NEURAL INFORMATION PROCESSING SYSTEMS

KAIST

Hypergraph Propagation and *Community Selection* for *Objects Retrieval*

Guoyuan An, Yuchi Huo, Sung-Eui Yoon

Challenging in revisited Oxford & Paris

Current achievement

Query

Top 20 items of the initial search result; mAP 0.077 (M) and 0.062 (H)

Top 20 items of the result after CS and HD; total 43 SPs; mAP 0.988 (M) and 0.987 (H)

SOTA and the opportunities

- We have the current SOTA result.

Table 1: Results (% mAP) on the ROxf/RPar datasets and their large-scale versions ROxf+1M/RPar+1M, with both Medium and Hard evaluation protocols.

	ROxf		ROxf+R1M		RPar		RPar+R1M	
Method	M	H	M	H	M	H	M	H
DELG (Global) [5]	76.3	55.6	63.7	37.5	86.6	72.4	70.6	46.9
DELG (Global + Local) [5]	81.2	64.0	69.1	47.5	87.2	72.8	71.5	48.7
Average QE [9]	77.2	57.1	68.5	43.0	87.6	74.3	75.4	54.8
Average QE with decay [13]	78.4	58.0	70.4	44.7	88.2	75.3	76.2	56.0
α QE [27]	65.2	43.2	57.0	30.2	91.0	81.2	81.0	64.1
Diffusion [16]	81.0	59.3	71.5	46.8	91.4	82.7	79.2	64.7
Hypergrah Propagation (Ours)	**85.7**	**70.3**	**78.0**	**60.0**	**92.6**	**83.3**	**86.6**	**72.7**

- There are still a lot challenges / opportunities.
- Check our result to find more opportunities:

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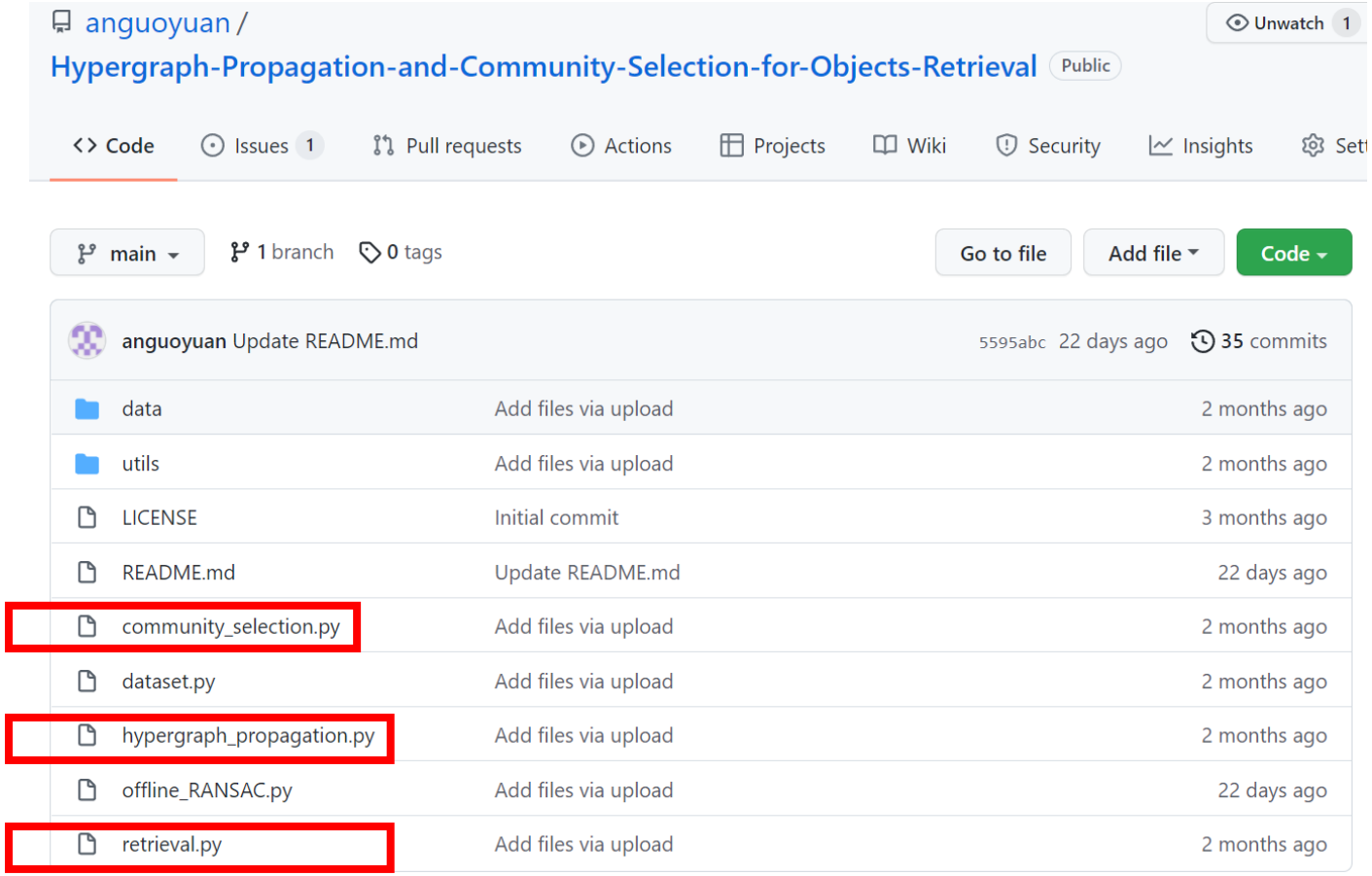
Tips for reading the code

