

NEAR²: A Nested Embedding Approach to Efficient Product Retrieval and Ranking

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Abstract

E-commerce information retrieval (IR) systems struggle to simultaneously achieve high accuracy in interpreting complex user queries and maintain efficient processing of vast product catalogs. The dual challenge lies in precisely matching user intent with relevant products while managing the computational demands of real-time search across massive inventories. In this paper, we propose a Nested Embedding Approach to product Retrieval and Ranking, called NEAR², which can achieve up to 12 times efficiency in embedding size at inference time while introducing no extra cost in training and improving performance in accuracy for various encoder-based Transformer models. We validate our approach using different loss functions for the retrieval and ranking task, including multiple negative ranking loss and online contrastive loss, on four different test sets with various IR challenges such as *short and implicit queries*. Our approach achieves an improved performance over a smaller embedding dimension, compared to any existing models.

Keywords

E-commerce, Search, Matryoshka, Representation Learning

1. Introduction

In e-commerce platforms like Amazon, eBay, and Walmart, effective information retrieval (IR) is crucial for matching user queries with relevant products. However, IR systems face dual challenges of accuracy and efficiency. Accurately interpreting the user intent and ranking search results are complicated by ambiguous, repetitive, and alphanumeric queries [1, 2, 3]. For example, “iPhone 13” often fails to clarify user intent, leading to irrelevant results like “iPhone 13 case” being ranked alongside the intended product. Repetition of query terms in both relevant and irrelevant titles exacerbates this issue. For instance, the term “iPhone 13” might appear in unrelated accessory titles, confusing embedding-based models. Additionally, alphanumeric queries, such as “S2716DG”, pose problems because slight variations (*e.g.*, changing “DG” to “DP”) signify different product features, which semantic similarity models struggle to interpret without an exact match. These challenges reflect the difficulty of aligning query interpretation with user intent.

At the same time, the computational demands of processing massive product catalogs in real time make efficient retrieval a pressing concern [4]. Balancing accuracy with efficiency remains a significant hurdle for modern IR engines. On the efficiency front, current IR systems often rely on computationally intensive models, such as deep neural networks or large-scale embedding computations, to evaluate semantic similarities between queries and product titles [5, 6]. For instance, calculating embeddings for millions of product titles during a live query can create latency, especially when combined with re-ranking stages that refine results. This latency impacts user experience, as delays of even a fraction of a second

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can lead to dissatisfaction or abandoned searches. Optimizing these systems to handle large-scale data efficiently without compromising accuracy is a critical challenge in e-commerce search.

In this paper, we propose a **Nested Embedding Approach** to product **Retrieval and Ranking**, called NEAR², which can achieve efficient product retrieval and ranking using much smaller embedding sizes of encoder-based Transformer models [7]. This approach maintains performance comparable to the full model without incurring additional training costs. Our evaluation results on various test sets that contain different types of challenging queries, such as implicit and alphanumeric queries, indicate that NEAR² can improve model performance on these challenging datasets using significantly smaller embedding dimension sizes. Our contributions can be summarized as follows:

- We propose NEAR², a nested embedding approach, which can achieve up to 12× efficiency in embedding size and 100× smaller in memory usage during inference while introducing no extra cost in training.
- We evaluate NEAR² on four different test sets that contains various types challenging queries. Evaluation results show that our approach achieves an improved performance using a much smaller embedding dimension compared to any existing models.
- We conduct ablative experiments on different encoder-based models fine-tuned using different IR loss functions. We find that NEAR² is robust to different IR losses or loss combinations for continued fine-tuning.
- We perform a qualitative analysis on retrieved product titles using challenging queries. Our analysis re-affirms the superior performance of our approach and reveals that the similarity scores from NEAR² models are more reliable than those of baseline models.

2. Related Work

Modern IR systems encounter several challenges that hinder their performance, particularly in dealing with complex queries and data representation. Ambiguities in natural language, vocabulary mismatches, and the need for scalable real-time processing pose significant challenges [5]. Traditional term-based models often fail due to lexical gaps and polysemy, necessitating the transition to advanced semantic models. Semantic retrieval with dense representations, powered by neural networks and pre-trained language models (PTLMs) like BERT [8], has shown remarkable improvements in handling context and semantics. However, these models demand substantial computational resources and struggle with implicit or alphanumeric queries [5]. Similarly, interaction-based approaches focus on capturing query-document dynamics through deep neural networks, such as the Deep Relevance Matching Model [9], but often sacrifice efficiency and scalability due to their inability to cache document embeddings offline and their reliance on real-time computation [10]. To gap the mismatch of user intent and retrieved product titles in search queries, Saadany et al. [3] curated a dataset annotated with user-intent centrality scores, and proposed a dual loss optimization strategy to fine-tune PTLMs on the dataset in a multi-task learning setting, to solve such challenges.

To address the efficiency issue, researchers have proposed a range of solutions aimed at enhancing efficiency while maintaining accuracy at the same time. Efficiency issues can be tackled through using DUET models that employ local and distributed deep neural networks, which learns dense lower-dimensional vector representations of the query and the document text for efficient retrieval [10]. Knowledge distillation, where smaller models inherit knowledge from larger PTLMs, has proven effective in reducing resource requirements without compromising performance for IR systems [11]. To mitigate computational overhead, Wan et al. [12] proposed to use dimension reduction and distilled encoders to create lightweight models for fast and efficient question-answer retrieval. Kusupati et al. [13] proposed Matryoshka representation learning (MRL) which is able to encode information at different granularities, to adapt to the computational constraints of various downstream tasks. In this paper, we tackle the challenges of accuracy and efficiency using a nested embedding approach based on MRL to create lightweight embedding models for IR tasks.

3. Methodology

This section describes our nested embedding approach in § 3.1 and the backbone models in § 3.2.

3.1. Nested Embedding Training

We utilize MRL with a ranking loss to train nested embeddings of different sizes on various models.

Matryoshka Representation Learning MRL develops representations with diverse capacities within the same higher-dimensional vector by explicitly optimizing sets of lower-dimensional vectors in a nested manner, as illustrated in Figure 1.

