☕ ESE: ESPRESSO SENTENCE EMBEDDINGS

Anonymous authors
Paper under double-blind review

ABSTRACT

High-quality sentence embeddings are fundamental in many natural language processing (NLP) tasks, such as semantic textual similarity (STS) and retrieval-augmented generation (RAG). However, most existing methods leverage fixed-length sentence embeddings from full-layer language models, which lack the scalability to accommodate the diverse available resources across various applications. Viewing this gap, we propose a novel sentence embedding model Espresso Sentence Embeddings (ESE) with two learning processes. First, the **learn-to-express** process encodes more salient representations to shallow layers. Second, the **learn-to-compress** process compacts essential features into the initial dimensions using Principal Component Analysis (PCA). This way, ESE can scale model depth via the former process and embedding size via the latter. Extensive experiments on STS and RAG suggest that ESE can effectively produce high-quality sentence embeddings with less model depth and embedding size, enhancing embedding inference efficiency. [1]

1 INTRODUCTION

Sentence embedding learning (Cer et al., 2018; Reimers & Gurevych, 2019; Gao et al., 2021; Li & Li, 2024a;b) is a crucial yet challenging task in the NLP research. It aims to capture essential semantic and syntactic information in language, benefiting various scenarios such as clustering (Reimers & Gurevych, 2019), semantic textual similarity (STS) (Li & Li, 2024a; Zhang et al., 2024), and retrieval-augmented generation (RAG) (Gao et al., 2023).

In the common deployment practices, the pipeline of applying sentence embeddings unfolds in two typical stages: (i) computing the sentence embeddings via a forward pass and (ii) employing these embeddings in downstream tasks. Existing work (Reimers & Gurevych, 2019; Gao et al., 2021; Li & Li, 2024a, *etc.*) typically adopts entire Transformer (Vaswani et al., 2017) layers and full embedding sizes for all tasks to ensure optimal performance, regardless of the varying resources and requirements across applications. It can result in computational redundancy and fails to scale well to the diverse resources available in downstream scenarios (Kusupati et al., 2022). To address this challenge, Matryoshka Representation Learning (MRL) concurrently trains multiple embeddings with cascading dimensions to enable scalable embedding sizes while preserving maximum semantics (Kusupati et al., 2022). However, MRL employs full Transformer layers for embedding inference, in which high computational costs persist when using Large Language Models (LLMs) with very deep architectures (Wang et al., 2023; Li & Li, 2024a;b; Lee et al., 2024).

We propose a novel Espresso Sentence Embeddings (ESE) to further improve inference efficiency by enabling scalability on model depth. ESE consists of two key processes. First, the **learn-to-express** process allocates more crucial latent representations to shallow layers by weighting embeddings at different levels. Second, the **learn-to-compress** process condenses essential features into initial dimensions by exploring the inner dependencies of embedding dimensions through Principal Component Analysis (PCA). Figure 1 illustrates ESE's overview and its differences from the MRL (Kusupati et al., 2022) and traditional embeddings (Reimers & Gurevych, 2019; Gao et al., 2021; Li & Li, 2024a). As depicted, ESE is designed to encode more salient features into shallow layers and small embedding dimensions simultaneously. Thus, it enables scalable sentence embeddings that adapt to various settings of model depth and embedding size, allowing for more flexible accommodation of diverse computing resources. In contrast, MRL focuses solely on scaling embedding

[1] The code is available at `https://anonymous.4open.science/r/Espresso`.

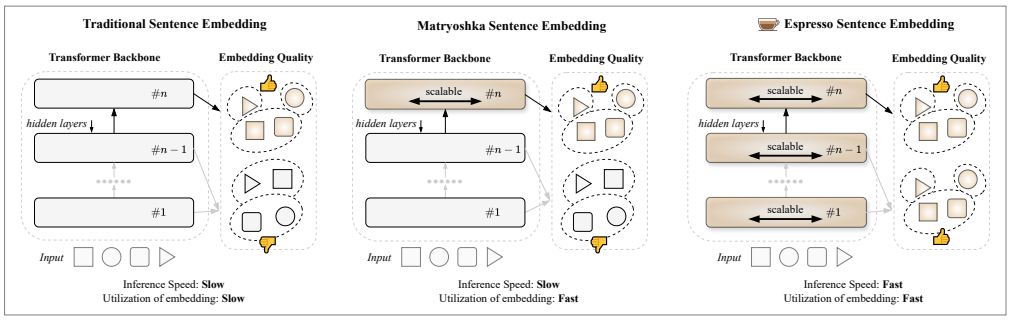


Figure 1: The comparison of traditional (left), MRL (middle), and ESE (right) sentence embedding models. The gray blocks indicate Transformer layers fine-tuned in the full setting, while the coffee-colored ones indicate scalable settings. ESE can scale both model depth and embedding size.

size, while traditional models lack scalability. Additionally, the PCA implementation of ESE at various layers of embedding learning can help organize the learned features in order according to their significance; it allows easier training than MRL by jointly training multiple varying-dimension embeddings to scale embedding sizes.

To the best of our knowledge, *we are the first to learn sentence embedding with information compression, presenting scalable embedding inference to both model depths and embedding dimensions.*

We extensively experiment across STS and RAG tasks to evaluate ESE. First, the main results on the STS benchmarks show that ESE performs competitively in full settings than non-trivial baselines and shows significantly better results with shallow model depth or smaller embedding size. For instance, ESE enhances BGE's (Xiao et al., 2023) shallow-layer embeddings from 45.60 to 66.27, showcasing the effectiveness of our method. Then, ablation studies indicate that all modules positively affect ESE, and its performance is sensitive to smaller PCA compression sizes. Moreover, the RAG experiments show that ESE improves retrieval across varying embedding sizes and model depths, underscoring the potential in various application scenarios. Finally, we further discuss ESE and present the following findings: (i) The scaled embeddings from ESE work better than trained embeddings with the same-sized model; (ii) ESE shows better inference efficiency on both STS and RAG tasks; (iii) In visualization, ESE's scaled embeddings exhibit greater overlap with the unscaled ones, indicating its effectiveness in information compression and superiority in scaling embeddings. In summary, our contributions are as follows:

- We are the first to employ the information compression technique to scale sentence embeddings.
- Our novel ESE model allows for scalable embeddings in both model depth and embedding size.
- Extensive experiments on STS and RAG show ESE's superiority in producing effective embeddings with reduced model depth and embedding size, enhancing inference efficiency.

2 Related Work

Our work is in line with the sentence embedding learning research. While early efforts primarily focused on word embeddings (Mikolov et al., 2013), the recent trend has shifted towards sentence embeddings as they can capture representations from richer contexts. In the training methods, many studies adopted supervised approaches to align embeddings to human senses (Conneau et al., 2017; Cer et al., 2018; Reimers & Gurevych, 2019; Li & Li, 2024a). And **contrastive learning** techniques (Carlsson et al., 2020; Gao et al., 2021; Chuang et al., 2022; Xu et al., 2023; Liu, 2024) have recently become popular to involve in-batch comparison of positive and negative pairs. As for model architectures, with the LLMs breakthrough in NLP (OpenAI, 2022; Touvron et al., 2023), **LLM-based** sentence embedding models have drawn a growing attention (Li & Li, 2024a; Wang et al., 2023; Li & Li, 2024b; Muennighoff et al., 2024) for a more effective context exploration.

