

# Acquiring Social Knowledge about Personality and Driving-related Behavior

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## Abstract

In this paper, we introduce our psychological approach for collecting human-specific social knowledge (particularly personality and driving-related behavior) from a text corpus, using natural language processing (NLP) techniques. Although this social knowledge is not usually explicitly described, it is often shared among people. We used the language resources that were developed based on psychological research methods: a Japanese personality dictionary (317 words) and a driving experience corpus (8,080 sentences) annotated with behavior and subjectivity. We then automatically extracted collocations of personality descriptors and driving-related behavior from a driving corpus (1,803,328 sentences after filtering) to obtain 5,334 unique collocations. Furthermore, we designed four step-by-step crowdsourcing tasks to evaluate the adequacy of the collocations as social knowledge. The crowdsourcing resulted in 266 pieces of social knowledge, which included knowledge that might be difficult to recall by crowdworkers but is easy with which to agree. Finally, we discussed the acquired social knowledge and its implementation into systems.

**Keywords:** social knowledge, driving, psychology, personality

## 1. Introduction

The properties of the human mind, such as personality and individual differences, have long been studied in psychology. Many psychologists have focused on understanding personality construct and human behavior. However, this interest has recently expanded to other fields. Understanding individual human differences in mind and behavior is one of the important topics in robotics, artificial intelligence (AI), and natural language processing (NLP). In the field of NLP, many studies have examined human subjectivities, such as emotions (Tokuhisa et al., 2009), personality (Golbeck et al., 2011; Nasukawa and Kamijo, 2017; Nasukawa et al., 2016; Plank and Hovy, 2015; Schwartz et al., 2013), opinion mining (Sun et al., 2017), and polarity (Higashiyama et al., 2008; Kobayashi et al., 2005). In this study, we introduce our psychology-integrative approach for acquiring human-specific knowledge, referred to as *social knowledge*, about personality and driving-related behavior. We acquire social knowledge from a large volume of user-generated content (UGC), especially those written by non-professional authors. UGC is posted by users and is available to the public (Moens et al., 2014). UGC, such as blog articles, includes a wide variety of descriptions of personal experiences and meanings (Higashiyama et al., 2008), although it is often deemed noisy and particularly unstructured, with the frequent omissions of subjects in Japanese because of its highly casual writing tone.

Social knowledge is required for machines to interact or collaboratively work with humans to improve the quality of daily human lives. In human development, people acquire social knowledge through experiences and learning in social environments (Turiel, 1983). Social knowledge enables people to infer the intentions of other people and predict their behavior through natural communication and joint actions (Tomasello, 1999). For example, people may decide that those who are shy are unwilling to make a presentation first among other people. On the basis of social knowledge, humans predict psychological states, such as intentions and emotions, based on the behaviors of others, to predict subsequent behaviors, introspect, and become attuned to contexts and

others. The others also behave themselves in a similar manner. Such reciprocal and continuous adjustment of behaviors establish interactions that are natural to humans. To understand user and accomplish natural interactions between humans and machines, it is critical to implement human social knowledge in machines.

We focus on social knowledge, especially about personality and driving-related behavior, for three reasons. First, our approach is novel; thus, it is ideal to start with a restricted domain. Driving is one of the domains where systems are expected to assist humans. Second, it is feasible to scope driving situations and related texts out of a large volume of texts using driving-related words or expressions. Finally, system implementations in vehicles are critical for safety, as autonomous car developments are becoming highly competitive.

This paper is organized as follows: We present related work and then describe the development process. The process consists of two steps. First, we automatically extract collocations between personality and driving-related behaviors from a large corpus. Next, we evaluate them through crowdsourcing. With these results, we discuss our novel integrative approach and conclude the paper.

## 2. Related Work

In this section, we present related work in personality, driving, and social knowledge.

### 2.1 Personality

Big Five is one of the most widely accepted frameworks generally used to understand human personality. It was developed through a lexical approach where researchers collected personality-descriptive adjectives from a dictionary and five broad human personality traits are identified (Goldberg, 1992): (1) Extraversion, (2) Agreeableness, (3) Conscientiousness, (4) Neuroticism, and (5) Openness-to-Experience.<sup>1</sup> EX is the degree to which a person is extraverted, sociable, and active; AG

<sup>1</sup> In this paper, Extraversion is hereinafter abbreviated as EX, Agreeableness as AG, Conscientiousness as CO, Neuroticism as NE, and Openness-to-Experience as OP.

indicates agreeableness, warmth, and sympathy; CO indicates self-discipline, organization, and motivation; NE indicates sensitivity, worry, and anxiety; OP is an aspect of curiosity and intelligence (Gosling et al., 2003). Furthermore, a similar five-broad structure has been confirmed in Japanese (Kashiwagi et al., 2005; Oshio et al., 2014).

