A longitudinal sentiment analysis of the #FeesMustFall campaign on Twitter

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Declaration

I, Yaseen Khan, hereby declare that the content within this thesis is my own work. All sources that I have used or quoted have been acknowledged in the text by the means of completed references. This study has not been previously submitted in any form to the Durban University of Technology or to any other institution for assessment or for any other purpose.

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Dedication

I begin in the name of Allah ﷻ, The Most Compassionate, The Most Merciful, and everlasting Blessings and Peace be upon Muhammad ﷺ, The Beloved of Allah. All praises directed towards me are for Allah and all faults are my own.

I hereby dedicate this thesis to my loving parents, brothers, extended family and friends. The network of support offered from these personalities motivates me to continuously strive for excellence.

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The financial assistance of the NEMISA towards this research is hereby acknowledged. Opinions expressed and conclusions arrived at, are those of the author and should not necessarily to be attributed to the NEMISA.

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Abstract

The #FeesMustFall campaign began in 2015 to lobby government to provide students with free university education in order to redress past imbalances. It rapidly progressed to become a widespread national phenomenon that attracted international attention and sympathetic support. However, certain unsavoury incidents marred the campaign and attempted to derail it from achieving its goals. The campaign did reach many of its targets with the South African government eventually announcing free education for the poor and working class in December 2017. #FeesMustFall has been well documented and researched, however, no literature offered a quantitative insight into the opinions of social media users during this campaign, although a unique feature of #FeesMustFall was leveraging social media platforms to coordinate the campaign. This study addresses this gap by undertaking a longitudinal sentiment analysis of textual conversations expressed on the Twitter social media platform.

This longitudinal study analyses the Twitter #FeesMustFall campaign through the acquisition of 576 583 tweets posted between 15 October 2015 and 10 April 2017. These tweets were pre-processed and cleaned by removing exact duplicates and unintelligible data. The research method to analyse the “cleaned” #FeesMustFall data utilises, *inter alia*, descriptive statistics, sentiment analysis using a natural language programming (NLP) approach called Valence Aware Dictionary sEntiment Reasoner (VADER) and code written in Python. VADER is a lexicon rule-based sentiment analysis tool particularly suited to social media. To detect multiple changes in this large historical dataset, the Change Point Analysis method (CPA) is applied using a Cumulative Sum Analysis (CUSUM) method to identify changes across time.

The research question is whether and for what reason the online sentiment changed during the observation period. The sentiment expressed is triangulated with perceived real-life negative events, such as the burning of the University of KwaZulu-Natal (UKZN) library and the University of Johannesburg (UJ) Hall, to understand whether online activism sentiment reflected or reacted to real-life events. The study finds that sentiment did change in relation to these two events, one on the day of the UKZN library event and one prior to the UJ Hall event.

Social robots (bots) are automatic or semi-automatic computer programs that mimic human behaviour in online social networks. Their deployment exposes online activism to manipulation. A further research question addressed whether bots played a role in the #FeesMustFall campaign. A review of bots, their characteristics, behaviour, and detection methods was undertaken. The study does indeed establish the presence of bots during #FeesMustFall.

The study's contribution is significant as this is the first longitudinal study of the #FeesMustFall campaign which observes the sentiment distribution and changes. It is also the first study to investigate and find evidence of bots in the #FeesMustFall campaign.

Key words

#FEESMUSTFALL, OPINION MINING, SENTIMENT ANALYSIS, NATURAL LANGUAGE PROCESSING, SOCIAL ROBOTS, TWITTER BOTS, CYBORGS.

List of Acronyms

Bots	Software robots
BOP	Bottom Of The Pyramid
COTS	Commercial-off-the-shelf
CPUT	Cape Peninsula University of Technology
DM	Direct Message
DUT	Durban University of Technology
IEEE	Institute of Electronic and Electrical Engineers
ML	Machine Learning
MUT	Mangosuthu University of Technology
NEMISA	National Electronic Media Institute of South Africa
NLP	Natural Language Processing
POS	Parts of Speech
SA	Sentiment Analysis
SNA	Social Network analysis
SMA	Social Media Analytic
SML	Supervised Machine Learning
RT	ReTweet
RTed	Retweeted
UCT	University of Cape Town
UFS	University of the Free State
UJ	University of Johannesburg
UKZN	University of Kwazulu-Natal
UML	Unsupervised Machine Learning
UP	University of Pretoria
URL	Uniform Resource Locator
US	University of Stellenbosch
UWC	University of the Western Cape
VADER	Valence Aware Dictionary and sEntiment Reasoner
Wits	University of the Witwatersrand

Output

Journal papers submitted arising from this study (Under review)

Khan, Y. and Thakur, S. 2019. A longitudinal analysis of the #FeesMustFall campaign.

Conferences arising from this study

Khan, Y. and Thakur, S. 2018. The presence of Twitter bots and cyborgs in the #FeesMustFall campaign. In: *2018 International Conference on Intelligent and Innovative Computing Applications (ICONIC)*. Plaine Magnien, Mauritius, 6-7 December 2018. IEEE, 543-547.

Presentations arising from this study

Khan, Y. 2018. Preliminary analysis of the #FeesMustFall. *Knowledge for innovation.* Post Graduate Seminar. Nelspruit, 12-14 March 2018.

Khan, Y. 2018. Sentiment and bot analysis of the #FeesMustFall. *The digital being.* Lecture. Coastlands Hotel, Durban, 2-3 May 2018.

Recognition arising from this study

Peters, W. 2018. Khan's research on #FeesMustFall Twitter campaign gains recognition in parliament. *DUT.ac.za*, 22 May 2018. Available: https://www.dut.ac.za/khans-research-on-feesmustfall-twitter-campaign-gains-recognition-in-parliament/ (Accessed 11 July 2019).

The 2017-2018 Deputy Minister of the Department of Telecommunication and Postal Services (DPTS), Ms Stella Ndabeni-Abrahams mentioned the importance of this study in her speech to the South African Parliament during the DTPS Budget speech on 17 May 2018 and further requested the author to stand up in recognition of his work.

Newspaper articles arising from this study

Khan, Y. and Thakur, S. 2019. Who's tweeting whom?. *Voices360*, 18 June 2019. Available: https://www.voices360.com/technology/whos-tweeting-whom-26594429 (Accessed 11 July 2019).

Khan, Y. and Thakur, S. (Under Review). Tweeting a storm: analysing online campaigns.

Conflict of Interest

It is important to point out that the researcher is employed by Durban University of Technology (DUT) (where he is a student), and DUT is one of the Higher Education Institutions involved in the #FeesMustFall campaign. Further, the researcher was a student for two undergraduate degrees (between 2006 and 2009) at another university, University of KwaZulu-Natal. The researcher was (and remains) a keen observer of the online campaign. He neither participated in nor was tagged by any #FeesMustFall post related to this study. There was no conflict of interest.

Chapter 1 Introduction

1.1 Introduction

This thesis undertakes a longitudinal analysis of the sentiment opinion of Twitter users during the South African #FeesMustFall campaign using a natural language programming (NLP) based sentiment analysis model called Valence Aware Dictionary sEntiment Reasoner (VADER). The #FeesMustFall campaign is studied primarily through the acquisition of 576 583 tweets posted between the 15 October 2015 and 10 April 2017. In addition, the study also determines whether, or if, these tweets originated from humans or automotive software known as software robots or bots.

The #FeesMustFall campaign is the largest and longest social media campaign in Africa (Workman, 2017). It was triggered in 2015 because poor students could not afford their university fees and associated costs of accommodation, books, travel and meals. The campaigners argued that higher education entrenched a new form of apartheid based on a class system (Heher, 2017). The movement enjoyed support across the political spectrum (including the rich, poor, business, academia, and civil society), but it is celebrated as a leaderless, non-partisan, student-driven protest movement (despite many political parties trying to gain mileage out of the campaign) (Makhafola, 2015; Booysen, 2016; Mqadi, 2016; Buttelli and Le Bruyns, 2017; Langa *et al.*, 2017; Wessels, 2017).

The #FeesMustFall campaign seemingly culminated in 2017 after relentless pressure from the protestors leading government to eventually announce ‘Free Education’ in mid-December 2017 (Mlambo, Hlongwa and Mubecua, 2018), following earlier attempts to ease tensions with alternative solutions (Zuma, 2017). #FeesMustFall leveraged significant use of social media during the campaign (Jacobs and Wasserman, 2015) with Twitter emerging of particular interest due its hashtag feature (Perez, 2018) which was inherent within the campaign’s slogan ‘#FeesMustFall’.

Twitter is a flat, open communication platform generating large volumes of data comprising words of tweets, often linked by a prefix or keyword hashtag (#) to enjoin and encourage conversations e.g. #FeesMustFall. The hashtags provide a many-to-many communication mechanism for connecting and updating conversation threads between users (Bruns and Burgess, 2011). Twitter tweets may also contain emoticons, emojis, images, audio and video. This type of data is now called big data and provides a rich research opportunity for historical as well as contextual analysis. One type of contextual analysis is Sentiment Analysis.

Social Media has been largely accredited as a tool which precipitated democracy in the Middle East, through the sustained #ArabSpring or “Arab Spring” campaign. Twitter has evolved from a source of “pointless babble” to something that Dorsey[1] says “did rather well” during disasters and elections (Rogers, 2013; Weller *et al*., 2014: 9-21). Microblogging platforms such as Twitter assisted the Japanese in 2011 when they endured a combination of an earthquake (Cho, Jung and Park, 2013), followed by a tsunami (Acar and Muraki, 2011), all but collapsing the communication infrastructure except for Twitter and Facebook. The Queensland floods (2010) and Christchurch earthquakes (2011) also demonstrates how the minimalist Twitter platform can assist search and rescue efforts by restraining emotion while leveraging the geolocation metadata (Acar and Muraki, 2011; Bruns and Liang, 2012; Bruns and Burgess, 2014).

These events have demonstrated the value of Twitter in crisis communication. The minimalist 140-character tweet length conveniently mediates emotion while encouraging factual requests for support thereby saving first responders limited time and their scarce resources (Acar and Muraki, 2011; Cho, Jung and Park, 2013). Nevertheless, during the 2011 London Riots criminals or yobs used social media and the secure encrypted communication feature of Blackberry Messenger to surreptitiously incite violence and plan looting (Thakur and Millham, 2017). The 2017 Barcelona terror attack had a reactive sequel when Twitter users united to post pictures of “cute cats” to thwart activists from spreading pictures of the death and the mayhem (Woods, 2017). These incidents demonstrate the use-abuse, exploit-leverage chasm of Twitter and highlight the societal need for methods to monitor sentiment expressed on the platform.

Sentiment Analysis computationally identifies whether a given piece of text (such as a Facebook post or a Twitter tweet) contains any subjective information by using computational methods such as NLP (Breck and Cardie, 2014). It discerns whether the text is positive, negative or neutral in sentiment. Sentiment Analysis provides a new form of early warning system of mounting anger, joy, emerging opportunity or

[1] Jack Dorsey is the co-founder of Twitter.

threat and even a post-mortem. To study #FeesMustFall this thesis uses the following three-way sentiment classification:

- Positive – Text is perceived as encouraging and uplifting
- Neutral – Text has a balanced mood or is uninterpretable
- Negative – Text is perceived as harmful and adverse

In this study, sentiment analysis is applied to the *same topic*, in this case, #FeesMustFall tweets, over a *sustained period of time* and represents a longitudinal study which informs how views on the *same* topic (#FeesMustFall) evolve.

The advent of social media management platforms such as Hootsuite, together with the development of automated software such as social robots or bots, has enabled voluminous tweets which could (and have) influenced online campaigns. Given the popular nature of social media, bots have emerged as protagonists in international and local campaigns as they purposefully seek to influence public opinion to further their creators' interests (Ferrara *et al*., 2016). This is termed social media manipulation. Formally**,** social bots are defined as automatic or semi-automatic computer programs that mimic humans and/or human behaviour in online social networks (Wagner *et al*., 2012).

There have been high profile incidents in which social bots were created to influence public opinion. Social bots may be identified through temporal characteristics such as irregular volume, unnaturally high frequency and repeated retweets of the same content. Communication company Bell Pottinger deployed Twitter bots to troll and attack South Africans perceived to speak negatively about their clients, the Guptas, who were accused of 'state capture' (which is a term for an outsider who usurps governmental functionality for their own, usually financial, benefit) (IOL News, 2018). The outcry that resulted cost the company its corporate license and it is now bankrupt (IOL News, 2018). Treré (2016: 131), in a two-year ethnographic longitudinal study of the Mexican socio-political system through the #YoSoy132 networked movement, unravels the algorithmic manufacturing of consent and points to the role of bots noting "massive deployment of strategies including: the creation of a false universe of followers; the use of software robots (bots) to automatically generate tweets; and the hiring of trolls (people who tweet in favour of a candidate, or against their opponent);

and ghost followers (empty accounts that boost a candidate's followers)". In the 2016 US Presidential election bots were deployed to actively participate in the online discussion, with some bots supporting the eventual victor Trump, while other bots supported the challenger Clinton (Bessi and Ferrara, 2016; Howard, Woolley and Calo, 2018).

This research is executed using Python software, Tableau and Microsoft Excel and some algorithms. VADER is used to compute sentiment polarity. A Change Point Analysis (CPA) is used to detect multiple changes; CPA is particularly useful when analysing large historical data sets such as #FeesMustFall. A cumulative sum (CUSUM) chart, which is a type of control chart used to monitor small shifts in the process mean, is applied. It uses the cumulative sum of deviations from a target (Taylor, 2000; Bendat and Piersol, 2011). DeBot, a specialised bot detector, is deployed in a South African context to identify bot activity in #FeesMustFall. The study thus contributes to the body of knowledge of the identification of bots and their activity relevant to South Africa, which is significant especially since the study of bots is still in its infancy.

This chapter now introduces the research problem (section 1.2), provides key definitions (section 1.3), elaborates the aim and objectives of the research (section 1.4), and outlines the research questions (section 1.5). Thereafter the research methodology (section 1.6) is outlined briefly (it is elaborated in detail in chapter 3 and 4). The significance of the study (section 1.7), the contribution of the study (section 1.8), and delimitations of the study (section 1.9) are then outlined. The chapter concludes with a synopsis of the rest of the thesis (section 1.10).

1.2 Research problem

South Africa is the civil protest capital of the world, with one of the highest rates of public protests in the world (Rodrigues, 2010). Civil protest is now augmented by online platforms which introduce engagement opportunities as well as threats (Bosch, 2017; Luescher, Loade and Mugume, 2017). The #FeesMustFall movement is the first South African significant online social media national campaign and is also the largest and longest in the African continent (Workman, 2017). The simultaneous private-public nature of social media allowed student leaders to amplify their network and mobilise offline physical protests on particular campuses at particular times without the knowledge of authorities.

The research interest is to explore if one can, by tracking online tweets, determine the sentiment and if it changed. It is evident that the analysis of large Twitter data sets is non-trivial. Indeed given the volume of tweets, it is simply not feasible for a human or a group of humans to analyse real-time tweets even with the benefit of considerable time (Mondal, 2016). Hence, there is a need to use automated techniques. There are commercial-off-the-shelf products (COTS) that provide black box sentiment analysis solutions. The challenge of COTS analytical tools is the cost, hidden algorithms, and perceived vendor lock-in which detracts from the bona fide of the results and adoption of the framework (Thakur, 2015). COTS may even create or entrench distrust providing a rationale for using open source algorithms such as VADER.

Social robot deployment and activity on social platforms, known as social bots, has increased in recent years and has impacted sentiment in many domains, including politics and economic markets (Ferrara *et al.*, 2016). International campaigns have already purposefully deployed social bots aimed at shaping public opinions to boost their creators' interests such as the notorious 2016 US Presidential election online discussion (Bessi and Ferrara, 2016). Given the increasing prevalence of bots, the research also seeks to establish if bots played a role during this campaign.

The "exact" #FeesMustFall campaign was trending and viral and generated a large volume of data with over 289 458 tweets alone in October 2015 (Table 6). Although other similar hashtags such as #WitsMustFall and #nationalshutdown emerged, the #FeesMustFall prevailed. Consequently, this research focusses only on #FeesMustFall for analysis and tracks the tweets through the positive and negative events in the campaign in order to extract information assumed to be reflective of the popular opinion. Society from across all spectrums was largely in favour of the #FeesMustFall campaign until the advent of perceived negative events such as the burning of the library at the University of KwaZulu-Natal (UKZN) and the Hall at the University of Johannesburg (UJ) which created a negative atmosphere (Langa *et al.*, 2017).

This study contributes to scientific knowledge by answering the following important research problem:

Can we make use of sentiment analysis methods to provide trends and insights into evolving public opinion of the Twitter #FeesMustFall campaign while being mindful of the possible presence and influence of software robots?

1.3 Definitions

It is necessary to provide a working definition of frequently used terms in this research.

Click Bait is a text or thumbnail link that is designed to entice users to follow that link and then read, view, or listen to the linked piece of online content.

Change Point Analysis is a statistical method capable of detecting multiple changes particularly when analysing large historical data sets.

Direct Message is a messaging function on Twitter that allows a user to send a private message to a specific user.

A **Hashtag** is a word or phrase preceded by a hash sign (#). It is used on social media platforms, especially Twitter, to identify messages on a specific topic. Multiple tags are possible in the same tweet.

Natural Language Processing (NLP) is the application of computational techniques to the analysis and synthesis of natural language and speech.

Sentiment Analysis can be defined as a process that automates mining of attitudes, opinions, views and emotions from text, speech, tweets and database sources through Natural Language Processing.

Slacktivist are keyboard activists who support online campaigns through posts and acumen though with little physical engagement.

A **Software Robot** is an artificial intelligence-based system that runs on a host device rather than existing as a standalone machine.

A **Social bot** is a computer algorithm that automatically produces content and interacts with humans on social media.

Structured Data is data that has been organized into a formatted repository, typically a database, so that its elements are addressable for effective processing and analysis.

Tweeps are used to describe a Twitter ‘tweet’ + people ‘peeps’. Tweeps is a portmanteau of the words 'tweet' and 'peeps’.

A **Tweet** is a post on Twitter containing 280 characters or less.

A **Tweeter** is a user who posts one or more tweets on Twitter.

Twitter is a social media platform that allows registered users to send and receive tweets.

Twitterati are avid or frequent users of the social media application Twitter.

Twitterbots, also called Twitter bots, is a term used to refer to bot software that controls a Twitter account via the Twitter API which executes actions such as tweeting, re-tweeting, favouriting, following, unfollowing, or direct messaging other accounts

Twittersphere is the totality of users and messages on the Twitter microblogging platform.

Twar refers to two Twitter users arguing on social media with direct reference to each other.

VADER, or Valence Aware Dictionary and sEntiment Reasoner, is a parsimonious rule-based model for sentiment analysis of social media text that is specifically attuned to sentiments expressed in social media.

1.4 Research Objectives

The overarching aim of this study is to develop a longitudinal analytic technique for online sentiment analysis of a corpus of social media Twitter tweets for the #FeesMustFall campaign, while also determining whether the tweeters included software robots.

In order to accomplish this research aim, the following research objectives are set:

Objective 1: To analyse the prevailing sentiment of Twitter users’ opinions during the #FeesMustFall campaign.

Objective 2: To examine changes in sentiment on Twitter in relation to the burning of the University of KwaZulu Natal (UKZN) library and University of Johannesburg hall events during the #FeesMustFall campaign.

Objective 3: To determine if online sentiment trends on Twitter were affected by the deployment of social bots during the #FeesMustFall campaign.

The following sub-objectives were constructed to assist in addressing the objectives:

- To describe the distributive pattern of the longitudinal data
- To determine the most influential users on Twitter in terms of volume of tweets
- To examine the days closely related to the events in Objective 2 in terms of sentiment
- To determine the sentiment trend for the longitudinal data
- To determine the prominent associative hashtags

1.5 Research Questions

The following research questions are constructed to achieve each of the objectives:

1.5.1 Research question 1

Research question 1 asks:

> **What was the prevailing sentiment of Twitter users during the #FeesMustFall campaign?**

In order to answer research question 1, the following subsequent questions were added:

a) *Who were the dominant tweeters and how did they tweet during this study?*

b) *Were news media part of the dominant tweeters?*

c) *What were the tweeting characteristics of the top tweeter?*

1.5.2 Research question 2

Research question 2 asks:

> **How did perceived negative events such as the burning of the UJ Hall and the UKZN Library impact online sentiment trends and polarity?**

In order to answer research question 2, subsequent questions were constructed and divided into two parts. Part A dealt with the overall sentiment polarity and Part B dealt with the negative sentiment polarity.

Part A: Overall Sentiment Polarity

a) Where there any changes in sentiment trend and polarity during this period?

b) What were the dates that signified the beginnings of these changes?

c) How do these change dates relate to dates of real-life significant events?

Part B: Negative Sentiment Polarity

a) Where there any changes in negative sentiment trend and polarity during this period?

b) What were the dates that signified the beginnings these changes?

c) How do these change dates relate to dates of real-life significant events?

1.5.3 Research question 3

Research question 3 asks:

Were social robots deployed on Twitter during the #FeesMustFall campaign?

1.6 Research methodology

This study adopts a post-positivist philosophy, a quantitative methodology, a deductive research approach and a longitudinal time horizon. In total 576 823 tweets from the #FeesMustFall campaign posted on the Twitter microblogging platform over a 14-month-year period are acquired, downloaded, pre-processed, filtered, cleaned and examined. Descriptive methods and sentiment techniques that analyse frequency, volume and mood of tweets are utilised in order to determine sentiment and bot activity. The aim is to observe the evolving online sentiments of protesters over time and particularly before, during and after perceived negative events such as the burning of the UJ hall and a library at UKZN. Extracting the type of mood from tweets are accomplished using sentiment analysis. Further, the study attempts to determine whether and how software robots played a role in #FeesMustFall.

A corpus of tweets differs to transcripts or questionnaire data in terms of ethical and privacy implications, since tweets posted publicly and are readable by anyone with an Internet connection (Thelwall, 2014). Despite this, it was only the sentiment of the tweets that are analysed not the identity.

A quantitative approach is used on the hashtag, #FeesMustFall, obtained from Twitter between its first public mention to when this research began from 1 March 2015 to 9 April 2017. Sentiment analysis is conducted computationally using the NLP method, along with the VADER model which is particularly suited to use with microblogging platforms (Hutto and Gilbert, 2014). In addition, an examination of the temporal behaviours of Twitter users is also conducted (Roenneberg, 2017).

1.7 Significance of the study

The ultimate goal of sentiment analysis[2] (SA) is to detect opinion towards with near perfect levels of accuracy, and to be utilised as an influential component in predictive analytics. Predictive analytics in social media encompasses a variety of statistical, natural language and mathematical techniques with data and opinion mining to analyse current and historical facts to make predictions about future or otherwise unknown events (Nyce, 2007; Bekker, 2019). In the context of #FeesMustFall campaign the intrigue was to establish if one can, by monitoring voluminous online tweets, ascertain the relative sentiment polarity changes and pin-point sentiment changes. As noted in chapter 2, the researcher has found, to the best of his knowledge that Sentiment Analysis research of this nature on a protest campaign has not been undertaken in South Africa to date. This research thus addresses this gap and supports the body of knowledge by presenting a computational approach to sentiment analysis on the Twitter #FeesMustFall campaign data.

The #FeesMustFall campaign ranks as a protest movement seeking social change. This study restricts itself to the #FeesMustFall campaign which was the largest, longest-run hashtag campaign in Africa at the time of data collection (June 2017), with the second being #ArabSpring. The length of the campaign provided an opportunity for a unique longitudinal study which is the significant gap. These facts provide the scope and enticing reason for research. As is noted in chapter 2, several researchers

[2] Sentiment analysis is also used with the acronym SA. South Africa also uses the acronym SA. This thesis consequently avoids the acronym SA to prevent ambiguity or confusion.

have already undertaken #FeesMustFall studies, including Findlay (2016) and Baillie-Stewart (2017) who focussed on the role of news media, and Bosch (2017) who examined online protest and participatory citizenship etc. However, there has not yet been a longitudinal study of Sentiment Analysis of #FeesMustFall.

A third significant aspect of this study is that it analyses the presence of social robots within this campaign. The emergence of social robots complicates sentiment analysis and this thesis scientifically investigates if social bots, in terms of Twitterbots and Cyborgs, existed in #FeesMustFall. As a result of different types of social bots, the sensitivity around fake news or agenda-driven influencers is high in the current context of South Africa. Given the country's volatile climate, and the size of the information there is a need to separate fact from fiction in order to detect and prevent social manipulation or widespread diffusion of misinformation (Nguyen *et al.*, 2012). This means that bots need to be identified by developing appropriate tools, techniques and algorithms.

1.8 Contribution of the study

This longitudinal study could arguably serve as an exemplar for social media sentiment analytics. An analysis of the #FeesMustFall sentiment ultimately examines the reflective and reactive impact that Twitter has on society. The always-on, always-connected society discusses and debates challenges in new ways which places an additional requirement on communication staff in business, government and also universities. They now have to monitor a continual medium quite distinct from previous daily single-edition newspapers or period-based news bulletins.

This study informs on how to conduct similar studies on Twitter and social media campaigns, by providing detailed technical discussion. Social media, viewed critically, also generates legitimate discourse contrary to popular belief that only 'fake news' and digital noise arrive through these channels (Wessels, 2017), though one must be aware of the presence and the impact of bots (Khan and Thakur, 2018).

To date, packages have been developed that produce 'black-box' analysis of Twitter campaigns. Some crisis-ridden confrontational situations occur in a fishbowl environment with wary protagonists. Therefore using closed-tools may either introduce distrust or be opportunistically distrusted. On the other hand, open software and algorithms fortuitously introduce transparency and engender trust while informing and educating stakeholders. This effort concurs with Booysen (2016: 155) who argues “that we should not wait for the longer-term impacts” of the #FeesMustFall “to show themselves – while the early and illuminating trends congeal.”

A particular contribution which emerges from this study is the provision of the first known published literature concerning the existence of social robots on Twitter during the #FeesMustFall campaign (Khan and Thakur, 2018).

1.9 Delimitations

This thesis only measures sentiment polarity of the corpus of tweets and not the veridicality of the sentiment (Ladusaw, 1980). Veridicality is a semantic or grammatical assertion of the truth of an utterance such as a tweet (Dawson and Medler, 2010). Nothing is said about the truthfulness of the sentiment. This is important to understand in social media analytics. Veridicality is delimited and noted given the important current research around fake news and the perceived role media play in amplifying campaigns.

A further delimitation is that tweets from Twitter arrive with embedded video, audio, and images as well as metadata such as geolocations. These are not analysed in this study. It is also fair to assume that Twitter was not the preferred social media platform for everyone who conversed about #FeesMustFall; nonetheless other social media platforms are excluded from this study, and this is a further delimitation. Note also that not all Twitter users impacted by the #FeesMustFall campaign tweeted about it.

In addition, the #FeesMustFall campaign had associated hashtags such as FeesMustFall (without the #), #Fees2017, #FMF, #WitsFeesMustFall, etc. Unless these hashtags were tagged in conjunction with #FeesMustFall they were omitted from the study.

Twitter allows one to retrieve tweets using hashtags. However, the retrieved data may be spam which is extraneous or ambush content, posted as clickbait on social media. This means even the keyword #FeesMustFall may have content irrelevant to the campaign itself.

Further one may assume when one uses Twitter that having all the tweets is equivalent to having the tweets of the population. This may be true if indeed this is all the tweets.

The challenge is that tweets may also be the output of software robots (bots) which were deliberately written to amplify a particular agenda by either amplifying or rebutting a view. This is why Research Question 3 was added. An additional delimitation is that when attempting to retrieve data from Twitter the collected dataset may not be reflective of the population of posted tweets since tweets can be deleted, made private or user accounts suspended all of which prevents access to these tweets.

1.10 Chapter Synopsis

The rest of this thesis is organised as follows:

Chapter 2 provides a comprehensive overview of literature on Twitter hashtags and the history of #FeesMustFall. It also reviews literature on automated tweets and software bots.

Chapter 3 discusses the literature that explains sentiment analysis and provides extensive technical detail on these methods. Since this is a “longitudinal study of sentiment analysis” it is important to provide a detailed overview of sentiment analysis methods, algorithms, software, tools and programming languages. The discussion of these methods is included in its own chapter due to the length of chapter 4.

Chapter 4 presents a detailed account of the research methodology and design. It includes a detailed elaboration of the data sources and how the data is handled in the study. It elaborates on the nine steps of the data analytics lifecycle as it applies to this study. The discussion of sentiment analysis in chapter 3 is further extended to also discuss the descriptive analysis and change point analysis that was applied.

Chapter 5 presents the findings and results of each question asked in this study.

The discussion of the findings on each question, together with relevant literature, is elaborated in Chapter 6.

Finally, chapter 7 provides a summary of how the research has achieved its objectives and identifies future areas for research before concluding the study.

Chapter 2 Literature review

2.1 Introduction

This chapter begins with a brief technical background to Twitter (section 2.2), followed by a review of literature on the positive and negative influence of Twitter hashtags on society (section 2.3). Thereafter, the context and historical origins of the #FeesMustFall movement is outlined (section 2.4), before discussing how #FeesMustFall has been studied in the literature (section 2.5). Finally, the characteristics and profiles of automated and social bots are introduced and their behaviour and how it can be detected is explained (section 2.6). (The relevant literature on Sentiment Analysis is discussed in chapter 3 and builds on the content in this chapter).

2.2 Twitter, tweets and taxonomy

Twitter is a popular social networking and micro blocking tool which was released in 2006. The tweet-rate on Twitter has risen from 5,000 tweets per day in 2007 (Weil, 2010) to 500m tweets per day in 2018 (Internet Live Stats, 2018). This represents a six-fold increase in the order of magnitude. In 2017, Twitter had 7.9m South African users, up from 5.9m in 2016 and 4.81m in 2015 (Goldstuck, 2018). The comparative worldwide figures were 328m in 2017, 246.9m in 2016, and 237.4m in 2015 (Clement, 2019a).

Twitter encourages users to share whatever is on their mind in easily readable, bite-sized chunks called tweets. A tweet used to be 140 characters in length but has since increased to 280 characters[3]. These tweets are sometimes annotated with a tag called a hashtag represented by the symbol #. A hashtag (#) is a type of metadata tag used on Twitter, to allow users to apply dynamic, user-generated tagging which makes it possible for others to easily find messages with a specific theme or content (Perez, 2018).

Twitter has nurtured the use of abbreviations, emoticons, wit, irony and humour, slang, colloquialisms, a combination of upper and lower cases, multiple hashtags and

[3] This was implemented on 7 Nov 2017 (Rosen, 2017).

multiple languages (Saif, Ortega and Fernández, 2016). This is why such data is called unstructured data. Analysing Twitter data, however, is a non-trivial challenge.

More than one hashtag may be used in a tweet. Note the hashtag title does not have case sensitivity so #FEESMUSTFALL, #FEESmustfall, #feesmustfall and #FeesMustFall all refer to the same tag. The last is arguably the most syntactically readable hence its popularity.

A user on Twitter has their addressable username proceeded by an @ so Barack Obama's Twitter username is *BarackObama.* The full name also called handle is *@BarackObama*. Figure 1 and Table 1 combine to describe the taxonomy of a tweet.

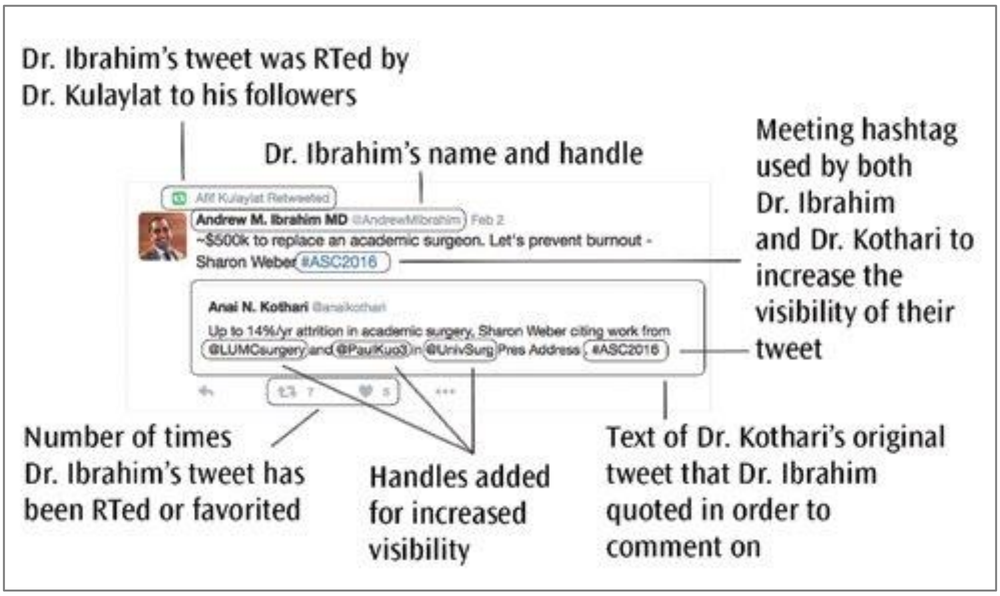

Figure 1 Annotated Taxonomy of a tweet

Twitter has two kinds of directed relationships - *friend* and *follower.* In the case where the user A adds B as a friend, A is a follower of B while B is a friend of A. B can also add A as his friend (namely, following back or returning the follow), but it is not required. From the standpoint of information flow, tweets flow from the source (author) to subscribers (followers). More specifically, when a user posts tweets, these tweets are displayed on both the author's homepage and those of his followers (Chu *et al.*, 2012).

Table 1 defines and clarifies the intention of the metadata of a tweet.

Table 1 Metadata of a tweet

Data	Description
Tweet	A message containing texts, emoticons and symbols limited to 280 characters (140 previously)
Time Stamp	Gregorian calendar date and the time of the tweet
User name/handle	Unique identification of the user who tweeted
Source of Tweet	The device used to send through a tweet
Favourite	Tweet tagged as favourite
Retweeted	Tweet that has been reposted or forwarded
Hashtag	An optional metadata tag a user may use to aggregate a topic or join a conversation with a particular topic.

Aside from microblogging social media platforms such as Twitter and Tumblr, there are a wide range of other social media platforms, including online social networks such as Facebook, WhatsApp and LinkedIn; blogs like WordPress; social news such as Reddit; social bookmarking such as Pinterest and StumbleUpon; sharing service sites such as Uber and Airbnb; sites media sharing such as Instagram, Flikr and YouTube; wikis such as Wikipedia; question-and-answer sites such as Quora and review sites such as TripAdvisor (Barbier and Liu, 2011; Gundecha and Liu, 2012; Gandomi and Haider, 2015: 142). As this study focuses only on Twitter hashtags (and #FeesMustFall in particular), literature studying Twitter hashtags is the focus of the review of literature that follows in section 2.3.

2.3 Review of literature on Twitter hashtags

Social media and in particular, Twitter, are known to have a positive and negative influence on society. There have been a number of studies on the influence of Twitter and Twitter hashtags, including in disaster management and terrorism (section 2.3.1), infodemiology (disease outbreaks) (section 2.3.2) and anti-government protests (section 2.3.4) and these are outlined in this section. (Discussion of Twitter and elections is covered in the discussion of bots in section 2.6).