However, the common practices deploy embeddings with full model layers and predefined embedding sizes. It inevitably constrains the scalability of sentence embedding use in downstream applica-

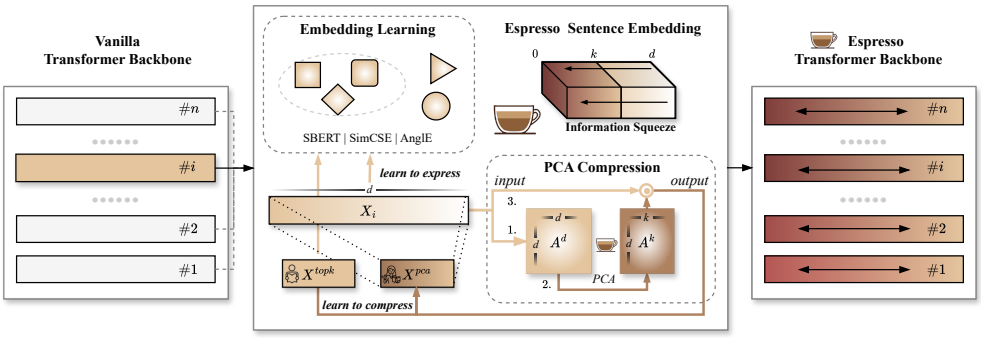


Figure 2: The ESE framework. The left part is the vanilla Transformer backbone, where each layer is not scalable. The center part is the ESE training with the **learn-to-express** (to scale model depths) and **learn-to-compress** (to scale embedding sizes) processes. The right part is the trained Espresso Transformer backbone, where each layer is scalable (marked with double-ended arrows).

tions, particularly in scenarios where resources are limited. To address this constraint, Matryoshka Representation Learning (MRL) was introduced to allow scalable embedding sizes (Kusupati et al., 2022). Yet, it still relies on full Transformer layers for embedding inference. In contrast, ESE has dual scalability in both model depth and embedding size, largely enhancing the efficiency of embedding inference. Moreover, MRL trains multiple embeddings in varying sizes, whereas ESE employs PCA for embedding size compression. Here, the PCA in training can help organize the features in order and allow more effective embedding learning. While some other methods (Zhu et al., 2018; Gupta et al., 2019; Zhao et al., 2022) applied PCA-alike compression to pre- or post-process trained embeddings, ESE is the first to integrate PCA into sentence embedding training.

3 ESPRESSO SENTENCE EMBEDDINGS

This section describes how ESE learns scalable sentence embeddings by elaborating the learn-to-express and learn-to-compress processes. Figure 2 depicts its framework.

3.1 ENCODER

We start the discussion with how we process the input, where the pretrained language model are used as an encoder to transform the text into dense sentence embeddings. Here, BERT (Devlin et al., 2019) or LLMs (Touvron et al., 2023; Bai et al., 2023) serves as the backbone to encode text x as follows:

$$\mathbf{X}_i^k = \text{Pooling}(\text{Encoder}^{1:i}(x)) \in \mathbb{R}^{k \times 1}, \tag{1}$$

where $i \in [1, n]$ is first-i layers of the n-layer Transformer backbone, and $k \in [1, d]$ denotes first-k-dimensional sub-embeddings of the full d-dimensional embeddings. For BERT-based models, we use the "CLS" pooling strategy following Li & Li (2024a). For LLM-based models, we follow previous practices (Li et al., 2023; Li & Li, 2024b) to transform all layers into bidirectional and adopt the mean pooling. Here, we select BERT and LLMs like Qwen and LLaMA as the encoder since they are widely used Transformer-based models for sentence embeddings. It allows for evaluating the effectiveness and generalization of the proposed ESE across various model scales.

3.2 LEARN TO EXPRESS

The encoded embeddings $\mathbf{X}_i^k$ will then go through a **learn-to-express** process to allow scalable model depths. Our idea is to encode more essential representations into shallow layers. Concretely, we cache each layer's sentence embeddings obtained by Eq. 1 for $i \in [1, n-1]$ and then jointly train their first-k-dimension sub-embeddings by a weighted loss. The loss is computed as follows:

$$\mathcal{L}_{le} = \sum_{i=1}^{n-1} w_i * \text{loss}(\mathbf{X}_i^k, \mathcal{G}) + \text{loss}(\mathbf{X}_n^k, \mathcal{G}). \tag{2}$$

Here w_i denotes the weight for i-th layer. We provide two implementations for the weights w_i. The first implementation is to parameterize w_i so that the weights can be adjusted dynamically during the model training. The second implementation sets $w_i = \frac{1}{1+\ln(i)}$. This way, the weights decrease as the layer depth increases, allowing the shallow layers to capture more crucial information for embedding scalability in model depths. Note that we leave the last layer unweighted due to its critical role in capturing sentence-level semantics (Li & Li, 2024b). The second implementation is applied by default as it does not introduce any additional parameters, making the implementation more efficient as the efficiency is always an important factor for the proposed ESE. The $\text{loss}(\cdot)$ can be any loss function for sentence embedding learning, e.g., contrastive loss (Gao et al., 2021) or AnglE loss (Li & Li, 2024a). We use the latter one by default. $\mathcal{G}$ is the positive or negative sample indicators for loss computation.

3.3 Learn to Compress

The learn-to-express method (Section 3.2) focuses on scaling embeddings across layers for model depths. Then, the **learn-to-compress** aims to enable scalable embedding sizes within each layer while preserving maximum semantics. The goal is to allow ESE to condense more essential information into sub-vectors of the initial embedding dimensions, as shown in the "Information Squeeze" box in Figure 2. It shows information distributions, where the left-hand-side part contains higher "information density" and a richer representation than the right-hand-side.

To achieve the above, we use Principal Component Analysis (PCA) to reduce embeddings' dimensionality from size d to k while preserving the crucial semantics, where d and k denote full and compressed embedding sizes, respectively. We compress the inner dependencies within embedding dimensions instead of directly compressing the sentence embeddings. This step aims to enable ESE to capture nuanced cross-dimension interactions without oversimplifying the embedding structure.

Concretely, we first compute the embedding inner-dependency matrix by scaled dot product:

$$\mathbf{A}_i^d = \text{softmax}(\frac{\mathbf{X}_i^d \cdot \mathbf{X}_i^{d^T}}{\sqrt{d}}) \in \mathbb{R}^{d \times d}, \tag{3}$$

where i denotes first-i Transformer layers. $\mathbf{X}_i^d \in \mathbb{R}^{d \times 1}$ are full sentence embeddings obtained from Eq. 1. The design pertains to the self-attention of Transformer Vaswani et al. (2017) reflecting the weights across varying dimensions. Then, we employ PCA, implemented with Singular Value Decomposition (SVD), to compress its information. It thus results in $\mathbf{A}_i^d = \mathbf{U}_i \mathbf{\Sigma}_i \mathbf{V}_i^T$, based on which we obtain top-k principal components (i.e. dependencies) for each embedding, as follows:

$$\mathbf{A}_i^k = \mathbf{U}_i^{1:d,1:k} \mathbf{\Sigma}_i^{1:k,1:k} \in \mathbb{R}^{d \times k}, \tag{4}$$

where $1 \leq k \leq d$. $1:d, 1:k$ means the selection of the first-d rows and first-k columns, and $\mathbf{A}_i^k$ indicates the compressed inner-dependency matrix. The diagonal matrix $\mathbf{\Sigma}_i$ displays the singular values $\sigma_{i,1}, \sigma_{i,2}, \ldots, \sigma_{i,k}$ on its diagonal, arranged in descending order according to their magnitude.

