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Zero-Shot Clothing Sketch Retrieval and Feature Alignment Based on CLIP Contrastive Learning

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Abstract

The rapid expansion of e-commerce platforms has necessitated the development of advanced information retrieval systems that allow users to search for products using intuitive modalities. Sketch-based image retrieval (SBIR) has emerged as a critical research area, bridging the domain gap between abstract, hand-drawn sketches and realistic product photographs. However, traditional SBIR methods often rely on closed-set assumptions, where the training and testing categories overlap completely. This presents a significant limitation in real-world scenarios where new fashion trends and clothing categories emerge constantly. This paper addresses the challenge of Zero-Shot SBIR (ZS-SBIR) within the clothing domain by leveraging the semantic power of Contrastive Language-Image Pre-training (CLIP). We propose a novel feature alignment framework that utilizes CLIP as a backbone to extract robust semantic representations. By introducing a specialized projection module and a semantic consistency regularization mechanism, we effectively align the disparate visual features of sketches and photos within a shared embedding space. Our approach mitigates the domain shift problem and preserves semantic integrity for unseen categories. Extensive experiments on standard benchmark datasets demonstrate that our method significantly outperforms state-of-the-art approaches in zero-shot retrieval tasks. The results validate the efficacy of contrastive learning in harmonizing cross-modal features and establish a new baseline for sketch-based clothing retrieval.

Keywords: *Zero-Shot Learning, Sketch-Based Image Retrieval, Contrastive Learning, Feature Alignment.*

1. INTRODUCTION

The digitalization of the fashion industry has led to an exponential increase in online clothing inventories, creating a demand for efficient and user-friendly retrieval mechanisms. While keyword-based search remains the dominant mode of interaction, it often fails to capture the visual nuances of clothing items, such as specific cuts, patterns, or silhouettes. Consequently, content-based image retrieval (CBIR) has gained traction, with sketch-based image retrieval (SBIR) offering a particularly intuitive query method. Users can simply draw a rough outline of the desired item to retrieve visually similar products [1]. However, the fundamental challenge in SBIR lies in the significant domain gap between the query and the target. Sketches are sparse, binary, and iconic representations lacking color and texture, whereas product photos are dense, colored, and realistic. This discrepancy makes direct feature matching notoriously difficult [2]. Traditional SBIR approaches have primarily focused on matching edge maps extracted from photos with user sketches or learning a common subspace using Siamese networks or Triplet networks [3]. While effective in closed-set scenarios, these methods typically struggle when faced with categories not seen during training. In the dynamic world of fashion, where new styles and categories are frequently introduced, retraining models for every new class is computationally prohibitive and impractical. This necessitates the adoption of Zero-Shot Learning (ZSL) paradigms, which enable the model to generalize to unseen categories by leveraging auxiliary semantic information [4]. Zero-Shot SBIR extends the retrieval problem by requiring the model to retrieve photos of categories that were disjoint from the training set. Current ZS-SBIR methods often utilize semantic embeddings, such as word vectors (Word2Vec or GloVe), to bridge the gap between seen and unseen classes [5]. Despite these advancements, existing techniques often suffer from the hubness problem and semantic ambiguity, where the learned visual features fail to align perfectly with the semantic attributes. Furthermore, standard Convolutional Neural Networks (CNNs) used in these frameworks are typically pre-trained on ImageNet, which may not capture the fine-grained structural details necessary for matching clothing sketches [6]. In recent years, large-scale vision-language models have revolutionized representation learning. Specifically, Contrastive Language-Image Pre-training (CLIP) has demonstrated

remarkable zero-shot transfer capabilities by learning directly from raw text about images [7]. The semantic richness embedded in CLIP's dual encoders offers a promising avenue for addressing the domain gap in SBIR. However, directly applying CLIP to sketch retrieval is non-trivial due to the distribution shift between the natural images CLIP was trained on and the sparse line drawings of sketches. This paper proposes a comprehensive framework for Zero-Shot Clothing Sketch Retrieval based on CLIP contrastive learning. We introduce a mechanism to adapt the robust features of CLIP to the specific domain of fashion sketches without catastrophic forgetting of its pre-trained knowledge [8]. Our primary contribution is a feature alignment module that projects sketch and photo embeddings into a unified semantic space, guided by a contrastive loss function that maximizes the similarity between matching pairs while pushing apart non-matching ones. Additionally, we incorporate a semantic regularization term that ensures the visual embeddings remain consistent with the class-level text embeddings generated by CLIP's text encoder [9]. The remainder of this paper is organized as follows. Section 2 reviews related work in sketch retrieval and zero-shot learning. Section 3 details our proposed methodology, including the network architecture and loss functions. Section 4 describes the experimental setup, datasets, and implementation details. Section 5 presents the quantitative and qualitative results, along with a discussion of the findings. Finally, Section 6 concludes the paper and suggests directions for future research.