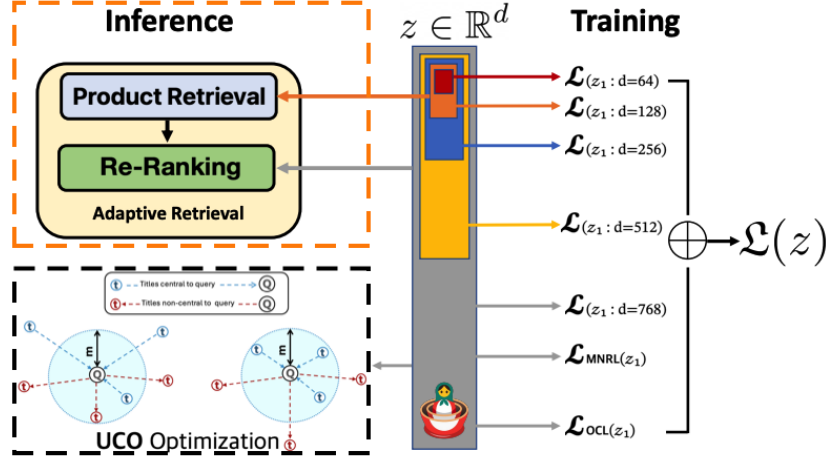


Figure 1: NEAR² combines UCO optimisation [3] with MRL [13] to learn multiple nested embedding representations of different sizes ($z \in \mathbb{R}^d$ as the full embedding representation) with multi-task learning, which are adaptive to different downstream tasks such as retrieval or ranking during inference.

The initial m -dimensions of the Matryoshka representation, where $m \in M$, the set of nested representation sizes, form a compact and information-dense vector that matches the accuracy of a separately trained m -dimensional representation, but requires no extra training effort. As dimensionality increases, the representation progressively incorporates more detailed information, providing a nested coarse-to-fine representation. This approach maintains near-optimal accuracy relative to the full dimensional scale, while avoiding substantial training or deployment costs [14].

The MRL loss is formally defined in Equation 1, where L_{task} is the loss for downstream tasks such as the cross-entropy loss for classification tasks. $f_m(x)$ is the output of the m -th nested embedding representation, and c_m is the importance weight for the m -th embedding representation.

$$L_{MRL} = \sum_{m \in M} c_m L_{task}(f_m(x), y) \quad (1)$$

MRL learns multiple nested embedding representations, each with a different size $m \in M$. The final MRL loss is a weighted sum of the task losses for each of the nested representations. For our product retrieval and ranking task, we set the multiple negative ranking loss (MNRL) [15] as our L_{task} .

Multiple Negative Ranking Loss MNRL measures the difference between relevant (positive) and irrelevant (negative) examples associated with a given query. This technique ensures a clear separation by reducing the distance between the query and positive samples while increasing the distance from negative samples. Using multiple negative examples enhances the model’s ability to discern varying levels of irrelevance, refining its optimization. The MNRL objective function is formulated as follows:

$$MNRL = \sum_{i=1}^P \sum_{j=1}^N \max(0, f(q, p_i) - f(q, n_j) + \text{margin}) \quad (2)$$

In Equation 2, P represents the number of positive samples; N denotes the number of negative samples; q is the query; f is the similarity metric (cosine similarity in our case), and the *margin* is a hyperparameter defining the ideal distance between positive and negative samples based on the relevance score. The goal of MNRL is to minimize the similarity between (q, p_i) while simultaneously maximizing the difference between (q, n_j) for all positive and negative samples.

3.2. Backbone Models

We used encoder-based Transformer models as our backbone for training nested embeddings for efficient product retrieval and ranking.

Pre-trained Language Models We initially leveraged BERT [8], a publicly available pre-trained encoder Transformer model. For our specific use case in e-commerce, we also employed eBERT¹, a proprietary multilingual language model pre-trained internally at eBay. This custom model was pre-trained on a corpus of approximately three billion product titles, supplemented by data from general domain sources like Wikipedia and RefinedWeb.

Expanding our experimental approach, we also incorporated eBERT-siam, a fine-tuned variant of eBERT using a Siamese network architecture. This model aims to generate semantically aligned embeddings for item titles, making it particularly effective for similarity-based search and retrieval tasks. Consistent across all models, we maintained a uniform architectural design of 12 layers with a dimension size of 768.

User-intent Centrality Optimized (UCO) Models Saadany et al. [3, 16] show how current IR systems have problems in achieving user-centric product retrieval and ranking due to implicit or alphanumeric queries. They curated a dataset with user-intent centrality scores (see Section 4.1) and proposed a few models optimized for user-intent using an MNRL loss for retrieval and ranking, and an online contrastive loss (OCL) for user-intent centrality. OCL builds on the traditional contrastive loss (CL) [17] approach but introduces a more focused strategy. While conventional CL uses a twin network to evaluate similarities between all data point pairs from the same and different classes, OCL targets only the most challenging and informative pairs within a batch. By prioritizing such cases, OCL refines the loss calculation to focus on the most critical and complex relationships between data points.

They applied the two losses in a transfer learning setup for eBERT and eBERT-siam models, and performed fine-tuning for centrality classification. Their results indicate that the UCO models achieve an improved performance for retrieval and ranking. Details can be found in Saadany et al. [3].

To improve model efficiency and meanwhile leverage optimized performance of the UCO models, we continued training them using NEAR² for both eBERT-UCO and eBERT-siam-UCO models.

4. Experimental Setup

This section explains the datasets we used for training, validating and testing our approach in § 4.1. Implementation details and evaluation metrics are presented in § 4.2 and § 4.3 respectively.

