Software Metric Pattern Discovery for Text Mining

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ABSTRACT

The mining techniques are proposed for the purpose of developing effective mining algorithms to find particular patterns within reasonable and acceptable time frame. With a large number of patterns generated by using data mining approaches, how to effectively use and/or update these patterns is still an open research issue. In the existing system is an effective pattern discovery technique introduced which first calculates discovered specificity patterns and then evaluates the term weight according to the distribution of terms in the discovered patterns rather than the distribution in documents for solving the misinterpretation problem. It also considers the influence of patterns from the negative training examples to find noisy patterns and try to reduce their influence for the low-frequency problem. The process of updating uncertain modes can be referred as pattern evolution. Those approaches improve the accuracy of the evaluating term weights because discovered patterns are more specific than whole documents. This technique uses two processes, one pattern deploying and another pattern evolving, to improve the discovered patterns in text documents. But they do not consider the time series to rank the given sets of documents. In the proposed system, temporal text mining approach is introduced. The system terms of its capacity is evaluated to predict forthcoming events in the document. Here the optimal decomposition of time period associated with the given document set is discovered, where each subinterval consists of sequential time points having identical information content. Extraction of sequences of the events from new and other documents based on the publication times of these documents has been shown to be extremely effective in tracking past events.

1.INTRODUCTION

Discovery of knowledge is process of extraction of nontrivial information from large databases, where information is unknown and useful for user. Data mining is the first and essential step in process of knowledge discovery. Various data mining methods are available such as association rule mining, sequential pattern mining, and closed pattern mining, frequent item set mining to perform different knowledge tasks. Use of discovered patterns effectively is research issue; therefore, proposed system will apply various data mining methods for effective knowledge discovery for text mining.

Text mining is method that takes useful information from a large amount of digital text data. Therefore it is critical that a good text mining model should retrieve the information that users require with relevant efficiency. Conventional Information Retrieval (IR) has same purpose of automatically retrieving as many proper documents as possible whilst filtering out insignificant documents at the same time. However, IR-based systems not provide users with what they really need. Many text mining methods which have been developed for retrieving useful information for the users. Highly text mining methods use the keyword based methods, where as others choose the phrase technique to build a text representation for the set of documents. The phrase-based methods execute better than the keyword-based as it is considered, that more information is carried by single phrase than by a single term. New studies have been focus on finding superior text representatives from a textual data collection. One solution is to use data mining methods, such as sequential pattern mining for representation with the new type of attributes. Such data mining-based methods use the concept of closed sequential patterns and non-closed patterns to decrease the attribute set size by removing noisy patterns. New technique, Pattern Discovery Model for the object of

effectively using discovered patterns is proposed. Proposed system will estimate the measures of patterns using pattern deploying process as well as finds patterns from the negative training examples using pattern evolving process.

2. REVIEW OF LITERATURE

As the volume of electronic data increases, there is increasing interest in developing tools to help people to find better, manage, and filter these resources. Text are sorted [9] Specifies the natural language texts to predefined categories or more based on their content and an important component in many management tasks and organize information. Machine learning methods, including "support vector machines" (SVMs), has tremendous potential for helping people to organize effective electronic resources. Text mining often involves extracting key words with regard to the degree of importance. Weblog data text content with clear and significant temporal aspect. Important text are sorted automatically sort a set of documents into categories from a predefined set. This task to various applications, including automated indexing of scientific articles according to the thesaurus already defined technically, selective dissemination of information to consumers, and the filing of patents to the patent-related directories, population manalfhars hierarchical automated network resources, author attribution, spam filtering, select the type of document and scan coding, automated article so tagged. Automatic text classification is attractive because it frees organizations from having to manually organize rules document,That could be simply useless or too expensive to issue documents or time constraints. The accuracy of modern text classification systems that trained human mnavsihalmhniin, thanks to the Union of information retrieval (IR) technology and machine learning (ML) technology. This outline the basic qualities of the relevant technologies, applications that can be addressed effectively through text classification tools and resources that are available to the researcher and developer who are interested in taking these technologies to deploy applications in the real world. A web technology[4] extracts the statistical information and discovers interesting user patterns, discover potential correlations between web pages and user groups, cluster the user into groups according to their navigational behavior identification of potential customers for E-commerce, enhance the delivery and quality of Internet information services to the end user, site design and facilitate personalization and improve web server system performance.

