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Towards Keyword Based Recommendation System

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Abstract: ***Recommender systems have been shown as valuable tools for providing appropriate recommendations to users. In the last decade, the amount of customers, services and online information has grown rapidly, yielding the big data analysis problem for recommender systems. Consequently, traditional service recommender systems often suffer from scalability and inefficiency problems when processing or analyzing such large-scale data. Moreover, most of existing recommender systems present the same ratings and rankings of items to different users without considering diverse users' preferences, and therefore fails to meet users personalized requirements. This project proposes a Keyword based Recommendation method, to address the above challenges. It aims at presenting a personalized recommendation list and recommending the most appropriate items to the users effectively. Specifically, keywords are used to indicate users' preferences, and a user-based Collaborative Filtering algorithm is adopted to generate appropriate recommendations. To improve its scalability and efficiency in big data environment, it is implemented on Hadoop, a widely-adopted distributed computing platform using the MapReduce parallel processing paradigm. Proposed system is used to improve the accuracy and scalability of service recommender systems over existing approaches.***

Keywords: recommender system, preference, keyword, Big Data, MapReduce, Hadoop, Naive Bayes classification algorithm

1. Introduction

In recent years, the amount of data in real world has been increasing explosively, and analysing large data sets—so called "Big Data" becomes a key basis of competition underpinning new waves of productivity growth, innovation, and consumer surplus [1]. Then, what is "Big Data"?, Big Data refers to datasets whose size is beyond the ability of current technology, method and theory to capture, manage, and process the data within a tolerable elapsed time. "Big data" refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze [2]. This definition is intentionally subjective and incorporates a moving definition of how big a dataset needs to be in order to be considered big data—i.e., big data size is not defined in terms of being larger than a certain number of terabytes (thousands of gigabytes).

Today, Big Data management stands out as a challenge for IT companies. The solution to such a challenge is shifting increasingly from providing hardware to provisioning more manageable software solutions [2]. Big Data also brings new opportunities and critical challenges to industry and academia [3],[4]. Similar to most big data applications, the big data tendency also poses heavy impacts on service recommender systems. Every day, people are inundated with choices and options. What to buy? Which book to buy? Where to travel? Which blog post to read? Which movie to watch? And so on. Each of these questions has many alternative solutions. With the growing number of alternative services, effectively recommending services that users preferred have become an important research issue. Service recommender systems are software tools and techniques providing suggestions for items to be of use to user. 'Item' is the general term used to denote what the system recommends to user. Recommender systems have been shown as valuable tools to help users deal with services overload and provide appropriate recommendations to them. Examples of such practical applications include CDs, books, web pages and various other products now use recommender systems [5],[6],[7]. Recommender systems are directed towards individuals who lack sufficient personal experience or competence to evaluate the potentially overwhelming number of alternative items.

Cloud Computing and MapReduce:

Cloud computing is a successful paradigm of service oriented computing and has revolutionized the way computing infrastructure is abstracted and used. The major goal of cloud computing is to share resources, such as infrastructure, platform, software, and business process.

Cloud computing can provide effective platforms to facilitate parallel computing, which has gained significant attention in recent years to process large volume of data. There are several cloud computing tools available, such as Hadoop Mahout, MapReduce of Google [8], the Dynamo of Amazon.com, the Dryad of Microsoft and Neptune of Ask.com, etc. Among these tools, Hadoop is the most popular open source cloud computing platform inspired by MapReduce and Google File System papers, which supports MapReduce programming framework and mass data storage with good fault tolerance. MapReduce is a popular distributed implementation model proposed by Google, which is inspired by map and reduce operations in the Lisp programming language.

Recommender Systems and Collaborative Filtering Recommender systems developed as an independent research area in the mid1990s when recommendation problems started focusing on rating models. In their simplest form, non-personalized recommendations are used. These are much simpler to generate and normally featured in magazines or newspapers recommender systems. Typical examples include the top selection of books, CD's from particular category. While they may be useful and effective in certain situations, these types of non-personalized recommendations are easy to implement but inefficient. To make recommendation more useful to user, personalized

recommendations are offered as ranked list of items. In performing this ranking, recommender systems try to predict what the most suitable products or services are, based on the user's preferences and constraints.

