International Journal on Advanced Science Engineering Information Technology

Vol.10 (2020) No. 4
ISSN: 2088-5334

The Role of Trust to Enhance the Recommendation System Based on Social Network

Muhammed.E Abd Alkhalec Tharwat[a,*], Deden Witarsyah Jacob[b], Mohd Farhan Md Fudzee[a], Shahreen Kasim[a], Azizul Azhar Ramli[a], Muharman Lubis[b]

[a] *Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia, 86400, Malaysia*
*E-mail: *muhammead@gmail.com*

[b] *Department Information System, Telkom University,Bandung Indonesia*

Abstract— **Recommendation systems or recommender system (RSs) is one of the hottest topics nowadays, which is widely utilized to predict an item to the end-user based on his/her preferences primary. Recommendation systems applied in many areas mainly in commercial applications. This work aims to collect evidence of utilizing social network information between users to enhance the quality of traditional recommendation system. It provides an overview of traditional and modern approaches used by RSs such as collaborative filter (CF) approach, content-based (CB) approach, and hybrid filter approach. CF is one of the most famous traditional approaches in RSs, which is facing many limitations due to the lack of information available during a performance such as Cold start, Sparsity and Shilling attack. Additionally, this content focused on the role of incorporating a trust relationship from the social network to enhance the weaknesses of CF and achieve better quality in the recommendation process. Trust-aware Recommendation Systems (TaRSs) is a modern approach proposed to overcome the limitations of CF recommendation system in a social network. The trust relationship between users can boost and enhance CF limitations. Many researchers are focusing on trust in the recommendation system but fewer works are highlighting the role of trust in the recommendation system. In the end, limitations, and open issues of the current picture of the recommendation system come across.**

Keywords— **recommendation system; recommender system; trust; distrust; social network.**

I. INTRODUCTION

With the IT revolution and the huge information available online, extracting suitable information to the active users become one of the biggest challenges that need to be overcome. Recommendation system (RS) is a software tool deal with an overloaded challenge by suggesting and discovering the best suitable items that match the interests of the active user [1]**.** It becomes an important tool to reduce the time of accessing the interesting items and to overcoming the drawbacks of the overload issue, and finally increase the sales of e-commerce [2], [3]. RS has been implemented in many companies such as Netflix, Amazon, YouTube, Spotify, LinkedIn, Facebook, TripAdvisor, and Google news. Amazon said "We use recommendation algorithms to personalize the online store for each customer and 35% sales from RSs", Netflix 2/3 of movies watched are recommended, Google news RS generates 38% more click through.[4].The main aim of RSs is to suggest items to active users based on his/her preferences [5]. Nowadays, RS is important for online businesses to increase profits and sales, to sell a more diverse range of items, to increase user satisfaction, to increase user fidelity, and to better understand what the user wants. On the other side, RS is also important for users to find certain items, to find all good items for Influencing and helping others, to provide useful annotations for the customers, to provide a sequence of items matching a user's interests, and to receive recommending a bundle. This work can be classified as traditional RS approaches and the modern RS approaches, which are based on social network.

A. *Traditional Recommendation System Approaches*

The recommendation system is a subpart of information retrieval (IR), which helps to navigate the information through a complex large-scale available by making an individual prediction to the users, i.e., study, visit, watch [1]. Currently, there are many classifications of recommendation system (RS) that began to appear based on whether it is a personal recommendation or not, roots and background of data, the input data. Generally, RSs classified as three approaches: Collaborative filter approach, Content-based filter approach, and Hybrid approach [6]. Figure1 represents the classification of traditional recommendation system approaches.

1) Collaborative Filtering (CF) Approach: This approach is the most popular and successful technique used in RS, which is mainly based on a multi-user environment. CF focus on finding similar neighbors to get prediction based on users historical, preference, likes, dislikes, and rating to different products [7]. Moreover, the CF approach is easy to understand and implement, it's working well in the real-life scenario mainly in online businesses like Amazon [8], and eBay [9]. There are many types of researches have been proposed based on CF approach in different areas such as, in IoT [10], CR-IIA [11], Smart Radio [12] and time-aware [13]. Based on [14] RS based on the collaborative filter are still play an important role in all kinds of applications such as online business, online shopping, digital library, tourism technology. Generally, the CF approach divided into three different methods based on (Memory, Model and Hybrid) [15]. The main difference between Memory-based and Model-based is their way of processing the data. Memory-based utilizes heuristic rules to predict the ratings while Model-based utilize machine learning (ML) techniques and statistic. Hybrid-based is combination of Memory-based and Model-based in order to maximize the advantage by complement each other.

