Compressing Transformer-Based Semantic Parsing Models using Compositional Code Embeddings

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Abstract

The current state-of-the-art task-oriented semantic parsing models use BERT or RoBERTa as pretrained encoders; these models have huge memory footprints. This poses a challenge to their deployment for voice assistants such as Amazon Alexa and Google Assistant on edge devices with limited memory budgets. We propose to learn compositional code embeddings to greatly reduce the sizes of BERT-base and RoBERTa-base. We also apply the technique to DistilBERT, ALBERT-base, and ALBERT-large, three already compressed BERT variants which attain similar state-of-the-art performances on semantic parsing with much smaller model sizes. We observe 95.15\% \sim 98.46\% embedding compression rates and 20.47\% \sim 34.22\% encoder compression rates, while preserving >97.5\% semantic parsing performances. We provide the recipe for training and analyze the trade-off between code embedding sizes and downstream performances.

1 Introduction

Conversational virtual assistants, such as Amazon Alexa, Google Home, and Apple Siri, have become increasingly popular in recent times. These systems can process queries from users and perform tasks such as playing music and finding locations. A core component in these systems is a task-oriented semantic parsing model that maps natural language expressions to structured representations containing intents and slots that describe the task to perform. For example, the expression Can you play some songs by Coldplay? may be converted to Intent: PlaySong, Artist: Coldplay, and the expression Turn off the bedroom light may be converted to Intent: TurnOffLight, Device: bedroom.

Task-oriented semantic parsing is traditionally approached as a joint intent classification and slot filling task. Kamath and Das (2018) provide a comprehensive survey of models proposed to solve this task. Researchers have developed semantic parsers based on Recurrent Neural Networks (Mesnil et al., 2013; Liu and Lane, 2016; Hakkani-Tür et al., 2016), Convolutional Neural Networks (Xu and Sarikaya, 2013; Kim, 2014), Recursive Neural Networks (Guo et al., 2014), Capsule Networks (Sabour et al., 2017; Zhang et al., 2019), and slot-gated attention-based models (Goo et al., 2018).

The current state-of-the-art models on SNIPS (Coucke et al., 2018), ATIS (Price, 1990), and Facebook TOP (Gupta et al., 2018) datasets are all based on BERT-style (Devlin et al., 2018; Liu et al., 2019) encoders and transformer architectures (Chen et al., 2019; Castellucci et al., 2019; Rongali et al., 2020). It is challenging to deploy these large models on edge devices and enable the voice assistants to operate locally instead of relying on central cloud services, due to the limited memory budgets on these devices. However, there has been a growing push towards the idea of TinyAI\textsuperscript{1}.

In this paper, we aim to build space-efficient task-oriented semantic parsing models that produce near state-of-the-art performances by compressing existing large models. We propose to learn compositional code embeddings to significantly compress BERT-base and RoBERTa-base encoders with little performance loss. We further use ALBERT-base/large (Lan et al., 2019) and DistilBERT (Sanh et al., 2019) to establish light baselines that achieve similar state-of-the-art performances, and apply the same code embedding technique. We show that our technique is complementary to the compression techniques used in ALBERT and DistilBERT. With all variants, we achieve 95.15\% \sim 98.46\% embedding compression rates and 20.47\% \sim 34.22\% encoder compression rates, with >97.5\% semantic

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\textsuperscript{1}https://www.technologyreview.com/technology/tiny-ai/
parsing performance preservation.

2 Related Compression Techniques

2.1 BERT Compression

Many techniques have been proposed to compress BERT (Devlin et al., 2018). Ganesh et al. (2020) provide a survey on these methods. Most existing methods focus on alternative architectures in transformer layers or learning strategies.

In our work, we use DistilBERT and ALBERT-base as light pretrained language model encoders for semantic parsing. DistilBERT (Sanh et al., 2019) uses distillation to pretrain a model that is 40% smaller and 60% faster than BERT-base, while retaining 97% of its downstream performances. ALBERT (Lan et al., 2019) factorizes the embedding and shares parameters among the transformer layers in BERT and results in better scalability than BERT. ALBERT-xlarge outperforms BERT-large on GLUE (Wang et al., 2018), RACE (Lai et al., 2017), and SQUAD (Rajpurkar et al., 2016) while using less parameters.

