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SENTIPEDE: A Smart System for Sentiment-based Personality Detection from Short Texts

Adi Darliansyah
(Auckland University of Technology, Auckland, New Zealand
adi.darliansyah@gmail.com)

M. Asif Naeem
(Auckland University of Technology, Auckland, New Zealand
mnaeem@aut.ac.nz)

Farhaan Mirza
(Auckland University of Technology, Auckland, New Zealand
farhaan.mirza@aut.ac.nz)

Russel Pears
(Auckland University of Technology, Auckland, New Zealand
russel.pears@aut.ac.nz)

Abstract: Personality distinctively characterises an individual and profoundly influences behaviours. Social media offer the virtual community an unprecedented opportunity to generate content and share aspects of their life which often reflect their personalities. The interest in using deep learning to infer traits from digital footprints has grown recently; however, very limited work has been presented which explores the sentiment information conveyed. The present study, therefore, used a computational approach to classify personality from social media by gauging public perceptions underlying factors encompassing traits. In the research reported in this paper, a Sentiment-based Personality Detection system was developed to infer trait from short texts based on the 'Big Five' personality dimensions. We exploited the spirit of Neural Network Language Model (NNLM) by using a unified model that combines a Recurrent Neural Network named Long Short-Term Memory (LSTM) with a Convolutional Neural Network (CNN). We performed sentiment classification by grouping short messages harvested online into three categories, namely positive, negative, and nonpartisan. This is followed by employing Global Vectors (GloVe) to build vectorial word representations. As such, this step aims to add external knowledge to short texts. Finally, we trained each variant of the models to compute prediction scores across the five traits. Experimental study indicated the effectiveness of our system. As part of our investigation, a case study was carried out to investigate the existing correlation of personality traits and opinion polarities which employed the proposed system. The results support the prior findings of the tendency of persons with the same traits to express sentiments in similar ways.

Key Words: personality detection, five-factor model, sentiment analysis, deep learning, neural network language model, global vectors, smart system

Category: E.0

1 Introduction

The phenomenon represented by the buzzwords *social media* seems to have influenced human interaction and communication on an individual and a community level [van Dijck 2013]. Twitter, for instance, with nearly 330 million active users, has become one of the most popular social media platforms today [Kemp 2018], allowing users to collaborate, exchange content, and disseminate information on social spaces in everyday life. This often includes thoughts, feelings, and behaviour, which signal their personalities [Carducci et al. 2018].

Referring to the combination of the aforementioned characteristics, personality defines a unique individual. A person hence can be described as shy, open, or friendly as determined by a relatively stable features called *traits*. Among the available measurements, the Five-Factor Model (FFM) [McCrae and John 1992] emerged as the most broadly accepted personality traits model today. Also known as the Big Five, the FFM is derived from five high-order traits comprises of *Openness* (OPE) which refers to as being emotional, curious, imaginative, and creative; *Conscientiousness* (CON) describes as being organised, dependable and motivated; *Extroversion* (EXT), a person with the trait has a tendency to be sociable, active, and willing to take risks; *Agreeableness* (AGR) indicates individuals who are cooperative, helpful, and trusting; and, *Neuroticism* (NEU), the trait defines a continuum from emotional stability to instability [Burton et al. 2014].

As language features play an important role in an individual's personality development, researchers thus conducted studies to examine either the correlation between language use and a person's personality or the language features themselves [Argamon et al. 2005, Schwartz et al. 2013]. The classical approach for assessing personality entails participants to answer self-report questionnaires or describe themselves or a person's personality [Burton et al. 2014]. The Big Five Inventory (BFI) [John and Srivastava 1999], for instance, has 44-item of personality inventory consists of short phrases with a relatively accessible vocabulary. This pencil-and-paper test, however, requires adequate time and resources. Social media, nevertheless, are presently considered a promising instrument to infer traits. The open nature of social media in which users can contribute and share interests has also made its platforms a flourishing space of personal expression.

The prior modelling on trait inference from social media was dominated by algorithms on word usage patterns recognition. Among these are the Linguistic Inquiry and Word Count (LIWC) [Tausczik and Pennebaker 2010], a transparent text count analysis program that counts words in psychology-relevant categories. Studies have shown that the LIWC categories correspond with the FFM [Golbeck et al. 2011, Schwartz et al. 2013, Sumner et al. 2012]. However, this bag-of-linguistic-features approach is usually language-dependent and comprises of intensive processing and thus takes time [Liu et al. 2016]. In addition, the approach often requires vast amounts of data to learn, e.g., around 200 posts from a Facebook user [Schwartz et al. 2013], or 100,000 words, in predicting a user's personality [Yarkoni 2010]; consequently, they might not entirely applicable in the real usage scenario of social media, in particular, in Twitter, where every tweet has a cap of 280 characters. Researchers have therefore moved towards deep learning methods.

Over the last few years, the interest in using deep learning for user profiling has grown. For example, it has been used in the business sector to build up a customer demographic profile for each type of user [Smith et al. 1999]. Marketers have attempted to analyse the consumer's buying pattern and its relation with geographical, demographic, and psychological characteristics. Neural network learning approaches, which provide a robust method to compute such behaviour patterns on a nonlinear, parallel task [Mitchell 1997], are able to uncover that valuable information. The approach has been successfully applied to problems entailing real-world sensor data such as face recognition [Lawrence et al. 1997] and handwritten character classification [Ciresan et al. 2011]. Furthermore, in natural language processing (NLP) applications, neural network learning has been shown to be effective in text classification [Conneau et al. 2016, Kim 2014]. In regard to personality detection from self-authored text, a variant of neural networks known as Convolutional Neural Network (CNN) [LeCun and Bengio 1998] has demonstrated promising performance [Majumder et al. 2017, Kalghatgi et al. 2015]. Although the research has been devoted to entailing document-level features, rather less attention has been paid to infer trait at the sentence-level. Taken together, the results thus far reveal the need for further empirical study.

Personality has been found to influence an individual's choice of words. As highlighted by [Stemmler and Wacker 2010], persons with same personality traits tend to express similar sentiments. While this observation has already drawn attention to investigating sentiment analysis based on personality traits, such as the work of [Lin et al. 2017], there is a general lack of research in exploring the role of opinion polarity in trait inference. Besides, in practice the existing models tend to ignore the sentiment information in sentences [Carducci et al. 2018].

Driven by above-mentioned motives, this work presents a smart system called SENTIPEDE, stands for *Sentiment-based Personality Detection*. The term SENTIPEDE is used to refer to the proposed system in the rest of the paper. This new system employs Neural Network Language Model (NNLM) to predict user personality from a self-authored text incorporating sentiment information conveyed. Moreover, to better understand the existing correlation of personality and public perceptions, we further conduct a case study-based investigation. This research, therefore, makes the following contributions:

– **SENTIPEDE: A smart system for personality detection.** We develop a smart system using a *Python* web framework for extracting user personality traits from short texts. The main tasks of the system include *Twitter data scraping*, *Sentiment analysis*, and *Personality detection*. We use pre-trained word representations named Global Vectors (GloVe) to transform the given texts into an embedding matrix, and later feed them onto a neural network with CNN and a recurrent network called Long Short-Term Memory (LSTM). The system returns prediction scores across the five board personality dimensions. SENTIPEDE can be accessed online at the following link: http://sentipede.dsrg.ac.nz.

