Out with the Old?

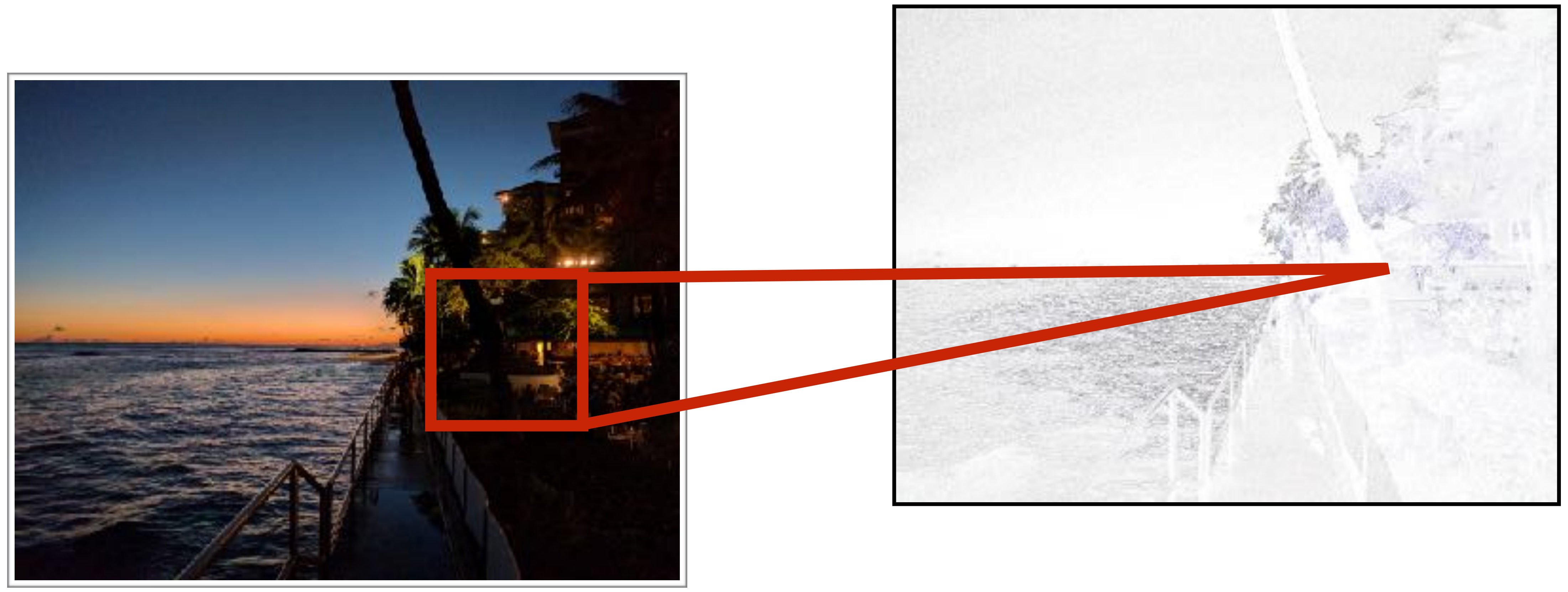
Convolutional Neural Networks for Feature Matching and Visual Localization

Torsten Sattler

Computer Vision and Geometry (CVG) Lab
ETH Zürich

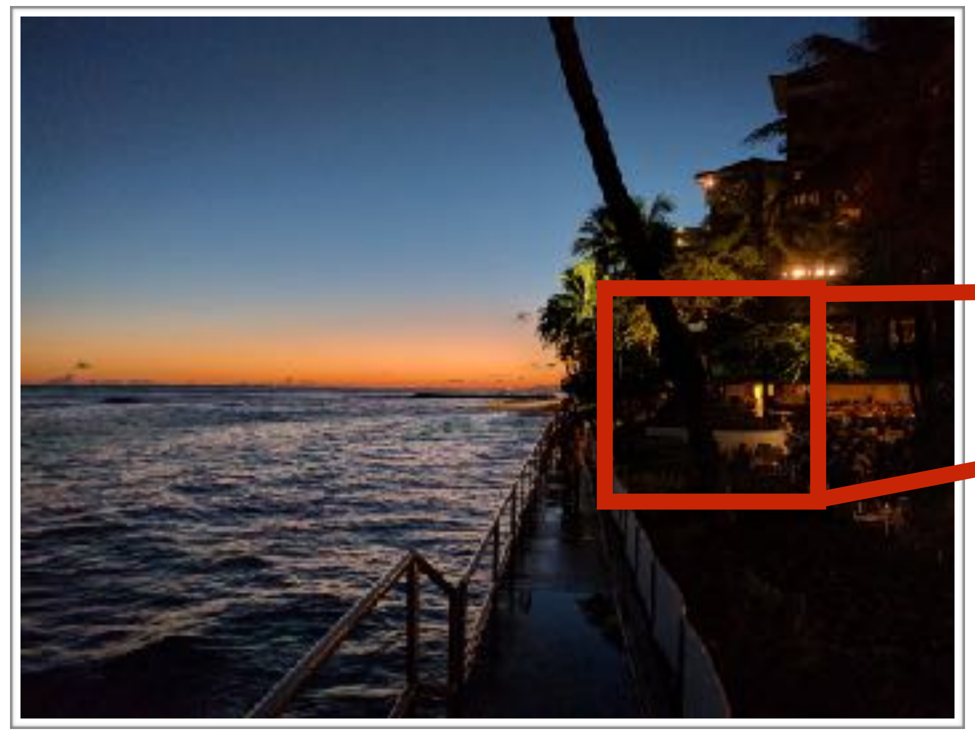
Convolutional Neural Networks

Convolutional Neural Networks



convolutions +
non-linearity

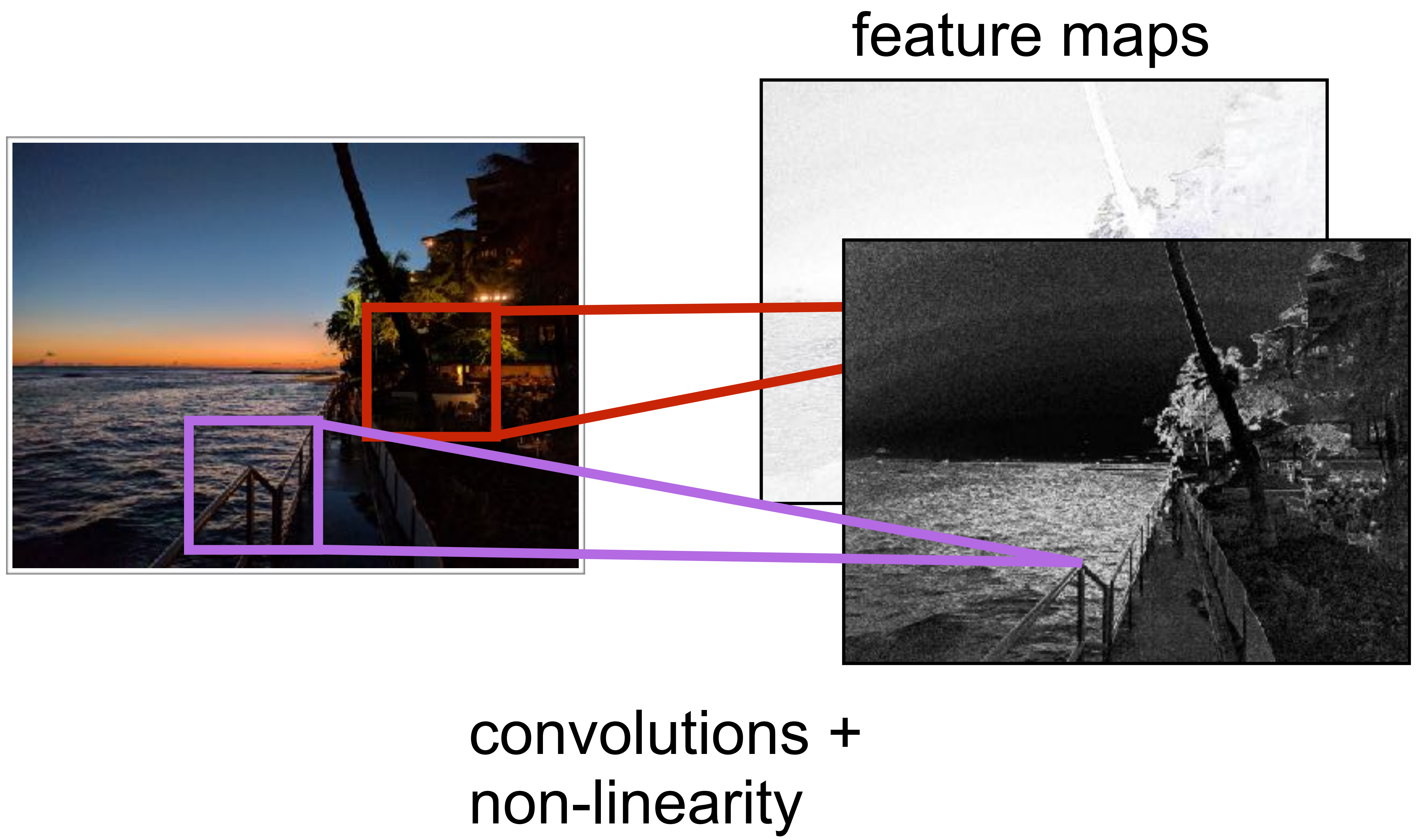
Convolutional Neural Networks



feature maps

convolutions +
non-linearity

Convolutional Neural Networks



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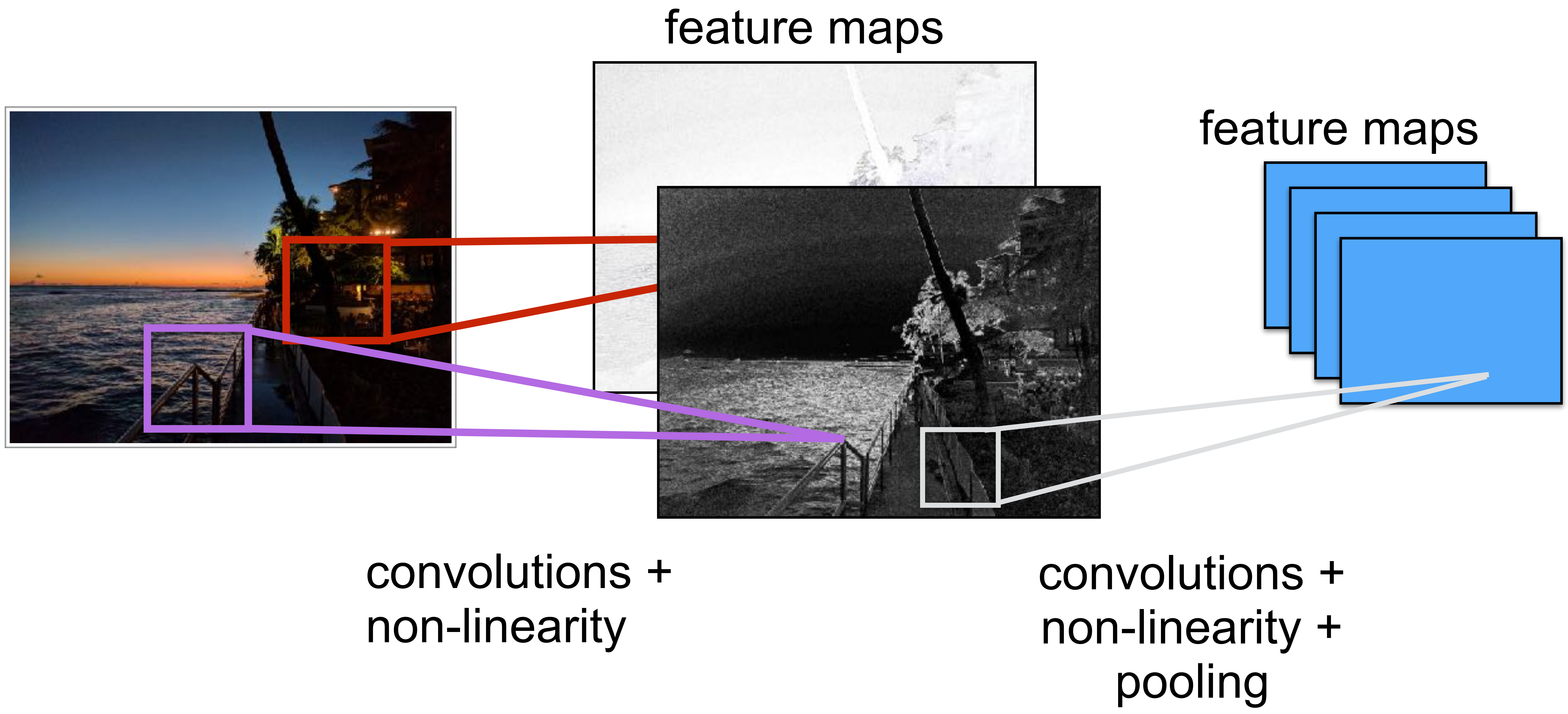

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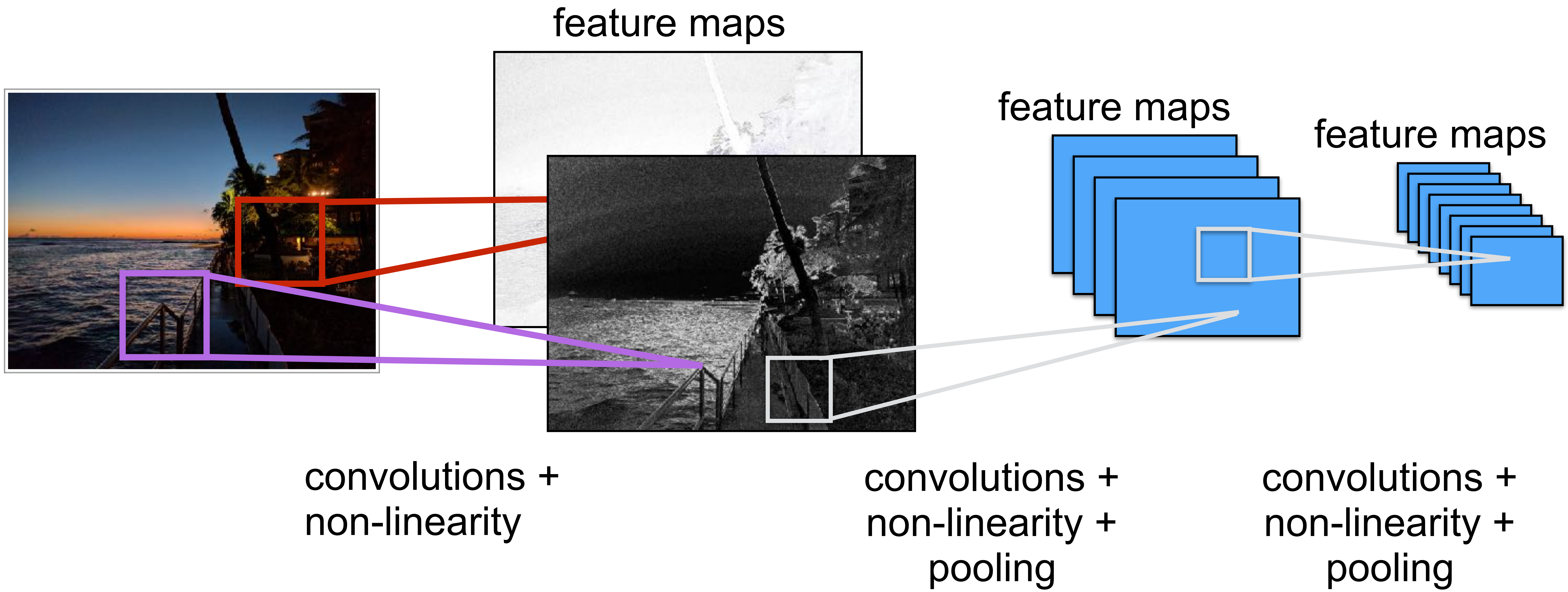

Convolutional Neural Networks

Convolutional Neural Networks

Deep Learning Revolution

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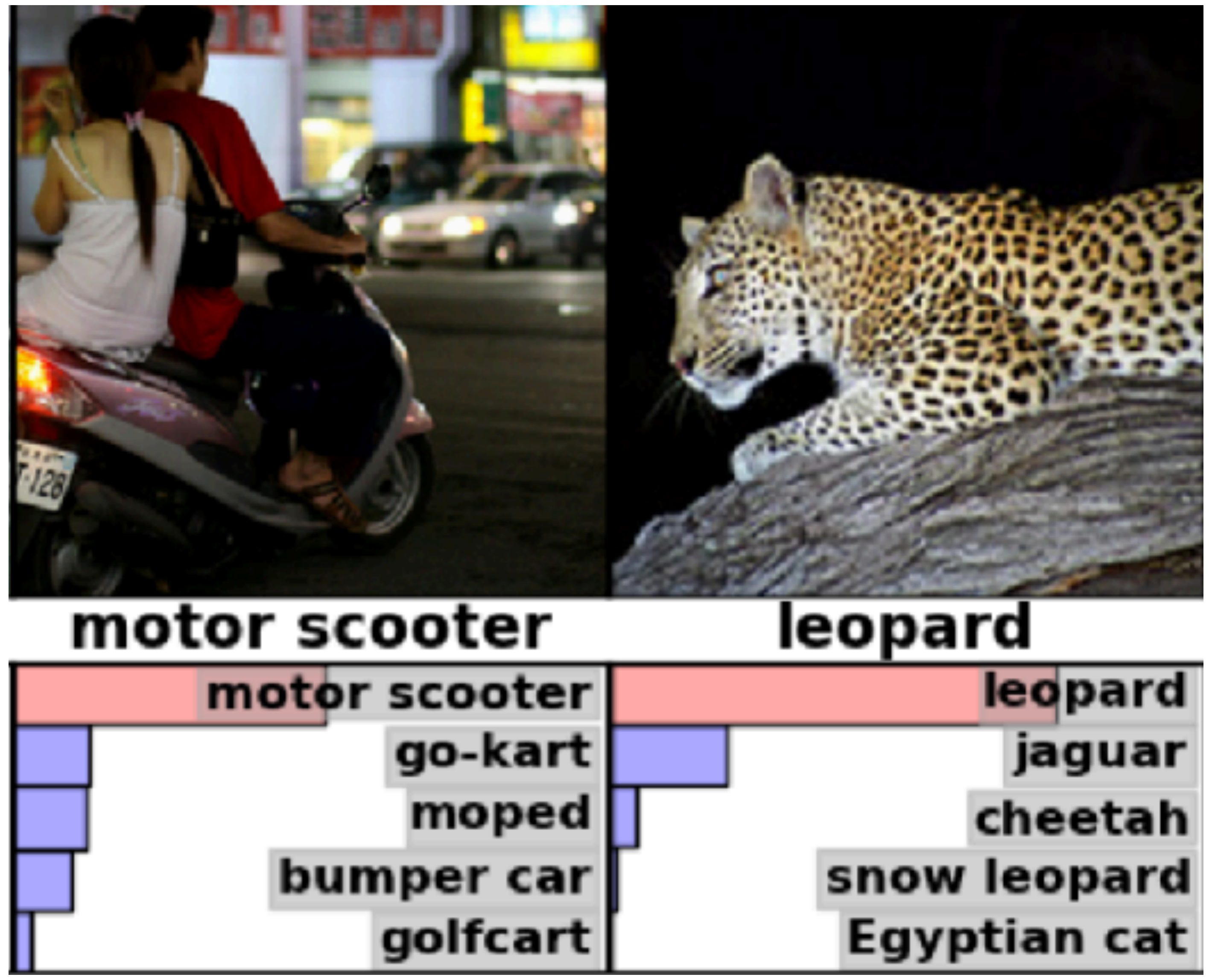
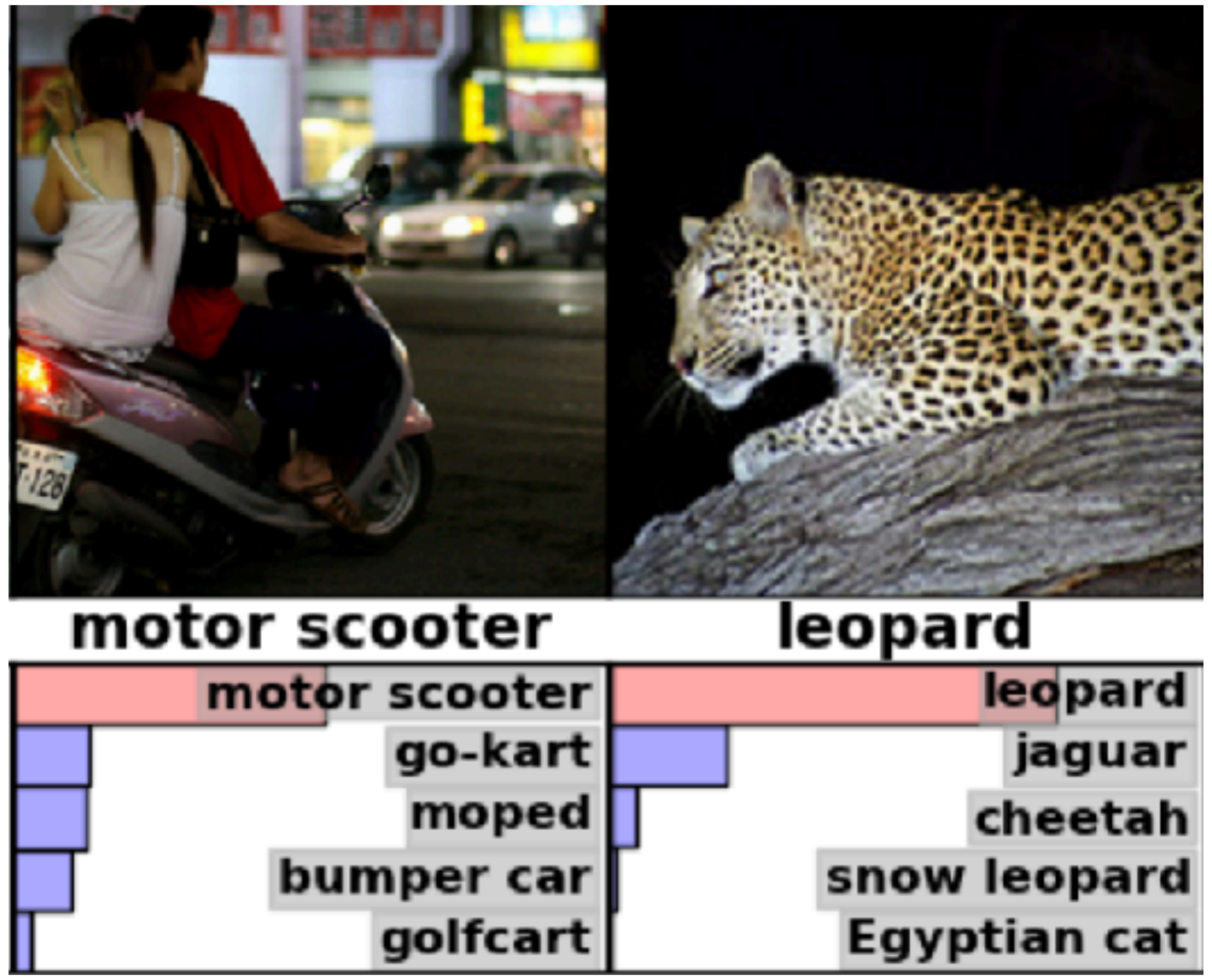


[Krizhevsky et al., ImageNet Classification with Deep Convolutional Neural Networks , NIPS 2012]

Deep Learning Revolution



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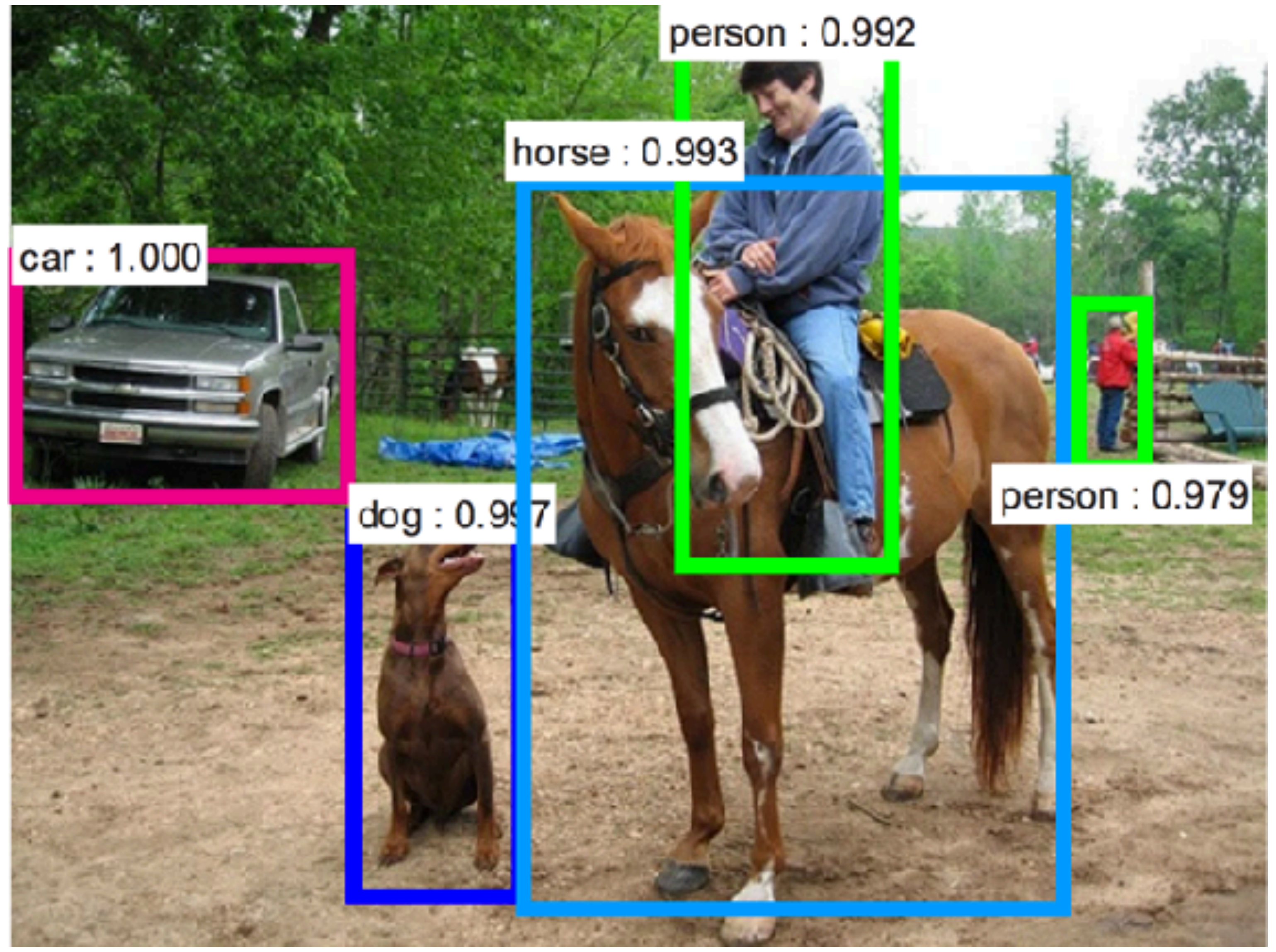

