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# Personalized Healthcare Recommender Based on Social Media

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***Abstract*— Social media is rapidly changing the nature and speed of healthcare interaction. As more and more people go online to search for their health-related issues, providing them with appropriate information would save them from being overwhelmed by mountains of information. For this purpose, in this paper we propose a personalized healthcare recommending system to recommend highly relevant and trustworthy healthcare –related information to users. The system identifies key factors impacting the recommendation in a healthcare social networking environment, and uses semantic web technology and fuzzy logic to represent and evaluate the recommendation. Experiments were conducted and demonstrated that our approach can generate good outcomes in making recommendation and predicting the scope and impact of different factors.**

***Keywords—recommendation; social network; healthcare; semantics***

## I. INTRODUCTION

Social media are playing an increasingly prominent role in healthcare. Social networks have enabled communication, collaboration and information sharing in the healthcare domain [1]. According to a recent survey, approximately one-third of Americans who go online to research their health problems are using social networks to find fellow patients and discuss their conditions [2, 3]. Thirty-six percent of social network users evaluate and leverage other consumers' knowledge before making healthcare decisions [4]. With the explosion of Web 2.0, application such as blogs, social and professional networks are being developed to enable social networking for healthcare. For example, an online social networking site called *PatientsLikeMe* provides users with tools to track disease progress, and access disease information. Users can also learn from other patients' experience on similar medical conditions, and share their findings with fellow patients, healthcare professionals and industry organizations. Another consumer-directed social site is *MedHelp* which offers a number of tracking tools for pain, weight and other chronic conditions. *CureTogether* is another site that helps people anonymously track and compare health data to better understand their health, make more informed treatment decisions and contribute data to research. *DailyStrength* is also a social networking website centered on support groups, where users provide one another with emotional support by discussing their struggles and successes with each other. The site contains online communities that deal with different medical conditions or life challenges.

Meanwhile, healthcare professionals, hospitals and academic medical centers are diving into social networks: sixty percent of surveyed physicians are interested in using social networks for professional studies [5]; approximately one out of every six U.S. physicians are members of *Sermo*, an online physicians network [6]; and sixty-five percent of surveyed nurses indicate they are planning to use social networks for their work [7, 8].

While the ever increasing information sources and various information types on the social media hold tremendous promise, how to find and select right information becomes critical as users are easily overwhelmed by a vast amount of information. Recommender systems can help users deal with information overload problem efficiently by suggesting items (e.g., information and products) that match users' personal interests. The recommender technology has been successfully employed in many applications such as *Amazon*'s book suggestions, *Netflix*'s movie recommendations, *Pandora*'s music suggestions, *YouTube*'s video recommendations, *Facebook*'s friend suggestions etc.

Although recommender systems have been extensively applied to recommend appropriate products to users in the past decade, recommendation for healthcare-related items is still challenging because of the following reasons. (a) Unlike movies or music, it is rare to see a person vote on different kinds of healthcare items; this creates difficulties for adopting collaborative filtering-based mechanism which only utilize large amount of rating information to generate recommendations. (b) Health-related data and personal profile are very sensitive. People normally would not disclose such information to public or even colleagues and friends; this creates difficulties for adopting classic social network-based recommendation systems that uses friend-of-friend relationship to recommend. (c) People often express their preferences and interests in items/services using linguistic terms, such as ‘‘good’’, ‘‘very good’’, or “bad”. To deal with the aforementioned difficulties and help people to choose the most appropriate products/services to address their health concerns, in this paper we propose an intelligent recommendation system for personalized healthcare. Based on a particular user's profile, this system extract information from the healthcare social media and then applies semantic web technology and fuzzy logic to filter and evaluate the information to make appropriate recommendations.

The rest of the paper is organized as follows. In Section II, we survey the existing work on recommender systems. Section III gives an overview of the system. Section IV describes the details of our semantics-enhanced fuzzy-based

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recommender. Section V discusses the proposed model for providing healthcare-related recommendations for healthcare social networks. We conclude our paper with future work in Section VI.

