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# BAG-OF-DISCRIMINATIVE-WORDS (BODW) REPRESENTATION VIA TOPIC MODELING

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Abstract:

Words in a document are sometimes classified as objective (delivering facts) or subjective (expressing ideas) based on the context in which they appear. If we have a collection of papers on the order Hemiptera, and someone assigns the term "bug" to that subject, it likely refers to a specific kind of insect, but when used to the topic of "software," it likely communicates a negative view. In this research, we propose a model called discriminatively objective-subjective LDA (dosLDA) based on the intuitive premise that various words have varied degrees of discriminative strength in providing the objective meaning or the subjective sense with regard to their assigned themes. In order to capture the relationship between themes and discriminative power for the words in a document in a supervised way, the proposed dosLDA makes use of a pair of objective and subjective selection factors. Therefore, each text should be shown as a "bag-of-discriminatory-words" (BoDW). Experiments with both textual and visual data show that dosLDA not only outperforms conventional methods in terms of topic modeling and document categorization, but can also determine if a given word has a more objective or subjective meaning in relation to its assigned topic.

*Keywords: Topic modeling, latent Dirichlet allocation, objective and subjective classification, bag-of-discriminative-words representation*

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## 1. INTRODUCTION

Multimedia data, such as copious amounts of news and a wide variety of photographs, is readily available on the Internet, which has led to the formidable issue of automatically grouping, analyzing, and summarizing this data. Numerous machine learning techniques have been used so far to try to solve the problem. In particular, topic models have received a lot of interest in recent decades due to their ability to uncover latent structures (i.e., topics) and give low-dimensional representation in terms of the learnt topics. By using a "Bag-of-Words" (BoW) representation, as used by topic models, each data sample is modeled as a disorganized assortment of relevant

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features. Therefore, topic models can not only analyze texts, but also any other data modalities that can be represented as "documents" and "words" (such as images represented by a bag of visual words). Probabilistic latent semantic analysis (pLSA) and latent Dirichlet allocation are the two most prominent and influential efforts in topic modeling (LDA). pLSA is the first topic model that develops out of latent semantic analysis (LSA) and uses a probabilistic generating process to uncover the hidden meanings of words. By associating each document's words with latent topics, pLSA projects the documents onto a low-dimensional topic space, where topics are often represented as multinomial distributions over a predetermined vocabulary. The LDA model is based on the same principle as pLSA, but it adds a generative process to the topic fraction of each document and models the whole corpus inside a hierarchical Bayesian framework. While LDA is superior at modeling large-scale documents because to its well-defined a priori, pLSA turns out to be a specific example of LDA with a uniform Dirichlet prior in a maximum a posteriori model. Over the last decade, the LDA model has been the subject of much research and several practical applications. The grammatical relationships between words are disregarded by the BoW representation. In an unsupervised setting, LDA's learnt representations of documents are generally not very predictive. Unfortunately, from a prediction standpoint, unsupervised LDA overlooks the nature of the discriminative job of interest, such as classification, therefore it offers no assurance that the extracted information will be useful. Many methods aim to overcome this restriction by using supplementary information (such category labels or author ratings) to better model the associated articles in a supervised setting. It is common for LDA versions to use the supplementary data as a response variable anticipated from the latent representation of the text (i.e., the percentage of topics), with the topic assignments to individual words serving as the active mechanism rather than the words themselves. The "Bag-of-Topics" (BoT) model has supplanted the "Bag-of-Words" (BoW) representation for characterizing large texts in predictive tasks like regression and classification. The supervised linear discriminant analysis (sLDA), the scene understanding model, the multi-class sLDA, and the LDA are the most prominent models presented in the idea of BoT. It is intuitive that many words in a given document either deliver facts (objective) or express opinions (subjective) depending on the topics they are involved with, but this is not reflected in the BoT representation, in which any two words drawn from the vocabulary are treated equally if they are assigned with the same topic. Assigning the term "bug" to the subject "order Hemiptera" seems