We use compositional code learning (Shu and Nakayama, 2017) to compress the model embeddings, which contain a substantial amount of model parameters. Previously ALBERT uses factorization to compress the embeddings. We find more compression possible with code embeddings.

2.2 Embedding Compression

Varied techniques have been proposed to learn compressed versions of non-contextualized word embeddings, such as, Word2Vec (Mikolov et al., 2013) and GLoVE (Pennington et al., 2014). Subramanian et al. (2018) use denoising k-sparse autoencoders to achieve binary sparse interpretable word embeddings. Chen et al. (2016) achieve sparsity by representing the embeddings of uncommon words using sparse linear common combination of common words. Lam (2018) achieve compression by quantization of the word embeddings by using 1-2 bits per parameter. Faruqui et al. (2015) use sparse coding in a dictionary learning setting to obtain sparse, non-negative word embeddings. Raunak (2017) achieve dense compression of word embeddings using PCA combined with a post-processing algorithm. Shu and Nakayama (2017) propose to represent word embeddings using compositional codes learnt directly in end-to-end fashion using neural networks. Essentially few common basis vectors are learnt and embeddings are reconstructed using their composition via a discrete code vector specific to each token embedding. This results in 98% compression rate in sentiment analysis and 94% - 99% in machine translation tasks without performance loss with LSTM based models. All the above techniques are applied to embeddings such as WordVec and Glove, or LSTM models.

We aim to learn space-efficient embeddings for transformer-based models. We focus on compositional code embeddings (Shu and Nakayama, 2017) since they maintain the vector dimensions, do not require special kernels for calculating in a sparse or quantized space, can be finetuned with transformer-based models end-to-end, and achieve extremely high compression rate. Chen et al. (2018) explores similar idea as Shu and Nakayama (2017) and experiment with more complex composition functions and guidances for training the discrete codes. Chen and Sun (2019) further show that end-to-end training from scratch of models with code embeddings is possible. Given various pretrained language models, we find that the method proposed by Shu and Nakayama (2017) is straightforward and perform well in our semantic parsing experiments.

3 Method

3.1 Compositional Code Embeddings

Shu and Nakayama (2017) apply additive quantization (Babenko and Lempitsky, 2014) to learn compositional code embeddings to reconstruct pretrained word embeddings such as GloVe (Pennington et al., 2014), or task-specific model embeddings such as those from an LSTM neural machine translation model. Compositional code embeddings \( E^C \) for vocabulary \( V \) consist of a set of \( M \) codebooks \( E^C_1, E^C_2, ..., E^C_M \), each with \( K \) basis vectors of the same dimensionality \( D \) as the reference embeddings \( E \), and a discrete code vector \( (C^1_w, C^2_w, ..., C^M_w) \) for each token \( w \) in the vocabulary. The final embedding for \( w \) is composed by summing up the \( C^i_w \)th vector from the \( i \)th codebook as \( E^C_w = \sum_{i=1}^{M} C^i_w E^C_i(C^i_w) \). Codebooks and discrete codes are jointly learned using the mean square distance objective:

\[
(C^*, E^{C^*}) = \arg \min_{C, E^C} \frac{1}{|V|} \sum_{w \in V} \| E^C(C^*_w) - E(w) \|^2.
\]

For learning compositional codes, the Gumbel-softmax reparameterization trick (Jang et al., 2016; Maddison et al., 2016) is used for one-hot vectors corresponding to each discrete code.
### 3.2 Transformer-Based Models with Compositional Code Embeddings

