Neural Language Priors

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Abstract
The choice of sentence encoder architecture reflects assumptions about how a sentence’s meaning is composed from its constituent words. We examine the contribution of these architectures by holding them randomly initialised and fixed, effectively treating them as hand-crafted language priors, and evaluating the resulting sentence encoders on downstream language tasks. We find that even when encoders are presented with additional information that can be used to solve tasks, the corresponding priors do not leverage this information, except in an isolated case. We also find that apparently uninformative priors are just as good as seemingly informative priors on almost all tasks, indicating that learning is a necessary component to leverage information provided by architecture choice.

1 Introduction
Sentence representations are fixed-length vectors that encode sentence properties and allow models to learn across many Natural Language Processing (NLP) tasks. These representations enable learning procedures to focus on the training signal from specific “downstream” NLP tasks (Conneau and Kiela, 2018), circumventing the often limited amount of labelled data. Naturally, sentence representations that can effectively encode semantic and syntactic properties into a representations are highly sought after, and are a cornerstone of modern NLP systems.

In practice, sentence representations are formed by applying an encoding function (or encoder) provided by a Neural Network (NN) architecture, to the word vectors of the corresponding sentence. Encoders have been successfully trained to predict the context of sentence (Kiros et al., 2015; Ba et al., 2016), or to leverage supervised multi-task objectives (Conneau et al., 2017; Dehghani et al., 2018).

The choice of encoder architecture asserts an inductive bias (Battaglia et al., 2018), and reflects assumptions about the data-generating process. Different encoders naturally prioritise one solution over another (Mitchell, 1991), independent of the observed data, trading sample complexity for flexibility (Geman et al., 2008). Given that NNs, which are able to generalise well, can also overfit when presented with random labels (Zhang et al., 2016), we expect that architecture plays a dominant role in generalisation capability (Lempitsky et al., 2018).

The inductive biases of encoder architectures reflect assumptions about how a sentence’s meaning is composed from its constituent words. A plethora of architectures have been investigated, each designed with a specific set of inductive biases in mind. Bag of Embeddings (BOE) architectures disregard word order (Harris, 1954; Salton et al., 1975; Manning et al., 2008), Recurrent Neural Network (RNN) architectures can leverage word positional information (Kiros et al., 2015; Ba et al., 2016), Convolutional Neural Network (CNN) architectures compose information at the $n$-gram level (Collobert et al., 2011; Vieira and Moura, 2017; Gan et al., 2016), self-attention models leverage explicit positional information with long range context (Vaswani et al., 2017; Ahmed et al., 2017; Shaw et al., 2018; Dehghani et al., 2018; Radford et al., 2019; Devlin et al., 2018; Cer et al., 2018), and graph-based models can exploit linguistic structures extracted by traditional NLP methods (Tai et al., 2015; Li et al., 2018; Zhang et al., 2019; Teng and Zhang, 2016; Kim et al., 2018a; Ahmed et al., 2019; Bastings et al., 2017; Marcheggiani and Titov, 2017; Marcheggiani et al., 2018; Marcheggiani and Perez-Beltrachini, 2018). This list is far from exhaustive.

Given the critical role of encoder architectures
in NLP, we set out to examine their contribution to downstream task performance independent of biases induced by learning processes. We find that even architectures expected to have extremely strong language priors yield almost no gains when compared to architectures that are equipped with apparently uninformative priors, consistent with the results found in Wieting and Kiela (2019). This suggests that for NLP tasks, relying on the prior is insufficient, and the learning process is necessary, in contrast to what was found in the vision field (Lempitsky et al., 2018). In short, although there are known strong inductive biases for language, there is no best language prior, and in practice there is surprisingly little correspondence between the two.

To show this, given a set of pre-trained word embeddings, we evaluate the classification accuracy of a variety of architectures on a set of NLP tasks, only updating the parameters specific to the task, holding the parameters of the architecture fixed at their random initialisation.

