# Emotion Prediction From Readers Perspective Using Data Mining Algorithm

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***Abstract***- *Many documents given by readers' emotions have been generated through new portals. If we compare to the earlier studies which focused on author's viewpoint, our research focuses on readers' emotions invoked by news articles. Research done by us provides helpful assistance to the social media application such as election prediction, opinion summarization, and Sentiments recovery and so on. On the news based on social opinion network, we predict the readers' emotion through this paper. Specifically we construct the opinion network based on the semantic distance.*

*Communities in the news network show the specific events related to the emotions. So, the opinion network serves as reference between the events and its related emotions. To predict reader's emotions we control neighbor relationship in network. So compare to all available methods, we think our method obtain better results. Also we developed a growing strategy to trim the network for practical applications. The experiment checks the reasonability of the reduction of application.*

***Keywords***- Recognition of group emotion, affective text mining, complex network, Affect sensing and analysis,

## I. INTRODUCTION

Filtering the web containing an assets of product reviews, is a difficult task. Normally, an opinion mining tool generates a list of product attributes and aggregate opinions of each by processing the set of search results for a given time. We begin by noting the unique properties of this problem and develop a method for automatically distinguishing between positive and negative reviews. Our classifier draws on Information retrieval techniques by out classifier is used for feature extraction and scoring, and the results for various metrics and heuristics vary depending on the testing condition.

The best methods work as same as or better than traditional machine learning method. When operating on individual sentences collected from web searches, performance is limited due to noise and uncertainty. But in the context of a complete web-based tool and aided by a simple method for grouping sentences into attributes, the results are useful more efficiently.

People are getting used to consuming online and writing comments about their purchase experiences on merchant/review Websites, due to boom of e-commerce in today's digital world. These consumer opinions are valuable resources both to future customers for decision-making and to merchants for improving their products and/or service. But, as the size of reviews grows rapidly, then there is problem of severe information overload. Opinion summarization, opinion polling, and comparative analysis are the opinion mining techniques to solve this problem of overload. The maintest is how to accurately predict the sentiment orientation of review sentences.

Lexicon-based methods and machine learning methods are the two main categories of the famous sentiment classification general methods. Lexicon-based methods normally take the tactic of first constructing a sentiment lexicon of opinion words (e.g. "wonderful", "disgusting"), and then design classification rules based on appeared opinion words and prior syntactic knowledge. Though this methods are effective, they require considerable efforts in lexicon construction and rule design. Besides, lexicon-based methods cannot well handle implicit opinions, i.e. objective statements such as "I bought the mattress a week ago, and a valley appeared today". As pointed out in, this is also amain form of opinions.

True/original information is more helpful than subjective feeling. Lexicon-based methods can only deal with implicit opinions in an ad-hoc technique. Popular machine learning algorithms such as Naïve Bayes were applied by the first machine based classification work to the problem. Further, most research in this direction revolved around feature engineering for better classification performance. Feature such as - n-grams Part-of-speech (POS) information and syntactic relations etc. were discovered. Feature engineering also costs a lot of human hard work, and a feature set suitable for one domain will not work for the other domains.

In current years, deep learning has developed as an effective means for solving sentiment classification problems. A deep neural network intrinsically learns a high-level representation of the data, thus avoiding difficult work such as feature engineering. A 2ndbenefit is that deep models have stronger expressive power than shallow models. Though, the success of deep learning heavily depends on the availability of large-scale training data. Labeling large number of sentences is much difficult.

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## II. OBJECTIVE

- To study of the product data that we are passing as data.
- Main objective is to study the product review based on available dataset and generate result in terms of negative or positive.

## III. LITERATURE SURVEY

For proposed work to be better, one following literature is analyzed for existing systems working and critically evaluated on some evaluation method to find weaknesses from them

To make proposed work to be better,

[1] P. S. Yu. A holistic, and X. Ding, B. Liu. ,universal lexicon-based approach to opinion mining. In WSDM, pages 231–240, 2008.