Subsequently, we apply the top-k inner-dependency matrix $\mathbf{A}_i^k$ (with compressed self-attention-alike weights) to the original $\mathbf{X}_i^d$. It results in compressed sentence embeddings as follows:

$$\mathbf{X}_{i_{pca}}^k = \mathbf{A}_i^{k^T} \cdot \mathbf{X}_i^d \in \mathbb{R}^{k \times 1}. \tag{5}$$

Although the above process works only in training, PCA may cause higher computational costs in embedding inference. To tackle this issue, we align the truncated first k-dimensional sub-embeddings to the PCA-compressed ones to reduce the cost. The alignment involves mean squared error and Kullback-Leibler divergence losses (Kim et al., 2021). As an innovative approach, we employ a weighted strategy across layers, in alignment with the learn-to-express process, to coherently

coordinate the compression of embedding sizes across scalable model depths, as follows:

$$\mathcal{L}_{lc} = \sum_{i=1}^{n-1} w_i * \text{align}(\mathbf{X}_i^k, \mathbf{X}_{i\,pca}^k) + \text{align}(\mathbf{X}_n^k, \mathbf{X}_{n\,pca}^k), \\ \text{align}(x, y) = \text{MSE}(x, y) + \text{KLDiv}(x, y), \tag{6}$$

where $\text{MSE}(\cdot)$ and $\text{KLDiv}(\cdot)$ denote the mean squared error and Kullback-Leibler divergence, respectively. w_i means the weight for the i-th layer. It has the same setting as Eq. 2. By optimizing $\mathcal{L}_{lc}$, the truncated first k-dimensional sub-embedding will be aligned to be similar to the PCA-compressed ones. It allows the direct use of the first k-dimensional sub-embeddings at inference without repeatedly performing PCA and improves inference efficiency.

3.4 Joint Learning

Finally, we jointly train the learn-to-express and learn-to-compress processes within a unified framework. Their respective objectives are seamlessly integrated into the overall learning objective of the proposed ESE, as follows:

$$\mathcal{L} = \alpha\mathcal{L}_{le} + \beta\mathcal{L}_{lc}, \tag{7}$$

where α and β are the weights trading off the two processes. We set both to 1 by default. By jointly optimizing the two objectives, ESE trains its sentence embeddings to be scalable in both model depths and embedding sizes.

4 Experiment

In the experiments, we first present the main intrinsic results of STS in Section 4.1. Then, we probe into more details of ESE output via an ablation study in Section 4.2. Next, we present extrinsic evaluation with RAG in Section 4.3. Finally, we further discuss ESE from varying perspectives in Section 4.4 to provide more insight.

Table 1: STS benchmark results. The last column ($\prec$ Avg.) is the average results of shallow layers (except the last one), while the remaining correspond to the last-layer results. Avg.: average results over varying benchmark datasets. RAW: the original model; MRL: Kusupati et al. (2022). The coffee-colored cells: the best results for each backbone model; boldfaced numbers: the overall best results. For $\prec$ Avg., ESE performs significantly better than baselines: p-value $< 5\%$ (paired t-test).

Model	STS12	STS13	STS14	STS15	STS16	STS-B	SICK-R	Avg.	$\prec$ Avg.
bge-base-en-v1.5 (Xiao et al., 2023)									
RAW	78.03	84.18	82.27	87.96	85.47	86.41	79.88	83.46	45.60
+ MRL	75.90	87.87	83.97	88.92	85.07	87.17	79.18	84.01	46.18
+ ESE	77.70	86.97	83.57	89.43	86.16	87.27	80.32	84.49	**66.27**
UAE-Large-V1 (Li & Li, 2024a)									
RAW	79.09	89.62	85.02	89.51	86.61	**89.06**	**82.10**	85.86	44.80
+ MRL	78.26	90.19	84.91	89.48	86.17	88.49	79.28	85.25	44.97
+ ESE	**79.64**	**90.40**	**85.76**	**90.33**	**86.64**	88.54	81.09	**86.06**	59.12
Qwen1.5-0.5B (Bai et al., 2023)									
RAW	75.91	83.77	80.04	86.05	82.91	85.32	78.98	81.85	56.59
+ MRL	76.30	85.04	80.68	86.15	83.12	85.65	79.45	82.34	58.22
+ ESE	76.43	85.70	81.75	86.30	83.67	85.76	80.16	82.82	59.99

4.1 STS Experiments

Following common practices Gao et al. (2021); Li & Li (2024a), we adopt STS for intrinsic evaluation to assess the quality of trained sentence embeddings. It measures how well embeddings capture semantic similarity between sentences, indicating their capacity for effective text representation.

Setup. In the comparison, we include two baselines: the scalable embeddings MRL (with scalable embedding sizes) (Kusupati et al., 2022) and RAW embeddings (without any scaling operations).

For the *datasets*, we train sentence embeddings on MultiNLI (Williams et al., 2018) and SNLI (Bowman et al., 2015) datasets following previous studies. Evaluation of model performance is conducted on the STS benchmark computed by SentEval (Conneau & Kiela, 2018), where Spearman's correlation in the "all" setting is reported as the evaluation metric. To enable comprehensive evaluation, this benchmark comprises seven widely used STS datasets: STS 2012-2016 (Agirre et al., 2012; 2013; 2014; 2015; 2016), SICK-R (Marelli et al., 2014), and STS-B (Cer et al., 2017).

For *model settings*, we examine two popular BERT-based backbones, *bge-base-en-v1.5* (Xiao et al., 2023) and *UAE-Large-V1* (Li & Li, 2024a) , and an LLM-based backbone, *Qwen1.15* (Bai et al., 2023). We use the recent popular AnglE (Li & Li, 2024a) loss as the sentence embedding training loss. The initial learning rates are set to $5e-5$ and $2e-4$ to train BERT-based and LLM-based models, respectively. For efficient LLM fine-tuning, we utilize LoRA (Hu et al., 2021; Dettmers et al., 2024) with parameters $lora_r = 32$, $lora_alpha = 32$, and $lora_dropout = 0.1$. For the ESE setup, the compression dimension k is set to 128 by default, and the weights α and β for joint learning (Eq. 7) are set to 1.

Main Results In the main STS experiments, we extract embeddings from the last 12 Transformer layers for comprehensive analyses. Then, we follow common practices to report results from the last layer of all benchmark datasets, including their average (Avg.). Moreover, we report the average results from the shallow layers (excluding the last one) to assess the scalability of ESE across model depths ($\prec$ Avg.). The results are shown in Table 1, where we can draw the following observations.

