THE DESIGN OF MUSIC RECOMMENDER SYSTEM BY USING USER-BASED COLLABORATIVE FILTERING METHOD

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ABSTRACT

Recommender system is an aplication model from the results of an observation towards users' condition and desire, therefore recommender system needs an appropriate recommendation model so the recommendations fit the users' desire. Recently, music industries experienced a significant change. Consumers tend to access and buy contents by online, compared to go to a store, this is obviously triggers very fast data development problem on the internet so it causes too many information available.

On this research recommender system is analyzed and built by using user-based collaborative filtering method, since by this algorithm it involves user subjectivity so that the recommendations which are created have a good quality. However, this user-based collaborative filtering method still has a weakness which is the existence of scalability (a condition where there is a high number of users and items increase on the database) and sparsity (the void of data matrix user-item occurrences). Therefore, it is needed to use additional algorithm which is K-Means clustering and smoothing process which aim to handle those two major problems.

Based on the implementations and test results, we could conclude that based on the use of user-based collaborative filtering method, this algorithm could handle the void of data with sparsity level as much as 70%. However, for the final result from this testing method, it used MAE (Mean Absolute Error) which have the range of values from 0 – 1, and the result is 0,6713 which means the use of this method generate values more than 0,5, then it is concluded that this method is still less accurate, so it is needed to use the other algorithms which is more accurate or generate values no more than 0,5.

Keywords : Recommender System, User-based collaborative filtering.

1. INTRODUCTION

The music industry recently experienced a very significant change. Consumers now tend to access and buy content online than go to a store, it is obviously raises issues of data growth very quickly on the Internet cause too much information available. This causes a person to experience difficulty in obtaining information about the music quickly and as needed. It required a recommender system that can help a person find music information according to their needs (Saptariani, Trini. 2014).

In this study the recommender system will be analyzed and constructed using user-based collaborative filtering algorithm because it involves the user subjectivity in the calculation so that the resulting recommendations have a good quality. But the method of user-based collaborative filtering it still has the disadvantage that it is :

1. Scalability, which is a state where a high number of user increase and the items in the database that affect computational algorithms declining user-based collaborative filtering.
2. sparsity, ie the data gaps user-item matrix, due to rate a user in a small amount of the number of items available in the database.

Therefore it is necessary to use additional algorithms yaiitu K-Means clustering and smoothing process which aims to address the two major problems. Music recommender system is built on the web platform, with consideration of software that is built must have the ability to handle many users.

Based on the above the problems that occur, then the system hope these recommendations will help and provide information about the music that is appropriate for the user.

2. THEORETICAL BASIS

2.1 *Information Retrieval* dan *Information Filtering*

The rapid development of the Internet indirectly provide the ability for users to choose among a lot of information available on the internet. This information can be related to their profession, events in the world, or even information related to lifestyle. Information needed by Internet users is constantly increasing and this could be coming from a variety of

different sources. For example through web pages, email, articles, newsletters, journals, shopping sites, and multimedia sites. These developments lead to information explosion in cyberspace that complicate the user in finding a quick and relevant information. This problem is the reason developed several techniques for information retrieval and information filtering (Mortensen, Magnus. 2007).

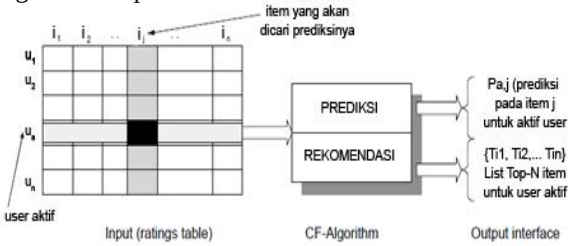
2.2 *Recommender System*

Recommender System is an information filtering applications to locate and provide recommendations in the form of items of information, products or services to users based on predictions that are personal (Sarwar, Badrul. 2001). Recommender system development by various online vendors is a step to attract more attention of users and improve user satisfaction on the results of the search for information online. On e-commerce, for example, where the system is used extensively recommendations to suggest products to customers and to provide customers with information to help customers decide which products will be purchased option (Mortensen, Magnus. 2007). It has become very important to the success of the industry in the field of information technology and e-commerce today that gradually bring benefits in terms of popularity in various applications such as Netflix project, Google News, and Amazon.

