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Identifying Social Relationships using Text Analysis for Social Chatbots*

Jeonghun Kim
School of Management,
Kyung Hee University
(*adsky0719@khu.ac.kr*)

Ohbyung Kwon
School of Management,
Kyung Hee University
(*obkwon@khu.ac.kr*)

A chatbot is an interactive assistant that utilizes many communication modes: voice, images, video, or text. It is an artificial intelligence-based application that responds to users' needs or solves problems during user-friendly conversation. However, the current version of the chatbot is focused on understanding and performing tasks requested by the user; its ability to generate personalized conversation suitable for relationship-building is limited. Recognizing the need to build a relationship and making suitable conversation is more important for social chatbots who require social skills similar to those of problem-solving chatbots like the intelligent personal assistant. The purpose of this study is to propose a text analysis method that evaluates relationships between chatbots and users based on content input by the user and adapted to the communication situation, enabling the chatbot to conduct suitable conversations. To evaluate the performance of this method, we examined learning and verified the results using actual SNS conversation records. The results of the analysis will aid in implementation of the social chatbot, as this method yields excellent results even when the private profile information of the user is excluded for privacy reasons.

Key Words : Social Chatbot; Relationship Awareness; Text Analysis; Privacy Protection

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1. Introduction

A chatbot is a computer-based program that allows a device to have an intelligent conversation with a user in the form of voice, images, video, or text over SNS. Chatbots are used in education, games, and many other settings. iPhone's Siri, Google's Assistant, Amazon's Alexa, and Galaxy S8's Bixby are recent representative examples. With the rapid development of natural language processing and speech recognition technologies, companies are considering adoption of chatbots in customer service applications and employee training.

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When chatbots are used as social agents, users may feel like chatting with them at the beginning of a conversation, but they may also feel that the conversation gradually becomes a struggle. For a social chatbot, it is difficult to learn from past conversational records to improve the quality of the current conversation (Hill et al., 2015). Collection of customer information and improving customer satisfaction may also be difficult. To alleviate this problem, chatbots need the ability to probe users' backgrounds and form a rapport with them. Doing so is not only important in successful human-to-human communication, but can also play an important role in human–agent communication (Cerekovic et al., 2017) with agents such as chatbots. Positivity, attentiveness, and coordination are also necessary to form a rapport, as is knowledge of the human circumstances of the conversation, especially the nature of the relationship (e.g., secretary, friend, relative, etc.).

Context-aware technology automatically collects environmental data about people, time, and location related to interactions between applications (Dey, 2001). One of the contextual perceptions is the ability to recognize the relationships between people or between people and machines, which will foster sustainable and natural personalized communication (Koerner, 2006). In this study, we estimate these relationships between users and objects, hoping to provide users with convenient, timely, high-quality services from social chatbots.

Relationships are also evident in important situational information. However, there is almost no existing research that has investigated this aspect of the relationship between users and chatbots. Developers of social chatbots assume a conversational style chosen by the developer, which may be provider-oriented or obtrusive, thereby decreasing user satisfaction and acceptance.

The purpose of this study is to propose a method which automatically infers how a user interacts with a chatbot during a conversation, assuming a relationship based on written unstructured sentences. We utilize the text analysis function, analyzing sentences provided by the conversant, and the inference function, inferring the relationship. Relationships are classified into four types of social collectives according to the research of Kirkpatrick and Ellis (2001): instrumental coalitions, mating relationships, kin relationships, and friendships. In addition, the user profile, which aids in recognizing the relationship during context recognition, may cause privacy problems; therefore, we herein describe how to avoid these problems.

This paper is organized as follows. In Section 2, we review existing research on relationship recognition with chatbots. In Section 3, we describe the proposed methodology. Validation of the results to verify the feasibility and superiority of our research method is performed in Section 4. Finally, a discussion and description of possible future research directions are provided in Section 5.

2. Literature Review

2.1 Chatbots

Chatbots, also called "conversational agents" and "conversational systems", analyze natural language processing of text or voice data entered by the user and analyze the contents of the text, answering via software (Griol et al., 2013). In recent years, chatbots have been used in increasingly diverse business areas in addition to customer service (Sandbank et al., 2017).

There are three types of chatbots: scenario-based, rule-based, and artificial intelligence-based, depending on how users select responses to queries. First, the scenario-based chatbot is a type in which queries and responses are made according to a predetermined order and content. Second, the rule-based chatbot recognizes the user's answers as a condition and then responds with a conclusion matching the condition type. However, these two types of chatbots have the disadvantage that they cannot respond to exceptional user queries. On the other hand, the artificial intelligence approach can provide the most suitable answer to a new type of query, or if a new conversation is created, its contents may be learned. This method has the advantage of excellence in terms of flexibility and expandability. A chatting service based on the artificial intelligence approach is more sustainable than one based on the other two methods. Early versions of chatbots such as Eliza, for example, were very difficult to understand and respond to in a conversational context because of the pattern matching inherent in conversations. However, the development of natural language processing techniques and artificial intelligence has improved interactive performance, resulting in the birth of intelligent chatbots like Alexa, Apple’s Siri, and Samsung’s Bixby (Hirschberg & Manning, 2015).

Chatbots can also be categorized according to function. There is the IPA (intelligent personal assistant) type, which is a kind of electronic secretary that solves problems, and the social chatbot, which carries on a conversation while establishing and maintaining a relationship with the user. With the IPA, the chatbot uses situational and personal information to perform tasks requested by the user in conjunction with music, movies, calendars, and emails to provide convenience to users (Shum et al., 2018). Representative examples of IPAs include Google’s Assistant, Amazon’s Alexa, Apple’s Siri, and Samsung’s Bixby. Siri, developed by Apple and embedded in the smartphone, can notify the user about events on his or her schedule stored in the calendar and execute requested applications. Siri also provides relevant information about sports, movies, and restaurants as well as smartphone features. Similarly, Bixby works on Samsung's Android phone, and, like Siri, its voice can be changed according to individual preferences. Alexa is an IPA that has the ability to notify users of weather forecasts, news, calendar events, and shopping It can access Wikipedia and provide users with desired information. In addition, Alexa is a cross-platform chatbot that is compatible with various devices.

IPA-type chatbots have minimal difficulty in performing tasks requested by users. However, in order to use chatbots effectively, users must understand and respond to the chatbot’s questions (Shum et al., 2018). For effective communication with chatbots, conversational quality must be high and emotional exchanges must occur (Oliver, 2014). For example, Microsoft's XiaoIce has the skills to understand the user’s emotional state and conduct the conversation accordingly, but empathy is still lacking.

Social chatbots, on the other hand, communicate freely with users and perform requested tasks using acquired human social skills. As a social chatbot, Microsoft's XiaoIce is representative. When interacting with this device, the device can input conversational content, analyze the emotional state of the user, and respond to changes in emotional state. One essential technology for social chatbots is the ability to grasp current human perceptions about the relationship and respond accordingly. Depending on how it is perceived, the relationship between the chatbot and the user will differ and responses to the chatbot’s speech will vary. In this study, we present a method for automatically recognizing this relationship, a function not currently available in the social chatbot.

2.2 Relationship Inferencing

A relationship is formed when a social connection is made for its own sake, for the benefit of each person from a sustained association with the other (Jamieson, 1999). Establishing relationships is essential to constructing a network. People use both verbal and nonverbal means to form relationships. In everyday conversation, gestures can be used as a nonverbal form of communication, but this is difficult in non-face-to-face situations. In some cases, people often use emoticons or images in order to express their feelings and form relationships with others. In addition, as the amount of unstructured data acquired in the non-face-to-face channel increases, more research is being conducted to grasp opinions and understand emotional states through written articles (Choi et.al, 2015; Choi et.al, 2016; Cui et.al, 2016; Seo and Kwon, 2018).

