Large Scale Deep Convolutional Neural Network Features Search with Lucene

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Abstract

In this work, we propose an approach to index Deep Convolutional Neural Network Features to support efficient content-based retrieval on large image databases. To this aim, we have converted these features into a textual form, to index them into an inverted index by means of Lucene. In this way, we were able to set up a robust retrieval system that combines full-text search with content-based image retrieval capabilities. We evaluated different strategies of textual representation in order to optimize the index occupation and the query response time. In order to show that our approach is able to handle large datasets, we have developed a web-based prototype that provides an interface for combined textual and visual searching into a dataset of about 100 million of images.

1 Introduction

Deep Convolutional Neural Networks (DCNNs) have recently shown impressive performance on a number of computer vision problems, such as image classification and object recognition. A very profitable way of exploiting the potentialities of this technology is to use the representation of one of the CNN internal states, when it is excited with a given input (image). These “intermediate” representations can be successfully used as global features in generic recognition or visual similarity search tasks. In general, it is possible to extract multiple layers of features. The first layers are typically able to recognize low-level characteristics of images such as edges and blobs. While higher levels have demonstrated to be more suitable for semantic similarity search.

However, one major obstacle to the use DCNN features for indexing large datasets of images is its internal representation, which is high dimensional leading to the curse of dimensionality [8]. For instance, in the well-known AlexNet architecture [13] the output of the sixth layer (fc6) has 4,096 dimensions, while the fifth layer (pool5) has 9,216 dimensions. An effective approach to tackle the dimensionality curse
problem is the application of approximate access methods such as permutation based indices \[7, 1\].

However, a drawback of these approaches is on one hand the dependence of the index on a set of reference objects (or pivots), and on the other hand the need to reorder the result set of the search according to the original feature distance. The former issue requires the selection of a set of reference objects, which represents well the variety of dataset that we want to index. The latter issue forces to use a support database to store the original objects, which requires efficient random I/O on a fast secondary memory (such as flash-based storages).

Deep learning and Convolutional Neural Networks (CNNs) are considered today a great step forward towards the development of effective techniques for understanding multimedia content. The idea of using the representations extracted from Convolutional Neural Nets is quickly gaining ground on Local Features (as for instance SIFT \[15\] and SURF \[3\]) as favoured state-of-the-art global image descriptors for image instance retrieval \[2, 5, 14\].

In this paper, we propose an approach to specifically index DCNN Features to support efficient content-based on large datasets. The proposed approach exploits the ability of inverted files to deal with the sparsity of the Convolutional features. To this end, we make use of the efficient and robust full-text search library Lucene\[^1\]. The idea is to associate each component of the feature vector with a unique alphanumeric keyword and to generate a textual representation in which we boost the relative term proportionally to its intensity.

The paper is organized as follows. Section 2 introduces the proposed approach. Section 3 discusses the validation tests. Section 4 concludes.

## 2 Text Representation for Deep Convolutional Neural Network Features

In this paper, we propose to index DCNN features using a text encoding that allows us to use a text retrieval engine to perform image similarity search. As discussed later, we implemented this idea on top of the Lucene text retrieval engine; however any full-text engine supporting vector space model is acceptable.

In order to perform similarity search on DCNN features, in principle, we should to compare the feature extracted from the query with all the features extracted from the image of the dataset and take the nearest images according to L2 distance. However, if database is large, this approach can become time-consuming. Taking advantage of the sparsity of the DCNN features, which contain mostly zeros (about 75%), we are able to efficiently perform such a search without affecting the precision. To this end, we observe that, since typically DCNN feature vectors exhibits better results if they are L2-normalized to the unit length \[17, 8\], if two vectors \(x\) and \(y\) have length equal to 1 (such as in

\[^1\]http://lucene.apache.org
our case), the following relationship between the L2 distance $d_2(x, y)$ and the inner product $x \ast y$ exists:

$$d_2(x, y)^2 = 2(1 - x \ast y)$$

The advantage of formulating the L2 distance in terms of inner product is that allows us to efficiently exploit the sparsity of the vectors by accumulating the product of non-zeroes entries in the vector $x$ and their corresponding non-zeroes entries in the vector $y$. Moreover, Lucene, as other search engines, computes the similarity between documents using the cosine similarity, which is dot product of the two vectors divided by their lengths product. Therefore, in our case, cosine similarity and dot product are the same. The idea now is to force, in same way, Lucene to fill the vector of its internal inverted index with the entries of the DCNN feature vectors. Therefore, if a query feature transformed in this way is submitted to Lucene engine, we receive as result a ranked list of documents (i.e., the images) sorted by decreasing values of the cosine similarity, i.e. by increasing values of the L2. For space-saving reasons, however, text search engines do not store float numbers in the posting entries of the inverted index representing documents, but they store the term frequencies, which are represented as integers. Therefore, we must guarantee that posting entries will contain numeric values proportional to the float values of the deep feature entries.