Meanwhile, NLP researchers have used Big Five to develop language models from a certain volume of texts from social media to infer author personality (e.g., Golbeck et al., 2011; Park et al., 2015; Plank and Hovy, 2015; Schwartz et al., 2013). This NLP approach requires texts for personality inference. We, however, need what personality a person is described with a personality descriptor.

Accordingly, we developed a personality dictionary where word entries have weights that can be used to infer the five traits from each entry (Iwai et al., 2020). First, we developed a 20-item Big Five questionnaire, Trait Descriptors Personality Inventory (TDPI), based on the responses of 17,591 people (Iwai et al., 2019b). Each item contains a personality word obtained from English personality adjectives, using word embeddings and phrase-based statistical machine translation. We collected 527 personality words from the seeds of 116 personality descriptors obtained in the development process (Iwai et al., 2017; Iwai, Kumada et al., 2018; Iwai, Kawahara et al., 2019b), using word embeddings trained with 200 million Japanese sentences. Furthermore, we conducted a web-survey on 1,938 participants to evaluate their personality based on each personality descriptor in addition to TDPI (Iwai, Kawahara et al., 2019b), using a 7-Likert scale from 1 (totally disagree) to 7 (totally agree). Meanwhile, Iwai, Kumada, Kawahara et al. (2019) identified five-factor structures among the items in the personality questionnaire and 317 personality descriptors based on the responses. Thus, we calculated weights for 323 personality descriptors, including those in the personality questionnaire, to predict the five traits and develop a personality dictionary.

## 2.2 Driving and Psychology

Previous studies have demonstrated that Big Five personality is related to different aspects of car driving. Jovanović et al. (2011) found that 400 Serbian drivers with NE, CO, and AG personalities exhibited driving-related anger. Moreover, Ge et al. (2014) observed that stress and personality induced dangerous driving behavior in Chinese drivers. Furthermore, the effects of different personalities on prosocial and aggressive driving behaviors have also been investigated (e.g., Clarke and Robertson, 2011; Shen et al., 2018). These empirical studies indicated that driving behaviors are related to personality. However, they do not provide insights for implementing them with NLP. In performing experiments or questionnaires, researchers can select items and behaviors that reflect differences in personality because of the shared social knowledge about personality and behaviors.

## 2.3 Language Resources in Driving

Language resources in driving can be divided into two groups: rule-focused and psychology-focused.

Rule-focused language resources are developed based on traffic rules and environments. Sugimura and Sasaki

(2013) formulated solvers of traffic rules. Taira et al. (2014) constructed a car license text corpus for textual entailment. Using traffic regulation texts, Kawabe et al. (2015) proposed transportation terminology recognition for semi-automatic traffic ontology expansion, to obtain necessary knowledge on traffic, such as traffic regulations and transportation manners necessary for traveling. Suzuki et al. (2015) converted questions into SPARQL queries for traffic ontology. Takayama et al. (2017) constructed a traffic ontology-based Q&A dataset. These datasets, however, are not publicly available. Furthermore, human-centered or human experiential foci are not highlighted.

In contrast, we developed driving-related language resources based on a driving-related dictionary (DRD), driving experience corpus (DEC), and driving behavior and subjectivity corpus (DBSC). These are briefly explained as follows:

**DRD.** Iwai, Kumada, Takahashi et al. (2019) developed a driving-related dictionary (DRD) that includes psychological expressions such as “飛び出しに気をつける/be careful of jump-outs” and “スピードが怖い/speed is scary.” In the process, we also developed driving-related words and driving behavioral words which also include psychological expressions such as “不安/anxiety” and “心配/worry.”

**DEC.** Iwai, Kawahara, et al. (2019a) developed DEC annotated with behavior and subjectivity. The corpus consists of 261 blog articles that include manually-annotated tags of driving behaviors and their psychological reactions (=subjectivity: SJ). For annotation, we differentiated who exhibited each behavior, the author (self-behavior: SB) or others (others' behavior: OB). A conditional random field (CRF) model (Lafferty et al., 2001) was then applied on the test dataset and the F-values are 0.556, 0.549, and 0.741 for OB, SB, and SJ respectively.

**DBSC.** Iwai, Kumada, Takahashi et al. (2019) developed a corpus that includes not only driving-related behavior but also the psychological reactions (subjectivity) to such behavior based on the authors' views or their experiences. We used a list of driving behavioral words, the CRF model developed with DEC (Iwai, Kawahara et al., 2018), and support vector machine (SVM). Moreover, we used crowdsourcing to evaluate the corpus. In the result, 31.3% of the articles were judged to have both driving-related behaviors and subjectivity.

