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Multimedia recommendation using Word2Vec-based social relationship mining

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Abstract
This study proposes the multimedia recommendation method using Word2Vec-based social relationship mining. This is to analyze users with a similar tendency on the basis of the keywords related to multimedia content and sentiment words of comments, to build a trust relationship, and to recommend multimedia. In order to solve the problem of data sparsity, metadata of multimedia content are collected and then are clustered by genre. User's evaluate a preference for multimedia content. With the use of evaluation data, the attributes preferred by users are predicted. In terms of propensities, the sentiment words in users comments are classified by SVM on the basis of sentiment dictionary. The classified sentiment words are presented in vector with the use of Word2Vec. In terms of the vector of sentiment words, the dynamic relationship between users of words in the same preference by the similarity using the distance scale. It helps to build a trust relationship between users with preferences that can change with a lapse of time. Accordingly, multimedia content are recommended to users with a similar tendency. In terms of performance evaluation, F-measure is compared with the uses of precision and recall for a recommendation. As the result of evaluation, the social relationship mining method is evaluated to be better than explicit and implicit recommendation methods. With the proposed method, it is possible to search with metadata of content and make a intelligent recommendation explicitly and implicitly according to user's tendency.

Keywords Multimedia · Recommendation · Word2vec · Social relationship mining

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1 Introduction

With the development of network and the penetration of smartphones, the number of social networking service(SNS) users is increasing. User's create various relationships online through SNSs. A social networking service is an online platform that makes it possible for not only users close with each other but anonymous users to communicate freely, share information and build interpersonal relationship [29]. In a SNS, users are able to share a variety of information such as something in particular interest, activities of daily living, and emotional expressions. Through social mining [30], reliability and sharing between users, information extraction, change in preference over time, time-series prediction of social stream are applied to a recommendation system. Social mining is the process of obtaining user data from social media and processing them in order to extract meaningful patterns or knowledge. It consists of the following steps: source search, document extraction, keyword definition, analysis option, and search. In this way, it is possible to find user's behavior, thinking, and desires, and thereby understand a social flow and trend. Accordingly the process, it is possible to predict sales, promotions, and social changes [14]. Social media are an open online platform where users can share their thinking, opinions, experiences, and information with each other, and create or expand mutual relationship. In the platform, various kinds of data, such as text, images, and video, are shared [14, 30]. Multimedia include myriads of media information and are created, saved, and processed in a digital form. For this reason, multimedia data can be obtained, saved, and processed with the use of a digital device. With the development of SNSs, it is possible to interact with other users, freely communicate, share information, transmit emotions, and build a relationship in an online environment [6].

In a multimedia platform, the problems of sparsity and first rating are addressed on the basis of precise content classification in order to provide a personalized recommendation. For content classification, YouTube has such content rating labels as Strong language (L), Nudity (N), Sexual situations (S), Violence/disturbing (V), Drug use (D), and Flashing lights (F). With the rating labels, YouTube control users' access when video content is uploaded. In addition, with green (monetizing) and yellow (limited or no ads) icons, YouTube decides monetization, and therefore an inappropriate video is unable to be monetized [35]. With the increase in content makers, there is less reliability of precision of content classification. In order to extract important information from multimedia content, importance is calculated through information relationship modeling and then information noise is removed [6].

In terms of online characteristics, massive data can be generated depending on a purpose, and the reward of achieving the purpose is mostly larger than the cost for data generation. It is hard to detect a user for a particular purpose, because of anonymity using the roundabout method using SNS characteristics. For example, when content is uploaded, irrelevant content is inserted and the number of hits is manipulated in order to get the original content exposed to the top rank of a portal site. As a result, general users are able to get exposed to malicious content. A method of improving precision of content classification based on content user information has been researched. For instance, deep learning based classification has the limitations of calculation time and cost and has difficulty in filtering distorted information. Clustering using nearest neighborhood in collaborative filtering causes the problem of initial evaluator and lowering calculation efficiency [9, 10]. At present, online portal sites are prone to easily occurs Abusing, a dictionary definition of abuse and misuse of content. That is because content is easily changed, added, and updated by multiple users. Abusing is the action of increasing the number of hits through intentional search, continuous transmission of the content with the same title, or the manipulation of the hit number to put keywords in the top ranking of portal sites in real time [20]. It causes user's confusion about proper information collection and decreases precision of recommendations. Therefore, this study proposes the multimedia recommendation using Word2Vec-based social relationship mining. The proposed method collects metadata from multimedia content by genre, title, and keyword, and then clusters them by genre. In addition, it classifies sentiment keywords of user comments depending on user tendency. By analyzing user's preference to content cluster, it classifies a user tendency into positive, negative, and neutral on the basis of content metadata. In user's comments, their preferences that can be changed with a lapse of time are analyzed, and thereby a trust relationship between users with a similar tendency is created. By using the trust relationship, it is possible to find their preferences, and search for multimedia content with the use of keywords. After a vector is given to the word presenting a tendency in a user's comment, the trust relationship between users with a similar tendency is created through similarity of words. In this way, the multimedia content that has reliability of users with a similar tendency is recommended.

