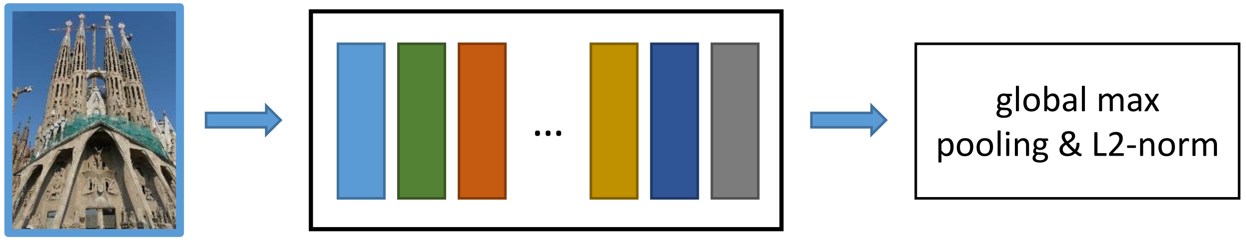

CNN Image Retrieval Learns from BoW: Unsupervised Fine-Tuning with Hard Examples

Filip Radenović Giorgos Tolias Ondřej Chum

Center for Machine Perception, CTU in Prague

ECCV 2016

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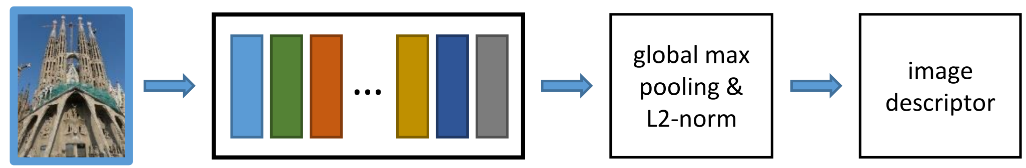
CNN Image Retrieval

- compact image descriptors
- Nearest Neighbor search



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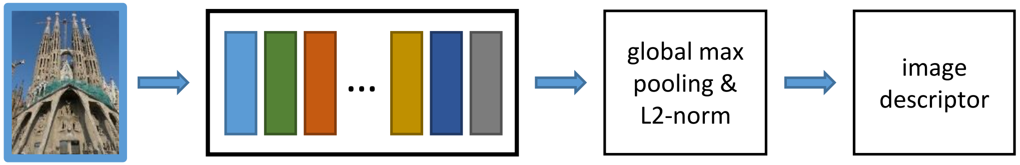

CNN Learning (Fine-Tuning)

start with CNN trained for different but similar task (reasonable parameters)

re-train with data relevant to your task

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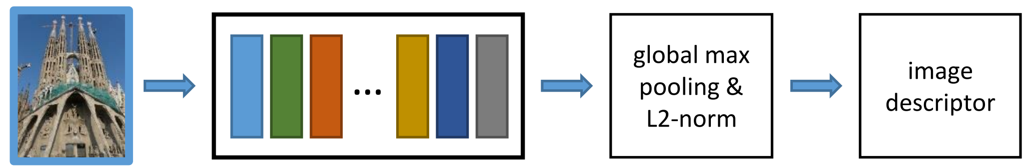

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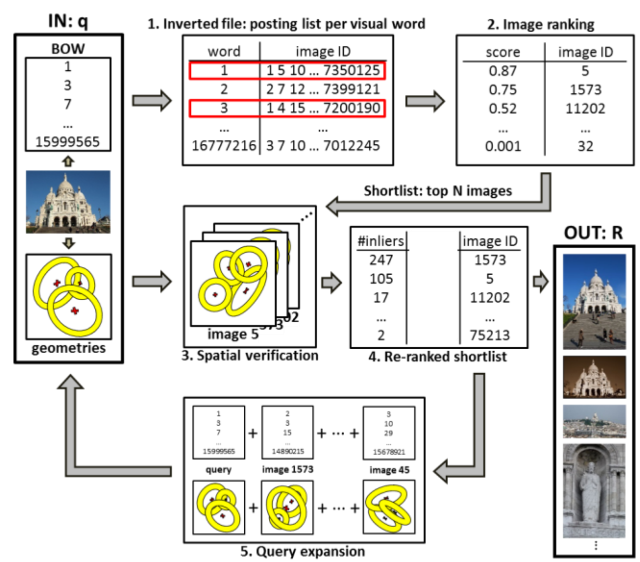
Bag of Words

state-of-the-art retrieval performance

couples well with SfM



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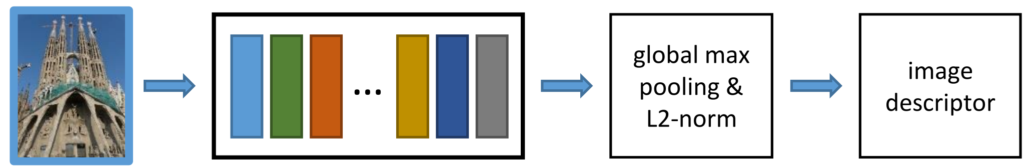
CNN Image Retrieval



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Unsupervised training data generation

- no human interaction

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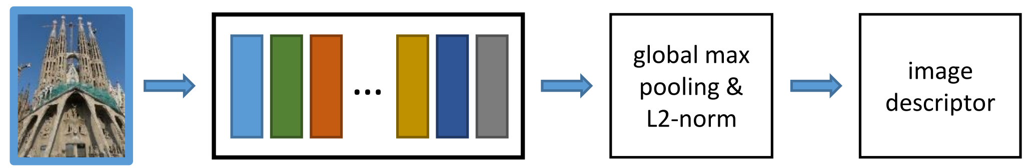

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Hard Examples

Instance Retrieval Challenges

- ➡ Significant viewpoint and/or scale change
- Significant illumination change
- Severe occlusions
- Visually similar but different objects

BoW: affine co-variant local features, invariant descriptors
CNN: lots of training examples





Instance Retrieval Challenges

Significant viewpoint and/or scale change

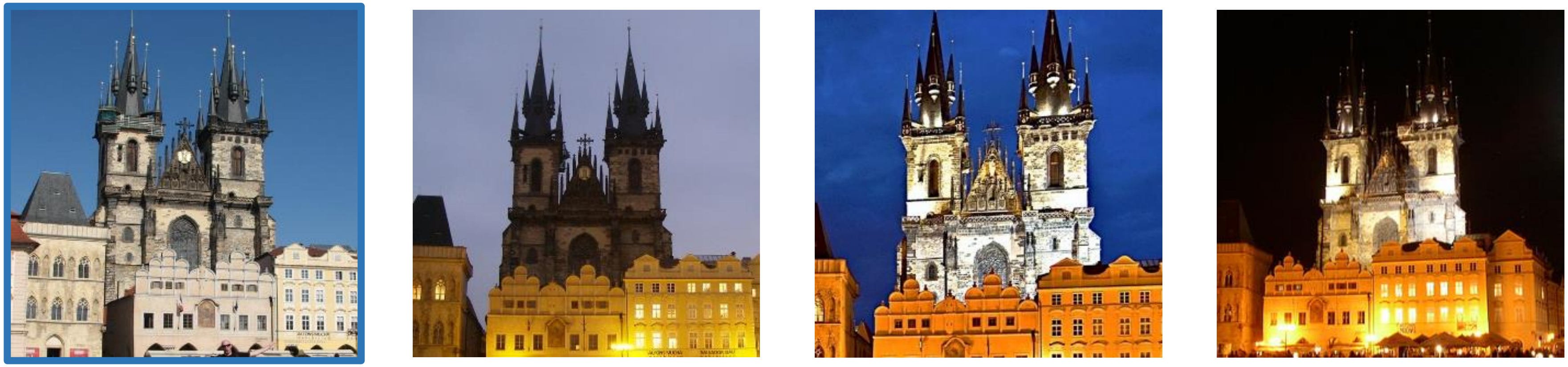
Significant illumination change

Severe occlusions

Visually similar but different objects

BoW: color-normalized feature descriptors

CNN: lots of training examples



Instance Retrieval Challenges

Significant viewpoint and/or scale change

Significant illumination change

➡ Severe occlusions

Visually similar but different objects

BoW: locality of the features, geometric verification

CNN: lots of training examples

Instance Retrieval Challenges

Significant viewpoint and/or scale change

Significant illumination change

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➡ Visually similar but different objects

BoW: discriminability of the features, geometric verification

Instance Retrieval Challenges

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CNN: lots of training examples

“Lots of Training Examples”

Large Internet
photo collection

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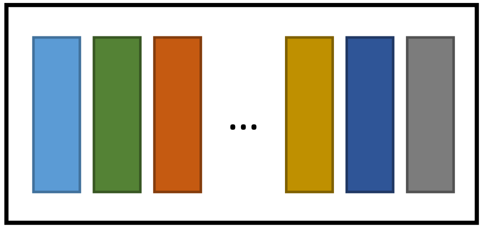


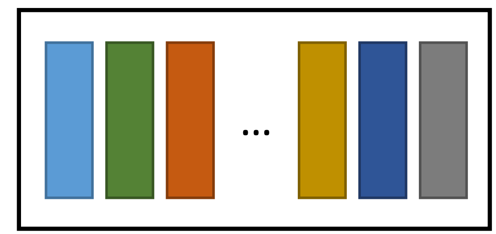
Convolutional Neural Network (CNN)

“Lots of Training Examples”

Large Internet photo collection

Training

Image annotations



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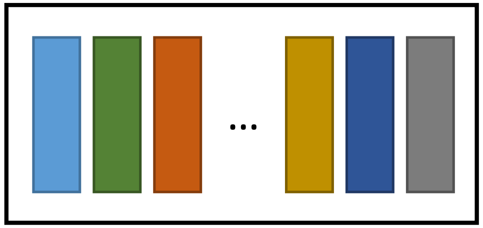
amazon mechanicalturk™
Artificial Artificial Intelligence

Not accurate
Expensive $$



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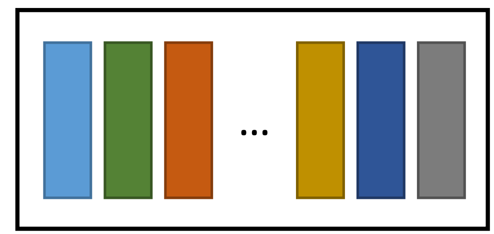

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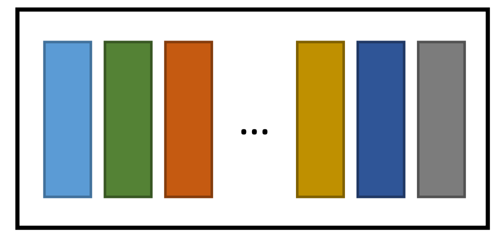


Convolutional Neural Network (CNN)

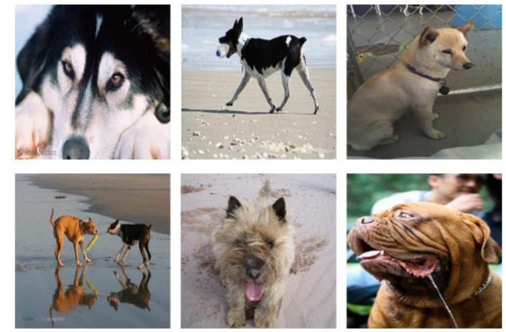
Automated extraction of training data

Very accurate

Free ~~$~~

Off-the-shelf CNN

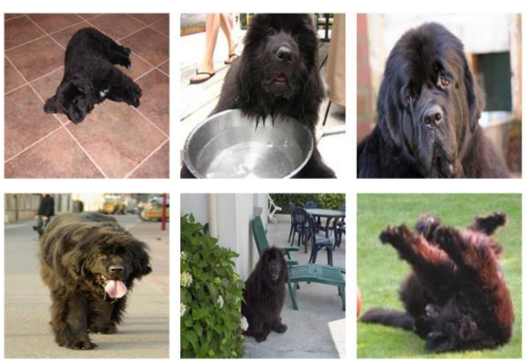
- Target application: classification
- Training dataset: ImageNet
- Architecture: AlexNet & VGG



Images from ImageNet.org

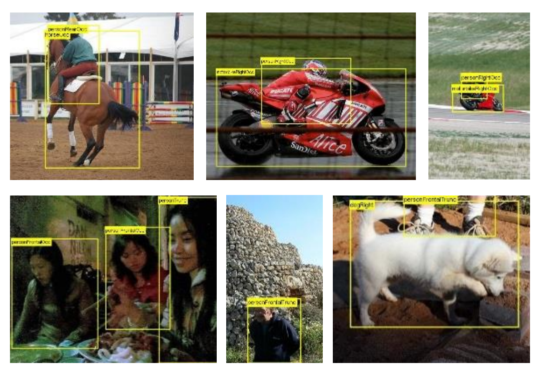
- Directly applicable to other tasks

Fine-grain classification



Images from ImageNet.org

Object detection



Images from PASCAL VOC 2012

Image retrieval

Annotations for CNN Image Retrieval

- CNN pre-trained for classification task used for retrieval
  [Gong et al. ECCV'14, Babenko et al. ICCV'15, Kalantidis et al. arXiv'15, Tolias et al. ICLR'16]

