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Ontology-based Conversational Recommender System for Movie domain

Marendra Septianta*[1], Z. K. A. Baizal*[2], Kemas M. Lhaksmana*[3]

*School of Computing, Telkom University
Bandung, West Java, Indonesia

[1]marendra@student.telkomuniversity.ac.id
[2]baizal@telkomuniversity.ac.id
[3]kemasmuslim@telkomuniversity.ac.id

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Abstract

A conversational recommender system created to help a user find information in a domain through the use of conversational mechanism. This system helps a user get recommendations of what he/she wants by selecting items that are best suited to the user's preference by asking for his/her needs. The recommendations are generated by eliciting user's interest e.g. his/her preferred movie, actor, and director. The system will then give the user an item that is related to his/her interest. There are many methods to obtain an appropriate recommendation that corresponds to the user's preference. In this paper, we use ontology, which represents knowledge, to obtain a recommendation that matches to the user's preferences by determining the user's needs using knowledge-based filtering. We implement our system in a movie domain. The accuracy of our system is tested by studying user's acceptance.

I. Introduction

Conversational recommender system is one of many types of recommender systems [1, 2]. It provides recommendation based on user preferences elicited from conversation between system and user. While each user may have different preferences, they sometimes have similarities [3]. One of the basic recommendation methods for recommender systems is user-based collaborative filtering. It gives recommendations on the basis of the rating of certain items given by users [1, 3, 5]. Users who rate the same items are likely to have the same interest. Due to the simplicity of collaborative filtering algorithm, the system often provides recommendations that does not match the user preference, or the system takes a long time to make recommendation when there are multiple users or items, particularly in the movie domain. Knowledge-based filtering is another known recommendation method, in which the system determines user preferences by asking questions related to user needs, and gives recommendations by taking measure any available variables. It is a more effective method compared to collaborative filtering, due to the cold start problem that occurs in collaborative filtering. Thus, we use knowledge-based filtering in this research. Using the knowledge-based filtering, the system determines user preference in the movie domain by asking some questions and finds any relation between individuals in ontology.

II. Overview of Ontology Model

The proposed ontology model consists of some of the main aspects in the movie domain. It contains five hierarchies that represent movie, director, actor, origin and age rating. Each main class has subclasses and individuals (instances).

