

# RATING PREDICTION BASED ON SOCIAL SENTIMENT FROM TEXTUAL TENSOR FACTORIZATION MODEL ON SOCIAL SENTIMENT FROM TEXTUAL REVIEWS

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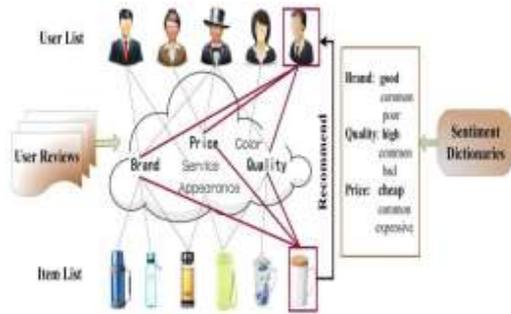
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**Abstract**— Consumers' reviews in E-commerce systems are usually treated as the important resources that re-effect user's experience, feelings, and willingness to purchase items. All this information may involve consumers' views on things that can express interest, sentiments, and opinions. Many kinds of research have shown that people are more likely to trust each other with the same attitude toward similar things. In this paper, we consider seeking and accepting sentiments and suggestions in E-commerce systems somewhat implies a form of trust between consumers during shopping. Following this view of point, an E-commerce system reviews mining oriented sentiment similarity analysis approach is put forward to exploring users' similarity and their trust. We divide the trust into two categories, namely direct trust, and propagation of trust, which represents a trust relationship between two individuals. The direct trust degree is obtained from sentiment similarity, and we present an entity-sentiment word pair mining method for similarity feature extraction. The propagation of trust is calculated according to the transitivity feature. Using the proposed trust representation model, we use the shortest path to describe the tightness of trust and put forward an improved shortest path algorithm to configure the propagation trust relationship between users. A large-scale E-commerce website reviews dataset is collected to examine the accuracy of the algorithms and feasibility of the models. The experimental results indicate that the sentiment similarity analysis can be an efficient method to find trust between users in E-commerce systems.

## I. INTRODUCTION

Reviews from consumers are very important information in E-commerce systems. Many online shops have developed reviews system for users to post their reviews. With the rapid development of social networking media, more and more people are willing to share their feelings, opinions and suggestions on their bought items with their friends or even strangers in social network applications or E-commerce systems. These reviews can be very useful for people's

decision making in many different scenarios such as users' preference mining and personalized recommendation. At present, more and more review mining based applications are being applied to make our decision process easier than before. These applications have greatly changed people's behavior patterns, especially in E-commerce activities. For example, when people want to buy a product, book a hotel or restaurant, they usually not only ask for advice from their friends but also refer to reviews available online. To adapt to this change, many famous E-commerce companies, such as Amazon, eBay and Taobao(China), have built up well-function consumer review systems. Online experience from various people can help one make decisions. In this case, people and their experience are required to be trusted by others. It makes sense that we usually ask for advice from our friends or family members before we make a decision. But the question is, why individuals are inclined to rely on strangers in cyber space to make decision? Scholars find a primary reason for that is their lack of trust in companies that they only experience through the web medium. The virtual nature of the web medium challenges traditional understanding of customer trust. In E-commerce scenario, customers have no chance to have a face-to-face interaction with a salesman or a direct physical experience with the store and the products they want to buy. On one hand, their experience is mediated through the web which is a two-dimensional graphical display. They usually feel somewhat lost and need someone to give them advices. On the other hand, reviews from consumers who purchase an item have direct physical experiences with it, are seem to be more reliable than vendor's promotions or advertising words.



**Fig.1: System Architecture**

The users are usually the consumers who have involved in E-commerce activities. They may have purchased some items or services and posted reviews on these objects, as shown in figure 1. Typically, a user can post multiple reviews on multiple items. Therefore, these reviews for specify items can be expressed in several texts. These reviews can usually be obtained by collecting network information. To end the trust, including direct and propagation, based on sentiment similarity of reviews by users in E-commerce systems, we propose a generally four-step computing framework.

## II. EXISTING SYSTEM

An information propagation mechanism in semantic web to semantic trust score computation. Entire trust is measured by a combined trust score from both subjective and objective sides of information [20]. The objective side of trust is semantic trust of information, and the subjective side is trust relationship between peers. And trust relationship is based on the historical interactions between peers. A trust management model which will take factors like direct, indirect and global trust of the service to find out the final trust value of the service.

### DRAWBACKS OF EXISTING SYSTEM

- In the existing work, the analysis, both at the document level and at the sentence level, cannot exactly discover the specific objects whether people like or dislike..
- An Existing methods concern directly in overall trend which is insufficient when the system calculates the trust based on sentiment similarity.