2.3.1 Twitter use in disaster management and terrorism

The ease and real-time nature of Twitter makes it an attractive tool for disaster management, as both victims and rescuers can place their problems and solutions in the same place. The limited length mitigates emotion while encouraging unemotional factual tweets. The present system of Twitter can be extended for use in other natural disaster situations, such as floods, typhoons, earthquake, tsunami and even man-made disasters such as riots, terrorist attacks (Singh *et al.*, 2017). For example Japan endured a combination of an earthquake (Cho, Jung and Park, 2013), followed by a tsunami (Acar and Muraki, 2011), which collapsed the communication infrastructure but Twitter and Facebook remained working, showing the value of Twitter in many-to-many crises communication (Bruns and Liang, 2012). Twitter has also been used for earthquake detection by applying semantic analysis on data retrieved from search queries using keywords like 'earthquake' and 'shaking' (Sakaki, Okazaki and Matsuo, 2010).

Internationally, Twitter has also been utilized to investigate terrorism and social unrest (Compton *et al.*, 2014). Criminals leveraged social media during the so-called 2011 London Riots when mobs used secure encrypted communication provided by Blackberry Messenger to secretly incite violence and looting (Thakur and Millham, 2017). The yobs[4] became known as the "Blackberry mob" and the Blackberry became known as the "riot phone." The 2017 Barcelona terror attack had a sequel where Twitter users united to post pictures of "cute cats"[5] to thwart activists from spreading pictures of the death and the mayhem (Woods, 2017).

In South Africa, Twitter has also been successfully used to assist the rescue of a "carjacked victim[6]" after the hostage tweeted from the trunk of his hijacked car to his girlfriend, who in turn, retweeted the message. The tweet message went viral and the victim along with his vehicle was saved within 3 hours (Thakur and Millham, 2017).

---

[4] The British disparagingly refer to these noisy, rude aggressive rude young men as "yobs" (Urban Dictionary)

[5] This must not be confused with deadcatting which refers to the introduction of a dramatic, shocking, or sensationalist topic to divert discourse away from a more damaging topic (section 2.6.3.2).

[6] The term carjacked is used in SA to describe a vehicle hijacked or taken under forceful conditions.

2.3.2 Twitter and disease outbreaks

Ahmed (2018) reports that Twitter research has been socially beneficial within the health sector, and studies have included positive and negative views about vaccination sentiments (Salathé and Khandelwal, 2011), dementia (Robillard *et al.*, 2013), sexual risk behaviours (Young, Rivers and Lewis, 2014) and marijuana (Cavazos-Rehg *et al*., 2015).

Ahmed, Demartini and Bath (2017), Ahmed (2018) and Ahmed *et al*. (2019) have highlighted how social media platforms such as Twitter can be utilised for monitoring public views and opinions related to disease outbreaks such as swine flu, Ebola, and the Zika virus. This can potentially support health authorities to discern potential misinformation, understand public concerns and collect unanswered questions. Ahmed (2018) used a qualitative method to analyse data and had to carefully and manually go through each tweet and code it. This was time- as well as person-intensive (Mondal, 2016). In the health context, Ahmed's work is an important contribution. The Zika and Ebola viruses continue to overwhelm the world with increasing mortalities and the seeming lack of a cure despite best efforts. It is therefore reasonable for victims, their families and colleagues to post about their experiences. In a South African context, the health authorities' aggressive search of food factories to identify the source of the life threatening Listeria infection triggered the #Listeria trend on Twitter. The source was eventually identified at a factory in Polokwane (Van Dyk and Malan, 2018).

Social media postings on the experiences with epidemic outbreaks help increase infodemiology or knowledge of diseases, although its impact and value are still being evaluated. Infodemiology is the science of electronic Internet distribution and determinants of information with the goal of informing and influencing public health and public policy (Eysenbach, 2009). The use of infodemiology data for surveillance purposes is called infoveillance and provides the opportunity for analysts to monitor pandemics (Ahmed, 2018), with a goal of elimination or containment. While the threat of Ebola and Zika is ostensibly far-yet-possible, the threat of Listeria, on the other hand, was near-and-possible. The researcher speculates that infodemiology may well have helped track the source quicker and is grounds for future research, suggesting that analysis of Twitter posts about food and health risks can make a positive contribution to society.

2.3.3 Twitter and anti-government protests

Twitter is an attractive medium for protestors to maximise awareness about an issue with relative ease. As Boynton (2014) points out:

> *"Twitter messages are easy to write and easy to read, are by default public and messages can be found and read in a variety of ways. Unlike email, unlike texting, unlike messages on Facebook, these messages are in the public domain (Ahmed, 2018: 79)."*

The link between social media and activism is highlighted by Alsaedi, Burnap and Rana (2017) who used Twitter to research the tracking and prediction of riots and protests.

There is anecdotal and literature evidence that the Twitter medium is an enabler for activism (Meijer 2017; Van der Vyver 2017) with perceived positive (Bosch 2017) and negative benefits (Rotman *et al.*, 2011; Woode-Smith, 2016: 20; Taghavi, 2018). The Arab Spring was a series of anti-government protests, uprisings, and armed rebellions, which spread across the Middle East in late 2010. It began as a response to oppressive regimes where citizens endured a low standard of living. From its origins in Tunisia it quickly spread throughout the Middle Eastern region. This was the first time since 1927 that four of the world's longest serving Arab leaders were overthrown by their own people after decades in power (Comninos, 2011; González-Bailón *et al.*, 2011; Howard and Hussain, 2013).

Howard and Hussain (2013) posit three reasons for the success of the Arab Spring. Firstly, social media played a central role in shaping political debates in the Arab Spring. Secondly, a spike in online revolutionary conversations often preceded major events on the ground. Thirdly, social media helped spread democratic ideas across international borders.

The most powerful evidence that digital media mattered in the Arab Spring comes from activists themselves. The Arab Spring was a *bottom-up* campaign that excluded the traditional political hierarchy including opposition leaders and other out-of-power leaders, a similarity it shares with #FeesMustFall. The regime change that resulted from the Arab Spring placed these nations at the birth of the new era associated with rising expectations, and socio-economic and political consequences, some unintended (Ibid).

In summary, Twitter hashtags have been effectively used to influence the public in disasters, epidemic outbreaks and anti-government protests. (As noted, politically oriented Twitter hashtag campaigns are discussed later under the bots discussion in section 2.6).

In the next section, the historical origins of Twitter in the #FeesMustFall campaign are discussed.

2.4 The Historical origins of #FeesMustFall

The #FeesMustFall campaign was started by South African students in October 2015 to lobby government to fund student university education. The intention was to challenge government to redress past imbalances created by a discredited discriminatory system (called Apartheid) that treated citizens unequally (Booysen, 2016).

This discussion of the historical origins of #FeesMustFall includes the following sections: The context of the Freedom Charter (section 2.4.1); Roots in #RhodesMustFall (section 2.4.2); October university fee increases prompt the first #FeesMustFall protests (section 2.4.3); the #FeesMustFall campaign becomes violent (section 2.4.4), and MTN zero rates Twitter data (section 2.4.5).

2.4.1 Context of the Freedom Charter

In order to contextualise the rise in prominence of the #FeesMustFall campaign a brief history around the dynamics surrounding education in South Africa is required. In 1955 the oppressed people of South Africa gathered in Kliptown and passed several resolutions, including the basic right to free education, in a document which was called the Freedom Charter (Mandela, 1990). Over the next three decades a protracted struggle by the people led to the establishment of the new South Africa in 1994, when Nelson Mandela was inaugurated as South Africa's first president (South African History Online, 1994).

Unfortunately, the new government faced many competing compelling priorities, including needs for housing and social grants, and this meant that the government's delivery on the Freedom Charter promise of free education was delayed (Suttner, 1985; Suttner and Cronin, 2006). The continued passage of time without delivery on the Freedom Charter promises precipitated an increasing number of sometimes violent service delivery protests within South Africa. This violence had the effect, in many instances, of forcing the government to react, unintentionally lending credibility to the notion that riotous protest is an acceptable method (perhaps even the only effective method) to garner government's attention and reaction (Engh and Settler, 2016; Pillay, 2016).

2.4.2 Roots in #RhodesMustFall

According to Booysen (2016) and Bosch (2017), the #FeesMustFall movement rose on the back of the #RhodesMustFall movement at the University of Cape Town (UCT). The #RhodesMustFall campaign was premised on the decolonization of education in South Africa and focused on Cecil John Rhodes, who was labelled a colonizer that plundered Africa in order to become wealthy. His statue on the UCT campus consequently became a target for the protesting students (Nyamnjoh, 2015). Chumani Maxwele is credited with starting the #RhodesMustFall movement when he protested against Cecil John Rhodes on 9th of March 2015 by throwing faeces at the statue (Heher, 2017). The campaign resulted in the removal of the Cecil John Rhodes statue from the campus of UCT (Bosch, 2017).

There is early evidence of the term #FeesMustFall being used on Twitter during the #RhodesMustFall campaign. The first was a tweet on 21 March 2015 at 16:28 pm by Hectare Peterson which was retweeted 3 times and liked 5 times[7] (Figure 2).

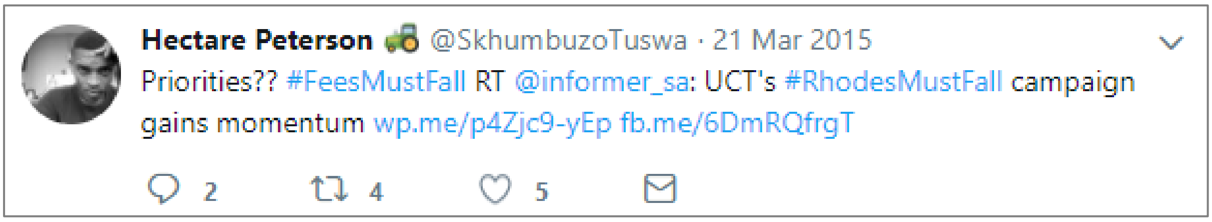

Figure 2 First Tweet of #FeesMustFall

[7] As Twitter accounts are "live", downloading the data at a particular point in time may not produce an exact copy with a download at some point in the future. Figure 2 taken in May 2018 shows 4 Retweets whereas according to the data captured in April 2017 the number is 3.

The second tweet was on 7 April 2015 at 6:30 am by Simangaliso S Sibiya and was retweeted 2 times and liked 4 times (Figure 3) during the #RhodesMustFall campaign, arguably supporting the assertion that this campaign gave birth to the FeesMustFall hashtag.

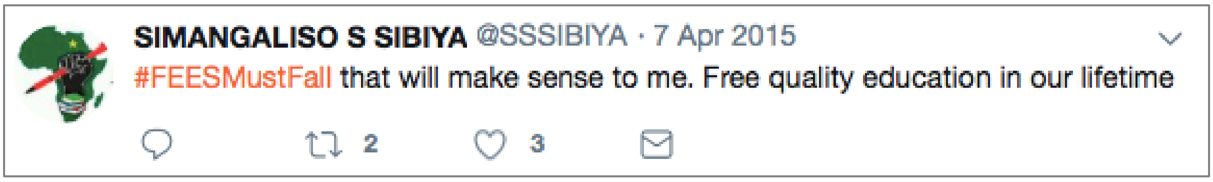

Figure 3 Second Tweet of #FeesMustFall

Sibiya later claimed ownership of the #FeesMustFall (Figure 4) declaring "I own the #feesmustfall hashtag I tweeted it at times when it appeared unfamous."

Figure 4 Alleged ownership of #FeesMustFall

In terms of syntax, it is important to note how "#FEESMustFall" is stated in Figure 3 and #feesmustfall" in Figure 4 by Sibiya, as compared to the (now) generally accepted tweet syntax of #FeesMustFall. These differences only demonstrate preferential styling of tweeters since Twitter does not apply case-sensitivity when treating hashtags and therefore tweets in Figure 3 and 4 are indexed the same by Twitter (Fishman, 2019).

2.4.3 October university fee increases prompt the first #FeesMustFall protests

The first #FeesMustFall protest commenced in Johannesburg after the University of Witwatersrand (Wits) declared what students believed to be an unaffordable 10.5% rise in students' fees for 2016 (South African History Online, 2016; Heher, 2017). The Wits university administration, in its defence, claimed that the subsidy it received from the government would not be enough to accommodate the real increase in costs incurred by the university, for *inter alia* library books, journal subscriptions, research equipment, infrastructure and staff salaries. Rhodes University similarly announced a minimum initial upfront 50% fees payment for 2016 (Mpulo and Pela, 2015).

The #FeesMustFall campaign commenced with the aim of lobbying against fee increases and then expanded to remind the government of its free education pledge through the Freedom Charter (Booysen, 2016; Heher, 2017). The #FeesMustFall protestors argued that higher education fees discriminated against poor students who could not afford the totality of fees, accommodation, travel and food costs (Malabela, 2017). The #FeesMustFall movement thus quickly escalated to a wider rallying cry against financial exclusion and debt traps for economically disadvantaged students (Pillay, 2016; Heher, 2017).

Findlay (2016) and Baillie-Stewart (2017) argue adamantly that although #FeesMustFall was initially spurred by activists at Wits, they were operating mostly in isolation. Wits activists managed to keep the discussions alive for about a week before UCT-based protestors stormed parliament in Cape Town (Heher, 2017). It was the storming of parliament that catapulted the protests onto the national stage and other universities joined the fray one-by-one.

Digital online activism aided and nurtured the bourgeoning #FeesMustFall movement because social media's instant messaging services enabled supporters to instantly communicate, and covertly coordinate and organize meetings as well as protest marches (Loader and Mercea, 2012). The day of 16 October 2015 witnessed #FeesMustFall going viral, triggering a sustained movement. On 23 October 2015, thousands of supporters marched to the Union Buildings, the administrative seat of the South African government, to demand free education from State President Jacob Zuma, and the Minister of Higher Education Blade Nzimande (Pillay, 2016; Heher, 2017).

2.4.4 The #FeesMustFall campaign becomes violent

The campaign pitched students against university administration, and sometimes required police intervention and backing. This is ironic given that previously both the students and administrators were philosophically in support of the campaign (Luescher, Loade and Mugume, 2017). In spite of general support from society, students believed that social media offered more support and provided more awareness of the #FeesMustFall movement than other physical forms of activism, with related literature defining this perfunctory online support as 'slacktivism' (Lee and Hsieh, 2013). Pillay (2016:156) is unequivocal about the perceived lack of support and asserts that “silence is (also) violence.” One can speculate that this slacktivism laid the embryonic seed for the violence. However, this speculation is beyond the researcher’s expertise and is delimited for further work.

It must be mentioned that students distrusted the university administrations, perhaps because they felt that the respective university administrations were not doing enough to support their cause. However, academics were largely considered to be on the side of students and were also among those that were arrested (Figure 5).

Figure 5 Academics Arrested (@DasenThathia, 2016)

There were some particularly horrifying events during the stand-off between students and universities which saw emotions swaying towards the students when they were tear-gassed and rubber bullets were fired (Luescher, Loade and Mugume, 2017). On the other hand, society reacted with horror when two security guards were burnt at CPUT (Langa *et al.*, 2017); there was the torching of a University of Johannesburg (UJ) Hall (Dlamini *et al*., 2018); and an irreplaceable historic library was burnt at the University of KwaZulu Natal (UKZN) (Engh and Settler, 2016). There was an uncomfortable nexus between physically violent protests to demand attention and a peaceful #FeesMustFall campaign.

Higher education and Training Minister Naledi Pandor, in a written reply to a question, said that the damage caused by protesting students in the #FeesMustFall movement cost universities more than R786 million, which she contextualised as being equivalent to the annual state subsidy provided to a small university (Kahn, 2018). The government’s agreement to make university education free as a result of #FeesMustFall, means that South Africa has a new fiscal expense which for the 2018 year was estimated at R12 billion according to then Finance Minister Gigaba (Omarjee, 2018).

2.4.5 MTN zero rates traffic and data on its Twitter platform

MTN, a telecommunications network provider, between May 2014 and September 2018[8], froze charges and zero-rated traffic and data on its Twitter platform (Rangongo, 2018). As this was during the window of this study's observational period it is relevant to mention. This decision formed part of a marketing strategy by MTN to drive social media adoption to retain and increase their subscriber base. This "free data" proved beneficial to the #FeesMustFall movement as it allowed students and campaigners to post and tweet wherever and whenever they wished without cost. It also facilitated amplifying the traffic and noise which may well have "persuaded" other ambivalent campaigners to participate. It is important to point that MTN is a significant cellular provider on the South African landscape. Further, the activism was mostly on campuses which in some cases, had free WiFi (Jordaan, 2018).

In summary, #FeesMustFall's origins lie in the Freedom Charter. The hashtag #FeesMustFall has its roots in #RhodesMustFall, but the campaign was triggered by university fee increases in October 2015 which prompted the first #FeesMustFall protests, and it escalated as more universities joined and the campaign became violent. Finally, the coincident introduction of zero rated traffic by MTN enabled the student campaign by providing free data with which to tweet about the protest.

The next section (2.5) reviews the literature on #FeesMustFall.

2.5 Review of #FeesMustFall in the literature

The #FeesMustFall movement is recognised as the first South African national struggle that was waged almost entirely on social media platforms (Luescher, Loade and Mugume, 2017). During its duration, the #FeesMustFall campaign was one of the five largest hashtag campaigns in the continent, and it has also been the longest hashtag campaign (to the date of this study). These top 5 hashtags were 1) #FeesMustFall 2) #ArabSpring (North Africa, Middle East); 3) #ThisFlag (Zimbabwe); 4) #BringBackOurGirls (Nigeria); and 5) #SayNotoXenophobia (South Africa) (Workman, 2017).

A unique feature of #FeesMustFall was the leveraging of social media platforms or social networks to coordinate the campaign, inform and lobby both students and

[8] Twitter had a meltdown with #RIPFreeTwitter trending at that time.

activists, and garner support through sustained media and community attention. Social media platforms were used to mobilize students through virtual tools to amplify their physical presence at various locations on particular campuses at particular times. At the same time, media houses were strategically informed to ensure that the event occurred in the glaring public eye. The simultaneous private-public nature of social media allowed students to network and coordinate protests without the knowledge of authorities. Jacobs and Wasserman (2015) point out that because students made up no more than 1 million of the country's nearly 55 million people, they needed to use social media to form alliances and capture energies and ensure the protests had an impact or effect beyond campuses.

This research study focuses only on the Twitter component of the #FeesMustFall campaign, primarily because the researcher was able to acquire 576 583 tweets posted between years 2015 and 2017[9] with attempts to retrieve #FeesMustFall data from Facebook and other platforms proving too costly and restrictive. As already noted, there is evident proof that the #RhodesMustFall campaign fuelled #FeesMustFall with the first mention of #FeesMustFall coming 6 months before the "official" October 2015 start of #FeesMustFall (Figure 2 and Figure 3). It can thus be argued that youth were already increasingly using social networking platforms such as Twitter to develop a new biography of citizenship which is characterised by more individualized forms of activism. In the #FeesMustFall case, Twitter afforded youth the opportunity to conduct political discussions on broader relevant socio-political topics in a contemporary South African society, "reflecting a form of sub-activism" (Bosch, 2017: 221).

#RhodesMustFall spawned #FeesMustFall which, in turn, gave rise to more 'must fall' hashtags such as #EndOutSourcing; the satirical #ZumaMustFall (*Everything Must Fall*, 2018) and the comedic #StudentsMustFall (Wessels, 2017). The 'Must Fall' theme is evident in these campaigns with Healy-Clancy (2016) using the term 'fallism' to refer to the political atmosphere in South Africa during the #RhodesMustFall and #FeesMustFall campaigns. This 'must fall' pattern in hashtags is further enunciated by Taghavi (2017) as "fallism" that is explained as the need for decolonised education.

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[9] The specific dataset range is from 21 March 2015 to 10 April 2017. See Section 4.5.2.3

This term evolved to represent anyone connected with trying to dismantle some perceived abhorrent aspect of society such as #FeesMustFall (Taghavi, 2017). Fallism supports the assertion that Twitter is evolving as a social awareness medium with clout in South Africa.

Booysen (2016) adds: “The students themselves often use the term “movement” in relation to their multi-campus, cross-province and international action under the banner #FeesMustFall. Loader and Mugume (2016) as well as Leuscher (2017) use the more comprehensive term “internet-age student movement” while Twitter uses the generic term “campaign” to signify hashtag-driven activities. This thesis uses the terms campaign and movement interchangeably.

There have been many studies on #FeesMustFall to date. The following is a non-exhaustive list of diverse scholarly efforts researching the #FeesMustFall in fields such as: governance (Godsell, Chikane and Mpofu-Walsh, 2016); politics (Booysen, 2016; Buttelli and Le Bruyns, 2017; Meijer, 2017); cultural studies (Pillay, 2016); sociology (Naicker, 2016; Wessels, 2017); journalism (Bosch, 2016; De Jager, 2016; Baillie-Stewart, 2017; Luescher, Loade and Mugume, 2017); language (Linden, 2017), thematic analysis (Van der Vyver, 2017); and data science (Findlay, 2016; Fraser, 2017; Ramluckan, Ally and van Niekerk, 2017; Khan and Thakur, 2018).

Some of the relevant insights of this research for this study include the following:

In the area of governance, Godsell *et al*. (2016) examined #FeesMustFall and its impact on governance between October 2015 and mid-2016 and argued that the nation must react as a matter of urgency.

In political studies, Booysen (2016: 155) added “that we should not wait for the longer-term impacts of the FeesMustFall to show themselves – while the early and illuminating trends congeal.” Meijer (2017) examined the dark or violent side of the #FeesMustFall. However, the paper does not inform on how to measure the sentiment before, during or after these violent episodes, however.

In cultural studies, Pillay (2016: 156) undertook a critical psychological assessment of the RhodesMustFall and FeesMustFall student protest arguing that the pervasive lack of public expression by Vice Chancellors is wrong even claiming “silence is quiet violence.”

In sociology, Wessels' (2017) research uses discourse analysis theory to understand the social processes during #FeesMustFall protest action, and finds that there was miscommunication and a failure on the part of universities to make use of social media for dialectical, constructive, engagement with students.

In the field of journalism, Ramluckan, Ally and van Niekerk (2017) and Bosch (2017) studied the Twitter impact on the protest movement in general with an overview of the #FeesMustFall campaign. Luescher, Loade and Mugume (2017) use the term 'internet-age student movement' and conducted an extended study of #FeesMustFall by examining the specific University of Free State context and experience of the campaign, and focus on #SteynMustFall and #UFSFeesMustFall. Bosch (2017) undertook a qualitative study of the #RhodesMustFall campaign using Microsoft Excel and NodeXL. Bosch (2017) further contributes to understanding the role of the viral internet in fostering political participation and activism to strengthen or undermine public discourse and concludes that Twitter afforded #FeesMustFall youth with an opportunity to participate in politics and set mainstream news agendas.

A particularly relevant journalism study is that of Baillie-Stewart (2017) who interrogated the most robust 9-day #FeesMustFall campaign period between the 15th and 23rd October 2015. This was a purposefully selected observation period which analysed the campaign from a news media and journalistic perspective. By comparison, this current thesis is a longitudinal study that covers a period of 545 days instead of just 9 days. This thesis intends that its observations corroborate and even extend Baillie-Stewart's (2017) work on the role of media.

It is worth noting that Baillie-Stewart's (2017) study exclusively utilised a commercialised data visualisation software called Tableau which requires a professional license fee for non-academic usage (Murray, 2013). Although Ballie-Stewart received special permission to use the software royalty-free, its license fees might prove unaffordable for certain civil and non-research organisations. The aim of this thesis however, is to undertake research that both academic and non-academic researchers could use with open ICT knowledge. Therefore this study will make a contribution by using the open programming language Python and VADER which has a zero cost for "open" data analysis. The reason for the choice is discussed in chapter 3.

In the area of thematic analysis, Van der Vyver (2017) and others such as Bosch (2017) asserted that activism has gone online, using the phrase ‘e-activism’. Bosch (2017) labels this activism as participatory citizenship. In both these studies the analysis did not include sentiment analysis, although Van der Vyer uses an intriguing thematic analysis approach.

In conflict-ridden mass protest situations such as #FeesMustFall, which did escalate into violence on several occasions, it can be argued that real-time analysis of tweets over a long period of time to get a handle of the sentiment of the protesters with qualitative methods has utility and such a study has not yet been done. The researcher was unable to find any longitudinal Sentiment Analysis of the #FeesMustFall campaign. (Sentiment Analysis, and the related data science studies relevant to #FeesMustFall, is discussed chapter 3).

In summary, a review of the literature reveals that there is cursory evidence of Twitter usage being studied in South Africa. The literature provides some rich non-ICT and a few data science research efforts on the #FeesMustFall campaign which shaped this thesis’s direction. However, the review of the #FeesMustFall literature reveals that there is an opportunity to extend recent work where Twitter research on #FeesMustFall has been used, and the gap is to conduct the first, to the researcher’s knowledge, longitudinal sentiment analysis study of Twitter Social Media in the #FeesMustFall campaign in South Africa.

In the course of reviewing the literature, the researcher also identified that automated tweets and software robots might also have been used during the campaign. This led to the addition of Research Question 3. The relevant literature in this regard is discussed next in section 2.6.

2.6 Review of literature on Automated Tweets and Software Robots

Given that this study has a particular interest in the Twitter platform, research question 3 sought to establish whether bots or cyborgs played a role in #FeesMustFall. In this section different types of bots are introduced (section 2.6.1), and their characteristics, indicators and profiles, together with discussion of bot detection algorithms and techniques, follows (section 2.6.2). Thereafter, the impact of bots and bot networks on social media and society is outlined (section 2.6.3) with the importance of bot research and its influence (section 2.6.4) finalising this section.

2.6.1 Types of bots

The growing number of users and the “open nature” of Twitter has rendered the Twitter platform an ideal target for exploitation by automated bots. A software robot or bot is an artificial intelligence-based system that runs on a host device rather than existing as a standalone machine (Margaret, 2016). Some bots are harmless; others are malicious, while some can be both (Singer and Brooking, 2018). There are several types of bots namely chatbots, internet bots, trolls, cyborgs and social bots. Each is now described.

2.6.1.1 Chatbots

A chatbot is a computer program or an artificial intelligence application that conducts a conversation via auditory or textual methods; in other words, chatbots can recognise and decipher human voice and requests for information. Apple’s Siri and Amazon’s Alexa are the best examples (Shawar and Atwell, 2007).

2.6.1.2 Internet bots

An Internet bot or web bot, also known as web robot, WWW robot or simply bot, is a software application that runs automated tasks (scripts) over the Internet. There is also an unsavoury version called a spambot, which is a computer program designed to assist in the sending of spam. Spambots usually create accounts as well as spam messages which they send together (Dunham and Melnick, 2008; AFP, 2018; Khan, 2018).

2.6.1.3 Trolls or ‘sockpuppets’

‘Sockpuppets’ are illicitly appropriated fake identities through which members of Internet communities praise or create the illusion of support or opposition towards a cause or work. Its detection is non-trivial (Bu, Xia, and Wang, 2013). Sockpuppets or ‘trolls’ are often fake identities used to interact with ordinary users on social networks. Sockpuppets can assume a fabricated identity to promote a cause, spread malicious links or generate advertisements.

2.6.1.4 Social Bots

Social bots are the scope of this thesis. A social bot is an automatic or semi-automatic computer algorithm that automatically produces content, mimics humans or interacts with humans on social media (Wagner *et al.*, 2012; Davies *et al.*, 2016). The fully automatic type of social bots, referred to as 'bots' or 'Twitterbots' on Twitter, require no human intervention, while the semi-automatic type, sometimes referred to as 'cyborgs' or 'hybrid bots', combine automation with human input (Chu *et al.*, 2010). Cyborgs have emerged as an intermediary between humans and bots, and are either human-assisted bots or bot-assisted humans (Chu *et al.*, 2010; Khan, 2018; Singer and Brooking, 2018). They have become a feature on Twitter and display interwoven hybrid characteristics of both manual and automated behaviour (Chu *et al.*, 2010; 2012).

The perversity and ease of deployment of social bots make them an important tool to understand for use as well as abuse. This is why social bots, and in particular political bots, are important to examine in the context of #FeesMustFall. In order to undertake an analysis of this depth, first the presence of social bots needs to be established. This study utilizes characteristics and profiles outlined in section 2.6.2 to detect social robots, however, the intention and content of social bots are not examined as it is not part of this research and is delimited for further work.

2.6.2 Characteristics of bots and how to detect them

As noted, a tweet may derive from a fake software social robot (bot) pretending to be a human, or from a human who uses bot technology to help boost posts more frequently, faster, and longer (also known as a cyborg). Each has some characteristics that assist in distinguishing between them (Chu *et al.*, 2012).

Chu *et al.* (2012) observed that a typical human user on Twitter is very likely to follow "famous" or reputable accounts.

$$\boldsymbol{Account\ Reputation} = \boldsymbol{follower\_no}/(\boldsymbol{follower\_no} + \boldsymbol{friend\_no})$$

A celebrity has many followers and few friends. An example is Barack Obama who has a reputation value of close to one[10]. In contrast, a bot has few followers and many

[10] At the time of writing @ BarackObama had an Account Reputation = (104M)/(104M+616K)=0.994 (1 Feb 2019)

friends. This has a reputation close to zero. It follows that humans should have the highest Account Reputation, followed by cyborgs, and then bots.

Bots and cyborgs depict easy-to-understand distinctive characteristics and behavioural traits, which aid in their identification. The technical indicators of a bot (section 2.6.2.1); characteristics of bot profiles (section 2.6.2.2) and bot detection systems (sections 2.6.2.3 and 2.6.2.4) are now discussed in the context of Twitter as this detail is important in understanding the study's choice of methodology and findings.

2.6.2.1 Indicators of a bot

Unsurprisingly, a key characteristic of a typical bot is that it displays repetitive behaviour, has a high volume of output and very frequent behaviour. A Twitterbot is a type of bot software that uses a Twitter API to control a Twitter account (Chu *et al*., 2012). Twitterbots are capable of performing tasks autonomously such as tweeting, retweeting, liking, following, unfollowing, or direct messaging other accounts. Twitter imposes a set of automation rules that cap Twitter bot behaviour (Twitter Inc., 2018a), and some bot accounts are now being suspended for extreme or aggressive activity (Chu *et al*., 2010; 2012), but Twitter does not effectively remove all malicious bots (Shao *et al*., 2017).

In terms of the number of tweets, it turns out, for example, that cyborgs generate the most tweets, followed by humans and finally bots. At a superficial level this is surprising, but on reflection it is evident that bots tweet frequently in a small sustained period, which is higher than humans would do, and then hibernate for a long period, perhaps to avoid detection. Gilani *et al.* (2017) suggest clear distinctions between a bot and human activity across the following metrics:

- Age of Account
- User Tweets or tweet rate
- User Retweets
- User replies and mentions
- URLs in tweets[11]

[11] Uniform Resource Locator (URL) is commonly known as a website address

- Content uploaded
- Likes per tweet
- Retweets per tweet
- Tweets Favourited
- Friend-follower ratio
- Activity sources count

Users have begun to use automated tools in order to boost their profiles on social media and in particular, there are such tools for Twitter that follow and un-follow users automatically (Karlson, 2017).

It is argued that the indicators of Twitter bots are that they:

1. Follow very few accounts which are in turn followed by very few,
2. Are usually topic or cause-specific,
3. Exhibit excessive duplicate or near-duplicate tweets on a profile's stream,
4. Tweet in patterns such as:
    a. By fixed-interval time periods between tweets using timers,
    b. Short intense tweet bursts,
    c. Tweet at an exact time in a day, every day using timers,
5. Have low Account Reputation.

(Chu *et al.*, 2012; Kramar, 2017).

Bots also have profiles, and these are discussed next.

2.6.2.2 Bot profiles

Makara (2013) and Fraser (2017) suggest that a fake or automatically generated bot has the following profile characteristics:

- The avatar or User Profile's picture remains with Twitter's default of an "egghead." This may suggest the profile is either a very new account, a fake bot account, or evidence that the Twitter account is not a serious one.
- A bot creator may also use stock profile images from the internet. One may use Google Images to determine if the image is 'stock'.

- The user profile usually contains no biographic data in the account section.
- There are strange user names such as males with female names, or a transnational combination of first names and surnames.

There are framework for detecting bots, and two are explained next.

2.6.2.3 DeBot detection system

Chavoshi, Hamooni and Mueen (2016) have developed a Twitter Bot detection system called DeBot. DeBot detects abnormalities in Twitter behaviour of users based on activity correlation which requires no pre-trained or labelled datasets (ibid). The researchers also boast a 94% precision for their DeBot system in the detection of bots and has made the system accessible via an API[12]. The system is built on the premise that humans, in general, cannot display highly synchronous activities on Twitter without automated support (Ibid). Furthermore, DeBot operates by clustering user accounts into correlated sets utilising a lag-sensitive hashtag technique which occurs in near real-time and then detects for warped correlation amongst user accounts. A warped correlation represents an unusual high synchronous correlation between user accounts based on Twitter activity (Ibid).

2.6.2.4 Botometer detection system

A framework for bot detection, called Botometer[13], has further been constructed to evaluate the degree to which a Twitter account is similar in characteristics to known social bots (Davis *et al.*, 2016). The Botometer system uses a random forest machine learning model that incorporates 1,150 features derived from user account metadata, friend/follower data, network characteristics, temporal features, content and language features, and sentiment analysis. Botometer was previously called Botornot (Davis *et al.*, 2016; Kramar, 2017).

Davis, lead developer of Botometer explains that users have this heuristic where they automatically assign more credence to opinions which appear to have been widely shared (Davis *et al.*, 2016). This is, in fact, the central tenet of deception that bots aspire to create, in order to lend artificial credibility to an agenda that the bot creator wants to influence or amplify (Shao *et al*., 2017; Block, 2018). Within the context of

[12] Available at https://www.cs.unm.edu/~chavoshi/debot/api.html and requires registration
[13] Available at https://botometer.iuni.iu.edu/#!/ and is free to use online.

generic bot influence, the goal is to identify the top influencer(s). Identifying top influences will provide strategic insight into researchers and authorities alike. University authorities, for example, may alternatively be the benefactors or the targets of bot behaviour. The impact of bots and bot networks on social media and society is important and is discussed next.

2.6.3 The impact of bots and bot networks on social media and society

Twitter tweets, as electronic data, may be automatically tweeted or retweeted by software such as Hootsuite or Tweetdeck, as well as by bots**.** The same tweet may be tweeted periodically by the same user for as long as they choose, which allows for someone to influence an agenda.

A bot is considered to be amoral. It exhibits the intent of the developers who themselves may be agenda-based or disinterested hired guns. Bots are also sophisticated enough to fool social media users into thinking they are human. Of course, bots are not always bad; they are often benign, or even useful, although some are created to harm, by tampering with, manipulating, influencing, and deceiving social media users (Davis *et al.*, 2016). As humans regrettably view information generated by Twitter bots as a credible source of information (Edwards *et al.*, 2014) bots can have significant potential influence on society.

According to Gilani *et al.* (2017), bots have been observed to have a profound influence on social media, and online media has become influential in affecting the sentiment of users. This capacity to influence is, in all likelihood, a reason why bot creators have been targeting websites and social media to either promote products, causes or even spread fake news. Since a sentiment shared in social media has been recognized to affect external events (section 3.3.1) such as financial markets and political affinity, it is perhaps unsurprising to witness the emergence of bots that aggressively lobby viewpoints or spread malicious information.

