Randomly Removing 50% of Dimensions in Text Embeddings has Minimal Impact on Retrieval and Classification Tasks

Sotaro Takeshita[1], Yurina Takeshita[2], Daniel Ruffinelli[1], Simone Paolo Ponzetto[1]
[1]Data and Web Science Group, University of Mannheim, Germany
[2]Independent researcher
{sotaro.takeshita, druffinelli, ponzetto}@uni-mannheim.de

Abstract

In this paper, we study the surprising impact that truncating text embeddings has on downstream performance. We consistently observe across 6 state-of-the-art text encoders and 26 downstream tasks, that randomly removing up to 50% of embedding dimensions results in only a minor drop in performance, less than 10%, in retrieval and classification tasks. Given the benefits of using smaller-sized embeddings, as well as the potential insights about text encoding, we study this phenomenon and find that, contrary to what is suggested in prior work, this is not the result of an ineffective use of representation space. Instead, we find that a large number of uniformly distributed dimensions actually cause an increase in performance when removed. This would explain why, on average, removing a large number of embedding dimensions results in a marginal drop in performance. We make similar observations when truncating the embeddings used by large language models to make next-token predictions on generative tasks, suggesting that this phenomenon is not isolated to classification or retrieval tasks. Our code is attached to the submission.[1]

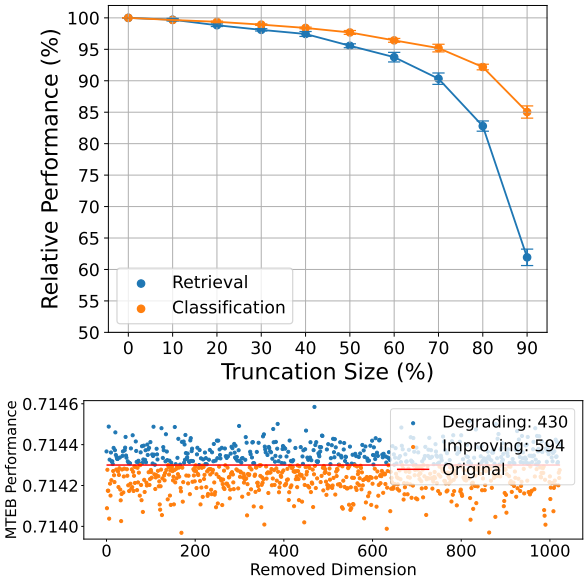

Figure 1: (top) Regardless of the selection, removing 50% of embedding dimensions results in less than 5% performance drop. (bottom) This seems related to is due to many dimensions that lower performance (depicted in blue).

1 Introduction

As text embeddings are used in various applications such as retrieval augmented generation (Li et al., 2025), question answering (Karpukhin et al., 2020), or text retrieval (Liu et al., 2021), there have been extensive research efforts not only aiming at improving their performance but also to understand them. A number of works explore *what* text embeddings encode, such as using probing methods in well-controlled setups to check the information encoded by embeddings (Hewitt and Manning, 2019; Kulmizev et al., 2020). However, less has been explored on *how* information is encoded. Existing works in this direction often assess isotropy (or anisotropy) in text embeddings, that is, whether text embeddings are scattered (or concentrated) in representation space (Ait-Saada and Nadif, 2023; Godey et al., 2024). While these works provide insights into geometric properties of text embeddings, they often focus less on the impact that these properties have on downstream tasks.

To fill this gap, we look at how text embeddings use the representation space *through the lens of their impact on downstream task performance.* In our first experiment, we examine how well text encoders use the embedding space by measuring performance when removing K% of embedding dimensions. Through extensive testing with 6 text encoders, including a large language model (LLM), and 26 embedding-based tasks (e.g., passage retrieval and intent classification), we find that, surprisingly, the resulting embeddings still achieve

[1]https://sotaro.io/papers/trunbed

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comparable performance to the original embeddings even when more than half of the dimensions are removed. Regardless of the selection of removed dimensions, reduced embeddings can retain 95% and 90% of the original performance, in classification and retrieval tasks, respectively (Fig. 1: top). By measuring Spearman correlation, we find that indeed, truncation seems to preserve the properties of the space well enough that the rankings used for retrieval and classification are mostly unaffected. These results suggest an inefficient use of the representation space by text encoders.

To study whether embeddings use the representation space effectively, we integrate three well-studied concepts into our study. Specifically, we test if the cause is (i) embeddings gathering in a narrow cone in representation space (Xiao et al., 2023), (ii) redundancy in dimensions (Jing et al., 2021), or (iii) a few outlier dimensions that determine performance (Kovaleva et al., 2021). While all of these properties are present in every models, we do not find strong relations to our initial observation, calling for a new perspective.

To this end, we take inspiration from input attribution methods (Sundararajan et al., 2017; Bastings et al., 2022), and analyze the contribution of each embedding dimension on downstream performance. We find that every model contains many dimensions that negatively impact performance, dubbed degrading dimensions. For instance, we identify 430 degrading dimensions (out of 1024) in E5-large (Wang et al., 2022) (Fig. 1: bottom). The degrading dimensions are uniformly distributed across embedding features. This suggests a possible reason for our initial observation, that is, when we remove dimensions randomly, both the positively and negatively contributing features are removed, resulting in a marginal performance drop. Indeed, when removing only the degrading dimensions, the performance drop is much slower compared to removing random dimensions, or the performance improves from the original embeddings. We also find that a significant number of degrading dimensions are shared across tasks, indicating the potential for further improvements in text encoders.

While our focus is on embeddings produced by text encoders, we also find similar results when truncating the embeddings used by LLMs for next-token prediction in text generation tasks, i.e., tasks where these truncated embeddings are repeatedly used. However, the results in this case are more task-dependent, as we find that in some tasks, performance is severely degraded.

Our contributions are the following:

- We consistently find across several models and downstream tasks, that text embeddings retain more than 90% of their original performance even after randomly removing 50% of their dimensions. We make similar but less consistent findings about the embeddings used by causal language models.
- We identify that the representations obtained from state-of-the-art text embedders can contain a significant amount of dimensions that have a negative impact on many downstream tasks, but more research is needed to understand their role in text representations and to possibly improve existing text encoders.

2 Impact of Embedding Truncation

In this section, we study how well text embeddings use their dimensions by considering a simple hypothesis: if text encoders are effectively using embedding dimensions, removing some features in an arbitrary manner should have a noticeably negative effect on performance. To test this hypothesis, we look at the impact that different methods of embedding truncation have on downstream performance.

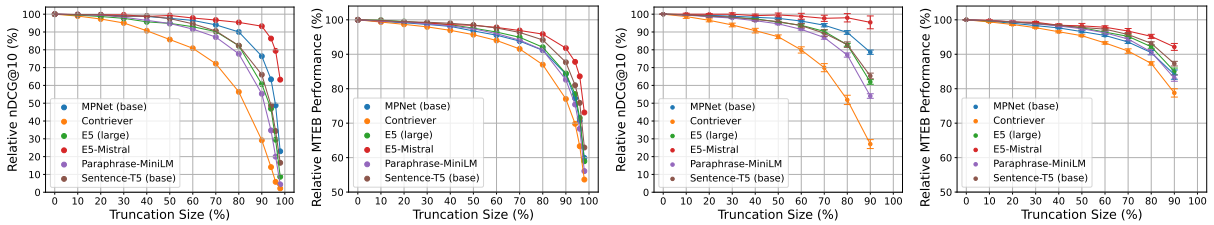
2.1 Experimental Settings

Models. We consider 6 state-of-the-art models, including an LLM-based model, with various sizes and training configurations. All models are contrastively trained after pre-training (see Table 5 for a list of models).

