Discriminatory Expressions to Produce Interpretable Models in Microblogging Context

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Abstract

Social Networking Sites (SNS) are one of the most important ways of communication. In particular, microblogging sites are being used as analysis avenues due to their peculiarities (promptness, short texts...). There are countless researches that use SNS in novel manners, but machine learning (ML) has focused mainly in classification performance rather than interpretability and/or other goodness metrics. Thus, state-of-the-art models are black boxes that should not be used to solve problems that may have a social impact. When the problem requires transparency, it is necessary to build interpretable pipelines. Arguably, the most decisive component in the pipeline is the classifier, but it is not the only thing that we need to consider. Despite that the classifier may be interpretable, resulting models are too complex to be considered comprehensible, making it impossible for humans to comprehend the actual decisions. The purpose of this paper is to present a feature selection mechanism (the first step in the pipeline) that is able to improve comprehensibility by using less but more meaningful features while achieving a good performance in microblogging contexts where interpretability is mandatory. Moreover, we present a ranking method to evaluate features in terms of statistical relevance and bias. We conducted exhaustive tests with five different datasets in order to evaluate classification performance, generalisation capacity and actual interpretability of the model. Our results shows that our proposal is better and, by far, the most stable in terms of accuracy, generalisation and comprehensibility.

Keywords: interpretability, interpretable models, feature selection, discriminatory expressions, text mining, microblogging

1. Introduction

Nowadays, information flow is huge. From traditional media such as newspaper and television to blogs and forums, sources of information have grown to
| year | no. of papers |
|------|--------------|
| 2019 | 4635         |
| 2018 | 4212         |
| 2017 | 3746         |
| 2016 | 3554         |
| 2015 | 2930         |
| 2014 | 2578         |
| 2013 | 2308         |
| 2012 | 1652         |
| 2011 | 1080         |
| 2010 | 617          |
| 2009 | 187          |
| 2008 | 36           |
| 2007 | 10           |

Table 1: Number of publications that results from the search of the word “Twitter” in the title, abstract and/or keywords in Scopus. Updated October 24th 2020.

a point where we cannot conceive our reality without them. Social Media has become one of the most important ways to communicate. Users from all around the world can now manifest their opinions and share content regardless of their socioeconomic status. This makes Social Networking Sites (SNS) a baseline to analyse people’s interest and opinion trends.

Microblogging sites are prone to analysis applications such as environmental problem detection and sentiment analysis at different levels (Perinán-Pascual & Arcas-Túnez, 2019; Alharbi & de Doncker, 2019). They can be understood as a combination of blogging (since general public can access your history of publications) and instant messaging (because messages are supposed to be short enough to keep a fluid communication). Messages may include media such as images and videos.

Arguably, the most popular one is Twitter, with 126 million daily active users as of 2018 and almost 6000 tweets being sent per second (Twitter Inc., 2019; Internet Live Stats, 2020). In recent years, Twitter has become a very important tool for research. The number of papers published regarding this topic has increased substantially since the platform was born in 2007 (see table 1). However, tweets show clear handicaps when performing analysis of their content that impoverish machine learning (ML) models capacities: lack of context; abundance of misspelled words, contractions and acronyms; and new semantic units (like hashtags), among others.

Along with these handicaps, another problem arises when considering domains where interpretability is required. Mainly, any decision that may have a social impact is subject to being audited and should be transparent and fair. For example, censor algorithms are a controversial topic regarding this matter, since preemptive closing of accounts limits free speech and should have explicit
| year | no. of papers |
|------|---------------|
| 2019 | 1637          |
| 2018 | 1040          |
| 2017 | 807           |
| 2016 | 614           |
| 2015 | 564           |
| 2014 | 484           |
| 2013 | 469           |
| 2012 | 449           |

Table 2: Number of publications that results from the search of the word “interpretability” in the title, abstract and/or keywords in Scopus. Updated October 24th 2020.

reasoning (Phillips, 2018; Hanff, Alexander, 2018). Recommendation systems also present this kind of issue as filtering the content that is shown to a user may impact their interests and opinions, and even affect third parties (O’Dair & Fry, 2019; Zhao et al., 2018; Lee & Hosanagar, 2014, 2016). For industries and businesses, complying with regulations and ethic constraints may also imply interpretability.

However in recent years, machine learning research has focused mostly in accuracy and goodness metrics (such as accuracy, $f_1$-score or ROC AUC), forgetting about interpretability. State-of-the-art language models (such as ELMo or BERT (Peters et al., 2018; Devlin et al., 2018), presented by Google, and GPT-2 or GPT-3 (Radford et al., 2019; Brown et al., 2020), presented by OpenAI) are based on deep techniques and thus they are not interpretable. These models are extremely powerful in terms of potential uses, and they have proven to be effective in tasks in which they were never trained for, such as language translation and code writing. To achieve this outstanding capabilities, they use cutting-edge techniques such as Transformers, that are based on the concept of Attention, but they require billions of hyperparameters that need to be optimised and fine-tuned to each specific task (Vaswani et al., 2017).

At the same time, researches are noticing the vast moral implications of taking high stakes decisions with ML models. Lately, numerous events and studies regarding interpretability are emerging, giving this field more relevance both between scientists and citizens, as can be seen in the list gathered by Carvalho et al. (2019). Table 2 reflects the increasing number of papers related to interpretability.

Instead of developing new interpretable models, there is a growing tendency to explain current black-box models with subordinated ones (post-hoc models trained to give reasons on why the original model behaves that way); this approach may preserve bad practices over time that can lead to potential harm (Rudin, 2018).

There are several ways to build ML models, but the typical procedure includes: several preprocessing steps (obtaining features, removing outliers, re-
ducing dimensionality...), training the model and validating it. It is common belief that model accuracy is directly related to its complexity. Rudin (2018) established that this statement is not necessarily true, since well-structured significant features often yields the same results regardless of the complexity of the classifier. In this paper, we will focus on the features used to train a model that is required to be interpretable, to obtain a feature selection method that is able to:

1. Improve classification performance using a low number of features.
2. Improve generalisation capacity using a low number of features.
3. Improve comprehensibility by using less but more meaningful features.

We will measure these items in terms of mean value and stability through different classifiers and datasets to ensure that the method is versatile enough. We refer to generalisation capacity as the ability of a model to obtain good classification performance when training with a much lower number of instances. This is the typical situation when working with social media.

We believe that we can use expressions biased towards a class in order to achieve our targets. An expression will be a sequence of words (not necessarily contiguous) with a specific order. This is partially what linguists consider when analysing text: not only the words but also the order in which they are presented. In fact, they also take into account stop words, on the contrary to machine learning models where stop words are removed in most scenarios while preprocessing. Moreo et al. (2012a) tried a similar approach with success, although in a different domain. Additionally, we will need a new measure that is able to maximise statistical relevance and discriminatory performance in order to rank the expressions in a massive search space.

In this article, we present an algorithm that is able to obtain and select expressions from short texts like tweets. Since they will be sequence of natural language words, features will be easy to interpret. Moreover, selected expressions will be biased towards a class to ensure classification performance while decreasing model complexity. Thus, we introduce a ranking method called CF-ICF that is able to rank words taking into consideration the bias towards the class whose expressions we are looking for, while maximising statistical relevance.

Our results show that our proposal has one of the best classification performance between the compared methods. They also show that it has one of the lowest deviations and it manages to reduce the complexity of the resulting models in some cases, hereby improving comprehensibility. Decreasing model complexity is important because not all models are interpretable in practice (e.g. a huge decision tree with a lot of leaves is potentially interpretable, but it is impossible to do it effectively).

The rest of this paper is organised as follows. In section 2, we review literature related to feature selection methods and introduce concepts on interpretability.
Section 3 shows results on a preliminary study to check if current interpretable models are comprehensible enough. In section 4, we present our algorithm of Discriminatory Expressions, as well as a ranking method based on the classic TF-IDF. We performed several experiments as mentioned in section 5 and we discuss results in section 6. Section 7 presents our main contributions and limitations of our work. Sections 8 and 9 sum up our proposal and present several lines of future work.

2. Related Work

Text mining research in Social Media has become very relevant in the last few years, as they are ground for quite a few computer science applications. From analysing human behaviour to stock prediction, there are a lot of ongoing projects and researches based on topic detection (Periñán-Pascual & Arcas-Túnez, 2019; Castellanos et al., 2017; Nassar et al., 2016; Xie et al., 2016), measuring user’s influence (Alsaig et al., 2019; Qasem et al., 2016; Jorgens et al., 2016; Subbian et al., 2016), sentiment analysis (Alharbi & de Doncker, 2019; Xiaomei et al., 2018; Rosenthal et al., 2017; Saif et al., 2016; Supriya et al., 2016), opinion mining (Li et al., 2016; Gasco et al., 2019; Takahashi et al., 2016; Kumar et al., 2016), and text summarisation (Qian et al., 2019; Arroyo-Fernández et al., 2019), among others. However, NLP processing techniques may not be good enough under microblogging circumstances, since they result in highly-dimensional and very sparse feature matrices (Zheng et al., 2018). Applications like authorship identification (duplicate accounts, inter-network identification...) have demonstrated that traditional methods are not feasible in short-message contexts like Twitter, as they tend to assume a minimum text extension under which models would not be suitable enough. Alternative techniques like style markers have been proved better (Green & Sheppard, 2013).

Other document-pivot methods present similar problems, and recent approaches based on co-occurrence, TF-IDF and/or pattern recognition techniques (such as FP-Growth (Han et al., 2000)) are being used for this purpose (Li et al., 2012; Sayyadi & Raschid, 2013).

In any case, when dealing with natural language models, the feature space is usually extremely wide. Normally, a set of documents has a few thousand unique words that are used as features, despite many of them can be considered noisy or not relevant at all. It is required to select and/or recombine them, not only to decrease the complexity of the problem but also to improve classification performance (Wang & Hong, 2019).

There are several classes of feature selection (FS) methods, but they are generally grouped into three categories (Xue et al., 2013):

- Filtering methods. Given a set of features, they apply an evaluation function and select the $k$ best, where $k$ is an hyperparameter. They score each feature taking into consideration different aspects of them, like document frequency (DF) or TF-IDF.
• Wrapper methods. Given a set of features, they select different subsets of them to train a classifier and check out how good its performance is. Since selected features are tested directly within the classifier, they normally achieve better performance than filters.

• Hybrid methods. They combine both techniques: first, they perform a filter to reduce the number of features; then, optimal subset is computed by feeding a classifier.

There is another group of feature selection techniques called embedded methods (Liang et al., 2017). These methods are inherent to the classification stage, since they take part in the training process (e.g. decision trees), and they are usually not considered independently.

There are loads of filtering methods available and backed by the scientific community. We have selected a few of them based on their current relevance, goodness metrics and community acceptance. They are presented below:

**CHI2 (chi-square).** $\chi^2$ is one of the most popular filtering methods for feature selection problems. It is possible to use the statistical test in order to check the independence of two events ($p(AB) = p(A)p(B)$), in this case, a feature and a class.

$$\chi^2_{(t,c)} = \frac{D \times \left[p(t|c)p(\overline{t}|\overline{c}) - p(t|\overline{c})p(\overline{t}|c)\right]^2}{p(t)p(\overline{t}) - p(c)p(\overline{c})}$$  \hspace{1cm} (1)

$\chi^2$ is defined for text classification through equation[1] where: $D$ stands for the total number of documents, $t$ is a feature and $c$ is a class (Rutkowski et al., 2008; Senthil Kumar B & Bhavitha Varma E, 2016; Zheng et al., 2004).

