A Ubiquitous Recommender System Based on Collaborative Filtering and Social Networking Data

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Abstract: The use of mobile devices and the rapid growth of the internet and networking infrastructure has brought the necessity of using ubiquitous recommender systems. However in mobile devices there are different factors that need to be considered in order to get more useful recommendations and increase the quality of the user experience. This paper gives an overview of the factors related to the quality and proposes a new hybrid recommendation model. The proposed model is based on Collaborative filtering and social rating network data. Furthermore it includes an approach to protect user privacy when context parameters are used, by transferring a subset of the users and ratings in the mobile device and applying the algorithm and context parameters locally. In addition we recommend the use of classical user-based Collaborative filtering, enhanced by the trust network, which is a method that performs better in terms of accuracy when compared with user-based Collaborative filtering and Trust-aware Collaborative filtering. Our approach has been experimentally evaluated and is shown that is both practical and effective.

Keywords: Ubiquitous Recommender Systems, Collaborative Filtering, Social Rating Networks, Context Awareness, User Experience, Privacy

Reference to this paper should be made as follows…

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1 Introduction

Recommender systems are software algorithms aiming at filtering information (Ekstrand et al., 2011; Polatidis & Georgiadis 2013b). Their job is to propose items or services, utilizing information based on user preferences. Recommender systems main algorithms are based on collaborative filtering, which is the most widely used algorithm. The items or services are recommender according to preferences of other users that have similar preferences (Polatidis & Georgiadis 2014; Jannach et al., 2010). Other important recommendation algorithms include content based filtering where the recommendations depend on previous items found in the history of the user and the top matching are proposed by the system (Jannach et al., 2010) and knowledge based filtering where the system uses a knowledge based attitude to generate recommendations. It is an algorithm where the user pre defines a set of requirements that the system will use to create the list of the recommendations. Moreover the knowledge database can be built by recording the user preferences while he is browsing or by asking him to complete a questionnaire (Jannach et al., 2010).

Hybrid recommender systems use a combination of the above methods and look the most promising due to the fact that can take advantage of each method and improve the overall output. The hybridization can occur in different ways such as using the output of one algorithm as the input for the other or by combining the recommendations of each algorithm for a single input hybrid algorithm (Ekstrand et al., 2011).

Ubiquitous recommender systems assist the user of a mobile device by providing him with personalized recommendations of items or services that are in his device, while context is taken into consideration (Mettouris & Papadopoulos, 2014, Polatidis & Georgiadis 2014). These recommendations usually include mobile tourism related services such as tourist guides, shopping recommenders and route finders (Mettouris & Papadopoulos, 2014; Ricci 2011). A clear example of ubiquitous recommendations can be found in Takeuchi & Sugimoto (2007) where a city guide is proposed by the authors for mobile device users that are equipped with GPS in their devices. Moreover it has been proposed that ubiquitous recommender systems can make smoother the buying process in the actual store by recommending items that are of the user interest (Reischach et al., 2009). Such recommenders can suggest items, display their ratings and comments.

The idea of ubiquitous computing as proposed by Want and Pering (Want & Pering, 2005) is to move away from traditional desktop environments to distributed computing, using a variety of devices. In addition it usually referred as pervasive computing (Polatidis & Georgiadis 2014; Mettouris & Papadopoulos 2014; Want & Pering, 2005). A critical part of ubiquitous recommendations is context awareness, which has to be taken into consideration in order to provide accurate recommendations (Bilandzic et al., 2008; Burrel & Gay, 2001, Mettouris & Papadopoulos, 2014). This brings us to a critical point where if we want to have quality recommendations we have to let the system use the location and at the same time have our privacy respected. Such systems aim to solve the information overload problem found nowadays on the internet and do it successfully up to a point. However different quality factors have to be ensured in order to improve the user experience and increase the overall quality. Figure 1 gives an overview of a ubiquitous recommender system.