The sophistication of bots has grown to circumvent social media platforms and develop networks of their own, known as bot networks. The recent Trump and Russia allegations revealed bot networks in Twitter that targeted journalists' and other users' accounts that opposed Donald Trump, with some human accounts temporarily suspended after being attacked by a network of bots (Krebs, 2017). This means that a bot network is capable of suspending human accounts by triggering a breach in the rules of Twitter. Twitter suspends accounts based on the following three criteria (Twitter Inc., 2018b):

- Spam
- Account security at risk
- Abusive tweets or behaviour

In retaliation to bots and bot networks, Twitter has established security measures to detect unusual patterns and activities within its platform (Roth and Harvey, 2018). Nevertheless, bots adapt and evolve and continue to plague social media platforms. Libicki (2007), Singer and Brooking (2018) highlight the weaponization of social media through bots and note that digital information has become an integral component of the arsenal in warfare.

It is interesting to note that a decade before the proliferation of computers, McLuhan (1970: 66) ominously predicted that the next World War will be a guerrilla information war with no discernible division between military and civilian participation. With the advent of the social media, this prediction may have some merit as the global digital village has elevated any online poster to a potential influencer.

Marketers, lobbyists, and activists use or deploy bots to amplify their agenda by attempting to manipulate social media users' opinions through automated social engagements. The agenda may be personal, cause-related, political or financial (Davis *et al.*, 2016; Howard, Woolley and Calo, 2018; Khan and Thakur, 2018). University students arguably also have agendas, and are generally considered to be intelligent and have access to software tools with knowledge and capability to programme them. It is conceivable that they could have created automated bot software to support an agenda such as #FeesMustFall; although, this is speculative.

In the sections that follow, the impact of bots on politics in the USA (section 2.6.3.1) and in South Africa (section 2.6.3.2) is elaborated. Thereafter, the case for the importance of bot research is argued (section 2.6.4).

2.6.3.1 Political bots in the USA

Howard, Woolley and Calo (2018) use the phrase 'political bots' to describe automated scripts designed to manipulate public opinion. They show how political bots have been used in the US context to surreptitiously coordinate campaigns, illegally solicit contributions or votes, and even violate rules on disclosure. The first unequivocal deployments of political bots occurred during the 2010 Massachusetts Senate Election ending in the election of Scott Brown. These bots drew journalist as well as donor interest from across the country (Khan, 2018).

In the 2016 US Presidential election campaign, election bots were deployed to actively participate in online discussions, with some bots supporting the eventual victor Trump, while other bots supported the challenger Clinton (Bessi and Ferrara, 2016; Howard, Woolley and Calo, 2018). Shao *et al.* (2017) purposefully researched this bot-battle and determined that this bot battle was uneven, with pro-Trump bots outnumbering and out-tweeting pro-Clinton bots by 4:1 and 7:1 respectively. Bessi and Ferrara (2016) found that as many as 400 000 social bots participated in the 2016 US elections, supporting both contestants Trump and Clinton. These bots generated at least 3.8m tweets or 19% of the total number of tweets during their study observation period.

In addition, there was a widely publicized investigation into whether the 2016 US Presidential election was influenced by an organisation called Cambridge Analytica, perhaps with external forces (Gonzalez, 2017). To help clients manipulate election voters during the 2016 US Presidential election, it is alleged that Cambridge Analytica built psychological profiles from data that it surreptitiously harvested from the accounts of 50 million Facebook users (Zunger, 2018). Whilst the target was Facebook, such clandestine profile building behaviour can be extended to Twitter. Cambridge Analytica remains a 'textbook reference case' of the abuse of big data social media analytics for nefarious reasons. The fallout from this is ongoing as governments engage with Facebook, Twitter and Google over covert consumer monitoring (Klien, Rao and Dalvi, 2018). Indeed, the US government eventually decided to fine Facebook $5 billion (BBC News, 2019).

2.6.3.2 Political bots in South Africa: Bell Pottinger and #Guptabots

In South Africa, Twitter has also experienced the emergence of bot activities which aim to influence government, financial markets and society. A key example of this is the Bell Pottinger incident (ANCIR, 2017; Child, 2017; IOL News, 2018; Ziller, 2018). Ireton and Posetti (2018:112) describe this incident as follows:

> *"A wealthy family accused of capturing key state enterprises and politicians in South Africa hired UK Public Relations firm, Bell Pottinger, to devise an*

elaborate propaganda campaign. It spread its messages via a disinformation empire involving websites, media and a paid Twitter army which targeted journalists, business people and politicians with abusive, hostile messages and photoshopped images, designed to humiliate and counter their investigations into state capture (Ireton and Posetti, 2018: 112)".

It is widely believed that the Bell Pottinger incident was the first widespread, large-scale, post-apartheid fake news propaganda war to use social bots to manipulate public opinion in South Africa. As noted, Bell Pottinger was a public relations company employed to manage the Gupta family brand after the family faced serious multi-billion dollar state looting allegations[14] in South Africa. Their Gupta campaign was said to have adversely affected the country's politics and economy, even resulting in a Commission of Enquiry. This network of fake news is said to have produced at least 220 000 tweets and Facebook posts to confuse the public between July 2016 and July 2017 (ANCIR, 2017; IOL News, 2018).

In 2016, Fraser (2017) exposed the network of at least 800 fake accounts and identified bots who trolled citizens or organisations who were perceived to be against the Guptas, and they gained the name #Guptabots. Fraser (2017) analysed the #GuptaLeaks bots, and said that they are easy to identify by their strange names, identical profiles and their identical tweets sent at the same or similar time. Using online tools, Fraser (2017) found that these #Guptabots emanated from 'troll farms' in India (Gupta Leaks, n.d.; Child, 2017; Ziller, 2018). Fraser (2017) determined that a Fake Name Generator, which can create 3 000 names in seconds, was deployed and showed that bots follow accounts with hundreds of thousands of followers so as to appear legitimate. For example, an analysis of one protagonist, Jimmy Manyi, determined that 60% of his followers were fake. The researchers themselves were trolled and attacked with a website 'White Monopoly Capital Leaks' that accused the researchers of being on the payroll of white-run media companies.

Child (2017) suggests that Twitterati came to the defence of South Africa's democracy and outed fake pro-Gupta Twitter bot accounts which were used to promote the family

[14] This discussion is beyond the scope of this research but is presented to show that Twitter has negative consequences

by praising pro-Gupta supporters and selectively targeting journalists and others perceived to be anti-Gupta.

One such Twitter account, “Esaia Theron”, was shown to be fake (Child, 2017). Theron praised known Gupta supporter Andile Mngxitama, in the following tweet:

> *@Mngxitama “We all have to admit that is the greatest of all so much passion he has for the improvement of the country. #BLF”*

On the other hand, journalist Barry Bateman was trolled by the bots, picking up 500 new fake followers daily forcing him to lock his account. Theron condemned Bateman for locking his account and blocking Theron.

The #GuptaBots campaign is known alternatively as ‘deadcatting’ or a ‘dead cat strategy’. This refers to the introduction of a dramatic, shocking, or sensationalist topic to divert discourse away from a more damaging topic. By alleging that white monopoly capital was responsible for state looting, it took attention away from the major players (Gupta Leaks, n.d.; Head, 2018; PRCA, 2018).

The Public Relations and Communications Association was dismayed by Bell Pottinger’s actions suggesting that the company had shamed the public relations and communications industry with its actions. Bell Pottinger consequently received the worst possible sanction of immediate membership termination (PRCA, 2018).

2.6.4 Bot influence and the importance of bot research

As has been intimated, the massive spread of digital misinformation has been identified as a global risk which could impact elections, national security, company and individual reputation (Shao *et al.*, 2017). Therefore, much research is being undertaken to understand the viral diffusion of misinformation by social bots (e.g. the Bessi and Ferrara (2016) and Shao *et al.* (2017) studies on 2016 US Presidential election). Bots may not all be malicious and their presence on Social Media may even be used productively such as to legally monitor activity for medical evidence of the spread of an ‘illness.’ Chew and Eysenbach (2010) termed this infoveillance (section 2.3.2). Some bot accounts are entertaining, helpful, or at least harmless, although nefarious uses for social bots abound, particularly when multiple bot accounts are used in a coordinated fashion to perform an orchestrated campaign (Davis *et al.*, 2016; Ferrara *et al.,* 2016).

It is argued that there is a need for more research in this area as malicious bots aim to influence societies, governments and economies and can have negative social impact. Twitterbots have been known to attempt to influence the sentiment of Twitter users by associating the *hashtag* (#) with positive or negative text together with fake news and even additional hashtags (such as #FeesMustFall).

A review and analysis of literature and the media during #FeesMustFall and the observational period did not find evidence that the terms 'software robots', 'social bots' or 'bots' have yet been studied along with the term #FeesMustFall. This connection, to the author's knowledge, was also not mentioned in the media or any relevant study during the #FeesMustFall campaign.

It is therefore argued that there is a gap in the literature in this area – and this discovery led to the inclusion of Research Question 3 to examine bot behavioural characteristics and basic bot identification algorithms in relation to #FeesMustFall. To the authors' knowledge, this is the first ICT thesis that studies bots and the influence of bots in a country-wide movement or campaign such as #FeesMustFall.

2.7 Conclusion

This chapter embarked on a literature review, inter alia, on Twitter and its potential uses and abuses. It found that Twitter hashtags have been effectively used to influence the public in disasters, epidemic outbreaks and anti-government protests. A historical overview of the number one hashtag during the study period, #FeesMustFall, revealed that the campaign's origins lie in the Freedom Charter. Whilst the use of the hashtag has early roots in #RhodesMustFall, the #FeesMustFall movement was triggered by university fee increases in October 2015 which prompted the first #FeesMustFall protests. These protests escalated across more universities and the campaign became violent. The campaign was further enabled by free Twitter data as a result of a marketing campaign by cellular provider MTN.

A specific review of the academic literature on #FeesMustFall on Twitter revealed that there have been a number of rich non-ICT and a few data science research efforts on the #FeesMustFall campaign. However, the review identified that there is an opportunity to extend recent work and the gap is to conduct the first (to the researcher's knowledge) longitudinal study of Twitter Social Media in the

#FeesMustFall campaign in South Africa. In the course of the review the possible role of software robots in the #FeesMustFall campaign became apparent. The literature review revealed that the terms “software robots”, “social bots” or “bots” had yet been studied along with the term #FeesMustFall. This led to the identification of a further gap for additional research.

The literature pointed to the value of Sentiment Analysis as a theoretical framework and analysis tool for the study. Given the length of this chapter, as well as the technical detail involved, the discussion of Sentiment Analysis is covered in chapter 3.

Chapter 3 Analysis framework - Sentiment analysis

3.1 Introduction

Chapter 2 reviewed research on Twitter and social media bots in relation to #FeesMustFall in particular. It built the argument that the social medium of Twitter can have a positive or negative influence on society in areas such as disasters, epidemics, anti-government protests and politics. Literature was provided to make the case that malicious bots aim to influence societies, governments and economies and can have negative social, economic and political impact. In addition, the review found that Twitterbots have been known to attempt to influence the sentiment of Twitter users by associating the *hashtag* (#) with positive or negative text together with fake news and even additional hashtags. In chapter 2, these findings were discussed in relation to the #FeesMustFall campaign in South Africa, and it was that there is merit in undertaking a longitudinal sentiment analysis of #FeesMustFall and combining this with analysis of bot and cyborg activity to fill a gap in the literature.

This chapter builds on chapter 2 to justify the use of sentiment analysis as a theoretical lens and data analysis method. The key reason sentiment analysis is discussed before presenting the research methodology (chapter 4) is to provide literature to defend the choice of sentiment analysis. The length of chapter 2 and chapter 4 also mitigated against discussing it in these chapters. Since this is a longitudinal study of sentiment analysis, the literature and technical detail of it needs to be fully elaborated and therefore, the pragmatic decision was made to discuss it in its own chapter.

The rest of the chapter is organised as follows: First Twitter analysis techniques are briefly outlined (section 3.2). Thereafter sentiment analysis is more fully explained (section 3.3), with discussion of its usefulness (section 3.3.1), how it is defined (section 3.3.2), the forms of data that can be utilised (section 3.3.3), methods for mathematically coding tweets for sentiment analysis (section 3.3.4), and sentiment analysis methods (section 3.3.5). Section 3.4 discusses the VADER algorithm and detail is provided on VADER as an automated sentiment rater; as a method to compute the sentiment score of a sentence using a lexicon; and as a means for factoring emoticons into sentiment. The challenge of the open-ended hard research problem is then discussed, together with motivation for choosing the VADER lexicon classifier, before concluding the chapter (section 3.5).

3.2 Twitter data analysis techniques and #FeesMustFall

Social media, Twitter in particular, contains large amounts of textual and non-textual information (data) that can be analysed utilising several possible techniques. The limitations of this study (section 1.9) dictates that these techniques be discussed within a textual context as the researcher only obtained a dataset comprised of textual tweets (section 4.5.2.2). The study therefore excludes audio, image and video references.

Possible analytical techniques include Content Analysis (section 3.2.1), Thematic Analysis (section 3.2.2), Social Network Analysis (section 3.2.3) and Sentiment Analysis (section 3.2.4). The Twitter and/or #FeesMustFall studies that have used these methods are briefly mentioned as they were discussed in chapter 2. Sentiment analysis is then more fully elaborated in section 3.3.

3.2.1 Content analysis

Content analysis studies the meaning of the words. This includes the grammar and the relationships amongst the words. The Internet Age supports content analysis to draw valid conclusions from data by interpreting frequency distributions and patterns according to the context of their use (Krippendorff, 2004: 18). It also has emerging uses in plagiarism detection (Grimmer and Stewart, 2013). Baillie-Stewart (2017) utilised computer-assisted content analysis (Einspänner, Dang-Anh and Thimm, 2014) to study the #FeesMustFall campaign.

Content analysis examines the meanings rather than sentiment of expressed words and was therefore omitted from this study.

3.2.2 Thematic analysis

Braun and Clarke (2006:79) define thematic analysis as:

> *"A method to identify, analyse and report patterns (themes) within data. Thematic analysis shows what is being written about most, which topics are trending, and even determine the influencers that is who is bringing up which subjects the most (Ahmed, 2018)."*

Van der Vyver (2017) used thematic analysis to analyse tweets that were collected during the second wave of the #FeesMustFall campaign between October–November 2016. He purposefully sampled 300 tweets from citizen journalists and 150 tweets from professional journalists finding that citizen journalists who were not bound by newsroom ethical constraints enjoyed a lot more freedom of expression than their official media counterparts.

Thematic analysis was not selected for this study as it is suited for research that aims to examine themes as opposed to analysing sentiment of phenomena and events.

3.2.3 Social network analysis (SNA)

Wasserman and Katherine (1994:3) explain social network analysis (SNA) as methods to examine the relationships amongst social entities. SNA has the potential to examine the users who were most influential, and whom they influenced during a campaign. Ediger *et al.* (2010) conducted SNA on Twitter using algorithms and unique tools built upon networks and graph theory. Graph theory is used to identify nodes who direct, convey and amplify information (Otte and Rousseau, 2002; Grandjean, 2016). Bosch (2016) applied SNA methodology to over a million tweets collected at the height of the protests, to identify key actors and relationships using a qualitative content analysis method to explore the purpose and nature of the online conversations via the hashtag #FeesMustFall.

SNA focuses on relationships as opposed to opinions of social entities and was therefore not selected for this study.

3.3 Sentiment analysis

Sentiment analysis measures the mood of online conversations, and provides insight into the emotion behind the words by categorizing tweets into positive, neutral or negative categories.

Different studies on #FeesMustFall (see section 2.5 for a list of these studies) have utilised various techniques apart from sentiment analysis (some which have been outlined in section 3.2). As noted in chapter 2, a review of the literature revealed that sentiment analysis has not yet been used in a longitudinal study of #FeesMustFall. It is for this reason that the sentiment analysis theoretical lens and technique was chosen for this study. The interest is also influenced by a desire to understand if or whether there are any cause-causality relations between online protest and offline events, and a longitudinal analysis using sentiment analysis would enable the researcher to study this.

This section begins with a discussion of the utility of sentiment analysis (section 3.3.1), before progressing to a technical definition (section 3.3.2). Thereafter, the forms of data that can be analysed using sentiment analysis are outlined (section 3.3.3) and methods for coding sentiments mathematically are outlined (in section 3.3.4 and 3.3.5).

3.3.1 Why sentiment analysis is useful

The capturing of public opinion in social events, political movements, company strategies, and marketing campaigns is garnering increasing interest from scientific, business and now government entities. About 95% of data is labelled as unstructured (Mayer-Schönberger and Cukier, 2013; Gandomi and Haider, 2015) and is hardly analysed (Rizkallah, 2017; Taylor, 2018). Sentiment analysis aims to analyse people's sentiments, attitudes and opinions, emotions on elements such as products, individuals, topics, organizations, and services. Sentiment analysis studies have predominantly centred on the market and perceived consumer reaction to commercial brands. This is exemplified by Van de Kruis (2014) who focused on sentiment analysis and brand attitude. Barnaghi, Ghaffari and Breslin (2016), however, are representatives of the decentralised position on sentiment analysis research and undertook a correlation study between sentiment polarity on Twitter data and real-life events. The #FeesMustFall campaign is similarly researched in this thesis to establish a link between Twitter sentiment and real-life events (section 1.5.2).

#FeesMustFall was a movement which riveted the South African nation due to its arguably coordinated virtual-online campaign, as well as the physical-offline human approach. Students protested in person at various universities, while sustaining and maintaining the campaign in traditional media and the public eye through instant reporting on social media platforms from the protest sites. Journalists amplified these posts by reposting them as well as adding their own reporting (Baillie-Stewart, 2017). During the course of the movement, a wide range of sentiments, attitudes and opinions were expressed in tweets.

Having a corpus of #FeesMustFall related tweets implies that one can establish the sentiment of the tweets for various intervals. Sentiments can change through persuasion (such as from the lobbyist in the campaign), perceived positive events (such as a university or government capitulation on a specific or a set of demands) or negative events (such as police or security violence, violence, and destruction of property) (Gilani *et al.*, 2017).

The research interest in any sentiment analysis or opinion mining study is to understand what the sentiment is, and when and why the sentiment changed. Research on sentiment is already being done in relation to the stock market (Smailović *et al*., 2013), and Swamy (2017) has shown that it is possible to retrospectively predict outcomes where the choice-decision-options are known in advance, e.g. who will win the Oscar awards. A number of studies have focused on sentiment in relation to elections to assess whether it is possible to predict outcomes (Chung and Mustafaraj, 2011). In particular, Larsson and Moe (2014) studied Twitter along with the Scandinavian Political Elections in Sweden, Denmark and Norway. There is anecdotal evidence that the destruction of property does change the perceived public opinion. Given the destruction of property during #FeesMustFall, there is an opportunity to identify whether opinion changed over the longitudinal period and sentiment analysis offers a way to do this.

3.3.2 Sentiment analysis defined

Sentiment analysis can be defined as a process that automates mining of attitudes, opinions, views and emotions from text, speech, tweets and database sources through natural language processing (NLP) (Kharde and Sonawane, 2016). Sentiment analysis is also called opinion mining or appraisal extraction. It is unlike semantic analysis which analyses meanings and contexts, and it does not examine the truthfulness of the data. Semantic analysis and truthfulness of the data are delimited in the discussion around fake news and given that media played a large role in amplifying the event[15], even though this was purposeful.

There are many sentiment analysis tools *inter alia* Sentiwords, Linguistic Inquiry and Word Count (LIWC), Pattern, IBM Watson Natural Language Understanding and various Python instances such as TextBlob and VADER (Davydova, 2017).

Sentiment analysis of text is the process of analysing the unstructured text, to extract relevant information, and transform it into useful business intelligence. Sentiment analysis may also be applied to non-textual feedback such as video, audio, and

[15] Lies, fake news or gossip can evoke sentiments of anger or joy. The originator may be a person or a social bot (section 2.6)

images; for example, a picture of an angry person with a bloody knife would receive a lower sentiment score than an image of a smiling person offering a white rose (Sigler, 2015).

There are existing limitations in sentiment analysis due to the complex nature of human communication and language and while NLP is improving there remains and probably will forever be factors that curb its efficiency (Bell *et al.*, 2014). Factors such as irony detection, emotion detection, and tweet sentiment are complex to interrogate but machine learning offers some relief and by utilising efficient algorithms together with NLP this gap becomes narrower (Giachanou and Crestani, 2016).

3.3.3 Forms of data that can be analysed using sentiment analysis

A unit of data on its own is not very useful. Combining data creates information, then knowledge and ultimately wisdom (Hey, 2004). Data has two extreme forms, structured and unstructured with semi-structured a combination of the two (Erl, Khattak and Buhler, 2016: 19). Structured data is data that is comprised of clearly defined data types whose pattern makes them easily searchable. It often resides in a database (Mayer-Schönberger and Cukier, 2013). Text files, images, audio, video and social media are examples of unstructured data (Rizkallah, 2017; Taylor, 2018), which sometimes lack the structural organization required by machines for analysis. Data may be textual (social media, email) or non-textual (video), and human- or machine-generated.

Semi-structured data are considered to be largely unstructured data but contain small amounts of structured elements within their metadata that allow for analysis using some traditional structured methods (Erl, Khattak and Buhler, 2016: 19). JSON and XML are examples of semi-structured data.

Unstructured data has internal structure but is not structured via pre-defined data models or schema (Gandomi and Haider, 2015; Taylor, 2018). Unstructured data remains one of the major unsolved problems of Information Technology (Blumberg and Atre, 2003), although much current research is taking place (Madhoushi, Hamdan and Zainudin, 2015). It comprises 95% of all data (Mayer-Schönberger and Cukier, 2013; Gandomi and Haider, 2015). As this study examines Twitter data, the data is considered unstructured.

The next section (3.3.4) outlines a framework to mathematically code tweets for sentiment analysis. Thereafter sentiment analysis methods are discussed (section 3.3.5).

3.3.4 Methods for coding sentiments mathematically

Typical English sentences have a subject and a predicate. This syntax is also frequently used in tweets. Sentiment analysis unpacks the sentence (tweet) in an effort to find the words that express the sentiment. Consider the following sentence as a tweet:

<SENTENCE>	=	The story of the movie was weak and boring

It unpacks into the following components:

<OPINION HOLDER>	=	<author>
<OBJECT>	=	<movie>
<FEATURE>	=	<story>
<OPINION >	=	<weak><boring>
<POLARITY>	=	<negative>

Mathematically we now represent an opinion as a quintuple (***o, f, so, h, t***), where

o	=	object;
f	=	feature of the object ***o***;
so	=	orientation or polarity of the opinion on feature ***f*** of object ***o***;
h	=	opinion holder;
t	=	time when the opinion is expressed.

These elements can be defined as follows:

Object: An entity which can be a person, event, product, organization, or topic

Feature: An attribute (or a part) of the object with respect to which evaluation is made.

Opinion orientation or polarity: The orientation of an opinion on a feature ***f*** represents whether the opinion is positive, negative or neutral.

Opinion holder: The holder of an opinion is the person or organization or an entity that expresses the opinion (Kharde and Sonawane, 2016).

This syntax now provides researchers with a method to parse sentences or phrases for sentiment analysis.

3.3.5 Sentiment analysis methods

Sentiment analysis uses one of two methods: Machine learning (ML) or a lexicon-based approach. A decision tree depicting sentiment analysis approaches and techniques can be seen in Figure 6 (Medhat, Hassan and Korashy, 2014).

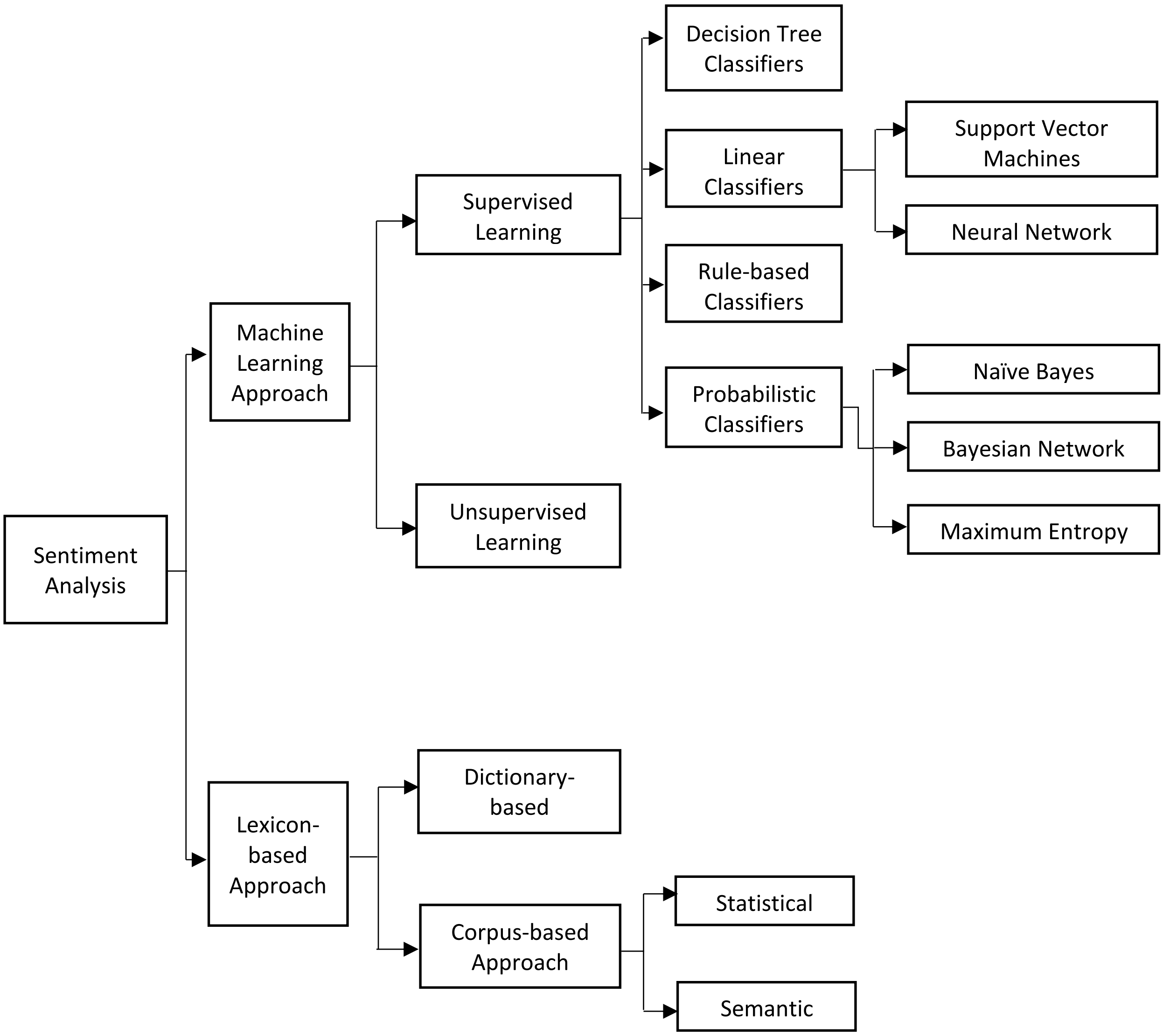


Figure 6 Sentiment classification techniques (Medhat, Hassan and Korashy, 2014)

3.3.5.1 Sentiment analysis using a machine learning approach

Machine learning (ML) can be utilized to automatically categorise tweets based on a pre-trained dataset (Pennacchiotti, and Popescu, 2011). ML typically breaks the data into two sets – one set where 80% of the data is subjected to the training of the data for patterns and observations and analysis while the remaining 20% of the actual data is used to test the trained data (Kharde and Sonawane, 2016). This works well in image processing. Using ML to automatically code large volumes of Twitter data with ease is a common big data exercise. This is flagged as important future work. ML may be used for sentiment analysis, content analysis, thematic analysis, and social network analysis (SNA) as discussed in 3.2.

Post-facto research is a useful tool to search for cause and causality if it exists. The purpose of this approach is to see the impact and triangulate with real-life events. The goal of ML is to establish relationships between features. The features themselves may be continuous, categorical or binary. If instances are given with known labels and corresponding outputs the method is called supervised machine learning. If they are not labelled it is called unsupervised approaches machine learning (Figure 6).

3.3.5.2 Sentiment analysis using a lexicon-based approach

A sentiment lexicon is a list of lexical features (e.g. words) which are generally labelled according to their semantic orientation as either positive (love, nice, great, good) or negative (hurt, ugly, sad, bad, worse) (Hutto and Gilbert, 2014). Manually creating and validating such lists of opinion-bearing features, although being amongst the most robust methods for generating reliable sentiment lexicons, remains the most time-consuming. For this reason, much of the applied research leveraging sentiment analysis relies heavily on pre-existing manually constructed lexicon dictionaries such as VADER, LIWC, GI and Hu-Liu04 Dictionary (Pennebaker, Francis and Booth, 2001; Hutto and Gilbert, 2014; Ribeiro *et al.*, 2016). They categorize words by their text free semantic orientation into binary opposites of positive or negative (Hutto and Gilbert, 2014).

This study uses the lexicon-based approach, and more specifically the VADER method is chosen. This is detailed in section 3.4.

3.4 VADER

Valence Aware Dictionary and sEntiment Reasoner, also known as VADER, is a parsimonious rule-based model for sentiment analysis of social media text (Hutto and Gilbert, 2014). It measures the sentiment and polarity (intensity) of the text by examining a list of lexical features (e.g. words) which are labelled according to their semantic orientation as either positive or negative. This is because VADER not only gives information about the positivity and negativity score but it also informs on the polarity or degree of positivity or negativity of a sentiment (Ibid).

The technical aspects and effectiveness of VADER are elaborated next in this section as follows: First the VADER algorithm is explained (section 3.4.1), then VADER as an automated sentiment rater is discussed (section 3.4.2). VADER's process to compute the sentiment score of a sentence using a lexicon is elaborated thereafter (section 3.4.3), followed by an explanation of how VADER factors emoticons into sentiment (section 3.4.3.1). Having outlined how emoticons are factored into the sentiment, reasons for sentiment analysis being an open-ended hard research problem is provided (section 3.4.4), together with reasons for choosing the VADER lexicon classifier (section 3.4.5).

3.4.1 The VADER algorithm

VADER is an example of a lexical method for sentiment analysis and its algorithm is based on the following principles.

$$E \in [-4; 4], where\ E\ represents\ the\ Sentiment\ Score\ per\ word$$

- Sentiment score or Emotion intensity of a word is measured on a scale from -4 to +4, where -4 is the most negative and +4 is the most positive. The midpoint 0 represents a neutral sentiment.
- The overall sentiment (S) is normalized using the formula,

$$S = {}^{\sum Ei}\Big/_{\sqrt{(\sum Ei)^2 + \alpha}} \quad i = 0,1,2, \dots, n$$

$Ei\ represents\ the\ Sentiment\ score\ of\ the\ i^{th}\ word$

$S \in [-1; 1], where\ S\ is\ the\ overall\ sentiment$

$\alpha\ is\ a\ normalization\ parameter\ set\ at\ a\ value\ of\ 15$

$S > 0.05\ is\ Positive \quad S < 0.05\ is\ Negative \quad -0.05 \leq\ S \leq 0.05\ is\ Neutral$

(Huttto and Gilbert, 2014; Calderon, 2017).

The overall sentiment score of a sentence is the normalization of the sum of the sentiment score of each sentiment-bearing word.

VADER incorporates colloquialism, emoticons and punctuations into its sentiment algorithm by considering five heuristics (Calderon, 2017). These are as follows:

1. Punctuation
2. Capitalization
3. Degree modifiers
4. Shift in polarity due to "but"
5. Tri-gram examination before a sentiment-laden lexical feature to catch polarity negation.

The application of VADER as an automated sentiment rater can now be discussed (section 3.4.2).

3.4.2 VADER as an automated sentiment rater

The credibility of VADER was enhanced by the inclusion of 20 pre-screened and appropriately trained human sentiment raters during its development (Hutto and Gilbert, 2014). VADER performs as well (correlation coefficient r = 0.888) as human raters (r = 0.888) in the social media domain and even performs better in classification accuracy ($F1$ = 0.96) of positive, neutral or negative than human raters ($F1$ = 0.84). This provides VADER with enough credibility to be utilized as an automated rater for sentiment.

VADER is, however, based on the English language which limits its effective application towards other languages and therefore it lacks linguistic diversity. In an attempt to address this gap, Hutto and Gilbert have now incorporated an online translation service within the VADER Python library on their Github webpage[16]. The VADER Python library (Hutto, n.d.; Python Software Foundation, n.d.a) is an open source collection of functions and methods built by Hutto and Gilbert (2014) that allows for the VADER model to be computationally utilised through the Python programming language.

An automated rating method provides a timesaving solution when the requirement is to rate large volumes of data within a short period of time. The #FeesMustFall dataset used in this study contained large volumes of tweets which attracted the researcher towards an automated method for rating sentiment, hence the eventual choice of

[16] The VADER Python library can be found at https://github.com/cjhutto/vaderSentiment

VADER. This software-type approach to analyse tweet content is recommended by Pak and Paroubek (2010).

VADER computes the sentiment score of a sentence using a lexicon and this process is elaborated next (section 3.4.3).

3.4.3 Computing the sentiment score of a sentence using a lexicon

Section 3.4.1 demonstrates how the VADER algorithm was applied to derive a sentiment score for a sentence. VADER achieves this by making use of its valence aware dictionary which comprises of lexicons that contain values for an extensive list of texts, emoticons and emojis. Each text, emoticon or emoji in a sentence is parsed through this dictionary and successful matches are replaced with corresponding values while unsuccessful matches return a zero value.

Manually creating and validating a comprehensive sentiment lexicon is a labour intensive and sometimes error-prone process which prompted researchers to use existing lexicons. A list is compiled by Mohammad (2019) which provides existing well-established sentiment word-banks namely LIWC, ANEW, and GI.

The compound score is computed by summing the valence scores of each word in the lexicon, adjusted according to the rules, and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive). This is the most useful metric if one wants a single unidimensional measure of sentiment for a given sentence. This is termed a 'normalized, weighted composite score'. The positive, neutral, and negative scores are ratios for proportions of text that fall in each category. Therefore these should all add up to be 1 or very close to it with float operation. These are the most useful metrics if one requires multidimensional measures of sentiment for a given sentence.

Emoticons are also factored in by VADER to compute sentiment and is discussed next (section 3.4.3.1)

3.4.3.1 Factoring emoticons into the sentiment

Numerous lexical features common to sentiment expression in microblogging platforms like Twitter are incorporated by VADER, including:

- A full list of Western-style emoticons, e.g., :-) denotes a smiley face and generally indicates positive sentiment while :-(denotes the opposite

- Sentiment-related acronyms and initialisms (e.g., LOL and WTF are both examples of sentiment-laden initialisms)
- Commonly used slang with sentiment value (e.g., Nah, meh and giggly).

(Pandey, 2018)

Having outlined how emoticons are incorporated by VADER into the sentiment, reasons why sentiment analysis is an open-ended hard research problem are now explained (section 3.4.4).

3.4.4 Why sentiment analysis is an open-ended hard research problem

Understanding the emotional intent of text is a non-trivial task. Text may a range of sentiments all at once. For instance,

> “The intent behind the movie was great, but it could have been better”.

The above sentence comprises two polarities, i.e., Positive as well as Negative. So how do we conclude whether the review was positive or negative?

Automated software is not (yet) capable of comprehending wit, sarcasm, similes, metaphors, hyperboles, understated or figurative speech**.** Heavy, creative or playful use of emoticons and slang with sentiment values in social media texts like that of Twitter and Facebook also makes text analysis difficult.

These are a few of the open-ended problems encountered not only with sentiment analysis but also with NLP as a whole. Rosenthal, Farra and Nakov (2017: 504) explain that while one is currently able, “Given a tweet and a topic, [to] classify the sentiment conveyed in the tweet towards that topic”, can one “Given a set of tweets about a topic, estimate the distribution of tweets across?”, they ask.