2 Method

2.1 Priors from Random Sentence Encoders

The line of investigation we take follows Wieting and Kiela (2019) closely. We treat randomly initialized NNs as handcrafted priors for how the meaning of a sentence is composed from its constituent words. Concretely, let each word \( w \) have a pre-trained and fixed \( D \)-dimensional word representation \( \theta_w \in \mathbb{R}^D \). Consider a sentence \( S \) consisting of \( T_S \) words \( S = w_1, \ldots, w_{T_S} \). Using an encoding function \( f_{\text{enc}} \), the meaning of the sentence is distilled into a sentence representation \( h_S \):

\[
h_S(\theta) = f_{\text{enc}}(e_1, \ldots, e_{T_S}; \theta),
\]

where \( \theta \) are the parameters of the encoding function. For NN architectures that output a matrix \( H_S \in \mathbb{R}^{T_S \times D'} \), where \( D' \) is an output dimensionality and \( T_S \) is a temporal dimensionality\(^1\), we pool along the temporal dimension using a pooling function \( f_{\text{pool}} \). For our main results we use max pooling \( h_S = f_{\text{pool}}(H_S) = \max(H_S) \in \mathbb{R}^{D'} \) throughout, as it has been successful in InferSent (Conneau et al., 2017).

The \( \theta \) are typically learned using e.g. Maximum Likelihood Estimation (MLE) on sentence context, resulting in \( h_S(\theta) \) representing a sample from the encoder’s posterior over functions applied to \( S \) given a corpus. Instead of learning \( \theta \), we simply sample \( \theta \) from its own prior. \( h_S(\theta) \) then represents a sample from the encoder’s prior over functions applied to \( S \).

For each encoding function, we take multiple samples of \( \theta \). For each sample, the resulting encoder function is used to produce sentence embeddings for a set of downstream tasks. These downstream tasks are the supervised transfer tasks of the SentEval (Conneau and Kiela, 2018) framework, where the transfer model is a simple logistic regression model or a MLP\(^2\). Combining the results from multiple samples then gives a performance estimate of each encoder’s prior.

2.2 BOREPs, Random LSTMs and ESNs

We take the architectures investigated in (Wieting and Kiela, 2019) as a starting point: Bag of Random Embedding Projections (BOREP), Random Long Short Term Memory (LSTM) Neworks and Echo State Networks (ESNs). BOREP is simply a random projection of word embeddings to a higher dimension, RandLSTM is a randomly initialised bi-directional LSTM (Hochreiter and Schmidhuber, 1997), and ESN is a hypertuned randomly initialised bi-directional ESN (Jaeger, 2001). For more details please see (Wieting and Kiela, 2019).

2.3 Random CNNs

Although CNNs are more famously used in the image domain (Simonyan and Zisserman, 2014; He et al., 2015), they have also enjoyed much success as sentence encoders (Collobert et al., 2011; Vieira and Moura, 2017; Gan et al., 2016). A temporal one-dimensional convolution is performed by applying a \( D' \)-channel filter \( W \in \mathbb{R}^{D \times k \times D'} \) to a window of \( k \) words and a bias added. This weight \( W \) is initialised uniformly at random from \([ -\frac{1}{\sqrt{d}}, \frac{1}{\sqrt{d}} ] \), where \( d \) is the word embedding dimension. The representation \( h_S \) is then obtained by pooling

\[
h_S = f_{\text{pool}}[\text{CNN}(e_1, \ldots, e_{T_S})] \in \mathbb{R}^{D'}.
\]

Note that using a window size \( k = 1 \) corresponds to BOREP.

\(^1\) In practice \( T_S \) may not directly correspond to the length of the input sentence due to e.g. finite kernel sizes in convolution operations.

\(^2\) For emphasis: the parameters of these logistic regression model and MLP are updated by the task.
2.4 Random Self-Attention

Attention mechanisms have been employed on many NLP tasks with tremendous success (Vaswani et al., 2017; Ahmed et al., 2017; Shaw et al., 2018; Dehghani et al., 2018; Radford et al., 2019; Devlin et al., 2018; Cer et al., 2018). Self-attention in particular has enabled the incorporation of incredibly long ranged contexts, as well as hierarchical contextualisations of word embeddings within a highly parallel setting.