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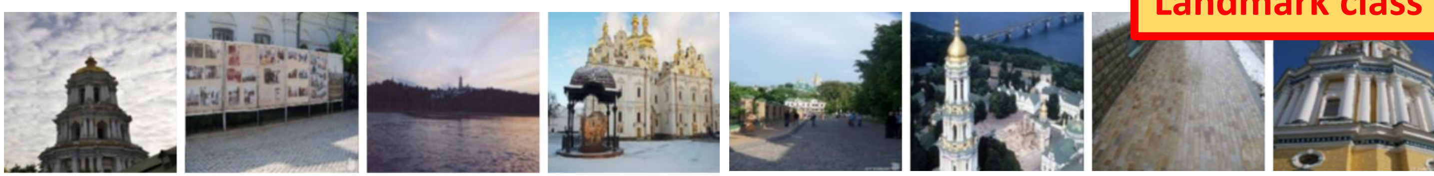
Building class

- Fine-tuned CNN using a dataset with landmark classes

Landmark class



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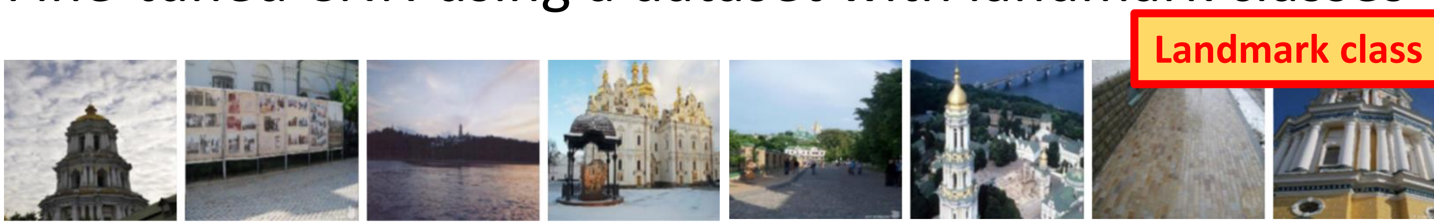
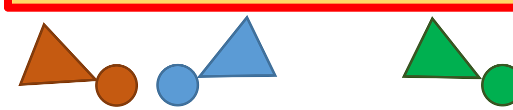


- NetVLAD: Weakly supervised fine-tuned CNN using GPS tags

spatially closest ≠ matching



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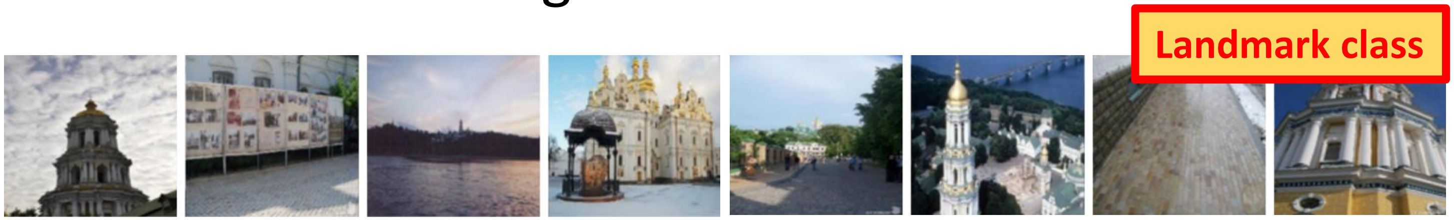

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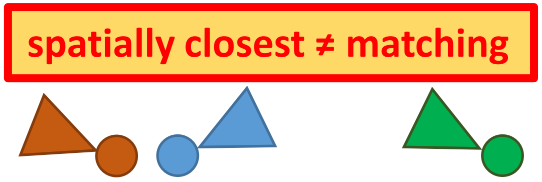


- We propose: automatic annotations for CNN training

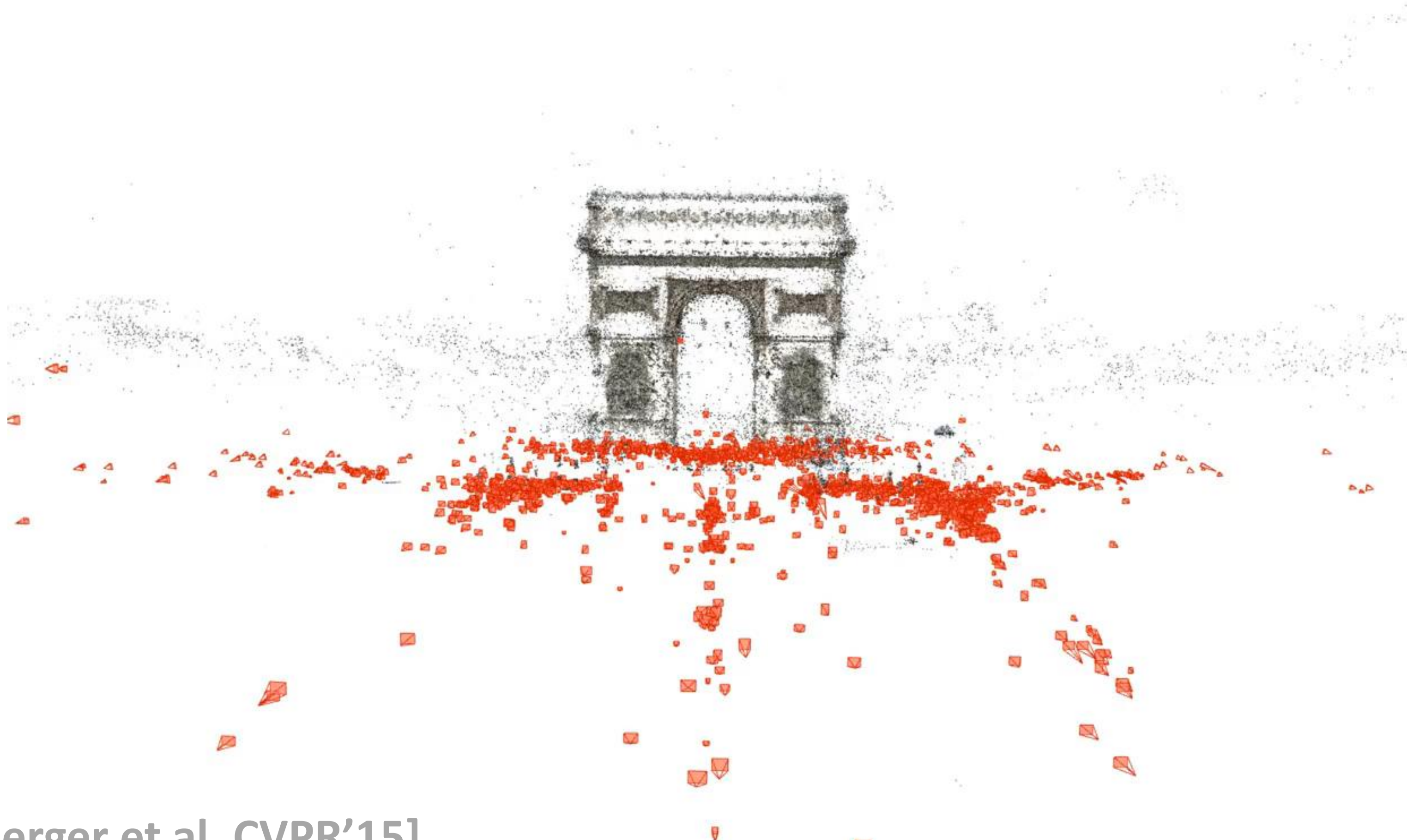
CNN learns from BoW – Training Data

[Schonberger et al. CVPR’15]
[Radenovic et al. CVPR’16]

7.4M images → 713 training 3D models

CNN learns from BoW – Training Data

Camera Orientation Known
Number of Inliers Known



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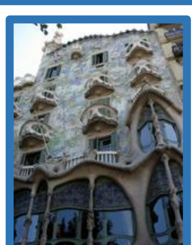
7.4M images → 713 training 3D models

Hard Negative Examples

Negative examples: images from different 3D models than the query
Hard negatives: closest negative examples to the query
Only hard negatives: as good as using all negatives, but faster

query



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query | **the most similar CNN descriptor**

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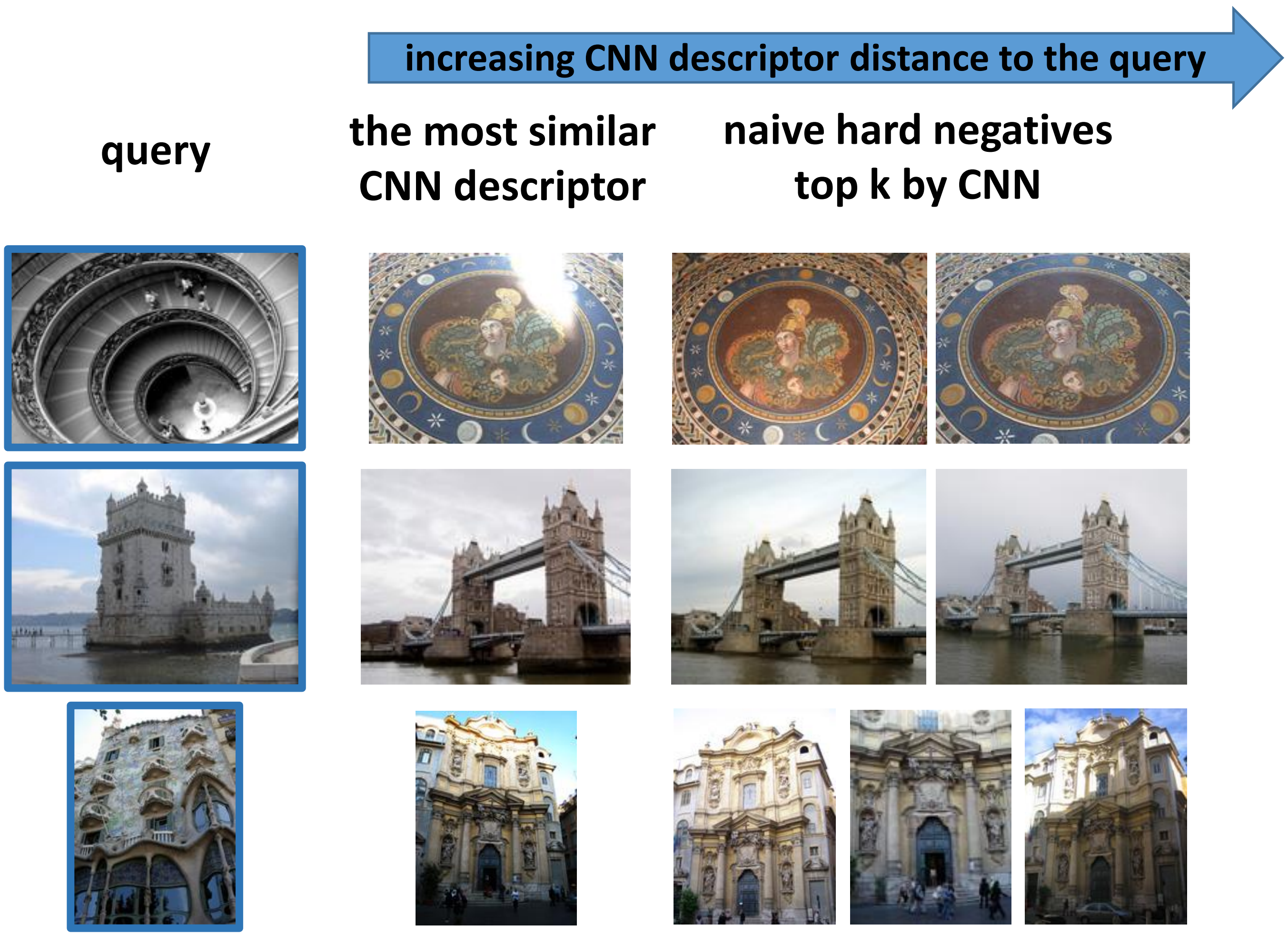

