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Designing a Flexible System for Automatic Detection of Categorical Student Sentiment Polarity Using Machine Learning

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Abstract

Writing is one of the most effective tool to express ideas, feelings, and opinions by human beings. With the growth of social media and blogs, human beings now express their feeling in writing that is accessed across the globe. There are so many research that has been published to perform opinion mining, subjectivity analysis, and to generate some values out of it in the form of future trends. Higher education may also use this subjectivity analysis for course delivery effectiveness. It can be achieved by generating knowledge from student's comment about their feelings about a course delivery. The simple approach towards this objective is to classify the sentiment polarity of students that fits in a category (such as positive or negative comment). Machine learning has proved itself a good choice for such solution. Designing a flexible (modifiable and extensible) system for the said purpose is one of the challenging task. It needs expertized and experience. One can exploit the expertise and experience of the developer using design pattern that is a documented literature to construct flexible systems. The aim of this research is to design a flexible system for curriculum delivery evaluation by extracting the hidden knowledge of words from students' comments about a particular course delivery. This extraction of hidden knowledge may be used for the purpose of the assessment, to further improve quality of teaching learning process.

Keywords*: Machine learning, Sentiment analysis, Effective course delivery, Teaching assessment, Design Pattern*

1. Introduction

Humans often rely on information and experiences before making an important decisions. Pervasive use of the Internet and digital media has made access to this kind of information available at a touch. It is very easy to find out opinion and experiences of a pool of people about the services and products available on various social networking sites.

Exponential growth of blogs and social sites (like Twitter and Facebook) provide answers to almost every subjective as well as objective query. These opinions enunciated by the consumers can immensely influence the business of major companies by affecting the opinions of other consumers. These opinions ultimately create their brand loyalties and help users in making purchase decisions. Companies can also monitor consumer sentiments about their products or services by modifying their marketing messages, brand positioning, product development, and other activities accordingly.

Use of computers to categorize the text according to the meaning it conveys is known as Sentiment Analysis. Opinion Mining is the process of discovering the opinion or mental state of the writer. Mining Opinions associated with text can be useful to know the experience of user about a place, about any event or any product. This information about users' opinions can be of immense value to business houses, government *etc*. The processes of Sentiment Analysis and Opinion Mining can be considered as a sub area of subjectivity analysis [1].

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A university system can also analyze student's comment about the teaching methodologies applied on a particular course and can be used as a feedback for assessment and quality improvement of teaching learning process. Creating such automated systems that can analyze texts and indicate whether the student has a positive/negative/neutral opinion about a particular course delivery is a very challenging task. It is because the one has to mine the meaning the sentence of each students and then inferring the meaning that they want to convey. Machine learning can be used to solve this challenging task that will extract the meaning automatically based on algorithm and improves quality of output with experience.

2. Problem Statement

Sentiment analysis of text has many real life applications. It is one of the most active research areas in Natural Language Processing (NLP), Computational Linguistics, Data Mining and Information Retrieval. It is in fact an interdisciplinary research and also has its applicability in computer science and in management sciences ([3-6]). A large number of research which deal with subjectivity classification, sentiment analysis and opinion mining have been published till date. In [7], the authors have used feedback of users as input data and the feedback was classified as positive or negative. In [8], the minimum cut algorithm on a graph was employed to help sentiment classification. In [9], syntactic relations between the words and parts of speech used by the writer were used together with traditional features. In [10], the contextual valence and sentiment shifters were employed for classification. In [11], a genetic algorithm was used to select features in the text written in different languages. In [12], a non-negative matrix factorization method was proposed. In [13], semi-supervised learning and/or active learning were experimented. In [14], labeled features were exploited for classification. In [15], a dependency tree-based classification method was proposed, which used Conditional Random Fields (CRF) [16] with hidden variables. In [17], automatically generated annotator rationales was used to help in classification. In [18], the authors proposed a graph-based hashtag approach to classifying Twitter post sentiments, and in [19] linguistic features and features that capture information about the informal and creative language used in microblogs were also utilized. In [20], the authors used word vectors which can capture some latent aspects of the words to help classification. In [21], sentiment classification was performed based on supervised latent n-gram analysis.

Since, it is an emerging area of research, and still evolving and there are various algorithms that may be applied on opinion mining about a course delivery from the comments of students. Further, as researchers are constantly exploring the possibilities of improvement of these algorithms. a system that implements these algorithms must be designed keeping flexibility in mind, where one algorithm may be replaced by another for overall quality improvement; if required. Very little research have been done that explores the techniques that may be applied in machine learning system for flexibility of change. So, the focus of this research is not explaining algorithms for such system, but design of a system that supports the replacement of algorithm with ease.