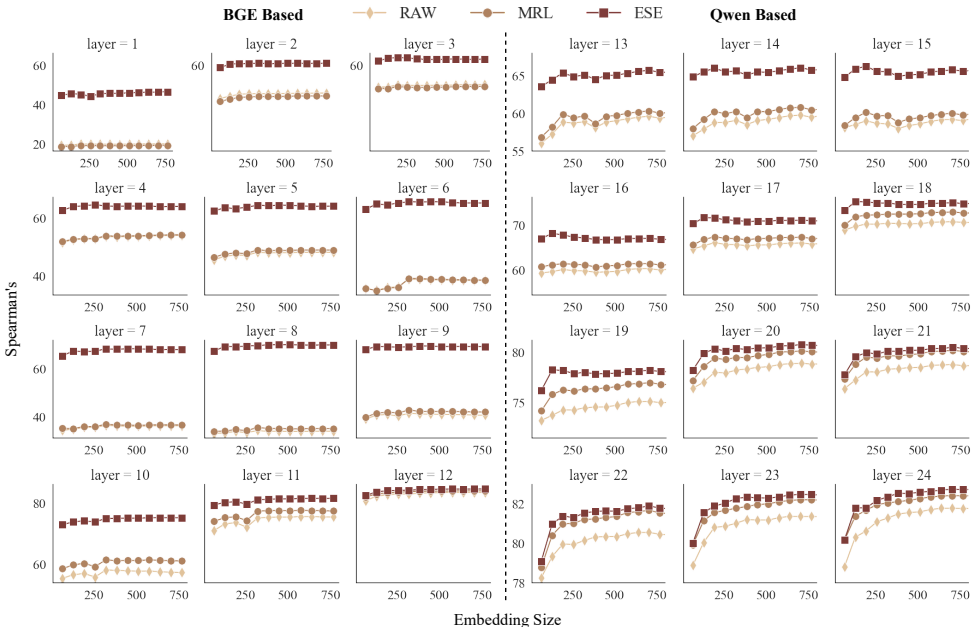
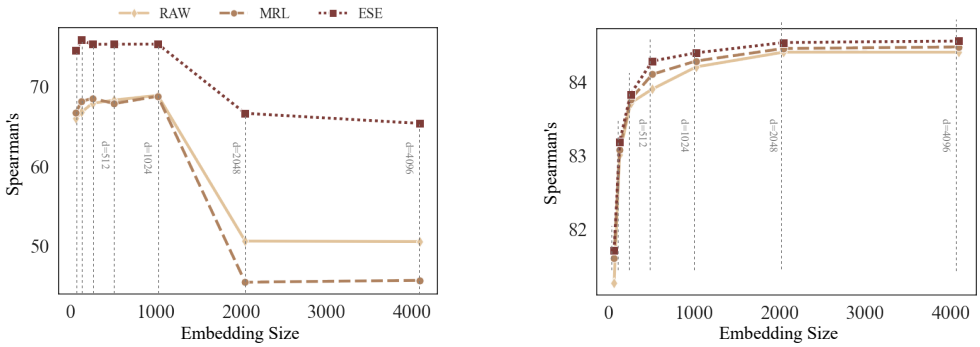


Figure 3: Results of the STS benchmark for each of the last 12 layers of BGE-based backbone (left part) and Qwen-based backbone (right part). For each layer's result, the x-axis shows the embedding size, and the y-axis shows the average Spearman's correlation over varying benchmark datasets.

First, ESE shows competitive and even better performance compared to RAW across every backbone in the last layer results. It indicates that the scalability learning of ESE does not adversely impact its last-layer performance. The marginal performance gain could be attributed to the use of PCA in organizing features, which potentially facilitates more effective embedding learning even in an unscaled setup. In contrast, MRL fails to outperform RAW in UAE's last layer, possibly due to chaos introduced by its multi-embedding learning strategy. Second, ESE significantly outperforms baselines in the $\prec$ Avg. setup , with a 20.67 gain to BGE. It indicates ESE's capability of effectively



(a) layer=16 (b) layer=32

Figure 4: The average STS benchmark results of various embedding sizes for the half layer (first 16 layers) and last layer (full 32 layers) of LLaMA2 7B (Touvron et al., 2023) with the RAW, MRL, and ESE training.

scaling embeddings across different layers. The improvement is less notable in LLM-based models than in BERT-based models, possibly due to LoRA's limitation on updating parameters in LLMs.

To further examine the scalability of ESE in model depths and embedding sizes, we show the STS results over embedding sizes from every layer in Figure 3. While all the models achieve competitive results using the full-sized embeddings from the last layer, RAW and MRL exhibit inferior performance in the shallow layers. They even demonstrate performance fluctuations as the layers deepen. In contrast, ESE can significantly improve the performance of the shallow layers. For example, the BGE achieves a result over 60.00 at the 11th layer, while BGE-MRL requires ten layers to reach that level. In contrast, BGE-ESE only requires two layers and consistently improves until the last layer, reaching a score of 84.49. This shows the effectiveness of ESE's learn-to-express process in encoding the more important information into shallow layers.

Moreover, ESE consistently performs better over embedding sizes at each layer, indicating the effectiveness of its learn-to-compress process. The performance gain is more significant at shallow layers, potentially because they contain richer information, resulting in more effective compression. Notably, ESE's stable performance since the 128 dimension suggests that a 128-dimensional embedding may capture the majority of salient features.

Furthermore, considering the *Qwen1.5* 0.5B is a relatively small LLM (Lu et al., 2024), we also evaluate the effectiveness of ESE on larger LLMs by testing LLaMA2 7B (Touvron et al., 2023) on the STS benchmark, as shown in Figure 4. Here, we report the results of two typical layers, i.e. the half layer (layer=16) and the last layer (layer=32). It is evident that the proposed ESE consistently outperforms baselines across different model depths and embedding sizes. Notably, ESE achieves a significant improvement at shallow layers, demonstrating its superior scalability. We can also see that there is a performance drop observed at the half layer for baselines and ESE. This could be attributed to the LoRA's limitation in sentence embedding learning. Nevertheless, ESE can mitigate this limitation, as evidenced by its lower drop rate than baselines.

4.2 Ablation Study

While Section 4.1 shows the overall effectiveness of ESE, we conduct ablation studies of ESE on the STS benchmark to assess the effectiveness of each component. The results are presented in Table 2.

We first evaluate different compression strategies to scale embedding sizes: the default PCA on embedding dependencies, PCA on sentence embeddings directly (i.e., PCA on $\mathbf{X}_i^d$), the max-k embedding dependencies (i.e., max k of dependency matrix $\mathbf{A}_i^d$ in Eq. 3 without PCA), and the ablation without any compression. All components contribute positively to the learning of both the last-layer and the shallow-layer embeddings. Interestingly, the performance drops substantially without compression, suggesting that compression can also help the learning of scaling across layers.

As to the weighting strategies, we compare the performance of without, dynamic, and default layer weighting. The results indicate that without layer weight performs worse than dynamic and default in both the last layer and shallow layer learning, particularly the latter. It suggests that assigning different layer weights allows shallow layers to capture more essential information. While the dynamic layer weighting strategy outperforms the default strategy in the last layer, it performs worse for shallow layers. This might be because dynamic weighting places more importance on the last layer of learning, which negatively affects the shallow layers' performance, thereby hurting the scalability of model depth. The default layer weighting strategy consistently improves the performance of both the last and shallow layers. This could be because the performance improvements in the shallow layers propagate to the deeper layers, resulting in an overall performance improvement.