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to comment on a specific item (a group of insects), but using the same word in reference to "software" is likely to express a negative judgment, based on a sample of relevant papers. In this study, we claim that systematically identifying the objective or subjective discriminatory power of the words with regard to their included subjects aids in the construction of better predictive representations for each text. Thus, this study presents a method known as discriminatively objective-subjective LDA (dosLDA). The central concept is encoding the relationship between themes and discriminative capacity of words in a supervised way using a set of objective and subjective selection criteria. The innovative "bag-of-discriminativewords" (BoDW) representations are produced for each document by the dosLDA, which has the alluring capacity to naturally choose out those words that are discriminative in giving either an objective or a subjective sense in a particular text. Through a series of studies, we show that our proposed BoDW is more predictive for discriminative tasks than the conventional BoW and BoT representations used in the state-of-the-art approaches.

## 2. LITERATURE SURVEY

Although the original LDA model was established as a method for evaluating documents, numerous of its extensions have been presented and have been effectively employed for analyzing a wide variety of different modalities of data. Computer vision, which includes the analysis of pictures [16], [21], videos [22], [23], and the concurrently modeling of images and words (for example, annotations) [24], is one of the areas in which LDA and its derivatives are used the most often. For example, [25] provides two LDA-based models that represent one picture and the annotations of it in a combined framework. These models are called Gaussian-multinomial LDA (GM-LDA) and correspondence LDA. Both of these models are based on LDA (Corr-LDA). In GM-LDA, each picture (and its accompanying annotations) contains one mixture of themes, which is where the latent factors are formed from. After the latent factors have been produced, each word and image area has the potential to be generated from the factors. In contrast, corr-LDA adopts the assumption that the latent factor (also known as the "topic") of each visual area is the same as one of those factors responsible for producing the annotations. As a result, the visual factors are picked at random from the textual themes. In the paper [17], the multi-class sLDA model is used to classify images into various categories. The authors also propose the multi-class sLDA with annotation, which combines the previously mentioned Corr-

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LDA and softmax regression in order to simultaneously model the images, the class labels, and a varying number of annotations attached to the images. This allows the authors to model the images, the class labels, and the varying number of annotations attached to the images. While the "words" that are used to represent images and scenes are generated from visual features such as SIFT and region descriptors, the basic form of the graphical models for computer vision problems are typically very similar to those modeling texts. This is true even though the basic form of the graphical models for computer vision problems is typically very similar to those modeling texts.

The earliest and most typical work among the supervised topic models is the supervised LDA model [15], which was developed in the past. As a natural supervised extension of the traditional LDA model, sLDA inherits the hierarchical Bayesian structure adopted in LDA, while the afore-mentioned BoT representation is also conducted, which enables it to properly handle labelled documents. This allows sLDA to perform better than traditional LDA when it comes to document classification. When using sLDA, the documents and their accompanying auxiliary information are simultaneously modeled. The auxiliary information is viewed as answers anticipated by the latent themes found in the documents, and the documents themselves are modeled as replies to those latent topics. For documents with unconstrained real-valued labels, such as the ratings towards various movies on IMDb, the original sLDA model was presented as a solution. This model is used in situations where the response value is created from a normal linear model. When used in conjunction with a generalized linear model, however, it has been shown in a theoretical sense that sLDA can accept a wide variety of responses (such as real or discrete values, nonnegative values, multi-class labels, and so on) [26]. As a result, getting stretched for the many jobs that need to be done is convenient. The multi-class sLDA and the multi-class sLDA with annotation that were just stated are both examples of extensions that may be made to the basic sLDA. tLDA [18] is another well-known variation of sLDA that was developed with the intention of bridging the language barrier that exists between papers of varying sophistication (e.g., a news report and its related journal article). Each word is given a binary selector in the tLDA model so that it may be determined whether or not the word is a technical term. The latent representation of a single document is made up of all the assignments of the selectors in that document (instead of the subjects), and the technicality of the text is the answer that was anticipated based on the representation using a cosine regression model.

