Semantic Analysis of Context Attributes for Recommender System using Ontology

[1]Pallab Dutta, [2]Dr. A. Kumaravel
[1]Research Scholar, Department of CSE, Bharath University, Chennai, India
[2]Dean-School of Computing, Bharath University, Chennai, India

Abstract

There has been anunprecedented expansion of Internet in last couple of decades; huge amount of information and content isavailable in almost all domains and subjects and is ever expanding in both breadth and depth. On the flip side, this colossal expansion has resulted in data overloading problem; due to which it has become an increasingly difficult task toretrieve useful information from internet and separate out the unwanted ones. Recommender systems have evolved as a solution to the data overload problem that persists today in World Wide Web. Context aware recommender system has been an active research hotspot in current times. It has been found that when contexts parameters are induced appropriately in recommender system, the prediction accuracy increases but if contexts are not properly assimilated, the accuracy of recommender system suffers.The contexts always do not match exactly, but when contexts are meaningfully similar or nearer within a givenknowledge domain, these can be considered and exploited for further processing. This paper discusses the semantic analysis of context attributes of recommender system towards increasing the prediction accuracy and overcome data sparseness.

Keywords

Context, Recommender System, Context Aware Recommender System, Trust Network

I. Introduction

In our everyday life, it is often necessary and evident to make choices about some items (e.g.; book, movie, place, restaurants etc.) without sufficient personal experience.Under such situations, we rely on recommendations from other people (family, friends, and neighbors) either by word of mouth, recommendation letters, reviews printed in newspapers and so on. Recommender systems assist and augment this natural social process. Recommender Systems (RSs) are software tools and techniques that provide suggestions for items to be of use and interest to a user. In a typical recommender system people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipient. RSs are primarily directed towards individuals who lack sufficient personal experience or competence to evaluate the potentially overwhelming number of alternative items that a Web site, for example, may offer.Amazon.com, Flipkart.com are the example sites which provides recommendation about items to the users.There are many different types and uses for recommender systems. Recommender systems use various types of information to generate a recommendation, such as, past purchase records, click stream analysis, user profiles, explicit ratings of items, or social network information. Recommender systems use various methods to process the input data, and output recommendations to the user. The recommender systems are broadly categorized in to two types: Content based and collaborative filtering.Content based recommender systems operate by comparing description of recommendable items. This type of recommender system relies on rich content description of items those are being recommended. Here items may be products or services. Collaborative filtering based on the observation that in real life scenario, people typically rely on the friends who have similar taste or preferences. It is built on the assumption that a possible way to determine interesting content for a user, is to find other users who have similar interest, and then recommend item that those similar users liked. There are issues for both these types of RSs. There are many approaches to overcome these issues by using trust network based approach, hybrid methods, Context aware RS to improve the recommendation accuracy and overcoming data sparseness issue.

A. Context Aware RS

As discussed in [4], context has many definitions and is a multidimensional concept that has been studied and analyzed across different research domains including Computer Science, Cognitive Science, linguistic, philosophy, psychology and organizational context. Since context has been studied in multiple disciplines, each of them view the context in their own premise and are distinctive from each other. In the domain of RS, we try to interpret and dissect the term ‘context’. In the case of RS, context parameters are heavily dependent on whether it is a movie RS or a Tourist RS etc.Brown et al. [26] widened the scope of context information totemperature, time, season and many other factors. As number of context parameterscan be unlimited, the definition of context by Anhind K. Dey in [27] is oneof the most relevant and commonly used:

“Context is any information that can be used tocharacterize the situation of an entity. An entityis a person, place, or object that is consideredrelevant to the interaction between a user andan application, including the user and applicationthemselves. [27]”

In movie RS, the contexts are typically: Day of watching, Place (Theatre) of watching, Time of Watching, Seasonal info (during festival etc.), companion (friends, family etc), Important pre & post events. In musicRS, the contexts are typically: mood, time_of_day, companion, important pre & post events. Traditional recommender systems usually compute the similarity using two-dimensional user-item matrix and do not take into consideration contextual information which plays pivotal role towards influencing the decisions. The contextualinformation is time, location, companions, weather, and so on. Infusing context information appropriately is very important towards enhancing the prediction accuracy. Adomavicius and Tuzhilin proposed a multidimensional approach to incorporate contextual information into the design of recommender systems.