In this work, we learn compositional code embeddings to reduce the size of the embeddings in pretrained contextualized language models. We extract the embedding tables from pretrained RoBERTa-base (Liu et al., 2019), BERT-base (Devlin et al., 2018), DistilBERT-base (Sanh et al., 2019), ALBERT-large-v2 and ALBERT-base-v2 (Lan et al., 2019) from the huggingface transformers library (Wolf et al., 2019) and follow the approach presented by Shu and Nakayama (2017) to learn the code embeddings. We then replace the embedding tables in the transformer models with the compositional code approximations and evaluate the compressed language models by finetuning on downstream tasks. When Shu and Nakayama (2017) feed compositional code embeddings into the LSTM neural machine translation model, they fix the embedding parameters and train the rest of the model from random initial values. In our experiments, we fix the discrete codes, initialize the transformer layers with those from the pretrained language models, initialize the task-specific output layers randomly, and finetune the codebook basis vectors with the rest of the non-discrete parameters.

### 3.3 Size Advantage of Compositional Code Embeddings

An embedding matrix \( E \in \mathbb{R}^{|V| \times D} \) stored as 32-bit float point numbers, where \(|V|\) is the vocabulary size and \(D\) is the embedding dimension, requires \(32|V|D\) bits. Its compositional code reconstruction requires \(32MKD\) bits for \(MK\) basis vectors, and \(M \log_2 K\) bits for codes of each of \(|V|\) tokens. Since each discrete code takes an integer value in \([1, K]\), it can be represented using \(\log_2 K\) bits.

Table 1 illustrates the size advantage of compositional code embeddings for various pretrained transformer models (Wolf et al., 2019) used in our experiments. While the technique focuses on compressing the embedding table, it is compatible with other compression techniques for transformer models, including parameter sharing among transformer layers and embedding factorization used in ALBERT and distillation for learning DistilBERT. In our experiments, we apply the code learning technique to compress embeddings in five pretrained BERT variants by 95.15% ~ 98.46% to build competitive but significantly lighter semantic parsing models.

### 4 Datasets

Following Rongali et al. (2020), we evaluate our models on SNIPS (Coucke et al., 2018), AIRline Travel Information System (ATIS) (Price, 1990), and Facebook TOP (Gupta et al., 2018) datasets for task-oriented semantic parsing (Table 2). For SNIPS and ATIS, we use the same train/validation/test split as Goo et al. (2018).

| Dataset   | Train | Valid | Test | #Intent | #Slot |
|-----------|-------|-------|------|---------|-------|
| ATIS      | 4,478 | 500   | 893  | 26      | 83    |
| SNIPS     | 13,084| 700   | 700  | 7       | 39    |
| Facebook TOP | 31,279| 4,462 | 9,042| 25      | 36    |

Table 2: Statistics for semantic parsing datasets.

### 5 Experiments and Analyses

For transformer model training, we base our implementation on the huggingface transformers library v2.6.0 (Wolf et al., 2019). We use the AdamW optimizer (Loshchilov and Hutter, 2017) with 10% warmup steps and linear learning rate decay to 0. For code embedding learning, we base our implementation on that of Shu and Nakayama (2017). By default we learn code embeddings with 32 codebooks and 16 basis vectors per codebook. Unless otherwise specified, hyperparameters are found according to validation performances from one random run. We conduct our experiments on a mixture of Tesla M40, TITAN X, 1080 Ti, and 2080 Ti GPUs. We use exact match (EM) and intent accuracy as evaluation metrics. Exact match requires correct predictions for all intents and slots in a query, and is our primary metric.
Uncased BERT and DistilBERT perform better than the cased versions. We experiment with different transformer encoders to establish strong baselines which achieve EM values that are >99% of the state-of-the-art. We implement a joint sequence-level and token-level classification layer for pretrained transformer models. The intent probabilities are predicted as \( \hat{y}_i = \text{softmax}(W^h h_0 + b^h) \), where \( h_0 \) is the hidden state of the [CLS] token. The slot probabilities for each token \( j \) are predicted as \( \hat{y}_j = \text{softmax}(W^s h_j + b^s) \). We use the cross-entropy loss to maximize \( \mathbb{E} \left[ \log p(y_i | x) \prod \log p(y_j | x) \right] \) where \( j \) is the first piece-wise token for each word in the query. We learn code embeddings for \( \{500, 700, 900, 1100, 1300\} \) epochs. We train transformer models with original and code embeddings all for 40 epochs with batch size 16 and sequence length 128.