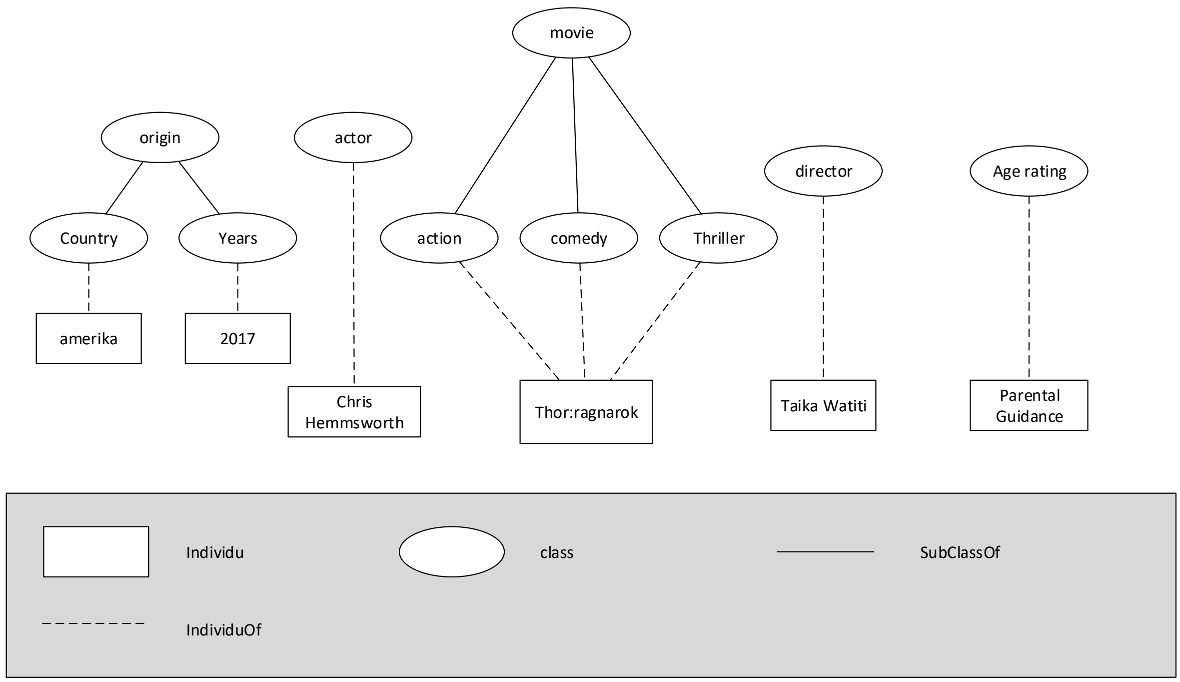

Fig. 1. A Part of Ontology

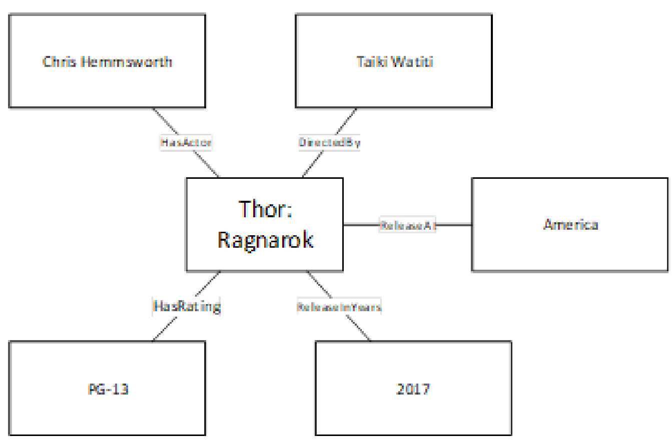

Fig. 2. The Relations Between Individual

Figure 1. and 2. illustrate the structure of ontology and the relations between individuals. In ontology, there are two types of set of relations. First, a set of inter-hierarchy relations comprised of relations between two nodes in a hierarchy, such as *subClassOf*, *individualOf* and *hasChild*. Second, a set of inter-hierarchy relations comprised of relations between two individuals in different hierarchies [6].

III. RECOMMENDER SYSTEM

In this paper, we combine collaborative and knowledge-based filtering. Our ontology represents that of the movie domain ontology, which can be used for movie recommendation for viewers around the world, as well as in Indonesia. The movie recommender system recommends movies based on user preferences. It will elicit user preference based on the genre chosen by the user. To calculate user interest on a movie, we construct an equation based on DOI (degree of interest) equation presented by Blanco-Fernández et al [7]. The DOI equation is as follows,

$$DOI(C_{m+1}) = \frac{DOI(C_m)}{1+\#sibDOI(C_{m+1})} \quad (1)$$

- C_m : the class of chosen genre
- C_{m+1} : the subclass/individual of chosen genre
- $DOI(C_{m+1})$: the DOI of chosen class. It will be 1 if the genre is chosen.

Figure 2. shows the relation between individual for each hierarchy, which includes *HasActor*, *DirectedBy*, *ReleasInYears*, *CameFrom*, and *HasRating*. *HasActor* relation represents who the actor in the movie is. The *DirectedBy* relation represents who the director is. The *ReleasInYears* represents the movie release date in year. The *CameFrom* explains the origin of the movie. The *HasRating* represents the movie rating by MPAA (Motion Picture Association of America) for age restriction. Currently, the rating system used by MPAA are G (General Audience), PG (Parental Guidance Suggested), PG-13 (Parental Guidance Strongly cautioned 13 years old), R (Restricted), and NC-17 (adult only, No Children and 17+). After the genre and the rating of the movie is chosen, the user will then be asked to choose one of the movies that the user likes from the given list of movies related to the chosen genre. The system will then process the similarity of needs between individuals, and will calculate DOI score with a slight modification to match collaborative filtering algorithm. We use a slightly modified similarity equation presented by Blanco-Fernández et al [7] to match our system preference.

$$Sim_{(a,b)} = \left[\left(\frac{Common(a,b)}{Max(a,b)}\right) * \left(\frac{DOI_a+DOI_b}{2}\right)\right] \quad (2)$$