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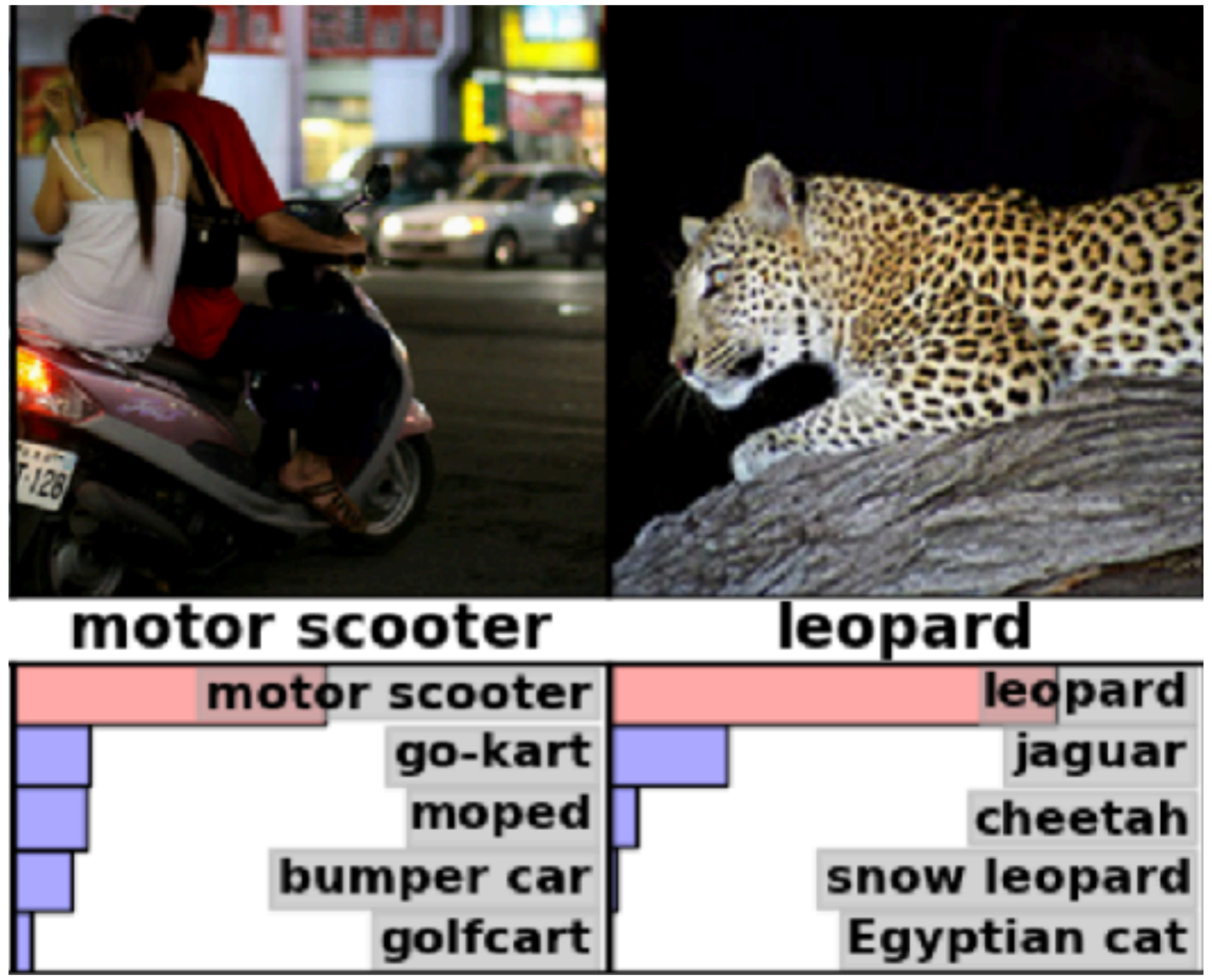
Deep Learning Revolution



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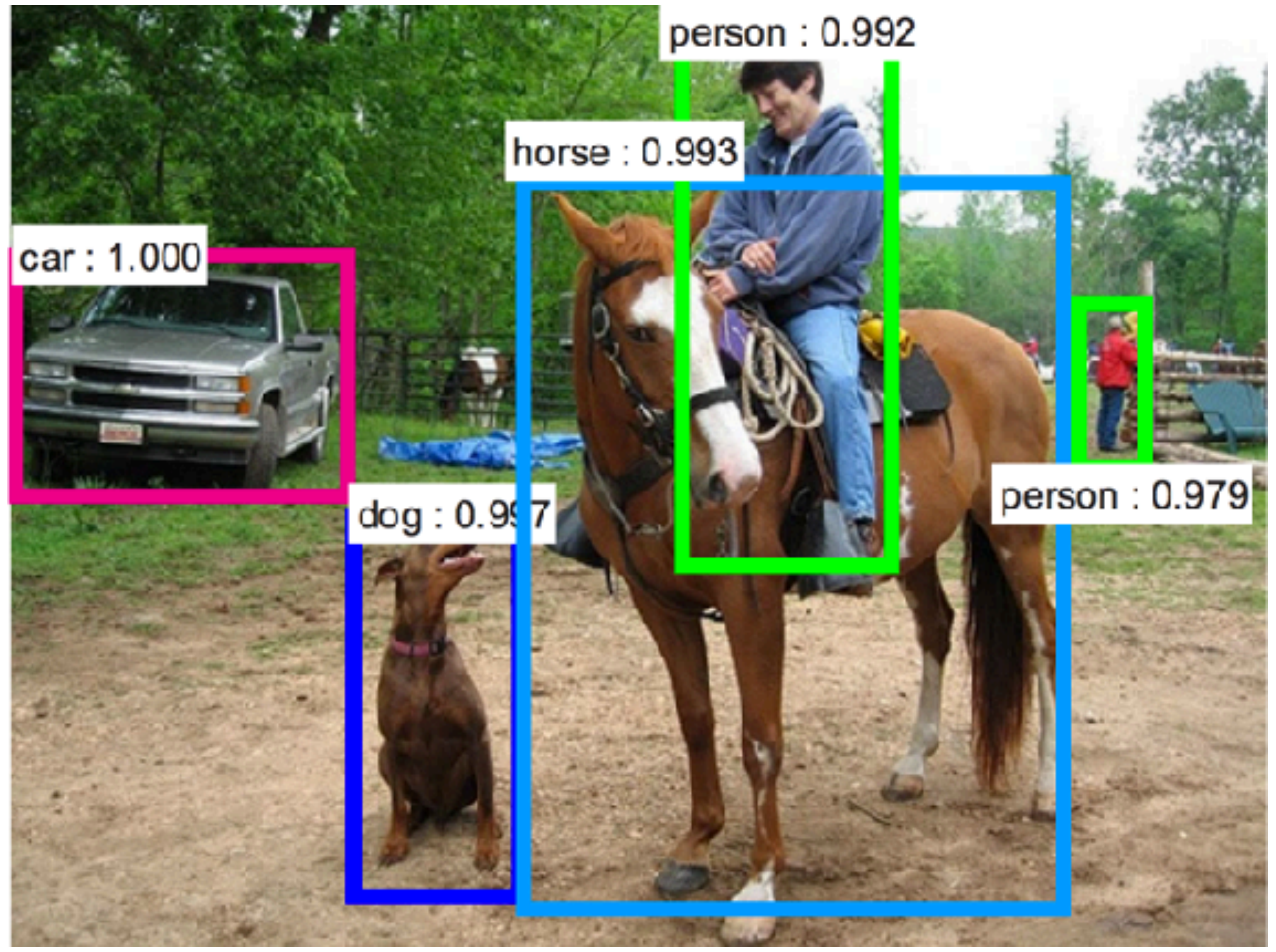

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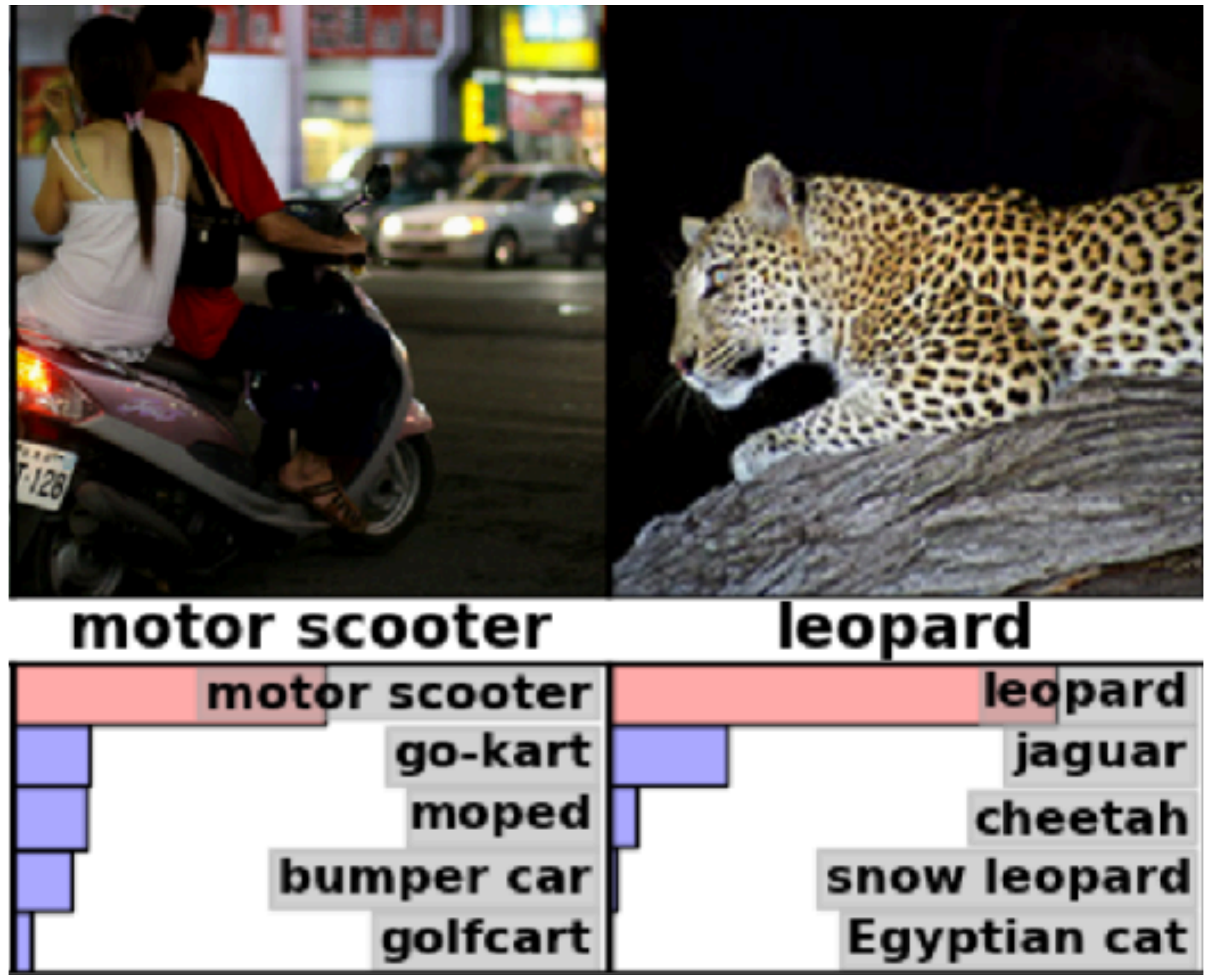

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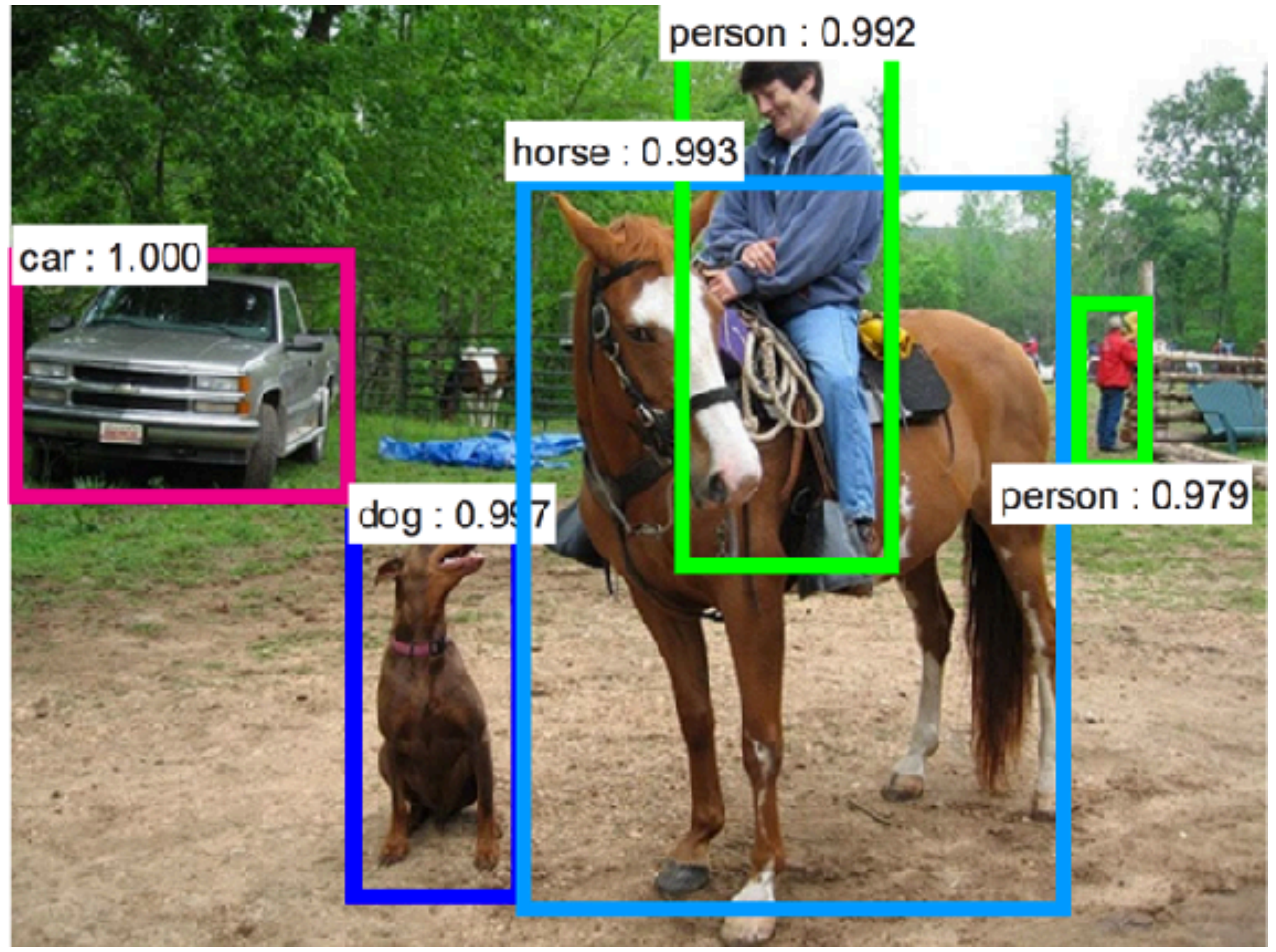

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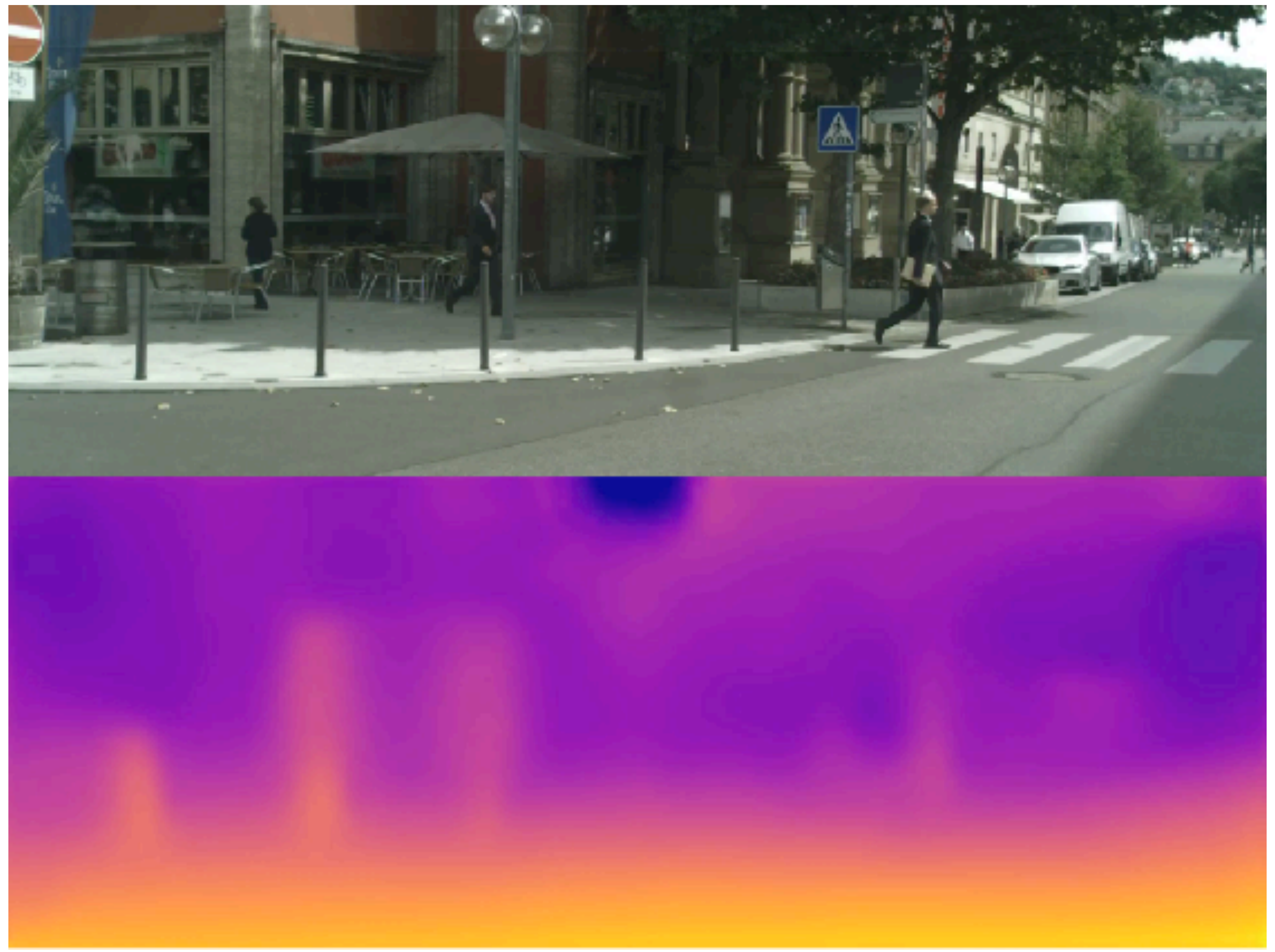


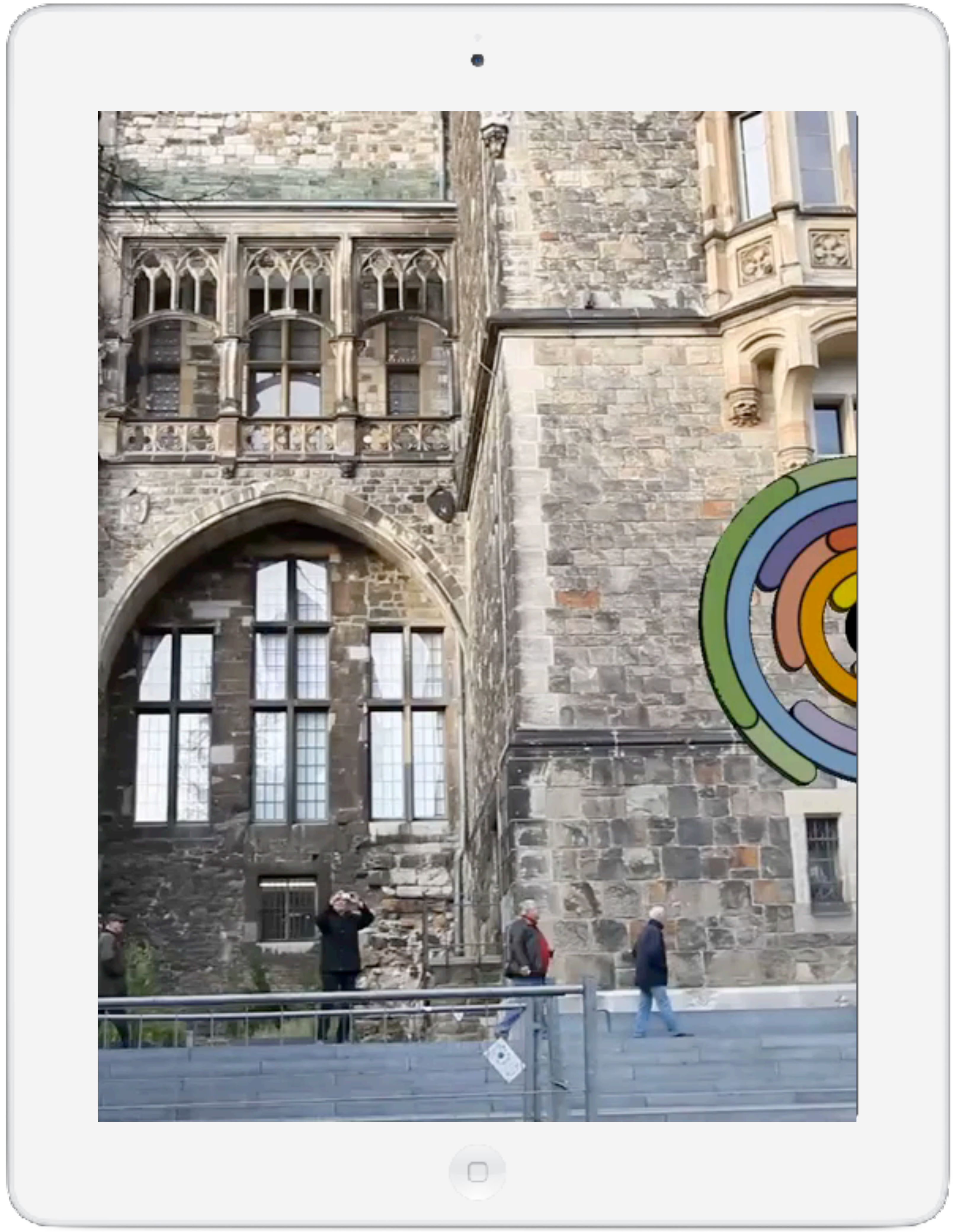
[Zhou et al., Unsupervised Learning of Depth and Ego-Motion from Video, CVPR 2017]

Overview

I. **CNNs for Visual Localization**

II. CNNs for Feature Detection & Description

Visual Localization



[Middelberg, **Sattler**, Untzelmann, Kobbelt, Scalable 6-DOF Localization on Mobile Devices. ECCV 2014]

