

e-CLIP: Large-Scale Vision-Language Representation Learning in E-commerce

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ABSTRACT

Understanding vision and language representations of product content is vital for search and recommendation applications in e-commerce. As a backbone for online shopping platforms and inspired by the recent success in representation learning research, we propose a contrastive learning framework that aligns language and visual models using unlabeled raw product text and images. We present techniques we used to train large-scale representation learning models and share solutions that address domain-specific challenges. We study the performance using our pre-trained model as backbones for diverse downstream tasks, including category classification, attribute extraction, product matching, product clustering, and adult product recognition. Experimental results show that our proposed method outperforms the baseline in each downstream task regarding both single modality and multiple modalities.

CCS CONCEPTS

• **Applied computing** → **Electronic commerce**.

KEYWORDS

Multimodal pre-training; Large-scale pre-training

1 INTRODUCTION

Product search engines and recommendation systems satisfy millions of users daily and facilitate billion-level transaction records [34, 55, 71]. As shown in Figure 1, a diverse set of unimodal and multimodal tasks, including category classification, attribute extraction, product matching, and product clustering, play an integral role in improving the search quality to organize billions of products and enhance user experience systematically [20, 31, 44].

In the industry, training a unified deep neural network jointly across such heterogeneous tasks has been widely applied due to benefits such as reduced operational overhead in managing fewer models, higher accuracy via multi-task learning, and usage as a

transferable backbone model for a new downstream task [1, 2, 47]. However, previous production use cases have mainly focused on training with a single modality [2, 47] or with a framework that is not symmetric for all modalities, thereby restricting the individual use of unimodal models [33].

Recently, large-scale vision and language pre-training methods, such as CLIP [46] and ALIGN [23], have gained considerable research interest in learning a transferable model for multiple downstream tasks. This line of research trains multimodal models jointly based on a contrastive loss such that embedding representations of paired images and texts are similar while those of non-paired images and texts are dissimilar, and these methods exhibit several advantages: (1) They demonstrate promising accuracy on multiple downstream tasks. In some instances, high accuracy can be achieved without fine-tuning on task-specific data [45]. (2) These methods comprise two independent models for each modality so that each unimodal model can be used independently for a modality-specific downstream task. (3) These methods can leverage vast amounts of readily available data in an unsupervised manner without labels.

Despite their remarkable benefits, the application of these large-scale multimodal pre-training methods has yet to be studied or implemented in the industry. Applying them in the e-commerce industry is nontrivial and poses five challenges concerning the ‘quality’ and ‘scale’ of real-world e-commerce data¹:

1. **Noisy Data.** Numerous people register products, resulting in noisy data and even product text and image pairs mismatches. The product title can contain irrelevant information about the product, thus hindering the generalization of the model.
2. **Duplicate and Similar Products.** The same product can be registered multiple times by different sellers. These products with slightly different attributes, such as their size or volume, constitute a great proportion of data. However, these duplicate products are problematic for contrastive learning, because they are the same but treated as different products during training; the contrastive loss pushes away embeddings of the same product.
3. **Irregularity and Sparsity.** Product text in e-commerce consists of condensed details about products and lacks grammatical structure. They are usually short and have a sparse context [75]. For instance, 50% of product titles in our dataset contain fewer

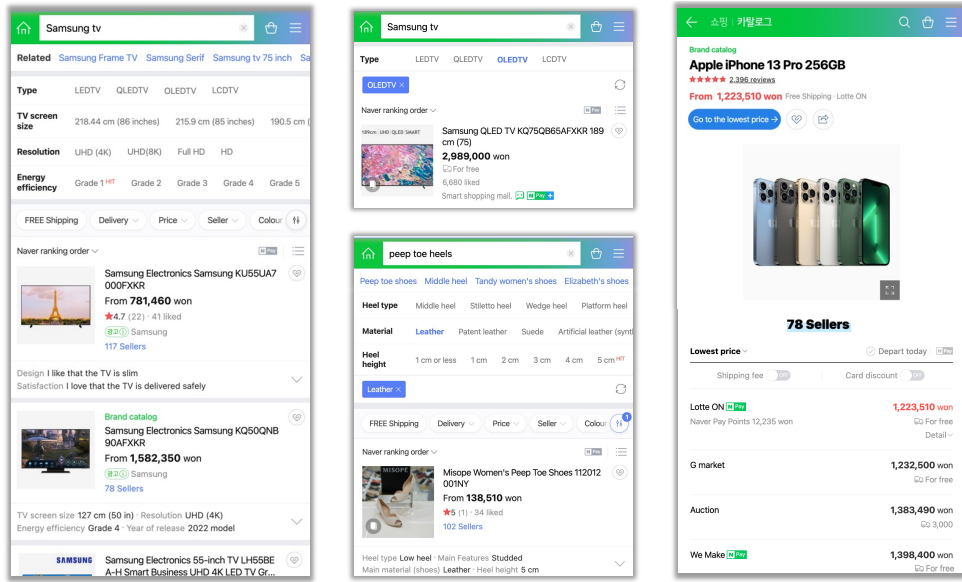
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¹NAVER Shopping has over 1.5 billion products with 500,000 sellers and affiliate malls, such as eBay Korea and Coupang. NAVER Shopping has more than 30 million weekly active users and over 2 billion monthly searches.



(a) Query-based Search.

(b) Filter-based Search.

(c) Price Comparison.

Figure 1: NAVER Shopping is a shopping portal service that provides product search, price comparison, and shopping content so that users can easily access products and sellers registered on NAVER Shopping: (a) shows a search results page with the keyword ‘samsung tv’. There are various search filters such as categories (i.e., type) and attributes (e.g., screen size, resolution, and energy efficiency), improving the user’s ability to browse relevant products and producing accurate product rankings; (b) shows a search results page after applying category and attribute filters; (c) shows an example of a group of the same products we call ‘catalog’, which helps provide price comparison over multiple sellers on the same product.

than eleven words. Therefore, capturing the correct semantics from product titles can be difficult.