4.1. Data

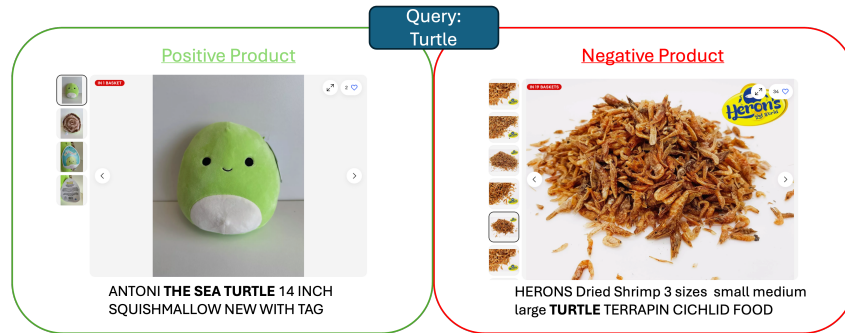
We utilized eBay’s internal graded relevance (IGR) datasets to train our nested embedding representation. These datasets comprise user search queries alongside the product titles retrieved on the platform. They

¹eBERT Language Model

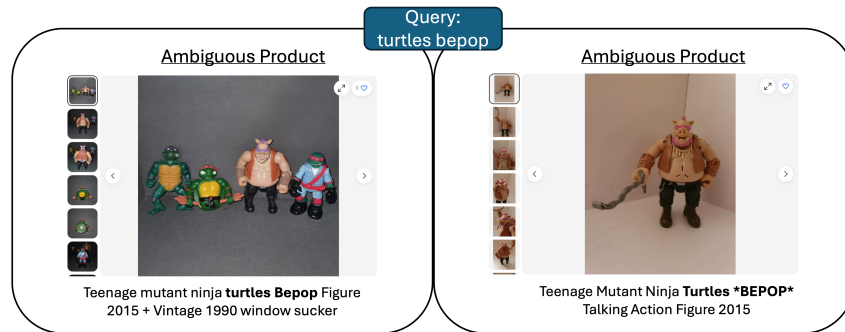
are annotated by humans following specific guidelines to generate two types of buyer-focused relevance labels.

The first is a relevance ranking scheme, where query-title pairs are assigned a rank from (1) Bad, (2) Fair, (3) Good, (4) Excellent, to (5) Perfect. A “Perfect” rating signifies an exact match between the query and title, indicating high confidence that the user’s needs are fully met, whereas a “Bad” rating indicates no alignment between the query and the product title. This ranking methodology aligns with previous studies [18, 19]. The second annotation type is a binary centrality score, derived through majority voting among multiple annotators, indicating whether a product aligns with the user’s expressed query intent. Centrality scoring differs from relevance ranking in that it assesses whether an item is an outlier or unexpected in the retrieval set versus being a core match to user expectations.

To compare the results of our approach with those reported in Saadany et al. [3], we utilized the Common Queries (CQ), CQ Balanced (CQ-balanced), CQ Common String (CQ-common-str), and CQ Alphanumeric (CQ-alphanum) test sets proposed in their paper. The CQ test set was constructed using queries with both positive (relevancy > 3) and negative (relevancy < 3) titles, resulting in a dataset skewed toward positive pairs due to the nature of e-commerce data collection. To address this imbalance, a new version, CQ-balanced, was created with approximately equal numbers of positive and negative query-title pairs. The CQ-common-str set was derived by selecting queries where the exact query string appeared in both positive and negative titles, ensuring a strong correlation between relevance scores (both graded relevance and binary centrality). Finally, CQ-alphanum was created to include only query-title pairs containing alphanumeric characters, allowing for a more focused evaluation. Details about their formulation can be found in Saadany et al. [3]. An example of the datasets and the size for each test set can be seen in Figure 2 and Table 1.



- (a) The query “turtle” is a part of both positive and negative titles with very different product search outputs. It could also be a part of the ambiguous query “turtles bepop”.



- (b) The query “turtles bepop” is ambiguous as it could be referred to the major antagonist, “Bepop” or together with other Ninja Turtles.

Figure 2: Examples of query-title pairs from the *CQ-common-str* test set. The search queries can be very short and ambiguous, but the retrieved products can be very different as shown in (a), or their titles can be quite close in semantic relation as shown in (b).

Test Name	# Corpus	# Queries
<i>CQ</i>	187469	17325
<i>CQ-balanced</i>	46561	17325
<i>CQ-common-str</i>	12508	6351
<i>CQ-alphanum</i>	162115	12333

Table 1
The size of the four test sets.

4.2. Implementation Details

We continued training the PTLMs and the UCO models in § 3.2 for 2 epochs, using our nested embedding approach at dimension sizes of 768, 512, 256, 128 and 64, on the query-title pairs using only the relevance ranking scores (excluding pairs with a score of 3) of the IGR datasets.

During training, we ran a sequential evaluator on the ranking score data to validate for all dimension sizes. First, the evaluator computes the embeddings for both query and title and uses them to calculate the cosine similarity. Then, it finds the most relevant product title to the query (top 3, 5 and 10 titles) in the corpus of all titles with a max corpus size of 200,000. For all experiments, we set a batch size of 32, a margin of 0.75 for the MNRL loss with the AdamW optimizer [20] and the learning rate as $5e - 05$. Training one model using the above hyperparameters takes ≈ 1.5 hours on a single NVIDIA V100 GPU.

4.3. Evaluation Metrics

We evaluated the model effectiveness through multiple established evaluation metrics including precision, recall, normalized discounted cumulative gain (NDCG) [21] and mean reciprocal rank (MRR).

Precision@ k quantifies the ratio of pertinent items within the top- k recommended products, focusing on their individual relevance. Conversely, recall@ k assesses the proportion of successfully retrieved relevant items compared to the total number of applicable products, regardless of their positioning. NDCG provides a comprehensive assessment of recommendation quality by analyzing both the relevance and positioning of suggested items. This metric compares the actual recommendation order against an idealized ranking, offering a nuanced evaluation of recommendation performance. MRR focuses on measuring the average ranking position of the first relevant item across different queries. A superior MRR indicates the model’s capability to prominently feature highly relevant products, thereby enhancing user experience and recommendation effectiveness.

5. Results and Discussion

Results achieved using NEAR² with a dimension size of 64 are shown in Table 2. Since BERT and eBERT were not fine-tuned on e-commerce data², improvement achieved using our approach is huge, as listed in Table A.1 in Appendix A. The values are shown as the percentage of increase (delta) of the evaluation metrics in comparison of those without using NEAR² presented in Saadany et al. [3].

Comparing results upon using NEAR² vs existing models, we find that our approach remarkably improves performance on all test sets for all models in § 3.2, even using embeddings with a dimension size of 64, which is 12× smaller in size and more than 100× smaller in memory usage than the full model (see Table 3).

When comparing results of different dimension sizes from the largest (768) to the smallest (64), as shown in Table 4³ for the **CQ test** set, we discover that the drop in performance is not significant. Embeddings of some smaller dimensions are even slightly better than larger ones. For example, the performance of the eBERT-siam model using NEAR² at dimension 512 is slightly better than 768 for

²eBERT was only pre-trained on e-commerce data.