### 5.1 SNIPS and ATIS

We implement a joint sequence-level and token-level classification layer for pretrained transformer models. The intent probabilities are predicted as \( \hat{y}_i = \text{softmax}(W^h h_0 + b^h) \), where \( h_0 \) is the hidden state of the [CLS] token. The slot probabilities for each token \( j \) are predicted as \( \hat{y}_j = \text{softmax}(W^s h_j + b^s) \). We use the cross-entropy loss to maximize \( \mathbb{E} \left[ \log p(y_i | x) \prod \log p(y_j | x) \right] \) where \( j \) is the first piece-wise token for each word in the query. We learn code embeddings for \( \{500, 700, 900, 1100, 1300\} \) epochs. We train transformer models with original and code embeddings all for 40 epochs with batch size 16 and sequence length 128. Uncased BERT and DistilBERT perform better than the cased versions. We experiment with peak learning rate \( \{2e^{-5}, 3e^{-5}, \ldots, 6e^{-5}\} \) and weight decay \( \{0.01, 0.05, 0.1\} \). As shown in Table 3 and 4, we use different transformer encoders to establish strong baselines which achieve EM values that are within 1.5% of the state-of-the-art.

On both datasets, models based on our compressed ALBERT-large-v2 encoder (54MB) preserves >99.6% EM of the previous state-of-the-art model (Chen et al., 2019) which uses a BERT encoder (420MB). In all settings, our compressed encoders preserve >97.5% EM of the uncompressed counterparts under the same training settings. We show that our technique is effective on a variety of pretrained transformer encoders.

### 5.2 Facebook TOP

Table 5 presents results on Facebook TOP. We follow Rongali et al. (2020) and experiment with Seq2Seq models. We use different pretrained BERT-variants as the encoder, transformer decoder layers with \( d_{model} = 768 \) (Vaswani et al., 2017), and a pointer generator network (Vinyals et al., 2015) which uses scaled dot-product attention to score tokens. The model is trained using the cross-entropy loss with label smoothing of 0.1. For simplicity, we always train code embeddings for 900 epochs offline. Learning rate 2e-5 and weight decay 0.01 are used for transformer training. BERT and DistilBERT are used in these experiments. During inference, we employ beam decoding with width 5. Our greatly compressed models present 98–99% performances of the original models.

#### Table 3: Results on SNIPS. “cc” indicate models with code embeddings. “epo” is the epoch number for offline code embedding learning. “lr” and “wd” are the peak learning rate and weight decay for whole model finetuning. “EM-v”, “EM”, “Intent” indicate validation exact match, test exact match, and test intent accuracy.

| Model                     | EM | Intent |
|---------------------------|----|--------|
| Joint-BiRNN (Hakkani-Tür et al., 2016) | 92.14 | 98.71 |
| Attention-BiRNN (Liu and Lane, 2016) | 92.29 | 97.50 |
| Slot Gated Full Attention (Goo et al., 2018) | 92.14 | 98.71 |
| CapsuleNLU (Zhang et al., 2019) | 90.90 | 98.69 |
| BERT-Seq2Seq-Ptr (Rongali et al., 2020) | 91.00 | 98.69 |
| RoBERTa-Seq2Seq-Ptr (Rongali et al., 2020) | 87.10 | 98.00 |
| BERT-Joint (Castellucci et al., 2019) | 91.60 | 99.00 |
| Joint BERT (Chen et al., 2019) | 92.80 | 98.60 |

