NetVLAD: CNN architecture for weakly supervised place recognition

Relja Arandjelović INRIA *
Petr Gronat INRIA*
Akihiko Torii Tokyo Tech †
Tomas Pajdla CTU in Prague ‡
Josef Sivic INRIA*

Abstract

We tackle the problem of large scale visual place recognition, where the task is to quickly and accurately recognize the location of a given query photograph. We present the following three principal contributions. First, we develop a convolutional neural network (CNN) architecture that is trainable in an end-to-end manner directly for the place recognition task. The main component of this architecture, NetVLAD, is a new generalized VLAD layer, inspired by the "Vector of Locally Aggregated Descriptors" image representation commonly used in image retrieval. The layer is readily pluggable into any CNN architecture and amenable to training via backpropagation. Second, we develop a training procedure, based on a new weakly supervised ranking loss, to learn parameters of the architecture in an end-to-end manner from images depicting the same places over time downloaded from Google Street View Time Machine. Finally, we show that the proposed architecture significantly outperforms non-learnt image representations and off-the-shelf CNN descriptors on two challenging place recognition benchmarks, and improves over current state-of-the-art compact image representations on standard image retrieval benchmarks.

1. Introduction

Visual place recognition has received a significant amount of attention in the past years both in computer vision [5, 10, 11, 24, 35, 62, 63, 64, 65, 79, 80] and robotics communities [16, 17, 44, 46, 74] motivated by, *e.g*., applications in autonomous driving [46], augmented reality [47] or geo-localizing archival imagery [6].

The place recognition problem, however, still remains extremely challenging. How can we recognize the same street-corner in the entire city or on the scale of the entire country despite the fact it can be captured in different illuminations or change its appearance over time? The fundamental scientific question is what is the appropriate representation of a place that is rich enough to distinguish similarly looking places yet compact to represent entire cities or countries.

(a) Mobile phone query (b) Retrieved image of same place

Figure 1. Our trained NetVLAD descriptor correctly recognizes the location (b) of the query photograph (a) despite the large amount of clutter (people, cars), changes in viewpoint and completely different illumination (night vs daytime). **Please see the appendix [2] for more examples.**

The place recognition problem has been traditionally cast as an instance retrieval task, where the query image location is estimated using the locations of the most visually similar images obtained by querying a large geotagged database [5, 11, 35, 65, 79, 80]. Each database image is represented using local invariant features [82] such as SIFT [43] that are aggregated into a single vector representation for the entire image such as bag-of-visual-words [53, 73], VLAD [4, 29] or Fisher vector [31, 52]. The resulting representation is then usually compressed and efficiently indexed [28, 73]. The image database can be further augmented by 3D structure that enables recovery of accurate camera pose [40, 62, 63].

In the last few years convolutional neural networks (CNNs) [38, 39] have emerged as powerful image representations for various category-level recognition tasks such as object classification [37, 49, 72, 76], scene recognition [89] or object detection [22]. The basic principles of CNNs are known from 80's [38, 39] and the recent successes are a combination of advances in GPU-based computation power together with large labelled image datasets [37]. While it has been shown that the trained representations are, to some extent, transferable between recognition tasks [20, 22, 49, 68, 87], a direct application of CNN representations trained

*WILLOW project, Departement d'Informatique de l'École Normale Supérieure, ENS/INRIA/CNRS UMR 8548.
†Department of Mechanical and Control Engineering, Graduate School of Science and Engineering, Tokyo Institute of Technology
‡Center for Machine Perception, Department of Cybernetics, Faculty of Electrical Engineering, Czech Technical University in Prague

for object classification [37] as black-box descriptor extractors has so far yielded limited improvements in performance on instance-level recognition tasks [7, 8, 23, 60, 61]. In this work we investigate whether this gap in performance can be bridged by CNN representations developed and trained directly for place recognition. This requires addressing the following three main challenges. First, what is a good CNN architecture for place recognition? Second, how to gather sufficient amount of annotated data for the training? Third, how can we train the developed architecture in an end-to-end manner tailored for the place recognition task? To address these challenges we bring the following three innovations.

First, building on the lessons learnt from the current well performing hand-engineered object retrieval and place recognition pipelines [3, 4, 25, 79] we develop a convolutional neural network architecture for place recognition that aggregates mid-level (conv5) convolutional features extracted from the entire image into a compact single vector representation amenable to efficient indexing. To achieve this, we design a new trainable generalized VLAD layer, NetVLAD, inspired by the Vector of Locally Aggregated Descriptors (VLAD) representation [29] that has shown excellent performance in image retrieval and place recognition. The layer is readily pluggable into any CNN architecture and amenable to training via backpropagation. The resulting aggregated representation is then compressed using Principal Component Analysis (PCA) to obtain the final compact descriptor of the image.

Second, to train the architecture for place recognition, we gather a large dataset of multiple panoramic images depicting the same place from different viewpoints over time from the Google Street View Time Machine. Such data is available for vast areas of the world, but provides only weak form of supervision: we know the two panoramas are captured at approximately similar positions based on their (noisy) GPS but we don't know which parts of the panoramas depict the same parts of the scene.

Third, we develop a learning procedure for place recognition that learns parameters of the architecture in an end-to-end manner tailored for the place recognition task from the weakly labelled Time Machine imagery. The resulting representation is robust to changes in viewpoint and lighting conditions, while simultaneously learns to focus on the relevant parts of the image such as the building façades and the skyline, while ignoring confusing elements such as cars and people that may occur at many different places.

We show that the proposed architecture significantly outperforms non-learnt image representations and off-the-shelf CNN descriptors on two challenging place recognition benchmarks, and improves over current state-of-the-art compact image representations on standard image retrieval benchmarks.

1.1. Related work

While there have been many improvements in designing better image retrieval [3, 4, 12, 13, 18, 25, 26, 27, 29, 32, 48, 51, 52, 53, 54, 70, 77, 78, 81] and place recognition [5, 10, 11, 16, 17, 24, 35, 44, 46, 62, 63, 64, 74, 79, 80] systems, not many works have performed learning for these tasks. All relevant learning-based approaches fall into one or both of the following two categories: (i) learning for an auxiliary task (*e.g.* some form of distinctiveness of local features [5, 16, 30, 35, 58, 59, 88]), and (ii) learning on top of shallow hand-engineered descriptors that cannot be fine-tuned for the target task [3, 10, 24, 35, 57]. Both of these are in spirit opposite to the core idea behind deep learning that has provided a major boost in performance in various recognition tasks: end-to-end learning. We will indeed show in section 5.2 that training representations directly for the end-task, place recognition, is crucial for obtaining good performance.

Numerous works concentrate on learning better local descriptors or metrics to compare them [45, 48, 50, 55, 56, 69, 70, 86], but even though some of them show results on image retrieval, the descriptors are learnt on the task of matching local image patches, and not directly with image retrieval in mind. Some of them also make use of hand-engineered features to bootstrap the learning, *i.e.* to provide noisy training data [45, 48, 50, 55, 70].

