Deep Learning for Augmented Reality

Vincent Lepetit

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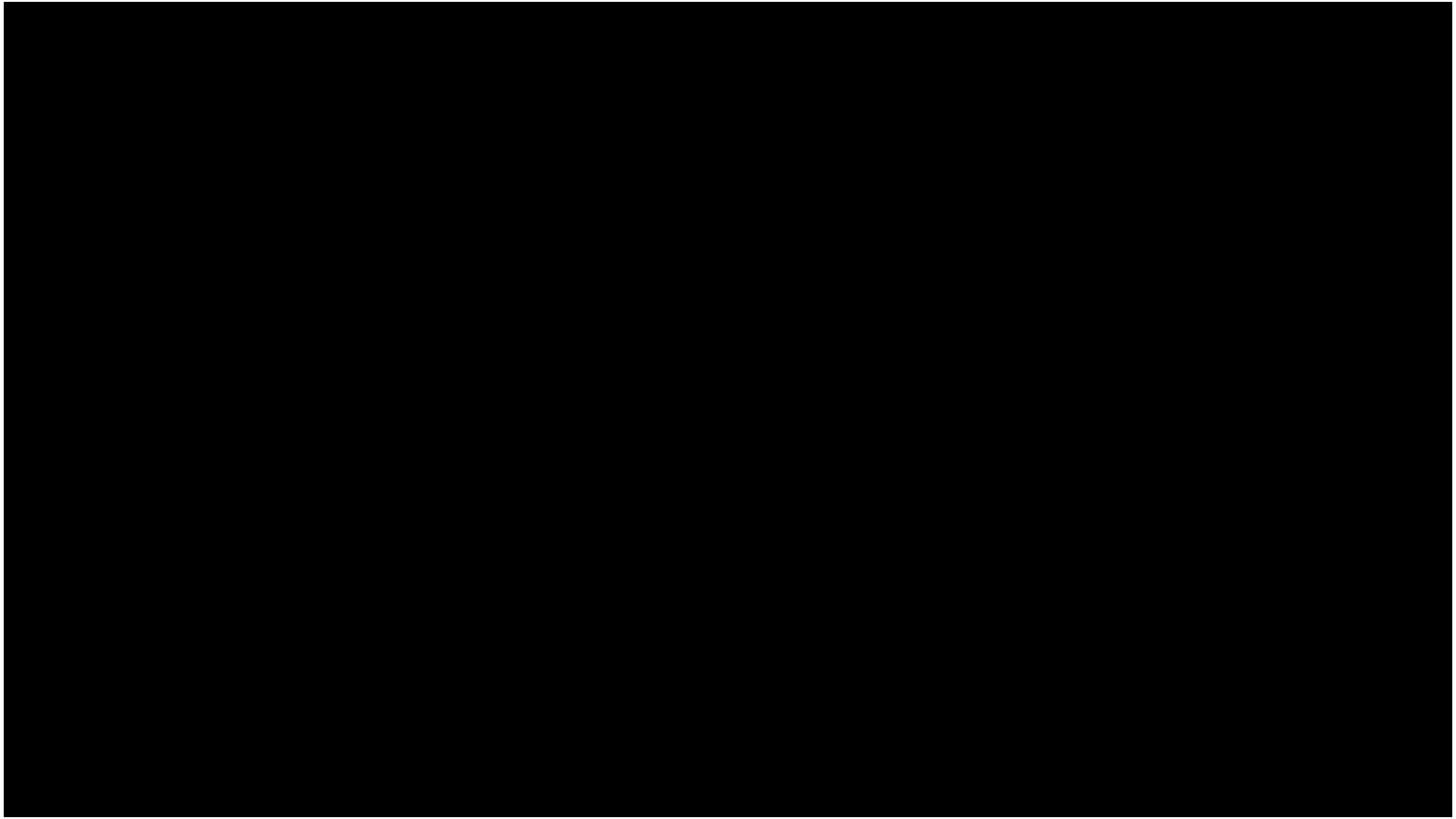
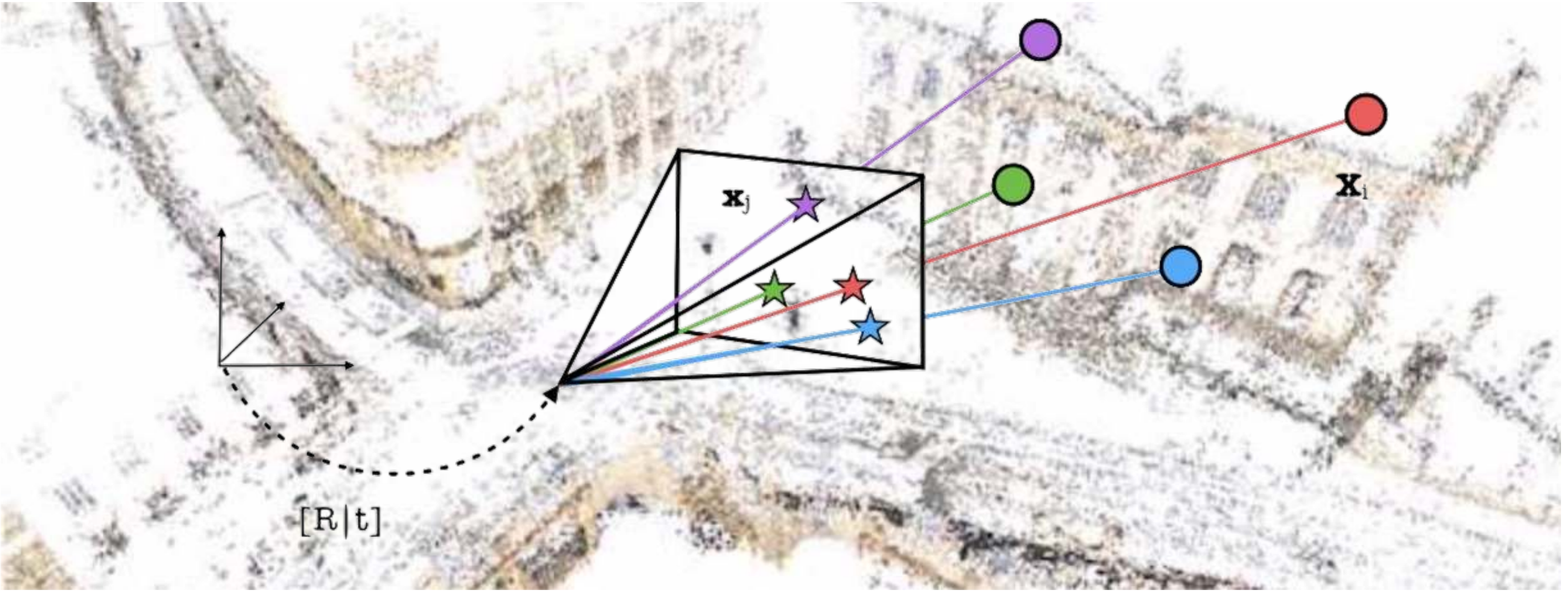
Image Retrieval





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Hierarchical Localization

Query Image

Nearest Neighbour Retrieval

Sparse 3D Model

Local 2D-3D Matching

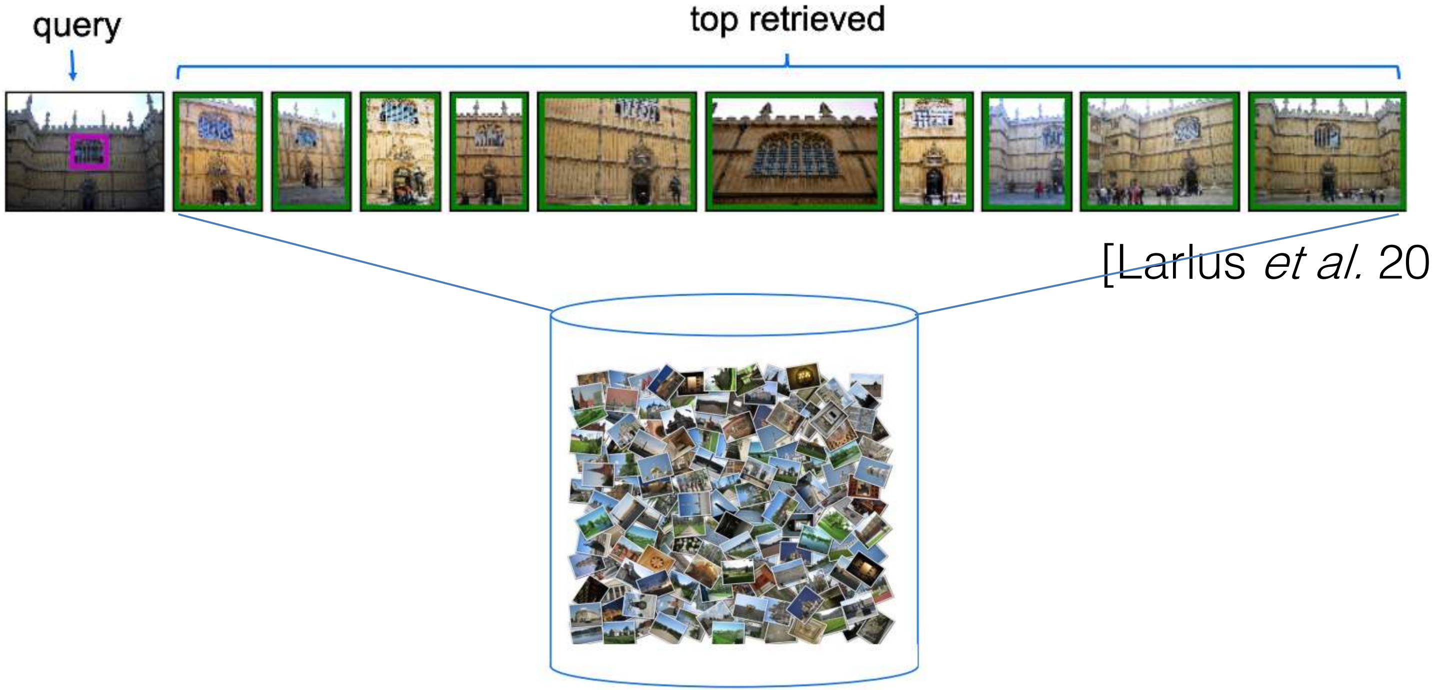
Camera Pose Estimation (P*n*P)

NetVLAD [Arandjelovic *et al.*, CVPR 2016]:

Application to Camera Localization

Localization by Image Retrieval

Matching a query image against a database



[Larlus *et al.* 2017]

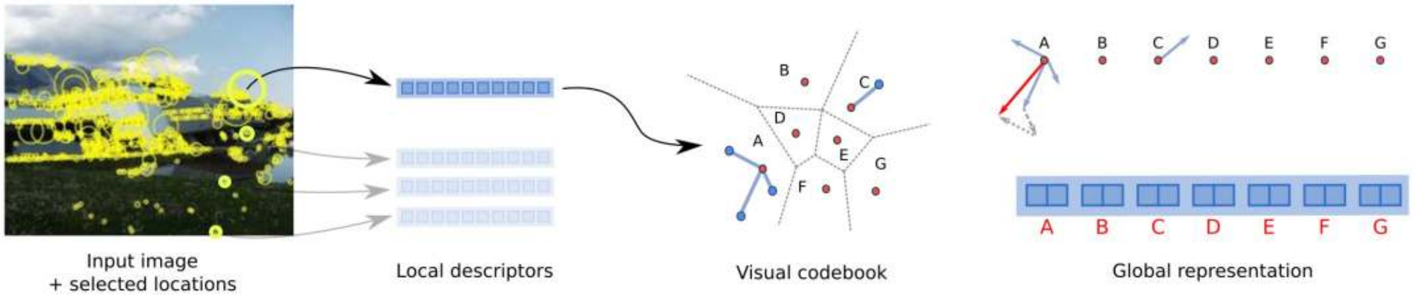
Aggregating Local Representations

A popular approach: VLAD (Vector of Locally Aggregated Descriptors)

- Assign local descriptors to *visual words;*

- Concatenate vectors for individual words by computing *residuals;*

- Store a 2D vector per cluster as part of final descriptor.



