Modeling Credibility in Social Big Data using LSTM Neural Networks

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Abstract: Communication accounts for a vital need among people in order to express and exchange ideas, emotions, messages, etc. Social media fulfill this necessity as users can make use of a variety of platforms like Twitter, to leave their digital fingerprint by uploading personal data. The ever humongous volume of users claims for evaluation and that is why the subject of user credibility or trust in a social network is equally vital and meticulously discussed in this paper. Specifically, a trust method, as we measure user credibility and trust in a social environment using user metrics, is proposed. Our dataset is derived from Twitter and consists of tweets from a popular television series. Initially, our text data are analyzed and preprocessed using NLP tools and in following, a balanced dataset that serves in model evaluation and parameter tuning, is constructed. A deep learning forecasting model, which uses LSTM/BiLSTM layers along with classic Artificial Neural Network (ANN) and predicts user credibility, is accessed for its worth in terms of model accuracy.

1 INTRODUCTION

Internet growth is rapidly developing and undoubtedly affects every single sector of our lives. This development is chaotic and continues to increase day after day due to the exploding volume of data and information. Most of these data are created through human interaction in social networks where social media platforms like Twitter, Facebook and Linkedin make distant communication feasible. Specifically, in UK, an astonishing 82% of Internet users maintain a profile or account either at one or more social media sites or applications and another astonishing 84% resort daily to messaging chats or applications[1].

One of the most popular social network applications is Twitter, which provides all sorts of information and allows its users to post text messages called "tweets". Its user database is extremely vast as 330 millions use it on a monthly basis and another 145 millions on a daily basis creating over 500 millions tweets everyday[2]. As a result, these characteristics make Twitter an excellent choice for knowledge extraction since users can post anything they feel and thus it's of great importance to identify their credibility.

Nevertheless, despite its advantages, Twitter is often deemed as an untrustworthy news resource because tweets are posted directly by users and not by verified authorities (Zhao et al., 2016). Moreover, most approaches for trust or credibility measurement utilize statistic metrics such as the number of followers and retweets of tweets (Cardinale et al., 2021). We should bear in mind that Twitter interactions, like following, mentioning and retweeting, can be forged from malicious users. On the other hand, content-based approaches can be problematic due to the fact that tweets don't regularly follow classic linguistic rules.

Trust assessment is mandatory especially for applications such as Twitter because it is considered a complex relationship (Sherchan et al., 2013). There are multiple ways to decide trusting someone; most of the times, we trust someone with which we had common experiences or share the same ideas. Psychology and human emotions play an important role too, since introvert people struggle with trusting others. Moreover, in social networks like Twitter, user interactions show to what extend an individual feels since one can demonstrate trust by forwarding their post. Thus, a model that can identify highly trustworthy users based on both text and arithmetic data of Twitter's platform, is crucial.

Machine learning is one of the most common ways for pattern recognition in complex data. In re-

[1] https://www.ofcom.org.uk/__data/assets/pdf_file/0025/217834/adults-media-use-and-attitudes-report-2020-21.pdf

[2] https://www.internetlivestats.com/Twitter-statistics/

cent years, computational costs reduced while memory capacity has increased leading to real-world applications that benefit from these techniques. Deep learning is a sub-category of machine learning (Hinton et al., 2006) that has exhibited a novel idea of translating matrix pixels to a fresh new form that is based on iterative learning. The algorithms related to the Deep Learning field follow a high-level generalization of the available data, by using a hierarchical stack of processing layers (Aggarwal, 2018).

As mentioned before, this paper addresses the problem of user credibility or trust in Twitter. We have measured it by exploiting user metrics in order to predict human trustworthiness. A real dataset is created from Twitter that consists of both numerical and text data (tweets). The pre-processing steps along with the utilization of deep learning models, have been implemented in the proposed methodology and have been evaluated in terms of model accuracy. Last but not least, another contribution constitutes the development of various models and the exploration for identifying the best implementation for different number of layers.