#### Table 4: Results on ATIS. Refer to the caption of Table 3 for abbreviation explanations.

| Model                     | EM | Intent |
|---------------------------|----|--------|
| Joint-BiRNN (Hakkani-Tür et al., 2016) | 90.70 | 92.60 |
| Attention-BiRNN (Liu and Lane, 2016) | 78.90 | 91.10 |
| Slot-Gated (Goo et al., 2018) | 82.20 | 93.60 |
| CapsuleNLU (Zhang et al., 2019) | 83.40 | 95.00 |
| BERT-Seq2Seq-Ptr (Rongali et al., 2020) | 86.40 | 97.40 |
| RoBERTa-Seq2Seq-Ptr (Rongali et al., 2020) | 87.10 | 97.40 |
| BERT-Joint (Castellucci et al., 2019) | 88.20 | 97.80 |
| Joint-BERT (Chen et al., 2019) | 88.20 | 97.50 |

#### Table 5: Results on Facebook TOP. The SR models are by Einolghozati et al. (2019). Refer to the caption of Table 3 for abbreviation explanations.

| Model                     | EM | Intent |
|---------------------------|----|--------|
| SR ensemble + ELMo + SVMRank | 87.25 | - |
| Shift Reduce (SR) Parser | 80.86 | - |
| SR with ELMo embeddings | 83.93 | - |
| BERT-Seq2Seq-Ptr (Rongali et al., 2020) | 83.13 | 97.91 |
| RoBERTa-Seq2Seq-Ptr (Rongali et al., 2020) | 86.67 | 98.13 |
1000 epochs, the mean Euclidean distance between the original and reconstructed embeddings decrease with a decreasing rate. The average number of shared top-20 nearest neighbours according to cosine similarity and Euclidean distances between the two embeddings increase with a decreasing rate. We apply code embeddings trained for different numbers of epochs to ALBERT-base-v2 and fine-tune on semantic parsing. On SNIPS and ATIS, we find the best validation setting among learning rate $\{2, 3, 4, 5, 6\} \times 10^{-5}$ and weight decay $\{0.01, 0.05, 0.1\}$. We observe that the test exact match plateaus for the embeddings from pretrained ALBERT-base (Table 6). During the first 1000 epochs, the mean Euclidean distance between the embeddings to ALBERT-base-v2 and fine-tune on semantic parsing. On SNIPS and ATIS, we apply Dis-tilBERT (256MB), ALBERT-large (68MB), and ALBERT-base (45MB), and observe near state-of-the-art performances. We learn compositional code embeddings to compress the model embeddings by 95.15% $\sim$ 98.46%, the pretrained encoders by 20.47% $\sim$ 34.22%, and observe 97.5% performance preservation on SNIPS, ATIS, and Facebook TOP. Our compressed ALBERT-large is 54MB and can achieve 99.6% performances of the previous state-of-the-art models on SNIPS and ATIS. Our technique has potential to be applied to more tasks including machine translation in the future.

**Table 6:** Analyses for the code embedding learning process (M=32, K=16). MeanEucDist, NN-cos, and NN-Euc are averaged across 5 runs. “SNIPS”, “ATIS”, and “TOP” are the test exact match achieved on the three datasets.

| Epoch | MeanEucDist | NN-cos | NN-Euc | SNIPS | ATIS | TOP |
|-------|-------------|--------|--------|-------|------|------|
| 100   | 0.367±0.25% | 0.66±1.90% | 0.65±2.00% | 79.29 | 82.31 | 78.09 |
| 200   | 0.325±0.08% | 2.20±0.69% | 2.30±0.84% | 85.43 | 84.99 | 81.59 |
| 300   | 0.302±0.09% | 3.66±0.92% | 3.96±0.55% | 86.86 | 86.11 | 83.17 |
| 400   | 0.284±0.23% | 4.84±0.58% | 5.26±0.83% | 89.71 | 87.01 | 83.45 |
| 500   | 0.268±0.26% | 5.72±0.48% | 6.21±0.78% | 87.71 | 87.23 | 83.82 |
| 600   | 0.257±0.12% | 6.20±0.39% | 6.72±0.18% | 88.14 | 85.69 | 83.41 |
| 700   | 0.249±0.20% | 6.42±0.49% | 6.94±0.33% | 88.00 | 87.35 | 84.27 |
| 800   | 0.244±0.07% | 6.54±0.39% | 7.07±0.15% | 88.57 | 86.90 | 84.09 |
| 900   | 0.240±0.10% | 6.62±0.31% | 7.14±0.14% | 88.57 | 86.56 | **84.42** |
| 1000  | 0.238±0.07% | 6.65±0.39% | 7.16±0.10% | 89.14 | 87.12 | 83.86 |

