Beyond one shot recommendations: The seamless interplay of environmental parameters and Quality of recommendations for the best fit list

Minakshi Gujral[1], Satish Chandra[2]
[1] **Department of Computer Science and Engineering, Jaypee Institute of Information Technology, Noida, UP-201307, INDIA.**
minakshigujral2011@gmail.com

[2] **Department of Computer Science and Engineering, Jaypee Institute of Information Technology, Noida, UP-201307, INDIA.**
satish.chandra@jiit.ac.in

Abstract

The Knowledge discovery tools and techniques are used in an increasing number of scientific and commercial areas for the analysis and knowledge processing of voluminous Information. Recommendation systems are also one of Knowledge Discovery from databases techniques, which discovers best fit information for appropriate context. This new rage in Information technology is seen in area of E-commerce, E-Learning, and Bioinformatics, Media and Entertainment, electronics and telecommunications and other application domains as well. Academics, Research and Industry are contributing into best-fit recommendation process enrichment, thereby making it better and improvised with growing years. Also one can explore in depth for qualitative and quantitative analysis of E-World Demand and Supply chain with help of recommendation systems. Lot has been talked about effective, accurate and well balanced recommendations but many shortcomings of the proposed solutions have come into picture. This Paper tries to elucidate and model Best Fit Recommendation issues from multidimensional, multi-criteria and real world's perspectives. This Framework is Quality Assurance process for recommendation systems, enhancing the recommendation quality. The proposed solution is looking at various dimensions of the architecture, the domain, and the issues with respect to environmental parameters. Our goal is to evaluate Recommendation Systems and unveil their issues in quest for the Best Fit Decisions for any application domain and context.

Keywords: *Recommendation Systems, Best fit decisions, Issues in Recommendations, Expert recommendations, best fit decisions.*

1. Introduction

The Recommendation systems are the new search paradigm which has stormed the E-world with semantic preferences and excellent information services. Some of the renowned recommendation systems are Amazon, last.fm, Netflix, Cinematch, yahoo and Google. Recommendation Systems lays strong foundation for the commercially rich and ever expanding Recommendation culture with ever growing online commerce. Not only it proves solution for Information Overload problems but also provides users with novel and preferred products, concepts and services relevant to their preferences. The Social aspect of Recommendations shapes the cultural flow. As our culture moves online, the creativity, evolution and augmentation of connection centric recommendation process grows four folds. Rightly said by Fortune magazine writer Jeffrey M. O'Brien, in an article published in CNN Money, entitled "The race to create 'smart' Google","The Web, they say, is leaving the era of search and entering one of discovery. What's the difference? Search is what you do when you're looking for something. Discovery is when something wonderful that you didn't know existed, or didn't know how to ask for, finds you". The quest for best fit decisions is about moving ahead of search engines in the world of recommendation.

This proposed solution analyzes some selected but generic recommendation systems of varied application environments, and their recommendation methods, performance, user and item profile, rating structures, similarity measure, and other issues. This gives a Multi dimensional evaluation framework to model optimized system for the best fit recommendations. This kind of approach has cropped from recommendation system's evaluation and research for optimized recommendations. It started from way back mid 1990 to this current era but no concrete, balanced and feasible solution from multidimensional perspective has been given till date. This analysis can be extended with no of issues, systems and their changing context. There are viable paths of improvements and extensions, which can be implemented, mixed and matched for feasible, environmentally tailor made best fit recommendations.

The recommendation Quality has multilingual aspects to it while diving deep in research, innovation and novel ideas for recommendations. It is the search for best fit solution for any application, technology, for varying demography of users. The need is to explore Multi dimensional issues for Multi criteria parameters to produce best fit optimized recommendations. This paper tried to ponder on best fit recommendation issues in section 2, evaluates it in section 3 and gives a knowledge prototype approach in section 4.