The rest of the text is outlined as follows: In Section 2, we provide a literature view of trust metrics on Twitter and on social networks in general, while Section 3 focuses on the trust model along with the basic concepts and algorithms utilized in this paper. Section 4 details our implementation and presents the forecasting model as well as the deep learning techniques we implemented, whereas Section 5 presents the various research results. In Section 6, we summarize our contributions and future directions.

2 Related Work

It is a fact that there have been a great number of recent studies regarding trust in computer and social science. Trust models are considered a popular field in which researchers try to predict human credibility. In (Kamvar et al., 2003), authors present a method to measure trust in peer-to-peer networks where their algorithm is called EigenTrust and it creates a trust matrix with information for every pair of nodes in the network. They calculate trust propagation by computing an eigenvector matrix which is actually based on the trust matrix.

In (Adali et al., 2010), a model using statistical data which is based on timestamps and messages between two users, is developed. This trust model, entitled behavioral trust, can be described by two metrics: the conversational and the propagation trust. The conversational trust is measured based on how long and how frequent two users communicate, while the propagation trust is estimated based on the propagation of the information. The basic idea is that an indication of trust is considered when a user propagates messages of a third user.

Some similar works that implement models for calculating trust based on additional dimensions like the sentiment, are presented in following. Authors in (Alowisheq et al., 2017) investigate the relationship between trust and sentiment as they initially figure the trust score based on (Adali et al., 2010). Then, the sentiment agreement matrix score is computed using the hashtags of every user and by comparing these two matrices, the authors can assess the relation between users and whether they agree on different topics they are interested in. Similarly, the aim of (Boertjes et al., 2012) is to develop a model that takes into account both textually expressed sentiment and source authority. The final degree of trust is calculated based on situational trust, behavioral trust momentary sentiment and authority. Specifically, situational trust is determined by the opinions and the resulting trust utterances of people with higher authority whereas, behavioral trust is the degree of trust that is observable from trust utterances of people in general. Finally, the momentary sentiment is an instance of sentiment and authority that reflects the user popularity as it is calculated purely based on followers.

Delving further in sentiment analysis, authors in (Roy et al., 2016) have developed a TSM algorithm for measuring individual users' trust levels in a social network where a pair of complementary scores is assigned to each actor in the network. The scores are defined as trustingness and trustworthiness; the first one specifies the propensity of an actor to trust others in the network while the latter refers to how trustworthy an actor thinks others can be. Furthermore, the TSM algorithm takes as input a directed graph and computes both scores for every node. In following it converges, after some iterations or when a convergence criterion is met like the maximum difference among all actors.

A novel topic-focused trust model in order to evaluate trustworthiness of users and tweets is also presented in (Zhao et al., 2016); in this work, authors take into account data from heterogeneous topics that derive from multiple users. Trust scores are computed for both users and tweets where the trustworthiness of a tweet can be estimated by whether its content refers to things that actually took place and in following, users score by its posts. This proposed method is scalable unlike traditional graph-based trust ranking approaches.

MarkovTrust, a recommender system that estimates trust from Twitter interactions between users in a social network, is proposed in (Lumbreras and Gavaldà, 2012). This system utilizes Markov chains which make computation more efficient and effective and particularly, the trust score is measured based on interactions like mentioning and retweeting. More specifically, authors apply a random-walk algorithm to measure the propagation trust between distant users. Moreover, in (Kang et al., 2012), three models for recommending credible topic-specific information are introduced. Concretely, the first model computes user credibility using a multi-weight formula that takes into account data from tweets in terms of various topics. The second model focuses on tweet content to compute user credibility and the third one combines the former two techniques in a hybrid method.

In numerous real-world applications, complex pattern recognition problems are required to be executed in our personal computers, such as visual pattern recognition. Since the conventional strategies are clearly not appropriate for this type of problems, we therefore adopt characteristics and features from brain physiology and in following use them as a premise for novel processing models. This is well known as Artificial Neural Systems (ANS) technology or essentially just as Neural Networks (Freeman and Skapura, 1991).

