ANALYTIC SYSTEM BASED ON PREDICTION ANALYSIS OF SOCIAL EMOTIONS FROM USERS

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ABSTRACT - *Over social media there are lots of symbols are used as compared to text this is an unstructured type of which get considers day by day increase in such symbols is moving the towards the new data prediction determination technique.*

Due to the rapid development of Web, large numbers of documents assigned by readers' emotions have been generated through new portals. Comparing to the previous studies which focused on author's perspective, our research focuses on readers' emotions invoked by news articles. Our research provides meaningful assistance in social media application such as sentiment retrieval, opinion summarization and election prediction. In this paper, we predict the readers' emotion of news based on the social opinion network. More specifically, we construct the opinion network based on the semantic distance. The communities in the news network indicate specific events which are related to the emotions. Therefore, the opinion network serves as the lexicon between events and corresponding emotions. We leverage neighbor relationship in network to predict readers' emotions. As a result, our methods obtain better result than the state-of-the-art methods. Moreover, we developed a growing strategy to prune the network for practical application. The experiment verifies the rationality of the reduction for application.

In this paper, we implement social opinion prediction by generating a real-time social opinion network. In more details, first, we train word vectors according to the most recent Wikipedia word corpus. Second, we calculate semantic distance between news via word vectors. As a metric between opinions, semantic distance allows us to construct the opinions growing network to describe the dynamical social opinions. Last, we predict follow-up

EXISTING WORK

In existing paper it is proposed that the system can do the prediction of emotions of the users they are taken the reference of the news article which help us to know about the users emotions regarding to such a article .In this the experiment get proposed on datasets. Social opinion prediction is a difficult research endeavor. As the initial research work on social opinion prediction, "affective text" in SemEval-2007 Tasks. Intend to annotate news headlines for the evoked emotion of read-ers. Another research focus on readers' emotion evoked by news sentences. Existing methods of social opinion prediction can be divided into three categories: knowledge-based techniques, statistical methods and hybrid approaches. Because of the deficiency of information of news text. it is unmanageable to annotate the emotions consistently. Knowledge-based techniques utilize existing emotional lexicon to supplement the prior knowledge for annotating the emotions. The popular emotional lexicon includes Affective Lexicon, linguistic annotation scheme, Word Net-Affect, Senti Word Net, and Sentic Net. The drawback of knowledge-based techniques is the reliance on the coverage of the emotional lexicon. These techniques cannot process terms that do not appear in the emotional lexicon. Statistical methods predict social opinion by training a statistical model based on a large number of well-labeled corpuses.

PRAPOSED WORK

By looking towards the technique given in existing we are proposed a business intelligence analytic module based on emotion detection regarding to the product reviews based on mining with reviews , feedback, complaints given by users this will help us the user for giving the instant and fast response and which also become very proper for business development. In proposed we can implement the opinion network and emotion opinion model on the datasets retrieved from business data. Opinion prediction system will helps to predict and decision making in business intelligence.

In this paper, our proposed work is to malicious post blocking using pattern matching algorithms, ration calculation based naïve baise classification for the classification of malicious user, determination of malicious user using social icon prediction, prediction analysis for the user post based on review in social icon, determination of malicious user link based on web context extraction technique.

Methods Used

1. LDA
2. Social Opinion Mode

Algorithm Used

1. Pattern Matching Algorithm

OBJECTIVE

- Development of analytic algorithmic work for the business analytics
- Implementation of network based semantic distance.
- Implementation of Predictive decision making based on iconinc patter matching
- Development of business intelligence tools for predictive analyss

EXPERIMENTS AND ANALYSIS

In this section, we present the experimental result and evaluate the performance of the proposed models for social opinion prediction, then compare it with state of the art models. Moreover, we design the experiments to analyze the impact of network size on social opinion prediction. Experiment Setup To test the effectiveness of the proposed model, we utilize two datasets for testing (The dataset is available in public:

github.com/lixintong1992/SocialEmotionData). One dataset used here is Yanghui Rao's corpus which col- lected 4570 news articles from the Society channel of Sina. The attributes of each article include the URL address, publishing date (from January to April of 2012), news title, content, and user ratings over 8 emotion labels: "touching", "empathy", "boredom", "anger", "amusement", "sadness", "surprise" and "warmness". The other dataset is collected from the Society channel of Sina from January to December of 2016, a total of 5258 hot news data. User ratings over 6 emotion labels: "touching", "anger", "amusement", "sadness", "surprise" and "curiosity". The average votes per news represent the number of votes for label. The average votes in dataset2016 is 770.41 which means that the labels in each news are generated by approximate 770 readers on average. By contrast, the average votes in dataset2012 is 71.21, which means that the labels in each news are generated by only 71 readers on average. The label generated by more reader seems more credible. In addition, Fig. 8 shows the overall distance distribution between news. Both of the datasets obey normal distribution. But the expectation and vari- ance of the normal distribution of dataset2016 are greater than dataset2012, which indicates the semantic correlation is relatively small. In summary, compared to dataset2012, dataset2016 has large time interval, less semantic correlation, more credible label.

