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SRS: Social Correlation Group based Recommender System for Social IoT Environment

Deok-Hee Kang, Hoan-Suk Choi, Sang-Gyu Choi, Woo-Seop Rhee
Department of Multimedia Engineering
Hanbat National University, Deajeon, 34158, Republic of Korea

ABSTRACT

Recently, the Social Internet of Things (IoT), the follow-up of the IoT, has been studied to expand the existing IoT services, by integrating devices into the social network of people. In the Social IoT environment, humans, devices and digital contents are connected with social relationships, to guarantee the network navigability and establish levels of trustworthiness. However, this environment handles massive data, including social data of humans (e.g., profile, interest and relationship), profiles of IoT devices, and digital contents. Hence, users and service providers in the Social IoT are exposed to arbitrary data when searching for specific information. A study about the recommender system for the Social IoT environment is therefore needed, to provide the required information only. In this paper, we propose the Social correlation group based Recommender System (SRS). The SRS generates a target group, depending on the social correlation of the service requirement. To generate the target group, we have designed an architecture, and proposed a procedure of the SRS based on features of social interest similarity and principles of the Collaborative Filtering and the Content-based Recommender System. With simulation results of the target scenario, we present the possibility of the SRS to be adapted to various Social IoT services.

Key words*: Social IoT, Social Correlation, Recommender System, Similarity Calculation and Correlation Prediction.*

1. INTRODUCTION

The Internet of Things (IoT) has strong potential strength by enabling interaction among devices [1]. It connects a large number of heterogeneous devices and integrates them to give humans new dynamic services. Therefore, the IoT has improved the quality of human's life such as living, e-health and e-learning. Meanwhile, it has been changed over three generations. In the first generation, it uses the Radio-Frequency Identification (RFID) technology to tag non-electric objects and give them identification [2]. While the RFID-based IoT environment was ongoing, technologies of remote sensing in the Wireless Sensor Networks (WSN) also had key roles in the IoT. In the second generation, the IoT had evolution by giving general devices capabilities to be directly connected to the Internet. As the web applications was rapidly emerging, devices are integrated into the Web with peer-to-peer networking [3]. Finally, in the third generation of the IoT, a new paradigm about the social network of devices has been referred to as the future Internet [4].

Because the future Internet will be people-centric and resource-centric [5], it is important to understand social relationship, interest and resource consuming patterns of humans. Thus, many researches start to study the Social IoT as the follow-up of the IoT. Based on existing social network of human, the Social IoT environment has identified types and characteristics of social relationship among humans, devices and digital contents. Likewise, various features of Social Networking Services (SNSs) are reflected in the Social IoT environment, such as Facebook, Twitter and Instagram. SNSs offer functions that generate social relationship and share the personal interests, activities among users [6]. According to social relationship, information can be spread out rapidly and be consumed easily. Moreover, information is clearly identified with existing relationship among humans. Therefore, the Social IoT can guarantee the network navigability to find specific devices or digital contents, and establish levels of trust-worthiness to leverage the degree of interaction among devices [7], [8].

However, there are still numerous challenges that must be faced for providing real Social IoT environment [9]. One of issues is about data discovery. It should handle massive data including sensing data, social profile and relationship. In this environment, users and service providers are exposed to indiscriminate data when searching some required information. However, there are same issues about discovery for digital contents in media recommendation services. It should find tasty contents to get users more interested in them. Therefore, like media recommendation services, the Social IoT needs a study about the recommender system to find expected information.

* *Corresponding author, Email: wsrhee@hanbat.ac.kr*
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In this paper, we propose the Social correlation group based Recommender System (SRS) for the Social IoT Environment. The SRS generates a target group depending on the social correlation about service requirement. The social correlation group includes more correlative information expected by target service to reduce excessive search for users. It contains several profiles of users and devices which can be potential customers, or services and contents which can be required resources for target services. To extract the social correlation group, we design an architecture and propose a procedure of the SRS. Based on several features of the social interest similarity, the SRS proceed with principles about two main recommender systems of media streaming services, which are the Collaborative Filtering and the Content-based Recommender System. But the existing recommender systems have content lack and newly service problems. Thus, the proposed SRS is designed to combine each pros of existing recommender systems and support the content lack and newly service situation. Finally, we show simulation results to prove its feasibility by setting the target service scenario.

The rest of paper is organized as follows. In the section 2, we provide some related work that focus on the integration of the Social IoT environment and existing recommender systems. In the section 3, we show the definition of the social correlation group, and propose the SRS. The section 4 provides simulation results based on the one of target service scenarios. Finally, we conclude with remarks on future works in the section 5.