2. Exploring Multi Dimensional Issues in Recommendation Systems [1-4]:

2.1 Evaluating Recommendation system's algorithm:

The evaluation of various recommender systems' algorithm is done for jargoning and validating the issues. Thereby the focus is on two kinds of evaluations:
1) The first one concerns the performance accuracy with respect to changing context and knowledge levels.
2) The second concerns user satisfaction, retaining the interest of users and formulating the requirement model of the problem task.

Several approaches are compared by the tool used in experiments on two real movies rating datasets i.e. Movie Lens and Netflix. The collaborative and content filtering algorithms, used in recommender system, are complementary approaches. Thus this motivates the design and implementation of hybrid systems. And thus this new hybrid system is tested with real users.

Following deductions give some focal points to this approach:
1) Similarity Measure cannot be implemented for all users of varying preferences.
2) An unresolved issue is to explore criteria that try to capture quality and usefulness of recommendations from the user satisfaction perspectives like coverage, algorithmic complexity, scalability, novelty, confidence and trust. This all is important along with user-friendly interaction.
3) The need to design an efficient, user friendly user interface which keeps the user from quitting and extracting important information for making requirement model of the problem task.
4) Traditional Recommendation Methods i.e. content, collaborative and hybrid [depending on rating system], with their advantages and shortcomings contribute towards Possible extensions. This capacitates them for large scale application domains like recommending vacations, financial services. The flipside is although these Extensions are introduced but till date neither implemented nor explained concretely and explicitly in recommendation system's research. Also the changing context and knowledge level influences the recommendation results.

2.2 Issues hindering best fit Recommendations:

The study of various recommendation issues in this scenario gives a new dimension through some formulations. Firstly the various unresolved extensions introduced:
a) Comprehensive Understanding of Users and Items
b) Model Based recommending techniques
c) Multidimensionality of Recommendations
d) Multi-criteria Rating
e) Non-intrusiveness
f) Flexibility
g) Trustworthiness
h) Scalability
i) Limited Content Analysis
j) Over specialization
k) New Item/User Problem
l) Sparsity

Various extensions in recommendation capabilities are rightly focused but not justified because:
1) Problems and Extensions are introduced theoretically but not yet solved from multi dimensional real world scenario. The thematic profiles of Users and Product Attributes are evaluated and updated theoretically with synthetic data sets but real life transactions give the clear picture. These formulations need further validation with effective feedback of real world data.
2) Introduction of Contextual, critiquing and Conversational Recommendations should be incorporated.
3) These extensions should be balanced with increase in information, user, network and addition of complex cross application networks.

2.3 Background study of some recommendation systems:

1) An innovative approach for developing reading material recommendation systems is by eliciting domain knowledge from multiple experts. To evaluate the effectiveness of the approach, an article recommendation expert system was developed and applied to an online English course.
But the flipside measured in this case: Learning preferences or needs are not the same. Online e-learning

module provides fixed learning content for all students with varying aptitude and knowledge level.

2) Technique using the repertory grid method assists the domain experts to better organize their knowledge and experiences. This is significant approach but with ever changing and evolving nature of user and item model there arises doubts on this approach being successful. It's difficult to calculate recommendation best for different learning levels. Other factors like Authenticity of data filled, coverage of application domain with increase in courses and students, absence of Justification of choice by users also contribute to this discussion and points towards Multi dimensional issues.

3) Another novel research problem which focuses on the personalization issue is the problem of recommendation under the circumstance of a blog system. It is a comprehensive investigation on recommendation for potential bloggers who have not provided personalized information in blog system. This talks about registered and unregistered bloggers (personalized/non personalized) given recommendations for services in blog environment.

4) Another Recommendation Method presents an algorithm on the inhomogeneous graph to calculate the important value of an object, and then combined with similarity value to do recommendation.

This is a random work in inhomogeneous graph thereby this cannot be generalized with increasing users and resources. The following points come in front:

a) There is no information about what happens to recommendations with new users and resources.

b) There is no clear picture about how one can calculate best recommendations for a particular item type which does not match neighbor nodes?

c) The issues like scalability and trustworthiness of the system are at stake. Normally any blogger can register and can create imperfect/illegal data or change information which is again one contradictory point.

d) Furthermore the methodology is too voluminous, complex to implement for large application domains.