**Information Gain (IG).** IG is based on entropy (information theory). It measures the gain of a feature with respect to a given class (decrease in entropy between considering the feature or not) (Forman, 2003). IG is defined as stated in equation[2] where $t$ is a feature and $c$ a class (Caropreso et al., 2001; Ding & Fu, 2018; Deng et al., 2019; Largeron et al., 2011).

$$IG_{(t,c)} = p(t|c) \log \frac{p(t|c)}{p(t)p(c)} + p(\overline{t}|c) \log \frac{p(\overline{t}|c)}{p(\overline{t})p(c)}$$ \hspace{1cm} (2)

**Mutual Information (MI).** MI measures how much information two variables share, in this case, a feature $t$ and a class $c$. It is defined in equation[3] (Deng et al., 2019; Al-Salemi et al., 2016). It can be proved equal to IG for binary problems (Senthil Kumar B & Bhavitha Varma E, 2016).

$$MI_{(t,c)} = \log \frac{p(t|c)}{p(t)p(c)}$$ \hspace{1cm} (3)

with $t$ and $c$ being a feature and a class, respectively.
Odds Ratio (OR). OR measures the probability of a term $t$ and a class $c$ co-occurring normalised by the probability of $t$ occurring in other classes (Al-Salemi et al., 2016; Zheng et al., 2004).

\[
OR_{(t,c)} = \log \frac{p(t|c)(1 - p(t|\overline{c}))}{(1 - p(t|c))p(t|\overline{c})}
\]  

where $t$ is a feature and $c$ is a class.

Expected Cross Entropy (ECE). ECE computes the distance between the class $c$ distribution and the class distribution co-occurring with the feature $t$. Wu et al. (2015) defined ECE as in equation 5.

\[
ECE_{(t,c)} = p(t) \times \left( \frac{p(c|t)}{p(c)} \log \frac{p(c|t)}{p(c)} + \frac{p(\overline{c}|t)}{p(\overline{c})} \log \frac{p(\overline{c}|t)}{p(\overline{c})} \right)
\]

ANOVA F-value. It is used to check if there is a significant difference between the variance of two variables (Misangyi et al., 2016). In one-way ANOVA, the F-statistic is defined as in equation 6:

\[
F\text{-statistic} = \frac{\text{variance between groups}}{\text{variance within groups}}
\]  

Galavotti-Sebastiani-Simi coefficient (GSS). Galavotti et al. (2000) proposed a simplified version of $\chi^2$ given by equation 7 (Largeron et al., 2011).

\[
GSS_{(t,c)} = p(t|c)p(\overline{t}|\overline{c}) - p(t|\overline{c})p(\overline{t}|c)
\]

where $t$ is a feature and $c$ is a class.

All these filters present similar drawbacks. Mainly, features are selected regardless of the classifier, so the selected feature subset may not be ideal for every classification stage. However, they are quicker computing the aforementioned subset than other categories of FS mechanisms.

On the other hand, wrappers assess the relevance of each subset of features within the context of a given classifier. Goodness metrics for the classification model determine how good each feature subset is. Hence, the FS method will choose the subset of features that yields the best performance. There are tons of generic wrappers for feature selection, such as (Dy & Brodley 2004; Shah & Kusiak 2004; Meiri & Zahavi 2006; Hans et al. 2005). They usually achieve better performance than filtering methods.

However, the complexity of evaluating each subset is quite high (exponential). To overcome this disadvantage, they are usually combined with meta-heuristics such as genetic algorithms, ant colony optimisation, particle swarm optimisation and/or iterated local search (AK & Zongker 1997). Despite the complexity of performing a search, they still are suboptimal approaches and classifier-dependant.

Wrapper approaches can also be combined with filters in order to narrow the space search to a promising area (hybrid methods). Hence, they are suitable for
early convergence (which can lead to local extrema) and prone to overfitting (at least with small datasets) (Lee et al., 2019).

Most of the techniques we have reviewed regarding feature selection were focused in reducing dimensionality and improving classification performance. However, little attention has been paid to how interpretable are the selected features. It is possible to obtain a set of features that are easier to understand by humans without significantly affecting classification performance (Rudin, 2018).

In fact, for some text classification problems, there are features that should not be selected at all, at least in microblogging context. For examples, those related to typing errors or contractions, when these are due to the limit of characters. In order to ensure model integrity, they should be transparent (FAT/ML, 2019).

There is no general consensus on how to measure interpretability. Doshi-Velez & Kim (2017) defined it as “the ability to explain or to present in understandable terms to a human”. They elaborated a taxonomy on how to evaluate interpretability:

1. Application level, consisting in an expert evaluation of the model itself.
2. Human metrics, where any human can perform such evaluation without the need of being a domain expert. It is normally performed by comparison with other models/explanations.
3. Proxy tasks, when we make the assumption that the user understands the model and we only compare parameters within it (e.g. depth of a decision tree).

It is particularly interesting to perform evaluations at application level. Nevertheless, this is a very expensive task that most studies do not contemplate unless it is strictly necessary.

Our proposal focuses in a functional evaluation (proxy task), but we consider performing a more in-depth evaluation for a specific domain in future work. We based our proposal in Moreo et al. (2012a). They tried a similar approach in a frequent answered questions (FAQ) retrieval method and continued with Moreo et al. (2017, 2013, 2012b). However, this model computes the whole set of minimal differentiator expressions, which is computationally eager and it is only viable in closed domains like the one proposed by the authors. It is not a valid solution for an open, always-growing environment like Social Media.

3. Preliminary Study

There are interpretable classifiers, such as decision trees (DT) or k-nearest neighbours (kNN), that can be used to build interpretable models. However, this is only doable in theory as actual models are too complex to be understandable. We justify in this section the necessity of new approaches that yield more comprehensible models.

There is a neat question regarding how many aspects can be handled by humans. In 1956, Miller (1956) established precedent in what would be considered
working memory. The article shows that $7 \pm 2$ is the number of chunks that a person can remember for a short time. The author referred to that number as a unitary measure but not in terms of minimum possible unit. That means that any human can handle between 5 and 9 concepts, situations, facts, melodies, etc., rather than words, movements or sounds (minimum expression). Further research proved that this number could be smaller (Cowan 2001).

Interpretability is not a general concept, and it should be understood within the domain of the studied problem (Rudin 2018; Freitas 2014; Huysmans et al. 2011). Consequently, there is no formula that can be used to measure how interpretable a model is. In order to evaluate it, we need to consider its characteristics.

We have selected three classifiers that can be considered interpretable (Molnar 2018). They are widely used and capable of handling different type of relations between features:

1. k-nearest neighbours (kNN). Given an instance, it retrieves the $k$ most similar instances within the training set. The resulting class (output) would be the mode between the classes of the $k$ closest instances. It can be considered self-explanatory, as it only compares through individuals of the same type. The complexity can be measured in two dimensions, being (1) the number of neighbours ($k$) and (2) the individual itself (number of features required to represent the document).

2. Decision Tree (DT). The particulars regarding how a DT works depend on the algorithm used to build it. In general, they split data into several partitions regarding some criteria. In order to interpret them, one will start in the root node. Each node represent a condition over an attribute with two (or more) possible outcomes (edges). Leaf nodes stand for the output of the classification process. Each path from the root to the leaves can be represented as a rule of AND clauses, each of them being a node. They can be measured in two dimensions: (1) number of leaves (equivalent to number of rules) and (2) length of the path (equivalent to length of the rule).

3. Random Forest (RF). They are collections of Decision Trees. Each DT will be trained with a subset of the training instances. The output can be obtained through the mode or the weighted addition of the individual outputs from decision trees. It is possible to interpret this classifier as individual decision trees with different perspectives of the same reality, as it would happen with a jury of humans. The complexity of the model can be measured in three dimensions: (1) number of trees, (2) number of leaves of each tree and (3) length of each path.

There are another two dimension that we need to consider to measure complexity. They affect all the classifiers mentioned above: comprehensibility and number of features. It is easy to argue that, within the context of our problem, features are as understandable as they can be, since they are sets/sequences of words. That leaves us with number of features.
Table 3: Number of features required to achieve the median $f_1$-score (approx. 0.54) for each feature selection method. Results shown are arithmetic mean and standard deviation through different folds (iterations), classifiers and datasets. See section 5 for more details.

| fs method | mean $f_1$-score | std $f_1$-score | number of features |
|-----------|------------------|-----------------|--------------------|
| CHI2      | 0.551399         | 0.111377        | 20                 |
| ECE       | 0.557570         | 0.061533        | 100                |
| ANOVA     | 0.564128         | 0.074548        | 20                 |
| IG        | 0.546856         | 0.108496        | 20                 |
| MI        | 0.550547         | 0.107467        | 20                 |
| OR        | 0.553999         | 0.071509        | 100                |

Table 4: Out-of-the-box mean performance and complexity measure for several classifiers. Results are obtained as a mean through different feature selection methods and datasets. See section 5 for more details.

| Classifier | $f_1$-score | Complexity Measure |
|------------|-------------|--------------------|
| kNN        | 0.5481      | 20 features        |
| DT         | 0.6277      | 366 rules of 12 clauses |
| RF         | 0.6501      | 100 trees          |

We have conducted several experiments to measure the complexity of the models built with the aforementioned classifiers. We followed a 5-cross fold validation scheme using python 3.8.1 and other libraries (see section 5). All tweets were tokenised and stemmed before selecting features.

Results show that there are still room for improvement. Table 3 shows that it is necessary to deal with at least 20 features in order to have acceptable performance metrics (above median value). Table 4 shows that default methodology yields models that are too complex to be actually comprehensible, despite that they are interpretable models. Since human capacities are limited, it is necessary to find new methods that enhance complexity measures.

4. Discriminatory Expressions

Taking into account aforementioned reasons, we present in this section our proposal to obtain significant feature sets that improve model comprehensibility in microblogging contexts. Words are a tool used to abstract reality. As such, we are the ones that give sense to them, even creating new meanings. However, they require context: it is impossible to communicate effectively without sentences. Given a word, depending on the words that precede or follow it, the meaning can vary from one end to the other. Meaning is not only influenced by the order of the words but also by adjectives, prepositions and even stop words (that are usually removed in preprocessing steps). Some expressions are prone to be interpreted in several ways but they maintain the bias to some extent. We rely on this bias to find the set of expressions that defines a class.
Let \( X = \{d_1, d_2, \ldots, d_n\} \) be a set of documents where each document \( d \in X \) belongs to a class \( C \). We consider \( S \) as the set of stop words.

**Definition 4.1 (Expression).** Given a document \( d \in X \) as a sequence of words \( d = (t_1, t_2, \ldots, t_n) \), \( e \) is said to be an expression of the document, noted as \( e \ expr \ x \), iff:

1. It is not composed strictly by stop words.
2. All words of the expression can be found in the document and the order is preserved (\( e \) is a regular expression that matches the document).

\[
e \ expr \ d \longleftrightarrow \exists t_i \in e : t_i \not\in S \land \frac{|e \ expr \ d|}{|C|} / t_1 \ast t_2 \ast \ldots \ast t_n / \ matches \ d
\] (8)

**Definition 4.2 (Discriminatory expression).** Given \( r \) (minimum relevance or recall) and \( p \) (minimum precision), an expression \( e \) is said to be \((r, p)\)-discriminatory for the class \( C \), noted as \( e \ dexpr_{r, p} \ C \) iff:

1. Recall of \( e \) for the class \( C \) is over a given threshold \( r \).
2. Precision of \( e \) for the class \( C \) is at least \( p \).

\[
e \ dexpr_{r, p} \ C \longleftrightarrow \frac{|e \ expr \ d; d_i \in C|}{|C|} > r \land \frac{|e \ expr \ d; d_i \in X|}{|e \ expr \ d; d_i \in X|} > p
\] (9)

Despite expressions may be an intuitive way to look at microblogging documents, the search space is too complex to be explored completely. There are several ways to obtain suboptimal solutions to this problem (metaheuristic techniques). We used a greedy approach with a custom ranking function based on TF-IDF.

### 4.1. Ranking Method: CF-ICF

We build discriminatory expressions from the words present in the documents of a class. Usually, there are several expressions that can accomplish our criteria, but a few of them are more useful than the rest. As we want to maximise statistical relevance and discriminatory performance, we propose a ranking method based on TF-IDF that takes into consideration the class whose expression we are looking for.

Let \( X \) be a set of documents \( X = \{d_0, d_1, \ldots, d_n\} \) where \( n = |X| \). \( L \) is a binary property that can be present (or not) in each document, such that for a given document \( d_i \in X \), \( L(d_i) \in \{0, 1\} \). We will now define the sets \( X^+_L \subseteq X \) and \( X^-_L \subseteq X \) such that:

\[
X^-_L = \{d \in X : L(d) = 0\}
\] (10)

\[
X^+_L = \{d \in X : L(d) = 1\}
\] (11)
where $n^+_L$ and $n^-_L$ stand for $|X^+_L|$ and $|X^-_L|$, respectively.

