

Master thesis

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Master thesis

Fake news detection using machine learning

Simon Lorent

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Master thesis

Fake news detection using machine learning

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Abstract

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Chapter 1

Introduction

1.1 What are fake news?

1.1.1 Definition

Fake news has quickly become a society problem, being used to propagate false or rumour information in order to change behaviours of peoples. Before stating to work on detecting fake news, it is needed to first understand what they are. It has been shown that propagation of fake news has had a non-negligible influence of 2016 US presidential elections[1]. A few facts on fake news in the United States:

- 62% of US citizens get their news for social medias[2]
- Fake news had more share on Facebook than mainstream news[3].

Fake news has also been used in order to influence the referendum in the United Kingdom for the "Brexit".

In this paper I experiment the possibility to detect fake news based only on textual information by applying traditional machine learning techniques[4, 5, 6] as well as bidirectional-LSTM[7] and attention mechanism[8] on two different datasets that contain different kinds of news.

In order to works on fake news detection, it is important to understand what are fake news and how they are charaterized. The following is based on *Fake News Detection On Social Media: A Data Mining Perspective*[9]. The first is characterization or what is fake news and the second is detection. In order to build detection models, it is need to start by characterization, indeed, it is need to understand what is fake news before trying to detect them.

Fake news definition is made of two parts: authenticity and intent. Authenticity means that fake news content false information that can be verified as such, which means that conspiracy theory is not included in fake news as there are difficult to be proven true or false in most cases. The second part, intent, means that the false information has been written with the goal of misleading the reader.

1.1.2 Fake News Characterization

Definition 1 *Fake news is a news article that is intentionally and verifiable false*

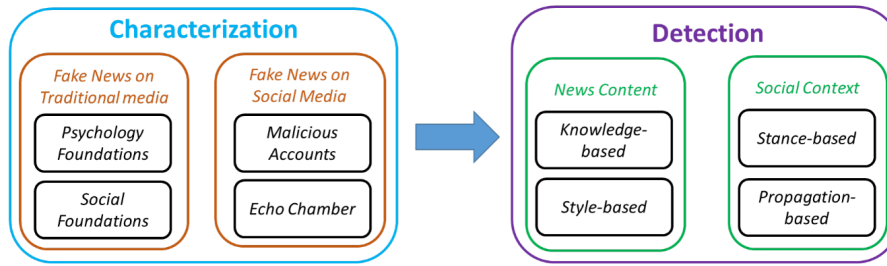


Figure 1.1: Fake news on social media: from characterization to detection.[9]

The part of the definition introducing the intent of misleading the reader automatically discard satire news media, that is why this work will focus on the first part, the fact that the piece of information is verifiable false or true. Indeed, even if satire news media does not have the intent to mislead the readers, not all of them have the ability of making criticism and not taking it to the first degree. On the other hand, in the case of political media, even if it clearly tries to influence the consumer, verifying the authenticity of there claims is usually harder as, in most of the cases, openly lies.

1.2 Feature Extraction

1.2.1 News Content Features

Now that fake news has been defined and the target has been set, it is needed to analyse what features can be used in order to classify fake news. Starting by looking at news content, it can be seen that it is made of four principal raw components:

- **Source:** Where does the news come from, who wrote it, is this source reliable or not.
- **Headline:** Short summary of the news content that try to attract the reader.
- **Body Text:** The actual text content of the news.
- **Image/Video:** Usualy, textual information is agremented with visual information such as images, videos or audio.

Features will be extracted from these four basic components, with the mains features being linguistic-based and visual-based. As explained before, fake news is used to influence the consumer, and in order to do that, they often use a specific language in order to attract the readers. On the other hand, non-fake news will mostly stick to a different language register, being more formal. This is linguistic-based features, to which can be added lexical features such as the total number of words, frequency of large words or unique words.

The second features that need to be taken into account are visual features. Indeed, modified images are often used to add more weight to the textual information. For example, the **Figure 1.2** is supposed to show the progress of deforestation, but the two images are actually from the same original one, and in addition the WWF logo makes it look like to be from a trusted source.



Figure 1.2: The two images provided to show deforestation between two dates are from the same image taken at the same time. [10]

1.2.2 Social Context Features

In the context of news sharing on social media, multiple aspect can be taken into account, such as user aspect, post aspect and group aspect. For instance, it is possible to analyse the behaviour of specific users and use their metadata in order to find if a user is at risk of trusting or sharing false information. For instance, this metadata can be its centre of interest, its number of followers, or anything that relates to it.

Post-based aspect is in a sense similar to users based: it can use post metadata in order to provide useful information, but in addition to metadata, the actual content can be used. It is also possible to extract features from the content using latent Dirichlet allocation (LDA)[11].

1.3 News Content Models

1.3.1 Knowledge-based models

Now that the different kinds of features available for the news have been defined, it is possible to start to explain what kinds of models can be built using these features. The first model that relate to the news content is based on knowledge: the goal of this model is to check the truthfulness of the news content and can be achieved in three different ways (or a mixture of them):

- **Expert-oriented:** relies on experts, such as journalists or scientists, to assess the news content.
- **Crowdsourcing-oriented:** relies on the wisdom of crowd that says that if a sufficiently large number of persons say that something is false or true then it should be.
- **Computational-oriented:** relies on automatic fact checking, that could be based on external resources such as DBpedia.

These methods all have pros and cons, hiring experts might be costly, and expert are limited in number and might not be able to treat all the news that is produced. In the case of crowdsourcing, it can easily be fooled if enough bad annotators break the system and automatic fact checking might not have the necessary accuracy.

1.3.2 Style-Based Model

As explained earlier, fake news usually tries to influence consumer behaviour, and thus generally use a specific style in order to play on the emotion. These methods are called deception-oriented stylometric methods.

The second method is called objectivity-oriented approaches and tries to capture the objectivity of the texts or headlines. These kind of style is mostly used by partisan articles or yellow journalism, that is, websites that rely on eye-catching headlines without reporting any useful information. An example of these kind of headline could be

You will never believe what he did !!!!!

This kind of headline plays on the curiosity of the reader that would click to read the news.

1.4 Social Context Models

The last features that have not been used yet are social media features. There are two approaches to use these features: stance-based and propagation-based.

Stance-based approaches use implicit or explicit representation. For instance, explicit representation might be positive or negative votes on social media. Implicit representation needs to be extracted from the post itself.

Propagation-based approaches use features related to sharing such as the number of retweet on twitter.

1.5 Related Works

1.5.1 Fake news detection

Current research focus mostly on using social features and speaker information in order to improve the quality of classifications.

Ruchansky et al.[12] proposed a hybrid deep model for fake news detection making use of multiple kinds of feature such as temporal engagement between n users and m news articles over time and produce a label for fake news categorization but as well a score for suspicious users.

Long et al. [13] proposed to apply attention mechanism to the speaker profile in a hybrid way with an LSTM on the textual information.

Tacchini et al.[14] proposed a method based on social network information such as likes and users in order to find hoax information.

Thorne et al.[15] proposed a stacked ensemble classifier in order to address a subproblem of fake news detection which is stance classification. It is the fact of finding if an article agree, disagree or simply discuss a fact.

Granik and Mesyura[16] used Nave-Bayes classifier in order to classify news from buzzfeed dataset.

In addition to texts and social features, Yang et al.[17] used visual features such as images with a convolutional neural network.

Wang et al.[18] also used visual features for classifying fake news but uses adversarial neural networks to do so.

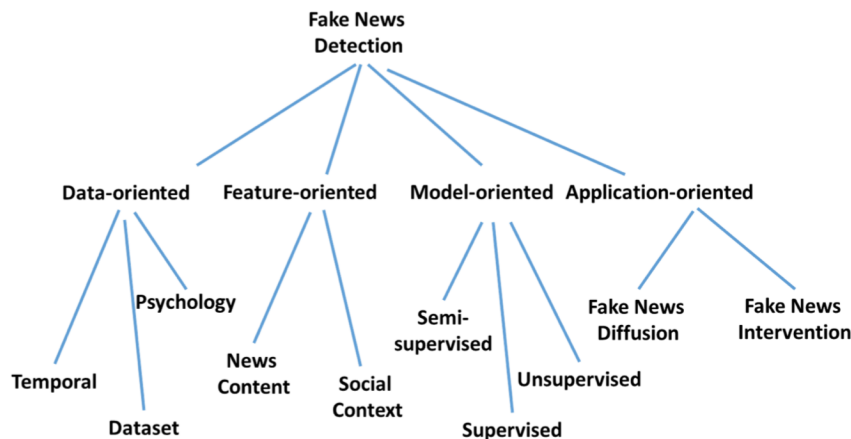


Figure 1.3: Different approaches to fake news detection.

1.5.2 State of the Art Text classification

There are two main categories of state of the art that are interesting for this work: previous work on fake news detection and on general text classification. Works on fake news detection is almost inexistent and mainly focus in 2016 US presidential elections or does not uses the same features. That is, when this work focus on automatic features extraction using machine learning and deep learning, other works make use of hand crafted features[19, 20] such as psycholinguistic features[21] which is not the goal here.

When it comes to state of the art for text classification, it includes Long short-term memory (LSTM)[7], Attention Mechanism[22], IndRNN[23], Attention-Based Bidirectional LSTM[8], Hierarchical Attention Networks for Text Classification[24], Adversarial Training Methods For Supervised Text Classification[25], Convolutional Neural Networks for Sentence Classification[26] and RMDL: Random Multimodel Deep Learning for Classification[27]. All of these models have comparable performances.

1.6 Conclusion

As it has been shown in **Section 1.2** and **Section 1.3** multiple approaches can be used in order to extract features and use them in models. This work focus on textual news content features. Indeed, other features related to social media are difficult to acquire. For example, users information is difficult to obtain on Facebook, as well as post information. In addition, the different datasets that have been presented at **Section 2.2** does not provide any other information than textual ones.

Looking at **Figure 1.3** it can be seen that the main focus will be made on unsupervised and supervised learning models using textual news content. It should be noted that machine learning models usually comes with a trade-off between precision and recall and thus that a model which is very good at detected fake news might have a high false positive rate as opposite to a model with a low false positive rate which might not be good at detecting them. This cause ethical questions such as automatic censorship that will not be discussed here.

Chapter 2

Data Exploration

2.1 Introduction

A good starting point for the analysis is to make some data exploration of the data set. The first thing to be done is statistical analysis such as counting the number of text per class or counting the number of words per sentence. The second step consist of doing Latent Dirichlet Allocation[11] in order to make unsupervised clustering of the text and see if there is some kind of correlation between the clusters to which a text belongs and its labels.

2.2 Datasets

2.2.1 Fake News Corpus

This works uses multiples corpus in order to train and test different models. The main corpus used for training is called Fake News Corpus[28]. This corpus have been automatically crawled using `opensources.co` labels. In other words, domains have been labeled with one or more labels in

- Fake News
- Satire
- Extreme Bias
- Conspiracy Theory
- Junk Science
- Hate News
- Clickbait
- Proceed With Caution
- Political
- Credible

These annotations have been provided by crowdsourcing, which means that they might not be exactly accurate, but are expected to be close to the reality. Because this works focus on fake news detection against reliable news, only the news labels as fake and credible have been used.

2.2.2 Liar, Liar Pants on Fire

The third and last dataset is **Liar, Liar Pants on Fire** dataset[29], which is a collection of twelve thousand small sentences collected from various sources and hand labeled. They are divided in six classes:

- pants-fire
- false
- barely-true
- half-true
- mostly-true
- true

This set will be used a second test set. Because in this case there are six classes against two in the other cases, a threshold should be used in order to fix which one will be considered as true or false in order to be compared with the other dataset.

It should be noted that this one differ from the two other dataset is it is composed only on short sentences, and thus it should not be expected to have very good results on this dataset for models trained on Fake News Corpus which is made of full texts. In addition, the texts from the latest dataset are more politicaly oriented then the ones from the first one.

2.3 Dataset statistics

2.3.1 Fake News Corpus

General Analysis

Because **Fake News Corpus** is the main dataset, the data exploration will start with this dataset. And the first thing is to count the number of items per class. Before starting the analysis, it is needed to cleanup the dataset. As it is originaly given in a large 30GB CSV file, the first step is to put everything in a database in order to be able to retrieve only wanted peice of information. In order to do so, the file have been read line by line. It appears that some of the lines are badly formatted, preventing them to be read correctly, in this case they are dropped without being put in the database. Also, each line that is a duplicate of a line already read is also dropped. The second step in cleaning the set consist of some more duplicate removal. Indeed, dropping same lines remove only exact duplicate. It appears that some news does have the same content, with slight variation in the title, or a different author. In order to remove the duplicate, each text is hashed using SHA256 and those hash are compared, removing duplicates and keeping only one.

Because the dataset have been cleaned, numbers provided by the dataset creators and number computed after cleaning will be provided. We found the values given at **Table 2.1**. It shows that the number of fake news is smaller by a small factors with respect to the number of reliable news, but given the total number of items it should not cause any problems. But it will still be taken into account later on.

| Type | Provided | Computed |
|----------------------|-----------|-----------|
| Fake News | 928,083 | 770,287 |
| Satire | 146,080 | 855,23 |
| Extreme Bias | 1,300,444 | 771,407 |
| Conspiracy Theory | 905,981 | 495,402 |
| Junk Science | 144,939 | 79,342 |
| Hate News | 117,374 | 65,264 |
| Clickbait | 292,201 | 176,403 |
| Proceed With Caution | 319,830 | 104,657 |
| Political | 2,435,471 | 972,283 |
| Credible | 1,920,139 | 1,811,644 |

Table 2.1: Number of texts per categories

In addition to the numbers provided at **Table 2.1**, there are also two more categories that are in the dataset but for which no description is provided:

- Unknwon: 231301
- Rumor: 376815

To have a better view of the distribution of categories, an histogram is provided at **Figure 2.1**.

In addition, the number of words per text and the average number of words per sentences have been computed for each text categories. **Figure 2.2** shows the boxplots for these values. It can be seen that there is no significative difference that might be used in order to make class prediction.

Before counting the number of words and sentences, the texts are preprocessed using gensim[30] and NLTK[31]. The first step consist of splitting text into an array of sentences on stop punctuation such as dots or questions mark, but not on commas. The second step consist on filtering words that are contained in these sentences, to do so, stopwords (words such as 'a', 'an', 'the'), punctuation, words or size less or equal to tree, non alpha-numeric words, numeric values and tags (such as html tags) are removed. Finnaly, the number of word still present is used.

An interesting features to look at is the distrubtion of news sources with respect to their categories. It shows that in some case some source a predominant. For instance, looking at **Figure 2.3** shows that most of the reliable news are from *nytimes.com* and in the same way, most of the fake news are coming from *beforeitsnews.com*. That have to be taken into account when training and testing models as the goal is not to distinguish between these two sources but between fake news and reliable news.