The rest of this paper is organized as follows. Section 2 provides a personalization classification through social big data analysis and a discovery of trust relationships in social networks. Section 3 provides a multimedia recommendation using Word2vec-based social relationship mining. Also, section 4 provides evaluation results. Finally, conclusions are given in Section 5.

2 Related work

2.1 Personalization classification through social big data analysis

With the development of internet, it is possible to share information with other users in the world, and people's characteristics are considered important according to diverse occupations and situations. People have different preferences for music, films, food, and video. Based on the personalized information, various techniques of social big data indexing, classification, and search are researched. S. Pang et al. [27] suggested the personalized model conversion method using SVM classification tree. It uses the knowledge created by SVM based classification tree in order to classify Personalized Transductive Learning (PTL) effective for new test instances. The method is able to reduce a size of tree of social big data and solve the problem of overfitting. Through the feature extraction and learning with the use of users' preferences, knowledge base is created, and information is offered through personalized

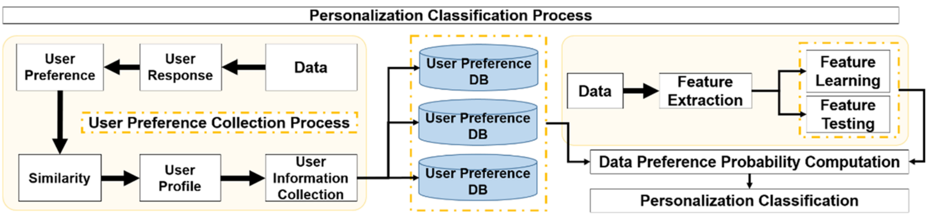

Fig. 1 Personalized classification process through social big data analysis

classification. Figure 1 shows the personalized classification process through social big data analysis [2].

G. Sanghani, K. Kotecha [28] proposed the personalized email spam classification method in internet. This method solves the error cost imbalance of email spam, frequent content change, the problem of personalized situations. Using TFDCR(Term Frequency Difference and Category Ratio), it extracts the features based on term frequency and category ratio. In addition, a classifier dynamically updates discriminant functions, and a heuristic algorithm is applied to identify an e-mail set in order for precise classification. Also, the method is able to reduce the error of classifying necessary e-mail messages in spam.

2.2 Discovery of trust relationships in social networks

With the wide penetration of smartphones, people's way of communication has been changed. Since SNSs including Twitter, Instagram, and blogs were developed, it has been to make communication with many and unspecified persons. As a relationship between them, a social network is created. SNSs are classified into open type and close type. Open SNSs help to make relationships with many and unspecified users. Close SNSs help to create relationships with acquaintances [15, 30]. Social mining makes it possible to analyze users on the basis of the multimedia content of social media, including text, photos, and video, and investigate the change flow and patterns of issues. With the uses of various analysis results and patterns, a changing social flow, a management strategy, marketing, and other things are intelligently determined [30]. The result predicted with the use of a trust relationship between users is applied to various areas, including decision making, marketing, and financing. Trust relationship is divided into direction connection and indirect connection. Direct connection means a relationship with close persons, presenting a high degree of reliability. Indirect connection means a relationship with the high possibility of obtaining new information in the aspect of information acquisition, although it has a low degrees of reliability [37]. Reliability is more important in an online environment than in offline environment in terms of information transactions with the persons never seen before. It involves the issue of truth of the content to be offered. Information shared by users with a similar tendency makes it possible to create a consensus and thereby has a higher likeliness of reliability. Based on the similarity of users, it is possible to build a trust relationship. Accordingly, how to build and develop trust in an

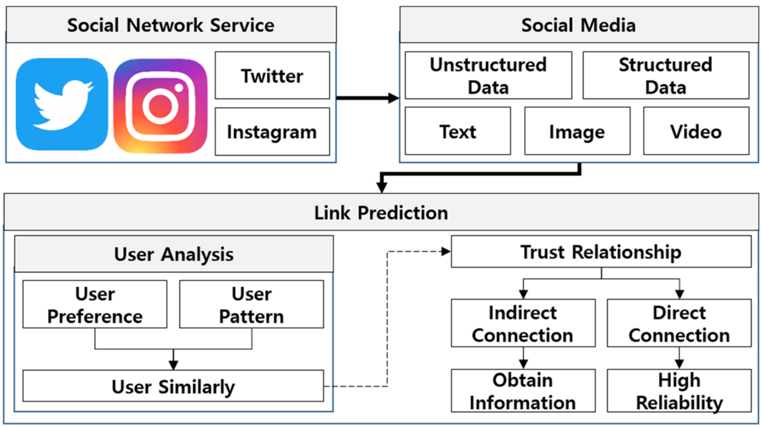

Fig. 2 Discovery of trust relationships in social networks

online environment is researched [1]. Figure 2 shows discovery of trust relationships in social networks.

