

CNN-based descriptors

A horizontal timeline illustrating the evolution of computer vision research from 2000 to 2016. The timeline is divided into three main background regions: a light blue region for the early years (2000-2008), a light blue region for SIFT-based methods (2008-2012), and a light orange region for CNN-based methods (2012-2016). A black line with dots represents the timeline, with specific years and research milestones labeled above and below it. Below the timeline, two boxes labeled 'SIFT-based' and 'CNN-based' are positioned under their respective time periods.

Year	Research Milestone	Category
2000	"The end of the early years" Smeulders et al.	Early Years
2003	Video Google Slivic and Zisserman	Early Years
2006	Hierarchical K-Means Stewénius and Nistér	Early Years
2007	Approximate K-Means Philbin et al.	Early Years
2008	Hamming Embedding Jégou et al.	SIFT-based
2010	VLAD Jégou et al.	SIFT-based
2012	CNN for ImageNet Krizhevsky et al.	CNN-based
2014	CNN off-the-shelf Razavian et al.	CNN-based
2015	Neural codes Babenko et al.	CNN-based
2016	VLAD-CNN Ng et al.	CNN-based
2016	R-MAC Tolias et al.	CNN-based

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• 3-channel RGB input, 224 x 224

A 5x5 grid of 25 small images. The first row shows purple flowers. The second row shows elephants. The third row shows ships. The fourth row shows jack-o'-lanterns (pumpkins). The fifth row shows dogs.

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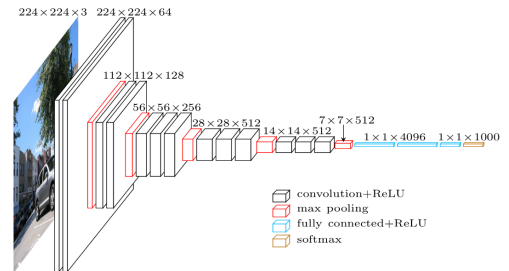
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CNN features Off-the-shelf

- For each image, extract multiple sub-patches of different sizes at different locations
- For each extracted sub-patch, its CNN representation is the L2 normalized output of the first fully connected layer (dim=4096)
- PCA dimensionality reduction → whitening → L2 renormalization (500-D)

A. Sharif Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, "Cnn features off-the-shelf: an astounding baseline for recognition," in CVPR Workshops, 2014.

VGG-16

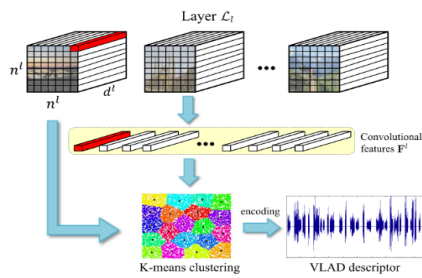


- Depth increased up to 19 layers,
- Kernel sizes reduced to 3, strides to 1

Simonyan and Zisserman 2014. Very Deep Convolutional Networks for Large-Scale Image Recognition.

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VLAD-CNN

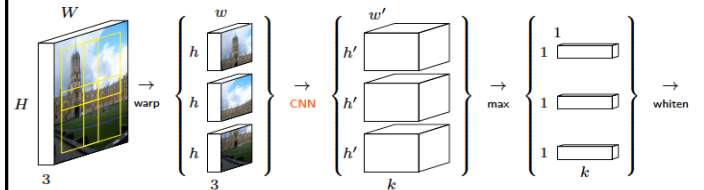


- Consider different layers of VGG-16
- For each layer, VLAD encoding ($k=100$)
- L2-normalization, PCS-whitening (128-D)

J. Ng, F. Yang, and L. Davis, "Exploiting local features from deep networks for image retrieval," CVPR Workshops, 2015.

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Regional CNN features

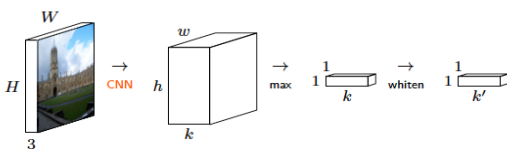


- 3-channel RGB input, largest square region extracted
- fixed multiscale overlapping regions, **warped** into $w \times h = 227 \times 227$
- each region** yields a $w' \times h' \times k = 36 \times 36 \times 256$ dimensional feature at the last convolutional layer of AlexNet
- global spatial **max**-pooling
- L2-normalization, PCA-whitening of each descriptor

Razavian, Sullivan, Maki and Carlsson 2015. Visual Instance Retrieval with Deep Convolutional Networks.

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Global max-pooling (MAC)



- VGG-16 last convolutional layer, $k = 512$
- global spatial **max**-pooling
- L2-normalization, PCA-whitening, L2-normalization
- MAC**: maximum activation of convolutions

Tolias, Sirc and Jegou. ICLR 2016. Particular Object Retrieval with Integral Max-Pooling of CNN Activations.

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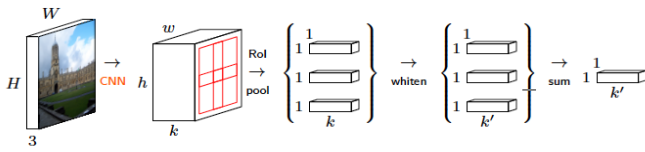
Global max-pooling (MAC)



- receptive fields of 5 components of MAC vectors that contribute most to image similarity

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Regional max-pooling (R-MAC)

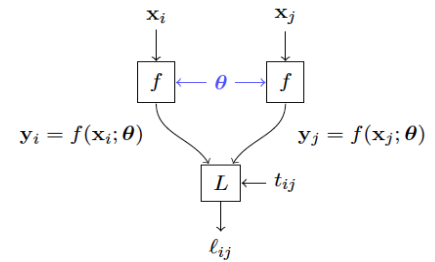


- VGG-16 last convolutional layer, $k = 512$
- fixed multiscale overlapping regions, spatial **max**-pooling
- L2-normalization, PCA-whitening, L2-normalization
- **sum**-pooling over all descriptors, L2-normalization

Tolias, Sivic and Jegou. ICLR 2016. Particular Object Retrieval with Integral Max-Pooling of CNN Activations.

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Siamese architecture



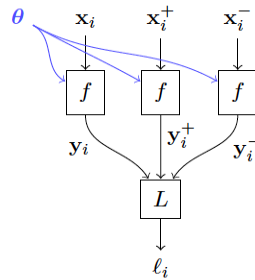
- an input sample is a **pair** (x_i, x_j)
- both x_i, x_j go through the **same** function f with **shared** parameters θ
- **Contrastive** loss l_{ij} is measured on output pair (y_i, y_j) and target t_{ij}

Chopra, Hadsell, Lecun. CVPR 2005. Learning a Similarity Metric Discriminatively, with Application to Face Verification.

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Triplet architecture

- an input sample is a triplet (x_i, x_i^+, x_i^-)
- x_i, x_i^+, x_i^- go through the **same** function f with **shared** parameters
- loss l_i measured on output triplet (y_i, y_i^+, y_i^-)



Wang, Song, Leung, Rosenberg, Wang, Philbin, Chen, Wu. CVPR 2014. Learning Fine-Grained Image Similarity with Deep Ranking.

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