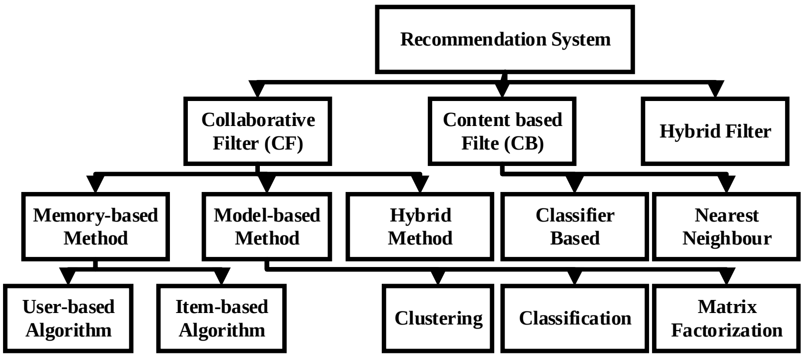

Fig 1. Traditional Recommendation System Approaches

Memory-Based Method. It is a computation method which computes the relationships between items/users with help of rating matrix (user or item rating matrix). There are two ways to represent the Memory-based method 'User-based methods' [16] and 'Item-based methods' [17] to predict the recommendation for active users. Generally, there are three processing steps of this method, First is measuring the similarity between active users which represent the core work of the CF approach, the second step is selecting the most similar users between all available to predict the items to the active user [21] using the appropriate algorithm such as k-nearest neighbor's algorithm (KNN), the last step is based on the set of neighbors identified. finally, the recommendation process generates a recommendation of N-item list for the active user based on the average weighted of all users' ratings.

Model-Based Method: Data mining and Machine learning algorithms are utilized to find the predictions patterns based on training data. Many model-based CF methods are proposed, Such as Latent Factor Model [22], Clustering Model [23], Bayesian Networks [24], Restricted Boltzmann Machines (RBM) [25], and Auto-Encoder Based Solutions [26]. It's also known as eager recommendation algorithms. Researchers in the recommendation area have introduced different learning models based on machine learning algorithms mainly are three models used widely. First is clustering models its unsupervised learning technique. A clustering method defined as an operation of collecting similar objects in spaces into groups, members of the same group is similar and different from other groups.

Clustering algorithms are used widely in many different applications such as, in computer science the clustering method used in software evolution, data mining search result grouping, crime analysis, and find the nearest target. The clustering methods become very useful for many tasks and especially for CF which have been extensively studied by several researchers. In [27] the authors proposed the RS approach based on clustering model by using K-mean method to reduce the scalability in traditional RSs. The second Classification techniques are used widely in various purposes such as for classification, decision, neural network, Bayesian network, prediction and estimation. It is also applied in many domain areas like education, health, marketing, social network, and finance. In [18] a new framework based on data segmentation through ontology classification and GMM has been proposed known as (CTRS) using trust network and the probabilistic matrix factorization approach to enhance the quality of RSs. To reduce the sparsity problem of the classical recommendation system, the matrix factorizing approach is found which represent the most accurate solution in RSs [19].

Hybrid-Based Method: The blended memory-based and the model-based CF algorithms defeat the limitation of the native CF algorithms. Performance enrichment in the prediction of the result is achieved by hybrid based CF algorithm but the implementation is more expensive due to algorithm complexity. [20] Hybrid CF systems combine the CF techniques (memory and model) based to enhance the predictions of each technique.

