A NOVEL STUDY FOR SUMMARY/ATTRIBUTE BASED BUG TRACKING CLASSIFICATION USING LATENT SEMANTIC INDEXING AND SVD IN DATA MINING

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ABSTRACT

This paper presentsa Latent Semantic Indexing (LSI) method for learningBug tracking concepts in document data. Each attribute in a vector provides the mark of participation of the document in data or term in the parallel concept .The objective to describe the concepts summary based, but to be capable to signify the documents and relations in a combined way for showing document-similarity, document-term, and term-term similarities or semantic relationship.Many technique for the implementing our research i.e. NLP, STEMMING, LUD, &SVD to the relevant similarity like bug report bug title, report summary etc., sinceevery bug report, and mined developer's name who fixed the bug reports from the developers activity data. We processed the mined textual data, and got the term-to-document matrix. Our proposed model different machine learning methods for on the basis of summary and attribute based classification of bug reports which produce the outlier bugs from large amount of data that improved accuracy and efficiency bug classification and relevant base bug indexing which is similar in meaning by using LSI and SVD Technique.

Keyword: BTS, LSI, SVD, LUD etc

I. INTRODUCTION

A bug tracking system is used for justification and sharing of bug reports to the maximum appropriate designers. An LSI based bug trackingscheme may decrease the software preservation time and advance its value by correct and timely task of new bug reports to the suitable reporters.

Figure 1: Diagram Shows Some use Cases Related to Bug Tracking and Fixing

In this paper, we presentthe current techniques overdue an LSI bug tracking system, which is based on the labelingof summary bug reports. In order to gets an attribute bugtracking system we used these techniques and performed comparative experiments.

Latent Semantic Analysis arose from the problem of how to find relevant documents from search words. The fundamental difficulty arises when we compare *words* to find relevant documents, because what we really want to do is compare the *meanings or concepts behind the words*. LSA attempts to solve this problem by mapping both words and documents into a "concept" space and doing the comparison in this space.

Most NLP applications such as information extraction, machine translation, sentiment analysis and question answering, require both syntactic and semantic analysis at various levels. The motivation for LU decomposition is based on the observation that systems of equations involving triangular coefficient matrices are easier to deal with.

1.1 Indexing for Documents

Indexing is an essential part of the IR systems for two reasons. First, it optimizes the query performance and improves the respond times considerably by storing terms in an inverted file structure.

1.2 Searching

In this phase, the query terms are searched against the inverted index. All the documents that contain the occurrences of the query terms are retrieved. Depending on the application, the retrieval can be done even for the partially matched documents.

1.3 Ranking

The documents retrieved in the previous step are given scores according to the matching quality between the query terms and the documents. The documents are sorted according to this score, so that the most relevant documents are presented to the user on top of the retrieval list. Ranking process is highly dependent to the IR model.Semantic analysis at various levels. Traditionally, NLP research has focused on developing algorithms that are either language-specific and/or perform well only on closed-domain text.

II. LITRATURE REVIEW

Literature reviews are the maximum basic, yet very significant concept to set a theoretical basis. Their quality and usefulness greatly depends on the literature research process:-

Turney [2, 9] proposed the Latent Relational Analysis (LRA) by covering VSM-based methodsin three ways: a) lexical patterns are mechanically extracted from a corpus, b) the Singular ValueDecomposition (SVD) is used to smooth the frequency data, and c) synonyms are used to travelvariants of the word-pairs.

DanushkaBollegala*et al.* [11] planned the method which accepted web text wastes to mechanically extracts lexical patterns that describe the relation obscure by the two words in aword-pair and calculates the relational similarity between two word-pairs using a machine learningapproach.

Shuji [10] shape a model to detect defect correction effort based on protracted association rule mining. They defined defect fixing effort as a variable and appropriate association rule mining to treat with such variables. Data used are supported from Japans Ministry of Economy, Trade and Industry (METI).

