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Enhancing the Classification Accuracy in Sentiment Analysis with Computational Intelligence Using Joint Sentiment Topic Detection with MEDLDA

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ABSTRACT
Web mining is the process of integrating the information from web by traditional data mining methodologies and techniques. Opinion mining is an application of natural language processing to extract subjective information from web. Online reviews require efficient classification algorithms for analysing the sentiments, which does not perform an in–depth analysis in current methods. Sentiment classification is done at document level in combination with topics and sentiments. It is based on weakly supervised Joint Sentiment-Topic mode which extends the topic model Maximum Entropy Discrimination Latent Dirichlet Allocation by constructing an additional sentiment layer. It is assumed that topics generated are dependent on sentiment distributions and the words generated are conditioned on the sentiment topic pairs. MEDLDA is used to increase the accuracy of topic modeling.

KEYWORDS: Accuracy, Classification, Machine Learning methods, Reviews, Sentiments, Sentiment analysis

1 INTRODUCTION

SENTIMENT analysis is the territory of research that endeavors to make programmed frameworks to decide human assessment from content written in common natural language. It decides the opinion of a person concerning the general view of a document. This demeanor might be the though or assessment, full of feeling state (the passionate condition of the writer when composing), or the proposed enthusiastic correspondence. Given an arrangement of evaluative content reports that contain conclusion or assumptions around a question, sentiment mining expects to separate properties and some of the posts marked on the contents, that is used to decide whether the posts on the content are positive, negative or neutral. Classifying the given text document as positive, negative or neutral is considered as the basic task in sentiment analysis. This may be done at the sentence, aspect and document.

In the present decades, Opinion mining or Sentiment analysis has attracted with more research topics on classifying the polarity with improved accuracy. It is a really tough to do the test for views posted on different topics in different views , and accomplishing success is really a difficult task then what people think. Considering the posts/ contents written in a natural languages into a positive or negative opinion is not so easy, as the feeling or subjectivity in some cases differ based on the human annotators on the grouping to be relegated to a given content. Individual elucidation by each individual is not quite the same as others, and this is influenced by many social aspects and the involvement of individual about the content. What's more, the shorter the content, and the more regrettable composed, the more troublesome the errand moves toward becoming, as on account of messages on informal communities like Twitter or Facebook.

The primary favorable position of semantic methodologies is that mistakes are moderately simple to remedy, including the same number of words as vital, and hypothetically, this could get a high accuracy as needed, with some additional time in constructing the dictionary for the words. For such cases, approaches in machine learning concepts are regularly used, where to correct mistakes or to include

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information which is new is more complex. This is just possible by growing the gathering of writings and re-preparing the existing model. On the other hand, the learning-based methodology has the advantage that it is very simple and quick to construct a notion/supposition prepared with the gathering of labeled writings. It is consequently generally simple to fabricate classifiers adjusted to a specific area. Conversely, the need to generate a vocabulary for a specific topic, without any preparation, is difficult, since it is done manually k, so these structures are less flexible.

2 LITERATURE REVIEW

CHRISTOPHER and Dorbin (2011) investigated the density-based algorithm and proposed the scalable distance-based algorithm for analysing Web opinions. Although SDC achieves good performance in clustering Web opinions, it has own limitations. SDC does not require a predefined number of clusters and two parameters used for identifying clusters have impacts on micro and macro accuracy.

A lexicon enhanced method was proposed by Chen and Dang (2010) for sentiment classification which combines machine learning and semantic orientation approaches into one framework that significantly improves sentiment classification performance It generates a set of sentiment words based on a sentiment lexicon as a new feature dimension.

A new hybrid approach was proposed by Swati and Manali (2012) which has a rule based supervised learning and machine learning method for sentiment analysis. The hybrid approach was experimented with movie reviews and produced maximum accuracy.