5) Some recommendation algorithm tried to incorporate "thinking of out of the box recommendations" [5]. This Concept introduces TANGENT, a novel recommendation algorithm, which makes reasonable, yet surprising, horizon-broadening recommendations. The main idea behind TANGENT is to envision the problem as node selection on a graph, giving high scores to nodes that are well connected to the older choices, and at the same time well connected to unrelated choices.

Extensive comparison of the numerous alternatives; while all seem reasonable on paper, several of them suffers from subtle issues. Computational cost being one of them. Also at some undesired situation, if neighbor's nodes are at complex positions, complexity, overhead and computational cost increases. Practical problems arise in this case i.e.

-New user new item problem
-Cold Start Problem
-Coverage Issues
-Computational Cost

6) Some recommendation research also tried to explore Singular Value Decomposition (SVD) to reduce the dimensionality of recommender system databases to increase performance of recommendations [6]

a) SVD can be very expensive and is suitable for offline transactions. Its complex architecture, differentiating results for different setups also hinders good recommendation approach. This does not take into account the Top N Predictions in a cot effective way to enhance quality of recommendations. Here Recommendation Evaluation speaks of more issues to ponder. For example Best Fit Recommendations in changing E-WORLD, security issues, measuring user satisfaction, efficiency, and persuasiveness of recommendation process, scalability, coverage, and these points are not fulfilled in such evaluations.

b) The Concept of [Rating, Prediction Elicitation, and Similarity Measure] is vague and difficult in practical scenario. They are taken from synthetic Datasets. Real world transactions say reservation system, registration is far better than synthetic datasets; this approach fails to implement it. The thematic profiles of Users and Product Attributes are implemented theoretically but not from real life transactions. These calculations further needs to be checked with effective feedback of real world data.

c) Overhead of Computation of Similarity Measures is also there. Out of Box thinking is needed to measure Similarity not only in the thematic profiles of Users and Product Attributes theoretically but also from real life transactions. These calculations further needs to be checked with effective feedback of real world data.

3. Evaluating multidimensional issues of recommendation process:

3.1. The Cold Start Problem

The cold start problem occurring when a new user has not provided any ratings yet or a new item has not yet received any rating from the users. The system lacks data to produce appropriate recommendations. [1][2].To remove over specialization problem when there is use of diversification in explanations [11] this gives chance to new items in the group which is good testament to solution of cold start problem. CBR plus Ontology [12] concepts reasons out the current and old status of items as per logic based calculations rather than ratings. This increases the system complexity and even if it gives cold start solution to 15% it increases scalability sparsity and other issues. This 15% also is viable when information is well fed by past cases. Knowledge based Models[6] hits hard on usage of rating structure by Implicit recommendation methods[1,2] and proposes evaluating explicit user/item models to take care of cold start problem. The excellent analysis done by knowledge Model framework[16] which says that as new products of various categories arrive in market, this can further ignite cold start, over specialization and sparsity problem. Even clubbing Intelligent Agents and mining Semantic web [18] leads to cold start problem and with increase in scalability the system suffers. The Cold start problem is apparent in systems depicted by Table 1.

3.2. Coverage

While preferences can be used to improve recommendations, they suffer from certain drawbacks, the most important of these being their limited coverage. The coverage of a preference is directly related to the coverage of the attribute(s) to which it is applied. An attribute has a high coverage when it appears in many items and a low coverage when it appears in few items [1] [2]. Table 1 depicts the coverage problems.

3.3. Overspecialization

Content-based approaches can also suffer from overspecialization. That is, they often recommend items with similar content to that of the items already considered, which can lead to a lack of originality. [5][6]. Moreover Table 1 depicts the Overspecialization problems in some systems. As per Conversational strategy also which is best of above mentioned lot, all the preferences to be specified upfront, at the beginning of the interaction. This is a stringent requirement, because users might not have a clear idea of their preferences at that point. New Preferences and servicing needs to be feed in, system itself cannot predict or recommend and again presents with old strategies and products [14]. Overspecialization is said to be solved effectively by attribute based diversity and explanation based diversity[11], of which explanation based diversity strategy reigns supreme as it takes care of computational cost, provides coverage for even social domain, and is better in efficiency and performance. But needlessly explanation is also criteria added to content or collaborative based technologies, so it cannot escape from its structural disadvantages. Furthermore explanations need logic or reasoning to calculate satisfaction which is an inexplicable concept.