The function $f(t, d)$ yields the number of times that a word $t$ appears in the document $d$. From here, we can define classic TF-IDF as follows:

$$tf(t, d, X) = \frac{f(t, d)}{\max\{f(t, d'), \forall d' \in X\}} \quad (12)$$

$$df(t, X) = |\{d \in X : t \text{ in } d\}| \quad (13)$$

$$idf(t, X) = \log \frac{n}{df(t, X)} \quad (14)$$

$$tfidf(t, d, X) = tf(t, d, X)idf(t, X) \quad (15)$$

Now, let $cf(t, L)$ be a function that returns the number of times that the word $t$ appears in the documents of $X^+_L$ and let $d_L = \bigcup_{d \in X^+_L} d$ (meaning that $d_L$ is the result of concatenating all the documents in $X^+_L$). We can define $cf$ as a function of $tf$ using the concatenated $d_L$ as follows:

$$cf(t, L) = \sum_{d \in X^+_L} f(t, d) = tf(t, d_L) \quad (16)$$

In the same way, let $n^-_L(t) = |\{d \in X^-_L : t \text{ in } d\}|$ and $n^+_L(t) = |\{d \in X^+_L : t \text{ in } d\}|$. We can also express IDF as follows:

$$idf(t, X) = \log \frac{n}{n^-_L(t) + n^+_L(t)} \quad (17)$$

Now, $idf$ can be modified to define $icf$, as shown below:

$$icf(t, L, X) = \log \frac{n}{n^-_L(t) + 1} \quad (18)$$

$$cficf(t, L, X) = cf(t, L)icf(t, L, X) \quad (19)$$

The proposed ranking method can be seen in equation (19). It is straightforward to notice that

$$idf(t, X) = icf(t, L, x) \iff n^+_L = 1 \quad (20)$$

$$cficf(t, L, X) = \sum_{d \in X'} tfidf(t, d, X'), \text{ where } X' = \{d_L\} \cup X^-_L \quad (21)$$

We can now study the relation between both methods:

a) If $t$ is only in one document of $X^+_L$ (or none), then:

$$cficf(t, L, X) = \sum_{d \in X^+_L} tfidf(t, d, X) \quad (22)$$
b) If \( t \) is in more than one document of \( X_L^+ \), then:

\[
  cf-icf(t, L, X) > \sum_{d \in X_L^+} tfidf(t, d, X)
\]  

(23)

Note that if \( t \) is in several documents of \( X_L^+ \), then \( CF-ICF \) only depends on the number of times that this word appears in those documents. If \( t \) only appears in \( X_L^+ \), \( ICF \) will be the maximum possible (\( \log n \)), which implies that the maximum possible value for \( CF-ICF \) will also be \( \log n \), since \( cf \) is normalised between [0, 1] and it will only be achieved if exists a word \( t \) that is the most frequent in the class \( L \) and it is not present in the documents of \( X_L^- \).

Figures 1 and 2 describe the behaviour of \( CF-ICF \) when keeping \( cf \) and \( icf \) fixed, respectively. It shows that is more important for the expression to be discriminatory than relevant (\( icf \) decreases faster than \( cf \) grows).

4.2. Discriminatory Expressions Algorithm

The algorithm (1) we propose for feature extraction will compute a set of discriminatory expressions \( D \) taking into consideration that each expression needs to meet some frequency and distinguishability criteria with respect to a class. In other words, each expression \( e \) should be skewed towards a class, such that the frequency in which that expression appears in the class exceeds a certain threshold \( (r) \) meanwhile the ratio between the matches in the class and the total number of matches is above a given boundary \( (p) \).

Once we have the set of discriminatory features, we can transform each document to a binary vector \( (v_i) \) where each component \( v_i \) stands for the appearance of the \( i \)-th discriminatory expression in the document.

Our python implementation can be found in our project’s repository 1.

5. Experiments

We conducted experiments to evaluate the performance of our proposal in terms of classification performance, generalisation capacity and comprehensibility. Through this section, we introduce the datasets we used to run our experiments, along with the specific settings of these.

5.1. Datasets

We used several popular datasets to test our proposal within different contexts and topics. Since it is not feasible to generate synthetic datasets (we extract and select the relevant features directly from plain text), we chose them taking into account dataset diversity (airlines sentiment, IMDB reviews, gender classification...), preciseness and acceptance within scientific community.

1https://github.com/nutcrackerugr/discriminatory-expressions
Figure 1: Behaviour of the CF-ICF ranking method when keeping cf fixed. It can be seen that the function decrease faster than a linear one.

Figure 2: Behaviour of the CF-ICF ranking method when keeping icf still, showing that function grows linearly.
Algorithm 1 DE algorithm

Require: Training set of documents $X$, vector of labels $y$ for each document, minimum required precision $p$, minimum required recall $r$, maximum number of words in an expression $\alpha$, set of stop words $STOPW$

Ensure: Set of discriminatory expressions $D$

1: $D \leftarrow \emptyset$ $\triangleright$ Initialise set of DE
2: for all $d \in X$ do
3: \qquad $o \leftarrow$ QUEUE $\triangleright$ Initialise queue of candidates
4: \qquad $t \leftarrow$ tokenize $d$
5: \qquad stem words from $t$
6: \qquad sort elements in $t$ by $eficf$
7: \qquad put all elements of $t$ in $o$
8: \qquad repeat
9: \qquad \qquad $e \leftarrow$ pop $o$
10: \qquad \qquad $tp \leftarrow$ count $e$ matches in $\{X_i: y_i = True\}$
11: \qquad \qquad $fp \leftarrow$ count $e$ matches in $\{X_i: y_i = False\}$
12: \qquad \qquad $R \leftarrow \frac{tp}{|\{y_i = True\}|}$
13: \qquad \qquad $P \leftarrow \frac{tp}{tp + fp}$
14: \qquad \qquad if $R \geq r$ then $\triangleright$ Check if $e$ is relevant enough
15: \qquad \qquad \qquad if $P \geq p$ and $e \not\subseteq STOPW$ then $\triangleright$ Check if $e$ is discriminatory enough and discard those that are entirely stop words
16: \qquad \qquad \qquad \quad accept $e$
17: \qquad \qquad \qquad $D \leftarrow D \cup e$
18: \qquad \qquad \qquad else if $|e| < \alpha$ then $\triangleright$ Keep exploring until maximum length
19: \qquad \qquad \qquad \quad $n \leftarrow e \times t$
20: \qquad \qquad \qquad \quad put all elements of $n$ in $o$
21: \qquad \qquad end if
22: \qquad end if
23: \qquad until $e$ is accepted
24: end for
25: return $D$
All of these datasets are publicly available, except for Villena-Roman et al. (2015) which can be requested to the authors through their website. Although they all have different feature set, we only used plain text and target class in our experiments.

- **US Airlines Sentiment.** A collection of approximately 15k tweets from Crowdflower’s Data for Everyone library[^1] tagged for sentiment towards US airlines. It contains three classes (positive, neutral and negative, with 2363, 3099 and 9178 instances, respectively) and a total of 14640 tweets.

- **Twitter User Gender.** A dataset of around 25k tweets labelled as *male*, *female*, *brand* or *unknown* from Crowdflower’s Data for Everyone library[^2]. Distribution of instances between classes is as follows: 6700 females, 6194 males, 5942 brands and 1117 unknown samples for a total of 19953 tweets.

- **Sentiment140 dataset** (Go et al., 2009)[^3]. 1.6M instances tagged as *positive* or *negative* sentiment, with 800k instances for each class (balanced).

- **Sentiment Labelled Sentences (SLS) dataset** (IMDB subset) (Kotzias et al., 2015)[^4]. A collection of 3000 instances of sentences labelled into positive and negative classes (balanced).

- **TASS Sentiment Analysis dataset** (Villena-Roman et al., 2015)[^5]. A collection of 7k Spanish tweets gathered by SEPLN, classified in positive, neutral and negative sentiment. Each class has a total of 2884, 2153 and 2182 tweets, respectively.

### 5.2. Feature Selection Methods and Classifiers

We chose to compare our algorithm with several filter methods used in state-of-the-art research articles. These are $\chi^2$ (CHI2), Information Gain (IG), Mutual Information (MI), Odds Ratio (OR), Expected Cross Entropy (ECE), ANOVA F-value ($f$-ANOVA) and Galavotti-Sebastiani-Simi (GSS) coefficient. We described them in section 2.

DE is a filtering method and we should compare it with algorithm of the same category. However, we wanted to evaluate how would it perform against wrappers methods. Per expert recommendation, we also included in the evaluation of the performance a stochastic method called Monte Carlo Features Selection (MCFS). It select features by training classifiers with random subsets of the training instances in order to count how many times a feature is selected (Dramiński et al., 2008).

We used four classifiers that are widely considered interpretable. *k*-nearest neighbours (kNN), Decision Trees (DT), Random Forest (RF) and Logistic Regression (LR). We did not perform hyperparameter tuning on any of them.

[^1]: https://www.figure-eight.com/data-for-everyone
[^2]: https://www.kaggle.com/kazanova/sentiment140
[^3]: https://archive.ics.uci.edu/ml/datasets/Sentiment+Labelled+Sentences
[^4]: https://archive.ics.uci.edu/ml/datasets/Sentiment+Labelled+Sentences
[^5]: http://tass.sepln.org/2017
Although many authors consider LR an interpretable technique, we only used it to check accuracy within a linear model. It is possible to interpret how LR works, but we think it will not be easy for non-technical users to comprehend how it weights the features.

On the contrary, we chose RF since (1) it is straightforward to understand it once you know how DT works, (2) it is easier to comprehend by non-expert users with the analogy that each DT is an individual with its own perspective and (3) it is a more complex model widely used in classification problems which is capable of solving intricate classification scenarios.

5.3. Settings

We performed exhaustive experiments with four different purposes:

- In order to evaluate mean classification performance of the different methods.
- In order to evaluate generalisation capacity.
- In order to check how comprehensible the resulting models are.

We measured all three aspects in terms of mean values and dispersion rate. Performance and comprehensibility test were conducted following a 5-fold cross-validation scheme over four datasets (airlines, gender, IMDB and TASS). In performance-related tests, we included a stochastic method (Monte Carlo FS) that is widely used and can be helpful as a comparison between filters and wrappers. We did not include it in further scenarios since it is not in the same category than the rest.

For the generalisation test, we used a 100-fold cross-validation reversed approach. That means that each partition will have approximately 16000 instances and we will use one partition to train and the 99 remaining ones to validate the model. With this decision, we simulated a situation in which the model has been trained with a small dataset but has to face a real world scenario. It will not be realistic to train supervised models with datasets larger than that, since expert-labelled datasets are expensive to ensemble.

All experiments where run using python 3.8.1, pandas 0.25.3, Natural Language Toolkit (NLTK) 3.4.5 and scikit-learn (sklearn) 0.22. The set of stop words that NLTK offers for each language was enriched with several custom stop words collected by ourselves. All tweets were tokenised using NTLK’s TweetTokenizer class and stemmed using SnowballStemmer from the same package. Tweet classes were binarised.

We used the classifiers and feature selection methods present in sklearn and we implemented those who were not available in the package. Although Information Gain (IG) and Mutual Information (MI) can be proved equal for binary classification problems, we studied them both since they are approximated with different formulas.