To employ this idea, we provide a textual representation for the DCNN feature vectors that guarantees the direct proportionality between the feature components and the term frequencies. Firstly, we associated each component of the vector, say $e_i$, with a unique alphanumeric term $\tau_i$. We chose, for instance, as term the prefix 'f' followed by the numeric values corresponding to the index $i$ of the $i$-th vector component. We form the text representation of $e_i$ by repeating the term $\tau_i$ for the non-zero components a number of times directly proportional to the its values. This process introduces a quantization error due to the representation of float components in integers. However, as we will see, this errors does not affect the retrieval effectiveness. Therefore, the number of repetitions $\text{rep}(fi)$ of the term $fi$ corresponding the the component $e_i$ is given by:

$$\text{rep}(fi) = \lfloor Qx_i \rfloor$$

Where $\lfloor \rfloor$ denotes the floor function and $Q$ is a multiplication factor $> 1$ that works, as explained, as a quantization factor. For instance, if we fix $Q = 2$, for $x_i < 0.5$, $\text{rep}(fi) = 0$, while for $x_i \geq 0.5$, $\text{rep}(fi) = 1$. The accuracy of this approximation depends on the factor $Q$, we used to transform the vectors entries. In contrast, the smaller we set $Q$ the smaller the inverted index will be. This is because the truncation will set to zero more entries of the posting lists. Hence, we have to find a good compromise between the effectiveness of the retrieval system and its space occupation.

For example, if we set $Q = 30$ and and we have for instance a feature vector with just three components $(0.01, 0.15, 0.09)$ the corresponding
integer-representation of the vector will be (042) and its textual representation will be: "f2 f2 f2 f3 f3 f3". Since the first component of the vector is equal to 0, so we do not consider it.

Since typically the 25% of the DCNN features are greater than zero (in our specific case of fc6 layer), the size of their corresponding textual representation will have a small fraction of the unique terms present in the whole dictionary composed of 4,096. In our case, in average a document contains about 275 unique terms, which is about 6.7% of the dictionary because of quantization that set to zero the feature components smaller than $1/Q$. When we have to process similarity search, therefore the search engine have to tread query of that size. These unusually long queries, however, can affect the response time if the inverted index contains millions of items.

A quite intuitive way to overcome this issue is to reduce the size of the query by exploiting the knowledge of the $tf*idf$ (i.e., term frequency * inverse document frequency) statistic of the features textual representation, which comes for free in standard full-text retrieval engines. We can retain the elements of the query that exhibit greater values of $tf*idf$ and eliminate the others. For instance, for a query of about 275 unique term in average, we can take the first ten terms that exhibit the highest $tf*idf$, with a query time reduction of the 96%.

This query reduction comes, however, with a price: it decreases the precision of results. To alleviate this problem, for a top-$k$ query, we reorder the results using the cosine similarity between the original query (i.e., the one without reduction) and the first $C_r \times k$ candidates documents are retrieved. Where $C_r$ is an amplification factor that we refer to as reordering factor. For instance, if we have to return $k = 100$ images and we set $C_r = 10$, we take and reorder the first $10 \times 100 = 1000$ candidate documents returned by the reduced query.

In order to calculate the cosine similarity of the original query and the $C_r \times k$ candidates, we have to reconstruct the quantized features by accessing to the posting list of the document returned by the search engine. As we will see, this approach does not affect significantly the efficiency of the query but can offer great improvements in terms of effectiveness.

3 Experiments

3.1 Setup

For the evaluation of the effectiveness of the proposed approach, we have used the INRIA Holidays dataset [12, 10]. It is a collection of 1,491 holiday images. The authors selected 500 queries and for each of them a list of positive results. As in [9, 11, 10], to evaluate the approaches on a large scale, we merged the Holidays dataset with the Flickr1M collection. SIFT features have been extracted by Jegou et

\[http://press.liacs.nl/mirflickr/\]
al. for both the Holidays and the Flickr1M dataset. All experiments were conducted on a Intel Core i7 CPU, 2.67 GHz with 12.0 GB of RAM a 2TB 7200 RPM HD for the Lucene index. We used Lucene v4.7 running on Java 6 64 bit.