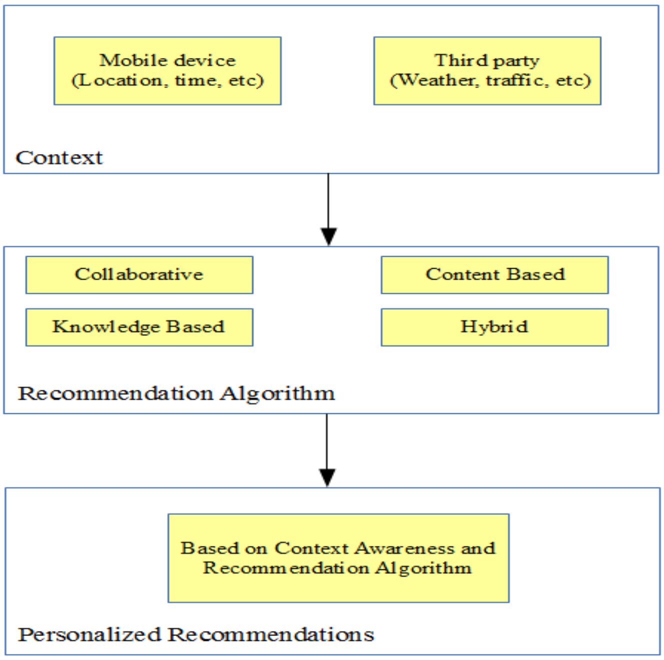

Fig. 1. Ubiquitous recommender system

1.1 Application Domains

Mobile recommender systems have become very popular and different domains have started to use such systems. M-commerce is the process of conducting e-commerce transactions of any kind using a wireless network. The use of recommenders in that field is important for their success and includes mainly context variables such as the environment and the activities (Polatidis & Georgiadis 2013a). Also tourism is a sector that supports the economy at an international level and the fact that each travelers has specific needs that need to be satisfied makes it natural to use a ubiquitous recommender system to provide personalized information in his mobile device. Gavalas et al., (2014) states that mobile recommender systems that are context aware can be used to provide different kind of services such as tour recommendations, points of interest, route recommendations, locate attractions and many more. Museum guides is a sector that recommender systems could be employed to provide context aware related information to users within a museum to display data about monuments or to provide multimedia experience of archeological artifacts

2 Influencing Factors

The user experience is influenced by several factors, some of which are of technical and some of psychological nature. These factors include context awareness, privacy (Polatidis & Georgiadis 2014; Mettouris & Papadopoulos 2014).

It is noted that the factors that affect considerably the quality of the user experience in ubiquitous recommender systems are not found in other environments and are primarily to the size of the device, the physical resources and the amount of time the user is willing to use a small size device.

2.1 Context Awareness

Context can be used by ubiquitous recommender systems to produce more personalized recommendations (Adomavicius et al., 2011). Recommender systems use collaborative and content filtering methods most of the time to produce recommendations, however this methodology does not take into consideration the contextual information and how this can be applied to the current situation and increase the overall quality of recommendations. According to the same scholars contextual recommender systems can be categorized in three main types. Fully observable, partially observable and unobservable. Moreover, a point is to discover the changes in the contextual factors and how to represent them in a mobile environment. Ubiquitous recommender systems vary and include different factors such as location, time, weather and emotional status of the user. The contextual information is very important if we want to provide recommendations that are based on Location Based Services (Adomavicius et al., 2011).

Information regarding context parameters can be collected either explicitly, which is by asking the user directly to provide data using a questionnaire. Moreover data can collected implicitly by environment data, such as historical information and changes that occur during the use of the service (Adomavicius et al., 2011). Required values may be taken into the system by using the sensors of the device such as the camera and the Global Positioning System (GPS) (Gavalas et al., 2014). Context is considered to be the most important aspect in ubiquitous recommender systems (Adomavicius at al., 2011; Mettouris & Papadopoulos, 2014; Benou & Vassilakis 2010). We strongly believe that if context is utilized properly more useful recommendations will occur and the user will be highly satisfied.

2.2 Privacy

Privacy means that the user is ensured and decides on what ways his data will be processed (Kobsa 2007; Polatidis & Georgiadis, 2013a, Toch et al., 2012). Privacy concerns direct users towards a negative behaviour when they are asked to provide more data in order to receive personalized recommendations.

In Recommender Systems users are divided in three main categories (Polatidis & Georgiadis 2013a, Kobsa 2007):

- Users that will provide any kind of information in exchange with the highest level of personalization possible.

- Users that will give some information so they can receive some kind of personalized recommendations.

- Users that will not give any kind of information due to privacy concerns.

Privacy is a crucial factor that is possible to be addressed using the right techniques. If this issue didn't exist then the user would supply any necessary information and his experience using the recommender system would be of a very high standard.

3 Less Influencing Factors

Factors that also influence the quality of the user experience, but in a less important manner can be found in the literature as well. Also a challenge that is found in traditional recommender systems but also applies to ubiquitous recommendations is the 'new user' problem, which is an important factor that plays a vital role in the development of such systems. The new user problem occurs frequently in recommender systems when a new user is registered with the service and he has not provided any ratings yet. Therefore classical collaborative filtering techniques are unable to provide recommendations to such a user. Furthermore a less critical factor but considered essential is multilingual personalization (Ghorab et al., 2011).

3.1 Factors Related to User Experience

3.1.1 Perceived accuracy

A factor that needs some consideration is perceived accuracy which is a point where a user feels that the recommendations match his preferences (Pu et al., 2011). It is considered to be a measuring assessment of how good the recommender performed and how accurate is to find the interests of a particular user.

3.1.2 Familiarity and novelty

Familiarity is a description of the previous experience that user had with the recommended item or service (Pu et al., 2011). However familiarity might mean that all the recommendation categories must be familiar to the user. Novelty must be introduced and balanced with familiarity so the user would be as satisfied as possible.

3.1.3 Attractiveness

Attractiveness is conserved with the process of irritating the user and evoke positive imaginations and increase the possibility of desiring. Attractiveness is concerned on how well the recommendations will be delivered to the user and not the recommendations provided (Pu et al., 2011).

3.1.4 User interface

Limitations found in the user interface, where different devices may be used, the task would be to develop suitable and user friendly interfaces (Gavalas et al., 2014). User interfaces are tightly related to the attractiveness as described above and could improve the quality. The more attractive is the user interface the user will be satisfied more.