L. Guo, B. Zhang [15] Developed the structural influence analysis method for analyzing a meaningful relationship in a social network. In this method, after a degree of influence between nodes is judged in a low-density network, structural influence is analyzed in order to predict a degree of influence between a center node and a different node. A. Helal et al. [17] proposed the efficient algorithm for community search in a social network. This method is used to search for a leader of a social network and create a community based on the leader. Members of the same community are detected to share common behavior. In terms of the detection of the community reflecting a person's behavior, similarity is measured in consideration of the added data of nodes in order to improve the quality of a detected community. Therefore, the proposed algorithm is able to detect the number of similar communities more precisely than the algorithm that fails to consider the added data of nodes.

3 Multimedia recommendation using Word2Vec-based social relationship mining

3.1 Composition of multimedia contents

As the data for multimedia recommendation, in this study the metadata of movies, user's comments, and the content of users' conversations were used. As metadata of multimedia content, the open data offered by TMDb(The Movie Database) [32] were collected. TMDb stores a database of films and TV programs the contents of which were created in communities and provides data for companies related to developers to create a recommendation service. The metadata of movies and TV programs are continuously updated for users, and are provided in a variety of languages, allowing everyone to use them. As an open platform accessed daily by numerous users, TMDb offers a variety of metadata of multimedia content. These metadata consist of 24 attributes, including budget, genre, keyword, and language. Table 1 shows the schema composition of multimedia contents.

In this study, from among the 24 attributes genre, keyword, and title were used. Keywords were used to search for multimedia content. For example, the metadata for the movie "Avatar" are classified into Action, Adventure, Fantasy, and Science Fiction genres. Its title is Avatar, and the search keywords are Culture Clash, Future, Space War, Space Colony, Society, Space Travel, and Futuristic. Users' comments and conversation contents related to a movie are collected using a Web crawler. From the collected comments, words representing sentiments are extracted. Through preprocessing, stop words and special expressions are removed. Using the extracted words, a sentiment analysis dictionary based on KoSAC [21] is created to analyze the propensities of users' comments. Only the meanings of sentiment words showing a tendency, regardless of their forms, are taken into account, and thus, the words are classified into positive, negative, and neutral propensities. Table 2 shows a part of the sentiment dictionary for tendency analysis. NEG represents a negative tendency, NEUT a neutral tendency, and POS a positive tendency. In addition, *max.prop* represents a maximum probability and *max.value* represents a maximum value. *Max.prop* means the

Table 1 Schema composition of multimedia contents

Data	Type	Description
adult	Boolean	[FALSE, TURE]
belongs_to_collection	String	[String]
budget	String	[String]
genres	String	[String]
homepage	String	[String]
id	Numeric	[Num]
imdb_id	String	[String]
original_language	String	[English, Korean]
original_title	String	[String]
overview	String	[String]
popularity	Numeric	[Num]
poster_path	String	[String]
production_companies	String	[String]
production_countries	String	[String]
release_date	Date	[YYYY-MM-DD]
revenue	Numeric	[Num]
runtime	Numeric	[Num]
spoken_languages	String	[String]
status	String	[String]
tagline	String	[String]
title	String	[String]
video	Boolean	[FALSE, TURE]
vote_average	Numeric	[0~10]
vote_count	Numeric	[Num]

maximum value among the NEG, NEUT, and POS probability values. *Max.value* means the maximum value among the NEG, NEUT, and POS values.

For example, in case of the word "baseless," the probability of NEG is 0.470, the probability of NEUT 0.235, and the probability of POS 0.294. In this case, the probability

Table 2 Sentiment dictionary for tendency analysis

Word	NEG	NEUT	POS	Max.value	Max.prop
Honesty	0	0	1	POS	1
Joyful	0	0	1	POS	1
Baseless	0.470	0.235	0.294	NEG	0.470
Adverse	0.364	0.273	0.364	NEG	0.364
Conventional	0	1	0	NEUT	1
Incredulous	0	1	0	NEUT	1
Urgent	1	0	0	NEG	1
Imaculate	0	0	1	POS	1
Disappoint	0.667	0.167	0.167	NEG	0.667
Enjoin	0.556	0.056	0.278	NEG	0.556
Frazzle	0.500	0.500	0	NEG	0.5
...	...	...	...	...	...

of NEG is the highest, and therefore *max.prop* is 0.470 and *max.value* is the value of NEG. Therefore, the tendency of "baseless" is negative.

3.2 SVM-based user tendency classification model

Using unstructured, semi-structured, and structured data types of multimedia content, including nonverbal sounds, such as accent and tone, verbal conversation content of text, video, and photos, a persons' sentiment can be analyzed. In addition, sentiment tendency can change over of time, and therefore, it has a dynamic feature. Through social relationship mining, sentiments are analyzed in sequential patterns. Regarding the verbal conversation content of text, context analysis can be applied repeatedly to analyze the sentiments that are found as they change with time. Therefore, the sentiment words in contexts are analyzed by algorithms, such as support vector machine (SVM), k-nearest neighbor (KNN), decision tree, and naïve Bayes classification, to infer a tendency and classify the sentiment words into positive, negative, and neutral types.

