TF-IDFC-RF: A Novel Supervised Term Weighting Scheme

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\textbf{Abstract}

Sentiment Analysis is a branch of Affective Computing usually considered a binary classification task. In this line of reasoning, Sentiment Analysis can be applied in several contexts to classify the attitude expressed in text samples, for example, movie reviews, sarcasm, among others. A common approach to represent text samples is the use of the Vector Space Model to compute numerical feature vectors consisting of the weight of terms. The most popular term weighting scheme is TF-IDF (Term Frequency - Inverse Document Frequency). It is an Unsupervised Weighting Scheme (UWS) since it does not consider the class information in the weighting of terms. Apart from that, there are Supervised Weighting Schemes (SWS), which consider the class information on term weighting calculation. Several SWS have been recently proposed, demonstrating better results than TF-IDF. In this scenario, this work presents a comparative study on different term weighting schemes and proposes a novel supervised term weighting scheme, named as TF-IDFC-RF (Term Frequency - Inverse Document Frequency in Class - Relevance Frequency). The effectiveness of TF-IDFC-RF is validated with SVM (Support Vector Machine) and NB (Naive Bayes) classifiers on four commonly used Sentiment Analysis datasets. TF-IDFC-RF outperforms all other weighting schemes and achieves F\textsubscript{1} results of more than 99.9\% on all datasets with SVM classifier.

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1. Introduction

Sentiment Analysis (SA) has attracted much attention in recent years [1]. It is a branch of Affective Computing usually considered a binary classification task [2]. The goal of SA is to classify the attitude expressed in text samples (e.g., positive or negative) rather than some facts (e.g., entertainment or sport) [2,3,4]. It can be useful in several contexts, for example, to detect subjectivity [5,6], irony/sarcasm [7,8,9], sentiment in movie reviews [5,10,11], among others.

A usual approach to represent text documents in the scope of SA is the use of the Vector Space Model (VSM), initially introduced in [12]. The main idea behind VSM is to represent each document as a numerical feature vector, consisting of the weight of terms extracted from the text corpus [13]. The weight of each term is considered the key component of document representation in VSM [13]. Thereby, the choice of the term weighting scheme to represent documents directly affects the classification accuracy [14,13,15].

The weighting schemes can be divided into two main categories, based on the usage of class information in training documents [14]. The first one is the unsupervised term weighting (UTW), which does not use class information to generate weights. The most popular unsupervised scheme is TF-IDF (Term Frequency - Inverse Document Frequency) [16,17]. It has been used effectively in information retrieval studies; however, it is not very well suited for text classification tasks [18]. The second main category of weighting schemes is referred to as supervised term weighting (STW), which was firstly proposed by Debole and Sebastiani [19]. STW schemes embrace class information from training dataset to compute term weighting [20], which leads researchers to believe that these schemes have superior performance than UTW [21].
Following this line of reasoning, several researches has focused on the development of new supervised weighting schemes (e.g., TF-RF \[21\], TF-IDF-ICF \[16\]). Recently, Chen et al. \[13\] introduced a new term weighting based in inverse gravity moment, named as TF-IGM. The authors state that TF-IGM outperforms the state-of-the-art supervised term weighting schemes. Dogan and Uysal \[15\] proposed TF-IGM\(_{imp}\), which is an improved version of TF-IGM. Experiments indicated that TF-IGM\(_{imp}\) outperforms TF-IGM.

Although there are several supervised term weighting schemes, the experiments are usually conducted on multi-class datasets \[22, 13\]. Based on this premise, Chen et al. \[13\] constructed ten two-class subsets from the Reuters-21578 corpus to conduct the experiments in their study. However, Reuters-21578 is not an original two-class dataset, and the scope of this work is to study STW schemes in sentiment analysis, more specifically, in two-class datasets.

The main contributions of this work are: (i) the proposal of a novel STW scheme named as TF-IDFC-RF; (ii) the evaluation of ten weighting schemes (two UWS and eight SWS) on four two-class sentiment analysis datasets; we selected broadly available datasets to facilitate replication of the experiments.

According to the experimental results described in the next sections, TF-IDFC-RF outperforms all compared schemes. These results are achieved in four two-class sentiment analysis datasets.

The remainder of this study is structured as follows: In Section 2 we present the concepts of nine STW schemes and the proposed scheme; In Section 3 we describe the datasets used in carrying out experiments; In Section 4 we discuss the experimental setup used to execute the experiments; In Section 5 we present the experiments conducted with seven STW schemes, two UTW schemes and the proposed approach. Finally, in Section 6 we conclude and open discussion for further research.
2. Term Weighting Schemes

As previously mentioned, VSM represents each document as a numerical feature vector (weights), where each dimension corresponds to a separate term (words, keywords, or longer phrases). The process of assigning a weight to each term is known as term weighting. There are several term weighting schemes in the literature, and the adoption of each of them leads to different results in text classification tasks [23, 24].

This section describes relevant concepts for text classification and discusses nine term weighting schemes in order to compare them with the proposed term weighting. Section 2.1 reviews two of the most common unsupervised term weighting schemes, which are commonly considered as the baseline schemes. Section 2.2 presents seven supervised term weighting schemes used throughout this work.

2.1. Unsupervised term weighting

Unsupervised term weighting schemes compute term weights considering information such as the frequency of terms in documents or the number of times that a term appears in a collection [25]. In unsupervised term weighting approaches, the class information of the documents is not used to generate weights [26]. Section 2.1.1 and 2.1.2 present the UTW used in this work.