³BERT and eBERT results are in Table A.2 in Appendix A.

Model	Precision@ k			Recall@ k			NDCG@ k			MRR@ k
	3	5	10	3	5	10	3	5	10	10
CQ test										
eBERT-siam	+11.80%	+11.79%	+11.49%	+9.99%	+9.72%	+9.07%	+11.50%	+11.23%	+10.65%	+9.06%
eBERT-UCO	+2.98%	+3.28%	+3.90%	+3.12%	+2.99%	+3.16%	+3.27%	+3.34%	+3.47%	+3.03%
eBERT-siam UCO	+2.82%	+2.75%	+3.16%	+2.72%	+2.45%	+2.50%	+2.91%	+2.77%	+2.80%	+2.58%
CQ-balanced test										
eBERT-siam	+8.85%	+8.45%	+7.31%	+8.85%	+8.43%	+7.28%	+10.28%	+10.03%	+9.56%	+10.48%
eBERT-UCO	+3.19%	+2.87%	+2.42%	+3.15%	+2.81%	+2.41%	+3.36%	+3.19%	+3.03%	+3.25%
eBERT-siam UCO	+2.77%	+2.45%	+2.09%	+2.75%	+2.48%	+2.05%	+3.06%	+2.93%	+2.77%	+3.01%
CQ-common-str test										
eBERT-siam	+6.62%	+4.90%	+3.00%	+6.59%	+4.84%	+3.01%	+8.57%	+7.70%	+6.99%	+8.51%
eBERT-UCO	+1.69%	+1.53%	+0.81%	+1.68%	+1.51%	+0.86%	+1.56%	+1.48%	+1.27%	+1.38%
eBERT-siam UCO	+1.49%	+1.22%	+0.81%	+1.48%	+1.18%	+0.83%	+1.86%	+1.72%	+1.59%	+1.85%
CQ-alphanum test										
eBERT-siam	+5.82%	+5.84%	+6.15%	+4.70%	+4.59%	+5.01%	+5.52%	+5.40%	+5.35%	+4.41%
eBERT-UCO	+3.64%	+3.75%	+3.92%	+3.61%	+3.55%	+3.60%	+3.30%	+3.33%	+3.40%	+2.57%
eBERT-siam UCO	+2.32%	+2.13%	+2.68%	+2.15%	+1.87%	+2.36%	+2.33%	+2.13%	+2.38%	+2.28%

Table 2

Delta in precision, recall, NDCG, and MRR at k on all the test sets for different encoder-based models fine-tuned using NEAR² at 64 dimensions of the entire embedding size (768).

Embedding Size	Memory Usage (MB)
768	398.03
512	2.77
256	4.09
128	0.55
64	1.56

Table 3

Memory usage at different embedding sizes for eBERT-siam.

precision, NDCG and MRR. This is also true for other models such as BERT, eBERT and eBERT-UCO, which further indicates the effectiveness of our approach for product retrieval and ranking.

To further validate our approach, we qualitatively compared some product titles retrieved with and without NEAR². The comparison consistently confirmed the superior performance of our method. Full details are presented in Appendix B.

6. Ablation Study

To verify whether continual training using NEAR² can help improve performance and efficiency when models are initially trained with other losses, we conducted several experiments using eBERT and eBERT-siam for ablation studies. First, we continued training the models using NEAR², which have been fine-tuned using the MNRL and OCL losses respectively to test if our approach works on each of the two individual losses. Second, we tested training these models using the MRL loss first, and then continued fine-tuning on the MNRL and OCL losses in a multi-task learning setting. The results are contrasted with training without using NEAR², which are presented as the percentage of increase (delta) in the evaluation metrics in Table 5.

Our ablative results suggest that applying the nested embedding approach to training embeddings with lower dimensions can improve performance for all models fine-tuned using the MNRL or OCL losses for retrieval and ranking, with much obvious improvement on the models trained using the OCL loss. However, models trained with the MRL loss first, then fine-tuned using the MNRL and OCL losses, show slight performance degradation in terms of NDCG and MRR. This suggests that our approach is most effective when used after training the model with an IR task loss first.

Model	Dimension	Precision@5	Recall@5	NDCG@5	MRR@10
eBERT-siam	768	+13.33%	+11.77%	+13.10%	+10.20%
	512	+13.35%	+11.87%	+13.16%	+10.30%
	256	+13.26%	+11.68%	+13.05%	+10.19%
	128	+13.10%	+11.37%	+12.80%	+10.16%
	64	+11.79%	+9.72%	+11.23%	+9.06%
eBERT-UCO	768	+4.25%	+4.04%	+4.34%	+3.50%
	512	+4.27%	+3.97%	+4.37%	+3.57%
	256	+4.18%	+3.83%	+4.23%	+3.49%
	128	+3.86%	+3.52%	+3.97%	+3.42%
	64	+3.28%	+2.99%	+3.34%	+3.03%
eBERT-siam-UCO	768	+3.85%	+3.75%	+3.82%	+3.05%
	512	+3.85%	+3.72%	+3.81%	+3.00%
	256	+3.62%	+3.47%	+3.61%	+2.96%
	128	+3.46%	+3.27%	+3.46%	+2.96%
	64	+2.75%	+2.45%	+2.77%	+2.58%

Table 4

Delta in precision, recall, NDCG, and MRR at k on CQ test set for different encoder-based models fine-tuned using NEAR² for all dimension sizes.

Method	eBERT		eBERT-siam	
	NDCG@5	MRR@10	NDCG@5	MRR@10
MNRL	+4.26%	+3.48%	+2.98%	+2.51%
OCL	+32.09%	+22.50%	+25.86%	+15.66%
MNRL + OCL	+3.34%	+3.03%	+2.77%	+2.58%
MRL: MNRL + OCL	-3.29%	-1.51%	-3.26%	-1.58%

Table 5

Delta in NDCG@5 and MRR@10 on the CQ test set for eBERT and eBERT-siam trained using NEAR² on different loss functions. We continued training these models using NEAR² at 64 dimensions of the entire embedding size (768) after they were fine-tuned on the MNRL and OCL losses separately or together (MNRL + OCL). We also trained them on the MRL loss first and then on the MNRL and OCL losses (MRL: MNRL + OCL).