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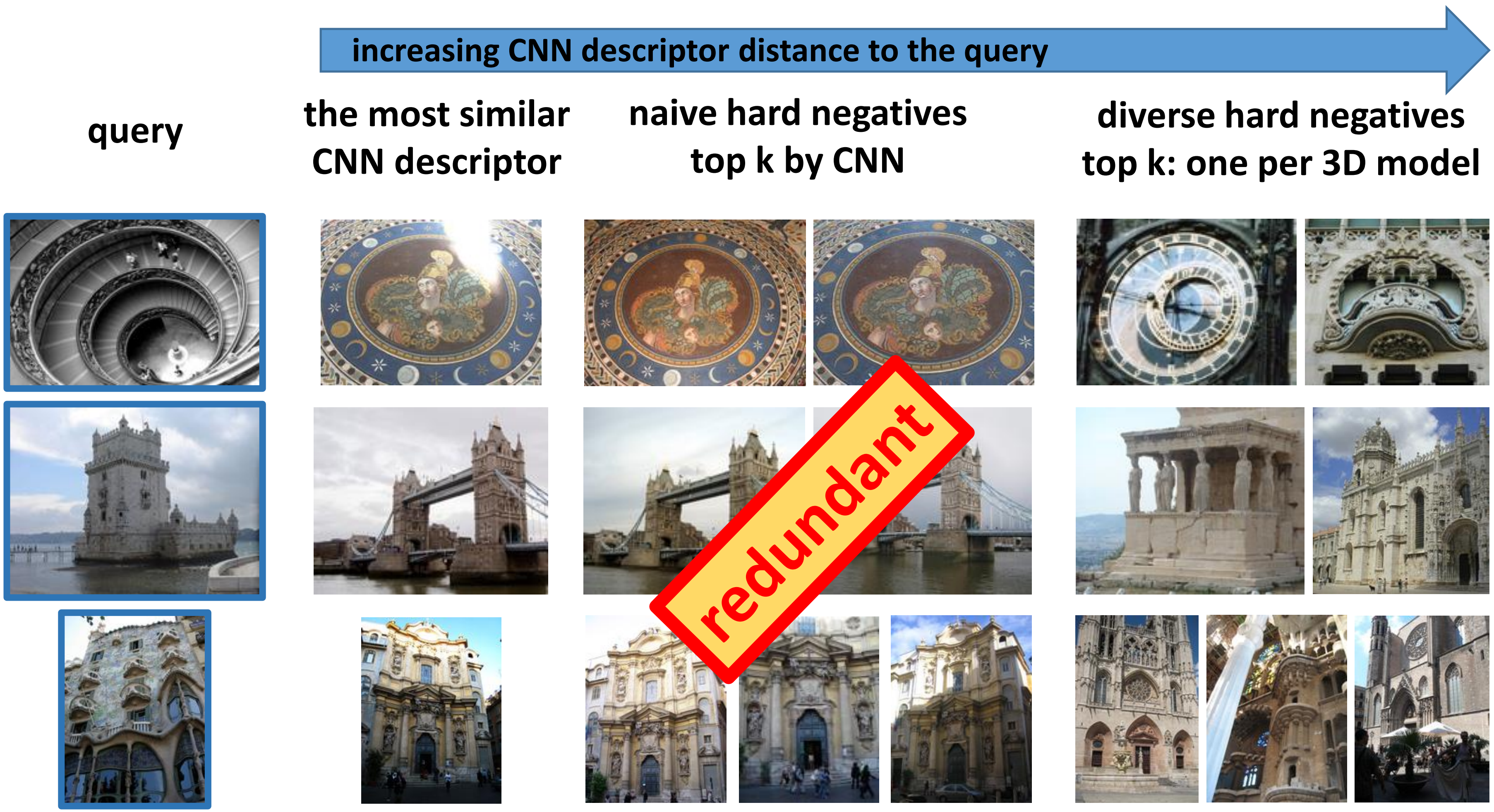
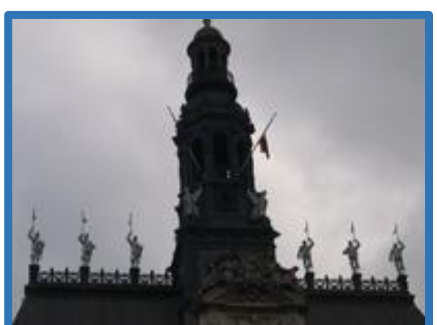


Hard Positive Examples

Positive examples: images that share 3D points with the query
Hard positives: positive examples not close enough to the query

query



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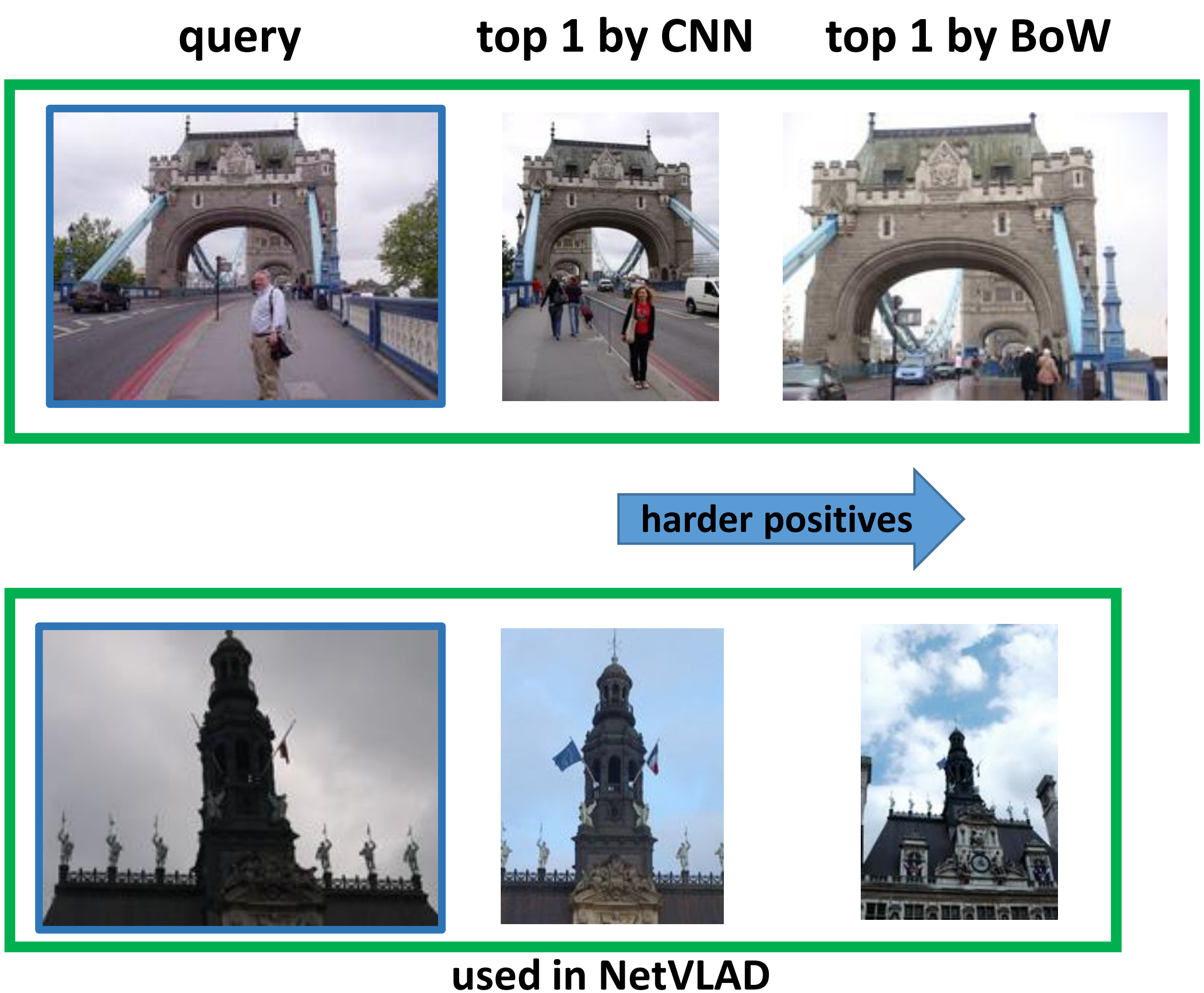

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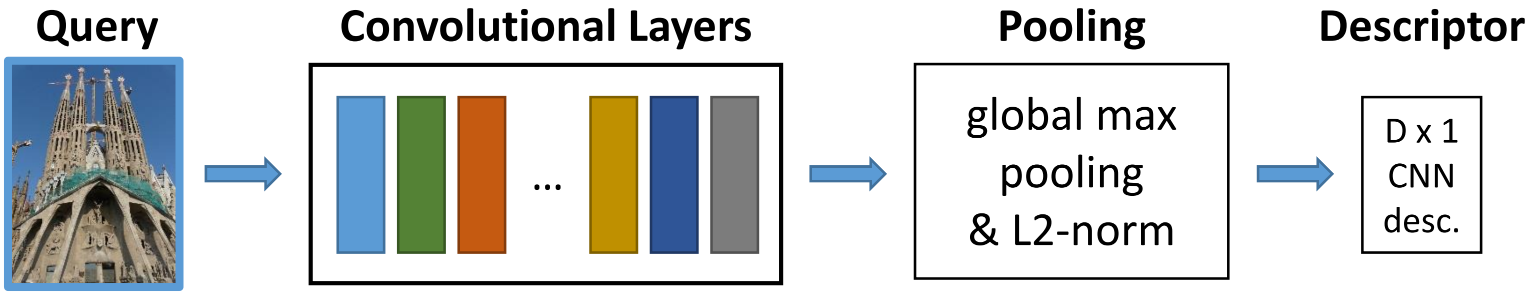
query **top 1 by CNN** **top 1 by BoW** **random from top k by BoW**

used in NetVLAD

CNN Siamese Learning



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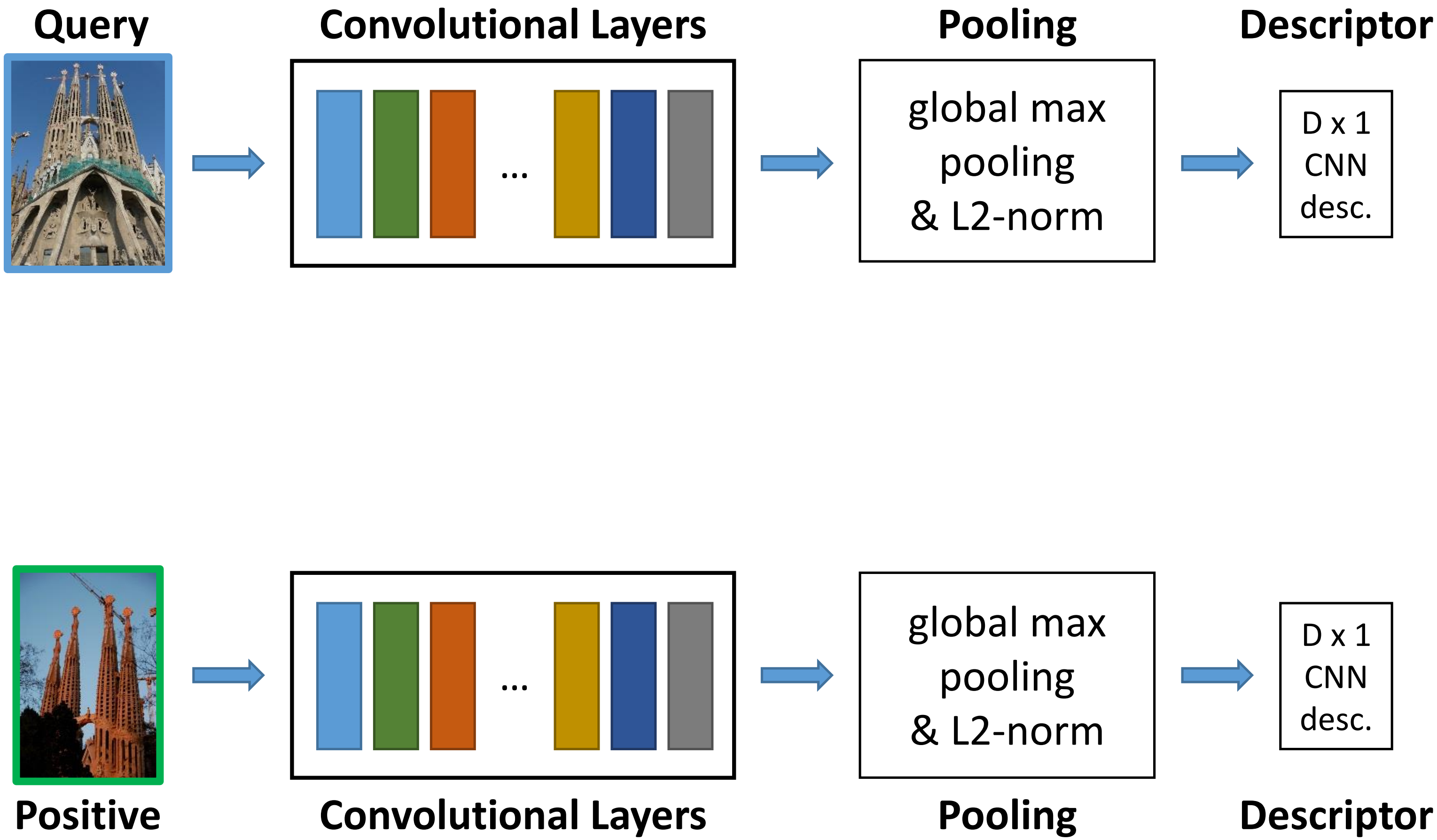

