Explicitly Modeling Adaptive Depths for Transformer

Yijin Liu\textsuperscript{1*}, Fandong Meng\textsuperscript{2}, Jie Zhou\textsuperscript{2}, Yufeng Chen\textsuperscript{1} and Jinan Xu\textsuperscript{1†}

\textsuperscript{1}Beijing Jiaotong University, China
\textsuperscript{2}Pattern Recognition Center, WeChat AI, Tencent Inc, China
adaxry@gmail.com
\{fandongmeng, withtomzhou\}@tencent.com
\{chenyf, jaxu\}@bjtu.edu.cn

Abstract

The vanilla Transformer conducts a fixed number of computations over all words in a sentence, irrespective of whether they are easy or difficult to learn. In terms of both computational efficiency and ease of learning, it is preferable to dynamically vary the numbers of computations according to the hardness of the input words (Dehghani et al., 2019). However, how to find a suitable estimation for such hardness, then explicitly modeling adaptive computation depths are still not investigated. In this paper, we try to solve this issue, and propose two effective approaches, namely 1) mutual information based estimation and 2) reconstruction loss based estimation, to measure the hardness of learning the representation for a word and determine its computational depth. Results on the classic text classification task (24 datasets in various sizes and domains) show that our approaches achieve superior performance while preserving higher efficiency in computation over the vanilla Transformer and previous depth-adaptive models. More importantly, our approaches lead to more robust depth-adaptive Transformer models with better interpretability of the depth distribution.

1 Introduction

Generally, in a sentence, certain words are usually more ambiguous than others and thus need more layers of abstraction to refine feature representations. While simply training a very deep neural model is not easy, due to the problem of vanishing/exploding gradient (Pascanu et al., 2013a). One alternative solution is to dynamically modulate the number of computational steps at different word positions, which is known as ACT (Adaptive Computation Time) (Graves, 2016). Specifically, the ACT employs a halting unit upon each word when reading a sentence, then this halting unit determines a probability that computation should continue or stop layer-by-layer. Recently, the ACT has cut a figure and attracted more and more attentions, under the trend of bigger and bigger neural models nowadays. For instance, the ACT has been extended to reduce computations either by exiting early or by skipping layers for the ResNet (Figurnov et al., 2017), the SkipNet (Wang et al., 2018) and the Universal Transformer (Dehghani et al., 2019).

Despite its success, how to properly estimate the hardness of each word and adaptively determine its computation depth still remains a core issue in the ACT. This can be attributed to no explicit supervision for the modeling of the adaptive depth, since typically, the core component of the ACT (i.e., the halting unit) is implicitly trained together with other downstream tasks, which may yield under-optimized parameters and weak robustness to random initialization\textsuperscript{1}. Intuitively, it is preferable to provide an explicit supervision for the depth estimation according to the hardness of learning representation for each input word, in addition to the supervision of downstream tasks. Since the explicit supervision can directly guide the estimation of the adaptive depth to make the model learning easier and more interpretable.

To this end, we investigate two effective approaches, namely 1) mutual information based estimation, and 2) reconstruction loss based estimation, to measure the hardness of learning representation for each input word. Next, we use the estimated value to calculate a synthetic label for the depth selection. Then we treat this ‘fake’ label as an approximation of the golden label (actually unaccessible), and name it as ‘depth oracle’. In doing so, we can simply step in the supervised learning

\textsuperscript{*}This work was done when Yijin Liu was interning at Pattern Recognition Center, WeChat AI, Tencent Inc, China
\textsuperscript{†}Jinan Xu is the corresponding author of the paper.

\textsuperscript{1}Our preliminary experiments show a relatively high variance with different random seeds on a text classification task.
paradigm, and significantly reduce the difficulty to train a good halting unit. We conduct extensive experiments on the text classification task (24 datasets in various sizes and domains). Results show that our approaches bring in consistent improvements over the vanilla Transformer and previous depth-adaptive models in terms of accuracy and efficiency. More importantly, our approaches lead to more robust depth-adaptive Transformer models with better interpretability of the depth distribution.