7. Conclusion and Future Work

E-commerce IR systems face the challenge of balancing accurate interpretation of complex user queries with efficient processing of large product catalogs. To address this, we introduced NEAR², a nested embedding approach for efficient product retrieval and ranking. NEAR² improves accuracy and achieves up to 12× efficiency in embedding size and 100× smaller in memory usage during inference, without any increase in pre-training costs. Tested across diverse datasets, including short and implicit queries and alphanumeric queries, our method outperforms existing models with smaller embedding dimensions, demonstrating its robustness across challenging evaluation sets, and with efficiency. Our qualitative analysis reinforces the superior performance of our approach, demonstrating that embeddings generated by NEAR² models are significantly more reliable than those of baseline models when evaluated based on similarity scores. For future work, we plan to: 1) evaluate our model performance through A/B testing in deployment, 2) leverage internal data to refine larger decoder-based generalist embedding models like NV-embed-v2 [22], and 3) optimize these models using our NEAR² approach.

Declaration on Generative AI

During the preparation of this work, the author(s) used ChatGPT (GPT-4) and Grammarly in order to: Grammar and spelling check. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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A. Additional Figures and Tables

Model	Precision@ <i>k</i>			Recall@ <i>k</i>			NDCG@ <i>k</i>			MRR@ <i>k</i>
	3	5	10	3	5	10	3	5	10	10
CQ test										
BERT	+244.88%	+274.90%	+296.75%	+261.89%	+278.42%	+277.64%	+230.75%	+251.93%	+263.34%	+164.96%
eBERT	+185.18%	+198.72%	+196.57%	+204.36%	+202.87%	+185.80%	+180.69%	+191.63%	+190.49%	+124.19%
CQ-balanced test										
BERT	+261.57%	+239.27%	+207.46%	+262.23%	+239.63%	+207.94%	+273.74%	+261.24%	+245.48%	+262.73%
eBERT	+178.60%	+151.73%	+121.33%	+178.84%	+151.59%	+121.06%	+197.78%	+181.60%	+164.85%	+186.77%
CQ-common-str test										
BERT	+230.82%	+206.66%	+171.23%	+230.87%	+206.58%	+171.61%	+238.59%	+226.38%	+210.68%	+226.68%
eBERT	+148.89%	+125.23%	+98.80%	+148.64%	+125.10%	+98.64%	+167.57%	+154.43%	+141.09%	+160.48%
CQ-alphanum test										
BERT	+176.19%	+202.04%	+215.87%	+177.55%	+199.48%	+201.58%	+164.68%	+181.94%	+188.90%	+117.16%
eBERT	+160.04%	+176.97%	+181.05%	+161.56%	+170.52%	+165.06%	+152.21%	+163.12%	+164.35%	+104.15%

Table A.1

Delta in precision, recall, NDCG, and MRR at *k* on all the test sets for BERT and eBERT fine-tuned using NEAR² at 64 dimensions of the entire embedding size (768).

Model	Dimension	Precision@5	Recall@5	NDCG@5	MRR@10
BERT	768	+286.80%	+296.32%	+265.40%	+170.99%
	512	+287.11%	+296.11%	+265.57%	+171.13%
	256	+286.80%	+295.49%	+264.91%	+170.52%
	128	+284.27%	+291.95%	+262.16%	+169.54%
	64	+274.90%	+278.42%	+251.93%	+164.96%
eBERT	768	+192.17%	+197.60%	+185.11%	+119.88%
	512	+192.41%	+197.45%	+185.24%	+120.00%
	256	+192.17%	+196.98%	+184.72%	+119.50%
	128	+190.26%	+194.32%	+182.58%	+118.71%
	64	+183.19%	+184.16%	+174.59%	+114.99%

Table A.2

Delta in precision, recall, NDCG, and MRR at *k* on CQ test set for BERT and eBERT models fine-tuned using NEAR² for all dimension sizes.

B. Detailed Qualitative Analysis

To understand the performance improvements of our approach compared to existing models, we conducted a qualitative analysis using examples from the **CQ test** set. Specifically, we generated inferences for all instances in the CQ test set with eBERT and eBERT-siam⁴ using or not using the NEAR² approach at a dimension size of 64 (NEAR²@64). For each query, we retrieved the top 10 product titles and ranked them based on their cosine similarity scores. To evaluate real-world performance, we selected two representative queries: one short and implicit query and one long and detailed query. These examples provided insights into how our approach performs relative to eBERT or eBERT-siam in practical scenarios.

Short and Implicit Query Table B.1 illustrates the retrieved titles, their rankings (from 1 to 10), and their normalized⁵ similarity scores for the short and implicit query “plants” with eBERT. Based on the gold label, the expected product title should include “potted plants”. For the model using NEAR²@64, all retrieved product titles contained relevant keywords such as “plant” or “pot”, along with detailed product descriptions. In contrast, the titles retrieved by the model without using NEAR²@64 were significantly

⁴We mainly analyze results from eBERT. Results from eBERT-siam can be seen in Tables B.3 and B.4.

⁵Against the minimum value.

Method	Retrieved Title	Ranking	Sim_Score _{Norm}
NEAR ² @64	Philodendron Micans Rooted Cutting Trailing House Plant Cuttings Rare Plants	1	0.3935
	Tillandsia Mix 5 Plants Indoor Air Plant for House Vivarium Terrarium	2	0.3880
	Big leaf philodendron pink princess plant cutting 1 leaf cutting	3	0.3760
	2 NEON PINK SALVIA PLANT PERENNIAL SAGE HIGHLY FRAGRANT	4	0.3725
	Spathiphyllum Peace Lily Indoor Plants 1 x Potted Lily House Plant 9cm Pot	5	0.3693
	Cissus Discolor aka Rex Begonia Vine 6 inch pot	6	0.3687
	3 Plant 4 Pots Great Houseplant Assorted Rex Begonia Easy to grow housepl	7	0.3684
	PHILODENDRON MELANOCHRYSUM VERY LARGE 25 3 FEET TALL STUNNING PLANT	8	0.3679
	Spathiphyllum Peace Lily House Plant Live Indoor House Potted Tree In 9cm	9	0.3620
	PHILODENDRON PINK PRINCESS LARGE PLANT IN 15CM POT HOUSE PLANT	10	0.3593
W/o NEAR ² @64	Avocado plant	1	0.0604
	coins	2	0.0520
	Begonia Butterfly	3	0.0494
	drinks cabinet	4	0.0487
	Eucalyptus tree	5	0.0483
	portfolio landscape lights	6	0.0479
	Nico the marble index	7	0.0469
	car assessories	8	0.0468
	Begonia Curly Q	9	0.0465
	Houseplant and Pot Package	10	0.0454
Gold label	Aloe Vera Plant - Large Plant in Pot	/	/

Table B.1

Retrieved titles for the short and implicit query “plants” using or not using NEAR²@64 on eBERT.

