An Investigation of Users' Actions

Expressed in Tweets Submitted by Using Music Player Applications

Yasuhiko Watanabe, Kenji Yasuda, Ryo Nishimura, and Yoshihiro Okada
Ryukoku University
Seta, Otsu, Shiga, Japan
Email: watanabe@rins.ryukoku.ac.jp, t130522@mail.ryukoku.ac.jp,
r_nishimura@afc.ryukoku.ac.jp, okada@rins.ryukoku.ac.jp

***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 investigated what users described in these tweets. We found 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. Furthermore, we examined whether we can detect tweets where two kinds of action phases, start and middle, were described. In both cases, we obtained the high accuracy and precision. 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. 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, we investigated tweets submitted by using music player applications and show what Twitter users are thinking and doing while listening to music [1]. In this paper, we conduct a detailed investigation on tweets submitted by using music player applications and discuss whether they can be classified by using machine learning techniques.

The rest of this paper is organized as follows: In Section II, we survey the related works. In Section III, we investigate tweets submitted by music player applications and show what 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 users are doing and what action phases they are in 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]. Furthermore, Twitter data was used for inferring on-line Internet service availability [7], measuring public interest and concern about health-related events [8], observing information diffusion in social media [9], and examining situational features during emergency events [10].

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 [11]. Kamath et al. studied the spatio-temporal dynamics of Twitter hashtags by using a sample of 2 billion geo-tagged tweets [12]. However, Watanabe et al. reported that less than one percent of Twitter posts are associated with a geolocation [13]. This is because Twitter users have been slow to adopt geospatial features and only a small amount of tweets comes with location information [14]. As a result, recent work has focused on geoinference for predicting the locations of posts. Yamaguchi et al. pointed out that most existing methods can be categorized into two kinds of approaches: a content-based approach or a graph-based approach [15].

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 [14]. Eisenstein et al. proposed a method of multi-level generative model that enables prediction of an author's geographic location from tweets [16]. Hecht et al. reported that user's home country and state can be reasonably inferred by using simple machine learning techniques [17]. Han et al. proposed a method of finding location indicative words via feature selection and examined whether the reduced feature set boosts geolocation accuracy [18]. 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 [19]. Yamaguchi et al. proposed an online location inference method that can update inference results using only newly arriving contents without using previous contents [15].

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 [20]. 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 [21]. 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 [22]. Rout et al. proposed an approach to geolocating users of online social networks, based solely on their friendship connections [20]. 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 [23].

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 [24]. 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 predicting what users are thinking and doing while many studies have been made on predicting 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 [25]:

- 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, (exp 3), (exp 4), and (exp 5) are normal tweets. Normal tweets are generally submitted to general public.

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

- 1,000 Japanese normal tweets including hashtag [26]
  - #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 a 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.

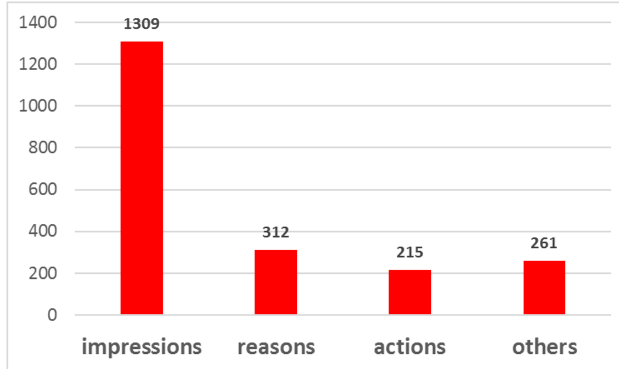

Figure 1. The classification result of the 2,000 tweets which users submit when they use music player applications (by human experts).

Figure 1 shows the classification result of the obtained 2,000 Japanese tweets. 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.

(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.

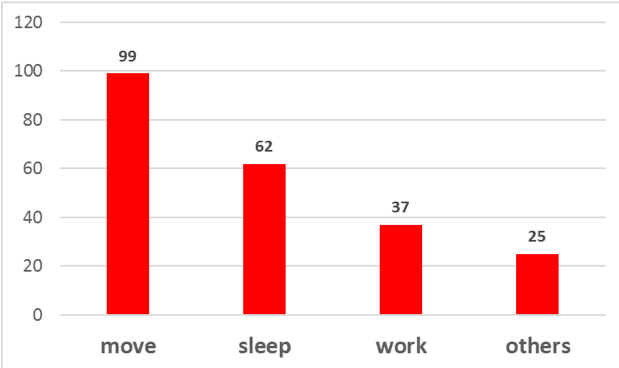

Figure 2. The classification result of the 215 tweets expressing users' actions (by human experts).