2. RELATED WORK

2.1 Social IoT

Recently, many researches have defined social relationship to form the Social IoT environment. An ontology-based platform for the Social IoT, called Lilliput, is proposed to construct user interface of devices by using existing SNSs [10]. It provides information of SNSs (e.g., profiles, social relationship of user) and devices (e.g., context, location) as a social graph based on ontology. To manage information, it conducts a research about what social relationship among humans, devices and places will be, and represents them in the form of N-Triples. Thus, the Lilliput leads to infer more complex context and authentication of control access using proposed relationships.

Our previous study [11] proposes the social relationship model which consists of human, devices and digital contents. Because all digitals such as social media, video clips and IoT services are provided for humans, we define human-centric relationship and show a simulation result about the Social IoT graph. We expect this relationship can be applied to provide Social IoT services without human's control.

However, this kind of researches only defines relationship models of the Social IoT, and do not indicate specifically how to find required information with the model.

2.2 Social Interest Similarity

With the evolution of SNSs, it is important to figure common interests out among users for the maintenance of vibrant services. By using interest similarity of users, service providers of SNSs can support friend recommendation. On the other hands, the social interest similarity between two users benefits various applications in SNSs and even Social IoT by advertising attractive contents. For example, the video liked by users who share many interests could be recommended to the target user in order to arouse his interests. Moreover, targeted online advertising can use the analysis of social interest similarity by finding users who will be potential clients.

X. Han [12] presents a study on correlations between interest similarity and various social features of users depending on three interest domains (i.e., movie, music and TV). C. Yang [13] learns to predict how similar interests of two users about videos are by using video access patterns. Two studies rely on dataset aggregated from Facebook and QQ.

With analyses, they reveal that the interest similarity between two users is related with three types of social features:

- Profile similarity: Users tend to show more similar tastes if they have same demographic information (e.g., age, gender and location).
- Friend similarity: Users have more similar friendship, community membership and interaction history when they have same tastes.
- Interest individuality: Users show similar interest as they have past long-term similarity or high individuality of interest.

These results seem that we can improve users' satisfaction of recommendation about expected information in the Social IoT environment by utilizing social features.

2.3 Recommender Systems

In case of existing media streaming services, users have difficulties to find what they want among a lot of items such as music, movies and TV programs. Thus, several recommender systems have studied to select proper items by analyzing interest of user and attributes of item. There are two main recommender systems, the Collaborative Filtering [14] and the Content-based Recommender System [15]. The Collaborative Filtering shows the best performance by using rating history of user. It selects some items which have high rating values from other users with similar tastes. Thus, it can offer various types of items to the target user if there are enough rating history. But, if not, such as new user or new content, it cannot perform properly. On the other hand, the Content-based Recommender System provides items in the same category which contains similar contents liked by target user. It does not have to use rating history. But, new user cannot perform recommendation owing to a lack of user's rating history. Likewise, two recommender systems have pros and cons depending on service conditions as shown in the Table 1.

Like media streaming services, the Social IoT environment also has several conditions when users find required information. Therefore, with existing recommender systems, we can apply them to the proposed recommender system for the Social IoT environment depending on service conditions.

Table 1. Existing Recommender Systems

	Collaborative Filtering [14]	Content-based Recommender System [15]
Features	- Select other users who have similar tastes by analyzing interest of target users. - Recommend contents which similar users liked before.	- Classify similar contents about profiles with target content. - Predict interest of target content by using existing interest history between target user and contents in the category.
Pros	Can show the best performance when interest history information of target user exists enough.	Can be used if there are any interest history between target user and content.
Cons	Cannot guarantee the performance if the target user or content is newly entered in the service.	Cannot guarantee the performance if profile information of the content is lack.

3. SRS: THE PROPOSED RECOMMENDER SYSTEM FOR SOCIAL IOT

3.1 Social Correlation Group in the Social IoT Environment

The Fig. 1 shows the Social IoT graph to represent the Social IoT environment. Each node (i.e., human, device and digital content) is linked by social relationship based on several behaviors, contexts and resource consuming patterns of humans. Likewise, massive data in this environment can be generated and managed through the relationship. Thus, there are similar features among aggregated data and they can be converted into useful information for new adaptive services. But, there is no way to find more correlative information in flood of information.

Therefore, our previous study [16] defined the social correlation group which selects highly correlative nodes with the target service. The type of nodes contained in the group can be different depending on the service requirement. For example, one of social correlation group contains information of humans who often visit same restaurant. The restaurant can use this group to receive ratings of a new menu. On the other hand, another social correlation group has a list of some actuators that can raise the temperature in the target room. Thus, the user can send the request messages to the group to find available actuators.

