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Dual Sentiment Analysis with Three-Stage Model for Complex Polarity Shift Patterns with Two Sides of One Review

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ABSTRACT: Sentiment classification is a unique process of text categorization whose objective is to categorize a text related to the sentimental polarities of opinions it consists of constructive or adverse, positive or negative. Bag-of-words (BOW) is now the major famous method to form text in numerical machine learning methods in Sentiment Analysis (SA). On the other hand, the accuracy of BOW sometimes still remains lesser because of various basic disadvantages in handling the polarity shift problem. To deal with this problem, Dual Sentiment Analysis (DSA) is proposed in the recent work and it is used for SA classification. However in DSA is should consider more difficult polarity shift patterns are middle, subjunctive and sentiment-inconsistent sentences in forming reversed reviews. To solve this problem a Three-Stage Model (TSM) is combined to Dual Sentiment Analysis (DSA) classifier named as DSA-TSM. Initially divide the each set of documents into a set of sub-sentences and build a hybrid classifier which creates the rules and machine learning model to distinguish precise and hidden polarity shifts, correspondingly. Secondly, corpus based method is introduced to build a pseudo-antonym dictionary in the direction of polarity shift elimination technique, to remove polarity shift in negations. Finally, dual training and dual prediction algorithm is proposed for learning a sentiment classifier which classifiers the polarity into three major classes such as positive-negative-neutral by considering the neutral reviews into consideration. The results of the proposed DSA-TSM model are significantly improved when compared to DSA schema and other methods in terms of accuracy, precision, recall and f-measure.

INDEX TERMS: Natural language processing, machine learning, sentiment analysis, opinion mining, Three-Stage Model (TSM).

1. Introduction

Sentiment Analysis (SA) is the computation method of opinions and sentiments discussed in text [1]. SA is generally carryout depending on sentiment words which specify the sentiment polarity of a text documents. The major challenge of this approach is with the purpose of the vocabulary polarity of an emotion word might be reversed by means of sentence perspective [2]. Several methods have been proposed in the recent work for SA classification. These work demonstrated to discover the sentiment of entire text documents. Recognize the polarity of language in the direction of a specific topic, on the other hand, no longer needs recognizing the sentiment of a complete set of documents text, however moderately the background sentiment close a target expression. Document polarity categorization provides a new issue to data-driven models; opposes conventional text-classification methods [3]. Recent review works focused on choosing investigative lexical features, categorizing a text documents related to the number of such features which happen somewhere inside it. On the contrary, introduce the following procedure: (1) label the sentences in the texts as whichever subjective or objective, removal the later; and then (2) relate a typical machine-learning model in the direction of the resultant extract. This is able to stop the polarity categorization from considering unrelated or still potentially misleading text.

Accordingly, a huge number of works in SA aimed to increase BOW by integrating linguistic information [4-6]. On the other hand, appropriate to the basic issues in BOW, many of these efforts demonstrate extremely small results in increasing the categorization accuracy. One of the majorities of distinguished difficulties is the polarization shift problem. Polarity shift is a category of linguistic occurrence which is able to reverse the sentiment polarity of the text. Exclusion is the mainly significant form of polarity shift. For instance by means of count a negation word "don't" in the direction of a positive text "I like this book" in obverse of the word "like", the sentiment of the text determination be reversed beginning positive to negative. On the other hand, the two sentiment-opposite texts are measured to be extremely related by means of the bag-of-words. This the major reason when the standard classification algorithm may fail to solve polarity shift problem and many works have been done in the recent work to solve this problem [7-8]. On the other hand, many of them needed moreover complex linguistic knowledge. Such an advanced dependency on external resources create the systems becomes very difficult to be extensively used in many works. Many of the work have been proposed in the literature to solve this polarity shift problem [9-11] with the nonexistence of extra annotations and linguistic information. On the other hand, to the best of the information, the conventional method results are still extreme starting suitable.

This research work proposed a new TSM model which reversed reviews of the text documents for solving polarity shift classification problem which classifies the class into two major classes such as positive and negative. The unique and reversed reviews are created in a single-to-single correspondence. Dual training and prediction algorithm is proposed to classify original and reversed sentences in pairs for training and testing model. In DT stage, the categorization is learnt by maximizing a grouping of likelihoods of the unique and reversed training samples. In DP stage, the testing is performed by considering two sides of one review. With the purpose of calculate not only how positive/negative the unique analysis is there, however moreover how negative/positive, subjective and partial the reversed evaluation. Additional enlarge DSA into three stage positive negative- neutral classification by considering the neutral reviews addicted is introduced to together DT and DP stage. To decrease DSA's addiction on an external antonym dictionary, corpus-based method is proposed for creating a pseudo-antonym dictionary. This dictionary is language-free and area adaptive. It formulates the DSA model potential to be functional into a several range of applications. The results of the proposed DSA-TSM model are significantly improved when compared to DSA schema and other methods in terms of accuracy, precision, recall and f-measure.

