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Development of a Japanese Personality Dictionary based on Psychological Methods

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Abstract

We propose a new approach for constructing a personality dictionary with psychological evidence. In this study, we collect personality words by using word embeddings and construct a personality dictionary with weights for the Big Five traits. The weights are calculated based on the responses of the large sample (N = 1,938, female = 1,004, M = 49.8 years old: 20–78, SD = 16.3). All the respondents answered a 20-item personality questionnaire and 537 personality items derived from word embeddings. We present the procedures to examine the qualities of responses with psychological methods and to calculate the weights. Using these, we develop a personality dictionary with two sub-dictionaries. We also discuss an application of the acquired resources.

Keywords: personality, psychology, weights

1. Introduction

When describing ourselves or others, we usually use certain abstract terms such as “she is a *sociable* person” or “he is *kind*.” With such cues, we expect that the person is friendly or warm. We can also imagine that they accept an invitation to a party or help their classmates without hesitation. These assumptions can be made because social knowledge about latent traits are shared among humans. This is critical in human social perceptions, and even unconsciously affects human behavior (Ferguson and Bargh, 2004). It allows them to infer others’ personalities based on the words that describe their personalities.

For understanding human personality based on the trait descriptions of others, computers need knowledge on the relationships between personality descriptors and personality traits. However, to the best of our knowledge, such a personality dictionary does not exist, which is applicable to natural language processing (NLP).

In this study, we develop a Japanese personality dictionary with weights for Big Five traits, incorporating psychological methods. Moreover, our approach is the first NLP study that has theoretical and statistical evidence tolerant to psychological research standards. The Big Five is one of the most widely used framework to understand universal personalities (e.g., McCrae and Costa, 1997). The Big Five assumes that human individual differences in personalities can be described in five broad traits: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness-to-Experiences[1] (Goldberg, 1992). EX indicates the degree to which a person is extraverted; AG indicates that for agreeable, warmth, and sympathetic; CO for self-disciplined, organized, and motivated; NE for sensitivity, worrisome, and anxious; OP for the aspects of curiosity and intelligence (Gosling et al., 2003). We calculate the weights of personality words per the Big Five traits to infer a person’s personality based on the personality word they are described by. With such weights, researchers can see detailed differences of the personality words in each trait. These weights are useful in enabling computers to understand the personality of a person described by a personality word.

The procedure comprises the following two steps:

1. We collect dictionary entries related to personality, using NLP techniques (word embeddings).
2. We ask a large sample to evaluate self-personality and personality words. We calculate the weights of each personality word based on the results of exploratory factor analyses.

2. Related Work

We introduce the three related domains of previous studies in personality; (1) in psychology, (2) in NLP, and (3) in an incorporative approach of (1) and (2).

2.1 Psychological Approach

The Big Five has been developed through lexical studies in psychology. In this approach, researchers select the word entries describing individual differences in personality using dictionaries. Researchers repeated surveys to evaluate respondents’ personality and identified the five broad traits (e.g., Goldberg, 1992; Saucier and Goldberg, 2001; Norman, 1963). In Japan, Murakami, (2002) and Kashiwagi et al. (2005) conducted such a lexical approach and identified the five-factor structure.

However, a problem remains for NLP researchers. Psychological interest is the latent and mutually exclusive structure of the personality, which results in specifying the words or expressions that represent one’s trait. NLP resources, however, prefer dictionaries of wider coverage, regardless of the complexity of the structure.

2.2 NLP Approach

Regarding NLP, previous studies focused on social media services such as Facebook and Twitter to predict the users’ personalities by using a certain amount of texts (e.g., Golbeck et al., 2011; Nasukawa et al., 2016; Nasukawa and Kamijo, 2017; Park et al., 2015; Plank and Hovy, 2011; Schwartz et al., 2013). They developed models to infer the self-evaluated personalities. However,

[1] In this paper, Extraversion is hereinafter referred to as EX, Agreeableness as AG, Conscientiousness as CO, Neuroticism as NE, and Openness-to-Experiences as OP.

this approach does not provide information on what words represent the personality or the weights for personality inference. Our goal was to acquire personality words that allow computers to infer an individual's personality from a single personality word.

