Generic Sketch-Based Retrieval Learned without Drawing a Single Sketch

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Abstract

We cast the sketch-based retrieval as edge-map matching. A shared convolutional network is trained to extract descriptors from edge maps and sketches, which are treated as a special case of edge maps. The network is fine-tuned solely from edge maps of landmark images. The training images are acquired in a fully unsupervised manner from 3D landmark models obtained by an automated structure-from-motion pipeline.

The proposed method achieves the state-of-the-art results on a standard benchmark. On two other fine-grained sketch-based retrieval benchmarks, it performs on par with or comes just after the method specifically designed for the dataset.

1. Introduction

Deep neural networks have recently become very popular for computer-vision problems, mainly due to their good performance and generalization. These networks have been first used for image classification in Krizhevsky et al. [25], then their application spread to other related problems. Instead of training from scratch, the task-specific network is initialized by a classification network and fine-tuned for the new problem. The fine-tuning approach reduces the amount of the task-specific annotation and has shown to be practical for image retrieval (query by image) as well as for sketch-based image retrieval (query by sketch).

The first successful image-retrieval application based on convolutional neural network (CNN) dates back to the work of Babenko et al. [3]. Since then, CNNs became a popular choice for image retrieval and different aspects of the training and search were addressed [24, 2, 35, 48]. Lately, the efficiency of the training data acquisition stage has attracted research attention [1, 34, 19].

Until recently, the sketch-based image retrieval has been handled with hand-crafted descriptors [18, 21, 37, 30, 51, 6, 32, 38, 52, 47]. Deep learning methods have been applied to the task of sketch-based retrieval [5, 33, 53, 39, 41, 27, 7] much later than to the related task of image retrieval. We attribute the delay to the fact that the training data acquisition for sketch-based retrieval is much more tedious compared to image retrieval because it not only includes labeling the images, but also sketches must be drawn in large quantities.

Most of the “shallow” methods of sketch-based image retrieval represent images with detected edge maps. Various algorithms of explicit edge-segments alignment were used to perform the retrieval [30, 9, 45]. Recent approaches based on deep neural networks exploit the end-to-end training of the network. It typically has two branches that embed
images and sketches respectively to a common descriptor space [7, 39]. These approaches use multi-stage training heuristics that combine a number of loss functions to overcome the lack of training data. The loss functions often include a category-level loss, which makes the sketch retrieval category/object dependent.

This paper addresses shape-based sketch retrieval. Instead of training two separate branches, we propose to unify the image and sketch domains by transforming images into edge maps. The key advantage of such a design is the ability to learn the shape similarity by fine-tuning an off-the-shelf CNN on cheap-to-obtain realistic training data using a simple contrastive loss function. Matching and non-matching training pairs are extracted from automatically generated 3D models of landmarks [34]. Edge maps detected on these images provide training data for the network. Example of positive and negative pairs of edge maps is shown in Figure 1.

We argue that the intermediate representation of edge maps is natural for sketch-based image retrieval. Looking at different sketch datasets, most of the drawings show outer boundaries of the objects and dominant edges within the objects, see Figure 2. Avoiding the category level penalty makes the proposed method generic and applicable beyond a fixed set of categories, or even beyond object search. On the contrary, methods using the category level loss in training are capable of retrieving images of objects from the same category as the sketch (if the category is included in the training set), even though the shape of the sketch does not match the shape of the depicted object. The proposed method does not have this capability. Nevertheless, it is questionable, whether a sketch is the best input for category search, if the shape does not matter.

Our trained network – identical network used for all tasks – achieves the state-of-the-art results on a standard sketch-based image retrieval benchmark. With no human annotation for the fine-tuning, it outperforms methods using man-years worth annotation and sketching in training. On two recent fine-grained benchmarks, the network performs on par with or comes after the methods specifically trained for the specific task, outperforming all other methods.

The applicability of the proposed method reaches beyond the sketch-based retrieval to problems, where the relevant information is carried by shape. Even though this is not the main focus of the paper, we show cases where standard image retrieval fails, while our proposed edge-map retrieval performs well. Namely, cross-modal retrieval with painting and retrieval under significant change of illumination.

The rest of the paper is organized as followed. Related work for sketch-based image retrieval is discussed in Section 2 and our training and search approach is presented in Section 3. Finally in Section 4 we evaluate our network on sketch-based retrieval and compare to the state of the art.

