Emotional Intensity Estimation based on Writer’s Personality

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Abstract

We propose a method for personalized emotional intensity estimation based on a writer’s personality test for Japanese text. Existing emotion analysis models are difficult to accurately estimate the writer’s subjective emotions behind the text. We personalize the emotion analysis using not only the text but also the writer’s personality information. Experimental results show that personality information improves the performance of emotional intensity estimation. Furthermore, a hybrid model combining the existing personalized method with ours achieved state-of-the-art performance.

1 Introduction

Emotional intensity estimation (Strapparava and Mihalcea, 2007; Bostan et al., 2020; Kajiwara et al., 2021) is one of the major challenges in the natural language processing community with many applications in dialogue systems (Tokuhisa et al., 2008) and social media mining (Stieglitz and Dang-Xuan, 2013). Emotional intensity estimation predicts the (often discretized) intensities of finer-grained emotions, such as Ekman’s basic emotions, i.e., joy, sadness, surprise, anger, fear, and disgust (Ekman, 1992) and Plutchik’s basic emotions, i.e., joy, sadness, expectation, surprise, anger, fear, disgust, and trust (Plutchik, 1980).

WRIME† (Kajiwara et al., 2021; Suzuki et al., 2022) is a corpus from Social Networking Service (SNS) text in Japanese for emotional intensity estimation. As exemplified in Table 1, the corpus adopts Plutchik’s basic emotions from both the writers’ (subjective) and the readers’ (objective) points of view. Their experimental results showed that estimating subjective emotion is more difficult than objective emotion. This fact renders an additional challenge to subjective emotional intensity estimation. That is, there can be a latent factor that modulates the superficial emotion perceived from the text per se.

A straightforward hypothesis to explain the difference is that the writer’s personality affects their writing. This hypothesis seems plausible as the same text can have different meanings depending on who wrote it, the contexts such as the writer’s preceding SNS text and the circumstance the writer is in; etc; the writer’s personality can influence all these aspects and can alter how they author text.

This hypothesis inspires us to design a model specialized for subjective emotion. The model uses the personality test result of each writer, which is fortunately included in the corpus. Specifically, given the personality test result, which is answers to 60 questions (Saito et al., 2001) based on the Big Five personality five-factor model (Goldberg, 1992), we embed 60 answers into a high-dimensional feature vector. Our model, shown in Figure 1 combines feature vectors from the SNS text and the personality to improve the estimation performance.

Figure 1: An overview of the proposed method.
I often have expectations for people I meet in real life, not on the web, and am a little disappointed due to overly high expectations. What should I do?

|          | Joy | Sadness | Anticipation | Surprise | Anger | Fear | Disgust | Trust |
|----------|-----|---------|--------------|----------|-------|------|---------|-------|
| Subjective | 0   | 3       | 0            | 0        | 0     | 0    | 0       | 0     |
| Objective A | 0   | 1       | 0            | 0        | 0     | 0    | 1       | 0     |
| Objective B | 0   | 1       | 2            | 0        | 0     | 0    | 0       | 0     |
| Objective C | 0   | 2       | 0            | 0        | 0     | 0    | 0       | 0     |
| BERT      | 0   | 1       | 1            | 0        | 0     | 0    | 3       | 0     |
| + Personality | 0   | 3       | 0            | 0        | 0     | 0    | 0       | 0     |

Why can’t people who work hard be rewarded for their efforts? It’s so frustrating.

|          | Joy | Sadness | Anticipation | Surprise | Anger | Fear | Disgust | Trust |
|----------|-----|---------|--------------|----------|-------|------|---------|-------|
| Subjective | 0   | 3       | 0            | 0        | 2     | 0    | 1       | 0     |
| Objective A | 0   | 2       | 0            | 0        | 0     | 2    | 2       | 0     |
| Objective B | 0   | 2       | 0            | 0        | 0     | 0    | 3       | 0     |
| Objective C | 0   | 3       | 0            | 0        | 0     | 0    | 0       | 0     |
| BERT      | 0   | 3       | 0            | 0        | 0     | 0    | 0       | 0     |
| + Personality | 0   | 3       | 0            | 0        | 2     | 0    | 3       | 0     |

Table 1: The upper rows of each table show examples of emotional intensity labels, consisting of subjective and objective ones, where three annotators (A–C) were invited for this sample (0: none, 1: weak, 2: medium, 3: strong). The lower part of each table shows the prediction results of the baseline model and our method.