- $Sim_{(a,b)}$ is similarity score between movie *a* and movie *b*
- $Common(a,b)$ represents the number of similar properties value between movie *a* and movie *b*
  Example:
  A={(*HasActor*)=>Chris Evan, (*HasRating*)=>PG-13}
  B={(*HasActor*)=>Chris Hemsworth, (*HasRating*)=>PG-13}
  Common (A, B) = 1
- $Max(a,b)$ Represents the maximum of relations between movie *a* and movie *b*.
- DOI_a represents the DOI value of movie *a*
- DOI_b represents the DOI value of movie *b*

The system will make recommendation by combining the similarity value from (2) with user's actor and director preference (see (3)). The chosen actor and director each contributes 1 score to the similarity between the chosen movie and another movie. Equation (3) is created based on the work of Carrer-Neto et al [8].

$$FinalSim_{(a,b)} = (w_1 * sim_{(a,b)} + w_2 * La_b + w_3 * Ld_b) * 10 \quad (3)$$

where
- $FinalSim_{(a,b)}$ represents the final score of recommendations after adding user's preference
- $sim_{(a,b)}$ represents the similarity score between movie *a* and b from (1)
- La_b Represents the points of actor. If movie *b* has the chosen actor it value change to 1. If not, the value will be 0.
- Ld_b represents the scores of director. Same as L_a , if movie b has the chosen director it value change to 1. Otherwise, the value will be 0.
- W represents the weight. Based on experiment, $w_1 = 0.4$, w_2=w_3=0.3

Example

- A user wants to watch an action-packed movie with a 13-years-old kid. The system will ask the user to choose the appropriate genre and age restriction, and the system will return the list of movies related to the chosen genre and age restriction, in this case, "Action" movies with the "PG-13" rating. The movie list consists of "Avengers: Infinity Wars", "Captain America: The First Avenger", "Dunkirk", "Furious 7", "Inception", "Iron Man", "Iron Man 2", "Iron Man 3", "The Avengers", and "The Dark Knight".
- The system will then ask the user to choose one of the movies he/she likes from the movie list.
- If the user chooses "Iron Man", the similarities between "Iron Man" and another "Action" genre movies with a "PG-13" rating will be calculated by the system automatically.
- The system will then create a list of actors for the user to choose. The list of actors contains those that are related to the "Action" genre and a "PG-13" rating by searching the relation between gnre, actor, and age restriction rating.
- Once the user has selected one of the actors from the previous list, the system will display a list of directors that are also related to the "Action" genre. The user must choose one of the directors that he/she prefers from the list, and then equation (3) can be calculated.
- The system will then automatically find a movie that has the previously chosen actor and director, and apply the previously calculated recommendation score. The higher the score, the higher the relation between the movies.

IV. RESULT

The M.O.R.E.S. (our system's name) creates a recommendation by calculating (1) followed by (2) and (3). Figure 3, 4, 5, 6 and 7 show our system's user interface. The data used in the system is stored in rdf format using apache jena fuseki, with a total number of 20 movies. It is applied to the system by using SPARQL. The experiment was conducted with the students as the respondents.