2. Related work

In this section we review prior work related to sketch-based image retrieval. It is divided into two categories based on whether a learning stage (training data) is involved or not. The methods with no learning typically carry no assumptions on the depicted categories, while the learning based methods often include the category recognition into training. The proposed method aims at generic sketch-based retrieval, not limited to a fixed set of categories; it is, actually, not even limited to objects.

**Learning-free methods.** As in the traditional image search, the line of research of sketch-based image retrieval has followed the same initial steps. These include the construction of either global [10, 37, 32] or local [17, 36, 21, 8, 51] image and/or sketch representations. Local representations are also using vector quantization to create a Bag-of-Words model [28]. The domain gap between hand-drawn sketches and images is handled by applying representations that are easily applicable on both domains. Histogram of Gradients [13] is a popular choice for both global [37, 32] and local representations [21]. The latter was also extended to color instances [6]. Further cases are symmetry-aware and flip invariant descriptors [8], and descriptors that are based on local contours [36] or line segments [51]. Recently, asymmetric feature maps (AFM) were used to derive a short vector image representation, that supports efficient scale and translation invariant sketch-based image retrieval [47]. Despite their small dimensionality, these short codes provide query localization in the retrieved image.

An efficient approximation of Chamfer matching allows [9, 45] to scale the searchable collections to millions or even billion images. However, precision is sacrificed along with the transformation invariance. In contrast, the method proposed in this paper offers high precision, is fully translation invariant, and scalable, because it reduces to a nearest-neighbor search in a descriptor space.

**Learning-based methods.** The learning-based approaches require annotated data in both domains. These typically come for a fixed set of object categories which makes the methods [50, 5, 33, 53, 39, 41, 27, 7] to be category specific and may limit good performance to those categories. End-to-end learning methods are applied to both
category level [27, 7] and to fine-grained, i.e. sub-category level [53, 39, 41] retrieval. In order to achieve high accuracy for specific tasks, even different models per category [26, 53, 44] are learned.

A common characteristic of these deep-learning methods [53, 39, 41, 27, 7] is that a sequence of different learning and fine-tuning stages is applied. These include training with a category loss on images and/or sketches, ranking loss of category level similarity, fine-grained similarity, and cross-view pairwise loss. Training data for all these stages are required, which involves massive manual effort at various stages. For example, the Sketchy dataset [39] required first going through 69,495 images and selecting those that are “sketchable”. For each of 12,500 sketchable images, around 5 sketches were drawn by 644 different users who collectively spent 3,921 hours sketching. Then, again, going through 75,741 sketches was required to exclude incorrect ones from the training. On the contrary, our proposed fine-tuning does not require any manual annotation.

An interesting concept was introduced in work by Shrivastava et al. [42] where discriminative features are learned by an exemplar classifier. There are no assumptions on the visual content but a different model needs to be trained per query. Design choices and datasets used are discussed in Section 4.4 for the most related approaches to ours.

3. Method

In this section we describe the proposed approach. First, the details of image pre-processing are given because it is common to both learning and search stage. Then, the process of fine-tuning the CNN is described in Section 3.1 and the sketch-based image search mechanism is detailed in Section 3.2.

Image representation. As discussed earlier, we break the end-to-end process of image description into two parts. In the first part, the images are turned into edge maps. In particular, throughout all our experiments we used the edge detector of Dollár and Zitnick [14] due to its great trade-off between efficiency and accuracy, and the tendency not to consider textured regions as edges.

An image is represented as an edge map, which is a 2D array containing the edge strength in each image pixel. The edge strength is in the range of $[0, 1]$, where 0 represents background. Sketches are represented as a special case of an edge map, where the edge strength is either 0 for the background or 1 for a contour.

3.1. Training

We use a network architecture previously proposed for image classification [43], in particular, we use all convolutional layers and the activations of the very last one, i.e., the network is stripped of the fully-connected layers. The CNN is initialized by the parameters learned on a large scale annotated image dataset, such as ImageNet [15]. This is a fairly standard approach adopted in a number of problems, including image search [1, 34, 19]. Our experiments show that such an approach already outperforms most prior hand-crafted work on a standard benchmark. The network is then fine-tuned to the specific task of sketch retrieval.

The network. The image classification network expects an RGB input image, while the edge maps are only two dimensional. We sum the first convolution filters over RGB. Unlike in RGB input, no mean pixel subtraction is performed to the input data.

