Learning a Unified Embedding for Visual Search at Pinterest

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Figure 1: Three visual search products on Pinterest (Flashlight, Lens, and Shop-the-Look) allowing users to browse content related to web or camera images and search for exact products within home scenes for shopping. Visual search is one of the fastest growing products at Pinterest with over 600M searches per month.

ABSTRACT
At Pinterest, we utilize image embeddings throughout our search and recommendation systems to help our users navigate through visual content by powering experiences like browsing of related content and searching for exact products for shopping. In this work we describe a multi-task deep metric learning system to learn a single unified image embedding which can be used to power our multiple visual search products. The solution we present not only allows us to train for multiple application objectives in a single deep neural network architecture, but takes advantage of correlated information in the combination of all training data from each application to generate a unified embedding that outperforms all specialized embeddings previously deployed for each product. We discuss the challenges of handling images from different domains such as camera photos, high quality web images, and clean product catalog images. We also detail how to jointly train for multiple product objectives and how to leverage both engagement data and human labeled data. In addition, our trained embeddings can also be binarized for efficient storage and retrieval without compromising precision and recall. Through comprehensive evaluations on offline metrics, user studies, and online A/B experiments, we demonstrate that our proposed unified embedding improves both relevance and engagement of our visual search products for both browsing and searching purposes when compared to existing specialized embeddings. Finally, the deployment of the unified embedding at Pinterest has drastically reduced the operation and engineering cost of maintaining multiple embeddings while improving quality.

KEYWORDS
multi-task learning; embedding; visual search; recommendation systems

ACM Reference Format:
Andrew Zhai, Hao-Yu Wu, Eric Tzeng, Dong Huk Park, Charles Rosenberg. 2019. Learning a Unified Embedding for Visual Search at Pinterest. In The 25th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD ’19), August 4–8, 2019, Anchorage, AK, USA. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3292500.3330739

1 INTRODUCTION
Following the explosive growth in engagement with online photography and videos, visual embeddings have become increasingly critical in search and recommendation systems. Content based image retrieval systems (visual search) is one prominent application that heavily relies on visual embeddings for both ranking and retrieval as users search by providing an image. In recent years, visual search has proliferated across a portfolio of companies including Alibaba’s
These applications support a wide spectrum of use cases from shopping where a user is searching for the exact item to Discovery [32] where a user is browsing for inspirational and related content. These interactions span both real world (phone camera) and online (web) scenarios.

Over 250M users come to Pinterest monthly to discover ideas for recipes, fashion, travel, home decor, and more from our content corpus of billions of Pins. To facilitate discovery, Pinterest offers a variety of products including text-to-pin search, pin-to-pin recommendations [14], and user-to-pin recommendations. Throughout the years, we’ve built a variety of visual search products (Figure 1) including Flashlight (2016), Lens (2017), and automated Shop-the-Look (2018) to further empower our users to use images (web or camera) as queries for general browsing or shopping [32]. With over 600 million visual searches per month and growing, visual search is one of the fastest growing products at Pinterest and of increasing importance.

We have faced many challenges training and deploying generations of visual embeddings over the years throughout the search and recommendation stack at Pinterest. The difficulties can be summarized to the following four aspects:

**Different Applications have Different Objectives**: Pinterest uses image embeddings for a variety of tasks including retrieval (pin and image), ranking (text, pin, user, image queries), classification or regression (e.g. neardup classification, click-through-rate prediction, image type), and upstream multi-modal embedding models (PinSAGE [19]). One observation we made with these multiple applications is that optimization objectives are not the same. Take our visual search products in Figure 1 as examples: Flashlight optimizes for browsing relevance within Pinterest catalog images. Lens optimizes for browsing Pinterest catalog images from camera photos; hence overcoming the domain shift of camera to Pinterest images is necessary. Finally Shop-the-Look optimizes for searching for the exact product from objects in a scene for shopping.

**Embedding Maintenance/Cost/Deprecation**: Specialized visual embeddings per application are the clearest solution to optimizing for multiple consumers and is the paradigm operated at Pinterest prior to 2018. This however has significant drawbacks. For our visual search products alone, we developed three specialized embeddings. As image recognition architectures are evolving quickly [13] [21] [7] [28] [10], we want to iterate our three specialized embeddings with modern architectures to improve our three visual search products. Each improvement in embedding requires a full back-fill for deployment, which can be prohibitively expensive. In practice, this situation is further exacerbated by downstream dependencies (e.g. usage in pin-to-pin ranking [14]) on various specific versions of our embeddings, leading us to incrementally continue to extract multiple generations of the same specialized embeddings. All these considerations make the unification of specialized embeddings into one general embedding very attractive, allowing us clear tracking of external dependency in one lineage along with scalability to support future optimization targets.

