A Language-independent and Compositional Model for Personality Trait Recognition from Short Texts

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Abstract

Many methods have been used to recognise author personality traits from text, typically combining linguistic feature engineering with shallow learning models, e.g. linear regression or Support Vector Machines. This work uses deep-learning-based models and atomic features of text – the characters – to build hierarchical, vectorial word and sentence representations for trait inference. This method, applied to a corpus of tweets, shows state-of-the-art performance across five traits and three languages (English, Spanish and Italian) compared with prior work in author profiling. The results, supported by preliminary visualisation work, are encouraging for the ability to detect complex human traits.

1 Introduction

Techniques falling under the umbrella of “deep-learning” are increasingly commonplace in the space of Natural Language Processing (NLP) (Manning, 2016). Such methods have been applied to a number of tasks from part-of-speech tagging (Ling et al., 2015; Huang et al., 2015) to sentiment analysis (Socher et al., 2013; Kalchbrenner et al., 2014; Kim, 2014). Essentially, each of these tasks is concerned with learning representations of language at different levels. The work we outline here is no different in essence, though we choose perhaps the highest level of representation – that of the author of a given text rather than the text itself. This task, modelling people from their language, is one built on the long-standing foundation that language use is known to be influenced by sociodemographic characteristics such as gender and personality (Tannen, 1990; Pennebaker et al., 2003). The study of personality traits in particular is supported by the notion that they are considered temporally stable (Matthews et al., 2003), and thus our modelling ability is enriched by the acquisition of more data over time.

Computational personality recognition, and its broader applications, is becoming of increasing interest with workshops exploring the topic (Celli et al., 2014; Tkalčić et al., 2014). The addition of personality traits in the PAN Author Profiling challenge at CLEF in 2015 (Rangel et al., 2015) is further evidence. Much prior literature in this field has used some variation of enriched bag-of-words; e.g. the Open vocabulary approach (Schwartz et al., 2013). This is understandable as exploring the relationship between word use and traits has delivered significant insight into aspects of human behaviour (Pennebaker et al., 2003). Different levels of representation of language have been used such as syntactic, semantic, and higher-order such as the psychologically-derived lexica of the Linguistic Inquiry and Word Count (LIWC) tool (Pennebaker et al., 2015).

One drawback of this bag-of-linguistic-features approach is that considerable effort can be spent on feature engineering. Moreover, such linguistic features are mostly language-dependent, such as LIWC (Pennebaker et al., 2015), making the adoption to multi-lingual models more time-consuming. Another issue is an unspoken assumption that these features, like the traits to which they relate, are similarly stable: the same language features always indicate the same traits. However, this is not the case. As Nowson and Gill (2014) have shown, the relationship between language and personality is not consistent across all forms of communication the relationship is more complex.

In order to better explore this complexity in this work we propose a novel deep-learning feature-engineering-free modelisation of the problem of
personality trait recognition, making the model language independent and enabling it to work in various languages without the need to create language-specific linguistic features. The task is framed as one of supervised sequence regression based on a joint atomic representation of the text: specifically on the character and word level. In this context, we are exploring short texts. Typically, classification of such texts tends to be particularly challenging for state-of-the-art BoW based approaches due, in part, to the noisy nature of such data (Han and Baldwin, 2011). To cope with this we propose a novel recurrent and compositional neural network architecture, capable of constructing representations at character, word and sentence level. We believe a latent representation inference based on a parse-free input representation of the text seen as a sequence of characters can balance the bias and variance of such sparse dataset.

The paper is structured as follows: after we consider previous approaches to the task of computational personality recognition, including those which have a deep-learning component, we describe our model. We report on two sets of experiments, the first of which demonstrates the effectiveness of the model in inferring personality for users, while the second reports on the short text level analysis. In both settings, the proposed model achieves state-of-the-art performance across five personality traits and three languages.

2 Related Work

Early work on computational personality recognition (Argamon et al., 2005; Nowson and Oberlander, 2006) used SVM-based approaches and manipulated lexical and grammatical feature sets. Today, according to the organisers (Rangel et al., 2015) “most” participants to the PAN 2015 Author Profiling task still use a combination of SVM and feature engineering. Data labelled with personality data is sparse (Nowson and Gill, 2014) and there has been more interest in reporting novel feature sets. In the PAN task alone¹ there were features used from multiple levels of representation on language. Surface forms were present in word, lemma and character n-grams, while syntactic features included POS tags and dependency relations. There were some efforts of feature curation, such as analysis of punctuation and emoticon use, along with the use of latent semantic analysis for topic modelling. Another popular feature set is the use of external resources such as LIWC (Pennebaker et al., 2015) which, in this context, represents over 20 years of psychology-based feature engineering. When applied to tweets, however, LIWC requires further cleaning of the data (Kreindler, 2016).