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It would seem that the sLDA model and all of its possible versions are capable of performing practically any sort of discriminative job, including classification and regression. However, when dealing with difficulties in the area of sentiment analysis that are more nuanced and complex, sLDA is unable to execute object and sentiment identification of provided data at the same time because it lacks the capacity to simultaneously analyze both types of information. As a result, a number of different strategies have been offered in order to identify themes (in the sense of the objective) as well as feelings (in the sense of the subjective) in a way that is collaborative. For example, Mei et al. [19] provide a method to describe the combination of themes and feelings expressed in weblogs. They call it the topicsentiment mixing approach (TSM). After that, a Multi-grain LDA [27] is constructed, the purpose of which is to extract and collect certain emotive words connected to a variety of subjects. The joint sentiment-topic model (JST) [28] and its re-parameterized version (reversed JST) [29] are designed to explicitly identify the sentimental polarities expressed by words in documents. It is also capable of mining the content of different sentiments in terms of one given topic. [28] and [29] respectively. [28] [29] [28] [29] [28] [28] [29] [28] [28] [29] [28] [28]. All of these previously stated algorithms uncover the latent attitudes and themes in an unsupervised way, and they represent the documents using BoT or its equivalent (i.e., the representation that is made up of the percentage of latent variables). As a result, their predictive power is less to that of the standard sLDA model.

When compared to the progress made with textual data, the amount of work that has been put into doing sentiment analysis on visual information is quite limited. The research that is most closely related to sentiment analysis for visual content may be the analysis of aesthetic [30], interestingness [31], and affect or emotions [32]. In this type of study, either the low-level visual features (such as color based schemes) or detected emotions and facial expressions are used to predict the aesthetic perception, memorability, or affect of the whole image. When compared to the ones that focus on specific problems in visual content analysis, [33] provides a large-scale ontology of semantic concepts that are strongly correlated with strong sentiments, such as "beautiful landscape" and "dark clouds," forming a visual sentiment dictionary that is able to serve in general analysis on visual sentiments. [33] also provides a visual sentiment dictionary that is able to serve in general analysis on visual sentiments. However, there is currently a lack of work that adds to the identification of significant areas that convey the predominate feeling of a single image, much alone the combined finding of regions that are relevant both objectively and

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subjectively. While the dosLDA model that has been presented makes an effort to choose out the visual words that are discriminative in conveying either an objective or a subjective sense, it is also, to the best of our knowledge, the first topic model that is capable of doing visual sentiment analysis.

In addition to GM-LDA and Corr-LDA, there are a number of other probabilistic graphical models that have been developed to determine the correlation between information presented in various modalities. Some examples of these models are topic regression. The Multimodal Document Random Field (MDRF) [36], Multimodal LDA (tr-mmLDA) [34], and nonparametric Bayesian upstream supervised (NPBUS) multimodal topic model [35]. They try to learn joint representation for multi-modal data by introducing latent variables that indicate the shared portion of semantic space in an effort to do so.

There are also a number of strategies that are based on the process of learning dictionaries [37], ranking [38], or hashing [39]. It is important to take note of the fact that many deep architectures have been suggested to learn the combined representation for textual and visual data, and that these designs have successively attained state-of-the-art performance [40], [41], [42]. While the goal of the dosLDA model is to learn the representation for mono-modal data in virtually any modalities, it would be desirable to further apply the suggested BoDW representation to the joint modeling of multimodal data. This would be accomplished by combining the two models.

## 3. PROPOSED SYSTEM

The study that is being offered is a method that has been given the label discriminatively objective-subjective LDA (dosLDA). A pair of objective and subjective selection variables are explicitly used to encode the interaction between themes and discriminative power with regard to the words in a supervised way, and this is the core principle that underpins it. The dosLDA possesses the attractive power of naturally selecting out those words that are discriminative in delivering either an objective or a subjective sense in a given document, and it generates the novel "bag-of-discriminative words" (BoDW) representations for each document, as shown in Figure. This power allows the dosLDA to possess the attractive power of naturally selecting out those words that are discriminative in delivering either an objective or a subjective sense. It has been established via a number of studies that the standard BoW and BoT representations used in

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the methodologies that are currently in use are inferior to our suggested BoDW in terms of its predictive ability for discriminative tasks.

