Modelling of the Fake Posting Recognition in On-line Media Using Machine Learning

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Abstract. Discuss content in the online web space has a significant impact on social life in recent years, especially in the political world. The impact of social networks has its advantages and disadvantages. An important disadvantage is a rising of the antisocial content in online communities. The antisocial content represents a serious and actual problem that is reinforced by a simplifying the process of creating and disseminating of antisocial posts. A typical example is a spreading of fake reviews. Detection of fake reviews is becoming one of the most important areas of research in last years. It is easier to track the impact of fake reviews than to detect them. The aim of this paper is to create suitable models for the fake reviews recognition using machine learning algorithms particularly decision tree, random forests, support vector machine and naïve Bayes classifier. Using a confusion matrix, several indicators of binary classification efficiency were quantified in the process of these models testing.

Keywords: Social media mining · model for fake reviews identification · machine learning methods · antisocial posting

1 Introduction

In today's technology, nearly three and a half billion people have access to the Internet. At its beginning, the web was used to spread knowledge and education, first among academics and later among the general public. When the social networks began to emerge later, their goal was similar. Over time and with their rapid development, they have become not only a communication channel but also a means of sharing photos, videos, articles, opinions, even though a mobile phone. Many people do things in their lives just to share it on social networks. Unfortunately, this communication tool also has a dark side. It has become the home of fake reviews, gossip, or nonsense, which unfortunately users continue to share without validation. Every day, falsehood and deceit are spread through social networks for a variety of reasons as a financial gain or a gain the favor of the greatest number of people. And consumer users are just helping.

The concept “fake reviews” is neologism, which is very often used to refer to a fictive message. The fictive information is distributed mainly by social media, but it can be also distributed through the conventional media. Fake reviews is written and published in order to mislead and sometimes to harm the reputation of a company, entity or person, and to profit from it either financially or politically. They usually have sensational headlines to increase readability of posts.

The effort to manipulate people's minds is very old. In ancient times, tribal leaders, princes, kings, and pharaohs wanted to manipulate power. In these times, it was enough to influence those who had some power. With the arrival of the city states, it was necessary to manipulate wider groups of people as senators or ambassadors. With the oncoming of democratic regimes, it was necessary to persuade the masses of the people about their truth by means of books or daily newspapers. The problem at that time was that the reader had to buy a book or newspaper with lies. When the radio and television came, the manipulation was easier, because they allowed the information to be spread among masses without necessity to pay for the content so much. The mass manipulation began to fall slowly with the oncoming of the Internet. Suddenly it was also very easy and quick to find out what was true.

After some time, the mass manipulation took on a new form, for example the form of fake reviews. Social networks provided an ideal environment for the fake reviews. If misleading information comes from multiple sources in a similar period, it is not difficult to believe that it is serious information. Most social networks users give them only a quick look. Time and space to confront the source of information is significantly low. Large number of users do not verify the truth of information because the information is already enjoyed by thousands of users. Everybody who has a social network account can create a professionally looking posts, which are spread quickly and for free.

News characteristics such as timeliness and oddity indicate that there is a difference between detection of fake reviews and fake news, and thus bring new challenges. The challenges point out the potential resources (e.g., fact-checking websites) and techniques (e.g., deep learning). Future research directions can improve the performance of fake reviews detection, and promote our understanding of them and identifying check-worthy content [1].

2 Fake Reviews

2.1 Fake Reviews in Online Space

The fake reviews under mines serious media companies and make it difficult for journalists to report significant reviews stories. BuzzFeed, an American Internet media and reviews agency, found that the top twenty fake reports of the 2016 US presidential election received more engagement on Facebook than the first twenty election stories from nineteen major social media. Also, well known publishers have been anonymously attacked by sites that published fake reviews because it was difficult to detect sources of them. During and after the presidential election, Donald Trump began using the term "fake reviews" to describe negative information about his presidency.

