Disentangling Nonlinear Perceptual Embeddings
With Multi-Query Triplet Networks

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Abstract

We propose Multi-Query Networks to answer questions like “Find a shoe precisely like this, but with higher heel”. To respond to a question like this, one needs an image representation that captures all the different notions of similarities that shoes can be compared to. However, when learning such similarity based embeddings with siamese or triplet networks the simplifying assumption is commonly made that images are only compared to one unique measure of similarity. A main reason for this is that contradicting notions of similarities cannot be captured in a single space. To address this shortcoming, we propose Multi-Query Networks (MQNs) that learn embeddings differentiated into semantically distinct subspaces that capture the different notions of similarities. In addition, MQNs make the representation interpretable by encoding different similarities in separate dimensions. We show that our approach learns visually relevant semantic subspaces. Further, when evaluating on triplet questions from multiple similarity notions our model even outperforms the accuracy obtained by training individual specialized networks for each notion separately.

1. Introduction

When learning nonlinear features from constraints of object similarities and dissimilarities, objects are embedded in a feature-vector space, in which their distances preserve the relative dissimilarity. The similarities can be encoded pairwise or in higher order relationships such as triplets. Commonly, convolutional neural networks are trained to transform the visual stimuli into the feature-vectors. When learning from (dis-)similarity constraints, the simplifying key assumption is commonly made that all objects are compared according to one unique measure of similarity. However, objects have various attributes and can be compared according to a multitude of semantic aspects.

An illustrative example to consider is the comparison of coloured geometric shapes, a task toddlers are regularly exposed to with benefits to concept learning. Consider, that a red triangle and a red circle are very similar in terms of color, more so than a red triangle and a blue triangle. However, the triangles are more similar to one another in terms of shape than the triangle and the circle.

An optimal embedding should minimize distances between perceptually similar objects. In the example above and also in the practical example in Figure 1 this creates a situation where the same two objects are semantically repelled and drawn to each other at the same time. A standard triplet embedding ignores the sources of similarity and cannot jointly satisfy the competing semantic aspects. Thus, a successful embedding necessarily needs to take the visual concept into account that objects are compared to.
One way to address this issue is to learn separate triplet networks for each visual task. However, the idea of building a separate perceptual system for each aspect of similarity is wasteful in terms of parameters needed, redundancy of parameters, as well as the associated need for training data.

An ideal system would combine both of the above: deal with multiple aspects of similarity within a shared embedding using a shared feature extractor. In this work, we introduce Multi-Query Networks (MQNs) a joint architecture to learn a nonlinear embeddings that gracefully deals with multiple notions of similarity in an integrated fashion. Different aspects of similarity are incorporated by assigning responsibility weights to each embedding dimension with respect to each aspect of similarity. This can be achieved through a masking operation leading to separate semantic subspaces. Figure 2 provides an overview of the proposed framework. Images are passed through a convolutional network and projected into a nonlinear embedding. Subsequent masks indicate which dimensions of the embedding are responsible for separate aspects of similarity. We can then compare objects according to various notions of similarity by selecting an appropriate masked subspace.

In our experiments we evaluate the quality of the learned embeddings by their ability to embed unseen triplets. We demonstrate that MQNs clearly outperform single triplet networks, and even sets of specialist triplet networks where a lot more parameters are available and each network is trained towards one similarity notion. Further we show MQNs make the representation interpretable by encoding different similarities in separate dimensions.

Our contributions are a) formulating Multi-Query Networks, an approach that allows to to learn nonlinear embeddings that incorporate multiple aspects of similarity within a shared embedding using a shared feature extractor, b) demonstrating that the proposed approach outperforms standard triplet networks and even sets of specialist triplet networks in a variety of hard predictive visual tasks and c) demonstrating that our approach successfully disentangles the embedding features into meaningful dimensions so as to make the representation interpretable.

