Medicine recommender system for the purpose of suggesting new and alternate medicines

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Introduction

This paper contains reflection of concepts that were taught in *SI 583 – Recommender Systems* course and an approach to apply these concepts into a new domain for coming up with an efficient recommender. Recommender Systems has been extensively applied to e-commerce websites (Amazon.com) but its application in other domains is very limited. The reason behind these phenomena is the interest in increasing ROI with e-commerce websites. However the potential of applying recommender systems to public benefit domain should also be explored and researched upon.

This paper uncovers one such domain, i.e. application of recommender systems for recommending medicines to patients. The medical application of the recommender systems would not only allow one to make wise decisions while purchasing medicines but would also provide a platform for global collaboration of medical experience between doctors.

However, the criticality of the medical profession and side effects of a wrong medicine should also be considered and challenges for this system should be predicted and dealt with in advance. Otherwise a bad design could even have adverse impacts on the patients.

A Medical Recommender

The need for a medical recommender system emerges because of two primary reasons: The inefficiency of patients to take a medical decision and the financial and accessibility restrictions imposed by economical and geographical conditions. One can argue that vastness of the resources present online is sufficient but the problem lies with the amount of content one has to read and verify before taking a decision.

A major challenge of such a recommender system is also to work synchronously with three prominent medical branches, i.e., Ayurvedic, Homeopathy and Allopathic. Having these three different resources for medicines creates confusion for what treatment to go for. People on allopathic treatment always find lack of resources for gaining information on Ayurvedic medicines that might be better for them. Scarcity of doctors who are trained in all three fields also creates further difficulty in switching. Having established that, the need for a recommender system is not only for making meaningful suggestion within same type of treatment but also to integrate Ayurvedic, Homeopathic and Allopathic fields and allow user to easily switch between them.

The issue of privacy associated with recording users medical data poses a major challenge to such a system. A patient might not be comfortable with sharing his/her medical history. In such case the system would lack sufficient data for generating recommendations. This paper would address these issues through deriving implications from the concepts taught in the *Recommender Systems* class.

The paper would first try to make arguments about the recommendations algorithms that are appropriate for such a system. Then further arguments about evaluating the recommender would be made. Further challenges particularly those related with privacy would be discussed in the concluding sections of this paper.

Recommender Algorithms

This section analyzes various recommendation algorithms based on their efficiency in a medical setting. The items being recommender are mainly medicines. As discussed above, medicine can be recommended in two different situations. Firstly, medicine in a similar type of treatment could be suggested. For ex. For a patient who is on a particular type of treatment or seeking one (ex. Allopathic) can be recommended better allopathic medicines. Secondly, the medicines from other type of treatments could also be recommended. For ex. A person not convenient with allopathic treatments could be recommended Ayurvedic substitutes.

The three main recommendation systems namely content-based, collaborative and their hybrid SVD can be used in the following way:

1. Content Based Filtering

   A content-based filter works on manually entered description of items. In this situation a content-based system could be used for matching the medicines with similar compositions and/or associated with the same diseases. This approach would be effective in recommending medicines within same type of treatment. The advantage of following the content-based model would be that it would not require the medical history for its database. Also the computations could be performed offline and hence the recommendations would be generated at a good pace.

   However, Content-based Filtering would be inappropriate for generating recommendation for switching the type of treatment, as the composition is totally different in different fields. Also since the content-based filtering does not provide weights to the recommendation through ratings, it would also be inappropriate for those users who want to switch medicines within the same field. In short, it could be summarized that content-based filtering would work fine only for new patients but not for existing patients.

2. Collaborative Filtering

   Collaborative filtering is one in which a user is matched with other users for recommending further items. Collaborative filtering can be achieved in two ways: User-User in which a users are matched with other users based on their similarity with items and item's ratings, and item-item in which an item is matched with other items based on the similar users.

   User-user algorithm would not be efficient because generally a person does not get medication for a single disease. For ex. An asthma patient might take pain-relievers for other purposes. However using item-item would be more suitable as it matches the users. This would particularly helpful in the case where the recommender has to find similar users who have switched type of treatments.

3. Using Single Value Decomposition (SVD) Algorithm

   While using SVD algorithm [1], for the medicines within same treatment type, clustering features could be based on the chemical composition. Also type of disease relieved by that medicine could also serve as a clustering feature. This feature has to be interpreted and fed by the doctors who are experts at translating the chemical composition to the type of disease. Once the type of disease associated with a particular feature has been found, various features from Ayurvedic, Homeopathic and Allopathic medicines could also be integrated to generate cross-recommendations.