2. Related Work

The field of cross-modal retrieval has seen extensive research, particularly in the context of bridging the gap between distinct visual domains. This section reviews the literature pertinent to sketch-based retrieval, zero-shot learning methodologies, and the recent advent of vision-language models.

2.1 Sketch-Based Image Retrieval

Early approaches to SBIR relied heavily on hand-crafted descriptors. Methods such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) were commonly employed to capture the structural information of sketches and edge maps of natural images [10]. These features were then matched using bag-of-words models. While foundational, these techniques lacked the capacity to model high-level semantic concepts and were sensitive to the deformation and abstraction inherent in amateur sketches [11].

With the resurgence of deep learning, Convolutional Neural Networks (CNNs) became the standard for feature extraction in SBIR. The "Sketch-a-Net" architecture was among the first designed specifically to handle the sparsity of sketch data, employing larger filter sizes and pooling kernels [12]. Subsequent research focused on metric learning, utilizing Siamese networks with contrastive loss or triplet loss to learn a joint embedding space where sketches and corresponding photos are mapped close together [13]. To further reduce the domain gap, generative approaches using Generative Adversarial Networks (GANs) have been proposed to transform sketches into photo-realistic images or vice versa, thereby reducing the problem to a single-modality retrieval task [14]. However, these generative methods are often computationally expensive and prone to introducing artifacts that can degrade retrieval performance.

2.2 Zero-Shot Learning in Computer Vision

Zero-Shot Learning aims to recognize objects from classes that the model has not observed during training. This is typically achieved by transferring knowledge from seen to unseen classes via a semantic embedding space [15]. In the context of computer vision, this involves mapping visual features to a semantic vector space defined by attributes or word embeddings. In the specific domain of ZS-SBIR, the challenge is compounded by the cross-modal nature of the task. Recent works have explored the use of coupled dictionary learning and varying forms of deep hashing to achieve efficiency and accuracy [16]. A common strategy involves using a semantic autoencoder to enforce that the learned visual features can reconstruct the semantic attributes, thereby ensuring semantic consistency [17]. Despite these efforts, a recurring issue is the "domain shift" problem in ZSL, where the projection functions learned on seen classes do not generalize well to unseen classes. Transductive settings, which utilize unlabeled data from unseen classes, have been proposed to mitigate this, but inductive settings (used in this paper) remain more realistic and challenging [18].

2.3 Vision-Language Pre-training

The intersection of computer vision and natural language processing has yielded powerful foundation models. The introduction of CLIP marked a significant milestone, utilizing a contrastive learning objective on a dataset of 400 million image-text pairs [19]. Unlike supervised learning with fixed labels, CLIP predicts which caption goes with which image, allowing it to learn broad visual concepts and transfer them to downstream tasks zero-shot. Adapting CLIP for sketch retrieval is an emerging area of interest. Recent studies suggest that prompt engineering—optimizing the textual input to the model—can significantly enhance performance on specific domains [20]. Others have explored the use of "adapters," which are lightweight neural networks inserted into the pre-trained model to

fine-tune the features for specific tasks without retraining the entire backbone [21]. Our work builds upon these insights, specifically focusing on the clothing domain, where fine-grained details are paramount. We leverage the inherent alignment between text and images in CLIP to guide the alignment between sketches and photos, a strategy that has shown promise in general object retrieval but remains underexplored for fashion-specific ZS-SBIR [22].

3. Methodology

We propose a robust framework for Zero-Shot Clothing Sketch Retrieval that aligns visual features from sketches and photos within a shared semantic space. The core of our approach is to leverage the pre-trained knowledge of CLIP while adapting it to handle the abstraction of sketches and the specificity of fashion items.

