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Classification and Regression Tree Method for Forecasting

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Abstract: ***Sentiment classification is a special task of text classification whose objective is to classify a text according to the sentimental polarities of opinions it contains e.g., favorable or unfavorable, positive or negative. This is especially a problem for the tweets sentiment analysis. Since the topics in Twitter are very diverse, it is impossible to train a universal classifier for all topics. Twitter is an online social networking service that enables users to send and read short 140-charcters messages called "tweets". Moreover, compared to product review, Twitter lacks data labeling and a rating mechanism to acquire sentiment labels. The extremely sparse text of tweets also brings down the performance of a sentiment classifier. Twitter, attracts more people to post their feelings and opinions on various topics. The posting of sentiment contents cannot only give an emotional snapshot of the online but also have potential commercial, financial and sociological values. In social media, a Twitter user may have different opinions on different topics using a method called CART (classification and Regression Tree) method. CART analysis is a tree-building technique which is unlike traditional data analysis methods. Other factors which limit CART's general acceptability are the complexity of the analysis and, until recently, the software required to perform CART analysis was difficult to use.***

Keywords: Sentiment classification, social media, topic-adaptive, CART method.

I. Introduction:

The booming micro-blog service, twitter, attracts more people to post their feelings and opinions on various topics. The posting of sentiment contents can not only give an emotional snapshot of the online world but also have potential commercial, financial, and sociological values. However, facing the massive sentiment tweets, it is hard for

people to get overall impression without automatic sentiment classification and analysis. Therefore, there are emerging many sentiment classification works showing interests in tweets.

Topics discussed in Twitter are more diverse and unpredictable. Sentiment classifiers always dedicate themselves to a specific domain or topic named in the paper. Namely, a classifier trained on sentiment data from one topic often performs poorly on test data from another .One of the main reasons is that words and even language constructs used for expressing sentiments can be quite different on different topics. Taking a comment "read the book" as an example, it could be positive in a book review while negative in a movie review. In social media, a Twitter user may have different opinions on different topics. Ad-hoc Micro-blog search in Text Retrieval Conference (TREC) 2011 and 2012 is hopefully a choice for people to query tweets on emerging topics, and sentiment classification can be conducted afterwards.

Problem for the tweets sentiment analysis. Since the topics in Twitter are very diverse, it is impossible to train a universal classifier for all topics. Moreover, compared to product review, Twitter lacks data labeling and a rating mechanism to acquire sentiment labels. The extremely sparse text of tweets also brings down the performance of a sentiment classifier. We proposed in this paper CART (classification and Regression Tree) method. CART analysis is a tree-building technique which is unlike traditional data analysis methods. It is ideally suited to the generation of clinical decision rules. Other factors which limit CART's general acceptability are the complexity of the analysis and, until recently, the software required to perform CART analysis was difficult to use. Luckily, it is now possible to perform a CART analysis without a deep understanding of each of the multiple steps being completed by the software. In a number of studies, I have found CART to be quite effective for creating clinical decision rules which perform as well or better than rules developed using more traditional methods. In addition, CART is often able to uncover complex interactions between predictors which may be difficult or impossible to uncover using traditional multivariate techniques.

II. Related Work:

2.1 Opinion Word Expansion and Target Extraction through Double Propagation:

Analysis of opinions, known as opinion mining or sentiment analysis, has attracted a great deal of attention recently due to many practical applications and challenging research problems. In this article, we study two important problems, namely, opinion lexicon expansion and opinion target extraction. For example, in the opinion sentence I am not happy with the battery life of this phone, battery life is the target of the opinion.

2.2 Modeling Review Comments:

Writing comments about news articles, blogs, or reviews have become a popular activity in social media.. Experiments using Amazon review comments demonstrate the effectiveness of the proposed models. These reviews are also used by other consumers and businesses as a valuable source of opinions.

The problem of modeling review comments, and presented two models TME and ME-TME to model and to extract topics (aspects) and various comment expressions. These expressions enable us to classify comments more accurately, and to find contentious aspects and questioned aspects. These pieces of information also allow us to produce a simple summary of comments for each review.

