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A Review on Integrated Control and Protection System for Photovoltaic Microgrids

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Abstract- Availability of the huge amount of unstructured data accessible online today, there is much to be picked up from the mining frameworks that can effectively sort out and order this information, so it can be utilized by clients. Sentiment investigation has attracted awesome attention for many researches for blog entries, film and eatery surveys, and so forth. So these papers solve issues of sentiment identification by using particle swarm optimization algorithm. Identification of sentiment was done by using pattern feature of text mining. So based on clustered patterns obtain from generic algorithm sentiment identification was done. Experiment was done on real dataset and results shows that proposed work has improved the various evaluation parameters of sentiment analysis.

Keywords- Classification, Sentiment analysis, Ontology, Text Mining , Un-directed Classification.

I. INTRODUCTION

Sentiment or opinion mining refers to the type of natural language processing used to understand the moods, opinions and sentiments of the public regarding a particular product or a movie or an event. The availability of large amounts of data and the human tendency to always manipulate what other people think has been influential in a decision making process. This unique feature plays a vital role in deciding on matters that have financial, medical, social or other implications. Seeking second or third or many more opinions have fuelled the interest of researchers in the field of sentiment mining.

With multiple reviews available for a single product and the enormous growth in the number of internet users it has become indispensable to develop a system that collects, builds, analyzes, and classifies the comments or a review posted online. Usually these kinds of reviews are written by customers who have used the particular product or service. An individual's interests, opinions and perceptions greatly influence the nature of the review. There are instances where people are biased in their Opinion's and automatically that has an impact on the content they contribute to the number of such

people contributing content surges it has become

a huge challenge to classify and organize the real problems and prospects of the product which makes the user to doubt the reliability of the content. Big companies rely on personal review of customers to improve the scope of their product and deem it to be of great importance in placing content based ads on sites that easily aid a prospective buyer. The same applies to movie enthusiasts and voters as more and more people are using the social networking sites, online shopping and trend analysts who after reading the reviews available decide on various issues.

For example placing the ad of a Kitchen Aid Mixer on a food blog not only influences purchase decisions but also goes a long way in modifying the marketing strategy. The marketing division of a company enthusiastically promotes reviewers by sending samples of product to be reviewed or sponsoring giveaways in blogs or in social networking sites like Face book and Twitter. This has lead to the increase in the volume of data available and the need to classify the available information efficiently as these have a larger impact. The subjective nature of opinion makes a single opinion insufficient in decision making [6]. Also, the writing skills and choice of words by contributors largely depend on the language proficiency and the temperament of the writer. Online reviews that are usually the voice of the customer are written from their angle of interests and preferences can be a combination of a positive and negative opinion which may not help in deciding whether it is a positive or a negative review. For example, consider the sentence "This restaurant's Chinese dishes are not as good as their Thai dishes". These kind of comparative opinions are different in natural language processing. When a positive word „good" is negated like „not as good as a reader will also find it difficult to comprehend on how good the Thai dishes were as this decides the taste of the Chinese dishes too.

Levels and duration. On the other hand, these controllers actions' have to be coordinated with system protective schemes. An important design objective for protection engineers is to always ensure good coordination between the protection schemes of DERs, their controls and load capabilities in order to achieve reliable and stable operation of the modern power distribution [1]. This coordination requires a detailed and in-depth strategy to ensure that the protective relays are fully coordinated with the excitation systems of the DERs.

In addition, the relays' settings must consider the full load capabilities and steady-state stability limits [1]. Besides, the protection schemes are also required to be coordinated with the network interconnections of neighboring DERs [2]. It has been also reported in [3] that malfunction of generator protection and lack of coordination were the main contributors of 2003 US and Canada blackout. The design details for necessary coordination shapes that ensure reliability of modern power systems.