2. Literature Review

Chen et al [12] proposed a new optimization-based approach which automatically mine sentiment expressions on behalf of a known target (e.g., movie, or person) from a corpus of unlabeled tweet documents. Specifically, this proposed optimization-based approach is performed three major stages: (i) To identify the a different and richer set of sentiment-behavior expressions in tweets together with recognized and slang words/phrases, not restricted to pre-specified syntactic examples; (ii) As opposed to related in emotion with an complete tweet, we review the object-dependent polarity of every sentiment expression. The polarity of sentiment expression is strong-minded by the character of its target; (iii) it also gives a new formulation of assigning polarity toward a sentiment expression as a constrained optimization problem for tweet corpus. The results are conducted and validated on two domains, tweets reveals on movie and person entities; results demonstrate that the proposed approach obtains higher results when compared with traditional methods and it becomes more important with increased corpus sizes.

Cui et al [13] proposed a new machine learning algorithms for online review datasets, which is used to estimate several trades-offs in experimentally and used roughly 100K product reviews from the internet. Choi & Cardie [14] proposed a new learning-based approach for subsentential interactions in light of compositional semantics which incorporates structural inference. The results demonstrated that the proposed work was a simple and performs better than other learning methods, produces accuracy results of 89.7% vs. 89.1% for single semantics, for integrated compositional semantics it produces accuracy results of 90.7%. The results also demonstrated that it performs better for content-word negators.

Maas et al [15] proposed a new hybrid model which combines the procedure of unsupervised and supervised techniques in the direction of study word vectors capturing semantic term–document information in addition to rich sentiment substance. The proposed hybrid model might control together constant and multi-dimensional sentiment data in addition to non-sentiment annotations. This hybrid model makes use of the text-level sentiment polarity explanation current in various online documents. This work validated the hybrid model using small, extensively used emotion and bias corpora, it discover it performs better when compared to state of art methods for sentiment categorization. The results are validated using the movie reviews to serve as an additional strong benchmark designed for work in this part.

Sentiment analysis seeks to recognize the viewpoint(s) fundamental a text span; an instance application is categorizing a movie review as “thumbs up” or “thumbs down”. Pang and Lee [16] proposed a new machine-learning method for solving polarity shift problem in text-classification. Extracting these portions has been experimented using many techniques for discovering minimum cuts in graphs; this significantly helps the integration of cross-sentence appropriate constraints.

Harihara et al [17] proposed a new dual-classifier approach in the direction of appropriate sentiment analysis on the SemEval-2013 Task 2. Contextual investigation of polarities paying attention on a word rather than the broader task of identifies the sentiment of an entire text. The Task 2 description consists of target word spans with the purpose of range in size starting a single word toward entire sentences. On the other hand, the perspective of a single word is dependent on the words nearby syntax, at the same time as a phrase consists of the majority of the polarity inside itself. So explain a separate treatment by means of two self-determining classifiers, outperforming the results of a single classifier. This proposed dual-classifier approach ranked 6th out of 19 teams on SMS message categorization, and 8th of 23 on twitter data provides higher results when compared to the other methods with little quantity of word context is required for high-results polarity extraction.

Vakali et al [18] developed a new SA classifier which classifies the samples as positive and negative polarity. It provides higher and wider expressive scales in the direction of present’s new smart services over mobile devices which make use of micro-blogging data study for selected topics, locations and time. It is helpful designed for many communities such as rule makers, establishment and the public. When faced by means of the task for creating NLP model, it is frequently valuable in the direction of turn to dynamic learning to get human annotations at reduced costs. Conventional active learning methods query a human designed for labels of brightly selected samples. On the other hand, human attempt be able to moreover be finished in collecting different forms of annotations.

Jagtap and Dhotre [19] proposed new polarity shift classifiers which automatically teacher feedback evaluation scheme. As know, teacher is significant measurement of education. Consequently development and performance monitoring of teacher is also significant factor of teaching scheme. It might be calculated by considering feedback from student designed for specific teacher. The dataset samples were collected from student with larger size to concluding result is major difficult task. At this time, SA plays a major important role so hybrid sentiment classification is performed by considering Hidden Markov Model(HMM) and Support Vector Machine (SVM) classifier.