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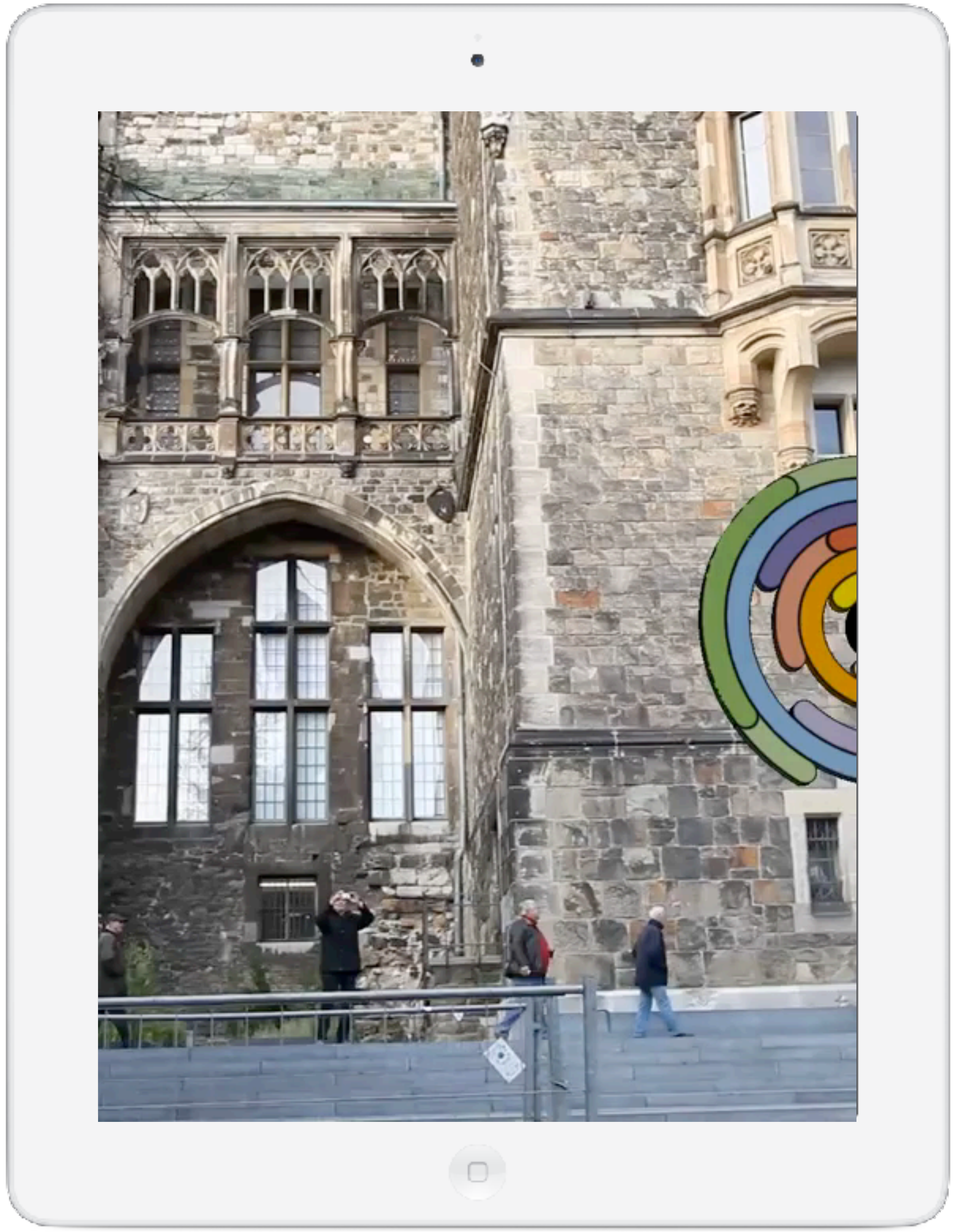

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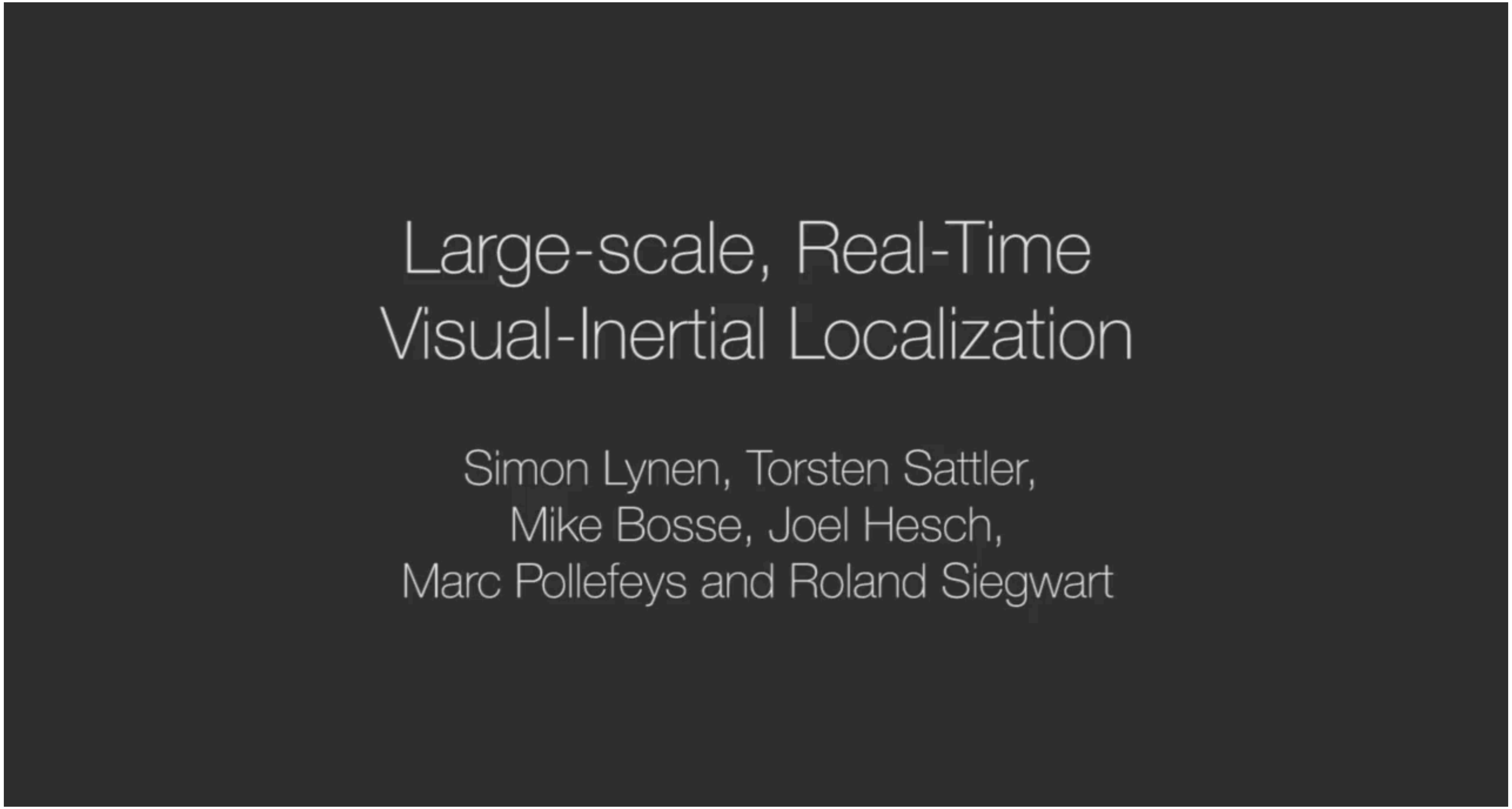

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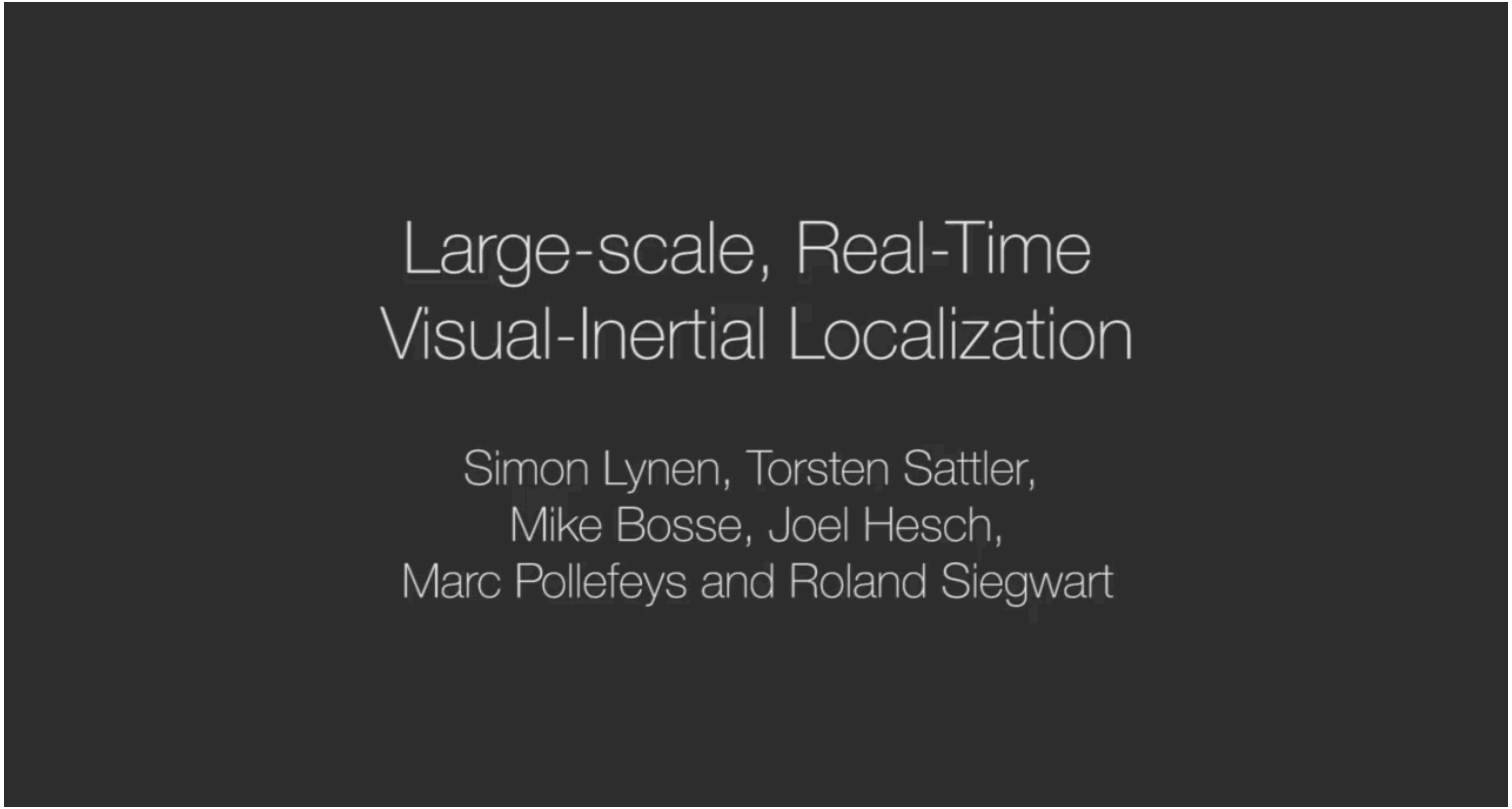

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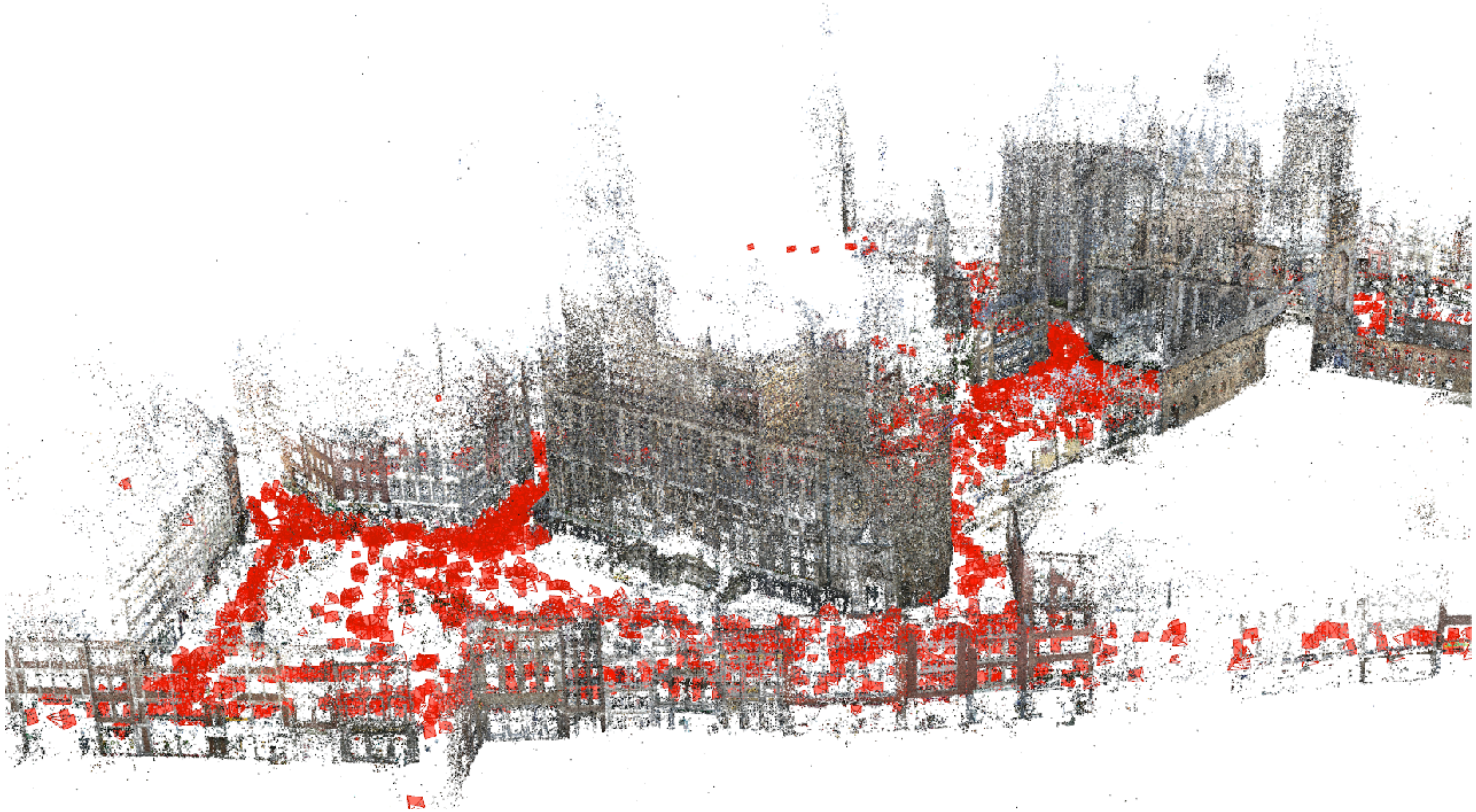
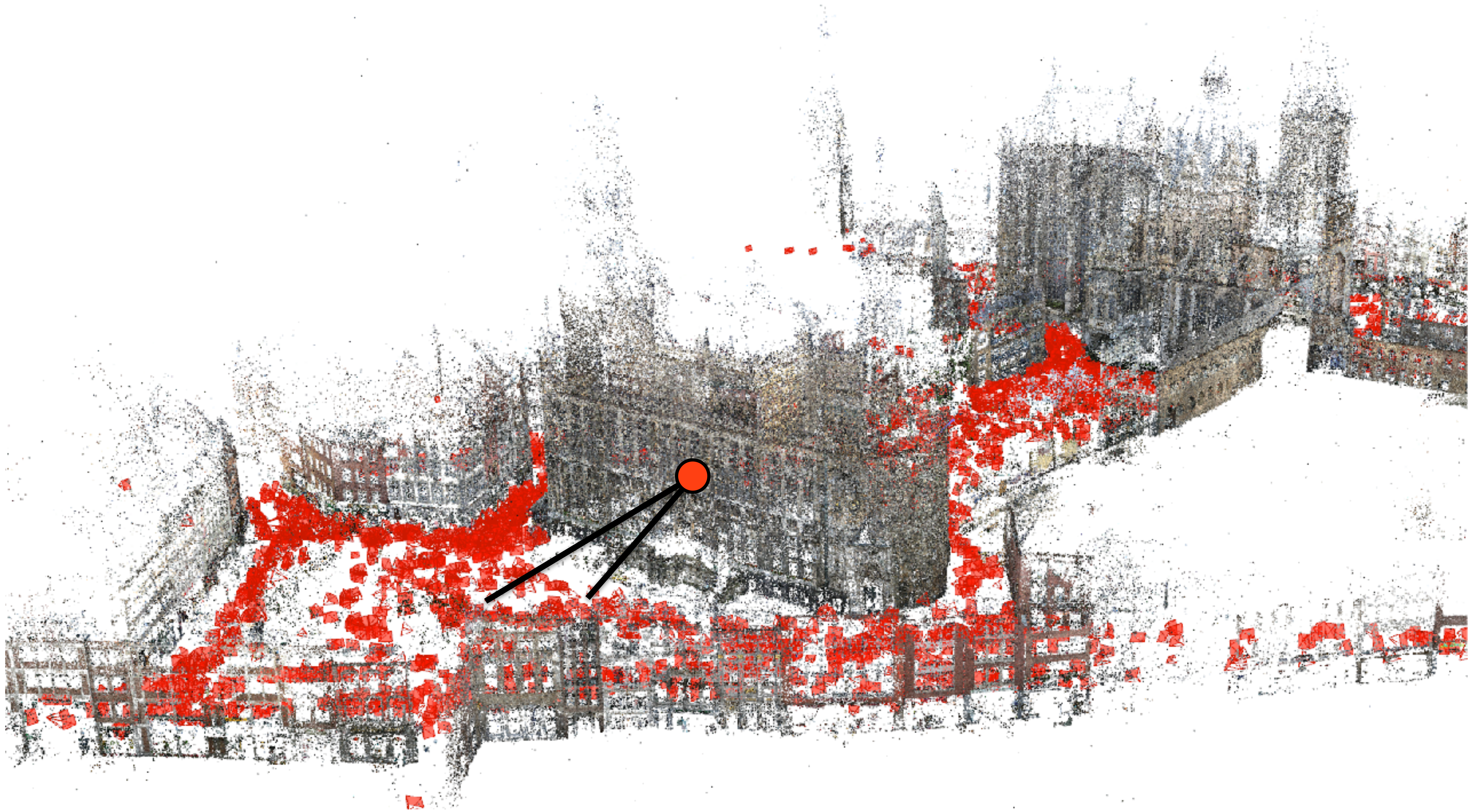
Classic Localization Pipeline



- Offline: Reconstruct scene using Structure-from-Motion

Classic Localization Pipeline



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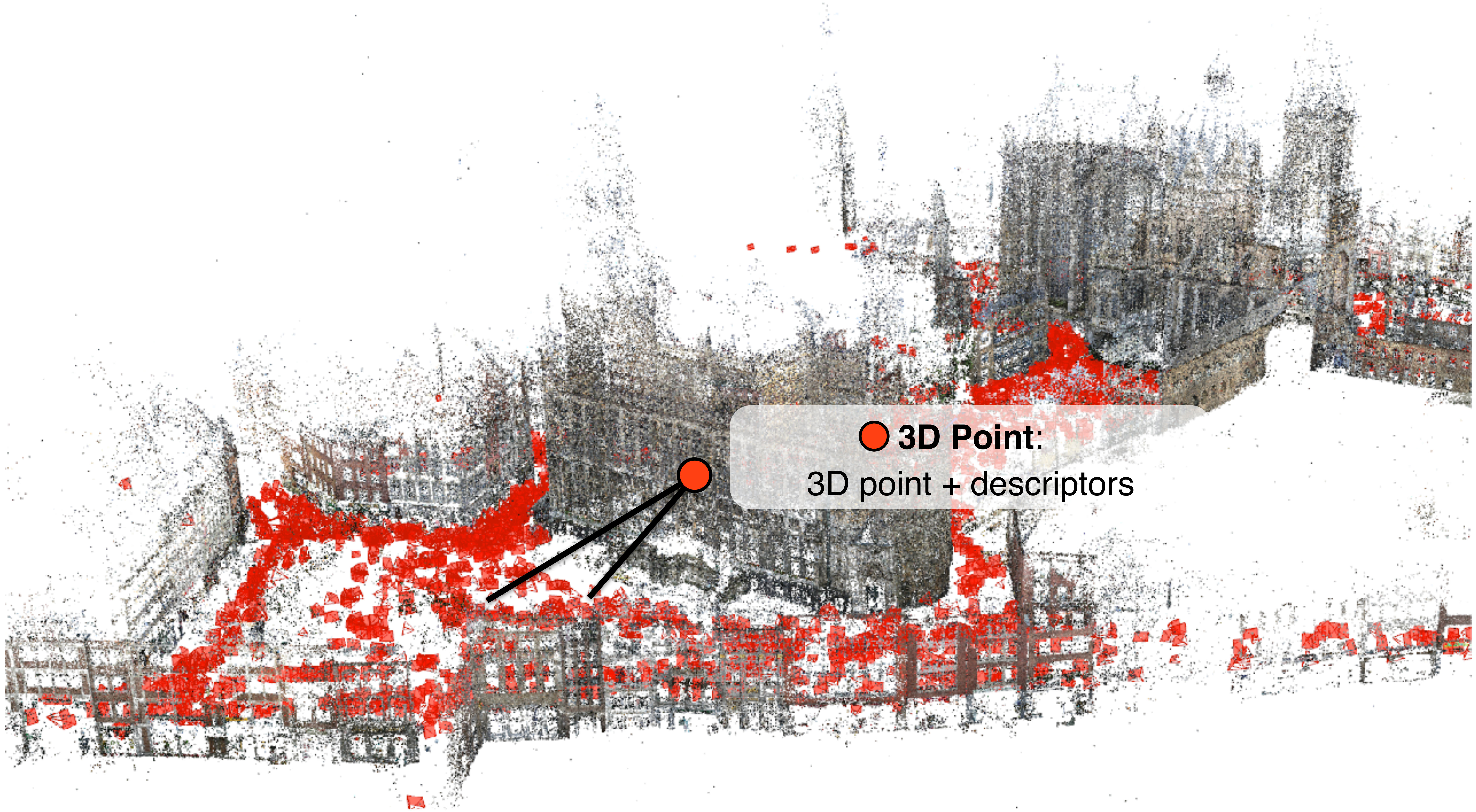
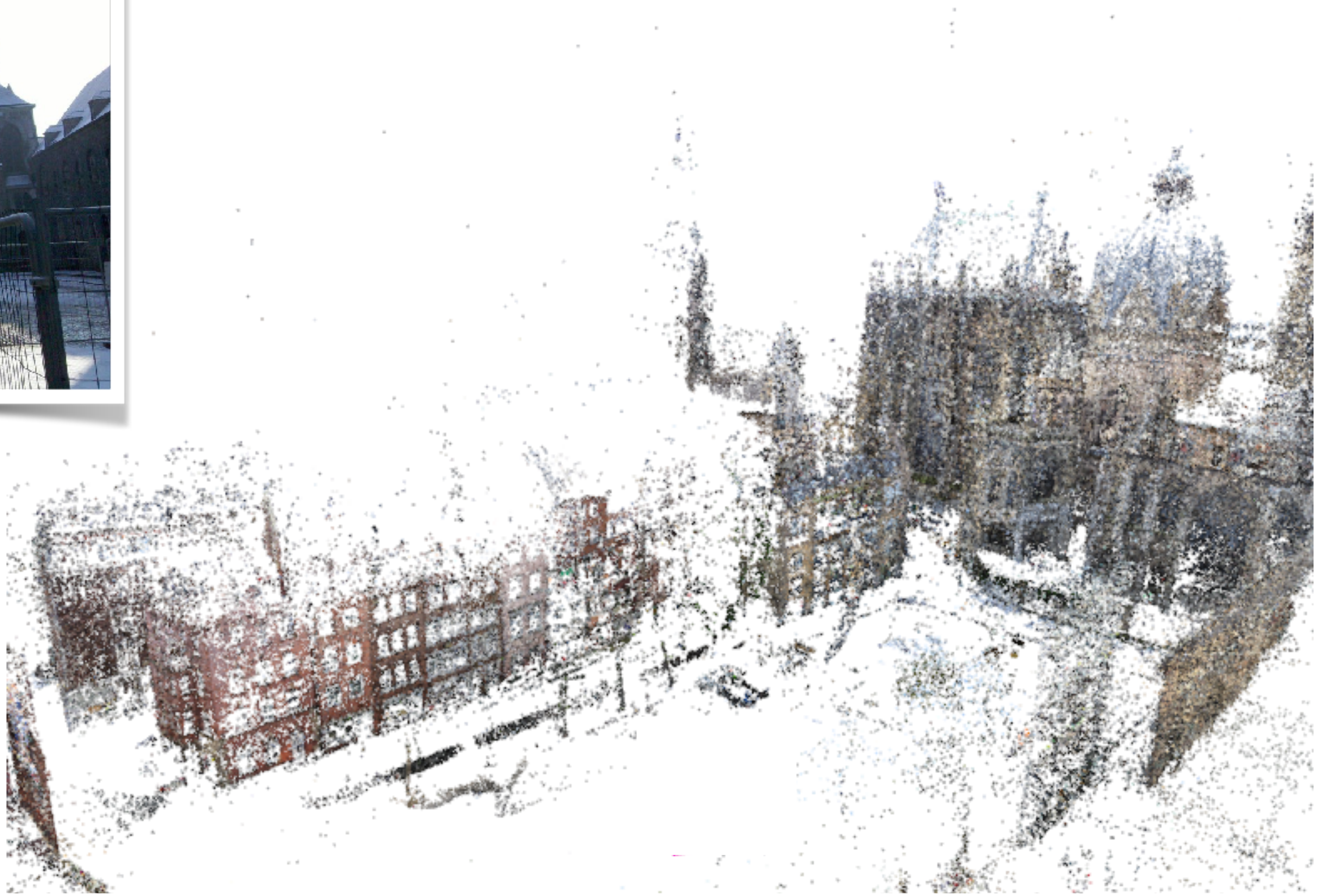


- Offline: Reconstruct scene using Structure-from-Motion
- Associate each 3D point with local image descriptors (SIFT)