The quality of the retrieved images is typically evaluated by means of precision and recall measures. As in many other papers [9, 16, 10], we combined this information by means of the mean Average Precision (mAP), which represents the area below the precision and recall curve.

### 3.2 Effectiveness and Quantization factor $Q$

In a first experimental analysis, we have evaluated the optimal value of $Q$ over the Flickr1M dataset. As explained above, by keeping the value $Q$ to the minimum, we can reduce the space occupation of the inverted index. Figure 1 analyzes this aspect, and shows the mAP as function of $Q$ and the corresponding space occupation of the inverted index. From this analysis, we conclude that an optimal choice of the quantization factor $Q$ is 30, which leads to a mAP of 0.62 and a space occupation of 2.31GB. It is important to know that the mAP using the L2 on the exact DCNN feature vectors is about 0.59. This means that our quantization error leads to an slight improvement of the precision for $Q \geq 30$. Another important aspect is that, this effectiveness was obtained using forcing Lucene to use the standard inner product on $tf$ weight without $idf$ and any other document normalization. A further improvement can be obtained using the similarity function of Lucene called LMDirichlet, which provided a mAP of about 0.64.

Figure 2 shows the document frequency distribution of the terms $\tau_i$ (i.e., component $e_i$), sorted in decreasing order for the Flickr1M dataset. It basically shows, the number of image features each component had non-zero values (to be precise, less than 1/30, because of the quantization error). As can be seen, the distribution is quite skewed and some terms (components) are much more frequent than others ranging from 313 of $i = 2435$ to about 378,876 of $i = 464$ in a collection of about one million features. This aspect has some impact to the performance of the inverted index, since it means that the posting list of the term $\tau_{464}$ has 378,876 items since it appears in as many as documents (i.e., image features).

The observation about terms document frequency leads to the idea of using $tf*idf$, as already mentioned above, to reduce the query length by cutting off terms with lower $tf*idf$ weight. Since in inverted files the query time is usually proportional with the length of the query [4], this approach gives a great improvement in terms of query response time.

Figure 3 shows the mAP values at different levels of reordering factors $C_r$ and query lengths $L_q$. Note that, $C_r = 0$ means no reordering, $C_r = 1$, reordering of the first $k$ candidates, $C_r = 2$, reordering of the first $2k$ candidates, and so on. Concerning, $L_q$, we have considered a range of values between 2 and 50. Since the average document length

[http://lear.inrialpes.fr/~jegou/data.php](http://lear.inrialpes.fr/~jegou/data.php)
is about 275, this corresponds to an average length reduction from 0.3% to 80%. In the graph of Figure 3, we have also plotted the mAP level obtained with query without reduction (namely fullQ) and the mAP obtained with sequential scan using L2. In all experiments we have set $k = 100$. As these experiments show, the configuration $C_r = 10$ and $L_q = 8$ exhibits a mAP comparable to the case of sequential scan using L2.

### 3.3 Evaluation of the Efficiency

In order to evaluated the efficiency of our solution, in Figure 4, we have plotted the average response time for the same queries of previous experiments. As we can see, there is a big improvement in efficiency even for the case in which the reorder factor is maximum, i.e., $C_r = 10$.

In order to further validated our approach, we test our index on a large dataset that contains almost 100 millions of the images. The dataset is the Yahoo Flickr Creative Commons 100 Million Dataset (YFCC100M) and it is available at [https://bit.ly/yfcc100md](https://bit.ly/yfcc100md). We have extracted the DCNN features of the fc6 layer and indexed them with lucene using a quantization factor $Q = 30$. Since for this dataset a ground-truth is not available, we only reported the performance of the query in terms of average response time (see Figure 5). From this experiment, we see that for instance for the configuration $L_q = 10$ and $C_r = 10$, we have an average query time of less than 4 seconds (without any parallelization), which is quite encouraging considering that using a modern PC the query time is of order of 10 minutes for the same dataset.
4 Conclusions and Future Work

In this work, we propose an efficient approach to build a content-based image retrieval on top of a text search engine specifically developed for Deep Convolutional Neural Network Features. This approach is very straightforward and does not demand costly elaborations during the indexing process, as for instance the permutation-based approaches such as \cite{1}, which requires to order a set of predefined reference objects for each object to be indexed. Moreover, in our approach, we can tune the query costs versus the quality of the approximation by specifying the length of the query, without the need of maintaining the original features for reordering the result set.