II. RELATED WORK

In [4] paper proposes a advanced framework for opinion mining that correlates all the merits of semantic web guided solutions to tremendously improve the overall results of traditional NLP (Natural Language Processing). The proposed framework makes use of domain ontology at feature extraction stage. This enhancement makes huge changes in the feature based sentiment classification. Existing machine learning techniques classify the words into limited category such as positive/negative. Existing system also performs sentiment classification at the document level (i.e.) if the document includes huge no of positive than negative terms, then it will be considered to be a positive document otherwise negative document. Dataset of Movie Reviews is used to check the performance of proposed model.

In [5] paper the proposed framework provide a clear understanding about the polarity shift problem. Sentiment Analysis is affected by many factors. Among that polarity shift problem is considered to be very dangerous factor that destroys the complete classification performance of traditional machine learning based sentiment classification. Usually the review data is represented in the form of Bag of Words (BOW) that entirely terminates the semantic correlation between the texts. The existing system makes use of term counting method addressing the polarity shift problem. The proposed polarity shift Detection, Elimination and Ensemble (PSDEE) performs detection of hybrid polarity shifts. To perform hybrid polarity shift detection it makes use of 3 levels of cascading model. Polarity shift problem arises if there is a polarity shifters or valance shifters such as negation, contrast, sentiment inconsistency in the text review. Proposed methodology make use of Rule based Method is used for detecting negations and contrast polarity shift and statistical methods are used for detecting implicit inconsistency. The proposed PSDEE was examined in four domains which are extracted from the Amazon website.

In [6] paper proposes a framework for aspect/feature based sentiment analysis along with the sentence compression technique. Aspect based sentiment analysis is performed based on syntactic features which poses a chance for over natural problem. This type of issue makes the sentiment analysis too difficult to handle the syntactic parsers used in the opinion mining technique. The proposed framework develops an innovated sentence compression technique before the sentiment analysis. For compressing a text for sentiment analysis 2 schemes are used. That is syntactic compression and extractive compression technique. Compared to extractive compression technique syntactic is considered to be more efficient because it compress the text by removing the unimportant words. The proposed technique makes use of Aspect-Polarity (A-P) collection based sentiment analysis. Most of the aspect based sentiment analysis focus on the relationship between the aspects and the polarity words which extremely affects the efficiency. To solve this problem the proposed framework makes use of syntactic patterns.

In [12] propose an innovative method to do the sentiment computing for news events. More specially, based on the social media data (i.e., words and emoticons) of a news event, a word emotion association network (WEAN) is built to jointly express its semantic and emotion, which lays the foundation for the news event sentiment computation. Based on WEAN, a word emotion computation algorithm is proposed to obtain the initial words emotion, which are further refined through the standard emotion thesaurus. With the words emotion in hand, we can compute every sentence's sentiment.

III. PROPOSED WORK

In this work sentiment of tweets were identify by using pattern based approach where sentiment representative patterns were clustered into respected class. For clustering of identified pattern hybrid genetic algorithm was used which is a combination of butterfly and particle swarm optimization.

1. Preprocessing

Preprocessing is initial filtration of input data where un-wanted or noisy data get remove from dataset. Here work has adopt stop-word removal technique. This approach takes each tweet in as input and remove stop words {a, an, of, the, for, to, from, in... etc. } present in it. This step remove noise of input data so important words which gives meaning to sentence are separate. This can be understand by "Ram is not happy because he loose cricket trophy", "My brother will be more happy if we loose this game", so after pre-processing set of words will be: {Ram, Happy, Loose, Cricket, Trophy}, {Brother, Happy, Loose, Game}.