## 2.4 Social Knowledge

In social psychology, attributing personality traits to behaviors is called perception or trait inference. Humans recognize other humans only when they recognize them as minded agents. Subsequently, they infer or attribute personality traits to them (Fiedler and Schenck, 2001). For example, Malle and Holbrook (2012) indicated that humans have the ability to infer personality traits from explicit personality behaviors as well as neutral and general behaviors. In their psychological experiments, they demonstrated that participants attributed personality traits to those who were in the queue in front of an ATM. This was possible because people have social knowledge that those who can wait might be patient or wait if they are patient. This attribution is possible because people have past experiences and use the social knowledge derived from these experiences.

### 3. Automatic Extractions

In this section, we describe the steps to extract collocations of personality trait words (PTW) and behavioral predicates automatically. First, we filtered the DBSC. Second, we extracted personality trait words from the personality dictionary. Third, we trained a CRF model based on the DEC (Iwai, Kawahara et al., 2019a) to extract the behaviors. For the model, personality and DRD were used as features. Fourth, we applied the model to the DBSC and extracted behavioral predicates. Fifth, we extracted collocations from personality traits and behavioral predicates.

#### 3.1 Driving Behavior and Subjectivity Corpus

Before automatic extraction, we reviewed, evaluated, and filtered the DBSC.

**Evaluation.** We randomly selected 20 blog articles regardless of the automatic evaluations of their relevance to driving experiences. These articles were evaluated with reference to the guidelines (Iwai, Kawahara et al., 2019a), to judge their adequacy for driving experiences. The results were lower (20.0%, 4 out of 20 articles) than that of Iwai, Kumada, Takahashi et al. (2019). However, the corpus developed by Iwai, Kumada, Takahashi et al. (2019) was the best one available at the time when the experiments were conducted. Therefore, we used their DBSC.

**Filtering.** Next, we filtered the DBSC in four steps. First, we eliminated the dates. Second, we eliminated the top 1,000 sentences that appeared most frequently in the corpus. Third, we eliminated blogs with peculiar expressions (e.g., 続きを読む/read more). Finally, we eliminated lines that consist of only alphabets and numbers. Table 1 indicates corpus statistics after filtering.

	Total	Mean	SD
Sentences	1,803,328	80.2	39.7
Words	19,178,772	853.3	463.7
Content Words	10,581,708	470.8	253.2
Type Token Ratio	---	0.232	0.090

Table 1: Corpus statistics ( $N = 23,622$  blog articles)

#### 3.2 Traits

We extracted personality traits from the DBSC using the TDPI and PTW words in the personality dictionary (Iwai et al., 2020) only when nominatives were inferred as humans, using zero anaphora analysis in the Japanese dependency and predicate-argument structure analyzer, KNP<sup>2</sup>. The extractions also included negation information. The procedure resulted in 297 entries of personality trait words (frequency = 34,325). While the most variety of CO words were found in the corpus, NE words most frequently appeared in the corpus.

### 3.3 Behaviors

We trained the CRF model with all 261 blog articles in DEC (L1,  $c = 1$ ), using CRF++ version 0.561<sup>3</sup>. We then applied the model to DBSC. Table 2 presents the total number of each tag and descriptive statistics per blog article. As this study focuses on social knowledge about personality and driving-related behavior, we did not use SJ data although we extracted it. Next, we extracted predicate-argument structures (PASs) only when the sentence parts have driving experience tags, using KNP. These tagged data included words and predicates. Thus, the obtained results included behavioral predicates that were not in the driving-related dictionary, such as 後ろにトラック/a truck is behind (OB), バイク便を横目で見送る/look sideways like a motorbike messenger (OB), and ダンプが対向車でやってくる/a dump truck comes from the opposite (OB).

