Class-Weighted Convolutional Features for Image Retrieval

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DATA 61 CSIRO

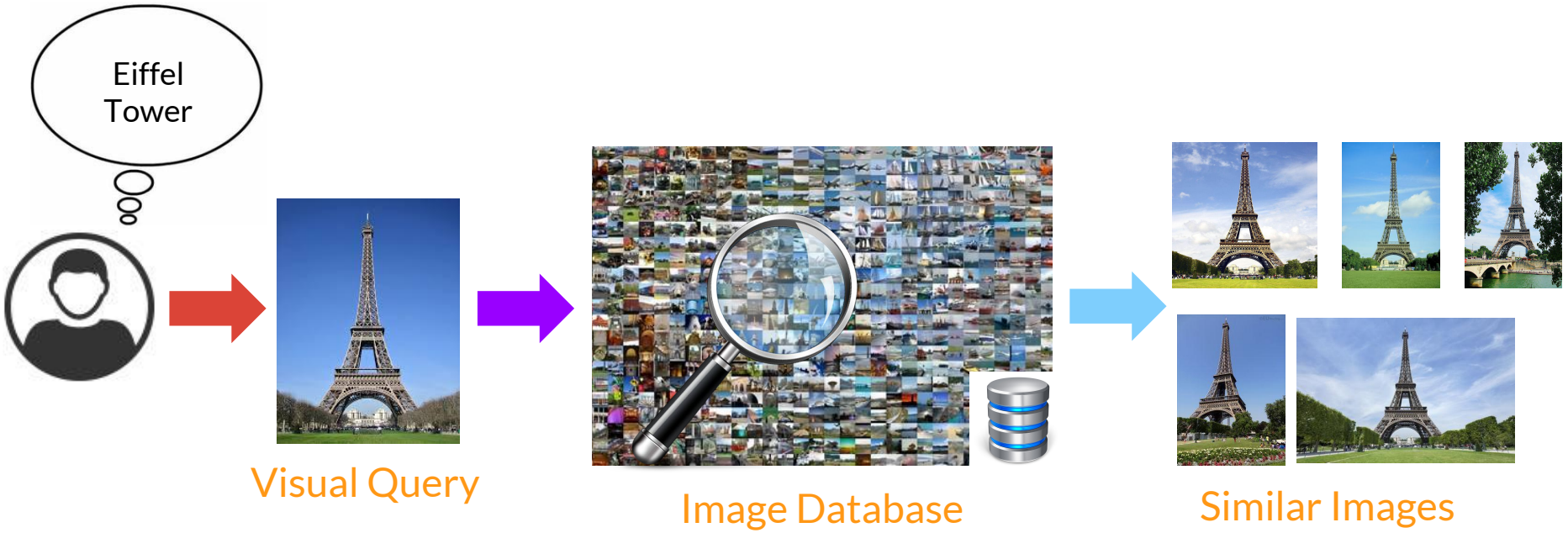
Code available at GitHub

Outline

- Introduction
- Related Work
- Our Proposal
- Experiments
- Conclusions

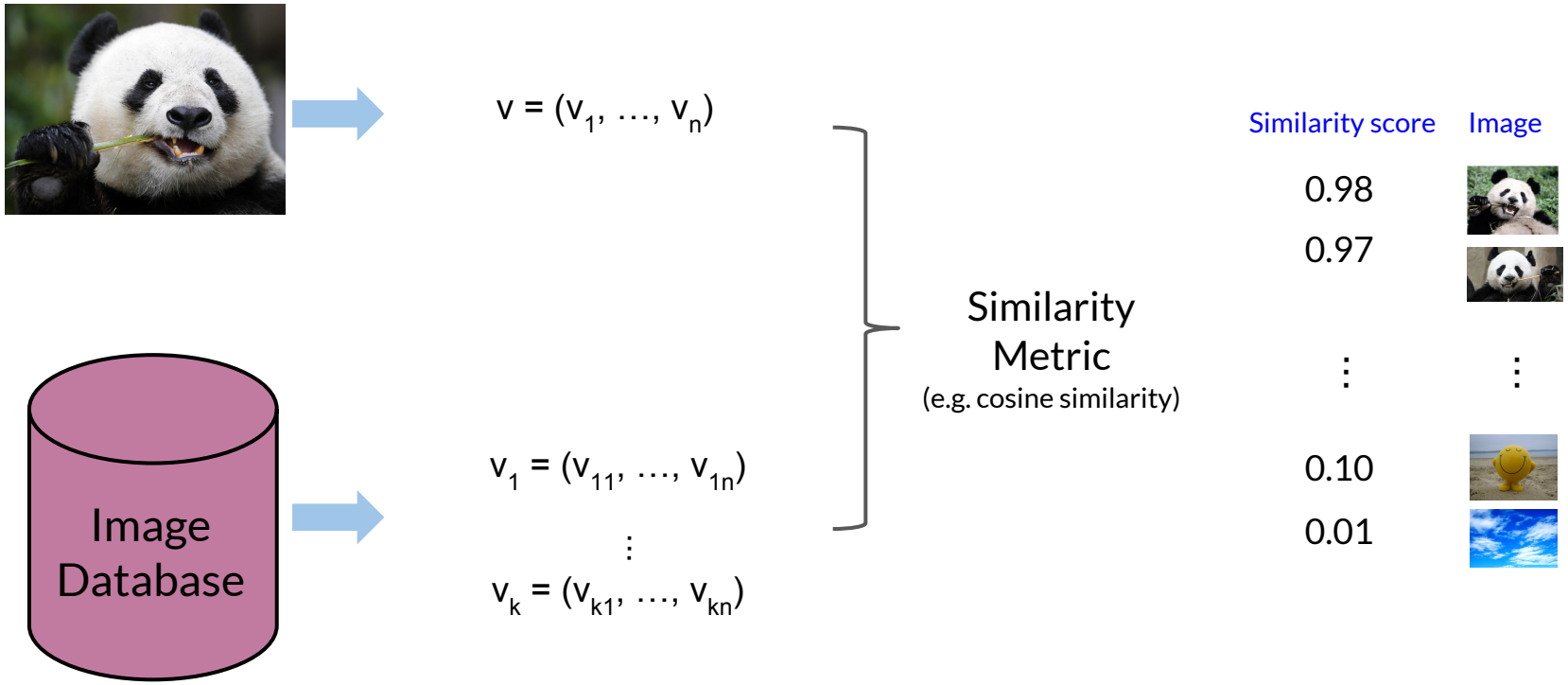
1. Introduction

Visual Instance Retrieval

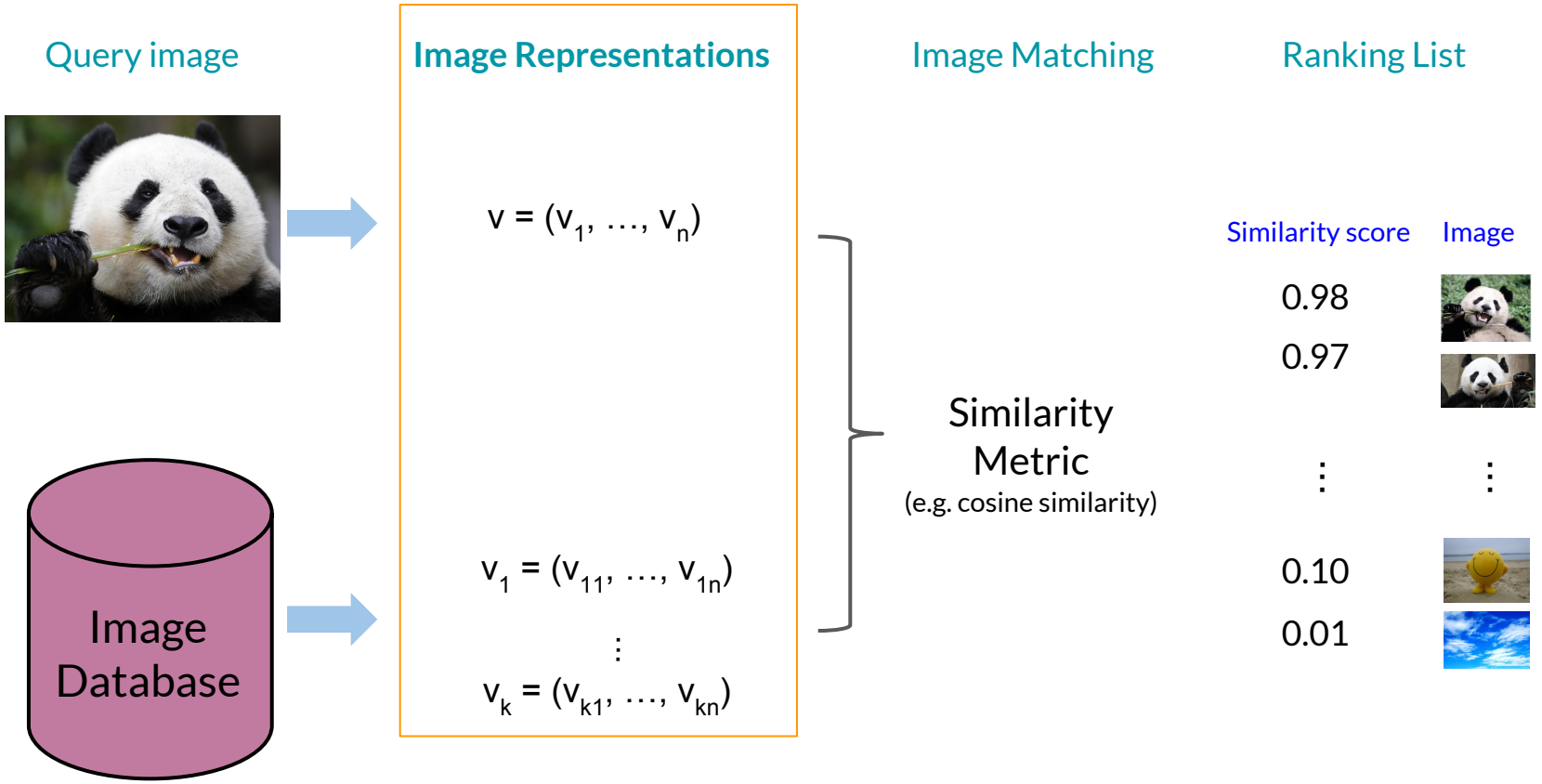


Given an image query, generate a ranked list of similar images

Visual Instance Retrieval



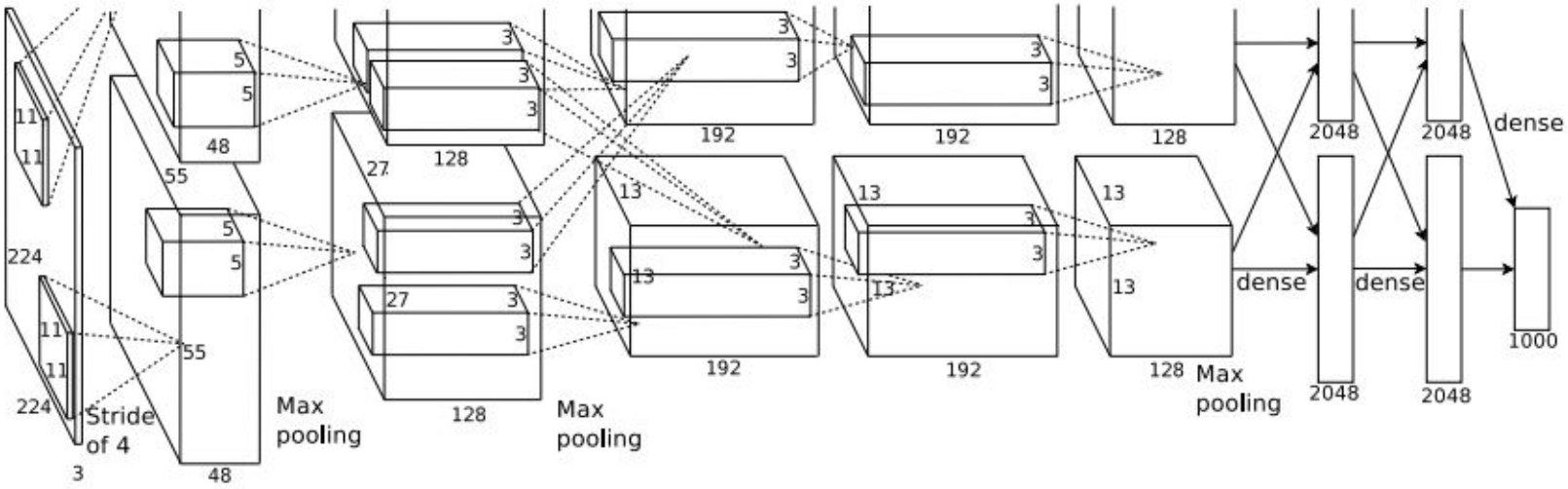
Visual Instance Retrieval



2. Related Work

Image Representations