– **The case study of Uber.** A case study-based investigation is conducted employing the recommended system. We opted for a ride-sharing company of Uber as the subject of this study. The topic is selected on the basis of a degree of attention received from the online community which provides us with enough variability to be explored. The selected case study, therefore, is expected to provide an insight into the relationship between personality traits and opinion polarity.

– **Performance evaluation.** Several well-known deep learning approaches under the umbrella of NNLM are implemented in this work: CNN, LSTM, and a unified model combining the two models. We compare the performance of each variant under both sentiment classification and personality detection tasks, and determine the best models to predict the personality traits from social media.

The rest of the paper is organised as follows: Section 2 provides an overview of the related literature used to support the current study. In this section, we identify the research gap as the starting point for further examination. A proposed system including design framework and implementation is described in Section 3. Next, in Section 4, a case study-based investigation is presented. Section 5 discusses the experimental setup and the evaluation results. Some limitations of the study are also considered. Finally, the conclusions drawn from this study and suggestions for future work are provided in Section 6.

2 Related Work

2.1 Personality and Public Perceptions

Personality trait assessment can be a valuable resource and has been used in a wide range of studies. This is exemplified in the work undertaken by [Chamorro-Premuzic and Furnham 2003] in examining students' academic performance, and studies in the workplace to investigate the correlation between an applicant's aptitude and achievement [Goldberg 1993, Judge et al. 2001]. In some cases, personality dimensions are related to the types of products or services that are offered, such as a game to match a players personality [Yang et al. 2017]. In the realm of public opinion, an individual's behaviour is closely related to any of the sentiment polarity carried in a sentence, namely positive, negative, and nonpartisan.

The early work on the correlation between personality and sentiment undertaken by [Golhamer 1950] has shown that a person's orientation to expressing opinions may be accompanied by their characteristics. Psychological research reveals that psycho-linguistics have strong correlations with individuals' self-disclosure, particularly in influencing their choice of words, suggesting that persons with the same trait tend to express their sentiments by using similar words [Stemmler and Wacker 2010]. Additionally, the study [Schoen 2007] stated that personality traits merit serious attention in sentiment analysis, particularly towards public policy [Gerber et al. 2011, Gravelle et al. 2014].

In support of prior studies, the work [Lin et al. 2017] constructed a sentiment classifier using features grouped by different personality traits, and the results show their effectiveness in refining the performance. The authors claimed to be among the first to explore the role of user personality in social media sentiment analysis. In contrast, in computational personality research thus far, the existing models tend to ignore the sentiment information embedded in texts [Carducci et al. 2018]; this reveals the need for further empirical investigation. To fill the gap, this study therefore explore the role of opinion polarity in trait inference.

2.1.1 Measuring the Big Five from Social Media

The conventional personality assessment relies on self-report and empirical investigation through questionnaires [John and Srivastava 1999]. In spite of the fact that it has a profound theoretical significance, such an approach can be tedious. Social media, on the other hand, unprecedentedly provide the digital footprint of human behaviours and social interactions that were not previously possible in both scale and extent. For this reason alone, it is imperative to harness the potential of social media as a tool or method with the intention of understanding user behaviours within the platform.

There has been extensive research conducted in an attempt to assess user personality from digital traces, particularly using the FFM. With Twitter and Facebook dominating as the two main platforms, most researchers have explored syntactic and lexical features from social media content as mentioned in Table 1.

In the study carried out by [Celli 2011], twelve cross-linguistic features were extracted from Twitter using the list of linguistic features developed by [Mairesse et al. 2007]. The author evaluated the co-occurrence of Twitter features with most frequent personality models and obtained an average of 66.51% accuracy. In a similar case, the study [Schwartz et al. 2013] investigated the correlation of language features with continuous or ordinal dependent variables such as gender

Table 1: Studies of personality prediction from social media

Sources	Study	Methods	Evaluation	Result
Twitter	[Golbeck et al. 2011]	LIWC, Twitter usage, psycho-linguistic features, sentiment.	MAE	0.1192
	[Sumner et al. 2012]	LIWC, Twitter usage.	Accuracy	0.919
	[Celli et al. 2013]	Cross-linguistic features.	Co-ocurrence	0.6651
	[Lima and de Castro 2014]	Word embeddings, Twitter meta attributes.	Accuracy	0.83
Facebook	[Schwartz et al. 2013]	LIWC, open vocabulary, extracted topics.	R	0.42
	[Liu et al. 2016]	Latent topics from n-grams, word representations.	RMSE	0.479
	[Farnadi et al. 2016]	LIWC, social network features.	Precision	0.54
Twitter and Facebook	[Carducci et al. 2018]	Word embeddings, SVM.	MSE	0.537

Note. MAE=Mean absolute error, MSE=Mean squared error, RMSE=Root mean squared error, R=Correlation coefficient

and age from Facebook users. A text analysis tool called LIWC (pronounced 'Luke') was utilised to calculate the percentage of words along with different linguistic categories, e.g., pronouns, verbs, and adverbs [Pennebaker and King 1999]. The study revealed that the use of language is influenced by the preceding factor variables.

Several other studies involved social media platform features including time and content usage, notably from Twitter and Facebook [Farnadi et al. 2016, Golbeck et al. 2011, Sumner et al. 2012]. The results indicated that the nature of each platform in which messages are usually incorporated with informal language and abbreviations tends to affect the prediction effectiveness. As shown in Table 1, a model to infer personality from Facebook developed by [Farnadi et al. 2016] suffered from low precision, whereas [Golbeck et al. 2011] and [Sumner et al. 2012], utilising tweets to predict personality, achieved an overall good performance.

In the context of automated prediction systems, various methods have been proposed to identify personality from user generated content. This can be seen in [Carducci et al. 2018]. Relying on Twitter content, the authors developed a supervised learning-based system called *TwitPersonality* to assess the Big Five model from cross-platform posts. They trained the Facebook status corpus employing Support Vector Machine (SVM), and used them to classify from Twitter. This system obtained significant results with an average of 0.537 MSE. In alignment with those authors, [Lima and de Castro 2014] built a multi-label classifier system called *PERSOMA*, adopting semi-supervised learning techniques with Naive Bayes Classifier (NBC) and SVM, which resulted in an approximately 83% accurate prediction. In their study, Twitter's meta-attributes were entailed, however, and rather than a single tweet, the system works with groups of tweets.

2.1.2 Trait Inference from Short Texts

Compared to documents, short updates such as tweets contain limited context which does not always observe linguistic rules, in contrast to what is expected in a written language [dos Santos and Gatti 2014]. Consequently, traditional techniques may not provide significant results when required to handle such peculiarities. Another issue is a tendency of Twitter users to use abbreviated words or phrases, idioms, and informal languages which are embedded with emoticons and folksonomies (e.g., social tags and social bookmarking). This makes the task of personality profiling more challenging.

Notwithstanding this, neural networks learning has been found to perform well when dealing with small amounts of training data and able to carry out NLP tasks, despite large corpora not being available [Gungor 2010, Liu et al. 2016]. A variety of approaches entailing neural networks learning have been recently proposed to automatically infer users' personalities. The study [Majumder et al. 2017], for instance, adopted a CNN model on document level features. Employing a collection of stream-of-consciousness essays deployed by [Pennebaker and King 1999], the model can achieve up to 62.68% accuracy.

