

Activating Group Discussion by Topic Providing Bots

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SUMMARY Online chat systems, e.g., Twitter and Slack, have been used in academic conferences or study meetings as a means of instant discussion and sharing related information alongside a real presentation. We propose a system for activating online discussion by providing a bot that suggests webpages related to current timeline of the discussion. Our system generates keyword vectors according to discussion timeline, searches best related webpages from several web sites, and timely provides these pages to the discussion timeline. This paper describes deployments of our system in two types of meetings: lightning talk format meetings and group meetings; and daily exchanges using online chat system. As a result, we could not find good enough reactions to the bot's postings from meeting participants at the lightning talk format meetings, but we could observe more reactions and progress of discussion caused by the bot's postings at the relaxed meetings and daily exchanges among group members.

key words: online bot, activating discussion, keyword extraction, documents provision

1. Introduction

Along with the spread of computers and the Internet, network computers has increasingly become the place of our cooperative work [1], [2]. In academic conferences and study meetings, many participants join instant discussion and share information in the online chat systems like Twitter in the context of current presentation [3]. The use of the online chat systems facilitates relaxed and timely discussion from various types of participants (experts/non-experts, presenters/audiences, onsite participants/online participants) even in the meetings with hard time-constraints.

Figure 1 is an example of using Twitter in the meeting where we deployed our system. We facilitated our participants to use Twitter for sharing quick questions and comments, and discussion related to the presentation done in the front of them since we did not have enough time to discuss for each presentation.

Thanks to it, our participants could exchange instant question-answer along the presentation without time-consuming interrupt of real-world presentation, and record and share related information timely among the participants. However, if you do a search etc. during a meeting, it will cause a difficulty to keep up with the topic in a timely manner due to the temporal restrictions.

In order to eliminate the time and labor required for

searching during a time-limited meeting, we developed a bot system that automatically provides information related to the content of the meeting. By deploying this bot at the actual meetings, it is expected that information provision will help solve potential questions and promote understanding, and invoke discussions between users.

Our bot system firstly analyzes the tweets/messages in online discussion then extracts keywords which are determined to be at the center of the discussion. It secondly searches related information according to the keywords from websites of digital library and online news. Finally, it provides searched results for participants in the form of tweet/message.

We deployed our system to three types of situations: lightning talk format meeting; relaxed meeting among group members; and daily exchanges among the group members. We analyzed how the proposed system affected online discussion by observing whether the bot's posts promote new discussion between participants and users' responses (like, retweet, and reply) to them.

In the rest of the paper, we describe previous work, the implementation of our proposed system, and deployments of it to three types of situations, i.e., lightning talk format meeting; relaxed meeting among group members; and daily exchanges among the group members. Lastly, we discuss the results of our deployments and future directions.



Fig. 1 Overview of the study meeting where our system deployed.

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2. Related Work

2.1 Support of Group Meetings

The main aim of the conferences and meetings is to develop our knowledge by exchanging mutual thoughts and experiences through discussion and chat among participants. Many systems have been proposed for facilitating online/offline meetings [4], [5]. These systems are helpful for better organizing the meeting structure, but they do not intend to provide additional contents on behalf of the meeting participants. The purpose of our research is to timely provide related information of the current discussion done by participants.

Twitter has grown as a platform for an open discussion. Takeuchi et al. developed a system to visualize the spread of information by recursively clustering tweets displayed in chronological order [6], and Jussila et al. visualized Twitter data for increasing the awareness among conference participants [7]. These systems could present the flow of online chats clearly, but did not intend to provide new tweets. This paper aims to provide new tweets as stimulus from outsider viewpoints.

Kurihara developed a system that automatically tweets each time its user (i.e., presenter) shows new slides on behalf of her/him[†]. The tweets are prepared in advance by the presenter by embedding them as notes for each slide. The system can provide hooks to the Twitter timeline to initiate discussion among audiences embedded in the presentation context. The system is suitable for controlling online discussions according to the presentation in the viewpoints of the presenter, but it does not provide a new viewpoint influenced by the audience's discussion. We aim to broaden the views of participants by providing new information related to the discussion contexts.