We evaluated different strategies of textual representation in order to optimize the index occupation and the query response time. In order to show that our approach is able to handle large datasets, we have developed a web-based prototype that provides an interface for combined textual and visual searching into a dataset of about 100 million of images.

References

[1] Giuseppe Amato, Claudio Gennaro, and Pasquale Savino. MI-File: using inverted files for scalable approximate similarity search. Multimedia Tools and Applications, 71(3):1333–1362, 2014.
Figure 3: Effectiveness (mAP) for various level of query lengths $L_q$ and reordering factor $C_r$ (with $k = 100$) vs the query without reduction (fullQ), and the mAP obtained with sequential scan using L2 ($C_r = 0$ means no reordering).

[2] Artem Babenko, Anton Slesarev, Alexandr Chigorin, and Victor Lempitsky. Neural codes for image retrieval. In Computer Vision–ECCV 2014, pages 584–599. Springer, 2014.

[3] Herbert Bay, Tinne Tuytelaars, and Luc Van Gool. SURF: Speeded Up Robust Features. In Ales Leonardis, Horst Bischof, and Axel Pinz, editors, Computer Vision - ECCV 2006, volume 3951 of Lecture Notes in Computer Science, pages 404–417. Springer Berlin Heidelberg, 2006.

[4] Stefan Böttcher, Charles LA Clarke, and Gordon V Cormack. Information retrieval: Implementing and evaluating search engines. Mit Press, 2010.

[5] Vijay Chandrasekhar, Jie Lin, Olivier Morère, Hanlin Goh, and Antoine Veillard. A practical guide to cnns and fisher vectors for image instance retrieval. arXiv preprint arXiv:1508.02496, 2015.

[6] Ken Chatfield, Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. Return of the devil in the details: Delving deep into convolutional nets. arXiv preprint arXiv:1405.3531, 2014.

[7] G.E. Chavez, K. Figueroa, and G. Navarro. Effective proximity retrieval by ordering permutations. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 30(9):1647–1658, sept. 2008.

[8] ZongYuan Ge, Chris McCool, Conrad Sanderson, and Peter Corke. Modelling local deep convolutional neural network features to improve fine-grained image classification. In Image Pro-
Figure 4: Average response time (sec) for various level of query lengths $L_q$ and reordering factor $C_r$ (with $k = 100$) vs the query without reduction (fullQ), and the mAP obtained with sequential scan using L2 ($C_r = 0$ means no reordering).

[9] H. Jégou, M. Douze, and C. Schmid. Packing bag-of-features. In Computer Vision, 2009 IEEE 12th International Conference on, pages 2357–2364, 29 2009-oct. 2 2009.
[10] H. Jégou, F. Perronnin, M. Douze, J. Sánchez, P. Pérez, and C. Schmid. Aggregating local image descriptors into compact codes. IEEE Transactions on Pattern Analysis and Machine Intelligence, 34(9):1704–1716, Sept 2012.
[11] Hervé Jégou, Matthijs Douze, and Cordelia Schmid. Improving bag-of-features for large scale image search. International Journal of Computer Vision, 87:316–336, May 2010.
[12] Hervé Jégou, Matthijs Douze, Cordelia Schmid, and Patrick Pérez. Aggregating local descriptors into a compact image representation. In IEEE Conference on Computer Vision & Pattern Recognition, pages 3304–3311, jun 2010.
[13] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, pages 1097–1105, 2012.
[14] Jie Lin, Olivier Morère, Julie Petta, Vijay Chandrasekhar, and Antoine Veillard. Tiny descriptors for image retrieval with unsupervised triplet hashing. arXiv preprint arXiv:1511.03055, 2015.
Figure 5: Average query response time (sec) for the YFCC100M dataset using lucene.

[15] David G. Lowe. Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, 60(2):91–110, 2004.

[16] F. Perronnin, Yan Liu, J. Sanchez, and H. Poirier. Large-scale image retrieval with compressed fisher vectors. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, pages 3384–3391, June 2010.

[17] Ali Sharif Razavian, Hossein Azizpour, Josephine Sullivan, and Stefan Carlsson. Cnn features off-the-shelf: An astounding baseline for recognition. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, June 2014.

[18] Bart Thomee, Benjamin Elizalde, David A Shamma, Karl Ni, Gerald Friedland, Douglas Poland, Damian Borth, and Li-Jia Li. Yfcc100m: The new data in multimedia research. *Communications of the ACM*, 59(2):64–73, 2016.