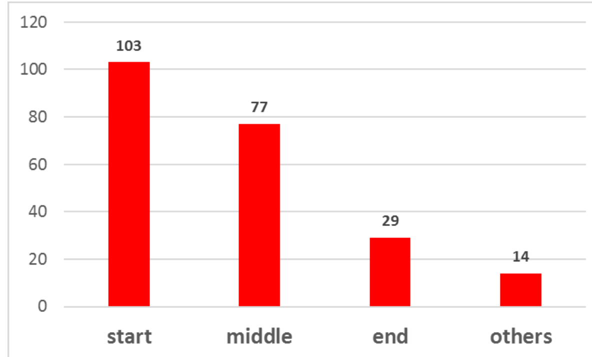

Figure 3. The classification result of the stages of users' actions in the 215 tweets expressing users' actions (by human experts).

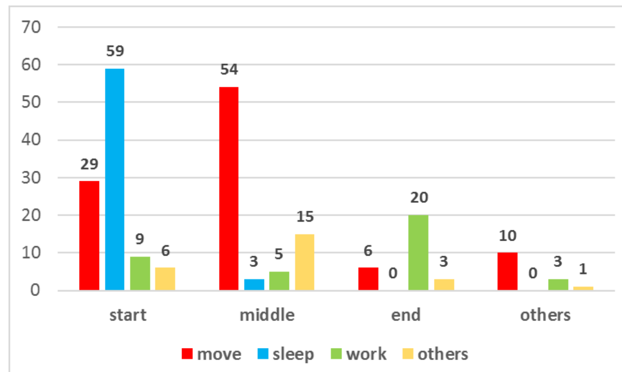

Figure 4. The classification result of the stages of users' actions: move, sleep, work, and others (by human experts).

2) Comments expressing actions: Psychology research has shown that people can attend only one task at a time [27]. Hyman et al. reported that people talking on their cell phones while walking they ran into people more often, and did not notice what was around them [28]. 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.*
(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, and 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 [29]. The survey was conducted on 72 college students. The result of their survey had partially in common with ours. In their investigation result, 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 a user who were shopping while listening to music.

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

Many tweets expressing users' actions showed the phases of their actions. For example, (exp 13) showed that the tweet was submitted just before the user started his/her action. On the other hand, (exp 12) showed that the tweet was submitted when user's action was ongoing. As a result, we classified the 215 tweets expressing users' actions in Figure 1 into four types: start, middle, end, and others. Figure 3 shows the classification result of the tweets expressing users' actions. As shown in Figure 3, many tweets were classified into user's phase (start) and phase (middle). Some tweets expressing users' actions can be classified into two types. For example, (exp 14) was classified into user's phase (end) and phase (start).

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 user's phase (end). On the other hand, user's action expressed in *kiro he* (On my way home) of (exp 14) was classified into user's phase (start). Furthermore, Figure 4 shows the classification result of the phases of user's actions expressed in 215 tweets (Figure 2), move, sleep, work, and others. Figure 4 shows that

- there were many tweets expressing users' action (sleep) in the tweets classified into user's phase (start),
- there were many tweets expressing users' action (move) in the tweets classified into user's phase (middle), and
- there were many tweets expressing users' action (work) in the tweets classified into user's phase (end).

Both (exp 17) and (exp 18) were classified into user's action (move) in Figure 2. On the other hand, (exp 17) and (exp 18) were classified into user's phase (middle) and phase (start) in Figure 4, respectively. The number of tweets expressing the phase (middle) of user's action (move), such as (exp 17), was more than twice the number of those expressing the phase (start) of user's action (move), such as (exp 18).

(exp 17) *kiki nagara doraibu now –*
(I am driving a car now while listening to music –)
(exp 18) *yakin! chikusho- itte kuru!*
(Night shift! Damn it. Let's go!)

As shown in Figure 4, most of tweets expressing users' action (sleep) were classified into user's phase (start). However, there was a small number of tweets classified into user's phase (middle), such as (exp 19).

(exp 19) *nere masen*
(I can't sleep.)

Many of tweets expressing user's action (work) were classified into user's phase (end). However, we found some tweets classified into user's phase (middle), such as (exp 20) and (exp 21).

