Acquisition of Periodic Events with Person Attributes

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***Abstract*—In this paper, we aim to acquire "periodic events" that represent significant actions that are happened by groups of people in particular seasons or timing. Recently, the importance of knowledge acquisition is increasing. Many studies about human action knowledge and temporal commonsense knowledge have been carrying out. We need a dataset to acquire periodic events. However, manually building the dataset with human attribute labels is costly. Therefore, we construct a human attribute classifier of Twitter users and create a large labeled tweets dataset automatically. Periodic events with specific human attributes are collected with our proposed method. Finally, we obtained commonsense event knowledge; e.g., "Students often go to college at 1 P.M." and "Workers often work overtime on weekdays."**

***Index Terms*—Knowledge Acquisition, Text Mining, Commonsense Knowledge**

I. Introduction

Recently, the importance of knowledge acquisition is increasing. Many researchers have studied this task; e.g., knowledge of numerical commonsense [1] and knowledge of object pairs typically found near each other in real life [2]. In addition, some large scale knowledge bases are constructed, such as [3] and [4]. These studies reported that common sense knowledge is effective for question answering [5], non-task oriented dialogue [6], and NLP benchmark tasks [7].

Yamamoto and Shimada [8] have acquired knowledge of human actions, natural phenomena, and social phenomena that occur in specific timing (hereinafter this is called "periodic event"). This knowledge is pairs of action/event and season/timing, such as "{*action/event, season/timing*}". They used data on Twitter[1] that is one of the most popular social media in Japan. They analyzed tweets, namely posted sentences with a timestamp on Twitter, and extracted candidates about actions and events. Finally, they applied some scoring rules based on frequency distribution to the ranking of candidates. They obtained knowledge pairs; for example, {*sleep, night*} and {*recruit, April*} (April is the beginning season of the recruitment process in Japan).

One problem of their acquired knowledge is just generalized human action knowledge. For instance, {*finish-the-work, 7PM*} is probably correct as human action knowledge. However, this knowledge does not fit students. Similarly, {*go-to-school, weekday*} is not appropriate for office workers. Thus, periodic event knowledge needs the attributes of the target persons.

In this paper, we incorporate human attributes with the acquisition of periodic events. We need large amounts of data with human attributes for the acquisition. However, the construction of such data is costly. We generate an attribute classifier of users from small amounts of labeled data. Then, we automatically construct large amounts of data with human attributes by using the classifier. As the first step of knowledge acquisition with human attributes, we define three attributions of people; students, workers, and parents. We apply BERT [9] to the attribute classification. Finally, we extract periodic event knowledge with human attributes from the large dataset that is divided by the attribute classifier.

II. Related work

The purpose of this paper is to obtain periodic event knowledge that contains the characteristics of each human attribute. Ge et al. [10] have collected event knowledge from Wikipedia data. Their target is major events, such as earthquakes and Olympic events. Such event information is important because it has significant influence on society. However, most of the events do not relate to particular seasons and timing. Events occurring in people's daily life are also important. Therefore, we acquire event knowledge centered on human activity.

Tandon et al. [11] have proposed an acquisition method of knowledge about activities from narratives, such as movies. However, there were few types of time information for extraction, such as morning and night, and time information definitions were obscure. In this paper, we set up a wide variety of time spans from weekday/weekend to hour. Yao and Huang [12] have proposed a method for acquiring rich temporal "before/after" event knowledge across sentences in narrative stories. Information of time in their paper is relative time information between actions. Hence, the information is knowledge of event relation rather than knowledge of event and timing. Moreover, these studies did not consider attributes of persons who take the action. Our task is to acquire knowledge with human attributes.

[1]https://twitter.com

Zhou et al [13] have focused on a wide variety of temporal commonsense. They trained a model on event duration, frequency, and typical time. The model obtained better performance on several tasks that need knowledge of temporal commonsense, as compared with a BERT model. Knowledge of periodic event in this paper is one temporal commonsense knowledge of their definition. Their purpose is to create a model with temporal commonsense. On the other hand, our purpose in this paper is to acquire the structured knowledge with temporal commonsense.