Experimental results on the WRIME corpus show that our model performs better than both Bag-of-Words (BoW) and BERT (Devlin et al., 2019) baselines without personality information, which suggests the advantage of using writers’ personality information for subjective emotional intensity estimation. Furthermore, a hybrid model combining the existing personalized method (Milkowski et al., 2021) with ours achieved state-of-the-art performance in emotional intensity estimation. The performance is on par with the performance of our human annotators.

Personalized emotion analysis has been studied in recent years. Milkowski et al. (2021) personalized the emotion analysis by focusing on the labeling variation among annotators. They proposed Personal Emotional Bias (PEB) as a measure of labeling variation and showed that such user-specific information contributes to emotional intensity estimation. Kajiwara et al. (2021) personalized the emotion analysis by focusing on the personality of the text writer. They considered personality information based on the Big Five personality five-factor model (Goldberg, 1992) in a simple way (concatenation or attention) and showed that such user-specific information contributes to emotional intensity estimation. This study advances the latter approach and proposes a more effective method to model personality information for this task.

2 Related Work

Human emotions are subjective and have personal biases depending on many factors such as the first language, age, education (Wich et al., 2020; Al Kuwatly et al., 2020), gender (Bolukbasi et al., 2016; Tatman, 2017), race (Sap et al., 2019; Davidson et al., 2019), and personality (Kajiwara et al., 2021). Due to the nature of such personal biases, writers may express different emotions even if they wrote the same text (Milkowski et al., 2021; Ngo et al., 2022). Taking into account the emotional differences between writers is important for a high-quality emotional analysis.

3 Methods

As argued in Section 1, we hypothesize that the writer’s personality influences how they express themselves. We thus propose to leverage the personality of the writer as auxiliary information, especially for subjective emotional intensity estimation.

Figure 1 shows the overall structure of our model, which consists of the text stream and personality.
stream, fused together for estimating personality-aware emotional intensities. The text stream is the feature extractor of a basic emotional intensity estimation model, and the personality stream can also be seen as the feature extractor of regression model, trained to predict individual personality traits of the Big Five taxonomy (Goldberg, 1992).

3.1 Text Stream
Our text stream is a part of simple BERT pre-trained model (Devlin et al., 2019)-based emotional intensity classifiers. The 768-dimensional feature vector $h_t$ corresponding to [CLS] token is fed into a linear classifier for each emotion to predict one of the four-level intensities of the emotion (as in Table 1). We use $h_t$ as text features.

3.2 Personality Stream
The WRIME (Kajiwara et al., 2021; Suzuki et al., 2022) corpus provides a personality assessment result for each writer during the curation process. This personality assessment is based on the Big Five model (Goldberg, 1992), and our writers were asked to answer 60 questions related to talkativeness, anxiousness, etc. (Saito et al., 2001) over a seven-point scale. The answers are collectively mapped into continuous likeliness values (Big Five Scales) of the writer having the five personality traits (i.e., extraversion, neuroticism, openness, conscientiousness, and agreeableness).

For embedding a writer’s personality in a feature vector, we mimic the process of computing the likeliness values from the 60 answers using a 3-layer multilayer perceptron with a 60-dimensional input layer and a 5-dimensional output layer, as shown in Figure 2. The middle layer’s dimensionality is 768, which is the same as the output of BERT. We use the middle layer as personality feature $h_p$.

3.3 Fusion of Text and Personality Streams
The feature vectors $h_t$ and $h_p$ are fused for personality-aware emotional intensity estimation, where the dimensionality of the feature vectors are both $d = 768$. We exploratively evaluate the following four approaches for fusion.

1. **Difference** uses $h_{\text{diff}} = |h_t - h_p|$ as a fused vector. This approach retains the dimensionality of the fused vector $h$.

