# Personality Estimation from Japanese Text

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## Abstract

We created a model to estimate personality trait from authors' text written in Japanese and measured its performance by conducting surveys and analyzing the Twitter data of 1,630 users. We used the Big Five personality traits for personality trait estimation. Our approach is a combination of category- and Word2Vec-based approaches. For the category-based element, we added several unique Japanese categories along with the ones regularly used in the English model, and for the Word2Vec-based element, we used a model called GloVe. We found that some of the newly added categories have a stronger correlation with personality traits than other categories do and that the combination of the category- and Word2Vec-based approaches improves the accuracy of the personality trait estimation compared with the case of using just one of them.

## 1 Introduction

There has been a growing interest in the analysis of text in social media. If you can determine the personality trait of a writer, you can apply the result to various purposes, such as how you should contact this person in the future and how you should advertise your products to them. However, most of these personality trait analyses have been done for English text only, with studies focusing on the Big Five (Yarkoni, 2010; McCrae and John, 1992; Golbeck et al., 2011), Needs (Yang and Li, 2013), and Values (Boyd et al., 2015; Chen et al., 2014). In this work, we analyze Japanese text to investigate the differences in personality trait analyses based on language by considering what kind of textual features in Japanese are relevant to personality trait, and report the results of our analysis on Big Five personality. Figure 1 shows the overview of our system for personality trait estimation. We perform a survey to determine personality trait while a crawler obtains the author's tweet data, as discussed in detail in Section 3. The survey results and tweet data are saved to a storage for later analysis. After a certain amount of data is gathered, we perform linguistic analysis on it and then calculate the correlation (relationship) between the analyzed data and the survey results, after which we can estimate the personality trait.

We discuss related work in Section 2, how we collected the training data in Section 3, our personality estimation model in Section 4, and the analysis results in Section 5. We conclude in Section 6 with a brief summary.

## 2 Related Work

Ever since the significance of the relationship between people's personality traits and the textual features of how they write or talk (Mairesse et al., 2007) became known, there have been attempts to analyze personality traits from written texts. Moreover, as some indices of personality traits (such as the Big Five model) have been standardized, workshops for shared tasks on computational personality recognition have been organized to evaluate features and learning techniques and even to compare the performances of systems for personality recognition on a common benchmark (Celli et al., 2013; Celli et al., 2014).

The Big Five model describes personality on the basis of five traits formalized as bipolar scales (Norman., 1963), namely:
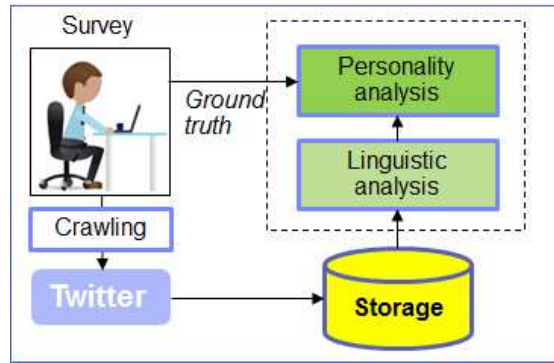
Figure 1: System overview of personality trait estimation model.

- **Agreeableness** (friendly vs. uncooperative)
- **Conscientiousness** (organized vs. careless)
- **Extraversion** (sociable vs. shy)
- **Neuroticism** (neurotic vs. calm)
- **Openness** (insightful vs. unimaginative)

Even though this Big Five model has been widely adopted on the global level, most of the personality recognition work has been conducted in English. Only a little work has been done on this area in the Japanese language, such as three papers written in Japanese (Fujikura et al., 2013; Okamoto et al., 2014; Okumura et al., 2015). This is problematic because the relationship between people's personality traits and textual features depends highly upon both language and cultural background. We therefore believe it is necessary to analyze the relationship in each language.