Our main contributions are as follows:

- We are the first to investigate the supervised paradigm to depth-adaptive neural network, specifically on the Transformer.
- We propose two simple yet effective approaches to estimate the hardness of learning representation for each word, and explicitly model the adaptive depths with the help of these estimations.
- Our approaches achieve a good trade-off between accuracy and speed, and bring interpretability and robustness over baselines.
- We provide thorough analyses to offer more insights and elucidate the properties of our approaches.

2 Model

2.1 How to Estimate the Hardness and Obtain the Depth Oracle?

In this section, we introduce two estimations to measure the hardness of learning representations for input words, and then generate the depth oracle for each word according to the estimated values.

Mutual Information Based Estimation. The Mutual Information (MI) is a measure of the mutual dependence between the two variables. Formally, the MI value of two jointly discrete random variables \( X \) and \( Y \) is calculated as:

\[
\text{MI}(X; Y) = \sum_{y \in Y} \sum_{x \in X} p(x, y) \cdot \log \left( \frac{p(x, y)}{p(x) \cdot p(y)} \right)
\]

(1)

The MI has been widely used for feature selection in the statistic machine learning literature (Peng et al., 2005). In our case of text classification, a larger MI value of a word indicates a greater certainty between this word and the labels, and thus fewer computations are needed to learn a adequate representation for this word. For example, ‘terrible’ could decide a ‘negative’ label with high confidence, thus does not need to take a very deep transformation in a neural model. Based on the above assumptions, it is intuitive to choose the MI as an estimation approach to measure the difficulty of learning a word.

Formally, given a set of sentences with vocab \( W \) and label set \( C \), the MI value for word \( w \) is calculated as follows:

\[
\text{MI}(w) = \sum_{c \in \{0, 1\}} \sum_{e_c \in \{0, 1\}} P(e_w, e_c) \cdot \log \left( \frac{P(e_w, e_c)}{P(e_w) \cdot P(e_c)} \right)
\]

(2)

where \( e_w \) is a boolean indicator that whether word \( w \) exists in a sentence. Similarly, \( e_c \) refers to the existence of label \( c \). In practice, the probability formulas \( P(\cdot) \) in Equation (2) are calculated by frequencies of words, labels, or their combinations in the whole corpus, and a smooth factor is introduced to avoid zero division. Note that we only calculate the MI values on the train set for each dataset to avoid injecting information of golden labels of test set.

After acquiring the MI value \( \text{MI}(w) \) for each word, we proceed to generate the depth oracle \( d(w) \) according to \( \text{MI}(w) \). As the histogram of MI values shown in Figure 1 (the upper part). The obvious long tail exposes that the distribution is extremely imbalanced. To alleviate this issue, we first perform negative log scale for the original MI values as:

\[
\text{MI}_{\log}(w) = -\log(\text{MI}(w))
\]

(3)

Next, we binning the scaled \( \text{MI}_{\log}(w) \) into \( L \) fixed-width buckets, where \( L \) denotes a predefined number of maximum depth. The larger is the value \( \text{MI}_{\log}(w) \), the smaller is the number of depth oracle \( d(w) \).
Figure 1: The histogram of MI values of partial words from the IMDB dataset (the upper part), and the histogram of output depths of these words by using the reconstruction loss based estimation (the bottom part). We can clearly observe the different distributions and bias for these two estimation methods. The MI based one could easily calculate out most of label-relevant words (e.g., opinion words in this semantic analysis dataset), and then could assign fewer computational resources properly. While the reconstruction based one is good at recognizing common words, due to its powerful contextual modeling ability.

Reconstruction Loss Based Estimation. Generally, in a sentence, several words may bring redundant information that has been included by their contexts. Thus if we mask out these trivial words, it would be easier to reconstruct them than others. Based on this principle, we use the reconstruction loss (i.e., cross entropy) to measure the hardness of learning the representation for a masked word. Firstly, we train a masked language model (MLM) following the experimental setup of BERT (Devlin et al., 2019) with two major differences: 1) we make predictions at every layer with a shared classifier instead of only at the final layer in BERT, 2) we train MLMs only with each individual datasets instead of using additional corpora, as we only need a suitable estimation for learning representation of a word rather than boosting a huge pre-trained LM. We take the weighted sum \(^4\) of loss from each layer as the final loss of our MLMs. After training the MLMs, we sequentially mask out each word \(x_i\) in an input sentence, and then select the number of layer with the minimum loss as the depth oracle \(d(x_i)\):

\[
d(x_i) = \arg \max_n (\text{loss}_i - \lambda n)
\]

where \(\lambda\) is the penalty factor to encourage a lower selection.