According to the definition of recommender system, recommender system can be defined as system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful services in a large space of possible options. Current recommendation methods usually can be classified into three main categories: content based, collaborative, and hybrid recommendation approaches. Content based approaches recommend services similar to those the user preferred in the past. Collaborative filtering (CF) approaches recommend services to the user that users with similar tastes preferred in the past. Hybrid approaches combine content based and CF methods in several different ways.

CF algorithm is a classic personalized recommendation algorithm, which is widely used in many commercial recommender systems [9]. In CF based systems, users receive recommendations based on people who have similar tastes and preferences, which can be further classified into item-based CF and user-based CF. In item-based systems; the predicted rating depends on the ratings of other similar items by the same user. While in user-based systems, the prediction of the rating of an item for a user depends upon the ratings of the same item rated by similar users. And in this work, user-based CF algorithm is accepted to deal with above mentioned problem.

A. *Motivation*

Over the last decade, there has been much research done both in industry and academia on developing new approaches for service recommender systems [10].With the success of the Web 2.0, more and more companies capture large-scale information about their customers, providers, and operations. The rapid growth of the number of customers, services and other online information yields service recommender systems in "Big Data" environment, which poses critical challenges for service recommender systems. Moreover, in most existing service recommender systems, such as hotel reservation systems and restaurant guides, the ratings of services and the service recommendation lists presented to users are the same. They have not considered users' different preferences, without meeting users' personalized requirements. And many times such recommendations are not useful for the user. [11] And so, there is a need of personalized recommendation system, which will help out the user with the selection of products.

B. *Problem Statement and Objective*

Service recommender systems have been shown as valuable tools for providing appropriate recommendations to users. In the last decade, the amount of customers, services and online information has grown rapidly, yielding the big data analysis problem for service recommender systems. Consequently, traditional service recommender systems often suffer from scalability and inefficiency problems when processing or analysing such large-scale data. Moreover, most of existing service recommender systems present the same ratings and rankings of services to different users without considering diverse users' preferences, and therefore fails to meet users personalized requirements. The project proposes a novel method of personalized recommendation system. In which Keyword-candidate List and Domain Thesaurus are maintained for particular system. Preferences are taken from user. And similar users are searched out by keyword extraction method and similarity calculations. Then the keywords are classified, and weights of reviews of similar users are calculated. Then finally, recommendation list of top-k items is generated.

Chapter 1 contributes an introductory part. Chapter 2 describes literature survey; it includes study of existing system for recommendation, its advantages, disadvantages and limitations. Chapter 3 describes proposed system, its flow and expected results of system.

2. Literature Survey

There have been many recommender systems developed in both academia and industry. An analysis of a number of techniques used to incorporate trust into recommender systems in comparison to standard recommendation algorithms. In this work trust inference formula is used. By measuring Mean Absolute Error, Root Mean Square Error and the prediction coverage and thus analyse the effects of these techniques on three different datasets with increasing numbers of ratings removed. Which showed that trust based systems is more accurate and efficient than traditional recommender algorithm of ratings.

In [12], the authors propose a Bayesian inference based recommendation system for online social networks. They show that the proposed Bayesian inference based recommendation is better than the existing trust based recommendations and is comparable to Collaborative Filtering recommendation. In [9], Adomavicius and Tuzhilin give an overview of the field of recommender systems and describe the current generation of recommendation methods. They also describe various limitations of current service recommendation methods, and discuss possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications. Most existing service recommender systems are only based on a single numerical rating to represent a service's utility as a whole. In fact, evaluating a service through multiple criteria and taking into account of user feedback can help to make more effective recommendations for the users.

