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## Authorship Authentication of Short Messages from Social Networks Using Recurrent Artificial Neural Networks: Message Batches

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### Abstract

500 tweets from Twitter are collected by using the software Nvivo, from each of 34 authors that meet certain criteria. Dataset consists of 17000 tweets is preprocessed to extract frequencies of 72 features. Since artificial neural networks are more successful distinguishing two classes, for N authors,  $N \times N$  neural networks are trained for pair wise classification. These experts then organized as N special competing teams (CANNT) to aggregate decisions of these  $N \times N$  experts. Then to improve the accuracy of author authentication, a novel technique, batch identification is used and up to 100% accuracy is achieved.

## 1. INTRODUCTION

The Internet has become dramatically significant. Social Networks have taken interest of billions and their effect grows each day. Users reach each others, share their opinions and transmit the information. Online networks like Twitter and Facebook serve as virtual environment with simplicity and became rich and easy content platforms that provide knowledge. Nonetheless, there are several security issues that occur with the wide usage of these sites. It can be considered that these sites have trustable environments but they are accessible to virtual attacks. Detecting fake and compromised accounts, and distinguishing them are the main problems in authorship authentication for social networks.

This work aims the study of developing a system which is able to operate for finding the author of anonymous messages by providing to the system posts written by a list of suspected users on social media and choosing the matched author.

Related studies investigated mostly focusing on longer text documents rather than what is intended to do by this research (Can, 2012). This study is important by combining stylometry which is more than a century-old science with current computational capacity for short text messages. The stylometry regarding text classification of short social network messages, appropriate methods applied in relevant and contemporary research were investigated as the base of this study.

Stylometry, also known as authorship analysis purposes to determine the original author of a given text which studies linguistic style. The methods of it have been primarily applied to analyze letters and literary works such as Federal Papers (Hamilton, et. al., 2008). The analysis in the vocabulary of an author and the use-frequency of words in it are known as a general method in stylometry which is later compared with the vocabulary of another author. The specific analysis of the use-frequency of function words including numerals, pronouns, prepositions, auxiliary verbs, and conjunctions is also possible with it. The analysis of average sentence length or the use of very unusual words is another method applied with stylometry for comparing texts.

There are three main perspectives regarding today's applications. These are authorship attribution, authorship verification, and authorship profiling. Authorship attribution aims to determine a probable author from a multitude of several other authors. On the other hand, authorship verification finds if an author's linguistic style matches to another linguistic style of the author. Authorship profiling has the purpose of determining attributes which are likely to reveal an anonymous authors origin, age, gender, and so on. This work focuses on the first perspective, i.e. authorship attribution.

The detection of the authorship for a document which is fewer than 1000 words was thought to be difficult in the time of the early 19th century. In the early 21st century, the number decreased and the determination of the authorship of a document with 250 words was thought to be possible. There is also a need for decreasing this limit because of spreading usage of many shorter communication tools such as Twitter, Facebook etc.

There are differences between authorship attribution of online documents and the authorship attribution of traditional work. This occurs in two ways. The first is that the online documents or text collection are frequently informal and unstructured which are not necessarily grammatically correct as a comparison to literature texts. The second is that the quantity of authorship disputes regarding a single online document is much more as a comparison to traditional published documents. In this situation, the scarcity of standardized data to test the accuracy of results underlies as the reason that is one of the challenges of authorship attribution.

For the researchers, the increasing of the popularity of social media has made it easier directing the focus on authorship attribution in micro-blogs. Various studies have been published as a respect to the use of authorship analysis in social network recently.

The problem of authorship attribution for an online social network Twitter is studied in this work. Twitter has had an increase with its popularity recently by reporting to have over 500 million user base that share almost the same quantity of messages daily which is called as tweets

(internet live stats). Twitter differs from other social networks in terms of publishing limitation. Users are able to publish only 140 characters for each tweet.

Various classification methods are implementable to the authorship attribution problem. An important transition from statistical methods into machine learning based approaches is demonstrated by the authorship attribution techniques (Usha et al, 2017). Supervised classification methods are preferred in the current literature (Rocha et al, 2016). In this study, machine learning based approach was used.