With boom in e-commerce over the last 10 years, Products selling on Web is increasing, and more people are buying products online. It has become a common practice for online merchants to enable their customers to write reviews on products in order to improve customer shopping experience. With large numbers of users becoming comfortable with the Web, the more number of people are writing reviews. As a result, the number of reviews that a product receives grows rapidly. Some popular products can get hundreds of reviews or more at some large merchant sites.

Many reviews are too long, which makes it hard for a potential customer to read them to make an informed decision on whether to purchase the product. If he/she only reads a few reviews, he/she will not get true view. The large number of reviews makes it difficult for the product manufacturers or businesses to keep track of customer opinions and sentiments on their products and services. In a lexicon-based method is suggested to use opinion bearing words (or simply opinion words) to perform task. Words that are commonly used to express positive or negative opinions (or sentiments), e.g., “amazing”, “great”, “poor” and “expensive” are called Opinion words. The method mainly counts the number of positive and negative opinion words that are near the product feature in each review sentence. If there are more positive opinion words compare to negative opinion words, the final opinion on the feature is positive and otherwise negative. The opinion lexicon or the set of opinion words was achieved through a bootstrapping process using WordNet (http://wordnet.princeton.edu/). WordNet method is simple and effective, and gives reasonable results. Though, this technique has some major drawbacks.

[2] R. Collobert, J. Weston, L. Bottou, M. Karlen, K. Kavukcuoglu, P. Kuksa. And R. Collobert, J. Weston, Natural language processing (almost) from scratch. JMLR, 12:2493–2537, 2011.

Can a computer program will be able to translate a piece of English text into a programmer friendly data structure that describes the meaning of the natural language text? Unfortunately, there are no consensus developed about the form or the presence of such a data structure. Till such fundamental Artificial Intelligence problems are determined, computer scientists must settle for the reduced objective of extracting simpler representations, which will explain limited features of the textual information. These simpler representations are often motivated by specific applications (for instance, bag of words options for information retrieval), or by our belief that they capture something more general about natural language. They can describe syntactic information (e.g., part-of-speech tagging, chunking, and parsing) or semantic information (e.g., word-sense disambiguation, semantic role labeling, named entity extraction, and anaphora resolution). Text corpora have been physically explained with such data structures in order to compare the performance of various systems. Availability of standard benchmarks has inspired research in Natural Language. For all these task, Processing (NLP).and effective systems have been designed. This systems are often observed as software components for constructing real-world NLP solutions.

Many of the majority of the state-of-art systems states their single benchmark task by applying linear statistical models to ad-hoc features. In other words, the researchers themselves discover halfway representations by engineering task-specific features. These features are often derived from the output of established systems, leading to complex runtime dependencies. This approach is very effective, as researchers influence a large body of linguistic knowledge. On the other hand, there is a great attraction to improve the performance of a system for a specific benchmark. Even though such performance improvements can be very useful in practice, they teach

Very little about the means to progress toward the broader goals of natural language understanding and the mysterious goals of Artificial Intelligence.

In this case, we try to do best on multiple benchmarks while avoiding task-specific engineering. In its place we use a single learning system able to learn suitable internal representations. Actually we view the benchmarks as indirect measurements of the importance of the internal representations discovered by the learning procedure, and we suggest that these intermediate representations are more general than any of the benchmarks. Our wish to avoid task-specific engineered features prevented us from using a large body of linguistic knowledge. In its place we reach good performance levels in most of the tasks by transferring intermediate representations discovered on large unlabeled data sets. This approach we can consider “almost from scratch” to highlight the reduced (but still important) dependence on a priori NLP knowledge.

[3] Y. Singer and J. Duchi, E. Hazan, Adaptive sub gradient methods for online learning and stochastic optimization. JMLR, 12:2121–2159, 2011.

In the current eras of social colonization and connectedness, publics becoming more enthusiastic about interacting, sharing, connecting and collaborating through online cooperative media. In current scenario, this collective intelligence has spread too many different areas, with particular focus on fields related to everyday life such as commerce, tourism, health and education causing the size of the Social Web to expand rapidly. The distillation of knowledge from such a large amount of unstructured information, though, is a tremendously difficult task, as the contents of today’s Web are perfectly suitable for human consumption, but remain hardly understandable to machines. In many applications of online and stochastic learning, the input instances are of very high dimension, yet within any particular instance only a few features are non-zero. In rare cases, occasionally occurring features are highly informative and discriminative. Formativeness of rare features has led practitioners to craft domain-specific feature weightings, such as TF-IDF (Salton and Buckley, 1988), which pre-emphasize infrequently occurring features. We use this old idea as a motivation for applying modern learning-theoretic techniques to the problem of online and stochastic learning, concentrating concretely on (sub) gradient methods.