With the exception of those test that explicitly evaluate some variable against the number of features, we conducted our experiments using 9 features as much, as we established earlier (see section 3).
Table 5: Classification performance of our proposal (DE) against the rest of the selected methods measured with accuracy, precision, recall, \( f_1 \)-score and area-under-curve ROC when training with 9 features.

| FS method | accuracy | precision | recall | \( f_1 \)-score | ROC AUC |
|-----------|----------|-----------|--------|-----------------|---------|
|           | mean     | std       | mean   | std             | mean    | std     | mean   | std     | mean   | std     |
| CHI2      | 0.6692   | 0.1273    | 0.6763 | 0.1461          | 0.4979  | 0.2845  | 0.5030 | 0.1472  | 0.6226 | 0.0720  |
| DE        | 0.6869   | 0.1156    | 0.6309 | 0.0955          | 0.5367  | 0.1472  | 0.5610 | \textbf{0.0624} | 0.6370 | 0.0540  |
| ECE       | 0.6353   | 0.1267    | 0.5872 | 0.1196          | 0.3950  | 0.2485  | 0.4228 | 0.1525  | 0.5714 | 0.0607  |
| f-ANOVA   | 0.6787   | 0.1198    | 0.6829 | 0.1370          | 0.5282  | 0.2754  | 0.5295 | 0.1306  | 0.6306 | 0.0680  |
| GSS       | 0.6608   | 0.1311    | 0.6691 | 0.1168          | 0.3869  | 0.2189  | 0.4449 | 0.1322  | 0.6102 | 0.0743  |
| IG        | 0.6793   | 0.1194    | 0.7006 | 0.1350          | 0.4756  | 0.2637  | 0.5040 | 0.1335  | 0.6286 | 0.0695  |
| MI        | 0.6784   | 0.1223    | 0.7014 | 0.1456          | 0.4707  | 0.2698  | 0.5044 | 0.1379  | 0.6280 | 0.0694  |
| OR        | 0.6500   | 0.1229    | 0.6033 | 0.1079          | 0.4214  | 0.2200  | 0.4591 | 0.1330  | 0.5927 | 0.0649  |
| MCFS      | 0.6194   | 0.1396    | 0.5900 | 0.1139          | 0.5182  | 0.2754  | 0.4906 | 0.1479  | 0.5789 | 0.0655  |

6. Results and Discussion

In this section, we analyse the results of the experiments described above. We evaluated classification performance, stability across experiments, generalisation capacity and comprehensibility. Generally, plots show dataset mean results meanwhile tables have a more detailed perspective (separated by datasets). Conducted experiments depend on four dimensions: dataset, feature selection method, number of features, and classifier. Although, we have set fixed conditions for some of them (see section 5).

6.1. Classification Performance

There are several ways of measuring how good a classification model is, but we are going to focus on \( f_1 \)-score because its ability to work with imbalanced classes. Table 5 shows accuracy, precision, recall, \( f_1 \)-score and area-under-curve ROC. Presented values correspond to the mean between cross-validation folds, datasets and classifiers. Figure 3 shows \( f_1 \)-score evolution against the number of features.

Features selected by Discriminatory Expressions (DE) are more useful to train a classifier with a reduced feature space. As the number of features increases, the rest of methods get closer and even surpass DE in some cases. This happens when the number of features is higher than the amount that we can consider feasible to be managed by humans (see section 3). When varying the classifier, table 6 shows that our proposal works better than the rest for 3 out of 4 classifiers.

In order to prove that a new feature selection method performs well, it is also necessary to consider measures of dispersion. In the aforementioned tables, it is possible to check that DE dispersion is the lowest among the rest. Table 7 shows additional deviation measurements. Discriminatory Expressions (DE) is significantly more stable than the rest of them. Figure 4 depicts the dispersion of the performance for each feature selection method while varying the number of features. They show that our proposal is more stable through different
| Classifier | accuracy | precision | recall | f1-score | ROC AUC |
|------------|----------|-----------|--------|----------|---------|
| CHI2       |          |           |        |          |         |
| DT         | 0.6805   | 0.6912    | 0.1333 | 0.5277   | 0.6329  |
| LR         | 0.6782   | 0.6951    | 0.1382 | 0.4566   | 0.6257  |
| RF         | 0.6806   | 0.6906    | 0.1328 | 0.5289   | 0.6368  |
| kNN        | 0.6374   | 0.6283    | 0.1743 | 0.4782   | 0.5981  |
| DE         |          |           |        |          |         |
| DT         | 0.6791   | 0.5970    | 0.1032 | 0.5184   | 0.6359  |
| LR         | 0.7070   | 0.6871    | 0.0930 | 0.5342   | 0.6571  |
| RF         | 0.6970   | 0.6557    | 0.0832 | 0.5302   | 0.6501  |
| kNN        | 0.6644   | 0.5837    | 0.0646 | 0.5641   | 0.6649  |
| ECE        |          |           |        |          |         |
| DT         | 0.6398   | 0.5942    | 0.1281 | 0.3978   | 0.5769  |
| LR         | 0.7066   | 0.6909    | 0.0948 | 0.3800   | 0.5802  |
| RF         | 0.6413   | 0.5909    | 0.1205 | 0.4222   | 0.5781  |
| kNN        | 0.6095   | 0.5365    | 0.1209 | 0.3799   | 0.5503  |
| f-ANOVA    |          |           |        |          |         |
| DT         | 0.6822   | 0.6797    | 0.1360 | 0.5748   | 0.6354  |
| LR         | 0.6830   | 0.6842    | 0.1318 | 0.5476   | 0.6325  |
| RF         | 0.6826   | 0.6796    | 0.1353 | 0.5756   | 0.6360  |
| kNN        | 0.6670   | 0.6883    | 0.1521 | 0.4149   | 0.6183  |
| GSS        |          |           |        |          |         |
| DT         | 0.6792   | 0.6973    | 0.0922 | 0.3321   | 0.6251  |
| LR         | 0.6814   | 0.7075    | 0.0843 | 0.3104   | 0.6117  |
| RF         | 0.6806   | 0.6928    | 0.0872 | 0.3407   | 0.6269  |
| kNN        | 0.6020   | 0.5789    | 0.1472 | 0.5644   | 0.5769  |
| IG         |          |           |        |          |         |
| DT         | 0.6818   | 0.6952    | 0.1347 | 0.5307   | 0.6346  |
| LR         | 0.6774   | 0.6971    | 0.1302 | 0.3964   | 0.6230  |
| RF         | 0.6819   | 0.6948    | 0.1344 | 0.5326   | 0.6355  |
| kNN        | 0.6762   | 0.7155    | 0.1475 | 0.4426   | 0.6213  |
| MI         |          |           |        |          |         |
| DT         | 0.6845   | 0.7156    | 0.1407 | 0.4987   | 0.6365  |
| LR         | 0.6813   | 0.7166    | 0.1421 | 0.3965   | 0.6275  |
| RF         | 0.6847   | 0.7153    | 0.1403 | 0.5001   | 0.6373  |
| kNN        | 0.6632   | 0.6582    | 0.1585 | 0.5236   | 0.6374  |
| OR         |          |           |        |          |         |
| DT         | 0.6543   | 0.6082    | 0.1058 | 0.4565   | 0.6014  |
| LR         | 0.6576   | 0.6288    | 0.0949 | 0.3574   | 0.5921  |
| RF         | 0.6564   | 0.6098    | 0.1021 | 0.4628   | 0.6039  |
| kNN        | 0.6317   | 0.5965    | 0.1235 | 0.4087   | 0.5734  |
| MCFS       |          |           |        |          |         |
| DT         | 0.6242   | 0.6042    | 0.1118 | 0.5216   | 0.5848  |
| LR         | 0.6305   | 0.6110    | 0.1128 | 0.5297   | 0.5902  |
| RF         | 0.6255   | 0.6016    | 0.1064 | 0.5330   | 0.5860  |
| kNN        | 0.5975   | 0.5432    | 0.1177 | 0.4887   | 0.5547  |

Table 6: Detailed performance of the feature selection methods for each classifier, trained with 9 features. Listed metrics are the mean values across datasets and folds. Our proposal has the best results for 3 out of 4 classifiers.
6.2. Generalisation Capacity

In order to measure how good a method models reality when training with small datasets, we used a reversed 100-fold cross-validation scheme. We split our data into 100 partitions and we measure the performance when classifying 99 partitions having trained with only one of them. This means that, for each fold, the model trained with approximately 16k instances and it was asked then to classify 1.5 million instances. As in the rest of the experiments, we considered 9 features. We considered mean and dispersion rates for accuracy, precision, recall, $f_1$-score and area under the curve ROC. Table 8 shows the behaviour of the feature selection method for our biggest dataset (Sentiment140). Results show that our proposal not only has the best mean generalisation capacity but also the lowest deviation.

6.3. Comprehensibility

As we established earlier, there is no global measure of interpretability. In this section, we will perform an analysis on the practical interpretability of the
Table 7: Further measurements of performance dispersion for our proposal (DE) against the rest of the selected methods measured with range, interquartile range (IQR), standard deviation (STD) and coefficient of variation (CV) when training with 9 features.

| FS method | range | IQR   | STD   | CV (%) |
|-----------|-------|-------|-------|--------|
| CHI2      | 0.6730| 0.1732| 0.1472| 29.2623|
| DE        | **0.2977** | **0.1008** | **0.0624** | **11.1313** |
| ECE       | 0.5772| 0.2161| 0.1525| 36.0694|
| f-ANOVA   | 0.6276| 0.1829| 0.1306| 24.6674|
| GSS       | 0.4964| 0.1330| 0.1322| 29.7014|
| IG        | 0.5860| 0.2020| 0.1335| 26.4790|
| MI        | 0.6420| 0.1625| 0.1379| 27.3400|
| OR        | 0.5174| 0.1801| 0.1330| 28.9810|
| MCFS      | 0.6479| 0.2634| 0.1479| 30.1403|

Figure 4: f1-score dispersion between iterations for each fold, classifier and dataset while varying the number of features. Our proposal shows a lower dispersion and, generally, better performance while working with a low number of features.
Table 8: Mean generalisation capacity and its deviation for a reversed 100-fcv using 9 features with Sentiment140 dataset. Results are the mean between folds and classifiers. Our proposal has a slightly superior \( f_1 \)-score than the rest. It is also the most stable one.

| FS method | accuracy | precision | recall | \( f_1 \)-score | ROC AUC |
|-----------|----------|-----------|--------|----------------|---------|
|            | mean     | std       | mean   | std            | mean    | std   |
| CHI2       | 0.5781   | 0.0071    | 0.5672 | 0.0672         | 0.8805  | 0.2320 |
| DE         | 0.6526   | 0.0161    | 0.6313 | 0.0198         | 0.7446  | 0.0988 |
| ECE        | 0.5370   | 0.0068    | 0.5790 | 0.0553         | 0.4557  | 0.2946 |
| f-ANOVA    | 0.5776   | 0.0097    | 0.5684 | 0.0702         | 0.8750  | 0.2378 |
| GSS        | 0.5865   | 0.0208    | 0.7009 | 0.0438         | 0.3324  | 0.1274 |
| IG         | 0.5784   | 0.0085    | 0.5605 | 0.0606         | 0.9092  | 0.1936 |
| MI         | 0.5784   | 0.0086    | 0.5650 | 0.0670         | 0.8941  | 0.2176 |
| OR         | 0.5549   | 0.0155    | 0.6559 | 0.0645         | 0.3059  | 0.1941 |
| MCFS       | 0.6194   | 0.1396    | 0.5900 | 0.1139         | 0.5182  | 0.2754 |

models that result from each feature selection method.

\( k \)-nearest neighbours (kNN) get the \( k \) most similar neighbours to the one that is being classified and outputs the majority class. The interpretation is straightforward, since it is a mere comparison. Hence, the fewer neighbours you need to consider, the better. Likewise, the lower the number of features the better, because that means there will be less dimensions when comparing similarities. In order to measure overall performance versus complexity, we will use equation (24):

\[
\text{comprehensibility rate} = \sum_k \frac{f_1 \text{-score}}{k}
\]

since the comprehensibility decays with the number of neighbours \( k \) considered.

Table 9 shows performance results for different number of neighbours and 9 features. Figure 5 shows different dispersion measures between folds and datasets for \( f_1 \)-score values with respect to the number of considered neighbours. Discriminatory Expressions (DE) method has its better comprehensibility rate grouped under 9 neighbours, without significant difference than when using 5 of them.