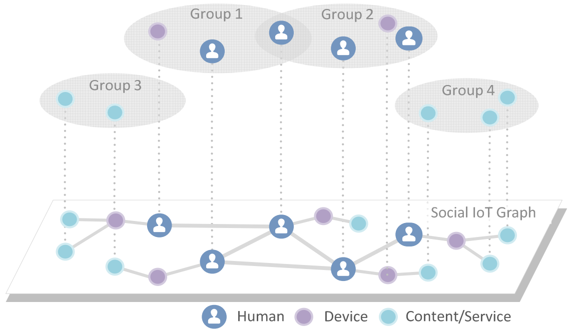


Fig. 1. Social correlation group in the Social IoT environment

According to several roles in the Social IoT, we can classify nodes into an entity and a content. The entity is a subject generating and consuming the content. For instance, humans and devices can be entities, on the other hand, media and services can be contents. As shown in the table 2, we classify types in datasets from Facebook [17], Twitter [18], IoTMakers [19] and IMDb (Internet Movie Database) [20]. Page, User and Group of Facebook in the SNS domain can be entities which generate some contents such as Post, Comment. Moreover, Device of IoTMakers in the IoT service domain can be an entity which aggregates sensing data called TagStream.

Thus, we can also classify the requirement of the social correlation group into the entity and the content. In the view of the entity, if we need similar tasty consumers of media and services, some humans or devices are chosen as group members like Group 1, Group 2 as shown in the top of Fig. 1. In the view of the content, when we need interesting resources which we like to consume, some resources are chosen as group members like Group 3, Group 4 as shown in the top of Fig. 1.

Table 2. Classification between entity and content

	SNS		IoT Service	Media Service
	Facebook	Twitter	IoTMakers	IMDb
Entity	Page, User, Group	Users	Device	People
Content	Post, Comment	Tweets, Comment	TagStream	Media

To generate the social correlation group, we propose an architecture and a procedure of the SRS as follows.

3.2 Architecture of the SRS Platform

Fig. 2 shows the proposed architecture of the SRS platform. As shown in the bottom of Fig. 2, data from three different service domains (i.e., SNS, IoT service, media service) are aggregated to each repository of the Social IoT platform by the Data Aggregation function. Because each domain has a unique data structure, the Data Abstraction function should provide the common abstracted data structure which is able to represent whole data from every service domain. Moreover, aggregated data is managed in the form of ontology model by the Ontology Graph Manager. Thus, we can query the required information easily by the Graph Query Manager function and generate the social correlation group by the Target Group

Generation function according to the service requirement. The SRS platform can provide information of the group by the Web API.

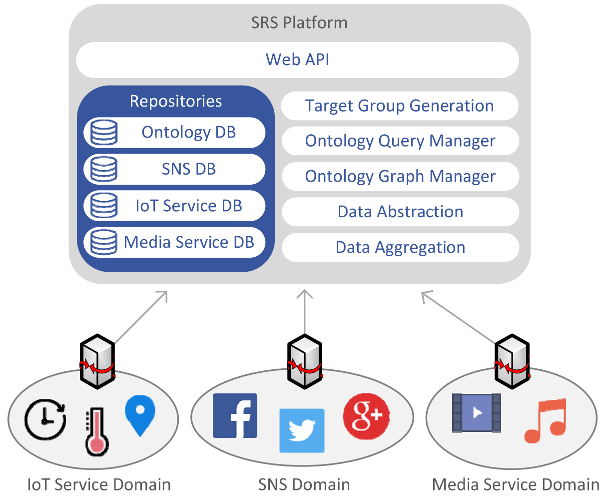


Fig. 2. Architecture of the SRS platform

3.3 Procedure of the SRS

As shown in the Fig. 3, the SRS proceeds with the following four phases. However, the proposed procedure is conducted depending on three conditions of the service requirement.

- s1: when the service requirement is for a new entity, there is no data to calculate correlation values.
- s2: when the service requirement is for a new content, there is no data to calculate correlation values.
- s3: when the service requirement is for the existing entity or content, it has enough data history to calculate correlation values.

Thus, if the condition is s1 or s2 which corresponds with a new entity or a new content, it should go through the phase 2) to fill scarce information.

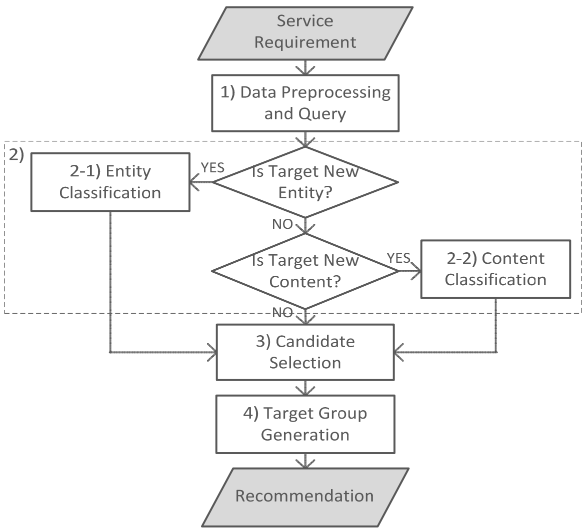


Fig. 3. Procedure of the SRS

1) Data Preprocessing and Query: When the service requirement is requested to the SRS platform, it should be preprocessed in the shape of proper forms to query it. For example, if a specific movie is selected as the service requirement, the platform extracts title or IMDb ID of the movie to query relevant data.