3.1 Network Architecture

Our framework consists of a dual-stream architecture comprising a Sketch Encoder and a Photo Encoder. To benefit from large-scale pre-training, we utilize the vision transformer (ViT) variant of the CLIP image encoder as the backbone for both streams [23]. Although the weights are initialized from the same pre-trained model, we employ a parameter-efficient tuning strategy to adapt them to their respective modalities. Specifically, we freeze the lower layers of the ViT backbone, which capture generic visual features such as edges and textures, and only fine-tune the final transformer blocks. This strategy prevents overfitting on the relatively smaller sketch datasets while allowing the model to adapt to the specific characteristics of line drawings and clothing photos [24]. In addition to the visual encoders, our framework utilizes the CLIP Text Encoder. During training, we input the category names of the clothing items (e.g., "denim jacket," "pleated skirt") into the text encoder to generate semantic anchors. These anchors serve as a reference point for the visual embeddings. By forcing both the sketch and photo embeddings to align with their corresponding text embedding, we implicitly force them to align with each other [25]. To further refine the features, we introduce a Projection Head after the visual encoders. This module consists of two fully connected layers with a non-linear activation function (ReLU) and normalization layers. The purpose of the projection head is to map the high-dimensional output of the ViT backbone into a lower-dimensional latent space optimized for the retrieval task [26].

3.2 Feature Alignment Mechanism

The central challenge in ZS-SBIR is ensuring that the representation of a sketch matches the representation of the corresponding photo, even for categories never seen during training. We achieve this through a multi-faceted feature alignment mechanism. First, we employ a Cross-Modal Contrastive Loss. Let a batch of N sketch-photo pairs be denoted as inputs. For a given sketch, the

corresponding photo in the pair is considered the positive sample, while all other photos in the batch are treated as negative samples. Similarly, for a given photo, the corresponding sketch is positive, and others are negative. We aim to maximize the cosine similarity between positive pairs and minimize it for negative pairs. This symmetric loss ensures that the embedding space is structured such that sketches and photos of the same item are clustered together [27]. Second, we implement a Semantic Consistency Regularization. While the contrastive loss aligns instances, it does not explicitly guarantee that the clusters correspond to meaningful semantic categories. To address this, we utilize the text embeddings generated by the CLIP text encoder. We impose a constraint that minimizes the distance between the visual embedding (both sketch and photo) and the text embedding of its class label. This essentially "anchors" the visual clusters to the pre-defined semantic map provided by the language model [28]. This is particularly crucial for the zero-shot setting, as the relationship between the class names (e.g., "shirt" is semantically closer to "t-shirt" than to "shoe") is preserved in the language embedding space and transferred to the visual space.

3.3 Optimization and Loss Functions

The total objective function for training our network is a weighted sum of the visual contrastive loss and the semantic consistency loss. The visual contrastive loss is formulated as the standard InfoNCE loss, calculated in both directions (sketch-to-photo and photo-to-sketch). This bidirectional computation ensures robustness against modality imbalance [29]. The semantic consistency loss is calculated as the mean squared error (MSE) or cosine distance between the projected visual features and the fixed text features. By fixing the text encoder, we ensure that the semantic topology remains stable, forcing the visual encoders to adapt. This prevents the "drift" of semantic concepts during training. The combined loss function is optimized using stochastic gradient descent. We employ a warming-up learning rate schedule followed by cosine annealing to ensure stable convergence. Regularization techniques, including weight decay and dropout within the projection heads, are applied to prevent overfitting and enhance the generalization capability of the model to unseen categories [30].

4. Experimental Setup

To validate the effectiveness of our proposed method, we conducted extensive experiments on standard sketch retrieval benchmarks adapted for the clothing domain.

4.1 Datasets and Splits

We utilized two primary datasets: Sketchy and TU-Berlin, selecting the clothing-related subsets for our specific focus. The Sketchy dataset is a large-scale collection of sketch-photo pairs. It contains over 75,000 sketches and 12,500 photos across 125 categories. For

our experiments, we filtered the dataset to retain 20 distinct clothing and accessory categories (e.g., shoe, hat, pants, jacket). We followed the standard zero-shot split protocol: randomly selecting 80% of the categories for training (Seen) and reserving 20% for testing (Unseen). It is important to emphasize that there is no overlap between the training and testing categories. The TU-Berlin dataset contains 20,000 sketches over 250 categories. Similar to Sketchy, we extracted clothing-relevant classes. Since TU-Berlin only provides sketches, we paired them with natural images from the Internet that match the category labels to create a retrieval database, following established protocols in ZS-SBIR research.