2) Content-*Based Filtering (CBF) Approach:* This approach is mainly utilized with a textual field such as news, scholarly paper [21]. Content-Based Filtering approach is useful for extracting topics or information from the user profile and history content [22]. It is based on the similarity of the previous preference profiles between the members and the active user. CBF approach recommends and suggests similar items to the active user based on the user preferred and what has been used in the past. Content-based approaches suffer the limitation of making accurate recommendations to users with very few ratings [23]. Moreover, two different items are indistinguishable if they are represented by the same tags[24]. This approach based on three steps: first content analyzer which is work to map the non-structural information to represent it, the second step is profile learning module which uses the output of the previous step as input to generate this data and construct the user profile. Filtering component utilizes user profile to suggest relevant items as the last step in the content-based recommendation process. Generally, there are two strategies to recommend the items to an active user based CBF approach according to[25] which are classifier based and machine learning-based.

3) Hybrid *Approach:* To gain more accuracy, the hybrid approach contains two or more recommendation techniques which would enable to overcome the limitation of CF and CB approaches [26]. Generally, there are three aspects can be described as a hybrid approach. First aspect CB and CF each one works alone and then combine their predictions to generate the final recommendations [27]. The second aspect adds some of CF characteristics inside of CB and then CB generates the recommendation [28]. The last one adds some of the CB characteristics inside of CF and then CF generates the recommendation [29]. In [30] the authors proposed a hybrid novel approach based on CF and context-aware using the trust relationship to capture multifaceted and asymmetry trust relationships known as haTrust. This work improves the performance rating prediction and more robust to the cold-start problem.

B. The Modern Recommendation System Approaches

Based on the traditional recommendation system approaches there are many other types of RSs introduced in bellow, see Figure 2 which represent the modern RSs approaches.

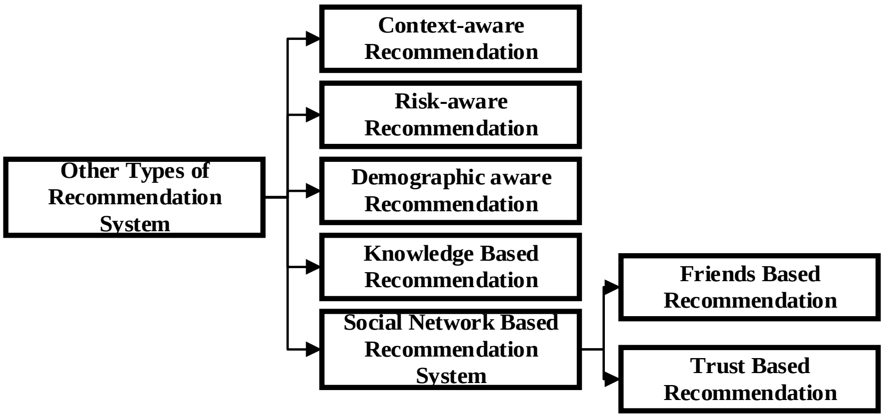

Fig 2. Modern Recommendation Approaches

1) Context-Aware Recommendation: Exploiting the context information in the recommendation system generation leads to having context-based recommendation methods. Besides, users profiles and rating history context information also would affect the recommendation system consumption such as movie recommendation, user's behavior could be affected by the environment factors (when, where and with whom) to watch the movie. Researchers notice the improvement of the context and information for the use of recommendation quality. In [18] based on the probabilistic matrix factorization the authors propose a new context-aware recommendation framework called (CTRS) via ontology and Gaussian mixture models. CTRS proved the achievement of good recommendation quality.

2) Risk-Aware Recommendation: Risk-aware recommendations are a subpart of context-aware recommendation, which is based on critical context information such as user vital signs. It is known as a risk due to the wrong decision may menace user's life or cause harm such as recommend medical drugs for sale or purchase. In [31] to solve the exploration/exploitation trade-off (Exr/Exp) problem, the authors propose an algorithm called R-UCB that considers the risk level of the user's situation to adaptively balance between Exr and Exp, the result of this work is an improvement of recommendation system performance.

3) Demographic-Aware Recommendation: Demographic-aware recommendation system (DRS) provides recommendations based on the user's demographic data like age, gender, date of birth, education, language, or any other personalized information[32]. This approach categorizes users into clusters based on their demographic characteristics and then recommend the items based on these similarity factors[1]. More precisely, the demographic approach assumes users in the same category have the same preferences. based on our investigation very few works are focusing on this approach, so it is important to go deep and discover it. In [33] present a point of interest POI recommendation method based on trust enhancement in social networks known as social pertinent trust walker (SPTW).