Comparisons Between Two Estimation. In this section, we make detailed comparisons about these two estimations. When we focus on computational expense, the MI based approach does not rely on additional trainable module, thus is highly efficiency in computation. While the reconstruction loss based approach has to train several MLMs in advance, which yields extra computational resources. Next, we compare the different features of the distribution of depth oracles generated by both approaches. As the histogram shown in Figure 1 (upper part), the words with high MI values
tend to be highly label-relevant words (e.g., opinion words ‘perfect’ and ‘horrible’ in the IMDB semantic dataset), which could easily predict the correct label. Thus it is reasonable to allocate relatively fewer computations for these words. For the sake of comparisons, we also pick out the corresponding depth oracles outputted by using the reconstruction loss based estimation, and shown them in Figure 1 (bottom part). There is clear that both distributions measure the hardness for a word in different views. Unlike the preference for label-related words in the MI based approach, the reconstruction based one measures purely rely on the unsupervised context. Therefore it is good at to recognizes common words (e.g., ‘today’, ‘one’ and ‘me’), then assigns smaller numbers of depth and vice versa.

2.2 Depth-Adaptive Mechanism

We stacked $L$ layers of the Transformer encoder to model a sentence. The Transformer encoder is consist of two sub-layer in each layer. The first sub-layer is a multi-head dot-product self-attention and the second one is position-wise fully connected feed-forward network. We refer readers to the original paper (Vaswani et al., 2017) for more details. In particular, we build a depth classifier upon the first layer of our encoder. This classifier is used to dynamically predict the number of depth for each word position, and is fully supervised by our proposed depth oracle $d(x_i)$. Unlike the continuous prediction of the stop probability layer-by-layer in the ACT, we directly predict the depth distribution for the sake of computational efficiency.\(^5\) The classifier calculates the probability of predicted depths $p$ by following:

$$h^1 = \text{Transformer}(x)$$

$$p = \text{softmax}(W_d h^1 + b_d)$$

(5)

where $h^1$ is the output hidden state of the first encoder layer, and $W_d \in \mathbb{R}^{d_{\text{model}} \times N}$ and $b_d$ are trainable parameters of the classifier. The depth classifier is trained with cross entropy loss.

$$L_{\text{depth}} = - \sum_{i=1}^n d(x_i) \log(p_i)$$

(6)

At training stage, the depth oracle $d(x_i)$ are chosen to determinate the actual depth to conduct, and the predicted one is used when testing.

$$\hat{d}_i = \arg \max_n (p + \lambda n)$$

(7)

To make sure all hidden states of the same layer are available to compute self-attention, once a word $x_i$ reaches its own maximal layer $\hat{d}_i$, it will stop state transition, and simply copy its state to the next layer until all words stop or the predefined maximal layer $N$ is reached. Formally, for the $i$-th word, its hidden state $h_i$ are updated as follows:

$$h_i^n = \begin{cases} h_i^{n-1} & \text{if } l > \hat{d}_i \\ \text{Transformer}(h_i^{n-1}) & \text{else} \end{cases}$$

(8)

where $n \in [1, N]$ refers to the number of current layer. Specially, $h_i^0$ is initialized by the word embedding, which is the concatenation of the glove and character-level embeddings.