   Accuracy is an important issue while making such recommendations. More the features used to form clusters in SVD larger is the accuracy. It should also be noted that reducing the composition feature while making cross-recommendations would affect the accuracy of such predications. Hence such predictions should only be made when the item being recommended has no side effects.

Collecting Data

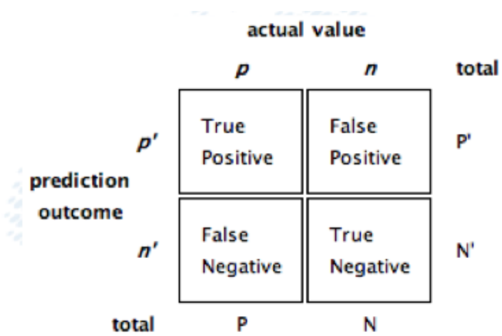
For content-based algorithms, collecting data would not be a problem as it would be fed into the system by pharmaceutical firms, which would in turn benefit them for showcasing their products. However for collaborative filtering algorithms, Collecting users data and their medical history would be a major challenge because of lack of motivation and issue with the privacy of data. For motivating users to feed data and rating into the system, one major strategy could be to allow them to store their medical profile online for permanent reference. The system can also allow them to send their medical history online to remote doctors and get advisory. Doctors can charge a nominal fee for this type of advisory as they would get a high number of patients everyday and they would be spending little time per patient. This would also remove the hassle of maintain physical medical records.

Following a reputation based model for doctors would also encourage feeding data into the system. Doctors can recommend their patients to maintain their data online and keep rating the medicines and doctors in turn can be awarded reputation points based on the number of patients they are handling.

In progress this system could serve as a centralized record archive of medical history of individuals that can be accessed anywhere by any doctor with proper authorization. A firm assurance could be provided to the patients that their name and other profile related information would be well hidden from everyone except their doctors.

Evaluation of the Recommender System

Once the recommendations system is defined in place it is very important to evaluate this system for any possible inconsistency. The medical profession is critical and any error should be checked and eliminated beforehand. Recommendations can be evaluated through the confusion metrics [2] as shown below:



(from wikipedia.org)

This metrics give opportunity to evaluate both accuracy and recall behavior of the system. However since the outcome of an incorrect recommendation might be dangerous, it is important to evaluate the recommender based on accuracy especially when the recommended medicines have prominent side-affects. The accuracy of the recommendation is given by:

TP/(TP+FP)

Where TP = Number of positive events that were predicted as true

FP = Number of positive events that were predicted as false

However in ayurvedic and homeopathic recommendations and especially in small scale diseases like cold/cough, recall should also been given importance over accuracy as user would need to be presented with a good number of option to choose from as he might have tried other things before. In such a case the following formula could be used for evaluating both accuracy and recall

2pr/(p+r) where

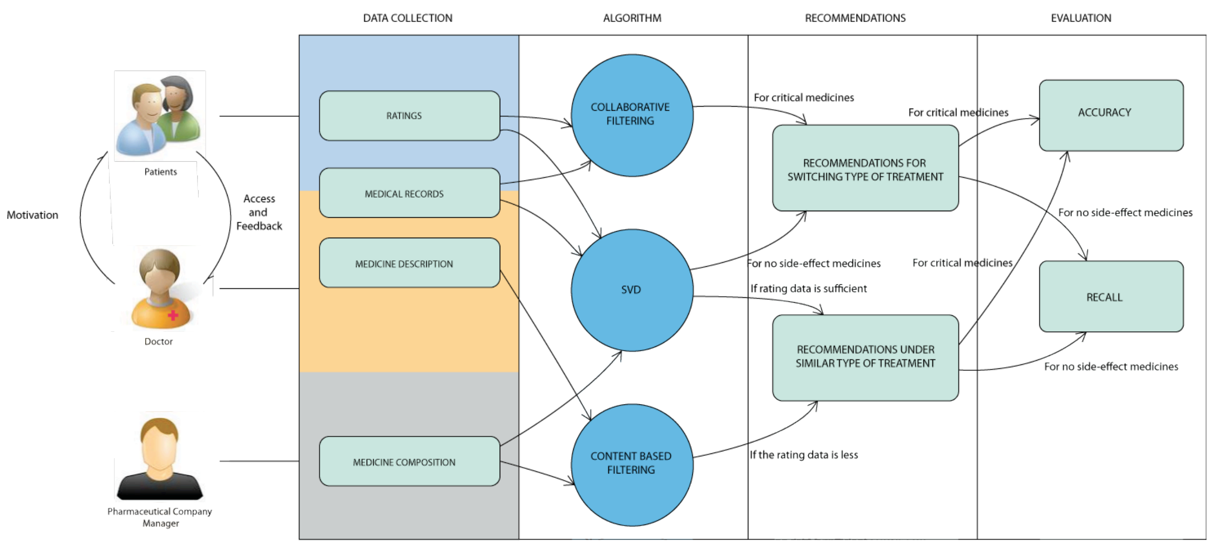
p= precision calculated above

r= recall calculated above

Hence it can be inferred that both side affects of the recommended medicine and type of disease plays an important role in determining the evaluation metrics.