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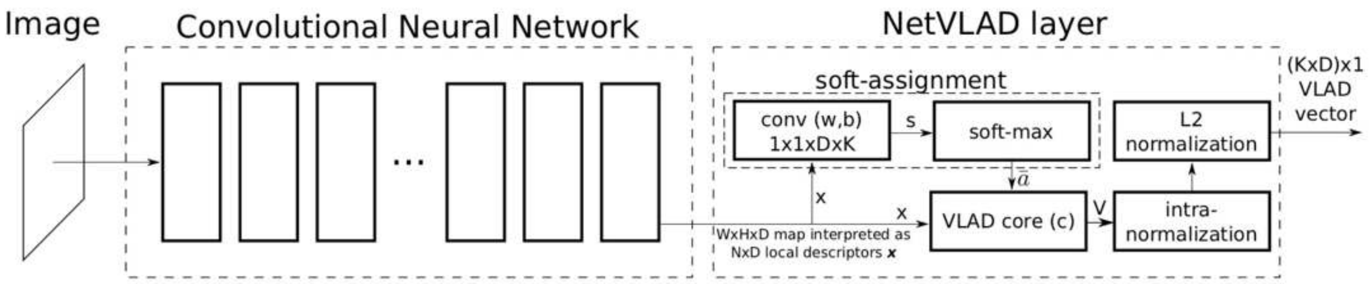
[Jégou et al. CVPR 2010]

Improving VLAD: *Learning* to extract local features and to aggregate them

NetVLAD: Apply VLAD on features learned end-to-end

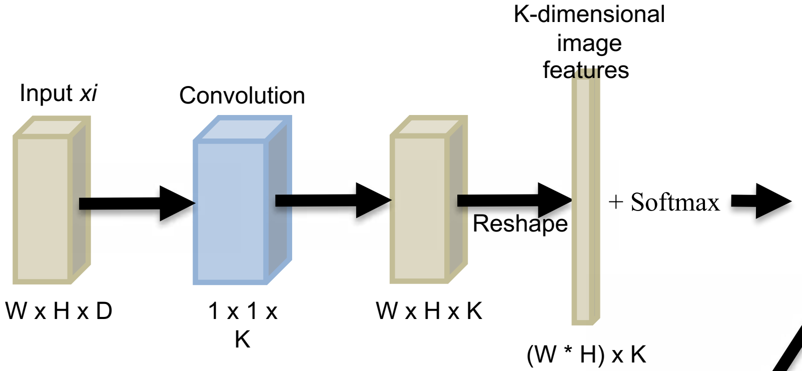
Define a differentiable VLAD layer, append it to a Siamese Network



[Arandjelovic et al. CVPR16]

NetVLAD in practice

$\{\mathbf{w}_k\}$, $\{b_k\}$ and $\{\mathbf{c}_k\}$ are sets of trainable parameters



"Soft" assignment of features to 1 of K cluster centers

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

Compute the residuals between the features and the centroid of their clusters (as in VLAD)

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

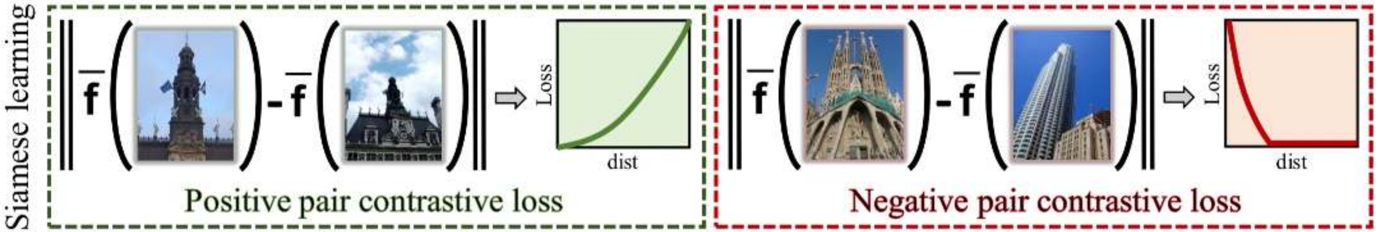
Normalization

$(K \times D) \times 1$ descriptors

Training NetVLAD

The network is trained on pairs of images, either *positive* or *negative;*

- For positive pairs, minimize the distance between the output descriptors.
- For negative pairs, maximize it.



$$\mathcal{L}(i,j) = \begin{cases} \frac{1}{2}||\bar{\mathbf{f}}(i) - \bar{\mathbf{f}}(j)||^2, & \text{if } Y(i,j) = 1 \\ \frac{1}{2}\left(\max\{0, \tau - ||\bar{\mathbf{f}}(i) - \bar{\mathbf{f}}(j)||\}\right)^2, & \text{if } Y(i,j) = 0 \end{cases}$$

[Radenovic et al. TPAMI2018]

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NetVLAD: Results

[Arandjelovic et al. CVPR16]

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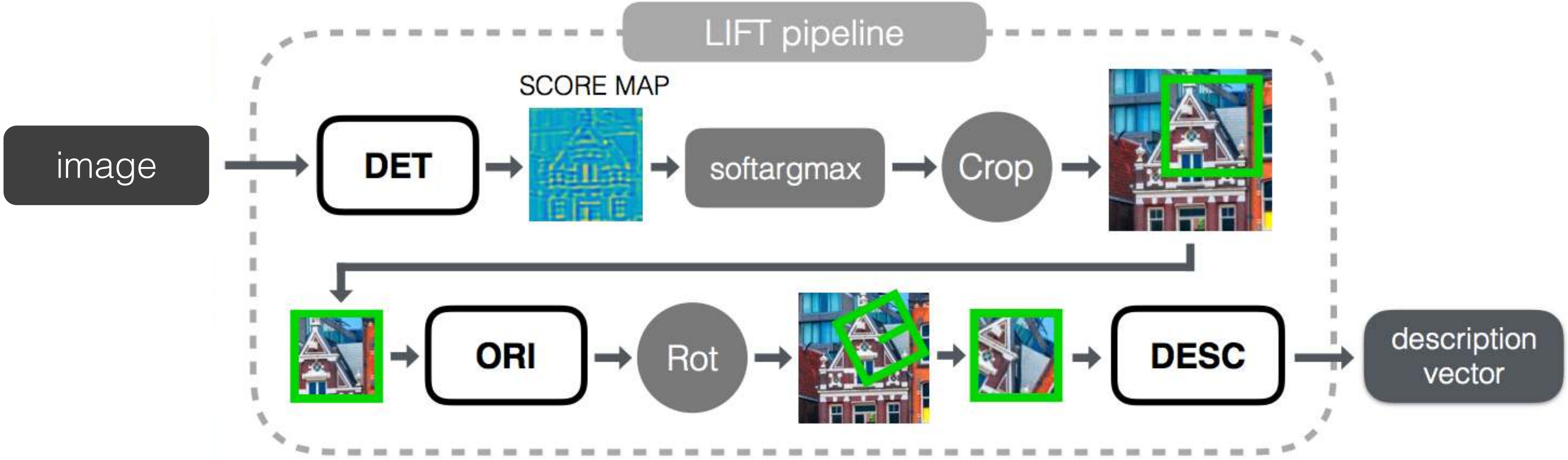
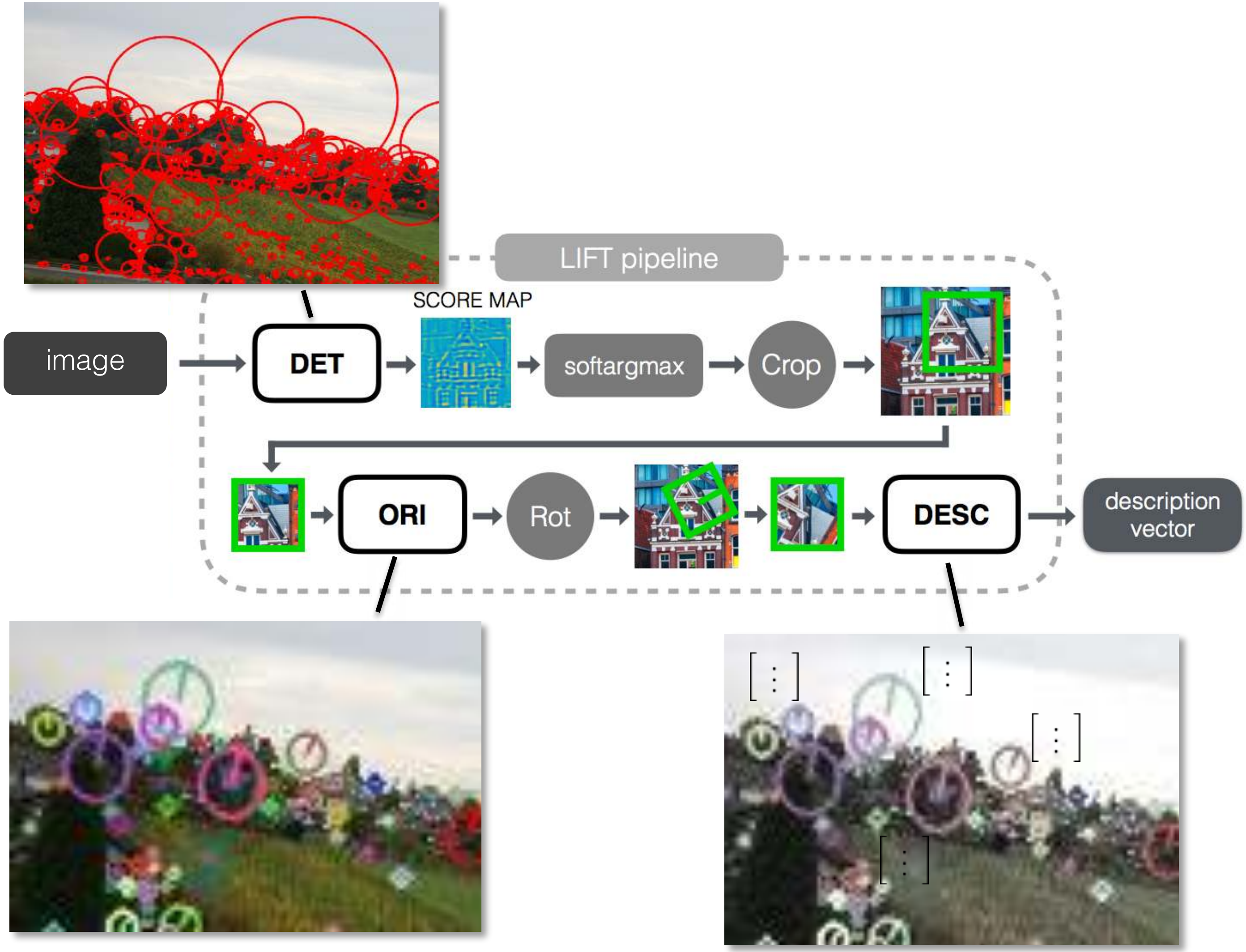
LIFT