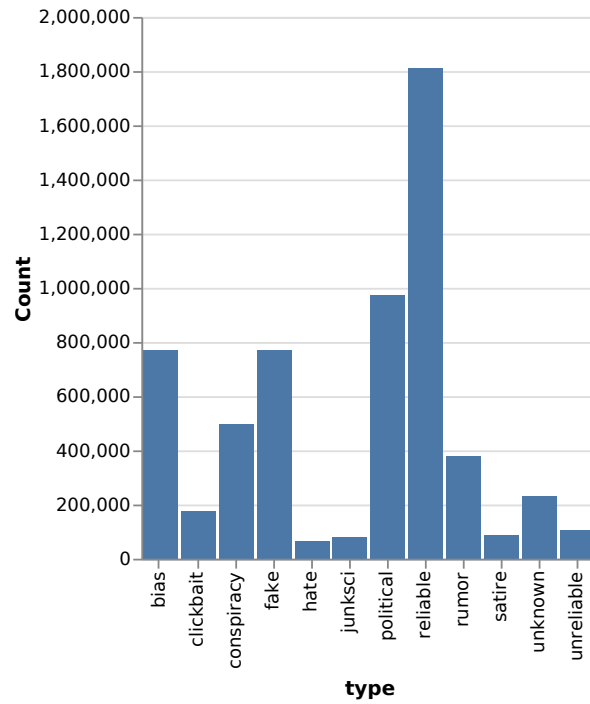
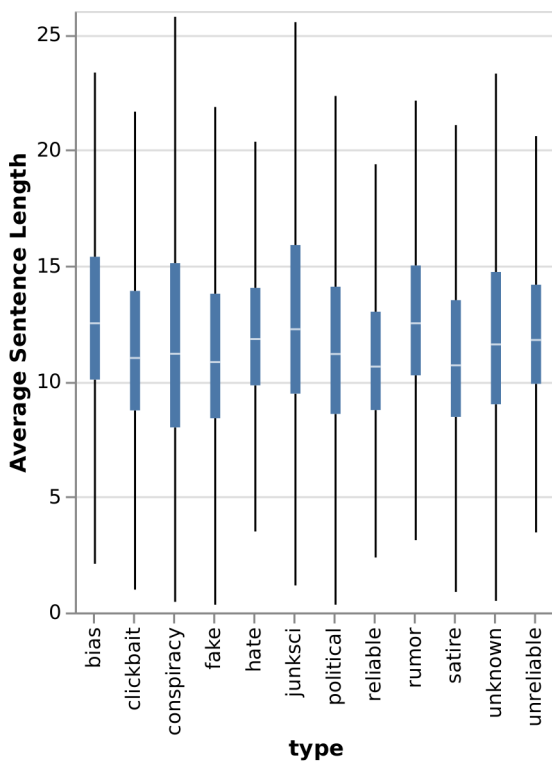
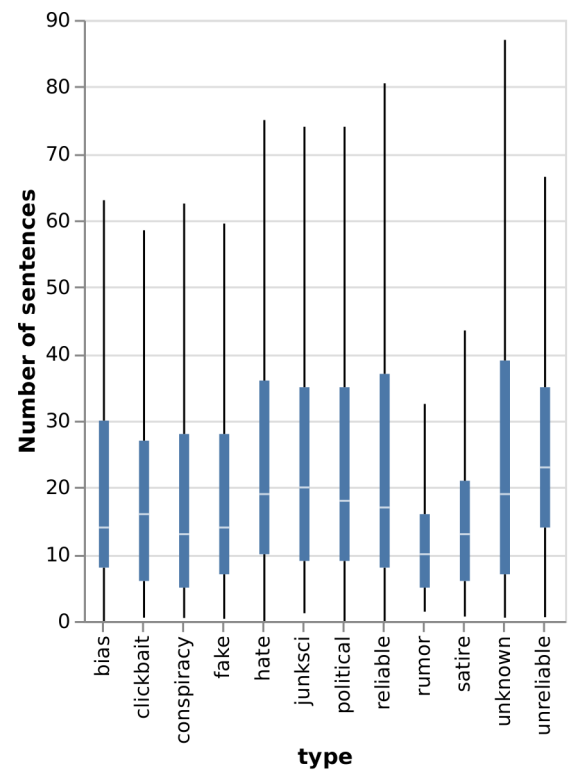


Figure 2.1: Histogram of text distribution along their categories on the computed numbers.

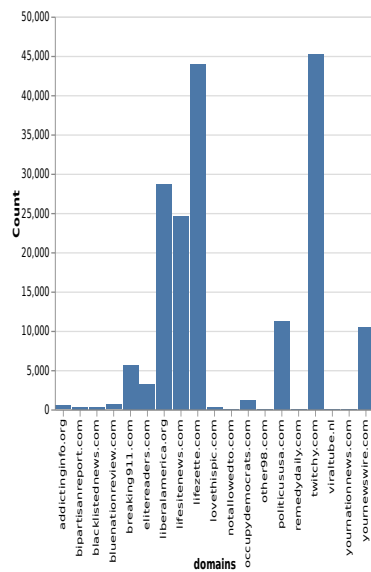


(a) Boxplot of average sentence length for each category.

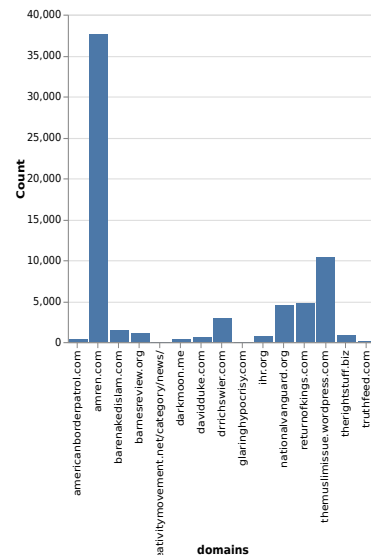


(b) Boxplot of number of sentences for each category.

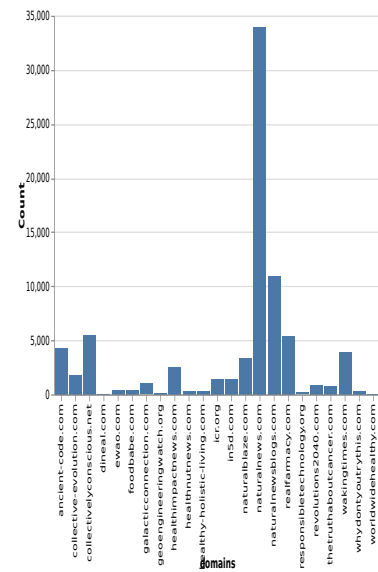
Figure 2.2: Summary statistics



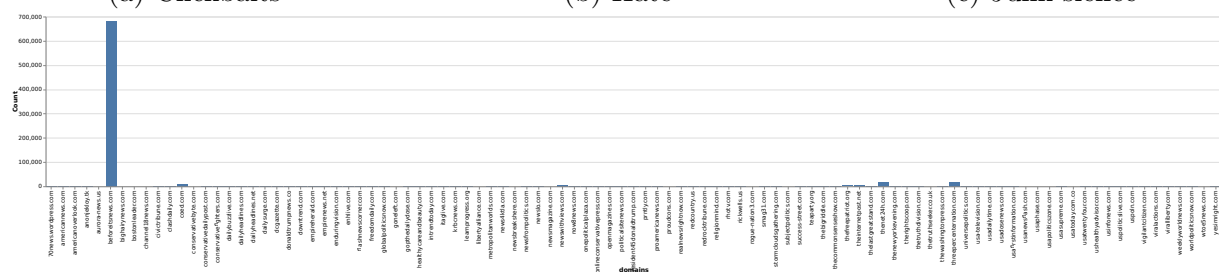
(a) Clickbaits



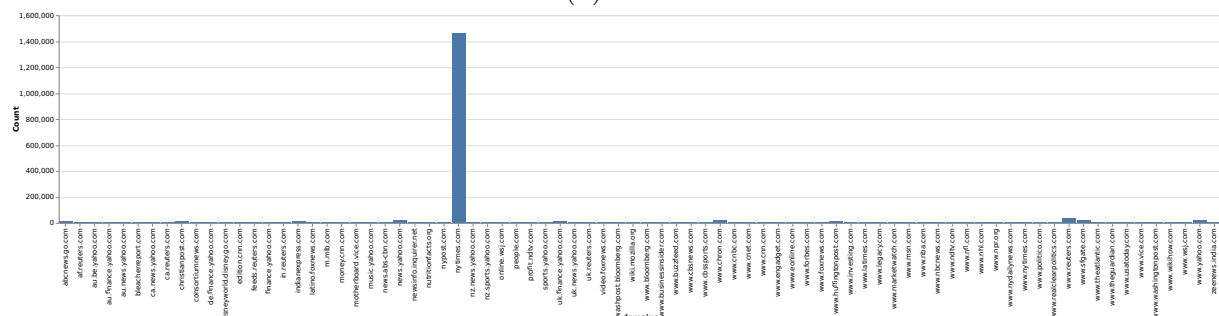
(b) Hate



(c) Junk science



(d) Fake



(e) Reliable

Another important feature to look at is the distribution of the number of words in the text. Indeed, at some point it will be needed to fix a constant length for the texts and using too small length would mean a lot of cutting and using too long size would mean too much padding. It is thus needed to investigate the length of the texts in order to choose the right one. It can be seen at **Figure 2.4** that reliable news have slightly more words than fake news, but the difference is minimal.

Fake News analysis

In this section, the analysis will focus on fake news and reliable news. Because of what shows **Figure 2.3**, that is, some categories are almost all from the same source, an analysis of what happens when dropping these sources. First, lets compare the number of news while and while not taking into account majors sources. Comparing **Figure 2.5** and **Figure 2.6** shows that even by removing *nytimes.com* and

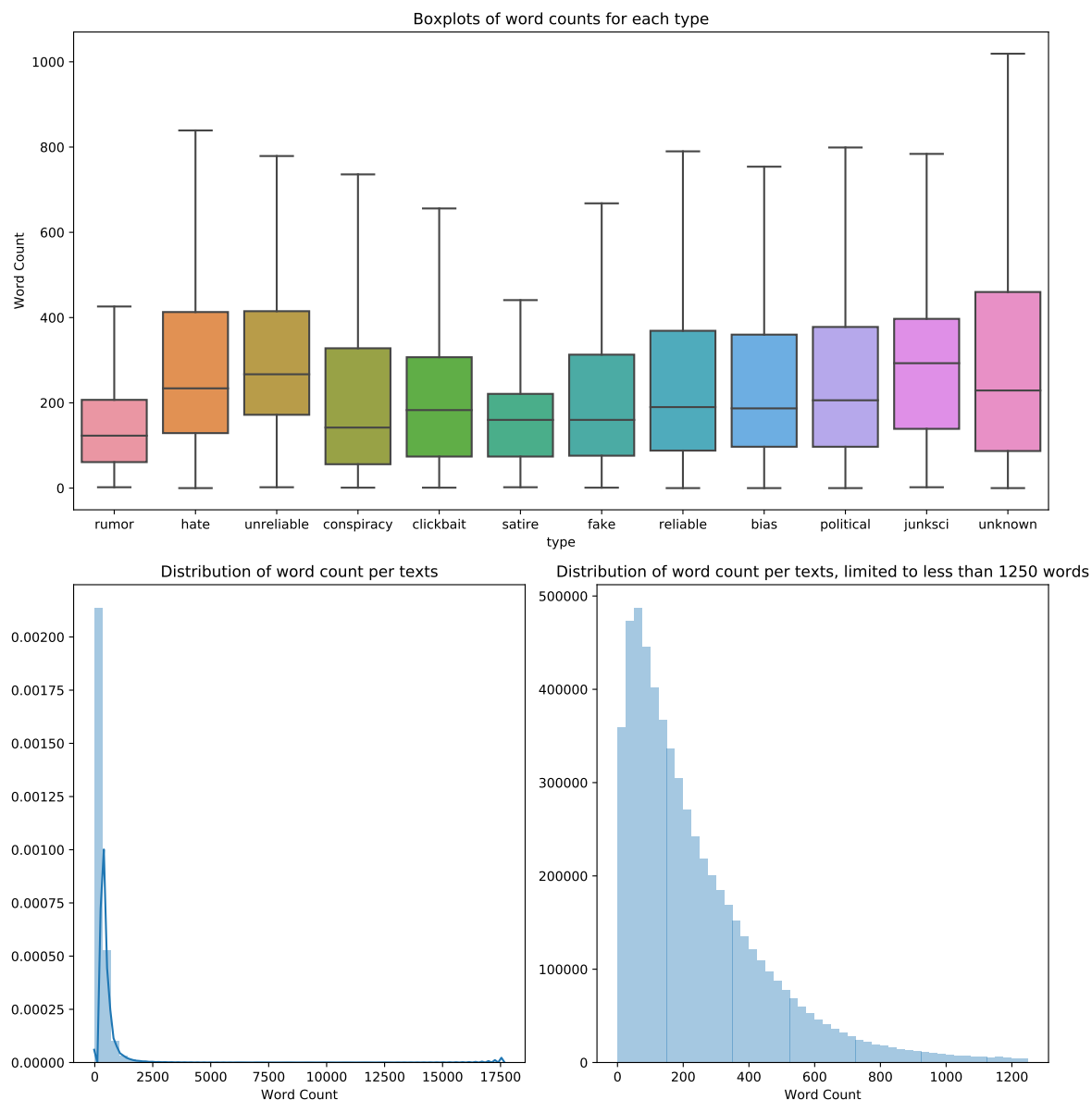


Figure 2.4: Distribution of the number of words per text

beforeitsnews.com news from the dataset still leave enough texts to train the different models without the risk of learning something unwanted such as only separating these two sources. But one drawback is that the ratio between fake news and reliable news is going from around one half to around one fourth.

2.3.2 Liar-Liar corpus

As said in **Chapter 1**, this dataset is made of small text of one or two sentences at most. Which means that they are smaller than the ones in *fake news corpus*. The distribution of words length can be seen at **Figure 2.7**. In addition, this dataset is not unbalanced as the other corpus is, which means that precautions does not have to be taken.

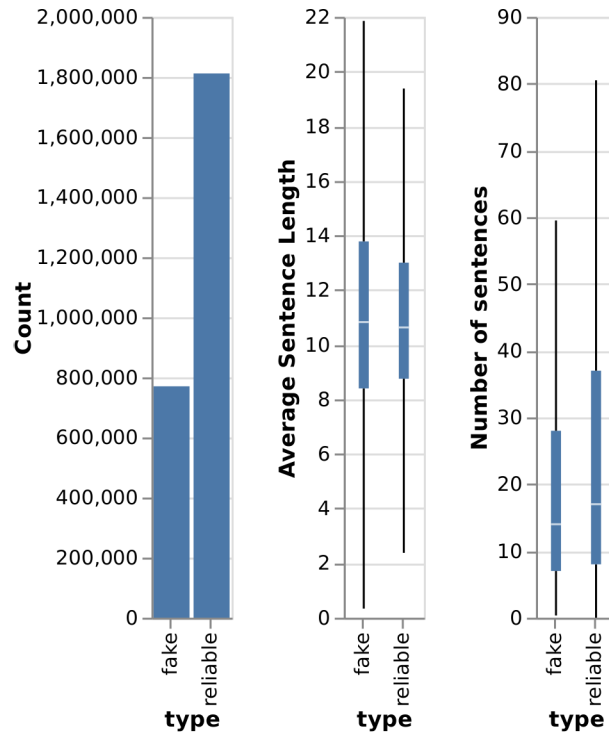


Figure 2.5: Summary statistics for not downsampled fake and reliable news.

2.4 Visualisation with t-SNE

In order to visualize the data it is needed to transform text in a numerical way and eventually reduce the dimension in order to allow it to be plotted on a 2D or 3D plot. Here TF-IDF (term frequency, inverse document frequency[5, 32]) is used. How it works will be details later on. This produce a sparse matrix with each document being represented as an array, each value of the array being a value for one term. That is, the more term in the corpus, the longer the array becomes. For example, a corpus of 10.000 text with 20.000 uniques words would be represented as a 10000×20000 sparse matrix. As said before, plotting in 20000 dimension is not possible. In order to do so, the number of dimension needs to be reduced. Here, principal component analysis before t-SNE[33] will be used together.