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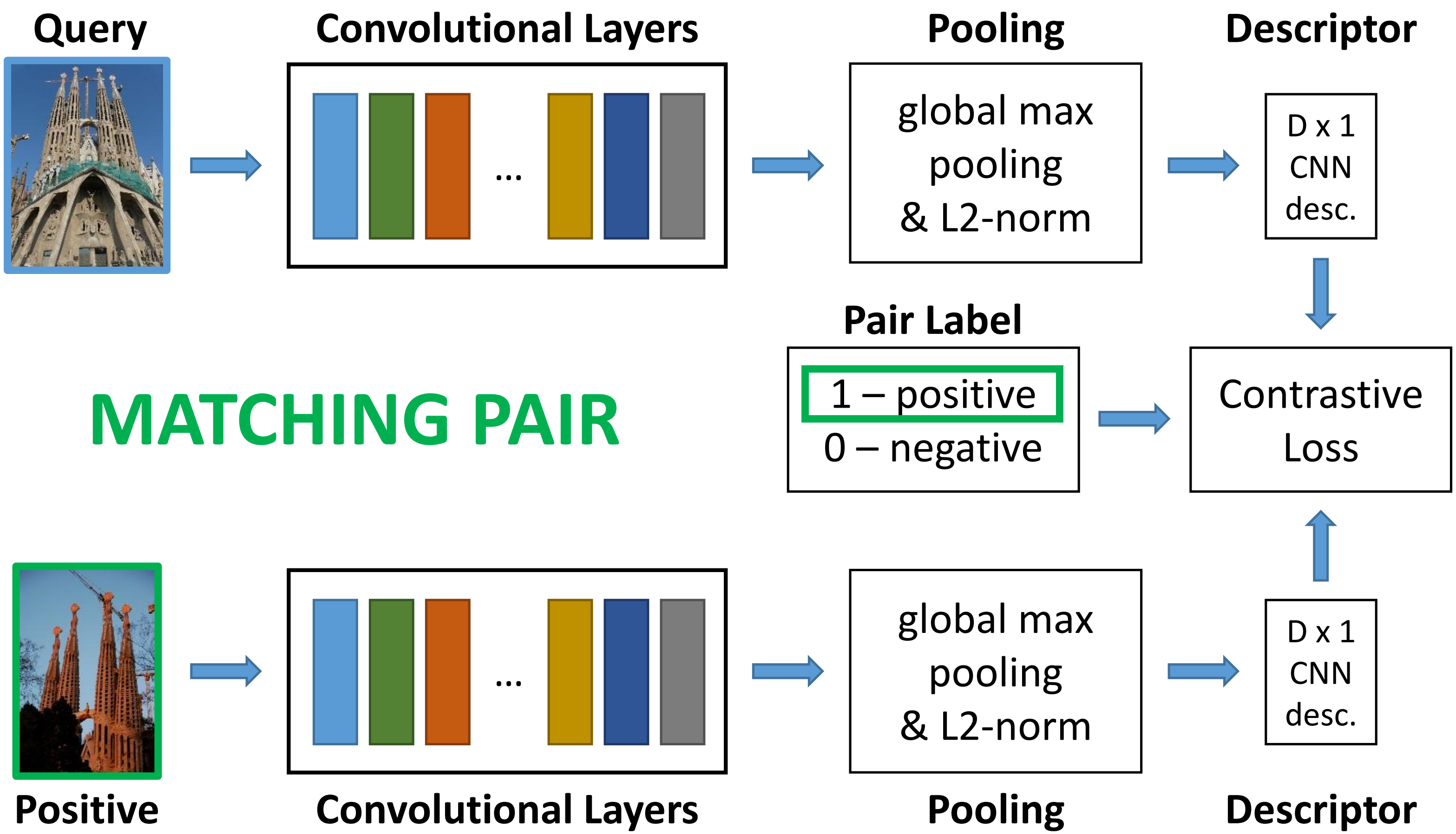

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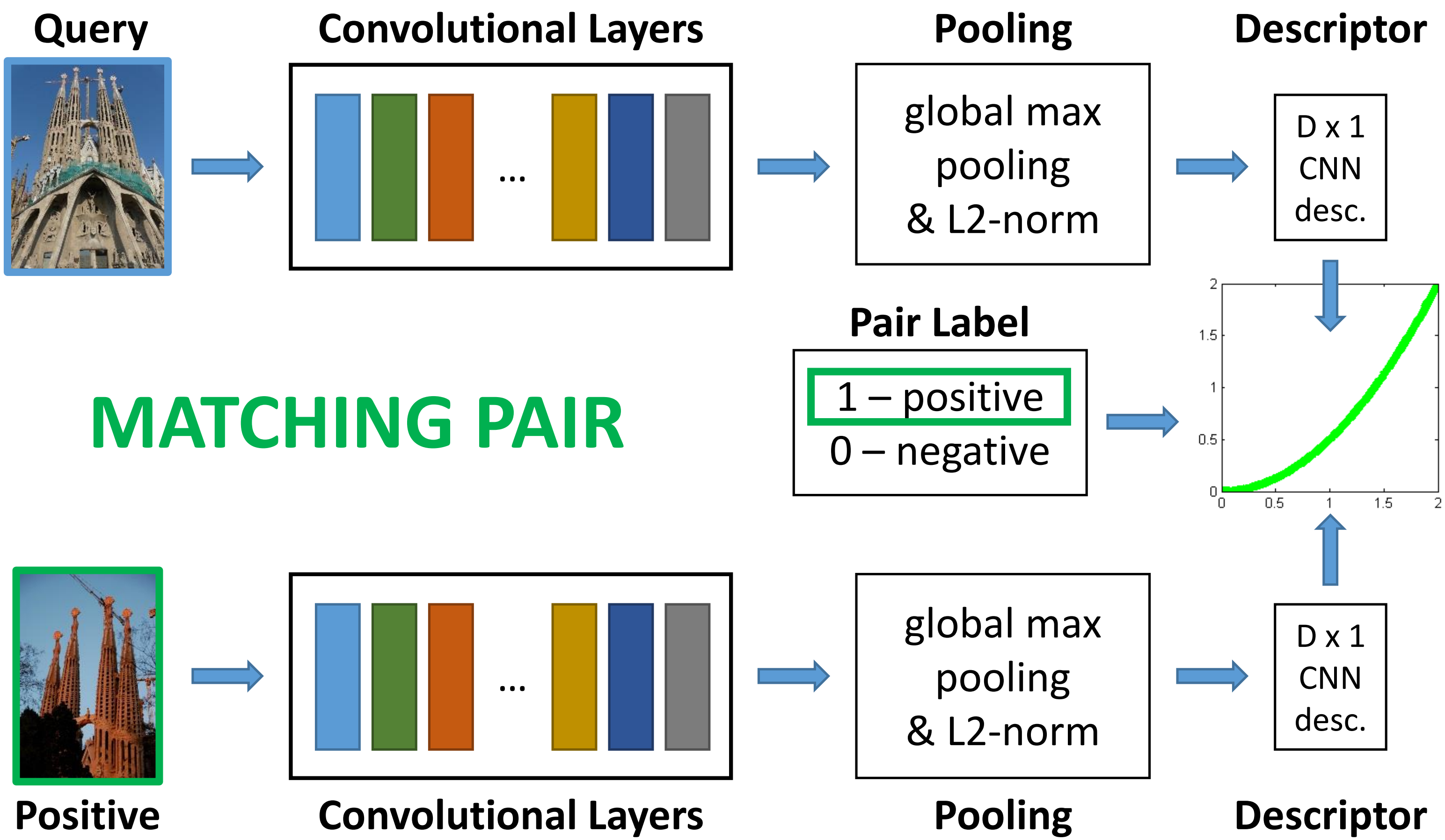

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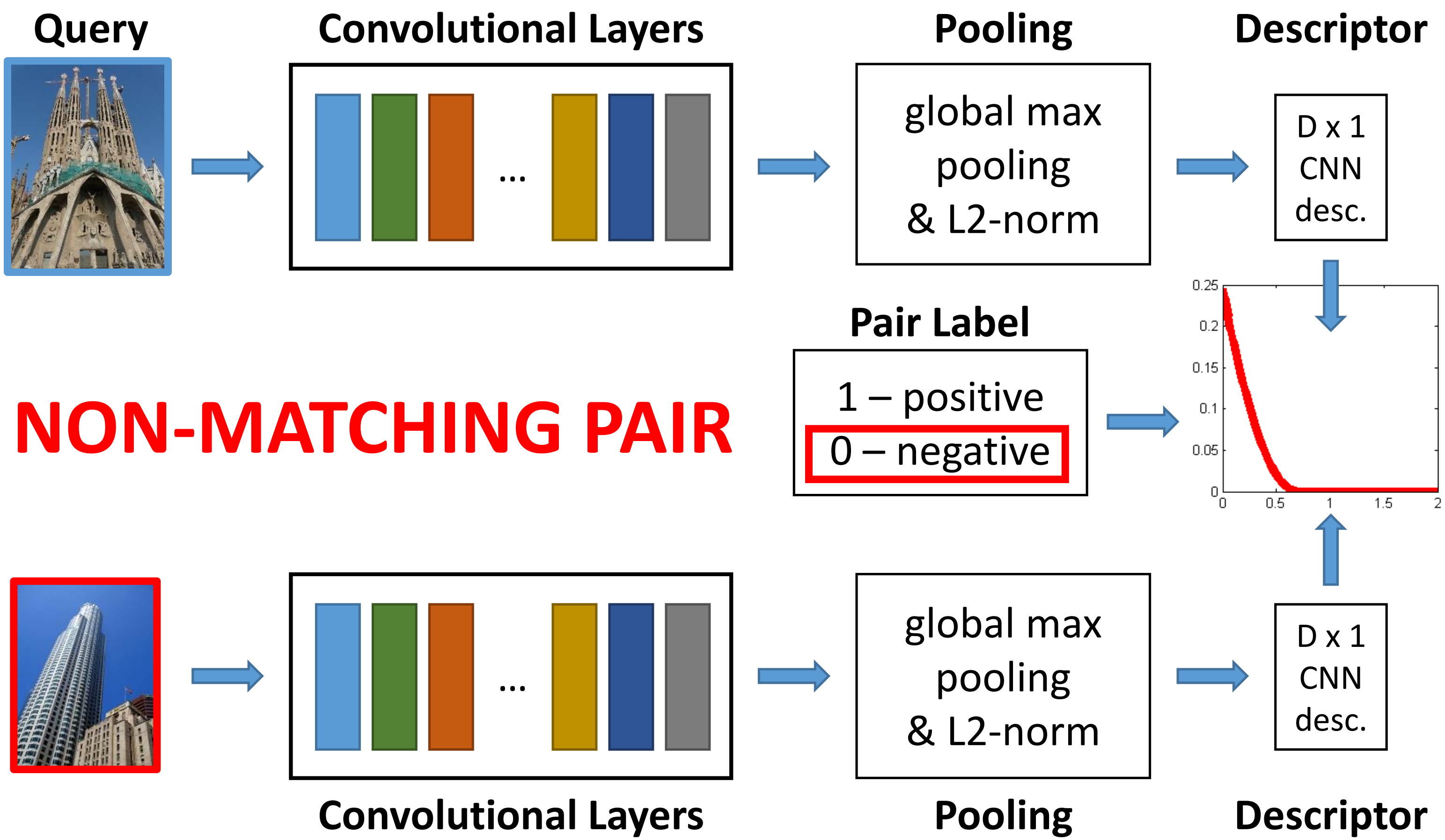

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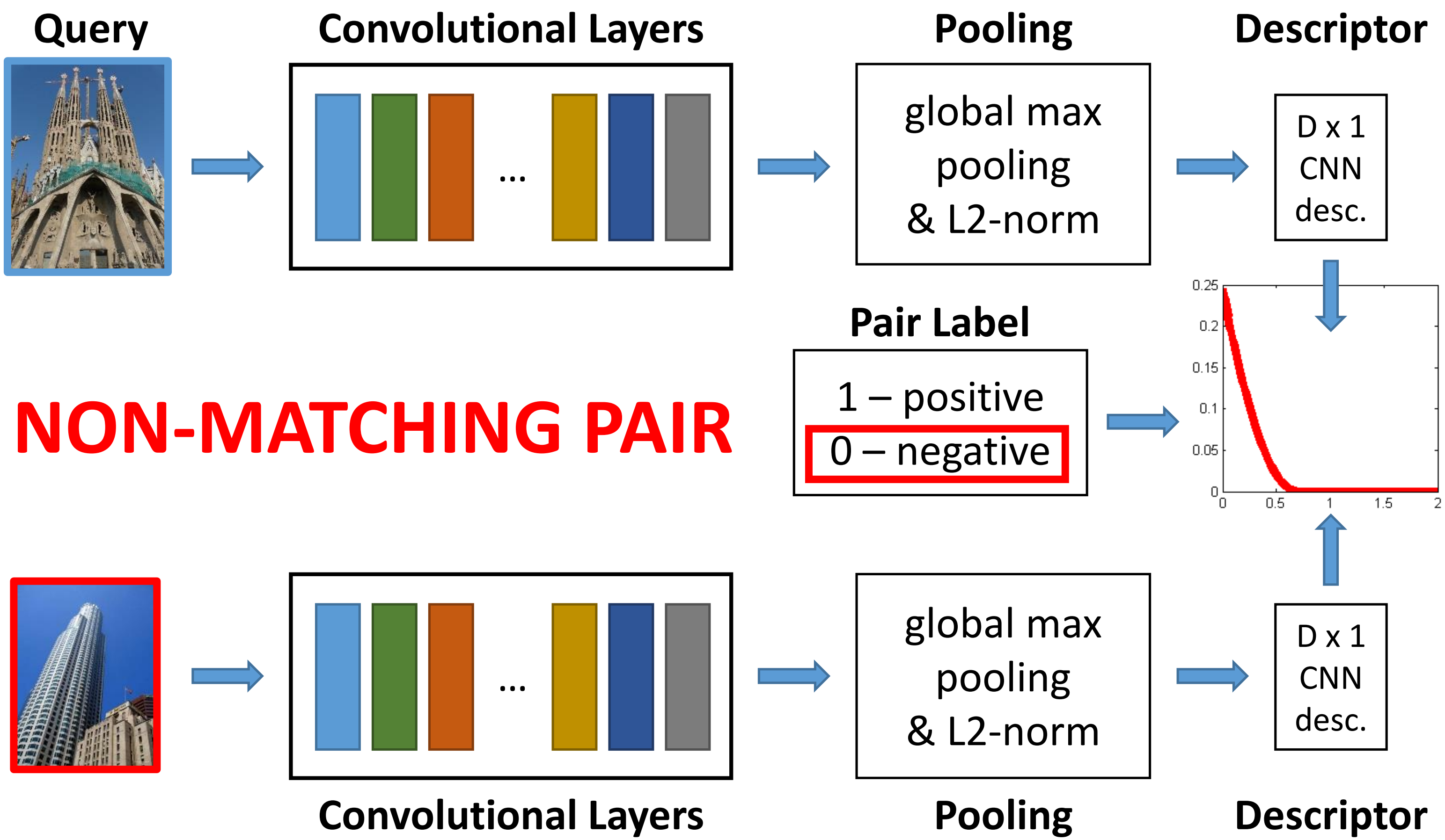
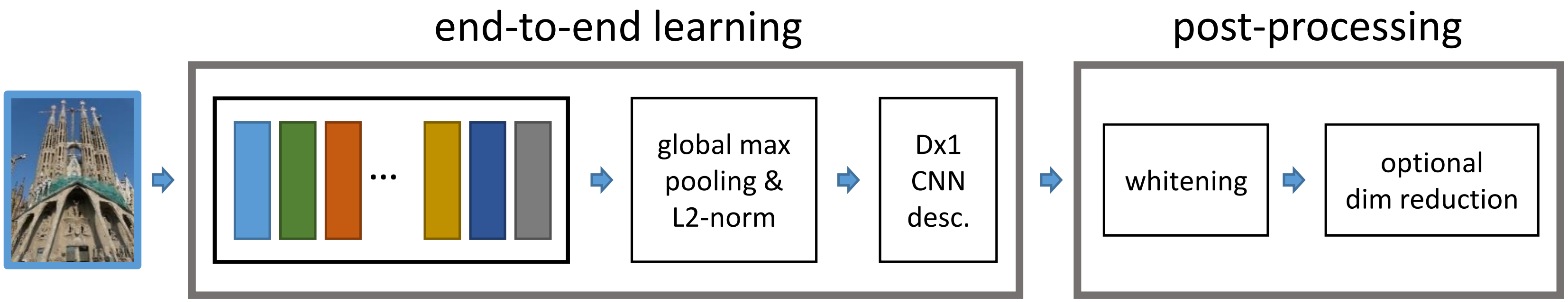


