ABSTRACT

Creating meta-embeddings for better performance in language modelling has received attention lately, and methods based on concatenation or merely calculating the arithmetic mean of more than one separately trained embeddings to perform meta-embeddings have shown to be beneficial. In this paper, we devise a new meta-embedding model based on the self-attention mechanism, namely the Duo. With less than 0.4M parameters, the Duo mechanism achieves state-of-the-art accuracy in text classification tasks such as 20NG. Additionally, we propose a new meta-embedding sequence-to-sequence model for machine translation, which to the best of our knowledge, is the first machine translation model based on more than one word-embedding. Furthermore, it has turned out that our model outperform the Transformer not only in terms of achieving a better result, but also a faster convergence on recognized benchmarks, such as the WMT 2014 English-to-French translation task.

1 Introduction

Transformer [38], Recurrent neural networks with long short-term memory [17] and gated recurrent neural networks [11], have been firmly established as state of the art approaches in sequence modelling and machine translation [35, 4, 10]. Without one single exception, these models use the distributed vector representations of words, referred to as word embeddings, as their cornerstone. Furthermore, researches have shown that a word embedding set with better quality can benefit the whole model [22], and methods of “meta-embedding”, first proposed by [43], can yield an embedding set with improved quality. Therefore, meta-embedding can benefit the language modelling.

To yield an embedding set with better quality, several methods have been proposed in terms of meta-embeddings, e.g., 1toN+ [43] takes the ensemble of $K$ pre-trained embedding sets, and use a neural network to recover its corresponding vector within each source embedding set. An unsupervised approach is employed by [5]: for each word, a representation as a linear combination of its nearest neighbours is learnt. Other methods, despite their simplicity, such as concatenation [43], or averaging source word embedding [12] has been used to provide a good baseline of performance for meta-embedding. In this work, we explore a new way of meta-embedding, namely, the Duo. To the best of our knowledge, our model is the first meta-embedding method based on self-attention mechanism.

Our meta-embedding language learning model uses the Transformer as our back stone, which is a model architecture eschewing recurrence and relying only on attention, of which the mechanism is drawing of global dependencies between input and output. As recurrence is deducted, the parallelization is greatly enhanced. Because we use two times the embeddings to learn, the number of heads in the Transformer doubles and better performance is gained. Moreover, we use weight sharing in duo multi-head attention; thus the number of parameters is reduced.

The mechanism of the Duo is that instead of merely adding the dimension of word embedding, which leads to enormous increasing number in parameters, we use separately trained embedding as key and value for each word in the self-attention mechanism of the Transformer. As the number of word embedding doubles, the information in attention also
doubles. The discrepancy between the two pieces of independent embedding describes two different aspects of the same information. As our results demonstrate, this independence is quite beneficial to the training of the model.

Moreover, recent research [36] has shown that the Transformer has shortcomings in long sequence learning, the Transformer-XL and other methods [9,34] are therefore proposed to address the long sequence problem. The good news is that our model is very general that the Transformer-XL, along with other language models based on the Transformer, can employ the Duo mechanism to perform meta-embedding learning.

We examine our model in two representative tasks: the text classification task and the machine translation task. When it comes to a text classification problem, the Duo mechanism exploits the information in two pieces of word embedding, each separately trained, e.g., GloVe [30] and fastText [18]. This meta-embedding model allows the language model to have more previous knowledge in independent aspects, thus leading to a better result. The machine translation task is more tricky for meta-embedding learning, as it concerns the devising of a decoder. However, in this paper, we proposed a sequence-to-sequence meta-embedding language model to handle this problem, and the experiment shows that learning in such a way leads to better performance and a faster convergence.

All in all, the contributions of us are threefold:

- We propose an attention-based way of meta-embedding for a better language modelling.
- To the best of our knowledge, we devise the first sequence-to-sequence encoder-decoder language model which directly uses two independent embeddings.
- The Duo mechanism we propose is very general and can be employed on any language model based on the Transformer.