B. Context Parameter and Context Attribute

In our research work, we used two terminologies and are listed in this paper; these are: ‘Context parameters’ and ‘Context attributes’. Context parameters are individual situational parameters, e.g.; in a movie recommender system, ‘daytype’, ‘weather’, ‘location’, ‘time’ etc. are individual context parameters. Each ofthese individual context parameterscan take different values (categorical or continuous); e.g.; time : Morning, Afternoon, Evening, Night; daytype : Working day, Weekend, Holiday; season : Spring,

Summer, Autumn, Winter; location : Home, Public place, Friend's house; weather : Sunny / clear, Rainy, Stormy, Snowy, Cloudy.
These different possible values of each context parameters are called context attributes. In this case, 'morning', 'afternoon', 'evening', 'night' are context attributes for the context parameter 'time'.We propose an approach to calculate the semantic similarity of context attributes by constructing the domain knowledge structure, the knowledge structure is formed using ontology. We then appropriatelyinfusethe context variables in a trust network based recommender system and analyze the effect of the same in the metrics used.
Rest of the paper is structured as follows: Section II of this paper gives the related work done the area of semantic similarity and RS. Data sparsity and cold start problem is listed in Section III, the concept of ontology in our application context is described in section IV. Our approach towards semantic analysis and infusing the same in RS is given in section V along with experiment and results in section VI. Section VII gives conclusion.

II. Related Works

In this section, we review some of the works related to Context aware Recommender System (RS) and semantic analysis of context attributes. A considerable amount of work has been done in the area of Context aware RS and continues to be a research hotspot. Context aware RS is discussed by G. Adomaviciusand AlexanderTuzhilin in [4]. Their work details about modeling contextual information in RS. They also describe contextual pre-filtering, post-filtering and Contextual modeling. In [4], they mention about possibility of combining post-filter, pre-filtering and contextual modeling in order to achieve higher accuracy in RS output. They also proposed a multidimensional rating estimation method based on the reduction based approach, and tested their methods on a movie recommendation application that took time, place, and companion contextual information into consideration. Here, recommendations are generated using only the ratings made in the same context of the target prediction. However, in fact, it is rarely the same context occurs in the future but instead the similar context. The disadvantage of that method is the increase of data sparsity. Umberto and Michele have analysed post filtering, pre filtering and contextual modeling for context-aware recommender system. There are research done on selecting relevant context features, relevant contexts increases the accuracy of recommender system while the irrelevant ones actually degrades the performance both in terms of output accuracy and computational load. Ante Odic et al. in [19], describes different methods for elicitation of relevant context selection for a movie recommender system. Rhul Gupta et al. in [20] points out the naïve Bayes classifiers and SVD for context aware recommender system. Feature reduction for product recommendation is given in [21]. Matthias, Gernot Bauer explore the design space of RS for mobile applications and describe different dimensions and techniques for capturing the users, the items, the contexts etc. in [5]. In [28-30], ontology based semantic similarity concepts are given. In [28], to improve accuracy of semantic similarity measurebetween ontology concepts, four main factors namely semantic distance, semantic depth, semantic coincidence andsemantic density that impact onsemantic similarity measure is taken into considerations. At First, they were preprocessed to obtainfour basic methods for calculating semantic similarity. Andthen Multi Expression Programming algorithm is used tocombine and optimize the four basic methods. After experiments, it has been shown that only three out of four factors are significant. Feature based semantic similarity is described in [32]. To the best of our knowledge, we did not find any literature on semantic analysis of context attributes for a recommender system.

III. Data Sparsity Problem

Data sparsity in generic terms means lack of sufficient data points.In the domain of RS, it refers to the difficulty in finding sufficientreliable similar users, since in general the active usersonly rate a small portion of items. This data sparsity problem is very dominant in Collaborative Filtering based Recommender system. In a Trust based RS also, the direct trusted elements/users may be less and thus data sparsity problem can manifest provided appropriate trust propagation models are not implemented. In context ware RS, context information is also used along with user similarity/trust. Data sparsity is a major issue is context aware RS. One hindrance towards achieving high prediction accuracy in context aware RS in many practical scenariosis due to high sparsity of contextual information. High sparsity is caused by various naturesof users and their preferences and also due to fine grained context attributes. Some users do not wantto share their personal information such as location, thuscausing missing contextual information. Poor context information leads to low accuracy in prediction. On the otherhand, some users are willing to expose even personal contextual information such as emotions. They are willing toanswer question and explicitly express contextual information, which is then useful in context-aware recommendation. Along with context elicitation problems, when context attributes are fine grained (defined and used in very granular way), the probability of matching the context attributes reduces and there by data sparsity issue manifests further.

