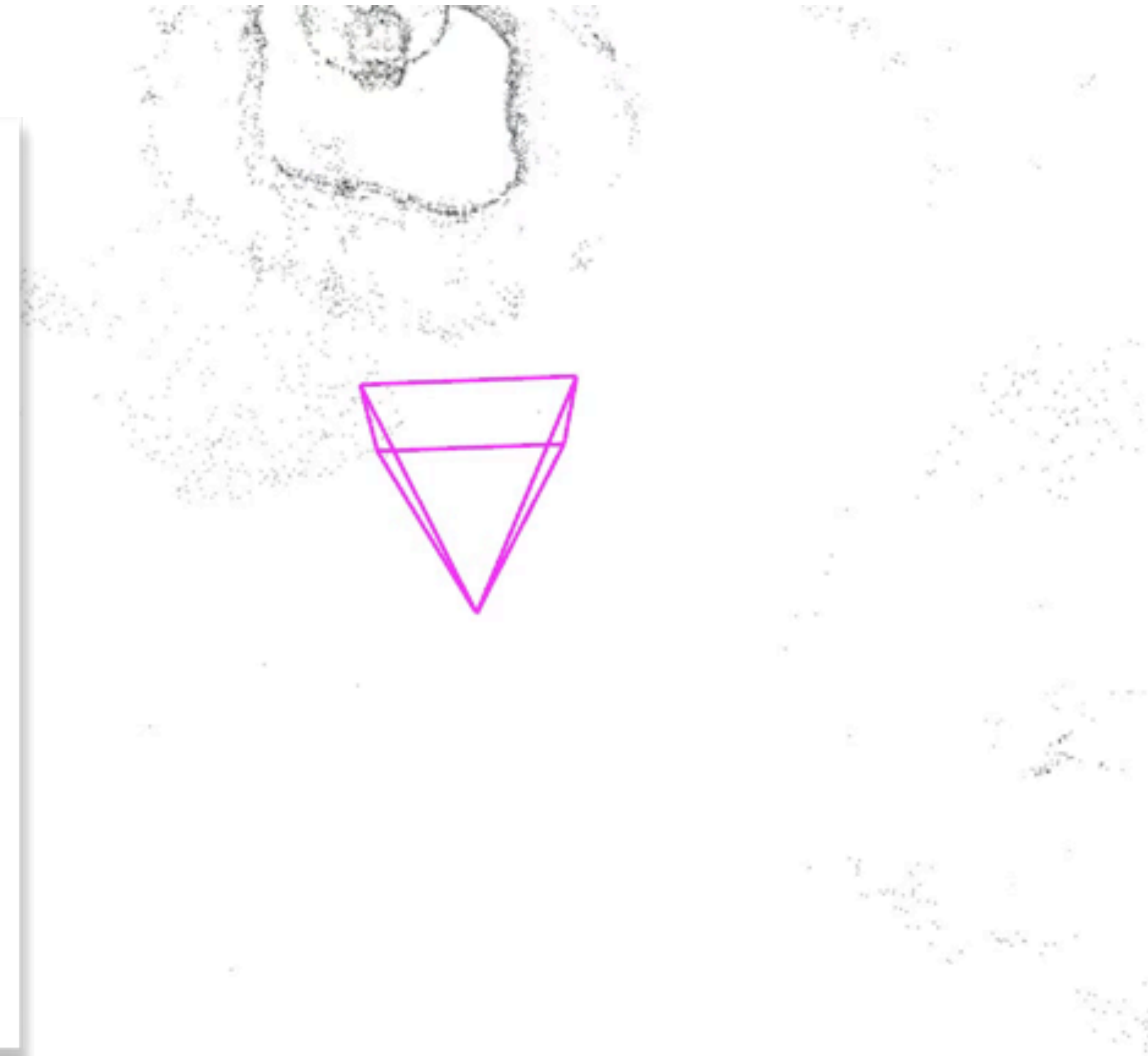
Has the (Large-Scale) Image-based Localization Problem been solved?

Torsten Sattler
Computer Vision & Geometry Lab
ETH Zurich

The Image-Based Localization Problem



Compute **exact position and orientation** of query image relative to 3D scene model.

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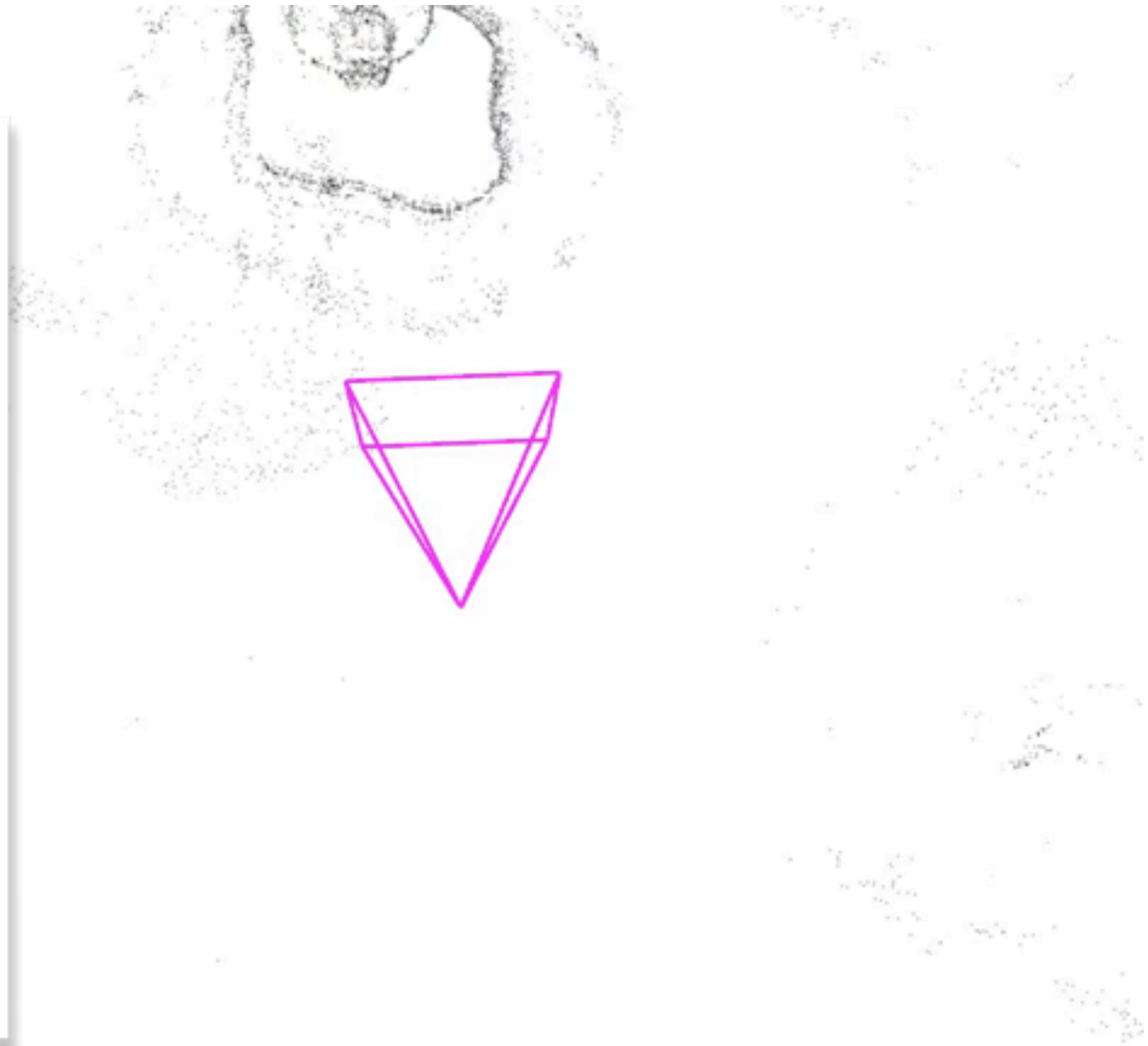

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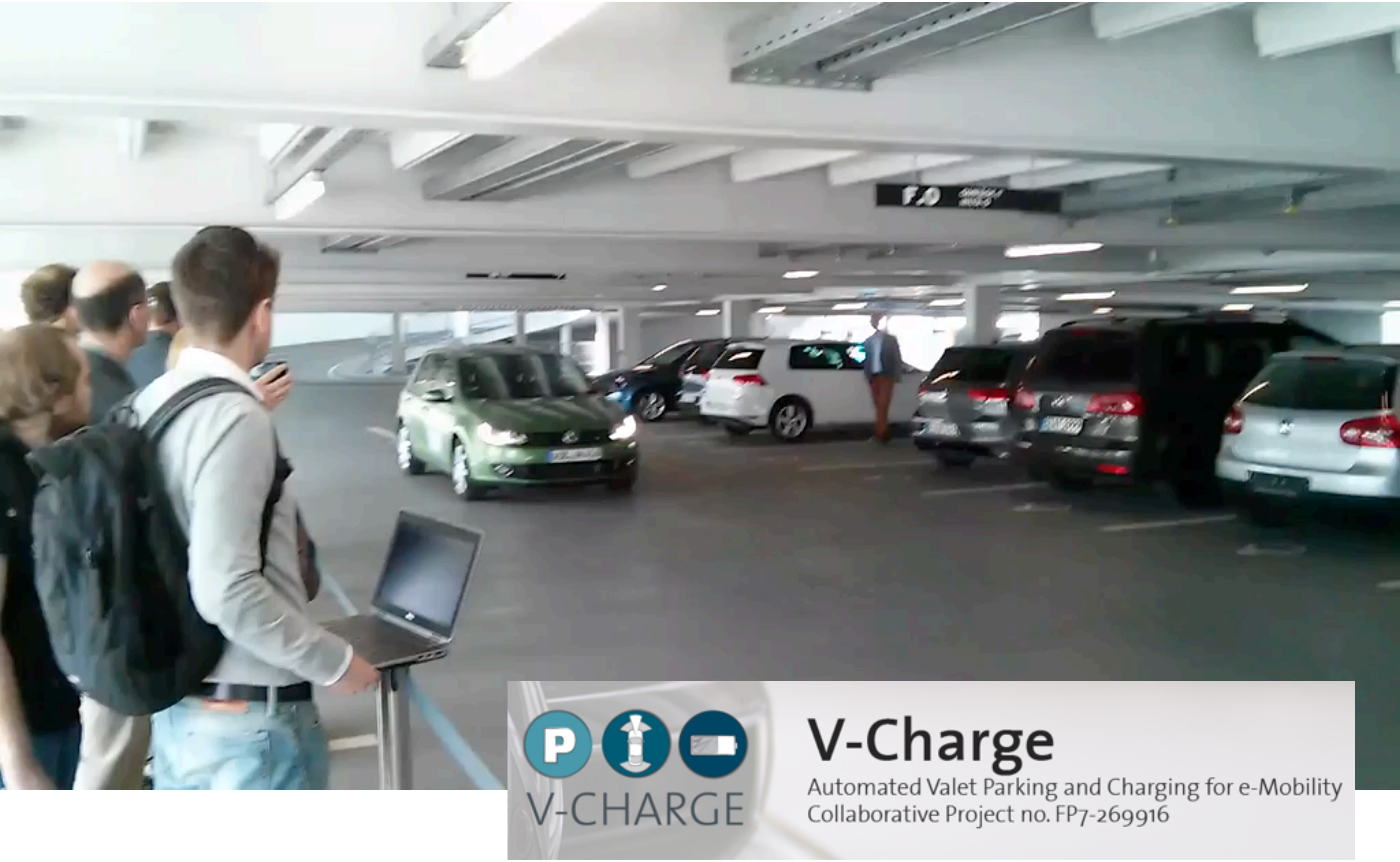

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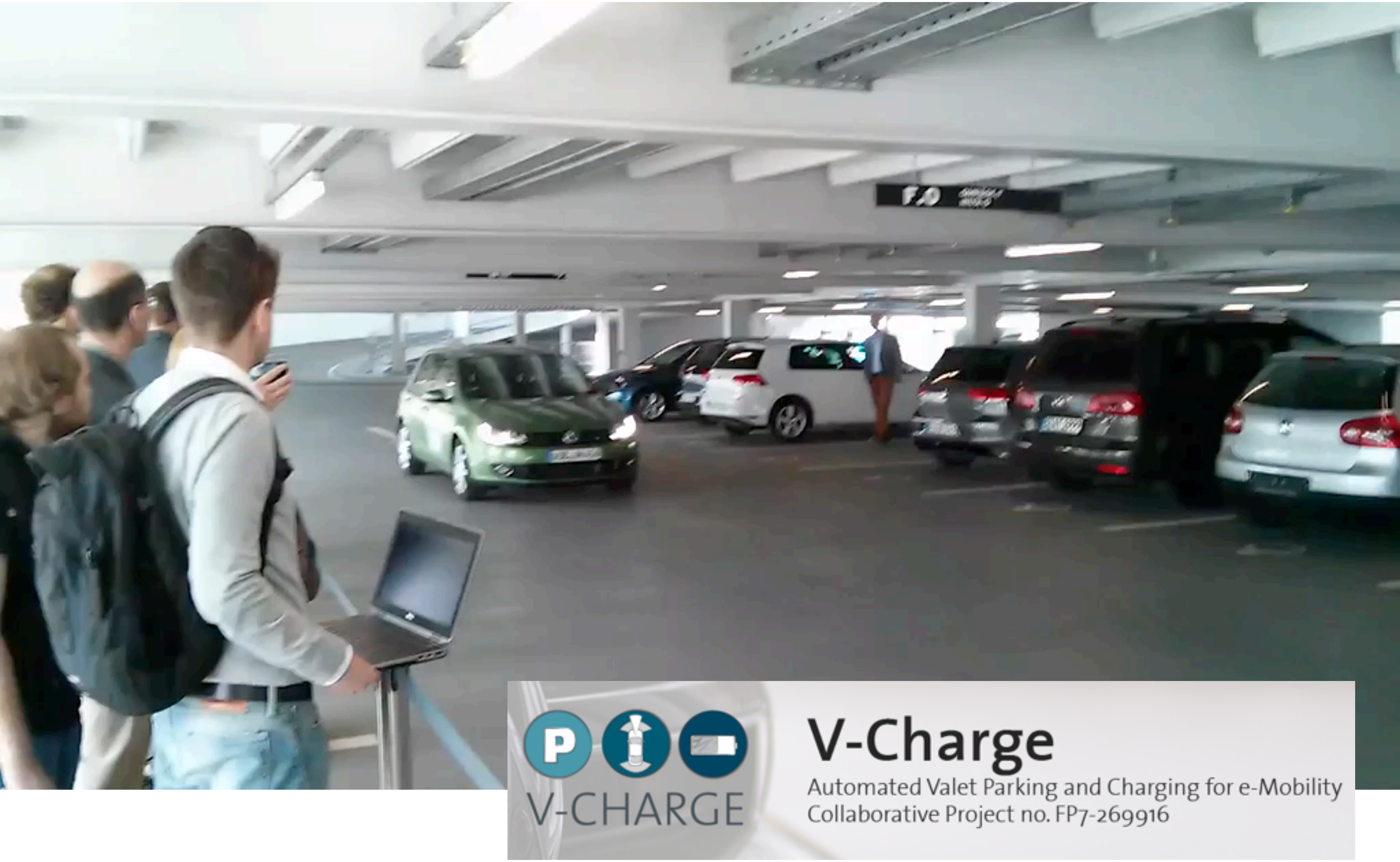

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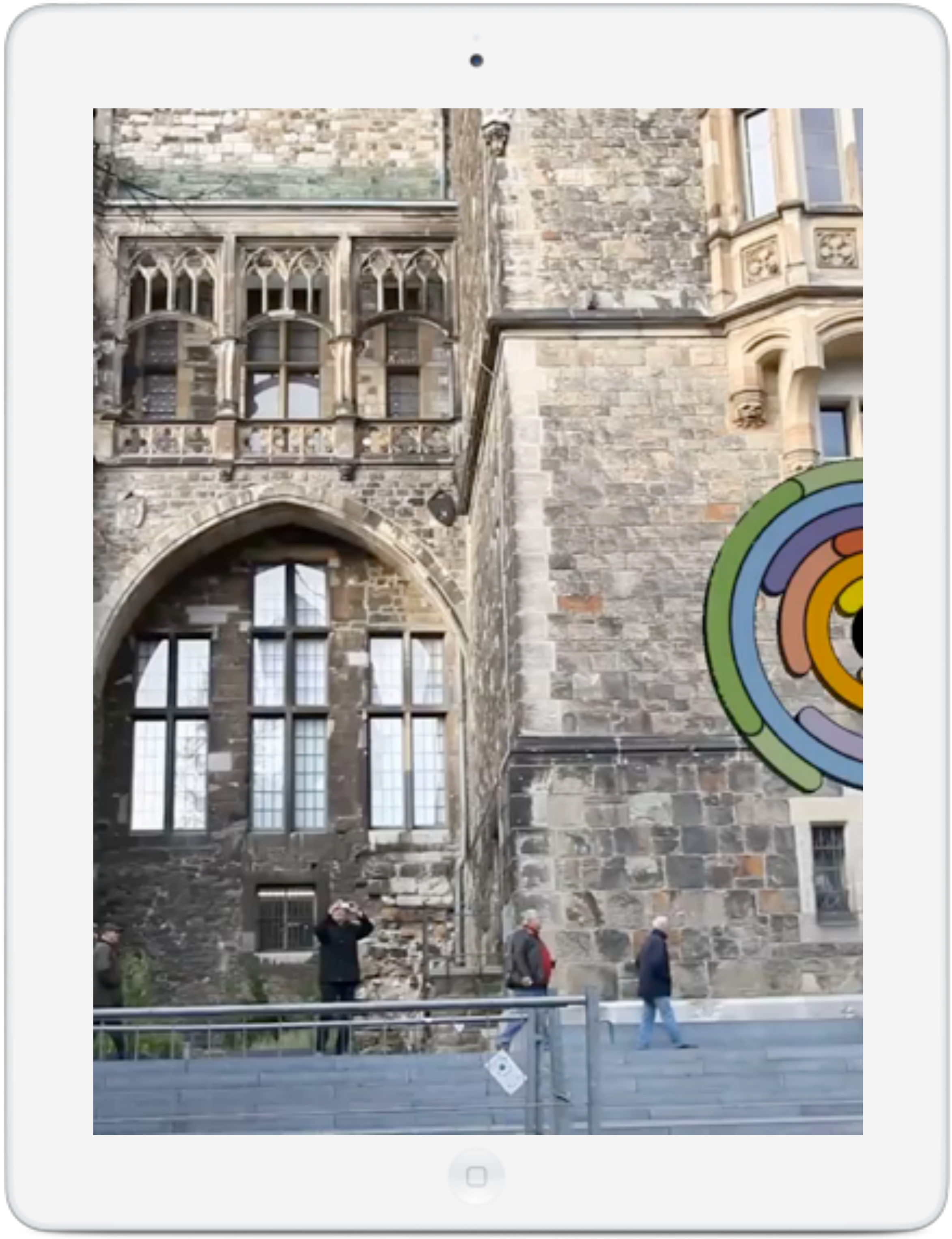

[Middelberg et al., ECCV'14]

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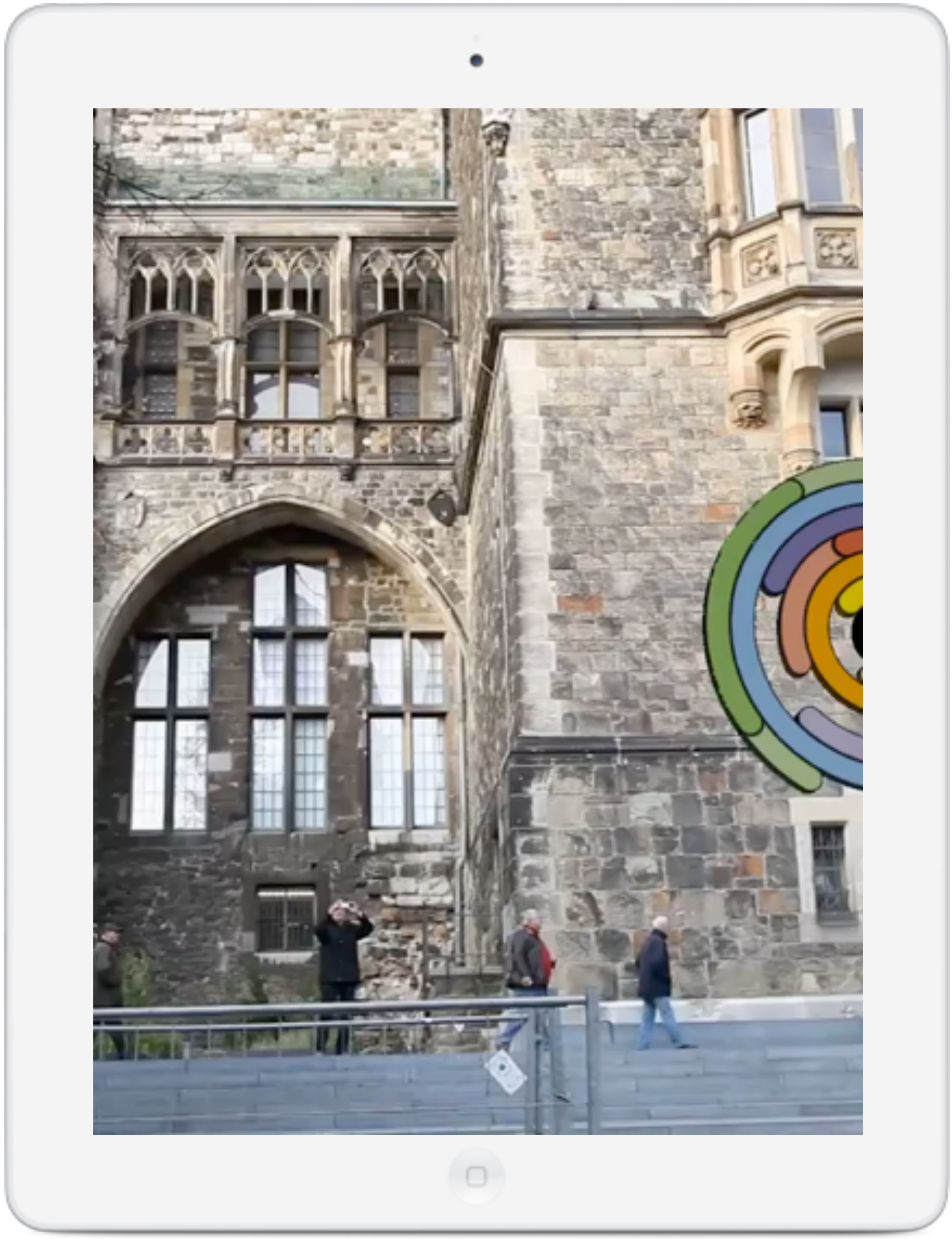

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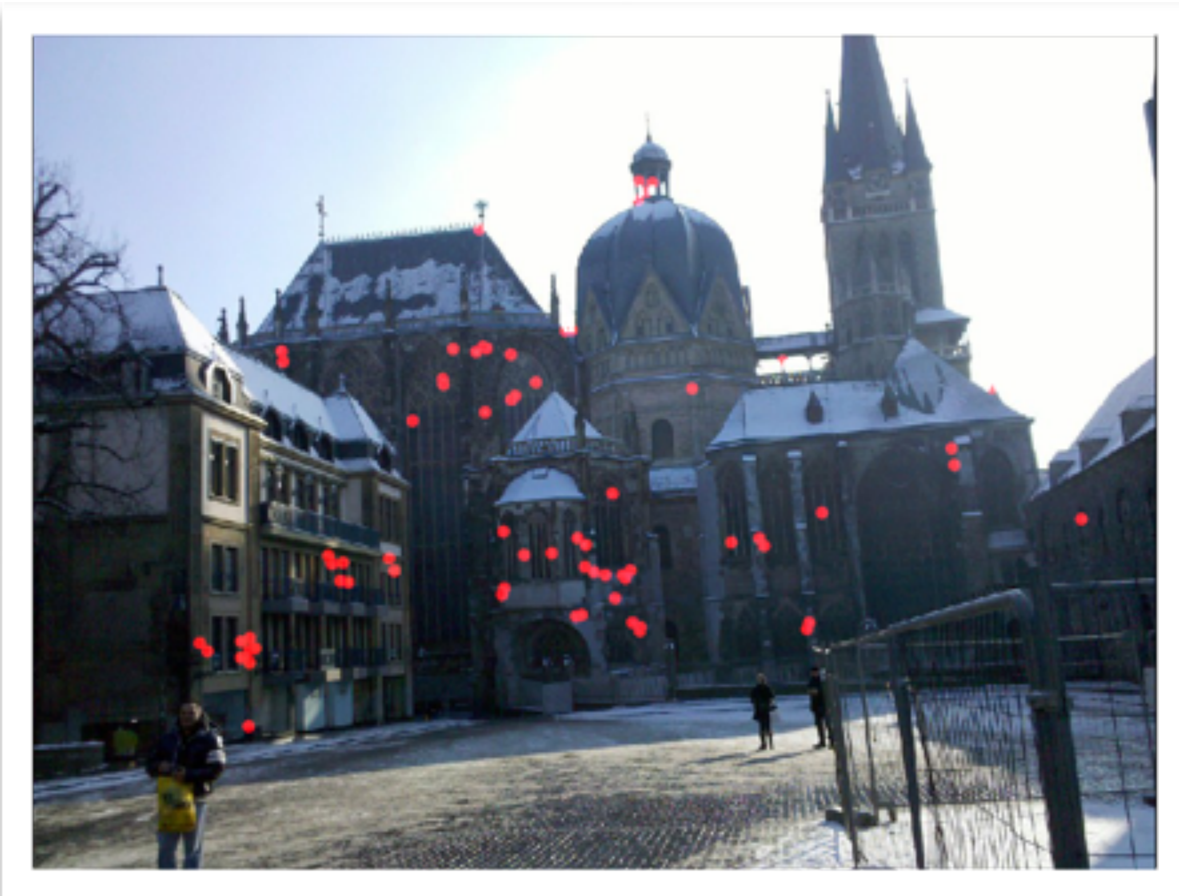
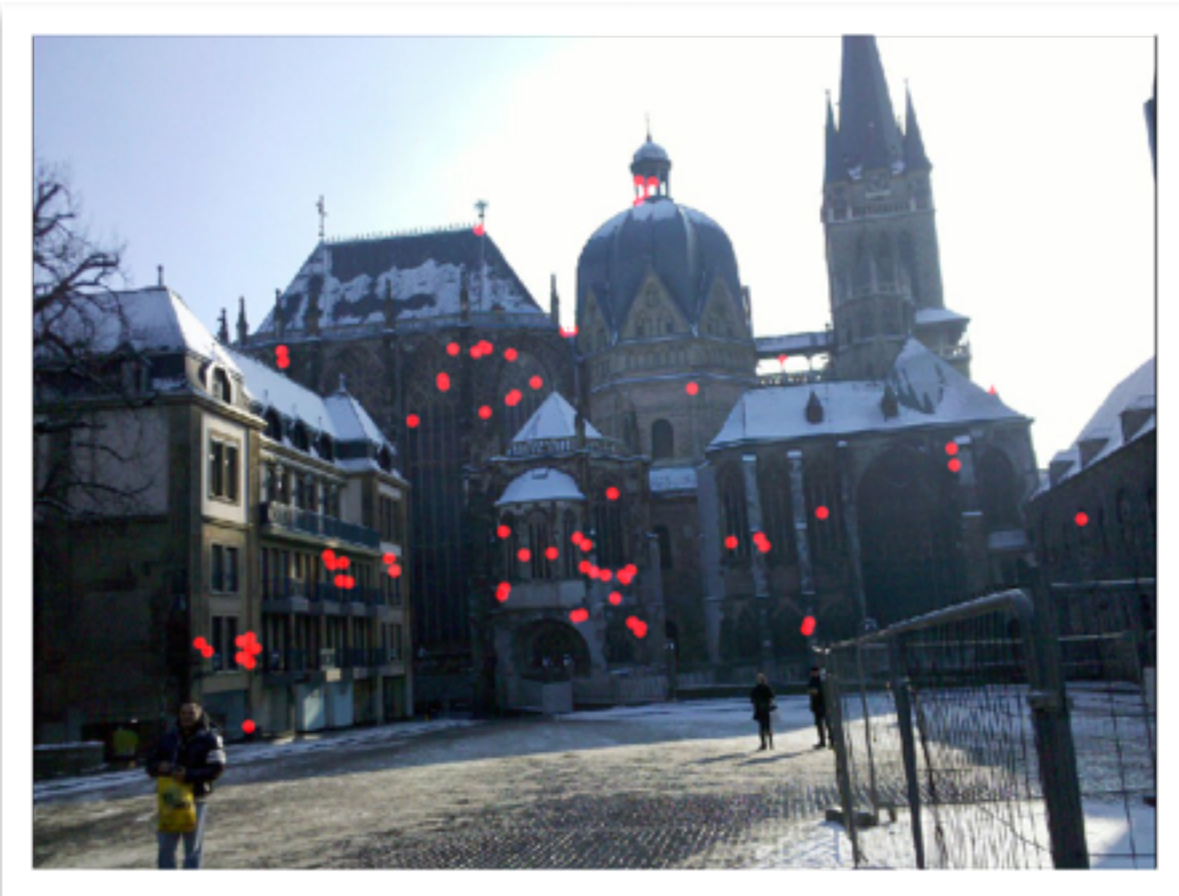


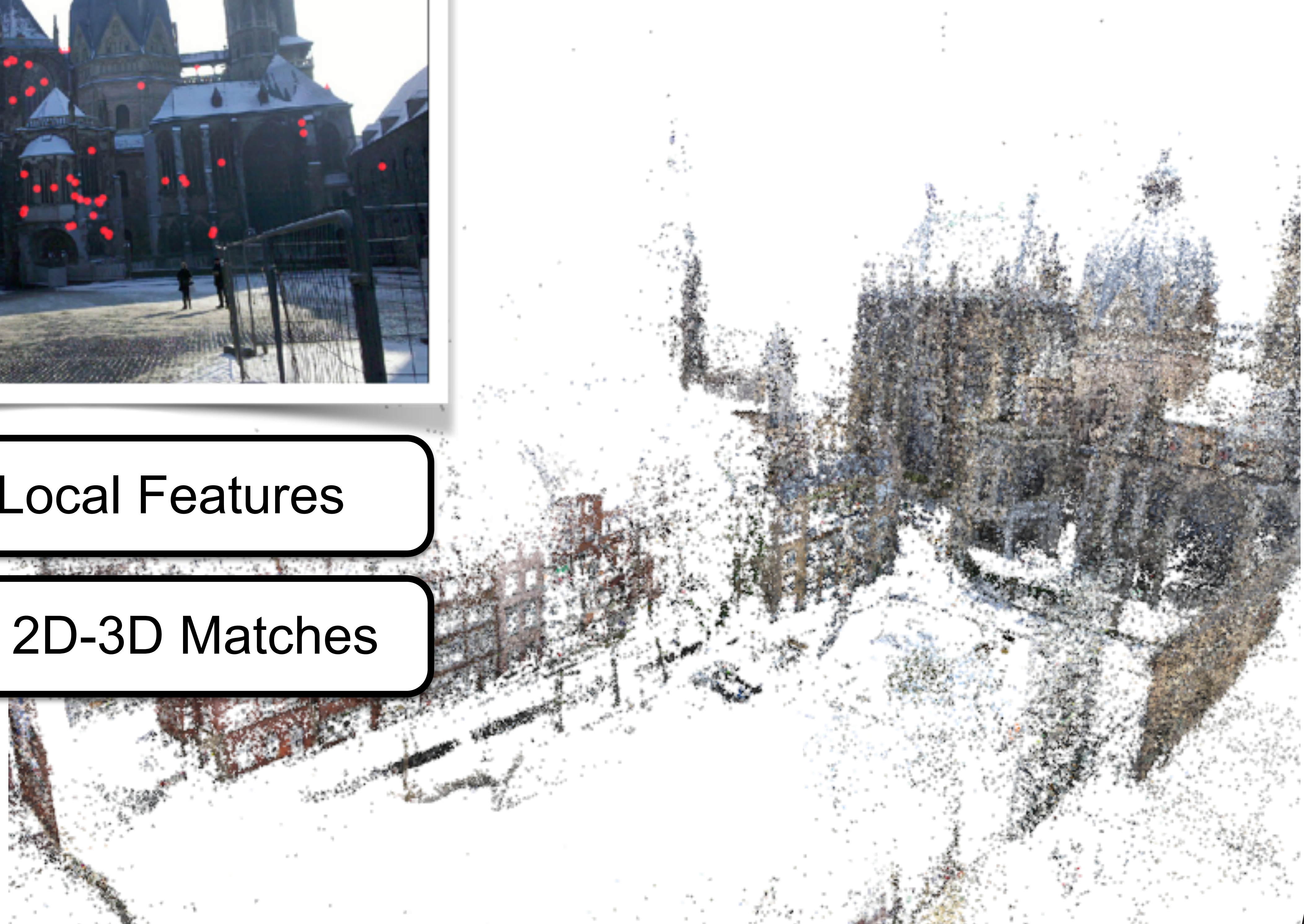
Extract Local Features

Image-Based Localization Pipeline



Extract Local Features

Establish 2D-3D Matches



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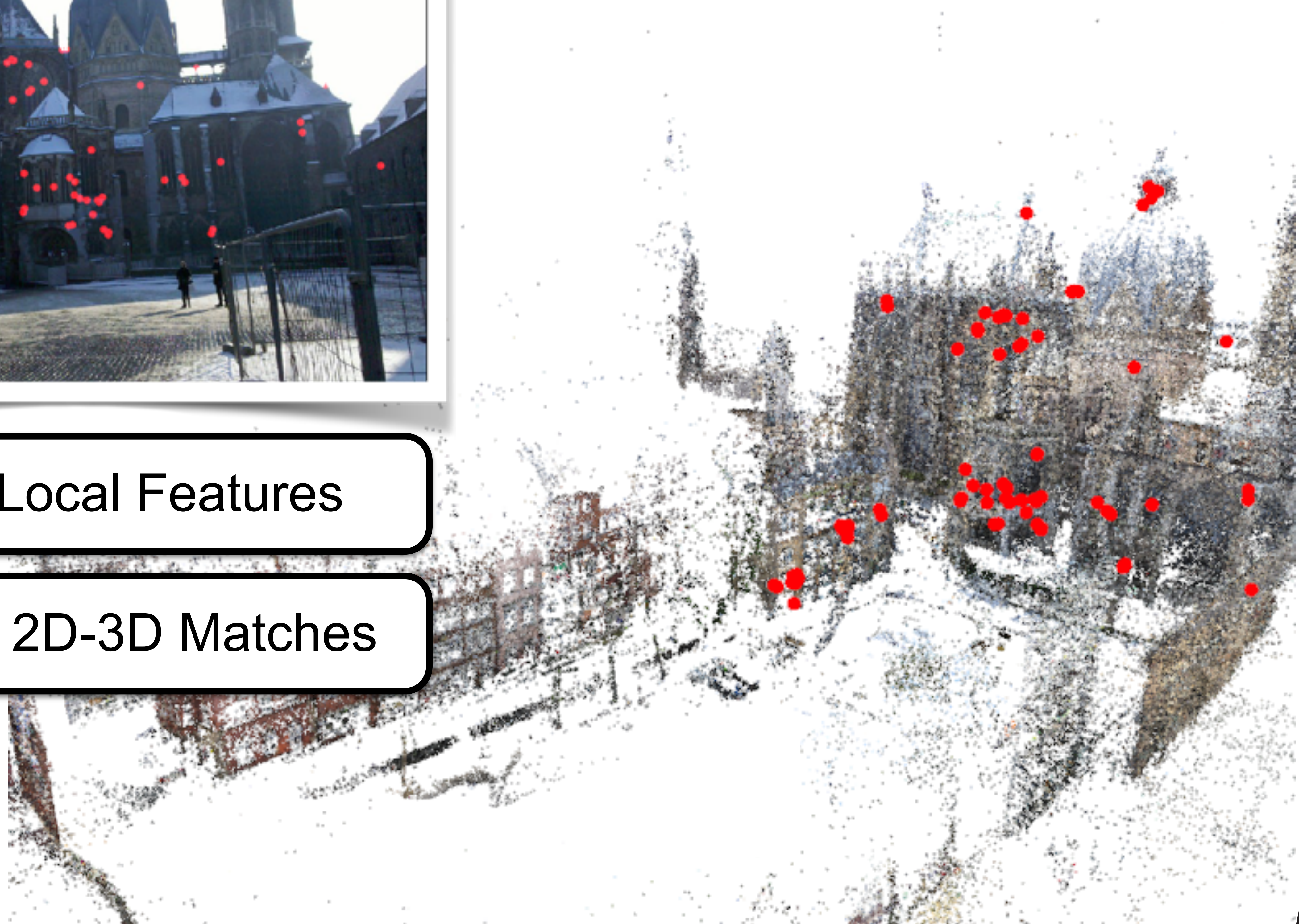

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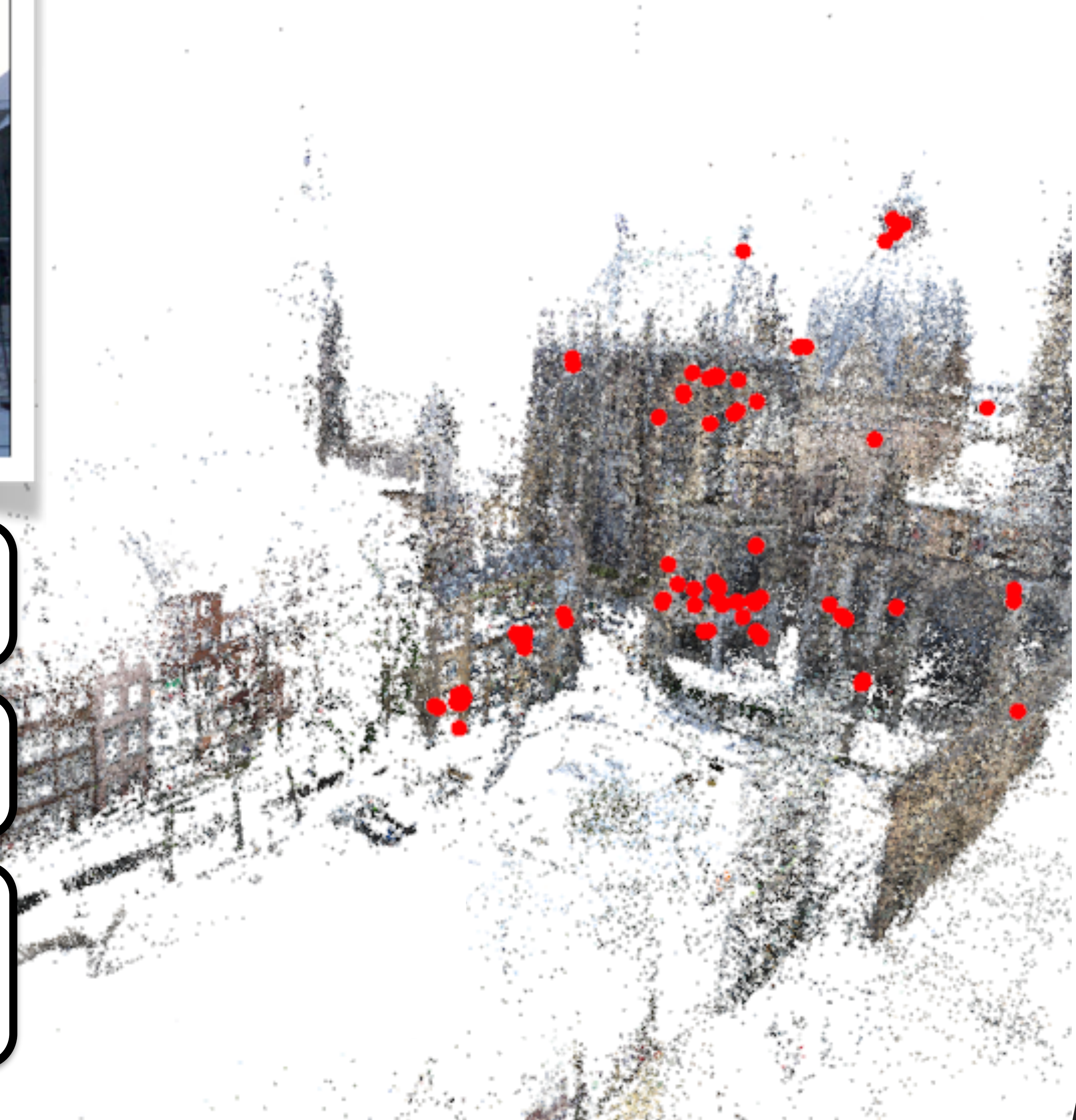

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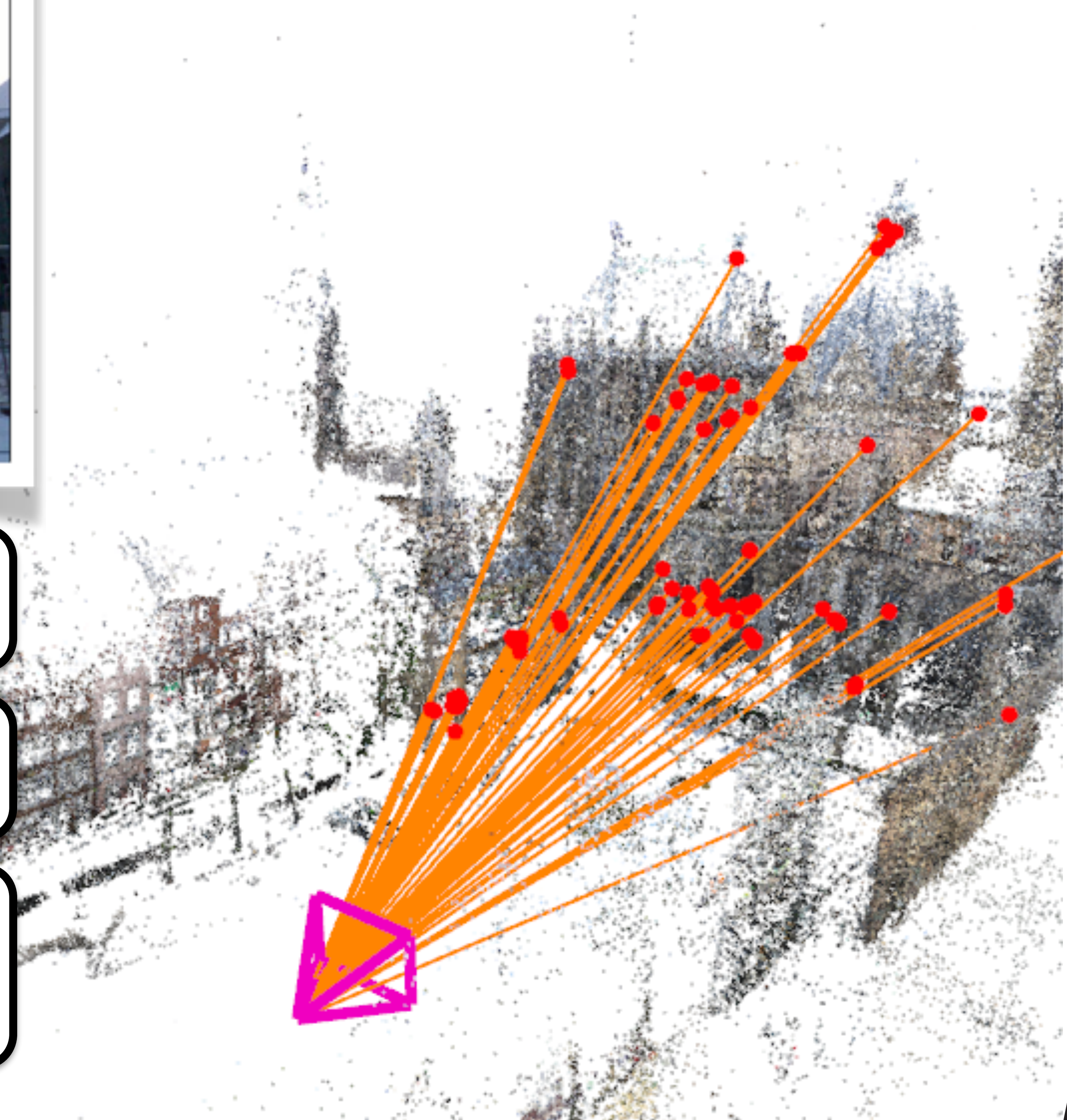

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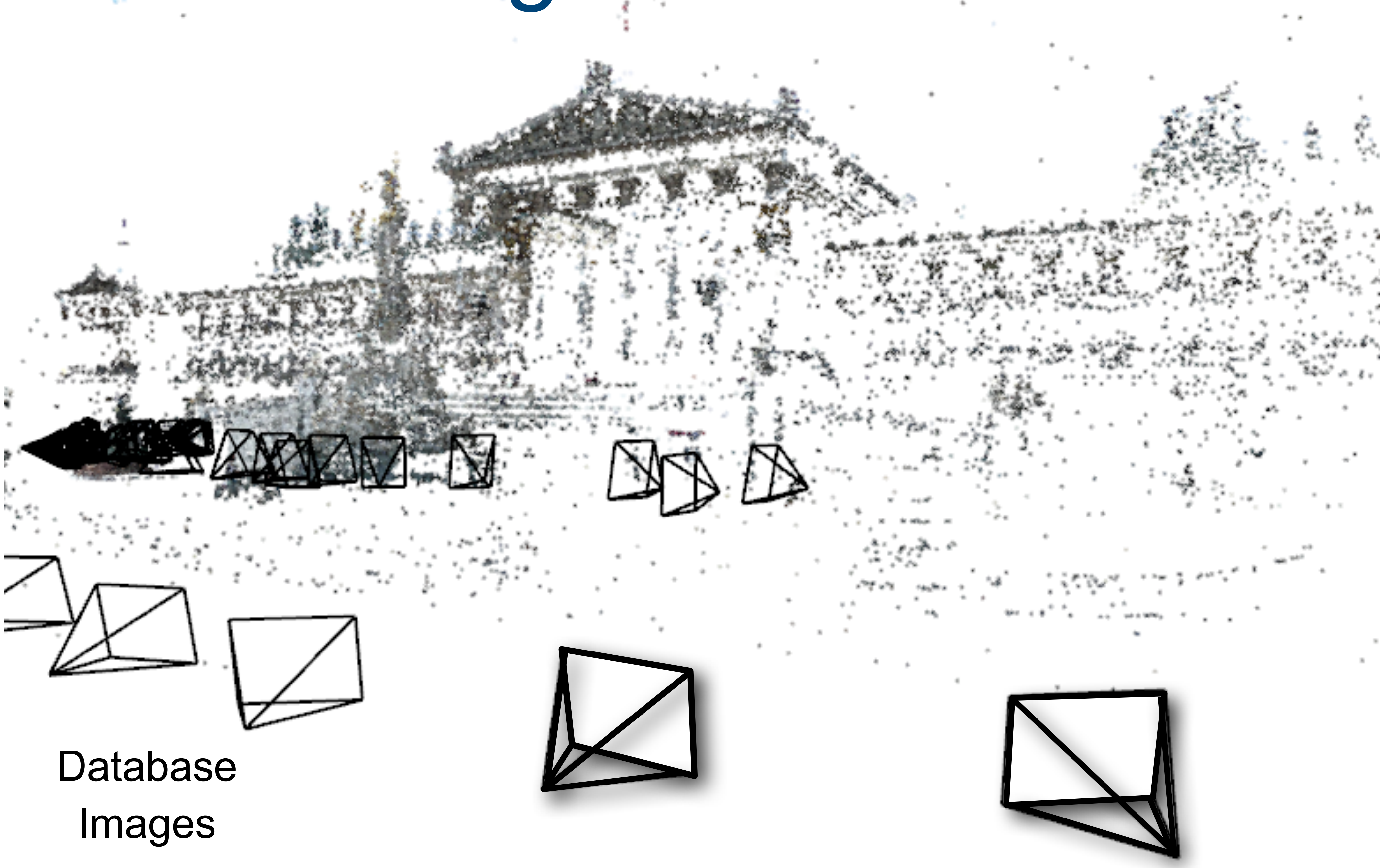

- 3D model from SfM

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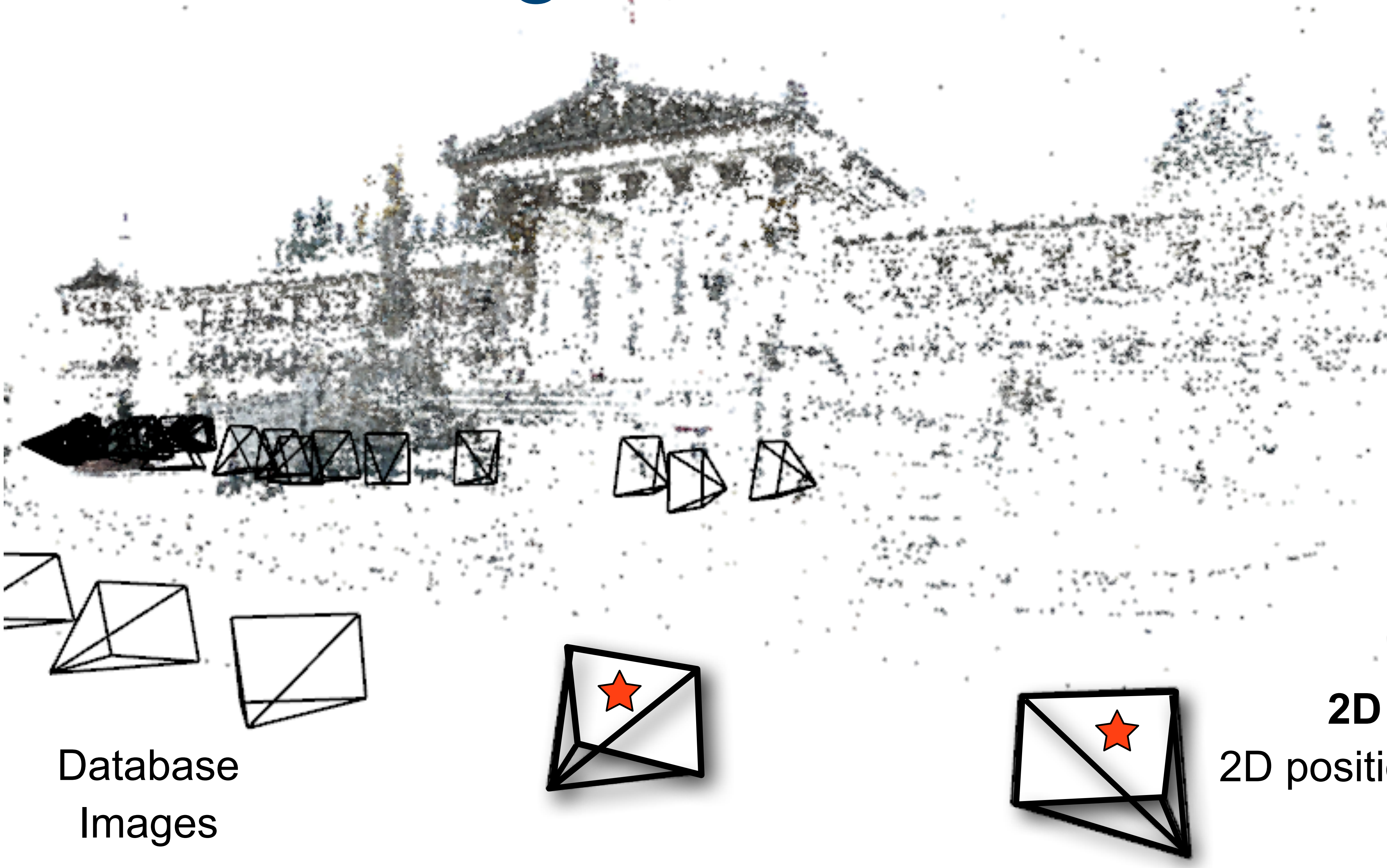

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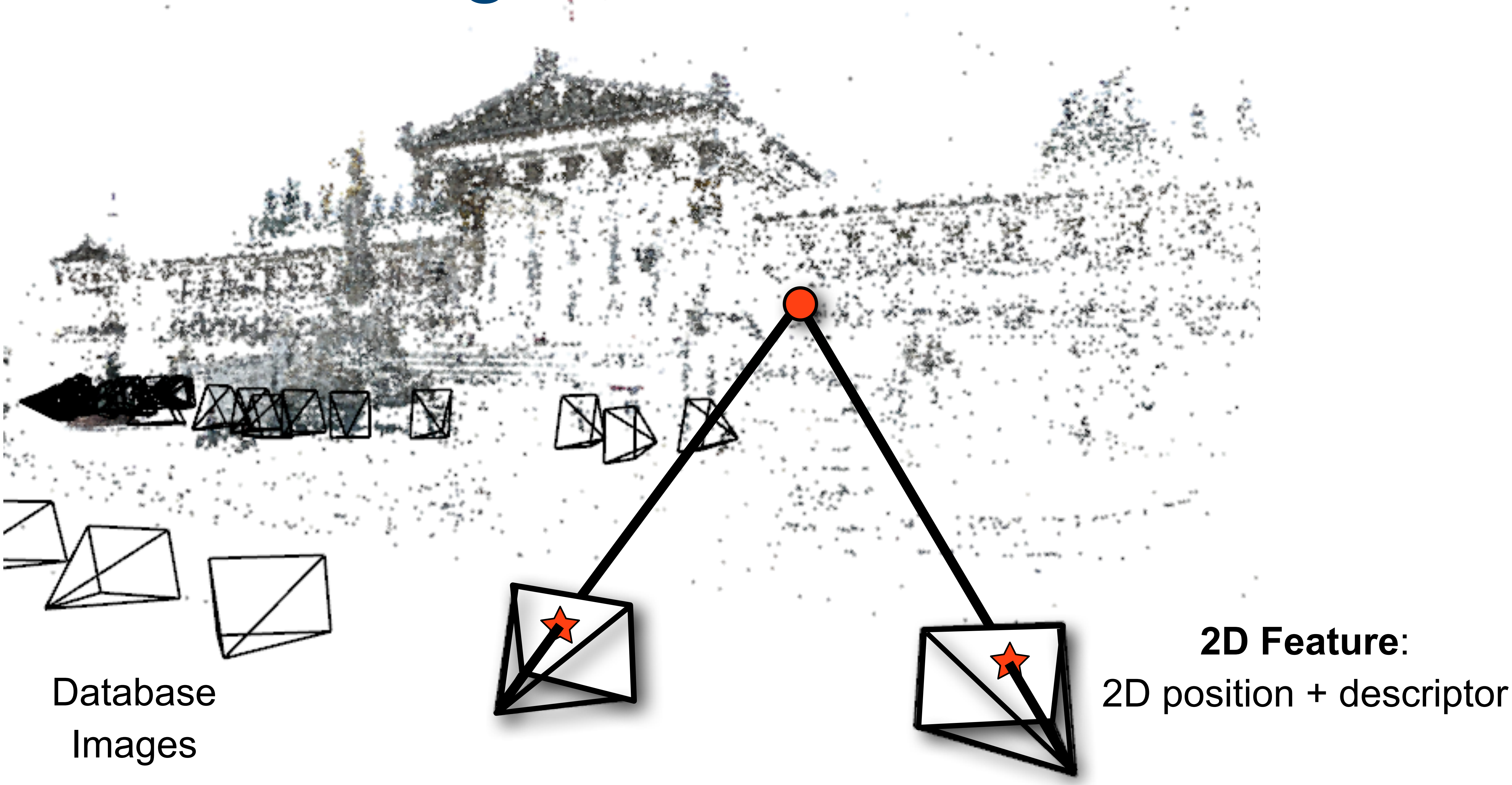

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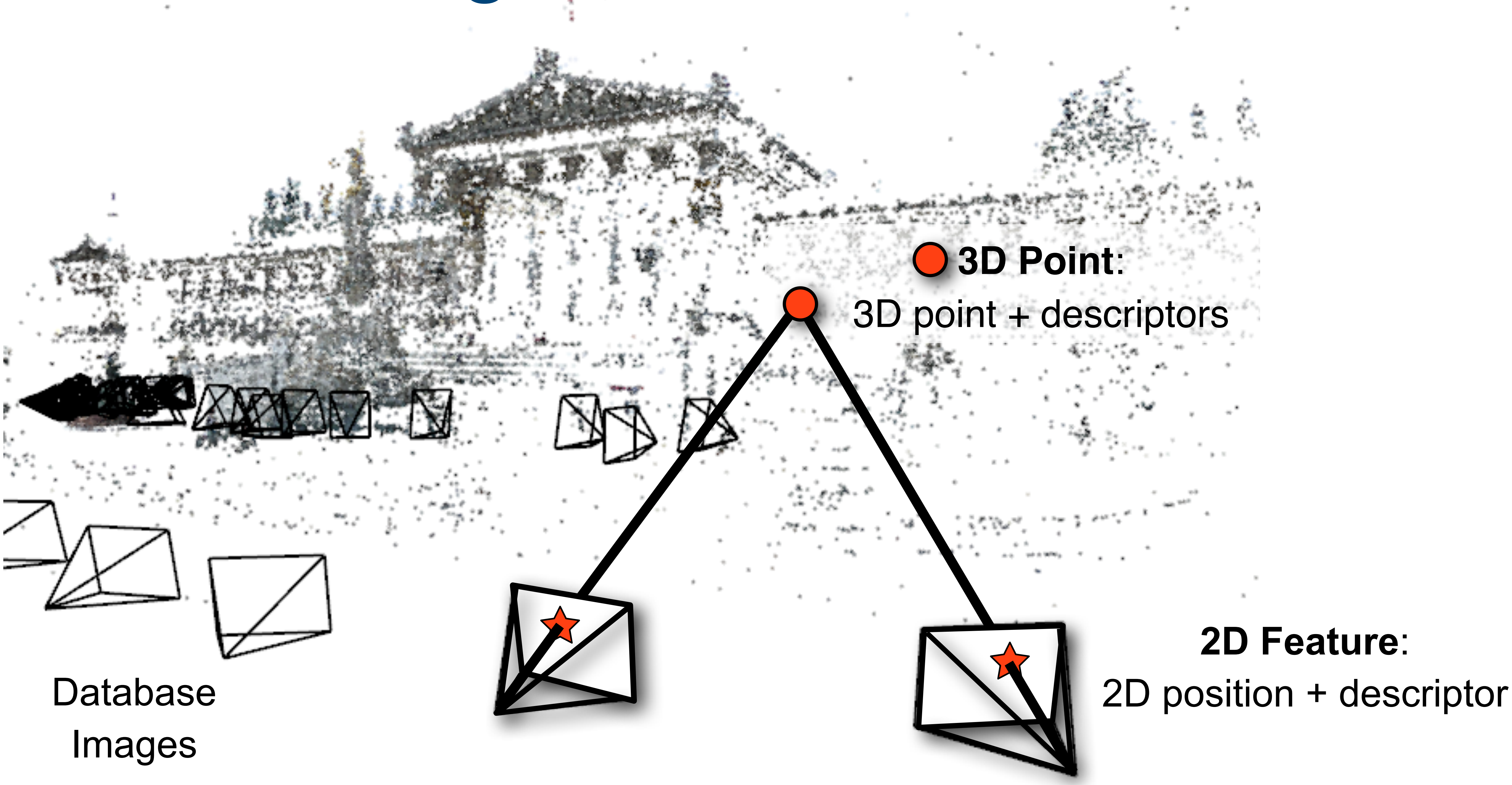

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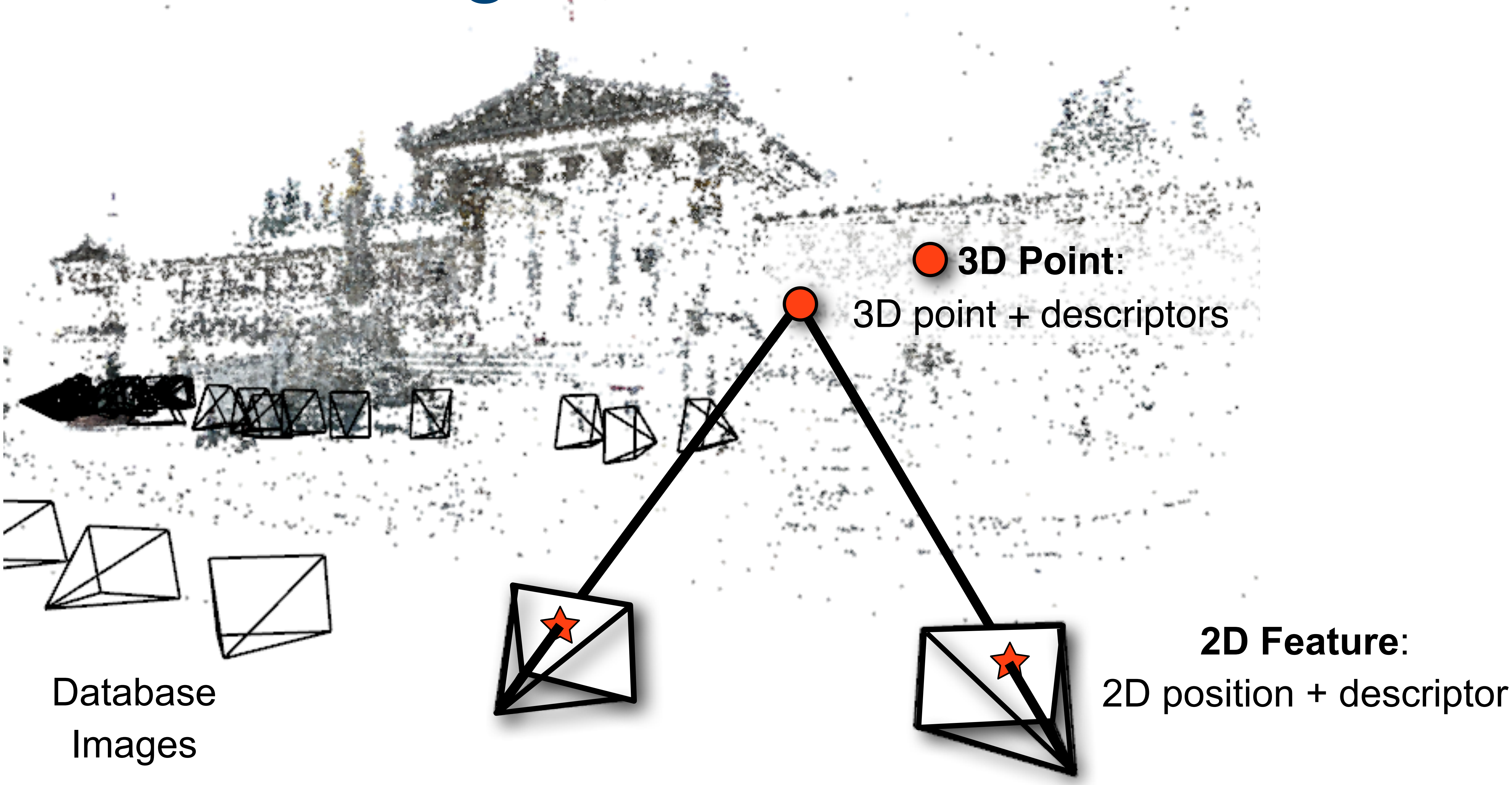

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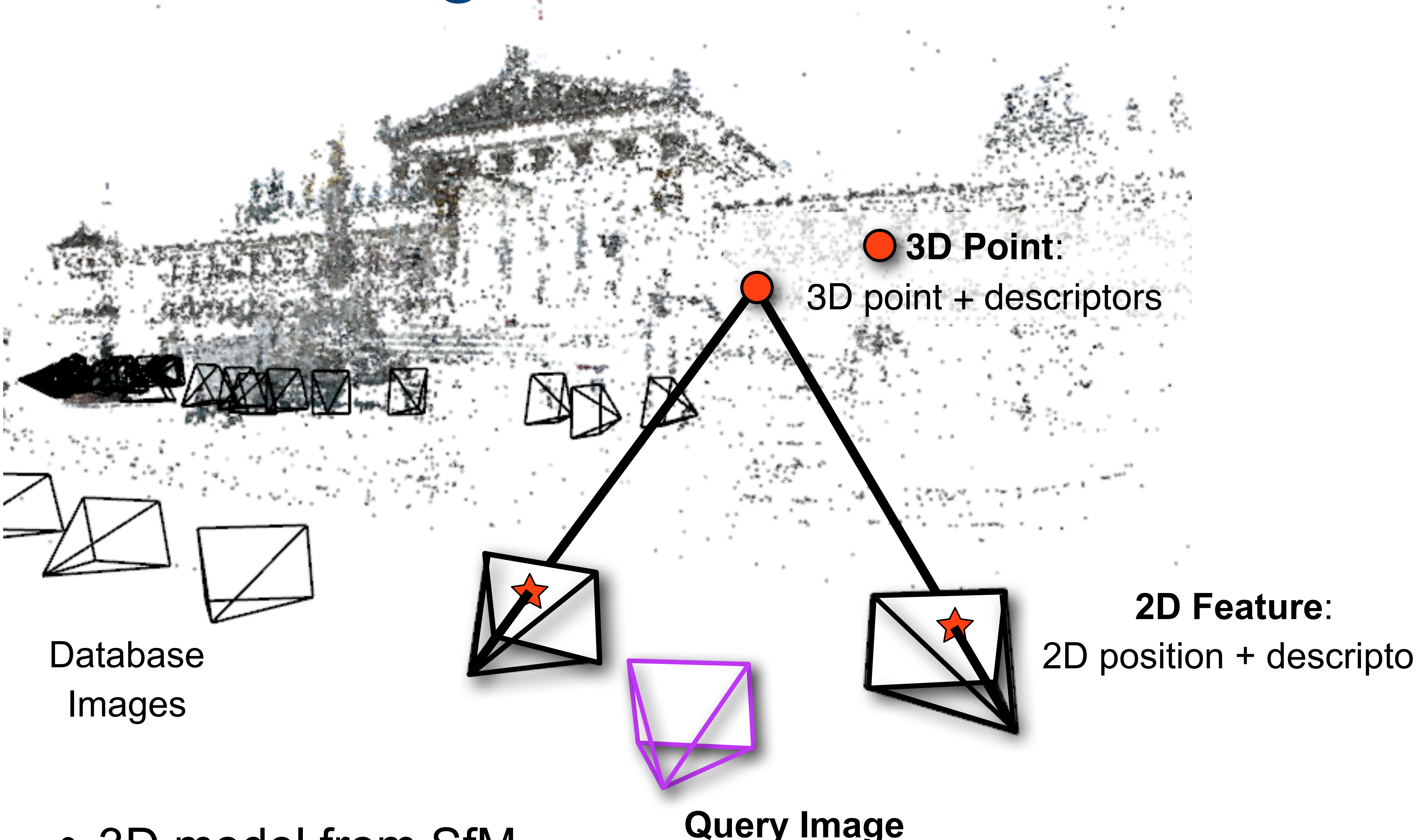

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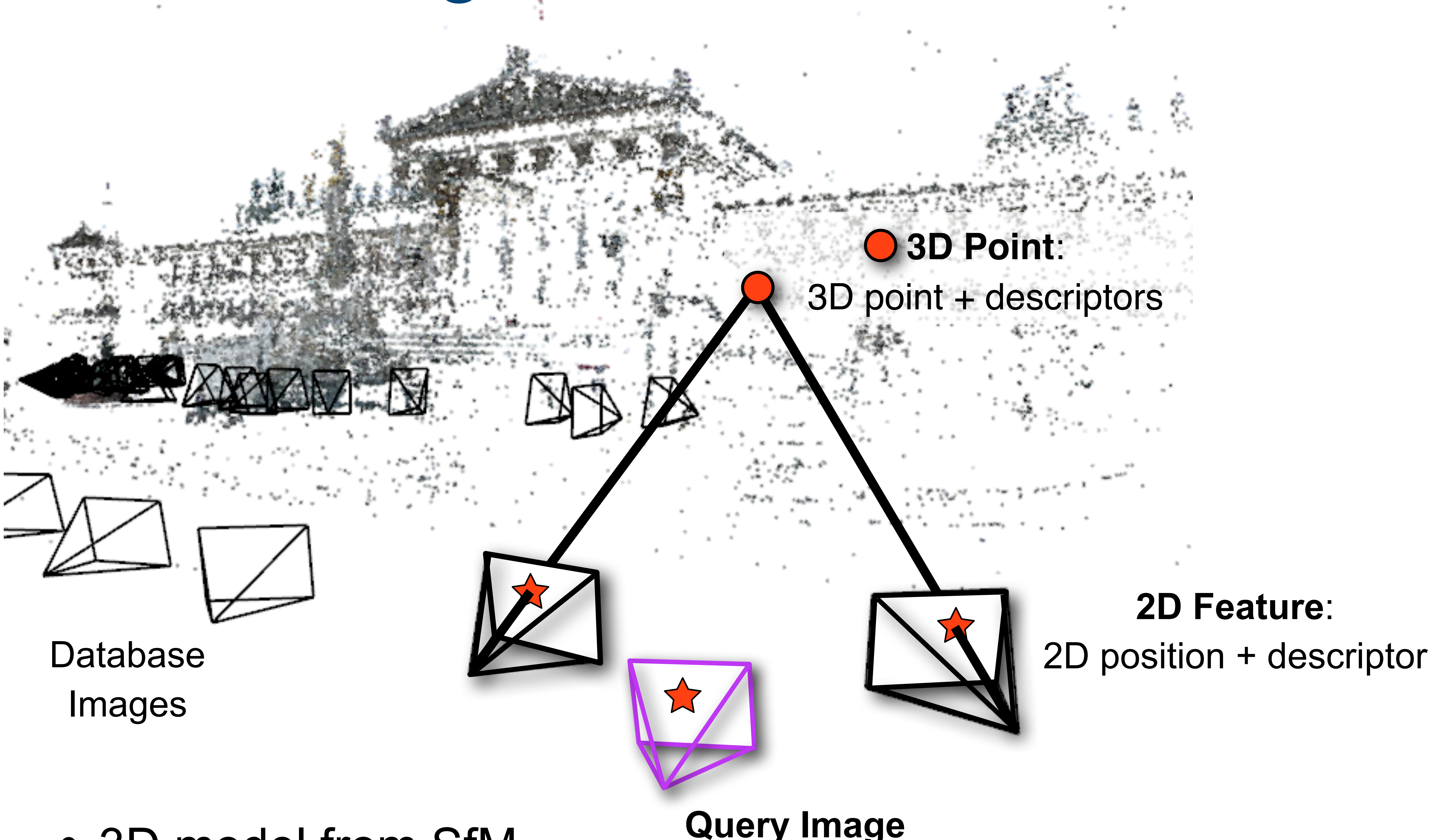

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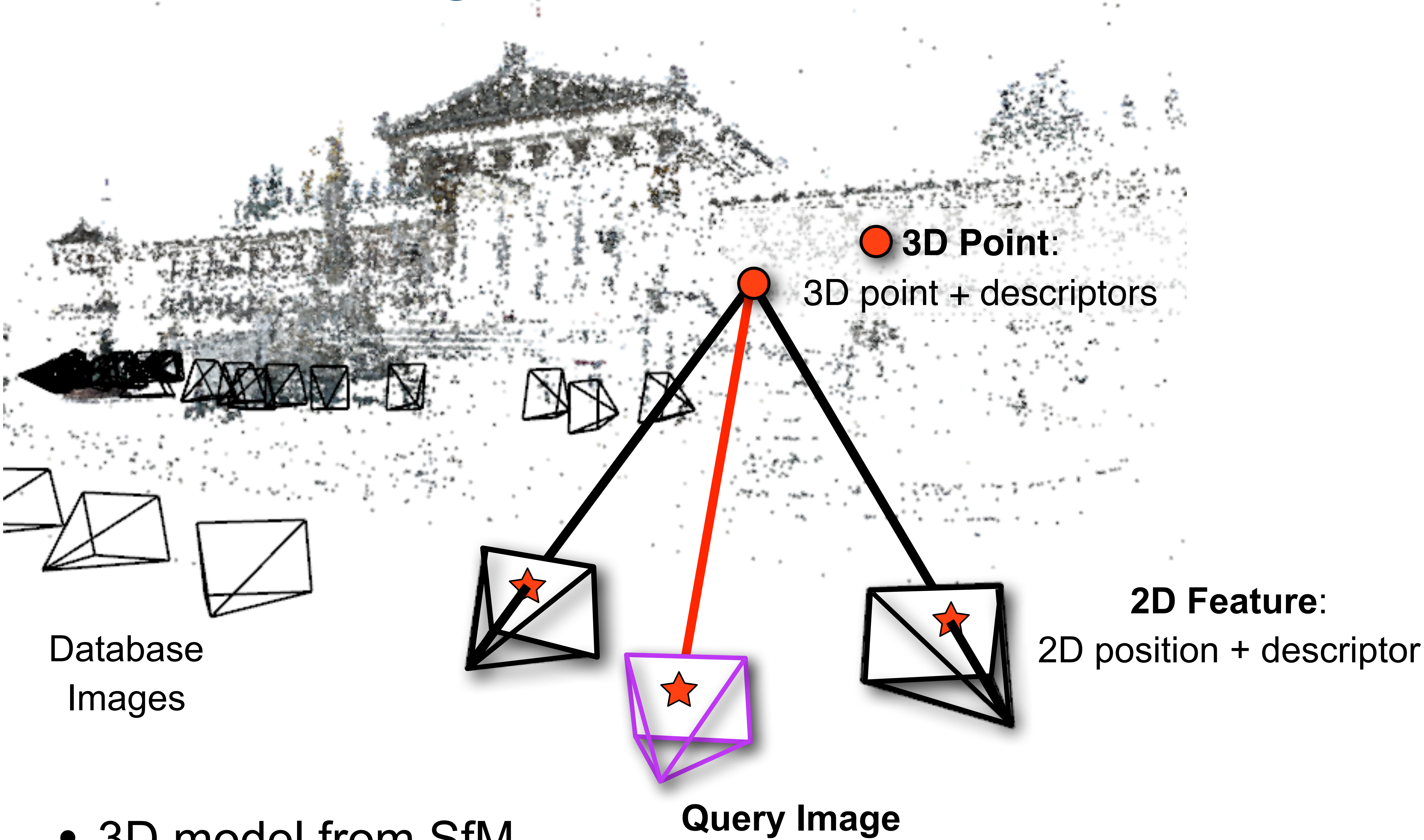

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Challenges

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- **Effectiveness**: Localize all query images

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- **Effectiveness**: Localize all query images
- **Accuracy**: Accurately recover camera pose

Overview

- Efficient & Effective Large-Scale Localization
- Real-Time Mobile Localization
- Open Challenges

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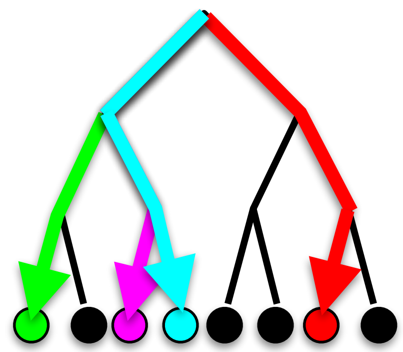
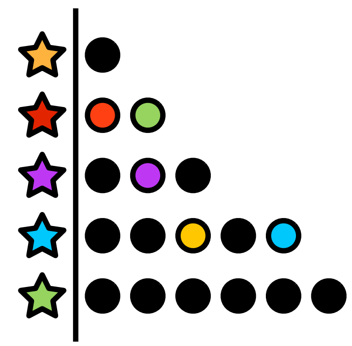
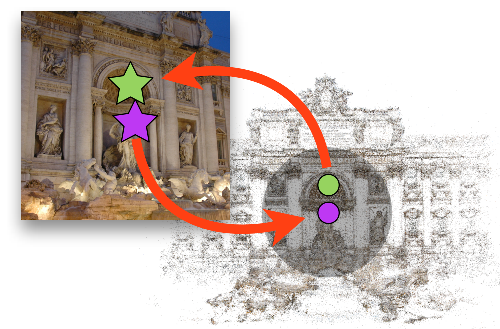
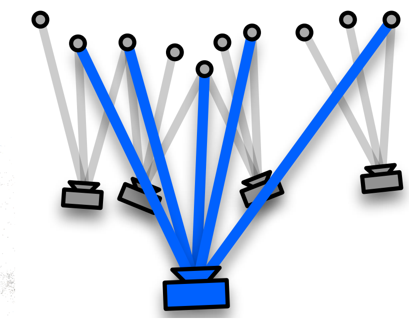
Localization - Overview









	Baseline: kd-tree search	**VPS**	**Active Search**	**+ Visibility Filtering**
	[Sattler et al., ICCV'11]	[Sattler et al., ICCV'11]	[Sattler et al., ECCV'12]	
effectiveness	✓	✗	✓✓	✓✓
efficiency	✗ ✗	✓	✗	✓

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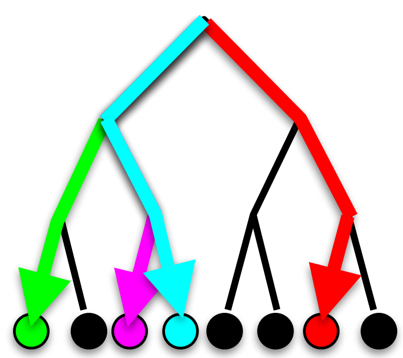