Qiu et al [20] proposed a new approach for polarity shift problem, which is mechanically approximation the sentiment of environment posts, learns sentiment modify patterns in CSN members, and permits examination of factors with the purpose of influence the sentiment alteration. This is the initial study of sentiment benefits and dynamics in a huge-scale health-associated electronic community discovers with the purpose of an estimated 75%–85% of Cancer Society Cancer Survivors Network (CSN) discussion participants modify their sentiment in a helpful way during online interactions with additional neighborhood members. Two new features, Name and Slang, not formerly second-hand in SA, make easy recognizing positive sentiment in posts. This work concludes that the initial concepts designed for additional studies of sentiment impact of OHC contribution and gives higher results to emotional support to their members

Nakagawa et al [21] proposed a new semi-supervised model for subsentential SA with the purpose of calculate polarity related on the interactions among nodes in dependency graphs, which potentially be able to stimulate the scope of exclusion. Dependency tree-based method is proposed for sentiment categorization of Japanese and English subjective sentences with conditional random fields by means of hidden variables. A subjective sentence frequently encloses words which reverse the emotion polarities of other words. So, interactions among words should be considered in sentiment categorization, which is complex to be deal with easy bag-of-words approaches, and the syntactic dependency formation of subjective sentences are exploited in this tree-based method. The experimentation results concludes that the proposed semi-supervised model for SA of Japanese and English subjective sentences provides better results when compared to other methods based on bag-of-features.

Ikeda et al [22] proposed a machine learning based method for polarity shift problem. The words meaning is determined from lexical dictionary extracted from General Inquirer in the direction of form polarity-shifters designed for both word-wise and sentence-wise sentiment categorization. There were still some methods with the purpose of addressed polarity shift not including of complex linguistic study and additional annotations. For instance, Li and Huang [23] introduced a new method to categorize each sentence in a text addicted to a polarity-unshifted part and a polarity-shifted part related to specific rules, then to characterize them as two bags-of-words for sentiment categorization. Negation and difference alteration are two types of linguistic occurrence which are widely used in the direction of reverse the sentiment polarity of a number of words and sentences.

3. Proposed Methodology

This work introduces a novel three stage model (TSM) for sentimental analysis in reviews which solves the polarity shift problem. This TSM model classifies the review dataset into three major classes such as positive-negative-neutral. This TSM model is performed in three major stages, in the initial stage of the work split the each text documents into a set of sub-sentences .For this purpose, hybrid model is introduced which combines the rules and statistical method to identify the explicit and implicit polarity shifts, correspondingly. Secondly a polarity shift elimination method is introduced to remove polarity shift in negations. At finally , base classifiers is introduced on training dataset divided by varied types of polarity shifts, and make use of a weighted mixture of the hybrid classifiers designed for dual sentiment categorization. The results demonstrated that the proposed TSM model work extensively performs better on existing methods for polarity shift identification and forming reversed reviews in the direction of help supervised sentiment categorization.

Data expansion method is proposed with the purpose of extraction of data for sentiment analysis. Varied from the other methods discussed in the literature, the unique and reversed reviews are created in a one-to-one correspondence.

Text reversion: If there is exclusion, initial distinguish the capacity of negation. Each and every one sentiment words out of the capacity of negation are reversed in the direction of their antonyms. In the capacity of negation, negation words (e.g., “no”, “not”, “don’t”, etc.) are removed, however the emotion words are not reversed;

Label reversion: For every of the training dataset, the class label is moreover reversed in the direction of its opposite (i.e., positive to negative, or viceversa), as the class label of the reversed review. Note with the purpose of the formed sentiment-reversed review might not be as good as the one created by human beings. Since together the original and reversed review texts are denoted by the BOW demonstration in classifier, the word order and syntactic structure are completely disregarded. Consequently, the constraint designed for maintenance the grammatical superiority in the formed reviews is lesser as with the purpose of human languages. Furthermore, determination makes use of a trade-offs parameter in the direction of control the unique and reversed reviews in double prediction. Assigning a comparatively lesser weight in the direction of the reversed review is able to protect the representation from being broken through integrating low-quality review samples. This work presents a TSM for text-level sentiment categorization. The three stages are 1) hybrid polarity shift detection, 2) polarity shift elimination in negations and 3) polarity shift based categorization model designed for solving conflicting difficulty from the dual SA process.