IV. Ontology and Semantic Similarity

Ontology:In recent years, ontology has received attention from both academic and industrial fields and has been in intense research focus. The word 'ontology' has been originated from the field of philosophy, where it is used to mean the basic characteristics of existence in the world. It is now defined in different perspectives. Ontologies are used in many domains of computer and information science, namely artificial intelligence, the Semantic Web, systems engineering, software engineering, biomedical informatics and information architecture as a method of knowledge representation about the world or some part of it. The core meaning of ontology within computer science is a model for describing the world that consists of a set of types, properties, and relationship types. In general, it is expected that the features of the model in ontology should closely resemble the real world (related to the object).Manytechnologies offer good data-sharing solutions for thesyntactic level, for example XML, but do not workeffectively at the semantic level. Ontology offers a goodsolution for using data and sharing it at the semantic level.Ontology is a modeling tool that provides a formaldescription of concepts and their relations, as a foundationfor semantic integration and interoperability.
Common components of ontologies are:

- **Individuals:** Instances or objects (the basic or "ground level" objects)
- **Classes:** Sets, collections, concepts, types of objects, or kinds of things.
- **Attributes:** Aspects, properties, features, characteristics, or parameters that objects (and classes) can have.
- **Relations:** Ways in which classes and individuals can be related to one another.
- **Function Terms:** Complex structures formed from certain

relations that can be used in place of an individual term in a statement.

- **Restrictions:** Formally stated descriptions of what must be true in order for some assertion to be accepted as input.
- **Rules:** Statements in the form of an if-then (antecedent-consequent) sentence that describe the logical inferences that can be drawn from an assertion in a particular form.
- **Axioms:** Assertions (including rules) in a logical form that together comprise the overall theory that the ontology describes in its domain of application. This definition differs from that of "axioms" in generative grammar and formal logic. In these disciplines, axioms include only statements asserted as a priori knowledge. As used here, "axioms" also include the theory derived from axiomatic statements.
- **Events:** The changing of attributes or relations.

Ontologies are commonly encoded using ontology languages. Examples [32] of general purpose ontology are "Wordnet", "Sensus", domain specific ontology are UMLS, SNOMED, GO.The Unified Medical Language System (UMLS) is a multi-purpose and multilingual metathesaurus containing information. SNOMED is a widely used clinical health care terminology and infrastructure and this enables easy access of health care knowledge, Gene Ontology (GO) describes gene proteins and all concerns of organisms in a structured way in terms of defined terms.

A. Semantic Similarity

Semantic similarity between concepts is a measure ofmeaningful connotational similarity (or commonality) between two concepts according to a given ontology. Semantic similarity is used to identify concepts having common "characteristics" or "features". Although human beings may not be aware of the formal definition of similarity and relatedness between concepts, he/she can intuitively understand and infersimilarity or relatedness between objects/items/concepts. As an example [32], a small child can tell that "apple" and "peach" have more related to each other than "apple" and "tomatoes". Semantic similarity is widely used for most applications of intelligent knowledge-based, semantic information retrieval systems and Bioinformatics.Semantic similarity and semantic relatedness are two related terms although not the same, but semantic similarity is more specific than relatedness and can be considered as a type of semantic relatedness. For example 'Player' and 'Coach' are the related terms, which are not similar. All the similar concepts are related but the vice versa is not always true. Several methods of determining semantic similarity measures have been proposed in the last few decades. Structure based measure, Information content measure, Feature based measure are the most common ones.

B. Structure Based Semantic Similarity Measure

There are many approachesto measure semantic similarity using structure based methodologies. We analyze and adapt the approach as given in [28] based on semantic distance, semantic depth and semantic coincidence. As shown in [28], the semantic density has minimum impact and is ignored for calculation of affective semantic similarity.

Semantic Distance:In an ontology hierarchy structure, semantic distance is defined as the number of directed arcs included in the shortest path which connects two concept nodes of ontology. E.g.; in Fig. 1, the semantic distance between snowy and stormy is 2, denoted as: l(snowy, stormy)=2.It can be very easily and intuitively established that Semantic distance is one of the impacting factorsin the determination of semantic similarity. As given in [28], there is nonlinear negative correlation between semantic distanceand semantic similarityand take negative exponentialfunction.The relation between semantic similarity andsemantic distance lis given by the function (1):

$$f_1(l) = e^{-\alpha l} \qquad (1)$$

where α is a constant coefficient(α>0). The range ofsemantic distance l is [0,∞], and the range of correspondingsemantic similarity is [0,1]. It has been proved through experiments [33] that when α is equal to 0.25, the semantic similarity got thehighest accuracy.