Despite the above mentioned studies, little progress has been made on short messages, particularly tweets. This is exemplified in the study carried by [Liu et al. 2016]. Instead of exploiting CNN, the authors developed a recurrent network-based model with LSTM for personality recognition from short texts. Another example body of work by [Kalghatgi et al. 2015] entails social behaviours and grammatical features such as the text length and word usage on a multilayer perceptron network model. The authors concluded by claiming to have successfully predicted personality by employing a group of tweets. However, the study did not include detailed evaluations. There is no clear explanation of the data collection used, of how the authors evaluated the model, or of how validity was achieved. Therefore, the present study extends the empirical approach to address research gaps in previous studies, particularly with a focus on this level of granularity.

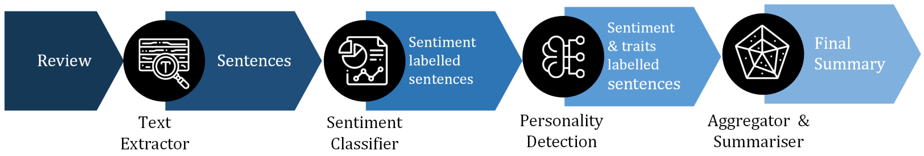

Figure 1: System overview: Predicting a user's personality from opinionated texts.

3 Sentiment-based Personality Detection

The concept of a smart system for predicting a person's personality based on the way tweets are written has been emphasised by recent initiatives [Carducci et al. 2018, Lima and de Castro 2014]. It has emerged as a response to the perceived problem that classification is a complex process in which data must undergo in a smart system [Silvis-Cividjian 2017]. Sentiment-based Personality Detection (SENTIPEDE) is a web-based system which allows users to input a string, or a file containing opinionated texts, while providing the tools for automated personality prediction. The system seamlessly enables functions to be made available pervasively via the Internet. As illustrated in Figure 1, the proposed system contains multi-functional modules that can perform data extraction, sentiment classification and traits detection to present a personality assessment. It was designed to react upon input data, and adapt the output based on external input parameters. This ability is considered to be computationally intelligentor *smart*. Hence, a system that depends on such computational intelligence can be described as a smart information system [Hopfgartner 2015].

3.1 Design Framework

In the system developed in this paper, deep learning-based models with neural networks and a single embedding layer are used to forecast personality traits. Each model is made up of a number of parameters that tune the outcomes. The system has three layers working in sequential mode, as explained below. The full description for the modelling design is illustrated in Figure 2.

3.1.1 Layer 1: Data Collection

In the first layer, we implement Twitter data collection and pre-processing. We use Twitter API[1] to download the tweets, and under the pre-processing phase we remove stop-words and apply text stemming to the original tweets.

[1] https://developer.twitter.com/en/docs.html

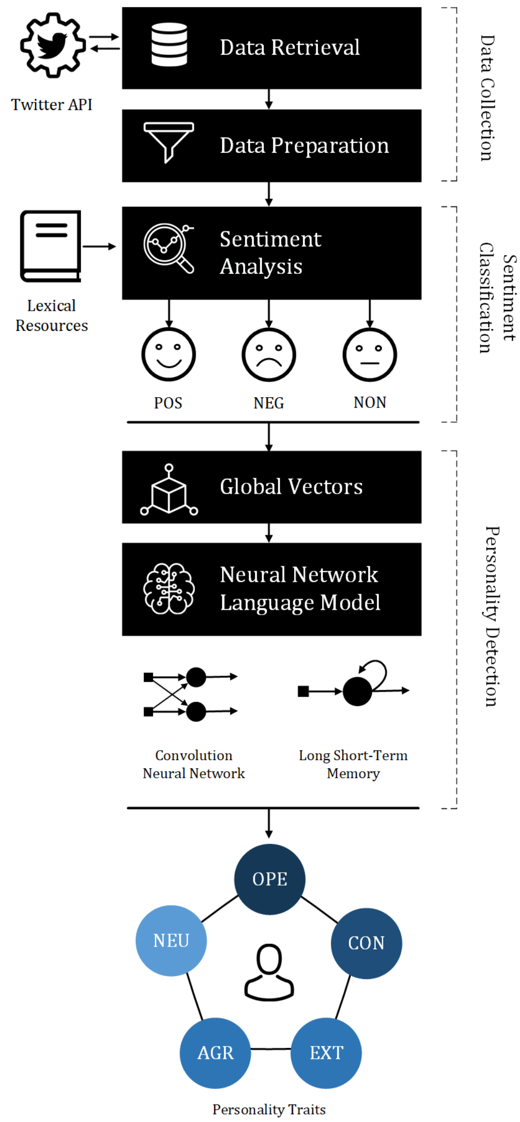

Figure 2: Proposed system architecture for Sentiment-based Personality Detection (SENTIPEDE).

3.1.2 Layer 2: Twitter Sentiment Classification

Once the collected data is cleaned, it moves to the second layer called *Twitter sentiment classification*. We utilised a lexicon for the English language named Valence Aware Dictionary and Sentiment Reasoner (VADER)—a rule-based framework developed by [Hutto and Gilbert 2015]. It contains necessary sentiment scores associated with words, emoticons and slang, with a total of over 9,000 lexical features. Each feature is rated on valence scores of an integer between "[-4] Extremely Negative" and "[4] Extremely Positive", with an allowance for "[0] Neutral (or Neither, N/A)". Based on the sentiment analysis, the system determines whether a given texts reflects positive (POS), negative (NEG), or nonpartisan (NON); thus, the output produced by this layer is in the form of three groups of tweets categorised by their polarities.

3.1.3 Layer 3: Personality Detection

In the third layer, a *predictive model* is implemented. As the processed data has been bundled together in categories, the system then transforms these categories into a word embeddings matrix before feeding them into neural networks and training the networks with several predictors. Pre-trained word vectors of tweets provided by Global Vectors (GloVe) were used. GloVe[2] is a count-based model wherein the algorithm works on aggregated global word co-occurrence statistics from a corpus [Pennington et al. 2014]. GloVe from Twitter[3] contains two billion tweets with 27 billion tokens and over 1.2 million vocabulary items.

In developing this layer, we experimented with Convolutional Neural Network (CNN) [LeCun and Bengio 1998]. A CNN is typically a feed-forward neural network, a nonlinear function in which the information flows in the forward direction. Generally, CNN consists of convolution and relevance weight, and pooling layers followed by fully connected layers [Kim 2014]. In this study, we combined it with a Long Short-Term Memory (LSTM) layer [Hochreiter and Schmidhuber 1997]. The aim was to take advantage of LSTM in maintaining state by adding the past information to the present state. LSTM has the capability of learning the relationships between elements in an input sequence to overcome the vanishing gradient problem which often occurs when the network is deep enough so that, at some point, the information for learning vanishes. The system returns the final scores for each personality dimension, i.e., Openness (OPE), Conscientiousness (CON), Extroversion (EXT), Agreeableness (AGR), and Neuroticism (NEU).