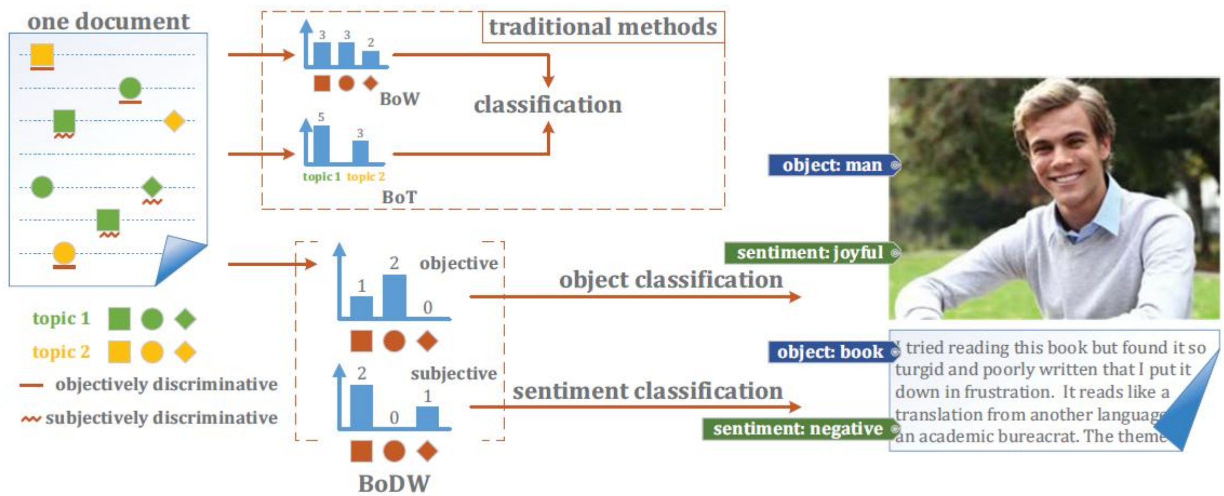


**Figure 1: Architecture for Proposed System**

## 4. RESULTS

**Table 1: Comparison of Object Classification**

| | BoW +SVM | BoW +LR | sLDA | LDA +SVM | LDA +LR | LSTM | 2CONV-4FC | PCNN | dosLDA⁻ | dosLDA |
|---|---|---|---|---|---|---|---|---|---|---|
| **Multi-Domain Sentiment Dataset** | | | | | | | | | | |
| Accuracy | 0.6878 | 0.6161 | $0.6233_{\pm0.0022}$ | $0.6768_{\pm0.0004}$ | $0.6136_{\pm0.0007}$ | **0.7015** | - | - | $0.6857_{\pm0.0012}$ | $0.6923_{\pm0.0009}$ |
| Micro-AUC | 0.8012 | 0.7055 | $0.7383_{\pm0.0024}$ | $0.7892_{\pm0.0005}$ | $0.7035_{\pm0.0009}$ | 0.8090 | - | - | $0.8041_{\pm0.0021}$ | **0.8119**$_{\pm0.0022}$ |
| Macro-AUC | 0.7782 | 0.6724 | $0.7160_{\pm0.0022}$ | $0.7601_{\pm0.0004}$ | $0.6757_{\pm0.0012}$ | **0.7927** | - | - | $0.7674_{\pm0.0018}$ | $0.7814_{\pm0.0018}$ |
| Micro-F1 | 0.7908 | 0.7540 | $0.7628_{\pm0.0030}$ | $0.8043_{\pm0.0010}$ | $0.7568_{\pm0.0015}$ | **0.8246** | - | - | $0.7980_{\pm0.0024}$ | $0.8173_{\pm0.0029}$ |
| Macro-F1 | 0.7930 | 0.6703 | $0.7018_{\pm0.0028}$ | $0.7707_{\pm0.0008}$ | $0.6932_{\pm0.0013}$ | **0.8154** | - | - | $0.7571_{\pm0.0024}$ | $0.7938_{\pm0.0024}$ |
| **Flickr Dataset** | | | | | | | | | | |
| Accuracy | 0.5077 | 0.4532 | $0.5344_{\pm0.0036}$ | $0.5234_{\pm0.0006}$ | $0.5144_{\pm0.0009}$ | - | 0.5274 | 0.5477 | $0.5574_{\pm0.0017}$ | **0.5696**$_{\pm0.0019}$ |
| Micro-AUC | 0.6163 | 0.5459 | $0.5825_{\pm0.0033}$ | $0.5531_{\pm0.0010}$ | $0.5431_{\pm0.0015}$ | - | 0.5756 | 0.5789 | $0.6007_{\pm0.0024}$ | **0.6241**$_{\pm0.0026}$ |