LIFT pipeline
SCORE MAP
image
DET
softargmax
Crop
ORI
Rot
DESC
description vector



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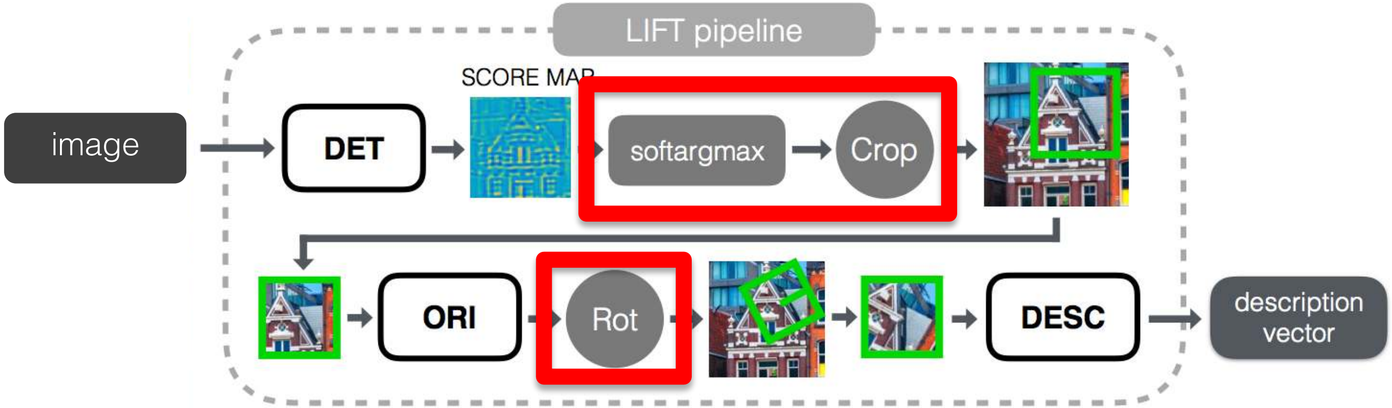

"Differentiable glue"

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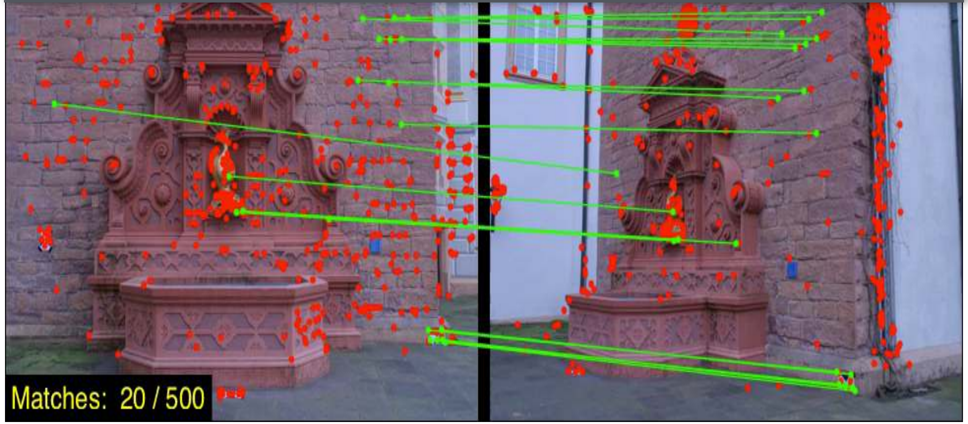
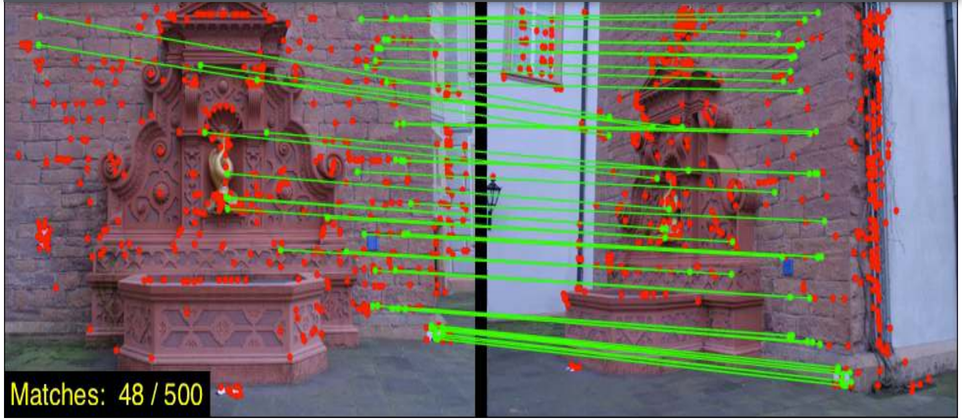
SIFT. Average: 60.2 matches



+64%

LIFT (Ours). Average: 98.6 matches



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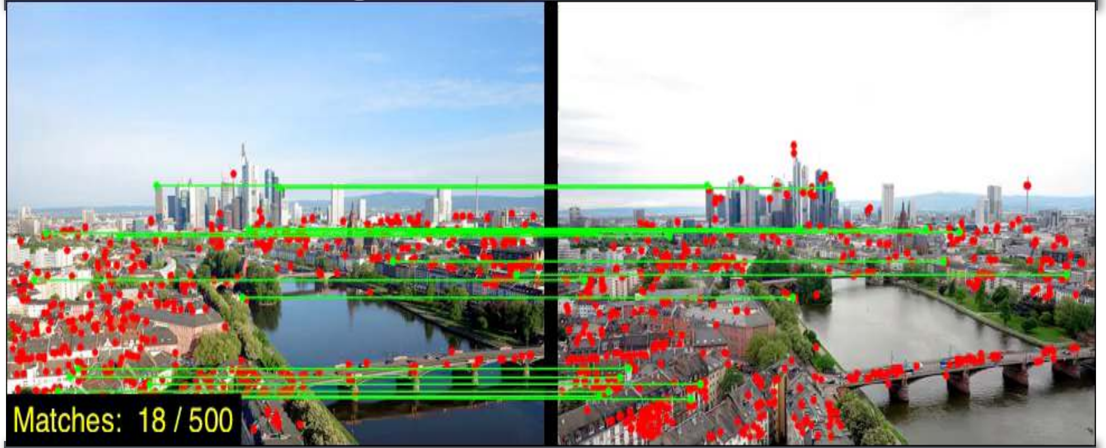
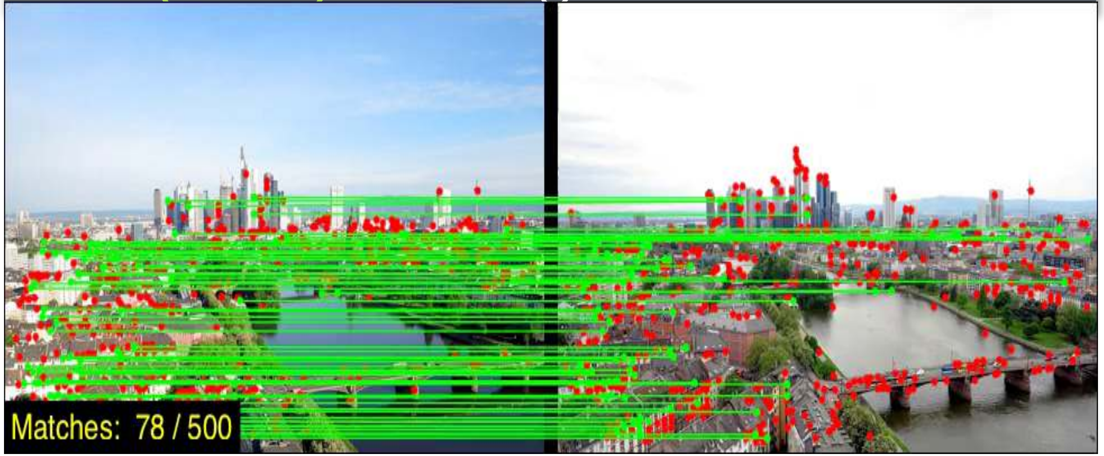
SIFT. Average: 23.1 matches