Tags	Total	Mean	SD
OB tags	107,784	4.8	4.0
SB tags	265,739	11.8	7.8
SJ tags	792,462	35.3	19.6
TG tags	1,581	0.1	0.3

Table 2: Results of automatic annotation (per article)

	Tags	Total	DRD	NRT
Token	OB tags	51,064	18,652	32,412
	SB tags	157,036	50,436	106,600
	SJ tags	428,098	102,041	326,057
	Total	636,198	171,129	465,069
Types	OB tags	15,547	4,318	11,229
	SB tags	40,912	8,902	32,010
	SJ tags	107,495	16,746	90,749
	Total	163,954	29,966	133,988

Table 3: Summary of automatically acquired predicates  
Note: DRD = predicates in DRD; NRT = predicates not in DRD

#### 3.4 Collocations

We extracted the collocations of trait phrases and PASs when a PAS appeared within the window of five sentences that included a trait phrase in the middle. Then, we counted the frequencies and obtained the pointwise mutual information (PMI) for each pair. However, we did not use PMI to select pairs of personality words and driving-related behavior (see Section 5.3.2 for discussion). Table 4 summarizes the number of collocations. The PMI ranged from 3.173 to 22.179. Meanwhile, the number of OB predicates was approximately twice that of the newly extracted predicates and SB predicates. Moreover, the number of SJ predicates was thrice that of the other predicates. Compared with the number of behavioral predicates and corpus size, collocations were seemingly limited. However, similar to the previous section, the results indicated that the extracted collocations included those that could not be acquired using only the DRD.

<sup>2</sup> <http://nlp.ist.i.kyoto-u.ac.jp/EN/index.php?KNP>

<sup>3</sup> <https://taku910.github.io/crfpp>

	Tags	Total	DRD	NRT
Frequency	OB tags	3,692	1,122	2,570
	SB tags	8,801	2,521	6,280
	SJ tags	32,988	6,764	26,224
	Total	45,481	10,407	35,074
Types	OB tags	1,595	478	1,117
	SB tags	3,739	1,064	2,675
	SJ tags	12,978	2,717	10,261
	Total	18,312	4,259	14,053

Table 4: Summary of automatically extracted collocations

In summary, some collocations could be considered as social knowledge of personality traits. Examples are: 他者が自分勝手だ\_直進車を妨害している/the other person is selfish\_interfere a straight-going car, 他者が自分勝手だ\_車がレーンに止まっている/the other person is selfish\_a car stops in the lane, and 他者が知らん顔\_真横に居る/the person ignores\_the other person is just next to me.

Next, we reviewed the original blog articles from which we extracted the collocations to examine whether the collocations actually reflect plausible social knowledge about personality and driving-related behaviors. Example (1) is a successfully acquired collocation. The bolded spans indicate the portion that the CRF model identifies as behavior while the italicized and underlined spans are personality trait words.

- (1) 今日の会社帰りに、右折レーンで右折待ちをしていた車が、突然直進レーンに戻ってきて走り始めた為、前を走っていた車が危うく追突するところだったし、自分も危うく前の車に追突するところだった。  
その少し先では、交差点の手前で突然直進レーン2本を横切って右折レーンに入ろうとした車が、右折レーンに入りきれずに直進レーンをふさいだまま止まっていて、**直進車を妨害して**る。

盆と正月の時期は、車が少なくなって通勤が楽なんだけど、なぜかこういう**自分勝手な**運転手が増えるんだよなあ。

On my way home from work, a car that was about to turn to the right-turn lane suddenly drove straight. So the car that was running ahead was about to clash and it was dangerous. I was about to crash into a car.

A little further ahead, another car tried to cross two straight lanes to enter the right-turn lane, which was located immediately before the intersection. It was unable to enter the right-turn lane and stopped, thereby **blocking the cars that were driving straight**.

During Bon and New Year, there are few cars, which makes commuting easy; however, for some reason, the number of *selfish* drivers increases.

Meanwhile, example (2) did not indicate clear associations between personality and behaviors in the actual blog articles, although the literal collocations seemed reasonable. “道に出る,” and “清々しい”

are not directly related. The author felt refreshed because s/he viewed a landscape.

- (2) いつになく日光がまばゆい気がしたので工場の前の**道に出て**みてガラにもなく**清々しく**景色などをながめていると50Mくらい先で7~8歳の子供がこちらを見ている。

Being unusually dazzled by the sunlight, I **got out on the road** in the front of the factory and was *refreshed* by the landscape. I found a 7- to 8-year-old child looking at me from about 50 meters ahead.

The results revealed many overlapping contents in the corpus. Although the collocation “他者が自分勝手だ\_直進車を妨害している/the other person is selfish\_interfere a straight-going car” in example (1) appeared 20 times in the corpus (PMI = 17.787), the 20 articles were the same article from different sources. Therefore, we evaluated all the behavioral collocations with crowdsourcing rather than automatic filtering and PMI.

#### 4. Human Evaluations

We used crowdsourcing to evaluate all the automatically extracted collocations of personality and behaviors (both OB and SB) regardless of PMI. The human evaluations were conducted in the manner described in Figure 1. To evaluate the acquired knowledge, we prepared crowdsourcing tasks through Yahoo Crowdsourcing. Our ultimate goal was to evaluate the automatically extracted collocations as general social knowledge about driving behaviors and personality using human assessments. Thus, we carefully designed the crowdsourcing tasks, considering the goal and limitations of crowdsourcing tasks.