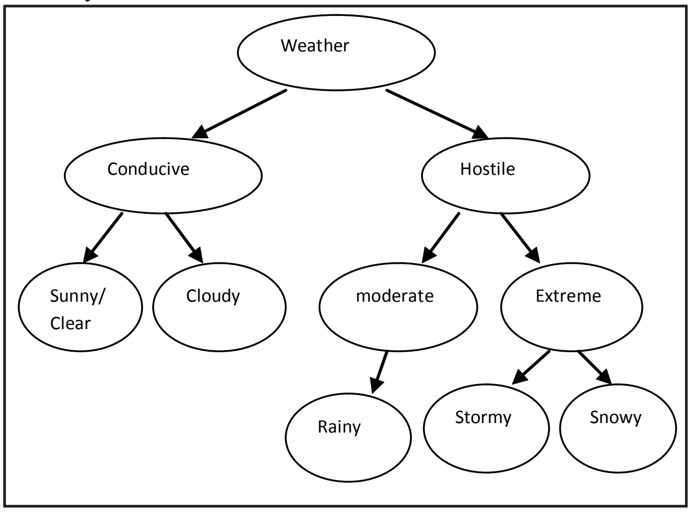

Fig. 1: Hierarchical Structure for Context attribute of Movie RS.

Semantic Depth:For concept hierarchical structure, Semantic depth is defined as the number of concept nodes included in the longest path from the node to the top node of structure. The semantic depth of the top node is 0. From the top node of hierarchical structure, the depth of the child node in next layer is equal to the depth of the current node plus 1. As shown in Figure 1, the semantic depth of rainy is 4, denoted as: h(rainy)=4.Semantic similarity depends not only on semantic distance but on other factors too. It can be seen that, the larger semantic depth ofthe most close common ancestor node of the two concepts is,the larger semantic similarity between two concepts is. That is, they are directly proportional. Li [33] proposed hyperbolic tangentfunction as relation function between semantic similarity andsemantic depth h:

$$f_2\,(h) = \frac{e^{\beta h} - e^{-\beta h}}{e^{\beta h} + e^{-\beta h}} \qquad (2)$$

Whereis a constant coefficient (>0). The range ofsemantic depth h is [0, ∞], and the range of correspondingsemantic similarity is [0,1]. It has been proved through experiments [33] that when is equal to 0.15, the semantic similarity got thehighest accuracy.

Semantic Coincidence:Concept semantic coincidence is defined as the ratio of the number of nodes in intersection to the number of nodes in union of common ancestor concepts of the two concepts in ontology for a given hierarchical structure. Let the collection of ancestor concepts of concept ci be p(ci), and the collection of ancestor concepts of concept cj be p(cj), then Semantic Coincidence, c(ci, cj) is as per equation (3) as below:

$$c(c_i\,,\ c_j) = \frac{|P(c_i) \cap P(c_j)|}{|P(c_i) \cup P(c_j)|} \qquad (3)$$

Semantic coincidence between rainy and cloudy is ¼.Semantic coincidence represents the same degreebetween concepts, which

ISSN : 0976-8491 (Online) | ISSN : 2229-4333 (Print)

can be directly used to measuresemantic similarity between concepts [34]. Thelarger semantic coincidence between two concepts results in higher semantic similarity between two concepts and vice-versa. That is, semantic similarity and semantic coincidence is directly proportional. Also the rangeof semantic coincidence is [0,1], which is the same as the range of semantic similarity.As shown in [28, 34], it is directly used to calculate semanticsimilarity. The relation between semanticsimilarity and semantic coincidence c is represented by the function as given in (4) below:

$f_3(c) = c$ (4)

As elaborately discussed and shown in [28], using Multi Expression Programming (MEP) andappropriately training MEP algorithm, comprehensive semantic similarity calculating formula between concepts is determined as given by equation (5) below:

$f(l,h,c)= \sqrt{f_1(l).f_2(h).f_3(c)}$ (5)

$Sim_T(C1, C2) = \sqrt{f_1(l).f_2(h).f_3(c)}$ (6)

Where $Sim_T(C1, C2)$ is the structure based semantic similarity between the concepts C1 and C2.