2.2 Information Provision by Agents

There are many research for realizing agents, i.e., autonomous system as virtual participants, to promote mutual understanding among participants of online communication [8]–[11]. We aim not only to promote mutual understanding but also to facilitate their discussion by providing information related to the current context.

Yamada developed a Twitter bot which provides paper titles stored in academic database named CiNii^{††}. This bot searches for CiNii with a trend keyword periodically extracted from Twitter's open timeline. By focusing the scope of extraction of keywords, it is expected to respond to specific discussions.

In previous work on bots that automatically answer to users' questions, FAQ Finder [12] automatically generated

FAQ (frequently asked questions) from dialogues of question and answer, and dialog navigator [13] focused on disambiguation of question and answer. Feng et al. [14] proposed a discussion-bot for answering queries of course students. These work tried to identify users' queries that were given consciously. Our attempt focused on not such conscious question-answering but information providing related to unconscious tweets.

Nishimoto et al. [15], [16] proposed a system that stimulates narrow-view discussion by providing articles based on outsider model, that aims to search articles having not only evident relevance but also hidden relevance to current topics. Our aim is to realize more open and flexible system by utilizing today's platform such as Twitter as a discussion forum.

Kitamura et al. proposed a system that provides related information by using character agents [17] and competing information recommendation [18]. These systems had plural types of agents, and helped users to search information with various viewpoints corresponding to each agent having different features about search areas. We also aim to provide multiple viewpoints derived from the current discussion contexts by using various websites such as academic archives, web magazines, etc.

2.3 Keyword Extraction from Online Meetings

We need to extract appropriate keywords from participants' postings in order to select webpages related to the contents. There has been proposed various techniques for extracting keywords from text such as tf-idf [19], Key Graph [20], machine learning by SVM [21], LDA [22], and DTM [23]. There has been also work on summarizing single documents by using lexical chains [24].

These techniques, however, require text resources of target domain beforehand and then not realistic to deal with open-end Web resources as target resources. We employ an API for keyword extraction from given sentences developed Yahoo! JAPAN^{†††} since it is easy to use for Web-based system and good enough to extract appropriate keywords from any sentences as far as we know.

Before employing the Yahoo! API, we have tried to build a subsystem for keyword extraction using tf-idf technique with approximately 30,000 articles from Gigazine^{††††}. However, the result of keyword extraction by our trial system depended on the given articles from Gigazine, and we could not get better results than the Yahoo! API. Therefore, we decided to use the Yahoo! API for extracting keywords at the moment.