III. Dataset

We need a corpus for the attribute classification and periodic event acquisition. The corpus needs the human attribute label of each Twitter user. In this section, we explain the corpus construction process. The process consists of data acquisition and labeling.

A. Data acquisition

We collect tweets randomly from Twitter by using Twitter API. For the labeling process, we extract Japanese users with profile information. For the users, we extract the timeline of them. In addition, we ignore users with the following constraints for the extraction

- The number of tweets is less than 100.
- The duration of use of Twitter is less than one year.

As a result, we obtained 200,000 users and 55 million tweets. We call this corpus "original dataset".

B. Attribute labeling

Next, we annotate user attributes for users in the original dataset. We prepare three labels as the attributes that we handle in this paper. The labels, Students, Workers, and Parents, are shown in Table I. The definitions of each attribute are as follows.

- Students are persons who learn in elementary school, junior high school, high school, vocational school, college, or university. However, we eliminate the person if he/she is a student on leave.
- Workers are persons who earn a salary. Full-time homemakers also are included in this label. We eliminate the persons if he/she is a student.
- Parents are persons who raise a child/children 15 and under.

We manually collected keywords that are used in profile fields of Twitter users. The keywords that we used in this paper are also shown in Table I. Our target is Japanese tweets. Hence, the keywords are also Japanese and we translate the keywords to English in the table. We extract users with these keywords from the original dataset. For the extracted users, we manually annotate the labels. We extracted approximately 1,000 users for each attribute. Table II shows the statistics of the annotated data. We call this dataset "labeled dataset".

From the definitions, some users contain two labels, namely Workers+Parents and Students+Parents. It was, however, minority; less than 5% about Workers+Parents and 0% about Students+Parents in the dataset.

TABLE I
KEYWORDS FOR MANUAL LABELING.

Attributes	Keywords
Students	student (学生), college/university (大学), junior college (短大), vocational school (専門学校), student of graduate school (院生), faculty (学部), department (学科)
Workers	worker (社会人), company (会社), enterprise (企業), work (勤務), business (業務)
Parents	child rearing (育児), child care (子育て), son (息子), daughter (娘), 's father (の父), 's mother (の母), 's dad (のパパ), 's mom (のママ)

TABLE II
THE NUMBER OF USERS AND TWEETS WITH PERSON ATTRIBUTE LABELS.

Attributes	Uses	Tweets
Students	1,032	1.0 million
Workers	1,216	1.2 million
Parents	1,182	1.1 million

IV. Method

Our method consists of two parts: (1) attribute classification of Twitter users and (2) periodic event acquisition with the attributes. In this section, we describe the two parts in Section IV-A and Section IV-B. The overview of our method is shown in Figure 1. First, our method generates an attribute classifier from the labeled dataset explained in Section III-B. We apply this attribute classifier to the original dataset, namely a non-labeled dataset. We obtain large amounts of virtual data with attributes through this process. We can capture knowledge from the original dataset with the estimated attribute labels. For the acquisition process, we extract event words that consist of verbs or pairs of verb-noun. Then, we compute a score of each event word on the basis of the frequency. Finally, we rank the score to extract the periodic events in each attribute for several time segments.

A. Attribute classifier

Although we require large amounts of data with human attributes for the acquisition, the construction is costly. To solve this problem, we introduce an automatic large data construction approach. For the purpose, we constructed a small dataset with labels in Section III-B. We apply machine learning to the labeled dataset. We use the BERT pre-trained model [9] for the task.

Figure 2 shows the outline of our classification model with BERT. We add a linear layer on the BERT. Then, we fine-tune the model by the one-vs-rest person label classification task for each tweet. In other words, we generate three BERT based models, namely "students or others", "workers or others", and

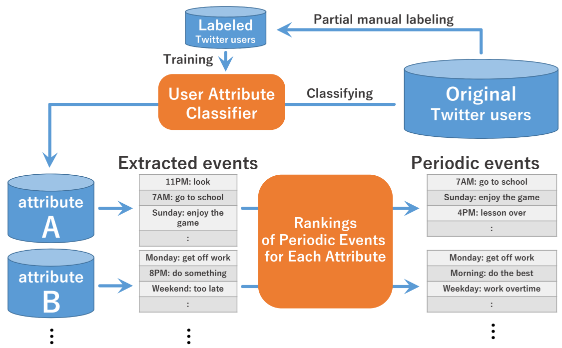

Fig. 1. Overview of our method.