2.3 Task-specific Settings

After dynamic steps of computation among all word positions, we make prediction upon the final exit layer for the classification task. The feature vector $v$ consists of mean and max pooling of output hidden states $h_i^{n_{\text{max}}}$, and is activated by the ReLU. Finally, a softmax classifier are built on $v$. Formally, the above-mentioned procedures are computed as follows:

$$v = \text{ReLU}([\max(h_i^{n_{\text{max}}}); \mean(h_i^{n_{\text{max}}})])$$

$$P(\hat{y}|v) = \text{softmax}(W_{\text{cls}} v + b_{\text{cls}})$$

(9)

where $W_{\text{cls}}$ and $b_{\text{cls}}$ are parameters of classifier, and $P(\hat{y}|v)$ is the probability distribution. Afterwards, the most probable label $\hat{y}$ is chosen from above probability distribution described by Equation (9):

$$\hat{y} = \arg \max P(\hat{y}|v)$$

(10)

At training stage, we use the cross entropy loss that is computed as:

$$L_{\text{cls}} = -\sum_{i=1}^{|S|} y_i \log(p_i)$$

(11)

where $y_i$ and $|S|$ are the golden label of and the size of the label set.

The total loss of our model is the sum of $L_{\text{depth}}$ and $L_{\text{cls}}$ with a balanced factor $\alpha$:

$$\text{loss} = L_{\text{cls}} + \alpha \cdot L_{\text{depth}}$$

(12)

\(^5\)Our preliminary experiments show that both methods work well.
Table 1: Dataset statistics. ‘CV’ refers to 5-fold CV. There are 16 subsets with the same size in Amazon-16.

| Dataset                        | Classes | Type  | Average Lengths | Max Lengths | Train Sample | Test Sample |
|--------------------------------|---------|-------|-----------------|-------------|--------------|-------------|
| TREC (Li and Roth, 2002)       | 6       | Question | 12             | 39          | 5,952        | 500         |
| AGs News (Zhang et al., 2015)  | 4       | Topic  | 44             | 221         | 120,000      | 7,600       |
| DBPedia (Zhang et al., 2015)   | 14      | Topic  | 67             | 3,841       | 560,000      | 70,000      |
| Subj (Pang and Lee, 2004)      | 2       | Sentiment | 26            | 122         | 10,000       | CV          |
| MR (Pang and Lee, 2005)        | 2       | Sentiment | 23            | 61          | 10,622       | CV          |
| Amazon-16 (Liu et al., 2017)   | 2       | Sentiment | 133           | 5,942       | 31,880       | 6,400       |
| IMDB (Maas et al., 2011)       | 2       | Sentiment | 230           | 2,472       | 25,000       | 25,000      |
| Yelp Polarity (Zhang et al., 2015) | 2       | Sentiment | 177           | 2,066       | 560,000      | 38,000      |
| Yelp Full (Zhang et al., 2015) | 5       | Sentiment | 179           | 2,342       | 650,000      | 50,000      |

Table 2: Accuracy scores (%) on the Amazon-16 datasets. † is our implementations with several recent advanced techniques (e.g., label smoothing) under the unified setting. Our model achieves better results than strong baseline Transformer models.

| Data / Model | MS-Transformer | Transformer † | Star-Transformer † | Ours |
|--------------|----------------|---------------|--------------------|------|
| Apparel      | 86.5           | 87.3          | 88.7               | 91.0 |
| Baby         | 86.3           | 85.6          | 88.0               | 89.8 |
| Books        | 87.8           | 85.3          | 86.9               | 89.0 |
| Camera       | 89.5           | 89.0          | 91.8               | 92.3 |
| Dvd          | 86.5           | 86.3          | 87.4               | 88.8 |
| Electronics  | 84.3           | 86.5          | 87.2               | 88.3 |
| Health       | 86.8           | 87.5          | 89.1               | 90.8 |
| Imdb         | 85.0           | 84.3          | 85.0               | 89.5 |
| Kitchen      | 85.8           | 85.5          | 86.0               | 88.5 |
| Magazines    | 91.8           | 91.5          | 91.8               | 94.3 |
| Mr           | 78.3           | 79.3          | 79.0               | 79.8 |
| Music        | 81.5           | 82.0          | 84.7               | 86.5 |
| Software     | 87.3           | 88.5          | 90.9               | 91.5 |
| Sports       | 85.5           | 85.8          | 86.8               | 87.0 |
| Toys         | 87.8           | 87.5          | 85.5               | 91.0 |
| Video        | 88.4           | 90.0          | 89.3               | 90.2 |
| Avg          | 86.2           | 86.4          | 87.4               | 89.3 |