3.4. User Satisfaction Issue

An important issue in recommender system now is to explore criteria that try to capture quality and usefulness of recommendations from the user's satisfaction perspectives like coverage, algorithmic complexity, scalability, novelty, confidence and trust, user interaction. The need to design an efficient, user-friendly user interface: [1-3, 5]

1) For Mixed hybrid approach to implement again there is a decision i.e. which items should be rated to optimize the accuracy of collaborative filtering systems, and which item attributes are more critical for optimal content-based recommendations, are issues that are worth exploring.

2) Even if the recommender system is accurate in its predictions, it can suffer from the 'one-visit' problem, if users become frustrated that they cannot express particular preferences or find that the system lacks flexibility. Creating a fun and enduring interaction experience is as essential as making good recommendations.

Moreover Table 1 depicts this problem in some systems.

3.5. Personalization as potent factor in Recommendations.

As depicted by Table 1, personalization is a potent factor to be solved:

Processing of User Preference is Difficult due to:

1) Different User Background
2) Registered/Unregistered Users (TRUST ISSUE)
3) Dynamic Remodeled Information.
4) Willingness/Decision making criteria of user for best fit preference.
5) Personalization should be clubbed with security issues.

3.6. Scalability

Some of the systems have limitation of scalability as depicted by Table 1. By increasing load on the recommendation in terms of growing item, users, the system slows down effective process. This degrades system performance, efficiency and throughput of recommendation system. In using Explanation Facility to solve over specialization[13] and to bring in diversity in product choice[11], the recommendation quality improve but with increase in users, items and modules of system, the result is complexity and overhead which further breaks the performance. Same happens with other systems.

Increase in load or scalability is real test of system potential and capacity. Research solutions on small scale or fewer loads are feasible from all perspective but with scalability of system it is a different scenario in itself.

3.7. Scrutability

There are Recommendation Frameworks which exhibit absence of scrutability criteria as per Table 1. Scrutability is one of recommendation quality parameter which permits user to alter his query to tailor fit his recommendations. [13] The user is giving his authentic feedback for the recommendations via scrutability. Many recommendation process do not allow user feedback or scrutability. This can lead to dissatisfaction of user.

3.8. Sparsity

There are Recommendation Frameworks, in which there are sparsity issues as shown by Table 1. The Concept of sparsity leads to a situation when enough transactional data is not there for any type of correlation or mapping of [item/user] data. Be it recommendation technique of recommendation using diversification [11], explanation facility[13], tags[15] and others, most of them lack transactional, linking data to map or correlate user/item models. In other words calculating the distance between entities [user/item] becomes difficult.

3.9. Introducing the concept Recommendation shilling attack [7, 8]

This is a Novel Contribution, which is a part of the proposed Solution. But the background research for this formulation is given by study of some of such issues coming from fake ratings systems of research citations and E-Commerce world.

E-Commerce Security Issues like “shilling attack” can also be found in well known research context issues like Matthew Effect, self citations, citation circles and ceremonial citations.

Recommendations in ratings can be faked just as publication numbers, citations and references are inserted for good results. Ratings can be added to high numbers of desired products, and even decreased. There arises a need for semantic structuring and authenticity.

As shown in Table 1, some of the Systems suffer from Recommendation Shilling attack. Unscrupulous producers in the never-ending quest for market penetration may find it profitable to shill recommender. The Affiliate marketing and other E-Commerce profit gain concepts also fall in this category. This all is done to have their products recommended more often than those of their competitors. Such acts are known as shilling attack on recommendations. Also the concepts from a well known recommendation work on research domain elucidates some unwanted situations and the framework for shilling attack as a recommendation issue and the respective formulations given below. This work defines a new issue named shilling attack on quality of recommendation on the basis given below. Method Citation is considered equivalent to rating phenomenon. Four Formulations [F1-F4] is given on these grounds:

a) Matthew Effect describes the fact that frequently cited publications are more likely to be cited just because the author believes that well-known papers should be included.