Convolutional Neural Networks



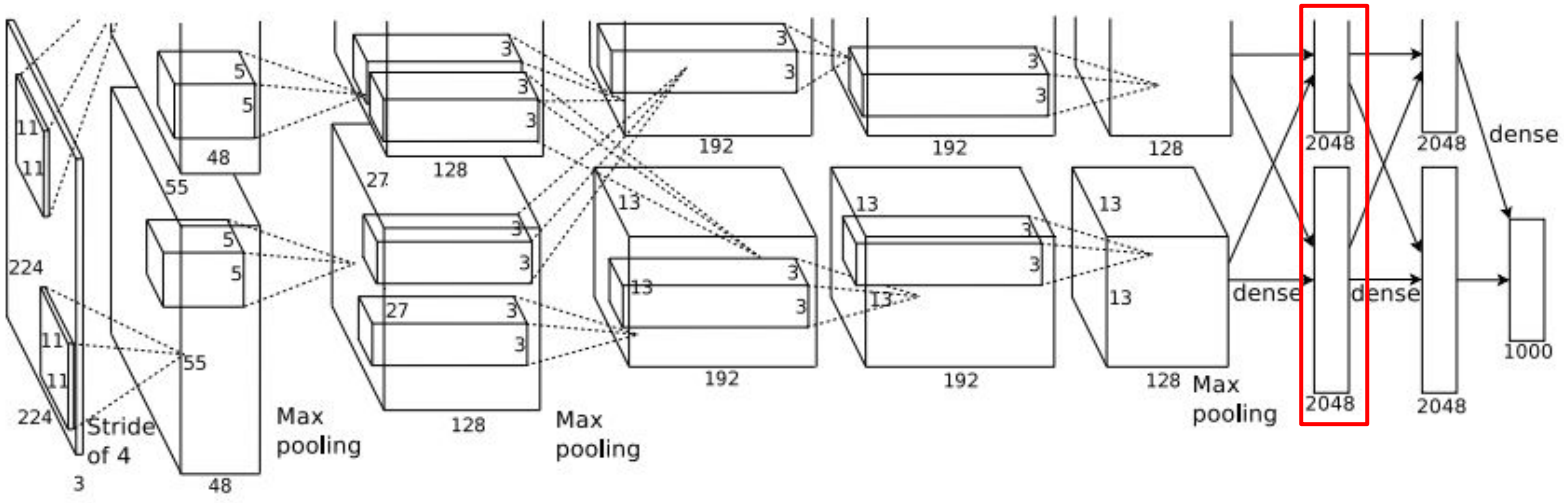
Example of a CNN: AlexNet

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105).

Image Representations

Convolutional Neural Networks

Fully-Connected features as global representation



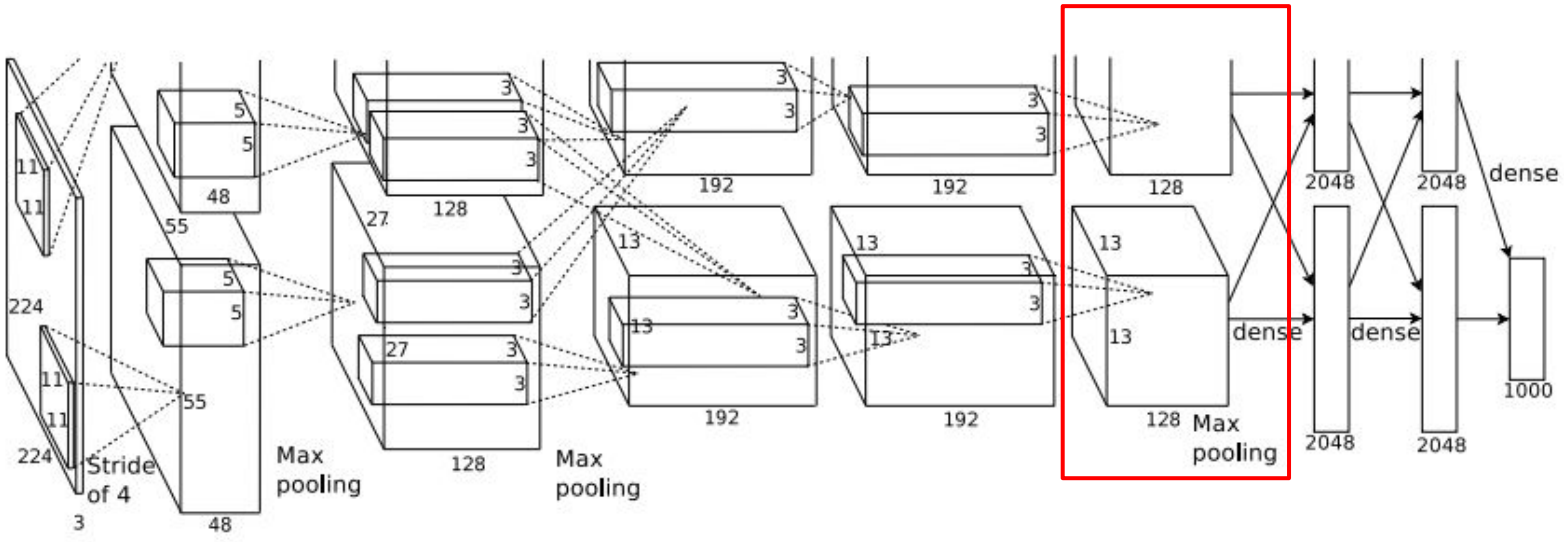
Babenko, A., Slesarev, A., Chigorin, A., & Lempitsky, V. (2014). Neural codes for image retrieval. In *ECCV 2014*

Razavian, A., Azizpour, H., Sullivan, J., & Carlsson, S. (2014). CNN features off-the-shelf: an astounding baseline for recognition. In DeepVision *CVPRW 2014*