3.2 Factors Related to Technical Characteristics

3.2.1 New user and item

The new user and item problem are very important when the algorithm used is based solely in collaborative filtering (CF). They occur when a new user or item is added to the database there is no history about the user or no rating history about the item or service. If a user wants higher quality from a recommender from the very beginning of joining a service, then this is a very important issue that needs to be faced and this can be dealt with the use of hybrid algorithm that utilize data from social networks (Massa & Avessani 2006).

3.2.2 Multilingual Personalization

Given the fact that there is a vast amount of data found on the internet, these data can exist in different languages (Ghorab et al., 2011). It is possible that the data requested from a user will not be available in his native language but be available in a foreign language. Research has been done towards the field of personalized multilingual information retrieval (Ghorab et al., 2011). It is a field where if suitable research occurs then more useful recommendations could be delivered.

4 Proposed Model

User experience becoming more and more an essential part in the attention of the research community. However there isn't much work done on how the quality of the user experience in ubiquitous recommender systems can be increased and what kind of standards could be specified to work towards that direction. The criteria need to be combined into a comprehensive framework that could be potentially used to provide better quality ubiquitous recommender systems. The framework should take into consideration all the major criteria which should be satisfied. A comprehensive model identifying all the aforementioned essential qualities could be established as a standard, which will convince potential users to adapt such a system.

4.1 Problem Statement

Nowadays with the growth of the internet and the development of high capability mobile devices the information overload problem is becoming serious. Recommender systems have become widely known and used in recent years to overcome this problem, with the use of collaborative filtering (CF) as the most widely known and used (Ekstrand et al., 2011). Furthermore the technology nowadays has become ubiquitous and a vast majority of users tend to use a mobile device to use the internet. All these users need recommendation technologies that can be used in their device by taking in consideration a broader context. However there exist a number of important factors that influence the quality of the user experience and should be handled. Most notable issues can be found in collaborative filtering it is not capable of making any predictions about new users, which have not rated any products or services yet and about new items that have not received any ratings yet. To address this problem the use of data from a social rating network is considered in combination with the collaborative filtering method. Social rating networks are made of a rating network and a friendship network, which means that still recommendations can be made even when there are no ratings available. Furthermore privacy is an issue that is important to users of ubiquitous recommender systems. Last but not least is the use of contextual parameters since the main usage target will be recommendations in ubiquitous environments.

4.2 Collaborative Filtering Preliminaries

Collaborative filtering is the most widely used approach in recommender systems (Jannach et al., 2010). The recommender using this approach will make recommendations based on users that have similar preferences or tastes using ratings provided from those users (Ekstrand et al., 2011). The overall idea is to make recommendations that the user is likely to be interested. In user based collaborative filtering a database is created, which contains the nearest neighbor of the user requesting the recommendations. It is a simple idea where a table stores the user id, the item id and the rating. Table 1 is such an example. Then the algorithm will identify similar users using a similarity function. Figure 2 represents the Pearson correlation. Sim (a, b) is the similarity of users a and b, $r_{a,p}$ is the rating of user a for product p, $r_{b,p}$ is the rating of user b for product p and $\bar{r}a$, $\bar{r}b$ represent user's average ratings. P is the set of all products.

	Product1	Product2	Product3	Product4	Product5
User1	5	3	4	4	Empty
User2	3	1	2	3	3
User3	4	3	4	3	5
User4	3	3	1	5	4
User5	1	5	5	2	1

Table 1. Product ratings

$$Sim\ (a,b) = \frac{\sum p \in P(ra,p - \bar{r}a)(rb,p - \bar{r}b)}{\sqrt{\sum p \in P(ra,p - \bar{r}a)^2}\sqrt{\sum p \in P(rb,p - \bar{r}b)^2}}$$

Fig. 2. Pearson correlation

Assuming that we want to calculate similarities of users to user number 1. Then the similarity values are created, ranging from -1 to 1. As shown in table 2 the user closest to User1 is User3.

	User1	User2	User3	User4	User5
User1	1	0.70	0.85	0.2	-0.79

Table 2. Similarity table

4.3 Social Rating Networks Preliminaries

A social rating network is a service that helps people to connect between them, exchange information and most importantly rate products (Massa and Avessani, 2006). One of the most know social rating networks is Epinions. In such a network a Truster-Trustee network is created and it is clear that User1 trusts User2. Although this does not mean that User2 trusts User1. It is a one way network. See table 3 for such a network example.

Truster	Trustee
1	2
2	3
3	2

Table 3. Truster-Trustee network

Then a different number of methods can be applied to this data and include get recommendations. From the trust network only could be an option or go further down to the network and include friend of a friend. Finally, similarity methods can be applied that perform different techniques to retrieve the nearest user neighbourhood.

Finally it should be highlighted that two different types of social relationships exist in social rating network. The first one is the user, item and rating relationship and has been described in section 4.2 and the second one is the Truster-trustee network.

4.4 Proposed Method

It should be noted that the quality of recommendations and hence an increased user experience is heavily based on the algorithm used. A hybrid algorithm based on collaborative filtering is necessary due to the better prediction of such algorithms (Ricci et al., 2011). However there is a problem in collaborative filtering with the new user and item issues, which can be solved with the use of data from social rating networks such as Epinions. In addition the proposed algorithm will incorporate contextual information that aims to be useful in ubiquitous environments. Figure 3 gives a high level architecture of the proposed recommender system that utilizes social media data.