2. Identify Pattern

As text content classification is done by two approach first was term and other was pattern feature. This approach use pattern feature to classify tweets where instead of assigning

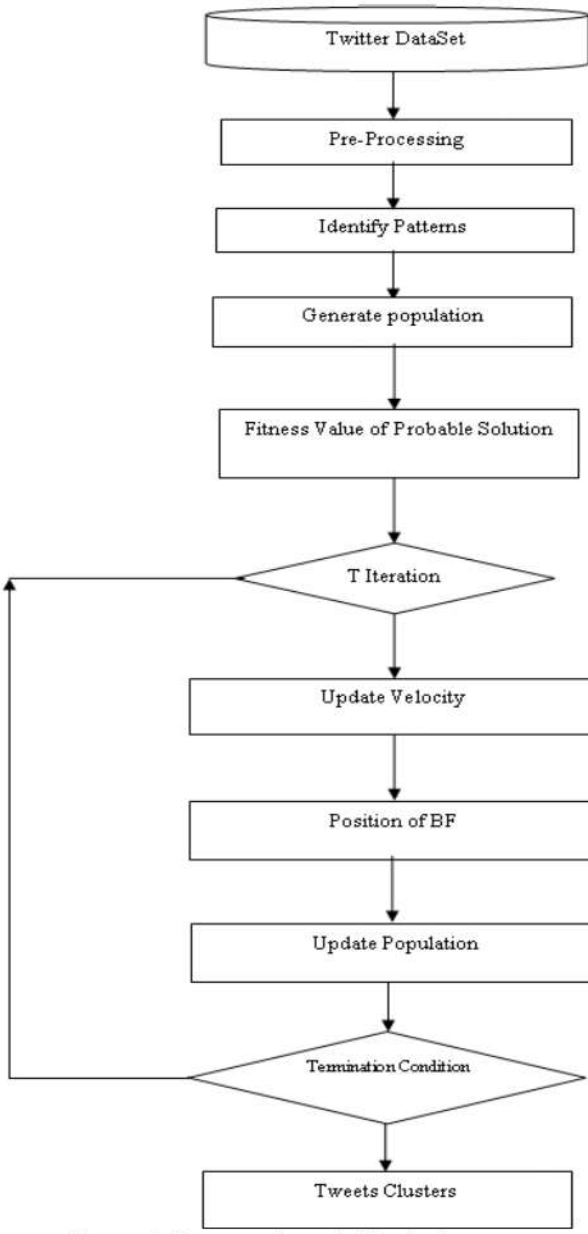

Figure 1 Proposed work Block diagram.

Sentiment to a term pattern is more effective. So based on this concept patterns were identify by the successive words in a tweets. Hence successive set of words present in multiple tweets are considers as the pattern. This can be understand by an example let sentence be: {Ram, Happy, Loose, Cricket, Trophy}, {Brother, Happy, Loose, Game}, so as per sets of words patterns are {'Ram Happy', 'Happy Loose', 'Loose Cricket', 'Cricket Trophy'}, {'Brother Happy', 'Happy Loose', 'Loose Game'}. Finally common pattern is 'Happy Loose' which is present in more than one sentence.

3.Generate Population

Generate Population: Here expect some probable solutions which are set of nodes act as cluster center. Randomization of this population was done by Gaussian function shown in eq. 1. This can be understand as let the number of sentiment be m so number of cluster is m and number of initial population is IP, then one of the possible solution is Cc ={Tp1, Tp5,..... Tpm} this can be assume as the solution set where Tp is text patterns obtained from above steps. While IP = [Cc1, Cc2,......Ccn] is an population obtain randomly by eq. 1.

IP←Rand(m, n)----Eq. 1

4. Iteration Steps

This involve calculation of Sensitivity of Butterfly by eq. 2 [17] than cognitive values with constriction factor and inertia weight were evaluate by eq. 3, 4 [17]. Here velocity and position of the butterfly also get update which are parameters of PSO. So as per position matrix crossover is done to update population.

5.Update velocity V

$$V_{i+1} = F_i * (W * V_i) \text{-----Eq. 2}$$

Update Position X of each probable solution

X = R*P*V_(i+1)-----Eq. 3

In above equation V is velocity, X is position while R and R' are random number whose values range between 0-1. p is probability of nectar for the butterfly selection. So as per X and V values crossover operation were performed.

6.Crossover

In this work population P is updated as per X column wise and V values update P row wise. Change in column help to assign new position for the cluster center in same probable solution.

