New Students on Sesame Street:
What Order-Aware Matrix Embeddings Can Learn from BERT

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Abstract
Large-scale pretrained language models (PreLMs) are revolutionizing natural language processing across all benchmarks. However, their sheer size is prohibitive in low-resource or large-scale applications. While common approaches reduce the size of PreLMs via same-architecture distillation or pruning, we explore distilling PreLMs into more efficient order-aware embedding models. Our results on the GLUE benchmark show that embedding-centric students, which have learned from BERT, yield scores comparable to DistilBERT on QQP and RTE, often match or exceed the scores of ELMo, and only fall behind on detecting linguistic acceptability.

1 Introduction
Large-scale pretrained language models (Devlin et al., 2019; Raffel et al., 2020) (PreLMs) have emerged as de-facto standard methods for natural language processing benchmarks (Wang et al., 2018, 2019). The common strategy is to pretrain models on enormous amounts of unlabeled text before fine-tuning them for downstream tasks. However, the drawback of PreLMs is that the models are becoming larger and larger with up to several billions of parameters (Brown et al., 2020). This comes with high environmental and economic costs (Strubell et al., 2019) and shifts the development and research in the hand of a few global players only (Bommasani et al., 2021).

Even though a single pretrained model can be reused for multiple, so-called downstream tasks, the sheer model size is often prohibitive. The immense resource requirements prevent using those models in small-scale laboratories and on mobile devices, which is tied to privacy concerns (Sanh et al., 2020b). Thus, there is a need for more efficient models, or compressed versions of large models that can make AI research more inclusive and energy-friendly, while fostering deployment in real-world use cases.

Reducing the size of PreLMs using techniques such as knowledge distillation (Hinton et al., 2015) or model compression (Bucila et al., 2006) is an active area of research (Sanh et al., 2020a; Jiao et al., 2020; Sun et al., 2020). Both knowledge distillation and model compression can be described as teacher-student setups. The student is trained to imitate the predictions of the teacher while using less resources. Typically, a large-scale PreLM takes the role of the teacher while the student is a smaller version of the same architecture. Sharing the same architecture between student and teacher has certain advantages, i.e., dedicated distillation techniques may be employed for intermediate layers (Sanh et al., 2020a; Sun et al., 2020). However, downstream tasks can often also be well addressed by more efficient architectures than transformers (Tang et al., 2019; Wasserblat et al., 2020).

Distilling PreLMs into simpler architectures has already shown promising results (Tang et al., 2019; Wasserblat et al., 2020). In these works, the students are LSTMs (Hochreiter and Schmidhuber, 1997) or models based on the continuous bag-of-words (CBOW) (Mikolov et al., 2013). However, LSTMs are difficult to parallelize as they need at least \(O(n)\) sequential steps to encode a sequence of length \(n\). On the other side, CBOW-based models are not order-aware, i.e., cannot distinguish sentences with the same words but in different order (“cat eats mouse” vs. “mouse eats cat”).

There are, however, efficient models such as continual multiplication of words (CMOW) (Mai et al., 2019) that are order-aware as they represent each token as matrix and a sequence is modeled by non-commutative matrix multiplication. Furthermore, Mai et al. (2019) have shown that a continuous ma-
trix space model (Rudolph and Giesbrecht, 2010) can be pretrained on unlabeled text.

This paper complements the existing body of works by investigating how order-aware embeddings can be used as student models of large-scale PreLM teachers. We aim to understand to which extent order-aware embeddings are better suited than the traditional bag-of-word models (Mikolov et al., 2013) to capture the teacher signal of a large-scale PreLM. To this end, we extend Mai et al. (2019)’s CMOW/CBOW-Hybrid model by bidirection and the ability to emit per-token representations to facilitate using a modern masked language model objective (Devlin et al., 2019). We investigate both general distillation, i.e., the distillation is applied during pretraining on unlabeled text, as well as task-specific distillation, when an already fine-tuned PreLM is distilled on a per-task basis.

Our results show that large-scale PreLMs can be distilled into efficient order-aware embedding models and achieve performance comparable to ELMo on the GLUE benchmark. On certain tasks, embedding-based models even challenge other size-reduced BERT models such as DistillBERT. In summary, our contributions are:

• We extend order-aware embedding models with bidirection and make them amenable for masked language model pretraining. Thus, the models can learn from the BERT’s teacher signal both during pretraining and fine-tuning.

• We explore various downstream classifiers on-top of the matrix embeddings including a novel 2D-CNN approach along with a siamese encoding strategy for two-sentence tasks.

• Our results show that simple embedding models can be on-par with more complex models such as ELMo or DistillBERT on certain tasks from the GLUE benchmark.

Below, we summarize the related works. Section 3 introduces our embedding models, downstream classifiers, and teacher-student architecture. The experimental apparatus is described in Section 4. Results and ablation studies are reported in Sections 5 and 6. Section 7 discusses the results.

2 Related Work

Order-aware Embeddings The continuous bag-of-words (CBOW) model (Mikolov et al., 2013) provides dense representations, i.e., embeddings of words and their context within a text. CBOW embeddings are accurate in encoding word content and relatively easy to compute. However, they do not capture the word order. In contrast, continual multiplication of words (CMOW) embeddings can capture word order, but are less accurate in encoding word content (Mai et al., 2019). Therefore, the authors propose a CMOW/CBOW-Hybrid model that combines the advantages of both kinds of embeddings. Word2rate (Phua et al., 2021) is an extension of CMOW where the matrices are considered as statistical transitions (rate matrices) in a Taylor series, with comparable results.

General Distillation In general distillation, a PreLM is distilled into a student model during pretraining. Then, the student model is fine-tuned for each downstream task without teacher supervision. DistilBERT (Sanh et al., 2020a) is such a general-purpose language model that has been distilled from BERT-base using multiple loss terms. Apart from masked language modeling and distillation objectives, they also introduce a cosine loss term to align the student’s and teacher’s hidden states (layer transfer). Furthermore, the student is initialized with selected layers of the teacher. As another general distillation approach, MobileBERT (Sun et al., 2020) introduces a bottleneck to the teacher such that layer-wise knowledge distillation objectives can be used.

Task-specific Distillation When performing task-specific distillation, the teacher signal is used during fine-tuning on downstream tasks. The distillation has to be performed on each downstream task separately. In BERT-PKD, Sun et al. (2019) use layer-wise distillation objectives and initialize with teacher weights to train BERT students with fewer layers. They explore which layers from the teacher supply the most information, i.e., using upper layers or learning from every $k$th-layer. TinyBERT (Jiao et al., 2020) is trained by applying knowledge distillation in both stages, pretraining and fine-tuning. General distilled models serve as initialization for task-specific fine-tuning. Additionally, TinyBERT uses a data augmentation technique to enrich the training data. LadaBERT (Mao et al., 2020) combines knowledge distillation with iterative weight pruning and matrix factorization. During fine-tuning, LadaBERT learns through knowledge distillation, which is ap-
plied on the embedding, attention, hidden, and prediction layer.