2 Background

For the deep learning method in the text classification problem, word embedding has been a focus of much research [26,30] as several studies showed that the text classification task depends enormously on the effectiveness of the work embedding [33,40]. The first part of our work focuses on combining different pre-trained word embedding for text classification. In other words, the Duo mechanism enables two different pieces of pre-trained word embedding to perform on the same stage.

As for methods for the meta embedding [43], they concern conducting a complementary combination of information from an ensemble of distinct word embedding sets, each trained using different methods, and resources, to yield an embedding set with improved overall quality [19,28,12,27,2]. Thus we believe this is one of the benefits of applying Duo.

There have also been exhausted studies on the refinement of the architecture of the Transformer. Adversarial training has been proved to be beneficial to language modelling [39]. Additionally, to deal with the fix-length problem, [13] extend the vanilla Transformer with recurrent units, which greatly enhances the original model. The Duo mechanism is a meta-embedding way to approach the Transformer.

The Duo is the first meta embedding language architecture based on attention to the best of our knowledge. In the following sections, we will describe the Duo text classification model in section 3.1 and then we will explore its implementation on encoder-decoder architecture in section 3.2.

3 Model Architecture

3.1 Duo Classifier

3.1.1 Duo Word Embedding

As is demonstrated in figure 1, we use different embedding namely, Spongebob and Patrick, to represent the word embedding of the same input sequence \( x_i = (x_1, x_2, ..., x_{l_i}) \), where \( l_i \) is the unified length of the \( i \)-th sentence. Later, we use embedding Spongebob and Patrick to represent separately trained word embedding, e.g., Spongebob can be GloVe 300d, and Patrick can be Word2Vec 30d. For the simply of notation, we use \( S_i \in \mathbb{R}^{l_i \times d_{model1}} \), \( P_i \in \mathbb{R}^{l_i \times d_{model2}} \) to represent the text with different word embedding.
Figure 1: The Duo Classifier Model Architecture

3.1.2 Duo Classifier Attention

We will simply let the model to learn the parameter of attention to balance the weight of different dimension in our text classifier. In practice, we initialize two parameter $w^S \in \mathbb{R}^{d_{model1}}$ and $w^P \in \mathbb{R}^{d_{model2}}$.

$$a^P = \text{Attention}(w^S, S, P) = \text{Softmax}(w^S S^T) P$$  \hspace{1cm} (1)  \\
$$a^S = \text{Attention}(w^P, P, S) = \text{Softmax}(w^P P^T) S$$  \hspace{1cm} (2)  

In our later experiment, we will drop the softmax function, because doing this will have even faster computation while maintaining satisfying results.

3.1.3 Duo Sentence Embedding

The duo sentence embedding would be a fusion layer of $a^P$ and $a^S$, so, we will introduce another fusion parameter $W^O \in \mathbb{R}^{(d_{model1} + d_{model2}) \times d_{ff}}$.

$$e = [a^P, a^S]W^O$$  \hspace{1cm} (3)  

where $[\cdot, \cdot]$ is concatenate operation.

The $e$ is the final representation of sentence embedding. Its value is the weighted sum of $P, S$ based on the attention of each other. In other words, we learn the attention and value separately by giving them different embedding.

3.1.4 Model Complexity

The number of parameters to be learned in our model is $d_{model1} + d_{model2}$ in Duo Classifier Attention layer, $(d_{model1} + d_{model2}) \times d_{ff}$ in Sentence Duo Embedding layer and $d_{ff} \times \text{label\_num}$ in the final softmax layer. If we set $d_{model1} = d_{model2} = 300$, $d_{ff} = 600$ and number of label = 20. The number summed up is no more than 0.4M parameters. When running on a machine with 8 GPUs, we can achieve a state-of-the result on text classification tasks 20NG in less than half an hour.

3.2 Duo Transformer

3.2.1 Duo Attention

After reviewing on the duo classifier, the Duo multi-head attention seems simple and straight-forward.