2. Related Work

Similarity based learning has emerged as a broad field of interest in modern computer vision and has been used in many contexts. Disconnected from the input image, triplet based similarity embeddings, can be learned using crowd-kernels [24]. Further, Tamuz et al. [21] introduce a probabilistic treatment for triplets and learn an adaptive crowd kernel. Similar work has been generalized to multiple-views and clustering settings by Amid and Ukkonen [1] as well as Van der Maaten and Hinton [23]. A combination of triplet embeddings with input kernels was presented by Wilber et al. [27], but this work did not include joint feature and embedding learning. An early approach to connect input features with embeddings has been to learn image similarity functions through ranking [4].

A foundational line of work combining similarities with neural network models to learn visual features from similarities revolves around Siamese networks [6, 10], which use pairwise distances to learn embeddings discriminatively. In contrast to pairwise comparisons, triplets have a key advantage due to their flexibility in capturing a variety of higher-order similarity constraints rather than the binary similar/dissimilar statement for pairs. Neural networks to learn visual features from triplet based similarities have been used by Wang et al. [25] and Schroff et al. [17], where use of supervised features with crowd-inferred similarities boosts performance in face verification and fine-grained visual categorization tasks. A key insight from these works is that semantics as captured by triplet embeddings are a natural way to represent complex class-structures when dealing with problems of high-dimensional categorization and greatly boost the ability of models to share information be-
Disentangling representations is a major topic in the recent machine learning literature and has for example been tackled using Boltzmann Machines by Reed et al. [16]. Chen et al. [5] propose information theoretical factorizations to improve unsupervised adversarial networks. Within this stream of research, the work closest to ours is that of Karalekos et al. [12] on representation learning which introduces a joint generative model over inputs and triplets to learn a factorized latent space. However, the focus of that work is the generative aspect of disentangling representations and proof of concept applications to low-dimensional data. Our work introduces a convolutional embedding architecture that forgoes the generative pathway in favor of exploring applications to embedding high-dimensional image data. We thus demonstrate that the generative interpretation is not required to reap the benefits of Multi-Query Networks and demonstrate in particular their use in common computer vision tasks.

A theme in our work is the goal of modeling separate learning signals within the same system by factorizing (or disentangling) latent spaces. We note the relation of these goals to a variety of approaches used in representation learning. Multi-view learning [20, 26] has been used for 3d shape inference and shown to generically be a good way to learn factorized latent spaces. Multiple kernel learning [3, 19] employs information encoded in different kernels to provide predictions using the synthesized complex feature space and has also been used for similarity-based learning by McFee and Lanckriet [15]. Multi-task learning approaches [7] are used when information from disparate sources or using differing assumptions can be combined beneficially for a final prediction task. Indeed, our gating mechanism can be interpreted as an architectural novelty in neural networks for multi-task triplet learning. Similar to our work, multilinear networks [14] also strive to factorize representations, but differ in that they ignore weak additional information. An interesting link also exists to multiple similarity learning [2], where category specific similarities are used to approximate a fine-grained global embedding. Our global factorized embeddings can be thought of as an approach to capture similar information in a shared space directly through feature learning.

We also discuss the notion of attention in our work, by employing gates to attend to the mentioned subspaces of the inferred embeddings when focusing on particular visual tasks. This term may be confused with spatial attention such as used in the DRAW model [9], but bears similarity insofar as it shows that the ability to gate the focus of the model on relevant dimensions (in our case in latent space rather than observed space) is beneficial both to the semantics and to the quantitative performance of our model.

3. Multi-Query Triplet Networks

Our goal is to learn a nonlinear feature embedding \( f(x) \), from an image \( x \) into a feature space \( \mathbb{R}^d \), such that for a pair of images \( x_1 \) and \( x_2 \), the Euclidean distance between \( f(x_1) \) and \( f(x_2) \) reflects their semantic dis-similarity. In particular, we strive for the distance between images of semantically similar objects to be small, and the distance between images of semantically different objects to be large. This relationship should hold independent of imaging conditions.