2) Entity/Content Classification: The SRS calculates the similarity to classify nearest neighbors with the service requirement. This phase is conducted to fill required information by the closest neighbors instead of a new entity or a new content. Thus, we use the cosine similarity as shown in the Eq. (1) which is used in the social interest similarity [12] and Content-based Recommender System [15]. In this equation, the similarity value, $sim(s,n)$, means how close the service requirement s and each neighbor n are. If the service requirement is about entities, we go through the phase 2-1) and utilize information sets p_s , p_n including social profile of humans (e.g., age, gender and location) or profile of devices (e.g., type, location and owner). And, if the service requirement is about contents, we go through the phase 2-2) and use information sets p_s, p_n including media metadata (e.g., released year and genre) to compare similarity.

$$sim(s,n) = \frac{\overrightarrow{p_s}\cdot\overrightarrow{p_n}}{|p_s||p_n|} = \frac{\sum p_s \times p_n}{\sqrt{\sum {p_s}^2}\times\sqrt{\sum {p_n}^2}} \quad (1)$$

3) Candidate Selection: It selects candidates of the social correlation group by using correlation history such as rating, comments and likes. If the service requirement is s3, it uses own correlation history. On the other hand, if the service requirement is s1 or s2, it uses correlation history of classification members generated in the phase 2). Thus, we can suppose that some entities or contents related with correlation history have a possibility to be highly correlative information with service requirement.

4) Target Group Generation: Finally, it generates the social correlation group for the service requirement. To extract highly correlative information, we use two equations of the Collaborative Filtering. When the correlation history is about entities, the Eq. (2) is used [21]. Where v_{e1} is correlation value of entity e_1 on content c and v_{e2} is rating of user e_2 on content c, set E indicates contents that entity e_1 and e_2 co-evaluated. It calculates predicted correlation $p_{e_1,c}$ on the content c. The correlation is computed by a weighted average of the correlation history of neighbors. Otherwise, when the correlation history is about contents, the Eq. (3) is used [22]. This equation computes predicted correlation p_{e,c_1} on the content c_1 for the entity e by computing predicted correlation given by the entity e on the contents c_2 similar to c_1. Each correlation history is weighted by the similarity $sim(c_1,c_2)$ between contents c_1 and c_2. With two equations, it can select highly correlative information with the service requirement and generate the social correlation group.

$$p_{e_1,c} = \overline{v_{e_1}} + \frac{\sum_{e_2 \in E} sim(e_1,e_2)(v_{e_2,c} - \overline{v_{e_2}})}{\sum_{e_2 \in E}|sim(e_1,e_2)|} \quad (2)$$

$$p_{e,c_1} = \frac{\sum_{c_2 \in C} sim(c_1,c_2) \cdot v_{e,c_2}}{\sum_{c_2 \in C} |sim(c_1,c_2)|} \quad (3)$$

Consequently, we can recommend correlative information which meets the service requirement by using the social correlation group.

4. PERFORMANCE EVALUATION

In this section, we explain one of service scenarios in the Social IoT environment to show the feasibility of the SRS. According to the scenario, we build the simulation environment for the Social IoT graph. Moreover, based on the graph, we show simulation results to generate the social correlation group with each phase as shown in the Fig. 3. Consequently, we reveal how the social correlation group perform relative to the service requirement: 1) prediction accuracy of expected preferences; 2) preference evaluation of the social correlation group; 3) hit ratio of the social correlation group.

4.1 Simulation Scenario

Fig. 4 shows one of service scenarios in the Social IoT environment. In the company, there are various coworkers connected with social relationship such as same company and same location. They have high possibility to like similar interests because they often spend time in the company. Meanwhile, a service provider of the movie recommendation service needs to find potential viewers of a new released movie. Therefore, it generates the social correlation group which includes similar tasty humans and advertises new movie.

When the service provider only sends a trailer of new movie to Alice who is fully connected with other group members, Alice can share the trailer within the social correlation group. It can minimize the delivery costs by avoiding redundancy delivery to each person.

According to the scenario, the service requirement is about a new movie which is the content. Thus, we perform the movie advertisement based on the SRS in the condition s2 mentioned at the section 3.3.