Pang and Lee (2008) focused on the methods that seek to address the new challenges raised by sentiment aware applications, as compared to those that are already present in more traditional fact based analysis. It includes summarization of evaluative text and on broader issues regarding privacy, manipulation, and economic impact that the development of opinion oriented information access services gives rise to.

Daniel, et al. (2009) introduced Labelled LDA, a topic model that constraints Latent Dirichlet Allocation by defining a one–to–one correspondence between LDA’s latent topics and user tags and allows Labelled LDA to directly learn word tag correspondences. It shows Labelled LDA’s improved expressiveness over traditional LDA and Labelled LDA outperforms SVMs by more than 3 to 1 when extracting tag specific document snippets.

Zhu, et al. (2012) proposed the Maximum Entropy Discrimination Latent Dirichlet allocation (MED**L**DA), a supervised topic model leveraging the maximum margin principle for making more effective use of side information during estimation of latent topical representations.

A new topic model was proposed by Li, et al. (2019) to do entity relation detection (ERD) and use of the latent semantics of text. The approach considers pairs of named entities (NEs) and features associated with them as mini documents, and aims to utilize the underlying topic distributions as indicators for the types of relations that may exist between the NE pair. ERD-MEDLDA, adapts Maximum Entropy Discriminant Latent Dirichlet Allocation (MEDLDA) with mixed membership for relation detection. ERD-MEDLDA is a topic model that combines the benefits of both, maximum likelihood estimation (MLE) and maximum margin estimation (MME), and the mixed-membership formulation enables the system to incorporate heterogeneous features.

Applying a sentiment classifier trained using labeled data for a particular domain to classify sentiment of user reviews on a different domain often results in poor performance because words that occur in the train (source) domain might not appear in the test (target) domain. A method was proposed by Bollegala and Weir (2013) to overcome this problem in cross-domain sentiment classification. A sentiment sensitive distributional thesaurus was created using labeled data for the source domains and unlabeled data for both source and target domains. Sentiment sensitivity is achieved in the thesaurus by incorporating document level sentiment labels in the context vectors used as the basis for measuring the distributional similarity between words.

A novel probabilistic modeling framework called joint sentiment-topic (JST) model was proposed by Lin and He (2012 is based on Latent Dirichlet allocation (LDA), which detects sentiment and topic simultaneously from text. The weakly supervised nature of JST makes it highly portable to other domains. JST model even outperforms existing semi-supervised approaches in some of the data sets despite using no labeled documents. Moreover, the topics and topic sentiment detected by JST are indeed coherent and informative.

Document level sentiment classification is done in conjunction with topic detection and topic sentiment analysis of bigrams simultaneously. This model is based on the weakly supervised Joint Sentiment-Topic model, and it extends the Latent Dirichlet Allocation by adding the sentiment layer. Bigrams are considered in order to increase the accuracy of sentiment analysis was proposed by Pavitra and Kalaivaani (2015).

Latent Dirichtlet Allocation method is used with Joint Sentiment Topic detection for classification in weakly supervised sets. In the proposed method this is used with naïve Bayes algorithm was proposed by Kalaivaani and Thangarajan (2016) to further improve the accuracy of classification. The naïve Bayes algorithm is created based on weakly supervised learning techniques. So it is portable to all other domains. It produces good performance results which demonstrate the flexibility of hybrid model for sentiment analysis task.

All of the above mentioned works has the following limitations:

- In most of the previous research works, supervised learning techniques used needs labeled data for training
- Opinions were classified without topics which lowers the success of classification of the sentiments
- Only Lexicon or word net based methods were used for classification by most of the works
- They considered mostly unigrams for sentiment analysis which does not give accurate sentiment analysis for negative words such as “not good”

3 JOINT TOPIC SENTIMENT DETECTION FROM TEXT WITH LDA

A significant part of the current research on content data handling has been centered on mining and recovery of real data, e.g., data recovery, Web seek, and numerous other content mining and normal dialect preparing undertakings. Recognizing point and slant helps clients by giving more enlightening sentiment–theme mining comes about. The primary goal is the archive level opinion arrangement for general areas in conjunction with subject identification and point slant investigation, in light of the proposed pitifully directed Joint Sentiment Topic (JST). To build the model the following steps are performed.