## 3   Collection of the Training Data

In order to determine the correlation between tweet data and the author's personality trait, we first performed a Web-based survey of personality trait diagnosis for authors having a certain amount of writing ($\geq$150 tweets) on Twitter (Fig. 1). Such surveys have previously been performed in English and Spanish, but we did this Japanese one separately, since the usage of the language, nationality, culture, and the like is so different. We announced our survey on our Facebook and home page as well as directly announcing the survey to Twitter users. The survey included a questionnaire for the Big Five Personality, Needs, and Values, including 50 questions for Big Five. The sources of the survey for Big Five and Values are (IPIP., 2016) and (Schwartz, 2003), respectively.

Values is typically defined as a network of ideas that a person views to be desirable and important (Boyd et al., 2015; Rokeach, 1973). This network, as developed by Schwartz (Schwartz, 1992; Schwartz, 2006; Schwartz, 2012), includes four high-level values (Self-transcendence, Conservation, Self-enhancement, Open to change) and ten values (Self-direction, Stimulation, Hedonism, Achievement, Power, Security, Conformity, Tradition, Benevolence, Universalism). Needs is typically defined as the relationship between human needs and the social value; it includes 12 profiles (Challenge, Closeness, Curiosity, Excitement, Harmony, Ideal, Liberty, Love, Practicality, Self-(expression), Stability, Structure) based on Kevin Ford's universal needs map (Ford, 2005).

Figure 2 shows examples of questions for Big Five, where respondents were asked to select one from "Strongly Agree", "Agree", "Neutral", "Disagree", or "Strongly Disagree". When the respondents completed the survey, they were provided with a quick personality diagnostic result, which functioned as an incentive for them to complete the survey. Figure 3 shows an example of the quick personality diagnostic result. Our system also collected respondents' tweet data and stored it for later analysis (Fig. 1). As these survey and tweet data include private data, they were securely stored and treated in our system so that they would not be exposed to the outside, and obviously they will not be published. We included a few dummy questions (e.g., the sixth question in Fig. 2) to exclude those who might have been answering

1. I am the life of the party.
2. I feel little concern for others.
3. I am always prepared.
4. I get stressed out easily.
5. I have a rich vocabulary.
6. Sorry, another question to make sure you are still reading these. Select "Agree" for this one.

Figure 2: Survey example.



**Big Five**

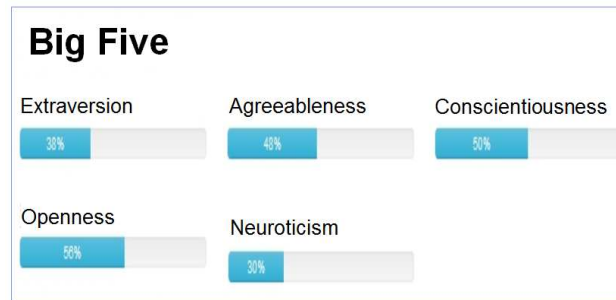| Extraversion | Agreeableness | Conscientiousness |
| 38% | 48% | 50% |

| Openness | Neuroticism |
| 56% | 30% |

Figure 3: An example of the quick personality diagnostic result shown after the respondent completes the survey.

without looking at the questions. We collected training data for Big Five from 1,630 persons ($n$=1,630). Distribution of respondents' ages was 6.4% (under 18), 42.6% (18–24), 29.6% (25–34), 20.1% (35–54), and 1.3% (55+). Gender ratio was 61.9% (Male) and 38.1% (Female). Figure 4 shows the distribution of (a) the number of words in all respondents' tweets per user, (b) the number of tweets per user, and (c) the average of number of words per tweet. The averages of (a), (b), and (c) are 26092.6, 1315.0, and 20.5, respectively.

## 4　Personality Estimation Model

Two approaches were utilized to realize the estimation of personality traits from user text: a category-based approach and a Word2Vec-based one.