LIFT (Ours). Average: 60.6 matches

+162%



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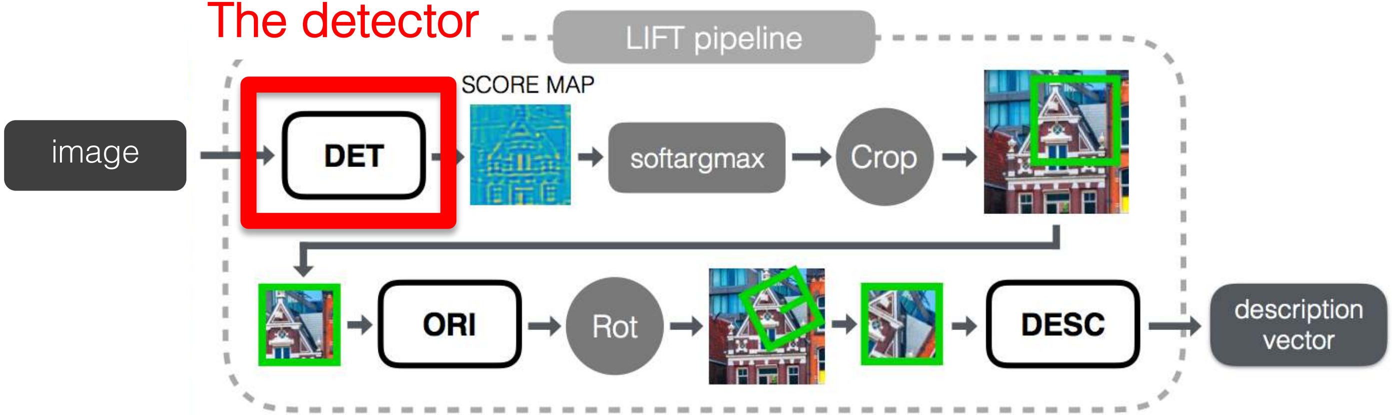
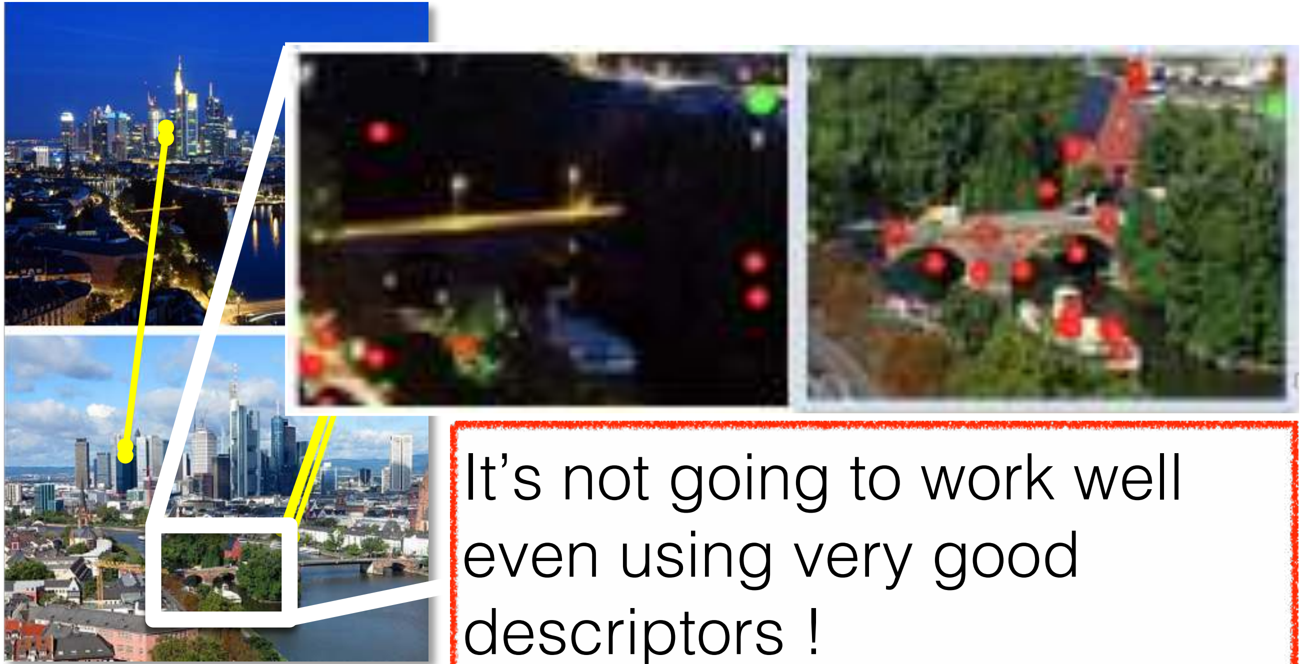
The detector



Detection under Severe Illumination Changes

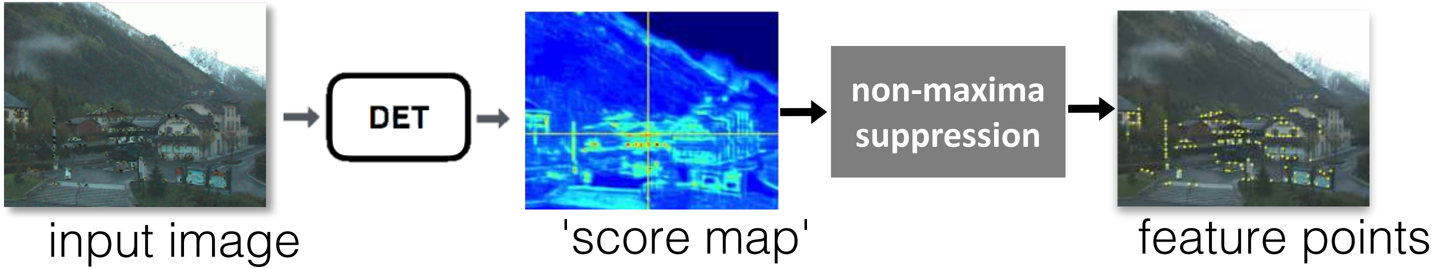
Detection under Severe Illumination Changes



It's not going to work well even using very good descriptors !

Learning to Detect under Severe Illumination Changes

How the Detector is Used at Run-Time



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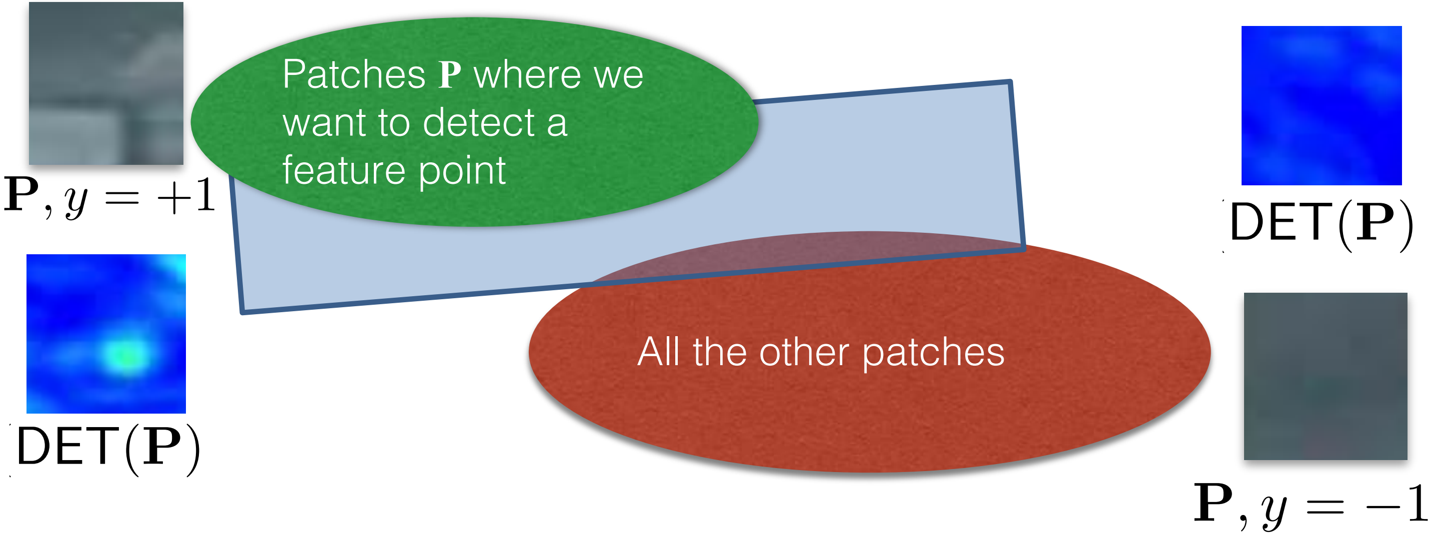
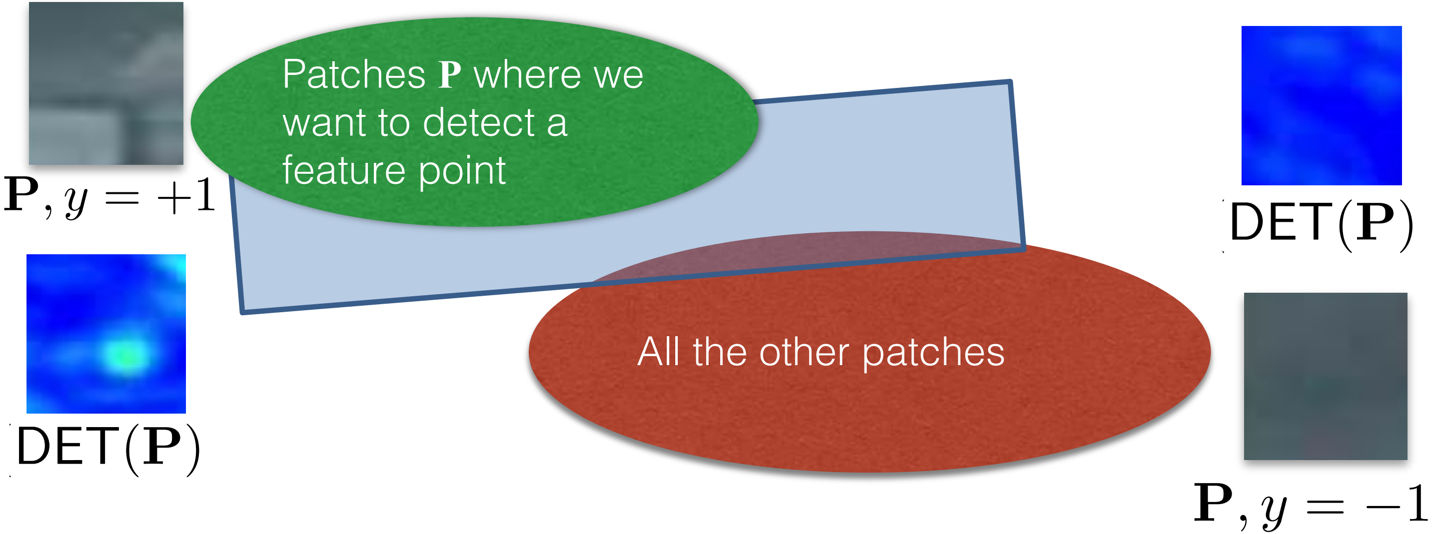
Cost Function (1)



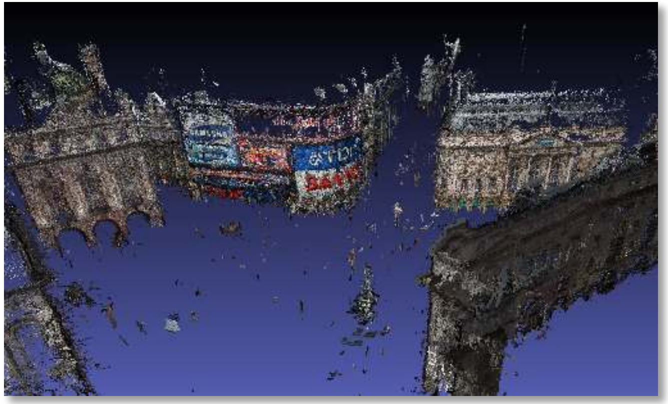
$$\mathcal{L}_{\text{class}}(\mathbf{P}) = \max(0, 1 - y \max(\text{DET}(\mathbf{P})))^2, y \in \{-1, +1\}$$

Cost Function (1)

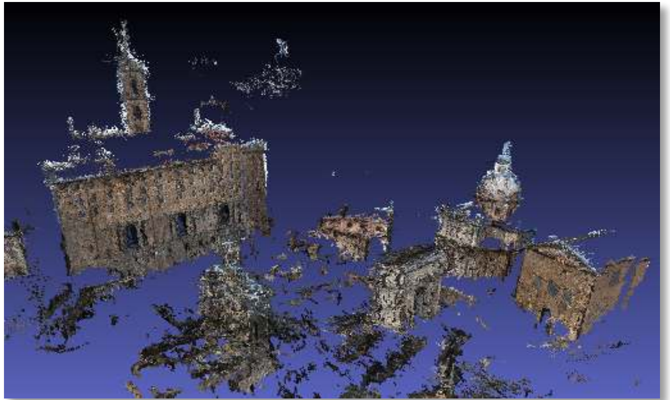


$$\mathcal{L}_{\text{class}}(\mathbf{P}) = \max(0, 1 - y\ \underline{\text{softmax}}(\text{DET}(\mathbf{P})))^2, y \in \{-1, +1\}$$