**Effective Usage of Datasets**: At Pinterest, there are various image data sources including engagement feedback (e.g. pin-to-pin click data [14], Pin-to-Board graph when users save Pins into collections called Boards [2]) and human curation. When training specialized embeddings for a specific task, deciding what datasets to use or collect is a non-trivial issue, and the choice of data source is often based on human judgement and heuristics which could be suboptimal and not scalable. Multi-task learning simplifies this by allowing the model to learn what data is important for which task through end-to-end training. Through multi-task learning, we want to minimize the amount of costly human curation while leveraging as much engagement data as possible.

**Scalable and Efficient Representation**: With billions of images and over 250M+ monthly active users, Pinterest has a requirement for an image representation that is cheap to store and also computationally efficient for common operations such as distance for image similarity. To leverage the large amount of training data that we receive from our user feedback cycles, we also need to build efficient model training procedures. As such, scalability and efficiency are required both for inference and training.

In our paper, we describe our implementation, experimentation, and productionization of a unified visual embedding, replacing the specialized visual embeddings at Pinterest. The main contributions of this paper are (1) we present a scalable multi-task metric learning framework (2) we present insights into creating efficient multi-task embeddings that leverage a combination of human curated and engagement datasets (3) we present lessons learned when scaling training of our metric learning method and (4) comprehensive user studies and AB experiments on how our unified embeddings compare against the existing specialized embeddings across all visual search products in Figure 1.

## 2 RELATED WORKS

### 2.1 Visual Search Systems

Visual search has been adopted throughout industry with Ebay [30], Microsoft [9], Alibaba [34], Google (Lens), and Amazon launching their own products. There has also been an increasing amount of research on domain-specific image retrieval systems such as fashion [29] and product [1] recommendations. Compared to others, Pinterest has not just one but a variety of visual search products (Figure 1), each with different objectives. We focus on addressing the challenges of unifying visual embeddings across our visual search products.

### 2.2 Metric Learning

Standard metric learning approaches aim to learn image representations through the relationships between images in the form of pairs [4] [1] or triplets [8] [20]. Similarity style supervision are used to train the representation such that similar images are close in embedding space and dissimilar images apart. Sampling informative negatives is an important challenge of these pair or triplet based approaches, a focus of recent methods such as [23] [22] [26].

An alternative approach to metric learning are classification based methods [16][33] which alleviate the need of negative sampling. These methods have recently been shown to achieve SOTA results across a suite of retrieval tasks [33] compared with pair or triplet based methods. Given the simplicity and effectiveness of formulating metric learning as classification, we build off the
architecture proposed in [33] and extend it to multi-task for our unified embeddings.

2.3 Multi-Task Learning

Multi-task learning aims to learn one model that provides multiple outputs from one input [25] [18]. By consolidating multiple single-task models into one multi-task model, previous work have seen both efficiency [25] and performance [12] [15] [18] improvements on each task due to inherent complementary structure that exists in separate visual tasks [31]. Prior work also investigate how to learn to balance multiple loss objectives to optimize performance [12] [3]. In the context of metric learning, [24] and [35] explore the idea of learning a conditional mask for each task to modulate either the learned embedding or the internal activations. In our paper, we experiment with multi-task metric learning and evaluate its effects on our web scale visual search products.

3 METHOD

3.1 Problem Setup

Pinterest is a visual discovery platform in which the contents are predominantly images. To empower the users on Pinterest to browse visually inspired contents and search for an exact item in the image for shopping, we have built three services shown in Figure 1: Flashlight, Lens, and Shop-The-Look (STL). Flashlight enables the users to start from the images on Pinterest (or web), and recommends relevant Pins inspired by the input images for the users to browse. Similarly, Lens aims to recommend visually relevant Pins based on the photos our users take with their cameras. STL, on the other hand, searches for products which are best match to the input images for the users to shop. The three services either serve images from different domains (web images v.s. camera photos), or with different objectives (browsing v.s. searching).

With both cost and engineering resource constraints and the interest of improved performance, we aim to learn one unified image embedding that can perform well for all three tasks. In essence, we would like to learn high quality embeddings of images that can be used for both browsing and searching recommendations. The relevance or similarity of a pair of images is represented as the distance between the respective embeddings. In order to train such embeddings, we collected a dataset for each task addressing its specific objective (Figure 2), and frame the problem as multi-task metric learning that jointly optimizes the relevance for both browsing and searching. We will describe how we collect the dataset for each task, the detailed model architecture, and how we set up multi-task training in the following sections.

3.2 Training Data

We describe our training datasets and show some examples in Figure 2.