4) Knowledge-Based Recommendation: Knowledge-based recommendation (KBRS) or rule-based recommendation systems is a very useful approach in the context of the items which have not used or liked by the users such as real estate, automobiles, tourism requests, financial services, or expensive luxury goods. In some case, there is no enough rating of feedback information about these items which affect the recommendation process. Due to the low percentage of the buyers for those items, it will be very hard to give sufficient rating information. This limitation is also encountered in the context of the cold-start problem. For that, knowledge-based RS is proposed. its utilize user specification, item attributes and domain knowledge as input to give the recommendation. Knowledge-based recommendation systems can be categorized based on the kind of interface: constraint-based recommendation systems and case-based recommendation systems.

5) Social Network-Based Recommendation: It is necessary to have in mind the important role of social media when considering enhancing the recommendation systems. Specifically, social networks are an instantiation of the new social network-based recommendation methods, by considering the enormous number of information and relations. Social recommendation system (SRS) proposed to address the limitations of previous work by using social information to boost the performance of RSs. [34]. SRS is the original term for personalized recommendation techniques. It's widely utilized such as recommendation systems implemented at LinkedIn [35] which based on SRS. Generally, SRS can be categorized into two types: friends-based recommendation, and trust-based recommendation methods.

- *Friends-Based Recommendation:* The concept of SRSs depends on social friendship relations among users within the network, in which the relationship is exchanged among the parties in the social network. The friendship relations represent how the concerned users reprieve in mutual interaction on social networks, which differs from the trust relationship that can be one-sided trust value. Some researchers have adopted the collaborative filtering capabilities to recommend the items to users, and the advantages of social relations between users should be included in the recommendation process. In [36] the authors propose an approach by incorporating the social information with a collaborative filter to increase the effectiveness of recommendation system, the authors utilize the close friendship relation with user rating to have data from Cyworld social networking.
- *Trusts- Based Recommendation:* In a real-life scenario, users like to get information from trusted sources such as parents, *friends* and relatives. The social network is playing an important role in our daily routine and contains much useful information which can support the recommendation system for better prediction. The trust relationship is utilized with a trust-aware recommendation system to mitigation the limitation of the collaborative filter approach such as sparsity and cold start [52]. More precisely, trust perspective in recommendation systems has a major role in overcoming some of the limitations and issues especially cold start and sparsity. Consuming trust increases systems productivity and supports the reliable influence of online behavior to produce recommendations [58]. Particularly, there are two different uses of trust in the recommendation domain: first, trust relationships between users and second trust in the system's output/recommendations. Many researchers introduce the trust relationship to enhance the traditional recommendation system such as, in [37] propose an algorithm based on trust network which can be used instead of the similarity weight, the proposed work proved the accuracy and coverage of the traditional work. In [38] the authors propose a model known as Trust Walker based on a random walk which combines trust and item-based collaborative filtering approach, the proposed model proved the performance of RSs in terms of precision. [39] The authors propose a hybrid technique to eliminate the issue of data sparsity in an online community of practices (CoPs) based on trust recommendation system, the proposed work provides more accurate recommendations compare to content-based technique**.** In [40] the authors propose a method based on matrix factorization technique and the trust relationship which combine the interest of the active user with the favors of the trusted friends. In [41] the authors introduce SocialMF, it's one of the most common social recommendation techniques. SocialMF based on probabilistic matrix factorization model with the trust propagation to enhance the prediction accuracy to a large extent. In [42] the authors propose a new method which is based on trust and distrust relationships between users. In [43] the authors propose a model based on the matrix factorization by using trust and distrust relationships. In [44] the authors introduce a TrustSVD model which based on explicit and implicit trust relationship using the SVD++ algorithm. In [45] the authors propose a hybrid approach based on social trust and distrust relationship for better recommendations. The proposed work shows the benefit of utilizing the distrust for better prediction and effectively enhances the recommendation system performance.