Recommendation system built with the aim of helping the user to select items that likes of the many items available. Search techniques recommended items that will be carried out based on similarity, resemblance could be an item with other items, based on the content or similarity of tastes of a user to another user based on the rating given on the item.

2.3 *Collaborative FilteringAlgorithm*

Collaborative filtering (CF) is a recommender system technology the most successful and popular today, as well as the use of CF is very successful for various recommender systems on the Internet. This technique uses statistical techniques to find a set of users, known as neighbors, where each user has the same interests and opinions with the target user (ie, they have a few rating the same item or user tendencies like the same item). After neighbors formed environment, the system will use some algorithm to produce a recommendation.



Picture 2.1. Collaborative Filtering process (Sarwar, Badrul. 2001).

In the scenario, a list of user m CF user U = {u1, u2, ..., um} and a list of items I = {p1, p2, ..., pn}. Each user ui express his opinion on a list of items. Set of the set of that opinion referred to the rating of the user ui and denoted with IUI. Once the system is determining the nearest adjacency, then the system will continue to represent an item which may be preferably user in two forms, namely:

1. Prediction, is a numeric value where Pa, j is the predicted value j rating of items that might be favored by active user (Ua). This predicted value is used with the same scale with the value provided (eg, on a scale of 1 to 5).
2. The Recommendation is a list of N items that may be preferred by the user Ua. Recommended list usually consists of items that have been purchased or rated by the active user. The output of the CF algorithm is also known as the Top-N Recommendation.

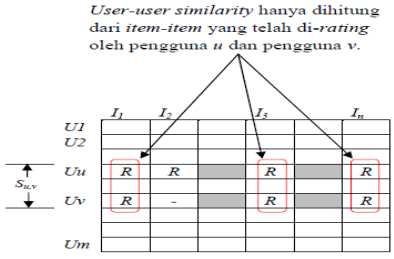
Figure 2.1 shows the schematic diagram of the process of collaborative filtering. CF algorithms represent all mxn as user-item rating matrix where each entry is a value rating of the user for each item. Active users (Ua) in this scheme is that users will look for items that might be preferred by using algorithms CF (Sarwar, Badrul. 2001)

2.4 *User-Based Collacborative Filtering Method*

User-based Collaborative filtering uses statistical techniques to find a set of users, known as neighbors (neighbor), which has a history agrees with the target users. Having a set of neighbor formed, the system uses different algorithms to combine favorite neighbors to generate predictions or recommendation N-top for the active user. (Sarwar, Badrul. 2001).

Friendly approach based on collaborative filtering systems provide recommendations to the user preferred items or user-rated by other users who have a lot of similarities with it. For example, a user likes or rate the items 1, 2 and 3, then the user b liked items 1, 2 and 4, the system will merekomedasikan item 3 to the user b and item 4 to a user.

Pendekantan the advantages of user-based collaborative filtering is able to produce a good quality recommendations. Here is a user-based collaborative filtering scheme.



Picture 2.2 The pattern of user-based collaborative filtering (Sarwar, Badrul. 2001).

2.4.1 *K-Means Clustering Algorithm*

The algorithm used in the formation of the cluster user is K-means algorithm. K is the number of inputs used an algorithm to determine how much the number of clusters to be formed. The steps of the K-means clustering are as follows (Xue, Gui-Rong, 2005):

1. Determine some user k is used as a centroid.
2. Any user who is not a centroid compared to the nearest centroid based on the similarity.
3. Calculation birthday centroid value based on the average value of a collection of users in each cluster is formed.
4. Make the process of reshaping the cluster centroid new value until the value is stable or approaching centroid centroid previous value.

Value centroid similarity between the user and the other user-defined using the Pearson correlation coefficient, is as follows:

$$Sim_{u,u'} = \frac{\sum_{t \in T(u) \wedge T(u')} (R_u(t) - \overline{R_u}) \cdot (R_{u'}(t) - \overline{R_{u'}})}{\sqrt{\sum_{t \in T(u) \wedge T(u')} (R_u(t) - \overline{R_u})^2} \sqrt{\sum_{t \in T(u) \wedge T(u')} (R_{u'}(t) - \overline{R_{u'}})^2}} \quad (2.1)$$

2.4.2 *Smoothing Data*

Sparsity is fundamental problems that exist in collaborative filtering, applying a smoothing of data on the system CF then this problem can be minimized. Smoothing is done by filling in the missing value in the dataset with shadow rating.