Abbasi, and Chen (2005) collected 20 web forum messages from each 20 authors. Average length was 76.6 words. They used 5 authors and randomly chosen 30 messages in their experiment for comparing feature types and classification techniques. 301 features were chosen and C4.5 and SVM were used. Accuracy for C4.5 was 90% while it was 97% for SVM. Calix et al. (2008) updated an existing C# based stylometry system for verifying author of e-mails. They used 55 style features and K-nearest neighbor algorithm for classification. The average length of e-mails was 150 words.

Layton (2010) evaluated current techniques and identifies some new preprocessing methods. They stated that existing authorship attribution technique SCAP (Source code authorship profile) performs well. A threshold quantity of tweets regarding to attribution task is determined in the paper and informed that 120 tweets per author is an important threshold and there is not a significant improvement in accuracy even in the case of increasing the tweet number greater than the threshold value.

Bhargava, et al (2013) grouped various tweets for increasing the text size under consideration. They prefer to analyze features over a group of tweets instead of a single one. They used syntactic, lexical, tweet specific and emoticon features as author style in which firstly the model was trained by applying SVM as classifier. By increasing the length of each block, they reached 81.42% accuracy for 10 users with 200 tweets each and 77.7% accuracy after increasing tweets number to 250 each. If they increased number of users to 20 with 300 tweets per user, they achieved 64.54% accuracy. Also they informed that while group of 10 tweets received the best result, using each tweets alone resulted with 78.1% accuracy.

Green, and Sheppard(2013) focused on messages collected from Twitter to analyze most effective feature sets for authorship verification. They used sequential minimal optimization (SMO) algorithm included in Weka for classification 10 authors with 120 tweets from each and had 44% accuracy rates. They compared style makers (SM) feature sets and bag-of-words (BOW) feature sets and informed that SM features are more effective than BOW features for authorship verification. Further, the analysis of the authorship traits for verifying the

legitimacy of Twitter accounts was examined by Barbon et al (2017). By aiming that, the syntactic, lexical, idiosyncratic and content specific features were applied.

Arakawa et al (2014) investigated a Twitter specific approach which evaluates the category and number of re-tweets. Afroz et al (2014) prepared a large scale study related to posts on forums and malicious search engine optimization. They proposed several features which are suitable to social network messages as word-level bigrams, numbers used in place of letters, capitalization, and existence of foreign words. Azarbyonad et al (2015) drew attention to the dynamicity of authors and examined the temporal changes of word usage by authors of tweets and emails and based on this examination they suggested a way to measure the dynamicity of authors' word usage.

Li, et al (2016) used short posts from Facebook. Facebook post, average 20.6 words was applied as the dataset in order to determine whether user is authenticated or not among 30 users in the work. Further, SVM Light with 233 features was applied and 12 tests were conducted. They discussed the challenge of using traditional stylometry on short texts. They examined different feature sets. The success for 10 users with 233 features was 81.6%. When the author number was increased to 20 and 30, the success was slightly dropped to 79.8% and 79.6% respectively (Demir, 2016, 2017).

For the determination of traits in multi authored documents, Macke, and Hirshman (2015) used deep learning techniques that is at the sentence level. The vocabulary and grammatical structure with the application of recurrent neural network model (RNN) is modeled by the authors and it is noticed that application has less performance in the case the number of authors increases. Schwartz, et al (2013) trained SVM classifier for classification of Twitter messages and n-gram features set was used. The tweets that have fewer than 3 words were removed in the preprocessing process and k-signature of authors that appears in at least k% of author's training set but not appear in others' was defined and used as a feature. Authorship attribution in tweets with a focus on unique signature related with users was studied in the research. In the experiments different number of authors and tweets were used. 65% accuracy was achieved for 50 authors and 500 tweets and 72% was archived for 1000 tweets. Decreasing size of submitted data and increasing author number resulted with decreasing the accuracy rate.

Rocha A. et al (2016) compared several algorithms to classify tweets and discussed an extensive review for the existing authorship analysis techniques in micro blogs. They concluded that PMSVM had the best accuracy rate. The success was 48% for 50 authors with 100 tweets. Using more number of tweets increased the accuracy rate; 500 tweets 55% and 1000 tweets 65%. The results offered for the necessity of a plenary method which allows the application of the data context and process it irrespective of its multimodality and further a system which tolerates

the lack regarding availability for all author data during training.