II. MATERIAL AND METHOD

Many weaknesses in the traditional recommendation system mainly the poor of resources. Reliable resources can be utilized to boost up the performance of RSs. Based on the truth that most of the people like to have information from the trusted sources to get a recommendation. Sense has to focus on the trust relationship to enhance the traditional recommendation system. This section started with understanding the general terms of trust and how we can use it the social network, and then move to the limitations of the current works. This can help the researchers to find interesting areas to research in.

A. Understanding the Trust

To understand the trust, in this sub-sections, definitions, properties and aspect of trust highlighted below.

1) Trust Definitions: It's one of the essential factors of human being behavior [46]. Trust is one of an important concept in our daily routine. There are many a definition of trust word, depend on which domain the trust used. Trust has been defined in various ways based on the disciplines and contexts of computation [47]. In psychology, trust is referred to the psychological state of the individual, when the trustor can accredit the trustee's intention or conduct [48]. In sociology, trust is defined as “an about the future contingent actions of the trustee” [49]. Trust in computer science is derived from psychology and sociology, the standard definition is “a subjective expectation an entity has about another’s future behavior”[50].

2) Trust Properties: Trust has many properties which are useful and affect the level of trust between users, which are listed below [69].

- *Context-specific:* Trust is context-specific in its scope. Suppose, Sam, trusts Thar as his travel guide, but he doesn’t trust Thar as a mechanic to fix his car.
- *Dynamic:* Negative or positive evidence respectively can increase or decrease trust level between users. A trust relationship is usually hard to build and easy to crash. Time and location could change it. Keeping up to date experience is important since old experience might become old or obsolete...etc. This property is widely utilized in computer science and needs always to care about it.
- *Propagative:* In real-life situations when someone trusts his friends, it could also tend to trust the friends of friends. Suppose we have three persons: Sam, Thar, and Alex, Sam has direct trust connection with Thar, on the other hand, Thar has also direct trust connection with Alex. Propagative property can be created between Same and Alex depending on the degree of direct trust connectivity. Generally, in social network trust relationship can be propagated which lead to creating chains of trust.
- *Transitivity:* Generally, trust is not the transitive and important property of the trust. Suppose Sam trusts Thar and Thar trusts Alex this does not necessarily imply that Sam will trust Alex. Trust transitive is not the same as propagative.
- *Composable:* In some conditions, there will be not any direct trust available between the users, but there is propagated trust available from one source to another. The compostable trust property represents the solution for this condition by composing all the propagation trust available in one trust score. Suppose Sam doesn't have a direct trust relationship with Alex, Thar and Sony inform Sam about Alex's trustworthiness**.** In this case, Sam has to combine all suggestion of his friends about Alex's to generate his own decision trust relationship degree based on Thar and Sony suggestions, taking into account differences of opinion. This is known as aggregation which based on composability property.
- *Subjective:* Generally, trust relationships between users are subjective. Suppose, Thar gives the Viewpoints about the last movie he saw, and Sam believes in Thar's Viewpoints, so he will trust Thar's opinion but with Alex which he has a different level of belief with Thar he may ignore and distrust of viewpoints of Thar. So trust is personalization matter. Simply we can say C trust A, but B doesn't trust A.
- *Asymmetric: Trust relationship is asymmetric.* It can be happed Z trust B, but B doesn't trust Z in the same level of trust. Whenever both sides are trustworthy, this type of relationship between both sides will change to high mutual trust after frequent interaction, vice versa. If one of the parties does not act in a trustworthy manner. Asymmetry can happen due to the difference of opinions, believes, expectation and perceptions of the peoples.
- *Self-Reinforcing:* Trust can be self-reinforcing. Uses deal positively with people they trust. Similarly, when the trust level between users is less than the threshold, it will be very hard to interact with each other, leading to even less trust in each other. Based on the literature, this property is taking less attention compared to others.
- *Event Sensitive:* Trust relationships need a long time to build between the members, but it is easy to destroy it. Simply need a long time to build and fast to destroy it. This property has taken less attention compared to others.