C. Feature based Semantic Similarity Measure

Feature based similarity measure is one of the important approaches towards the calculation of semantic similarity in a knowledge structure. The study of the features of a term/concept is very important, because it contains valuable information concerning knowledge about the same. Feature based measure assumes that each term is described by a set of terms indicating its properties or features. The similarity measure between two terms/concepts is defined as a function of their properties (e.g., their definitions or "glosses" in WordNet) or based on their relationships to other similar terms in hierarchical structure. There are various methods for semantic similarity calculations within feature based approach. Here we discuss and adapt Tversky method. The Tversky measure takes into account the features of terms to compute similarity between different concepts. Feature for each term/conceptare described by a set of words. Common features tend to increase the similarity and non-common features tend to decrease the similarity of two concepts [35]. The similarity is calculated as per equation (7) below.

$$Sim_F(C1, C2) = \frac{|C1 \cap C2|}{|C1 \cap C2| + \alpha|C1 - C2| + (\alpha - 1)|C2 - C1|} \quad (7)$$

Where C1 and C2 are the corresponding description sets of two concepts.is the relative importance of the non-common characteristics and its range is [0,1]. This value increases with commonality and decreases with the difference between the two concepts. The determination of is based on the that similarity is not necessarily a symmetric relation.

V. Our Approach

The approach of semantic similarity calculations between ontology concepts as given in [28] is adapted along with feature based semantic similarity measure [32] and used here in the domain of context aware RS. Here ontology is used to construct the knowledge structure for context variables and then determine the semantic similarity between context attributes.

It can be seen that [28] semantic similarity is the function ofsemantic distance, semantic depth, semantic coincidence as per (6).

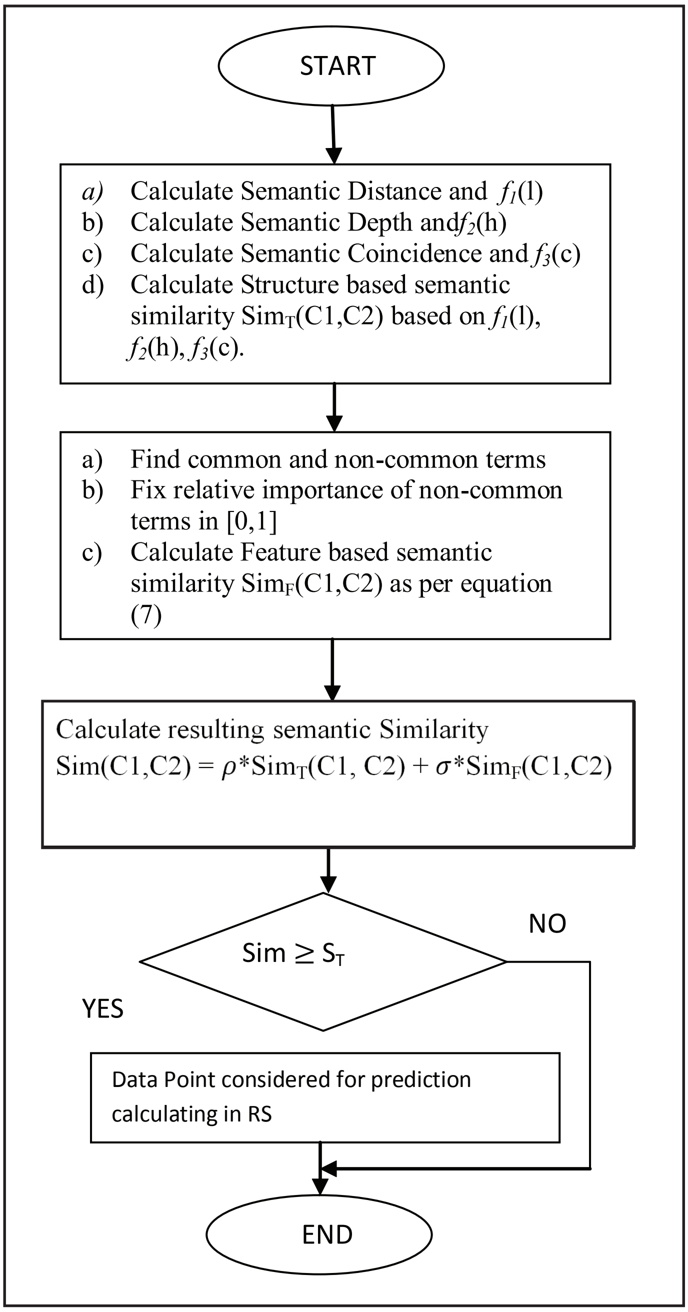

Fig. 2: Semantic Similarity Calculation

For a given context parameter, we calculate the semantic similarity between the context attributes. If the target context attribute does not match with any of the available data points and calculated semantic similarity is more than a specified threshold STH, we use the same for prediction calculation in Recommender system.

In our approach, we consider both structure based and feature based semantic similarity for calculating the resulting semantic similarity.

