In Depth Analysis of Semantic Similarity for Context Attributes in Recommender Systems

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Abstract—**Internet has perhaps been the most outstanding innovation and technological marvel in the field of ICT in last couple of decades; huge amount of information and content is available in almost all domains and is ever expanding gigantically across dimensions. On the other hand, as a disadvantageous after effect, this uncontrolled proliferation has resulted in data overloading problem. Recommender systems have been designed in-order to overcome the data overloading problem that exists today in World Wide Web, by aiding the users towards seamlessly narrowing down to the required information and discard the unwanted ones. Research output demonstrate that context aware recommender systems are useful and enhances the prediction accuracy when context parameters are induced appropriately, but if contexts are not properly assimilated, the objectives of context aware recommender system are not met, rather it gives rise to unwanted complications and reduces the quality of output. In this paper, we discuss and analyze the semantic similarity of context attributes of recommender system towards increasing the prediction accuracy and overcoming data sparseness. The context attributes, in many cases are meaningfully similar or semantically closer within a given knowledge domain; in such situations, these semantically closer attributes can be consciously be considered and exploited for further processing and thereby enhancing the veracity of Recommender system. A hybrid method consisting of both structure based approach and weighted feature based approach is proposed and analyzed here for determining the semantic similarity and its effect on the quality of Recommender system is also analysed.**

Keyword - Recommender system, Semantic similarity, Context aware Recommender System, data mining, Ontologies.

I. INTRODUCTION

In our day to day life, we as human beings make enormous number of choices, consciously or sub-consciously, in order to fulfil our normal living requirements.While unfolding the landscaping of life in general, it is often necessary and becomes evident to make choices about some items (e.g.; book, movie, place, restaurants etc.) without sufficient personal experience on a particular item or subject matter. In such situations, we rely on inputs or recommendations from other player in our social eco system (family, friends, and neighbours) either by word of mouth, recommendation letters, reviews and opinion printed in newspapers and so on. When the amount of data is vast and the real world social contacts and the eco-system is not very strong, Recommender systems aids, augment and complement 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. Today World Wide Web contains virtually infinite number of Web sites for consumers to choose from. Recommender systems are designed and developed in-order to solve the problem of information overloading and are gaining a lot of prominence in recent times. This would ease out the effort required on part of the user to extract the useful information, aid in interpretation and converge towards an informed conclusion. RSs are useful when individuals 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 provide recommendation about items to the users. There are many types of Recommender Systems and have evolved over a period of time and still evolving. Traditionally 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 requires rich content description of items. Here items may be products or services. Collaborative filtering,on the other hand, evolved and inspired from a real life scenario that people typically rely on the friends who have similar taste or preferences. It is built on the premise 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. None of these approaches are perfect and there are issues associated with both these types of RSs in terms of prediction accuracy, coverage, data sparsity, cold start problem etc. There are different approaches to overcome these issues by using trust network based approach, hybrid methods, Context aware RS. Recommender system has been a research hotspot in the recent years.

Generic Concept of Context aware RS

Context Aware RS has been in research interest in both academia and industry for sometimes now; it is evolving towards a practical solution with more and more enhancements and improvisations. We will try to decipher and understand the term ‘context’ first; then the concept of context aware RS is explored. As discussed in [4]byAdomaviciusandTuzhilin, ‘context’ has many definitions and is a multidimensional concept and a complex abstraction. This abstraction has been studied and analyzed across many diverse research domains including Computer Science, Cognitive Science, linguistic, philosophy, psychology and organizational context. Since context has been studied in multiple disciplines, each of them views the context in their own premise and perceptionresulting in distinctive semantics. In the premise of RS, we try to interpret the term ‘context’.Context aware recommender system takes into consideration contextual information, such as time, place and company of other people (such as watching a movie with friend or family etc) along with user and item. 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 application themselves. [27]”. In a 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 touristRS, the contexts are typically: mood, season, companion, weather, cost. Traditional recommender systems usually compute the similarity using two-dimensional user-item matrix and do not take into consideration contextual information while generating the recommendation. The contextualinformation is time, location, companions, weather, and so on. When context information is appropriately captured and factored in RS, it enhances the prediction accuracy. Adomavicius and Tuzhilin proposed a multidimensional approach to incorporate contextual information into the design of recommender systems. As described in [39], there are different types of contexts namely Physical context, social context, interaction media context, modal context. These context types when characterized and infused in RS, it yields better accuracy.