Image Representations

Convolutional Neural Networks

Convolutional features (Sum/Max Pooled) as global representations

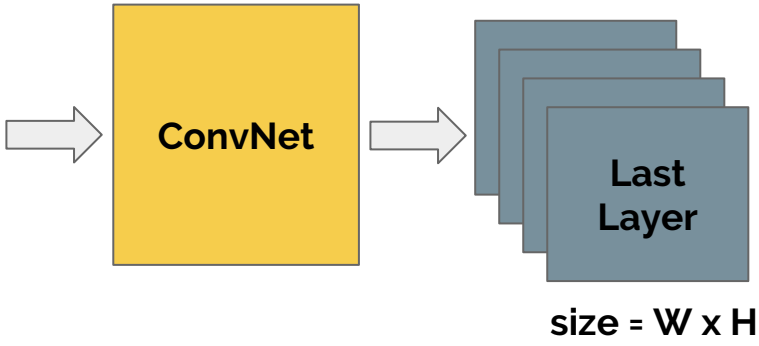


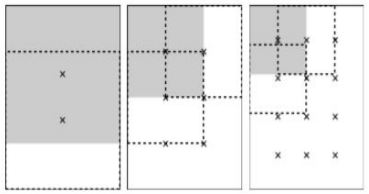
Babenko, A., & Lempitsky, V. (2015). Aggregating local deep features for image retrieval. *ICCV 2015*

Tolias, G., Sicre, R., & Jégou, H. (2015). Particular object retrieval with integral max-pooling of CNN activations. *ICLR 2016*

Kalantidis, Y., Mellina, C., & Osindero, S. (2015). Cross-dimensional Weighting for Aggregated Deep Convolutional Features. *arXiv preprint arXiv:1512.04065*.