3.2.1 Flashlight Dataset. The Flashlight dataset is collected to define browse relevance for Pinterest (web) images. As a surrogate for relevance, we rely on engagement through feedback from our users in a similar manner to Memboost described in [14] to generate the dataset. Image sets are collected where a given query image has a set of related images ranked via engagement, and we assign each image set a label (unique identifier) that is conceptually the same as semantic class label. We apply a set of strict heuristics (e.g. number of impressions and interactions for each image in the set) to reduce the label noise of the dataset, resulting in around 800K images in 15K semantic classes.

3.2.2 Lens Dataset. The Lens dataset is collected to define browse relevance between camera photo images and Pinterest images. When collecting the training dataset for prototyping Lens, we found that camera photo engagement on Pinterest is very sparse and as such any dataset collected via user engagement would be too noisy for training. The main obstacle we need to overcome is the domain shift between camera photos and Pinterest images, so for the training set, we collected a human labeled dataset containing 540K images with 2K semantic classes. These semantic classes range from broad categories (e.g. tofu) to fine-grained classes (e.g. the same denim jacket in camera and product shots). Most importantly, this dataset contains a mix of product, camera, and Pinterest images under the same semantic label so that the embeddings can learn to overcome the domain shifts.

3.2.3 Shop-The-Look Dataset. The Shop-The-Look dataset is collected to define search relevance for an object in a home decor scene to its product match. To bootstrap the product, we collected a human labeled dataset containing 340K images with 189 product class label (e.g. Bar Stools) and 50K instance labels. Images with the same instance label are either exact matches or are very similar visually as defined by an internal training guide for criteria such as design, color, and material.
3.3 Model Architecture

Figure 3 illustrates our overall setup for multi-task metric learning architecture. We extend the classification-based metric learning approach of Zhai et al. [33] to multi-task. All the tasks share a common base network until the embedding is generated, where each task then splits into their own respective branches. Each task branch is simply a fully connected layer (where the weights are the proxies) followed by a softmax (no bias) cross entropy loss. There are four softmax tasks, Flashlight class, Shop-the-Look (STL) product class, STL instance class, and Lens category class. For the Flashlight class and STL instance tasks, the proxies are subsampled using our subsampling module before input to the fully connected layer for efficient training.

There are two essential modules for web-scale applications: a subsampling module to make our method scalable to hundreds of thousands of classes, and binarization module to make learned embedding storage and operation efficient.

3.3.1 Subsampling Module. Given N images in a batch and M proxies to target each with an embedding dimension of D, to compute the similarity (dot product) of embeddings to proxies, we do a NxM by DxM matrix multiplication in the fully connected layer. As such, computation increases with the number of proxy classes (M), an undesirable property as we scale M. Furthermore, we may not even be able to fit the proxy bank (MxD matrix) in GPU memory as we scale M to millions of classes (user engagement training data can easily generate this many classes). To address these issues, we store the proxy bank in CPU RAM (more available than GPU memory and disk can be used later if necessary) along with also implementing class subsampling. As shown in Figure 4, for each training batch, the subsampling module samples a subset of all classes for optimization. The sampled subset is guaranteed to have all the ground truth class labels of the images in the training batch (the label index slot will change however to ensure the index is within bounds of the number of classes sampled). The pseudocode for the forward pass is provided in Algorithm 1. During the training forward pass for efficiency, the proxies of the sampled classes are moved to GPU for computation asynchronously while the embedding is computed from the base network. The softmax loss only considers the sampled classes. For example, if we subsample only 2048 classes for each iteration, the maximum loss from random guessing is $\ln(2048) \approx 7.62$.

**Algorithm 1 Subsampling Proxy Indices**

**Input:** targets, num_samples  
**Output:** sampled_proxy_idx, remapped_targets  
**Require:** len(targets) $\leq$ num_samples  
1: sampled_proxy_idx $\leftarrow$ set(targets)  
2: while len(sampled_proxy_idx) $\leq$ num_samples do  
3:    s $\leftarrow$ sample(all_labels)  
4:    if s $\notin$ sampled_proxy_idx then  
5:      sampled_proxy_idx.add(s)  
6:    end if  
7:  end while  
8: sampled_proxy_idx $\leftarrow$ list(sampled_proxy_idx)  
9: remapped_targets $\leftarrow$ list([])  
10: for all t $\in$ targets do  
11:    for all index, label $\in$ enumerate(sampled_proxy_idx) do  
12:      if t = label then  
13:        remapped_targets.add(index)  
14:      end if  
15:    end for  
16:  end for  
17: return sampled_proxy_idx, remapped_targets

3.3.2 Binarization Module. At Pinterest, we have a growing corpus of billions of images and as such we need efficient representations to (1) decrease cold storage costs (e.g. cost of AWS S3) (2) reduce...
we balance a uniform mix of each of the datasets with an epoch.