3 Experiments

3.1 Task and Datasets

Text classification aims to assign a predefined label to text (Zhang et al., 2015), which is a classic task for natural language processing and is generally evaluated by accuracy score. Generally, The number of label may range from two to more, which correspond to binary and fine-grained classification. We conduct extensive experiments on the 24 popular benchmarks collected from diverse domains (e.g., topic, sentiment), and range from modestly sized to large-scaled. The statistics of these datasets are listed in Table 1.

3.2 Implementation Details

For the MI-based approach, we calculate depth oracles in the token level in advance, and use them at both training and testing stages. For the reconstruction loss based approach, we only use depth oracle for training, and utilize the predicted depth for testing. Dropout (Srivastava et al., 2014) are applied to word embeddings and hidden states with a rate of 0.3 and 0.2 respectively. Models are optimized by the Adam optimizer (Kingma and Ba, 2014) with gradient clipping of 3 (Pascanu et al., 2013b). The initial learning rate $\alpha$ is set to 0.001, and linearly decays with the increment of training steps. One layer CNN with a filter of size 3 and
Table 3: Accuracy scores (%) on modestly sized and large-scaled datasets. † is our implementations with several recent advanced techniques and analogous parameter sizes. ‘Uni-Transformer’ is the Universal Transformer. ‘Transformer’ is the vanilla Transformer with 6 layers. Our model brings consistent improvements over the baseline models w/ or w/o depth-adaptive mechanism, and achieves comparable results with state-of-the-art models.

### Results on Larger Benchmarks

As the results on larger corpora listed in Table 3, we also observe consistent improvements over the conventional Transformer (+0.53%) and other strong baseline models (e.g., the universal transformer (+0.63%), the star-transformer (+0.85%). Apart from the high accuracy, we further investigate the time efficiency in section 4.1, which suggest our model achieves a good accuracy-speed trade off and is more robustness for depth selection than the conventional ACT.

### Analysis

We conduct analytical experiments on a modestly sized benchmark (i.e., IMDB) to offer more insights and elucidate the properties of our approaches.

#### 4.1 Accuracy and Speed analysis

To investigate the effective of our proposed estimations for depth selection, we use the conventional depth-adaptive mechanism (i.e., the ACT) on a nine-layered Transformer without supervision of depth as baselines, and then apply MI based estimation and reconstruction loss based estimation, respectively. We run each model variant for three times and report the mean and variance.
Figure 2: Results of the conventional depth-adaptive mechanism w/o any depth estimation (i.e., ACT), ‘w/ MI estimation’ and ‘w/ reconstruction estimation’ on the IMDB sentiment dataset. The solid line indicate the mean performance and the size of colored area indicates variance.

Figure 3: Speeds of the conventional depth-adaptive mechanism w/o any depth estimation (i.e., ACT), ‘w/ MI estimation’ and ‘w/ reconstruction estimation’ on the IMDB sentiment dataset. The solid line indicate the mean speed and the size of colored area indicates variance. ‘Speed’: the number of samples calculated in one second on one Tesla P40 GPU with the batch size of 100.

4.2 Case Study

We choose a random sentence from the IMDB dataset, and show the depth oracles outputted by both kinds of estimations in Figure 4. We observe that the MI based estimation is able to reduce depths for the opinion words, such as ‘anticipated’ and ‘thriller’. While the reconstruction loss based estimation successfully reduces depths for all common words, such as ‘this’, and conducts more computation for more ambiguous words, like ‘Sci-fi’.

5 Related Work

Our work is inspired by conditional computation, where only parts of the network are selectively activated according to gating units (Bengio et al., 2013) or a learned policy (Bengio et al., 2015). A related architecture known as Adaptive Computation Time (ACT) (Graves, 2016). It employs a halting unit upon each word when sequentially reading a sentence. The halting unit determines the probability that whether computation should continue or stop step-by-step. ACT has been extend to control the layers of the Residual Networks (Figurnov et al., 2017) and the Universal Transformer (Dehghani et al., 2019). The major difference between our work and previous depth-adaptive mechanism lies in the explicit estimation of depth distribution and train the adaptive depth module in the supervised paradigm. Unlike the continuous layer-wise prediction to determine a stop probability in the ACT, we provide an effective alternative method with more straightforward modeling, which directly predicts the depth distribution among words simultaneously.