**Cross-architecture Distillation** Previously described works have exploited that teacher and student share the same architecture and used techniques such as layer transfer and loss terms to align hidden states. However, the student model does not need to have commonalities with the teacher architecture. In example, Wasserblatt et al. (2020) use a simple feed forward network with CBOW embeddings and a bidirectional LSTM model as students. Both models perform well in several downstream tasks. Tang et al. (2019) explore distilling BERT into a single layer BiLSTM without using any additional training data or modifications to the teacher architecture. Their distillation-based approach yields improvements compared to a plain BiLSTM without teacher signal: about 4 points on all reported tasks (QQP, MNLI, and SST-2). This motivates us to investigate whether even simpler models can be used as students of a BERT teacher. So far, all cross-architecture approaches are task-specific, while we also explore general distillation.

**Pruning and Quantization** Pruning approaches such as (Sanh et al., 2020b) are effective at reducing the number of parameters. Still, the resulting smaller models use the same complex architecture as their large-scale counterparts and do not necessarily improve inference speed. Quantization is a common post-processing step to reduce model size by decreasing the floating point precision of the weights (Wu et al., 2020). As shown in these works (Sanh et al., 2020b; Sun et al., 2020), pruning and quantization can be applied in conjunction with distillation. In our work, we focus on distillation, while pruning and quantization could even further increase the efficiency of our proposed method.

**Efficient Transformers** Another path for improving the efficiency of transformer models is to reduce the number of comparisons in sentence-pair regression tasks like semantic textual similarity (Reimers and Gurevych, 2019). Although BERT is a powerful and influential transformer model, it does not perform efficiently on all downstream tasks. Especially pair regression tasks are time and resource consuming. Therefore, SentenceBERT (Reimers and Gurevych, 2019) modifies BERT such that semantically meaningful sentence embeddings are derived which can then be compared using standard cosine-similarity. This allows SentenceBERT to perform sentence-pair regression tasks more efficiently. We borrow the siamese encoding strategy from SentenceBERT and combine it with our embedding models. Numerous other methods have been proposed to improve the general efficiency of transformer models, for which we refer to a recent survey (Tay et al., 2020).

**Summary** To summarize, the existing body of literature primarily focuses on reducing the size of PreLMs via distillation, pruning, and quantization. So far, only few recent works consider distilling PreLMs into other architectures such as bag-of-words feed-forward nets and LSTMs. In this work, we explore cross-architecture distillation with order-aware embedding models as students.

3 Methods

We present order-aware matrix embedding models and downstream classifiers, before we describe the teacher-student training procedure. For every student model, a specific classifier is trained, herein referred to as the decoder. The decoder operates on a specific kind of sentence embedding (i.e., embedding of a sequence of tokens) generated by an encoder. While we describe the encoder and decoder in isolation, we consider all possible combinations of embedding models and classifiers.

3.1 Embedding Models (Encoder)

For the order-aware matrix embeddings, we extend the CMOW/CBOW-Hybrid variant of Mai et al. (2019). Compared to classic vector-based embeddings, the word order can be captured because matrix multiplication is non-commutative. The embedding model is also efficient as the $O(n)$ steps to encode a sequence of length $n$ can be parallelized to $O(\log n)$ sequential steps, as matrix multiplication is associative. Below, we briefly introduce the CMOW/CBOW-Hybrid embeddings before describing our extensions.

**CMOW/CBOW-Hybrid Embeddings** Given a sequence of $n$ tokens, matrix-space embeddings $X_j \in \mathbb{R}^{d \times d}$ (we use $d = 20$) for each different token $j$, and vector-space embeddings $x_j \in \mathbb{R}^{d_{vec}}$ (we use $d_{vec} = 400$). Then the CMOW/CBOW-Hybrid embedding of a sequence of length $n$ is computed as the multiplication of embedding matrices $X_i$, concatenated (symbol $\cdot\parallel\cdot$) to the summation
of the embedding vectors $x_i$:

$$H^{(CMOW)} = X_1^{(CMOW)} \cdot X_2^{(CMOW)} \cdots X_n^{(CMOW)}$$

where $\cdot \parallel \cdot$ denotes concatenation. The output of the encoder is then fed into the decoder. This may be $H^{(CMOW)}$ for bidirectional CMOW or $h^{\text{hybrid}}$ in case of bidirectional CMOW/CBOW-Hybrid.

3.2 Downstream Task Classifiers (Decoder)

The sequence representation serves as input for the downstream classifier for the final predictions. Note, we also experimented with a BiLSTM as classifier, which overall showed lower accuracy compared to all other students.

Input representations The original input processing of BERT (Devlin et al., 2019), which jointly encodes two sequences, may be less useful in combination with our matrix-space embeddings. Therefore, we also explore a siamese variant inspired by SentenceBERT (Reimers and Gurevych, 2019), in which any two sentences $a$ and $b$ are encoded separately before combining them. As combination function, we use the absolute elementwise differences and concatenate it to the representations of $a$ and $b$, which we denote as siamese DiffCat:

$$h^{(\text{DiffCat})} = h^{(a)} \parallel h^{(b)} \parallel |h^{(a)} - h^{(b)}|$$

Linear Probe and MLP We consider linear probe and multi-layer perceptron (MLP) as straightforward downstream classifiers. Linear probe directly maps the pooled (eventually siamese) sequence embeddings to the output dimension. Our MLP classifier uses a hidden layer of 1,000 hidden units with ReLU activation. In the general distillation case, we employ dropout with probability 0.2 for regularization. In both cases, we make use of layer normalization (Ba et al., 2016) on the pooled embeddings to ease optimization.

CNN We explore a 2D-CNN classifier that induces a bias for learning two-dimensional structures within the (aggregated) embedding matrices. The CNN consists of one transposed convolution, which increases the matrix dimensions by a factor of four. Following that, we employ a block of three convolutional layers, the first one having a single filter (or two, for hybrid variants) and a kernel size of four, with the remaining two layers having 3 (4) kernels with stride 2. To avoid distorting the input embeddings, no padding is applied. ReLU is used for all activation functions. We apply BatchNorm for regularization before the last convolutional layer’s output is flattened and passed into a linear layer, which produces the predictions. We add a dropout of 0.4 before the last linear layer.

3.3 Teacher-Student Architecture

The idea of knowledge distillation (Hinton et al., 2015; Sanh et al., 2020a) is to distill the knowledge of a large teacher model into a smaller student model. The teacher’s logits may convey more information than the mere ground truth labels because they also supply values for the 2nd/3rd/... highest scores, and thus, may hint at semantic relationships among outputs. In practice, knowledge distillation is performed as a combination of hard loss $L_{\text{hard}}$, the cross-entropy to the ground truth, and soft loss as cross-entropy to the teacher’s logits:

$$L_{\text{soft}} = \sum_{i} t_i \cdot \log(s_i),$$

where $t_i$ is the teacher’s logit for output $i$ and $s_i$ is the student’s. The soft loss can further be adjusted by dividing both teacher and student logits with a temperature before computing the cross-entropy. The resulting loss function is:

$$L = \alpha \cdot L_{\text{hard}} + (1 - \alpha) \cdot L_{\text{soft}} \cdot \frac{1}{T^2}$$

We follow Jiao et al. (2020) and distinguish between general distillation and task-specific distillation. In general distillation (as in DistilBERT or
MobileBERT), we use the teacher signal only during the pretraining phase of the model. Therefore, the large-scale PreLM teacher model can be discarded as it is not necessary for fine-tuning. In task-specific distillation, we use the teacher signal separately for each downstream task. Note, TinyBERT and MobileBERT use further techniques to support distillation such as exploiting teacher weights as initialization or using an additional layer-wise distillation loss. We cannot employ these tricks, as our student’s architecture differs from the teacher.