To obtain a compact, shift invariant descriptor, a global max-pooling [35] layer is appended after the last convolutional layer. This approach is also known as Maximum Activations of Convolutions (MAC) vector [48]. After the MAC layer, the vectors are $\ell_2$ normalized.

Edge filtering. A typical output common to edge detectors is a strength of an edge in every pixel. We introduce an edge filtering layer to address two frequent issues with edge responses. First, the background often contains close-to-zero responses, which typically introduce noise into the repre-
representation. This issue is commonly handled by thresholding the response function. Second, the strength of the edges provides ordering, \(i.e.\) higher edge response implies that the edge is more likely to be present, however its value typically does not have practical interpretation. Prior to the first convolution layer, a continuous and differentiable function is pre-pended. This layer is trained together with the rest of the network to transform the edge detector output with soft thresholding by a sigmoid and power transformation. Denote the edge strength by \(w \in [0, 1]\). Edge filtering is performed as

\[
f(w) = \frac{w^p}{1 + e^{\beta(\tau - w)}},
\]

where \(p\) controls the contrast between strong and weak edges, \(\tau\) is the threshold parameter, and \(\beta\) is the scale of the sigmoid choosing between hard thresholding and a softer alternative. The final function (1) with learned parameters is plotted in Figure 3 (right). The figure also visually demonstrates the effect of application of the filtering. The weak edges are removed on the background and the result appearance is closer to a rough sketch (see Figure 2), while the uncertainty in edges is still preserved.

**Fine tuning.** The CNN is trained with Stochastic Gradient Descent in a Siamese fashion with contrastive loss [11]. The positive training pairs are edge maps of matching images (similarity of the edge maps is not considered), while the negative pairs are similar edge maps (according to the current state of the network) of non-matching images.

Given a pair of vectors \(x\) and \(y\), the loss is defined as their squared Euclidean distance \(|x - y|^2\) for positive examples, and as \(\max\{m - |x - y|^2, 0\}\) for negative examples. Hard-negative mining is performed several times per epoch which has been shown to be essential [34, 19].

**Training data.** The training images for fine tuning the network are collected in a fully automatic way. In particular, we use the publicly available dataset used in Radenovic et al. [34] and follow the same methodology, briefly reviewed in the following.

A large unordered image collection is passed through a 3D reconstruction system based on local features and Bag-of-Words retrieval [40]. The outcome consists of a set of 3D models which mostly depict outdoor landmarks and urban scenes. For each landmark, a maximum of 30 six-tuples of images are being selected. The six-tuple consists of: one image as the training query, then one matching image to the training query, and five similar non-matching images. This gives arise to one positive and five negative pairs. The geometry of the 3D models, including camera positions, allows the mine of the matching images, \(i.e.\) those that share adequate visual overlap. Negative-pair mining is facilitated by the 3D models, too: negative images are chosen only if they belong to a different model.

**Data augmentation.** A standard data-augmentation, \(i.e.\) random horizontal flipping (mirroring) procedure is applied to introduce further variance in the training data and to avoid over-fitting. The training query and the positive example are jointly mirrored with 50% probability. Negative examples are sought after eventual flipping.

In order to bring the edge maps and the sketches closer, we propose an additional augmentation technique that simulates sketch queries. For selected training queries, the edge map responses are thresholded with a random threshold uniformly chosen from \([0, 0.2]\) and the result is binarized. Matching images (in positive examples) are left unchanged; negative images are selected after the transformation. This augmentation process is applied with a probability of 50%. It mimics the asymmetry of sketch-to-edge map matching. The randomized threshold can be also seen as an approximation of the stroke removal in [53].

### 3.2. Indexing and Search

**Sketch pre-processing.** The sketches come in the form of strokes, thin line drawings, or brush drawings, depending on the input device (or the dataset). To unify the sketch input, a simple morphological filter is applied to a binary sketch image. Specifically, a morphological thinning followed by dilation is performed. After the pre-processing, the sketch is treated as an edge map.

**Indexing.** Each image is first passed to an edge detector. The edge map is then transformed by the CNN into a descriptor, which is stored in the database. For multi-scale representation with mirroring, MAC descriptors are extracted for a number of edge maps obtained from re-scaled and mirrored versions of the image. The individual descriptors are sum-aggregated into a single descriptor, which is finally \(l_2\) re-normalized.