We have multi-head attention:

$$A^S = \text{MultiHead}(Q^P, K^P, V^S)$$  \hspace{1cm} (4)  

Figure 2: The Duo Transformer Model Architecture

\[ A^P = \text{MultiHead}(Q^S, K^S, V^P) \]  (5)

We can use similar formulation to calculate the Duo multi-head attention.

From figure 2, it seems that the number of parameters has doubled compared to vanilla attention. In order to eschew this overcomplexity, we share weight in multi-head attention of each layer. Specifically, \(K^P\) and \(V^P\), and \(V^S\) and \(K^S\) in each layer share the same projection parameters. So in the final multi-head attention, we only have \(\frac{1}{3}\) more projection parameters, and our experiments show that the weight sharing result in faster convergence.

3.3 Duo Decoder

The Duo Decoder is quite similar to the original Transformer decoder, except the fact that the original Transformer has the same \(K\) and \(V\), while the Duo Decoder has different ones. We interpret that each \(K\) and \(V\) encode different information from each word embedding. Thus they need to be decoded separately.

The vanilla Transformer has the same weights matrix between the two embedding layers and pre-softmax linear transformation similar to [31]. However, as we have a fusion layer, we still share weights, but after a linear projection of the original concatenated duo embedding layer, and the parameters of this projection is to be learnt in the training step.

3.4 Duo Layer Normalization

Another intriguing part is the Duo Layer Normalization. The output of the traditional layer normalization [3] and residual connection [16] is \(\text{LayerNorm}(x + \text{Sublayer}(x))\) in each unit. However, considering the dimensional difference in different word embedding, meanwhile guaranteeing more fluid cross information flow. We modify the original LayerNorm to the following formula:
\[
\text{DuoLayerNorm}(x^S, x^P) = \text{LayerNorm}(x^S + \text{Sublayer}(x^P))
\]  
(6)

This mechanism is used in the decoder layer between the masked multi-head attention, and the feed-forward unit demonstrated in figure 2.

3.5 Why Duo

Attention is undoubtedly a good idea in natural language processing. However, even the author of the Transformer is aware of the limitation of equaling attention value to the word value. Thus, we have multi-head attention to deal with the problem, where the embedding is linearly transformed and then fed into the scaled dot-product attention. However, such a linear transformation may not contain as much information; after all, it is linear, meaning there are still unbreakable constrains in the attention value and word value.

For example, when we think of the abstract word 'duo', the concrete word 'Spongebob', 'Patrick', 'Tom' and 'Jerry' are among the things we come up. However, in order to let the noun 'duo' to pay close attention to these concrete examples, this word should be among the 'name cluster' in the embedding space. However, 'duo' is undoubtedly not a name; it should be among these names in the abstract attention space, but not in the value space.

Another example is we have a word vector 'Spongebob' by adding a vector to the word vector 'Patrick'. Moreover, we get 'Tom' by adding the same vector to 'Jerry' due to the linear substructure of the embedding space. However, we have no idea what we will get by adding this vector to the word 'duo'.

Loosening the attention-value constrains enables the model to have diversity in concrete embedding space while maintaining the homogeneity in abstract embedding space, which we use to calculate attention.

4 Experiment

In this section, we will first demonstrate the performance of our Duo Classifier on public text classification tasks. Then, we will show the results of running our model on machine translation tasks. We ran our models on 8 NVIDIA RTX 2080 Ti GPUs.

4.1 Duo Classifier

We compare our model with multiple state-of-the-art baselines on many public datasets in terms of accuracy. We use GloVe 50d and GloVe 300d as pre-trained embedding, which we find are the best duo couple. Then, we will run a series of self-compare experiment on different combinations of word embedding.