R-MAC

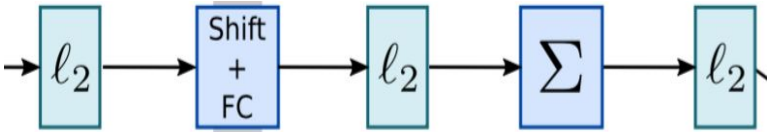




- Regions selected using a rigid grid
- Compute a feature vector per region
- Combine all region feature vectors
  - Dimension → 256 / 512
  - AlexNet / VGG-16

maximum activation

$$\mathbf{f}_{\mathcal{R}} = [\mathrm{f}_{\mathcal{R},1} \ldots \mathrm{f}_{\mathcal{R},i} \ldots \mathrm{f}_{\mathcal{R},K}]^\top$$

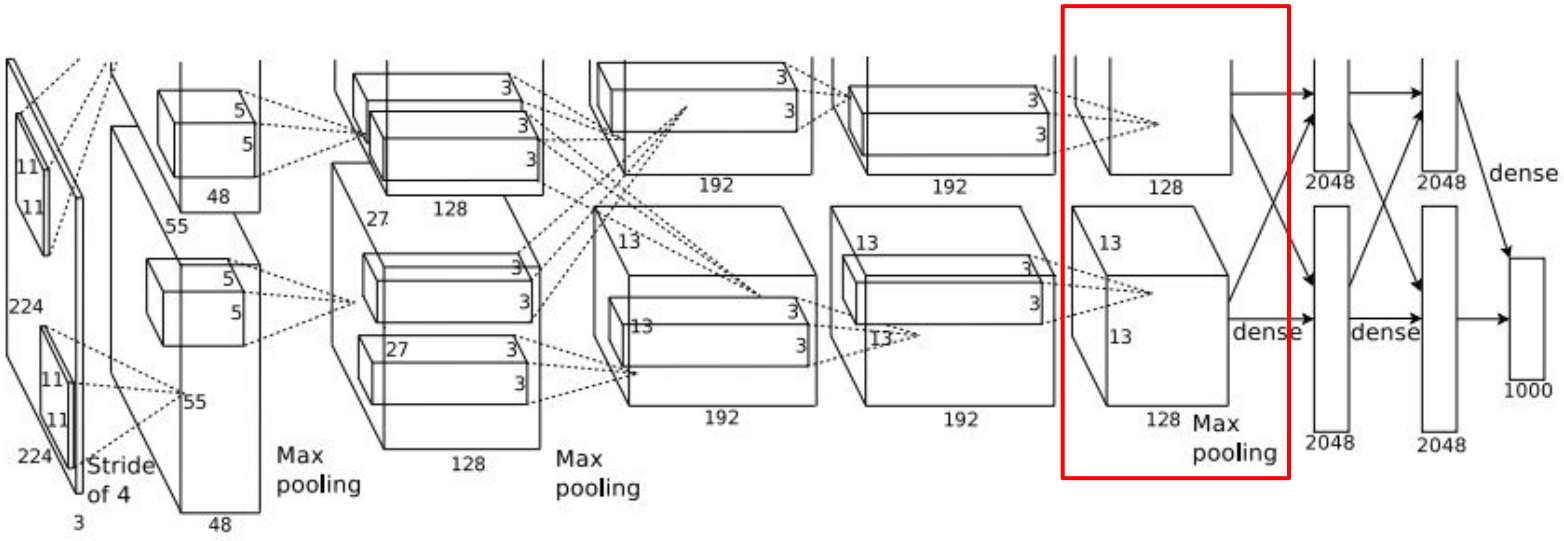


Tolias, G., Sicre, R., & Jégou, H. (2015). Particular object retrieval with integral max-pooling of CNN activations. *ICLR 2015*

Image Representations

Convolutional Neural Networks

Convolutional features - Encoded with VLAD or BoW



Ng, J., Yang, F., & Davis, L. (2015). Exploiting local features from deep networks for image retrieval. In *DeepVision CVPRW 2015*

E. Mohedano, A. Salvador, K. McGuinness, F. Marques, N. E. O'Connor and X. Giro, Bags of Local Convolutional Features for Scalable Instance Search. In ICMR 2016