Emad and Walid [13] have developed an approach for predicting re-opened defects through Eclipse projects, their study depend upon some factors such as work habits dimension like: day which issue is closed, the bug report features dimension like: components, the bug correction dimension like: time needed to fix bug.

Weiß et al. predict the "fixing effort" or person-hours spent addressing a defect [7]. They leverage existing bug databases and historical context information. To make their prediction, they use pre-recorded development cost data from the existing bug report databases.

III. PROBLEM STATEMENT

The Software development corporations have to face a lot of problems while preservingphysically all the preservation of the projects, their bugs and their status. This type of problem kinds the whole system an incompetent one and thus making a poor and unorganized working. In order to remove this type of problem, So that the paper is deliberate to develop. The LSI mechanism that resolves the problem contains simply of helpful a very large number of local Data. It also permits the manager of the system to modify the tracking procedure so that unnecessary documentation on the part of the problem solvers does not develop a waste of time.

IV. SYSTEM MODEL

The system model in linear algebra that decomposes a matrix into three factor matrices. SVD is a much more complex approach than other; however, once the original matrix has been moldy, operations on the matrix are rather quick.

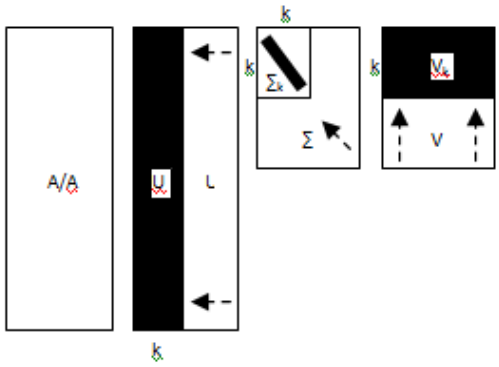


Fig 2: Singular Value Decomposition is a Mathematical

SVD is an extension of Latent Semantic indexing (LSI). LSI is a technique of investigating a group of terms and documents to find relationships between the two [7].

SVD takings as input a matrix of size *m* x *n*. This matrix is spoiled into three different matrices: $U\sum V_T$. The output of these three matrices is a relationship to the original matrix.

S and V_T are both orthogonal matrices and $\sum$ is a diagonal matrix. These three matrices are added identified as:

- S is the right singular vectors
  - Sized: *m* x *r*
- V_T is the left singular vectors
  - Sized: *r* x *r*
- $\sum$ is the singular values
  - Sized: *n* x *r*

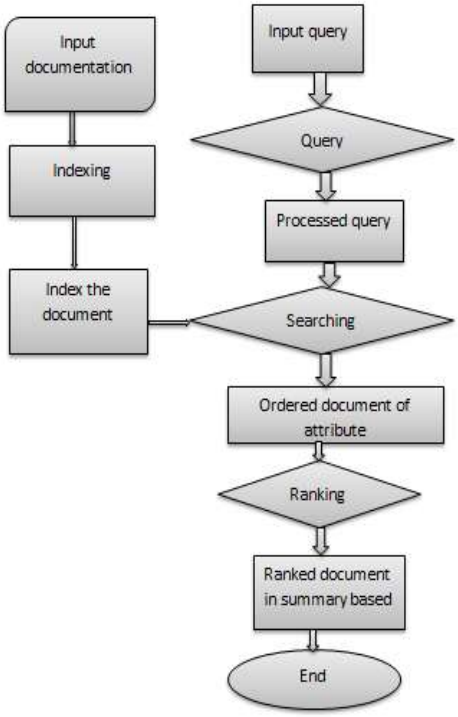
For SVD, "*r*" is measured to be the rank of the matrix, which is the minimum of the original matrix dimensions. In overall, all matrices necessityis full rank, meaning *r* is equal to either *m* or *n*. In this case, we can accuratelyrebuild the original matrix given the three decomposed matrices.