Algorithm 2

Algorithm 1

run



Content

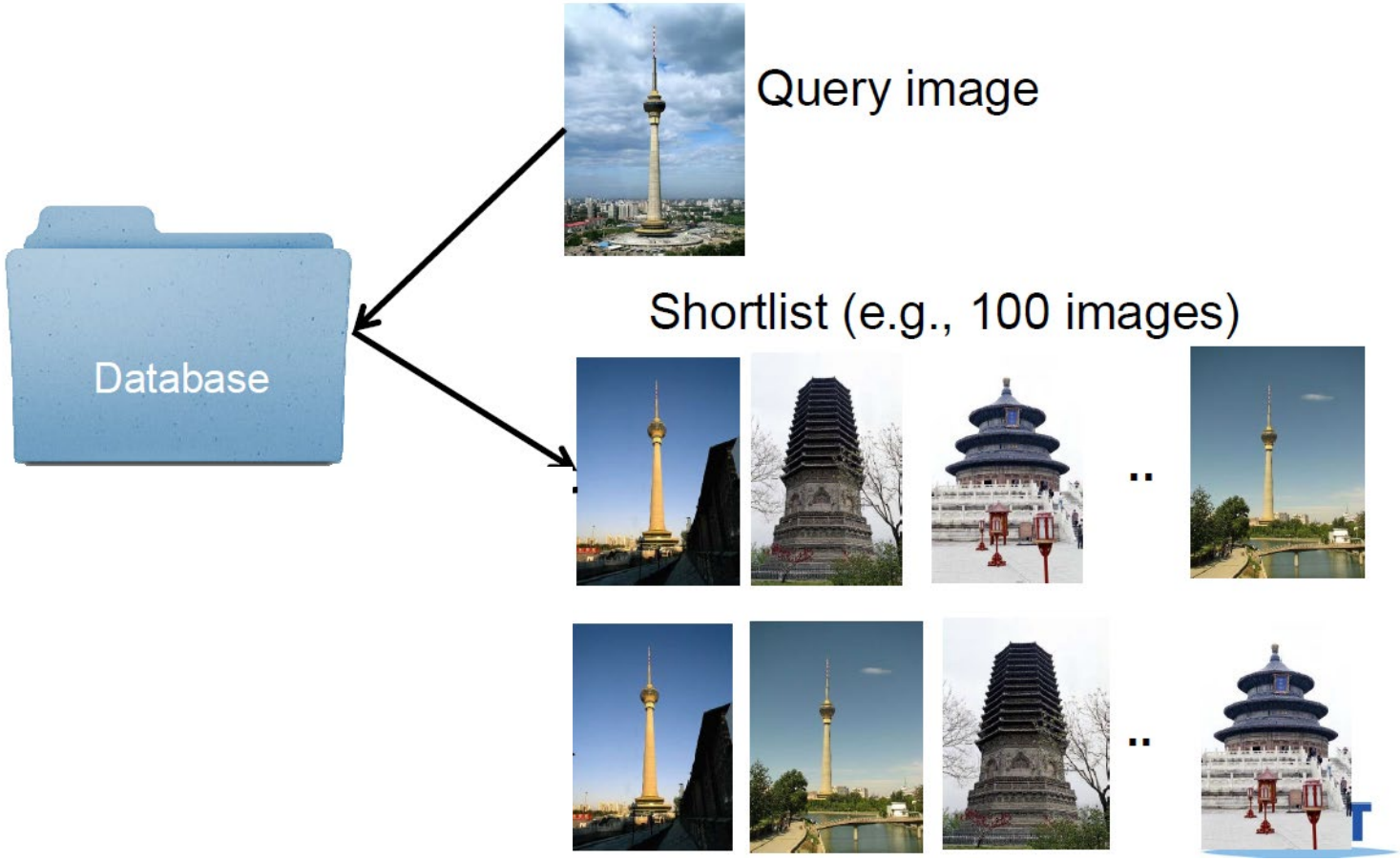
- Review: pipeline of image retrieval

- Problem of diffusion
- Solution: hypergraph propagation

- Problem of spatial verification
- Solution: community selection

Review: pipeline of image search

Pipeline of image retrieval

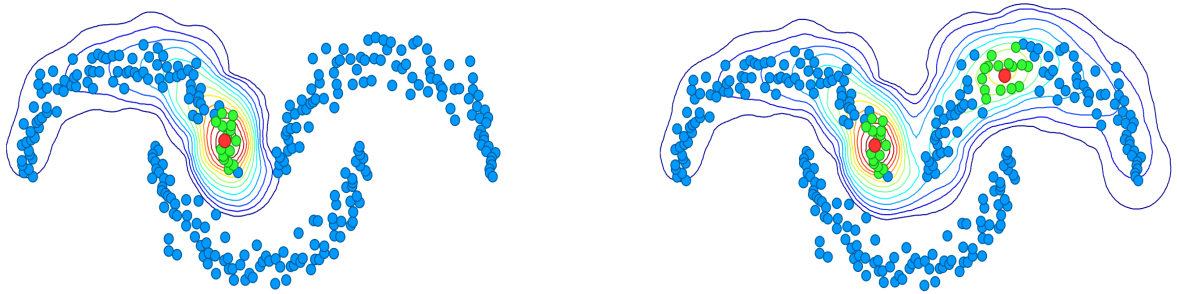


Re-ranking:
1. Diffusion & query expansion
2. Spatial verification

Problem of diffusion

Problem

- Diffusion captures the image manifold in the feature space.
- It is a popular and powerful technique to improve the quality of image retrieval.



Iscen, … Efficient Diffusion on Region Manifolds: Recovering Small Objects with Compact CNN Representations, CVPR 2017