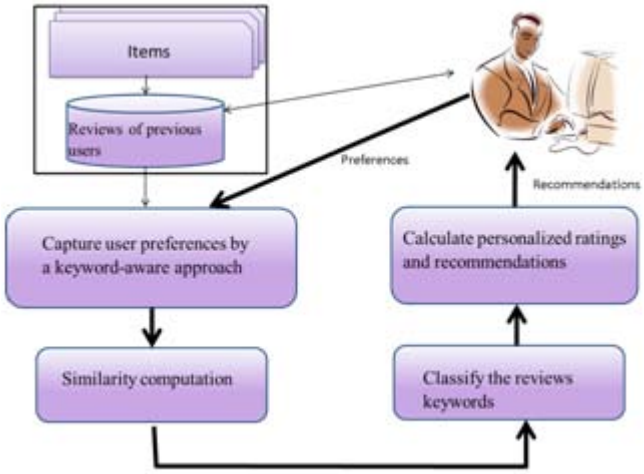
With the development of cloud computing software tools such as Apache Hadoop, MapReduce, and Mahout, it becomes possible to design and implement scalable recommender systems in "Big Data" environment. The authors of [13] implement a CF algorithm on Hadoop. They solve the scalability problem by dividing dataset. But their method doesn't have favourable scalability and efficiency if the amount of data grows. It presents a parallel user profiling approach based on folksonomy information and implements a scalable recommender system by using MapReduce and Cascading techniques. Jin et al. [14] propose a large scale video recommendation system based on an item based CF algorithm. They implement their proposed approach in

Qizmt, which is a .Net MapReduce framework, thus their system can work for large scale video sites.

Moreover, MapReduce has favourable scalability and efficiency. Hadoop MapReduce is a software framework for easily writing applications which process vast amounts of data (multi-terabyte datasets) in parallel on large clusters (thousands of nodes) of commodity hardware in a reliable, fault tolerant manner. A MapReduce job usually splits the input dataset into independent chunks which are processed by the map tasks in a completely parallel manner. The framework sorts the outputs of the maps, which are then input to the reduce task

3. Proposed Recommendation Method

The project proposesa novel method of personalized recommendation system. In which Keyword-candidate List and Domain Thesaurus are maintained for particular system. Preferences are taken from user. And similar users are searched out by keyword extraction method and similarity calculations. Then the keywords are classified, and weights of reviews of similar users are calculated. Then finally, recommendation list of top-k items is generated.



In proposed method, keywords are used to indicate both of users' preferences and the quality of candidate services. A user based CF algorithm is adopted to generate appropriate recommendations. Proposed system aims at calculating a personalized rating of each candidate service for a user, and then presenting a personalized service recommendation list and recommending the most appropriate services to him/her.

Table 1Summarizes the basic symbols and notations used in next algorithms.

Table 1: The basic symbols and notations

Symbol	*Definition*
K	The keyword candidate list, K={k1, k2, …,kn}
APK	The preference keyword set of the active user
PPK	The preference keyword set of a previous user
sim(APK,PPK)	The similarity between APK and PPK
$\overrightarrow{W_P}$	A preference weight vector
$\overrightarrow{W_{AP}}$	Preference weight vector of the active user
$\overrightarrow{W_{PP}}$	Preference weight vector of a previous user

3.1 Keyword Candidate List and Domain Thesaurus

In our method, two data structures, “keyword candidate list” and “specialized domain thesaurus”, are introduced to help obtain users' preferences.

Keyword candidate list: The keyword candidate list is a set of keywords about users’ preferences and multi-criteria of the candidate services [11], which can be denoted as K= 1 where n is the number of the keywords in the keyword candidate list. An example of a simple keyword candidate list of the hotel reservation system is described in Table 2.

Table 2: sample keyword candidate list

No.	*Keyword*	*No.*	*Keyword*
1.	Service	6.	Transportation
2.	Room	7.	Location
3.	Food	8.	Cleanliness
4.	Shopping	9.	Environment
5.	Value	10.	Fitness

Keywords in the keyword candidate list can be a word or multiple words related with the quality criteria of candidate services. In this method, the preferences of previous users will be extracted from their reviews for candidate services and formalized into a keyword set. Usually, since some of words in reviews cannot exactly match the corresponding keywords in the keyword candidate list which characterize the same aspects as the words. The corresponding keywords should be extracted as well. In KASR [11], specialized domain thesauruses are built to support the keyword extraction, and different domain thesauruses are built for different service domains.

Domain thesaurus: A domain thesaurus is a reference work of the keyword candidate list that lists words grouped together according to the similarity of keyword meaning, including related and contrasting words and antonyms.

3.2 User Preferences/ choices

In this step, the preferences of active users and previous users are formalized into their corresponding preference keyword sets respectively. In this method, an active user refers to a current user needs recommendation.