Classic Localization Pipeline



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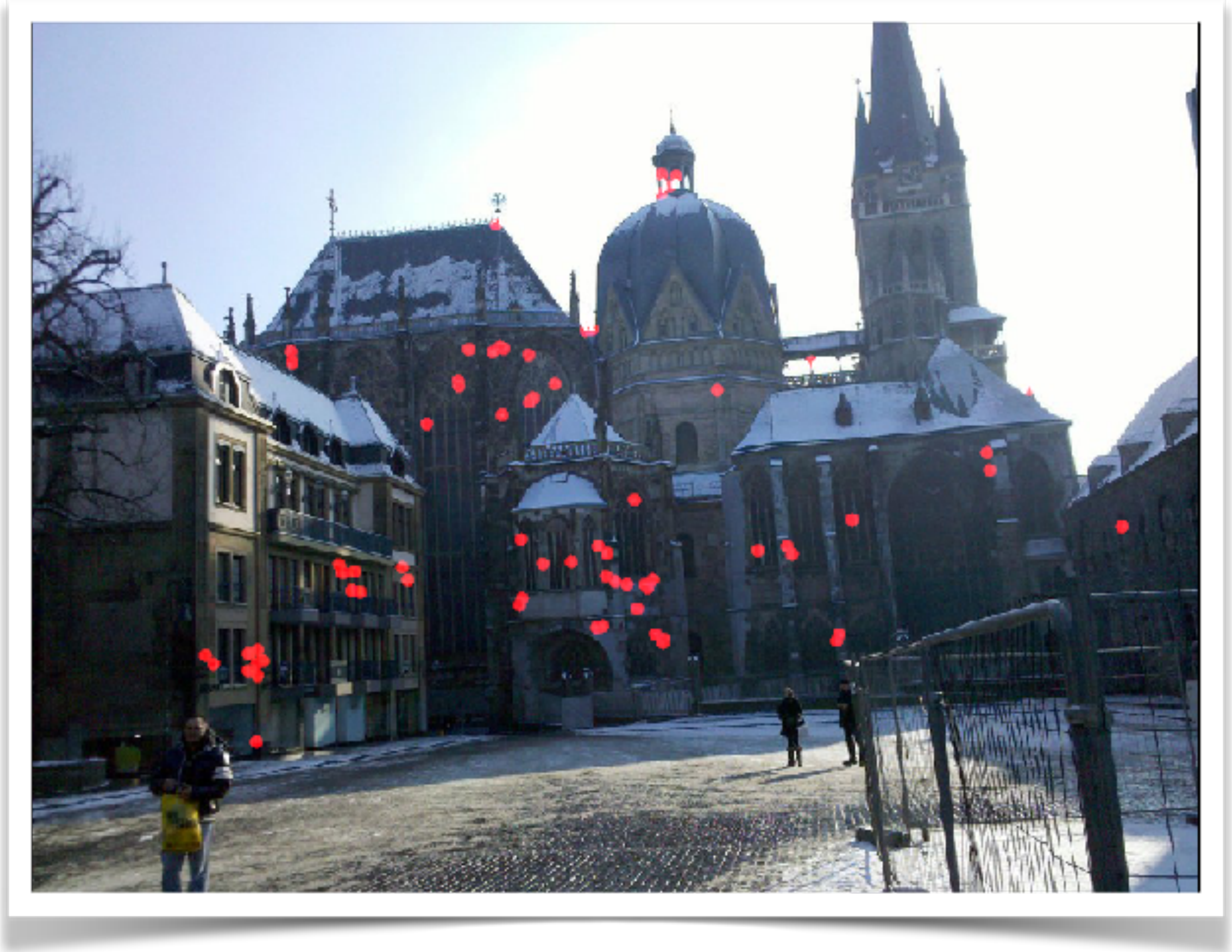
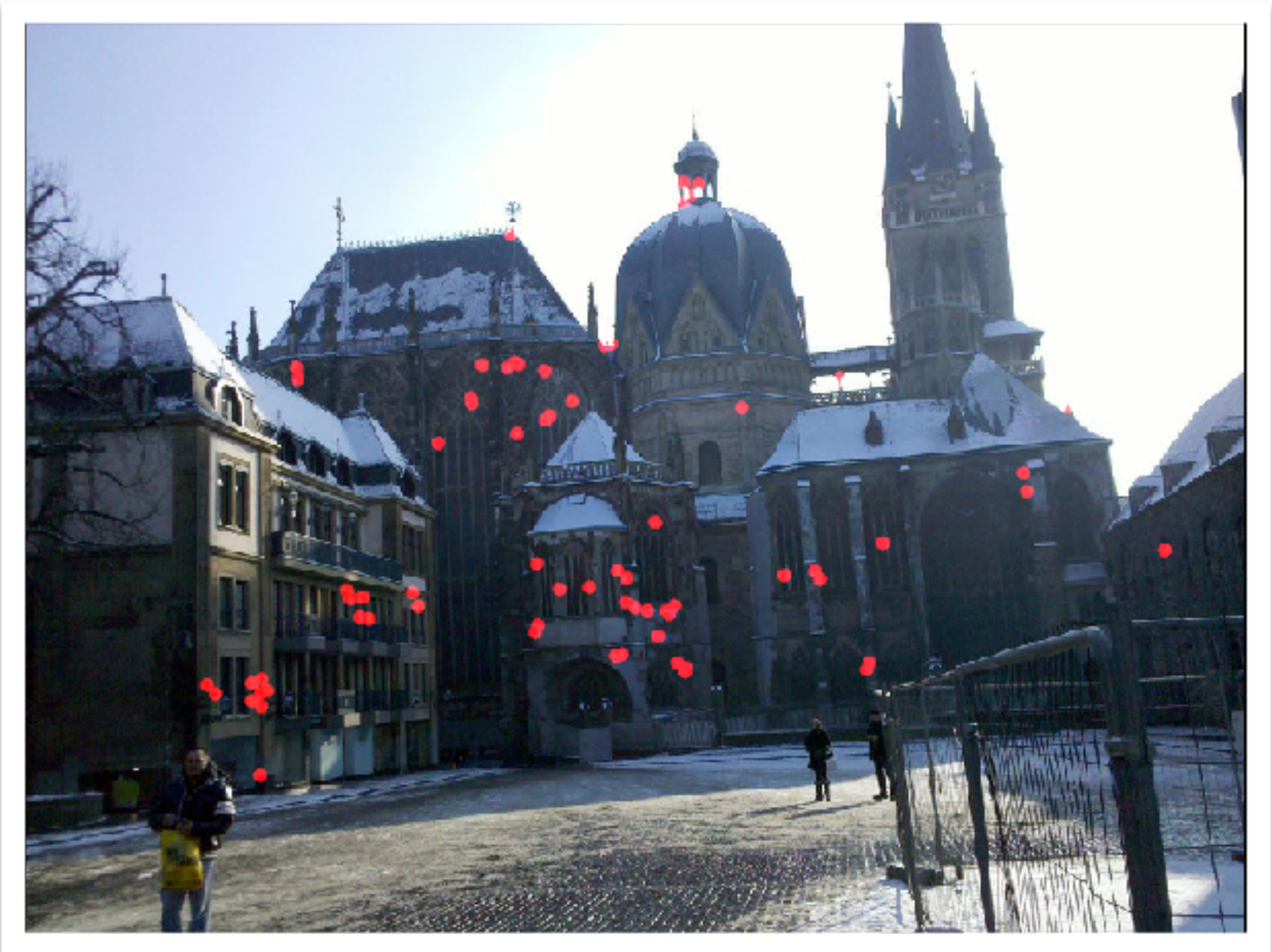


Extract Local Features

Classic Localization Pipeline



Extract Local Features

Establish 2D-3D Matches

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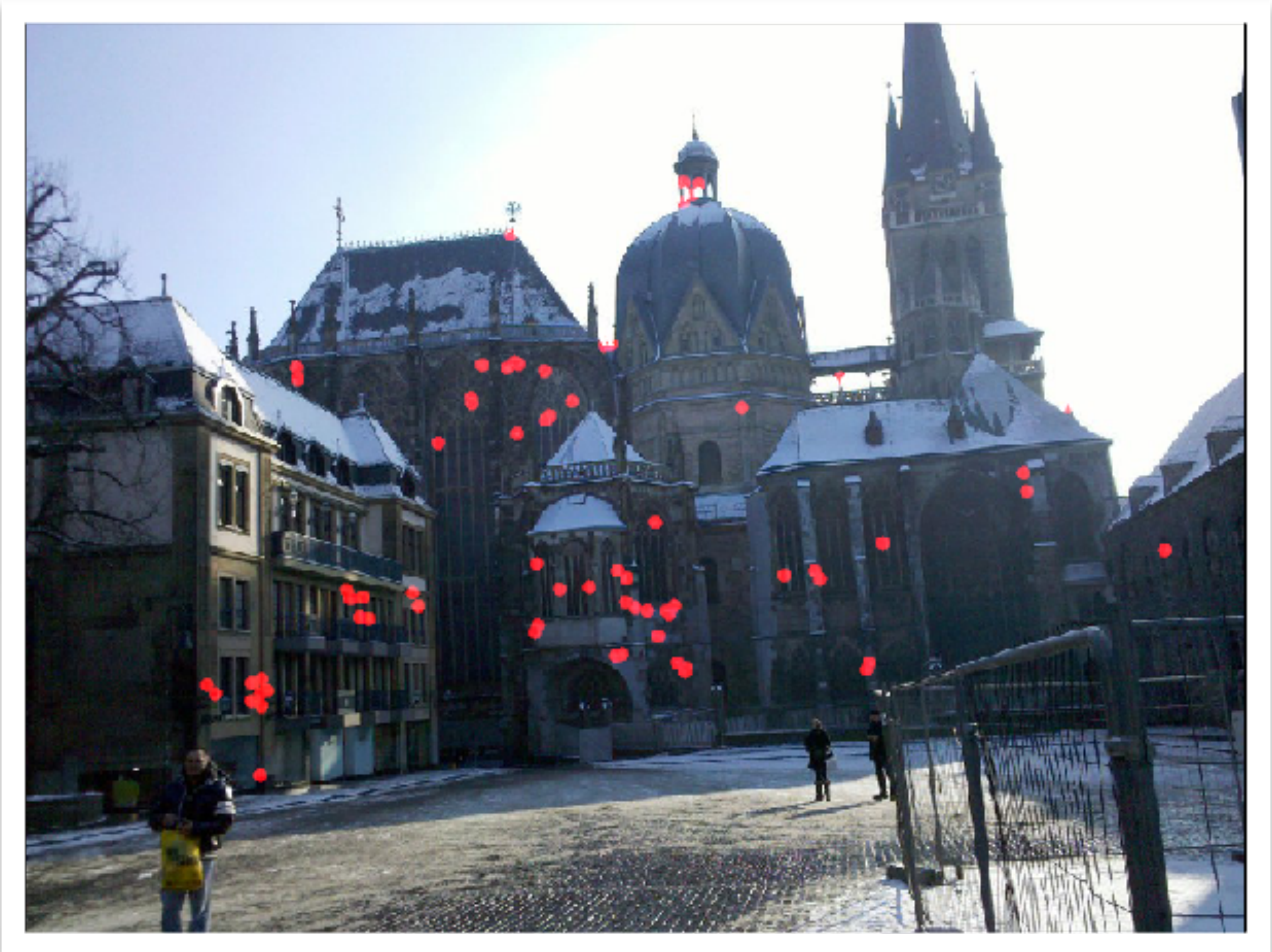

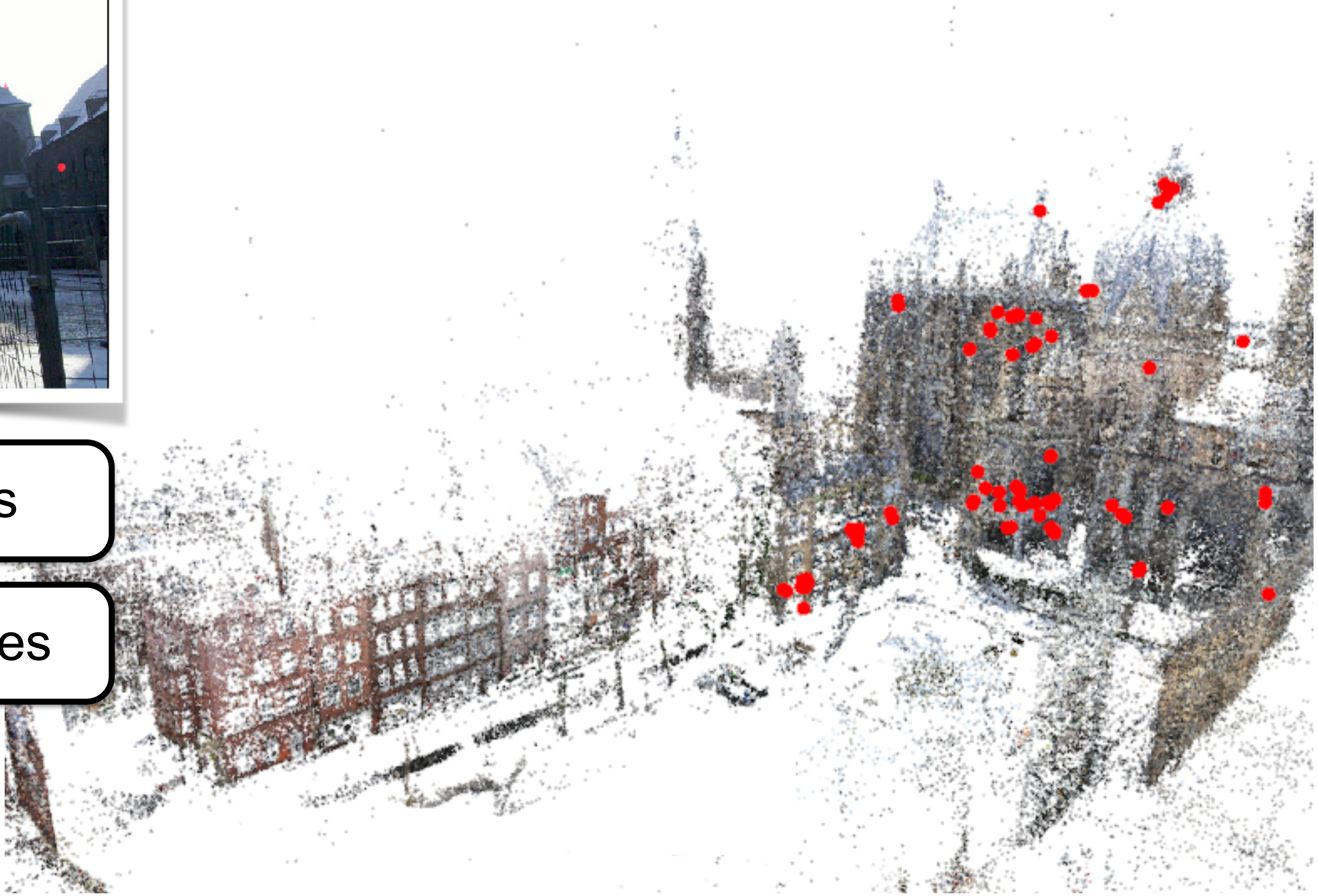

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Classic Localization Pipeline

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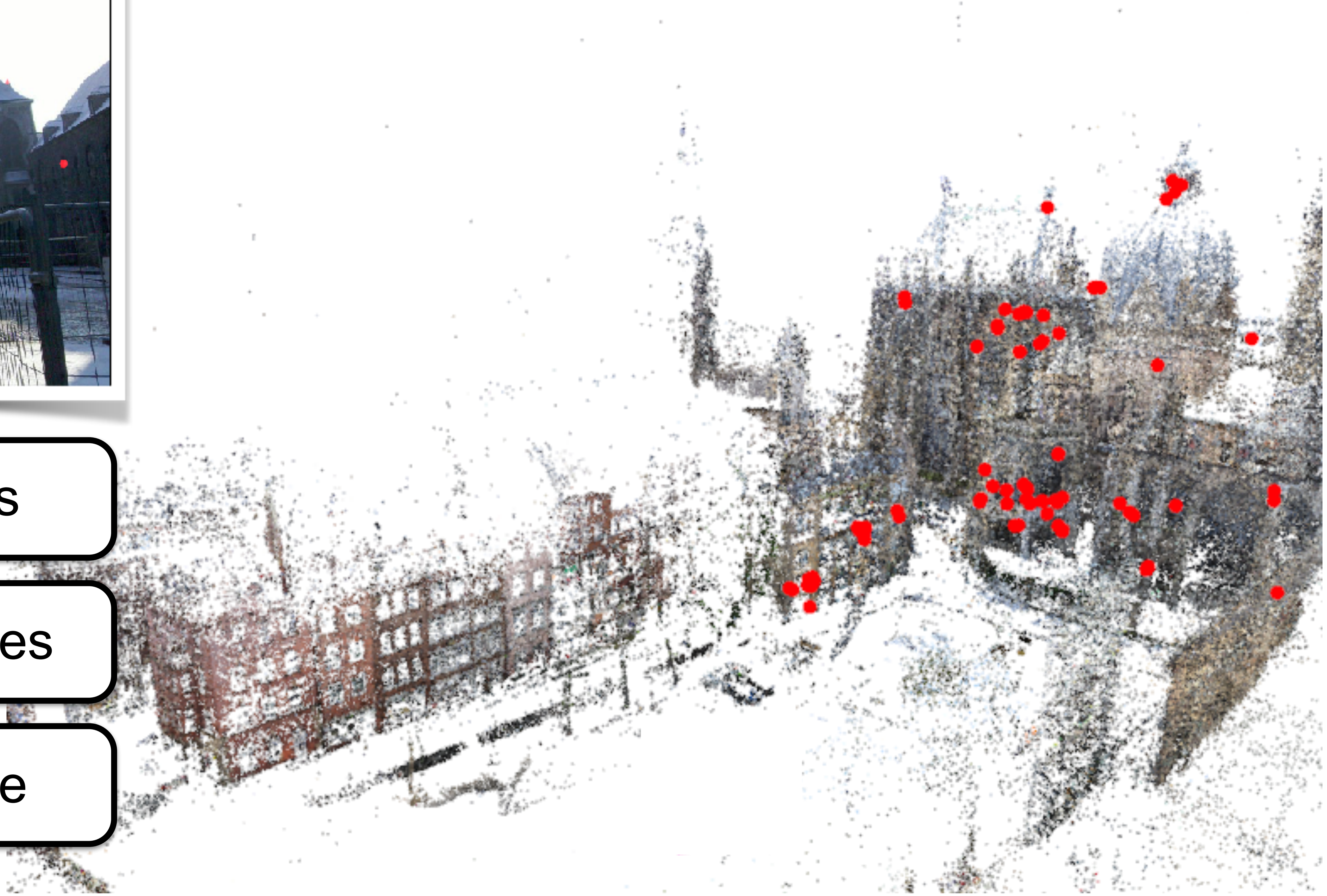
Estimate Camera Pose



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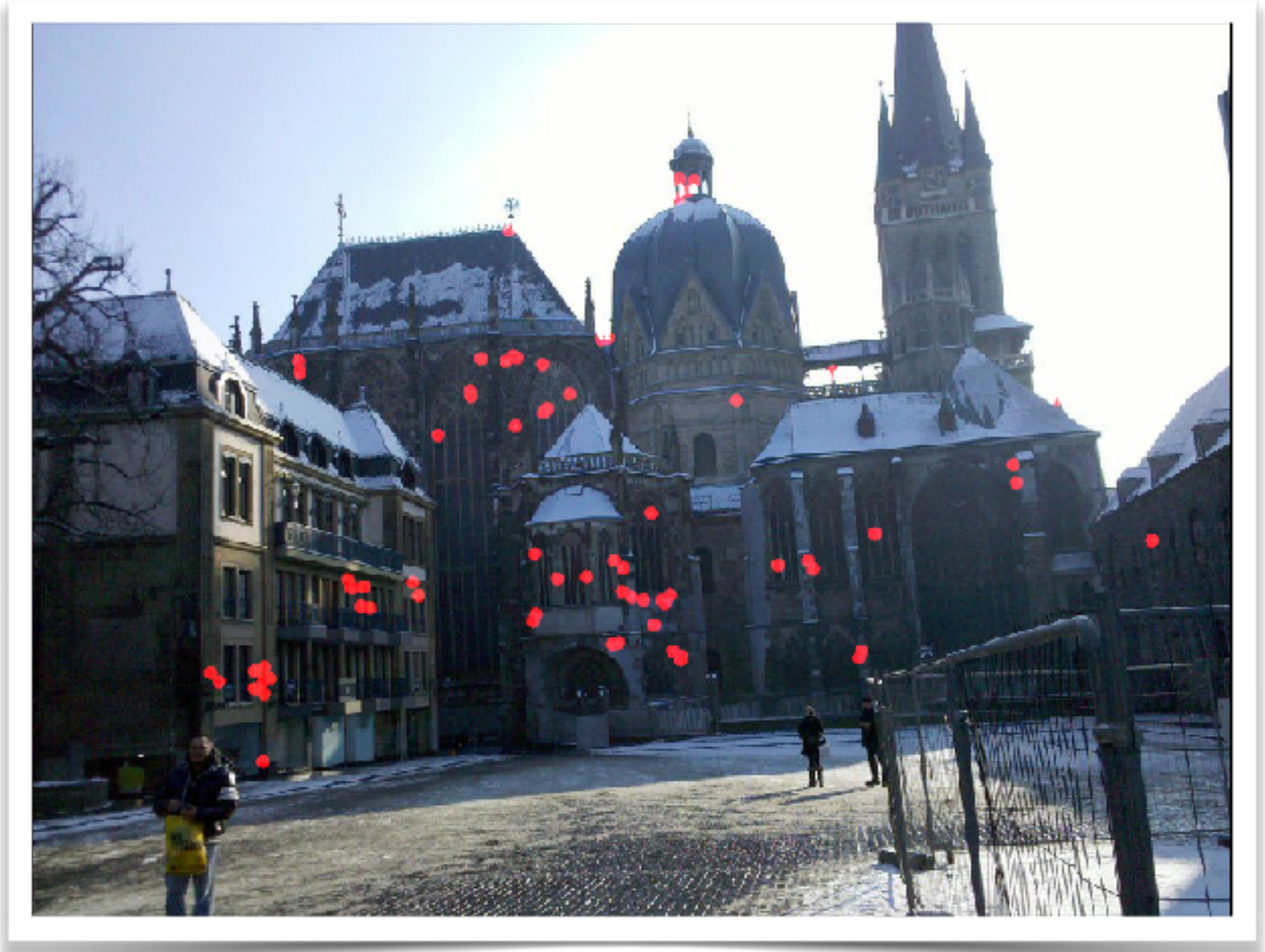

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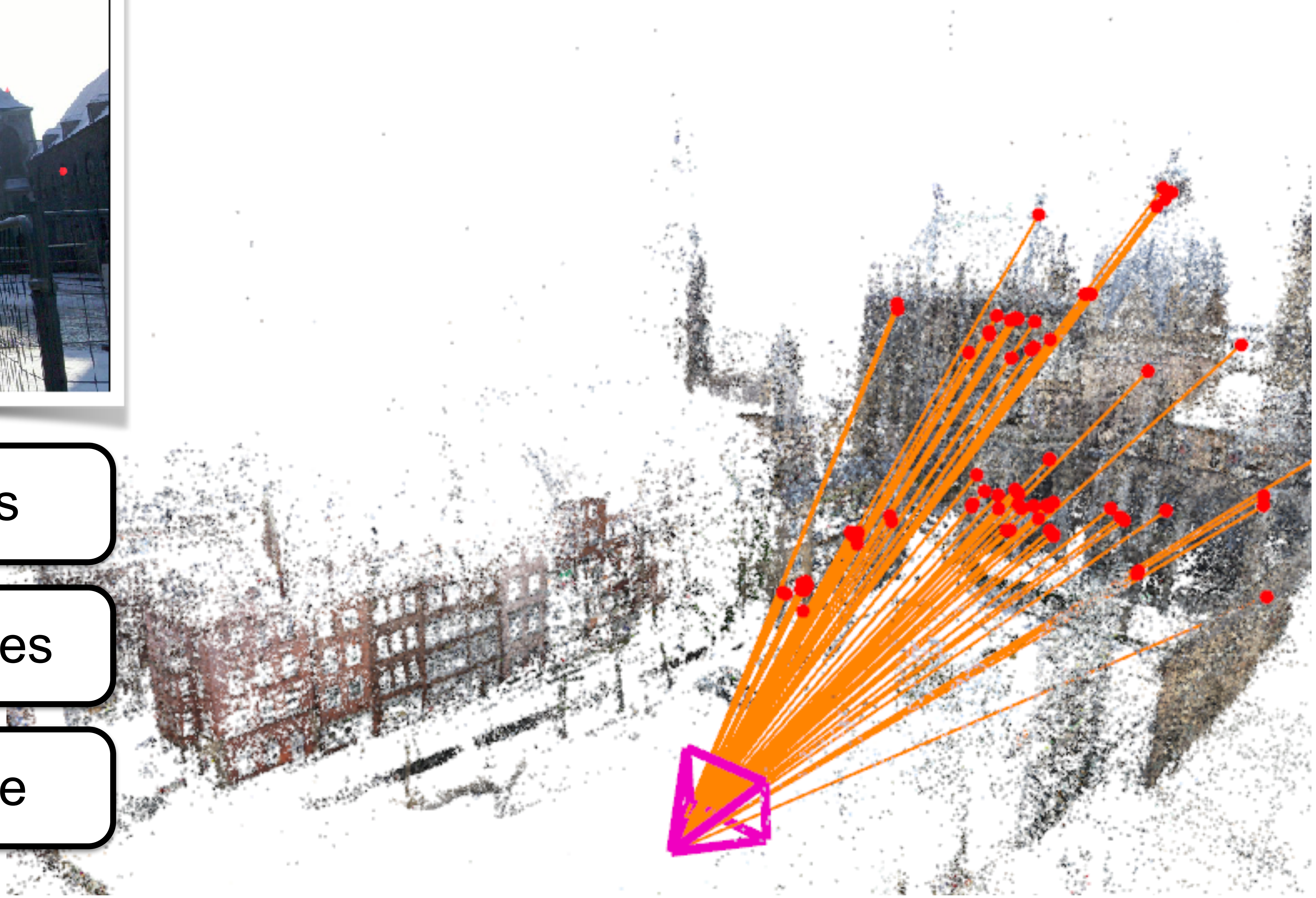