Furthermore, we assess the impact of different PCA compression sizes (k) during training. We train ESE on NLI datasets with varying compression sizes and evaluate their STS performance in the full setting. For comparison with the baselines, we report ESE's and baseline's results in Figure 5. The results indicate that ESE consistently outperforms the baselines across different compression sizes, highlighting the effectiveness of information compression in enhancing sentence embeddings. However, there exhibits a first-increase-then-decrease trend (peaked at 128). This is because the model with large compression sizes may overlook critical details, whereas that with small compression sizes might not have adequate capacity to retain all essential information.

Table 2: Ablation study of ESE on STS benchmark. Avg. and $\prec$ Avg. denote the average Spearman's correlation of the last layer and shallow layers (except the last), respectively.

Model	Avg.	$\prec$ Avg.
Compression Strategies		
PCA on dependencies (default)	**84.49**	**66.27**
PCA on sentence embeddings	84.30	65.69
max-k embedding dependencies	84.22	65.47
none (w/o compression)	84.13	50.18
Layer Weighting Strategies		
without weight	84.25	64.56
dynamic weight	**84.63**	65.94
default weight	84.49	**66.27**

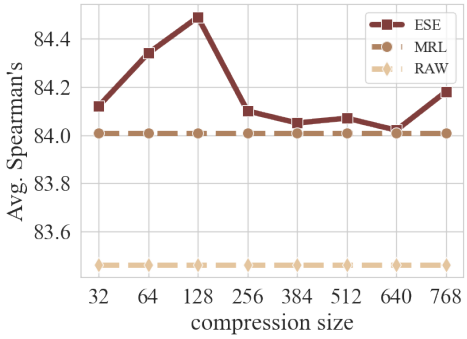


Figure 5: The STS benchmark results of ESE trained on different PCA compression sizes. Dashed lines indicate baseline results, serving as reference points.

4.3 RAG Experiments

The previous discussions center on the intrinsic evaluation in STS. We conduct an extrinsic evaluation to examine how ESE helps downstream retrieval and generation deployment. We compare different sentence embedding models based on *bge-base-en-v1.5* (Xiao et al., 2023) on HotpotQA dataset. It contains 113k Wikipedia-based factoid question-answer pairs. We employ faiss (Johnson et al., 2019) to index and retrieve documents based on sentence embeddings. Since our sentence embeddings are normalized, cosine similarity or Euclidean distance can be used. We follow the common practice (Douze et al., 2024) of using Euclidean distance, i.e., IndexFlatL2 in faiss, as the similarity measurement. For each query, we retrieve the most relevant context from all Wikipedia documents in HotpotQA and generate responses using LLaMA2-7B (Touvron et al., 2023) via a prompt in Table 3. For the QA evaluation, we adopt the popular metric *Exact Match*.

The RAG results of the last layer with various embedding sizes are listed in Table 4. We observe that ESE outperforms baselines in all embedding sizes. The improvements are more evident with smaller embedding sizes, for example, 2.42% and 1.80% higher than RAW and MRL with 64-dimensional embedding, respectively. Moreover, we compare the performance when using the sentence embeddings from the half layer ($n = 6$). ESE shows 0.72% and 0.44% improvement compared to RAW and MRL, respectively. These results demonstrate that effective ESE sentence embeddings, scalable in terms of both embedding sizes and model depths, can further benefit RAG.

Table 3: The prompt used in LLaMA2-7B for the RAG task. The "{context}", and "{question}" are the placeholders for the input context and question.

As an advanced QA system, your role is to provide accurate and straightforward answers based on the provided context. Utilize the following information to answer the given question, directly output the straightforward answer, and do not explain it:
Context: {context}.
Question: {question}.
Requirement: For 'yes/no' question, directly output 'yes' or 'no'. For the 'who' question, directly output the people's names. For the 'when' question, directly output the date or time, so on and so forth.
Output:

Table 4: RAG exact matching scores with different embedding sizes of different sentence embedding models on HotpotQA. *bge-base-en-v1.5* serves as the backbone sentence embedding model (marked with RAW).

embedding size	**Model**		
	RAW	+ MRL	+ ESE
64	29.86	30.48	**32.28**
128	38.85	38.90	**39.28**
256	42.05	42.20	**42.50**
512	44.16	44.20	**44.44**
768	45.06	45.09	**45.31**

Table 5: Results of different model scales and their independently trained counterparts.

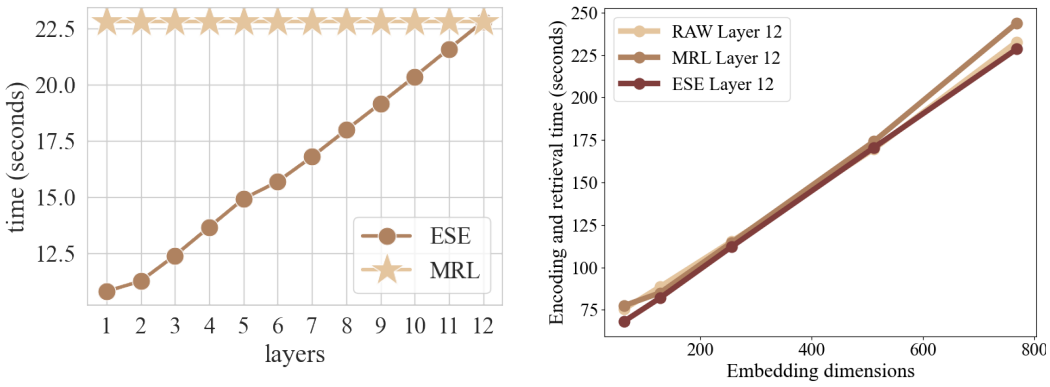
Model	**Avg. Spearman's Corr.**	
Small Scale ($n = 4$, $d = 512$)		
BERT_{small}	74.01	
MRL w/ BERT_{base}	54.91	(-19.10)
ESE w/ BERT_{base}	**74.46**	$(+0.35)$
Tiny Scale ($n = 2$, $d = 128$)		
BERT_{tiny}	69.85	
MRL w/ BERT_{base}	54.90	(-14.95)
ESE w/ BERT_{base}	**71.64**	$(+1.79)$

4.4 Discussion

Scalability. We scale down the trained BERT_{base} (Devlin et al., 2019) ESE model to BERT_{small} and BERT_{tiny} sizes by truncating the model depth and embedding size. Then, we compare the scaled-down ESE models with BERT_{small} and BERT_{tiny} models trained independently on MultiNLI and SNLI datasets, and show the results in Table 5. Scaled MRL performs poorly primarily due to its inability to support model depth truncation. It is noted that our scaled ESE consistently outperforms both trained BERT_{small} and BERT_{tiny} models. It demonstrates that the proposed ESE can be truncated and adapted to various scenarios while achieving competitive performance compared to a trained smaller model.