Motivation: Image Semantics

Dog

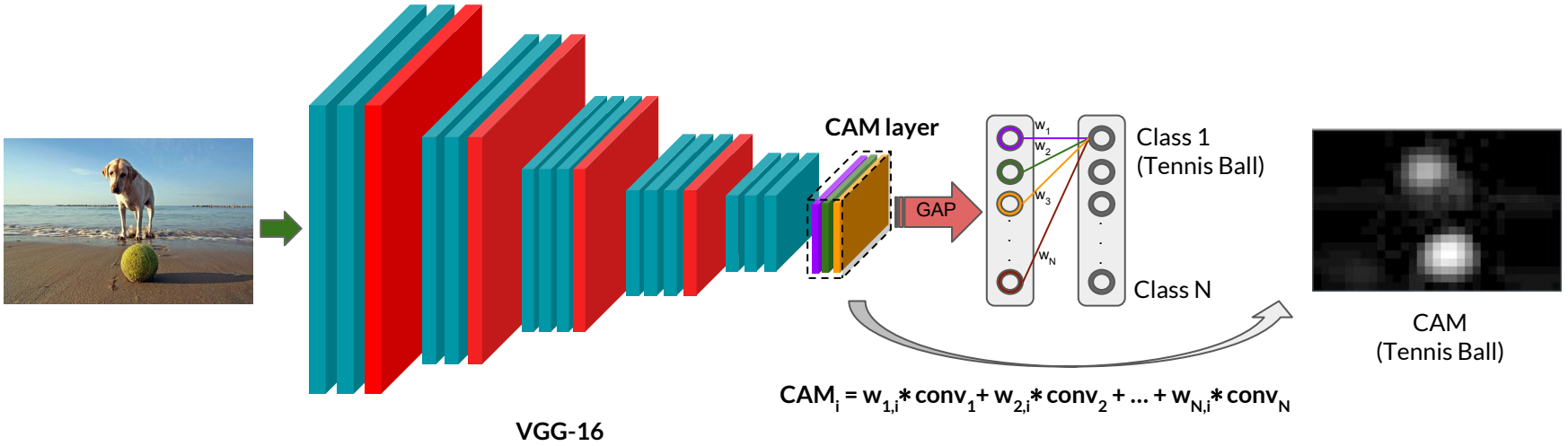
Seashore

Tennis Ball

Sand bar

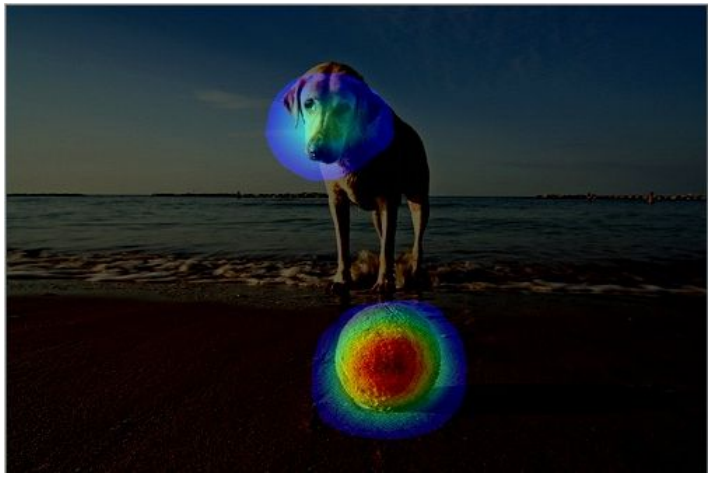
Motivation: Image Semantics

Class Activation Maps



B. Zhou, A. Khosla, Lapedriza. A., A. Oliva, and A. Torralba. 2016. Learning Deep Features for Discriminative Localization. CVPR (2016).

Motivation: Image Semantics



Tennis Ball

Chesapeake Bay Retriever

Simple Classes

Motivation: Image Semantics

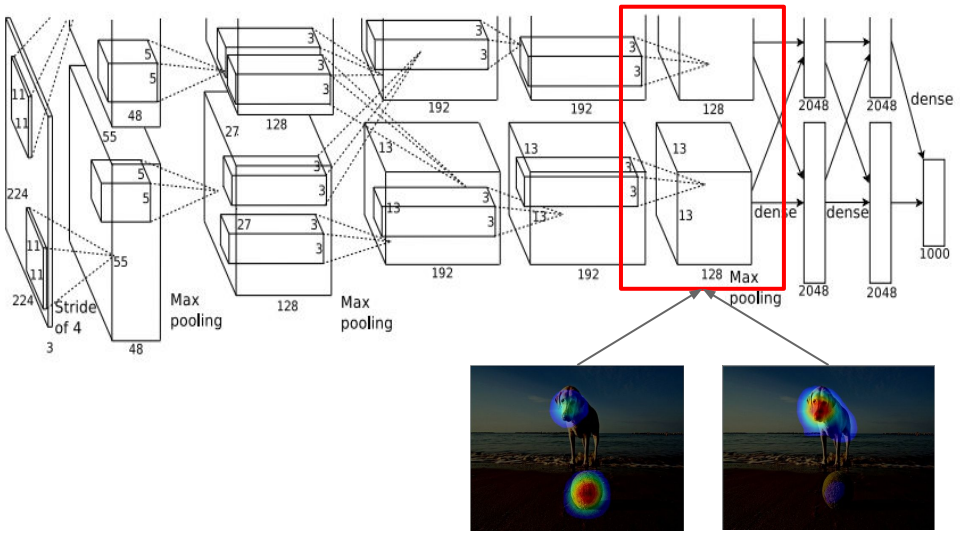
Sand Bar

Seashore

Complex Classes

3. Proposal

Proposal



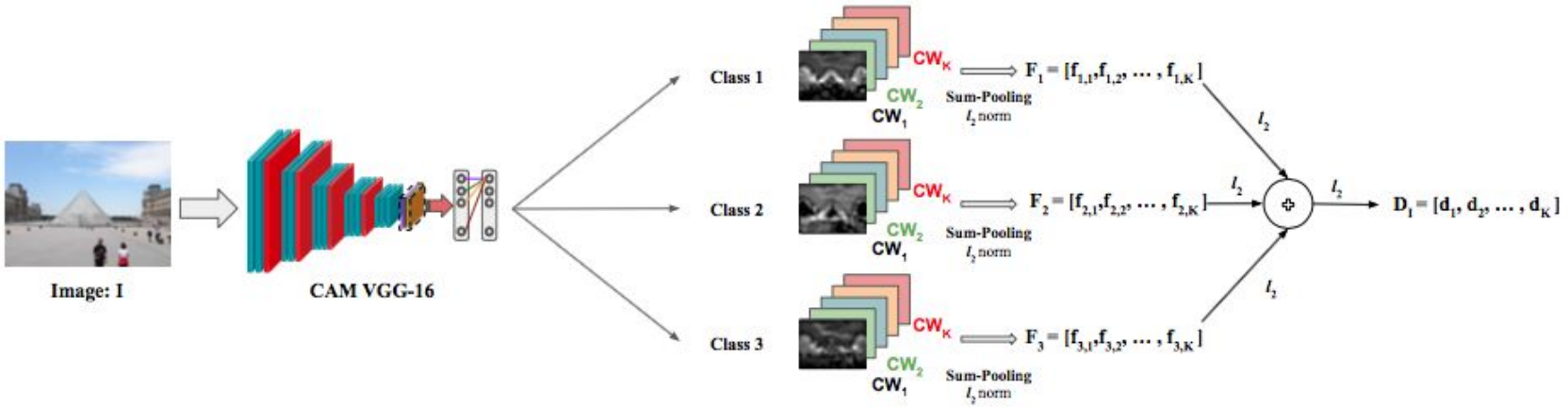
Compact Descriptor

Class-Weighted Convolutional Features

Encode images combining **image semantics** knowledge with **convolutional features**