Brocardo. et al (2013, 2014, 2015, 2016) proposed a supervised technique used n-gram feature set for authorship identification. They used Enron e-mail dataset. They prepared their data as each block contains 500 characters and each user has 50 blocks. They used 87 users and the EER (equal error rate) was 14.35%. In their late work (2017), they analyzed the use of deep belief networks for authorship verification model of continuous authentication. They achieved 16.73% ERR for 10 user with 140-character-length 100 blocks per user.

An authorship attribution method is offered by Usha et al (2017) in which the tone and personality patterns related with an author is modeled. Method is acquired with the application of convolutional neural network trained on tone and personality data. Data of the authors from Twitter is employed on the models and then psycholinguistic features were united with the final level features. Obtained features were applied for training a linear SVM classifier for prediction of an unknown tweet's author. Their results showed that if data number increased, better results were obtained. However increasing the number of authors has reverse impact. 15 Users with 250 tweets had 51% accuracy and with 800 tweets results increased to 80% accuracy. However 50 Users with 250 tweets achieved 50% accuracy and 50 Users with 800 tweets achieved 71% accuracy.

Sirinivasan and Nalini (2017) evaluated the effects of different classification methods for online messages. They used lexical, syntactic, structural and n-gram features and as classifier they examined C4.5, fuzzy classifier and Ada boost classifier. 40 Amazon review messages were collected from each 5 authors and evaluated by using cross validation. Ada boost classifier received the best results with 84% accuracy for 5 authors.

## 2. A BRIEF NOTE ON ANNS

This brief presentation of artificial neural networks will focus on a particular structure of ANNs, multi-layer feedforward networks, which is the most popular and widely-used network paradigm in many applications including forecasting volatilities and prices in markets. For a general introductory account of ANNs, readers are referred to Wasserman (1989); Hertz et al. (1991); Smith (1993). Rumelhart et al. (1986a), (1986b), (1994), (1995); Lippmann (1987); Hinton (1992); Hammerstrom (1993); Haykin 1999 illustrate the basic ideas in ANNs.

### 2.1 Recurrent Neural Networks (RNN)

Financial time series mostly dependent nonlinearly on time and hence recurrent neural networks (RNN) are particularly useful (Szkoła, et al, 2011; Lipton, 2015). They are constructed by taking a feedforward network and

adding feedback connections from output and/or hidden layers to input layers. The standard backpropagation algorithm also trains these networks conditional that patterns must always be presented in time sequential order. The one difference in the structure is that there are extra neurons in the input layer that is connected to the hidden layer and/or output layer just like the other input neurons. These extra neurons hold the contents of one of the layers as it existed when the previous pattern was trained. In this way, the network takes into account previous knowledge it has about previous inputs. These extra neurons are called the context unit and it represents the network’s long-term memory (Balkin 1997).

There are three types of RNNs: Jordan, Elman, and Jordan/Elman recurrent networks. A Jordan neural network (JNN) has additional neurons in the input layer, which are fed back from output layer (Carcanoa, et al, 2011). While an Elman neural network (ENN) has additional neurons in the input layer, which is fed back from hidden layer (Elman, 1990). The mixture of the two, Jordan/Elman recurrent networks (JENN) has additional neurons in the input layer, which is fed back from hidden layer, and output layer.

2.2 Jordan Recurrent Neural Networks (JNN)

A Jordan neural network (JNN) has several feedback connections from the output layer to the input layer. The input layer has additional neurons, which are fed back from the output layer (Carcanoa, et al, 2011).