### 4.1　Category–based

We categorized Japanese expressions by referring to the English Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2001). Among the 68 categories in the LIWC2001 dictionary, we excluded the *Article* category, as articles do not exist in the Japanese language, and *Fillers*, which can hardly be distinguished from *Non-fluencies*. For the remaining 66 categories, we defined corresponding Japanese expressions to create a dictionary that we call Japanese Categories for Personality Identification (JCPI). We also implemented a mechanism to identify the emergence of each expression in the text using the language processing function of the IBM Watson Explorer Advanced Edition Analytical Components V11.0 ("WEX" hereinafter) (Zhu et al., 2014). To create the JCPI, instead of simply translating English expressions in the LIWC2001 dictionary, we have defined appropriate expressions for each category in the LIWC2001 by taking the Japanese nationality and culture into consideration and created various new categories and subcategories on the basis of this.

First, from the psychological viewpoint considering Japanese culture, we added the following six categories:

- *Event* (such as "festival", "fireworks")
- *Relax* (such as "hot spring", "healing")
- *Move* (such as "train", "commuting")
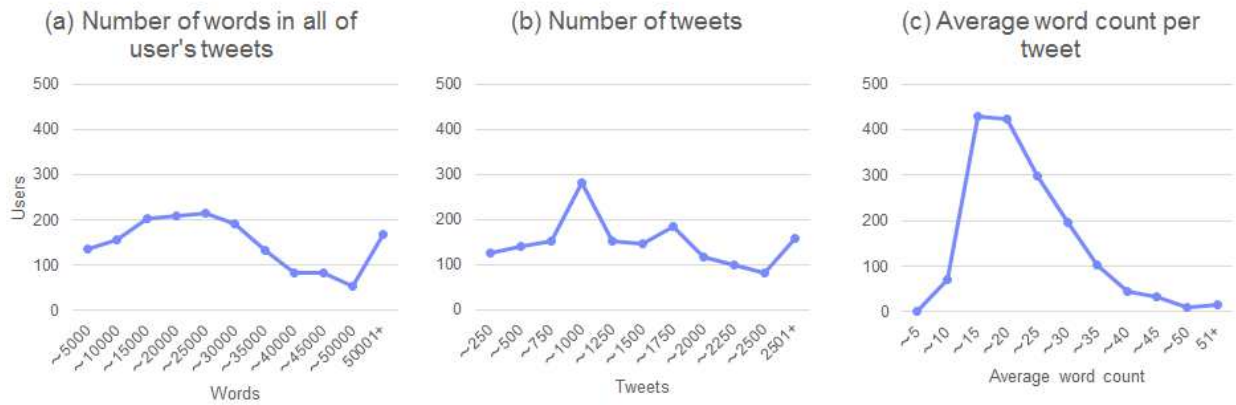- *Position Conversion* (such as "career change", "change")

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Figure 4: Statistical distribution data for survey respondents: (a) number of words in all a respondents' tweets, (b) number of tweets, (c) average word count per tweet.

- *Reading* (such as "read", "book")
- *Playing* (just "game" and "playing" only)

We also added the following four categories, including three Japanese-specific representations (excluding *Alphabet*):

- *Kanji* (Chinese character)
- *Hiragana* (cursive syllabary)
- *Katakana* (often used to express foreign proper nouns)
- *Alphabet*

Second, since Japanese does not have any *Prepositions*, we defined instead a *Particle* category for postpositional particles. Unlike in English, where word order plays an important role for indicating grammatical roles, as in the basic subject-verb-object pattern, word order in Japanese is flexible, and it is particles that play the more important role in terms of indicating the grammatical and semantic function of preceding words. In light of this importance of particles, we added the following subcategories:

- *Kakujoshi* (case markers: indicating subject, object, etc.)
- *Keijoshi* (binding particles: indicating inclusion, emphasis, etc.)
- *Fukujoshi* (adverbial particles: indicating degree, constraint, etc.)
- *Shuujoshi* (sentence-ending particles: indicating question, inhibition, etc.)