Instead of LayerNorm as proposed in [33], we propose to use

effect of the gradients of the current iteration increasing the learning rate. Assuming we choose

tion, we approximate the momentum update for sparse tensor by
tensors will be aggregated and become expensive dense gradient up-
abling momentum update on the sparse tensor, the sparse gradient
backward propagation.

An additional optimization is the handling of momentum. By en-
abling momentum update on the sparse tensor, the sparse gradient
tensors will be aggregated and become expensive dense gradient up-
dates. Since momentum is crucial for deep neural network optimiza-
tion, we approximate the momentum update for sparse tensor by
increasing the learning rate. Assuming we choose momentum \( m = 0.9 \),
the gradients of the current iteration \( \hat{G} \) will roughly have net update effect of 10x learning rate over the coarse of training:

\[
\sum_{n=1}^{\infty} lr \times \hat{G} \times 0.9^n = 10.0 \times lr \times \hat{G}
\]

Although increasing learning rate will affect the optimization tra-
jectory on the loss function surface, thus affect the subsequent gradients, we find this approximation decreases our training time by 40% while retaining comparable performance.

3.5 Model Deployment

We train our models using the PyTorch framework and deploy mod-
els through PyTorch to ONNX to Caffe2 conversion. For operations
where ONNX does not have a compatible representation for, we
directly use the Aten operator, a shared backend between PyTorch
and Caffe2, to bypass and deploy our Caffe2 model.

4 EXPERIMENTS

In this section, we measure the performance of our method on a
suite of evaluations including offline measurement, human judg-
ments, and A/B experiments. We demonstrate the efficacy and the
impact of our unified embeddings at Pinterest.

4.1 Implementation

Our model is trained using PyTorch on one p3.16xlarge Amazon
EC2 instances with eight Tesla V100 graphic cards. We use the
DistributedDataParallel implementation provided by the PyTorch
framework for distributed training.

We train our models with largely the same hyperparameters
as [33] with SE-ResNeXt101 [10] as the base model pre-trained
on ImageNet ILSVRC-2012 [5]. We use SGD with momentum of
0.9, weight decay of 1e-4, and gamma of 0.1. We start with a base
learning rate of 0.08 (0.01 x 8 from the linear scaling heuristic of [6])
and train our model for 1 epoch by updating only new parameters
for better initialization with a batch size of 128 per GPU. We then
train end-to-end with a batch size of 64 per GPU and apply the
gamma to reduce learning rate every 3 epochs for a total of 9 epochs
of training (not counting initialization). During training, we apply
horizontal mirroring, random crops, and color jitter from resized
256x256 images while during testing we center crop to a 224x224
image from the resized image.

4.2 Offline Evaluation

Offline measurements are the first consideration when iterating on
new models. For each product of interest (Shop-the-Look, Flashlight,
and Lens), we have a retrieval evaluation dataset. Some are derived
based on the training data while others are sampled according
to usage in product. The difference in approach is due to either
bostrapping a new product versus improving an existing one.

The evaluation dataset for Shop-the-Look is generated through
human curation as we looked to build this new product in 2018. We
sampled home decor scenes according to popularity (# of closeups)
on Pinterest and used human curation to label bounding boxes
of objects in scene along with ground truth whole image product
matches to the objects (criteria determined by our developed inter-

nal training guide). This resulted in 600 objects with 1421 ground
truth product matches. We measure Precision@1 [17] for evalua-
tion where for each of the objects, we extract its embedding and
generate the top nearest neighbor result in a corpus of 51421 prod-
uct images (50k sampled from our product corpus + the ground
We noticed a significant drop in performance between raw float and
with a SE-ResNeXt101 featurizer and multi-task heads (Section 3.3).

| Table 1: Model architecture experiments on offline evaluations |
|---------------------------------------------------------------|
| Model            | STL  | Flashlight | Lens |
|------------------|------|------------|------|
| Baseline (f)     | 47.5 | 60.1       | 18.6 |
| Baseline (b)     | 41.9 | 55.6       | 17.7 |
| + sm + gn (b)    | 48.4 | 59.3       | 17.8 |
| + sm + gn + r (b)| 49.7 | 61.1       | 17.6 |
| + sm + gn + r + dp (b) (Ours) | 52.8 | 60.2 | 18.4 |

Table 1: Model architecture experiments on offline evaluations (f = float, b = binary). We compare binary embeddings for deployment.

truth whole product images). Precision@1 is then the percent of objects that have a ground truth whole product image retrieved.