Determine the relative provisions is also useful in practice because direct comparisons are one of the most convincing ways of evaluation of the text, which may be more important than opinions on each individual object. Experiment results using the three types of documents, consumer reviews of products, news articles, and Internet forum postings, show a precision of 79% and

recall of 81%. Comparison is the most convincing ways for the text evaluation. Extracting comparative sentences from the text is useful for many applications.

For example, in the business environment, the product manufacturer wants to know the views of consumers on the product, whenever a new product comes to market, and how it compares with those products from its competitors. Much of this information is readily available on the Internet in the form of customer feedback, and discussion forum, a blog, etc. This information can be extracted much help companies in marketing and product measurement efforts. Clearly, product comparisons are not only useful for manufacturers of products, but also to potential customers because they enable customers to make better purchasing decisions.

A statistical pattern called Latent Semantic Indexing (LSI)[3] which models the implicit higher-order structure in the association of words and objects and improves retrieval performance by up to 30%. In supplementary large performance improvements of 40% and 67% can be achieved using differential term weighting and iterative retrieval methods. These methods include restricting the allowable indexing and retrieval vocabulary and training intermediaries to generate terms from these restricted vocabularies, hand-crafting field-specific thesauri to provide synonyms for users search terms, constructing definite models of domain-relevant knowledge, and automatically clustering documents and terms. The rationale for controlled or restricted vocabularies is that they are by design relatively unambiguous. However they have high costs and marginal if any benefits compared with automatic indexing based on the full content of texts. The use of a dictionary is intended to improve retrieval by expanding terms that are too specific.

Here we studied mining frequent patterns in time-series databases, transaction databases, and many other kinds of popular databases in the field of research and data mining. Most of the previous studies adopt an Apriori-like candidate set test and generation approach. However, the appointment of the candidate generation is still expensive for a large number of patterns and / or long patterns. The structure of the novel pattern repeated tree (FP-tree), and crucial information about patterns of frequent, extended tree structure prefix for storing compressed, and the development of efficient and family planning - a tree, mining based on the pattern, FP-growth, for mining a complete set of common patterns of growth pattern heartbreaking . Is to achieve efficiency of mining with the techniques of the three: Compressed [I] a large database in a data structure brief, smaller, tree pattern repeated that avoids database frequent, expensive scans, [II] our mining FP-based tree-based method of growth pattern - heartbreaking To avoid generation expensive from a large number of groups candidate, and the division [III] - method uses the building, and divide, conquer to solve mining task to a

group of tasks younger patterns mining confined to the database cop, which reduces a large degree area of research. To Dinadrash performance shows that the method of family planning - efficient and scalable growth for mining both long and short repetitive patterns, and is about order of magnitude faster than the Apriori algorithm and also faster than some recently reported new frequent-pattern mining methods. SVM can be used to learn a variety of representations, such as neural nets, polynomial estimators, splines, etc, one of the best approaches to data modeling.

$$X \subseteq dp$$
$$\ulcorner X \urcorner = \{dp | dp \in PS(d), X \subseteq dp\}.$$

A knowledge discovery model is developed for effectively use and update the discovered patterns and apply it to the field of the text mining. Text mining is the discovery of interesting knowledge in text documents. It is a challenging issuance to find accurate features in text documents to help users to find what they want. The Rocchio relevance feedback algorithm is one of the most popular and widely applied learning methods from information retrieval. Here is to provide a probabilistic analysis of this algorithm in the text classification framework. Theoretical analysis gives intuition in the reasoning used in the algorithm Rocchio, especially word weighting scheme and similarity metric. It also suggests improvements that lead to potential alternative for the Rocchio classifier. And Rocchio classifier, it's based on the theory of alternative possibilities, and are compared to the naive Bayes classifier on six text classification tasks. The results show probabilistic algorithms are better than Rocchio classifier heuristic, not only because it is more justified, but also because they gain better performance.