2.3 An Incorporative Approach

Recently, Iwai, Kawahara et al. (2019) introduced a new Big Five questionnaire in Japanese named as Trait-Descriptors Personality Inventory (TDPI). To the best of our knowledge, it is the only personality measurement developed by NLP techniques such as word embeddings and phrase-based statistical machine translation. It was constructed based on the responses of more than 40,000 Japanese people (Iwai et al., 2017, 2018; Ueda et al., 2016). In addition, Iwai, Kawahara et al. (2019) demonstrated reliability and the five-factor structure replications among different samples. However, it only included 20 items, and one personality word per item, which are too small to be used as a language resource.

3. Acquisition of Dictionary Entries

We prepared the candidate words using a word2vec model and manually annotated them to select the dictionary entries.

3.1 Acquisition of Candidate Words

We prepared two sets of seed personality words, 116 words in total, derived from Ueda et al. (2016) and Iwai et al. (2018). All the words were acquired based on English personality adjectives (Goldberg, 1992; Gosling et al., 2003), using word embeddings and phrase-based statistical machine translation. The words were tested in web-surveys, and it was confirmed that they have the Big Five structure (Iwai, Kumada, et al, 2018; Iwai, Kawahara, et al., 2019b). Japanese personality trait words were acquired from the English Big Five personality trait adjectives by using phrase-based statistical machine translation. We fed each set to a word2vec skip-gram model that was trained using approximately 200 million Japanese web sentences. The adjectives were, however, abstract and polysemous, and not only limited to personality descriptions. Therefore, we combined from one to four words to the averaged vectors within the same trait. We acquired 667 candidate words in total, with cosine similarities higher than .6.

3.2 Manual Annotation

We manually annotated the candidate words for the personality dictionary and modified them to be adequate for a web survey.

First, three annotators conducted manual annotations. They excluded words that did not describe human personalities (e.g., 死球 "hit by pitch"). They also annotated the most commonly written forms of each candidate word.

In addition, by reviewing the candidates, we decided to classify each candidate into two sub-categories: personality trait words (PTW) and personality-related words (PRW). PTW refers to words that can be used to describe the personality with minimum modifications, i.e., by using the words directly or by adding only function words, such as 動揺 "*upset*" and 不信 "*disbelief*." In contrast, PRWs may describe personality aspects in part but require additional information with some content words, such as 絵画 "*drawings*" and 本質 "*essence*." In other words, PRW requires more context than PTW.

Next, following the general principles of developing psychological questionnaires, two psychologists modified the words into sentences to allow the respondents to evaluate their personalities. All the items ended with the phrase …と思う/"*I think* …." 不信, a PTW, was modified to 不信になりがちだと思う "*I think I tend to disbelieve*." 絵画 "*drawings*," a PRW, was modified to 絵画に感心があると思う "*I think I am interested in drawings.*"

The procedure resulted in 526 words and questionnaire items (PTW = 317 words and PRW = 209 words).

4. Weight Calculations

We conducted a web survey and calculated the weights by using calculation methods that were determined based on the results of exploratory factor analysis.

For developing a personality-related language resource with trait weights, we adopted psychology methods. To evaluate psychological concepts, one method is conducting web surveys. To calculate the weights shared by the general population, we designed a web survey for a comparatively large sample size of different age groups and acquired reliable and valid responses from the same participants. We prepared the survey for at least 300 participants from different age groups (20s, 30s, 40s, 50s, 60s, and over 70s) to represent the shared knowledge of a wide range of Japanese people. In addition, we conducted a web survey twice after a one-week interval for two reasons. First, the number of items (526) and TDPI are too large for the participants to complete the survey in one sitting. Second, we examined the test–retest reliability and factor invariance with the data at two time points, which is reported in Section 4.3.

4.1 Web-survey

We conducted a web survey in February 2018 with a one-week interval. Participants (N = 1,938, female = 1,004, M = 49.8 years old: from 20 to 78, SD = 16.3) completed the first TDPI and the randomized 317 PTW items in (Time 1). One week later, the same participants also responded to the second TDPI and the randomized 209 PRW items (Time 2). All the items were evaluated based on a Likert scaling from 1 (strongly disagree) to 7 (strongly agree).