Tasks. For downstream task evaluation, we take 14 retrieval and 12 classification datasets from BEIR (Thakur et al., 2021)[2] and MTEB (Muennighoff et al., 2023) benchmarks (see Table 6 for a list of datasets).

Truncation methods. We evaluate with two different truncation approaches: (i) last K% truncation: we simply remove the last K% of dimensions from embeddings, and (ii) random K% truncation: we uniformly sample K% of the features to be removed. We repeat this process ten different times and report standard deviation in Fig. 2c and 2d.

[2]Due to its high computational demand, for the E5-Mistral model, we use NanoBEIR, which is a subset of the BEIR.



(a) Last K%, BEIR (b) Last K%, MTEB (c) Random K%, BEIR (d) Random K%, MTEB

Figure 2: Relative performance when (a, b) last and (c, d) random K% of dimensions are removed. Error bars in (c, d) are drawn from the results of ten different random removals. The results per dataset are shown in Fig. 9, 10.

2.2 Results and Discussion

Last K% truncation. Fig. 2a and 2b show the results on each benchmark. Relative performance only drops to below 80% when 80% of the dimensions are removed for five out of six models. In an extreme case, E5-Mistral retains 90% of its original performance even when 90% of its dimensions are removed. This suggests that most of the features in these text embeddings do not have a big impact on downstream performance. We further compare the two rankings of retrieved documents produced by original embeddings and truncated embeddings, and indeed see that Spearman's rank-order correlation remains high even after truncating 50%, higher than 0.8 for all models (details in Fig. 8).

Random K% truncation. Fig. 2c and 2d show a very similar pattern in performance reduction curves compared to our previous experiments, and the standard deviations of relative performance between ten random runs are small. This means that regardless of the selection of removed dimensions, models are able to retain most of their downstream performance. In the next section, we look at existing theories in the literature that may explain this phenomenon.

3 Effective Use of Representation Space

In this section, we investigate why text embeddings can be significantly reduced in size without much performance loss. We do this from the perspective of three different concepts from prior works that explore how embeddings (in)effectively use the representation space: anisotropy, dimensional collapse, and outlier dimensions.

3.1 Anisotropy in Embeddings

A number of existing works report that neural network-based encoders, not only for texts (Rudman et al., 2022; Hämmerl et al., 2023; Godey et al., 2024) but also for images (Wang and Isola, 2020), tend to produce anisotropic embeddings, meaning that the encoders map different input data points into a narrow cone without fully exploiting the representation space. The two main characteristics of anisotropic embeddings are (i) distorted variance in values taken by different dimensions and (ii) high correlations between different dimensions (i.e., features) (Rudman and Eickhoff, 2023). As this property may explain our earlier observations, we explore if anisotropy in text embeddings can be a predictor of performance with truncated embeddings.

Experimental setup. Prior work has shown that contrastively training models makes their embeddings less anisotropic, which in turn improves downstream performance (Ni et al., 2022; Chen et al., 2023). So, to obtain embeddings with different levels of anisotropy, we contrastively train two pre-trained models, BERT (Devlin et al., 2019) and T5 (Raffel et al., 2020), storing intermediate checkpoints along the way. The expectation is that, as anisotropy decreases with more training, performance should increase for full-size embeddings, but decrease for truncated embeddings, as less anisotropy means the model is making more effective use of the representation space. We train the models with a mixture of SNLI (Bowman et al., 2015) and MultiNLI (Williams et al., 2018) as training and validation data (Reimers and Gurevych, 2019; Gao et al., 2021), and use InfoNCE as a loss function (Oord et al., 2019). The training is terminated upon convergence of the validation loss. To measure anisotropy, we use two common metrics: uniform loss (Wang and Isola, 2020; Ni et al., 2022) and IsoScore (Rudman et al., 2022), the former decreases and the latter increases its values as the target embeddings become less anisotropic. We apply the last K% truncation to obtain reduced embeddings, and use 13 datasets from NanoBEIR

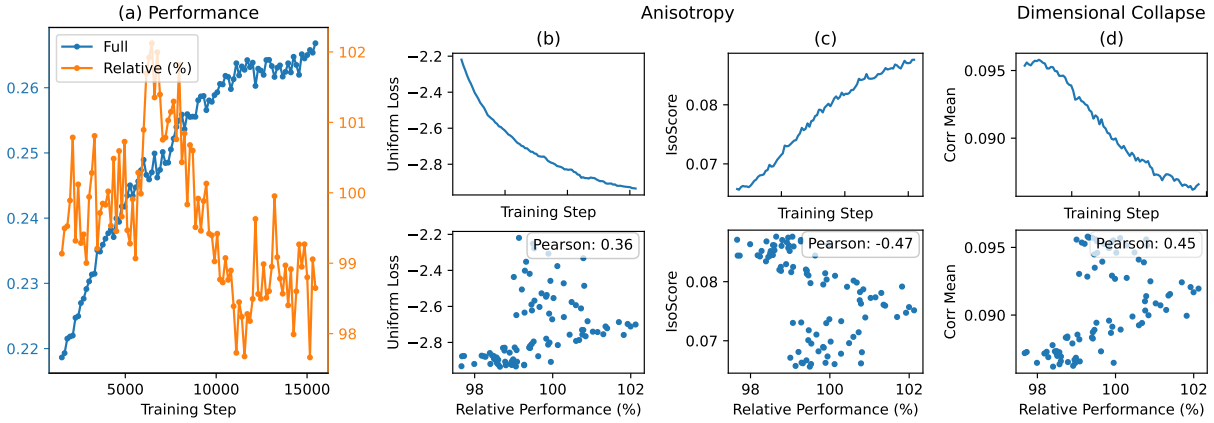


Figure 3: As a result of contrastive learning for T5, downstream task performance increases (a: Full), and the use of embedding space measured through Uniform Loss (↓) and IsoScore (↑) for anisotropy (b, c: top) and Corr Mean (↓) for dimensional collapse (d: top) also improves. However, the relative performance does not change over the training (a: Relative), therefore, there is no strong correlation between relative performance and representation quality measures (b, c, d: bottom).

to evaluate the final performance.

Results. Fig. 3a shows how the full-sized embeddings improve performance during the training together with the decrease in anisotropy as shown in Fig. 3b, c (top) for T5 (result for BERT is shown in Fig. 11). As expected, more training results in increased downstream performance and decreased anisotropy. However, the relative performance achieved by half-sized embeddings does not change over training steps. Fig. 3b, c (bottom) shows the relation between the relative performance and two anisotropy measures. We do not see correlating patterns because even though different checkpoints have different degrees of anisotropy, their relative performance is quite stable. We also compute the Pearson correlation between relative performance and the two anisotropy metrics, but do not observe any strong correlation (0.36 for uniform loss, -0.47 for IsoScore). These results indicate that even when models make better use of the representation space, as measured by anisotropy, truncated embeddings still result in marginal performance drops.

3.2 Dimensional Collapse

Existing works, especially in the computer vision community, report that the representations produced by neural network-based encoders have certain dimensions collapsed, and use only a lower-dimensional subspace (Huang et al., 2023; Hua et al., 2021; He and Ozay, 2022). While this is conceptually similar to anisotropy, dimensional collapse focuses on the correlation between dimensions. In this section, we explore the relation of dimensional collapse in text embeddings to the high relative performance we observe, as the embeddings with highly correlated dimensions can be robust to feature removal.