**General Distillation** We explore distilling the knowledge of BERT into a CMOW/CBOW-Hybrid model already during a pretraining phase with a masked language modeling objective (MLM). For this, we need token-level representations that are amenable for distillation. Therefore, we modify our bidirectional CMOW/CBOW-Hybrid model such that the intermediate representations can serve as token-level inputs to a linear decoder. For each position \( i \) in a sequence of length \( n \), we use the continual matrix multiplication up to \( i \), along with the partial sum of vector embeddings up to token \( i \). Analogously, in backward direction, the matrices are multiplied in reverse order from position \( n \) thru \( i \). Then, we compose our training objective of a MLM objective with respect to the ground truth along with cross-entropy to teacher’s logits as distillation loss. For the general distillation, we use unit temperature and equal weights (\( \alpha = 0.5 \)) for the hard MLM loss and the soft distillation loss.

**Task-specific Distillation** In addition to general distillation, we also consider task-specific distillation as suggested by Jiao et al. (2020). In this case, a fine-tuned BERT model serves as a teacher for adapting the order-aware embeddings models to the downstream tasks. The hard loss is provided by the ground truth class labels, while the soft loss is computed by cross-entropy with the fine-tuned BERT’s logits. Again, we use equal weights between soft and hard loss \( \alpha = 0.5 \) along with unit temperature as often used in the literature (Hinton et al., 2015; Mao et al., 2020; Jiao et al., 2020; Mishra and Marr, 2018; Polino et al., 2018). In regression tasks, there is no standard way of exploiting the teacher’s prediction. Therefore, we follow (Raffel et al., 2020) and apply binning to cast regression tasks into classification tasks.

### 4 Experimental Apparatus

**Datasets**

The GLUE benchmark consists of nine tasks for English language comprehension (Wang et al., 2018). These tasks comprise natural language inference (MNLI, QNLI, WNL, RTE), sentence similarity (QQP, STS-B, MRPC), linguistic acceptibility (CoLA), and sentiment analysis (SST-2). All tasks are based on pairs of sentences except for CoLA and SST-2, which are single-sentence tasks.

**Experimental Procedure**

**Tokenization and Binning** We use the BERT tokenizer and its vocabulary such that teacher and student use the same vocabulary. The BERT tokenizer relies primarily on the WordPiece algorithm (Wu et al., 2016), which yields a high coverage while maintaining a small vocabulary. To facilitate distillation on regression tasks, we follow Raffel et al. (2020) and cast STS-B from regression to classification by binning scores into intervals of 0.2.

**Initialization** For the CMOW and CMOW/CBOW-Hybrid models, we initialize with pretrained embeddings from Mai et al. (2019), which cover 54% of BERT’s vocabulary. As initialization for the newly developed bidirectional CMOW/CBOW-Hybrid models, we pretrain an own model on TorontoBooks+EnWiki using general distillation with BERT. We evaluate pretrained embeddings against random initialization to analyze whether pretraining helps for embedding-based models in the same way as it does for transformer-based language models.

**Teacher Model** In both general and task-specific distillation, a BERT model (Devlin et al., 2019) served as the teacher model. For task-specific distillation, we use uncased BERT-base models from the Huggingface repositories\(^2\) that were fine-tuned for every task of the GLUE benchmark. We have fine-tuned a BERT model ourselves on the tasks STS-B, where we applied binning, and MNLI, where the downloaded model led to sub-par results. For a fair comparison, we use the same fine-tuned BERT model as a teacher for all our student models.

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1. Downloaded from Zenodo: [https://zenodo.org/record/3933322#.YKJ_uKxXJU](https://zenodo.org/record/3933322#.YKJ_uKxXJU)
2. [https://huggingface.co/textattack](https://huggingface.co/textattack)
Hyperparameter Optimization For each task, we optimize the learning rate (range \([10^{-3}, 10^{-6}]\)) for all combinations of embedding types, i.e., CBOW, CMOW, CMOW/CMOW-Hybrid, and bidirectional CMOW-Hybrid, downstream classifiers: Linear, MLP, and CNN. We complement these combinations with either sequential or siamese encoding for the two-sentence tasks, as well as using pretrained embeddings vs random initialization where applicable. In total, we have conducted 306 training and evaluation runs for hyperparameter optimization of each GLUE task. To determine the best model, we use each task’s evaluation measure on the development set. We run each model for 20 epochs with early stopping (5 epochs patience). We select appropriate batch sizes on the basis of preliminary experiments and training data sizes. The hyperparameter configurations for the best-performing models are depicted in Table 1.

4.3 Measures
For evaluating teacher and student models, task-specific measures defined for the GLUE benchmark are used (Wang et al., 2018). The performance on all four NLI tasks as well as SST-2 is measured in accuracy. CoLA is evaluated by Matthews correlation coefficient. Similarity tasks are measured by the average between Pearson and Spearman correlation for the STS-B task, or as the average between accuracy and F1-score for MRPC and QQP.

5 Results
Table 2 shows the results of the general distillation and task-specific distillation experiments. The table also shows the results from two ablation studies, which are described in Section 6. The reported scores for each task correspond to the task-specific metric as given by GLUE. We report baseline metrics for all our BERT models on all tasks. Detailed results can be found in the supplementary material.

Comparison with baselines from the literature
Our embedding-based models were able to come close to DistilBERT for all tasks, except CoLA. As described by Wasserblat et al. (2020), a model needs to capture context and linguistic structure to perform well on CoLA. We achieved better results on CoLA and SST-2 than Wasserblat et al. (2020). Our best models scored higher than ELMo (Peters et al., 2018) on the tasks MRPC, QNLI, QQP, RTE, and WNLI. We achieve comparable results to DistilBERT for the task RTE, and got better results on WNLI than DistilBERT. Our embedding-based models yield lower scores than the distilled BiLSTM by Tang et al. (2019) on those tasks that they have reported, namely MNLI-m, QNLI, STS-B.

General vs. Task-specific Distillation General distillation compared to task-specific distillation leads to better results on MNLI, MRPC, QQP, STS-B, and RTE. For the other tasks, namely CoLA, QNLI, SST-2, and WNLI, task-specific distillation achieves higher scores. While task-specific distillation leads in 4 out of 9 tasks, the average score is higher when using only general distillation.

Siamese DiffCat vs. Non-Siamese The best scores were achieved with models using siamese DiffCat embeddings, with the exception of SST-2 and WNLI. On those two tasks, CNNs using non-siamese CMOW embeddings performed better. Note, that stronger improvement over the non-siamese architecture can be observed only in scores produced by the MLP student classifier.

Linear Probe vs. MLP vs. CNN The scores among the student classifiers varied more when siamese DiffCat embeddings were used vs. when it was not used. Considering the average GLUE score, the MLP student classifier performed better by at least 4.8 points than all other classifiers in combination with all embedding types. The good performance of the MLP student classifier is also visible when inspecting the best score for every single task: For 7 out of 9 tasks, a model using the MLP student classifier produced the highest score. When siamese DiffCat is not used, the differences are overall smaller. Looking at the average GLUE score, the difference in performance is never more than 3.2. All of the best scores were produced by the MLP classifier, except in combination with CMOW embeddings. There, the CNN student achieves the best score.