Data Pre-processing: This is mainly done to remove the stop words and stemming was performed to remove the unnecessary words and to bet the actual verbs or adjective of the views.

Bigram generation: A bigram is sequence of two adjacent words in a string of tokens, which are usually letters, syllables, or word. This is generally called as n-grams with n=2. Bigrams are used to categorize the text effectively and classify the opinions accurately.

The steps used to generate bigrams are as follows.

- Preprocess the documents considered for classification
- Identify the positive and negative words (S)
- Combine the adjacent words
- For each pair of words, check whether if any one of the word is present in S then add list of Bigrams

Latent Dirichlet Allocation (LDA): In LDA, there is just a single subject conveyance for every individual record. In Joint Sentiment Topic method, every report generated is related with S theme disseminations, every one of which compares to a feeling mark with a similar number of points. This component basically gives intends to the JST model to anticipate the assessment related with the removed subjects. At long last, it takes a word from the per– corpus word which is based on both subject and belief of the word. This is different from LDA, that here a word is reviewed from the word circulation which is based on a concept.

Joint Sentiment Topic Model: Joint Sentiment Topic model is developed by introducing an additional sentiment layer which lies between the topic and sentiment layers. So, this is an effective model with four layers, where sentiment labels are related with documents, in which topics are connected with sentiment labels and words are allied with both sentiment labels and topics.

The algorithm for the Gibbs sampling procedure of joint sentiment and topic is given below

Require: Corpus

Confirm: Ensure that the sentiment and topic label assigned for all words are in the corpus.

1: Set the following initial terms

$S \times V \times T$ matrix as φ

$D \times S \times T$ matrix as θ

$D \times S$ matrix as π and

$C \times V$ matrix as η

2: repeat for i from 1 to max Gibbs sampling iterations

3: for all the documents in do

4: for all the words do

5: Eliminate the word that is linked with sentiment label l and topic label z fromvariables Nk,j,i,Nk,j, Nd,k,j, Nd,k,Nc,j,i, Nc,j and Nd

6: Model a new sentiment and topic pair ~l and ~z

7: do update the variables Nk,j,i,Nk,j, Nd,k,j, Nd,k, Nk,j,i, Nc,j and Nd using the new sentiment label ~l and topic label ~z

8: end for

9: end for

10: for every 25 iterations do

11: keep modifying the hyperparameter with the maximum likely hood estimation

12: end for

13: for every 100 iterations do

14: Now update the matrix and with new sampled results;

15: end for

16: end for

Newly generated sentiment topic pairs are tested using

$$\varphi_{i,j} * \theta_{d,k,j} * \pi_{d,k} * \eta_{i,j}$$

$$\text{where } \varphi_{i,j} = \frac{N_{k,j,i} + \beta}{N_{k,j} + V\beta} \tag{1}$$

$$\theta_{d,k,j} = \frac{N_{d,k,j} + \alpha_{k,j}}{N_{d,k} + \sum_j \alpha_{k,j}} \tag{2}$$

$$\pi_{d,k} = \frac{N_{d.k} + \gamma}{N_d + S_\lambda} \tag{3}$$

$$\eta_{i,j} = \frac{N_{c,j,i} + \beta}{N_{c,j} + V\beta} \quad (4)$$

Nk,j,i- Number of times word i is identified in topic j and the sentiment label k
Nk,j - Number of times the words are allotted to topic j and the sentiment label k
Nd,k,j -Number of times a word from document d being linked with topic j and sentiment label k
Nd,k - Number of times the sentiment label k is identified with the words in document d
Nc,j,i- Number of times word i appeared in topic j and relational type label c
Nc, j- Number of times words are assigned to topic j and relational type label c
Nd- Number of words in document d
α = Past observation count on number of times topic j is associated with the sentiment label l

$$\beta = 0.01 \text{ and } \gamma = (0.05*L)/S$$

where L is the document length and S is the number of sentiment labels which is positive or negative.