In our random setting, the word embeddings \( e_1, \ldots, e_{T_s} \) are first projected up to a \( D' \) dimensional space. We then optionally add sinusoidal positional encodings (Vaswani et al., 2017). We then apply two layers of random self-attention with residual connections, each followed by layer normalisation. A single head of a self-attention layer produces new embeddings for each query representation \( q \in \mathbb{R}^{d_k} \) out of the value representations \( v_i \in \mathbb{R}^{D'} \), controlled by the key representations \( k_i \in \mathbb{R}^{d_k} \).

\[
q' = \sum_{i=1}^{T_s} \exp \left( \frac{q^T k_i}{\sqrt{d_k}} \right) v_i / \text{constant.} \tag{3}
\]

The \( d_k \)-dimensional key and query representations are given by independent random projections acting upon the self-attention layer input. We use eight heads of attention in each layer. The pooling function is applied to this output to produce the sentence representation \( h_S \).

We keep the default initialisation of the FairSeq implementation, which is Xavier uniform (Glorot and Bengio, 2010) for the weights of the self-attention layer.

2.5 Random TreeLSTMs

The final architecture we consider is the TreeLSTM. This architecture is particularly interesting as it can potentially incorporate syntactic information into the sentence representations (Tai et al., 2015; Li et al., 2018; Zhang et al., 2019; Teng and Zhang, 2016; Kim et al., 2018a; Ahmed et al., 2019).

We specifically consider the Binary Constituency TreeLSTM (Tai et al., 2015). This differs from a regular LSTM by having a two forget gates - one for each child node given by the structure of the parsed sentence.

Word representations are first presented to a random bi-directional LSTM of combined dimensionality \( D' \) to provide contextualised representations \( E_S' \in \mathbb{R}_{T_s \times D} \)

\[
E'_S = \text{BiLSTM}(e_1, \ldots, e_{T_s}). \tag{4}
\]

The contextualised representations are then presented to a random TreeLSTM, whose outputs are pooled to produce the sentence representation

\[
h_S = f_{pool} \left[ \text{TreeLSTM}(E'_S) \right]. \tag{5}
\]

Both weights of the bi-directional LSTM and the TreeLSTM are initialised uniformly at random from \( [-\frac{1}{\sqrt{d}}, \frac{1}{\sqrt{d}}] \). We used the Stanford parser (Manning et al., 2014) to parse each sentence. Punctuation and special characters were removed, and numbers were only kept if they formed an independent word and were not part of a mixed word of letters and numbers. Then, in the length of a word was reduced to zero, the word was replaced with a placeholder \( * \) character. After parsing, the prepossessing described in (Kim et al., 2018a) was used to compute the parse tree for the TreeLSTM.

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Table 1: Performance (accuracy) for \( f_{pool} = \text{max} \) on all eight tasks. The results indicated by \(^†\) are taken from (Wieting and Kiela, 2019). Mean (standard deviation) for each model is reported across five seeds. Our ESN was evaluated using a spectral radius of 1.0, a maximum kernel deviation from 0.0 of 0.1, and a sparsity 0.5, whereas the result from (Wieting and Kiela, 2019) is the best performing model from a hyperparameter search.