$Sim(C1,C2) = \rho * Sim_T(C1, C2) + \sigma * SimF(C1,C2)$ (8)

Where,

Sim(C1,C2) = ResultingSemantic similarity between C1 and C2.

$Sim_T(C1, C2)$ = Structure based semantic Similarity as given by equation (6)

$Sim_F(C1, C2)$ = Feature based semantic similarity as given by equation (7)

$\rho,\sigma \in [0,1]$ and $\rho+\sigma = 1$.ρ, σ are relative weighing factors for structure based and feature based semantic analysis.

Resulting similarity Sim(C1,C2) measure is within [0,1].
Let us calculate Semantic Similarity between 'Rainy' & 'Stormy'.
Semantic distance = l = 4.As per equation (1), $f_1(l) = 0.368$.
Semantic depth of common ancestor= h = 2.
As per equation (2), $f_2(h) = 0.2913$.
As per equation (3)& (4), $f_3(c) = 0.3333$.
Using equation (6):

$$Sim_T(Rainy, Stormy) = \sqrt{f_1(l).f_2(h).f_3(c)} = 0.1890 \quad (9)$$

For SimF(Rainy, Stormy) calculation,
Feature for 'rainy' = requires rain coat, requires umbrella, low temperature.
Feature for 'stormy' = requires rain coat, requires umbrella, windy, hostile, destructive.
Using equation (7) with $\alpha = 0.5$

$$SimF(Rainy, Stormy) = 0.4 \quad (10)$$

Using (8), (9), (10), with $\rho = \sigma = 0.5$, we get, Sim(Rainy,Stormy) = 0.2945
Calculating only structure based semantic similarity or only feature based similarity is not suitable in the domain of RS in general and the hybrid approach is suitable.

VI. Experiment and Result

In our experiments, we have considered modified LDOS-CoMoDa dataset that is a movie dataset and is rich in context information also. As per our previous work [31], not all context parameters are relevant and the relevant context parameters are selected using PCA (Principal Component Analysis) along with feature extraction method. Relevant context parameters in LDOS-CoMoDa dataset as per our analysis are:Social, Mood, Weather and Location. There are different context attributes for these context parameters as given in Table 1. We construct the knowledge domain for each of the context parameters using ontology. We construct both hierarchical structure and also add features to the classes/concepts (context attributes). We have used Protégé 4.3 tool for the ontology construction. In a movie recommender system, context parameters and context attributes are as follows:

Table 1: Context Parameters and Context Attributes

S. no	Context Parameters	Context attributes
1	Time	Morning, Afternoon, Evening, Night
2	daytype	Workingday, Weekend, Holiday
3	season	Spring, Summer, Autumn, Winter
4	location	Home, Public place, Friend's house
5	weather	Sunny / clear, Rainy, Stormy, Snowy, Cloudy
6	social	Alone, My partner, Friends, Colleagues, Parents, Public, My family
7	endEmo	Sad, Happy, Scared, Surprised, Angry, Disgusted, Neutral
8	dominantEmo	Sad, Happy, Scared, Surprised, Angry, Disgusted, Neutral
9	mood	Positive, Neutral, Negative
10	physical	Healthy, Ill
11	decision	User decided which movie to watch, User was given a movie
12	interaction	first interaction with a movie, n-th interaction with a movie

The usefulness of a recommender system depends on the accuracy of prediction. We measure the Mean Absolute Error (MAE) after implementing our approach. MAE measures the average absolute deviation between predicted ratings and users true ratings. If MAE is small, it indicates high prediction accuracy. MAE is simple but a very effective measure the accuracy of recommender system. MAE is also most commonly used metric for quantification of recommender system accuracy.

$$MAE = \frac{\sum_{i=1}^{N} |p_i - r_i|}{N} \quad (8)$$

Where,
p_i = Predicted rating, r_i = user's actual ratings, N = total number of items for which prediction is made.