Deep-learning based approaches to personality trait recognition are, unsurprisingly given the typical size of data sets, relatively few. The model detailed in Kalghatgi et al. (2015) presents a neural network based approach to personality prediction of users. In this model, a Multilayer Perceptron (MLP) takes as input a collection of hand-crafted grammatical and social behavioral features from each user and assigns a label to each of the 5 personality traits. Unfortunately no evaluation of this work, nor details of the dataset, were provided. The work of Su et al. (2016) describes a Recurrent Neural Network (RNN) based system, exploiting the turn-taking of conversation for personality trait prediction. In their work, RNNs are employed to model the temporal evolution of dialog, taking as input LIWC-based and grammatical features. The output of the RNNs is then used for the prediction of personality trait scores of the participants of the conversations. It is worth noting that both works utilise hand-crafted features which rely heavily on domain expertise. Also the focus is on the prediction of trait scores on the user level given all the available text from a user. In contrast, not only can the approach presented in this paper infer the personality of a user given a collection of short texts, it is also flexible to predict trait scores from a single short text, arguably a more challenging task considering the limited amount of information.

The model we present in Section 3.2 is inspired by Ling et al. (2015), who proposed a character-level word representation learning model under the assumption that character sequences are syntactically and semantically informative of the words they compose. Based on a widely used RNN named long short-term memory network (LSTM) (Hochreiter and Schmidhuber, 1997), the model learns the embeddings of characters and how they can be used to construct words. Topped by a softmax layer at each word, the model was applied to the tasks of language modelling and part-of-speech tagging and successful in improving upon traditional baselines particularly in morphologically rich languages. Inspired by this,
Yang et al. (2016) introduced Hierarchical Attention Networks where the representation of a document is hierarchically built up. They construct the representation of a sentence by processing a sequence of its constituent words using a bi-directional gated recurrent unit (GRU) (Cho et al., 2014). The representations of sentences are in turn processed by another bi-directional GRU at the sentence level to form the representation of the document. The work of (Ling et al., 2015) provides a way to construct words from their constituent characters (Character to Word, C2W) while Yang et al. (2016) describe a hierarchical approach to building representations of documents from words to sentences, and eventually to documents (Word to Sentence to Document, W2S2D). In this work, inspired by the above works, we present a hierarchical model situated between the above two models, connecting characters, words and sentences, and ultimately personality traits (Character to Word to Sentence for Personality Trait, C2W2S4PT).

3 Proposed Model

To motivate our methodology, we review a commonly-used approach to representing sentences and discuss some of its limitations and motivation. Then, we propose the use of a compositional model to tackle the identified problems.

3.1 Current Issues and Motivation

One classical approach for applying deep learning models to NLP problems involves word lookup tables where words are typically represented by dense real-valued vectors in a low-dimensional space (Socher et al., 2013; Kalchbrenner et al., 2014; Kim, 2014). In order to obtain a sensible set of embeddings, a common practice is to train on a large corpus in an unsupervised fashion, e.g. Word2Vec (Mikolov et al., 2013a; Mikolov et al., 2013b) and GloVe (Pennington et al., 2014). Despite the success in capturing syntactic and semantic information with such word vectors, there are two practical problems with such an approach (Ling et al., 2015). First, due to the flexibility of language, previously unseen words are bound to occur regardless of how large the unsupervised training corpus is. The problem is particularly serious for text extracted from social media platforms such as Twitter and Facebook due to the noisy nature of user-generated text – e.g. typos, ad hoc acronyms and abbreviations, phonetic substitutions, and even meaningless strings (Han and Baldwin, 2011). A naive solution is to map all unseen words to a vector UNK representing the unknown word. Not only does this approach give up critical information regarding the meaning of the unknown words, it is also difficult for the model to generalise to made up words, such as beautification, despite the components beautiful and -ification having been observed. Second, the number of parameters for a model to learn is overwhelmingly large. Assume each word is represented by a vector of \(d\) dimensions, the total size of the word lookup table is \(d \times |V|\) where \(|V|\) is the size of the vocabulary which tends to scale to the order of hundreds and thousands. Again, this problem is even more pronounced in noisier domain such as short text generated by online users. To address the above issues, we adopt a compositional character to word model described in the next section.