Experimental setup. We follow Hua et al. (2021) and use the mean of the correlation coefficient between dimensions, computed over embeddings obtained by encoding 10K English paragraphs from Wikipedia[3]. Same as our experiments on anisotropy in §3.1, we use the contrastively trained checkpoints of two model families and NanoBEIR evaluation. We hypothesize that the impact of dimension truncation can remain low for the models where the dimensions are highly correlating.

Results. Fig. 3d (top) shows that the contrastive training reduces correlations between dimensions for T5 (result for BERT is shown in Fig. 11 in the Appendix). As shown in existing works (Jing et al., 2021; He and Ozay, 2022), downstream task performance improves as the correlations weaken. However, as shown in Fig. 3d (bottom), we do not observe any relation between feature correlations and how performance drops after truncating the last 50% of dimensions; the Pearson correlation between them is 0.45. Given these results, we conclude that dimensional collapse, i.e. correlation between dimensions, does not explain the success of truncated embeddings.

[3] sentence-transformers/simple-wiki

	# of Outliers	Outlier	Non-outlier
MPNet (base)	5	0.576	0.576 ± 9e-04
Contriever	3	0.525	0.524 ± 1e-03
E5 (large)	1	0.577	0.577 ± 4e-04
E5-Mistral	32	0.651	0.626 ± 6e-04
Para-MiniLM	2	0.483	0.483 ± 6e-04
ST5 (base)	2	0.489	0.489 ± 9e-04

Table 1: Effect of removing outlier dimensions on downstream task performance. As a comparison, we also remove the same number of ten different non-outlier dimensions and report the average and standard deviation of achieved performance.

3.3 Outlier Dimensions in Embeddings

Several papers report that there are a few dimensions in the weights of pre-trained language models (PLMs) that take abnormally high or low values, known as outlier dimensions (Kovaleva et al., 2021; Puccetti et al., 2022; Hämmerl et al., 2023). PLM weights are often redundant and can be removed without much performance loss (Michel et al., 2019; Bian et al., 2021); however, Kovaleva et al. (2021) show that removing such outlier dimensions from models, even though there are only a few, can massively reduce performance. A follow-up work by Hämmerl et al. (2023) reports that a similar trend exists in multilingual models as well. While they study outlier dimensions in model weights, in this paper, we extend this concept to identify outlier dimensions in text embeddings and explore their interactions with our interest, the high relative performance.

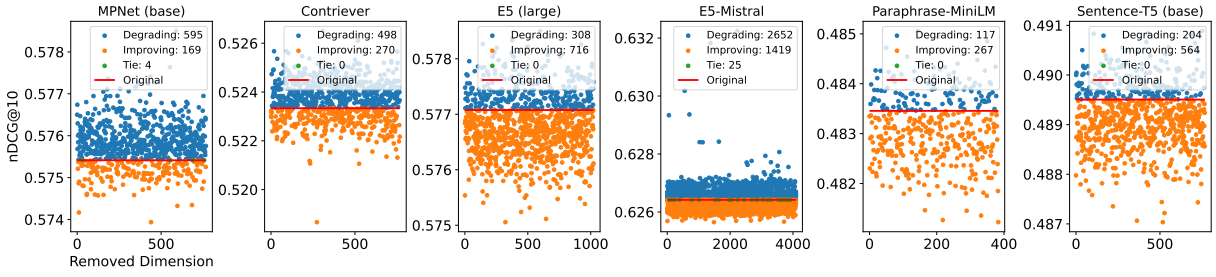
Experimental setup. First, we aim to identify outlier dimensions within text embeddings produced by text encoders. To this end, we examine the embedding obtained by averaging the embeddings of all the query texts from the NanoBEIR datasets. We follow the definition of outlier dimensions used by Kovaleva et al. (2021), that is, the dimensions that deviate more than 3σ from the standard deviation of all values in the average embedding. After identifying them, we assess their effects on downstream tasks by comparing the performance achieved by: (i) the embeddings without outlier dimensions, and (ii) the embeddings without non-outlier dimensions, the same number as outlier dimensions. The second configuration is our control trial. We experiment by removing ten different sets of non-outlier dimensions.

Results. The number of outlier dimensions for each model and their effect on performance are shown in Table 1. The number of outlier dimensions changes with different models; however, it remains low in all cases. This is similar to the outliers within weights reported by Kovaleva et al. (2021). The highest proportion of outlier dimensions to the full embedding is observed with E5-Mistral, that is 0.8% (32 out of 4096 dimensions). The figure also shows that, for five out of six models, the effect of removing outlier dimensions is not beyond the ones where we remove non-outlier dimensions, indicating that, outlier dimensions do not play a critical role. The exception is E5-Mistral, where removing outlier dimensions results in a slight increase in performance with regard to non-outlier removal counterparts, but the gap to the average performance non-outlier removal runs is too small, 0.025 in nDCG@10, to explain our initial observation. These observations are strong indications that the outlier dimensions are unlikely to be the reasons for the low drop rate, which is our interest in this paper.

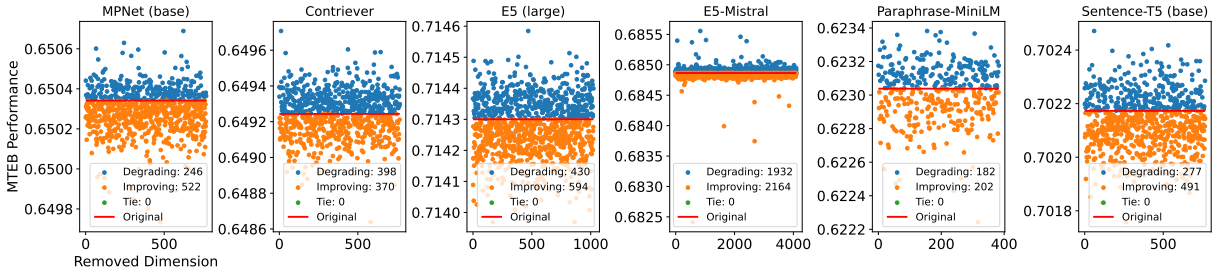
4 Dimension Attribution Analysis

Our previous experiments suggest that truncated embeddings perform well on downstream tasks, even when they seem to make good use of the representation space through existing concepts, e.g. when embeddings are better spread across the representation space, or when there is less correlation between features, or when outlying dimensions are considered. Since this implies that whatever dimensions are left after truncation are still useful, in this section, we study the impact that each dimension has on downstream performance.

Method. We take inspiration from existing works on input attribution, a family of methods that rely on perturbing inputs to determine feature importance to explain model predictions (Sattarzadeh et al., 2021; Wu et al., 2023). Specifically, we repeatedly evaluate performance by disabling one dimension at a time. This enables us to measure the contribution of each dimension to the downstream task performance in isolation. Zeroing model weights is the common way to analyze their role in model behavior (Serrano and Smith, 2019; Zhang et al., 2024b). However, as we focus on dimensions only in embeddings, we simply remove the target dimension from the embeddings. This is a preferred approach because, as each dimension can take a wide variety of values, zeroing values may have varying impacts on final performance.



(a) NanoBEIR



(b) MTEB

Figure 4: Average performance on all datasets in the NanoBEIR and MTEB benchmarks after removing each dimension in the input embeddings. The red horizontal line indicates the performance achieved by the original embedding, and each point is the performance without the corresponding dimension. Blue points indicate that they are negatively impacting the performance as they are above the red line.

Experiments setup. We take 13 retrieval and 12 classification datasets from NanoBEIR and MTEB, respectively, and perform our analysis with the same six models used in Section 2, 3.