[†]<https://sites.google.com/site/pptwiofficial/en>

^{††}<https://twitter.com/ronbuntter>

^{†††}<http://developer.yahoo.co.jp/webapi/jlp/keyphrase/v1/extract.html>

^{††††}<http://gigazine.net/>

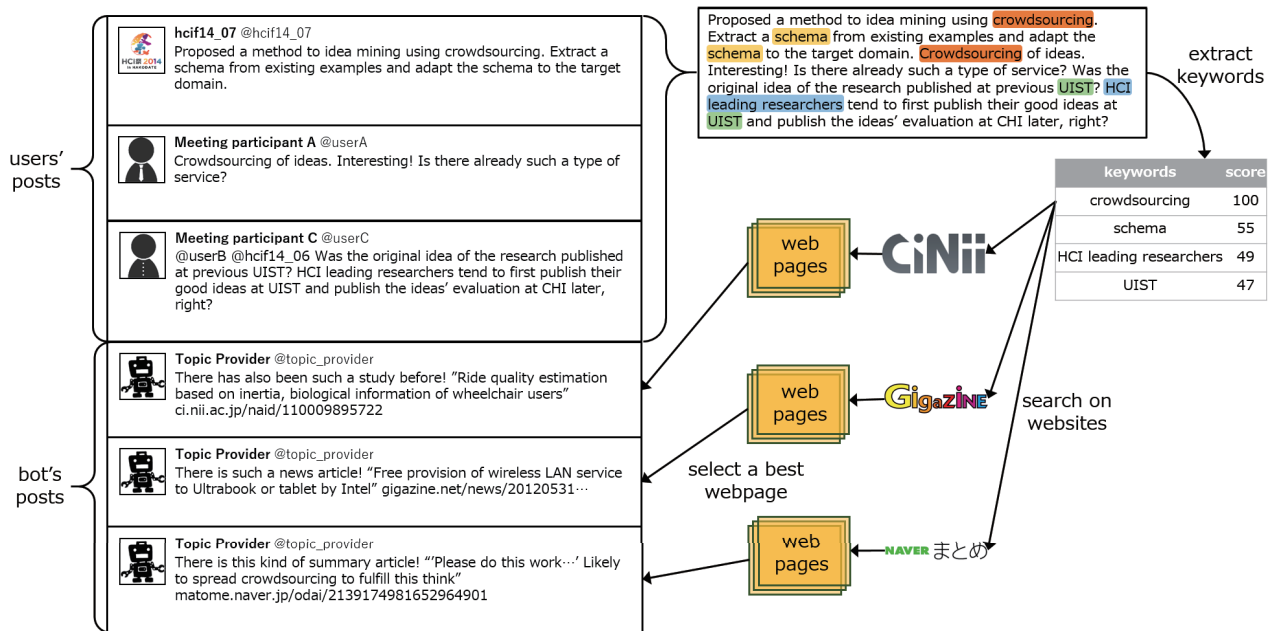


Fig. 2 System configuration based on actual deployment (Tweets were posted in Japanese. They are translated and anonymized here).

3. Bot System to Support Online Meeting

3.1 Overview of Our Bot System

The important role of academic conferences and study meetings is to provide a venue for participants to get new information and join to active discussion. However, in some types of conferences or meetings, participants do not have enough time to search additional information and extend discussion because of time constraints.

For resolving the problem, we propose a bot system which takes part in online meetings, and timely provides participants with related webpages. The bot gets participants' posts and analyzes them to extract a keyword meaning of the central topic. Next, the extracted keyword is used for searching in webpages such as academic information databases or big news sites. Many numbers of obtained webpages are compared with the participants' posts and calculated the degree of similarity, and then the webpage whose degree of similarity is the highest is posted by the bot.

By taking part in online discussion and providing participants with related webpages in real-time, participants can get more related information without taking time out from attending to presentations to make searches. We also expect the provided information gives a trigger for better discussion among participants.

Figure 2 is a system configuration of our system. The descriptions of detailed processing are explained below.

3.2 Keyword Extraction from Participants' Posts

The first stage in this process is getting all participants'

posts. In the Twitter, some conferences or meetings have hash tags to share their posts. Participants use these hash tags to search or tweet related information and ideas. In a group chat platform like Slack, it is easier to get all posts.

The second stage in the process is storing posts as text data, while removing excess information such as hash tags or URLs, until a certain amount has been stored.

The final stage is to analyze the stored posts and extract a keyword. A text analysis API provided by Yahoo! JAPAN to extract a keyword. By using this API, it is possible to analyze given texts and extract characteristics expressions (key-phrases) and their corresponding degrees of importance (score). Other methods for extracting characteristic keywords are conceivable, for example, calculating the term frequency or document frequency. But these methods have no real-time property. So, this API is used in this research.

We had a problem using the API that unknown words tend to be selected, which are useless keywords for representing the trend of timeline. To avoid this problem, our system selects only the highest scoring keyword from among those that exist as titles of Japanese Wikipedia articles. A list of titles from Japanese Wikipedia is summarized and stored in the database in advance. Extracted key-phrases are checked in order of score, beginning with the highest, until one is found that exists in the database.