If attributes that are irrelevant to the input and output attributes and that have a mutual relationship are included in classification, overfitting, which reduces the precision and reliability of classification, may result. In addition, if many attributes are included in the classification, the operation cost can increase. Therefore, regression analysis is conducted to maintain the classification precision and decrease the level of dimensions. Regression analysis [16] is a statistical technique for estimating the influence of one or multiple independent variables on dependent variables. The technique can be applied to various areas that involve prediction. The regression analysis applied in this study utilizes an SVM algorithm. SVM is a machine learning approach and is applicable in linear and non-linear classification. Its output is a set of hyperplanes for classification or regression analysis [22]. A hyperplane consists of an n-dimension plane for separating data in a multi-dimensional space. In this study, the SVM algorithm was used to find a hyperplane for classifying words precisely into each tendency type. Based on the hyperplane, words are classified into positive, negative, and neutral tendency types. Figure 3 shows the SVM-based user tendency classification model.

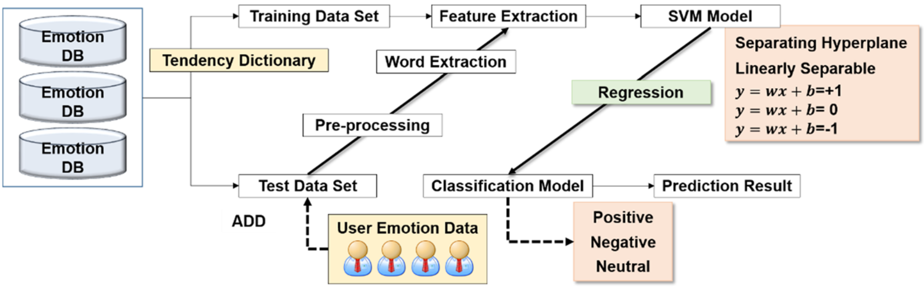

Fig. 3 SVM-based user tendency classification model

First, the tendency data of a sentiment dictionary are used as the dataset to train the SVM-based sentiment tendency classification model, and then, features are extracted from the test data set through preprocessing. Using a suitable hyperplane, the SVM model linearly separates the training data. If an observed value is larger than the hyperplane, it signifies a positive tendency and if smaller, it signifies a negative tendency. If an observed value is equal to the hyperplane, it signifies a neutral tendency. To determine a new user's tendency, features are extracted, and then the extraction results are classified into the positive, neutral, or neutral tendency type by means of the SVM model according to the training dataset. The classification result is saved in the database. Second, the classification technique predicts a tendency according to a genre of multimedia content to estimate a user's preference tendency for genres. For the analysis, the multimedia data are classified into 20 genres: Action, Adventure, Animation, Comedy, Crime, Drama, Family, Fantasy, History, Horror, Music, Mystery, Romance, Science Fiction, Thriller, War, Western, Documentary, TV Movie, and Foreign. The multimedia content is clustered according to genres. In clustering analysis [4], the similarity of each of the data items is measured, and then, they are grouped into clusters. The similarity of objects in a cluster and the association of objects in a different cluster are determined. Multimedia content can belong to multiple different genres, or to one or two genres. For instance, the movie "Avatar" belongs to four genres: Action, Adventure, Fantasy, and Science Fiction. For this reason, overlapping clustering is applied. Overlapping clustering is the simplest and most efficient clustering technique; it uses a K-means algorithm. By using a K-means algorithm, the technique creates clusters according to the genres of multimedia content. The implementation of K-means algorithms [11, 19] is very simple and clustering is based on a distance scale. The algorithm uses K as an input parameter and splits K clusters into N datasets. The mean value of the data is based on similarity. In this study, K was set to "10"

Table 3 Representative values of clusters using genres

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
G1	1.0000	0.0000	0.4949	1.0000	1.0000	0.0000	0.5078	0.4958	0.0000	1.0000
G2	1.0000	0.0000	1.0000	1.0000	0.0000	0.0000	0.0000	1.0000	1.0000	0.0000
G3	1.0000	1.0000	0.5051	1.0000	1.0000	0.0000	0.0000	0.5042	0.0000	1.0000
G4	0.0000	0.0000	0.4949	0.0000	0.0000	0.0000	0.0000	0.4958	1.0000	0.0000
G5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.0000	1.0000
G6	1.0000	1.0000	0.5051	1.0000	0.0000	1.0000	0.0000	0.5042	1.0000	0.0000
G7	0.0000	1.0000	0.0000	1.0000	1.0000	1.0000	1.0000	0.0000	0.0000	1.0000
G8	0.0000	1.0000	0.5051	0.0000	1.0000	1.0000	0.4922	0.5042	0.0000	1.0000
G9	1.0000	1.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000
G10	0.0000	0.0000	1.0000	1.0000	0.0000	1.0000	1.0000	1.0000	0.0000	0.0000
G11	1.0000	0.0000	0.4949	1.0000	1.0000	1.0000	0.0000	0.4958	0.0000	1.0000
G12	1.0000	0.0000	0.0000	1.0000	1.0000	1.0000	0.0000	0.0000	1.0000	1.0000
G13	1.0000	0.0000	0.0000	1.0000	1.0000	0.0000	0.0000	0.0000	1.0000	1.0000
G14	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	1.0000
G15	0.0000	0.0000	0.0000	1.0000	1.0000	0.0000	1.0000	0.0000	0.0000	1.0000
G16	1.0000	0.0000	0.0000	1.0000	1.0000	1.0000	1.0000	0.0000	0.0000	1.0000
G17	0.0000	0.0000	0.5051	0.0000	1.0000	0.0000	1.0000	0.5042	0.0000	1.0000
G18	0.0000	0.0000	1.0000	0.0000	1.0000	1.0000	0.5078	1.0000	0.0000	1.0000
G19	0.0000	0.0000	1.0000	0.0000	1.0000	0.0000	0.5078	1.0000	0.0000	1.0000
G20	0.7017	0.4528	0.6027	0.7016	0.6027	0.4526	0.5792	1.0000	0.4526	1.0000

