An Investigation of Tweets Submited by Using Music Player Applications

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***Abstract*—What users are doing at a certain point in time is important for designing various services and applications in social media, such as targeted advertisement, news recommendation, and real-world analysis. As a result, in this study, we investigated tweets which users submitted when they were listening to music by using music player applications. We collected 2,000 tweets including hashtags generated by music player applications and found about 65% of them were tweets where impressions were described, 15 % of them were tweets where reasons why users were listening to music were described, and 10 % of them were tweets where actions while listening to music were described. We applied machine learning techniques to detect tweets where two kinds of actions while listening to music, moving to somewhere or going to bed, were described. The experimental result shows that our method is useful for providing behavior based services and applications in social media.**

***Keywords*–music player application; music content; behavior based service; Twitter; social media.**

I. Introduction

Social media, such as Twitter and Facebook, generate large quantities of data about where users are and what they are thinking or doing at a certain point in time. Take tweets on Twitter, (exp 1) and (exp 2), for example. We can understand the submitters of these two tweets were listening to music. This is because #nowplaying in (exp 1) and (exp 2) show that these tweets were submitted by using music player applications. Users who are using music player applications are thought to be listening to music.

(exp 1) *#nowplaying: "soundscape" from "soundscape - Single" by TRUE (saisei kaisuu: 35) #songsinfo*
(#nowplaying: "soundscape" from "soundscape - Single" by TRUE (plays: 35) #songsinfo)

(exp 2) *#nowplaying kagerou by ONE OK ROCK on #onkyo #hfplayer*

#nowplaying is a hashtag generated by various music player applications [1]. Furthermore, #songsinfo in (exp 1) is a hashtag generated by a music player application, SongsInfo. Also, #onkyo and #hfplayer in (exp 2) are hashtags generated by a music player application, HF Player. These hashtags and the other words in (exp 1) and (exp 2) were all generated and embedded into these tweets automatically by music player applications when users submitted these tweets by using them. As a result, these hashtags enable us to understand that these users were listening to music when they submitted these tweets by using music player applications. As mentioned, (exp 1) and (exp 2) consist of words and hashtags all of which were generated by music player applications. On the other hand, (exp 3), (exp 4), and (exp 5) include words generated not only by music player applications but by users.

(exp 3) *#nowplaying: "Grow Slowly" from "Hafa Adai" by iguchi yuka (saisei kaisuu: 3) #songsinfo suki desu motto kiiteiru*
(#nowplaying: "Grow Slowly" from "Hafa Adai" by Iguchi Yuka (plays: 3) #songsinfo I like and listen to it so many times)

(exp 4) *basu wo nogashita node aruki masu !!#nowplaying: "walk on Believer ♪" from "walk on Believer ♪" by toyosaki aki (saisei kaisuu: 96) #songsinfo*
(I will walk because I missed the bus !! #nowplaying: "walk on Believer ♪" from "walk on Believer ♪" by toyosaki aki (plays: 96) #songsinfo)

(exp 5) *tenshon age te yakin ikuzo #nowplaying NIGHT FLIGHT by Perfume on #onkyo #hfplayer*
(I cheer myself up and go to night shift #nowplaying NIGHT FLIGHT by Perfume on #onkyo #hfplayer)

Specifically, the following words in (exp 3), (exp 4), and (exp 5) were generated not by music player applications but by users.

- *suki desu motto kiiteiru* (I like and listen to it so many times) in (exp 3),
- *basu wo nogashita node aruki masu !!* (I will walk because I missed the bus !!) in (exp 4), and
- *tenshon age te yakin ikuzo* (I cheer myself up and go to night shift) in (exp 5)

In this study, we describe user generated words in tweets submitted by using music player applications as *comments*. We will explain comments in tweets submitted by using music player applications in Section III. The comments in (exp 3), (exp 4), and (exp 5) express user's impression, action, and reason, respectively.