## II. RELATED WORK

Recommender Systems are a subclass of information filtering system that aim to predict users' preference or ratings for a particular item. Recommender systems have been extensively used in a variety of domains and applications, such as movies [9], books [10], videos [11], news [12], research articles [13], search queries [14], social tags [15], social links/friends [16], and products in general. In general, recommendation systems can be divided into two categories: content-based filtering and collaborative filtering.

Content-based filtering approaches are based on information about and characteristics of the items that are going to be recommended [17, 18, 19]. These approaches try to recommend items that are similar to content that the user has previously viewed or selected. In particular, various candidate items are compared with items previously rated by the user and the best-matching items are recommended. This approach has its roots in information retrieval and information filtering research. For example, a content-based movie recommender will typically rely on information such as genre, actors, director, and producer to match the learned preferences of the user, and recommend related movies to users.

Collaborative filtering has emerged as a key technology adopted by many modern recommendation system [20, 21, 22, 23, 24]. Collaborative filtering is a method of making automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many users (collaborating). The underlying assumption of the collaborative filtering approach is that if a person *A* has the same opinion as a person *B* on an issue, *A* is more likely to have *B*'s opinion on a different issue *x* than to have the opinion on *x* of a person chosen randomly.

Collaborative filtering approaches are often classified as memory-based and model-based. In the memory-based approach, all user ratings are stored into memory. Based on the ratings of these similar users or items, a recommendation can be generated. Examples of memory-based collaborative filtering include user-based methods [25, 26, 27, 28] and item-based methods [29, 30]. In user-based collaborative filtering algorithms, correlations or similarities between user records and the test user are calculated to select a set of nearest neighbors of the test user. Then, these neighbor item ratings are combined to generate recommendations for the test user on unvisited or unrated items. Item-based collaborative filtering approaches attempt to find similar items that are co-rated or visited by different users. Predictions for a target item then can be generated by taking a weighted average of the active user's ratings on these neighbor items. The memory-based methods suffer from the feedback scarcity issue that arises in practice because a typical user may only provide feedbacks for a limited number of items. Model-based approaches alleviate the feedback scarcity problem by generating a global model based on the given training data and use the model to predict the test user's preference on the unknown items. Typical models include aspect models [31], latent factor models [32], Bayesian models [33], and decision trees [34]. A major issue with the existing model-based approaches is their high computational overheads to tune a large number of parameters.

With the explosion of Web 2.0 and the population of crowdsourcing, there has been a tremendous increase in user-generated content. It is now well recognized that the user-generated content (e.g., product reviews, tags, forum discussions and blogs) contains valuable user opinions that can be exploited for many applications [35]. There has appeared research using collaborative filtering, data mining, and trust measurement technology to generate high quality and reliable recommendations. For example, recommendation systems have been increasingly adopted to support decision making by effectively leveraging the social network structure captured by social network sites. [36].

## III. SYSTEM OVERVIEW

First let us use an example to illustrate the rationale behind the methodology. Suppose Alice is overweight and she wants to take some actions to lose weight. Alice has no clue what is an easy and effective way to do that, so she calls a friend she trust, Betty, for some suggestions. Betty used to be overweight as well. Betty once used a diet pill - *SlimVox* and it worked well for her. In addition, Betty knows that her friend Cathy also used this pill. Therefore, Betty highly recommends this pill to Alice. Alice is willing to take Betty's recommendation, so she searches this pill over the Internet and finds that this pill is highly-rated. Therefore, Alice finally decides to try *SlimVox*.