4. **Limited Memory.** The limited memory of deep learning accelerators such as GPUs and TPUs can act as a bottleneck when training a large model along with a large batch size [11, 45]. Furthermore, due to the large data size, data cannot be fully loaded and can exceed the memory capacity during training.
5. **Model Convergence.** Training with a large batch usually results in lower model accuracy and slow convergence speed, even for a large number of epochs [22, 54]. Therefore, there remains a need for faster convergence.

In this work, we provide insights from our experience and a series of successfully implemented techniques to overcome the above challenges. We first introduce the overall system architecture of NAVER Shopping, and propose a contrastive learning framework named **e-CLIP** that learns visual concepts in the product image using the textual product information. We improve upon this framework by proposing new algorithmic and technical approaches, namely ‘catalog-based soft labeling’, ‘category-based negative sampling’, ‘multi-stream accumulation’, and ‘batch size scheduler’ (see Section 3.3 for details). They successfully save memory and expedite model convergence, enabling efficient training with satisfactory performance on multiple e-commerce downstream tasks. In addition to the framework, we present effective data preprocessing methods, including cleaning noisy data by removing invalid, duplicate, and inappropriate products. We conduct extensive experiments on five downstream tasks in NAVER Shopping, i.e., product matching, product clustering, attribute extraction, category classification, and

adult product recognition. Experimental results demonstrate the effectiveness of the proposed system and confirm our contributions to the improvement in accuracy and efficiency.

In summary, our main contributions are as follows:

- To the best of our knowledge, this is the first large-scale industry study investigating a unified multimodal transformer model which is symmetric for both modalities.
- We present an efficient yet effective contrastive learning framework e-CLIP, which exploits the large-scale NAVER Shopping dataset regardless of the presence of duplicate products.
- We identify five main challenges of adopting a large-scale vision and language pre-training in e-commerce and suggest algorithmic and technical approaches to tackle the issues.
- We conduct extensive offline and online experiments to validate the effectiveness of e-CLIP in single and multiple modalities. The results show that the proposed framework boost the performance of both visual and language tasks.
- We apply e-CLIP to multilingual downstream classification and clustering tasks in a real industrial scenario and obtain positive feedback, which may benefit further research.

2 RELATED WORKS

2.1 Deep Learning in E-commerce

Deep learning has been applied to numerous fields and has achieved great improvement in performance [14, 24]. Similarly, in the e-commerce industry, there has been a high demand in applying deep learning methods to real-world downstream tasks, such as category classification [20], product attribute extraction [16, 44, 64], product

clustering [63], product matching [31, 61], and product knowledge graph embedding [17, 66]. In particular, matching and discovering the same products play an important role in user experience and price comparison. Product categories and attributes are also core pieces of information that become a major source for search retrieval, ranking, and recommendation systems. However, there has been a challenge in making high-quality product embeddings with existing deep learning-based methods for e-commerce.

With the purpose of reducing maintenance and computational costs, prior work in e-commerce has also focused on adopting a single unified model for various downstream applications. For example, GrokNet [2] and Shop the Look [51] use multi-task learning to optimize a single embedding or computer vision model for a diverse set of applications. Likewise, [1] pre-trains a unified backbone model via multi-label classification for visual search systems. These production use cases focus on training with a single modality for visual search systems, while our work investigates pre-training with multiple modalities for both visual and language applications.

2.2 Transfer Learning

Transfer learning with pre-trained weights has been successfully used in natural language processing and computer vision [65, 73]. The main idea is to borrow knowledge learned from a large corpus into a new downstream task. This learning scheme shows better performance and faster convergence than learning from scratch.

Transfer learning generally proceeds in two stages. 1) *Pre-training*: training with weakly-labeled or self-supervised loss on large amounts of data. 2) *Fine-tuning*: supervised learning using labels from the downstream task that is to be applied.

In recent years, researchers have developed a variety of pre-training methods to learn and discover representations from large data. In the field of natural language processing, a transformer-based model is commonly trained with a self-supervised objective using masked (or replaced) tokens [3, 9, 10, 13, 35, 47, 70]. The computer vision field uses a self-supervised contrastive learning method using image augmentations [4, 5, 19, 21]. Recently, to reduce the **spatial inductive bias of CNN**, the self-attention structure has been applied to images with a transformer architecture called vision transformers (ViT) [18]. ViT-based pre-training is known to improve the performance of numerous downstream tasks in computer vision [36, 53]. In addition to the standard learning setup, the large-scale pre-trained model works well on few-shot learning and operates robustly in learning with imbalanced data [25].

2.3 Multimodal Learning

E-commerce data comprises rich multimodal data but has not been fully leveraged in the industry. As product data are composed of pairs of product images and text information, multimodal-based representations must be learned for visual and language tasks.

Multimodal learning employs multiple modalities such as text, image, and audio and has gained much attention, especially after the rise of transformers [50, 57, 58]. Recent works have pre-trained models on large-scale multimodal data to learn generic representations that capture cross-modality relationships [8, 30, 46].

Field	Description	Example
Product title	Title of product	Galaxy watch 4 40mm bluetooth
Brand name	Brand of product	Galaxy
Maker name	Maker of product	Samsung
Mall name	Seller mall	11 street
Mall category	Categories registered by sellers	Electronics > Watch
Price	Price	205,000
Registration time	Date of registration	2022-01-04
Popularity	Popularity based on click-through rate	32.4
Image path	Image URL	http://image_server/image_id
Product category	Category assigned by NAVER Shopping	Electronics > Wearable device

Table 1: Key fields of product information.