We can know that the submitters of (exp 3), (exp 4), and (exp 5) were listening to music when they submitted these tweets into Twitter. Furthermore, comments in these tweets enable us to understand what they were thinking and doing while listening to music. What users are thinking and doing at a certain point in time is important for designing various services and applications on social media, such as targeted advertisement, news recommendation, and real-world analysis. As a result, in this paper, we investigate tweets submitted by using music player applications and show what Twitter users are thinking and doing while listening to music. Furthermore, we discuss whether tweets submitted by using music player applications can be classified by using machine learning techniques.

The rest of this paper is organized as follows: In Section II, we survey related works. In Section III, we investigate tweets submitted by music player applications and show what the users are thinking and doing while listening to music. In Section IV, we apply machine learning techniques to classify tweets submitted by music player applications and discuss whether we can detect what the users are doing while listening to music. Finally, in Section V, we present our conclusions.

II. Related works

Twitter enables us to easily submit short messages in real time from anywhere with internet access. As a result, Twitter data is a valuable resource for predicting various trends and events. Taking this in consideration, there are many studies that have treated Twitter as a social sensor [2]. Aramaki et al. reported that Twitter messages reflect the real world and influenza related tweets can be extracted by using Twitter API and NLP techniques [3]. Also, Culotta showed that influenza-related Twitter messages can be identified by using a document classification method and a small number of flu-related keywords can forecast future influenza rates [4]. Sakaki et al. investigated the real-time nature of Twitter and proposed an event notification system that monitors tweets and delivers notification promptly [5]. Jansen et al. reported that microblogging is an online tool for customer word of mouth communications and potentially rich for companies to explore as part of their overall branding strategy [6].

Timestamps and geotags embedded into tweets are useful for treating Twitter as a social sensor. Some researchers conducted studies for event detection using geotags embedded into tweets. Lee and Sumiya proposed a method for detecting local events by applying a k-means clustering method to geotagged Twitter documents [7]. Kamath et al. studied the spatio-temporal dynamics of Twitter hashtags by using a sample of 2 billion geo-tagged tweets [8]. However, Watanabe et al. reported that less than one percent of Twitter posts are associated with a geolocation [9]. This is because Twitter users have been slow to adopt geospatial features and only a small amount of tweets comes with location information [10]. As a result, recent work has focused on geoinference for inferring the locations of posts. Yamaguchi et al. pointed out that most existing methods can be categorized into two kinds of approaches [11].

- a content-based approach or
- a graph-based approach

First, we discuss studies based on the content-based approach. The content-based approach leverages user-generated contents in the form of texts. Cheng at al. proposed a method for estimating a Twitter user's city-level location based purely on the content of the user's tweets [10]. Eisenstein et al. proposed a method of multi-level generative model that enables prediction of an author's geographic location from tweets [12]. Hecht et al. reported that user's home country and state can be reasonably inferred by using simple machine learning techniques [13]. Han et al. proposed a method of finding location indicative words via feature selection and examined whether the reduced feature set boosts geolocation accuracy [14]. Schulz et al. proposed a multi-indicator approach for determining the location where a tweet was created and the location of the user's residence [15]. Yamaguchi et al. proposed an online location inference method that can update inference results using only newly arriving contents without using previous contents [11].

Next, we discuss studies based on the graph-based approach. The graph-based approach is based on the structure of social graphs where friends are connected. This approach is based on an idea: users' social networks are useful for revealing their locations. For example, Twitter users are more likely to follow others that are geographically closer to them. As a result, Rout et al. described this approach as network-based approach [16]. Wang et al. used communication records of 6 million mobile phone subscribers and found that the similarity between individuals' movements, their social connectedness and the strength of interactions between them are strongly correlated with each other [17]. Backstrom et al. pointed out that, by using user-supplied address data and the network of associations between members of the Facebook social network, we can directly observe and measure the relationship between geography and friendship [18]. Rout et al. proposed an approach to geolocating users of online social networks, based solely on their friendship connections [16]. Sadilek et al. reported that we can infer people's fine-grained location, even when they keep their data private and we can only access the location of their friends [19].