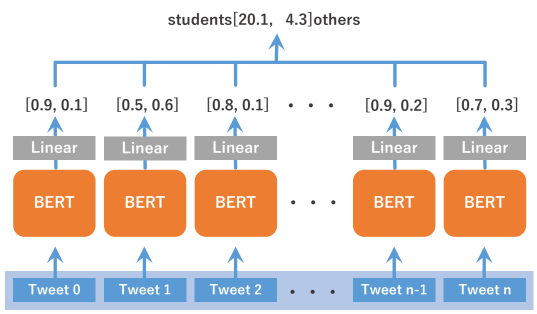

Fig. 2. Overview of our model.

"parents or others". "others" denotes a set of users randomly extracted from the original dataset. We identify the attribute label of each user. In this process, each input is each tweet of the target user. As a result, we obtain the outputs based on the number of tweets of the user; e.g., [0.9, 0.1], [0.5, 0.6], ..., [0.7, 0.3] in Figure 2. Finally, we calculate the sum of the outputs; e.g., [20.1, 4.3] in Figure 2. If the value of the target is larger, we assign the label to the user. If the value of the target is smaller, we do not assign the label to the user. In Figure 2, our model classifies the user to "students" since the value is larger than that of others (20.1 vs. 4.3). We perform this calculation for all attributes, namely students, workers, or parents.

B. Periodic event acquisition

1) Event extraction: Most events are explained by verbs or pairs of verb-noun with dependency relation. Therefore, we extract them from the original dataset. We call the extracted verbs and pairs "Event word".

Here the modality of verbs has an important role. For example, a verb with epistemic modality is not suitable as the event word because it is not always the real experience of the user. The expressions of their own desire are also not suitable, e.g., "I'd like to do". Therefore, we remove the verbs and pairs that express these meanings from the event word list.

2) Event ranking: We calculate the frequency of each event word in 36 time segments. The segments are daytime/weekend, days of the week, morning/noon/night, and 24 hours. The ratios of the frequency in each time segment denote the scores of the event words. We perform this process for tweets with each attribute that is classified by the attribute classifier explained in Section IV-A.

Finally, we rank the event words on the basis of the score. As a result, we obtain ranked event word lists for each attribute. Here we delete the words that match the following constraints.

Const1: The frequency is less than a threshold fq. We set $fq = 50$.

Const2: $n\%$ or more of the frequency of the word is occupied by one user. We set $n = 20$

Const3: The variance of the ratio of a day frequency to the year frequency is more than a threshold var. We set $var = 5e-5$.

Const4: The event word appears in two rankings or more.

Since low frequency words are usually not important, we delete them by Const1. If a word is dominant by specific users, the event based on the word is not general. Hence, we delete the word by Const2. Const3 is similar to a burst situation. Hence, the frequency captures the characteristic of periodic events that we want to handle even if the value is large. Our purpose is to detect periodic events that relate to each human attribute. The words that appear in some rankings are not suitable for the purpose because the words are common periodic events for people. Therefore, we adopt Const4 in this process.

V. Experiments

We evaluate the attribute classifier first. Then we discuss the ranking results based on the automatically labeled data by the attribute classifier.

A. Attribute classification

First, we explain the dataset for the evaluation. As the positive data for the evaluation, we randomly divided the labeled data (Table II) into 8:2 (training:test). In other words, we used 80% of the labeled data (e.g., approximately 800 users for students) and then evaluated the model with 20% of the labeled data (approximately 200 users for students) as the positive data. As the negative data for the evaluation, we randomly extracted users and their tweets from the original dataset (approximately 200,000 users). As the negative data, we extracted the same number of users in the positive data.

