Using Social Networks to Improve Language Variety Identification with Neural Networks

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Abstract

We propose a hierarchical neural network model for language variety identification that integrates information from a social network. Recently, language variety identification has enjoyed heightened popularity as an advanced task of language identification. The proposed model uses additional texts from a social network to improve language variety identification from two perspectives. First, they are used to introduce the effects of homophily. Secondly, they are used as expanded training data for shared layers of the proposed model. By introducing information from social networks, the model improved its accuracy by 1.67–5.56. Compared to state-of-the-art baselines, these improved performances are better in English and comparable in Spanish. Furthermore, we analyzed the cases of Portuguese and Arabic when the model showed weak performances, and found that the effect of homophily is likely to be weak due to sparsity and noises compared to languages with the strong performances.

1 Introduction

Language identification is a fundamentally important natural language processing (NLP) task that is usually applied before more sophisticated grammatical or semantic analyses. It is especially important in cases when analyzing user generated contents such as social media, which include various languages often, without accurate language information. General purpose language identification tools such as TextCat (Cavnar and Trenkle, 1994) and langid.py (Lui and Baldwin, 2012) can identify 50–100 languages with accuracy of 86–99%. However, these tools have not considered discrimination between closely related language varieties.

Recently, language identification among similar languages or language varieties has been studied actively to realize more advanced language identification (Goutte et al., 2016). Since 2014, VarDial workshops, which specifically examine linguistic variation, have organized shared tasks of discriminating between similar languages (Zampieri et al., 2014). More recently, language variety analysis has attracted an author profiling community to include it in a PAN shared task that targets social media (Rangel Pardo et al., 2017). A language variety that a person uses often depends on his or her regional and cultural backgrounds. The identification of language variety can enhance a social media analysis by providing such background information.

We tackle this language variety identification in Twitter with a hierarchical neural network model (Lin et al., 2015; Yang et al., 2016b) integrating information from a social network. The use of social network information has shown effectiveness in analyzing various user attributes (Wang et al., 2014; Li et al., 2014, 2015; Rahimi et al., 2015a,b) where homophily (McPherson et al., 2001) exists. Neural networks have recently shown superior performance for solving a variety of problems in NLP. However, for language variety identification, sparse traditional models have shown stronger performance than deep neural models (Medvedeva et al., 2017). Numerous parameters in neural network models make it difficult to apply to language variety identification where the training data are sparse.
limited to a maximum number of several thousands.

We expect to obtain two effects by introducing additional texts from a social network into our model. First, we introduce additional texts that are likely to share the same language variety by homophily. Secondly, we let several layers of our model be trained with more texts by sharing several layers of the model among the processes of a target user and its linked users with a social network. The contributions of this paper are the following:

1. We propose a novel neural network model that uses social network information for language variety identification in Twitter.
2. We show that additional texts of linked users can improve language variety identification.
3. We reveal that a neural network model can be efficiently trained by sharing layers within the processes of a target user and its linked users.

2 Related Works

2.1 Language Variety Identification

The increase of web documents in various languages has raised interest in identifying language varieties automatically. Inspired by some early works in Malay and Indonesian (Ranaivo-Malançon, 2006), south Slavic languages (Ljubešić et al., 2007), and Chinese varieties (Huang and Lee, 2008), studies of language varieties, similar languages, or dialects have expanded to examine numerous languages. The recent expansion of language variety identification has been well surveyed in works by Goutte et al. (2016) and Zampieri et al. (2017). As in other NLP tasks, various neural network models have been applied recently to language variety identification (Belinkov and Glass, 2016; Bjerva, 2016; Cianflone and Kosseim, 2016; Criscuolo and Aluisio, 2017; Medvedeva et al., 2017). However, these neural network models have shown inferior performance compared to sparse traditional models in comparisons (Malmasi et al., 2016; Zampieri et al., 2017).

2.2 NLP with Social Network Information

Social media have attracted numerous NLP studies to analyze its texts. Social media contain interactions among users such as follow, hashtag, mention, reply, and retweet. Many studies have exploited such social network information to enhance NLP models. The use of social networks has shown effectiveness for strengthening NLP tasks such as sentiment analysis (Speriosu et al., 2011; Tan et al., 2011; Vanzó et al., 2014; Ren et al., 2016; Yang and Eisenstein, 2017), skill inference (Wang et al., 2014), user attribute extraction (Li et al., 2014, 2015), geolocation prediction (Rahimi et al., 2015a,b), and entity linking (Yang et al., 2016a).