CMOW vs. CBOW vs. CMOW/CBOW-Hybrid For most classifiers, CMOW embeddings produce higher scores than CBOW embeddings, regardless of their initialization (pretrained or random). Hybrid embeddings can further improve the performance on 5 out of 9 tasks by a small margin. Word order seems to be not so important for the MRPC and STS-B tasks. This is suggested by the already strong performance of the CBOW model with siamese encoding. Our observation is in line with, e.g., Conneau et al. (2018), who found...
that ‘Word Content’ within sentence embeddings is most correlated with downstream task performance, particularly on STS-B.

Effect of Pretraining The results show that using pretrained embeddings instead of randomly initialized embeddings for task-specific knowledge distillation does not necessarily lead to higher scores. For all embedding types, differences between scores resulting from pretrained and randomly initialized embeddings vary depending on the task as well as on the student classifier. The biggest gain for pretrained embeddings among all model combinations can be found for CoLA.

Unidirectional vs. Bidirectional Siamese For most tasks, the bidirectional hybrid model leads to better results than the unidirectional hybrid model. This holds true for pretrained and randomly initialized embeddings. It is important to note that bidirection doubles the word embedding dimension and thus increases parameter count.

Runtime Performance Mai et al. (2019) reported that CMOW is 5x faster than using a simple RNN and can process 12k tokens per second. We run our own performance comparison with random sequences of length 512. On our infrastructure with a batch size of 10, a siamese CMOW/CBOW-Hybrid-MLP processes 99.36 sequences per second, whereas BERT predicts 60.47 sequences per second, resembling a 67% speed-up.

Parameter Count Both the embeddings and the student classifier our models consisted of 25M parameters compared to DistilBERT’s 66M. The majority of our parameters comes from the embeddings, which can be accessed efficiently via table look-up. In comparison, the sizes of the classifier models are negligible (<10k parameters). We provide more details in the supplementary material.

6 Ablation Studies

We perform two ablation studies for the best performing model combination for every task (see Table 1) to explore ideas of further increasing task-specific model performance. In case two models lead to the same score, the one with less parameters is chosen. Thus, in total we have nine highest scoring models, one per task. For the ablation studies, we keep the hyperparameters the same, except for the learning rate. We optimize over all six initial learning rates, namely $\{10^{-3}, 5 \cdot 10^{-4}, 10^{-4}, 5 \cdot 10^{-5}, 10^{-5}\}$. The ablation studies’ results are shown in Table 2. Note, the average score is calculated based on the nine selected, best models.

Using Only Soft Loss We study the influence of the alpha value used in the loss function, based on the best results obtained with the initial $\alpha = 0.5$. The goal is to investigate whether using only soft loss, i.e., setting $\alpha = 0.0$ leads to different results. As Table 2 shows, using only soft loss improves only the MRPC task by a small margin.

Data Augmentation Although technically not an ablation, we conduct a further study with data augmentation as in TinyBERT (Jiao et al., 2020). We employ their technique of replacing words by similar word embeddings and nearest predictions from BERT to augment the GLUE training datasets. We find that the effect of data augmentation is small. An improvement was only observed on SST-2 (+1.2 points) and STS-B (+3.6).

7 Discussion

Key Results We have shown that matrix-space embedding models can benefit from cross-architecture distillation with BERT as a teacher model. Our results show that general distillation and task-specific distillation lead to comparable results, but the average score for general distillation was higher than for task-specific distillation. This

| Task   | Score | Classifier | Emb. type | Emb. initialization | Siamese | Bidirectional | Learning rate |
|--------|-------|------------|-----------|---------------------|---------|---------------|---------------|
| CoLA   | 23.3  | MLP        | CMOW/CBOW-Hybrid | pretrained | true   | true         | 1.0E-4        |
| MNLI-m | 63.3  | MLP        | CMOW/CBOW-Hybrid | not pretrained | true   | true         | 1.0E-4        |
| MRPC   | 78.2  | MLP        | CBOW      | pretrained         | true   | false        | 1.0E-4        |
| QNLI   | 72.6  | MLP        | CMOW/CBOW-Hybrid | not pretrained | true   | true         | 5.0E-5        |
| QQP    | 86.6  | MLP        | CMOW/CBOW-Hybrid | not pretrained | true   | false        | 1.0E-4        |
| RTE    | 59.9  | MLP        | CMOW/CBOW-Hybrid | pretrained     | true   | true         | 5.0E-4        |
| SST-2  | 86.8  | CNN        | CMOW      | not pretrained     | false  | false        | 5.0E-4        |
| STS-B  | 66.0  | MLP        | CBOW      | pretrained         | true   | false        | 1.0E-4        |
| WNLI   | 69.0  | CNN        | CMOW      | pretrained         | false  | false        | 1.0E-5        |

Table 1: Hyperparameter configurations for best-performing models
Table 2: Scores on the GLUE benchmark development set. Our best performing general distillation and task-specific distillation models are highlighted in bold font per task. References indicate sources of scores. The ⋆-symbol indicates numbers on the official GLUE test set. CMOW/CBOW-Hybrid is abbreviated as 'Hybrid'.