3.3 Searching on Websites and Posting

The extracted keyword is searched on three websites: CiNii[†], Gigazine and NAVER^{††}. CiNii is a database of

[†]<http://ci.nii.ac.jp/>

^{††}<https://matome.naver.jp/>

Japanese academic publication, Gigazine is a news site in blog format, and NAVER is a CGM-type web curation service. These three websites were chosen to provide relevant past research papers from CiNii, and recent related topics from Gigazine or NAVER. When searching, the API provided by each website is used, or in the case of there being no provided API, the Bing Search API provided by Microsoft Azure is used.

Search results can be considered in order of relevance or date, but it is not guaranteed that the highest ranked website will be related to the content of the meeting. To resolve this issue, our system obtains a maximum of ten search results from each website in order of date, and selects the best webpage by using tf-idf and cosine similarity estimation method to determine the degree of similarity between the content of posts made at the time of keyword extraction and the content of the webpages.

Tf-idf is a weighting method of words in the document, calculated by the product of tf (term frequency) and idf (inverse document frequency). The tf-idf of the word t in the document d is given by the following expression.

$$tf(t, d) = \frac{n_{t,d}}{\sum_k n_{k,d}} \quad (1)$$

$$idf(t) = \log \frac{|D|}{df_t} + 1 \quad (2)$$

$$tf-idf(t, d) = tf(t, d) \cdot idf(t) \quad (3)$$

$n_{t,d}$ indicates the number of occurrences of the word t in the document d . D indicates the total number of documents. df_t indicates the number of documents in which the word t appears.

Cosine similarity is an index of similarity between documents. The cosine similarity between the feature vector x of the document d_1 and the feature vector y of the document d_2 is given by the following expression.

$$\cos(x, y) = \frac{\sum_k x_k y_k}{\sqrt{\sum_k x_k^2 \sum_k y_k^2}} \quad (4)$$

The webpage with the highest degree of similarity is chosen as the best. By taking this approach, it is possible to select a webpage which is closer to the contents of the discussion, as this method does not depend solely on the highest scoring keyword, but also considers words which were not chosen as keywords yet which are nonetheless distinctive and relevant to the meeting.

After the webpages have been selected, the bot provides posts including the titles and URLs of obtained webpages for users taking part in online discussion. The bot provides one post per website. If there are no search results, the bot does not post anything. If a useful keyword cannot be obtained, no search is carried out and the bot does not post.

4. Deployment at Lightning Talk Format Meetings

4.1 Detailed Setting of Deployment

We deployed our bot system at a lightning talk format meeting, “CHI study meeting 2016”. This meeting was a study meeting in which a huge number of papers presented at an academic conference, CHI 2016, were introduced in presentations of 30 seconds per paper. This meeting was divided into 139 sessions consisting of three to six papers, and each participant was responsive for one session and presented. The title and a short summary were tweeted for each papers. The summaries of individual papers were prepared by presenters beforehand, and provided as tweets each time the presenter showed new slides by volunteer participants. Our bot provided tweets when the number of characters in participants’ tweets was greater than a certain number.

This meeting was done in Japanese, and distributedly held at three venues, Hokkaido, Tokyo and Osaka, on June 26, 2016. The three venues were connected by Skype and slides and sounds were shared in real time. We had about 200 participants, including students, professors and researchers. About 50 of them actively used Twitter for sharing their ideas with a hash tag related to this meeting.

We deployed our bot using the hash tag. Our bot kept watching the participants’ tweets, and provided related articles when the number of characters of the acquired tweets exceeded the predetermined number of characters (3000 characters). We did not announce the participants about our bot in advance, but it was naturally accepted in the timeline.