Integration of social network information into neural network models is accomplished in these studies through joint training (Li et al., 2015), context-based sub-networks (Ren et al., 2016), embedding of social network components (Yang et al., 2016a), and social attention (Yang and Eisenstein, 2017). These are effective approaches in terms of accuracy but they make models more difficult to train with additional parameters. We designed our model to share layers among different processes to facilitate training of the neural network model.

3 Models

3.1 NN-HIER

We prepare a basic neural network model NN-HIER, which is a variant of known hierarchical models (Lin et al., 2015; Yang et al., 2016b). NN-HIER in Figure 1 portrays the architecture of this model. For each user, the model accepts the words of user tweets. The words are embedded with a word embedding layer and are processed with a recurrent neural network (RNN) layer, a max-pooling layer, an attention mechanism (Bahdanau et al., 2014) layer, and fully connected (FC) layers. As an implementation of RNN, we used Gated Recurrent Unit (GRU) (Cho et al., 2014) with a bi-directional setting.

The bi-directional GRU outputs $h$ and $\overline{h}$ are concatenated to form $g$ where $g_t = \overline{h}_t || h_t$. $g$ is further processed with a max-over time process in MaxPooling to obtain a tweet representation $m$. Attention$_U$ computes a user representation $o$ as a weighted sum of $m_n$ with weight $\alpha_n$:

$$o = \sum_n \alpha_n m_n$$

$$\alpha_n = \frac{\exp (v_t^T u_n)}{\sum_l \exp (v_t^T u_l)}$$

$$u_n = \tanh (W_n m_n + b_n)$$
where \( v_n \) is a weight vector, \( W_\alpha \) is a weight matrix, and \( b_\alpha \) a bias vector. \( u_n \) is an attention context vector calculated from \( m_n \) with a single FC layer (Eq. 2). \( u_n \) is normalized with softmax to obtain \( \alpha_n \) as a probability (Eq. 1). Finally, the user representation is passed respectively to FC1 and FC2.

### 3.2 NN-HIER-SNET

We extend NN-HIER by adding an additional level of hierarchy to process linked users of a target user. This extension is intended to introduce effects of homophily into our model. NN-HIER-SNET in Figure 1 presents this extended model. NN-HIER-SNET includes additional attention layers \( \text{Attention}_{UL} \) and \( \text{Attention}_{UL} \) to process linked users. \( \text{Attention}_{UL} \) accepts multiple user representations and combined them as in \( \text{Attention}_{UL} \) to form a linked users representation. \( \text{Attention}_{UL} \) further merges a target user representation (an output of \( \text{Attention}_{UL} \)) and \( \text{Attention}_{UL} \) to obtain an updated target user representation.

An important characteristic of NN-HIER-SNET is that the weights of WordEmbed and RNN are shared across the target user process and the linked users process. This sharing allows the weights to be trained with more texts than those of NN-HIER. Attention processes over tweets are separated \( (\text{Attention}_{UL} \text{ and } \text{Attention}_{UL}) \) so that the target user process and the linked users process can pick tweets differently between the two kinds of user processes.

### 4 Data

We used PAN@CLEF 2017 Author Profiling Training Corpus\(^1\) to train the proposed models. The dataset consists of 11,400 Twitter users labeled with language variety of English (en), Spanish (es), Portuguese (pt), and Arabic (ar). Because the proposed model of Section 3.2 integrates texts of linked users, we additionally collected timelines of mentioned users in this dataset as linked users using Twitter REST APIs. #mention in Table 1 are the numbers of users mentioned for each language. Avg degree is an average node degree and isolated nodes are the percentage of labeled nodes that are not connected to other labeled nodes.

### Table 1: Numbers of training data, development data, test data, entire data (total), language varieties (langvar), and mentioned users (mention).

|       | en  | es  | pt  | ar  |
|-------|-----|-----|-----|-----|
| #train\(_1\) | 2,880 | 3,560 | 960 | 1,920 |
| #dev\(_1\)   | 360  | 420  | 120 | 240  |
| #test\(_1\)  | 360  | 420  | 120 | 240  |
| #total       | 3,600 | 4,200 | 1,200 | 2,400 |
| #langvar     | 6    | 7    | 2   | 4    |
| #mention     | 73,897 | 59,685 | 11,541 | 20,287 |

|       | en    | es    | pt    | ar    |
|-------|-------|-------|-------|-------|
| #node | 77,497 | 63,885 | 12,741 | 22,687 |
| avg degree | 3.12 | 3.45 | 2.26 | 2.59 |
| isolated nodes | 3.92% | 5.83% | 6.33% | 28.88% |

### Table 2: Characteristics of nodes in mention networks for each language. Avg degree is an average node degree and isolated nodes are the percentage of labeled nodes that are not connected to other labeled nodes.