Arguments can now be provided for the choice of the VADER lexicon classifier (section 3.4.5).

3.4.5 The choice of the VADER lexicon classifier

VADER is the model of choice for lexicon based analysis of social media campaigns because of the intense size, range and variety of data (Hutto and Gilbert, 2014). The VADER lexicon dictionary is extensible which allows for the detections of particular words or phrases and even configuration to a body of study (Daniulaityte *et al.*, 2016). Other analytic models such as ML become useful as social media campaigns prolong.

In addition, Hutto and Gilbert (2014) refer to the sentiment lexicon of VADER as the "gold standard" which included manual validation by humans. Hutto and Gilbert (2014) compared the effectiveness of VADER to eleven typical sentiment analysis models such as Affective Norms for English Words (ANEW), LIWC, SentiWordNet (SWN) and also those that utilise machine learning techniques that depend on Naïve Bayes, Maximum Entropy and Support Vector Machine (SVM) algorithms. They found that VADER ranked the highest in predictive accuracy when tested on 4 200 tweets from Twitter, 3 708 product review snippets from Amazon.com, 10 605 movie review snippets and 5 190 article snippets from NY Times Editorials. Parikh and Movassate (2009) assert this effectiveness of VADER further justifying its selection for usage on social media type data such as the #FeesMustFall tweets in this study.

Further, Twitter, much like any other social media platform, contains text that does not necessarily abide by proper grammar, correct word spelling or punctuations. An example of this can be seen in the following tweet:

> *"Y nt Join the #FeesmustFall http://www.fmf2016.org.za ☺"*

This tweet contains an emoticon (☺) a hashtag (#FeesmustFall) and a URL all of which may require appropriate handling prior to the sentiment analysis phase depending on the sentiment model being applied. The advantage of the VADER model is that the tweet requires no such handling prior to the sentiment analysis phase. Characters, as well as languages outside the lexicon of VADER, are treated with a zero score and reflected as a neutral sentiment.

After considering all of the above, VADER was selected as the model to analyse sentiment for this study due to its higher accuracy performance levels and effectiveness when compared to various other sentiment models. Furthermore, VADER was designed specifically to examine sentiment of microblog type texts such as tweets from Twitter which fits in well when attempting to analyse a longitudinal dataset compromising of #FeesMustFall related tweets.

Having argued the case for the choice of VADER, the choice of software, tools and programming languages for sentiment analysis can now be elaborated (section 3.5)

3.5 Software, tools and programming languages for sentiment analysis

A brief review of some commercial and non-commercial computer products capable of conducting sentiment analysis are now presented for completeness. Table 2 lists various commercial and free software thereafter commercial and open-sourced products (section 3.5.1) followed by related programming languages (section 3.5.2) discussed next. In addition, the decision to use open-source programming tools (section 3.5.3) for this study are explained.

Table 2 Commercial and free software for sentiment analysis

Product	Service Type	Free/Paid	Website Hyperlink
DiscoverText	Cloud-based	Paid	www.discovertext.com
Google Cloud Natural Language API	Cloud-based	Paid	cloud.google.com/natural-language
Hootsuite	Cloud-based	Paid	www.hootsuite.com
IBM Watson Natural Language Understanding	Cloud-based	Paid	www.ibm.com/watson/services/natural-language-understanding
Microsoft Text Analytics API	Cloud-based	Paid	azure.microsoft.com/en-us/services/cognitive-services/text-analytics
Rapidminer	On premise	Paid	www.rapidminer.com/solutions/text-mining
NCSU Tweet Visualizer	Cloud-based	Free	www.csc2.ncsu.edu/faculty/healey/tweet_viz/tweet_app
Sentiment Analyzer	Cloud-based	Free	www.danielsoper.com/sentimentanalysis/default.aspx
SentiStrength	On premise	Free[17]	sentistrength.wlv.ac.uk

The cost associated with the commercial products from Table 2 prevented their usage in this study with SentiStrength the only free product from this list capable of processing large volumes of data. It was not selected due to its inferior lexicon size of 2 698 compared to VADER's 7 517 and being domain dependant (Ribeiro *et al.*, 2016).

[17] SentiStrength is free for academic research only

3.5.1 Commercial and open-source products for sentiment analysis

Prominent commercial and open-source products capable of performing sentiment analysis include Apache Hadoop, SAS, NodeXL and Talkwalker. They were purposely not mentioned in Table 2 in order to be briefly described below.

3.5.1.1 Apache Hadoop or Hadoop

Hadoop is a collection of open-source software tools using networked computers to solve problems involving massive amounts of data and computation (White, 2012). Furthermore, it is free for download and commercial use, however the complexity associated with utilising and operating Hadoop in enterprises often requires skilled support which generally comes at a certain cost. The researcher was unfamiliar with Hadoop and therefore opted against its use for this study.

3.5.1.2 SAS

SAS is a proprietary comprehensive statistical and data management tool developed by the SAS Institute. It is used internationally by government, private industry, and academia. SAS is the largest privately-owned software company in the world (Brittain *et al.*, 2018). The cost precluded this option being selected for this study.

3.5.1.3 NodeXL

NodeXL is a free but limited visualization software package for Microsoft Excel in order to conduct SNA. NodeXL Pro is a fee-based fully featured version of NodeXL that includes access to social media network data importers, advanced network metrics, automation and sentiment analysis. It is useful to follow influencers in a campaign but it has a restriction of 18 000 tweets (Hansen, Shneiderman and Smith, 2010), which made it unsuitable for this study.

3.5.1.4 Talkwalker

Talkwalker is a commercial product that offers comprehensive social media analytics services capable of undertaking sentiment analysis across various social media platforms (Talkwalker, n.d.). The closed nature of its functions together with the cost made it unfeasible to be used for this study.

3.5.2 Programming languages for sentiment analysis

Sentiment analysis requires programming languages that are suited to NLP and three of the most common, Python, R and Java are presented next. Python is selected for this study and discussed first.

3.5.2.1 Python

Python is an open-source programming language meant for software integration and development (Brittain *et al.*, 2018). Further, it has an extensive range of online libraries (packages) and reference materials with an active helpful online research community. A package is a collection of modules which in turn contain definitions and statements to execute functions or determine classes. Python has a better coding and syntax for the author (Python Software Foundation, n.d.b.; Brittain *et al.*, 2018). Natural Language Toolkit (NLTK) and TextBlob are two famous NLP packages for Python that are capable of performing sentiment analysis on text (Bird, Klein and Loper, 2009; Loria *et al.*, 2014).

Python was selected for use in this study due to the researcher's familiarity with the programming language.

3.5.2.2 R

R is an open-source programming language that was initially developed mainly for statistical learning but has since evolved to include extensive areas such as AI and NLP (RC Team, 2013). Further, R, like Python, plays a significant role in big data and text mining analytics. It also possesses a large and growing collection of NLP-related algorithms which can perform sentiment analysis.

R was not selected for this study due to the researcher being more familiar with Python than with other NLP capable programming languages.

3.5.2.3 Java

Java is a class-based and object-oriented programming language which is recognized as the most popular programming language for Android smartphone. It has many NLP libraries such as Stanford CoreNLP (Manning *et al.*, 2014) and Apache OpenNLP (Reese, 2015) that allow text to be automatically clustered, tagged and tokenised for Sentiment Analysis.

As noted earlier (section 3.5.2.2) Python was selected ahead of many programming languages, including Java, over familiarity concerns.

3.5.3 The decision of an open source software approach

Ahmed's research (2017) is novel as it takes the Ebola and Zika challenge, and uses qualitative methods to examine the tweets. The work was time intensive due to the need for individual analysis of the tweets. The lack of automation may discourage or mitigate adoption or even replication of such a study. Further the volume of tweets (576 583) discourages this option. Therefore, a decision was made to use software and an algorithmic approach to determine the sentiment of the #FeesMustFall activists. This affirmed the quantitative approach for this study, which is discussed in more detail in chapter 4.

Many studies use an application programming interface (API) to access web-based software applications or web-based tools (Gaffney and Puschmann, 2014). There are also several tools for analysing social media, some commercial and some open source such as SAS, Hadoop, etc (White, 2012). The challenge of common-off-the-shelf-software (COTS) analytical tools is cost and hidden algorithms which raises concerns in verifying produced results and adopting a framework (Thakur, 2015). This influenced the decision to use the Python programming language. This study, therefore, uses a combination of user-developed Python, and the VADER Python library code (Hutto, n.d.; Python Software Foundation, n.d.a) to prepare the data for interrogation and analysis.

It must be pointed out that other software applications are capable of undertaking the data analysis, however, the closed box nature of certain commercial applications implies the researcher was unaware of their algorithm. This is an important point since non-transparent algorithms prevent researchers from rigorously assessing its credibility which is often required to provide reliable analysis particularly on sensitive topics.

3.6 Conclusion

Chapter 3 provided the definition for Sentiment analysis together with its multiple uses and its rationale for this study. Sentiment analysis can be applied in many ways (section 3.3.5) mainly utilizing a lexicon or machine learning approach which has already been successfully utilized in research topics (section 3.3.1) such as disease outbreaks, financial stock markets and public protests. The lexicon based model, VADER, was chosen for use in this study which was explained and justified (section 3.4). Several other software and tools were discussed (section 3.5) for completeness with the VADER library in Python the preferred choice adopted for this study due to its open source nature and exempt from commercial costs.

Chapter 4 discusses the study's research methodology. As noted, since sentiment analysis is the study's data analysis method, the details of sentiment analysis are not outlined in chapter 4. The focus is instead on the study's philosophy and methodology and the data analytics process that was followed to generate the study data and convert it into a form on which sentiment analysis could be undertaken.

Chapter 4 Research Methodology

4.1 Introduction

In chapter 2, a review of the literature on #FeesMustFall on Twitter revealed that there have been a number of rich non-ICT and a few data science research efforts on the #FeesMustFall campaign, but to date there has been no longitudinal study of Twitter in the #FeesMustFall campaign, and no study of the role of social robots during the campaign. In addition, a review of the history of #FeesMustFall suggested that there were real world events that may have shifted perceptions of #FeesMustFall. The literature pointed to the value of sentiment analysis as a theoretical framework and analysis tool for studying shifts in sentiment during #FeesMustFall over a longitudinal period. Given the length of this chapter, as well as the technical detail involved, and the fact that the investigation of sentiment analysis influenced the choice of methodology for the study, the discussion of sentiment analysis was covered in chapter 3.

This chapter provides a comprehensive discussion of the study's research philosophy, design, data sources and data analytics method and ethical considerations.

The identification, acquisition, range, pre-processing and processing of the corpus of tweets is described. This includes issues relevant to data-mining of Twitter. The pre-processing involved the removal of non-discernible tweets, exact duplicates and non-English tweets. The processes for sentiment analysis, change-point analysis and bot detection are also described and defended. The chapter is deliberately pedantic given the relative newness of sentiment analysis.

This study was guided by the main research questions previously outlined in chapter 1 which are as follows:

- *Question 1: What was the prevailing sentiment of Twitter users during the #FeesMustFall campaign?*
- *Question 2: How did the burning of the UJ Hall and the UKZN Library relate to online sentiment trends and polarity?*
- *Question 3: Were social robots deployed on Twitter during the #FeesMustFall campaign?*

This chapter is organised as follows: First the research paradigm is explained (section 4.2), followed by research strategies and research design (section 4.3), data sources and the selection of Twitter data (section 4.4), and the data sources and Data Analytics Lifecycle that was applied to the data (section 4.5). The chapter concludes with a summary of the main arguments made (section 4.6).

4.2 Research paradigm: Post-Positivism

This study's chosen philosophic research paradigm is post-positivist. Post-positivism is distinct from positivism. Positivism sees the universe as deterministic with only the scientific method rules of cause and effect (Hacking, 1983; Creswell, 2013). On the other hand, post-positivism recognises that the manner in which both scientists and non-scientists operate, think and work are not different. Post-positivism argues that scientific reasoning and common sense reasoning is essentially the same process. Post-positivism recognises that not all observations are free from fallibility and error and that theory is revisable and reversible. Where the positivist believes that empirical science is the only way to uncover the truth about reality, the post-positivist believes that the role of science is to hold steadily onto the goal of getting it right about reality, even without ever achieving a goal; and that absolute knowledge of reality cannot be achieved through empirical sciences alone (Creswell, 2013; Creswell and Creswell, 2017).

Post-positivism suits social media research as both the underlying infrastructure (Internet Web 2.0, established in 2004) and the application (Twitter, established in 2006) are in their infancy at the time of writing. Further, natural language processing (NLP) tools and techniques to analyse the huge amount of social media are also in a developmental state with respect to technique (machine learning or lexical), scale (big data) and scope (content analysis, sentiment analysis etc) (Mayer-Schönberger and Cukier, 2013).For these reasons, this research study applies a post-positivist paradigm.

4.3 Research strategies and research design

This section outlines the study's methodology choice (section 4.3.1), research approach (section 4.3.2) and time horizon (section 4.3.3).

4.3.1 Methodological choice: Quantitative

Research methodology is the systematic process of information collection, analysis and interpretation. It usually comprises of two types, qualitative and quantitative methodologies, but there is a third methodology, mixed methodology, which is a combination of qualitative and quantitative methodologies (Creswell, 2013; Creswell and Creswell, 2017). This research study adopts a quantitative methodology due to the researcher's intention of providing a numerical and statistical outlook into opinions expressed in large volumes of social media type data. The view is that an empirical approach to understanding sentiment trends and patterns not only significantly reduces the amount of time and effort usually found in manual approaches but also can be utilised on a broader scale due to its portability.

Quantitative methodology utilises mathematical and statistical analytical methods to measure collected data by employing pre-existing statistical and computational techniques (Creswell and Creswell, 2017). It also aligns with the post-positivist worldview (Ibid). In quantitative research the core focus is on obtaining numerical data in order to explain a particular phenomenon or to generalize across many domains (Creswell, 2013; Creswell and Creswell, 2017).

In the particular context of #FeesMustFall, the study's ultimate goal was to automatically analyse sentiment which perfunctorily points to a quantitative mode of study. Can one, by monitoring online sentiment, mediate or leverage a sentiment? Predicative analytics would say yes and these analytics are already being used with respect to stock markets (Smailović *et al.*, 2013). In addition, Swamy (2017) showed that it is possible to retrospectively predict outcomes where the choice-decision-options are known in advance e.g. who will win the Oscar awards.

Qualitative methodology, on the other hand, is not selected for this study. Qualitative methodology focuses on interpretation and the quality of things (Creswell and Creswell, 2017). Hamad *et al.* (2016) argues that "text is always qualitative to begin with and the quantification of text alone is insufficient for successful understanding of content." This suggests that the study could also use qualitative methods, which means it could be a mixed mode of study involving both qualitative and quantitative modes of study. In fact, the mixed-mode methodology was used in studies by Bosch

(2016), Ballie-Stewart (2017) and Ahmed (2018) who included a mixed qualitative mode approach to their Twitter analysis.

That said, for the purposes of this study, it is quite apparent that human analysis of the huge #FeesMustFall longitudinal dataset is impractical. Indeed, 576 583 tweets is a cumbersome task to examine manually and not a portable solution, hence the need for an automated method (Mondal, 2016). This is also an ICT thesis that is confronted with a rich albeit large data set which demands a software approach which is well suited to quantitative methodology.

Finally, Gardner and Galanouli (2004: 148) bemoan the lack of quantitative studies in ICT and are dismissive of the debate around the “either-or” approach insisting “that the fit-for-purpose principle should be the central issue in methodological design.” It is argued that a mono-method quantitative methodology is fit for the purpose for this study. For all of these reasons, this study follows a quantitative research methodology.

4.3.2 Research approach: Deductive

This study follows a deductive approach to analysis since the selected research methodology is quantitative (section 4.3.1) and quantitative analysis requires deductive approaches (Creswell, 2013). A deductive approach requires that a theoretical structure be developed from which hypotheses are then constructed and tested by empirical observation using instruments that measure variables defined from the developed theory (Ibid). This flow is depicted in Figure 7.

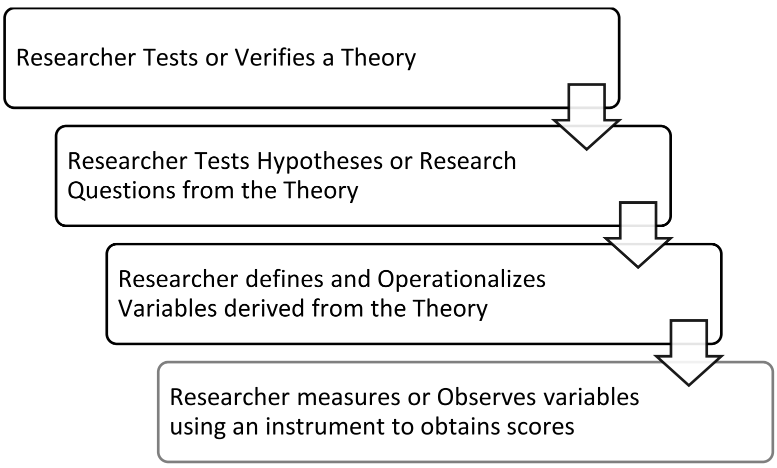


Figure 7 Typical deductive approach utilised in Quantitative studies

Furthermore, this study adopts a deductive approach because it quantitatively examines changes in sentiment trends based on real-life events. Its premises are that Twitter at a macro level reflects sentiment which is adversely affected by perceived negative events. Further a meso study of some of the tweet behaviour will be analysed to determine if social bot behaviour attempted to influence sentiment change.

4.3.3 Time horizon: Longitudinal

A longitudinal study is an observational research method in which data is gathered for the same entity repeatedly over an extended period of time. Longitudinal research projects can extend over a time horizon of several years (Dawber, Kannel, and Lyell, 1963). As data was collected for a period of 14 months in this research, its time horizon is longitudinal. The entity that is studied is the Twitter #FeesMustFall campaign.

4.4 Data sources and Twitter as a data source

In this section, an overview of the study's data sources is provided (section 4.4.1) and the choice of Twitter as a data source is explained together with the challenges this choice brings (section 4.4.2). Thereafter the data handling process for this study is elaborated.

4.4.1 Overview of data sources used in the study

The data sources used during the various phases of this thesis include accredited electronic databases and search engines such as Google Search, Google Scholar Search, conference publications, popular, traditional[18] and online media, and textbooks due to the newness of the topic and Twitter.

Table 3 illustrates which data sources are used during the various stages of the study.

[18] For the purposes of this study traditional news comprises newspapers, radio news and television news.

Table 3 Data sources used during the research

Research phase	Data source
Literature Review	Relevant publications in electronic databases, search engines such as Google Search, Google Scholar Search, conference publications, popular, traditional and online media, textbooks and user manuals
Review of software options for analysis	Google Scholar Search, Conference publications, Twitter, available experts, GitHub Python, textbooks and user manuals
Analysis of Tweets	Twitter, VADER, Python, MS Excel 2016 and Change Point Analyzer
Visualisation	Tableau, MS Excel 2016

4.4.2 Twitter as a data source

Twitter is increasingly being used as a data source for diverse research purposes in various areas such as finance, health, disaster management, public management and national elections (Sakaki, Okazaki and Matsuo, 2010; Acar and Muraki, 2011; Chung and Mustafaraj., 2011; Bruns and Liang, 2012; Cho, Jung and Park, 2013; Smailović *et al.*, 2013; Singh *et al.*, 2017; Swamy, 2017; Ahmed, 2018). Twitter has and continues to attract researchers with large amount of literature[19] in support of utilizing this platform for research. This is one contributing factor for the selection of Twitter as the data source for this study with the others related to the convenient nature of searching, retrieving and analysing information from Twitter (section 2.2).

The social media popularity landscape for South Africans during years 2015, 2016 and 2017 showed that Twitter was always ranked 3rd amongst the top three most popular social media platforms with Facebook ranked 1st and Youtube 2nd (StatCounter, n.d.; Businesstech.co.za, 2016; 2017). These years coincide with this #FeesMustFall longitudinal study.

Twitter was selected over other social media platforms because #FeesMustFall inherently adopted the '#' symbol as part of its slogan (name) which is synonymous to the hashtag feature associated with Twitter. Whether this was a deliberate attempt to promote Twitter activity around the campaign or not is beyond the scope of this study

[19] A search on Google Scholar: http://scholar.google.com with Twitter as the keyword reveals hundreds of related studies that utilise Twitter as a data source

but it is intriguing to point out that the popularity of Twitter grew in South Africa from 7.4m to 8.0m during this campaign (Businesstech.co.za, 2016; 2017). Instagram also makes use of the hashtag feature; however, Twitter outranked Instagram as the more popular social media platform for South Africans in years 2015, 2016 and 2017 (Businesstech.co.za, 2016; 2017). The interesting hashtag feature of the #FeesMustFall campaign together with its popularity in South Africa prompted the researcher to eventually select Twitter ahead of other social media platforms such as Facebook and Instagram. Further, although Twitter is a numeric minnow (Clement, 2019b) when compared to Facebook's more than two billion worldwide active users, Twitter arguably is still seen as an influential platform for various stakeholders such as journalists, politicians and academics who have a major presence on the platform with active engagement (Carpenter and Krutka, 2015; Park, Reber and Chon, 2016; Hu and Hong, 2017; Murthy, 2018; Bane, 2019). In addition, Twitter is now certainly as important as print media given that daily newspaper sales account for 1.051 million papers per day (or about 5 million readers) (Manson, 2018) whereas Twitter has an average of 7.9m users tweeting every day. These figures add to the justification of using the Twitter platform for this study.

There are, however, some challenges with using Twitter as a data source. Twitter analytics are exacerbated by challenges surrounding the long-term availability of data, research ethics, the interpretation of user-generated information, and the relation of qualitative and quantitative, as well as user-based and content-based research approaches (Ahmed, 2018). These challenges are not uncommon in social media research (Giglietto, Rossi and Bennato, 2012), however, they do not prevent research but rather offer opportunities when carefully factored in (Sinnenberg *et al.*, 2016).

In terms of credibility, Bruns and Stieglitz (2014) reveal that Twitter is often accused of being an unreliable scientific source and is generally a product of minority groups often lacking broader representation. However, as the popularity and usage of Twitter grow in events such as epidemics, protests and political voting, research on Twitter data gains value as information from this platform may be used for analysis such as prediction and causality (O'Leary, 2015). This researcher assumes the latter view due to the national impact of the #FeesMustFall campaign and the digital age we currently live in (Gregorian Year 2019).

Twitter is also a public platform which means that it contains rich information about online communities otherwise not easily accessible through interviews, surveys and questionnaires (McKenna, Myers and Newman, 2017). This together with its other beneficial features outweighs its limitations when considered as a credible data source for research (Anderson, Bell and Shirky, 2015; Ahmed; 2017; AFP, 2018).

The significance of the #FeesMustFall campaign in South Africa is well documented and continues to attract researchers who aim to extract meaningful information regarding the different aspects (Booysen, 2016; Naicker, 2016 ; Langa *et al.*, 2017; Ramluckan, Ally and van Niekerk, 2017; Khan and Thakur, 2018). This study makes use of Twitter as a data source and extracts from it sentimental information surrounding the #FeesMustFall campaign over a longitudinal period.

4.5 Data analytics: How data is handled in this study.

Ahmed (2013) and Vis (2017) strongly suggest that it is important during social media research to document the date and types of data retrieved as well as the source code. This means that it is important for this study to document the procedures of when, how, why and what data was retrieved, cleaned and analysed because other researchers may duplicate this present study for similar social media campaigns**.**

In this study, the Data Analytics Lifecycle suggested by Erl, Khattak and Buhler (2016: 55), which compromises nine stages as illustrated in Figure 8, will be used to explain the data handling process. There are other suggested data analytics lifecycles with Dietrich (2013) and Prajapati (2013) outlining six and five phases respectively. The approach by Erl, Khattak and Buhler (2016) is preferred for this study due to its pedantic outline of stages which can also be applied to big data analytics.

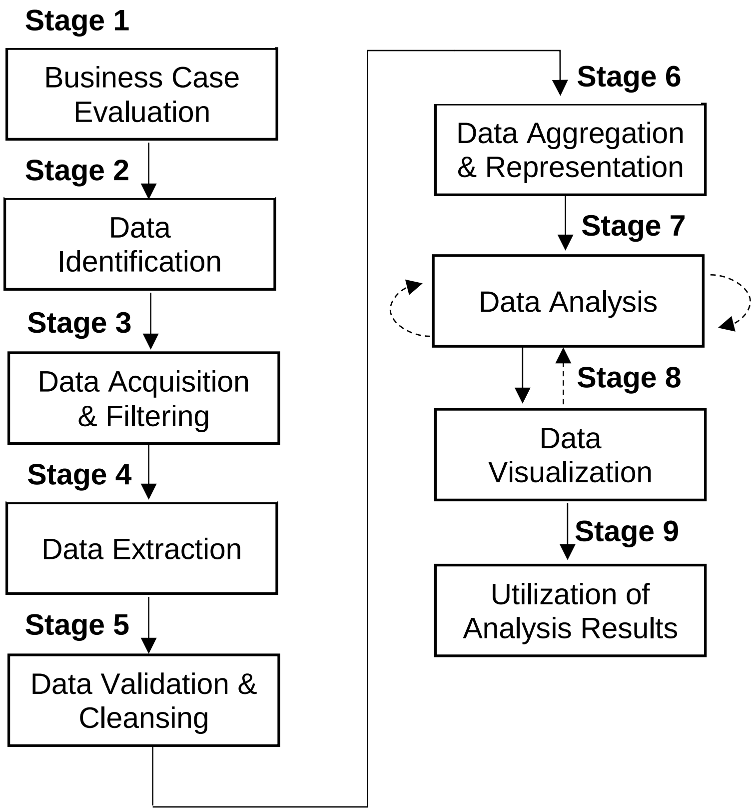


Figure 8 The Big Data Analytic Lifecycle (Erl, Khattak and Buhler, 2016)

In the rest of this section, Stage 1 Business case evaluation (section 4.5.1); Stage 2 Data identification (section 4.5.2); Stage 3 Data acquisition (section 4.5.3); Stage 4 Data Extraction (section 4.5.4); Stage 5 Data validation and cleansing (section 4.5.5); Stage 6 Data aggregation and representation (section 4.5.6) and Stage 7 Data analysis (section 4.5.7) will be elaborated. Stage 8 Data visualisation (section 4.5.8) and Stage 9 Utilization of analysis results (section 4.5.9) are only briefly elaborated as the evidence of these stages is outlined in the findings in chapter 5.

4.5.1 Stage 1: Business case evaluation

The first stage in the Data Analytics Lifecycle is business case evaluation. In this stage, the justification, motivation and goals of the analysis need to be clearly presented (Erl, Khattak and Buhler, 2016). In relation to this study, the research problems, questions, aims and objectives outlined in chapter 1 together with a review of relevant literature covered in chapter 2, provided the justification, motivation and goals for the selection of the #FeesMustFall campaign as a business case. In chapter 3 the choice to examine the sentiment of the social participants and commentators during a defined period and to examine the nature and extent of bot impact in driving influence using Sentiment Analysis was clearly explained.

The term *Literature Review* is typically used to describe the written component of a research plan or information which discusses the reviewed documents. Aveyard (2014) states that these documents can include articles, abstracts, reviews, monographs, dissertations, other research reports, and electronic media. Gay, Mills and Airasian (2011) found that the major purpose of reviewing literature is to determine what has already been done that relates to a topic, preventing any unintentional duplicating of another person's work. Hence, it can be advocated that the overall function of the literature review is to provide a justification of the proposed research project, indicating how it will be different to that which is already published and to identify a gap of knowledge in the research focus area (Creswell and Creswell, 2017). The case justifying the relevance of this study has, it is argued, been clearly articulated and supported in chapter 2 and the choice of sentiment analysis has been clearly argued in chapter 3.

4.5.2 Stage 2: Data identification

Stage 2 of the Data Analytics Lifecycle is data identification. This stage refers to identifying datasets and their sources required for the analysis (Erl, Khattak and Buhler, 2016). For this study, it was decided to analyse the #FeesMustFall tweets given the high Twitter activity and the fact that tweets are largely public (section 2.2). Twitter was, therefore, selected as the target social media platform (section 4.4.2) to source out a dataset for analyses. Creating a corpus of tweets does not have the same ethical and privacy implications as interview transcripts or questionnaire data, because tweets are inherently public and readable, when posted to a public account, by anyone with an Internet connection unless the messages are direct messages (DMs), protected or private accounts (Thelwall, 2014).

Some of the decisions that were made in regard to data identification for this study are now elaborated. Specifically the discussion outlines the choice of hashtag '#FeesMustFall' (section 4.5.2.1); the dataset (section 4.5.2.2) and the data range of the dataset (section 4.5.2.4).

4.5.2.1 The Choice of #FeesMustFall

This section provides rationale for selecting the hashtag '#FeesMustFall' for analysis (The #FeesMustFall campaign's significance and importance already discussed in section 2.4).

In order to conduct research on data from Twitter, it is possible to retrieve information and create a corpus via keywords or metadata such as hashtags, account handles, time frames, etc. (Burgess and Bruns, 2012). It is important to note that using limited hashtags or keywords to search for all data related to a relevant topic on Twitter such as #FeesMustFall may not be fully retrieved if users referred to the topic using alternate hashtags or keywords. For instance, '#fees2017' and #WitsMustFall relates to the #FeesMustFall campaign but will be excluded when searching for '#FeesMustFall' as the keyword. This researcher has used the keyword '#FeesMustFall', which is not case sensitive on Twitter, to retrieve data as it was deemed the most popular (Langa *et al.*, 2017). Other related hashtags were excluded due to their lesser popularity and additional costs associated in acquiring their historical data (section 4.5.3.1). Furthermore, the hashtag '#FeesMustFall' is cited across most, if not all, literature that references the #FeesMustFall campaign. This makes it the core keyword when querying information about the campaign.

In terms of retrievability, Twitter's hashtag feature conveniently allows for aggregating and harvesting data about the #FeesMustFall campaign by simply utilizing the term "#FeesMustFall" in Twitter search queries (section 2.2). Furthermore, tweets with this hashtag allows for contextual searches, grouping of responses, identification of trends and other forms of meta-analysis. For example, consider the following tweet by user, African Princess (2015) with Twitter handle @MaqCrazyNerd:

"8am DUT steve biko campus that's where imma be at tomorrow #FeesMustFall #DUT #MUT #UKZN #DurbanShutDown"

This tweet contains multiple hashtags with university acronyms which can be considered opportunistic tagging that was intended to attract and create awareness about the #FeesMustFall campaign amongst personnel affiliated across the Durban University of Technology (DUT), Mangosuthu University of Technology (MUT) and UKZN.

4.5.2.2 The dataset

The dataset for this study comprised only of a corpus of text data (tweets) embedded with emojis and emoticons and audio, images and videos were not considered, as noted in delimitations in section 1.9. This was guided by the selection of VADER (section 3.4) for this study which does not analyse audio, images and videos. Further, audio and visual processing require different forms of analysis which is beyond the scope of this study. These are also delimited.

The dataset also only compromises of tweets that contain the hashtag '#FeesMustFall' since it was the only hashtag requested for acquirement (section 4.5.2.1 and 4.5.3.1). Furthermore, specific requirements were outlined regarding the dataset's date range (section 4.5.2.3). There were no further conditions applied when requesting the dataset such as geolocation and specific users. The related metadata for each tweet (section 4.5.3.3) completes the dataset makeup.

4.5.2.3 Date range of the dataset

The literature review revealed the timeline of key historical events in #FeesMustFall. The timeline determined for the collection of Twitter data was set from the first mention of the #FeesMustFall, on 21 March 2015, until the 10 April 2017, despite the fact that the actual movement started on 15 October 2015. There were 2 outlier tweets between March and October 2015 which provided historical context (Figure 2 and 3).

The entire #FeesMustFall data were not extended until year end of 2018 due to the following reasons:

1. Financial cost
2. Length of time to get further research grant(s) to purchase data
3. This research proposal was designed in May 2017
4. Getting a second set of data from April 2017 to 2018 or the current date will introduce two disparate data sets albeit on the same campaign. Connecting the two "live" online data sets is not the same as one contiguous set. This is because data may be deleted, suspended or made private in the time span between the first and second download. This was deemed a research risk and delimited.

In summary, the data identification stage consisted of identifying the data source, data type and data range. These were identified as Twitter, #FeesMustFall tweets (excluding audio, images and videos) and 21 March 2015 until 10 April 2017 respectively.

In section 4.5.3 the data acquisition process is elaborated. In particular, the purchasing of data is discussed (section 4.5.3.1); how Twitter data is usually harvested is explained (section 4.5.3.2); the acquired tweet metadata is elaborated (section 4.5.3.3).

4.5.3 Stage 3: Data acquisition and filtering

Stage 3 of the Data Analytics Lifecycle is data acquisition and filtering. Erk, Khattak and Buhler (2016) consider this stage as the collection or gathering of all identified data sources and the filtering of irrelevant and corrupt data. Corrupt or irrelevant data are records which contain invalid data types or missing or nonsensical values and the “filtering” means removing corrupt data wherever detected.

After sustained efforts to retrieve credible longitudinal data on the campaign at no extra cost, the researcher eventually purchased 576 583 data points or tweets from a professional data service provider, Podargos,[20] with financial support (section 4.5.3.1) having conditions outlined in section 4.5.2. The obvious choice to purchase from Twitter itself was not possible due to high comparative costs (Twitter Inc., n.d.b).

The public-private dichotomy of Twitter data implies all tweets posted are accessible to anyone accessing the Twitter website or using a third-party client. For this study, the request to Podargos regarding the acquisition of #FeesMustFall from Twitter was explicit meaning all FeesMustFall-related references of the campaign were ignored if they did not contain the ‘#FeesMustFall’ hashtag. This is a significant decision which excluded many records. Time, complexity and cost were factors that drove this decision. Thus “FeesMustFall” (without the #), “WitsFeesMustFall” and the like were excluded unless they were paired with #FeesMustFall. The dataset acquired was in an ASCII delimited format. Further, data deemed corrupt or irrelevant data were removed from the dataset. This is where neither the researcher nor the software could make sense of a particular tweet. It is important to provide statistics of data that is excluded.

[20] www.podargos.com

4.5.3.1 Data purchase

As noted, data had to be purchased from Podargos for this study. The purchasing of data is not ideal. However, Jud Valeski CEO of Gnip, says “data is not free, and there’s always someone out there that wants to buy it” (Steele, 2011). Twitter limits direct access to their data and until this is removed the data-accumulation process will always be restricted. It thereafter does not matter who acquired the data as one will never be sure if the data is the population. An entire commercial ecosystem is forming around social data, and includes analytics companies such as Gnip and Podargos (Burgess and Bruns, 2012; Gaffney and Puschmann, 2014; Puschmann and Burgess, 2014; Hawamdeh and Chang, 2018).

4.5.3.2 How Twitter data is usually harvested

Typically, the majority of Twitter data is harvested using retrieval methods such as the Streaming API or the Search API (Gaffney and Puschmann, 2014). The Streaming API is utilised most widely for quantitative research (Gaffney and Puschmann, 2014; Ahmed, 2018). The Streaming API is known as a push-based service as data is typically captured live, and is provided through three bandwidths: ‘Spritzer’, ‘Garden-hose’ and ‘Firehose’, which can deliver 1%, 10% and 100% of available tweets respectively, over a short period of time (Gaffney and Puschmann, 2014; Ahmed, 2018).

It was not possible to use ‘Spritzer’ or ‘Garden-hose’ in this study because the gathering of data is restricted to short intervals and limited to approximately 3 200 points (Hernandez-Suarez *et al.*, 2018). These are mentioned for completeness and are not pursued further.