2.3 A Semi-supervised Word Alignment Algorithm with Partial Manual Alignments:

Mining opinion targets from online reviews is an important and challenging task in opinion mining. This paper proposes a novel approach to extract opinion targets by using partially-supervised word alignment model (PSWAM). We apply PSWAM in a monolingual scenario to mine opinion relations in sentences and estimate the

associations between words. Then, a graph-based algorithm is exploited to estimate the confidence of each candidate, and the candidates with higher confidence will be extracted as the opinion targets.

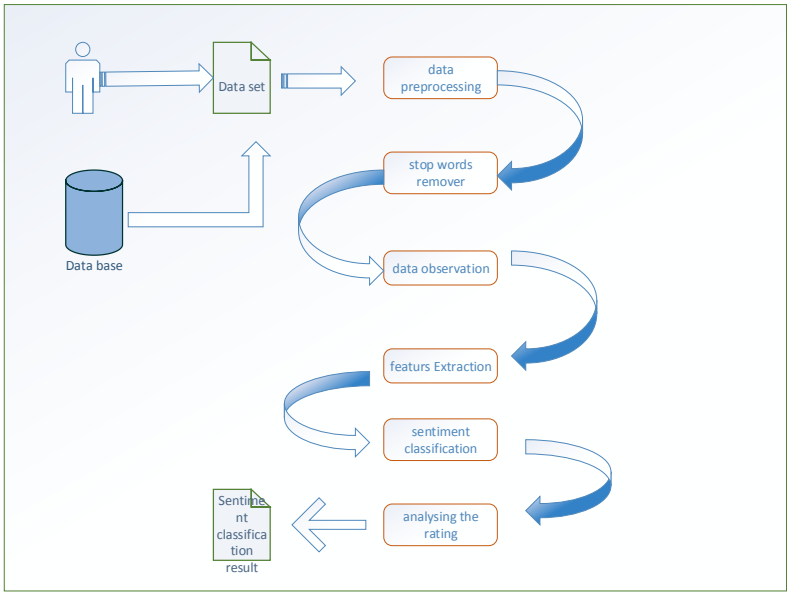
2.4 OPINION TARGET EXTRACTION USING PARTIALLY-SUPERVISED WORD ALIGNMENT MODEL:

Here the user's feedback and satisfaction is playing a vital role. In some cases the user may not give the feedback or reviews which they have viewed or downloaded directly. Instead of that the user is just searching the available things based on their interest. So there is no possibility for capturing the domain interest behavior of the user explicitly.

III. Proposed System:

CART analysis has a number of advantages over other classification methods, including multivariate logistic regression. First, it is inherently non-parametric. In other words, no assumptions are made regarding the underlying distribution of values of the predictor variables. Thus, CART can handle numerical data that are highly skewed or multi-modal, as well as categorical predictors with either ordinal or non-ordinal structure. This is an important feature, as it eliminates analyst time which would otherwise be spent determining whether variables are normally distributed, and making transformation if they are not. As discussed below, CART identifies "splitting" variables based on an exhaustive search of all possibilities. Since efficient algorithms are used, CART is able to search all possible variables as splitters, even in problems with many hundreds of possible predictors. [While some listeners may shudder at possible problems with over-fitting and data dredging, these issues are dealt with in depth later]. CART also has sophisticated methods for dealing with missing variables. Thus, useful CART trees can be generated even when important predictor variables are not known for all patients. Patients with missing predictor variables are not dropped from the analysis but, instead, "surrogate" variables containing information similar to that contained in the primary splitter are used. When predictions are made using a CART tree, predictions for patients with missing predictor variables are based on the values of surrogate variables as well.

System Architecture:



3.1 Data Collection:

Opinion text in blog, reviews, comments etc. contains subjective information about topic. Reviews classified as positive or negative review. Opinion summary is generated based on features opinion sentences by considering frequent features about a topic. It is the process of collecting review text from review websites. Information retrieval techniques such as web crawler can be applied to collect the review text data from many sources and store them in database. This step involves retrieval of reviews, micro-blogs, and comments of user.