- However, some works observed that diffusion degrade the retrieval performance of the hard cases.

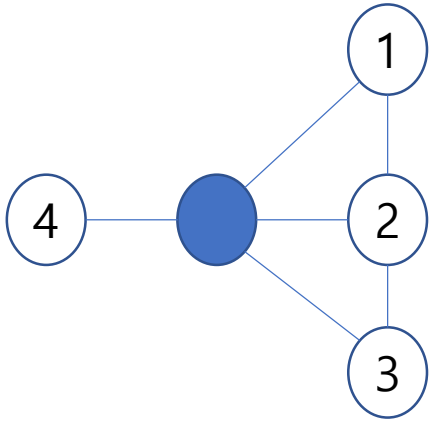
Radenovic, … Efficient Diffusion on Region Manifolds: Recovering Small Objects with Compact CNN Representations, CVPR 2018

How does diffusion work?

- Manifold: even though the images of the sequence contain the same object, the descriptors may be completely unrelated after a certain point.
- Diffusion performs similarity propagation to improve the performance.

How does diffusion work?

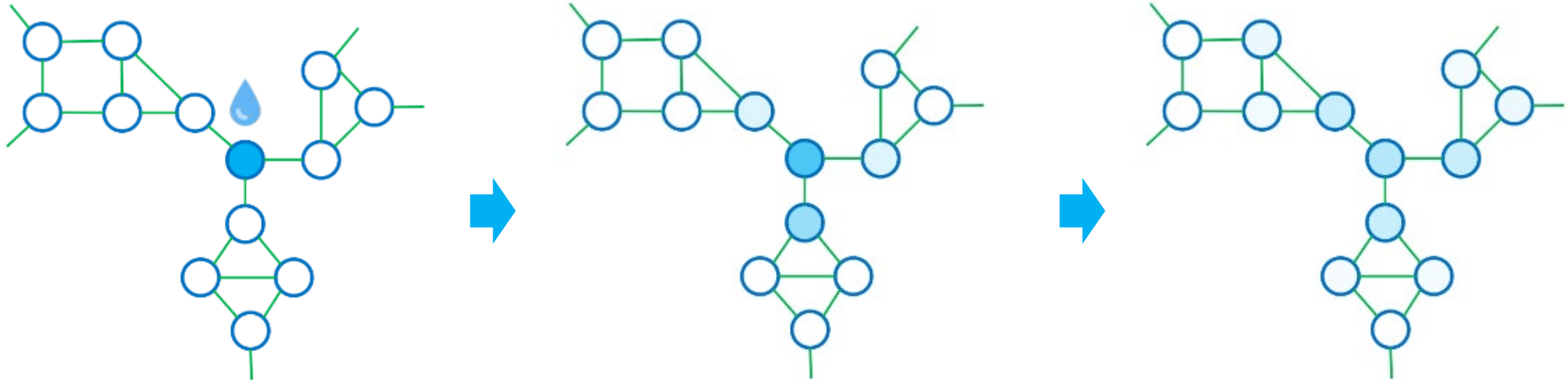
- Think about a droplet of ink into the water.
- Node 4 will get larger score than 1,2,3.
- Same theory with Markov Chain, PageRank,…



How does diffusion work?