Training with SfM Keypoints



Piccadilly (pic)



Roman Forum (rf)

- We need variability (illumination, perspective, etc). We build SfM reconstructions from **photo-tourism sets.**

- We keep only **points with SfM correspondences** as positive examples, that is, we **learn to find repeatable points.**

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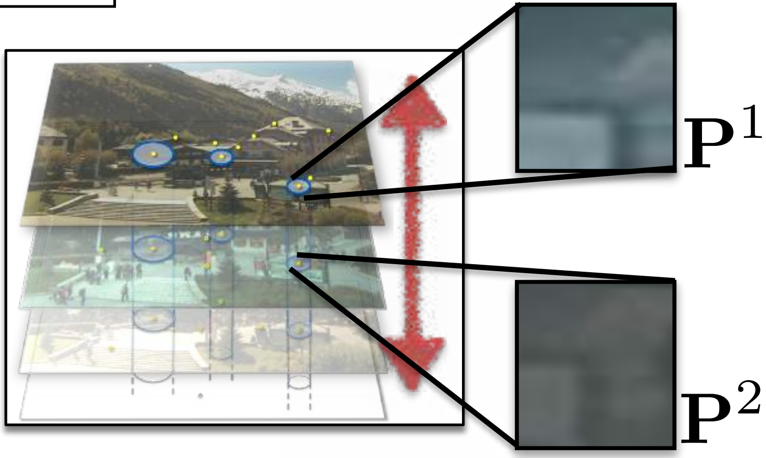
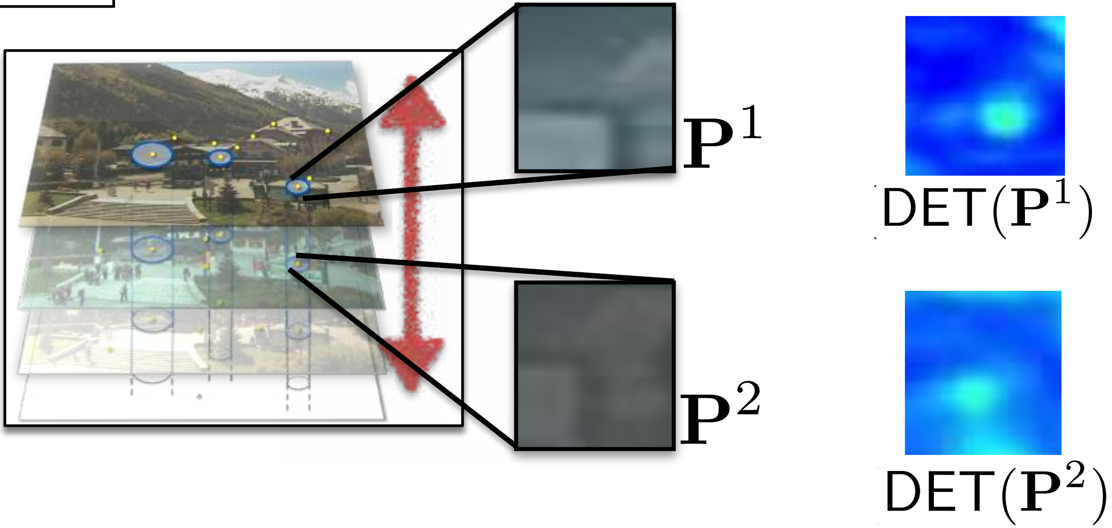
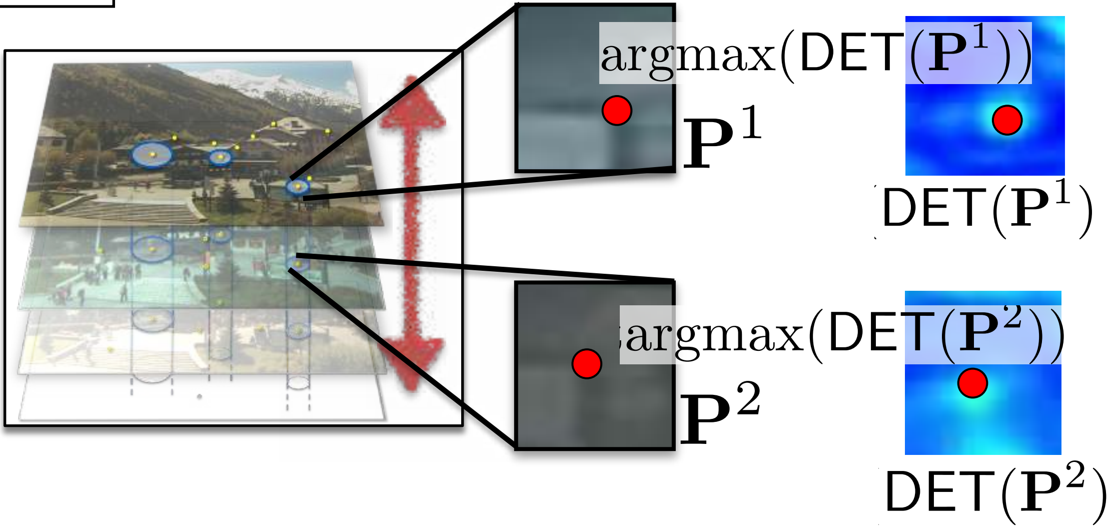
Cost Function (2)



Cost Function (2)



Cost Function (2)



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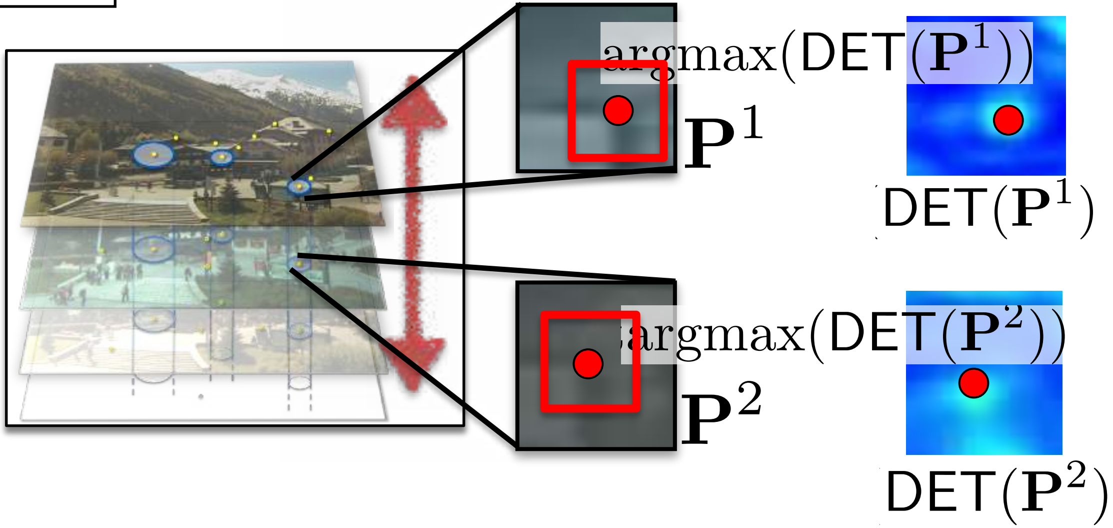
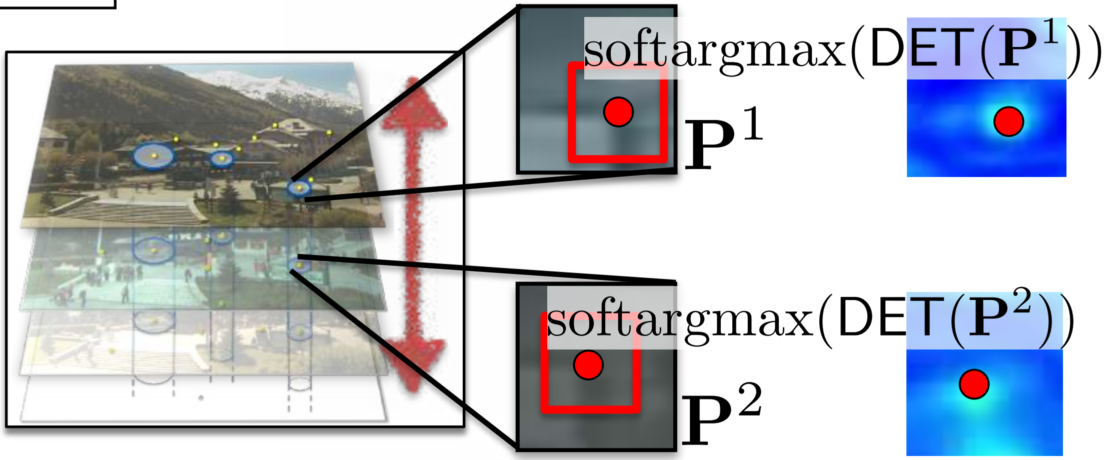


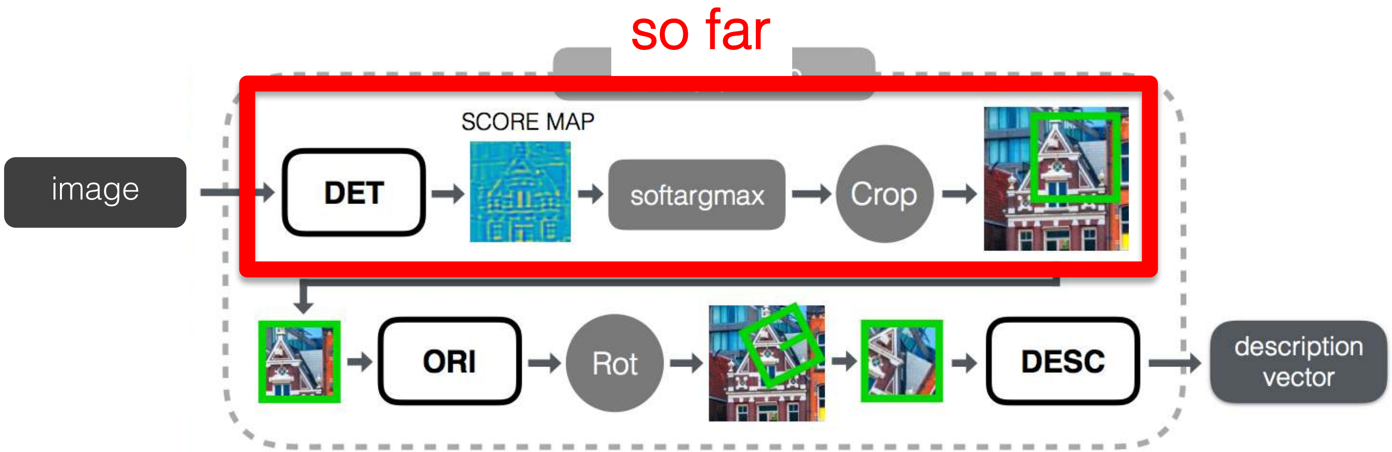
$$\mathcal{L}_{\text{pair}}(\mathbf{P}^1,\mathbf{P}^2) = \| \ \text{DESC}(\text{Crop}(\mathbf{P}^1, \text{argmax}(\text{DET}(\mathbf{P}^1)))) - \text{DESC}(\text{Crop}(\mathbf{P}^2, \text{argmax}(\text{DET}(\mathbf{P}^2)))) \ \|^2$$

