Logographic Information Aids Learning Better Representations for Natural Language Inference

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Abstract

Statistical language models conventionally implement representation learning based on the contextual distribution of words or other formal units, whereas any information related to the logographic features of written text are often ignored, assuming they should be retrieved relying on the cooccurrence statistics. On the other hand, as language models become larger and require more data to learn reliable representations, such assumptions may start to fall back, especially under conditions of data sparsity. Many languages, including Chinese and Vietnamese, use logographic writing systems where surface forms are represented as a visual organization of smaller graphemic units, which often contain many semantic cues. In this paper, we present a novel study which explores the benefits of providing language models with logographic information in learning better semantic representations. We test our hypothesis in the natural language inference (NLI) task by evaluating the benefit of computing multimodal representations that combine contextual information with glyph information. Our evaluation results in six languages with different typology and writing systems suggest significant benefits of using multi-modal embeddings in languages with logographic systems, especially for words with less occurrence statistics.

1 Introduction

The essential idea in statistical language modeling is to represent the meaning of a word as a function of its context. The function, modeled via the conditional probability of observing a word in a given utterance, has most efficiently been approximated with a neural network based architecture (Mikolov et al., 2013a,b; Bengio et al., 2003; Mikolov et al., 2010; Sundermeyer et al., 2012). The outstanding performance of neural methods in language modeling and their recent development (Peters et al., 2018; Tenney et al., 2019) have them a preliminary component in various downstream NLP tasks.

One of the main limitations in the formulation of language models lies however in the choice of orthographic units in calculating the contextual distribution, which is usually convenient in English and other languages using phonetic scripts. On the other hand, many languages rely on logographic writing systems, where surface forms are represented as a visual organization of smaller graphemic units and the word meaning can be changed through compositional variations of these units. Although a direct segmentation of these units has been found quite challenging due to visual compositions in the final form of the grapheme, previous studies have found potential benefits of using visual information to aid NLP models in sentence representation (Liu et al., 2017a; Meng et al., 2019; Dai and Cai, 2017; Salesky et al., 2021). On the other hand, none of these studies have focused on isolating the effects of different linguistic features in relation to their correlation to visual features.

As shown in Figure 1, logographic information often contain important features related to the word meaning. In this paper, we perform the first focused analysis to measure the significance of logographic features specifically to the semantic information encoded in token or character-level language representations by evaluating the performance of multi-modal embeddings in the NLI task. In particular, we aim to answer the following research questions:

1) How important may logographic information be to for an accurate representation of semantic information in word or character-level language units

2) Whether the contribution of logographic information to semantic representations may depend on the language typology and writing system

In order to answer these questions we implement a multi-modal representation learning model where
each written text segment is representation as a combination of visual embeddings obtained from prominent convolutional neural network (CNN) based models (Liu et al., 2017a; Meng et al., 2019; Salesky et al., 2021), and contextual representations obtained from multilingual pre-trained language models (Devlin et al., 2019; Conneau et al., 2020a). We evaluate the contribution of visual information to the performance in the NLI task under few-shot learning settings in six languages with varying typology and writing systems: English, Spanish, Hindi, Urdu, Vietnamese and Chinese. We also study the optimal representation granularity for semantic information by comparing word or character-level multi-modal representations in our experiments.

In conclusion, we find that taking into account the visual information improves the performance in NLI tasks especially in logographic languages like Chinese and that the improvements are correlated with the factors that determine the quality of token representations, such as the occurrence of the tokens in training data as well as language model capacity and hyperparameters. Our findings suggest multi-modal processing is a promising direction, especially for processing languages where conditions of data sparsity may create fall backs in assumptions undertaken in statistical formulations.

2 Computing Visual Glyph Embeddings

Our multi-modal embedding model is composed of two components: (i) the visual encoder, which computes embeddings based on the input images representing each text segment, and (ii) the pre-trained language model providing the text-based embeddings.

Image conversion Text segments consisting of complete sentences are split into words (or characters) and then converted into images. Sentences are split into 30 x 60 pixel word images using the Jieba\(^1\) tool. All graphemes are centralized to the middle of the image.

Visual Embeddings In order to extract the glyph information from text images, we use the CNN model developed by (Liu et al., 2017b; Sutskever et al., 2014) to generate visual embeddings. The model consists of a three-layer CNN, augmented with a two-layer feed-forward network. The full details of the network is given below.

The visual features extracted by the CNN are further encoded in a long-short term memory (LSTM) (Hochreiter and Schmidhuber, 1997) network to learn the glyph embeddings.

For a sequence consisting of \(t\) tokens \(x_0, x_1, \ldots, x_t\), the visual embedding \(v\) is computed by concatenating (Su et al., 2020; Lu et al., 2019) the hidden states of the LSTM and averaging them as

\[
v = \text{mean}([h_0; h_1; \ldots; h_t])
\]

Embedding composition In order to isolate the learning of representations from two modalities and measure their effect on the learning task in a controlled setting, we deploy late fusion in combining the visual embeddings with the text embeddings obtained by the pre-trained model for prediction in the down-stream task. The two embeddings are linearly composed through a simple affine projection and then concatenated. For the down-stream prediction task we use a multi-layer perceptron classifier.