| Score CoLA | MNLI-m | MRPC | QNLI | QQP | RTE | SST-2 | STS-B | WNLI |
|------------|--------|------|------|-----|-----|-------|-------|------|
|            | large-scale pre-trained language models | | | | | | | |
| ELMo (Sanh et al., 2020a) | 68.7 | 44.1 | 68.6 | 76.6 | 71.1 | 86.2 | 53.4 | 91.5 | 70.4 | 56.3 |
| BERT-base (Sanh et al., 2020a) | 79.5 | 56.3 | 86.7 | 91.7 | 89.6 | 69.3 | 69.3 | 92.7 | 89.0 | 53.5 |
| BERT-base (our teacher model) | 78.9 | 57.9 | 84.2 | 84.6 | 91.4 | 89.7 | 67.9 | 91.7 | 88.0 | 54.9 |
| DistilBERT (Sanh et al., 2020a) | 77.0 | 51.3 | 82.2 | 87.5 | 89.2 | 88.5 | 59.9 | 91.3 | 86.9 | 56.3 |
| MobileBERT (Sun et al., 2020) | 67.7 | 51.1 | 84.3 | 88.8 | 91.6 | 70.5 | 70.4 | 92.6 | 84.8 | — |
|            | general distillation baselines | | | | | | | |
| DistilBERT (Sanh et al., 2020a) | 77.0 | 51.3 | 82.2 | 87.5 | 89.2 | 88.5 | 59.9 | 91.3 | 86.9 | 56.3 |
| MobileBERT (Sun et al., 2020) | 67.7 | 51.1 | 84.3 | 88.8 | 91.6 | 70.5 | 70.4 | 92.6 | 84.8 | — |
|            | task-specific distillation baselines | | | | | | | |
| TinyBERT (Jiao et al., 2020) | 54.0 | 54.0 | 84.5 | 90.6 | 91.1 | 88.0 | 70.4 | 93.0 | 90.1 | — |
| BiLSTM (Tang et al., 2019) | 73.0 | — | 78.2 | — | — | — | 79.1 | — | — |
| CBOW-FFN (Wasserblat et al., 2020) | 10.0 | — | — | — | — | — | 79.1 | — | — |
| CBOW-FFN (Wasserblat et al., 2020) | 10.0 | — | — | — | — | — | 79.1 | — | — |
|            | general distillation (ours) | | | | | | | |
| Bidi. Hybrid + Linear | 65.1 | 15.0 | 63.6 | 80.9 | 70.7 | 84.3 | 56.7 | 84.0 | 71.1 | 59.2 |
| Bidi. Hybrid + MLP | 66.6 | 16.7 | 66.6 | 79.7 | 71.7 | 87.2 | 61.0 | 82.9 | 76.9 | 56.3 |
|            | task-specific distillation (ours) | | | | | | | |
| CMOW + CNN (rand. init.) | 54.6 | 13.4 | 45.6 | 72.3 | 61.2 | 82.6 | 56.3 | 86.8 | 15.0 | 57.8 |
| CMOW + CNN (pretrained) | 56.2 | 18.3 | 50.1 | 71.8 | 60.5 | 80.6 | 57.0 | 85.0 | 13.2 | 69.0 |
| CBOW + MLP (pretrained) | 53.8 | 14.0 | 61.7 | 78.2 | 70.8 | 86.2 | 57.4 | 83.8 | 66.0 | 56.3 |
| Hybrid + MLP (rand. init.) | 62.5 | 13.1 | 62.5 | 74.3 | 71.5 | 86.6 | 58.1 | 83.1 | 58.6 | 56.3 |
| Hybrid + MLP (rand. init.) | 63.2 | 13.0 | 63.3 | 75.7 | 72.6 | 86.1 | 57.4 | 83.3 | 59.7 | 57.7 |
| Hybrid + MLP (pretrained) | 64.6 | 23.3 | 61.8 | 75.0 | 72.0 | 86.3 | 59.9 | 82.9 | 62.9 | 57.7 |
|            | further experiments on best-performing task-specific distillation models | | | | | | | |
| Only soft loss (α = 0) | 64.0 | 19.9 | 62.3 | 78.7 | 72.4 | 68.5 | 56.3 | 86.6 | 62.4 | 69.0 |
| Data augmentation | 63.5 | 21.2 | 47.3 | 76.2 | 72.1 | 86.6 | 52.7 | 88.0 | 69.6 | 57.7 |

suggests that the extra effort of performing task-specific distillation step may not even be necessary for most tasks. Finally, we confirm observations from Mai et al. (2019) that certain GLUE tasks are more sensitive to word order than others, namely SST-2 and STS-B.

Threat to Validity An alternative approach to distillation is training small models from scratch. However, recent studies have shown that it is better, i.e., more efficient and more effective to train a large model first and then compress it (Sanh et al., 2020b). Generally, it is challenging to distill large models into a small student model because its capacity is easily exceeded. Especially the CoLA requires sophisticated linguistic knowledge, which explains our students’ poor performance on this task. To our knowledge, most of the distilled models so far performed poorly on the single-sentence task CoLA, such as DistilBERT or the models by Wasserblat et al. (2020). In the case of LadaBERT, the distillation on CoLA was not reported and it was confirmed by the authors to have not worked well (Mao et al., 2020). Another reason why distillation on CoLA does not work well is that the task does not provide much training data. We applied data augmentation following Jiao et al. (2020), however not all tasks could benefit from this. Particularly, it did not improve CoLA.

Generalization We expect our results to be transferable to other classification tasks since the student learns from a teacher that is already fine-tuned on the given task. For every task, where a fine-tuned teacher model is available, knowledge distillation can be performed. Tasks that require world-knowledge (such as CoLA) might not be suited for task-specific distillation, as the small, task-specific corpus might not provide enough knowledge itself and indirect world-knowledge has been shown to be induced by training on large datasets, usually in self-supervised manners. Our results on CoLA can be seen as an indicator for this.

Future Work Our work demonstrates how large-scale pretrained language models can be distilled into order-aware embedding models. In future work, one could further improve efficiency by applying pruning (Sanh et al., 2020b) and/or quantization (Wu et al., 2020) techniques on the learned matrices to allow sparse matrix multiplication during encoding. Furthermore, it would be interesting to explore what components would be necessary to improve the scores on particularly challenging downstream tasks such as detecting linguistic acceptability. This might include the re-introduction of a small attention module as in gMLP (Liu et al., 2021). Since we have shown how to emit (and train) per-token representations with CMOW, an-
other interesting direction of future work would be to explore whether CMOW representations are suited as order-aware embedding in transformer models, which might alleviate the need for a dedicated position encoding.

8 Conclusion

We distilled large pretrained language models into smaller order-aware matrix embeddings. The results indicate that our order-aware embeddings offer an alternative to CBOW embeddings, achieving better results in most of our experiments. We achieve comparable scores to DistilBERT on QQP and RTE and often match or exceed the scores of ELMo, using classifiers with low parameter counts.

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Supplementary Material

A Extended Results

We show detailed results of the hyperparameter optimization in Tables 4, 5, 6 and list the parameter counts for the used models in Table 7 and 8. The overall best performing model per task over the hyperparameter search space (see Tables 4, 5, 6) are marked in bold. We abbreviate CMOW/CBOW-Hybrid as 'Hybrid'.

B Overview of Architectural Choices

Figure 1 provides an overview of the architectural choices explored in this paper. We use pretrained BERT (Devlin et al., 2019) as well as the embeddings from Mai et al. (2019) as teacher for general distillation. Additionally, we pretrain a model CMOW/CBOW-Hybrid with our extension of masked language model training and bidirection on the same English Wikipedia + Toronto Books dataset. These pretrained embeddings may serve as initialization for the downstream classification models. We also evaluate downstream classification models that have been initialized randomly. For the downstream classification models, we consider three types of embeddings along with four types of classifiers. For training on the downstream task, we use once again BERT as a teacher for task-specific distillation, while our experiments on general distillation only benefit from the initialization of the MLM-pretrained CMOW/CBOW-Hybrid model.

LSTM We have further experimented with pooling the sequence embeddings via LSTMs. In the past, BiLSTM models have been successfully used in sentiment analysis tasks (Xu et al., 2019; Hameed and Garcia-Zapirain, 2020). In an LSTM network, the information at hand is propagated in the forward direction. Thus, each state \( t \) depends on its predecessor \( t - 1 \). BiLSTM are LSTM networks, in which the inputs are processed twice: once in forward direction and once in backward direction, generating a set of two outputs. In order to generate the output vectors, the output of a single BiLSTM block is fed into an MLP, consisting of two consecutive linear layers with ReLu activation functions. Note that the BiLSTM operates on a sequence of token embeddings, instead of operating on pooled sentence embeddings like the other student models. To reduce overfitting, a dropout of 0.5 is applied after the first linear layer.

C Hyperparameters

We list hyperparameter search spaces along with their optimization methods in Table 3. Note, we also optimized over using warmup steps versus no warmup. As the warmup did not improve the results, we did not use it.