Another concurrent work named ‘Depth-Adaptive Transformer’ (Elbayad et al., 2019) propose to dynamically reduce computational burdens for the decoder in the sequence-to-sequence framework, and uses task-specific likelihood as an estimation of depth selection. Our independently proposed approaches are different with this work in two leading aspects: 1) our mutual information estimation does not need to train an extra modules,
I have anticipated the various Sci-fi and thriller movies this summer.

Figure 4: The histogram of a random sample from the IMDB dataset, where the orange blocks indicate depth oracles outputted by the mutual information based estimation, and the green blocks indicate depth oracles outputted by the reconstruction loss based estimation. The two kinds of estimation show different preference and views to measure the hardness of learning a word. Unlike the preference for opinion words in MI based approach, the reconstruction based one successfully recognizes common words (e.g., ‘today’, ‘one’ and ‘me’), then assigns smaller numbers of depth and vice versa.

and is highly efficiency in computation. 2) Our reconstruction loss estimation is purely unsupervised, and can be cast as a generalization of the task-specific likelihood.

Another group of works explore to conduct conditional computation inside the dimension of neural networks, (Jernite et al., 2017; Shen et al., 2019), instead of activating partial layers of model, e.g., adaptive depths in our method.

6 Conclusion

We investigate the supervised paradigm to depth-adaptive neural network. Specifically, we propose two effective approaches, namely the mutual information based estimation and the reconstruction loss based estimation, to measure the hardness of learning representation for each input word. And then generate the adaptive computation depth for each word corresponding to the estimated values.

We conduct extensive experiments on the text classification task (24 datasets in various sizes and domains), and the results show that our approaches bring consistent improvements over the vanilla Transformer and previous depth-adaptive models in terms of accuracy and efficiency. More importantly, our approaches lead to more robust depth-adaptive Transformer models with better interpretability of the depth distribution.

Therefore, our main contributions four-fold: (1) We are the first to investigate the supervised paradigm to depth-adaptive Transformer. (2) We propose two simple yet effective approaches to estimate the hardness of learning representation for each word, and explicitly model the adaptive depths with the help of these estimations. (3) Our model brings consistent improvements over baselines in four aspects, i.e., accuracy, efficiency, interpretability and robustness. (4) We provide thorough analyses to offer more insights and elucidate the properties of our approaches.

References

Reinald Kim Amplayo, Kyungiae Lee, Jinyeong Yeo, and Seung-won Hwang. 2018. Translations as additional contexts for sentence classification. In Proceedings of IJCAI.

Emmanuel Bengio, Pierre-Luc Bacon, Joelle Pineau, and Doina Precup. 2015. Conditional computation in neural networks for faster models. arXiv.

Yoshua Bengio, Nicholas Loner, and Aaron Courville. 2013. Estimating or propagating gradients through stochastic neurons for conditional computation. arXiv.

Mostafa Dehghani, Stephan Gouws, Oriol Vinyals, Jakob Uszkoreit, and ukasz Kaiser. 2019. Universal transformers. In Proceedings of ICLR.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of NAACL.

Maha Elbayad, Jiatao Gu, Edouard Grave, and Michael Auli. 2019. Depth-adaptive transformer. arXiv preprint arXiv:1910.10073.
Michael Figurnov, Maxwell D. Collins, Yukun Zhu, Li Zhang, Jonathan Huang, Dmitry Vetrov, and Ruslan Salakhutdinov. 2017. Spatially adaptive computation time for residual networks. In Proceedings of CVPR.

Alex Graves. 2016. Adaptive computation time for recurrent neural networks. arXiv.

Qipeng Guo, Xipeng Qiu, Pengfei Liu, Yunfan Shao, Xiangyang Xue, and Zheng Zhang. 2019a. Star-transformer. In Proceedings of NAACL.