Decision Trees (DT) interpretation relies not only in the number of features selected but also in (1) the number of leaves (equivalent to number of rules) and (2) the length of the path from the root to each leaf node. In both cases, less is better. We consider that the desired decision tree will be have approximately 10 rules of 5 clauses each. Hence, we will be measuring the complexity with equation (25):

\[
\text{complexity} = \frac{\text{no. rules}}{\text{baseline rules}} \left( \frac{\text{no. clauses}}{\text{baseline clauses}} \right)^2
\]

We used the squared relation between the number of clauses and the desired one because the length of the rule would affect more to the comprehensibility than the number of rules. The relation between accuracy and complexity will respond to equation (26).
Table 9: Classification performance measure with $f_1$-score against $k$-nearest neighbours (kNN) feature selection method. The lower the number of neighbours and the higher the $f_1$-score, the better.

| FS method | 5     | 7     | 9     | 10    | 25    | $\sum \frac{f_1}{k}$ mean |
|-----------|-------|-------|-------|-------|-------|---------------------------|
| CHI2      | 0.5091| 0.19  | 0.5120| 0.18  | 0.5285| 0.16                      | 0.4442 | 0.15 | 0.5353 | 0.10 | 0.2995 |
| DE        | 0.5693| 0.14  | 0.5641| 0.13  | 0.5702| 0.14                      | 0.3616 | 0.24 | 0.5722 | 0.14 | 0.3169 |
| ECE       | 0.5056| 0.12  | 0.3808| 0.20  | 0.3957| 0.20                      | 0.2946 | 0.13 | 0.3721 | 0.14 | 0.2438 |
| f-ANOVA   | 0.5285| 0.15  | 0.5749| 0.12  | 0.5729| 0.11                      | 0.5722 | 0.11 | 0.5058 | 0.12 | 0.3289 |
| GSS       | 0.4360| 0.21  | 0.4278| 0.22  | 0.4513| 0.21                      | 0.3987 | 0.18 | 0.4295 | 0.17 | 0.2555 |
| IG        | 0.6148| 0.05  | 0.6271| 0.04  | 0.5935| 0.09                      | 0.5391 | 0.08 | 0.5351 | 0.08 | 0.3538 |
| MI        | 0.4691| 0.23  | 0.4781| 0.22  | 0.4676| 0.23                      | 0.3799 | 0.20 | 0.4583 | 0.23 | 0.2704 |
| OR        | 0.5595| 0.08  | 0.5293| 0.08  | 0.5228| 0.09                      | 0.4838 | 0.10 | 0.5094 | 0.10 | 0.3144 |

Figure 5: Performance comparison between kNN models generated using different feature sets. The plot shows the number of neighbours considered (less is better) against $f_1$-score. Our proposal performance remain between the top approaches for this classifier while needing a low number of features and neighbours.
Table 10: Performance and complexity measures of DT-based models. Number of leaves (rules) and path length (clauses) can be used to compare how comprehensible are the models that result from training with different feature sets.

TABLE 10

| FS method | f1-score mean (std) | rules mean (std) | clauses mean (std) | complexity compr. rate mean (std) |
|-----------|---------------------|-----------------|-------------------|----------------------------------|
| CHI2      | 0.5995 (0.08)       | 95.2500 (142.71)| 8.6858 (3.41)     | 28.74 (2.08)                    |
| DE        | 0.5711 (0.14)       | 27.2500 (10.43) | 6.8067 (0.32)     | 5.05 (11.30)                    |
| ECE       | 0.4623 (0.13)       | 346.2500 (398.57)| 11.74 (5.3)       | 28.74 (2.08)                    |
| f-ANOVA   | 0.5939 (0.09)       | 78.7500 (104.26)| 8.590 (3.02)      | 23.23 (2.55)                    |
| GSS       | 0.4486 (0.19)       | 37.5000 (14.88) | 7.8571 (0.70)     | 9.26 (4.84)                     |
| IG        | 0.6051 (0.08)       | 99.7500 (141.43)| 8.6970 (3.15)     | 30.17 (2.00)                    |
| MI        | 0.5927 (0.09)       | 95.5000 (138.48)| 8.2910 (3.37)     | 26.25 (2.25)                    |
| OR        | 0.5167 (0.12)       | 323.7500 (363.75)| 10.8829 (2.75)    | 153.37 (0.33)                   |

Comprehensibility rate = 100 - \( \frac{f1\text{-score}}{\text{complexity}} \) \hspace{1cm} (26)

Table 10 shows \( f1\text{-score} \) against complexity measures (number of leaves and mean length of the path). Our proposal is the only filter that manages to score good in classification performance while keeping a simple DT, both in terms of mean and dispersion measures.

Figure 6 shows centrality and dispersion measurements on the number of rules and their length. It also shows the classification performance. It is possible to notice that Discriminatory Expressions method is (1) the feature set that produces the simpler trees (the closer to the bottom left corner, the better), (2) the most stable in both dimensions (shortest whiskers) and (3) the feature set that produces one of the best performing models (dot size).

Finally, Random Forests (RF) are basically collections of DTs. Their complexity can be evaluated in the same way than decision trees, but it is necessary to consider an additional dimension, that is the number of trees in the forest (fewer is better). Hence, complexity measure will now reflect this new dimension as in equation \( \text{27} \):

\[
\text{complexity} = \frac{\text{no. trees} \cdot \text{no. rules}}{\text{baseline trees} \cdot \text{baseline rules}} \left( \frac{\text{no. clauses}}{\text{baseline clauses}} \right)^2
\] \hspace{1cm} (27)

The comprehensibility rate will not suffer further changes. Table 11 shows \( f1\text{-score} \) and complexity measures. Discriminatory Expressions method manages to perform well in terms of accuracy while keeping a minimum deviation. Figure 7 shows centrality and dispersion measurements for each feature set, while figure 8 shows the rate between accuracy and complexity. Our proposal has the best behaviour among the tested methods.

7. Contributions and Limitations

In this section, we summarise the contributions and limitations of our work.
Figure 6: Complexity measures comparison between DT models generated using different feature sets. The plot shows the mean number of leaves (fewer is better) as well as the mean length of the paths to those leaves (less is better). The size of each marker stands for the $f_1$-score and the error bars represent the dispersion (standard deviation) for each dimension. Our proposal keeps the lowest complexity of the model while keeping one of the best performances.

| FS method | $f_1$-score | leaves | length | complexity compr. rate |
|-----------|-------------|--------|--------|------------------------|
|           | mean | std | mean | std | mean | std | mean | mean |
| CHI2      | 0.6039 0.08 | 105.3000 126.73 | 9.2564 3.18 | 36.08 | 1.67 |
| DE        | 0.5707 0.14 | 41.9000 19.93 | 7.4953 0.62 | 36.08 | 1.67 |
| ECE       | 0.4681 0.13 | 368.9000 377.17 | 11.7672 2.82 | 204.32 | 0.22 |
| F-ANOVA   | 0.5954 0.10 | 98.3000 104.34 | 9.1386 2.47 | 32.83 | 1.81 |
| GSS       | 0.4485 0.18 | 58.6500 28.79 | 8.4637 0.82 | 16.80 | 2.66 |
| IG        | 0.6102 0.08 | 111.2000 118.40 | 9.4097 2.30 | 39.38 | 1.54 |
| MI        | 0.5937 0.09 | 109.8500 124.97 | 9.4794 3.01 | 39.48 | 1.50 |
| OR        | 0.5309 0.13 | 341.1000 349.87 | 11.5126 2.68 | 180.83 | 2.29 |

Table 11: Performance and complexity measures of RF-based models when training with 5 trees. Number of leaves (rules) and path length (clauses) can be used to compare how comprehensible are the models that result from training with different features selection mechanisms.
Figure 7: Comprehensibility comparison between the inner trees of RF models generated using different feature sets. The plot shows the mean number of leaves (less is better) as well as the mean length of the paths to those leaves (less is better). The size of each marker stands for the $f_1$-score and the error bars represent the dispersion (standard deviation) for each dimension. Our proposal keeps the lowest complexity of the model while keeping one of the best performances and stabilities.

Figure 8: Comprehensibility rate for RF models when varying the number of trees in each forest. The rate decreases as the number of trees increases.
We proposed the use of expression as features instead of words or other tokens. We based this decision on the work of linguists when analysing text. They consist on sequences of words in a certain order that may have others words in between. Not only these features are more interpretable to humans but they also add certain context to document encoding that may help classifiers in disambiguation. Moreover, we take advantage of stop words, since we do not discard them immediately as most models do. Instead, we use them to specialise expressions so that they are more accurate. Despite most of the methods we tested were filters, they proved to be more sensible to the classifier (and dataset) than ours. Discriminatory Expressions (DE) would be less disrupted by external facts like context and/or classifier.

The decision of using a filtering method is also influenced by interpretability. The notion of optimising the feature subset to the classifiers is against transparency to some extent. Wrappers adapt their selection to the performance of the subsequent classifier, while filters are based on a priori information.

Moreover, current interpretable machine learning (ML) models are not so interpretable in actual fact. Due to the complexity of our reality, trained models result in a vast number of rules with a large number of chained clauses that are nearly impossible to understand in practice. We presented a method that is capable of maintaining an acceptable performance while diminishing the complexity of the subsequent classifier. This is specially noticeable when using Decision Trees.

However, our method selects a relevant feature set but the classification performance does not improve much with the number of features. In other words, discriminatory expressions enhance accuracy with a low number of features but reaches a performance ceiling when augmenting the number of features. We believe this may be related to target recall and relevance and may be overcome by gradually decreasing both parameters.

Summing up, we would recommend the use of our method:

- When actual interpretability is required.
- With any classifier, but specially with decision trees.
- When features need to be explainable by itself.
- When fewer features are preferred.

8. Conclusions

Nowadays, Social Media has become one of the most important sources of information and a crucial way of communication. Microblogging sites are being used to analyse certain aspects of our reality, due to their peculiarities such as promptness and versatility. However, short-text messages present handicaps when training machine learning models, such as contractions or misspelled words. In recent years, machine learning has focused mainly on improving
classification performance rather than coping with these handicaps in an interpretable manner. Thus, state-of-the-art approaches are black-box models that should not be used to take or assist decisions that may have a social impact.

Despite that we may think that there are interpretable classifiers that can be used to build interpretable models, the fact is that the resulting ones are too complex to be actually interpretable. They usually require a large number of rules with several clauses, which reduces the comprehensibility since we humans have limited capacity. It is necessary to obtain new approaches that lead us to authentic transparency in artificial intelligence. We thought that feature selection was a good starting point, provided that it is the initial step in machine learning pipelines.

We selected several methods and classifiers that are widely used, both in scientific literature and commercial solutions, and we conducted several experiments in order to perform a preliminary study to check whether current methods are good enough to be comprehensible when combined with interpretable classifiers. Our results showed that there was still room for improvement.

We developed a feature selection algorithm for microblogging contexts where interpretability is mandatory that focused in obtaining a well-structured set of significant features in order to improve the comprehensibility of the model while offering good classification performance. We used expressions (sequences of words) that are biased towards specific classes, inspired in linguists procedures when analysing text. In order to assemble those expressions, we introduced a word ranking method that we have called CF-ICF. This method is capable of scoring words in two dimensions: statistical relevance and discriminative power (that is, bias towards an specific class).

We conducted exhaustive experiments to compare current methods with our proposal, in terms of classification accuracy, generalisation capacity and comprehensibility of the resulting models. We compared eight different feature selection methods using five different popular datasets. We followed a cross-validation scheme to ensure the integrity of the results with four different classifiers.

Results showed that our algorithm achieves a good baseline performance (without hyperparameter tuning) while being the most stable method regardless of the context and classifier used. For each iteration and fold, our algorithm yields close results, minimising deviations in almost every case, with a big difference with respect to the rest of the studied methods. It happens the same with the generalisation capacity, since our algorithm is the best both in terms of mean value and dispersion rate. It is also noticeable that classification performance does not improve significantly with the number of features, which proves that our feature set is quite relevant from the beginning.