We used BERT-Base whole-word-masking Japanese pre-trained model that is released by Tohoku university[2]. For the fine-tuning, the batch size was 32, the optimization function was Adam, the learning rate was $2e-5$ and the number of epochs was 3.

Table III shows the experimental result of the attribute classification. The tendency of the results was the high recall rate for the target attributes but the low precision rate. One reason was the construction of negative data for the evaluation. We randomly selected tweets from the original dataset for the negative data. Therefore, the selected negative data contained

[2]https://github.com/cl-tohoku/bert-japanese

TABLE III
RESULTS OF OUR FINE-TUNED CLASSIFIER.

Attributes	Precision	Recall	F1
Students	0.54	1.00	0.71
Others	1.00	0.37	0.54
Workers	0.47	1.00	0.64
Others	1.00	0.24	0.39
Parents	0.62	1.00	0.76
Others	1.00	0.69	0.71

TABLE IV
GENERATED DATASET WITH PERSON ATTRIBUTES AUTOMATICALLY.

Attributes	Users	Tweets
Student	32,404	17.2 million
Worker	29,697	14.1 million
Parent	19,897	7.9 million

false-negative users. For example, the negative data incorrectly contained many real student users for the student attribute classification task because there are essentially many student users on Twitter. As a result, the models tended to be the low precision rate because the test data contained real student users in the negative data of the student attribute task.

Here our purpose of this process is to construct large amounts of data with attributes automatically. In this situation, the high recall rate is preferred, as compared with the high precision situation, because we need a dataset that contains many tweets with users' attributes. The high recall classifier denotes the possibility that the model almost entirely collects the necessary users for the event acquisition. Therefore, the result was expedient and acceptable.

B. *Periodic event acquisition by ranking*

From the previous section, we obtained a high recall attribute classifier. By using the classifier, we generated a large and new labeled dataset from the original dataset. Table IV shows the statistics of the automatically labeled dataset.

We generate labeled Twitter user dataset by attributes classifying for unknown person attributes users with the classifier. Details of the dataset are shown in Table IV. We applied our periodic event acquisition method that was explained in Section IV-B. Due to limitations of space, we selected several results for the discussions; weekday/weekend of three attributes (Table V), Tuesday and Wednesday of three attributes (Table VI), morning/noon/night of three attributes (Table VII), and 24 hours of students (Table VIII). Each table contains the top four event words.

As mentioned above, our target is Japanese. Therefore, the result is also Japanese. For readers that cannot recognize Japanese, we add English translation of each event word. Since the extracted event words were, however, fragments of phrases[3], the direct translation of event words tended to be difficult to grasp the original meanings. Therefore, we tried to be idiomatic translation for the words. Nevertheless, there are several words that were difficult to translate to English. In the tables, "*" denotes the "hard-to-translate" words.

[3]Word sense ambiguity also appears in this situation.

For weekday/weekend of three attributes (Table V), event words of "Students" expressed the attribute, namely "attend a class", "be absent from school" and "lesson being over" in weekday. For "Workers", we obtained good results, such as "work overtime" and "go home after overtime work". The results for "Students" and "Workers" were relatively favorable. On the other hand, we did not obtain characteristic event words for the "Parents" attribute.

For Tuesday and Wednesday of three attributes (Table VI), we did not capture characteristic event words for all attributes, The extraction on day-of-week level is a difficult task for periodic event acquisition,

For morning/noon/night of three attributes (Table VII), the tendencies of the ranking were similar to the weekday/weekend rankings (Table V). The results for "Students" and "Workers" were expressed about the attributes although that for "Parents" was insufficient.

For 24 hours of "Students" (Table VIII), we obtained a positive result, such as "lesson being over" at 4 P.M. For 24 hours of "Workers", we obtained a good example, such as "work hard afternoon (午後，頑張る)" (the top event word of 12 P.M. and 1 P.M.), "do the best today (今日，頑張る)" (the top of 7 A.M.) and "survive today (今日，乗り切る)" (the top of 8 A.M.).