Furthermore, authors in (Kanavos et al., 2021) incorporate deep neural networks for the problem of forecasting aviation demand time series, where they utilized various models and identified the best implementation among several strategies. One of the most recent works exhibits an LSTM-CNN based system for classification (Savvopoulos et al., 2018). Specifically, the classification task was improved as the proposed method reduced the execution time by values ranging from 30% to 42%. Thus, the effectiveness of LSTM neural network and its important contribution for specific tasks was proved.

3 Proposed Architecture

Initially, the user credibility measurement along with the model equations, is introduced. The data pipeline, where exploratory analysis is applied, is considered a major aspect and has been taken into consideration in our proposed methodology. Furthermore, data preprocessing is utilized and the deep learning model is fully presented.

3.1 Measuring Credibility

The trust model for measuring social credibility of Twitter users, which is computed in two steps, is utilized. Initially, the Twitter domain is considered as the quintuple (U, F_o, F_e, T, X) where U represents the users, F_o, F_e represents the user's followers and friends respectively, T represents tweets and X is the set of topics of the corresponding domain. The model consists of the following Equations 1 to 6 that employ Twitter metrics like retweets, friends, followers (Kafeza et al., 2020; Kafeza et al., 2014; Kang et al., 2012).

In detail, we measure the retweet deviation for every user from the average retweet rate in Equation 1. Retweets constitute an important sign of credibility and are mapped to a log-log scale to handle large outliers.

$$Cred_{RT}(u,x) = |RT_u - \overline{RT_x}| \quad (1)$$

In equation 2, we measure the distance of the retweet rates multiplied by the number of followers normalized by tweets.

$$Utility_{RT}(u,x) = |\frac{RT_{u,x} \times F_o(u)}{t_{u,x}} - \frac{\overline{RT_x} \times \overline{F_{o,x}}}{t_x}| \quad (2)$$

Likewise to equation 1, a social score utilizing the number of followers divided by the number of tweets is computed in equation 3.

$$Cred_{social}(u) = |\frac{F_o}{t_u} - \frac{\overline{F_o}}{t}| \quad (3)$$

In equation 4, the ratio of followers to friends as a deviation is measured. In this way, accounts with many friends but few followers can be filtered out.

$$Balance_{social}(u) = |\frac{F_o(u)}{F_e(u)} - \frac{\overline{F_o}}{\overline{F_e}}| \quad (4)$$

Social credibility in computed in equation 5, which is similar to equation 4, although it takes into account different topics. In our study, a single topic is considered, so these two metrics have the same value.

$$Cred_{social(u,x)} = |\frac{F_o(u,x)}{t_{u,x}} - \frac{\overline{F_{o,x}}}{t_x}| \quad (5)$$

The last metric addresses the behavior of a user towards a given topic against all topics. Equation 6 is equal to 1 because we have a specific theme.

$$Focus(u,x) = |\frac{\sum_{t \in T} t_{u,x}}{\sum_{t \in T} t_u}| \quad (6)$$

We should bear in mind that user credibility is measured based on Equation 7.

$$C_u = \alpha(Focus(u,x) + \beta(Balance(u) \times Cred_{social}(u)) + \gamma(Utility_{RT}(u,x) \times CredRT(u,x)) \quad (7)$$

The users that have been manually verified by Twitter constitute a small minority. This verification is initiated by Twitter and it cannot be requested by a specific user as it signifies a trustworthy person (Morozov and Sen, 2014). In the second step, the trust score *only* for verified users as presented in equation 8 is updated; this weighted formula boosts verified credibility based on the score of the most credible and verified persons.

$$C_u(ver) = 0.2 \cdot C_u(ver)_{max\_ver} + 0.8 \cdot C_u(ver) \quad (8)$$

3.2 Data Pipeline Procedure

The major modules of our proposed methodology are presented in following. Initially, we gather our data based on tweets regarding a specific topic as will be presented in Section 4.1. The exploratory analysis in our dataset for investigating and summarizing its main characteristics will be then applied; this will help in avoiding any assumptions as patterns will be identified and outliers or anomalous events will be detected. Later on the credibility, based on the common metrics of the Twitter dataset, will be measured as discussed in Section 3.1.