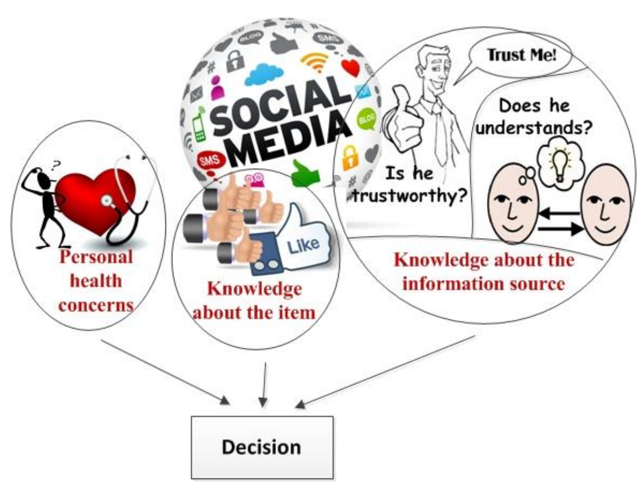


Figure 1. Factors that influence healthcare-related decisions

If we review this example, we will find that at least three factors that contribute to Alice's final decision. The first factor is Alice's concern for her overweight problem. If Alice does not have this concern, she would be less likely to try some diet pills. The second factor is the recommendation from Betty. This factor also include some sub-factors: (a) Betty is not a random friend of Alice. Betty had the same health concern as Alice, so she really understands Alice's problem, and (b) Alice knows she can trust Betty. Interestingly, Betty's opinion is also influenced by people she knows. Finally, the third factor is the public reviews on this product. If the pill received bad reviews, Alice may hesitate to take her friend's suggestion. If we recall decisions that we make in our daily life, such as picking a dentist, choosing healthy food, looking for remedies, or deciding a treatment, many of them are actually influenced by these factors.

Figure 1 further illustrates how these three factors influence a person's healthcare-related decisions. Intuitively, a person's decision on whether or not to accept a healthcare-related recommendation is based on (1) if the recommended item matches the person's health concerns. For example, diet pill for Alice's overweight issue; (2) if the recommender really understands this person's health concern. For example, Betty was also overweight and she understands Alice's concern; (3) if the recommendation is from trustworthy sources, such as from a well-known doctor, or from a close friend, (4) if the recommended item has been recognized by many others, for example, *SlimVox* gets good reviews in the Internet. With such an understanding in mind, we are going to propose a recommender system based on the social influences.

In this paper, we use fuzzy logic model to assist making personalized recommendation. In this model, recommendation is expressed by linguistic terms, such as "highly recommended", "not recommended" rather than numerical values. Fuzzy logic is suitable for recommendation using social media and social relationship as it takes into account the uncertainties of the data (for example, human relationships). People naturally use linguistic expressions when they are asked if they would recommend something. Fuzzy inference copes with imprecise inputs, such as assessments of quality or relevance, and allows inference rules to be specified using imprecise linguistic terms, such as "very knowledgeable" or "not useful". More importantly, as shown in [39], fuzzy-based modeling performs better in combining contradictory information. Recommendation has a certain degree of vagueness and involves truth degrees that one requires to present and reason about. The fuzzy model will be used to collectively analyze and interpret these uncertain values.

## IV. A Fuzzy-based Healthcare Recommender

### A. Identify Factors Contributing to the Recommender.

Our model identified of three important factors which impact the healthcare recommendation in an evolving healthcare social community.

**Trust** to information provider: for personalized healthcare to be truly effective, we need a certain level of trust. Trust is an important factor that determines if a person will take the suggestion given by others. For example, people normally give different trust levels to different users with different roles in a healthcare social network. Based on a recent survey [37], 61% of patients trust information posted by physicians on social media. This was well above the amount who said they are likely to trust drug companies (37%). There has been extensive research on trust evaluation. Adopting our previous social network-based trust model [38, 39], we can evaluate the trustworthiness of a particular user in a healthcare social network based on factors such as role and reputation of the user in the social community.

**Similarity** between information requestor and provider: In an online health social network, one of the striking benefits is the emphasis on common experience among participants [40]. Studies have suggested that perceived similarity is associated with increased levels of affect and trust [41]. In healthcare social networking, people with similar health issues may find it easier to connect with each other, and be more comfortable in sharing factual information and emotional feelings [42]. Moreover, people with similar condition would be viewed more capable and honest in terms of sharing their experience.