F1: Branded/well known items are given more preference/rating not even knowing that they match the demography of users and context of his query. This can further lead to Over specialization, cold start and sparsity. For example any new shoe category branded X Company has to be rated 8/10, without actually checking out the product. This can be termed as RecommBrandedRating Effect.

b) Self citations: Sometimes self citations are made to promote other publications of the author, although they are irrelevant for the citing publication.

F2: At times when items are recommended, there are some complementary things which are presented along with that, which may not match the preference elicitation or context. This is just done for gaining profit from other company/advertising. This can lead to Computational cost, decay in performance, efficiency, user satisfaction, coverage and personalization issues. Ratings/Preferences or recommendation results are more biased towards own company product thereby to increase brand value. This can be termed as RecommSelfRating Effect.

c) Citation circles: In some cases Citation circles occur if citations were made to promote the work of others, although they are pointless.

F3: Group Recommendations following F1 and F2 can be construed in this category. This can further ignite sparcity, cold start, and overspecialization. Even the corporate world revert their direction towards ‘give and take’ phenomenon where other products are rated high, who in turn favors you with high recommendation value of home products. This can be termed as RecommAffiliateRating Effect.

d) Ceremonial citations: The Ceremonial citations are citations that were used although the author did not read the cited publications.

F4: At times raters or recommendations are just listed for increased brand name in market without Comprehensive understanding of user and items. Without calculating the similarity measure/personalization/preference of recommendations some items are rated arbitrarily.
All Four factors affect recommendation quality, even discourage future extensions. This intensely affects the comprehension understanding of users and Items and also inversely affects User Satisfaction level. This can be termed as RecommAstractRating Effect.

This Four Formulations has been grouped under the concept Recommendation shilling attack. This has been applied to concept of shilling attack with perspective of quality framework. One can well imagine if such fake entries enter in recommendation process, what will be the overall effect on item preferences, cold start, over specialization and other issues. It would be disastrous.

3.10. The Central Processing Unit of Recommendation Framework: Quality of Recommendations. [1-3, 6, 9, 10-17, 21, 23]

The Quality of Recommendations is measured by some primary component such as Novelty, flexibility, scrutability, transparency, effectiveness, efficiency, persuasiveness. But presence of issues depicted by Table 1 fails the most tailor made recommendations also. So the need arises to evaluate the recommendation quality from Multi dimensional qualitative perspectives as well. These are given by primary components of recommendation quality parameters as described above. The various learning techniques i.e. ontology, repertory grid etc of these algorithms are evolved to resolve recommendation issues. Recommendation strategies also encompasses evaluations grounded in mathematical logic such as Pearson's co-efficient, top N Model, but they are algorithmically striking a balance among prediction, recommendation, relevance, diversity of items and measuring of issues which is not viable. This requires feasible real world modeled framework.

The quality of Recommendation is a Multi dimensional evaluation from all these twelve perspective. The quality evolution started from content, collaborative and hybrid techniques. Ratings helped to calculate user satisfaction, Personalization brought semantic understanding to it. Recommendation Quality research further saw similarity measure, preference elicitation, difference between search recommend and predict to ascertain the exact co-relation between user characteristics and item attributes. Tagging facility solved the understanding of item background to an extent and Explanation facility, further augmented this approach. The Concept of Search Algorithms, repertory grids and Graph models also participated to churn out optimized best fit recommendations. Conversational, Context and Critiquing process brought a see saw change in recommendation quality research. Even Case Base reasoning, Ontology, Intelligent Agents also contributed towards this direction. The innovation and feasible technique illuminated by knowledge based models is a show stopper. It models.
The Learning Techniques are described by the strategy of recommendation process. Various systems used in Table 1 have following learning Techniques.
a) Traditional systems based on [1, 2] Rating structures, User/item profile analysis [Content/ Collaborative/hybrid]
b) Personalization-User Demography [19]
c) Search Algorithms
d) Tagging Concept in Recommendations [15]
e) Explanation Facility [11, 13]
f) Knowledge Models [4, 16, 22]
g) Repertory Grids [3]
h) Graphs [6, 9, 10]
i) Capturing Context through Conversational/Critiquing Strategies [14, 23]
j) Capturing Context using semantic web [17]
k) Using CBR+ONTOLOGY Combination [2]
l) Using intelligent agents for Recommendations [18, 21]
m) Blogs/Social Groups based Connection Centric Recommendations.
Example: Orangut/twitter/LinkedIn/Wayn [9]