Hybrid Polarity Shift Detection

In this work at primary, proposes a hybrid method in the direction of distinguish varied types of polarity shifts, which is discussed as follows, polarity shifters, also named “valence shifter” and “sentiment shifter” words and phrases with the purpose be able to modify emotion orientations of texts. Polarity shift is a difficult linguistic structure with the purpose of might contain precise negations, difference, intensifiers, diminishers, irrealis, etc [24]. In [24] reviewed a statistic on the division of varied types of polarity shift, and reported with the purpose of precise negations and difference covers more than 60% polarity shift construction.

Negation is the most regular category of polarity shifts. For instance, in the review

Review 1 (Explicit Negation): “I don’t hate my job”,

The negator “don’t” transfer the division of the emotion word “hate”. It generally has explicit hints (i.e., negators) in negation. Consequently, this work is able to confine the open negation by means of using some rule-based methods with the presence of a number of pre-defined negators.

Contrast is one more significant class of polarity shifts. For instance in the review:

Review 2 (Explicit Contrast): “Honestly very hard to do, but job is very interesting”,

The contrast indicator “however” shifts the emotion polarity of the earlier phrase “Honestly very hard”. Parallel as explicit negations, this might moreover use rule-based method in the direction of detects the precise contrasts related to a number of pre-defined contrast indicators. At the same time as some polarity shift structures such as explicit negations and contrasts are comparative simple toward detect, there still be present a huge part of implicit polarity shifts with the purpose it is very difficult to identify based on simple rule-based methods. For instance in the review

Review 3 (Sentiment Inconsistency): "I don't hate my job. Great reputation company, less salary",

The initial expression "I don't hate my job" states a positive sentiment in the direction of the career, the second expression "great reputation company" demonstrate a positive sentiment in the direction of work place, and the third expression "less salary" states the negative sentiment in the direction of characteristic of situation. In this case, people hold a positive attitude in the direction of one secondary characteristic, which is reverse in the direction of the sentiment of the complete review. This names this category of polarity shift "sentiment changeability".

In [25] referred to these issues as "thwarted expectation", which is identical to not consistent or mixed emotion patterns in the analysis text. This occurrence is particularly general in extensive review texts, where people may have diverse opinions in the direction of diverse characteristic of one result. However in emotion variation, the attitude is not consistent to with the purpose of its neighbours, and is always different in the direction of the emotion expressed on the product generally. In this case, there are not open hints designed for polarity shift detection. However, accordingly these work might use a statistical method in the direction of identify them. The methods in the direction of handle diverse types of polarity shifts in sentiment categorization.

Algorithm 1 presents the pseudo-code of the polarity shift detection algorithm

1. **Input:** document $c = (d_1, d_2, d_3 \ldots . d_n)$, negation indicator set $I = (i_1, i_2, \ldots i_m)$, and contrast indicator set $S = (s_1, s_2, \ldots . S_t)$
2. **Output:** ,$doc_{contrast}$, $doc_{inconsistence}$ and $doc_{noshift}$
3. for $= 1, \ldots ., n$:
4. for $j = 1, \ldots, |d_i|$:

(1) 5. if $u_{ij} \in I$: put d_i into$doc_{negation}$; # capture negations

5. continue;
6. if $u_{ij} \in S_1$: put d_{i-1} into $doc_{contrast}$; # capture contrasts (fore-contrast)
7. continue;
8. if $u_{ij} \in S_2$: put d_i into $doc_{contrast}$; # capture contrasts (post-contrast)
9. continue;
10. compute $r(u_{ij})$;
11. compute $h(d_i)$;
12. if $h(d_i) < 0$: put d_i into $doc_{inconsistence}$; #capture sentiment inconsistency
13. let $doc_{no\ shift} = doc - doc_{negation} - doc_{contrast} - doc_{inconsistence}$