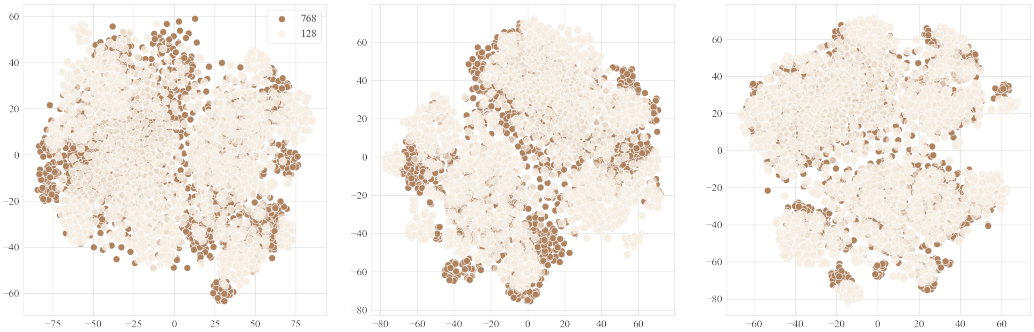
Efficiency. We compare ESE with MRL (Kusupati et al., 2022) in terms of efficiency on STS, as shown in Figure 6a. ESE's trend is almost linear and outperforms MRL. The results imply that it is scalable for ESE to choose shallow layers for efficiency considerations. We also examine how ESE affects RAG efficiency. Figure 6b illustrates the time consumed by the encoding and retrieval stages of the RAG pipeline with various embedding sizes. The results indicate that smaller embedding sizes are more efficient than larger ones, and ESE is slightly more efficient than baselines. The possible reason is the ESE's high-quality embeddings in varying scaled sizes allow easier and more effective indexing, thus improving RAG efficiency.

Compression Quality. To intuitively compare the information compression quality between ESE and baselines, we use t-SNE (Van der Maaten & Hinton, 2008) to visualize 768-dimensional (full) and 128-dimensional (scaled) sentence embeddings in 2D space, as shown in Figure 7. ESE exhibits a higher overlapping rate between the dark- and light-color dots than baselines, showing ESE's high fidelity in the compressing process, i.e., ESE's first-128 sub-embeddings carry most key information



(a) (b)

Figure 6: (a) The inference time of ESE over different layers on STS. MRL serves as a reference. (b) The encoding and retrieval time with different embedding sizes on the HotpotQA dataset.



(a) RAW (Avg. distance=32.63) (b) MRL (Avg. distance=25.75) (c) ESE (Avg. distance=10.36)

Figure 7: The t-SNE visualization of sentence embeddings on the STS-B test set. *bge-base-en-v1.5* serves as the backbone for RAW, MRL, and ESE models. The dark-color dots denote the full 768-dimensional sentence embeddings, while light-color ones represent the first 128-dimension sub-embeddings. The Avg. means the average distance between the 768-dimensional and the 128-dimensional embedding points.

from their full embeddings. To quantitatively measure the difference, we calculate the average distance between the 768- and 128-dimensional embedding points and put the numbers in Figure 7. It is evident that the proposed ESE achieves the lowest average distance among the baselines. This indicates that ESE can effectively condense essential information into the initial embedding dimensions by the learn-to-compress process. It can reduce information loss when using small first-k sub-embeddings for downstream applications.

5 Conclusion

In this paper, we have presented a novel sentence embedding model called Espresso Sentence Embeddings (ESE). It is the first work to support both model depth and embedding size scaling with two novel processes. First, the learn-to-express enables model depth scaling by allowing more important features to be captured by shallow layers. Second, the learn-to-compress allows embedding size scaling by employing information compression to compress embeddings' inner dependencies. The dual scalability of ESE enables it to be truncated into different scales, making it adaptable to varying computational resource requirements. Extensive experiments on STS and RAG have suggested that ESE can effectively produce high-quality embeddings with less model depth and embedding size, enhancing embedding inference efficiency.

REFERENCES

Eneko Agirre, Daniel Cer, Mona Diab, and Aitor Gonzalez-Agirre. SemEval-2012 task 6: A pilot on semantic textual similarity. In **SEM 2012: The First Joint Conference on Lexical and Computational Semantics – Volume 1: Proceedings of the main conference and the shared task, and Volume 2: Proceedings of the Sixth International Workshop on Semantic Evaluation (SemEval 2012)*, pp. 385–393, Montréal, Canada, 7-8 June 2012. Association for Computational Linguistics. URL https://aclanthology.org/S12-1051.

Eneko Agirre, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, and Weiwei Guo. *SEM 2013 shared task: Semantic textual similarity. In *Second Joint Conference on Lexical and Computational Semantics (*SEM), Volume 1: Proceedings of the Main Conference and the Shared Task: Semantic Textual Similarity*, pp. 32–43. Association for Computational Linguistics, 2013.

Eneko Agirre, Carmen Banea, Claire Cardie, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Weiwei Guo, Rada Mihalcea, German Rigau, and Janyce Wiebe. SemEval-2014 task 10: Multilingual semantic textual similarity. In *Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014)*, pp. 81–91, Dublin, Ireland, August 2014. Association for Computational Linguistics. doi: 10.3115/v1/S14-2010. URL https://aclanthology.org/S14-2010.

Eneko Agirre, Carmen Banea, Claire Cardie, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Weiwei Guo, Iñigo Lopez-Gazpio, Montse Maritxalar, Rada Mihalcea, German Rigau, Larraitz Uria, and Janyce Wiebe. SemEval-2015 task 2: Semantic textual similarity, English, Spanish and pilot on interpretability. In *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015)*, pp. 252–263, Denver, Colorado, June 2015. Association for Computational Linguistics. doi: 10.18653/v1/S15-2045. URL https://aclanthology.org/S15-2045.

Eneko Agirre, Carmen Banea, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Rada Mihalcea, German Rigau, and Janyce Wiebe. SemEval-2016 task 1: Semantic textual similarity, monolingual and cross-lingual evaluation. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pp. 497–511, San Diego, California, June 2016. Association for Computational Linguistics. doi: 10.18653/v1/S16-1081. URL https://aclanthology.org/S16-1081.

Jinze Bai, Shuai Bai, Yunfei Chu, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023.

Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. A large annotated corpus for learning natural language inference. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pp. 632–642, Lisbon, Portugal, September 2015. Association for Computational Linguistics. doi: 10.18653/v1/D15-1075. URL https://aclanthology.org/D15-1075.

Fredrik Carlsson, Amaru Cuba Gyllensten, Evangelia Gogoulou, Erik Ylipää Hellqvist, and Magnus Sahlgren. Semantic re-tuning with contrastive tension. In *International conference on learning representations*, 2020.

Daniel Cer, Mona Diab, Eneko Agirre, Iñigo Lopez-Gazpio, and Lucia Specia. SemEval-2017 task 1: Semantic textual similarity multilingual and crosslingual focused evaluation. In *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, pp. 1–14, Vancouver, Canada, August 2017. Association for Computational Linguistics. doi: 10.18653/v1/S17-2001. URL https://aclanthology.org/S17-2001.

Daniel Cer, Yinfei Yang, Sheng-yi Kong, Nan Hua, Nicole Limtiaco, Rhomni St. John, Noah Constant, Mario Guajardo-Cespedes, Steve Yuan, Chris Tar, Brian Strope, and Ray Kurzweil. Universal sentence encoder for English. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pp. 169–174, Brussels, Belgium, November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-2029. URL https://aclanthology.org/D18-2029.

Yung-Sung Chuang, Rumen Dangovski, Hongyin Luo, Yang Zhang, Shiyu Chang, Marin Soljacic, Shang-Wen Li, Scott Yih, Yoon Kim, and James Glass. DiffCSE: Difference-based contrastive

learning for sentence embeddings. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 4207–4218. Association for Computational Linguistics, July 2022. doi: 10.18653/v1/2022.naacl-main.311. URL https://aclanthology.org/2022.naacl-main.311.