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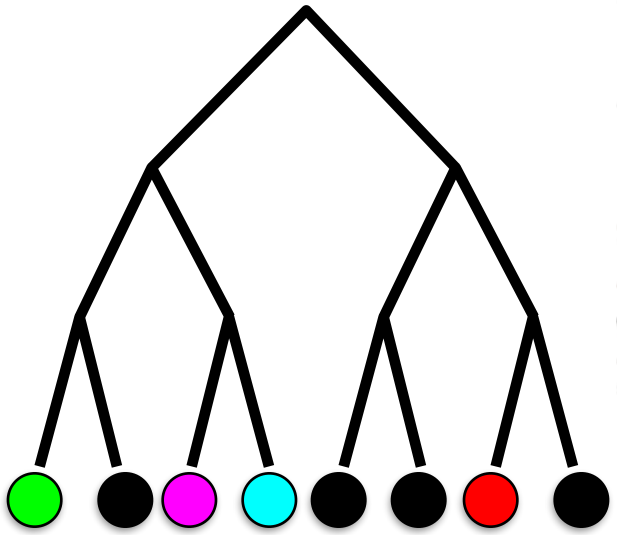
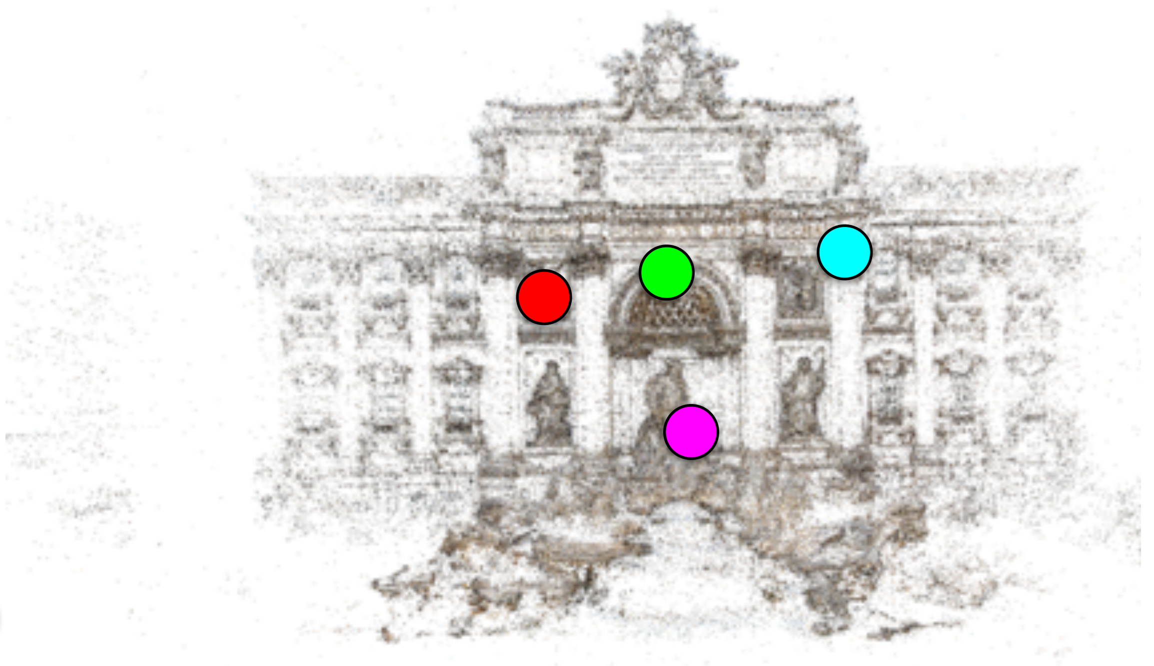
Baseline: Tree-Based Search



kd-tree



3D Model

[Sattler et al., ICCV'11] [code]

photo credit: Ming Li

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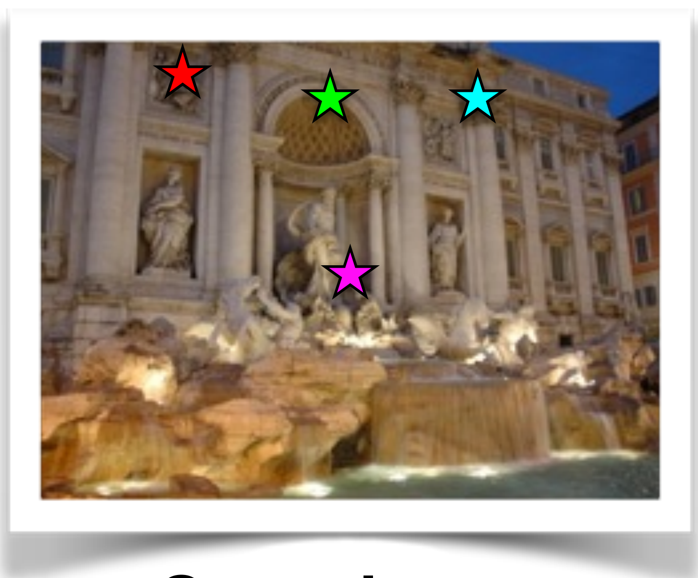
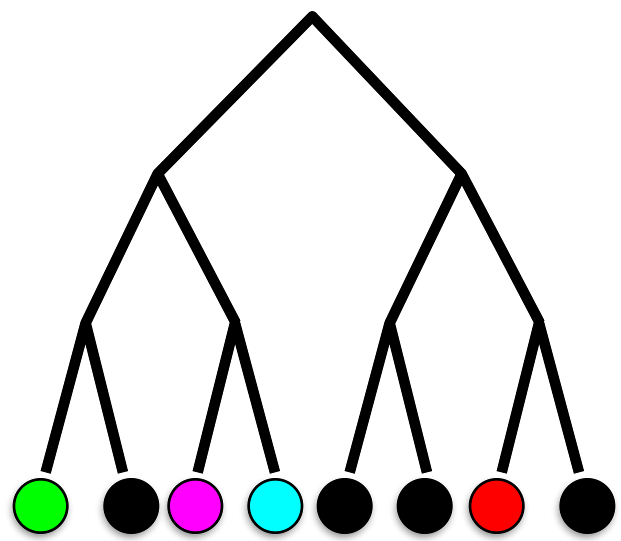
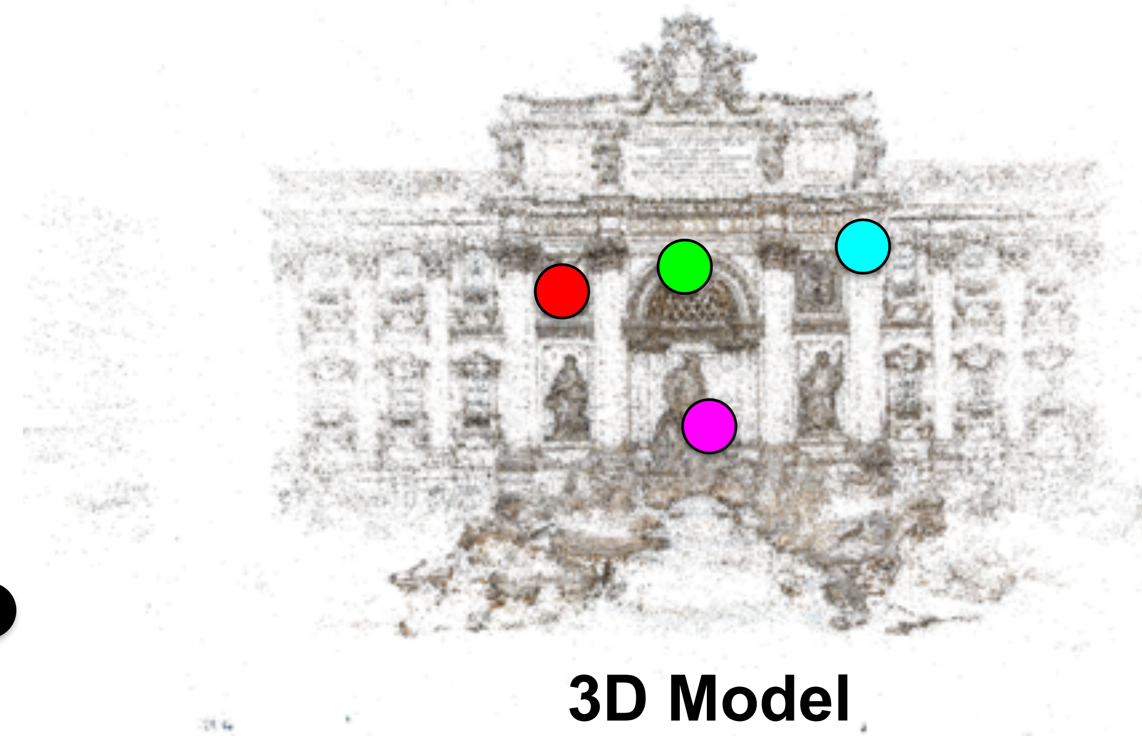


Query Image



kd-tree



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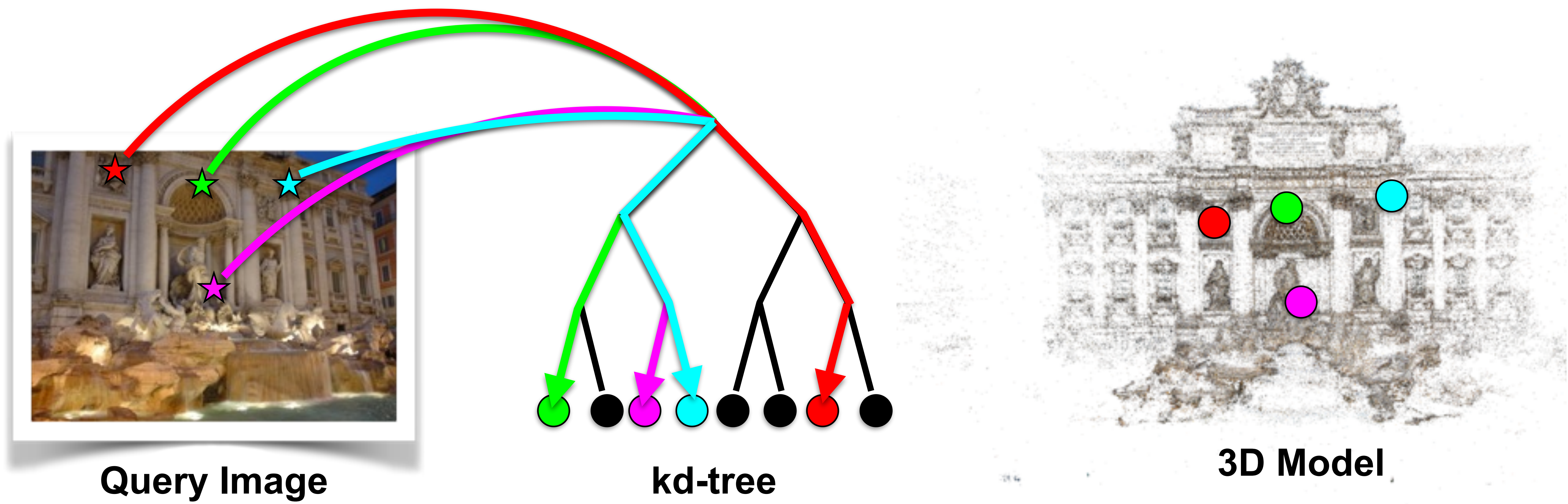

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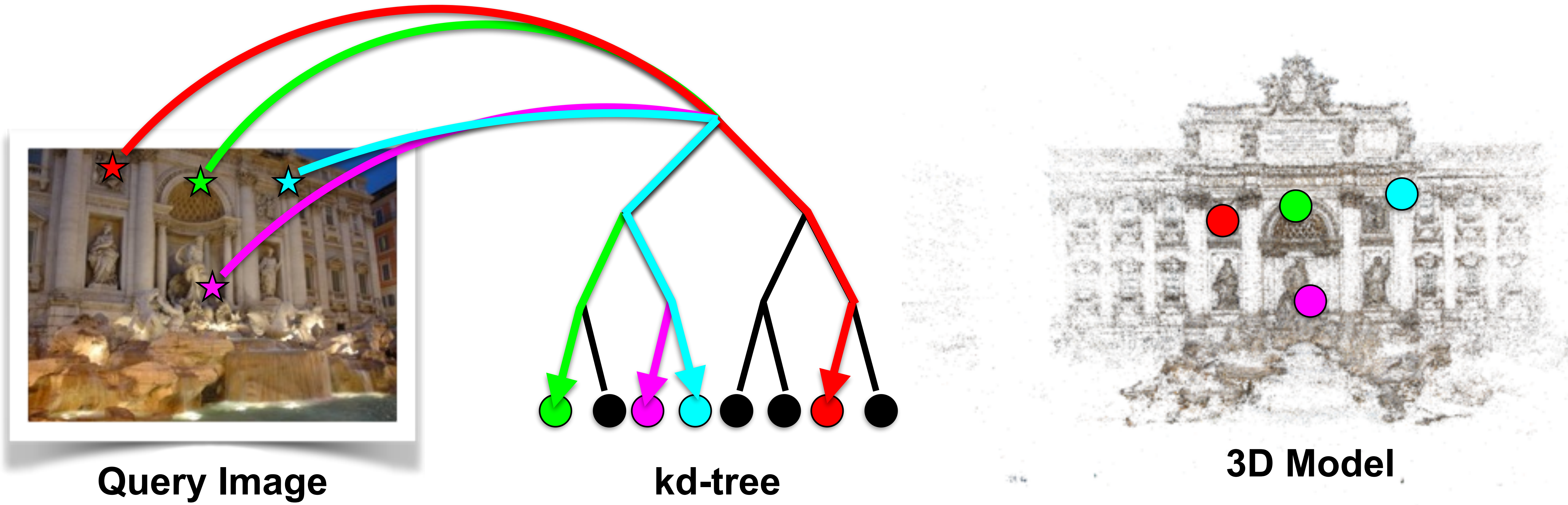

2-nn search & ratio test

$$\frac{||d - d_1||_2}{||d - d_2||_2} < 0.7$$

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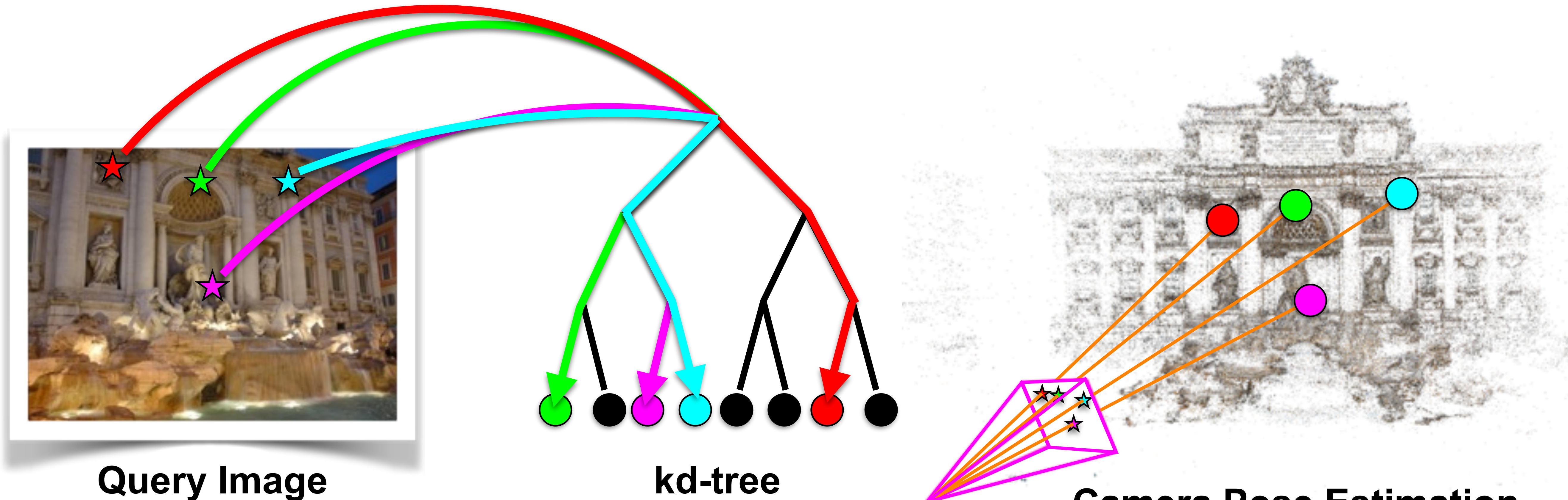

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LO-RANSAC + $T_{1,1}$ + p6p

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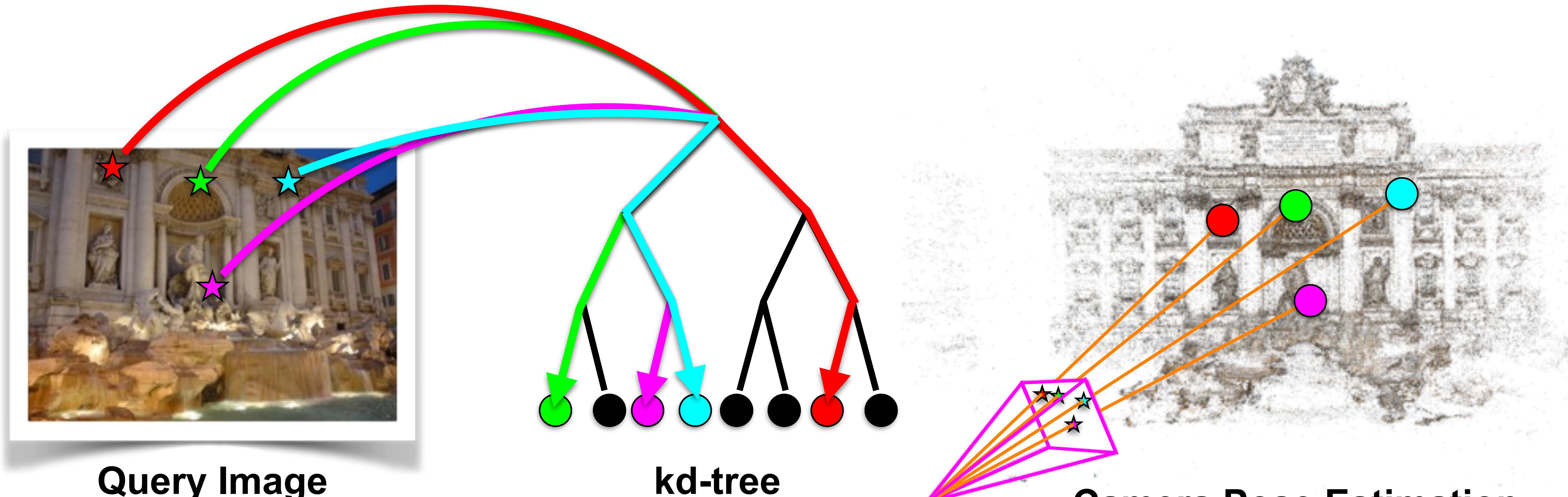

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Camera Pose Estimation

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pose valid if ≥ 12 inliers

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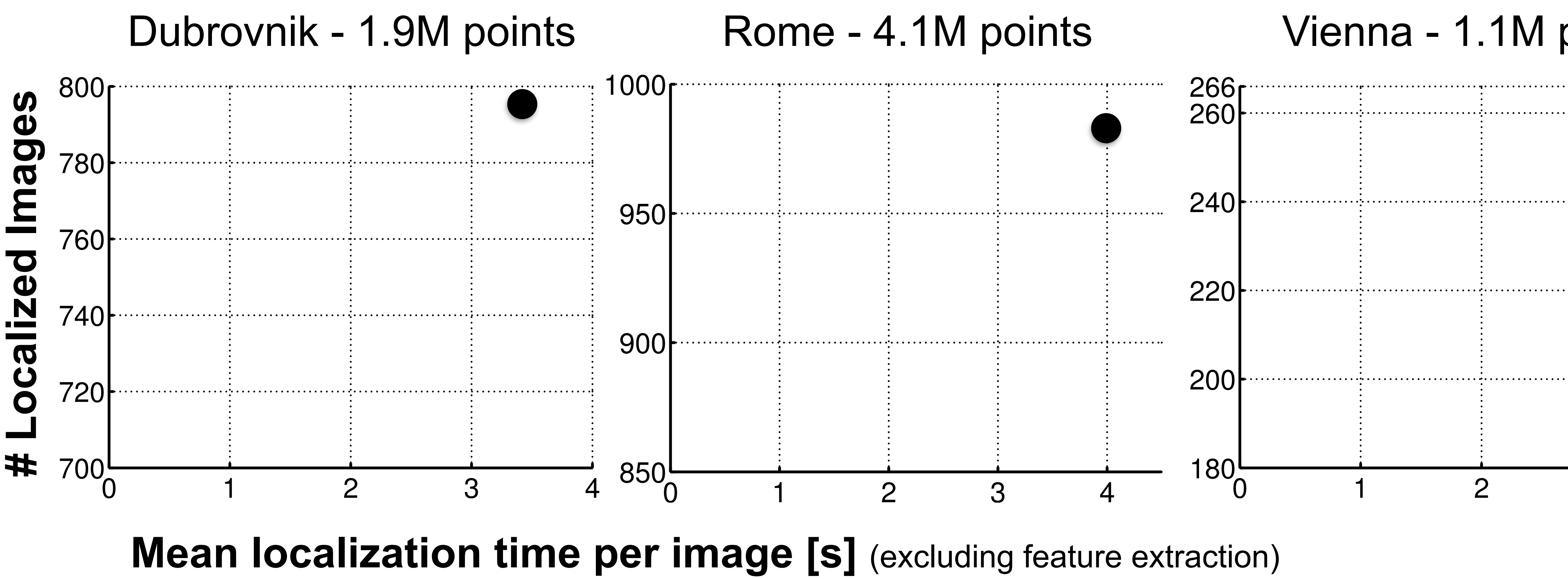
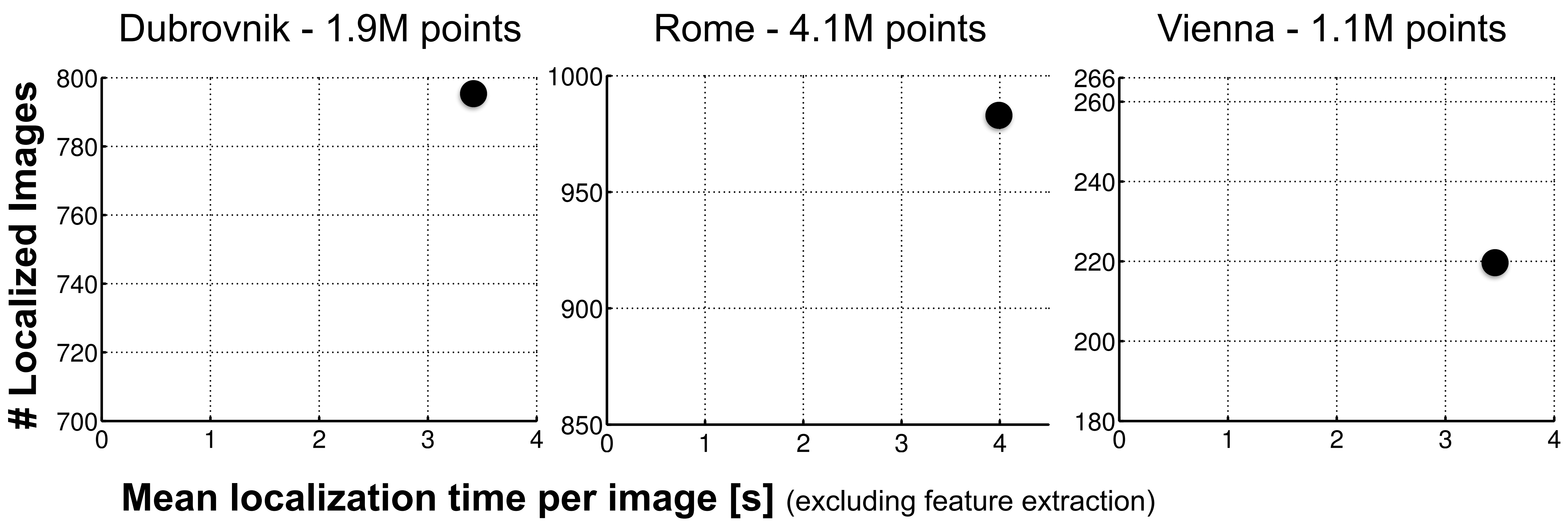
Results



Dubrovnik - 1.9M points
Rome - 4.1M points
Vienna - 1.1M points
Localized Images
800
780
760
740
720
700
1000
950
900
850
266
260
240
220
200
180
0
1
2
3
4
Mean localization time per image [s] (excluding feature extraction)

Results



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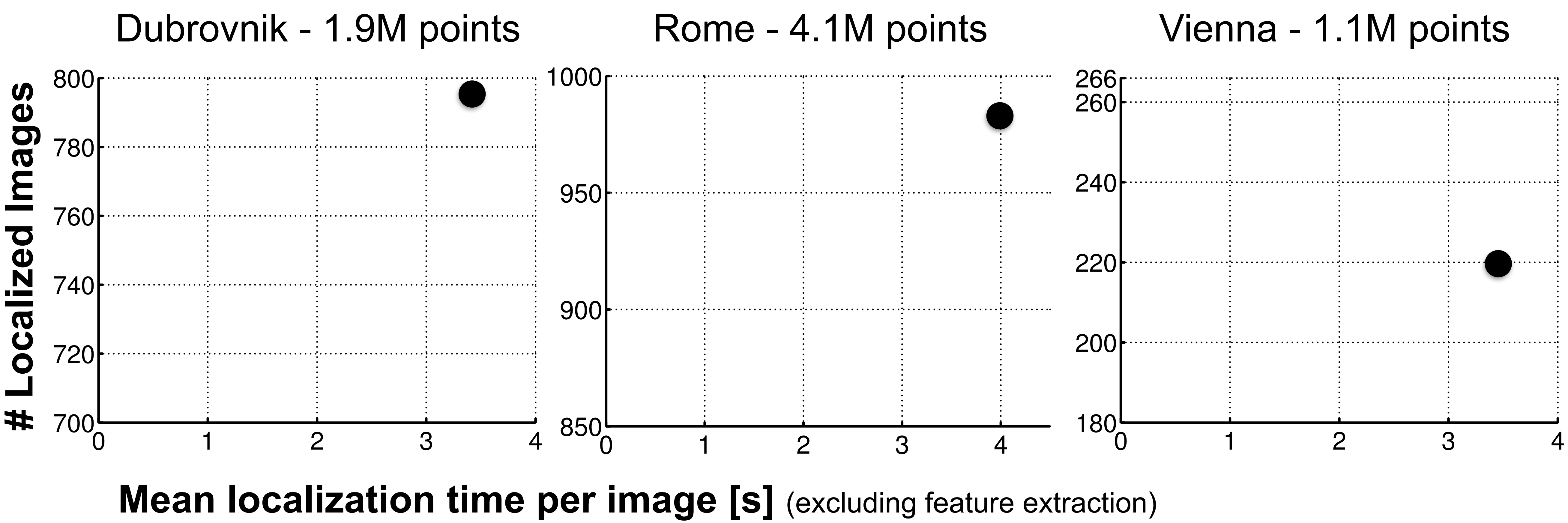

✓ Excellent localization effectiveness…

✗ … but very slow!

Potential for Faster Search

[Sattler et al., ICCV'11]

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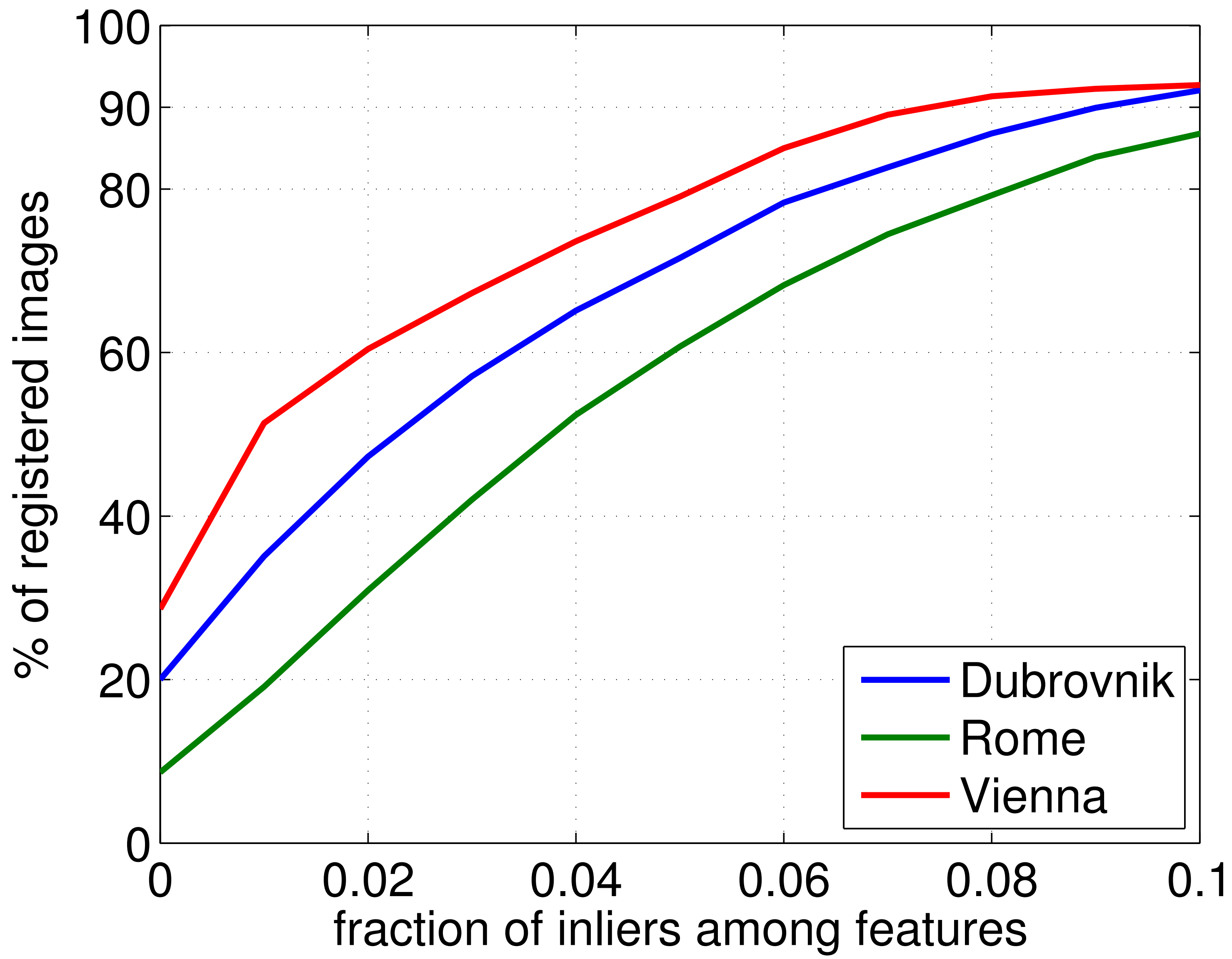

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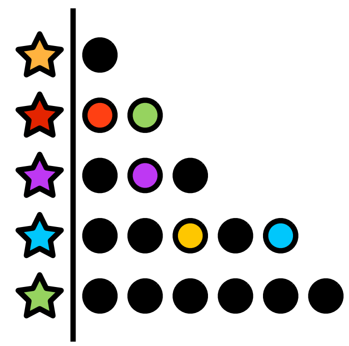

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$$\min \sum_i X_i c_i \quad \text{s.t.} \quad \sum_i X_i p_i \geq N_t \text{ with } X_i \in \{0, 1\}$$

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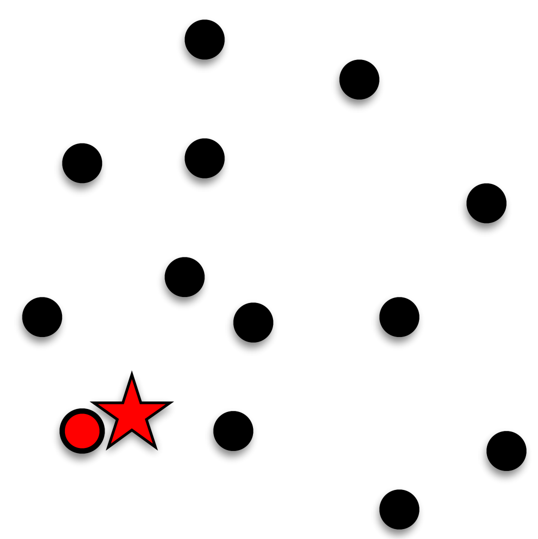

Efficient computation of p_i, c_i

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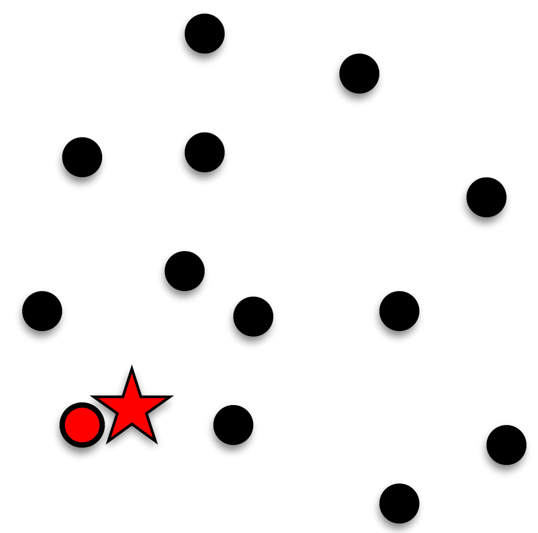

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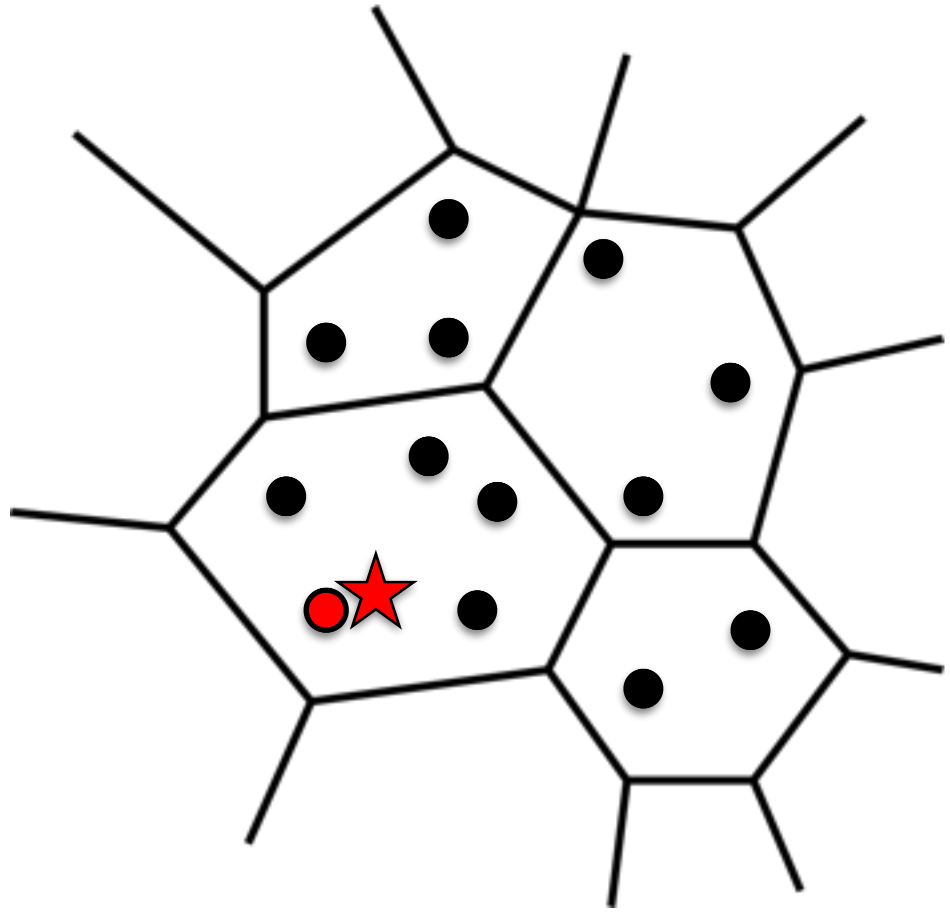

Fixed & Precomputed Visual Vocabulary

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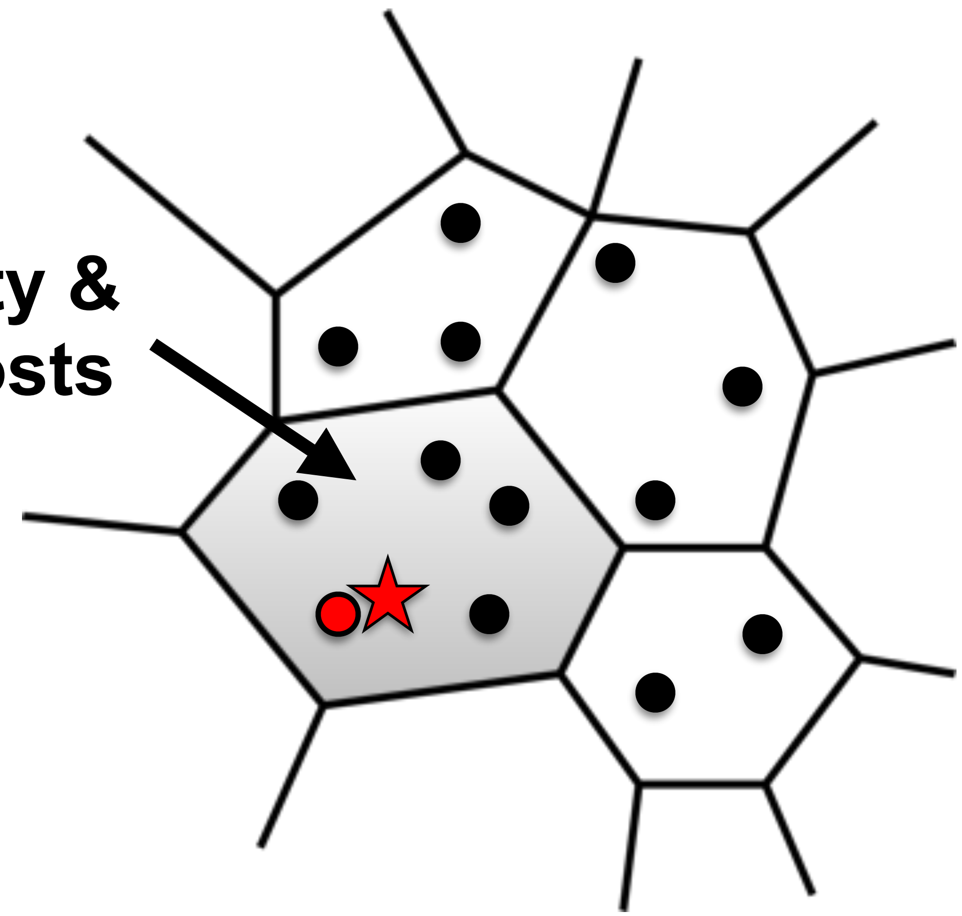
Constant probability & constant search costs



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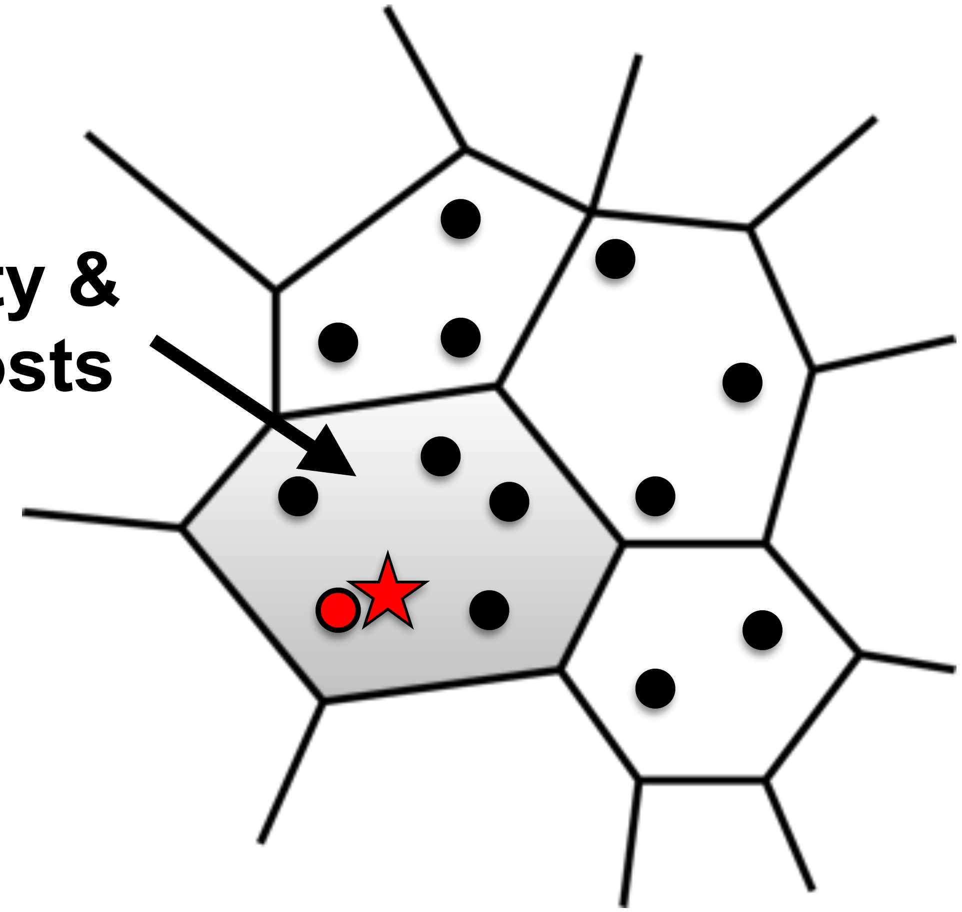

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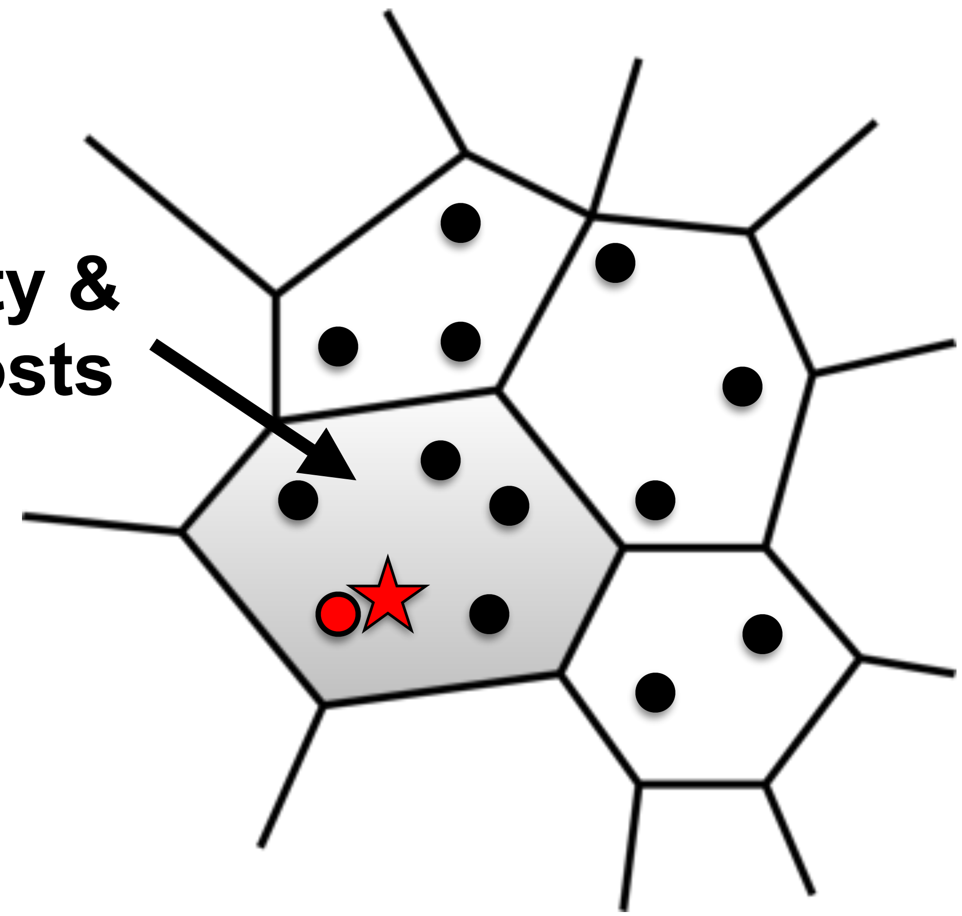

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- Precompute probabilities for **regions** in descriptor space
- Limit nearest neighbor search to same cell (**Quantized Search**)
- Computation in constant time for fixed-size vocabulary

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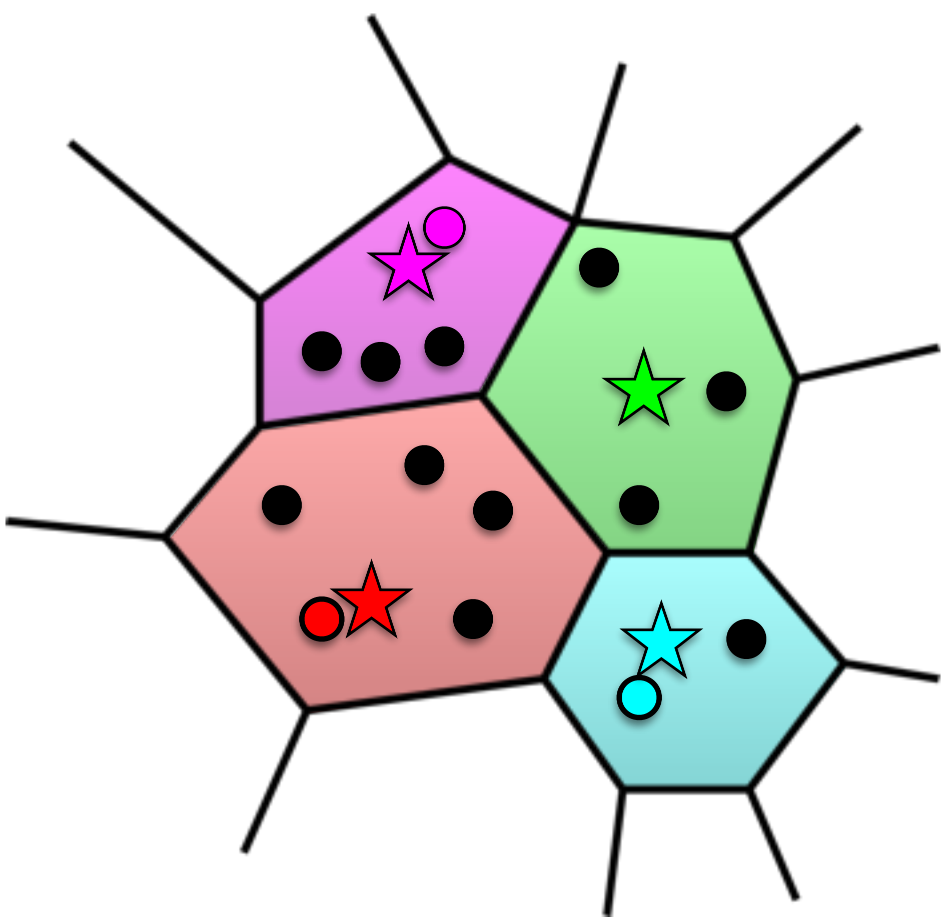

Resulting order:

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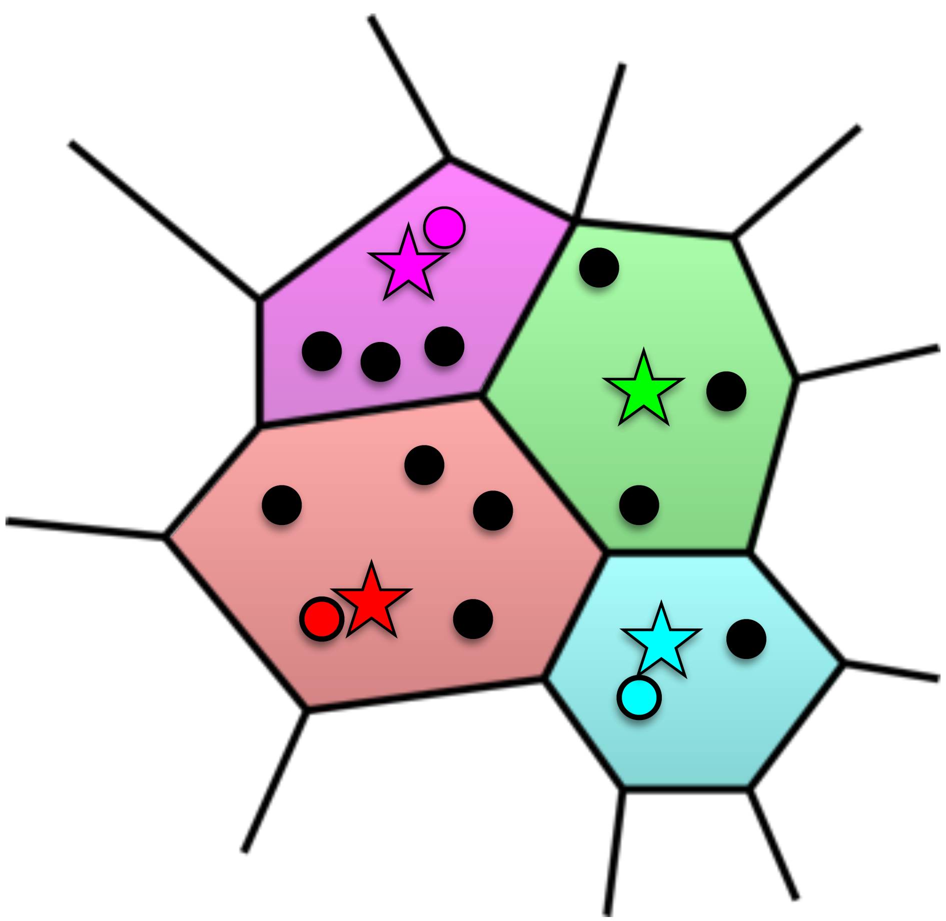

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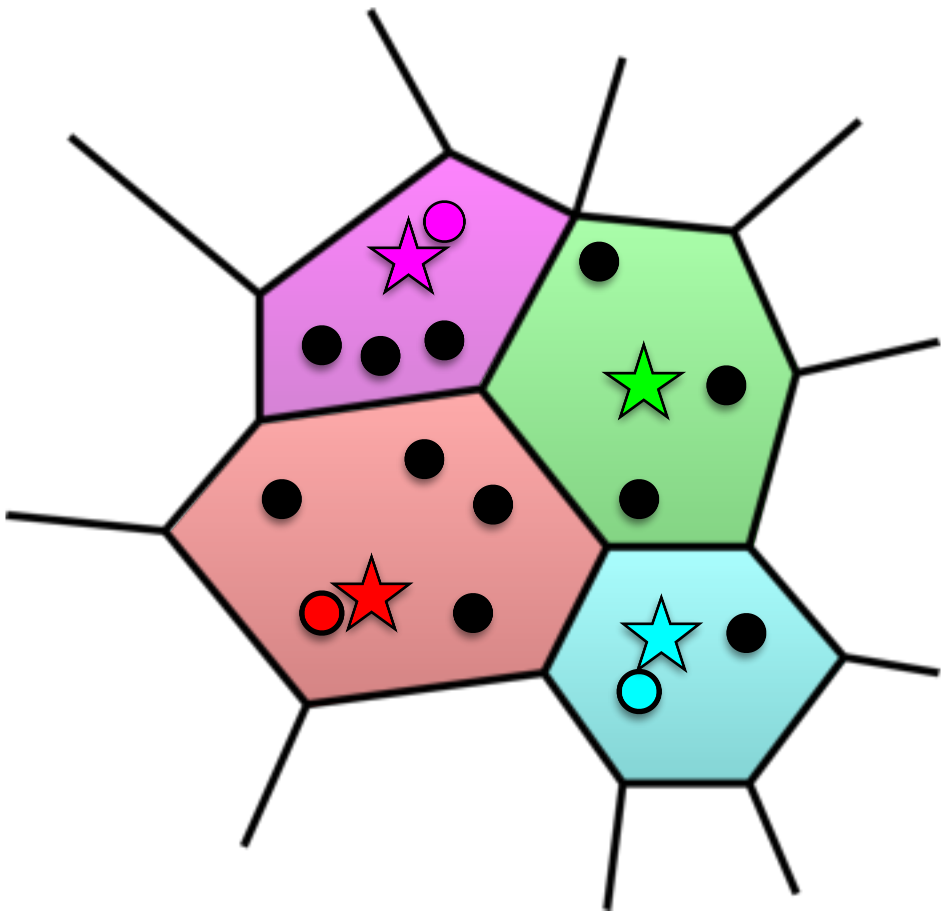
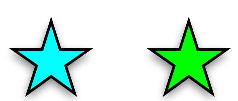
  - Sort features with $p_i>0$ in ascending order of search costs
  - Select first m features such that $\sum_{i=1}^{m} p_i \geq N_t$



Resulting order:



A Greedy Approach

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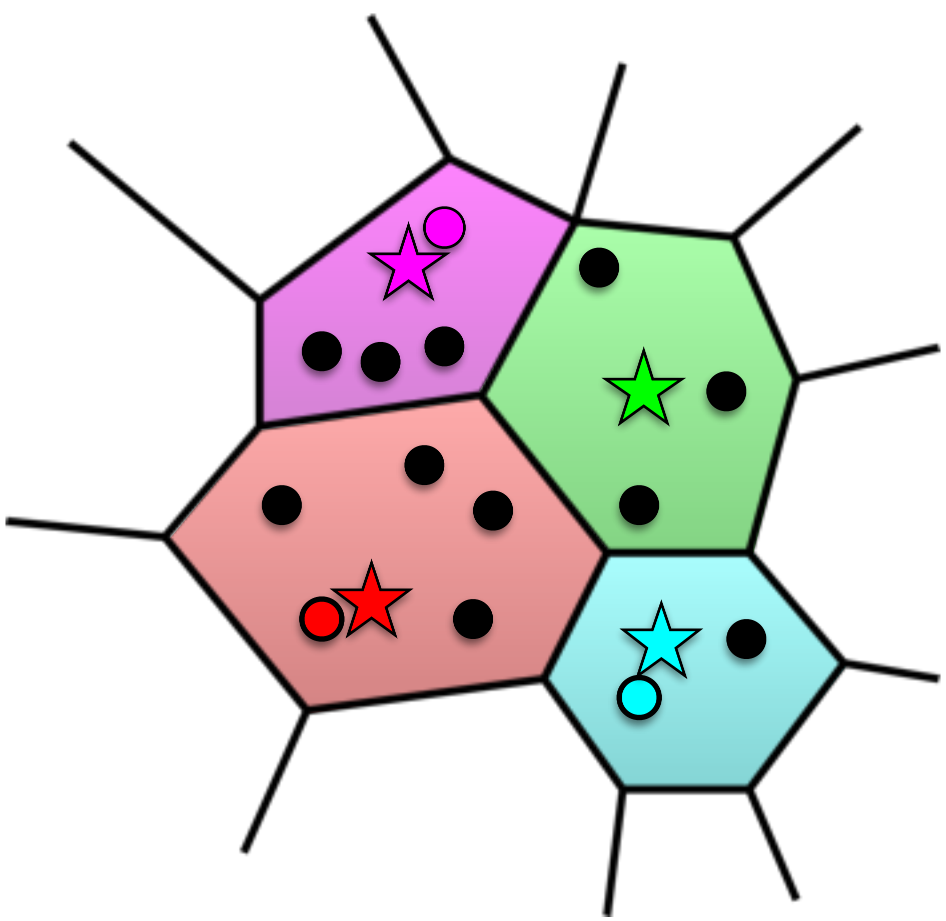
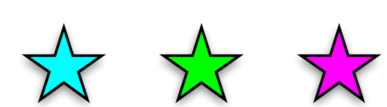


Resulting order:



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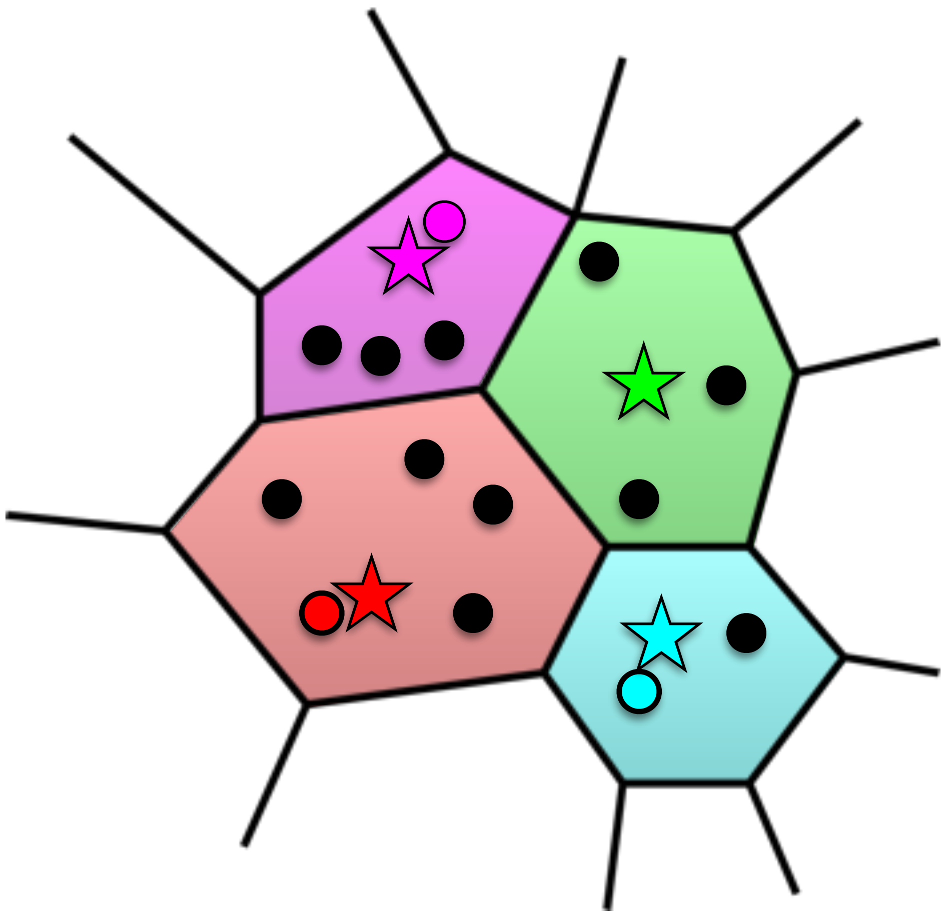
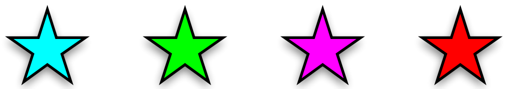


Resulting order:



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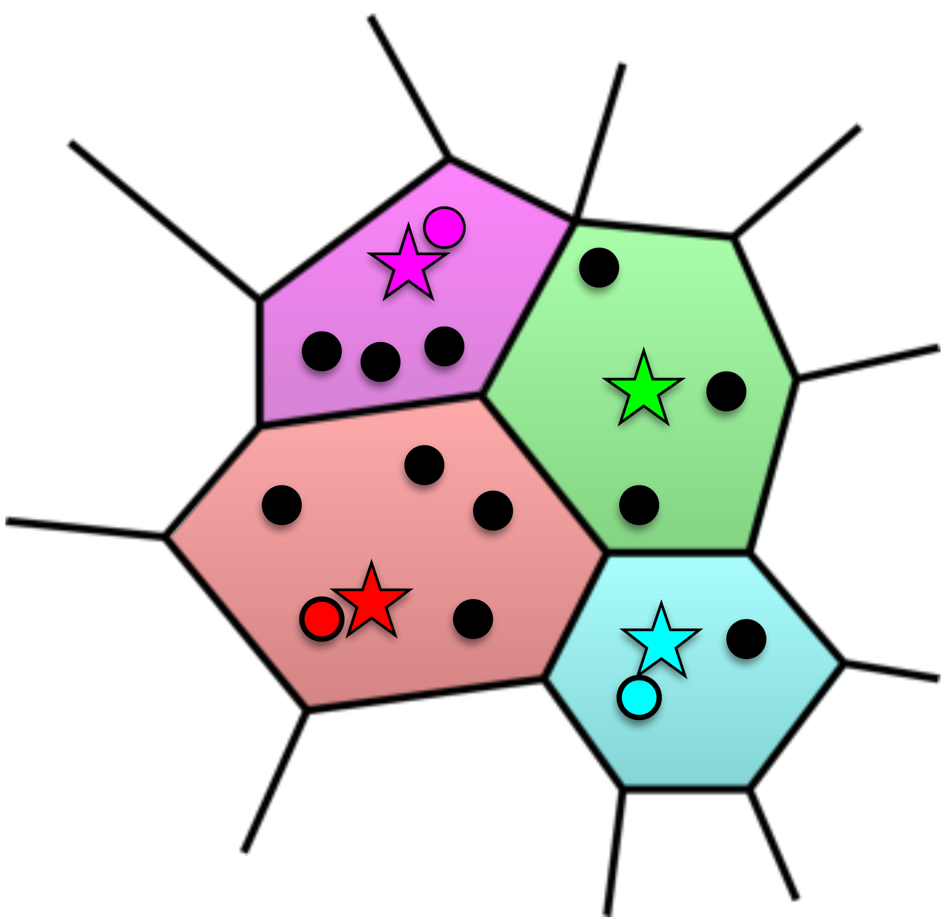
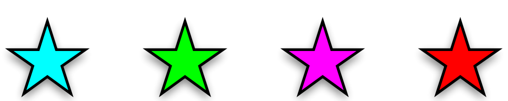


Resulting order:



Globally unique

A Greedy Approach

- Solving $\min \sum_i X_i c_i \text{ s.t. } \sum_i X_i p_i \geq N_t$ is **NP-complete**
- Simple Greedy strategy:
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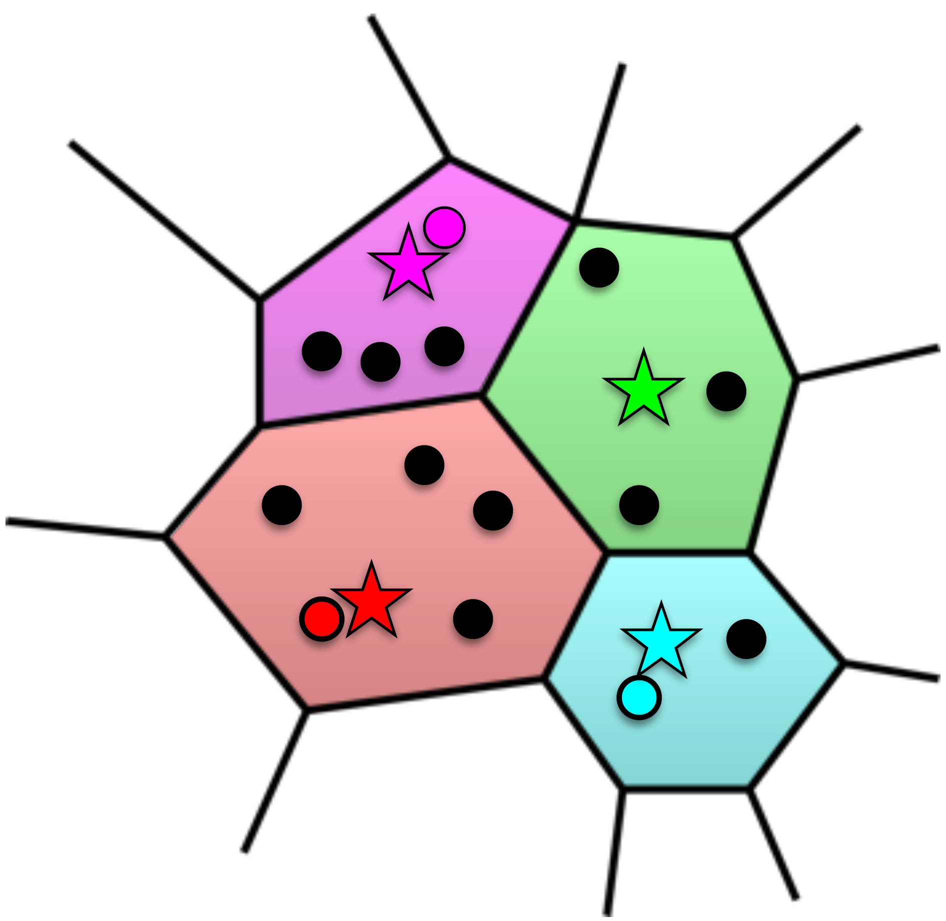

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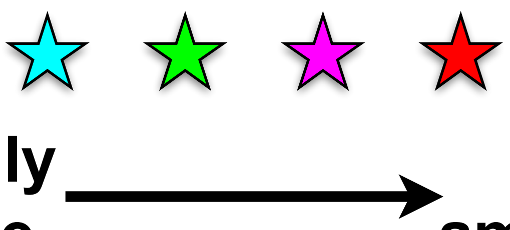
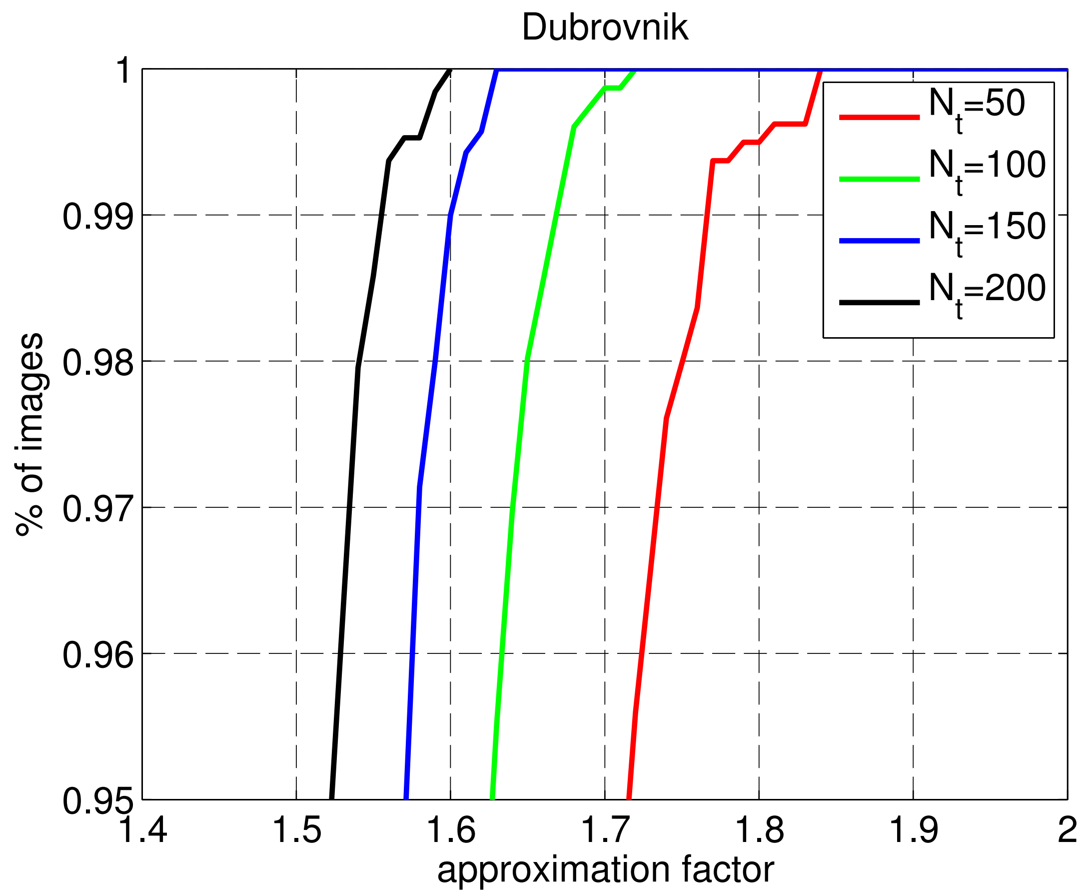
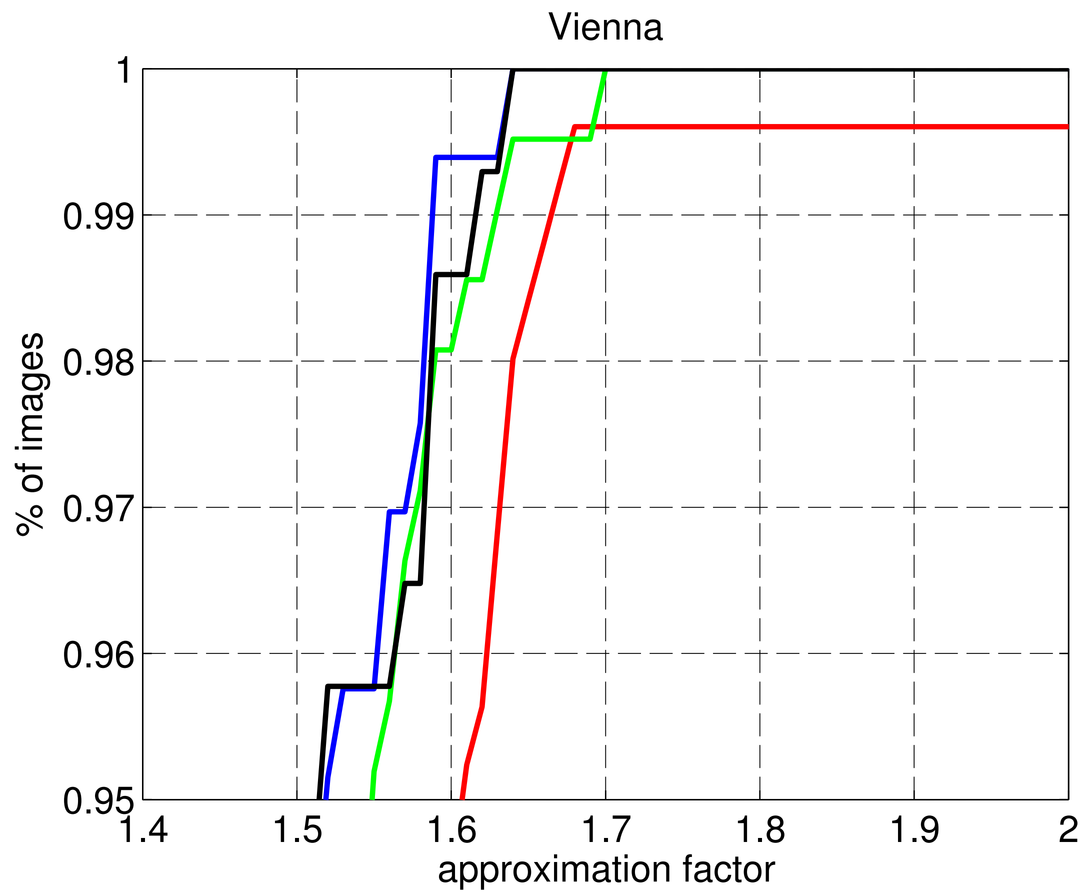


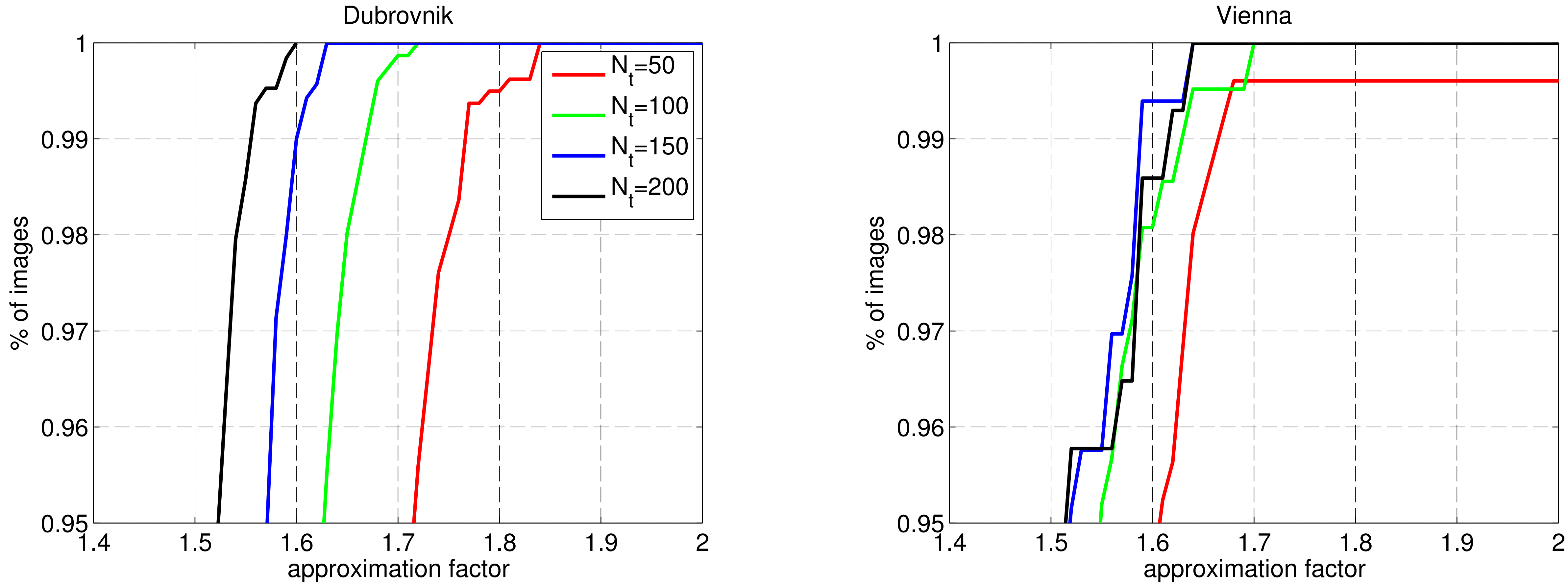
Globally unique → **Highly ambiguous**

Greedy vs. OPT



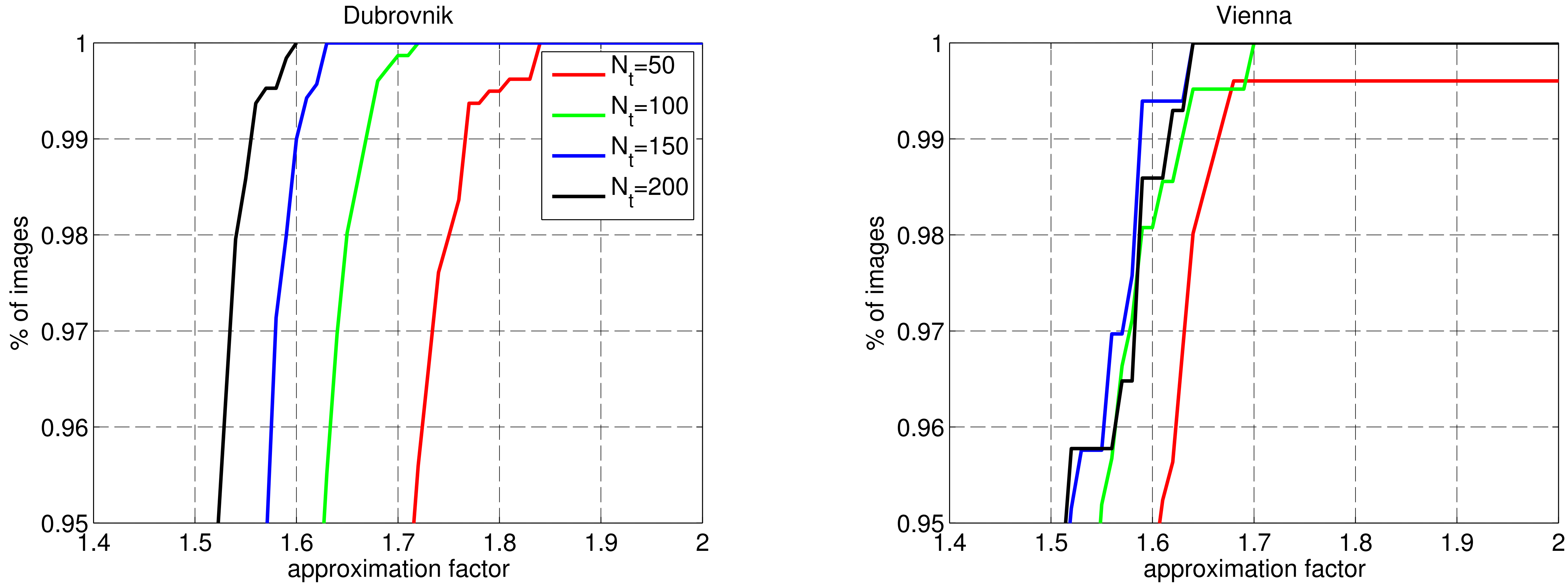


Greedy vs. OPT



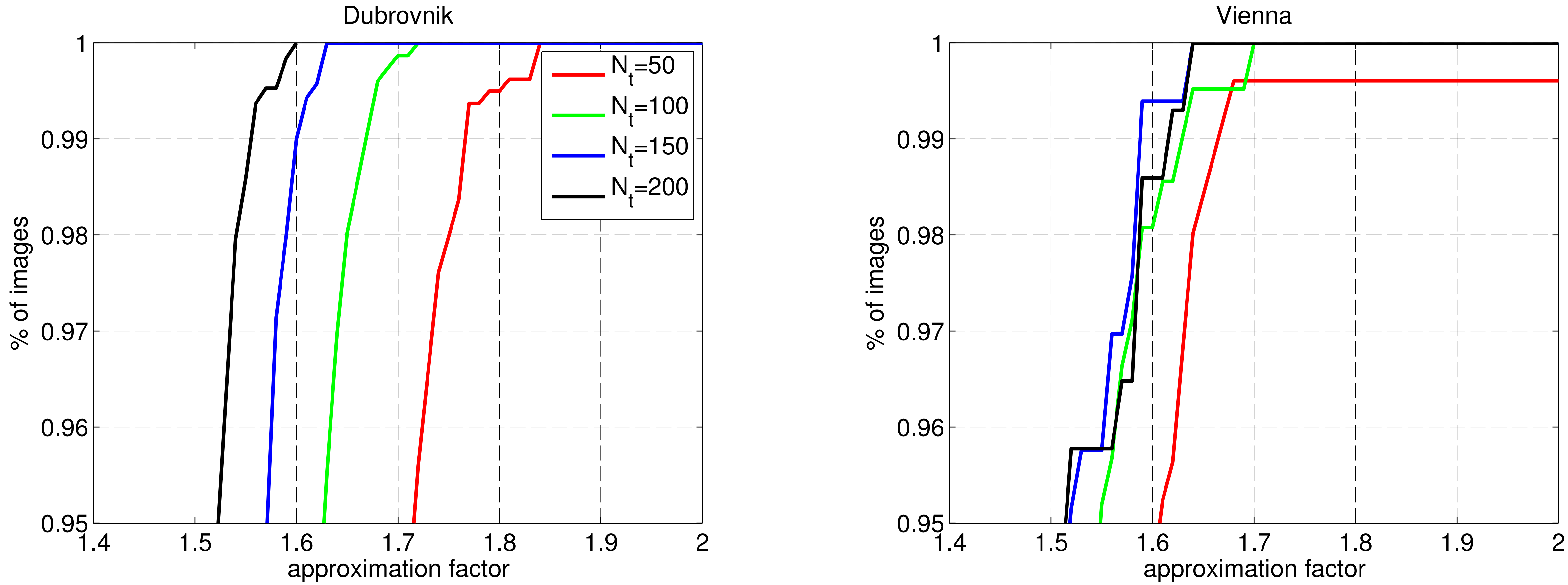
- Greedy performs close to optimal!