This study thus uses Search API and the ‘Firehose’ bandwidth method albeit through a vendor because Twitter does not grant access to its historical data for free (See 3.5.3).

4.5.3.3 Tweet metadata

Formally each tweet (data point) that was analysed comprised of metadata that included the Tweet text; Date Timestamp; Username; Tweet Source; Favourite[21]; Retweet, User Language and Tweet Language (Figure 5 and Table 1).

[21] The Facebook equivalent term is “Liked”

The following list is adapted from Table 1 that briefly describes the aforementioned metadata:

Tweet: A message containing texts, emoticons and symbols limited to 280 characters (140 previously)

Date Time Stamp: Gregorian calendar Date and the time of the tweet

User name: Unique identification of the user who tweeted

Tweet Source: The device used to send through a tweet

Favourite: Tweet tagged as favourite

Retweet: Tweet that has been reposted or forwarded

User Language: A user's associated language according to their profile

Tweet Language: Most dominant language expressed in a tweet e.g. English

In summary, the data was acquired using the services of a commercial data service provider, and harvested using Search API and the 'Firehose' bandwidth method albeit through a vendor. Tweet metadata for analysis was described.

In the next section (4.5.4), stage 4 (data extraction) is explained.

4.5.4 Stage 4: Data extraction

Stage 4 of the Data Analytics Lifecycle is data extraction. This stage involves the extraction of inappropriate formatted data into a format that is suited for analysis (Erl, Khattak and Buhler, 2016). Frequently, companies extract data in order to process it further, and migrate the data to a data repository such as a data warehouse or a data lake for further analysis (Alley, 2018).

In this study, data extraction involved extracting the harvested #FeesMustFall tweets from an ASCII delimited file (section 4.5.3) to a Microsoft Excel format which made it convenient for each analysis phase (section 4.5.7). For instance, the sentiment analysis phase required the dataset to be extracted into a Microsoft Excel file and thereafter imported into Python for further analysis. Further, some of the data visualisations (section 4.5.8) required importing the Microsoft Excel formatted dataset into Tableau whilst others required the extraction of information from Microsoft Excel into the CPA (section 4.5.7.4).

In summary, the data extraction phase involved transforming the original formatted dataset into an appropriate format for analysis. This was achieved by extracting all data from the ASCII delimited dataset into a Microsoft Excel file.

The next section (4.5.5) discusses Stage 5 – data validation and cleaning

4.5.5 Stage 5: Data validation and cleansing

Stage 5 in the Data Analytics Lifecycle is data validation and cleansing. This stage cleans invalid data found in the datasets by either correcting or removing them depending on the analysis to be performed as they may skew and even falsify results (Erl, Khattak and Buhler, 2016). Further, this stage pre-processes data into meaningful forms that are sometimes required prior to the analysis phases (section 4.5.7).

In this section the validity of the tweets (section 4.5.5.1), the population and sample (section 4.5.5.2), ethical considerations such as Tweet copyright (section 4.5.5.3) and user anonymity and privacy (section 4.5.5.4) are outlined. Thereafter data pre-processing (section 4.5.5.5) is discussed, before elaborating on data security (section 4.5.5.6).

4.5.5.1 Validity of the tweets

Given that the data was received from a third-party source, the reliability of the company comes into question. The credibility of Podargos as a professional data service provider is recognized by Chahal and Kapur (2018) that mentioned the company when elaborating on emerging data service providers due to API limitations imposed on Twitter and Facebook. This together with the company's services utilised in peer reviewed papers by Valli, Uma and Sasikala (2017); Khan and Thakur (2018) and an accepted thesis by Mtchedlidze (2019), reassured the researcher.

4.5.5.2 The population and sample under review

Traditional research paradigms identify the population, calculate a statistically appropriate sample size, and obtain the sample using an appropriate sampling method. The sample points may be purposeful or random. Thereafter the relevant analysis is done. This study uses all the available Twitter #FeesMustFall data obtained at a particular point in time, for the observational period. It is important to note that the available corpus of tweets does not equate to the entire population of #FeesMustFall tweets for the following reasons:

- Tweets become unavailable when deleted by the user (by choice) or
- A User account is suspended by Twitter. This is likely given Twitters anti-bot stance
- A User deletes account
- A User changes privacy settings
- The hashtag #FeesMustFall is exact and discriminatory. Even spelling errors are excluded. For instance, campaigners who omitted the '#' symbol and just typed "FeesMustFall" or similar words in conversations would be excluded.

(Roth and Harvey, 2018)

There were a number of ethical considerations considered in the data validity with copyright concerns discussed next (section 4.5.5.3) and privacy concerns (section 4.5.5.4) is discussed thereafter.

4.5.5.3 Tweet Copyright

Ahmed (2018) asserts that using tweets for non-commercial research is possible and ethical by citing the United Kingdom's Copyright, Designs and Patents Act (1988). The Act allows exceptions to the use and analysis of copyrighted work, for:

- Non-commercial research and private study
- Text and data mining for non-commercial research
- Criticism, review and reporting current events

This Act thus allows for the legal usage of Twitter data in this study since it meets these criterion. Further, Twitter data that are made private or deleted cannot be accessed through both of its APIs except public data which can be viewed or retrieved by anyone with access to the internet. There is no need to subscribe, enter a password, or pay to access the data[22]. This study only researched tweets that were marked as public. Twitter informs new users in its 'terms of service' that public tweets

[22] Although this study paid for a large volume of the data (Section 4.1.8.1)

are visible to anyone regardless of whether they have a Twitter account or not. Thus the researcher is pacified that no copyright was deliberately infringed.

4.5.5.4 User anonymity and privacy

The discussion of Twitter being public notwithstanding, Beurskens (2014) implores that the researcher must make best efforts to remove any personal references such as names and replace them with pseudonyms. As the researcher analyses the tweets for sentiments through software there is little likelihood of their identities being revealed. Further, the tweets are not displayed – just the sentiments. It is only the top tweeters who are identified. The tweets published are minor celebratory instances e.g. the first tweet.

Beurskens (2014) further suggests one should anonymize location data. The lack of location metadata in the dataset fortuitously, therefore, has turned into an advantage. The data was not shared with any researcher. It will only be shared through the university guidelines.

The Library of Congress has, in collaboration with Twitter, decided to archive every single public tweet since 2006 the year of the launch to preserve American History (Osterberg, 2013), highlighting the public nature of Twitter data.

4.5.5.5 Pre-processing data

In order to pre-process Twitter data, this study filtered and removed exact duplicates. "Near-duplicate tweets" or identical tweets with different timestamps were allowed because it is observed that Twitter influencers routinely repeatedly tweet (retweet) a thought to amplify a message (Bild *et al.*, 2015). Retweets were therefore analysed despite the suggestion by Bruns and Liang (2012) that retweets be omitted from analysis as they only concentrate attention to the most retweeted content. Here, retweets demonstrate amplification which may point to the presence of bot activity and this is important to this study.

The identification and removal of exact duplicate tweets was a non-trivial task because two or more users may simultaneously tweet the same content. Bots may also display this kind of behaviour.

4.5.5.6 Data Security

Transparency and reproducibility are fundamental principles of any scholarly research.

When dealing with Twitter data, this seemingly implies that researchers must make their whole data set available. Twitter, however, disapproves of shadow databases and has even tried to ban their dissemination (Beurskens, 2014). The researcher, therefore, decided to store the data at the university. While the data will be available for collaborative work, its distribution or reuse will be subject to the institutional research rules as they stand.

The researcher had complete control of the #FeesMustFall data and acted as its custodian. The data was stored on a secure hard disk drive within a protected laptop and was backed up on Google Drive using a protected account. All data analysis was conducted solely by the researcher. Limited data were shared with the supervisor for marking or administrative purposes.

In summary, the validation and cleansing stage involved proving the reliability of Podargos as a recognized data service provider (section 4.5.5.1) which gives credibility to the retrieved data. This was followed by an explanation of why retrieving a dataset from Twitter may not be representative of the population and is non-trivial (section 4.5.5.2). Thereafter, supporting literature were discussed that provided legal use regarding the ethical usage of tweets (section 4.5.5.3 and 4.5.5.4) before pre-processing the data by removing identical duplicates from the dataset (section 4.5.5.5). Finally, the security of the dataset was outlined (section 4.5.5.6) which described how the data was secured in order to avoid tampering and provide longevity. All of these sections contained satisfactory reasons in relation to the validation of the #FeesMustFall dataset and provided it with credibility for utilisation.

The next section discusses Stage 6 - data aggregation and representation.

4.5.6 Stage 6: Data aggregation and representation

Stage 6 in the Data Analytics Lifecycle is data aggregation and representation. This stage involves the integration of multiple datasets to form a single consolidated dataset (Erl, Khattak and Buhler, 2016). Complexity may arise when attempting to reconcile various datasets due to different data structures and semantics. In the context of this study, there was no need to merge separate datasets, however, the single acquired dataset required the creation of additional fields to facilitate and reflect sentiment polarity scores and sentiment classes for each respective tweet.

The next section discusses Stage 7 – Data analysis.

4.5.7 Stage 7: Data analysis

Stage 7 of the Data Analytics Lifecycle is data analysis. This stage is where the actual analysis is conducted which may be iterative and usually involves more than one type of analytics (Erl, Khattak and Buhler, 2016).

Before embarking on the data analysis, a pilot was undertaken to determine if #FeesMustFall was a topic worthy of sentiment analysis, and this is discussed first (section 4.5.7.1). Thereafter, the data analysis stages of this study are discussed. These are sentiment analysis (section 4.5.7.2), descriptive analysis (section 4.5.7.3), change point analysis and the CUSUM method (section 4.5.7.4) and the social bots identification methods (section 4.5.7.5). These three phases are each illustrated in Figures 9, 10 and 11. Thereafter, how these methods were used to answer research questions 1, 2 and 3 is explained (section 4.5.7.6) (This is a long section but technically necessary to elaborate).

4.5.7.1 Pilot study

In[23] (2017) suggests that the researcher embark on a small scale enquiry, referred to as a pilot study, in order to identify possible problems and risks and gain practical knowledge of and insight into the research area. Arain *et al.* (2010) agree that the execution of a pilot study ensures that observational categories are appropriate, exhaustive and effectively operationalised for the purpose of the study.

A pilot study was therefore undertaken which conducted sentiment analysis on 3 200 #FeesMustFall-related Twitter data points. The 3 200 data points were selected due to this quantity being the maximum number that Twitter allows via its API for free download (Twitter Inc., n.d.a). The researcher used NodeXL Basic which is a free open-source network analysis and visualization software package (Hansen, Shneiderman and Smith, 2010). The results convinced the researcher that sentiment analysis was feasible and desirable. Furthermore, the limited data points meant that more data was required to provide deeper insights into the online conversations about #FeesMustFall. This then pointed towards a longitudinal study which was consequently chosen. The resulting volume of data meant that a qualitative approach

[23] Researcher's name is Junyong In

on an unrestricted dataset was not feasible and that manual analysis would be prohibitively long. The following conclusions were drawn from the pilot:

- Images and embedded videos and audio clips, though potentially rich sources of information, require different analytic methods.
- Numerous hashtags abounded but #FeesMustFall was dominant
- The choice of NodeXL, though useful to understand #FeesMustFall in a social networking aspect, was also abandoned due to its data retrieval limitations (NodeXL, n.d.) with a maximum of 18 000 data points within a 9 day period. Further, the research focused on sentiment analysis and not SNA.

In light of the above, some delimitations and qualifications were added to the study (as was noted in chapter 1, section 1.9).

4.5.7.2 Data analysis phase 1: Sentiment analysis

Chapter 3 explained the sentiment analysis data analysis method in detail, and thus this section focuses on providing a summary of the process. The output data was subjected to a series of analysis. The analytical method utilised included, *inter alia*, descriptive statistics, sentiment analysis using Python programming language, NLP, timeline analysis, time series analysis, and hashtag data analysis. The results were also triangulated with real-life events.

This is a desktop research thesis and sentiment was determined computationally using Python and the VADER library which is aligned to the VADER model for classifying tweets into 3 categories, namely: positive, neutral and negative. As noted, VADER is an NLP lexicon and rule-based sentiment analysis model that is specifically attuned to sentiments expressed in social media and works well on texts from other domains (Python Foundation, 2018). Python was used to analyse the data with specific algorithms written to parse the metadata into appropriate datasets based on multiple search criteria. The VADER library was used to computationally extract the sentiment from the tweets and its selection was primarily based on the researcher's familiarity with Python and the package being attuned to micro-blog like text.

Tweets were filtered into sentiment classes according to sentiment polarity scores[24] supported by Hutto and Gilbert (2014) as follows:

- If **polarity score < -0.05** then the sentiment is classed as **Negative**
- If **-0.05 ≤ polarity score ≤ -0.05** then the sentiment is classed as **Neutral**
- If **polarity score > 0.05** then the sentiment is classed as **Positive**

The sentiment analysis and classification processes for this study are depicted in Figure 9. It began with the acquisition of the Twitter data, which was pre-processed before input to the VADER model. The pre-processing stage is where duplicates and corrupted data were removed. The VADER model then computed and assigned sentiment polarity scores for each tweet. Thereafter, predetermined thresholds stratified the data according to one of three sentiment classes (*viz*. positive, negative, neutral)

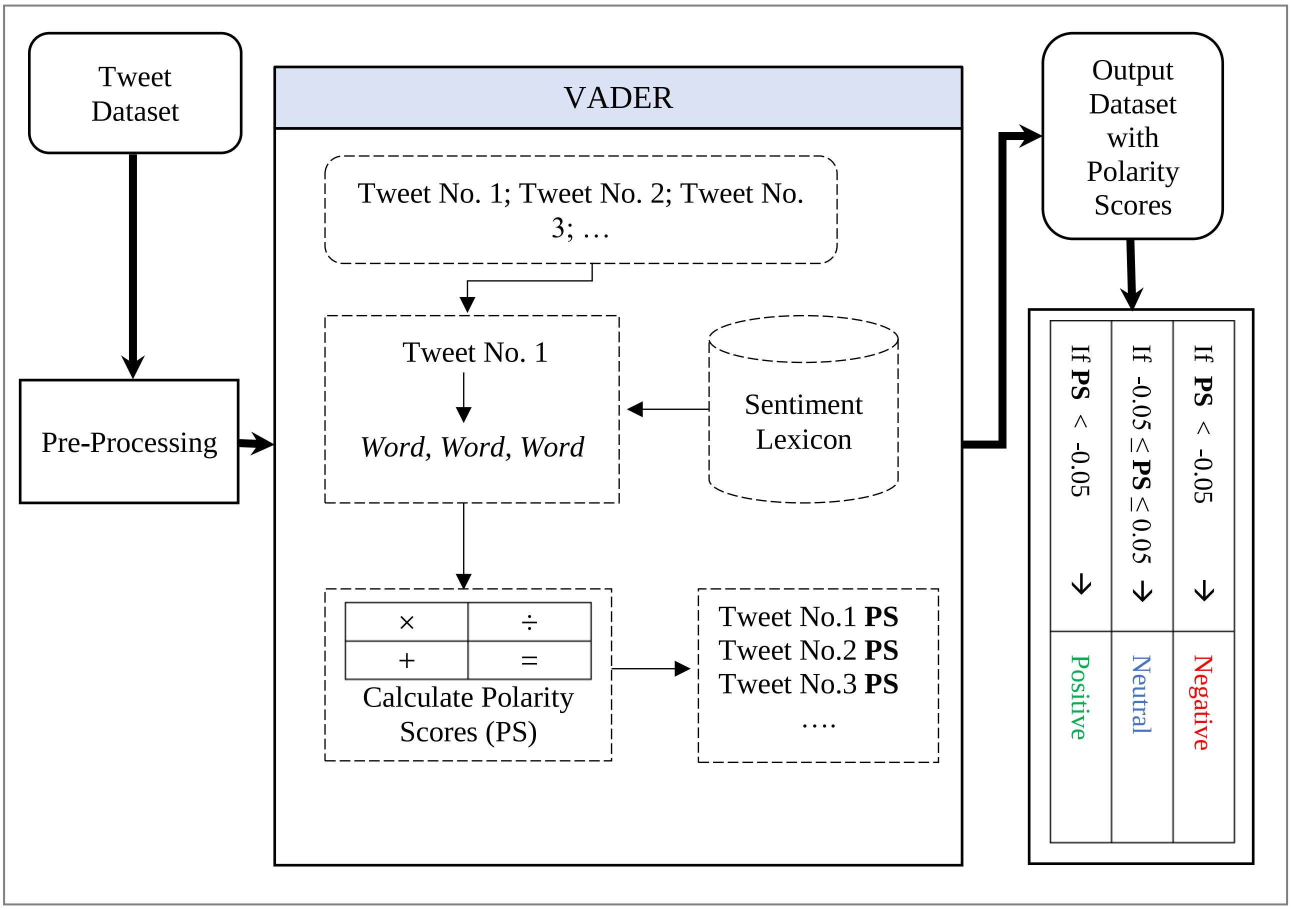


Figure 9 Sentiment Analysis process for Twitter data

[24] The threshold of 0.05 was recommended by Hutto. It may be changed depending on sensitivity required.

The sentiment polarity scores and sentiment classification fields were consequently added to the dataset.

4.5.7.3 Data analysis: Descriptive analysis

A description of the dataset post the sentiment analysis stage is described in this section. The number of corrupt and identical duplicate data are described together with the total number of data points removed from the dataset. Furthermore, the distribution of the dataset is tested against a log-normal form. The number of data points, linguistic makeup and prominent secondary hashtags are described. In addition, the volume of tweets per weekday is also described.

Descriptive analytics manipulate raw data from multiple data sources providing valuable insights into the past (Bekker, 2019). These provided key insights over the longitudinal observation period and supplemented the other analytics. The focussed was on what happened.

Observing the distribution of social media data, provides opportunities for further contextual analysis. In terms of distributive patterns related to Twitter, Bild *et al.* (2015) have found that campaigns on Twitter exhibit a log-normal form. The #FeesMustFall data in this study was assumed to follow a log-normal pattern which required statistical confirmation. Consequently, the log-normal test was used to determine the monthly distributive nature of the data between October 2015 and September 2016, a span of 12 months. The following hypothesis was used in the statistical test:

$$\mathcal{H}_0 = The\ data\ follows\ a\ lognormal\ distribution$$
$$\mathcal{H}_1 = The\ data\ does\ not\ follow\ a\ lognormal\ distribution$$

The following fields were further added to the dataset:

- Number of Hashtags
- Number of URLs

These fields were required to provide insight into the nature of tweets posted and to describe the tweeting behaviour of users.

A monthly tally of tweet frequency was calculated to determine the pattern and significant months with the most number of tweets. With similar intent, tweets per day of the week were calculated based on the respective volumes of tweets experienced for each day from Monday to Sunday.

Associated tweet hashtags were determined by converting all tweets into lowercase to avoid case-sensitivity hashtag counts. Thereafter a Python script was applied that filtered out all the respective hashtags and then tabulated them in descending order. The research questions of this study were then analysed.

4.5.7.4 Data analysis phase 2: CPA using CUSUM method

CPA analysis became important when analysing research question 2. Figure 10 depicts the phases required to undertake the CPA analysis which consists of a data pre-processing, data mining and data analysis phase.

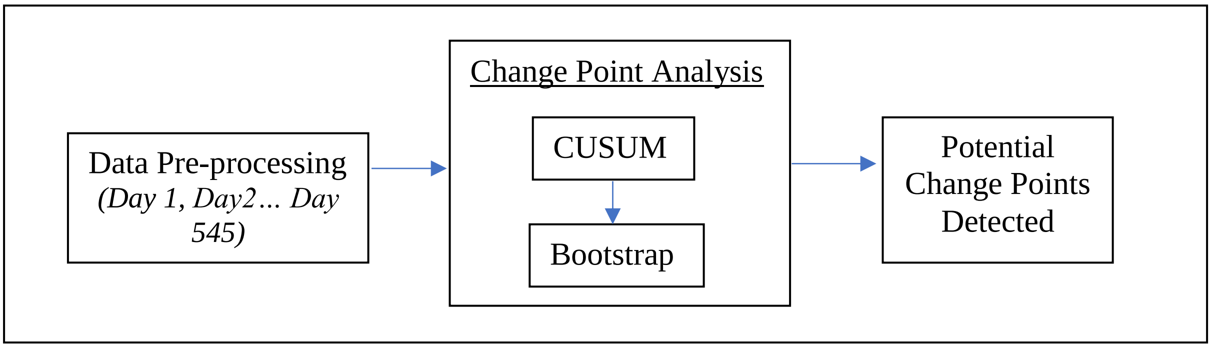


Figure 10 Change Point Analysis process flow

4.5.7.4.1 Change point analysis (CPA)

Scientists cannot determine whether an earthquake is a foreshock until the larger earthquake, called the mainshock, happens (Sykes, 1971). Similarly in campaigns such as #FeesMustFall smaller contributing events get “lost” in the shadow of larger events. Researchers consequently need to mine the longitudinal data to find these “foreshocks” using an appropriate statistical method. The CPA was conducted and used the bootstrapped based Cumulative Sum Analysis (CUSUM) method.

For the #FeesMustFall campaign the particular research interest was if and when and with what confidence level did the sentiment change(s) occur? CPA has the added advantage of controlling the change-wise error rate. As a result, each change detected is likely to be real (Taylor, 2000).

A CPA is a probability distribution - either a stochastic process or a time series of ordered data - to detect whether any change(s) have occurred. A CPA is capable of detecting multiple changes particularly when analysing large historical data sets (Taylor, 2000; Bendat and Piersol, 2011). CPA has the added advantage of controlling the change-wise error rate. As a result, each change detected is likely to be real (Taylor, 2000).

Traditional change detection methods use control charts or curves to detect changes because they are generally better at detecting isolated abnormal points or a major change quickly. In contrast, a change-point analysis can detect subtle changes sometimes missed by control charts. The researcher therefore decided to use CPA to answer research question 2 (Taylor, 2000; Bendat, and Piersol, 2011).

Change point dates were triangulated with historic #FeesMustFall timelines that contain significantly known real-life events in order to determine a plausible relationship between online sentiment and real-life events. The magnitude and mathematical correlation of the relationship is beyond the scope of this study, however, results obtained by the triangulation provide possible explanations and research opportunities about the influence of social media sentiment on real-life events and vice versa. For example, if the sentiment change occurred prior to the event, it may indicate a scope for sentiment analysis hashtag studies to be modelled to forecast real-life outcomes and if the change occurred after, then this may be used to ascertain the impact of events on sentiment.

One may argue that CPA, as post-facto research, is research after the proverbial horse has bolted. The researcher argues otherwise, as CPA provides context or the contributing factors - the foreshocks when something started to happen - to the larger event. CPA may (and should) also be customized for each individual university e.g. #Wits and its variants to get further contextual meaning. This is delimited as this research focus is on the national sphere.

4.5.7.4.2 Bootstrap and Cumulative Sum of charts (CUSUM) algorithm

Taylor (2000) employs a non-parametric CPA method that is based on the mean-shift model with the assumption that residuals are independent and identically distributed with a zero mean. This method adopts an iterative application of CUSUM methods and bootstrapping analysis in order to determine changes in time-series data (Ibid). It is advantageous as multiple changes can be detected regardless of the distribution of the data and is therefore selected for CPA in this study.

CUSUM charts were constructed by calculating and plotting a cumulative sum based on the data. The timeline of the data were 545 days (section 4.5.7.2.3). Let d_i represent the i^{th} day in the 545-day period, $i = 1,2, \ldots ,545,\ i \in \mathbb{N}$. A day is measured using the conventional timescale denoted by [00:00:00AM; 23:59:59 PM], where the time is in 24-hour format.

Then the average sentiment of the i^{th} day is represented by X_i. From this, the cumulative sums $S_0, S_1, \ldots, S_{545}$ are calculated. The cumulative sums are calculated as follows (Taylor, 2000; Granjon, 2013; Taylor, 2018);

1. First calculate the overall average sentiment, $\bar{X}$

$$\bar{X} = \frac{\sum_{i=1}^{i=N} X_i}{N}\ ,\ N = 545$$

2. Commence the cumulative sum at zero by setting $S_0 = 0$.

$$S_i = S_{i-1} + (X_i - \bar{X})$$

3. Calculate the other cumulative sums by adding the difference between current value and the average to the previous sum, i.e. for $i = 1, 2, \ldots, 545$.

The bootstrap analysis will be performed using an estimator (S_{diff}) which determines the magnitude of the change. The estimator makes no assumptions on the distribution of the data and is defined as follows:

$$S_{diff} = S_{max} - S_{min}\ \text{, where}$$

$$S_{max} = \max_{i=0,\ldots,545} S_i \qquad \text{and} \qquad S_{min} = \min_{i=0,\ldots,545} S_i$$

A single bootstrap is performed using the following steps:

1. Generate a bootstrap sample of 545 units and denote it as $X_1^0, X_2^0, \ldots, X_{545}^0$ by reordering the 545 values randomly. A bootstrap sample is dependent on the timeline points which are in this case 545 days (i).
2. Use the bootstrap sample to calculate the bootstrap CUSUM, denoted as $S_0^0, S_1^0, \ldots, S_{545}^0$
3. Calculate the maximum, minimum and difference of the bootstrap CUSUM, denoted as S_{max}^0, S_{min}^0 and S_{diff}^0
4. Determine whether $S_{diff}^0 < S_{diff}$

The bootstrap analysis used in the study generates 10 000 bootstrap samples and from these samples the confidence level is calculated on the percentage of occurrences where $S_{diff}^{0} < S_{diff}$ out of the 10 000 samples. A 95% level of confidence is used to assess the data for significant changes (Taylor, 2000; Granjon, 2013; Taylor, 2018).

4.5.7.4.3 Accepting a change point date change

Granjon (2013) presents the following algorithm to explain the process behind the acceptance of a change point date:

initialization
  if necessary
end
While *the algorithm is not stopped* **do**
  Measure the current sample x[k]
  Decide between $\mathcal{H}_0$ (no change) and $\mathcal{H}_1$ (one change)
  If $\mathcal{H}_1$ *decided* **then**
    store the detection time $n_d \leftarrow k$
    estimate the change time n_c
    stop or reset the algorithm
  end
end
CPA Algorithm : general form of a sequential change detection algorithm

4.5.7.5 Data analysis phase 3: Social bots identification

This section is in relation to research question 3. This data analysis phase utilises four methods to identify social bots. Three methods are applied on the pre-processed dataset with the remainder utilising the DeBot API. This is illustrated in Figure 11.

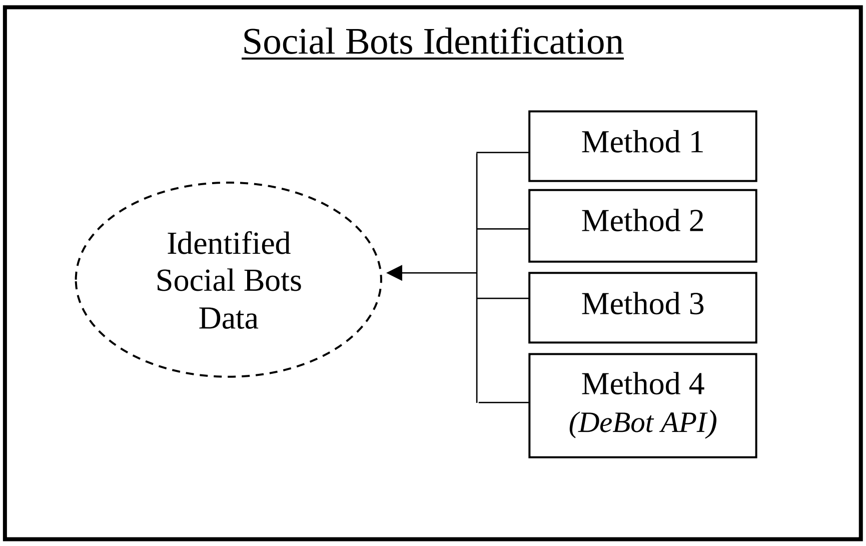


Figure 11 Social bots identification

The mathematical notations follow on from Method 1 through to Method 4.

Method 1: Identify tweeters who posted more than once in a single timestamp. Instances of this nature are improbable for human type tweeters given that a minimum lag in time is required to manually generate successive tweets, however, instances of this nature are achievable with the use of automatic assistance, a feature synonymous with the characteristics of bot and cyborg tweeters. The mathematical notation for this method is as follows:

Let a tweet = $(tw)_i \;\; where\; i \; \in \; \mathbb{N}$

$$\sum_i (tw)_i = Total\ No.of\ tweets$$

Let a user for a tweet = u_j , $where\ j \; \in \; \mathbb{N}\ and$

$$\sum_j u_j = Total\ No.of\ users$$

Let a Timestamp for a tweet = $t_k,\;\; where\ k \; \in \; \mathbb{N} \;\; and$

$$\sum_k t_k = Total\ No.of\ Timestamps$$

Each Timestamp is representative of the Gregorian Calendar and Coordinated Universal Time (UTC) and follows the format (*year/month/day hour:minute:second*)

$$A\ user, u_j\ is\ assumed\ a\ bot\ or\ cyborg\ if\ at\ Timestamp, t_k:$$

$$\sum_i (tw)_{ijk} > 1$$

Method 2: Identify tweeters that generate many instances of duplicate tweet content (i.e. a tweeter who duplicates tweet content more than once). Tweeters with a volume of 29 or less were filtered out from the results. This threshold was determined by the researcher and purposely selected to exclude tweeters with perceived insignificant volume in tweets. The rationale behind Method 2 is based upon a known spamming trait of certain bots and cyborgs which is to schedule or trigger posting of tweets. This means that bots and cyborgs who deploy sequential and repetitive tweeting mechanisms are expected to generate multiple occurrences of duplicate tweet content of a higher frequency than that of human tweeters.

It is possible that a human tweeter may duplicate tweet content several times, however, it is unlikely that such duplication occurs significantly often enough. Therefore, it is validly assumed that a tweeter whose duplicate tweet content comprises of 30% or more of its total tweets in a fixed period is considered to be a bot or cyborg. This is mathematically notated as follows:

Let each unique tweet = $\left(\overline{\overline{\mathrm{tw}}}\right)_{\mathrm{i}}$ $\text{ where } \mathrm{i}\,, \left(\overline{\overline{\mathrm{tw}}}\right)_{\mathrm{i}} \in \mathbb{N}$

$$\sum_{\mathrm{i}} (\overline{\overline{\mathrm{tw}}})_{\mathrm{i}} = \text{Total No. of unique tweets}$$

$$\text{A user, } \mathrm{u_j} \text{ is assumed to be a bot or cyborg if :}$$

$$\sum_{\mathrm{i}} (\mathrm{tw})_{\mathrm{ij}} \geq \frac{10 * \sum_{\mathrm{i}} (\overline{\overline{\mathrm{tw}}})_{\mathrm{ij}}}{7} \text{ , and } \sum_{\mathrm{i}} (\mathrm{tw})_{\mathrm{ij}} \geq 30$$

Method 3: Identify tweeters that utilize automated applications for the majority of their tweets. Cyborgs and bots utilize automation software to purposely drive their intended cause(s) by amplifying their tweet volume. Tasks are automated on Twitter in relation to posting messages, retweeting, following and replying to posts. It may be argued that if a tweeter utilized a known automated software then why is the concern placed on how much? This is because tweeters may use an automated application infrequently for reasons other than to amplify an intended cause e.g. setting up an auto-reply feature to engage Twitter followers whilst on holiday. This may be seen as cyborg behavior, however, the volume of tweets posted automatically are significantly less than the volume of tweets posted manually since the tweeter generally posts manually which falls outside the cyborg parameter of posting tweets largely through automation. It is for this reason that an appropriate threshold is assigned when using automated applications as a variable to investigate cyborgs. An appropriate threshold was selected that searches for tweeters who have posted a minimum of 30 tweets with 70% or more of their tweets originating from known automated software. This is to increase the likelihood of the results being related to bots and cyborgs. Tweet sources were retrieved as part of the metadata (section 3.6.3.2) making these parameters valid for utilization when analyzing the data.

“IF This Then That” (IFTTT), Hootsuite, TweetDeck, TweetCaster and Buffer were used as the set of known automated software for analysis. IFTTT creates applets that automate tasks such as tweeting and retweeting on Twitter (IFTTT, n.d.). Buffer and Hootsuite are Social Media managers with automation features that include scheduling of posting tweets on Twitter (Buffer, n.d.; Hootsuite, n.d.). TweetDeck is a Social Media application that allows for multiple Twitter accounts to be managed with a feature to schedule the posting of tweets (Tweetdeck, n.d.). Tweetcaster is an application that manages a user account on Twitter offering the feature to schedule posting of their tweets (TweetCaster, n.d.). The mathematical notation for this method is as follows:

Let $A = \{\text{IFTTT; Hootsuite; TweetDeck; TweetCaster; Buffer}\}$,

$where\ A\ is\ a\ set\ of\ automating\ tweet\ sources$

Let the sum of the number of times an automating tweet source appears for the j^{th} user be denoted as $(ats)_j$, $where\ (ats)_j \in A,\ j \in \mathbb{N}$

$$A\ user, u_j\ is\ assumed\ to\ be\ a\ bot\ or\ cyborg\ if\ :$$

$$\frac{(ats)_j}{\sum_i (tw)_{ij}} \geq 0.7\ , and\ \ \sum_i (tw)_{ij} > 29$$

Method 4: Utilize the DeBot API to identify Twitter Bots and cyborgs. The DeBot API is publicly available and requires an ‘api key’ which is provided upon registration at their website (Chavoshi, Hamooni and Mueen, 2016). A keyword like ‘#FeesMustFall’ is then required to search for related bots. The following code was used in Python:

$$import\ debot$$

$$db\ =\ debot.DeBot('your\_api\_key')$$

$$db.get\_related\_bots('\#FeesMustFall')$$

In summary, this study uses the data analysis methods of sentiment analysis, descriptive analysis, change point analysis and the CUSUM method, and the social bots identification method. The next section explains how these data analysis methods were used to answer research questions 1, 2 and 3.

4.5.7.6 Data analysis methods and the research questions

Data analysis proceeded through three main phases as noted in Table 4 and illustrated in Figure 12.

Table 4 Main analysis phases, data analysis method used and output

Data analysis phase	**Data analysis method used and where discussed**
Phase 1: To answer research question 1	Sentiment analysis and descriptive analysis (4.5.7.2 and 4.5.7.3)
Phase 2: To answer research question 2	Change point analysis using bootstrap and CUSUM methods (4.5.7.4)
Phase 3: To answer research question 3	Social bots identification (4.5.7.5)

In this section, each research question and subsidiary questions are revised, and the specific data analysis steps followed are outlined in detail. One might be of a view that this discussion might rather have been included in chapter 5 with the findings, but due to the length of chapter 5, and the proximity to the technical discussion, it was decided to rather elaborate on this here.