Terminologies introduced for context information processing in RS

In Context Aware Recommender systems, contexts need to be processed and induced along with user and item information. In our research work, we used two terminologies and are listed in [37]; these are: ‘Context parameters’ and ‘Context attributes’. Here we define and describe these terms. 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’.The context attributes may be sometimes similar in semantic sense and do not required to be processed differently. 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 use a hybrid method consisting of both structure based approach and weighted feature based approach.In a context aware recommender system, we analyze the effect of these semantic similarity calculations for context attributes.

Rest of the paper is organized as follows: Section II of this paper gives the related work done in the area of semantic similarity and RS. Problem domain is listed in Section III, the concept of ontology in our application context is described in section IV. Our approach towards semantic similarity calculation for context attributes is given in section V along with experiment and results in section VI. Section VII gives conclusion.

II. RELATED WORK

In this section, we review some of the works related to Context aware Recommender System (RS) and context information processing. Also different approaches of semantic similarity analysis are reviewed. 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. Adomavicius and Alexander Tuzhilin in [4]. Their work details about modeling contextual information in RS. They also describe contextual pre-filtering, post-filtering and Contextual modelling. In [4], they mention about possibility of combining post-filter, pre-filtering and contextual modelling 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 a real life scenario, it is rarely the same context repeats but instead the similar context reoccurs. The disadvantage of that method is the increase of data sparsity. Umberto and Michele have analysed post filtering, pre filtering and contextual modelling 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. Rahul Gupta et al. in [20] points out the naïve Bayes classifiers and SVD for context aware recommender system. As per [39] Context gives rise to a behaviour that is observable, though context itself may not be observable (it's "intentional") Context exists (usually implicitly) in relation to the ongoing interaction of the user with the system; it is not static, can be derived. Feature reduction for product recommendation is given in [21]. Matthias, Gernot Bauer [5] 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 [28, 29, 30], ontology based semantic similarity concepts are given. In [28], to improve accuracy of semantic similarity measure between ontology concepts, four main factors namely semantic distance, semantic depth, semantic coincidence and semantic density that impact on semantic 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]. In [34], the determination of semantic similarity by a number of information sources is explored, which consist of structural semantic information from a lexical taxonomy and information content from a corpus. A comparison of four main types of models: the geometric model, the feature model, the network model, and the transformational model are done in [38].To the best of our knowledge, we did not find any literature detailing on semantic analysis of context attributes for a recommender system. In our previous work [37], we have introduced the concept of semantic similarity of context attributes in RS, here we do further analysis and enhances the semantic similarity model within a given knowledge domain.

III. Problem Domain

Although Recommender System has been evolving over a period of time, still it has few impediments towards practical usage. Accuracy is one of the main such impediments along with coverage. There are reasons such as data sparcity problem, due to which it is often difficult to achieve high recommender accuracy in spite of having sophisticated prediction algorithm. Data sparsity in generic terms means lack of sufficient data points. In the domain of RS, it refers to the difficulty in finding sufficient reliable similar users, since in general the active users only 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 and item data. Data sparsity is a major issue is context aware RS. High sparsity is caused due to various real world reasons, many a times driven by socio cultural factors. Behavioural characteristics of users and their preferences and also fine grained context attributes lead to very less useable data points for recommendation calculations. Some users do not want to share their personal information such as location, thus causing missing contextual information. Poor context information leads to low accuracy in prediction; also many a times, the prediction cannot be generated and thus coverage also suffers. It has been observed that in some cases, 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 generating data points for context-aware recommendation to work properly. 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. If the context attributes are not granular enough, this also negatively impact the prediction accuracy. Hence, the engineering challenge lies in appropriately differentiating the context attributes and also meaningfully combining them with the aim of enhancing the prediction accuracy of a context aware RS.