What is t-SNE? It stands for **t-distributed stochastic neighbor embedding**. The goal of this method is that two points to are closed in \mathcal{R}^Q should be close in \mathcal{R}^S , $S \ll Q$. In order to do so, the algorithm starts by fitting a probability distribution on the input points. It starts by computing

$$p_{i|j} = \frac{\frac{\exp(-||x_i - x_j||^2)}{2\sigma_i^2}}{\sum_{k \neq i} \frac{\exp(-||x_i - x_k||^2)}{2\sigma_i^2}}$$

Each of the $y_i, i \in 0 \dots N$ being a point of dimension Q .
Then

$$p_{ij} = \frac{p_{i|j} + p_{j|i}}{2N}$$

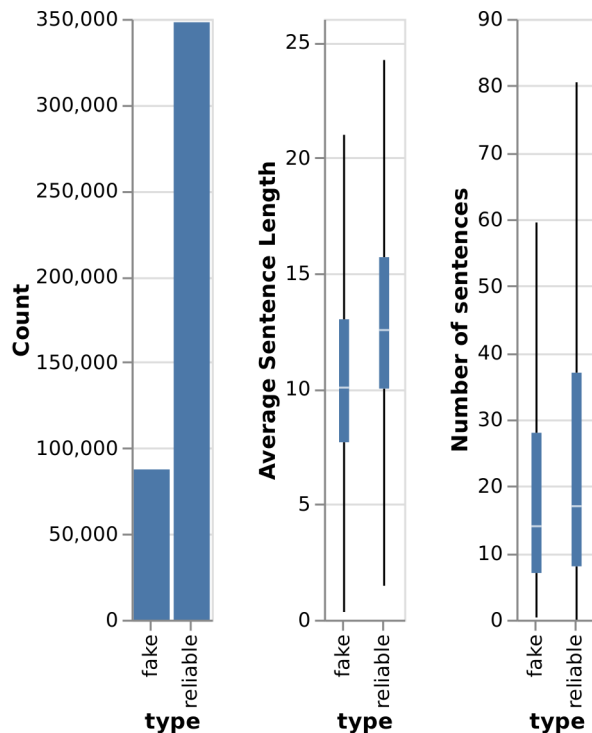


Figure 2.6: Summary statistics for downsampled dataset on fake and reliable news

is computed.

The probability distribution for the low density map is given by

$$q_{ij} = \frac{(1 + ||y_i - y_j||^2)^{-1}}{\sum_{k \neq l} (1 + ||y_k - x_l||^2)^{-1}}$$

And in order to have a low dimension probability distribution as close as possible to the high dimension one, it minimize the KullbackLeibler divergence of the two distributions.

$$KL(P||Q) = \sum_{i \neq j} p_{ij} * \log\left(\frac{p_{ij}}{q_{ij}}\right)$$

The minimization of KL divergence is acheived by gradient descent.

The documentation of the module of scikit-learn[34] used for computing this value recomand to apply PCA first in order to reduce the original dimension and speed-up computation. The result of these computation can be seen at **Figure 2.8**. These 500 firsts PCA components explains around 47% of the total variance. The figure shows that there is no clear clustering of the classes.

Increasing the number of PCA components to 1750 gives the results at **Figure 2.9** and does not shows more clustering, even if it explains 75% of the variance. This shows that classifying the dots might not be easy, but it should be reminded that it is a dimensionality reduction and that there is a loss of information. Some of the original data dimension can have a better separation of the classes.

It is not possible to use t-SNE on the *Fake News Corpus* because the algorithm is quadratic with respect to the number of samples. Which make it impossible to compute

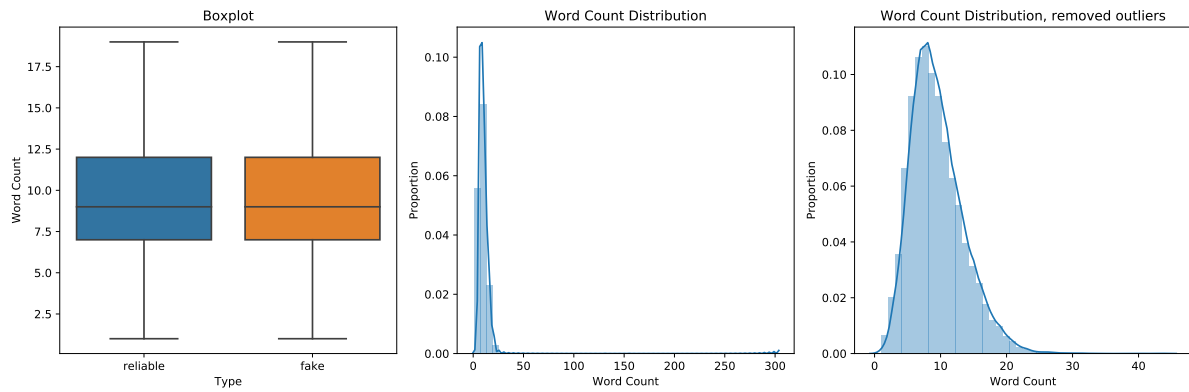


Figure 2.7: Number of words distributions for liar-liar dataset. On the first and the third plots, a few outliers with length greater than 50 have been removed in order to make the plots more readable.

for that corpus which is larger than the *liar-liar* corpus. But it is still possible to try to make some vizualisation using truncated singular v alues decomposition.

2.5 Conclusion

Data exploration have shown that there is no real statistical differences between text metadata for fake and reliable news, and thus make it not interesting for using it for classifying new texts. In addition, dimensionality reduction does not show any sign of helpfulness for the classification.

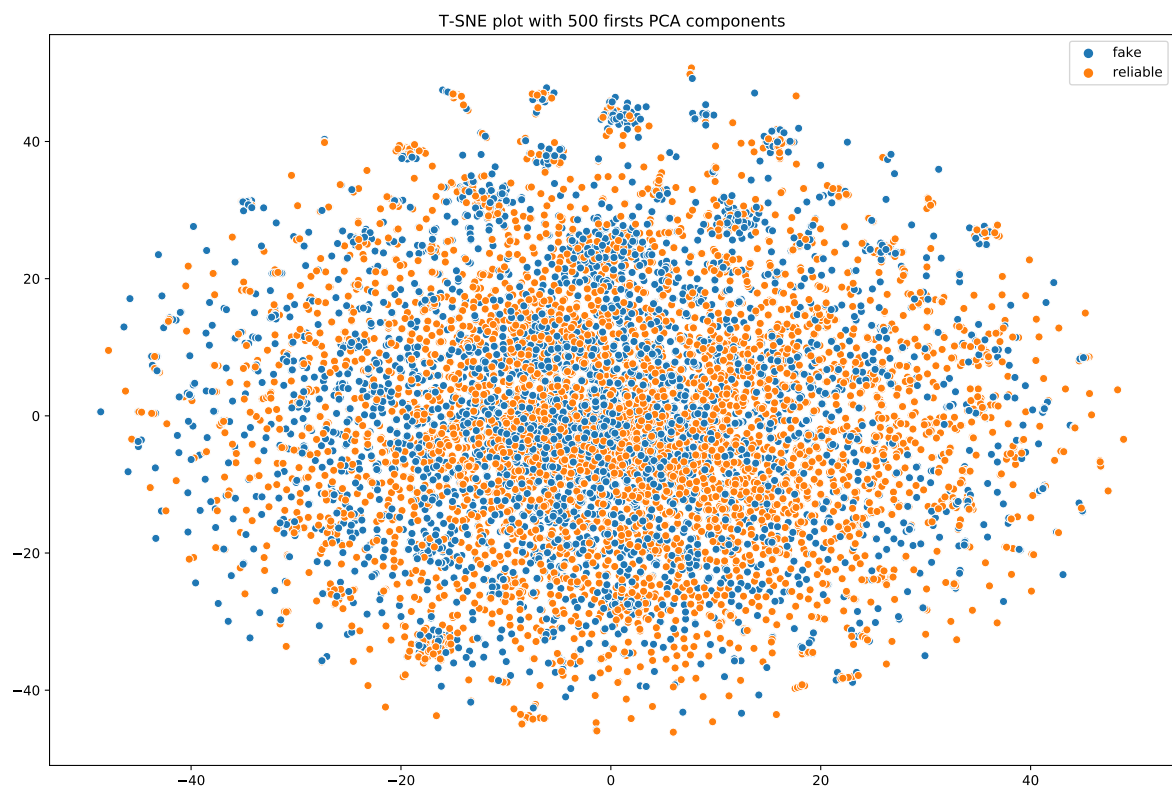


Figure 2.8: t-SNE plot for liar-liar dataset.

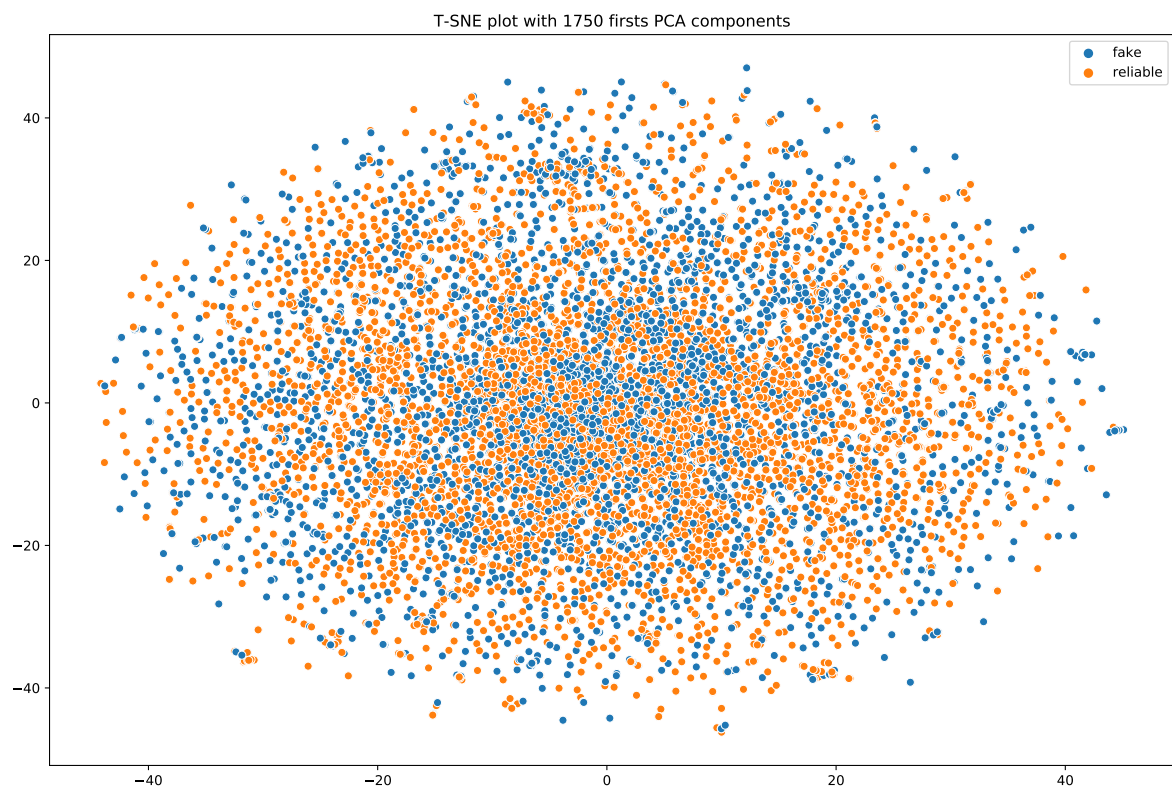


Figure 2.9: t-SNE plot for liar-liar dataset.

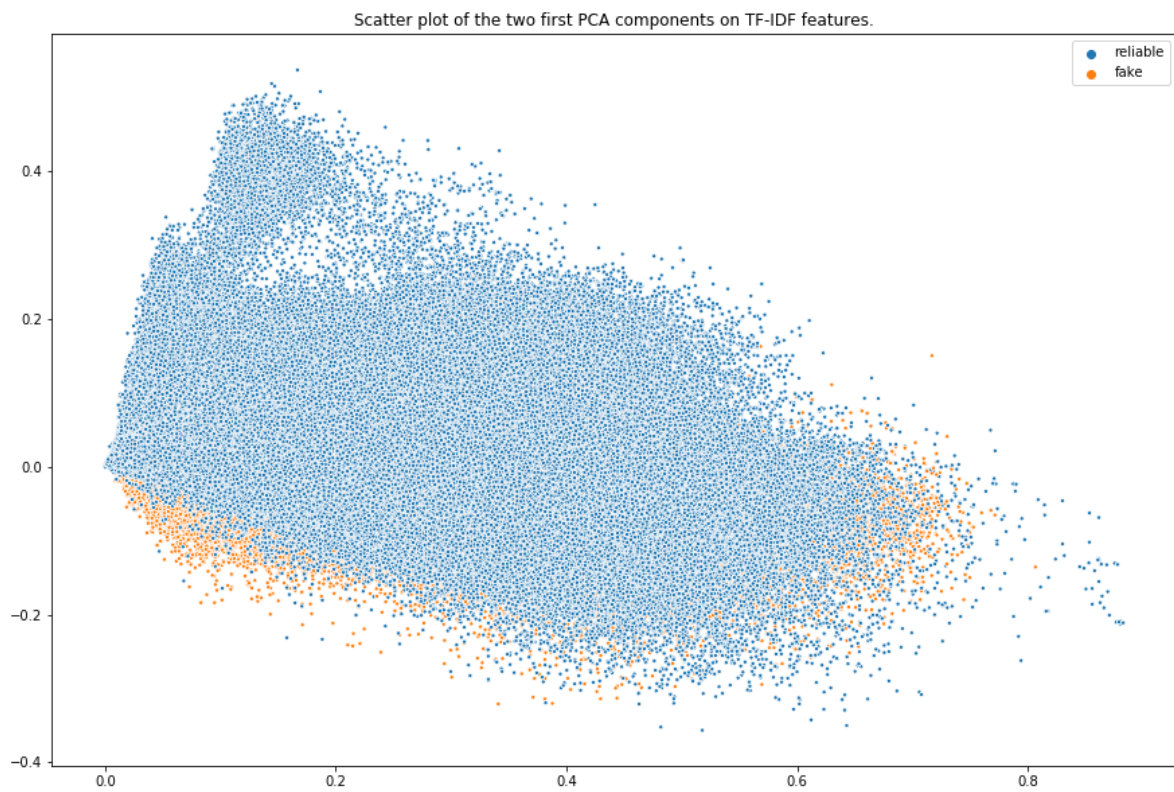


Figure 2.10: First two LSA compnoents for fake news corpus

Chapter 3

Machine Learning techniques

3.1 Introduction

In this chapter, we will focus on the more traditional methods used in natural language processing such as Nave-Bayes, decision trees, linear SVM and others. These will serve as baseline for comparing the performances of the more two advanced models that will be analyse later on: LSTM and Attention Mechanism. The first thing to do when working with text is the do words and texts embedding, indeed, in order to use machine learning algorithms on texts, a mathematical representation of these texts is required.

3.2 Text to vectors

As explained before, text need to be represented in a way that gives more meaningful information than a simple sequence of bits, which have additional drawbacks such that for a given word, the sequence of bits representing it depends on the coding. The first and simplest coding that come to mind is a one-hot encoding: a matrix M of size number of texts \times number of words where $M_{ij} = 1$ if the word j is present in the text i and 0 in the other case. But this is till not enough as each word is given the same weight, no matter how often it appears in the text.

In order to overcome this problem, term-frequency might be used, that is, rather than setting M_{ij} to 0 or 1 we set it to the number of time it appears in the text.

It is possible to use even better text embedding. It is called term-frequency, inverse document frequency. The main idea is that a word that appears often in all the documents is not helpful in order to classify the documents. For example, if the task is to classify books of biology and physics, words atom, cell or light are more useful than today or tomorrow.