4.1.1 Results

Settings

We explored a variety of duo couple, and it turns out the GloVe 50d and GloVe 300d can yield the best results. Other parameters including dropout, learning rate are the same as the original transformer. We randomly selected 10% of the training set a validation. We trained our model for a maximum of 200 epochs using Adam \cite{21} and stop if the validation loss does not decrease for ten consecutive epochs. The results of other models on the same datasets are from \cite{42}. We run out models for ten times and calculate its mean. We will then further explore the result of different combinations of duo couple.

Datasets

We ran our experiments on five popular benchmark corpora including 20-Newsgroups (20NG)\footnote{http://qwone.com/ jason/20Newsgroups/}, Ohsumed\footnote{http://dist.unin.it/moschitti/corpora.htm}, R52 and R8 of Reuters 21578\footnote{https://www.cs.umb.edu/ smimarog/textmining/datasets/} and Movie Review (MR)\footnote{http://www.cs.cornell.edu/people/pabo/movie-review-data/}. These datasets are widely used and recognized in recent publications, and we will skip the details of them. The readers could go to \cite{42} for more detailed settings.

Performance

\[\text{(continued)}\]
As it turns out, our model achieves the best results on 4 out of 5 benchmarks\textsuperscript{1}. It still ranks second in R8 dataset, and we think it is because the words number in this datasets are less than the others (with only 7,688 words) that information simply from word embedding are not enough.

The main reasons why duo model works well are obvious. Firstly, we use separately trained embedding. And previous research has shown that this meta embedding technology can greatly improve the performance. Secondly, we use Transformer to combine these embedding and this model is proved to be more efficient than traditional RNN-based models. Let alone we simply calculate the average of the word embedding in each documents for text classification in way of meta embedding way.

\textbf{Which Couple Is The Best}

We explored various couples of word embedding on datasets. Including different dimensions of embedding from GloVe \textsuperscript{30}, CBOW \textsuperscript{26}, and fastText \textsuperscript{18}, and the results are demonstrated on 2, 3 and , and 4. And it turns out that the GloVe 50d and GloVe 300d duo win the competition. The result is obtained by running 10 times of different couples and calculating their mean performance on 20NG, Ohsumed and MR dataset. Without any exceptions, the Duo couple of GloVe 50d and GloVe 300d has the best results on all the tasks. These results further proves the advantages of GloVe word embedding. Additionally, it is no surprise to us that the the diagnose of the table shows relatively less satisfying results, . Because the duo embedding employs the same embedding, they are simple one-layer single-head transformer models.

\textbf{4.2 Duo Machine Translation}

After exploring the performance of Duo in the text classification task, we further investigate whether this meta-embedding mechanism could be applied to the machine translation tasks. The potential of the model is considerable, as a good performance in task classification tasks means such a mechanism could encode a sentence much better. However, the real difficulties lay in the design of the decoder. We finally figure out a meta embedding decoder architecture based

\textsuperscript{5}bag-of-words model with term frequency-inverse document frequency weighting. Logistic Regression is used as the classifier.

\textsuperscript{6}CNN-non-static uses pre-trained word embeddings
on the backbone of the Transformer demonstrated in [32]. In this part, we will examine the Duo Translator in terms of its BLEU score, and its convergence speed.

### 4.2.1 Results

#### Settings

For the machine translation models, we followed the same hyper-parameter setup described in [38]. Specifically, we set the $d_{\text{model}} = 512$, and the $d_{\text{ff}}$ was set to 2048. The number of layers for the encoder and the decoder was set to 8. Additionally, we use weight sharing in the Duo Multi-head to decrease the model complexity. Worth mentioning, we use gloVe 300d word embedding followed by a $300 \cdot 512$ feed-forward neural networks to fix the discrepancy of dimensionality.

#### Datasets

On the machine translation task, we report results on three mainstream benchmark datasets: WMT 2014 English to German (En-De) consisting of about 4.5 million sentence pairs, and WMT 2014 English to French (En-Fr) of 36M sentences. We used byte-pair encoding [6] of size 32K and 40K tokens for each task.