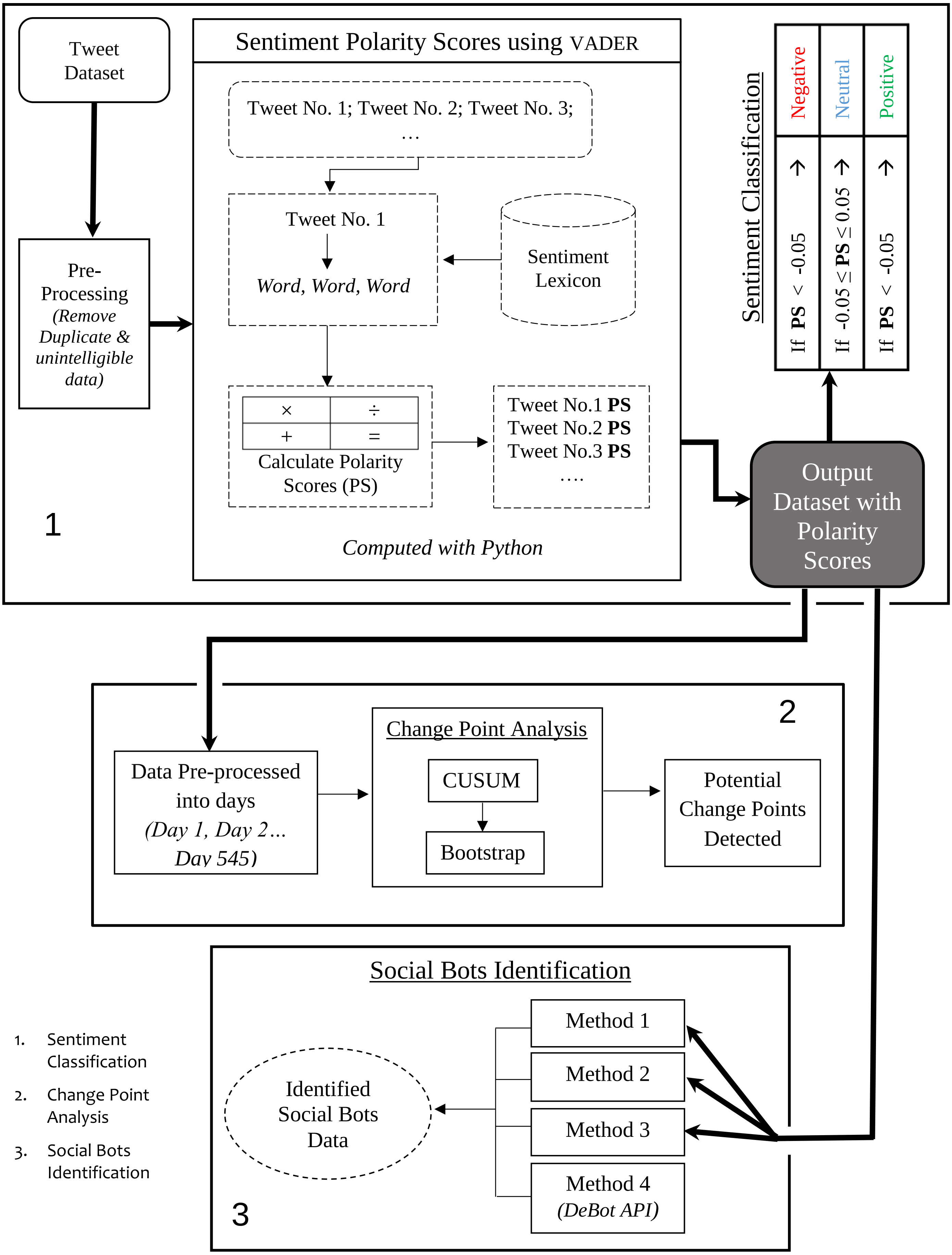


Figure 12 Main analysis phases for this study from sentiment analysis towards change point analysis and social bots identification.

4.5.7.6.1 Research question 1

Research question 1 asks:

> **What was the prevailing sentiment of Twitter users during the #FeesMustFall campaign?**

This question had resonance because there were a huge number of tweets that captivated the nation as the campaign played out. #FeesMustFall was Africa's biggest hashtag campaign during this study period (Workman, 2017).

To analyse question 1, the VADER model was applied on the data using the algorithm in section 3.4.1 which computed each tweet into a sentiment polarity score. These were stratified into three sentiment classes: positive, negative and neutral (This is discussed in section 4.5.7.2).

The total count of each sentiment provided the overall sentiments view during the longitudinal period of this study and is subjective depending on the time-frame of analysis. Therefore, a more segmented approach in terms of months was required to provide prevailing sentiment on a granular scale.

Taking the average of all the tweets in a month is not recommended as the negative polarity will cancel positive polarity and all one will see is the prevailing "mood." Therefore, the next step involved computing the monthly average sentiment polarity of each separate class and plotting this on three distinct curves. Calculations were applied on months having more than 1 tweet which therefore excluded March 2015 and April of 2015 as these months only contained a single tweet each. The tweet volume was also superimposed on the graph over the 14 month period. Each vertical value of positive, negative and neutral curves totalled 100% of the tweets for that point. Therefore, the relative volume for each sentiment can be viewed over the time x-axis. These sentiments were separately investigated. This was important because observing the extent and range of the divergent views for any given month is an important contribution to sentiment analysis.

A further set of subsequent questions were constructed to provide additional insight into research question 1. These questions and the reasons for their inclusion are as follows:

a. *Who were the dominant tweeters and how did they tweet during this study?*

The prevailing online sentiment is driven by the tweet volume of tweeters. It was important to determine the most prolific tweeters who were potential influencers. The dominant tweeters were identified by measuring their respective tweet volumes. The top-ten ranked tweeters were filtered together with their corresponding metadata. The metadata comprised inter alia Retweets, Favourites, Average Sentiment, Number of Hashtags and Number of URLs. These metadata were used to describe each tweeter’s #FeesMustFall-related tweet characteristics posted during this study.

b. Were News Media part of the dominant tweeters?

This sub-question was constructed to provide a quantitative analysis on the role of news media in the #FeesMustFall campaign, as opposed to the qualitative analysis of the role of news media in the thesis by Baillie-Stewart (2017).

The usernames identified from the top ten highest tweeters were analysed to determine if they were public news media handles or not. If matched, their metadata was filtered and analysed.

c. What were the tweeting characteristics of the top tweeter?

It is worth providing insight to the tweeter who generated the most number of tweets which may reveal otherwise unnoticeable information. This subsequent question was therefore constructed and the tweeter’s average sentiment trend in conjunction with the corresponding volume was analysed. This was done across a monthly scale beginning from October 2015 and ending in March 2017. The metadata of the top tweeter was also analysed.

Rates for the Retweets (RT), Hashtags, URLs and Favourites were calculated to provide further insight into the tweeting behaviour for the aforementioned questions. A RT rate was calculated by dividing the number of tweets by the RT count for each respective tweeter. Similarly, the other rates were also calculated.

4.5.7.6.2 Research question 2

Research question 2 investigates relations between perceived real-life events and the computed sentiment polarity. It asks:

> **How did the burning of the UJ Hall and the UKZN Library relate to online sentiment trends and polarity?**

Answering this question required a number of steps. Before this question could be answered the changes in sentiment and polarity and the change dates needed to be identified.

In order to determine the changes of sentiment during the period of this study, a time series analysis was first performed on the average sentiment per day and thereafter a change point analysis (CPA) was conducted using the CUSUM method (as described technically in section 4.5.7.4).

The time series analysis and CPA was achieved by utilising dates as the scale of measurement between 13 October 2015 and 09 April 2017[25], a total of 545 days. These dates were purposely selected to avoid dates that had less than 5 tweets, with 10 April 2017 also excluded due to it being incomplete when the data retrieval process began.

The UKZN incident occurred on 6 September 2016 and the burning of the UJ Hall occurred on 29 September 2016. These dates were then benchmarked against dates pertaining to changes in overall average sentiment polarity during the 545 day period and their closeness was analysed. Since these events were perceived as negative, the negative sentiment polarity trend was particularly used.

In order to answer research question 2, subsequent questions were constructed and divided into two parts. Part A dealt with the *overall* sentiment polarity and Part B dealt with the *negative* sentiment polarity. The associated sub-questions are as follows:

Research question 2, Part A: Overall sentiment polarity

a) *Where there any changes in average sentiment trend and polarity during this period?*

b) *What were the dates that signified the beginnings of these changes?*

c) *How do these change dates relate to dates of real-life significant events?*

Research question 2, Part B: Negative sentiment polarity

a) *Where there any changes in negative sentiment trend and polarity during this period?*

---

[25] The researcher recommends the sample of at least 5 tweets to mitigate single tweet bias.

b) *What were the dates that signified the beginnings these changes?*

c) *How do these change dates relate to dates of real-life significant events?*

This section of the study comprised of a data pre-processing, data mining and data analysis phase as depicted in Figure 10. The data pre-processing phase filtered the timeline into days and evaluated the average sentiment per day in preparation for data mining.

In the data mining phase, a CPA (section 4.5.7.4) was applied and the subsequent results examined in the data analysis phase. The sentiments were computed as an average for each day, although the period granularity may be adjusted. The corpus of #FeesMustFall tweets, while expressing a sentiment, is viewed as ordered data. Thus, CPA is performed on a series of time ordered data to detect if and when any sentiment changes have occurred. The time series range is the 545 consecutive days reflecting each day's average sentiment. The CPA algorithm was then applied with no other training or adjustment. The CPA was conducted using the Cumulative Sum Analysis (CUSUM) and bootstrap methods.

These methods are described and defended. CPA was selected as the appropriate method to statistically detect changes in the sentiment given the longitudinal nature of this study. Further CPA is capable of not only detecting changes but also of detecting the points of change together with the magnitude and the confidence level.

Part A sought to establish overall average sentiment polarity and had three subsidiary questions:

a. *Where there any changes in sentiment trend and polarity during this period?*

b. *What were the dates that signified the beginnings of these changes?*

c. *How do these change dates relate to dates of real-life significant events?*

To answer sub-questions (a) and (b), a Time Series Plot (Figure 17) was used to depict the average sentiment trends per day over the 545 day longitudinal period. This was required in order to visually inspect potential patterns.

In order to determine changes in overall sentiment polarity during the timeline, a time series analysis was performed on the overall average sentiment polarity per day using a CPA through the CUSUM method.

This also produced the significant points that represent beginnings of changes. Overall, average sentiment polarity per day was produced by respectively adding the negative, neutral and positive sentiment scores together and dividing them by the total number of tweets for the respective day. These two sub questions were statistically examined using the following constructed hypothesis:

$$H_0 = There\ were\ no\ changes\ in\ the\ overall\ average\ sentiment\ polarity$$

$$H_1 = There\ were\ change(s)\ in\ the\ overall\ average\ sentiment\ polarity$$

To answer sub-question (c) (*How do these change dates relate to dates of real-life significant events?)* the change points outputted from the CPA were utilised and closeness was compared to dated real-life events pertaining to the #FeesMustFall campaign.

The identification of these real-life events emanated from desktop research. In addition, an examination of the temporal behaviours and features from Twitter users was also conducted. This was determined by triangulating the dates of such events with the sentiment trend line. It is reasonable for authorities to use social media to determine the range and polarity of sentiments of the online feelings of protesters as this will inform and prescribe an appropriate reaction. In particular this method was developed to understand perceived negative events such as the burning of the UKZN Library and the UJ Hall and its influence on online sentiment trends.

Results from the subsidiary questions were compared to the dates from the UJ Hall and UKZN incidences. The sentiment trends in terms of their volume per classification were then analysed 3 days before and after each of the dated UJ Hall and UKZN Library burning events. The number three was purposely selected in order to closely inspect the data.

4.5.7.6.3 Research Question 3

Research question 3 asked:

> **Where social robots significantly involved on Twitter during the #FeesMustFall campaign?**

'Significantly', here, refers to the amount of expressed sentiment on Twitter. Since, a sentiment is derived from a tweet, naturally, the more volume in tweets means the more sentiments were expressed. Therefore, identifying a portion of the highest tweeters on Twitter to be social bots will satisfy as an answer to this research question.

Social robots were investigated in terms of Twitterbots and Cyborgs by utilising techniques built upon their general characteristics highlighted in section 2.6.2. Methods 1 to 4 outlined in section 4.5.7.5 represent the techniques involved to identify a Twitterbot and Cyborg. To answer research question 3, results from Methods 1, 2, 3 and 4 were then analyzed against the Top 10 tweeters in order to determine if social robots existed as a significant influencer in amplifying the hashtag #FeesMustFall. These methods were accepted at the double blind peer reviewed IEEE 2018 Mauricon Conference (Khan and Thakur, 2018).

In summary, in long section discussed the pilot study to determine if #FeesMustFall was a topic worthy of sentiment analysis. It then outlined, technically, the data analysis stages of sentiment analysis, descriptive analysis, change point analysis and the CUSUM method, and the social bots identification method before explaining how these methods were applied practically to answer the research questions set by this study.

Having now concluded data analysis, the final two stages - Stage 8 – Data visualisation and Stage 9 – Utilisation of data results, can now be elaborated.

4.5.8 Stage 8: Data visualisation

Stage 8 of the Data Analytics Lifecycle is data visualisation. It is used to graphically visualise the analysis performed in order for verification and alternative interpretation opportunities by different analysts (Erl, Khattak and Buhler, 2016). For this study, software such as Tableau software, Microsoft Excel and Change-Point-Analyzer were used to achieve this. Visualisation included the creation and compilation of graphical representation and tables respectively such as the sentiment analysis trends (section 5.3.2), frequency of tweets (section 5.3.1), time-series plot (section 5.4.1) and change-point analysis tables (section 5.4.1).

This stage is evident in chapters 5 and 6 of this study.

4.5.9 Stage 9: Utilisation of analysis results

Stage 9 is the Utilisation of Analysis Results and completes the Data Analytics Lifecycle. It is where the results of the analysis are presented and made available to relevant stakeholders such as researchers and business owners in order to support decision making as well as further leverage the data (Erl, Khattak and Buhler, 2016).

This stage is related to chapters 5 and 6 of this study.

4.6 Conclusion

This chapter explained the study's methodological and design choices. It noted that this study is guided by the post-positivist philosophy, adopts a quantitative research methodology, follows a deductive research approach and has a longitudinal time horizon.

The key focus of this chapter was to explain the data collection and data analysis process required to answer the research questions. It was noted that #FeesMustFall tweets posted during the observational periods from 15 October 2015 until 10 April were purchased for the study. The dataset did not contain any audio, image and video content for analysis. This dataset further excluded corrupted and identical duplicated data points prior to sentiment analysis, CPA and social bots identification.

This chapter elaborated in detail the nine stages of the Data Analytics Lifecycle as they applied to this study, explained the technical detail of the data analysis stages, and explained how these were applied in answering the research question. The associated decisions that were made to ensure the rigour and ethicality of the data analytics process was also justified.

In the next chapter (Chapter 5), the study's findings are presented.

Chapter 5 Findings and Results

5.1 Introduction

This chapter presents the findings to the study's research questions. It begins with a descriptive analysis of the corpus of tweet data (section 5.2). Thereafter the findings regarding the prevailing sentiment of Twitter users during the #FeesMustFall campaign (research question 1) are presented in section 5.3. In section 5.4, the findings on how the real life events of the burning of UJ Hall and the UKZN library relate to online sentiment trends and polarity (research question 2) are outlined. This corresponds to the longest section of this chapter 4 where findings for the 6 sub-questions are also presented. Finally, in section 5.5 the results on whether or not social bots were deployed on Twitter during the #FeesMustFall campaign (research question 3) is presented. A discussion of the findings and their implications, can be found in chapter 6. The technical details on how these findings were generated were explained in chapters 3 and 4.

5.2 Results of the descriptive analysis of the #FeesMustFall tweets

This section reports on the descriptive analysis findings and results based upon the utilisation of methods outlined in section 4.5.7.3. These descriptive traits provides assistance to answer the study's key research questions. Initially, the retrieved dataset contained 576 583 #FeesMustFall tweets posted during the observational periods from 15 October 2015 until 10 April 2017[26]. The cleaning of the corpus of tweets yielded a final sample of 490 449 tweets. No corrupted data was detected and the reduction was due to the removal of 86 134 duplicates.

The results of the linguistic analysis (section 5.2.1); tweet volume (section 5.2.2), tweet distribution (section 5.2.3), daily rates (section 5.2.4) and multiple hashtags (section 5.2.5) are presented next.

5.2.1 Linguistic analysis

The algorithm used by Podargos (as noted in sections 4.5.2 and 4.5.3) discerned that 27 distinct-languages were used during the #FeesMustFall campaign, of which English was the dominant language commanding 432 942 tweets, representing 88.3%

[26] There were two tweets shown in Figure 1 and 2 posted in March 2015 with historical significance (section 2.4.2).

of the total tweets. This demonstrates that linguistically the #FeesMustFall hashtag on Twitter was overwhelmingly communicated in an English language text.

The number of tweets for each language detected is presented in Table 5 along with the overall number of tweets. The discernible defined non-English tweets numbered 9 331, with Dutch being identified as the second largest defined language.

There were 48 176 tweets flagged as undefined due to the inability of the algorithm to decipher texts not part of its code.

Table 5 Tweets distribution by language

Language	Total		Language	Total
English	432 942		Norwegian	188
Undefined	48 176		Czech	153
Dutch	3 366		Arabic	152
Spanish	941		Swedish	152
German	791		Hungarian	53
Portuguese	744		Japanese	26
French	523		Russian	12
Polish	517		Chinese	11
Romanian	398		Ukrainian	11
Turkish	349		Vietnamese	6
Hindi	245		Urdu	5
Finnish	241		Greek	2
Danish	226		Korean	1
Italian	217		Persian	1
TOTAL 490 449				

5.2.2 Tweet volume

The tweet distribution for every month in the dataset was computed and is reflected in Table 6. The months of March 2015 and April 2015 each consisted of one tweet. The highest number of tweets belonged to October 2015 with a tally of 289 458 which represents 59.02% of the 490 449 analysed tweets. October 2016 marked the anniversary of the #FeesMustFall campaign and contained 82 712 tweets or 16.8% of the total tweets.

Table 6 Tweet Distribution

Year of Date	Month	Number of Tweets
2015	March	1
	April	1
	October	289 458
	November	13 452
	December	3 922
2016	January	13 318
	February	7 215
	March	3 898
	April	2 076
	May	900
	June	1 551
	July	2 238
	August	6 541
	September	38 472
	October	82 712
	November	9 505
	December	3 626
2017	January	4 113
	February	2 244
	March	2 843
	April	2 363
Total		**490 449**

5.2.3 Tweet distribution

The tweet distribution was calculated using the following hypothesis:

$$\mathcal{H}_0 = The\ data\ follows\ a\ lognormal\ distribution$$

$$\mathcal{H}_1 = The\ data\ does\ not\ follow\ a\ lognormal\ distribution$$

A log-normal statistical test from October 2015 until September 2016 concluded that for this 12 month period the data did indeed follow a lognormal distribution.

The descriptive statistics together with the lognormal distribution fit results can be seen in Table 7:

Table 7 #FeesMustFall descriptive and distribution test results for total tweets per month from October 2015 until September 2016 (α = 0.05)

Descriptive Statistics							
Count	*Mean*	*StDev*	*Median*	*Min*	*Max*	*Skew*	*Kurt*
12	31920	81762	5231.5	900.0	289 458	3,370	11,50
Distribution Results							
Location	*Scale*	*Log-Likelihood*	*AD*	*p Value*	*AIC*		
8821	1,515	-127,9	0,394	0,317	259,7		

The distribution results yielded a p-value > 0,317 which meant that the null hypothesis cannot be rejected at a 5% level of significance and therefore it can be concluded that the tweet distribution for the aforementioned parameters followed a lognormal distribution as indicated in Figure 13.

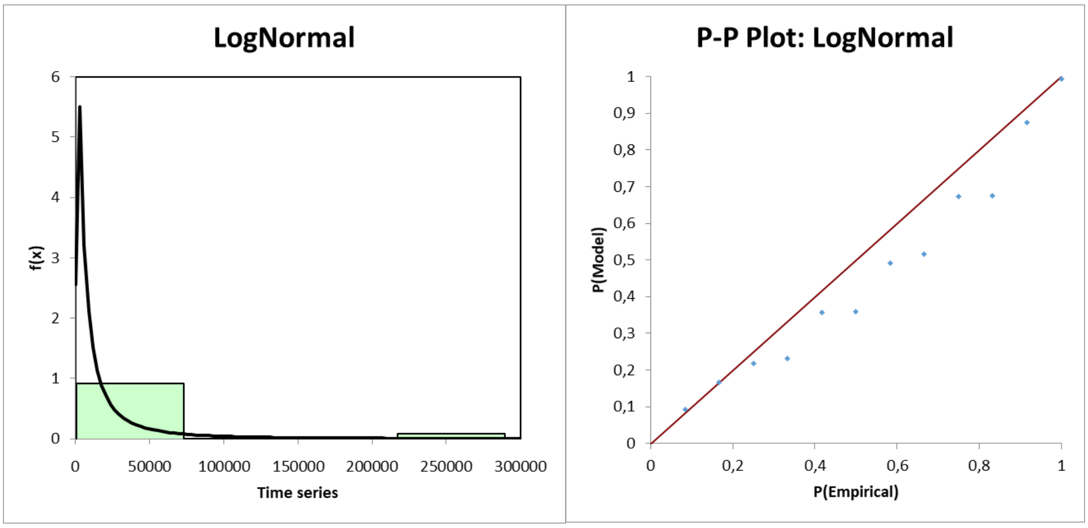


Figure 13 #FeesMustFall lognormal distribution curve (left) and lognormal P-P Plot (right) for October 2015 - September 2016 Monthly tweets.

5.2.4 Daily tweet distribution

The results indicate that total tweets were distributed over conventional days of the week as displayed in Figure 14, with a noticeable decline in tweet volume over the weekend days of Saturday and Sunday. This indicated a significant pattern in which the tweeting behaviour increased daily from Monday through Friday, and declined over the weekend.

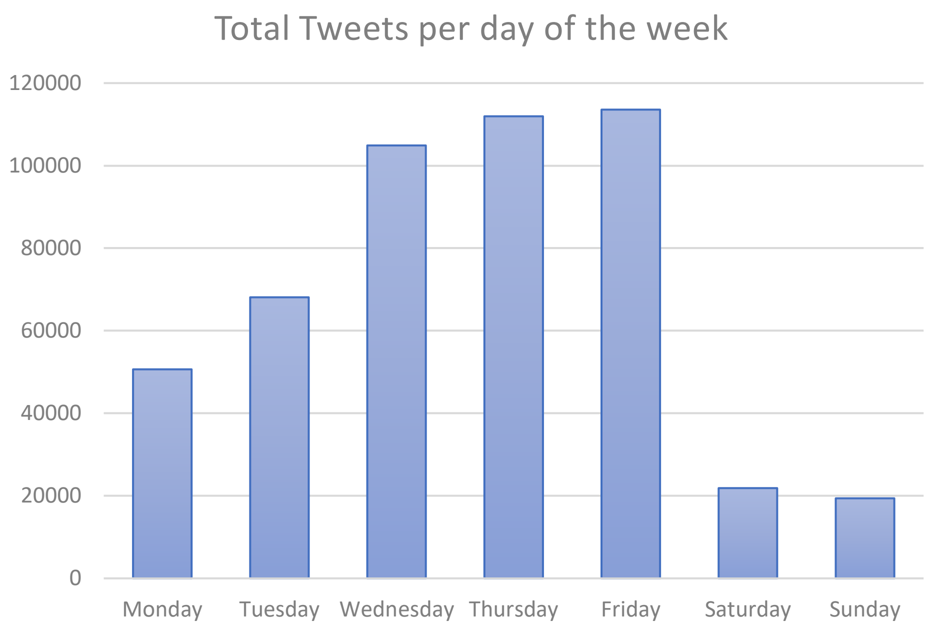


Figure 14 Tweet distribution per day of the week

5.2.5 Tweets with multiple hashtags

Table 8 represents the hashtag counts greater than 4 000 as per methods described in section 4.5.7.3. The four dominant secondary hashtags were found to be #nationalshutdown, #southafrica, #wits and #fees2017 respectively.

Table 8 Dominant secondary hashtags posted along with primary hashtag #FeesMustFall

Hashtag	Primary Hashtag Count	Secondary Hashtag Count
#feesmustfall	497 916	
#nationalshutdown		28 054
#southafrica		16 500
#wits		12 352
#fees2017		12 100
#unionbuilding		6 921
#leadership		5 527
#ancmustfall		5 486
#zumamustfall		5 209
#asinamali		4 353
#occupy		4 222
#freeeducation		4 166

The next section (5.3) discusses the findings of research question 1.

5.3 Findings of research question 1: Prevailing sentiment

Research question 1 asks:

> **What was the prevailing sentiment of Twitter users during the #FeesMustFall campaign?**

In the discussion below each of the high level findings to research question 1 regarding overall sentiment over the longitudinal period (section 5.3.1) and the tweet frequency and sentiment trend (section 5.2.2), are presented. Thereafter answers are provided to three additional sub-questions that were created to provide additional insight.

5.3.1 Finding: The stratified sentiment over the longitudinal period

The results indicate that Neutral sentiment represented 41.5% of the total dataset with a 29.4% count for Positive sentiment and a 29.1% count for Negative sentiment.

Table 9 presents the three classified sentiments and the overall total for the classified sentiments as follows:

Table 9 Sentiment Classification Count

Sentiment	Count
Negative	142 730
Neutral	203 693
Positive	144 026
Total	**490 449**

5.3.2 Finding: The tweet frequency and sentiment trend

The results from Table 6 (Tweet distribution) and Table 9 (Sentiment classification count) are combined with the average sentiment per month to produce a volume and percentage based sentiment distribution of tweets (Figure 15). This method follows that outlined in section 4.5.7.2. As noted earlier, March and April in the year 2015 were omitted due to each containing only one tweet. Furthermore, April in 2017 was also left out since the study period culminated at 10 April 2017 leaving the month with insufficient days to compute an appropriate average.

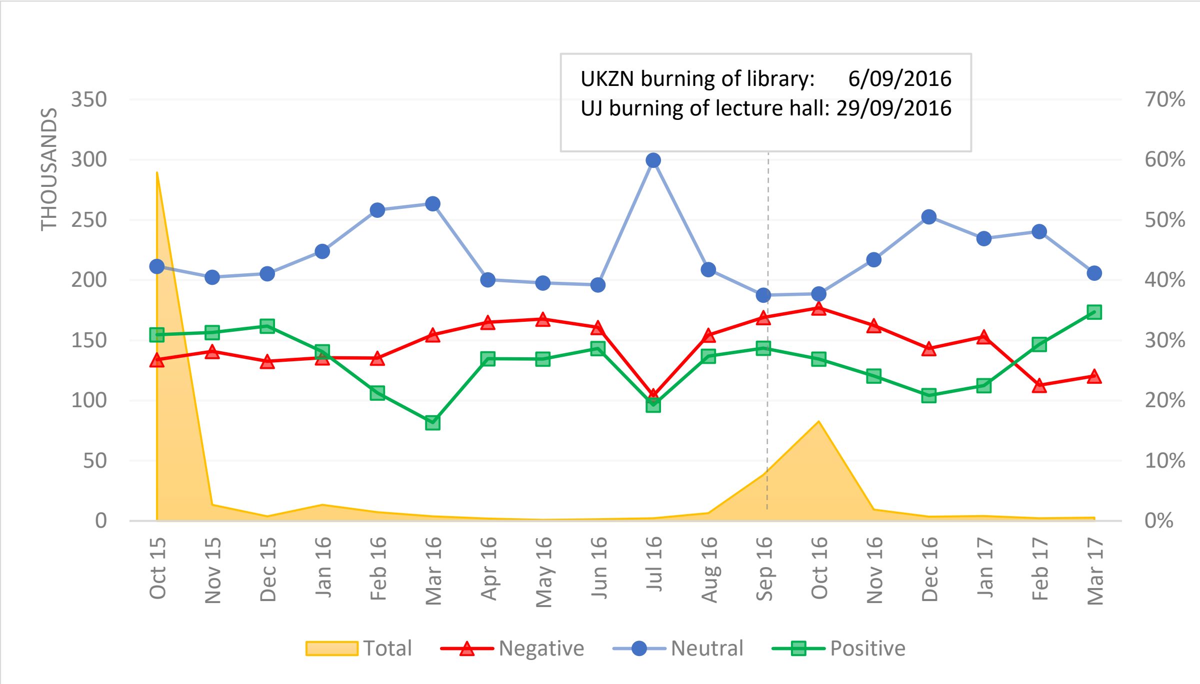


Figure 15 Sentiment analysis Time Series Plot (by month) October 2015 to March 2017

The left-side vertical axis measures the tweet volume of tweets for each month (as drawn from Table 6). The right-hand vertical axis measures the average sentiment percentage for a month. Thus for example, the extractable data for October 2016 has volume of approximately 80 000 tweets (Table 6 affirms this to be 82 712); of which 38% represents neutral tweets; 36% is negative tweets; and about 26% is positive tweets, totalling 100%. In other words, at any given point the sum of the three sentiments (positive, negative and neutral) is 100%.

The dashed vertical line represents two significant perceived negative events that occurred during the #FeesMustFall in September 2016, viz. the arson attacks on the UKZN library (6 September 2016) and the burning of the UJ Hall (29 September 2016). (The findings in this regard are analysed as part of Research Question 2).

A further set of subsequent sub-questions were constructed with its rationale elaborated in section 4.5.7.6 and are provided here for context. These were as follows:

a. *Who were the dominant tweeters and how did they tweet during this study?*
b. *Were news media part of the dominant tweeters?*
c. *What were the tweeting characteristics of the top tweeter?*

The analysis of sub-questions (a) to (c) are now reported in section 5.3.3; section 5.3.4 and section 5.3.5 together with the respective findings.

5.3.3 Finding 1(a): The leading tweeters

Sub-question 1(a) asked:

(a) Who were the dominant tweeters and how did they tweet during this study?

Table 10 provides an analysis of the volume for the Hashtag, Favourite, URL and Retweet of the most prolific (top 10) tweeters as identified following the methodology outlined in section 4.5.7.6.1.

Table 10 The most prolific #FeesMustFall tweeters

User Name	Avg. Sentiment Score	No. of Hashtags (#)	No. of Favourites	No. of URLs	No. of Retweets	Number of Tweets
Camaren Peter	-0.07	63 817	488	15 362	242	**15 403**
EduFunder	0.05	13 665	146	4 111	319	**7 018**
Wake up SA!!	0.00	15 684	1 013	2 215	1 025	**2 318**
Jou Ma Se Party	-0.09	533	56	2 294	70	**2 258**
#AFRICA	-0.09	7 355	426	2 221	100	**2 193**
Jacaranda News	-0.01	3 388	2 035	712	7 185	**2 063**
EWN Reporter	-0.04	2 206	6 532	969	28 974	**1 739**
The Daily VOX	-0.02	1 561	3 523	1 096	12 034	**1 053**
POWER987News	0.00	1 297	1 371	298	6 622	**1 041**
ANN7	-0.01	2 590	1 114	366	4 171	**949**

The columns in Table 10 can be explained as follows:

Average Sentiment Score was calculated by taking and adding the sentiment score of every tweet by each user and dividing it by the total number of tweets.

No. of hashtags is the sum total of hashtags (#) of a user.

Favourite refers to the sum total of all the user tweets that was selected as favourite by a user

No. of URLs in Tweet shows the sum total of the number of URLs of a user.

No. of Tweets refers to the sum total of the number of tweets of a user.

Retweets indicates the sum total of all the user tweets that were retweeted.

5.3.4 Finding 1(b): The role of news agencies in tweets

Research sub-question 1(b) asked:

(b) Were News Media part of the dominant tweeters?

By applying calculations outlined section 4.5.7.6.1, the analysis of news media usernames identified that Jacaranda News (2 063), EWN Reporter (1 739), The Daily VOX (1 053), POWER987News (1 041) and ANN7 (949) (Table 11, rows 6 to 10) were handles of specific news media. The presence of five news media among the list of the Top 10 tweeters (Table 11) indicates that news media played a significant role in generating tweets related to #FeesMustFall.

Table 11 Top 10 tweeters and their respective Rates

Username	No. of Tweets	Hashtag Rate	Fav Rate	URL Rate	RT Rate
Camaren Peter	15 403	4.14	0.03	1.00	0.02
EduFunder	7 018	1.95	0.02	0.59	0.05
Wake up SA!!	2 318	6.77	0.44	0.96	0.44
Jou Ma Se Party	2 258	0.24	0.02	1.02	0.03
#AFRICA	2 193	3.35	0.19	1.01	0.05
Jacaranda News	2 063	1.64	0.99	0.35	3.48
EWN Reporter	1 739	1.27	3.76	0.56	16.66
The Daily VOX	1 053	1.48	3.35	1.04	11.43
POWER987News	1 041	1.25	1.32	0.29	6.36
ANN7	949	2.73	1.17	0.39	4.40

The columns in Table 10 can be explained as follows and the findings are then discussed:

No. of tweets refers to the sum total of the number of tweets of a user

Hashtag rate indicates the average number hashtags per tweet

Fav rate is the average number of Favourites per tweet

URL rate is the average number of URLs per tweet

RT rate indicates the average number of Retweets per tweet

5.3.4.1 Hashtag rates

ANN7 was the only news media account with a Hashtag rate greater than 1.94, with a value of 2.73. Jou Ma Se Party was the only non-news media account with a Hashtag rate less than 1.94 with a value of 0.24.

5.3.4.2 Favourite rates

The news media accounts had Favourite rates greater than 0.98. By comparison, the non-news media accounts had Favourite Rates of less than 0.45.

5.3.4.3 URL rates

Three of the non-news media accounts yielded URL rates of 1 or more, with The Daily Vox being the only news media account with an URL rate of 1.04.

5.3.4.4 Retweet (RT) rates

Collectively, the news media's top 5 handles tweeted 6 485 times (Table 11) which were, in turn, retweeted (RTed) 58 986 times (9.1 per post). EWN posted 1 739 tweets which was retweeted 28 974 times with an RT rate of 16.66 (Table 11). RT rates for Daily Vox and POWER987News were 11.43 and 6.36 respectively demonstrating the role of media as influencers. Significantly, RT rates for the top-5 non-news media accounts were less than 0.45 compared to news media-related accounts being all greater than 3.47.

5.3.5 Finding 1(c): Tweeting characteristics of the top tweeter?

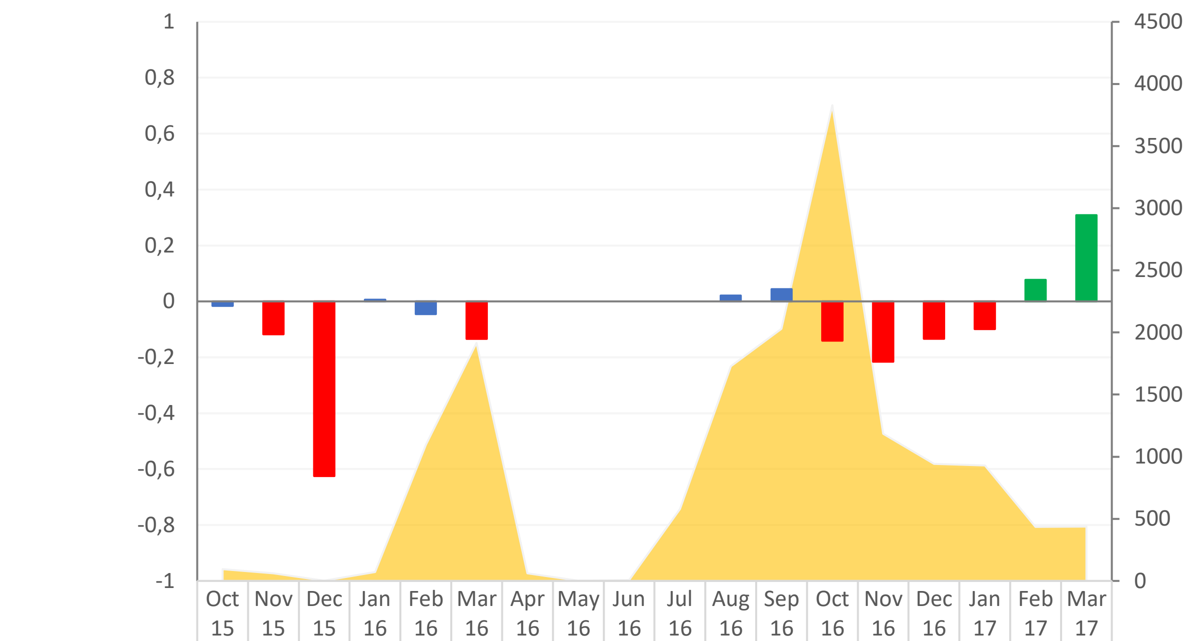
Sub-question (c) asked:

> (c) *What were the tweeting characteristics of the top tweeter?*

5.3.5.1 The top tweeter: Camaren Peter

The top tweeter was Camaren Peter, who posted 15 403 tweets which were favourited 488 times. Each tweet had an average of 4.14 hashtags with one URL This tweeter also had the 3rd lowest retweet total of 242, and the second lowest average negative sentiment score of -0.07 (Table 10).