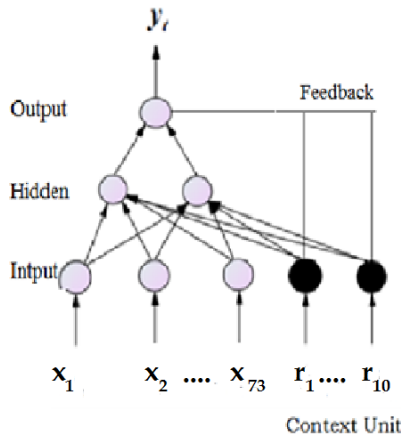


Figure 1. JNN with a single hidden layer representing a nonlinear regression model

3. DATA

Dataset in this research consists of 17000 tweets collected from Twitter, as 500 tweets for each of 34 authors that meet certain criteria. Raw data collected using the software Nvivo. The collected raw data is preprocessed in order to obtain same structure and improve classification accuracy. 72 features (Demir, and Can 2018) in four types are

integrated into feature set and used for e-mail authentication. They are selected from the list that was prepared by Zheng et al. (2006). The features are extracted by a program in Java, and registered to a text file. Later this text file was reached by our program for training the classifiers and to implement author attribution.

The features that are evaluated are combinations of character-based lexical features, word-based lexical features, syntactic features, structural features and social networking-based features. We collected only textual inputs and did not collect metadata like date of posting, location of user, application for posting, and id. because of the research’s extent. Further, data set is collected without any tendency to any particular content or user.

Studies showed that different types of features have different power of discrimination. Therefore, it is important to identify the key features.

Feature vectors, created by extracting from Twitter messages, were used as input for modeling artificial neural network (ANN).

4. A CLASSIFIER FOR TEN AUTHORS

To train a recurrent artificial neural network that will be able to distinguish tweets of the authors  $a_i$ , and  $a_j$ , we choose an appropriate network architecture.

The input vector is 72 dimensional, for bias, 1 is added as the first element of each data vector, and we add one component for the recurrent information. Therefore the neural network will have 74 input neurons. This input vector is multiplied by a  $74 \times 74$  synaptic weight matrix  $W_1$ , to create vector of 74 numbers at 74 hidden layer nodes.

4. 1. A Pair Wise Classifier

If the data entered to ANN belongs to a tweet authored by the author  $a_i$ , and the output is +1, it is OK, otherwise it is erroneous, and synaptic weights must be adjusted by back propagation of the error through iterations, till ANN creates enough correct results at the output node. In Table 2, the accuracies achieved by 100 experts that trained to distinguish tweets by ten authors( $a_i, a_j$ ) are shown.

Table 2. The accuracies achieved by 100 experts that trained to distinguish tweets by author pairs ( $a_i, a_j$ ).

%	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10
a1	0	84	86	77	96	89	95	89	78	80
a2	88	0	88	82	88	90	92	93	92	72
a3	86	79	0	78	88	90	95	90	96	78
a4	74	83	82	0	80	86	88	91	92	67
a5	84	82	90	85	0	80	88	92	86	78
a6	83	87	85	82	73	0	84	84	86	72
a7	92	92	86	94	90	91	0	93	92	92
a8	82	91	89	89	80	82	93	0	88	86
a9	74	92	93	80	86	91	89	92	0	86
a10	86	81	78	73	58	71	83	78	72	0

4. 2. Aggregating Expert Votes

To create a authentication device from these 100 experts for tweets by 10 authors, two approaches are discussed: 1) on a single tweet from an author, 2) on a bundle of several tweets from an author.

4.2.1. Deciding on a Single Tweet

Expert  $e_{ij}$  is trained to distinguish tweets by authors ( $a_i, a_j$ ). If the data vector  $v$ , belongs to a tweet by  $a_i$ , he most probably rises a flag written 1, If the data vector  $v$ , belongs to a tweet by  $a_j$ , he most probably rises a flag written -1. If the data vector  $v$ , belongs to a tweet by  $a_k$ ,  $k \neq i$ , and  $k \neq j$ , although he is not so sure, he rises a flag written either 1, or -1. Since he is not trained to distinguish tweets by the authors ( $a_i, a_k$ ), or ( $a_k, a_j$ ), his vote will be a mixed signal.