Cost Function (2)



$$\mathcal{L}_{\text{pair}}(\mathbf{P}^1, \mathbf{P}^2) = \| \quad \text{DESC}(\text{Crop}(\mathbf{P}^1, \underline{\text{softargmax}}(\text{DET}(\mathbf{P}^1)))) - \text{DESC}(\text{Crop}(\mathbf{P}^2, \underline{\text{softargmax}}(\text{DET}(\mathbf{P}^2)))) \quad \|^2$$

$$\text{softargmax}(\mathbf{S}) = \frac{\sum_{\mathbf{x}} \exp(\beta \mathbf{S}(\mathbf{x}))\mathbf{x}}{\sum_{\mathbf{x}} \exp(\beta \mathbf{S}(\mathbf{x}))}$$



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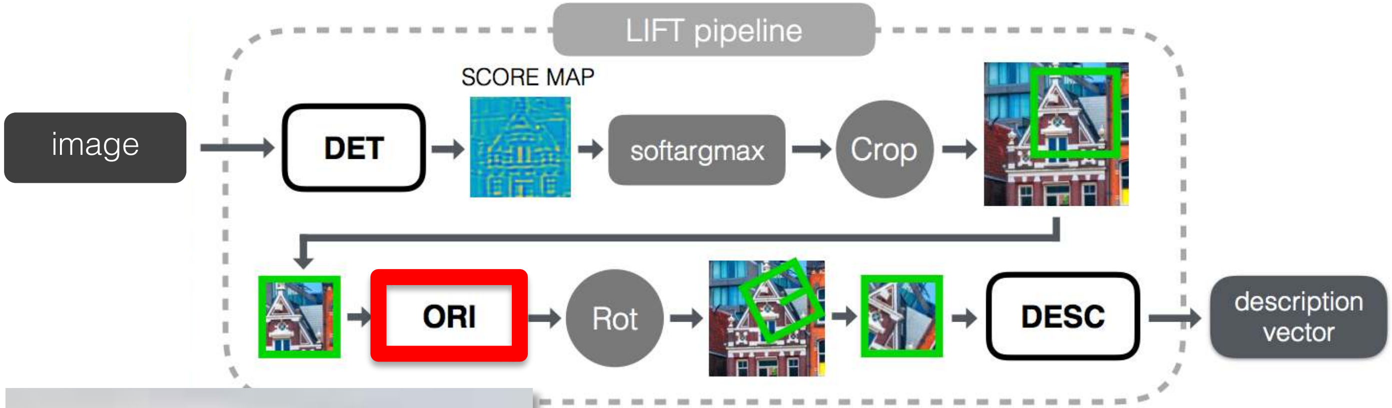
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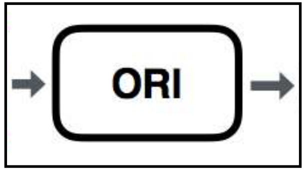
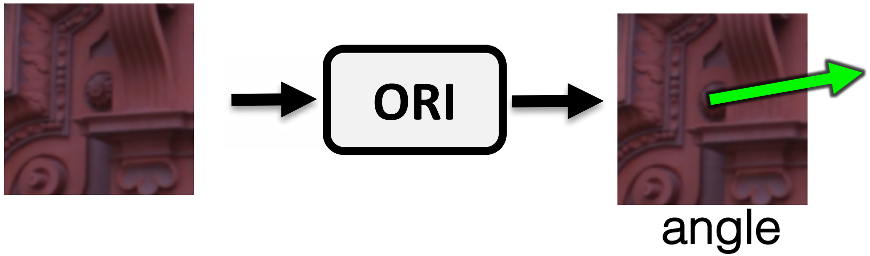
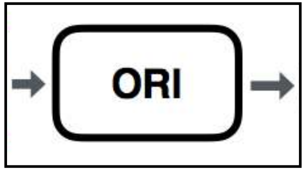


Learning Orientations Implicitly

We want the orientation estimator to provide **consistent** results, regardless of imaging changes





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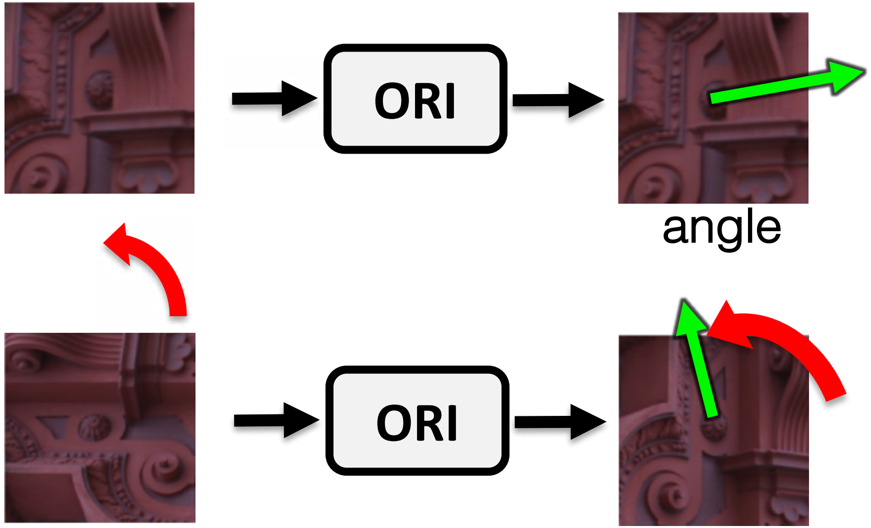

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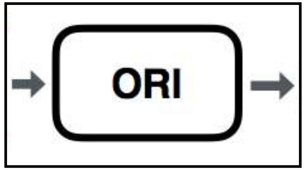
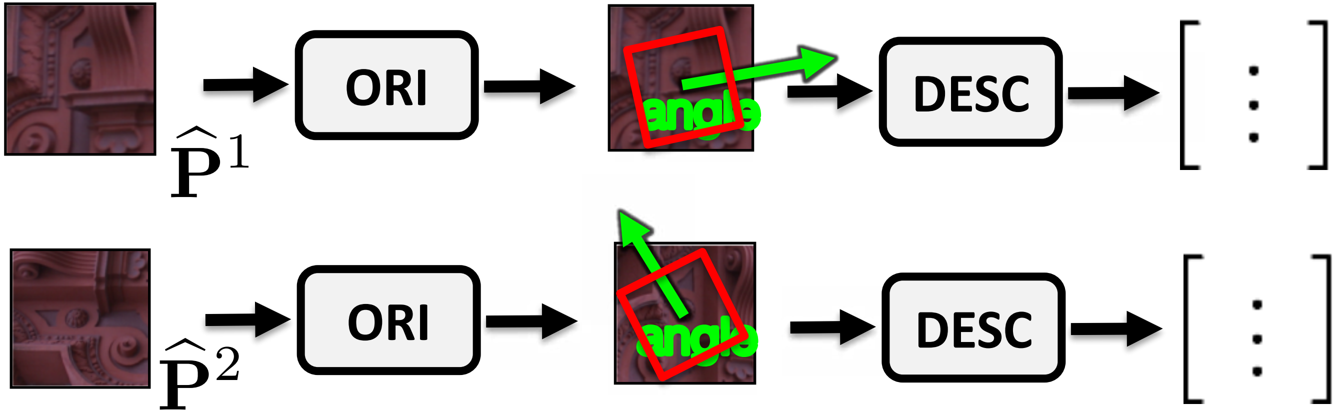
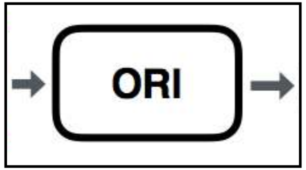


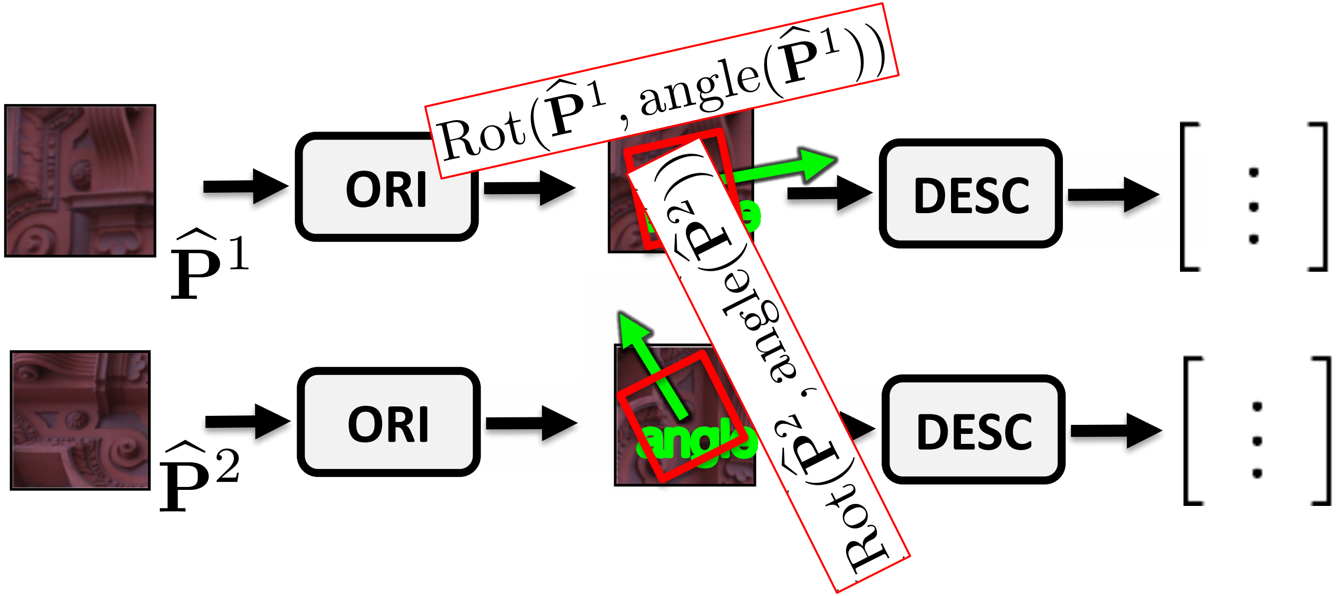
Learning Orientations Implicitly: A Siamese Network with a Twist

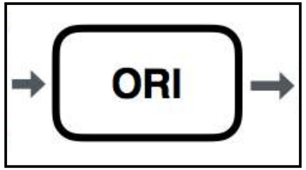




Learning Orientations Implicitly: A Siamese Network with a Twist

$$\mathcal{L}_{\text{pair}}(\widehat{\mathbf{P}}^1, \widehat{\mathbf{P}}^2) = \| \ \text{DESC}(\text{Rot}(\widehat{\mathbf{P}}^1, \text{angle}(\widehat{\mathbf{P}}^1))) - \text{DESC}(\text{Rot}(\widehat{\mathbf{P}}^2, \text{angle}(\widehat{\mathbf{P}}^2))) \ \|^2$$