(exp 20) *shigoto tiu nano yo ne*
(Working now.)
(exp 21) *kore wo kiki tutu tabunya no eigo no kyokasho wo hitasura yakushite iru*
(I have been listening to this song and translated English textbooks in other areas entirely.)

We found some tweets which expressed users' actions, however, did not show the phases of them. For example, (exp 22) did not show the phase of user's action.

(exp 22) *asa undou*
(morning exercise)

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

(exp 23) *kibun teki ni kikitaku natta*
(I have a craving for music)
(exp 24) *katte shimatta*
(I finally bought it!)

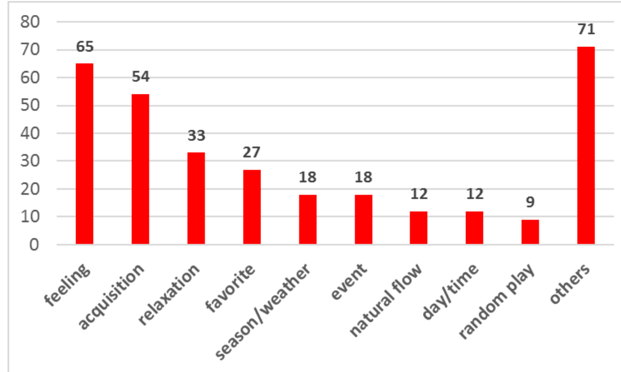

Figure 5. The classification result of users' results in the 312 tweets expressing users' reasons (by human experts).

(exp 23) and (exp 24) 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 23) felt an impulse and listened to music. On the other hand, the submitter of (exp 24) bought music contents and listened to it.

As shown in Figure 1, we found 312 tweets expressing users' reasons in the obtained 2,000 tweets which users submit when they use music player applications. We classified these 312 tweets expressing users' reasons why they were listening to music by using music player applications into ten types: (1) feeling, (2) acquisition, (3) relaxation, (4) favorite, (5) season/weather, (6) event, (7) natural flow, (8) day/time, (9) random play, and (10) others.

Figure 5 shows the classification result of the tweets expressing users' reasons why they were listening to music by using music player applications.

We classified (exp 23) into user's reason (feeling). This is because we thought the submitter of (exp 23) felt like listening to music. Also, we classified (exp 25) into user's reason (feeling). This is because we thought the submitter of (exp 25) did not listen to the song for a long time, and so, he/she felt like doing it.

(exp 25) *sugoku hisashiburi ni kiku.*
(I listen to this song after a long interval.)

We classified (exp 24) into user's reason (acquisition) because the submitter of (exp 24) bought and obtained the music content. Also, we classified (exp 26) into user's reason (acquisition) because the submitter of (exp 24) could not find the CD for a long time and found it.

(exp 26) *I found CD*

We classified (exp 27) and (exp 28) into user's reason (relaxation). In these tweets, the submitters played musics for relaxation.

(exp 27) *kibun tenkan ♪*
(relaxation ♪)
(exp 28) *toriaezu tenshon age*
(Let's get going)

(exp 29) and (exp 30) are examples of tweets classified into user's reason (favorite). This is because both the submitters of (exp 29) and (exp 30) addicted to the songs that they played.

(exp 29) *kinou kara do hamari shite iru*
(I have been addicted to the song since yesterday)
(exp 30) *1 nichi 1 kai ha kikanaito ikite ikenai karada ni*
(I will die if I do not play this song at least once a day)

(exp 31) and (exp 32) are examples of tweets classified into user's reason (season/weather). We thought both the submitter of (exp 31) and (exp 32) felt like listening to the song and submitting the tweets because they felt the sense of the season. As shown in Figure 5, 18 tweets were classified into this type. Seven of these tweets, including (exp 32), were submitted on November/24/2016, the first snow day of the winter. All these seven tweets touched the snow.

(exp 31) *kono kisetsu ha kore yana*
(This music suits the mood of the season)
(exp 32) *yuki to ieba kojinteki niha kore*
(I listen to the song when it snows)

We classified (exp 33) and (exp 34) into user's reason (event). The reasons why the submitter of (exp 33) and (exp 34) play the songs were the birthday of his/her friend and Halloween, respectively.