Kinsella et al. pointed out that understanding where users are can enable a variety of services that allow us to present information, recommend businesses and services, and place advertisements that are relevant to where they are [20]. We also may say that understanding what users are thinking and doing can enable a variety of services that are relevant to what they are thinking and doing. However, few studies have been made on inferring what users are thinking and doing while many studies have been made on inferring where users are. As a result, in this paper, we investigate tweets submitted by using music player applications and show what Twitter users are thinking and doing while listening to music. Furthermore, we discuss whether tweets submitted by using music player applications can be classified by using machine learning techniques.

III. Investigation of tweets submitted by using music player applications

In this section, we investigate tweets submitted by music player applications and show what the users are thinking and doing while listening to music.

A. The investigation object

Tweets can be classified into three types [21]:

- reply
  A reply is submitted to a particular person. It contains "@username" in the body of the tweet. For example, (exp 6) is a reply to @eitaso.

  (exp 6) *@eitaso ore to nagoya de seigi no uta wo utawanaika ?* (^L^) *#nowplaying futten toppa ☆ LOVE IS POWER ☆ / chikyu bouei bu*
  (@eitaso Let's sing a song of justice in Nagoya? (^L^) #nowplaying futten toppa ☆ LOVE IS POWER ☆ / chikyu bouei bu)

- retweet
  A retweet is a reply to a tweet that includes the original tweet.

- normal tweet
  A normal tweet is neither reply nor retweet. For example, (ex 3), (ex 4), and (ex 5) are normal tweets. Normal tweets are generally submitted to general public.

In order to investigate tweets submitted by music player applications and what users are thinking and doing while listening to music, we collected the following 2000 tweets:

- 1,000 Japanese normal tweets including hashtag
  - #nowplaying
  - #songsinfo

  obtained from 13 October 2016 to 11 December 2016. These 1,000 tweets were submitted by 244 users.
- 1,000 Japanese normal tweets including hashtag
  - #nowplaying
  - #onkyo
  - #hfplayer

  obtained from 13 October 2016 to 1 December 2016. These 1,000 tweets were submitted by 345 users.

We did not collect the following tweets even if they include the hashtags above.

- replies,
- retweets, and
- tweets that include no comments generated by users.

As a result, (exp 1), (exp 2), and (exp 6) were not included in the collected 2000 tweets. Then, we extracted user generated comments from them by eliminating the following words.

- Uniform Resource Locators (URL),
- hashtags, and
- words generated automatically by music player applications.

As a result, we extracted *suki desu motto kiiteiru* (I like and listen to it so many times) from (exp 3) as an user generated comment. Also, we extracted *basu wo nogashita node aruki masu !!* (I will walk because I missed the bus !!) and *tenshon age te yakin ikuzo* (I cheer myself up and go to night shift) from (exp 4) and (exp 5), respectively.

B. Tweets which users submit when they use music player applications

We classified comments in tweets submitted by using music player applications into the following four types:

- impressions — comments expressing users' impressions and evaluations of contents which they played by using music player applications,
- reasons — comments expressing reasons why users played contents by using music player applications,
- actions — comments expressing actions which users carried out when they used music player applications, and
- others — comments that cannot be classified into the three types above.

Figure 1 shows the classification result of the obtained 2,000 Japanese tweets. These tweets were classified by human experts. We should notice that some comments can be classified into two types. For example, *yoi kyoku da!* (Good music!) in (exp 7) is classified into impressions. On the other hand, *ekurea katte kaero!* (Let's buy an eclair and go home!) is classified into actions.