Relationships between humans and machines have been extensively studied (Kwon & Lee, 2011). Experiments have been conducted to examine how machines interact with humans to form a specific relationship (Reeves & Nass, 1996; Cassell et al., 2000; Breazeal, 2002). Specific mathematical functions have been developed to infer relationships with friends (Yu et al., 2017), colleagues (Zhuang et al., 2012; Diehl et al., 2007), co-authors (Zhuang et al., 2012; Wang et al., 2010), and others.

Many researchers have attempted to infer relationships using network analysis of traffic (Yu et al., 2013; Yu et al., 2017; Zhuang et al., 2012; Wang et al., 2010; Diehl et al., 2007), as shown in Table 1. Although social network reasoning based on traffic data estimates intimacy according to volume and temporal patterns of contact, accuracy in reasoning of correct relationships is problematic. For example, traffic data may indicate numerous business contacts in formal relationships, but individual connections are difficult to establish.

Various studies have clarified the situation by further analyzing factors related to proximity (time, location) (Yu et al., 2013; Yu et al., 2017). For example, during work hours, people often interact

〈Table 1〉 Related Studies on Relationship Inferencing

Researchers	Content	Data for Learning	Input Feature	Class	Algorithm
Yu et al. (2013)	- real-world sensing data using Bluetooth technique - classified friends or non-friends (simple problem) - inadequate detail about social relationships (family, formal relationship, or lover)	- MIT Reality Mining project data	- Outgoing calls - Outgoing text messages - Incoming calls - Incoming text messages - proximity (time, location)	- Friend, non-friend	SVM
Yu et al. (2017)	- performance comparison using ensemble technique and PCA (principal component analysis) - improved performance using semi-supervised learning - no inference of detailed social relationships with unstructured data such as text messages	- MIT Reality Mining project data	- Outgoing calls - Outgoing text messages - Incoming calls - Incoming text messages - proximity (time, location)	- Friend, non-friend	SVM + Naïve Bayes
Zhuang et al. (2012)	- compared with the previous studies, proposed an improved algorithm - inference based on network analysis, requires continuous data collection - proposed a relationship inference method using various domains, but no inferences about social relationships	- Publication: Wang et al. (2010) - Email: Diehl et al. (2007) - Mobile: Eagle et al. (2009)	- Publication: paper count/paper ratio/ co-author ratio/ conference coverage/first-paper-year-diff - Email: Traffic - Mobile: Voice calls/messages/ proximity (time)	- Publication: co-advisor/ co-advisee - Email: co-recipient/ co-manager/ co-subordinate - Mobile: co-location/ related-call	SVM TPFG PLP-FGM-S PLP-FGM
Wang et al. (2010, July)	- potential publishing networks identified by applying time-series elements not previously considered in network research - difficult to apply to relationships that change in real time like Web or SNS	- DBLP computer science bibliography database	- Sent, received	Colleague/Ph.D./ teacher/advisor/ advisee	SVM Ind Max TPFG
Diehl et al. (2007)	- content-based reasoning is superior to traffic-based method - inference using unstructured data with no consideration of proximity	- Enron email dataset	- Traffic/content	Manager/subordinate	Supervised ranking approach

with their colleagues; for those with closer relationships, they may meet outside of work hours. Diehl et al. (2007) found that the results were better when traffic-based analysis and inference and comparison of content-based relationships were combined.

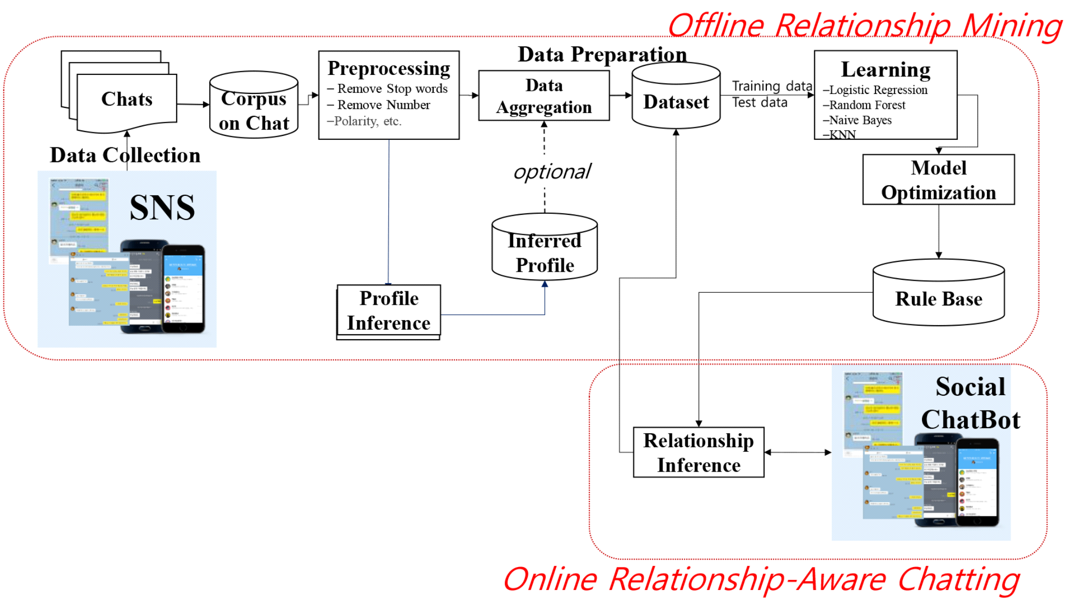
Traffic-based network reasoning has the advantage of verifying relationships between users and machines, but grasping the detailed nuances of relationships remains difficult. In addition, various dynamic factors affect human relationships; thus, constant observation of the network is required. On the other hand, with relational reasoning using irregular data, relationships can be instantly deduced. This method is also suitable for deducing individual relationships and can be changed according to the dynamics among various factors. The secret is the vocabulary used, which depends on the type of relationship. For example, emails in the workplace involve words like "please", "report", "project", "termination", and "executed" (Diehl et al., 2007). In more casual relationships, words like "hey", "game", and "music" are used.

3. Methods

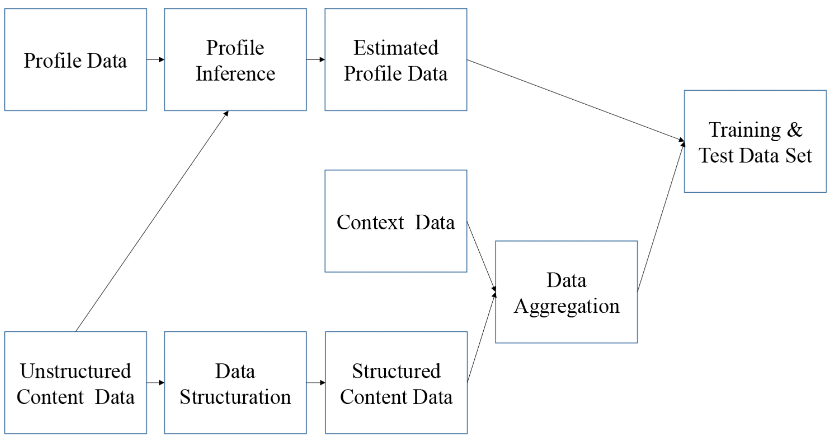
3.1 Process

The proposed method of recognizing relationships in this study is shown in Figure 1. First, actual messages were collected from users of KakaoTalk. Data was collected using the chat export function in KakaoTalk, and the profile of each user was input by the data provider. Note that the user profile data are not used in the proposed method. Second, message information was classified in preprocessing the text after constructing the corpus. The preprocessing stage involved extraction of idiomatic words, the number of words, morphemes, polarity, and nouns, from which metrics were constructed. The data set was then randomly divided using the 10-fold method to generate a prediction model based on the training data set. Lastly, test data was applied to the generated prediction model, and the final evaluation was performed.

The process of preparing data to be used for relationship inferencing is shown in Figure 2. First, inferences about the user's profile data were based on content obtained from the existing learning data. Therefore, at the stage of actually recognizing the relationship, only the inferred profile can be estimated irrespective of the exact profile of the user. The profile information is not included based on the assumption that obtaining the user's profile data or utilizing it for service enhancement causes privacy concerns. Next, unstructured data corresponding to the dialogue is formulated and aggregated according to sessions composed of various conversational contents in combination with contextual information (e.g., time zone during conversation). Finally, the collected, inferred profile data and the data aggregated in session units are combined and used in learning and verification processes to deduce the relationship.