Alexis Conneau and Douwe Kiela. SentEval: An evaluation toolkit for universal sentence representations. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, Miyazaki, Japan, May 2018. European Language Resources Association (ELRA). URL https://aclanthology.org/L18-1269.

Alexis Conneau, Douwe Kiela, Holger Schwenk, Loïc Barrault, and Antoine Bordes. Supervised learning of universal sentence representations from natural language inference data. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pp. 670–680, Copenhagen, Denmark, September 2017. Association for Computational Linguistics. doi: 10.18653/v1/D17-1070. URL https://aclanthology.org/D17-1070.

Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. Qlora: Efficient finetuning of quantized llms. *Advances in Neural Information Processing Systems*, 36, 2024.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 4171–4186, 2019.

Matthijs Douze, Alexandr Guzhva, Chengqi Deng, Jeff Johnson, Gergely Szilvasy, Pierre-Emmanuel Mazaré, Maria Lomeli, Lucas Hosseini, and Hervé Jégou. The faiss library. *arXiv preprint arXiv:2401.08281*, 2024.

Tianyu Gao, Xingcheng Yao, and Danqi Chen. Simcse: Simple contrastive learning of sentence embeddings. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 6894–6910. Association for Computational Linguistics, 2021.

Yunfan Gao, Yun Xiong, Xinyu Gao, Kangxiang Jia, Jinliu Pan, Yuxi Bi, Yi Dai, Jiawei Sun, and Haofen Wang. Retrieval-augmented generation for large language models: A survey. *arXiv preprint arXiv:2312.10997*, 2023.

Rohit Gupta, Patrik Lambert, Raj Patel, and John Tinsley. Improving robustness in real-world neural machine translation engines. In *Proceedings of Machine Translation Summit XVII: Translator, Project and User Tracks*, pp. 142–148, Dublin, Ireland, August 2019. European Association for Machine Translation. URL https://aclanthology.org/W19-6727.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*, 2021.

Jeff Johnson, Matthijs Douze, and Hervé Jégou. Billion-scale similarity search with GPUs. *IEEE Transactions on Big Data*, 7(3):535–547, 2019.

Taehyeon Kim, Jaehoon Oh, Nakyil Kim, Sangwook Cho, and Se-Young Yun. Comparing kullback-leibler divergence and mean squared error loss in knowledge distillation. In *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, IJCAI 2021, Virtual Event / Montreal, Canada, 19-27 August 2021*, pp. 2628–2635. ijcai.org, 2021.

Aditya Kusupati, Gantavya Bhatt, Aniket Rege, Matthew Wallingford, Aditya Sinha, Vivek Ramanujan, William Howard-Snyder, et al. Matryoshka representation learning. In *Advances in Neural Information Processing Systems*, volume 35, pp. 30233–30249. Curran Associates, Inc., 2022. URL https://proceedings.neurips.cc/paper_files/paper/2022/file/c32319f4868da7613d78af9993100e42-Paper-Conference.pdf.

Jinhyuk Lee, Zhuyun Dai, Xiaoqi Ren, Blair Chen, Daniel Cer, Jeremy R Cole, Kai Hui, Michael Boratko, Rajvi Kapadia, Wen Ding, et al. Gecko: Versatile text embeddings distilled from large language models. *arXiv preprint arXiv:2403.20327*, 2024.

Xianming Li and Jing Li. Aoe: Angle-optimized embeddings for semantic textual similarity. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1825–1839, 2024a.

Xianming Li and Jing Li. Bellm: Backward dependency enhanced large language model for sentence embeddings. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics*. Association for Computational Linguistics, 2024b.

Zongxi Li, Xianming Li, Yuzhang Liu, Haoran Xie, Jing Li, Fu-lee Wang, Qing Li, and Xiaoqin Zhong. Label supervised llama finetuning. *arXiv preprint arXiv:2310.01208*, 2023.

Kang Liu. SetCSE: Set operations using contrastive learning of sentence embeddings. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=zEHGSN8Hy8.

Zhenyan Lu, Xiang Li, Dongqi Cai, Rongjie Yi, et al. Small language models: Survey, measurements, and insights. *arXiv preprint arXiv:2409.15790*, 2024.

Marco Marelli, Stefano Menini, Marco Baroni, Luisa Bentivogli, Raffaella Bernardi, and Roberto Zamparelli. A SICK cure for the evaluation of compositional distributional semantic models. In *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14)*, pp. 216–223. European Language Resources Association (ELRA), May 2014. URL http://www.lrec-conf.org/proceedings/lrec2014/pdf/363_Paper.pdf.

Tomás Mikolov, Ilya Sutskever, Kai Chen, Gregory S. Corrado, and Jeffrey Dean. Distributed representations of words and phrases and their compositionality. In *27th Annual Conference on Neural Information Processing Systems 2013.*, pp. 3111–3119, 2013.

Niklas Muennighoff, Hongjin Su, Liang Wang, Nan Yang, Furu Wei, et al. Generative representational instruction tuning. *arXiv preprint arXiv:2402.09906*, 2024.

OpenAI. Introducing chatgpt, 2022. URL https://openai.com/blog/chatgpt.

Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*, pp. 3980–3990. Association for Computational Linguistics, 2019.

Nandan Thakur, Nils Reimers, Andreas Rücklé, Abhishek Srivastava, and Iryna Gurevych. Beir: A heterogenous benchmark for zero-shot evaluation of information retrieval models. *arXiv preprint arXiv:2104.08663*, 2021.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(11), 2008.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

Liang Wang, Nan Yang, Xiaolong Huang, Linjun Yang, Rangan Majumder, and Furu Wei. Improving text embeddings with large language models. *arXiv preprint arXiv:2401.00368*, 2023.

Adina Williams, Nikita Nangia, and Samuel Bowman. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pp. 1112–1122. Association for Computational Linguistics, June 2018. doi: 10.18653/v1/N18-1101. URL https://aclanthology.org/N18-1101.

Shitao Xiao, Zheng Liu, Peitian Zhang, and Niklas Muennighoff. C-pack: Packaged resources to advance general chinese embedding, 2023.

Jiahao Xu, Wei Shao, Lihui Chen, and Lemao Liu. DistillCSE: Distilled contrastive learning for sentence embeddings. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 8153–8165. Association for Computational Linguistics, December 2023.

Marina Zhang, Owen Skipper Vallis, Aysegul Bumin, Tanay Vakharia, and Elie Bursztein. RETSim: Resilient and efficient text similarity. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=23b9KSNQTX.

Xuandong Zhao, Zhiguo Yu, Ming Wu, and Lei Li. Compressing sentence representation for semantic retrieval via homomorphic projective distillation. In *Findings of the Association for Computational Linguistics: ACL 2022*, pp. 774–781, 2022.

Yonghua Zhu, Xuejun Zhang, Ruili Wang, Wei Zheng, and Yingying Zhu. Self-representation and pca embedding for unsupervised feature selection. *World Wide Web*, 21:1675–1688, 2018.