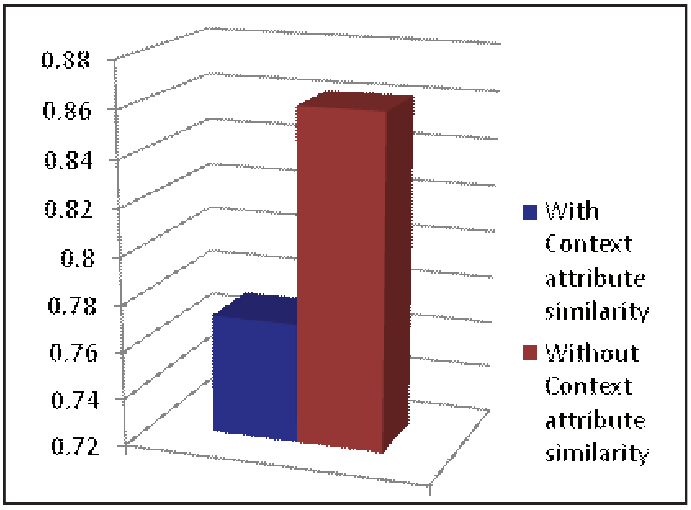

Fig. 3: Mean Absolute Error

We use MAE to measure the accuracy of our proposed approach with different parameters. We calculate MAE with and without considering context attribute similarity.
We have taken $\rho = \sigma = 0.5$
We divide the total dataset into training set and Test set. For our experiment, we consider the following splits: 80% Training data and 20% Test data.

VII. Conclusion

In this paper, we have discussed and analyzed semantic similarity of context attributes. Various approaches of semantic similarity calculations are discussed and an approach for semantic similarity calculation is proposed. The proposed approach is based on both hierarchical structure based and also on feature based semantic similarity methods. For structure based semantic similarity method, three parameters are considered, namely semantic distance, semantic depth and semantic coincidence. Feature based method takes into consideration relative importance of non-common characteristics. The proposed resulting semantic similarity method reduces the data sparsity problem found in context aware recommender system and thereby increases the accuracy and hence reduces the Mean Absolute Error (MAE). In future course, we plan to do further analysis and optimize the values and , the relative weighing factors of structure based similarity values and feature based similarity values respectively in the resulting semantic similarity determination so that the overall maximum accuracy of RS can be obtained.

References

[1] Adomavicius, G., Tuzhilin, A.,"Toward the Next Generation of Recommender Systems:A Survey of the State-of-the-Art and Possible Extensions", IEEE Transactionson Knowledge and Data Engineering 17, pp. 734–749, 2005.

[2] J. Herlocker, J. Konstan, B. A., J. Riedl,"An algorithmic framework for performing collaborative filtering", In Proc. ACM-SIGIR Conf., pp. 230–237, 1999.

[3] Q. Li, B. Kim,"An approach for combining content-based and collaborative filters", In Proc. of IRAL 2003.

[4] Adomavicius, G., Tuzhilin, A.,"Context-Aware Recommender Systems", In Recommender Systems Handbook, ed. F. Ricci, L. Rokach, B. Shapira, and P. Kantor, pp. 217–256. Berlin: Springer Verlag, 2011.

[5] Matthias, Gernot Bauer et.al.,"Exploring the Design Space of Context-aware Recommender Systems that Suggest Mobile Applications", In CARS-2010, September 26, 2010, Barcelona, Spain, 2010.

[6] Abbar Sofiane, Bouzeghoub Mokrane, Lopez Stéphane, "Context-Aware Recommender Systems: A Service-Oriented Approach", Very Large Data Bases-VLDB conference, 2009.

[7] [Online] Available: http://www.protege.standford.edu Protégé tool 4.3

[8] EmmanouilVozalis, K.G. Margaritis,"Analysis of Recommender Systems' Algorithms", Parallel and Distributed Processing Laboratory.

[9] Elizabeth Chang, Tharam S Dillon, Farookh Khadeer Hussain,"Trust and Reputation Relationships in Service-Oriented Environments", In Proceedings of the Third International. Conference on Information Technology and Applications (ICITA'05) 2005 IEEE.

[10] Kristen Mori,"Trust Networks in Recommender Systems", Masters Project, San Jose State University, 2008.

[11] Jonathan L. Herlocker, Joseph A Konstan, Loren G Terveen, John T Riedl,"Evaluating Collaborative Filtering Recommender Systems", In ACM ACM Transactions on Information Systems, Vol. 22, No. 1, pp. 5–53, 2004.

[12] Pallab Dutta, A Kumaravel,"A Review of Recommender System: From Past to the Future", International Journal of Computer Science And Technology, Vol. 5, Issue 3, July - Sept 2014.

[13] Qing Li, Byeong Man Kim,"Clustering Approach for Hybrid Recommender System", Proceedings of the IEEE/WIC International Conference on Web Intelligence (WI'03)© 2003 IEEE.

[14] John O'Donovan, Barry Smyth,"Trust in recommender systems", IUI'05 Proceedings of the 10th international conference on Intelligent user interfaces, pp. 167-174, 2005.