<u>Contrastive vs. Triplet loss</u>: Contrastive better with our data

Contrastive loss more strict, requires accurate training data

Triplet loss less sensitive to inaccurate annotation

Whitening and dimensionality reduction



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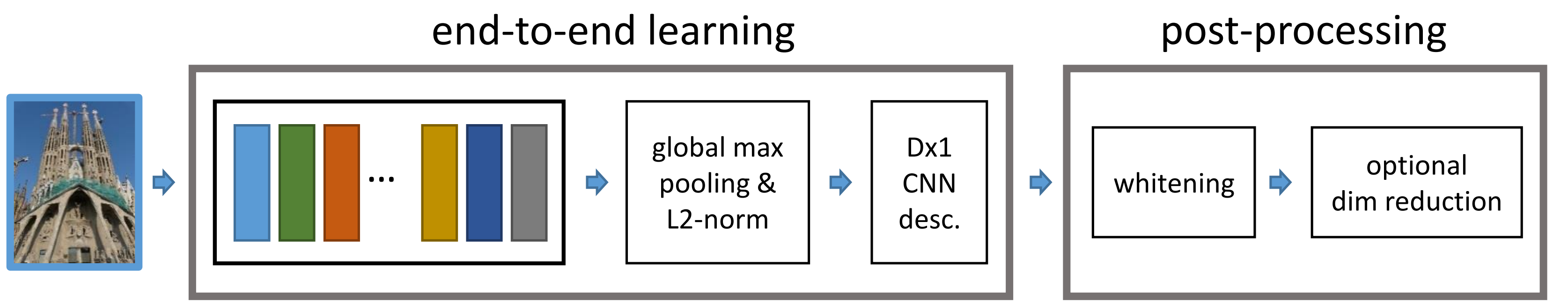
Whitening and dimensionality reduction



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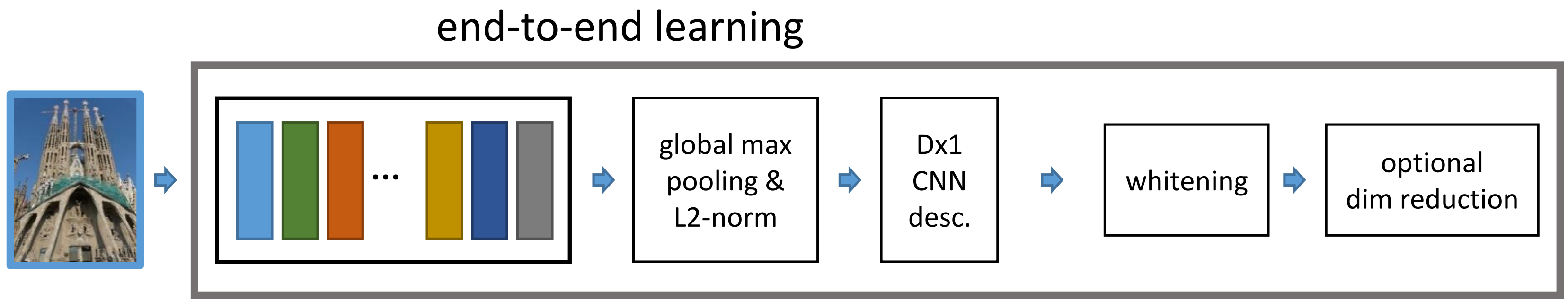

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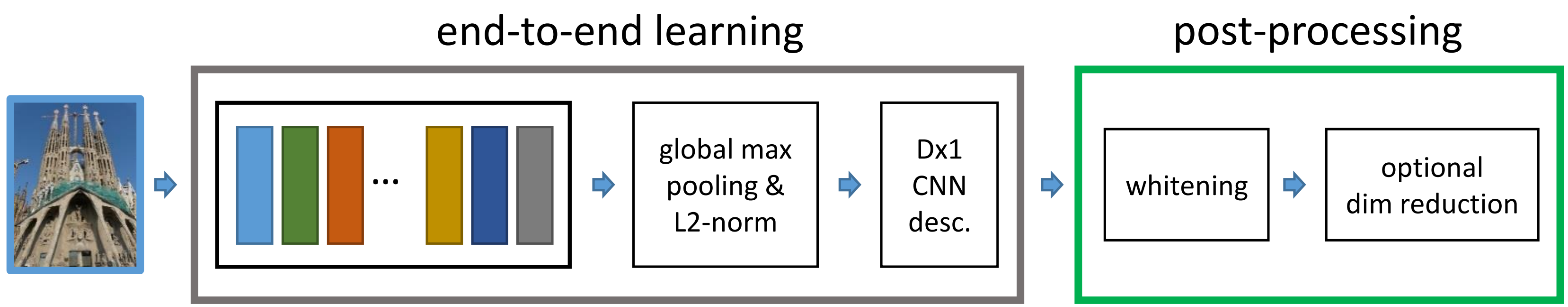
Whitening and dimensionality reduction



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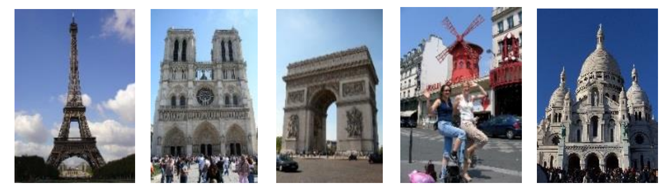
Experiments – datasets

- **Oxford 5k dataset**
  [Philbin et al. CVPR’07]

- **Paris 6k dataset**
  [Philbin et al. CVPR’08]



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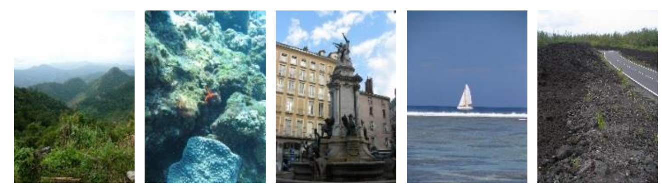

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- **Protocol:** mean Average Precision (mAP)

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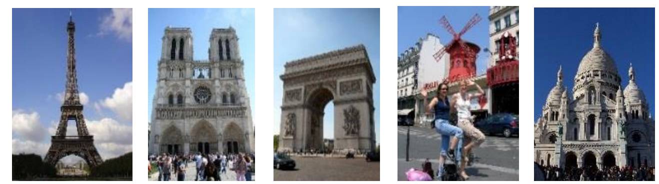

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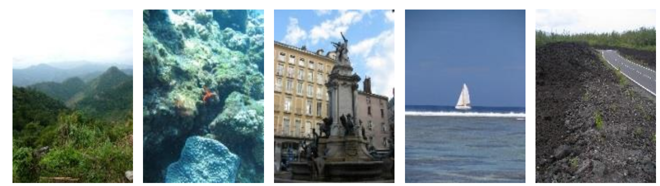

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Training 3D models do not contain any landmark from these datasets

- **Protocol:** mean Average Precision (mAP)

Experiments – Learning (AlexNet)

- Careful choice of **positive** and **negative** training images makes a difference

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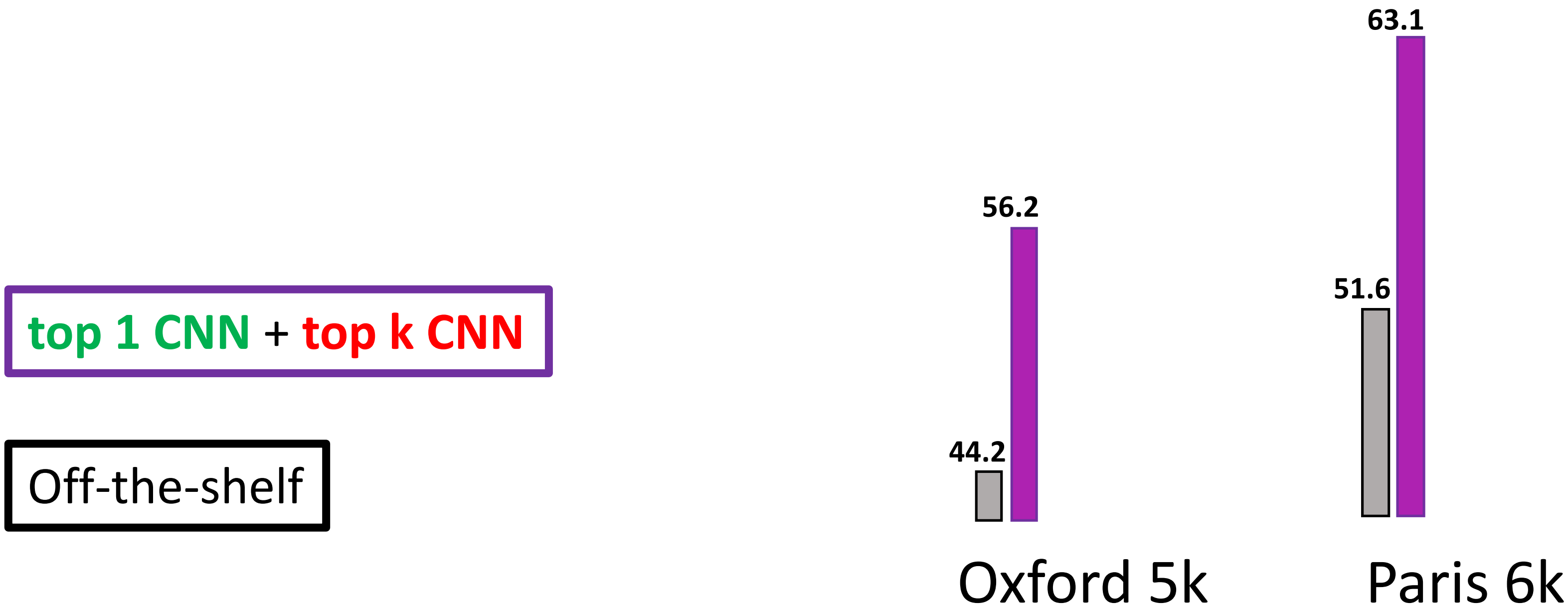