Several works have investigated using CNN-based features for image retrieval. These include treating activations from certain layers directly as descriptors by concatenating them [9, 60], or by pooling [7, 8, 23]. However, none of these works actually train the CNNs for the task at hand, but use CNNs as black-box descriptor extractors. One exception is the work of Babenko *et al.* [9] in which the network is fine-tuned on an auxiliary task of classifying 700 landmarks. However, again the network is not trained directly on the target retrieval task.

Finally, recently [34] and [41] performed end-to-end learning for different but related tasks of ground-to-aerial matching [41] and camera pose estimation [34].

2. Method overview

Building on the success of current place recognition systems (*e.g.* [5, 11, 35, 62, 63, 64, 65, 79, 80]), we cast place recognition as image retrieval. The query image with unknown location is used to visually search a large geotagged image database, and the locations of top ranked images are used as suggestions for the location of the query. This is generally done by designing a function f which acts as the "image representation extractor", such that given an image I_i it produces a fixed size vector $f(I_i)$. The function is used to extract the representations for the entire database $\{I_i\}$, which can be done offline, and to extract the query image representation $f(q)$, done online. At test time, the visual search is performed by finding the nearest database image to the query, either exactly or through fast approximate nearest neighbour search, by sorting images based on the Euclidean distance $d(q, I_i)$ between $f(q)$ and $f(I_i)$.

While previous works have mainly used hand-engineered image representations (*e.g.* $f(I)$ corresponds to extracting SIFT descriptors [43], followed by pooling into a bag-of-words vector [73] or a VLAD vector [29]), here we propose to learn the representation $f(I)$ in an end-to-end manner, directly optimized for the task of place recognition. The representation is parametrized with a set of parameters θ and we emphasize this fact by referring to it as $f_\theta(I)$. It follows that the Euclidean distance $d_\theta(I_i, I_j) = \|f_\theta(I_i) - f_\theta(I_j)\|$ also depends on the same parameters. An alternative setup would be to learn the distance function itself, but here we choose to fix the distance function to be Euclidean distance, and to pose our problem as the search for the explicit feature map f_θ which works well under the Euclidean distance.

In section 3 we describe the proposed representation f_θ based on a new deep convolutional neural network architecture inspired by the compact aggregated image descriptors for instance retrieval. In section 4 we describe a method to learn the parameters θ of the network in an end-to-end manner using weakly supervised training data from the Google Street View Time Machine.

3. Deep architecture for place recognition

This section describes the proposed CNN architecture f_θ, guided by the best practises from the image retrieval community. Most image retrieval pipelines are based on (i) extracting local descriptors, which are then (ii) pooled in an orderless manner. The motivation behind this choice is that the procedure provides significant robustness to translation and partial occlusion. Robustness to lighting and viewpoint changes is provided by the descriptors themselves, and scale invariance is ensured through extracting descriptors at multiple scales.

In order to learn the representation end-to-end, we design a CNN architecture that mimics this standard retrieval pipeline in an unified and principled manner with differentiable modules. For step (i), we crop the CNN at the last convolutional layer and view it as a dense descriptor extractor. This has been observed to work well for instance retrieval [7, 8, 61] and texture recognition [14]. Namely, the output of the last convolutional layer is a $H \times W \times D$ map which can be considered as a set of D-dimensional descriptors extracted at $H \times W$ spatial locations. For step (ii) we design a new pooling layer inspired by the Vector of Locally Aggregated Descriptors (VLAD) [29] that pools extracted descriptors into a fixed image representation and its parameters are learnable via back-propagation. We call this new pooling layer "NetVLAD" layer and describe it in the next section.

3.1. NetVLAD: A Generalized VLAD layer (f_{VLAD})

Vector of Locally Aggregated Descriptors (VLAD) [29] is a popular descriptor pooling method for both instance level retrieval [29] and image classification [23]. It captures information about the statistics of local descriptors aggregated over the image. Whereas bag-of-visual-words [15, 73] aggregation keeps counts of visual words, VLAD stores the sum of residuals (difference vector between the descriptor and its corresponding cluster centre) for each visual word.

Formally, given N D-dimensional local image descriptors $\{\mathbf{x}_i\}$ as input, and K cluster centres ("visual words") $\{\mathbf{c}_k\}$ as VLAD parameters, the output VLAD image representation V is $K \times D$-dimensional. For convenience we will write V as a $K \times D$ matrix, but this matrix is converted into a vector and, after normalization, used as the image representation. The (j, k) element of V is computed as follows:

$$V(j,k) = \sum_{i=1}^{N} a_k(\mathbf{x}_i)\left(x_i(j) - c_k(j)\right), \qquad (1)$$

where $x_i(j)$ and $c_k(j)$ are the j-th dimensions of the i-th descriptor and k-th cluster centre, respectively. $a_k(\mathbf{x}_i)$ denotes the membership of the descriptor $\mathbf{x}_i$ to k-th visual word, *i.e.* it is 1 if cluster $\mathbf{c}_k$ is the closest cluster to descriptor $\mathbf{x}_i$ and 0 otherwise. Intuitively, each D-dimensional column k of V records the sum of residuals $(\mathbf{x}_i - \mathbf{c}_k)$ of descriptors which are assigned to cluster $\mathbf{c}_k$. The matrix V is then L2-normalized column-wise (intra-normalization [4]), converted into a vector, and finally L2-normalized in its entirety [29].

In order to profit from years of wisdom produced in image retrieval, we propose to mimic VLAD in a CNN framework and design a trainable generalized VLAD layer, *NetVLAD*. The result is a powerful image representation trainable end-to-end on the target task (in our case place recognition). To construct a layer amenable to training via backpropagation, it is required that the layer's operation is differentiable with respect to all its parameters and the input. Hence, the key challenge is to make the VLAD pooling differentiable, which we describe next.

The source of discontinuities in VLAD is the hard assignment $a_k(\mathbf{x}_i)$ of descriptors $\mathbf{x}_i$ to clusters centres $\mathbf{c}_k$. To make this operation differentiable, we replace it with soft assignment of descriptors to multiple clusters

$$\bar{a}_k(\mathbf{x}_i) = \frac{e^{-\alpha\|\mathbf{x}_i - \mathbf{c}_k\|^2}}{\sum_{k'} e^{-\alpha\|\mathbf{x}_i - \mathbf{c}_{k'}\|^2}}, \qquad (2)$$

which assigns the weight of descriptor $\mathbf{x}_i$ to cluster $\mathbf{c}_k$ proportional to their proximity, but relative to proximities to