The recommendation Quality is much more than these seven primary factors. They are affected by 12 issues of Table 1 framework. Quality needs to be seen from multidimensional perspectives.
Quality of recommendations depends on many factors;
1) Recommendation Issues.
2) The Learning Techniques and the variables used in it.
3) The real time evolution of Application Framework.
Therefore the 12 factors of Table 1 have quality parameters embedded in them.

3.11 Environmental parameters of Recommendation Evaluation. [25-27]

Issues like Multidimensionality of Recommendation system, Multi criteria Rating and Model based Recommendation techniques calls for a Frame work which takes information from user with user friendly GUI in conversational stages/increments. This further processes contextual ratings using KBB technique from

ACSIJ Advances in Computer Science: an International Journal, Vol. 3, Issue 1, No.7 , January 2014
ISSN : 2322-5157
www.ACSIJ.org

E-COMMERCE Databases thereby processing in knowledge Grid.

This Concept refers to Recommendations which fits in the Multi Dimensional Criteria's of user and application domain. For example demography of user, object attributes, social, legal and environmental rule based structure, understandable and cost-effective navigational links. It has Multi-User Flexible Interface to cater to user needs i.e. stop the user from one visit problems and assist him to decide. This further assists to create homogenous environment of interaction. But some of the Recommendation systems lacks in one way or the other in this type of evaluation point. As depicted by Table 1. In this work, the novel contribution is the 3M Model which has been identified from the above stated concept. This is of Multidimensional Multi-criteria modeling: The 3M-Model.

From the perspective of E-Business point of view: Recommendation System's Maintenance Model [Business Model]: This deals with business model perspective of recommendations thereby taking care of real-time transactions and the cost incurred.

a) Maintenance Model 1: charge recipients of recommendations either through subscriptions or pay-per-use [Danger of fraud].

b) Maintenance Model 2: A second model for cost recovery is advertiser support. [Danger of fraud]

c) Maintenance Model 3: A third model is to charge a fee to the owners of the items being evaluated. [Partial Danger]. This 3M Model can also take care of TRUST Issues.

We can look at recommendation system from social and technical evaluation perspective. For this the author has taken 5 recommender systems Grouplens, Fab, Referral web, PHOAKS AND SITECEER.

This evaluation metrics further illuminates various recommendation methodologies, architecture and their implementation and processing strategies with two main goals:

1) Recommendation system's quality evaluations
2) Recommendation system's maintenance in real world.

For this the evaluation metrics are categorically divided into three major parts of evaluations:

The Technical Design Space: This consists of Contents of recommendation, use of recommendations, explicit entry, anonymous and aggregation,

The domain space and characteristics of items evaluated: This consists of type, quantity, and lifetime and cost structure of Recommendations.

The domain space and characteristics of the participants and the set of evaluations: This consists of Recommendation density, consumer taste, and consumer taste variability and consumer type.