\(^1\)https://github.com/fxsjy/jieba
3 Experiments

3.1 Character recognition

As an initial verification, we implement the visual encoder and evaluate it individually in the character recognition task. We use the CASIA Chinese Handwriting Database (Liu et al., 2011) and obtain competitive results (93.23% accuracy) on this task, confirming the visual encoder works sufficiently in extracting character features from input images.

3.2 NLI

Data We evaluate our model under few-shot learning settings using the XNLI dataset (Conneau et al., 2020b), using only a small portion of the testing data for training and development, and test the effect of logographic information to contribute to resolve the high level of semantic ambiguity.

| Datasets     | Number of Sentences |
|--------------|---------------------|
| Training     | 4509                |
| Development  | 501                 |
| Test         | 2490                |

Table 1: Data statistics for training, development and test sets.

Model settings and hyper-parameters In training the multi-modal models, the learning rates of both XLM-R and mBERT based pre-trained models are set to 1e-6. The visual encoder is trained on the images captured from the training sentences, either at word or character-level resolution, with a learning rate of 4e-6 (for XLM-Roberta) and 1e-6 (for mBERT). The hidden size of the LSTMs used is 128 and we use dropout of with 0.3 in this layer. All hyper-parameters are tuned with grid-search. For each task we train 30 epochs and always choose the results with smallest validation loss.

Languages We pick six languages with varying typology and writing systems, including English, Spanish, Urdu, Vietnamese, Chinese and Hindi. English and Spanish use the Latin script; Urdu is written with the Arabic alphabet, whereas Hindi uses Devanagari, all of which are phonetic writing systems. Chinese uses logographic writing. Vietnamese, although traditionally have used logographic writing, recently and in the XNLI data set is written with the Latin script.

Contextual representations We verify the significance of logographic information for contributing to enrich the language representations by testing our multi-modal approach with two different pre-trained language models, including the mBert-base and the XLM-R-base both available from Huggingface2. We also investigate the effects of different segmentation methods for processing sentence images either at the level of words or characters.

4 Results and Discussion

Our experiment results are given in Table 2. At a first glance, we observe the performance of the models are much lower than reported in (Conneau et al., 2020b), since we have significantly less training and development data available. Under these challenging evaluation settings with high amount of sparsity, we observe that the logographic information improves the performance obtained using the mBert-base model in all languages that do not deploy the Latin script, including Chinese, Urdu, Hindi and Vietnamese. In case

2https://huggingface.co
Table 2: Results in the XNLI benchmark. base models represent baseline pre-trained language model performance in the down-stream task. base-CNN models represent the multi-modal system performance. (C) denotes character and (W) denotes word level input representations. Random stands for comparisons to multi-modal systems where random images were input to the visual encoder to verify the effect of visual information on the overall performance.

| Languages       | English | Chinese | Urdu | Hindi | Vietnamese | Spanish |
|-----------------|---------|---------|------|-------|------------|---------|
| mBERT-base      | 65.86   | 55.28   | 51.29| 56.48 | 57.08      | 62.27   |
| mBERT-base-CNN (W) | 62.87   | 58.88   | 53.49| 57.68 | 59.88      | 60.47   |
| mBERT-base-CNN (C) | 64.07   | 59.08   | 53.69| 57.48 | 60.07      | 61.67   |
| mBERT-base-CNN (C) — Random | -       | 54.33   | -   | -     | -          | -       |
| XLM-Roberta-base| 69.86   | 64.27   | 59.88| 63.87 | 63.07      | 65.66   |
| XLM-Roberta-base-CNN (W) | 69.26   | 66.66   | 57.88| 62.87 | 61.67      | 65.46   |
| XLM-Roberta-base-CNN (C) | 68.26   | 62.07   | 56.28| 61.67 | 63.07      | 65.26   |
| XLM-Roberta-base-CNN (C) — Random | -       | 61.36   | -   | -     | -          | -       |

Models | Accuracy | # of UNK  
---|---------|---------
 mBERT-base (C) | 45.31   | 128     
mBERT-base-CNN (C) | 52.43   |         

Table 3: Results for targeted evaluation, UNK represents unknown tokens.

As an additional analysis investigating the effects of token frequency on the positive effects of logographic information integrated in the language model, we sample sentences in the test set that have unknown words in the model vocabulary and compute the targeted accuracy on this sample of sentences. The results shows in table 3 further illustrate the boosted performance on the sample test, suggesting that data sparsity is an important obstacle to learning high-quality contextual representations, and such conditions can be the ideal place where logographic information might be useful to improve the semantic features embedded in representations.

5 Conclusion

In this paper, we evaluated the benefits of using logographic information in language modeling by implementing a multi-modal representation learning model which combines contextual language representations with visual embeddings. Our experiments in the NLI task in six languages confirmed the benefits of logographic information in obtaining more reliable semantic representations, especially under sparse learning settings. As future work we hope to contribute to the development of larger multilingual benchmarks to evaluate the effect of visual information on more languages and linguistic phenomena. Our software and the experimental data will be available upon publication.
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