Legend Action = G1, Adventure = G2, Animation = G3, Comedy = G4, Crime = G5, Drama = G6, Family = G7, Fantasy = G8, History = G9, Horror = G10, Music = G11, Mystery = G12, Romance = G13, Science Fiction = G14, Thriller = G15, War = G16, Western = G17, Documentary = G18, TV Movie = G19, Foreign = G20 for clustering. As a representative value, the distance between objects in the same cluster is extracted using Euclidean distance. Table 3 shows the representative values of clusters using genres. Genres are represented as {G1, G2, G3, ..., G20} and clusters as {C1, C2, C3, ..., C10}.

In Table 3, the representative value of Cluster 1 is 1 for {G1, G2, G3, G5, G6, G9, G11, G12, G13, G14, G16}, 0 for {G4, G7, G8, G10, G15, G17, G18, G19}, and 0.7017 for G20. The representative value of Cluster 3 is 0.494 for {G1, G4, G11}, 1 for {G2, G5, G10, G18, G19}, 0. 5051 for {G3, G6, G8}, 0 for {G7, G9, G12, G13, G14, G15, G16}, and 0.602 for G20. Based on the Euclidean distance, it is possible to predict that the multimedia of Cluster 1 and of Cluster 3 contain something similar.

Third, the classification technique classifies a user's preference tendency for each content cluster. It finds users' propensities by analyzing their preferred genres. For example, if a user has a negative tendency for G7, it can be predicted that the user also has a negative tendency for contents M1, M2, and M4, which are clustered in G7. Therefore, to evaluate users' tendency for a cluster, preference transactions with the users were performed. Table 4 shows the transactions for multimedia content clustering. Users were presented with {U1, U2, U3, ..., Un}. The data for evaluation preference were collected in a questionnaire survey, and the preferences were evaluated on a scale from 1 to 10 points. A lower preference value signifies "dislike," and a higher preference value signifies "like."

Using Table 4, a user's tendency for multimedia content was analyzed based on the hyperplane of the SVM algorithm that learned tendency data from a sentiment dictionary. If the preference score is larger than the hyperplane, the user has a positive tendency, if smaller, the user has a negative tendency, and if equal, the user has a neutral tendency. Table 5 shows the user tendency analysis algorithm for multimedia contents. As input, the preference for multimedia content, represented by PC[m], is used. The result signifies a user's tendency.

3.3 Word2vec-based social relationship mining in social stream

Through a variety of SNSs, including Facebook, Instagram, and KakaoStory, a social network can be created in an online environment. In a social network, as previously mentioned a user can communicate with other users by sharing a particular interest, activities of daily living, comments, and other emotional expressions [30]. A social network can influence information diffusion, and the degree of information diffusion is determined by the influence of the user posting the

Table 4 Transactions on multimedia content clustering

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	…
U1	1	3	2	2	4	5	3	4	1	7	4	…
U2	4	5	7	2	5	7	1	1	3	4	10	…
U3	3	1	3	3	3	5	3	7	7	7	2	…
U4	8	7	2	7	2	2	4	6	5	5	3	…
U5	7	5	4	1	2	5	6	7	8	1	8	…
U6	3	4	4	5	3	1	3	9	7	10	7	…
…	…	…	…	…	…	…	…	…	…	…	…	…

Table 5 User tendency analysis algorithm for multimedia contents

```
Input : Preference of Multimedia Contents → PC[m]
Output : User Tendency → UT

PreferenceSum[Num_Contents] ← 0
PreferenceCount[Num_Contents] ← 0

for m is multimedia contents that user rated do
    for g is the multimedia contents of PC[m] do
        PreferenceSum[g] ← PreferenceSum[g] + PC[m]
        PreferenceCount[Num_Contents] = PreferenceCount[Num_Contents] + 1
    endfor
endfor
for i = 1 to Num_Contents do
    UT ← MAX(UT, ContentsSum[i] / ContentsCount[i])
    if (UT < Separating Hyperplane)
        UT = Negative
    else if (UT == Separating Hyperplane)
        UT = Neutral
    else
        UT = Positive
endfor
Representative Attribute[UT] ← PC[m]
return
```