This has given a balanced structure to evaluate and satisfy various recommendation parameters. Therefore following analysis holds true:

a) Recommendation Quality Framework: Good Evaluation Matrix which enhances recommendation quality. It talks about the parameters of quality evaluations which can provide sound base to explain issues. For example: Recommenders Density of recommendations tells you about over all coverage or sparsity criteria's.

b) It also evaluates the Cost structure therefore evaluating the remuneration of each approach and strategy.

c) Consumer Taste parameter evaluates the over specialization issue also to some extent can help to solve collaborative filtering disadvantages due to inconsideration of different user background.

d) Recommendation system's implementation, usage and evaluation are a costly transaction. This has to be strategically managed by structuring balanced quotient of multidimensional Recommendation quality criteria's and Business Model's needs. Cost and quality parameters should be managed according to application domain's need and user's perspective.

e) Qualative parameters alone cannot justify best fit recommendations; they need to work with issues. They need justification for analysis and an architectural framework for generation of recommendations.

ISSUES	***S1***	***S2***	***S3***	***S4***	***S5***	***S6***	***S7***	***S8***	***S9***	***S10***	***S11***	***S12***
Accurate Rating	1	1	0.5	1	1	1	1	1	1	0.5	1	1
Preference Elicitation	1	1	0.5	1	1	1	1	1	1	0.5	1	1
Similarity Measure	1	1	0.5	1	1	1	1	1	1	0.5	1	1
Building of item/ user profile	1	1	0	1	0.5	1	0	1	1	1	1	1
Personalized recommendation	1	1	0	1	0.5	1	0	1	1	1	1	1
Implicit/ Explicit Data Collection	1	1	0	1	0.5	1	0	1	1	1	1	1
Cold Start Problem	1	0	0	1	1	1	1	0	0	0	0	0
Coverage	0	0	0	1	0	1	1	0	0	0	0	1
Sparsity	0	0	0	1	0	1	1	1	1	0	0	1
Over specialization	1	0	0.5	0	1	0	1	1	0	0	0	1
Recommend -ation Quality	1	1	0.5	1	0	1	1	1	0.5	0	1	1
User Satisfaction/1 Visit Problem	1	0	0.5	0	0	1	1	1	0	1	0.5	1

Scrutability	1	1	1	1	0	0	1	1	0	0	1	1
Scalability	0	0	0	0	0	0	1	0	0	0	0	1
Real World Modeling	0	0	0	0	0	1	1	1	0	0	1	1
Shilling Attack	0	0	0	0	0	0	0	0	0	1	0	0

Table 1: Multi Dimensional Issues in Recommendation Systems Matrix. Here Systems S1..S12 refers to systems and concepts depicted by research papers [11-22] at back reference in same order. The number 0 marks presence of issue. 1 means system is working fine with respect to following issue. The table can be read as: a) Coverage Problems are there in some systems [11-13, 15, 18-21]. b) Overspecialization problems are there in some systems [12, 14, 16, 19, 20, and 21]. c) User Satisfaction Issue are prevalent in systems [12, 14, 15, 19].d) Personalization problem is there in systems [13, 17].e) Scalability is there in some of the systems [11-16, 18-21]. f) Scrutability problem present in systems [15, 16, 19, 20]. g) Sparsity is shown by some of the Recommendation Frameworks [11, 12, 13, 15, 20, and 21]. h) As shown in Table 1, some of the systems [11-19, 21-22] also suffer from Recommendation Shilling attack. i) System in References [12, 13, 18-22] depicts Cold start problem. Real world Modeling problem is shown by the systems [1-5, 9, 10].

4. The Recommendation evaluation framework by Multi Layer Architecture:

This Evaluation prototype paves the way for measuring the recommendation process of best fit recommendations. This is a generic, abstract framework which can further be extended by increasing number of systems, architecture, issues, measurement criteria's and viable solution sets. This can be further given the shape of Knowledge Grid. This Consists of 8 layers and 3 Knowledge Bases.
Referring to Table 1, the working of the framework is explained with respect to system S1.

Layer 1: Extracts all the Algorithmic Detail of system S1 i.e. Architecture {Knowledge Model, Ontology, Repertory Grid etc}, Domain Application {E-Commerce, E-learning}, Quantitative Parameters [25][26] {Number, type, Cost and lifetime of recommended items, Contents and density of Recommendation, User taste variability etc} and store in Knowledge Base as KB1.