2. **Product** applies the element-wise multiplication $h_{\text{prod}} = h_t \odot h_p$. This approach retains the dimensionality of the fused vector $h$.

3. **Concatenation** is given by $h_{\text{conc}} = [h_t, h_p]$, where $[\cdot, \cdot]$ is the operator for concatenation. This approach doubles the fused vector’s dimensionality.

4. **All** concatenate all these fused vectors, i.e., $h_{\text{all}} = [h_{\text{diff}}, h_{\text{prod}}, h_{\text{conc}}]$. This approach results in a $4d$-dimensional fused vector.

For fusion approach $f \in \{\text{diff, prod, conc, all}\}$, emotional intensity is estimated by

$$y_e = \text{softmax}(W_e h_f + b_e), \quad (1)$$

where $y_e \in [0, 1]^4$ is the confidences of four intensity levels for emotion $e$ in Plutchik’s basic emotions (Plutchik, 1980), and $W_e \in \mathbb{R}^{4 \times D_f}$ and $b_e \in \mathbb{R}^4$ are parameters of the classifier for emotion $e$ ($D_f$ is size of fused vector for approach $f$).

4 Experiments
Using WRIME (Kajiwara et al., 2021; Suzuki et al., 2022), a corpus for estimating the emotion analysis in Japanese, we conduct an experiment to evaluate a four-class (i.e. none, weak, medium, and strong) classification of writers’ emotional intensity.

4.1 Setting
4.1.1 Dataset
For a fair comparison with the previous work (Młkowski et al., 2021), we first split 35,000 SNS posts by 60 writers into two parts: One is for training/evaluating the models, while the other is for computing the user representation in PEB. Following Młkowski et al. (2021), the latter part thus contains past 15% of SNS posts authored by each writer. The former is further split into training, validation, and evaluation sets. The training, validation, and evaluation sets respectively contain 25,500 posts from 40 writers, 2,125 posts from 10 writers, and 2,125

![Figure 2: Mapping from 60 answers to Big Five personality traits.](image-url)
Table 2: Quadratic weighted kappa of the writer’s subjective emotional intensity estimation.

|                | Joy  | Sadness | Anticipation | Surprise | Anger  | Fear   | Disgust | Trust | Overall |
|----------------|------|---------|--------------|----------|--------|--------|---------|-------|---------|
| BoW            | 0.307| 0.181   | 0.151        | 0.132    | 0.165  | 0.145  | 0.178   | 0.080 | 0.227   |
| + Difference   | 0.313| 0.206   | 0.164        | 0.144    | 0.151  | 0.117  | 0.168   | 0.108 | 0.229   |
| + Product      | 0.293| 0.233   | 0.139        | 0.145    | 0.164  | 0.154  | 0.200   | 0.037 | 0.231   |
| + Concat       | 0.294| 0.217   | 0.148        | 0.120    | 0.144  | 0.145  | 0.188   | 0.101 | 0.236   |
| + All          | 0.300| 0.231   | 0.169        | 0.111    | 0.167  | 0.108  | 0.178   | 0.097 | 0.230   |
| + Pc           | 0.292| 0.193   | 0.153        | 0.121    | 0.175  | 0.153  | 0.151   | 0.066 | 0.219   |
| + Pa           | 0.310| 0.192   | 0.130        | 0.121    | 0.138  | 0.093  | 0.180   | 0.067 | 0.213   |
| + PEB          | 0.329| 0.292   | 0.207        | 0.198    | 0.147  | 0.174  | 0.181   | 0.142 | 0.260   |
| + Personality (All) | 0.336| 0.312   | 0.199        | 0.200    | 0.147  | 0.185  | 0.249   | 0.115 | 0.281   |
| BERT           | 0.551| 0.419   | 0.352        | 0.341    | 0.375  | 0.302  | 0.431   | 0.206 | 0.437   |
| + Difference   | 0.559| 0.444   | 0.368        | 0.336    | 0.381  | 0.313  | 0.410   | 0.225 | 0.440   |
| + Product      | 0.573| 0.468   | 0.363        | 0.351    | 0.384  | 0.311  | 0.439   | 0.240 | 0.459   |
| + Concat       | 0.558| 0.453   | 0.332        | 0.331    | 0.359  | 0.303  | 0.433   | 0.222 | 0.444   |
| + All          | 0.573| 0.476   | 0.373        | 0.345    | 0.404  | 0.328  | 0.425   | 0.153 | 0.454   |
| + Pc           | 0.564| 0.443   | 0.377        | 0.316    | 0.358  | 0.290  | 0.403   | 0.243 | 0.438   |
| + Pa           | 0.560| 0.430   | 0.359        | 0.322    | 0.392  | 0.284  | 0.413   | 0.206 | 0.429   |
| + PEB          | 0.576| 0.455   | 0.377        | 0.336    | 0.421  | 0.327  | 0.429   | 0.198 | 0.451   |
| + Personality (All) | 0.588| 0.469   | 0.389        | 0.343    | 0.394  | 0.311  | 0.451   | 0.214 | 0.462   |
| Annotator 1    | 0.622| 0.461   | 0.423        | 0.348    | 0.363  | 0.333  | 0.394   | 0.089 | 0.439   |
| Annotator 2    | 0.633| 0.526   | 0.432        | 0.339    | 0.386  | 0.361  | 0.442   | 0.153 | 0.465   |
| Annotator 3    | 0.624| 0.450   | 0.459        | 0.396    | 0.374  | 0.380  | 0.467   | 0.134 | 0.463   |