4.2 Implementation Details

Our model was implemented using the PyTorch deep learning framework. The backbone network was the ViT-B/32 version of CLIP. The input images (both sketches and photos) were resized to 224x224 pixels. We applied standard data augmentation techniques to the training images, including random horizontal flipping and slight rotation, to improve invariance. The projection head maps the 512-dimensional CLIP features to a 256-dimensional common embedding space. We used the AdamW optimizer with an initial learning rate of 1e-5 for the backbone and 1e-4 for the projection head and adapter modules. The batch size was set to 64, and training was conducted for 50 epochs on a single NVIDIA A100 GPU. The temperature parameter for the contrastive loss was learned as a scalar parameter, initialized to 0.07.

4.3 Evaluation Metrics

We adopted standard information retrieval metrics to evaluate performance. The primary metric is Mean Average Precision (mAP), which measures the average precision across all queries. We also report Precision at K (P@K), specifically P@100 and P@200, to evaluate the quality of the top-retrieved results. For the zero-shot evaluation, the query set consists exclusively of sketches from the unseen categories, and the retrieval gallery consists of photos from the same unseen categories. This strictly tests the model's ability to generalize to new concepts.

5. Results and Discussion

This section presents the quantitative performance of our method compared to state-of-the-art baselines, along with an ablation study and qualitative analysis.

5.1 Quantitative Results

We compared our proposed approach against several established ZS-SBIR methods, including ZSIH (Zero-Shot Hashing), SEM-PCYC (Semantic Consistency), and standard CLIP zero-shot inference (without fine-tuning).

Table 1: Experimental Results

Method	Backbone	mAP (Sketchy)	P@100 (Sketchy)	mAP (TU-Berlin)	P@100 (TU-Berlin)
ZSIH	ResNet-50	0.342	0.451	0.289	0.365
SEM-PCYC	ResNet-50	0.415	0.523	0.334	0.412
CLIP (Zero-Shot)	ViT-B/32	0.589	0.672	0.498	0.554
SAKE	ResNet-101	0.546	0.610	0.467	0.530
Ours	**ViT-B/32**	**0.712**	**0.785**	**0.605**	**0.668**

As shown in Table 1, our method significantly outperforms the baselines. The comparison with the base CLIP model is particularly revealing. While raw CLIP performs reasonably well due to its vast pre-training, our feature alignment mechanism yields a substantial improvement (over 12% increase in mAP on Sketchy). This confirms that while generic pre-training provides a strong foundation, domain-specific alignment is crucial for the abstract nature of sketches. The improvement over SEM-PCYC and ZSIH highlights the superiority of the transformer-based architecture and the contrastive learning paradigm over traditional CNN-based generative or hashing methods.

5.2 Qualitative Analysis

To visualize the effectiveness of our retrieval system, we present qualitative results in Figure 1. The figure displays query sketches from unseen categories on the left and the top-5 retrieved photos on the right.