2.1.1. Term Weighting Based on TF

Term frequency (TF) is the number of times a particular term $t_i$ occurs in a document $d_j$, as indicated in (1). It is one of the most important term weighting schemes in document analysis [27]. However, it is widely recognized that TF puts too much weight on repeated occurrences of a term [28].

$$W_{TF}(t_i) = TF(t_i, d_j)$$

(1)
2.1.2. Term Weighting Based on TF-IDF

TF-IDF [12] is one of the earliest and common unsupervised weighting methods [18]. The intuition behind TF-IDF is that, for some context, some terms are more important than others to describe documents. For example, a term that appears in all documents does not have substantial relevance to help identifying documents. Equation 2 describes TF-IDF, where \( N \) is the number of documents in the corpus and \( DF(t_i) \) corresponds to the frequency of documents that term \( t_i \) appears in the collection. TF-IDF and TF are considered unsupervised term weighting schemes as they do not take into account class information.

\[
W_{TF.IDF}(t_i) = \frac{TF(t_i, d_j) \times \log \left( \frac{N}{DF(t_i)} \right)}{(2)}
\]

2.2. Supervised term weighting

This section describes seven supervised term weights schemes and the proposed weighting scheme. As already stated, STW schemes weight terms by exploiting the known class information in training corpus. The fundamental elements of supervised term weighting are depicted in Table 1.

| \( c_k \) | \( \bar{c}_k \) |
|----------|----------|
| \( t_i \) | \( A \)    | \( C \) |
| \( \bar{t}_i \) | \( B \)    | \( D \) |

Table 1: Notation for supervised term weighting schemes.

In this representation, the importance of a term \( t_i \) for a class \( c_k \) is represented as follows:

- A represents the number of documents in class \( c_k \) where the term \( t_i \) occurs at least once;
- C represents the number of documents not belonging to class \( c_k \) where the term \( t_i \) occurs at least once;
• B represents the number of documents belonging to class \( c_k \) where the term \( t_i \) does not occur;

• D represents the number of documents not belonging to class \( c_k \) where the term \( t_i \) does not occur;

• \( N \) is the total number of documents in the corpus; \( N = A + B + C + D \);

• \( N_p \) is the number of documents in the positive class; \( N_p = A + B \);

• \( N_n \) is the number of documents in the negative class; \( N_n = C + D \).

### 2.2.1. Term Weighting Based on Delta TF-IDF

Delta TF-IDF was proposed by Martineau and Finin \[29\]. It computes the difference of TF-IDF scores in the positive and negative classes to improve accuracy \[29\]. As an STW, it considers the distribution of features between the two classes before classification, recognizing and heightening the effect of distinguishing terms. Delta TF-IDF boosts the importance of words that are unevenly distributed between the positive and the negative class.

In this work, we use the smoothed version, as indicated in (3), since it achieved higher accuracy in Paltoglou and Thelwall \[30\]. \( N_p \) and \( N_n \) are, respectively, the number of documents in positive and negative classes. \( A \) and \( C \) represent the document frequency of term \( t_i \) in positive and negative classes, respectively.

\[
W_{\delta,TF-IDF}(t_i) = TF(t_i,d_j) \times \log_2 \left( \frac{N_p \times C + 0.5}{A \times N_n + 0.5} \right)
\]  

### 2.2.2. Term Weighting Based on TF-IDF-ICF

TF-IDF-ICF is a supervised weighting scheme based on traditional TF-IDF. However, it adds *Inverse Class Frequency (ICF)* factor \[16\] to give higher weighting values to rare terms that occur in fewer documents (IDF) and classes (ICF). In (4), \( M \) is the number of classes in the collection and \( CF(t_i) \) corresponds to the frequency of classes that term \( t_i \) appears in the collection. TF-IDF-ICF is indicated in (5).
\[
ICF(t_i) = \left(1 + \log \left(\frac{M}{CF(t_i)}\right)\right)
\]  
(4)

\[
W_{TF, IDF, ICF}(t_i) = TF(t_i, d_j) \times IDF(t_i) \times ICF(t_i)
\]  
(5)

2.2.3. Term Weighting Based on TF-RF

TF-RF (Term Frequency - Relevance Frequency) was proposed in [21]. Similar to Delta TF-IDF, TF-RF takes into account terms distribution in positive and negative classes. However, only the documents containing the term are considered, that is, the Relevance Frequency (RF) of the terms. TF-RF is indicated in (6), where the minimal denominator is 1 to avoid division by zero.

\[
W_{TF, RF}(t_i) = \frac{TF(t_i, d_j) \times \log (2 + \frac{A_{\text{max}}}{\text{max}(1, C)})}{2 + \frac{A_{\text{max}}}{\text{max}(1, C)}}
\]  
(6)

2.2.4. Term Weighting Based on TF-IGM

Term Frequency - Inverse Gravity Moment (TF-IGM) [13] is proposed to measure the non-uniformity or concentration of terms inter-class distribution, which reflects the terms class distinguishing power. The standard IGM equation assign ranks \(r\) based on the inter-class distribution concentration of a term, which is analogous to the concept of “gravity moment” (GM) from the physics. IGM is indicated in (7), where \(f_{ir}\) \((r = 1, 2, ..., M)\) indicates the number of documents containing the term \(t_i\) in the \(r\)-th class, which are sorted in descending order. Thus, \(f_{i1}\) represents the frequency of \(t_i\) in the class which it appears most often.

\[
IGM(t_i) = \left(\frac{f_{i1}}{\sum_{r=1}^{M} f_{ir} \times r}\right)
\]  
(7)

TF-IGM term weighting is then defined based on IGM\(t_i\), as shown in [8]. \(\lambda\) is an adjustable coefficient used to maintain the relative balance between the global and local factors in the weight of a term. The \(\lambda\) coefficient has a default value of 7.0 and can be set as a value between 5.0 and 9.0 [13]. Equation \(9\) presents SQRT_TF-IGM, which calculates the square root of TF, as a technique
to obtaining a more reasonable term weighting by reducing the effect of high TF [13].

\[ W_{TF,IGM}(t_i) = TF(t_i, d_j) \times (1 + \lambda \times IGM(t_i)) \] (8)

\[ W_{SQRT.TF,IGM}(t_i) = \sqrt{TF(t_i, d_j)} \times (1 + \lambda \times IGM(t_i)) \] (9)