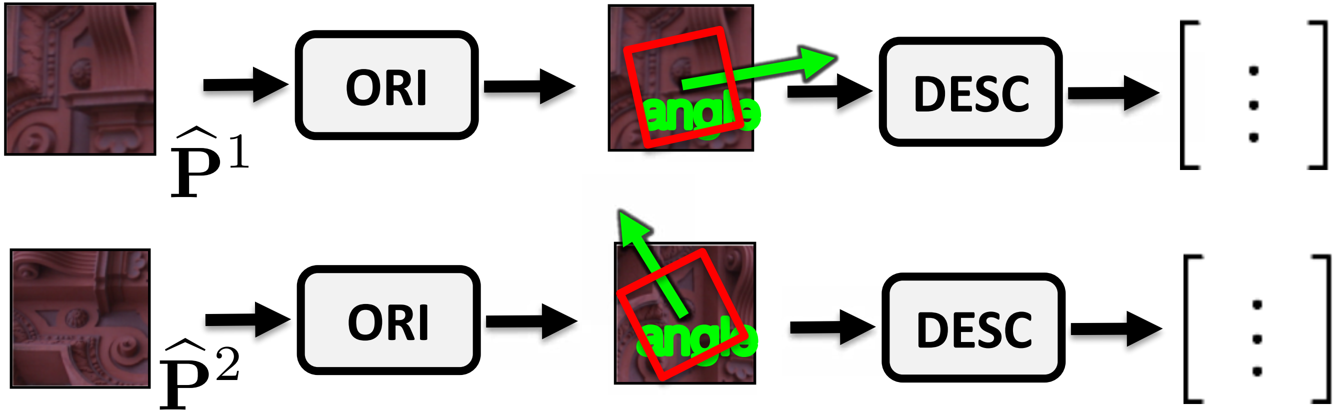


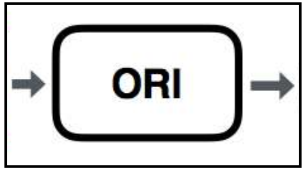


Learning Orientations Implicitly: A Siamese Network with a Twist

$$\mathcal{L}_{\text{pair}}(\widehat{\mathbf{P}}^1, \widehat{\mathbf{P}}^2) = \| \ \mathsf{DESC}(\text{Rot}(\widehat{\mathbf{P}}^1, \text{angle}(\widehat{\mathbf{P}}^1))) - \mathsf{DESC}(\text{Rot}(\widehat{\mathbf{P}}^2, \text{angle}(\widehat{\mathbf{P}}^2))) \ \|^2$$

$$\text{with angle}(\widehat{\mathbf{P}}) = \text{arctan2}(\mathsf{ORI}(\widehat{\mathbf{P}})^{[1]}, \mathsf{ORI}(\widehat{\mathbf{P}})^{[2]})$$



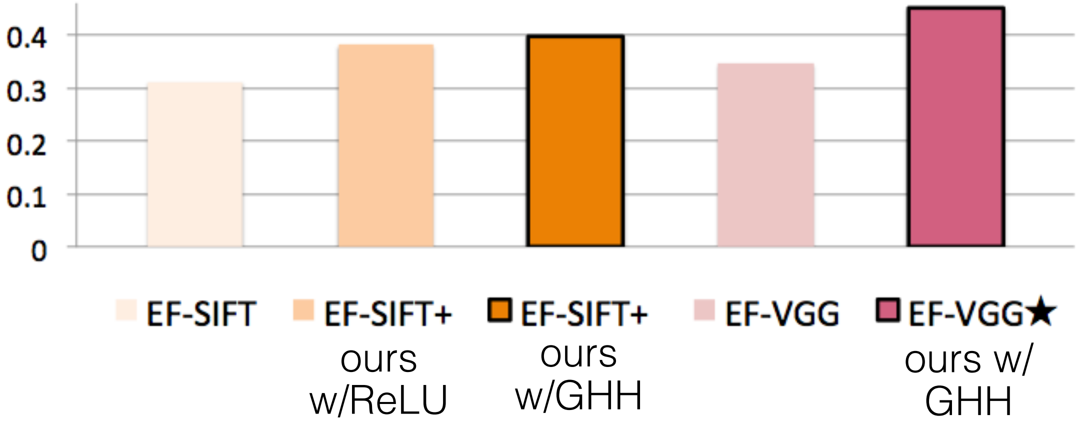


Performance Gain with Learned Orientations

mAP

(higher is better)

Average performance



Descriptor matching performances (mAP) with nearest neighbor matching (Mikolajczyk & Schmid, IJCV'04).

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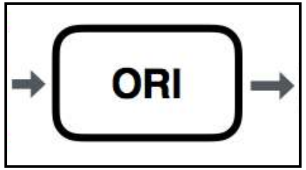
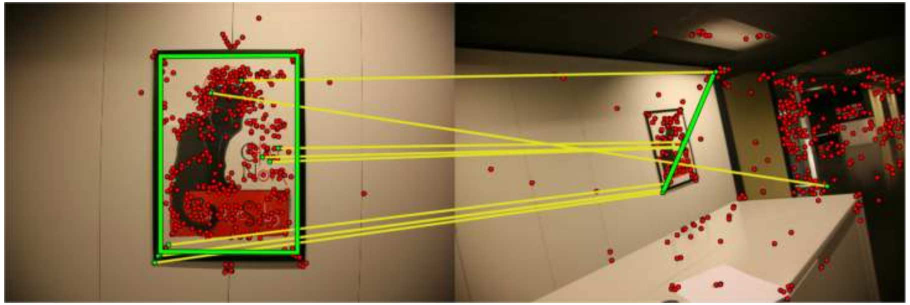
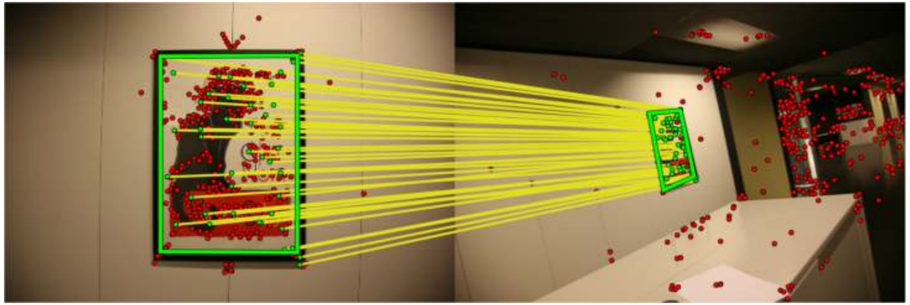


Learned Orientations



Dominant Gradient Orientations



Our Learned Orientations

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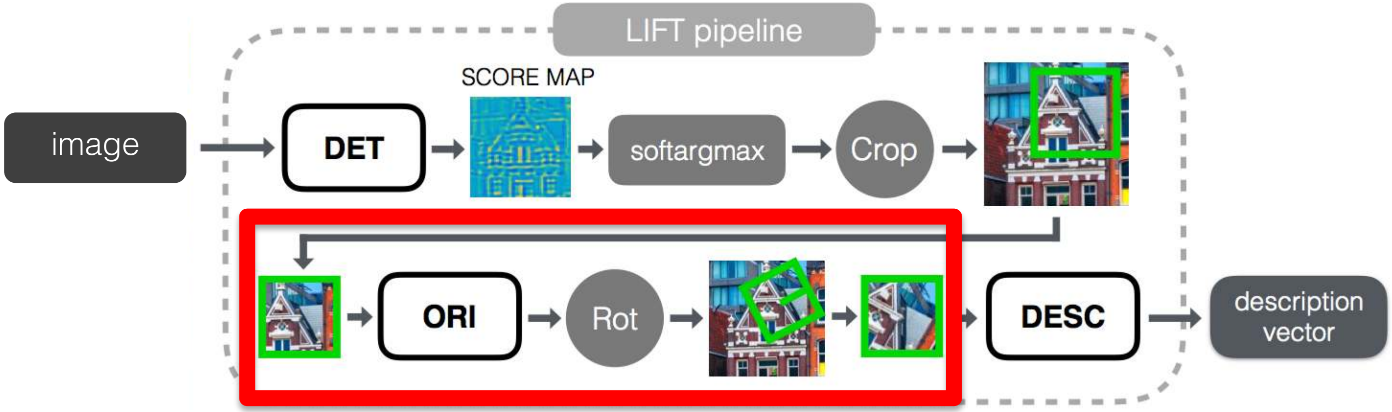
LIFT pipeline
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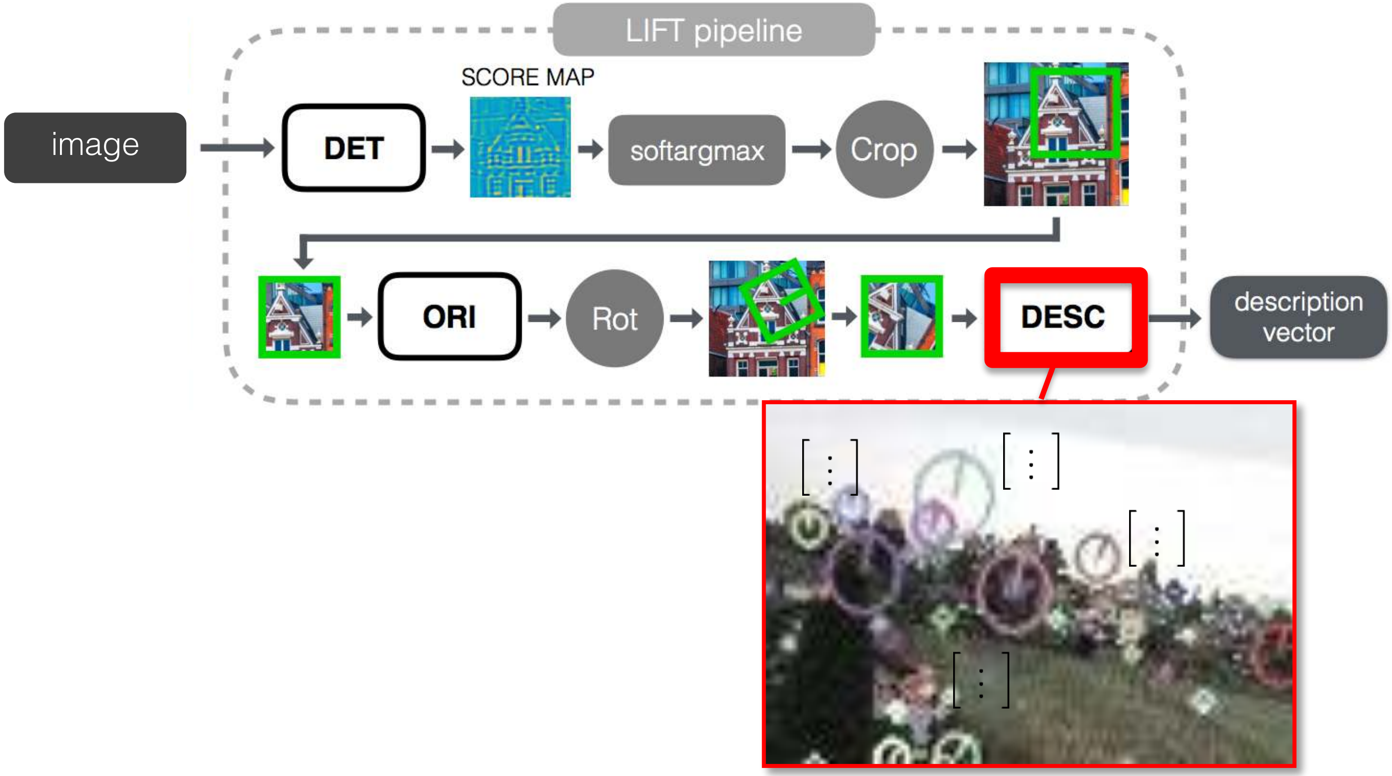