[4] B. Liu andM. Hu,Mining and summarizing customer reviews. In SIGKDD, pages 168–177, 2004.

E-commerce fast popularity, more and more products are sold on the Web, and more and more enthusiastic are also buying products online. With the motive to increase customer satisfaction and shopping experience, it has become a common practice for online merchants to enable their customers to review or to express opinions on the products that they have purchased. The number of reviews that a product receives is growing rapidly. It makes it hard for a potential customer to read such a large scale reviews and makes it difficult to make a decision regarding purchase the product. If he/she only reads a few reviews, he/she may get a true view. The large number of reviews also makes it hard for product manufacturers to keep track of customer opinions of their products. For a product manufacturer, there are additional difficulties because many merchant sites may sell its products, and the manufacturer may (almost always) produce many kinds of products making production excess compare to its demand.

So in this research assignment, we study the problem of developing feature-based summaries of customer reviews of products sold online. Here, features broadly mean product features, specifications (or attributes) and functions. Given a set of customer reviews of a particular product, the task involves 3 subtasks: (1) Recognizing features of the product that customers have expressed their opinions on (called product features); (2) Recognizing review sentences that give positive or negative opinions for each product review; and (3) Generating a summary by using the discovered information.

[5] S. T. DumaisS. Deerwester, G. W. Furnas, T. K. Landauer, and. Harshman. Indexing by latent semantic analysis. Journal of the American society for information science, 41(6):391, 1990.

Here we describe a new approach to automatic indexing and retrieval. It is design to overcome a fundamental problem that plagues existing retrieval techniques that try to match words of queries with words of documents. The problem is that users want to retrieve on the basis of conceptual content, and individual words provide untrustworthy evidence about the conceptual topic or meaning of a document. There are usually many ways to express a given concept as all people don’t think in same manner, so the exact terms in a user’s query may not match those of a relevant document available. Also, most words have multiple meanings, so terms in a user’s query will literally match terms in documents that are not of interest to the user, ultimately making it of no use.

[6] J. Schmidhuber and S. Hochreiter Long short-term memory. Neural computation, 9(8):1735–1780, 1997.

User reviews available on large web sites where authors provide quantitative or binary ratings are perfect for training and testing a classifier for sentiment or orientation. We want to focus our future mining efforts on is exactly same to the range of language used in such bodies. The two sites we chose were Amazon and Caned, based on the number of reviews, number of products, review quality, ease of spearing and available metadata.

[7] K. Dave, S. Lawrence, and D. M. Pennock. Mining the peanut gallery: Opinion extraction and semantic classification of product reviews. In WWW, pages 519–528, 2003.

One main objective of applying statistical inference techniques to large networked datasets is to know how behavioral contagions spread in human social networks. More exactly, understanding how people influence or are influenced by their lords can help us understand the flow of market trends, product adoption and diffusion and also rejection. The spread of health behaviors such as smoking and Exercise, the productivity of information workers, and whether particular individuals in a social network have an unbalanced amount of influence on the system.

In case of movie review domain, sites like Rottentomates.com have jumped up to try to impose some order positive/negative, providing ratings and brief quotes from numerous reviews and generating an aggregate opinion and also changing opinions of consumers and influencing on its way. Such sites even have their own category—"Review Hubs"—on Yahoo! On the commercial side, Internet clipping services like Web clipping. Com, eWatch.com, and TracerLock.com watch news sites and discussion areas for mentions of a given company or product, trying to track "buzz." clipping services have been providing competitive intelligence for some time. The simplicity of publishing on the web led to an outburst in content to be surveyed, but the same technology makes automation much more possible.

## IV. PROBLEM DEFINITION

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 se-mantic 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.