3.2 Software Architecture

Most available platforms used for machine learning are focused on functionalities for developing and tuning models. Less attention is paid to presenting the trained models as an end-user product. In this paper, we attempted to deliver

[2] https://nlp.stanford.edu/projects/glove/
[3] http://nlp.stanford.edu/data/glove.twitter.27B.zip

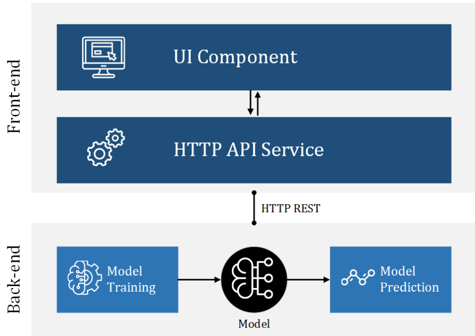

Figure 3: Descriptive diagram of deployment of a machine learning model in a web application.

an interactive web application embedded with Neural Network Language Models. We developed our system based upon the architecture diagram proposed by [Elsner 2018], which can be seen in Figure 3. The diagram exhibits the deployment of machine learning modelling into a web application. We built our model on Tensorflows framework[4] and used Keras[5] as the neural network library. A micro-framework for Python called Flask[6] was used to develop the web application. Finally, we followed a Continuous Delivery (CD) [Daya et al. 2015] approach—in which the system was reliably built, tested, and deployed—to deliver the proposed system to production.

3.3 Implementation

The SENTIPEDE was designed to allow the user to set parameters through a user interface. In response, the trained models compute and present users with the predicted probabilities. There are four main functionalities included in this system. Isolated in *modules*, they are: (1) *Main Module*, (2) *Twitter Data Scraper Module*, (3) *Sentiment Classifier Module*, and (4) *Personality Detection Module*. Each module consists of one or more components and works independently at the same time on the same flow of information, as shown on Figure 4.

3.3.1 Main Module

The main page of the web interface shows the inputs form for the sentence-level sentiment-based personality detection task. The module provides a text

[4] https://www.tensorflow.org/
[5] https://keras.io/
[6] http://flask.pocoo.org/

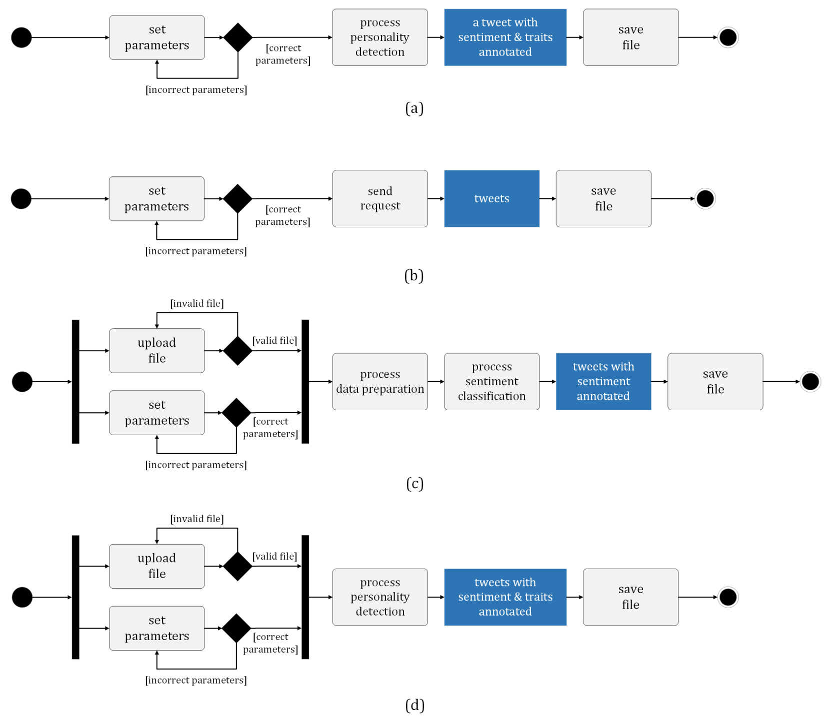

Figure 4: Activity diagrams representing the flow of each function the system offered: (a) Sentence-level sentiment-based personality detection, (b) Twitter data scraper, (c) Sentiment analysis, and (d) Personality detection.

input to be filled with string. Users can also choose a classification method and a language model available from drop-down lists. The screenshot of the main page can be seen in Figure 5. The module processes the prediction task based on the parameter values. First, it cleans the inputted string, and passes it to the sentiment classifier, which annotating the string with a sentiment polarity. The personality traits detection is performed once the string is labelled. This returns the scores for each trait, as shown in Figure 6.

3.3.2 Twitter Data Scraper Module

The aim of this module is to extract tweets related to a given query, historical data and users' specific timelines. The tweet is gathered based on the username, hashtag or mention, fetching dates, and the maximum number of tweets. The request is sent to Twitter through the HTTP Server. Following this process, Twitter issues a response by rendering tweets into the web, which enabling user to download or save a file in comma-separated values (CSV) format.

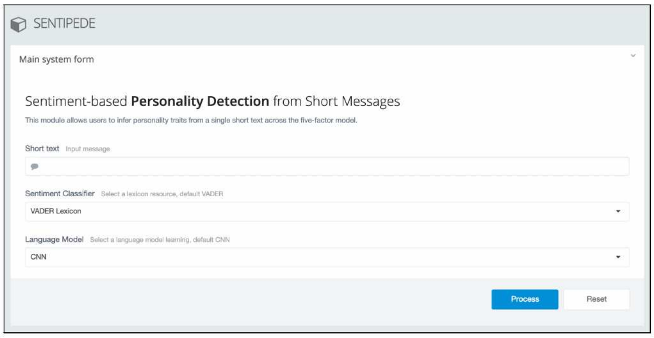

Figure 5: A screenshot of the main page. The module allows users to infer personality from a sentence.

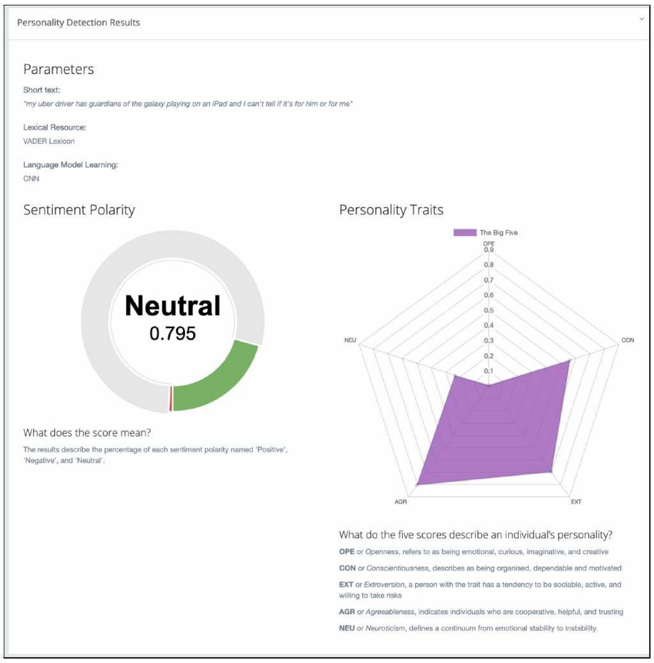

Figure 6: Screenshot shows the results of the personality detection from short text.

3.3.3 Sentiment Classifier Module

In this module, a sentiment analysis is performed. The Natural Language Toolkit (NLTK)[7] was used to statistically process the given tweets. In order to deter-

[7] https://www.nltk.org/

mine sentiment polarity, we utilised a valence-based sentiment analysis tool library (VADER) [Hutto and Gilbert 2015]. The outputs of this module are tweets annotated with sentiment scores, namely positive, negative, and nonpartisan.