To be able to detect fake reviews, at first the concept has to be characterized. There are more types of fake reviews:

- Satire or parody - no intention to cause harm, but there is a possible craziness
- False link - subtitles and headlines do not support content
- Misconception - use of misleading information to confront a problem or an individual

- False context - if a true content is shared with a false context information
- Fraudulent content - if original sources are supplied with false resources
- Manipulated content - when original information or images intend for fraud are manipulated, for example in a "modified" photo
- Invented content - the new content is 100% false, designed to deceive and damage

According the source, the fake reviews on traditional media has psychology and social foundations. On the other hand, the fake reviews on social media can be characterized by malicious accounts and its echo chamber [2].

2.2 Fake Reviews Detection

There are different approaches to fake reviews detection. The first approach is based on a *content analysis* using knowledge (an external source can be used for check-up the truth of reviews) and the style analysis (a spreading of fake and misleading information requires the special writing style). The second approach is based on a *social context analysis* of a stance, attitude and a propagation of reviews. Detecting false messages on social networks is a relatively new area of research. The survey [2] addresses related research areas, open issues, and future research directions from a data mining perspective.

The fake reviews detection can be oriented on data, feature, model and application:

- Data oriented – oriented on different aspects of fake reviews such as collecting data, psychological verification and early detection.
- Feature oriented - goal is to explore effective features to detect fake reviews from multiple sources, such as reviews content or social context.
- Model oriented - opens the door to the creating practical and effective models for detecting fake reviews using supervised, partially supervised and unsupervised machine learning.
- Application oriented - includes a research that goes beyond the detection of fake reviews, such as its diffusion and interventions.

Social media such as Facebook and Twitter are undoubtedly main channels for spreading misleading information. Facebook has attempted to implement detection tools. The first is, that users have the option to mark reviews they consider to be a fake reviews. To identify the source, badges are created that mark the lie and allow users to learn more about the story. When enough users label a story to be fake, the frequency of the shared article decreases. To prevent the spread of fake reviews, the company reduces the number of tagged posts and thus reduces their spreading. Repeated offenders, who spread often misleading messages, have removed advertising rights, thereby reducing their distribution as well as earning.

Another possibility is to implement an artificial intelligence to detect fake messages. The artificial intelligence can learn quickly and efficiently to determine words and phrases most relevant to fake reviews - using the trial-and-error method. The artificial intelligence can be used to identify inappropriate posts and to recognize extremism, violence, hatred, threats and other forms of misleading information in online discussions.

2.3 Related Works

The work [3] represents an approach which integrates content and usage information to detect fake products reviews. The model is based also on a reviewer's behavioural trails interlinked by specific spam indicators as an extreme evaluation, a big number of post in a short time period and a similarity of posts of the reviewer.

Another study is based on the detection of online fake reviews using a text analysis approach based on n-gram models and machine learning techniques. It compares six different classification techniques, namely, K-nearing neighbors (KNN), logistic regression, linear support vector machine (SVM), decision trees and stochastic gradient descent. To reduce the size of the lexical profile of texts, two methods were used TF and TF-IDF weightings. The authors collected 12,600 false and 12,600 true reviews on the 2016 political situation. The study showed linear models are better than nonlinear ones. The highest accuracy was achieved using the SVM algorithm (92%) and the lowest accuracy (47%) was achieved using the KNN algorithm [4].

The work [5] is focused on an uncovering fake reviews by classifying it using naive Bayes classifier and random forests. The reviews were obtained from Amazon and included the seller's website, product name, rating, reviewer ID, review topic, review content, date added, review impact (how many people consider it useful), and whether the purchase was verified. The experiments showed that the random forests model achieved better results than the naive Bayes classifier.

3 Used Machine Learning Methods

The term “machine learning” was established by Arthur Samuel in his paper titled ”Some Studies in Machine Learning Using the Game of Checkers” in 1959 [6]. Machine learning and artificial intelligence are gaining massive attention due to its progress in the last few decades. Machine learning methods can be divided into supervised and unsupervised learning methods. The *supervised learning* is a task where computer is given input-output examples and attempts to learn a model, which can be used for mapping given new input into unknown output values. Input-output samples used to train a model are called training samples. The *Unsupervised learning* is explained as a task where computer learns patterns given only input values. A typical frequent task of the unsupervised learning is clustering [7].