The problem about social opinion predictions well defined, including the relevant general terms and notations.

### *A. Motivation*

Current study was designed to verify whether or not, the use of causality heuristics and representativeness in decision making results from insufficient and not so trusted information processing rather than information from an integral deficiency in human processing ability. It was imagined that subjects which were distracted while making predictions.(Field-dependent subjects who were continuously aware of other subjects 'performance in the experimental session) wound fail to use the base rate to a greater extent than wound no distracted subjects (field-dependent subjects who were not aware of the other subjects 'performance, and field-independent subjects).As predicted, when other subjects" performance was public, field-independent subjects followed more to the base rate than did field-dependent subjects. In the private condition, however, the opposite pattern emerged. The results were discussed in terms of the drive theory of social facilitation and no cautious information processing.

### *B. Goals*

We will construct an opinion network to find user generated social emotion by structures of opinion network, all based on the similarity. There is important connection between emotion and structures of news network as we expected. The performance of the prediction based on opinion network is more stable, accurate and reliable than existing models.

## V. PROPOSED SYSTEM

Social opinion prediction is a difficult research field. Initially, research work on social opinion prediction, "affective text", intend to interpret news headlines for the evoked emotion of readers. Additional research focus on readers 'emotion evoked by news sentences. Current methods of social opinion prediction can be divided into three categories: 1) knowledge-based techniques, 2) statistical methods and 3) hybrid approaches. It is impossible to interpret the emotions consistently due to lack of information of news text. Knowledge-based technique utilize existing emotional lexicon to increase the prior knowledge for explaining the emotions. The popular emotional lexicon includes Affective Lexicon linguistic annotation scheme, WordNet-Affect, Sent WordNet, and Sentinel. The disadvantage 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 statistical model based on a large number of well-labeled body. There are two principal categories of statistical methods: word-level and topic-level methods. Word-level methods focus on exploiting the sentiment of individual words on the idea that words are the foundation of user sentiments. A variant of Naïve Bays model named Emotion-Term (ET) is created in order to model the word emotion association.

The words extracted from the news articles are considered as independent features which show the emotion. Though, word-level features in social opinion prediction are always obstructed by the background noise words. In particular, the methods treat each word in-dividedly, many emotional words are usually mixed with background noise words. In addition, the methods usually utilize the bag of words model to represent the text. A large number of explanations are required in order to ensure the accuracy of emotional recognition. More recently, topic-level methods try to achieve the sentiment of topics. A real-world event, object, or abstract entity that is the primary subject of the opinion as intended by the opinion holder can be considered as a topic in the topic-level social opinion prediction. The machinery of la-tent topic models like the Latent Dirichletian Allocation (LDA) is agreed in the Emotion-Topic Model (ETM). To make a topic became vitally relevant to an emotion, the ETM is added to an intermediate layer into LDA.. According to the experiments on grouping topics into different emotions, ETM improves several other methods including SVM for social opinion prediction.

Author-Topic Model (ATM), Labeled LDA and Joint Sentiment/Topic Model (JSTM), are the homologous model to ETM designed. Comparative to LDA, ATM assumes that each author complies with a Dirichletian distribution over topics while each topic com-plies with a Multinomial distribution over words. Labeled LDA integrates correspondence between LDA's latent topics and user tags. JSTM works well expressly for sentiment analysis of movie reviews. All the model above are formed from point of view of the authors. Writers may have their favored topics or personal impression before writing an article or a review. It means that emotions can predefined and be showed in the latent topics and observable words. This lack of explanatory leads to poor apprehension and confusion about what concepts or features should be involved in the text analysis. Though the methods are difficult to obtain satisfactory results, if insufficient data volume condition.