〈Figure 1〉 Research Framework



〈Figure 2〉 Data Preparation Procedure

3.2 Preprocessing

In this study, formalized data to be used as input features for classification was extracted from unstructured text through the following process. The first input feature is the number of words, which represents the length of the sentence. By treating the number as a spacing unit, we can determine the word length more objectively by counting how many sentences are used regardless of the length of each word. Second, the number of morphemes is calculated. Since there can be more than one morpheme in a given word, it is desirable to know the number of morphemes in order to determine the length of the text more objectively. However, since morphemes only indicate auxiliary meaning, not the central meaning, the length of the text is also used as an indicator of meaning in addition to the number of words and morphemes. Various kinds of analyses were made possible by including these grammar units.

Emoticons are another means of expressing emotions in addition to pictures, special symbols, and other elements which cannot be conveyed through text. Using emoticons, the speaker can express his or her emotions both more directly and indirectly. Emoticons convey meaning that is difficult to express in words and can convey intimacy while keeping communication appropriate. Because of this feature of emoticons, the same sentence can convey feelings differently. The frequency of their use is expected to be high between friends because they are relatively easy to use and freely available in private conversations; however, because it is not a traditional method of expression, its use in public interactions is expected to be low. In addition to the emoticons provided by Messenger, we also examine "!", "...", and "~". In this study, emoticons were extracted and categorized using the *Mild* symbol and the *Tough* symbol. The *Mild* symbol is a function that softens expressions and is difficult to express directly. They enable the speaker to convey his/her direct attitude for easy interpretation by the listener, so that communication is successful. On the other hand, symbols such as the exclamation point are represented by the *Tough* symbol, which is a more direct sign used for more emphatic expression. The ability to amplify and express feelings without inhibition indicates that the listener is not a difficult person or some kind of opponent. Using this system, it is possible to determine users' class and level of intimacy.

Lastly, emotional analysis was performed to extract values related to the emotional elements of the conversation. Positive or negative words in the conversation provide information about the emotional value of the conversation. Using SentiWordNet, emotional words were extracted by three coders who are graduate students specializing in data analytics. Emotional values were calculated by assigning a value of +1 to affirmative words and a value of -1 to negative adverbial/adjectival words, aggregating the overall value for all affirmative words and subtracting the overall value for all adverbial/adjectival words, and dividing the result by the total number of vocabulary words related to emotion in the conversation. This study used the stringr package of R, an open source statistical program, and the RHINO 2.5.4 morphological analyzer was used. RHINO 2.5.4 can be downloaded from "https://github.com/SukjaeChoi/RHINO". RHINO 2.5.4 supports R, Java and Python languages. Table 2 shows the input features in the content category obtained through the above process.

〈Table 2〉 Class and Input Features

Category	Features	Definitions	Data Type
Class	Perceived relationship	Human perceptions of the relationship between humans and chatbots	Categorical (1=family/2=public/3=non-public/ 4= lover/5=friend)
Content (Session)	Average number of words	The average number of words in the message written by the speaker	Real
	Average number of morphemes	The average number of morphemes in the message written by the speaker	Real
	Average respect level	The average level of respect in the message written by the speaker	Real (0~4)
	Average number of emoticons	Number of times emoticons were used in messages created by the speaker	Real (1=false/2=true)
	Average number of mild symbols	The number of times the mild symbol is used in the message written by the speaker	Real
	Average number of tough symbols	The number of times the tough symbol is used in the message written by the speaker	Real
	Average polarity	The polarity value of the message created by the speaker	Real (1=positive/ 2=negative)

3.3 Profile Inferencing

In this study, we utilized inferred personal profiles rather than actual personal profiles because use of real profiles can cause privacy concerns, which may be a barrier to chatbot system acceptance. However, doing the opposite increases the possibility of inferior performance of our proposed method. Therefore, we profiled the user as much as possible using the proposed method of reasoning without securing personal information that is sensitive to disclosure. Of course, in this study, deducing the user's identity is not allowed.

To infer the personal profiles, we first divided the corpus into training data and test data. Second, each dialogue unit was separated into text and classification categories. Third, a DTM (document term matrix) was generated for each conversation including content and keyword lists. Fourth, each DTM was divided into categories. Last, the frequency of each column of the DTM was determined for each conversation unit. Conversations with column sums of zero were excluded. By repeating the above procedure, we deduced each personal profile with its cumulative DTM. The resulting inferred user profile is shown in Table 3.

〈Table 3〉 Input Features in Inferred User Profile

	Features	Definitions	Data Type
Inferred User Profile	Gender	Gender of the speaker (human)	Binary (1=man/0=woman)
	Age	Age of the speaker (human)	Category (10's, 20's, 30's, 40's, 50's, 60's, 70's)
	Homogeneity	Whether the gender of both parties is the same	Binary (0=homogeneity/1=heterogeneity)

3.4 Contextual information

Even for the same content, relationships may differ depending on the context of the conversation. For example, in a formal relationship, conversations may not often occur on weekends. Also, the later the time of a conversation, the more informal it is likely to be. Therefore, in this study, contextual information (e.g., location) was obtained automatically without any direct input from the user to avoid privacy concerns.

First, we determined the time of the conversation. In close personal relationships, communications are frequently and easily exchanged regardless of time. However, in other relationships, it is common to avoid texts or phone calls in the evening and after a certain time of night. Therefore, it is safe to assume high intimacy in cases where communication occurred frequently and at night time. In the same vein, we also considered the day of the week. Frequent communication on both weekdays and weekends indicates a high level of intimacy. In most public, formal relationships, weekends are considered a private time in which people must refrain from attempting to communicate.

Second, the presence of nighttime conversation is a powerful factor with which to gauge the intimacy of a relationship. Night time was designated as from 21:00 to 08:59, which is the time of day when most people are sleeping, and day time was designated as from 09:00 to 20:59.

Table 4 summarizes the three variables described above.

〈Table 4〉 Input Features in Inferred User Context

	Features	Definitions	Data Type
User Context	Conversation time	Time of day at which conversation occurs	Time
	Conversation at night	Whether or not message is sent after 21:00	Real [0,1] (0=daytime/1=evening or midnight)
	Date of conversation	Date when the speaker sent the message/made the call	Real [0,1] (0=weekday,1=weekend)