Compared with the other data collection methods, the crowdsourcing included more satisficing respondents. We designed relatively simple tasks and conducted the crowdsourcing step-by-step (Figure 1).

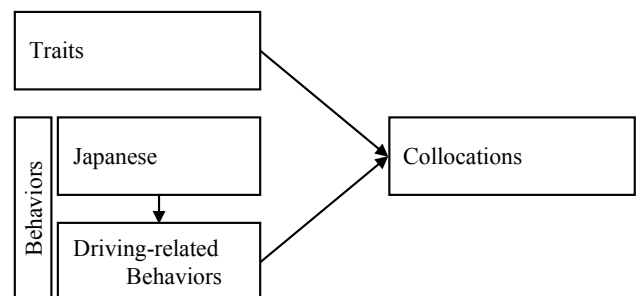


Figure 1: The four steps of crowdsourcing

##### 4.1 Traits

First, we conducted crowdsourcing to investigate whether the trait words described individual personalities in the blog articles.

##### 4.1.1 Method

**Preparation of tasks and questions.** We extracted trait words and randomly chose one paragraph, including each

of the words. Subsequently, we created task sets of 219 trait words. However, the variations of nominatives and negation resulted in 575 expressions. Assessing whether the expressions describe personality traits requires contexts. Hence, each question included trait words and two sentences preceding the trait-included sentence. The crowdworkers were instructed to select “YES/NO” when reading the questions. Meanwhile, one task consisted of five questions and one filtering question.

**Procedure.** A total of 317 crowdworkers completed the tasks and 117 crowdworkers did not pass the filtering question. All the crowdworkers were instructed to read the sentences and select “YES/NO” to indicate whether or not the expressions enclosed in parentheses “[ ]” represent human traits or the human mind. The crowdworkers received a few points only when they selected the correct answers in the filtering question.

#### 4.1.2 Results and Discussion

Based on the numbers of YES responses of each question, we set the cut-off value to a value greater than or equal to 4. After this filtering, only 461 expressions remained (80.2%).

Examples (3) and (4) are questions in which all crowdworkers judged whether the expressions indicate the human mind or a trait. おっちょこちよい/careless in Example (3) was regarded as a trait expression while 対立/dichotomy in example (4) was considered not to express either human mind or a trait.

- (3) 良く風水などで言われるように方位ってあるのでしょうか？  
うる覚えの風水で北に机を向けると冷静思考になれると記憶しています。  
【おっちょこちよいな】私なので北向きに座っていましたが、プラス思考というよりはマイナス思考気味でした。  
Do directions matter as it is often said in Feng Shui?  
I remember vaguely that in Feng Shui, if I turn my desk to the north, I can think calmly.  
Although I sat in the north-facing direction because I'm [careless], I was a more negative than a positive thinker.

- (4) 誰かに話したかったと。  
仕事と生活を分けることは出来ないと、施設長を辞めた彼は、自分の哲学を貫ける施設を準備中。  
介護する側とされる側という二項【対立】を作らない施設。いつになく日光がまばゆい気がしたので  
I wanted to tell someone.  
He cannot separate work from life. He left the facility director and is preparing a facility that can carry out his philosophy.

A facility that does not create a [dichotomy] between the side to care and the one being cared for.

## 4.2 Japanese

To filter out unnatural Japanese PASs owing to analysis errors, we conducted crowdsourcing.

### 4.2.1 Method

**Preparation of tasks and questions.** We prepared tasks to select only predicates that are natural Japanese. Each crowdworker was allowed to complete a maximum of 10 tasks. Meanwhile, one task consisted of nine questions and one filtering question. We prepared a total of 506 tasks and 61 filtering questions for 4,554 respondents.

### 4.2.2 Results and Discussion

It took 2 h 10 min to obtain the answers. A total of 1,079 respondents completed the tasks, and 170 respondents were filtered out during data collection. Based on the results, we set the cut-off value at equal to or more than 5. After this, 3,441 (74.6%) remained in the list.

## 4.3 Driving Behavior

The purpose of this crowdsourcing was to select the driving-behavioral predicates.

### 4.3.1 Method

One task consisted of five questions and one filtering question. We prepared 715 tasks with 3,585 questions. Each crowdworker completed a maximum of 10 tasks.