As the majority of messages in online health communities are narrative and story-telling, the messages create a multidimensional profile of a patient. To measure the similarity between users, we compare their profiles. Profiles include personal information and users' opinions and ratings of online information. This information can be used to compute how similar two users are. We adopt our previous semantics-based profile similarity metric [43] to measure the similarity between patients and between patients and doctor's expertise. In the context of socialized health care, profile of a user $u$ is basically a vector which may include the user's disease, symptoms, conditions, etc. Assume that the profile of user $u$ can be represented as a vector of keywords $P_u=\{C_1, C_2, \dots C_n\}$. The semantic distance between two concepts $C_a$ and $C_b$ is defined as:

$$dis(C_a, C_b) = \frac{1}{2}\left(\frac{\sum_{i\in \text{path}(C_a \text{ to } C_p)} w_i dis(C_i, C_{i+1})}{\sum_{i\in \text{path}(C_a \text{ to } C_{root})} w_i dis(C_i, C_{i+1})} + \frac{\sum_{j\in \text{path}(C_b \text{ to } C_p)} w_j dis(C_j, C_{j+1})}{\sum_{j\in \text{path}(C_b \text{ to } C_{root})} w_j dis(C_j, C_{j+1})}\right),$$

where $C_p$ is the common ancestor of $C_a$ and $C_b$ in the hierarchical ontology graph, $C_{root}$ is the root of the tree, $C_{i+1}$ is $C_i$'s parent, and $w_i$ is the weight of edge presented as a distance factor. The concept similarity between two concepts $C_a$ and $C_b$ is defined as:

$$sim(C_a, C_b) = 1 - dis(C_a, C_b).$$

Given two profiles $P_x$ and $P_y$, the similarity between the two profiles is defined as:

$$sim(P_x, P_y) = \frac{\sum_1^n \max_{j\in[1,m]} sim(Cx_i, Cy_j)}{n},$$

where $n$ is the number of concepts in profile $P_x$ and $m$ is the number of concepts in $P_y$. If $sim(P_x,P_y)$ is larger than a user-defined similarity threshold $t$ ($0<t\leq 1$), the profile $P_x$ is said to be semantically related to $P_y$.

**Review** or rating of the test item is another important factor affecting user's acceptance of the item. It is a collective measure of the goodness of an item based on the recommendations from other agents. We must understand that our system does not require users of the system to do review or rating on all the items in question. Instead, the review can be collected from anywhere in the Internet. Therefore, the review defined here is quite different from the ratings used in collaborative filtering approaches.

## B. Define Linguistic Variables

The input of the fuzzy model includes the aforementioned key recommendation indicators: (1) trust to information provider, (2) similarity between information requestor and provider, and (3) review of the test item. The output is the goodness of the recommendation.

TABLE I: INPUT AND OUTPUT VARIABLES AND THEIR RANGE

| **Input variable: Trust, *t*** | | |
|---|---|---|
| Value | Notation | Range (normalized) |
| Very Low | VL | [0 0.3] |
| Low | L | [0.15 0.42] |
| Moderate | M | [0.35 0.62] |
| High | H | [0.51 0.82] |
| Very High | VH | [0.69 1] |
| **Input variable: Similarity, *s*** | | |
| Value | Notation | Range (normalized) |
| Very Low | VL | [0 0.33] |
| Low | L | [0.19 0.49] |
| Moderate | M | [0.39 0.72] |
| High | H | [0.51 0.81] |
| Very High | VH | [0.67 1] |
| **Input variable: Review, *w*** | | |
| Value | Notation | Range (normalized) |
| Bad | B | [0 0.3] |
| Unsatisfactory | U | [0.21 0.49] |
| Average | A | [0.34 0.64] |
| Good | G | [0.57 0.83] |
| Excellent | E | [0.69 1] |
| **Output variable: Recommendation, *r*** | | |
| Value | Notation | Range (normalized) |
| Not Recommended | NR | [0 0.4] |
| Recommend | R | [0.25 0.76] |
| Highly Recommend | HR | [0.65 1] |

As we mentioned earlier, the inputs and the output constitute vague estimates rather than crisp values; such vague estimates defined general categories, as opposed to rigid, fixed collections. Valid ranges of the inputs are considered and divided into classes, or fuzzy sets. These categories have more flexible membership requirements that allow for partial membership to a category. The degree to which a value is a member of a category can be any value between 0 and 1. In fuzzy logic, these categories are called fuzzy sets. We cannot specify clear boundaries between classes. The degree of belongingness of the values of the variables to any selected classes is called the degree of membership [44]. Table I lists the input and output variables and their ranges.