Main results. Fig. 4 shows the results on NanoBEIR and MTEB. Each point indicates the downstream task performance achieved without the corresponding dimension. The red line is the original performance achieved by the full-sized embeddings. Points are highlighted in blue (or orange) when they are better (or worse) than the original performance. There are two main observations in the figures. (i) In all model-benchmark combinations, a surprisingly large number of dimensions improve the performance when they are removed (blue in the figures). In other words, there are a large number of dimensions, more than half in some cases, that are degrading the embeddings' performance. In the remainder of the paper, we call them degrading dimensions. For instance, we find 498 and 398 degrading dimensions in embeddings produced by Contriever on NanoBEIR and MTEB, that is, 65% and 52% of the whole embeddings. (ii) The degrading dimensions are uniformly distributed across embedding dimensions without clustering in some areas.

These observations provide an explanation for why removing a large number of dimensions has minimal impact on performance. Since there are many degrading dimensions spread across embedding dimensions, random dimension removal leads to removing dimensions that both improve and degrade performance, resulting in a marginal performance drop as a whole. We further conduct an experiment where we only remove the degrading dimensions. As the results shown in Fig. 5 (blue plot), we observe that the relative performance

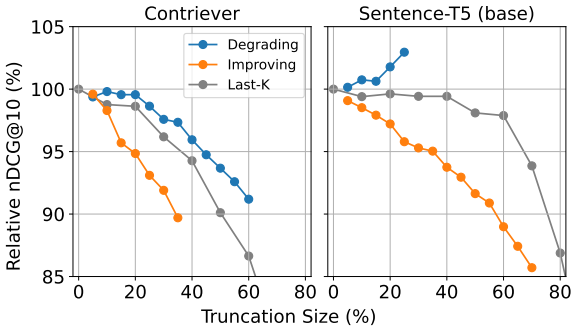


Figure 5: As we remove the degrading dimensions (blue plot), the relative performance for Sentence-T5 (figure on right) improves over the original embeddings. For Contriever (figure on left), while we do not see the improvements, however, the decay is slower than the last-k truncation. On the other hand, when only the improving dimensions are removed (orange plot), the performance decreases rapidly for both models. Results for other models are shown in Fig. 12.

keeps improving for some models (e.g., Sentence-T5), and even for the models whose truncated embeddings drop their performance (e.g., Contriever), the speed of decay is slower than random truncation. Conversely, when we remove only the dimensions that are improving the performance (dimensions in orange in Fig. 4a), the performance drops rapidly compared to the random truncation (Fig. 5: orange plot).

These results indicate that there is a new aspect of improvements in current text embedding models, as many of the dimensions are damaging performance. Future work can explore training objectives or model architectures that can reduce degrading dimensions to boost the model performance, similarly to how the training objective proposed by Jing et al. (2021) mitigates dimensional collapse or the novel Transformer architecture introduced by He et al. (2024) that can reduce the number of outlier dimensions.

Outlier degrading dimensions in E5-Mistral. Some degrading dimensions in E5-Mistral's embeddings have higher impacts compared to other models when evaluated on NanoBEIR (Fig. 4a). As we observe the outlier dimensions in E5-Mistral also have stronger impacts than other models (§3.3), we draw a connection from the outlier dimensions to the degrading dimensions. As shown in Fig. 13, there are 19 degrading dimensions that have stronger negative impacts than the other degrading dimensions (ODD: Outlier degrading dimensions), i.e., performance degraded at least 3σ from the mean of the performance, and 12 of them also take outlying values (ODD $\cap$ OD in the figure). This explains our earlier observation in §3.3: not all outlier dimensions (OD) have a strong impact on downstream task performance, however, some indeed have outlying impacts. We speculate that the model's extremely high relative performance (e.g., 90% relative performance when 90% of the dimensions are truncated) may be due to these outlier degrading dimensions.

Shared degrading dimensions. We test if the same dimension appears as a degrading one in multiple datasets. To this end, we independently identify degrading dimensions for each dataset in NanoBEIR and count the ones shared in multiple datasets. Fig. 6 shows the result. We can see that while there is no degrading dimension shared across all 13 datasets in any models, they are indeed commonly degraded dimensions across some

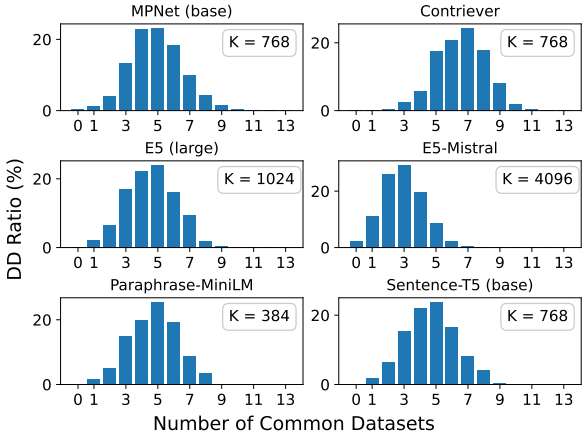


Figure 6: The ratio of degrading dimensions to the size of original embedding sizes (K in the figure) that are shared across a certain number of datasets.

	BEIR		MTEB	
	Trun. (%)	PCA (%)	Trun. (%)	PCA (%)
MP	97.7	99.4	96.6	99.6
Cont	87.3	77.3	95.4	98.5
E5-L	95.9	90.6	97.7	99.8
E5-M*	99.6	100.6	98.2	100.4
Para	94.6	99.3	97.4	99.5
ST5	95.9	100.2	97.8	99.9

Table 2: Comparison of relative performance between random truncation (Trun.) and PCA when reducing embedding size by 50%. We use NanoBEIR for E5-Mistral.

datasets, i.e., MPNet's more than 20% of dimensions degrade performance in five datasets. This observation hints at a possibility to explore domain-specific methods to identify degrading dimensions, which is left for future work.

Random Truncation vs PCA. We explore the practical value of embedding truncation by comparing it to a popular dimension reduction method: PCA (Raunak et al., 2019; Zhang et al., 2024a). To this end, we compare the performance of embeddings that are halved by the PCA and the average of ten different runs of random truncation (see §2). We use the implementation from scikit-learn (Pedregosa et al., 2011), and use 20k sentences from the all-nli dataset for training[4]. Table 2 shows the results on BEIR (NanoBEIR for E5-Mistral) and MTEB. While random truncation does not require any training or additional computation at inference time, their relative performances are surprisingly close to PCA, even outperforming it in some cases,

[4] sentence-transformers/all-nli

Model	Dataset	Method	Perf (Relative)
Llama	MMLU (acc)	Full	0.681 (1.000)
		First	0.580 (**0.852**)
		Last	0.586 (**0.861**)
	SQUAD-V2 (best exact)	Full	51.87 (1.000)
		First	50.07 (**0.965**)
		Last	50.07 (**0.965**)
	GSM8K (exact match (strict))	Full	0.764 (1.000)
		First	0.009 (0.012)
		Last	0.014 (0.018)
Qwen	MMLU (acc)	Full	0.718 (1.000)
		First	0.709 (**0.988**)
		Last	0.709 (**0.987**)
	SQUAD-V2 (best exact)	Full	50.12 (1.000)
		First	50.07 (**0.999**)
		Last	50.07 (**0.999**)
	GSM8K (exact match (strict))	Full	0.766 (1.000)
		First	0.045 (0.059)
		Last	0.011 (0.014)

Table 3: Performance on three benchmark datasets when the last hidden representations and the unembedding layer are reduced by half. Relative performance is bolded when it reaches 80% of the original performance. The results on the rest of the datasets are shown in Table 4 in the Appendix.

e.g., Contriever on BEIR. This result exhibits random truncation as an extremely simple and cheap approach to reduce text embedding's dimensionality.