3.3.4 Personality Detection Module

This module runs personality detection tasks based on arguments. Once it is started, the module calls the Twitter sentiment classification model which is responsible for data cleaning and pre-processing, and classifying the given tweets. The process is completed when the module applies the prediction models and assigns the tweets with personality trait scores following the selected language model learning.

3.4 Deployment

This phase aims to deploy a releasable built application n which the process is manually guided by Puppet Pipelines.[8] In this work, we adopted the CD approach to ensure a rapid pipeline from development to test and production, as can be seen in Figure 7. It began by connecting the application to the source control, which is a git repository.[9] This grants an administrator access to auto-build commits and pull request by adding a *webhook*—a HTTP push API. The second step entailed selecting a *docker image*[10] to build a production-ready application. The final version of the application was released after running a series of tests on the application. This then was made live on the production environment of an existing server in the cloud known as an *instance.*[11]

4 The Uber Case

The sharing economy has rapidly emerged as a viable alternative and, inevitably, is shifting the face of the asset-lending market. Through a convergence of ideas and technologies, it has provided new value to economic agents who were previously had limited access to the market or were even excluded from it [Kasprowicz 2016]. This on-demand business model is enabled over a shared marketplace, collaborative platform, or peer-to-peer application. However, the emergence of the sharing economy not only benefits the marginal market participants, but also is disrupting traditional businesses. Uber's disruption of the taxi industry is a case in point.

[8] https://puppet.com/products/puppet-pipelines
[9] https://bitbucket.org/product
[10] https://hub.docker.com/
[11] https://aws.amazon.com/ec2/

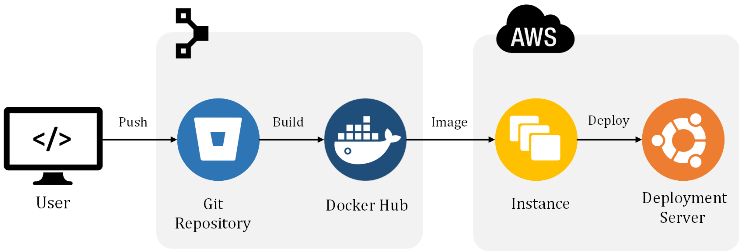

Figure 7: Software deployment pipeline adopting the Continuous Delivery approach wherein users push codes to build and deploy an application into production.

Founded as UberCab by Travis Kalanick and Garrett Camp,[12] Uber's penetration in the transportation sector began in 2009. This new entrant offers an arguably more affordable, better user experience than public transit. By utilising the company's mobile application, passengers can hail a ride from private vehicle owners. With over 75 million passengers in 65 countries worldwide, Uber was reported to have reached net revenue of 2.8 billion USD in 2018, bigger than its competitors such as Lyft[13] and Grab[14] [Iqbal 2019]. However, while Uber was defending its market dominance, the long-established taxi industry was struggling. The sharing economy dramatically damaged their conventional business model. Taxi and rental car companies have become antiquated. The incumbents were compelled to adopt the collaborative economy platform [Kasprowicz 2016]. This disruptive force, in turn, leverages tension which often leads to public demonstrations and roadblocks, sometimes involving violence. France, Spain, Indonesia, and Brazil are some of many countries that have taken a rather hostile stand against this archetype of service [Palling 2016].

Nevertheless, the public perception of sharing economy-based companies has changed considerably in the past few years. Uber's self-inflicted controversies has attracted the attention of social groups across the globe as streamed on social media, particularly via Twitter. While, many patronised the collaborative platform as reported in several European countries [Csaba and Reiner 2016], the controversies surrounding the company throughout the years come at a price: public loyalty. This was clearly illustrated in 2017 when customers were urged to completely eliminate the service. As reported by [Cresci 2017], social tags like *#BoycottUber* and *#DeleteUber* topped the 2017's trending topic in the U.S as

[12] https://www.uber.com
[13] https://www.lyft.com/
[14] https://www.grab.com/

public reaction to the company's surge pricing during a taxi strike. A similar case happened in Australia with Uber reportedly increasing its fares after Sydney's hostage crisis [Vinik 2014]. The calls to boycott the brand continued recently in the Gulf region, following the disappearance of a journalist from Saudi Arabia—a country which is listed as one of the Uber's major investors [Lomas 2018]. Together, these reports signify that Uber, as a globally renowned company, has attracted considerable attention in society, especially through social media where news spreads rapidly. However, thus far, no study has been done on the effect of user personality on public perceptions relating to the brand.

In this paper, therefore, a case-based investigation into the relationship between personality traits and opinion polarity was conducted employing the proposed system. We opted for the ride-sharing company Uber as the subject of this study. The topic was selected on the basis of the degree of attention received, which provided us with enough variability in the concepts we wanted to study. More specifically, this investigation intended to answer the following questions: (a) *What do the results tell us about the trend in the public opinion of the brand?*, (b) *What are the characteristics of users responding to the topic?*, and (c) *Were there any correlations between users' personalities and their perceptions?*.

5 Experiment and Results

5.1 Choice of Data Sets

The first challenge encountered when working on profile information is to find a relevant, publicly accessible data set, as acquiring such data can be problematic, particularly in terms of privacy. The recent Facebook privacy scandal involving a political consulting and strategic communication firm, Cambridge Analytica,[15] is a clear example. In early 2018, the company had harvested personally identifiable information from 50 million Facebook profiles through a personality quiz application called *thisisyourdigitiallife* [Granville 2018]. However, it was revealed later that Cambridge Analytica exploited the data without authorisation to build a system tailored specifically to deliver personalised political advertisements [Greenfield 2018]. Consequently, this attracted public attention and became a global headline which has led to an ongoing debate surrounding the illicit use of such sensitive data. In order to avoid this type of issue, we thus relied on the community to crowd-source a gold standard data set labelled with the Big Five called *myPersonality*. The collection is part of a project of the same name initiated by [Kosinski et al. 2012]. Harvested from an online personality assessment application that was specifically built for Facebook platform, the

[15] https://cambridgeanalytica.org/

Table 2: Statistics about the personality traits of the myPersonality data set

	OPE	CON	EXT	AGR	NEU
Maximum	5	5	5	5	4.75
Minimum	2.25	1.45	1.33	1.65	1.25
Average	4.0786	3.5229	3.2921	3.6003	2.6272
σ	0.5751	0.7402	0.8614	0.6708	0.7768

Notes. OPE=Openness, CON=Conscientiousness, EXT=Extraversion, AGR=Agreeableness, NEU=Neuroticism, σ=Standard deviation.

myPersonality data has been made publicly available through the project's web site.[16]

Twitter and Facebook shared the same characteristics as they are platforms for users to broadcast ideas and opinions. Thus, the myPersonality corpus met the criteria for data sets used in this study. Additionally, [Carducci et al. 2018] trained the same corpus to investigate personality detection from Twitter users. The author applied a transfer learning approach by reusing the trained model to predict personality traits using tweets as inputs. In correspondence with that work, we based our study on the same sample of the myPersonality data set. The data retrieval process is explained in detail in the following section.

5.2 Data Retrieval and Preparation

5.2.1 The MyPersonality Corpus

We used a collection of 9,913 status updates posted by 250 anonymised Facebook users. The myPersonality corpus was tagged with the five personality traits along with social networking features. The copy of this data set was downloaded in February 2018. The statistics and the distributions of the myPersonality corpus are shown in Table 2 and Figure 8 respectively. To predict the traits of the FFM, we first applied the data cleaning process. Then, we drop non-normalised scores of social network features such as '*brokerage*' and '*betweenness*'. Stop words were removed by utilising the words list for English language provided by a module corpus from NLTK. This process resulting in 9,847 cleaned data.