- Diffusion uses the structure information to rank the database images.

- Random walk

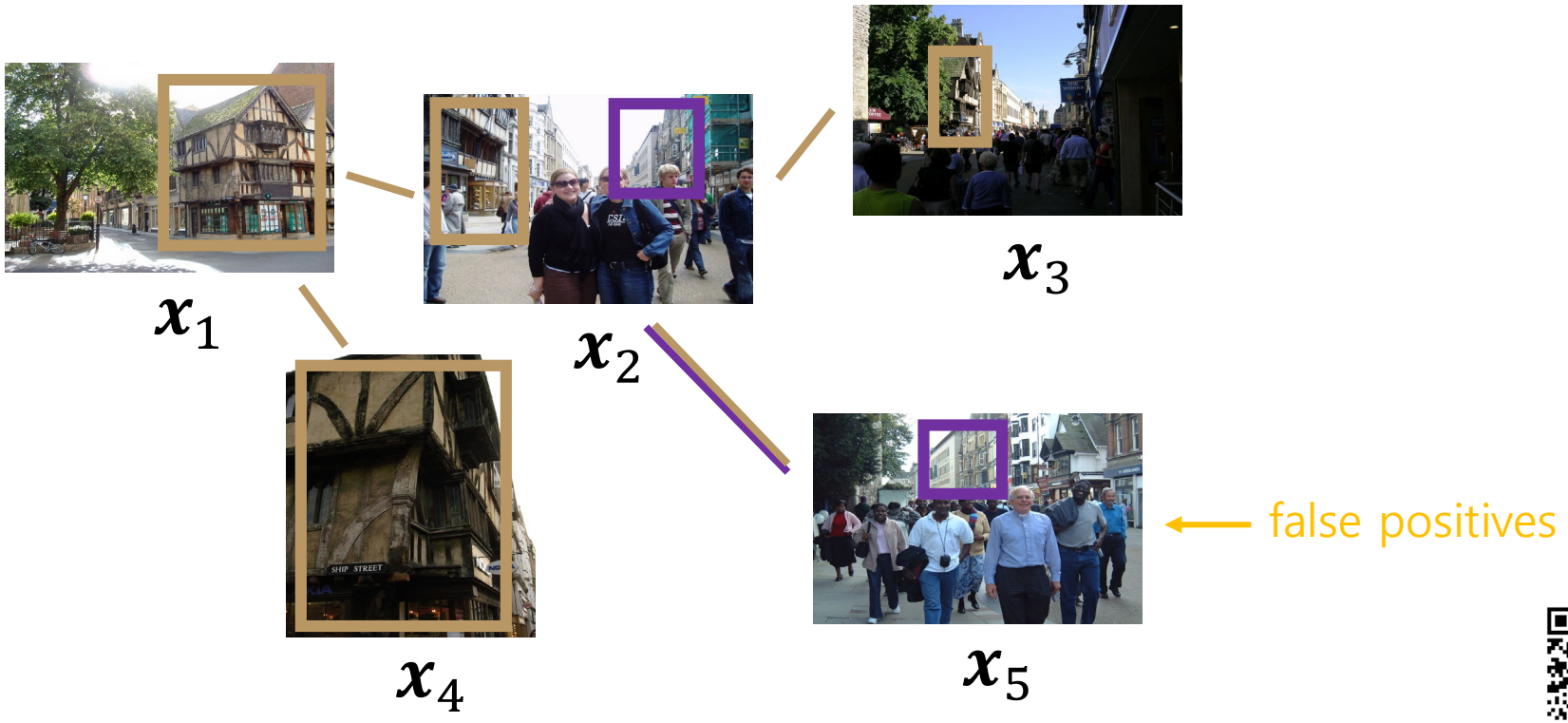


Node: image

Edge: transition probabilities

Where does diffusion fail?