## C. Determine Fuzzy Sets

Each fuzzy set has a corresponding membership function that returns the degree of membership for a given value within a fuzzy set. We choose trapezoid-triangle-trapezoid membership function. Figs 2-5 show how we can represent the inputs and outputs by means of membership functions.

## D. Specify Fuzzy Rules

Having specified the recommendation and its indicators, the logical next step is to specify how the recommendation level varies as a function of the factors. Experts provide fuzzy rules that relate recommendation to various levels of indicators based on their knowledge and experience. Below are two example rules used in our fuzzy model:

If (*t* is *VH*) and (*s* is *VH*) and (*w* is *E*) then (*r* is *HR*)

If (*t* is *VL*) and (*s* is *VL*) and (*w* is *B*) then (*r* is *NR*)

Meanwhile, a detailed analysis of the system may enable us to derive more rules that represent complex relationships between variables used in the system. Table II contains these rules. In our system, there are three input and one output variables. For a three-by-one system (three inputs and one output), the representation of the rule metrics takes the shape of a 5*5*5 cube called FAM (fuzzy associative memory). The number of rules has been found to be the key parameter in overcoming problems of over-fitting and generalization arising from uncertainties due to incomplete or non-representative data. For this particular system, the performance indices have shown its best performance compared to two other possible methods of solution – a traditional normal ratio method and artificial neural network (ANN) solution.