2.5 *Mean Absolute Error* (MAE)

Mean Absolute Error is an equation that includes the type of statistical accuracy metrics, where MAE is the most commonly used metrics for the measurement accuracy of recommender system. As the name implies, MAE calculate the value of the average difference between the predicted value with the actual value (Xue, Gui-Rong, 2005). MAE own values, ranging from 0 to 1. The smaller the value MAE indicates the accurate prediction rating value of a recommender system (Xue, Gui-Rong, 2005).

$$MAE = \frac{\sum_{u \in T} |R_u(t_j) - \widetilde{R_u}(t_j)|}{|T|}$$

3.1 Analysis Systems

Analysis system can be defined as the decomposition of a system whose whole into its component parts with a view to identifying and evaluating problems-problems, opportunities, barriers that occur and needs that are expected to be proposed improvements. Analysis can also be interpreted to understand the complex system of thought by breaking it down into elements more simple so that the relationship between the elements it becomes clear.

As the analysis of the current system, will discuss how the procedures were or were already running on the system earlier. Analysis of functional systems covering the data needs analysis, and modeling system that will be described in the form of charts and analysis of non-functional system that includes hardware needs analysis, requirements analysis software is used and the analysis of user needs.

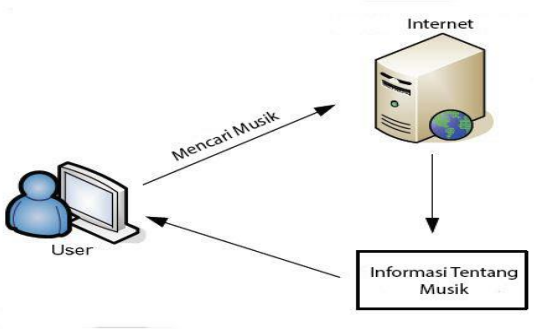
3.1.1 Problem Analysis

Based on the system analysis of the problem in this study, the analysis of the problems found are as follows:

1. As the development of the music industry these days consumers are now more likely to buy / looking for music content online than went to a store.
2. Search music today mostly only put emphasis on a tagging or labeling alone.
3. By varying levels of knowledge about the musical information of each user then dibutuhkanya a recommendation system that will be able to provide information personal music.

3.1.2 Similar analysis of other research.

The music industry recently experienced a very significant change. Consumers now tend to access and buy content online than going to a store. Examples of other music subscription services between iTunes Radio, Grooveshark, Pandora, Spotify, and Google Play Music All-Access. For locally based services, Guvera provide similar services. Services - these services have in common is a search feature songs by tagging or labeling which is stored as additional information on each song and emphasis to the search feature. (Saptariani, Trini. 2014) so that the user will get general information / not personal.



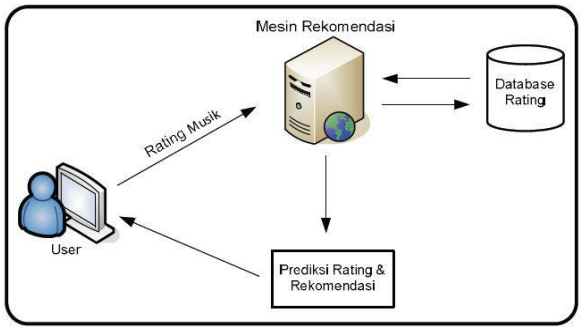
Picture 3.1 Analysis of similar studies.

(Saptariani, Trini. 2014).

3.1.3 Analysis System To Be Built

Music Recommender System is a web-based application that aims to provide music recommendations based on the rating that may be

preferred by the user. This system also facilitates the user to provide a specific rating to the music in it. Therefore, the provision of a personal rating value is done, then the recommended music will also be given personally. Simply put, a user is very possible to have the results of different recommendations with other users.



Picture 3.2 Flow System To Be Built.