(exp 33) *Mikakoshi Happy Birthday !!!*
(My Mikako, Happy Birthday !!!)
(exp 34) *happi- harouin*
(Happy Halloween)

In both of (exp 35) and (exp 36), the submitters described that they selected and played the songs naturally. Take (exp 35) for example. *kotti mo* (this song) in (exp 35) meant implicitly that the submitter just before listened to the other song that had some kind of connection to this song. The connection let him/her select and play it. As a result, we classified (exp 35) and (exp 36) into user's reason (natural flow).

(exp 35) *kotti mo kika naku cha*
(I have to listen to this song)
(exp 36) *touzen no nagare*
(natural course)

We classified (exp 37) and (exp 38) into user's reason (day/time). The submitters of (exp 37) and (exp 38) listened to the songs because it was Sunday morning and night, respectively.

(exp 37) *nichiyoubi no asa ha, sawayaka ni heavy metal!! (((o(* ◦▽ ◦*)o)))*
(let's play heavy metal music refreshingly in Sunday morning!! (((o(* ◦▽ ◦*)o))))
(exp 38) *ichiou mada yonaka nano de kiku*
(I listen to this song because it is still night time)

We classified (exp 39) and (exp 40) into user's reason (random play). Both (exp 39) and (exp 40) were touched the songs that were selected randomly by music player applications.

(exp 39) *kyou no 1 kyoku me (random kettei)*
(Today's first song (random selection))
(exp 40) *soshite randam saisei de nagarete kita noga kore to iu*
(Then, random play and this song comes)

As shown in Figure 5, we found many tweets the comments of which were classified into user's reason (feeling) and (acquisition). This investigation result is not in good agreement with the survey on the use of portable music player conducted by Hamamura and Iwamiya [29]. They conducted the survey on 72 college students and reported that the reasons why the students used portable music players were relaxation (56 students), to kill time (51 students), to intercept environmental sound (27 students), to sharpen concentration (18 students), to improve operational efficiency (14 students), to avoid being talked to (13 students). The common reason of this survey and our investigation is only relaxation. This is because we investigated each tweets and the reason why the submitter listened to the song. On the other hand, Hamamura and Iwamiya did not survey every single use of portable music player. They surveyed the reasons why the college students used portable music players in their daily lives.

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

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 comments expressing users' actions, especially, move and sleep, from those including hashtags generated by music player applications by using machine learning techniques. Furthermore, we discuss whether we can detect tweets including comments expressing the phases of users' actions.

In this study, we used the 2,000 tweets investigated in Section III for the experimental data. The experimental data include 216 comments expressing users' actions. In this experiment, we used the support vector machine (SVM) and maximum entropy method (ME) for data training and classifying. Table I shows feature $s1$ to $s15$ used in machine learning on experimental data. $s1$ to $s7$ were obtained by using the results of morphological analysis on experimental

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

(a) SVM classification result

	SVM results		
users' comments	action	others	recall
action	127	88	0.59
others	9	1776	0.99
precision	0.93	0.95	

(b) ME classification result

	ME results		
users' comments	action	others	recall
action	123	92	0.57
others	7	1778	1.00
precision	0.95	0.95	

data. In the experiments, we used a Japanese morphological analyzer, JUMAN, for word segmentation of tweets [30]. $s8$ to $s10$ and $s12$ to $s14$ were obtained by extracting character N-gram from experimental data. Odaka et al. reported that character 3-gram is good for Japanese processing [31]. $s4$ to $s7$ and $s12$ to $s15$ 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 [32] and maxent [33]. Table II shows the SVM and ME classification results of users' actions in the 2,000 tweets. The experimental result was obtained with 10-fold cross-validation. As shown in Table II, we obtained 95% accuracy each when we applied SVM and ME machine learning techniques to detect tweets including comments expressing user's actions. The SVM and ME precision of tweets including comments expressing user's actions were 93% and 95%, respectively. On the other hand, the SVM and ME recall of tweets including comments expressing user's actions were 59% and 57%, respectively. The experimental results show that our method failed to detect many tweets expressing users' actions. However, the precisions of our method show that our method is useful to collect tweets expressing users' actions precisely. In order to discuss the experimental result, we examined whether we can detect tweets including comments expressing users' actions, move and sleep, from those including hashtags generated by music player applications by using machine learning techniques.