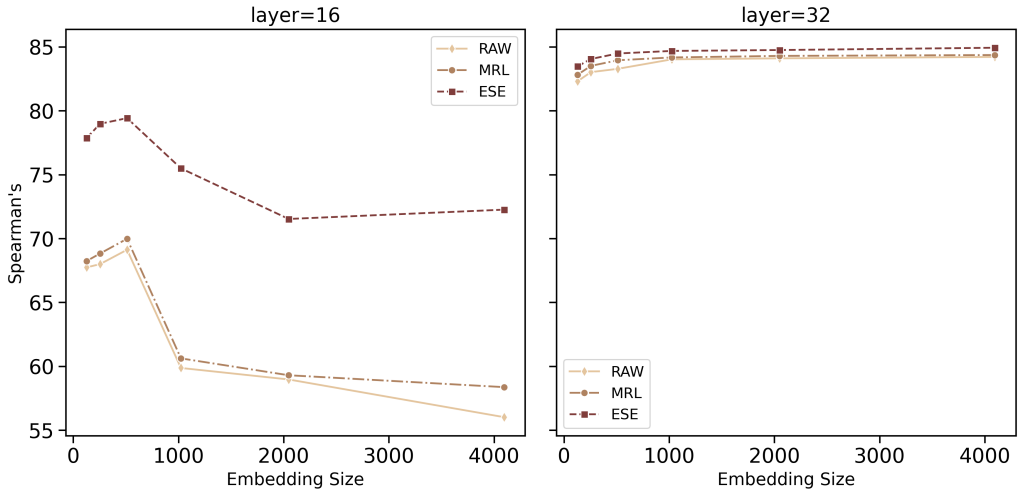


Figure 8: The average STS benchmark results of various embedding sizes for the half layer (first 16 layers) and last layer (full 32 layers) of LLaMA3.1 8B (Touvron et al., 2023) with the RAW, MRL, and ESE training.

A LLaMA3.1 STS Results

To evaluate the ESE performance on larger LLMs, we conducted an STS experiment using LLaMA3.1 8B [2], as shown in Figure 8. Here, we reported the results for the half layer (layer=16) and the last layer (layer=32). It is evident that ESE consistently outperforms baselines across different model depths and embedding sizes. Notably, ESE significantly improves at shallow layers. A performance drop was observed at the half layer, which could be attributed to the LoRA's limitation in sentence embedding learning. However, ESE can mitigate this limitation, as evidenced by its lower drop rate than baselines.

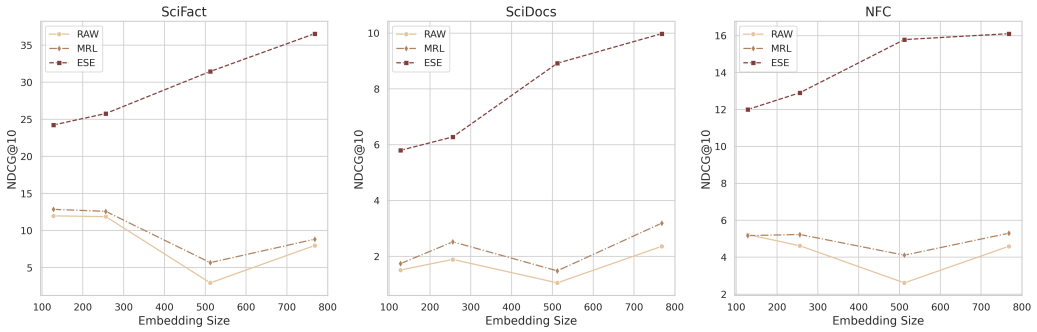
B BEIR Results

We also test ESE on information retrieval datasets, including SciFact, SciDOCS, and NFCorpus from the BEIR benchmark (Thakur et al., 2021), as shown in Figure 9. We can see that ESE can effectively improve the performance of the shallow layer and is more stable than the baselines in the shallow layers. In the last layer, ESE also consistently outperforms the baselines. This shows the effectiveness of ESE in information retrieval.

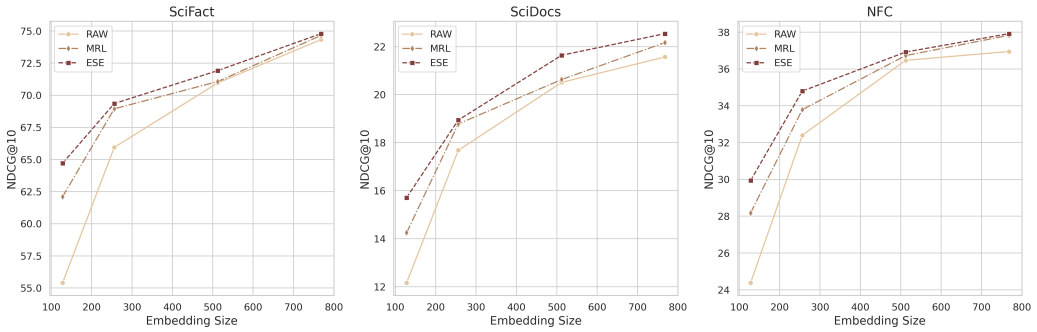
C Shallow Layer Performance

Figure 10 depicts the inference time and STS performance of different layers in MRL and ESE models. Although the inference times at different layers are largely the same, the performance gaps between MRL's and ESE's embeddings are significant. This shows that our approach can effectively improve the shallow layer's task-specific representation, underscoring the scalability of the ESE model.

[2] meta-llama/Llama-3.1-8B



(a) layer=6



(b) layer=12

Figure 9: The information retrieval results on SciFact, SciDOCS, and NFCorpus (NFC) datasets from BEIR benchmark (Thakur et al., 2021). *bge-base-en-v1.5* serves as the backbone.

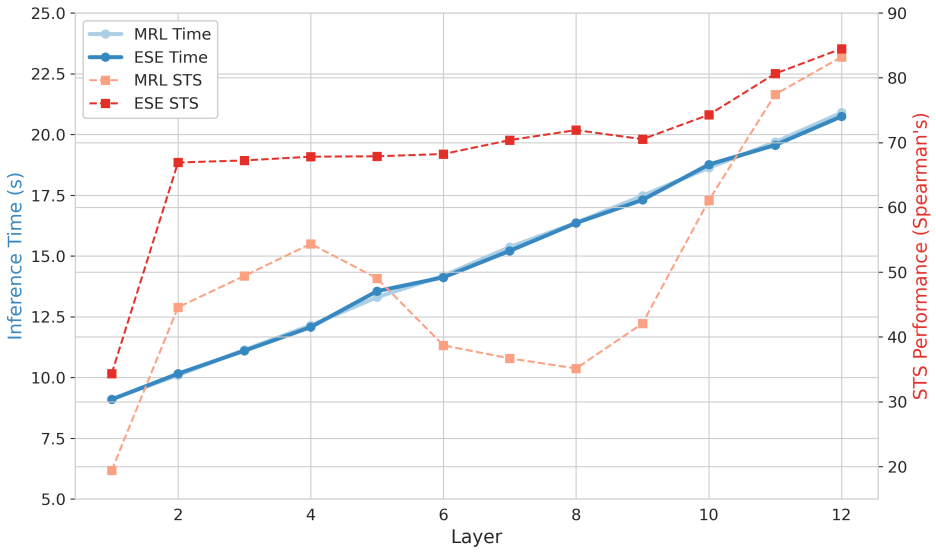


Figure 10: Inference time and STS performance *vs* layers.