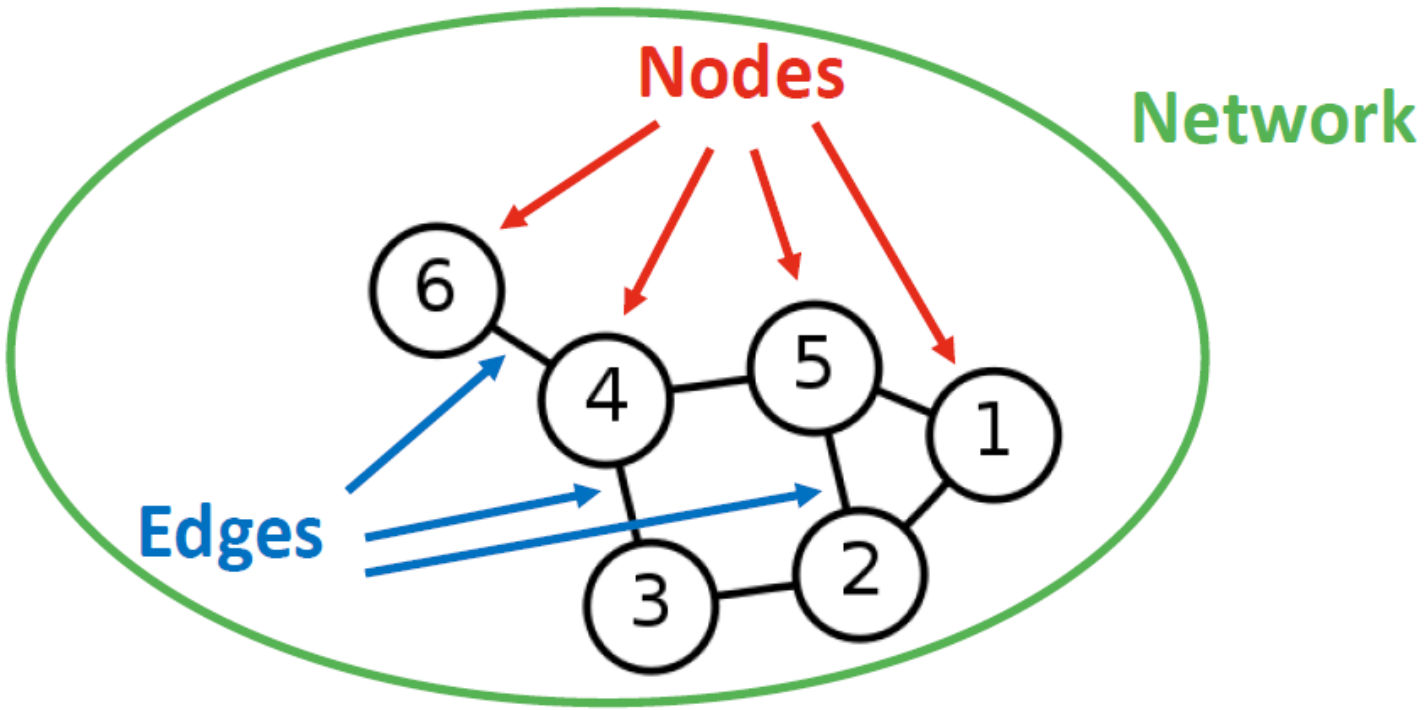
- However, if the dataset is difficult, some images in a manifold may not contain a same object.
- Thus, diffusion inevitably includes false positives.



Solution: hypergraph propagation

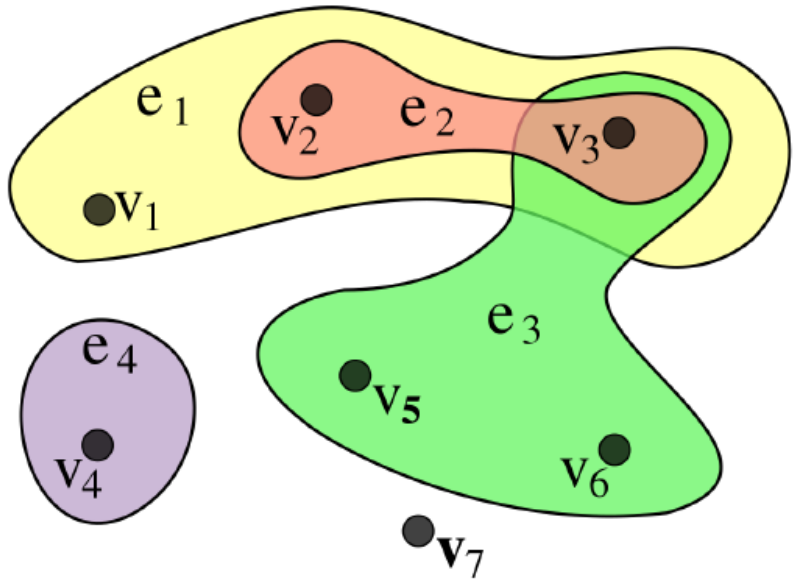
Networks (Graphs)