First, the λ matrix of size S x V is initialized with all value of 1. This is used to code the word with prior sentiment information into JST and Reverse JST models.

For each term w in the corpus vocabulary V and for each sentiment label l in S, if w is found in the sentiment lexicon, the element

$$\lambda_{1w} = \begin{Bmatrix} 1, if S(w) = 1 \\ 0, otherwise \end{Bmatrix} \quad (5)$$

where the function S(w) returns the past sentiment label of w in sentiment lexicon, which may be either neutral, positive, or negative. For an example, the word “best” in the vocabulary has a positive sentiment polarity. With this example the corresponding row vector in the above equation will be set as λ is [0, 1, and 0] with its element representing neutral, positive, and negative prior polarity.

For each topic j in T, multiplying λ li with β lji, only the value of β lposji is set to 1, and β lneuji and β lnegji are set to 0 respectively.

Thus, “best” can only be derived from the positive word generated from a Dirichlet distribution with parameter β lpos.

For the datasets Book, DVD and kitchen review, the sentiment score is calculated based on the following steps.

- Find the count of the positive and negative words
- If positive count is less than the negative count then

$$ratio = -1 * \left(positivecount \middle/ negativecount \right)$$

- If positive count is greater than the negative count then

$$ratio = -1 * \left(positivecount \middle/ negativecount \right)$$

- else $ratio = 0$
- If ratio value calculated is less than -10 then ratio is set as -10
- else ratio set as 10

Incorporation of prior information: The positive and negative lexicons which are considered as the past information is given to the JST model.

Prediction: For the Book, DVD and Kitchen datasets the sentiment polarities have been obtained using this model. The model designed for sentiment analysis is shown in the Fig 1.

New data is appended to the topic and sentiment distribution based on every iteration using incremental algorithm. This is available in different versions. Here instead of Latent Dirichlet Allocation (LDA), Maximum Entropy Discrimination Latent Dirichlet Allocation (MEDLDA) is used to improve the efficiency of topic modelling. This is designed by adding an additional layer for entity relationship detection. In order to provide the supervised information, response variable is connected to each of the document.

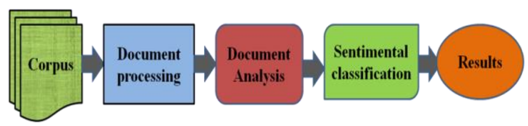

Figure 1. **Sentiment Analysis model**

The LDA is a hierarchical Bayesian model, where the topic words for a document are drawn from a Dirichlet distribution. The words in the document in turn are sampled repeatedly from a topic that is derived from those topic proportions. Response variables are introduced by MEDLDA topic model to LDA for each document. K ×M matrix denotes K with be the number of topics and M be the number of terms in a vocabulary and each β is a distribution over the M terms. The response variable y in R, is generated in MEDLDA is as follows:

1. Generate topic proportions
2. For each word:
   (a) Derive a topic assignment Z
   (b) Derive a word W
3. Generate a response variable: Y

In order to estimate the unknown constants (α,β,Ꞃ), MEDLDA maximizes the joint likelihood p(Y,W| α,β,Ꞃ), where Yis the vector of response variables in a corpus D and W is the words. The pros of using MEDLDA is that it discovers sparse and highly discriminative cal representation of topics, which achieves a state of art prediction in performance and is more effective than existing supervised approaches.

The procedure for generating a word in a document in MEDLDA is done in two stages.

(i) For a document, choose a distribution over a mixture of T topics.
(ii) Next it picks a topic randomly from the topic distribution, and picks a word from that topic according to the corresponding topic word distribution.