To solve the problem of fake reviews detection, we have selected machine learning algorithms with the supervised learning, namely naive Bayes, decision trees, random forests and support vector machines. We have chosen them for a number of reasons: they are the most reliable, understandable, often used with success, and easy to implement [8].

3.1 Naïve Bayes Classifier

Naive Bayes is a probabilistic classifier based on Bayes' theorem and the independence assumption between features. Let us assume that event A and event B are independent, than their conditional probability is defined using Bayes theorem (1).

$$P(A|B) = \frac{P(A)P(B|A)}{P(B)} \tag{1}$$

In practice P(B) can be estimated from the dataset. Replacing P(B) with a constant β^{-1}, formula (1) is then expressed as

$$P(A|B) = \beta P(A)P(B|A). \tag{2}$$

Let us assume that A represents class and B represents a feature relating to this class A. Than the equation (2) handles only one feature. Let us extend the rule with more features. Then the conditional probability of class A on features B, C is following (3).

$$P(A|B,C) = \beta P(A)P(B,C|A) = \beta P(A)P(B|A)P(C|A) \tag{3}$$

If we assume that features B and C are independent of each other, than a simplifying of expression P(B,C/A) to P(B/A)P(C/A) is possible. For n observations – features $x_1, \ldots, x_n$ the conditional probability for any class y_j can be expressed as below.

$$P(y_j|x_1, \ldots, x_n) = \beta P(y_j) \prod_{i=1}^{n} P(x_i|y_j) \tag{4}$$

This model is called naive Bayes classifier. The naive Bayes is often applied as a baseline for text classification, however its performance is reported to be outperformed by support vector machines [9].

3.2 Decision Tree Classifier

Another Decision tree is a model which uses a tree of decisions to predict a label for a new sample. Tree is learned on the training set using a standard top-down approach, which starts with a full dataset in one root (parent) node A question divides a node to sub-nodes - each representing answers to the question. Typical questions are one-feature focused (for example "temperature" with two values divides a set to two subsets "warm" and "cold").

Focusing on subsets, they are generated in variety of degrees of a disorder or an impurity. The impurity of a node is a measure representing class diversity while also taking into account their ratio. There are two most commonly used types of disorder functions, information entropy and Gini index [10]. If E is a subset of the dataset, m is number of classes and p_i is probability distribution of class i in the subset, then information entropy H is defined as follows.

$$H_{entropy}(E) = -\sum_{i=1}^{m} p_i \log_2(p_i) \tag{5}$$

Best ranked questions generate minimal disorder. Difference between the entropy of a parent node and the sum of weighted entropy of all subsets after applying the question is called information gain. Method continues to select most suitable questions recursively splitting samples into smaller and smaller sets, resulting in a tree like graph, hence the name decision tree.

The most known decision tree generator is C4.5 algorithms developed by Ross Quinlan. The advantages of decision tress are their intuitive interpretation and the non-linear solution. The disadvantage of the decision trees in text processing is, that text processing includes a large amount of words as features, and generated tree can be very robust. The decision trees were successfully used for part-of-speech tagging [11] and text documents categorization and parsing [12].

3.3 Random Forests

Random Forests [13] represents a learning of a set of classifiers – decision trees. Random forests represent so-called the composed learning. It builds a set of *de-correlated* trees. It averages results of the set of decision trees without pruning. To ensure the condition that individual tree models have to be independent, the random forests technique uses a random selection of attributes for each tree generation. Since these trees are independent, it is suitable and easier to generate them in parallel.

The classification result is determined by voting. The random selection of a training set for training of each decision tree enable to validate (to test) it on data, which was not used for training. It facilitates validation. This approach is fast and accurate - so it has been used very often in recent years.

From the beginning following parameters have to be given:

- The number of decision trees in the model
- The number of randomly selected attributes for each tree generation

The specificity of random forests is that only the decision tree machine learning method can be used as a particular classifier.