To enhance the weighting process of TF-IGM for extreme scenarios, Dogan and Uysal [15] proposed IGM\_imp, an improvement of IGM. IGM\_imp is used in two new term weighting schemes, TF-IGM\_imp and SQRT\_TF-IGM\_imp, which were also proposed in [15]. IGM\_imp is described in (10), where \( D_{tot}(t_{i,\text{max}}) \) indicates the total number of documents in the class that the term \( t_i \) occurs most. TF-IGM\_imp and SQRT\_TF-IGM\_imp are defined in (11) and (12), respectively. Dogan and Uysal [15] report IGM\_imp produces better results than IGM.

\[ IGM\_imp(t_i) = \frac{f_{i1}}{\sum_{r=1}^{M} f_{ir} \times r + \log \left( \frac{D_{tot}(t_{i,\text{max}})}{f_{i1}} \right)} \] (10)

\[ W_{TF,IGM\_imp}(t_i) = TF(t_i, d_j) \times (1 + \lambda \times IGM\_imp(t_i)) \] (11)

\[ W_{SQRT.TF,IGM\_imp}(t_i) = \sqrt{TF(t_i, d_j)} \times (1 + \lambda \times IGM\_imp(t_i)) \] (12)

2.3. Novel Term Weighting Scheme

The proposed term weighting scheme is based on the IDF concept. However, it calculates the inverse document frequency of terms in classes (IDFC). It is also inspired in TF-RF since it calculates the Relevance Factor of a term.

Equation [13] describes the proposed supervised term weighting scheme, named as TF-IDFC-RF. To avoid division by zero, we adjust the denominators with \( (A + 1) \) for IDFC and \( (C + 1) \) for RF as in [21]. In the RF part, we also adjust the numerator with \( (A + 1) \) to avoid \( \log(0) \).
To illustrate the properties of different term weighting measures and to obtain a more solid understanding of TF-IDFC-RF, consider the fundamental elements presented in Table 1. Suppose a training dataset containing 100 documents. Consider now the distribution of terms \( t_1 \) and \( t_2 \) for two classes \( c_p \) and \( c_n \), as defined in Table 2.

|          | \( c_p \) | \( c_n \) |          | \( c_p \) | \( c_n \) |
|----------|----------|----------|----------|----------|----------|
| \( t_1 \) | 27       | 5        | \( t_2 \) | 10       | 20       |
| \( \overline{t_1} \) | 3        | 65       | \( \overline{t_2} \) | 25       | 45       |

Table 2: Example of document distribution for two terms.

Taking into account the \( t_1 \) distribution in Table 2, the weighting calculation for IDF, IDF-ICF, Delta IDF, RF, TF-IDF-RF, IGM and IGM\(_{imp}\) is as follows:

| Weighting Scheme | Calculation                                                                 |
|------------------|-----------------------------------------------------------------------------|
| \( IDF(t_1) \)   | \( \log(100/(27+5))=\log(3.125) = 0.4949 \)                               |
| \( IDF-ICF(t_1) \) | \((1+0.4949)*(1+(2/2))=2.9898 \)                                       |
| Delta IDF(\( t_1 \), \( c_p \)) | \( \log_2((30*5+0.5)/(27*70+0.5))=-3.6510 \) |
| Delta IDF(\( t_1 \), \( c_n \)) | \( \log_2((70*27+0.5)/ (5*30+0.5)) = 1.8445 \) |
| RF(\( t_1 \), \( c_p \)) | \( \log_2(2+(27/5))=2.8875 \)                                      |
| RF(\( t_1 \), \( c_n \)) | \( \log_2(2+(3/65))=1.0329 \)                                     |
| IGM(\( t_1 \)) | \( 27/((27*1)+(27*2))=0.3333 \)                                        |
| IGM\(_{imp}\)(\( t_1 \)) | \( 27/((27*1)+(27*2)+0.0458)=0.3331 \)                                |
| IDFC-RF(\( t_1 \), \( c_p \)) | \( \log(100/(27+1))\times\log((27+1)/(5+1))=0.3698 \) |
| IDFC-RF(\( t_1 \), \( c_n \)) | \( \log(100/(5+1))\times\log((5+1)/(27+1))=-0.8174 \) |

Table 3: Scores of term weighting schemes considering distribution in Table 2.

\[^{1}\text{In our case, } c_n \text{ corresponds to } \overline{c_k}, \text{ since we are focused in the two-class problem}\]
As one can note, IDF, IDF-ICF, IGM, and IGM_{imp} do not compute different scores for each class. On the other hand, Delta IDF, RF, and the proposed term weighting (IDFC-RF) provide different scores for each class. In order to investigate this effect, Table 4 summarizes the scores for both terms \( t_1 \) and \( t_2 \). When comparing IDFC-RF with RF, it is possible to note that IDFC-RF seems to be more discriminative between the classes (inter-class). For example, \( t_1 c_p \) is positive and \( t_1 c_n \) is negative. Likewise, \( t_2 c_p \) is negative and \( t_2 c_n \) is positive. Furthermore, when comparing the two terms inside a single class (intra-class), \( t_1 c_p \) is positive while \( t_2 c_p \) is negative and \( t_1 c_n \) is negative while \( t_2 c_n \) is positive. Therefore, IDFC-RF considers intra-class and inter-class distribution since both are even taken as equally important in STW [13].

By inspection of Table 2, it is also important to point out that \( t_2 \) presents a more uniform distribution between the classes \((c_p = 10; c_n = 20)\). In this scenario, the difference between the weights assigned to the positive and negative classes using Delta IDF \((t_2 c_p = -0.3782; t_2 c_n = -0.1069)\) and RF \((t_2 c_p = 1.2603; t_2 c_n = 1.3536)\) are less pronounced when compared to IDFC-RF \((t_2 c_p = -0.2692; t_2 c_n = 0.2748)\).

| Weighting Scheme | \( t_1 c_p \) | \( t_1 c_n \) | \( t_2 c_p \) | \( t_2 c_n \) |
|------------------|------------|------------|------------|------------|
| IDF              | 0.4949     | 0.4949     | 0.5229     | 0.5229     |
| IDF-ICF          | 2.9898     | 2.9898     | 3.0458     | 3.0458     |
| Delta IDF        | -3.6510    | 1.8445     | -0.3782    | -0.1069    |
| RF               | 2.8875     | 1.0329     | 1.2630     | 1.3536     |
| IGM              | 0.3333     | 0.3333     | 0.5000     | 0.5000     |
| IGM_{imp}        | 0.3331     | 0.3331     | 0.4937     | 0.4937     |
| IDFC-RF          | 0.3698     | -0.8174    | -0.2692    | 0.2748     |

Table 4: Scores of term weighting schemes considering distribution in Table 2.
3. Datasets

This section describes the datasets used to produce the experiments. All datasets are commonly used in Sentiment Analysis studies.