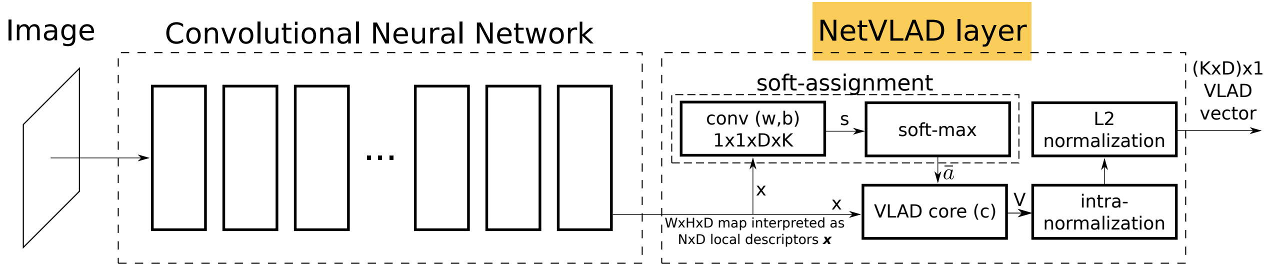


Figure 2. **CNN architecture with the NetVLAD layer.** The layer can be implemented using standard CNN layers (convolutions, softmax, L2-normalization) and one easy-to-implement aggregation layer to perform aggregation in equation (4) ("VLAD core"), joined up in a directed acyclic graph. Parameters are shown in brackets.

other cluster centres. $\bar{a}_k(\mathbf{x}_i)$ ranges between 0 and 1, with the highest weight assigned to the closest cluster centre. α is a parameter (positive constant) that controls the decay of the response with the magnitude of the distance. Note that for $\alpha \to +\infty$ this setup replicates the original VLAD exactly as $\bar{a}_k(\mathbf{x}_i)$ for the closest cluster would be 1 and 0 otherwise.

By expanding the squares in (2), it is easy to see that the term $e^{-\alpha\|\mathbf{x}_i\|^2}$ cancels between the numerator and the denominator resulting in a soft-assignment of the following form

$$\bar{a}_k(\mathbf{x}_i) = \frac{e^{\mathbf{w}_k^T\mathbf{x}_i+b_k}}{\sum_{k'} e^{\mathbf{w}_{k'}^T\mathbf{x}_i+b_{k'}}}, \tag{3}$$

where vector $\mathbf{w}_k = 2\alpha\mathbf{c}_k$ and scalar $b_k = -\alpha\|\mathbf{c}_k\|^2$. The final form of the NetVLAD layer is obtained by plugging the soft-assignment (3) into the VLAD descriptor (1) resulting in

$$V(j,k) = \sum_{i=1}^{N} \frac{e^{\mathbf{w}_k^T\mathbf{x}_i+b_k}}{\sum_{k'} e^{\mathbf{w}_{k'}^T\mathbf{x}_i+b_{k'}}} \left(x_i(j) - c_k(j)\right), \tag{4}$$

where $\{\mathbf{w}_k\}$, $\{b_k\}$ and $\{\mathbf{c}_k\}$ are sets of trainable parameters for each cluster k. Similarly to the original VLAD descriptor, the NetVLAD layer aggregates the first order statistics of residuals $(\mathbf{x}_i - \mathbf{c}_k)$ in different parts of the descriptor space weighted by the soft-assignment $\bar{a}_k(\mathbf{x}_i)$ of descriptor $\mathbf{x}_i$ to cluster k. Note however, that the NetVLAD layer has three independent sets of parameters $\{\mathbf{w}_k\}$, $\{b_k\}$ and $\{\mathbf{c}_k\}$, compared to just $\{\mathbf{c}_k\}$ of the original VLAD. This enables greater flexibility than the original VLAD, as explained in figure 3. Decoupling $\{\mathbf{w}_k, b_k\}$ from $\{\mathbf{c}_k\}$ has been proposed in [4] as a means to adapt the VLAD to a new dataset. All parameters of NetVLAD are learnt for the specific task in an end-to-end manner.

As illustrated in figure 2 the NetVLAD layer can be visualized as a meta-layer that is further decomposed into basic CNN layers connected up in a directed acyclic graph. First, note that the first term in eq. (4) is a soft-max function $\sigma_k(\mathbf{z}) = \frac{\exp(z_k)}{\sum_{k'}\exp(z_{k'})}$. Therefore, the soft-assignment of the input array of descriptors $\mathbf{x}_i$ into K clusters can be seen as a two step process: (i) a convolution with a set of K filters $\{\mathbf{w}_k\}$ that have spatial support 1×1 and biases $\{b_k\}$, producing the output $s_k(\mathbf{x}_i) = \mathbf{w}_k^T\mathbf{x}_i + b_k$; (ii) the convolution output is then passed through the soft-max function σ_k to obtain the final soft-assignment $\bar{a}_k(\mathbf{x}_i)$ that weights the different terms in the aggregation layer that implements eq. (4). The output after normalization is a $(K \times D) \times 1$ descriptor.

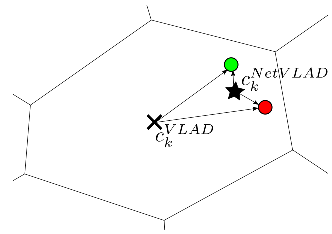


Figure 3. **Benefits of supervised VLAD.** Red and green circles are local descriptors from two different images, assigned to the same cluster (Voronoi cell). Under the VLAD encoding, their contribution to the similarity score between the two images is the scalar product (as final VLAD vectors are L2-normalized) between the corresponding residuals, where a residual vector is computed as the difference between the descriptor and the cluster's anchor point. The anchor point $\mathbf{c}_k$ can be interpreted as the origin of a new coordinate system local to the the specific cluster k. In standard VLAD, the anchor is chosen as the cluster centre ($\times$) in order to evenly distribute the residuals across the database. However, in a supervised setting where the two descriptors are known to belong to images which should not match, it is possible to learn a better anchor ($\star$) which causes the scalar product between the new residuals to be small.

Relations to other methods. Other works have proposed to pool CNN activations using VLAD or Fisher Vectors (FV) [14, 23], but do not learn the VLAD/FV parameters nor the input descriptors. The most related method to ours is the one of Sydorov *et al.* [75], which proposes to learn FV parameters jointly with an SVM for the end classification objective. However, in their work it is not possible to learn the input descriptors as they are hand-engineered (SIFT), while our VLAD layer is easily pluggable into any CNN architecture as it is amenable to backpropagation. "Fisher Networks" [71] stack Fisher Vector layers on top of each other, but the system is not trained end-to-end, only hand-crafted features are used, and the layers are trained greedily in a bottom-up fashion. Finally, our architecture is also related to bilinear networks [42], recently developed for a different

(a) (b) (c)

Figure 4. **Google Street View Time Machine examples.** Each column shows perspective images generated from panoramas from nearby locations, taken at different times. A well designed method can use this source of imagery to learn to be invariant to changes in viewpoint and lighting (a-c), and to moderate occlusions (b). It can also learn to suppress confusing visual information such as clouds (a), vehicles and people (b-c), and to chose to either ignore vegetation or to learn a season-invariant vegetation representation (a-c). More examples are given in [2].

task of fine-grained category-level recognition.