Layer 2: The Issues are recorded in a grid framework with severity of issues mapped as {X=0, √=1, 1/2 √ =50%}. The Issues are given a Tag which consists of Issue Number. The Issues are stored in Knowledge Base as KB2, according to their sequence Number and Issue details.
The Cold Start Problem - 01
Coverage - 02
Overspecialization - 03
User Satisfaction Issue - 04
Personalization- 05
Scalability- 06
Scrutability- 07
Sparsity- 08
Real World Modeling of data. - 09

Layer 3: The Recommendation Density and other Quantitative parameters are referred as:
Function F= {A1…..AN} where N is all the quantitative parameters. This Function F is further checked with the information overload problem due to social networking. This is done with the viewpoint of Social Centric View of World Wide Web i.e. harnessing the Recommendation linkages from social centric network [25][26][27]. This step is important to recover from problems of Personalization, Navigational links and Social Networks.

Layer 4 and 5:
For system S1 the tags allocated going through various layers starting from Layer 1 to Layer 5.
To solve the probability of Recommendation shilling attacks, tags are further extended by adding extensions F1..F4 {Formulations discussed in section Recommendation shilling attack} -> For S1 We have S1%26789%F2F3.

Layer 6: Here we resolve the fake rating structure or data due to recommendation shilling attack. We remove the redundant data added due to fake ratings thereby adding Clear Flag giving S1%26789%Clr.

Layer 7: further matches the Solution set Knowledgebase SKB3 which consists of strategies to resolve issues. This is future work and this may give rise to many other research directions. For system S1 we have to resolve issues 2, 6, 8, 9. This may further give solution sets in terms of architectural, environmental, qualitative or quantitative changes to rectify the given problems.

Layer 8: tests the validity of the recommendations. In case of failure, it sends this to layer 1 or exits the system.
Each Recommendation Data goes through maturation effect i.e. data change due to environment or knowledge level of people so layer 1 again tracks all the system information. Thereby it is customary to update KB1, KB2 and SKB3 with evolution in recommendation data and strategies.

5. Conclusions

Recommendation System can be termed as Information Filtering KDD Technique which evolves with E-world. It is a way ahead of smart search. Every Recommendation Algorithm in spite of anomalies have basic Learning Technique, Issues creating problems in good recommendations, parameter to evaluate recommendations, social centric point of view, all contributing to quality framework for best fit recommendations.

This paper categorizes recommender systems semantically on large scale. This includes applications ranging from e-commerce to social networking, platforms from web to mobile, healthcare to differential diagnosis, project management to quality assurance and beyond, and a wide variety of technologies ranging from collaborative filtering, content based, hybrid approaches, explanations facility, tags terminology, ontology, case-based reasoning to Knowledge Models.

Thus a need arises to evaluate and explore recommendation architecture with perspective of issues, quality parameters of evaluation.

The main goal is trust worthy, user friendly, conversational, context enriched, novel best fit recommendations. This all contributes to Multi dimensional evaluation architecture which filters cost effective, application/domain based best fit recommendations. The summary Table 1 encompasses semantic analysis of some selected systems and can be extended with n number of systems and other issues as well. The era of best fit recommendations tailor made for any application domain will see the user asking for," what you suggest for me? Rather than, "I am X ,I have used Y, and can you suggest something like Y?.

Further Recommendation system needs more cross dimensional analysis from the perspective of: Issues, Qualitative and Quantitative Framework, Business Model, Architecture and Application Domains.

In this Paper the evaluation frameworks of very few architecture with respect to issues and quality parameters have been evaluated. The prototype of evaluation is present but this consists of core areas of research, precise measurements and boundary definition which is a future extension. The main focus of this paper has mainly been discussion of issues and trying to eradicate them by giving an algorithm for filtering the issues through tags. This algorithm needs to be extended to a bigger architecture with respective functions simulated with datasets. There are many Issues and some of them are overlapping as well. The accurate and best fit recommendation generating evaluation framework is future work. There is lot more to be done and more importantly issues have to be clearly and broadly classified and worked out for approximate, contextually best fit decision.

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