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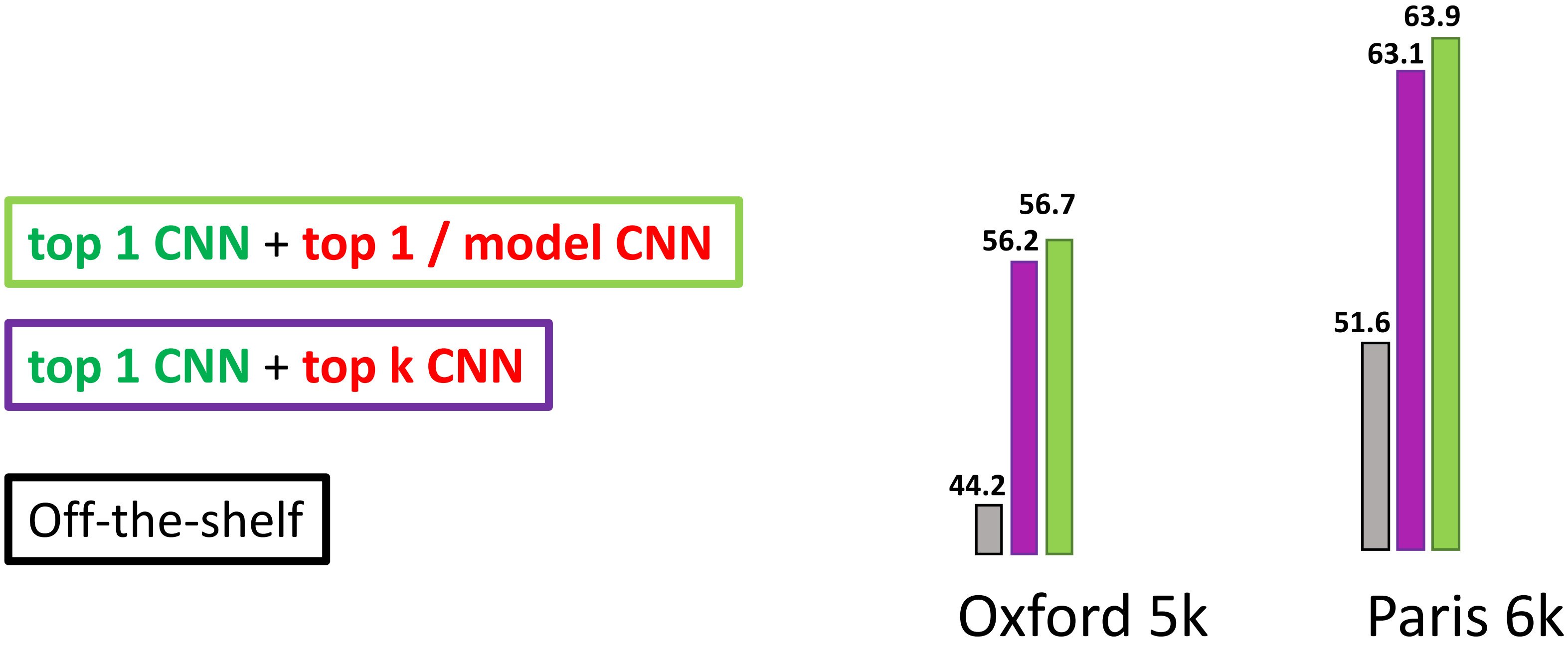

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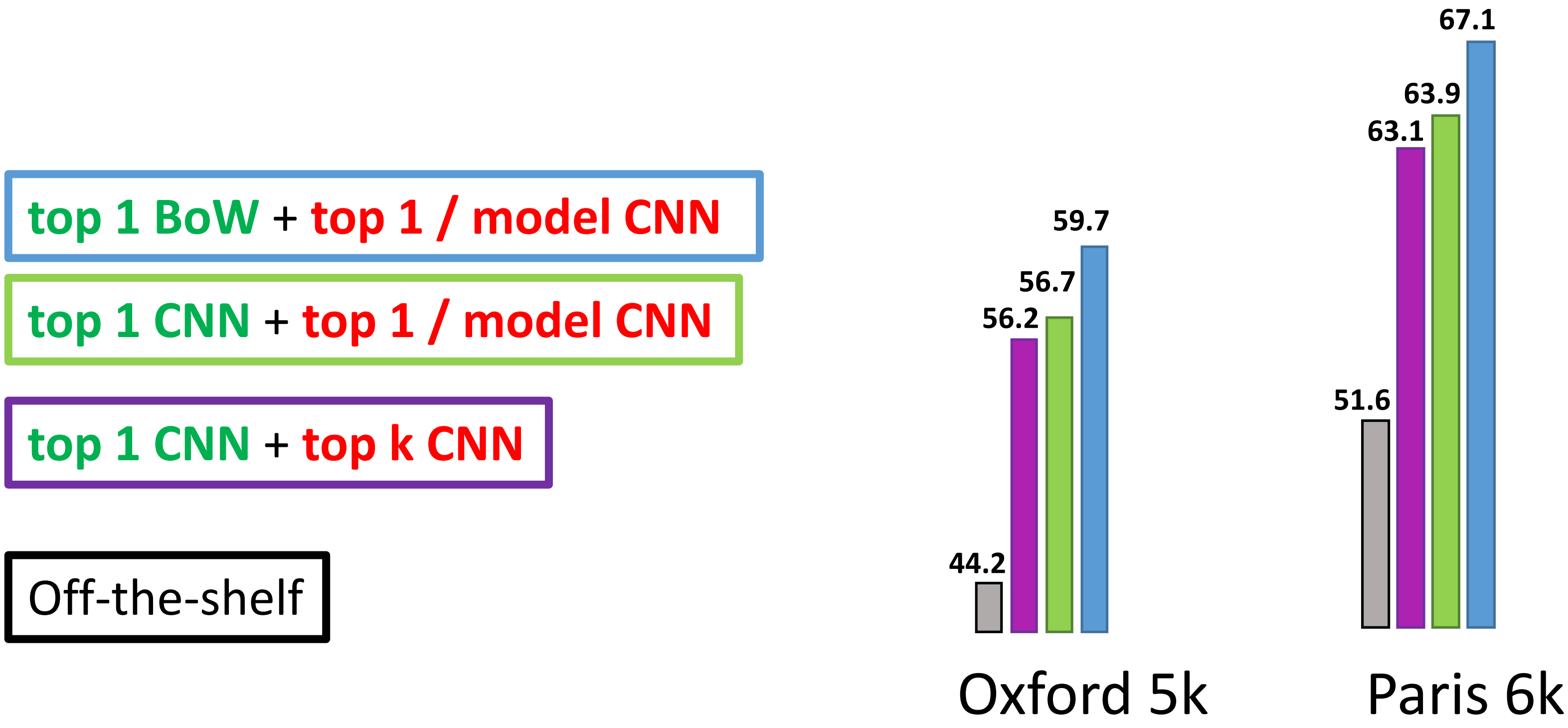

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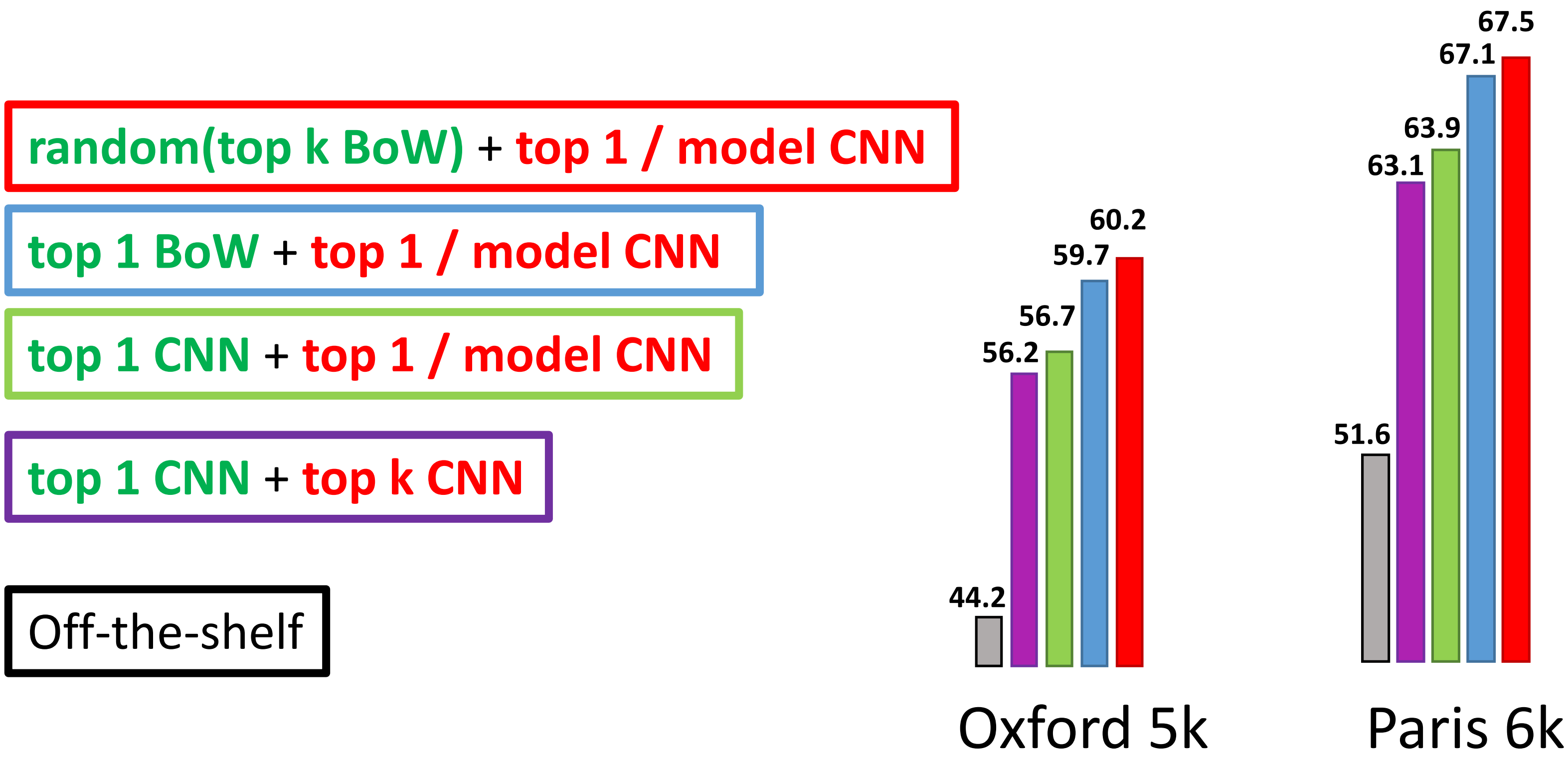

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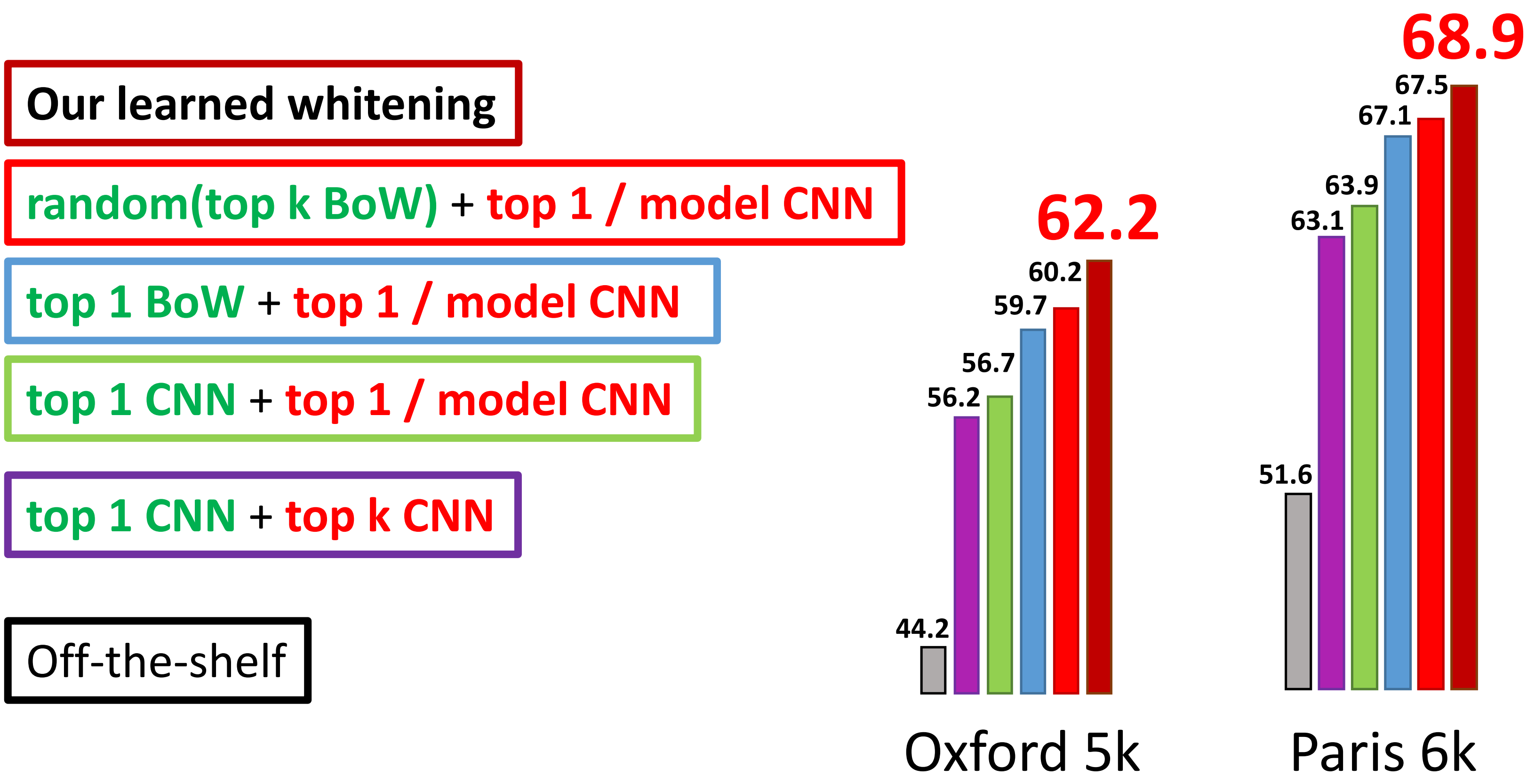
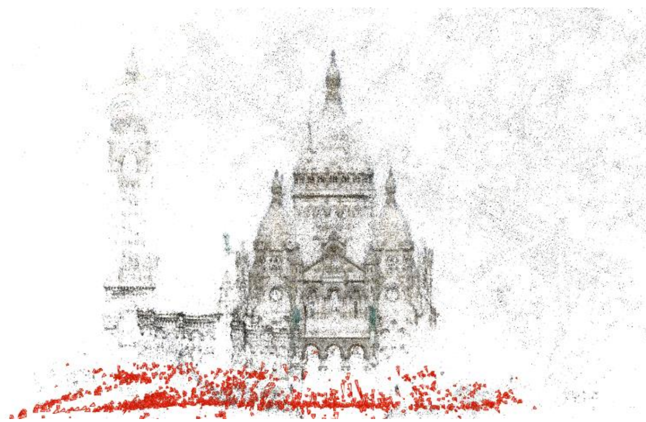