We consider \( y = Wg(x) \) to be an embedding of observed images \( x \) into coordinates in a feature space \( y \). Here, \( f(x) = Wg(x) \) clarifies that the embedding function is a composition of an arbitrarily nonlinear function \( g(\cdot) \) and a linear projection \( W \), for \( W \in \mathbb{R}^{d \times b} \), where \( d \) denotes the dimensions of the embedding and \( b \) stands for the dimensions of the output of the nonlinear function \( g(\cdot) \). In general, we denote the parameters of function \( f(x) \) by \( \theta \), denoting all the filters and weights.

3.1. Query-Dependent Triplets

Apart from observing images \( x \), we are also given a set of triplet constraints sampled from an oracle such as a crowd. We define triplet constraints in the following.

Given an unknown query-dependent similarity function \( s_Q(x_1, x_3) \), an oracle such as a crowd can compare images \( x_1 \), \( x_2 \) and \( x_3 \) according to a query \( Q \). A query is a certain notion of similarity according to which images can be compared. Figure [1] gives a few example queries according to which images of fashion products can be compared. The query \( Q \) serves as a switch between attended visual concepts and can effectively gate between different similarity functions \( s_Q \). Using image \( x_1 \) as reference, the oracle can apply \( s_Q(x_1, x_2) \) and \( s_Q(x_1, x_3) \) and decide whether \( x_1 \) is more similar to \( x_2 \) or to \( x_3 \) according to query \( Q \). The oracle then returns an ordering over these two distances, which we call a triplet \( t \). A triplet is defined as the set of indices \( \{x_1, x_3, x_2\} \) if \( s_Q(x_1, x_3) \) is larger than \( s_Q(x_1, x_2) \).
We define the set of all triplets related to query $Q$ as:

$$ T_Q = \{(i, j, l; Q) \mid s_Q(x_i, x_j) > s_Q(x_i, x_l)\}. \quad (1) $$

We do not have access to the exhaustive set $T_Q$, but can sample $K$-times from it using the oracle to yield a finite sample $T_Q^K = \{t_k\}_{k=1}^K$.

Triplets have also been generalized to quadruplets to encode analogical reasoning, but the key insight is that using more than pairwise relationships encodes higher-order knowledge with weak and distant supervision effectively. Therefore, triplets are at the core of the exhibition of our method as the simplest sufficient element to use implicit oracles for learning.

### 3.2. Learning From Triplets

The feature space spanned by our model is given by function $f(\cdot)$. To learn this nonlinear embedding and to be consistent with respect to the observed triplets, we define a loss function $L_T(\cdot)$ over triplets to model the similarity structure over images. The triplet loss function commonly used is

$$ L_T(x_i, x_j, x_k) = \max\{0, D(x_i, x_j) - D(x_i, x_k) + h\} \quad (2) $$

where $D(x_i, x_j) = \|f(x_i; \theta) - f(x_j; \theta)\|_2$ is the Euclidean distance between the representations of images $x_i$ and $x_j$. The scalar margin $h$ helps to prevent trivial solutions. The generic triplet loss is not capable of capturing the structure induced by multiple visual concepts, notions of similarities.

To be able to model the query-dependence, we introduce masks $m$ over the embedding with $m \in \mathbb{R}^{d \times n_q}$ where $n_q$ is the number of possible notions of similarities. We define a set of parameters $\beta_m$ of the same dimension as $m$ such that $m = \sigma(\beta)$, with $\sigma$ denoting the sigmoid function which ensures that mask values lie between 0 and 1. As such, we denote $m_q$ to be the selection of the $q$-th mask column of dimension $d$ (in pseudocode $m_q = m[:, q]$). The mask plays the role of an element-wise gating function selecting the relevant dimensions of the embedding required to attend to a particular concept. The role of the masking operation is visually sketched in Figure 3.

The query-aware masked distance function between two images $x_i$ and $x_j$ is given by

$$ D(x_i, x_j; m_q, \theta) = \|f(x_i; \theta)m_q - f(x_j; \theta)m_q\|_2. \quad (3) $$

While appearing to be a small technical change, the inclusion of a masking mechanism for the triplet-loss has a highly non-trivial effect. The mask induces a subspace over the relevant embedding dimensions, effectively attending only to the relevant dimensions for the visual concept being queried. In the loss function above, that translates into a modulated cost phasing out Euclidean distances between irrelevant feature-dimensions while preserving the loss-structure of the relevant ones. We borrow a term from neural network ensemble training and coin this procedure triplet distillation, since it leads to one joint network distilling multiple triplet networks into a compact architecture.