4. Experiment

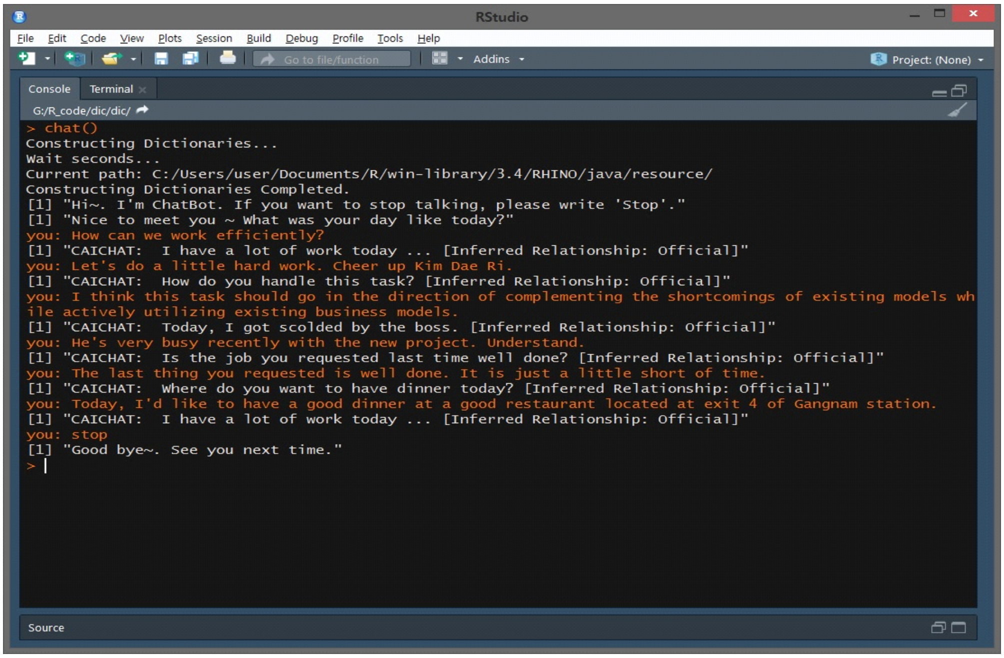
4.1 Prototype System

We implemented a prototype system to show the feasibility of the relationship-aware social chatbot system proposed in this study. This system was programmed in R3.5.0 running on 64-bit computers. When the system is started, contextual data (time, day, and time domain) at the time of use is automatically received. Then, when the user's input message is received, a morphological analysis is carried out to determine the number of morphemes, special characters, etc. included in the text, after which the user's age and gender are deduced. Next, when collection of necessary data is completed, the relation-inferred result is shown in parentheses through the model, which has already been learned. This process is designed to stop the system when the user indicates that it is not in use. A sample screen shot for the prototype system is shown in Figure 3 and the pseudo code for the drive operation process is shown in Appendix A. Figure 3 shows an example of Chatbot communicating with humans using the method proposed in this study. Figure 3 (a) is an example of public dialogue, and Figure 3 (b) is an example of a dialogue with family. When chatting with a long sentence, Chatbot recognizes it as a public conversation and responds accordingly. Figure 3 (b) shows a relatively short conversation in which the conversation partner is inferred as a family member . The prototype proposed in this study combines characteristics of the text input by the opponent, profile information, and context information so that the user can communicate according to the social relation assumed by the user. In this study, the relationship consists of friends, family, public, private, and lover relationships.

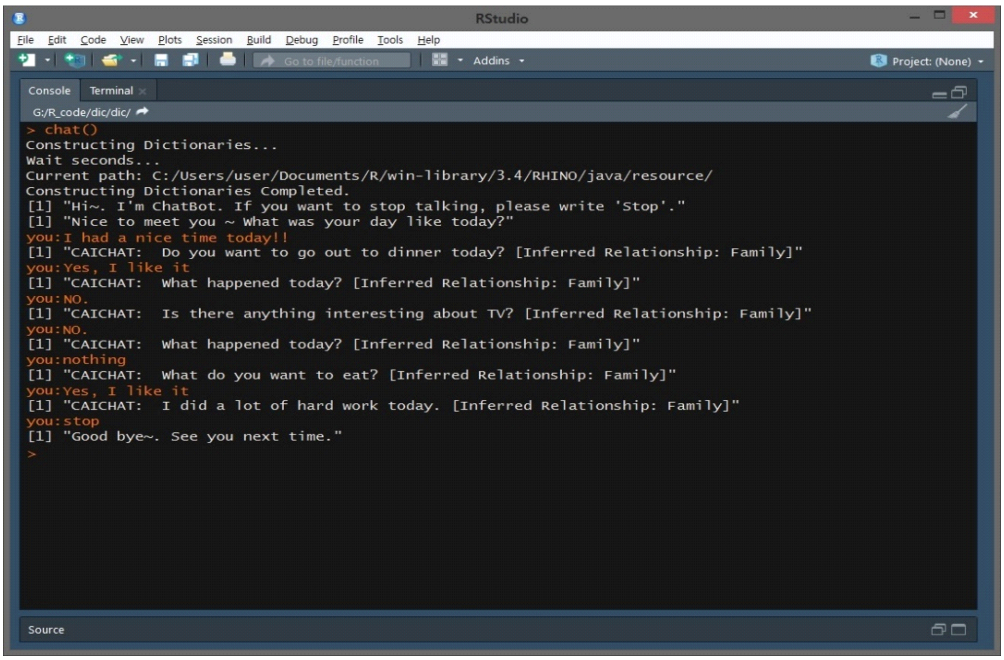
4.2 Experimental Methodology

In this study, we combined and compared three things: personal profile information (inferred or not), features extracted from content, and features extracted from context. We considered two possible methods as options: combining the three features using factors from actual user profiles which do not present privacy concerns − gender and age (Method 7) and combining these three features using inferred user profiles − inferred gender and inferred age (Method 8). We did not compare our methods with previous methods because of the lack of research into relationship inferencing. Overall accuracy was selected as the variable of interest. The following is a list of the methods examined:

Method 1: Personal profile only
Method 2: Content data only
Method 3: Content only
Method 4: Combining Method 1 and Method 2
Method 5: Combining Method 1 and Method 3
Method 6: Combining Method 2 and Method 3
Method 7: Combining Method 1, Method 2, and Method 3 (Proposed 1)
Method 8: Combining inferred personal profile, Method 2 and Method 3 (Proposed 2)



(a) Formal conversation



(b) Informal conversation

〈Figure 3〉 Examples of Relationship Inferencing during Conversation

4.3 Data Collection

The data used in this study involved users of KakaoTalk, a smartphone messenger application used by more than 50 million users around the world. Actual conversational content was collected over a period of 30 days from data shared by the sponsored participants. In total, 33,160 conversations were collected and saved as the .txt file by KakaoTalk application program. To make the raw data suitable for analysis, a data set is reconstructed, as shown in Figure 4. Personal information such as name, dialogue relations, age, gender, personality, etc. was declared by the participants, and raw data about the time, day, and date of the conversation was transferred to a spreadsheet. In addition, we used RHINO 2.5.4 as the morphological analyzer to compute the number of morphemes, number of emoticons, number of mild and tough symbols, and polarity. The relationships are distributed as shown in Table 5, and Table 6 is an example of the dialogue contents of the collected data.

〈Table 5〉 Relation Frequency

	Frequency
Family	5,159
Friend	11,155
Public Relations	4,691
Non-Public Relations	7,922
Lover	4,233
Total	33,160