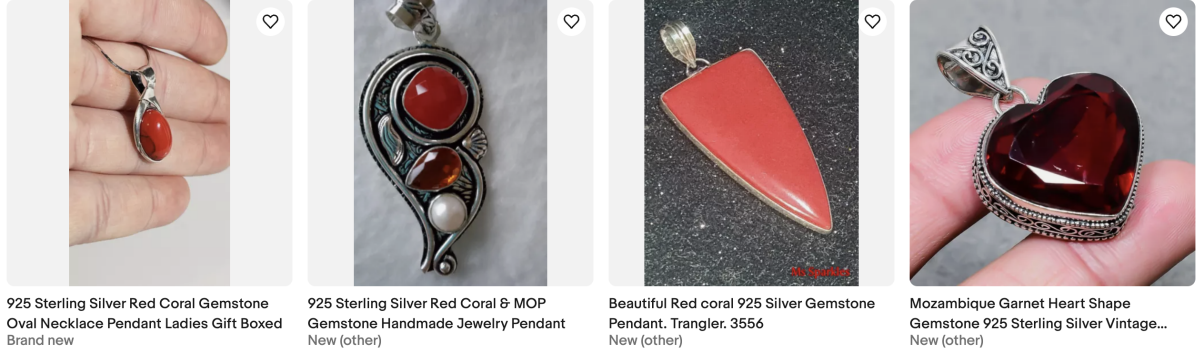
shorter, with many lacking the keyword “plant” and some, such as “coins”, being entirely irrelevant to the query. Notably, the normalized similarity scores from without using NEAR²@64 are much lower than those of using NEAR²@64, which is responsible for those irrelevant titles retrieved. This highlights the unreliability of the similarity scores from models without using NEAR².

Method	Retrieved Title	Ranking	Sim_Score _{Norm}
NEAR ² @64	Vintage 925 Sterling Silver Fiery Boulder Opal Ring Uk Size P	1	0.3561
	Sterling Silver 925 Signed Opal Heart Pendant Necklace 19 Chain	2	0.3406
	Vintage Possibly Opal Pendant On Gold Tone Necklace Chain	3	0.3376
	Ethiopian OPAL 083 carat sterling silver solitaire pendant	4	0.3373
	Vintage Ring White Opal Fire Lustre Genuine Natural Gems Sterling Silver Size L	5	0.3347
	Australian Triplet Opal Gemstone 925 Sterling Silver Handmade Ring All Size	6	0.3342
	Moonstone Opal Pendant 925 Sterling Silver Necklace Earring Women Jewellery Gift	7	0.3314
	Green Triplet Fire Opal Peridot 925 Sterling Silver Jewelry Pendants 27 v957	8	0.3283
	Gemporia Mosaic Opal White Topaz Sterling Silver Pendant Aggl98	9	0.3144
	Coober Pedy Semi Black Opal pendant 094 carats 179 grams of 925 Sterling Sil	10	0.3125
W/o NEAR ² @64	GENUINE 9ct gold gf garnet hoop earringsPacked full of dazzling stones 7b Y64 7d	1	0.0973
	GENUINE 9ct gold gf garnet hoop earringsPacked full of gemstones 7b Y64 7d	2	0.0965
	Large Vintage Sterling silver cabochon amethyst garnet pendant chain 155g	3	0.0929
	Gold diamante encrusted large round pendant 80 cm long chain rope necklace	4	0.0925
	Vintage 70s sterling silver and oval amethyst pendant and 925 chain necklace	5	0.0919
	9ct yellow gold reversible small crystal puffy love heart pull through earrings	6	0.0918
	CLASSIC 9ct Gold gf Aquamarine hoop earringsTRULY STUNNING EARRINGS 7b J067 7d	7	0.0917
	STUNNING 9ct Gold Opal toe ring gf WHILE STOCKS LAST DONT MISS 7b TO88 7d	8	0.0915
	Vintage Art Nouveau style sterling silver 925 and onyx stone scroll leaf brooch	9	0.0914
	Brand new set of two pair of earrings one butterfly one little girlin a gift box	10	0.0911
Gold label	925 Sterling Silver Red Coral Gemstone Handmade Jewelry Vintage Pendant S120	/	/

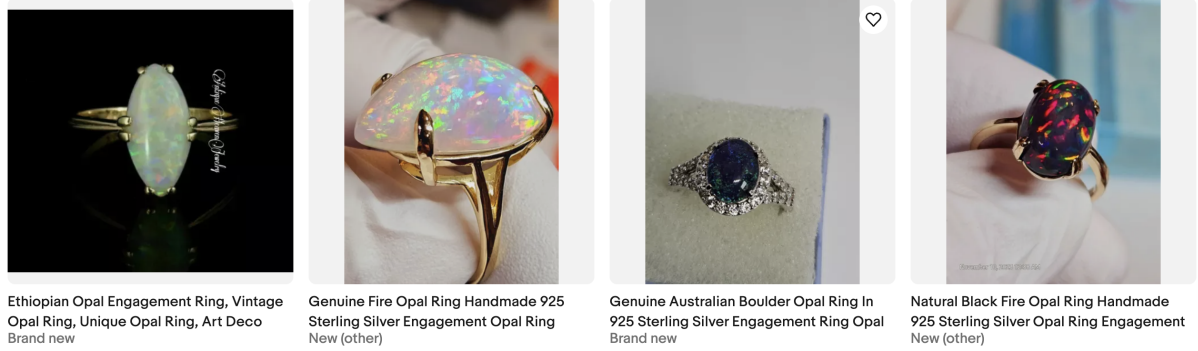
Table B.2

Retrieved titles for the long and detailed query “925 sterling silver triplet opal gemstone jewelry vintage pendant s-1.20” using or not using NEAR²@64 on eBERT.