4.2 Evaluation of Responses

We carefully investigated the reliability and validity of TDPI based on psychological methods by evaluating the responses. The advantage of our study is the number of items associated with the personality scores. Meanwhile, the quality of responses is critical because a person responds to many items at the same time. Reliability and validity of TDPI were indicated repeatedly in the previous study (Iwai et al., 2018). Supporting evidence for these properties imply that the responses are reliable and valid in return.

Traits	*M*	*SD*	*α*
EX	15.6/15.6	4.5/4.9	.86/.85
AG	17.9/18.0	4.1/4.0	.81/.82
CO	18.2/18.3	4.4/4.0	.80/.81
NE	17.0/16.6	3.7/3.8	.68/.70
OP	17.2/17.1	4.0/3.9	.76/.76

Table 1: TDPI statistics (Time 1/Time 2).

Data	*M*	*SD*
TDPI-Time 1	3.1–4.7	1.2–1.6
PTW-Time 1	2.8–4.9	1.1–1.5
TDPI-Time 2	3.1–4.7	1.2–1.6
PRW-Time 2	2.7–5.1	1.0–1.5

Table 2: Ranges of means and standard deviations of response scores at item-level

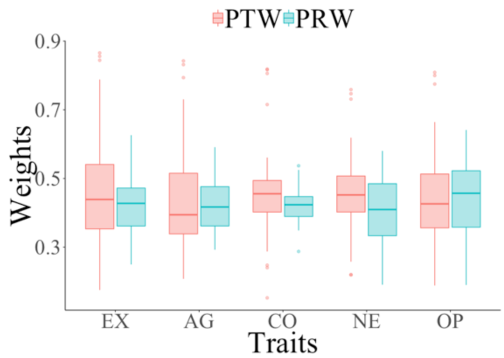

Figure 1: Weight distributions (absolute weights).

In this paper, we provide two reliability metrics: internal consistency and test-retest correlations. Both values were calculated using the responses within the same traits. Internal consistency assumes that a person tends to similarly answer items within the same trait, which is indicated by Cronbach's α (Cronbach, 1951). The test–retest reliability is coherency across time. Furthermore, validity is also important that those items measure factors as hypothesized, i.e., the Big Five traits.

Reliability: Table 1 summarizes the descriptive statistics and internal consistencies (α) at Times 1 and 2. The internal consistency is substantial. Moreover, the correlations within the same traits between Times 1 and 2 are high and statistically significant at $p < .001$ (r =.823, .744, .779, .704, .746 for EX, AG, CO, NE, and OP respectively).

Validity: We conducted exploratory factor analysis (EFA) at two time points with factor loading invariance and correlated residuals across time, using maximum likelihood with a robust standard error method and a geomin rotation. EFA is a statistical approach for extracting common factors across measured variables based on correlation coefficients (Fabrigar et al., 1999). The results indicated good replication of the five-factor structure with excellent model fits (CFI[2] =.965, TLI[3] = .956, RMSEA[4] [90% CI[5]] = .029 [.028, .031])[6]. These supported that the measured latent factors (i.e., five factors) are replicated across Times 1 and 2.

4.3 Weight Calculations

Before weight calculations, we investigated the means and standard deviations of the response scores at the item-level (Table 2). Although the means of PTW and PRW were slightly wide-ranging compared with TDPI-Time 1 and TDPI-Time 2, there were no floor and ceiling effects or extremely biased distributions. This suggests that the collected words reflected the individual differences in personalities. Thus, it is considered that the seed words (described in Section 3.1) are good.

We conducted EFA for Times 1 and 2 items to investigate if the acquired expressions share common factors as the Big Five. After reviewing the results, we conducted multivariate single regression analyses for PTW items and calculated correlation coefficients for PRW. Figure 1 illustrates the distributions of absolute weights that are the highest among the five traits.

PTW: We conducted an EFA with a promax rotation using maximum likelihood including the TDPI items (i.e., 20 TDPI items + 317 PTW items = total 337 items). The 20 items of TDPI were loaded on the hypothesized factors as in the study of Iwai et al. (2018). The results suggest that the latent five-structure underlies in the 337 items. This supports that the five common factors underlie in the measured variables.