For the softmax temperature, we find that \( T = 1 \) is often used (Hinton et al., 2015; Mao et al., 2020; Jiao et al., 2020; Mishra and Marr, 2018; Polino et al., 2018). Since a higher temperature also flattens the curve over all predictions, it could add too much noise and it is therefore better to use a smaller temperature (Chen et al., 2017). Setting the weight \( \alpha = 1 \) corresponds to only using hard loss and \( \alpha = 0 \) to only using soft loss. Since we do not want to discard any information stemming from the hard loss, we do not follow the approach of Wasserblat et al. who only use the soft loss (Wasserblat et al., 2020) but instead, we employ a vanilla knowledge distillation approach following Hinton et al. (Hinton et al., 2015).

Hinton et al. (2015) state, that using cross-entropy loss on the softmax-temperature with a large temperature, for example \( T = 20 \), corresponds to only using the Mean Square Error (MSE) loss on the raw student and teacher logits. Therefore it is also common to use this loss for the soft distillation loss (Tang et al., 2019; Wasserblat et al., 2020; Mukherjee and Awadallah, 2020). While Tang et al. (Tang et al., 2019) used the weighted hard cross-entropy loss in the overall loss calculation, Wasserblat et al. and Mukherjee et al. only used the soft loss (Tang et al., 2019; Wasserblat et al., 2020; Mukherjee and Awadallah, 2020). A disadvantage of MSE loss, is that every error has a huge effect on the overall loss, since it is squared. Another point is, that Hinton et al. found it beneficial to use small temperature values if the teacher is way bigger than the student (Hinton et al., 2015). Since using MSE loss corresponds to using big \( T \) values, this loss does not apply to our use case of using small students for lower bound knowledge distillation, but with cross-entropy loss, we still have the possibility to achieve the behavior of the MSE loss by setting the value of \( T \) to a big value.
Figure 1: Options for embeddings and downstream classifiers, pretraining and distillation.

Table 3: Hyperparameter search space and optimization method

| Hyperparameter          | Search space                          | Opt. method   |
|-------------------------|---------------------------------------|---------------|
|                         | — General Distillation —              |               |
| Learning rate           | $\{10^{-3}, 5 \cdot 10^{-4}, 10^{-4}, 5 \cdot 10^{-5}, 10^{-5}\}$ | grid search   |
| Warmup steps            | $\{0, 500\}$                         | grid search   |
| Embedding dropout       | $\{0, 0.1\}$                         | grid search   |
| Hidden unit dropout     | $\{0.2\}$                            | fixed         |
| Batch size              | $\{1, 8, 32, 64, 128, 256\}$         | manual        |
|                         | — Task-specific Distillation —        |               |
| Learning rate           | $\{10^{-3}, 5 \cdot 10^{-4}, 10^{-4}, 5 \cdot 10^{-5}, 10^{-5}, 5 \cdot 10^{-6}\}$ | grid search   |
| Embedding type          | Hybrid, CMOW, CBOW, CONV              | grid search   |
| Embedding initialization| random, pretrained                   | grid search   |
| Siamese                 | true, false                          | grid search   |
| Bidirectional           | true, false                          | grid search   |
| Classifier              | Linear Probe, MLP, CNN, BiLSTM        | grid search   |
### Table 4: Scores on the GLUE benchmark development set (without siamese DiffCat)

| Task-Specific Distillation | Score | CoLA | MNLI-m | MRPC | QNLI | QQP | RTE | SST-2 | STS-B | WNLI |
|----------------------------|-------|------|--------|------|------|-----|-----|-------|-------|------|
| Teacher BERT-base          |       |      |        |      |      |     |     |       |       |      |
| **— task-specific finetuning (ours) —** |       |      |        |      |      |     |     |       |       |      |
| Linear probe               | 52.8  | 12.2 | 43.0   | 72.3 | 60.1 | 74.8| 55.6| 82.8  | 17.7  | 56.3 |
| MLP                        | 53.2  | 13.0 | 46.3   | 71.3 | 59.7 | 76.9| 54.5| 82.9  | 17.5  | 56.3 |
| CNN                        | 52.8  | 11.7 | 43.0   | 72.1 | 60.1 | 77.5| 54.5| 82.7  | 17.2  | 56.3 |
| BiLSTM                     | 52.1  | 10.9 | 44.9   | 70.8 | 59.8 | 78.1| 54.5| 81.3  | 12.3  | 56.3 |
| **— task-specific distillation (ours) CBOW not pretrained —** |       |      |        |      |      |     |     |       |       |      |
| Linear probe               | 52.4  | 11.0 | 43.2   | 72.1 | 58.8 | 74.8| 54.9| 82.5  | 14.0  | 60.6 |
| MLP                        | 54.0  | 14.3 | 46.3   | 71.3 | 60.1 | 76.9| 58.5| 83.1  | 14.8  | 60.6 |
| CNN                        | 53.0  | 12.0 | 43.5   | 71.6 | 59.2 | 77.5| 55.2| 82.6  | 18.8  | 56.3 |
| BiLSTM                     | 50.8  | 0    | 44.9   | 71.3 | 59.4 | 78.0| 54.0| 81.0  | 12.0  | 56.3 |
| **— task-specific distillation (ours) CBOW pretrained —** |       |      |        |      |      |     |     |       |       |      |
| Linear probe               | 52.4  | 11.0 | 43.2   | 72.1 | 58.8 | 74.8| 54.9| 82.5  | 14.0  | 60.6 |
| MLP                        | 54.0  | 14.3 | 46.3   | 71.3 | 60.1 | 76.9| 58.5| 83.1  | 14.8  | 60.6 |
| CNN                        | 53.0  | 12.0 | 43.5   | 71.6 | 59.2 | 77.5| 55.2| 82.6  | 18.8  | 56.3 |
| BiLSTM                     | 50.8  | 0    | 44.9   | 71.3 | 59.4 | 78.0| 54.0| 81.0  | 12.0  | 56.3 |
| **— task-specific distillation (ours) CMOW not pretrained —** |       |      |        |      |      |     |     |       |       |      |
| Linear probe               | 53.7  | 13.8 | 45.3   | 72.1 | 62.5 | 80.9| 53.4| 84.1  | 15.2  | 56.3 |
| MLP                        | 54.8  | 15.1 | 45.6   | 72.8 | 60.6 | 82.6| 55.6| 84.3  | 20.0  | 56.3 |
| CNN                        | 54.6  | 13.4 | 45.6   | 72.3 | 61.2 | 82.6| 56.3| 86.8  | 15.0  | 57.8 |
| BiLSTM                     | 53.2  | 16.7 | 44.9   | 72.1 | 64.8 | 80.6| 54.2| 82.9  | 7.9   | 54.9 |
| **— task-specific distillation (ours) CMOW pretrained —** |       |      |        |      |      |     |     |       |       |      |
| Linear probe               | 54.3  | 20.8 | 48.6   | 71.3 | 60.3 | 78.4| 54.9| 84.5  | 13.8  | 56.3 |
| MLP                        | 55.4  | 18.9 | 50.4   | 72.3 | 61.3 | 79.3| 55.2| 83.0  | 17.9  | 60.6 |
| CNN                        | 56.2  | 18.3 | 50.1   | 71.8 | 60.5 | 80.6| 57.0| 85.0  | 13.2  | 69.0 |
| BiLSTM                     | 51.4  | 0    | 44.2   | 68.4 | 59.8 | 81.1| 55.2| 82.3  | 15.0  | 56.3 |
| **— task-specific distillation (ours) CMOW/CMOW-Hybrid not pretrained —** |       |      |        |      |      |     |     |       |       |      |
| Linear probe               | 54.4  | 17.0 | 47.0   | 72.6 | 61.1 | 81.4| 53.4| 84.5  | 15.1  | 57.8 |
| MLP                        | 54.4  | 13.8 | 50.0   | 73.0 | 60.4 | 78.6| 53.8| 84.9  | 18.5  | 56.3 |
| CNN                        | 53.6  | 12.0 | 42.1   | 72.6 | 60.9 | 79.6| 52.7| 85.7  | 16.3  | 60.6 |
| BiLSTM                     | 52.4  | 0    | 43.2   | 72.1 | 61.2 | 80.0| 57.4| 83.0  | 18.1  | 56.3 |
| **— task-specific distillation (ours) CMOW/CMOW-Hybrid pretrained —** |       |      |        |      |      |     |     |       |       |      |
| Linear probe               | 53.9  | 19.1 | 41.0   | 71.8 | 57.6 | 78.7| 57.8| 83.7  | 16.2  | 59.2 |
| MLP                        | 55.3  | 22.1 | 47.4   | 71.6 | 60.0 | 79.5| 57.8| 84.1  | 18.1  | 56.3 |
| CNN                        | 54.0  | 20.7 | 44.5   | 71.8 | 59.9 | 79.7| 54.9| 85.9  | 9.9   | 59.1 |
| BiLSTM                     | 53.7  | 17.0 | 40.6   | 71.8 | 61.3 | 80.3| 57.4| 82.5  | 14.0  | 59.2 |
Table 5: Scores on the GLUE benchmark development set (with siamese DiffCat aggregation)