3. Sentiment Classification Approaches

Text sentiment classification is the process of ascribing one or more classes to a document as per their content. There are two common approaches of sentiment classification: Machine learning and Lexicon-based approach. Machine learning can further be broadly classified as supervised and unsupervised learning. There are various techniques of supervised learning: Decision tree classifiers, Linear classifiers (Support Vector Machine, Neural networks), Rule based classifiers, and Probabilistic classifiers (Naïve Bayes, Maximum Entropy, Bayesian Network).

Sentiment classification can be framed as a supervised learning problem having three classes, positive, negative and neutral. Datasets containing user reviews of products, services, events can be used for training Naive Bayesian classifier and Support Vector Machines (SVM) can be used for this classification. For example, the early work reported in [22] performed subjectivity classification using the naïve Bayes classifier with a set of binary features (the presence in the sentence of a pronoun, an adjective, a cardinal number, a modal other than will and an adverb other than not). Supervised learning in general, involves huge effort in labeling a large number of training examples. [23] classified the subjectivity of tweets (on Twitter) based on traditional features with the inclusion of some Twitter specific clues such as re-tweets, hashtags, links, upper case words, emoticons, and exclamation and question marks.

An SVM model represents examples as points in space so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. [24] took this approach to classify movie reviews into two classes, positive and negative. A machine learning solution for sentiment classification has to find an effective set of features. A feature is an aspect or quality of the text that is used by the algorithm to find sentiment orientation of the text. One of the feature that [25] proposed is Syntactic dependency. A score function [26] can be used based on words in positive and negative reviews. In [27], feature weighting schemes are used.

Unsupervised learning methods (that use only unlabeled training data) consist of three steps [28] generally: 1. Extraction of phrases containing adjectives or adverbs as indicators of opinions. 2. Estimation of the semantic orientation of the extracted phrases using the Point wise Mutual Information (PMI) measure. 3. Given a review, the algorithm computes the average Sentiment Orientation (SO) [25] of all phrases in the review, and classifies the review as positive if the average SO is positive; negative otherwise.

Lexicon based approach uses sentiment lexicons. Sentiment lexicons is a collection of known and precompiled sentiment terms. Lexicon based approach is further classified as dictionary-based approach, and corpus-based approach. In dictionary based approach a small set of seed opinion words (seed list) and an online dictionary, *e.g.*, WordNet [29] or thesaurus is used. First, a small set of opinion words are collected manually with known orientations, and then this set is grown by searching in the WordNet or thesaurus for their synonyms and antonyms. The newly found words are added to the seed list. The corpus-based approach use syntactic or co-occurrence patterns and also a seed list of opinion words to find other opinion words in a large corpus.

Hu and Liu [30] proposed a lexicon-based algorithm for aspect level sentiment classification, but the method can determine the sentiment orientation of a sentence as well. It was based on a sentiment lexicon generated using a bootstrapping strategy with some given positive and negative sentiment word seeds and the synonyms and antonyms relations in WordNet. The sentiment orientation of a sentence was determined by summing up the orientation scores of all sentiment words in the sentence. A positive word was given the sentiment score of +1 and a negative word was given the sentiment score of -1. Negation words and contrary words (*e.g.*, but and however) were also considered. A method was reported in [31] that learns from the document level labeling only but performs both sentence and document level sentiment classification. The method is thus partially supervised.

Additional works on subjectivity classification of sentences has also been done in Arabic [32] and Urdu languages [33] based on different machine learning algorithms using general and language specific features.

4. Proposed System Architecture and Candidate Design Patterns for Flexibility

Quality of the system is an important criteria that has to be considered while developing a system. Many quality model and various attributes has been proposed for this purpose. One of such attribute is the flexibility of the system. McCall in its Quality Model [34] defines flexibility as "the ability to make changes required as dictated by the business". At the same time flexibility defined in Boehm's Quality Model [35],[36] means "the ease of changing the software to meet revised requirements". Based on above definition, the present research has taken flexibility as modifiability and extensibility in general terms.

4.1. Role of Design Patterns in Flexible System

Design patterns are a modern software engineering problem-solving methodology that emerged from the object-oriented community and was popularized by Erich Gamma *et. al.* [37]. The design pattern is the excellent design method. A software based on design patterns could easily deal with specific changes to achieve the flexible software [38]. Patterns are gleaned from the experiences of experts and they facilitate developers to reiterate a thriving design and hence aid in pulling off the flexibility. It can be considered a very high form of reuse because of it is domain-independent and can be reused in designing diverse software packages.

4.2. Proposed System Architecture and Overall Workflow

A machine learning system may also apply design patterns, leading to truly open systems where algorithms and various components may be interchange. To find out the candidate design patterns applicable in machine learning systems, one may apply the following steps:

i. Decompose a machine learning system into major sub-systems.
ii. Modularize these sub-systems based on their functionalities.
iii. Represent these modules with set of object-oriented classes.
iv. Identify the parts of the system that are subject to future modification or extension (may referred as "*Flexible Cube*").
v. Name these flexible cube and also describe the reasons leading to flexibility.
vi. Mine appropriate design patterns which can be applied to each flexible cube.