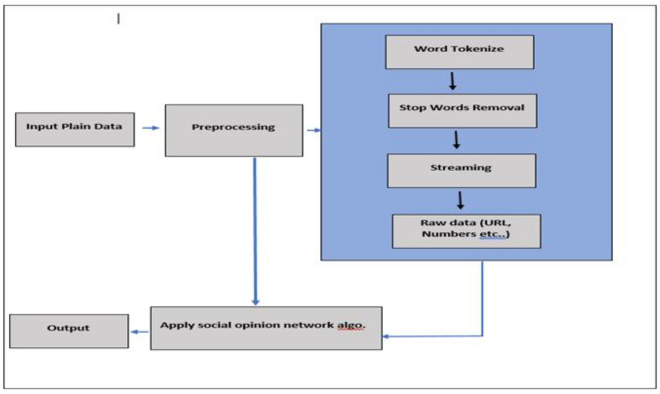



**Fig 1: System Architecture**

## VI. MATHEMATICAL MODEL

We define the following notations for describing the social opinion prediction: An online news collection consists of news, and the emotion ratings labels. The list of emotion labels is denoted by, and indicates emotion titled "joy", "anger", "fear", "surprise", "touching", "empathy", "boredom", "sadness", "warmness" etc. In particular, a news is a set of word tokens, and a set of ratings over Emotion labels denoted by. The value of is the number of online users who have voted the kth emotion label for news

1. Let S be a system that describes Cross-Language Opinion Mining

S={..}

2. Identify input as I

I = context in terms of train data {i1}

The input will be Text and parameters.

3. Identify output as O

O = Emotion prediction {o1}

4. Identify the processes as P

S={I,O,P,..}
P={ Data Collection : p1,
Data Processing : p2,
Prediction Process :p3,
}

5. Identify failure cases as F

S={I,O,P,F,.}

F=Failure occurs when the trained data not found.

6. Identify success as s. S={I,O,P,F,s..}

s=When comment is posted by authorized user.

### *A. Algorithm*

#### *1) Force Atlas 2:*

- Is a continuous algorithm, that allows you to manipulate the graph while it is rendering.
- Has a linear-linear model (attraction and repulsion proportional to distance between nodes).
- Features a unique adaptive convergence speed that allows most graphs to converge more efficiently
- Proposes summarized settings, focused on what impact the shape of the graph (scaling, gravity).
- Default speed should be the good one.

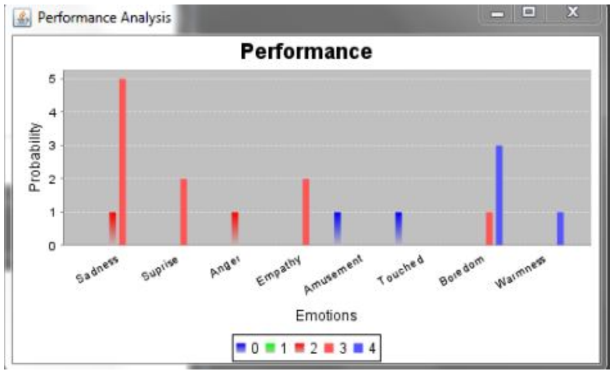
### *B. Related Work*

Based on the connection between opinions, we construct an opinion network, in which nodes indicate opinions and edges indicate relation between opinions. The opinion network acts as conventional knowledge which can serve as the lexicon between events and corresponding emotions. Social opinion can be predicted through the network.

To make the opinion network, we add the edge between nodes to denote distance. Presents the distribution of opinions distance from a real- world data. The figure shows that the distribution of opinions distance obeys Gaussian distribution. Then we explore the relationship between network structure and social emotions. As the opinion network here is fully connected net-works, we filter the edge to visualize the network structure trim edges shorter than threshold and label the nodes of 8 emotion In this case, we choose the threshold forth visualization of the network. The thresholds chosen as 0.7 manually for visualization of network.

We utilize ForceAtlas2 algorithm to arrange the layout of nodes. The color of the nodded-notes the most voted emotion labeling each news. The weights of edges reflect the value of distance.

## VII. RESULT ANALYSIS




The dataset used in this experiment consists of 784,349 samples of informal short English messages (i.e. a collection of English tweets), with 8 emotion classes: anger, surprise, sadness ,empathy, amusement, touched, boredom, warmness.

## VIII. CONCLUSION

The development of emotion prediction that can judge the type of emotion present in the input data. The data is categorize into different categories like: Happy, Sad, Angry, excited etc. For preprocessing point, we will use NLP (Natural language processing). Also, we propose a threshold-based net-work growing strategy for pruning (trimming) the network.

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