**Table 7:** Effects of M and K. Mean squared errors (MSE) are averaged over 5 runs. Best validation exact match (EM) is presented for compressed transformer models trained with 0.05 weight decay and $\{3, 4, 5, 6\} \times 10^{-5}$ peak learning rates on SNIPS.

| M     | K     | epochs | MSE (±) | EM    |
|-------|-------|--------|---------|-------|
| 8     | 16    | 700    | 0.3155±0.05% | 85.43 |
| 8     | 32    | 700    | 0.3032±0.04% | 87.43 |
| 8     | 64    | 700    | 0.2944±0.04% | 87.43 |
| 16    | 16    | 700    | 0.2855±0.05% | 88.57 |
| 16    | 32    | 700    | 0.2727±0.09% | 88.00 |
| 16    | 64    | 700    | 0.2669±0.08% | 88.14 |
| 32    | 16    | 700    | 0.2409±0.12% | 89.00 |
| 32    | 32    | 700    | 0.2421±0.20% | 89.14 |
| 32    | 64    | 700    | 0.2396±0.27% | 88.29 |
| 64    | 16    | 700    | 0.2543±0.47% | 88.29 |
| 64    | 100   | 700    | 0.2256±0.06% | 89.71 |
| 64    | 32    | 700    | 0.2557±0.37% | 89.86 |
| 64    | 32    | 1000   | 0.2159±0.43% | 89.71 |

**5.3 Analysis for Code Convergence**

We study the relationship among a few variables during code learning for the embeddings from pretrained ALBERT-base (Table 6). During the first 1000 epochs, the mean Euclidean distance between the original and reconstructed embeddings decrease with a decreasing rate. The average number of shared top-20 nearest neighbours according to cosine similarity and Euclidean distances between the two embeddings increase with a decreasing rate.

We apply code embeddings trained for different numbers of epochs to ALBERT-base-v2 and fine-tune on semantic parsing. On SNIPS and ATIS, we find the best validation setting among learning rate $\{2, 3, 4, 5, 6\} \times 10^{-5}$ and weight decay $\{0.01, 0.05, 0.1\}$. We observe that the test exact match plateaus for code embeddings trained for more than 400 epochs. On Facebook TOP, we use learning rate $2 \times 10^{-5}$ and weight decay 0.01, and observe the similar trend.

**5.4 Effects of M and K**

We use embeddings from pretrained ALBERT-base-v2 as reference to learn code embeddings with M in $\{8, 16, 32, 64\}$ and K in $\{16, 32, 64\}$. As shown in Table 7, after 700 epochs, the MSE loss for embeddings with larger M and K converges to smaller values in general. With M=64, more epochs are needed for convergence to smaller MSE losses compared to those from smaller M. We apply the embeddings to ALBERT-base-v2 and finetune on SNIPS. In general, larger M yields better performances. Effects of K are less clear when M is large.

**6 Conclusion**

Current state-of-the-art task-oriented semantic parsing models are based on pretrained RoBERTa-base (478MB) or BERT-base (420MB). We apply DistilBERT (256MB), ALBERT-large (68MB), and
References

Artem Babenko and Victor Lempitsky. 2014. Additive quantization for extreme vector compression. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 931–938.

Giuseppe Castellucci, Valentina Bellomaria, Andrea Favalli, and Raniero Romagnoli. 2019. Multilingual intent detection and slot filling in a joint bert-based model. arXiv preprint arXiv:1907.02884.

Qian Chen, Zhu Zhuo, and Wen Wang. 2019. Bert for joint intent classification and slot filling. arXiv preprint arXiv:1902.10909.