Data pre-processing constitutes an essential part of the proposed model since the text is cleaned and any redundant features are totally eliminated. Moreover, the NLP characteristics such as the number of verbs, nouns, and symbols will be extracted with the use of spaCy python linguistic tool (Hotho et al., 2005). These features will be then used as input in our proposed deep learning model in order to forecast credibility for each particular user.

3.3 Data Pre-processing

The data pre-processing phase consists of several steps as we aim to reduce the noise of the data and thus, the complexity of our proposed model. Specifically, in order for the model to be more robust and efficient, all characters are converted to lowercase, and the hyperlinks along with the stop words are removed as they don't add any useful linguistic information (Kaur and Buttar, 2018; Luhn, 1960). Furthermore, mentions and hashtags that are often used on Twitter messages to attract other users' attention, are also removed.

Part-of-Speech (POS) tagging was in following implemented for extracting the useful features and enhance our deep learning model. Tokenization and lemmatization were also considered, where the first one is the process of turning text data into tokens and is performed in order to obtain tokens and prepare a vocabulary, which consists of the unique tokens of the corpus and the latter is the process of replacing a given word with its root in order to reduce the vocabulary size.

As previously mentioned, spaCy library[3] with its English vocabulary set called "en_core_web_lg" was employed. Six different dataset instances were created according to the vocabulary size, with 10.000, 20.000, 30.000, 40.000, 50.000 and 60.000 different words respectively.

3.4 Deep Learning Model

The deep learning model we utilized for predicting user credibility is illustrated in Figure 1 consisting of two different modules (Patterson and Gibson, 2017). Specifically, the first module takes as input the preprocessed text and adds an embedding layer. This layer transforms words into their corresponding word embeddings with the aim of compressing the input feature space into a smaller one. Word embeddings are in fact a set of processes, where individual words are represented as real-valued vectors in a predefined vector space.

After the embedding layer, the spatial dropout, the LSTM or BiLSTM layers and the normal dropout (Buduma and Locascio, 2017) were added. In our model, we employ both LSTM and bidirectional LSTM neural networks. Long Short Term Memory networks are a special kind of Recurrent Neural Networks that are capable of learning long term dependencies and provide impressive performance especially on Natural Language Processing problems (Hochreiter and Schmidhuber, 1997; Savvopoulos et al., 2018). The difference is that LSTM networks preserve information from the past while BiLSTM networks preserve information from both past and future. The second module consists of the classic ANN network, that takes as input arithmetic features.

Both models concatenate in a single artificial neural network that can fit on both textual and numeric data. Here, Keras deep learning library was used for implementing our proposed methodology.