Greedy vs. OPT



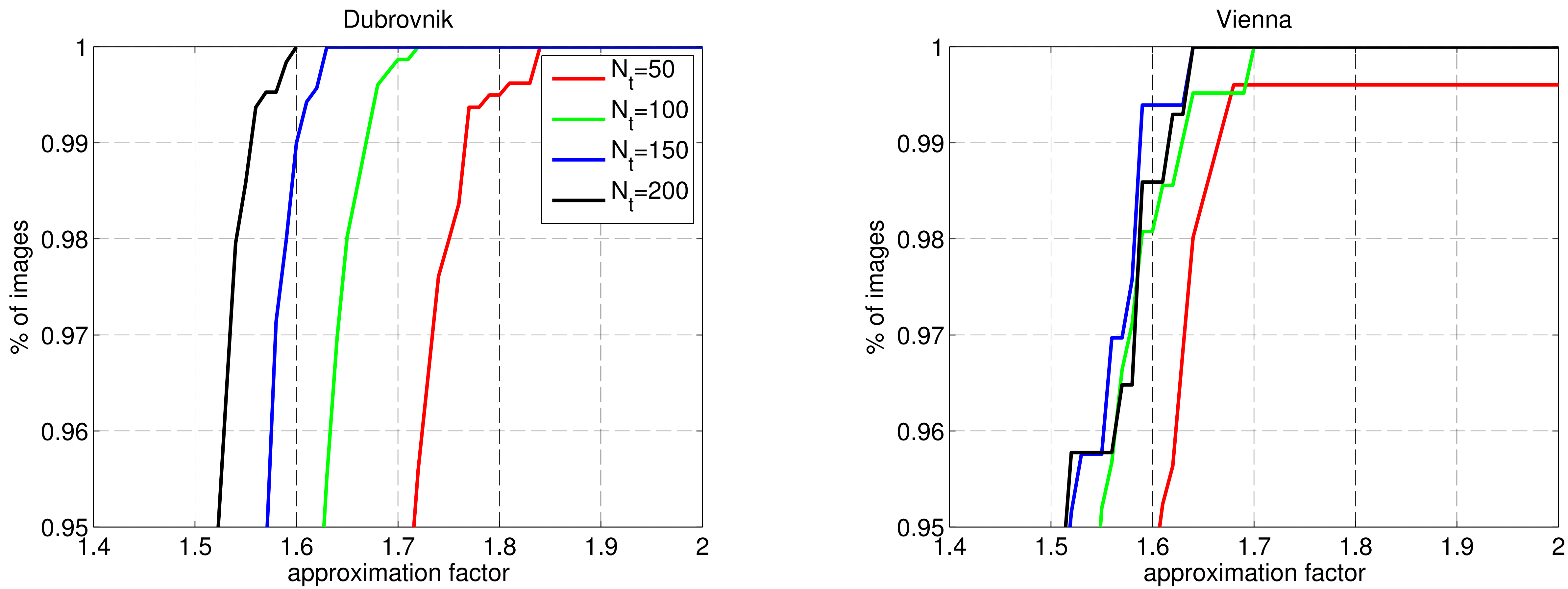
- Greedy performs close to optimal!
- Here: Probabilities learnt from query images

Greedy vs. OPT



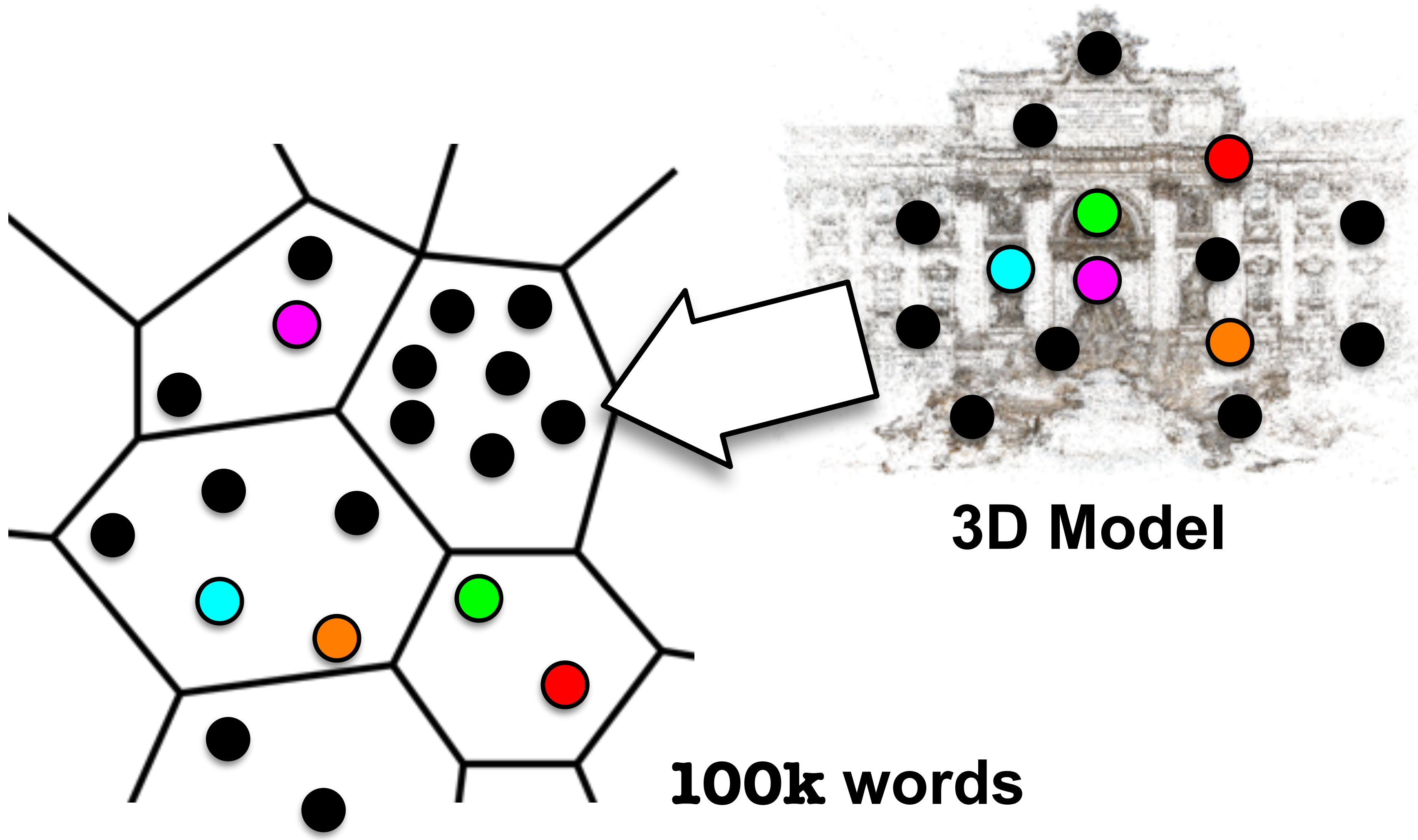
- Greedy performs close to optimal!
- Here: Probabilities learnt from query images
- In practice: Hard to find good training data

Greedy vs. OPT



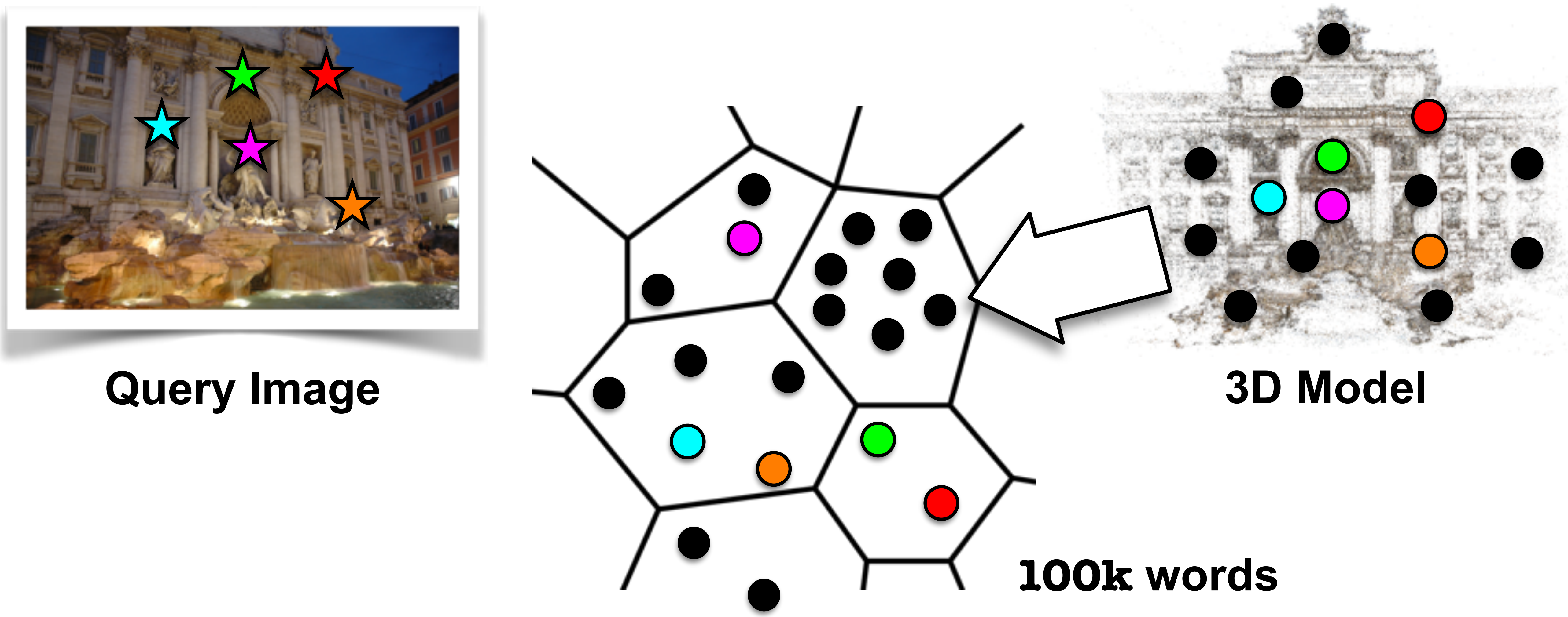
- Greedy performs close to optimal!
- Here: Probabilities learnt from query images
- In practice: Hard to find good training data
  - … but Greedy does not really need probabilities

Vocabulary-Based Prioritized Search (VPS)



[Sattler et al., ICCV'11] [code]

Vocabulary-Based Prioritized Search (VPS)



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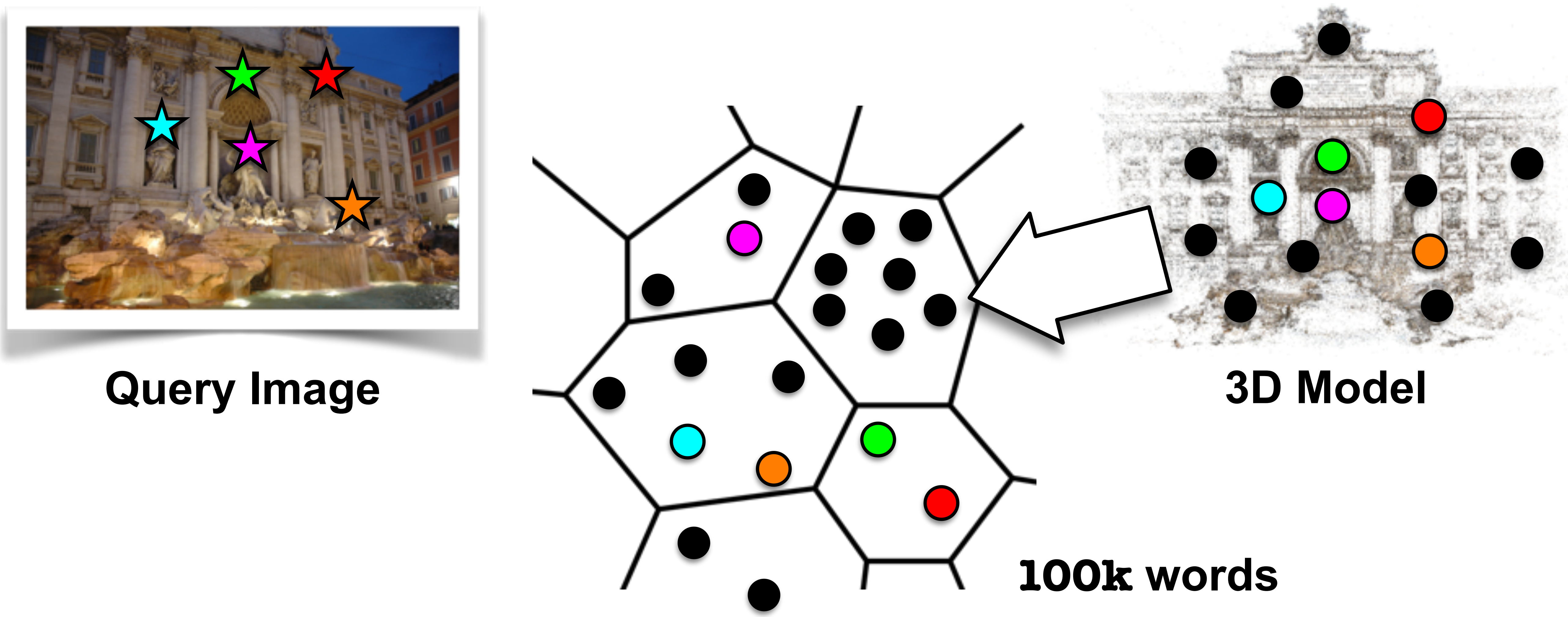

Assign features to words

[Sattler et al., ICCV'11] [code]

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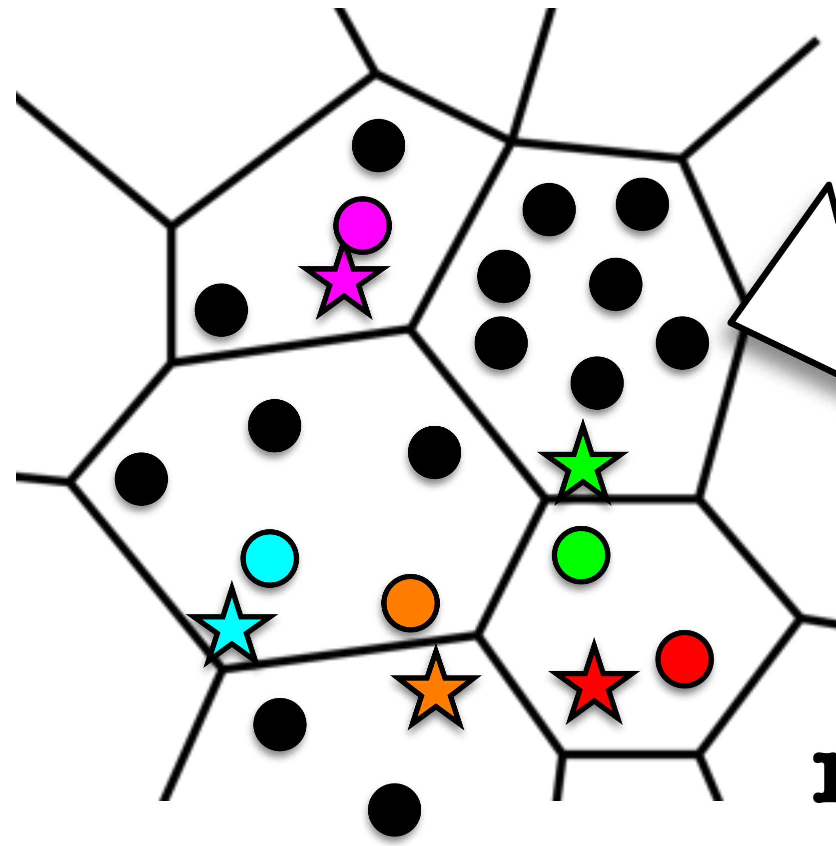
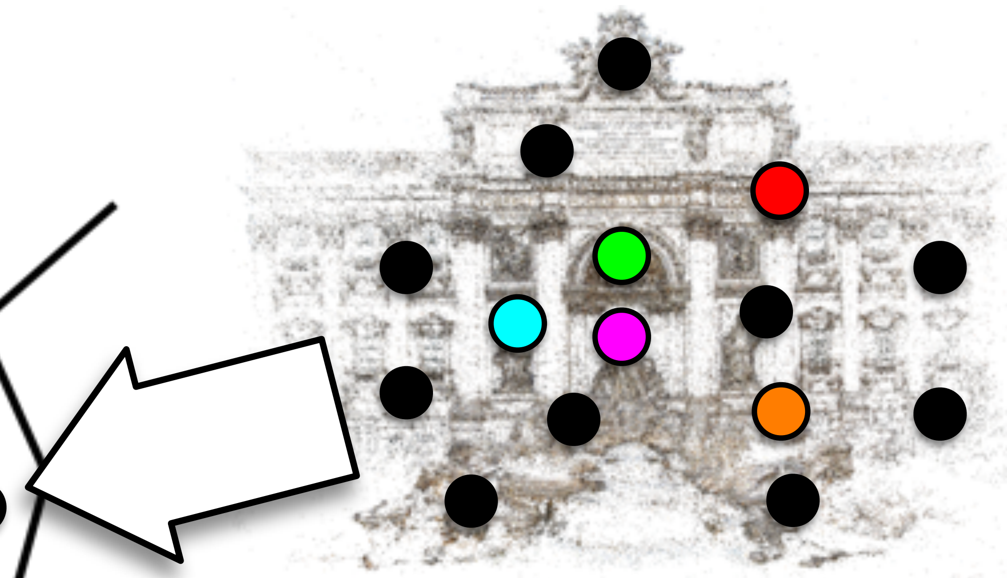
Vocabulary-Based Prioritized Search (VPS)

Query Image



100k words

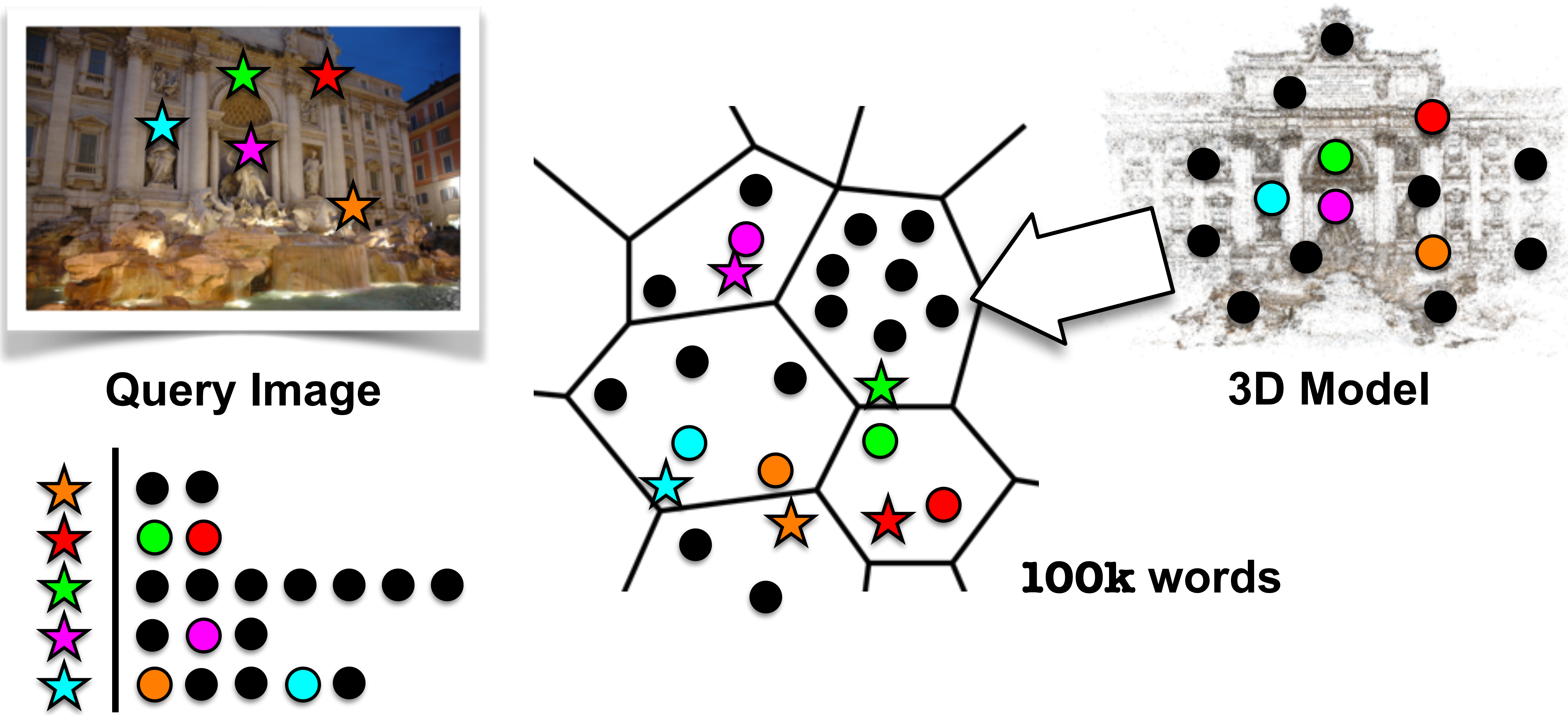


3D Model

Assign features to words

[Sattler et al., ICCV'11] [code]

Vocabulary-Based Prioritized Search (VPS)



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[Sattler et al., ICCV'11] [code]

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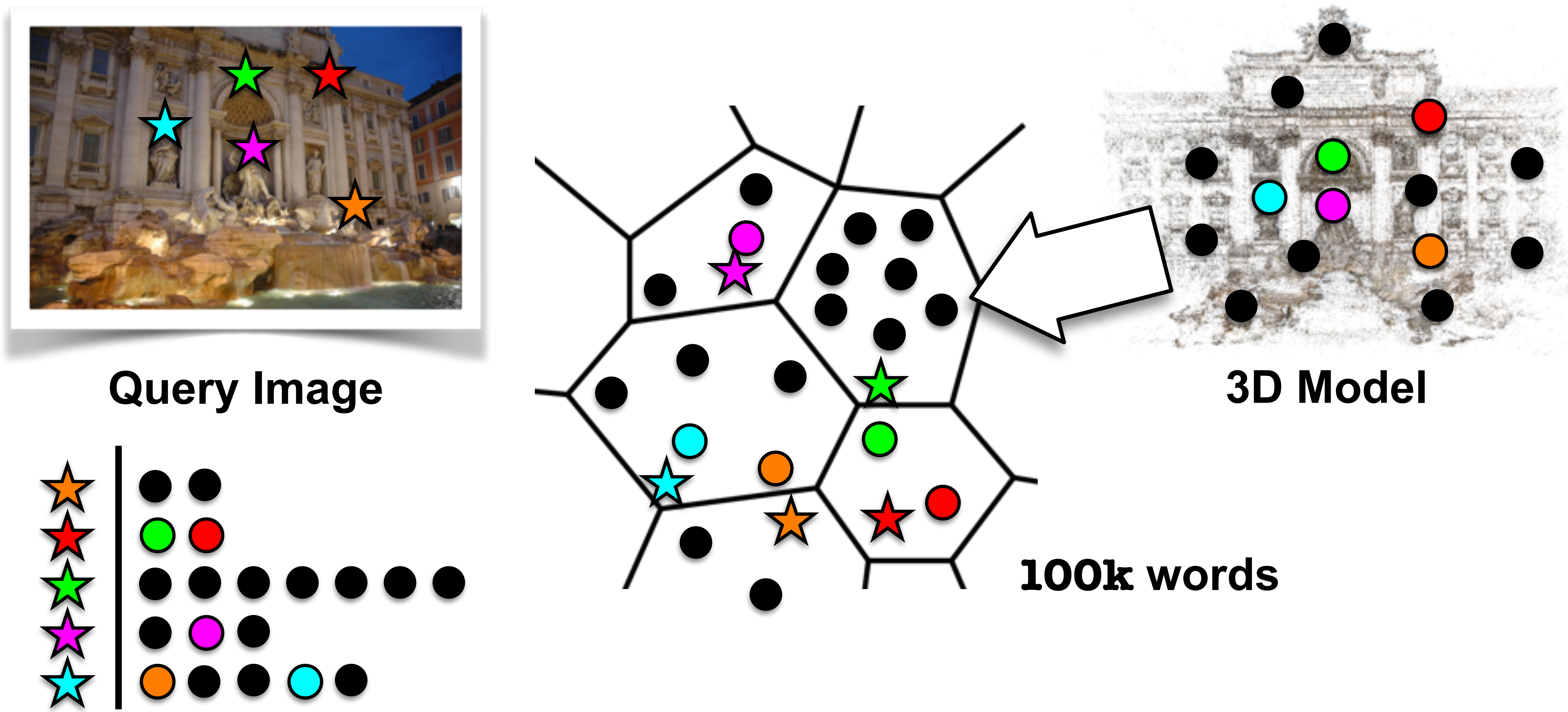


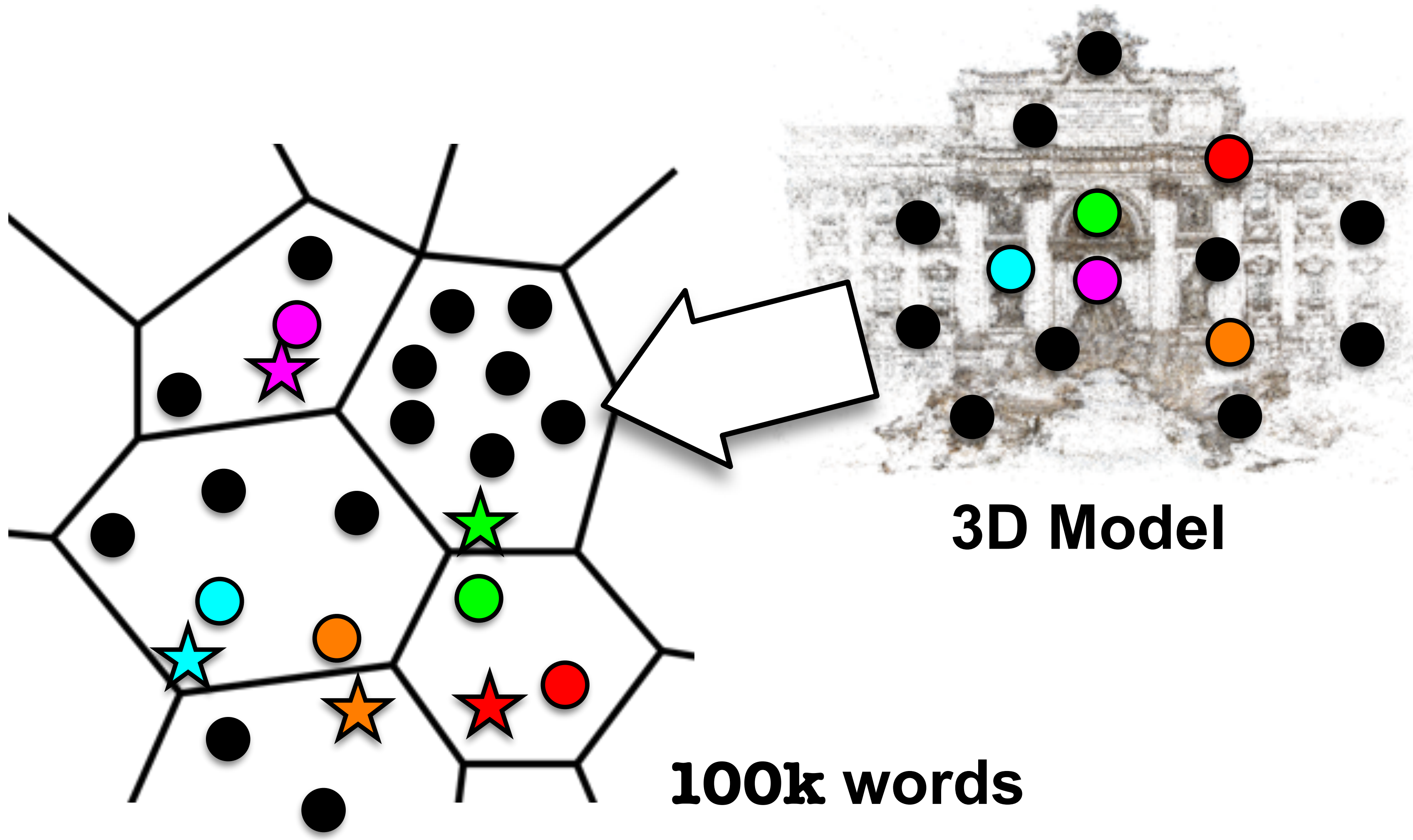
Assign features to words

Sort based on costs

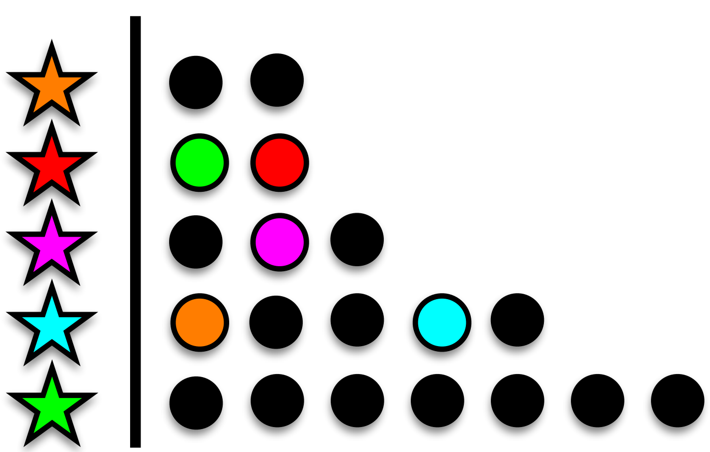
[Sattler et al., ICCV'11] [code]

Vocabulary-Based Prioritized Search (VPS)

Query Image



3D Model



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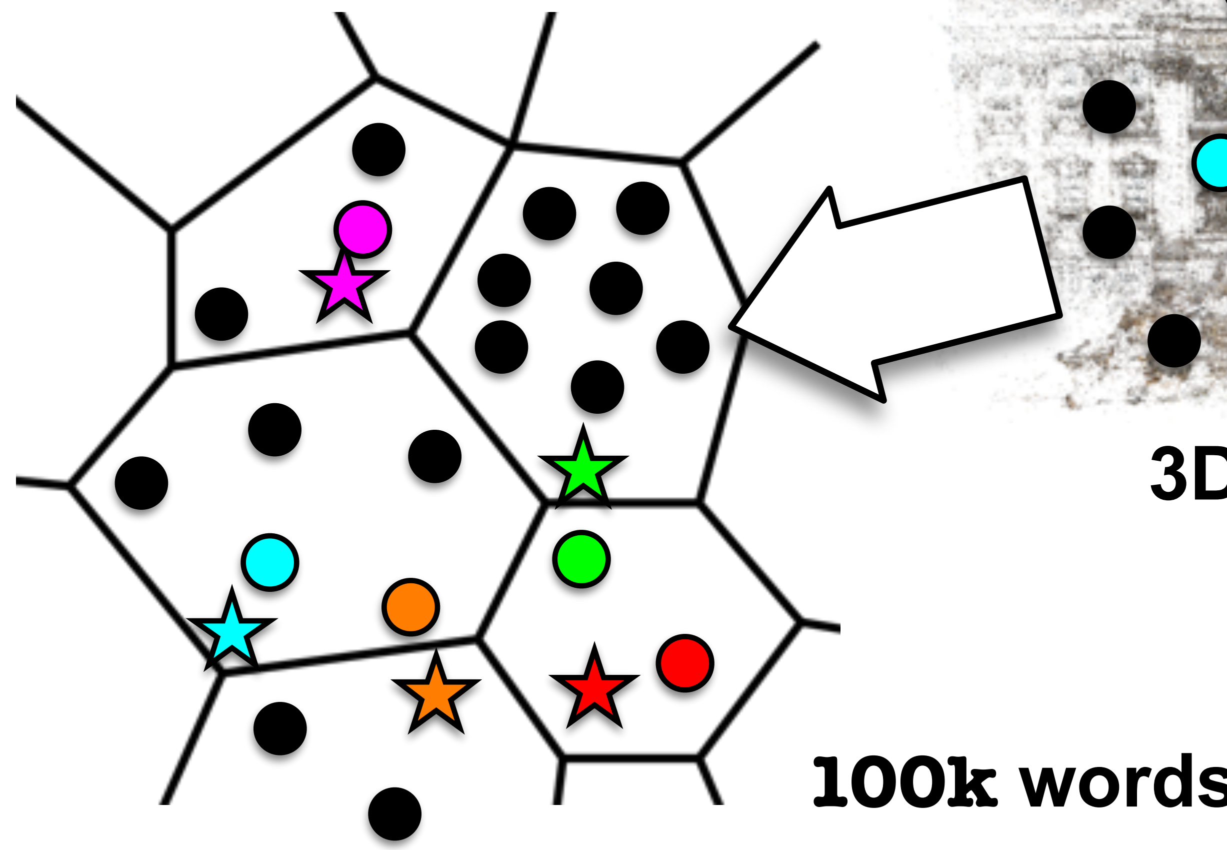

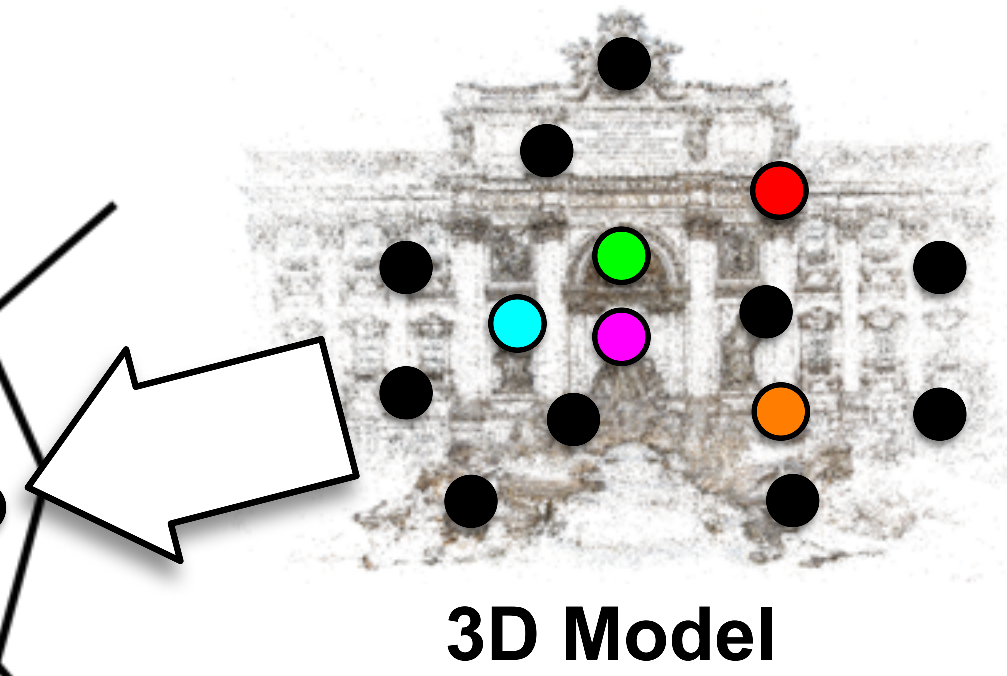

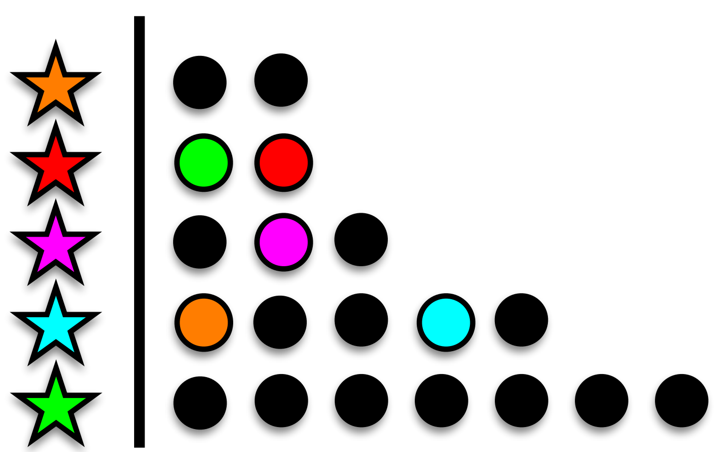

Assign features to words

Sort based on costs

Linear search through words

[Sattler et al., ICCV'11] [code]

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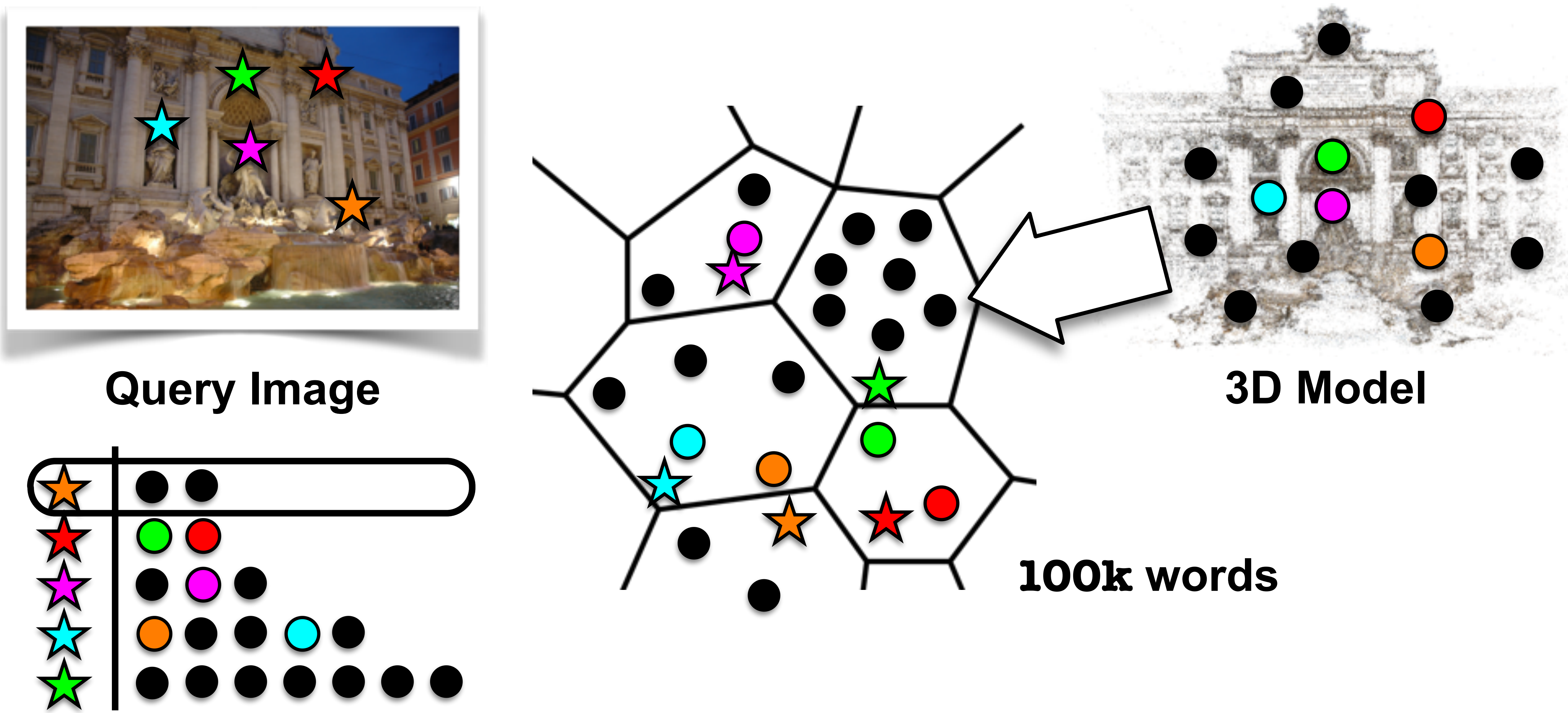

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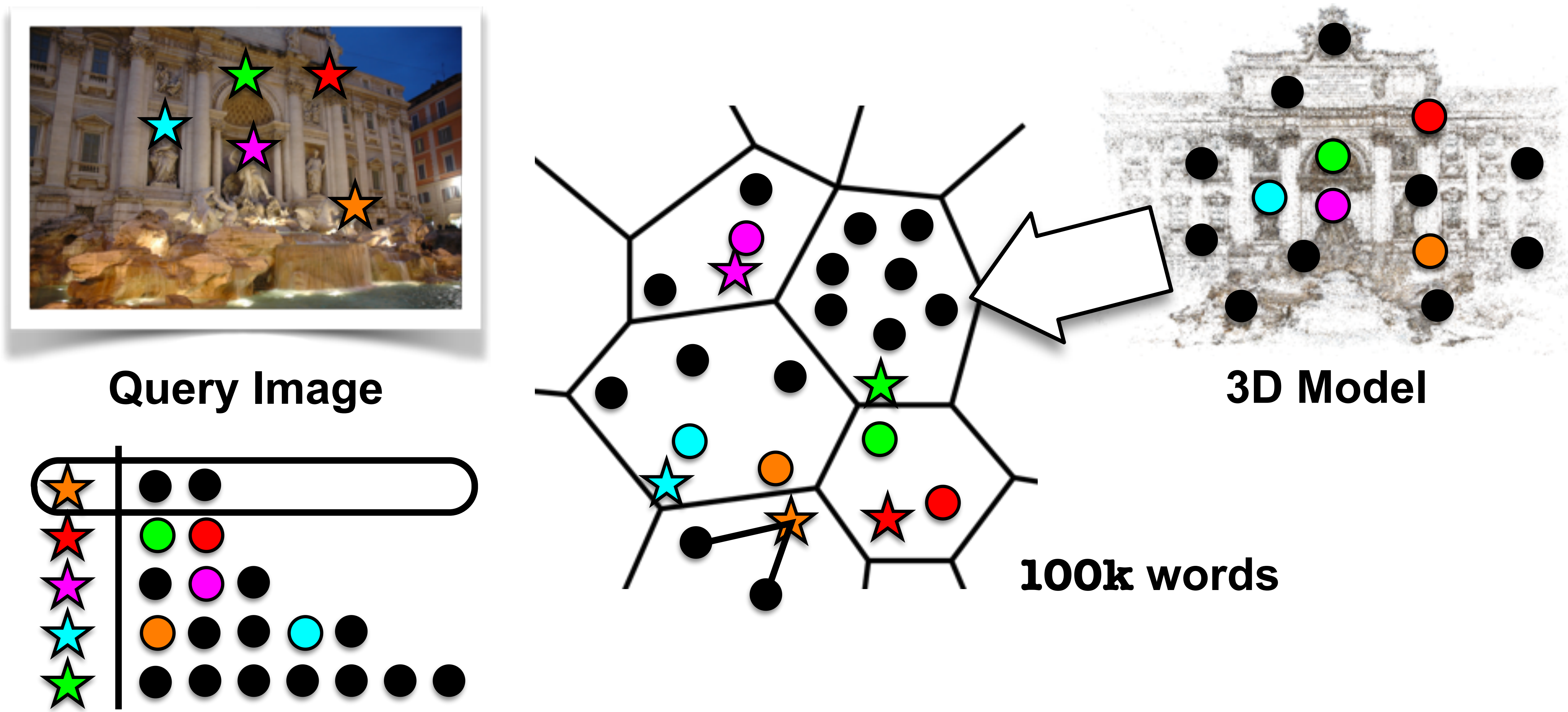

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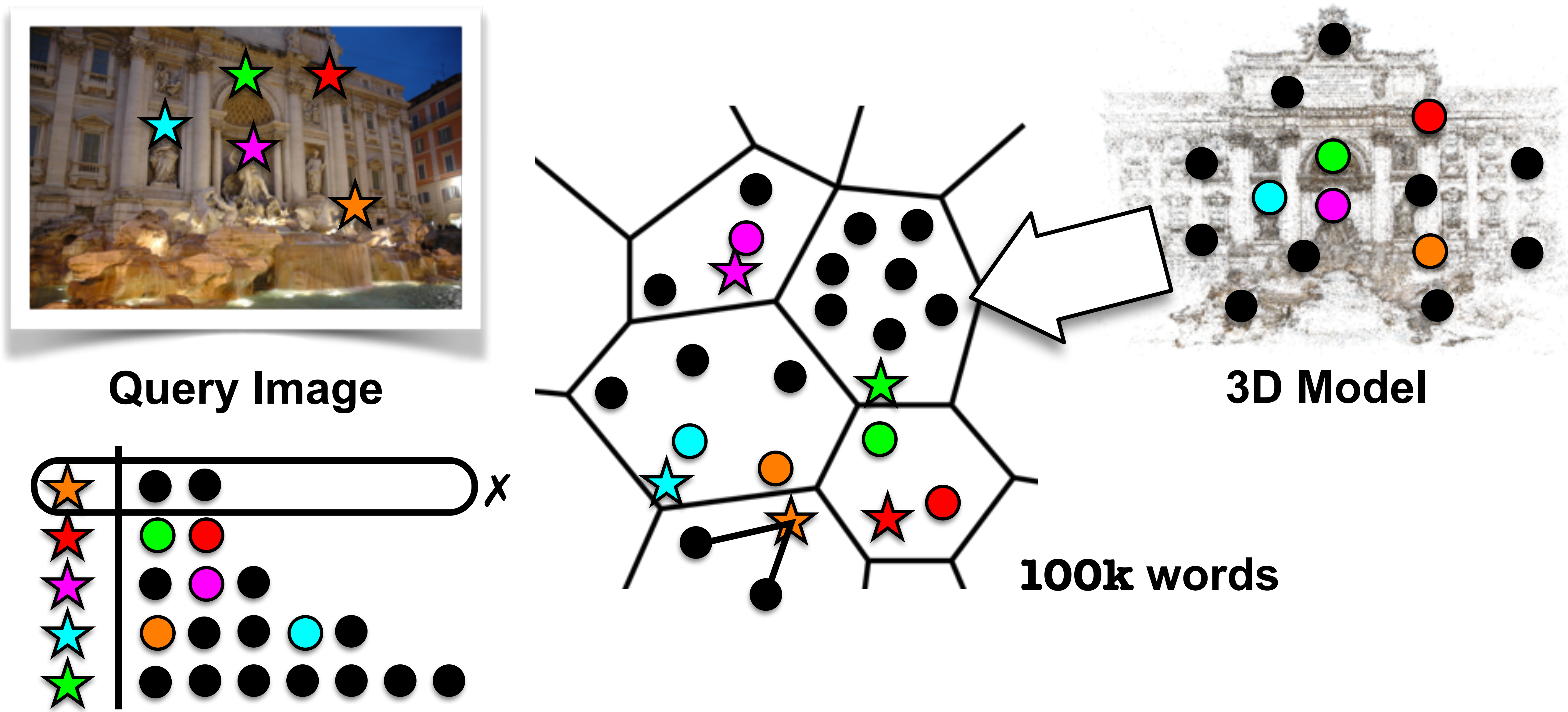

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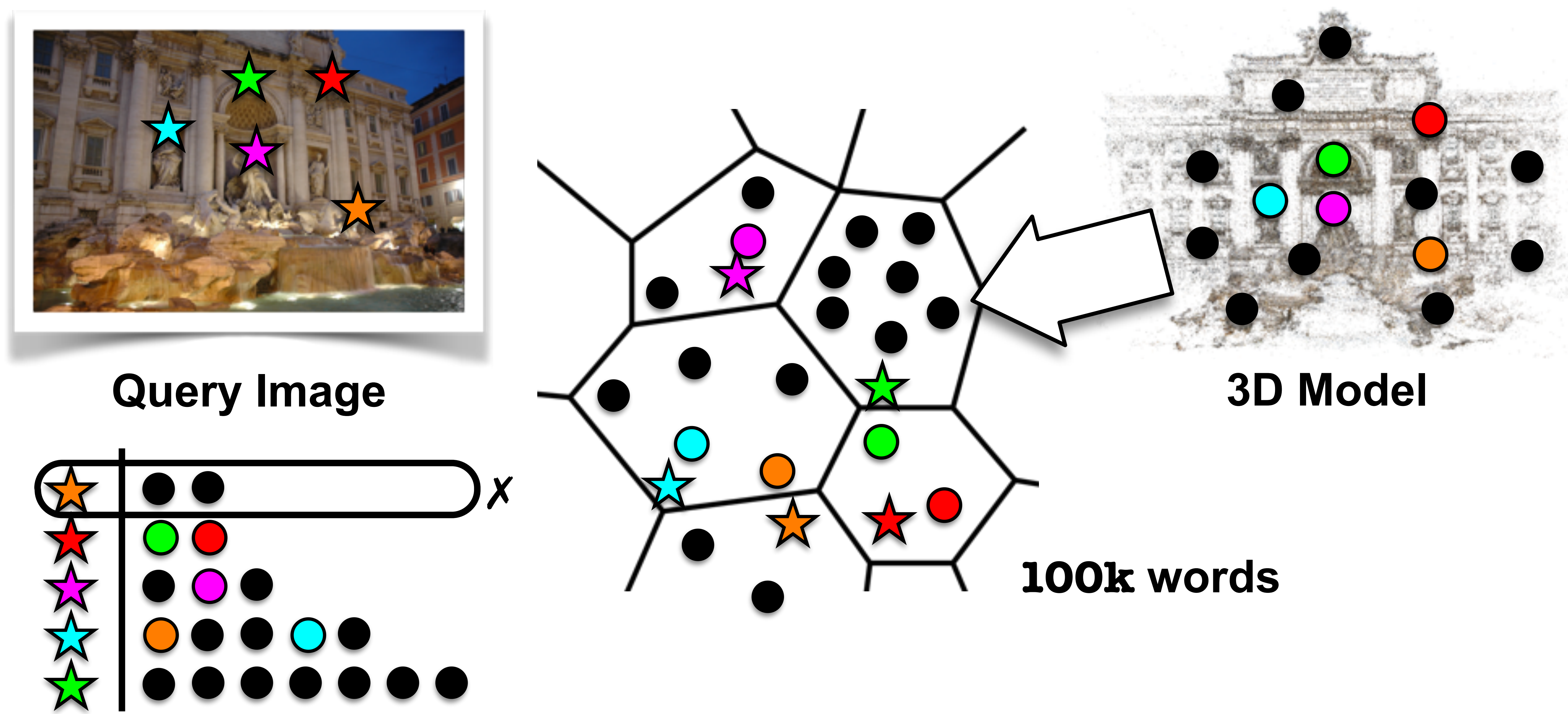

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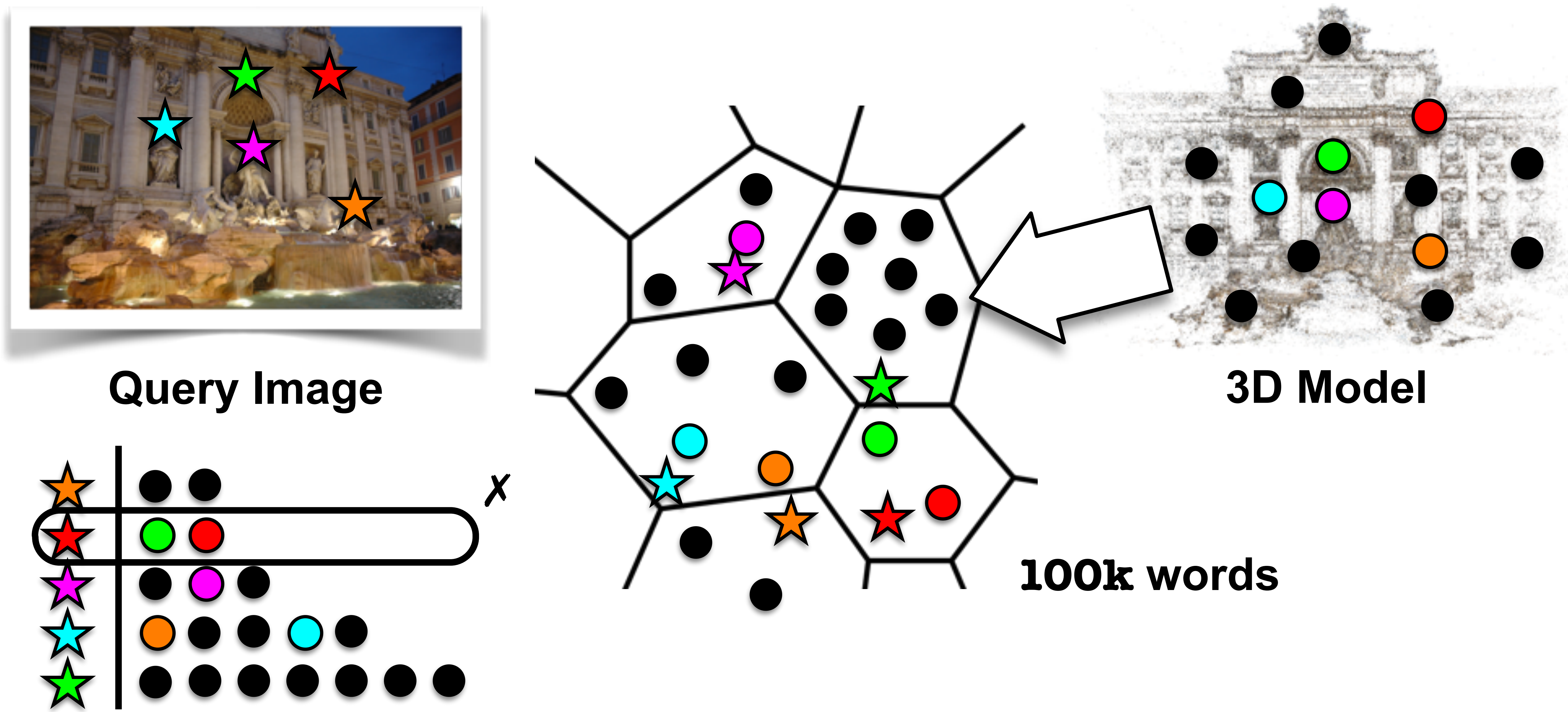

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[Sattler et al., ICCV'11] [code]

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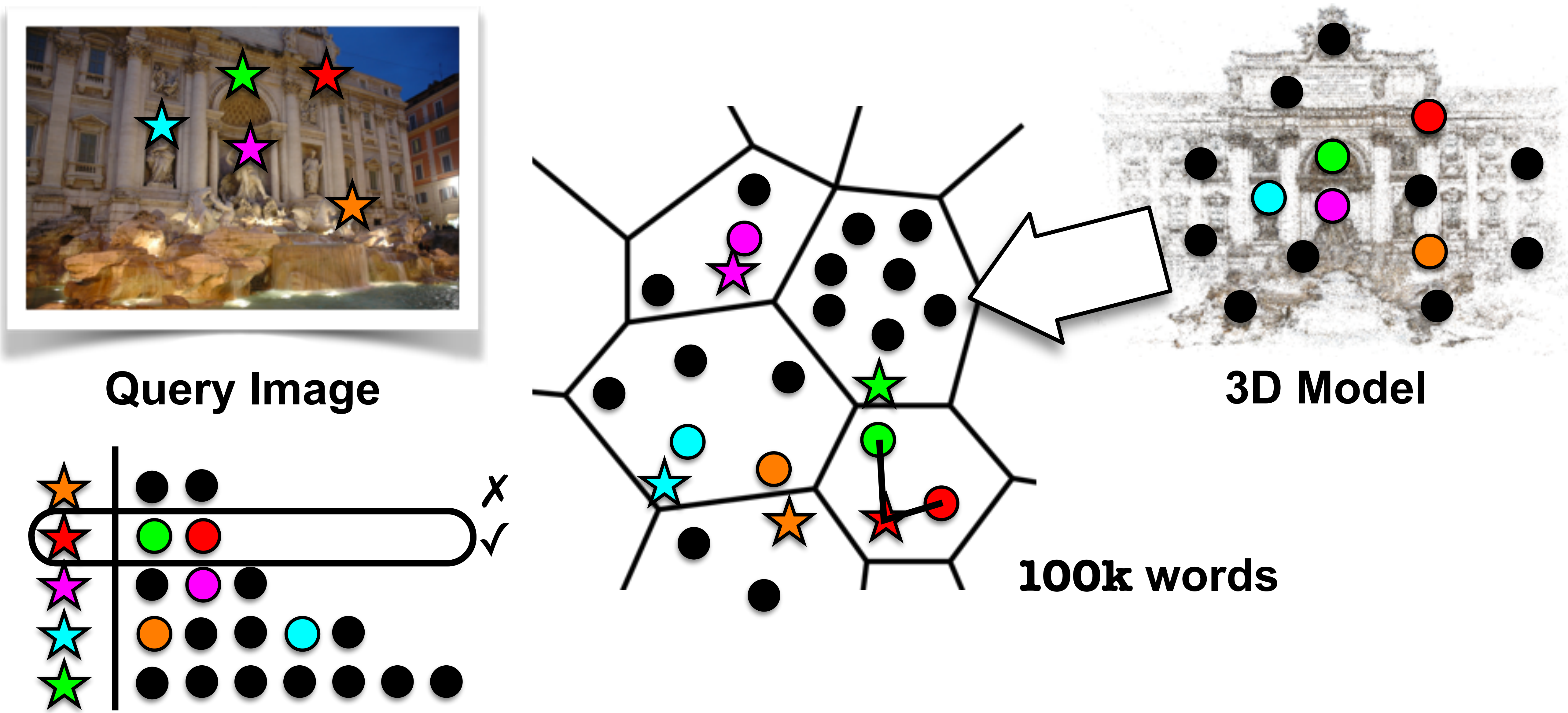

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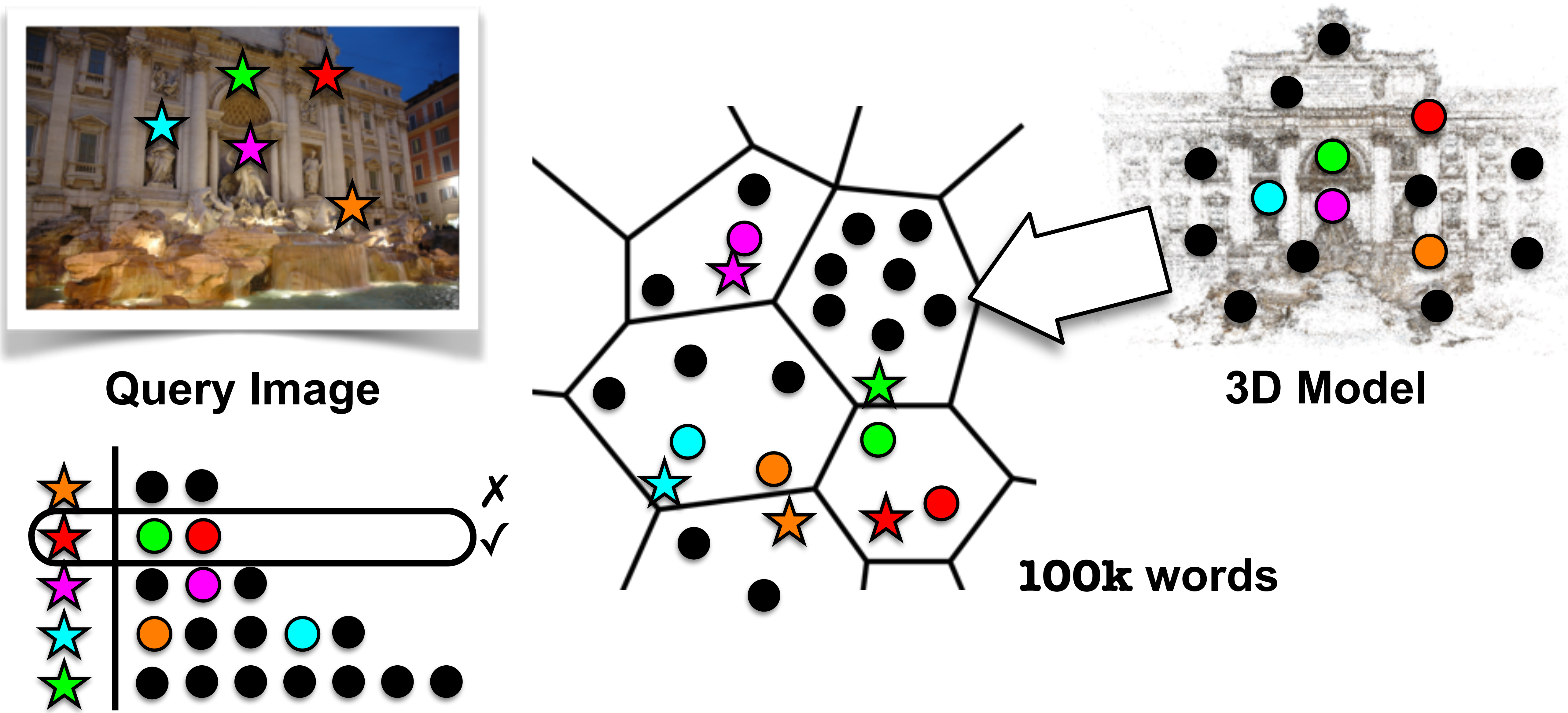

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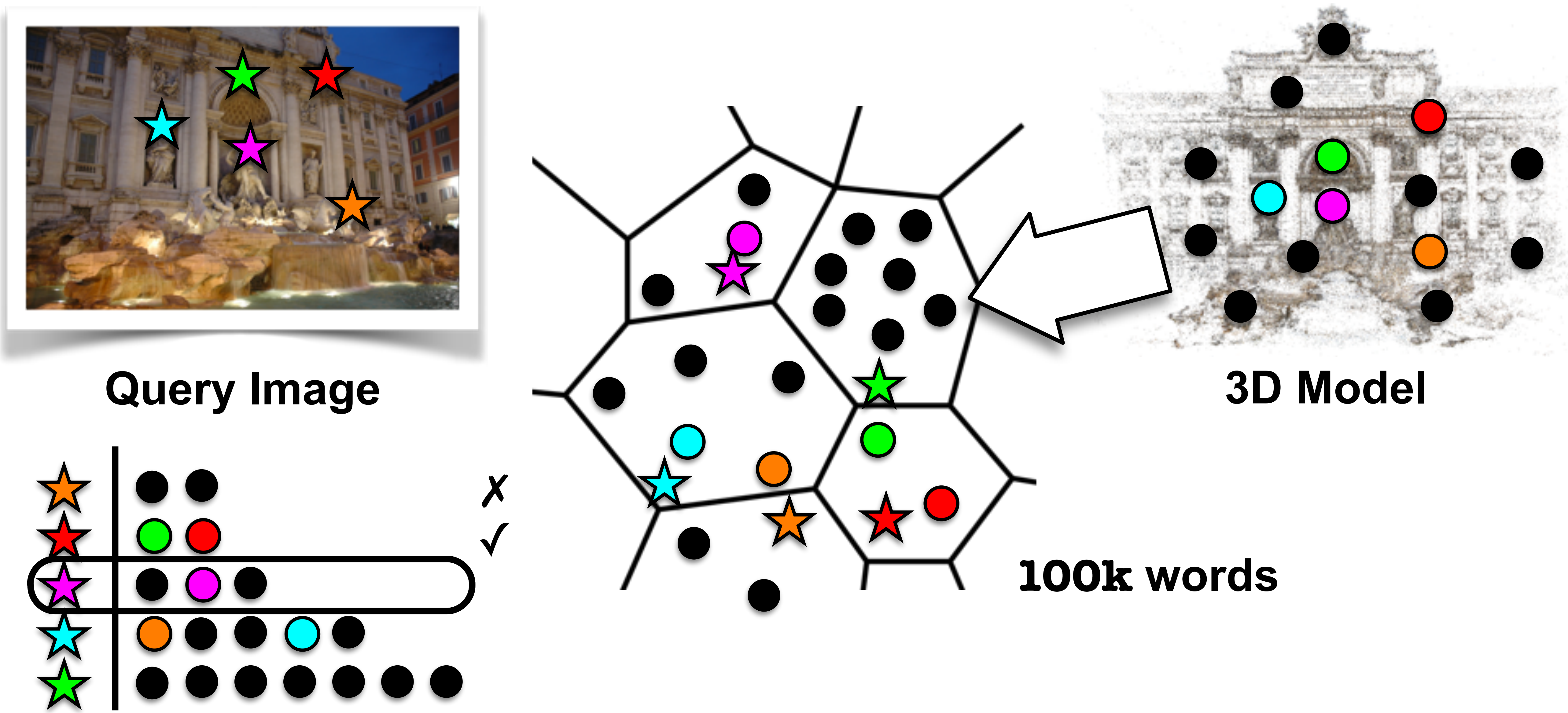

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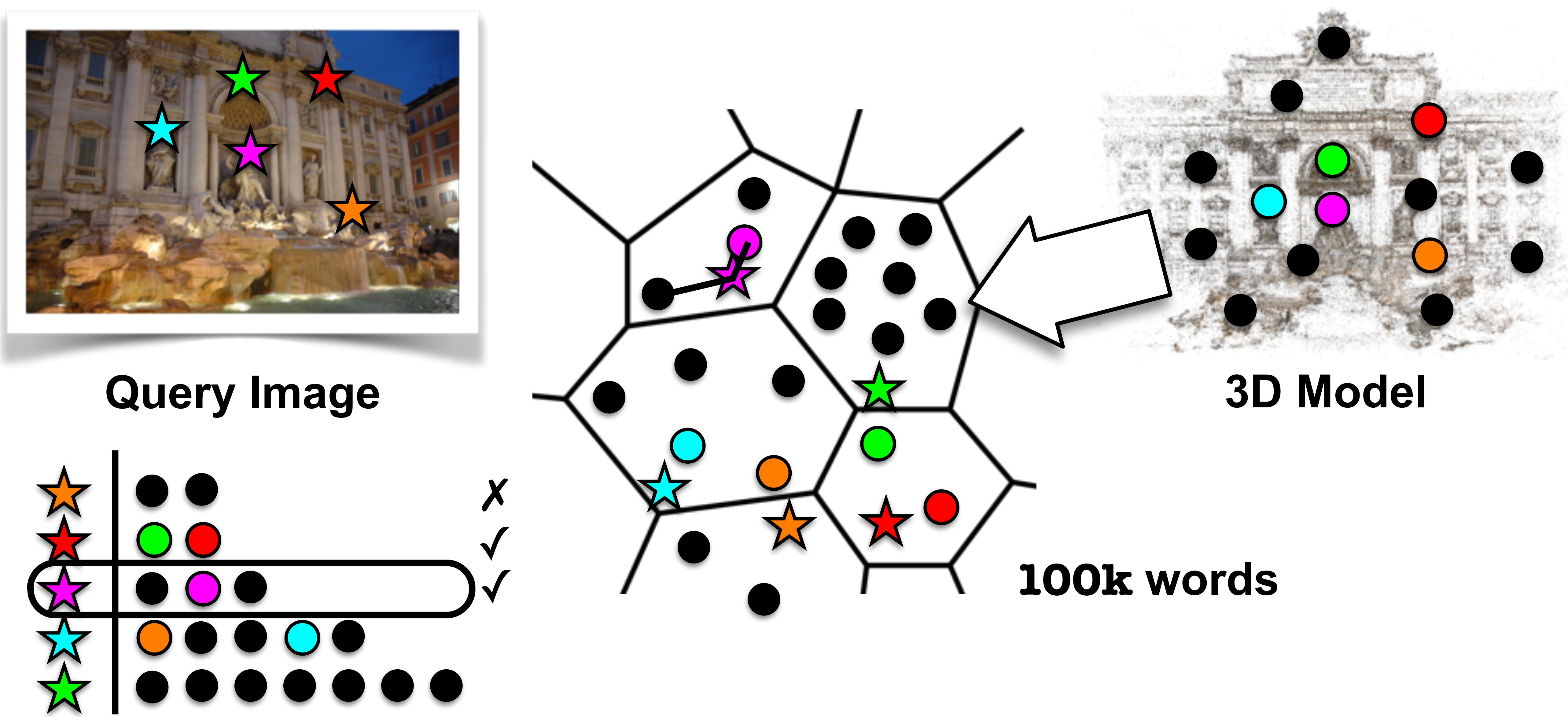

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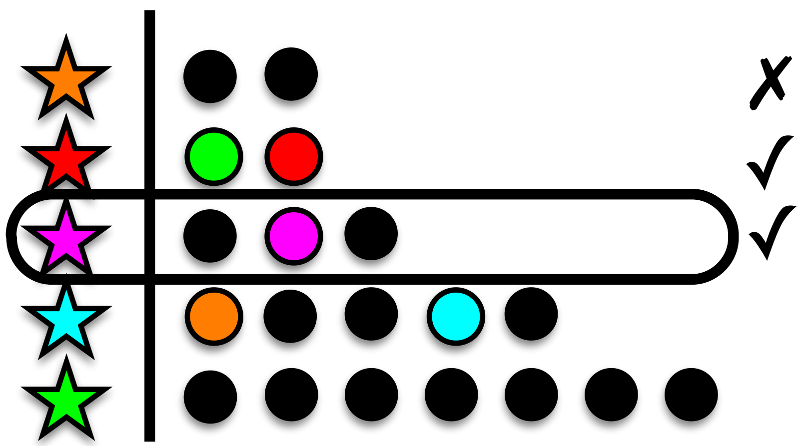
Sort based on costs

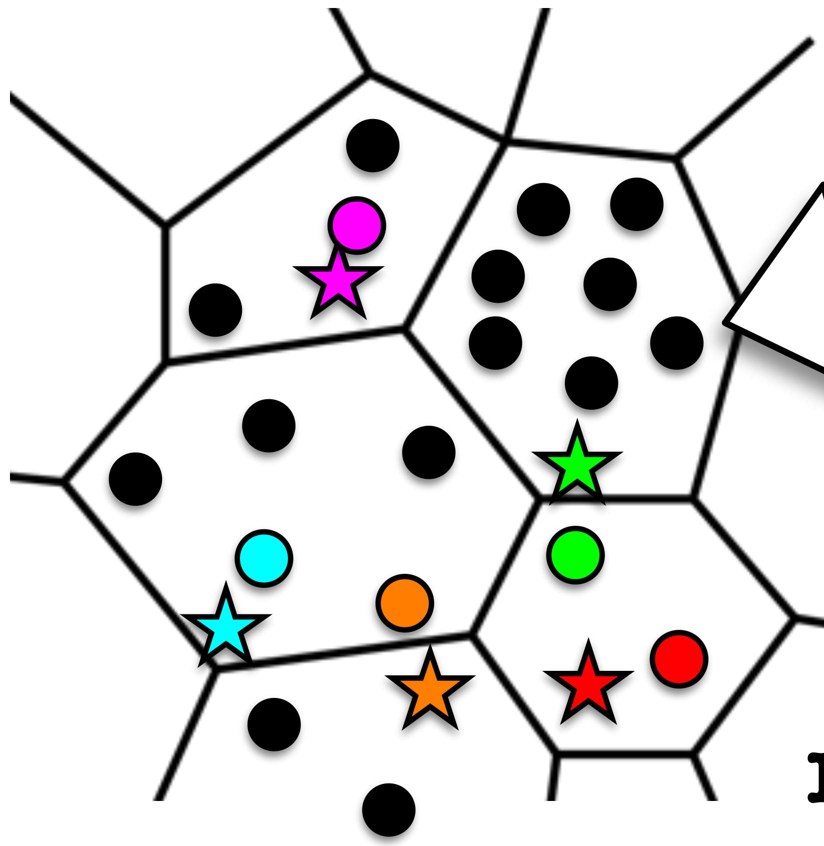
Linear search through words

[Sattler et al., ICCV'11] [code]

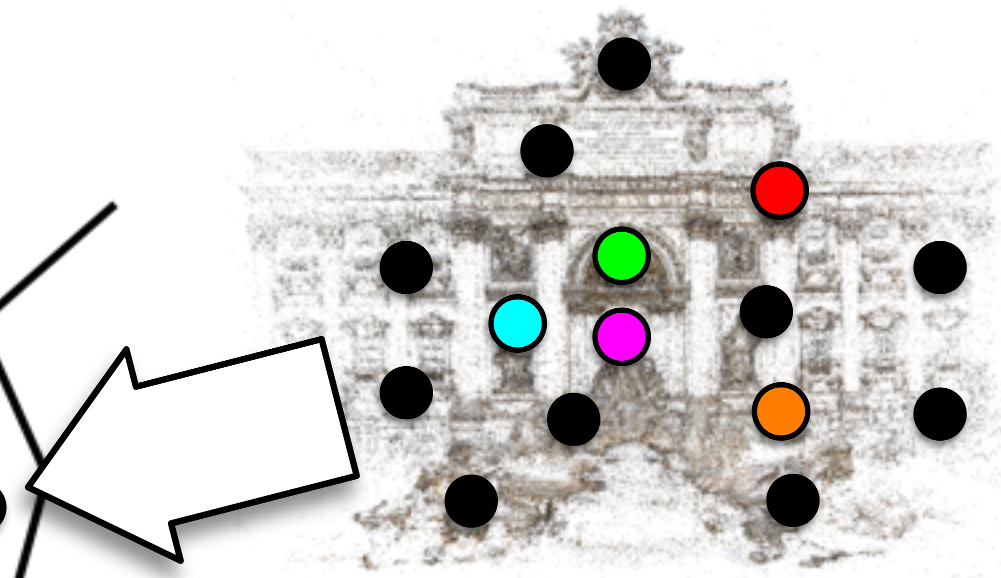
Vocabulary-Based Prioritized Search (VPS)

Query Image





100k words



3D Model

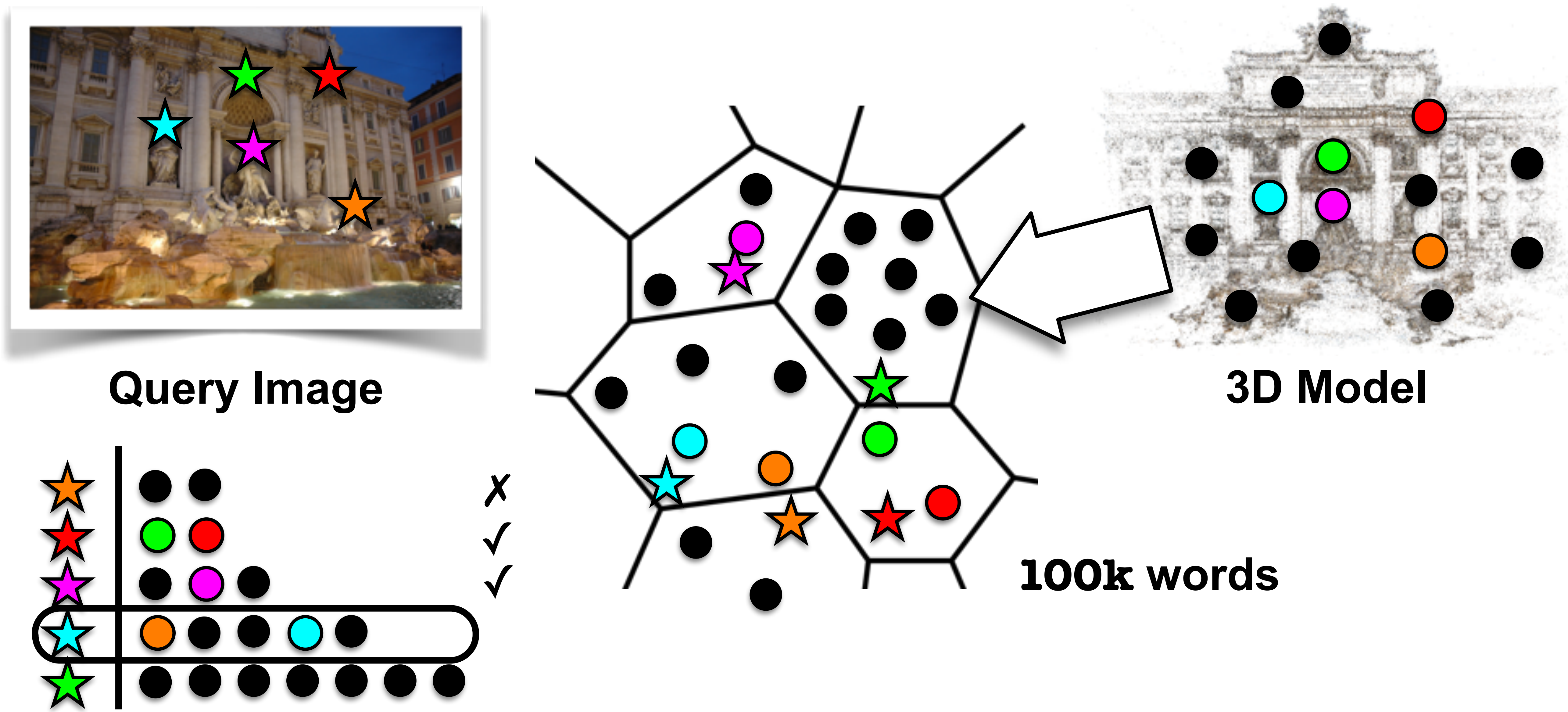
Assign features to words

Sort based on costs

Linear search through words

[Sattler et al., ICCV'11] [code]

Vocabulary-Based Prioritized Search (VPS)



Assign features to words → **Sort based on costs** → **Linear search** through words

[Sattler et al., ICCV'11] [code]

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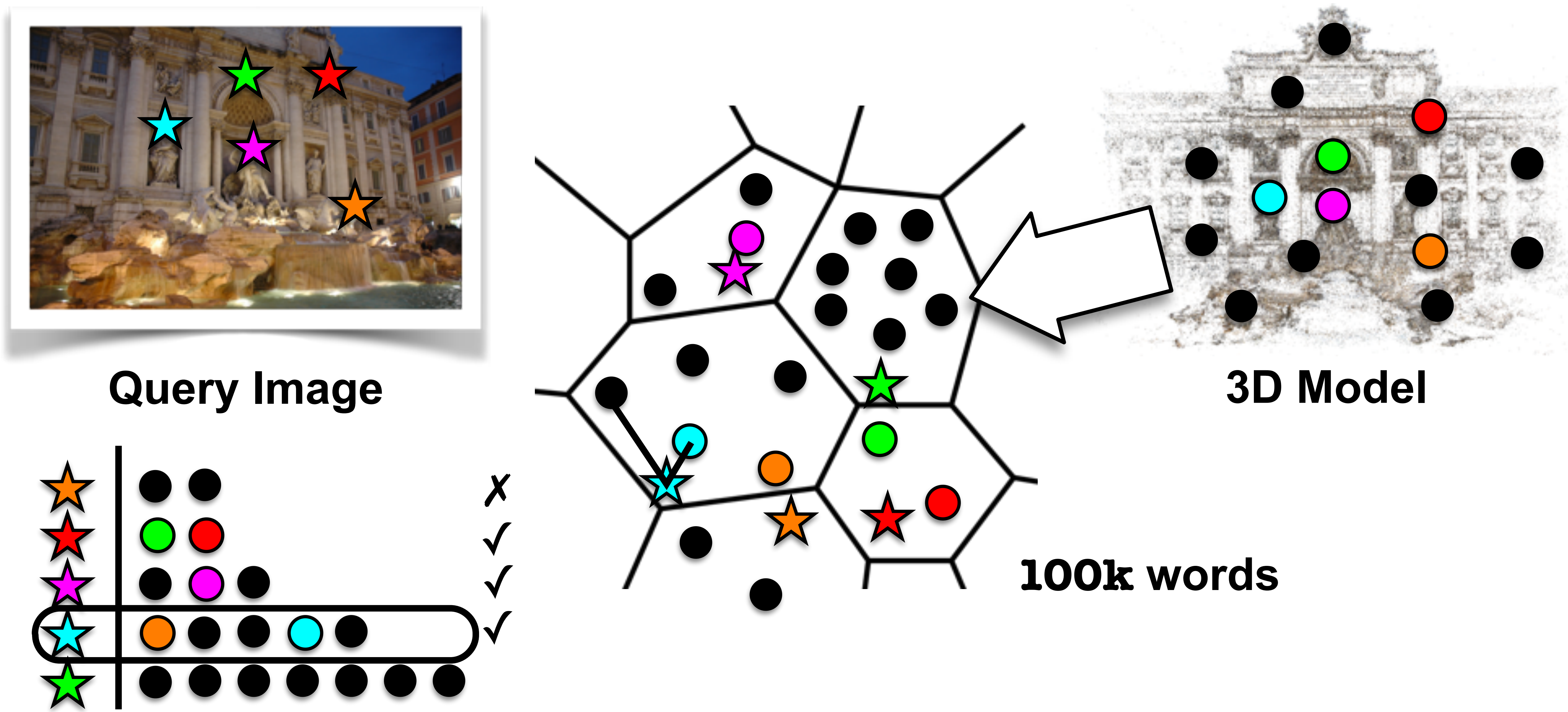
Vocabulary-Based Prioritized Search (VPS)



Assign features to words

Sort based on costs

Linear search through words

[Sattler et al., ICCV'11] [code]

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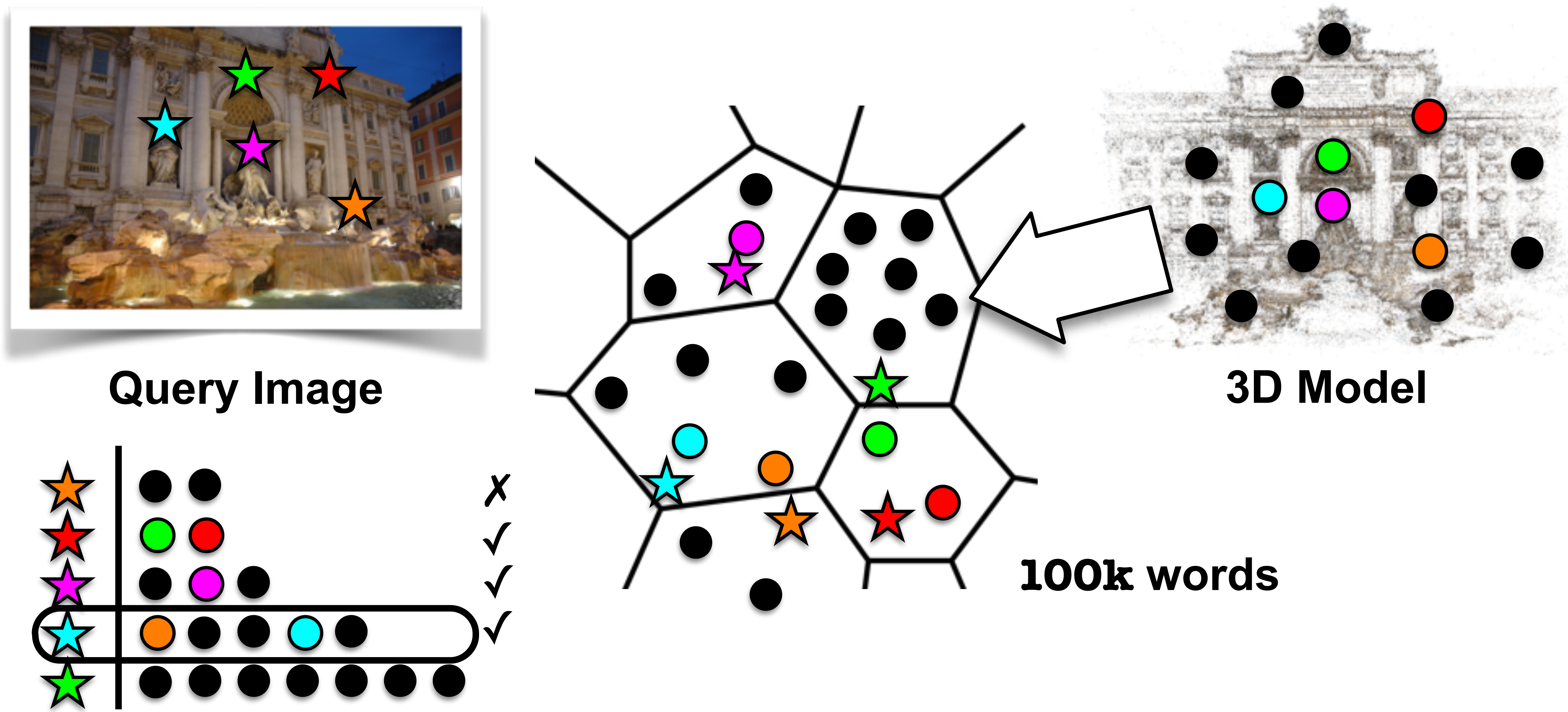

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Linear search through words

[Sattler et al., ICCV'11] [code]

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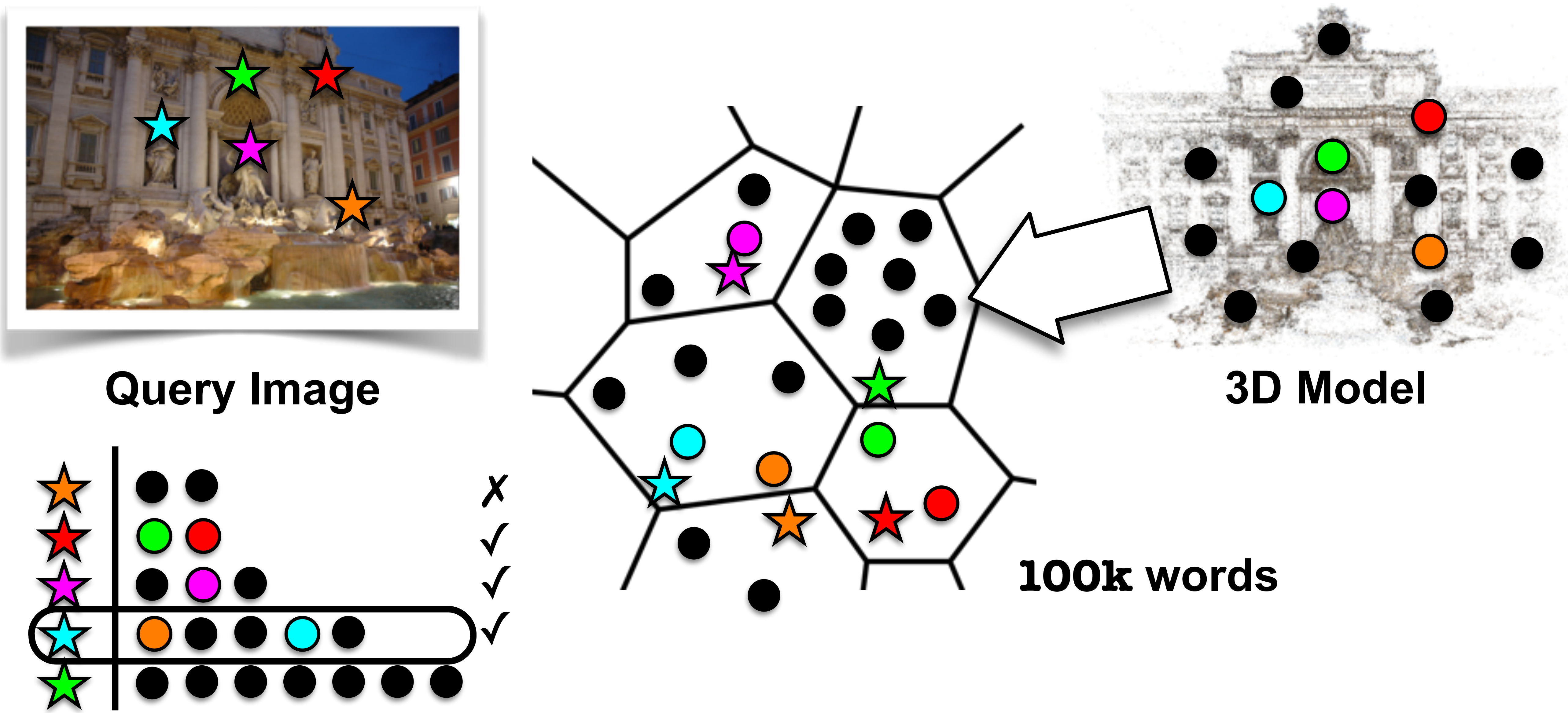