| Macro-AUC | 0.6782 | 0.6225 | $0.6593_{\pm0.0030}$ | $0.6548_{\pm0.0008}$ | $0.6396_{\pm0.0013}$ | - | 0.6473 | 0.6846 | $0.6841_{\pm0.0025}$ | **0.6893**$_{\pm0.0025}$ |
| Micro-F1 | 0.6280 | 0.6237 | $0.6917_{\pm0.0031}$ | $0.6889_{\pm0.0010}$ | $0.6771_{\pm0.0014}$ | - | 0.6800 | 0.7091 | $0.7201_{\pm0.0021}$ | **0.7245**$_{\pm0.0029}$ |
| Macro-F1 | 0.7467 | 0.7355 | $0.7989_{\pm0.0032}$ | $0.7935_{\pm0.0009}$ | $0.7875_{\pm0.0013}$ | - | 0.7625 | 0.7998 | $0.8064_{\pm0.0023}$ | **0.8229**$_{\pm0.0027}$ |
| **Twitter Dataset** | | | | | | | | | | |
| Accuracy | 0.4195 | 0.3356 | $0.4282_{\pm0.0025}$ | $0.4392_{\pm0.0009}$ | $0.4035_{\pm0.0012}$ | - | 0.4579 | 0.4613 | $0.4698_{\pm0.0018}$ | **0.4714**$_{\pm0.0014}$ |
| Micro-AUC | 0.5916 | 0.5453 | $0.6208_{\pm0.0017}$ | $0.6264_{\pm0.0010}$ | $0.5812_{\pm0.0012}$ | - | **0.6712** | 0.6694 | $0.6590_{\pm0.0019}$ | $0.6509_{\pm0.0020}$ |
| Macro-AUC | 0.7221 | 0.5944 | $0.7045_{\pm0.0016}$ | $0.7349_{\pm0.0009}$ | $0.7064_{\pm0.0011}$ | - | 0.7426 | 0.7477 | $0.7387_{\pm0.0015}$ | **0.7480**$_{\pm0.0017}$ |
| Micro-F1 | 0.5982 | 0.5272 | $0.6357_{\pm0.0026}$ | $0.6526_{\pm0.0009}$ | $0.6035_{\pm0.0009}$ | - | 0.6550 | 0.6476 | $0.6658_{\pm0.0023}$ | **0.6709**$_{\pm0.0018}$ |
| Macro-F1 | 0.7071 | 0.6367 | $0.7527_{\pm0.0022}$ | $0.7658_{\pm0.0007}$ | $0.7274_{\pm0.0010}$ | - | 0.7651 | 0.7681 | $0.7689_{\pm0.0022}$ | **0.7721**$_{\pm0.0016}$ |