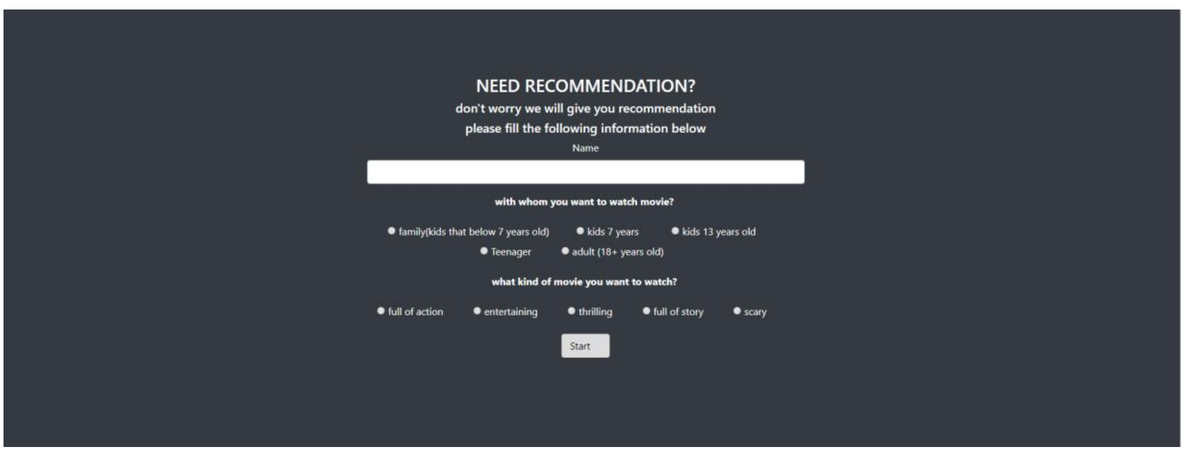

Fig. 3. The GUI of M.O.R.E.S to Determine the User Needs

please choose one of the movie which you ever been watch and you like it

silahkan memilih film yang sudah pernah di tonton dan anda menyukainya

title	synopsis	rating	choose
Avengers: Infinity War	The Avengers and their allies must be willing to sacrifice all in an attempt to defeat the powerful Thanos before his blitz of devastation and ruin puts an end to the universe.	8.8	pilih
Captain America: The First Avenger	Steve Rogers, a rejected military soldier transforms into Captain America after taking a dose of a 'Super-Soldier serum'. But being Captain America comes at a price as he attempts to take down a war monger and a terrorist organization.	6.9	pilih
Dunkirk	Allied soldiers from Belgium, the British Empire and France are surrounded by the German Army, and evacuated during a fierce battle in World War II.	8.0	pilih
Furios 7	Deckard Shaw seeks revenge against Dominic Toretto and his family for his comatose brother.	7.2	pilih
Inception	A thief, who steals corporate secrets through the use of dream-sharing technology, is given the inverse task of planting an idea into the mind of a CEO.	7.9	pilih
Iron Man	After being held captive in an Afghan cave, billionaire engineer Tony Stark creates a unique weaponized suit of armor to fight evil.	7.0	pilih
Iron Man 2	With the world now aware of his identity as Iron Man, Tony Stark must contend with both his declining health and a vengeful mad man with ties to his father's legacy.	8.1	pilih
Iron Man 3	When Tony Stark's world is torn apart by a formidable terrorist called the Mandarin, he starts an odyssey of rebuilding and retribution.	9.0	pilih
The Avengers	Earth's mightiest heroes must come together and learn to fight as a team if they are going to stop the mischievous Loki and his alien army from enslaving humanity.	6.8	pilih
The Dark Knight	When the menace known as the Joker emerges from his mysterious past, he wreaks havoc and chaos on the people of Gotham. The Dark Knight must accept one of the greatest psychological and physical tests of his ability to fight injustice.	5.2	pilih

Fig. 4. List of Movie After Select the First Option

here is a list of movie actor artist according to your choice.please select your favorite artist

berikut ini adalah jajaran artis pemeran film action silahkan pilih artis favorit anda

artis	pilih
Chris_Hemsworth	pilih
Chris_Evans	pilih
Barry_Keoghan	pilih
Vin_Diesel	pilih
Leonardo_DiCaprio	pilih
Robert_Downey_Jr.	pilih
Christian_Bale	pilih
Edward_Norton	pilih

Fig. 5. List of Actor Related to Previous Choice

The following is the line of film directors according to your choice. please select your favorite director

berikut ini adalah jajaran sutradara film sesuai dengan pilihan anda. silahkan pilih sutradara favorit anda

artis	pilih
Anthony_Russo	pilih
Joe_Johnston	pilih
Christopher_Nolan	pilih
James_Wan	pilih
Jon_Favreau	pilih
Shane_Black	pilih
Joss_Whedon	pilih
Louis_Leterrier	pilih
Kenneth_Branagh	pilih
D.J._Caruso	pilih