(1) Rule-based polarity detection for negations and explicit contrasts

Propose a rule-based method for polarity shift detection. Let $I = (i_1, i_2, \ldots i_m)$ which describes the set of negation indicators (i.e., negators), $S = (s_1, s_2, \ldots . S_t)$ represents the set of contrast indicators (i.e., disjunctive conjunctions). Here this used the disjunctive conjunctions, which includes "but", "however", "yet", "unfortunately", "thought", "although" and "nevertheless". Let us consider that the a document doc is composed of subsentences $c = (d_1, d_2, d_3 \ldots . d_n)$, where each subsentence d_i is represented by a list of words consisting in the sentence $d_i = (w_{i1}, w_{i2}, \ldots ., w_{i|d_i|})$. Let us consider $doc_{negation}$ and $d_{contrast}$ as subsets with the purpose of consists of negations and contrasts, respectively. From step 3 to step 10 in Algorithm 1 shows the rule-based methods for detecting negations and explicit contrasts. Specifically, put the subsentence d_i that contains a negation indicator into $d_{negation}$. For a subsentence consisting of the "fore-contrast" indicators, put its previous subsentence d_{i-1} into $c_{contrast}$; for a subsentence consisting of the "post-contrast" indicators, put the current subsentence d_i into $doc_{contrast}$. Finally, each document doc in the training and test text-documents is categorized into three parts: $doc_{negation}, doc_{contrast}$, and $doc_{no\ shift}$, it is suitable to solve only explicit polarity shift problem. In the next step a statistical method is proposed to identify the hidden sentiment variation.

(2) Statistical polarity shift detection for implicit contrasts

The statistical method is proposed to identify the implicit sentiment inconsistency of Dual Sentiment Analysis(DSA). The basic procedure is performed based on the phenomenon with the purpose of the sentiment changeability has the different polarity to with the purpose of its neighbouring subsentences in addition to the entire review . The subsentences with the purpose of have the different sentiment polarities in the direction of the entire review are labeled as sentiment changeability. From step 11 to 12 algorithm 1 shows the procedure of statistical method for identifying sentiment changeability. Particularly, this work proposes a weighted log-likelihood ratio (WLLR) algorithm in the direction of identify conflicting sentiment in the text. WLLR is considered as the feature selection method for text categorization [26]. Formally, WLLR measures the relevance of the feature f_i to the class label cl_j as follows:

$$r(f_i, cl_j) = p\left(f_i \middle| cl_j\right)\log\frac{p(f_i|cl_j)}{p(f_i|\overline{cl_j})} \quad (1)$$

In this proposed approach, make use of WLLR in the direction of acquire the relevance of each feature and two classes, i.e., Positive (+) and Negative (-), ,then calculate a WLLR score regarding a feature f_i as:

$$r(f_i) = r(f_i, +) - r(f_i, -) \quad (2)$$

Second, this work calculates the direction of each subsentence based on the WLLR score. Let us consider that the document as doc is consists of n subsentences $c = (d_1, d_2, d_3 \dots . d_n)$, where each sentence d_i is denoted by a list of words considered in the subsentence $d_i = (w_{i1}, w_{i2}, \dots, w_{i|d_i|})$. This work describe the positive relevance and negative relevance of a sub-sentence d_i as

$$g(d_i) = \sum_{h=1}^{|d\_i|} r(w_{ih}) \quad (3)$$

Lastly, this work describe the sentiment changeability indicator functions $h(d_i) = xg(d_i)$ where x is the class label. Note with the purpose of training document c_k, the class label x_k is already given as $x\epsilon\{+1, -1\}$. For each test document doc_i use the sum of relevance scores in the document as the estimated of the true class label:

$$\bar{x} = \text{sign}\left(\sum_{j=1}^{n}\sum_{k=1}^{|d_j|} r(w_{jk})\right) = \text{sign}\left(\sum_{k=1}^{|doc_i|} r(w_k)\right) \quad (4)$$

If $h(d_i) < 0$, (i.e., the sentiment polarity of d_i and doc are different), and say, sentence d_i is sentiment not consistent by means of the document doc. Or else, it believe d_i does not have sentiment changeability.

Negation Polarity Shift Elimination

The second stages of this system propose a polarity shift elimination algorithm to remove negations in the reviews. The idea is to use the antonym words, so some antonym dictionary is needed to remove words. In this part, introduce a totally corpus-based method to construct a “corpus-sense” antonym dictionary, without using any lexical resources.

The Lexicon-Based Antonym Dictionary

In the languages where lexical resources are abundant, a simple system is toward obtaining the antonym dictionary straightforwardly from the distinct lexicon with WordNet. WordNet is a lexical database which clusters English words into sets of synonyms called synsets, provides short, general description, and records the many semantic relations among these synonym sets. Using the antonym thesaurus it is potential in the direction of attain the words and their opposites. From the English words this dictionary is not be readily available. So corpus based method is proposed to construct a pseudo-antonym dictionary and can be learned by using training data. The basic procedure is to make use of MI in the direction of recognize the most helpful appropriate and the mainly negative-relevant features, rank them in two major classes, and pair the features with the intention of have the similar level of sentiment strength as pair of antonym words.