As for comprehensibility, our proposal manage to score among the best for every case. When combined with decision trees, our algorithm reduces drastically the complexity of the models without loosing $f1$-score. Complexity deviation is also one the lowest of the eight selected methods, one order of magnitude lower than the majority of them. When used to train random forests, our proposal gives the best overall results of accuracy versus complexity.
9. Future Work

There are several lines of future work, including a more in-depth evaluation of interpretability, focusing in an application-level analysis within a specific application. We also plan to perform analytical studies on hyperparameter fine-tuning to maximise both performance and comprehensibility. This is also the first step towards an interpretable pipeline, and we plan to continue proposing novel methods and/or modifications of current ones to obtain a fully comprehensible classification pipeline.

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References

AK, J., & Zongker, D. (1997). Feature Selection: Evaluation, Application, and Small Sample Performance. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 19, 153–158. doi:10.1109/34.574797.

Al-Salemi, B., Mohd Noah, S. A., & Ab Aziz, M. J. (2016). RFBoost: An improved multi-label boosting algorithm and its application to text categorisation. Knowledge-Based Systems, 103, 104–117. doi:10.1016/j.knosys.2016.03.029.

Alharbi, A., & de Doncker, E. (2019). Twitter sentiment analysis with a deep neural network: An enhanced approach using user behavioral information. Cognitive Systems Research, 54, 50–61. doi:10.1016/j.cogsys.2018.10.001.

Alsaig, A., Alsaig, A., Alsadun, M., & Barghi, S. (2019). Context based algorithm for social influence measurement on Twitter. Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST, 266, 136–149. doi:10.1007/978-3-030-06152-4_12.

Arroyo-Fernández, I., Curiel, A., & Méndez-Cruz, C.-F. (2019). Language features in extractive summarization: Humans Vs. Machines. Knowledge-Based Systems, 180, 1–11. URL: http://www.sciencedirect.com/science/article/pii/S0950705119302205 doi:10.1016/j.knosys.2019.05.014.

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J.,
Winter, C., Hesse, C., Chen, M., Sigler, E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I., & Amodei, D. (2020). Language Models are Few-Shot Learners. *arXiv:2005.14165 [cs]*, [URL](http://arxiv.org/abs/2005.14165). ArXiv: 2005.14165.

Caropreso, M. F., Matwin, S., & Sebastiani, F. (2001). A Learner-Independent Evaluation of the Usefulness of Statistical Phrases for Automated Text Categorization.

Carvalho, D. V., Pereira, E. M., & Cardoso, J. S. (2019). Machine Learning Interpretability: A Survey on Methods and Metrics. *Electronics, 8*, 832. [URL](https://www.mdpi.com/2079-9292/8/8/832) doi:10.3390/electronics8080832.

Castellanos, A., Cigarrn, J., & Garca-Serrano, A. (2017). Formal Concept Analysis for Topic Detection. *Inf. Syst., 66*, 24–42. doi:10.1016/j.is.2017.01.008.

Cowan, N. (2001). The magical number 4 in short-term memory: a reconsideration of mental storage capacity. *The Behavioral and Brain Sciences, 24*, 87–114; discussion 114–185.

Deng, X., Li, Y., Weng, J., & Zhang, J. (2019). Feature selection for text classification: A review. *Multimedia Tools and Applications, 78*, 3797–3816. [URL](https://doi.org/10.1007/s11042-018-6083-5) doi:10.1007/s11042-018-6083-5.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv:1810.04805 [cs]*, [URL](http://arxiv.org/abs/1810.04805) ArXiv: 1810.04805.

Ding, J., & Fu, L. (2018). A Hybrid Feature Selection Algorithm Based on Information Gain and Sequential Forward Floating Search. *Journal of Intelligent Computing, 9*, 93. [URL](http://www.dline.info/jic/fulltext/v9n3/jicv9n3_1.pdf) doi:10.6025/jic/2018/9/3/93-101.

Doshi-Velez, F., & Kim, B. (2017). Towards A Rigorous Science of Interpretable Machine Learning. *arXiv:1702.08608 [cs, stat]*, [URL](http://arxiv.org/abs/1702.08608) ArXiv: 1702.08608.

Dramiński, M., Rada-Iglesias, A., Enroth, S., Wadelius, C., Koronacki, J., & Komorowski, J. (2008). Monte Carlo feature selection for supervised classification. *Bioinformatics (Oxford, England), 24*, 110–7. doi:10.1093/bioinformatics/btn486.

Dy, J. G., & Brodley, C. E. (2004). Feature Selection for Unsupervised Learning. *The Journal of Machine Learning Research, 5*, 845–889.
FAT/ML (2019). Principles for accountable algorithms and a social im-
impact statement for algorithms. URL: http://www.fatml.org/resources/
principles-for-accountable-algorithms

Forman, G. (2003). An extensive empirical study of feature selection metrics 
for text classification [J]. Journal of Machine Learning Research - JMLR, 3.

Freitas, A. A. (2014). Comprehensible classification models: a position paper. 
ACM SIGKDD Explorations Newsletter, 15, 1–10. URL: https://doi.org/
10.1145/2594473.2594475 doi:10.1145/2594473.2594475.

Galavotti, L., Sebastiani, F., & Simi, M. (2000). Experiments on the Use of 
Feature Selection and Negative Evidence in Automated Text Categorization. In J. Borbinha, & T. Baker (Eds.), Research and Advanced Technology for 
Digital Libraries Lecture Notes in Computer Science (pp. 59–68). Berlin, 
Heidelberg: Springer. doi:10.1007/3-540-45268-0_6

Gasco, L., Clavel, C., Asensio, C., & de Arcas, G. (2019). Beyond sound level 
monitoring: Exploitation of social media to gather citizens subjective response 
to noise. Science of the Total Environment, 658, 69–79. doi:10.1016/j.
scitotenv.2018.12.071

Go, A., Bhayani, R., & Huang, L. (2009). Twitter sentiment classification using 
distant supervision. Processing, 150.

Green, R., & Sheppard, J. (2013). Comparing frequency- and style-based fea-
tures for twitter author identification. In FLAIRS Conference (pp. 64–69).

Han, J., Pei, J., & Yin, Y. (2000). Mining Frequent Patterns Without Can-
idate Generation. In Proceedings of the 2000 ACM SIGMOD International 
Conference on Management of Data SIGMOD ’00 (pp. 1–12). New York, NY, 
USA: ACM. doi:10.1145/342009.335372

Hanff, Alexander (2018). The Cold World of Algorithmic Censorship 
- Alexander Hanff - Medium. URL: https://medium.com/@a.hanff/
the-cold-world-of-algorithmic-censorship-5d63d8d4748

Hans, C., Dobra, A., & West, M. (2005). Shotgun Stochastic Search for “Large 
p” Regression. Journal of the American Statistical Association, 102. doi:10.
2307/27639881

Huysmans, J., Dejaegere, K., Mues, C., Vanthienen, J., & Baesens, B. (2011). 
An empirical evaluation of the comprehensibility of decision table, tree and 
rule based predictive models. Decision Support Systems, 51, 141–154. doi:10.
1016/j.dss.2010.12.003

Internet Live Stats (2020). Twitter usage statistics - internet live stats. URL: 
https://www.internetlivestats.com/twitter-statistics/
Jorgens, H., Kolleck, N., & Saerbeck, B. (2016). Exploring the hidden influence of international treaty secretariats: using social network analysis to analyse the Twitter debate on the Lima Work Programme on Gender. *Journal of European Public Policy, 23*, 979–998. doi:10.1080/13501763.2016.1162836

Kotzias, D., Denil, M., Freitas, N. d., & Smyth, P. (2015). From Group to Individual Labels Using Deep Features. In *KDD ’15* (pp. 597–2013). doi:10.1145/2783258.2783380

Kumar, P., Choudhury, T., Rawat, S., & Jayaraman, S. (2016). Analysis of Various Machine Learning Algorithms for Enhanced Opinion Mining Using Twitter Data Streams. In *2016 International Conference on Micro-Electronics and Telecommunication Engineering (ICMETE)* (pp. 265–270). doi:10.1109/ICMETE.2016.19

Largerón, C., Moulin, C., & Géry, M. (2011). Entropy based feature selection for text categorization. In W. C. Chu, W. E. Wong, M. J. Palakal, & C.-C. Hung (Eds.), *ACM Symposium on Applied Computing* (pp. 924–928). TaiChung, Taiwan: ACM. URL: https://hal.archives-ouvertes.fr/hal-00617969 doi:10.1145/1982185.1982389

Lee, D., & Hosanagar, K. (2014). *Impact of Recommender Systems on Sales Volume and Diversity.*

Lee, D., & Hosanagar, K. (2016). When Do Recommender Systems Work the Best?: The Moderating Effects of Product Attributes and Consumer Reviews on Recommender Performance. In *Proceedings of the 25th International Conference on World Wide Web* WWW ’16 (pp. 85–97). Republic and Canton of Geneva, Switzerland: International World Wide Web Conferences Steering Committee. URL: https://doi.org/10.1145/2872427.2882976 doi:10.1145/2872427.2882976 event-place: Montréal, Québec, Canada.

Lee, J., Park, J., Kim, H.-C., & Kim, D.-W. (2019). Competitive Particle Swarm Optimization for Multi-Category Text Feature Selection. *Entropy, 21*, 602. URL: http://adsabs.harvard.edu/abs/2019Entrp..21..602L doi:10.3390/e21060602

Li, C., Sun, A., & Datta, A. (2012). Twevent: Segment-based Event Detection from Tweets. In *Proceedings of the 21st ACM International Conference on Information and Knowledge Management* CIKM ’12 (pp. 155–164). New York, NY, USA: ACM. doi:10.1145/2396761.2396785

Li, Q., Jin, Z., Wang, C., & Zeng, D. D. (2016). Mining opinion summarizations using convolutional neural networks in Chinese microblogging systems. *Knowledge-Based Systems, 107*, 289–300. URL: http://www.sciencedirect.com/science/article/pii/S0950705116301782 doi:10.1016/j.knosys.2016.06.017
Liang, H., Sun, X., Sun, Y., & Gao, Y. (2017). Text feature extraction based on deep learning: a review. EURASIP Journal on Wireless Communications and Networking, 2017. URL: https://jwcn-eurasipjournals.springeropen.com/articles/10.1186/s13638-017-0993-1 doi:10.1186/s13638-017-0993-1

Meiri, R., & Zahavi, J. (2006). Using simulated annealing to optimize the feature selection problem in marketing applications. European Journal of Operational Research, 171, 842–858. URL: http://www.sciencedirect.com/science/article/pii/S0377221704005892 doi:10.1016/j.ejor.2004.09.010

Miller, G. A. (1956). The magical number seven, plus or minus two: some limits on our capacity for processing information. Psychological Review, 63, 81–97. doi:10.1037/h0043159

Misangyi, V. F., LePine, J. A., Algina, J., & Francis Goeddeke, J. (2016). The Adequacy of Repeated-Measures Regression for Multilevel Research: Comparisons With Repeated-Measures ANOVA, Multivariate Repeated-Measures ANOVA, and Multilevel Modeling Across Various Multilevel Research Designs. Organizational Research Methods, . URL: https://journals.sagepub.com/doi/10.1177/1094428105283190 doi:10.1177/1094428105283190

Molnar, C. (2018). Interpretable Machine Learning. Leanpub. URL: https://leanpub.com/interpretable-machine-learning

Moreo, A., Castro, J., & Zurita, J. (2017). Towards portable natural language interfaces based on case-based reasoning. Journal of Intelligent Information Systems, 49, 281–314. doi:10.1007/s10844-017-0453-8

Moreo, A., Eisman, E., Castro, J., & Zurita, J. (2013). Learning regular expressions to template-based FAQ retrieval systems. Knowledge-Based Systems, 53, 108–128. doi:10.1016/j.knosys.2013.08.018

Moreo, A., Navarro, M., Castro, J. L., & Zurita, J. M. (2012a). A high-performance FAQ retrieval method using minimal differentiator expressions. Knowledge-Based Systems, 36, 9–20. URL: http://www.sciencedirect.com/science/article/pii/S0950705112001657 doi:10.1016/j.knosys.2012.05.015

Moreo, A., Romero, M., Castro, J., & Zurita, J. (2012b). FAQtory: A framework to provide high-quality FAQ retrieval systems. Expert Systems with Applications, 39, 11525–11534. doi:10.1016/j.eswa.2012.02.130

Nassar, L., Ibrahim, R., & Karray, F. (2016). Enhancing Topic Detection in Twitter Using the Crowdsourcing Process. In 2016 International Conference on Collaboration Technologies and Systems (CTS) (pp. 196–203). doi:10.1109/CTS.2016.0049.
O’Dair, M., & Fry, A. (2019). Beyond the black box in music streaming: the impact of recommendation systems upon artists. *Popular Communication*, . doi:10.1080/15405702.2019.1627548

Periñán-Pascual, C., & Arcas-Túnez, F. (2019). Detecting environmentally-related problems on Twitter. *Biosystems Engineering, 177*, 31–48. doi:10.1016/jbiosystemseng.2018.10.001

Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., & Zettlemoyer, L. (2018). Deep contextualized word representations. *arXiv:1802.05365 [cs]*, . URL: [http://arxiv.org/abs/1802.05365](http://arxiv.org/abs/1802.05365) ArXiv: 1802.05365.