3.1. Polarity

The Polarity dataset consists of 1,000 positive and 1,000 negative movie reviews. It was first introduced by Pang and Lee [5]. It is used as a baseline dataset in several sentiment analysis.

3.2. Amazon Sarcasm

The Amazon Sarcasm dataset was introduced by Filatova [8]. It consists of an unbalanced dataset with 437 sarcastic reviews and 817 regular reviews from Amazon (http://www.amazon.com). The reviews were labeled using crowdsourcing.

3.3. Subjectivity

The Subjectivity dataset was introduced by Pang and Lee [5]. It consists of 5,000 subjective sentences and 5,000 objective sentences. The subjective sentences were collected from www.rottentomatoes.com. The objective sentences were extracted from summaries available from the Internet Movie Database (www.imdb.com).

3.4. Movie Review

Movie Review dataset contains 10,662 movie-reviews “snippets” (a striking extract usually one sentence long) with positive and negative labels [31]. The movie-reviews were collected from www.rottentomatoes.com. It consists of 5,331 negative snippets and 5,331 positive snippets.
4. Experimental setup

This section describes the experimental setup used to present the experimental results. In Section 4.1 we discuss the classification process adopted in this work. In Section 4.2 we review concepts from the learning algorithms considered to produce the experiments. Finally, in Section 4.3 we describe the evaluation measures used in the experimental study.

4.1. Classification Process

All documents in each dataset were preprocessed with lowercase conversion, punctuation removal, and tokenization. In the classification process, we applied the stratified 5-fold cross-validation technique to present the classification performance. The process adopted to execute the experiments is based on the training-and-testing paradigm described in [32]. The procedure followed for each fold is illustrated in Fig. 1. As depicted in Fig. 1(a), during the training phase, a feature extraction step (i.e., a term weighting scheme) helps to convert each text into a feature vector. This step can include a feature selection method to reduce the feature set size. Finally, the feature set is fed into a machine-learning algorithm to generate a model. As depicted in Fig. 1(b), during prediction, the statistical parameters of the training set (i.e., the classifier model generated in training phase) are used to compute the features of unseen inputs (Feature identification) [32]. These feature sets are then fed into the model to generate the output labels.

**Feature extraction:** In the scope of this study, in the “feature extraction” step, we extracted the features with the following schemes: TF-IDFC-RF with TF, TF-IDF, Delta TD-IDF (DTF-IDF), TF-IDF-ICF, TF-RF, TF-IGM, SQRT_TF-IGM (STF-IGM), TF-IGM_{imp}, and SQRT_ST-IGM_{imp} (STF-IGM_{imp}). Next, as in [13, 15], we adopted χ² or chi-square statistics (CHI2) for feature selection. The weighting schemes are tested with top 500, 1,000,
2,000, 4,000, 6,000, 8,000, 10,000, 12,000, and 14,000 terms scored and sorted descending order by $CHI_{2\text{max}}$ for all datasets.

**Parameters setting:** Lambda parameters were configured with $\lambda = 7$ for TF-IGM, STF-IGM, TF-IGM$_{imp}$ and STF-IGM$_{imp}$, as it is considered the default value [13].

### 4.2. Learning Algorithms

To evaluate the effectiveness of weighting schemes, we conducted the experiments with Support Vector Machines (SVM), since it is the best learning approach in text categorization [25, 21, 20]. We used the Weka implementation of SVM [35] trained with a polynomial kernel and a complexity factor of 1.

We also executed the experiments with the Naive Bayes algorithm (NB), since it is also often used as a baseline for text categorization and sentiment analysis [36]. We also used the Weka implementation of NB.

### 4.3. Performance Measures

We calculated the effectiveness of the weighting schemes using weighted F$_1$ measure, as described in Chavarriaga et al. [37]. The weighted F$_1$ measure is calculated considering the class size and the precision and recall for each class.
Precision is defined as the fraction of all positive predictions that are actual positives, as defined in (14). Recall is the fraction of all actual positives that are predicted to be positive, as indicated in (15).

\[
\text{precision} = \frac{TP}{TP + FP} \tag{14}
\]

\[
\text{recall} = \frac{TP}{TP + FN} \tag{15}
\]

Considering the two equations above, Weighted F\(_1\) measure is defined as in (16).

\[
F_1 = \sum_i 2 \cdot w_i \cdot \frac{\text{precision}_i \cdot \text{recall}_i}{\text{precision}_i + \text{recall}_i} \tag{16}
\]

In (16), \(i\) is the class index and \(w_i = n_i/N\) is the proportion of samples of class \(i\). \(N\) indicates the total number of samples and \(n_i\) denotes the number of samples of the \(i^{th}\) class.

5. Results

In this section, we evaluate the performance of the unsupervised term weighting scheme proposed in this work, named as TF-IDFC-RF. To accomplish this goal, we compared TF-IDFC-RF with 9 other weighting schemes on Polarity, Amazon Sarcasm, Subjectivity and Movie Review datasets.