Max pooling (f_{max}). We also experiment with Max-pooling of the D-dimensional features across the $H \times W$ spatial locations, thus producing a D-dimensional output vector, which is then L2-normalized. Both of these operations can be implemented using standard layers in public CNN packages. This setup mirrors the method of [7, 61], but a crucial difference is that we will learn the representation (section 4) while [7, 60, 61] only use pretrained networks. Results will show (section 5.2) that simply using CNNs off-the-shelf [60] results in poor performance, and that training for the end-task is crucial. Additionally, VLAD will prove itself to be superior to the Max-pooling baseline.

4. Learning from Time Machine data

In the previous section we have designed a new CNN architecture as an image representation for place recognition. Here we describe how to learn its parameters in an end-to-end manner for the place recognition task. The two main challenges are: (i) how to gather enough annotated training data and (ii) what is the appropriate loss for the place recognition task. To address theses issues, we will first show that it is possible to obtain large amounts of weakly labelled imagery depicting the same places over time from the Google Street View Time Machine. Second, we will design a new weakly supervised triplet ranking loss that can deal with the incomplete and noisy position annotations of the Street View Time Machine imagery. The details are below.

Weak supervision from the Time Machine. We propose to exploit a new source of data – Google Street View Time Machine – which provides multiple street-level panoramic images taken at different times at close-by spatial locations on the map. As will be seen in section 5.2, this novel data source is precious for learning an image representation for place recognition. As shown in figure 4, the same locations are depicted at different times and seasons, providing the learning algorithm with crucial information it can use to discover which features are useful or distracting, and what changes should the image representation be invariant to, in order to achieve good place recognition performance.

The downside of the Time Machine imagery is that it provides only incomplete and noisy supervision. Each Time Machine panorama comes with a GPS tag giving only its approximate location on the map, which can be used to identify close-by panoramas but does not provide correspondences between parts of the depicted scenes. In detail, as the test queries are perspective images from camera phones, each panorama is represented by a set of perspective images sampled evenly in different orientations and two elevation angles [11, 24, 35, 80]. Each perspective image is labelled with the GPS position of the source panorama. As a result, two geographically close perspective images do not necessarily depict the same objects since they could be facing different directions or occlusions could take place (*e.g.* the two images are around a corner from each other), *etc*. Therefore, for a given training query q, the GPS information can only be used as a source of (i) *potential* positives $\{p_i^q\}$, *i.e.* images that are geographically close to the query, and (ii) *definite* negatives $\{n_j^q\}$, *i.e.* images that are geographically far from the query.[1]

Weakly supervised triplet ranking loss. We wish to learn a representation f_θ that will optimize place recognition performance. That is, for a given test query image q, the goal is to rank a database image I_{i*} from a close-by location higher than all other far away images I_i in the database. In other words, we wish the Euclidean distance $d_\theta(q, I)$ between the query q and a close-by image I_{i*} to be smaller than the distance to far away images in the database I_i, *i.e.* $d_\theta(q, I_{i*}) < d_\theta(q, I_i)$, for all images I_i further than a certain distance from the query on the map. Next we show how this requirement can be translated into a ranking loss between training triplets $\{q, I_{i*}, I_i\}$.

From the Google Street View Time Machine data, we obtain a training dataset of tuples $(q, \{p_i^q\}, \{n_j^q\})$, where for each training query image q we have a set of potential positives $\{p_i^q\}$ and the set of definite negatives $\{n_j^q\}$. The

[1] Note that even faraway images can depict the same object. For example, the Eiffel Tower can be visible from two faraway locations in Paris. But, for the purpose of localization we consider in this paper such image pairs as negative examples because they are not taken from the same place.

set of potential positives contains *at least one* positive image that should match the query, but we do not know which one. To address this ambiguity, we propose to identify the best matching potential positive image p_{i*}^q

$$p_{i*}^q = \underset{p_i^q}{\operatorname{argmin}}\, d_\theta(q, p_i^q) \tag{5}$$

for each training tuple $(q, \{p_i^q\}, \{n_j^q\})$. The goal then becomes to learn an image representation f_θ so that distance $d_\theta(q, p_{i*}^q)$ between the training query q and the best matching potential positive p_{i*}^q is smaller than the distance $d_\theta(q, n_j^q)$ between the query q and *all* negative images q_j:

$$d_\theta(q, p_{i*}^q) < d_\theta(q, n_j^q), \quad \forall j. \tag{6}$$

Based on this intuition we define a *weakly supervised ranking loss* L_θ for a training tuple $(q, \{p_i^q\}, \{n_j^q\})$ as

$$L_\theta = \sum_j l\left(\min_i d_\theta^2(q, p_i^q) + m - d_\theta^2(q, n_j^q)\right), \tag{7}$$

where l is the hinge loss $l(x) = \max(x, 0)$, and m is a constant parameter giving the margin. Note that equation (7) is a sum of individual losses for negative images n_j^q. For each negative, the loss l is zero if the distance between the query and the negative is greater by a margin than the distance between the query and the best matching positive. Conversely, if the margin between the distance to the negative image and to the best matching positive is violated, the loss is proportional to the amount of violation. Note that the above loss is related to the commonly used triplet loss [66, 67, 84, 85], but adapted to our weakly supervised scenario using a formulation (given by equation (5)) similar to multiple instance learning [21, 36, 83].

We train the parameters θ of the representation f_θ using Stochastic Gradient Descent (SGD) on a large set of training tuples from Time Machine data. Details of the training procedure are given in the appendix [2].

5. Experiments

In this section we describe the used datasets and evaluation methodology (section 5.1), and give quantitative (section 5.2) and qualitative (section 5.3) results to validate our approach. Finally, we also test the method on the standard image retrieval benchmarks (section 5.4).

5.1. Datasets and evaluation methodology

We report results on two publicly available datasets.

Pittsburgh (Pitts250k) [80] contains 250k database images downloaded from Google Street View and 24k test queries generated from Street View but taken at different times, years apart. We divide this dataset into three roughly equal parts for training, validation and testing, each containing around 83k database images and 8k queries, where the division was done geographically to ensure the sets contain independent images. To facilitate faster training, for some experiments, a smaller subset (Pitts30k) is used, containing 10k database images in each of the train/val(idation)/test sets, which are also geographically disjoint.