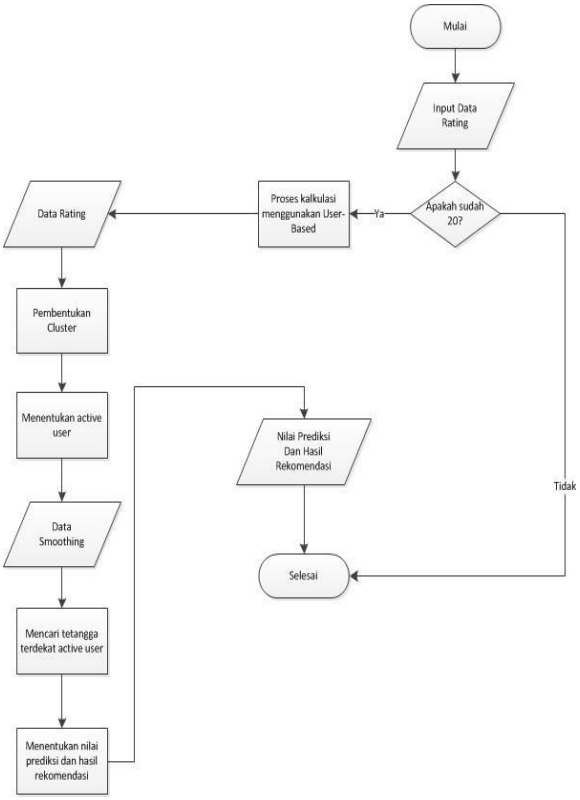
(Saptariani, Trini. 2014).

Basically this system has for the music data in the rating by the user. While the ratings data used were obtained from user rating enrolled into the system. Based on the rating, the system will perform calculations by using algorithms on the method of User-Based Collaborative Filtering to give recommendations.

Methods User-Based Collaborative Filtering group various users who have a very high similarity in some clusters with K-means clustering algorithm. The purpose of the application of clustering algorithm is to address the issue of scalability that is, the current state of the high number of improved user and the items in the database rating that affects the decrease computational algorithms Collaborative Filtering, this method utilizes the process of smoothing to reduce the problem of sparsity, ie a vacuum in the data matrix-friendly items due to rate a user in a small amount of the number of items available in the database. To calculate the level of accuracy and quality of the music recommender system is to use the calculation of MAE (Mean Absolute Error). As the name implies MAE calculating the difference in value between the predicted value with the actual value (Xue, Gui-Rong, 2005).

3.1.4 Analysis User-Based Collaborative Filtering

Application of the method User-Based Collaborative Filtering is done in several stages. Implementation of User-Based Collaborative Filtering can be seen in picture 3.3 below :



Picture 3.3 Flowchart Application User-Based Collaborative Filtering

3.1.5 Modeling System

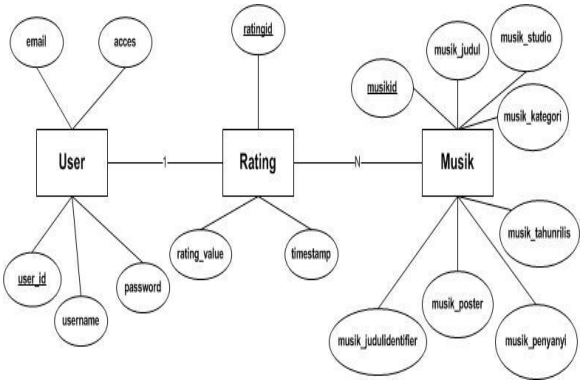
At this stage, the modeling system to determine the functions that can be performed by the system and determining the class required for the realization of system functions that have been previously analyzed and described it in the form of a diagram.

3.1.6 Analysis Database

The database, or often called database is one of the important components in computerized information systems. Analysis of the data base used to model and link relationships among the data.

3.1.6.1 Entity Relationship Diagram (ERD)

Entity Relationship Diagram (ERD) is used to systematically describe the various entities and components of data the system and the relationship between each of these entities. To see the connectedness between entities are then described as follows :



Picture 3.4 *Entity Relationship Diagram*

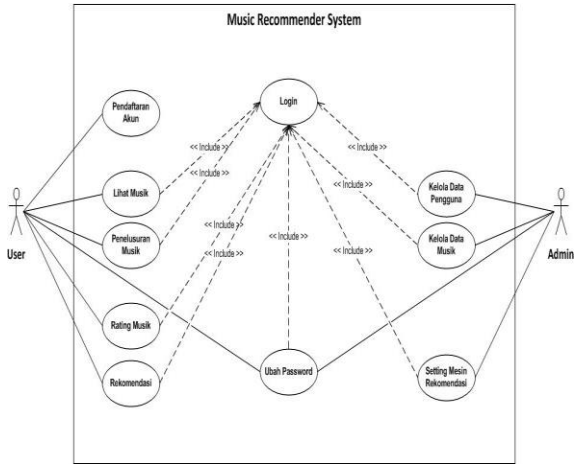
A. *Use Case* Diagram

Use Case diagram is a description of the function of a system and a user perspective. The diagram also describes what will be done by the system. Use Case consists of three parts, namely the identification of actors, identification and the Use Case Use Case scenario.