A large body of work has trained multimodal models using language modeling and image captioning datasets [7, 12, 33, 62]. Although these methods can learn specific representations for image-text pairs, the framework is not symmetric for all modalities and thus limits the generalization to single-modal scenarios [67]. Many works have also embedded image and text in the homogeneous feature space using their concatenated tokens as input to a transformer [28, 38, 72]. Still, learning representations is challenging due to the distribution difference between the visual and text inputs.

As an alternative approach, CLIP [46] demonstrates the effectiveness of pre-training on a large crawled dataset of approximately 400 million image and text pairs from the internet. CLIP uses contrastive learning by maximizing the similarity between two embeddings generated by image and language encoders for the same item and minimizing the similarity for other items. Several methods have also been proposed to improve performance and resolve scalability challenges. Some researchers presented methods that scale up the model and data size [23, 45]. Some studies add self-supervised learning methods, such as SimCLR [5], SimSiam [6], and MLM [13], to the existing CLIP loss [32, 43]. LiT improves the performance of CLIP by locking the weights of the image model and learning only the text representations [69]. Meanwhile, ZeroVL presents ways to train CLIP with limited resources [11].

A CLIP-based method can be a potential solution for representation learning due to its simple data preparation and effective training method. However, this family of methods does not provide satisfactory performance in terms of robustness and scalability issues associated with e-commerce data.

3 SYSTEM ARCHITECTURE

3.1 Overview

Our methodology involves training and deploying a unified model and powers understanding visual and language representations for search and recommendation systems at NAVER Shopping². Figure 2 illustrates the architecture with three main subsystems: **data preparation, modeling, and applications.**

The first stage is data preparation, which is responsible for collecting and managing products daily. NAVER Shopping receives product content and descriptions, including product titles and images from sellers. The data is then processed and stored systematically in a distributed database.

From the abundant source of data provided by sellers, data is extracted and preprocessed to train our unified multimodal model, as described in 3.2.2. Multimodal transformer models are pre-trained on this data using a contrastive loss detailed in Section 3.3 and saved

²<https://shopping.naver.com/>

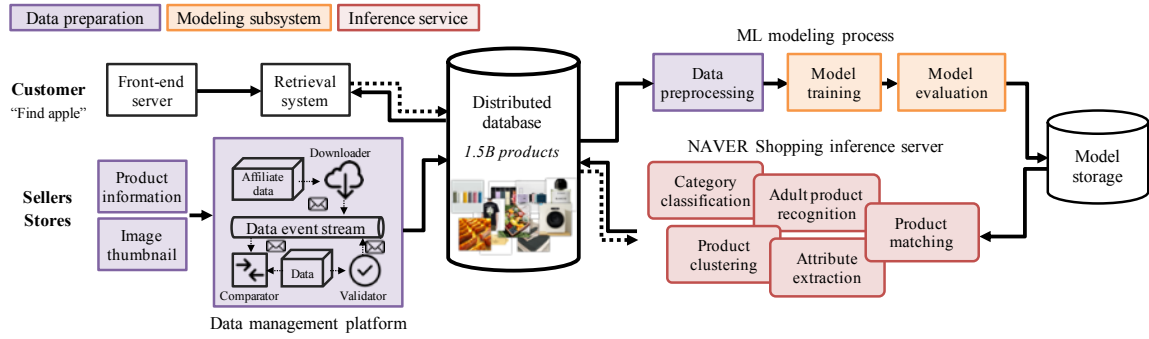


Figure 2: System architecture of NAVER Shopping.

to storage. If the quality bar is met, the updated model becomes a reliable source model to build upon for downstream modeling tasks, where fine-tuning can be applied to enhance performance.

Lastly, these downstream applications are used to augment product descriptions with predicted attributes and categories, dramatically impacting the retrieval and ranking of search results. We dive into the details of our framework below, describing each component that participated in significantly improving the performance of applications.

3.2 Data Preparation

3.2.1 Data Collection. Over a billion products from hundreds of thousands of sellers are deployed, and millions of new products are continuously uploaded, deleted, and modified daily on NAVER Shopping platform. More and more products are registered every day from a growing number of affiliated online shopping malls as well as individual sellers.

According to NAVER Shopping’s registration guide, sellers register product content and descriptions, including the product title, price, brand name, and a set of images, as shown in Table 1. When the registration request is received, product images are stored after processing and resizing to meet the thumbnail image standards of NAVER Shopping.

The next stage consists of examining whether products are sellable or have been sold out. If products are confirmed to be valid, products are assigned predicted categories through classification and checked if there are similar products in the database for product comparison. Because product information is surprisingly sparse and limited, many parts of NAVER Shopping’s product management pipelines are operated with AI-based recommendation and matching systems that use both product images and its textual information (*i.e.*, multimodal input). More details about the prediction tasks are described in Section 3.4. Products that have passed verification and classification processes are considered serviceable. Detailed information about the product, such as brand name, category, and product image path, are saved into separate tables and uploaded to the database.

A snapshot of the NAVER Shopping database is generated every day and uploaded to the Hadoop distributed storage engine [15]. We collect and refine product data from the snapshot data for training. Product data is later used as pairs of a product image and textual information, such as the product title and brand name. To deal with billions of product data, we use Spark [68] and mainly work on the Hadoop ecosystem [39].

3.2.2 Data Preprocessing. We use the large volume of collected product data by extracting the product text and image as pairs. We then preprocess the dataset due to common problems that plague e-commerce datasets, including corrupted data, duplicate products, and skewed data distributions. We execute preprocessing regarding the following three types of data, which is necessary to improve data quality for better representation learning.