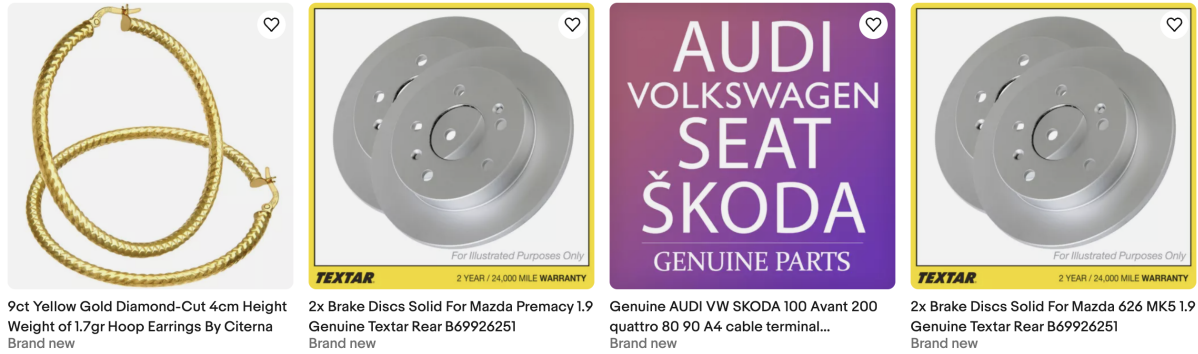
Long and Detailed Query Table B.2 presents the retrieved titles, their rankings, and their normalized similarity scores for the long and detailed query “925 sterling silver triplet opal gemstone jewelry vintage pendant s-1.20” with eBERT. Given the specificity of the query, even using the exact gold label title did not yield the exact product on eBay. However, the model using NEAR²@64 retrieved similar products, as shown in Figure B.1(b). In contrast, the products retrieved using top-ranked title from eBERT without NEAR²@64, shown in Figure B.1(c), were significantly less relevant compared to those retrieved using the gold label title in Figure B.1(a). These results further demonstrate the effectiveness of NEAR²@64. As with the short query example in Table B.1, normalized similarity scores from eBERT without using NEAR²@64 are much lower than those using NEAR²@64, further underscoring its limitations.



(a) Products retrieved using the gold label title.



(b) Products retrieved using the first title from NEAR²@64.



(c) Products retrieved using the first title from eBERT without NEAR²@64.

Figure B.1: Products retrieved on eBay using the gold label title (a), the top one title from eBERT using NEAR²@64 (b) and eBERT not using NEAR²@64 (c) for the query-title pairs in Table B.2.

Performance Disparity To investigate the root cause of performance disparity, we plotted the distribution of original similarity scores based on eBERT for all retrieved query-title pairs in the CQ test set, as shown in Figure B.2. The scores from the model using NEAR²@64 are well-distributed between 0.5 and 1.0, reflecting nuanced relevance evaluations. In contrast, scores from eBERT without using NEAR²@64 are clustered between 0.9 and 1.0, with most query-title pairs assigned a score near 0.95. This uniform distribution suggests that eBERT fails to effectively differentiate between relevant and irrelevant titles, leading to poor ranking performance. These findings further validate the superiority of NEAR²@64 in the evaluation metrics for product retrieval and ranking tasks.

For product titles retrieved by eBERT-siam, whether for the short, implicit query or the long, detailed query, the differences in appearance between using and not using NEAR²@64 are less pronounced compared to those observed with eBERT. However, the similarity scores still show a notable distinction. As illustrated in Figure B.3, the model using NEAR²@64 produces scores that are well-distributed between 0.45 and 1.0. In contrast, the scores from the model without this approach are more tightly clustered between 0.65 and 1.0, with the majority of query-title pairs receiving scores between 0.75 and

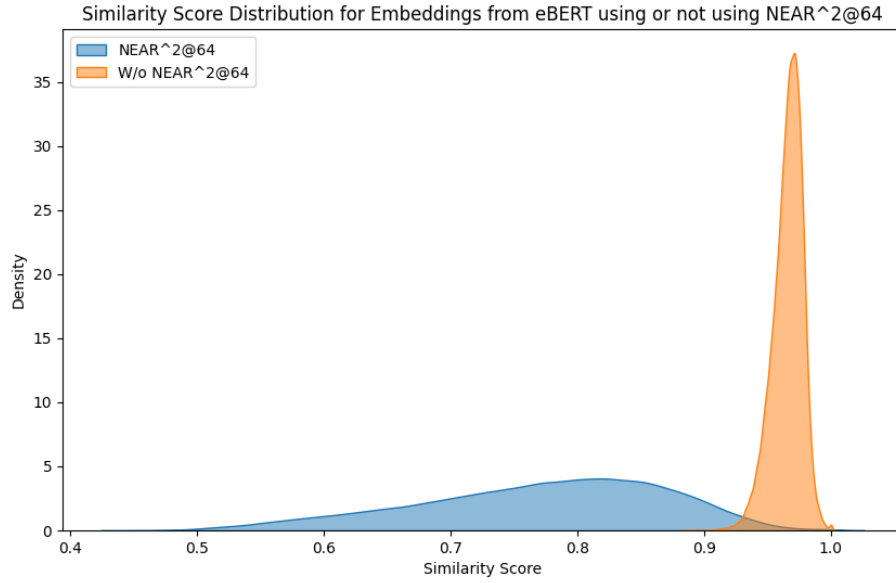


Figure B.2: Similarity score distribution for embeddings from models using vs not using NEAR²@64 with eBERT on the CQ test set.