Qipeng Guo, Xipeng Qiu, Pengfei Liu, Xiangyang Xue, and Zheng Zhang. 2019b. Multi-scale self-attention for text classification. arXiv preprint arXiv:1912.00544.

Yacine Jernite, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Variable computation in recurrent neural networks. In Proceedings of ICLR.

Rie Johnson and Tong Zhang. 2017. Deep pyramid convolutional neural networks for text categorization. In Proceedings of ACL.

Yoon Kim. 2014. Convolutional neural networks for sentence classification. In Proceedings of EMNLP.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv.

Hung Le, Truyen Tran, and Svetha Venkatesh. 2019. Learning to remember more with less memorization. In Proceedings of ICLR.

Xin Li and Dan Roth. 2002. Learning question classifiers. In Proceedings of COLING, pages 1–7.

Pengfei Liu, Xipeng Qiu, and Xuanjing Huang. 2017. Adversarial multi-task learning for text classification. In Proceedings of ACL.

Lajanugen Logeswaran and Honglak Lee. 2018. An efficient framework for learning sentence representations. arXiv.

Andrew L Maas, Raymond E Daly, Peter T Pham, Dan Huang, Andrew Y Ng, and Christopher Potts. 2011. Learning word vectors for sentiment analysis. In Proceedings of ACL, pages 142–150.

Bryan McCann, James Bradbury, Caiming Xiong, and Richard Socher. 2017. Learned in translation: Contextualized word vectors. In Proceedings of NeurIPS.

Bo Pang and Lillian Lee. 2004. A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts. In Proceedings of ACL.

Bo Pang and Lillian Lee. 2005. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. In Proceedings of ACL.

Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio. 2013a. On the difficulty of training recurrent neural networks. In Proceedings of ICML, pages 1310–1318.

Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio. 2013b. On the difficulty of training recurrent neural networks. In Proceedings of ICML.

Hanchuan Peng, Fuhui Long, and Chris Ding. 2005. Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy. IEEE Transactions on pattern analysis and machine intelligence, 27(8):1226–1238.

Chao Qiao, Bo Huang, Guocheng Niu, Daren Li, Daxiang Dong, Wei He, Dianhai Yu, and Hua Wu. 2018. A new method of region embedding for text classification. In Proceedings of ICLR.

Dinghan Shen, Guoyin Wang, Wenlin Wang, Martin Renqiang Min, Qinliang Su, Yizhe Zhang, Chunyuan Li, Ricardo Henao, and Lawrence Carin. 2018. Baseline needs more love: On simple word-embedding-based models and associated pooling mechanisms. In Proceedings of ACL.

Yikang Shen, Shawn Tan, Alessandro Sordoni, and Aaron Courville. 2019. Ordered neurons: Integrating tree structures into recurrent neural networks. In Proceedings of ICLR.

Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: A simple way to prevent neural networks from overfitting. The journal of machine learning research.

Yi Tay, Luu Anh Tuan, and Siu Cheung Hui. 2018. Recurrently controlled recurrent networks. In Proceedings of NeurIPS.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in neural information processing systems.

Baoxin Wang. 2018. Disconnected recurrent neural networks for text categorization. In Proceedings of ACL.

Xin Wang, Fisher Yu, Zi-Yi Dou, Trevor Darrell, and Joseph E. Gonzalez. 2018. Skipnet: Learning dynamic routing in convolutional networks. In The European Conference on Computer Vision (ECCV).

Min Yang, Wei Zhao, Jianbo Ye, Zeyang Lei, Zhou Zhao, and Soufian Zhang. 2018. Investigating capsule networks with dynamic routing for text classification. In Proceedings of EMNLP, Brussels, Belgium.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V Le.
2019. Xlnet: Generalized autoregressive pretraining for language understanding. *arXiv preprint arXiv:1906.08237*.

Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. In *Advances in neural information processing systems*, pages 649–657.

Han Zhao, Zhengdong Lu, and Pascal Poupart. 2015. Self-adaptive hierarchical sentence model. In *Proceedings of IJCAI*.