In order to compute tf-idf, it is separated in two part, the first one being term-frequency and the second one inverse document frequency. We have that

$$tf_{ij} = \#(W_j | W_j \in D_i) \quad (3.1)$$

That is, tf_{ij} is the number of time the word j appears in the document i . Secondly, we have that

$$idf_j = \log\left(\frac{\#D}{\#(D_i | W_j \in D_i)}\right)$$

This is the log of the total number of documents, over the number of documents that contains the word j . Finally, the value $tfidf$ value is computed by

$$tf - idf_{ij} = tf_{ij} * idf_j \quad (3.2)$$

This the text embedding methods that will be used in this section.

3.3 Methodology

All the methods presented will be tested in three different ways:

- On the liar-liar dataset
- On the fake corpus dataset, excluding the news from *beforeitsnews.com* and *ny-times.com*
- On the fake corpus dataset, including the two previous domains.

To be more precise, in the first case, the models will be trained on a training set, tuned using validation set and finally tested using test set. In the second case, the same methodology will be used, the dataset have been split by choosing 60% of the text from each domain for training, and 20% for validation and testing. This way of splitting has been chosen because of the uneven representation of each domain in the dataset in order to ensure representation of all the domains in the three subsets.

In the last case, the model is trained on all the news but the two domains previously cited and tested on these two domains.

3.3.1 Evaluation metrics

In order to evaluate each model, multiple evaluation metrics have been used. There are recall, precision and f1-score. It is needed to use multiple metrics because they don't all account for the same values. For instance, it is possible to have a model with a recall of 1 that behaves extremely bad because it simply classifies all the inputs in the same single class.

Remember that precision is defined as

$$Precision = \frac{TP}{TP + FP} \quad (3.3)$$

Which means that we can have two different precisions, depending on which classes is considered as being positive. This is the proportion of correctly classified positive elements over the number of elements classified as positive. It equals to 1 when there is no false positive, but it does not mean that all the positive elements are correctly classified as it might be some false negative. The recall helps to solve these problems.

It is defined as

$$recall = \frac{TP}{TP + FN} \quad (3.4)$$

The f1-score combines the recall and the precision. It is defined by

$$f1 - score = \frac{2 * precision * recall}{precision + recall} \quad (3.5)$$

It is also possible to look at the weighted average of all these values. For instance, it is possible to compute a global recall by averaging the recall for both classes by the respective class ratio.

Finally, raw output can be used by looking at the confusion matrix.

The first parameters to tune is the max number of features used by tf-idf. This is the maximum number of words that will be kept to create the text encoding. The words that are kept are the most frequent words.

3.4 Models

Four models have been used in order to classify texts represented as a TF-IDF matrix. These are Multinomial Nave-Bayes, Linear SVM, Ridge Classifier and Decision Tree.

3.4.1 Naïve-Bayes[6]

The basic idea of Nave-Bayes model is that all features are independent of each other. This is a particularly strong hypothesis in the case of text classification because it supposes that words are not related to each other. But it works well given this hypothesis. Given an element of class y and vector of feature $\mathbf{X} = (x_1, \dots, x_n)$. The probability of the class given that vector is defined as

$$P(y|\mathbf{X}) = \frac{P(y) * P(\mathbf{X}|y)}{P(\mathbf{X})} \quad (3.6)$$

Thanks to the assumption of conditional independence we have that

$$P(x_i|y, x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n) = P(x_i|y) \quad (3.7)$$

Using Bayes' rules we have that

$$P(y|x_1, \dots, x_n) = \frac{P(y) \prod_{i=1}^n P(x_i|y)}{P(x_1, \dots, x_n)} \quad (3.8)$$

Because $P(x_1, \dots, x_n)$ is constant, we have the classification rule

$$\hat{y} = \underset{y}{\operatorname{argmax}} P(y) \prod_{i=1}^n P(x_i|y) \quad (3.9)$$

3.4.2 Linear SVM

Linear SVM is a method for large linear classification. Given pairs of features-label (\mathbf{x}_i, y_i) , $y_i \in \{-1, 1\}$, it solves the following unconstrained optimization problem.

$$\min_w \frac{1}{2} \mathbf{w}^T \mathbf{w} + \mathbf{C} \sum_{i=1}^l \xi(\mathbf{w}; \mathbf{x}_i, y_i) \quad (3.10)$$

Where ξ is a loss function, in this case L2 loss function has been used, and $\mathbf{C} > 0$ a penalty parameter.

Class of new examples are assigned by looking at the value of $\mathbf{w}^T \mathbf{w}$. The class 1 is assigned if $\mathbf{w}^T \mathbf{w} \geq 0$ and the class -1 if $\mathbf{w}^T \mathbf{w} < 0$.

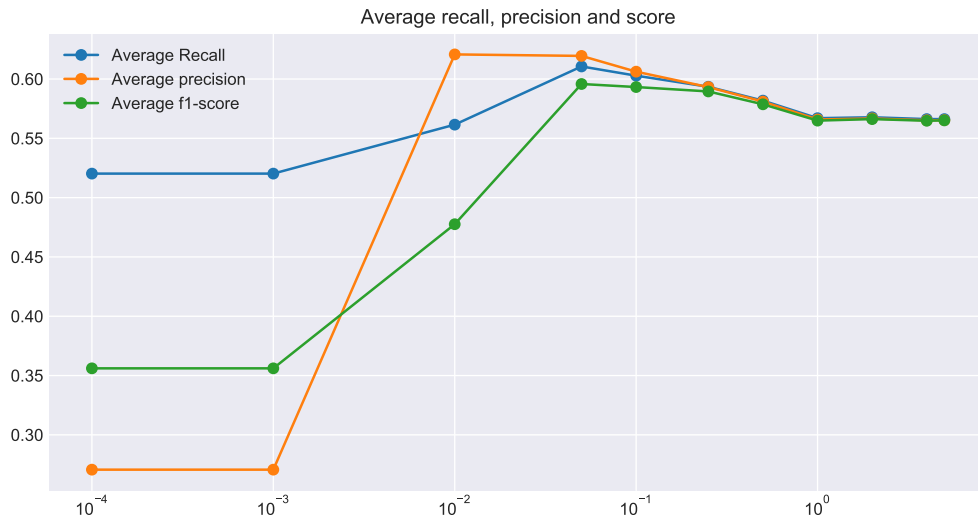


Figure 3.1: Tuning linearSVC parameters

3.4.3 Decision Tree

3.4.4 Ridge Classifier

Ridge classifier works the same way as ridge regression. It states the problem as a minimization of the sum of square errors with penalization. It can be expressed as in **Equation 3.11**.

$$\min_w ||Xw - y||_2^2 + \alpha ||w||_2^2 \quad (3.11)$$

The predicted class is positive if Xw is positive and negative otherwise.

3.5 Models on liar-liar dataset

3.5.1 Linear SVC

In the case of linear SVC there is one parameter to tune up, which is the penalty parameter for the error term. **Figure 3.1** shows the tree main metrics with respect to the penalty parameter. This shows that a parameter of around 0.1 is the best one.

3.5.2 Decision Tree

With decision tree, it is possible to reduce overfitting by pruning the tree. It is possible to do prepruning or post pruning. Prepruning means that a stopping criterion is used to stop tree growth earlier and post pruning cuts the tree once it has been fully grown. In this case, prepruning is done by limiting the maximum depth of the tree.

Figure 3.2 shows metrics values for different depths. It seems that trees of depth 1000 are the best ones.



Figure 3.2: Tuning decision tree parameters

3.5.3 Ridge Classifier

With the ridge classifier model it is also possible to tweak the pennality value of the optimization problem. At **Figure 3.3** we can see that the optimal parameter is around 10 or 20, depending of the metrics that we want to maximize. Later on, the value of 10 will be chose as a comprimse between precision and recall. It is the value that maximize the f1-score.

3.5.4 Max Feature Number

Starting with the maximum number of features, the precision of each model can be analyzed when limiting the maxium number of words. The results for each model can be seen at **Figure 3.4**, **3.5** and **3.6**. Shows that depending on the metrics we want to optimize it is better to choose different parameters. For instance, in order to maximize F1-score, it is better to use a maximum number of features of 1000.

The results are slightly different if the goal is to optimize the precision because if the best value stay the same for Linear SVM and Ridge Classifier, the Nave-Bayes works better when using the maxium number of features and it goes the same way for recall. Based on **Figure 3.4** we can say that when it comes to precision and recall, Nave-Bayes is the one that perform the best.

Row results for max features selection are available at **Appendix A**. It goes differently when we focus on a single class. For example, the precision for fake detection is at its maxium for Linear SVM and Ridge Classifier when only 10 features are used. But at the same time, it is at its minium for reliable class. Its shows that when trying to optimize the overall model and not only for a single clas, it is better to look at the weighted average than at the value for a single clas. But it is still important to look at the metrics for a single class because it indicate how it behave for this class. For instance, in the case of automatic fake news detection, it is important to minimize the number of reliable news

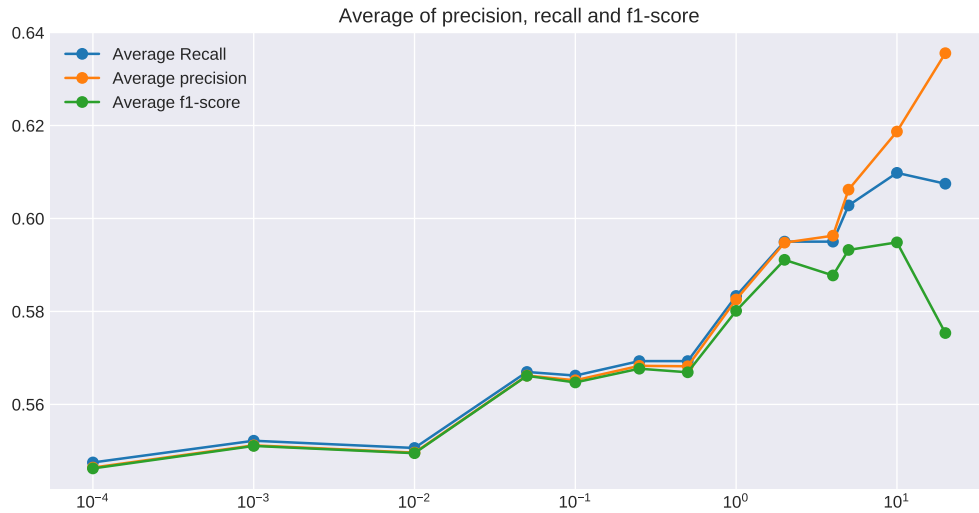


Figure 3.3: Average metrics for ridge classifier with respect to the penalty parameter.

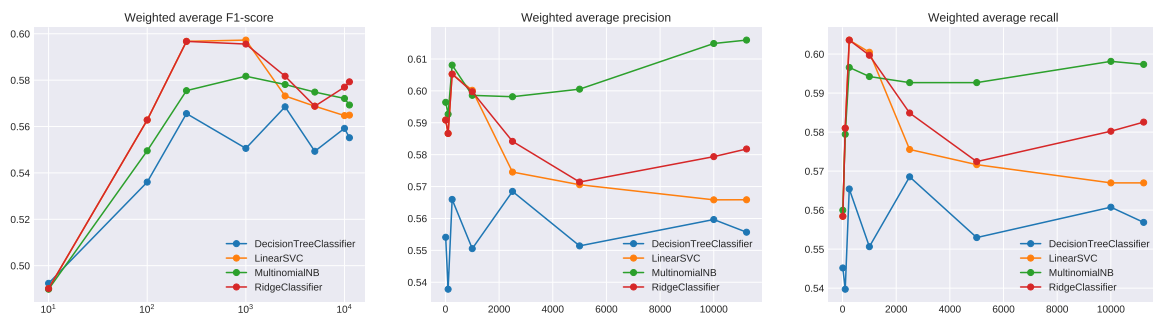


Figure 3.4: Weighted average of f1-score, precision and recall of each classes.

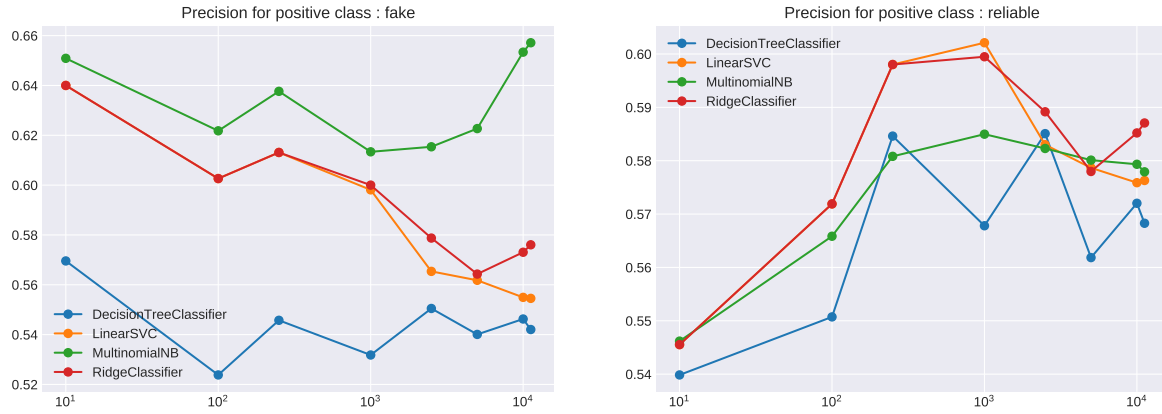


Figure 3.5: Precision of the model for each classes, the x axes is log scale of the number of features

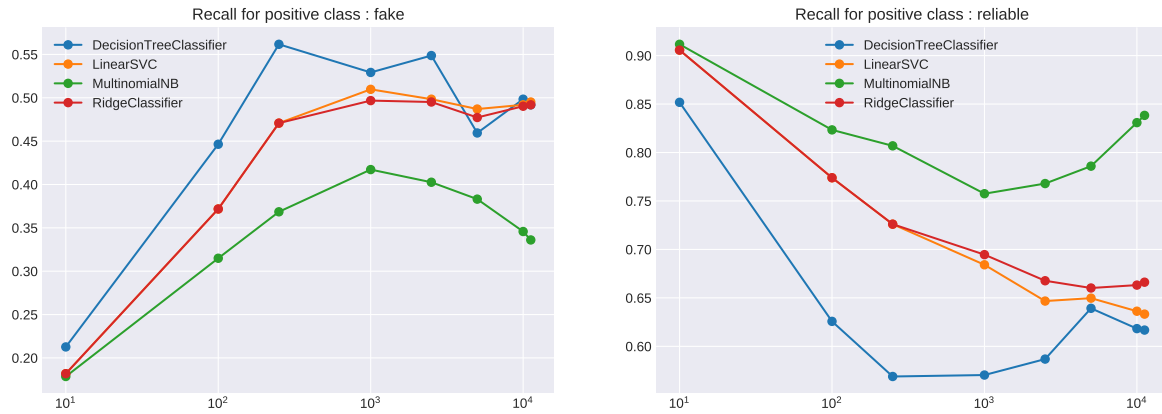


Figure 3.6: Precision of the model for each classes, the x axes is log scale of the number of features

missclassified in order to avoid what could be called censorship.

3.6 Models on fake corpus dataset

3.6.1 SMOTE: Synthetic Minority Over-sampling Technique[35]

As it have been show in **Chapter 2**, the fake news corpus is inbalanced. Synthetic minority over-sampling is a technique that allows to generate fake samples from the minor class. It works by randomly choosing one or many neirest neighbor in the minority class. For instance, if the algorithm is set to use 5 nearest neighbours, for each samples it will choose one of its nearest neighbours, and generate a new sample on the segment joining the sample and its neighbour.

Algorithm 1 and **2** shows how it works. The first one compute the k-nearest neighbors and the second one compute a new element by randomly choosing one of this neighbors.