4.2 Results of Deployment

Table 1 shows a part of timeline as a successful example. At the moment, the presenter has been showing a paper on individual authentication using acoustic characteristics of the skull, and then the audiences, i.e., User01-05 in the Table, responded on the timeline. Our bot instantly extracted

Table 1 Example of an appropriate information provided (part of timeline of lightning talk format meeting, translated from Japanese).

Name	Tweet
User01	“SkullConduct: Biometric User Identification Using Bone Conduction Through the Skull” Very impressed title.
User02	“Enhancing Mobile Content Privacy with Proxemics Aware Notifications and Protection” The system notifies when the others try to peek the user’s mobile phone in order to prevent the shoulder hack.
User03	Security is insufficient with just ID and password. Skull-Conduct is a type of biometric authentication, using the vibration pattern of the skull as a password. They say its recognition rate is 97%.
User04	Using the vibration pattern of the skull for authentication. Wow...
User05	Such a high rate 97%!
Bot	There is such a news article! “Biometric authentication using the ‘skull’ as a password...” (URL)

bot's postings (131)

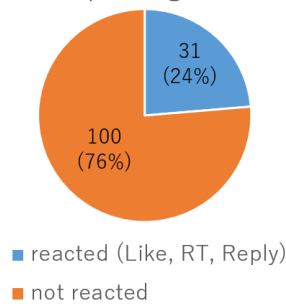


Fig. 3 Users reactions to the bot's postings (lightning talk format meeting).

participants' tweets (1352)

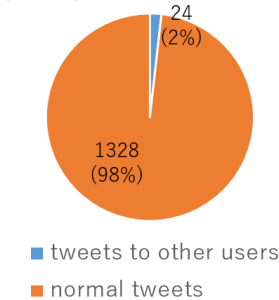


Fig. 4 Tendency of users' tweets (lightning talk format meeting).

several keywords (e.g., “password”, “skull”, “individual authentication”, etc.) from the timeline, and “password” was the best keyword. And then, the bot retrieved articles up to ten from each three sites using the best keyword “password” out of above candidates and selected best article based on cosine similarity of keyword vectors: “Biometric authentication using the skull” from Gigazine as shown in the Table. That was Japanese article introducing the research that has just presented at that moment, and it facilitated for the participants to easily understand and evaluate social reputation from the online news article. Actually, many participants reacted to the bot tweet (i.e., like, retweet, and reply).

Figures 3 and 4 show the results of the deployment at CHI study meeting 2016. Figure 3 illustrates the tendency of reactions by the meeting participants to posts by the bot. Approximately a quarter of bot's postings were reacted by the participants. Compared to it, tweets by the human participants rarely received reactions by others as shown in Fig. 4. The reason is thought that the progress of the meetings was too fast to deepen their discussion. These results show our bot played a role to provide meaningful information enough to receive reactions from participants, but we still had a problem to facilitate our users to deepen their discussion triggered by our bot's postings.

5. Deployment at Relaxed Meeting among Group Members

In a lightning talk format meeting, posts by our bot received

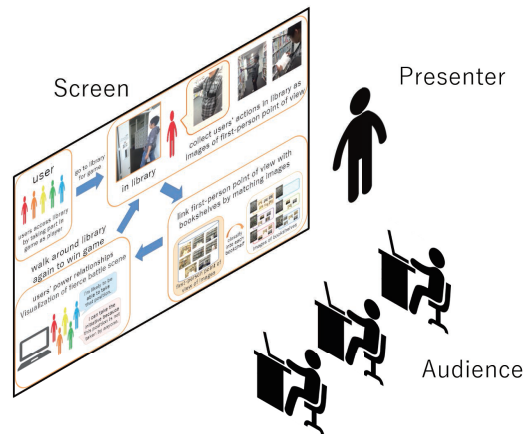


Fig. 5 Setting of group meeting supported by our bot system.

successful reactions such as like and retweet, but did not lead to evoke participants' discussion. The reasons of it were thought that the progress of the meeting was too fast and many of the participants did not know each other for exchanging easy chats or deepening discussion. Therefore, we attempted to deploy our system to other situations, namely, more relaxed group meetings and daily exchanges on a chat system.