| Model          | Dim | MR    | CR    | MPQA  | SUBJ  | SST2  | TREC   | SICK-E | MRPC |
|----------------|-----|-------|-------|-------|-------|-------|--------|--------|------|
| BOE\(^†\)      | 300 | 77.3(2)| 76.6(3)| 87.6(1)| 91.3(1)| 80.6(5)| 81.5(8)| 78.7(1)| 72.9(3)|
| BOREP\(^†\)    | 4096| 77.4(4)| 79.5(2)| 88.3(2)| 91.9(2)| 81.8(4)| 88.8(3)| 82.7(7)| 73.9(4)|
| BOREP (ours)   | 4096| 75.3(2)| 78.2(5)| 85.5(2)| 90.3(4)| 79.3(1)| 86.5(13)| 82.1(2)| 71.8(7)|
| RandLSTM\(^†\) | 4096| 77.2(5)| 78.7(5)| 87.9(1)| 91.9(2)| 81.5(3)| 86.5(1)| 81.8(5)| 74.1(5)|
| RandLSTM (ours)| 4096| 76.9(2)| 80.9(3)| 88.7(1)| 91.7(1)| 81.3(5)| 89.2(4)| 81.7(5)| 71.8(6)|
| ESN\(^†\)      | 4096| 78.1(3)| 80.9(6)| 88.5(2)| 92.6(1)| 83.0(5)| 87.9(10)| 83.1(4)| 73.4(4)|
| ESN (ours)     | 4096| 70.4(1)| 76.9(8)| 86.3(1)| 88.7(4)| 76.4(5)| 88.9(12)| 78.4(3)| 67.4(7)|
| CNN Window = 3 | 4096| 74.9(3)| 76.9(7)| 85.4(2)| 88.6(1)| 75.6(5)| 88.7(12)| 79.1(2)| 69.4(5)|
| CNN Window = 4 | 4096| 74.3(3)| 74.8(8)| 84.2(3)| 86.8(3)| 75.5(5)| 85.2(1)| 78.0(2)| 69.2(3)|
| Self-Attention | 4096| 68.0(3)| 77.1(5)| 82.0(5)| 90.1(3)| 78.8(12)| 84.9(13)| 73.7(7)| 67.1(1)|
| TreeLSTM       | 4096| 75.6(2)| 78.5(3)| 87.7(1)| 91.4(0)| 79.9(5)| **90.3(7)** | 80.7(9)| 71.1(5)|
Figure 1: Performance (accuracy) for $f_{pool} = \max$ on all eight tasks across five seeds. We observe: 1) Almost every encoder architecture performs at best, similarly to the relatively uninformative BOREP, and at worst, much worse. 2) Taking BOREP as CNN with a window size of 1, we note that increasing CNN window size impairs performance. This indicates that any gains to be made from employing n-grams over word representations as a basis for distilling meaning needs to be learned. 3) The performance of the Self-Attention Network with and without positional encoding is fairly similar. This indicates that although the encoder architecture has positional information available, the transfer model cannot learn to use it. It would be interesting to look at the BShift task to probe this directly (Conneau et al., 2018). 4) Random Self-Attention networks perform poorly even though they form a cornerstone of modern state of the art NLP systems. Considering Equation (3), we see that the random contextualisation can be any linear combination of the input, with none selected by an inductive bias. There is no reason to expect this random combination to outperform BOREP. 5) The TreeLSTM performs noticeably better than other encoder architectures on TREC, a question-type task which relies heavily on sentence syntax to solve (Li and Roth, 2002). It appears that in this instance, the encoder may be using the syntactic information available, however, its performance on all other tasks is comparable to BOREP.

2.6 Evaluation

The SentEval tasks we evaluate on are sentiment analysis (MR, SST), question-type (TREC), product review (CR), subjectivity (SUBJ), opinion polarity (MPQA), paraphrasing (MRPC), and entailment (SICK-E). We use the default SentEval settings defined in (Conneau and Kiela, 2018). We evaluate for five samples (seeds) per architecture per task.

We follow the FairSeq implementation (Ott et al., 2019) to build our CNN and self-attention networks. We also follow the implementation of (Kim et al., 2018b) without the structure-aware tag representations to build our TreeLSTMs.

3 Results

Our investigation is concerned with the priors of encoder architectures, rather than the posteriors they may learn from data; we only compare untrained encoders acting upon word embeddings.

Table 1 contains the performance of architectures discussed in Section 2 at dimensionality 4096 on the selected SentEval tasks, together with the results from Wieting and Kiela (2019). Figure 1 contains the performance for these architectures across a range of dimensionalities.

As a sanity check, we evaluated BOREP and CNN with a window size of 1 and found the performance indistinguishable.

In general, we find that even if encoders have inductive biases that present additional information that can be used to solve a task, the corresponding priors do not leverage this information, except in an isolated case. This strongly indicates that learning is an essential component of building encoder architectures if any gains are to be made beyond apparently uninformative priors.

4 Conclusion

We have evaluated randomly initialised architectures to measure the contribution of priors in distilling sentence meaning. We find that apparently uninformative priors are just as good as seemingly informative priors on almost all tasks, indicating that learning is a necessary component to leverage information provided by architecture choice.
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