When selecting a test attribute in a tree node, *m* attributes from the total number of *p* attributes are considered. But only one of the attributes is selected. For the next node only *m* attributes are considered, but it is another subset of m attributes as in the previous case. So, it is not allowed to consider many predictors - attributes for each tree division. Why? Let us assume one very strong predictor - attribute within a group of slightly strong predictors. Then most particular trees use it as a test attribute. Individual particular trees would be then similar with the strong tree correlation. It is unwanted situation, because an averaging the results of highly correlated trees cannot bring an advantage compared to using a single tree.

The principle of the tree de-correlation is, that the probability of a strong predictor will be only (p-m) / p and hence other attributes – predictors get more chances. Trees (regression, classification) are notoriously noisy. They become more accurate in the process of being averaged in the random forests technique, what is the basis of the learning by a set of methods.

3.4 Support Vector Machines

The Support vector machines represents a classification model based on support vectors. Models approach is to separate the sample space into two or more classes with the widest margin possible. Method is often called the ’widest street approach’. Support vector machine is originally a linear classifier – Maximal Margin Classifier based on “widest street principle. The wider street the classifier has, the more accurate it is. However, the classifier can relatively efficiently perform a non-linear classification. There are two such support vector machine***s*** [14]:

- Classifier with non-linear decision boundaries
- Support vector machine using kernel function

Kernel is a method which maps features into a higher dimensional space specified by the used kernel function. For the model building, we need training samples labelled -1 or 1 for each class. Support vector machines attempts to divide the classes with a parametrized linear boundary in such a way to maximize the margin between given classes.

So, the widest margin between samples has to be found. It was observed, that only nearest points to the separating street determines its width. It can be expressed as a difference vector of these points multiplied by the vector of the street W and its magnitude ||W||. The objective is to maximize the width of the street, which is known as the primal problem of support vector machines [15].

4 Models Building

The main aim of this work was to find the most accurate machine learning algorithm for learning the model that could detect the fake reviews. We used CRISP-DM methodology [16] for the data mining process. We had a dataset that contained the title, the text and the label of the posts in the form of marks False and True. The attributes Title and Text of the posts have been pre-processed. The main part was the modelling phase. Input to the modelling was in two forms: a *document term matrix* and a *document term matrix with a TF-IDF weighting.* The input data was divided into a training and a test set where *naive Bayes*, *decision tree*, *random forests* and *support vector machine* were applied to the training set. We have verified the created models on the test set using several indicators of binary classification.

4.1 Data Source

We have chosen a dataset that was freely available at https://www.kaggle.com/. Dataset, *Fake News Detection,* contained 4009 records and 4 attributes. The message tag was specified using the *Label* attribute, which takes two values, 0 - indicates fake reviews, and 1 - indicates true post. The attribute represents the target attribute. The proportion of false and true posts was 51.31% to 46.69%. It also contained attributes: *URLs*, which indicates the location of the post on the Internet, the *Headline* and *Body* of a post. The dataset contains reviews about the new USA President Donald Trump. The dataset was divided into two datasets. First data set contains only bodies of all reviews and the second dataset contains only headlines of reviews. These two datasets were used for testing. We wanted to figure out which machine learning methods are better for extremely short texts and which methods can be used for all reviews.

4.2 Data Preprocessing

The data pre-processing is one of the most time consuming phases of the process of data mining. The quality of pre-processed input data affects the quality of output. The description of data pre-processing follows:

- *Removing unsuitable symbols*. As we examined the datasets more closely, we found symbols that had to be removed. The data contained „*â€™, â€* " were removed.
- *Creating a source vector*. We created a source vector, referred to as a corpus, into which we inserted a text attribute.
- *Conversion to lowercase*. Lettering is needed when working with text, so all characters have
- been changed to lowercase.
- *Delete punctuation*. In general, punctuation does not add any value to text analysis using classification models. For this reason, punctuation from data sets was deleted.
- *Remove "stop words"*. The next stage of the text data pre-processing was to remove "stop words". These are words that are not meaningful, which are commonly used in sentences and their information value is zero. Members, prepositions, clutches and some pronouns are considered as so-called the stop words.
- *Remove unnecessary gaps*.
- *Document term matrix*. The document term matrix (DTM) is the most common way of representing of an input text for further processing. In our case, we exported pre-processed data to the form of "Bag of words". This model does not take into account the order of words in the document. The matrix describes the frequency of words that occur in the document file. The matrix lines represent selected texts and columns represent words.
- *Document term matrix with weighting*. Nowadays, the most popular is the weighting scheme TF-IDF (term frequency - inverse document frequency). The aim is to express the importance of a word for a post text in a corpus. It increases proportionally with the number of a word frequency in the post text but it decreases with the frequency of the word in the overall collection of texts. The metric does not take into account the position or context of the word [16].

5 Models Testing

Four models were trained using following four machine learning methods: naive Bayes (NB), decision tree (DT), random forests (RF) and support vector machine (SVM). The input data, process of models learning and testing are illustrated in Fig. 1. The input of the training was consisted from tests of posts (attribute Body) from dataset described above. The data were pre-processed to the form of document term matrix (DTM) and processed by four above mentioned machine learning methods under two different conditions: with and without TF-IDF waiting. Using a confusion matrix, following indicators of binary classification were quantified: Accuracy, Interval of accuracy (Table 1). Experiments presented in both Table 1. and Table 2. showed that in the case when the input of the learning are whole texts of reviews or posts the best model is model learned by random forests algorithm. The random forests method is best in all results of the monitored parameters of effectivity: Recall, Precision, F1 measure and Accuracy. Also Intervals of accuracy are narrowest and smallest for random forests model. A smaller range of the Interval of accuracy means a better model. Precision, Recall and F1 measure as a harmonic average of precision and recall (see Table 2).

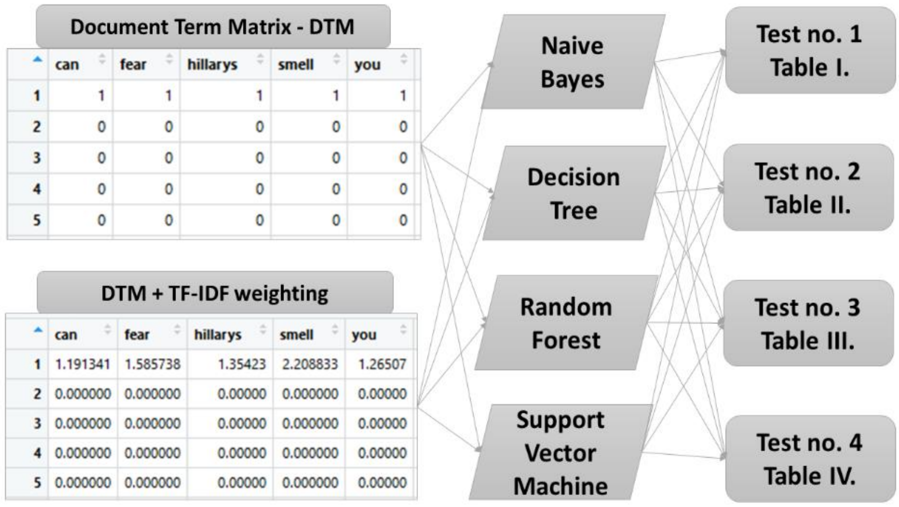

Figure 1. Illustration of input data and generated model testing

Table 1. Accuracy and Interval of Accuracy of models learned from the body of posts

Body of posts	DTM		DTM + TF-IDF	
	Accuracy	*Interval of Accuracy*	*Accuracy*	*Interval of Accuracy*
NB	0.844	(0.822, 0.864)	0.904	(0.886, 0.920)
DT	0.881	(0.862, 0.899)	0.904	(0.886, 0.920)
RF	**0.978**	**(0.969, 0.988)**	**0.983**	**(0.973, 0.989)**
SVM	0.782	(0.758, 0.805)	0.944	(0.930, 0.957)

Table 2. Recall, Precision and F1 measure of models learned from the body of posts