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Ext

Estab

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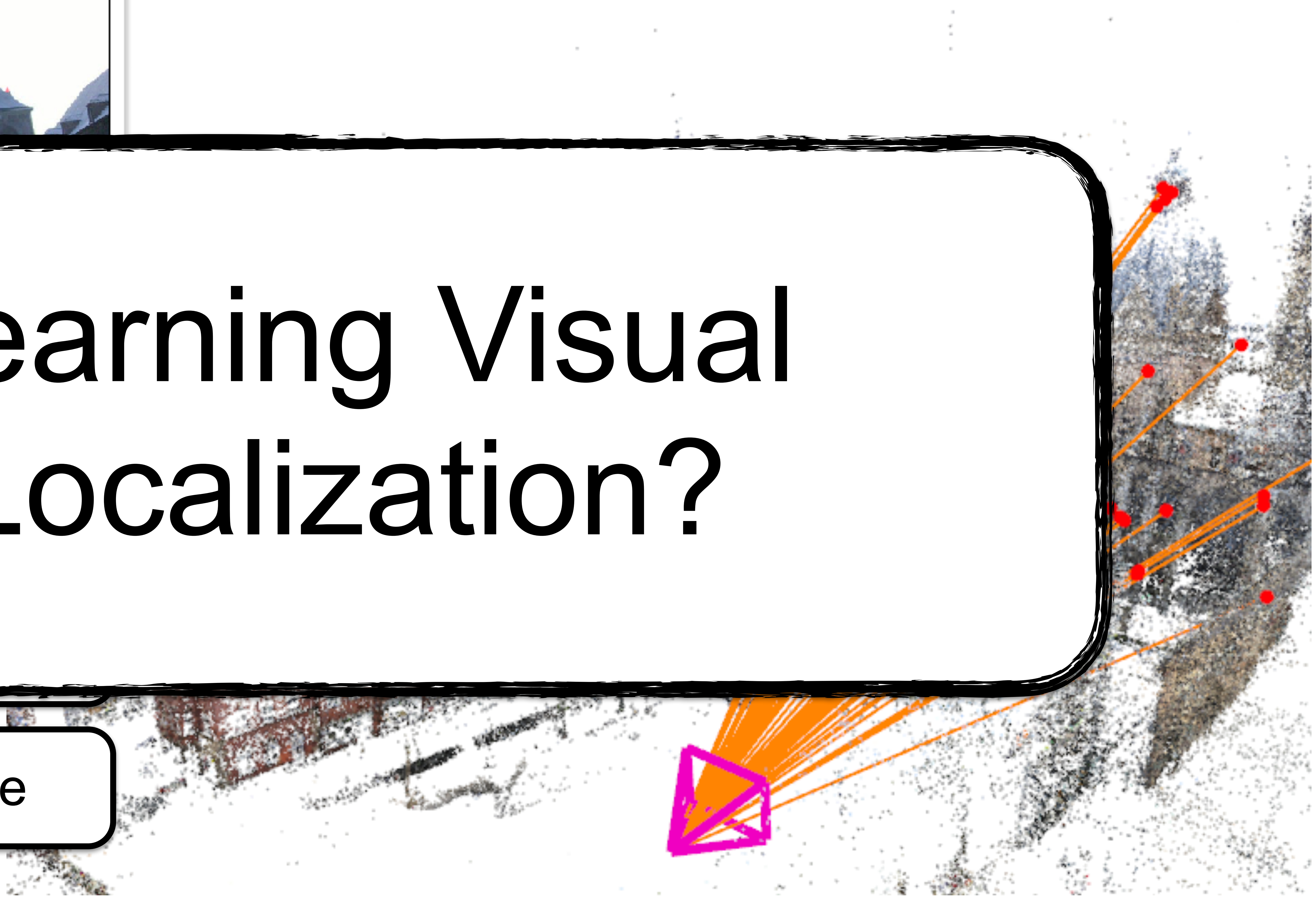
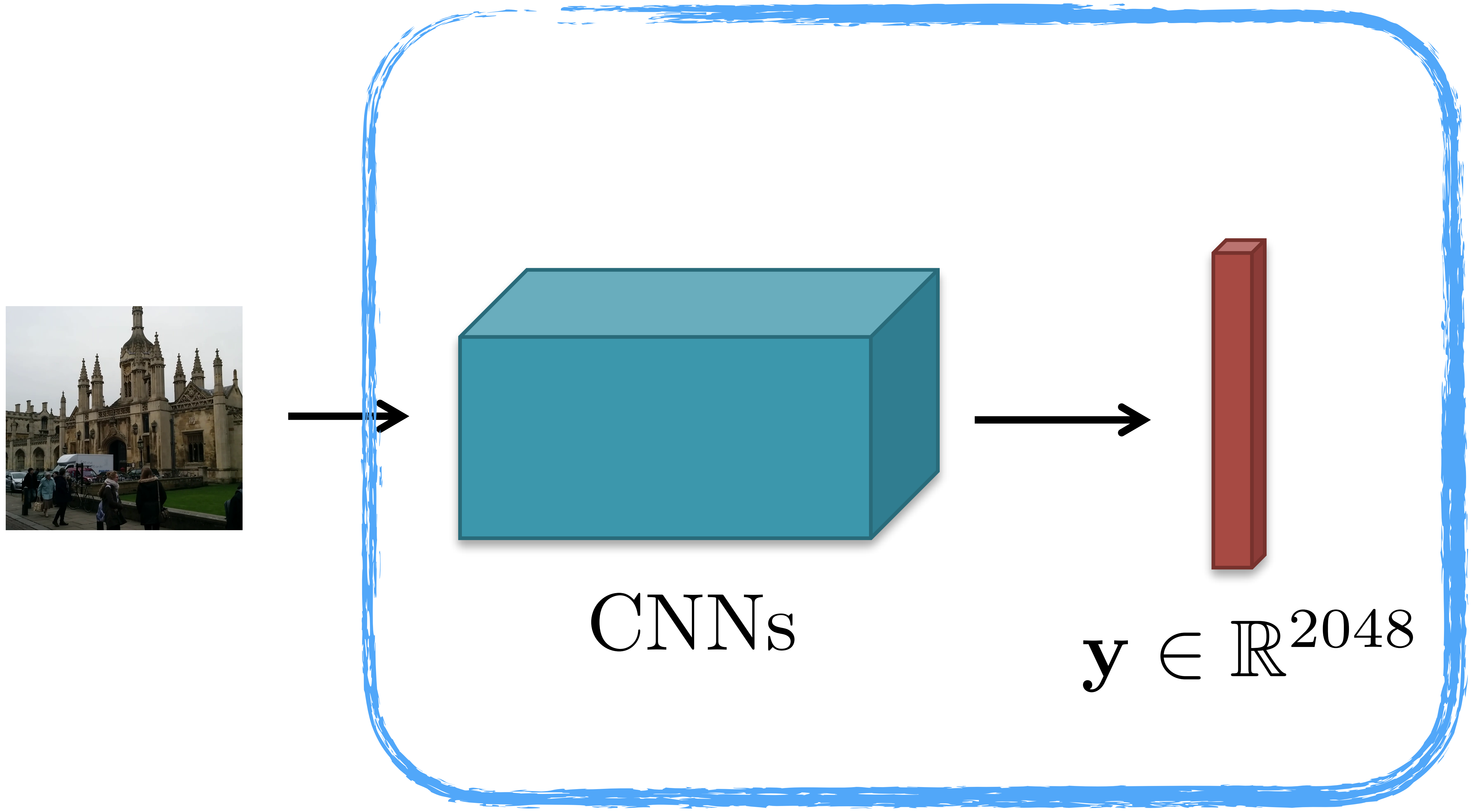


Learning Visual Localization?

CNN-based Localization (PoseNet)



Non-Linear Embedding

[Kendall, Grimes, Cipola, PoseNet: A convolutional network for real-time 6-dof camera relocalization. ICCV 2015]

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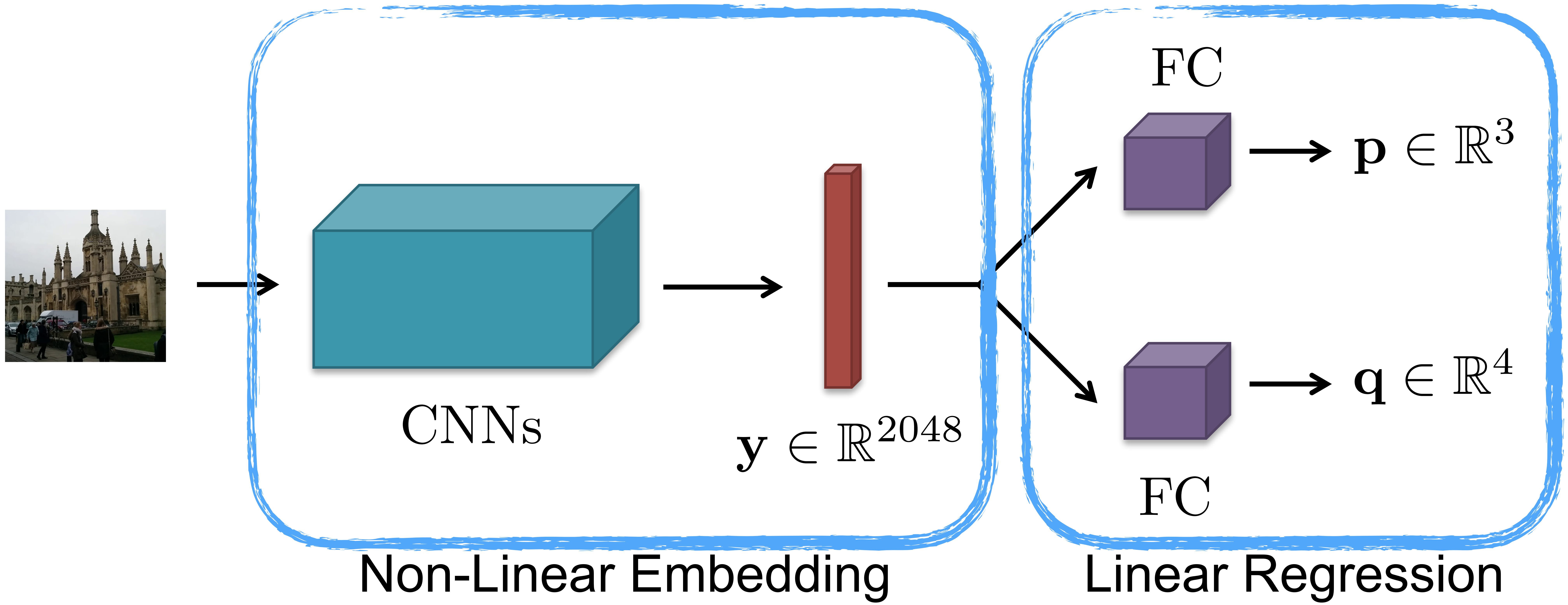

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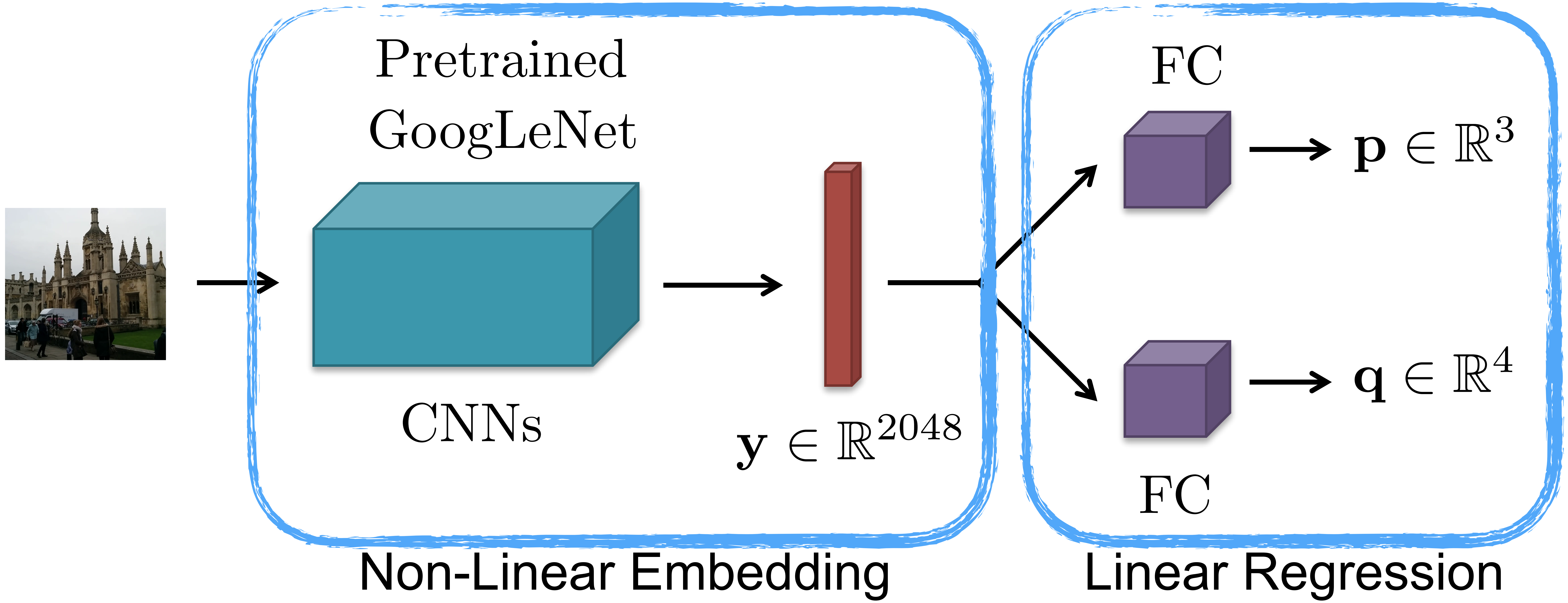

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CNN-based Localization

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Training PoseNet

- Input: Images I_i with known 6DOF camera pose $(\hat{\mathbf{c}}_i, \hat{\mathbf{q}}_i)$

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- Non-geometric loss function:

$$L_i = \|\mathbf{c}_i - \hat{\mathbf{c}}_i\|_2 + \beta \cdot \left\| \mathbf{q}_i - \frac{\hat{\mathbf{q}}_i}{\|\hat{\mathbf{q}}_i\|} \right\|_2$$

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- Geometric loss function: Minimize re-projection error of 3D points visible in image

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Deep vs. Classical Localization

Measure: Median position [m] / orientation [deg] error

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Deep vs. Classical Localization

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original PoseNet	1.92m 5.40°	2.31m 5.38°	1.46m 8.08°	2.65m 8.48°	0.32m 8.12°	0.47m 14.4°	0.29m 12.0°	0.48m 7.68°	0.47m 8.42°	0.59m 8.64°	0.47m 13.8°

Cambridge Landmarks (outdoor)

7 Scenes (indoor)

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PoseNet + geometric loss	0.88m 1.04°	3.20m 3.29°	0.88m 3.78°	1.57m 3.32°	0.13m 4.48°	0.27m 11.3°	0.17m 13.0°	0.19m 5.55°	0.26m 4.75°	0.23m 5.35°	0.35m 12.4°

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[Sattler et al., PAMI 2017]	**0.42**m **0.55**°	**0.44**m **1.01**°	**0.12**m **0.40**°	**0.19**m **0.54**°	**0.04**m **1.96**°	**0.03**m **1.53**°	**0.02**m **1.45**°	**0.09**m **3.61**°	**0.08**m **3.20**°	**0.07**m **3.37**°	**0.03**m **2.22**°

Cambridge Landmarks (outdoor) — first four result columns; 7 Scenes (indoor) — last seven result columns

[Walch, Hazirbas, Leal-Taixé, **Sattler**, Hilsenbeck, Cremers, Image-based localization using LSTMs for structured feature correlation. ICCV, 2017]

Deep vs. Classical Localization

Results on Dubrovnik dataset:

	Quantile Errors [m]		
	25%	50%	75%
PoseNet + geometric loss	-	7.9	-

[**Sattler**, Torii, Sivic, Pollefeys, Taira, Okutomi, Pajdla,Are Large-Scale 3D Models Really Necessary for Accurate Visual Localization? CVPR 2017]

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[Sattler et al., PAMI 2017]	0.5	1.3	5.0

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[Sattler et al., PAMI 2017]	0.5	1.3	5.0
[Zeisl et al., ICCV 2015]	0.2	0.6	2.1

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A Hard Example

[Walch, Hazirbas, Leal-Taixé, **Sattler**, Hilsenbeck, Cremers, Image-based localization using LSTMs for structured feature correlation. ICCV, 2017]

A Hard Example

original PoseNet	1.87m, 6.14○
PoseNet + LSTM	**1.31**m, **2.79**○
[Sattler et al., PAMI 2017]	SfM failed

[Walch, Hazirbas, Leal-Taixé, **Sattler**, Hilsenbeck, Cremers, Image-based localization using LSTMs for structured feature correlation. ICCV, 2017]

My Take

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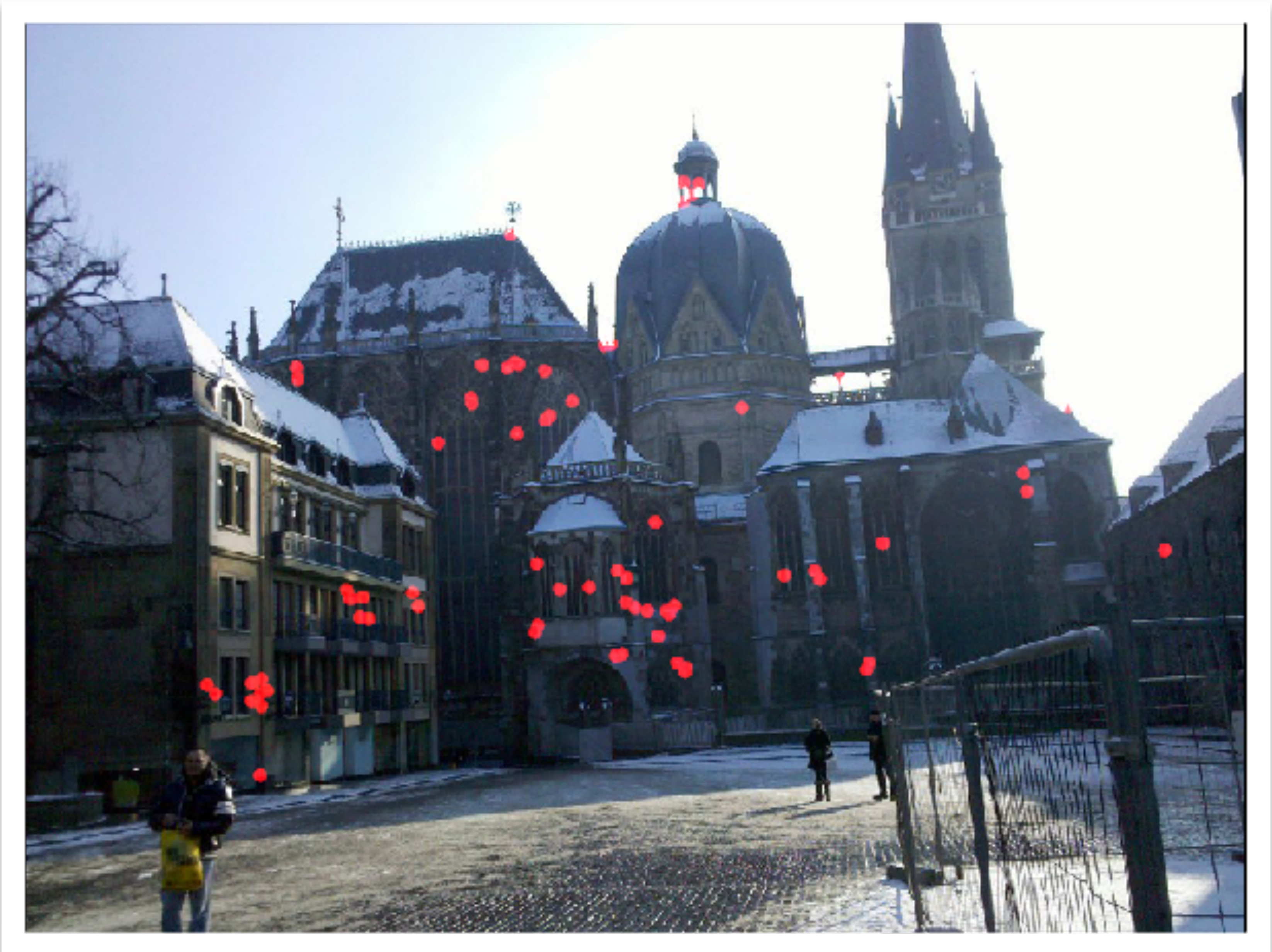
- Promising results for hard scenes in which feature-based approaches fail
- Why learn full pose estimation pipeline?

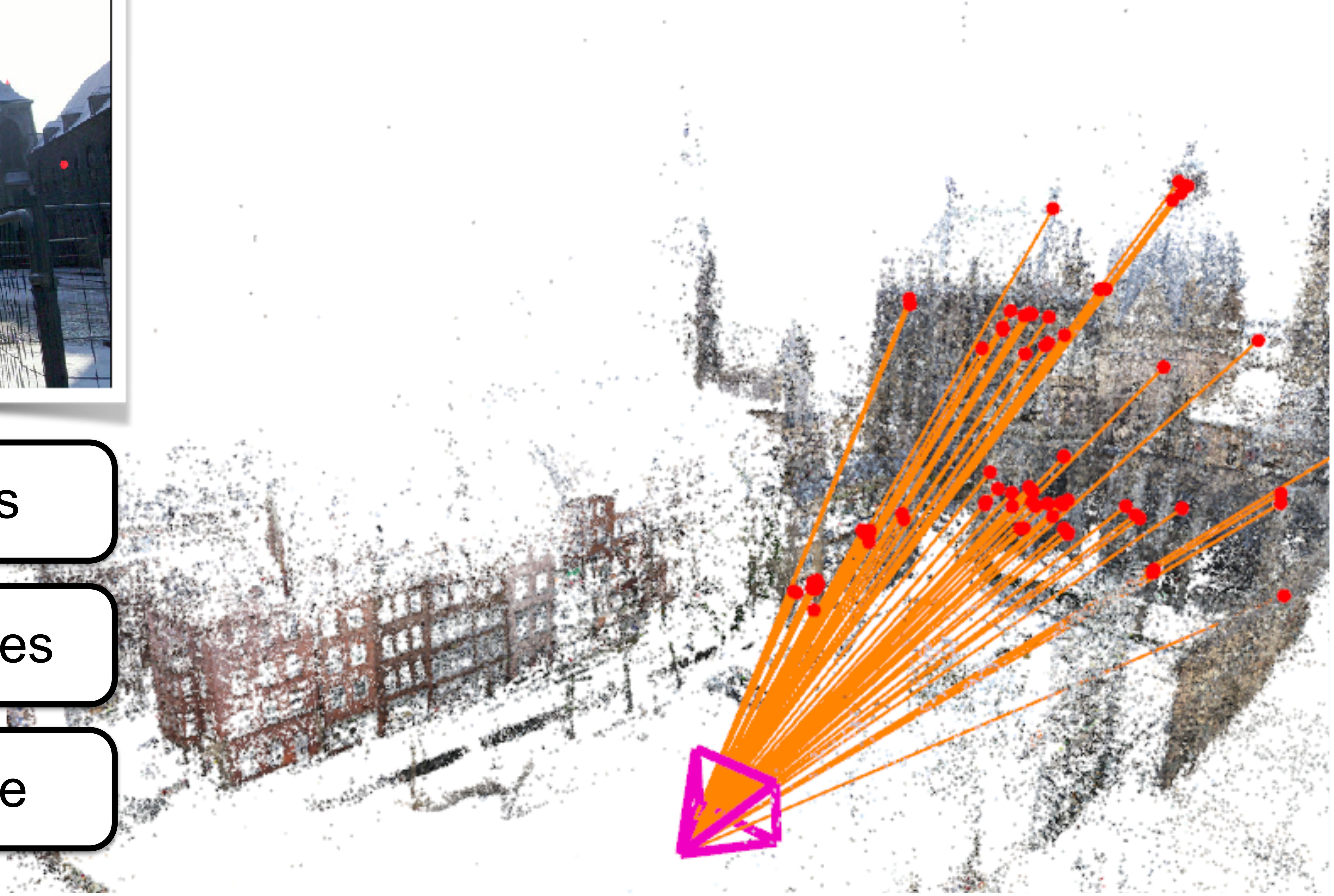
Classic Localization Pipeline



Extract Local Features

Establish 2D-3D Matches

Estimate Camera Pose



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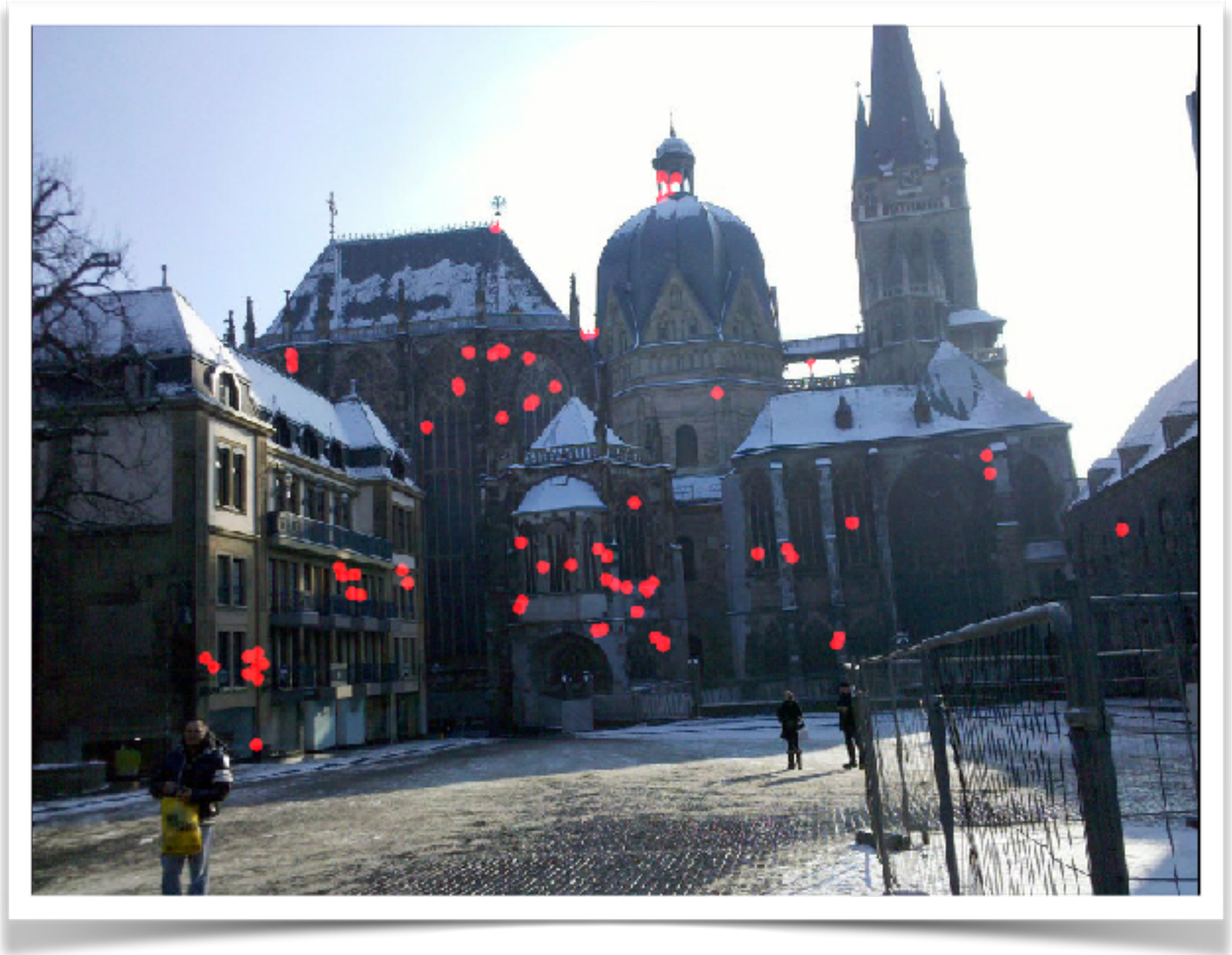