Truncated Representations in Causal Language Models. While the focus of this paper is on embeddings produced by text encoders, in this section, we study the impact that embedding truncation has on causal language modeling.

To this end, we consider two LLMs, Llama 3.1 8B (Grattafiori et al., 2024) and Qwen 2.5 7B (Qwen et al., 2025), and evaluate on various six tasks after removing half of the last hidden representations before they are projected to the vocabulary space (Hendrycks et al., 2020; Rajpurkar et al., 2018; Dua et al., 2019; Gordon et al., 2012; Cobbe et al., 2021; Zellers et al., 2019). We test removing the first and last half of the representations, and reduce the unembedding matrix correspondingly. We use Language Model Evaluation Harness (Gao et al., 2024) for our evaluation.

Table 3, 4 shows the results. On three out of six tasks, both models retain more than 80% of the original performance, and in these cases, similarly to our embedding-based experiments, how to reduce representations (removing first or last) does not have an impact, indicating the presence of inefficient representation space usage by LLMs. However, contrary to our embedding-based evaluation results, the high relative performance is not observed in all datasets, e.g., on GSM8K, the original performance is heavily lost with all models and reducing methods, leaving a dedicated study on LLMs for our future studies.

5 Related Works

Inefficient use of representation space within the weights of PLMs and LLMs is hinted at by a number of papers showing these models are robust to pruning (Michel et al., 2019; Budhraja et al., 2020; Chen et al., 2021; Zheng et al., 2022). In the context of text embeddings, several studies analyze their geometric properties, such as anisotropy (Hämmerl et al., 2023; Godey et al., 2024; Razzhigaev et al., 2024). However, their influence on downstream tasks is under exploration. Ait-Saada and Nadif (2023) show a limited influence of anisotropy on text clustering. Our work adds more evidence of such limited influence of anisotropy on 26 embedding-based tasks.

The work closest to ours is Kovaleva et al. (2021) in which the authors identify a few dimensions within BERT's weights that are more impactful than the others. Its successor works analyze outlier dimension in multilingual models (Hämmerl et al., 2023), analyze their properties (Rudman et al., 2023), or identify similar dimensions in LLMs (He et al., 2024). Differently, in this paper, we focus on properties of embedding dimensions instead of model weights, and while we observe outlier dimensions in embeddings, we show that they do not have a strong influence on task performance compared to the ones in model weights.

A concurrent work by Tsukagoshi and Sasano (2025) shows how little dimension truncations impact performance with prompt-based text encoders. They approach this observation from a perspective of redundancy in embeddings. They take two concepts, namely isotropy and intrinsic dimensionality, and show that the models with higher redundancy in produced embeddings are more robust to truncation. In addition, they show that prompt design has an influence on this phenomenon. Our work complements this work by (i) conducting experiments with a more diverse set of models, including non-

prompt-based encoders and LLM text generators, (ii) conducting additional controlled experiments, such as the use of a continuous set of contrastively trained models to analyze redundancy (anisotropy and dimensional collapse) which allows us to have more comparable models, and finally (iii) shedding light on a new perspective to analyze the model's use of embeddings space, namely dimensional attribution analysis.

6 Conclusion

In this paper, we explored a surprisingly small effect of randomly removing dimensions from text embeddings on downstream task performance. We showed that 6 text encoders can retain 90% of the original performance even when 50% of the dimensions are removed, consistently for 26 embedding-based downstream tasks. Through a series of analyses, we identified a significant number of dimensions in text embeddings that are lowering downstream performance, distributed across embeddings, which would explain our initial observation. We also observed a similar effect during the text generation by causal language models in some cases.

Limitations

This work has the following limitations: (i) The cause of the degrading dimensions is still unknown. While we find that there is a large number of dimensions in text embeddings that lower the downstream task performance, this work does not explore how they emerge. For instance, identifying in which stage of model construction (e.g., early stage of pre-training) such degrading dimensions start to appear remains as future work for us. (ii) We focused on removing one dimension at a time in our dimension attribution analysis experiments (§4) without taking combinations of multiple dimensions into account. While such complex analysis may provide us with more insights about degrading dimensions, this would require an extremely high computational resource, preventing us from exploring this direction. (iii) Our experiments only cover models trained for the English language and datasets that are in English. While we confirm our findings through extensive experiments, the language is limited to English, without covering other languages, leaving a possibility of different behaviours in non-English languages. (iv) The relation to models trained with the Matryoshka Representation Learning (MRL) method (Kusupati et al., 2022) is not explored. The MRL models are trained with a tailored objective function so that their output representations can be truncated without large performance loss. In our preliminary experiment, we compared two MPNet variants trained with standard and MRL objectives, and observed that the performance of truncated embeddings from both models was comparable; also, the change in relative performance with different degrees of truncation was comparable to non-MRL encoders. While larger-scale experiments to assess the impact of MRL on text encoders are interesting, such experiments require powerful computational infrastructure with large GPU memories, therefore, we are unable to pursue this direction.

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A Appendix

A.1 Relative Performances by Different Seeds

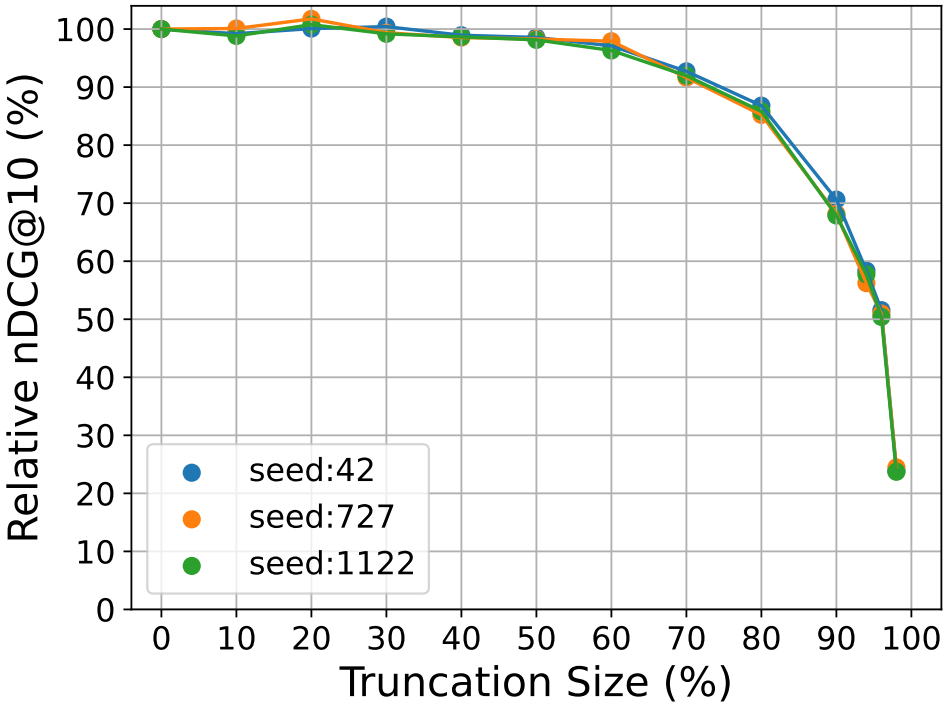

Figure 7: Relative performance of three differently-seeded models on NanoBEIR benchmark with different truncation sizes.