1. **Invalid Products:** Valid pairs of product image and text are essential for cross-modal e-commerce representation learning, but a number of mismatched pairs are included during collection due to system abuse. To improve data validity, we first removed image-text pairs with no images, too small images, and corrupted images, as exemplified in Figure 3(a), using a rule-based system. We also discarded the pairs with invalid text by comparing the token set of product titles; After replacing special characters with white-space in the product titles, we eliminated products with titles consisting of less than two tokens.
2. **Duplicate Products:** We aimed to eliminate duplicate products, exemplified in Figure 3(b), based on product titles and images. We first dropped products with identical titles. To eliminate products with duplicate images, we reshaped a product image into (5,5) patches and created one-digit hash keys from the mean color value of each patch. We also took the image size into consideration, resulting in a 29-digit hashed value. Images with the same hashed values were removed. Moreover, as suggested by [59], we retrieved compressed embeddings extracted from the last layer of ResNet-34 pre-trained on ImageNet for all images and eliminated duplicate images with the same embeddings.
3. **Inappropriate Products:** Product data collected from various sellers contain inappropriate products that are non-compliant with organizational policies, including adult products, promotional products, social issue products, and immoral products (see Figure 3(c)). Not only do these products show distributions that deviate from the general distribution of normal products, but they are also manipulated not to be filtered. For example, sellers blur or mask the critical parts of the image but use product titles that look like normal products. We excluded these products by checking whether the products had been flagged according to the moderation system.

As a result of preprocessing, our dataset was reduced from 1B pairs to 330M pairs, and we call this dataset ‘NAVER Shopping data.’ To shorten training time and compare with baseline methods with the same amount of e-commerce data, we also created a smaller

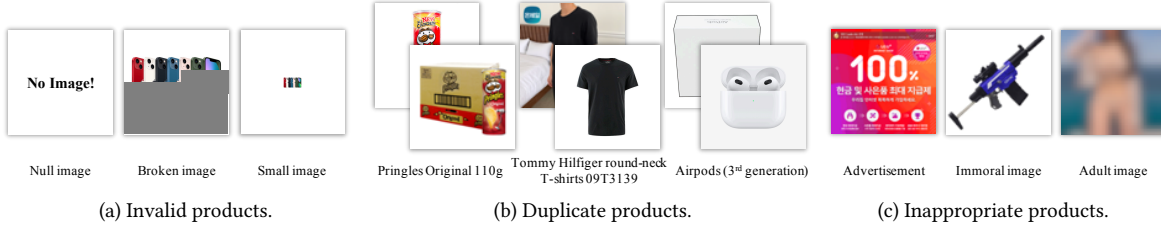


Figure 3: Examples of filtered products during data preprocessing.

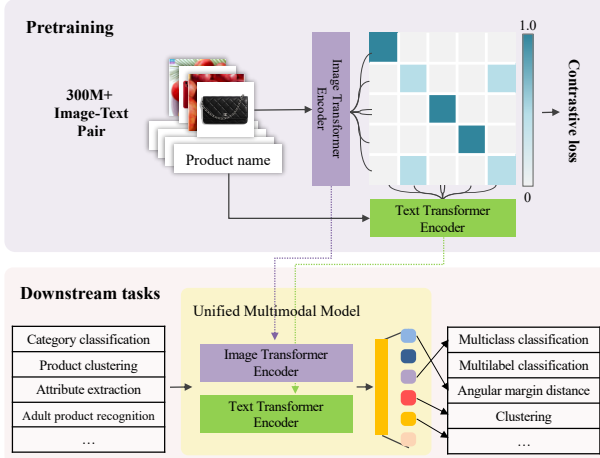


Figure 4: Overview of e-CLIP framework.

dataset of 270M products. For the latter, we additionally removed products that were predicted to be the same by the product matching system³. The details of the product matching procedure are explained in Section 3.4. For evaluation during pre-training, 41K products were randomly sampled according to the square root of the natural distribution of product categories and split as test data.

3.3 Pre-training Method: e-CLIP

Our pretraining-finetuning framework e-CLIP is summarized in Figure 4. We first pre-train our multimodal model based on a contrastive loss as suggested in CLIP [46] and LiT [69], but consider the presence of duplicate products and optimize the training speed and memory usage of computational resources. Our pre-trained model is later distributed for diverse downstream applications.

3.3.1 Model architecture. Our proposed method e-CLIP follows the original dual-encoder structure of CLIP consisting of a visual encoder and text encoder, which return the learned embeddings of the visual and text inputs, respectively.

For computational efficiency, the image encoder is ViT-B/32, a vision transformer (ViT) mostly composed of multi-head attention blocks [18, 32]. Although convolutional neural networks (CNNs) are also popular in computer vision tasks, ViTs require shorter training time and fewer GPUs than CNNs in the dual-encoder multimodal pre-training task [11, 46]. To tackle irregularity and sparsity of

the data and accelerating model convergence, we fine-tune a pre-trained multilingual BERT-base model [13] as our text encoder like [69] and leverage learned weights of multiple languages.

Rather than using the representation of the [CLS] token like ALIGN and CLIP [23, 46] or averaging representations of all steps like BASIC [45], we compute the average of representations across steps of token length at the top layer of our model.

3.3.2 Training objective. InfoNCE loss is a popular objective for learning visual models with text supervision [45, 46]. Image and text encoders are jointly trained using a symmetric cross-entropy loss by maximizing the cosine similarity of paired image and text embeddings while minimizing the similarity of non-paired embeddings in a batch. This contrastive loss expects each sample in the batch to be different from other samples. However, our NAVER Shopping datasets have high volumes of ‘duplicate’ data even after preprocessing. Therefore, the same products can become their respective negative pairs, making our contrastive learning pipeline inefficient and ineffective.