- A **network** (or a **graph**) G consists of
  - V: set of **nodes (or vertices)**
  - E: set of **edges (or links)**
    - Each edge is associated with a pair of nodes



Hypergraphs

- A **hypergraph** (or a **hypernetwork**) G consists of
  - V: set of **nodes (or vertices)**
  - H: set of **hyperedges**
    - Each hyperedge is associated with a non-empty subset of nodes
    - Each hyperedge can contain an **arbitrary** number of nodes

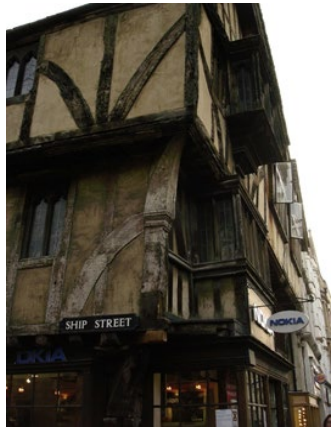


Solution: hypergraph

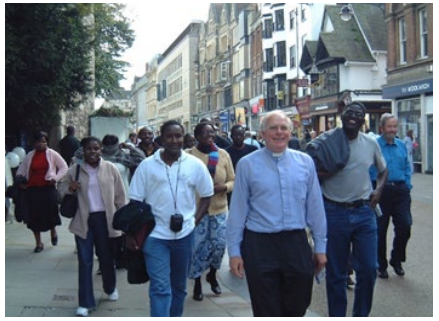
x_1

x_2

x_3

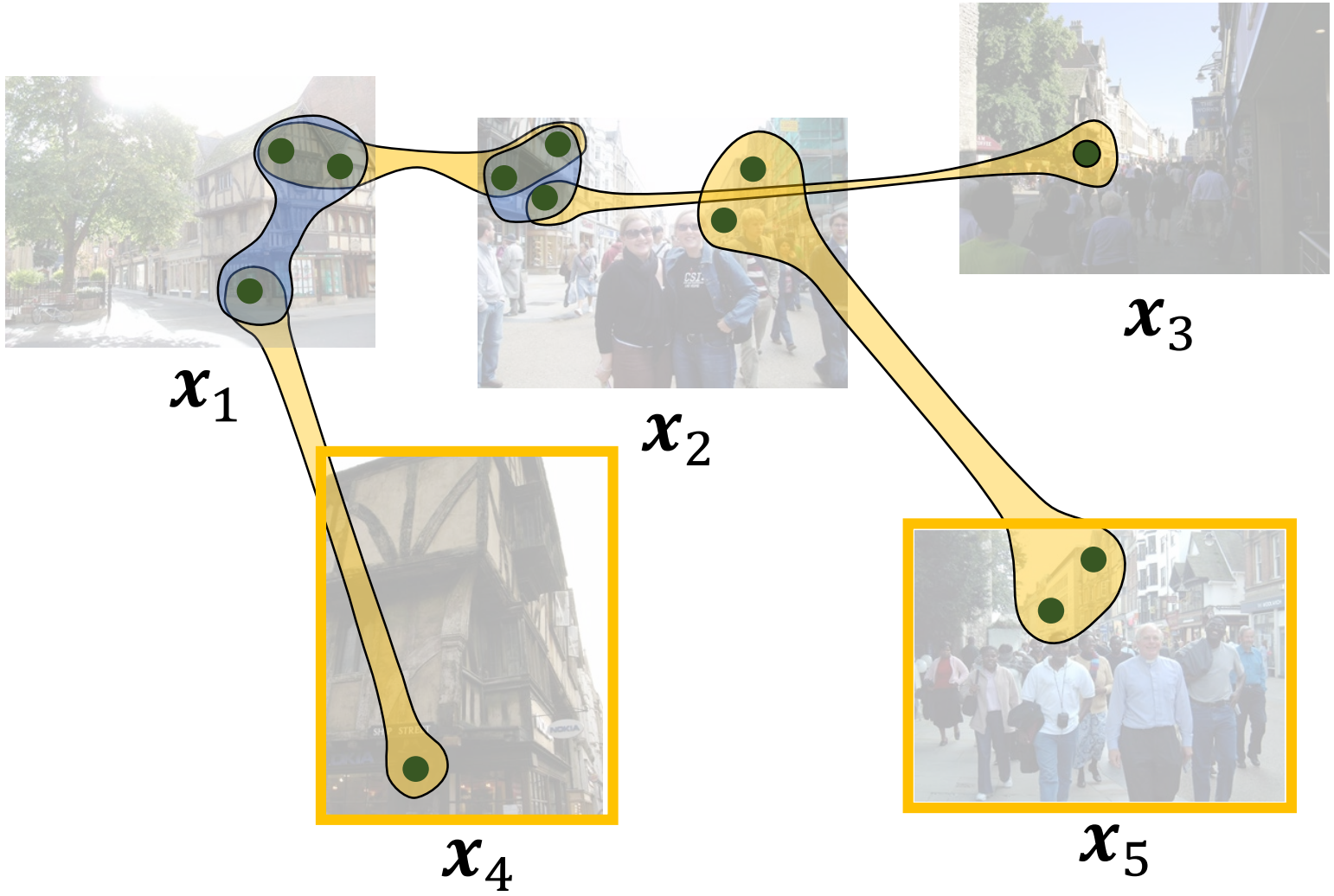


x_4



x_5

Solution: hypergraph



Quantitative result

- Accuracy: significant performance improvement