4 MAXIMUM ENTROPY DISCRIMINATION LATENT DIRICHLET ALLOCATION

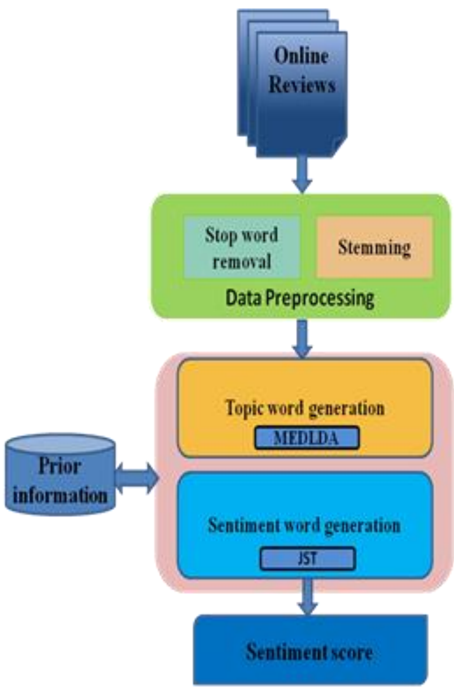

Figure 2. Architectural Framework

At the start of the process the stop words like punctuation, numbers, and non-alphabet characters were removed and stemming is done in ordered to reduce the vocabulary size. This is given as an input to the model. Using MEDLDA topic model word extraction is done without any sentiment layer as in JST. This sentiment layer is additionally included in JST.

As a semantic orientation, the prior information is provided to the JST model. The topic generation is based on sentiment labels in JST, where the polarity assigned to the words as positive, negative or neutral is treated as prior information, based on the sentiment opinion delivered. The sentiment score is calculated for each dataset, and at last the result is compared with the existing supervised models.

Prior information is referred as labeled features and used directly to constrain model's predictions on unlabeled instances using generalized expectation criteria.

The topics are assigned to the words in the document. The sentiment layer is added to get the sentiment polarity of the reviews. The algorithm of the generative process in JST corresponding to the graphical model is given in the following steps

Step 1: For every sentiment label $l \in \{1,\ldots,S\}$

For each topic draw $j \in \{1,\ldots,r\}$

Step 2: For every document d, choose distribution

$$\pi_d \sim Dir(\gamma)$$

Step 3: For every sentiment label l under document d, choose a distribution $\theta_{l,d} \sim Dir(\alpha)$

Step 4: For every word W_i in document

- choose a sentiment label $l_i \sim Mult(\pi_d)$
- choose a topic $Z_i \sim Mult(\theta_{l_i})$
- choose a response variable $Y_i \sim Mult(\eta_d)$ choose a word W_i from a multinomial $\varphi_{l_i Z_i}$ distribution over words conditioned on topic Z_i and sentiment label l_i.

Maximum Entropy Discrimination Latent Dirichlet allocation is a productive model that allows sets of observations to be described by unobserved groups, that explains as why some parts of the data are same. For an example, if the words collected into documents are the observations, it suggests that each document is a combination of a small number of topics and each word's creation is related to one of the document's topics.

The topic distribution is chosen from the parameter of Dirichlet distribution. The topic label Z is chosen from the topic distribution. A relational type label Y is chosen from the distribution over relational types. The relational distribution is the collection of similar to related words. This is done with the help of prior information.