To address this challenge, we add a modification to the InfoNCE loss that we call *catalog-based soft labeling*. Let z_{ij} be a label matrix to define whether the image of i -th product and the text of j -th product are the positive pair. Then, the original CLIP forces only the diagonal entry to be 1, otherwise 0 (i.e., hard labeling). In NAVER Shopping data, the i -th and j -th product can be the same product, which breaks the assumption of hard labeling. Hence, we internally maintain a list of catalogs, where each catalog is a cluster of the same product in our database and has its unique id. When each product is provided as input to e-CLIP, its catalog id is used to find the same products in the batch. Based on the catalog id c_id , and given a batch of length N , we generate a soft label $\tilde{z}_{ij} = 1/|\{j \leq N : c_id[i] = c_id[j]\}|$, where $c_id[i]$ is the catalog id of the i -th product and $\sum_{j=1}^N \tilde{z}_{ij} = 1$ for soft labeling. The catalog and its id are created in a weakly supervised manner since catalog (product) clustering and matching are part of downstream tasks (refer to Sections 4.2.1 and 4.2.2).

Let (x, y) be image-text features pairs in a batch of size N , and x_i and y_j be image and text features of the i -th and j -th pair respectively. For the objective of e-CLIP, we first compute the cosine similarity between text and image representations as $sim_{i,j}$ for all N^2 image-text pairs in a batch. The softmax function is applied to the similarity matrix, and logits are scaled by a learnable temperature τ before computing a cross-entropy loss with respect to a uniform distribution over the same product soft labels $\tilde{z}_{ij} \in [0, 1]$. We formulate a symmetric e-CLIP loss as follows:

$$\mathcal{L}_{e-CLIP} = \frac{1}{2} \left(\mathcal{L}_{e-CLIP}^{I2T} + \mathcal{L}_{e-CLIP}^{T2I} \right), \text{ where} \quad (1)$$

³We name e-CLIP trained on 330M data ‘e-CLIP’ while filtered 270M data ‘e-CLIP (filter)’ throughout the paper.

$$\mathcal{L}_{e-CLIP}^{I2T} = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^N \tilde{z}_{ij} \log \left(\frac{\exp(\text{sim}_{i,j})/\tau}{\sum_{l=1}^N \exp(\text{sim}_{i,l})} \right), \quad (2)$$

$$\mathcal{L}_{e-CLIP}^{T2I} = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^N \tilde{z}_{ij} \log \left(\frac{\exp(\text{sim}_{i,j})/\tau}{\sum_{l=1}^N \exp(\text{sim}_{l,j})} \right). \quad (3)$$

Furthermore, it is well known that increasing the difficulty of contrastive learning through hard negative sampling can boost performance [48]. To improve the ability of learning representations, we introduce *category-based negative sampling* based on the product’s predicted categories, e.g., “electronics > wearable device.” Because we keep each product’s category data in our database, as mentioned in Section 3.2.1, we can easily sample batches composing products with similar category data that have been manually labeled or predicted via classification. Category-based hard negatives help contrast ‘confusing’ products with similar category information; hence, pre-training e-CLIP with this technique generally shows superior or comparable performance to its counterparts in the transfer learning setup. However, in some zero-shot transfer tasks, it somewhat degrades the performance. Since zero-shot transfer does not have any refinement process like fine-tuning, the pre-trained model with negative sampling can perform poorly because of some noise in the category data despite our efforts for data cleaning.

3.3.3 Implementation Design. Due to larger models and limited memory of computational resources, training with large batch sizes can be infeasible with limited resources. Memory problems mainly occur because of contrastive losses requiring the gradients of a $N \times N$ similarity matrix. Inspired by [11, 45], we thus implemented a way to train enlarged batches on limited GPU resources through multiple forward passes. Our key idea is *multi-stream accumulation*, which computes gradients related to the entire similarity matrix and gradients related to embeddings separately. First, embeddings from each forward pass are concatenated and used to calculate the similarity matrix without storing activation values. We then execute another stream of forward passes to calculate the gradients for each local batch using the formerly computed similarity matrix and update the model parameters. As a result, by sacrificing reasonable training time, we can successfully train our models with even up to 30x increased batch size.

Speeding up model convergence is challenging due to the large amount of training data, which requires longer training time and limited computational resources. To solve this problem, we develop a *convergence algorithm* that allows us to complete training models with fewer iterations.

Reducing gradient synchronization frequencies is a common approach in fastening distributed data parallel training [29, 54]. We thus propose a *batch size scheduler* that avoids unnecessary synchronization by replacing the typical learning rate decay scheduler using gradient accumulation. According to [52], increasing the batch size produces the same effect as decreasing the learning rate. The learning rate remains constant throughout training and the batch size B for each iteration t is altered as follows:

$$B_t \leftarrow B_0 \cdot \left\lceil 2 \cdot \left(1 + \cos\left(\frac{\pi \cdot t}{E}\right)\right)^{-1} \right\rceil, \quad (4)$$

where B_0 and E indicate the initial batch size and the number of epochs, respectively. Our batch size scheduling is based on the *cosine annealing scheduler* without restarts.

To further speed up training and save additional memory, we use mixed-precision [41]. The calculation of embedding similarities was also sharded by computing only the subset of the pairwise similarities necessary for each GPU’s local batch of embeddings.

We use the *AdamW optimizer* [37] with a constant learning rate of $3e-5$ and schedule the batch size as described in Eq. (4). The dual encoders of e-CLIP are trained on NVIDIA A100 GPUs.

3.4 Downstream Tasks

Our pre-trained model is employed in five applications, which are important in e-commerce and has a plethora of research in both academia and industry.

Product Clustering. Product clustering denotes grouping the same products and is used to identify new products. A group of products is displayed on a single page with information such as attributes, descriptions, and collected reviews, as shown in Figure 1c. Discovering new groups from billions of products is complex and requires deep learning models to detect similar products with great precision.

Product Matching. Product matching refers to the problem of matching products to an existing set of products in the database based on similarity. Identifying whether a product is the same as one from another seller creates the opportunity for users to select the best offer and prevents users from viewing duplicate products in the search results. Despite its importance, product matching is challenging to tackle, because similar products must be retrieved from a large dataset and product information can vary greatly.