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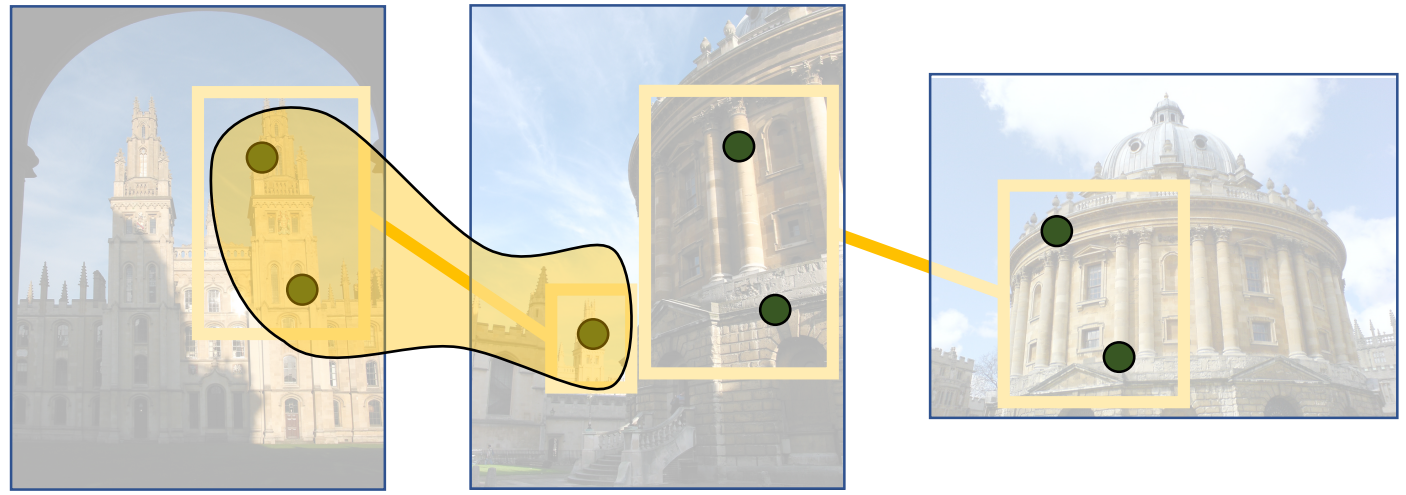
- Memory: no much extra storage required; smaller than the global feature

global feature	local features' matching information	local features
8192 B	2678 B	1040000 B

- Speed: significant performance improvement

initial search	hypergraph propagation	uncertainty calculation	spatial verification
0.62 s	1.07 s	0.0003 s	41.12 s

Qualitative result



Problem of spatial verification

Estimate the accuracy of initial search

- Estimating the accuracy of initial search is important for
  - Reranking with diffusion
  - Search engine improvement
  - User experience.
- Traditional way is doing the geometric verification for the top 100 searched images.

Query

(b) Breakdown of average time per query.