We, thus, conduct multivariate single regression analyses in that, each single item of TDPI and PTW predicts individual raw scores of the five traits. These procedures resulted in five weights for the Big Five personality. 動揺 "*upset*," for example, EX, AG, CO, NE, and OP had the weights of -.258, -.106, -.328, .572, -.156, respectively. The weights independently predicted each trait.

PRW: The EFA results of the TDPI and 209 items at Time 2 do not support the five-factor structure. The TDPI items do not load on the hypothesized factors. Thus, we decided to use Pearson's correlations coefficients between raw scores and each trait's score (i.e., sums of raw scores within the same traits).

4.4 Personality Dictionary

Based on the analyses, the personality dictionary was designed to comprise two subsidiary dictionaries: (1) a PTW dictionary including TDPI words and (2) a PRW dictionary (See examples in Table 3 at next page). After reviewing the results of PTW in Section 4.3, we re-classified 14 items into PRW. The two sub-dictionaries contained the canonical forms of words retrieved from the Japanese morphological analyzer, JUMAN++[7], human

[2] Comparative fit index
[3] Turker-Lewis index

[4] Root mean square error of approximation
[5] Confidential intervals
[6] The model fit indices are considered as excellent when CFI and TLI > .950, RMSEA < .03 and good when CFI and TLI > .900, RMSEA < .05 (Marsh et al., 2009).

[7] http://nlp.ist.i.kyoto-u.ac.jp/EN/index.php?JUMAN++

Entries	English	EX	AG	CO	NE	OP
Trait Descriptors Personality Inventory (Personality Questionnaire)						
活発	active	.866	.293	.212	-.190	.362
温和	warm	.292	.842	.161	-.140	.301
鈍感	dull, insensible, unaffected	-.198	.000	-.715	.192	-.247
心配	worried	-.126	.082	-.012	.759	.046
知性的	intellectual	.380	.354	.349	-.141	.775
Personality Trait Words (PTW)						
不信	distrust	-.322	-.265	-.301	.481	-.078
動揺	upset/unsettled/ agitated	-.258	-.106	-.328	.572	-.156
横暴	domineering	-.123	-.359	-.448	.242	-.139
革新的	innovative	.334	.098	.117	-.063	.400
卑劣	despicable	-.233	-.302	-.469	.256	-.211
創造的	creative	.342	.160	.140	-.046	.485
誤解	misunderstanding	-.166	-.193	-.386	.394	-.121
知的	intellectual	.282	.275	.278	-.114	.605
独善的	self-righteousness	-.031	-.182	-.247	.206	.096
優柔不断	hesitating/hesitant/indecisive	-.260	-.037	-.377	.429	-.139
臆病	cowardly	-.396	-.082	-.319	.471	-.144
焦る	impatient	-.238	-.158	-.326	.540	-.135
謙虚	humility	.151	.439	.255	-.034	.233
軽率	rash/hasty/careless	-.157	-.214	-.512	.300	-.176
混迷	chaos	-.254	-.169	-.377	.507	-.174
お人好し	good/soft-hearted/good-natured	.230	.384	.077	.148	.167
身勝手だ	selfish	-.205	-.328	-.494	.287	-.128
理不尽	unreasonable	-.214	-.306	-.420	.305	-.162
的外れだ	irrelevant	-.190	-.203	-.475	.312	-.196
懸念	concern	-.220	-.096	-.207	.448	.066
自分勝手だ	selfish	-.177	-.345	-.474	.318	-.122
恥知らず	shameless	-.147	-.235	-.469	.210	-.116
浅はか	shallow	-.218	-.237	-.497	.378	-.221
幼稚	childish	-.242	-.256	-.491	.358	-.202
困惑	puzzled	-.280	-.156	-.352	.517	-.157
物静か	quiet	-.359	.185	-.040	.065	.037
温厚	mild	.245	.668	.233	-.117	.304
傲慢	arrogant	-.149	-.323	-.428	.232	-.090
Personality Related Words (PRW)						
本質	essence/nature	.275	.259	.140	.074	.560
絵画	drawings	.237	.141	.048	.000	.290
力添え	Help/aid	.419	.420	.142	.028	.346
斬新	novel/original	.361	.176	.011	.041	.469
寒い	cold	-.281	-.255	-.429	.418	-.079
素養	grounding/sophistication	.377	.316	.169	-.044	.544
必要不可欠	essential/indispensable	.440	.302	.146	-.109	.313
論じる	discuss/argue	.350	.156	.049	.065	.508
技巧	skill/art/technique	.282	.232	.104	-.027	.446
美しい	beautiful/aesthetic	.309	.303	.163	.086	.387
とらわれる	be constrained	-.117	-.033	-.313	.483	.037
文化	culture	.292	.310	.119	.015	.412
緊密	close/intimate/tight-knit	-.281	-.255	-.429	.418	-.079
態度	attitude	.377	.316	.169	-.044	.544
オリジナリティ	originality	.440	.302	.146	-.109	.313