The experimental data include

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

Table III and Table IV show the classification result of users' action (move) and users' action (sleep) in the 2,000 tweets, respectively. As shown in Table III, we obtained 97% accuracy each when we applied SVM and ME machine learning techniques to detect tweets including comments expressing user's action (move). Also, as shown in Table IV, we obtained 99% accuracy each when we applied SVM and ME machine learning techniques to detect tweets including comments expressing user's action (sleep). Furthermore, the SVM and ME precision of tweets including comments expressing user's action (move) were 91% and 95%, respectively. Also, the SVM and ME precision of tweets including comments expressing user's action (sleep) were 100% each. On the other hand, the SVM and ME recall of tweets including comments expressing user's action (move) were 48% and 41%, respectively. However, the SVM and ME recall of tweets including comments expressing user's action (sleep) were 79% and 73%, respectively. The reason why the recall of tweets including comments expressing user's action (sleep) was better than user's action (move) was that typical expressions, such as "*oyasuminasai* (good night)", were often used in comments expressing user's action (sleep). The experimental result shows that our method is useful to detect and collect tweets including comments expressing user's action (sleep). On the other hand, the recall of tweets including comments expressing user's action (move) shows that our method failed to detect many of them. However, the precision of them shows that our method is useful to collect them precisely.

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

(a) SVM classification result

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

(b) ME classification result

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

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

(a) SVM classification result

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

(b) ME classification result

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

Next, we discuss whether we can detect tweets including comments expressing the phases of users' actions, start, mid-

TABLE V. The classification result of the phase (start) of users' actions in the 2,000 tweets including hashtags generated by music player applications.

(a) SVM classification result

action stages	SVM results: start	SVM results: others	recall
start	62	41	0.60
others	2	1895	1.00
precision	0.97	0.98	

(b) ME classification result

action stages	ME results: start	ME results: others	recall
start	59	44	0.57
others	1	1896	1.00
precision	0.98	0.98	

TABLE VI. The classification result of the phase (middle) of users' actions in the 2,000 tweets including hashtags generated by music player applications.

(a) SVM classification result

action stages	SVM results: middle	SVM results: others	recall
middle	33	44	0.43
others	3	1920	1.00
precision	0.92	0.98	

(b) ME classification result

action stages	ME results: middle	ME results: others	recall
middle	29	48	0.38
others	1	1923	1.00
precision	1.00	0.98	

TABLE VII. The classification result of the phase (start) of users' action (sleep) in the 2,000 tweets including hashtags generated by music player applications.

(a) SVM classification result

action (sleep)	SVM results: start	SVM results: others	recall
start	50	9	0.85
others	0	1941	1.00
precision	1.00	1.00	

(b) ME classification result

action (sleep)	ME results: start	ME results: others	recall
start	45	14	0.76
others	0	1941	1.00
precision	1.00	0.99	

TABLE VIII. The classification result of the phase (middle) of users' action (move) in the 2,000 tweets including hashtags generated by music player applications.

(a) SVM classification result

action (move)	SVM results: middle	SVM results: others	recall
middle	27	27	0.50
others	4	1942	1.00
precision	0.87	0.99	

(b) ME classification result

action (move)	ME results: middle	ME results: others	recall
middle	25	29	0.46
others	1	1945	1.00
precision	0.96	0.99	

dle, and end. This is because the phases of users' actions enable us to provide more precise services and applications relevant to users' actions. The experimental data include

- 103 comments expressing the phase (start) of users' actions and
- 77 comments expressing the phase (middle) of users' actions.

Table V shows the classification results of the phase (start) of users' actions in the 2,000 tweets. Table VI shows the classification results of the phase (middle) of users' actions in the 2,000 tweets. As shown in Table V and Table VI, both of the precision of tweets including comments expressing the phase (start) and phase (middle) of users' actions were good. On the other hand, the recall of tweets including comments expressing the phase (start) was better than that of tweets including comments expressing the phase (middle). In order to discuss the experimental result, we examined whether we can detect tweets including comments expressing the phases of specific actions, move and sleep. The experimental data include

- 59 comments expressing the start of users' sleep
- 54 comments expressing the middle of users' move

Especially, users who are in the middle of move are good targets for social media services, such as targeted advertisement and news recommendation. Table VII shows the classification results of the phase (start) of user's action (sleep) in the 2,000 tweets. Also, Table VIII shows the classification results of the phase (middle) of user's action (move) in the 2,000 tweets. In both cases, we obtained the high accuracy and precision. However, the recall of tweets including comments expressing the phase (start) of user's action (sleep) was good while that of the phase (middle) of user's action (move) was not good. This is because Twitter users often submit short messages including typical expressions, such as "*oyasuminasai* (good night)", in order to inform they cannot read any messages while they are sleeping. Nakao reported that there are many Japanese young SNS users who feel regret when they cannot reply to SNS messages rapidly [34]. As a result, many Twitter users submit messages including these typical expressions, such as "*oyasuminasai* (good night)", before they are sleeping.