SVD has astimulating property that permits for less than full rank of the matrices to approximate the original matrix. For the purposes of this project and LSA, we don't want the original data back (perfect reconstruction of the original matrix), but rather we want underlying relationships in the movie data.

V. PROPOSED IMPLEMENTATION

To complete Latent Semantic Indexing on a collection of documents, this paper performs the following steps:

- Main in first, change each document in your index into a vector of word occurrences. The number of dimensions your vector occurs in is equivalent to the number of exclusive words in the whole document set. Most document vectors will have great empty patches, some will be quite full. It is optional that common words (e.g., "this", "him", "that", "the") are removed.
- Next, scale each vector so that every term imitates the frequency of its occurrence in context. *I'll column the math for this step when I get home.* Seems he didn't ever get home ;-)
- Next, combine these column vectors into a large *term-document matrix*. Rows represent terms, columns represent documents.
- Execute SingularValueDecomposition on the term-document matrix. This will result in three matrices usually called U, S and V. S is of specific interest, it is a diagonal matrix of singular values for your document system.
- Recombine the terms to form the original matrix (i.e., U * S' * V(t) = M' where (t) signifies transpose).
- Break this reduced rank term-document matrix back into column vectors. Assistant these with their corresponding documents.
- Currently you have a Latent Semantic Index.



5.1 Indexing Process

A stemming algorithm is a process of languagestandardization, in which the differentprocedures of a word are summary to a common form, for example,

Connection

Connections

Connective --->connect

Connected

Connecting

It is important to grow that we use stemming with the meaning of improving the concert of LSIsystems. It is not an exercise in etymology or grammar. In fact from an etymological or grammatical viewpoint, a stemming algorithm is accountable to make many mistakes. In adding, stemming algorithms - at least the ones obtainable here - are appropriate to the written, not the spoken, form of the language.

For some of the world's languages, Chinese for example, the concept of stemming is not applicable, but it is certainly meaningful for the many languages of the Indo-European group. In these languages words tend to be constant at the front, and to vary at the end:

ion

ions

connect-ive

ed

ing

The adjustable part is the `ending', or `suffix'. Taking these endings off is called `suffix stripping' or `stemming', and the residual part is called the stem.

VI. RESULT

The performance evaluation in the thesis is being carried out by using standard Bug tracking of recall and precision for each word&sentence, interpolated average percentage is computed.

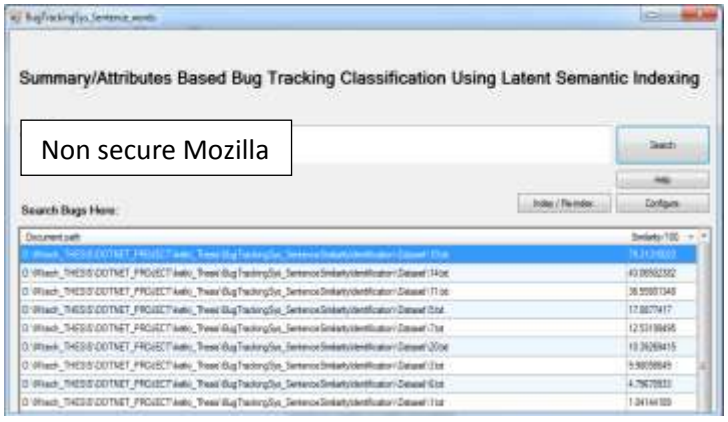


Figure 1: Semantic Search Sentence Based Similarity

In Figures 2 and 3, we have presented the results on evaluation of interpolated semantic search for each of the content queries in the database. Figure 3 represents the highlight of sentence for each query with respect to SVD and

LUD at, where we have recorded the maximum average percentageinFigure3.