1) Identification of Actors

To identify the actors, must be determined division of labor and tasks associated with the role in the system. Actor in a use case diagram music recommender application consists of two actors, namely user and admin. User is an actor who uses the frontend application, where actors can interact with the system such as registering an account, see the details of the music, browse through music lists, change passwords, rate the music, and obtaining the recommendation. While the administrators of an actor who can manage user data and music data, change passwords, and can set up the number of clusters in the system.

2) Identification Use Case

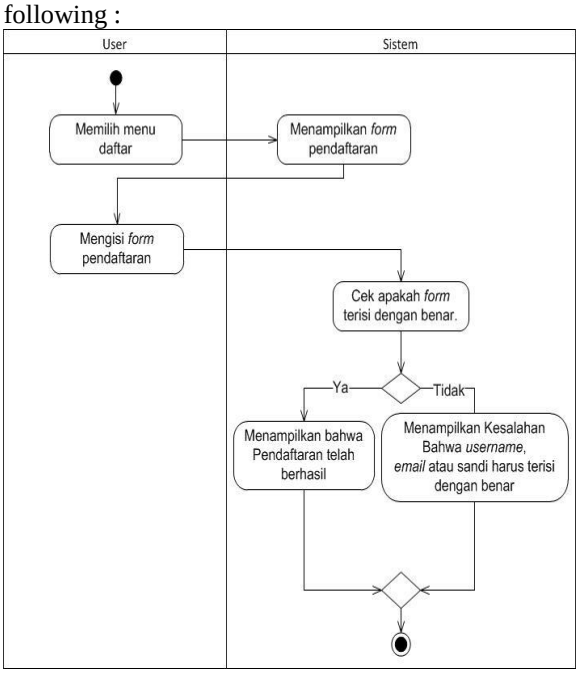


Picture 3.5 Use Case Diagram

B. Activity Diagram

Activity diagram is a diagram that describes procedural logic, business processes and work flows in many cases. Activity Diagrams such as flowcharts have a role, but the difference with the flowchart is a diagram activity can support parallel behavior while flowchart can not. Activity diagrams model the events that occur within a Use Case and used for modeling the dynamic aspects of the system

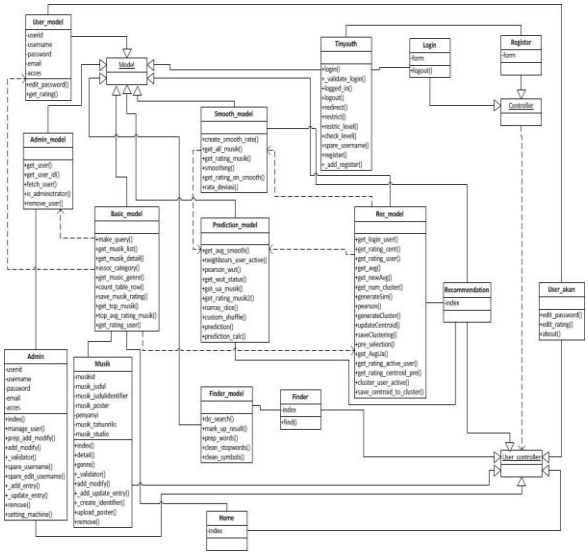
Activity Account Registration diagram describes the activities of actors in registering / user data input into the system. Pendafrataran Account Activity diagrams can be seen in Picture 3.6. The following :



Picture 3.6 Activity Diagram Account Registration

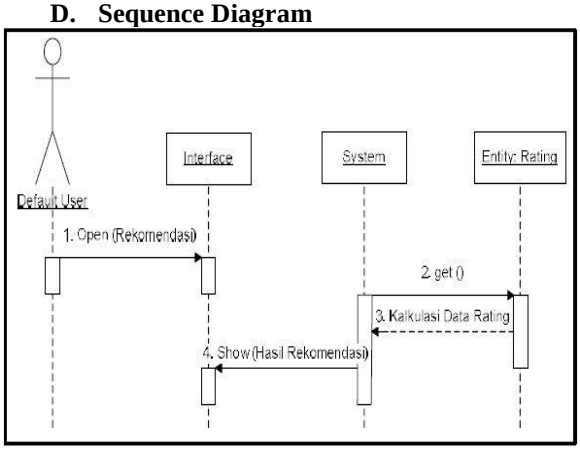
C. *Class Diagram*

Class diagrams describe the state of a system to explain the connection between a class with another class that is contained in the system. Class diagrams are static in the class diagram illustrated relation of each - each class but it does illustrate what happens when the class is related.