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\(^1\)http://pan.webis.de/clef17/pan17-web/author-profiling.html
Table 3: Accuracies of the proposed models and the baselines. Underlined values represent the best values for each language.

| Model               | en  | es  | pt  | ar  |
|---------------------|-----|-----|-----|-----|
| SVM-W2              | 83.06 | 95.74 | 98.61 | 80.00 |
| SVM-W2C6            | 85.56 | 95.71 | 98.99 | 82.08 |
| SVM-W2C6-SNET       | 82.69 | 92.86 | 99.17 | 82.08 |
| SVM-W2C6-SNET-R     | 86.11 | 93.33 | 99.17 | 82.71 |
| NN-HIER             | 85.83 | 93.57 | 99.17 | 78.75 |
| NN-HIER-SNET        | 91.29 | 95.48 | 93.33 | 80.42 |

Table 4: Accuracies of the label propagation approach and the comparison approaches.

| Model               | en  | es  | pt  | ar  |
|---------------------|-----|-----|-----|-----|
| Majority Baseline   | 16.67 | 13.29 | 50.00 | 25.00 |
| NN-HIER             | 85.83 | 93.57 | 99.17 | 78.75 |
| Label Propagation   | 75.28 | 78.81 | 83.33 | 60.42 |

5 Experiment

5.1 Baselines

We prepared four support vector machine based baselines: SVM-W2, SVM-W2C6, SVM-W2C6-SNET, and SVM-W2C6-SNET-R.

SVM-W2

A support vector machine model with tf-idf weighted word 1–2 grams. We prepared SVM-W2 with a soft margin setting and configured parameter $C \in \{0.1, 0.5, 1.0, 5.0, 1e^2, 5e^2, 1e^3\}$ using the development sets. For multi-class classification, we used an one-vs.-the-rest scheme.

SVM-W2C6

An extended model of SVM-W2 which additionally uses tf-idf weighted character 1–6 grams. This setting is simple, but similar models have shown state-of-the-art performance in past Var-Dial tasks (Malmasi et al., 2016; Zampieri et al., 2017).

SVM-W2C6-SNET

An extension of SVM-W2C6 with features of linked users. tf-idf weighted word 1–2 grams and tf-idf weighted character 1–6 grams of linked users were added to SVM-W2C6 with a feature space separated from other SVM-W2C6 features.

SVM-W2C6-SNET-R

A variant of SVM-W2C6-SNET with a restricted feature space for linked users. The size of feature space for linked users are restricted to be equal to the size of feature space for target users in this model. Since, in general, there are more texts of linked users than that of target users, this restriction suppresses the effect of social network information.

5.2 Model Configurations

We trained our model by stochastic gradient descent over shuffled mini-batches with cross-entropy loss as an objective function. Word embeddings were pre-training using streaming tweets by fastText (Bojanowski et al., 2016) using the skip-gram algorithm. The details of the model configurations including a text processor and layer unit sizes are described in Appendix A.

6 Discussions

6.1 Effects of Homophily

The experiment revealed the effectiveness of combining texts of a target user with social network information for language variety identification. For comparison, we additionally performed a label propagation experiment to observe performances of language variety identification without texts. Following the approaches by Rahimi et al. (2015a) and Rahimi et al. (2015b), we extracted an undirected graph of the social network from target users and their linked users. The labels of training users were propagated to test users using the algorithm of Zhou et al. (2004) with $\alpha = 0.99$.

Table 4 presents the performance of this label propagation approach. The performance are better than the majority baseline but are substantially lower than those from our text model (NN-HIER). Especially, the performance of Arabic is weak compared to other languages since the percentage of isolated nodes is high in Arabic (Table 2). The result suggests that social network information without texts is ineffective for language variety identification, at least in a dataset of several thousand users.
Table 5: Accuracies of NN-HIER-SNET with non-shared (NS) layers.

| Model            | en   | es   | pt   | ar   |
|------------------|------|------|------|------|
| NN-HIER-SNET     | 91.39| 95.48| 93.33| 80.42|
| NN-HIER-SNET-NS  | 75.56| 84.76| 93.33| 80.00|

6.2 Effects of Shared Layers

NN-HIER-SNET includes shared layers to suppress the increase of neural networks parameters. To ascertain the effects of these shared layers, we additionally evaluated NN-HIER-SNET with non-shared layers. NN-HIER-SNET-NS in Table 5 presents performances of this setting. As expected, the performances were fundamentally inferior to the shared layers architecture. They performed especially badly in English and Spanish, for which the numbers of mentioned users were high (Table 1). The result shows that the shared layer architecture is effective for language variety identification.