information [18]. In an SNS, it is possible to find users' similarity of birth date, birthplace, and interest, and interact with other social networking users. A social network can be characterized by its networking intensity, and the reliability of its users can be characterized by the results of user link prediction. Using link prediction, potential relationships between users can be found [3]. If the prediction shows the hierarchical relationship of users is similar, it implies that their relations are positive and trustful; if the similarity of the relationship is low, it implies negative and untrusting relations. Users' similarity is determined based on the similarity of words in comments, which show their tendency. It is difficult to extract a user's opinion and tendency. Therefore, Word2Vec-based social relationship mining is used to determine a trust relationship among users and then to find the users with a high reliability among users with a similar tendency. The analysis of the similarity of words, which considers the semantic relation between words, is used to find and quantify social relationships. Using Word2Vec, a word is converted to a vector to express the semantic relation. If random words appear in one sentence, they are considered to have semantic similarity, and the co-occurrence relationship between the words is determined. Based on the word tendency analysis results using a sentiment dictionary, a vector model is created according to the tendency words most frequently found in each user's comments and the frequency of the words. A vector model is an algebraic model represented by a vector of identifiers, such as a word index [7, 38]. Accordingly, the words in comments that indicate the user's tendency are converted into vectors in a high-dimensional space and then are presented in graph form. For example, on the assumption that a user who frequently uses negative words has a negative tendency, a user's tendency can be determined by analyzing his/her comments related to each multimedia content. Using word-vector operations, users' tendencies and similarities can be compared and a significant result can be extracted. As similarity operations, Euclidean distance [26], cosine similarity [12], Jaccard's coefficient [5], Pearson's correlation coefficient [39], and Spearman's correlation coefficient [33] are variously used according to the situation. In this study, Euclidean distance and cosine similarity were used to measure similarity. In Euclidean distance, the physical distance between words is calculated for measuring similarity. Cosine similarity represents a direction and is used to measure the similarity of vectors for multi-dimensional data [12].

The higher the similarity of users according to the results of the similarity operations, the greater is the trust between them. In addition, multimedia content can be precisely recommended to a user according to the similarity of his/her tendency with that of another user. Figure 4 shows the results of Word2Vec for the words extracted from users' comments. The horizontal and vertical axes represent the coordinates for expressing a vector of a word.

Figure 4 shows the coordinate plane of the sentiments extracted from each user's comments. If the words of User 1 are similar to those of User 2, it means that the two users have a similar tendency. Figure 5 shows the social relationship mining process in a social stream based on Word2Vec.

4 Evaluation results

4.1 Multimedia content recommendation in social stream

In a social networking service, it is possible to recommend multimedia content in consideration of preferences that change with a lapse of time. Multimedia is the integrated content of various types of information, including text, voice, and video. There are various ways of information awareness and expression. Multimedia content with a similar tendency is massively distributed, and an amount of accumulated information increases with a lapse of time. In this circumstance, users can have difficulty collecting and selecting information of their preferred multimedia content. A recommendation system is able to recommend and offer information and products by creating