Table 3. The accuracies achieved by 100 experts (10 of them are dummy) that trained to distinguish tweets by authors ( $a_i, a_j$ ).

no	1	2	3	4	5	6	7	8	9	10	R
1	0	-1	1	1	-1	-1	1	1	-1	1	10
2	-1	0	-1	-1	-1	-1	1	-1	-1	-1	3
3	1	-1	0	-1	-1	-1	-1	1	-1	-1	3
4	-1	1	1	0	1	-1	1	1	1	1	14
5	1	1	1	-1	0	-1	1	1	-1	1	12
6	1	0	-1	-1	-1	0	1	-1	-1	-1	10
7	-1	-1	0	-1	-1	-1	0	1	-1	-1	2
8	-1	1	1	0	-1	-1	1	0	1	-1	6
9	1	1	1	-1	0	-1	1	1	0	0	12
10	-1	1	1	-1	0	-1	1	1	-1	0	10

When a data vector  $v$ , belonging to a tweet by the author  $a_i$  the votes +1 at the  $i$ th row, and the votes -1 at the  $i$ th column will be more consistent than other row-column pairs. The number in  $i$ th row at the last R column, is the sum of the numbers of +1s at  $i$ th row, and -1s at  $i$ th column. These are called the rank of the row-column pairs. So, it is decided that the data vector  $v$ , belongs to a tweet by the author  $a_i$ , where  $i$  is the row number with highest rank. In Table 3., this author is  $a_4$ . We call this technique of aggregating decisions as competing artificial neural network teams (CANNT). In Table 4, the accuracy of 100 artificial neural networks to distinguish shuffled tweets by 10 authors is given.

Table 4. The accuracies in distinguishing shuffled tweets authored by 10 authors. The average is 79%

	a1	a2	a3	a4	a5
%	73	77	84	66	76
	a6	a7	a8	a9	a10
%	76	88	89	79	83

4.2.2. Deciding on a Batch of Tweets

In decision support systems, it is accustomed not to rely on only one sample item. For a more comprehensive aggregation of expert decisions, who are trained to distinguish tweets pairwise, a second voting mechanism is introduced.

To activate this second voting mechanism, instead of a single tweet from each author, batches of several tweets of each author is supplied.

Assume there are eight tweets in each batch, and tweets in a bundle are classified as in the below.

Tweet in batch	1	2	3	4	5	6	7	8
Decision	1	6	4	1	4	5	10	4

Figure 3. Tweets in a batch are classified as in this figure

Since 4 is most common in votes, it is decided that this batch of eight tweets belong to author 4.

When CANNT is followed by this second voting mechanism a 100% accuracy is easily achieved.

Table 5. Aggregated votes, and the most common votes in batches of eight tweets.

Tw/ Auth	1	2	3	4	5	6	7	8	MostC
1	9	1	1	9	1	1	4	1	1
2	4	2	2	2	2	2	2	2	2
3	3	10	3	3	3	3	3	3	3
4	1	6	4	1	4	5	10	4	4
5	5	9	5	5	5	9	6	7	5
6	6	6	6	6	6	3	6	6	6
7	7	7	7	7	7	4	7	7	7
8	8	8	8	8	8	8	8	1	8
9	9	9	9	9	9	9	9	9	9
10	6	10	10	6	1	10	6	2	10

If authentication is made by most common votes, it is seen that the outcome is 100% correct.

4.2.2. Further Averaging

Assume the experiment in 4.2.2 is repeated six times. In Table 6., we have six MC column of Table 5.

Table 6. Most common votes in six experiments. The overall accuracy is 100%.

Exp	1	2	3	4	5	6	7	8	9	10
1	4	2	3	4	6	6	7	8	9	9
2	4	2	3	4	5	6	7	8	9	10
3	1	2	3	4	5	6	7	8	9	10
4	1	2	3	4	5	6	7	8	9	10
5	1	2	3	4	5	6	7	8	9	10
6	1	2	3	4	6	6	7	8	9	1
MC	1	2	3	4	5	6	7	8	9	10

In the last row, most common votes in columns are listed. It is seen that the outcome is 100% correct.

CONCLUSION

Dataset consists of 17000 tweets collected from Twitter, as 500 tweets for each of 34 authors that meet certain criteria. Raw data is collected by using the software Nvivo. The

collected raw data is preprocessed to extract frequencies of 72 features. As an example ten of these 34 authors are selected. Since artificial neural networks are more successful distinguishing two classes, 100 neural networks are trained for pairwise classification. These experts then organized as ten special competing teams (CANNT) to aggregate decisions of these 100 experts. For ten authors 79% accuracy is achieved. If this decision mechanism is followed by batch decisions, 100% accuracy is achieved in 99.9% of the cases.

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