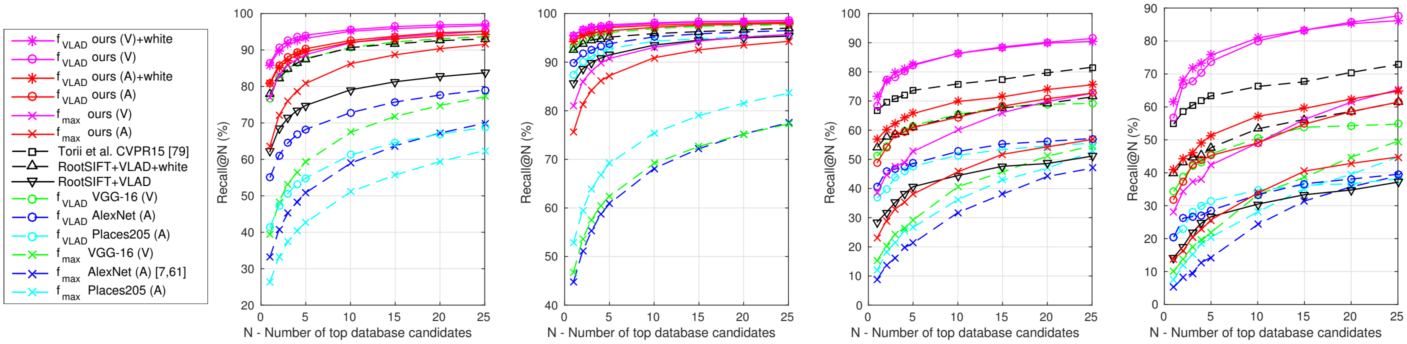
Tokyo 24/7 [79] contains 76k database images and 315 query images taken using mobile phone cameras. This is an extremely challenging dataset where the queries were taken at daytime, sunset and night, while the database images were only taken at daytime as they originate from Google Street View as described above. To form the train/val sets we collected additional Google Street View panoramas of Tokyo using the Time Machine feature, and name this set **TokyoTM**; Tokyo 24/7 (=test) and TokyoTM train/val are all geographically disjoint. Further details on the splits are given in the appendix [2].

Evaluation metric. We follow the standard place recognition evaluation procedure [5, 24, 64, 79, 80]. The query image is deemed correctly localized if at least one of the top N retrieved database images is within $d = 25$ meters from the ground truth position of the query. The percentage of correctly recognized queries (Recall) is then plotted for different values of N. For Tokyo 24/7 we follow [79] and perform spatial non-maximal suppression on ranked database images before evaluation.

Implementation details. We use two base architectures which are extended with Max pooling (f_{max}) and our NetVLAD (f_{VLAD}) layers: AlexNet [37] and VGG-16 [72]; both are cropped at the last convolutional layer (conv5), before ReLU. For NetVLAD we use $K = 64$ resulting in 16k and 32k-D image representations for the two base architectures, respectively. The initialization procedure, parameters used for training, procedure for sampling training tuples and other implementation details are given in the appendix [2]. All training and evaluation code, as well as our trained networks, is online at [1].

5.2. Results and discussion

Baselines and state-of-the-art. To assess benefits of our approach we compare our representations trained for place recognition against "off-the-shelf" networks pretrained on other tasks. Namely, given a base network cropped at conv5, the baselines either use Max pooling (f_{max}), or aggregate the descriptors into VLAD (f_{VLAD}), but perform no further task-specific training. The three base networks are: AlexNet [37], VGG-16 [72], both are pretrained for ImageNet classification [19], and Places205 [89], reusing the same architecture as AlexNet but pretrained for scene classification [89]. Pretrained networks have been recently used as off-the-shelf dense descriptor extractors for instance retrieval [7, 8, 23, 60, 61] and the untrained f_{max} network corresponds to the method of [7, 61].



(a) Pitts250k-test (b) TokyoTM-val (c) Tokyo 24/7 all queries (d) Tokyo 24/7 sunset/night

Figure 5. **Comparison of our methods versus off-the-shelf networks and state-of-the-art.** The base CNN architecture is denoted in brackets: (A)lexNet and (V)GG-16. Trained representations (red and magenta for AlexNet and VGG-16) outperform by a large margin off-the-shelf ones (blue, cyan, green for AlexNet, Places205, VGG-16), f_{VLAD} (-o-) works better than f_{max} (-x-), and our f_{VLAD}+whitening (-∗-) representation based on VGG-16 sets the state-of-the-art on all datasets. [79] only evaluated on Tokyo 24/7 as the method relies on depth data not available in other datasets. Additional results are shown in the appendix [2].

Furthermore we compare our CNN representations trained for place recognition against the state-of-the-art local feature based compact descriptor, which consists of VLAD pooling [29] with intra-normalization [4] on top of densely extracted RootSIFTs [3, 43]. The descriptor is optionally reduced to 4096 dimensions using PCA (learnt on the training set) combined with whitening and L2-normalization [25]; this setup together with view synthesis yields the state-of-the-art results on the challenging Tokyo 24/7 dataset (*c.f.* [79]).

In the following we discuss figure 5, which compares place recognition performance of our method to the baselines outlined above on the Pittsburgh and Tokyo 24/7 benchmarks.

Dimensionality reduction. We follow the standard state-of-the-art procedure to perform dimensionality reduction of VLAD, as described earlier, *i.e.* the reduction into 4096-D is performed using PCA with whitening followed by L2-normalization [25, 79]. Figure 5 shows that the lower dimensional f_{VLAD} (-∗-) performs similarly to the full size vector (-o-).

Benefits of end-to-end training for place recognition. Representations trained on the end-task of place recognition consistently outperform by a large margin off-the-shelf CNNs on both benchmarks. For example, on the Pitts250k-test our trained AlexNet with (trained) NetVLAD aggregation layer achieves recall@1 of 81.0% compared to only 55.0% obtained by off-the-shelf AlexNet with standard VLAD aggregation, *i.e.* a relative improvement in recall of 47%. Similar improvements can be observed on all three datasets. This confirms two important premises of this work: (i) our approach can learn rich yet compact image representations for place recognition, and (ii) the popular idea of using pretrained networks "off-the-shelf" [7, 8, 23, 60, 61] is sub-optimal as the networks trained for object or scene classification are not necessary suitable for the end-task of place recognition. We believe this could be attributed to the fact that "off-the-shelf " conv5 activations are not trained to be comparable using Euclidean distance.

Comparison with state-of-the-art. Figure 5 also shows that our trained f_{VLAD} representation with whitening based on VGG-16 (magenta -∗-) convincingly outperforms RootSIFT+VLAD+whitening, as well as the method of Torii *et al.* [79], and therefore sets the state-of-the-art for compact descriptors on all benchmarks. Note that these are strong baselines that outperform most off-the-shelf CNN descriptors on the place recognition task.

VLAD versus Max. By comparing f_{VLAD} (-o-) methods with their corresponding f_{max} (-x-) counterparts it is clear that VLAD pooling is much better than Max pooling for both off-the-shelf and trained representations. NetVLAD performance decreases gracefully with dimensionality: 128-D NetVLAD performs similarly to 512-D Max (42.9% vs 38.4% recall@1 on Tokyo 24/7), resulting in *four* times more compact representation for the same performance. Furthermore, NetVLAD+whitening outperforms Max pooling convincingly when reduced to the same dimensionality (60%). See the appendix [2] for more details.

Which layers should be trained? In Table 1 we study the benefits of training different layers for the end-task of place recognition. The largest improvements are thanks to training the NetVLAD layer, but training other layers results in further improvements, with some overfitting occurring below conv2.