5.2.2 The Uber Tweets

We gathered tweets that explicitly refer to the Uber brand as research data. The process commenced with the acquisition of data utilising the Twitter Data Scraper module in SENTIPEDE. This was performed by crawling tweets filtered by hashtag and mention with queries of *#uber* and *@uber*. We set the fetching

[16] http://mypersonality.org/wiki/doku.php

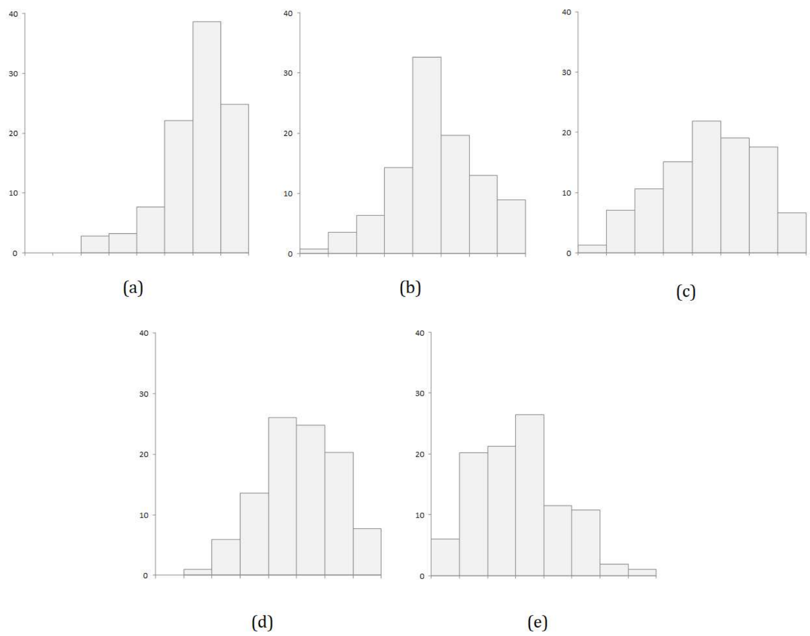

Figure 8: A histogram distribution for the five traits of personality: (a) Openness, (b) Conscientiousness, (c) Extraversion, (d) Agreeableness, and (e) Neuroticism.

dates from January to December 2018. Once the data were collected, we performed a data preparation process involving the elimination of URL links, numeric and special characters, mentions, and retweet identifiers. The final version of the data set was formed after applying tokenisation and stop word removal to the original corpus.

Figure 9 depicts the monthly volume of tweets gathered. A total of 120,975 tweets in the English language were collected containing tweet IDs, tweets, dates, mentions and permalinks. From the figure, it can be seen that the highest volume of tweets collected was recorded in March 2018, with 13,450 tweets collected, while the lowest was reported in July in the same year, with 5,676 tweets. On average, there were over 10,000 tweets mentioning or relating to Uber posted per month in 2018.

5.3 Experimental Setup

5.3.1 Configurations for Lexicon-based Sentiment Analysis

As the sentiment classification task relies heavily on the lexicon, setting standardised thresholds for classifying sentences is crucial. In this phase, we config-

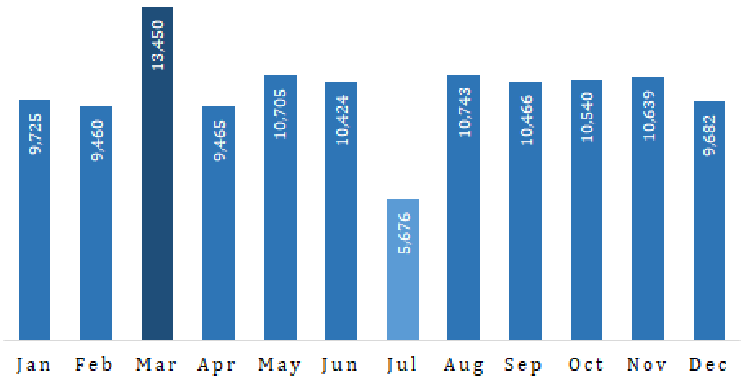

Figure 9: Monthly volume of tweets relating to Uber in 2018.

ured a classification threshold for the lexical resource included in this work to determine sentences as either positive (POS), neutral (NON), or negative (NEG). To score the polarity using VADER, we set the compound scores threshold for POS sentiment to be greater than [0.05]; for NON sentiment, scores were between [-0.05] and [0.05]; and for NEG sentiment score were less than [-0.05].[17] From 9,847 cleaned data, 4,243 were categorised as POS, 3,350 as NEG, and 2,254 as NON.

5.3.2 Model Tuning

Fine tuning a predictive model is an important step as it determines the accuracy of the predicted results. In this phase, we applied an approach that encompasses model tuning entailing data partitioning. We split the original data set into distinct sets which were used to create the model and for periodic evaluation of accuracy respectively. This process was crucial to prevent the occurrence of *over-fitting* or *under-fitting*. We allocated the data with an 80-20 split. To provide optimal coverage of each class in the data set, we also performed shuffling to both training and test data.

5.3.3 Defining and Compiling Networks

In this stage, hyper-parameters for the neural networks models were set. Once the network had been defined, it was ready to be compiled. Figure 10 illustrates

[17] https://github.com/cjhutto/vaderSentiment

the unified model of GloVe+CNN+LSTM for personality detection from short texts.

i. **Word Vector Initialisation**. To start this process, word vector initialisation was performed. In an NNLM, the use of a dense distributed representation for each word is the key to the method. The current work utilised GloVe **pre-trained word vectors** for Twitter with a dimensionality of 200. The study [Sahu and Anand 2015] revealed that 200 dimension distributed word representations perform better for NLP tasks entailing GloVe model. Only the top 20,000 most commonly occurring words in the data sets were used and the sequences were truncated to a maximum length of 1,000 words. The texts were selected randomly for training and the remaining texts were used for testing.

ii. **Neural Network Layers**. We used a simple **convolutional layer** consisting of 64 trainable filters that are convolved across the input matrix. Afterwards, outputs of the convolutional layer are sub-sampled by a **max-pooling layer**. So our next layer is an **LSTM layer** with 100 memory units.

iii. **Activation Functions**. We later experimented with dropout and an activation before concatenating to a fully connected layer. The goal of **dropout** is to randomly drop nodes along with their connections from the neural network during training. This can prevent nodes from co-adapting, a process by which two or more nodes behave as if they are a single node [Hahn and Choi 2018]. In general, softmax activation is used for multi-class classification. Although it can also be used for binary classification, in this stage, we used sigmoid funtion. A **sigmoid activation** is a logistic function that normalises the dimensional vectors of arbitrary real values to a probability distribution over predicted output classes that range from 0 to 1.

iv. **Dense Layer**. Finally at the end we have a dense layer with one node and a sigmoid activation as the output. As we are going to predict probabilities of each class, we used **binary cross-entropy** for the loss function. The optimiser is the standard one (**adam**) and the metrics are also the standard accuracy metric. We ran our test of every itinerary for 10 epochs.