Attribute Extraction. Product attributes are defined as the properties of a product. For example, as displayed in Figure 1b, attributes of a shoe include the material and heel type. Attribute extraction refers to identifying values of an attribute of interest from product data and is used to power faceted retrieval, ranking, and recommendation systems. The problem of solving attribute extraction, however, is that acquiring data is difficult; There are multiple attributes for a product, and attributes differ for each product. Attribute values are also often noisy and mostly incomplete with missing values.

Category Classification. E-commerce platforms generally use a predefined structured hierarchy of product categories to enhance user experience and organize products systematically. Accurately matching categories is crucial for improving search quality because categories are used in multiple tasks such as retrieval, ranking, and recommendation. NAVER Shopping manages over 5,000 categories using a hierarchical category system of up to four levels.

Adult Product Recognition. Identifying and filtering out adult products is necessary to provide appropriate and safe content for buyers. Because products are uploaded by numerous sellers, some product images can be inappropriate for minors, such as nudity and pornographic images. However, it is challenging to develop deep learning models because not only is collecting flagged products difficult, but the product distributions are heavily skewed; less than 0.01% of products turn out to be adult products in NAVER Shopping.

Method	Text model		Image model		# Pairs
	Hidden dim	# Params	Model	# Params	
BERT-multi	768	167M	-	-	-
BERT-dlarva	768	110M	-	-	-
CLIP	512	37M	ViT/B-32	87M	400M
KELIP	512	88M	ViT/B-32	87M	1.1B
e-LiT	768	167M	ViT/B-32	87M	270M
e-CLIP (filter)	768	167M	ViT/B-32	87M	270M
e-CLIP	768	167M	ViT/B-32	87M	330M

Table 2: Details of models and data size (# pairs).

4 EXPERIMENTS

We studied the effect of large-scale pre-training through the transfer performance of e-CLIP on the aforementioned five downstream tasks via zero-shot transfer, linear probe, and fine-tuning.

4.1 Experimental Settings

4.1.1 Comparing Methods. To validate the effectiveness of our e-CLIP method, we present the results of seven pre-trained models listed in Table 2, where “# pairs” indicate the total number of image-text pairs used for pre-training. For a fair comparison, we selected language models pre-trained on a Korean and English corpus. The five baseline models are summarized as follows:

- BERT-multi [13]: Multilingual BERT-base pre-trained on the largest Wikipedia dataset with 102 languages, including Korean and English.
- BERT-larva [27]: BERT-base model pre-trained on Korean and English conversation datasets from NAVER services.
- CLIP [46]: Multimodal transformer model which is pre-trained on 400 million image-text pairs and is publicly available.
- KELIP [26]: Multimodal transformer model pre-trained on 1.1 billion pairs (708 million in Korean and 476 million in English) including 270 million NAVER Shopping products. It should be noted that the product data used to train this model differs from our NAVER Shopping dataset, despite similarities in data size.
- e-LiT: Multimodal transformer model pre-trained on our small 270 million NAVER Shopping dataset using our contrastive loss. As proposed by [69], we freeze the pre-trained image model weights of CLIP [46] and fine-tune the language model for efficiency and performance.

We trained three different versions of e-CLIP on our NAVER Shopping dataset with the purpose of (1) *e-CLIP vs. e-CLIP (filter)*: examining the effect of rigorous deduplication of products, and (2) *e-CLIP vs. e-CLIP (hard)*: investigating the effectiveness of hard negative sampling.

- e-CLIP and e-CLIP (filter) are pre-trained on 330 million and 270 million NAVER Shopping datasets, respectively, where duplicated products are filtered out using the AI-based product matching system for the 270 million data.
- e-CLIP (hard) is pre-trained on the 330 million NAVER Shopping dataset similar to e-CLIP, but after a warmup stage of training, our category-based negative sampling technique is activated for batch sampling.

4.1.2 Evaluation Protocol. There are three evaluation schemes, namely zero-shot transfer, linear probe, and fine-tuning.

Category Modality	Electronics			Food		
	Text	Image	Multi-modal	Text	Image	Multi-modal
BERT-multi	17.4	-	-	24.3	-	-
BERT-larva	14.0	-	-	23.7	-	-
CLIP	30.9	36.5	40.2	30.8	41.9	43.0
KELIP	33.5	35.6	41.2	53.2	38.7	52.9
e-LiT	41.1	36.6	46.4	66.7	42.7	66.8
e-CLIP (filter)	39.6	32.9	43.7	64.9	49.4	66.1
e-CLIP	43.4	33.2	46.5	67.0	48.6	67.3
e-CLIP (hard)	46.6	34.5	48.7	68.2	50.9	68.9

Table 3: Top-1 accuracy (%) of product matching.

Zero-shot Transfer. To measure each method’s capability of capturing task-related representations, we evaluate all the methods through zero-shot transfer as proposed by [46]. Prior methods evaluated image encoders using the names of all the classes in the dataset and predicting the most probable (image, text) pair. We extend this method so that both the image and text encoders can be evaluated with multimodal inputs; The image and text representations are averaged to find the most probable class.

Linear Probe and Fine-tuning. Each task has different evaluation metrics, but the same strategy is used to evaluate learned representations. For linear probe, we freeze the pre-trained model and train a linear classifier to evaluate the embeddings extracted from the model. For fine-tuning, we perform end-to-end training on the entire model, including the encoders and linear classifiers [46].

4.2 Five Downstream Tasks

4.2.1 Task 1: Product Matching. Identifying identical products from existing products is highly valued for food products and is challenging for electronic products. We, therefore, validate the capability of recognizing the same product from 300K products from both categories. We average the matching results of almost 200K products for each category.