The experimental results show that our method could not detect many tweets expressing users' actions. However, the precisions of our method show that our method is useful to collect tweets expressing users' actions precisely. In other words, tweets detected by our method are useful to understand what users were doing and what phases users were in. As a result, our method is useful to provide social media services, such as targeted advertisement, news recommendation, and real-world analysis.

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. In this respect it 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 the 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 the users are doing and what action phases they are in while listening to music. In both cases, we obtained the high accuracy and precision, however, the low recall. The low recall shows that our method often failed to detect tweets expressing users' actions. However, the high accuracy and precision show that most of detected tweets were classified correctly. In other words, tweets detected by our method are useful to understand what users were doing and what action phases they are in. As a result, our method is useful to provide social media services, such as targeted advertisement, news recommendation, and real-world analysis. We intend to use the results of this study for further investigation of tweets expressing users' emotions and sentiments. This is because more than half of the investigated tweets were classified into ones expressing users' impressions.

REFERENCES

[1] Y. Watanabe, K. Yasuda, R. Nishimura, and Y. Okada, "An investigation of tweets submited by using music player applications," in Proceedings of the Ninth International Conference on Evolving Internet (INTERNET 2017), Jul 2017, pp. 24–29. [Online]. Available: https://www.thinkmind.org/index.php?view=article&articleid=internet_2017_2_30_40029 [accessed: 2018-5-25]

[2] T. Sakaki and Y. Matsuo, "Twitter as a social sensor : Can social sensors exceed physical sensors?" Journal of Japanese Society for Artificial Intelligence, vol. 27, no. 1, jan 2012, pp. 67–74.

[3] E. Aramaki, S. Maskawa, and M. Morita, "Twitter catches the flu: Detecting influenza epidemics using twitter," in Proceedings of the Conference on Empirical Methods in Natural Language Processing, ser. EMNLP '11. Stroudsburg, PA, USA: Association for Computational Linguistics, 2011, pp. 1568–1576. [Online]. Available: http://dl.acm.org/citation.cfm?id=2145432.2145600 [accessed: 2018-5-25]

[4] A. Culotta, "Towards detecting influenza epidemics by analyzing twitter messages," in Proceedings of the First Workshop on Social Media Analytics, ser. SOMA '10. New York, NY, USA: ACM, 2010, pp. 115–122. [Online]. Available: http://doi.acm.org/10.1145/1964858.1964874 [accessed: 2018-5-25]

[5] T. Sakaki, M. Okazaki, and Y. Matsuo, "Earthquake shakes twitter users: Real-time event detection by social sensors," in Proceedings of the 19th International Conference on World Wide Web, ser. WWW '10. New York, NY, USA: ACM, 2010, pp. 851–860. [Online]. Available: http://doi.acm.org/10.1145/1772690.1772777 [accessed: 2018-5-25]

[6] B. J. Jansen, M. Zhang, K. Sobel, and A. Chowdury, "Twitter power: Tweets as electronic word of mouth," J. Am. Soc. Inf. Sci. Technol., vol. 60, no. 11, Nov. 2009, pp. 2169–2188. [Online]. Available: http://dx.doi.org/10.1002/asi.v60:11 [accessed: 2018-5-25]

[7] M. Motoyama, B. Meeder, K. Levchenko, G. M. Voelker, and S. Savage, "Measuring online service availability using twitter," in Proceedings of the 3rd Workshop on Online Social Networks, ser. WOSN'10. Berkeley, CA, USA: USENIX Association, 2010, pp. 13–13. [Online]. Available: https://cseweb.ucsd.edu/˜savage/papers/WOSN10.pdf [accessed: 2018-5-25]

[8] A. Signorini, A. M. Segre, and P. M. Polgreen, "The Use of Twitter to Track Levels of Disease Activity and Public Concern in the U.S. during the Influenza A H1N1 Pandemic," PLoS One, vol. 6, no. 5, May 2011. [Online]. Available: http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0019467 [accessed: 2018-5-25]