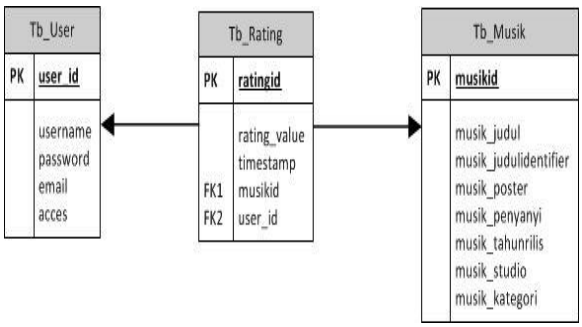
Picture 3.7 Class Diagram

D. Sequence Diagram



Picture 3.8 Sequence Diagram Recommendation

3.1.7.2 Relation Scheme



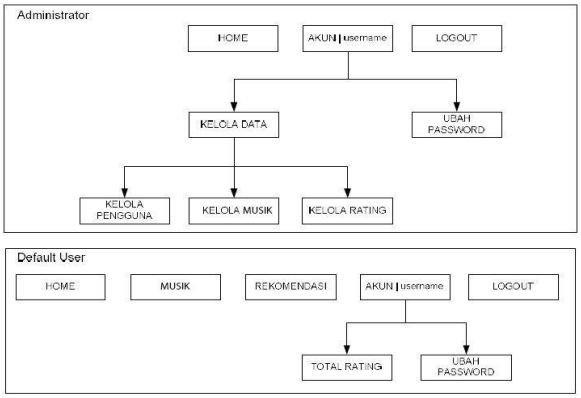
Picture 3.9 Relation Scheme

3.2 System Design

System design aims to specify the technical aspects of the solution in the planning. At this stage of the design will be defined in detail to address the problems more technical, relating to the implementation of activities such as database design and interface design.

3.2.1 Menu Structure

Music recommender system on this, there is a menu on the page after the user enters through the verification process, the following is the menu structure on a system that can be seen in Picture 3.10 below :

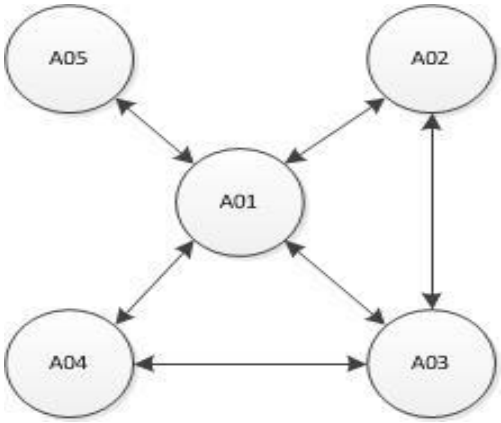


Picture 3.10 Menu Structure

3.2.2 Semantic Network

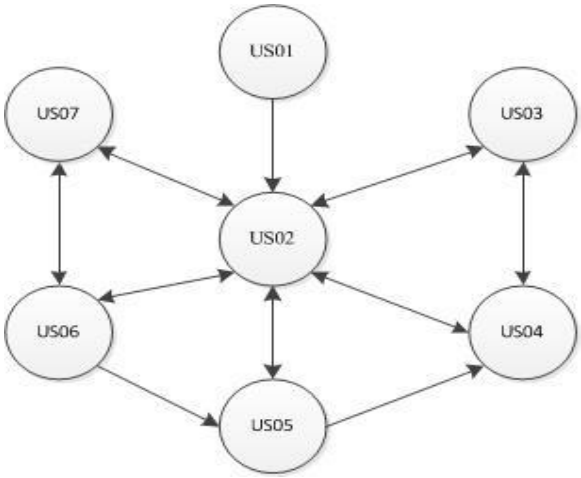
Semantic network is a network of data and information, which shows the relationship between the various objects. Here is a semantic network of music recommender system :