3.2 Preprocessing:

Preprocessing Algorithm receives user opinions in raw form. We implement some form of preprocessing in order to filter-out noise. Sentence splitting is a critical step in this module (opinion delimitation) since double propagation takes into account neighborhood sentences in order to propagate sentiment. Additionally in order to increase the efficiency of the extraction process we have adopted an on-line stemmer engine.

3.3 Feature Classification:

It defines the polarity of document, but a positive phrase does not indicates that the user likes everything and similarly a negative phrase does not indicate that the opinion holder dislikes everything. It is a fine-grained level of classification in which polarity of the sentence can be given by three categories as positive, negative and neutral. It is defined as product attributes or components. In this approach positive or negative opinion is identified from the already extracted features. It is a fine grained analysis model among all other models. It is having a drawback that it could really cut very badly if there used any grammatically incorrect text.

3.4 Sentence level Opinion Mining:

In sentence level Opinion Mining, the polarity of each sentence is calculated. The same document level classification methods can be applied to the sentence level classification problem also but Objective and subjective sentences must be found out. The subjective sentences contain opinion words which help in determining the sentiment about the entity. After which the polarity classification is done into positive and negative classes.

3.5 Feature Opinion:

The knowledge resource is useful for improving the performance of the opinion mining. Opinion words lexicon is adopted in the stage of identifying opinions regarding the product features. A domain independent Lexicon and manually constructed Emoticon dictionary is used to assign polarity score (positive, negative or neutral) to opinionated words and sentences. For deciding correct polarity class of such words, revised mutual information concepts are used. These words could strengthen, weaken the surrounding opinion words' extent or even transit its sentiment orientation.

IV. System Implementation:

In the experiments, we use the corpuses in Table 1 for evaluation. There are K ¼ 3 sentiment class labels in the corpuses, i.e., negative, neutral and positive. In order to show how our algorithm performs with a small amount of labeled data, we randomly sample some ratio p of labeled tweets on a topic, keeping proportions of sentiment classes. The sampled tweets from various topics are then mixed together as initially labeled data set L. And the rest tweets on each topic are used for testing.

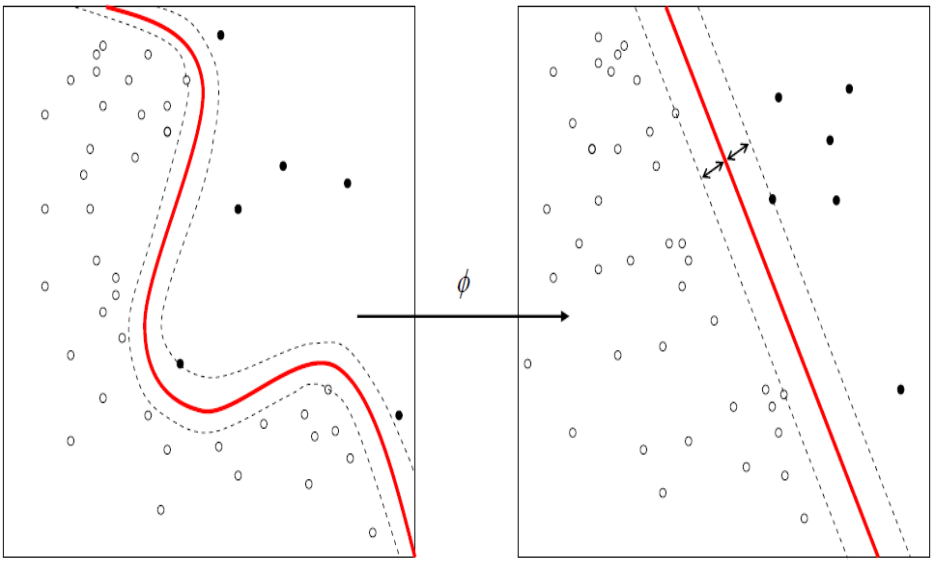
- DT. It is a Weak implementation of Decision Tree, which is a tree-like model in which internal node represents test on an attribute. –
- MSVM. It is a multiclass SVM classification based on Structural SVM and it is an instance of SVM structure.

- RF. It is a Weak implementation of Random Forest, which is an ensemble learning method for classification of a multitude of decision trees, and we tune the number of trees to be 10 for better performance.
- MS3VM. It is multiclass semi-supervised SVM which is our implementation of augmenting unlabeled tweets without adaptive features.
- CoMS3VM. It is MS3VM algorithm in a co-training scheme, by naturally splitting the common features into text and non-text views.