0.9. These results are consistent with the findings from the eBERT model.

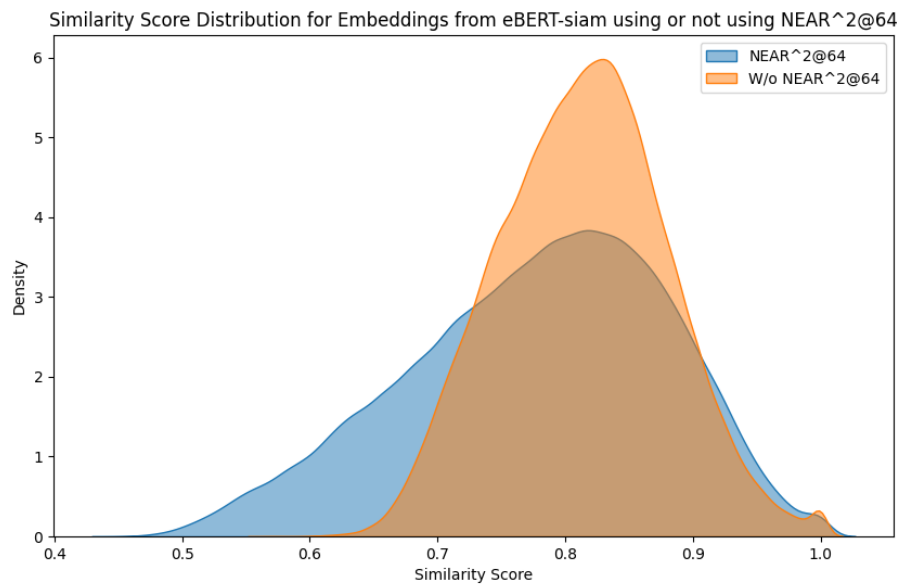


Figure B.3: Similarity score distribution for embeddings from models using vs not using NEAR²@64 with eBERT-siam on the CQ test set.

Method	Retrieved Title	Ranking	Sim_Score _{Norm}
NEAR ² @64	CRAZY DAISY Shasta daisies Qty 2 PLANTS Hardy Perennial Healthy plants	1	0.3967
	CRAZY DAISY Shasta daisies Qty 2 x Hardy Perennialhealthy plants	2	0.3824
	Streptocarpus MKsArktur09 young plant	3	0.3822
	Spathiphyllum Peace Lily Indoor Plants 1 x Potted Lily House Plant 9cm Pot	4	0.3731
	Houseplant and Pot Package	5	0.3723
	Spathiphyllum Peace Lily House Plant Live Indoor House Potted Tree In 9cm	6	0.3710
	Boston FernLive 10 Plants Lots Of Roots Air Purifier Reptile Terrarium ORGANIC	7	0.3696
	1 x CRAZY DAISY Shasta daisies Hardy Perennial Healthy plant	8	0.3671
	Leucanthemum Crazy Daisy Middleton Nurseries Flowering hardy Plants	9	0.3642
	Syngonium White Butterfly Arrowhead Goose Foot Plant House Plant Easy Care	10	0.3640
W/o NEAR ² @64	Houseplant and Pot Package	1	0.2665
	Spathiphyllum Peace Lily Indoor Plants 1 x Potted Lily House Plant 9cm Pot	2	0.2425
	Spathiphyllum Peace Lily House Plant Live Indoor House Potted Tree In 9cm	3	0.2417
	Cordyline Kiwi Ti Plant 7c Best Indoor Plants 7c Colourful 3040cm Potted Plant	4	0.2349
	68 Live Snake Plant Sansevieria Trifasciata Two Plants	5	0.2341
	Leucanthemum Crazy Daisy in plant in 13cm pot approx	6	0.2338
	Multi Listing Pond Plants Marginal Plants Water Bog Garden Oxygenator SALE	7	0.2317
	12 Succulent Flowers not Included Pots 12 Pcs 12 Fashion Practical	8	0.2267
	Avocado plant	9	0.2255
	3CM Succulent Cactus Live Plant Copiapoa Tenuissima Chile Home Garden Rare Plant	10	0.2239
Gold label	Aloe Vera Plant - Large Plant in Pot	/	/

Table B.3

Retrieved titles for the detailed query “plants” using or not using NEAR²@64 on eBERT-siam.

Method	Retrieved Title	Ranking	Sim_Score _{Norm}
NEAR ² @64	Moonstone Opal Pendant 925 Sterling Silver Necklace Chain Womens Jewellery Gifts	1	0.3934
	Green Triplet Fire Opal Peridot 925 Sterling Silver Jewelry Pendants 27 v957	2	0.3814
	Moonstone Opal Pendant 925 Sterling Silver Necklace Earring Women Jewellery Gift	3	0.3664
	Sterling Silver 925 Signed Opal Heart Pendant Necklace 19 Chain	4	0.3500
	Vintage Possibly Opal Pendant On Gold Tone Necklace Chain	5	0.3337
	Triplet Fire Opal Peridot Gemstone 925 Silver Jewelry Necklace 18 AQ269	6	0.3309
	BULK LOT Vintage 925 Silver Costume Jewellery Gemstones Opal Cloisonne Etc	7	0.3227
	Ethiopian Opal 925 Sterling Silver Choker Necklace Women Gemstone Jewelry Gift	8	0.2829
	Yellow Triplet Fire Opal Citrine 925 Sterling Silver Jewelry Earrings 21 s558	9	0.2691
	Blue Opal Pendant 925 Sterling Silver Minimalist Necklace Gift for Girlfriend	10	0.2688
W/o NEAR ² @64	Vintage Possibly Opal Pendant On Gold Tone Necklace Chain	1	0.2615
	Green Triplet Fire Opal Peridot 925 Sterling Silver Jewelry Pendants 27 v957	2	0.2561
	Moonstone Opal Pendant 925 Sterling Silver Necklace Chain Womens Jewellery Gifts	3	0.2558
	Triplet Fire Opal Peridot Gemstone 925 Silver Jewelry Necklace 18 AQ269	4	0.2505
	Moonstone Opal Pendant 925 Sterling Silver Necklace Earring Women Jewellery Gift	5	0.2475
	Sterling Silver 925 Signed Opal Heart Pendant Necklace 19 Chain	6	0.2472
	GemporiaGems TV Sterling Silver 157ct Ethiopian Blue Opal Pendant Necklace	7	0.2448
	NWT GEMPORIA GEMS TV AUSTRALIAN OPAL STERLING SILVER PENDANT	8	0.2381
	Vintage 925 Silver Opal Ring size J	9	0.2360
	Australian Triplet Opal Gemstone 925 Sterling Silver Handmade Ring All Size	10	0.2270
Gold label	925 Sterling Silver Red Coral Gemstone Handmade Jewelry Vintage Pendant S120	/	/

Table B.4

Retrieved titles for the detailed query “925 sterling silver triplet opal gemstone jewelry vintage pendant s-1.20” using or not using NEAR²@64 on eBERT-siam.