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Learning the Descriptor

- Positive pairs:  $\widehat{\mathbf{P}}^1$  $\widehat{\mathbf{P}}^2$

$$\mathcal{L}_{\text{pos}}(\widehat{\mathbf{P}}^1, \widehat{\mathbf{P}}^2) = \|\text{DESC}(\widehat{\mathbf{P}}^1) - \text{DESC}(\widehat{\mathbf{P}}^2)\|^2$$

Learning the Descriptor

- Positive pairs:

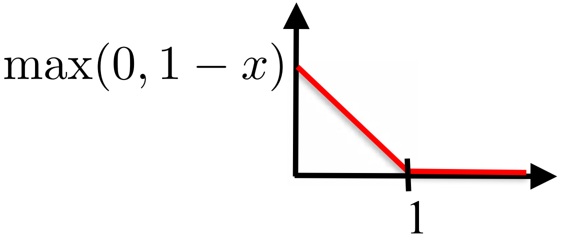
$\widehat{\mathbf{P}^1}$

$\widehat{\mathbf{P}^2}$

$$\mathcal{L}_{\text{pos}}(\widehat{\mathbf{P}^1}, \widehat{\mathbf{P}^2}) = \|\text{DESC}(\widehat{\mathbf{P}^1}) - \text{DESC}(\widehat{\mathbf{P}^2})\|^2$$

- Negative pairs:

$$\mathcal{L}_{\text{neg}}(\widehat{\mathbf{P}^1}, \widehat{\mathbf{P}^3}) = \max(0, 1 - \|\text{DESC}(\widehat{\mathbf{P}^1}) - \text{DESC}(\widehat{\mathbf{P}^3})\|^2)$$



$\widehat{\mathbf{P}^1}$

$\widehat{\mathbf{P}^3}$

Hard example mining is very important for training

A Single, Global Cost Function

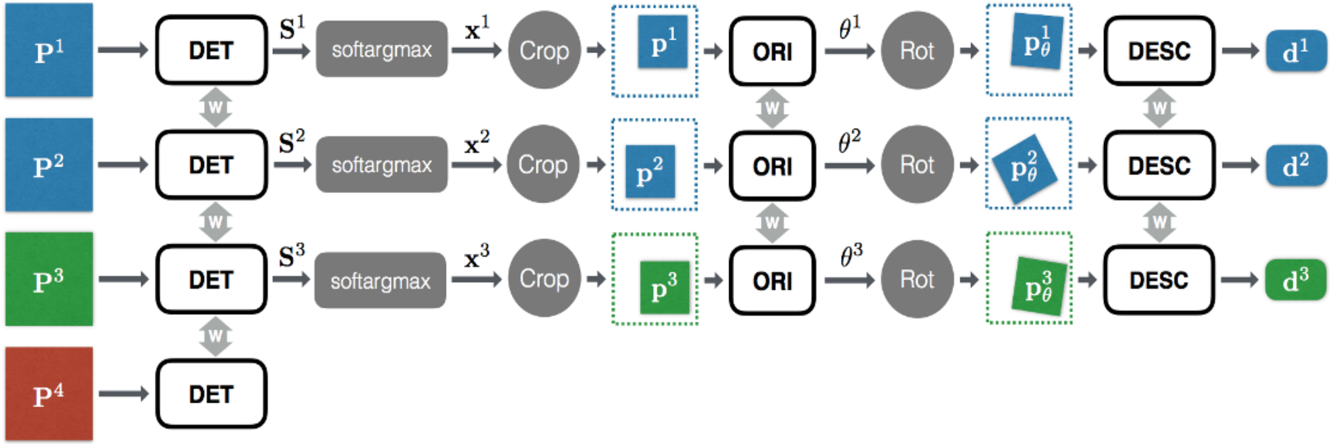
$$\min_{\{\mathsf{DET},\mathsf{ORI},\mathsf{DESC}\}} \sum_{\{(\mathbf{P},y)\}} \max(0, 1 - y \text{ softmax}(\mathsf{DET}(\mathbf{P})))^2 +$$

$$\sum_{(\mathbf{P}_1,\mathbf{P}_2)} \|\mathsf{DESC}\left(G(\mathbf{P}^1, \text{softargmax}(\mathsf{DET}(\mathbf{P}^1))\right) - \mathsf{DESC}\left(G(\mathbf{P}^2, \text{softargmax}(\mathsf{DET}(\mathbf{P}^2))\right)\|^2 +$$

$$\sum_{(\mathbf{P}_1,\mathbf{P}_3)} \max(0, 1 - \|\mathsf{DESC}\left(G(\mathbf{P}^1, \text{softargmax}(\mathsf{DET}(\mathbf{P}^1))\right) - \mathsf{DESC}\left(G(\mathbf{P}^3, \text{softargmax}(\mathsf{DET}(\mathbf{P}^3)))\right)\|^2)$$

$$G(\mathbf{P}, \mathbf{x}) = \text{Rot}\left(\mathbf{P}, \mathbf{x}, \text{angle}_{\mathsf{ORI}}(\text{Crop}(\mathbf{P}, \mathbf{x}))\right)$$

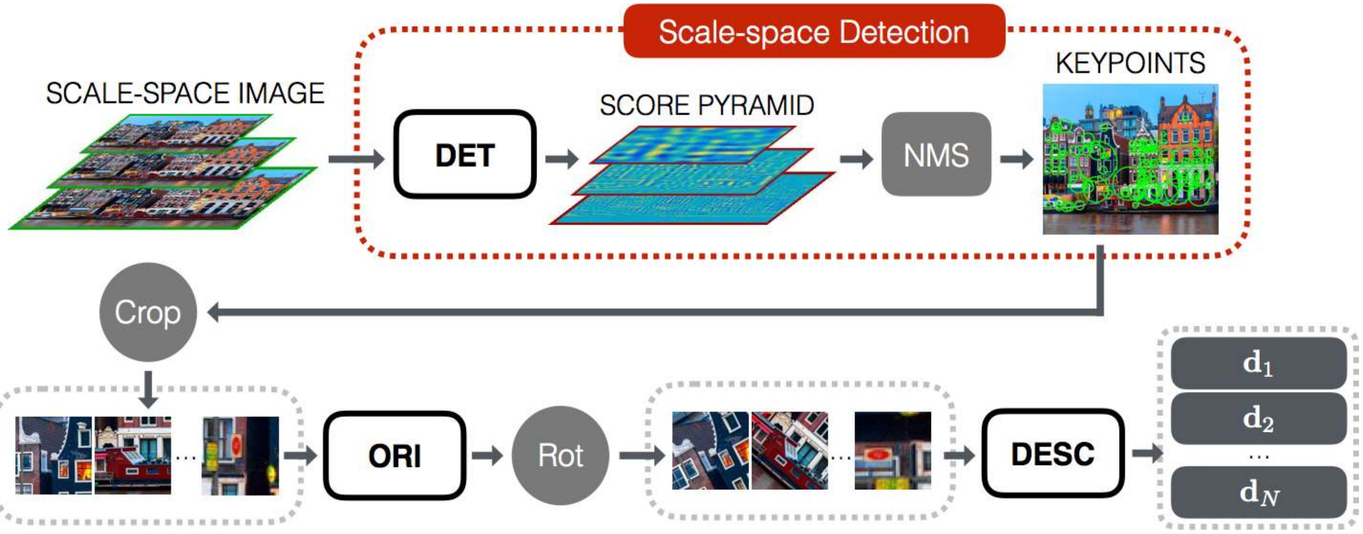
Problem-Specific Training



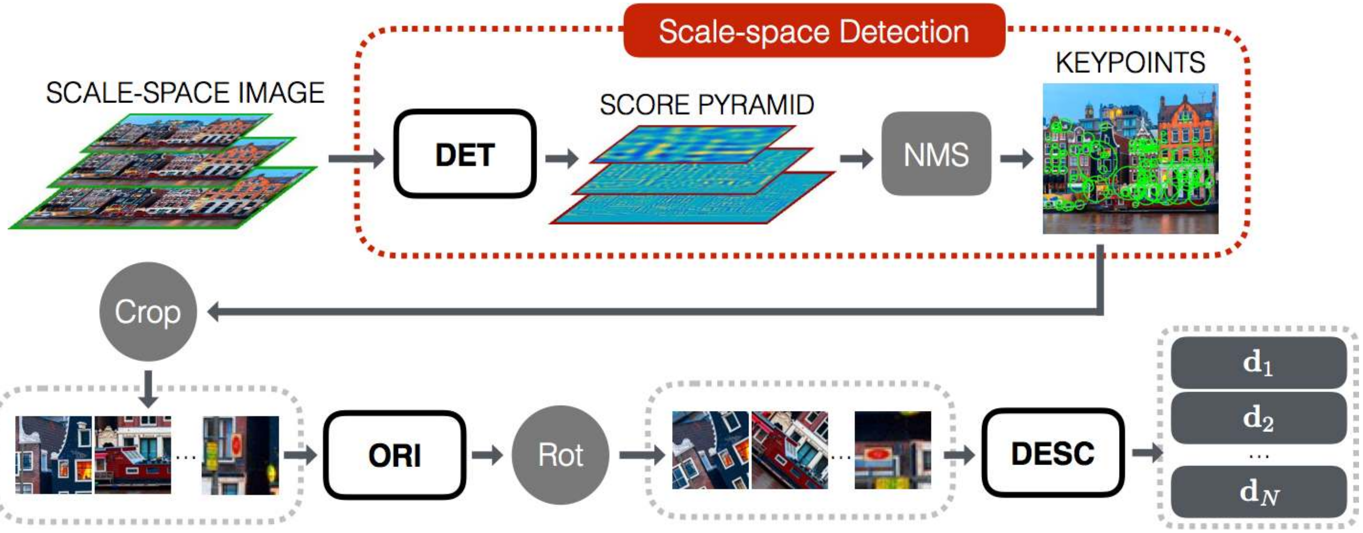
Run-Time Pipeline

Detector

- is purely convolutional, efficiently applied to the whole image;
- works in scale-space.



Run-Time Pipeline



The orientation estimator and the descriptor are applied only to keypoints.

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