The evaluation datasets for Flashlight and Lens are generated through user engagement. For Flashlight, we sampled a random class subset of the Flashlight training data (Section 3.2), and randomly divided it into 807 images for queries and 42881 images for the corpus across classes. For Lens, we generated the evaluation dataset using user engagement in the same manner as the Flashlight training dataset (Section 3.2) but filtering the query images to be camera images with human judgement. This resulted in 1K query images and 49K images for the corpus across classes. As these datasets are generated from noisy user engagement, we use the evaluation metric of Average Precision@20 where we take the average of Precision@1 to Precision@20 (Precision@K as defined in [32]). Empirically we have found that though these evaluations are noisy, significant improvements in this Average P@20 have correlated with improvements in our online A/B experiment metrics.

4.2.1 Binarization. We experiment with model architectures in Table 1. We are primarily interested in binarized embedding performance as described in Section 3.3.2. An alternative to binary features for scalability is to learn low dimensional float embeddings. Based on our prior work [33] however, we found that for the same storage cost, learning binary embedding led to better performance than learning float embeddings.

Our baseline approach in Table 1 was to apply the LayerNorm (ln) with temperature of 0.05 and NormSoftmax approach of [33] with a SE-ResNeXt101 featurizer and multi-task heads (Section 3.3). We noticed a significant drop in performance between raw float and binary features. We experimented with variations of the architecture including: Softmax (sm) to remove L2 normalized embedding constraint, GroupNorm [27] (group=256) for more granularity in normalization, ReLU (r) to ignore negative magnitudes, and Dropout (p=0.5) for learning redundant representations. As shown, our final binarized multi-task embeddings performs favorably to the raw float features baseline.

4.2.2 Multi-Task Architecture Ablations. We show our multi-task experiment results in Table 2. Instead of uniform sampling of each dataset in a mini-batch (Section 3.4.1), we experiment with sampling based on dataset size. Instead of assigning equal weights to all task losses, we experiment with GradNorm [3] to learn the weighting. We see our simple approach achieved the best balance of performance.

4.2.3 Multi-Task Dataset Ablations. We look at how training with multiple datasets affects our unified embeddings. In Table 3, we compare our multi-task embedding trained with all three datasets against embeddings (using the same architecture) trained with each dataset independently. When training our embedding with one dataset, we ensure that the total iterations of images over the training procedure is the same as when training with all three datasets. We see that multi-task improves all three retrieval metrics compared with the performance of embeddings trained on a single dataset.

4.2.4 Unified vs Specialized embeddings. We compare our unified embedding against the previous specialized embeddings [32] deployed in Flashlight, Lens, and Shop-the-Look in Table 4. We also include a SENet [10] pretrained on ImageNet baseline for comparison. We see our unified embedding outperforms both the baseline and all specialized embeddings for their respective tasks.

Although the unified embeddings compare favorably to the specialized embeddings, the model architectures of these specialized embeddings are fragmented. Flashlight embedding are generated from a VGG16 [21] FC6 layer of 4096 dimensions. Lens embedding are generated from a ResNeXt50 [28] final pooling layer of 2048 dimensions. Shop-the-Look embedding are generated from a ResNet101 [7] final pooling layer of 2048 dimensions. This fragmentation is undesirable as each specialized embedding can benefit from updating the model architecture to our latest version as seen in the dataset ablation studies in Section 4.2.3. However in practice, this fragmentation is the direct result of challenges in embedding maintenance from focusing on different objectives at different times in the past. Beyond the improvements in offline metrics from multitsk as seen in the Ablation study, the engineering simplification of iterating only one model architecture is an additional win.

4.3 Human Judgements

Offline evaluations allow us to measure, on a small corpus, the improvements of our embeddings alone. Practical information retrieval systems however are complex, with retrieval, lightweight
Table 4: Our binary unified embedding against the existing specialized binary embeddings for each application. We include an ImageNet baseline using a pre-trained SENet[10]

| Model          | STL P@1 | Flashlight P@20 | Lens Avg P@20 |
|----------------|--------|-----------------|---------------|
| Old Shop-the-Look | 33.0  | -               | -             |
| Old Flashlight   | -      | 53.4            | -             |
| Old Lens         | -      | -               | 17.8          |
| ImageNet         | 5.6    | 33.1            | 15.0          |
| Ours             | 52.8   | 60.2            | 18.4          |

score, and ranking components [11] using a plethora of features. As such it is important for us to measure the impact of our embeddings end-to-end in our retrieval systems. To compare our unified embeddings with the productionized specialized embeddings for human judgement and A/B experiments, we build separate clusters for each visual search product where the difference between the new and production clusters are the unified vs specialized embeddings.