IV. Semantic Similarity

Semantic similarity is a metric over a set of documents or terms, based on the likeliness of their meaning as opposed to similarity which can be estimated regarding their syntactical representation. This refers to similarity between two concepts in a taxonomy or ontology and it is achieved through ontology or taxonomies to define a distance between words or using statistical means.Semantic Similarity relates to computing the similarity between conceptually similar but not necessarily lexically similar terms. Typically, semantic similarity is computed by mapping terms to an ontology and by examining their relationships in that ontology. Similarity among concepts is a quantitative measure of information, computed based on the properties of the concepts and their relationships. Semantic similarity between concepts is a measure ofmeaningful connotational similarity (or commonality) between two concepts according to a given ontology. An ontology is a formal, explicit specification of a shared conceptualization. 'Formal' refers to the fact that theontology should be machine readable, while 'Shared' reflectsthe notion that an ontology captures consensual knowledge.The characteristics mentioned above make an ontology be areliable structured knowledge base. With the rapiddevelopment of the Semantic Web, a large number ofuniversal ontologies and domain ontologies are generatedand widely applied to knowledge-based systems, particularly,the measure of concept similarity.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. Psychological experimentsdemonstrate that similarity is context-dependent andmay be asymmetric also[36], [41]. Similarity between words isinfluenced by the context in which the words are presented.Similarity may also be asymmetric with respect todirection. People may give different ratings when asked tojudge the similarity of surgeon to butcher and the similarity ofbutcher to surgeon. Although similarity may be asymmetric,the “asymmetries are only observed under quite circumscribedconditions” [42]. Experimental results investigatingthe effects of asymmetry suggest that the average differencein ratings for a word pair is less than 5 percent [41]. It is a safe assumption that such a small difference will have little impacton the overall performance of computational methods, sowe do not consider the effects of asymmetry. This is in linewith many application areas of computational linguisticsand artificial intelligence.

As in Fig.1 similarity determination between concepts belonging to single ontology have different approaches such as:

- Structure based measure
- Information content based measure
- Hybrid measure
- Feature based measure.

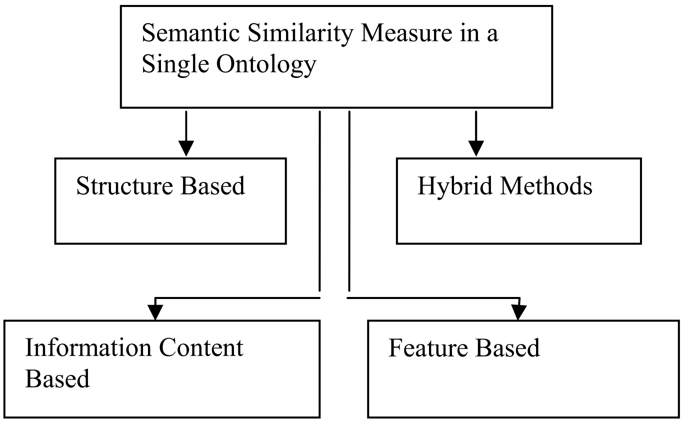

Figure 1: Methods of Semantic Similarity measure in a single Ontology

Depending on the application and use case scenarios, different methods are adopted and used.

Structure Based Semantic Similarity Measure:

There are many approachestomeasure semantic similarity using structure based methodologies.

Structure based semantic similarity methods are:

- Shortest Path
- Wu & Palmar method
- Leacock &Chodorow
- Lesk method etc.

In [37], we analyzed and adopted the approach as given in [29] based on semantic distance, semantic depth and semantic coincidence. As shown in [29, 37], 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 Figure 2, the semantic distance between snowy and stormy is 2, denoted as: *l*(snowy, stormy)=2.The relation between semantic similarity andsemantic distance *l*is given by the function (1):

$f_1(l) = e^{-\alpha l}$…………………………………..(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].

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 2, the semantic depth of rainy is 4, denoted as: h(rainy)=4.Relation function between semantic similarity andsemantic depth h:

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

Where β is a constant coefficient (β >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 β is equal to 0.15, α is equal to 0.25, the semantic similarity got thehighest accuracy.