From the personality perspective, character-based features have been widely adopted in trait inference, such as character n-grams (González-Gallardo et al., 2015; Sulea and Dichi, 2015), emoticons (Nowson et al., 2015; Palomino-Garibay et al., 2015), and character flooding (Nowson et al., 2015; Giménez et al., 2015). Motivated by this and the issues identified above, we propose in the next section a language-independent compositional model that operates hierarchically at the character, word and sentence level, capable of harnessing personality-sensitive signals buried as deep as the character level.

3.2 Character to Word to Sentence for Personality Traits

To address the problems identified in Section 3.1 we propose to extend the compositional character to word model first introduced by Ling et al. (2015) wherein the representation of each word is constructed, via a character-level bi-directional RNN (Char-Bi-RNN), from its constituent characters. The constructed word vectors are then fed to another layer of word-level Bi-RNN (Word-Bi-RNN) and a sentence is represented by the concatenation of the last and first hidden states of the forward and backward Word-RNNs respectively. Eventually, a feedforward neural network takes as input the representation of a sentence and returns a scalar as the prediction for a specific personal-
ity trait. Thus, we name the model C2W2S4PT (Character to Word to Sentence for Personality Traits) which is illustrated in Figure 1. Specifically, suppose we have a sentence $s$ consisting of a sequence of words \( \{w_1, w_2, \ldots, w_i, \ldots, w_m\} \). We define a function $c(w_i, j)$ which takes as input a word $w_i$, together with an index $j$ and returns the one-hot vector representation of the $j$th character of the word $w_i$. Then, to get the embedding $c_{i,j}$ of the character, we transform $c(w_i, j)$ by: $c_{i,j} = E_c(c(w_i, j))$ where $E_c \in \mathbb{R}^{d \times |C|}$ and $|C|$ is the size of the character vocabulary.

Next, in order to construct the representation of $w_i$, the sequence of character embeddings $\{c_{i,1}, \ldots, c_{i,n}\}$ is taken as input to the Char-Bi-RNN (assuming $w_i$ is comprised of $n$ characters). In this work, we employ GRU as the recurrent unit.

In this work, we employ GRU as the recurrent unit in the Bi-RNNs, given that recent studies indicate GRU achieves comparable, if not better, results to LSTM (Chung et al., 2014; Kumar et al., 2015; Jozefowicz et al., 2015). Concretely, the forward pass of the Char-Bi-RNN is carried out using the following:

$$
\tilde{z}^c_{i,j} = \sigma(W^c_{z} \cdot c_{i,j} + U^c_{hz} \cdot \tilde{h}^c_{i,j-1} + b^c) 
$$

(1)

$$
\tilde{r}^c_{i,j} = \sigma(W^c_{r} \cdot c_{i,j} + U^c_{hr} \cdot \tilde{h}^c_{i,j-1} + b^r) 
$$

(2)

$$
\tilde{h}^c_{i,j} = \tanh(W^c_{h} \cdot c_{i,j} + \tilde{r}^c_{i,j} \odot U^c_{hh} \cdot \tilde{h}^c_{i,j-1} + b^h) 
$$

(3)

$$
\tilde{h}^c_{i,j} = \tilde{z}^c_{i,j} \odot \tilde{h}^c_{i,j-1} + (1 - \tilde{z}^c_{i,j}) \odot \tilde{h}^c_{i,j} 
$$

(4)

where $\odot$ is the element-wise product, $W^c_{z}, W^c_{r}, W^c_{h}, U^c_{hz}, U^c_{hr}, U^c_{hh}$ are the parameters for the model to learn, and $b^c, b^r, b^h$ the bias terms. The backward pass, the hidden state of which is symbolised by $\tilde{h}^c_{i,j}$, is performed similarly, although with a different set of GRU weight matrices and bias terms. It should be noted that both the forward and backward Char-RNN share the same character embeddings. Ultimately, $w_i$ is represented by the concatenation of the last and first hidden states of the forward and backward Char-RNNs: $e_{w_i} = [\tilde{h}^c_{i,n}, \tilde{h}^c_{i,1}]^T$. Once all the word representations $e_{w_i}$ for $i \in [1, n]$ have been constructed from their constituent characters, they are then processed by the Word-Bi-RNN, similar to Char-Bi-RNN but on word level with word rather than character embeddings:

$$
\tilde{z}^w_i = \sigma(W^w_z e_{w_i} + \tilde{U}^w_{hz} \tilde{h}^w_{i-1} + b^w) 
$$