3. PROPOSED WORK

3.1 Features Selection Method

Here in this method, documents are considered as an input and the features for the set of documents are collected. Features are selected depends on the TFIDF method. The information retrieval has been developed based on many mature techniques which demonstrate the terms which are important features in the text documents. However, many terms with more weights (e.g., the term frequency and inverse document frequency (tf*idf) weighting scheme) are general terms because they can be frequently used in both relevant and irrelevant information. The features selection approach has been used to improve the accuracy of evaluating term weights because the discovered patterns are more specific than whole documents. In order to limit the features

are irrelevant and conducted several approaches to reduce the dimensions through the use of feature selection techniques.

3.2 Finding Frequent and Closed Sequential Pattern

When feature selection process is completed, the closed and frequent patterns are discovered based on the documents, the term set 'X' in document 'd', $\ulcorner X \urcorner$ is used to denote the covering set of X for d, which includes all paragraph 'dp' $\in$ PS(d) such that,

Its total support is the number of occurrences of X in PS(d) i.e.,

$$sup_a(X) = |\ulcorner X \urcorner|$$

Its relative support is the fraction of the paragraphs that contain pattern, which is,

$$sup_r(X) = \frac{|\ulcorner X \urcorner|}{|PS(d)|}$$

Patterns can be structured into taxonomy by using the subset relation. Smaller patterns in the taxonomy are normally more general because they could be used frequently in both positive and negative documents and larger patterns are usually more specific since they may be used only in positive documents. The semantic information will become used in the pattern taxonomy to improve the performance of using closed patterns in text mining.

The sequential pattern X is called frequent pattern if its relative support is a minimum support. Some property of closed patterns can be used to define closed sequential patterns. The algorithm for finding the support count is given as,

input : positive documents D^+; minimum support, min_sup

output: d-patterns DP, and supports of terms.

```
1   DP = ∅;
2   foreach document d ∈ D⁺ do
3       let PS(d) be the set of paragraphs in d;
4       SP = SPMining(PS(d), min_sup);
5       d̂ = ∅;
6       foreach pattern pᵢ ∈ SP do
7           p = {(t, 1)|t ∈ pᵢ};
8           d̂ = d̂ ⊕ p;
9       end
10      DP = DP ∪ {d̂};
11  end
12  T = {t|(t, f) ∈ p, p ∈ DP};
13  foreach term t ∈ T do
14      support(t) = 0;
15  end
16  foreach d-pattern p ∈ DP do
17      foreach (t, w) ∈ β(p) do
18          support(t) = support(t) + w;
19      end
20  end
```

3.3 Pattern Taxonomy Model

In PTM method, all the documents 'd' are spilted into paragraphs 'p' which yields PS (d). Patterns can be structured into taxonomy by using the subset or relation. From the set of paragraphs in documents the frequent patterns and the covering sets are discovered for each. Smaller patterns in taxonomy, patterns are usually more general because they could be used frequently in both negative and positive documents. Larger patterns, in the taxonomy are usually more specific since they may be used only in positive documents. The semantic information will become used in the pattern taxonomy to improve the performance of using closed patterns in text mining.

3.4 D-Pattern Discovery

D-pattern mining algorithm is used to discover the D-patterns from the set of documents. The efficiency of pattern taxonomy mining is improved by proposing an SP mining algorithm to find all the closed sequential patterns, which used as the well-known appropriate property in order to reduce the searching space. The algorithm describes training process of finding the set of d-patterns. For every positive document and the SP Mining algorithm is first called giving rise to a set of closed sequential patterns. The main focus on the deploying process, which is consists of the d-pattern discovery and term support evaluation. All the discovered patterns in a positive document are composed into a d-

pattern giving rise to a set of d-patterns .Thereafter, term supports are calculated based on the normal forms for all terms in d-patterns.