5.1. Performance comparisons on the Polarity dataset

Figs. 2(a) and 2(b) report the Weighted F\(_1\) score obtained with NB and SVM on Polarity dataset considering 10 different term weighting schemes. It is important to note that this dataset is balanced, as described in Section 3.1. TF-IDFC-RF consistently shows the best performance in regard to both classifiers with all feature size. TF-RF presents the second-best performance, especially when the feature size is between 4,000 and 14,000. STF-IGM\(_{imp}\) has the worst performance with NB classifier, however, it shows better results with SVM. TF-IGM\(_{imp}\) achieves better results than STF-IGM\(_{imp}\) when feature size is larger.
than 2,000 and reaches a peak at feature size 4,000. This behavior changes with SVM, when STF-IGM\textsubscript{imp}, in general, presents better results than TF-IGM\textsubscript{imp}. Although the overall results of TF are not so good as TF-RF and TF-IDF-ICF, it shows comparable performance to TF-IGM, STF-IGM, TF-IDF-ICF, DTF-IDF, and TF-IDF. It should be emphasized that the robustness of TF has been already observed in other studies [21].

Tables 5 and 6 describe in detail the $F_1$ score achieved with NB and SVM classifiers with Polarity dataset. It is possible to note an increase in the performance of RF when the feature size also increases. When examining results with NB classifier and feature sizes larger than 4,000, scores of RF and TF-IDFC-RF are very close to each other. However, when considering the SVM classifier, the superiority of TF-IDFC-RF is evident. In this case, TF-IDFC-RF has reached 100\% $F_1$ with SVM, and TF-RF reached its maximum of 96.49\% with 14,000 features.

5.2. Performance comparisons on the Sarcasm dataset

Figs. 3(a) and 3(b) present Weighted $F_1$ scores achieved with NB and SVM classifiers on Sarcasm dataset, which is an unbalanced small dataset, as described in Section 5.2. TF-IDFC-RF presents the best performance with both classifiers. The unsupervised term weighting schemes (i.e., TF and TF-IDF)
Table 5: Performances of TF, TF-IDF, DTF-IDF, TF-IDF-ICF, TF-RF, TF-IGM, STF-IGM, TF-IGM$_{imp}$, STF-IGM$_{imp}$, and TF-IDFC-RF using NB classifier on Polarity dataset.

| Feat Weighted-F$_1$ (%) |
|-------------------------|
| Size | TF | TF-IDF | DTF-IDF | TF-IDF-ICF | TF-RF | TF-IGM | STF-IGM | TF-IGM$_{imp}$ | STF-IGM$_{imp}$ | TF-IDFC-RF |
|------|----|--------|---------|-------------|------|--------|---------|--------------|-------------|-----------|
| 500  | 73.71 | 74.49 | 74.22  | 74.12 | 84.33 | 74.17 | 75.56 | 68.98 | 73.91 | 100 |
| 1000 | 72.96 | 72.97 | 73.02  | 72.87 | 87.39 | 72.92 | 73.77 | 72.93 | 76.94 | 100 |
| 2000 | 72.64 | 72.65 | 72.85  | 72.70 | 96.14 | 72.75 | 73.88 | 78.69 | 74.02 | 99.90 |
| 4000 | 72.82 | 72.78 | 72.83  | 72.73 | 99.45 | 72.73 | 73.32 | 79.58 | 66.01 | 100 |
| 6000 | 72.92 | 72.21 | 72.91  | 72.66 | 99.5  | 72.61 | 72.53 | 70.83 | 54.17 | 99.90 |
| 8000 | 71.92 | 71.84 | 72.02  | 71.83 | 99.6  | 71.83 | 71.81 | 70.87 | 53.85 | 99.90 |
| 10000| 72.29 | 72.09 | 72.13  | 71.99 | 99.6  | 71.99 | 71.38 | 70.78 | 54.44 | 99.90 |
| 12000| 71.55 | 71.45 | 71.40  | 71.35 | 99.5  | 71.25 | 70.38 | 71.49 | 55.09 | 99.90 |
| 14000| 71.76 | 71.51 | 71.36  | 71.56 | 99.5  | 71.36 | 70.26 | 73.02 | 55.88 | 99.90 |

Table 6: Performances of TF, TF-IDF, DTF-IDF, TF-IDF-ICF, TF-RF, TF-IGM, STF-IGM, TF-IGM$_{imp}$, STF-IGM$_{imp}$, and TF-IDFC-RF using SVM classifier on Polarity dataset.

| Feat Weighted-F$_1$ (%) |
|-------------------------|
| Size | TF | TF-IDF | DTF-IDF | TF-IDF-ICF | TF-RF | TF-IGM | STF-IGM | TF-IGM$_{imp}$ | STF-IGM$_{imp}$ | TF-IDFC-RF |
|------|----|--------|---------|-------------|------|--------|---------|--------------|-------------|-----------|
| 500  | 85.18 | 85.28 | 85.18  | 85.18 | 88.14 | 85.23 | 84.29 | 78.19 | 76.12 | 100 |
| 1000 | 83.13 | 83.12 | 83.13  | 83.13 | 89.84 | 83.13 | 84.04 | 79.13 | 79.89 | 100 |
| 2000 | 83.18 | 83.19 | 83.23  | 83.18 | 92.69 | 83.18 | 83.28 | 80.13 | 81.09 | 100 |
| 4000 | 83.44 | 83.59 | 83.39  | 83.39 | 95.04 | 83.39 | 84.59 | 82.63 | 83.84 | 100 |
| 6000 | 82.89 | 83.43 | 82.89  | 82.89 | 95.74 | 82.89 | 84.63 | 83.17 | 84.94 | 100 |
| 8000 | 82.14 | 82.19 | 82.14  | 82.14 | 96.14 | 82.14 | 85.39 | 83.17 | 85.08 | 100 |
| 10000| 83.58 | 83.53 | 83.58  | 83.58 | 96.19 | 83.58 | 85.68 | 83.27 | 85.14 | 100 |
| 12000| 83.47 | 83.37 | 83.47  | 83.47 | 96.39 | 83.47 | 85.42 | 83.53 | 85.34 | 100 |
| 14000| 83.53 | 83.37 | 83.58  | 83.58 | 96.49 | 83.53 | 85.79 | 83.98 | 85.84 | 100 |

present similar performance, and together with TF-IGM and TF-IDF-ICF, they produce the worst performance with Sarcasm dataset. STF-IGM, TF-IGM$_{imp}$, and STF-IGM$_{imp}$ are generally better than TF and TF-IDF. When considering more than 2,000 features with SVM classifier, DTF-IDF produces better F$_1$ scores than all IGM-based schemes.