Assign features to words

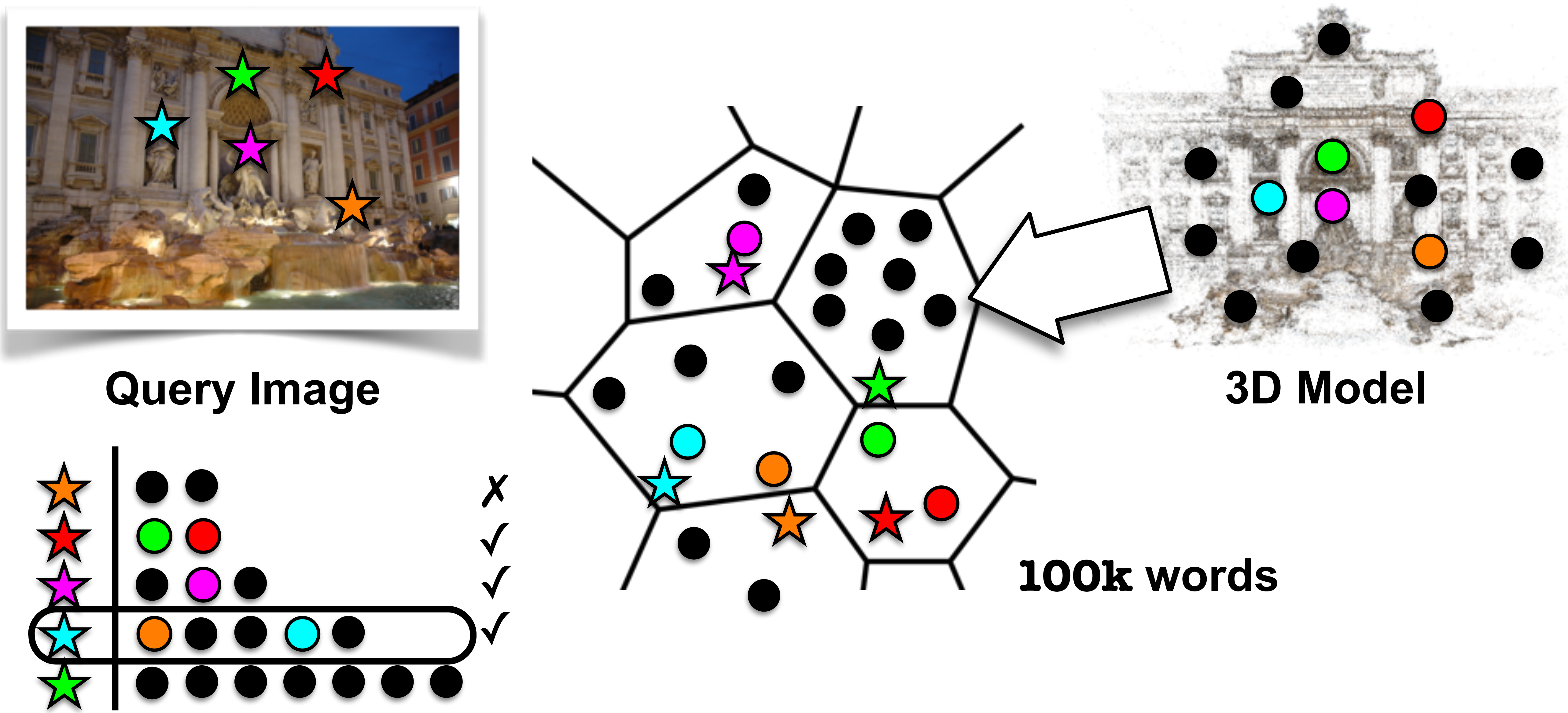
Sort based on costs

Linear search through words

Stop after 100 **matches**

[Sattler et al., ICCV'11] [code]

Vocabulary-Based Prioritized Search (VPS)



Assign features to words	Sort based on costs	Linear search through words	Stop after 100 matches	Pose estimation: RANSAC + p6p

[Sattler et al., ICCV'11] [code]

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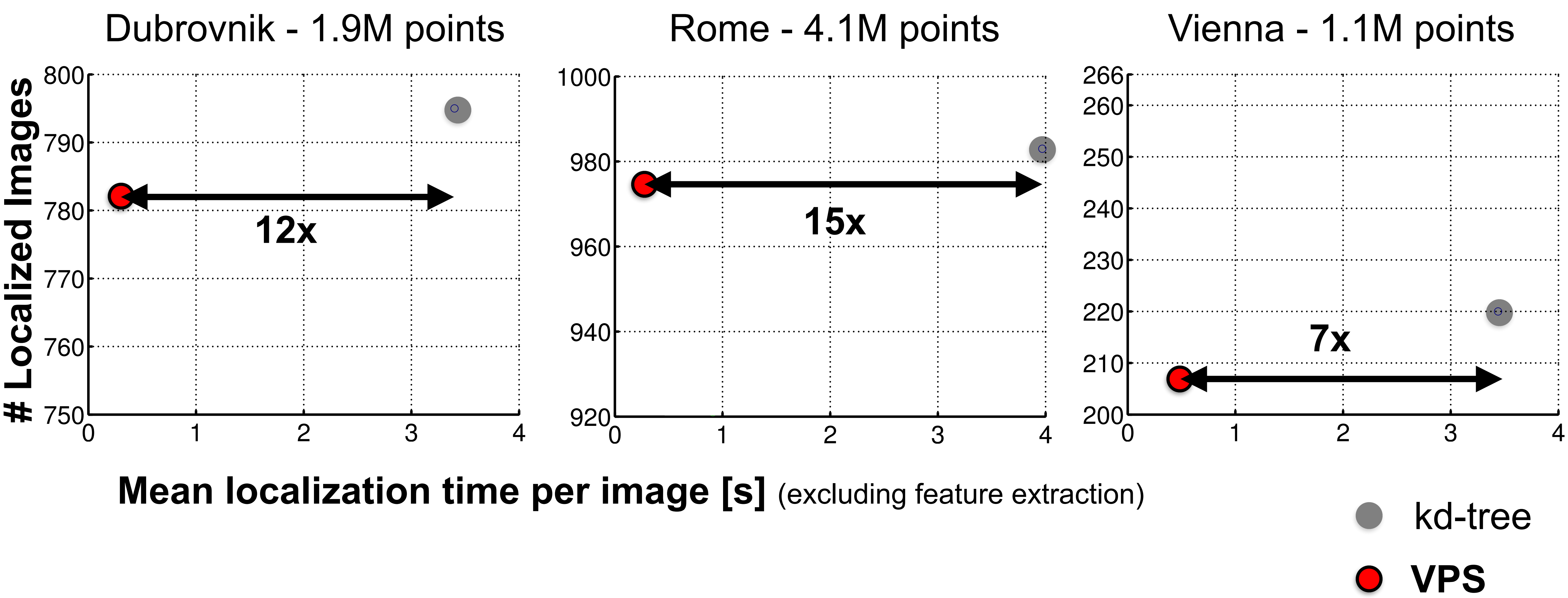
Results



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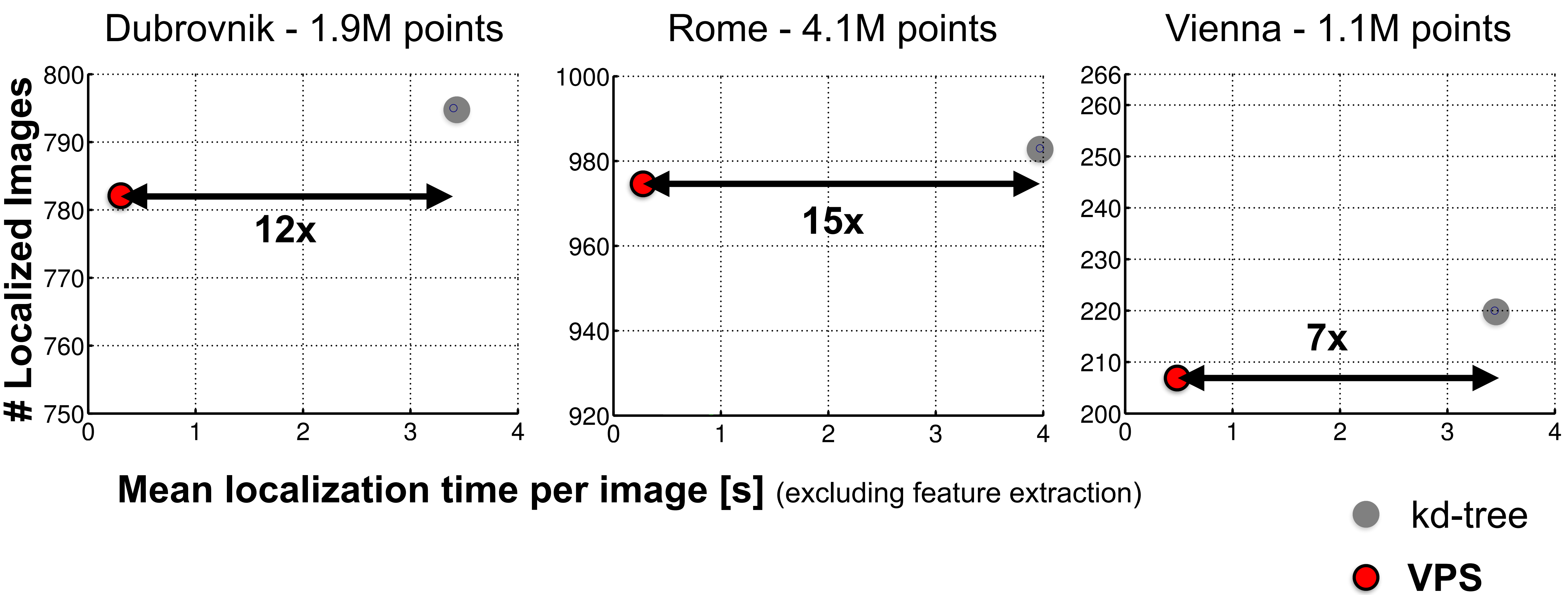
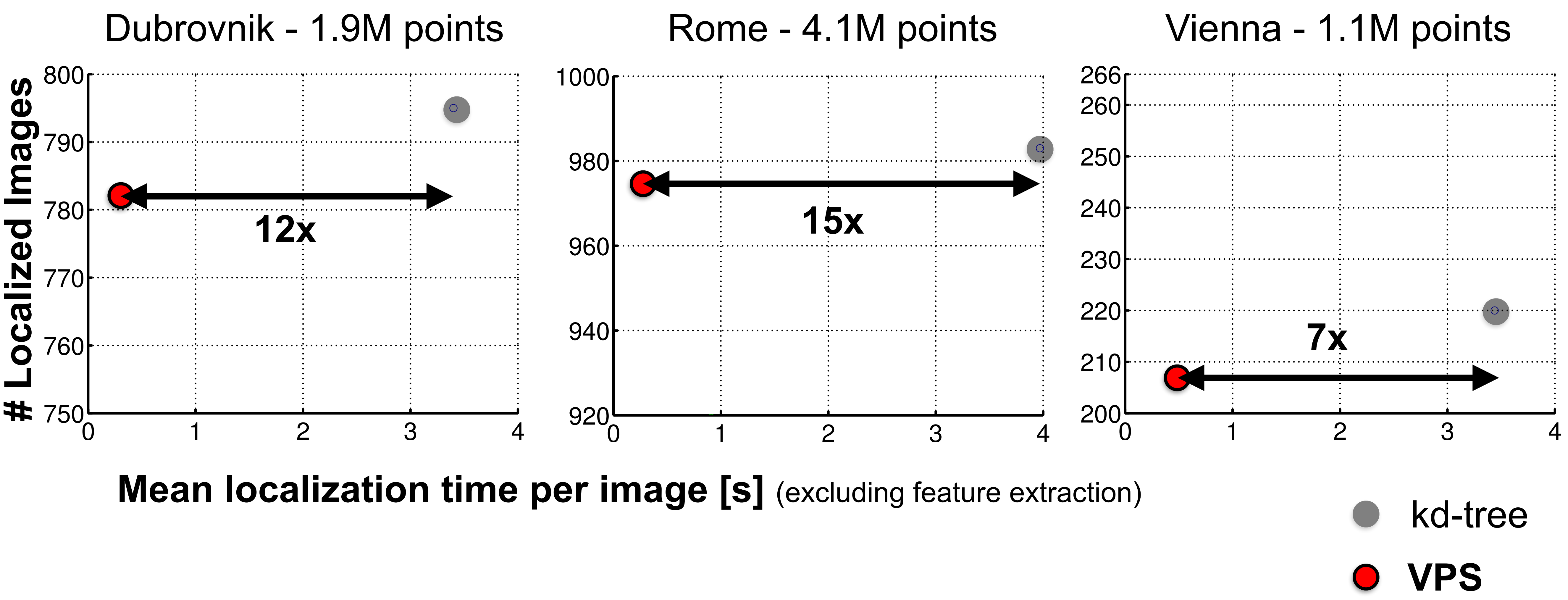
Results



✓ 10x faster than kd-tree

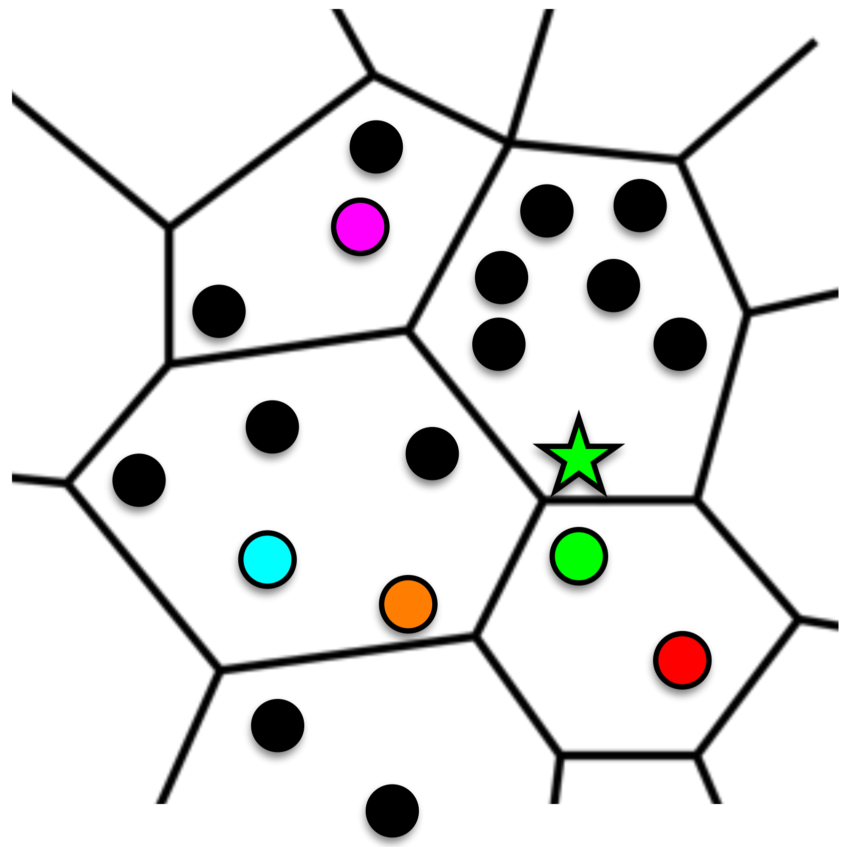
Results



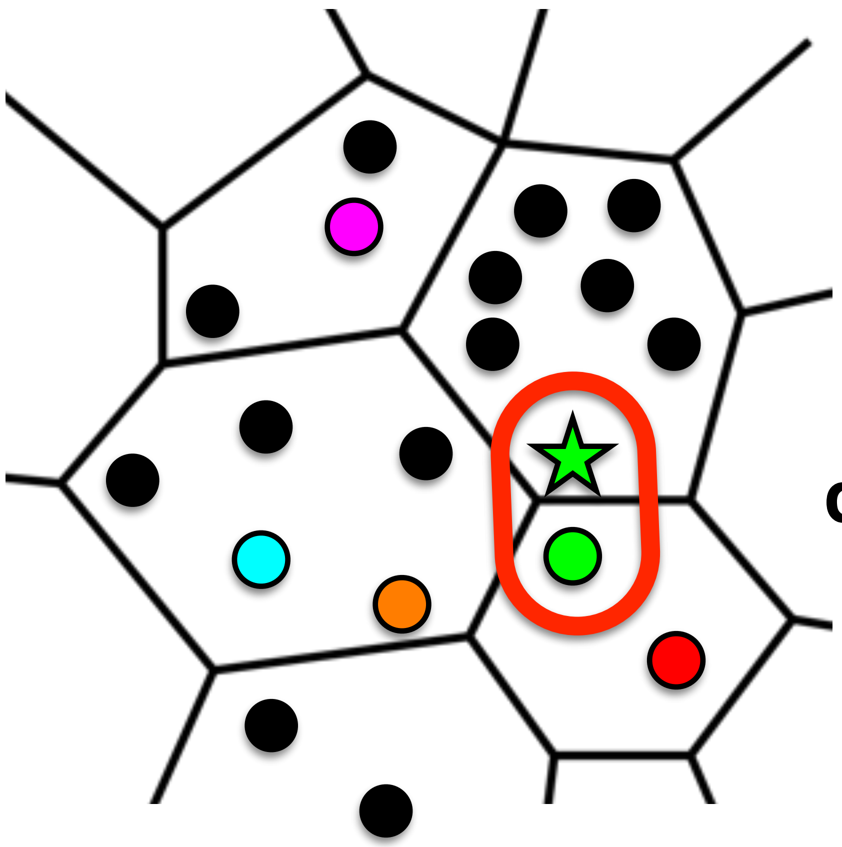
✓ 10x faster than kd-tree

✗ … but less effective than kd-tree

Quantization Artifacts

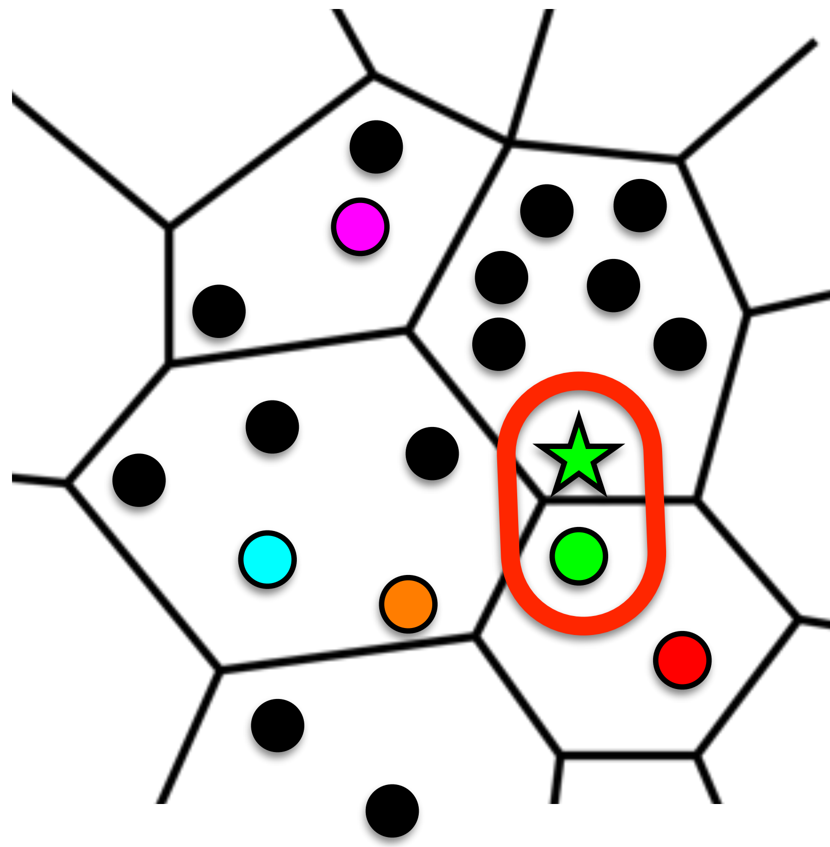


Quantization Artifacts



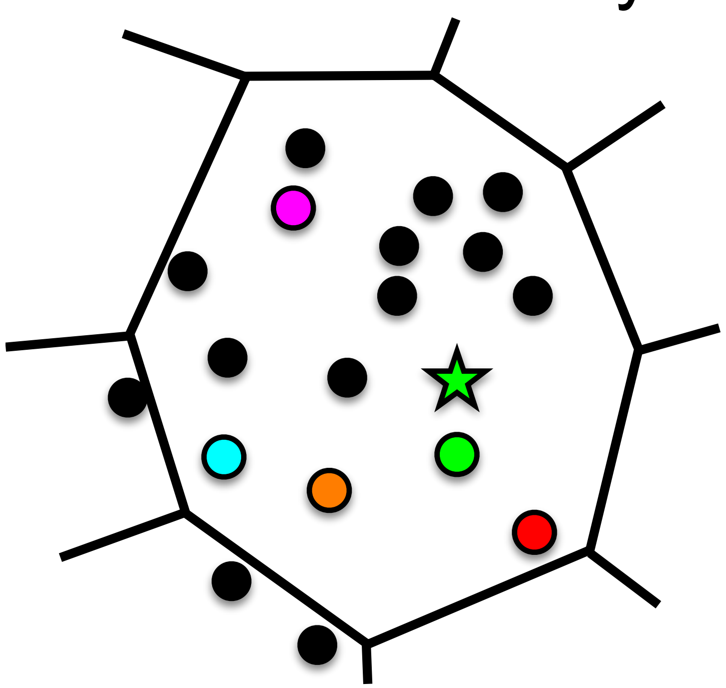
Match missed due to quantization!

Quantization Artifacts

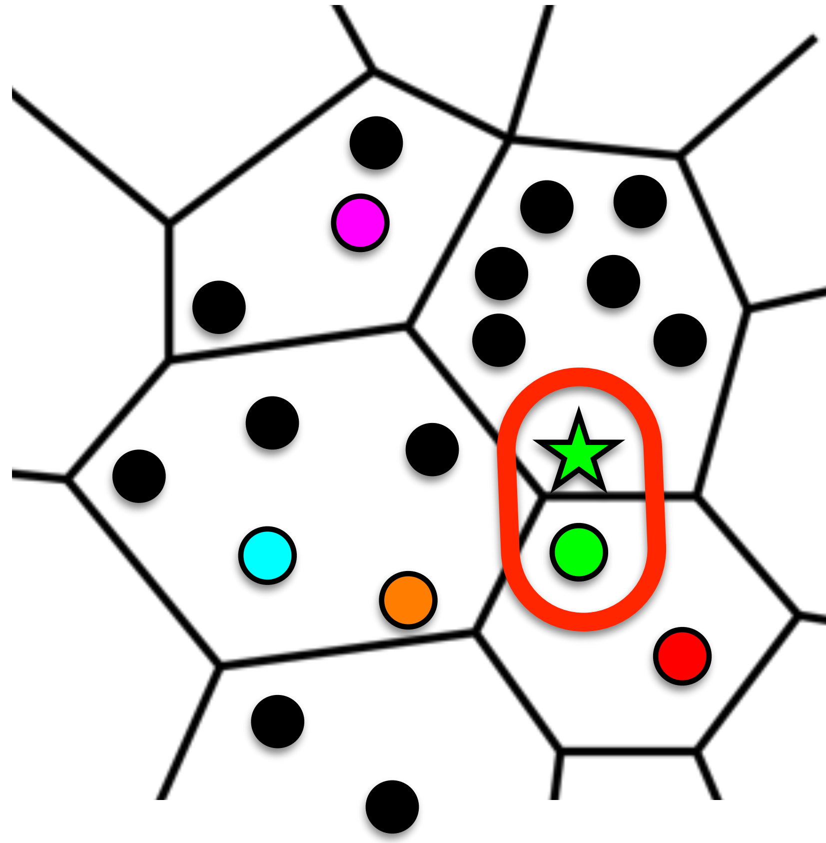


Match missed due to quantization!

Smaller Vocabulary



Quantization Artifacts



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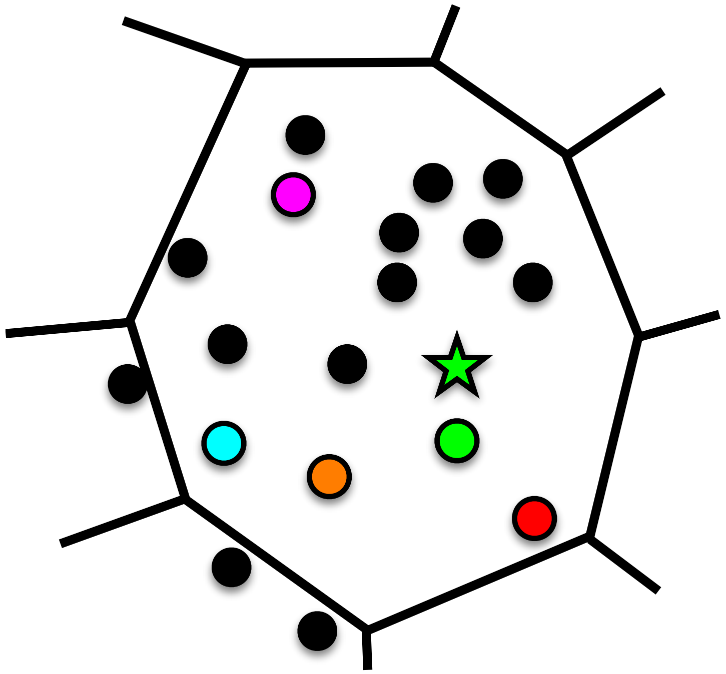
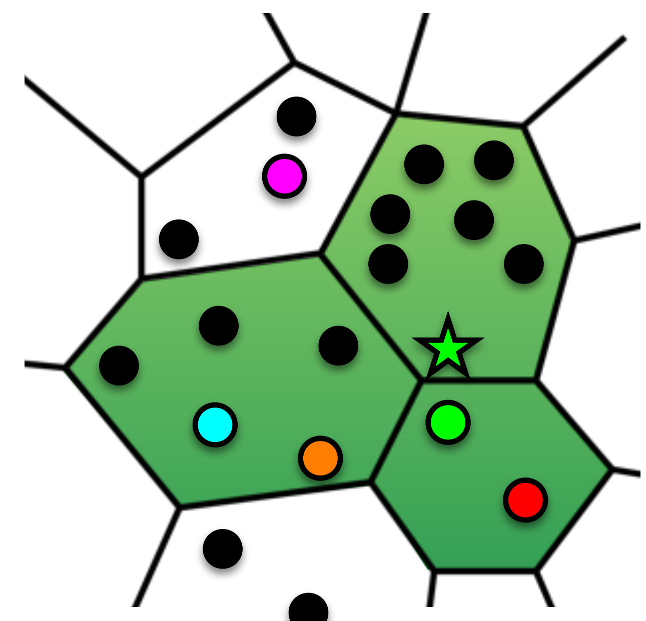
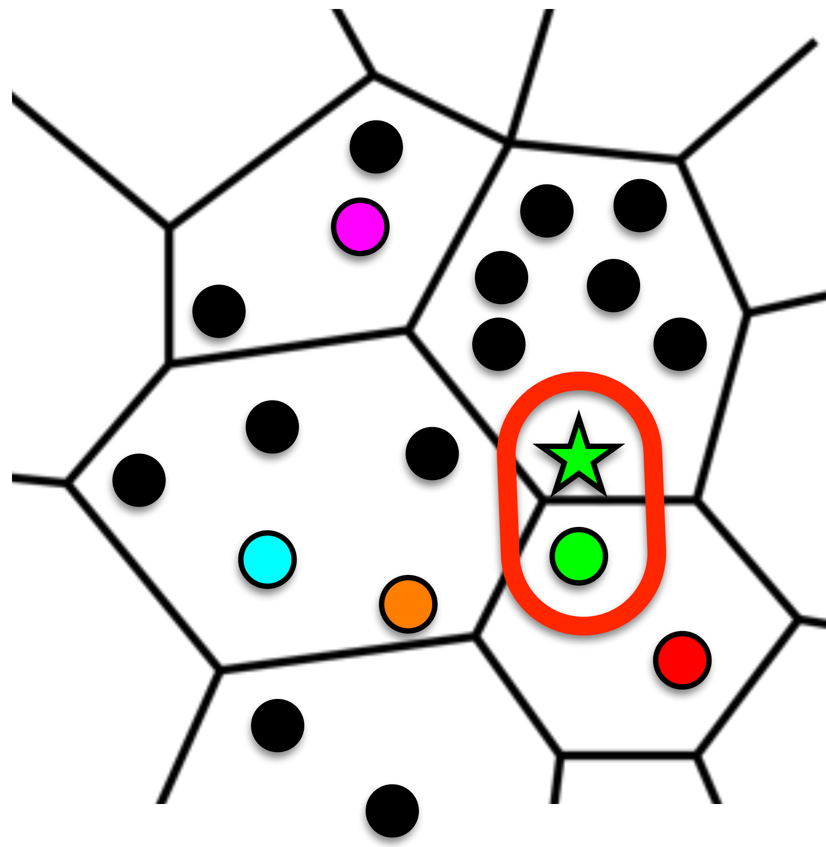


Soft Assignments



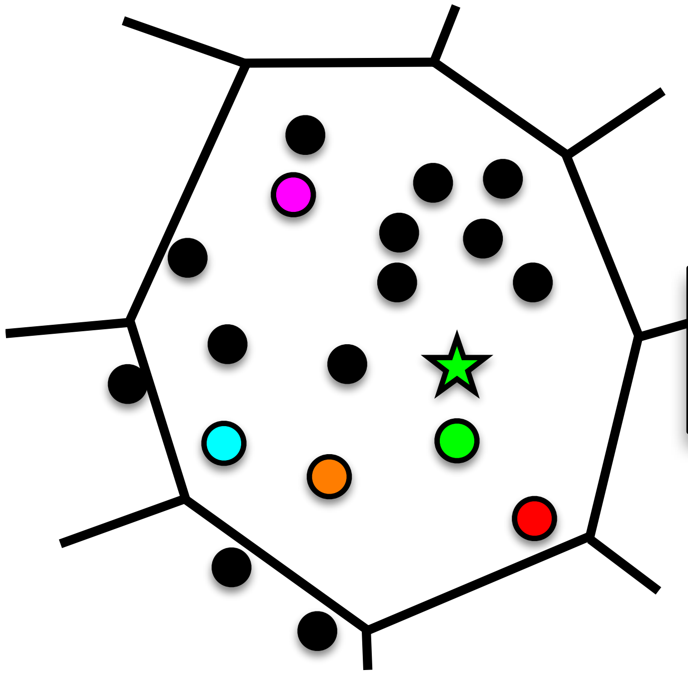
[Philbin et al., CPVR'08]

Quantization Artifacts



Match missed due to quantization!

Smaller Vocabulary



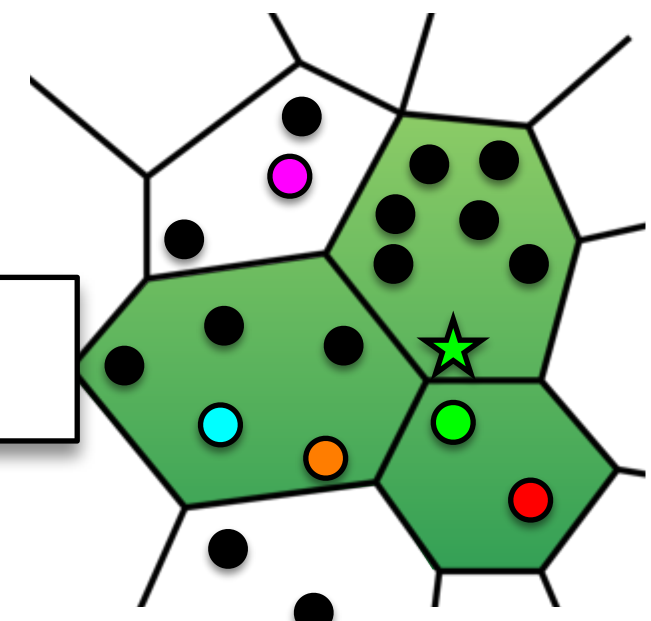
Additional costs

for each feature

$$\mathcal{O}(P/W)$$

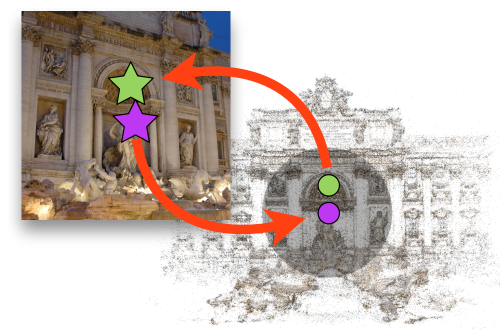
W words, P points

Soft Assignments



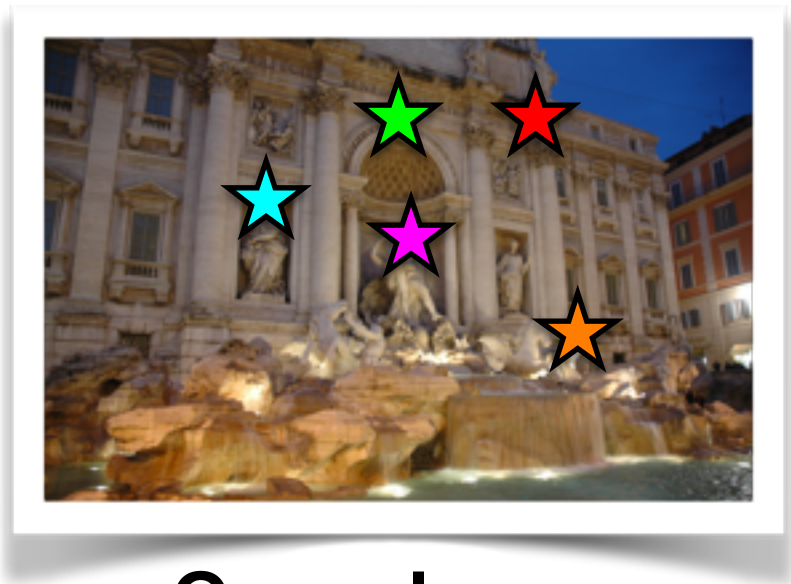
[Philbin et al., CPVR'08]

Localization - Overview

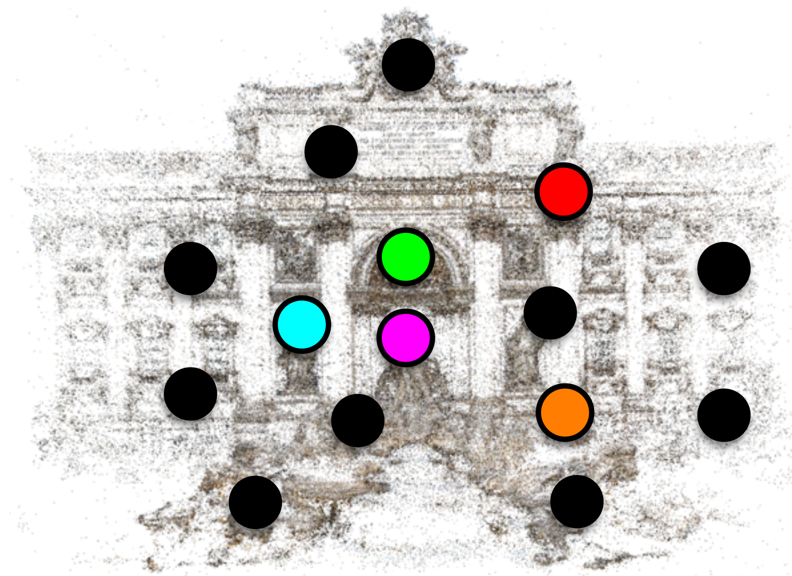
				
	Baseline: kd-tree search	**VPS**	**Active Search**	**+ Visibility Filtering**
	[Sattler et al., ICCV'11]	[Sattler et al., ICCV'11]	[Sattler et al., ECCV'12]	
effectiveness	✓	✗	✓✓	✓✓
efficiency	✗ ✗	✓	✗	✓

Active Search

Idea: Exploit **co-occurrence of matches** to recover matches



Query Image



3D Model

[Sattler et al., ECCV’12] [code]

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Active Search

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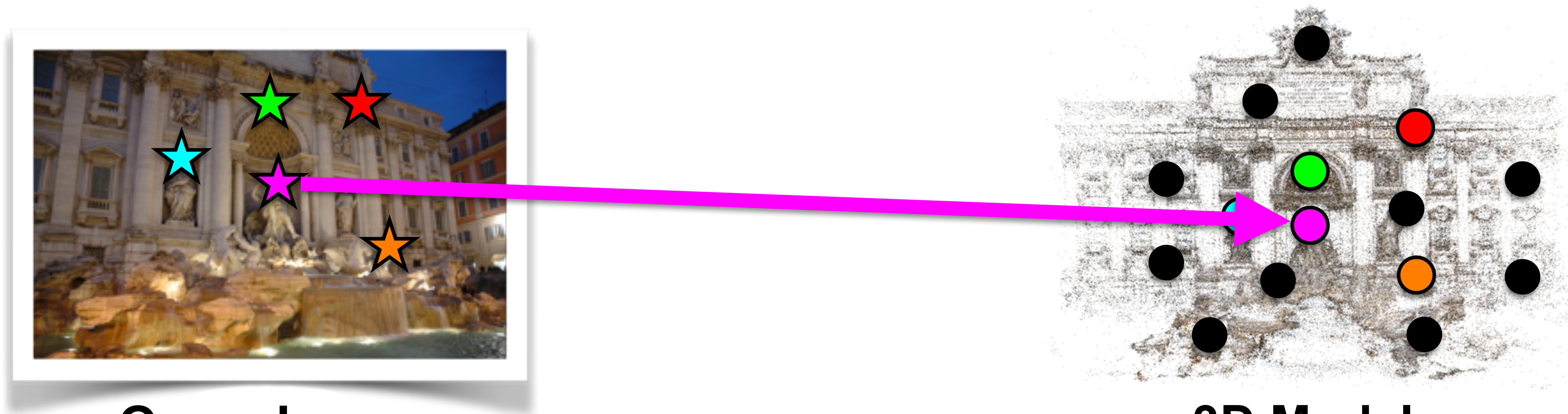

Query Image **3D Model**

[Sattler et al., ECCV’12] [code]

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- Points surrounding 2D-to-3D match should also be visible:

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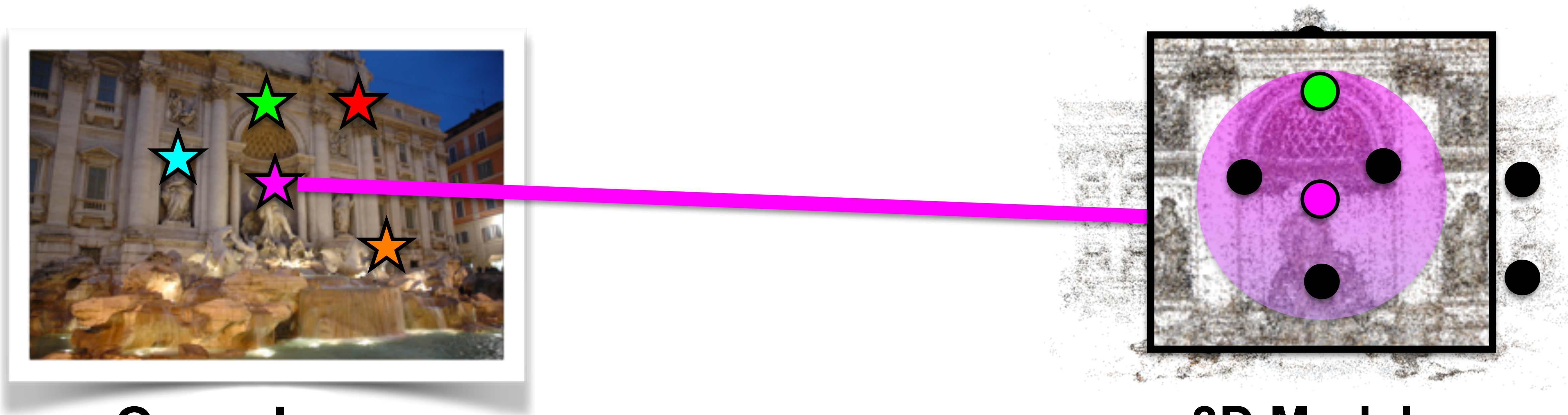

Query Image **3D Model**

- Points surrounding 2D-to-3D match should also be visible:
  - Find nearest neighbors in 3D around matching point

[Sattler et al., ECCV'12] [code]

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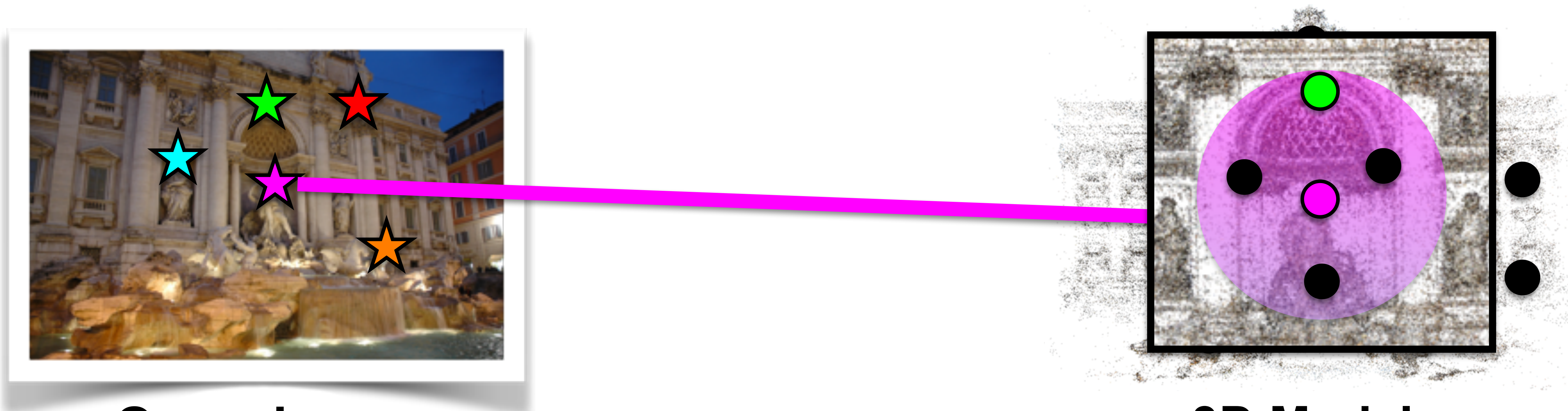

Query Image **3D Model**

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[Sattler et al., ECCV'12] [code]

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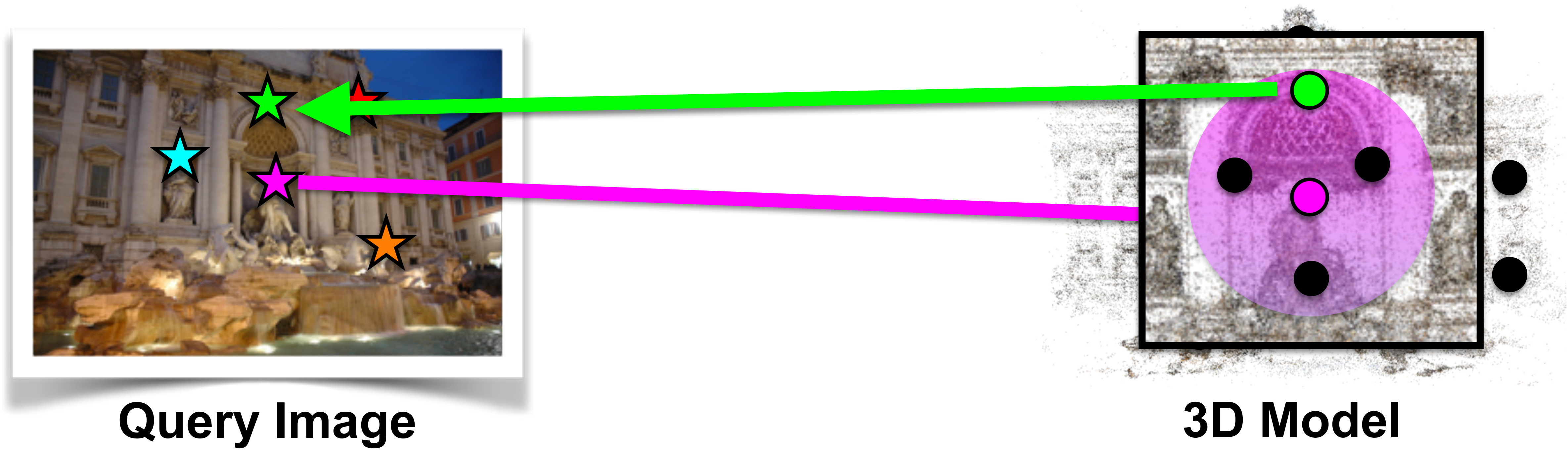

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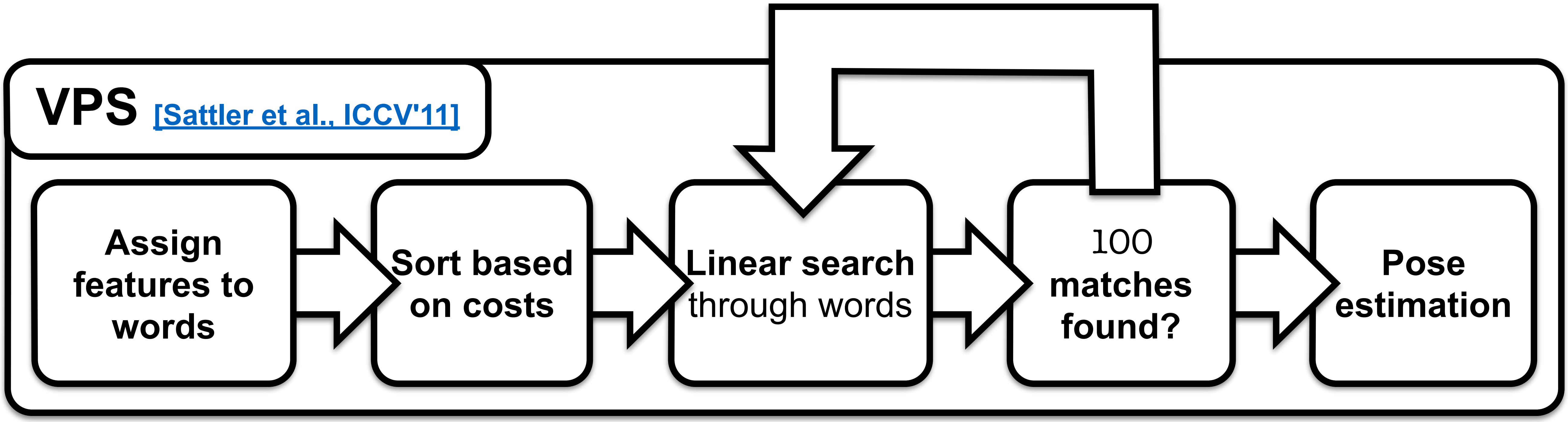
Integration Into VPS



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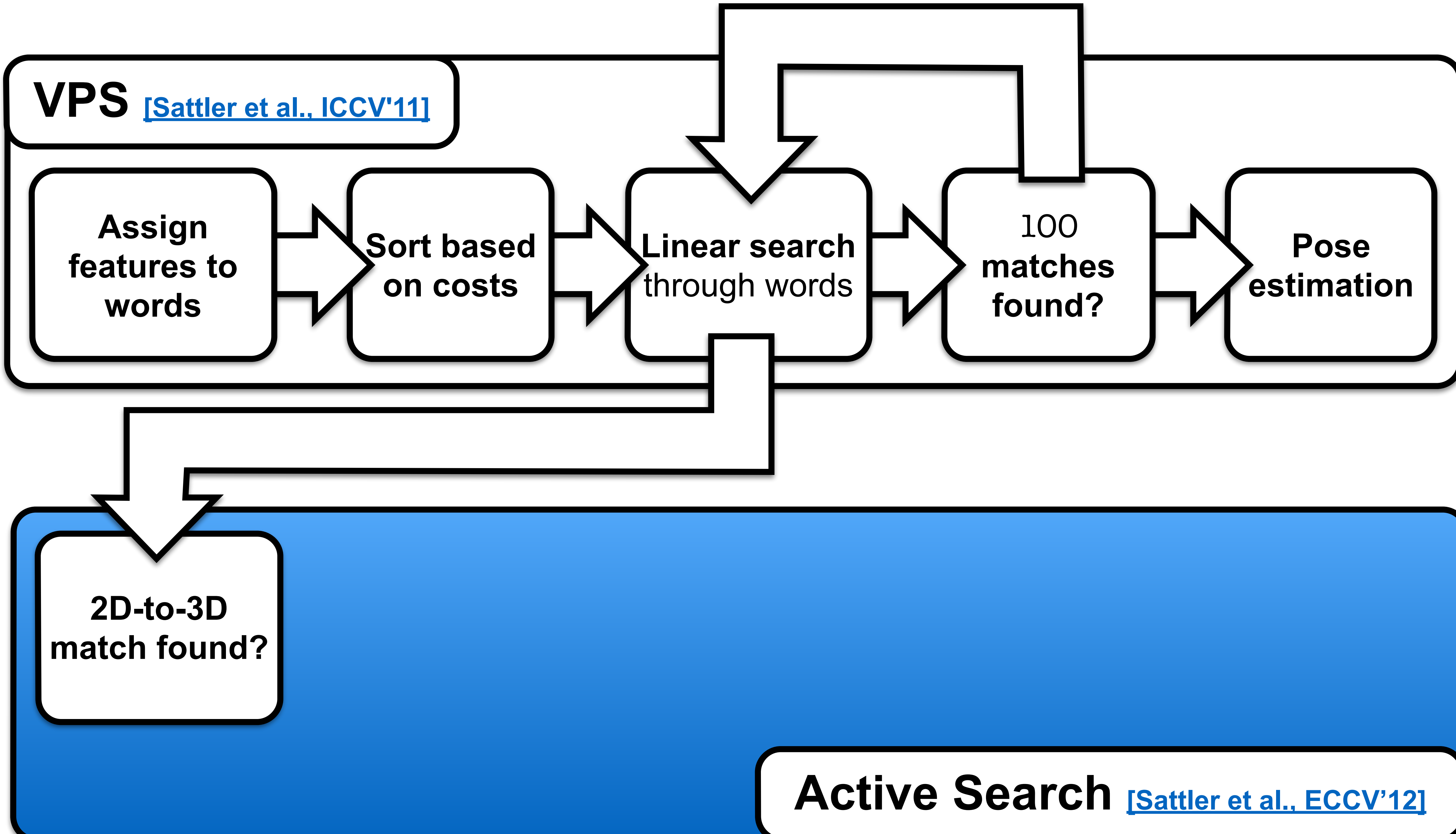

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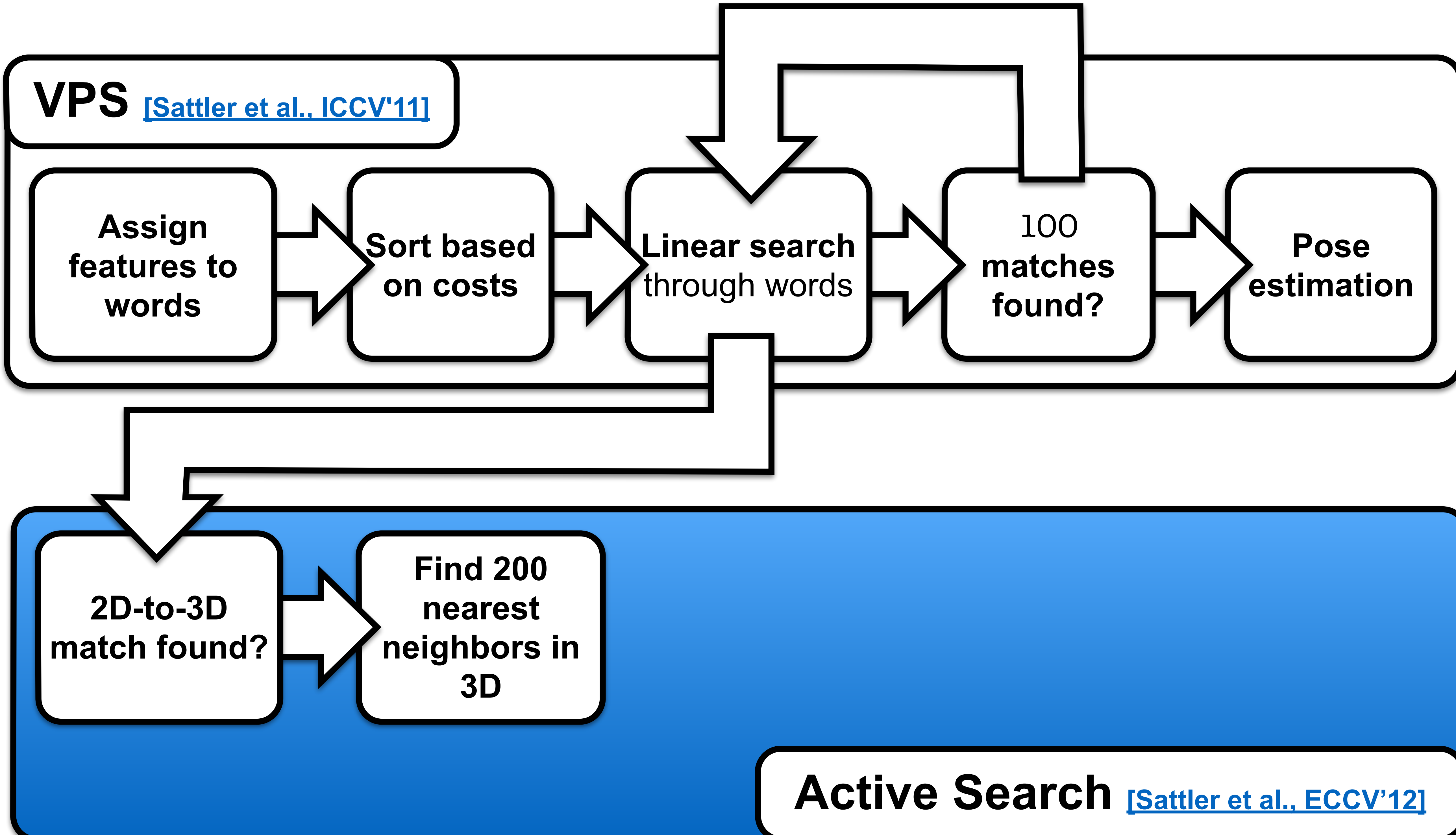

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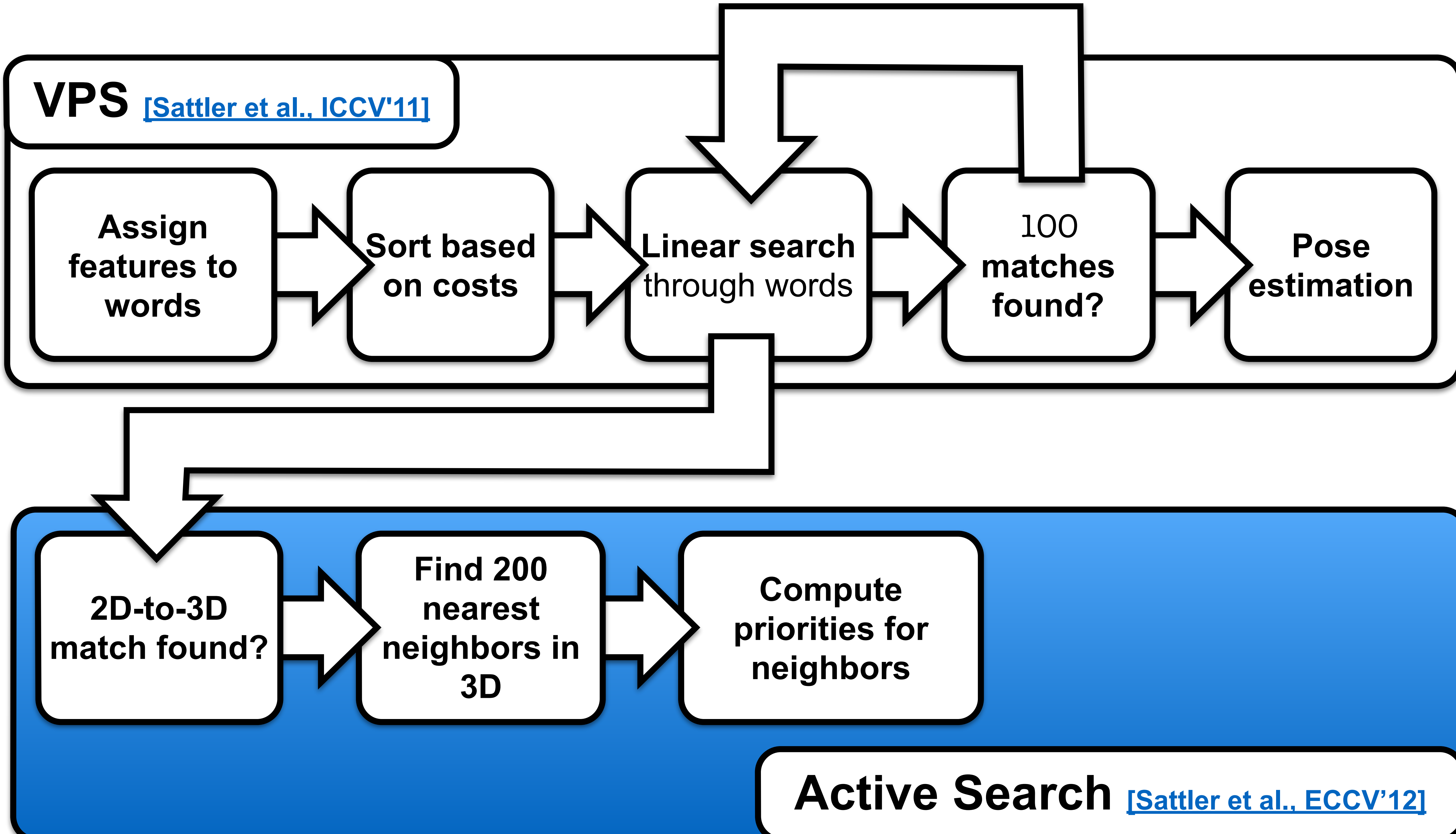
Integration Into VPS



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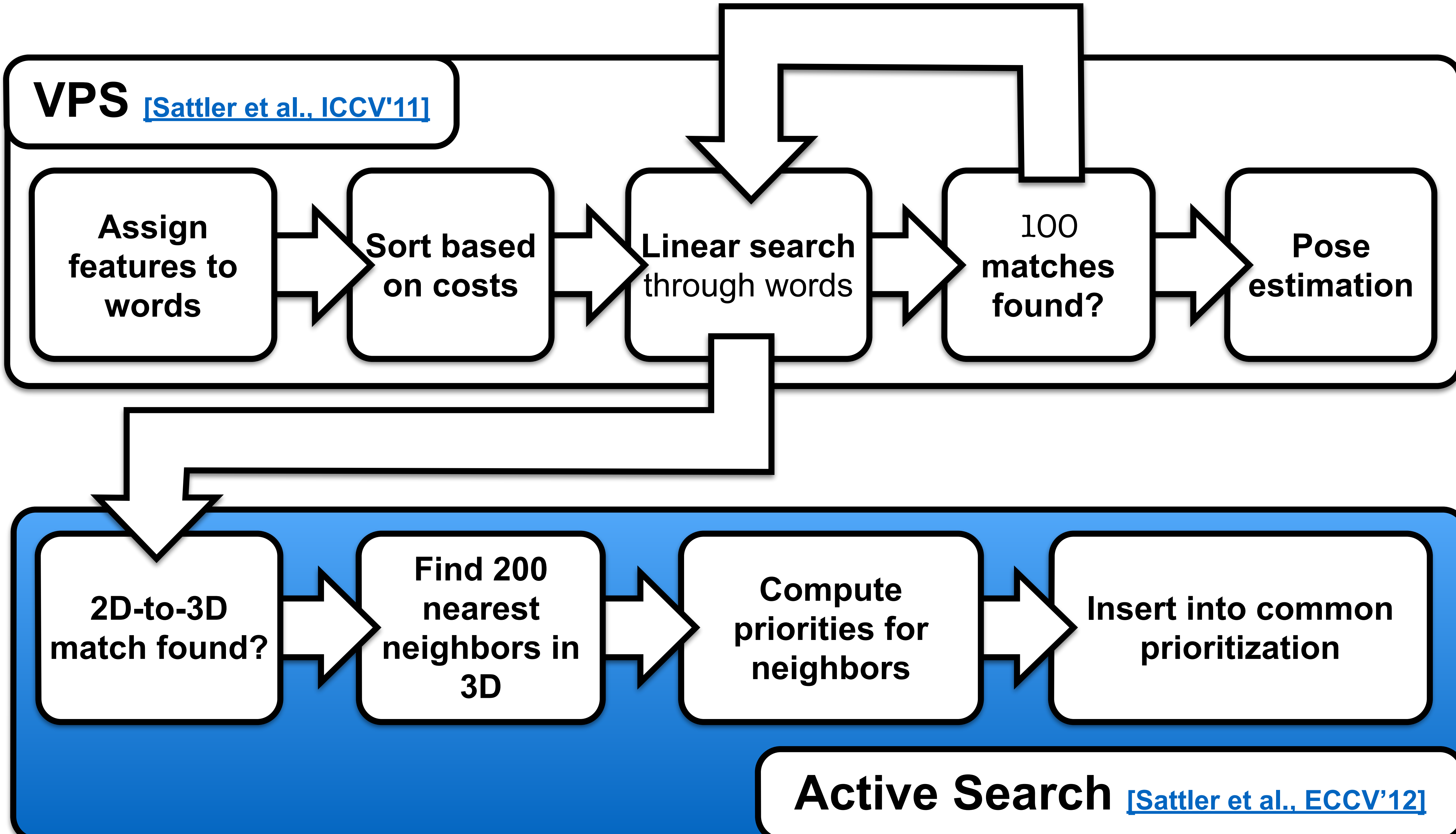

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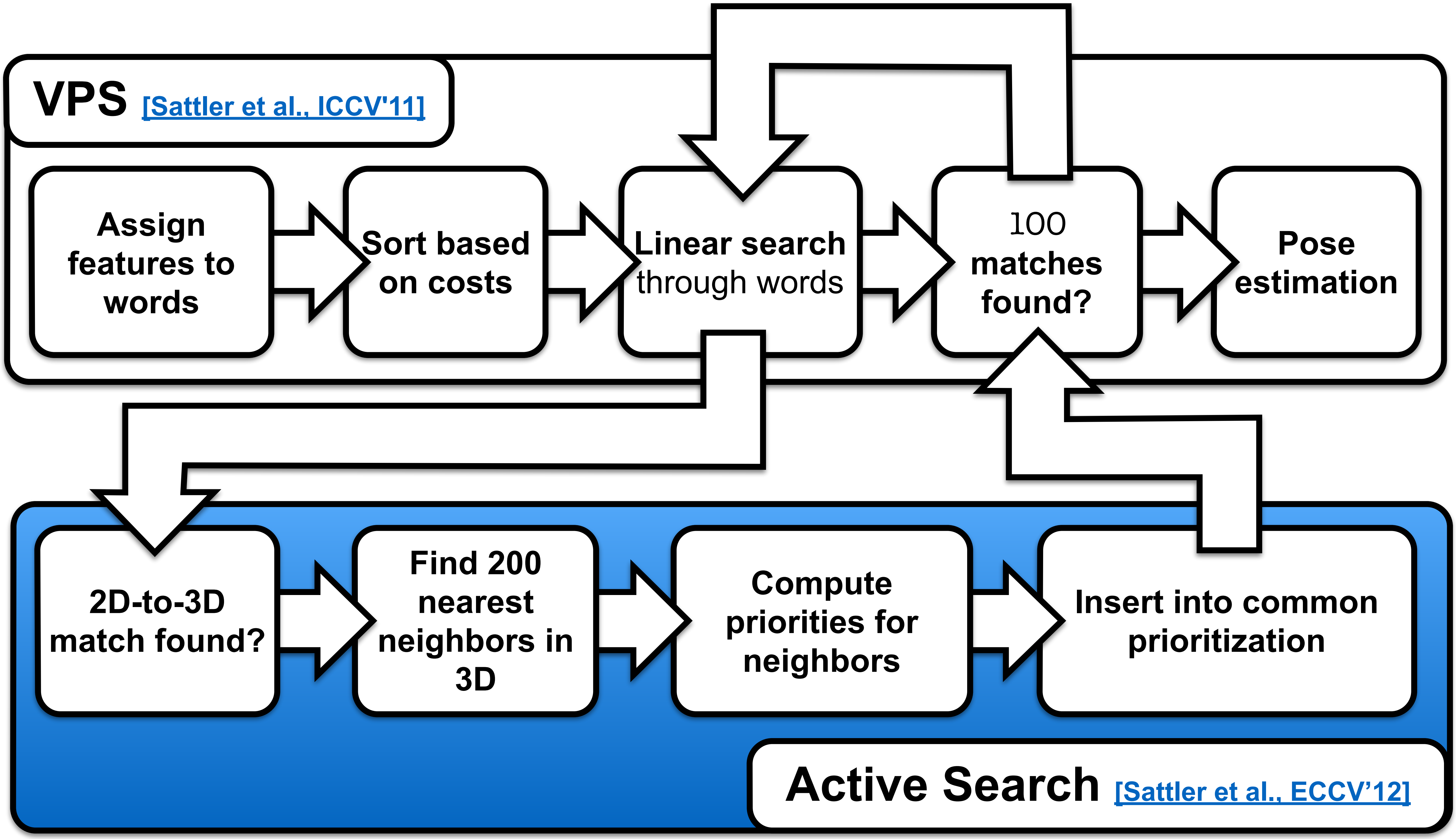

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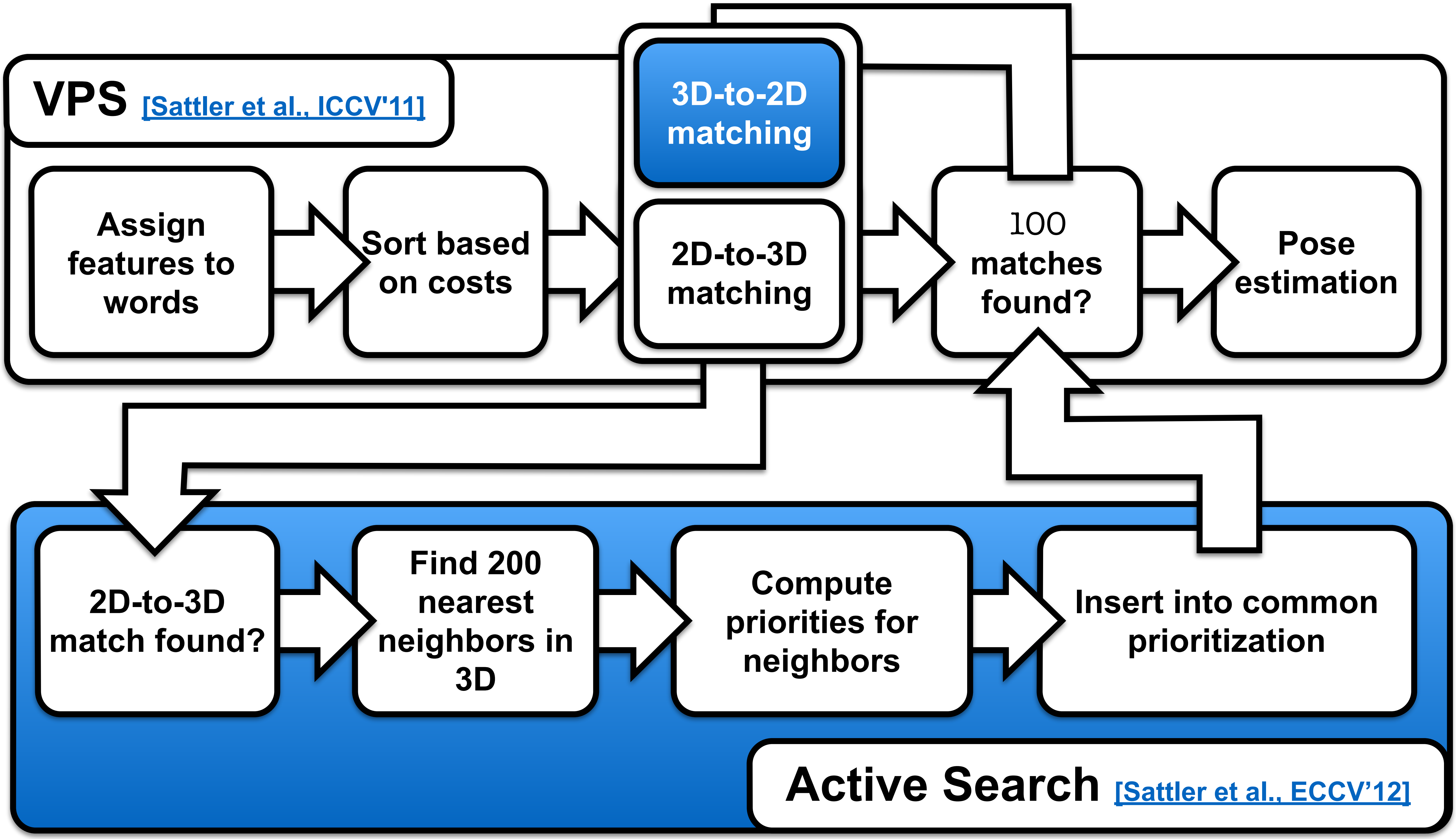

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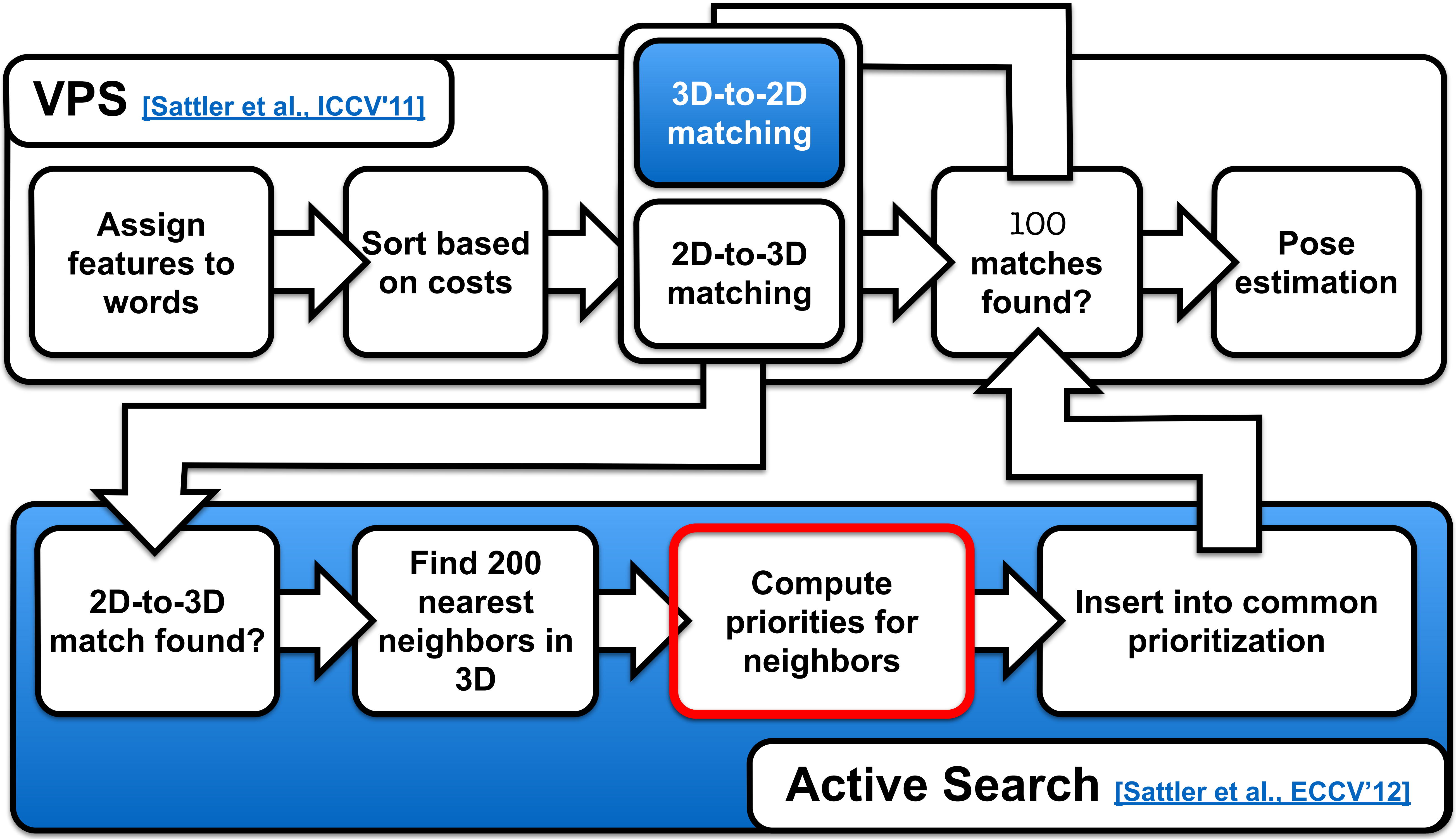

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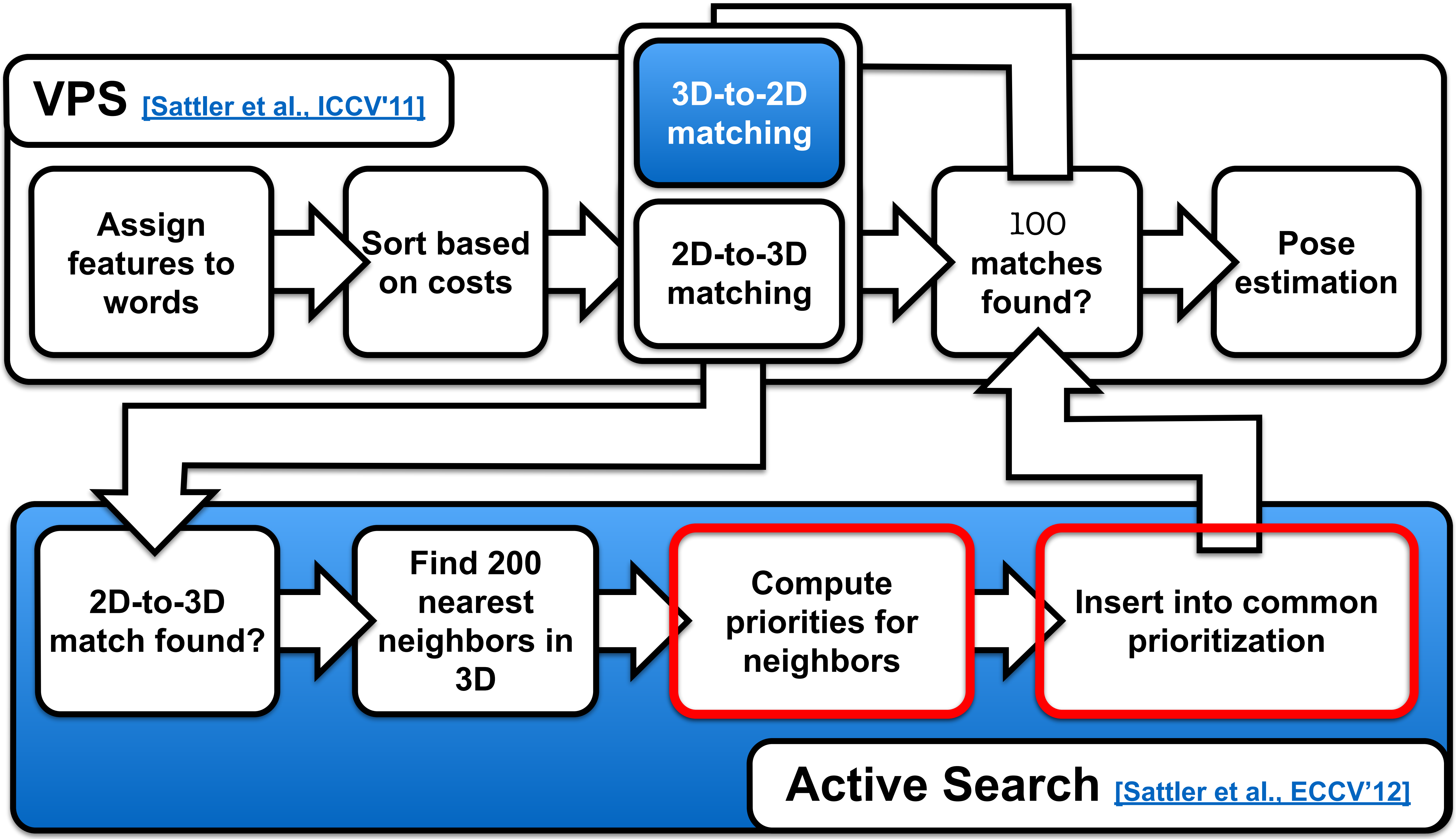

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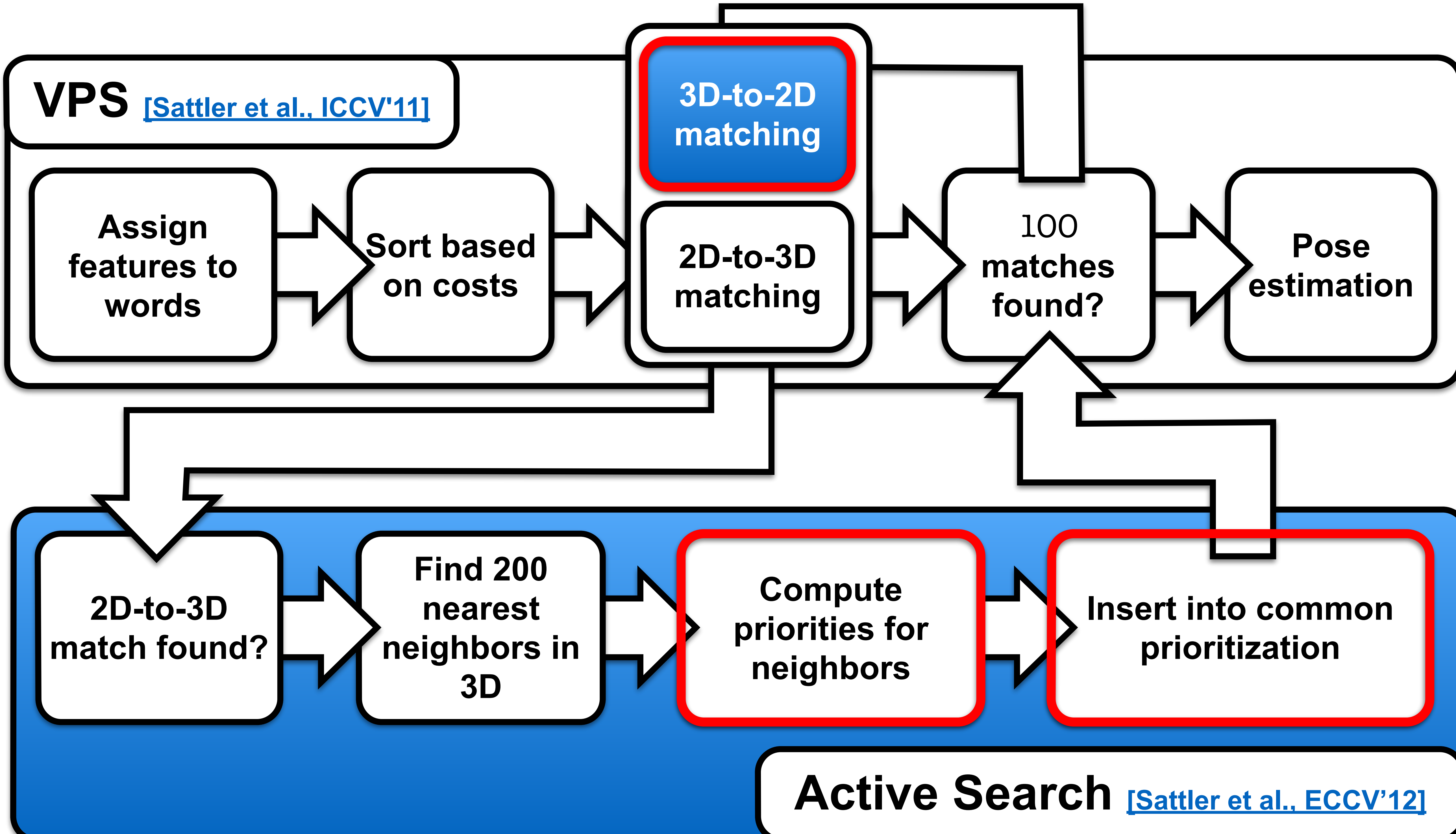