[15] Elizabeth Chang, Tharam S Dillon, Farook Khadeer Hussain,"Fuzzy and Dynamic Nature of Trust", Second International Conference, TrustBus 2005, Copenhagen, Denmark. August 22-26, 2005. Proceedings, pp. 161-174, 2005

[16] PallabDutta, A Kumaravel,"A Novel Approach to Trust Based Recommender Systems Leveraged by Context Attributes", International Journal of Engineering and Technology (IJET),Vol. 6, No. 3, 2014.

[17] Umberto Panniello, Michele Gorgoglione,"Context-Aware Recommender Systems: A Comparison of Three Approaches".

[18] Panniello, U., Tuzhilin, A.,"Experimental comparison of pre- vs. post-filtering approaches in context-aware recommender systems", In: Proceedings of the 3rd ACM conference on Recommender systems, pp. 265–268, 2009.

[19] Ante Odic, Marko Tkalcic, Jurij F, AndrejKosir,"Relevant Context ina Movie Recommender System: Users' Opinion vs. Statisticaldetection", CARS -2012.

[20] Rahul Gupta, ArpitJainJ, SatakshiRana, Sanjay Singh "Contextual Information based Recommender System using Singular Value Decomposition", ICACCI, pp. 2084-2089, 2013.

[21] Hyung Jun Ahn, Jong Woo Kim,"Feature Reduction for ProductRecommendation in Internet Shopping Malls", Proceedings of the fifthInternational Conference on Electronic Business, pp. 132-137, 2005.

[22] JØSANG, A., MARSH, S., AND POPE, S.,"Exploring different types oftrust propagation", Lecture Notes in Computer Science 3986, pp. 179–192, 2006.

[23] Guha, R.; Kumar, R.; Raghavan, P.; Tomkins, A., "Propagationof trust and distrust", In Proceedings of the 13th international conferenceon World Wide Web, pp. 403–412. ACM, 2004.

[24] Robin Burke,"Hybrid Recommender System: Survey and Experiments", California State University.

[25] ChavviRana,"New dimensions of temporal serendipity and temporal novelty in recommender system", Advances in Applied Science Research, 2013, 4(1), pp. 151-157.

[26] P. J. Brown, J. D. Bovey, X. Chen,"Context-awareapplications: From the laboratory to the marketplace", IEEE Personal Communication, Vol. 4, No. 5, Oct. 1997, pp. 58–64.

[27] A. Dey, G. Abowd,"Towards a better understandingof context and context-awareness", In CHI 2000 Workshopon The What, Who, Where, When, and How of Context-Awareness, 2000.

[28] Shixiong Xia et al.,"An Approach of Semantic Similarity Measure between Ontology Concepts Based on Multi Expression Programming", 2009 Sixth Web Information Systems and Application Conference.

[29] Sridevi. U.K et al."Ontology based Similarity Measure in Document Ranking", International Journal Of Computer Applications, Vol. 1, No. 26, 2010.

[30] MingxinGan et al.,"From Ontology to Semantic Similarity: Calculation of Ontology – Based Semantic Similarity", The Scientific World Journal, Volume 2013.

[31] A Kumaravel, PallabDutta,"Application of PCA for Context Selection For Collaborative Filtering", 2014, Middle-East Journal of Scientific Research 20 (1), pp. 88-93.

[32] ThabetSlimani,"Description and Evaluation ofSemantic similarity Measures Approaches".

[33] Y. H. Li, Z. Bandar, D. McLean,"An approach for measuring semantic similarity between words using multiple informationsources", IEEE Transactions on Knowledge and

Data Engineering, Vol. 15, No. 4, pp. 871-881, 2003.
[34] B. Y. Liang, J. Tang, J. Z. Li, et al,"Semantic Similarity Based Ontology", Cache. Heidelberg: Springer-Verlag, pp. 250-262, 2006.
[35] Tversky, A.,"Features of Similarity", Psycological Review, 84(4), pp. 327-352. 1977.

Pallab Dutta did his BTech in ECE from NIT Calicut (1997), ME from VMU, TN in Computer Science & Engineering (2007). Currently he is pursuing PhD from Bharath University. His research areas of interest includes Embedded systems, Cryptography, Multi agent system, Semantic Web, Recommender system etc. He has around two decades of experience in R&D.

Dr. A.Kumaravel received PG in Computer Science in Applied Sciences from the MIT Chennai , Ph.D in theoretical computer science from Anna university in 1988,1992 respectively. He was worked as a professor in CS for more than 20 years in Singapore. He has published many research papers, and he also presented numerous papers in national and international conferences. He has organized workshops, national and international conferences, seminars in various organizations. Now, he is working as Dean of Computing Studies. He had received senior fellowship in UGC.