	speaker	session_nc	words	morph	respect	respect_str	imo_stren	mild_num	tough_nur	polarity	top_positi	top_negat	weekend	hour	night	personalit	gender	ages	homo	h_gender	h_ages	class
1	Me	100	2	4	4	1	2	0	0	1.4142	1	0	1	0	0	1	0	3	1	1	2	5
2	You	100	4	11	4	1	2	0	0	1	1	0	1	0	0	1	1	3	1	1	2	5
3	Me	101	7.176471	14.41176	3.352941	0.588235	1.176471	0.058824	0	0.586747	1	0	0	13.23529	1	1	0	3	1	1	3	5
4	You	101	4.888889	15.22222	3.444444	0.444444	0.222222	0.222222	0	0.1762	1	1	0	13.33333	1	1	1	3	1	1	2	5
5	Me	102	1	2	4	1	0	0	0	0	0	0	0	1	0	1	1	3	1	1	2	5
6	You	103	6	21	3	1	2	0	0	1	1	0	0	10	1	1	0	3	1	0	3	5
7	Me	104	6.933333	14.8	3.333333	0.666667	0.933333	0.066667	0	0.29428	1	1	0	1	0	1	0	3	1	1	3	5
8	You	104	4.090909	11.18182	3.181818	0.818182	0.363636	0	0	0.181818	1	1	0	1	0	1	1	3	1	0.909091	3	5
9	Me	105	8.714286	18.42857	3.428571	1	0.857143	0	0	0.487743	1	1	1	8.428571	0.571429	1	0	3	1	1	3	5
10	You	105	4.714286	16	3.428571	0.428571	0.285714	0	0	-0.14286	1	1	1	8.285714	0.714286	1	1	3	1	0.857143	3	5
11	Me	106	2.4	5	1.6	0	0.4	0	0	-0.2	0	0	0	12.8	0.8	1	0	3	1	1	3	5
12	You	106	2	14	3	0.5	0	0	0	0.5	0	0	0	0	0	1	1	3	1	1	3	5
13	Me	107	3.727273	8.818182	2.454545	0.181818	0.545455	0	0	0.310382	1	1	0	9.090909	1	1	0	3	1	0.909091	3	5
14	You	107	2.875	9.125	2.375	0.125	0.5	0.625	0	0.301775	1	0	0	9	1	1	1	3	1	0.875	3	5
15	Me	108	2.333333	3.333333	0.666667	0	0	0	0	0	0	0	0	7	0	1	0	3	1	1	2	5
16	You	108	1.4	2.8	1	0	0.4	0	0	0	0	0	0	7.4	0.2	1	1	3	1	0.8	3	5
17	Me	109	2.666667	7.333333	2	0	0	0	0	0.666667	1	0	1	18	1	1	0	3	1	1	2	5
18	You	109	2	5.375	0.375	0	0.25	0	0	0.125	1	0	1	3.75	0.125	1	1	3	1	0.75	3	5
19	Me	10	10.5	23	4	1	0	0	0	0	0	0	1	8	0	-1	1	4	1	0.5	4	5
20	You	10	8	18.5	4	1.5	1	1	0	1	1	0	1	8.5	0.5	1	0	6	1	0.5	4	5
21	Me	110	1	9	4	1	0	1	0	1	1	0	0	4	0	1	0	3	1	1	2	5
22	You	110	4	19	3	0	0	1	1	0	0	0	0	1	0	1	1	3	1	1	2	5
23	Me	111	2.711409	6.912752	1.577181	0.214765	0.832215	0.114094	0	0.112942	1	1	0	9.791946	1	1	0	3	1	0.832215	3	5
24	You	111	2.45509	6.299401	1.245509	0.071856	0.335329	0.209581	0.05988	0.025556	1	1	0	9.724551	0.988024	1	1	3	1	0.856287	3	5
25	Me	112	6	17.33333	2.666667	0.333333	0.333333	0.333333	0	0.333333	1	0	1	21.33333	0.666667	1	0	3	1	1	2	5
26	You	112	1	6	4	0	0	0	0	1	1	0	1	22	0	1	1	3	1	1	2	5
27	Me	113	2.4	8.2	3.8	1.2	0.8	0.2	0	0.88284	1	0	0	13	1	1	0	3	1	1	3	5
28	You	113	6.2	9.8	1.4	0.8	0	0	0.2	0	0	0	0	13	1	1	1	3	1	1	2	5
29	Me	114	6.5	15	3.5	1.5	1	0	0	1.2071	1	0	0	21	1	1	0	3	1	0.5	2	5
30	You	114	5	9	3.5	0.5	0	0	0.5	0.5	1	0	0	18.5	1	1	1	3	1	1	2	5
31	Me	115	4.25	9.25	2.5	0.625	0.25	0.0625	0	0.213388	1	0	0	15.25	1	1	0	3	1	0.6875	3	5
32	You	115	3.818182	5.454545	1.727273	0.272727	0.181818	0	0.181818	0.181818	1	0	0	16	1	1	1	3	1	0.545455	3	5
33	Me	116	4.55	7.65	1.2	0.25	0.75	0.15	0	0.42071	1	0	1	18.65	1	1	0	3	1	0.85	2	5
34	You	116	7.818182	10.63636	1	0.227273	0.090909	0	0.045455	0.109736	1	0	1	18.90909	1	1	1	3	1	0.772727	3	5

〈Figure 4〉 Aggregated Data by Session

〈Table 6〉 Sample text by Relation

Relation	Sample Text
Family	- Are you tired? I loved it. Come on. - Have a bowl of seaweed soup. ^^
Public	- Manager Hi ^^ I sent you the list last time. I think the image was sent by the manager last time. I have not received it yet. Please send it once when you have time ^^ I did not have the file then ;;; And I asked you if you have OO. If you have two, I would like to ask for confirmation. - Hi? Can not you see the details of others yet? I do not have a contact for Professor OO yet ... Please complete this and send it to me ^^
Non Public	- How are you? I hope to see you sometime ..... Happy Christmas evening! - Seeing you soon.
Lover	- Baby, I like to look at anything! - Honey, I like that look. (heart)
Friend	- Buddy, doing something? - Where are you playing?

4.4 Causal Analysis

In this study, multinominal logistic regression was used to investigate the factors affecting relationship inference. Normal logistic regression is analyzed as two separate dependent variables, y = 0 and y = 1, while multinominal logistic regression is based on y = 0 and y = 1, y = 2, y = 3, y = 4. Multinominal logistic regression was performed because the dependent variable in this study consists of five categories. We evaluated the influence of three input feature categories: content, user context, and user profile, in predicting the user–chatbot relationship. Logistic regression analysis was performed for each model by using the full model (relationship ~ content + user context + user profile), reduced Model #1 (relationship ~ content), and reduced Model #2 (relationship ~ content + user context).

As shown in Table 7, the number of morphemes, the total number of honorifics, and the degree of honorification in the three models were statistically significant. Thus, these are important variables in predicting relationships. The use and strength of honorifics can be an important basis for speculating about relationships. For intimate relationships with friends or lovers, it is seldom used; however, this important variable enables us to appreciate fine distinctions in relationships because it is used in relationships with parents or grandparents or in public relationships. Comparing the adj-Mcfadden R^2 of each model, we see that the full model proposed in this study had the highest value at 0.331. Values for reduced Models #1 and #2 were 0.165 and 0.167, respectively; #2 is slightly higher, but the difference is not significant. Therefore, we can conclude that the contextual information of reduced Model #2 is more influential than the elements extracted from unstructured data. In addition, the R^2 value of the full model including profile information, which was excluded from reduced Models #1 and #2, was 0.331, which was twice as high as that of both models. This difference can be explained by the amount of profile information.

One interesting point in the results of the logistic regression analysis is that the magnitude of the quasi-linearity has a positive effect, but the age-dummy variables have no effect. This seems to be due to the fact that the boundaries of social relations are ambiguous. For example, among lovers, regardless of their age, there will be cases in which they do not show respect in their conversations; this is also true in public relationships. However, age may be a very important factor in predicting detailed relationships other than those proposed in this study.

As a result, the variables which are significantly associated with the user–chatbot relationship used in the proposed method for developing relationship aware social chatbot.

〈Table 7〉 Results of Logistic Regression Analysis

	Variables	Reduced Model #1	Reduced Model #2	Full Model
	(Intercept)	-0.2056	0.7028	-16.7649
Contents	words	-0.0887	-0.0873	-0.2661***
	morph	0.2522***	0.2462***	0.2627***
	respect	0.1944*	0.2076*	0.2728***
	respect_strength	2.1752***	2.1286***	1.7022***
	imo_strength	-0.1008	-0.088	0.2177
	mild_num	0.266	0.2837	0.201
	tough_num	-0.5364	-0.5114	-0.0234
	polarity	0.2848	0.2426	0.3293
Context	hour		-0.042***	-0.0436***
	night		-0.3156	-0.4053
	weekend		-0.0677	-0.0635
Personal Profile	gender			0.6923***
	age20's			17.4678
	age30's			19.0744
	age40's			19.1183
	age50's			17.7969
	age60's			16.3698
	age70's			35.3985
	homogeneity			-1.9209***
		adj–Mcfadden R^2 = 0.165	*adj*–Mcfadden R^2 = 0.167	*adj*–Mcfadden R^2 = 0.331