Preferences of an active user: An active user can give his/her preferences about candidate services by selecting keywords from a keyword candidate list, which reflect the quality criteria of the services he/she is concerned about. The preference keyword set of the active user can be denoted as APK= $\{ak_1, ak_2, .., ak_l\}$ where ak_i $(1 \leq i \leq l)$ is the ith keyword selected from the keyword candidate list by the active user, l is the number of selected keywords.

Preferences of previous users:
The preferences of a previous user for a candidate service are extracted from his/her reviews for the service according to the keyword candidate list and domain thesaurus. And a review of the previous user will be formalized into the preference keyword set of him/her, which can be denoted as PPK= $\{pk_1, pk_2, .., pk_h\}$ where pk_i $(1 \leq i \leq h)$ is the ith

keyword extracted from the review, h is the number of extracted keywords.

The keyword extraction process is described as follows:

a) Preprocess

Firstly, HTML tags and stop words in the reviews snippet collection should be removed to avoid affecting the quality of the keyword extraction in the next stage. And the Porter Stemmer algorithm (keyword stripping) is used to remove the commoner morphological and in flexional endings from words in English. Its main use is as part of a term normalization process that is usually done when setting up Information Retrieval systems.

b) Keyword Extraction

In this phase, each review will be transformed into a corresponding keyword set according to the keyword candidate list and domain thesaurus. If the review contains a word in the domain thesaurus, then the corresponding keyword should be extracted into the preference keyword set of the user. For example, if a review of a previous user for a hotel has the word “spa”, which is corresponding to the keyword ``Fitness'' in the domain thesaurus, then the keyword ``Fitness'' should be contained in the preference keyword set of the previous user. If a keyword appears more than once in a review, the times of repetitions will be recorded. In this method, it is regarded that keywords appearing multiple times are more important. The times of repetitions will be used to calculate the weight of the keyword in preference keyword set in the next step.

c) Classify Keywords

When a keyword is captured, it is classified into positive or negative keyword with respect to the meaning of particular word in sentence. For the classification, naive bayes algorithm will be used. Keyword classification is described later in section IV.

d) Similarity Calculation

The second step is to identify the reviews of previous users who have similar tastes to an active user by finding neighborhoods of the active user based on the similarity of their preferences. Before similarity computation, the reviews unrelated to the active user's preferences will be filtered out by the intersection concept in set theory. If the intersection of the preference keyword sets of the active user and a previous user is an empty set, then the preference keyword set of the previous user will be filtered out.

Two similarity computation methods are introduced in our recommendation method: an approximate similarity computation method and an exact similarity computation method. The approximate similarity computation method is for the case that the weights of the keywords in the preference keyword set are unavailable, while the exact similarity computation method is for the case that the weight of the keywords are available.

3.3 Approximate Similarity Computation

A frequently used method for comparing the similarity and diversity of sample sets, Jaccard coefficient, is applied in the approximate similarity computation. Jaccard coefficient is measurement of asymmetric information on binary (and nonbinary) variables, and it is useful when negative values give no information. The similarity between the preferences of the active user and a previous user based on Jaccard coefficient is described as follows:

$$sim(APK, PPK) = Jaccard(APK, PPK) = \frac{|APK \cap PPK|}{|APK \cup PPK|}$$

Where APK is the preference keyword set of the active user, PPK is the preference keyword set of a previous user. And the weight of the keywords is not considered in this approach.

Algorithm 1, SIM-ASC, illustrates the functionality of the approximate similarity computation method.

Algorithm 1: SIM-ASC (Approximate Similarity Computation)

Input: The preference keyword set of the active user APK
The preference keyword set of a previous user PPK_j
Output: The similarity of APK and PPKj, sim_{ASC}(APK, PPK_j)
1: $sim_{ASC}(APK, PPK_j) = \frac{|APK \cap PPKj|}{|APK \cup PPKj|}$
2: return similarity of APK and PPKj, sim_{ASC}(APK, UPK_j)

3.4 Exact similarity computation:

A cosine based approach is applied in the exact similarity computation, which is similar to the Vector Space Model (VSM) in information retrieval.