Body of posts	DTM			DTM + TF-IDF		
	Recall	*Precision*	*F1*	*Recall*	*Precision*	*F1*
NB	0.910	0.818	0.862	0.880	0.936	0.907
DT	0.938	0.854	0.894	0.920	0.902	0.911
RF	**0.964**	**0.995**	**0.979**	**0.972**	**0.995**	**0.983**
SVM	0.570	0.938	0.709	0.916	0.978	0.946

Other four models were trained using following four machine learning methods: naive Bayes (NB), decision tree (DT), random forests (RF) and support vector machine (SVM). The input of the training was created with headlines of posts (attribute Headline) from dataset described above. The data were pre-processed to the form of document term matrix (DTM) without and with TF-IDF waiting. Using a confusion matrix, following indicators of binary classification were quantified: Accuracy, Interval of accuracy (Table 3), Precision, Recall and F1 measure (Table 4).

Experiments presented in Table 3 shows that in the case when the input of the learning were extremely short texts as headlines or titles of posts the best model was model learned by Naïve Bayes learning method when Accuracy and Interval od accuracy was taken into account. The results in Table 4 are not so clear. When Recall and Precision was taken into account naïve Bayes model and decision tree model were the best alternately according the way of pre-processing: DTM or DTM with TF-IDF waiting. But when F1 measure was taken into account the naïve Bayes model was the best. We can close the evaluation by claim, that naïve Bayes model is best for Headlines of post, because F1 measure is harmonic means of Precision and Recall and so the F1 measure takes into account both types of mistakes – numbers of falls positive and falls negative classifications.

Table 3. Accuracy and Interval of Accuracy of models learned from the headlines of posts

Headline of posts	**DTM**		**DTM + TF-IDF**	
	Accuracy	***Interval of Accuracy***	***Accuracy***	***Interval of Accuracy***
NB	**0.802**	**(0.778, 0.824)**	**0.812**	**(0.788, 0.833)**
DT	0.551	(0.523, 0.580)	0.550	(0.521, 0.578
RF	0.749	(0.724, 0.773)	0.760	(0.735, 0.784)
SVM	0.762	(0.737, 0.786)	0.775	(0.750, 0.798)

Table 4. Recall, Precision and F1 measure of models learned from the headlines of posts

Headline of posts	**DTM**			**DTM + TF-IDF**		
	Recall	***Precision***	***F1***	***Recall***	***Precision***	***F1***
NB	0.792	**0.829**	**0.810**	**0.820**	0.826	**0.823**
DT	***1.000***	0.543	0.704	0.200	***0.898***	0.327
RF	0.830	0.734	0.779	0.710	0.827	0.764
SVM	0.718	0.814	0.763	0.766	0.802	0.783

Our results are not so good as in work [17] using novel automatic fake news detection model based on geometric deep learning. Presented algorithms are a generalization of classical CNNs to graphs, allowing the fusion of heterogeneous data such as content, user profile and activity, social graph, and news propagation. They achieved accuracy 0.927. Also according [18] the fake news detection as Natural Language Processing problem can be successfully solved using the Deep CNN. This approach could achieve very good results (accuracy 0,962) [19].

6 Conclusions

The approach to the fake reviews detection in online discussions was introduced. The approach was based on models for fake reviews classification generated by machine learning algorithms: naive Bayes, decision trees, random forests and support vector machines. Generated models have been tested. Experiments showed that input data representation is important, as in most cases models that worked with the document term matrix with a TF-IDF weighting (DTM + TF-IDF) achieved better results. The naive Bayes model appeared to be the best for a smaller data input sample for example in the form of headlines or titles of posts. On the other hand, the random forests model appeared to be the best for larger data input samples as whole texts of posts.

This work has produced results that could be further developed, as the problem of fake reviews steadily increases. These issues should be discussed, their dangers highlighted, and they can be resolved by finding and detecting them. For future, we would like to extend our experiments using deep neural networks. The problem of fake reviews detection could be also analyzed from the point of sentiment or opinion polarity [20].

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