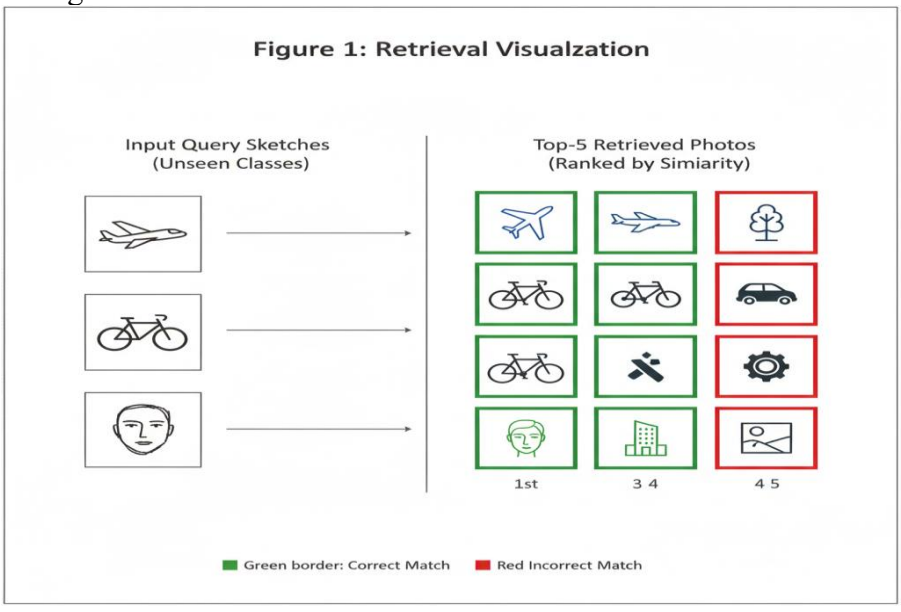

Figure 1: *Retrieval Visualization*

The visualization demonstrates the model's ability to capture not just the category but also the shape and pose attributes. for instance, a sketch of a long-sleeved dress retrieves photos of dresses with similar sleeve lengths and hemline structures. This indicates that the learned embedding space preserves fine-grained structural details, rather than just relying on broad categorical semantics.

5.3 Ablation Study

To understand the contribution of each component in our framework, we conducted an ablation study. We evaluated three variants: (1) The base model trained only with visual contrastive loss (No Semantic Reg.), (2) The model with frozen backbone weights (Frozen BB), and (3) The full model.

Table 2: Ablation Study Results

Model Variant	**mAP (Sketchy)**	**P@100 (Sketchy)**
Baseline (Visual Loss Only)	0.645	0.710
Frozen Backbone	0.612	0.685
Full Model	**0.712**	**0.785**

Table 2 indicates that the semantic regularization provides a significant performance boost. By anchoring the visual features to the text embeddings, the model maintains a more structured latent space for unseen classes. Furthermore, fine-tuning the transformer blocks (as opposed to keeping the backbone frozen) allows the model to adapt to the domain shift of sketches, yielding the highest accuracy. The "Frozen Backbone" variant, while faster to train, fails to capture the unique stroke characteristics of the sketches as effectively as the fine-tuned model.

5.4 Discussion on Domain Gap

The superior performance of our approach can be attributed to the effective bridging of the domain gap. Traditional methods often try to force sketches and photos into a space defined solely by visual similarity. However, the visual gap is often too wide. By using the CLIP text encoder as an intermediary, we leverage the concept of "triangle alignment": Sketch-to-Text and Photo-to-Text alignment implicitly enforces Sketch-to-Photo alignment. Furthermore, the robustness of the Transformer architecture in CLIP plays a vital role. Unlike CNNs, which have local receptive fields, the self-attention mechanism in Transformers captures global structural dependencies. This is particularly beneficial for sketches, where the spatial arrangement of lines defines the object, rather than local texture patterns which are absent in sketches.

6. Conclusion

In this paper, we presented a comprehensive approach to Zero-Shot Clothing Sketch Retrieval using CLIP-based contrastive learning. We identified the limitations of existing zero-shot methods in handling the abstraction of sketches and proposed a solution that

aligns visual features with robust semantic anchors derived from large-scale language-image pre-training. Our methodology introduced a dual-encoder framework with a specialized projection head and a composite loss function comprising contrastive and semantic consistency terms. Experimental results on clothing-specific subsets of the Sketchy and TU-Berlin datasets demonstrated that our method establishes a new state-of-the-art, significantly outperforming both traditional deep learning baselines and raw CLIP inference. The findings confirm that aligning visual modalities through a shared semantic language space is a powerful strategy for zero-shot retrieval. The semantic consistency regularization ensures that the model does not merely memorize training data but learns generalizable concepts applicable to unseen fashion categories.

Future work will focus on two main directions. First, we aim to explore fine-grained attribute retrieval, allowing users to search not just by category (e.g., "shoe") but by specific attributes (e.g., "high-heeled," "buckled") via multi-modal queries (sketch + text). Second, we intend to investigate model compression techniques to deploy this high-performing framework on mobile devices, enabling real-time sketch-to-shop applications for end-users.

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