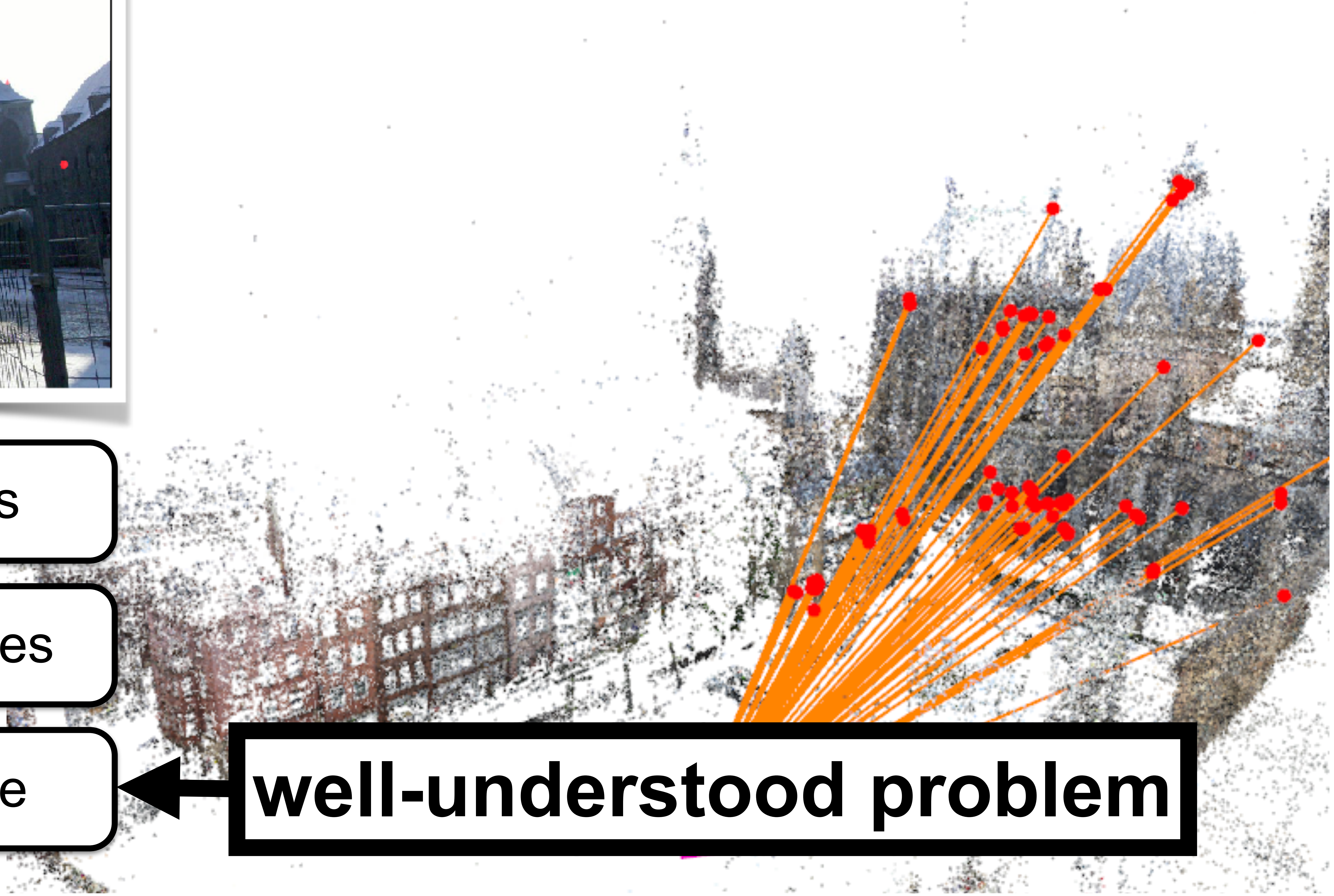

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well-understood problem

Classic Localization Pipeline

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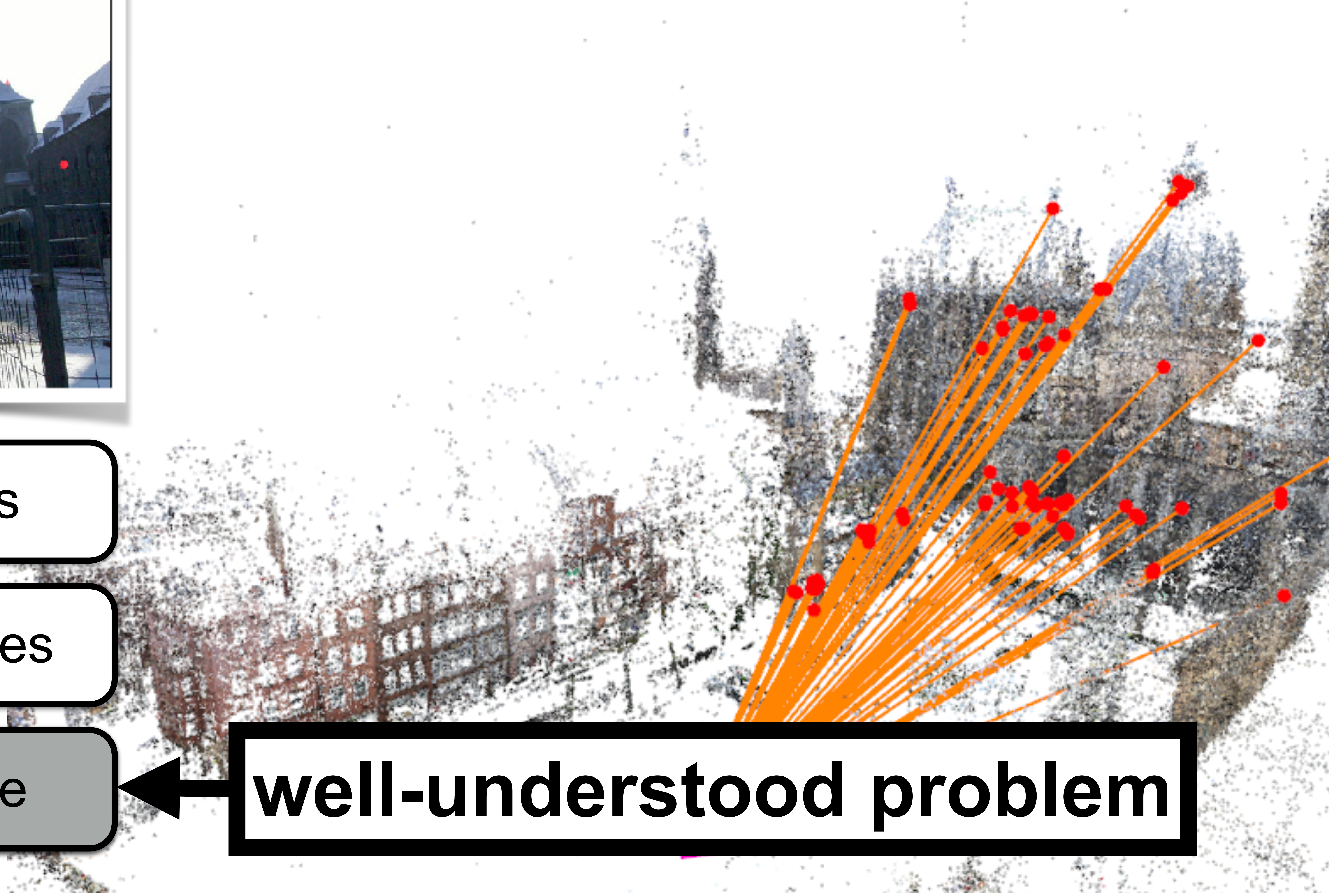

well-understood problem

Classic Localization Pipeline

Extract Local Features

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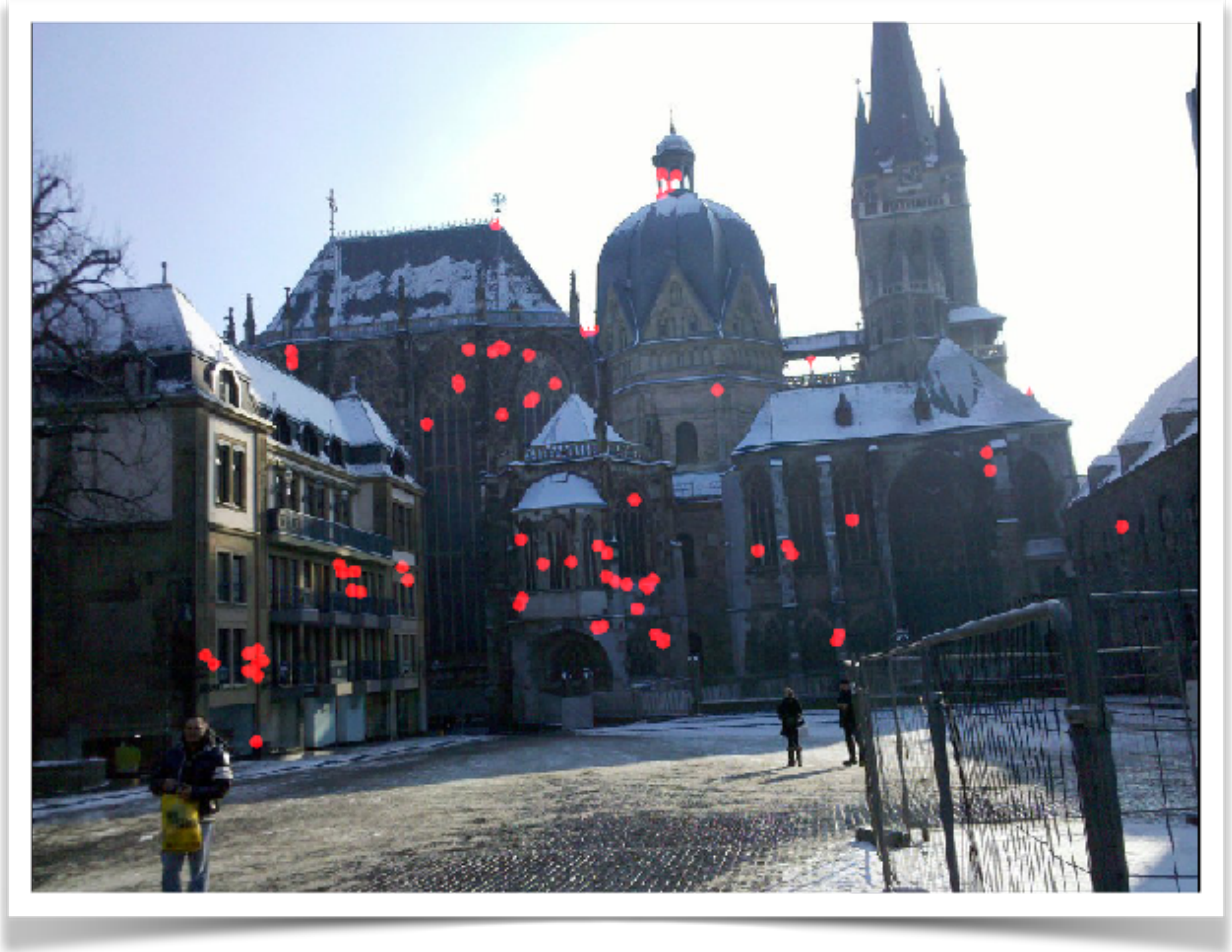

Extract Local Features

Establish 2D-3D Matches ← **nearest neighbor search**

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Overview

I. CNNs for Visual Localization

II. CNNs for Feature Detection & Description

Learning Feature Detectors

- What are properties of a good feature detector?

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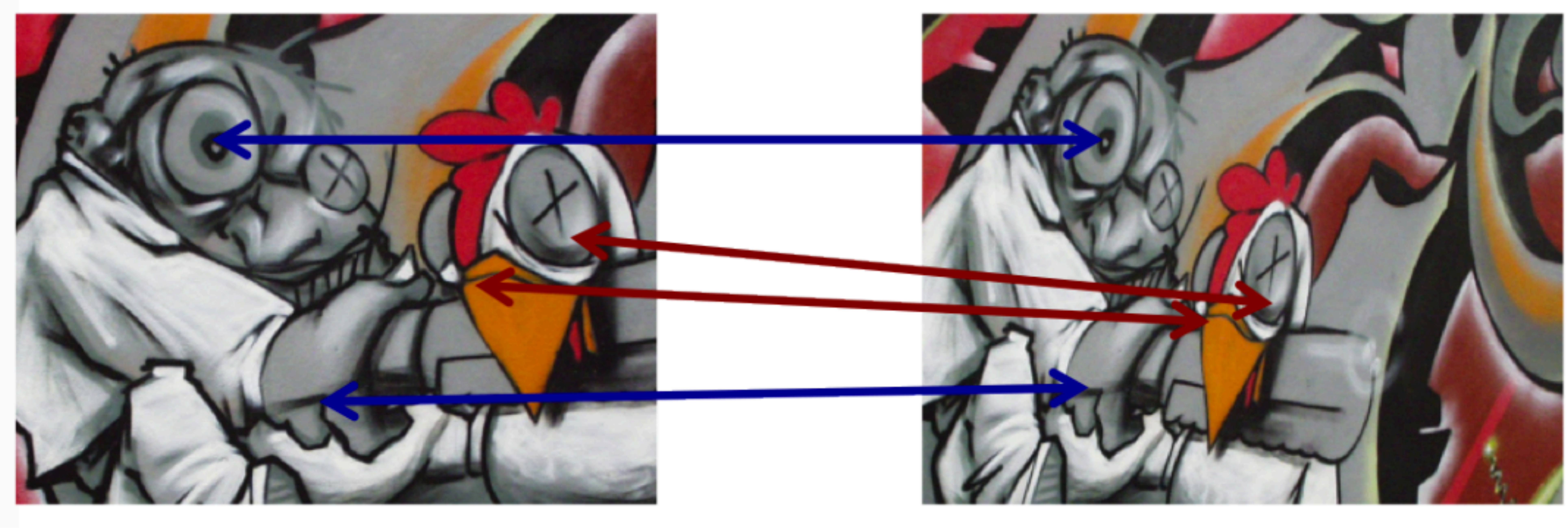
- How to train a detector from scratch without any bias to existing solutions?

Learning Feature Detectors



[Savinov, Seki, Ladicky, **Sattler**, Pollefeys, Quad-networks: unsupervised learning to rank for interest point detection, CVPR 2017]

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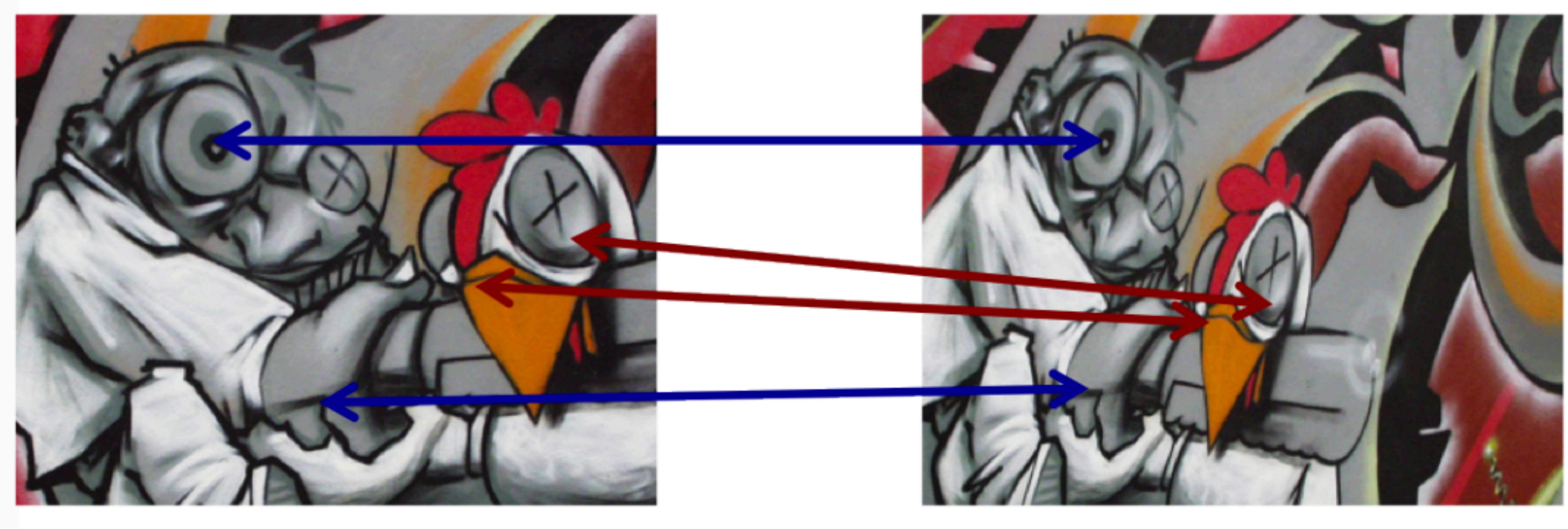

- Learn function $\mathtt{H(x|w)}\colon \mathtt{R}^2 \rightarrow \mathtt{[-1, 1]}$ with parameters $\mathtt{w}$

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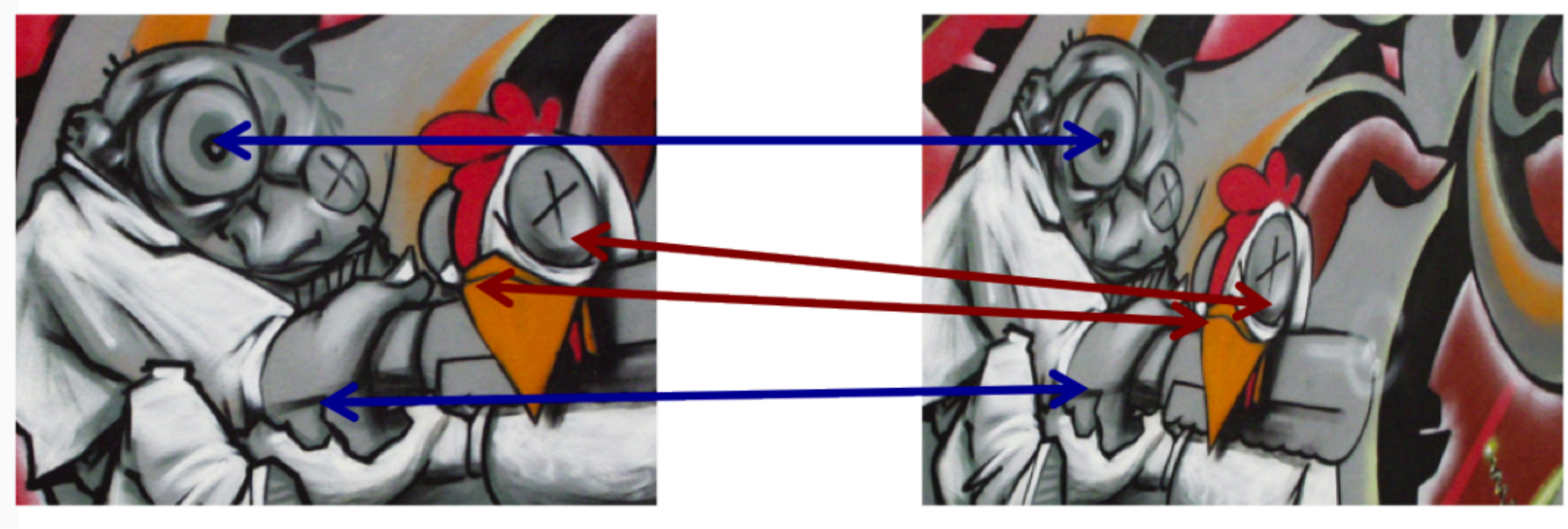

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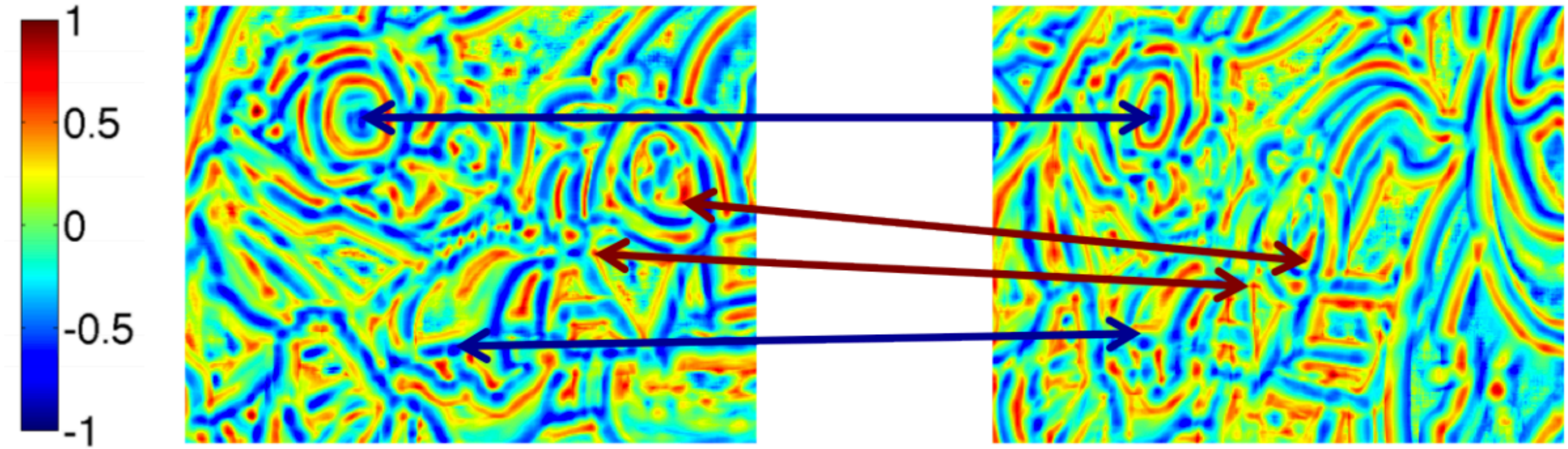

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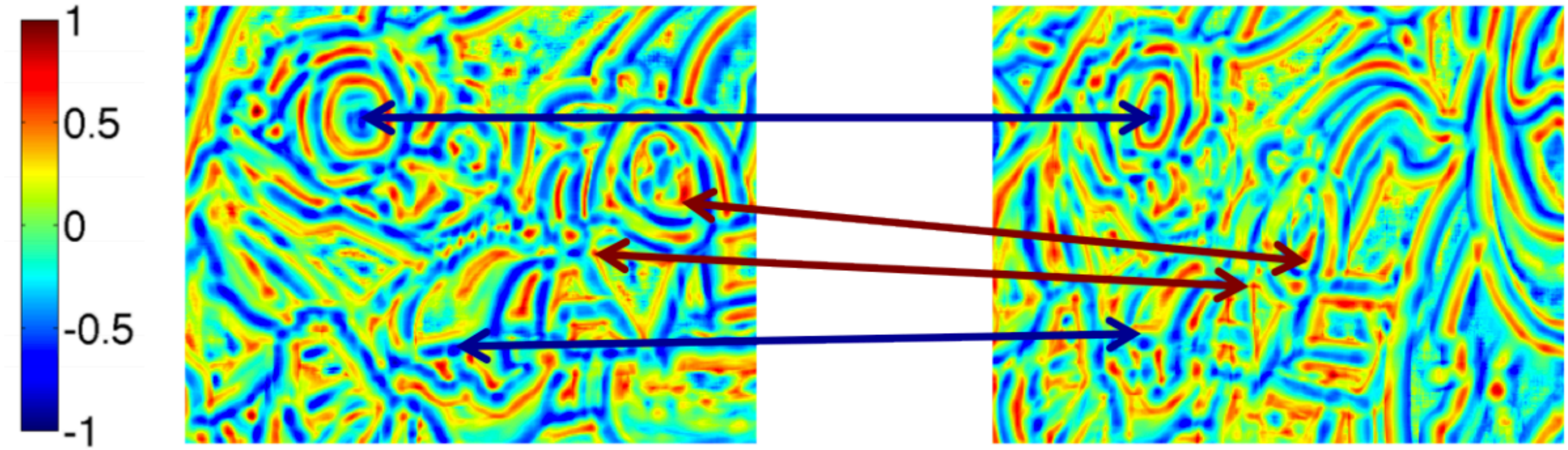