Phillips, A. (2018). The Moral Dilemma of Algorithmic Censorship. URL: [https://becominghuman.ai/the-moral-dilemma-of-algorithmic-censorship-6d7b6faefe7](https://becominghuman.ai/the-moral-dilemma-of-algorithmic-censorship-6d7b6faefe7)

Qasem, Z., Jansen, M., Hecking, T., & Hoppe, H. U. (2016). Detection of strong attractors in social media networks. *Computational Social Networks, 3*, 11. doi:10.1186/s40649-016-0036-9

Qian, X., Li, M., Ren, Y., & Jiang, S. (2019). Social media based event summarization by user-text-image co-clustering. *Knowledge-Based Systems, 164*, 107–121. URL: [http://www.sciencedirect.com/science/article/pii/S0950705118305148](http://www.sciencedirect.com/science/article/pii/S0950705118305148) doi:10.1016/j.knosys.2018.10.028

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language Models are Unsupervised Multitask Learners. URL: [paper/Language-Models-are-Unsupervised-Multitask-Learners-Radford-Wu/9405cc0d6169988371b2755e573cc28650d14dfe](paper/Language-Models-are-Unsupervised-Multitask-Learners-Radford-Wu/9405cc0d6169988371b2755e573cc28650d14dfe)

Rosenthal, S., Farra, N., & Nakov, P. (2017). SemEval-2017 Task 4: Sentiment Analysis in Twitter. In *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)* (pp. 502–518). Vancouver, Canada: Association for Computational Linguistics. URL: [http://www.aclweb.org/anthology/S17-2088](http://www.aclweb.org/anthology/S17-2088)

Rudin, C. (2018). Please Stop Explaining Black Box Models for High Stakes Decisions. *arXiv:1811.10154 [cs, stat]*, . URL: [http://arxiv.org/abs/1811.10154](http://arxiv.org/abs/1811.10154) ArXiv: 1811.10154.

Rutkowski, L., Tadeusiewicz, R., Zadeh, L. A., & Zurada, J. M. (2008). *Artificial Intelligence and Soft Computing – ICAISC 2008: 9th International Conference Zakopane, Poland, June 22-26, 2008, Proceedings*. Springer Science & Business Media. Google-Books-ID: cdBlypDgCK8C.

Saif, H., He, Y., Fernandez, M., & Alani, H. (2016). Contextual semantics for sentiment analysis of Twitter. *Information Processing & Management, 52*, 5–19. doi:10.1016/j.ipm.2015.01.005
Sayyadi, H., & Raschid, L. (2013). A Graph Analytical Approach for Topic Detection. *ACM Trans. Internet Technol.*, 13, 4:1–4:23. doi:10.1145/2542214.2542215

Senthil Kumar B, & Bhavitha Varma E (2016). A Different Type of Feature Selection Methods for Text Categorization on Imbalanced Data.

Shah, S. C., & Kusiak, A. (2004). Data mining and genetic algorithm based gene/SNP selection. *Artificial Intelligence in Medicine, 31*, 183–196. URL: http://www.sciencedirect.com/science/article/pii/S0933365704000521 doi:10.1016/j.artmed.2004.04.002

Subbian, K., Aggarwal, C., & Srivastava, J. (2016). Mining Influencers Using Information Flows in Social Streams. *ACM Trans. Knowl. Discov. Data, 10*, 26:1–26:28. doi:10.1145/2815625

Supriya, B. N., Kallimani, V., Prakash, S., & Akki, C. B. (2016). Twitter Sentiment Analysis Using Binary Classification Technique. In P. C. Vinh, & L. Barolli (Eds.), *Nature of Computation and Communication* Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering (pp. 391–396). Springer International Publishing.

Takahashi, S., Sugiyama, A., & Kohda, Y. (2016). A Method for Opinion Mining of Coffee Service Quality and Customer Value by Mining Twitter. In *Knowledge, Information and Creativity Support Systems* (pp. 521–528). doi:10.1007/978-3-319-27478-2_39

Twitter Inc. (2019). *Q1 2019 Earning Report*. Technical Report Twitter Inc. URL: https://s22.q4cdn.com/826641620/files/doc_financials/2019/q1/Q1-2019-Slide-Presentation.pdf

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention Is All You Need. arXiv:1706.03762 [cs], URL: http://arxiv.org/abs/1706.03762 ArXiv: 1706.03762

Villena-Roman, J., Lana-Serrano, S., Martinez-Camara, E., & Gonzalez-Cristobal, J. C. (2015). TASS - workshop on sentiment analysis at SEPLN. *Procesamiento del Lenguaje Natural, 50*, 37–44. URL: http://journal.sepln.org/sepln/ojs/ojs/index.php/pln/article/view/4657

Wang, H., & Hong, M. (2019). Supervised Hebb rule based feature selection for text classification. *Information Processing & Management, 56*, 167–191. URL: http://www.sciencedirect.com/science/article/pii/S0306457318305752 doi:10.1016/j.ipm.2018.09.004

Wu, G., Wang, L., Zhao, N., & Lin, H. (2015). Improved Expected Cross Entropy Method for Text Feature Selection. In *2015 International Conference on Computer Science and Mechanical Automation (CSMA)* (pp. 49–54). doi:10.1109/CSMA.2015.17 ISSN: null.
Xiaomei, Z., Jing, Y., Jianpei, Z., & Hongyu, H. (2018). Microblog sentiment analysis with weak dependency connections. Knowledge-Based Systems, 142, 170–180. URL: http://www.sciencedirect.com/science/article/pii/S095070511730566X doi:10.1016/j.knosys.2017.11.035

Xie, W., Zhu, F., Jiang, J., Lim, E., & Wang, K. (2016). TopicSketch: Real-time Bursty Topic Detection from Twitter. IEEE Transactions on Knowledge and Data Engineering, 28, 2216–2229. doi:10.1109/TKDE.2016.2556661

Xue, B., Zhang, M., & Browne, W. (2013). Particle Swarm Optimization for Feature Selection in Classification: A Multi-Objective Approach. IEEE transactions on cybernetics, 43, 1656–1671. doi:10.1109/TSMCB.2012.2227469

Zhao, Z., Gao, M., Yu, J., Song, Y., Wang, X., & Zhang, M. (2018). Impact of the Important Users on Social Recommendation System. Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST, 252, 425–434. doi:10.1007/978-3-030-00916-8_40

Zheng, H.-T., Wang, Z., Wang, W., Sangaiah, A. K., Xiao, X., & Zhao, C. (2018). Learning-based topic detection using multiple features. Concurrency and Computation-Practice & Experience, 30, e4444. doi:10.1002/cpe.4444 WOS:000438339700001.

Zheng, Z., Wu, X., & Srihari, R. (2004). Feature selection for text categorization on imbalanced data. ACM SIGKDD Explorations Newsletter, 6, 80–89. URL: https://doi.org/10.1145/1007730.1007741 doi:10.1145/1007730.1007741

Complementary Tables
| FS method | acc       | pre       | rec       | f1       | rocauc    |
|-----------|-----------|-----------|-----------|----------|-----------|
| **airlines dataset** |           |           |           |          |           |
| CHI2      | 0.8745    | 0.6364    | 0.5251    | 0.5696   | 0.7334    |
| DE        | 0.8664    | 0.6308    | 0.4640    | 0.5295   | 0.7039    |
| ECE       | 0.8696    | 0.6694    | 0.3795    | 0.4824   | 0.6717    |
| f-ANOVA   | 0.8771    | 0.6456    | 0.5406    | 0.5835   | 0.7413    |
| GSS       | 0.8686    | 0.6450    | 0.4816    | 0.5379   | 0.7123    |
| IG        | 0.8792    | 0.6537    | 0.5383    | 0.5869   | 0.7415    |
| MI        | 0.8786    | 0.6562    | 0.5257    | 0.5802   | 0.7361    |
| OR        | 0.8679    | 0.6488    | 0.4287    | 0.5113   | 0.6906    |
| **gender dataset** |           |           |           |          |           |
| CHI2      | 0.5361    | 0.4954    | 0.6805    | 0.5099   | 0.5417    |
| DE        | 0.5704    | 0.5401    | 0.7084    | **0.6100**| 0.5759    |
| ECE       | 0.5430    | 0.5073    | 0.7293    | 0.5706   | 0.5492    |
| f-ANOVA   | 0.5478    | 0.5153    | 0.7369    | 0.5685   | 0.5553    |
| GSS       | 0.5282    | 0.5636    | 0.2052    | 0.2436   | 0.5157    |
| IG        | 0.5372    | 0.5125    | 0.6883    | 0.5232   | 0.5429    |
| MI        | 0.5360    | 0.5022    | 0.6842    | 0.5176   | 0.5416    |
| OR        | 0.5343    | 0.5051    | 0.6631    | 0.5251   | 0.5386    |
| **imdb dataset** |           |           |           |          |           |
| CHI2      | 0.5792    | 0.7027    | 0.5326    | 0.4899   | 0.5829    |
| DE        | 0.6205    | 0.6748    | 0.5447    | **0.5790**| 0.6216    |
| ECE       | 0.5505    | 0.5781    | 0.4160    | 0.4635   | 0.5494    |
| f-ANOVA   | 0.5825    | 0.6567    | 0.6761    | 0.5598   | 0.5882    |
| GSS       | 0.5885    | 0.6927    | 0.4466    | 0.4989   | 0.5922    |
| IG        | 0.5852    | 0.7247    | 0.5081    | 0.4933   | 0.5894    |
| MI        | 0.5885    | 0.7319    | 0.5023    | 0.4874   | 0.5919    |
| OR        | 0.5725    | 0.6311    | 0.4234    | 0.4825   | 0.5737    |
| **tass dataset** |           |           |           |          |           |
| CHI2      | 0.6780    | 0.7735    | 0.3755    | 0.4729   | 0.6274    |
| DE        | 0.6901    | 0.6779    | 0.4299    | **0.5255**| 0.6467    |
| ECE       | 0.6067    | 0.5907    | 0.2251    | 0.2987   | 0.5433    |
| f-ANOVA   | 0.6930    | 0.7985    | 0.3438    | 0.4677   | 0.6340    |
| GSS       | 0.6594    | 0.7222    | 0.4005    | 0.4722   | 0.6153    |
| IG        | 0.6974    | 0.8062    | 0.3217    | 0.4583   | 0.6346    |
| MI        | 0.6945    | 0.8084    | 0.3433    | 0.4685   | 0.6352    |
| OR        | 0.6376    | 0.6158    | 0.2958    | 0.3882   | 0.5804    |