Data: k = Number of nearest neighbors
Data: T = number of minority class samples
for $i \leftarrow 1 \dots T$ **do**
 | Compute k -nearest neighbors of sample i ;
 | Populate(knn, i);
end

Algorithm 1: SMOTE

Data: knn = the k nearest neighbour of sample i
Data: s = i th sample
 $nn = \text{random_choice}(knn)$;
 $\text{newSample} = s + \text{rand}(0, 1) * (nn - s)$;

Algorithm 2: Populate

3.6.2 Model selection without using SMOTE

Hyperparameters tuning

As for the models trained on the **liar-liar corpus**, hyper-parameters can be optimized the same way. The average metrics for each models with respect to there paramters are shown at **Figure 3.7, 3.8** and **3.9**.

The optimal parameter for the ridge classifier is clearly 1. As well as for the decision tree trained on **liar-liar** dataset, the optimal maximum depth is of 1000. And finally, the optimal value for the penalty parameter of the svm is also 1.

By looking at **Figure 3.5, 3.6** and **3.4** we can find optimal parameters for the number of features used in TF-IDF. It shows that linear svm and ridge classifier are the ones that perform the best, having an average precision of slightly more than 94% for the linear svm and 94% for the ridge classifier. They acheive these performances from 50,000 features and does not decrease. On the other hand, Nave-Bayes reches a pike at 100,000 features and greatly decrease afterward.

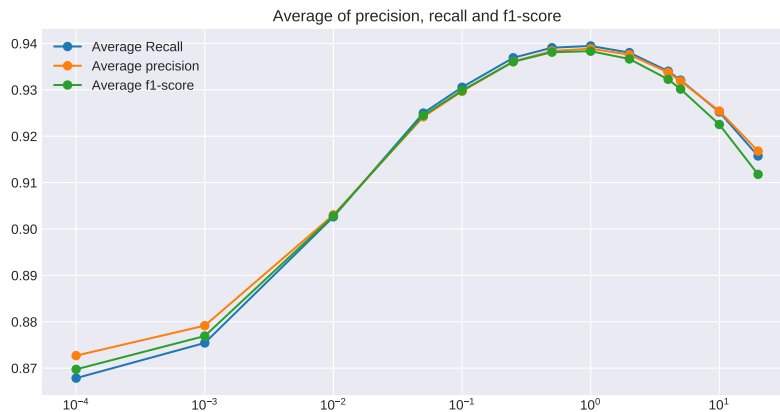


Figure 3.7: Metrics value with respect to the penalty paramter for ridge classifier

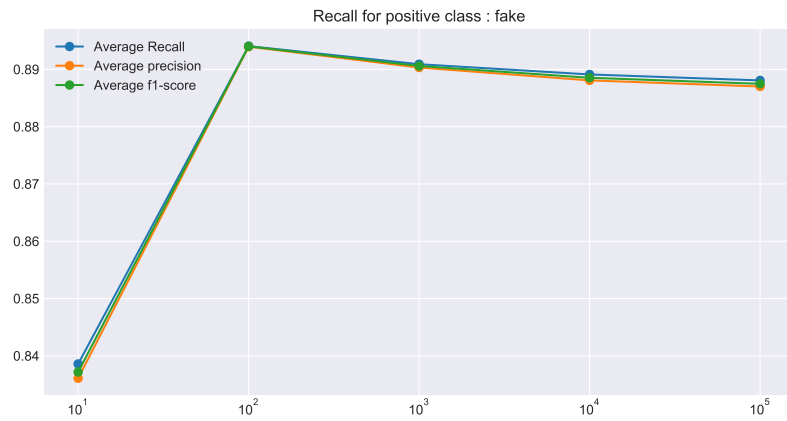


Figure 3.8: Optimal depth of decision tree.

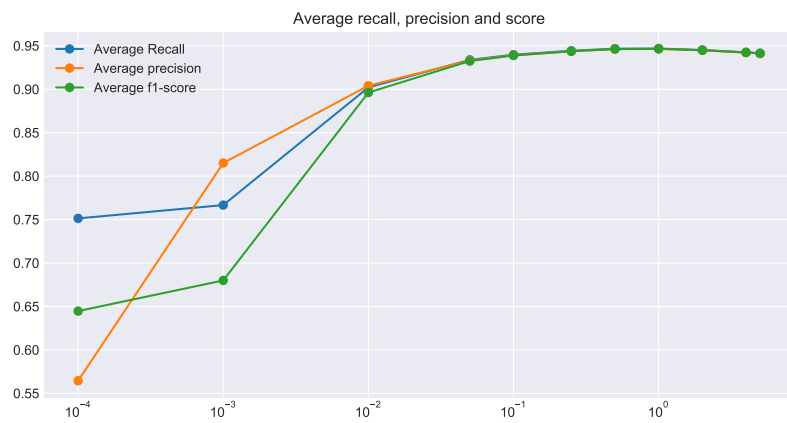


Figure 3.9: Optimal penalty parameters for linear svm

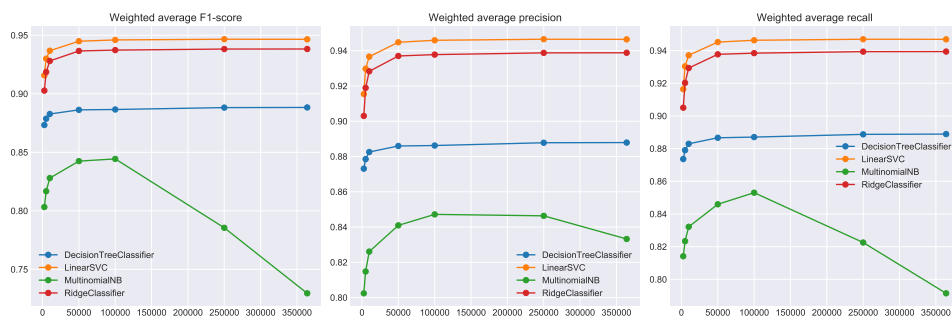


Figure 3.10: Average recall, precision and f1-score wti respect to the maxiumum number of features.



Figure 3.11: Precision for fake and reliable class for each model with respect to the maximum number of features

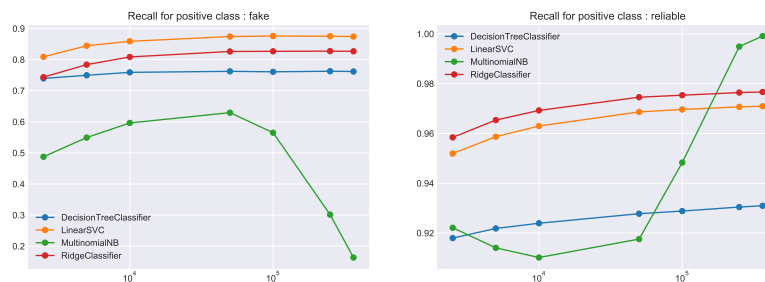


Figure 3.12: Recall for fake and reliable class for each model with respect to the maximum number of features

Figure 3.4 shows why it is important to look at all the metrics, because Nave-Bayes reaches a recall of 1 for the reliable class and close to 0 for the fake class, which means that almost all the text are classified as reliable. This can be verified by looking at **Figure 3.21**, only a small proportion of true fake are actually classified as it.

3.6.3 Model selection with SMOTE

The first thing that can be noticed at **Figure 3.14**, **3.15**, **3.16**, **3.17**, **3.18** and **3.19** is that the two models that worked the best without applying SMOTE method, linear SVM and ridge classifier are still the ones that perform the best. By comparing **Figure 3.9** and **Figure 3.16** we can see that it work better when applying a smaller regularization parameter. It goes from 0.66% of accuracy to 0.86% of accuracy thus acting as a regularization. The same does not apply to ridge classifier.

It also has a huge impact on how Nave-Bayes behaves as it removes overfitting when using a larger number of features in TF-IDF, leading to a few percent of accuracy increase.

It conclusion for SMOTE method we can say that it does help models that does not have regularization parameter or when the regularization parameter is low. Thus it does help preventing overfitting.

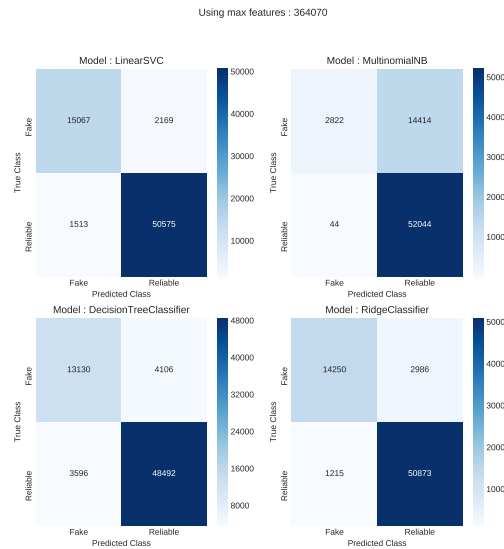


Figure 3.13: Confusion matrix for each model using 364,070 features

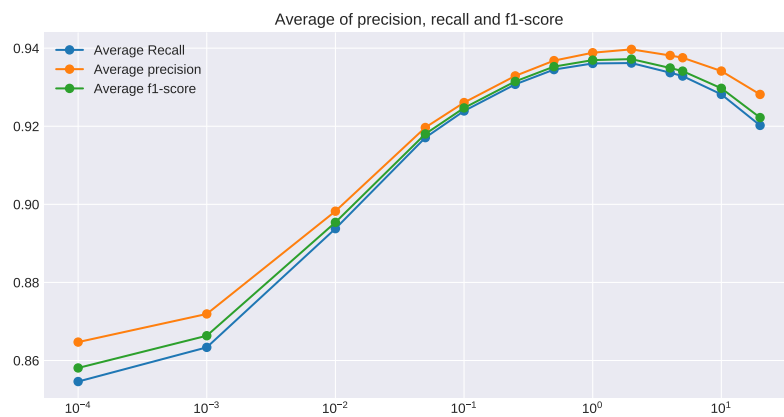


Figure 3.14: Metrics value with respect to the penalty paramter for ridge classifier when using SMOTE.



Figure 3.15: Optimal depth of decision tree when using SMOTE.

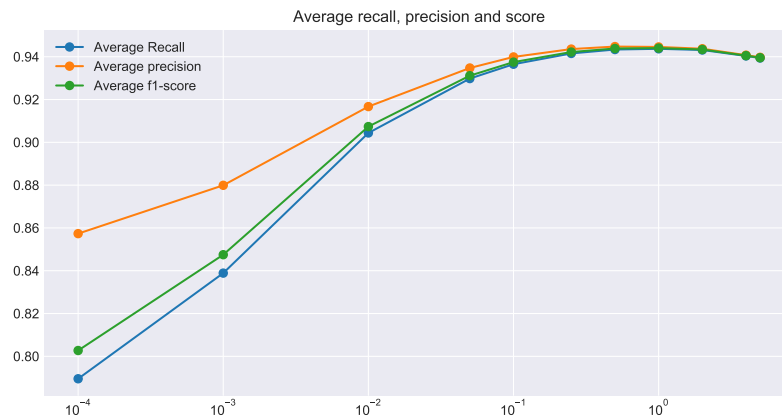


Figure 3.16: Optimal penalty parameters for linear svm when using SMOTE

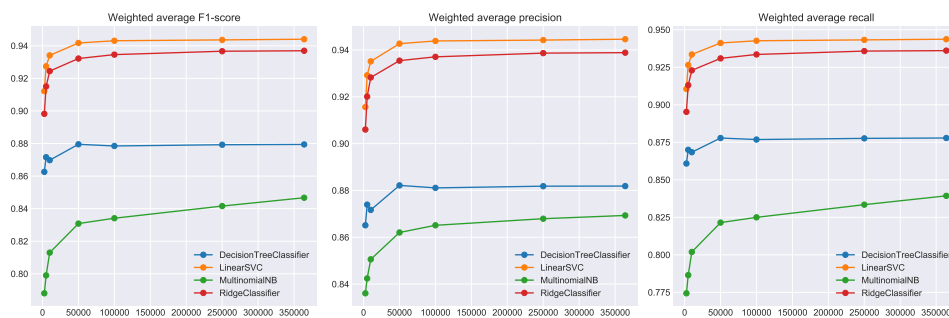


Figure 3.17: Average recall, precision and f1-score wti respect to the maximum number of features.

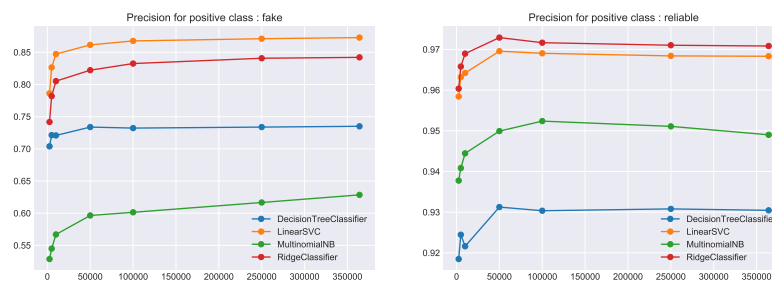


Figure 3.18: Precision for fake and reliable class for each model with respect to the maximum number of features

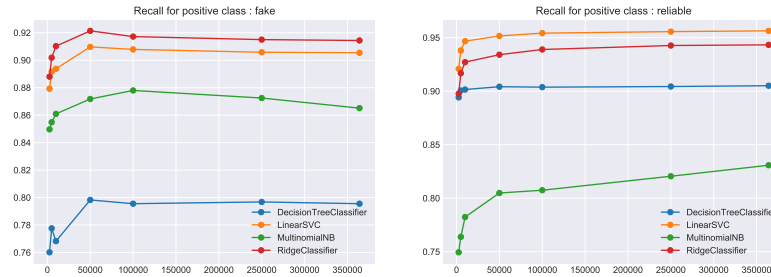


Figure 3.19: Recall for fake and reliable class for each model with respect to the maximum number of features

3.7 Results on testing set

3.7.1 Methodology

Now that all the models have been tuned, they need to be tested independently on testing set. Each datasets contains a testing set.

For the **liar-liar** dataset the following parameters will be used:

- Linear SVM with regularization parameters of 0.1 of a max TF-IDF features of 500,
- Ridge Classifier with $\alpha = 10$ and also max TF-IDF features of 500,
- Decision Tree with maximum depth of 1000 and the maximum number of features for TF-IDF,
- Nave-Bayes will also use the maximum number of features for TF-IDF.

For the **Fake News Corpus**, the following setting will be used:

- Linear SVM with regularisation parameters of 1,
- Ridge Classifier with $\alpha = 1$,
- Decision Tree with maximum depth of 100.

They will all be trained using 100,000 features for TF-IDF.

For the **Fake News Corpus** with SMOTE, the same parameters will be used, but the maximum number of features for TF-ISF will be used.

All the models will be trained on train and validation set and tested on test set.

3.7.2 Results

Liar-Liar Corpus

By looking at the row results, based on average accuracy Nave-Bayes, Linear SVM and ridge classifier perform very close, but when looking at the recall per class it shows that Nave-Bayes is bad at detecting fake news and classifies most of the text as reliable, when Linear SVM and Ridge classifier are more balanced.