Ting Chen, Martin Renqiang Min, and Yizhou Sun. 2018. Learning k-way d-dimensional discrete codes for compact embedding representations. arXiv preprint arXiv:1806.09464.

Ting Chen and Yizhou Sun. 2019. Differentiable product quantization for end-to-end embedding compression. arXiv preprint arXiv:1908.09756.

Yunchuan Chen, Lili Mou, Yan Xu, Ge Li, and Zhi Jin. 2016. Compressing neural language models by sparse word representations. arXiv preprint arXiv:1610.03950.

Alice Coucke, Alaa Saade, Adrien Ball, Théodore Bluche, Alexandre Caulier, David Leroy, Clément Doumouro, Thibault Gisselbrecht, Francesco Caltagirone, Thibaut Lavril, et al. 2018. Snips voice platform: an embedded spoken language understanding system for private-by-design voice interfaces. arXiv preprint arXiv:1805.10190.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Arash Einolghozati, Panupong Pasupat, Sonal Gupta, Rushin Shah, Mrinal Mohit, Mike Lewis, and Luke Zettlemoyer. 2019. Improving semantic parsing for task oriented dialog. arXiv preprint arXiv:1909.00600.

Maximilian Lam. 2018. Word2bits-quantized word vectors. arXiv preprint arXiv:1803.05651.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942.

Bing Liu and Ian Lane. 2016. Attention-based recurrent neural network models for joint intent detection and slot filling. arXiv preprint arXiv:1609.01454.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.

Ilya Loshchilov and Frank Hutter. 2017. Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101.

Chris J Maddison, Andriy Mnih, and Yee Whye Teh. 2016. The concrete distribution: A continuous relaxation of discrete random variables. arXiv preprint arXiv:1611.00712.
Grégoire Mesnil, Xiaodong He, Li Deng, and Yoshua Bengio. 2013. Investigation of recurrent-neural-network architectures and learning methods for spoken language understanding. In Interspeech, pages 3771–3775.

Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.

Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pages 1532–1543.

Patti Price. 1990. Evaluation of spoken language systems: The atis domain. In Speech and Natural Language: Proceedings of a Workshop Held at Hidden Valley, Pennsylvania, June 24-27, 1990.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. Squad: 100,000+ questions for machine comprehension of text. arXiv preprint arXiv:1606.05250.

Vikas Raunak. 2017. Simple and effective dimensionality reduction for word embeddings. arXiv preprint arXiv:1708.03629.

Subendhu Rongali, Luca Soldaini, Emilio Monti, and Wael Hamza. 2020. Don’t parse, generate! a sequence to sequence architecture for task-oriented semantic parsing. arXiv preprint arXiv:2001.11458.

Sara Sabour, Nicholas Frosst, and Geoffrey E. Hinton. 2017. Dynamic routing between capsules. CoRR, abs/1710.09829.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108.

Raphael Shu and Hideki Nakayama. 2017. Compressing word embeddings via deep compositional code learning. arXiv preprint arXiv:1711.01068.

Anant Subramanian, Danish Pruthi, Harsh Jhamtani, Taylor Berg-Kirkpatrick, and Eduard Hovy. 2018. Spine: Sparse interpretable neural embeddings. In Thirty-Second AAAI Conference on Artificial Intelligence.

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, pages 5998–6008.

Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015. Pointer networks. In Advances in neural information processing systems, pages 2692–2700.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2018. GLUE: A multi-task benchmark and analysis platform for natural language understanding. CoRR, abs/1804.07461.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, R’emi Louf, Morgan Funtowicz, and Jamie Brew. 2019. Huggingface’s transformers: State-of-the-art natural language processing. ArXiv, abs/1910.03771.

Puyang Xu and Ruhi Sarikaya. 2013. Convolutional neural network based triangular crf for joint intent detection and slot filling. In 2013 ieee workshop on automatic speech recognition and understanding, pages 78–83. IEEE.

Chenwei Zhang, Yaliang Li, Nan Du, Wei Fan, and Philip Yu. 2019. Joint slot filling and intent detection via capsule neural networks. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, Florence, Italy. Association for Computational Linguistics.