The Corpus-Based Pseudo-Antonym Dictionary

In information theory, the mutual information of two random variables is an amount with the purpose of measures the mutual measurement between variables. MI is extensively used as a feature selection procedure in sentiment categorization. Primary, select each and every one adjectives, adverbs and verbs in the training text documents as candidate features, and make use of the MI metric in the direction of determine the significance of each candidate feature w_i in the direction of the positive (þ) and negative (-) class, correspondingly. It is significant in the direction of notice with the purpose of rather than a common-sense antonym dictionary, it is a “pseudo” antonym dictionary, Here, “pseudo” means a pair of antonym words are not actually semantic-opposite, however contain opposite sentiment strong point just must in the direction of maintain the level of sentiment strength in review reversion. Actually, the MI gives a good evaluate of the appropriate sentiment strength. Consequently, the form of the similar level sentiment strength is able to be essential by means of pairing the positive and negative-relevant words among the same ranking positions. Furthermore, since the pseudo-antonym dictionary is learnt from the training text documents, it has a high-quality property: language- independent and domain-adaptive. This property formulates the DSA model potential in the direction of be applied into a various range, particularly when the lexical antonym dictionary is not obtainable across varied languages and domains. WLLR proposed work again in the direction of recognize the mainly positive and negative class in the training corpus, select adjectives, adverbs and verbs as candidate words, and rank the candidate words related to a decreasing order of $r(r(f_i) = r(f_i, +) - r(f_i, -))$and in Equation (5), respectively:

$\Upsilon_+ = [pwd_1, pwd_2 \ldots pwd_T]$, $\Upsilon_- =$ (5) $nwd_1, nwd_2 \ldots, nwd_T$,.

The antonym dictionary is then created through zipping Υ_+ and Υ_- . Each word pair $\{(pwd_i, nwd_i)\}_{i=1}^{T}$ in is measured as a pair of antonyms. It is significant in the direction of notice with the purpose of it is a corpus-sense antonym dictionary, moderately than an ordinary-sense antonym dictionary. For instance this work might learn an antonym word pair (interesting, hard) from the career review category data, thus, the negation text “the job is interesting” determination be converted into “the job is hard”. It must be noted with the purpose of though “hard” is not a high-quality opposite word of “interesting”, the WLLR system be able to promise with the purpose of “hard” and “interesting” has the similar level of sentiment strength depending on learning from the corpus, and consequently determination still make sense in sentiment categorization.

The Polarity Shift Based classification Model

Polarity shift detection model is proposed to find the negation polarity shift elimination approach. Each text documents both training and testing phase is performed with three major stages: 1) the eliminated negation division, 2) the contrast division, and 3) the sentiment inconsistency division and 4) the division not including polarity shift. Here ensemble model is proposed to train and test the dataset documents for sentiment categorization depending the above mentioned three parts of text, correspondingly. The ensemble technique with the purpose of integrates the outputs of some base classifiers to form a combined output have develop into a successful categorization method for several domains including sentiment categorization [26]. The detection of ensemble model is motivated by means of the perception with the purpose of a suitable combination of varied parts with respect to polarity shift capacity leverage dissimilar strengths in sentiment categorization. Let $o_{kj}(x)$ represents the result of the $k-th$ base-classifier for the j-th class. Subsequently, the weighted ensemble might be written as follows,

$$l_j \sum_{k=1}^{T} \theta_k o_{kj}(x), j = +, - \qquad (6)$$

where C and D are the number of classes and classifiers correspondingly, θ_k represents the weights designed for each parts. A successful ensemble system is proposed in the direction of give a comparatively larger weight in the direction of the base classifier trained on the polarity upshifted parts, at the same time as allocate a qualified smaller weight in the direction of the base classifiers trained on the polarity shifted parts. Following remove the polarity shift problems; one more novelty of this work is with the purpose of it determination expand the text documents not only in the training stage, but also in the test stage. The original and reversed test review is used in pairs for sentiment calculation.

4. Results and Discussion

In the experimental work, we will assess the results of the corpus based pseudo-antonym dictionary by performing experiments on diabetes datasets. The results are also compared with other Mutual Information (MI) and Word Net dictionaries on the multi-domain sentiment datasets. The results are experimented to three classification algorithms such as Dual Sentiment Analysis- MI (DSA-MI), DSA-WN and proposed DSA-TSM model. It concludes that the proposed DSA-TSM model is successful in discovering reversed and non reversed order topics. The results of these classifiers are measured using the performance metrics like precision, recall, f-measure and accuracy with respect to the ground truth.