Preference weight vector: In this cosine based approach, The preference keyword sets of the active user and previous users will be transformed into n-dimensional weight vectors respectively, namely preference weight vector, which can be denoted as $\overrightarrow{W}_P = [w_1, w_2, .., w_n]$, n is the number of keywords in the keyword candidate list,w_i is the weight of the keyword k_i in the keyword candidate list. If the keyword k_i is not contained in the preference keyword set, then the weight of k_i in the preference weight vector is 0, i.e., w_i=0. The preference weight vectors of the active user and a previous user are noted as $\overrightarrow{W}_{AP}$ and $\overrightarrow{W}_{PP}$ respectively.

In KASR method [11], the Analytic Hierarchy Process (AHP) model decides the weight of the keywords in the preference keyword set of the active user. AHP method is provided by Saaty in 1970s to choose the best satisfied business role for its hierarchy nature. The weight computing based on the AHP model is decided as follows:

Firstly, pairwise comparison matrix in terms of the relative importance between each two keywords is constructed. The pairwise comparison matrix QUOTE $A_m = (a_{ij})A_m = (a_{ij})$, where m must satisfy the following properties, a_{ij} represents the relative importance of two keywords:

a_{ij} = 1, i=j=1,2,3..,m

$a_{ij} = {}^{1}/_{a_{ji}}$, i,j =1,2,3..,m and i ≠ j

$a_{ij} = {}^{a_{ik}}/_{a_{jk}}$, i,j , k =1,2,3..,m and i ≠ j

After checking the consistence of the matrix, then calculate the weight by the following function:

$$w_i = \frac{1}{m}\sum_{j=1}^{m}\frac{a_{ij}}{\sum_{k=1}^{m} a_{kj}}$$

Where a_{ij} is the relative importance between two keywords, m is the number of the keywords in the preference keyword set of the active user. The weight vector of the preference keyword set of a previous user can be decided by the term frequency/inverse document frequency (TF-IDF) measure, which is one of the best known measures for specifying the weight of keywords in Information Retrieval.

In the TF-IDF approach, to calculate the preference weight vector of a previous user u', "all reviews" by user u' should be collected. Here, "all reviews" contain the reviews by user u' for the candidate services and similar services not in the candidate services. The reviews should also be transformed into keyword sets respectively according to the keyword candidate list and the domain thesaurus.

TF, the term frequency of the keyword pk_i in the preference keyword set of user u' is defined as

$$TF = \frac{N_{pk_i}}{\sum_g N_{pk_i}}$$

Where N_{pk_i} is the number of occurrences of the keyword pk_i in all the keyword sets of the reviews commented by the same user u', g is the number of the keywords in the preference keyword set of the user u'. The inverse document frequency (IDF) is obtained by dividing the number of all reviews by the number of reviews containing the keyword pk_i.

$$IDF = \log\frac{|R'|}{|r' : pk_i \in r'|}$$

where |R'| is the total number of the reviews commented by user u', and |r': pki∈ r'| is the number of reviews where keyword pk_i appears. So the TFIDF weight of the keyword pki in the preference keyword set of user u' can be decided by the following function:

$$w_{pk_i} = TF * IDF = \frac{N_{pk_i}}{\sum_g N_{pk_i}} * \log\frac{|R'|}{|r' : pk_i \in r'|}$$

Then the similarity based on the cosine-based approach is defined as follows:

$$sim(APK, PPK) = \cos(\vec{W}_{AP}, \vec{W}_{PP}) = \frac{\vec{W}_{AP} \bullet \vec{W}_{PP}}{\|\vec{W}_{AP}\|_2 \times \|\vec{W}_{PP}\|_2}$$

$$= \frac{\sum_{i=1}^{n} \vec{W}_{AP.i} \times \vec{W}_{PP;i}}{\sqrt{\sum_{i=1}^{n} \vec{W}^2_{AP,i}}\sqrt{\sum_{i=1}^{n} \vec{W}^2_{PP,i}}}$$

Where $\vec{W}_{AP}$and $\vec{W}_{PP}$ are respectively the preference weight vectors of the active user and a previous user. $\vec{W}_{AP.i}$is the ith dimension of $\vec{W}_{AP}$ and represents the weight of the keyword k_i in preference keyword set APK, $\vec{W}_{PP;i}$ is the i-th dimension of $\vec{W}_{PP}$ and represents the weight of the keyword k_i in preference keyword set PPK. Algorithm 2, SIM-ESC, illustrates the functionality of the exact similarity computation method.