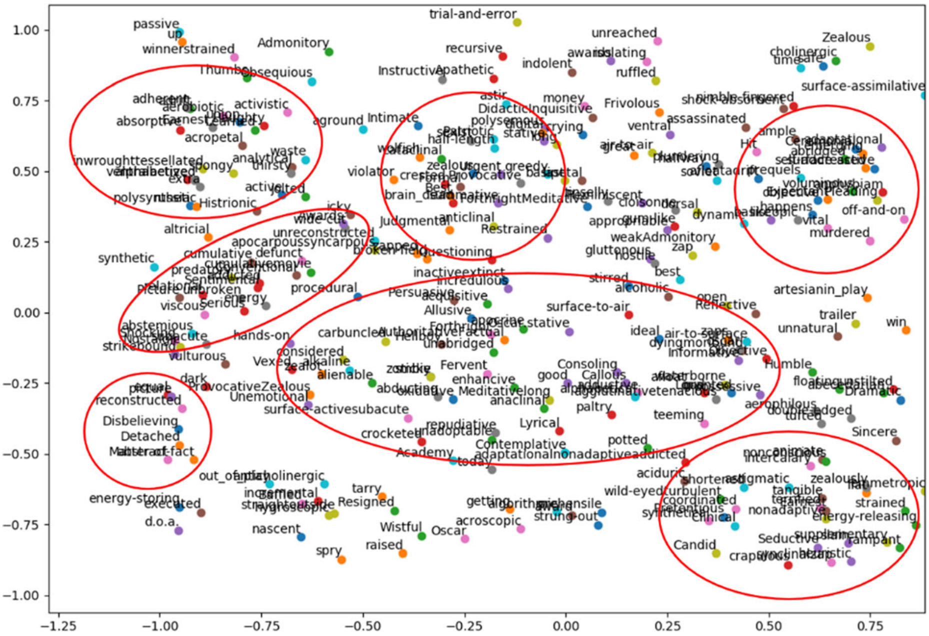

Fig. 4 Results of Word2Vec for words extracted from users' comments

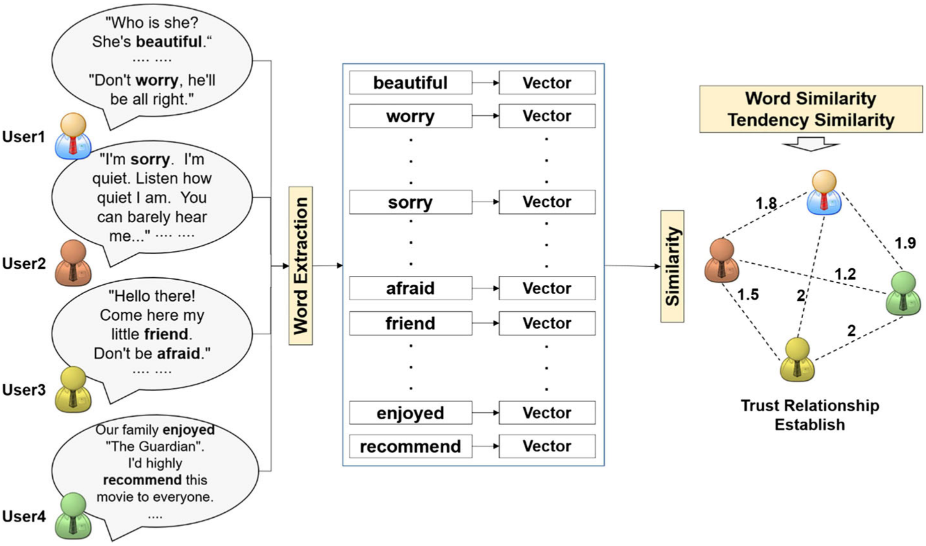

Fig. 5 Social relationship mining process based on Word2Vec in social stream

association relationships or rules through queries of a user's interest, tendency, and preference [34]. A system design process can be different depending on data types, predictive algorithms, and other factors. Types of data include a user's profile, metadata, and attributes of items. As predictive algorithms, there are collaborative filtering, content-based filtering, hybrid filtering, and others. According to social stream recommendation, there are explicit recommendation and implicit recommendation. Explicit recommendation is presented with the evaluation value with user preference information for content. Since a user's preference can be presented explicitly, it is possible to make recommendation intuitively [9, 10]. Implicit recommendation requires such information as a user's purchase history of content, history of views, attribution information, browsing action, web logs, and bookmarks. The recommendation method is able to clearly find a user's preference for content on the basis of the user's records [24]. This study uses the recommendation method that considers complementary factors of both implicit recommendation and explicit recommendation. Figure 6 shows the structure of multimedia recommendation in social stream.

As shown in Fig. 6, the multimedia recommendation method is used to collect metadata of content, extract keywords from user's comments, and save them in sentiment database. In the categories of positive, negative, and neural propensities, data are saved in sentiment database through SVM. And then, the step of tendency clustering of social stream, content metadata is clustered and user's preferences are collected. Preferences are predicted with evaluation values, comments, and patterns. In the step of trust relationship creation, user's similarity is measured in the sequence pattern for evaluation values, comments, and sentiments, in order to build a relationship. The sentiment words of users in comments are converted to vectors, and then similarity of vectors are used. To recommend content fitting a user's tendency, the evaluation values in explicit recommendation method, and user logs, comments and keywords for multimedia content in implicit recommendation method are used.

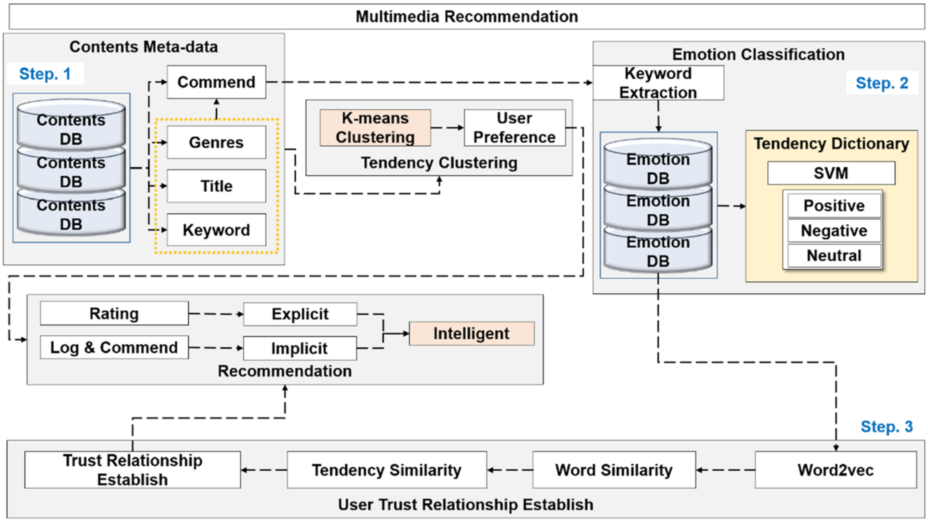

Fig. 6 Structure of multimedia recommendation in social stream

4.2 Performance evaluation

To evaluate the performance of the proposed method, the results extracted from the sentiment analyzer of Kosac [21] are used to make a sentiment dictionary. From the data of test for tendency analysis, semantic information is converted and extracted through morphological analysis. About 8600 words of tendency are classified in consideration of meanings only regardless of word morphology. In terms of the evaluation for the Word2Vec-based social relationship mining for recommending top 15 kinds of multimedia content in consideration of a user's tendency, F-measure using precision and recall for recommendation is applied [23]. As the preference data for evaluation, the evaluation data for the multimedia content collected already is used. In this study, among 4802 kinds of multimedia content, 3360 kinds are used as training data, and 1442 kinds of multimedia content as test data. Formula (1) presents the equation of calculating precision, recall, and F-measure. Precision is used to evaluate whether the recommendation list actually fits a user's tendency. Recall is used to evaluate how many kinds of content are recommended in line with a user's tendency.