#### Performance

We demonstrate the effectiveness of our model in table 5, which shows that meta embedding could clearly benefit the process of translation. Specifically, our model is able to achieve a state-of-the-art score on WMT 2014 En-De benchmark, and still competitive in WMT 2014 English to France benchmark. Worth mentioning, the meta-embedding Duo Transformer has outperformed the vanilla transformer by 1.3 and 1.1 BLEU score on each task, further proving the advantage of the meta-embedding mechanism.

Figure 3, alongside with table 8 and 7 also demonstrates the faster convergence, as well as better performance results by meta embeddings. The results are obtained by calculating the average of 3 separate runnings of each model on the WMT 2014 En-De Validation Set.

| Model                  | Param | WMT En-De | WMT En-Fr |
|------------------------|-------|-----------|-----------|
| ConvS2S [15]           | 216M  | 25.2      | 40.5      |
| Transformer big [38]   | 213M  | 28.4      | 41.0      |
| Weighted Transformer [1] | 213M  | 28.9      | 41.4      |
| RNMT+ [6]              | 379M  | 28.5      | 41.0      |
| Transformer with RPP [32] | -    | 29.2      | 41.5      |
| SNMT [29]              | 210M  | 29.3      | 43.2      |
| DynamicConv [41]       | 213M  | 29.7      | 43.2      |
| TaLK Convolution [42]  | 209M  | 29.6      | 43.2      |
| **Ours**               | 220M  | **29.7**  | **42.1**  |

Table 5: Machine translation accuracy in terms of BLEU for WMT En-De and WMT En-Fr on newestst2014.
In order to evaluate the function of different parts in our architecture, we did an ablation test on the WMT 2014 En-De Validation set. We used the same hyper-parameters as before, and the results are reported in Table 6. Initially, we add the meta embeddings to the Vanilla Transformer Model, and it seems that this gives the most salient advancement of the performance. However, the number of parameters increased quite a lot, and the improvement may merely come from the additional parameter numbers. Therefore, we decided to shrink the model’s size by using weight sharing in Duo Multihead. It turns out that this operation not only reduced the number of parameters but also improves the performance. The following Normalization and Fusion layer has also been proved to be beneficial.

Table 6: Ablation on WMT En-De validation set. (+) indicates that a result includes all preceding features.

| Model | Param | BLEU   |
|-------|-------|--------|
| Transformer | 213M  | 27.31 ± 0.01 |
| + Meta Embeddings | 246M  | 28.41 ± 0.2 |
| + Weight Sharing in Duo Multihead | 220M  | 28.58 ± 0.05 |
| + Duo Normalization | 220M  | 29.60 ± 0.07 |
| + Fusion Layer | 220M  | 29.68 ± 0.03 |

Table 7: Details of BLEU on WMT 2014 En-De Validation Set for the last 11 epoches

| # Epoch | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---------|----|----|----|----|----|----|----|----|----|----|----|
| Transformer | 25.55 | 25.59 | 26.49 | 26.78 | 26.69 | 27.2 | 27.05 | 27.69 | 27.21 | 27.55 | 27.21 |
| Duo(Ours) | 29.02 | 28.94 | 29.26 | 29.32 | 29.12 | 29.3 | 29.7 | 29.65 | 29.13 | 29.69 | 29.75 |

Table 8: Details of Perplexity on WMT 2014 En-De Validation Set for the last 11 epoches

| # Epoch | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---------|----|----|----|----|----|----|----|----|----|----|----|
| Transformer | 24.53 | 19.68 | 20.49 | 18.17 | 16.77 | 16.77 | 15.95 | 16.11 | 15.33 | 14.01 | 13.46 |
| Duo(Ours) | 18.72 | 16.94 | 16.89 | 15.64 | 15.03 | 14.43 | 14.15 | 12.06 | 11.82 | 11.58 | 11.13 |

5 Conclusion

In this work, we presented the Duo Model, the first meta-embeddings mechanism based on self-attention, which improves the performance of language modelling by exploiting more than one word-embedding.