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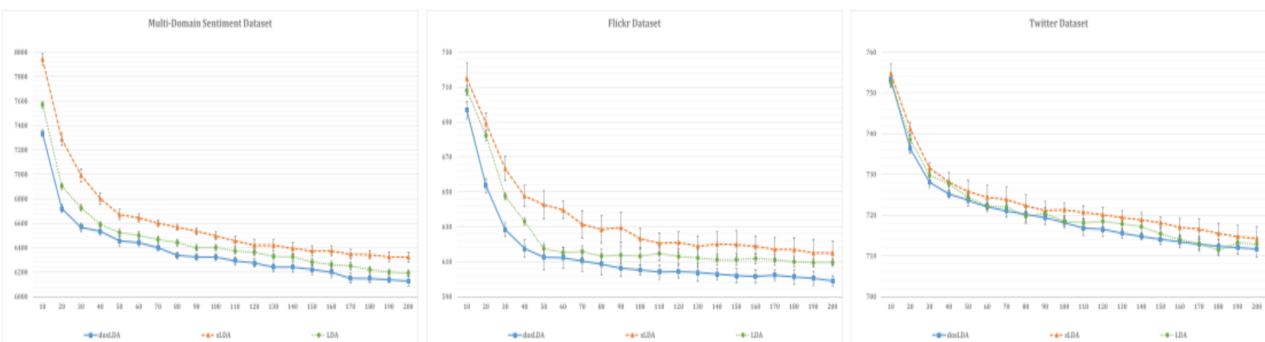
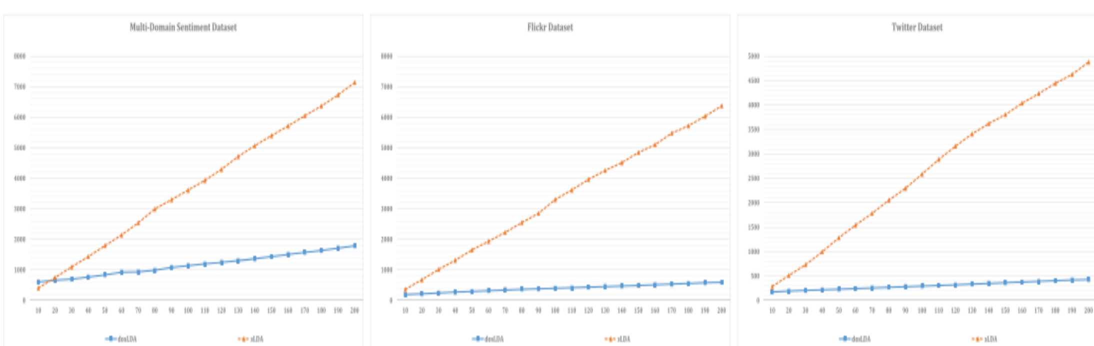
### Table 2: Comparison of sentiment classification