Fig. 6. List of Director Based on Previous Choices

This is list of the recommendation based on your favorite needs berikut ini adalah hasil rekomendasi berdasarkan kebutuhan/kesukaan(favorit) anda

film	synopsis	recommendations score
Iron Man 2	With the world now aware of his identity as Iron Man, Tony Stark must contend with both his declining health and a vengeful mad man with ties to his father's legacy.	4.7727272727273
Iron Man 3	When Tony Stark's world is torn apart by a formidable terrorist called the Mandarin, he starts an odyssey of rebuilding and retribution.	4.1818181818182
The Incredible Hulk	Bruce Banner, a scientist on the run from the U.S. Government, must find a cure for the monster he turns into, whenever he loses his temper.	4.1818181818182
The Dark Knight	When the menace known as the Joker emerges from his mysterious past, he wreaks havoc and chaos on the people of Gotham. The Dark Knight must accept one of the greatest psychological and physical tests of his ability to fight injustice.	4.1818181818182
Thor	The powerful, but arrogant god Thor, is cast out of Asgard to live amongst humans in Midgard (Earth), where he soon becomes one of their finest defenders.	3.5909090909091
The Avengers	Earth's mightiest heroes must come together and learn to fight as a team if they are going to stop the mischievous Loki and his alien army from enslaving humanity.	3.5909090909091
Avengers: Infinity War	The Avengers and their allies must be willing to sacrifice all in an attempt to defeat the powerful Thanos before his blitz of devastation and ruin puts an end to the universe.	3.5909090909091
Inception	A thief, who steals corporate secrets through the use of dream-sharing technology, is given the inverse task of planting an idea into the mind of a CEO.	3.5909090909091
Furios 7	Deckard Shaw seeks revenge against Dominic Toretto and his family for his comatose brother.	3.5909090909091
Dunkirk	Allied soldiers from Belgium, the British Empire and France are surrounded by the German Army, and evacuated during a fierce battle in World War II.	3.5909090909091
Captain America: The First Avenger	Steve Rogers, a rejected military soldier transforms into Captain America after taking a dose of a 'Super-Soldier serum'. But being Captain America comes at a price as he attempts to take down a war monger and a terrorist organization.	3.5909090909091
xXx: Return of Xander Cage	Xander Cage is left for dead after an incident, though he secretly returns to action for a new, tough assignment with his handler Augustus Gibbons.	3.5909090909091

Fig. 7. The Result of Recommendation Generated on M.O.R.E.S.

Table 1 shows a list of movies with its genre and age restriction from a survey, and the resulted DOI of each movie. The DOI score was calculated automatically by the system based on the movie's genre and age restriction rating based on the survey. Meanwhile, the example of final similarity generated by the system is shown in Table 2. The accuracy of the system is defined as the user's acceptance of the recommendation.

TABLE I
THE RESULTED DOI OF EACH MOVIE OBTAINED FROM THE SURVEY

Movie	Class	Age Restriction	DOI
Avengers: Infinity War	action	PG-13	0.091
Captain America: The First Avenger	action	PG-13	0.091
Dunkirk	action	PG-13	0.091
Furios 7	action	PG-13	0.091
Inception	action	PG-13	0.091
Moana	comedy	PG	0.333
Stand by Me Doraemon	comedy	PG	0.333
Furios 7	thriller	PG-13	0.333
xXx: Return of Xander Cage	thriller	PG-13	0.333
Deadpool	action	R	0.333
Deadpool 2	action	R	0.333
Stand by Me Doraemon	drama	PG	0.500
Grown Ups 2	comedy	PG-13	0.500
A Quiet Place	drama	PG-13	0.200
Dunkirk	drama	PG-13	0.200
Interstellar	drama	PG-13	0.200
The Dark Knight	drama	PG-13	0.200
Deadpool	comedy	R	0.250
Deadpool 2	comedy	R	0.250
The Intouchables	comedy	R	0.250
The Intouchables	drama	R	0.500

TABLE II
THE EXAMPLE OF GENERATED FINAL SIMILARITY BY SYSTEM

Chosen movie (*a*)	**Related movies (*b*)**	$Common(a,b)$	$Sim_{(a,b)}$	$FinalSim_{(a,b)}$
Avengers: Infinity War	Captain America: The First Avenger	1	0.148	0.359
Avengers: Infinity War	Dunkirk	1	0.148	0.359
Avengers: Infinity War	Furios 7	1	0.148	0.359
Avengers: Infinity War	Inception	1	0.148	0.359
Avengers: Infinity War	Iron Man	1	0.148	0.359
Avengers: Infinity War	Iron Man 2	1	0.148	0.359
Avengers: Infinity War	Thor	2	0.295	0.418