For text-classification tasks, a single-layer Duo Classifier can achieve the state-of-the-art results on many public benchmarks. Moreover, for machine translation tasks, we introduce the first encoder-decoder models with more than one embedding. Furthermore, we prove that this meta embedding mechanism benefits the vanilla transformer in terms of not only better performance but also a faster convergence.
Nowadays, though there is more and more attention paid to meta-embeddings in natural language processing, we still think that this mechanism has potential other than the text classification task. We sincerely expect more investigations into this field.

References

[1] Ahmed, K., Keskar, N. S., and Socher, R. Weighted transformer network for machine translation. *arXiv preprint arXiv:1711.02132* (2017).

[2] Artetxe, M., Labaka, G., Lopez-Gazpio, I., and Agirre, E. Uncovering divergent linguistic information in word embeddings with lessons for intrinsic and extrinsic evaluation. *arXiv preprint arXiv:1809.02094* (2018).

[3] Ba, J. L., Kiros, J. R., and Hinton, G. E. Layer normalization. *arXiv preprint arXiv:1607.06450* (2016).

[4] Bahdanau, D., Cho, K., and Bengio, Y. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473* (2014).

[5] Bollegala, D., Hayashi, K., and Kawarabayashi, K.-i. Think globally, embed locally—locally linear meta-embedding of words. *arXiv preprint arXiv:1709.06671* (2017).

[6] Britz, D., Goldie, A., Luong, M.-T., and Le, Q. Massive exploration of neural machine translation architectures. *arXiv preprint arXiv:1703.03906* (2017).

[7] Bruna, J., Zaremba, W., Szlam, A., and LeCun, Y. Spectral networks and locally connected networks on graphs. *arXiv preprint arXiv:1312.6203* (2013).

[8] Chen, M. X., Firat, O., Bapna, A., Johnson, M., Macherey, W., Foster, G., Jones, L., Parmar, N., Schuster, M., Chen, Z., et al. The best of both worlds: Combining recent advances in neural machine translation. *arXiv preprint arXiv:1804.09849* (2018).

[9] Child, R., Gray, S., Radford, A., and Sutskever, I. Generating long sequences with sparse transformers. *arXiv preprint arXiv:1904.10509* (2019).

[10] Cho, K., van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., and Bengio, Y. Learning phrase representations using rnn encoder-decoder for statistical machine translation. *arXiv preprint arXiv:1402.3130* (2014).

[11] Chung, J., Gulcehre, C., Cho, K., and Bengio, Y. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555* (2014).

[12] Coates, J., and Bollegala, D. Frustratingly easy meta-embedding—computing meta-embeddings by averaging source word embeddings. *arXiv preprint arXiv:1804.05262* (2018).

[13] Dai, Z., Yang, Z., Yang, Y., Cohen, W. W., Carbonell, J., Le, Q. V., and Salakhutdinov, R. Transformer-xl: Attentive language models beyond a fixed-length context. *arXiv preprint arXiv:1901.02860* (2019).

[14] Defferrard, M., Bresson, X., and Vandergheynst, P. Convolutional neural networks on graphs with fast localized spectral filtering. In *Advances in neural information processing systems* (2016), pp. 3844–3852.

[15] Gehring, J., Auli, M., Grangier, D., Yarats, D., and Dauphin, Y. N. Convolutional sequence to sequence learning. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70* (2017), JMLR. org, pp. 1243–1252.

[16] He, K., Zhang, X., Ren, S., and Sun, J. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (2016), pp. 770–778.

[17] Hochreiter, S., and Schmidhuber, J. Long short-term memory. *Neural computation* 9, 8 (1997), 1735–1780.

[18] Joulin, A., Grave, E., Bojanowski, P., and Mikolov, T. Bag of tricks for efficient text classification. *arXiv preprint arXiv:1607.01759* (2016).