We carefully considered the instructions because the definitions of behaviors were confusing. We assumed that human drivers controlled the vehicles. We also regarded driving actions as human behaviors when we expect human behaviors. For example, although the nominative in the phrase “the oncoming car was jumping out of the road toward us” is “the car”, we labeled it as behavior. Therefore, the crowdworkers judged whether or not the expression is the driver’s behavior or behavior of the car that is likely to be experienced while driving a car.

### 4.3.2 Results and Discussion

It took about 11 hours to collect data from 2,410 crowdworkers. Although we intended to filter out the crowdworkers that did not respond to the checkbox questions, we accepted all the respondents by mistake. Such respondents accounted for 32% (n = 771). Based on the responses, we set the cut-off value equal to or more than 0.7 and selected 1,218 (33.9%) of all the assigned predicates. The predicates include “クラクションを鳴らされる/be horned,” “他者を見る/look at others,” “右に曲がる/turn right,” “マンションに着く/get to an apartment”, and “ブレーキを踏んでいる/step on the brakes.” On the other hand, the following predicates were evaluated as non-related to driving; “彼が世界/he is the world,” “彼女が付き合ってる/she dates,” “魔神に変身される/transform into a genie,” “箱が新しい/the box is

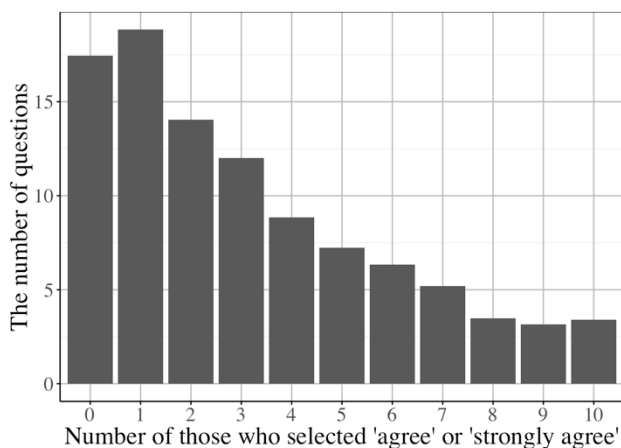


Figure 2: Distribution of the responses.

NR	Examples
10	パーキングに入る_運転手が落ち着く /enter the parking lot_the driver calms down, バックで追突する_運転手が謝る /collision at the back_the driver apologizes, 愛車に乗る_運転手が落ち着く/ride your favorite car_the driver is relaxed, 料金所で手間取る_運転手が焦る/take time at a toll gate_the driver is irritated, 同乗者がドアを閉めてないのに_運転手が焦る/a fellow passenger does not close the door_the driver is irritated
6 <i>Cut-off</i>	会話をしている_運転手が心配/have a conversation_the driver is worried, 海に家族で行く_その人が優しい/go with family to the sea_the person is kind, 顔を出す_運転手が焦る/pop the face up_the driver is upset, 警察が来る_その人が不安だ/the police comes_the person is anxious
0	雨が降り出す_その人が陽気だ/rain begins_the person is cheerful, 運転をするので_運転手がヘラヘラ/drive a car_the driver is foolish, 横を向く_運転手が情け無い/turn sideways_the driver is not good, 音が安定する_運転手が不安定だ/sound gets stable_the driver is unstable

Table 4: Examples of pairs of social knowledge. NR = number of those who selected “strongly agree” or “agree”.

new,” “著者がやらなかったからで/because the author did not do it,” and “一言を一族に旦那から伝えます/the husband tells a word to the family.”

#### 4.4 Social Knowledge

To evaluate the extracted collocations as social knowledge, we prepared tasks for crowdsourcing.

##### 4.4.1 Method

This task design was the most difficult among all the crowdsourcing tasks. We instructed the crowdworkers to evaluate whether the behaviors and trait descriptions are natural as social knowledge without clarifying our intentions. We labeled behavioral predicates as “A” and

trait descriptions as “B” and asked them to rate to what degree they generally agree with B when A happens while driving a car, using a 4-point Likert scaling from 1 (strongly disagree) to 4 (strongly agree).

One task consisted of five questions and one filtering question. It was also difficult to prepare the filtering questions, because the tasks involved evaluating human subjectivities. Therefore, we created combinations that most people totally disagree with; for example, “老人が飛び出す\_その人が親切だ/an older man jumps out\_the person is kind” and “警察に電話します\_運転手が陽気だ/the driver calls the police\_the driver is cheerful.” All the predicates and trait descriptions were in the DBSC but arranged in combinations. We found that several crowdworkers ignored unnatural spans and evaluated only the adequacy of meanings. This was considered because by chance, another task owner had repeated multiple tasks that asked the crowdworkers to read several sentences and choose spans that summarized the sentences most appropriately but not the accuracy of the spans. Therefore, we added one filtering question for the unnatural span.