5.4 Results and Findings

5.4.1 Model Performance

This section presents the results of model validation. All models were trained on a cleaned training set. We used the performance metric to measure the effectiveness of classification models. Experimental results of sentiment-based personality detection are shown in Table 3.

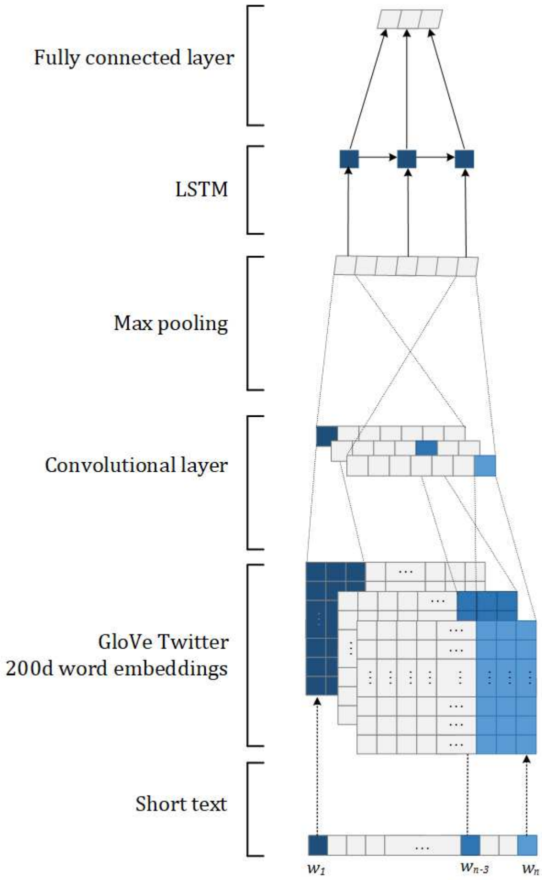

Figure 10: Overview framework of the proposed model: a unified model of GloVe+CNN+LSTM for personality detection from short texts.

From the table, the unified model (GloVe+CNN+LSTM) provided the highest accuracy (61.13%) for predicting personality traits from the NON category. The model also showed significant results in predicting the CON trait in all categories. Adding GloVe to CNN, has improved the prediction accuracy to 59.11% for the NEG category. An exception was made for LSTM. Although GloVe+LSTM obtained higher scores for the OPE trait in the NON category, the LSTM alone performed better than other models for two traits: the EXT trait in both POS and NEG categories, and the AGR trait in the POS and NON categories. In fact, the baseline model of LSTM achieved best in the POS group with 59.25% accuracy. The results of prediction accuracy obtained with different configurations are shown in Table 3.

Table 3: Validation accuracy for Sentiment-based Personality Detection

Method	OPE	CON	EXT	AGR	NEU	avgOCEAN
POS						
CNN	66.39	54.49	57.67	53.89	58.84	58.26
LSTM	65.57	56.96	**58.84**	**57.43**	57.43	**59.25**
CNN+LSTM	66.15	57.08	57.43	55.90	57.55	58.82
GloVe+CNN	**70.52**	57.19	55.07	52.00	57.55	58.47
GloVe+LSTM	68.75	55.90	54.36	56.13	**60.97**	59.22
GloVe+CNN+LSTM	68.28	**58.25**	54.85	53.42	58.84	58.73
NEG						
CNN	68.89	56.00	55.78	50.00	**60.22**	58.18
LSTM	60.89	54.00	**59.78**	52.00	55.33	56.40
CNN+LSTM	65.56	55.11	54.44	**55.33**	58.22	57.73
GloVe+CNN	**75.56**	54.89	55.78	51.78	57.56	**59.11**
GloVe+LSTM	68.67	56.44	56.67	51.11	58.44	58.27
GloVe+CNN+LSTM	70.67	**56.44**	54.67	50.89	58.22	58.18
NON						
CNN	68.06	56.27	57.01	57.46	58.96	59.55
LSTM	68.36	54.33	58.51	**57.91**	59.40	59.70
CNN+LSTM	70.15	55.97	57.46	57.31	**62.39**	60.66
GloVe+CNN	70.15	57.61	51.64	53.88	57.31	58.12
GloVe+LSTM	**74.63**	57.15	56.57	54.93	58.06	60.27
GloVe+CNN+LSTM	72.24	**57.91**	**58.51**	54.77	62.24	**61.13**

Note. POS=Positive, NEG=Negative, NON=Nonpartisan, OPE=Openness, CON=Conscientiousness, EXT=Extraversion, AGR=Agreeableness, NEU=Neuroticism, avgOCEAN=average accuracy. **Bold** highlights best performance.

Based on the experimental results obtained, we can state that our proposed model has performed significantly better than the majority of baseline models for all five traits, although, different settings for different traits were implied. This was strongly influenced by an insufficient sample size, as the data set used comprised only 9,913 sentences with over 146,000 words. Nevertheless, we found that using the GloVe word embeddings has improved prediction performance. GloVe gives additional knowledge by capturing semantic similarity between words from the given short texts. This is showed in the positive (POS) category, where the unified model achieved an overall 58.73% accuracy. A relative improvement after training with 10 epochs was also been observed in both NEG and nonpartisan (NON) sentiment groups as the model achieved 58.18% and 61.13% accuracy respectively. In general, then, we conclude that the smart system demonstrated satisfactory performance.

Table 4: Results for sentiment classification of tweets relating to Uber in 2018.

	POS	NEG	NON	Total
January	4,450	2,876	2,399	9,725
February	4,300	2,916	2,244	9,460
March	5,393	5,084	2,973	13,450
April	4,390	2,797	2,278	9,465
May	4,831	3,284	2,590	10,705
June	4,736	3,447	2,241	10,424
July	2,637	1,736	1,303	5,676
August	4,984	3,189	2,570	10,743
September	4,991	3,075	2,400	10,466
October	5,194	2,976	2,370	10,540
November	5,007	3,192	2,440	10,639
December	4,537	2,990	2,155	9,682
Total	55,450	37,562	27,963	120,975
Mean	4,620	3,130	2,330	10,081

Note. POS=Positive, NEG=Negative, NON=Nonpartisan

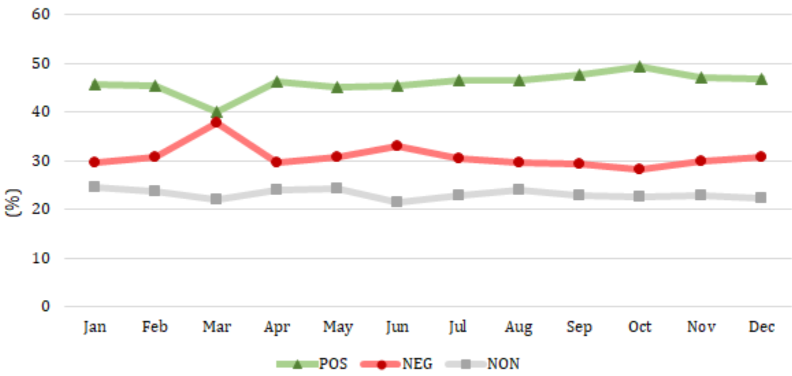

Figure 11: 2018 year in review: Sentiment towards Uber, analysed from tweets fetched between January and December.

5.4.2 Uber Case Evaluation

In this section, two processes were carried out: (1) sentiment analysis to determine public perceptions of Uber; and, (2) personality detection to infer the traits of users who tweeted about the company.