[3] `https://spacy.io/`

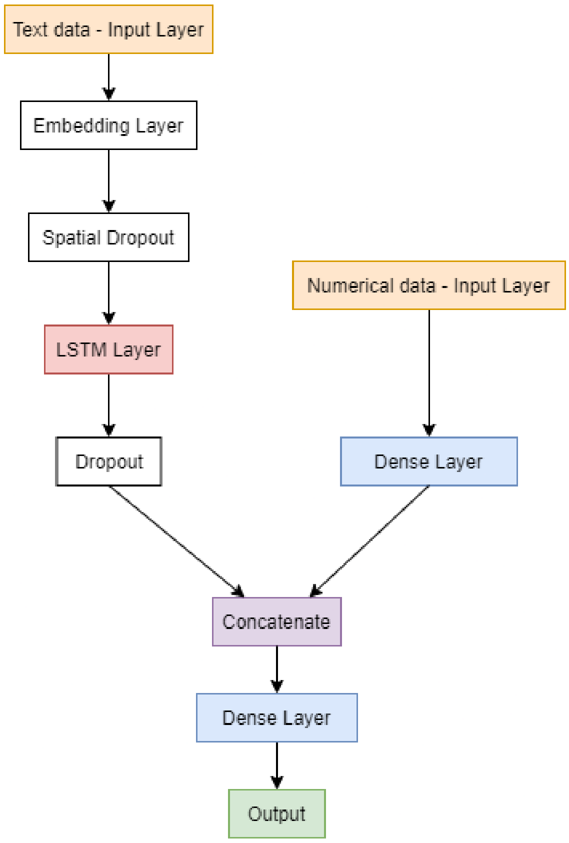

Figure 1: Deep Learning Model Architecture

4 Implementation

4.1 Dataset

We have used a dataset entitled “Game of Thrones S8”, which captures the release of all six Game of Thrones episodes from the popular television series that premiered on 14th of April, 2019[4]. It consists of 403.903 unique users that have contributed a number of tweets equal to 760.626.

This dataset was reconstructed as most features were removed and new linguistic characteristics were added. Specifically, every user was rated in a scale of 1 to 5 depending on the credibility score, where more trustworthy users are rated higher. Finally, a very small portion of the users was removed as they had zero followers or friends and thus, user credibility in this case could not be computed.

The distribution of the users is presented in Table 1; the majority of them were categorized as non trustworthy and slightly trustworthy.

[4]https://www.kaggle.com/monogenea/game-of-thrones-twitter

Table 1: User Categories of Initial Dataset

Classes	**Number of Users**
non trustworthy	285.793
slightly trustworthy	106.443
somewhat trustworthy	8.939
pretty trustworthy	1.253
most trustworthy	71
Total	**402.499**

4.2 Balanced Dataset

At a later stage, a new dataset was constructed because the initial dataset was exceptionally large and awfully imbalanced. This dataset is called the “balanced” one and was utilized in order to precisely evaluate and fine-tune our proposed deep learning model. Moreover, a more balanced dataset will provide us with more accurate results in terms of accuracy as well as validation accuracy.

In order to create this dataset, we had to deal with the problem of the extremely few values of the last category. To achieve this, we normalized the values within a new range in order to have a small difference between the classes.

The distribution of the users per each class after the balancing process, is presented in Table 2.

Table 2: User Categories of Balanced Dataset

Classes	**Number of Users**
non trustworthy	10.000
slightly trustworthy	10.000
somewhat trustworthy	10.000
pretty trustworthy	4.316
most trustworthy	686
Total	**35.002**

5 Evaluation

In this section, we evaluate our model on the two datasets for different vocabulary sizes and for different number of layers in terms of accuracy and validation accuracy, which are the most common metrics to evaluate deep learning models.

Primarily, the results regarding the initial dataset are presented; here 10 hidden layers in the corresponding LSTM network were implemented. We have to mention here that the evaluation with bidirectional LSTM neural networks performed almost the same and thus, the results are omitted. Table 3 presents the accuracy and validation accuracy on different ratio splits, where they assume values larger than 81% presuming that the dataset is large enough and as a result, we can not observe any actual differences.

Table 3: Accuracy and Validation Accuracy on different Ratio Splits on initial Dataset

Ratio Split	Accuracy	Validation Accuracy
0.05	0.8157	0.8132
0.10	0.8147	0.8189
0.15	0.8136	0.8139
0.20	0.8153	0.8143
0.25	0.8148	0.8160
0.30	0.8141	0.8186
0.35	0.8146	0.8160
0.40	0.8156	0.8159

In Table 4, we add, except text data and arithmetic features, several other features through NLP process like POS tagging. This is how the accuracy score of 81% is achieved, highlighting the significance of NLP procedure.