$$F\text{-}measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{1}$$

The proposed recommendation method using social relationship mining(SoR) is compared with the recommendation method using collaborative filtering(RCF) [9] and with the recommendation method using content-based filtering(CoF) [10] in terms of performance. Table 6 shows the evaluation results of precision, recall, and F-measure.

Table 6 Evaluation results of precision, recall, and F-measure

	SoR	RCF	CoF
Precision	0.685	0.615	0.552
Recall	0.755	0.592	0.575
F-measure	0.718	0.603	0.563

As the result of the comparative evaluation, the proposed method (SoR) has the best performance. It takes into consideration the complementary factors of both implicit recommendation and explicit recommendation. As a method of giving a sentiment value to an associated tendency in order for recommendation, the proposed one is able to respond to an unexpected situation. In terms of the recommendation for multimedia content, the proposed method has high precision and recall thanks to the synergy effect of social relationship mining. The collaborative filtering based recommendation method has low precision and recall, since it fails to solve the problems of initial evaluation and sparsity. The recommendation method using content-based filtering can predict a user's preference for multimedia content through the pattern detection using web browsing, web logs, and bookmarks. In this way, it is possible to recommend the multimedia content similar to a user's tendency. However, due to the large log update for pattern analysis, an error occurred due to information overproduction, which resulted in low reproducibility. Given the evaluation results, the proposed method is able to improve precision for the recommendation a user prefers. Also the user's tendency classification precision evaluate performance using ROC curve. ROC curve is common way to assess the accuracy of classification in supervised learning [13, 25, 31, 36]. Area under curve is used for classification in unbalanced classes [8]. The area of the ROC curve can be expressed as between 0.5 and 1, where 0.5 means a poor classifier, and a 1 indicates a very good classifier.

Figure 7 shows the evaluation results of classification using ROC. X-axis means false positive rate and Y-axis represents the true positive rate. The results in Fig. 7 are suitable for classifying dispositions as negative and positive. This means that the classification of the user's propensity words used in the model is appropriate.

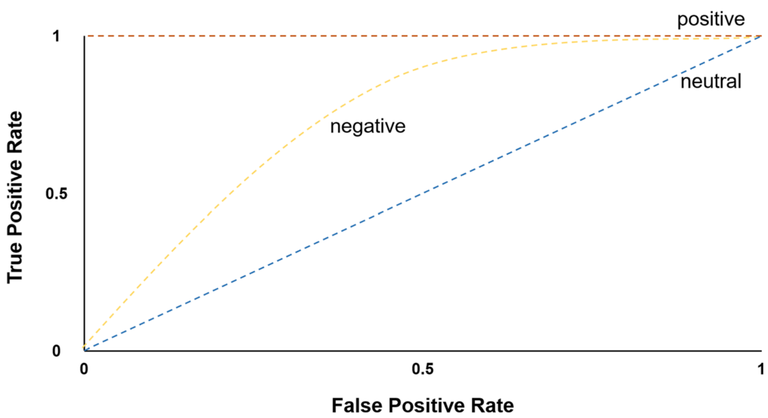

Fig. 7 Evaluation results of classification using ROC

5 Conclusions

A recommendation system needs to ensure precise recommendation in line with a user's tendency. This study proposed the multimedia recommendation method using Word2Vec-based social relationship mining. It collects information on genre, title, and keyword from metadata content. And then, users' preferences and comments are collected on the basis of multimedia content. Multimedia content is clustered by genre in order to solve the problem of data sparsity. One multimedia content can be clustered repeatedly in multiple genres. It is the process of recommending content intelligently through metadata search for a user's preference and multimedia content. Sentiment words are extracted from the comments related to content, and then are classified into positive, negative, and neutral types through SVM. In order for the precise and reliable recommendation of content fitting a user's tendency, similarity and trust relationship with other users are established. With the use of Word2Vec, sentiment words in the comments of each user are converted into vectors and are quantified. Since semantic relationships of words are taken into account, similarity of words is used to find a social relationship. For performance evaluation, the proposed method is compared with the recommendation method using collaborative filtering and the recommendation method using content-based filtering in terms of precision, recall, and F-measure. As the result of the evaluation, the proposed recommendation method using social relationship mining has the best performance, since it takes into account complementary factors of both implicit recommendation method and explicit recommendation method. Therefore, the Word2Vec-based social relationship mining is used to find a trust relationship, judge a similar tendency, and thereby recommend the most appropriate multimedia content. It is recommended to users who have a similar tendency than other recommendation methods so that the recommended user is recommended to the trusted content.

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