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|-------------|-------------|----------|-------------|--------------|
| f1-score | 0.514399 | 0.679764 | 0.614049 | 0.597082 | 0.607588 |
| precision | 0.570485 | 0.638376 | 0.614049 | 0.604430 | 0.608744 |
| recall | 0.468354 | 0.726891 | 0.614049 | 0.597623 | 0.614049 |
| support | 1106.000000 | 1428.000000 | 0.614049 | 2534.000000 | 2534.000000 |

Table 3.1: Raw results for Linear SVM

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|-------------|-------------|----------|-------------|--------------|
| f1-score | 0.412107 | 0.698507 | 0.601421 | 0.555307 | 0.573504 |
| precision | 0.578431 | 0.608741 | 0.601421 | 0.593586 | 0.595512 |
| recall | 0.320072 | 0.819328 | 0.601421 | 0.569700 | 0.601421 |
| support | 1106.000000 | 1428.000000 | 0.601421 | 2534.000000 | 2534.000000 |

Table 3.2: Raw results for Nave-Bayes

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|-------------|-------------|----------|-------------|--------------|
| f1-score | 0.496366 | 0.691279 | 0.617206 | 0.593822 | 0.606207 |
| precision | 0.582927 | 0.633606 | 0.617206 | 0.608266 | 0.611486 |
| recall | 0.432188 | 0.760504 | 0.617206 | 0.596346 | 0.617206 |
| support | 1106.000000 | 1428.000000 | 0.617206 | 2534.000000 | 2534.000000 |

Table 3.3: Raw results for Ridge Classifier.

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|-------------|-------------|----------|-------------|--------------|
| f1-score | 0.479354 | 0.591549 | 0.542226 | 0.535451 | 0.542580 |
| precision | 0.475936 | 0.594901 | 0.542226 | 0.535418 | 0.542977 |
| recall | 0.482821 | 0.588235 | 0.542226 | 0.535528 | 0.542226 |
| support | 1106.000000 | 1428.000000 | 0.542226 | 2534.000000 | 2534.000000 |

Table 3.4: Raw results for Decision Tree

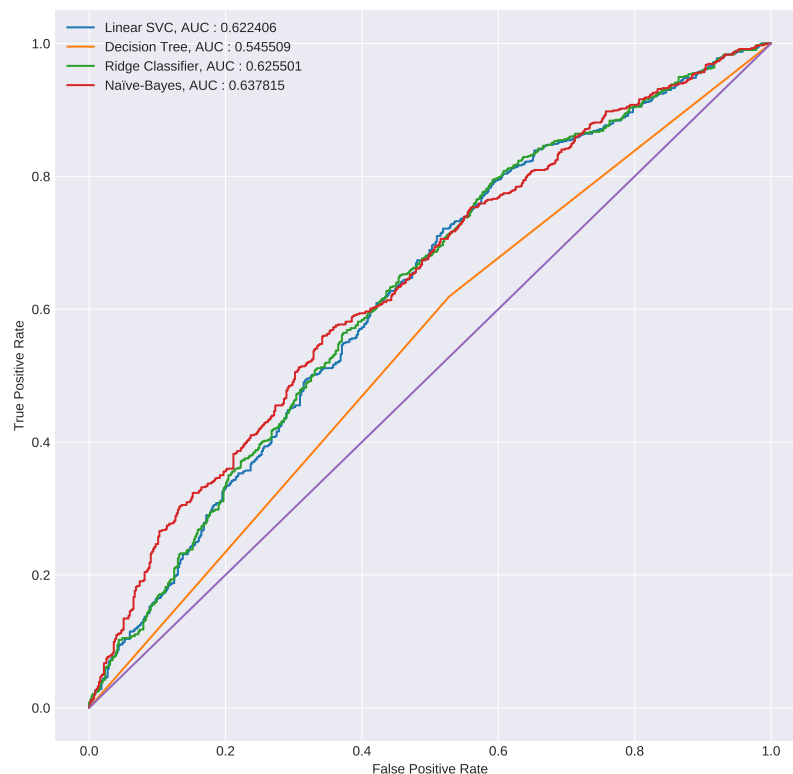


Figure 3.20: ROC curve for each model

Finally, it is possible to look at the ROC curve at **Figure 3.20**. One more time, it shows that Nave-Bayes, linear svm and rigde classifier have similar performance, but in this case it shows that NB has a little advantage, with a slightly larger AUC. There is only one point for the decision tree as it does not output probabilites for each classes.

When it comes to the **Fake news corpus**, linear model are still the ones that perform the best, with linear svm reaching an accuracy of 94.7% and ridge classifier 93.98%. Surprisingly decision tree outperform Nave-Bayes in this case, with an accuracy of 89.4% when Nave-Bayes only gets 85.3%.

In this case, the ROC curve (**Figure 3.22**) shows almost the same ranking of models,

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|--------------|--------------|----------|--------------|--------------|
| f1-score | 0.894700 | 0.965364 | 0.947874 | 0.930032 | 0.947620 |
| precision | 0.907861 | 0.960783 | 0.947874 | 0.934322 | 0.947494 |
| recall | 0.881916 | 0.969989 | 0.947874 | 0.925952 | 0.947874 |
| support | 17496.000000 | 52181.000000 | 0.947874 | 69677.000000 | 69677.000000 |

Table 3.5: Raw results for Linear SVM on **Fake News Corpus**

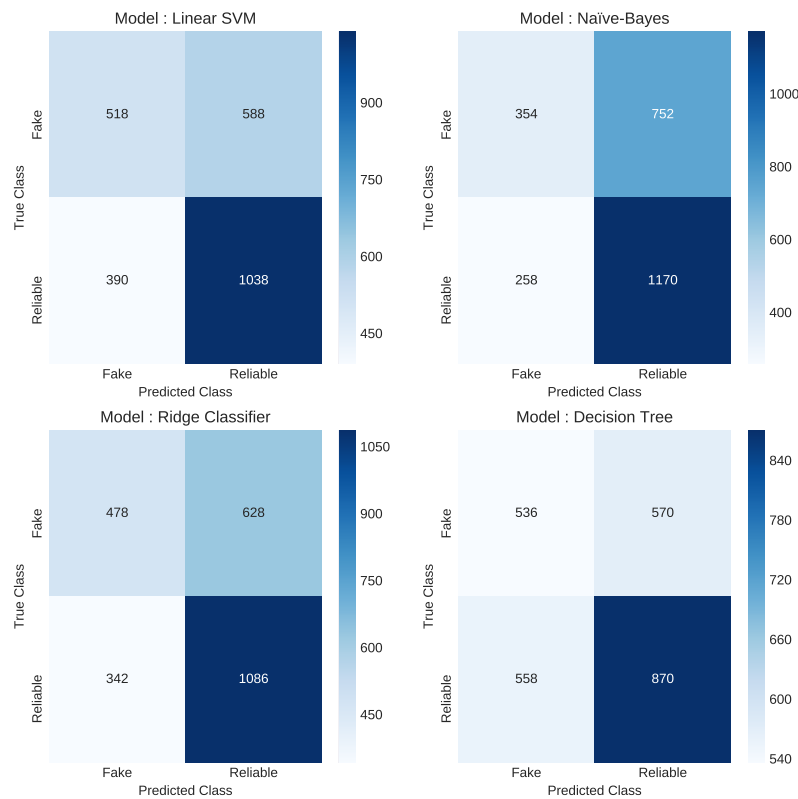


Figure 3.21: Confusion Matrix for each models

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|--------------|--------------|----------|--------------|--------------|
| f1-score | 0.674458 | 0.905634 | 0.853682 | 0.790046 | 0.847585 |
| precision | 0.764127 | 0.875841 | 0.853682 | 0.819984 | 0.847790 |
| recall | 0.603624 | 0.937525 | 0.853682 | 0.770574 | 0.853682 |
| support | 17496.000000 | 52181.000000 | 0.853682 | 69677.000000 | 69677.000000 |

Table 3.6: Raw results for Nave-Bayes on **Fake News Corpus**

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|--------------|--------------|----------|--------------|--------------|
| f1-score | 0.874220 | 0.960438 | 0.939808 | 0.917329 | 0.938788 |
| precision | 0.919674 | 0.945736 | 0.939808 | 0.932705 | 0.939192 |
| recall | 0.833048 | 0.975604 | 0.939808 | 0.904326 | 0.939808 |
| support | 17496.000000 | 52181.000000 | 0.939808 | 69677.000000 | 69677.000000 |

Table 3.7: Raw results for Ridge Classifier on **Fake News Corpus**

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|--------------|--------------|----------|--------------|--------------|
| f1-score | 0.791687 | 0.929799 | 0.894987 | 0.860743 | 0.895119 |
| precision | 0.788700 | 0.930987 | 0.894987 | 0.859844 | 0.895258 |
| recall | 0.794696 | 0.928614 | 0.894987 | 0.861655 | 0.894987 |
| support | 17496.000000 | 52181.000000 | 0.894987 | 69677.000000 | 69677.000000 |

Table 3.8: Raw results for Decision Tree on **Fake News Corpus**

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|--------------|--------------|----------|--------------|--------------|
| f1-score | 0.891373 | 0.962340 | 0.94407 | 0.926857 | 0.944520 |
| precision | 0.869960 | 0.970623 | 0.94407 | 0.920291 | 0.945346 |
| recall | 0.913866 | 0.954198 | 0.94407 | 0.934032 | 0.944070 |
| support | 17496.000000 | 52181.000000 | 0.94407 | 69677.000000 | 69677.000000 |

Table 3.9: Raw results of linear svm on **Fake News Corpus** when training using SMOTE

except for Decision Tree that is the last one, and Nave-Bayes being just above it. Confusion matrix (**Figure 3.23**) shows that Nave-Bayes has a tendency of classifying fake news as being reliable. And the other hand, ridge classifier is the one that makes the least missclassification for reliable news, which is a good point.

Finlay, there is the results of the models trained with SMOTE data augmentation. Using it shows little to no improvements. The only benefit is to balance a little bit the recall for Nave-Bayes on fake and reliable news.

3.8 Conclusion

In this chapter we have analyzed how traditional machine learning algorithms words on two different datasets, the second being imbalanced a data augmentation technique, called SMOTE, has been used in order to see if it improves the results.

We can conclude that in all the cases linear models are the ones that works the best, with a top accuracy of 61.7% on the **liar-liar corpus** using Ridge Classifier, and a top accuracy of 94.7% on the **Fake News Corpus** using linear svm. At the end, the results obtains on the second data set are really goods, when those obtains on the first when are mitigates.

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|--------------|--------------|----------|--------------|--------------|
| f1-score | 0.714816 | 0.873538 | 0.824777 | 0.794177 | 0.833683 |
| precision | 0.604424 | 0.950521 | 0.824777 | 0.777472 | 0.863615 |
| recall | 0.874543 | 0.808091 | 0.824777 | 0.841317 | 0.824777 |
| support | 17496.000000 | 52181.000000 | 0.824777 | 69677.000000 | 69677.000000 |

Table 3.10: Raw results of Nave-Bayes on **Fake News Corpus** when training using SMOTE

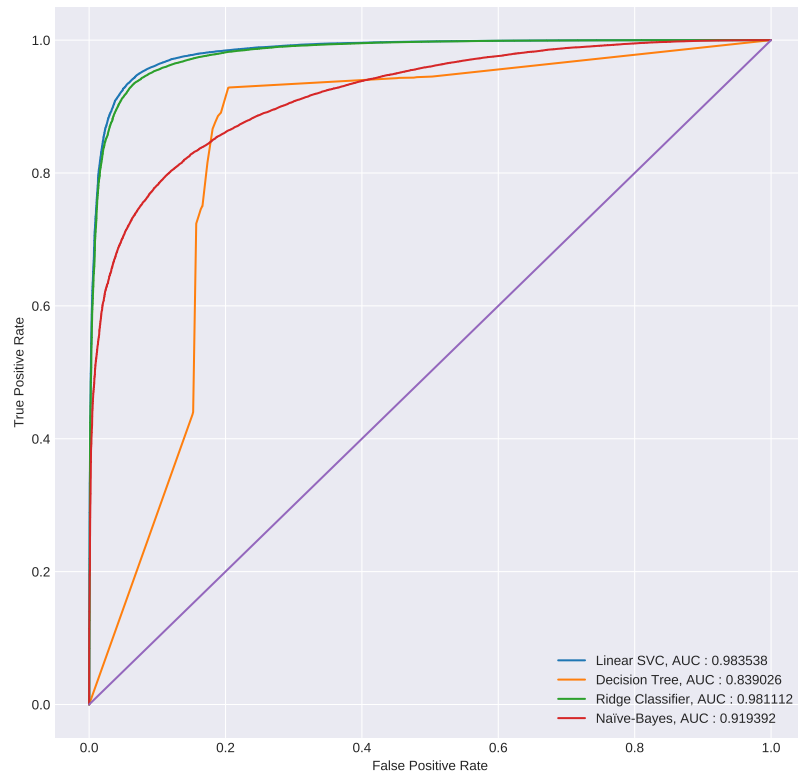


Figure 3.22: ROC curve for each model

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|--------------|--------------|----------|--------------|--------------|
| f1-score | 0.877755 | 0.956129 | 0.935431 | 0.916942 | 0.936449 |
| precision | 0.836588 | 0.973317 | 0.935431 | 0.904953 | 0.938984 |
| recall | 0.923182 | 0.939537 | 0.935431 | 0.931360 | 0.935431 |
| support | 17496.000000 | 52181.000000 | 0.935431 | 69677.000000 | 69677.000000 |

Table 3.11: Raw results of Ridge Classifier on **Fake News Corpus** when training using SMOTE

| | fake | reliable | accuracy | macro avg | weighted avg |
|-----------|--------------|--------------|----------|--------------|--------------|
| f1-score | 0.787226 | 0.921178 | 0.884969 | 0.854202 | 0.887542 |
| precision | 0.734992 | 0.946085 | 0.884969 | 0.840539 | 0.893079 |
| recall | 0.847451 | 0.897549 | 0.884969 | 0.872500 | 0.884969 |
| support | 17496.000000 | 52181.000000 | 0.884969 | 69677.000000 | 69677.000000 |

Table 3.12: Raw results of Decision tree on **Fake News Corpus** when training using SMOTE