(5)

$$
\tilde{r}^w_i = \sigma(W^w_r e_{w_i} + \tilde{U}^w_{hr} \tilde{h}^w_{i-1} + b^r) 
$$

(6)

$$
\tilde{h}^w_i = \tanh(W^w_h e_{w_i} + \tilde{r}^w_i \odot \tilde{U}^w_{hh} \tilde{h}^w_{i-1} + b^h) 
$$

(7)

$$
\tilde{h}^w_i = \tilde{z}^w_i \odot \tilde{h}^w_{i-1} + (1 - \tilde{z}^w_i) \odot \tilde{h}^w_i 
$$

(8)

where $W^w_z, W^w_r, W^w_h, \tilde{U}^w_{hz}, \tilde{U}^w_{hr}, \tilde{U}^w_{hh}$ are the parameters for the model to learn, and $b^w, b^r, b^h$ the bias terms. In a similar fashion to how a word is represented, we construct the sentence embedding by concatenation: $e_s = [\tilde{h}^w_m, \tilde{h}_y]^T$. Lastly, to estimate the score for a particular personality trait, we top the Word-Bi-RNN with an MLP which takes as input the sentence embedding $e_s$ and returns the estimated score $\hat{y}_s$:

$$
\hat{y}_s = W_{hy} e_s + b_y 
$$

(9)

$$
\hat{y}_s = \max(0, W_{eh} e_s + b_h) 
$$

(10)

where ReLU is the REctified Linear Unit defined as $\text{ReLU}(x) = \max(0, x)$. $W_{eh}, W_{hy}$ the parameters for the model to learn, $b_h, b_y$ the bias terms, and $h_s$ the hidden representation of the MLP. All the components in the model are jointly trained with mean square error being the objective function:

$$
L(\theta) = \frac{1}{n} \sum_{i=1}^{n} (y_{s_i} - \hat{y}_{s_i})^2 
$$

(11)

where $y_{s_i}$ is the ground truth personality score of sentence $s_i$ and $\theta$ the collection of all embedding and weight matrices and bias terms for the model to learn. Note that no language-dependent component is present in the proposed model.

4 Experiments and Results

We report two sets of experiments: the first a comparison at the user level between our feature-engineering-free and language-independent approach and current state-of-the-art models which rely on linguistic features; the second designed to evaluate the performance of the proposed model against other feature-engineering-free approaches on individual short texts. We show that in both settings, i.e., against models with or without feature engineering, our proposed model achieves better results across two languages (English and Spanish) and is equally competitive in Italian.
4.1 Dataset and Data Preprocessing

We use the English, Spanish and Italian data from the PAN 2015 Author Profiling task dataset (Rangel et al., 2015), collected from Twitter and consisting of 14,166 English (EN), 9,879 Spanish (ES) and 3,687 Italian (IT) tweets (from 152, 110 and 38 users respectively). Due to space constraints and the limited size of the data, the Dutch dataset is not included. For each user there is a set of tweets (average \( n = 100 \) and gold standard personality labels. The five trait labels, scores between -0.5 and 0.5, are calculated following the author’s self-assessment responses to the short Big 5 test, BFI-10 (Rammstedt and John, 2007) which is the most widely accepted and exploited scheme for personality recognition and has the most solid grounding in language (Poria et al., 2013).

In our experiments, each tweet is tokenised using Twokenizer (Owoputi et al., 2013), in order to preserve hashtag-preceded topics and user mentions. Unlike the majority of the language used in a tweet, URLs and mentions are used for their targets, and not their surface forms. Therefore each text is normalised by mapping these features to single characters (e.g., \( @\text{username} \to @ \), \( \text{http://t.co/} \to \)). Thus we limit the risk of modelling, say, character usage which was not directly influenced by the personality of the author.