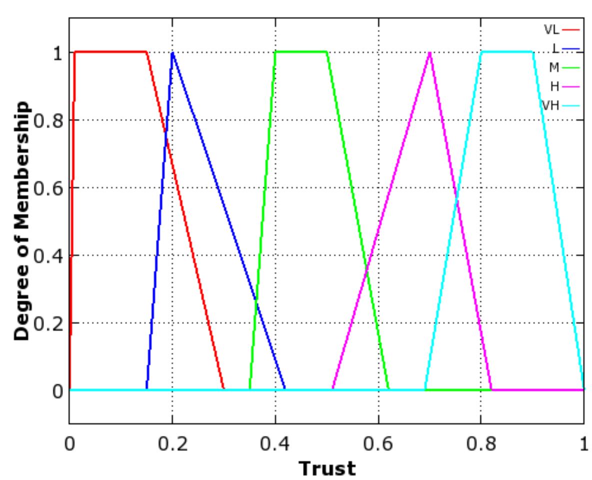


Figure 2. Fuzzy Sets of Trust

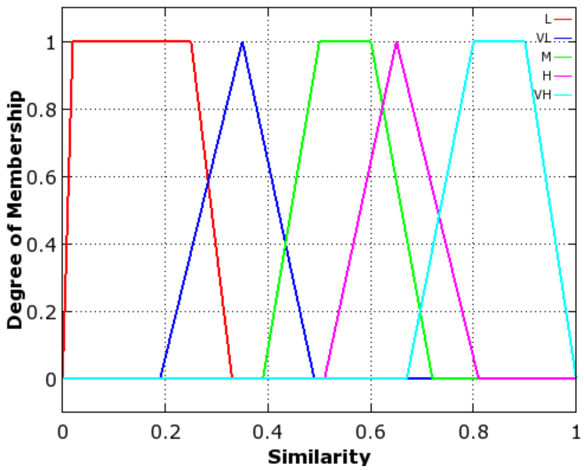


Figure 3. Fuzzy Sets of Similarity

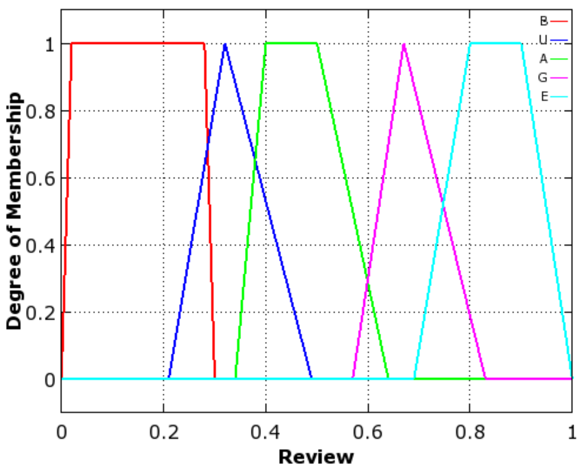


Figure 4. Fuzzy Sets of Review

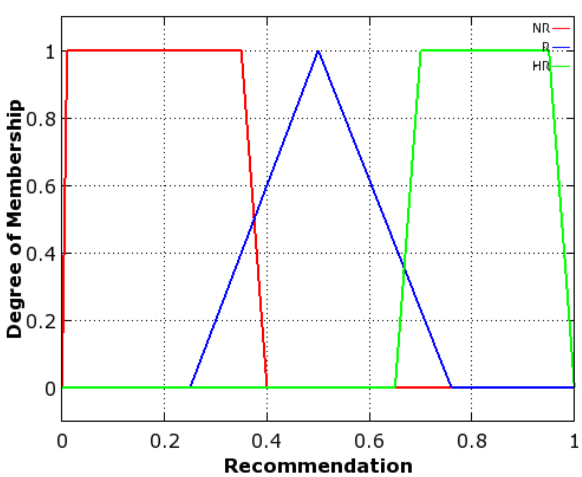


Figure 5. Fuzzy Sets of Recommendation

### *E. Specify Fuzzy Rules*

Having specified the recommendation and its indicators, the logical next step is to specify how the recommendation level varies as a function of the factors. Experts provide fuzzy rules that relate recommendation to various levels of indicators based on their knowledge and experience. Below are two example rules used in our fuzzy model:

If ($t$ is *VH*) and ($s$ is *VH*) and ($w$ is *E*) then ($r$ is *HR*)

If ($t$ is *VL*) and ($s$ is *VL*) and ($w$ is *B*) then ($r$ is *NR*)

Meanwhile, a detailed analysis of the system may enable us to derive more rules that represent complex relationships between variables used in the system. Table II contains these rules. In our system, there are three input and one output variables. For a three-by-one system (three inputs and one output), the representation of the rule metrics takes the shape of a 5*5*5 cube called FAM (fuzzy associative memory). The number of rules has been found to be the key parameter in overcoming problems of over-fitting and generalization arising from uncertainties due to incomplete or non-representative data. For this particular system, the performance indices have shown its best performance compared to two other possible methods of solution – a traditional normal ratio method and artificial neural network (ANN) solution.

TABLE II: RULE LIST

| Rule | Input | | | Output |
|---|---|---|---|---|
| | *t* | *s* | *w* | *r* |
| 1 | VL | VL | B | NR |
| 2 | L | VL | U | NR |
| 3 | M | VL | A | NR |
| 4 | H | VL | G | R |
| 5 | VH | VL | E | R |
| 6 | VL | L | B | NR |
| 7 | L | L | U | NR |
| 8 | M | L | A | NR |
| 9 | H | L | G | R |
| 10 | VH | L | E | R |
| 11 | VL | M | B | NR |
| 12 | L | M | U | NR |
| 13 | M | M | A | R |
| 14 | H | M | G | R |
| 15 | VH | M | E | HR |
| 16 | VL | H | B | NR |
| 17 | L | H | U | NR |
| 18 | M | H | A | R |
| 19 | H | H | G | R |
| 20 | VH | H | E | HR |
| 21 | VL | VH | B | NR |
| 22 | L | VH | U | NR |
| 23 | M | VH | A | NR |
| 24 | H | VH | G | R |
| 25 | VH | VH | E | HR |

### F. *Encode Fuzzy Model and Tune the System*

Lastly, we encode the fuzzy model and tune the system. This could be the most laborious step to evaluate and tune the system to let it meet the requirements specified at the beginning. To build our fuzzy expert system, we use Octave Fuzzy Logic Toolkit [45], a MATLAB-compatible fuzzy logic toolkit. It provides a systematic framework for computing with fuzzy rules and graphical user interfaces.