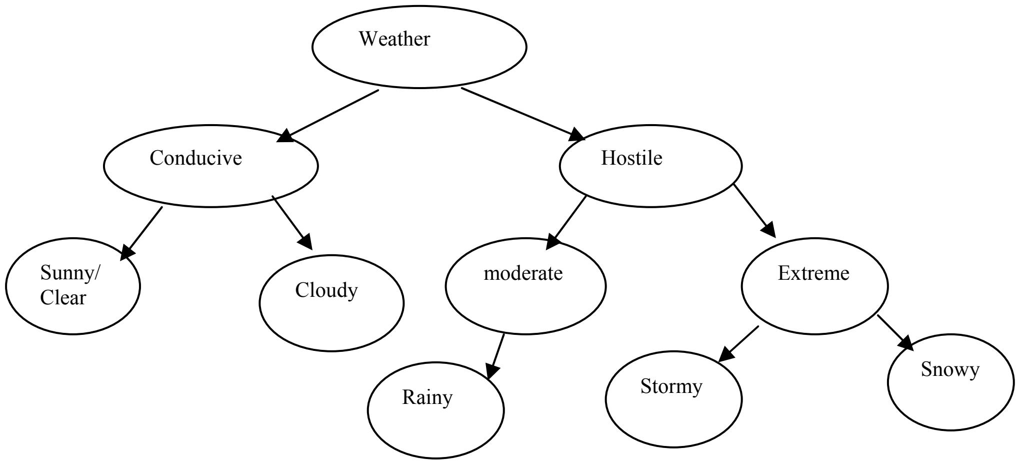

Figure 2: Hierarchical Structure for Context attribute of movie RS.

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 twoconcepts 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:

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

Semantic coincidence between rainy and cloudy is ¼. 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)

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

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

Information content based Measure:

Structure based measure use the knowledge solely captured by ontology to computationally determine the similarity between concepts. In Information content-based similarity measures, each of the measures attempts to exploit the information contained at best to evaluate the similarity between the pairs of concepts. Therefore how to obtain IC is crucial, which will affect the performance directly. One method is to obtain IC through statistical analysis of corpora, from where probabilities of concepts occurring are inferred. The various information content based measures are:

- Resnik Measure
- Lin Measure
- Jiang and Conrath measure

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. Feature-based measure is independent on the taxonomy and the subsumers of the concepts, and attempts to exploit the properties of the ontology to obtain the similarity values. Feature based measure assumes that each term is described by a set of terms indicating its properties or features. 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.

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

Where C1 and C2 are the corresponding description sets of two concepts.α 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 α is based on the that similarity is not necessarily a symmetric relation.

V. OUR APPROACH TO SEMANTIC SIMILARITY CALCULATION

Different semantic similarity measures have different characteristic. Most structure based measures are simple. But the accuracy is not high in all cases. IC based measures are effective. However they can't reflect structure information of concepts, such as the distance. Corpora dependency seriously limits the applicability of classic IC measures. Feature based measure can't work well when there is not a complete feature set. Hybrid method combines multiple approaches. But one or more parameters are needed and turning is required. In fact there are no absolute good performance measures. Different measures will show different performance in different applications. In specific application, whether a measure will hold all other aspects of the system well is indeed a matter of research investigation. In this paper, a hybrid method is proposed. 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). It is evident that not all features of a term will have same weightages, that is some features will have more weightage compare to other features. In the feature based similarity, we introduce this individual weightage factor.

Let there be n features of a term with weightages W_1, W_2, W_3,….W_n such that $W_1+W_2+ W_3+\ldots+W_n = 1$.

In equation (7):

$C1 \cap C2$ = Common features between the terms/concepts

C1 - C2 = Features available in C1 but not in C2

C2-C1 = Features available in C2 but not in C1

By considering the weightages of the features, the Tversky measure of semantic similarity can be modified as below:

$$Sim_F(C1,C2) = \frac{W_C\,|C1 \cap C2|}{W_C\,|C1 \cap C2| + W_{C1,2}(C1 - C2) + W_{C2,1}(C2 - C1)}$$

……………………………(8)

Where,

W_c = Sum of the weightages of the common features.