Integration 3D-to-2D Matching

- Reduce quantization artifacts

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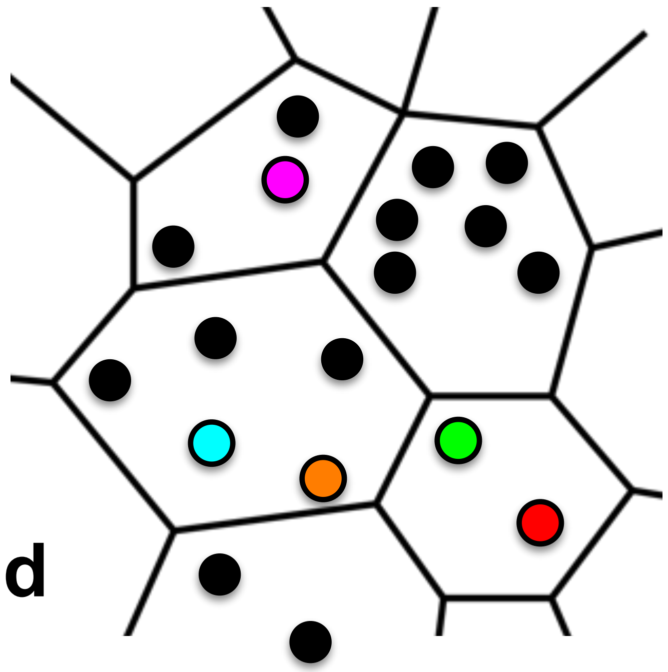

Large Vocabulary required for VPS (100k words)

Integration 3D-to-2D Matching

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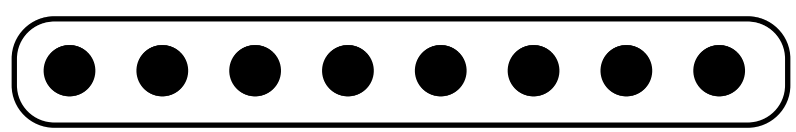
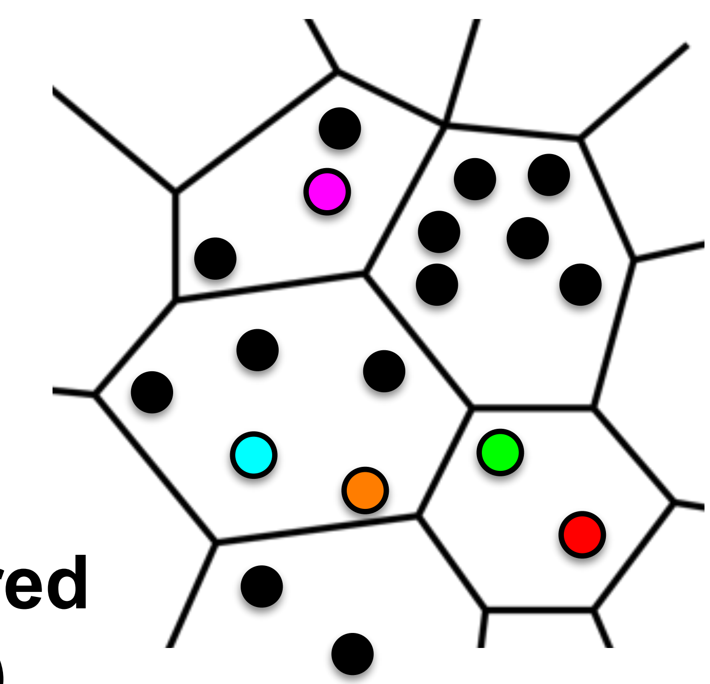
Vocabulary Tree





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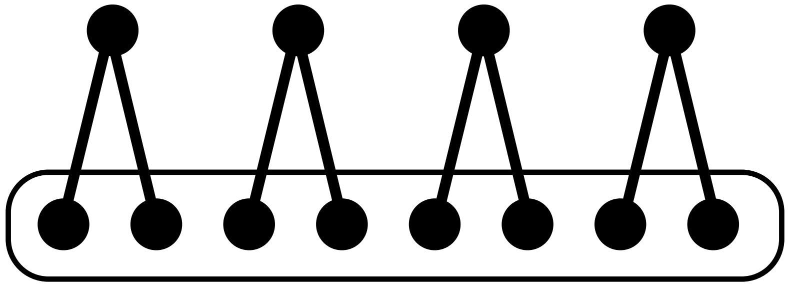

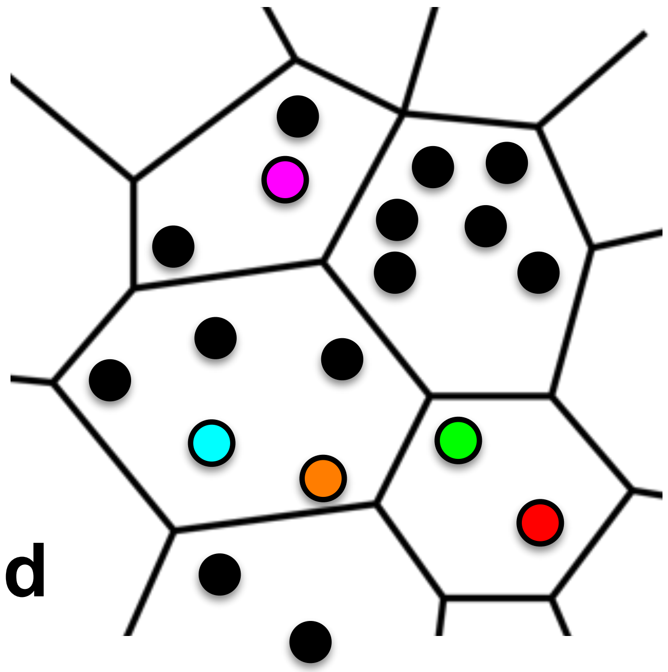

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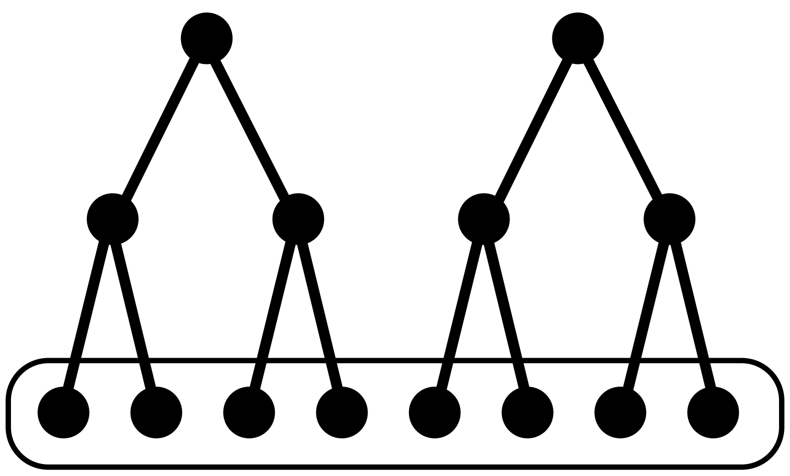

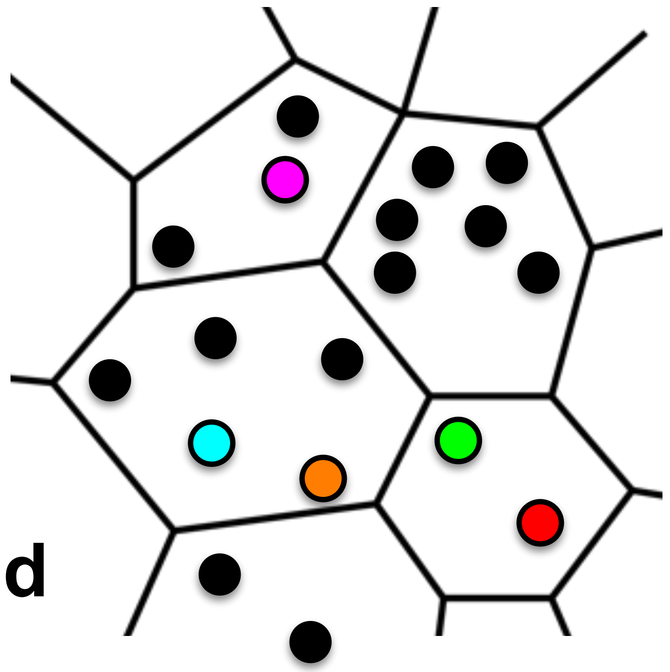

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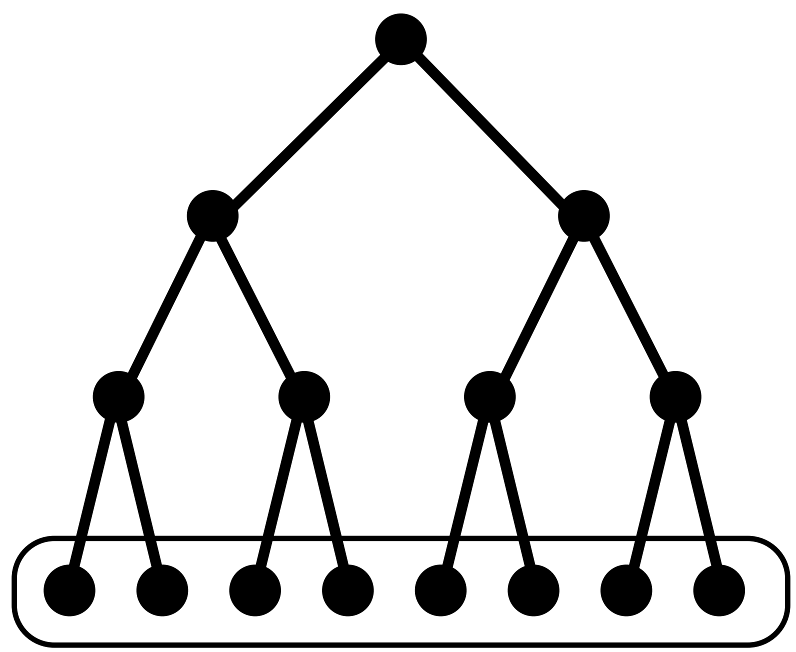

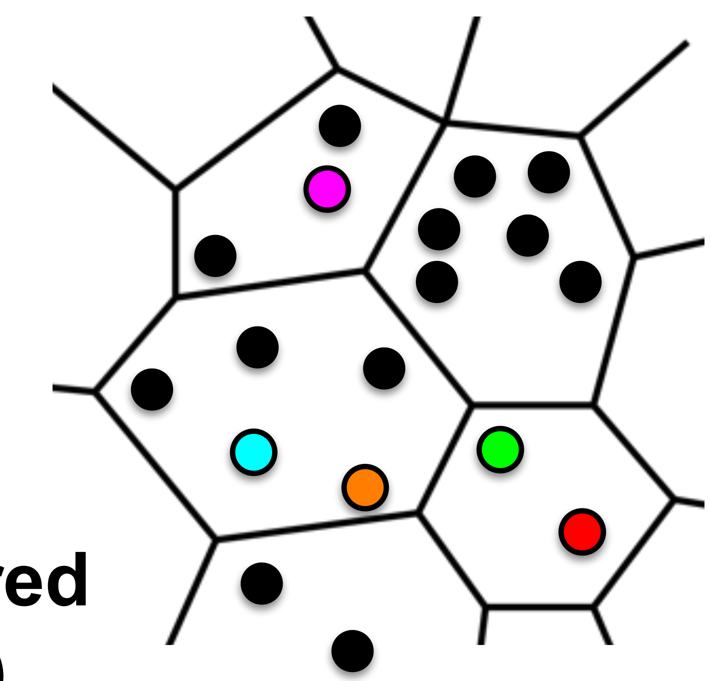

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Integration 3D-to-2D Matching

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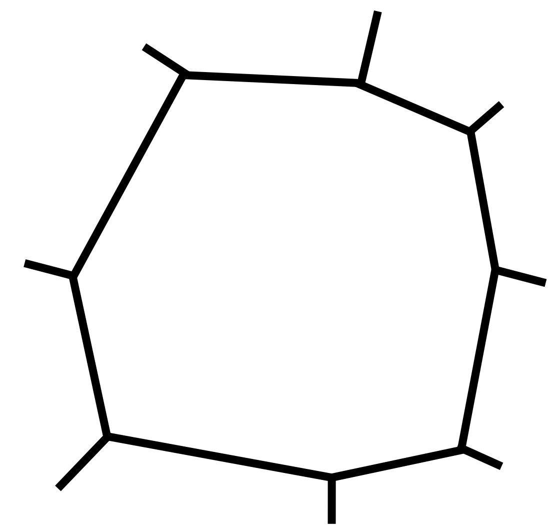
Small Vocabulary for 3D-to-2D search (100-1k words)



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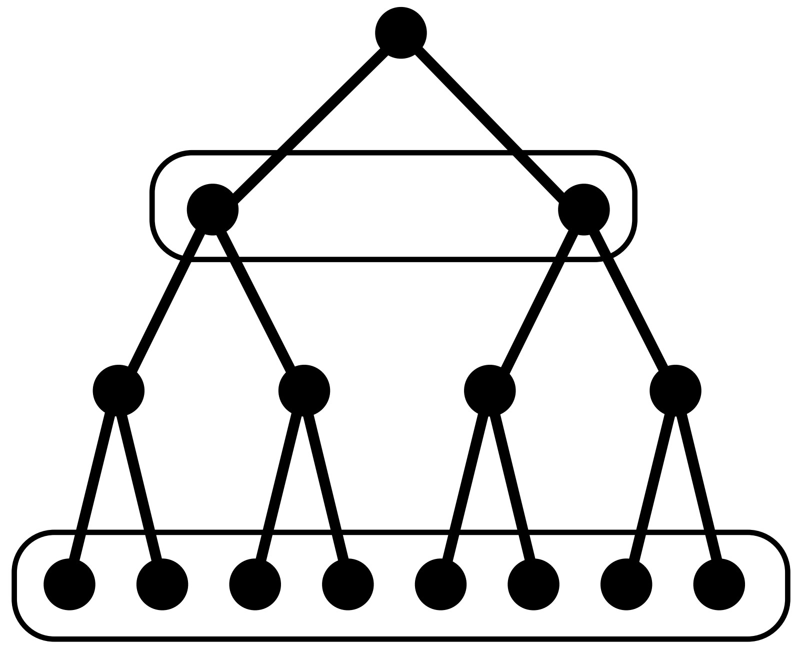

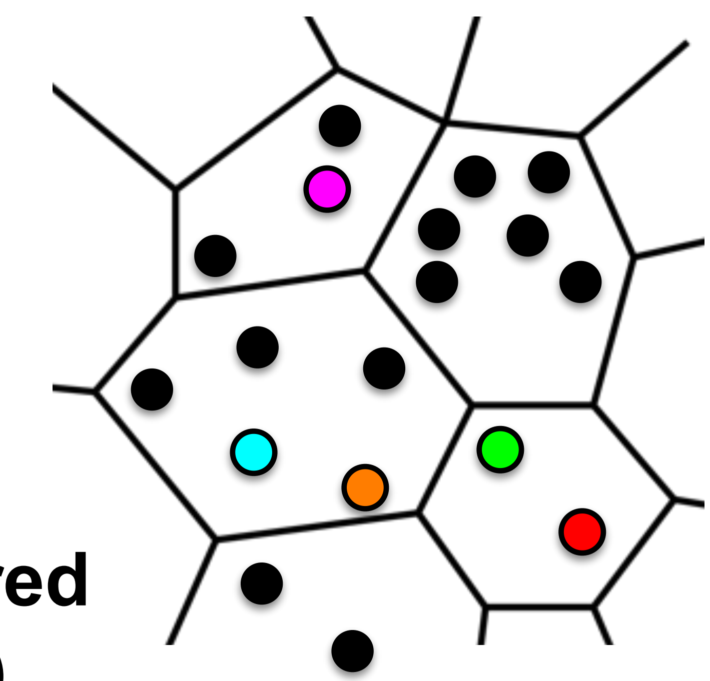

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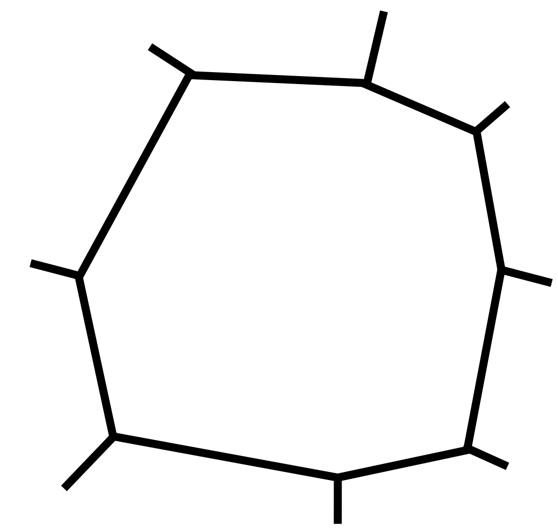
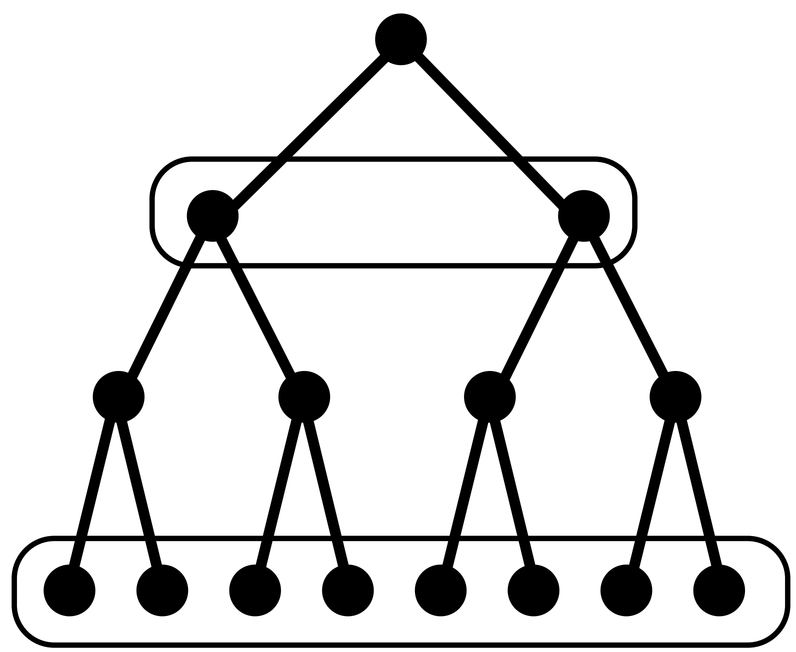
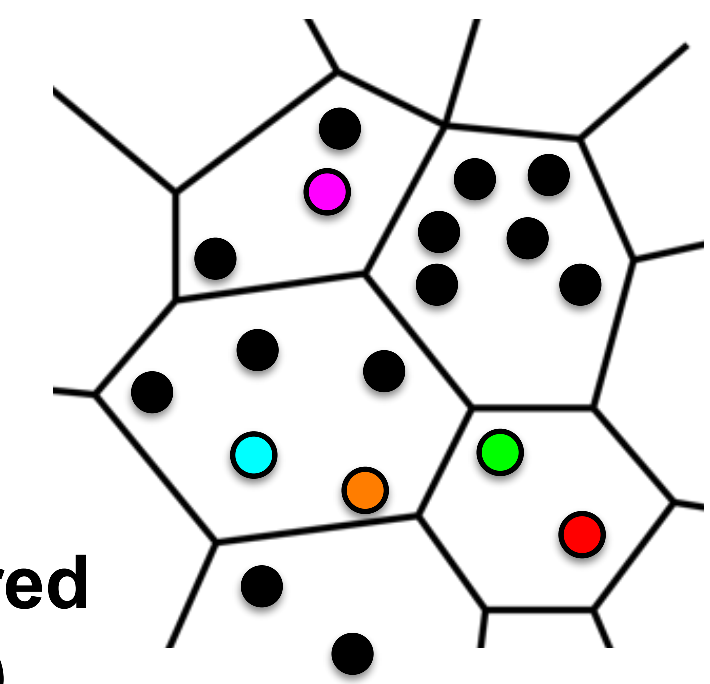


Query Image

Vocabulary Tree





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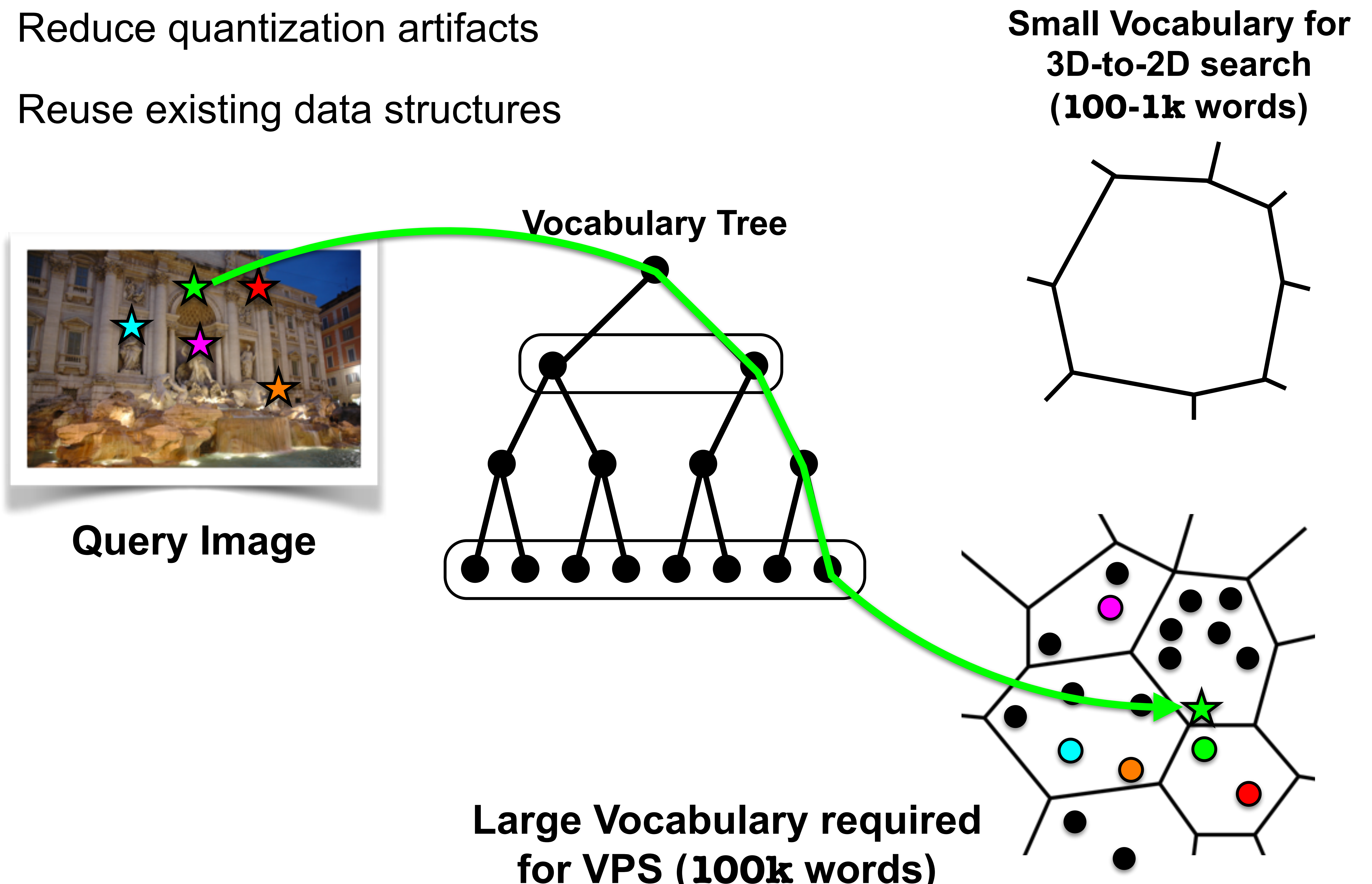

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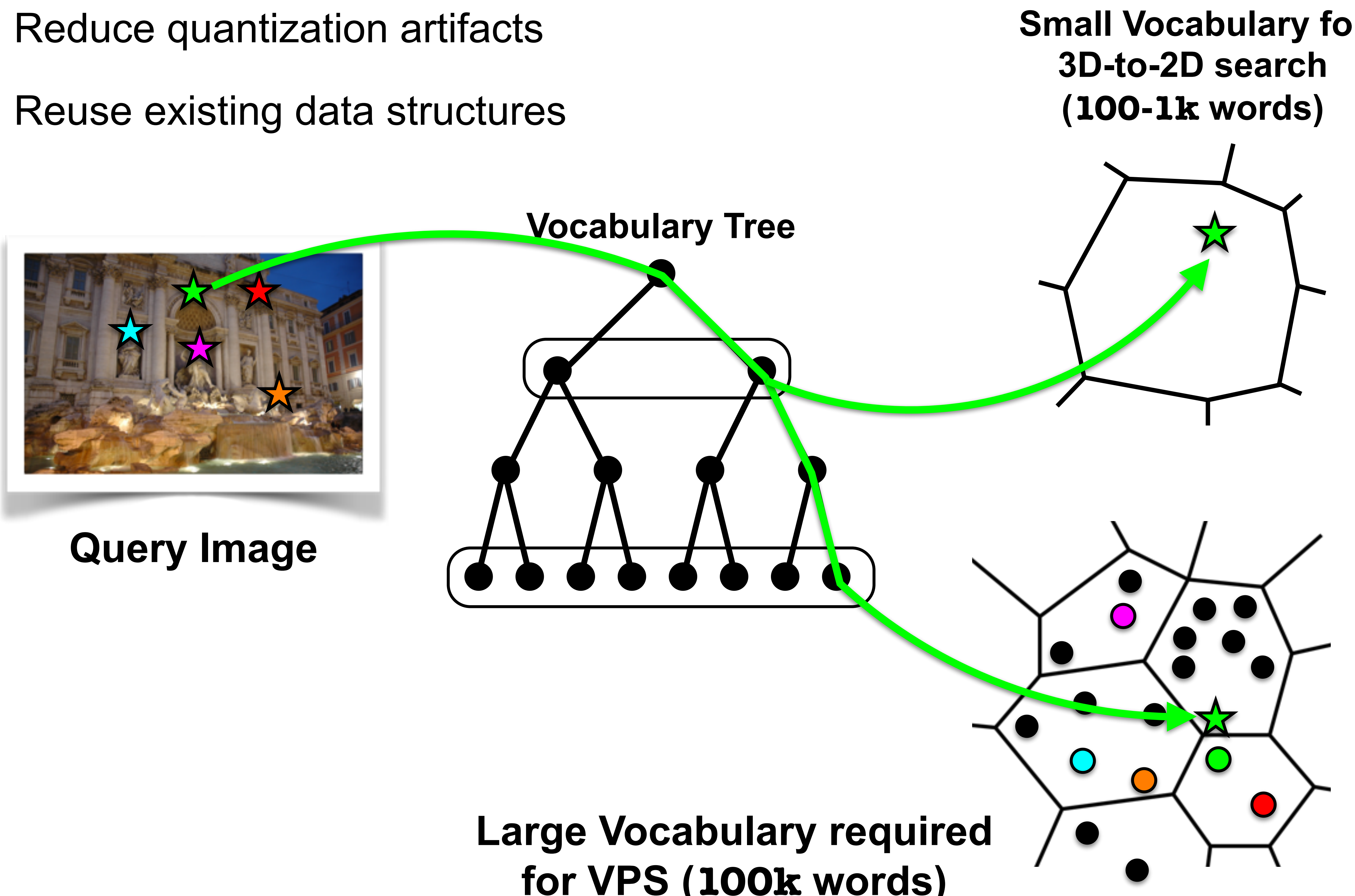

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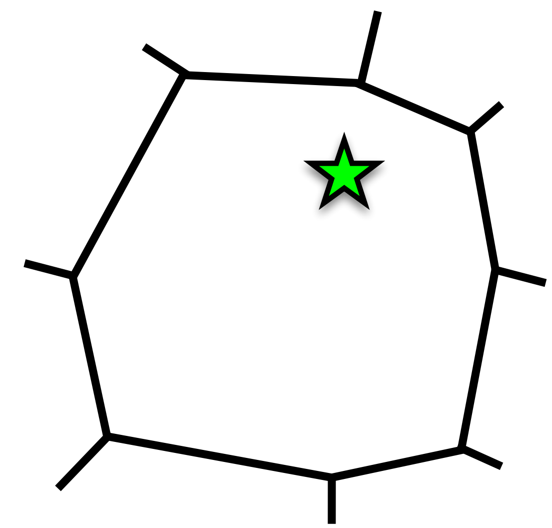
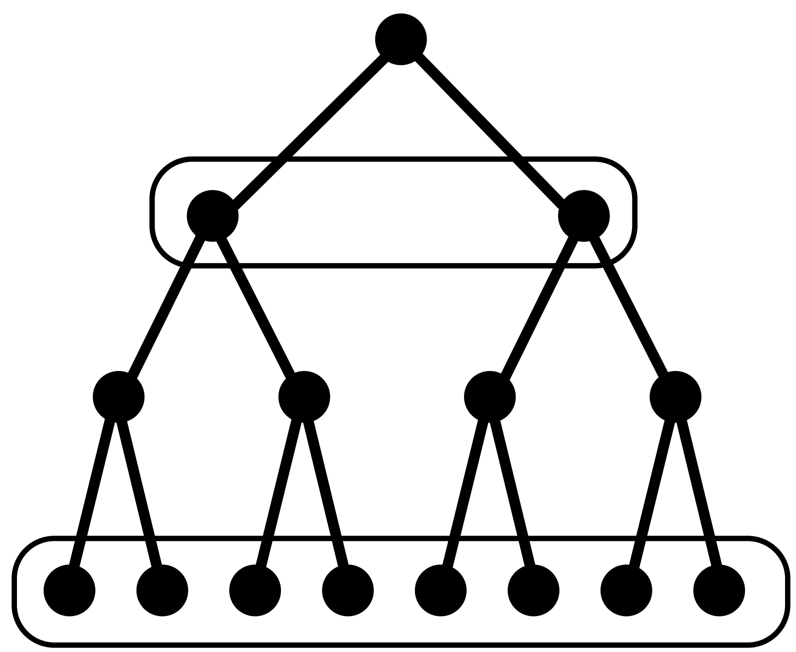
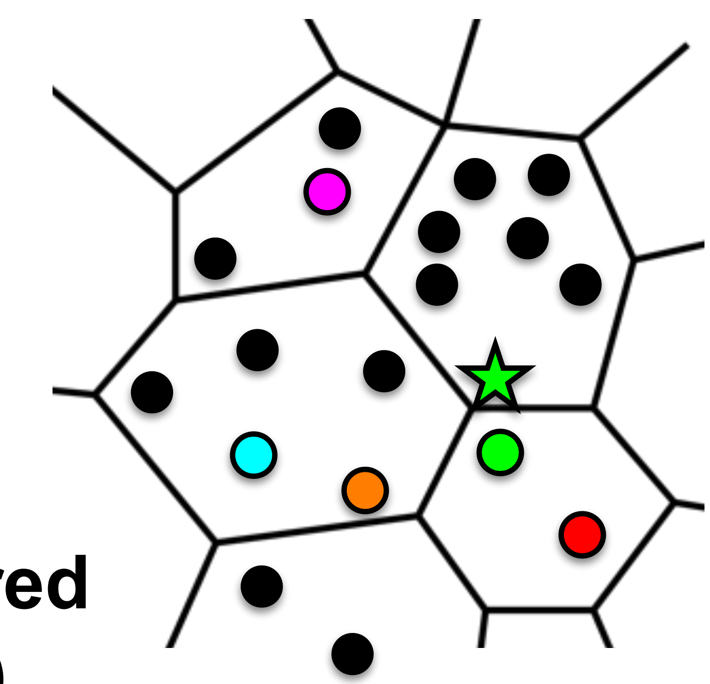
Small Vocabulary for 3D-to-2D search (100-1k words)



Query Image

Vocabulary Tree





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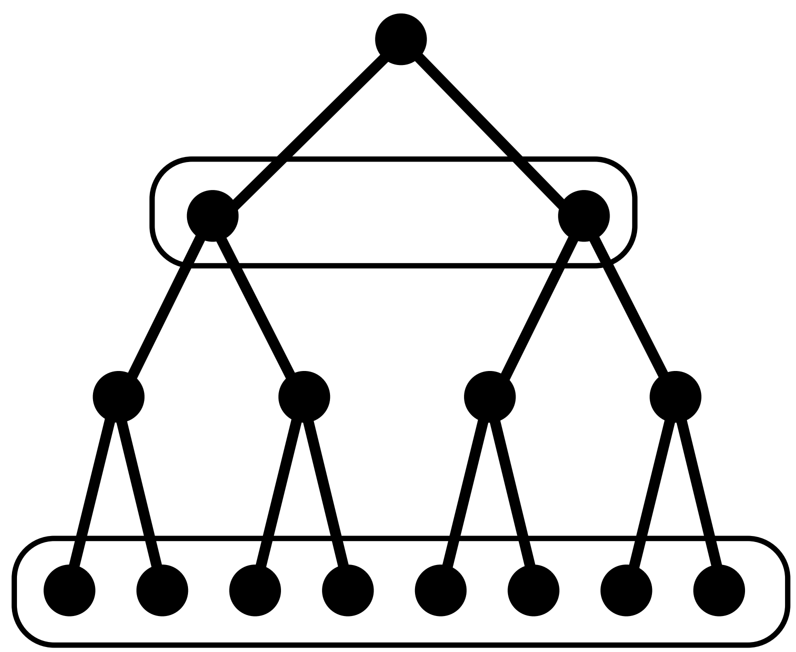

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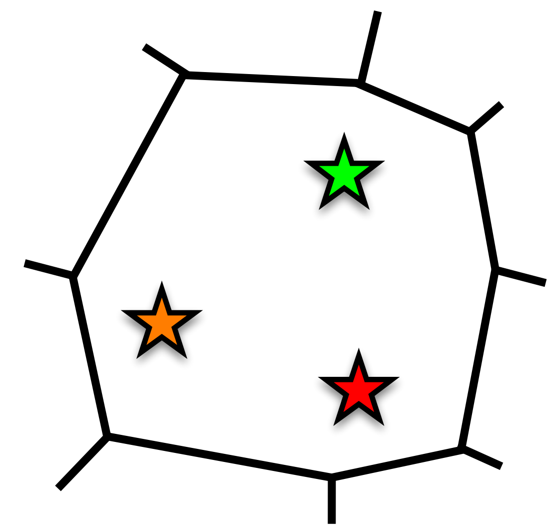

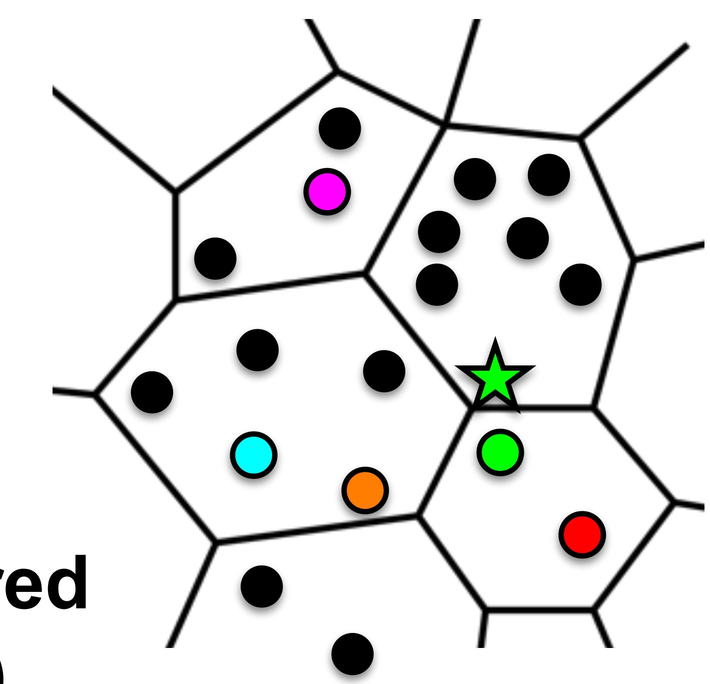

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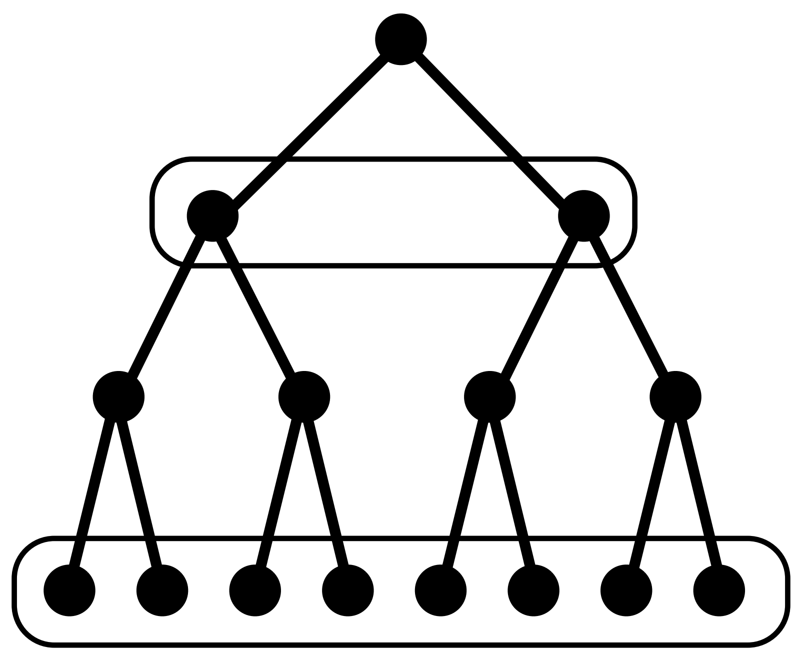

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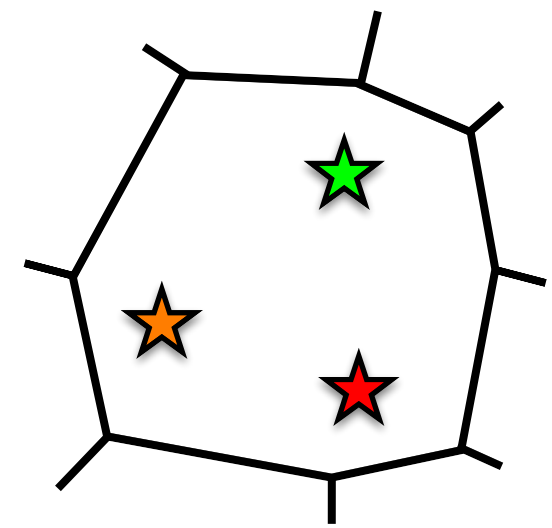

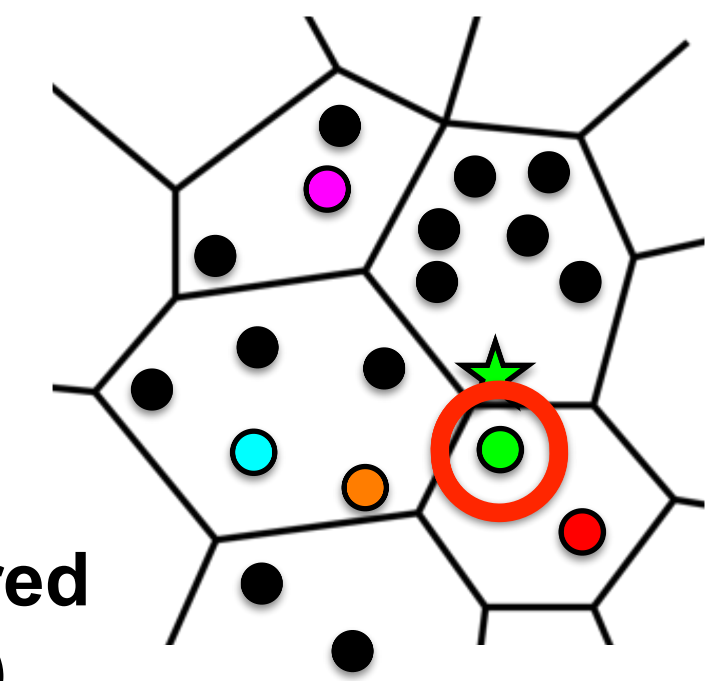

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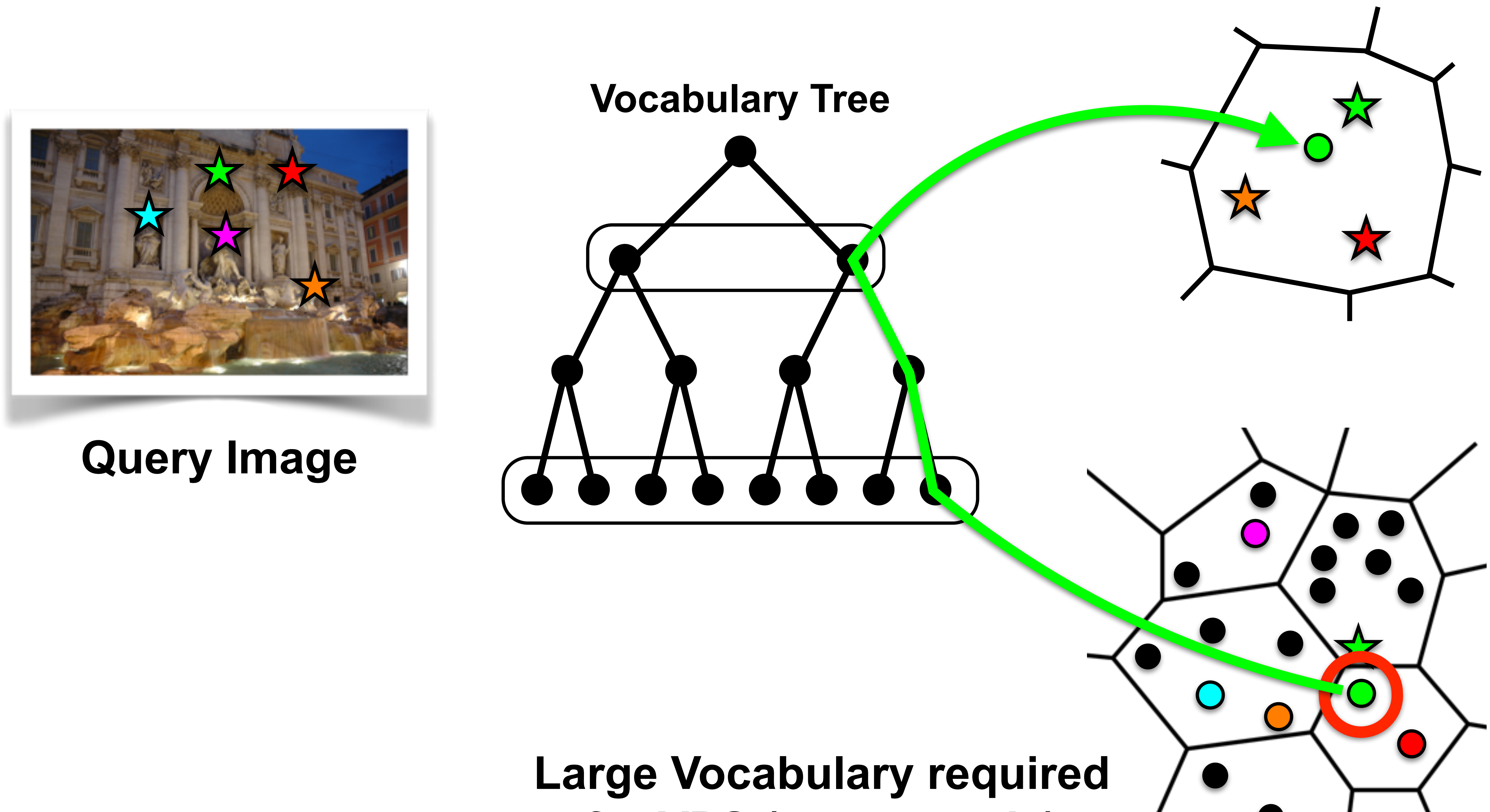

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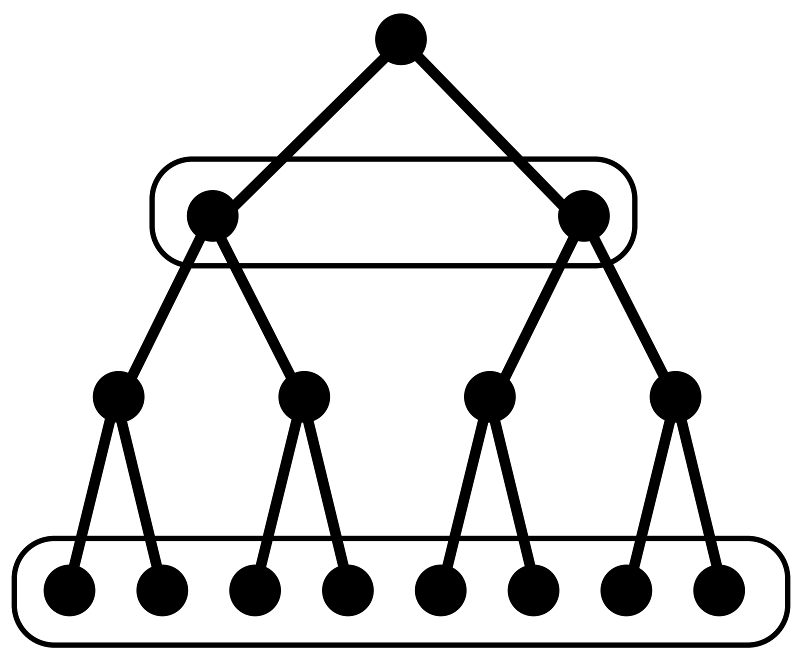

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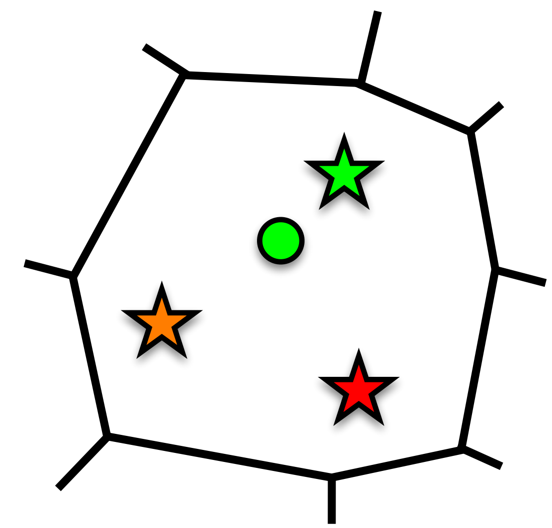

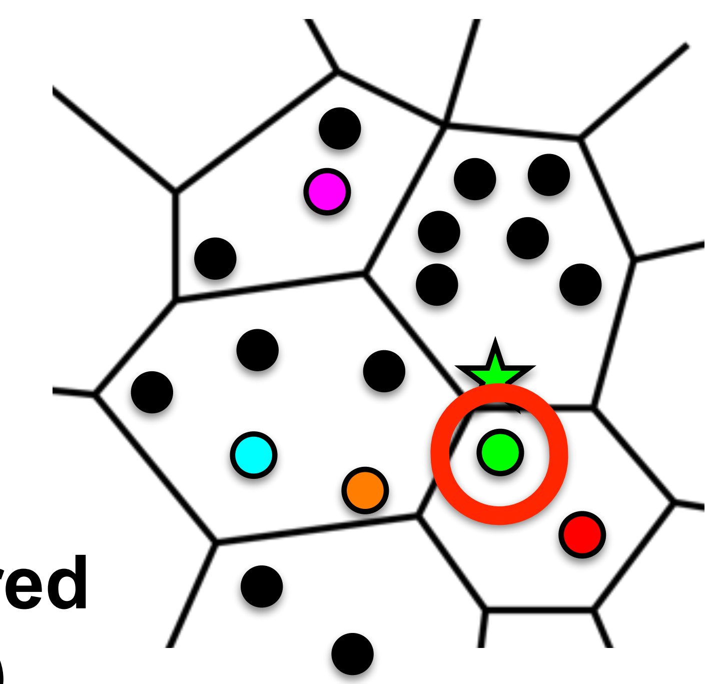

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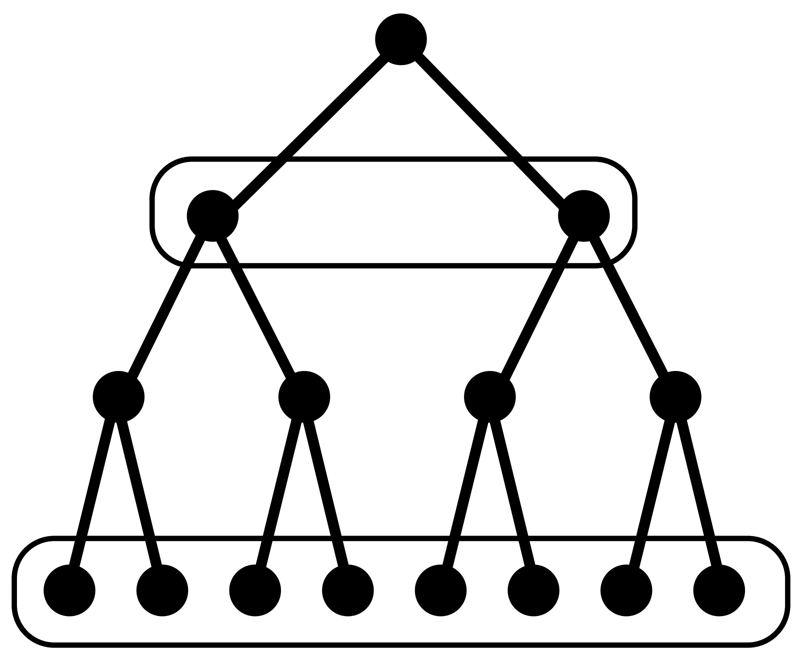

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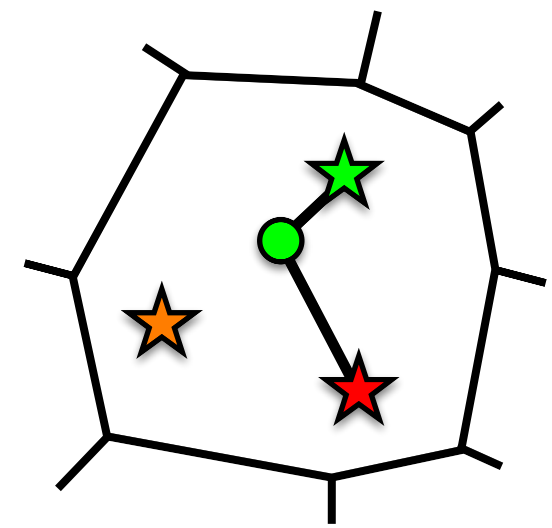
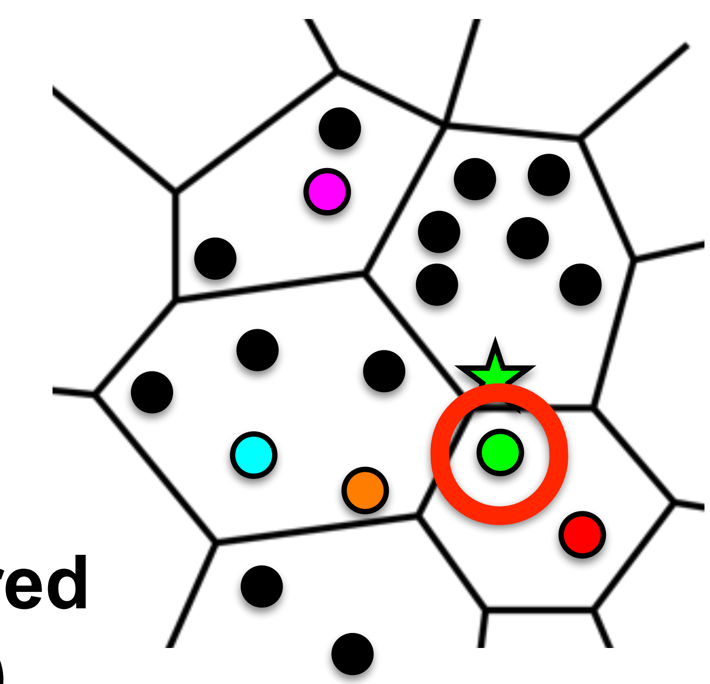
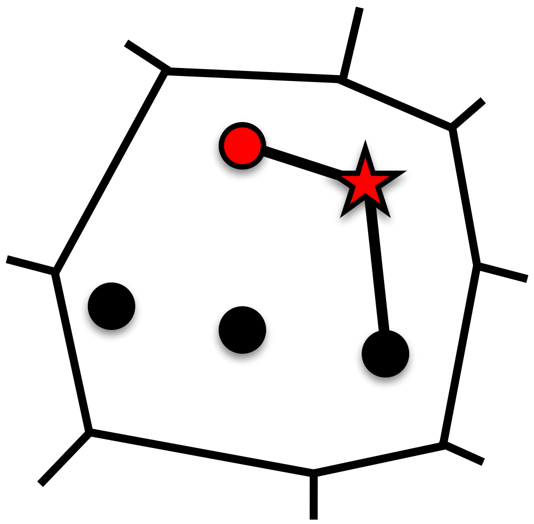




Large Vocabulary required for VPS (100k words)

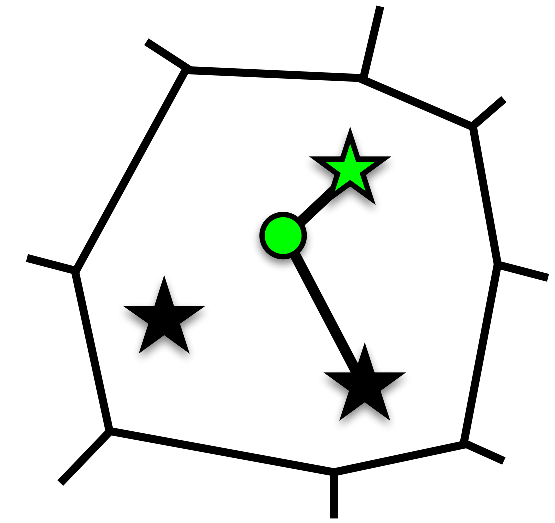
Common Prioritization Scheme

2D-to-3D Matching



- Find neighbors inside visual word
- Same definition of search costs

3D-to-2D Matching



[Sattler et al., ECCV'12]

Common Prioritization Scheme

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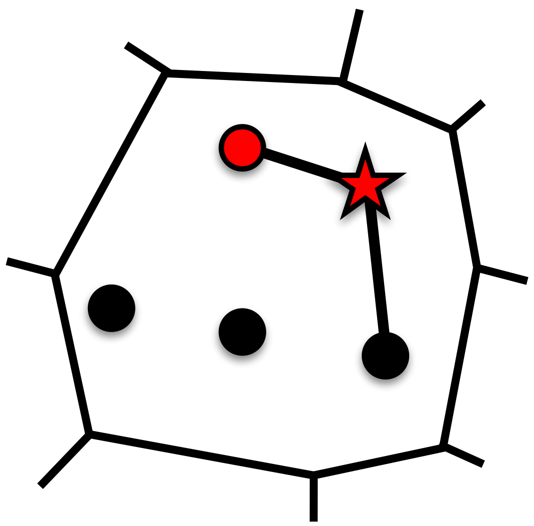
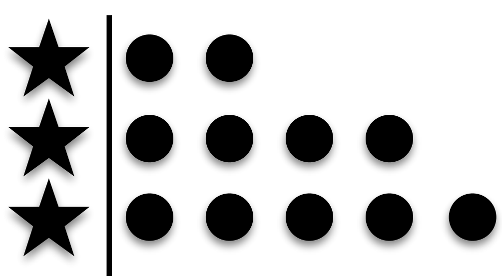


Priorities



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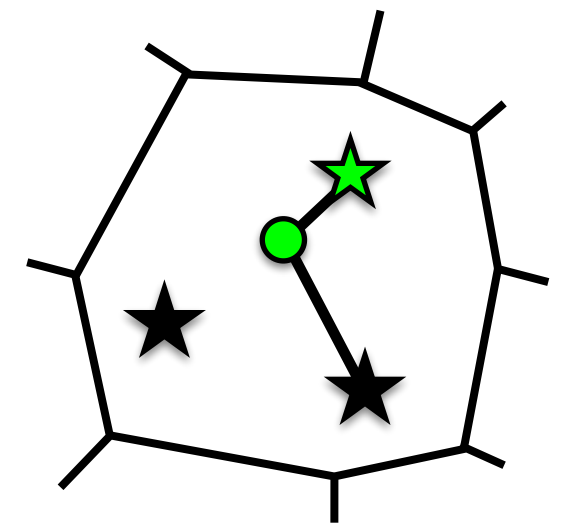

Priorities

[Sattler et al., ECCV'12]

Common Prioritization Scheme

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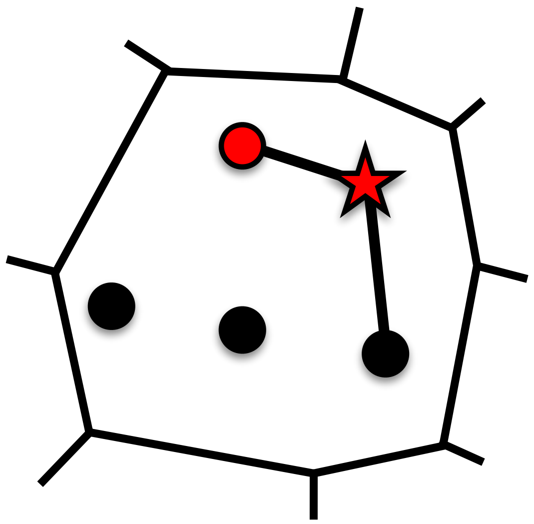

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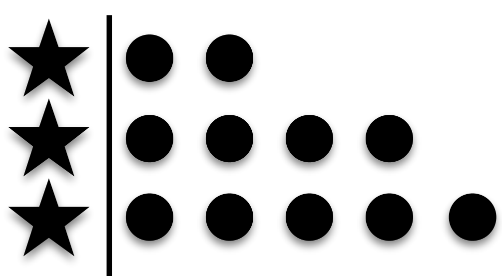

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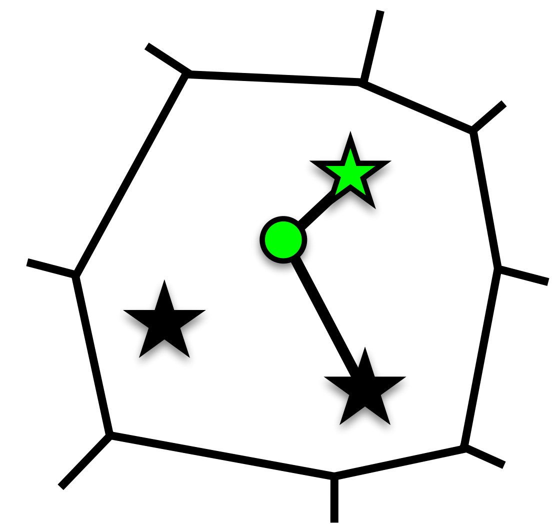

Priorities

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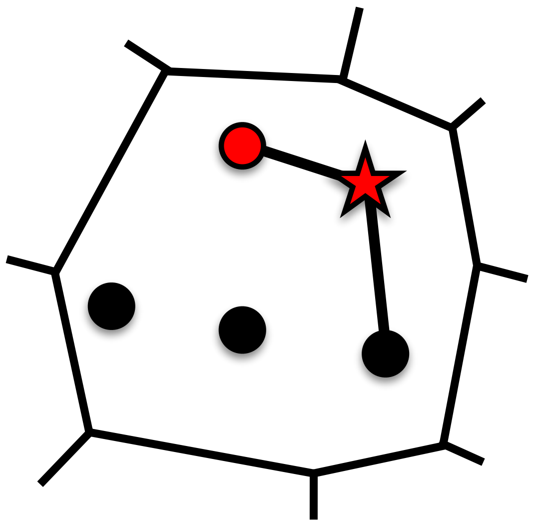
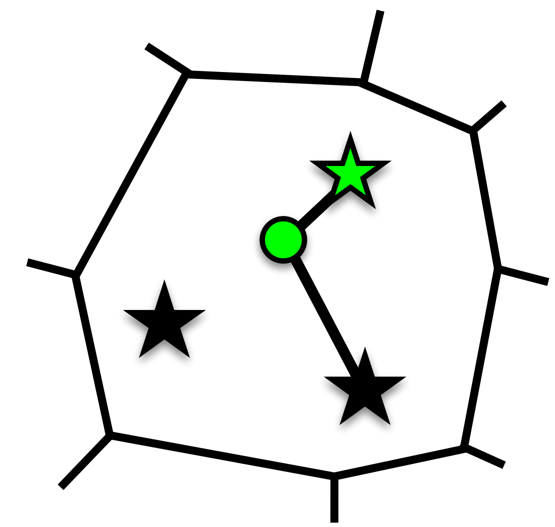
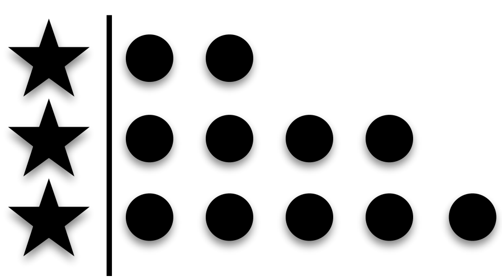


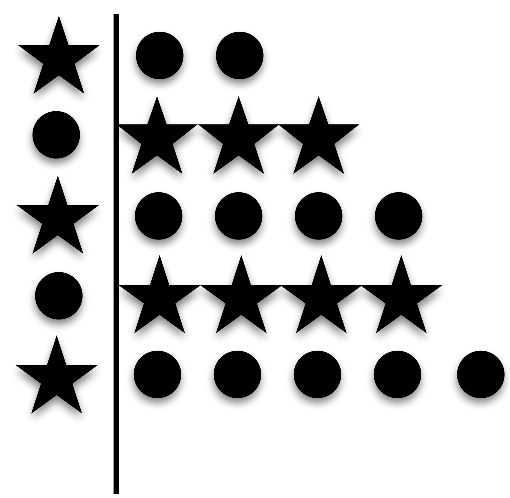
3D-to-2D Matching



- Find neighbors inside visual word
- Same definition of search costs

Priorities





Priorities

[Sattler et al., ECCV'12]

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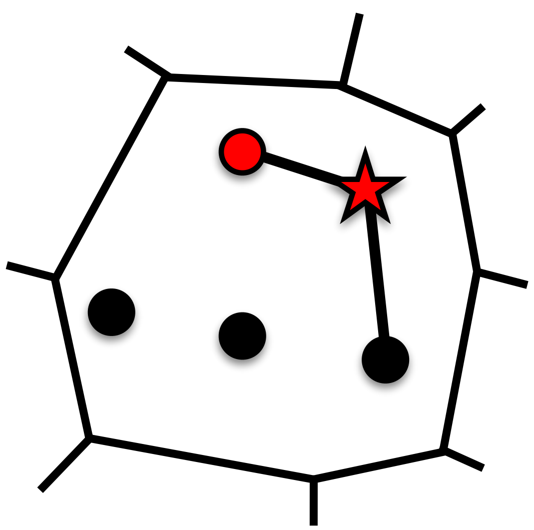
Common Prioritization Scheme

2D-to-3D Matching

3D-to-2D Matching



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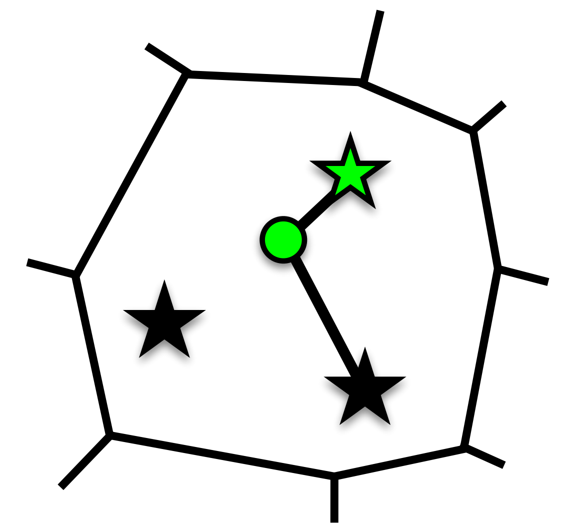

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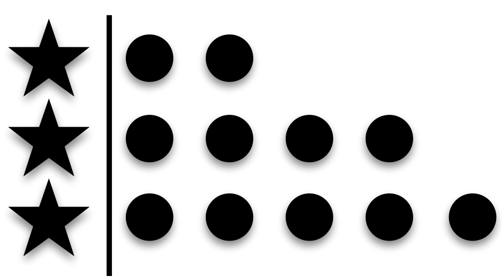

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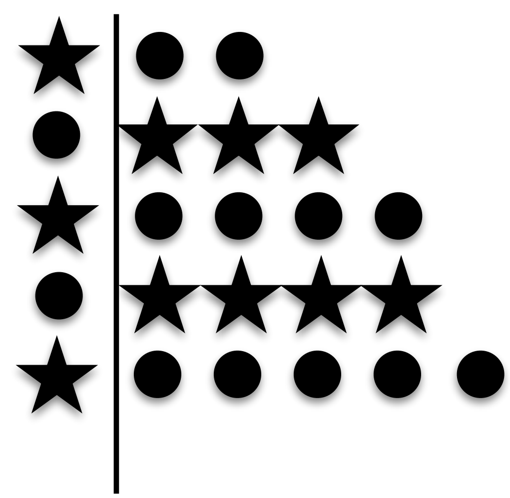
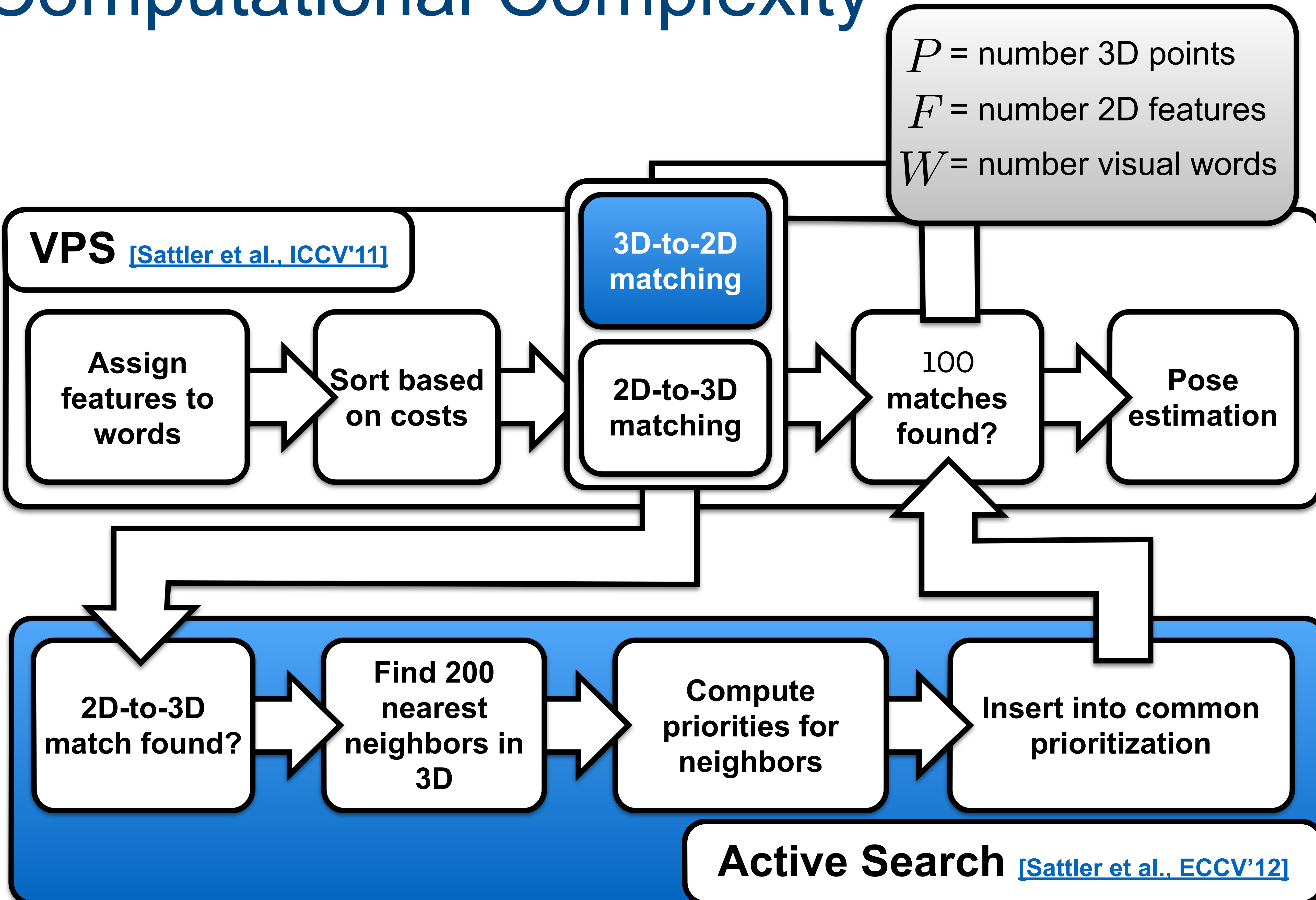


Common prioritization: Prefer cheaper search direction

[Sattler et al., ECCV'12]

Computational Complexity



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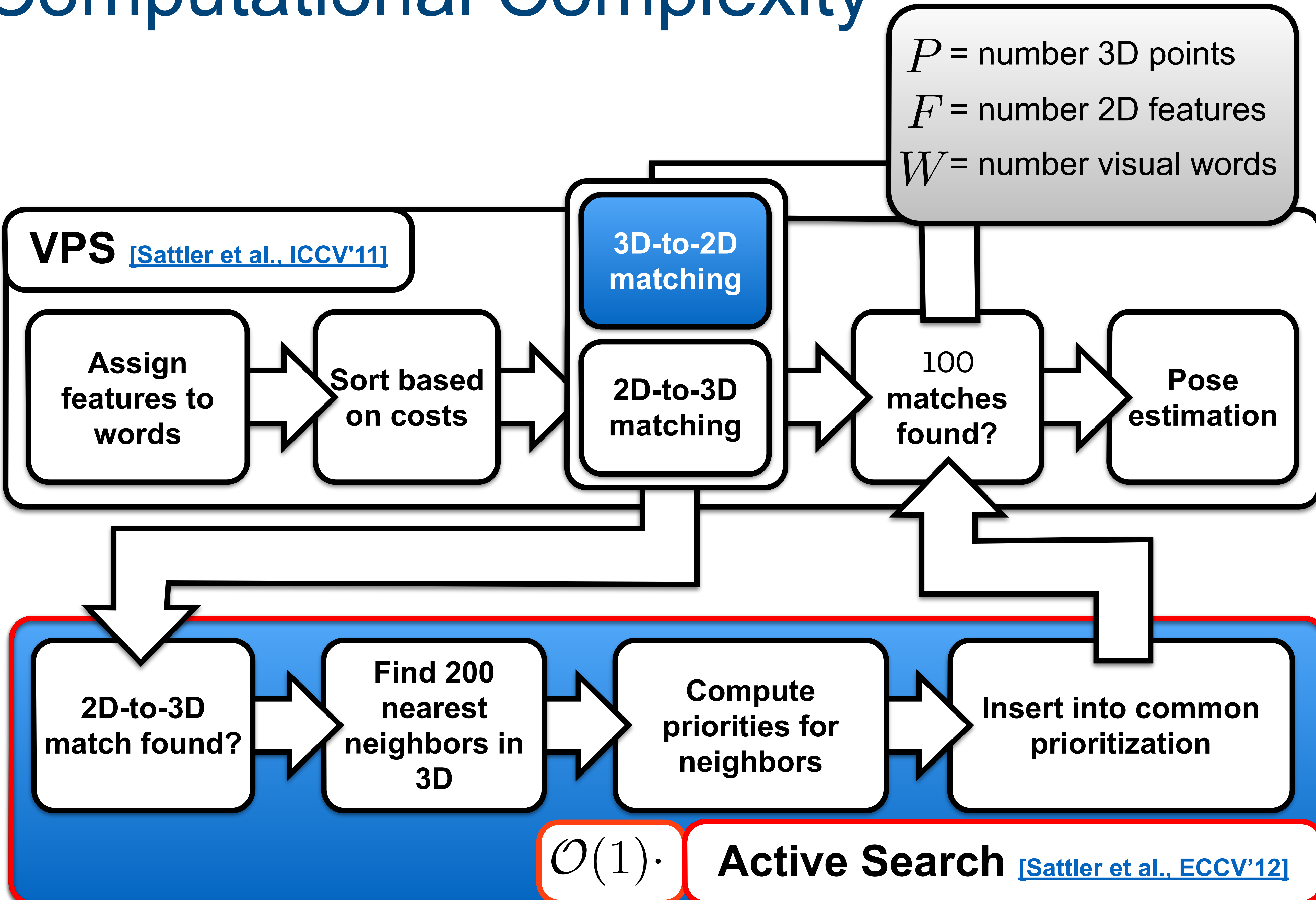

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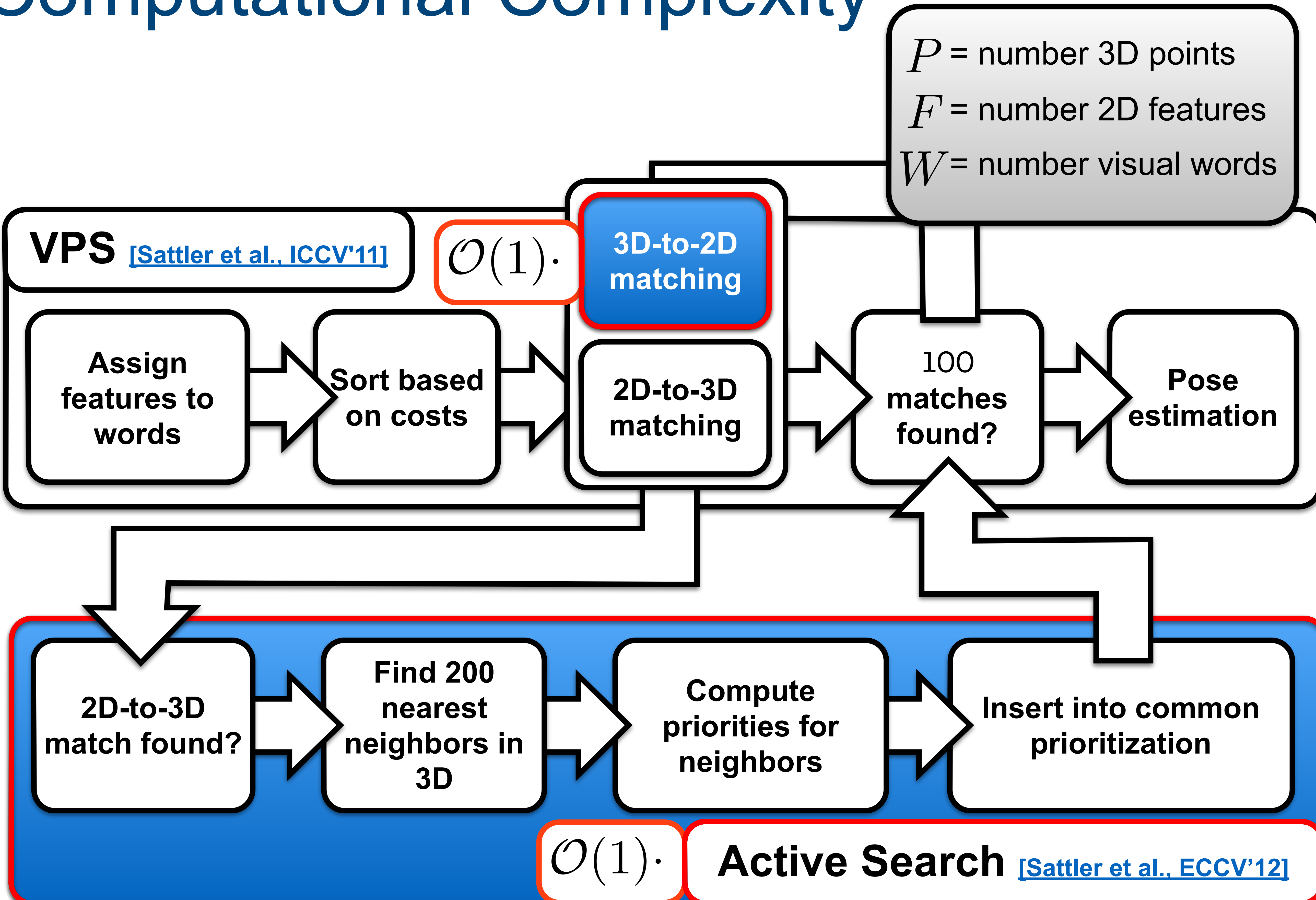

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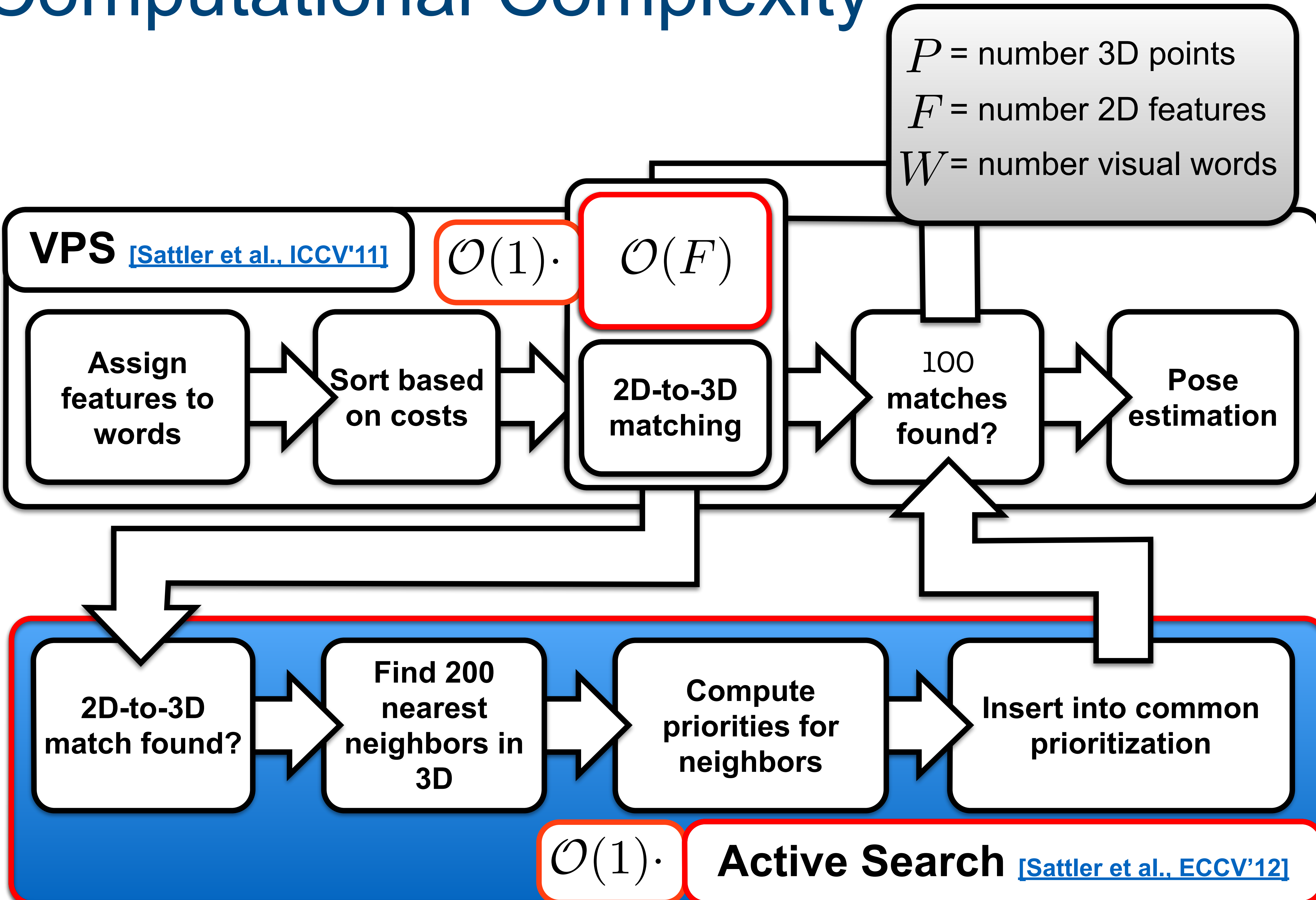