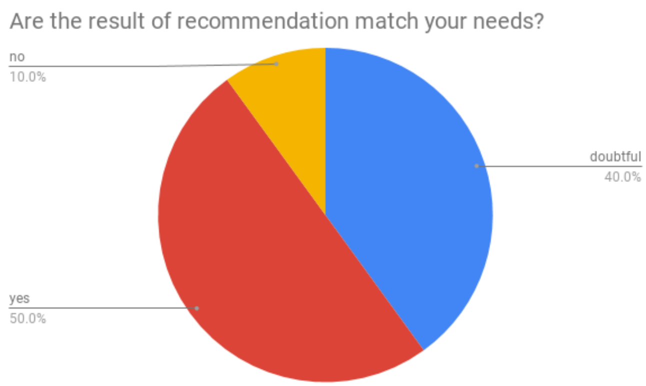

Fig. 9. Diagram of User's Acceptance About Recommendation

Based on Table 1, we can conclude that the sum of sibling (movies with the same genre and age restriction rating) affects the DOI score. The more the sibling is in a particular genre and age restriction, the more the DOI score of those movies propagated, which leads to a low DOI score. For example, movies with "comedy" genre with age restriction "PG" has a DOI score of 0.333 while movies with the genre "drama" and "R" age restriction has a DOI score of 0.500. This happens because the system determines that the user is interested in all movie related to the user's chosen genre. Table 2 shows that the value of *common(a,b)* affects the result of *FinalSim(a,b)*. For example, the chosen movie "Avengers: Infinity War" with a related movie "Thor" both have the same *common(a,b)* value of 2 and *FinalSim(a,b)* value of 0.418, while "Avengers: Infinity War" with another related movie "Iron Man" both have a *common(a,b)* value of 1 and *FinalSim(a,b)* value of 0.359. This implies the value of *common(a,b)* affects the value of *FinalSim(a,b)* positively. Referrring to Fig. 9, from the total of 30 respondent of the survey, 50% of those suggests that the system is capable of giving recommendation that match the user's preferences. While the 40% of respondents are still doubtful, and the rest declare that the system is not capable of giving recommendation based on their preference. We may infer from the survey that M.O.R.E.S is still unable to provide the users with the appropriate recommendation based on their preferences, because half of the respondents are still in doubt about the recommendation given by the system. Based on user study, users are still in doubt due to the few choices of movies, actors, and directors, and that the users can only choose one of each parameter.

V. DISCUSSION

One of the issues that we have encountered is scalability. The M.O.R.E.S generates recommendation by determining similarities between one movie and the other. A huge amount of data may lead to memory constraints and the system might fail to create recommendations if a relation is missing. Furthermore, adding those data one by one to a list will take a much longer time.

As mentioned earlier, the $Sim_{(a,b)}$ and DOI propagation equation are created on the basis of the equation introduced by Blanco-Fernández et al [7]. It saves user preference on ontology to generate recommendations. We use a different approach of saving user preference, by storing it on a variable (temporary memory) when the system finds relation between classes, individuals, and relations. We have tried using the same approach as that introduced by Blanco-Fernández et al [7] but it does not suit our ontology. We modified the equation of DOI and $Sim_{(a,b)}$ in order to be able to use it in our system.

VI. CONCLUSION AND FUTURE WORK

Based on the result, the ontology model that was created has represented the movie domain and was able to support interaction in the conversational recommender system. The interaction created using knowledge-based filtering is quite effective, able to give choices in the form of a list of movies, actors, and directors. Based on user study, the recommendation is accepted by 50% of users, but is still doubted by 40% of users and 10% is not satisfied with the recommendation. As previously explained, half the users doubted the recommendations due to the lack of choices. Users can choose only one from the list of movies, actors, and directors.

Our work can be advanced in many ways. First, to help determine the similarities between movies, the knowledge can be expanded to include more movies, actors, and directors. In addition, movies released by the same studios could receive a score in similarity. This can create more issues, however, because of overfitting.

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