4.5 Performance Evaluation

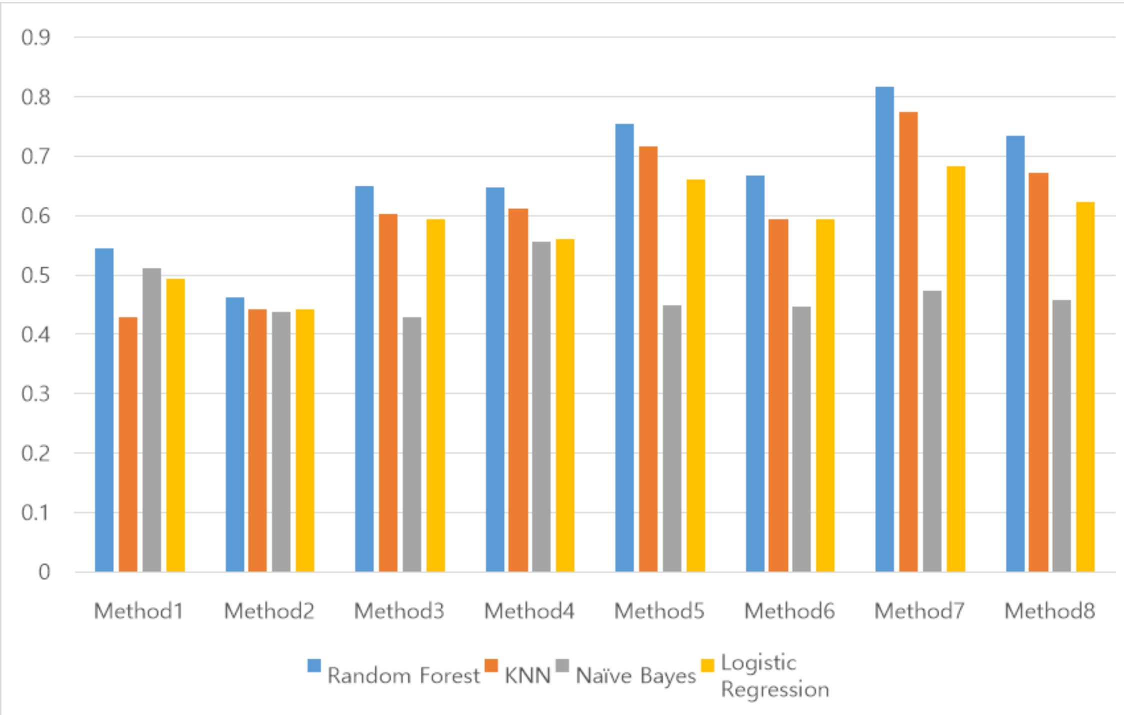
A performance comparison was conducted by comparing the accuracy of the relationship between the proposed method with functions of other chatbots. First, we compared the performance of the proposed methodologies. We used the 10-fold method as the input feature to obtain all or part of the unstructured data, contextual information, and personal profile details and to predict the perceived relationship (family, public relations, friends, lovers, and private relations). Table 8 shows the relationship prediction accuracy obtained by training and test data.

According to the results presented in Table 8 and Figure 5, Method 7 yielded the best inference accuracy (81.56%). On the other hand, Method 2 showed the lowest inference accuracy (46.3%). Also, when considering the economic feasibility of the model, we see that Method 3 exceeds other methods. Method 2 has the lowest accuracy because SNS enables users to communicate anytime and anywhere without restriction of time and space. Since Methods 4, 6, 7, and 8 show higher reasoning accuracy than Method 2, we may conclude that contextual information appears to be effective when combined with other information. In addition, the accuracy of Methods 4 and 6 is almost the same at 64.86% and 64.23%, respectively. Based on the accuracy of Method 5, we posit that there is a lower causality relation between profile information and information extracted from unstructured data.

Of Methods 4, 5, 7, and 8, which included profile information and unstructured data, Method 7 had the highest accuracy at 81.51%. Therefore, if profile information is available in the inferencing process, more inferential reasoning is possible, but it may cause privacy issues (Kwon, 2009; Faratin et al., 1998). To overcome this problem, Method 5, which does not use profile information, and Method 8, which uses profile

〈Table 8〉 Performance Comparison (Overall Accuracy)

Methods	Random Forest	KNN	Naïve Bayes	Logistic Regression
Method 1	**0.5439**	0.4279	0.5122	0.4943
Method 2	**0.4630**	0.4423	0.4383	0.4428
Method 3	**0.6497**	0.6023	0.4294	0.5942
Method 4	**0.6480**	0.6105	0.5561	0.5596
Method 5	**0.7544**	0.7162	0.4479	0.6606
Method 6	**0.6676**	0.5931	0.4473	0.5930
Method 7	**0.8156**	0.7746	0.4739	0.6832
Method 8	**0.7340**	0.6716	0.4583	0.6220



〈Figure 5〉 Performance Comparison

information through inference, can be suitable alternatives. Consequently, we conclude that if profile information is obtainable, Method 7 is superior. If profile information is unobtainable, Method 8 is superior.

Next, we compare the proposed system with other major chatbot systems. The evaluation items for chatbots include speech recognition and synthesis, rules built into the knowledge base, provision of help functions, presence of back buttons, connectivity with external databases (Kuligowska, 2015), user interface, and system aspects such as elapsed time. We also see the performance of chatbots resulting from human success. We did not consider features related to system commercialization and user interface, as they are not the focus of this paper. We compared systems from the viewpoint of personalization of conversation among functional viewpoints. In total, we evaluated items in five categories: personal information protection, use of context-awareness information, personalization of conversation, individual profile inferencing, and relationship recognition.

First, protecting personal information involves asking the user for personal information about things such as gender or age during a conversation, or taking user information from a third source and constructing a dialogue based on this information. Although accuracy of the conversation will increase, there is concern about privacy. Situational or context awareness concerns the current location or time. Personalization of a conversation involves changing its content (e.g., honorification, etc.) according to the characteristics of the user. Personal profile inferencing is the ability to attain profile information about things such as gender or age by various means safely without the user providing personal information, and to communicate based on that. Using all these tools, we assessed the chatbots' ability to recognize relationships between users during conversation.

5. Discussion

5.1 contributions

In this study, we proposed a method to deduce the relationship between chatbot users and a social chatbot system automatically. We combined a text analysis method and classification methods such as random forest, naïve Bayes, logistic regression, and KNN. The results reveal that using the formalized variable extracted from a text analysis, the proposed method showed very high performance in terms of accuracy for contextual information and the user profile. Moreover, since no personal profile information is provided by the user, and information about gender and age is obtained indirectly through text analysis, privacy problems are averted. Except for profile information, no factors caused a threat to privacy. Although Diehl et al. (2007) proposed a model to infer relationships by direct analysis of the content of emails, infringement upon the user's privacy is probable. In the case of a public for more formal relationship, it is highly possible that information will be leaked. On the other hand, since the method proposed in this study involves extraction and use of the characteristics of sentences such as the number of words, number of morphemes, the length of the text, and use of emoticons, the threat of personal information leakage and privacy infringement can be avoided.

Even without direct access to profile information, excellent results were obtained using our profile inferencing method that infers gender and age. The method proposed in this study is successful in extracting formal information needed for relationship recognition.

5.2 Future Research Issues

The relationship inferencing method proposed in this study can be used with social chatbots. Current use of chatbots focuses on the user's intention only. However, as Lindgaard (2003) pointed out, we must consider the issues of efficiency and effectiveness. Developing viable systems for use in business is much more complex than developing prototype systems aimed at demonstrating technical ability. Creating a technology-driven system for real users would undoubtedly be more attractive, but would require more time and money (Nielsen, 1994). For this reason, future researchers should focus more on business-driven concepts and profitability. In applying the relationship inferencing system proposed in this study, practitioners can provide a high-quality, business- and technology-oriented service.

A limitation of this study is that the data is used in a model constructed assuming a one-to-one dialogue. Although our proposed method solves the privacy problem that was often mentioned in previous big data and IoT studies, it may be difficult to use for inferring relationships in other contexts. In the context of personal terminals such as a smartphone or chatbot service, the proposed model can be applied because it is a one-to-one situation, but it may be difficult to apply it to artificially intelligent speakers or robots that provide services in open places. Second, this study focuses on proposing a method of inferring relationships. However, actual implementation remains at the development stage with a simple prototype system. Full implementation of the method in a sustainable dialogue with more than one user generating appropriate sentences should be conducted in future research.