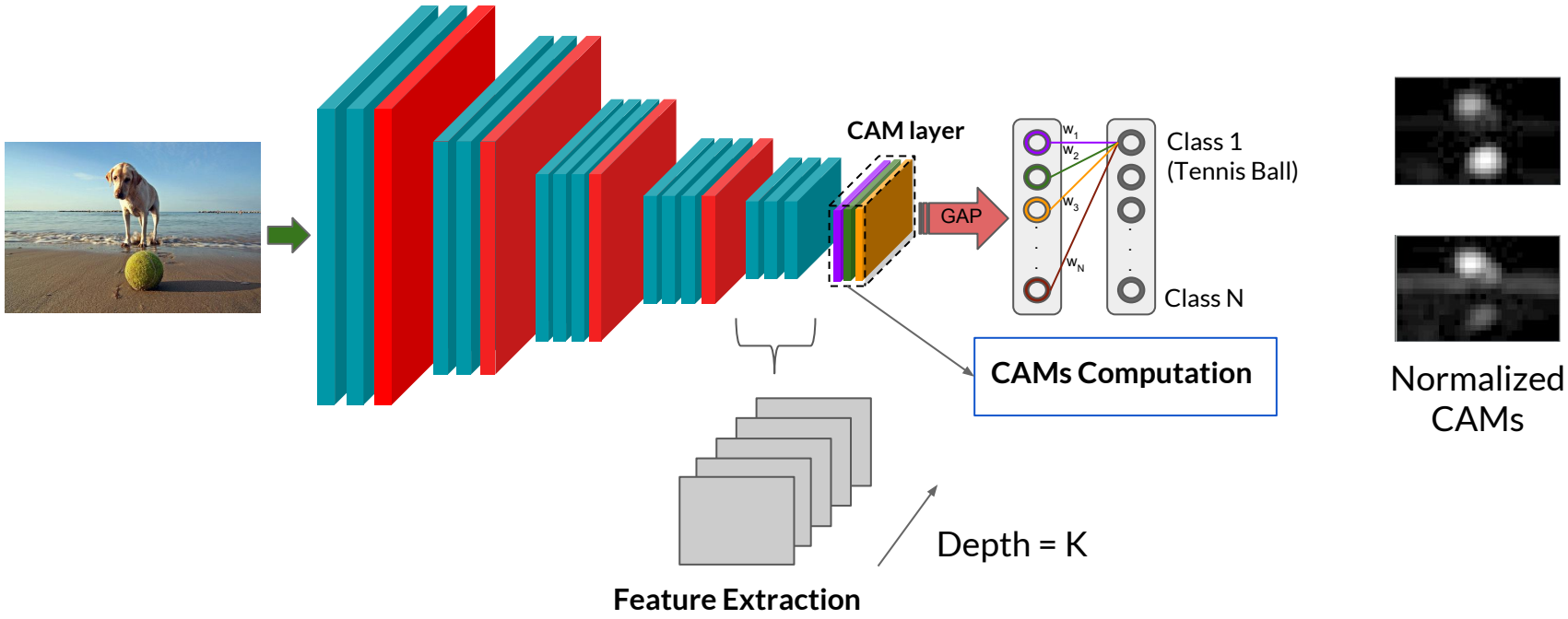
Retrieval Pipeline

1. Convolutional Features & CAMs Extraction
2. Channel & Class-Weighting
3. Feature Pooling
4. Descriptor Aggregation



Retrieval Pipeline

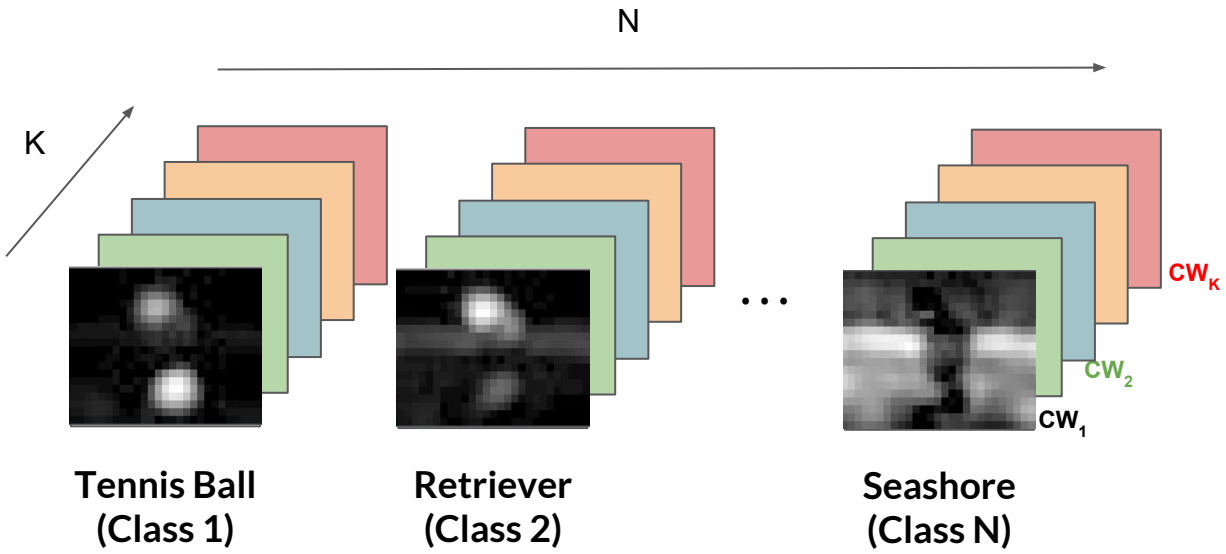
1. Convolutional Features & CAMs Extraction



In a **single forward pass** we extract convolutional features and image CAMs

Retrieval Pipeline

2. Channel & Class-Spatial Weighting

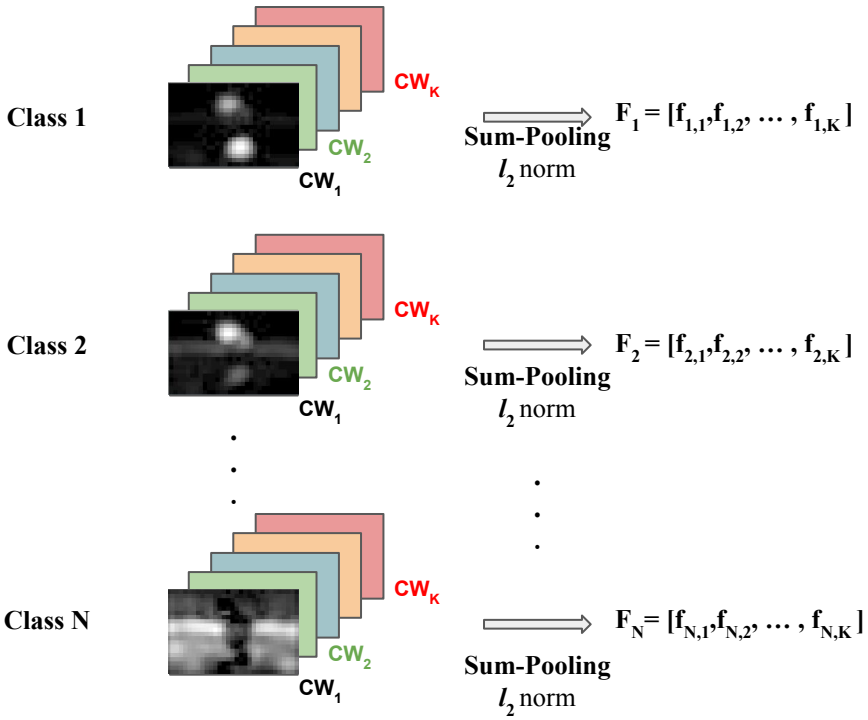


Spatial Weighting based on Class Activation Maps

Channel Weighting based on feature maps sparsity (as in CroW)