5.1 Detailed Setting of Deployment

We set up a meeting by members of the group to which the authors belong in order to evaluate the effect of our system at a relaxed group meeting. The meeting was done in December 25, 2015. 15 undergraduate students participated including seven fourth-year students and eight third-year students. The four fourth-year students made presentations of their own research in ten in ten minutes in each.

All participants were asked to use Twitter for taking notes and discussion during the presentation. We announced to use our bot system for supporting the meeting. Figure 5 shows the setting of the meeting. We prepared a big screen to display the presenter's slides and asked to use individual note PCs to for using Twitter.

5.2 Results of Deployment

Table 2 shows an example illustrating ideal interactions between participants including bot's postings observed in the meeting timeline. During the time that these tweets were being made, a research on activating library usage by gamification was being presented. The bot provided two webpages according to the timeline, one of which was a research paper about gamification in libraries, similar to the work being presented.

After posting by the bot, a chat occurred among three users. As shown in Table 2, User01 first reacted to the bot's post regarding a related paper. When the presenter (i.e., User15) returned to the seat after his presentation, he noticed it and reacted immediately. According to our interview

Table 2 Example of an appropriate information provided (part of timeline of group meeting, translated from Japanese).

Name	Tweet
User12	This is a research about activation of library usage by gamification.
User12	He wants to make users to visit real-world libraries more.
User12	Using territory based game
User14	Do games facilitate people to join?
User03	Combination of library usage and gamification
User04	Chance encounter with books sounds nice.
User08	A research of game application for collecting photos has existed.
User12	Users' purpose is first to play the game, but gradually, going to the library becomes their purpose.
User10	There exists such a previous research.
Bot	There is such a research paper! "Possibility of gamification as an 'escape game' in a university library" (<i>URL</i>)
Bot	There is such a summary page! "#Gamification Geeks 2015.12.08" (<i>URL</i>)
User01	The paper on the relationship between escape game and library usage looks interesting!
User15	@user01 Is there such a paper?
User01	@user15 Yeah
User14	@user15 @user01 The bot has just tweeted it.

Table 3 Extracted keywords during Table 2 (translated from Japanese).

Keyword	Score
gamification	100
library usage	44
real-world	40
territory	31
game	26
purpose	24
previous research	22

to him later, he did not know about the provided paper and noticed it deeply related to his research. From this example, it can be said that the bot was successfully able to provide useful information for meeting participants.

Table 3 shows highly scored keywords extracted at the time of Table 2. In this example, the highest scoring word was "gamification", and this word existed as a title of Japanese Wikipedia article. Therefore, this word was selected as a keyword for searching on websites by our bot.

Table 4 shows calculated cosine similarity between extracted webpages and users' tweets on the timeline presented in Table 2. This shows that top scored 10 webpages were firstly selected by using keyword "gamification", and the article having the highest similarity was finally chosen to be posted to the timeline.

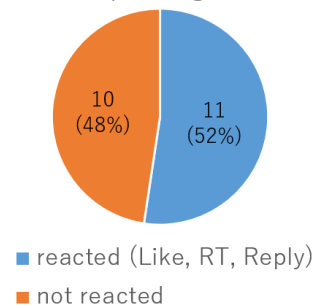
Figures 6 and 7 show the tweet behaviors of the meeting participants. Comparing Fig. 6 with Fig. 3, bot's postings received more reactions in the case of relaxed meeting by members who know well with each other. Likewise, the participants' tweets became more interactive, that is, including more numbers of reactions to other participants' tweets (like, retweet and reply) as shown in Fig. 7 compared to Fig. 4 in the case of the lightning talk format meeting.