$W_{c1,2}$ = Sum of the weightages of the features available in C1 but not in C2

$W_{c2,1}$ = Sum of the weightages of the features available in C2 but not in C1

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 S_{TH}, 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.

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

…………………………..(9)

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) = Weighted Feature based semantic similarity as given by equation (8)
$\rho,\sigma \in [0,1]$ 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].
Start:
Calculate Semantic Distance and f_1(l)
Calculate Semantic Depth andf_2(h)
Calculate Semantic Coincidence and f_3(c)
Calculate Structure based semantic similarity Sim_T(C1,C2) based on f_1(l), f_2(h), f_3(c).
Find common and non-common terms
Calculate Feature based semantic similarity Sim_F(C1,C2)
as per equation (8)
Calculate resulting semantic Similarity
Sim(C1,C2) = ρ*Sim_T(C1, C2) + σ*Sim_F(C1,C2)
If (Sim≥S_T)Then
Data Point considered for prediction calculating in RS
End if
End.
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 …………..(10)
For Sim_F(Rainy, Stormy) calculation,

TABLE 1

Attribute	Feature	Weightage
Rainy	Requires Rain Coat	0.2
	Requires Umbrella	0.2
	Low Temperature	0.25
	Wet Roads	0.35
Stormy	Requires Rain Coat	0.1
	Requires Umbrella	0.2
	Windy	0.2
	Hostile	0.25
	Destructive	0.25

Using equation (8) with weightages as given in table 1,

Sim_F(Rainy, Stormy) = 0.298. ……………… (11)

Using (9), (10), (11) with$\rho = \sigma = 0.5$, we get, Sim(Rainy,Stormy) = 0.244

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.

For every context parameter, we fix the similarity threshold value. If the calculated similarity value is more than the set threshold, the data points are considered to be same and taken for further processing. Similarity threshold setting is context parameter and RS specific. For a given context parameter, the threshold value may be different for different RS. E.g.; context parameter 'weather' will have different similarity threshold in a movie RS and in a Book RS. The threshold value plays a very crucial role in the accuracy of prediction of RS and this value requires to be set very judiciously. For a given RS, the optimum threshold value is different for different context parameters. The optimum threshold value is directly proportional to the weightage (importance) of the context parameter. That is, if a context parameter is less important/relevant compared to a more relevant context parameter, the optimum threshold value for this context parameter will also be less.This helps in determining the optimum similarity threshold values for context parameters.

Optimum similarity threshold value is different for different context parameters and depends on relative relevance weightage of the context parameter and the number of context attributes for the given context parameter.

S_{TO}= f (RW_{RP}, N_P) …………………….(12)

Where,

S_{TO}= Optimum Similarity Threshold.

RW_{RP}= Relative relevance weightage of the context parameter.

N_P= Number of context attributes for the given context parameter.

By experimenting with the dataset, we determine the function f().

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 in our experiment, we have used wordnet taxonomy to verify semantic similarity method.

WordNetis a lexical database for the English language. Nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets.Synsets, provides short, general definitions, and records the various semantic relations between these synonym sets. The specific meaning of one word under one type of POS (Part Of Speech) is called a sense. Each synset has a gloss that defines the concept it represents. For example, the words night, nighttime, and dark constitute a single synset that has the following gloss: the time after sunset and before sunrise while it is dark outside. The database can also be browsed online. Wordnet was created and is being maintained at the Cognitive Science Laboratory of Princeton University under the direction of psychology professor George A Miller. Development began in 1985. WordNet's latest version is 3.1. Each concept is described by a set of words indicating its properties or features , such as their definitions or “glosses” in WordNet. Generally there are different methods to evaluate a similarity measure approach. One is a theoretical examination of a computational measure for those mathematical properties thought desirable, such as whether it is a metric whether its parameter-projections are smooth functions, and so on. The second one is compare the measure by calculating the coefficients of correlation with human judgments. Although it is difficult to obtain a large set of reliable, subject independent judgments, it is a popular method. The similarity values of human judgments are deemed to be correct, which gives the best assessment of the performance of a measure. We evaluated the proposed method against Miller Charles (1998) dataset, a dataset of 30 word-pairs rated by a group of 38 human subjects. Wordpairs are rated on a scale from 0 (no similarity) to 4 (perfect synonymy). Miller-Charles' dataset is a subset of Rubenstein-Goodenough's (1965) original dataset of 65 word-pairs. Although Miller Charles' experiment was carried out 25 years later than Rubenstein-Goodenough's, two sets of ratings are highly correlated (Pearson correlation coefficient=0.97). Therefore, Miller-Charles ratings can be considered as a reliable benchmark for evaluating semantic similarity measures. In the proposed model, the similarity values are with in [0,1].