very slow

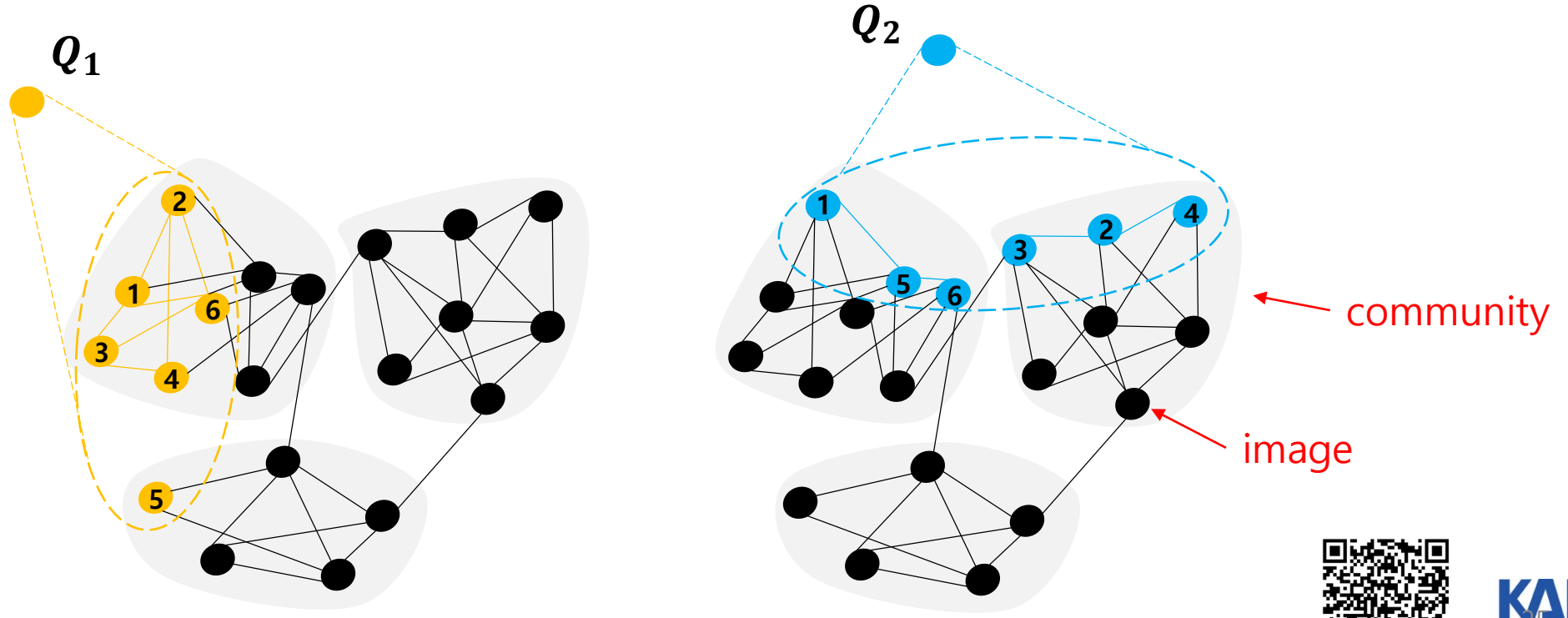
initial search	hypergraph propagation	uncertainty calculation	spatial verification
0.62 s	1.07 s	0.0003 s	41.12 s

geometric verification

Solution: community selection

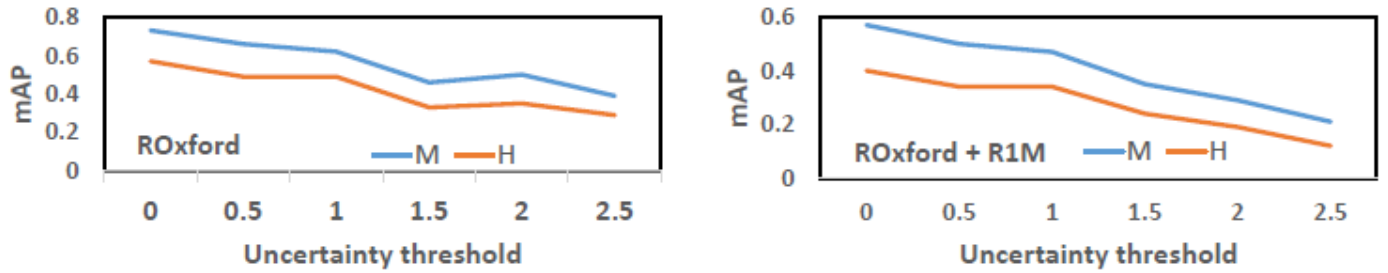
Graph approach: community selection

- We observe that the images containing a same object usually belong to a same community.
- By checking whether the searched images are in the same community, we can evaluate the quality of the initial search without query time spatial verification.



Quantitative result

- The uncertainty index predicts the quality of initial search without spatial verification or any user feedback.



- The speed of calculating the uncertainty index is very fast.

(b) Breakdown of average time per query.

initial search	hypergraph propagation	uncertainty calculation	spatial verification
0.62 s	1.07 s	0.0003 s	41.12 s

Thank you

Detail and code: https://sgvr.kaist.ac.kr/~guoyuan/hypergraph_propagation/