Comparing the results of two deployments, i.e., lightning talk format meeting and relaxed group meeting, reveals

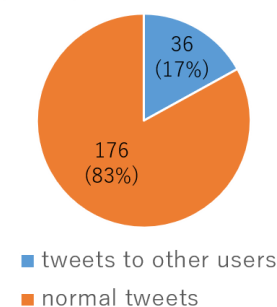
Table 4 Results of search for "gamification" in CiNii and cosine similarity between participants' posts and extracted webpages (translated from Japanese).

Article title	Similarity
Design for W-DIARY: A diary-style-application for English word learning with existing photos	0.0847
Demonstration of character rearing game application in delay tolerant networks	0.0570
Communication support with game-like methods	0.0544
The possibilities of using gamification in information literacy education: Examples from overseas libraries	0.0444
Effects of gamification-based teaching materials designed for Japanese first graders on classrooms	0.0365
Technology using gamification and verification in the business field	0.0134
Possibility of gamification as an 'escape game' in university library	0.2426
Active learning through discussion and negotiation: Using university education as materials	0.0120
Development and practice of gamified coursework design framework	0.0509
Effects of presenting rank order generated from subsets	0.0089

bot's postings (21)

**Fig. 6** Users reactions to the bot's postings (relaxed group meeting).

participants' tweets (212)

**Fig. 7** Tendency of users' tweets (relaxed group meeting).

that reaction of participants to the bot's posts as well as other participants' tweets was higher in the latter situation. According to our roughly browsing of participants' tweets in the two deployments, most participants used Twitter for personal notes, not for interactions with other participants in the lightning talk format meeting. It can be said that our bot is effectively working in more relaxed meeting by members who know well with each other than huge-sized and busy meeting.

6. Deployment on Daily Group Chats

In order to evaluate longer-term use, we deployed our system on daily group chats.

6.1 Online Daily Interaction

We deployed our bot system at the daily chats between members of the group to which the authors belong. Since we have been using Slack as daily chat system, we implemented another system running on Slack using the same method and data. Our system keeps watching messages posted on #general channel and posts messages on #provider channel when it finds articles related to the timeline of #general.

There were 13 active Slack users within the group during the time we deployed our system. They had a various kind of interactions on Slack including sharing personal notes as well as chatting with other members. We observed their interactions for two weeks from February 4 to February 20, 2017. During the period, our bot system monitored all the messages given by the group members, and posted relevant articles in the same manner of our previous system used for Twitter.

6.2 Results of Deployment

Our bot posted 27 times during the two weeks. During the period, there were not only daily activities within research group but also final presentation of graduation study in their university. They used Slack for exchanging daily messages as well as discussion about research presented in the meeting where they participated.

Figure 8 shows the tendency of users reactions to the bot's postings. Approximately a quarter of the posts received reactions from the users, that is interestingly similar with the deployment at lightning talk format meeting shown in Fig. 3. The reason is thought that the posts by our bot were overlooked by most users, or the users lost timing to react to the posts. In order to effectively utilize our bot in group communication, it can be said that the progress of the meetings must be at an appropriate speed, namely, not too fast and not too slow.

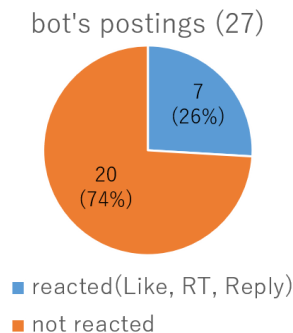


Fig. 8 Users reactions to the bot's postings (daily group chats on Slack in two weeks).

We present two examples that our bot timely provided good information related to group chats on Slack. The first example in Table 5 shows the chat on Slack during a research presentation given by a group member, User04 in the table. Group members chatted during User04 was presenting his research on service detection using IoT sensors, and then the bot presented an article showing the system similar to the research on timeline. Thanks to the bot's post, the presenter (User04) could meet an important work much related to his research.

