BREXIT: Psychometric Profiling the Political Salubrious through Machine Learning

Predicting personality traits of Boris Johnson through Twitter political text

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ABSTRACT

Whilst the CIA have been using psychometric profiling for decades, Cambridge Analytica showed that people's psychological characteristics can be accurately predicted from their digital footprints, such as their Facebook or Twitter accounts. To exploit this form of psychological assessment from digital footprints, we propose machine learning methods for assessing political personality from Twitter. We have extracted the tweet content of Prime Minster Boris Johnson's Twitter account and built three predictive personality models based on his Twitter political content. We use a Multi-Layer Perceptron Neural network, a Naive Bayes multinomial model and a Support Machine Vector model to predict the OCEAN model which consists of the Big Five personality factors from a sample of 3355 political tweets. The approach vectorizes political tweets, then it learns word vector representations as embeddings from spaCy that are then used to feed a supervised learner classifier. We demonstrate the effectiveness of the approach by measuring the quality of the predictions for each trait per model from a classification algorithm. Our findings show that all three models compute the personality trait "*Openness*" with the Support Machine Vector model achieving the highest accuracy. *"Extraversion*" achieved the second highest accuracy personality score by the Multi-Layer Perceptron neural network and Support Machine Vector model.

CCS CONCEPTS

• Human Centric Computing • Machine Learning • Deep Learning

KEYWORDS

BREXIT, OCEAN, Big Five Personality, Social Media

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1 INTRODUCTION

Today, the ability to source one's daily activities can be captured online from Twitter and Facebook and other social media. Political strategists and strategy-based operations are now able to observe human behaviour for statistical regularities or irregularities and underlying behaviour principles which has the potential to provide insight into otherwise unknown or unseen personality characteristics. The single biggest benefit is the ability to understand personality traits from digital footprints. This is known as psychometric profiling in the modern age. Psychometric profiling has been around in various forms since World War II. The CIA's Centre for the Analysis of Personality and Political Behaviour, an interdisciplinary behavioural science unit which provided assessments of foreign leadership and decision making, had been a pioneer in psychometric profiling for foreign leaders. [1] The centre provided psychometric profiling on political leaders such as Slobodan Milosevic, Yasir Arafat, Osama bin Laden, Saddam Hussein and Kim Jong-il. Whilst politics tells us that a politician's success largely depends on the impression made on others, it is the ability to understand what impression the public want to see that propels the politician's success. From a political perspective, the ability to understand the personality traits of the public or indeed your political adversaries gives politicians an advantage in how they portray and target their political philosophy. Psychometric profiling is the manner by which your behaviours are used to infer your personality. This technique was exploited heavily during BREXIT by Cambridge Analytica where online users' political beliefs, behaviours and motivations were extracted from social media and based on the personality traits discovered, persuasive literature was used to influence their vote on BREXIT referendum. [2,3,4] While other forms of personality-based gathering exist in the form of digit questionnaires such the use of *my personality* [5], we focus focusing on text-based psycholinguists psychometric profiling through the medium of Twitter.

This paper aims to provide machine learning and deep learning methods to access the political personality of Boris Johnson from his Twitter profile. It must be observed that we are only focused on the Twitter political text and the expected output is not an entirely reflective of the persons true personality traits but can be seen more as a political personality representation from their political Twitter text. The models use a Multi-Layer Perceptron neural network, a Naives Bayes multinomial model and a Support Machine Vector model to predict the OCEAN model (which consists of five personality factors, namely, "Openness", "Conscientiousness", "Extraversion", "Agreeableness" and "Neuroticism") from a sample of 3355 political tweets. Section 2 looks at related works. Section 3 looks at the Data Acquisition, Section 4 looks at the Methodology. Section 5 deals with the results and in Section 6, we conclude and discuss future work.