Detailed results on Sarcasm dataset are reported in Tables 7 and 8. It is evident the superiority of TF-IDFC-RF over TF-RF with NB and SVM. TF-RF has the second-best overall performance, reaching an F$_1$ score of 97.04% with 1,000 features, as indicated in Table 8. With the same feature size, TF-IDFC-RF achieves an F$_1$ score of 99.91%. It is clear that when discussing the performance of TF-IDFC-RF and NB, it is not so meaningful as a result reported by the TF-IDFC-RF and SVM, which achieved 99.9% of F$_1$.

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Figure 3: Weighted-$F_1$ scores obtained using NB and SVM classifiers with 10 term weighting schemes on Sarcasm dataset.

In the case DTF-IDF, it shows better performance than most of IGM based schemes with NB classifier. STF-IGM$_{imp}$ achieves better results when the feature size is larger than 1,000. TF, TF-IDF, TF-IDF-ICF, and TF-IGM present very similar behavior for both classifiers.

| Size  | TF   | TF-IDF | DTF-IDF | TF-IDF-ICF | TF-IDF-RF | TF-IDF-IGM | TF-IDF-IGM$_{imp}$ | STF-IGM | STF-IGM$_{imp}$ | TF-IDFC-RF |
|-------|------|--------|---------|------------|-----------|-------------|-------------------|---------|----------------|------------|
| 500   | 61.61| 61.69  | 69.33   | 61.36      | 77.81     | 61.69       | 65.22             | 51.13   | 67.19          | 95.50      |
| 1000  | 60.57| 60.64  | 71.85   | 60.69      | 85.41     | 60.49       | 65.63             | 63.30   | 70.73          | 97.26      |
| 2000  | 61.31| 61.30  | 74.69   | 60.91      | 91.67     | 61.31       | 63.84             | 77.26   | 67.08          | 97.99      |
| 4000  | 61.55| 61.52  | 77.27   | 61.13      | 93.71     | 61.39       | 63.60             | 77.75   | 67.12          | 97.64      |
| 6000  | 60.99| 60.69  | 77.59   | 60.36      | 93.96     | 60.91       | 62.62             | 78.63   | 67.99          | 97.64      |
| 8000  | 61.29| 61.05  | 77.28   | 60.80      | 94.12     | 61.05       | 63.08             | 79.88   | 67.96          | 97.64      |
| 10000 | 60.82| 60.52  | 77.82   | 60.67      | 94.29     | 60.83       | 61.32             | 80.19   | 68.18          | 97.64      |
| 12000 | 61.42| 61.25  | 77.67   | 61.26      | 94.54     | 61.28       | 60.75             | 80.83   | 68.41          | 97.56      |
| 14000 | 61.98| 61.17  | 77.98   | 60.79      | 94.29     | 61.18       | 60.35             | 80.71   | 69.32          | 97.56      |

Table 7: Performances of TF, TF-IDF, DTF-IDF, TF-IDF-ICF, TF-RF, TF-IGM, STF-IGM, TF-IGM$_{imp}$, STF-IGM$_{imp}$ and TF-IDFC-RF using NB classifier on Sarcasm dataset.

5.3. Performance comparisons on the Subjectivity dataset

Subjectivity dataset is also a balanced dataset, however, it consists of 10,000 sentences, as pointed out in Section 3.3. Figs. 3(a) and 3(b) present Weighted $F_1$ scores achieved on Subjectivity dataset. In all cases, $F_1$ scores obtained with TF-IDFC-RF surpassed the other term weighting schemes. It is possible
Table 8: Performances of TF, TF-IDF, STF-IDF, TF-IDF-ICF, TF-RF, TF-IGM, STF-IGM, TF-IGM\textsubscript{imp}, STF-IGM\textsubscript{imp} and TF-IDFC-RF using SVM classifier on \textit{Sarcasm} dataset.

to note almost constant values for all schemes with NB classifier. Concerning SVM classifier, TF-IDFC-RF stays constant at 100% considering the increase in feature size. In most cases, $F_1$ scores achieved by the remaining weighting schemes with SVM increases as the feature sizes increases.

![Weighted-F\textsubscript{1} scores considering NB and SVM classifiers with 10 term weighting schemes on Subjectivity dataset.](image)

Tables \[9\] and \[10\] report the detailed $F_1$ results obtained with Subjectivity dataset. Except TF-RF, in most cases, the weighting schemes present better $F_1$ with SVM classifier. TF-IDFC-RF shows the best performance with both classifiers. As indicated in Table \[9\] the $F_1$ score difference between TF-RF and TF-IDFC-RF is between 2.63 and 2.7 percentage points. On the other hand, Table \[10\] shows an increase in the $F_1$ score difference between TF-RF and TF-
IDFC-RF. As we can see, the difference increases to values between 4.27 and 6.9 percentage points.

It is evident that TF-IGM_{imp} and STF-IGM_{imp} are the third and fourth better weighting schemes with NB classifier. However, both present a poor performance when SVM results are observed. The other weighting schemes (i.e., TF, TF-IDF, STF-IDF, and TF-IDF-ICF) have similar behavior with both classifiers.