[9] J. Leskovec, L. Backstrom, and J. Kleinberg, "Meme-tracking and the dynamics of the news cycle," in Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ser. KDD '09. New York, NY, USA: ACM, 2009, pp. 497–506. [Online]. Available: http://doi.acm.org/10.1145/1557019.1557077 [accessed: 2018-5-25]

[10] S. Vieweg, A. L. Hughes, K. Starbird, and L. Palen, "Microblogging during two natural hazards events: What twitter may contribute to situational awareness," in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ser. CHI '10. New York, NY, USA: ACM, 2010, pp. 1079–1088. [Online]. Available: http://doi.acm.org/10.1145/1753326.1753486 [accessed: 2018-5-25]

[11] R. Lee and K. Sumiya, "Measuring geographical regularities of crowd behaviors for twitter-based geo-social event detection," in Proceedings of the 2Nd ACM SIGSPATIAL International Workshop on Location Based Social Networks, ser. LBSN '10. New York, NY, USA: ACM, 2010, pp. 1–10. [Online]. Available: http://doi.acm.org/10.1145/1867699.1867701 [accessed: 2018-5-25]

[12] K. Y. Kamath, J. Caverlee, K. Lee, and Z. Cheng, "Spatio-temporal dynamics of online memes: A study of geo-tagged tweets," in Proceedings of the 22Nd International Conference on World Wide Web, ser. WWW '13. New York, NY, USA: ACM, 2013, pp. 667–678. [Online]. Available: http://doi.acm.org/10.1145/2488388.2488447 [accessed: 2018-5-25]

[13] K. Watanabe, M. Ochi, M. Okabe, and R. Onai, "Jasmine: A real-time local-event detection system based on geolocation information propagated to microblogs," in Proceedings of the 20th ACM International Conference on Information and Knowledge Management, ser. CIKM '11. New York, NY, USA: ACM, 2011, pp. 2541–2544. [Online]. Available: http://doi.acm.org/10.1145/2063576.2064014 [accessed: 2018-5-25]

[14] Z. Cheng, J. Caverlee, and K. Lee, "You are where you tweet: A content-based approach to geo-locating twitter users," in Proceedings of the 19th ACM International Conference on Information and Knowledge Management, ser. CIKM '10. New York, NY, USA: ACM, 2010, pp. 759–768. [Online]. Available: http://doi.acm.org/10.1145/1871437.1871535 [accessed: 2018-5-25]

[15] Y. Yamaguchi, T. Amagasa, H. Kitagawa, and Y. Ikawa, "Online user location inference exploiting spatiotemporal correlations in social streams," in Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management, ser. CIKM '14. New York, NY, USA: ACM, 2014, pp. 1139–1148. [Online]. Available: http://doi.acm.org/10.1145/2661829.2662039 [accessed: 2018-5-25]

[16] J. Eisenstein, B. O'Connor, N. A. Smith, and E. P. Xing, "A latent variable model for geographic lexical variation," in Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing, ser. EMNLP '10. Stroudsburg, PA, USA: Association for Computational Linguistics, 2010, pp. 1277–1287. [Online]. Available: http://dl.acm.org/citation.cfm?id=1870658.1870782 [accessed: 2018-5-25]

[17] B. Hecht, L. Hong, B. Suh, and E. H. Chi, "Tweets from justin bieber's heart: The dynamics of the location field in user profiles," in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ser. CHI '11. New

York, NY, USA: ACM, 2011, pp. 237–246. [Online]. Available: http://doi.acm.org/10.1145/1978942.1978976 [accessed: 2018-5-25]

[18] B. Han, P. Cook, and T. Baldwin, "Geolocation prediction in social media data by finding location indicative words," in COLING 2012, 24th International Conference on Computational Linguistics, Proceedings of the Conference: Technical Papers, 8-15 December 2012, Mumbai, India, M. Kay and C. Boitet, Eds. Indian Institute of Technology Bombay, 2012, pp. 1045–1062. [Online]. Available: http://aclweb.org/anthology/C/C12/C12-1064.pdf [accessed: 2018-5-25]

[19] A. Schulz, A. Hadjakos, H. Paulheim, J. Nachtwey, and M. Mühlhäuser, "A multi-indicator approach for geolocalization of tweets." in ICWSM, E. Kiciman, N. B. Ellison, B. Hogan, P. Resnick, and I. Soboroff, Eds. The AAAI Press, 2013.