Here, we investigate whether the embeddings produced by all of the differently-seeded models during contrastive training achieve high relative performance by fine-tuning the T5's encoder with a contrastive learning objective as done in §3.1 with three different random seeds. The result is shown in Fig. 7. All three model instances have almost identical shifts in relative performance with different degrees of truncations. This result allows us to conclude that our observation, the embeddings' high robustness to the truncation operation, is present regardless of the randomness during contrastive training.

A.2 LLMs and Truncated Representations

Model	Method	COPA F1 (Relative)	DROP F1 (Relative)	HellaSwag Acc (Relative)
Llama	Full	0.194 (1.000)	0.194 (1.000)	0.681 (1.000)
	First	0.094 (0.487)	0.094 (0.487)	0.580 (**0.852**)
	Last	0.038 (0.198)	0.038 (0.198)	0.586 (**0.861**)
Qwen	Full	0.003 (1.000)	0.003 (1.000)	0.718 (1.000)
	First	0.001 (0.375)	0.001 (0.375)	0.709 (**0.988**)
	Last	0.001 (0.458)	0.001 (0.458)	0.709 (**0.987**)

Table 4: Performance on three benchmark datasets when the last hidden representations and the unembedding layer are reduced by half. Relative performance (scores in parenthesises) is bolded when it reaches 80% of the original performance.

Table 4 is a complementary table to Table 3, showing the impact of representation truncation on the three remaining datasets from §2.

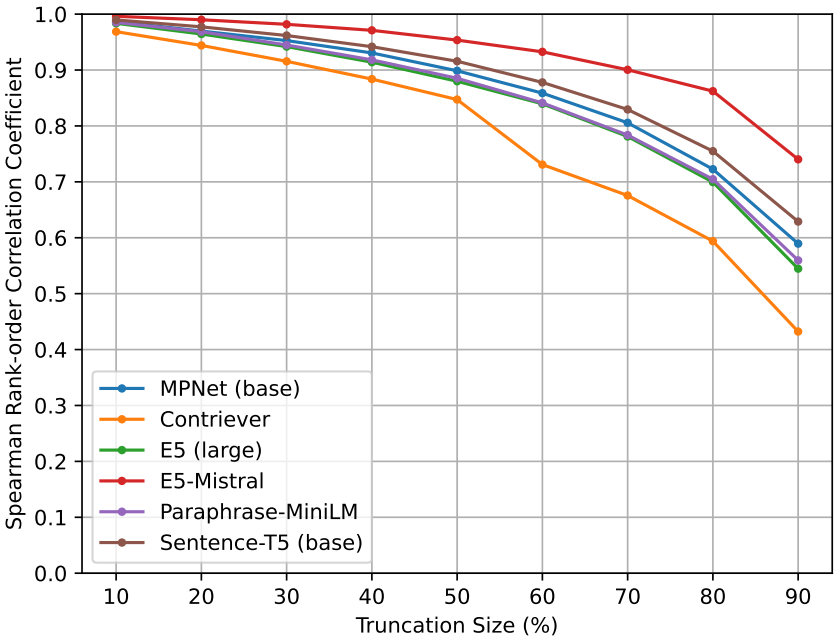

Figure 8: Spearman's rank-order correlation coefficient between the two rankings of documents for each query in NanoBEIR produced by full-sized embeddings and truncated embeddings.

A.3 Document Ranking by Truncated Embeddings

We compare two sets of document rankings. The first set is a result of standard text embedding-based retrieval, where we use the original full-sized embeddings to compute similarity between queries and documents. The second set is produced by using embeddings of which the last K% of the dimensions are truncated. We compute Spearman's rank-order correlation between the two and see how similar the rankings produced by truncated embeddings are to the original embeddings' rankings. The resulting curve is shown in Fig. 8. Similarly to our findings in §2, the behaviour of truncated embeddings is close to the original embeddings.

A.4 Truncated Embeddings' Performance Per Dataset

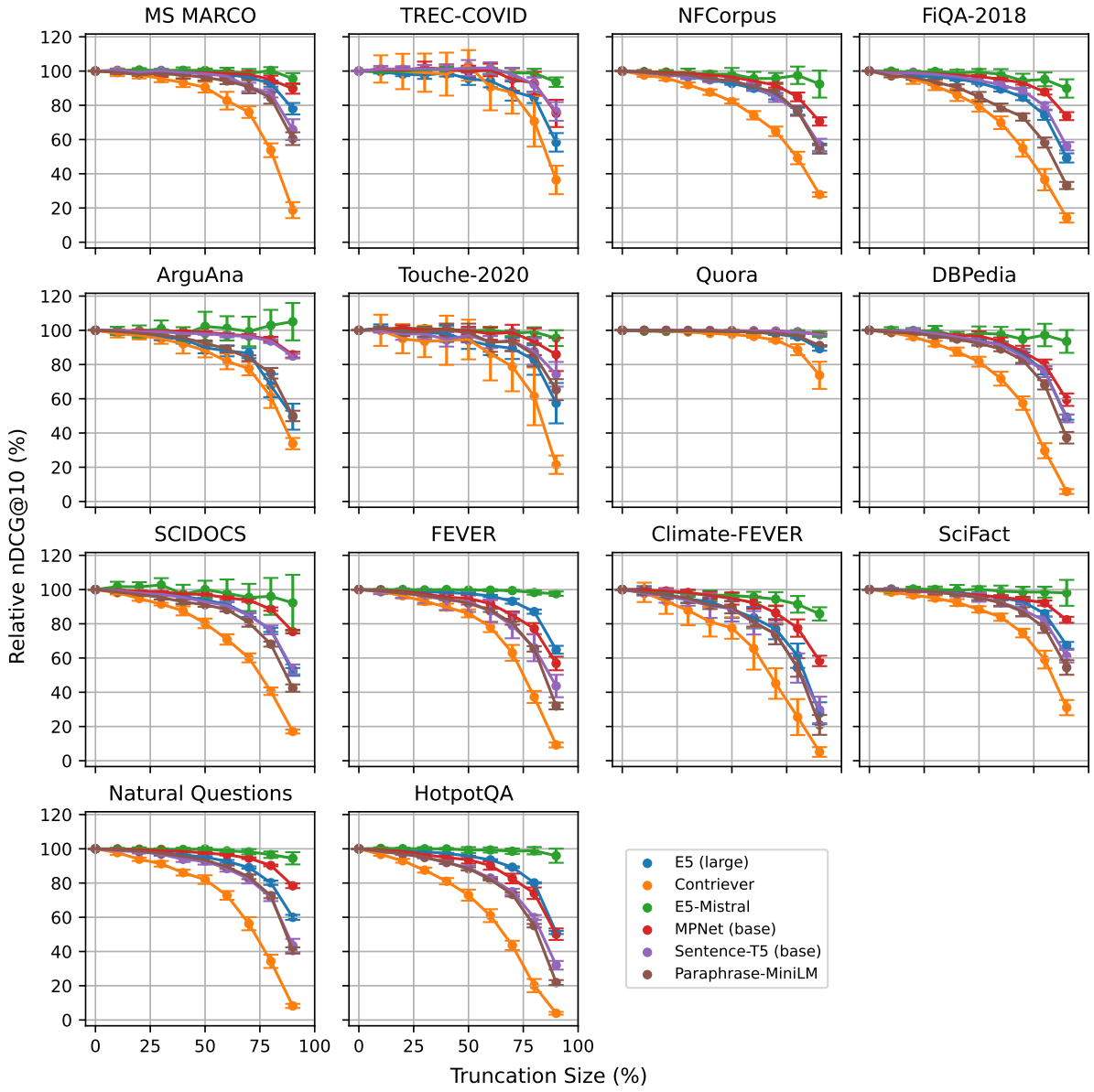

Figure 9: The relative performance achieved by randomly truncated embeddings per dataset from BEIR and NanoBEIR for E5-Mistral.