4.2 Evaluation Method

Due to the unavailability of the test corpus – withheld by the PAN 2015 organisers – we compare the \( k \)-fold cross-validation performance (\( k = 5 \) or 10) on the available dataset. Performance is measured using Root Mean Square Error (RMSE) on either the tweet level or user level depending on the granularity of the task:

\[
\text{RMSE}_{\text{tweet}} = \sqrt{\frac{\sum_{i=1}^{T} (y_{i,s} - \hat{y}_{i,s})^2}{n}}
\]

and

\[
\text{RMSE}_{\text{user}} = \sqrt{\frac{\sum_{i=1}^{U} (y_{i,s} - \hat{y}_{i,s})^2}{n}}
\]

where \( T \) and \( U \) are the total numbers of tweets and users in the corpus, \( y_{i,s} \) and \( \hat{y}_{i,s} \) the true and estimated personality trait score of the \( i \)-th tweet, similarly \( y_{user,i} \) and \( \hat{y}_{user,i} \) are their user-level counterparts. Each tweet in the dataset inherits the same five trait scores as assigned to the author from whom they were drawn. \( \hat{y}_{user,i} = \frac{1}{T_i} \sum_{j=1}^{T_i} \hat{y}_{j,s} \) where \( T_i \) refers to the total number of tweets of user \( i \).

In Section 4.3 and Section 4.4, we present the results measured at the user and tweet level using \( \text{RMSE}_{\text{user}} \) and \( \text{RMSE}_{\text{tweet}} \) respectively. It is important to note that, to enable direct comparison, we use exactly the same dataset and evaluation metric \( \text{RMSE}_{\text{user}} \) as in the works of (Sulea and Dichiù, 2015; Mirkin et al., 2015; Nowson et al., 2015).

4.3 Personality Trait Prediction at User Level

We test the proposed models on the dataset described in Section 4.1 and train our model to predict the personality trait scores based purely on the text without additional features supplied. To demonstrate the effectiveness of the proposed model, we evaluate the performance on the user level against models incorporating linguistic and psychologically motivated features. This allows us to directly compare the performance of current state-of-the-art models and C2W2S4PT. For 5-fold cross-validation, we compare to the tied-highest ranked (under evaluation conditions in EN, ranked 7th and 4th in ES and IT) of the PAN.
dropout rate to the embedding output: 0

On CON in ES, soundness of the approach. Without any hand-crafted features, underlining the ability (the inverse of Neuroticism), Agreeableness, are abbreviations for Extroversion, Emotional Stability (the inverse of Neuroticism), Agreeableness, Conscientiousness and Openness respectively.

**C2W2S4PT outperforms the current state of the art in EN and ES** In the 5-fold cross-validation group, C2W2S4PT is superior to the baselines, achieving better performance except for CON in ES. In terms of the performance measured by 10-fold cross-validation, the dominance of the proposed model is even more pronounced with C2W2S4PT outperforming the two selected baseline systems across all personality traits. Overall, in comparison to the previous state-of-the-art models in both groups, C2W2S4PT not only outperforms them, by a significant margin in the case of 10-fold cross-validation, but it also achieves so without any hand-crafted features, underlining the soundness of the approach.

**On CON in ES, 5-fold cross-validation** We suspect that the surprisingly good performance of Sulea and Dichiu (2015) may likely be attributed to overfitting. Indeed, the performance on the test set on CON in ES is even inferior to Nowson et al. (2015), further confirming our speculation.

The superiority of C2W2S4PT is less clear in IT This can possibly be caused by the inadequate amount of Italian data, less than 4k tweets as compared to 14k and 10k in the English and Spanish datasets, limiting the capability of C2W2S4PT to learn a reasonable model.

### 4.4 Personality Trait Prediction at Single Tweet Level

Although user-level evaluation is the common practice, we choose tweet-level performance to study the models’ capabilities to infer personality at a lower granularity level. To support our evaluation, a number of baselines were created. To facilitate fair comparison, the only feature used is the surface form of the text. Average Baseline assigns the average of all the scores to each tweet. Also, two BoW systems, namely, Random Forest and SVM Regression, have been implemented for comparison. For these two BoW-based baseline systems, we perform grid search to find the best hyper-parameter configuration. For SVM Regression, the hyper-parameters include: kernel ∈ {linear, rbf} and C ∈ {0.01, 0.1, 1.0, 10.0} whereas for Random Forest, the number of trees is chosen from the set {10, 50, 100, 500, 1000}.