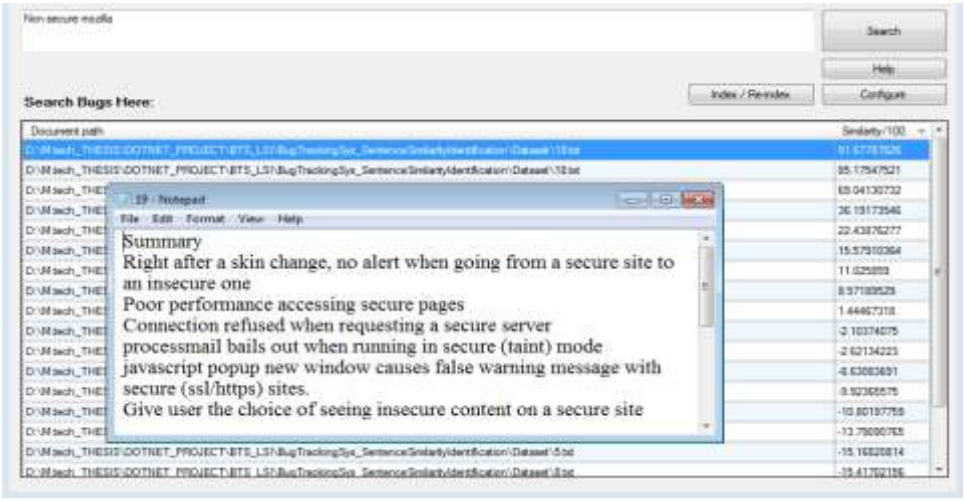


Figure2: Semantic Search Sentence Based Similarity with Document

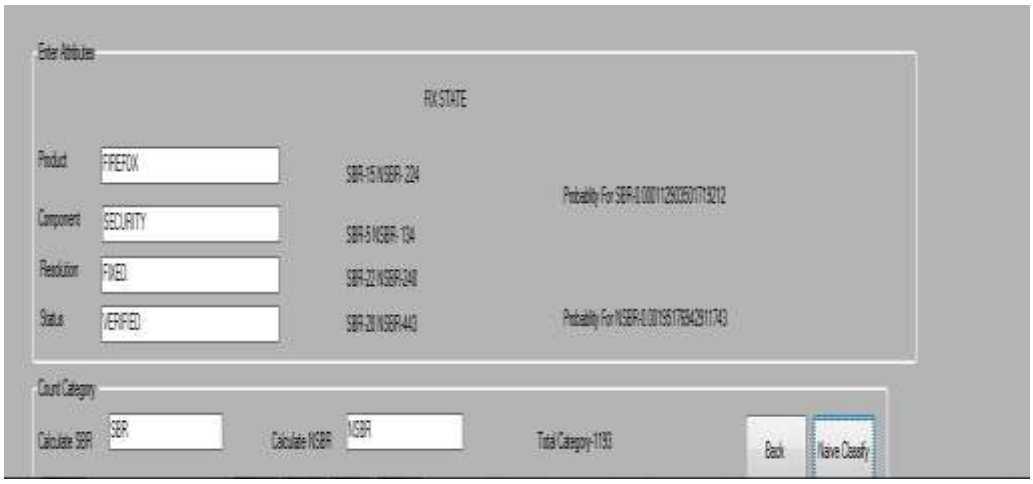


Figure 3: Bug Tracking with Random Attribute

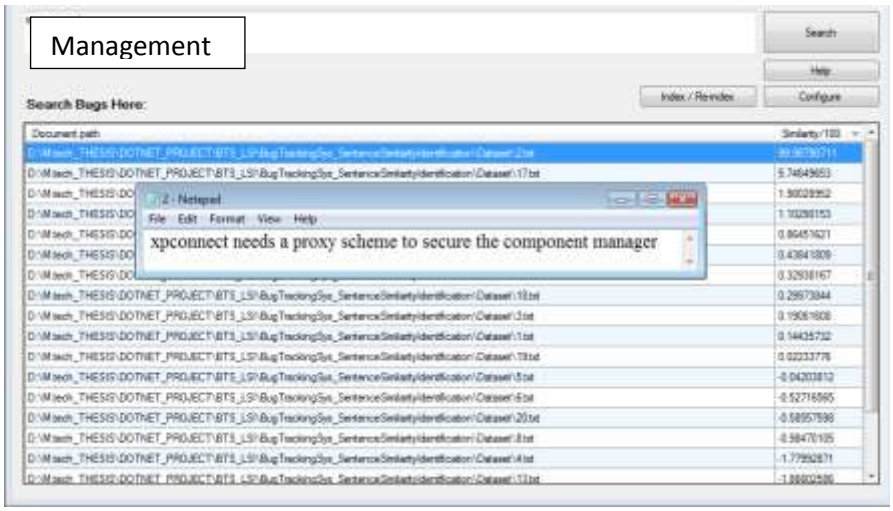


Figure 4: Semantic Search Word Based Similarity with Data

VII. CONCLUSION

Current bug tracking systems effectively elicit all of the information needed by user. Without this material developers cannot resolve bugs in a timely detect. We analyze the same bug summary attributes in different

ways. First we analyze the bug summary with the help of LSI Indexing & SVD classification which is simple to use and efficient to other classification algorithm. Natural language processing enables us to implements a more automated and more efficient bug training process. By analyzing same BUG summary with different methods it increase the efficiency of the system. While implementing a range of improvements from these areas may be ideal, bug tracking systems may instead prefer to specialize, thus providing a rich set of choices.

REFERANCES

[1] J. Anvik. I, Hiew, and G. C. Murphy, Who should fix this bug? In ICSE'06: Proceedings of the 28th International Conference on Software engineering, pages 361-370, 2006.

[2] P.D. Turney, Measuring semantic similarity by latent relational analysis, in Proc. Of IJCAT'05, pp-1136-1141, (2005).

[3] S. Artzi. S. Kim and M. D. Emst, Research: Making software failures reproducible by preserving object states. In Ecoop'08: Proceedings of the 22nd European Object-Oriented Programming Conference, pages 542-565, 2008. [CrossRef]