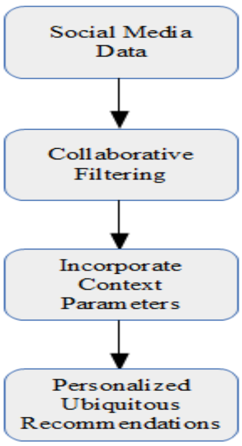

Fig. 3. Proposed Ubiquitous Recommendation Architecture

In our approach we use the data from the social rating network, which includes both the user-item network and the user trust network. The next step is to use the context parameters desired by the user, which is also known as contextual post filtering. Ubiquitous recommenders need to be context aware to be effective and capable of providing the correct results. Context as defined by Adomavicius et al., (2011) includes parameters such as:

- Location
- Time
- Date
- Weather
- Any other useful information

The contextual information is very important in ubiquitous environments and is crucial for location based services. Adomavicius et al., (2011) states that context can be incorporated either:

- Explicitly from the user
- Implicitly from changes in the environment such as location change
- Using data mining or statistical methods

4.4.1 Incorporating trust in Collaborative filtering

The first part of the proposed model is to utilize the data from the user-item rating network in order to identify the k-nearest neighbors of the user who is requesting the recommendations. This is done using equation 1 with a pre-defined number of user neighbors. The next step is to use the information acquired from the user-trust network in order to incorporate the information from the network (Who the user trusts) into the rating network. The values a, b are users, UTA it the set of the trust network of user a. UR is the set of all users and ratings. Figure 4 describes the definition of the enchased trust-based similarity.

$$Sim\ (a,b) = \begin{cases} Similarity\ value\ using\ equation\ 1, & if\ b \notin\ UTA \\ Similarity\ value\ using\ equation\ 1 + 0.50, & if\ b\ \in UTA \\ 0, & otherwise \end{cases}$$

Fig. 4. Trust-based Similarity

The algorithm modifies in positive manner the similarity value returned. If the comparing user belongs to the trust network of user requesting the recommendations then the similarity a value of 0.50 is added to the similarity value. It is noted that after experimentation using values from 0.1 to 0.6 the value 0.5 returned the best result for the Epinions dataset, which makes the accuracy of the algorithm better when compared to classical collaborative filtering. Further details are shown in the evaluation section. Moreover it should also be noted that if the addition returns a value greater than 1 then it is automatically converted to 1, which is the maximum. Also values above 0.60 where not used due to the reason that the method would only recommend items based on the trust network of the user.

Algorithm 1 Combining rating and trust network for user a $\in U$

1: Input
2: UR → the set of all users and ratings
3: UTA → the set of the user-trust network of user a
4: **for (i=0; i<UR; i++)**
5: Sim (a, i) // the similarity function using equation 1

```
double tempSimilarity = Sim (a, i) // a value between -1 to 1
if (i.isIn (UTA))
tempSimilarity + 0.50
finalSimilarity = tempSimilarity
else finalSimilarity=tempSimilarity
end for
return finalSimilarity
output: finalSimilarity
```

5 Privacy

Privacy is a crucial factor for personalized ubiquitous recommendations. In mobile environments, context parameters is the most important aspect of providing recommendations of better quality.

We propose an architecture with the following additions:

- The server will hold the user information, including the items, ratings and the trust network.
- When the user is requesting recommendations then the ratings, user neighborhood and trust network will be transferred to the mobile device.
- The algorithm will run on the mobile device and apply the recommendation method and any relevant context parameters in order to provide the recommendations.

We suggest that both the recommendation method and the application of the context parameters take place in the mobile device, in order to satisfy high privacy concerns. Moreover this solves the problem of the recommendation method or the merchant manipulating the recommendations and the user not wanting the merchant to know what was recommended to him. However while the user neighborhood gets larger then it will be time consuming to transfer all the user and item details over a, possibly, wireless connection. Therefore we use the k-means clustering approach using the Pearson correlation in equation 1 to form a k-nearest neighborhood of the user requesting the recommendations, with k being the number of neighbors. The set of users is represented as follows: U = {a, b, c, ... , n}. The cluster is represented as follows: C = {a, b, ...n}. The cluster C is a subset or equal to the set of the users such as $C \subseteq U$.

6 Experimental Evaluation

In this section, we experimentally compare our approach on a Pentium i3 2.13 GHz with 4GBs of RAM, running Windows 8.1. All algorithms were implemented in Java and where based on Apache Mahout (Anil et al., 2011) libraries. Our Collaborative filtering enchased approach is compared to the following methods:

- **User-Based Collaborative Filtering:** User-based Collaborative filtering is applied on the user-rating network only. In our approach we used the Apache mahout algorithm and used the Pearson Correlation similarity.

- **Trust-Aware Collaborative Filtering:** This is a simple approach where every recommendation is derived from users belong to the trust network of the requester.