6.3 Social Network Characteristics and Performances of Proposed Model

NN-HIER-SNET showed improvements over the baseline models in English and Spanish. These two languages are more dense than Portuguese and Arabic in terms of average node degree (Table 2), and are likely to obtain richer information from social networks. We further investigated the languages of tweets in linked users to capture additional characteristics of social networks for each language. Table 6 shows the summary of this investigation. In all four languages, the top linked language is same as a target language. However, their percentages vary from 78.08–94.26%, indicating differences in the amount of texts in different languages. These texts with different languages will likely be noises in the texts of linked users for language variety identification. As in average node degree, English and Spanish are in better conditions compared to Portuguese and Arabic with smaller noises. Sparsity and noises in social networks will likely to weaken the effect of homophily, resulting to small or negative improvements in performances.

7 Conclusion

We proposed a neural network model that integrates information from a social network for language variety identification. The model showed 1.67–5.56 improvements in accuracy from introducing additional texts with shared layers. Furthermore, compared to the performance of a state-of-the-art baseline model, the model performed better in English and comparably well in Spanish. In Portuguese and Arabic, the model performed weakly compared to the baseline models. We analyzed characteristic of social network in these languages and found that their sparsity and noises have possibly weakened the effect of homophily. The result underscores the promising future of applying neural network models to language variety identification.

As future works of this study, we plan to expand the use of the proposed models for application to other user attributes. We expect that a user attribute having a tendency for homophily is likely to benefit from the proposed model as in language variety identification. Additionally, we plan to perform a comparison of the model against an alternative approach to introduce social network information. Recently, neural network models like Graph Convolutional Networks (Kipf and Welling, 2016) are proposed to process graph data. We would like to observe the differences between a hierarchical approach and a graph process approach in a utilization of social network information.

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A Supplemental Materials

Text Processor We applied unicode normalization, Twitter user name normalization, and URL normalization for text pre-processing. Pre-processed texts were tokenized with Twokenize\(^2\) for English and NLTK\(^3\) WordPunctTokenizer for three other languages. Words are converted to lower case form, with ignored capitalization.

Pre-training of Embeddings
We collected tweets using Twitter Streaming APIs to pre-train the word embedding matrix of the models. Neural network models are known to perform better when word embeddings are pre-trained by a large-scale dataset. The following steps describe details of the collection process.

1. Tweets with lang metadata of en, es, pt, and ar were collected via Twitter Streaming APIs during March–May 2017.
2. Retweets are removed from the collected tweets.
3. Tweets posted by bots\(^4\) are deleted from the collected tweets.

Table 7 presents the number of resulting tweets. We pre-trained word embeddings with these tweets by fastText using the skip-gram algorithm. The pre-training parameters are dimension=100, learning rate=0.025, window size=5, negative sample size=5, and epoch=5.

Layer Unit Sizes & Maximum Linked Users
We set the following unit size of RNN = 100, unit size of $FC_1 = 100$, and the unit size of $FC_2$ to the number of labels. The context vector sizes of attention layers were set to $Attention_U = 200$, $Attention_{U1} = 200$, $Attention_{U2} = 200$, and $Attention_{UL} = 200$. To make our model tractable, we limited the maximum number of linked users to 3.

Optimization Strategy
We used cross-entropy loss as an objective function of the proposed models. The objective function was minimized through stochastic gradient descent over shuffled mini-batches with a learning rate of 0.01, momentum of 0.9, and gradient clipping of 3.0. The model parameters were set to the best performing parameters in terms of loss in the development data.

\(^2\)https://github.com/myleott/ark-twokenize-py
\(^3\)http://www.nltk.org/
\(^4\)We assembled a Twitter client list consisting of 80 clients that are used for manual postings.

| #tweet | en   | es   | pt   | ar   |
|--------|------|------|------|------|
|        | 12.30M | 3.71M | 3.16M | 2.87M |

Table 7: Number of tweets collected for each language with Twitter Streaming APIs.