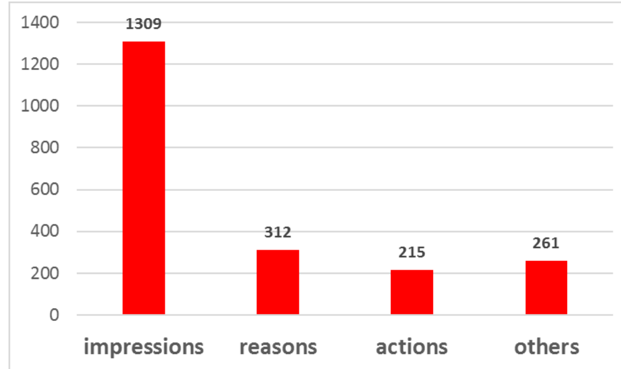

Figure 1. The classification result of the 2,000 tweets which users submit when they use music player applications (by human experts).

(exp 7) *yoi kyoku da! ekurea katte kaero!*
(Good music! Let's buy an eclair and go home!)

We shall discuss the following kinds of comments in detail.

- comments expressing impressions,
- comments expressing reasons, and
- comments expressing actions.

1) Comments expressing impressions: We found many comments expressing users' impressions and evaluations of contents which they played by using music player applications. Figure 1 shows that more than half of the obtained 2000 tweets were classified into ones expressing users' impressions, such as (exp 8) and (exp 9).

(exp 8) *yoi. suki.*
(Good. I like it.)
(exp 9) *natsukashi sugi te naki sou*
(I was close to tears)

In addition, we found that many comments expressing users' impressions were related to time, such as (exp 10) and (exp 11).

(exp 10) *kono jikantai ni kiku jazz ha, honto ni kimochi ga ii.*
(It's fun listening to jazz in this time period.)
(exp 11) *shinya no Neptunus ha kakubetsu.*
(It is wonderful to listen to Neptunus very late at night.)

Especially, most of them were related to time periods when users played music by using music player applications.

2) Comments expressing actions: For many years, psychology research has shown that people can attend to only one task at a time [22]. Hyman et al. reported that people talking on their cell phones while walking ran into people more often, and did not notice what was around them [23]. However, listening to music is an exception. We often do something while listening to music. Actually, we found many tweets where users described their actions while using music player applications. (exp 12), (exp 13), (exp 14), and (exp 15) are examples of comments expressing users' actions.

(exp 12) *tsuukin chu.. sawayakana hare.*

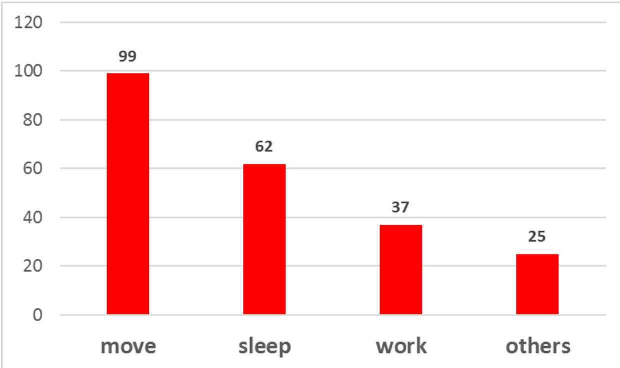

Figure 2. The classification result of the tweets expressing users' actions (by human experts).

(On my way to work.. It 's a crisp day.)
(exp 13) *oyasumi nasai*
(Good night)
(exp 14) *desaki deno gyomu shuryo. kiro he. yokohama live no set list.*
(I have finished my business out of the office. On my way home. The set list of the Yokohama live.)
(exp 15) *italo pop kiki nagara kare- shikomu yo*
(I will make curry with listening to Italo pop)

In our investigation, three kinds of most commonly actions described in tweets submitted by using music player applications are move, sleep, and work. For example, (exp 12) shows that the submitter was going to work with listening to music. (exp 13) shows that the submitter was going to sleep, and (exp 14) shows that the submitter had finished the job. As shown in Figure 1, we found 215 tweets expressing users' actions in the obtained 2,000 tweets which users submit when they use music player applications. We classified these 215 tweets expressing actions into four types:

- move
- sleep
- work
- others

Figure 2 shows the classification result of the tweets expressing users' actions. We found some tweets expressing users' actions can be classified into two types. For example, (exp 14) was classified into work and move. In particular, user's action expressed in *desaki deno gyomu shuryo* (I have finished my business out of the office) of (exp 14) was classified into work. On the other hand, user's action expressed in *kiro he* (On my way home) of (exp 14) was classified into move. Furthermore, some tweets expressing users' actions were classified into others. This is because they were classified into neither move, sleep, nor work. For example, (exp 15) was classified into others. As shown in Figure 2, many tweets expressing users' actions were classified into move and sleep. Hamamura and Iwamiya conducted the survey on the use of portable music player [24]. The survey was conducted on 72 college students, and 65 students and 39 students of them used portable music players while moving and working, respectively. This investigation result is in good agreement with ours. On the other hand, in their investigation result, there were no students who used portable music players while sleeping. The result is not in good agreement with ours. Furthermore, Hamamura and Iwamiya reported that 19 students used portable music players while shopping. On the other hand, we found only one comment, (exp 16), submitted by an user who were shopping while listening to music.

(exp 16) *osanpo & okaimono !*
(walk & shopping !)

3) Comments expressing reasons: We found many comments expressing users' reasons why they were listening to music by using music player applications.

(exp 17) *kibun teki ni kikitaku natta*
(I have a craving for music)
(exp 18) *katte shimatta*
(I finally bought it!)

(exp 17) and (exp 18) shows the reasons why the submitters of them were listening to music by using music player applications, feeling and acquisition, respectively. The submitter of (exp 17) felt an impulse and listened to music. On the other hand, the submitter of (exp 18) bought music contents and listened to it.

IV. Detection of Tweets Expressing Users' Actions

What users are doing at a certain point in time is important to design various services and applications in social media that are relevant to what they are doing. If we detect users' actions while listening to music automatically, we can design behavior based services and applications in social media more precisely. For example, users may have free time to use services and applications when they are listening to music and going to somewhere. On the other hand, users may not want to be disturbed when they are lying down on their beds and listening to music. As a result, in this section, we discuss whether we can detect tweets including hashtags generated by music player applications by using machine learning techniques.

In this study, we used the 2,000 tweets investigated in Section III for the experimental data. The experimental data include

- 99 comments expressing users' actions (move) and
- 62 comments expressing users' actions (sleep).

In this experiment, we used the support vector machine (SVM) and maximum entropy method (ME) for data training and classifying. Table I shows feature $s1 \sim s15$ used in machine learning on experimental data. $s1 \sim s7$ were obtained by using the results of morphological analysis on experimental data. In the experiments, we used a Japanese morphological analyzer, JUMAN, for word segmentation of tweets [25]. $s8 \sim s10$ and $s12 \sim s14$ were obtained by extracting character N-gram from experimental data. Odaka et al. reported that character 3-gram is good for Japanese processing [26]. $s4 \sim s7$ and $s12 \sim s15$ were obtained from first sentences of tweets. This is because, we thought, clue expressions of users' actions are often found at first sentences of tweets. We conducted this experiment using TinySVM [27] and maxent [28]. Table II and Table III show the SVM classification result of users' actions, move and sleep, in the 2,000 tweets, respectively. Also, Table IV and Table V show the ME classification result of users'

TABLE I. THE FEATURES USED IN MACHINE LEARNING METHODS FOR DATA TRAINING AND CLASSIFYING TWEETS EXPRESSING USERS' ACTIONS WHILE LISTENING TO MUSIC

$s1$	word unigrams of the comment
$s2$	word bigrams of the comment
$s3$	the number of words in the comment
$s4$	word unigrams of the first sentence of the comment
$s5$	word bigrams of the first sentence of the comment
$s6$	the number of words in the first sentence of the comment
$s7$	the last word of the first sentence of the comment
$s8$	character unigrams of the comment
$s9$	character bigrams of the comment
$s10$	character 3-grams of the comment
$s11$	the length of the comment
$s12$	character unigrams of the first sentence of the comment
$s13$	character bigrams of the first sentence of the comment
$s14$	character 3-grams of the first sentence of the comment
$s15$	the length of the first sentence of the comment

actions, move and sleep, in the 2,000 tweets, respectively. The experimental result was obtained with 10-fold cross-validation.