3) The Aspect of Trust: Mainly there is three aspects need to focus on which are:

- *Probabilistic Models and Gradual Approaches:* Probabilistic approaches maintain trust values in a black and white style. In this case, a higher probability indicates that a source can be trusted [51]. Moreover, gradual trust approaches are utilized to deal with estimation of trust values to a certain degree rather than it should be trusted or not. In real life scenario trust and distrust relationship is usually referred to as gradual trends, a nation like to represent their trusts relationship in term of trusting very much or less instead of trust or distrust [52].
- *Trust and Distrust*: The last decade has witnessed an increase in research on gradual trust as explained above. However, most of these studies focused on computing the only trust and ignored distrust; this is because modelling of distrust is considered a relatively unexplored area. After all, there is a growing opinion that distrust cannot be defined as a lack of trust [48]. Many gradual trust models including both trust and distrust are carried out, such as in [53] the author proposes a method based on a web of trust and distrust to solve the limitation of cold start by using analysis the social relationships of e-commerce.
- *Global and Local Trust**:*** Trust can be implemented as a global or local parameter local trust metrics compute trust according to the subjective beliefs of an active user in other users’ opinions. Hence, the local trust score will vary among users as they have different points of views towards each other[54]. Many models including global and local trust such as in [55] the authors merge global and local trusts into Collaborative Filter(CF) along with the trust computation based on the semantic features of items allows STARS to mitigate the Data Sparsity, Cold Start and MIMC problems.

4) Trust Computation: Trust can be computed as an estimation of how much one user trust another user by understanding their shared connections and behaviors within the networks. In the literature of trust-based recommenders, two strategies are used in building trust metrics propagation and aggregation [1]. The purpose of designing a trust metric is to quantify the degree of trust between users:

- Trust Propagation: Propagation help to achieve high performance and increase the coverage but have an inverse relationship with accuracy and F1 metrics, for that short propagation length will be good enough. In another word, increase the coverage by propagation will decrease the accuracy and F1 for that we have to make short propagation not to affect other factors [20]. Suppose user A doesn't have a direct trust relationship with user B. But there is need of having trust relationship between A and B. User A will try to search for trust relationship through his trust neighbours to build the connection with user B by using trust propagation. [56].
- Trust Aggregation: A trust metric may also use an aggregation strategy. To illustrate this technique, let us consider that several paths are linking to an active user, for whom the system is trying to predict a trust score in a large network. In this case, the trust prediction may be generated via different propagation paths, which must be integrated into one aggregation. Combining both strategies propagation and aggregation is often used, and the final trust evaluation might depend on the way they are used together. Classical aggregation and propagation can be used as weighted operators in a weighted sum, an average or a weighted average in the recommendations process.

5) Relation Between trust, Similarity and Distrust: The similarity is the backbones of the recommendation system which can increase the trust relationship between users. It is easily can get the best prediction from the recommendation system when the similarity stage build based on the trust relationship. Therefore, it is important to find the tradeoff between similarity and trust to reach effective performance. Trust and distrust have multiple aspects therefore trust is different than distrust relationship and they do not complement each other to incorporate the trust and distrust relationship it should base the work on weight. For example, A trusts B to some degree on the same time A may distrust B person to some degree. Simply can say trust and distrust are multi-faceted in nature [46].

B. Limitations of Recommendation System

The limitation of the recommendation system can be divided into two subsections the first represent the limitation of the classical recommendation system and the second represent the limitation of the trust-aware recommendation system

1) Traditional Recommendation System Limitations: Many limitations have been discovered in the recommendation system what are mainly listed below:

- Data Sparsity: The data sparsity is one of the serious limitations in a recommendation system which usually occurs due to the low rating information compared with the huge numbers of items available [57]. Many authors proposed a solution to come out with this limitation. Such as, [58] the authors proposed an algorithm based on a trust model to enhance the quality of ratings provided by a mobile ad hoc network (MANET). In [59] the authors propose a novel trust approach known as Effective Trust, which is a combination of trust neighbours and classical CF techniques to overcome the data sparsity limitation by using MoleTrust algorithm.
- Cold Start: Cold start is one of the common limitations of the recommendation system which mostly appears with data sparsity. It occurs when there is a lack of information about users or items. Usually, when there is a new user or item just registered in the system. In this situation, the recommendation systems do not have any information about new user or item based on that it will be hard to recommend what the user need or like to suggest for him. Generally, the cold start can be categories into two type based on the lack of information. If the lack with user information is known as user cold start, and if the lack with item information is known as item cold start [60]. However, several studies begin to overcome this limitation. Such as, to mitigate the cold start limitation of recommendation system the authors in [61] proposed a method based on trust calculation, neighbor filtering, and items rating prediction to overcome the cold start limitation and to improve the accuracy of RSs.
- Scalability: Scalability defines as the ability of the recommendation system methods to handle large data in real life. Increasing the number of users and items in traditional collaborative filter approach will suffer from scalability. Unlike the sparsity problem, the scalability problem may present a more resilient challenge, because the number of ratings will continue increasing over time. The scalability issue can be considered as a common problem among all the recommendation systems approaches. There are many researchers tried to solve this limitation such as. In [62] the authors propose a new algorithm using k-mean clustering techniques to address the scalability of traditional recommendation system. In [63] the authors propose a hybrid method using collaborative filter/item based to achieve a highly personalized product in the recommendation system. In [64] the authors propose an optimized MapReduce for item-based CF algorithm incorporated with empirical analysis to solve scalability and the processing efficiency of item based CF.
- Privacy-Preserving: Privacy is considered one of the challenges found in the recommendation system applications. When need to build a perfect recommendation system, it must keep in minds to violate user privacy and make them feel insecure. However, recommendation systems operate by collecting user data, creating user-profiles and storing user profiles to match them and find similar users. Several methods are proposed to preserve the privacy of users and their data. In [65] a multi-level data protection method is proposed for collaborative filtering systems, in which each evaluation intervenes before the individual ratings are sent to the server.
- Trustworthiness: Traditional recommendation systems facing trust issue between users and provider as well as between the users among themselves. Trustworthiness relationship in the recommendation system assumes that all the users in the system are in the friend's relationship

and rate item. The trust relationship is poor in current trust-based recommendation system [66]**.** To get the best recommendation which matches the user request, the users and the providers must cooperate. In [67] propose a Personalized Social Individual Explanation approach (PSIE) Which led to improve trustworthiness and users' satisfaction

- Gray-Sheep: When the user opinion is not clear or cannot be classified correctly, it is known as gray sheep information which means uncertain value. It's lead to a lack of benefit from this information. There are many researchers tried to highlight this limitation such as In [68] Propose a fuzzy trust computation model based on trust to enhance the RS by solving the gray sheep.
- Shilling Attack: The other limitation in recommendation systems is "Shilling Attack." There are many users in the recommendation system, every user can give rating information. Some of the users are given a positive rating to their items, this positive rating will use for recommendation item to the active user and negatively affect the competition items in a negative manner. It is hard to find those attackers as well as it is tough to find the fake and real users in the system. Many researchers propose a solution to overcome this limitation such as, in [69] propose a collective matrix factorization model (PN matrix and TD matrix) to integrate social trust relation and user rating information, while PM matrix avoids the shilling attack.
- Multiple-Interests and Multiple-Content(MIMC): Multiple-Interests and Multiple-content limitation happened when the target item of the active users are not matched with the popular neighbour interest[70]. To mitigation this limitation, it is important to find neighbours have the same flavour as the active user with the help of similarity selection. MIMC limitation affects the accuracy of the recommendation system. Based on literature this limitation has less attention compare to another. In [71] the authors propose a novel trust approach known as Semantic-enhanced Trust based Ant Recommender System (STARS) by using ant colony optimization to enhance the RS by solving the MIMC problem.