Another example is from chat between two members of the group. Table 6 shows the chat at that time. In the chat, User01 was first asking about a system that supports sketching in 3D virtual space developed by User02. Not

Table 5 Example of timely providing an article related to contents of research presentation (part of timeline on Slack, translated from Japanese).

Name	Post
User01	From the time difference between opening time of the card drawer and human detection at the e-studio, the system can determine if the person is group member or not. Sounds great.
User02	It can also detect someone is sitting next to the printer.
User03	(attach a link to an article of a product called "eRemote mini")
User01	eRemote seems a classical IoT service. I think the good point (of the presented research) is the service is embedded in the users' conversation, and they don't need directly manipulate the service.
Bot	There is such an article. "iRemocon" makes home electric appliances remotely controllable from the outside via iPhone and iPad - GIGAZINE" (URL)
User04	This is very important! QT: Bot "There is such an article. "iRemocon" makes home electric appliances remotely controllable from the outside via iPhone and iPad - GIGAZINE" (URL)"

Table 6 Example of providing a trigger of technical discussion (part of timeline on Slack, translated from Japanese).

Name	Post
User01	@User02 Good job! Now, we can do a demo anywhere.
User01	Is the sketch limited from the viewpoint firstly given? Do we have to reset the viewpoint for sketching after changing the viewpoint?
User02	Yes.
User01	The position of the pen seems slightly misaligned. The center of the sketch plane is correct, but pen stroke is beyond my expectation when I try to draw outside of the plane.
User02	I translated my earlier prototype to online demo. So, sketch is allowed in the front viewpoint only.
Bot	By searching with the keyword "viewpoint", the following article was found. "A JavaScript library 'jThree' enables viewers freely changes their viewpoint angles of MMD models on the web - GIGAZINE" (URL)
User01	Oh? Did you (User02) use this? QT: "By searching with the keyword "viewpoint", the following article was found. "A JavaScript library 'jThree' enables viewers freely changes their viewpoint angles of MMD models on the web - GIGAZINE" (URL)"
User02	No, I used "three.js". But it is nice to show "jThree" here. "jThree" is a library that allows us to handle "three.js" with jQuery notation.

only from the “viewpoint” used as a search keyword but also from the words such as “demo”, “change” and “drawing” that appeared in the interaction, an article on similar technology was offered. The bot’s post successfully gave the two members a chance to share technical details of collaborative research.

6.3 Comparison with Other Deployments

In deployment at daily group chats, it was not as good as responses to the bot’s posts at group meetings. Nevertheless, we could observe fruitful interactions triggered by the bot’s posts.

We sometimes observed posts by the bot caused our users confused. In the current system, set of keywords extracted from the timeline may be derived from two different topics since the topic division is not recognized correctly. In order to raise our bot’s performance at continuous timeline, we need to improve the bot to enable to provide information at an appropriate timing by checking the boundary of the topics.

7. Conclusions

We developed a bot system to activate online discussion and daily exchanges performed on chat systems by providing related articles. We presented deployments of our system in two types of meetings: lightning talk format meeting and group meeting; and daily exchanges using online chat system. We could not find good enough reactions to the bot’s postings from meeting participants at the lightning talk format meeting mainly because of hard time-constraint. On the other hand, we could observe more reactions (i.e., like, retweet and reply) to the bot’s postings and progress of discussion among users caused by them at the relaxed meetings and daily exchanges among group members who know well with each other.

We could observe our users’ reactions (i.e., like, retweet, and reply) to the posts by our bot system at various types of online communication. That means our bot could provide our users with appropriate information extracted from websites by sensing keywords representing contexts of timeline. Regarding the activation of discussion, however, the effect of our bot system was limited. We could observe some good discussion initiated by the bot’s posts at group meetings/chats between members who know well with each other and having no time constraints. At the same time, many posts were overlooked or lost timing to activate discussion among the users. Future work includes boundary detection between topics embedded in continuous timeline and flexible controlling of timing of bot’s postings in order to adapt to various types of timeline.

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