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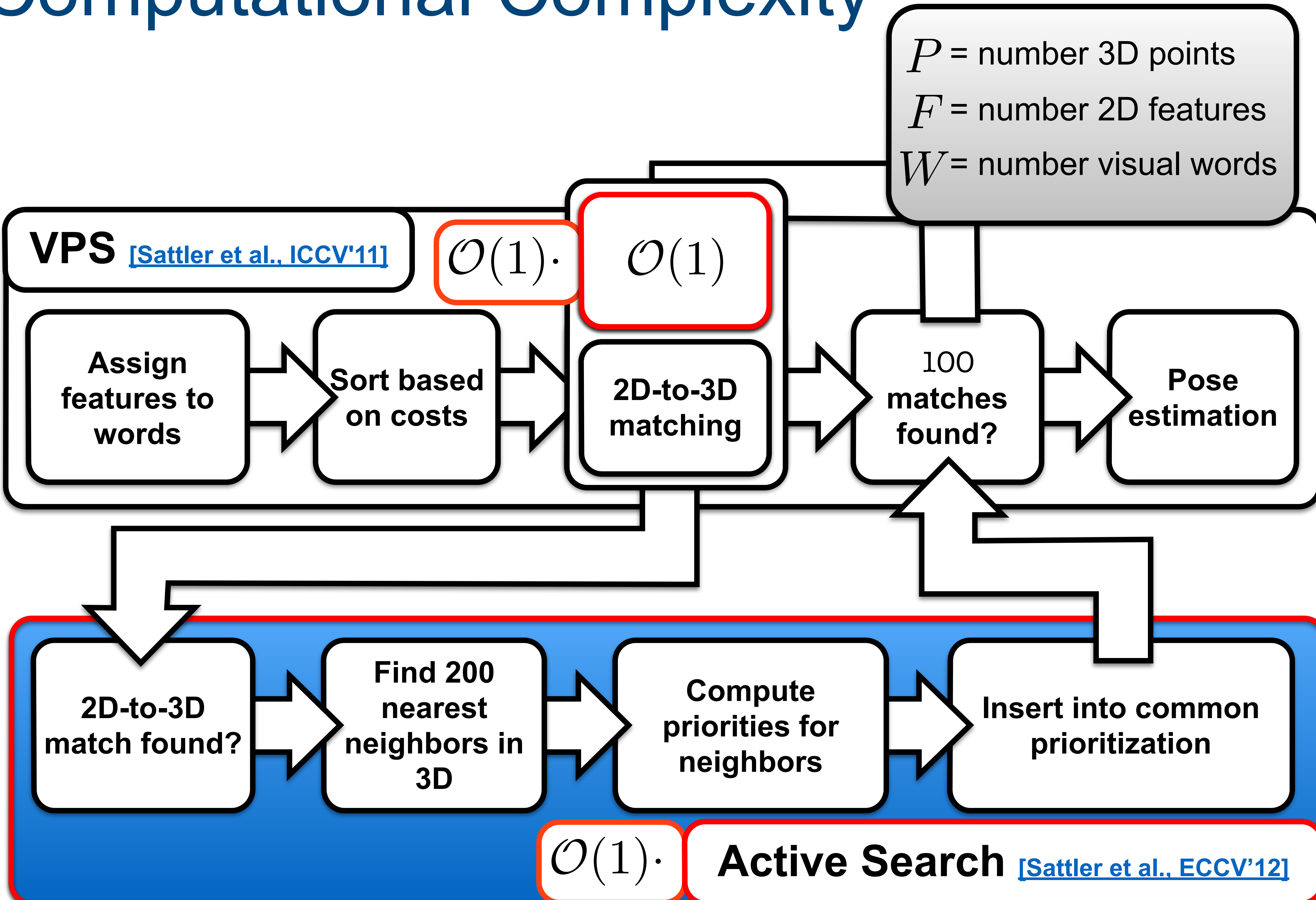

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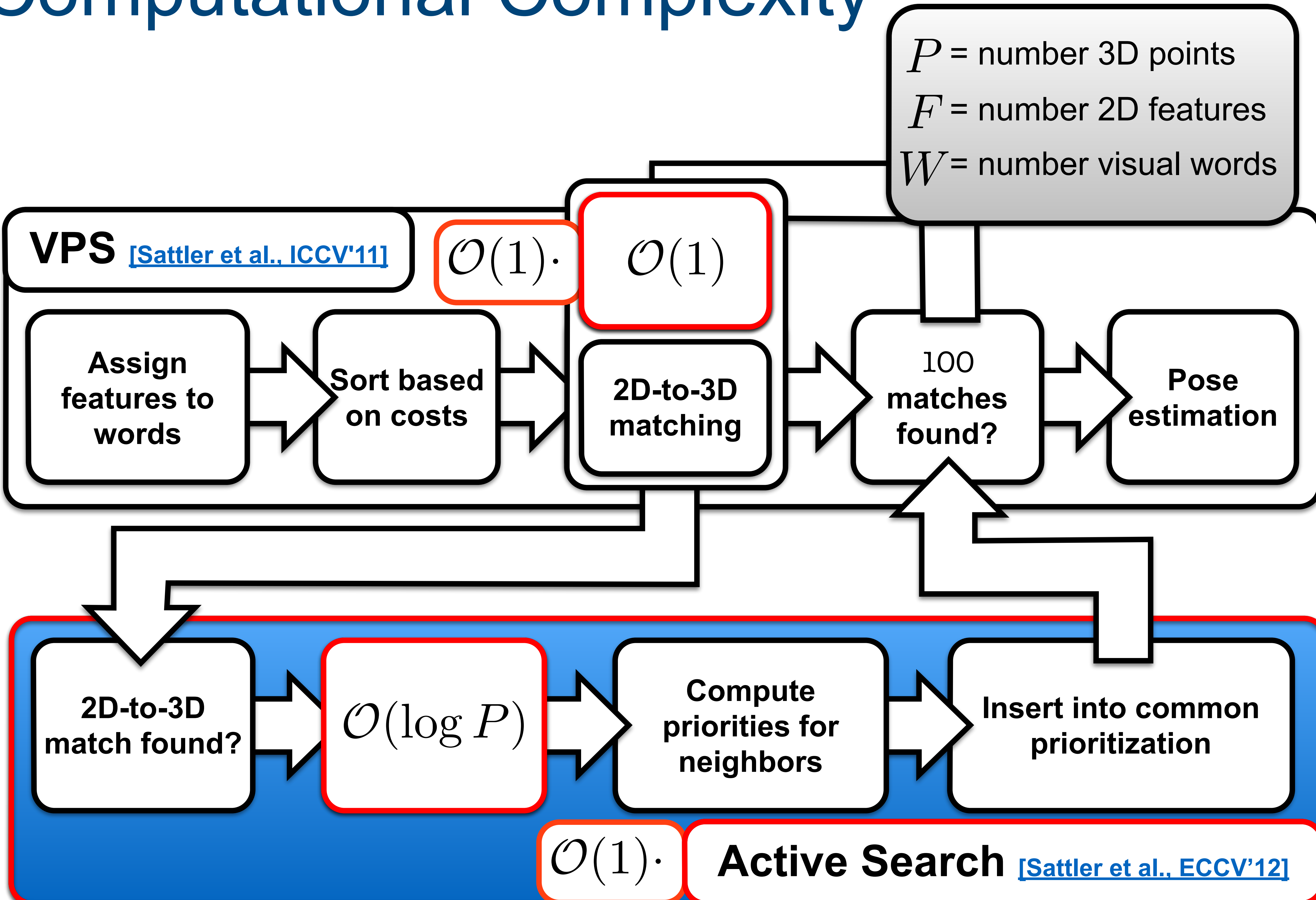

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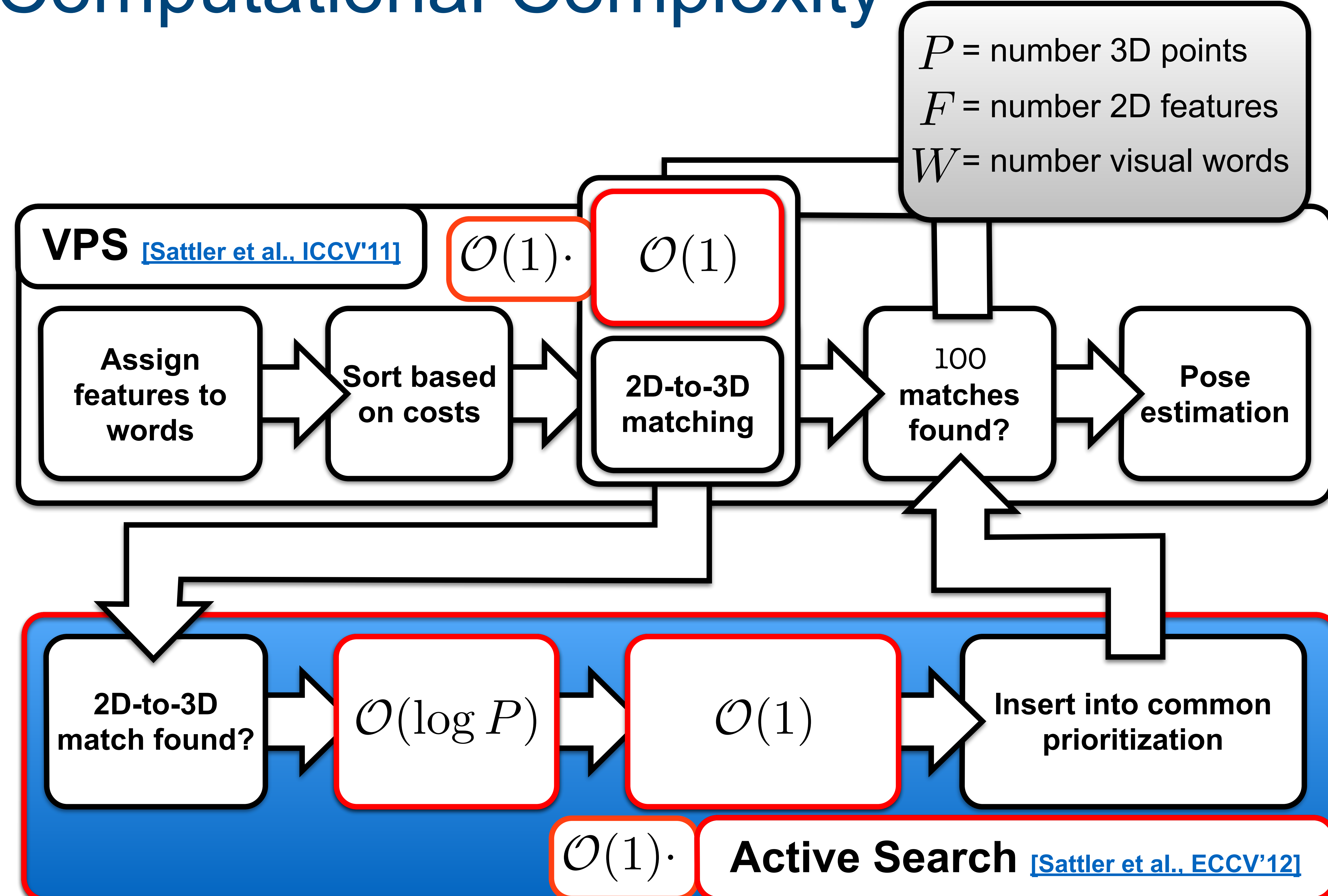

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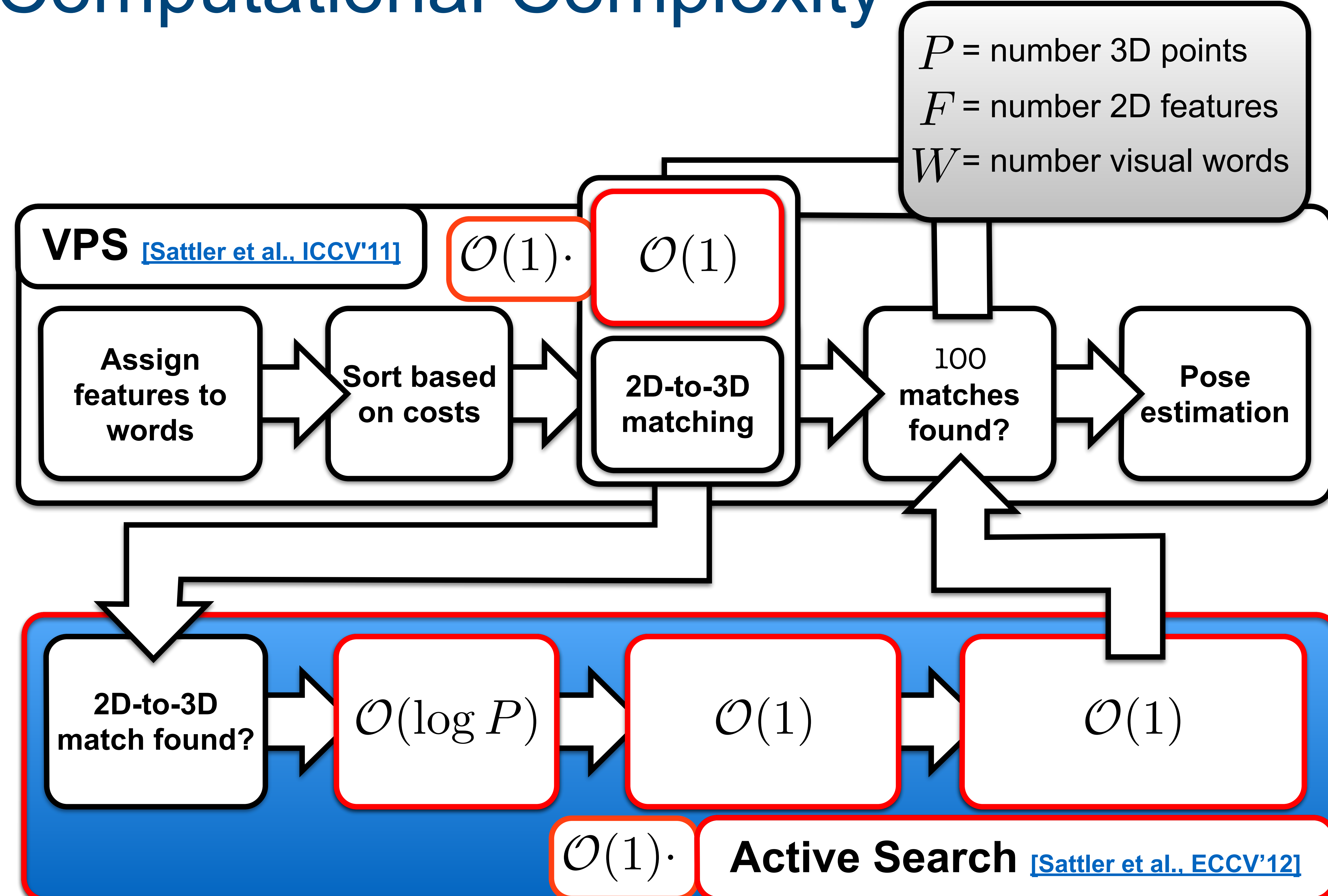
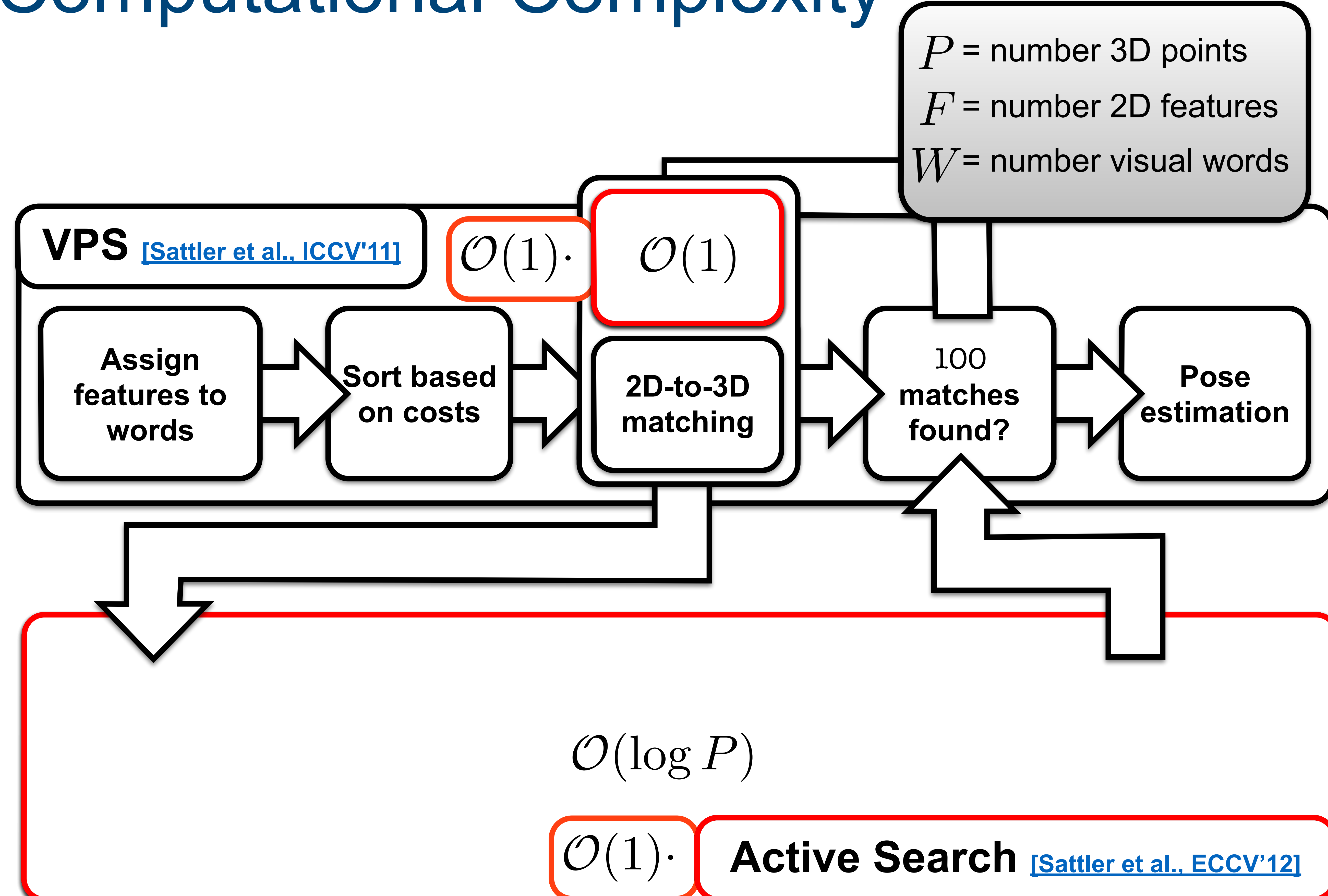


Computational Complexity



Computational Complexity

P = number 3D points

F = number 2D features

W = number visual words

VPS [Sattler et al., ICCV'11]

$\mathcal{O}(1)\cdot$ $\mathcal{O}(1)$

fe

on

Total effort added by Active Search: $\mathcal{O}(\log P)$

$\mathcal{O}(\log P)$

$\mathcal{O}(1)\cdot$ **Active Search** [Sattler et al., ECCV'12]

Computational Complexity

P = number 3D points
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VPS [Sattler et al., ICCV'11]

$\mathcal{O}(1)\cdot$ $\mathcal{O}(1)$

fe

on

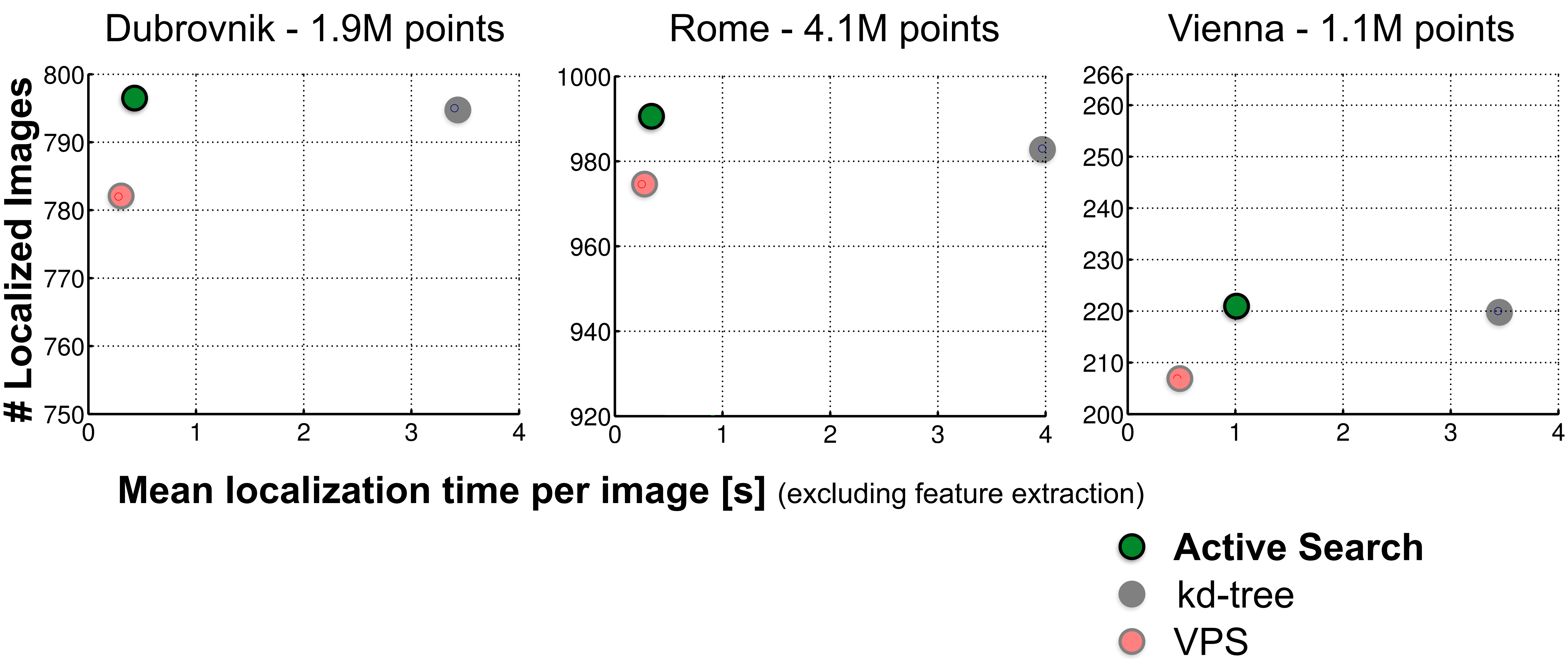
Total effort added by Active Search: $\mathcal{O}(\log P)$

Effort added by Soft Assignments: $\mathcal{O}(P/W)$ **per feature**

$\mathcal{O}(\log P)$

$\mathcal{O}(1)\cdot$ **Active Search** [Sattler et al., ECCV'12]

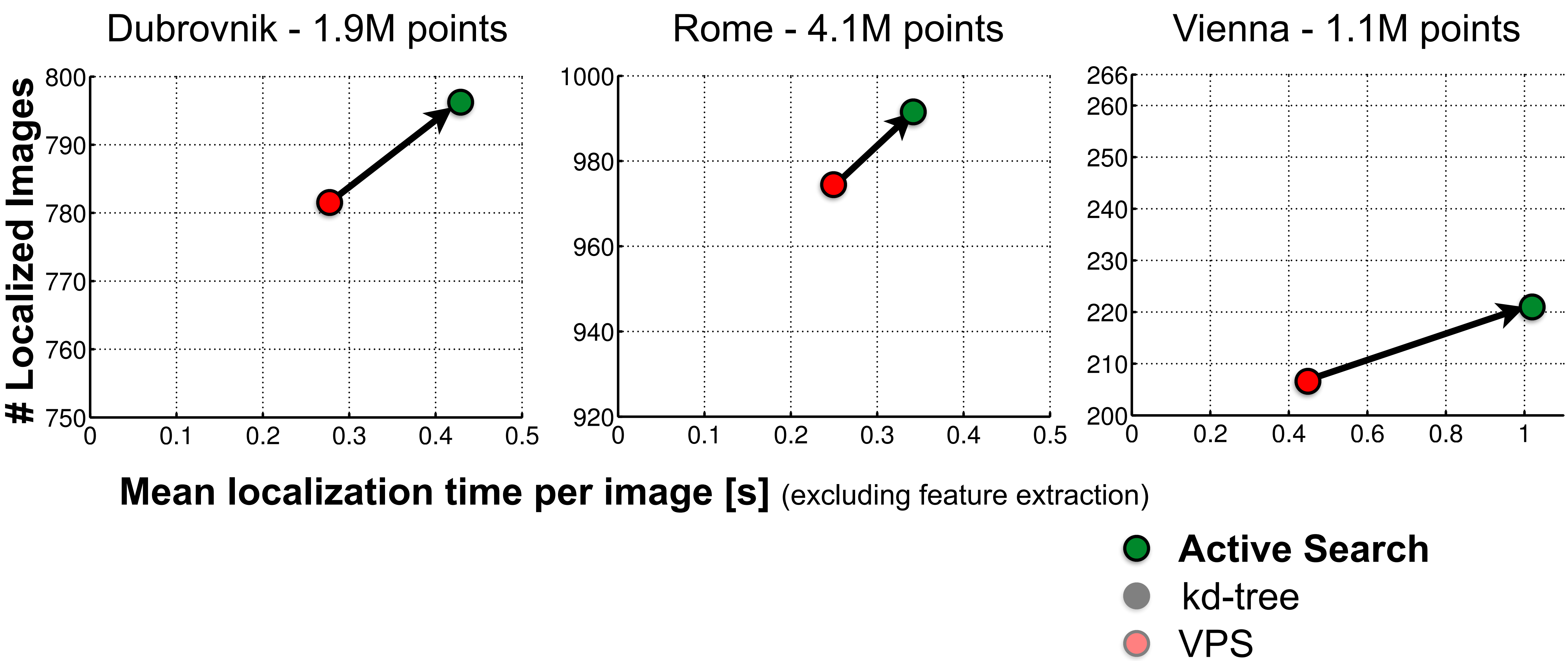
Results



✓ As effective as kd-tree or better

✗ Less effective than VPS due to additional computations

Results



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Localization - Overview

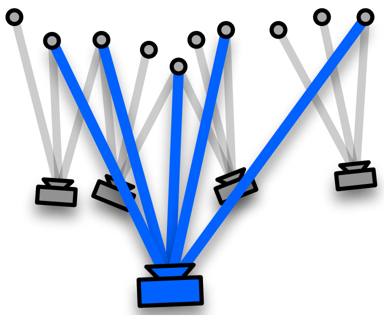
Baseline: kd-tree search

[Sattler et al., ICCV'11]

VPS

[Sattler et al., ICCV'11]

Active Search

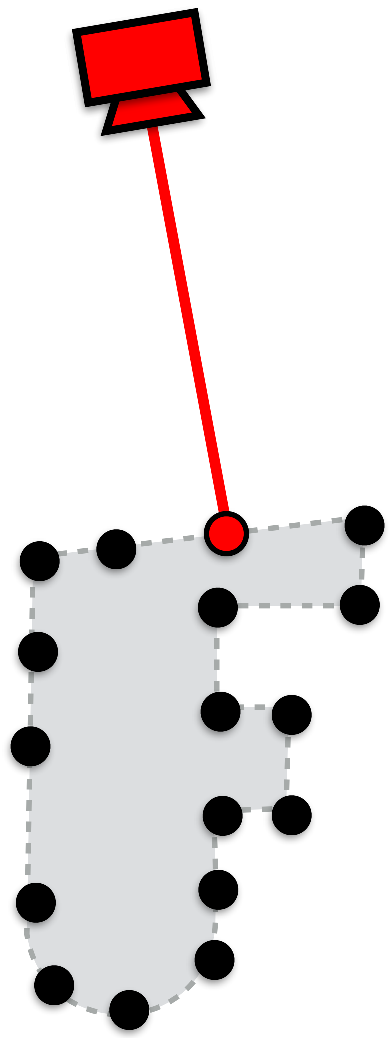


+ Visibility Filtering

[Sattler et al., ECCV'12]

	Baseline: kd-tree search	VPS	Active Search	+ Visibility Filtering
effectiveness	✓	✗	✓✓	✓✓
efficiency	✗ ✗	✓	✗	✓

Visibility Filtering



Filter out 3D-to-2D matching candidates

[Sattler et al., ECCV'12]

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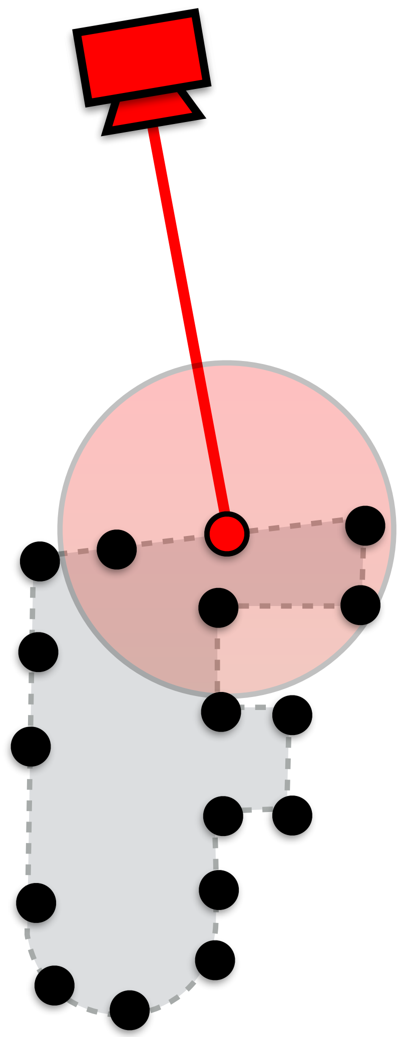
Visibility Filtering



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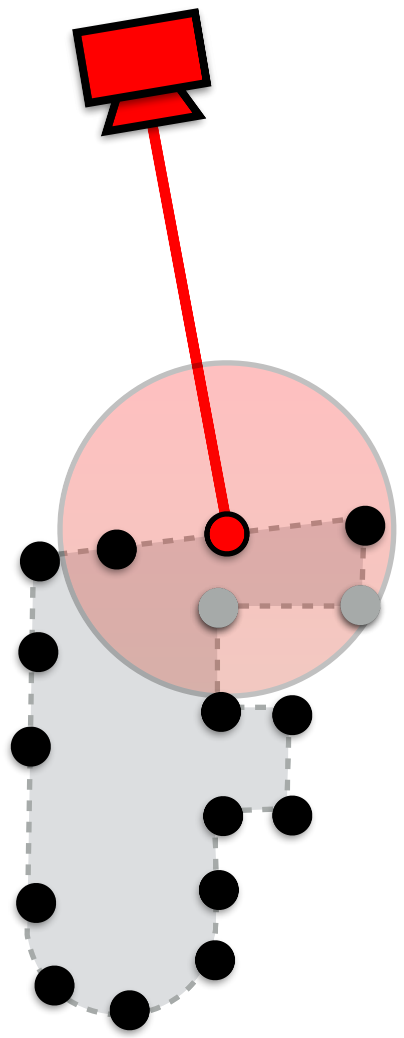

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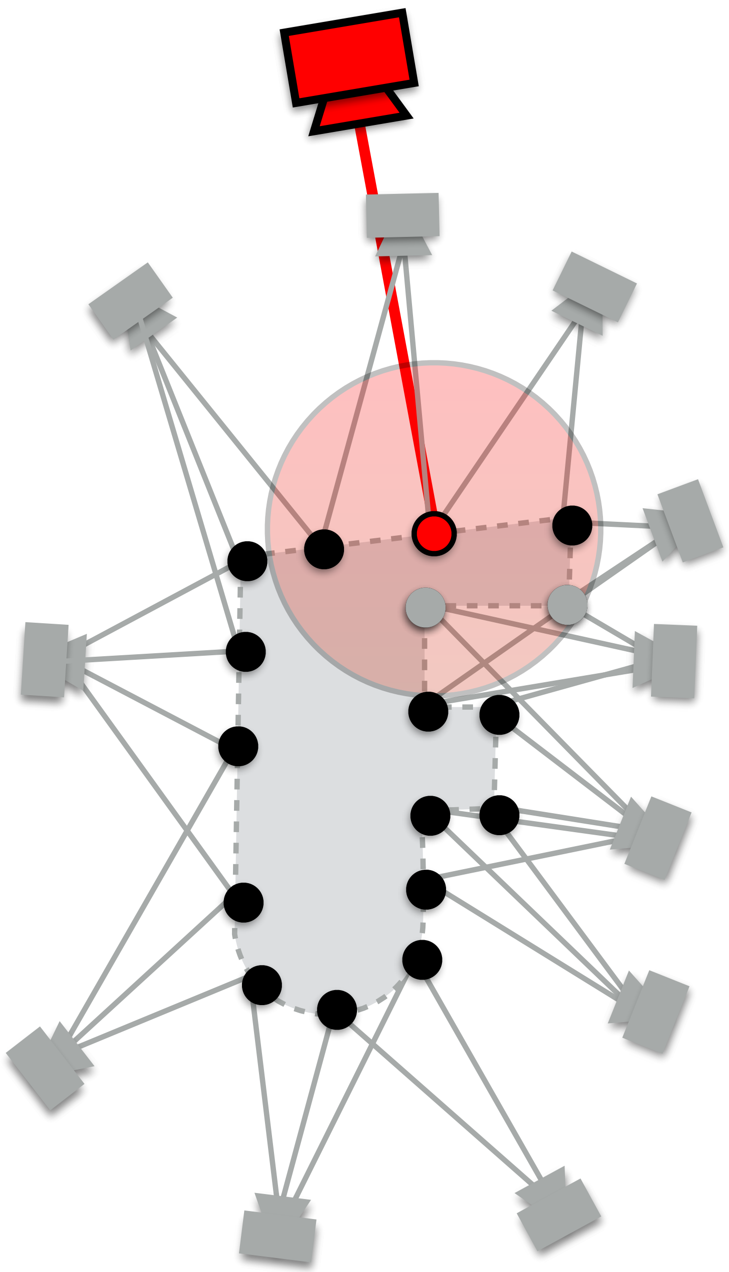

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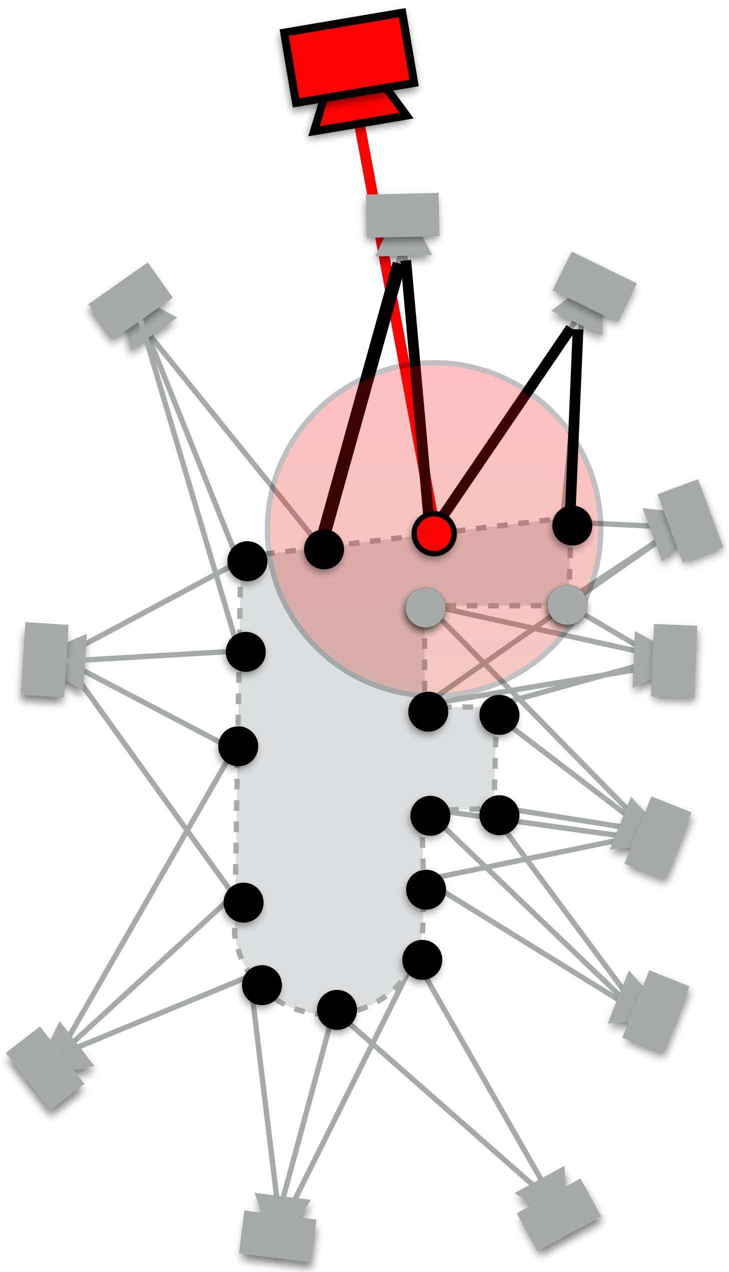

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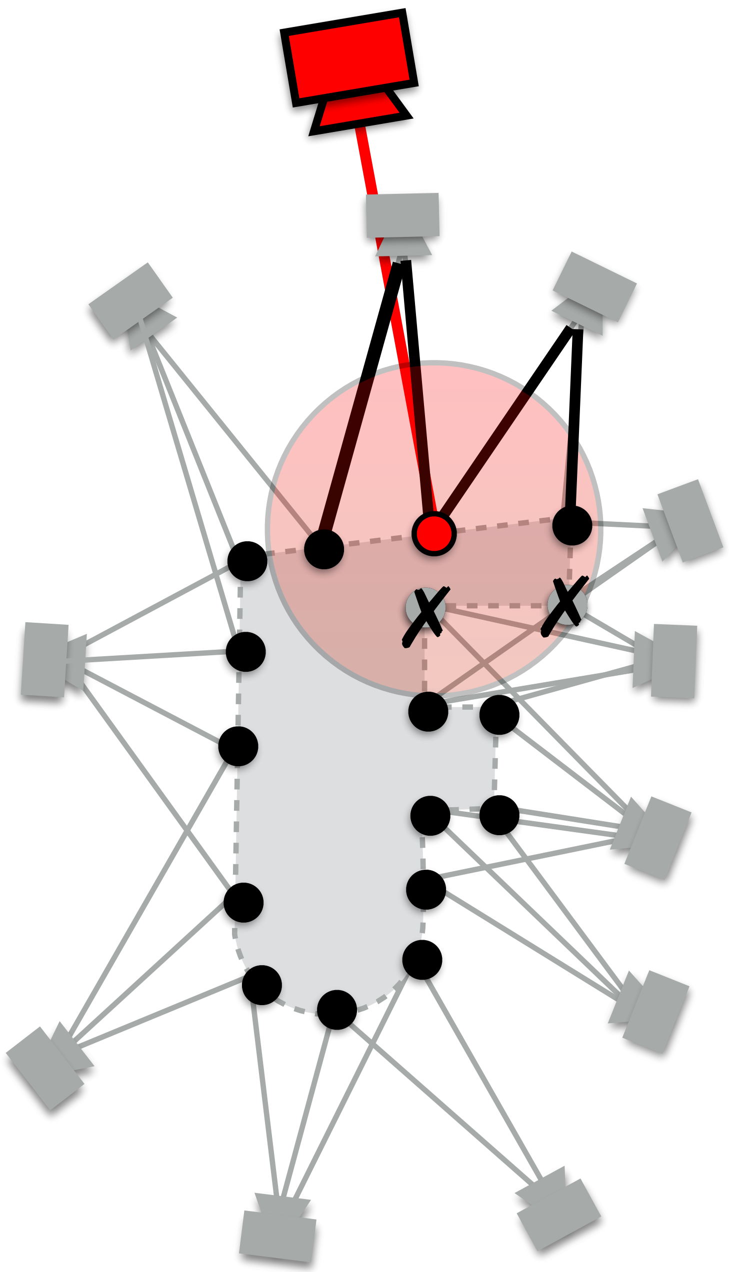

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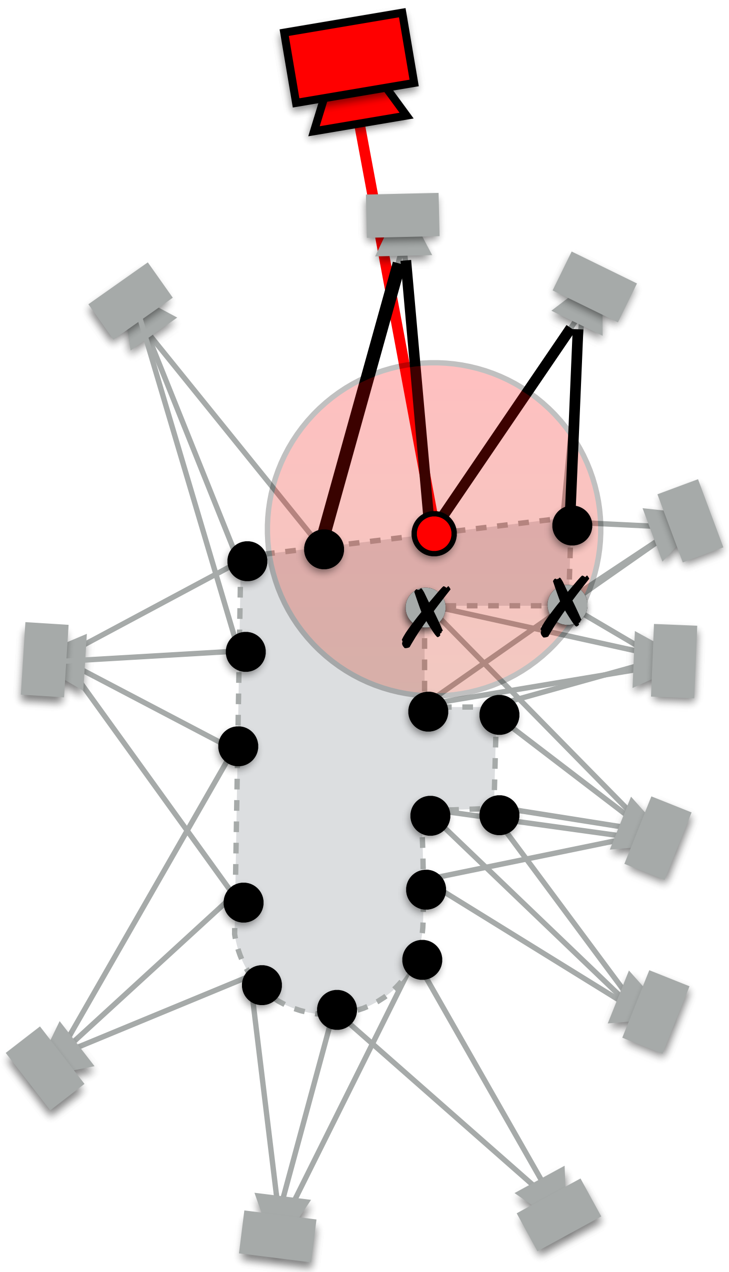

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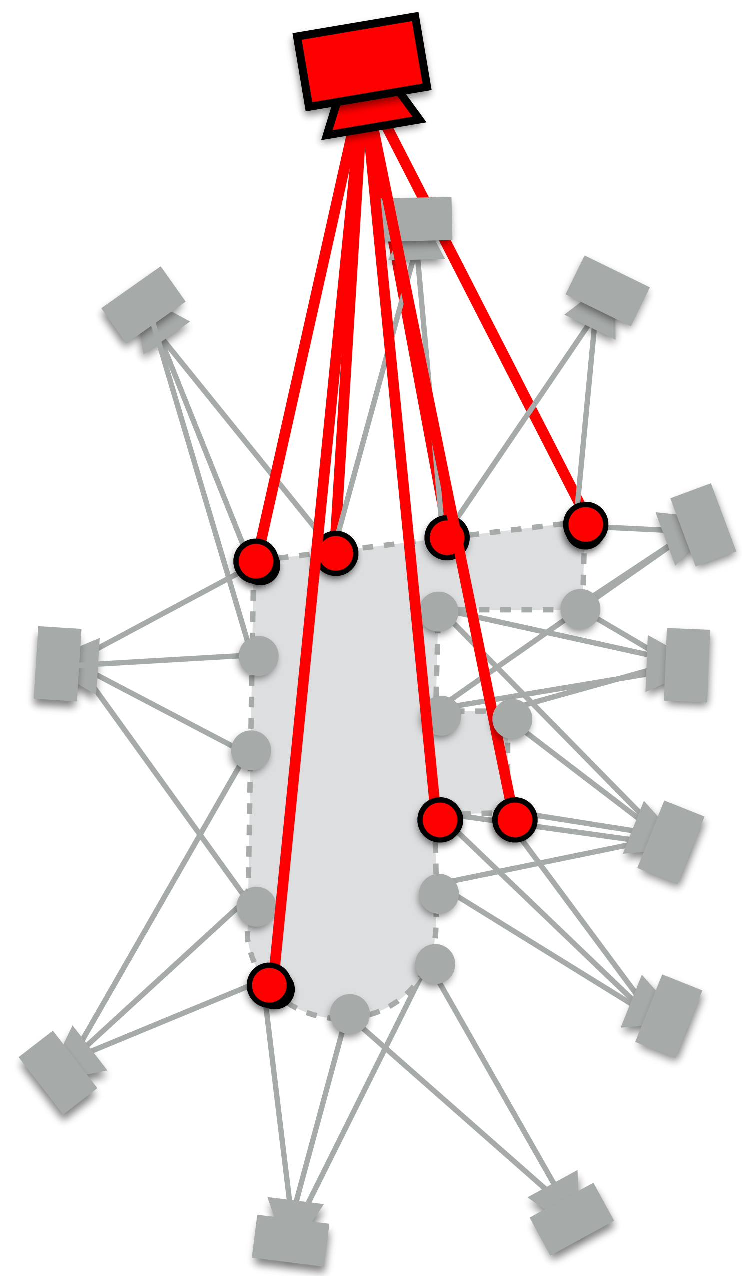
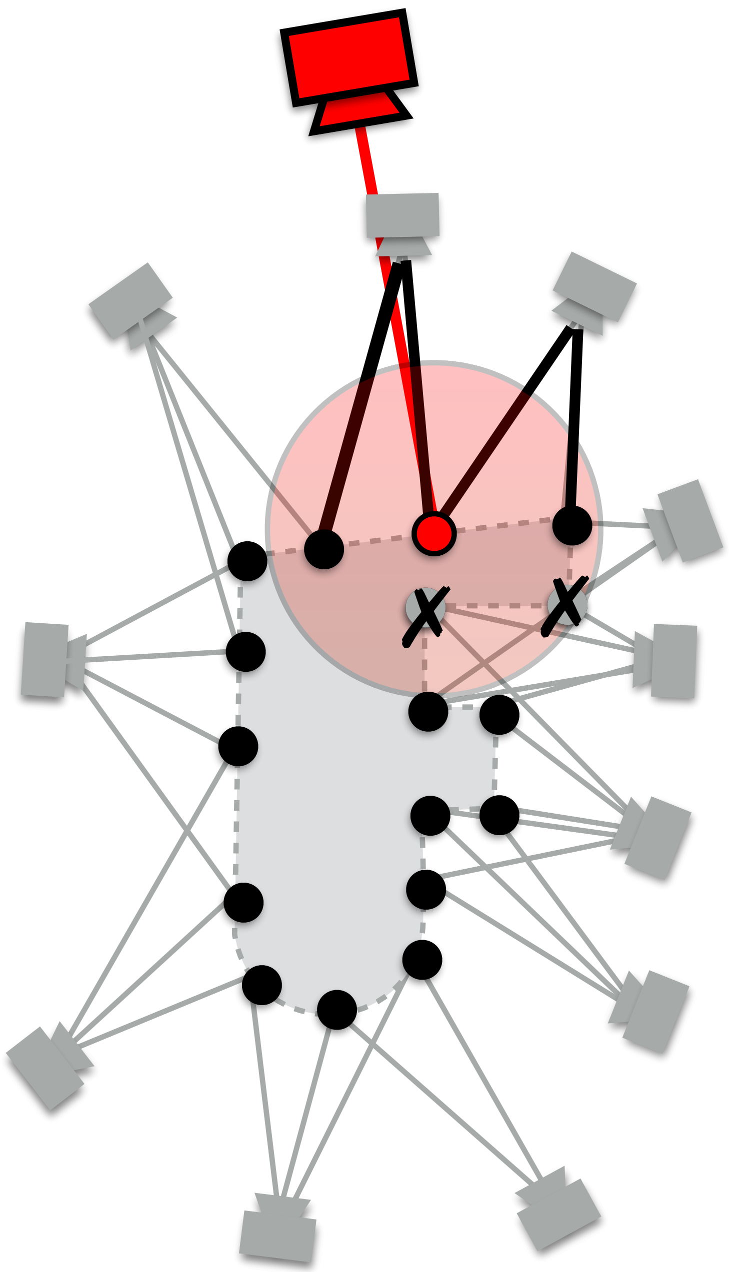


Remove wrong matches before RANSAC

[Sattler et al., ECCV'12]

Visibility Filtering



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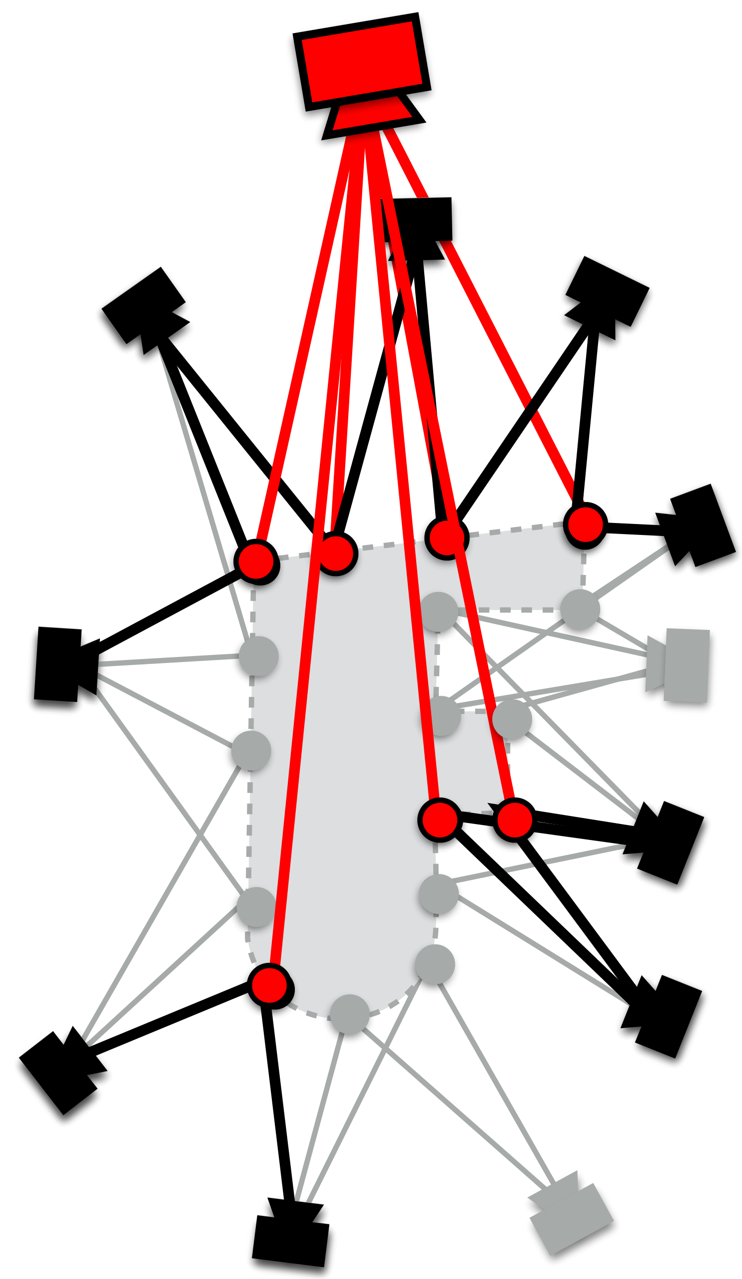

Remove wrong matches before RANSAC

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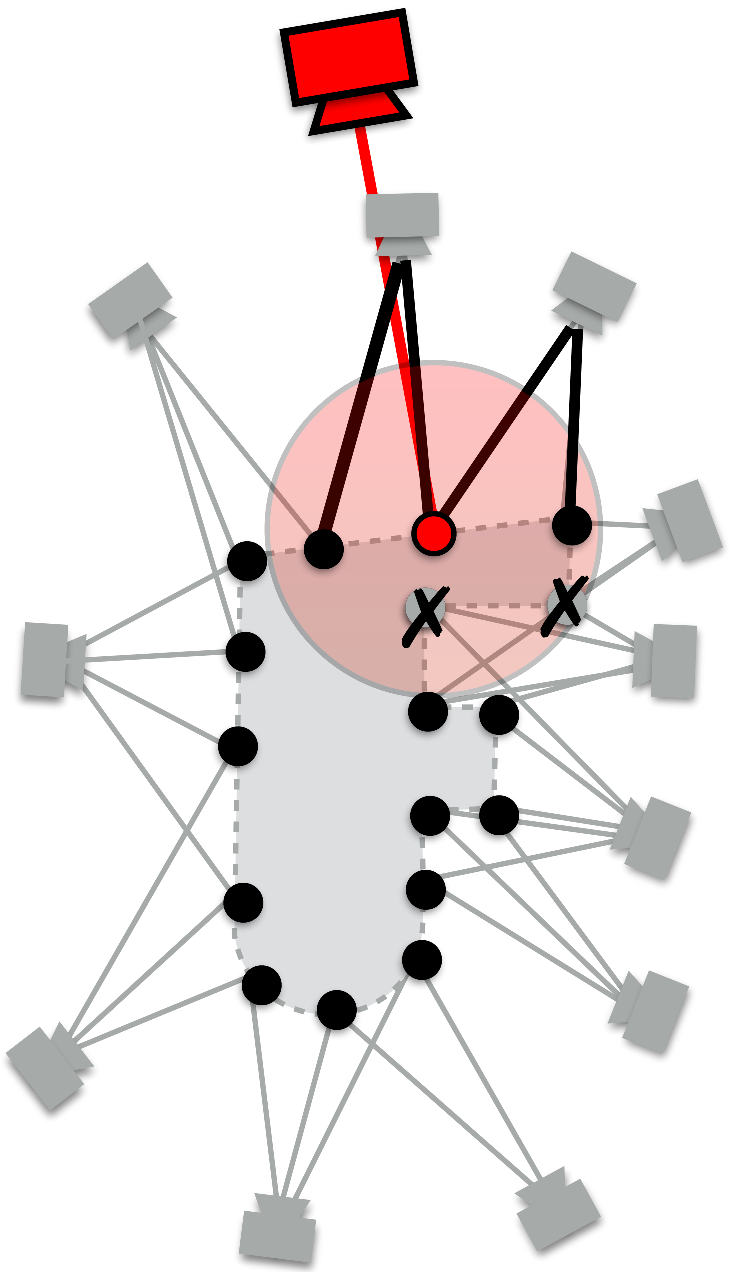
Visibility Filtering



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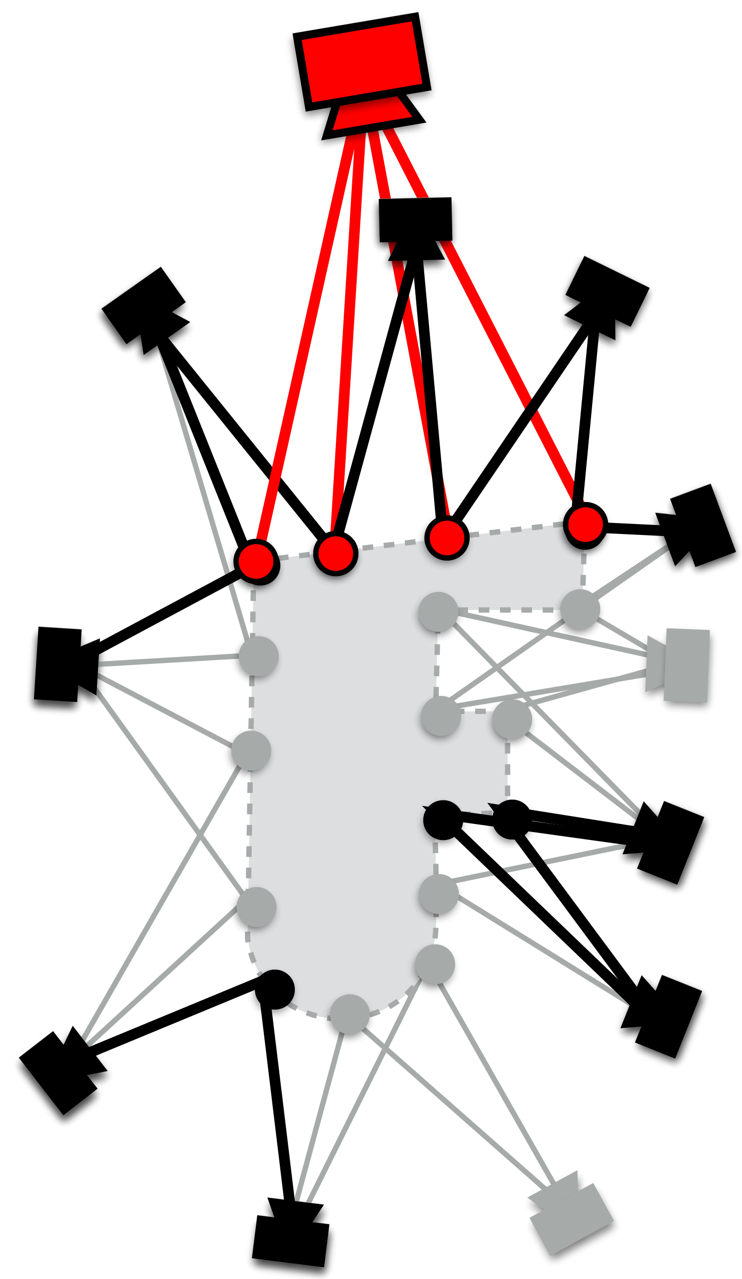

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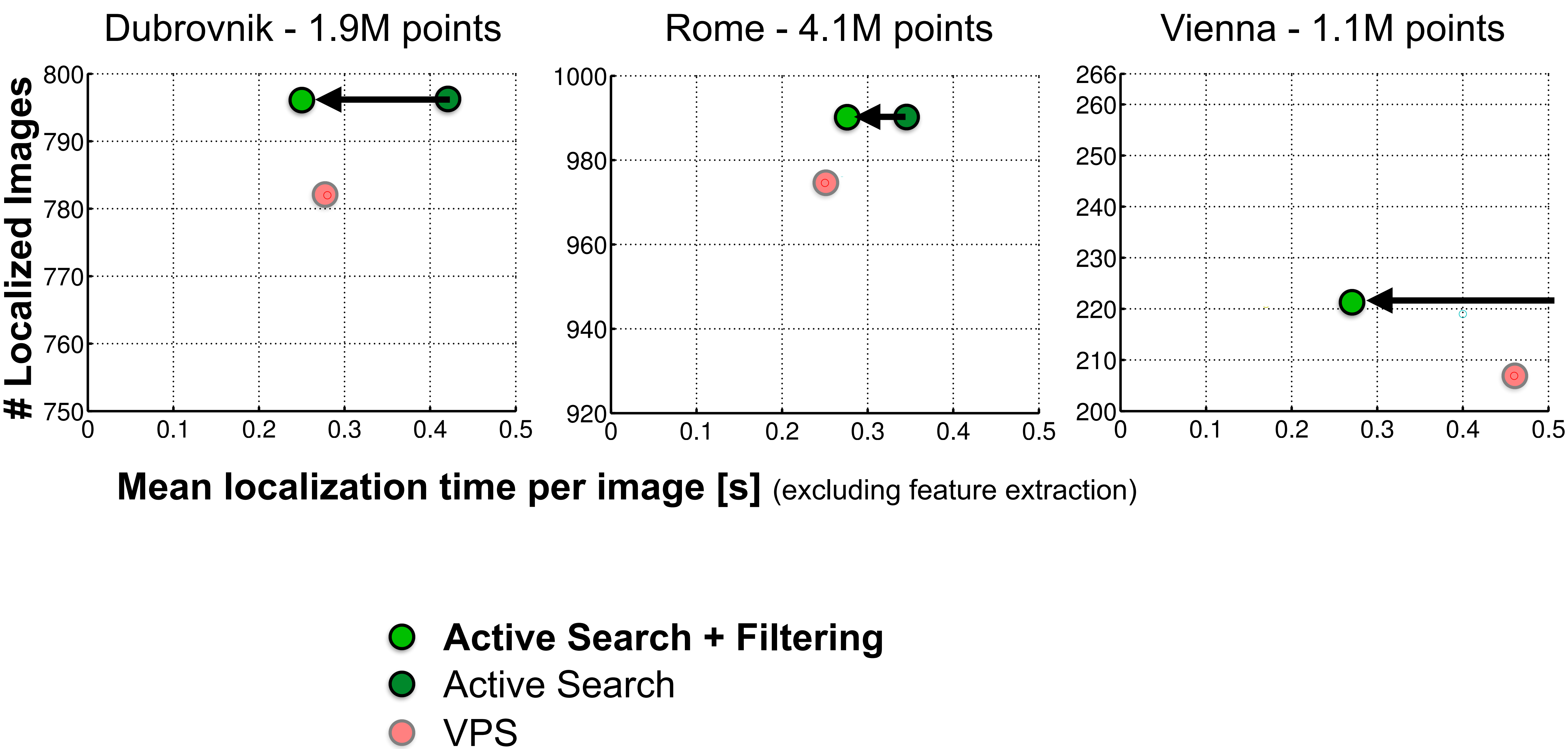
Results



code will be available “soon”

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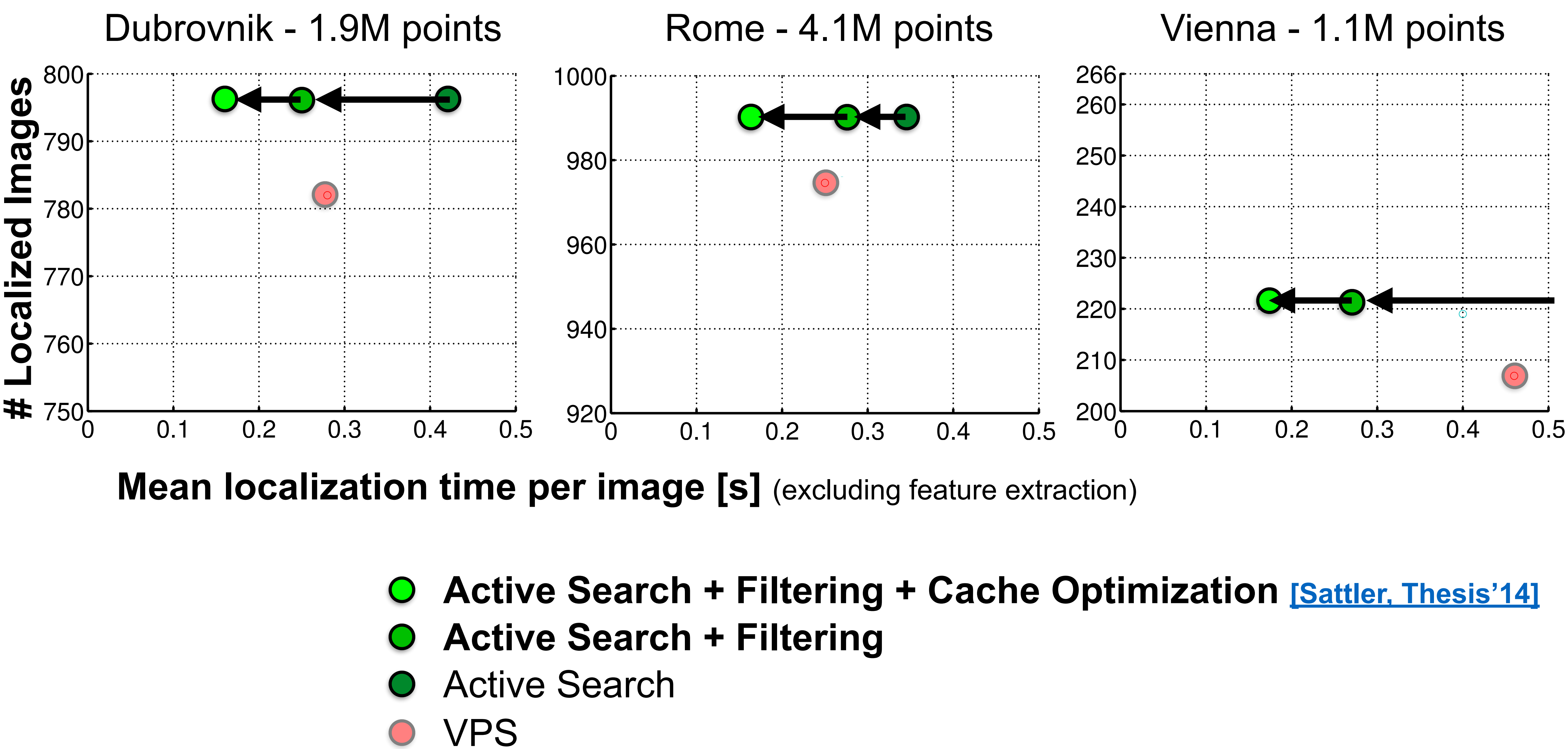
Results



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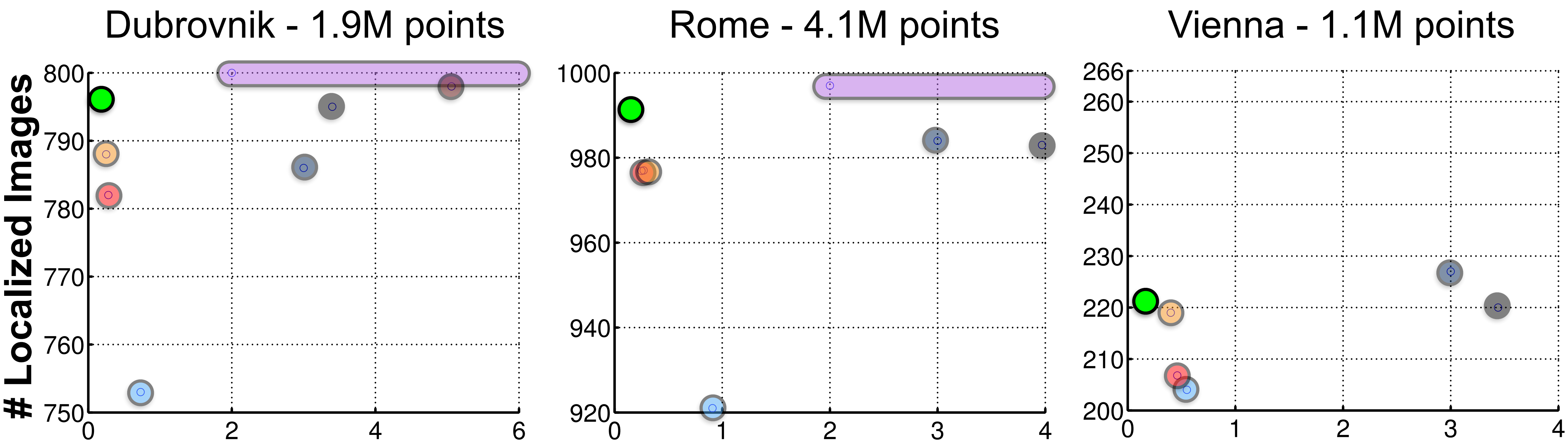
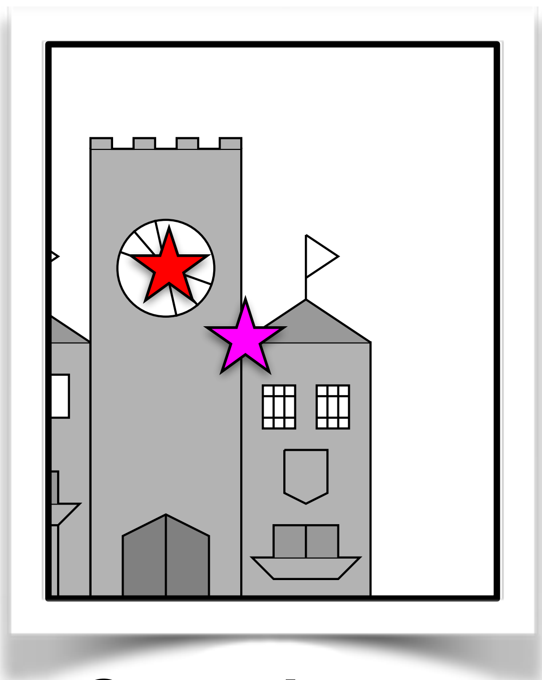


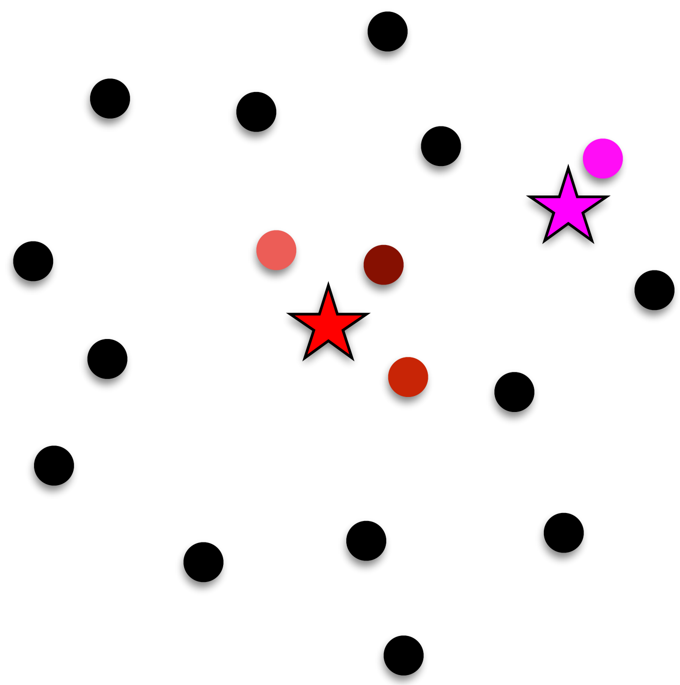
Mean localization time per image [s] (excluding feature extraction)

- **Active Search + Filtering + Cache Optimization** [Sattler, Thesis'14]
- kd-tree
- P2F [Li et al.,ECCV'10]
- VPS
- PGPM [Choudhary,ECCV'12]
- WPE [Li et al.,ECCV'12]
- Hamming Voting [Sattler et al.,BMVC'12]
- [Svarm et al.,CVPR'14]

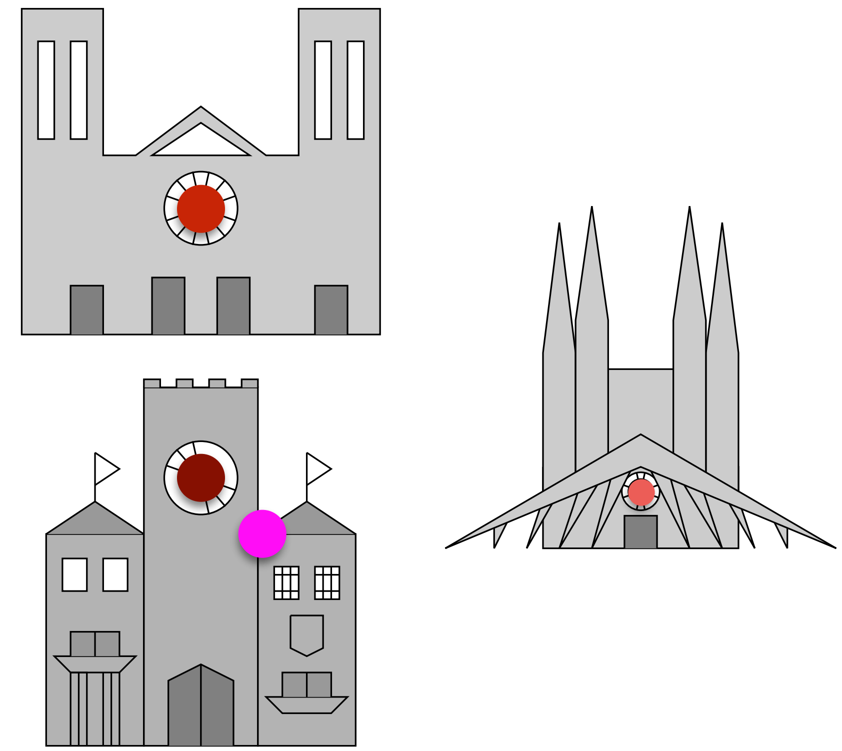
Active Search vs. Pure 2D-to-3D Matching



Query Image

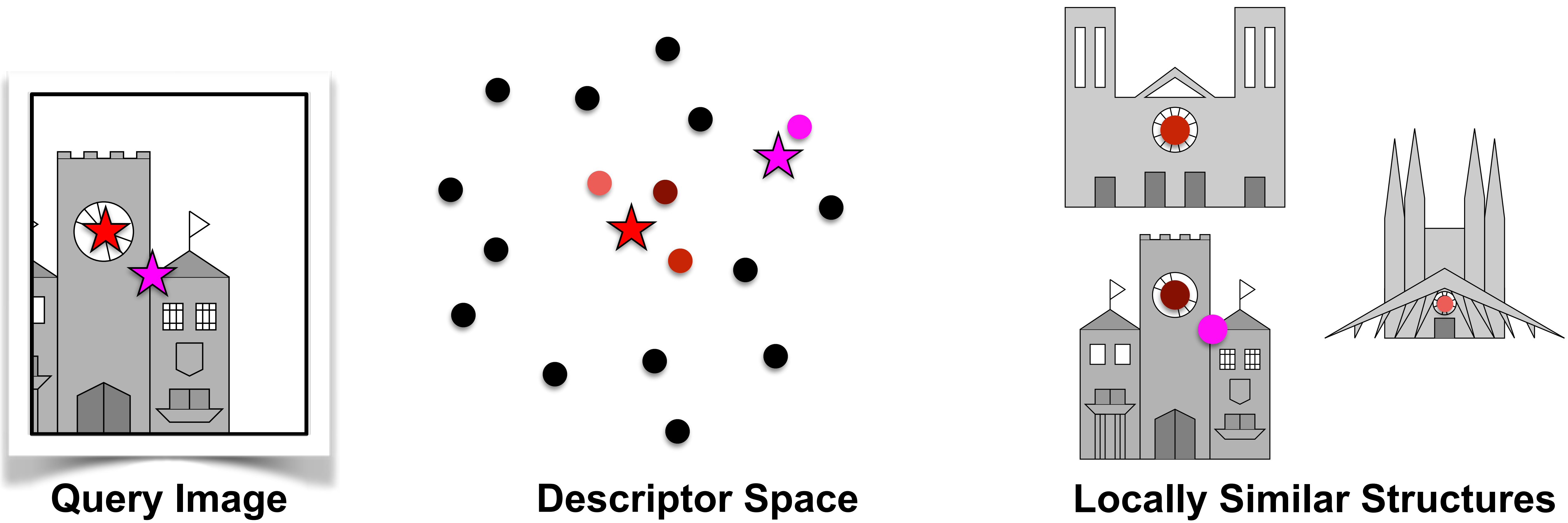


Descriptor Space



Locally Similar Structures

Active Search vs. Pure 2D-to-3D Matching



- Ratio test for 2D-to-3D matching rejects globally ambiguous matches

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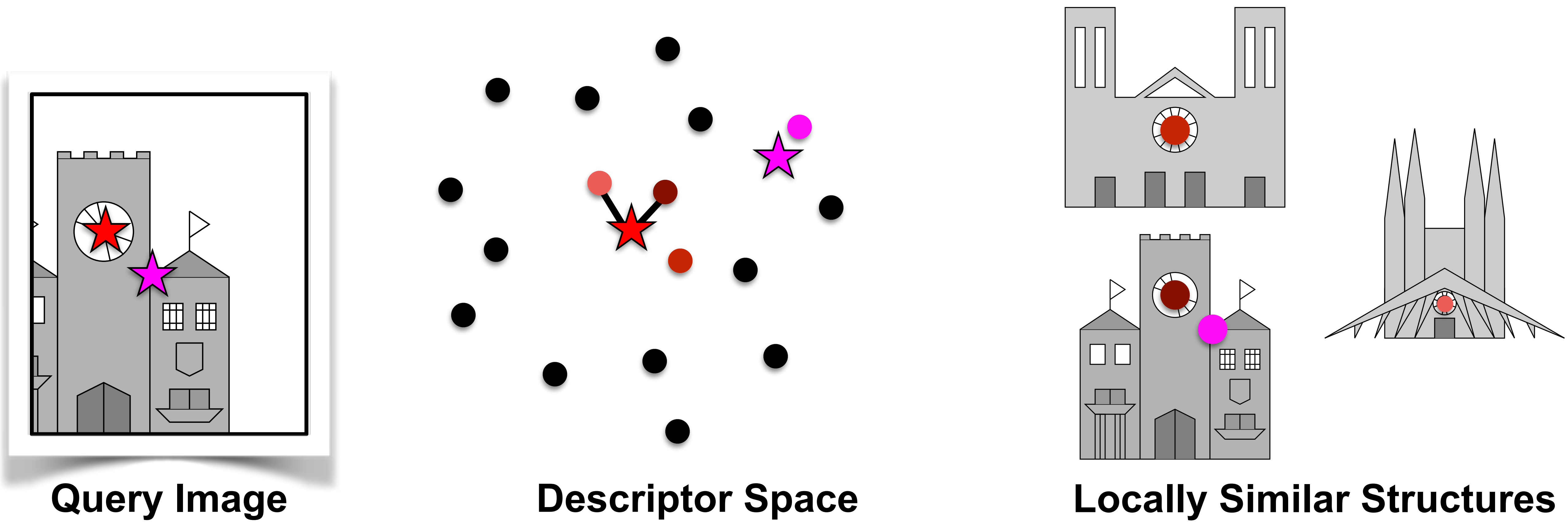

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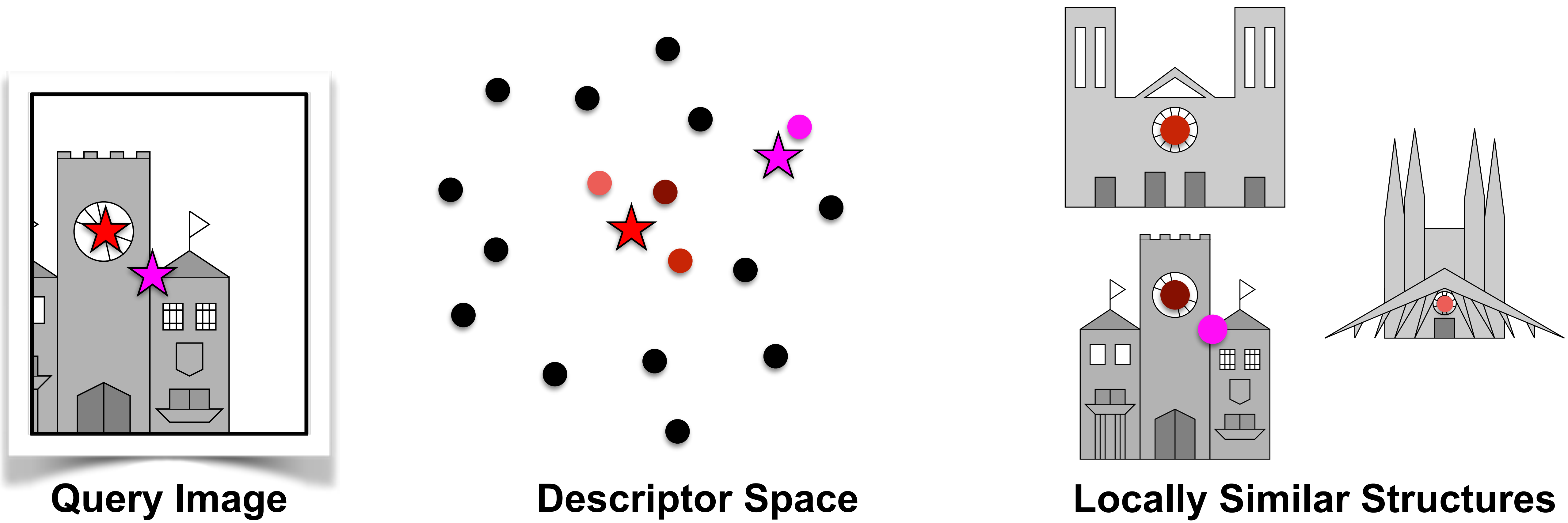

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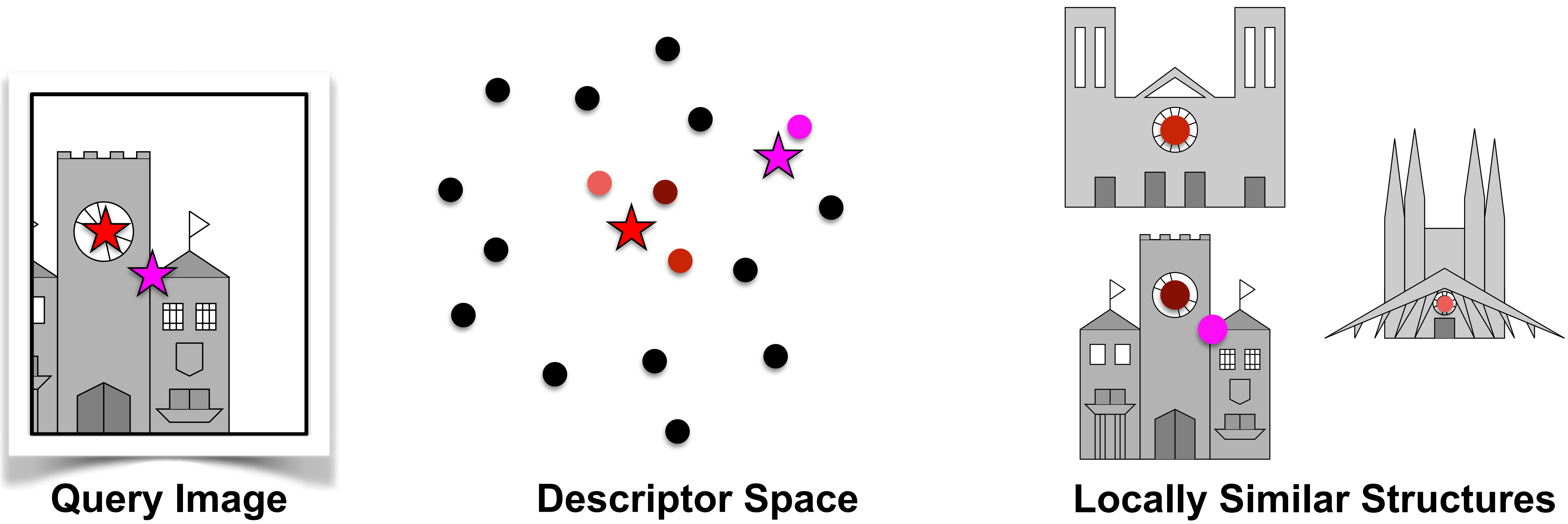