TABLE 2

Word pair	M&C ratings	Proposed model
Cord – Smile	0.13	0.023
Rooster-voyage	0.08	0.025
Noon - string	0.08	0.013
Glass-magician	0.11	0.145
Monk-slave	0.55	0.288
Coast-forest	0.42	0.342
Monk-oracle	1.1	0.443
Lad-wizard	0.42	0.367
Forest-graveyard	0.84	0.567
Food - rooster	0.89	0.345
Coast - hill	0.87	0.487
Car - journey	1.16	0.538
Crane - implement	1.68	0.857
Brother - lad	1.66	0.635
Bird - crane	2.97	0.822

Bird - cock	3.05	0.855
Food-fruit	3.08	0.907
Brother-monk	2.82	0.875
Asylum-madhouse	3.61	0.723
Furnace-stove	3.11	0.893
Magician-wizard	3.5	0.719
Journey-voyage	3.84	0.839
Coast-shore	3.7	0.671
Implement-tool	2.95	0.856
Boy-lad	3.76	0.827
Automobile-car	3.92	0.793
Midday-noon	3.42	0.714
Gem-jewel	3.84	0.906

We use Pearson Correlation Coefficient Calculator to determine the correlation between the M&C ratings and our proposed approach. This test is used to measure the strength of a linear association between two variables, where the value $r = 1$ means a perfect positive correlation and the value $r = -1$ means a perfect negative correlation. The value of R as calculated is 0.8737. This is a strong positive correlation, which means that high X variable scores go with high Y variable scores (and vice versa). The value of R^2, the coefficient of determination, is 0.7634. That is, our proposed model has strong correlation with already established human ratings given by Miller-Charles.

Relevant context parameters in LDOS-CoMoDa dataset as per our analysis (as carried out during our previous work in [32]) are:Social, Mood, Weather and Location. The weightages / importance factors of these relevant context parameters are [32]: W1(Social) = 0.2233, W2(Mood) = 0.2154, W3(Weather) = 0.1981, W4(Location) = 0.1944

There are different context attributes for these context parameters as given in Table 3. 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, relevant context parameters and context attributes are as follows:

TABLE 3

Sl. no	Context Parameters	Context attributes
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
9	mood	Positive, Neutral, Negative

TABLE 4

Sl. no	Feature	Weightage
Home	Flexibility of time	0.4
	No additional cost	0.2
	Normal multimedia system	0.4
Public Place	No flexibility of time	0.4
	Extra expenditure	0.3
	Superior multimedia setup	0.3
Friend’s House	Requires travel	0.3
	No additional cost	0.3
	Normal multimedia system	0.4

Sunny/clear	Generally not cold	0.2
	Do not Require Umbrella/rain coat	0.2
	Clear roads	0.3
	Not hostile	0.3
Rainy	Requires Rain Coat	0.2
	Requires Umbrella	0.2
	Low Temperature	0.25
	Wet Roads	0.35
Stormy	Requires Rain Coat	0.1
	Requires Umbrella	0.2
	Windy	0.2
	Hostile	0.25
	Destructive	0.25
Snowy	Requires Rain Coat	0.2
	Hostile	0.3
	Low Temperature	0.2
	Roads blockade	0.3
Cloudy	Low temperature	0.1
	Potentially hostile	0.4
	Requires Umbrella	0.5
Alone	Own Choice	0.3
	Travel alone	0.4
	expense	0.3
My Partner	Own/Shared Choice	0.3
	Travel companion	0.4
	High expense	0.3
Friends	Shared choice	0.3
	Travel companion	0.3
	Expense	0.2
	Fixed time	0.2
Colleagues	Limited choice	0.3
	Travel companion	0.3
	Fixed expense	0.2
	Fixed time	0.2
Parent	Shared choice	0.3
	Travel companion	0.2
	Expense	0.25
	Flexible time	0.25
Public	No choice	0.4
	Travel companion	0.2
	Expense	0.1
	Fixed time	0.2
	No privacy	0.1
My Family	Shared choice	0.3
	Travel companion	0.2
	Expense	0.25
	Flexible time	0.25
Positive	Any type movie	0.1