Normalized Mutual Information (NMI) is described as the harmonic mean of homogeneity (h) and completeness (c); i.e.,

$$V = \frac{hc}{(h+c)} \qquad (7)$$

where

$$h = 1 - \frac{H(C|L)}{H(C)}, C = 1 - \frac{H(L|C)}{H(L)} \qquad (8)$$

$$H(C) = \sum_{i=1}^{|C|} \frac{|c_i|}{N} log \frac{|c_i|}{N} \qquad (9)$$

$$H(L) = -\sum_{j=1}^{|L|} \frac{|w_j|}{N} log \frac{|w_j|}{N} \qquad (10)$$

$$H(C|L) = -\sum_{j=1}^{|L|}\sum_{i=1}^{|C|} \frac{|w_j \cap c_i|}{N} log \frac{|w_j \cap c_i|}{|w_j|} \qquad (11)$$

$$H(L|C) = -\sum_{i=1}^{|C|}\sum_{j=1}^{|L|} \frac{|w_j \cap c_i|}{N} log \frac{|w_j \cap c_i|}{|w_j|} \qquad (12)$$

Accuracy is calculated based on a combinatorial method which regards as each potential pair of data objects. Each pair be able to reduce into one of four groups: if together objects belong to the similar class and similar cluster in the pair is known as True Positive (TP); if both objects belong to the similar cluster however diverse classes the pair is known as False Positive (FP); if objects related to similar class however different pair of order is known as False Negative (FN); or else the data objects go to varied classes and diverse order then the pair is known as True Negative (TN). The Rand Index(RI) is also known as accuracy;

$$RI = Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \qquad (13)$$

The F-measure is defined as the harmonic mean of precision and recall is described as follows; i.e.,

$$F - measure = \frac{2PR}{(P+R)} \qquad (14)$$

$$Precision(P) = \frac{TP}{(TP+FP)} \qquad (15)$$

$$Recall(R) = \frac{TP}{(TP+FN)} \qquad (16)$$

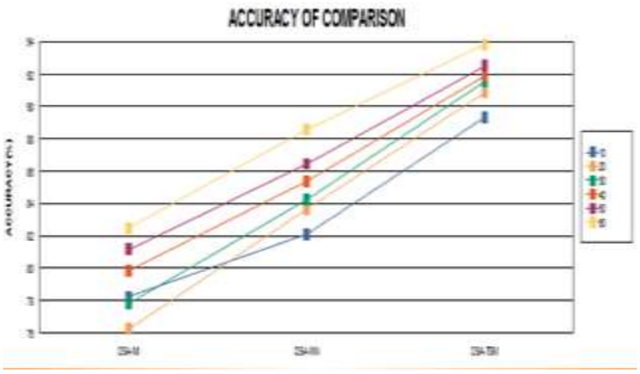

Figure 1. Accuracy of comparison vs. sentiment analysis methods

Figure 1 shows the accuracy comparison results of various sentiment analysis methods such as Dual Sentiment Analysis- Mutual Information (DSA-MI), Dual Sentiment Analysis- Word Net (DSA-WN) and Dual Sentiment Analysis- Three Stage Model (DSA-TSM). In compared with the lexical antonym dictionary, proposed corpus-based pseudo-antonym dictionary performs better across different languages and domains, results are tabulated in Table 1. It concludes that the DSA-TSM produces higher results of 93.84%, whereas other methods produce results of 88.58% and 82.48% for DSA-WN and DSA-MI methods respectively

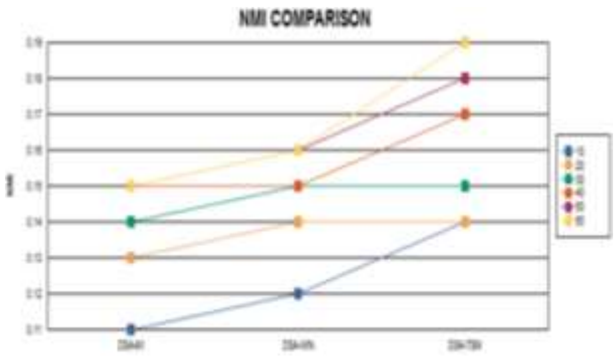

Figure. 2. NMI comparison vs. sentiment analysis methods

Figure 2 shows the results of different classification methods such as DSA-MI, DSA-WN and DSA-TSM in terms of NMI. It concludes that the DSA-TSM produces higher results of 0.19, whereas other methods produce results of 0.16 and 0.15 for DSA-WN and DSA-MI methods respectively. Since the proposed work uses a corpus based pseudo-antonym dictionary by learning the corpus, is also good NMI results are tabulated in Table 2.