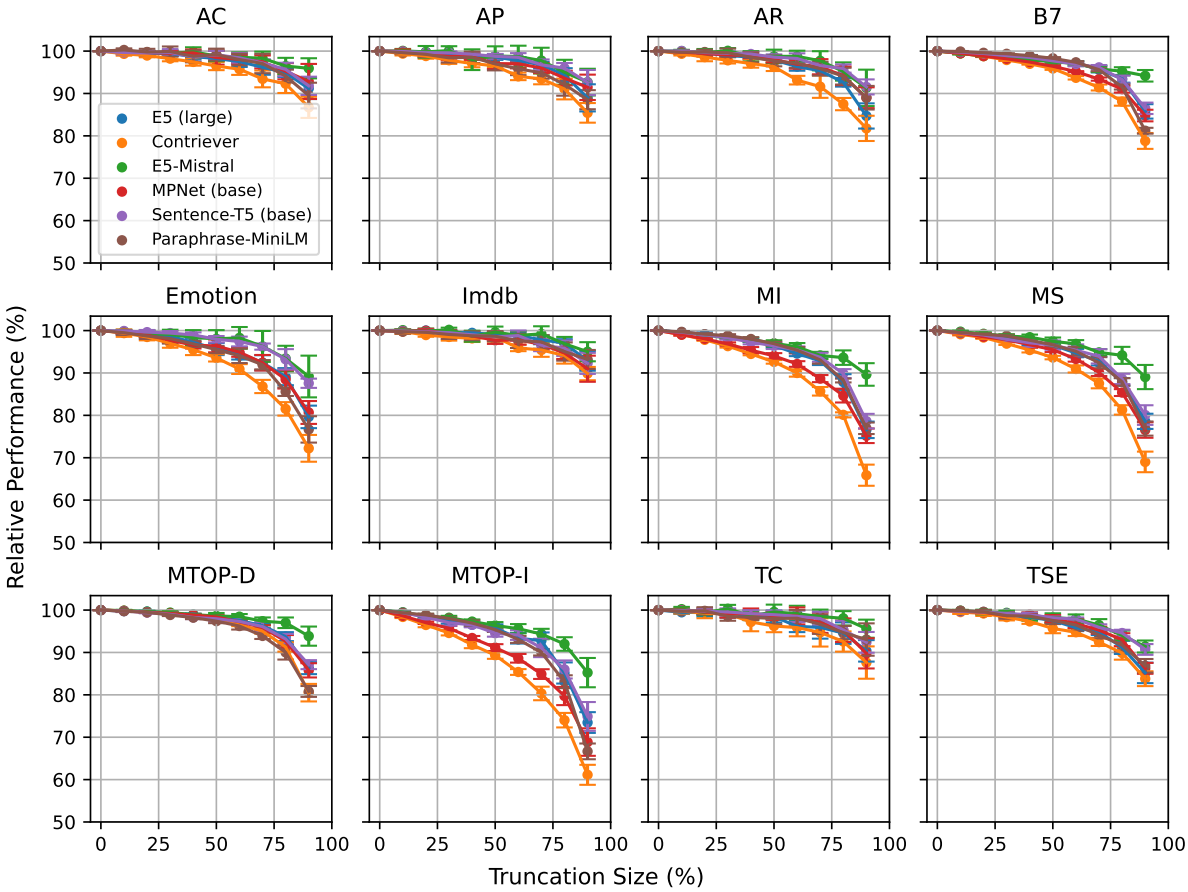

Figure 10: The relative performance achieved by randomly truncated embeddings per dataset from MTEB.

A.5 Effective Use of Representation Space (Figures for BERT)

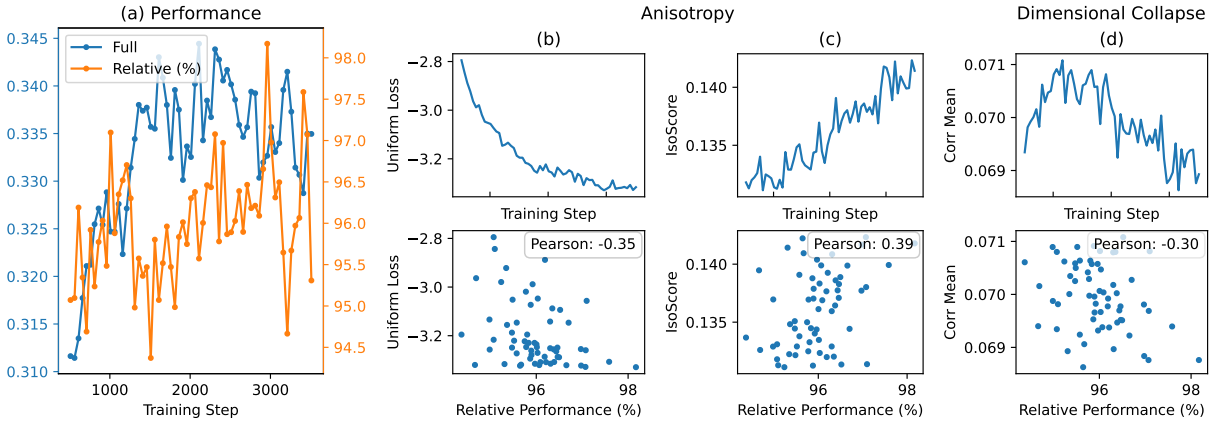

Figure 11: As a result of contrastive learning for BERT, downstream task performance increases (a: Full), and the use of embedding space measured through Uniform Loss (↓) and IsoScore (↑) for anisotropy (b, c: top) and Corr Mean (↓) for dimensional collapse (d: top) also improves. However, the relative performance does not change over the training (a: Relative), therefore, there is no strong correlation between relative performance and representation quality measures (b, c, d: bottom).