1. Semantic Network Admin



Picture 3.11 Semantic Network Admin

2. User Semantic Network



Picture 3.12 User Semantic Network

4.1. Hardware Requirement

Needs hardware used to implement the application program that is built can be seen in Table 4.1 below :

Table 4.1 Hardware Requirement

	Hardware	Specification
1	Processor	Intel i3
2	Monitor	Monitor 15 inch
3	Memory	DDR3 1Gb
4	Keyboard	Standart
5	Mouse	Standart
6	Modem	Standart

4.2. Software Requirement

The software used to implement this application can be explained in Table 4.2. below :

Table 4.2 Software Requirement

No	Software	In Use
1	Operating System	Windows 7
2	Programming language	PHP
3	Database Server	MySQL
4	Web Browser	Google Chrome and Mozila Firefox
5	Code Editor	Adobe Dreamweaver CS 6 dan Notepad ++

4.3 Testing

4.3.1 Testing With Blackbox

Phase of system testing is performed to determine whether the results of the implementation of the software has been running as expected.

4.3.1.1 Conclusion Results of Testing System Using Blackbox

Based on the results of system testing that has been done can be concluded that the application is built has been run in accordance with the initial design and run quite optimal, but did not rule out errors may occur, when the application is used, whether it was a mistake on the devices used, user error, or other errors. Thus requiring the treatment process and checks (maintenance) to keep an application running as expected.

4.3.2 Testing Level Accuracy Using MAE

Testing the accuracy of the data is done by taking a sample as many as 1,063 examples of the rating total rating that has been collected which amounted to 1,403 examples. The data sample used in this study had to meet the criteria for rating the data that comes from users who have a minimum of 20 rate the music to a maximum rating of each user are 30 music.

4.3.2.1 Accuracy Level Test Plan Using MAE

The first stage of testing the accuracy rate is to halve the existing dataset to 80% for training data and the remaining 20% as test data. Testing accuracy rate is calculated based on 3 parameters of the test is based on the number of clusters, k number of neighbors, and the level of sparsity. At each test parameters will be conducted the experiment as much as 5 times. The equation used to calculate the level of accuracy is the equation (2.9). Here's a testing procedure for each of the parameters used :

1. Based on the number of clusters
   The testing process is done for every cluster that has been determined, the cluster numbered 2, 3 and 4 cluster cluster. Number of k-neighbors used for each test parameter cluster is as much as 50%.
2. Based on the number of K-neighbors
   The testing phase is done by determining the percentage of the number of nearest neighbors of active users. Number of k-neighbors users who tested is taken from users who have a large degree of similarity to the active user that is as much as 30%, 50% and 70%. Number of clusters is used as much as 3 cluster.
3. Based on the sparsity
   Tests on samples of data will be selected ratings data to be emptied at random with sparsity level as much as 30%, 50% and 70%. Sparsity problem is a problem that often occurs in collaborative filtering, for it was through this testing will be seen how much influence the emptying of scores on ratings data or the data sparse state to the value of the prediction accuracy of the system. Testing is set to cluster number 3 and number k as 50%.

4.3.2.2 Level Accuracy Test Results

After testing with some parameters, then the test results for each parameter value MAE level of accuracy is obtained as follows :

1) Based on the number of clusters

Table 4.4 MAE based on the number of clusters

Jumlah *Cluster*	Percobaan ke-					Rata-rata
	I	II	III	IV	V	
2	0,6969	0,7088	0,7192	0,6634	0,6716	0,6919
3	0,6519	0,6894	0,6994	0,6429	0,6732	0,6713
4	0,7247	0,7601	0,7237	0,9584	0,7436	0,7821

Table 4.4 shows the test results in a database for a number of clusters that have been set at 2, 3 and 4 clusters. In this test it is known that the 4th iteration with the cluster number = 3 is a test with the lowest MAE value is 0.6429, while on the 4th iteration the

number of clusters = 4 was recorded as the test with the highest MAE value.

Of the average calculation MAE third cluster number is found the number of clusters = 3 is the producer of the smallest MAE value is 0.6713 and the resulting MAE value of 5 times of testing tends to be stable. In testing the number of clusters = 4 that divides the dataset into 4 clusters, where each cluster contains less data than other clusters cause a degree of accuracy is not stable due to nearest neighbor selection too little active user. In this test, the total number of users who will look for its cluster is as many as 40 users. The number of members of each cluster tends always different, which causes sometimes an active user into a cluster with a small number of members. For example active user to become a member of the cluster-x with total members just as much as 5 users. The logic is, if a member of a cluster there are only 5 users then the process of selecting the number of nearest neighbors of active users only candidate among the user 5.