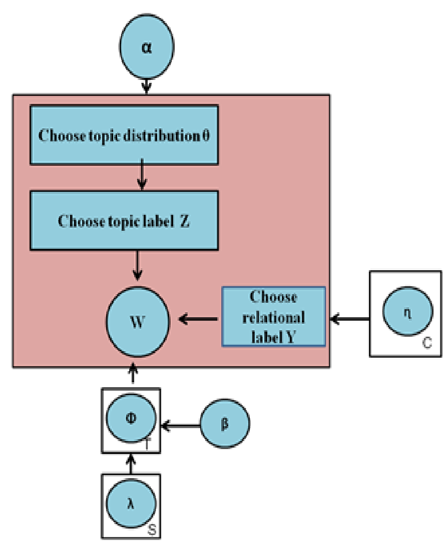

Figure 3. MEDLDA Architecture

In MEDLDA, for each individual document there is topic distribution and relational type label Y. But in case of JST each document is associated with the topic distributions, each of which corresponds to a sentiment label l with the same number of topics. This feature provides resources for the JST model to predict the opinions related with the extracted topics. Finally, a word is drawn from the per–corpus word distribution based on both topic and sentiment label. This is again different from LDA where a word is sampled from the word distribution based only on topic. The diagrammatic representation of MEDLDA process is shown in Fig. 3.

5 RESULTS AND DISCUSSION

FOR this work, multi domain sentiment dataset is used for analysis. The data set has 2000 reviews which is classified in terms of positive or negative orientation. This benchmark review dataset is collected from Cornell University.

The performance measure of sentiment or opinion classification is calculated using three factors: Accuracy, Precision, and Recall. The general way to compute these factors is based on the confusion matrix.

Table 1. Confusion Matrix

	Predicted Positives	**Predicted Negatives**
Actual Positive Instances	Number of True Positive instances (TP)	Number of False Negative instances (FN)
Actual Negative Instances	Number of False Positive instances (FP)	Number of True Negative instances (TN)

The two widely used metrics for evaluating performance in text mining, opinion mining and in information retrieval are mainly precision and recall. Precision and recall are extended versions of accuracy, and by using these measures the problem is solved for with skewed data for classifiers.

Precision is referred as the percentage of results which are relevant out of the predicted ones and recall is referred as the percentage of total relevant results classified correctly by the algorithm. The below equation(5) gives the number of examples correctly classified as positive divided by the total number that is classified as positive, while equation (6) is the number of examples correctly identified as positive divided by the total number of examples that are true positive. This is shown in the following formulas:

$$precision = \frac{TP}{TP + FP} \tag{5}$$

$$recall = \frac{TP}{TP + FN} \tag{6}$$

Accuracy is used to measure the performance in classification and error rate. It is the ratio of correctly classified examples to the total number of examples, but error rate gives the incorrectly classified examples instead of correct ones. The classification accuracy is used to determine the number of samples correctly classified and is calculated using the equation (7).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

where TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative.

TP (True positive): In a classification, if the observation tends to be positive and the predicted result is also positive then it is True Positive

True positive rate (TPR) =TP/P

P= (TP+FN)

where P – Positive TP –True Positive

TN (True negative): In a classification, if the actual observation tends to be negative and the predicted result is also negative, then it is called as True Negative

True negative rate (TNR) = TN/N

N= (TN+FN)

where N– Negative value, TN – True Negative.

FP (False positive): A result of classification indicates that it is positive but by observation it is negative. Then it is called as False positive.

False positive rate (α) = FP / (FP + TN)

FN (False negative): False negative (FN) is when the prediction result is negative but actually it is positive

False negative rate (β) =FN / (TP + FN)

A set of experiments were conducted on the proposed hybrid models with different number of documents. The proposed method used the existing thesaurus to expand feature vectors for training and testing in a binary classifier. The performance of the method depends on how far the sentiments are considered correctly and included in the thesaurus. From the predefined thesaurus, sentiment labels are extracted. While reading each sentence in the documents, sentiment topics are chosen randomly and the sentiment labels are found for each word using the thesaurus. The thesaurus contains both labeled and unlabeled data which may be collected from various domains.

Figure. 4, 5 and 6 shows the accuracy and result for Book, DVD and Kitchen

Bigrams are considered to increase the accuracy of the model with the correct identification of sentiment polarity compared to Unigrams. The related words are also considered in MEDLDA which is used for topic modeling, and this improves the efficiency of topic modeling.