The overall architecture of the system is depicted in Figure 1.

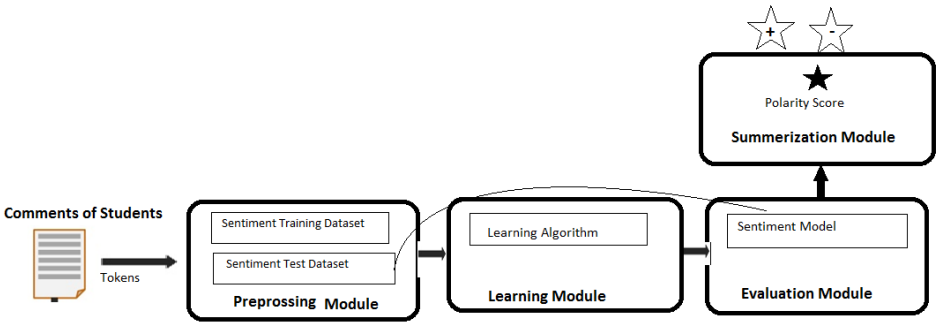

Figure 1. Architecture and Major Modules

The major modules that can be implemented for such systems are:

i. Preprocessing Module: This module to be implemented with an objective to identify and correct spelling errors. There are various algorithm for this purpose. One may

opt for Similarity / Edit distance or Weighted Edit distance for this purpose. Training dataset and test dataset is also identified in this module.

ii. Learning Module: Sentiment analysis is the process of identifying people's attitudes and emotional states from language. Various machine learning algorithms may be applied for this purpose. This module trains the model with the help of a machine learning algorithm.

iii. Evaluation Module: This module is responsible for analyzing the system based on objective function or scoring function. For this purpose testing data may be used.

iv. Summarization Module: This module calculates the polarity score based on positive and negative sentiment. A negation word decreases the polarity score by one whereas a positive word increase the score by one. Finally this module calculates the average opinion scores for each comment about a course of study.

4.3. Candidate Design Patterns

An experimental evaluation has been performed by [39] to measure the effect of design patterns on extensibility of system implementing decision tree learning algorithm with six cases of extensions. Total number of 8 Flexible Cube (referred as hot-spots) that are subject to change, 80 classes and 5 patterns were used to implement the system in [39]. The criteria used for evaluation were lines of code added in an extension, number of methods which are newly added or modified in an extension, and number of classes which are newly added or modified in an extension. The Flexible Cube and design patterns used by [39] is summarized in Table 1.

Table 1. Extensibility Requirements of Flexible Cube and Benefits Achieved by Application of Design Patterns

Sr. No.	Flexible Cube	Extensibility Requirements	Design Patterns Applied	Benefits
1.	Data set creation	For data set independence with data source.	Builder	Flexible representation of a data set object.
			Template Method	Allow reuse of the skeleton of the data creation algorithm.
			Strategy	Interchange of file parsing algorithm is easy.
2.	Attribute type	To support continuous as well as discrete attribute.	Abstract Factory	Allow the creation of an attribute object without depending on its type.
			Factory Method	Localizes knowledge of the connection between attributes and attribute values.
3.	Decision tree structure	To operate the decision tree without distinction of types of node.	Composite	Uniform treatment of primitive and composite structure.
			Visitor	Separates the operation of the decision tree from its structure.
4.	Test method	To support any kind of test for any type of attribute.	Command	Reusable code for creation of test.
5.	Test selection	To support a various	Template Method	Easy addition,

	method	interchangeable test selection methods.		modification and exchange the selection methods.
6.	Noise data Handling method	To support variety of noise data handling methods.	Strategy	Encapsulates a noise handling method for possible exchange.
			Abstract Factory	Makes it easy to change the noise handling methods.
7.	Decision tree pruning method	To support a variety of pruning methods and to make it exchangeable.	Visitor	Allows the easy addition of a new pruning method.
			Template Method	Easy to implementation of concrete visitor objects.
8.	Decision tree evaluation method	To provide a variety of evaluation methods.	Strategy	Addition of new evaluation method is easy.

5. Conclusion

It is a proven fact that machine learning techniques improve the accuracy of sentiment classification of written texts. There are a number of techniques in machine learning that may be applied for said purpose. One must keep flexibility in mind while developing a system based on machine learning that enable the replacement of one algorithm by other. As design patterns is a very powerful technique for improving flexibility of a software; it may be exploited in system design. This research has discussed the design aspects of the system for automatic detection of sentiment polarity about a course delivery using machine learning approach. Various design patterns have been identified for this purpose. The outcome of this research is a flexible system for sentiment analysis that may lead to improvement of course delivery method for effective teaching learning process.

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