The conclusion of testing the number of clusters is selecting the number of clusters on the application of user-based collaborative filtering-based smoothing need to pay attention to the amount to be diclusterisasi the maximum number of clusters to be created. So that after starting the process of charging the shadow rating, the selection of the nearest neighbors of active users and processes music prediction accuracy gets better with MAE value close to 0.

2) Based on the K-Neighbours

Table 4.5 MAE Based on the K-Neighbours

Jumlah K	Percobaan ke-					Rata-rata
	I	II	III	IV	V	
30%	0,6506	0,7496	0,7424	0,7520	0,7247	**0,7239**
50%	0,6519	0,6894	0,6994	0,6429	0,6732	**0,6713**
70%	0,7270	0,6790	0,7546	0,7034	0,7482	**0,7224**

Table 4.5 shows the results of testing the accuracy of the parameter number k is set as much as 30%, 50% and 70%. It appears that the average of these tests worth stable since the values of k> 30%. This can happen because there are many candidates for the nearest neighbors of active users. The cause of many of the candidate testing because it assumes if the similarity between the active user with the candidate nearest neighbor is 0 then the candidate nearest neighbor will be taken as the nearest neighbor on condition k maximum amount has not been fulfilled. Basically the similarity value <0 indicates that the user has little in common values of the active user.

The changes are not too drastic of the three test number k is also because the process generates predictions of this method using a dataset value rating that has been filled by rating shadows. So basically, since the training data is done, there is no music rating value = 0 is entered into the calculation of prediction..

3) Based on the level of sparsity

Table 4.6 MAE Based on the level of sparsity

Tingkat *Sparsity*	Percobaan ke-					Rata-rata
	I	II	III	IV	V	
30%	0,7540	0,7687	0,7802	0.7900	0,7696	**0,7725**
50%	0,7991	0,7722	0,7678	0.7523	0,7730	**0,7728**
70%	0,8552	0,8956	0,7864	0,8191	0,8244	**0,8361**

From Table 4.6 sparsity level testing showed an increase in the value of the data MAE when the vacancy rate increased. This occurs due to the increase in value when the condition data are sparse high, causing reduced ratings data that will be taken into consideration for granting the prediction. Application of smoothing technique in this situation also caused the data used to make the process more predictive filled by a recommendation engine than the sum of the actual rating dirating directly by the user. Nevertheless, the problem of data gaps on collaborative filtering can be resolved by applying a smoothing technique to the system built.

There are times when the value of similarity between the active user and other user-friendly in a cluster to meet the number 0, which affect the increase in the value of MAE. However, testing the accuracy of the sparsity of data can generate as much as 70% MAE value = 0.8361. It can be concluded that the system is able to handle data gaps up to 70% of the total existing ratings data.

4.3.2.3 Analysis of Test Results

Testing accuracy rate shows the music recommender system based on user-based collaborative filtering is built is able to overcome the problem of data gaps with the level of sparsity much as 70%, and testing the accuracy of the other can be concluded that the music recommender system will be built by setting the number of clusters = 3, and the number knearest neighbors as much as 50% due to testing done on both of these settings produce an average value MAE lower than others in the amount of 0.6713.

3. CLOSING

5.1 Conclusion

Based on the research that has been done, it can be concluded as follows :

1. To facilitate the user in finding music that is sought, then the user can use the search feature that exists or can be seen from the number of user ratings itself and can also see the list of the 10 most popular music or music outcome highest rating.
2. The results achieved in the accuracy of testing with this method is relatively inaccurate because by applying the number

of results smallest number of clusters k = 3 and number (the number of users which are the nearest neighbors of active user) = 50% can produce an average of MAE = 0 , 6713 means more than 0.5 to approach a value of 0, since MAE itself has a range of values from 0-1.

5.2 Suggestion

Some of the things suggested for the development of this study are as follows :

1. Based on these results it is advised to use other methods in order to produce better predictions music with MAE value close to 0 or not more than 0.5.
2. The testing procedure can be done in different ways, such as adding the number of datasets, and increase the amount of testing of testing in this study. This will affect the accuracy of recommender system to be built.
3. This method can be tried on research with other items, such as books, news on digital newspaper, movies, and more with a rating of collecting patterns similar to this test.

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