[20] D. Rout, K. Bontcheva, D. Preoţiuc-Pietro, and T. Cohn, "Where's @wally?: A classification approach to geolocating users based on their social ties," in Proceedings of the 24th ACM Conference on Hypertext and Social Media, ser. HT '13. New York, NY, USA: ACM, 2013, pp. 11–20. [Online]. Available: http://doi.acm.org/10.1145/2481492.2481494 [accessed: 2018-5-25]

[21] D. Wang, D. Pedreschi, C. Song, F. Giannotti, and A.-L. Barabasi, "Human mobility, social ties, and link prediction," in Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ser. KDD '11. New York, NY, USA: ACM, 2011, pp. 1100–1108. [Online]. Available: http://doi.acm.org/10.1145/2020408.2020581 [accessed: 2018-5-25]

[22] L. Backstrom, E. Sun, and C. Marlow, "Find me if you can: Improving geographical prediction with social and spatial proximity," in Proceedings of the 19th International Conference on World Wide Web, ser. WWW '10. New York, NY, USA: ACM, 2010, pp. 61–70. [Online]. Available: http://doi.acm.org/10.1145/1772690.1772698 [accessed: 2018-5-25]

[23] A. Sadilek, H. Kautz, and J. P. Bigham, "Finding your friends and following them to where you are," in Proceedings of the Fifth ACM International Conference on Web Search and Data Mining, ser. WSDM '12. New York, NY, USA: ACM, 2012, pp. 723–732. [Online]. Available: http://doi.acm.org/10.1145/2124295.2124380 [accessed: 2018-5-25]

[24] S. Kinsella, V. Murdock, and N. O'Hare, ""i'm eating a sandwich in glasgow": Modeling locations with tweets," in Proceedings of the 3rd International Workshop on Search and Mining User-generated Contents, ser. SMUC '11. New York, NY, USA: ACM, 2011, pp. 61–68. [Online]. Available: http://doi.acm.org/10.1145/2065023.2065039 [accessed: 2018-5-25]

[25] Y. Watanabe, K. Nakajima, H. Morimoto, R. Nishimura, and Y. Okada, "An investigation of a factor that affects the usage of unsounded code strings at the end of japanese and english tweets," in Proceedings of the Seventh International Conference on Evolving Internet (INTERNET 2015), Oct 2015, pp. 50–55. [Online]. Available: https://www.thinkmind.org/index.php?view=article&articleid=internet_2015_2_40_40038 [accessed: 2018-5-25]

[26] Twitter, "How to use hashtags," https://help.twitter.com/en/using-twitter/how-to-use-hashtags [accessed: 2018-5-25].

[27] S. Weinschenk, 100 Things Every Designer Needs to Know About People, 1st ed. Thousand Oaks, CA, USA: New Riders Publishing, 2011.

[28] I. E. Hyman, S. M. Boss, B. M. Wise, K. E. McKenzie, and J. M. Caggiano, "Did you see the unicycling clown? inattentional blindness while walking and talking on a cell phone," Applied Cognitive Psychology, vol. 24, no. 5, 2010, pp. 597–607. [Online]. Available: http://dx.doi.org/10.1002/acp.1638 [accessed: 2018-5-25]

[29] M. Hamamura and S. Iwamiya, "Survey on the use of portable audio devices by university students," The Journal of the Acoustical Society of Japan, vol. 69, no. 7, jul 2013, pp. 331–339.

[30] S. Kurohashi and D. Kawahara, JUMAN Manual version 5.1 (in Japanese). Kyoto University, 2005.

[31] T. Odaka et al., "A proposal on student report scoring system using n-gram text analysis method," The transactions of the Institute of Electronics, Information and Communication Engineers. D-I, vol. 86, no. 9, sep 2003, pp. 702–705. [Online]. Available: http://ci.nii.ac.jp/naid/110003171273/en/ [accessed: 2018-5-25]

[32] Taku Kudoh. TinySVM: Support Vector Machines. [Online]. Available: http://chasen.org/˜taku/software/TinySVM/index.html [accessed: 2018-5-25]

[33] M. Utiyama, "Maximum entropy modeling packages," http://mastarpj.nict.go.jp/˜mutiyama/software/maxent [accessed: 2010-7-27], 2008.

[34] M. Nakao, "Social media and children : Report from the world summit on media for children (wsmc)," The NHK monthly report on broadcast research, vol. 65, no. 3, mar 2015, pp. 76–80. [Online]. Available: https://ci.nii.ac.jp/naid/110009890194/en/ [accessed: 2018-5-25]