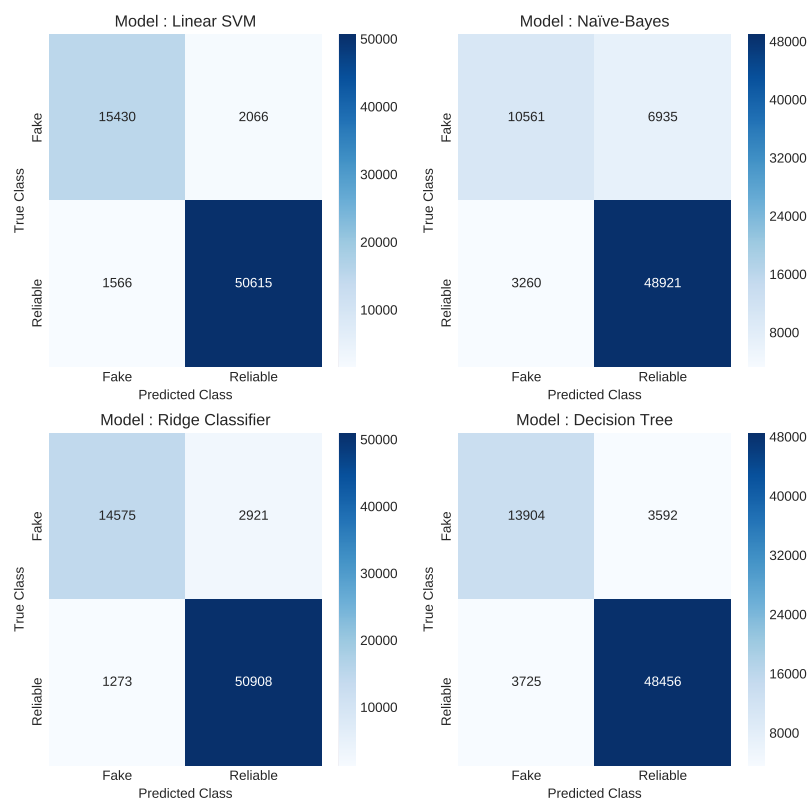


Figure 3.23: Confusion Matrix for each models

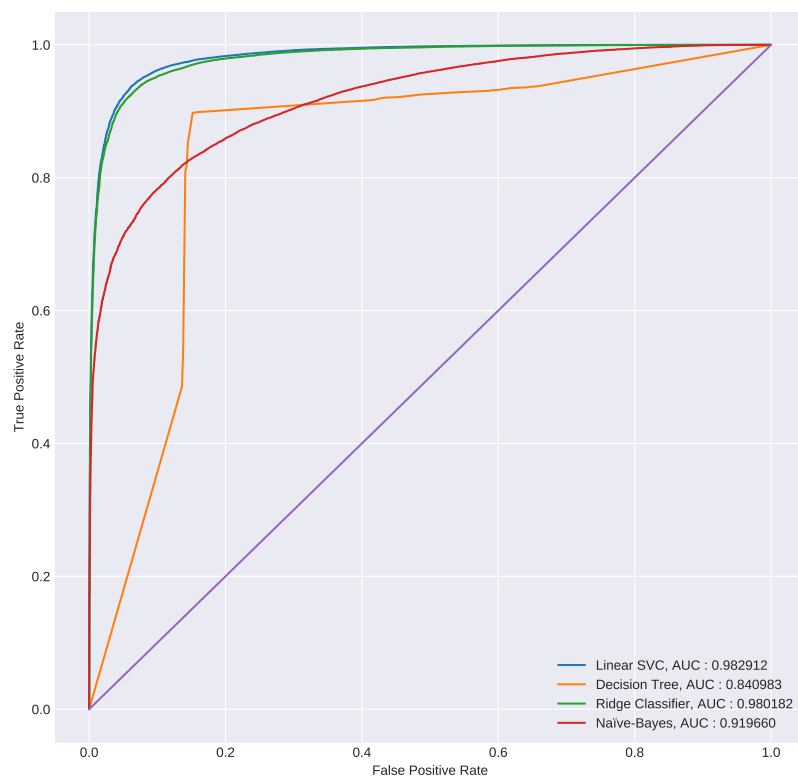


Figure 3.24: ROC curve for each model

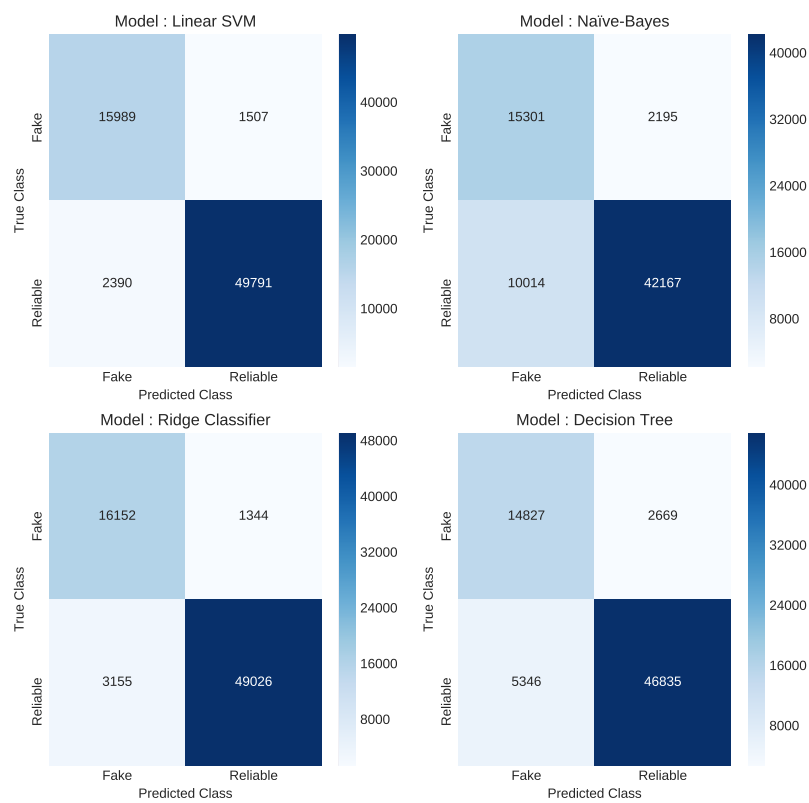


Figure 3.25: Confusion Matrix for each models

As explained earlier, it might be important to choose to model that make the smaller missclassification rate on reliable news in order to avoid possible censorship and confusion matrix shows that in both case Ridge Classifier is the ones that makes the less errors in that case.

In addition, we have shown that Synthetic Minority Over Sampling Techniques acts as a regularizers, as it does improve performance when the penalization term is small on linear models.

In the next section, the focus will be put on trying to improve results on the **Liar-Liar corpus** as there is room for improvement and that the second dataset already has very good results. But models will still be trying on it for comparison.

Chapter 4

Attention Mechanism

4.1 Introduction

In this section, we will focus on the deep learning models, the first one being a bidirectional LSTM and the second one an attention layer is added to this LSTM. But it is need to use an other text embedding in order to work with LSTM. Indeed, tf-idf create a sparse matrix with each row corresponding to a value for a given word. This means that the order of the words are lost. In order to solve this, word2vec[36] is used. It allows to match words to continuous vectors of a given size with interesting properties. An other methods, which consist in making word embedding as tuning parameters will be used.

4.2 Text to Vectors

4.2.1 Word2Vec

Word2Vec comes in two fashions: continuous bag of word (CBOW) and skip-gram. It is originally designed to predic a word given a context. For instance, given two previous words and the two next words, which word is the most likely to take place between them. But it appears that the hidden representation of these words works well as word embedding and have very interesting properties such that words with similar meaning have similar vector representation. It is also possible to perform arithmetic that captures informations such as singular, plural or even capital and countries. For example, we have that $dog - dogs \approx cat - cats$ but also $Paris - France \approx Berlin - Germany$.

It is possible to visualize these relationships by using t-SNE for projecting high dimentions word vectors in 2D space. The results of various relashionships can be see at **Figure 4.1**.

How does it works?

As the original authors did not inteded this kind of results, Xin Rong[37] did a good job explaing how it works.

Let V be the size of the vocabulary and that there is only one word in the CBOW model, it give **Figure 4.2** model.

Each words is encoded as a one-hot vector of size V . That means that it is a sparse vector full of zeros except for the position assigned to that word which is one. The hidden layers

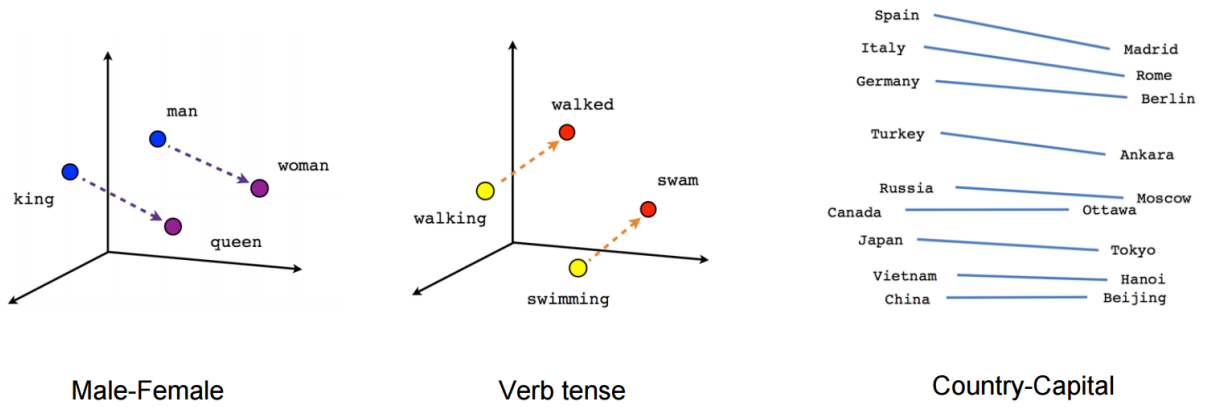


Figure 4.1: Relationships between different words with t-SNE dimensionality reduction.

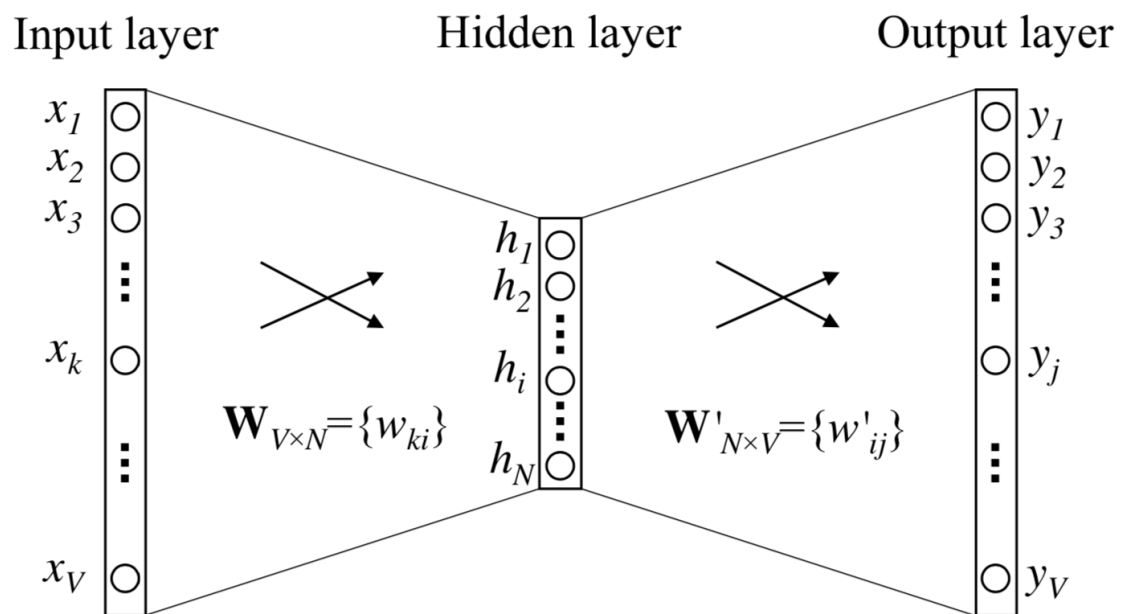


Figure 4.2: A simple CBOW model with only one word in the context

is computed as

$$\mathbf{h} = \mathbf{W}^T \mathbf{x} \quad (4.1)$$

Where $\mathbf{W}^{V \times N}$ is the weight matrix to optimize over.

The output layer values are computed as

$$\mathbf{Y} = \mathbf{W}'^T \mathbf{h} \quad (4.2)$$

As before $\mathbf{W}'^{N \times V}$ is also a weight matrix to optimize. The loss can be computed as softmax cross entropy.

It is also possible to make the oposite: predicting the context given a single input word. This is the skip-gram model. In this case the loss become **Equation 4.3**.

$$E = - \sum_{c=1}^C u_{j_c^*} + C \cdot \sum_{j'=1}^V \exp(u_{j'}) \quad (4.3)$$

j_c^* is the index of the c th output context word and $u_{j_c^*}$ is the score of the j th word in the vocabulary for the c th context word. Finly, the embedding that is used are the value of the hidden layers produced for a given word.

4.3 LSTM

LSTM or Long Short Term Memory[7] is a kind of reccurent neural network that fits well to temporal or sequential input such as texts. A RNN is a type of neural network where the hidden state is fed in a loop with the sequential inputs. There are usually shown as unrolled version of it (**Figure 4.4**). Each of the X_i being one value in the sequence.

Recurrent Neural Networks does not works very well with long-term dependencies, that is why LSTM have been introduced. It is made of an input gate, an output gate and a forget gate that are combined in **Equation 4.4**.

$$f_t = \sigma_g(\mathbf{W}_f x_t + \mathbf{U}_f h_{t-1} + b_f) \quad (4.4)$$

$$i_t = \sigma_g(\mathbf{W}_i x_t + \mathbf{U}_i h_{t-1} + b_i) \quad (4.5)$$

$$o_t = \sigma_g(\mathbf{W}_o x_t + \mathbf{U}_o h_{t-1} + b_o) \quad (4.6)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c(\mathbf{W}_c x_t + \mathbf{U}_c h_{t-1} + b_c) \quad (4.7)$$

$$h_t = o_t \circ \sigma_h(c_t) \quad (4.8)$$

Figure 4.5 shows how it works.

4.4 Attention Mechanism

4.5 Results

4.5.1 Methodology

In order to train the models and perform hyper parameters optimization grid search have been used when it was possibile (on the liar-liar dataset) and knowleadge aquiered there

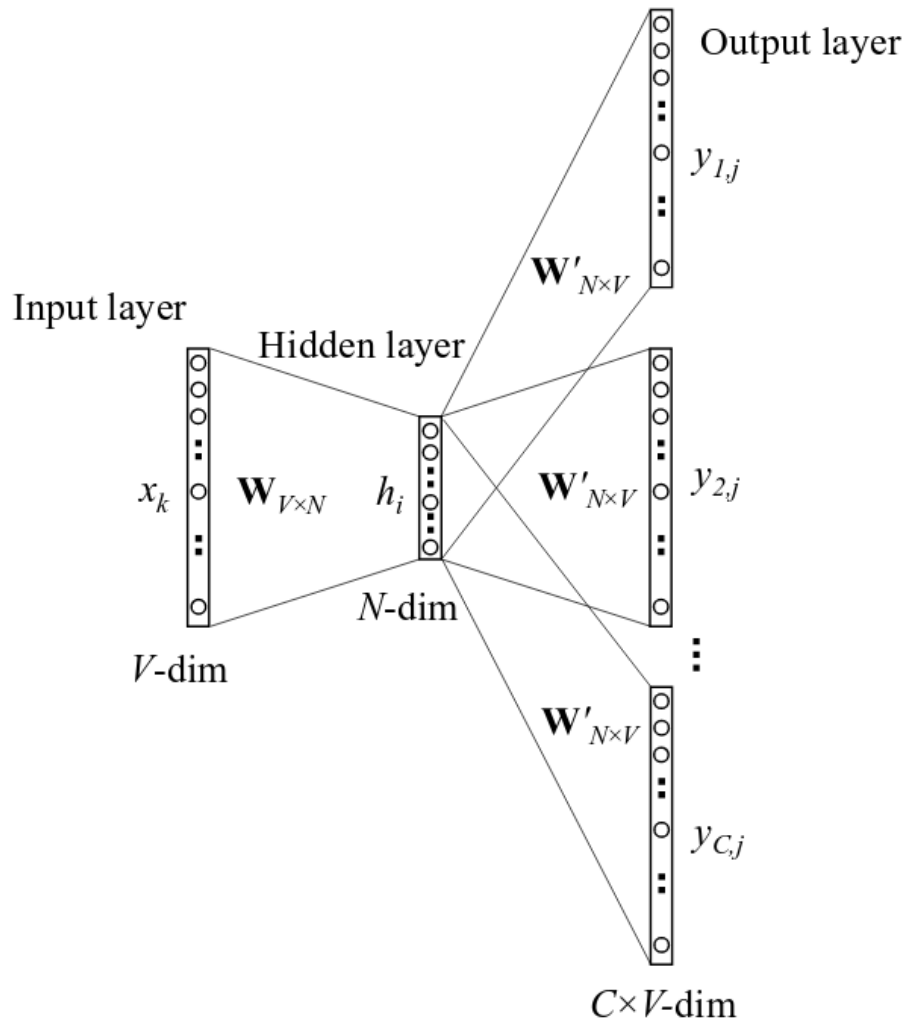
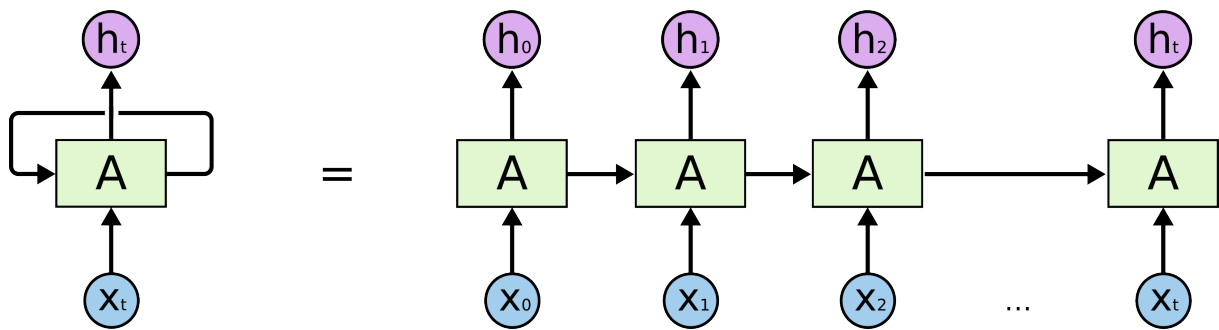


Figure 4.3: Skip-gram model with multiple outputs.