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Table. 1 Accuracy of comparison vs. sentiment analysis methods

Algorithm name		Percentage of documents					
		10	20	30	40	50	60
DSA-MI	Accuracy	78.25	76.24	77.81	79.84	81.15	82.48
DSA-WN		82.10	83.65	84.23	85.38	86.45	88.58
DSA-TSM		89.32	90.86	91.54	91.89	92.51	93.84

Table. 2. NMI of comparison vs. sentiment analysis methods

Algorithm name		Percentage of documents					
		10	20	30	40	50	60
DSA-MI	NMI	0.11	0.13	0.14	0.15	0.15	0.15
DSA-WN		0.12	0.14	0.15	0.15	0.16	0.16
DSA-TSM		0.14	0.14	0.15	0.17	0.18	0.19

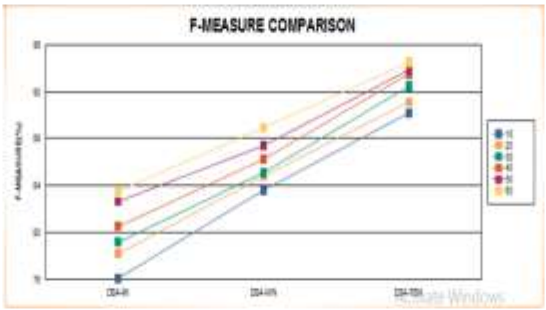

Figure.3. F-measure comparison vs. sentiment analysis methods

Figure 3 shows the results of different classification methods such as DSA-MI, DSA-WN and DSA-TSM in terms of F-Measure. It concludes that the DSA-TSM produces higher results of 94.52%, whereas other methods produce results of 88.94% and 83.52 % for DSA-WN and DSA-MI methods respectively. Since the proposed work uses a corpus based pseudo-antonym dictionary by learning the corpus, the results are tabulated in Table 3.

Table. 3. F-measure of comparison vs. sentiment analysis methods

Algorithm name		Percentage of documents					
		10	**20**	**30**	**40**	**50**	**60**
DSA-MI	**F-measure**	76.12	78.23	79.18	80.52	82.65	83.52
DSA-WN		83.61	84.82	85.12	86.25	87.41	88.94
DSA-TSM		90.21	91.14	92.48	93.51	93.87	94.52

5. Conclusion and Future Work

In this work, introduces a new data expansion model, called DSA-TSM model to solve polarity shift problem in SA classification as well as generating reversed reviews through subjunctive and sentiment-inconsistent sentences. In the initial stage of DSA-TSM model make use of a rule-based method toward distinguish explicit negations and contrasts. As well as the statistical method is proposed to distinguish the hidden sentiment variation. In the second stage of the work corpus based method is proposed to create a pseudo-antonym dictionary. This dictionary is able to be trained using the labeled training data itself. After the completion of these two stages, logistic regression model is proposed which classifies the training samples into positive, negative and neutral. The basic procedures of DSA-TSM model is toward form reversed reviews with the purpose of sentiment-opposite toward the original reviews, and creates use of the unique and reversed reviews in pairs toward train a SA classifier and formulate predictions.

Recognize together unique and reversed reviews in the form and make use of them for SA of text .DSA-TSM is highlighted by the model of one-to-one correspondence of information expansion and the way of using a pair of dataset samples in dual training and testing. Moreover expand the DSA-TSM algorithm, which might handle positive-negative-neutral based SA classification. Chinese sentiment datasets uses an external antonym dictionary, and the performance result of proposed DSA-TSM model provides higher results when compared to other existing DSA-MI and DSA-WN methods. In the future work proposed a context-aware method designed for investigating sentiment at the level of person sentences in together unique review and reversed review order. Modelling of difficult linguistic structures across sentences and frequently not succeed in the direction of confine nonlocal contextual cues are significant designed for dual emotion analysis; consequently it is also measured as one of the scope for future work. Encode insightful lexical and discourse information as meaningful constraints and incorporate them into the training of Conditional Random Field (CRF) technique via following regularization. In scope of the future work determination will discover better ways in creating less-noisy polarity shifting training data and testing data.

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