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- Repeatability = consistent ranking under transformations

[Savinov, Seki, Ladicky, **Sattler**, Pollefeys, Quad-networks: unsupervised learning to rank for interest point detection, CVPR 2017]

Learning to Rank

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[Savinov, Seki, Ladicky, **Sattler**, Pollefeys, Quad-networks: unsupervised learning to rank for interest point detection, CVPR 2017]

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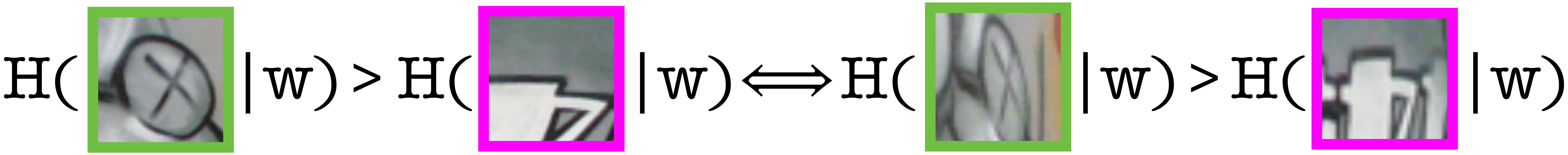

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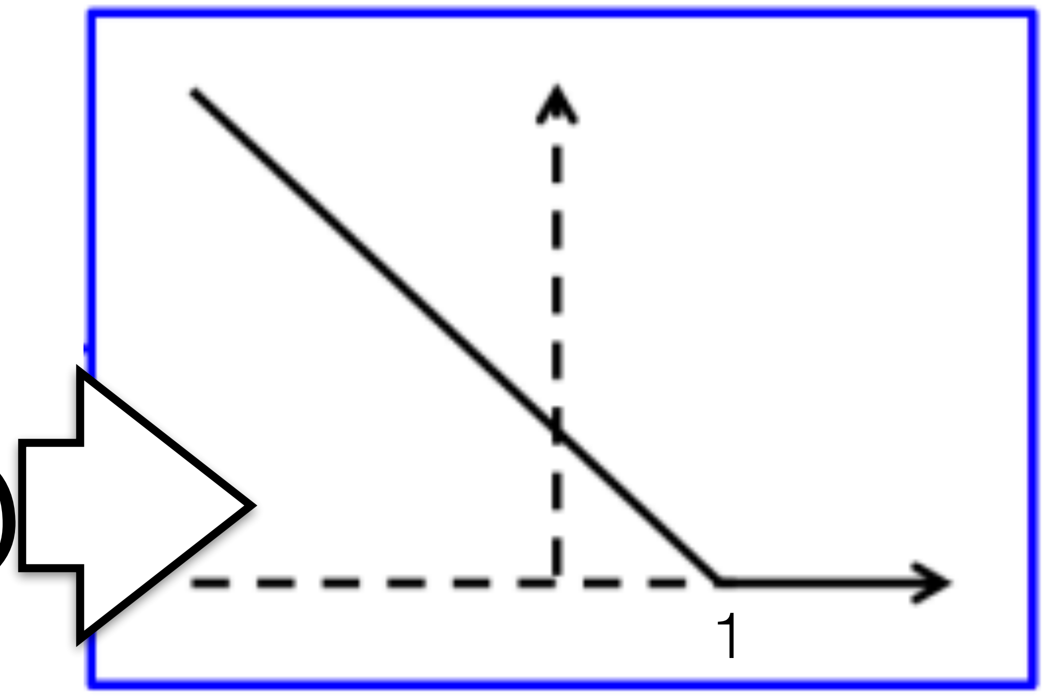
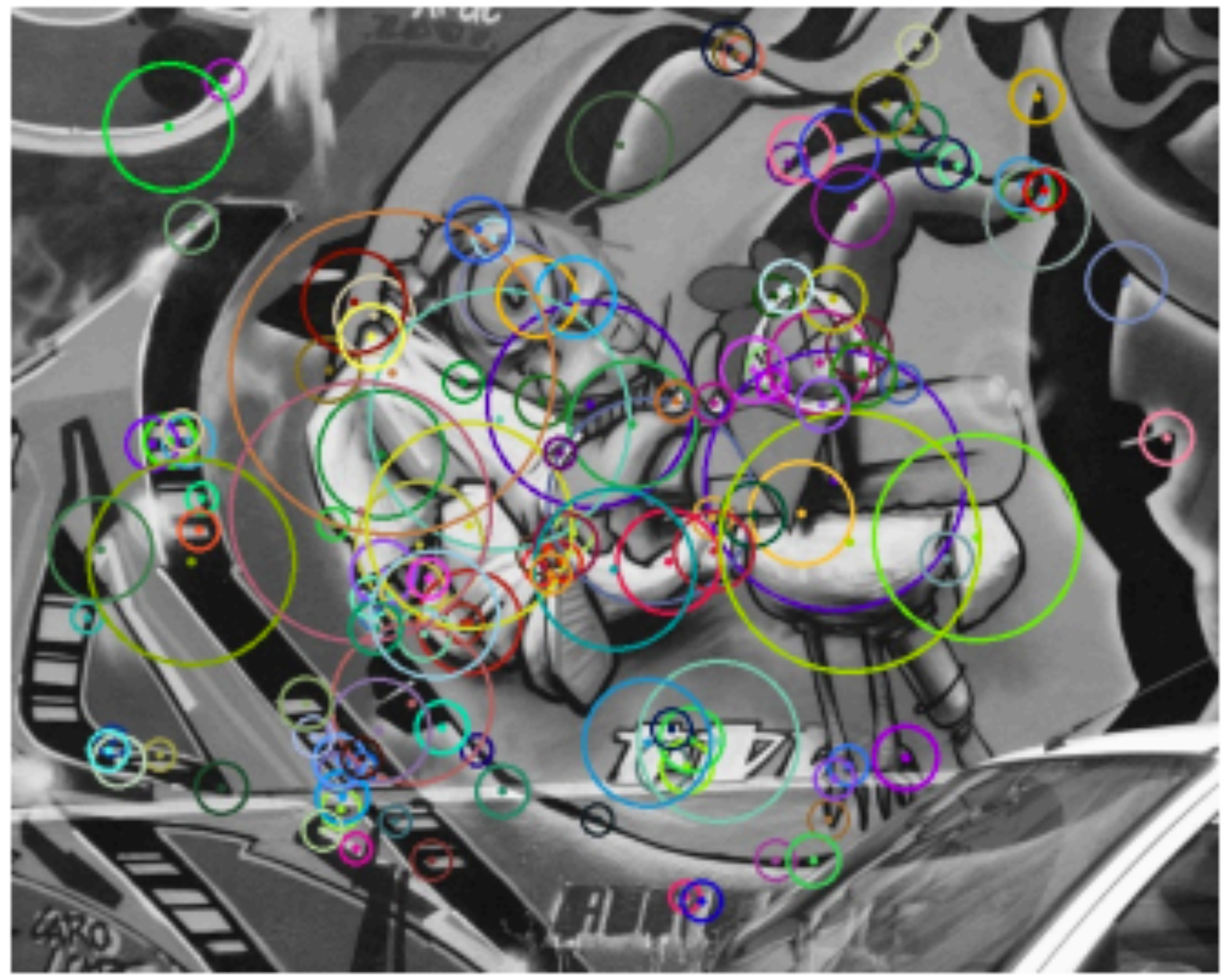
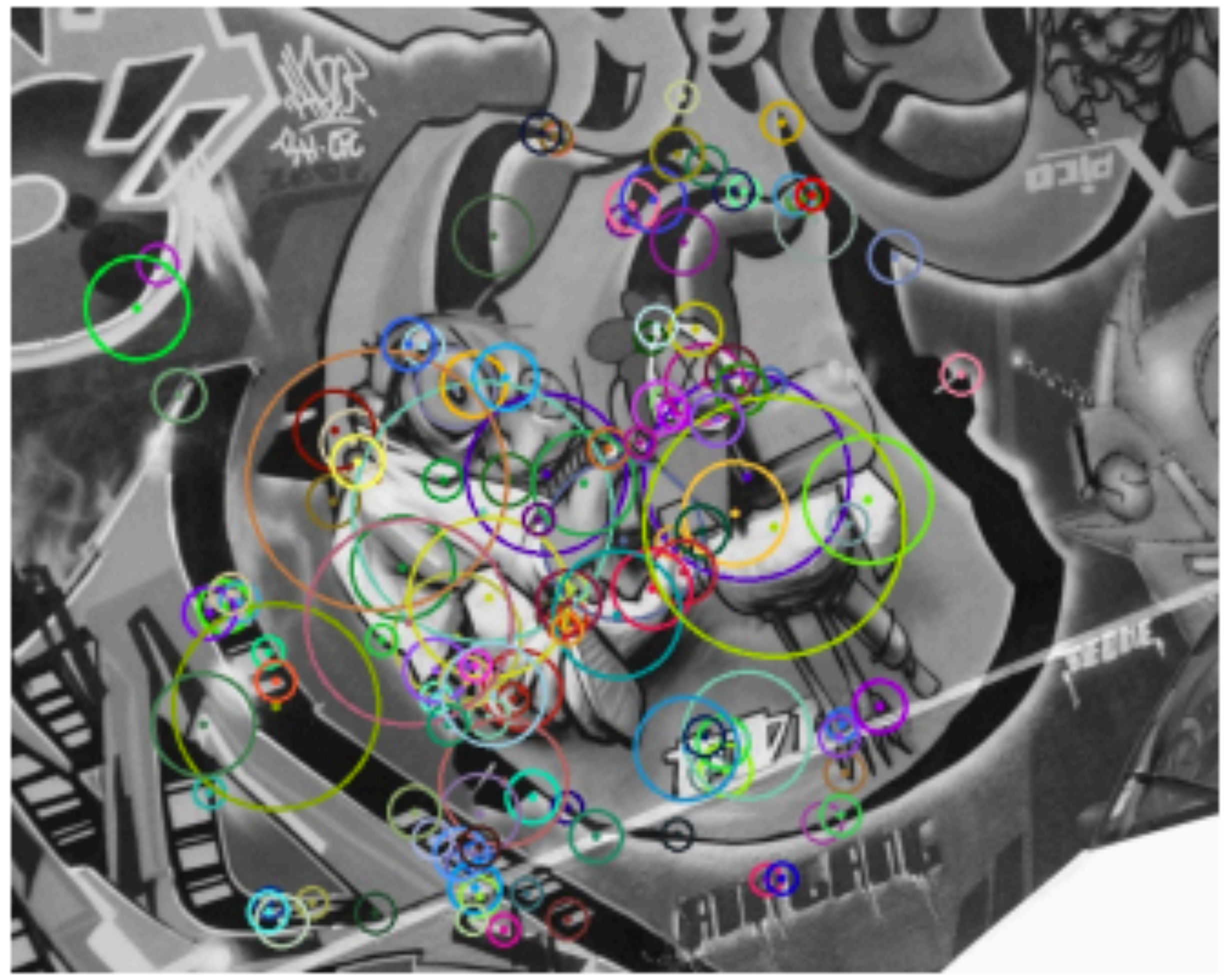


Hinge loss

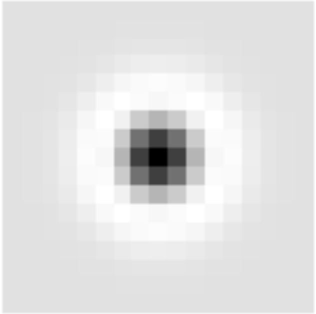
[Savinov, Seki, Ladicky, **Sattler**, Pollefeys, Quad-networks: unsupervised learning to rank for interest point detection, CVPR 2017]

Detection Results





Difference-of-Gaussians



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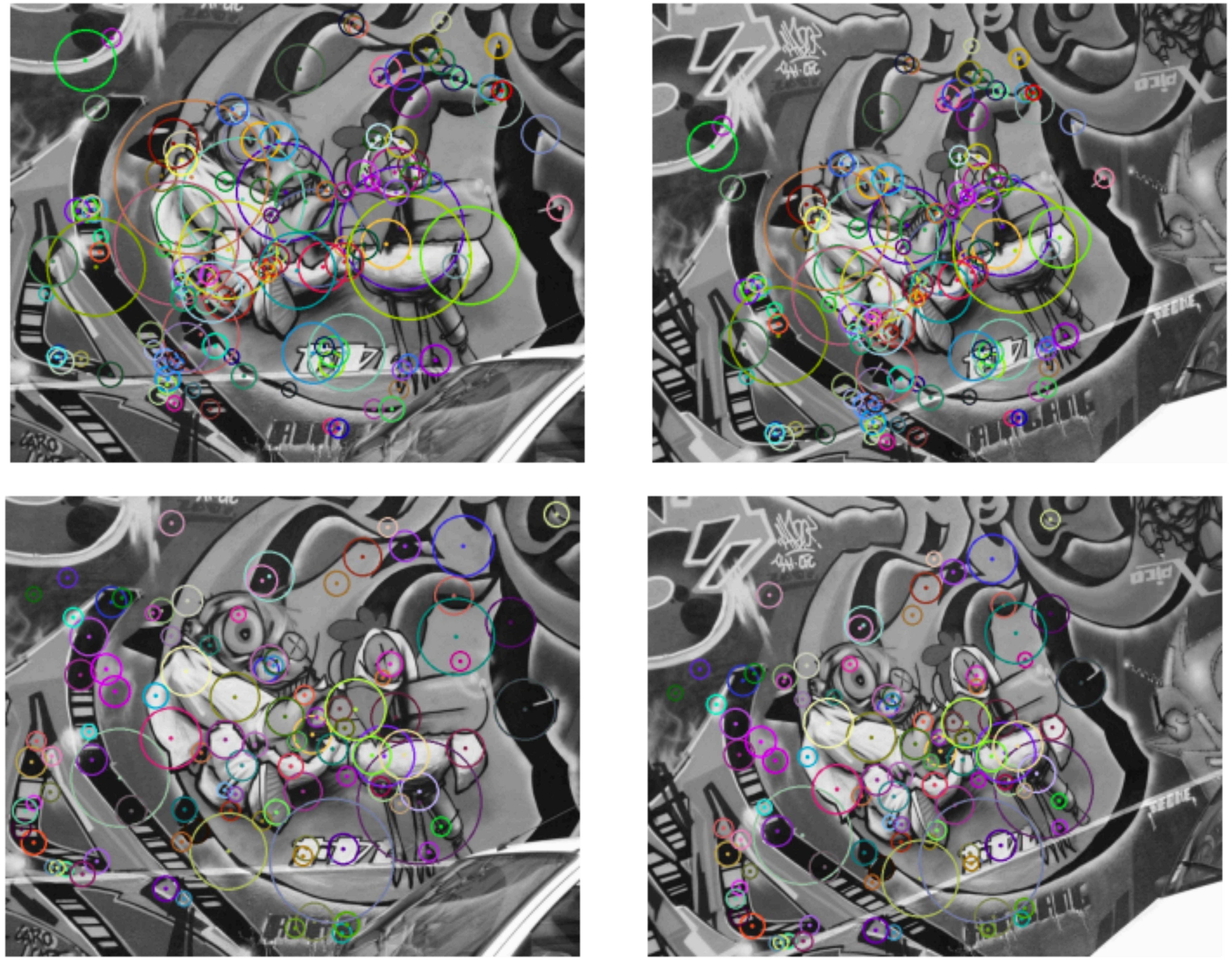

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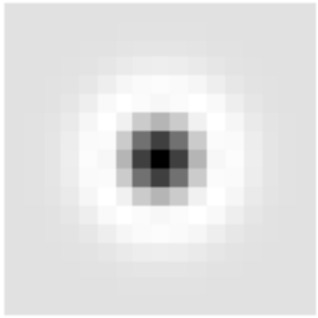
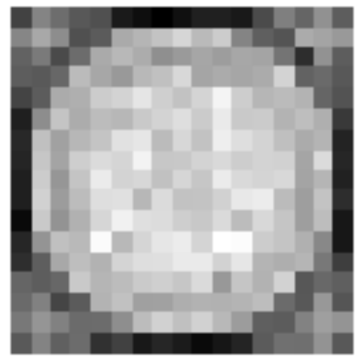


ours



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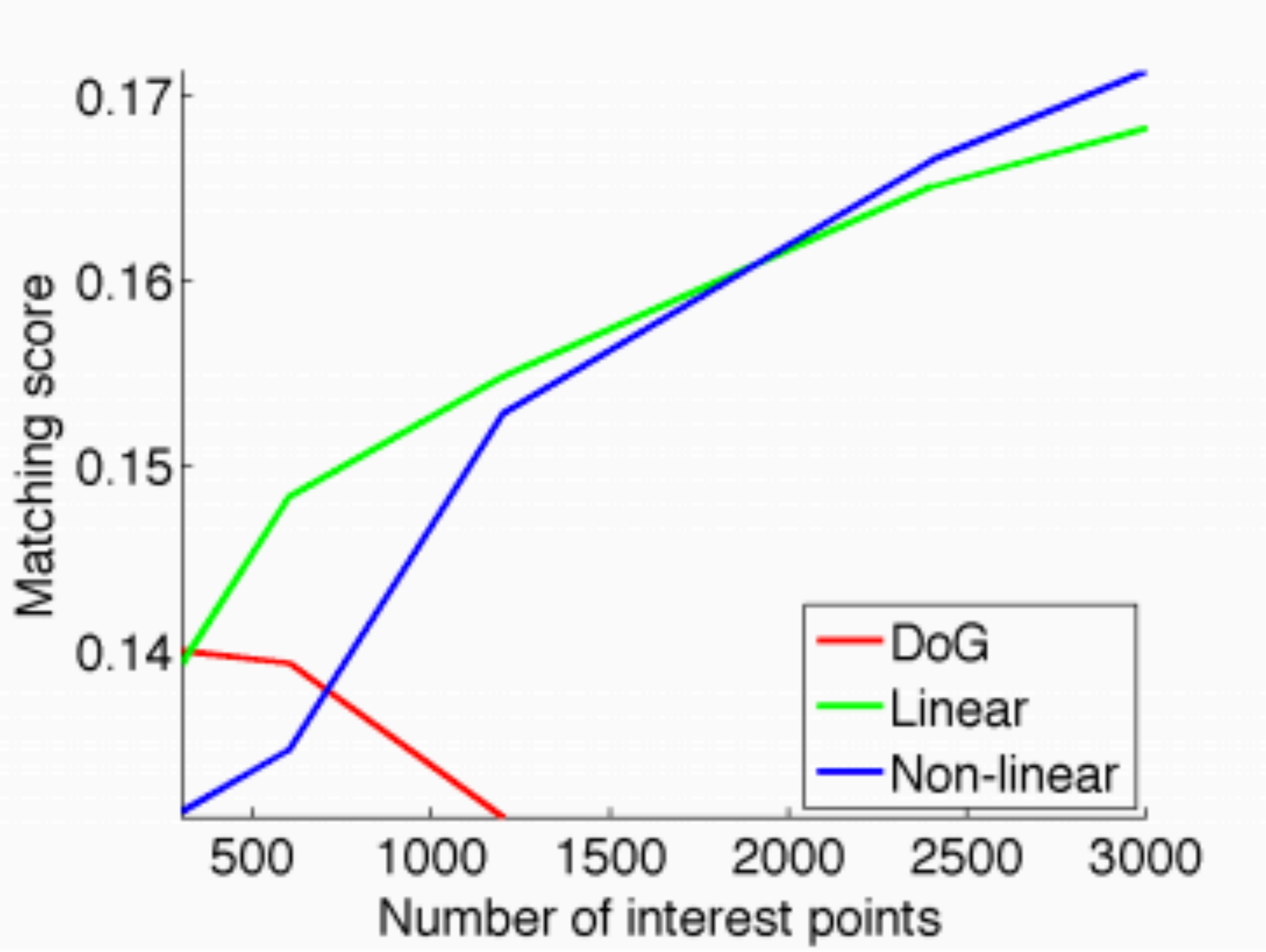
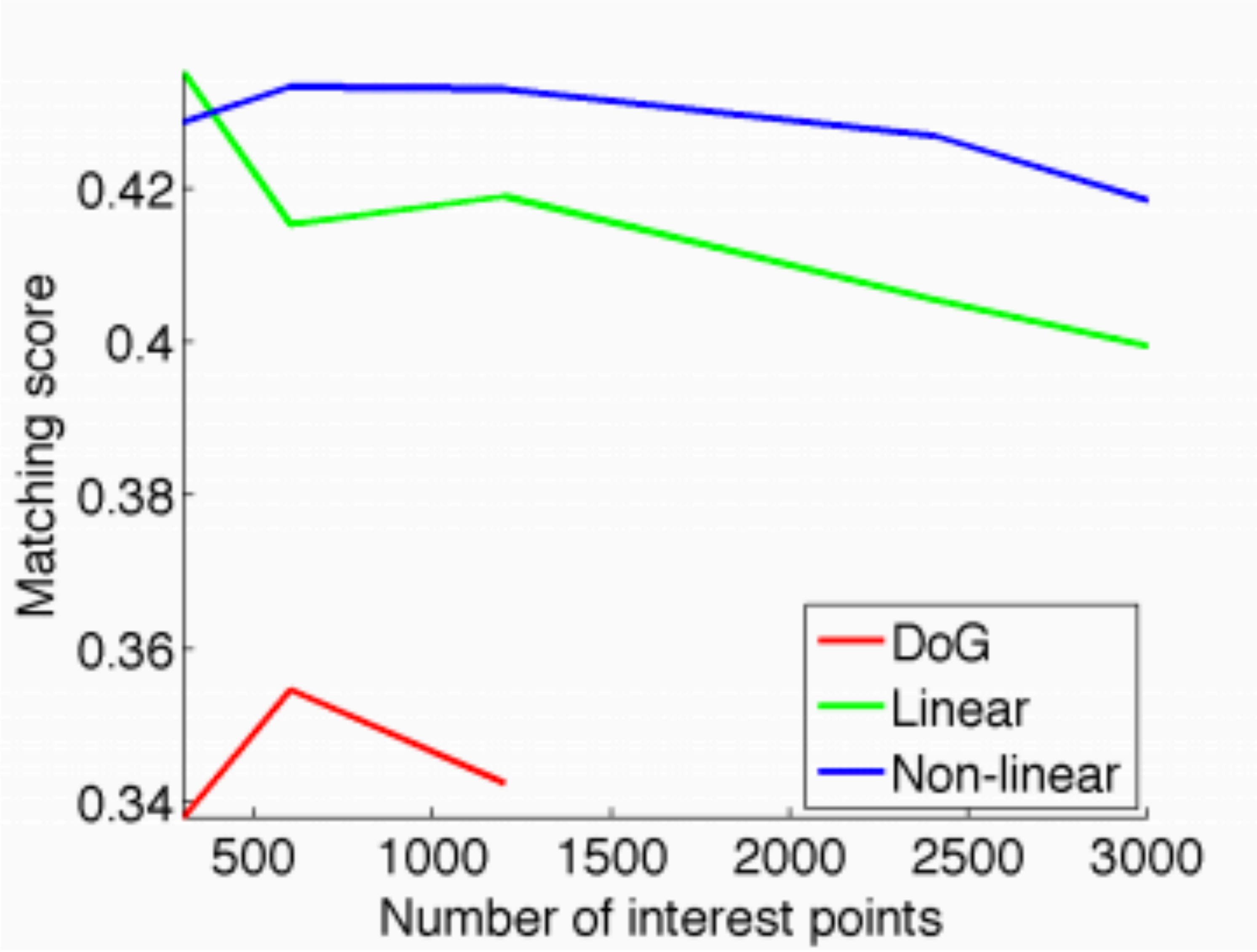


Wall (viewpoint)



Leuven (illumination)

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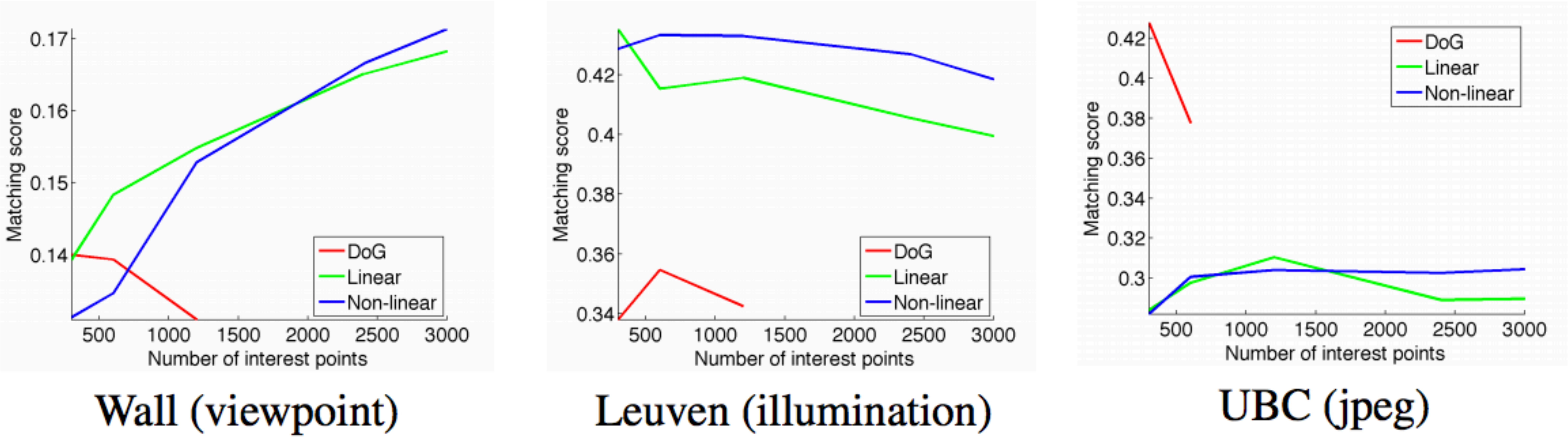