From the perspective of the results, we obtained favorable event words for "Students" and "Workers" attributes. On the other hand, the result of "Parents" tended to be insufficient. The reason was that persons with the "Parents" attribute were diverse in terms of the lifestyle habit, such as full-time homemakers and workers. Therefore, we need to consider other attributes for acquiring suitable periodic events. It leads to the improvement of the periodic events acquisition task.

VI. CONCLUSIONS

In this paper, we reported a periodic event acquisition task with person attributes. We defined three attributes; "Students", "Workers", and "Parents" as the first step of the task. For acquiring good knowledge from data, we need large amounts of data. However, the construction is costly. To solve this problem, we generated an attribute classifier from small amounts of labeled data. It was based on a BERT Japanese pre-trained model. We obtained the high recall attribute classifier. It led to the dataset construction that we desired, namely the high coverage dataset with attributes.

By using the attribute classifier, we obtained large amounts of data with attribute labels. The size of the dataset was approximately 82,000 users with 39.2 million tweets. We extracted event words of each attribute from the new dataset for several time segments, such as 24 hours and weekday/weekend. We obtained favorable event words for "Students" and "Workers" attributes. The results for the "Parents" attribute are important future work. One reason why the

TABLE V
WEEKDAY/WEEKEND RANKING.

Attributes	Week	Event words			
Students	weekday	attend a class (授業+出る)	attend the *n*-th class (限+する)	be absent from school (学校+休む)	lesson over (授業+終わる)
	weekend	do at last (ラスト+する)	go to town (街+行く)	line up for hours (時間+並ぶ)	go now (今+向かう)
Workers	weekday	work overtime (残業+なる)	go home after overtime work (残業+帰る)	do everyday (毎日+ある)	receive delivery (発送+くる)
	weekend	remove from (撤収+する)	finish club activities (部+終わる)	get on the expressway (高速+乗る)	go to a venue (会場+向かう)
Parents	weekday	get off work (会社+休む)	do something with a towel (タオル+する)	have a feeling (感+持つ)	read once * (一+読む)
	weekend	sleep in ages (久しぶり+寝る)	be awesome (最高+過ぎる)	win (勝利+する)	will go (いこう)

"*" denotes a word/phrase that is hard to translate.

TABLE VI
DAY OF WEEK RANKING, TUESDAY AND WEDNESDAY.

Attributes	DoW	Event words			
Students	Tuesday	weaken * (弱体+する)	eat beef (牛+食べる)	find the cause (原因+わかる)	feel stress (ストレス+感じる)
	Wednesday	take out at *n* o'clock (時+出す)	attend a class (授業+出る)	continue for *n* days (日+続ける)	drink protein shake (プロテイン+飲む)
Workers	Tuesday	see * (ん+みる)	forge a sword (鍛刀+する)	draw before * (前+描く)	can pick up (拾える)
	Wednesday	can do by *n* yen (円+できる)	I enter * (私+入れる)	swindle (詐欺+する)	do willpower (意思+する)
Parents	Tuesday	enter * (の+入れる)	Mr./Ms. stays (さん+居る)	dither over * (の+迷う)	hug (抱きつく)
	Wednesday	think about work (仕事+考える)	be rich * (とむ)	watch videos (動画+みる)	get bleeding (血+出る)

"*" denotes a word/phrase that is hard to translate.

acquisition sometimes did not work well is that the precision of the attribute classifier was not high. As a result, the dataset contained noise information, namely tweets of users with different attributes, although the coverage of our dataset was sufficient. To solve this problem, we have two choices; (1) the improvement of the attribute classifier and (2) the development of a robust event acquisition process for the noise information. For the first approach, we need to apply other pre-training models to our attribute classifier. For the second approach, we need to more discuss the constraints and the threshold values in the acquisition process. In addition, quantitative evaluation for the periodic event acquisition, improvement of readability for periodic words, and adaptation of the method for other user attributes are also important future work.