6.1 *Real Dataset*

For the evaluation of the algorithm we have used the Epinions dataset, which is a directed who trusts whom social network. In the website Epinions.com users can register and express their interest about products using ratings on a 1-5 scale. Moreover they can add other users in their trust network. However this is a directed network, which means that the user trusts does not work the other way around. The dataset was downloaded from trustlet.org (www.trustlet.org/wiki/Downloaded_Epinions_dataset) and is consisted of 49 thousand users and 487 edges between them. It also contains 140 thousand items with 665 thousand ratings.

6.2 *Measures*

For the task of measuring the accuracy of the recommendation algorithms we used the Mean Absolute Error (MAE) (Herlocker et al., 2004) and is shown in figure 5. The method is used to compute the deviation between the predicted ratings and the actual ratings. Pi is the predicted rating and ri is the actual rating in the summation. Finally it should be noted that lower values are better.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|pi - ri|$$

Fig. 5. Mean Absolute Error

In information retrieval systems such as recommender systems Precision and Recall are used. Precision is the portion of relevant recommendations that is relevant to the retrieval. Figure 6 defines Precision. Recall is the portion of recommendations that are relevant and where retrieved successfully. Figure 7 defines Recall. Finally it should be noted that higher values are better.

$$precision = \frac{|\{relevant\ recommendations\} \cap \{retrieved\ recommendations\}|}{|\{retrieved\ recommendations\}|}$$

Fig. 6. Precision

$$recall = \frac{|\{relevant\ recommendations\} \cap \{retrieved\ recommendations\}|}{|\{relevant\ recommendations\}|}$$

Fig. 7. Recall

6.3 Experiments

The MAE values for all algorithms, with a user neighborhood of 100 users based on the Epinions dataset are shown in table 4 and figure 8.

Algorithm	Value
Our Approach	**0.958**
Collaborative Filtering	0.981
Trust-aware	0.999

Table 4. MAE values with a 100 user neighborhood

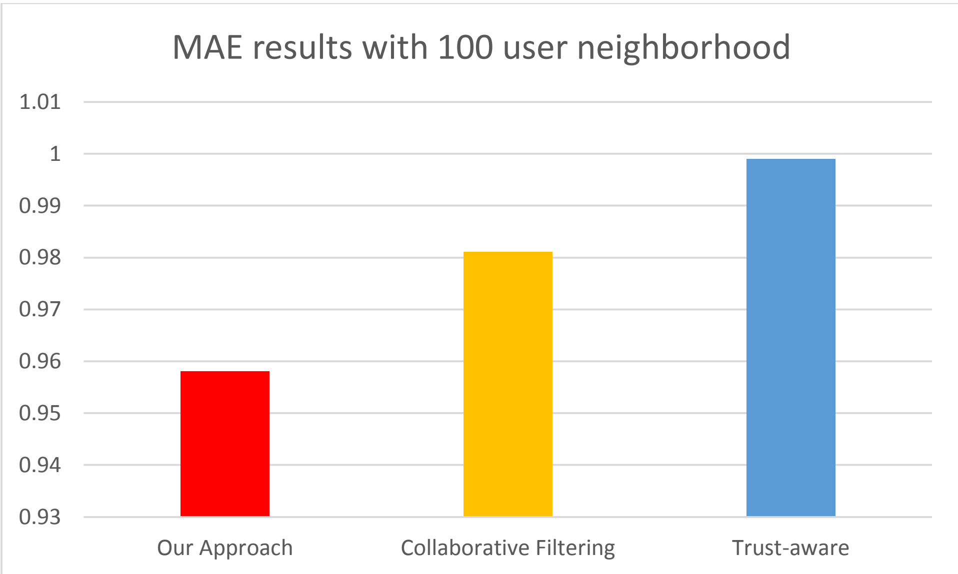

Fig. 8. MAE results with a 100 user neighborhood

The MAE values for all algorithms, with a user neighborhood of 20 users based on the Epinions dataset are shown in table 5 and figure 9.

Algorithm	Value
Our Approach	0.960
Collaborative Filtering	0.988
Trust-aware	**0.937**

Table 5. MAE values with a 20 user neighborhood

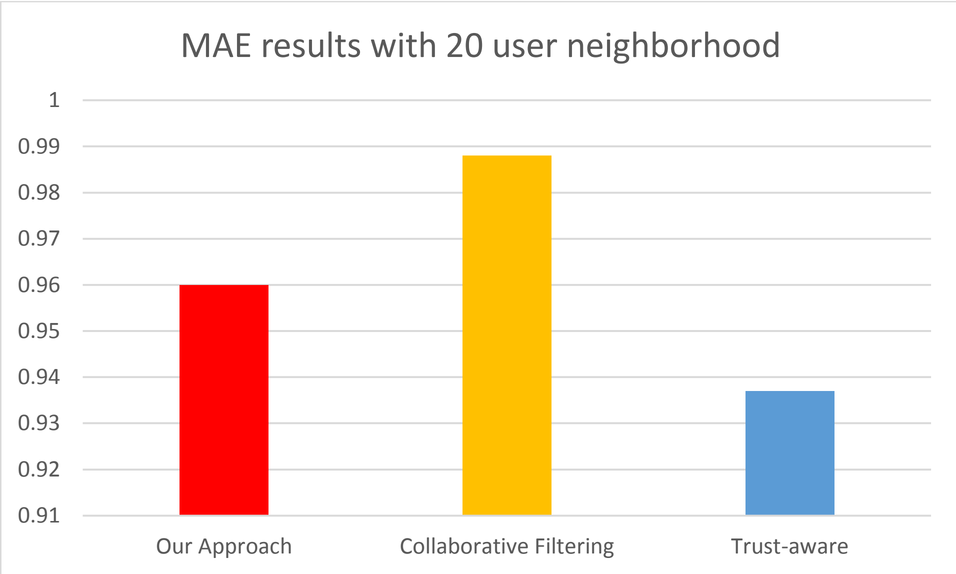

Fig. 9. MAE results with a 20 user neighborhood

The Precision and Recall values are shown in table 6 and figures 10 and 11.