As displayed in Table 3, all the e-CLIP models generally demonstrate substantial gains in top-1 zero-shot transfer accuracy for both categories. Our best models significantly improve the performance of other BERT-base models by up to 32.6% and 44.5% for electronic and food products, indicating that our models are exceptional at learning textual representations. Our e-CLIP models also show higher performance on multimodality than other pre-training methods. We can also observe that the performance of image experiments are lower, especially for electronic products, due to the task difficulty; For example, “RTX2080”, “RTX2080ti” are different products but their images are almost identical and difficult to distinguish for humans.

As for our three variations, the results show that catalog-based soft labeling makes e-CLIP robust to duplicate products since it generally outperforms e-CLIP (filter). The results of e-CLIP (hard) show that using a larger training dataset and category-based negative sampling can further enhance the performance of identifying similar products from a considerable number of products.

4.2.2 Task 2: Product Clustering. We evaluate the quality of clustered embeddings on both food and electronic products that

Modality Metric		Text			Image			Multimodal		
		ACC (↑)	NMI (↑)	ARI (↑)	ACC (↑)	NMI (↑)	ARI (↑)	ACC (↑)	NMI (↑)	ARI (↑)
Electronics	BERT-multi	0.30113	0.69736	0.15817	-	-	-	-	-	-
	BERT-larva	0.27077	0.69358	0.14677	-	-	-	-	-	-
	CLIP	0.52982	0.86198	0.43697	0.52150	0.85948	0.41423	0.58190	0.88571	0.49172
	KELIP	0.56415	0.88767	0.50492	0.52818	0.86788	0.43175	0.59765	0.90290	0.53277
	e-LiT	0.61519	0.91088	0.57202	0.51479	0.85446	0.40188	0.58451	0.90305	0.52882
	e-CLIP (filter)	0.59840	0.90691	0.55877	0.54582	0.87710	0.45887	0.57940	0.90275	0.53720
	e-CLIP	0.60619	0.91398	0.55831	0.52789	0.87488	0.44171	0.58197	0.90831	0.53834
	e-CLIP (hard)	0.63230	0.92481	0.60243	0.55043	0.88116	0.46199	0.61579	0.91609	0.56664
Food	BERT-multi	0.32305	0.72799	0.17194	-	-	-	-	-	-
	BERT-larva	0.32978	0.74063	0.18663	-	-	-	-	-	-
	CLIP	0.54439	0.87683	0.44835	0.54919	0.87505	0.44374	0.54076	0.87343	0.43057
	KELIP	0.63662	0.92114	0.59224	0.49241	0.84651	0.37045	0.59227	0.90459	0.53638
	e-LiT	0.70263	0.94864	0.68430	0.54838	0.87436	0.43045	0.66373	0.93910	0.63156
	e-CLIP (filter)	0.71346	0.95205	0.70110	0.62218	0.92105	0.56723	0.68449	0.94837	0.65927
	e-CLIP	0.69136	0.94825	0.66954	0.62607	0.92190	0.56503	0.71015	0.95184	0.68574
	e-CLIP (hard)	0.71091	0.95235	0.69348	0.63204	0.92443	0.58422	0.72024	0.95440	0.69640

Table 4: Test performance of product clustering with respect to ACC, NMI, and ARI. .

Attribute	Colors	Materials	Heel types	Toe shapes	Patterns
CLIP	70.2	46.1	42.0	41.8	90.2
KELIP	80.2	74.4	71.0	80.7	92.9
e-LiT	77.7	66.6	59.7	57.6	91.2
e-CLIP (filter)	80.5	77.5	77.8	82.3	90.9
e-CLIP	78.5	72.7	77.8	82.1	92.4
e-CLIP (hard)	79.5	77.8	78.6	82.4	92.9

Table 5: Test accuracy (%) of zero-shot attribute extraction.

have almost 1,000 and 2,000 clusters, respectively. Each target cluster contains 20 to 50 products. We evaluate product clustering tasks by extracting embeddings from frozen pre-trained models without additional training.

To assess product clustering, we obtain the multimodal embedding vector by concatenating the text and image embedding vectors and reducing the dimension to 128 using the PCA algorithm [42, 60]. The projected vectors are later clustered with the k -means algorithm [40]. We assessed the clusters using common metrics such as the clustering accuracy (denoted by ACC), normalized mutual information (denoted by NMI) [56], and adjusted Rand index (ARI) [49, 74]. Results in Table 4 show that e-CLIP outperforms baseline models and e-CLIP (hard) mostly yields the best performance in all cases, providing compelling evidence that (1) our methods are effective in distinguishing, and grouping similar products and (2) hard negative sampling can provide an additional performance boost.

4.2.3 Task 3: Attribute Extraction. To evaluate a method’s capability of capturing attributes from images, we used a dataset containing 3000 shoe products with five attributes: colors, main materials of the shoe, heel types, toe shapes, and patterns. We evaluate attribute extraction by creating Korean and English prompted attribute value texts as target classes for each attribute.

Table 5 summarizes the zero-shot transfer results. Inspection of the results indicates that most methods outperform CLIP, which

was not successful in understanding concepts specific to the e-commerce industry. Although e-CLIP (filter) was trained on the same number of e-commerce product pairs as KELIP, e-CLIP (filter) achieves higher accuracy than KELIP in most cases. Interestingly, our e-CLIP models are effective in predicting attributes such as materials, heel types, and toe shapes, which require capturing fine-grained features of a product and domain knowledge. These results imply that pre-training on domain-specific pairs is more effective in learning target concepts and understanding semantics.

4.2.4 Task 4: Category Classification. To verify the models’ performance on categories that are vital to NAVER Shopping, we evaluated models on three datasets: 10K samples of all the categories (denoted by All), 100K samples of fashion goods, and 50K children related products. For linear probe and fine-tuning, we trained models on training data of approximately 21 million products. Because categories are naturally imbalanced, the number of products in each category in the training data distribution was normalized to prevent extreme bias in popular categories.