Given an triplet $t = \{i, j, k\}$ defined over indices of the observed images and a corresponding query-index $q$, the final triplet loss function $L_T(\cdot)$ is given by:

$$ L_T(x_i, x_j, x_k, q; m_q, \theta) = \max\{0, D(x_i, x_j; m_q, \theta) - D(x_i, x_k; m_q, \theta) + h\} \quad (4) $$

### 3.3. Encouraging Regular Embeddings

The embedding function we use is $y = f(x)$. We want to encourage embeddings to be drawn from a unit ball in order to maintain regularity in the latent space. We encode this in an embedding loss function $L_W$ given by:

$$ L_W(x; \theta) = \|f(x; \theta)\|^2 = \|y\|^2 \quad (5) $$

Without this term, an optimization scheme may choose to inflate embeddings to create space for new data points instead of learning appropriate parameters to encode the semantic structure.

### 3.4. Joint Formulation For Convolutional MQNs

We define a loss-function $L_{MQN}$ for training MQNs by putting together the defined loss functions. Given images $x$, triplet constraints with associated queries $\{t, q\}$ as well as parameters for the masks $m$ and the embedding function $\theta$, the MQN loss is defined as
\[
\mathcal{L}_{MQN}(x, \{t, q\}; m, \theta) = \\
\mathcal{L}_T(x_{t_0}, x_{t_1}, x_{t_2}, q; m, \theta) + \lambda \mathcal{L}_W(x, \theta) \tag{6}
\]

The parameter \(\lambda\) weights the contributions of the triplet terms against the regular embedding terms.

In our paper, the nonlinear embedding function \(f(x)\) is defined as \(f(x) = W g(x)\), where \(g(x)\) is a convolutional neural network. The masked learning procedure leads \(f(\cdot)\) towards solutions which are consistent with triplets over varying notions of similarity. As a consequence, different dimensions in the embedding encode features associated to specific semantic notions of similarity. Then, during test time each image can be mapped into this embedding by \(f(\cdot)\). By looking at the different dimensions of the image’s representation, one can reason about the different semantic notions of similarity. We call a feature space spanned by a function with this property \textit{disentangled}, as it preserves the separation of the similarity notions through test time.

4. Experiments

We focus our experiments on evaluating the quality of the learned embeddings and the underlying convolutional filters. We present experiments highlighting the semantic structure of the embeddings and their subspaces, the ability to predict unseen triplets and fine-grained out-of-task classification performance.

4.1. Datasets

We perform experiments on two different datasets. First, for illustrative purposes we use a dataset of fonts\(^1\) collected by Bernhardsson. The dataset contains 3.1 million images of single characters in gray scale with a size of 64 by 64 pixels each. The dataset exhibits variations according to font style and character type. In particular, it contains 62 different characters in 50,000 fonts, from which we use the first 1,000. Second, we use the Zappos50k shoe dataset\(^{28}\) collected by Yu and Grauman. The dataset contains 50,000 images of individual richly annotated shoes, with a size of 136 by 102 pixels each, which we resize to 112 by 112. The images exhibit multiple complex variations. In particular, we are looking into four different characteristics: the \textit{type} of the shoes (i.e., shoes, boots, sandals or slippers), the \textit{suggested gender} of the shoes (i.e., for women, men, girls or boys), the \textit{height} of the shoes’ heels (numerical measurements from 0 to 5 inches) and the \textit{closing mechanism} of the shoes (buckle, pull on, slip on, hook and loop or laced up). We also use the shoes’ brand information to perform a fine-grained classification test.