**Search.** The sketch-based image retrieval is performed by a nearest-neighbors search of the query descriptor in the database. This makes retrieval compatible with approximate methods [29, 23] that can speed up search and offer memory savings.

**Performance boosting.** Query Expansion [12] (QE) is a popular technique in image retrieval to boost the recall of the retrieval system. It was shown that QE gives the best results with spatial verification, as it prevents from a topic drift. QE has been used in sketch-based image retrieval approach [47], where sketch matching is performed as an initial stage and then only image appearance matching is used to perform QE. A similar concept is used by Battacharjee et al. [5] who perform max-flow on a graph of top-K retrieved region proposals. To boost the recall of our sketch-based retrieval, we employ global diffusion, as recently proposed by Iscen et al. [22]. The ranking is based on a neighborhood graph, which is a mutual kNN-graph of
a dataset. We construct the neighborhood graph by combining kNN-graphs built on two different similarities [4, 55]: edge-map similarity and image similarity. The image descriptors are generated using an off-the-shelf CNN [43] and are used only for the kNN-graph construction, unlike [47, 5] where the image descriptors had to be stored together with the sketch descriptors.

4. Experiments

In this section we discuss implementation details and present the training and test datasets. We evaluate our method and show an improvement on different tasks, while we finally compare to the state of the art.

4.1. Training and implementation details

Training data. We use the same training set as in the work of Radenovic et al. [34]¹ which comprises landmarks and urban scenes. There are around 8k tuples, each containing a query, a positive and 5 negative images. Due to overlap of the landmarks contained in the training set and one of the test sets involved in our evaluation, we manually excluded these landmarks from our training data. We end up with with 5,969 tuples for training and 1,696 for validation. Hard negatives are re-mined 3 times per epoch [34] from a pool of around 22k images.

Training implementation. We use the MatConvNet toolbox [49] to implement the learning. We initialize the convolutional layers by VGG16 [43] trained on ImageNet and sum the filters of the first layer over the feature maps dimension to accommodate for the 2D edge-map input instead of the 3D image. The edge-filtering layer is initialized with values \( p = 0.5, \tau = 0.1 \) and \( \beta \) is fixed and equal to 500 so that it always approximates hard thresholding. Additionally, the output of the egde-filtering layer is linearly scaled from 0 to 1. \( \sqrt{\tau}, \sqrt{2}, \) and, with the additional mirroring, 6 edge maps are produced. Sum-aggregation and \( \ell_2 \)-normalization produce a single descriptor which we refer to as EdgeMAC descriptor. Multi-scale representation and mirroring offer improvements as shown in Table 1.

| Component          | Network |
|--------------------|---------|
| Train/Test: Edge filtering | O F F F F F F |
| Train: Query binarization   | ■ ■ ■ ■ ■ ■ |
| Test: Mirroring          | ■ ■ ■ ■ ■ ■ |
| Test: Multi-scale        | ■ ■ ■ ■ ■ ■ |
| Test: Diffusion           | ■ ■ ■ ■ ■ ■ |

mAP 25.9 27.9 38.4 42.0 43.8 45.6 46.3 68.9

Table 1. Performance evaluation of the different components of our method on Flickr15k dataset. Network: off-the-shelf (O), fine-tuned (F).

²Training data available at cmp.felk.cvut.cz/cnnimageretrieval

4.2. Test datasets and evaluation protocols

The method is evaluated on three standard sketch-based image retrieval benchmarks.

Flickr15k [21]. This dataset consists of 15k database images and 330 sketch queries that are related to 33 categories. Categories include particular object instances (Brussels Cathedral, Colosseum, Arc de Triomphe, etc.), generic objects (airplane, bicycle, bird, etc.), and shapes (circle shape, star shape, heart, balloon, etc.). The performance is measured via mean Average Precision (mAP) [31].

Shoes/Chairs [53]. These two datasets contain images from one category only, i.e. shoe/chair category respectively. It consists of pairs of a photo and a corresponding hand-drawn detailed sketch of this photo. There are 419 and 297 sketch–photo pairs of shoes and chairs respectively. Out of these, 304 (200) pairs are selected for training, and 115 (97) for testing shoes (chairs). We do not use the training set in this work, but only the test set for evaluation purposes. Performance is measured via the matching accuracy at the top K retrieved images, denoted by acc.@K. The underlying task is quite different compared to Flickr15k. The photograph used to generate the sketch is to be retrieved, while all other images are considered false positives.