Algorithm	Precision	Recall
Collaborative Filtering	0.009	0.0075
Our Approach	**0.0102**	**0.0082**

Table 6. Precision and Recall values

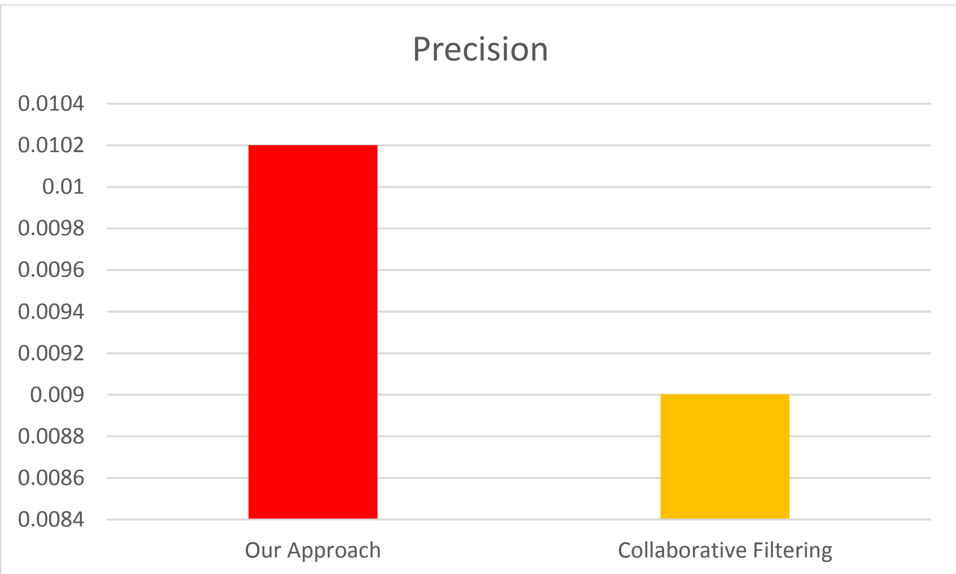

Fig. 10. Precision results

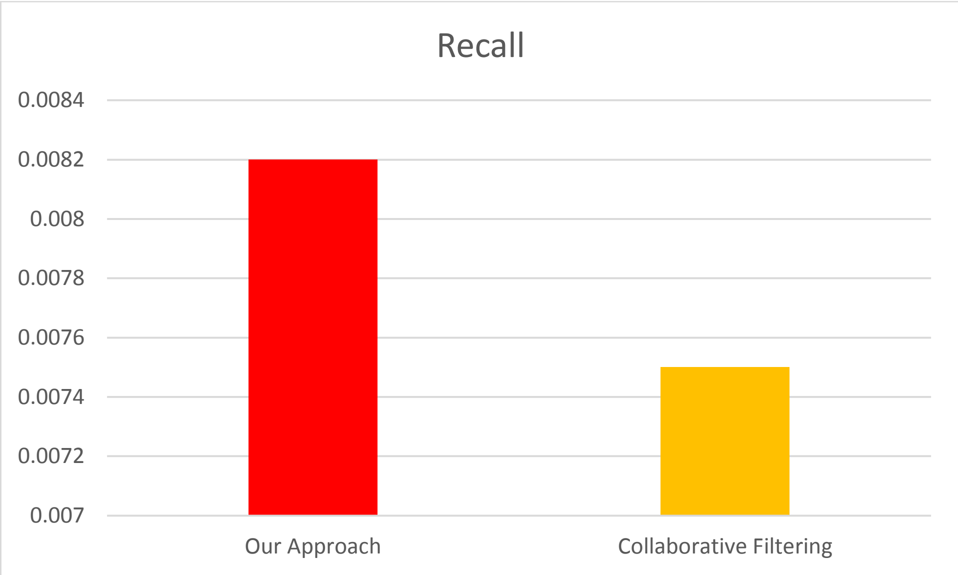

Fig. 11. Recall results

6.4 Case Study

In ubiquitous environments it means that a user with his mobile device can perform an action in any place and in anytime. Nowadays, everyone is in possession of such a device, which can be used for various tasks like communication, education and e-commerce. People become more and more attached to their device and want to keep using them in order to enjoy the services offered from various services such as ubiquitous recommender systems. We present a typical scenario which includes the user who uses his mobile phone to retrieve personalized recommendations. The scenario is about Bob who is a citizen of Fox city.