| | BoW | | sLDA | LDA | | LSTM | 2CONV-4FC | PCNN | dosLDA⁻ | dosLDA |
|---|---|---|---|---|---|---|---|---|---|---|
| | +SVM | +LR | | +SVM | +LR | | | | | |
| **Multi-Domain Sentiment Dataset** | | | | | | | | | | |
| Accuracy | 0.7326 | 0.6241 | 0.7538$_{\pm 0.0015}$ | 0.7894$_{\pm 0.0005}$ | 0.7599$_{\pm 0.0008}$ | 0.7898 | - | - | 0.8056$_{\pm 0.0015}$ | **0.8092**$_{\pm 0.0011}$ |
| Micro-AUC | 0.8032 | 0.6692 | 0.8411$_{\pm 0.0025}$ | **0.8625**$_{\pm 0.0008}$ | 0.8461$_{\pm 0.0011}$ | 0.8602 | - | - | 0.8542$_{\pm 0.0011}$ | 0.8520$_{\pm 0.0023}$ |
| Macro-AUC | 0.7280 | 0.6733 | 0.7551$_{\pm 0.0023}$ | 0.7725$_{\pm 0.0008}$ | 0.7657$_{\pm 0.0010}$ | 0.7713 | - | - | 0.7853$_{\pm 0.0011}$ | **0.7893**$_{\pm 0.0021}$ |
| Micro-F1 | 0.8469 | 0.7876 | 0.8533$_{\pm 0.0031}$ | 0.8656$_{\pm 0.0010}$ | 0.8592$_{\pm 0.0014}$ | 0.8506 | - | - | 0.8749$_{\pm 0.0012}$ | **0.8823**$_{\pm 0.0025}$ |
| Macro-F1 | 0.7475 | 0.6738 | 0.6993$_{\pm 0.0024}$ | 0.7738$_{\pm 0.0011}$ | 0.7165$_{\pm 0.0013}$ | 0.7667 | - | - | 0.7833$_{\pm 0.0011}$ | **0.7854**$_{\pm 0.0023}$ |
| **Flickr Dataset** | | | | | | | | | | |
| Accuracy | 0.4837 | 0.4397 | 0.4915$_{\pm 0.0032}$ | 0.4920$_{\pm 0.0009}$ | 0.4741$_{\pm 0.0013}$ | - | 0.4932 | **0.5219** | 0.5099$_{\pm 0.0014}$ | 0.5156$_{\pm 0.0023}$ |
| Micro-AUC | 0.6417 | 0.5929 | 0.6274$_{\pm 0.0026}$ | 0.6367$_{\pm 0.0011}$ | 0.6124$_{\pm 0.0013}$ | - | 0.6418 | 0.6232 | 0.6546$_{\pm 0.0017}$ | **0.6614**$_{\pm 0.0026}$ |
| Macro-AUC | 0.7388 | 0.6902 | 0.7280$_{\pm 0.0028}$ | 0.7422$_{\pm 0.0010}$ | 0.7362$_{\pm 0.0011}$ | - | 0.7269 | 0.7520 | 0.7466$_{\pm 0.0015}$ | **0.7616**$_{\pm 0.0021}$ |
| Micro-F1 | 0.6046 | 0.5615 | 0.6549$_{\pm 0.0031}$ | 0.6576$_{\pm 0.0012}$ | 0.6411$_{\pm 0.0017}$ | - | 0.6653 | 0.6695 | 0.6735$_{\pm 0.0016}$ | **0.6746**$_{\pm 0.0026}$ |
| Macro-F1 | 0.6502 | 0.6109 | 0.6884$_{\pm 0.0029}$ | 0.6949$_{\pm 0.0012}$ | 0.6946$_{\pm 0.0016}$ | - | 0.7081 | **0.7243** | 0.7114$_{\pm 0.0015}$ | 0.7179$_{\pm 0.0024}$ |
| **Twitter Dataset** | | | | | | | | | | |
| Accuracy | 0.7349 | 0.6879 | 0.7435$_{\pm 0.0021}$ | 0.7379$_{\pm 0.0006}$ | 0.7046$_{\pm 0.0009}$ | - | 0.7946 | **0.8081** | 0.7792$_{\pm 0.0008}$ | 0.7828$_{\pm 0.0014}$ |
| Micro-AUC | 0.6764 | 0.6102 | 0.6155$_{\pm 0.0020}$ | 0.7010$_{\pm 0.0007}$ | 0.6014$_{\pm 0.0012}$ | - | **0.7412** | 0.6912 | 0.7307$_{\pm 0.0013}$ | 0.7183$_{\pm 0.0020}$ |
| Macro-AUC | 0.5742 | 0.5346 | 0.5707$_{\pm 0.0018}$ | 0.6064$_{\pm 0.0006}$ | 0.5809$_{\pm 0.0010}$ | - | 0.6864 | **0.7027** | 0.6378$_{\pm 0.0012}$ | 0.6185$_{\pm 0.0013}$ |
| Micro-F1 | 0.7978 | 0.7153 | 0.8273$_{\pm 0.0019}$ | 0.8239$_{\pm 0.0008}$ | 0.8067$_{\pm 0.0011}$ | - | 0.7980 | 0.7397 | 0.8597$_{\pm 0.0012}$ | **0.8601**$_{\pm 0.0018}$ |
| Macro-F1 | 0.7380 | 0.6447 | 0.7511$_{\pm 0.0022}$ | 0.7451$_{\pm 0.0007}$ | 0.6579$_{\pm 0.0008}$ | - | 0.8854 | **0.8928** | 0.8031$_{\pm 0.0009}$ | 0.8181$_{\pm 0.0017}$ |




(a) (b) (c)

### Figure 2: Comparison of Mean and Standard Deviation




(a) (b) (c)

### Figure 3: Running Time of the Proposed Algorithm

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## 5. CONCLUSIONS

In this paper, a supervised topic model referred to as dosLDA is suggested with the purpose of identifying the words that have the capacity to convey either an objective or a subjective meaning in relation to the subjects to which they are allocated. The dosLDA model has the capability of obtaining the BoDW representations for documents, and each document is endowed with two distinct BoDW representations in terms of the objective senses and the subjective senses, respectively. The findings from a number of experiments indicate that the following three things are true: (1) the BoDW representation is more predictive than the traditional BoT representation for discriminative tasks; (2) dosLDA boosts the performance of topic modeling via the joint discovery of latent semantic structure of the whole dataset and the different objective and subjective discrimination among the words; and (3) dosLDA has lower computational complexity than sLDA, especially under an increasing number of topic categories.

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