Sketchy [39]. This dataset consists of 12,500 images and 75,471 sketches (roughly 5 sketches per photo), spanning 125 categories of common objects like horse, apple, axe, guitar etc. The held out test part consists of 1,250 database photos and 6,312 query sketches, still spanning the same 125 categories. We do not use the training set in this work, but only the test set for evaluation purposes. Each sketch query is associated to a single matching image, the one that
prompted the creation of this particular sketch. This puts the task somewhat between Flickr15k and Shoes/Chairs dataset task. Performance is measured via recall at various ranks, where recall@K is basically the same as acc.@K of the Shoes/Chairs dataset.

4.3. Analysis of the method

Impact of different components. Table 1 shows the impact of different components on the final performance of the proposed method as measured on Flickr15k dataset. Direct application of the off-the-shelf CNN on edge maps already outperforms most prior hand-crafted methods (see Table 2). Adding the edge-filtering layer to the off-the-shelf network improves the precision. The initial parameters for filtering are used. Fine-tuning brings significant jump to 38.4 mAP, which is already the state-of-the-art on this dataset. Random training-query binarization and multi-scale with mirroring representation further improve the mAP score to 46.3.

Finally, the diffusion process based on the combination of edge-map and image similarity kNN graphs boosts the performance to 68.9 mAP. To compute the image similarity, we extract CroW descriptors [24] from real images using the off-the-shelf VGG network. The proposed diffusion was superior to alternative methods: average QE on edge-map descriptors (57.3 mAP), average QE on image descriptors (61.7 mAP – needs additional set of descriptors), diffusion on edge-map kNN graph (66.2 mAP), and diffusion on image kNN graph (65.9 mAP).

Performance evolution during learning. We report the performance of the fine-tuned network at different stages (epochs) of training. The same network is evaluated for all datasets as we train a single network for all tasks. The performance is shown in Figure 4 for all three datasets. On all datasets, the fine-tuning significantly improves the performance already from the first few epochs.

As a sanity check, we also perform a non-standard sketch-to-sketch evaluation. On the Flickr15k dataset, each of the 330 sketches is used to query the other 329 sketches (the query sketch is removed from the evaluation), which attempts to retrieve sketches of the same category. On the Sketchy dataset, each of the 6,312 sketches is used to query the rest of the sketches. The goal is to retrieve sketches generated from the same image. Sketches from the same category but from different images are removed from the evaluation. The sketch-to-sketch retrieval is evaluated by mAP and the performance is presented in Figure 4. The evolution of the performance shows similar behavior as the sketch-to-image search, i.e., the learning on edge maps improves the performance on sketch-to-sketch retrieval.

4.4. Comparison with the state of the art

We extensively compare our method to the state-of-the-art performing methods on all three test datasets. Whenever code and trained models are publicly available, we additionally evaluate them on test sets they were not originally applied on. In cases that the provided code is used for evaluation on Flickr15k we center and align the sketches appropriately in order to achieve high scores, while our method is translation invariant so there is no such need. First we give a short overview of the best performing and most relevant methods to ours. Finally, a comparison via quantitative results is given.

Siamese network [33]. This is a two-branch network, with a newly proposed architecture that is similar to Sketch-a-Net [54]. Training is performed from scratch with contrastive loss on Flickr15k dataset. Training pairs are selected by randomly choosing a sketch and its category-level positive and negative image. Then, the sketch is fed in one and the image edge map in the other branch.
Shoes/Chairs network [53]. These two networks are obtained by training the Sketch-a-Net architecture from scratch. This is achieved by the following steps:\(^2\): (i) Training with classification loss for 1k categories from ImageNet-1K data with edge maps input. (ii) Training with classification loss for 250 categories of TU-Berlin [16] sketch data. (iii) Training a triplet network with shared weights and ranking loss on TU-Berlin sketches and ImageNet images. (iv) Finally, training separate networks for fine-grain instance-level ranking using the Shoes/Chairs training datasets. Their training involves various datasets with annotation at different levels.

TU-Berlin network [39]. This network is a baseline considered in [39]. It is a GoogLeNet [46] network fine-tuned for classification with the 250 sketch categories from TU-Berlin dataset. Edge maps are used as an input for photos during testing time. This is the only network in the work of [39] that is evaluated on the Sketchy test dataset without being trained on its training counter-part.