Additionally, two simpler RNN-based models, namely Bi-GRU-Char and Bi-GRU-Word, which only work on character and word level respectively but share the same structure of the final MLP classifier (hₙ and ̂yₙ), have also been presented in contrast to the more sophisticated character to word compositional model C2W2S4PT. For training, C2W2S4PT inherits the same hyper-parameter configuration as described in Section 4.3. For Bi-GRU-Char and Bi-GRU-Word, we set the character and word embedding size to 50 and 256 respectively. Due to time constraints, we did not perform hyper-parameter fine-tuning for the RNN-based models and C2W2S4PT. The \( RMSE_{\text{tweet}} \) of each effort, measured by 10-fold stratified cross-validation, is shown in Table 2.

**C2W2S4PT achieves comparable or better performance with SVM Regression and Random Forest in EN and ES** C2W2S4PT is state of the art in almost every trait with the exception of AGR in EN and STA in ES. This demonstrates that C2W2S4PT generates at least reasonably comparable performance with SVM Regression and Random Forest in the feature-engineering-free setting on the tweet
level and it does so without exhaustive hyper-parameter fine-tuning.

**C2W2S4PT outperforms the RNN-based baselines in EN and ES** This success can be attributed to the model’s capability of coping with arbitrary words while not forgetting information due to excessive lengths as can arise from representing a text as a sequence of characters. Also, given that C2W2S4PT does not need to maintain a large vocabulary embedding matrix as in Bi-GRU-Word, there are much fewer parameters for the model to learn (Ling et al., 2015), making it less prone to overfitting.

The performance of C2W2S4PT is inferior to Bi-GRU-Word in IT Bi-GRU-Word achieves the best performance across all personality traits with C2W2S4PT coming in as a close second and tying in 3 traits. Apart from the inadequate amount of Italian data causing the fluctuation in performance as explained in Section 4.3 further investigation is needed to analyse the strong performance of Bi-GRU-Word.

### 4.5 Visualisation

To further investigate into the learned representations and features, we choose the C2W2S4PT model trained on a single personality trait and visualise the sentences with the help of PCA (Tipping and Bishop, 1999). We also experimented with t-SNE (Van der Maaten and Hinton, 2008) but it did not produce an interpretable plot. 100 tweets have been randomly selected (50 tweets each from either end of the EXT spectrum) with their representations constructed by the model. Figure 2 shows the scatter plot of the representations of the sentences reduced to a 2D space by PCA for the trait of Extraversion (EXT), selected as it is the most commonly studied and well understood trait. The figure shows clusters of both positive and negative Extraversion, though the former intersect the latter. For discussion we consider three examples as highlighted in Figure 2:

- **POS7:** “@username: Feeling like you’re not good enough is probably the worst thing to feel.”
- **NEG3:** “Being good ain’t enough lately.”
- **POS20:** “O.O Lovely.”

The first two examples (POS7 and NEG3) are drawn from largely distinct areas of the distribution. In essence the semantics of the short texts are the same. However, they both show linguistic attributes commonly understood to relate to Extraversion (Gill and Oberlander, 2002): POS7

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| Lang. | k | Model | EXT | STA | AGR | CON | OPN |
|-------|---|-------|-----|-----|-----|-----|-----|
| EN    | 5 | Average Baseline | 0.166 | 0.223 | 0.158 | 0.151 | 0.146 |
|       |   | Sulea and Dichiu (2015) | 0.136 | 0.183 | 0.141 | 0.131 | 0.119 |
|       |   | C2W2S4PT | 0.131 | 0.171 | 0.140 | 0.124 | 0.109 |
|       | 10 | Mirkin et al. (2015) | 0.171 | 0.223 | 0.173 | 0.144 | 0.146 |
|       |    | Nowson et al. (2015) | 0.153 | 0.197 | 0.154 | 0.144 | 0.132 |
|       |     | C2W2S4PT | 0.130 | 0.167 | 0.137 | 0.122 | 0.109 |
| ES    | 5 | Average Baseline | 0.171 | 0.203 | 0.163 | 0.187 | 0.166 |
|       |   | Sulea and Dichiu (2015) | 0.152 | 0.181 | 0.148 | 0.114 | 0.142 |
|       |   | C2W2S4PT | 0.148 | 0.177 | 0.143 | 0.157 | 0.136 |
|       | 10 | Mirkin et al. (2015) | 0.153 | 0.188 | 0.155 | 0.156 | 0.160 |
|       |    | Nowson et al. (2015) | 0.154 | 0.188 | 0.155 | 0.168 | 0.160 |
|       |     | C2W2S4PT | 0.145 | 0.177 | 0.142 | 0.153 | 0.137 |
| IT    | 5 | Average Baseline | 0.162 | 0.172 | 0.162 | 0.123 | 0.151 |
|       |   | Sulea and Dichiu (2015) | 0.119 | 0.150 | 0.122 | 0.101 | 0.130 |
|       |   | C2W2S4PT | 0.124 | 0.144 | 0.130 | 0.095 | 0.131 |
|       | 10 | Mirkin et al. (2015) | 0.095 | 0.168 | 0.142 | 0.098 | 0.137 |
|       |    | Nowson et al. (2015) | 0.137 | 0.168 | 0.142 | 0.098 | 0.141 |
|       |     | C2W2S4PT | 0.118 | 0.147 | 0.128 | 0.095 | 0.127 |