| Task-Specific Distillation | Score | CoLA | MNLI-m | MRPC | QNLI | QQP | RTE | SST-2 | STS-B | WNLI |
|---------------------------|-------|------|--------|------|------|-----|-----|-------|-------|------|
| Teacher BERT-base         | 78.9  | 57.9 | 84.2   | 84.6 | 91.4 | 89.7| 67.9| 91.7  | 88.0  | 54.9 |
| — task-specific finetuning (ours) — | | | | | | | | | | |
| Linear probe              | 53.8  | 11.5 | 46.6   | 72.8 | 62.2 | 76.7| 52.7| 83.5  | 22.0  | 56.3 |
| MLP                       | 61.0  | 14.3 | 57.8   | 77.2 | 70.3 | 86.0| 56.7| 82.3  | 47.0  | 57.7 |
| CNN                       | 53.8  | 11.2 | 51.5   | 75.0 | 65.8 | 81.3| 53.1| 82.3  | 7.2   | 56.3 |
| BiLSTM                    | 48.4  | 11.5 | 31.8   | 68.3 | 66.8 | 63.2| 56.7| 83.5  | 1.5   | 56.3 |
| — task-specific distillation (ours) CBOW not pretrained — | | | | | | | | | | |
| Linear probe              | 56.3  | 9.0  | 47.1   | 72.8 | 64.8 | 77.1| 53.4| 82.5  | 43.4  | 56.3 |
| MLP                       | 63.8  | 14.0 | 61.7   | 78.2 | 70.8 | 86.2| 57.4| 83.8  | 66.0  | 56.3 |
| CNN                       | 53.7  | 10.9 | 55.0   | 73.8 | 66.2 | 81.1| 53.1| 82.2  | 3.8   | 56.3 |
| BiLSTM                    | 47.7  | 0    | 32.7   | 68.4 | 69.6 | 63.2| 55.6| 82.5  | 1.3   | 56.3 |
| — task-specific distillation (ours) CBOW pretrained — | | | | | | | | | | |
| Linear probe              | 56.3  | 10.9 | 54.3   | 71.8 | 62.7 | 80.9| 56.0| 85.2  | 17.6  | 56.3 |
| MLP                       | 63.2  | 14.2 | 61.9   | 75.5 | 72.4 | 86.3| 55.2| 83.7  | 62.7  | 56.3 |
| CNN                       | 55.4  | 12.4 | 45.3   | 72.3 | 61.5 | 82.6| 57.4| 84.3  | 26.1  | 56.3 |
| BiLSTM                    | 47.7  | 0    | 31.8   | 70.3 | 49.5 | 81.0| 55.6| 83.4  | 0     | 56.3 |
| — task-specific distillation (ours) CMOW not pretrained — | | | | | | | | | | |
| Linear probe              | 56.3  | 22.4 | 48.4   | 72.5 | 61.3 | 81.9| 54.5| 83.9  | 24.2  | 57.7 |
| MLP                       | 63.2  | 13.0 | 63.3   | 75.7 | 72.6 | 86.1| 57.4| 85.4  | 26.9  | 56.3 |
| CNN                       | 52.7  | 14.5 | 40.6   | 71.8 | 58.2 | 68.3| 54.9| 85.4  | 26.9  | 56.3 |
| BiLSTM                    | 49.7  | 0    | 32.7   | 68.3 | 67.2 | 82.9| 59.0| 82.5  | 0     | 56.3 |
| — task-specific distillation (ours) CMOW pretrained — | | | | | | | | | | |
| Linear probe              | 51.7  | 11.2 | 39.0   | 71.1 | 49.5 | 81.8| 56.0| 85.2  | 14.3  | 57.7 |
| MLP                       | 62.5  | 13.1 | 62.5   | 74.3 | 71.5 | 86.6| 58.1| 83.1  | 58.6  | 56.3 |
| CNN                       | 52.8  | 11.9 | 45.3   | 71.6 | 61.4 | 84.8| 55.2| 85.4  | 26.9  | 56.3 |
| BiLSTM                    | 50.9  | 0    | 42.6   | 70.1 | 60.3 | 79.3| 56.0| 84.4  | 9.3   | 56.3 |
| — task-specific distillation (ours) Hybrid not pretrained — | | | | | | | | | | |
| Linear probe              | 54.0  | 19.6 | 45.7   | 71.3 | 63.4 | 80.9| 54.2| 84.1  | 11.7  | 54.9 |
| MLP                       | 62.7  | 20.9 | 62.6   | 74.5 | 68.6 | 85.7| 56.3| 83.1  | 56.2  | 56.3 |
| CNN                       | 57.9  | 19.6 | 37.6   | 75.7 | 62.0 | 85.4| 54.9| 82.3  | 48.5  | 54.9 |
| BiLSTM                    | 52.1  | 0    | 48.0   | 68.4 | 71.9 | 85.3| 56.7| 82.5  | 0     | 56.3 |