posts from 10 writers. We employ quadratic weighted kappa\(^2\) (Cohen, 1968) as our evaluation metric, which assesses the agreement between the estimated and correct labels, considering the ordinal nature of our labels.

4.1.2 Implementation Details

For the text steam, we evaluated the two models.

- **BoW** extracts bag-of-words from a post and estimates emotional intensity by linear regression model. McCab (IPADIC-2.7.0)\(^3\) (Kudo et al., 2004) is used for word segmentation.

- **BERT** is a Japanese BERT\(^4\) (Devlin et al., 2019) with a structure of 12 layers, 12 attention heads, and 768 dimensions, pre-trained with mask language modeling objectives on 86 million Japanese Twitter posts.

The BoW model is implemented using scikit-learn\(^5\) (Pedregosa et al., 2011). The HuggingFace Transformers (Wolf et al., 2020) is used to implement the BERT model. BERT is fine-tuned using the cross entropy loss with the batch size of 32 posts and the dropout rate of 0.1. The learning rate is set to 2e-5 with the Adam optimizer (Kingma and Ba, 2015). Early stopping is used for training and training stops when the metric (quadratic weighted kappa) of the validation set does not improve for 3 epochs. For linear regressor of the BoW model is trained with the learning rate of 0.01.

Both BoW and BERT models are coupled with writers’ personality features in Section 3.2 by the four fusion approaches. For this personality embedding, the multilayer perceptron shown in Figure 2 with sigmoid activation is trained for 1,000 epochs with the SGD optimizer and the mean squared error loss.

4.1.3 Comparative Methods

We compare the following three existing methods with the proposed method.

- **Pc** (Kajiwara et al., 2021) uses \(h_c = W_c[u, v]\) as a feature vector, where \(v\) is a 768-dimensional textual representation corresponding to the \([\text{CLS}]\) token of BERT and \(u\) is a 786-dimensional personality representation computed by a linear mapping from the

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\(^2\)https://scikit-learn.org/stable/modules/generated/sklearn.metrics.cohen_kappa_score.html
\(^3\)https://taku910.github.io/mecab/
\(^4\)https://github.com/hottolink/hottoSNS-bert
\(^5\)https://scikit-learn.org/
5-dimensional Big Five personality traits. We use Equation (1) as classifier with replacing $h_f$ with $h_c$.

- **Pa** (Kajiwara et al., 2021) employs the scaled dot-product attention (Vaswani et al., 2017) as $h_a = \text{attention}(W^Q u, W^K v, W^V v)$ for feature extraction, so that textual representation corresponding to the $[\text{CLS}]$ token of BERT can be weighted based on the writer’s personality. Emotional intensity estimation is done in the same way as Pc but with $h_a$.