Figure 4.4: Unrolled RNN (Understanding LSTM Networks, <https://colah.github.io/posts/2015-08-Understanding-LSTMs/>)

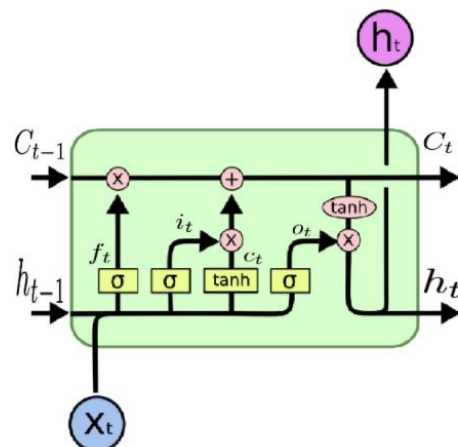


Figure 4.5: LSTM gates,

<https://hackernoon.com/understanding-architecture-of-lstm-cell-from-scratch-with-code-8da40f0b71f4>)

have been used in order to tune parameters for the networks on the **Fake News Corpus**. In addition, in order to find the best parameters among all tested with grid search, for each metrics, the training epochs having the highest validation value for that metrics have been chosen.

As SMOTE cannot be used on the **Fake News Corpus** due to the size of the corpus, in order to rebalance the dataset the minority class have been over sampled by feeding multiple times the same input by looping through them.

4.5.2 Liar-Liar dataset results

As explained earlier, both models have been trained using different embeddings: the first one being pre-trained word2vec vectors of size 300 and the second one being a tunable parameters with different embedding size.

Using word2vec embedding

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Appendix A

A.1 TF-IDF max features row results on liar-liar corpus

A.1.1 Weighted Average Metrics

| | model | max_features | recall | precision | f1 |
|----|------------------------|--------------|----------|-----------|----------|
| 0 | LinearSVC | 10 | 0.558411 | 0.590855 | 0.490108 |
| 1 | MultinomialNB | 10 | 0.559969 | 0.596418 | 0.489844 |
| 2 | DecisionTreeClassifier | 10 | 0.545171 | 0.554105 | 0.492387 |
| 3 | RidgeClassifier | 10 | 0.558411 | 0.590855 | 0.490108 |
| 4 | LinearSVC | 100 | 0.580997 | 0.586645 | 0.562808 |
| 5 | MultinomialNB | 100 | 0.579439 | 0.592686 | 0.549533 |
| 6 | DecisionTreeClassifier | 100 | 0.539720 | 0.537812 | 0.536041 |
| 7 | RidgeClassifier | 100 | 0.580997 | 0.586645 | 0.562808 |
| 8 | LinearSVC | 250 | 0.603583 | 0.605262 | 0.596719 |
| 9 | MultinomialNB | 250 | 0.596573 | 0.608079 | 0.575478 |
| 10 | DecisionTreeClassifier | 250 | 0.565421 | 0.565966 | 0.565582 |
| 11 | RidgeClassifier | 250 | 0.603583 | 0.605262 | 0.596719 |
| 12 | LinearSVC | 1000 | 0.600467 | 0.600183 | 0.597274 |
| 13 | MultinomialNB | 1000 | 0.594237 | 0.598593 | 0.581692 |
| 14 | DecisionTreeClassifier | 1000 | 0.550623 | 0.550539 | 0.550578 |
| 15 | RidgeClassifier | 1000 | 0.599688 | 0.599731 | 0.595559 |
| 16 | LinearSVC | 2500 | 0.575545 | 0.574544 | 0.573173 |
| 17 | MultinomialNB | 2500 | 0.592679 | 0.598169 | 0.578113 |
| 18 | DecisionTreeClassifier | 2500 | 0.568536 | 0.568482 | 0.568508 |
| 19 | RidgeClassifier | 2500 | 0.584891 | 0.584169 | 0.581693 |
| 20 | LinearSVC | 5000 | 0.571651 | 0.570574 | 0.568765 |
| 21 | MultinomialNB | 5000 | 0.592679 | 0.600539 | 0.574854 |
| 22 | DecisionTreeClassifier | 5000 | 0.552960 | 0.551400 | 0.549321 |
| 23 | RidgeClassifier | 5000 | 0.572430 | 0.571418 | 0.568760 |
| 24 | LinearSVC | 10000 | 0.566978 | 0.565837 | 0.564715 |
| 25 | MultinomialNB | 10000 | 0.598131 | 0.614854 | 0.572109 |
| 26 | DecisionTreeClassifier | 10000 | 0.560748 | 0.559664 | 0.559212 |
| 27 | RidgeClassifier | 10000 | 0.580218 | 0.579376 | 0.576984 |
| 28 | LinearSVC | 11222 | 0.566978 | 0.565860 | 0.564915 |
| 29 | MultinomialNB | 11222 | 0.597352 | 0.615925 | 0.569280 |

| | | | | | |
|----|------------------------|-------|----------|----------|----------|
| 30 | DecisionTreeClassifier | 11222 | 0.556854 | 0.555689 | 0.555171 |
| 31 | RidgeClassifier | 11222 | 0.582555 | 0.581782 | 0.579279 |

A.1.2 Per class Metrics

| | model | max_features | type | recall | precision | f1 |
|----|------------------------|--------------|----------|----------|-----------|----------|
| 0 | LinearSVC | 10 | fake | 0.181818 | 0.640000 | 0.283186 |
| 1 | LinearSVC | 10 | reliable | 0.905689 | 0.545537 | 0.680923 |
| 2 | MultinomialNB | 10 | fake | 0.178571 | 0.650888 | 0.280255 |
| 3 | MultinomialNB | 10 | reliable | 0.911677 | 0.546188 | 0.683118 |
| 4 | DecisionTreeClassifier | 10 | fake | 0.212662 | 0.569565 | 0.309693 |
| 5 | DecisionTreeClassifier | 10 | reliable | 0.851796 | 0.539848 | 0.660859 |
| 6 | RidgeClassifier | 10 | fake | 0.181818 | 0.640000 | 0.283186 |
| 7 | RidgeClassifier | 10 | reliable | 0.905689 | 0.545537 | 0.680923 |
| 8 | LinearSVC | 100 | fake | 0.371753 | 0.602632 | 0.459839 |
| 9 | LinearSVC | 100 | reliable | 0.773952 | 0.571903 | 0.657761 |
| 10 | MultinomialNB | 100 | fake | 0.314935 | 0.621795 | 0.418103 |
| 11 | MultinomialNB | 100 | reliable | 0.823353 | 0.565844 | 0.670732 |
| 12 | DecisionTreeClassifier | 100 | fake | 0.446429 | 0.523810 | 0.482033 |
| 13 | DecisionTreeClassifier | 100 | reliable | 0.625749 | 0.550725 | 0.585844 |
| 14 | RidgeClassifier | 100 | fake | 0.371753 | 0.602632 | 0.459839 |
| 15 | RidgeClassifier | 100 | reliable | 0.773952 | 0.571903 | 0.657761 |
| 16 | LinearSVC | 250 | fake | 0.470779 | 0.613108 | 0.532599 |
| 17 | LinearSVC | 250 | reliable | 0.726048 | 0.598027 | 0.655849 |
| 18 | MultinomialNB | 250 | fake | 0.368506 | 0.637640 | 0.467078 |
| 19 | MultinomialNB | 250 | reliable | 0.806886 | 0.580819 | 0.675439 |
| 20 | DecisionTreeClassifier | 250 | fake | 0.561688 | 0.545741 | 0.553600 |
| 21 | DecisionTreeClassifier | 250 | reliable | 0.568862 | 0.584615 | 0.576631 |
| 22 | RidgeClassifier | 250 | fake | 0.470779 | 0.613108 | 0.532599 |
| 23 | RidgeClassifier | 250 | reliable | 0.726048 | 0.598027 | 0.655849 |
| 24 | LinearSVC | 1000 | fake | 0.509740 | 0.598095 | 0.550394 |
| 25 | LinearSVC | 1000 | reliable | 0.684132 | 0.602108 | 0.640505 |
| 26 | MultinomialNB | 1000 | fake | 0.417208 | 0.613365 | 0.496618 |
| 27 | MultinomialNB | 1000 | reliable | 0.757485 | 0.584971 | 0.660144 |
| 28 | DecisionTreeClassifier | 1000 | fake | 0.529221 | 0.531811 | 0.530513 |
| 29 | DecisionTreeClassifier | 1000 | reliable | 0.570359 | 0.567809 | 0.569081 |
| 30 | RidgeClassifier | 1000 | fake | 0.496753 | 0.600000 | 0.543517 |
| 31 | RidgeClassifier | 1000 | reliable | 0.694611 | 0.599483 | 0.643551 |
| 32 | LinearSVC | 2500 | fake | 0.498377 | 0.565378 | 0.529767 |
| 33 | LinearSVC | 2500 | reliable | 0.646707 | 0.582996 | 0.613201 |
| 34 | MultinomialNB | 2500 | fake | 0.402597 | 0.615385 | 0.486752 |
| 35 | MultinomialNB | 2500 | reliable | 0.767964 | 0.582293 | 0.662363 |
| 36 | DecisionTreeClassifier | 2500 | fake | 0.548701 | 0.550489 | 0.549593 |
| 37 | DecisionTreeClassifier | 2500 | reliable | 0.586826 | 0.585075 | 0.585949 |
| 38 | RidgeClassifier | 2500 | fake | 0.495130 | 0.578748 | 0.533683 |
| 39 | RidgeClassifier | 2500 | reliable | 0.667665 | 0.589168 | 0.625965 |
| 40 | LinearSVC | 5000 | fake | 0.487013 | 0.561798 | 0.521739 |
| 41 | LinearSVC | 5000 | reliable | 0.649701 | 0.578667 | 0.612130 |
| 42 | MultinomialNB | 5000 | fake | 0.383117 | 0.622691 | 0.474372 |
| 43 | MultinomialNB | 5000 | reliable | 0.785928 | 0.580110 | 0.667514 |
| 44 | DecisionTreeClassifier | 5000 | fake | 0.459416 | 0.540076 | 0.496491 |

| | | | | | | |
|----|------------------------|-------|----------|----------|----------|----------|
| 45 | DecisionTreeClassifier | 5000 | reliable | 0.639222 | 0.561842 | 0.598039 |
| 46 | RidgeClassifier | 5000 | fake | 0.477273 | 0.564299 | 0.517150 |
| 47 | RidgeClassifier | 5000 | reliable | 0.660180 | 0.577982 | 0.616352 |
| 48 | LinearSVC | 10000 | fake | 0.491883 | 0.554945 | 0.521515 |
| 49 | LinearSVC | 10000 | reliable | 0.636228 | 0.575881 | 0.604552 |
| 50 | MultinomialNB | 10000 | fake | 0.345779 | 0.653374 | 0.452229 |
| 51 | MultinomialNB | 10000 | reliable | 0.830838 | 0.579332 | 0.682657 |
| 52 | DecisionTreeClassifier | 10000 | fake | 0.498377 | 0.546263 | 0.521222 |
| 53 | DecisionTreeClassifier | 10000 | reliable | 0.618263 | 0.572022 | 0.594245 |
| 54 | RidgeClassifier | 10000 | fake | 0.490260 | 0.573055 | 0.528434 |
| 55 | RidgeClassifier | 10000 | reliable | 0.663174 | 0.585205 | 0.621754 |
| 56 | LinearSVC | 11222 | fake | 0.495130 | 0.554545 | 0.523156 |
| 57 | LinearSVC | 11222 | reliable | 0.633234 | 0.576294 | 0.603424 |
| 58 | MultinomialNB | 11222 | fake | 0.336039 | 0.657143 | 0.444683 |
| 59 | MultinomialNB | 11222 | reliable | 0.838323 | 0.577915 | 0.684178 |
| 60 | DecisionTreeClassifier | 11222 | fake | 0.491883 | 0.542039 | 0.515745 |
| 61 | DecisionTreeClassifier | 11222 | reliable | 0.616766 | 0.568276 | 0.591529 |
| 62 | RidgeClassifier | 11222 | fake | 0.491883 | 0.576046 | 0.530648 |
| 63 | RidgeClassifier | 11222 | reliable | 0.666168 | 0.587071 | 0.624123 |

A.2 TF-IDF max features row results for fake news corpus without SMOTE

| | model | recall | precision | max_features | f1 |
|----|------------------------|----------|-----------|--------------|----------|
| 0 | LinearSVC | 0.744278 | 0.741135 | 10000 | 0.742519 |
| 1 | MultinomialNB | 0.638690 | 0.666131 | 10000 | 0.647986 |
| 2 | DecisionTreeClassifier | 0.649834 | 0.664873 | 10000 | 0.655847 |
| 3 | RidgeClassifier | 0.730762 | 0.739152 | 10000 | 0.734125 |
| 4 | LinearSVC | 0.757846 | 0.758336 | 50000 | 0.758086 |
| 5 | MultinomialNB | 0.658424 | 0.680365 | 50000 | 0.666197 |
| 6 | DecisionTreeClassifier | 0.668170 | 0.685830 | 50000 | 0.674751 |
| 7 | RidgeClassifier | 0.742044 | 0.756513 | 50000 | 0.746957 |
| 8 | LinearSVC | 0.757589 | 0.757112 | 100000 | 0.757346 |
| 9 | MultinomialNB | 0.657282 | 0.681421 | 100000 | 0.665562 |
| 10 | DecisionTreeClassifier | 0.669952 | 0.685943 | 100000 | 0.676058 |
| 11 | RidgeClassifier | 0.742437 | 0.754869 | 100000 | 0.746859 |
| 12 | LinearSVC | 0.757935 | 0.756228 | 250000 | 0.757021 |
| 13 | MultinomialNB | 0.660640 | 0.683517 | 250000 | 0.668590 |
| 14 | DecisionTreeClassifier | 0.668623 | 0.685926 | 250000 | 0.675103 |
| 15 | RidgeClassifier | 0.744877 | 0.754769 | 250000 | 0.748600 |
| 16 | LinearSVC | 0.753187 | 0.750750 | 500000 | 0.751847 |
| 17 | MultinomialNB | 0.672800 | 0.687760 | 500000 | 0.678584 |
| 18 | DecisionTreeClassifier | 0.673318 | 0.690695 | 500000 | 0.679764 |
| 19 | RidgeClassifier | 0.742800 | 0.751770 | 500000 | 0.746270 |
| 20 | LinearSVC | 0.753156 | 0.750642 | 1000000 | 0.751769 |
| 21 | MultinomialNB | 0.673599 | 0.688095 | 1000000 | 0.679241 |
| 22 | DecisionTreeClassifier | 0.673084 | 0.688515 | 1000000 | 0.679001 |
| 23 | RidgeClassifier | 0.742725 | 0.751611 | 1000000 | 0.746170 |