A.6 Effect of Removing Only Degrading (or Improving) Dimensions

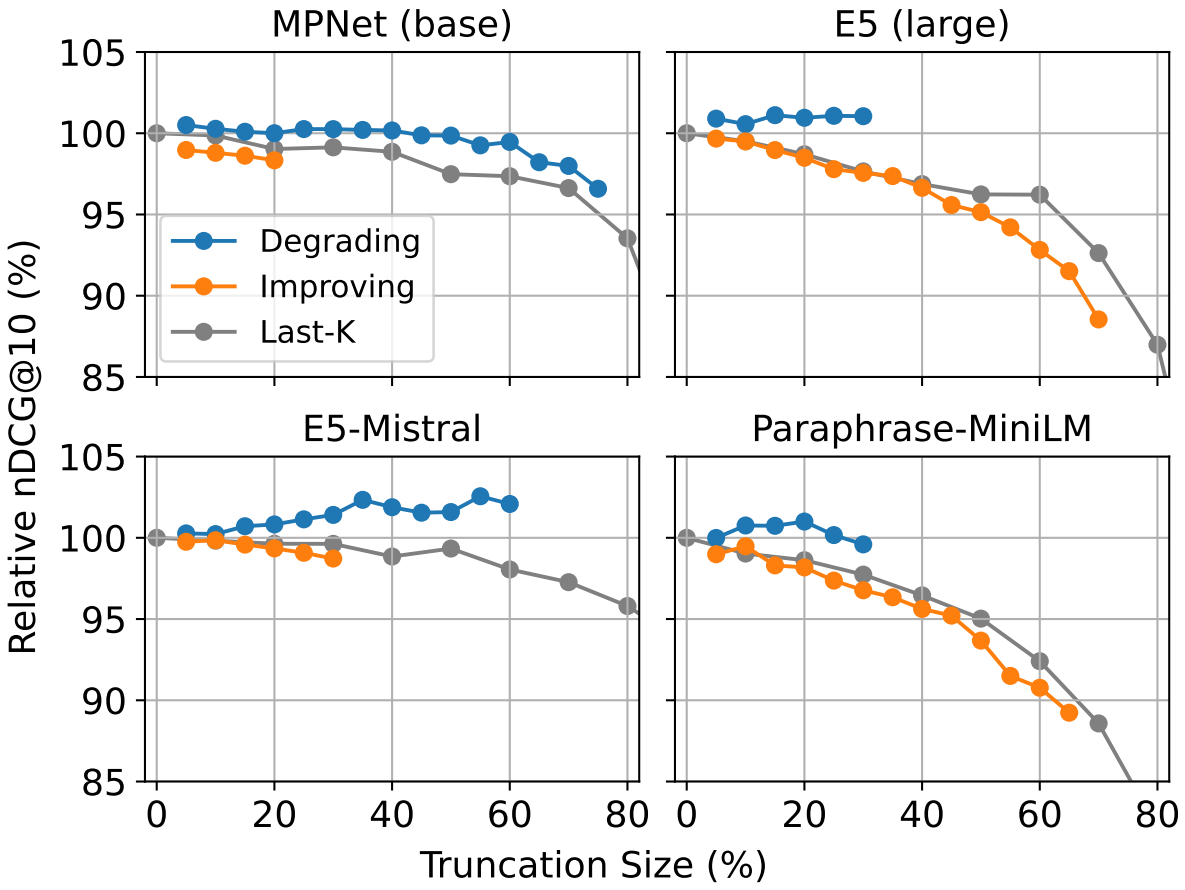

Figure 12: When only the degrading dimensions are removed (blue plot), the performance improves over the original embeddings first, and as more are removed, the performance starts to decay, however, more slowly than the last-k truncation. On the other hand, when only the improving dimensions are removed (orange plot), the performance decreases rapidly.

A.7 E5-Mistral's Outlier Dimensions.

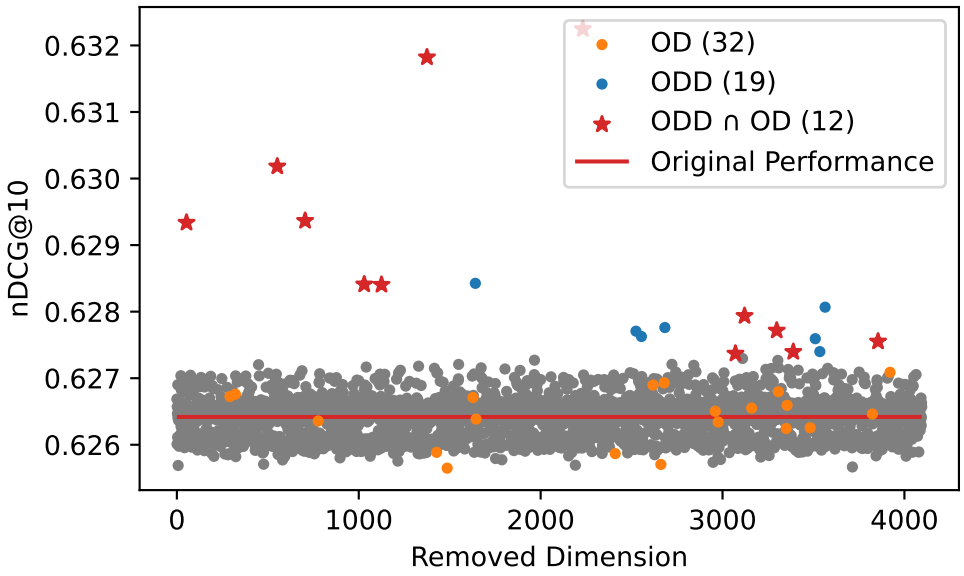

Figure 13: E5-Mistral's retrieval performance without one dimension. Outlier dimensions (ODs) take abnormal values within embeddings as defined in §3.3. Outlier degrading dimensions (ODDs) have negative impacts that are at least 3σ from the mean of performance. The numbers in parentheses indicate the count of each type of dimension.

A.8 Resources Used for Our Experiments

Name	Params	Emb Size	Licence
MPNet (base)	109M	768	Apache license 2.0
Contriever (Izacard et al., 2022)	110M	768	Attribution-NonCommercial 4.0 International
E5 (large) (Wang et al., 2022)	335M	1024	MIT
E5-Mistral (Wang et al., 2024)	7B	4096	MIT
Paraphrase-MiniLM (Reimers and Gurevych, 2019)	17M	384	Apache license 2.0
Sentence-T5 (base) (Ni et al., 2022)	110M	768	Apache license 2.0

Table 5: List of models used in our study.

	Name	Domain	Licence
Retrieval	MS MARCO (Nguyen et al., 2016)	Misc.	MIT
	TREC-COVID (Voorhees et al., 2021)	Bio-Medical	Dataset License Agreement
	NFCorpus (Boteva et al., 2016)	Bio-Medical	N/A
	FiQA-2018 (Maia et al., 2018)	Finance	N/A
	ArguAna (Wachsmuth et al., 2018)	Misc.	CC BY 4.0
	Touche-2020 (Bondarenko et al., 2020)	Misc.	CC BY 4.0
	Quora	Quora	N/A
	DBPedia (Hasibi et al., 2017)	Wikipedia	CC BY-SA 3.0
	SCIDOCS (Cohan et al., 2020)	Scientific	GNU General Public License v3.0
	FEVER (Thorne et al., 2018)	Wikipedia	CC BY-SA 3.0 l
	Climate-FEVER (Leippold and Diggelmann, 2020)	Wikipedia	N/A
	SciFact (Wadden et al., 2020)	Scientific	CC BY-NC 2.0
	Natural Questions (Kwiatkowski et al., 2019)	Scientific	CC BY-SA 3.0
	HotpotQA (Yang et al., 2018)	Scientific	CC BY-SA 4.0
Classification	AmazonCounterfactualClassification (O'Neill et al., 2021)	Reviews, Written	CC-by-4.0
	AmazonPolarityClassification (McAuley and Leskovec, 2013)	Reviews, Written	Apache 2.0
	AmazonReviewsClassification (Keung et al., 2020)	Reviews, Written	N/A
	Banking77Classification (Casanueva et al., 2020)	Written	MIT
	EmotionClassification (Saravia et al., 2018)	Social, Written	N/A
	ImdbClassification (Maas et al., 2011)	Reviews, Written	N/A
	MassiveIntentClassification (FitzGerald et al., 2023)	Spoken	Apache 2.0
	MassiveScenarioClassification (FitzGerald et al., 2023)	Spoken	Apache 2.0
	MTOPDomainClassification (Li et al., 2021)	Spoken	N/A
	MTOPIntentClassification (Li et al., 2021)	Spoken	N/A
	ToxicConversationsClassification (cjadams et al., 2019)	Social, Written	CC-by-4.0
	TweetSentimentExtractionClassification (Maggie et al., 2020)	Social, Written	N/A

Table 6: A list of datasets used in our evaluation.