Sketchy network [39]. This network consists of two asymmetric sketch and image branches, both initialized with GoogLeNet. The training involves the following steps:\(^3\):

(i) Training for classification on TU-Berlin sketch dataset. (ii) Separate training of the sketch branch with classification loss on 125 categories of Sketchy dataset and training of the image branch with classification loss on the same categories with additional 1000 Flickr photos per category. (iii) Training both branches in a triplet network with ranking loss on the Sketchy sketch–photo pairs. The last part involves approximately 100k positive and a billion negative pairs.

Quadruplet network [41]. This network tackles the problem in a similar way as Sketchy network, however, they use ResNet-18 [20] architecture with shared weights for both sketch and image branches. The training involves the following steps: (i) Training with classification loss on Sketchy dataset. (ii) Training a network with triplet loss on Sketchy dataset, while mining three different types of triplets.

Triplet no-share network [7]. This network consists of two asymmetric sketch and image branches initialized with Sketch-a-Net and AlexNet [25], respectively. The training involves the following steps: (i) Separate training of the sketch branch with classification loss on TU-Berlin and training of the image branch with classification loss on Im-

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\(^2\)Networks/code available at github.com/seulifeng/DeepSBIR

\(^3\)Network/code available at github.com/janesjanes/sketchy
Figure 5. We show retrieval examples for two query images collected from Flickr depicting Bridge of Sighs: a painting (top example), and a dark night image (bottom example). Retrieval is performed on the Oxford Buildings dataset with two networks: a network that expects RGB input and is trained for retrieval [34] (top row), and our network that expects edge-map input (bottom row). Correct matches are drawn with green border, incorrect with red.

ageNet. (ii) Training a triplet network with ranking loss on TU-Berlin sketches augmented with 25k corresponding photos harvested from the Internet. (iii) Training a triplet network with ranking loss on the Sketchy dataset.

Performance comparison. We compare our performance on all 3 test sets with other methods. For methods that have not reported scores on a particular data, we evaluate using the publicly available networks. Our results are achieved by the plain network to allow for a direct and fair comparison. Diffusion is only used to compare against other methods that perform re-ranking or QE and this is explicitly stated.

Results on the Flickr15k dataset are presented in Table 2, where our method significantly outperforms both hand-crafted descriptors and CNN-based that are learned on a variety of training data.

Results on Shoes/Chairs datasets are shown in Table 3, where our method that uses a single network for both cases is the best performing on Chairs and the second best on Shoes. This achievement supports the claim for generic purpose of our network which in contrast to [53] has not used the Shoes/Chairs training set. Interestingly, our method significantly outperforms the Sketchy network, even though its training data contained the shoe and chair category.

Finally, on the Sketchy dataset, our method is ranked right after methods specifically trained on Sketchy and designed for the particular task, see Table 4. The Sketchy network [39] and the Quadruplet network [41] are very well tuned for this particular task and dataset, outperforming other approaches by a large margin. On other datasets, the performance of these networks is good, but inferior to a number of other approaches.

Further applications. The proposed method can be applied beyond the sketch-based image retrieval, in the problems where the reliable information is represented by the shape. This includes the matching of the different modalities or severe changes in the illumination. We present two examples where retrieval is performed on the Oxford Buildings image retrieval dataset [31]. The queries are a painting and a night image of the Bridge of Sighs, downloaded from Flickr. We qualitatively compare our network (edge-map to edge-map retrieval) and a network that is particularly trained for the task of image retrieval [34] and takes an RGB image as an input, see Figure 5.

5. Conclusions

We have introduced a sketch-based image retrieval method that is based on edge maps matching. Image edge maps and sketches, which are treated as a special case of an edge map, are transformed into 512 dimensional descriptor by a shared CNN. The training data for the network are obtained in a fully automated manner exploiting edge maps of landmark images.

The proposed method achieves the state-of-the-art results on a standard benchmark, namely Flickr15k. On two other datasets it performs on par with or came just after the method specifically designed for the dataset. Training edge-map data, trained network, training, and testing code publicly available4.

We have further demonstrated the applicability beyond sketch-based image retrieval. Promising results were achieved for queries with different modality (painting) and significant change of illumination (day-night retrieval).

4Network/code available at cmp.felk.cvut.cz/cnnimageretrieval
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