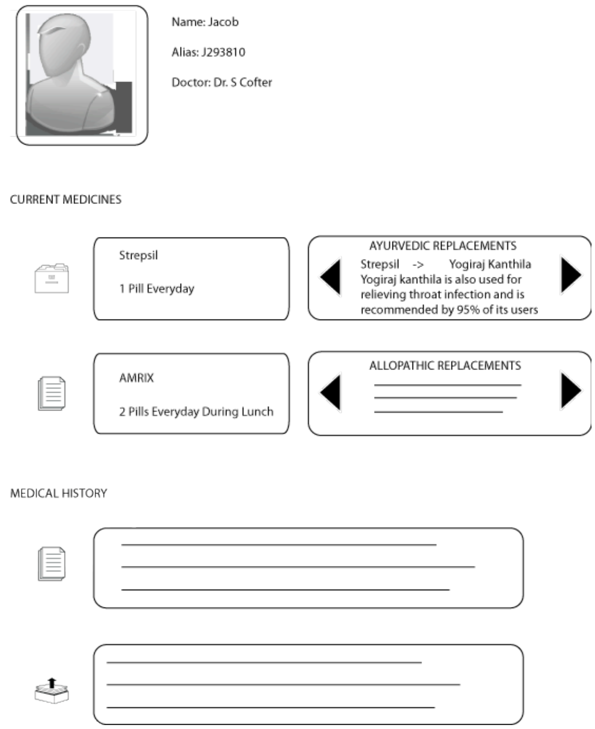
The Proposed System

The following figure represents the architecture of the whole system that has been laid so far.



MEDICINE RECOMMENDER SYSTEM

Figure 2 tries to give insights how the interface of the system is likely to be:



Even after establishing a recommendation system in place, further challenges could arrive even after the system is being implemented. Some of the major challenges to the system are mentioned in the in the next section.

Challenges

Privacy

Although it has been mentioned before that privacy of the users would be imposing a major threat for provide their medical records for collaborative filtering for cross-recommendations. This could be taken care of through hiding the users identity in the system. Also further steps could be taken to improvise the security. For example access rights would remain only with the users for deciding the doctors with whom they want to share their medical records. Notifications about this data through SMS/email would keep them updated about activities going on with their medical record, and also will make their medical notifications seamless.

Attackers

The business model of system would be attracting shilling primary from pharmaceutical and doctors who would try to manipulate it for increasing their business. While pharmaceutical company would be interested in promoting their products and new launches, doctors would be interested in creating multiple fake profiles of their patients for gaining more reputation within the online community.

The first problem could be addressed through “the influence limiter” [3]. The weights for the user ratings can be computed through the degree of informativeness he/she provides to the system. Informativeness could be measured based on the usefulness of the rating he/she provides to a product. The second issue could be addressed through restricting the user to signup only if they have a valid phone number and allowing a single account for one number. Also each of the users could be given options to add not more than two underage patients to the system. More underage patients could be added by requesting the administrator.

Accessibility of the recommendations

Since a good number of patients would be impaired, it is very essential that this medical recommender system is accessible to people with different disabilities.

Feedback

Easy maintenance of medical records would be an incentive to the user for joining the system but there lacks further motivation for feeding ratings for the medicines. In this case the intention of rating in supporting user’s own recommendation could be promoted. Also further motivation could be given to the patients through doctors asking them to rate the medicines and provide feedback online so that the he could monitor his patients regularly.

Conclusion

This paper has uncovered a new domain where recommendations could be applied. It should be noted that a vast difference exists between designing recommender system for medicines and other products. The criticality of medical practice and danger in making a bad decision should be given considered while proposing a design. Also it is very important that doctors and patients readily accept such a system. This paper does not only cover the medical recommender systems but also lay ground for further research work for applying recommender systems in critical domains.

For dealing with privacy related issues, it is very essential to give users assurance that the system would not expose their personal life to someone they do not want to. Further care should be taken that any unauthorized person like doctors are not present in the system nor they violate medical norms by exaggerating their medical profiles.

However, such a system would prove out to be useful in many ways. Not only people who are willing to shift to ayurvedic treatment would get resources but this system would also connect remote patients to appropriate doctors. In time this type of recommender system would have a major impact in improving the health conditions of people.

References

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