As shown in Table II and Table III, we obtained 97% and 99% accuracy when we applied SVM machine learning techniques to detect tweets including comments expressing user's move and sleep, respectively. Also, we obtained 97% and 99% accuracy when we applied ME machine learning techniques to detect tweets including comments expressing user's move and sleep, respectively. Furthermore, the SVM precision of tweets including comments expressing user's move and sleep were 91% and 100%, respectively. Also, the ME precision of tweets including comments expressing user's move and sleep were 95% and 100%, respectively. As a result, our method is useful to collecting tweets including comments expressing user's move and sleep, precisely. On the other hand, the SVM recall of tweets including comments expressing user's move and sleep were 48% and 79%, respectively. Also, the ME recall of tweets including comments expressing user's move and sleep were 41% and 73%, respectively. The reason why the recall of tweets including comments expressing user's sleep was better than that of move was that typical expressions, such as "*oyasuminasai* (good night)", were often used in comments expressing user's sleep than move. The experimental results show that our method is not enough to detect tweets expressing users' actions precisely. However, the precisions of our method show that tweets detected by our method are useful for understanding what users were doing. As a result, our method is useful for providing social media services, such as targeted advertisement, news recommendation, and real-world analysis.

TABLE II. THE SVM CLASSIFICATION RESULT OF USERS' ACTIONS (MOVE) IN THE 2,000 TWEETS INCLUDING HASHTAGS GENERATED BY MUSIC PLAYER APPLICATIONS.

	SVM results		
users' actions	move	others	recall
move	48	51	0.48
others	5	1896	1.00
precision	0.91	0.97	

TABLE III. THE SVM CLASSIFICATION RESULT OF USERS' ACTIONS (SLEEP) IN THE 2,000 TWEETS INCLUDING HASHTAGS GENERATED BY MUSIC PLAYER APPLICATIONS.

	SVM results		
users' actions	sleep	others	recall
sleep	49	13	0.79
others	0	1938	1.00
precision	1.00	0.99	

TABLE IV. THE ME CLASSIFICATION RESULT OF USERS' ACTIONS (MOVE) IN THE 2,000 TWEETS INCLUDING HASHTAGS GENERATED BY MUSIC PLAYER APPLICATIONS.

	ME results		
users' actions	move	others	recall
move	41	58	0.41
others	2	1899	1.00
precision	0.95	0.97	

TABLE V. THE ME CLASSIFICATION RESULT OF USERS' ACTIONS (SLEEP) IN THE 2,000 TWEETS INCLUDING HASHTAGS GENERATED BY MUSIC PLAYER APPLICATIONS.

	ME results		
users' actions	sleep	others	recall
sleep	45	17	0.73
others	0	1938	1.00
precision	1.00	0.99	

V. CONCLUSION

Social media, such as Twitter, generate large quantities of data about what users are thinking and doing at a certain point in time. What users are thinking and doing at a certain point in time is important to design various services and applications in social media, such as targeted advertisement, news recommendation, and real-world analysis. As a result, in this study, we investigate tweets submitted by music player applications and show what users are thinking and doing while listening to music. Furthermore, we apply machine learning techniques to detect tweets submitted by music player applications and discuss whether we can detect tweets expressing what users are doing while listening to music. The experimental results show that our method is not enough to detect tweets expressing users' actions precisely. However, tweets detected by our method are useful for understanding what users were doing. As a result, our method is useful for providing social media services, such as targeted advertisement, news recommendation, and real-world analysis. We are now investigating the phases of users' actions, such as start, middle, and end. This is because the phases of users' actions enable us to provide more precise services and applications relevant to users' actions.

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