Retrieval Pipeline

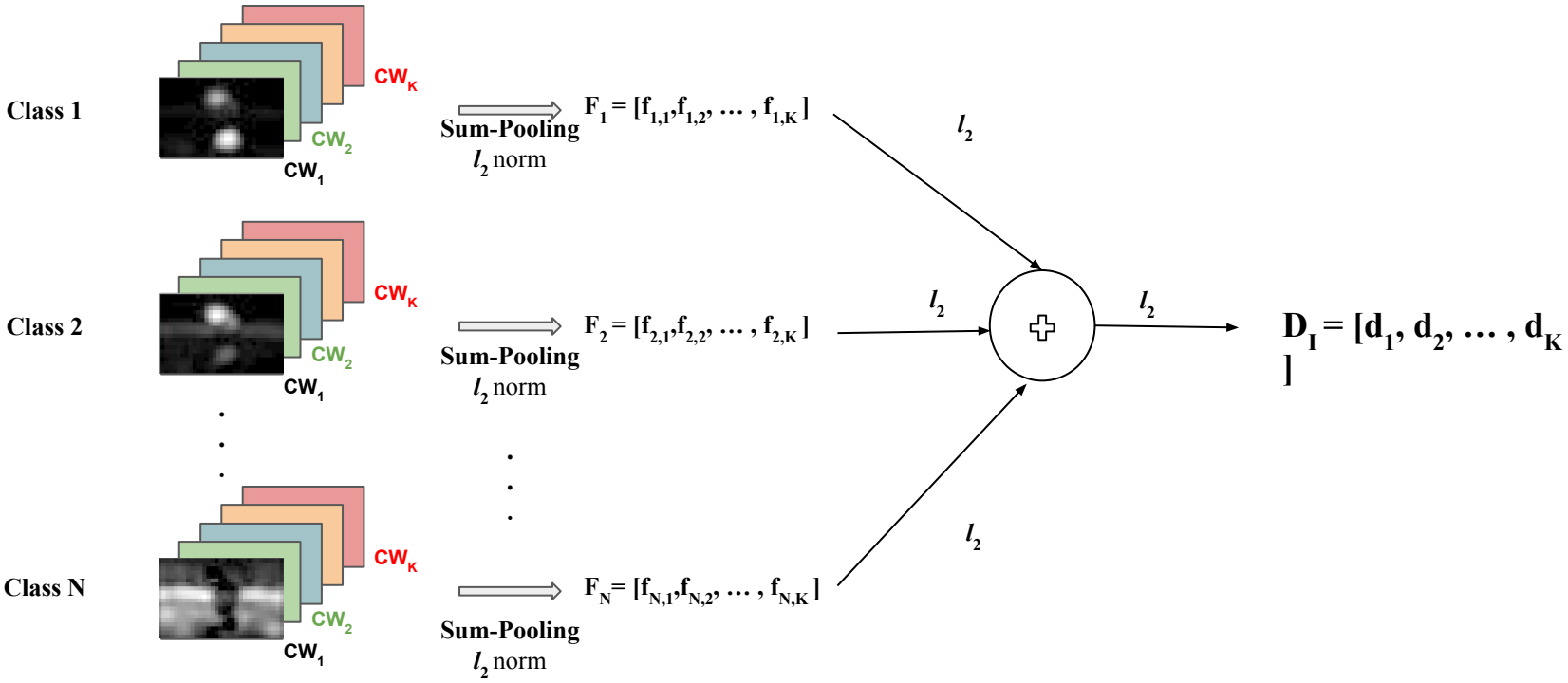
3. Feature Pooling



One vector per class: $F_c = [f_{c,1}, f_{c,2}, \ldots, f_{c,K}] \; \forall c \in [1, N]$

Retrieval Pipeline

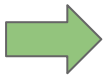
4. Descriptor Aggregation



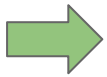
Descriptor Aggregation Strategies

Online Aggregation (OnA)

Image Dataset

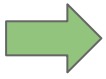


Our Retrieval Pipeline



Store all the class vectors (F_c)

Query



Our Retrieval Pipeline

Query Descriptor

Dataset Descriptor Aggregation

Scores

CNN Most Probable Classes Prediction from query (Retriever, seashore...)

Descriptor Aggregation Strategies

Offline Aggregation (OfA)

Image Dataset

Our Retrieval Pipeline

Dataset Descriptor Aggregation

Store final descriptor

CNN Most Probable Classes Prediction

Query

Our Retrieval Pipeline

Query Descriptor

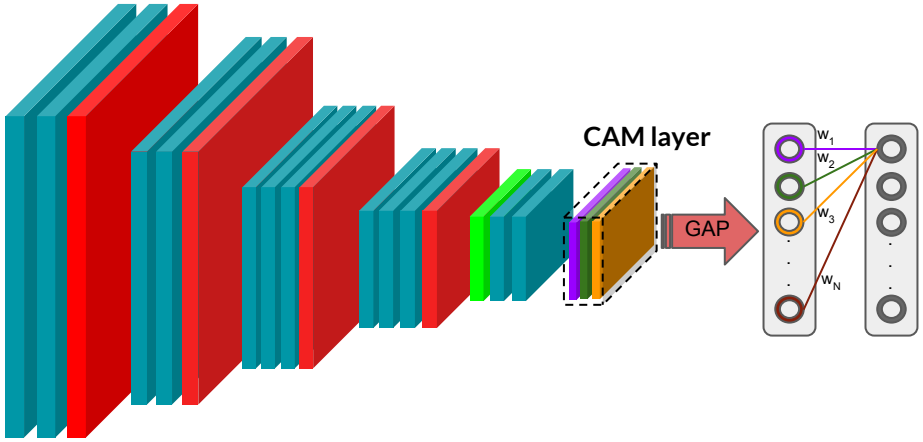
Pre-Computed Descriptors

Scores

4. Experiments

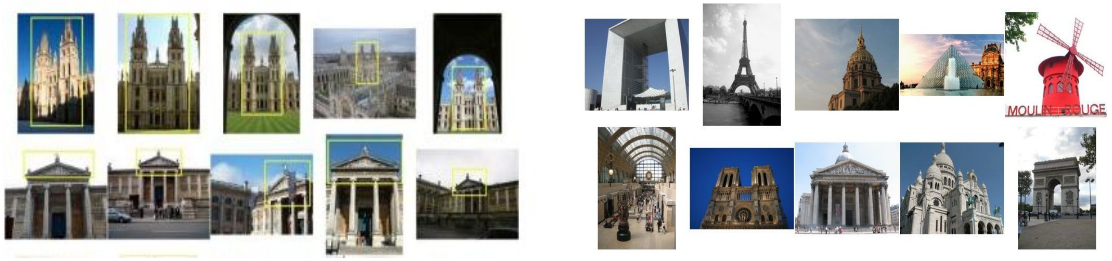
Experimental Setup

- Keras over Theano
- Images resized to 1024x720 (keeping aspect ratio)
- VGG-16 CAM model as feature extractor (ImageNet)
- Features from *Conv5_1* Layer