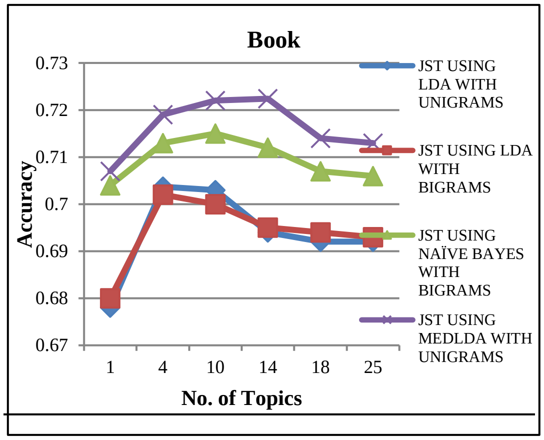

Figure 4. Comparison between Existing and Proposed Algorithm for Book

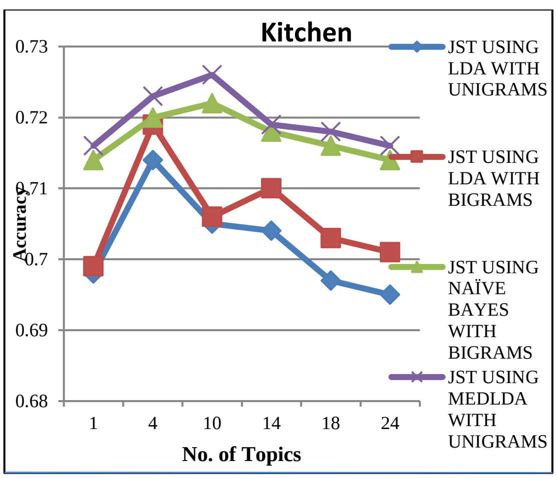

Figure 5. Comparison between Existing and Proposed Algorithm for Kitchen

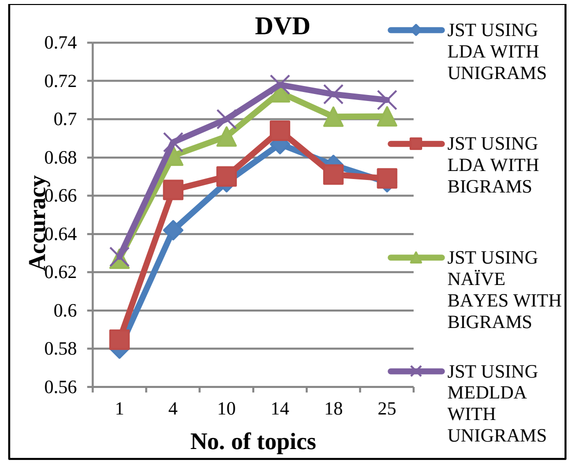

Figure 6. Comparsion between Existing and Proposed Algorithm for DVD

The main hypothesis is that most of the bigrams are no more informative than just combinations of unigrams, but their addition increases the variance. Highly discriminative bigrams do exist, but their ratio to "junk" bigrams is low. These "good" bigrams are indeed able to improve the classification results, but their contribution is weak in comparison to what hundreds of thousands of unigrams can contribute. So the efficiency is slightly improved and not too much extent. In proposed work the accuracy percentage has increased and the error rate has been decreased.

6 CONCLUSION

IN this work the ways to deal with sentiment analysis support administered learning. JST show targets notion and theme location all the while in a weekly directed manner. The broad investigations led on informational collections crosswise over various areas uncover that the model acts diversely when slant earlier learning is fused. For general area assumption arrangement, by consolidating a little measure of space autonomous earlier learning, the JST display with MEDLDA accomplished either better or comparable performance contrasted with existing semi– regulated methodologies regardless of utilizing no named records. It exhibits the adaptability of JST in the notion arrangement undertaking. In addition, the points and theme assessments distinguished by JST are to be sure reasonable and useful. Most of the nature inspired algorithms are used only for optimization. So machine learning algorithms alone is considered for classification improvement.

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