The volume and average sentiment trend per month for Camaren Peter is charted in Figure 16. The axis on the left measures the average sentiment during the longitudinal period and the right axis corresponds to the total number of tweets. This tweeter posted the most during the months of March 2016 and October 2016, with the respective volumes being 1 915 and 3 829. Peak months of March 2016 and October 2016 had an average sentiment of -0.13 and -0.14 respectively while March 2017 represented the most positive sentiment with an average score of 0.31.



	Oct 15	Nov 15	Dec 15	Jan 16	Feb 16	Mar 16	Apr 16	May 16	Jun 16	Jul 16	Aug 16	Sep 16	Oct 16	Nov 16	Dec 16	Jan 17	Feb 17	Mar 17
Total	95	61	2	71	1096	1915	62	1	8	578	1728	2029	3829	1184	941	930	436	437
Avg Sentiment	-0	-0,1	-0,6	0,01	-0	-0,1	0	0	0	0	0,02	0,04	-0,1	-0,2	-0,1	-0,1	0,08	0,31

Figure 16 Camaren Peter's tweet distribution and average sentiment per month

5.3.5.2 The second highest tweeter: EduFunder

EduFunder posted 7 018 tweets which were favourited 146 times. This is the lowest number in Table 11 suggesting the low impact these tweets had. Each tweet had an average of 1.95 hashtags and were barely retweeted (Average 0.05 times) (Table 11). This tweeter had a neutral sentiment score of 0.05 (Table 10).

5.4 Findings of research question 2: Changes in sentiment trends

Research Question 2 asks:

> **How did the burning of the UJ Hall and the UKZN Library relate to online sentiment trends and polarity?**

In order to analyse research question 2 subsequent questions were constructed and explained in section 4.5.7.6.2. These questions were divided into two parts and are presented for context as follows:

Part A: Overall Sentiment Polarity

a) *Where there any changes in sentiment trend and polarity during this period?*

b) *What were the dates that signified the beginnings these changes?*

c) *How do these change dates relate to dates of real-life significant events?*

Part B: Negative Sentiment Polarity

a) *Where there any changes in negative sentiment trend and polarity during this period?*

b) *What were the dates that signified the beginnings these changes?*

c) *How do these change dates relate to dates of real-life significant events?*

5.4.1 Findings: Question 2 Part A: Overall average sentiment polarity

Mathematical tests and conditions from section 4.5.7.4 were used to analyse research question 2. This resulted in 11 tweets being excluded and the remaining 490 438 tweets being examined across 545 days.

5.4.1.1 Finding A(a): Changes in sentiment trend and polarity

In response to sub-question (a), the analysis revealed that there were indeed changes in sentiment trend and polarity during the study period. This is visually indicated in Figure 17 and statistically in Table 12.

Figure 17 shows a time series plot of the combined **average sentiment per day** across the 545-day period. This is useful as it visually depicts changes with the peaks and troughs. The average changes are highlighted in blue while the upper and lower CUSUM limits are denoted by the top and bottom red lines. The yellow represents the background colour of the graphic.

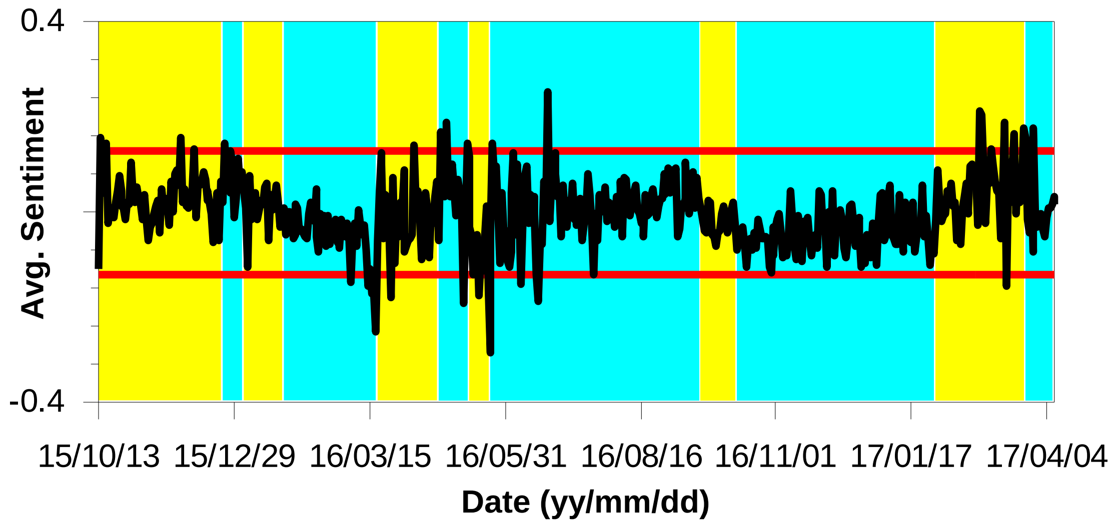


Figure 17 Average daily sentiment plot with CUSUM limits during #FeesMustFall

5.4.1.2 Finding A(b): The dates that signified the beginnings of changes

Sub-question (b) of Part A asked:

b) *What were the dates that signified the beginnings of these changes?*

The study was able to identify the beginnings of sentiment trend and polarity changes. Employing CPA using the CUSUM method (described in section 4.5.7.4) was able to detect 11 change points as seen in Table 12.

The alternate hypothesis H_1 (from section 4.5.7.4 and listed below) is therefore accepted at a 95% confidence level. This finding signifies that changes in sentiment did occur during the 545-day period with four of the changes having a confidence level of 100%.

$$H_0 = There\ were\ no\ changes\ in\ the\ overall\ average\ sentiment\ polarity$$

$$H_1 = There\ were\ change(s) in\ the\ overall\ average\ sentiment\ polarity$$

Table 12 Significant changes in average sentiment

(Confidence Level for Candidate changes= 50%, Confidence Level = 95%, CI=95%, Bootstrap = 10 000, Without Replacement, MSE Estimates)

	DATE	Confidence Interval (DD/MM/YY)	Conf. Level	From	To	Level
1	23/12/15	(29/10/15, 31/12/15)	98%	0.027693	0.077219	7
2	04/01/16	(28/12/15, 11/01/16)	98%	0.077219	0.012388	6
3	27/01/16	(19/01/16, 11/03/16)	100%	0.012388	-0.044778	9
4	20/03/16	(28/01/16, 21/04/16)	99%	-0.044778	-0.0052023	5
5	24/04/16	(25/03/16, 08/05/16)	98%	-0.0052023	0.060491	7
6	11/05/16	(05/05/16, 15/05/16)	100%	0.060491	-0.0997	8
7	23/05/16	(15/05/16, 31/05/16)	97%	-0.0997	0.014568	7
8	20/09/16	(24/05/16, 29/09/16)	96%	0.014568	-0.017547	8
9	10/10/16	(26/09/16, 30/01/17)	100%	-0.017547	-0.042322	3
10	01/02/17	(28/01/17, 11/02/17)	96%	-0.042322	0.052568	4
11	24/03/17	(02/02/17, 03/04/17)	100%	0.052568	0.0042626	5

5.4.1.3 Finding A(a) and (c): Change point beginnings and real world events

The data analysis identified 11 date points (section 5.4.1.2, listed in Table 12) at which average sentiment polarity changed during #FeesMustFall. These change points and their confidence levels are outlined individually in the following sections, together with plausible real-life events that may have precipitated this.

5.4.1.3.1 Change 1: 23 December 2015 (Confidence Level 98%): Neutral to positive

On 23 December 2015, average sentiment polarity increased by approximately 179% from 0.027693 to 0.077219, representing a shift in sentiment from neutral to positive. An online search identified that on 22 December 2015 the Student Representative Council (SRC) of Wits University appealed to students who were financially excluded to contact its organization for assistance (South African History Online, 2016). This indicates there was a significant real-life event around the 23 December 2015. Furthermore, 24 December 2015, a day later, the UCT's Vice Chancellor sent out a letter to funders and parents in relation to addressing financial sustainability over concerns of increasing tuition fees (Price, 2015).

5.4.1.3.2 Change 2: 04 January 2016 (Confidence Level 98%): Positive to neutral

Change point 2 occurs on 4 January 2016 when average sentiment decreased by 84% from 0.077219 to 0.012388 representing a shift in sentiment from positive to neutral. An online search identified that the SRC office at Wits officially opened on this date and its members met with the Wits University's hierarchy and reached agreements on a number of topics ranging from academic exclusion, finance and the First Payment Plan which were posted on Facebook (South African History Online, 2016). This indicates that there was a significant real life event that could be identified on this date. Furthermore, a week later on 11 January 2016 saw registrations at the Wits University disrupted by protest demonstrations (Whittles, 2016) and this follows social media posts by the Wits SRS on the 10 January 2016 which called for changes to the systematic process used in exclusions. This is also a recession from the previous change point 1.

5.4.1.3.3 Change 3: 27 January 2016 (100% Confidence Level). Inward neutrality shift

On 27 January 2016, average sentiment decreased by approximately 481% from 0.012388 to -0.044778 signalling an inward neutrality shift from near-positive to near-negative. An online search revealed that 26 January 2016 saw the #FeesMustFall campaign spread to the University of Namibia (UNAM) under different banners such as #Varsitylockdown and #Universitylockdown (South African History Online, 2016).

This is indicative of a significant real-life event closely related with this date. This is also a recession from the previous change point 2.

5.4.1.3.4 Change 4: 20 March 2016 (Confidence Level 99%). Neutral.

Average sentiment shifted from -0.044778 to -0.0052023 on 20 March 2016. This date corresponds to no identified significant real-life events and is in the defined neutral zone.

5.4.1.3.5 Change 5: 24 April 2016 (Confidence Level 98%). Shift to positive.

Average sentiment shifted from -0.0052023 to 0.060491 on 24 April 2016. This date does not correspond to any identified significant real-life events. It is represented a sentiment polarity shift from neutral to positive sentiment.

5.4.1.3.6 Change 6: 11 May 2016 (Confidence Level 100%). Shift to negative.

On 11 May 2016, average sentiment shifted from 0.060491 to -0.0997. This significant change point saw sentiment swing from a positive state into a negative one. On this date students of UCT appealed to the Supreme Court of Appeal (SCA) regarding UCT's interdict made final by the Western Cape High Court that prevented student protests at UCT (Langa *et al.*, 2017: 67). Furthermore, 5 days later on the 16 May 2016 represented the burning of SANLAM auditorium hall at University of Johannesburg which was later estimated to cost R100 million in damages and ranked as the single biggest act of arson at a university in the country's history (Chernick, 2017). Do note however that this event was not specifically linked to the #FeesMustFall campaign (Dlamini *et al*., 2018). Ultimately, a significant real-life event occurred on this date.

5.4.1.3.7 Change 7: 23 May 2016 (Confidence Level 97%). Shift to neutral.

Average sentiment shifted from -0.0997 to 0.014568 on 23 May 2016. On the evening of the 22 May 2016, homeless UJ students sheltering at UJ SRS offices were forcefully evicted by UJ protection services sparking outbursts on Twitter under the banner #UJeviction (The Daily Vox Team, 2016). This is the closest significant real-life event identified around this date.

5.4.1.3.8 Change 8: 20 September 2016 (Confidence Level 96%). Inward neutral shift

On 20 September 2016, average sentiment went from 0.014568 to -0.017547. This represents an inward neutrality shift from near-positive to near-negative. This date comes one day after the then South African Minister of Higher Education, Blade

Nzimande, made a controversial announcement on 19 September 2016 to allow hikes in tuition fees and asserted that universities could decide their own increases to a maximum of 8% for year 2017 (News24, 2016).

5.4.1.3.9 Change 9: 10 October 2016 (Confidence Level 100%). Neutral

Average sentiment shifted from -0.017547 to -0.042322 on 10 October 2016. Overall sentiment, although it remained neutral, tended towards negativity. Several incidents occurred on this date with the significant events being the torching of a bus at Wits University, the violent confrontations between #FeesMustFall protestors and police at UFS, as well as the burning of furniture at UKZN (Herman and Hess, 2016; News24, 2016).

5.4.1.3.10 Change 10: 1 February 2017 (Confidence Level 96%). Shift to positive.

On 1 February 2017, average sentiment shifted from -0.042322 to 0.052568. The overall sentiment changed from near-negative (still neutral) to positive. On the 30 January 2017, there was the opening of several universities with the Vice-Chancellor of Wits presenting a speech (Habib, 2016). Apart from this aspect there were no other significant real-life related events identified.

5.4.1.3.11 Change 11: 24 March 2017 (Confidence Level 100%). Shift to neutral

Average sentiment shifted from 0.052568 to 0.0042626 on 24 March 2017. Almost a week prior to this date, on the 18 March 2017, a skills convention was violently disrupted in relation #FeesMustFall (eNCA, 2017). This incident represents the closest significant real-life events around the change point date, 24 March 2017, which corresponded to a sentiment change from positive to neutral.

In summary, the study found 11 dates on which average sentiment shifted and was able to identify real-life events that might plausibly be linked to these shifts. Only 2 dates, 20 March 2016 and 24 April 2016, were detected that could not be linked to relatable real-life events.

5.4.2 Findings: Question 2 Part B: Negative sentiment polarity

The subsidiary questions for question 2 Part B were as follows:

a) *Where there any changes in negative sentiment trend and polarity during this period?*

b) *What were the dates that signified the beginnings these changes?*

c) *How do these change dates relate to dates of real-life significant events?*

The two questions (a and b) were statistically examined using the following constructed hypothesis, with the findings following:

$$H_0 = There\ were\ no\ changes\ in\ the\ average\ negative\ sentiment\ polarity$$

$$H_1 = There\ were\ change(s)\ in\ the\ average\ negative\ sentiment\ polarity$$

5.4.2.1 Finding: B(a): Changes in negative sentiment trend and polarity during this period

In response to Part B, sub-question (a), the study found in the affirmative. There were in fact *changes in negative sentiment trend and polarity during this period.* The utilisation of the CPA for the 142 730 negative tweets with parameters from section 4.5.7.4 detected 8 significant change points as seen in Table 13. Therefore, the null hypothesis is rejected and it is concluded that there were significant changes in the average negative sentiment trend during the 545 longitudinal days.

Table 13 Significant changes for average negative sentiment

(Confidence Level for Candidate changes= 50%, Confidence Level = 95%, CI=95%, Bootstrap = 10 000, Without Replacement, MSE Estimates)

	DATE	Confidence Interval (DD/MM/YY)	Conf. Level	From	To	Level
1	07/08/16	(30/07/16, 08/08/16)	99%	-0.42085	-0.29499	7
2	06/09/16	(05/09/16, 06/09/16)	100%	-0.29499	-0.43423	6
3	08/09/16	(08/09/16, 08/09/16)	98%	-0.43423	-0.27649	9
4	19/09/16	(19/09/16, 20/09/16)	100%	-0.27649	-0.43862	5
5	10/10/16	(24/09/16, 13/10/16)	97%	-0.43862	-0.46454	7
6	01/11/16	(31/10/16, 14/11/16)	99%	-0.46454	-0.42244	8
7	22/03/17	(09/03/17, 23/03/17)	95%	-0.42244	-0.52847	7
8	29/03/17	(27/03/17, 05/04/17)	98%	-0.52847	-0.43271	8

$$H_0 = There\ were\ no\ changes\ in\ the\ average\ negative\ sentiment\ polarity$$

$$H_1 = There\ were\ change(s)\ in\ the\ average\ negative\ sentiment\ polarity$$

5.4.2.2 Finding B(b) and (c): The beginnings of change points for negative sentiment polarity and how these relate to real world events

The findings in Part B, sub-question (b) were able to identify the dates that signified the beginnings of the changes in average negative sentiment polarity.

As noted in Table 13, the study has identified 8 date points at which negative sentiment polarity changed. These change points and their confidence levels are outlined individually in the following sections.

5.4.2.2.1 Change 1: 07 August 2016 (Confidence Level 99%). Decrease in negativity

On 7 August 2016, average negative sentiment shifted from -0.42085 to -0.29499 representing a significant decrease. However no discernible real-life events were found close to this date.

5.4.2.2.2 Change 2: 06 September 2016 (Confidence Level 100%). Increase in negativity

Average negative sentiment shifted from -0.29499 to -0.43423 on 6 September 2016 representing an increase in negativity. This date is the same date as the burning of the UKZN library. Therefore, the change point relates closely to a real-life event.

5.4.2.2.3 Change 3: 08 September 2016 (Confidence Level 98%). Decrease in negativity

Average negative sentiment shifted from -0.43423 to -0.27649 on 8 September representing a decrease in negativity. This is 2 days after the burning of the UKZN library incident. There were no other real-life significant events closely related to this date identified.

5.4.2.2.4 Change 4: 19 September 2016 (Confidence Level 100%). Increase in negativity

Average negative sentiment shifted from -0.27649 to -0.43862 on 19 September 2016 representing an increase in negativity. This date is the same date as the announcement by Blade Nzimande allowing hikes in student fees (News24, 2016). Therefore, the change point relates closely to a real-life event.

5.4.2.2.5 Change 5: 10 October 2016 (Confidence Level 97%). Increase in negativity

Average negative sentiment shifted from -0.43862 to -0.46454 on 10 October 2016, representing an increase in negativity. Multiple real-life incidents occurred on this date with the torching of a bus at Wits University being the most violent (Herman and Hess, 2016; News24, 2016). Therefore, the change point relates closely to a real-life event.

5.4.2.2.6 Change 6: 01 November 2016 (Confidence Level 99%). Decrease in negativity

Average negative sentiment shifted from -0.46454 to -0.42244 on 1 November 2016, representing a decrease in negativity. There were no real-life significant events closely related to this date that were identified.

5.4.2.2.7 Change 7: 22 March 2017 (Confidence Level 95%). Increase in negativity

Average negative sentiment shifted from -0.42244 to -0.52847 on 22 March 2017 representing an increase in negativity. There were no real-life significant events closely related to this date identified.

5.4.2.2.8 Change 8: 29 March 2017 (Confidence Level 98%). Decrease in negativity

Average negative sentiment shifted from -0.52847 to -0.43271 on 29 March 2017 representing a decrease in negativity. There were no real-life significant events closely related to this date identified.

In summary, when analysing negativity, only dates, 6 and 9 of September 2016 together with 10 October 2016, were detected as change points that corresponded with relatable real-life events.

5.4.3 Finding Question 2: Impact of perceived negative events on sentiment trends and polarity

Research Question 2 as a whole, sought to answer the question:

> **How did perceived negative events such as the burning of the UJ Hall and the UKZN Library impact online sentiment trends and polarity?**

Having identified the changes in sentiment and polarity and the change dates, this section analyses the two change points detected in relation to the UJ and UKZN arson attacks using the average negative sentiment with conditions outlined in section 4.5.7.6.2.

5.4.3.1 UKZN Burning of the Library: 6 September 2016

The burning of the library at UKZN occurred on the 6th September 2016. The results indicate that there was a significant change in the sentiment polarity on the same date, with a shift from -0.295 to -0.434 (Table 13) which yields a 47% increase in negative sentiment polarity.

This finding confirms that the degree of negative sentiment did change at the date of the UKZN incident. Table 14 represents the count for each sentiment class 3 days before and after the date of the UKZN Incident.

Table 14 Sentiment count during and near the UKZN Library Burning event

Sentiment	3 Sept 2016	4 Sept 2016	5 Sept 2016	6 Sept 2016	7 Sept 2016	8 Sept 2016	9 Sep 2016
Negative	35	38	52	152	112	76	88
Neutral	45	53	64	140	107	62	96
Positive	43	43	70	115	94	74	90
Total	***123***	***134***	***186***	***407***	***313***	***212***	***274***

In the days leading to the burning at the UKZN library the number of tweets were fairly static at around 120 per day, with the day before showing a small spike to 186. The destruction however doubled or quadrupled the spike to 407 tweets – depending on which day one analyses (Table 14). The “aftershock” remained on 7 September (313 tweets) as more people discovered this act (Table 14). The relatively small number of tweets may be explained by the fact that UKZN was far from the epicentre of the #FeesMustFall movement. Figure 18 shows a sharp drop in positive sentiments and concomitant rise in negative sentiments from 6 September 2016.

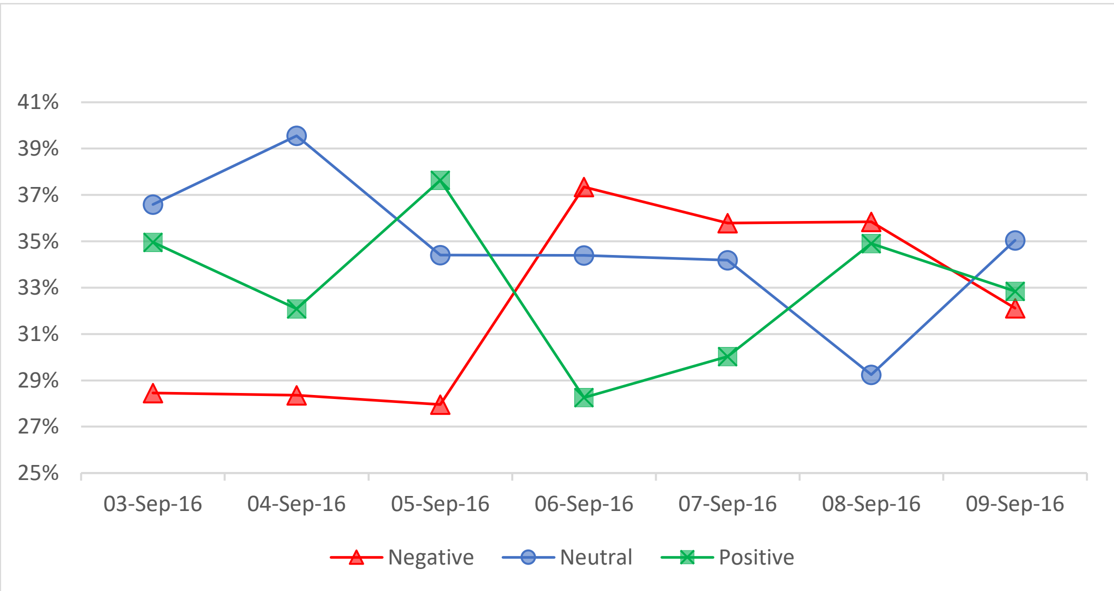


Figure 18 Average sentiment percentage per day during the UKZN library arson attack

5.4.3.2 UJ Burning of the Hall: 29 September 2016

The burning of the UJ Hall event occurred on the 29 September 2016. The number of tweets rose 349% from 25 September (984) to 26 September (3432) and remained above 2500 until the day of the UJ attack (Table 15). The days following 25 September

2016 saw negative sentiment soar by 364%, then experience a dip of 25% before increasing another 75% prior to the event at UJ on 29 September. Additionally, the volume of negative sentiments out-numbered the number of positive sentiments during these days. Table 15 represents the count for each sentiment class 4 days before and 3 days after the date of the UJ Incident.

Table 15 Sentiment count during and near the UJ Hall Burning event

Sentiment	**25 Sept 2016**	**26 Sept 2016**	**27 Sept 2016**	**28 Sept 2016**	**29 Sept 2016**	**30 Sept 2016**	**01 Oct 2016**	**02 Oct 2016**
Negative	109	506	382	671	498	347	140	85
Neutral	731	2613	1878	2781	2441	1590	959	618
Positive	144	313	243	351	405	228	127	114
Total	***984***	***3432***	***2503***	***3803***	***3344***	***2165***	***1226***	***817***

Figure 19 depicts the volume of tweets per day from 25 September 2016 until 02 October 2016 for the negative, neutral and positive sentiment classifications. A noticeable gap is seen between the volume in negative and positive sentiment tweets, with negative sentiment largely above the positive sentiment.

The decreasing trend is expected given that dates 1 October 2016 and 2 October 2016 represent the weekend and which Figure 19 confirms as low tweeting days. Table 15 provides the exact counts for dates in Figure 19.

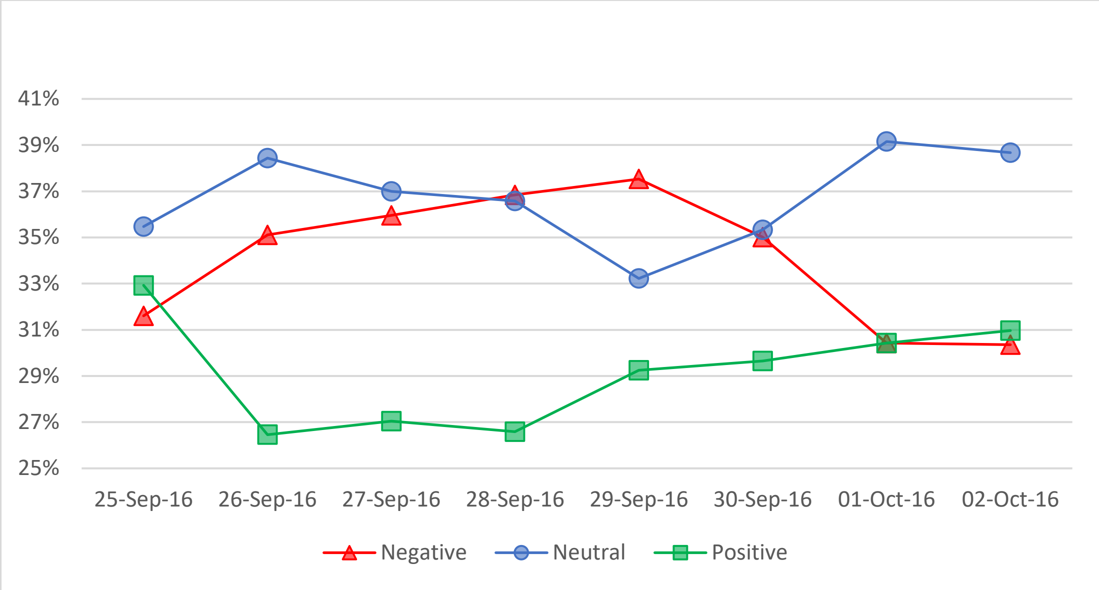


Figure 19 Average sentiment percentage per day during the UJ Senate Hall arson attack

The research question 2 findings are discussed in chapter 6.

5.5 Findings of Research Question 3

Research question 3 asked:

Were social robots deployed on Twitter during the #FeesMustFall campaign?

Social robots were investigated in terms of Twitterbots and Cyborgs by utilising Methods 1 to 4 outlined in section 4.5.7.5.

5.5.1 Finding Question 3: Deployment of social robots during #FeesMustFall

In response to Research Question 3, as to whether social robots were deployed on Twitter during the #FeesMustFall campaign, the study found in the affirmative. Methods explained in section 4.5.7.5 revealed that social robots were deployed during this longitudinal period. Method A returned a total of 283 Users that were either bots or cyborgs, while Method B and Method C returned 6 and 135 bot or cyborg prone accounts for further analysis. Method D returned a total of 4 bot accounts by the DeBot API.

These results from Methods A, B, C and D were analysed against the top tweeters in Table 10 and Camaren Peter and EduFunder were the two usernames that belonged to both grouping results.

Tweeting characteristics of Camaren Peter are illustrated in Figure 20 and show systematic patterns in tweeting behaviour within a one-hour time scale. Camaren Peter mainly tweeted via Hootsuite which assists in automating tasks on Twitter such as periodically tweeting multiple content.

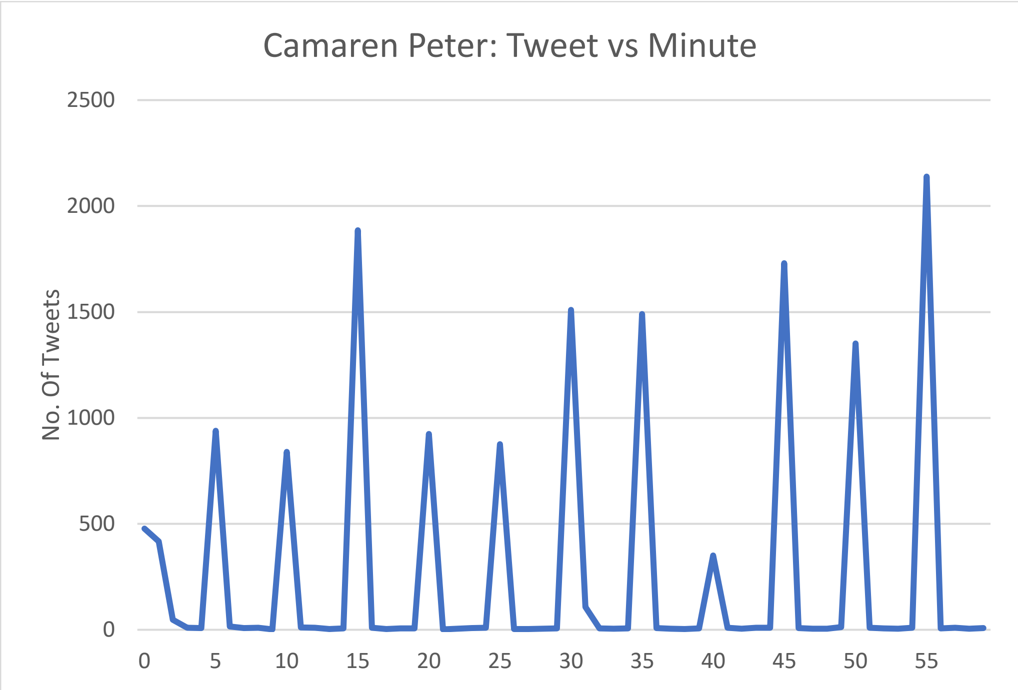


Figure 20 Timeline of tweets in a one-hour scale by Camaren Peter

EduFunder's tweeting behaviour, as seen in Figure 21, displays multiple tweets per second for 8 successive seconds within a 10 second interval on 21 October 2015 at 10:53 AM. The vertical axis represents time with format hour:minute:second and the horizontal axis represents the corresponding volume of tweets. Notice the significant amount of activity within 10 seconds and at least 2 tweets per second from this sample of data. EduFunder used the IFTTT (IF THIS THEN THAT) method to tweet. This is a widely used method in developing as well as creating bot applets.

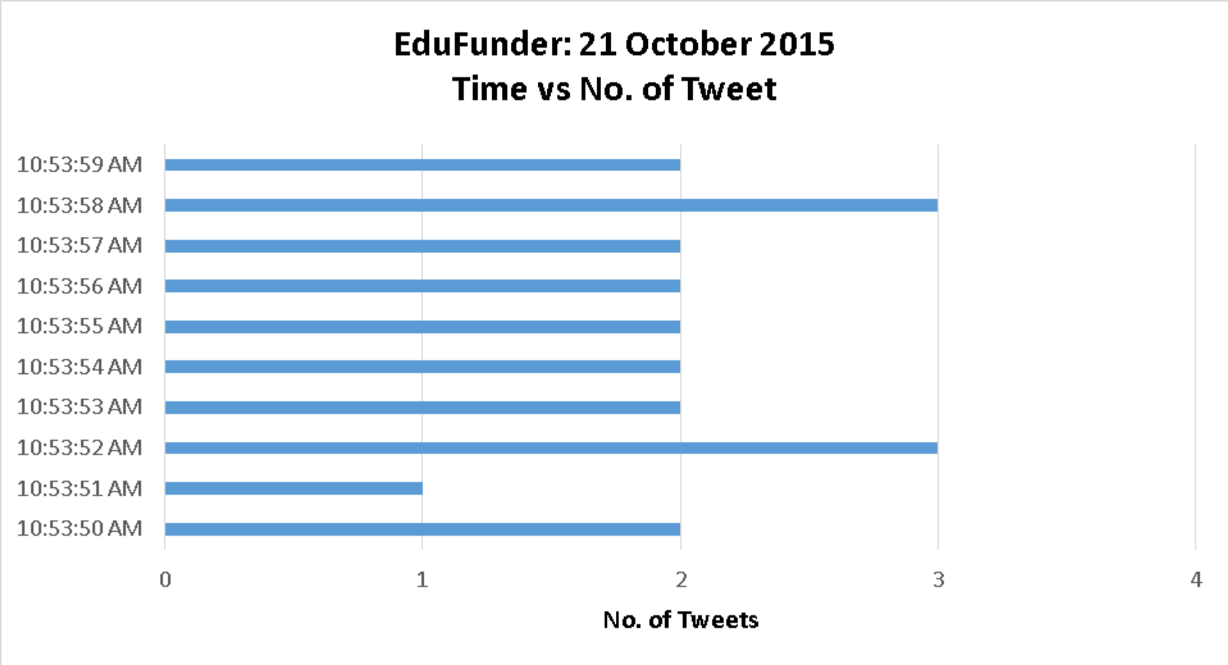


Figure 21 Volume of tweets in a 10-second burst by Edufunder

The research question 3 findings are discussed in chapter 6. This chapter concludes with the summary of the main findings of the study.

5.6 Conclusion: Main Findings

In summary, the study has three main findings.

5.6.1 There were fluctuations in sentiment

The main findings from chapter 5 revealed certain fluctuations in sentiment trends on Twitter during the 545 day study period that coincide with real-life events particularly when analysing only the negative sentiment class for perceived negative real-life incidents. These changes were after, on or even before perceived negative events, highlighting the potential for sentiment analysis to be used as a tool to mitigate perceived negative real-life outcomes.

5.6.2 The news media did amplify the campaign albeit neutrally

The study found that news media played a significant online role in the amplification of the #FeesMustFall campaign with news media user accounts comprising five out of the top ten highest tweeters during the period under study.

An analysis of the average sentiment score for each media outlets showed that their average sentiment was close to zero strongly suggesting that they tweeted positive, negative and neutral news without bias. This is an important finding for researchers and stakeholders who accuse the media or any particular sector or agenda setting.

5.6.3 Bots were deployed

The significant finding in this research was the uncovering of bots that were deployed in the #FeesMustFall campaign to at minimum amplify the #FeesMustFall campaign. It was found that social robots were deployed of which two bots played a significant role during this campaign. Accounts identified as social robots ranked first and second amongst the highest tweeters. These social robots played a dominant role affecting the volume of #FeesMustFall tweets which in turn affected sentiment. Their overall sentiment tended to be neural on Twitter during this period.

In summary, in this chapter, the data was analysed using sentiment analysis, descriptive analysis, CPA analysis and the CUSUM method, as well as bot identification methods, and the results were presented. Each research question and subsequent questions were answered methodically and significant outcomes highlighted. This chapter provided the evidence required to infer appropriate conclusions as well as suggest future work and recommendations to researchers and relevant stakeholders. Chapter 6 discusses the findings.