2) Trust-Aware Recommendation System Limitations: On the other side of the limitation the trust recommendation still suffering from many drawbacks which are listed bellow

- Trust Cold Start: Trust-aware recommendation system suffering from a cold start as well to find the trustees neighbours, to do so, new users should issue some trust statements to obtain suggestions from the system. In [72], Massa and Avessani said when there is a cold start in the traditional recommendation system it can provide mitigation with the help of a trust relationship. But in [73] the new user in trust recommendation system commonly suffer from the cold start.
- Supporting Visualization: How to start relations in a trusted network seems to be a problem. Using a visualization approach may address this problem by introducing a framework to visualize trust-based collaborative filtering. The system visualizes both information coming from the classical similarity computation (PCC) and information from trust values obtained from rating data. Based on the interactive interface to represent users in the system, this approach allows new users to indicate their tastes and obtain real-time trust information [74].
- Using Online Social Media: When information cannot be provided explicitly by the users, a new source of data should be explored. Diverse sources of social data can be investigated, like online friend's networks (e.g., Facebook or LinkedIn). Recommendation systems rely on different behaviour theories, such as the cognitive similarity between people and preferences, social capital in reputation systems and ties strength. All these social data may contribute successfully to the trust-based recommendation. However, the number of studies carried out in this area is still limited. Research should investigate further to identify how much of these data are useful to evaluate the performance of the new systems and those of the traditional trust-based recommendation approaches.
- Exploring the Potential of Distrust**:** Few efforts have been made in modelling distrust [75], and this is due to the limited availability of datasets that include distrust information, which represents the major issue. On the other hand, there is no general agreement about how to incorporate this type of data into recommenders.
- Time and Trust: Trust is a dynamic value, which can be high or low due to the cooperation and relationship affection. The trust value can be changed based on location, type, languages, situation and many more things can affect the trust value.
- Gray-Sheep of Trust Values: Sometimes the trust values cannot represent as trust and distrust (1 and 0). Because some time the user1 can trust user2 in some case and distrust in some other cases. Gray sheep of trust value refers to the users whose relationship do not consistently trust or distrust with any group of people and thus do not benefit from collaborative filtering. For this, we need to discover this type of value for better prediction. In [76] the author proposes Tunisian medical tourism ontology (TMT ontology) to overcome the shortage of semantic information of personalized recommendation in the tourism domain. Based on the literature review there is less attention for this type of information which can help to improve the recommendation system approaches.

III. Result and Discussion

Based on the fact, people like to have advice and recommendation from trusted sources. Trust-aware recommendation system (TaRSs) has been introduced to overcome some of the limitations in traditional recommendation system to produce the personalized prediction to the active users. At the beginning of this work, there are many approaches utilized with the recommendation system, the most famous and successful one is collaborative filter (CF) approach which based on open data in online systems. CF is suffering from many limitations such as cold start, data sparsity, grey-sheep, and shilling attack (Biases). The main successful part of the (TaRSs) due to the trust propagation not required any information about the new user but only required some explicit trust statements about his/her neighbors, this will boost to provide a better recommendation as to the old users. Social recommendation system introduced to Eases and enhances the collaborative filtering (CF) problem with the help of the open data available online. The trust-aware recommendation system is a subpart of the social recommendation system which based on the trust relationship between the users. There are many techniques utilized to apply trust in recommendation system .Trust metrics represent the most prominent and effective technique used to apply trust in RSs. Trust metrics has calculated the trust between users and also represent the building block of trust recommendation system. The trust metrics can be classified into three types first based on value (0, 1 or fuzzy values), second based on the medium of getting trust value (implicit or explicit trust), and third based on coverage (global or local).

IV. Conclusion

The task of this work describes the recommendation system approaches and the role of the trust relationship in a social network to overcome the limitation of the traditional approaches. Trust-aware recommendation system provides active users with the flavor he/she like based on his/her direct or indirect trust sources. At the first stage, these works start with traditional recommendation system and then move to the new modern approaches and finally focus on the trust recommendation system which has more attention in the current stage. Our future work will focus on how to utilize the explicit, implicit of trust sources with distrust relationship to enhance the current trust recommendation system. We also need to focus on how we can build trust sources to increase the input of the trustees in the recommendation system. Finally, many of unclear values are ignore which cannot be classified as trust or distrust, for that researchers need to have more attention to filter and discover this type of data in order increase the input sources.

Acknowledgement

This work is supported by Ministry of Higher Education (MOHE) under Fundamental Research Grant Scheme (FRGS) reference code FRGS/1/2018/ICT04/UTHM/02/3.

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