At Pinterest, we rely on human judgement to measure the relevance of our visual search products and use A/B experiments to measure engagement. For each visual search product, we build relevance templates (Figure 5) tuned with an internal training guide for a group of internal workers (similar to Amazon Mechanical Turk) where we describe what relevance means in the product at hand with a series of expected (question, answer) pairs. To control quality, for a given relevance template we ensure that workers can achieve 80%+ precision in their responses against a golden set of (question, answer) pairs. We further replicate each question 5 times, showing 5 different workers the same question and aggregating results with the majority response as the final answer. We also record worker consistency (WC) across different sets of jobs measuring given the same question multiple times, what percent of the questions were answered the same across jobs.

Questions for judgement are generated from a traffic weighted sample of queries for each product. Given each query (Pin image + crop for Flashlight, Camera image for Lens, and Pin image + crop for Shop-the-Look), we send a request to each product’s visual search system to generate 5 results per query. Each (query, result) pair forms a question allowing us to measure Precision@5. We generate two sets of 10K (question, answer) tasks per visual search product, one on the existing production system with the specialized embedding and another on the new cluster with our unified embedding. Our human judgement results are shown in Table 5 for Flashlight and Lens and Table 6 for Shop-the-Look. As we can see, our new unified embeddings significantly improve the relevance of all our visual search products.

One hypothesis for these significant gains beyond better model architecture is that combining the three datasets covered the weaknesses of each one independently. Flashlight allows crops as input while the engagement generated training data are whole images. Leveraging the Shop-the-Look dataset with crops helps bridge this domain shift gap of crop to whole images. Similarly for Lens, though the query is a camera image and we need to address the camera to pin image domain shift, the content in the corpus are all Pinterest content. As such additionally using Pinterest corpus training data like Flashlight’s can allow the embedding to not only handle camera to pin image matches but also better organize Pinterest content in general. Such dataset interactions are not immediately clear when training specialized embeddings. By learning a single unified embedding with all our training datasets, we let the model training learn how to effectively use the datasets for each task.

4.4 A/B Experiments
A/B experiments at Pinterest are the most important criteria for deploying changes to production systems.

Flashlight A/B experiment results of our unified embedding vs the old specialized embedding are shown in Figure 6. We present results on two treatment groups: (1) A/B experiment results on Flashlight with ranking disabled and (2) A/B experiment results on Flashlight with ranking enabled. Flashlight candidate generation is solely dependent on the embedding and as such, when disabling
Table 5: Human Judgements for Flashlight and Lens measuring Precision@5 delta comparing unified embedding vs existing specialized embedding along with the percent of queries that are better (Win), worse (Lose), or have the same (Draw) Precision@5. We see that our new unified embedding significantly improves the relevance of the two products.

| Application     | Win  | Lose | Draw | P@5 Delta | WC  |
|-----------------|------|------|------|-----------|-----|
| Flash (old vs new) | 41.3% | 13.9% | 44.8% | +22.2% | 98.0% |
| Lens (old vs new) | 54.0% | 7.9%  | 38.0% | +110.1% | 92.9% |

Table 6: Human Judgements for Shop-the-Look measuring Precision@5 comparing unified embedding vs existing specialized embedding. We see that our new unified embedding significantly improves the relevance overall with wins in all categories except one.

| Category          | Baseline | Ours | Delta |
|-------------------|----------|------|-------|
| Artwork           | 42.9%    | 75.5%| 76.0% |
| Beds & Bed Frames | 16.7%    | 45.7%| 173.7%|
| Benches           | 14.7%    | 51.4%| 249.7%|
| Cabinets & Storage| 22.9%    | 64.6%| 182.1%|
| Candles           | 60.0%    | 40.0%| -33.3%|
| Chairs            | 22.4%    | 63.3%| 182.6%|
| Curtains & Drapes | 39.6%    | 89.8%| 126.8%|
| Dresses           | 91.7%    | 100.0%| 9.1% |
| Fireplaces        | 40.4%    | 72.9%| 80.4% |
| Folding Chairs & Stools | 37.9%   | 46.7%| 23.2% |
| Lighting          | 33.3%    | 69.4%| 108.4%|
| Mirrors           | 30.6%    | 49.0%| 60.1% |
| Ottomans          | 50.0%    | 80.0%| 60.0% |
| Pillows           | 57.4%    | 75.5%| 31.5% |
| Rugs              | 71.4%    | 85.7%| 20.0% |
| Shelving          | 12.5%    | 42.9%| 243.2%|
| Sofas             | 18.4%    | 38.8%| 110.9%|
| Table & Bar Stools| 40.9%    | 82.2%| 101.0%|
| Tables            | 16.3%    | 40.8%| 150.3%|
| Vases             | 48.9%    | 69.4%| 41.9% |
| Overall           | 37.3%    | 64.2%| 72.1% |