6. Conclusion

For a social chatbot, one of the most important features in realizing a natural interface is to understand how the person is communicating, to do so accurately and unobtrusively, and then to create a conversation accordingly. In this study, we proposed a method to deduce perceived relationships with chatbots without using personal information submitted at the time of user registration. In this method, information is extracted from user-written messages and the number of words, number of morphemes, number of messages, and general contextual information (e.g., time, day of the week) are determined. In addition, we aggregated digitized and contextual information extracted from content to construct a data set for relationship inferencing. Our system automatically recognizes relationships and predicts chatbot performance without using personal information directly. Avoiding using personal data is important because if information is leaked while an individual is using IT services or devices, not only existing users, but also potential new customers may feel vulnerable and reject the service. Therefore, the method proposed in this study is expected to contribute to the enhancement of social chatbot performance. In the near future, this method may improve interaction between machines and users in fields such as the IoT (internet of things), AI (artificial intelligence), and enabled application systems, which make use of natural man–machine interaction. Most existing chatbot services are focused on improving accuracy with consideration of usage intentions rather than the factors that affect continuous use. However, chatbots with the features proposed in this study will increase satisfaction with the interaction.

References

Al-Zubaide, H., and Issa, A. A, "Ontbot: Ontology based chatbot," *Innovation in Information & Communication Technology (ISIICT), 2011 Fourth International Symposium on IEEE,* (2011, November), 7~12.

Araujo, T., "Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions," *Computers in Human Behavior*, Vol.85(2018), 183~189.

Breazeal, C., "Regulation and entrainment in human—robot interaction," *The International Journal of Robotics Research*, Vol.21, Issue.10-11(2002), 883~902.

Cassell, J., J. Sullivan, S. Prevost and E. Churchill, "Embodied Conversational Agents," *Cambridge*,MA: MIT Press, 2000.

Cerekovic, A., Aran, O., and D.Gatica-Perez, "Rapport with virtual agents: What do human social cues and personality explain?,". *IEEE Transactions on Affective Computing*, Vol.8, Issue.3(2017), 382-395.

Colby K.M, "Human-Computer Conversation in A Cognitive Therapy Program" In: Wilks Y. (eds) Machine Conversations. The Springer International Series in Engineering and Computer Science, vol 511. Springer, Boston, MA,1999.

Choi, S., Jeon, J., Subrata, B., Kwon, O., "An efficient estimation of place brand image power based on text mining technology," Journal of Korea Intelligent Information Systems, Vol. 21, No.2(2015), 113~129. (최석재, 전종식, 권오병, "텍스트마이닝 기반의 효율적인 장소 브랜드 이미지 강도 측정 방법," 지능정보연구, Vol.21, No.2(2015), 113~129.)

Choi, S. Song, Y., Kwon, O., "Analyzing contextual polarity of unstructured data for measuring subjective well-being," Journal of Intelligent Information Systems, Vol.22, No.1(2016), 83~105. (최석재, 송영은, 권오병, "주관적 웰빙 상태 측 정을 위한 비정형 데이터의 상황기반 긍부 정성 분석 방법," 지능정보연구, Vol. 22, No.1(2016), 83~105.)

Cui, M., Jin, Y. and Kwon, O., "A method of analyzing sentiment polarity of multilingual social media : A case of korean-chinese languages," Journal of Intelligent Information Systems, Vol.22, No.3(2016), 91~111. (최미나, 진윤선, 권오병, "다국어 소셜미디어에 대한 감성분석 방법 개발," 지능정보연구, Vol. 22, No.3(2016), 91~111.)

Diehl, C. P., Namata, G., and Getoor, L, Relationship identification for social network discovery, In *AAAI* ,Vol. 22, No. 1(2007, July), 546~552,.

Faratin, P., C.Sierra, and N. R.Jennings, "Negotiation decision functions for autonomous," agents. *Robotics and Autonomous Systems*, Vol.24, No.3-4(1998), 159~182.

Griol, D., J.Carbó, and J. M.Molina, "An automatic dialog simulation technique to develop and evaluate interactive conversational agents,". *Applied Artificial Intelligence*, Vol.27, No.9(2013), 759~780.

Haslam, N. and A.P. Fiske" Relational models theory: a confirmatory factor analysis," *Personal Relationships*, Vol.6, No.2(1999), 241~250.

Hill, J., W. R.Ford, and I. G.Farreras, “Real conversations with artificial intelligence: A comparison between human–human online conversations and human–chatbot conversations,” *Computers in Human Behavior*, Vol.49(2015), 245~250.

Hirschberg, J, and C. D.Manning,, “Advances in natural language processing,” *Science*, Vol.349(2015), 261~266.

Hung, V., M.Elvir, A.Gonzalez, and R.DeMara, “Towards a method for evaluating naturalness in conversational dialog systems,” *In Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on,* (2009, October), 1236~1241.

Jamieson, L. “Intimacy transformed? A critical look at the ‘pure relationship’,” *Sociology*, Vol.33(1999), 477~494.

Jong, A. D., and K.De Ruyter, “Adaptive versus proactive behavior in service recovery: the role of self-managing teams,” *Decision Sciences*, Vol.35(2004), 457~491.

Kirkpatrick, L. A. and B. J. Ellis. *An Evolutionary-Psychological Approach to Self-esteem: Multiple Domains and Multiple Functions,* Blackwell handbook of social psychology, Interpersonal processes, 409-436, 2001.

Koerner, A.F, “Models of relating – not relationship models: cognitive representations of relating across interpersonal relationship domains,” *Journal of Social and Personal Relationships*, Vol.23(2006), 629~653.

Kuligowska, K, “Commercial chatbot: Performance evaluation, usability metrics, and quality standards of embodied conversational agents,” *Professionals Center for Business Research 2*, 2015.

Kwon, O, “A two-step approach to building bilateral consensus between agents based on relationship learning theory,” *Expert Systems with Applications*, Vol.*36,* No.9(2009), 11957~11965.

Kwon, O., and N. Lee, “A relationship-aware methodology for context-aware service selection,” *Expert Systems*, Vol.28, No.4 (2011), 375~390.

Lindgaard,G, “The misapplication of engineering models to business decisions,” *INTERACT’03*, Zurich, Switzerland, (2003), 367~374.

López-Monroy, A. P., M.Montes-y-Gómez, H. J.Escalante, L.Villaseñor-Pineda, and E.Stamatatos, “Discriminative subprofile-specific representations for author profiling in social media,” *Knowledge-Based Systems*, Vol.89(2015), 134~147.

Madhu, D., Jain, C. N., Sebastain, E., Shaji, S., and A.Ajayakumar, “A novel approach for medical assistance using trained chatbot,” In *Inventive Communication and Computational Technologies (ICICCT), 2017 International Conference on,* (2017, March), 243~246.

Nielsen, J, *Usability heuristics, in Usability Engineering*, Academic Press, 1994, 115–164.

Oliver, R. L, *Satisfaction: A Behavioral Perspective on the Consumer: A Behavioral Perspective on the Consumer*. Routledge, 2014.

Perera, C., A.Zaslavsky, P.Christen, and D.Georgakopoulos, Context aware computing for the internet of things: A survey, *IEEE Communications Surveys & Tutorials*, Vol.16, No.1(2014), 414~454.

Pham, D. D., G. B.Tran, and S. B. Pham,. “Author profiling for Vietnamese blogs,” In *Asian Language Processing, 2009. IALP'09.*

International Conference on, (2009, December), 190~194).

Reddy, T. R., B. V.Vardhan, and P. V.Reddy, "Profile specific Document Weighted approach using a New Term Weighting Measure for Author Profiling," *International Journal of Intelligent Engineering & Systems*, (2016), 136-146.

Reeves, B. and C. Nass, The Media Equation: How People Treat Computers, Television, and New Media Like Real People and Places, *Cambridge: Cambridge University Press*, 1996.

Sandbank, T., M.Shmueli-Scheuer, D.Konopnicki, , J.Herzig, J.Richards, and D.Piorkowski, "Detecting Egregious Conversations between Customers and Virtual Agents," *arXiv preprint arXiv:1711.05780.*, 2017.