Module 1:

In our project first module is registration. This module is used for user. Firstly we need to create our account after that we can post our feeling.

Dig1: Registration of user

Module 2:

Second module is post of user. After successful registration user can post their comment. And in this module other user can like this module or dislike this module. We can post textual comment, link and images. If user continuously post the negative comment then this user will block automatically, because auto blocking process is available. And negative comment going into the malicious post.

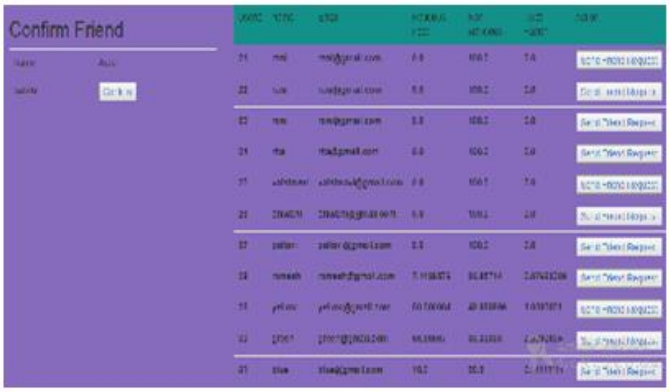
Dig2: Post of user

Module 3:

Third module of our project is calculation of trust factor. For the calculation of trust factor we need the calculation of malicious post as well as calculation of non-malicious post . From that post we can calculate the trust factor.

We calculate the trust factor for checking the person is good or bad for sending the friend request.If trust factor is good then person is good for sending firend request.

We can calculate the Percentage of malicious and non-malicious post by using their comment review.



Dig3: calculation of trust factor

$$\text{Trust factor} = \frac{\text{Number of malicious post}}{\text{Number of non malicious post}}$$

And for malicious post ,

$$\text{Malicious Post} = \frac{\text{Number of word matches}}{\text{Number of character in post}} * 100$$

Non-malicious post = 100 – Malicious post

Module 4:

In our project module 4 is view post. This module is come in admin login. Admin can view all the comment of user post, malicious as well as non-maliciious comment. view module show all post and their like dislike.

Dig4: View post

Module 5:

Fifth module is user malicious post calculator .In this module auto-blocking concept is present. After blocking admin have authority to unblock them and admin can view all percentage of malicious and non-malicious post. Again it show the graph of analysis.

Dig5: User malicious post calculator

Module 6:

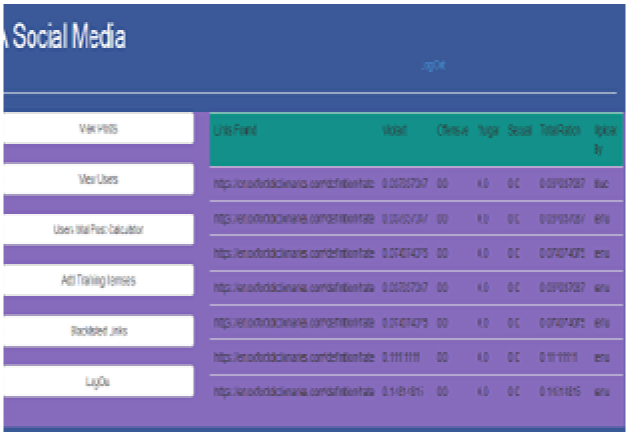
Module 6 is add training itemsets. we can add the malicious word in database and also we can describe their meaning and their category.

Dig6: Add training Itemsets

Module 7:

Module 7 is Blacklist link. And it is used for show the block link. our module predict the malicious link by using the pattern Matching algorithms.

If the miliciouness of link is more than 50% then this link will be block. and this block link is show in the blacklist link.



Dig7: Blacklist link

ADVANTAGES & DISADVANTAGES:

ADVANTAGES:

1. **Auto –blocking:**

   If someone post her photo ,but after posting this photo some people gives the bad/negative comment continuously then tis types of people will be block automatically.

2. **Security:**

   It block the malicious people by using the analysis of their post .it means it is secure as compared to the other social side.

3. **No need of man power:**

   We can analysis for the milions of post. if we need to analysis of one thousand post then need man power for read them but in our project we doesn't need the man power.

4. **Time saving**

   If we want the analysis of thousand comment then our project do this in within some second.

DISADVANTAGES

1. **Required net:**

For the total execution of this project we required the net.

CONCLUSIONS

By looking towards the technique given in existing we are proposed a business intelligence analytic module based on emotion detection regarding to the product reviews based on mining with reviews , feedback, complaints given by users this will help us the user for giving the instant and fast response and which also become very proper for business development.

In this paper, our proposed work is to malicious post blocking using pattern matching algorithms, ration calculation based naïve baise classification for the classification of malicious user, determination of malicious user using social icon prediction, prediction analysis for the user post based on review in social icon, determination of malicious user link based on web context extraction technique its my proposed work in this paper and I did this.

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