Finally, in the JCPI, we added the following subcategories to existing categories:

- To *Total_1st_person*: *Watashi* (such as "I" or "me", relatively formal), *Boku* (such as "I" or "me", relatively informal, mainly by boys), *Ore* (such as "I" or "me", informal, mainly by men)
- To *Causation*: *Good_causation* (such as "because of" or "achievements"), *Bad_causation* (such as "due to" or "caused by")
- To *Communication*: *Drinking_party* (such as "drinking" or "year-end party")
- To *Friends*: *Lover* (such as "boyfriend" or "girlfriend", relatively shallow relationship in Japan)
- To *Family*: *Children* (such as "son" or "daughter")
- To *Time*: *On_time* (such as "slow" or "late")

In all, we defined 89 categories including subcategories ($n_c$=89). The JCPI is not published, but part of it is discussed in (Yamamoto et al., 2016).

Table 1: Correlation between Big Five profiles and selected categories. *: newly added, *Italic*: $p < 0.01$, **bold**: $p < 0.001$.

|  | Kakujoshi* | Keijoshi* | Fukujoshi* | Drinking* | Hiragana* | Event* | Playing* | Motion | Job |
|---|---|---|---|---|---|---|---|---|---|
| **A** | **−0.128** | −0.071 | *−0.082* | 0.076 | −0.038 | **0.102** | **−0.148** | 0.053 | 0.059 |
| **C** | −0.037 | 0.027 | −0.029 | 0.076 | **−0.127** | 0.047 | *−0.084* | *0.082* | *0.088* |
| **E** | 0.018 | 0.007 | −0.059 | **0.128** | −0.026 | 0.062 | **−0.138** | *0.095* | **0.148** |
| **N** | **0.129** | **0.103** | −0.052 | **0.124** | −0.065 | −0.014 | *−0.086* | **0.166** | **0.155** |
| **O** | **0.257** | **0.178** | 0.014 | −0.048 | 0.014 | **−0.096** | 0.025 | 0.047 | 0.079 |

## 4.2 Word2Vec–based

We also used a vector representation of words (Word2Vec), since the category-based approach covers words and patterns that are relatively short, while Word2Vec is expected to cover up-to-date sentences relatively longer than what the category-based approach covers. For this purpose, we selected GloVe (Pennington et al., 2014), which was developed by Stanford University. GloVe is trained on aggregated global word-word co-occurrence statistics from a large corpus described in (Pennington et al., 2014), and the resulting representations capture semantic similarities and differences in the words by which we can keep up with the latest and emerging vocabulary on social media. In GloVe, we used only Japanese words whose lengths were between two and ten characters (taking the performance at the training stage into consideration) for 125,129 words in all, and used vectors whose dimensions were 200 ($n_w$=200). We did not convert the words into regular or formal expressions but used them as they are, since the words as they are, not the converted words, are better for expressing personality.

## 5 Analysis

For analysis, we used data from 1,630 Twitter users collected by means of a survey. We excluded retweets and URL addresses.

We analyzed the correlations between categories and personality in the category-based approach first, and then between words and personality in the Word2Vec-based approach, and finally we estimated overall performance accuracy.

### 5.1 Correlation and Matching Analysis

First we analyzed the correlation between categories and profiles. For each author $j$, we first performed a morphological analysis of $j$'s tweets using the WEX, counted the number of words/patterns included in each category $i$ used in $j$'s total tweets, and then divided each number by the number of words used in $j$'s total tweets (defined as $x_{ij}$) to obtain $\boldsymbol{x}_i = (x_{i1}, .., x_{in})^{\top}$, $i = 1, .., n_c$, where $^{\top}$ stands for Transpose. Also, we obtained a score vector, $\boldsymbol{s}_k = (s_{k1}, .., s_{kn})^{\top}$, where $s_{kj}$ ($0 \le s_{kj} \le 1$) is the ground truth score of $j$ for profile $k$ ($k = 1, .., n_s, n_s = 5$, which corresponds to Big Five file profiles) obtained from the survey. Then, we calculated Pearson's product-moment correlation coefficient ($r$), as well as $p$-value ($p$), between $\boldsymbol{x}_i$ and $\boldsymbol{s}_k$. Table 1 shows the $r$ and $p$ values for selected categories including newly added categories/subcategories and categories whose correlation ($|r|$) is larger in one of the profiles. Correlations that were statistically significant for $0.001 \le p < 0.01$ and $p < 0.001$ are in italics and bold, respectively. In Tables 1 and 2, **A**,**C**,**E**,**N**, and **O** stand for **Agreeableness**, **Conscientiousness**, **Extraversion**, **Neuroticism**, and **Openness**, respectively. From Table 1, we find the following:

- Subcategories of *Particle* (*Kakujoshi*, *Keijoshi*) have a strong relationship with **Agreeableness** (negatively), **Neuroticism** (positively), and **Openness** (positively). This suggests that agreeable people tend to be friendly and frank, so they often skip such formal particles, especially Kakujoshi. In contrast, neurotic people tend to be nervous and people who are open to experience tend to be highly educated, and both types rigidly use particles, even on social media platforms such as Twitter.
- *Drinking* has a strong positive relationship with **Extraversion** and **Neuroticism**. This suggests that extraverted people and neurotic people tend to drink, with others or alone.
- *Hiragana* has a strong negative relationship with **Conscientiousness**. This suggests that non-conscientious people tend to use Hiragana, which is often used for informal expressions.

| Length | Number of words | The ratio of words used at least once by each author | Most frequently used word (MFUW) | Meaning of the MFUW | The ratio of the MFUW being used at least once by each author |
|---|---|---|---|---|---|
| 10 | 3524 | 0.284 | ありがとうございまし | Part of formal "thank you" | 0.249 |
| 9 | 4683 | 0.387 | コミュニケーション | "Communication" | 0.108 |
| 8 | 7047 | 0.515 | になってしまった | "has become ..." | 0.106 |
| 7 | 10019 | 0.627 | と思ってたけど | "although I thought ..." | 0.086 |
| 6 | 14879 | 0.729 | かもしれない | "may be" | 0.091 |
| 5 | 19656 | 0.794 | とりあえず | "for now" | 0.091 |
| 4 | 26732 | 0.851 | なかった | "never been", "did not" | 0.074 |
| 3 | 22292 | 0.898 | なくて | "never", "not", etc. | 0.082 |
| 2 | 16297 | 0.933 | れる | Auxiliary verb for passive, active, possible, or respect | 0.123 |

Figure 5: Matching analysis between words in GloVe and in tweets.

- *Playing* has a strong negative relationship with **Agreeableness** and **Extraversion**. This suggests that non-agreeable or non-extraverted people tend to play indoor games alone. An important finding is that, although *Playing* includes just two words, 90% of the respondents (tweet authors) used either or both of the words in the *Playing* category at least once (not shown in table).

- *Job* has a strong positive relationship with **Extraversion** and **Neuroticism**. This suggests that extraverted people tend to discuss their working life with others and that neurotic people are worried about their jobs.

There are some prior works that examine the correlation between the LIWC categories and personality traits in English with a large dataset. For example, (Chen et al., 2014) used the data of 799 users on Reddit, a popular Web forum in the English-speaking world, to examine the correlations between LIWC categories and Values personality traits; the largest $|r|$ value was 0.184. Since the number of users is 1,630 in our case, it is not an accurate comparison, but still, these results are not much different from ours. Another example (Golbeck et al., 2011) used 50 users on Twitter data to study correlations between LIWC categories and Big Five personality traits, as well as to analyze its estimation performance. Its maximum $|r|$ value was 0.426, between **Openness** and *Work*, which is much larger than our case. However, the relative mean absolute (MAE) value for estimation performance with 10-fold cross validation was larger than our cases, as discussed in Section 5.2.

Next, we analyzed the matching between words in GloVe and in tweets. Figure 5 shows the number of words used for matching, the ratio of words used at least once by each author, the most frequently used word (MFUW), the meaning of the MFUW, and the ratio of the MFUW being used at least once by each author, for each length of the words in GloVe. From Fig. 5, we find the following:

- The ratio of words used at least once by each author simply increases as the word length decreases, and for length = 2, it is more than 90%, which is a very high ratio.