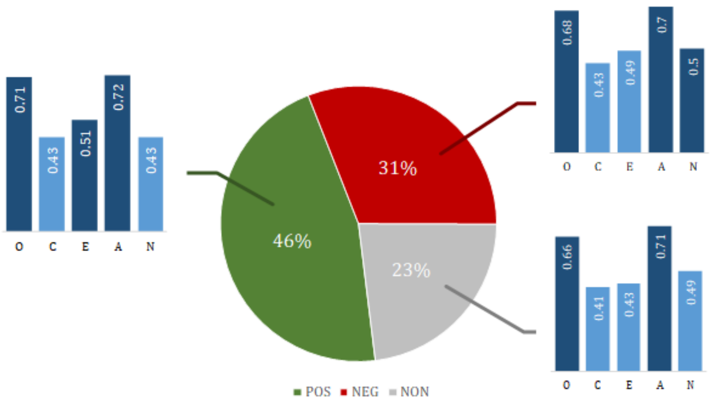

Figure 12: Sentiment towards Uber accompanied by the characteristics of each group of users. The results were analysed by SENTIPEDE.

5.4.2.1 Sentiment Analysis Results

Sentiment classification categorised the data into three groups, namely positive (POS), negative (NEG), and neutral or nonpartisan (NON). Table 4 shows the Uber sentiment classification results. As described in the table, at the start of 2018, the public perspective on Uber was positive but restrained. Almost half of tweets (45.75%) expressed positive sentiment towards the brand, and only 29.57% expressed a negative reaction, while around a quarter of tweets (24.67%) were categorised as neutral. However, in March, negative views reached their highest point with 38%, yet this trend changed quickly in the following months. Overall, through the year, the public grew more positive about Uber. A graphical representation of Uber sentiment month by month through 2018 can be seen in Figure 11.

5.4.2.2 User Personality and Perceptions Correlation

In order to examine the relationship between personality and sentiment, 100 personal Twitter accounts (anonymised) were selected randomly from each group, POS, NEG and NON. We picked 200 tweets from each user, in accordance with the study of linguistic measure variability conducted by [Haber 2015]. Following this, the personality detection process was then applied to each profile. We utilised the personality detection module of the proposed system. To obtain the prediction scores across the five traits, the unified model (GloVe+CNN+LSTM) was selected. SENTIPEDE then transformed the sentence from each given tweet into the corresponding word integers and then transformed it into GloVe's sparse word vectors. Next, the system fed the vectorial word representations into the model according to the sentiment polarity they carried. Each model then estimated the predicted probabilities for each trait, namely Openness (OPE), Conscientiousness (CON), Extraversion (EXT), Agreeableness (AGR), and Neuroticism (NEU). We ran aggregate tweets per profile by calculating the average score of each trait. Figure 12 visualises these results.

In the figure, the Big Five scores are presented in groups of sentiments. We found that Openness (OPE), Extraversion (EXT), and Agreeableness (AGR) scored high in the individuals who tweeted a positive review about Uber. In fact, the OPE score, which corresponds to receptivity to new ideas and approaches [Gross 1996], was found to be higher in this group than others. This finding supports the evidence that a person with high OPE tends to express a positive perception towards the company. The fact that Uber is a sharing economy company and is categorised as new business model platform, also explains why users who belong to this group were high scorers in EXT. A person with the EXT trait, which was only found to be high in this group, has a tendency to be sociable, active, and willing to take risks.

In contrast to OPE trait, we observed that persons in all groups scored low in Conscientiousness (CON)–a trait that indicates an individual to be organised, dependable and motivated. We also identified that a person who stays neutral about Uber is accompanied by a high-level of the AGR trait. High scorers in this trait tend to obey rules and adopt the conventions of society [Gross 1996]. Although, it might related, we cannot determine whether AGR sufficiently dominates users to the extent that it cause them to express their neutrality, as the trait also found to be continuously high in the other two groups. On the contrary, while Neuroticism (NEU) scored low in persons who showed positive and neutral feelings, the trait was revealed to be a slightly higher in the group of users with negative views of Uber. The NEU trait indicates an emotional instability, thus, a high scorer is characterised as being moody and experiencing feelings such as anxiety, worry, fear, or anger [Gross 1996]; these are more likely related to negative sentiment. In summary, the results of this study support previous findings in that individuals with the same personality traits tend to make similar sentiment expressions [Lin et al. 2017, Stemmler and Wacker 2010].

5.4.3 Limitations

Social media data is often publicly available; however, there were several aspects of the data that needed to be considered while doing this research. These included data control and privacy. Although these issues are much debated in the literature, the present study was designed with an awareness of those concerns. For example, while a personality test like the BFI is a fairly common approach for examining user personality, the current study does not imply nor present a comprehensive view of this assessment. Instead, our study relies on a crowd-sourced data set which was labelled with the five personality traits; although the trait scores might be seemingly different to the BFI scoring as we converted each score into a binary class for simplification purposes.

Furthermore, this study used data-driven machine learning techniques to extract activation patterns from training data. Hence, we acknowledge the importance of the representativeness of the data, which may account for the potentially biased results. Moreover, we have not analysed the results within a social theory framework. Such an approach could result in somewhat different interpretations. Therefore, the contribution of the current study in personality psychology might be limited.

6 Conclusions and Future Work

The conventional approach to measuring personality requires participants to answer a series of questions to evaluate their behaviours and preferences. This assessment process is tedious and labour-intensive. On the other hand, social media provides a vast amount of openly accessible social-related data that can be employed to infer a user's personality. In the real usage scenario, however, where on average users only have around twenty tweets on their timelines, this seems impractical. Also, while predicting user personality traits through text features on Twitter is promising, the character limit imposed on tweets makes the use of standard linguistic methods challenging and inefficient.

In this study, we developed a deep learning-based smart system for trait inference employing a Neural Network Language model (NNLM). The system was designed to forecast a person's personality traits based on the way that person tweets. In addition, we also explored the sentiment information at the sentence level, building upon the assumption that personality traits correlate to users' sentiments. To capture that information, we ran a lexicon-based sentiment classifier. This was followed by grouping the outputs into three main categories, namely positive, negative, and nonpartisan. Lastly, in order to detect personality traits, a collection of 9,913 Facebook status updates which were labelled with sentiment polarity and the Big Five personality scores was used in training.

A unified language model was defined combining Convolutional Neural Network (CNN) and the advantage of Long Short-Term Memory (LSTM) in maintaining information by adding past information to the present state. We applied the Global Vectors (GloVe) word embedding technique to add external knowledge by identifying similarities between words. Finally, we applied transfer learning by reusing the previously trained model to forecast traits using Twitter post as inputs. The result demonstrates the feasibility of inferring traits with reasonable accuracy from opinionated texts streamed online. Furthermore, to investigate the existing correlation between user personality and perception, we conducted a case study-based investigation which employed the proposed system. The experiment revealed that personality traits correspond to the way persons express their perceptions towards a topic.

In the future, we seek to expand our training data to better evaluate accuracy for various network architectures. Subsequently, we plan to involve participants to take personality assessments and use their Twitter posts as sample. Such an approach has been adopted by, for example, [Carducci et al. 2018] and [Qiu et al. 2012], and thus will give us a point of comparison for our predictive models. Finally, we mean to explore brand personality on social media using the proposed system. This future work is expected to set the stage for larger research projects such as investigate the relationship between brands' and customers' personalities.

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