Importance of Time Machine training. Here we examine whether the network can be trained without the Time Machine (TM) data. In detail, we have modified the training query set for Pitts30k-train to be sampled from the same set as the training database images, *i.e.* the tuples of query and database images used in training were captured at the same time. Recall@1 with f_{max} on Pitts30k-val for the off-the-shelf AlexNet is 33.5%, and training without TM im-

Lowest trained layer	f_{max} r@1	f_{max} r@5	f_{max} r@10	f_{VLAD} r@1	f_{VLAD} r@5	f_{VLAD} r@10
none (off-the-shelf)	33.5	57.3	68.4	54.5	69.8	76.1
NetVLAD	—	—	—	80.5	91.8	95.2
conv5	63.8	83.8	89.0	84.1	94.6	95.5
conv4	62.1	83.6	89.2	85.1	94.4	96.1
conv3	**69.8**	86.7	90.3	**85.5**	94.6	96.5
conv2	69.1	**87.6**	**91.5**	84.5	94.6	**96.6**
conv1 (full)	68.5	86.2	90.8	84.2	**94.7**	96.1

Table 1. **Partial training.** Effects of performing backpropagation only down to a certain layer of AlexNet, *e.g.* 'conv4' means that weights of layers from conv4 and above are learnt, while weights of layers below conv4 are fixed to their pretrained state; r@N signifies recall@N. Results are shown on the Pitts30k-val dataset.

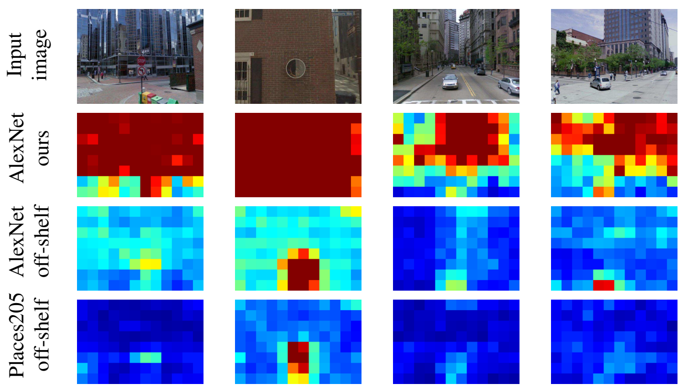


Figure 6. **What has been learnt?** Each column corresponds to one image (top row) and the emphasis various networks (under f_{max}) give to different patches. Each pixel in the heatmap corresponds to the change in representation when a large gray occluding square (100×100) is placed over the image in the same position; all heatmaps have the same colour scale. Note that the original image and the heatmaps are not in perfect alignment as nearby patches overlap 50% and patches touching an image edge are discarded to prevent border effects. All images are from Pitts250k-val that the network hasn't seen at training. Further examples are given in the appendix [2].

proves this to 38.7%. However, training with TM obtains 68.5% showing that Time Machine data is crucial for good place recognition accuracy as without it the network does not generalize well. The network learns, for example, that recognizing cars is important for place recognition, as the same parked cars appear in all images of a place.

5.3. Qualitative evaluation

To visualize what is being learnt by our place recognition architectures, we adapt the method of Zeiler and Fergus [87] for examining occlusion sensitivity of classification networks. It can be seen in figure 6 that off-the-shelf AlexNet (pretrained on ImageNet) focuses very much on categories it has been trained to recognize (*e.g.* cars) and certain shapes, such as circular blobs useful for distinguishing 12 different ball types in the ImageNet categories. The Place205 network is fairly unresponsive to all occlusions as it does not aim to recognize specific places but scene-level categories, so even if an important part of the image is occluded, such as a characteristic part of a building façade, it still provides a similar output feature which corresponds to an uninformative "a building façade" image descriptor. In contrast to these two, our network trained for specific place recognition automatically learns to ignore confusing features, such as cars and people, which are not discriminative for specific locations, and instead focuses on describing building façades and skylines. More qualitative examples are provided in the appendix [2].

5.4. Image retrieval

We use our best performing network (VGG-16, f_{VLAD} with whitening down to 256-D) trained completely on Pittsburgh, to extract image representations for standard object and image retrieval benchmarks. Our representation sets the state-of-the-art for compact image representations (256-D) by a large margin on all three datasets, obtaining an mAP of 63.5%, 73.5% and 79.9% on Oxford 5k [53], Paris 6k [54], Holidays [26], respectively; for example, this is a +20% relative improvement on Oxford 5k. The appendix [2] contains more detailed results.

6. Conclusions

We have designed a new convolutional neural network architecture that is trained for place recognition in an end-to-end manner from weakly supervised Street View Time Machine data. Our trained representation significantly outperforms off-the-shelf CNN models and significantly improves over the state-of-the-art on the challenging 24/7 Tokyo dataset, as well as on the Oxford and Paris image retrieval benchmarks. The two main components of our architecture – (i) the NetVLAD pooling layer and (ii) weakly supervised ranking loss – are generic CNN building blocks applicable beyond the place recognition task. The NetVLAD layer offers a powerful pooling mechanism with learnable parameters that can be easily plugged into any other CNN architecture. The weakly supervised ranking loss opens up the possibility of end-to-end learning for other ranking tasks where large amounts of weakly labelled data are available, for example, images described with natural language [33].

Acknowledgements. This work was partly supported by RVO13000 - Conceptual development of research organization, the ERC grant LEAP (no. 336845), ANR project Semapolis (ANR-13-CORD-0003), JSPS KAKENHI Grant Number 15H05313, the Inria CityLab IPL, and the Intelligence Advanced Research Projects Activity (IARPA) via Air Force Research Laboratory, contract FA8650-12-C-7212. The U.S. Government is authorized to reproduce and distribute reprints for Governmental purposes notwithstanding any copyright annotation thereon. Disclaimer: The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of IARPA, AFRL, or the U.S. Government.

References

[1] Project webpage (code/networks). http://www.di.ens.fr/willow/research/netvlad/. 6

[2] Supplementary material (appendix) for the paper. http://arxiv.org/abs/1511.07247. 1, 5, 6, 7, 8

[3] R. Arandjelović and A. Zisserman. Three things everyone should know to improve object retrieval. In *Proc. CVPR*, 2012. 2, 7

[4] R. Arandjelović and A. Zisserman. All about VLAD. In *Proc. CVPR*, 2013. 1, 2, 3, 4, 7

[5] R. Arandjelović and A. Zisserman. DisLocation: Scalable descriptor distinctiveness for location recognition. In *Proc. ACCV*, 2014. 1, 2, 6

[6] M. Aubry, B. C. Russell, and J. Sivic. Painting-to-3D model alignment via discriminative visual elements. *ACM Transactions on Graphics (TOG)*, 33(2):14, 2014. 1

[7] H. Azizpour, A. Razavian, J. Sullivan, A. Maki, and S. Carlsson. Factors of transferability from a generic ConvNet representation. *CoRR*, abs/1406.5774, 2014. 2, 3, 5, 6, 7

[8] A. Babenko and V. Lempitsky. Aggregating local deep features for image retrieval. In *Proc. ICCV*, 2015. 2, 3, 6, 7

[9] A. Babenko, A. Slesarev, A. Chigorin, and V. Lempitsky. Neural codes for image retrieval. In *Proc. ECCV*, 2014. 2