Scenes: Bob is at home: Bob is making use of his mobile phone app to retrieve personalized recommendations. However there are two cases that need to be taken into consideration:

1. Bob doesn't want to use any contextual information so the system generates the recommendations at the central server and then the results are provided through the wireless network to Bob's mobile device. In this case a larger neighborhood can be used if better accuracy is needed. Furthermore the experiments in section 6.3 show that a trust-enchased approach provides better results and also the larger the neighborhood is the results are more accurate.

2. Now, Bob has changed his mind and wishes to provide contextual information to get better recommendations. The server will create a k-nearest neighborhood subset, such as one of 20 users and pass the user ids the products and ratings to the mobile device. The clustering is done to improve the performance over a possible slow wireless network. Now the data have reached the mobile device of Bob and the algorithm will run at the device, including the post-contextual filtering.

6.4.1 Performance evaluation

Regarding the first part of the scene the recommendations are generated at the server and passed at the mobile device through the wireless network. However when privacy is necessary, particularly when context parameters are used then a subset of the data need to be transferred to the mobile device and the algorithm will run locally. For the performance evaluation part a Sony xperia U has been used with a dual core 1GHz processor, 512MBs of RAM, running Android 4.0.4. For simplicity reasons the dataset has been stored in the mobile device for user number 1 with the product ratings and the trust network. One subset with 100 user neighborhood was used and one with 20 user neighborhood. Five recommendations where requested. Figure 12 represents the results with a 100 user neighborhood and figure 13 with a 20 user neighborhood. The post-filtering of context parameters is not included in these metrics. Our approach takes 5 seconds in the first case and 4 seconds in the second case, whereas Collaborative filtering takes 2 seconds in both cases.

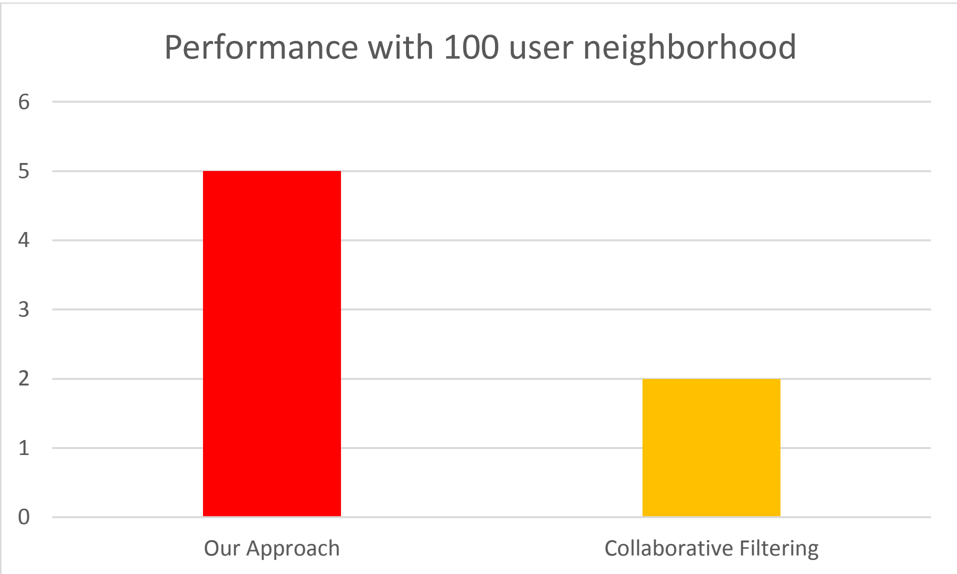

Fig. 12. Performance results with a 100 user neighborhood

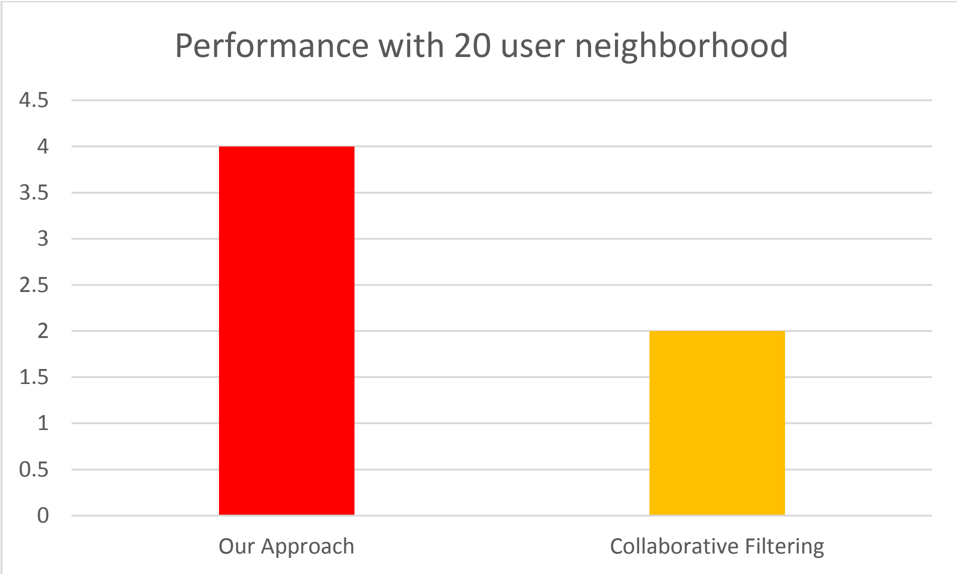

Fig. 13. Performance results with a 20 user neighborhood

Regarding context awareness we stored in a text file the following values for the locations: 1, 2, 3 and 4, each representing a different location such as home, office, friend's house and university. We also supplied the current time, which was retrieved programmatically from the mobile device. The next step is a series of IF statements to perform a rearranging of the recommendations.