To supervise and evaluate the triplet networks, we sample triplet constraints from the annotations of the datasets. For the font dataset, we sample triplets such that two characters are of the same type or font and one is different. For the Zappos dataset, we sample triplets in an analogous way for the three categorical attributes. For the heel heights we have numerical measurements so that for each triplet we pick two shoes with similar height and one with different height. Overall, we sample 500k triplets for the type of shoes, 400k triplets for the heel heights and 200k triplets for the suggested gender as well as for the closure mechanism. We split them each into three parts: 70% for training, 10% for validation and 20% in the test set.

4.2. Baselines and Model Variants

As a base model for our experiments we use an ImageNet pre-trained ConvNet that we fine-tune using the sampled triplet constraints. All model variants are trained on the same set of triplets and only differ in the way they are trained. We compare four different approaches. A schematic illustration of the different approaches is given in Figure 6.

\begin{itemize}
  \item **Standard Triplet Network**: The common approach to learn from triplet constrains is a single Convolutional Network where the embedding layer receives supervision from the triplet loss defined in Equation \ref{triplet_loss}. As such, it aims to learn from all available triplets jointly as if they come from
\end{itemize}

\(^1\)http://erikbern.com/2016/01/21/analyzing-50k-fonts-using-deep-neural-networks/
embedding layer
Convolutional Network
(a) (b) (c) (d)
Figure 6. We show the four different model variants used in our experiments with the example of three objects being compared according to two contradictory notions of similarity, green and red.
(a) A standard triplet network that treats all triplets equally (b) An ensemble of \( n_q \)-many triplet network experts specialized on green or red, respectively (c) A learned MQN, where a mask is learned to select features relevant to the notion of similarity by learning a weight for each feature (d) A disentangled MQN, where the embedding layer of the ConvNet is set to be factorized so that each dimension encodes a feature for a specific notion of similarity.

Set of Task Specific Triplet Networks: Second, we compare to a set of \( n_q \) separate triplet network experts, each of which is trained on a single notion of similarity. This overcomes the simplifying assumption that all comparisons come from a single measure of similarity. However, this comes at the cost of significantly more parameters. This is the best model achievable with currently available methods.

Multi-Query Networks - learned masks: We compare two different variants of Multi-Query Networks. Both variants extend a standard triplet network with a masking operation on the embedding vector and supervise the network with the masked triplet loss defined in Equation 4. The first variant is primarily used for exploration. It learns the convolutional filters, the embedding as well as the mask parameters together. It has the disadvantage that the representation might not be fully disentangled and thus not as easily interpretable. However, the learned masks can provide interesting insight in how different similarity notions are related.

Multi-Query Networks - disentangled: The second variant learns the convolutional filters and the embedding. The masks are pre-defined to be disjoint between the different notions of similarity. This ensures that the underlying convolutional features need to be fully disentangled, because each dimension must encode features that describe a specific notion of similarity. Enforcing the features to be semantically meaningful has the additional benefit of making the representation interpretable.

4.3. Training Details

We train different convolutional networks for the two datasets. For the font dataset, we use a variant of the VGG architecture [18] with 9 layers of 3 by 3 convolutions and two fully connected layers, which we train from scratch. For the Zappos dataset we fine-tune an 18 layer deep residual network [11] that is pre-trained\(^2\) on Imagenet [8]. We remove one downsampling module to adjust for the smaller image size. We train the networks with a mini-batch size of 96 and optimize using ADAM [13] with \( \alpha = 1E-5 \), \( \beta_1 = 0.1 \) and \( \beta_2 = 0.001 \). For all our experiments we use an embedding dimension of 128 and the weight for the embedding loss \( \lambda \) is 5E-4. In each mini-batch we sample triplets uniformly and for each query in equal proportions. We perform early stopping once validation performance decreases over the duration of 400k triplets.

For our MQN variants, we use two masks over the embedding for the fonts dataset and four masks for the Zappos dataset, one mask per concept-specific query. For models with pre-defined masks, we allocate \( 1/n_q \)th of the embedding dimensions to one task. When learning masks, we initialize \( \beta_m \) using a normal distribution with 0 mean and 0.005 variance. Following the sigmoid, this results in initial mask values centered closely around 0.5, representing uncertainty about whether a latent dimension is important or not to a particular concept.