V. Algorithm Protocol Used:

Decision tree learning uses a decision tree as a predictive model which maps observations about an item to conclusions about the item's target value. It is one of the predictive modeling approaches used in statistics, data mining and machine learning. Tree models where the target variable can take a finite set of values are called classification trees. In these tree structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels. Decision trees where the target variable can take continuous values (typically real numbers) are called regression trees. In decision analysis, a decision tree can be used to visually and explicitly represent decisions and decision making. In data mining, a decision tree describes data but not decisions; rather the resulting classification tree can be an input for decision making. This page deals with decision trees in data mining.

Decision tree learning is a method commonly used in data mining.[1] The goal is to create a model that predicts the value of a target variable based on several input variables. An example is shown below. Each interior node corresponds to one of the input variables; there are edges to children for each of the possible values of that input variable. Each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf.



A decision tree is a simple representation for classifying examples. For this section, assume that all of the features have finite discrete domains, and there is a single target feature called the classification. Each element of the domain of the classification is called a class. A decision tree or a classification tree is a tree in which each internal (non-leaf) node is labeled with an input feature. The arcs coming from a node labeled with a feature are labeled with each of the possible values of the feature. Each leaf of the tree is labeled with a class or a probability distribution over the classes..The dependent variable, Y, is the target variable that we are trying to understand, classify or

generalize. The vector x is composed of the input variables, x_1, x_2, x_3 etc., that are used for that task. Classification tree analysis is when the predicted outcome is the class to which the data belongs.

Regression tree analysis is when the predicted outcome can be considered a real number (e.g. the price of a house, or a patient's length of stay in a hospital).The term Classification And Regression Tree (CART) analysis is an umbrella term used to refer to both of the above procedures, first introduced by Breiman et al. Trees used for regression and trees used for classification have some similarities - but also some differences, such as the procedure used to determine where to split. Some techniques, often called ensemble methods, construct more than one decision tree. Bagging decision trees, an early ensemble method, builds multiple decision trees by repeatedly resampling training data with replacement, and voting the trees for a consensus prediction.[4]

A Random Forest classifier uses a number of decision trees, in order to improve the classification rate. Boosted Trees can be used for regression-type and classification-type problems. Rotation forest - in which every decision tree is trained by first applying principal component analysis (PCA) on a random subset of the input features.

A special case of a decision tree is a Decision list[8] which is a one-sided decision tree, so that every internal node has exactly 1 leaf node and exactly 1 internal node as a child (except for the bottommost node, whose only child is a single leaf node). While less expressive, decision lists are arguably easier to understand than general decision trees due to their added sparsity, permit non-greedy learning methods and monotonic constraints to be imposed. Decision tree learning is the construction of a decision tree from class-labeled training tuples. In summary, in this paper, we have presented and developed the following:

1) A three-layer model of social roles, which can provide a means to categorize the social roles in both the real world and cyber world for the collective decision-making support;
2) An integrated mechanism to improve the efficiency of the collective decision-making process by analyzing the social roles;
3) A Net Logo-based tool to simulate the negotiation process, which can be utilized to demonstrate and compare different decision-making methods.

As for our future work, we will improve the design and implementation of our proposed methods and related algorithms. We will conduct more experiments to evaluate the improved method and system as well.

Conclusion:

Diverse topics are discussed in Micro-blog services. Sentiment classifications on tweets suffer from the problems of lack of adapting to unpredictable topics and labeled data, and extremely sparse text. Therefore we formally propose an adaptive multiclass SVM model in co-training scheme, i.e., TASC, transferring an initial common sentiment classifier to a topic-adaptive one by adapting to unlabeled data and features. TASC-t is designed to adapt along a timeline for the dynamics of tweets. Compared with the well-known baselines, our algorithm achieves promising increases in mean accuracy on the six topics from public tweet corpuses. Besides a well-designed visualization graph is demonstrated in the experiments, showing its effectiveness of visualizing the sentiment trends and intensities on dynamic tweets

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