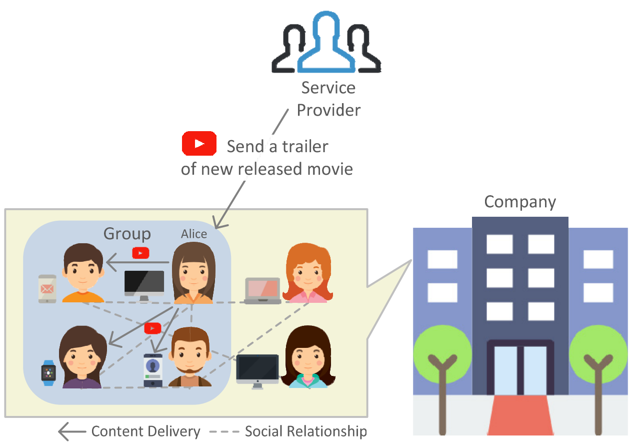


Fig. 4. Simulation scenario overview

4.2 Simulation Environment

As shown in the Table 3, we use open datasets to simulate the movie recommendation. First, social information in the SNS domain is based on a dataset of MovieLens [23] which recommends movies depending on personalized interest of each user. The MovieLens dataset contains demographic information of 6040 users (e.g., gender, age and occupation) and rating history about 3876 movies given by users in the past. Second, in cased of the IoT service domain, there is no device information. For the simulation, we assign one device for each user and distribute the target movie to them with the normal distribution. Finally, to calculate profile similarity and select closest movies with the target movie, we use IMDb API [24] to query detailed IMDb metadata of 3876 movies of MovieLens. Thus, it can connect IMDb movies to MovieLens users who has rating history about them.

Table 3. Simulation datasets

Service Domain	Service Name	Data Type	Description
SNS	Movie Lens	ID	The user's ID
		Gender	The user's gender
		Age	The user's age group
		Occupation	The user's job
IoT Service	Normal Distri-bution	ID	The device's ID
		Type	The device's type (e.g., smartphone, tablet, computer)
Media Service	IMDb	ID	The media's ID
		Released Year	The year that the media release
		Genre	The media's genre
		Director	Directors of the media
		Writer	Writers of the media
		Actor	Actors of the media
		Country	Countries where the media has been released

In the simulation environment, we used Microsoft Visual Studio to preprocess data and calculate similarity. Moreover, Eclipse Juno is used with Apache Jena 3.1.0 [25] framework to build ontology graph model, and includes Json-simple 1.1.1 [26] library to query IMDb metadata. Finally, we use Protégé 5.1.0 [27] to check outputs of the ontology graph.

4.3 Simulation Results

To simulate the SRS according to the scenario mentioned above, we generate the ontology graph which connects information from three service domains as shown in the Table 3. Fig. 5 shows an ontology graph model of the SRS which sets social relationships among MovieLens User, IMDb Movie and Device. For example, MovieLens User is connected to IMDb Movie by 'rates' relationship. With this graph model, we can query required information when generating the social correlation group. Thus, we can query required information when generating the social correlation group.

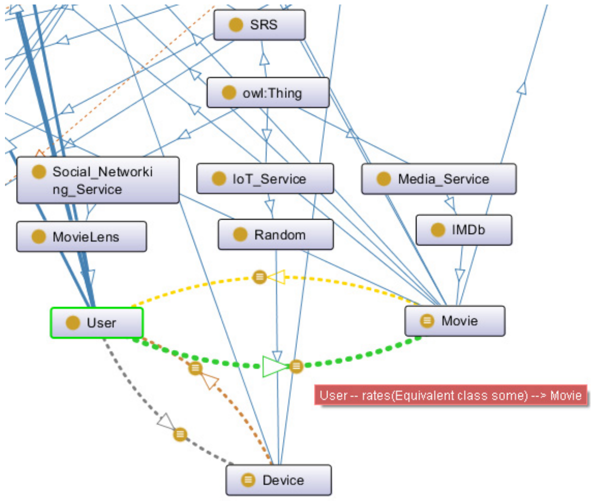
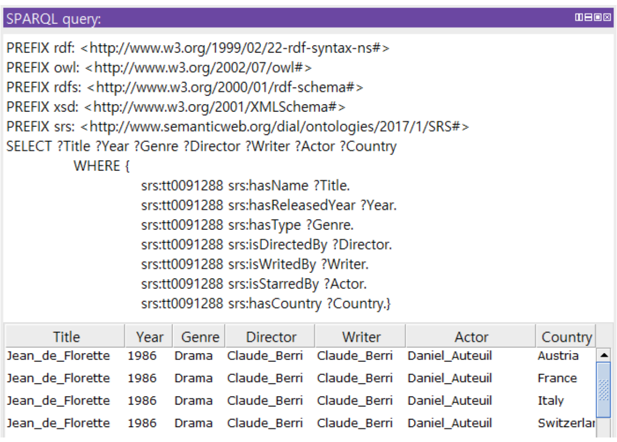


Fig. 5. Ontology graph model of the SRS

Based on the ontology graph, we proceed the SRS for the service requirement with the procedure as shown in the Fig. 3. In the service scenario, the requirement is a new released movie. Thus, we generate the social correlation group containing some users which expect to have as interesting to the movie.

However, since every movie generates different social correlation groups depending on its features, there is no point in averaging evaluation results about them. Therefore, we conduct one case of the simulation for the movie advertisement by selecting one of IMDb movies randomly as the target movie.