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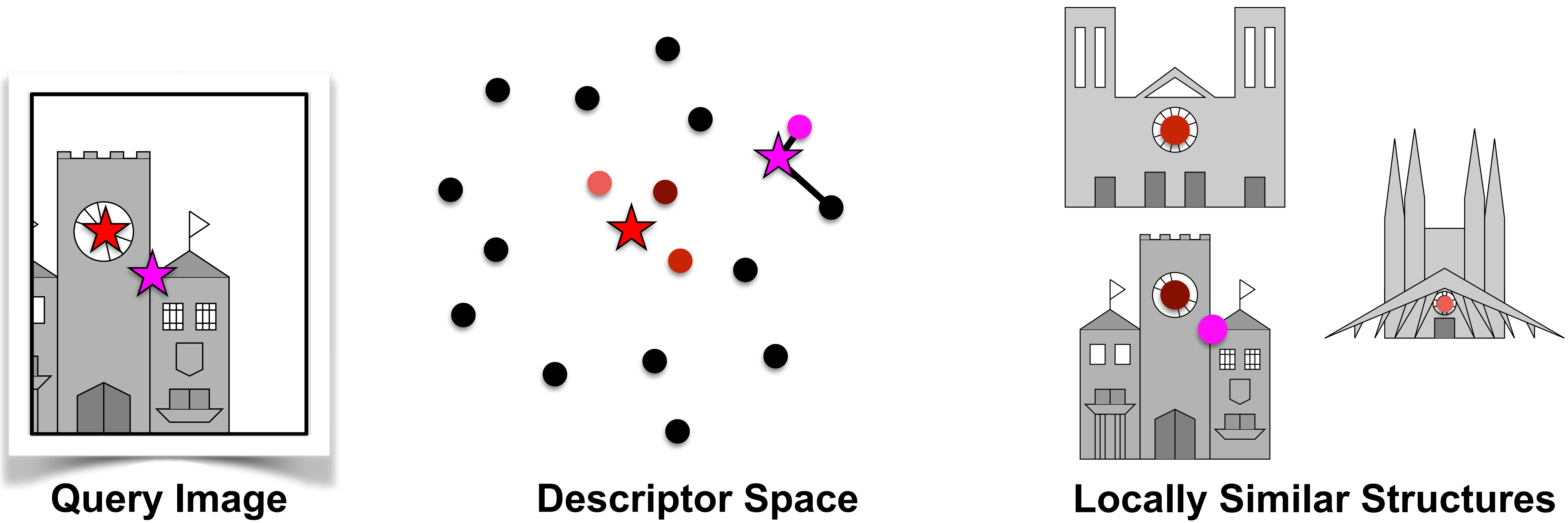
Active Search vs. Pure 2D-to-3D Matching



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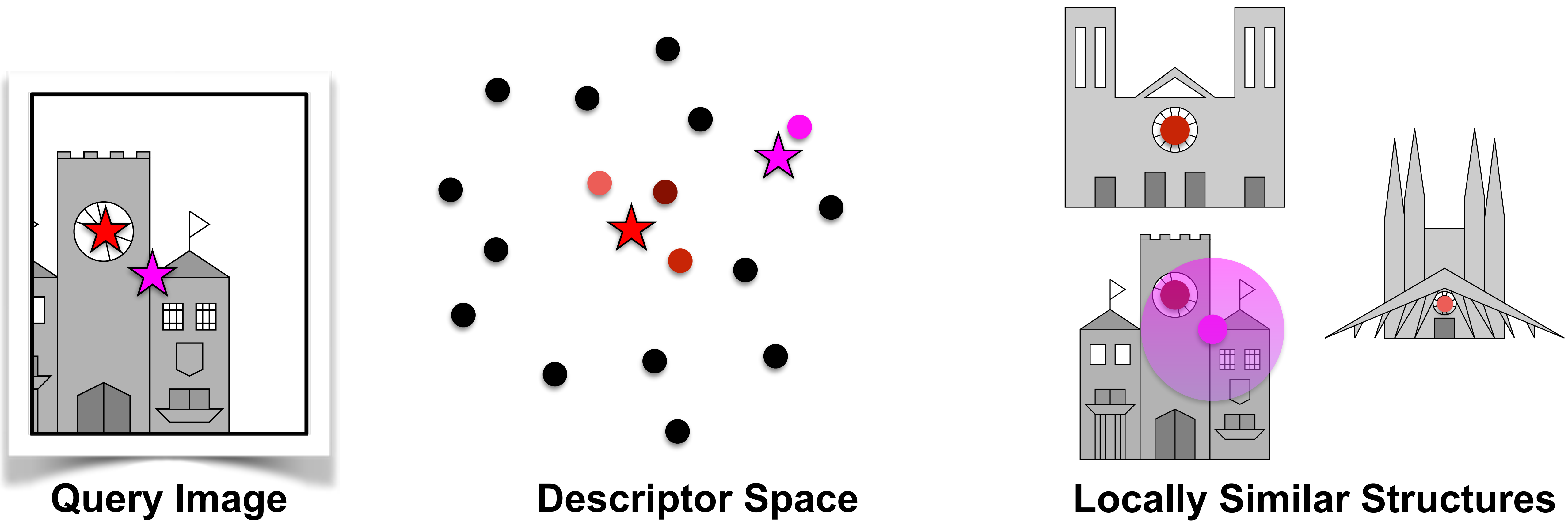

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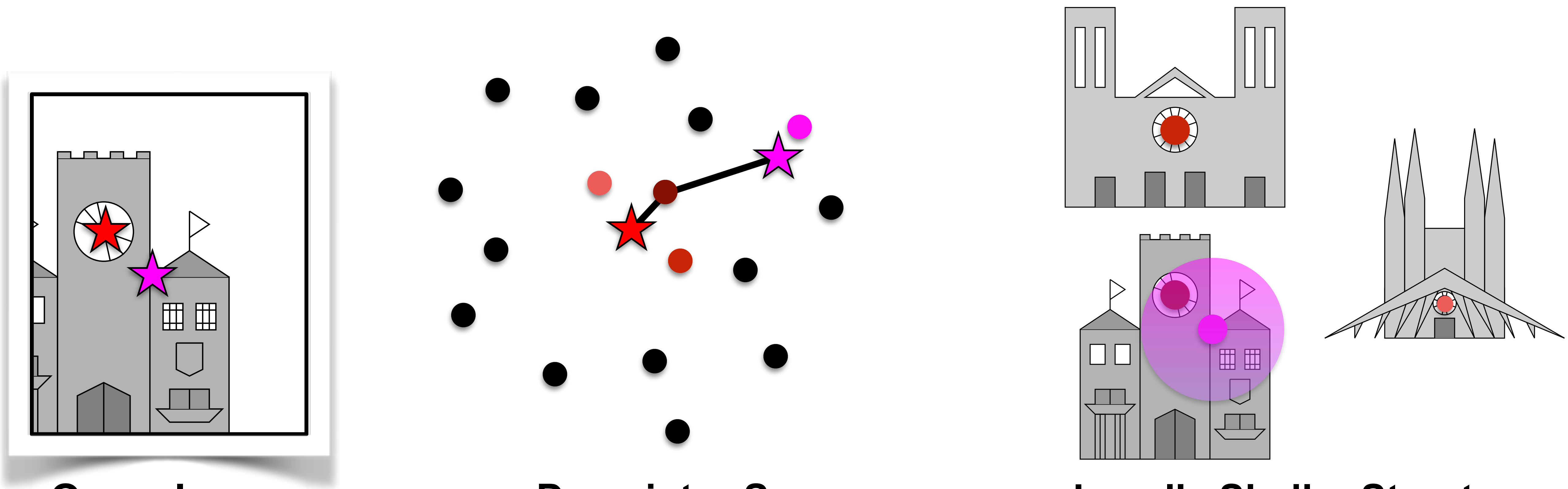

Query Image Descriptor Space Locally Similar Structures

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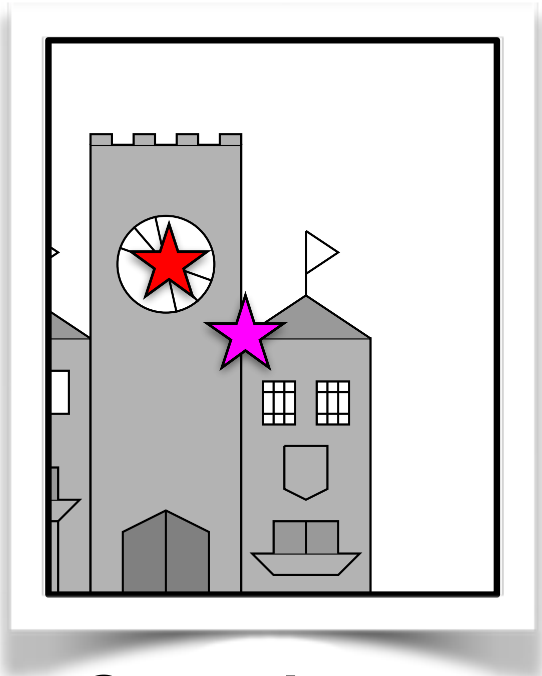
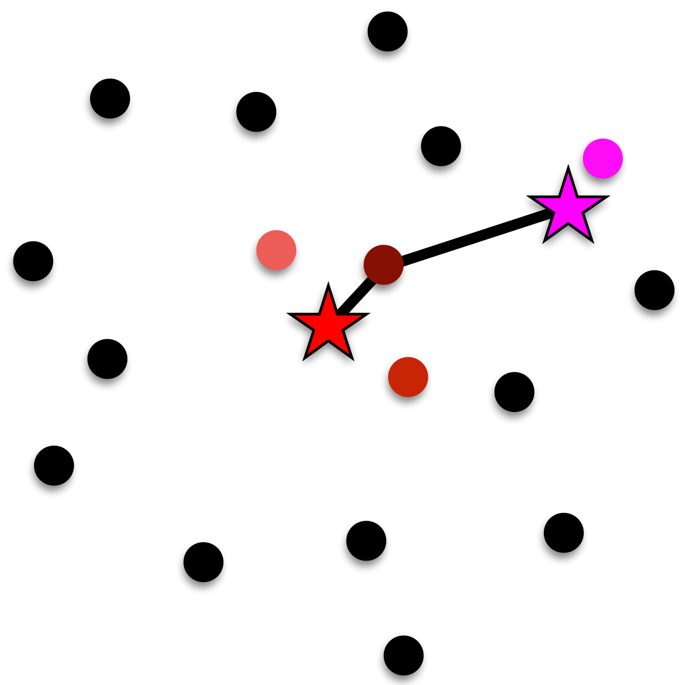
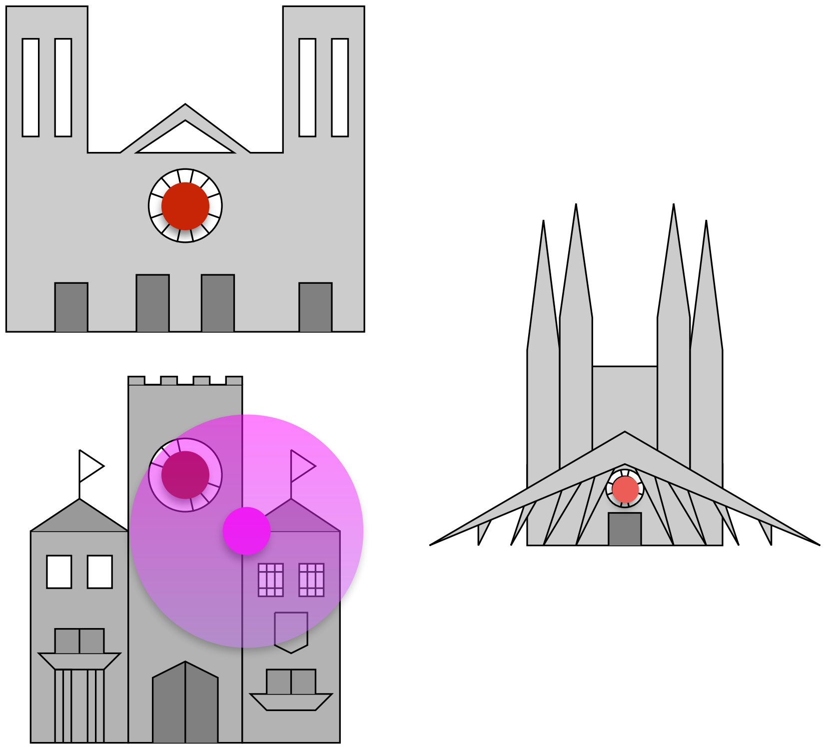


Query Image



Descriptor Space



Locally Similar Structures

- Ratio test for 2D-to-3D matching rejects globally ambiguous matches
- Active Search can recover rejected matches using 3D-to-2D matching
  - Scalability: Globally ambiguous structures more likely for larger models

Active Search vs. Pure 2D-to-3D Matching

Method	% Localized Images	Mean Localization Time [s]
kd-tree [Li et al., ECCV'12]	~87	"few seconds"
VPS	85.47	0.89
Active Search	**95.34**	**0.48**

Landmarks 1k dataset [Li et al., ECCV'12]

- Most popular 1k landmarks from Flickr
- 38M points reconstructed from 204k images
- 10k query images

Active Search vs. Pure 2D-to-3D Matching

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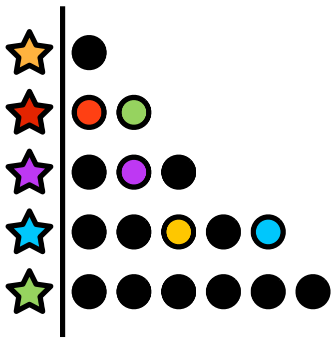
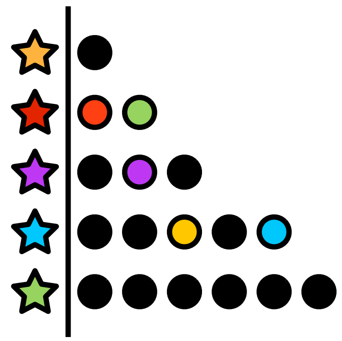
Key Insights



Prioritized Search

- 2D-to-3D matching more reliable than 3D-to-2D search
- Efficient search through **prioritization**
- Effectiveness reduced by **quantization**

Key Insights



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Active Search

- **Recover** missing matches via 3D-to-2D search

➡**State-of-the-art localization effectiveness**

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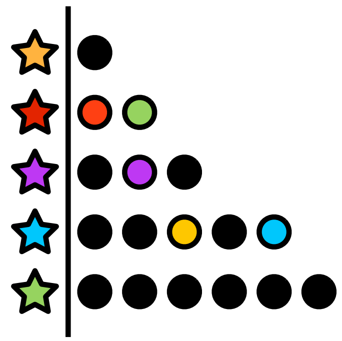
Key Insights



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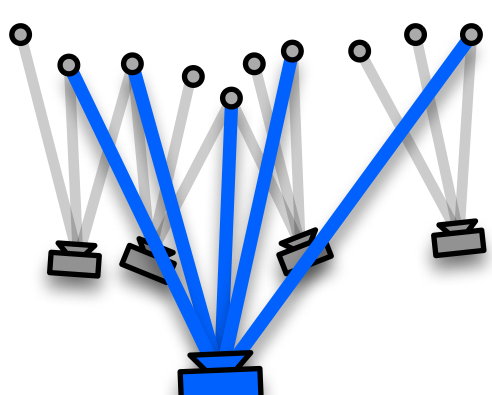

Visibility Filtering

- Accelerate both 3D-to-2D matching & pose estimation

➡**State-of-the-art localization efficiency & effectiveness**

Overview

- Efficient & Effective Large-Scale Localization
- Real-Time Mobile Localization
- Open Challenges

Localization On Mobile Devices

Goals:

- Real-time localization on mobile device
- Scalable, independent from scene size

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Challenges:

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- Limited memory

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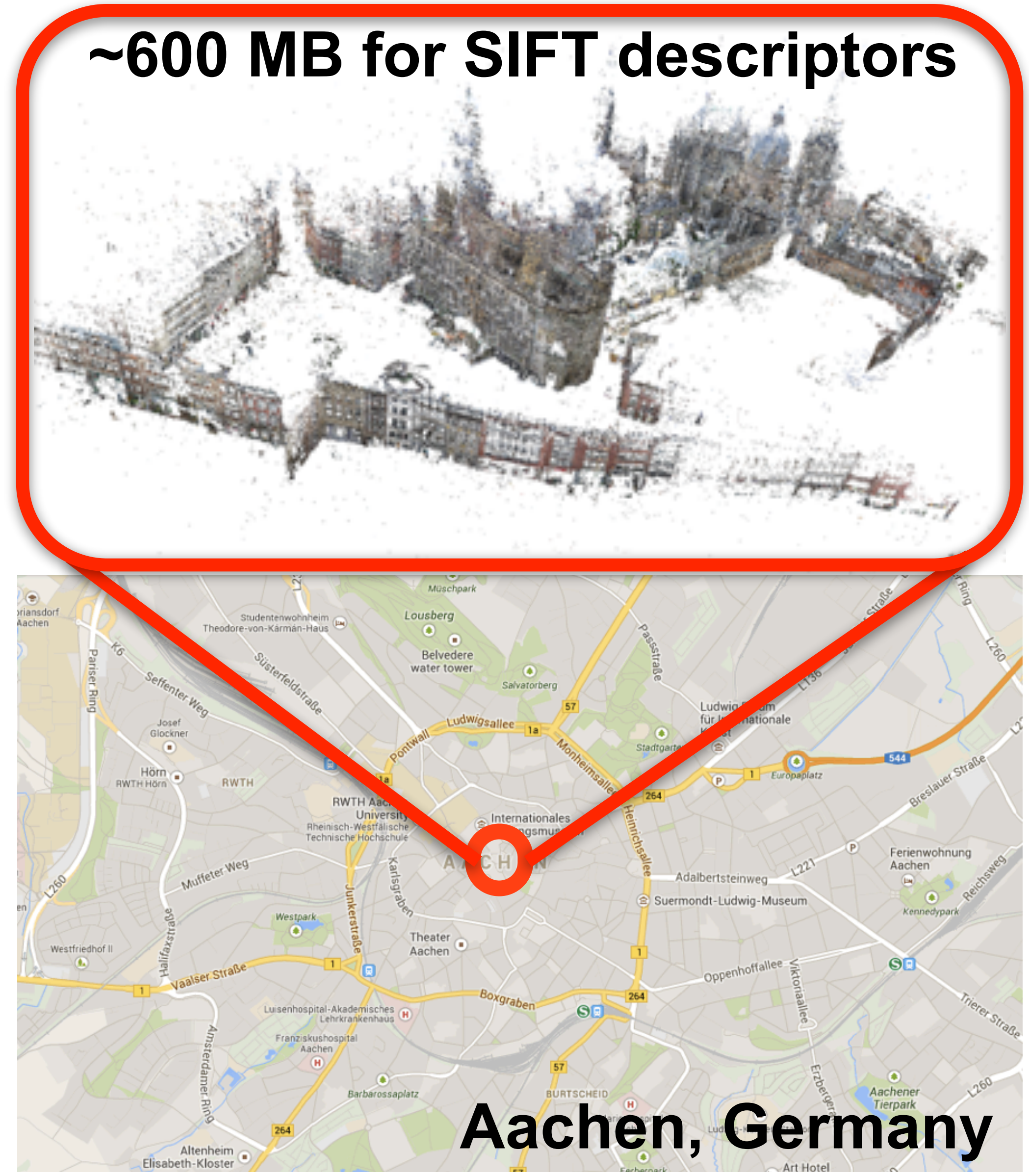

[Aachen dataset]

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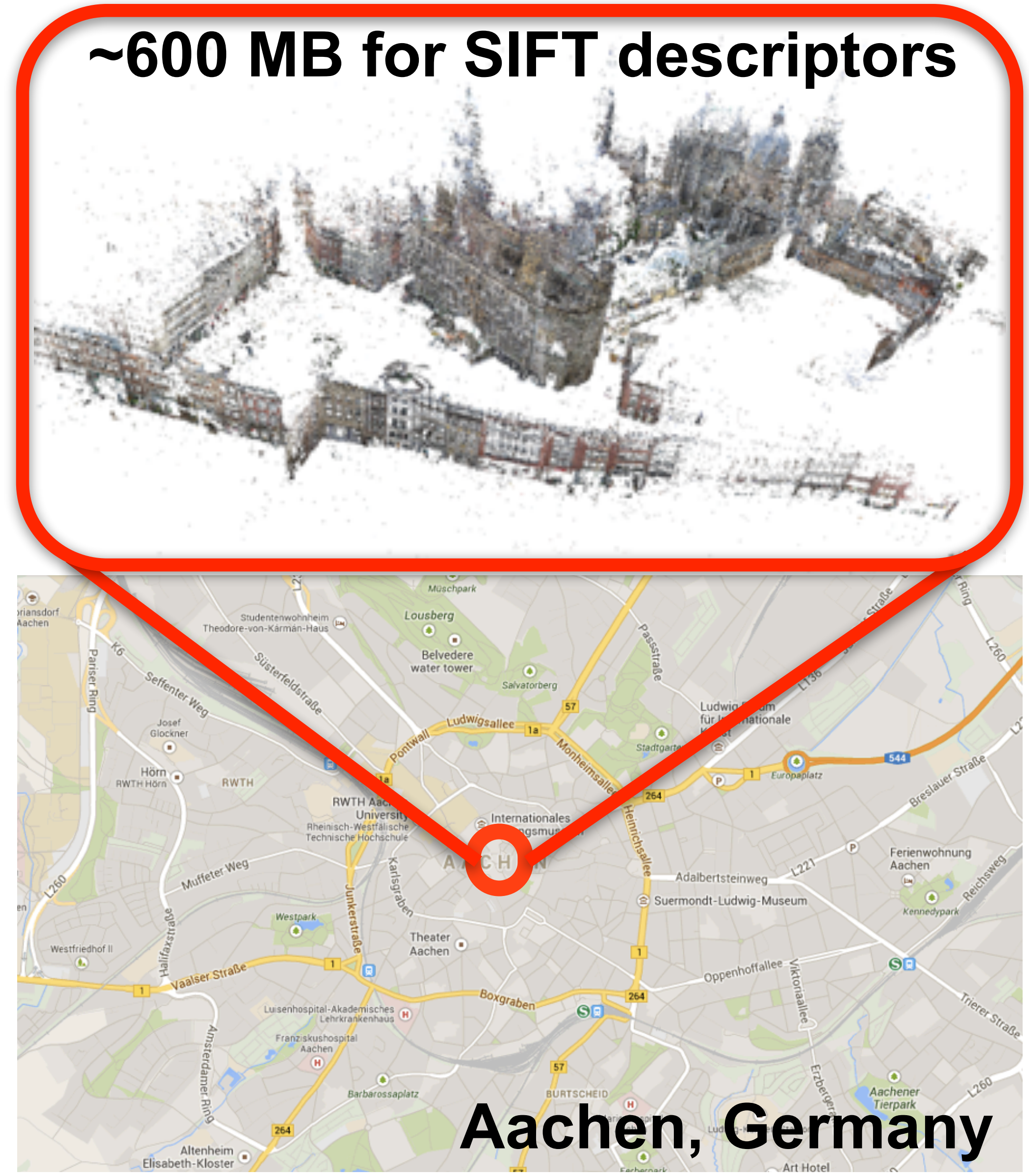
Localization On Mobile Devices

Goals:

- Real-time localization on mobile device
- Scalable, independent from scene size

Challenges:

- Limited memory
- Limited computational capabilities



[Aachen dataset]

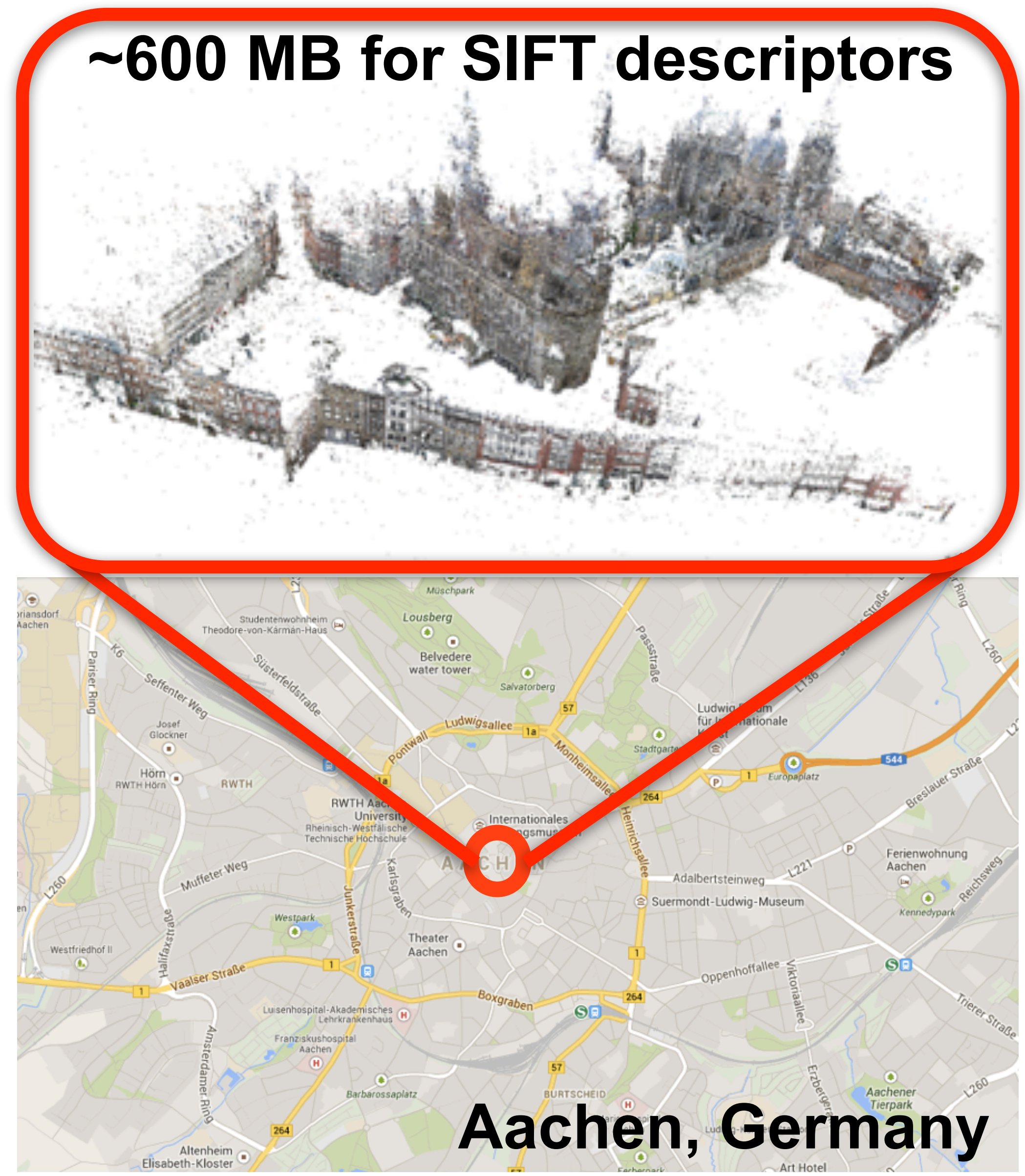
Localization On Mobile Devices

Goals:

- Real-time localization on mobile device
- Scalable, independent from scene size

Challenges:

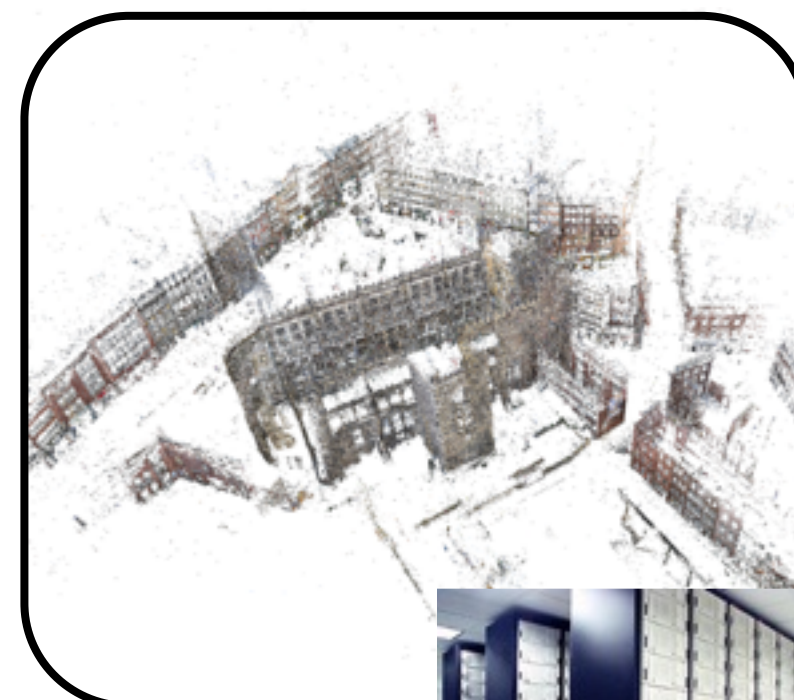
- Limited memory
- Limited computational capabilities
- Localization accuracy



[Aachen dataset]

A Scalable Mobile Localization Pipeline

Mobile Device



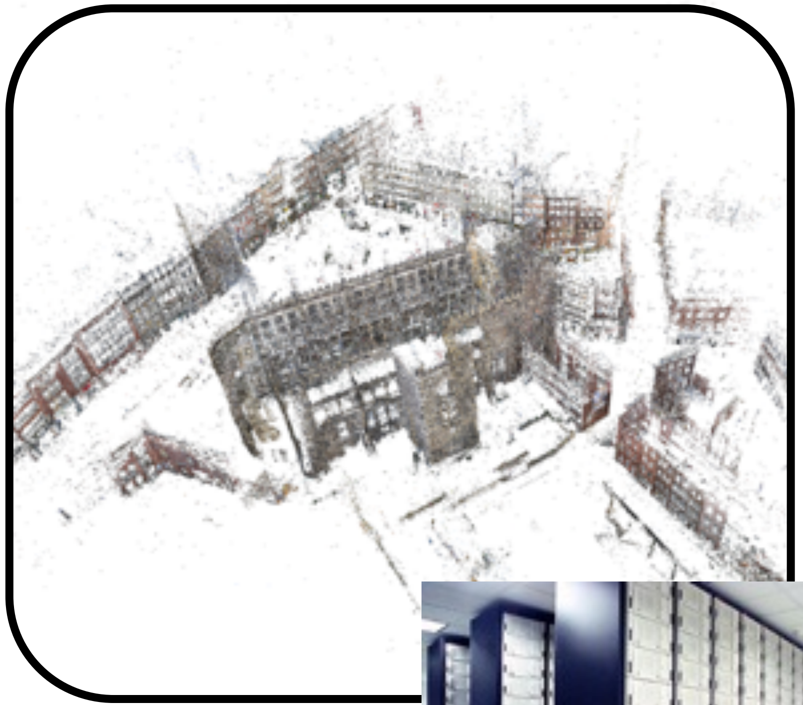
Localization Server

[Middelberg et al., ECCV'14]

A Scalable Mobile Localization Pipeline

Mobile Device

Send Image



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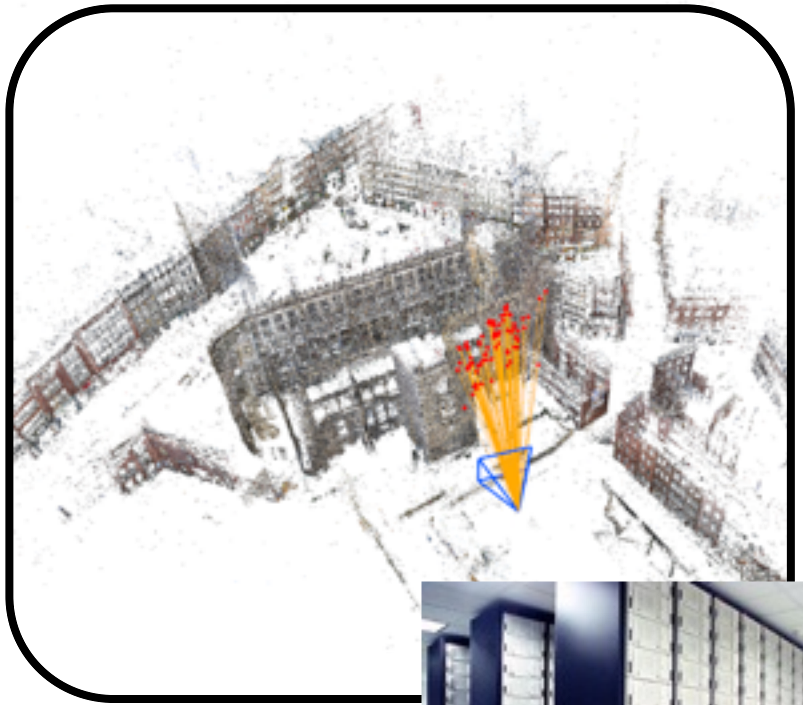

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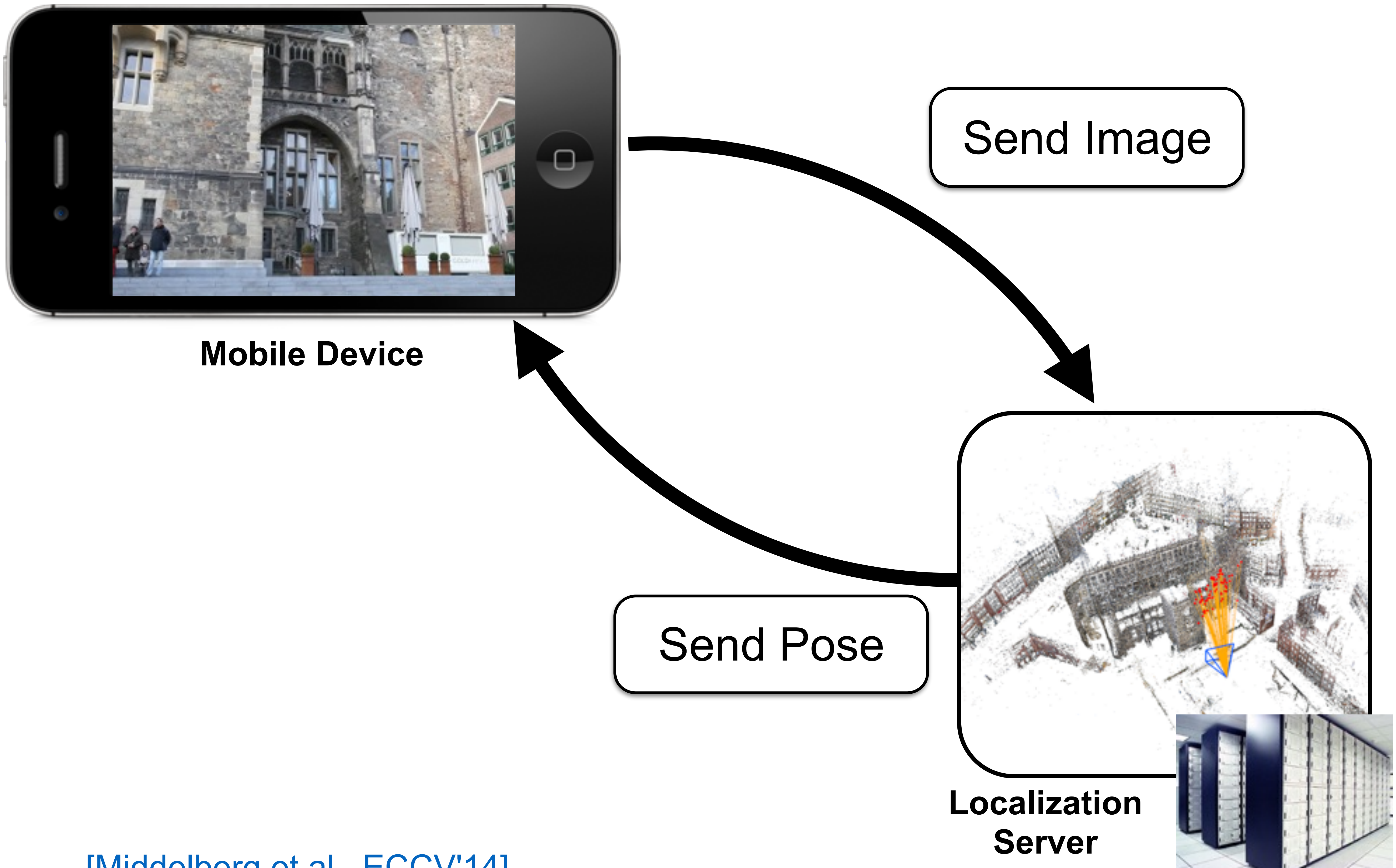
A Scalable Mobile Localization Pipeline



[Middelberg et al., ECCV'14]

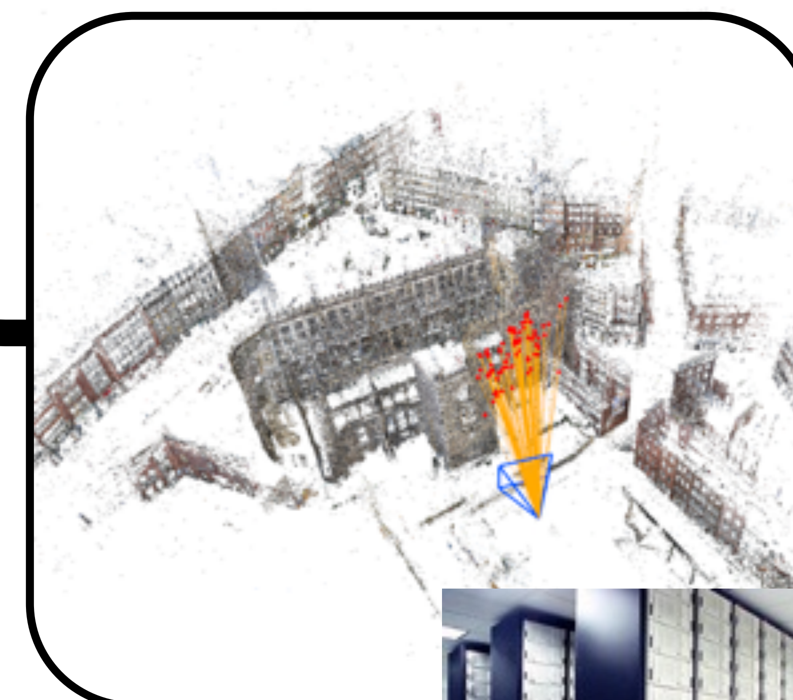
A Scalable Mobile Localization Pipeline

Mobile Device

Send Image

≥1s delay!

Send Pose



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[Middelberg et al., ECCV'14]

A Scalable Mobile Localization Pipeline

Mobile Device

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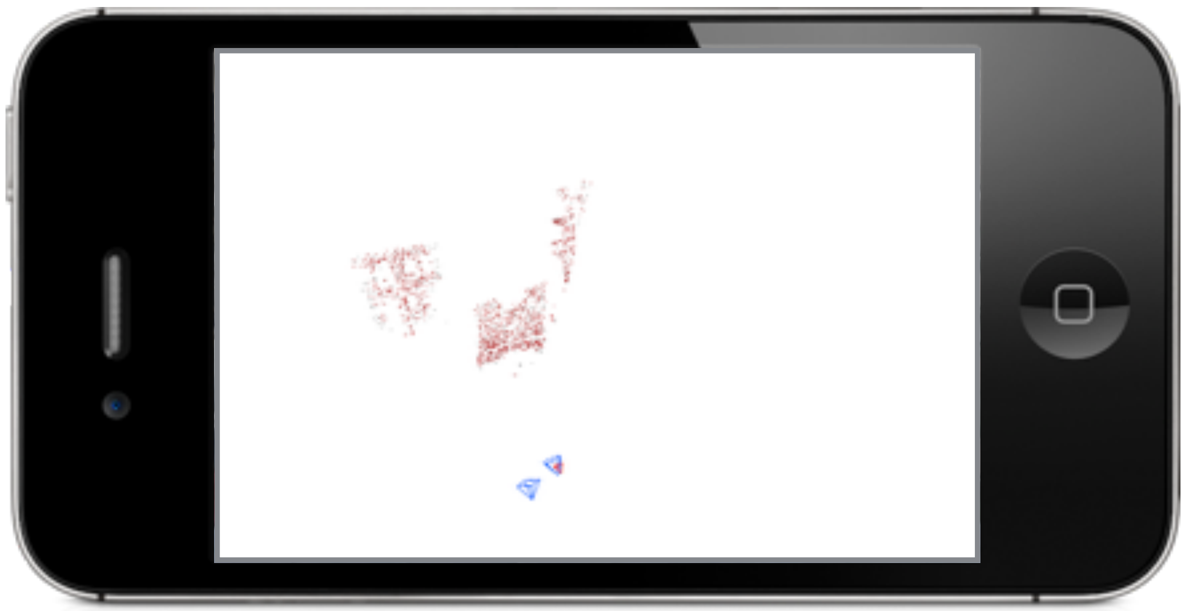
A Scalable Mobile Localization Pipeline



Mobile Device

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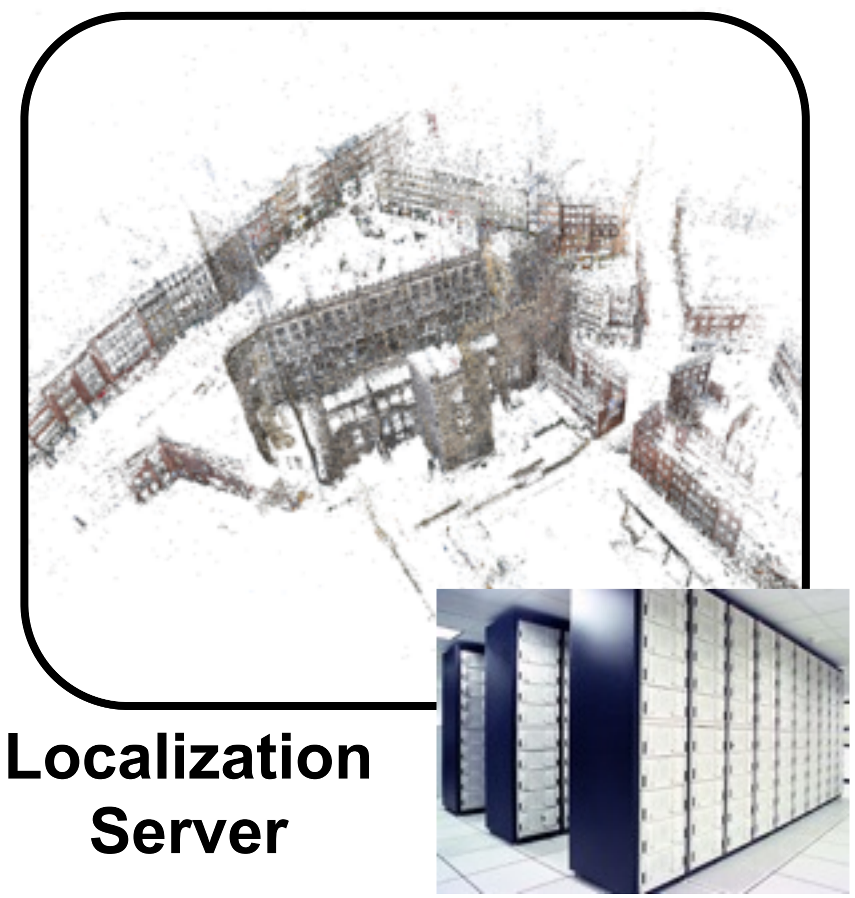

Localization Server

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A Scalable Mobile Localization Pipeline

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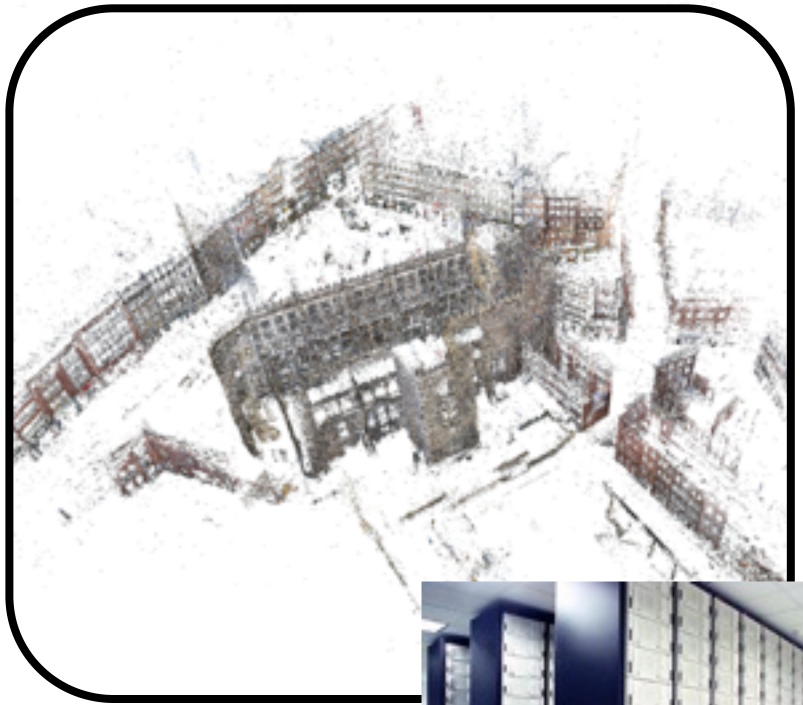

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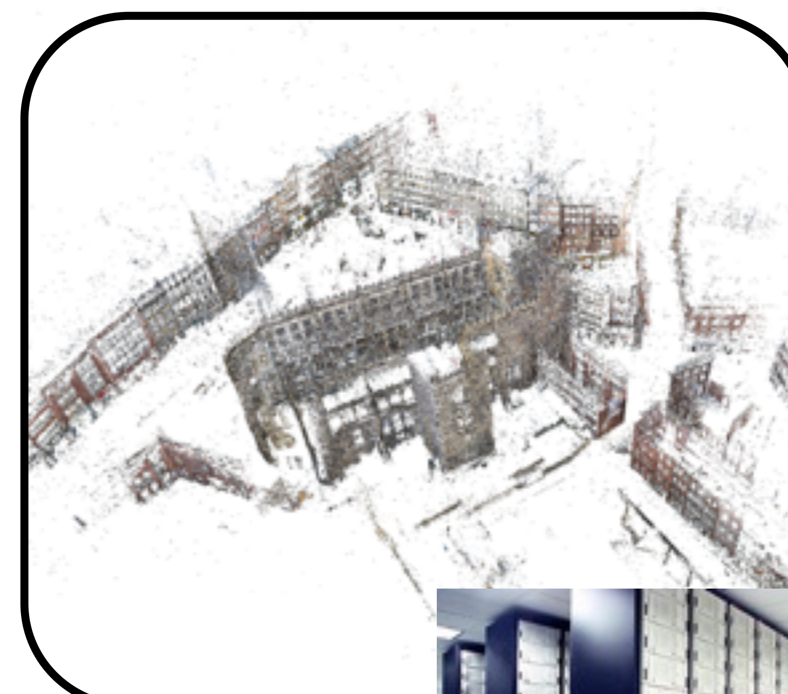

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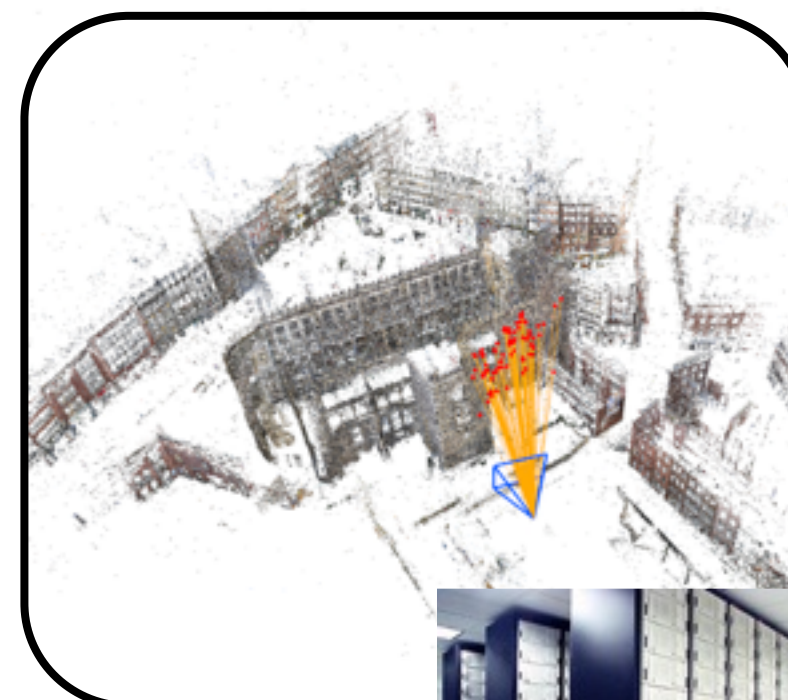

Localization Server

[Middelberg et al., ECCV'14]

A Scalable Mobile Localization Pipeline

Mobile Device

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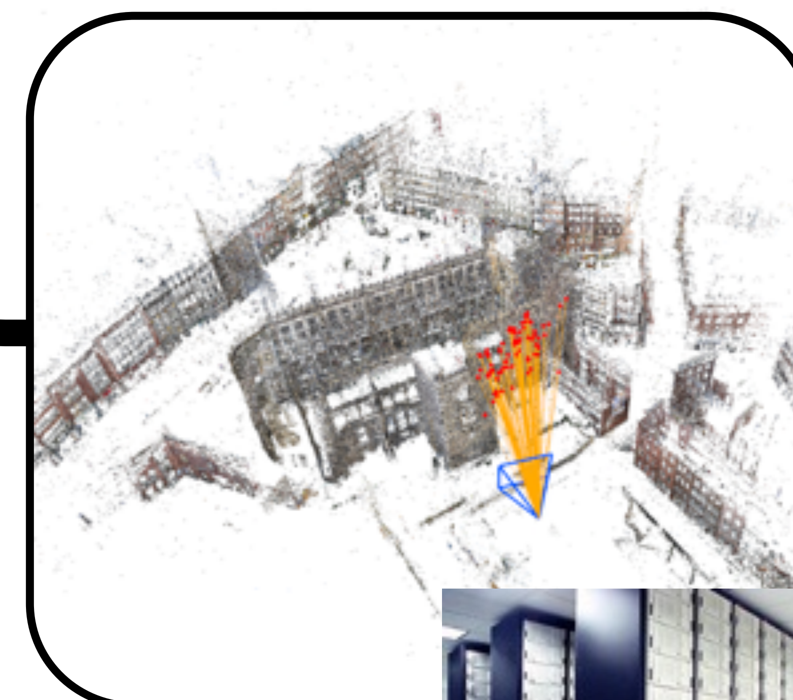
Send Image

Send Pose



Localization Server

[Middelberg et al., ECCV'14]

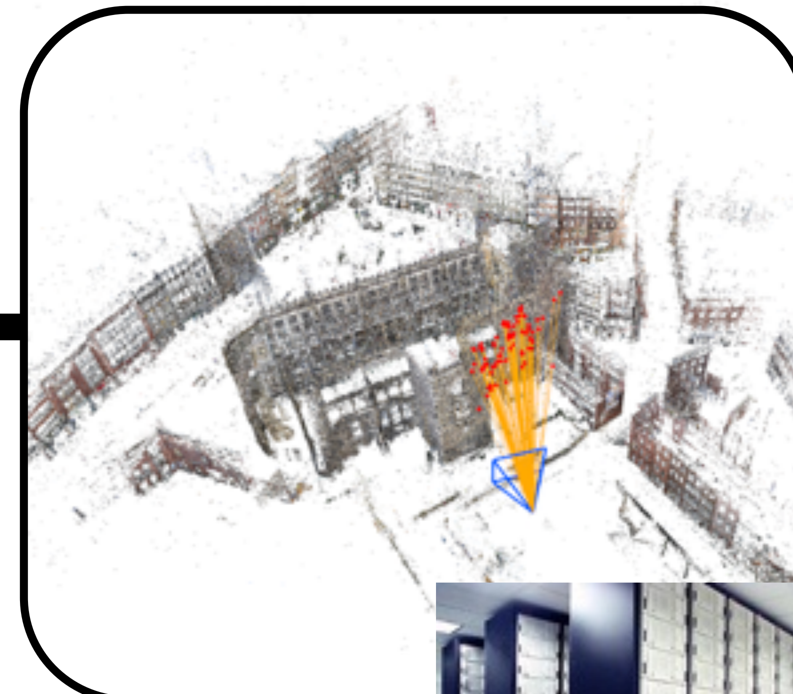
A Scalable Mobile Localization Pipeline

Mobile Device

Send Image

- Run SLAM / PTAM for **real-time camera tracking**
- Use global poses to **prevent drift**

Send Pose



Localization Server

[Middelberg et al., ECCV'14]

A Scalable Mobile Localization Pipeline

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  - Can be done in 2nd thread

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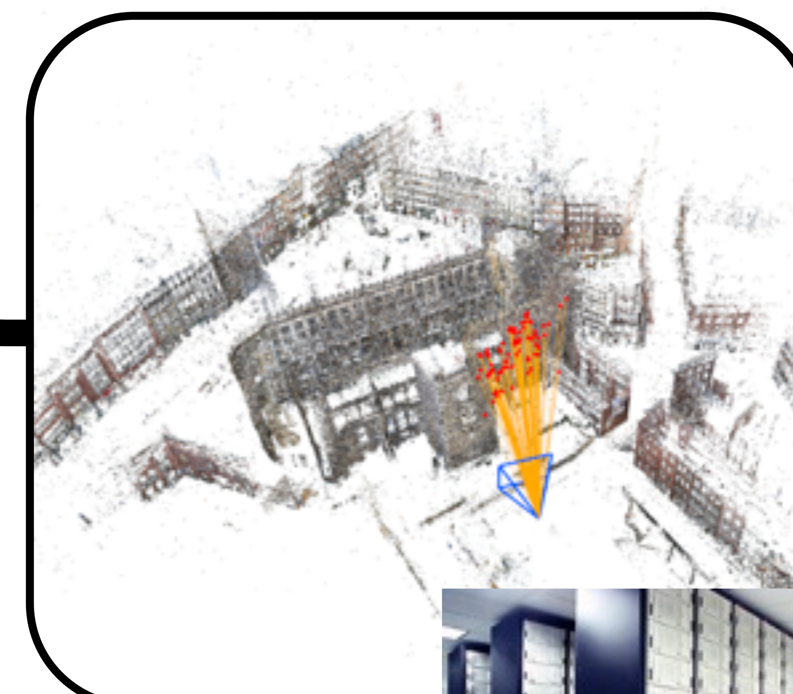

Localization Server

[Middelberg et al., ECCV'14]

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Mobile Device

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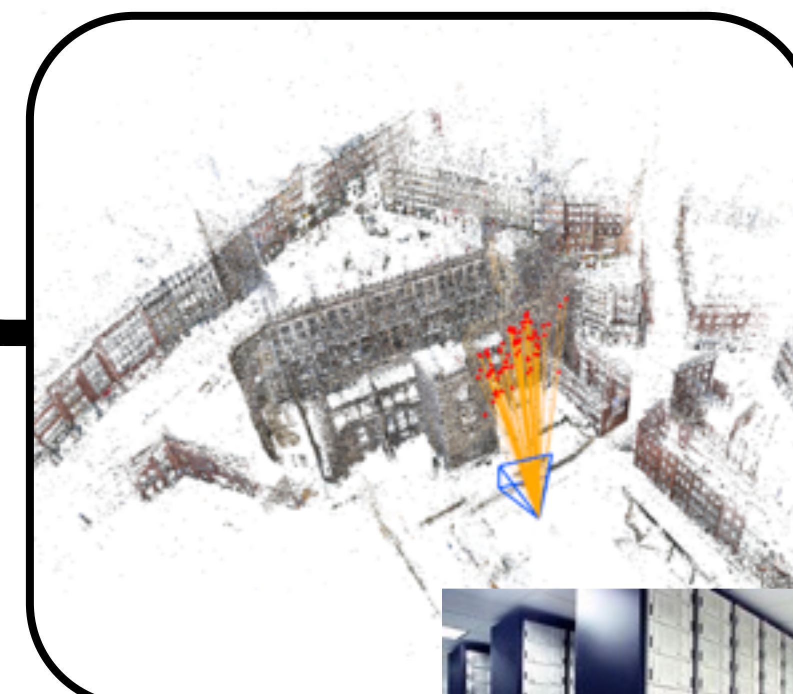
Send Pose



Localization Server

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Send Image

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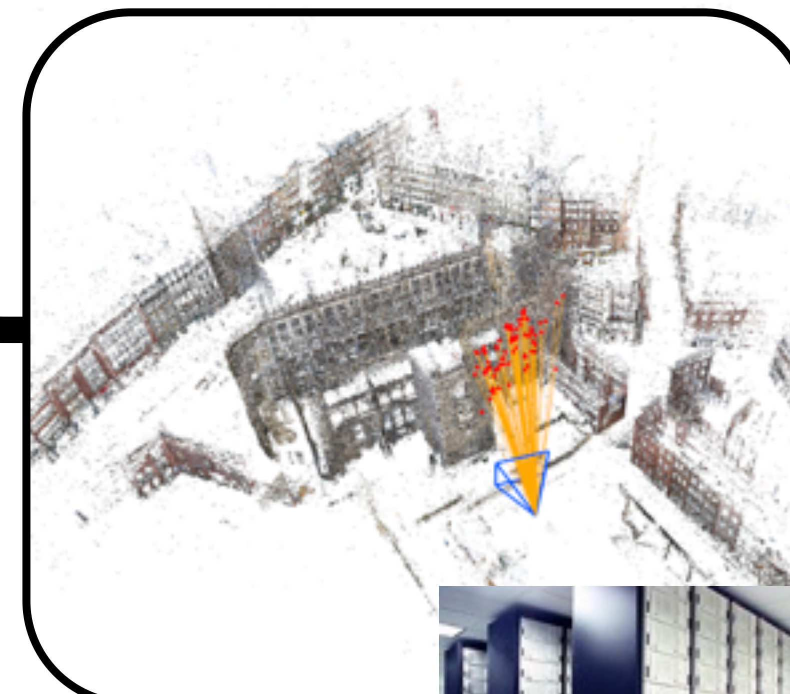

Localization Server

- Run SLAM / PTAM for **real-time camera tracking**
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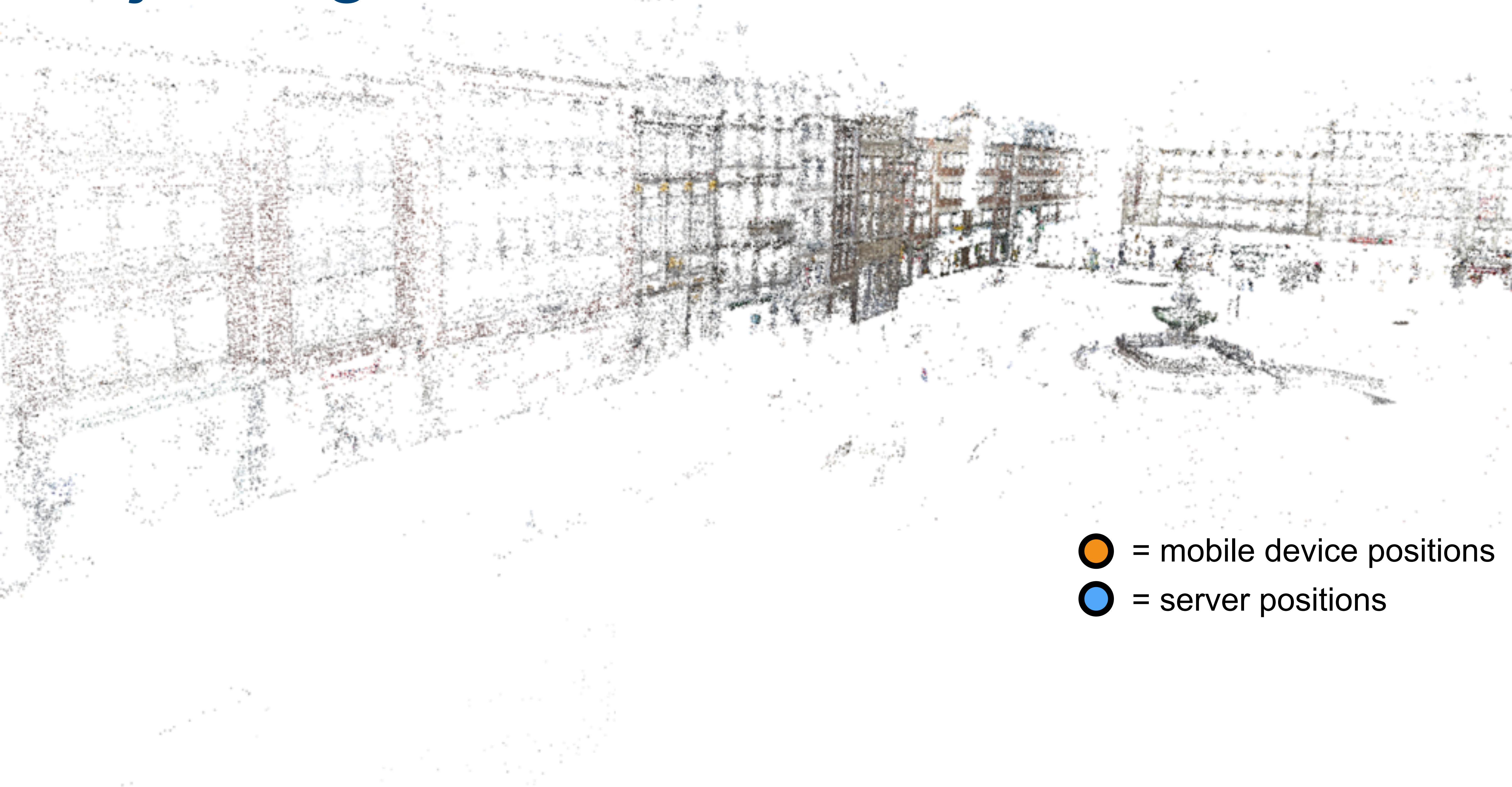
- [SLAM code available]

[Middelberg et al., ECCV'14]

Adjusting the Model



= mobile device positions

= server positions

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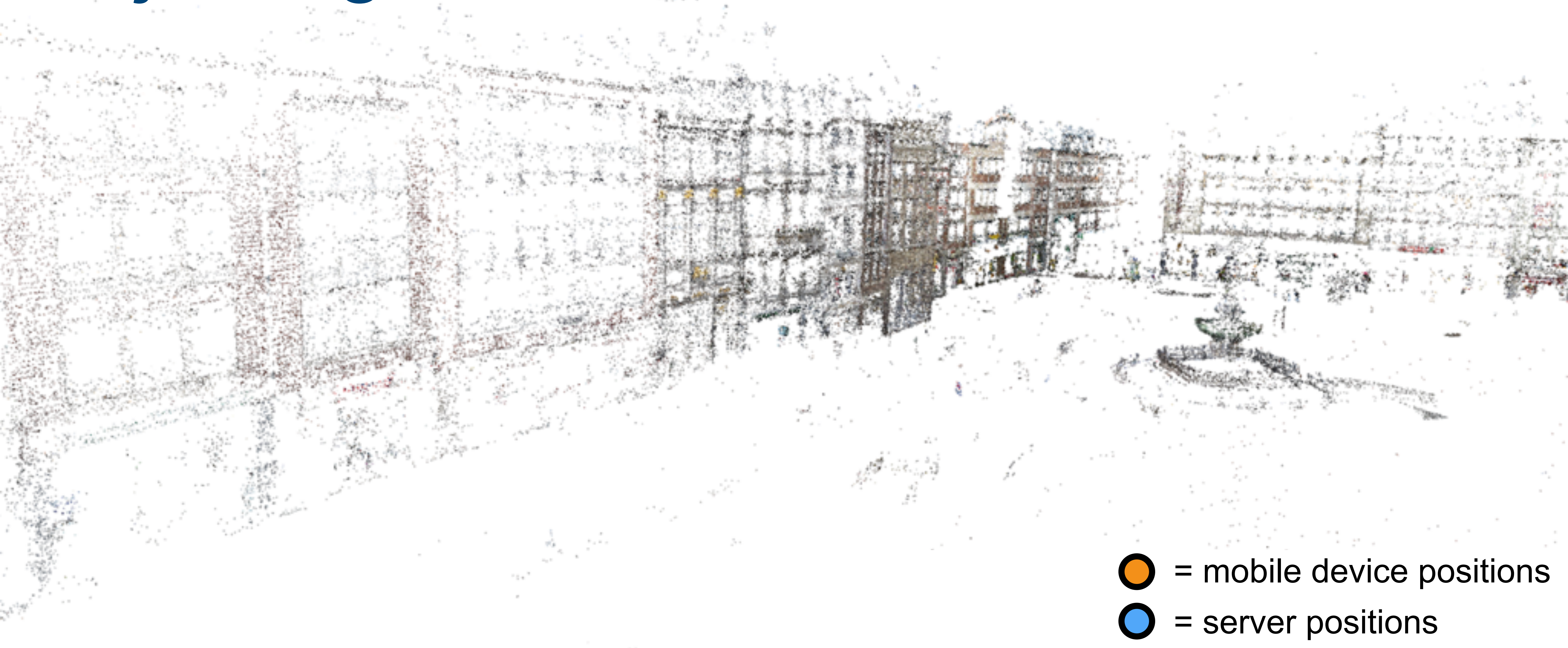
Adjusting the Model



- Initialization from first two keyframes + gravity direction

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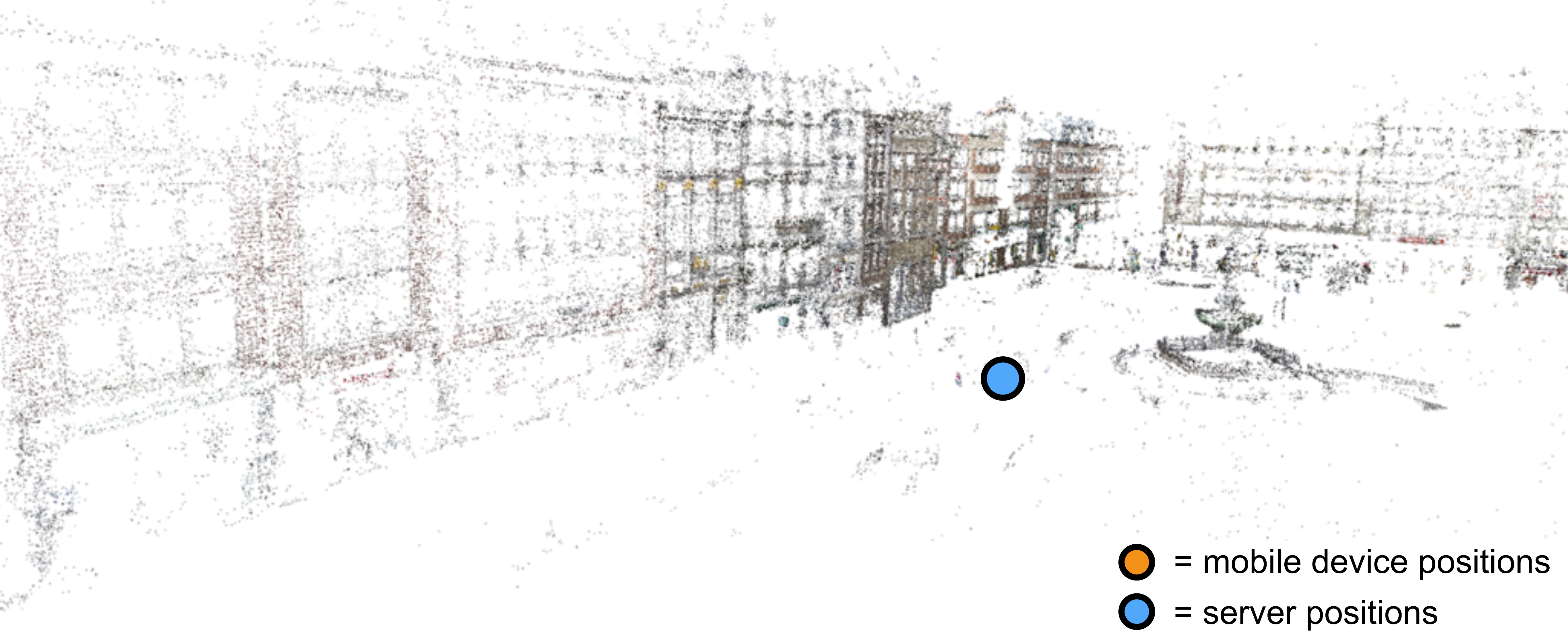

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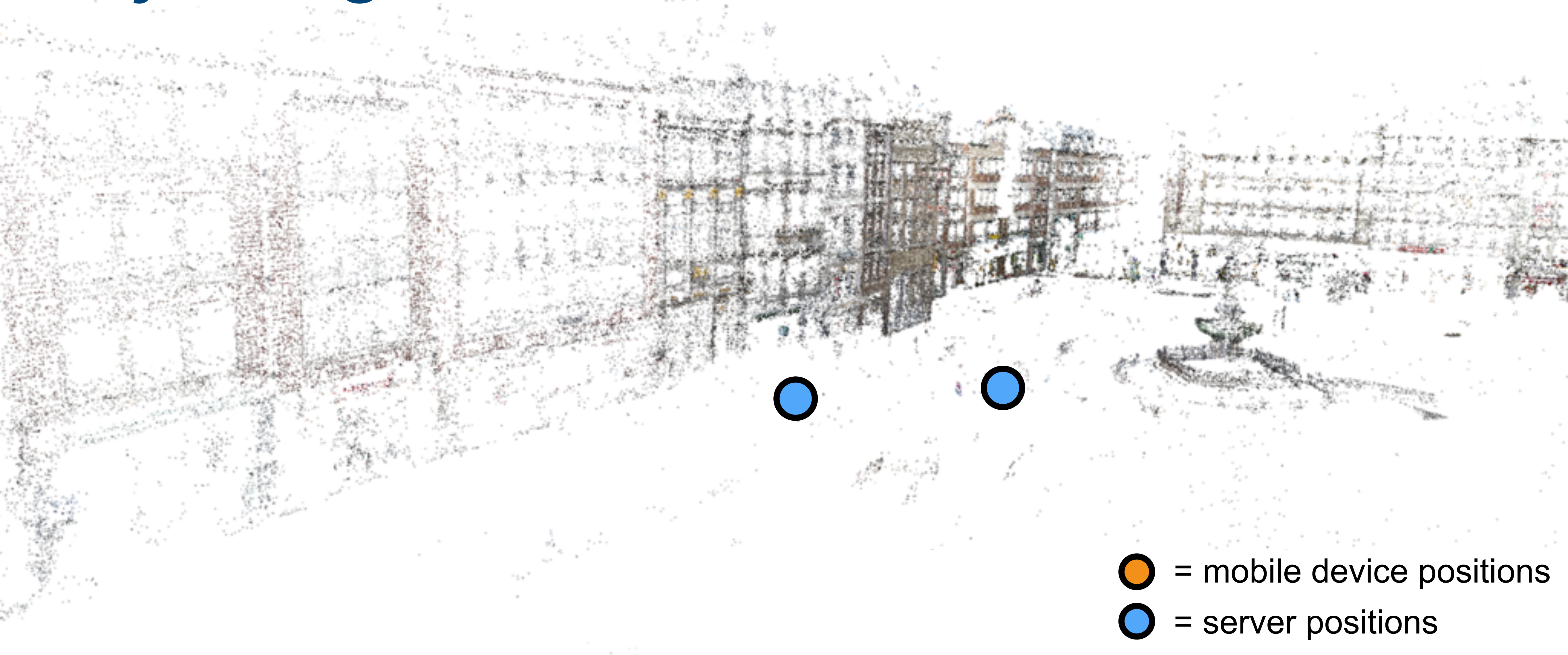

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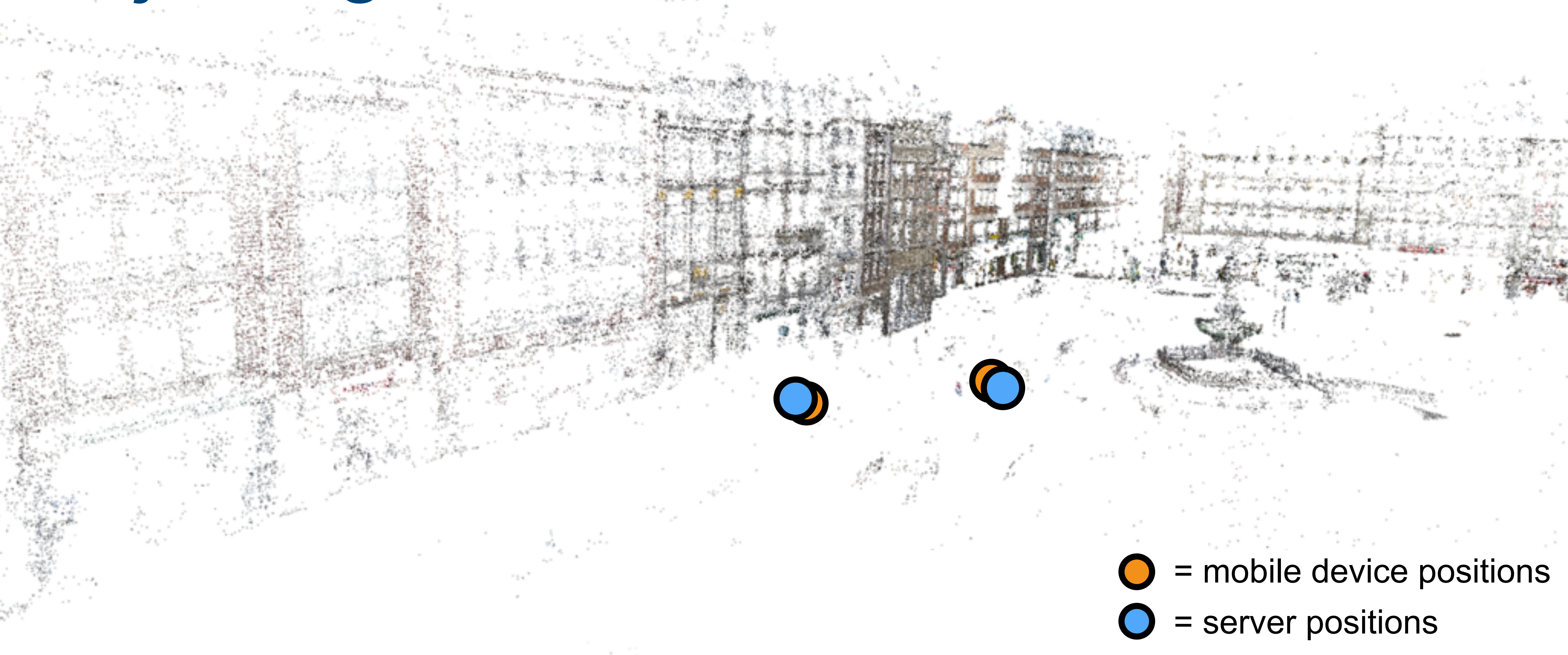

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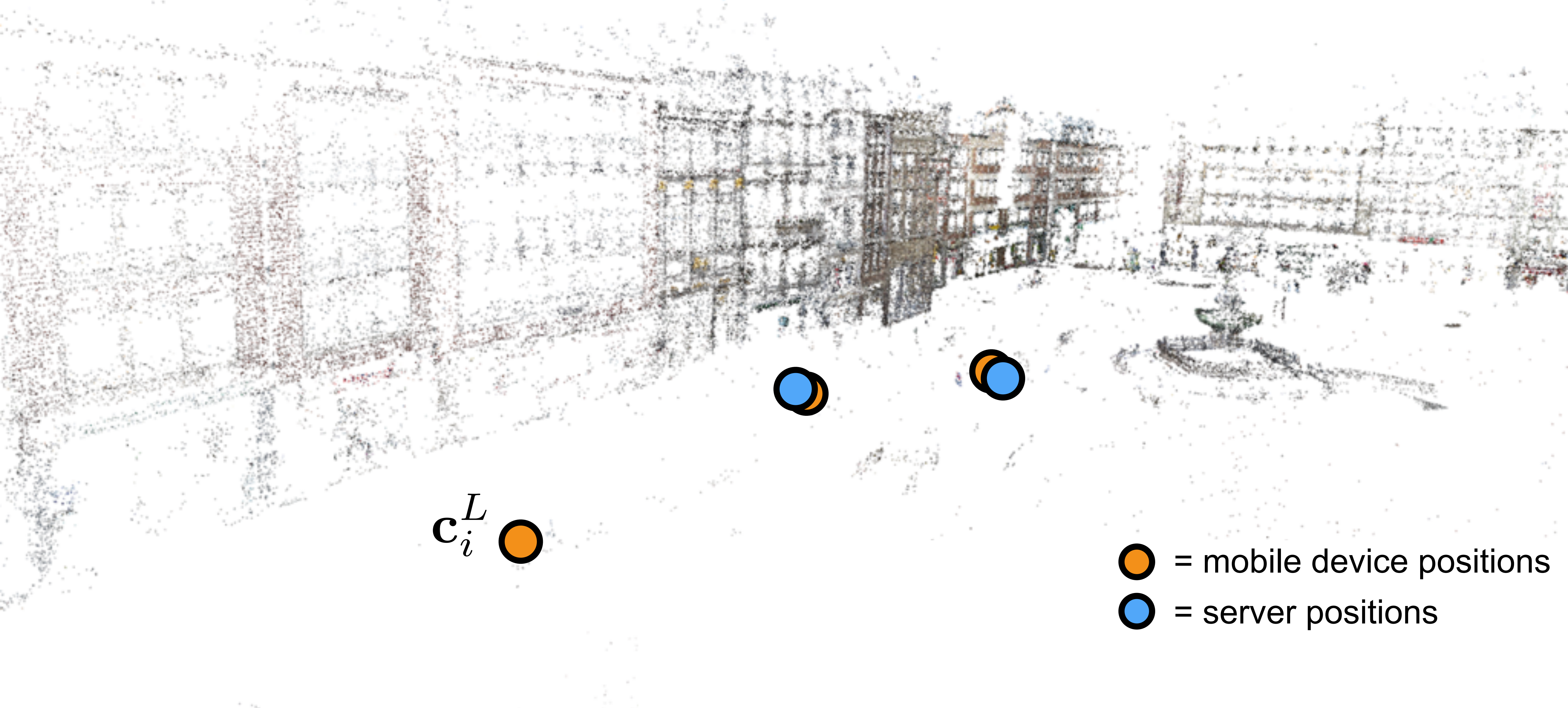

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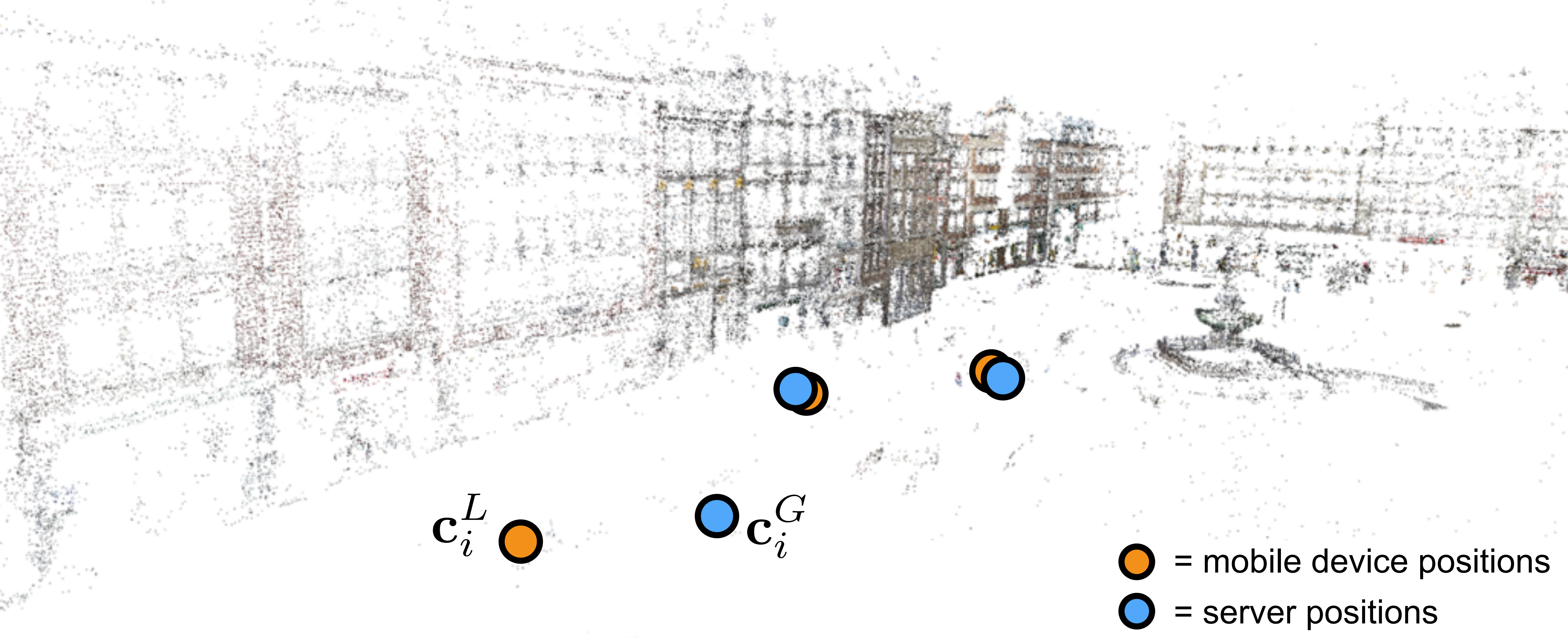