[10] S. Cao and N. Snavely. Graph-based discriminative learning for location recognition. In *Proc. CVPR*, 2013. 1, 2

[11] D. M. Chen, G. Baatz, K. Koeser, S. S. Tsai, R. Vedantham, T. Pylvanainen, K. Roimela, X. Chen, J. Bach, M. Pollefeys, B. Girod, and R. Grzeszczuk. City-scale landmark identification on mobile devices. In *Proc. CVPR*, 2011. 1, 2, 5

[12] O. Chum, A. Mikulik, M. Perďoch, and J. Matas. Total recall II: Query expansion revisited. In *Proc. CVPR*, 2011. 2

[13] O. Chum, J. Philbin, J. Sivic, M. Isard, and A. Zisserman. Total recall: Automatic query expansion with a generative feature model for object retrieval. In *Proc. ICCV*, 2007. 2

[14] M. Cimpoi, S. Maji, and A. Vedaldi. Deep filter banks for texture recognition and segmentation. In *Proc. CVPR*, 2015. 3, 4

[15] G. Csurka, C. Bray, C. Dance, and L. Fan. Visual categorization with bags of keypoints. In *Workshop on Statistical Learning in Computer Vision, ECCV*, pages 1–22, 2004. 3

[16] M. Cummins and P. Newman. FAB-MAP: Probabilistic localization and mapping in the space of appearance. *The International Journal of Robotics Research*, 2008. 1, 2

[17] M. Cummins and P. Newman. Highly scalable appearance-only SLAM - FAB-MAP 2.0. In *RSS*, 2009. 1, 2

[18] J. Delhumeau, P.-H. Gosselin, H. Jégou, and P. Pérez. Revisiting the VLAD image representation. In *Proc. ACMM*, 2013. 2

[19] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. ImageNet: A large-scale hierarchical image database. In *Proc. CVPR*, 2009. 6

[20] J. Donahue, Y. Jia, O. Vinyals, J. Hoffman, N. Zhang, E. Tzeng, and T. Darrell. DeCAF: A deep convolutional activation feature for generic visual recognition. *CoRR*, abs/1310.1531, 2013. 1

[21] J. Foulds and E. Frank. A review of multi-instance learning assumptions. *The Knowledge Engineering Review*, 25(01):1–25, 2010. 6

[22] R. B. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proc. CVPR*, 2014. 1

[23] Y. Gong, L. Wang, R. Guo, and S. Lazebnik. Multi-scale orderless pooling of deep convolutional activation features. In *Proc. ECCV*, 2014. 2, 3, 4, 6, 7

[24] P. Gronat, G. Obozinski, J. Sivic, and T. Pajdla. Learning and calibrating per-location classifiers for visual place recognition. In *Proc. CVPR*, 2013. 1, 2, 5, 6

[25] H. Jégou and O. Chum. Negative evidences and co-occurrences in image retrieval: the benefit of PCA and whitening. In *Proc. ECCV*, 2012. 2, 7

[26] H. Jégou, M. Douze, and C. Schmid. Hamming embedding and weak geometric consistency for large scale image search. In *Proc. ECCV*, pages 304–317, 2008. 2, 8

[27] H. Jégou, M. Douze, and C. Schmid. On the burstiness of visual elements. In *Proc. CVPR*, Jun 2009. 2

[28] H. Jégou, M. Douze, and C. Schmid. Product quantization for nearest neighbor search. *IEEE PAMI*, 2011. 1

[29] H. Jégou, M. Douze, C. Schmid, and P. Pérez. Aggregating local descriptors into a compact image representation. In *Proc. CVPR*, 2010. 1, 2, 3, 7

[30] H. Jégou, H. Harzallah, and C. Schmid. A contextual dissimilarity measure for accurate and efficient image search. In *Proc. CVPR*, 2007. 2

[31] H. Jégou, F. Perronnin, M. Douze, J. Sánchez, P. Pérez, and C. Schmid. Aggregating local images descriptors into compact codes. *IEEE PAMI*, 2012. 1

[32] H. Jégou and A. Zisserman. Triangulation embedding and democratic aggregation for image search. In *Proc. CVPR*, 2014. 2

[33] A. Karpathy and L. Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In *Proc. CVPR*, 2015. 8

[34] A. Kendall, M. Grimes, and R. Cipolla. PoseNet: A convolutional network for real-time 6-DOF camera relocalization. In *Proc. ICCV*, 2015. 2

[35] J. Knopp, J. Sivic, and T. Pajdla. Avoiding confusing features in place recognition. In *Proc. ECCV*, 2010. 1, 2, 5

[36] D. Kotzias, M. Denil, P. Blunsom, and N. de Freitas. Deep multi-instance transfer learning. *CoRR*, abs/1411.3128, 2014. 6

[37] A. Krizhevsky, I. Sutskever, and G. E. Hinton. ImageNet classification with deep convolutional neural networks. In *NIPS*, pages 1106–1114, 2012. 1, 2, 6

[38] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel. Backpropagation applied to handwritten zip code recognition. *Neural Computation*, 1(4):541–551, 1989. 1

[39] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998. 1

[40] Y. Li, N. Snavely, D. Huttenlocher, and P. Fua. Worldwide pose estimation using 3D point clouds. In *Proc. ECCV*, 2012. 1

[41] T.-Y. Lin, Y. Cui, S. Belongie, and J. Hays. Learning deep representations for ground-to-aerial geolocalization. In *Proc. CVPR*, 2015. 2

[42] T.-Y. Lin, A. RoyChowdhury, and S. Maji. Bilinear CNN models for fine-grained visual recognition. In *Proc. ICCV*, 2015. 4