Requesting 5 recommendations for user number 1, using our recommendation approach with a 20 user neighborhood the following recommendations where provided:

RecommendedItem [item: 14217, value: 5.0]
RecommendedItem [item: 676, value: 5.0]
RecommendedItem [item: 14215, value: 5.0]
RecommendedItem [item: 296, value: 5.0]
RecommendedItem [item: 515, value: 5.0]

User 1 is at location 1 and the time is 19:00. Under these parameters item number 5 is selected as the first option, while the other remained unchanged. To perform the rearrangement as described it took 1 second. The recommendations where rearranged as follows:

RecommendedItem [item: 515, value: 5.0]
RecommendedItem [item: 14217, value: 5.0]
RecommendedItem [item: 676, value: 5.0]
RecommendedItem [item: 14215, value: 5.0]
RecommendedItem [item: 296, value: 5.0]

7 Related Work

The interest in recommender systems and its related technologies, such as mobile devices, has increased the demand of personalization in different directions. Gamal (2010) proposed an enhanced K-means mobile recommender systems where he describes a system that provides the user with in store recommendations. Li and Beyong (2003) use clustering techniques to develop a hybrid recommender system that aims to solve the cold start problem. Gong (2010) combines user-based collaborative filtering and item-based collaborative filtering with a clustering based algorithm in order to provide higher quality recommendations. Kim et al., (2002) improves the performance of collaborative filtering by reducing the number of neighbors. This is done using the classical k-means algorithm.

Another indoor shopping recommender has been proposed by Fang et al., (2012). The recommender aims to use the position of the user inside a shop in order to provide recommendations that are of interest and are available. A good example of a recommender that utilizes social network data is SOMAR (Zanda et al., 2012) which aims to propose different activities to user and the data used are based on Facebook data and sensor data. Also an excellent approach of a mobile recommender system is PocketLens (Miller et al., 2004). This approach however utilizes peer-to-peer user networks to provide recommendations. Its main idea is to protect the user privacy and be able to work while an internet connection is not available.

However the use of social rating network data has not been proposed for use in mobile and ubiquitous environments but have been applied to web environments. Symeonidis et al., (2011) uses data from multi-modal social networks in order to provide personalized recommendations. Moreover he combines data from both the user-rating network and the trust network into a new hybrid model. Symeonidis et al., (2013) is the extended version of his previous work on multi-modal networks to provide friend recommendations as well and also to generalize his approach to use data from multiple social networks. Liu and Lee (2010) have developed an online social network and show through an evaluation with real data collected from their service that the use of a friendship network can used with Collaborative filtering to provide better results. Liu et al., (2014) shows that trust-aware recommendations that utilize data from the trust network provide more accurate results to the users. Carmagnola et al., (2013) delivered Sonars++, a social network based recommender system that provides recommendations of equal quality to classical Collaborative filtering. However this approach is not based on social rating networks.

8 Conclusions and Future Work

Recommender systems has matured to a full research area both in academia and in practice. However extended research has still to be done in ubiquitous environments and as the field grows, significant new challenges will be faced in terms of infrastructure and methodologies. This is due to the fact that two different areas have to be researched and as ubiquitous computing and recommender system develop further many more characteristics will appear and new solutions will have to be proposed. Ubiquitous recommender systems will have to combine different characteristics to become useful to our everyday lives and provide an improved user experience. Furthermore quality is a very important aspect found everywhere, including recommenders and ubiquitous environments. It is vital for the designer to be aware of the factors that relate to the improvement of the user experience.

Most important factors that need to be addressed include privacy and context awareness. Less important factors that if addressed could potentially improve the quality of the user experience include perceived accuracy, familiarity and novelty, attractiveness, improved user interfaces and multilingual personalization. However mobile devices and networking infrastructures are evolving constantly and new challenges arise. Both designers and developers should be aware of new open problems and implications. In addition it should be noted that although it is an important research field there is not much work in the literature regarding quality and serious work should be taken to define the required criteria that need to be satisfied.

Our proposed model was inspired from the important factors and was evaluated both in terms of accuracy and performance. The method uses the trust network to enchase the accuracy of the recommendations and is based on Collaborative filtering. Moreover we addressed the privacy problem using a client-based approach based on a smaller subset of the users, products and ratings in order for the algorithm to perform well in the mobile device, while maintaining an acceptable level of accuracy.

However we consider privacy being the most important issue in ubiquitous recommender systems. In a future work we would like to extend the privacy approach using multiple levels and make it more personalized to each user. Furthermore a privacy-aware Role Based Access Control (RBAC) tailored to the characteristics of ubiquitous recommender systems is essential.

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