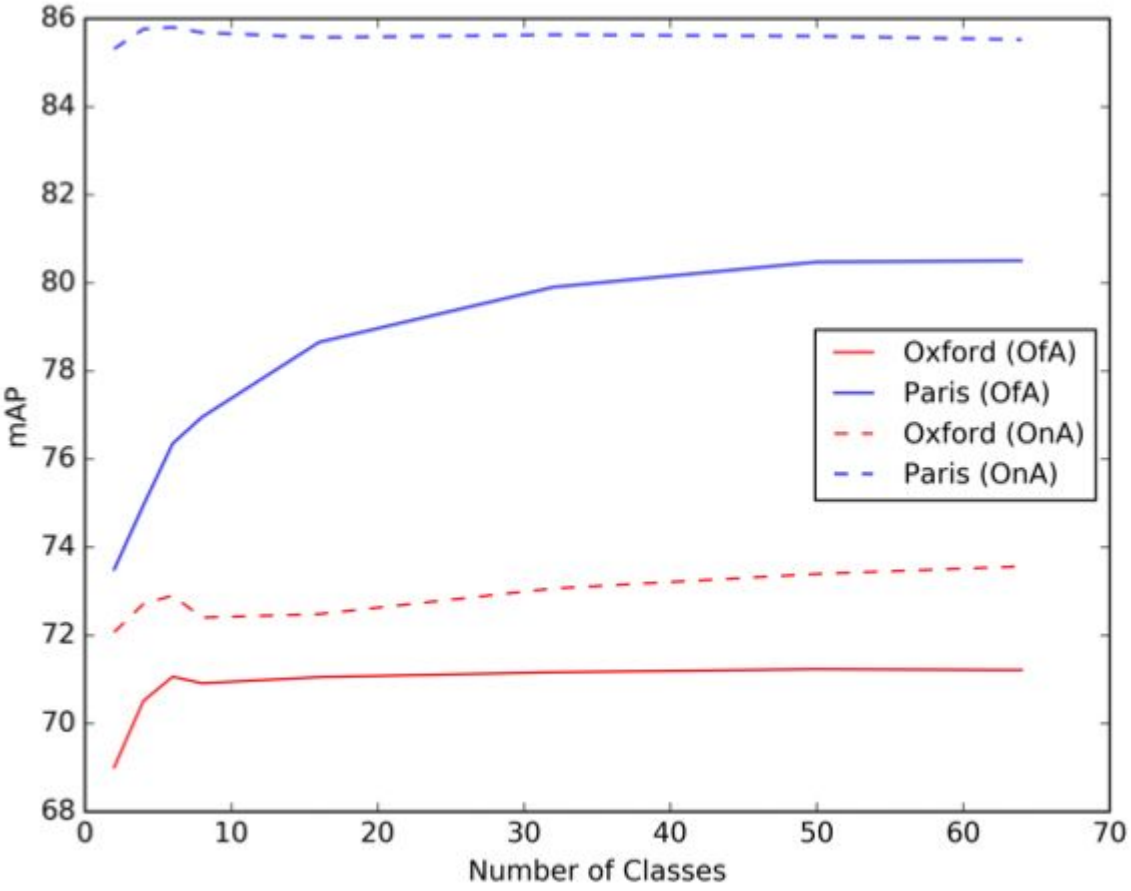
Experimental Setup

- Datasets
  - Oxford 5k
  - Paris 6k
  - 100k Distractors (Flickr)
- Scores computed with cosine similarity
- Evaluation metric: mean Average Precision (mAP)



Philbin, J. , Chum, O. , Isard, M. , Sivic, J. and Zisserman, A. Object retrieval with large vocabularies and fast spatial matching, *CVPR 2007*
Philbin, J. , Chum, O. , Isard, M. , Sivic, J. and Zisserman, A. Lost in Quantization: Improving Particular Object Retrieval in Large Scale Image Databases. *CVPR 2008*

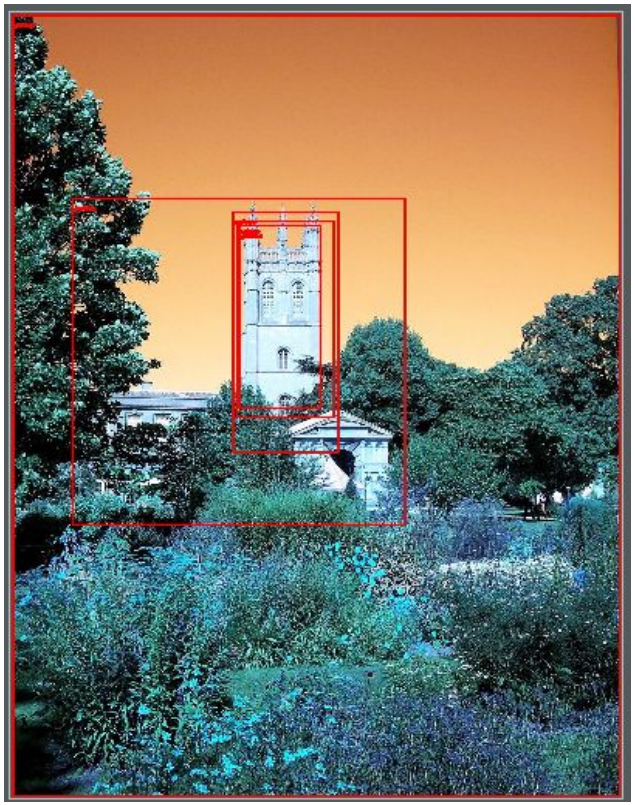
How many objects are relevant?



Comparison with State-of-the-Art

Method	Dim	Oxf5k	Par6k	Oxf105k	Par106k
SPoC[2]	256	0.531	-	0.501	-
CroW[10]	512	0.682	0.796	0.632	0.710
uCroW[10]	256	0.666	0.767	0.629	0,695
Razavian [19]	32k	**0.843**	0.853	-	-
R-MAC[27]	512	0.669	0.830	0.616	**0.757**
BoW[12]	25k	0.738	0.820	0.593	0.648
Ours(OnA)	512	0.729	**0.858**	-	-
Ours(OfA)	512	0.712	0.799	**0.672**	0.727

Re-Ranking



Comparison with State-of-the-Art

Method	Dim	R	QE	Oxf5k	Par6k	Oxf105k	Par106k
CroW	512	-	10	0.722	0.855	0.678	0.797
Ours(OnA)	512	-	10	0.766	**0.879**	-	-
Ours(OfA)	512	-	10	0.737	0.835	0.714	0.777
BoW	25k	100	10	0.788	0.848	0.651	0.641
Ours(OnA)	512	100	10	0.786	0.876	-	-
Ours(OfA)	512	100	10	0.772	0.836	0.744	0.777
RMAC	512	1000	5	0.770	0.877	0.726	**0.817**
Ours(OnA)	512	1000	5	**0.812**	0.874	-	-
Ours(OfA)	512	1000	5	0.803	0.854	**0.765**	0.778

5. Conclusions

Conclusions

- We propose to use the semantic information of images to encode them.
- We introduce the use of CAMs to spatially weight convolutional features inside a retrieval pipeline.
- We demonstrated that our retrieval system outperforms the previous state-of-the-art in off-the-shelf retrieval.


Thank
you