Experiments – Over-fitting and Generalization

- We added Oxford and Paris landmarks as 3D models and repeated fine-tuning



Experiments – Over-fitting and Generalization

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Only +0.3 mAP on average over all testing datasets

State-of-the-art

Method		D	Oxf5k		Oxf105k		Par6k		Par106k		Hol	Hol 101k
			Crop$_{\mathcal{I}}$	Crop$_{\mathcal{X}}$	Crop$_{\mathcal{I}}$	Crop$_{\mathcal{X}}$	Crop$_{\mathcal{I}}$	Crop$_{\mathcal{X}}$	Crop$_{\mathcal{I}}$	Crop$_{\mathcal{X}}$		
Compact representations												
mVoc/BoW [11]		128	48.8	–	41.4	–	–	–	–	–	65.6	–
Neural codes† [14]	(**fA**)	128	–	**55.7**	–	**52.3**	–	–	–	–	**78.9**	–
MAC‡	(**V**)	128	53.5	**55.7**	43.8	45.6	69.5	**70.6**	53.4	**55.4**	72.6	**56.7**
CroW [24]	(**V**)	128	**59.2**	–	**51.6**	–	**74.6**	–	**63.2**	–	–	–
⋆ MAC	(**fV**)	128	**75.8**	**76.8**	**68.6**	**70.8**	77.6	78.8	68.0	69.0	73.2	58.8
⋆ R-MAC	(**fV**)	128	72.5	76.7	64.3	69.7	**78.5**	**80.3**	**69.3**	**71.2**	**79.3**	**65.2**
MAC‡	(**V**)	256	54.7	56.9	45.6	47.8	71.5	72.4	55.7	**57.3**	76.5	**61.3**
SPoC [23]	(**V**)	256	–	53.1	–	**50.1**	–	–	–	–	80.2	–
R-MAC [25]	(**A**)	256	56.1	–	47.0	–	72.9	–	60.1	–	–	–
CroW [24]	(**V**)	256	**65.4**	–	**59.3**	–	**77.9**	–	**67.8**	–	83.1	–
NetVlad [35]	(**V**)	256	–	55.5	–	–	–	67.7	–	–	**86.0**	–
NetVlad [35]	(**fV**)	256	–	**63.5**	–	–	–	**73.5**	–	–	84.3	–
⋆ MAC	(**fA**)	256	62.2	65.4	52.8	58.0	68.9	72.2	54.7	58.5	76.2	63.8
⋆ R-MAC	(**fA**)	256	62.5	68.9	53.2	61.2	74.4	76.6	61.8	64.8	81.5	**70.8**
⋆ MAC	(**fV**)	256	**77.4**	**78.2**	**70.7**	**72.6**	80.8	81.9	72.2	73.4	77.3	62.9
⋆ R-MAC	(**fV**)	256	74.9	**78.2**	67.5	72.1	**82.3**	**83.5**	**74.1**	**75.6**	81.4	69.4
MAC‡	(**V**)	512	56.4	**58.3**	47.8	**49.2**	72.3	**72.6**	58.0	**59.1**	76.7	**62.7**
R-MAC [25]	(**V**)	512	66.9	–	61.6	–	**83.0**	–	**75.7**	–	–	–
CroW [24]	(**V**)	512	**68.2**	–	**63.2**	–	79.6	–	71.0	–	84.9	–
⋆ MAC	(**fV**)	512	**79.7**	80.0	**73.9**	**75.1**	82.4	82.9	74.6	75.3	79.5	67.0
⋆ R-MAC	(**fV**)	512	77.0	**80.1**	69.2	74.1	**83.8**	**85.0**	**76.4**	**77.9**	82.5	**71.5**
Extreme short codes												
Neural codes† [14]	(**fA**)	16	–	**41.8**	–	**35.4**	–	–	–	–	**60.9**	–
⋆ MAC	(**fV**)	16	**56.2**	**57.4**	**45.5**	**47.6**	57.3	62.9	43.4	48.5	51.3	25.6
⋆ R-MAC	(**fV**)	16	46.9	52.1	37.9	41.6	**58.8**	**63.2**	**45.6**	**49.6**	54.4	**31.7**
Neural codes† [14]	(**fA**)	32	–	**51.5**	–	**46.7**	–	–	–	–	**72.9**	–
⋆ MAC	(**fV**)	32	**65.3**	**69.2**	**55.6**	**59.5**	**63.9**	**69.5**	51.6	**56.3**	62.4	41.8
⋆ R-MAC	(**fV**)	32	58.4	64.2	50.1	55.1	**63.9**	67.4	**52.7**	55.8	68.0	**49.6**
Re-ranking (R) and query expansion (QE)												
BoW(1M)+QE [6]		–	82.7	–	76.7	–	80.5	–	71.0	–	–	–
BoW(16M)+QE [50]		–	84.9	–	79.5	–	82.4	–	77.3	–	–	–
HQE(65k) [8]		–	**88.0**	–	**84.0**	–	82.8	–	–	–	–	–
R-MAC+R+QE [25]	(**V**)	512	77.3	–	73.2	–	**86.5**	–	**79.8**	–	–	–
CroW+QE [24]	(**V**)	512	72.2	–	67.8	–	85.5	–	79.7	–	–	–
⋆ MAC+R+QE	(**fV**)	512	85.0	**85.4**	81.8	**82.3**	**86.5**	**87.0**	78.8	79.6	–	–
⋆ R-MAC+R+QE	(**fV**)	512	82.9	84.5	77.9	80.4	85.6	86.4	78.3	**79.7**	–	–

State-of-the-art

NetVLAD 256D

vs.

Our CNN 32D

63.5

69.2

Method		D	Oxf5k Crop$_\mathcal{I}$	Oxf5k Crop$_\mathcal{X}$	Oxf105k Crop$_\mathcal{I}$	Oxf105k Crop$_\mathcal{X}$	Par6k Crop$_\mathcal{I}$	Par6k Crop$_\mathcal{X}$	Par106k Crop$_\mathcal{I}$	Par106k Crop$_\mathcal{X}$	Hol	Hol 101k
Compact representations												
mVoc/BoW [11]		128	48.8	–	41.4	–	–	–	–	–	65.6	–
Neural codes† [14]	(**fA**)	128	–	**55.7**	–	**52.3**	–	–	–	–	**78.9**	–
MAC‡	(**V**)	128	53.5	**55.7**	43.8	45.6	69.5	**70.6**	53.4	**55.4**	72.6	**56.7**
CroW [24]	(**V**)	128	**59.2**	–	**51.6**	–	**74.6**	–	**63.2**	–	–	–
⋆ MAC	(**fV**)	128	**75.8**	**76.8**	**68.6**	**70.8**	77.6	78.8	68.0	69.0	73.2	58.8
⋆ R-MAC	(**fV**)	128	72.5	76.7	64.3	69.7	**78.5**	**80.3**	**69.3**	**71.2**	**79.3**	**65.2**
MAC‡	(**V**)	256	54.7	56.9	45.6	47.8	71.5	72.4	55.7	**57.3**	76.5	**61.3**
SPoC [23]	(**V**)	256	–	53.1	–	**50.1**	–	–	–	–	80.2	–
R-MAC [25]	(**A**)	256	56.1	–	47.0	–	72.9	–	60.1	–	–	–
CroW [24]	(**V**)	256	**65.4**	–	**59.3**	–	**77.9**	–	**67.8**	–	83.1	–
NetVlad [35]	(**V**)	256	[illegible]	[illegible]	[illegible]	–	–	67.7	–	–	**86.0**	–
NetVlad [35]	(**fV**)	[illegible]	[illegible]	[illegible]	[illegible]	–	–	**73.5**	–	–	84.3	–
⋆ MAC	(**fA**)	256	[illegible]	[illegible]	[illegible]	58.0	68.9	72.2	54.7	58.5	76.2	63.8
⋆ R-MAC	(**fA**)	256	62.5	68.9	53.2	61.2	74.4	76.6	61.8	64.8	81.5	**70.8**
⋆ MAC	(**fV**)	256	**77.4**	**78.2**	**70.7**	**72.6**	80.8	81.9	72.2	73.4	77.3	62.9
⋆ R-MAC	(**fV**)	256	74.9	**78.2**	67.5	72.1	**82.3**	**83.5**	**74.1**	**75.6**	81.4	69.4
MAC‡	(**V**)	512	56.4	**58.3**	47.8	**49.2**	72.3	**72.6**	58.0	**59.1**	76.7	**62.7**
R-MAC [25]	(**V**)	512	66.9	–	61.6	–	**83.0**	–	**75.7**	–	–	–
CroW [24]	(**V**)	512	**68.2**	–	**63.2**	–	79.6	–	71.0	–	84.9	–
⋆ MAC	(**fV**)	512	**79.7**	80.0	**73.9**	**75.1**	82.4	82.9	74.6	75.3	79.5	67.0
⋆ R-MAC	(**fV**)	512	77.0	**80.1**	69.2	74.1	**83.8**	**85.0**	**76.4**	**77.9**	82.5	**71.5**
Extreme short codes												
Neural codes† [14]	(**fA**)	16	–	**41.8**	–	**35.4**	–	–	–	–	**60.9**	–
⋆ MAC	(**fV**)	16	**56.2**	**57.4**	**45.5**	**47.6**	57.3	62.9	43.4	48.5	51.3	25.6
⋆ R-MAC	(**fV**)	16	46.9	52.1	37.9	41.6	**58.8**	**63.2**	**45.6**	**49.6**	54.4	**31.7**
Neural codes† [14]	(**fA**)	32	[illegible]	[illegible]	[illegible]	**46.7**	–	–	–	–	**72.9**	–
⋆ MAC	(**fV**)	32	[illegible]	[illegible]	[illegible]	**59.5**	**63.9**	**69.5**	51.6	**56.3**	62.4	41.8
⋆ R-MAC	(**fV**)	32	[illegible]	[illegible]	[illegible]	55.1	**63.9**	67.4	**52.7**	55.8	68.0	**49.6**
Re-ranking (R) and query expansion (QE)												
BoW(1M)+QE [6]		–	82.7	–	76.7	–	80.5	–	71.0	–	–	–
BoW(16M)+QE [50]		–	84.9	–	79.5	–	82.4	–	77.3	–	–	–
HQE(65k) [8]		–	**88.0**	–	**84.0**	–	82.8	–	–	–	–	–
R-MAC+R+QE [25]	(**V**)	512	77.3	–	73.2	–	**86.5**	–	**79.8**	–	–	–
CroW+QE [24]	(**V**)	512	72.2	–	67.8	–	85.5	–	79.7	–	–	–
⋆ MAC+R+QE	(**fV**)	512	85.0	**85.4**	81.8	**82.3**	**86.5**	**87.0**	78.8	79.6	–	–
⋆ R-MAC+R+QE	(**fV**)	512	82.9	84.5	77.9	80.4	85.6	86.4	78.3	**79.7**	–	–

State-of-the-art

NetVLAD 256D

vs.