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TABLE VII
MORNING/NOON/NIGHT RANKING.

Attributes	Segments	Event word			
Students	morning	a train is empty (電車+空く)	be in the morning (朝+ある)	go to the office (出社+する)	wake up (おきる)
	noon	eat lunch (昼飯+食う)	go to college (大学+来る)	attend a class (授業+出る)	go now (今+いく)
	night	drink tomorrow (明日+飲む)	gaze (見入る)	be in tomorrow (明日+いる)	cry (ちゃん+泣く)
Workers	morning	survive today (今日+乗り切る)	do the best today (今日+頑張れる)	say in morning (朝+言う)	do in early morning (早朝+する)
	noon	work hard afternoon (午後+頑張る)	remove from (撤収+する)	go shopping (買い出し+行く)	go to a venue (会場+向かう)
	night	a date changes (付け+変わる)	sleep for (ため+寝る)	watch it tomorrow (明日+観る)	drink rice wine (日本+飲む)
Parents	morning	miss a bus/train (乗り遅れる)	get swollen * (浮腫む)	use (用いる)	enjoy today (今日+楽しむ)
	noon	park a car (駐車+する)	be like * (人+似る)	do at dawn * (明け+する)	die * (の+死ぬ)
	night	finish a part-time job (バイト+終わる)	subscribe (申し込み+する)	have a dream (夢+見れる)	ready for tomorrow (明日+備える)

"*" denotes a word/phrase that is hard to translate.

TABLE VIII
STUDENT USER'S 24 HOUR RANKING (6 AM TO 11 PM)

Hours	Event words			
6 AM	sleep at n:30 (時半+寝る)	reply * (返事+なる)	do my best (日+頑張る)	finish the night-shift (夜勤+終わる)
7 AM	the train is empty (電車+空く)	commute (通勤+する)	do my best (日+頑張る)	forget really * (ホン+忘れる)
8 AM	train empty (電車+空く)	late n minutes (分+遅れる)	jolt (揺る)	in the morning (朝+迎える)
9 AM	arrive before (前+着く)	arrive at (分+着く)	finish yesterday (昨日+終わる)	attend the n-th period (限+する)
10 AM	attend the n-th period (限+する)	the n-th period is (限+ある)	go to college (大学+来る)	be turned up * (めくれる)
11 AM	change color (色+変わる)	pretend * (てらう)	exterminate (絶滅+する)	go to college (大学+来る)
12 PM	eat lunch (昼飯+食う)	scramble up (かき集める)	go to a pool (プール+行く)	do paperwork (書類+する)
1 PM	go to college (大学+来る)	have an effect (影響+出る)	eat lunch (昼飯+食う)	is a style * (系+ある)
2 PM	wear today (今日+着る)	drink tea (お茶+飲む)	recommend (推奨+する)	done the laundry (洗濯+終わる)
3 PM	go to buy (買い+来る)	do it a long time (散々+する)	doing now is too late (今更+する)	do a door (ドア+する)
4 PM	lesson over (授業+終わる)	go to buy (買い+来る)	set up (設ける)	tie up * (もやう)
5 PM	go off work (退社+する)	do with (ついで+する)	do a work * (ワーク+する)	well up (込み上げる)
6 PM	win n-day ticket (日+当たる)	do not make sense (意味+わく)	agree (同意+する)	at office (事務所+する)
7 PM	be a video game * (ゲー+なる)	pull up (引き上げる)	run today (今日+走る)	do mainly * (中心+する)
8 PM	the time comes (時代+来る)	understand (私+わかる)	be an element * (要素+する)	miss * (いっす)
9 PM	buy an album (アルバム+買う)	load * (こめる)	finish * (人+終わる)	watch the first (最初+見る)
10 PM	send (お送り+する)	I am * (わたし+いる)	help someone (お手伝い+する)	dry hair (髪+乾かす)
11 PM	watch a TV program (館+見る)	be tomorrow (明日+いる)	drink milk (牛乳+飲む)	have a sense of destiny (運命+感じる)

"*" denotes a word/phrase that is hard to translate.