Input: The preference keyword set of the active user APK
The preference keyword set of a previous user PPKj
Output: The similarity of APK and PPKj, sim_{ESC}(APK, PPKj)
1. for each keyword ki in the keyword-candidate list
2. if ki ϵ APK then
   Calculate $\vec{W}_{AP,i}$
3. Else
   $\vec{W}_{AP,i} = 0$
4. End If
5. if ki ϵ PPK then
   Calculate $\vec{W}_{PP,i}$
6. Else
   $\vec{W}_{PP,i} = 0$
7. End if
8. End for
9. Calculate sim_{ESC}(APK, UPKj)
10. Return the similarity of APK and PPKj, sim_{ESC}(APK, UPKj)

3.5 Generate Personalized Recommendation List

Based on the similarity of the active user and previous users, further filtering will be conducted. Given a threshold δ, if sim(APK, PPK_j) <δ , the preference keyword set of a previous user PPKj will be filtered out, otherwise PPKj will be retained. The thresholds given in two similarity computation methods are different, which are both empirical values. Once the set of most similar users are found, the personalized ratings of each candidate service for the active user can be calculated. Finally, a personalized service recommendation list will be presented to the user and the service(s) with the highest rating(s) will be recommended to him/her.

Here, a weighted average approach is used to calculate the personalized rating pr of a service for the active user.

$$pr = \bar{r} + k\sum_{PPKi \in \hat{R}} sim(APK, PPKj) \times (rj - \bar{r})$$

Where $k = 1/\sum_{PPKi \in \hat{R}} sim(APK, PPKj)$

Where sim(APK, PPK) is the similarity of the preference keyword set of the active user APK and the preference keyword set of a previous user PPK_j ; multiplier k serves as a normalizing factor; $\hat{R}$denotes the set of the remaining preference keyword sets of previous users after filtering; r_j is the rating of the corresponding review of PPKj, and r is defined as the average ratings of the candidate service.

Repeating the steps above, the personalized ratings of all candidate services for the active user are calculated. Then rank the services by the personalized ratings and present a personalized service recommendation list to him/her. Without loss of generality, it is assumed that the services with higher ratings are more preferable to the user.

4. Results

Expected results will include, most appropriate recommendation list. For simplification of expected results, some assumptions are made.

1) All keywords have same weight.
2) Weight of positive keyword is assumed to be +1.

3) weight of negative keyword is assumed to be -1.
Example: let's consider the following review for mobile phone model.
Preference keyword set of user: light sensor, battery backup, gesture sensor, internet speed, LED display

- **Review:** Overall performance is good..... Quad-core processor makes it superfast. I am amazed to see that this phone give me battery backup of 2 days but it don't have light sensors, gesture sensor and also its internet speed is only 21.1mbps which is slow compare to other smartphones at this price.
- **Keywords captured:** performance, processor, battery backup, light sensors, gesture sensor and internet speed

4.1 Output of existing System

5 keywords are extracted from particular review. And amongst them, 4 keywords matches with active user's preferences. It implies that weight of particular product is +4. So, there are more chances that the product will likely to fall in recommendation list.

4.2 Output of proposed System

The above review consists of 5 keywords. From these 5 keywords, 4 keywords match with user preferences. But by checking the sentences structure, one can easily find out the sense behind keyword use. On this basis, keywords are classified into positive and negative keywords

Classification of keywords:
Positive keywords: performance, processor, battery backup
Negative Keywords: light sensors, gesture sensor, internet speed
The weight of review = (+1) – (3) = (-2)

With this weight factor, there is not any chance that product will be recommended to user. In this way, a more personalized and appropriate recommendation list is generated for user. So, as per new method, output of recommendation system will be more personalized and efficient for user. And by parallelizing algorithm processing, system will be more time efficient, than existing system.

5. Conclusion

The proposed system is more efficient in terms of complexity. And the system gives more accurate results or recommendations to the users. This system is being developed for products based on amazon data set.

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