Fig. 6 shows the SPARQL query result about movie metadata of the target movie with the phase 1) of the procedure. According to the result, the target movie is "Jean de Florette" released in 1986. The movie genre is drama and it was made by one director (i.e., Claude Berri), three writers (i.e., Claude Berri, Gerard Brach, Marcel Pagnol) and four main actors (i.e., Yves Montand, Gerard Depardieu, Daniel Auteuil, Elisabeth Depardieu). Moreover, the movie released in France, Switzerland, Italy, Austria.



SPARQL query:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX srs: <http://www.semanticweb.org/dial/ontologies/2017/1/SRS#>
SELECT ?Title ?Year ?Genre ?Director ?Writer ?Actor ?Country
        WHERE {
                srs:tt0091288 srs:hasName ?Title.
                srs:tt0091288 srs:hasReleasedYear ?Year.
                srs:tt0091288 srs:hasType ?Genre.
                srs:tt0091288 srs:isDirectedBy ?Director.
                srs:tt0091288 srs:isWritedBy ?Writer.
                srs:tt0091288 srs:isStarredBy ?Actor.
                srs:tt0091288 srs:hasCountry ?Country.}
```

Title	Year	Genre	Director	Writer	Actor	Country
Jean_de_Florette	1986	Drama	Claude_Berri	Claude_Berri	Daniel_Auteuil	Austria
Jean_de_Florette	1986	Drama	Claude_Berri	Claude_Berri	Daniel_Auteuil	France
Jean_de_Florette	1986	Drama	Claude_Berri	Claude_Berri	Daniel_Auteuil	Italy
Jean_de_Florette	1986	Drama	Claude_Berri	Claude_Berri	Daniel_Auteuil	Switzerlai

Fig. 6. SPARQL query result about movie metadata

Because the target movie "Jean de Florette" is assumed as the new released movie, the service condition becomes the s2. Thus, we should go through the phase 2-2) which classify similar movies to fill rating history instead of the target movie.

For calculating the profile similarity between "Jean de Florette" and one of IMDb movies, we also query movie metadata of other movies. With query results, we use the Eq. (2) and compare six kinds of profile information (i.e., released year, genre, director, writer, actor and released country).

Therefore, Fig. 7 shows the number of IMDb movies with profile similarity. According to the graph, only one movie has the highest similarity which is 0.708. Moreover, two movies have the second-highest similarity which is 0.417 and two movies out of 44 have the third-highest similarity which is 0.375. Meanwhile, we limit number of movies to regulate the amount of ratings and take accurate calculation. Thus, according to the profile similarity, we select five closest movies mentioned above and appoint them to the classification.

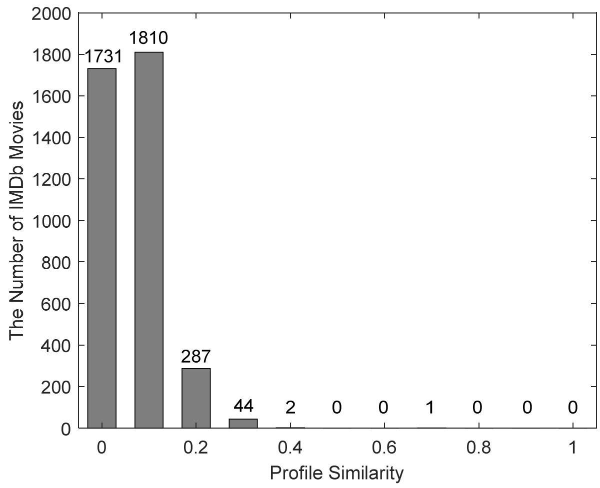


Fig. 7. The number of IMDb movies with profile similarity

For the phase 3) in the procedure, we aggregate rating information about five classification members. There are 510 ratings from 446 users in the past. To raise the accuracy of the correlation, we select 44 users as candidates who have rated more than twice.

The final phase 4) generates the social correlation group with ratings from 44 candidate users. To know who has more interests about the target movie "Jean de Florette", we calculate predicted ratings of 44 candidate users by using Eq. (3). Consequently, we extract 27 users who have an above-average predicted rating to the social correlation group.

4.4 Evaluations

With the social correlation group containing tasty users, we show how much they like the target movie "Jean de Florette" with three evaluations.

1) Prediction accuracy of expected preferences

To prove that we extract proper users who like the target movie, we calculate accuracy of predicted ratings. Thus, we use Mean Absolute Error (MAE) [28] as shown in the Eq. (4). It means average error between actual rating r_i and predicted rating $\overline{r_i}$. For this equation, we use actual ratings generated by 27 users about the "Jean de Florette".

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|r_i - \overline{r_i}| = \frac{1}{n}\sum_{i=1}^{n}|e_i| \quad (4)$$