2 RELATED WORK

Whilst Sir Francis Galton has been recognised as one of the first scientists to estimate personality descriptions, it was the work of Cantrell who furthered the research and found a dozen traits [6]. Further research was conducted by [7,8,9] and found that personality traits could be derived into what has become known as the Big Five model or the "OCEAN" model. The OCEAN model claims to reveal "the rudimentary structure underlying the distinctions in human behaviour and preferences." Psychologists such as [9] believe that these five traits contain more information about an individual or population's motivations and decision-making processes than any other five traits. This can be seen as quite advantageous when attempting to understand a foreign political leader or a political opponent. [10] demonstrates how digital footprints can infer the Big Five personality traits. The literature examined a plethora of highly sensitive personal attributes including: sexual orientation, ethnicity, religious and political views, personality traits, intelligence, happiness, use of addictive substances, parental separation, age, and gender. The use of Facebook likes was essential to the granular nature of the research and found the personality trait "Openness," prediction accuracy is close to the test–retest accuracy of a standard personality test trait. [11] measured the Facebook profile data of 180,000 users to ascertain the correlation of the user's digital personality traits and their Facebook network metrics such as density of their friendship network, number of group memberships, number of users tagged in photos and found the best personality prediction was "Extraversion". [12] examines the personality traits of the various types Twitter users with findings showing that both popular users and influential users are extroverts and emotionally stable indicating low levels of neuroticism. The study further found that popular users are imaginative indicating high in the "Openness" trait whilst influentials tended to be more organised which relates to high in "Conscientiousness". [13] successfully predicted users personability traits from their Facebook posts using machine learning. [14] found when selecting social media users, the selection process tends to involve selecting users with similar personability traits such as "Agreeableness," "Extraversion" and "Openness". [15] found that for Big Five personality dimensions to interpersonal conflicts "Agreeableness" was most closely associated with processes and outcomes during interpersonal conflict. Further research was carried out to examine the type of Big Five personality traits associated with people using social media such as Facebook. [16] found that people with high levels of narcissism engage in frequent use of Facebook however, this trend was attributable to the fact that Facebook encourages self-promotion and superficial behaviour. [17] investigated the correlation between the Big Five traits and users of social media and concluded that while "Extraversion" and "Openness" to experiences were positively related to social media use, emotional stability was a negative predictor, controlling for socio-demographics and life satisfaction. These findings differed by gender and age. While extraverted men and women were both likely to be more frequent users of social media tools, only the men with greater degrees of emotional instability were more regular users.

2.1 The Big Five Personality Model

We used the personality traits as defined by the NEO-PI-R Five factor model [18]: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. These are described as follows:

A. **Openness** is related to imagination, creativity, curiosity, tolerance, political liberalism, and appreciation for culture. People scoring high on openness like change, appreciate new and unusual ideas, and have a good sense of aesthetics.
B. **Conscientiousness** measures the preference for an organized approach to life in contrast to a spontaneous one. Conscientious people are more likely to be well organized, reliable, and consistent. They enjoy planning, seek achievements, and pursue long-term goals. Non-conscientious individuals are generally more easy going, spontaneous, and creative. They tend to be more tolerant and less bound by rules and plans.
C. **Extroversion** measures a tendency to seek stimulation in the external world, the company of others, and to express positive emotions. Extroverts tend to be more outgoing, friendly, and socially active. They are usually energetic and talkative; they do not mind being at the center of attention and make new friends more easily. Introverts are more likely to be solitary or reserved and seek environments characterized by lower levels of external stimulation.
D. **Agreeableness** relates to a focus on maintaining positive social relations, being friendly, compassionate, and

cooperative. Agreeable people tend to trust others and adapt to their needs. Disagreeable people are more focused on themselves, less likely to compromise, and may be less gullible. They also tend to be less bound by social expectations and conventions and are more assertive.

E. **Neuroticism** relates to emotionally unstable (neurotic) people who are more likely to experience stress and nervousness, whereas emotionally stable people (low neuroticism) tend to be calmer and self-confident

3 DATA ACQUISITION

A Twitter Dataset

Our dataset is obtained from Twitter using the Twitter API. Using the secure tokens obtained via the Oauth process, this provides authentication and thus allows the user to receive the requested Twitter data.[19] We utilise the "*Tweepy*" python library to accept the Twitter data. We customize our StreamListener API from the *Tweepy* library to capture tweets from *@BorisJohnson.* We collected 3,355 tweets from Boris Johnson's Twitter account from April 2015 to March 2020. For each tweet, these records provide a tweet identifier, the date-time-seconds of the submission (GMT), location, verified indictor, and the text content.

B Training Dataset

For training the models we use a labelled dataset, known as "essays" [20], which essentially is a large dataset of stream-of-consciousness texts (about 2400, one for each author/user), collected between 1997 and 2004 and labelled with the Big Five personality classes "Openness", "Conscientious", "Extraversion", "Agreeableness" and "Neuroticism". Texts have been produced by students who took the Big Five questionnaires. The labels, that are self-assessments, are derived by z scores computed by [21]. For our experiments, we have divided the dataset into a ratio of 1:3 i.e. 75% of the dataset is used for training and 25% for testing the accuracy of prediction models.

4 METHODOLOGY

Using the "*essays*" dataset as the training dataset described in Section 3, we derive a predictive model that is able to infer personality traits of Boris Johnson's Twitter political text. Considering the training dataset, we intend to use the stream-of-consciousness texts from authors essays; our approach is based on transfer learning, which essentially is modelling an algorithm for a context and applying the context to our Twitter political content. In our case, we derive a machine learning model for predicting personality of the authors of the essays, then we test it on Boris Johnson's political tweets. Essentially, we feed the tweet vectors to the trained "*essay*" model to obtain a prediction, to compute the final personality trait score. To derive the best performing predictive model, we use the classification library from scikit-learn to measure the quality of predictions for each trait per model from a classification algorithm.