4.4. Visual Exploration of the Learned Subspaces

We visually explore the learned embeddings regarding their consistency according to respective queries. We stress that all of these semantic representations are taking place within a shared space produced by the same network. The representations are disentangled so that each dimension encodes a feature for a specific notion of similarity. This allows us to use a simple masking operation to look into a specific semantic subspace.

Figure 4 shows embeddings of the two subspaces in the Fonts dataset, which we project down to two dimensions using t-SNE [22]. The learned features are successfully disentangled such that the dimensions selected by the first mask describe the character type (left) and those selected by the second mask the font style (right). Figures 5 and 7 show embeddings of the four subspaces learned with an MQN on the Zappos50k dataset. Figure 5(a) shows the subspace encoding features for the closure mechanism of the shoes. Figure 5(b) shows the subspace attending to the type of the shoes. The embedding clearly separates the different types of shoes into boots, slippers and so on. Highlighted areas reveal some interesting details. For example, the highlighted region on the upper right side shows nearby images of the same type (’shoes’) that are completely different according to all other aspects. This means the selected feature dimensions successfully focus only on the type aspect and do not encode any of the other notions. Figure 7(a) shows the subspace for suggested gender for the shoes. The subspace sep-

\(^2\)https://github.com/facebook/fb.resnet.torch
4.5. Qualitative Analysis Of Subspaces

The key feature of MQNs is the fact that they can learn separated semantic subspaces in the embeddings. The driving force for the separation is both the existence of triplet information regarding multiple concepts as well as the masking mechanism that allows the model to learn from all these concepts jointly. We visualize the masks for our common model choices in Figure 8. We show the traditional triplet loss, where each dimension is equally taken into account for each triplet. Further, we show pre-defined masks that are used to factorize the embedding into fully disjoint features. Lastly, we show a learned mask, which shows that the model learns private and some shared features for each query. This speaks for the pre-defined disjoint masks as the ideal choice to learn separate semantic subspaces. The learned masks can be used as an exploratory tool as it reveals the shared structure between the subspaces.

4.6. Results on Triplet Prediction

To evaluate the quality of the learned embeddings by the different model variants, we test how well they generalize to unseen triplets. In particular, we perform triplet prediction on a test set of hold-out triplets from the Zappos50k dataset. We first train each model on a fixed set of triplets, where triplets are sourced from the four different notions of similarity. After convergence, we evaluate for each triplet with associated query \( \{i, j, k, q\} \) in the test set whether the distance between \( i \) and \( k \) is smaller than between \( i \) and \( j \) according to query \( q \). Since this is a binary task, random guessing would perform at an error rate of 50%.

The error rates for the different models are shown in Table 1. Standard Triplet Networks fail to capture fine-grained similarity and only reach a top error rate of 15.81%. The ensemble of task specific triplet networks greatly improves on that, achieving an error rate of 12.9%. This shows that simply learning a single space cannot capture multiple similarity notions. However, this comes at the cost of \( n_q \) times more model parameters. Multi-Query Networks with learned masks achieve an error rate of 6.68%, significantly improving over standard triplet networks. This indicates they can learn multiple similarity notions without requiring substantially more parameters. However, as shown in Figure 8(c), the masks do not fully separate the shared structure between the subspaces. MQNs with fully disentangled features achieve a top error rate of 0.74%, clearly outperforming both the single query networks as well as the ensemble of specialist networks, which have a lot more parameters available for learning. This means by factorizing the embedding space into separate semantic subspaces, MQNs can successfully capture multiple similarity notions. Moreover, MQNs benefit from learning all concepts jointly within one model, utilizing shared structure between the concepts while keeping the subspaces separated.