Fig. 8 shows the number of social correlation group members with *MAE*. *MAE* values of 23 users who belong to almost 85 percent of the social correlation group members reveals under 0.1. Therefore, it is obvious that we properly predict expected rating values about the "Jean de Florette".

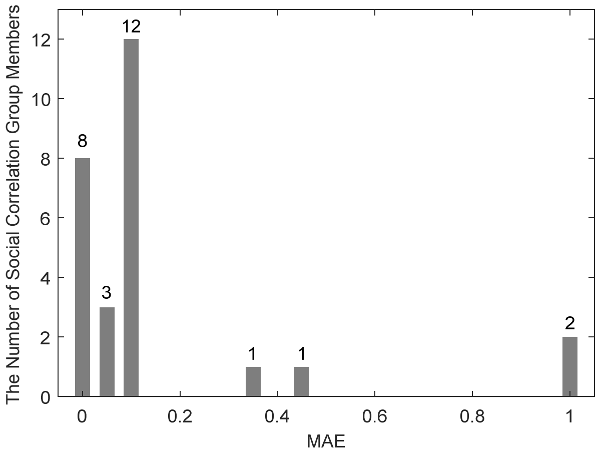


Fig. 8. The number of social correlation group members with *MAE*

2) Preference evaluation of the social correlation group

Fig. 9 shows mean values of actual ratings about the "Jean de Florette" in the MovieLens dataset. The mean value of the social correlation group reveals 0.4 higher than the mean value of whole area. With this result, we expect that members of the social correlation group have high possibility to like the trailer of "Jean de Florette".

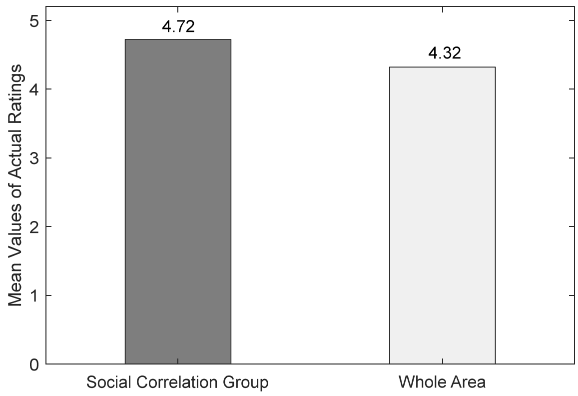


Fig. 9. Mean values of actual ratings

3) Hit ratio of the social correlation group

We reveal the hit ratio of 27 users in the social correlation group whether they have watched after receiving the trailer of the "Jean de Florette". For this evaluation, we conduct the SPARQL query result about device information owned by members of the social correlation group as shown in the Fig. 10.

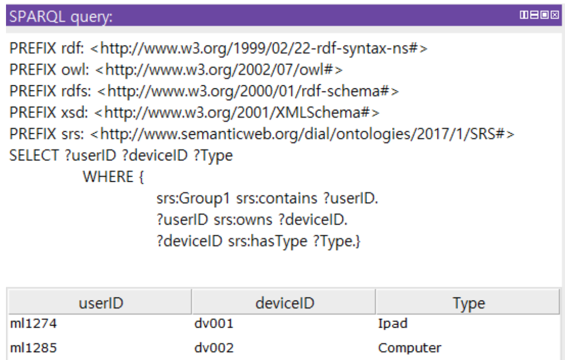


Fig. 10. SPARQL query result about device information

Based on the device information in the query result, we conduct the movie advertisement of the "Jean de Florette". To show the correlation between rating values and hit ratios, we query about the target movie. However, there is no real information about the distribution of the target movie file. Thus, we assume that the hit ratio of each user is related to the user preference such as rating value and comment.

We define the Eq. (6) modified the Eq. (5), the normal distribution, to generate the distribution model of hit ratios for each user. We make it more affordable for showing the relation between the rating value X and hit ratio $HitRatio(X)$. Moreover, we set X from 0 to 5 for representing rating values, and divide the Eq. (6) by $f(5)$ to leverage max $HitRatio(X)$ value to 1 for representing hit ratios. Finally, we set α as the standard deviation of the correlation between X and $HitRatio(X)$.

$$f(x) = \frac{1}{\sqrt{2\pi}\alpha} \cdot e^{-\frac{(X-5)^2}{2\alpha^2}} \quad (5)$$

$$HitRatio(X) = \frac{1}{\sqrt{2\pi}\alpha \cdot f(5)} \cdot e^{-\frac{(X-5)^2}{2\alpha^2}} \; (0 < X \leq 5) \quad (6)$$

Consequently, Fig. 11 shows mean hit ratio with correlations by using the Eq. (6). When we calculate the standard deviation based on the MovieLens dataset, α reveals 0.8258. When α is 0.8258, the mean hit ratio of the whole area reveals 68.178%. On the other hand, the mean hit ratio of the social correlation group reveals 88.453% which is 20.275% higher than the whole area. Moreover, to compare the mean hit ratio depending on correlations between rating values and hit ratios, we calculate them when α is from 0.1 to 1.5 as shown in the Fig. 11. With this result, the proposed SRS with the social correlation group shows better performance than the whole area.

Therefore, we expect that members of the social correlation group have high possibility to watch the "Jean de Florette" after the movie advertisement regardless of the correlation between the rating and the hit ratio.

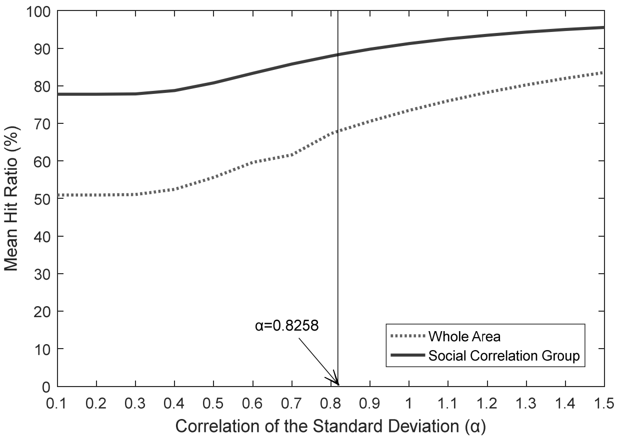


Fig. 11. Mean percentages of hit ratios with correlations

We compare the supporting status of service requirements between the existing recommender systems and the proposed SRS as shown in the Table 4. The Collaborative Filtering does not support the s1 and s2. Moreover, the Content-based Recommender System does not provide the s1. But, the proposed SRS supports every service conditions (i.e., s1, s2 and s3) as mentioned in section 3.3.

Table 4. Service requirement comparison between the existing recommender systems and the proposed SRS

	s1	s2	s3