Chapter 6 Discussion of the Findings

6.1 Introduction

Chapter 5 presented all the study's findings and answered the research questions. This chapter presents a discussion of these findings. First the findings of the descriptive analysis of the dataset is discussed (section 6.2), thereafter the findings of research question 1 (section 6.3), research question 2 (section 6.4) and research question 3 (section 6.5) are explored.

6.2 Discussion on the descriptive analysis of the data

Section 5.2 presented the results of the descriptive analysis of the #FeesMustFall tweets. These findings with regards to linguistic analysis (section 6.2.1) and tweet distribution (section 6.1.2) are discussed here.

6.2.1 Linguistic analysis

The linguistic analysis of the data (Table 5) found that English language texts were in the overwhelming majority. 'Undefined' was the second most detected language in the #FeesMustFall tweets. As South Africa is a multilingual country the likely explanation may be that the texts were composed using alternate or unique South African languages, jargon, emojis, emoticons, URLs or alphanumerical characters normally associated with linguistics outside of human languages, e.g. #FMF;☺; https://www.dut.ac.za; etc. The discernible non-English tweets numbered 9 331 (Table 5).

The second most defined tweeted language was reflected as Dutch and this is unsurprising since the Dutch language shares a very close resemblance to the Afrikaans language which is widely spoken in South Africa. Language detection algorithms, similar to the commercially applied algorithm applied by Podargos, require constant refinement and upgrades to achieve higher levels of accuracy and this is outside the scope of this study.

6.2.2 Tweet distribution

The distributive nature of #FeesMustFall was found to be lognormal (Figure 13). Bild *et al*. (2015) studied and quantitatively aggregated Twitter campaigns and found that tweet distribution, in general, exhibits a lognormal form over finite sample intervals.

Consequently, this suggests that the #FeesMustFall campaign on Twitter could not have been driven entirely by bot automated software since its distribution followed an expected lognormal form. Since the data in this study was purchased (section 4.5.3), Table 7 and Figure 13 provides mathematical comfort on the validity of the distribution of the data. The long tail demonstrates sustained interest from the protestors' side who maintained pressure on authorities providing a further reason for the study.

The tweet distribution for every month in the dataset is reflected in Table 6. March and April of the year 2015, each consisted of one tweet. These tweets occurred prior to the explosive increase in the volume of tweets experienced during October 2015. The first two tweets (Figure 2 and Figure 3) are historically significant as the seed for the hashtag #FeesMustFall which was planted during the height of the #RhodesMustFall campaign, as discussed section 2.4.2. These first two tweets were regarded as outliers when calculating the distribution of the data due to being significantly distant and isolated from the rest of the main data timelines.

The distribution of tweets from this study, therefore, conforms with and supports what Bild *et al*. (2015) found in their studies which was that tweet distributions of campaigns on Twitter generally follow that of a log-normal forma over limited intervals.

6.2.3 Tweet volume

The volume of tweets for October 2015 (Table 6) outweighed the combined total number of tweets for the entire 2016 year and marked the month that propelled the campaign to prominence. High volumes of this nature are expected at the peak of events and campaigns. It may well be that increases in the volume and rate of tweets were triggered by the physical protests occurring at prominent South African universities where these institutions provided "free" or cost effective Wi-Fi facilities which enabled easier access to online platforms such as Facebook and Twitter. Further MTN, a significant telecommunications network provider, coincidently allowed free Twitter usage on its platform during the time period of the longitudinal study (section 2.4.5) (Jordaan, 2018). Despite the free commercial and on campus transmission, volumes still dropped over time, as predicted by Bild *et al.* (2015).

The figure for October 2015 in Table 6 might seem contradictory to the 370 000 tweets analysed by Findlay (2015) between the 15th and 26th of October 2015. However, it must be reiterated that analysis by Findlay (2015) was conducted on *all*

#FeesMustFall-related Twitter hashtags. Consequently, the collection of tweets by Findlay (2015) is higher as it includes analysis of the associated hashtags such as #WitsFeesMustFall, #UCTFeesMustFall and #UKZNFeesMustFall which were generated by Twitter as separate discussions under new hashtags (Table 8).

October 2016, the anniversary of the #FeesMustFall campaign, represented a second spike in the volume of tweets compared to preceding months. October is also the month that universities commence with year-end examinations[27] and it is a time when subsequent results may be withheld due to outstanding tuition fees. Furthermore, a majority of South African universities announce their annual fee increases for the forthcoming year in October. All of these contextual circumstances revolve around fees and help to explain the heightened emphasis of the #FeesMustFall campaign during October 2015 and October 2016 corresponding to an amplification in the volume of tweets. These factors probably combined to revitalise the campaign.

6.2.4 Daily tweet distribution

#FeesMustFall Twitter activity was found to be more prevalent during weekdays as opposed to weekends (Figure 14). This may partially be explained by the fact that university classes are usually closed over weekends, which results in lack of free WIFI access. This argument is supported by the literature. Golder and Macy (2011: 1879) have highlighted the "the circadian activity and weekly cycles typical of social media chatter" that is seen in Figure 14. Chu *et al*. (2010) found that tweet volume also declined over university recess periods. An analysis of Findlay's (2016) tweet distribution (Figure 22) showed that even at the height of the campaign tweets were less over weekends (24-25 September 2016 and 1-2 October 2016). Ordinarily graphs from other sources do not appear in the results chapter, however Findlay (2016)'s findings in Figure 22 below, is revealing for discussion purposes as it validates the inferences from Figure 14 for the short peak period and also the tweet distribution finding in Table 6. The author's study extrapolates the tweet distribution behaviour found in the literature across a longer longitudinal duration which provides more assertiveness to the notion that frequency of tweets are significantly lower in recess periods compared to periods outside of recess.

[27] South African school and universities follow the Georgian calendar (January to December).

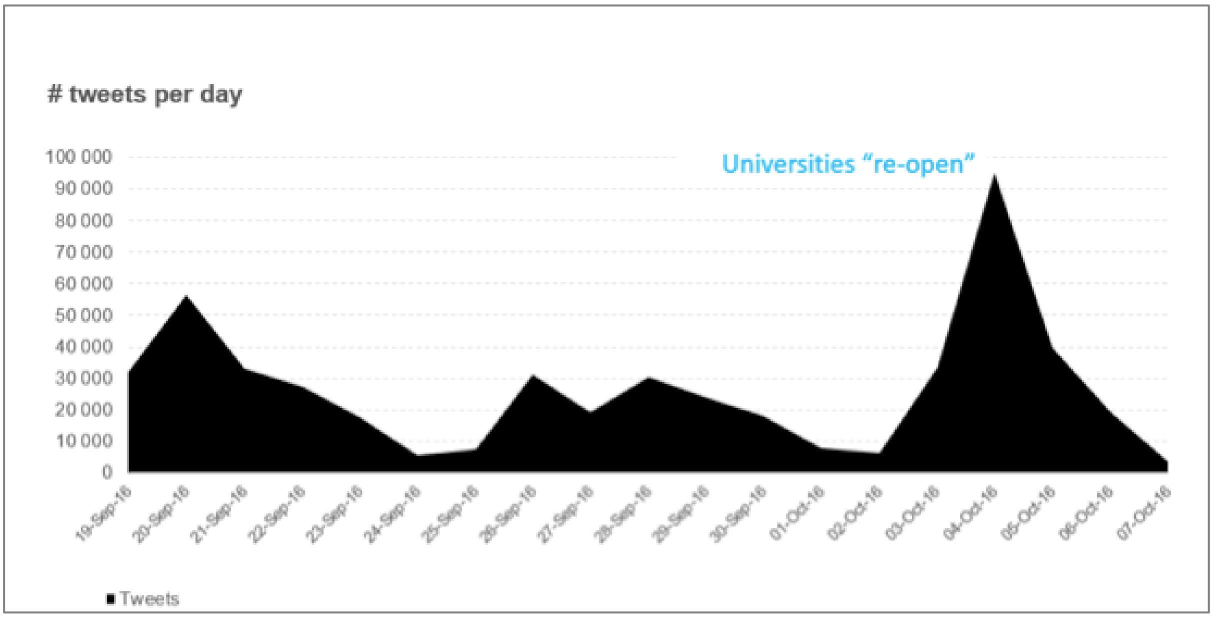


Figure 22 Daily tweet frequency between 19 Sept and 7 Oct 2016 (Findlay, 2016)

6.2.5 Tweets with multiple hashtags

Table 8 confirms that #FeesMustFall was the primary hashtag and that secondary hashtags played a partial role throughout the campaign.

Multiple hashtags in a tweet alternatively have either an amplifying or diminishing impact on the primary hashtag. This phenomenon can be seen in Figure 23 below where embedded secondary hashtags either served to increase the primary #FeesMustFall hashtag span by tagging other conversations in an attempt to lure in users otherwise affiliated with #RhodesMustFall, or served to shift focus away from #FeesMustFall towards another campaign, #EndOutSourcing which sought to end the outsourcing of university services. The tweet in Figure 23 is a reflection that leveraged the #FeesMustFall hashtag while also encouraging the protestors to promote secondary agendas.

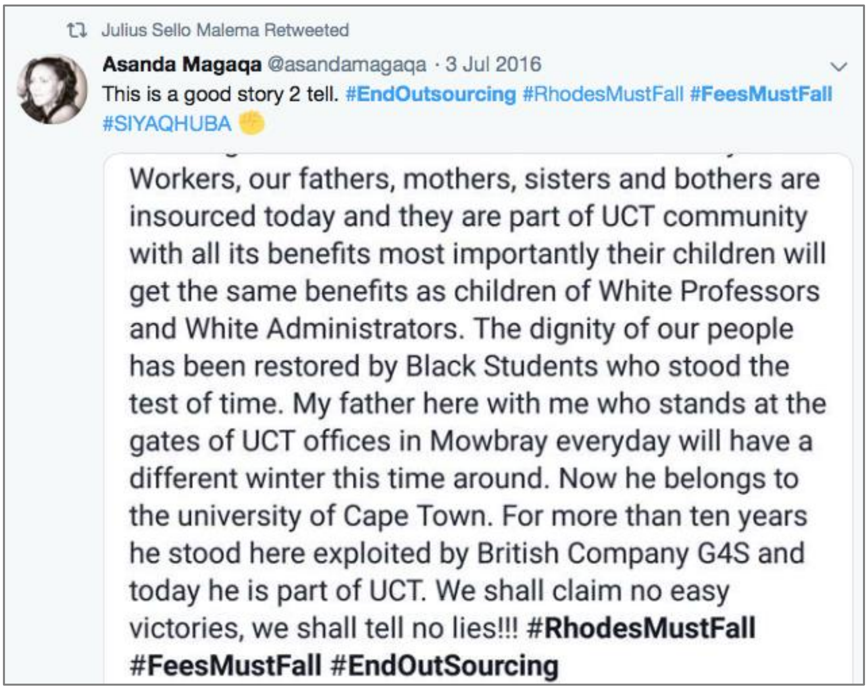


Figure 23 Tweet with multiple hashtags (Twitter, 2016)

Table 6 reflected a total tweet count of 490 449, whereas Table 8 reflected a primary hashtag count of 497 916 count for #FeesMustFall. This increase on Table 6 is due to many users utilising the hashtag more than once in a single tweet. This may be due to wanting to emphasize the term.

The dominant secondary hashtag was #nationalshutdown with a count of 28 054. Since #nationalshutdown was a well-known plea to conduct nationwide protests in South Africa, this represents a significant finding as it affirms that Twitter was indeed used as a platform to promote broader social activism during the #FeesMustFall campaign.

Wits University was the only tertiary institution that featured amongst the top ten entries in Table 8 with an associated hashtag, #Wits, with a tally of 12 352. This result supports the notion that the Wits University was at the epicentre of the #FeesMustFall campaign given the count tally in its favour compared to other tertiary institutions.

#fees2017 was closely tallied with #wits with a count of 12 100. This is unsurprising as the #FeesMustFall campaign attracted many related hashtags during its lifespan which covered many months following on from October 2015 with events towards the end of year 2016 refuelling the movement's cause for zero fees (*Everything Must Fall*, 2018). One such event was the statement by Blade Nzimande about capped increases in university tuition fees which reigniting the campaign and attracted related hashtags like #fees2017 along with the main #FeesMustFall hashtag (News24; 2016).

#asinamali, with 4 325 counts, has intellectual significance as it corresponds to Asinamali, a South African term, which means "we have no money" and is related to the apartheid-era prison, where black inmates shared their stories of persecution and rebellion in their pursuit for freedom (Makalela, 2018). This hashtag promotes a narrative that the #FeesMustFall was perceived to be associated with the freedom struggle.

Other hashtags, namely #leadership, #zumamustfall, #ancmustfall and #unionbuilding, may well have been a deliberate attempt to engage senior politicians on the fees matter.

6.3 Discussion on research question 1

This section discusses the stratified sentiment (section 6.3.1), the tweet frequency and the sentiment trend (sub section 6.3.2) findings of research question 1.

6.3.1 Stratified sentiment

Although the prevailing numerical sentiment was neutral over the longitudinal study period (Table 9), the stratified population provided rich analytical information. The exponential rise in tweets during October 2015 strongly suggests strong online interest, intrigue or participation.

An opportunistic feature and contribution of this research study is the stratifying and separate analysis of the positive, negative and neutral sentiment distributions. Mapping sentiments over a period becomes useful if one wants to look for aberrations which manifest through peaks and troughs within a trend. This cognitive data is particularly useful for non-technical stakeholders. Further, the aberrations become useful when tagged and contextualised together with real-life events. This must be done pragmatically. For instance, the big difference between neutral and positive sentiment in July 2016 is probably due to the university recess[28] where the media and other stakeholders continued covering news on the campaign, while students largely abstained (perhaps due to not having free Wi-Fi access off campus, as noted). The

[28] South African universities typically have a few weeks recess at midyear.

tweet count for July was also very low at 1 551. This is considered a “harmless” aberration.

6.3.2 The tweet frequency and sentiment trend

The perceived UJ and UKZN negative events of September 2016, created a spike (Figure 15) while the anniversary month maintained this upward trajectory (October 2016). A second lognormal distribution is discernible albeit at a lower rate from October 2016 until April 2017.

Visual inspection of (Figure 15) indicates noticeable changes in sentiment volumes over the longitudinal period. This observation cannot be presumed to be causality-based and requires scientific evidence to demonstrate what one “sees.” This was further expanded on in section 5.4.1.

When the volume of tweets and sentiment proportion are jointly taken into consideration, key patterns emerge particularly during the months of September, October and November of the year 2016. Negative sentiment grew higher in proportion to positive sentiment as the tweet volume substantially increased and was thereafter sustained for several months. The lack of positivity on the anniversary may be due to protestor dismay at the lack of progress as well as the perceived negative events such as the burning of the UKZN Howard library on the 06 September 2016 and the burning of a lecture hall in UJ Hall on 29 September 2016.

Sentiment analysis time series charts such as Figure 15 also provide an important opportunity for administrators to continually monitor sentiment trends as these charts will quickly show sentiment swings. This may provide for pre-emptive remedies when the online barometer demonstrates emerging negative sentiment, and may be useful to mitigate violence. Tweets drive sentiment while certain tweeters are more influential and prolific than others. It was therefore instructive to view the activity and respective average sentiment of the top tweeters during the campaign.

6.3.3 The role of news agencies in tweets

News media purvey news as this is their role. The media had a role in the amplifying the #FeesMustFall campaign, and generated a combined 58 986 retweets (indicated in Table 11). This finding is backed by Baillie-Stewart (2017). This role is an incidental, not accidental, and is a natural consequence of media behaviour. In South Africa, traditional news platforms in general, have a concomitant online presence. In 2014, some traditional news platforms reported that 100% of their journalists also used Twitter to perform their duty in providing news information to Twitter users (De Jager, 2016).

It was no surprise to find that news agencies did consider and cover the campaign as a newsworthy event. The high standing in the retweet rate elevated the media to the campaign's leading influencers. The high RT rate for media handles are not uncommon as communities consider the media as credible albeit with varying degrees of trust (Morris *et al*., 2012).

The ranking of news media accounts between fifth and tenth out of the top ten tweeters in Table 11, together with the high favourite rates of the media tweets support and affirms the influential role that the media plays. One should also remember that the news reporters are media savvy suggesting they either knew what "newsworthy" items to tweet or that they gauged what was newsworthy from tweet response and posted accordingly. This may add to the narrative that traditional news media had an agenda setting theory (De Jager, 2016).

The #FeesMustFall campaign experienced moments of tense standoffs between students and law enforcement, with stone throwing, burning of tyres and other violence, and destruction with the burning of cars and buildings. The campaign also had poignant moments of solidarity when all stakeholders concurred, converged and marched in unison.

Crucially the finding in this study is that while amplification did occur, the media was neutral with sentiment averages close to zero for all top 5 media houses (Table 10). A neutral sentiment score for a news agency is significant. An average sentiment score of close to zero suggests neutrality on the part of the poster. For example the EWN average sentiment was neutral (-0.04) signifying that it tweeted both positive, negative and neutral news exemplifying the neutral role of media that media should and did indeed play in the campaign. The other outlets also had neutral sentiment polarity scores namely Jacaranda News (-0.01), The Daily VOX (-0.02), POWER987News (0.00), and ANN7 (-0.01) (Table 10).

The news media accounts also did not try to ambush the #FeesMustFall with other extraneous or opportunistic tags, as indicated by the fact that their hashtag rates were between 1.25 and 2.73 (Table 10).

The researcher argues that the news media Twitter account for as ANN, EWN, and Power987News are commercial and self-serving, albeit with reasonable justification, because they direct traffic towards their online news articles as a marketing and sales exercise. The number of URL's indicates this type of tweet behaviour (Table 10). Indeed Twitter users view news media users as reputable sources of information and RT them (Morris *et al.*, 2012). There is nothing wrong with a self-serving self-interest when used ethically, it is argued.

6.3.4 The top tweeter

The top tweeter, Camaren Peter, displayed unusual patterns in tweet activity which can be seen in Figure 16, Table 10 and Table 11. The volume of tweets posted exceeded 15 000 (nearly double that of the second highest tweeter) and the hashtag rate of 4.4 indicates an emphasised attempt to market other related or non-related topics. These results affirms the construction of research question 3 to establish if the top tweeter was a social bot or cyborg.

6.4 Discussion on research question 2: Changes in average and negative sentiment

This section discusses changes found in the overall average sentiment (section 6.4.1) and changes in negative sentiment (section 6.4.2).

6.4.1 Changes in the overall average sentiment

Change points 1 to 11 (Table 12), excluding 4 and 5, were found to be closely related to significant real-life events. This indicates a strong connection between sentiment expressed on Twitter and real-life societal incidents including statements by government and university officials.

Change points 4 and 5 may be due to factors such as lobbyists or social robots attempting to aggressively push their views across thereby inflating the volume and affecting sentiment. Alternatively, cyclical periods of recess at universities which causes students to disperse lowered the focus on the campaign. Another possible factor could be because of news media who, like bots, played an amplified role during the campaign (Table 10 and 11) which may have sustained the online conversation during vocational periods. All of these factors would significantly impact sentiment results.

It is arguably logical to assume that perceived social negative events are a product of persistent and growing negative sentiment amongst people. Similarly, it is also logical to expect an increase in negative feedback following events of a negative nature. Therefore, the next section discusses change points only in respect of the average negative sentiment polarity. Changes will be triangulated to events such as the UJ Hall and UKZN arson attacks that have occurred during the #FeesMustFall campaign.

It could have been that nothing of significance happened – perhaps due to a correction from a previous change or a simple tweet reduction or a protestor distraction that the analysts should be aware of, but the two arson events providing a good research opportunity.

6.4.2 Changes in the negative average sentiment

Change points 2, 4 and 5 (Table 12) demonstrate that using average negative sentiment as the sentiment class to monitor perceived negative events yielded more accurate returns in terms of closeness to related real-life events. The CPA analysis proved that there is a relationship between negative sentiment changes on Twitter and perceived negative real-life events, although, not all the change points were identified to be in relation to significant real-life events. This may be due to many factors such as social robots and news media dominating the activity on Twitter during this period thereby impacting the sentiment analysis, or simply the researcher not being able to identify the triggers (The role of social bots was investigated in question 3).

The key negative events merit further discussion.

6.4.2.1 UKZN Burning of the Library: 6 September 2016

Results from Figure 18 and Figure 19 seems supportive of Engh and Settler (2016) and Kujeke (2016) who suggest that management were silent to UKZN's student demands and request of a meeting in 2016. UKZN management said security was 'beef[ed]-up' through several police vans, and a Nyala which is an armoured personnel carrier. Students reacted with "both fear and anger" (Engh and Settler, 2016). This led to incitement. Porta (2013) argues that there are two factors that cause protests to become violent: the escalation of policing and competitiveness. The latter refers to the fact that both student and police parties were highly competitive with respect to their respective power and authority. Govender (2016) alleges that academics had a hand in the student uprising at UKZN citing impeccable sources (Kujeke, 2016).

The burning of the UKZN library was another negative episode during the #FeesMustFall campaign. It occurred on 6 September 2016 and was successfully pinpointed by the CPA when analysing **only** the average negative sentiment polarity. This signifies the need to also conduct CPA on single sentiment classifications to provide further insights into data changes.

6.4.2.2 UJ Burning of the Hall: 29 September 2016

The destruction of the UJ Hall on the 29 September 2016 followed closely news media reports released on 26 and 27 September 2016 about the death of a worker at the Wits University linked to #FeesMustFall protests (Pijoos, 2016; TMG Digital, 2016). The link may well be tenuous but the reference is pragmatically pointed.

The burning of the UJ Hall event occurred on the 29 September 2016. This perceived negative event lies between the change point dates, 19 September 2016 and 10 October 2016 (change point 4 and 5 in Table 13), which detected an increase in the average negative sentiment polarity at both of these points. This is a significant statistic as it demonstrates the plausibility of utilising sentiment metrics on social media to trace early warnings to perceived negative real-life events.

The damage to the UJ Hall occurred on 29 September 2016 and this date is not directly pinpointed on Table 13 which records significant changes for average negative sentiment. However, the CPA identifies two nearby change points, 19 September 2016 and 10 October 2016 and their related significance is explained next.

On 19 September 2016 the controversial 8% capped increase in tuition fees announcement was made by Minister Blade Nzimande (News24, 2016). The significant sentiment change in *average* sentiment that resulted is reflected in Table 123 as an increase of 59% in the average negative sentiment score from -0.27649 to -0.43862. Table 13 detected this significant change in polarity much earlier than Table 12 and also detected a change point on the same date as the UKZN event affirming the alteration in application of the CPA for perceived negative events.

The day of 10 October 2016 was marred by various perceived negative events such as the torching of a bus in Wits University, damages to furniture at UKZN, violent confrontations with police at UFS and many more incidents across South Africa (Herman and Hess, 2016; News24, 2016). The nationwide reach of events helps explain the significant change in Table 13 (change point 5) with the average negative sentiment polarity increasing by 6% from -0.43862 to -0.46454.

The UJ Hall incident lies in-between the increasing trend in average negative sentiment polarity experienced from 19 September 2016 to 10 October 2016 (Table 13). This is significant in terms of using sentiment analysis as a means to monitor social media for preventative measures, because CPA detected an increased polarity shift well in advance to the burning of the UJ Hall demonstrating its capability of being used as an early warning mechanism to negative perceived outcomes.

Twitter is particularly useful for monitoring public opinion because (a) tweets are reliably time-stamped, unlike most of the rest of the Web, so that they can be analysed from a temporal perspective, (b) they are relatively easy to create, so that a wide segment of the population with Internet access could, in theory, create them, and (c) they are public and hence accessible to researchers, unlike most social network sites (Thelwall, 2014). Analysts and consultants argue that advanced statistical techniques will allow the detection of *ongoing* communicative events (natural disasters, political uprisings) (Bruns and Liang, 2012) and the reliable prediction of *future ones* (electoral choices, consumption) (Chung and Mustafaraj, 2011).

The South African nation had not experienced a campaign of the magnitude of #FeesMustFall since the advent of the digital age. The study's results indicate that sentiment on Twitter did change significantly throughout the #FeesMustFall campaign and certain changes triangulate successfully to real-life events.

6.5 Discussion on Research Question 3: Role of social robots

During the data analysis phase, intriguing social behaviour exhibited by the top tweeting users was found with respect to their frequency, volume and content, suggesting automated behaviour. Examples included tweeting messages with fixed constant intervals (Figure 20) and tweeting multiple times per second for several seconds producing an abnormal burst in tweeting activity (Figure 21). These tweet characteristics are synonymous with Twitter Bots or Cyborgs behaviour (Chu *et al*., 2012). Twitter software is specially written to troll social media and to *inter alia*, amplify certain tweets, or repeatedly tweet a boutique of tweets either in burst mode or with a certain time-based frequency. This is what piqued the researcher's interest to identify the nature and extent of the impact of Twitter Bots and Cyborgs within the dataset.

Results and analysis for Research Question 3 revealed that Camaren Peter and EduFunder were social robots. Camaren Peter portrayed symptoms of a cyborg since Hootsuite and Buffer were used to automate tweets for this account. Camaren Peter's tweeting activity displayed a tweet frequency unlike a completely human controlled Twitter account. In addition, Chavoshi, Hamooni and Mueen's (2016) DeBot system identified Camaren Peter as a bot when using its API on the 29 December 2016.

In summary, social robots (bots) did play a role during the #FeesMustFall campaign in at least amplifying the number of posts related to the movement, while their deployment may also have been intended to sustain the conversation on Twitter during off-peak intervals such as holidays and university recess periods. The existence of Twitter Bots and Cyborgs remains a significant finding emanating from this study since it is the first known research that undertook analysis and identification of social robots within a South African context, particularly about the famous #FeesMustFall campaign.

6.6 Conclusion

This chapter discussed the findings in more detail, drawing on additional literature. It expanded and offered explanations to results found in Chapter 5 such as the log-normal form for dataset distribution being an expected outcome with weekend periods ranking lowest in tweet volume due to factors such as lack of accessible Wi-Fi facilities for students. The results for multiple hashtags were noted to either have a diversion or awareness effect on the primary #FeesMustFall hashtag with #asinamali a peculiar presence amongst the highest ranking secondary hashtags.

Prevailing sentiment trends together with news media's role in the #FeesMustFall campaign were further discussed with links between changes in sentiment polarity and real-life events noted as a significant finding and an indicator for Twitter to be used a potential monitoring tool. Furthermore, the UKZN and UJ events analysed in this study were noted to be successfully detected using the CPA on sentiment polarity scores which were also discussed in detail.

A discussion concerning the role of social bots in the #FeesMustFall campaign completed the chapter which noted their amplification characteristics and highlighted their presence as a significant finding of this study.

In summary, the research questions analysed in this study (Chapter 5) produced results which were then discussed in this chapter. The discussions provided insightful explanations to the results and contributed towards successfully addressing the aims and objectives of this study.

The next chapter (Chapter 7) provides recommendations and scope for future research emanating from this study.

Chapter 7 Recommendations and future research

7.1 Introduction

This chapter reflects on the study in its entirety by summarising the work done, highlighting the research gaps, and explaining the unique contributions of this study. Further, this chapter reviews the aims and objectives outlined in chapter 1 and addresses their achievements. Moreover, the conclusions of this research are presented together with recommendations, and future work that is indicated by this study is elaborated.

A longitudinal sentiment analysis study of the #FeesMustFall on Twitter was successfully conducted in this research study. The study used computational techniques and methods to identify changes in sentiment trends as well as to detect social robots. Chapter 1 provided the introduction for this study and outlined its aims and objectives. Chapter 2 engaged with related #FeesMustFall literature and Chapter 3 discussed sentiment analysis literature which contextualised and provided a knowledge platform for this thesis. Chapter 2 also highlighted research gaps of which some have been fulfilled by this study. Chapter 3 provided a detailed explanation and justification of sentiment analysis and Chapter 4 elaborated the methodology and methods in detail, with a particular focus on data collection and data analysis. Chapter 5 presented the corresponding results and summarised the main findings of this study, and a discussion of the findings was provided in Chapter 6. The research objectives were reached and are summarised next.

a) Research Objective 1

To analyse the prevailing sentiment of Twitter users' opinions during the #FeesMustFall campaign

Sentiment trends serve as a barometer of the opinion of the online community, which may well reflect the opinion of the affected society. The study's results proved that the prevailing sentiment and associated volume can and did change for various reasons, some unidentifiable while others appear to react or reflect events. The stratifying of the sentiment into positive, negative and neutral classes provided further contextual views of the sentiment. The news media accounts displayed an admirable and overall neutral sentiment, despite being amongst the highest tweeters.

b) Research Objective 2

Examine changes in sentiment on Twitter in relation to the burning of the University of KwaZulu-Natal (UKZN) library and University of Johannesburg hall events.

The detection of changes in sentiment over the observational period was undertaken through the CPA analysis of either the average sentiment or the negative corpus of tweets. The first CPA analysis at UKZN used CPA on the overall sentiment classes while the second CPA analysis used only the negative sentiment class affirming the intrinsic value of stratified sentiment analysis. They together proved that online changes in sentiment trends were closely related to events at UKZN and UJ. CPA detected significant increases in negative sentiment trends on Twitter scientifically enforcing the view that negative events has a concomitant consequences.

c) Research Objective 3

Determine if online sentiment trends on Twitter were affected by the deployment of social bots during this longitudinal period

Social robots were detected and the top two highest tweeters were identified as social robots displaying unusual as well as abnormal tweeting patterns. The two social robots' prevalence in volume meant that ultimately the sentiment was directly affected and the bots did influence sentiment trends.

7.2 Future research

The study identifies a number of opportunities for future research.

7.2.1 The research should be extended to the full #FeesMustFall dataset

The research should be extended to include the complete years of 2017, 2018 and later years. A more complete dataset may yield other significant results, even though it may not be possible to ever retrieve the complete *in toto* dataset. Different observational periods of analysis may reveal different temporal features which can inform historical analysis. This is because a dataset retrieved at a given point in time may not be the same when retrieved at another date given that tweets are subject to being deleted, edited or removed from public view.

7.2.2 Analyse #FeesMustFall on other social media platforms

Twitter is not the only popular social media platform and studies should include other platforms such as Facebook and Instagram. Their Social media role in the #FeesMustFall campaign should be examined. Did Social media activism give rise to the #FeesMustFall Campaign or did it sustain it? This merits further research.

7.2.3 Analyse the media and metadata that Twitter provides

Twitter sentiment analysis may be extended to incorporate #FeesMustFall-related embedded data such as video, audio, images and location. For example, an angry person with a stone with an angry post would receive a higher sentiment score than a smiling person offering a white rose with a happy post. This also involves metadata such as location. Each part of the metadata may reveal unique or general patterns about Twitter activity and its communities which can then be further explored.

7.2.4 The #FeesMustFall dataset should be reanalysed using machine learning

Machine learning should be conducted for sentiment analysis of the data and be compared to this study. This may be in either supervised or unsupervised learning modes to determine how useful this method is when compared to VADER. It may well be that a combination of these methods including VADER could produce better results.

7.2.5 Each university should examine the data from its own context

The #FeesMustFall data should be analysed by each tertiary institution particularly Wits, UJ, UCT, CPUT and UWC. This will provide an institutional context as to how each constituency's campaigners participated in the campaign. Most campaigners added a second hashtag to signify their target. Thus #FeesMustFall and #Wits implies a comment on Wits which must be analysed by this institution.

7.2.6 Multi- and inter-disciplinary work is needed

The researcher had access to a rich set of data which requires different types of contextual, sociological, political and psychological analysis. Other experts should be drawn to do further study.

7.2.7 The role of bots should be examined in any analysis

The context of the bots and the interpretation of their intentions is flagged as important future work, because bots are created in different environments for different goals some overt, some covert, with alternatively noble or ominous intentions. Fake news is an example of content that social robots can exploit in order to influence sentiment and should be researched.

7.2.8 Extend study to “monitor” significant online protests and customer satisfaction

This method can be extended to other social media campaigns such as service delivery protest, customer satisfaction and medical disease monitoring. South Africa is the protest capital of the world with a long perturbing history with respect to service delivery protest. It may be useful and instructive to identify the pulse of the protestors, the reasons and the influencers, particularly if or whether the influencers are bots. Consumer satisfaction can be continually monitored.

7.2.9 Extend VADER to include South African languages

South Africa, like many other countries, is multilingual and requires specific lexicons to accurately examine sentiment. Therefore, VADER or other lexicon based sentiment models should extend their algorithms to include other languages like Afrikaans, Zulu and Xhosa.

VADER was based on the English language and therefore lacks diversity and continuous development is required to improve this area. As a result, tweets that cannot be identified by VADER have a zero-valence score and therefore languages such as Afrikaans, Zulu, and Xhosa which contain words outside the English lexicon will return a sentiment score of zero and be labelled as neutral.

7.3 Recommendations

The study makes the following recommendations based on the findings:

7.3.1 It is recommended that education authorities and national government departments such as Department of Higher Education, Universities South Africa, and National Treasury, as well as each individual university, add a further social media analytics component to its services that monitor and evaluate historical and real-time sentiment using the techniques outlined in this research.

7.3.2 It is recommended that the South African government increase the span and scope of this sentiment analysis technique to include *inter alia* service delivery protests and disease monitoring. This has value both during stable periods as well as periods of unease.

7.3.3 It is recommended that data science researchers and ICT professionals should conduct a series of workshops to teach the data science skills that sentiment analysis requires. Higher Education Institutions' communication staff and leadership should also be trained on social media, its usage and engagement techniques, as this is the medium of students and protestors.

7.4 Conclusion

This study finds that sentiment analysis is an important tool to understand online activism, such as the #FeesMustFall campaign on Twitter. Unlike laboriously manual labelling methods, the automated and cost effective nature of sentiment analysis techniques utilised in this study offers practical solutions to analysing large amounts of opinionated unstructured data typically associated with social media. Furthermore, this study demonstrated how longitudinal sentiment analysis on Twitter can provide useful insights into historical trends of public opinion for potential stakeholders.

Furthermore, it was found that during and post perceived negative events such as the burning incidents at the UKZN library and UJ hall, sentiment of #FeesMustFall tweets increased in negativity which resulted in significant changes to sentiment trends on Twitter. This together with other results (section 5.4) demonstrates a link between sentiment expressed on Twitter and real-life events during the campaign. In addition, this study found that sentiment analysis in conjunction with change detection algorithms can be extended for potential use as a real-time barometer to detect changes in sentiment.

Importantly, however, this study also identified the presence of social robots within the #FeesMustFall campaign on Twitter of which two were recognised to be influential and if not carefully factored in, may distort sentiment analysis results. The methods used in this study to identify social robots, analyse and detect significant changes in sentiment over a longitudinal period serves as beneficial framework that can be replicated to other Twitter campaigns.

A notable mention is that the sentiment analysis and bot identification techniques used in this study contained certain limitations which, although did not affect the credibility of this study's results, provides opportunities for future research

In conclusion, the objectives of this study have been met, its significance proven and its contribution to the body of knowledge highlighted. This thesis represents the first of its kind in South Africa to not only have undertaking a sentiment analysis study of the #FeesMustFall campaign but also identify social robots within the campaign thereby addressing a research gap. It provided information about the campaign's prevailing sentiment trends on Twitter and its significant change points in relation to real-life events. Finally, a longitudinal sentiment analysis of the #FeesMustFall campaign on Twitter demonstrated how quantitative approaches were successfully applied to research opinion on Twitter and provide beneficial insights into the #FeesMustFall campaign.

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