The fuzzy Logic Toolbox can generate surface to help us analyze the system's performance. We can generate a three-dimensional output surface by varying any two of the inputs and keeping other inputs constant, and observe the performance of our three-input one-out-put system on three three-dimensional plots. Figs 6-8 represent the three-dimensional plots of the system.

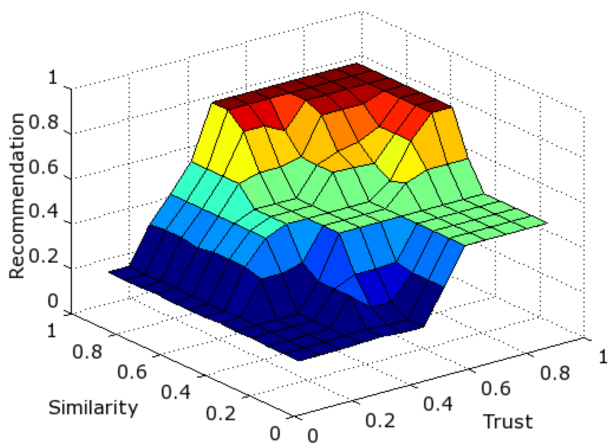


Figure 6. Three-dimensional Plots of Inference Rules in Terms of Trust and Similarity

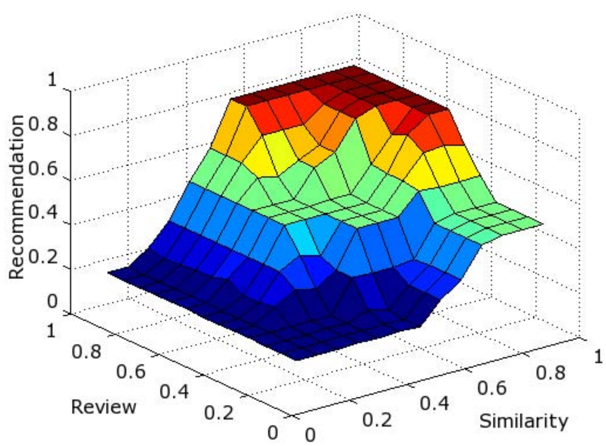


Figure 7. Three-dimensional Plots of Inference Rules in Terms of Similarity and Review

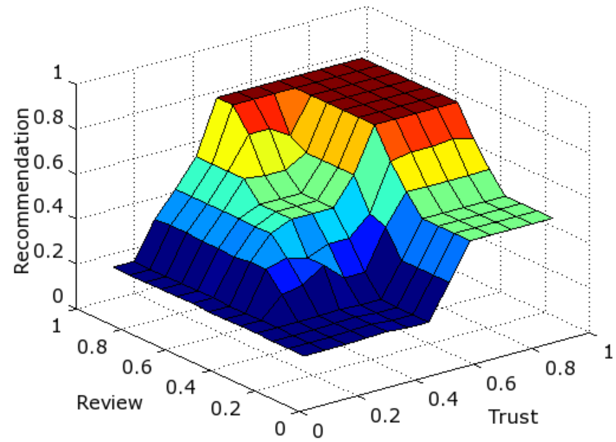


Figure 8. Three-dimensional Plots of Inference Rules in Terms of Trust and Review

## V. USING THE FUZZY SYSTEM TO RECOMMEND

The use of fuzzy model developed in Section IV to determine personalized recommendation in healthcare social network consists of four main steps: Fuzzification, Rule Evaluation, Aggregation, and Defuzzification. In the following, we use an example to illustrate how to use the system to make recommendation. Suppose in a healthcare social network, one patient user with type II diabetes looks for good doctors. Another user in a particular group recommends her doctor to the group. Should this doctor be recommended to the first user? Related to this problem, there are three input variable values: the trustworthiness of the information provider, assuming trust value of the provider is $t_1$ (0.84), the similarity between the provider and patient is $s_1$ (0.8) and the review/rating of the doctor is $w_1$ (0.78).