Our CNN 32D

Concurrent work:
[Gordo et al. ECCV'16]

63.5

69.2

Method		D	Oxf5k Crop$_\mathcal{I}$	Oxf5k Crop$_\mathcal{X}$	Oxf105k Crop$_\mathcal{I}$	Oxf105k Crop$_\mathcal{X}$	Par6k Crop$_\mathcal{I}$	Par6k Crop$_\mathcal{X}$	Par106k Crop$_\mathcal{I}$	Par106k Crop$_\mathcal{X}$	Hol	Hol 101k
Compact representations												
mVoc/BoW [11]		128	48.8	–	41.4	–	–	–	–	–	65.6	–
Neural codes† [14]	(fA)	128	–	55.7	–	52.3	–	–	–	–	78.9	–
MAC‡	(V)	128	53.5	55.7	43.8	45.6	69.5	70.6	53.4	55.4	72.6	56.7
CroW [24]	(V)	128	59.2	–	51.6	–	74.6	–	63.2	–	–	–
★ MAC	(fV)	128	75.8	76.8	68.6	70.8	77.6	78.8	68.0	69.0	73.2	58.8
★ R-MAC	(fV)	128	72.5	76.7	64.3	69.7	78.5	80.3	69.3	71.2	79.3	65.2
MAC‡	(V)	256	54.7	56.9	45.6	47.8	71.5	72.4	55.7	57.3	76.5	61.3
SPoC [23]	(V)	256	–	53.1	–	50.1	–	–	–	–	80.2	–
R-MAC [25]	(A)	256	56.1	–	47.0	–	72.9	–	60.1	–	–	–
CroW [24]	(V)	256	65.4	–	59.3	–	77.9	–	67.8	–	83.1	–
NetVlad [35]	(V)	256	[illegible]	[illegible]	[illegible]	–	–	67.7	–	–	86.0	–
NetVlad [35]	(fV)	[illegible]	[illegible]	[illegible]	[illegible]	–	–	73.5	–	–	84.3	–
★ MAC	(fA)	256	[illegible]	[illegible]	[illegible]	58.0	68.9	72.2	54.7	58.5	76.2	63.8
★ R-MAC	(fA)	256	62.5	68.9	53.2	61.2	74.4	76.6	61.8	64.8	81.5	70.8
★ MAC	(fV)	256	77.4	78.2	70.7	72.6	80.8	81.9	72.2	73.4	77.3	62.9
★ R-MAC	(fV)	256	74.9	78.2	67.5	72.1	82.3	83.5	74.1	75.6	81.4	69.4
MAC‡	(V)	512	56.4	58.3	47.8	49.2	72.3	72.6	58.0	59.1	76.7	62.7
R-MAC [25]	(V)	512	66.9	–	61.6	–	83.0	–	75.7	–	–	–
CroW [24]	(V)	512	68.2	–	63.2	–	79.6	–	71.0	–	84.9	–
★ MAC	(fV)	512	79.7	80.0	73.9	75.1	82.4	82.9	74.6	75.3	79.5	67.0
★ R-MAC	(fV)	512	77.0	80.1	69.2	74.1	83.8	85.0	76.4	77.9	82.5	71.5
Extreme short codes												
Neural codes† [14]	(fA)	16	–	41.8	–	35.4	–	–	–	–	60.9	–
★ MAC	(fV)	16	56.2	57.4	45.5	47.6	57.3	62.9	43.4	48.5	51.3	25.6
★ R-MAC	(fV)	16	46.9	52.1	37.9	41.6	58.8	63.2	45.6	49.6	54.4	31.7
Neural codes† [14]	(fA)	32	[illegible]	[illegible]	[illegible]	46.7	–	–	–	–	72.9	–
★ MAC	(fV)	32	[illegible]	[illegible]	[illegible]	59.5	63.9	69.5	51.6	56.3	62.4	41.8
★ R-MAC	(fV)	32	[illegible]	[illegible]	[illegible]	55.1	63.9	67.4	52.7	55.8	68.0	49.6
Re-ranking (R) and query expansion (QE)												
BoW(1M)+QE [6]		–	82.7	–	76.7	–	80.5	–	71.0	–	–	–
BoW(16M)+QE [50]		–	84.9	–	79.5	–	82.4	–	77.3	–	–	–
HQE(65k) [8]		–	88.0	–	84.0	–	82.8	–	–	–	–	–
R-MAC+R+QE [25]	(V)	512	77.3	–	73.2	–	86.5	–	79.8	–	–	–
CroW+QE [24]	(V)	512	72.2	–	67.8	–	85.5	–	79.7	–	–	–
★ MAC+R+QE	(fV)	512	85.0	85.4	81.8	82.3	86.5	87.0	78.8	79.6	–	–
★ R-MAC+R+QE	(fV)	512	82.9	84.5	77.9	80.4	85.6	86.4	78.3	79.7	–	–

Teacher vs. Student

Method	Oxf5k	Oxf105k	Par6k	Par106k
BoW(16M)+R+QE	**84.9**	**79.5**	**82.4**	**77.3**
CNN(512D)	79.7	73.9	**82.4**	74.6

Teacher vs. Student

Method	Oxf5k	Oxf105k	Par6k	Par106k
BoW(16M)+R+QE	**84.9**	**79.5**	**82.4**	**77.3**
CNN(512D)	79.7	73.9	**82.4**	74.6
CNN(512D)+R+QE	**85.0**	**81.8**	**86.5**	**78.8**

Our CNN with re-ranking (R) and query expansion(QE) surpasses its teacher on all datasets!!!

Teacher vs. Student

query

Teacher vs. Student

query

BoW

top 10 (correct | incorrect)

first incorrect at rank 127

Teacher vs. Student

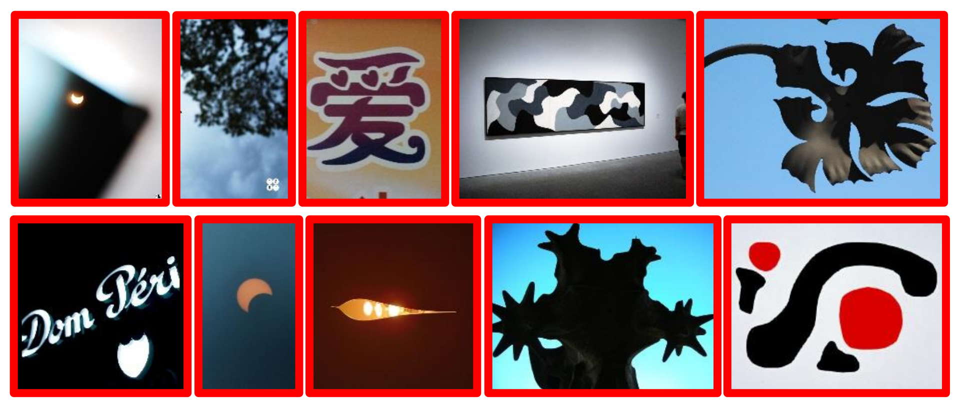
query

BoW

top 10 (correct | incorrect)

first incorrect at rank 127

CNN



Teacher vs. Student

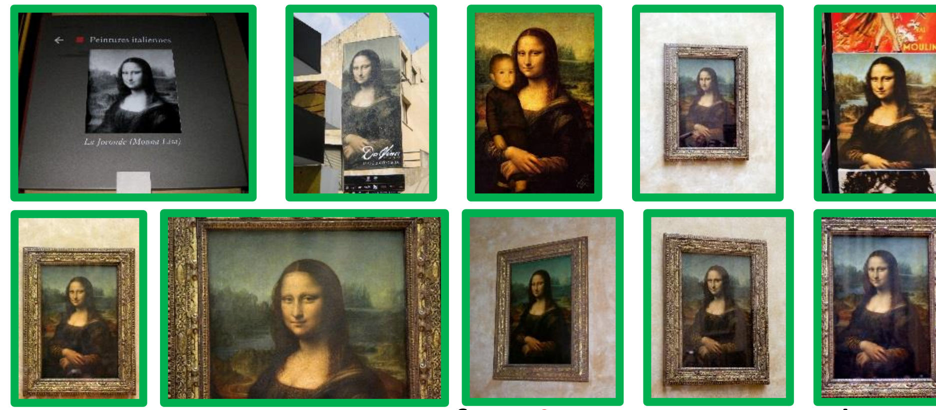
query

Teacher vs. Student

query

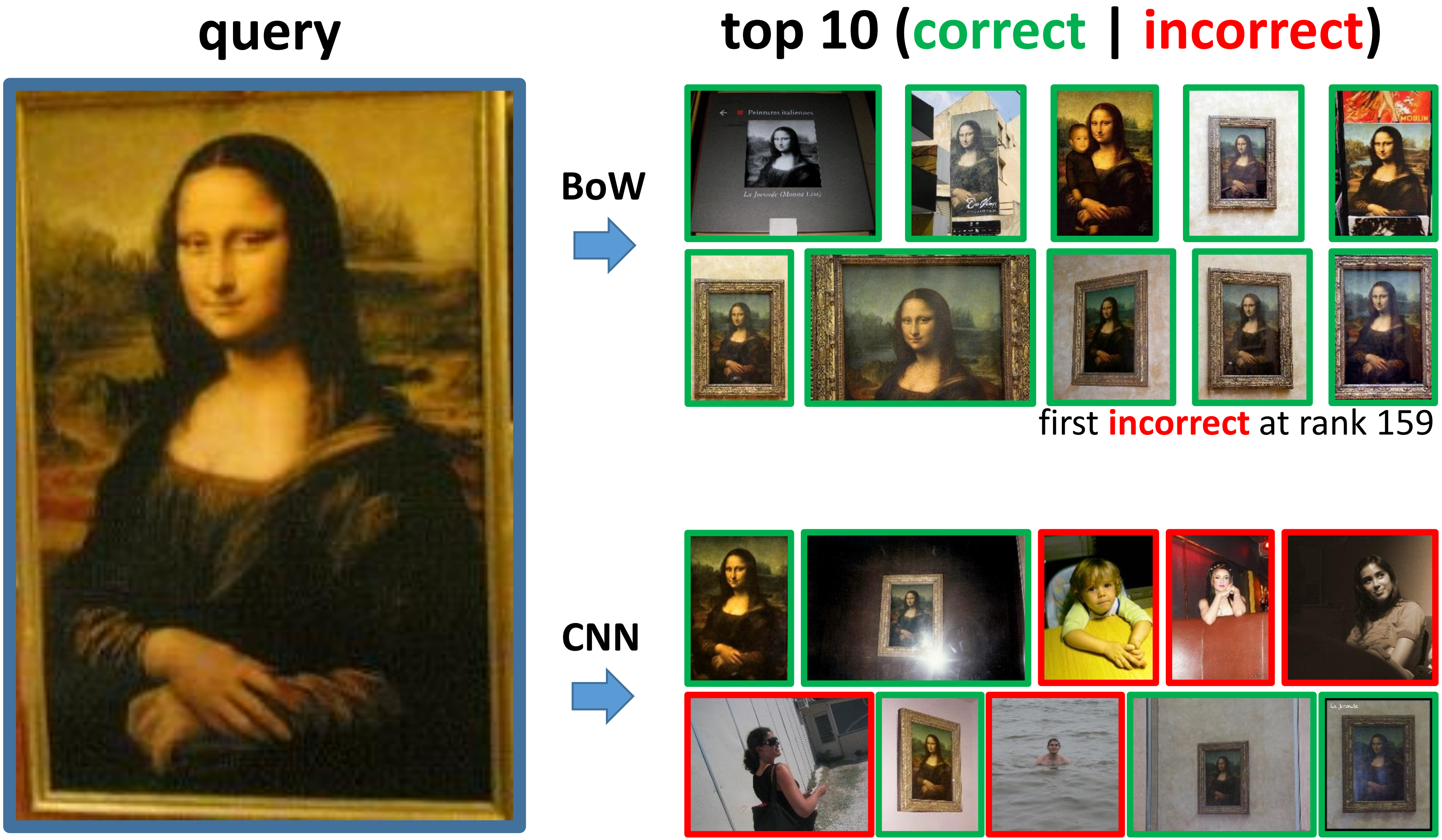
BoW

top 10 (correct | incorrect)



first **incorrect** at rank 159

Teacher vs. Student

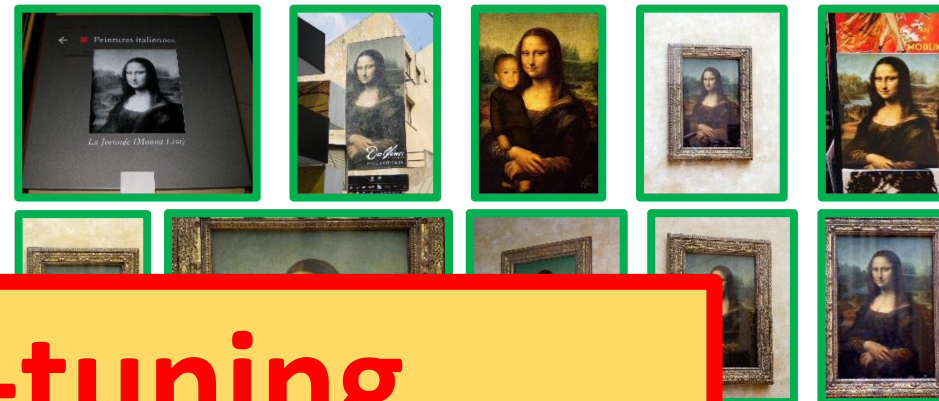


Teacher vs. Student

query

top 10 (correct | incorrect)

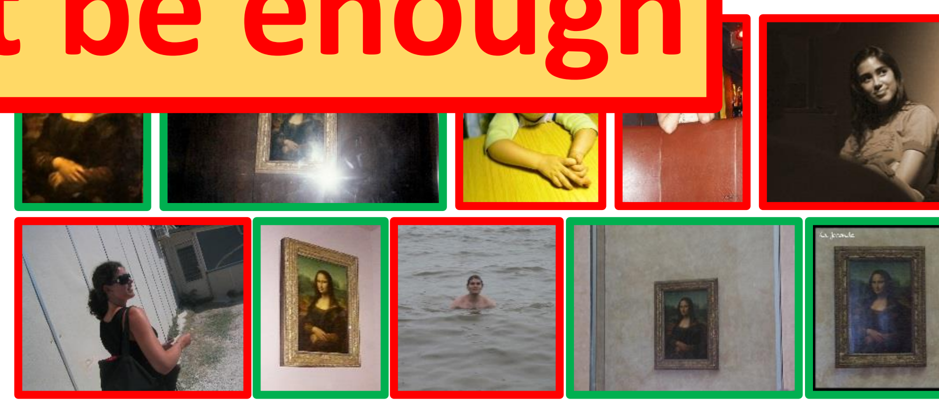
BoW



at rank 159

Fine-tuning might not be enough

CNN



Conclusions

- We propose a method to generate the necessary “lots of training examples” without any human interaction
- Strong supervision for hard negative, hard positive mining, and supervised whitening
- Data and trained networks available at: cmp.felk.cvut.cz/~radenfil/projects/siamac.html
- For more details about the paper visit **Poster O-1A-01**

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