	Any companion	0.2
	Varied Travel choice	0.2
Neutral	Some type movie	0.2
	Limited companion	0.2
	Some travel	0.25
	Fixed expense	0.35
Negative	limited type movie	0.4
	Limited companion	0.3
	Some travel	0.1
	Fixed expense	0.2

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.

$$MAE = \frac{\sum_{i=1}^{N} |p_i - r_i|}{N} \quad \text{.....................................(13)}$$

Where,

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

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 $= \sigma = 0.5$. We divide the total dataset into training set and Test set. For our experiment, we consider the following splits: 50% Training data and 50% Test data.

Prediction accuracy alone does not fully represent the effectiveness of the recommender system. It is also required to calculate the coverage factor for meaningful evaluation of the RS. Coverage is the measure of the percentage of items for which a recommender system can provide predictions. There are several ways to calculate coverage, for this research we compute coverage as number of items for which the recommender system can generate predictions, over the total number of item predictions that are requested. In Eq. (14), $P_i$represents the prediction that the recommender system generated on item i, and Srepresents the set of items for which recommender system is generating a prediction.

$$\text{Coverage} = \frac{|P_i \mid i \in S|}{|S|} \quad \text{.........................(14)}$$

Table 5, shows the effect on coverage value of the Recommender System with the inclusion of context attribute similarity of the relevant context parameters.

Similarity Threshold settings is one of the very important engineering decision in order to achieve high prediction accuracy. The Figure 4 shows the relation between similarity threshold settings (for context parameters) and the prediction accuracy for a given coverage value.

We use the weightage values of the relevant context parameters and considering the spread of their weighatges, we find their relative weightages as:

$$RW_{RP} = \frac{W_{RP} - W_{RMIN}}{W_{RMAX} - W_{RMIN}} + 1 \quad \text{..............................(15)}$$