5 CONCLUSION

Improving and maintaining different visual embeddings for multiple customers is a challenge. At Pinterest, we took one step to simplifying this process by proposing a multi-task metric learning architecture capable of jointly optimizing multiple similarity metrics, such as browsing and searching relevance, within a single unified embedding. To measure the efficacy of the approach, we experimented on three visual search systems at Pinterest, each with its own product usage. The resulting unified embedding outperformed all specialized embedding trained with individual task in comprehensive evaluations, such as offline metrics, human judgements and A/B experiments. The unified embeddings are deployed at Pinterest after observing substantial improvement in recommendation performance reflected by better user engagement across all three visual search products. Now with only one embedding to maintain and iterate, we have been able to substantially reduce experimentation, storage, and serving costs as our visual search products rely on a unified retrieval system. These benefits enable...
us to move faster towards our most important objective – to build and improve products for our users.

REFERENCES

[1] Sean Bell and Kavita Bala. 2015. Learning Visual Similarity for Product Design with Convolutional Neural Networks. *ACM Trans. on Graphics (SIGGRAPH)* 34, 4 (2015).

[2] Jerry Zita Liu Yuchen Liu Rahul Sharma Charles Sugnet Mark Ulrich Jure Leskovec Chantat Eksombatchai, Pranav Jindal. 2018. Pixie: A System for Recommending 3+ Billion Items to 200+ Million Users in Real-Time. In *Proceedings of the International Conference on World Wide Web*. 

[3] Zhao Chen, Vijay Badrinarayanan, Chen-Yu Lee, and Andrew Rabinovich. 2017. GradNorm: Gradient Normalization for Adaptive Loss Balancing in Deep Multi-task Networks. *CoRR* abs/1711.02257 (2017). arXiv:1711.02257 http://arxiv.org/abs/1711.02257

[4] Sumit Chopra, Raia Hadsell, and Yann LeCun. 2005. Learning a Similarity Metric Discriminatively, with Application to Face Verification. In *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR)*. Vol. 1. IEEE, 539–546.

[5] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. 2009. ImageNet: A Large-Scale Hierarchical Image Database. In *CVPR*.

[6] Paya Goyal, Piots Dollar, Ross B. Girshick, Pioter Noordhuis, Lukasz Wesolowski, Aapo Kyrola, Andrew Tulloch, Yangqing Jia, and Kaiming He. 2017. LargeMiniBatch SGD: Training ImageNet in 1 Hour. *CoRR* abs/1706.02677 (2017). arXiv:1706.02677 http://arxiv.org/abs/1706.02677

[7] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2015. Deep Residual Learning for Image Recognition. *arXiv preprint arXiv:1512.03385* (2015).

[8] Elad Hoffer and Nir Ailon. 2014. Deep metric learning using Triplet network. *CoRR* abs/1412.6622 (2014). http://arxiv.org/abs/1412.6622

[9] Houdong Hu, Yan Wang, Linjun Yang, Pavel Komelev, Li Huang, Xi (Stephen) Chen, Jianpei Huang, Ye Wu, Meena Merchant, and Arun Satchi. 2018. Web-Scale Responsive Visual Search at Bing. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. KDD 2018, London, UK, August 19-23, 2018. 359–367. https://doi.org/10.1145/3219819.3219843

[10] Jie Hu, Li Shen, and Gang Sun. 2017. Squeeze-and-excitation networks. *arXiv preprint arXiv:1709.01507* (2017).

[11] Y. Jing, D. Liu, D. Kuslyuk, A. Zhai, J. Xu, and J. Donahue. [n. d.]. Visual Search at Pinterest. In *Proceedings of the International Conference on Knowledge Discovery and Data Mining* (SIGKDD).

[12] Alex Kendall, Yarin Gal, and Roberto Cipolla. 2017. Multi-Task Learning Using Uncertainty to Weigh Losses for Scene Geometry and Semantics. *CoRR* abs/1705.07115 (2017).

[13] A. Krizhevsky, S. Ilya, and G. E. Hinton. 2012. ImageNet Classification with Deep Convolutional Neural Networks. In *Advances in Neural Information Processing Systems (NIPS)*. 1097–1105.

[14] David C. Liu, Stephanie Rogers, Raymond Shiau, Dmitry Kislyuk, Kevin C. Ma, Zhigang Zhong, Jenny Liu, and Yushi Jing. 2017. Related Pins at Pinterest: The Evolution of a Real-World Recommender System. *CoRR* abs/1702.07969 (2017).

[15] Ishan Misra, Abhinav Shrivastava, Abhinav Gupta, and Martial Hebert. 2016. Cross-stitch Networks for Multi-task Learning. *CoRR* abs/1604.05359 (2016).