Seo, H., and Kwon, O. Mining Intellectual History Using Unstructured Data Analytics to Classify Thoughts for Digital Humanities. Journal of Intelligent Information Systems, Vol.24, No.1(2018), 141~166.

(서한솔, 권오병, "디지털 인문학에서 비정형 데이터 분석을 이용한 사조 분류 방법," 지능정보연구, Vol. 24, No.1(2018), 141~166.)

Shawar, B. A., and E.Atwell, "Different measurements metrics to evaluate a chatbot system," *Proceedings of the Workshop on Bridging the Gap: Academic and Industrial Research in Dialog Technologies*, (2007, April), 89~96.

Shum, H. Y., X. D. He, and D. Li, From Eliza to XiaoIce: challenges and opportunities with social chatbots. *Frontiers of Information Technology & Electronic Engineering*, Vol.19, No.1(2018), 10~26.

Stevenson, M, "Individual Profiling Using Text Analysis," *University of Sheffield*, Sheffield United Kingdom, 2016.

Tan, L., and N.Wang, (2010, August). "Future internet: The internet of things," *In Advanced Computer Theory and Engineering (ICACTE), 2010 3rd International Conference on*, Vol. 5 (2010, August), V5~376.

Villegas, M. P., M. J.Garciarena Ucelay, M. L.Errecalde, and L.Cagnina, "A Spanish text corpus for the author profiling task," *XX Congreso Argentino de Ciencias de la Computación*, *(Buenos Aires, 2014)*.

Wang, C., J. Han, Y. Jia, J.Tang, D. Zhang, Y. Yu, and J. Guo, "Mining advisor-advisee relationships from research publication networks," *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, (2010, July), 203~212.

Weizenbaum, J, "ELIZA-A computer program for the study of natural language communication between man and machine," *Communications of the ACM*. Vol. 10, No. 8(1966), 36~45.

Yu, C., N. Wang, L. T.Yang, , D. Yao, C. H.Hsu, and H. Jin "A semi-supervised social relationships inferred model based on mobile phone data," *Future Generation Computer Systems*, Vol.76(2017), 458~467.

Yu, Z., X. Zhou, D. Zhang, G. Schiele, and C. Becker, "Understanding social relationship evolution by using real-world sensing data," *World Wide Web*, Vol.16, No.5-6(2013), 749~762.

Zhuang, H., J. Tang, W. Tang, T. Lou, A. Chin, and X. Wang, "Actively learning to infer social ties," *Data Mining and Knowledge Discovery*, Vol.25, No.2(2012), 270~297.

Appendix A. Pseudo-Code for the Proposed Prototype System

(1) LEARNING Module

```
chat<-function(test){
CALL packages
INITIALIZE Morphological analyzer
Neg <- GET ("negative_words.csv")
Pos<- GET ("positive_words.csv")

RANDOMIZE data set
GET test data set and training data set
Context (time, week) <- GET context info

WHILE (EOF) {
        Sentence <- READLINE( )
        Up <- INFER USER PROFILE (gender, ages)
        Rel <- INFER RELATIONSHIP (Sentence, Up)
        Polarity <- ANALYZE_SENTIMENT (Sentence, Up, Rel)
        Rules <- APPEND(Sentence, Up, Rel, Polarity)
}

SAVE Rules
```

(2) SERVICE Module

```
DO WHILE (Sentence NOT NULL) {
        PUT(Response)
        READLINE(Sentence)
        Up <- PREDICT_USERPROFILE(Response, Sentence)
        Rel <- PREDICT_RELATIONSHIP(Response, Sentence, Up)
        Polarity <- ANALYZE_SENTIMENT (Sentence, Up, Rel)
        Response <- GENERATE (Up, Rel, Sentence, Polarity)
        DISPLAY (Response)
}
```

(3) INFER USER PROFILE (Text, Class)

```
Count[Words] <- COMPUTE_COUNT (Text, WORD)
Count[Mild]<- COMPUTE_COUNT (Text, MILD)
Count[Tough]<- COMPUTE_COUNT (Text, TOUGH)
Count[Emoji]<- COMPUTE_COUNT (Text, EMOJI)
Cdtm <- RUN_CUMULATED_DTM(Text, Class) ## Cdtm : cumulated document term matrix
Up <- INFER(Count, Cdtm)
RETURN Up
```

(4) INFER RELATIONSHIP (Response, Sentence, User Profile)

```
RF<-RUN_CLASSIFICATION_ALGORITHM(class~.,data. BEST_ALGORITHM)
predicted_relation<-predict(RF, Sentence)
CASE (predicted_relation) "1" { Rel <- “Family” }
CASE (predicted_relation) "2” { Rel <- “Friend” }
CASE (predicted_relation) "3” { Rel <- “Public” }
CASE (predicted_relation) "4” { Rel <- “Private” }
CASE (predicted_relation) "5” { Rel <- “Lover” }
RETURN Rel
```

국문요약

소셜챗봇 구축에 필요한 관계성 추론을 위한 텍스트마이닝 방법

김정훈* · 권오병**

챗봇은 음성, 이미지, 비디오 또는 텍스트와 같은 다양한 매채를 이용하여 대화가 가능한 대화형 어시스턴트이자 인공지능을 기반으로 사용자의 질문에 답하거나 문제를 해결할 수 있는 사용자 친화적 프로그램이다. 하지만 현재 챗봇은 사용자가 요청한 작업을 정확하게 수행하는 기술적측면에 초점이 맞추어져 있으며, 개인화된 대화로 사용자와 챗봇간의 관계성 구축에는 제한적이어서 일부 사례에도 불구하고 소셜챗봇이 되기에는 미흡한 상태이다. 만약 인간의 사회성을 나타내는 특징 중 하나인 관계성을 챗봇이 인식하여 알맞게 대화를 하여 문제를 해결할 수 있다면, 개인화된 대화를 할 수 있을 뿐만 아니라 인간과 유사한 대화를 할 수 있을 것이다. 본 연구의 목적은 사용자가 입력한 내용을 기반으로 챗봇과 사용자 간의 관계성을 추론하고 대화 상황에 맞게 대화 상대가 적절한 대화를 수행 할 수 있는 텍스트 분석 방법을 제안하는 것이다. 본 연구의 실험 및 평가를 하기 위하여 실제 SNS대화 내용을 사용하였다. 분석결과 개인정보 보호를 위해 사용자의 개인 프로필 정보가 제외된 방법에서도 우수한 결과를 나타내어 소셜 챗봇에 적합한 방법으로 검증되었다.

주제어 : 소셜챗봇; 관계성인식; 텍스트분석; 개인정보보호

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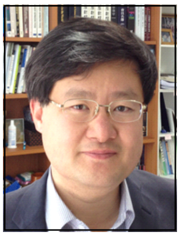
* 경희대학교 일반대학원 경영학과
** Corresponding Author: Ohbyung Kwon
School of Management, Kyung Hee University
26, Kyungheedae-ro, Dongdaemun-gu, Seoul, 130-701, Korea
Tel: +82-2- 961- 2148, Fax: +82-2- 961- 0515, E-mail: obkwon@khu.ac.kr

저 자 소 개

김정훈
현재 경희대학교 일반대학원 경영학과에서 박사과정을 수료하였다. 목원대학교 정보컨설팅학과에서 학사학위를 경희대학교에서 석사학위를 취득하였고, 로보틱스 및 행복지수 기반의 큐레이션 시스템 관련 정부과제를 수행한 바 있으며, 관심분야는 텍스트 분석, 휴먼로봇인터페이스, IT비즈니스, 빅데이터분석 등이다.



권오병
현재 경희대학교 경영대학 교수로 재직 중이다. 서울대학교 경영학과에서 학사학위를 한국과학기술원에서 석사 및 박사학위를 취득하였고, 카네기멜론대학 ISRI연구소에서 유비쿼터스 컴퓨팅 프로젝트를 수행한 바 있다. 관심분야는 텍스트 분석, 휴먼로봇인터페이스, 상황인식 서비스, IT비즈니스, 의사결정지원시스템 등이다.