[43] D. Lowe. Distinctive image features from scale-invariant keypoints. *IJCV*, 60(2):91–110, 2004. 1, 3, 7
[44] W. Maddern and S. Vidas. Towards robust night and day place recognition using visible and thermal imaging. In *Proc. Intl. Conf. on Robotics and Automation*, 2014. 1, 2
[45] A. Makadia. Feature tracking for wide-baseline image retrieval. In *Proc. ECCV*, 2010. 2
[46] C. McManus, W. Churchill, W. Maddern, A. Stewart, and P. Newman. Shady dealings: Robust, long-term visual localisation using illumination invariance. In *Proc. Intl. Conf. on Robotics and Automation*, 2014. 1, 2
[47] S. Middelberg, T. Sattler, O. Untzelmann, and L. Kobbelt. Scalable 6-DOF localization on mobile devices. In *Proc. ECCV*, 2014. 1
[48] A. Mikulik, M. Perďoch, O. Chum, and J. Matas. Learning a fine vocabulary. In *Proc. ECCV*, 2010. 2
[49] M. Oquab, L. Bottou, I. Laptev, and J. Sivic. Learning and transferring mid-level image representations using convolutional neural networks. In *Proc. CVPR*, 2014. 1
[50] M. Paulin, M. Douze, Z. Harchaoui, J. Mairal, F. Perronnin, and C. Schmid. Local convolutional features with unsupervised training for image retrieval. In *Proc. ICCV*, 2015. 2
[51] F. Perronnin and D. Dance. Fisher kernels on visual vocabularies for image categorization. In *Proc. CVPR*, 2007. 2
[52] F. Perronnin, Y. Liu, J. Sánchez, and H. Poirier. Large-scale image retrieval with compressed fisher vectors. In *Proc. CVPR*, 2010. 1, 2
[53] J. Philbin, O. Chum, M. Isard, J. Sivic, and A. Zisserman. Object retrieval with large vocabularies and fast spatial matching. In *Proc. CVPR*, 2007. 1, 2, 8
[54] J. Philbin, O. Chum, M. Isard, J. Sivic, and A. Zisserman. Lost in quantization: Improving particular object retrieval in large scale image databases. In *Proc. CVPR*, 2008. 2, 8
[55] J. Philbin, M. Isard, J. Sivic, and A. Zisserman. Descriptor learning for efficient retrieval. In *Proc. ECCV*, 2010. 2
[56] D. Qin, X. Chen, M. Guillaumin, and L. V. Gool. Quantized kernel learning for feature matching. In *NIPS*, 2014. 2
[57] D. Qin, Y. Chen, M. Guillaumin, and L. V. Gool. Learning to rank bag-of-word histograms for large-scale object retrieval. In *Proc. BMVC.*, 2014. 2
[58] D. Qin, S. Gammeter, L. Bossard, T. Quack, and L. Van Gool. Hello neighbor: accurate object retrieval with k-reciprocal nearest neighbors. In *Proc. CVPR*, 2011. 2
[59] D. Qin, C. Wengert, and L. V. Gool. Query adaptive similarity for large scale object retrieval. In *Proc. CVPR*, 2013. 2
[60] A. S. Razavian, H. Azizpour, J. Sullivan, and S. Carlsson. CNN features off-the-shelf: An astounding baseline for recognition. *CoRR*, abs/1403.6382, 2014. 2, 5, 6, 7
[61] A. S. Razavian, J. Sullivan, A. Maki, and S. Carlsson. A baseline for visual instance retrieval with deep convolutional networks. In *Proc. ICLR*, 2015. 2, 3, 5, 6, 7
[62] T. Sattler, M. Havlena, F. Radenović, K. Schindler, and M. Pollefeys. Hyperpoints and fine vocabularies for large-scale location recognition. In *Proc. ICCV*, 2015. 1, 2
[63] T. Sattler, B. Leibe, and L. Kobbelt. Fast image-based localization using direct 2D–to–3D matching. In *Proc. ICCV*, 2011. 1, 2
[64] T. Sattler, T. Weyand, B. Leibe, and L. Kobbelt. Image retrieval for image-based localization revisited. In *Proc. BMVC.*, 2012. 1, 2, 6
[65] G. Schindler, M. Brown, and R. Szeliski. City-scale location recognition. In *Proc. CVPR*, 2007. 1, 2
[66] F. Schroff, D. Kalenichenko, and J. Philbin. FaceNet: A unified embedding for face recognition and clustering. In *Proc. CVPR*, 2015. 6
[67] M. Schultz and T. Joachims. Learning a distance metric from relative comparisons. In *NIPS*, 2004. 6
[68] P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, and Y. LeCun. OverFeat: Integrated recognition, localization and detection using convolutional networks. *CoRR*, abs/1312.6229, 2013. 1
[69] E. Simo-Serra, E. Trulls, L. Ferraz, I. Kokkinos, and F. Moreno-Noguer. Fracking deep convolutional image descriptors. *CoRR*, abs/1412.6537, 2014. 2
[70] K. Simonyan, A. Vedaldi, and A. Zisserman. Descriptor learning using convex optimisation. In *Proc. ECCV*, 2012. 2
[71] K. Simonyan, A. Vedaldi, and A. Zisserman. Deep Fisher networks for large-scale image classification. In *NIPS*, 2013. 4
[72] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. In *Proc. ICLR*, 2015. 1, 6
[73] J. Sivic and A. Zisserman. Video Google: A text retrieval approach to object matching in videos. In *Proc. ICCV*, volume 2, pages 1470–1477, 2003. 1, 3
[74] N. Sunderhauf, S. Shirazi, A. Jacobson, E. Pepperell, F. Dayoub, B. Upcroft, and M. Milford. Place recognition with ConvNet landmarks: Viewpoint-robust, condition-robust, training-free. In *Robotics: Science and Systems*, 2015. 1, 2
[75] V. Sydorov, M. Sakurada, and C. Lampert. Deep fisher kernels – end to end learning of the fisher kernel GMM parameters. In *Proc. CVPR*, 2014. 4
[76] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In *Proc. CVPR*, 2014. 1
[77] G. Tolias, Y. Avrithis, and H. Jégou. To aggregate or not to aggregate: Selective match kernels for image search. In *Proc. ICCV*, 2013. 2
[78] G. Tolias and H. Jégou. Visual query expansion with or without geometry: refining local descriptors by feature aggregation. *Pattern Recognition*, 2014. 2
[79] A. Torii, R. Arandjelović, J. Sivic, M. Okutomi, and T. Pajdla. 24/7 place recognition by view synthesis. In *Proc. CVPR*, 2015. 1, 2, 6, 7
[80] A. Torii, J. Sivic, T. Pajdla, and M. Okutomi. Visual place recognition with repetitive structures. In *Proc. CVPR*, 2013. 1, 2, 5, 6
[81] T. Turcot and D. G. Lowe. Better matching with fewer features: The selection of useful features in large database recognition problems. In *ICCV Workshop on Emergent Issues in Large Amounts of Visual Data (WS-LAVD)*, 2009. 2
[82] T. Tuytelaars and K. Mikolajczyk. Local invariant feature detectors: A survey. *Foundations and Trends® in Computer Graphics and Vision*, 3(3):177–280, 2008. 1
[83] P. Viola, J. C. Platt, and C. Zhang. Multiple instance boosting for object detection. In *NIPS*, 2005. 6
[84] J. Wang, Y. Song, T. Leung, C. Rosenberg, J. Wang,

J. Philbin, B. Chen, and Y. Wu. Learning fine-grained image similarity with deep ranking. In *Proc. CVPR*, 2014. 6

[85] K. Q. Weinberger, J. Blitzer, and L. Saul. Distance metric learning for large margin nearest neighbor classification. In *NIPS*, 2006. 6

[86] S. Winder, G. Hua, and M. Brown. Picking the best DAISY. In *Proc. CVPR*, pages 178–185, 2009. 2

[87] M. D. Zeiler and R. Fergus. Visualizing and understanding convolutional networks. In *Proc. ECCV*, 2014. 1, 8

[88] J. Zepeda and P. Pérez. Exemplar SVMs as visual feature encoders. In *Proc. CVPR*, 2015. 2

[89] B. Zhou, A. Lapedriza, J. Xiao, A. Torralba, and A. Oliva. Learning deep features for scene recognition using places database. In *NIPS*, 2014. 1, 6