Further, we evaluate the impact of the number of unique triplets available during training on the performance. We compare models trained on 10k, 50k, 100k and all available unique triplets. Figure 9 shows that triplet networks generally improve with more available triplets.
Table 1. Triplet Prediction Results: We evaluate how many triplets of the testset are satisfied in the learned embeddings. Triplets come from four different similarity notions. The proposed Multi-Query Network clearly outperforms standard triplet networks. Moreover, MQNs even outperforms sets of specialist triplet networks where a lot more parameters are available during training and each network is specifically trained towards one similarity notion.

| Method                        | Error Rate |
|-------------------------------|------------|
| Standard Triplet Network      | 15.81%     |
| Set of Specialized Triplet Networks | 1.29%     |
| Ours learned masks            | 6.68%      |
| Ours fully disentangled        | 0.74%      |

### 4.7. Analysis of Convolutional Features Using Off-Task Classification

We now evaluate the convolutional features learned by our approach in comparison to standard triplet networks. Features learned with similarity-based methods such as triplet or siamese networks perform well in capturing subtle differences to learn semantic embeddings. However, they generally trade-off discriminating features for those fine-grained descriptive features. This could compromise the models’ classification performance and limit the transferability to other domains.

To evaluate the learned features, we perform an off-task classification task. In particular, we perform brand classification on the Zappos dataset, which is a task we did not collect any triplets for. We pick the 30 brands in the Zappos dataset with the most examples and select 254 each, split into 194 training, 20 validation and 40 test samples.

We compare standard triplet networks to fully disentangled MQNs, both initialized from the same ImageNet pretrained residual network. Both are fine-tuned using the same triplets and with their respective losses as described in Section 4.6. Then, we replace the last embedding layer for both networks with one hidden and one 30-way softmax classification layer. Finally, we train these layers for brand classification, keeping all convolutional filters fixed.

Table 2. Shoe brand classification accuracy using the ConvNet features fine-tuned with standard triplet networks and fully disentangled MQNs. Naively training a network with triplets from different similarity notions hurts the underlying convolutional features.

| Method                        | Top 1 Accuracy |
|-------------------------------|----------------|
| Standard Triplet Network      | 49.08%         |
| Ours fully disentangled        | 53.67%         |

The results are shown in Table 2. It is striking that the convolutional features fine-tuned by the standard triplet networks perform quite poorly compared to MQNs. In the triplet prediction experiment in Section 4.6 standard triplet networks do no perform well, as they are naturally limited by the fact that contradicting notions cannot be satisfied in one single space. This classification result documents that the problem reaches even deeper. The contradicting gradients do not stop at the embedding layer, instead, they expose the entire network to inconsistent learning signals and hurt the underlying convolutional features.

### 4.8. Further Discussion

Further, instead of being a black-box predictor, MQNs are qualitatively highly interpretable as evidenced by our exhibition of the semantic submanifolds they learn. Moreover, they provide a feature-exploration mechanism through the learned masks which surface the structure of the private and shared features between the different similarity aspects.

Lastly, we empirically find that naively training a triplet network with triplets generated through different similarity notions does not only limit the ability to correctly embed triplets, it also hurts the underlying convolutional features and thus generalization performance. The proposed MQNs are a simple to implement and easy to train end-to-end alternative to resolve these problems.

For future work, it would be interesting to consider learning from unlabeled triplets with a clustering mechanism to discover similarity substructures in an unsupervised way.

5. Conclusion

In this work, we propose Multi-Query Networks to learn nonlinear embeddings which incorporate multiple aspect of similarity within a shared embedding. The learned embeddings are disentangled such that each embedding dimension encodes semantic features for a specific aspect of similarity. This allows to compare objects according to various notions by selecting an appropriate subspace using an element-wise mask. We demonstrate that MQNs clearly outperform single triplet networks, and even sets of specialist triplet networks where a lot more parameters are available and each network is trained towards one similarity notion.

Further, instead of being a black-box predictor, MQNs are qualitatively highly interpretable as evidenced by our exhibition of the semantic submanifolds they learn. Moreover, they provide a feature-exploration mechanism through the learned masks which surface the structure of the private and shared features between the different similarity aspects.

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For future work, it would be interesting to consider learning from unlabeled triplets with a clustering mechanism to discover similarity substructures in an unsupervised way.
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