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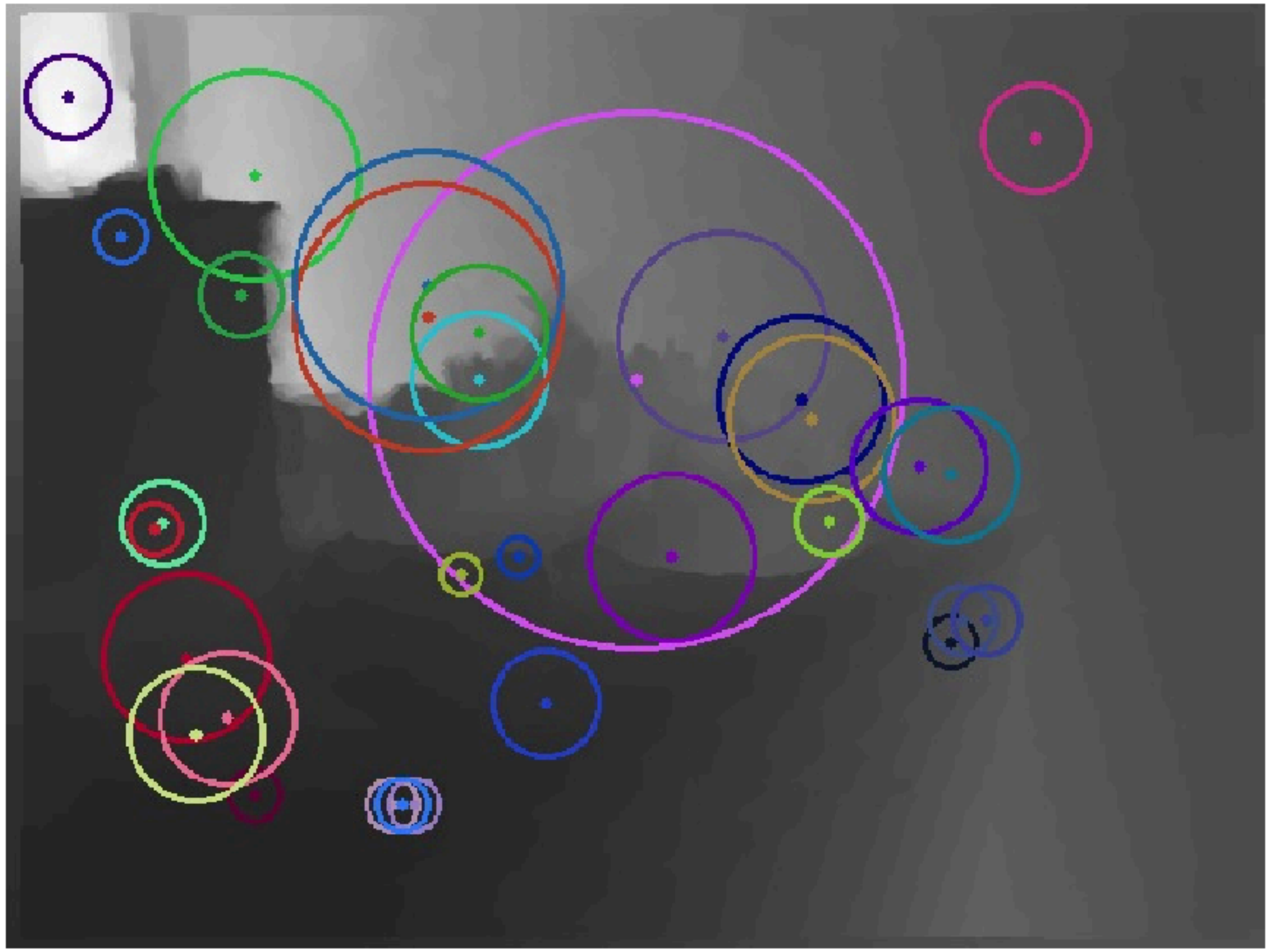
Multi-Modal Features



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Learning Patch Descriptors

- Learn mapping from patch to descriptor in $\mathbb{R}^n$

[Schönberger, Hardmeier, **Sattler**, Pollefeys, Evaluation of Hand-Crafted and Learned Local Features. CVPR 2017]

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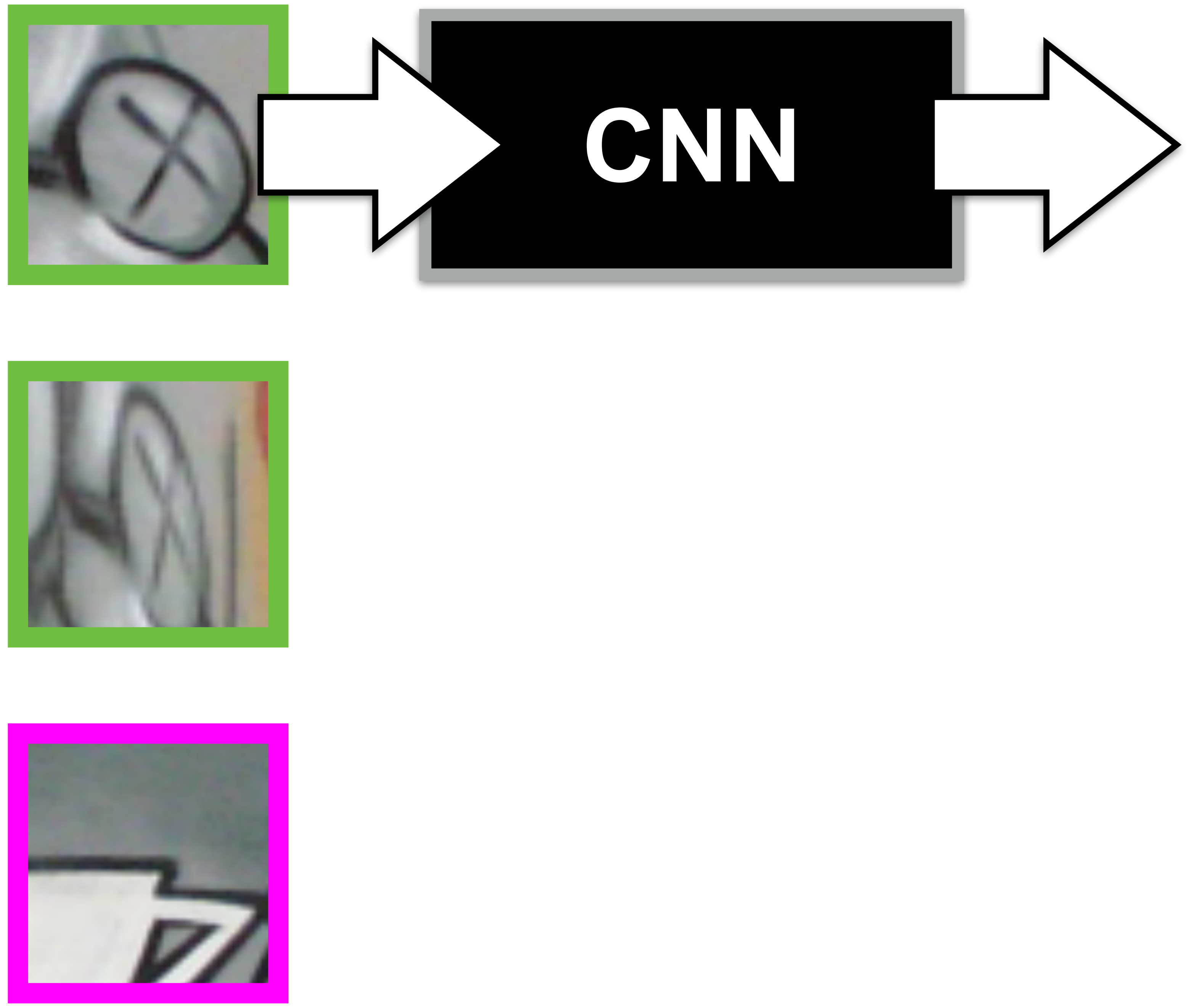

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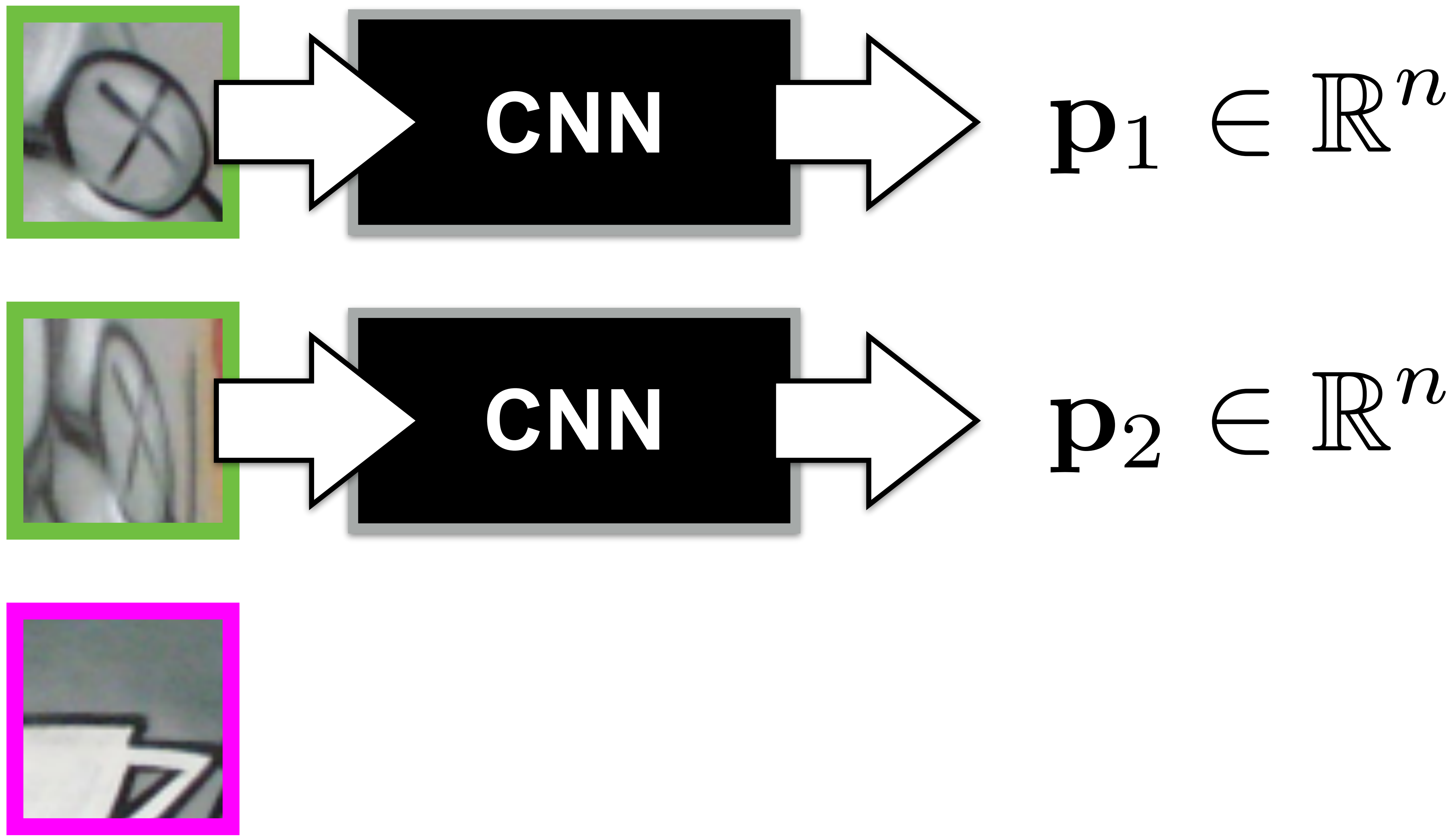

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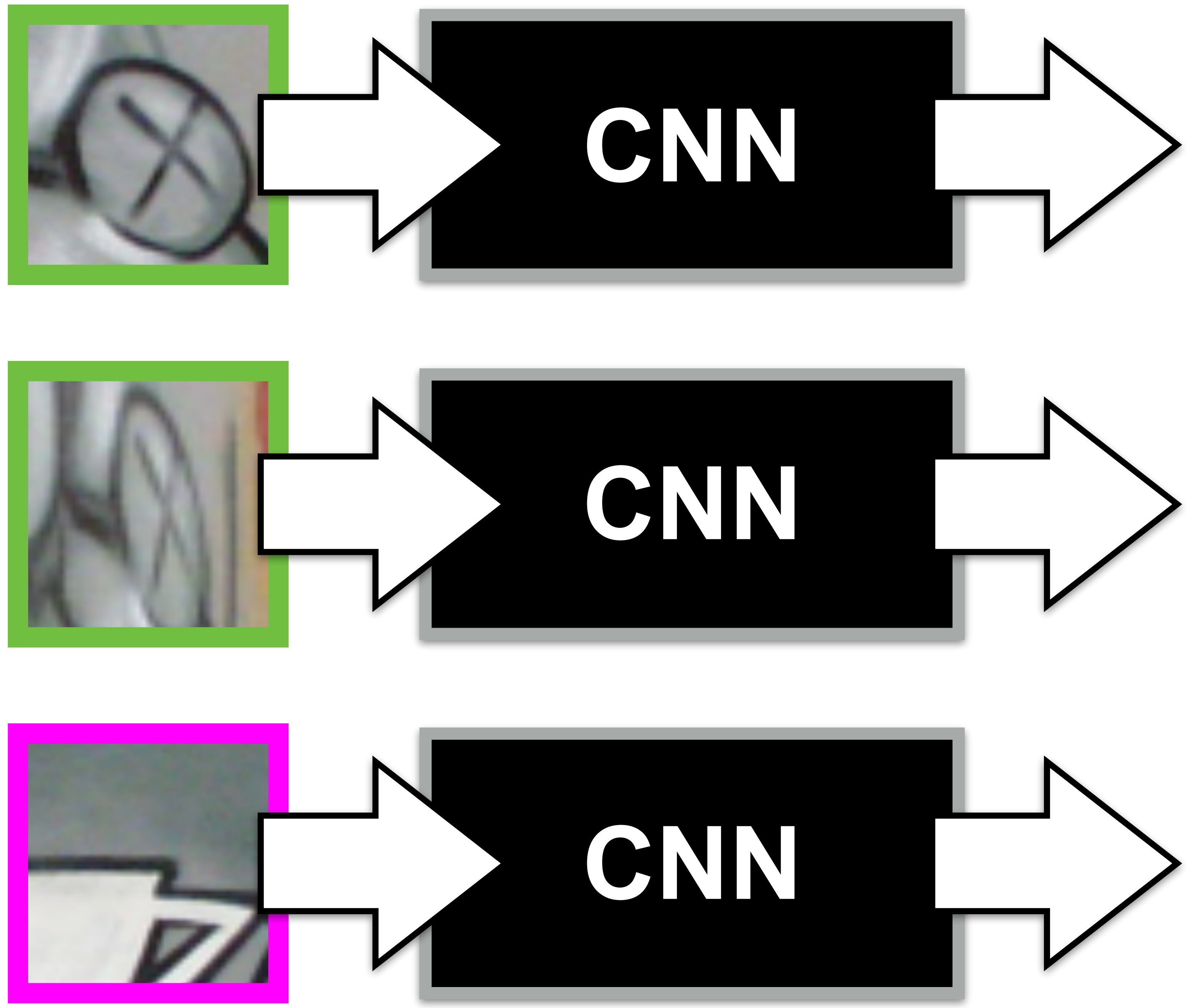

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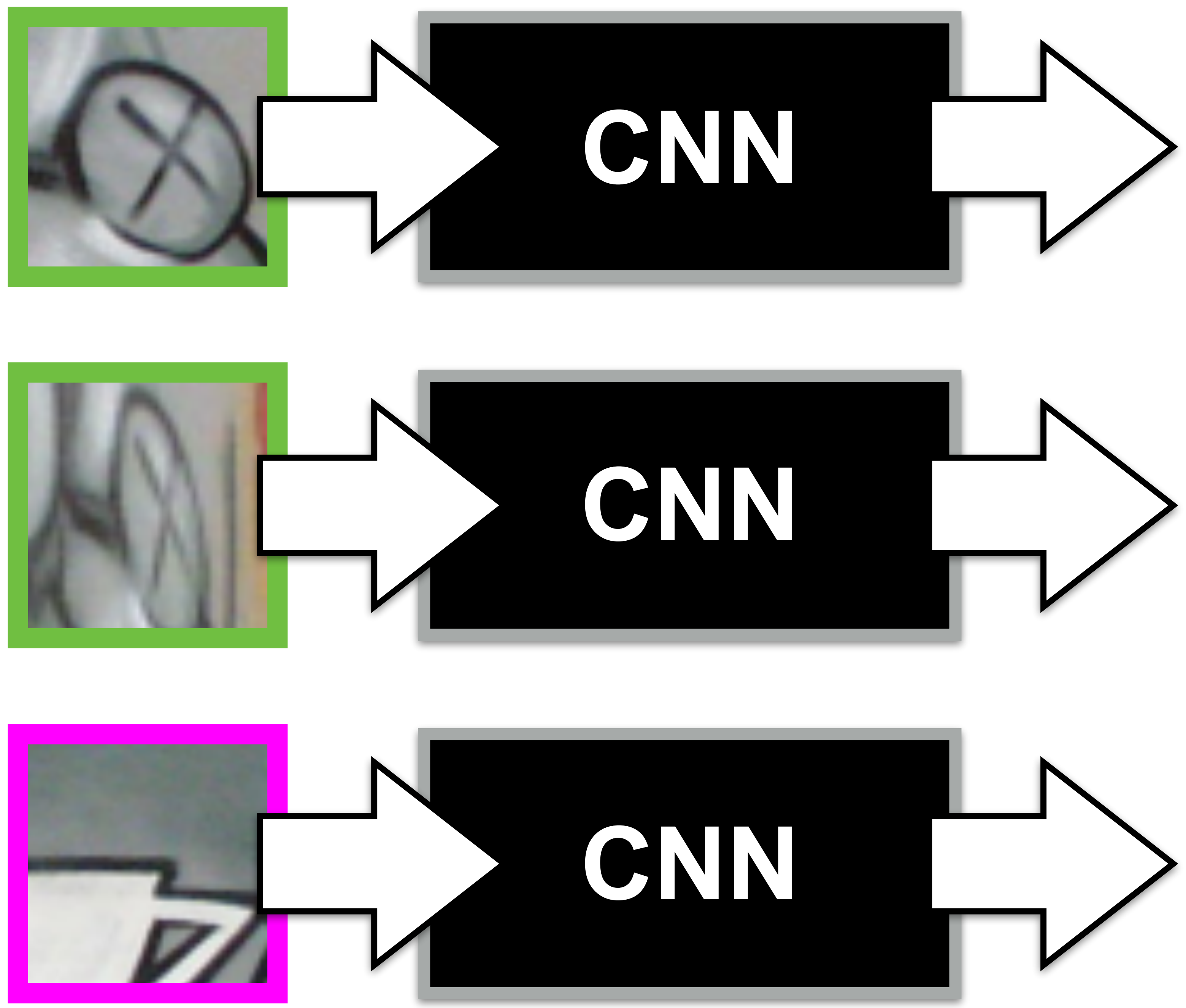

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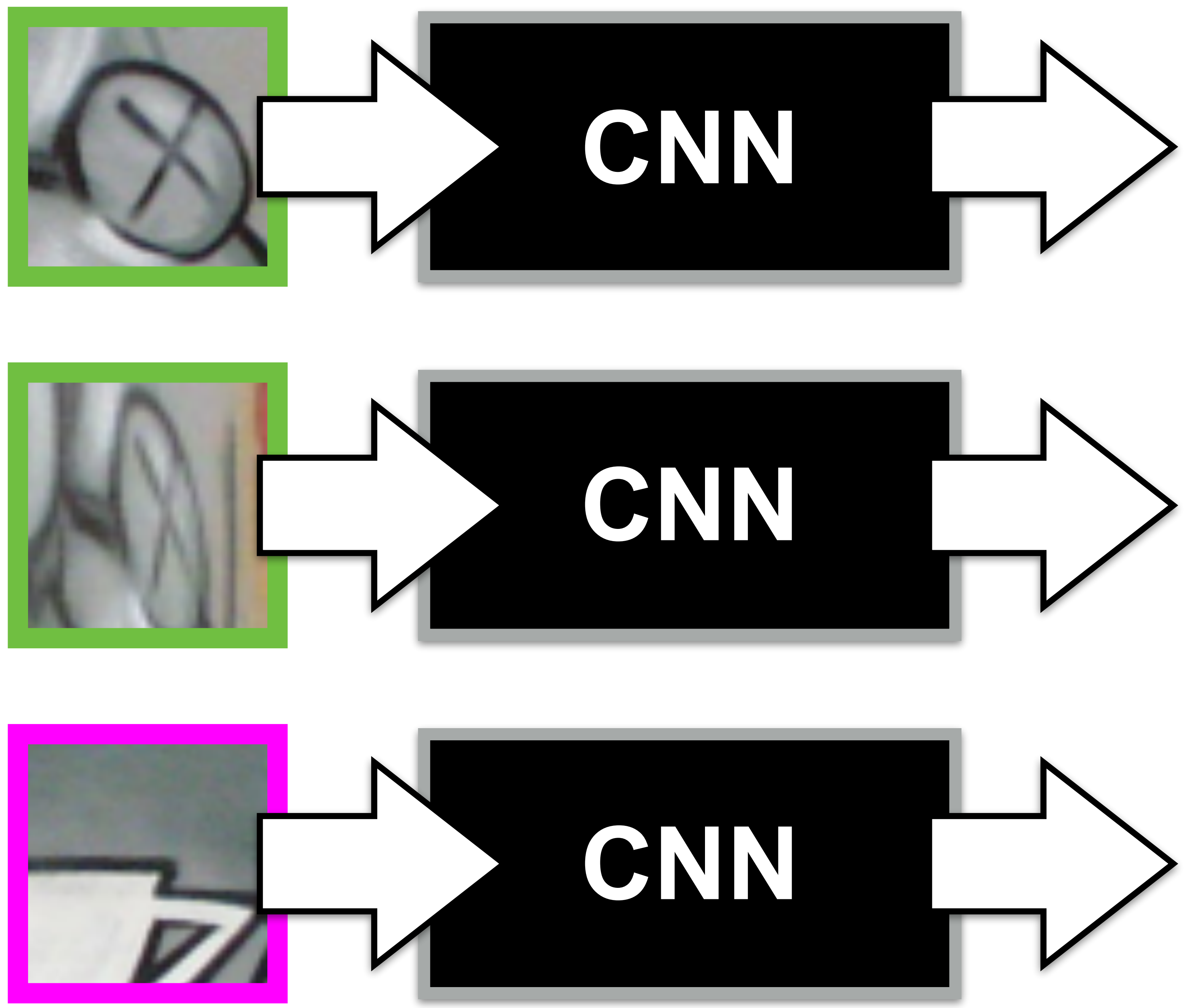

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margin

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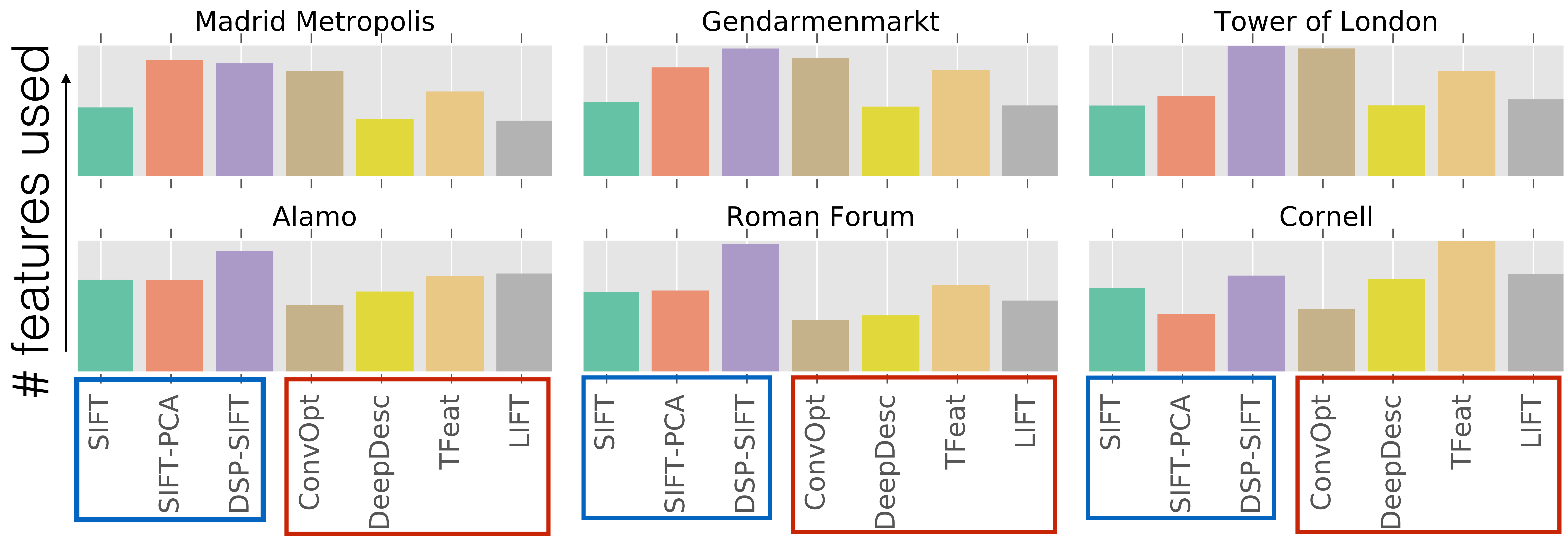

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- In any case: Compare against simple baselines!