7.Cluster Center

In this part best set of cluster center were obtained after T time iterations. So as per best cluster center solution all other nodes were distribute in respected clusters by using distance formula.

8.Cluster Tweets

Now as per cluster patterns center obtained tweets contents were identified and highly matching tweets were assign into respected class of sentiment.

9.Proposed Algorithm

Input: SD //Sentiment Dataset, m //Number of sentiment class.

Output: C // Cluster

- PSD←Pre-Processing(SD) //PSD: Processed Sentiment Dataset
- P←Pattern(PSD)
- IP←Generate_Population(m, n) //n: Number of Solution
- F←Fitness(IP)
- Loop 1:T // T: Number of Iteration
- [V X]←PSO(IP, W, F, V)
- IP←Crossover(IP, V, X)
- EndLoop
- F←Fitness(IP)
- C←Cluster (IP, F)

IV. EVALUATION PARAMETER

1. Data Set

In this work experiment is done on social dataset content obtained from https://twitter-sentiment-csv.herokuapp.com/, where as per the user query related twitter comments of respected user provided.

2. Evaluation parameters

In order to evaluate results there are many parameter such as accuracy, precision, recall, F-score, etc. Obtaining values can be put in the mention parameter formula to get results.

$$Precision = \frac{True\_Positive}{True\_Positive + False\_Positive}$$

$$Recall = \frac{True\_Positive}{True\_Positive + False\_Negative}$$

$$F\_Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

$$Accuracy = \frac{Correct\_Classification}{Correct\_Classification + Incorrect\_Classification}$$

In above true positive value is obtain by the system when the ranked tweet / comment is in favor of particular sentiment and system also says that tweet / comment is in favor of the same sentiment. While in case of false positive value it is obtain by the system when the input tweet / comment is in favour of particular sentiment and system do not rank that tweet / comment in similar sentiment class.

V. RESULTS

Table 1 Comparison of proposed technique under precision sentiment tweets.

Comparison Of Sentiment Precision Results		
Sentiments	Graph Based	PSO-SA
Joy	0.4	1
Love	1	0.909091
Sad	0.533	0.777778

Table1 shows that PSOSA(Particle Swarm Optimization algorithm Sentiment Analysis) has improved the precision parameters as compared to previous graph based approach [5]. Here use of genetic based clustering algorithm improved the accuracy of the work. This much of efficiency was achieved because of pattern based feature.

Table 2 Comparison of proposed technique under recall parameter for sentiment tweets.

Comparison of Sentiment Recall Results		
Sentiments	Graph Based	PSO-SA
Joy	0.461538	0.846154
Love	0.625	1
Sad	0.533	0.875

Table 2 shows that proposed work has improved the recall parameters as compared to previous graph based approach [5]. Here use of genetic based clustering algorithm improved the accuracy of the work. This much of efficiency was achieved because of pattern based feature.

Table 3 Comparison of proposed technique under Sad sentiment tweets.

Comparison Of Sentiment Precision Results		
Sentiments	Graph Based	PSO-SA
Joy	0.428571	0.916667
Love	0.769231	0.952381
Sad	0.695652	0.823529

Table 3 shows that proposed work PSO-SA (Particle Swarm Optimization algorithm Sentiment Analysis) has improved the f-measure parameters as compared to previous graph based approach [5]. Use of pattern based feature has worked well as compared to term based feature. So clustering of patterns into sentiment class for tweet identification by genetic is better as compared to graph based knowledge.

VI. CONCLUSION

This study examines the significance and impacts of content based sentiment examination challenges. Here paper has resolved a significant issue of content sentiment / emotion identification from un-organized data. Proposed work has classified the sentiment pattern feature by genetic algorithm which was a combination of particle swarm optimization. So proper iteration with fitness function efficiently cluster patterns into respective sentiment class. Result shows that proposed work has identify tweet sentiment. In future researcher can cluster tweets by using deep neural network.

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