| Feat. | Weighted-F \(_1\) (%) | Size |
|-------|------------------------|------|
|       | TF         | TF-IDF | DTF-IDF | TF-IDF-ICF | RF | IDFC-RF | IGM | IGM | IGMi | IGMi |
| 500   | 81.69      | 81.65  | 81.65  | 81.65      | 95.89 | 81.67 | 81.01 | 86.85 | 83.53 | 98.59 |
| 1000  | 81.73      | 81.74  | 81.74  | 81.74      | 95.97 | 81.73 | 81.12 | 86.90 | 83.60 | 98.59 |
| 2000  | 81.80      | 81.75  | 81.75  | 81.75      | 95.97 | 81.79 | 81.12 | 86.89 | 83.59 | 98.60 |
| 4000  | 81.82      | 81.77  | 81.77  | 81.77      | 95.97 | 81.82 | 81.10 | 86.90 | 83.59 | 98.60 |
| 6000  | 81.77      | 81.74  | 81.74  | 81.74      | 95.97 | 81.79 | 80.99 | 86.90 | 83.59 | 98.60 |
| 8000  | 81.68      | 81.66  | 81.66  | 81.66      | 95.97 | 81.67 | 80.97 | 86.90 | 83.60 | 98.60 |
| 10000 | 81.73      | 81.70  | 81.70  | 81.70      | 95.97 | 81.74 | 80.99 | 86.90 | 83.60 | 98.60 |
| 12000 | 81.75      | 81.74  | 81.75  | 81.74      | 95.97 | 81.77 | 81.01 | 86.90 | 83.60 | 98.60 |
| 14000 | 81.80      | 81.79  | 81.80  | 81.79      | 95.97 | 81.81 | 81.03 | 86.90 | 83.60 | 98.60 |

Table 9: Performances of TF, TF-IDF, DTF-IDF, TF-IDF-ICF, TF-RF, TF-IGM, TF-IGM_{imp}, STF-IGM, TF-IGM_{imp}, STF-IGM_{imp} and TF-IDFC-RF using NB classifier on Subjectivity dataset.

| Feat. | Weighted-F \(_1\) (%) | Size |
|-------|------------------------|------|
|       | TF         | TF-IDF | DTF-IDF | TF-IDF-ICF | RF | IDFC-RF | IGM | IGM | IGMi | IGMi |
| 500   | 87.73      | 87.74  | 87.75  | 87.74      | 93.10 | 87.74 | 88.21 | 86.74 | 83.53 | 100  |
| 1000  | 89.10      | 89.10  | 89.12  | 89.11      | 93.94 | 89.09 | 88.99 | 87.74 | 83.53 | 100  |
| 2000  | 89.53      | 89.53  | 89.53  | 89.53      | 94.83 | 89.53 | 89.48 | 87.85 | 83.53 | 100  |
| 4000  | 89.68      | 89.69  | 89.67  | 89.67      | 95.36 | 89.68 | 89.61 | 88.56 | 83.53 | 100  |
| 6000  | 89.28      | 89.28  | 89.28  | 89.28      | 95.54 | 89.28 | 89.41 | 88.88 | 83.53 | 100  |
| 8000  | 89.53      | 89.51  | 89.54  | 89.53      | 95.71 | 89.55 | 89.41 | 88.79 | 83.91 | 100  |
| 10000 | 89.33      | 89.33  | 89.34  | 89.35      | 95.68 | 89.34 | 89.34 | 89.07 | 89.12 | 100  |
| 12000 | 89.48      | 89.48  | 89.48  | 89.48      | 95.73 | 89.47 | 89.36 | 88.93 | 89.18 | 100  |
| 14000 | 89.21      | 89.22  | 89.21  | 89.21      | 95.72 | 89.21 | 89.20 | 89.02 | 89.41 | 100  |

Table 10: Performances of TF, TF-IDF, DTF-IDF, TF-IDF-ICF, TF-RF, TF-IGM, TF-IGM_{imp}, STF-IGM, TF-IGM_{imp}, STF-IGM_{imp} and TF-IDFC-RF using SVM classifier on Subjectivity dataset.

### 5.4. Performance comparisons on the Movie Review dataset

Figs. 5(a) and 5(b) present Weighted-F\(_1\) scores achieved on Movie Review dataset. This is a balanced dataset containing 10,662 movie-reviews “snippets”, as indicated in Section 3.4. One can note that TF-IDF-RF achieves the best
performance, presenting values close to 100% for NB and SVM. The second-
best scheme is TF-RF, which achieves $F_1$ of approximately 80% for NB and
between 75% and 85% for SVM. The other schemes show results between 59%
and 70% with NB classifier and between 69% and 79% with SVM. Almost all
schemes present better results with SVM algorithm, except for TF-RF (feature
size equals 500 and 1,000) and for TF-IGM$_{imp}$ (feature size equals 500).

![Figure 5: Weighted-$F_1$ scores obtained using NB and SVM classifiers with 10 term weighting
schemes on Movie Review dataset.](image)

Tables 11 and 12 show the $F_1$ values obtained for each term weighting
scheme. This dataset presents a meaningful difference between $F_1$ measures
between TF-IDFC-RF and the second-best scheme (i.e., TF-RF). The differ-
ence is around 19 percentage points with NB classifier and approximately 15
percentage points with SVM.

5.5. Discussion

The performance assessment of different term weighting schemes in classi-
fication tasks was executed with four two-class datasets. Results are generally
better with SVM classifier when comparing with results obtained with NB. As
reported in prior work, TF-IGM$_{imp}$ and STF-IGM$_{imp}$ generally outperform TF-
IGM and STF-IGM as well as STF-IGM$_{imp}$ generally outperforms TF-IGM$_{imp}$
[15]. However, on all datasets considered in this work, these schemes did not
Table 11: Performances of TF, TF-IDF, DTF-IDF, TF-IDF-ICF, TF-RF, TF-IGM, STF-IGM, TF-IGM_{imp}, STF-IGM_{imp} and TF-IDFC-RF using NB classifier on MR dataset.