## III. PROPOSED SYSTEM

In the proposed system, the system implements for sentiment similarity computations, we use a deep and more granular division to the reviews text. However other traditional sentiment analysis studies were able to find the propensity of sentiments, but this tendency concern in the overall evaluation and trend of the review. These cannot

reflect the perception of the specific attributes and characteristics of things in reviews. The system also propose a fine grained analysis method for the evaluation entity-sentiment word pairs by extracting the specific attribute words and feature in the reviews. The system proposed for direct trust computation, that is, one to one trust in the work, we use the weighted average method to compute them, which is similar to other existing works. However, at the same time, we introduce an accompanying factor of sentiment, the rating which widely exists in E-commerce reviews, for weights evaluation. Which is, the direct trust calculation impacted by the facts whether the users have the same sentimental tendency or not for the same thing.

### ADVANTAGES

- The system is affective since the sentiment similarity of reviews of two different users is firstly based on extracting the entity-sentiment word pairs of each review, and then performing similarity computing on the entity-sentiment word pairs.
- The system effectively proposes a system in which trust can be established according observations on whether the previous interactions among the subjects, and can be called direct trust.

### SYSTEM ARCHITECTURE



**Fig.2: Cloud Centric Authentication Architecture**

### MODULES

#### Generating Dataset

Two dataset were collected firstly, from Twitter tweets and secondly, from Online review Dataset. The online review dataset consists of around 800 user's review archived on the IMDB (Internet Movie Database) portal. And for, Twitter dataset around 1000 review were collected and each review were formatted according to .arff file where review text and class label are only two attributes. Class label represent the overall user opinion. Here, we set simple rules for scaling the user review. For dataset, a user rating greater than 6 is considered as positive, between 4 to 6 considered as neutral and less than 4 considered as negative.

#### Preprocessing

For doing the classification, Text preprocessing and feature extraction is a preliminary phase. Preprocessing involves 3 steps: I. Word parsing and tokenization: In this phase, each user review splits into words of any natural processing language. As movie review contains block of character which are referred to as token.

II. Removal of stop words: Stop words are the words that contain little information so needed to be removed. As by removing them, performance increases. Here, we made a list of around 320 words and created a text file for it. So, at the time of preprocessing we have concluded this stop word so all the words are removed from our dataset i.e. filtered.

**III. Stemming:** It is defined as a process to reduce the derived words to their original word stem. For example, “talked”, “talking”, “talks” as based on the root word “talk”. We have used Snowball stemmer to reduce the derived word to their origin.

**Classification**

Classification is a supervised learning method that helps in assigning a class label to an unclassified tuple according to an already classified instance set. Here, naïve bayes multinomial classifier has been used. Quality measure will be considered on the basis of percentage of correctly classified instances. For the validation phase, we use 10- fold cross validation method. Naïve bayes multinomial helps in generating dictionary and frequent set. It counts the occurrences of words in whole dataset and forms a dictionary of some most frequently occurring words.

**SYSTEM DESIGN**

**UML DIAGRAMS**

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems.

The UML is a very important part of developing objects oriented software and the

software development process. The UML uses mostly graphical notations to express the design of software projects.

**GOALS**

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modeling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

The development for the World Wide Web while making some things simpler has exacerbated these architectural problems.

- Class diagram
- Use case diagram
- Sequence diagram
- Activity diagram

**CLASS DIAGRAM**

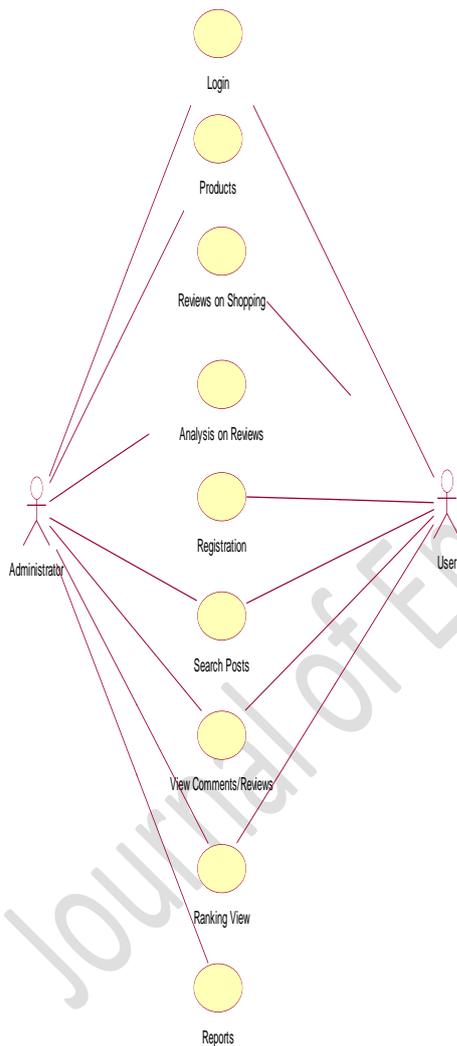
In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.