Table 6: Scores on the GLUE benchmark development set with siamese DiffCat + Bidirectional

| Task-Specific Distillation | Score | CoLA | MNLI-m | MRPC | QNLI | QQP | RTE | SST-2 | STS-B | WNLI |
|---------------------------|-------|------|--------|------|------|-----|-----|-------|-------|------|
| Teacher BERT-base         | 78.9  | 57.9 | 84.2   | 84.6 | 91.4 | 89.7| 67.9| 91.7  | 88.0  | 54.9 |
| — task-specific finetuning (ours) — | | | | | | | | | | |
| Linear probe              | 53.5  | 11.6 | 39.4   | 71.6 | 64.3 | 82.5| 56.3| 85.0  | 14.6  | 56.3 |
| MLP                       | 63.2  | 13.0 | 63.3   | 75.7 | 72.6 | 86.1| 57.4| 83.3  | 59.7  | 57.7 |
| CNN                       | 52.7  | 14.5 | 37.3   | 71.3 | 60.8 | 86.4| 55.2| 85.8  | 6.6   | 56.3 |
| — task-specific distillation (ours) Hybrid not pretrained — | | | | | | | | | | |
| Linear probe              | 55.5  | 18.1 | 42.4   | 72.1 | 64.9 | 81.2| 56.7| 85.2  | 22.5  | 56.3 |
| MLP                       | **64.6** | **23.3** | 61.8   | 75.0 | 72.0 | 86.3| **59.9** | 82.9  | 62.9  | 57.7 |
| CNN                       | 55.1  | 20.5 | 39.3   | 73.8 | 61.3 | 85.9| 56.3| 85.5  | 15.9  | 57.7 |
| — task-specific distillation (ours) Hybrid Bidirectional pretrained — | | | | | | | | | | |
| Linear probe              | 48.6  | 11.6 | 35.4   | 71.3 | 49.5 | 63.2| 84.6| 9.2   | 57.7  |      |
| MLP                       | 62.4  | 15.9 | 56.4   | 70.3 | 69.9 | 85.6| 53.4| 81.2  | 60.2  | **69.0** |
| CNN                       | 54.3  | 14.2 | 35.4   | 71.3 | 50.5 | 67.3| 52.7| 82.0  | 58.6  | 56.3 |
Table 7: Number of parameters without siamese DiffCat

| Model          | CoLA, MRPC, QNLI, QQP, SST-2, RTE, WNLI | MNLI | STS-B |
|----------------|----------------------------------------|------|-------|
| Linear probe   | 47,861,634                            | 47,862,419 | 47,876,549 |
| – only classifier | 3,138                                  | 3,923 | 18,053 |
| MLP            | 48,647,498                            | 48,648,499 | 48,666,517 |
| – only classifier | 789,002                                 | 790,003 | 808,021 |
| CNN            | 47,862,708                            | 47,864,737 | 47,901,259 |
| – only classifier | 4,212                                  | 6,241 | 42,763 |
| BiLSTM         | 53,704,002                            | 53,705,027 | 53,723,477 |
| – only classifier | 5,845,506                                | 5,846,531 | 5,864,981 |

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| Model          | CoLA, MRPC, QNLI, QQP, SST-2, RTE, WNLI | MNLI | STS-B |
|----------------|----------------------------------------|------|-------|
| Linear probe   | 23,932,386                            | 23,933,171 | 23,947,301 |
| – only classifier | 3,138                                  | 3,923 | 18,053 |
| MLP            | 24,718,250                            | 24,719,251 | 24,737,269 |
| – only classifier | 789,002                                 | 790,003 | 808,021 |
| CNN            | 23,933,460                            | 23,935,489 | 23,972,011 |
| – only classifier | 4,212                                  | 6,241 | 42,763 |
| BiLSTM         | 24,853,978                            | 24,854,371 | 35,022,869 |
| – only classifier | 924,730                                 | 925,123 | 110,936,21 |

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| Model          | CoLA, MRPC, QNLI, QQP, SST-2, RTE, WNLI | MNLI | STS-B |
|----------------|----------------------------------------|------|-------|
| Linear probe   | 24,420,802                            | 24,421,603 | 24,436,021 |
| – only classifier | 3,202                                  | 4,003 | 18,421 |
| MLP            | 25,222,602                            | 25,223,603 | 25,241,621 |
| – only classifier | 805,002                                 | 806,003 | 824,021 |
| CNN            | 24,420,558                            | 24,421,855 | 24,445,201 |
| – only classifier | 2,958                                  | 4,255 | 27,601 |
| BiLSTM         | 30,328,642                            | 30,329,667 | 30,348,117 |
| – only classifier | 5,911,042                               | 5,912,067 | 5,930,517 |
Table 8: Number of parameters siamese DiffCat

| Task Specific Distillation (Ours) | CoLA, MRPC, QNLI, QQP, SST-2, RTE, WNLI | MNLI | STS-B |
|---------------------------------|----------------------------------------|------|-------|
| Linear probe                    | 47,867,906                             | 47,870,259 | 47,912,613 |
| – only classifier               | 9,410                                  | 11,763 | 54,117 |
| MLP                             | 50,215,498                             | 50,216,499 | 50,234,517 |
| – only classifier               | 2,357,002                              | 2,358,003 | 2,376,021 |
| CNN                             | 47,865,932                             | 47,869,313 | 47,930,171 |
| – only classifier               | 7,436                                  | 10,817 | 71,675 |
| BiLSTM                          | 147,477,458                            | 147,479,811 | 147,522,165 |
| – only classifier               | 99,618,962                             | 99,621,315 | 99,663,669 |
| Linear probe                    | 23,938,658                             | 23,941,011 | 23,983,365 |
| – only classifier               | 9,410                                  | 11,763 | 54,117 |
| MLP                             | 26,286,250                             | 26,287,251 | 26,305,269 |
| – only classifier               | 2,357,002                              | 2,358,003 | 2,376,021 |
| CNN                             | 23,936,684                             | 23,940,065 | 24,000,923 |
| – only classifier               | 7,436                                  | 10,817 | 71,675 |
| BiLSTM                          | 123,548,210                            | 123,550,563 | 123,592,917 |
| – only classifier               | 99,618,962                             | 99,621,315 | 99,663,669 |
| Linear probe                    | 24,427,202                             | 24,429,603 | 24,472,821 |
| – only classifier               | 9,602                                  | 12,003 | 55,221 |
| MLP                             | 26,822,602                             | 26,823,603 | 26,841,621 |
| – only classifier               | 2,405,002                              | 2,406,003 | 2,424,021 |
| CNN                             | 24,424,990                             | 24,427,583 | 24,474,257 |
| – only classifier               | 7,390                                  | 9,983 | 56,657 |
| BiLSTM                          | 128,143,202                            | 128,145,603 | 128,188,821 |
| – only classifier               | 103,725,602                            | 103,728,003 | 103,771,221 |

— task-specific distillation (ours) CMOW —

| Task Specific Distillation (Ours) | CoLA, MRPC, QNLI, QQP, SST-2, RTE, WNLI | MNLI | STS-B |
|---------------------------------|----------------------------------------|------|-------|
| Linear probe                    | 36,640,802                             | 36,644,403 | 36,709,221 |
| – only classifier               | 14402                                  | 18003 | 82,821 |
| MLP                             | 40,231,402                             | 40,232,403 | 4,025,042 |
| – only classifier               | 3,605,002                              | 3,606,003 | 3,624,021 |
| CNN                             | 36,638,164                             | 36,641,729 | 36,705,899 |
| – only classifier               | 11,764                                 | 15,329 | 79,499 |
| BiLSTM                          | 451,437,602                            | 451,528,821 | 451,528,821 |
| – only classifier               | 414,811,202                            | 414,902,421 | 414,902,421 |