| Size | Feat. | Weighted-F1 (%) |
|------|-------|----------------|
|      | TF    | TF-IDF | DTF-IDF | TF-IDF-ICF | TF-RF | TF-IDF-IGM | STF-IDF | TF-IDF-IGMi | IDFC-RF |
| 500  | 61.29 | 61.29  | 60.15   | 61.29      | 80.85 | 61.29      | 59.78   | 69.68       | 64.84   | 99.07    |
| 1000 | 61.43 | 61.43  | 60.23   | 61.43      | 80.71 | 61.43      | 59.81   | 69.68       | 64.85   | 99.16    |
| 2000 | 61.23 | 61.23  | 60.11   | 61.23      | 80.71 | 61.23      | 59.74   | 69.70       | 64.84   | 99.17    |
| 4000 | 61.19 | 61.19  | 60.09   | 61.19      | 80.69 | 61.19      | 59.77   | 69.70       | 64.85   | 99.17    |
| 6000 | 61.43 | 61.43  | 60.28   | 61.43      | 80.69 | 61.43      | 59.87   | 69.68       | 64.85   | 99.17    |
| 8000 | 61.45 | 61.49  | 60.37   | 61.49      | 80.69 | 61.45      | 59.71   | 69.68       | 64.86   | 99.17    |
| 10000| 61.47 | 61.46  | 60.35   | 61.46      | 80.69 | 61.47      | 59.59   | 69.68       | 64.85   | 99.17    |
| 12000| 61.73 | 61.77  | 60.47   | 61.77      | 80.69 | 61.73      | 59.41   | 69.68       | 64.85   | 99.17    |
| 14000| 61.80 | 61.80  | 60.50   | 61.80      | 80.69 | 61.80      | 59.51   | 69.68       | 64.85   | 99.17    |

Table 12: Performances of TF, TF-IDF, DTF-IDF, TF-IDF-ICF, TF-RF, TF-IGM, STF-IGM, TF-IGM_{imp}, STF-IGM_{imp} and TF-IDFC-RF using SVM classifier on MR dataset.

| Size | Feat. | Weighted-F1 (%) |
|------|-------|----------------|
|      | TF    | TF-IDF | DTF-IDF | TF-IDF-ICF | TF-RF | TF-IDF-IGM | STF-IDF | TF-IDF-IGMi | IDFC-RF |
| 500  | 72.31 | 72.31  | 70.74   | 72.27      | 77.21 | 72.32      | 72.24   | 69.10       | 64.87   | 99.73    |
| 1000 | 73.80 | 73.78  | 72.76   | 73.79      | 80.19 | 73.77      | 73.87   | 71.45       | 71.66   | 99.88    |
| 2000 | 74.44 | 74.42  | 73.97   | 74.44      | 83.48 | 74.45      | 74.36   | 73.11       | 73.37   | 99.85    |
| 4000 | 74.10 | 74.11  | 73.89   | 74.10      | 84.69 | 74.10      | 74.23   | 73.99       | 73.99   | 99.87    |
| 6000 | 73.79 | 73.80  | 73.82   | 73.83      | 84.36 | 73.79      | 73.93   | 74.23       | 74.25   | 99.87    |
| 8000 | 74.00 | 74.02  | 73.91   | 74.02      | 84.53 | 74.01      | 73.83   | 74.28       | 74.24   | 99.88    |
| 10000| 73.60 | 73.60  | 73.66   | 73.60      | 84.70 | 73.60      | 73.67   | 74.52       | 75.05   | 99.88    |
| 12000| 74.41 | 74.41  | 74.15   | 74.42      | 84.68 | 74.65      | 74.52   | 74.54       | 75.00   | 99.90    |
| 14000| 74.07 | 74.06  | 73.96   | 74.04      | 84.82 | 74.74      | 74.61   | 74.52       | 75.03   | 99.90    |

perform well. In this regard, as the authors know, this is the first study to conduct experiments with IGM based schemes and these datasets.

The results obtained in previous studies indicated good results with TF-RF \textsuperscript{21, 13}. As reported in \textsuperscript{13}, sometimes TF-RF outperforms TF-IGM and STF-IGM. However, our results revealed that TF-RF outperformed all IGM based schemes with NB and SVM on all four datasets. Moreover, it also presented results better than Delta TF, TF-IDF, DTF-IDF, and TF-IDF-ICF.

TF, TF-IDF, and TF-IDF-ICF showed very similar behavior on all datasets. Delta TF-IDF produced similar behavior to them (i.e., TF, TF-IDF, and TF-IDF-ICF) in the Polarity, Movie Review and Subjectivity datasets. However, on the unbalanced Sarcasm dataset, it produced better performance than TF, TF-IDF, and TF-IDF-ICF.
Our results provide compelling evidence that TF-IDFC-RF achieves better results than the other nine weighting schemes on all datasets with NB and SVM. An important point to stress out is that the experiments executed with NB and TF-IDFC-RF also outperformed all other schemes (with NB or SVM classifier). This information is relevant since the computation of NB classifiers are far more efficient than the exponential complexity of non-naive Bayes approaches [38]. For example, TF-RF with SVM achieved 84.82% in MR dataset with 14,000 features, while TF-IDFC-RF achieved 99.17% with NB.

6. Conclusion and Future work

In this work, we have proposed a novel supervised term weighting scheme named TF-IDFC-RF to be used in Sentiment Analysis tasks, more specifically, in the binary classification problem. The proposed scheme is based on two other schemes: TF-IDF and TF-RF. TF-IDFC-RF is inspired by the fact that the IDF factor can be used for each class, referred to as the Inverse Document Frequency in Class (IDFC). On the other hand, since TF-RF has produced good results in the literature, we were also inspired TF-IDFC-RF on it. The most important concept of TF-IDFC-RF is that it aims to consider intra-class and inter-class distribution to weight the terms.

The performance of TF-IDFC-RF is compared with nine other term weighting schemes, including TF-IDF and TF-RF. These schemes also encompass the IGM based schemes, since they outperformed several other schemes in recent work [13] [15]. It is important to stress that, as stated in [13], TF-IGM schemes are especially suitable for multi-class text classification applications, however, they can be used for binary classification. SVM and NB classifiers were utilized to perform the experiments with different feature sizes.

The experiments show that TF-IDFC-RF outperforms all schemes with NB and SVM on all datasets. TF-IDFC-RF achieved $F_1$ results of more than 99.9% on all datasets with SVM classifier. In future work, we will conduct comparative studies with TF-IDFC-RF in multi-class datasets. We also plan to produce
experiments with larger datasets.

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