- **PEB** (Milkowski et al., 2021) extracts features by $h_{\text{PEB}} = W_{\text{PEB}}[z, v']$, where $v'$ is a textual representation given by linearly transforming $v$ into a 50-dimensional vector and $z$ is a user representation given by linear transformation of a 8-dimensional vector representing annotation for each emotion into a 50-dimensional vector. Again, Equation (1) is used with $h_{\text{PEB}}$ for emotional estimation.

### 4.2 Results

Table 2 shows the experimental results. The scores are the average of quadratic weighted kappa values over three training runs, where we trained the models five times with different parameter initialization and excluded the maximum and minimum kappa values. The table is divided into three blocks: The top two are for the emotional intensity estimation models, while the bottom block shows the human performance of three annotators in the WRIME corpus (Kajiwara et al., 2021; Suzuki et al., 2022). Note that these annotators do not know the writer’s personality or past posts.

Compared to the BoW model, the BERT model consistently achieves higher performance. This is a reasonable result for two reasons: feature extraction with BoW cannot take context into account, and BoW does not have the benefit of a large-scale corpus such as the one used for pre-training BERT.

The proposed methods showed improvement in many emotions compared to the baseline model, which does not take the writer’s personality into account. Our Difference method improved performance on five out of eight emotions for BoW and on six emotions for BERT. Our Product method improved performance on half of the eight emotions for BoW and consistently improved performance on all emotions for BERT. While our Concat method only improved performance on three out of eight emotions for BoW, it improved on five emotions for BERT. Our All method improved performance on half of the eight emotions for BoW and on six emotions for BERT. Furthermore, the proposed methods consistently improved performance in the overall evaluation. These experimental results confirm the effectiveness of the proposed methods for estimating subjective emotional intensity with the writer’s personality information.

Next, we discuss the results of a comparison of the proposed and existing methods. The existing methods for Pc and Pa (Kajiwara et al., 2021) did not show significant improvement from each baseline model in the overall evaluation in this experimental setting. Although these existing methods utilize the writer’s personality similar to our method, they differ in the method for feature extraction from the personality information. In contrast, our methods consistently improved performance in the overall evaluation.

Another existing method, PEB (Milkowski et al., 2021), achieves higher performance than our methods for BoW and comparable performance to our methods for BERT in the overall evaluation. Because our method, which takes into account the personality of the writer, and PEB, which takes into account labeling variations, take different approaches to personalize emotional intensity estimation, we can expect synergies from their combination. The bottom methods in Table 2, using $h_{\text{hybrid}} = [h_{\text{diff}}, h_{\text{prod}}, h_{\text{conc}}, h_{\text{PEB}}]$ instead of $h_f$, achieved the best performance for both BoW and BERT models in the overall evaluation. Furthermore, BERT with both writer’s personality and PEB achieved performance comparable to the human annotators in the overall evaluation. These experimental results demonstrate the usefulness of personality information in emotional intensity estimation and the effectiveness of our feature extraction method from the personality test.

The bottom row of each table in Table 1 shows examples of output from our model. By taking into account the personality of the writer, we succeeded in emphasizing the emotional intensity of sadness in the upper example and anger in the lower example, respectively. In the personality test, these writers answered strongly to the questions “pessimistic” and “irascible,” respectively.
5 Conclusions

To improve the performance of estimating subjective emotional intensity by writers, we propose an emotional intensity estimation model that takes into account the writer’s personality information. In the proposed method, we first extracted feature representations from the results of a personality test based on the Big Five personality five-factor model. Then, we fused that personality features with textual features from BoW or BERT to personalize the emotional intensity estimation. Experimental results on subjective emotional intensity estimation in Japanese SNS text reveal the effectiveness of the proposed methods in taking into account the personality of the writer.

Currently, our method requires writers to answer a 60-item personality test. Therefore, our future work includes studying methods for estimating the writer’s personality from their past posts, and how to combine them with the present method.

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