Table 1: $RMSE_{user}$ across five traits. **Bold** highlights best performance.
Table 2: $RMSE_{tweet}$ across five traits level. **Bold** highlights best performance.

| Lang. | Model               | EXT | STA | AGR | CON | OPN |
|-------|---------------------|-----|-----|-----|-----|-----|
| EN    | Average Baseline    | 0.163 | 0.222 | 0.157 | 0.150 | 0.147 |
|       | SVM Regression      | 0.148 | 0.196 | 0.148 | 0.140 | 0.131 |
|       | Random Forest       | 0.144 | 0.192 | **0.146** | 0.138 | 0.132 |
|       | Bi-GRU-Char         | 0.150 | 0.202 | 0.152 | 0.143 | 0.137 |
|       | Bi-GRU-Word         | 0.147 | 0.200 | **0.146** | 0.138 | 0.130 |
|       | C2W2S4PT            | **0.142** | **0.188** | 0.147 | **0.136** | **0.127** |
| ES    | Average Baseline    | 0.171 | 0.204 | 0.163 | 0.187 | 0.165 |
|       | SVM Regression      | **0.158** | **0.190** | 0.157 | 0.171 | 0.152 |
|       | Random Forest       | 0.159 | 0.195 | 0.157 | 0.177 | 0.158 |
|       | Bi-GRU-Char         | 0.163 | 0.195 | 0.158 | 0.178 | 0.155 |
|       | Bi-GRU-Word         | 0.159 | 0.192 | 0.154 | 0.173 | 0.154 |
|       | C2W2S4PT            | **0.158** | 0.191 | **0.153** | **0.168** | **0.150** |
| IT    | Average Baseline    | 0.164 | 0.171 | 0.164 | 0.125 | 0.153 |
|       | SVM Regression      | 0.141 | 0.159 | 0.145 | 0.113 | **0.141** |
|       | Random Forest       | 0.140 | 0.161 | **0.140** | 0.111 | 0.147 |
|       | Bi-GRU-Char         | 0.149 | 0.163 | 0.153 | 0.117 | 0.146 |
|       | Bi-GRU-Word         | **0.135** | **0.156** | **0.140** | **0.109** | **0.141** |
|       | C2W2S4PT            | 0.139 | **0.156** | 0.143 | **0.109** | **0.141** |

Figure 2: Scatter plot of sentence representations processed by PCA.

is longer and, with the use of the second person
pronoun, is more inclusive of others; NEG3 on
the other hand is shorter and self-focused, aspects
indicative of Introversion. The third sentence,
POS20, is a statement from an Extravert which
appears to map to an Introvert space. Indeed,
while short, the use of “Eastern” style, non-rotated
emoticons (such as $o.O$) has also been shown to
relate to Introversion on social media (Schwartz
et al., 2013). This is perhaps not the venue to
to consider the implications of this further, although
one explanation might be that the model has un-
covered a flexibility often associated with Ambi-
verts (Grant, 2013). However, it is important to
consider that the model is indeed capturing well-
understood dimensions of language yet with no
feature engineering.

5 Conclusion and Future Work

Overall, the results in the paper support our
methodology: C2W2S4PT not only provides
state-of-the-art results on the user level, but also
performs reasonably well when adapted to the
short text level compared to other widely used
models in the feature-engineering-free setting.
More importantly, one advantage of our approach
is the lack of feature engineering which allows us
to adapt the same model to other languages with
no modification to the model itself. To further
examine this property of the proposed model, we
plan to adopt TwiSty (Verhoeven et al., 2016), a
recently introduced corpus consisting of 6 languages
and labelled with MBTI type indicators (Myers
and Myers, 2010).
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