##### 4.4.2

#### 4.4.2 Results and Discussion

It took about seven hours to collect all the responses. A total of 1,239 crowdworkers completed the tasks and 1,065 workers were filtered out. Based on the results, we combined “strongly agree” and “agree” as “yes” and set the cut-off value equal to or more than 6 (Figure 2). Thus, we acquired 266 pieces of social knowledge. Table 4 shows examples of the number of yes responses.

## 5. Discussion

This study highlights the usefulness of crowdsourcing in social knowledge acquisition and the difficulty of automatic filtering.

### 5.1 Acquisition of Social Knowledge

The step-by-step evaluations confirmed that our proposed approach is valid and feasible for acquiring social knowledge about personality and driving-related behaviors from UGC. For personality-trait words in the blogs, 80.2% of the identified descriptions were evaluated as showing individual personality traits. Behavioral evaluations resulted in 56,459 types (76.7% of the acquired predicates are not in the DRD). We acquired interesting, not hypothesis- data-driven social knowledge about personality and driving-related behaviors derived from authors’ experiences. Thus, social knowledge is associated with the Big Five traits. Meanwhile, the acquisition rate of the social knowledge was very low: 266 collocations were regarded as social knowledge out of large text corpora (about 1.8 million sentences). These suggest the feasibility of our approach under a condition where we have a clean corpus with only unique blog articles that frequently includes personality adjectives and focuses on more the domain.

Social knowledge includes information that is difficult to recall in free writing; for example, “愛車に乗る\_運転手が落ち着く/get a ride on my beloved car\_the driver feels

at ease,” “猫を路地で発見\_運転手が慎重だ/find the cat in a small alley\_the driver is careful,” and “パーキングに入る\_運転手が落ち着く/the car enters a parking lot\_the driver is relaxed.” These pairs of “hard-to-recall” social knowledge suggest the difficulty of acquiring them by supervised or semi-supervised machine learning. It is difficult for annotators or crowdworkers to identify such unconscious or subtle knowledge from texts. Meanwhile, the classification of pairs as social knowledge is possible by machine learning if many extracted collocations are available. However, in this study, we extracted only 5,340 pairs. Hence, we conducted only crowdsourcing.

Social knowledge can be divided into two categories: (A) people infer the actor’s personality as personality descriptions when s/he behaves as in examples (5)–(8), and (B) people have similar psychological reactions when they are faced with some situations while driving a car (examples (9)–(11)). In our previous research, we derived the weights for each trait from the Japanese personality dictionary (Iwai et al., 2020). The numbers were calculated based on the responses of 1,938 people.

- (5) 物を見付ける\_運転手が慎重だ/The driver finds an object.\_The driver is careful.: 慎重 -0.08, 0.23, 0.23, 0.15, 0.24 for EX, AG, CO, NE, and OP, respectively
- (6) 道を戻って行ってくれる\_運転手が親切だ/ The car turns back\_the driver is kind: 0.38, 0.52, 0.37, -0.05, 0.30 for EX, AG, CO, NE, and OP, respectively
- (7) 車を止める\_運転手が親切だ/stop the car\_the driver is kind: 0.38, 0.52, 0.37, -0.05, 0.30 for EX, AG, CO, NE, and OP, respectively
- (8) 後続に知らせる\_その人が冷静だ/inform the car behind\_the person is calm: 0.13, 0.27, 0.21, -0.19, 0.38 EX, AG, CO, NE, and OP, respectively
- (9) 料金所で手間取る\_運転手が焦る/take time at a toll gate\_the driver is impatient: -0.24, -0.16, -0.33, 0.54, -0.14 EX, AG, CO, NE, and OP, respectively
- (10) 同乗者がドアを閉めてないのに\_運転手が焦る /a fellow passenger does not close the door\_the driver is irritated: -0.24, -0.16, -0.33, 0.54, -0.14 for EX, AG, CO, NE, and OP, respectively
- (11) 子供が外で遊んでる\_運転手が落ち着かない/a child plays outside\_the driver is restless: 0.16, 0.37, 0.26, -0.22, 0.35 for EX, AG, CO, NE, and OP, respectively

In addition, the weights of personality traits in each example suggest that we can infer the personality of the actor in the behavioral predicates. The driver in example (7), “車を止める/stop the car” is expected to be slightly extraverted, highly agreeable, moderately conscientious,

and moderately open to experiences. If the system recognizes this, it can return “you are kind” as feedback or predict that the driver will return to where s/he came from, as given in example (6).