**Fig.3:** Class Diagram

**USE CASE DIAGRAM**

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

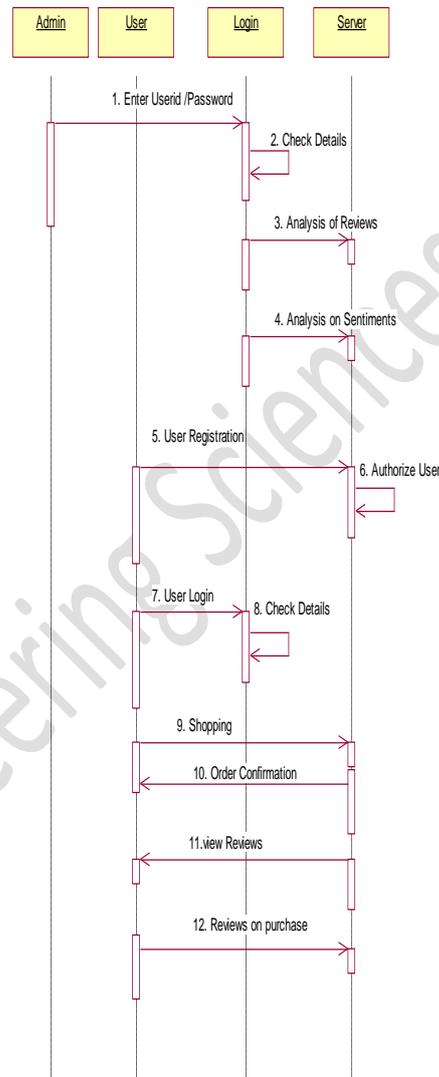


**Fig.4:** Use Case Diagram

**SEQUENCE DIAGRAM**

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes

called event diagrams, event scenarios, and timing diagrams.



**Fig.5:** Sequence Diagram

**ACTIVITY DIAGRAM**

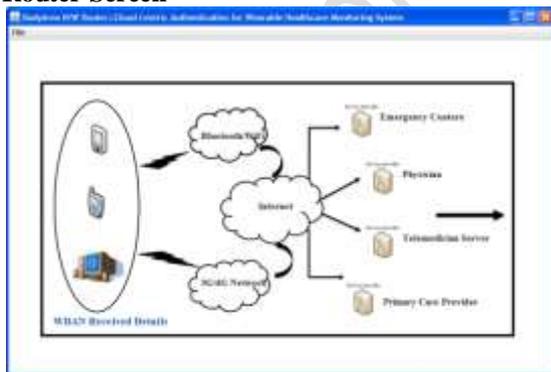
Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.



Fig.6: Activity Diagram

**IV. OUTPUTS**

**Router Screen**



Screen 1: Router Screen showing the connectivity between user and server

**Patient Details**

Patient ID	Patient No.	Diagnose Leds	BP Level	Temperature	HeartRate	Cholesterol
23985	8000	33	155	70	99.96	E
24001	8001	34	84	48	10226	T
40210	8009	35	81	50	80807	S
86534	8007	148	165	58	11187	T
86372	8004	120	150	59	00763	E

Screen 2: Patient Details showing Various Readings

**Emergency Details**

Patient ID	Patient No.	Diagnose Leds	BP Level	Temperature	HeartRate	Cholesterol
23985	8000	33	155	70	99.96	E
24001	8001	34	84	48	10226	T
40210	8009	35	81	50	80807	S
86534	8007	148	165	58	11187	T
86372	8004	120	150	59	00763	E

Screen 3: Router Showing Emergency Readings of Patients

**Physician Details**

Patient ID	Patient No.	Diagnose Leds	BP Level	Temperature	HeartRate	Cholesterol
23985	8000	33	155	70	99.96	E
24001	8001	34	84	48	10226	T
40210	8009	35	81	50	80807	S
86534	8007	148	165	58	11187	T
86372	8004	120	150	59	00763	E

Screen 4: Report Showing Physician Details

**Telemedicine Details**

Patient ID	Patient No.	Diagnose Leds	BP Level	Temperature	HeartRate	Cholesterol
23985	8000	33	155	70	99.96	E
24001	8001	34	84	48	10226	T
40210	8009	35	81	50	80807	S
86534	8007	148	165	58	11187	T
86372	8004	120	150	59	00763	E