4.1 Extraction

In our experiment, we use two of the most well-known Natural Language Processing tools namely NLP [22], and spaCy [23]. From a machine learning perspective, we are concerned with allowing our methods to learn and make predictions by finding patterns or statistical regularity. spaCy uses Convolutional Neural Networks (CNNs) with pre-trained word vectors to train its models. CNNs are Neural Networks (NNs). In terms of extraction we use:

A. Word Embeddings

spaCy uses its own embeddings which are trained models, therefore, we use pre-trained word embeddings. We used the English multi-task Convoluted Neural Network trained on OntoNotes, with GloVe vectors trained on Common Crawl, which assigns word vectors, context-specific token vectors, POS tags, dependency parse and named entities.[22] All word vectors are based on dimension 300 which is known as the most optimal for distributed word vectors.

B. TF-IDF

This is a technique to quantify a word in documents. We generally compute a weight to each word which signifies the importance of the word in the document and corpus.

C. Stop Word Removal

For stop-words removal, we use the Count Vectorizer module from scikit-learn library.

4.2 Models

We train five different models, i.e. one for each personality trait, built using the "*essay"* dataset as a training model for the three outlined models below using python libraries.

A. Naive Bayes

Naive Bayes is a straightforward model for classification. It is simple and works well on text categorisation. We adopt multinomial Naive Bayes in our project expressed in equation 1. It assumes each feature is conditional independent to other features given the class. That is

$$P\left(\frac{C}{T}\right) = \frac{P\,(C)\;\;P\,(T/C)}{P\,(T)} \qquad (1)$$

Where c is a specific class and t is the personality trait we want to classify. *P(c)* and *P(t)* is the prior probabilities of this class and this text. And *P(t |c)* is the probability the text appears given this class. In our case, the value of class c might be Openness, Conscientious, Extraversion, Agreeableness or

Neuroticism, and t is just a sentence. The goal is choosing value of c to maximize *P(c|t):* Where *P(wi|c)* is the probability of the *ith* feature in text t appears given class c. We need to train parameters of *P(c)* and *P(wi |c)*. It is relatively easy to achieve these parameters in the Naive Bayes model. They are simply the maximum likelihood estimation of each one. When making the prediction to a new sentence t, we calculate the log likelihood log *P(c) + ΣilogP(wi|c)* of different classes, and take the class with highest log likelihood as prediction. We run a Naive Bayes grid search to consider all combinations of hyper-parameters tuning which also utilises a 10 k-fold cross validation for optimisation to forecast the best possible values. We use the classification library from scikit-learn to calculate accuracy, precision, recall and f1 score. We subsequently ran the Naive Bayes classifier with an iterative search on each combination of values to determine the best grouping.

B. Support Machine Vector

Support Machine Vector (SMV) is a supervised machine learning model which is widely used in pattern recognitions and classifications. We deploy a linear SMV classifier model. The linear model is used here in a very close context to a linear regression model. Linear regression can be explained as the modelling of the relationship of a dependent variable and independent variables. Classes are defined as the list of the expected categorical values produced by the classification task. When this approach is applied to a regression problem, the goal of SMV is to compute Y_i, from the observation x_t with a margin of tolerance ϵ. The objective function is the following,

$$y(x) = \text{sign}\ \{\ \sum_{i=1}^{n}(\ a_k,\ x_k, \psi\ (x,\ x_k\ ) + b\} \tag{2}$$

where a_k are positive real constants and b is a real constant. For $\psi\ (\cdot, \cdot)$ and $\psi(x,\ x_k\ )= x_k^t\ x$ represents the linear SMV. To run this model, we use the SVC Linear library from sci-learn in conjunction with single-label One Vs All classifier library for each trait, which uses the subset of features that most linearly correlate to the classes they are labelled with. Additionally, in terms of hyper parameter tuning and optimisation, we perform a 10 k-fold cross validation to forecast the best possible values and calculate accuracy, precision, recall and f1 score.

C. Multi-Layer Perceptron Neural Network

A Multi-Layer Perceptron (MLP) neural network is a deep learning, artificial neural network. The model trains on a set of input-output pairs and learns to model the correlation (or dependencies) between those inputs and outputs. Training involves adjusting the parameters, or the weights and biases of the model in order to minimize error. Backpropagation is used to make those weigh and bias adjustments relative to the error, and the error itself can be measured in a variety of ways, Assuming that, we used an input layer with $n_{o\dots}$ neurons such that $x\ = (x_O,\ x_{1\dots}\ x_{n0})$ = neurons and a sigmoid activation function.