- The ratio of the MFUW being used at least once by each author is high even if the word length is long. This suggests that it does not depend on the length of the word but rather on what the word means. For example, the MFUW for the length of ten is a part of "thank you", which is frequently used in almost any circumstance.

## 5.2  Performance Analysis

Next, to examine the personality trait estimation accuracy of our model, we performed mean absolute error (MAE) and correlation (Corr) analysis to compare the trait scores calculated using our model with

Table 2: Performance comparison with (a) Category-based (new Japan-unique categories/subcategories only), (b) Category-based (All), (c) Word2Vec-based, and (d) Category-based + Word2Vec-based ((b)+(c)), average for each case, and mean and standard deviation of the survey scores.

| | (a) Category (JP) | | (b) Category (All) | | (c) Word2Vec | | (d) Category+W2V | | ZeroR | mean | sd |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | MAE | Corr | MAE | Corr | MAE | Corr | MAE | Corr | MAE | | |
| **A** | 0.1084 | 0.2003 | 0.1057 | 0.2958 | 0.1027 | 0.3278 | 0.1001 | 0.3602 | 0.1115 | 0.5792 | 0.1369 |
| **C** | 0.0977 | 0.1625 | 0.0962 | 0.2254 | 0.0941 | 0.2602 | 0.0939 | 0.2635 | 0.0999 | 0.4937 | 0.1248 |
| **E** | 0.1266 | 0.1682 | 0.1211 | 0.3227 | 0.1158 | 0.3862 | 0.1145 | 0.4005 | 0.1292 | 0.4791 | 0.1608 |
| **N** | 0.1220 | 0.2231 | 0.1186 | 0.3022 | 0.1147 | 0.3349 | 0.1122 | 0.3644 | 0.1258 | 0.3335 | 0.1572 |
| **O** | 0.1109 | 0.2719 | 0.1099 | 0.2591 | 0.1064 | 0.3067 | 0.1063 | 0.2817 | 0.1158 | 0.6225 | 0.1454 |
| Avg. | 0.1131 | 0.2052 | 0.1103 | 0.2810 | 0.1067 | 0.3231 | 0.1054 | 0.3341 | 0.1164 | 0.5016 | 0.1450 |

Table 3: Relative MAE comparison with (a) Category-based (new Japan-unique categories/subcategories only), (b) Category-based (All), (c) Word2Vec-based, (d) Category-based + Word2Vec-based , and Golbeck.

| | (a) Category (JP) | (b) Category (All) | (c) Word2Vec | (d) Category+W2V | Golbeck |
|---|---|---|---|---|---|
| **A** | 0.9715 | 0.9477 | 0.9213 | 0.8972 | 1.0053 |
| **C** | 0.9782 | 0.9630 | 0.9422 | 0.9401 | 0.9985 |
| **E** | 0.9804 | 0.9374 | 0.8968 | 0.8868 | 1.0000 |
| **N** | 0.9697 | 0.9428 | 0.9121 | 0.8921 | 0.9997 |
| **O** | 0.9577 | 0.9485 | 0.9183 | 0.9177 | 0.9999 |
| Avg. | 0.9715 | 0.9479 | 0.9181 | 0.9068 | 1.0008 |

the corresponding psychometric measures collected with the survey. Measurements were conducted for four cases:

(a) Category-based (newly added Japan-unique categories/subcategories only)
(b) Category-based (all categories/subcategories)
(c) Word2Vec-based
(d) Category-based + Word2Vec-based ((b) +(c))