W1(Social) = 0.2233 = 101

W2(Mood) = 0.2154 = 39

W3(Weather) = 0.1981 = 14

W4(Location) = 0.1944 = 1

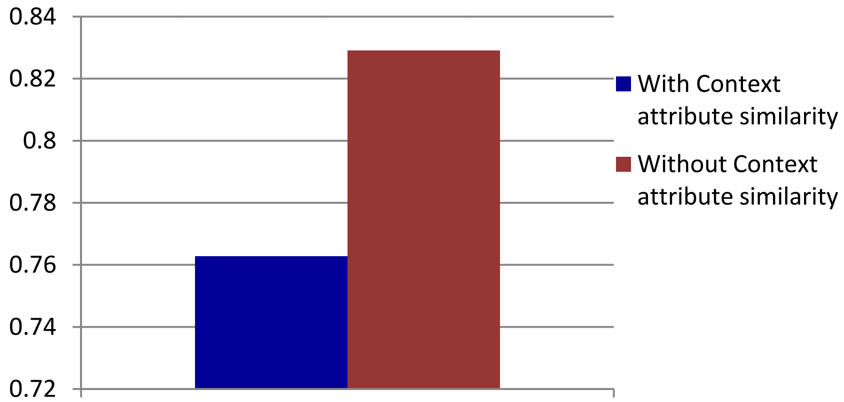

Figure 3: Mean Absolute error

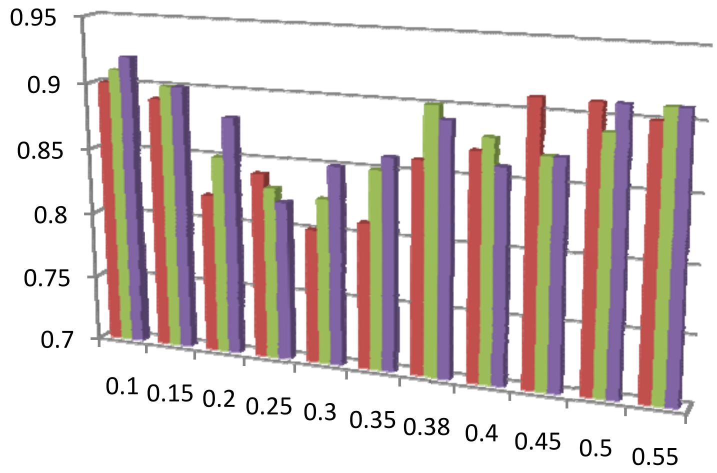

Figure 4: MAE Vs Similarity Threshold Value

The number of context attributes for these relevant context parameters are: 7, 3, 5, 3 respectively.

TABLE 5

Condition	**% Coverage**
Without Context attribute Similarity	61%
With Context attribute Similarity for context parameter-Location	72%
With Context attribute Similarity for context parameter-weather	71%
With Context attribute Similarity for context parameter-Social	76%
With Context attribute Similarity for context parameter-Mood	68%
With Context attribute Similarity for all 4 context parameters.	79%

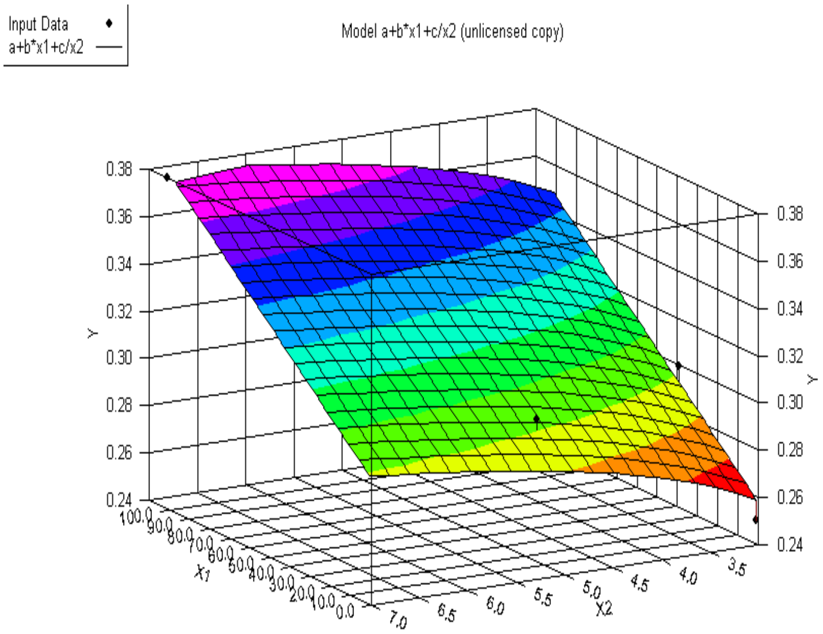

Figure 5: Optimum Similarity Threshold Vs Relative Context parameter weightage and No. of Context attributes.

From the experiments with the dataset, function 13 can be empirically derived as:

$S_{TO}= 0.32 + 8.9RW_{RP}-0.18 / N_P$

Figure 5 shows Optimum Similarity Threshold Vs Relative Context parameter weightage and No. of Context attributes.

VII. Conclusion

In this paper, various approaches of semantic similarity calculations are discussed and an approach for semantic similarity calculation is proposed for context attributes of Recommender system. The proposed approach is a hybrid method based on both hierarchical structure and also on Weightedfeature method. The proposed 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) and are close to human perceptional similarity values as given by Miller-Charles experiment. In future, we plan to optimize the values $\boldsymbol{\rho}$ and $\boldsymbol{\sigma}$, the relative weighing factors ofstructure based similarity values and feature based similarity values respectively in the proposed semantic similarity determination method so that the overall maximum accuracy of RS can be obtained for given knowledge structure.

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