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

To obtain the network output, we need to compute the output of each unit in each layer. We now consider ($h_i,\ h_{2\dots} \dots h_n$) assuming that n_i are the neurons number by each hidden layer h_i. For the output first hidden layer

$$h_i^j = f(\ \sum_{i=1}^{n}\ w_{k\ ,}^{o}\ j\ x_k)\ \ j{=}1, n_i \tag{4}$$

$$\text{Output } h_i^j f(\sum_{i=1}^{n}\ w_{k\ ,}^{i}\ h{,}xk_{i-1})\text{i=2, N and J=}\ n_1 \tag{5}$$

Where $w_{k,j}^{i}$ is the weight between the neuron k in the hidden layer i and the neuron j in the hidden layer + 1, n_j is the number of the neurons in the ith hidden layer. The output of the ith can be formulated as following: $h_i = (h_{i\ ,}^{1}\ h_{i\ ,}^{2}\ \dots\ h_{i\ ,}^{n_2}\ )$ (6)

The network output is computed by $y_{1=}\ f(\ \sum_{k=1}^{n}\ w_{k,j}^{n}\ h_{n,}^{k}\ )$

$$Y = (\ y_1,\ y_{j\dots}\ y_{n+1}) = F\ (W, X) \tag{7}$$

Where $w_{k,j}^{n}$ is the weight between the neuron k in the Nth hidden layer and the neuron j in the output layer, n_n is the number of the neurons in the Nth hidden layer, Y is the vector of output layer, F and W is the transfer function and is the matrix of weights. We needed to create a baseline for the model. For the baseline model, we used a semantic vector representation of the *essays* dataset, which was used to train a multi-label classifier. The F1 scored the model at approximately 57%. We train the Multi-Layer Perceptron neural network using spaCy's word embeddings, Tokenizer, TF-IDF and optimise the model parameters with a grid search. We further run an iterative search on each combination of values to determine the best grouping and calculate accuracy, precision, recall and f1 score for each trait.

5 RESULTS

We measure the predictive power of our approach for all three models assessed with the "*essay*" dataset over Boris Johnson's political Twitter content. We follow the methods described herein in Section 4. We tested for each of the Big Five personality traits per model. We compute the final personality trait accuracy, precision, recall and F1 score. Table 1 to 3 illustrates the scores per model and trait for Boris Johnson**.**

Table 1: Naive Bayes Model Boris Johnson

	O	C	E	A	N
Acc	**0.5964**	0.54132	0.54619	0.5705	0.57536
Prec	0.64	0.55	0.56	0.56	0.58
Recall	0.6	0.54	0.55	0.54	0.58
F1	0.57	0.52	0.52	0.5	0.57

Table 2: SMV Model Boris Johnson

	O	C	E	A	N
Acc	**0.6101**	0.54	**0.59**	0.53	0.55
Prec	0.61	0.54	0.59	0.54	0.56
Recall	0.64	0.63	0.67	0.80	0.55
F1	0.63	0.58	0.63	0.64	0.55

Table 3: MLP Model Boris Johnson

	O	C	E	A	N
Acc	**0.60453**	0.56239	**0.60129**	0.55105	0.56401
Prec	0.61	0.56	0.60	0.54	0.57
Recall	0.61	0.56	0.60	0.54	0.57
F1	0.60	0.56	0.60	0.54	0.56

6 CONCLUSION

In this study, we derive three predictive models to infer the personality traits of Boris Johnson's Twitter political text. We train five different models, one for each personality trait, built using the "*essay"* dataset as a training model for a Naive Bayes, Support Machine Vector and Multi-Layer Perceptron neural network using python libraries. Our finding show that all three models compute the personality trait "*Openness*" with the Support Machine Vector model achieving the highest accuracy. Openness is a popular trait according to [12] and could be seen as political advantage. Furthermore "*Openness*" is associated with political liberalism,change, and an appreciation for new and unusual ideas which could be seen to fit glove in hand for Boris Johnson's liberal mandate for BREXIT. *"Extraversion*" achieved the second highest accuracy personality score by the Multi-Layer Perceptron neural network and Support Machine Vector model. As per the definition extraverts are usually energetic and talkative, they do not mind being the center of attention and make new friends more easily. It could be argued that this could have been a defining personality factor in Boris Johnsons triumph in the Conservative party leadership race and the BREXIT Election in 2019. However, creating a digital political representation of oneself (as per Boris Johnson's tweets) is not fully represented of Boris Johnson. These tweets portray, at most, a political representation of the character. For future research we have collected a large BREXIT public tweet dataset and a BREXIT YouTube user dataset and would like to obtain the Facebook *mypersonality* dataset as a training model for same to conduct future user personality trait tests using a Convolutional Neural Network. The goal would be improving the model accuracy and applying the OCEAN model to *Bremainers* and *Brexiteers* alike.

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