*Step 1: Fuzzification:* The first step is to take the crisp input, $t_1$, $s_1$, $w_1$, and determine the degree to which these inputs belong to each of the appropriate fuzzy set. For example, the crisp input $t_1$ (trustworthiness of the provider, rated as 84%) corresponds to the membership function $T_1$ (*very high*) to the degree 1, the crisp input $s_1$ (similarity, rated as 80%) maps the membership functions $S_1$ and $S_2$ (*high, very high*) to the degree of 0.08 and 1 respectively and the crisp input $w_1$ (review, rated as 78%) maps the membership functions $W_1$ and $W_2$ of degree 0.29 and 0.82 (*high*, *very high*). In this manner, each input is fuzzified over all the membership functions used by the fuzzy rules.

*Step 2: Rule evaluation:* The second step is to take the fuzzified input $u$ ($t$=$T_1$) = very high, $u$ ($s$=$S_1$, $S_2$) = high, very high, $u$ ($w$=$W_1$, $W_2$) = high, very high and apply them to the fuzzy rules described in the following.

- Rule 1: If *t* is *very high* and *s* is *high* and *w* is *high* then *recommendation* is *very high*.

- Rule 2: If *t* is *very high* and *s* is *high* and *w* is *very high* then *recommendation* is *very high*.
- Rule 3: If *t* is *very high* and *s* is *very high* and *w* is *high* then *recommendation* is *very high*.
- Rule 4: If *t* is *very high* and *s* is *very high* and *w* is *very high* then *recommendation* is *high*.

*Step 3: Aggregation of the rule outputs:* Aggregation is the process of unification of the outputs of all rules. In other words, we take the membership functions of all rule consequents previously clipped or scaled and combine them into a single fuzzy set. Thus, the input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable. If we aggregate the output of the 8 rules mentioned above we will have an aggregated fuzzy output as shown in Figure 9.

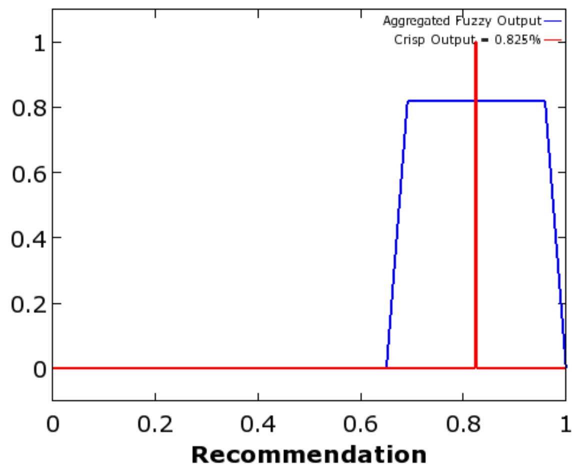

Figure 9. Aggregated Fuzzy output and Crisp output

*Step 4: Defuzzification:* The final output of a fuzzy system has to be a crisp number. The input for the defuzzification process is the aggregate output fuzzy set and the output is a single number. We adopt the most popular method, centroid technique to defuzzifize the output. For example, crisp output z is 0.825 which corresponds *HR* (Highly Recommended).

Through extensive examinations by human experts, the proposed fuzzy approach has demonstrated good performance in generating accurate and realistic outcomes in assessing recommendation and forecasting the scope and impact of different recommendation factors.

## VI. CONCLUSIONS

Healthcare-related social media provide a wide variety of information regarding people's health issues. These information sources are especially valuable to recommender systems. In this paper we presented a social media-based recommender system which makes recommendations by considering a user's own health concerns, the trustworthiness of the information providers, the similarity between the user and the information provider, and the test item's general acceptance in the social media. In particular, we proposed a semantics-enhanced fuzzy-based model to facilitate recommendation. The model consists of three important factors affecting recommendation in healthcare social networking environments: trust, similarity and review. Fuzzy logic is used in the model because it is tolerant of imprecisely defined data and can model non-linear functions of arbitrary complexity. Most importantly, fuzzy logic can accommodate vagueness, intuitive and experiences in modeling recommendation in a healthcare social network, because human observation forms the basis of recommendation assessments. Semantics-based profile similarity metric is adopted to measure the similarity.

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