[19] Kiela, D., Wang, C., and Cho, K. Dynamic meta-embeddings for improved sentence representations. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing* (Brussels, Belgium, Oct.-Nov. 2018), Association for Computational Linguistics, pp. 1466–1477.

[20] Kim, Y. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882* (2014).

[21] Kingma, D. P., and Ba, J. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980* (2014).
[22] Kočmi, T., and Bojar, O. An exploration of word embedding initialization in deep-learning tasks. *arXiv preprint arXiv:1711.09160* (2017).

[23] Le, Q., and Mikolov, T. Distributed representations of sentences and documents. In *International conference on machine learning* (2014), pp. 1188–1196.

[24] Lioutas, V., and Guo, Y. Time-aware large kernel convolutions. *arXiv preprint arXiv:2002.03184* (2020).

[25] Liu, P., Qiu, X., and Huang, X. Recurrent neural network for text classification with multi-task learning. *arXiv preprint arXiv:1605.05101* (2016).

[26] Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems* (2013), pp. 3111–3119.

[27] Muromagi, A., Sirts, K., and Laur, S. Linear ensembles of word embedding models. *arXiv preprint arXiv:1704.01419* (2017).

[28] Neill, J. O., and Bollegala, D. Angular-based word meta-embedding learning. *arXiv preprint arXiv:1808.04334* (2018).

[29] Ott, M., Edunov, S., Grangier, D., and Auli, M. Scaling neural machine translation. *arXiv preprint arXiv:1806.00187* (2018).

[30] Pennington, J., Socher, R., and Manning, C. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing* (EMNLP) (2014), pp. 1532–1543.

[31] Press, O., and Wolf, L. Using the output embedding to improve language models. *arXiv preprint arXiv:1608.05859* (2016).

[32] Shaw, P., Uszkoreit, J., and Vaswani, A. Self-attention with relative position representations. *arXiv preprint arXiv:1803.02155* (2018).

[33] Shen, D., Wang, G., Wang, W., Min, M. R., Su, Q., Zhang, Y., Li, C., Henao, R., and Carin, L. Baseline needs more love: On simple word-embedding-based models and associated pooling mechanisms. *arXiv preprint arXiv:1805.09843* (2018).

[34] Sukhbaatar, S., Grave, E., Bojanowski, P., and Joulin, A. Adaptive attention span in transformers. *arXiv preprint arXiv:1905.07799* (2019).

[35] Sutskever, I., Vinyals, O., and Le, Q. Sequence to sequence learning with neural networks. *Advances in NIPS* (2014).

[36] Tang, G., Müller, M., Rios, A., and Sennrich, R. Why self-attention? a targeted evaluation of neural machine translation architectures. *arXiv preprint arXiv:1808.08946* (2018).

[37] Tang, J., Qu, M., and Mei, Q. Pte: Predictive text embedding through large-scale heterogeneous text networks. In *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (2015), pp. 1165–1174.

[38] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. Attention is all you need. In *Advances in neural information processing systems* (2017), pp. 5998–6008.

[39] Wang, D., Gong, C., and Liu, Q. Improving neural language modeling via adversarial training. *arXiv preprint arXiv:1906.03805* (2019).

[40] Wang, G., Li, C., Wang, W., Zhang, Y., Shen, D., Zhang, X., Henao, R., and Carin, L. Joint embedding of words and labels for text classification. *arXiv preprint arXiv:1805.04174* (2018).

[41] Wu, F., Fan, A., Baevski, A., Dauphin, Y. N., and Auli, M. Pay less attention with lightweight and dynamic convolutions. *arXiv preprint arXiv:1901.10430* (2019).

[42] Yao, L., Mao, C., and Luo, Y. Graph convolutional networks for text classification. In *Proceedings of the AAAI Conference on Artificial Intelligence* (2019), vol. 33, pp. 7370–7377.

[43] Yin, W., and Schütze, H. Learning word meta-embeddings. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)* (2016), pp. 1351–1360.