3. 5 IP Evaluation and Shuffling

In the evaluation of internal style, and is measured by the similarity between the test and document estimated the internal use of the product concept. The relevance of t h e document'd' to the topic can be calculated by the function,

R (d) = d. V

To assign weights for all incoming documents 'd' based on their corresponding weight 'W' functions the following formulae is used,

$$weight(d) = \sum_{t \in T} W(t)\tau(t, d).$$

A computer is capable of generating a "perfect shuffle", a random exchange of the set of documents. For a given noise negative document 'nd', its time complexity is O (nm^2). The following algorithms are proposed for IP evaluation and for shuffling,

input : a training set $D = D^+ \cup D^-$; a set of d-patterns DP; and an experimental coefficient μ.

output: a set of term-support pairs np.

```
1   np ← ∅;
2   threshold = Threshold(DP);// see Eq. (5)
3   foreach noise negative document nd ∈ D⁻ do
4       if weight(nd) ≥ threshold then Δ(nd) = {p ∈ DP|termset(p) ∩ nd ≠ ∅};
5       NDP = {β(p)|p ∈ DP};
6       Shuffling(nd, Δ(nd), NDP, μ. NDP);//call Alg. 3
7       foreach p ∈ NDP do
8           np ← np ⊕ p;
9       end
10  end
```

input : a noise document nd, its offenders $\Delta(nd)$, normal forms of d-patterns NDP, and an experimental

coefficient μ.

output: updated normal forms of d-patterns NDP.

1 **foreach** d-pattern p in $\Delta(nd)$ **do**

2   **if** termset(p) $\subseteq$ nd **then** $NDP = NDP - \{\beta(p)\}$; //remove complete conflict offenders

3   **else** //partial conflict offender

4       $offering = (1 - \frac{1}{\mu}) \times \sum_{t \in (termset(p) \cap nd)} support(t);$

5       $base = \sum_{t \in (termset(p) - nd)} support(t);$

6   **foreach** term t in termset(p) **do**

7   **if** $t \in nd$ **then** $support(t) = (\frac{1}{\mu}) \times support(t);$ //shrink

8   **else** //grow supports

9             $support(t) = support(t) \times (1 + offering \div base);$

10

11   **end**

12

13 **end**

3.6 Temporal Sequential Pattern Mining

In pattern discovery model, a dynamic programming algorithm is used for finding optimal information preserving decomposition and optimal lossy decomposition. The closed relationship is discovered between the decomposition of time period associated with the document set and the significant information computed for temporal analysis, the problem of identifying the suitable time decomposition for a given document set which does not seem to have received adequate attention. So that the time point is defined in interval and decomposition. The time point is given by base granularity such as seconds, minutes, days etc. The time interval between t1 and t2 is defined as $t1 \leq t \leq t2$.

Decomposition of the time interval T is given as the sequence of time intervals
T1, T2, T3, T4… Tn
And **'T'** is computed by
T=T1*T2*T3*T4*……….*Tn.
The information is mapped with the keyword 'wi' and document dataset 'D' as,

$f_m(w_i, D) = v$ where $v \in R^+$.

4 PERFORMANCE EVALUATION

In this study document collection is used to evaluate the proposed approach. The various common measures are applied for performance evaluation. This evaluation defines and compares the following parameters such as precision, recall and F- measure which combines precision and recall with the existing system. Thus the experimental results show that the proposed method is better than the current system. The proposed system is more reliable and scalable for complex applications.

5 CONCLUSION

This model with new pattern discovery model for text mining mainly focuses on the implement of temporal text pattern. Here is a dynamic programming algorithm, knowledge and optimal lossless decomposition, decomposition introduced. This is used for analyzing the relationship between the decomposition of time period associated with the document set and the significant information computed for temporal analysis. It quickly finds the patterns for various ranges of the parameters. It focuses on using information extraction to extract a structured database from a corpus of natural language text and then discover patterns in the resulting database using traditional KDD tools. It also relates record linkage, a form of the data-cleaning that identifies equivalent but textually distinct items in the extracted data prior to mining. It is also related to the natural language learning. Further implementation will become focused on text mining for bioinformatics and it also includes applying the discovered patterns for various time series analysis domains such as prediction, serves as pattern templates for numeric- to-symbolic conversion and summarization of the time series.

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