For (a), we used just $\{\boldsymbol{x}_i | i \in \mathcal{C}_{new}\}$ for estimation, where $\mathcal{C}_{new}$ is the set of category numbers that belong to 24 categories and subcategories newly added for Japanese. For (b), we used all of the 89 categories and subcategories, i.e., $\{\boldsymbol{x}_1, .., \boldsymbol{x}_{n_c}\}$, for estimation. For (c), for each tweet, we counted the matched words from the longer ones in GloVe, created a vector for $j$ by weighting the $n_w$-dimensional GloVe vector by the count and dividing the coefficients of the vector by the number of words used in $j$'s total number of tweets, and obtained $\boldsymbol{y}_i = (y_{i1}, .., y_{in})^\top, i = 1, .., n_w$, where $y_{ij}$ is the coefficient for the $i$-th dimension of $j$. We then used $\{\boldsymbol{y}_1, .., \boldsymbol{y}_{n_w}\}$ for estimation. For (d), we used $\{\boldsymbol{x}_1, .., \boldsymbol{x}_{n_c}, \boldsymbol{y}_1, .., \boldsymbol{y}_{n_w}\}$ for estimation.

To estimate the score of each Big Five profile using the set of data described above for each case, we used a generalized linear regression model and performed 10-fold cross validation to calculate the MAE. Table 2 shows the results. In this table, "Corr" is the $r$ value between survey score and estimated score, and "ZeroR" is the MAE when the average of the survey scores is used as the estimated score for all users. Also, "mean" and "sd" are the average and standard deviation of the survey score data for each profile. These values are posted in the table as references.

The results shown in Table 2 yielded the following findings:

- Japan-unique (sub)categories were effective for estimating personality, especially for profiles that have a strong correlation with newly added (sub)categories. For example, in the case of **Openness**, the MAE of (a) was improved (reduced) 4.2% from ZeroR, and (b) improved only 0.95% from (a).
- By using all of the (sub)categories, the MAEs improved for all of the profiles, with 4.4% at maximum (**Extraversion**), compared with just using Japan-unique (sub)categories. This suggests that there is still room for improvement by using categories other than Japan-unique (sub)categories.
- The MAEs of the Word2Vec-based case were better (smaller) than those of the category-based for all of the profiles, with 4.3% at maximum (**Extraversion**), which suggests that Word2Vec covers

several words including up-to-date words that appear in the tweet data.

- Combining the category-based and Word2Vec-based approaches yielded the best result for all of the profiles, with a maximum improvement of 2.6% (**Agreeableness**) compared with the Word2Vec-based case.

In addition, we calculated the relative MAE, which is calculated as MAE/ZeroR, for each case and compared it with the case of (Golbeck et al., 2011). We used relative MAE for comparison since MAE and ZeroR values vary according to the dataset. Although the number of users was just 50 and the training algorithm is a Gaussian process in the Golbeck case, we find that ours had a more accurate performance (smaller relative MAE), even with (a).

## 6  Conclusion and Future Work

We analyzed the performance of personality estimation from category-based and Word2Vec-based approaches and found that, in Japanese, some personality traits are more highly correlated with how an author writes than what he or she writes. This is demonstrated by the fact that the *Particle* category, which is unique to Japanese, strongly correlates with several Big Five profiles. This is an important discovery because, since the Japanese language does not consider the grammatical order of words in a sentence, as English does, it is up to the authors to decide how formally and logically they write on social media, and this results in the usage of particles, which also exposes their personality traits. Moreover, not just the use of function words like particles but also the way of expressing content words in Hiragana characters is highly correlated with some personality traits. This is also a new aspect based on the characteristics of the Japanese language that we were able to find.

We also found that the Word2Vec-based approach performed better than the category-based approach, and that the combination of the two had the best estimation performance. We conclude that GloVe includes several longer words that are recently often used in tweets, and that the category-based approach covers other short words that Word2Vec-based does not. Also, we found that, when using a large data set ($n = 1,630$), the relative MAE values are smaller than those in a prior work in English, even when only Japan-unique categories.

As future work, we intend to further improve the estimation accuracy by adding and optimizing the categories as well as by optimizing Word2Vec. Also, in the present analysis, we found categories that are effective uniquely for Japanese and effective for English as well. By expanding this analysis, we aim to build a multi-language model that can be applied regardless of the languages.

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