Table 3: Examples of entries in the personality dictionary

written forms, and actual items used in the web survey commonly. The procedure and weights in each dictionary are explained in the next section.

PTW dictionary (323 entries): In addition to the common entries, this sub-dictionary includes the negative forms of each trait word and the following values per trait: standardized beta values, t-values for the betas, p-values for the betas, r squared, adjusted r squared, F values, and p-values for F-values for all five traits. The negative forms were annotated by a Japanese who holds an M.A. in psychology. Among the values, the standardized values are usable as weights, ranging from -1 to 1.

PRW dictionary (223 entries): We provide Pearson's correlation coefficients with raw scores of five traits as and when responses were obtained. The reclassified items from PTW to PRW are correlated with TDPI scores at Time 1. The other PRW items are correlated with TDPI scores at Time 2. The failure of the factor-structure replication is reasonable considering the classification standard of PRW. PRW items represent one aspect of personality, but they are actually insufficient for describing human personality only by themselves. Those interested in 本質 "*essence/nature*" of events or phenomena may have one similar aspect of personality, but it is difficult to identify what the personality trait is. The correlation coefficients range from very small such as 絵画 "*drawings*" to substantial 本質 such as "*essence/nature.*"

5. Discussion

In this section, we discuss the applicability of our dictionary, especially the PTW dictionary. Our dictionary will allow researchers to apply the resources to infer one's personality from behavior, cognition, perception, emotions, and polarity, in rather short spans compared with previous studies that predict authors' personality from certain volumes.

The Driving Behavior and Subjectivity Corpus (Iwai, Kumada, et al., 2019) is one example. It comprises 23,222 blog articles, which include human daily driving behaviors and their psychological states. It also includes substantial amounts of PTW. PTW entries appear 27,757 times. The example below indicates that the behavior in the first sentence is considered as 自分勝手だ "*selfish*," implying that the personality is disagreeable, disconscientious, and neurotic (weights = -.177, -.345, -.474, .318, -.122 for EX, AG, CO, NE, and OP, respectively).

> …車が、…直進車を妨害してる。…なぜかこういう***自分勝手な***運転手が増えるんだよなぁ。 *... a car, ..., is obstructing another straight traveling car. Somehow such **selfish** drivers increase.*

If computers know that a car obstructing another straight traveling car is *selfish* and disconscientious, computers can predict that the selfish driver causes similar disconscientious driving behaviors such as sudden turns at the corner of an intersection or lane changes without any signals. By using the personality dictionary and the Driving Behavior and Subjectivity corpus, we acquired social knowledge about personality and driving-related behavior (Iwai et al., 2020).

6. Conclusions

In this study, we developed a Japanese personality dictionary that comprises two sub-dictionaries, using psychological methods and statistical analyses. To the best of our knowledge, this is the first Japanese language resource developed based on theories and methodologies of personality psychology and has such weights. Furthermore, it is the only Japanese personality dictionary that is available for NLP researchers. The interests in human-machine interactions such as virtual agents, chat bots, and social robots are growing. Our dictionary and methodology will inspire those studying these fields. We are planning to make the developed dictionary available to the public through a website.

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