Screen 5: Patient Details at Telemedicine

**Primary Care Details**

Patient ID	Patient FL	Sugar Lvl	BP Level	Temp (F)	HeartBeat	Date & Tm
23195	West	155	136	99.99735	6	Fri Jan 1
20234	West	140	130	100.11107	1	Fri Jan 1
16272	West	120	116	99.00763	6	Fri Jan 1

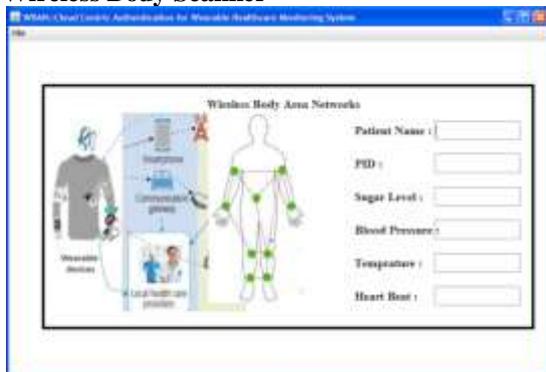
Screen 6: Patient Details at Primary Care

**Admin Login**



Screen 10: Admin Login

**Wireless Body Scanner**



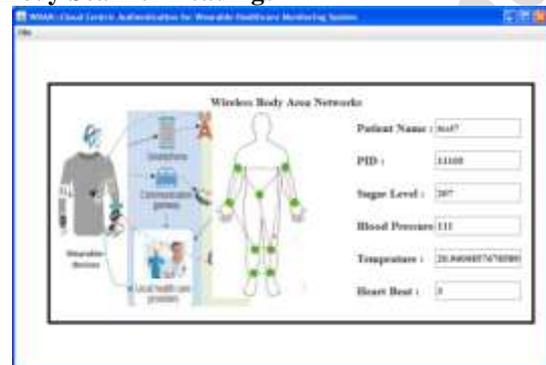
Screen 7: Showing Various Readings Scanned from Body

**Admin Menu**



Screen 11: Admin Menu Page

**Body Scanner Readings**



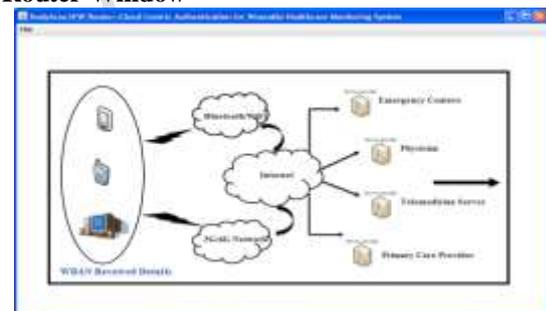
Screen 8: Body Scanner Readings

**Patient Sensor Details**

Health Care Centre - PATIENT SENSOR DETAILS									
Device ID	Readings	BP	Sugar	Temp	HR	Age	Sex	Status	Action
12345	120	130	100	99.9	60	30	Male	Active	View
67890	140	140	110	100.0	70	35	Female	Active	View
11111	150	150	120	100.1	80	40	Male	Active	View
22222	160	160	130	100.2	90	45	Female	Active	View

Screen 12: Health Care Patient Sensor Details

**Router Window**



Screen 9: Router Window with various Activities

**Emergency Details**

Health Care Centre - Emergency Details									
Device ID	Readings	BP	Sugar	Temp	HR	Age	Sex	Status	Action
12345	120	130	100	99.9	60	30	Male	Active	View
67890	140	140	110	100.0	70	35	Female	Active	View
11111	150	150	120	100.1	80	40	Male	Active	View
22222	160	160	130	100.2	90	45	Female	Active	View

Screen 13: Emergency Details of Patient

**Physician Details**



**Screen 14: Patient Details at Physician**

**Primary Care Details**



**Screen 15: Showing Patient Details at Primary Care**

**CONCLUSION**

In our work, we address the problem of mining users trust in E-commerce system. By dening two kinds of trust relationship, namely, direct trust and propagation trust, we transfer the point of exploring trust between users into calculation of sentiment similarity of their reviews. With the help of entity-sentiment word pairs mining, sentiment similarity of reviews can be calculated and direct trust relationships can be obtained through sentiment similarity analysis, which contains of sentiments and ratings aspect. These two aspects can be used jointly to analyse the sentiment direct trust relationship. We establish a weighed trust graph model for propagation trust computing. Propagation trust is the use of the propagation characteristics of trust. It is an indirect trust between two users without direct trust and is obtained through intermediate users who have direct trust between these two users. The propagation trust calculation approach is based on the improved shortest path algorithm, and the time complexity is  $O(V^2)$ , where  $V$  is the number of node in the graph. Ways to improve the computational complexity of the algorithm is a new problem that needs further study because the relatively large number of users in modern e-commerce system.

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