Table 12: Classification performance of our proposal (DE) against the rest of the selected methods measured with accuracy (acc), precision (pre), recall (rec), $f$1-score (f1) and area-under-curve ROC (rocauc) when training with 9 features. Results show that DE performs better in 3 out of 4 datasets.
| FS method | range | IQR  | STD  | CV (%) |
|-----------|-------|------|------|--------|
| **airlines dataset** |       |      |      |        |
| CHI2      | 0.2835 | 0.0290 | 0.0671 | 11.7734 |
| DE        | 0.1833 | 0.1018 | 0.0603 | 11.3899 |
| ECE       | 0.2158 | 0.0185 | 0.0478 | 9.9008  |
| f-ANOVA   | 0.2496 | 0.0242 | 0.0511 | 8.7641  |
| GSS       | 0.1740 | 0.0986 | 0.0570 | 10.6049 |
| IG        | 0.2306 | 0.0364 | 0.0501 | 8.5442  |
| MI        | 0.2273 | 0.0315 | 0.0474 | 8.1757  |
| OR        | 0.2366 | 0.0639 | 0.0608 | 11.8858 |
| **gender dataset** |       |      |      |        |
| CHI2      | 0.6253 | 0.1494 | 0.2537 | 49.7470 |
| DE        | 0.2185 | 0.0124 | 0.0471 | 7.7200  |
| ECE       | 0.5159 | 0.0188 | 0.1741 | 30.5157 |
| f-ANOVA   | 0.5760 | 0.0159 | 0.1939 | 34.1072 |
| GSS       | 0.4959 | 0.0260 | 0.1373 | 56.3815 |
| IG        | 0.5460 | 0.1397 | 0.2286 | 43.6941 |
| MI        | 0.5921 | 0.1404 | 0.2384 | 46.0551 |
| OR        | 0.4917 | 0.1248 | 0.2024 | 38.5512 |
| **imdb dataset** |       |      |      |        |
| CHI2      | 0.4921 | 0.3695 | 0.1849 | 37.7442 |
| DE        | 0.2283 | 0.0722 | 0.0618 | 10.6673 |
| ECE       | 0.3600 | 0.1852 | 0.1086 | 23.4350 |
| f-ANOVA   | 0.4719 | 0.3198 | 0.1813 | 32.3765 |
| GSS       | 0.2556 | 0.1483 | 0.0867 | 17.3774 |
| IG        | 0.4180 | 0.3076 | 0.1551 | 31.4443 |
| MI        | 0.4132 | 0.3603 | 0.1691 | 34.7056 |
| OR        | 0.3127 | 0.1125 | 0.0884 | 18.3206 |
| **tass dataset** |       |      |      |        |
| CHI2      | 0.1926 | 0.0275 | 0.0386 | 8.1571 |
| DE        | 0.1478 | 0.0558 | 0.0360 | 6.8562 |
| ECE       | 0.4576 | 0.0381 | 0.0880 | 29.4679 |
| f-ANOVA   | 0.1692 | 0.0346 | 0.0322 | 6.8889 |
| GSS       | 0.2002 | 0.0716 | 0.0492 | 10.4178 |
| IG        | 0.1029 | 0.0576 | 0.0298 | 6.5040 |
| MI        | 0.1725 | 0.0346 | 0.0324 | 6.9091 |
| OR        | 0.3455 | 0.1114 | 0.1015 | 26.1393 |

Table 13: Performance dispersion of our proposal (DE) against the rest of the selected methods measured with range, interquartile range (IQR), standard deviation (STD) and coefficient of variation (CV) when training with 9 features. Results show that DE performs better in 2 out of 4 datasets.
| FS method | airlines dataset | gender dataset | imdb dataset | tass dataset |
|-----------|------------------|----------------|--------------|-------------|
|           | CHI2 0.2653      | CHI2 0.6425    | CHI2 0.6763  | CHI2 0.4522 |
|           | DE 0.5608        | DE 0.6451      | DE 0.6966    | DE 0.6966   |
|           | ECE 0.3582       | ECE 0.6157     | ECE 0.6116   | ECE 0.6116  |
|           | f-ANOVA 0.3468   | f-ANOVA 0.6390 | f-ANOVA 0.6788 | f-ANOVA 0.4496 |
|           | GSS 0.5370       | GSS 0.1579     | GSS 0.6577   | GSS 0.3913  |
|           | IG 0.6000        | IG 0.6375      | IG 0.6788    | IG 0.5428   |
|           | MI 0.6000        | MI 0.6520      | MI 0.6764    | MI 0.6271   |
|           | OR 0.5335        | OR 0.5335      | OR 0.6071    | OR 0.4520   |

| no. of neighbours | f1-score | f1-score | f1-score | f1-score |
|-------------------|----------|----------|----------|----------|
| 5                 | 0.2763   | 0.6432   | 0.6763   | 0.4522   |
| 7                 | 0.3108   | 0.6555   | 0.6763   | 0.4522   |
| 9                 | 0.2638   | 0.6447   | 0.6763   | 0.4522   |
| 10                | 0.5918   | 0.6519   | 0.6763   | 0.4522   |
| 25                | 0.3024   | 0.3827   | 0.4138   | 0.3770   |

*Table 14: Classification performance against \(k\)-nearest neighbours (kNN) complexity for each dataset and feature selection method. The lower the number of neighbours is and the higher the \(f1\)-score, the better.*
| FS method | fl | rules | clauses | complexity | compr. rate |
|-----------|----|-------|---------|------------|-------------|
| **airlines dataset** | | | | | |
| CHI2      | 0.5981 | 34       | 7.4706  | 7.5901     | **7.8796** |
| DE        | 0.5698 | 41       | 7.2063  | 8.6638     | 6.5766      |
| ECE       | 0.5026 | 69       | 9.1159  | 22.9357    | 2.1912      |
| f-ANOVA   | 0.6083 | 44       | 7.6136  | 10.2023    | 5.9430      |
| GSS       | 0.5821 | 49       | 7.4082  | 10.7567    | 5.4111      |
| IG        | 0.6016 | 47       | 7.6383  | 10.9686    | 5.4845      |
| MI        | 0.6016 | 47       | 7.6383  | 10.9686    | 5.4845      |
| OR        | 0.5515 | 92       | 9.0543  | 30.1691    | 1.8280      |
| **gender dataset** | | | | | |
| CHI2      | 0.6429 | 309      | 13.7799 | 234.6999   | 0.2739      |
| DE        | 0.6444 | 28       | 6.5000  | 4.7320     | 13.6171     |
| ECE       | 0.6328 | 371      | 13.7278 | 279.6620   | 0.2263      |
| f-ANOVA   | 0.6381 | 234      | 13.0684 | 159.8524   | 0.3992      |
| GSS       | 0.1833 | 48       | 8.5417  | 14.0083    | 1.3087      |
| IG        | 0.6423 | 311      | 13.3698 | 222.3661   | 0.2889      |
| MI        | 0.6421 | 302      | 13.1623 | 209.2798   | 0.3068      |
| OR        | 0.6356 | 333      | 13.0541 | 226.9839   | 0.2800      |
| **imdb dataset** | | | | | |
| CHI2      | 0.6763 | 15       | 6.6667  | 2.6667     | 25.3597     |
| DE        | 0.6966 | 16       | 6.7500  | 2.9160     | 23.8899     |
| ECE       | 0.4082 | 44       | 10.0227 | 17.6801    | 2.3086      |
| f-ANOVA   | 0.6791 | 14       | 6.5000  | 2.3660     | 28.7026     |
| GSS       | 0.5976 | 17       | 7.1176  | 3.4449     | 17.3460     |
| IG        | 0.6889 | 16       | 6.5000  | 2.7040     | 25.4767     |
| MI        | 0.6764 | 11       | 5.4545  | 1.3091     | 51.6667     |
| OR        | 0.5385 | 36       | 8.0000  | 9.2160     | 5.8427      |
| **tass dataset** | | | | | |
| CHI2      | 0.4807 | 23       | 6.8261  | 4.2868     | 11.2146     |
| DE        | 0.3735 | 24       | 6.7083  | 4.3202     | 8.6457      |
| ECE       | 0.3055 | 901      | 14.0954 | 716.0488   | 0.0427      |
| f-ANOVA   | 0.4520 | 23       | 7.1739  | 4.7348     | 9.5465      |
| GSS       | 0.4316 | 36       | 8.3611  | 10.0668    | 4.2870      |
| IG        | 0.4877 | 25       | 7.2800  | 5.2998     | 9.2020      |
| MI        | 0.4509 | 22       | 6.9091  | 4.2007     | 10.7334     |
| OR        | 0.3414 | 834      | 13.4233 | 601.0936   | 0.0568      |

Table 15: Performance and complexity measures of DT-based models for each dataset. Number of leaves (rules) and path length (clauses) can be used to compare how comprehensible are the models that result from training with different feature sets. Our proposal is within the best of them and it produce the only feature set that can manage to keep a good classification performance while maintaining a simple model in the gender classification task.
| FS method | f1   | rules | clauses | complexity | compr. rate |
|-----------|------|-------|---------|------------|-------------|
| **airlines dataset** | | | | | |
| CHI2      | 0.6116 | 58.2000 | 8.2904 | 16.0004 | 3.8222 |
| DE        | 0.5691 | 65.8000 | 8.1672 | 17.5561 | 3.2417 |
| ECE       | 0.5057 | 160.2000 | 9.8588 | 62.2831 | 0.8120 |
| f-ANOVA   | 0.6057 | 68.0000 | 8.5646 | 19.9519 | 3.0356 |
| GSS       | 0.5749 | 87.4000 | 8.6319 | 26.0483 | 2.2070 |
| IG        | 0.6194 | 84.8000 | 9.2644 | 29.1130 | 2.1255 |
| MI        | 0.6031 | 84.2000 | 9.1788 | 28.3757 | 2.1255 |
| OR        | 0.5502 | 150.2000 | 9.5490 | 54.7826 | 1.0043 |
| **gender dataset** | | | | | |
| CHI2      | 0.6417 | 293.0000 | 13.8191 | 223.8153 | 0.2867 |
| DE        | 0.6442 | 41.8000 | 7.4090 | 9.1780 | 7.0187 |
| ECE       | 0.6321 | 365.6000 | 13.6071 | 270.7671 | 0.2334 |
| f-ANOVA   | 0.6385 | 251.2000 | 12.5725 | 158.8265 | 0.4020 |
| GSS       | 0.1892 | 53.0000 | 8.9622 | 17.0279 | 1.1109 |
| IG        | 0.6427 | 284.2000 | 12.5812 | 179.9404 | 0.3572 |
| MI        | 0.6411 | 292.4000 | 13.6436 | 217.7181 | 0.2945 |
| OR        | 0.6364 | 337.6000 | 13.1601 | 233.8737 | 0.2721 |
| **imdb dataset** | | | | | |
| CHI2      | 0.6810 | 14.4000 | 6.3957 | 2.3561 | 28.9034 |
| DE        | 0.6966 | 17.0000 | 6.6829 | 3.0370 | 22.9384 |
| ECE       | 0.4371 | 50.2000 | 8.8899 | 15.8692 | 2.7543 |
| f-ANOVA   | 0.6840 | 16.4000 | 6.6628 | 2.9122 | 23.4883 |
| GSS       | 0.5976 | 21.0000 | 7.2516 | 4.4172 | 13.5280 |
| IG        | 0.6889 | 19.4000 | 7.1179 | 3.9315 | 17.5221 |
| MI        | 0.6764 | 14.6000 | 6.4763 | 2.494 | 27.6129 |
| OR        | 0.5939 | 43.4000 | 8.9320 | 13.8499 | 4.2884 |
| **tass dataset** | | | | | |
| CHI2      | 0.4814 | 55.6000 | 8.5205 | 16.1460 | 2.9815 |
| DE        | 0.3730 | 43.0000 | 7.7223 | 10.2572 | 3.6366 |
| ECE       | 0.2974 | 899.6000 | 14.7129 | 778.9390 | 0.0382 |
| f-ANOVA   | 0.4533 | 57.6000 | 8.7544 | 17.6579 | 2.5673 |
| GSS       | 0.4324 | 73.2000 | 9.0092 | 23.7654 | 1.8196 |
| IG        | 0.4900 | 56.4000 | 8.6753 | 16.9789 | 2.8861 |
| MI        | 0.4542 | 48.2000 | 8.6188 | 14.3219 | 3.1714 |
| OR        | 0.3432 | 833.2000 | 14.4092 | 691.9755 | 0.0496 |

Table .16: Performance and complexity measures of RF-based models for each dataset when training with 5 trees. Number of leaves (rules) and path length (clauses) can be used to compare how comprehensible are the models that result from training with different features selection mechanisms.