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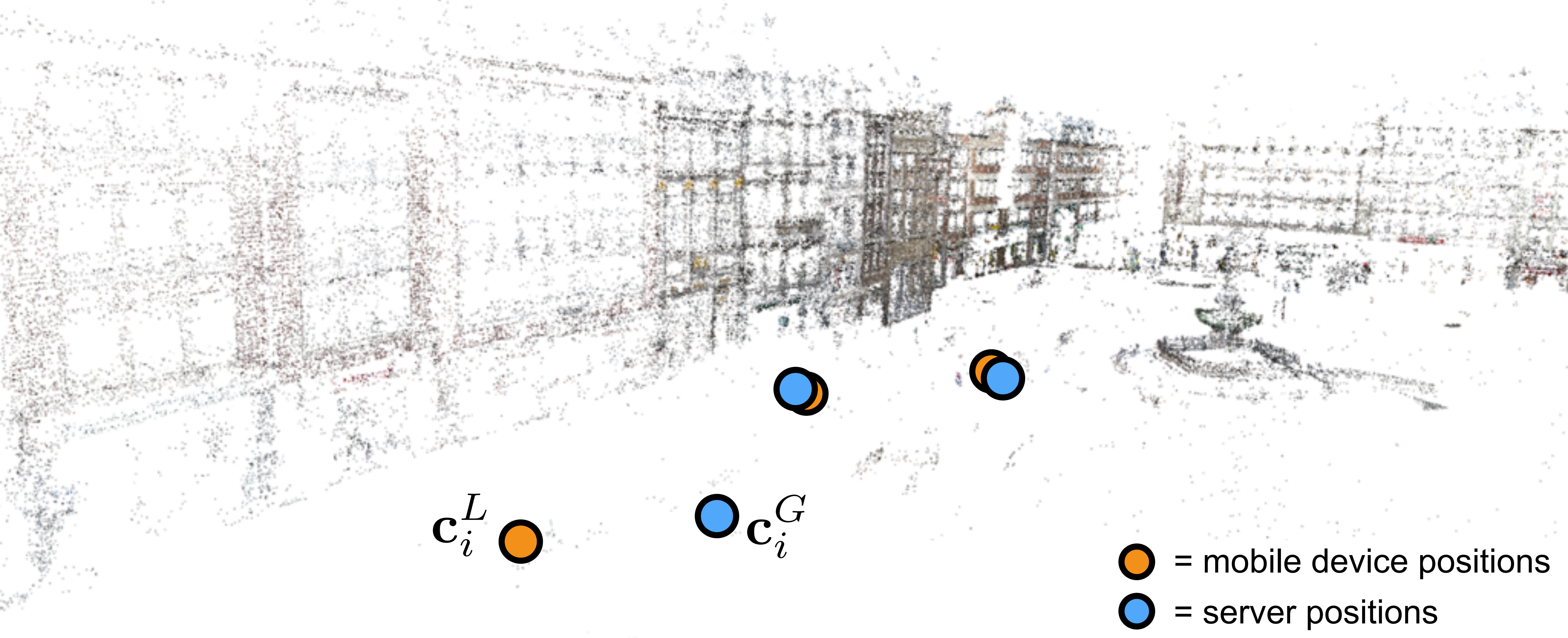
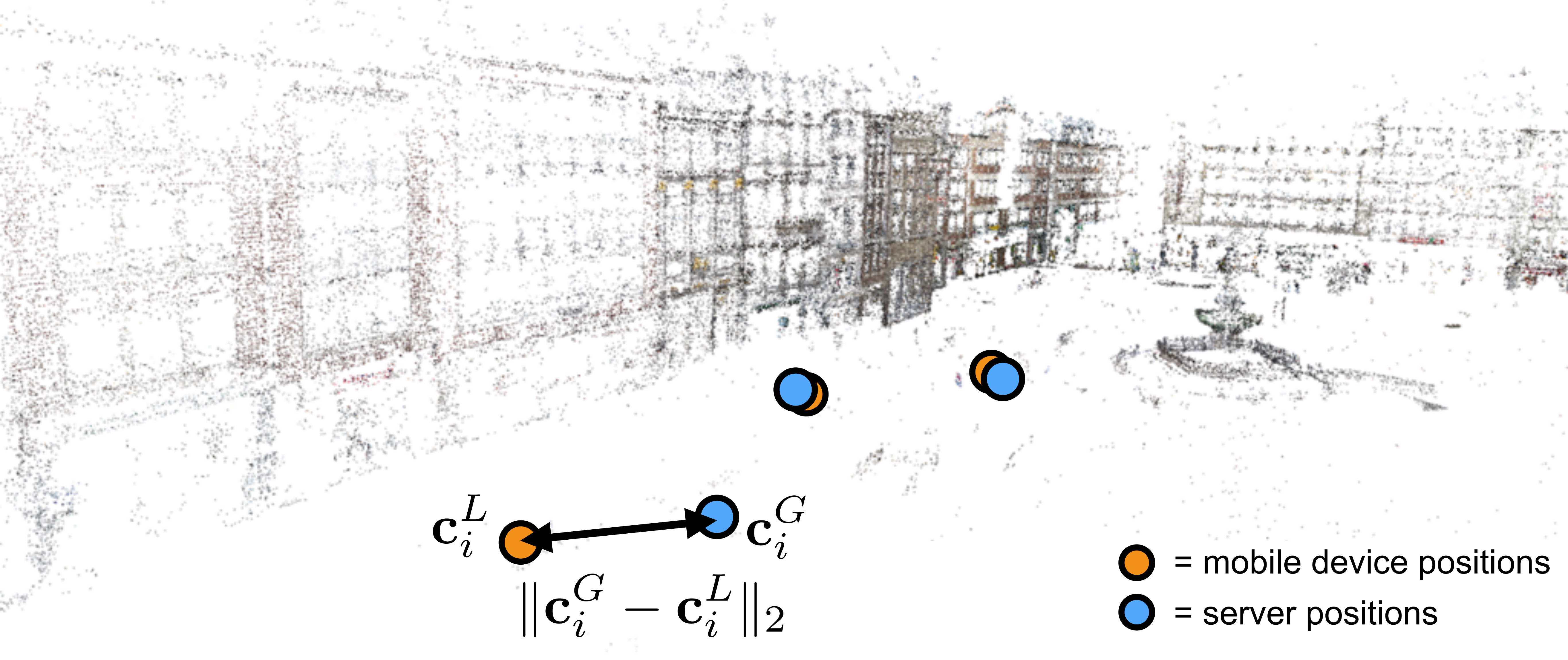


- Initialization from first two keyframes + gravity direction
- Try to minimize distance to camera positions reported by server

Adjusting the Model



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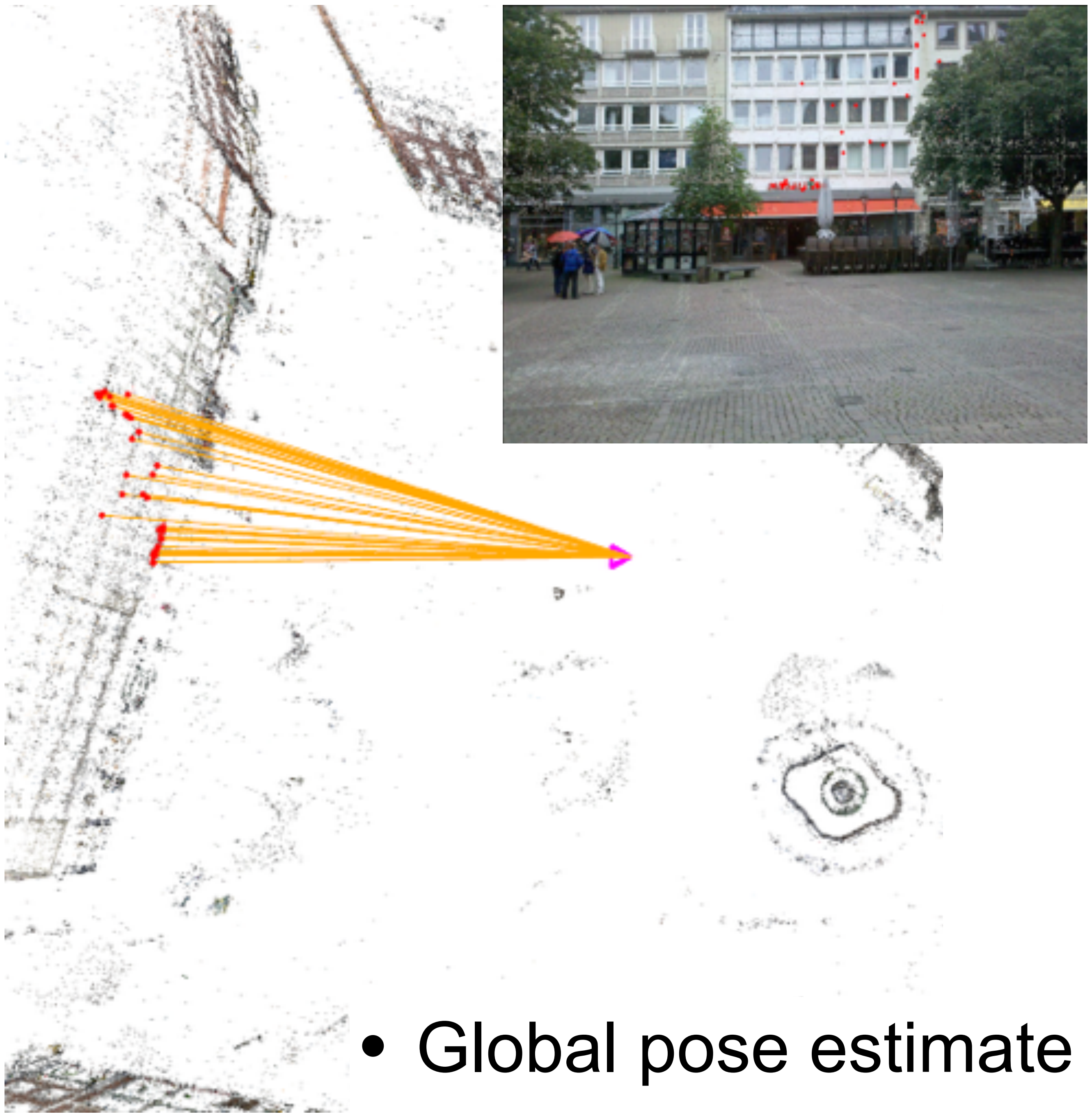
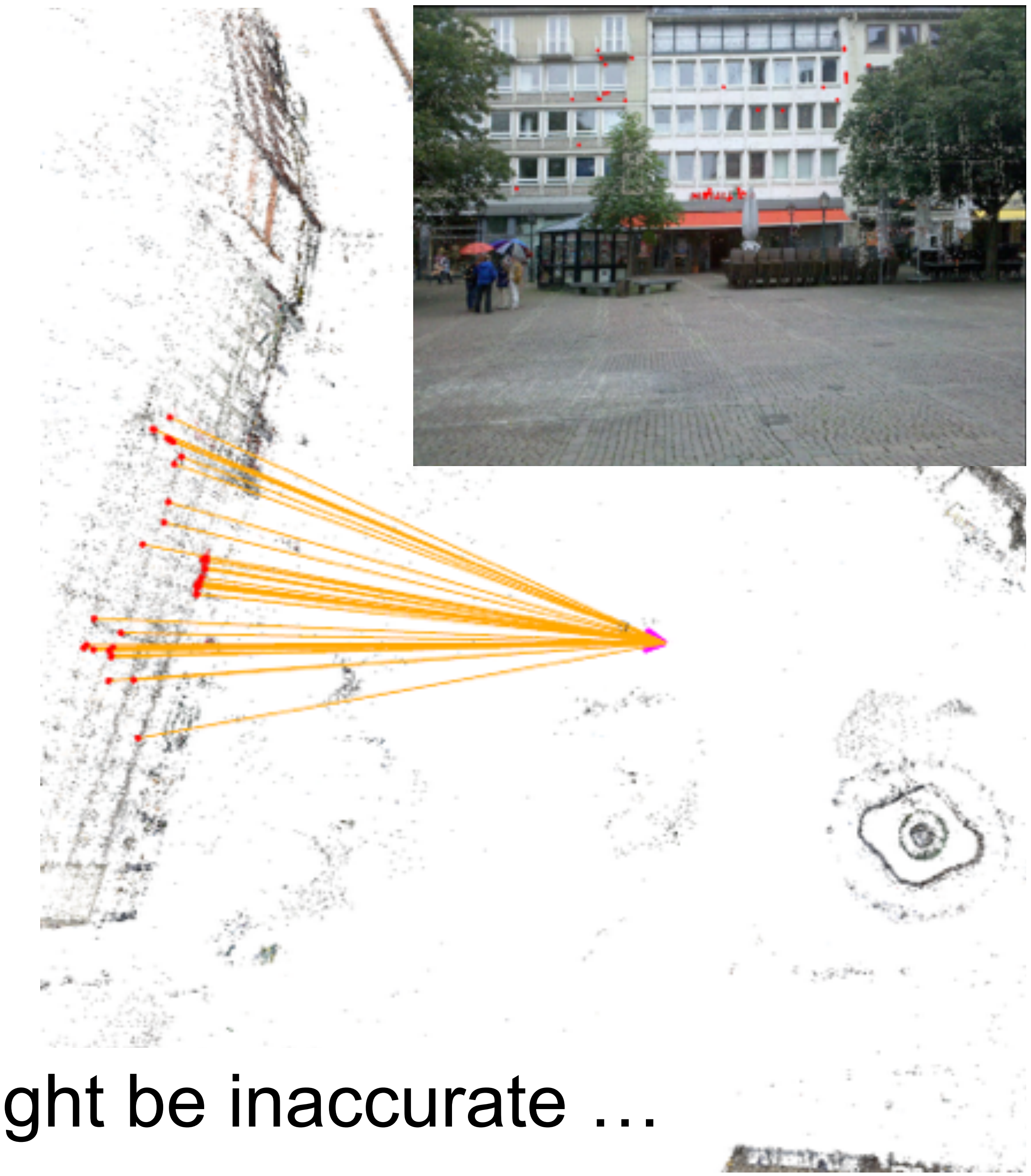
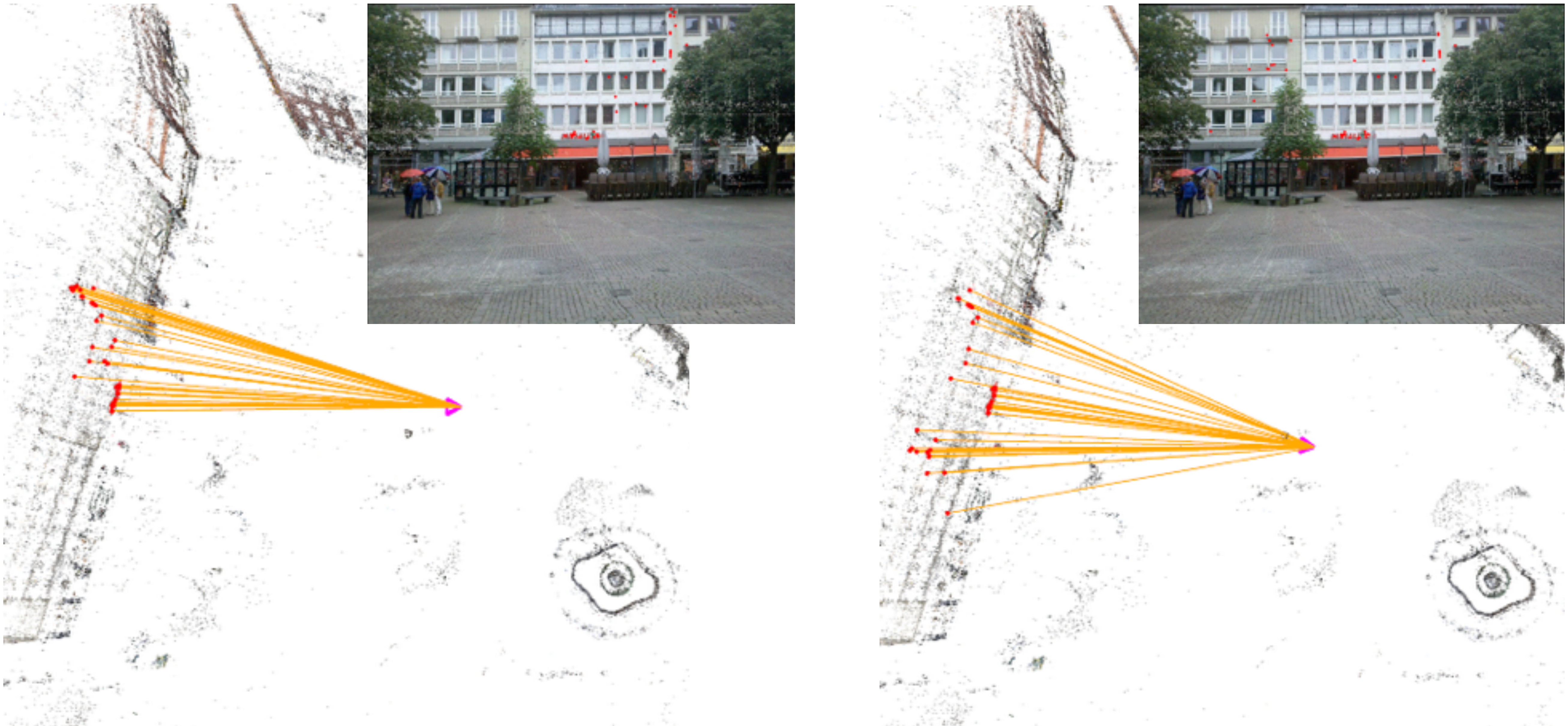




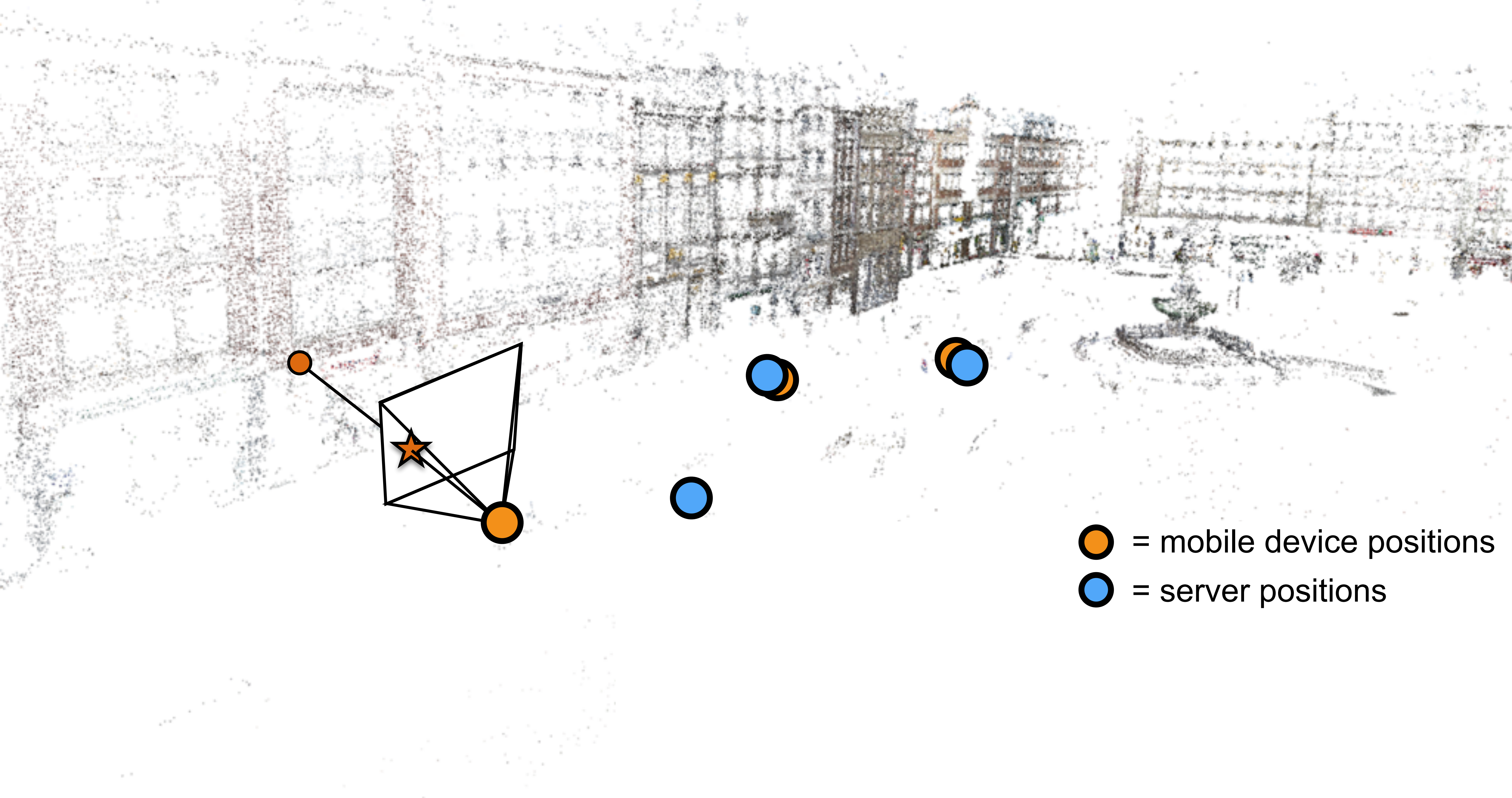
- Global pose estimate might be inaccurate …

Adjusting the Model



- Global pose estimate might be inaccurate …
- … but 2D-3D matches are still correct!

Adjusting the Model



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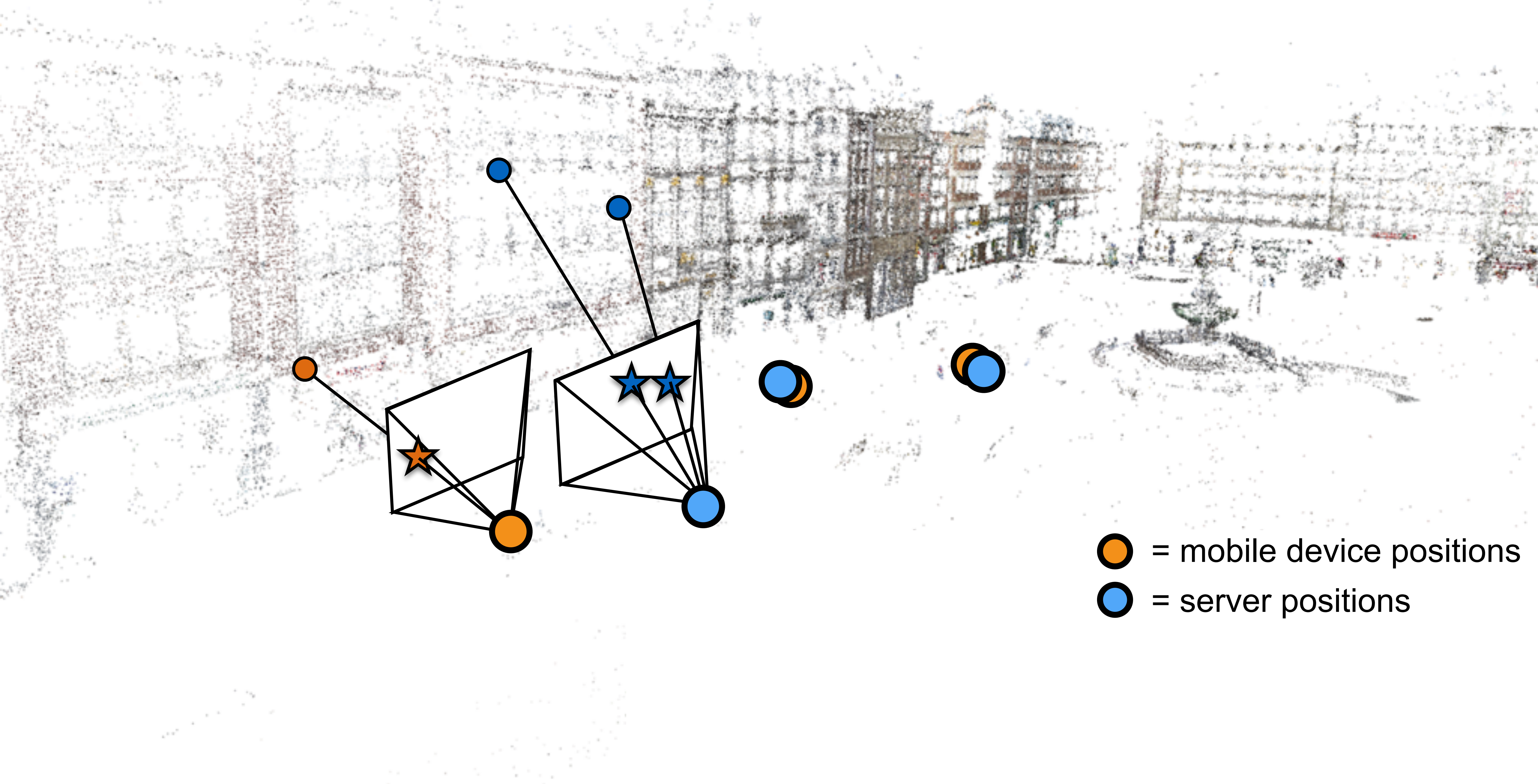

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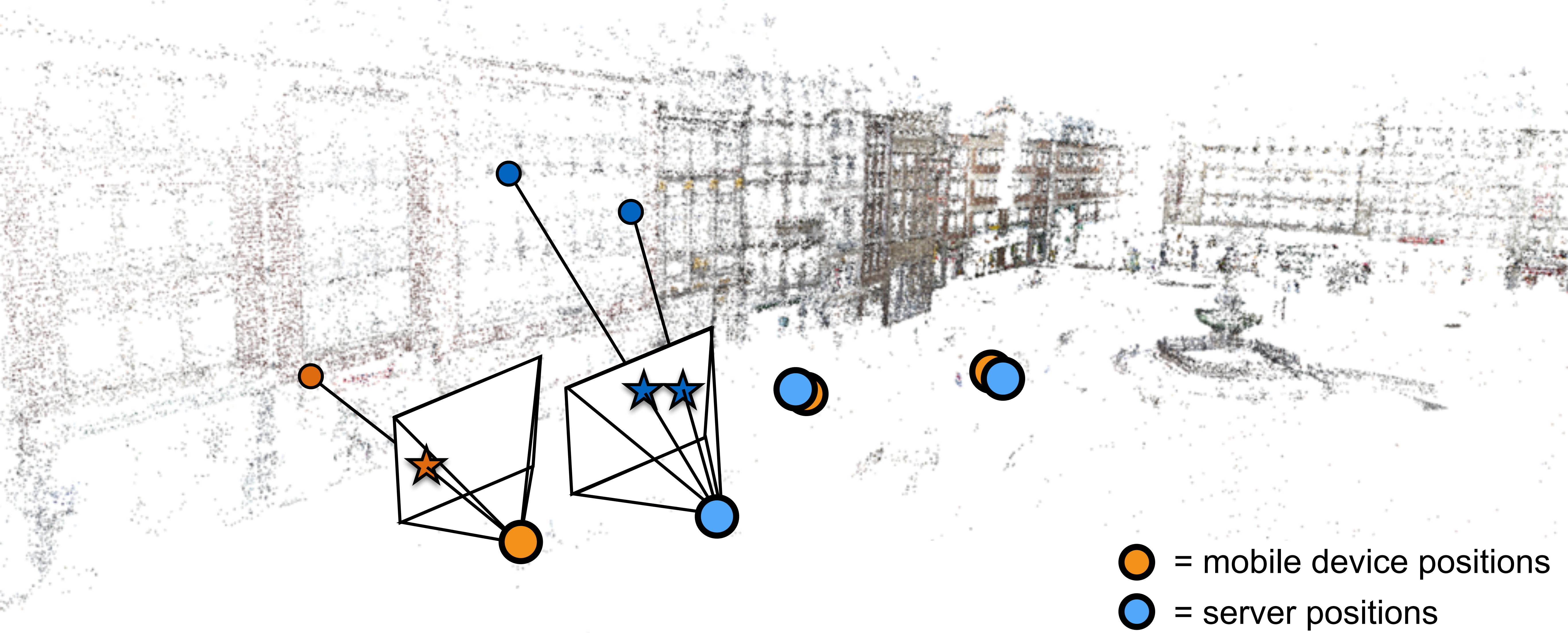
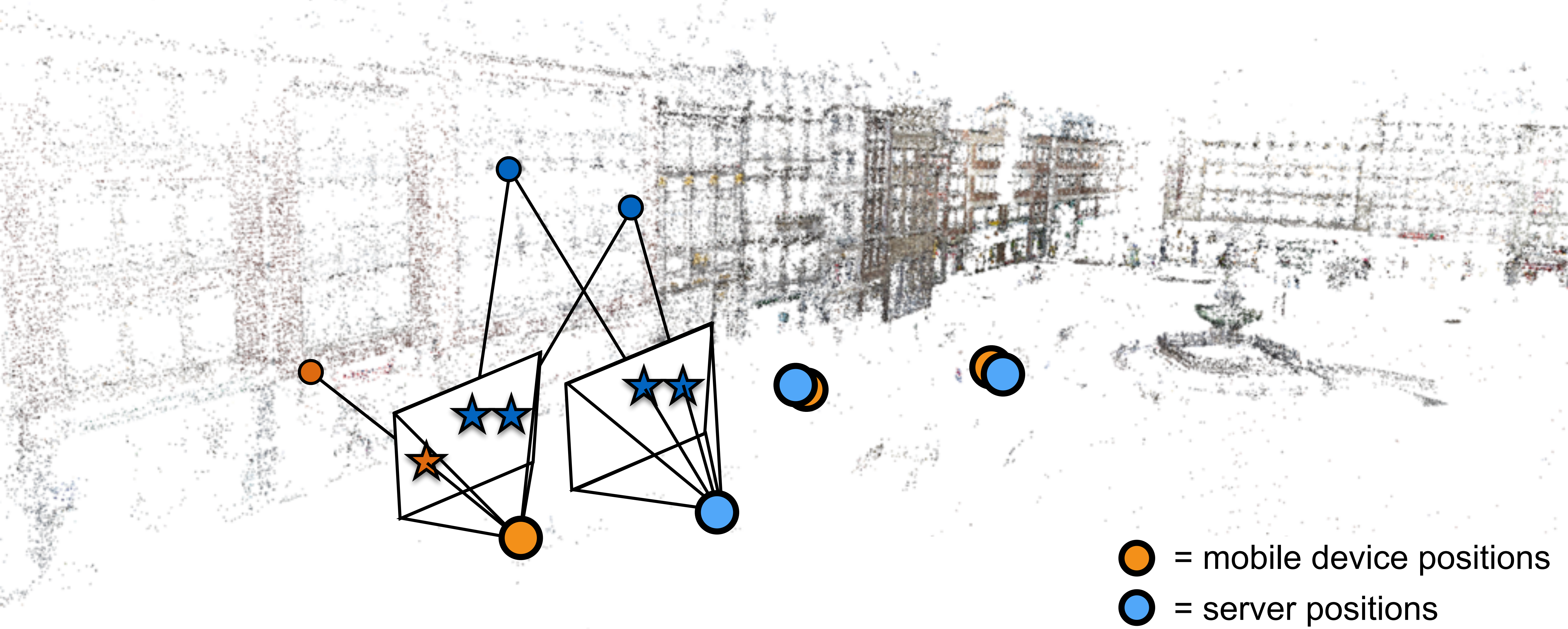
Adjusting the Model



- Use 2D-3D matches from server as control points

Adjusting the Model



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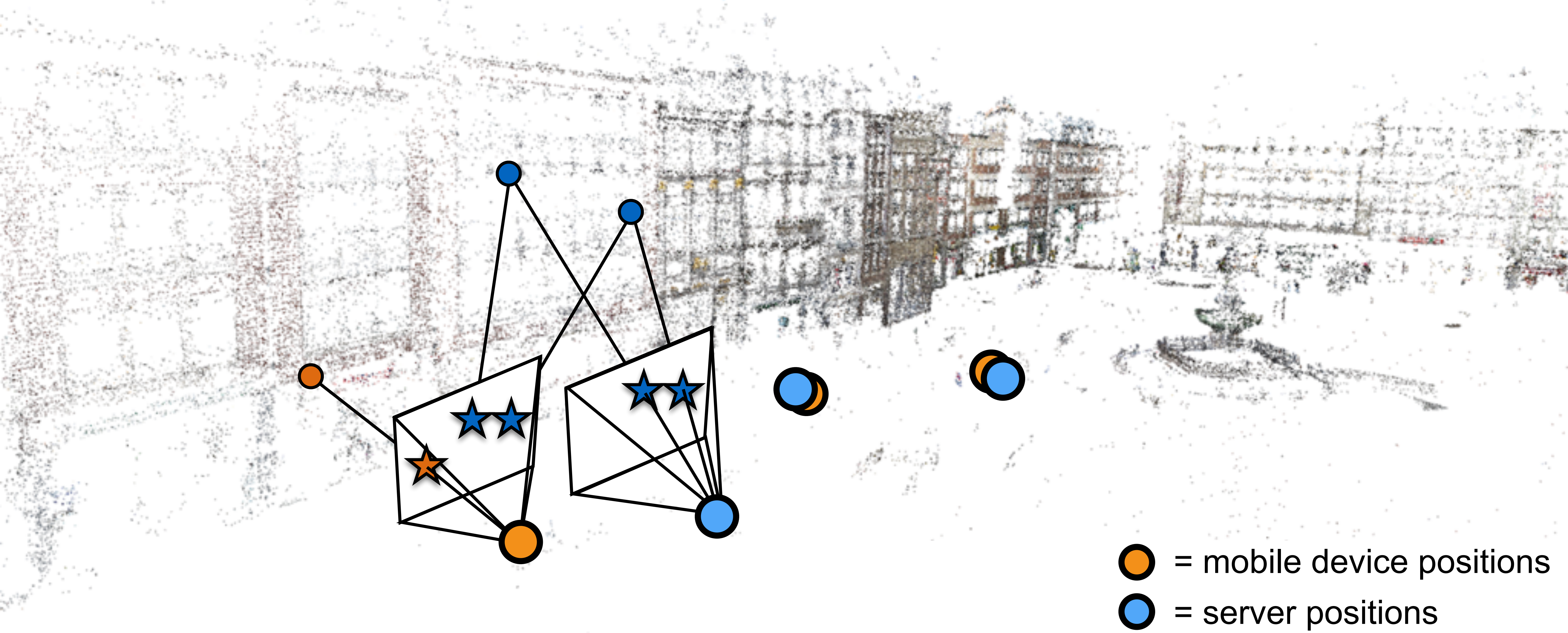
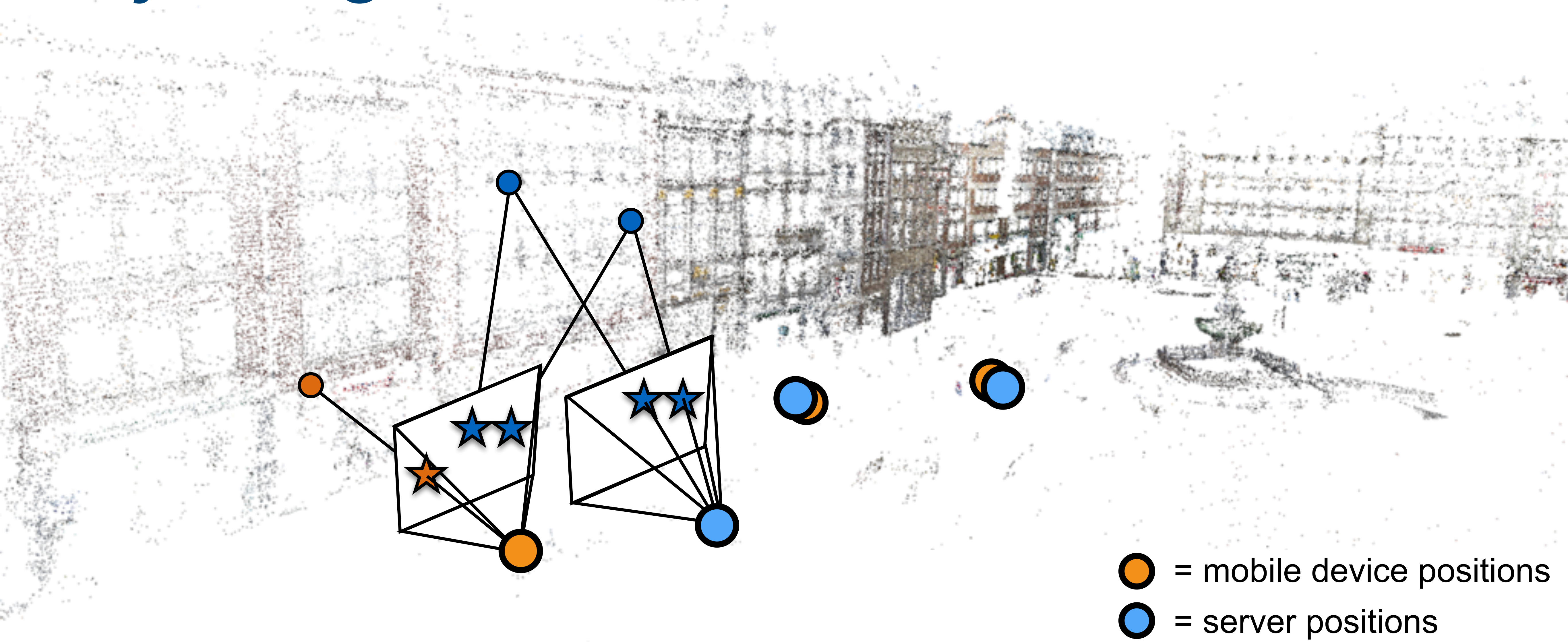


- Use 2D-3D matches from server as control points
  - Anchor local model, prevent drift

Adjusting the Model



- Use 2D-3D matches from server as control points
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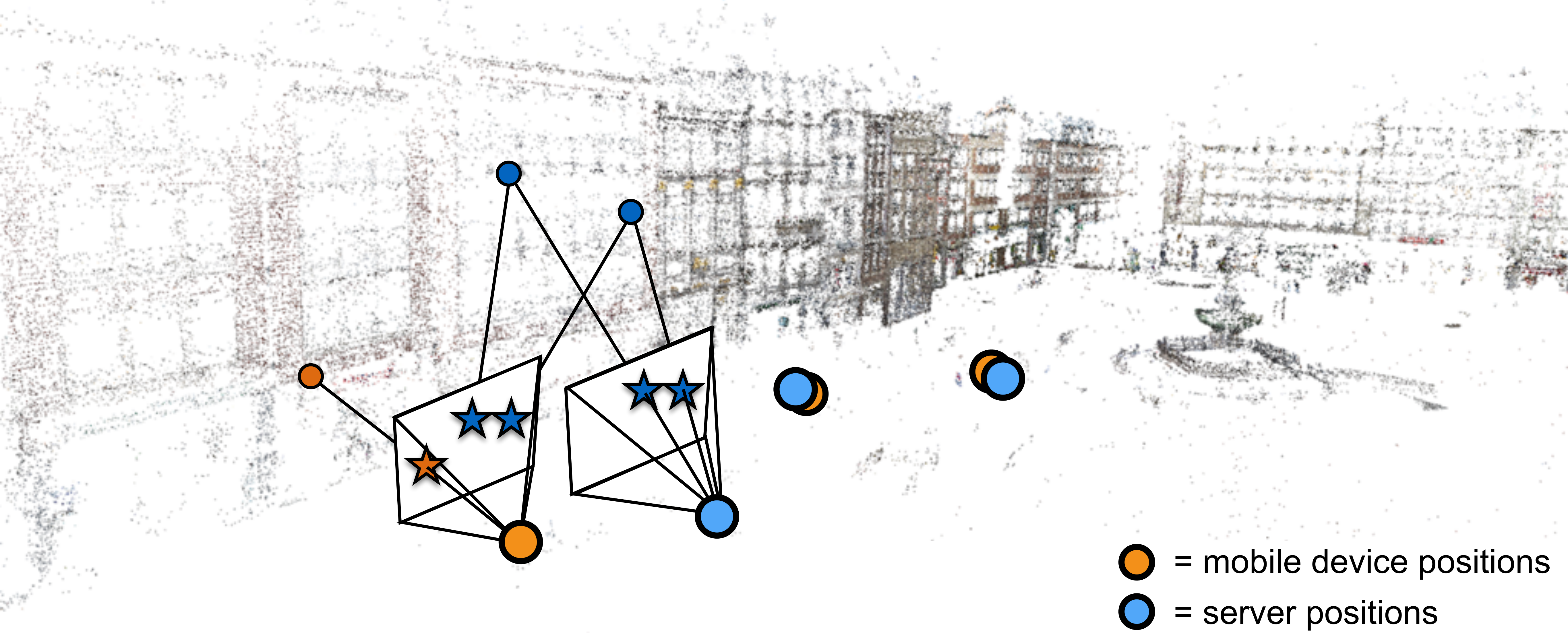
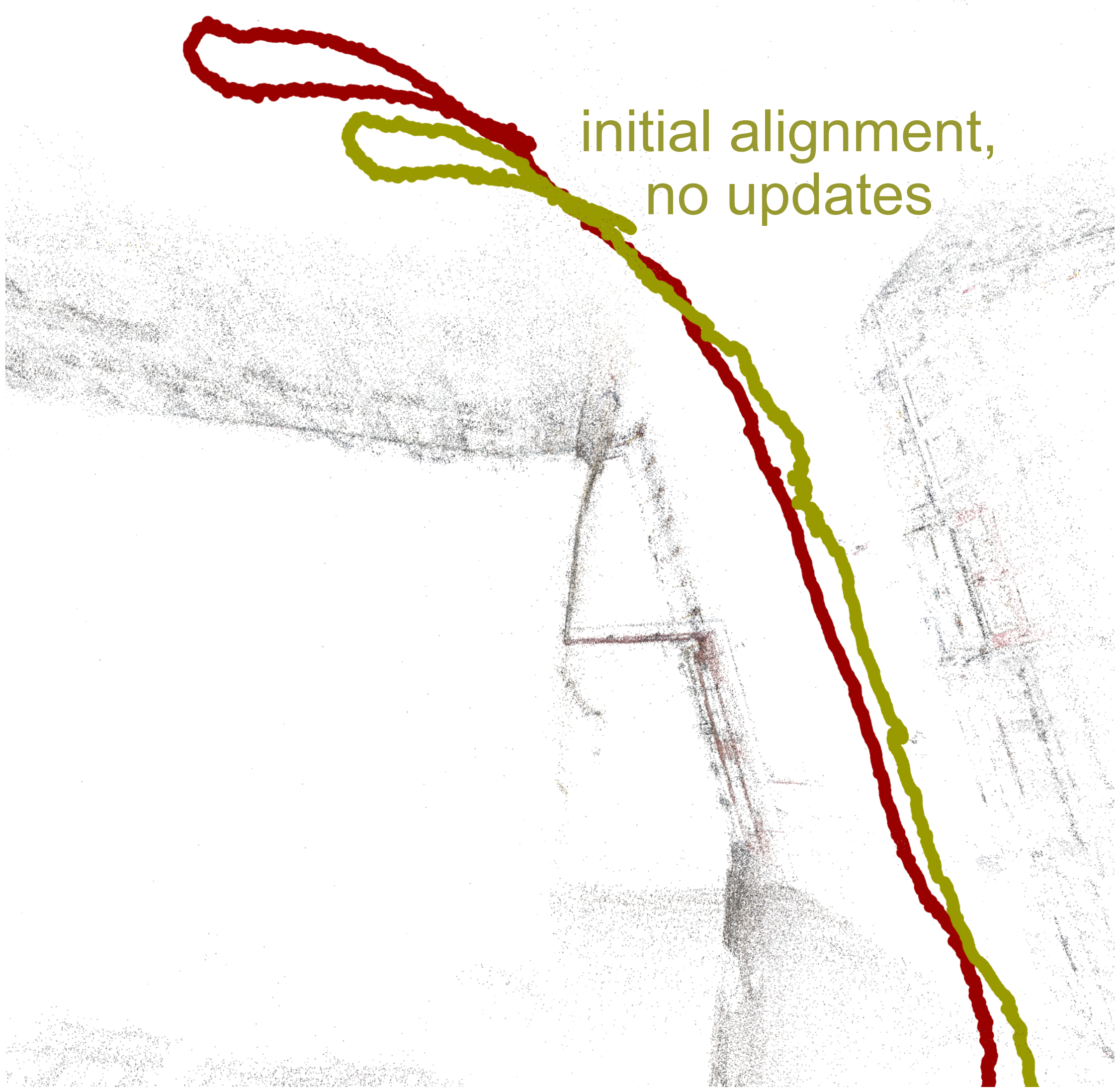


- Use 2D-3D matches from server as control points
  - Anchor local model, prevent drift
  - Little additional costs during Bundle Adjustment
- Still need weighting since fewer matches from server

Results



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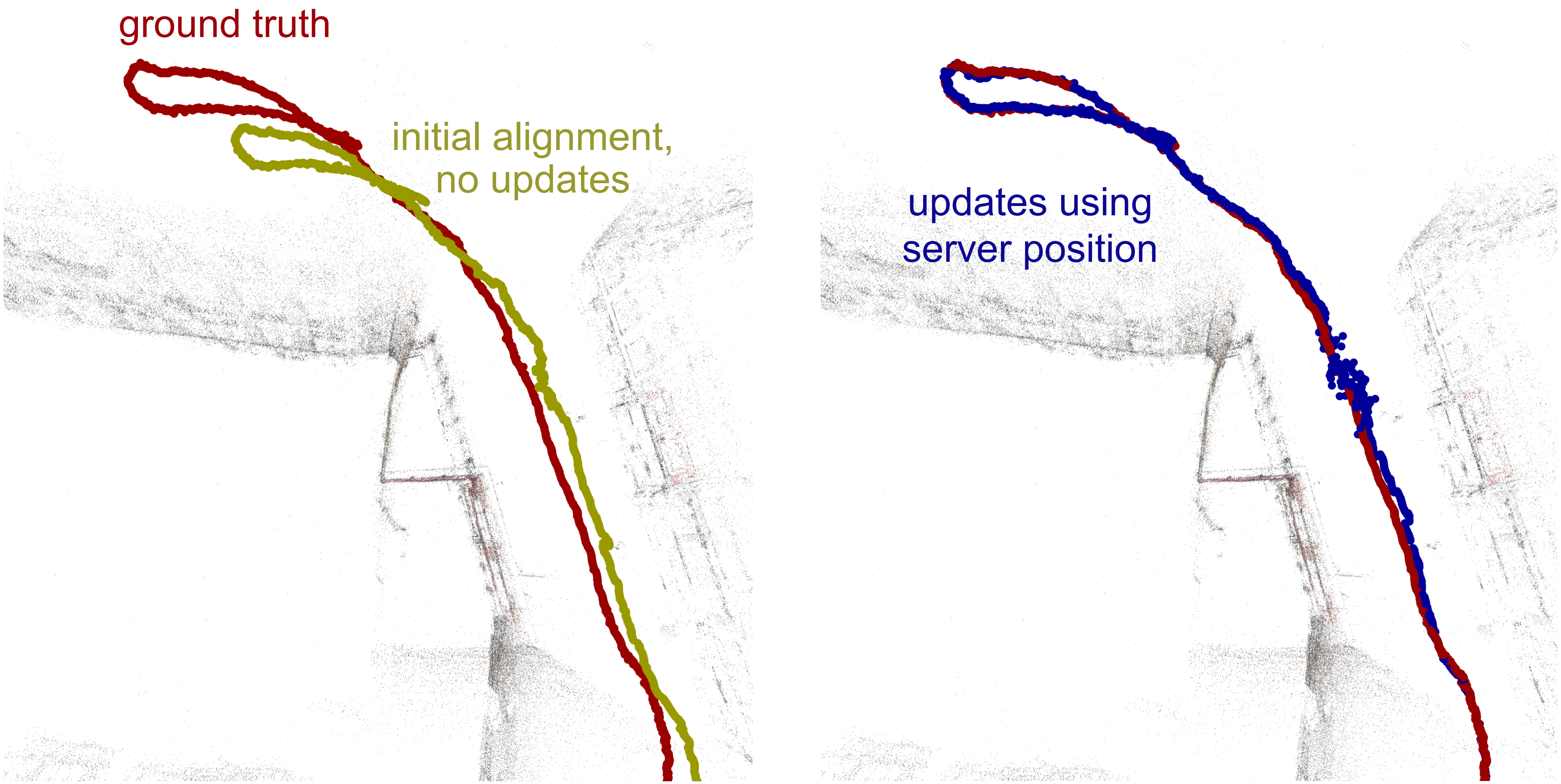
ground truth
initial alignment,
no updates
updates using
server position

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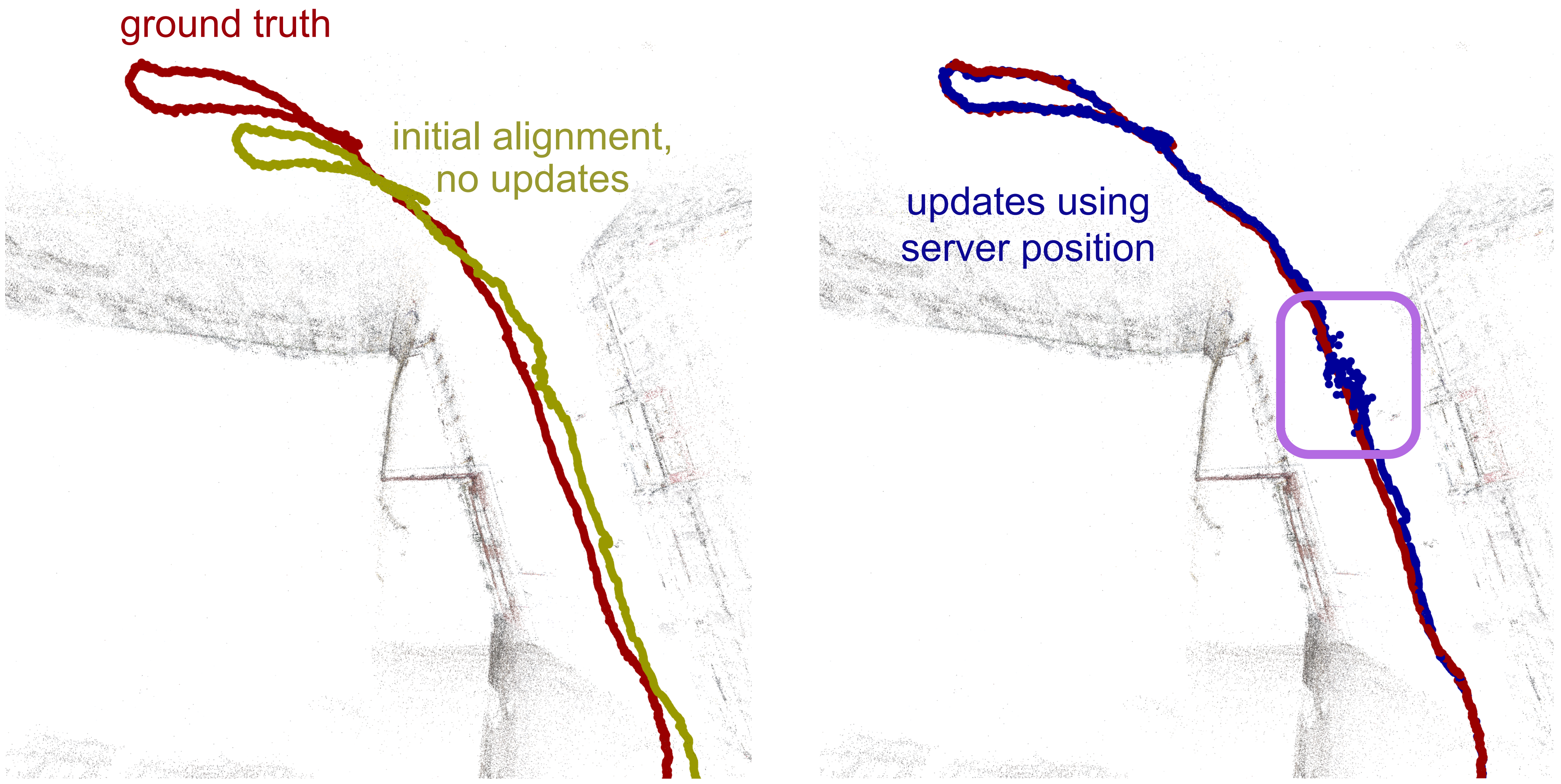

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and Geometry Group
ETH zürich

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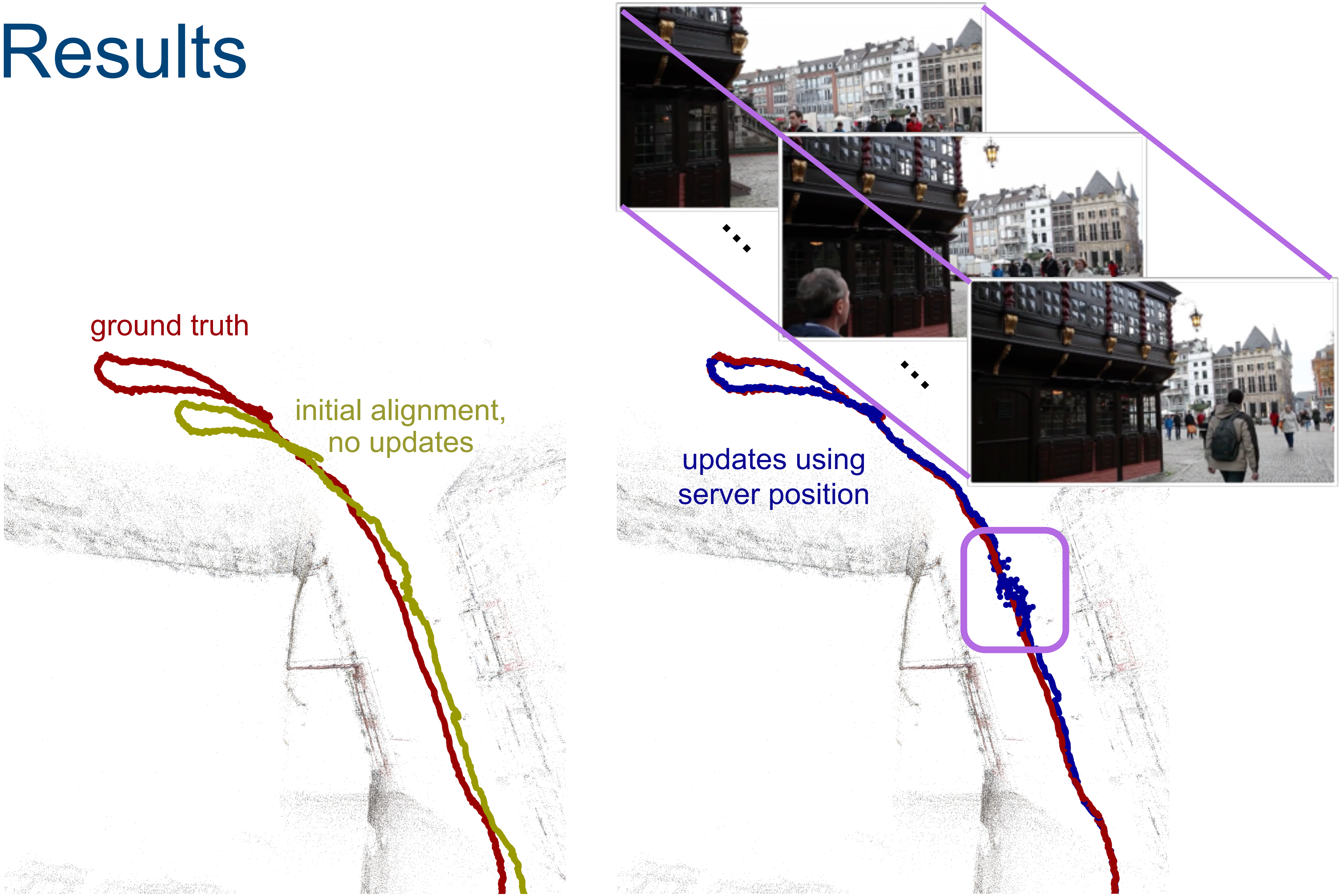

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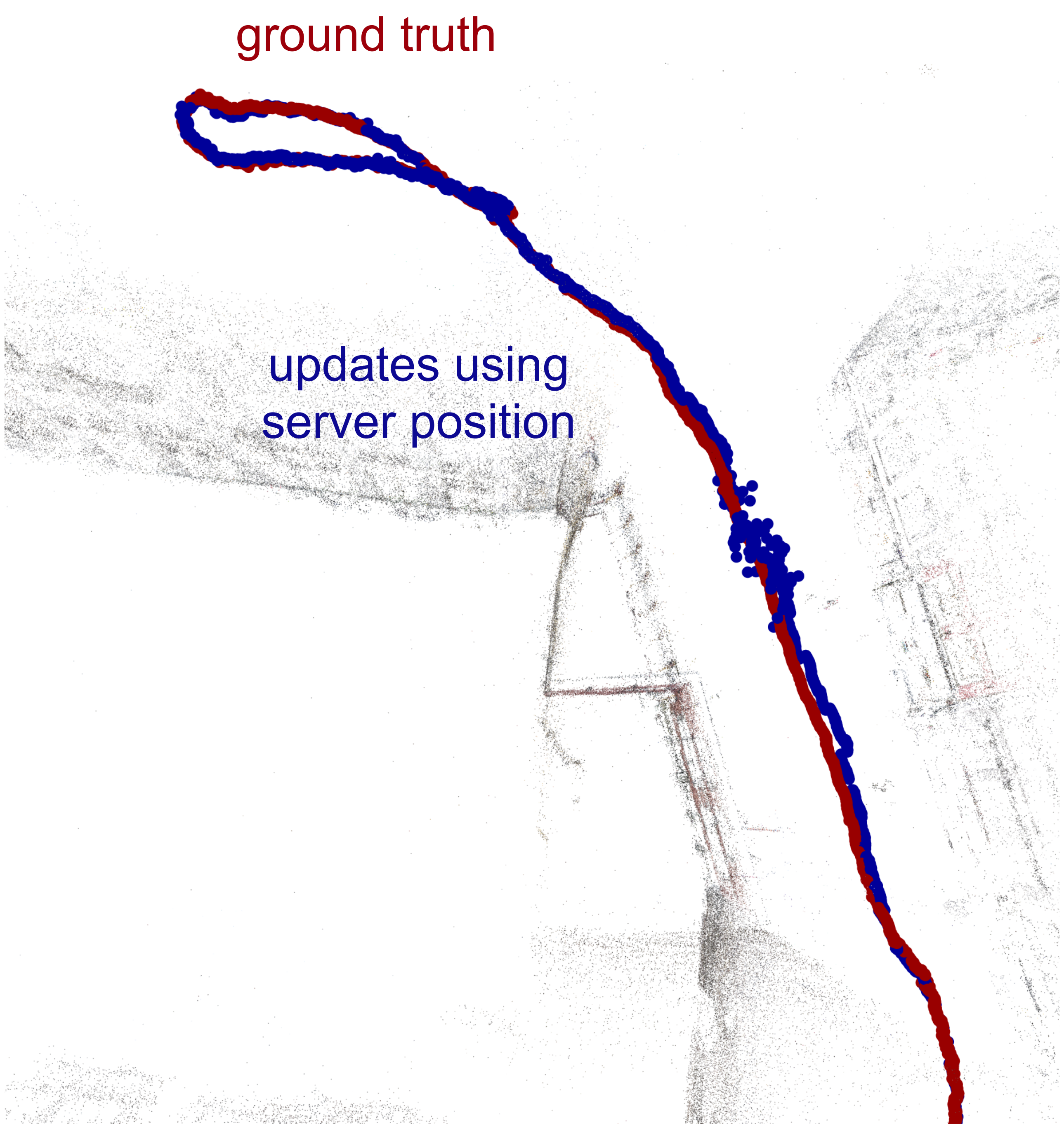
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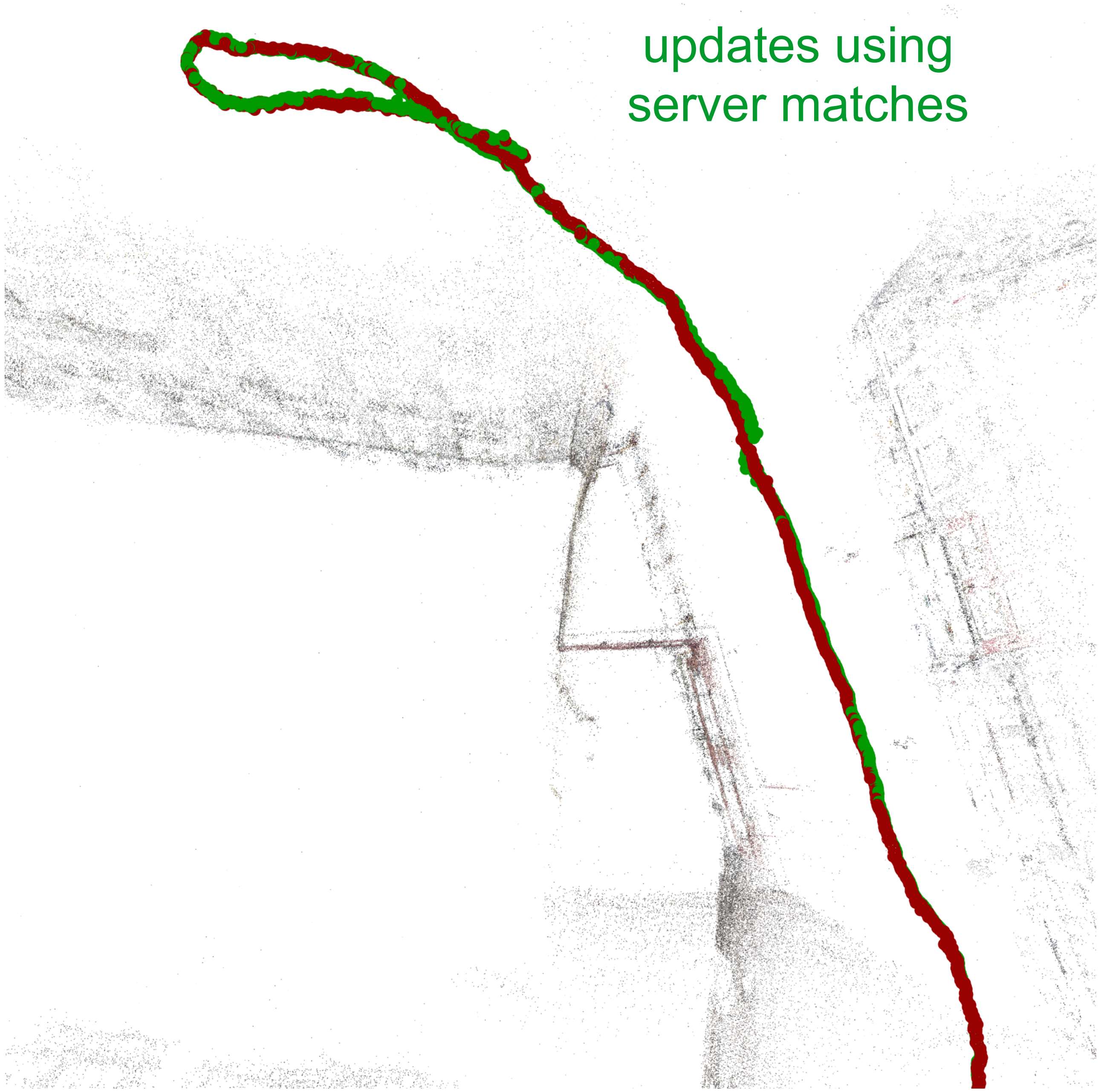
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Summary

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Overview

- Efficient & Effective Large-Scale Localization
- Real-Time Mobile Localization
- Open Challenges

The Ratio Test Problem

© Google

The Ratio Test Problem

© Google

- Larger models contain more locally similar structures

The Ratio Test Problem

© Google

- Larger models contain more locally similar structures

  ➡Ratio test for 2D-to-3D search rejects more and more matches

The Ratio Test Problem

© Google

- Larger models contain more locally similar structures
  - ➡Ratio test for 2D-to-3D search rejects more and more matches
- Happens already for Landmarks 1k dataset

The Ratio Test Problem

- Two possible solutions:

The Ratio Test Problem

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    - Promising results: [Li et al., ECCV'12] [Svärm et al., CVPR'14]

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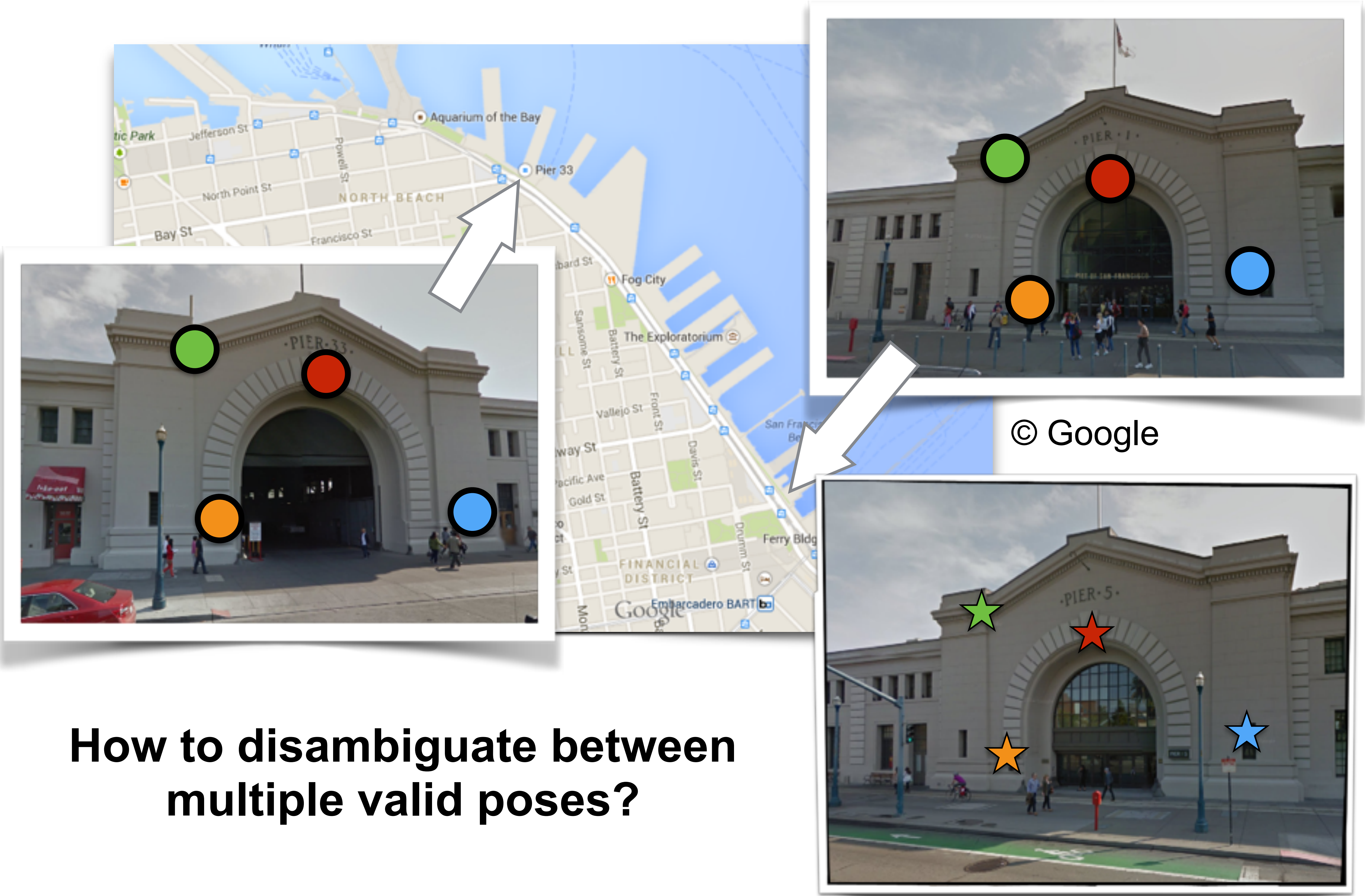
    - Promising results: [Li et al., ECCV'12] [Svärm et al., CVPR'14]
    - … pose estimation times grow too fast

(Quasi-)Identical Structures



How to disambiguate between multiple valid poses?

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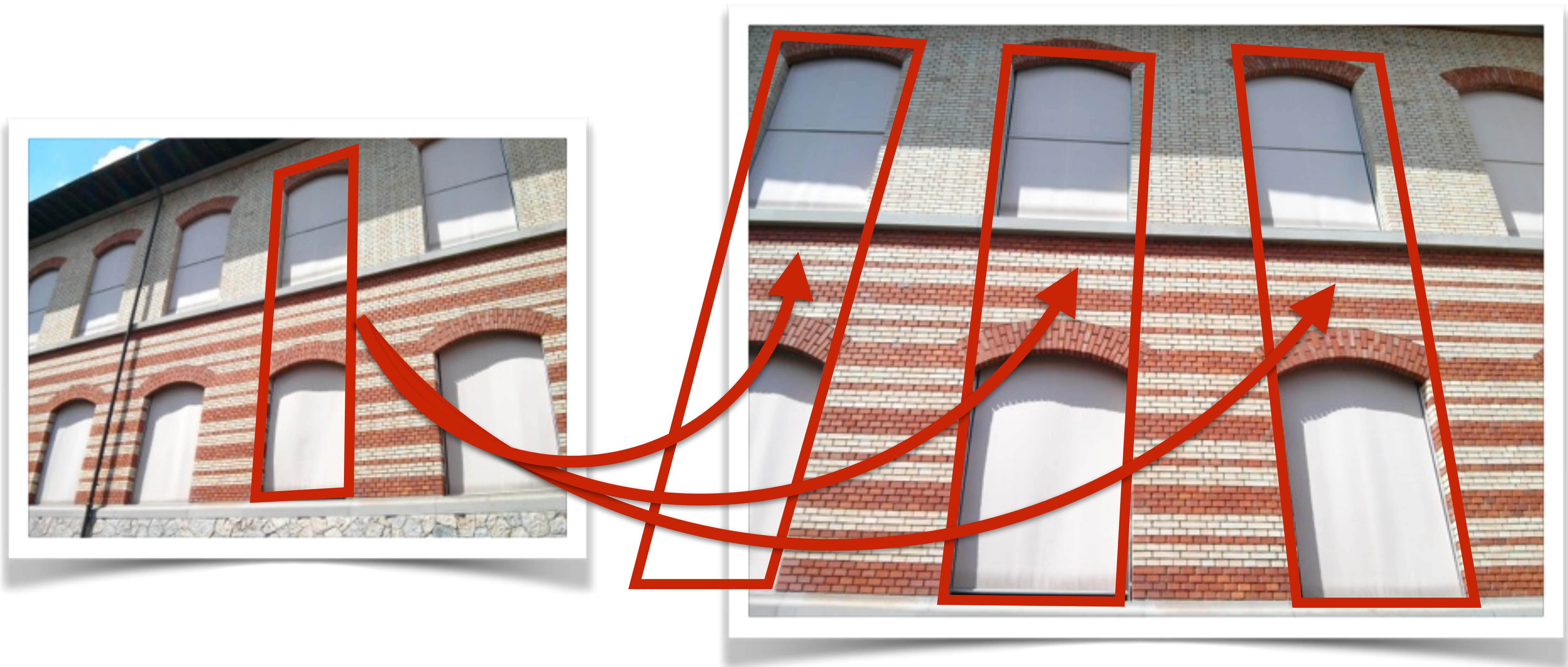
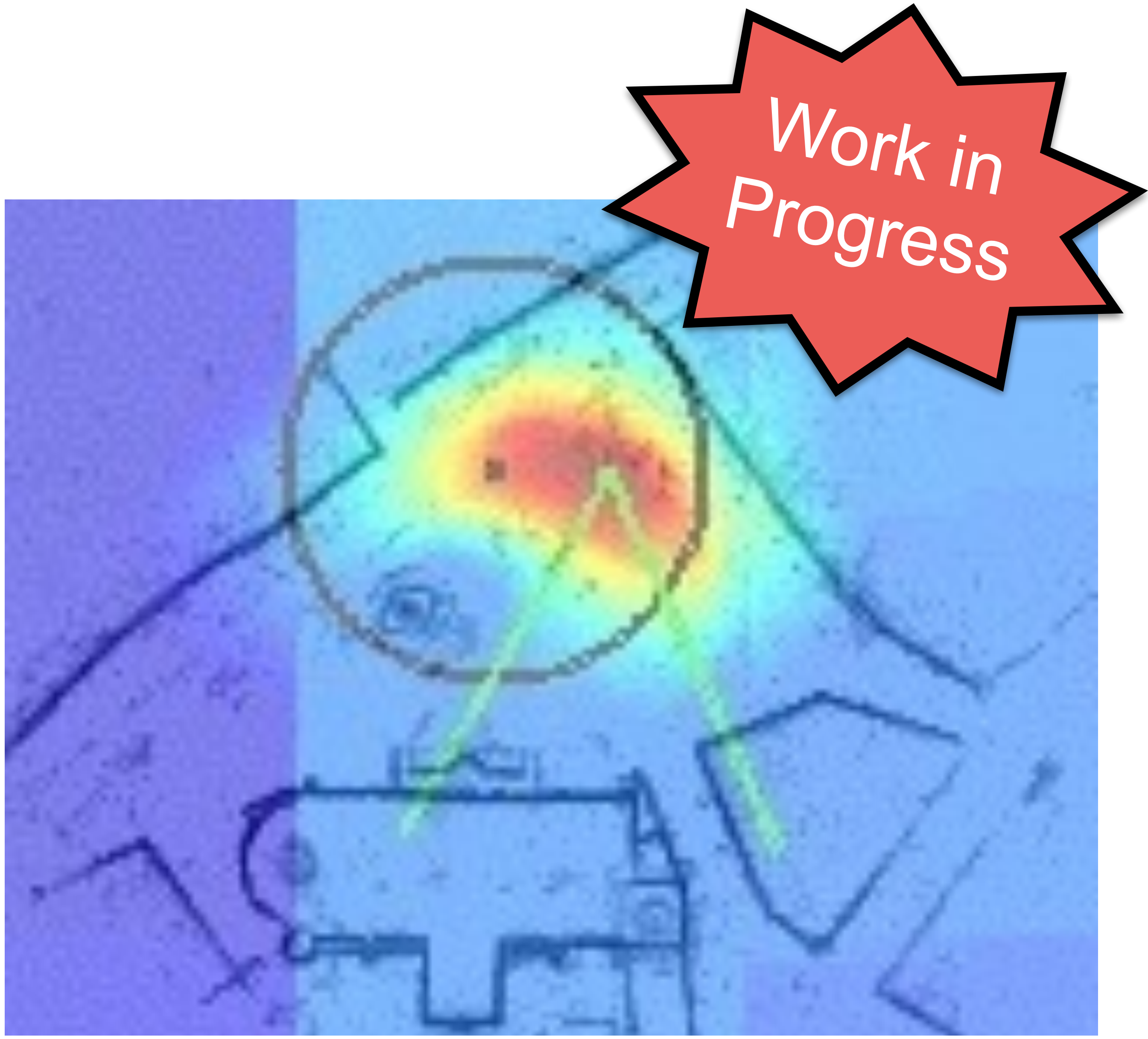
(Quasi-)Identical Structures



- What to do if we can't disambiguate?
- Can we get at least all plausible poses?

Camera Pose Voting



[Aachen dataset]

- Assume known gravity direction, ground plane
- Iterate over camera height, orientation, vote for position
- Linear in number of matches

Illumination Changes

© Google

- Feature detector fires at completely different positions
- Can we learn co-occurrence between day and night features?

General Changes

General Changes

- Can we learn co-occurrence / changes over time?

General Changes

- Can we learn co-occurrence / changes over time?
- What can we use to distinguish between places?

What Have We Solved?

Easy

Hard

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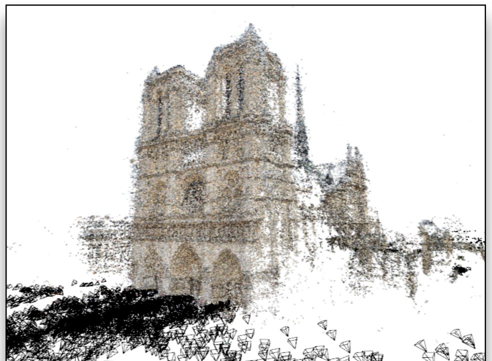
- Database & query images from same source, e.g., Flickr
- 97% - 100% localization rates
- *Challenges*: Run-time & memory consumption for large scale

Hard

What Have We Solved?

Easy



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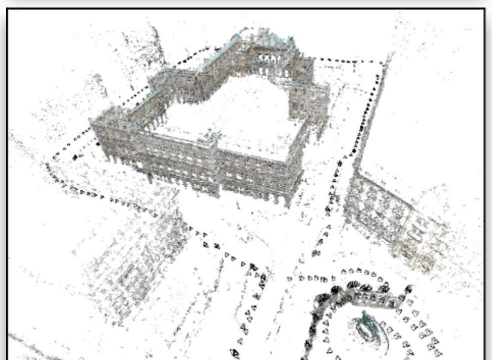

- Database & query images from different spatial distributions
- 70% - 90% localization rates
- *Challenges*: Deal with larger variety in viewpoints

Hard

What Have We Solved?

Easy

- Database & query images from same source, e.g., Flickr
- 97% - 100% localization rates
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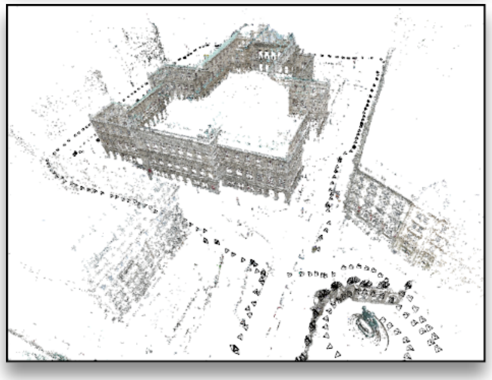

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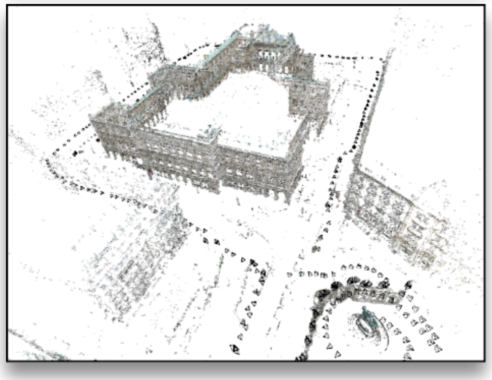

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Hard

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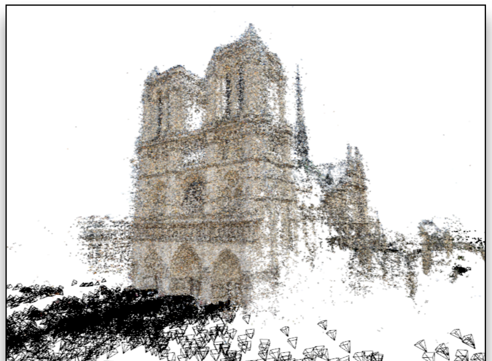

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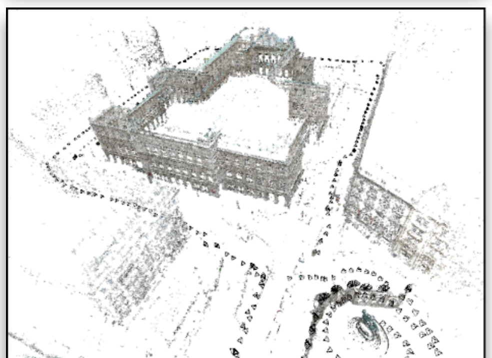

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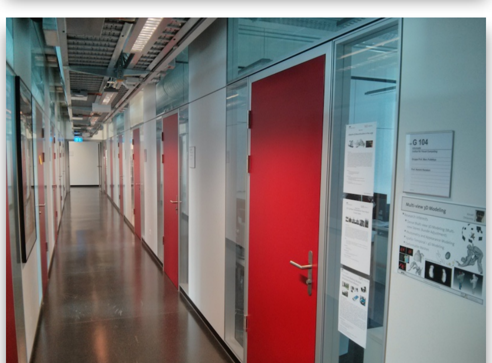

- Indoor scenarios
- *Challenges*: Identical structures, small distance to scene

Hard

Has the (Large-Scale) Image-based Localization Problem been solved?