[4] N. Bettenburg, S. Just. A. Schroter. C. Weiss. R. Premraj, and T. Zimmermann. What makes a good bug report? In FSE'08: Proceedings of the 16th International Symposium on Foundations of Software Engineering, pages 308-318, November 2008.

[5] N. Bettenburg. R. Premraj. T. Zimmermann. And S. Kim. Duplicate bug reports considered harmful…really? In ICSM'08: Proceedings of the 24th IEEE International Conference on Software Maintenance, pages 337-345, 2008.

[6] S. Breu, J. Sillito, R. Premraj, and T. Zimmermann. Frequently asked question in bug reports. Technical. Report, University of Calgary. March 2009.

[7] C. WeiB. R. Premraj. T. Zimmermann, and A Zeller. How Long will it take to fix this bug? In Workshop on Mining Software Repositories, May 2007.

[8] S. Kim and J. E. James Whitehead. How long did it take to fix bugs? In International workshop on Mining Software Repositories, pages 173-174, 2006.

[9] P.D. Turney, Similarity of semantic relations, Computational Linguistics, 32(3), 379-416, (2006).

[10] SHUJI M.AKITO M AND TOMOKO M, Defect data analysis based on extended association rulerning, In Proceeding of International Workshop on Mining Software Repositories (MSR), 2007

[11] D. Bollegala, Y. Matsuo, and M. Ishizuka. www site the sat: Measuring relational similarity on the web. In Proc. Of ECAI'08, pages 333-337, 2008.

[12] J.Aranda and G. Venolia. The secret life of bugs: Going past the errors and omissions in software repositories. In ICSE'09: Proceedings of the 31st International Conference on Software Engineering(to appear), 2009.

[13] EMAD S, AKINORI I, WALID I, AHMED H, Predicting reopened bugs: A case study on the eclipse Project. In Proceedings of the 17th Working Conference on Reverse Engineering WCRE 2010.