Collaborative Filtering [14]	X	X	O
Content-based Recommender System [15]	X	O	O
The proposed SRS	O	O	O

5. CONCLUSION

The Social IoT, the follow-up of the IoT, has been studied to autonomously establish social relationship of devices and create their own social network separated from human. This social relationship is expected to boost resource discovery and service composition from distributed devices. Likewise, the Social IoT can guarantee the network navigability to find specific devices or resources, and establish levels of trustworthiness to leverage the degree of interaction among devices. However, the Social IoT has problems about data discovery. It should handle massive data generated by human, devices and resources. Thus, users and service providers need to distinguish indiscriminate data when generating some required services.

In this paper, we proposed the SRS for the Social IoT Environment. The proposed system generated the social correlation group which includes more correlative information about service requirement. To extract the group, we designed the architecture and the procedure of the SRS. We utilized two main recommender systems of media streaming services, which are the Collaborative Filtering and the Content-based Recommender System. Moreover, we considered various factors about the social interest similarity to apply social features.

We generated the ontology graph model to connect datasets from three service domains (i.e., SNS, IoT service and media service). Thus, it provided query results including required information through social relationship. Moreover, according to the service scenario about the movie advertisement, we simulated the SRS according to the target movie “Jean de Florette”. The MAE of social correlation group members reveals under 0.1, which means most predicted rating are accurate. And, in view of mean values of actual ratings, the social correlation group had 0.4 higher mean than the whole area. It revealed that the social correlation group extract more correlative users with the “Jean de Florette”. Finally, when we distributed the “Jean de Florette” according to the random distribution, every hit ratios of the social correlation group shows higher than the whole area regardless of the correlation between ratings and hit ratios.

With simulation results of one Social IoT service scenario, we show the feasibility of the SRS. It can be used diversely when finding devices which is available to provide the target service or services which the target user will need. For the future work, the SRS will connect more various service domains such as transport, health care and medical treatment to provide adaptive services for users.

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Deok-Hee Kang
She holds the B.S., M.S. degrees in multimedia engineering from the Hanbat National University, Korea in 2015, 2017 respectively. Her main research interests include Social Internet of Things, recommender system, and multimedia services.

Hoan-Suk Choi
He is a Ph.D. candidate at the Hanbat National University, Korea. He received his M.S degree in multimedia engineering from the Hanbat National University in 2011. His research interests include Social Internet of Things, trust evaluation, semantic processing. He has been actively working for standardization in ITU-T since 2015.

Sang-Gyu Choi
He holds a Ph.D. degree from the Inha University, Korea in 1989. He is with the Hanbat National University, Korea as a professor. His research interests include Mathematical Analysis.

Woo-Seop Rhee
He holds a Ph.D. degree from the Chungnam National University, Korea in 2003. From 1983 to 2005, he was with the ETRI as a team leader. He is currently a Professor of the Hanbat National University. His research interests include Social Internet of Things, Trust management and evaluation, Context-aware Service. He has been actively working for standardization in ITU-T SG13, SG20 as an editor and oneM2M