Table 4: Accuracy and Validation Accuracy of Deep Learning Model with Text and NLP Features (initial Dataset)

Vocabulary Size (words)	Accuracy	Validation Accuracy
10.000	0.8172	0.8149
20.000	0.8153	0.8143
30.000	0.8155	0.8163
40.000	0.8163	0.8151
50.000	0.8144	0.8182
60.000	0.8156	0.8164

In following, the performance of our model in the balanced dataset using different numbers of LSTM and BiLSTM layers is depicted in Table 5. We observe that in the case of using more than 5 hidden layers on both textual and arithmetic data, the accuracy is maxed at 70% regarding LSTM networks whereas BiLSTM clearly outperforms this value as it consists of two LSTMs; one taking the input in a forward direction, and the other in a backward direction. BiLSTMs effectively increase the amount of information available to the network, improving the context available to the algorithm.

Finally, all the obtainable optimizers of Keras library were taken into consideration and the results are introduced in Table 6 showing that Adam is the best choice. Another outcome is the minimum number of epochs we need to train our model, which is 10 as illustrated in Figure 2.

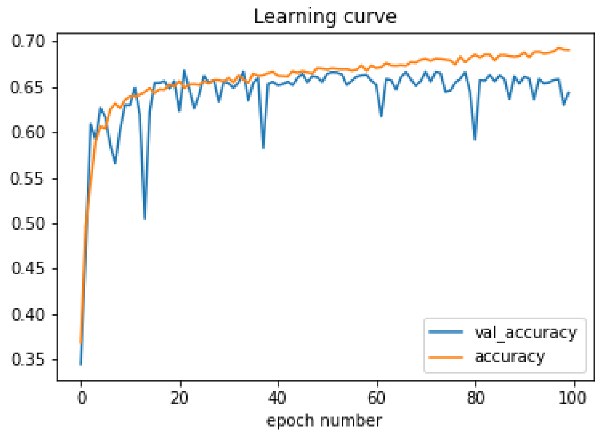

Figure 2: Learning Curve on balanced Dataset

6 Conclusions and Future Work

In our proposed work, we have presented a methodology that measures user credibility on Twitter and can predict human trustworthiness. We have included various features, such as numerical and text data utilizing the NLP process and have evaluated them in terms of accuracy. LSTM and BiLSTM neural networks have been implemented and experiments with different number of hidden layers were conducted. The results demonstrate that our proposed model can predict user credibility with high values of accuracy and this can be promising for such complicated problems as trust prediction.

Regarding future work, the proposed methodology can be augmented by incorporating Batch Normalization, which normally accelerates the training of deep networks. In addition to that, the inefficiencies of single models can be resolved by applying several combination techniques, which will lead to more accurate results.

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Table 5: Accuracy of Deep Learning Model with Text and NLP Features (balanced Dataset)

	Dense × 1	Dense × 3	Dense × 5	Dense × 10
LSTM × 1	0.4834	0.7099	0.7071	0.7100
LSTM × 3	0.6400	0.7032	0.7075	0.7050
LSTM × 5	0.7027	0.7129	0.7097	0.7099
LSTM × 10	0.7048	0.6900	0.7106	0.7083
BiLSTM × 1	0.9670	0.9688	0.9657	0.9702
BiLSTM × 3	0.9591	0.9491	0.9602	0.9522
BiLSTM × 5	0.8816	0.9267	0.9297	0.8865
BiLSTM × 10	0.6908	0.7094	0.7022	0.7111

Table 6: Accuracy and Validation Accuracy of Models with different Optimizers (balanced Dataset)

Optimizer	**Accuracy**	**Validation Accuracy**
Adadelta	0.2962	0.2896
Adagrad	0.2833	0.3337
Adam	0.6938	0.6980
Adamax	0.6841	0.6955
Ftrl	0.2873	0.2833
Nadam	0.6977	0.6907
Rmsprop	0.6828	0.6816
SGD	0.4812	0.5100

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