Table 6 reports the test accuracy results of zero-shot transfer. The results show that our models are more proficient at classifying the category of products than other baseline methods. With the same amount of e-commerce training data samples, our methods outperform KELIP by 1.3% to 30.1%. The baseline CLIP model scores less than 1%, presumably due to a lack of Korean training data and data related to the e-commerce domain. Unlike KELIP, our e-CLIP methods also achieve consistent and remarkable improvements in accuracy regarding multiple modalities compared to single modalities. These results could be interpreted that not only are representations for single modalities learned competently, but the text and image models are also better aligned in the multimodal feature space than other methods.

Table 7 displays the classification accuracy results for linear probe and fine-tuning. Our e-CLIP models outperform other baseline methods, including BERT-base models, CLIP, and KELIP, for both linear probe and fine-tuning experiments. It is also noteworthy that there is not a significant difference in accuracy for linear probe

Category Modality	All			Fashion			Children		
	Text	Image	Multimodal	Text	Image	Multimodal	Text	Image	Multimodal
CLIP	0.5	0.5	0.6	0.7	0.0	0.5	0.5	0.0	0.4
KELIP	28.9	17.9	28.7	42.6	29.7	43.0	36.0	24.9	36.2
e-LiT	20.9	31.9	35.2	34.4	37.7	42.5	32.0	31.5	38.8
e-CLIP (filter)	30.2	37.0	40.5	62.0	59.8	67.9	51.6	48.6	56.4
e-CLIP	32.0	32.7	36.3	45.4	48.7	53.3	39.0	39.7	45.2
e-CLIP (hard)	23.3	24.5	27.0	50.9	47.8	56.8	40.4	44.9	37.4

Table 6: Test classification accuracy (%) of zero-shot transfer for category classification.

Eval. Scheme Modality Category	Linear probe						Finetuning					
	Text			Image			Text			Image		
	All	Fashion	Children	All	Fashion	Children	All	Fashion	Children	All	Fashion	Children
BERT-multi	44.9	60.5	52.4	-	-	-	60.3	81.2	71.2	-	-	-
BERT-larva	52.9	66.4	61.5	-	-	-	63.0	81.8	74.0	-	-	-
CLIP	0.1	0.1	0.1	45.0	60.6	50.6	0.2	0.0	0.1	50.8	71.1	61.8
KELIP	67.8	83.3	75.1	55.4	73.7	61.9	67.4	83.3	76.1	53.6	74.2	64.5
e-LiT	69.4	83.6	77.0	44.0	50.8	59.3	70.0	84.9	78.2	49.8	60.4	70.3
e-CLIP (filter)	69.5	84.3	77.2	60.9	77.0	66.5	68.9	84.5	78.0	57.8	76.4	67.6
e-CLIP	70.3	85.0	77.5	60.6	77.1	66.8	69.1	84.7	78.3	58.6	76.7	67.8
e-CLIP (hard)	69.6	84.7	77.1	60.5	76.6	66.5	69.1	84.7	78.2	58.1	76.4	67.8

Table 7: Test classification accuracy (%) of linear probe and fine-tuning for category classification.

Eval. Scheme	Zero-shot	Linear Probe	Finetuning
CLIP	51.5	71.2	79.8
KELIP	57.5	73.0	81.3
e-LiT	53.2	71.2	79.8
e-CLIP (filter)	61.1	76.6	84.9
e-CLIP	63.8	78.4	83.8
e-CLIP (hard)	63.7	78.4	85.1

Table 8: F1-scores for adult product recognition.

and fine-tuning, which could be attributed to the large number of samples in the training data for category classification.

4.2.5 Task 5: Adult Product Recognition. We evaluate on adult products flagged by the NAVER Shopping monitoring system. We extract products collected for a year, sample non-adult products, and generate training data consisting of 10K adult products and 50K normal products. The test dataset consists of approximately 5000 normal products and 1000 adult product images. We use F1-scores for evaluation.

Table 8 displays the performance of zero-shot, linear probe and fine-tuning for adult product recognition. Our e-CLIP models outperform baseline models on F1-scores by remarkable margins for the zero-shot transfer task. Our models seem to learn domain-specific knowledge better than CLIP and KELIP because they significantly improve precision without damaging recall or detecting adult products excessively. For example, “lingerie” is usually treated as non-adult products in NAVER Shopping, but CLIP and KELIP may have been trained on “lingerie” images with more provocative texts, causing these products to be predicted as adult products. In addition, our models also achieve the best results for linear probe and fine-tuning.

4.3 Online Experiments

We confirmed the effectiveness of e-CLIP by running online experiments and integrating it with downstream applications. By leveraging our model embeddings directly and our model to train new models, we observed improvement in several applications and overall training efficiency. For example, we achieved a 14.11% relative improvement in F1-scores for adult product recognition. Our proposed models are a good fit because they have high-quality representations and are strong in transfer learning, as seen in our offline experiments. For category classification, we observed comparable performance by simply training a linear classifier.

Prior to employing e-CLIP, deep learning models in NAVER Shopping used different models and data per task. Even for the same task, it is often necessary to train the image and text models separately and retrain them regularly whenever product distributions change over time, thus consuming enormous resources. Our proposed e-CLIP framework can efficiently and jointly learn image and text representations through a single training process while showing comparable performance to previous models. Therefore, the proposed framework helps save vast resources by unifying NAVER Shopping’s model lifecycle from model management, training, validation, and serving.

5 CONCLUSION

We proposed e-CLIP to train a unified multimodal model by jointly training image and text models for large-scale e-commerce systems. We shared innovative ideas for preparing large training data through preprocessing and how to accelerate training and convergence with high accuracy. We evaluated the learned representations by transferring the model to important downstream tasks in the industry and demonstrate the effectiveness of e-CLIP with significant improvement over other competitive pre-training methods.

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