Meanwhile, we and the crowdworkers were not sure whether they or we have seen cats in a small alley while driving, and do not know that the person is truly careful. Of course, one might have had a similar experience. We know that cats can be in small alleys and we may not be aware of them if we judge from our past experiences or observations. Therefore, we assumed that the person who finds a cat in a small alley is careful. We assumed it based on our social knowledge and our approach allowed us to extract social knowledge candidates from UGC.

## 5.2 Social Knowledge and Implementation

In this section, we discuss social knowledge and its implementation, i.e., how social knowledge may contribute to society. We performed a series of studies, including this study (Iwai, Kawahara, et al., 2018, 2019a; Iwai, Kumada, Takahashi et al., 2019) to reflect users’ psychological and behavioral perspectives, not from manufacturers. Meanwhile, shared knowledge is often difficult to recall and write knowledge, although we can recognize such knowledge, as given in examples (12)–(16):

- (12) おまわりさんが傍に見える\_運転手がびくびく /see a police officer by the side\_the driver is nervous
- (13) おまわりさんがいない\_運転手が落ち着く /there is no police officer\_the driver is relaxed
- (14) 渋滞を後ろに作る\_運転手が焦る/a traffic jam occurs after the car\_the driver is irritated
- (15) スピードが落ちることない\_運転手が心配/the car does not slow down\_the driver is worried
- (16) スピードが出ていない\_運転手が焦る/do not increase the speed\_the driver is irritated

Examples (12) and (13) are contrasting. The given information does not describe situations where the author saw a police officer or reasons why the author was relaxed when s/he did not find a police officer. However, people often have such psychological reactions to police officers. The situation in example (14) is difficult to acquire with a rule-based approach because it depends on the situation. Examples (15) and (16) suggest that drivers prefer the speed which they regard as adequate, not too fast and not too slow. These examples are not directly related to mechanical designs. Hence, it is difficult for mechanical engineers to realize that people sometimes have psychological reactions that are unfamiliar in the design process. Even if they realize this, it is very important to ensure that the knowledge they acquire is accurate. Accidents often occur when people do something unexpected for manufacturers. Humans naturally agree with these examples and make a prediction of near future

behaviors from their social knowledge while machines cannot. Since humans consciously or unconsciously make such predictions, humans feel that something is wrong when machines do something unnatural for people.

While in previous NLP studies, personality inferences from a text corpus require the target person's own writing, our approach is applicable to descriptions of personality and behaviors. Considering its actual implementation in systems, it is necessary for machines to describe human behaviors. If this is achieved, machines will understand the personality of the person operating them and can predict their subsequent behaviors or attribute personality descriptors and personality attribution of human abilities to the person.

### 5.3 Limitations and Future Work

#### 5.3.1 Evaluation of the Acquired Social Knowledge to Infer Individual Personalities

This paper demonstrated that the synergetic approach is applicable to acquire "general" social knowledge about personality and driving-related-behaviors. Next, we need to examine if such inferred personality from driving behaviors will represent individual differences in personality. In other words, it is necessary to investigate those who drive a car. Hence, we plan to investigate the acquired general social knowledge to discover whether the behaviors predict individual differences in personality.

#### 5.3.2 Adequacy, Quality, and Evaluations of Corpora

The acquisition of social knowledge about personality and driving-related behaviors heavily depends on the adequacy and quality of the corpus. DBSC reflects a limited range of subjectivity and includes many noises and duplications. Hence, a new corpus that reflects the purposes is critical.

Moreover, it is unclear whether or not DBSC reflects all the possible driving experiences. Furthermore, the DBSC was regarded as reliable and valid due to poor standards. Acquiring the targeted expressions is like finding needles in haystacks. In this paper, we provided the corpus statistics of the number of sentences, words, content words, type token ratio, and results of CRF extraction. All of them were numeric facts but did not provide readers with insights into the contents. Therefore, it is necessary to develop evaluation methods to evaluate the contents. One example of this evaluation is the crowdsourcing proposed by Iwai, Kumada, Takahashi et al. (2019). Hence, it is important to discuss and establish methods, metrics, or standards to evaluate the quality of the corpus in the future.

## 6. Conclusions

This paper demonstrated the feasibility of our approach in acquiring social knowledge about personality and driving-related behaviors. Although it revealed the difficulty of scoping a large number of driving experiences and social knowledge due to the limited availability of a corpus, we acquired adequate social knowledge about personality and

driving-related behaviors. We are planning to make the social knowledge publicly available for research purposes.

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