[16] Yair Movshovitz-Attias, Alexander Toshiev, Thomas K. Leung, Sergey Ioffe, and Saurabh Singh. 2017. No Fuss Distance Metric Learning using Proxies. *CoRR* abs/1703.07464 (2017). http://arxiv.org/abs/1703.07464

[17] Henning Müller, Wolfgang Müller, David McG. Squire, Stéphane Marchand-Maillet, and Thierry Pun. 2001. Performance Evaluation in Content-based Image Retrieval: Overview and Proposals. *Pattern Recogn. Lett.* 22, 5 (April 2001), 593–601. https://doi.org/10.1016/S0167-8655(00)00128-5

[18] Zhongzheng Ren and Yong Jae Lee. 2017. Cross-Domain Self-supervised Multi-task Feature Learning using Synthetic Imagery. *CoRR* abs/1711.09882 (2017).

[19] Kaileng Chen Pong Eksombatchai William L. Hamilton Jure Leskovec Rex Ying, Ruining He. 2018. Graph Convolutional Neural Networks for Web-Scale Recommender Systems. In *Proceedings of the International Conference on Knowledge Discovery and Data Discovery (SIGKDD)*.

[20] Florian Schroff, Dmitry Kalenichenko, and James Philbin. 2015. FaceNet: A Unified Embedding for Face Recognition and Clustering. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[21] K. Simonyan and A. Zisserman. 2014. Very Deep Convolutional Networks for Large-Scale Image Recognition. *CoRR* abs/1409.1556 (2014).

[22] Kihyuk Sohn. 2016. Improved Deep Metric Learning with Multi-class N-pair Loss Objective. In *Advances in Neural Information Processing Systems 29*, D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett (Eds.). Curran Associates, Inc., 1857–1865.

[23] Huyun Ok Song, Yu Yang, Stefanie Jegelka, and Silvio Savarese. 2016. Deep Metric Learning via Lifted Structured Feature Embedding. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[24] Andreas Veit, Serge J. Belongie, and Theofanis Karaletsos. 2017. Conditional Similarity Networks. 2017 *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 1781–1789.

[25] Bin Yang Wenjie Luo and Raquel Urtasun. 2017. Fast and Furious: Real Time End-to-End 3D Detection, Tracking and Motion Forecasting with a Single Convolutional Net. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[26] Chao-Yuan Wu, R. Manmatha, Alexander J. Smola, and PhilippKrähenbühl. 2017. Sampling Matters in Deep Embedding Learning. *CoRR* abs/1706.07567 (2017). arXiv:1706.07567 http://arxiv.org/abs/1706.07567

[27] Yuxin Wu and Kaiming He. 2018. Group Normalization. *CoRR* abs/1803.08494 (2018).

[28] Saining Xie, Ross Girshick, Piotr Dollar, Zhuowen Tu, and Kaiming He. 2017. Aggregated residual transformations for deep neural networks. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 5987–5995.

[29] K. Yamaguchi, M. H. Kiapour, and Robinson Piramuthu. 2017. Visual Search at eBay. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Halifax, NS, Canada, August 13 - 17, 2017. 2101–2110. https://doi.org/10.1145/3097983.3098162

[30] Anir Ronan Zamb, Alexander Sax,William B. Shen, Leonidas J. Guibas, Jitendra Malik, and Silvio Savarese. 2018. Taskonomy: Disentangling Task Transfer Learning. *CoRR* abs/1804.08328 (2018).

[31] Andrew Zhao, Dimitry Kuslyuk, Yushi Jing, Michael Feng, Eric Tseng, Jeff Donahue, Yue Li Du, and Trevor Darrell. 2017. Visual Discovery at Pinterest. *arXiv preprint arXiv:1706.04680* (2017).

[32] Andrew Zhai and Hao-Yu Wu. 2018. Making Classification Competitive for Deep Metric Learning. *CoRR* abs/1811.12649 (2018). arXiv:1811.12649 http://arxiv.org/abs/1811.12649

[33] Yanhao Zhang, Pan Pan, Yun Zheng, Kang Zhao, Yingya Zhang, Xiaofeng Ren, and Rong Jin. 2018. Visual Search at Alibaba. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD 2018, London, UK, August 19-23, 2018. 993–1001. https://doi.org/10.1145/3219819.3219820

[34] Xiangyun Zhao, Haoxiang Li, Xiaohui Shen, Xiaodan Liang, and Ying Wu. 2018. A Modulation Module for Multi-task Learning with Applications in Image Retrieval. In *ECCV*. 

Figure 7: Qualitative results comparing the old embeddings vs our new multi-task embeddings in Flashlight. For each query on the left, the results from old embeddings are shown on the top row, and the new embeddings are shown on the bottom row.