QUERY EXPANSION WITH DIFFUSION ON MUTUAL RANK GRAPHS

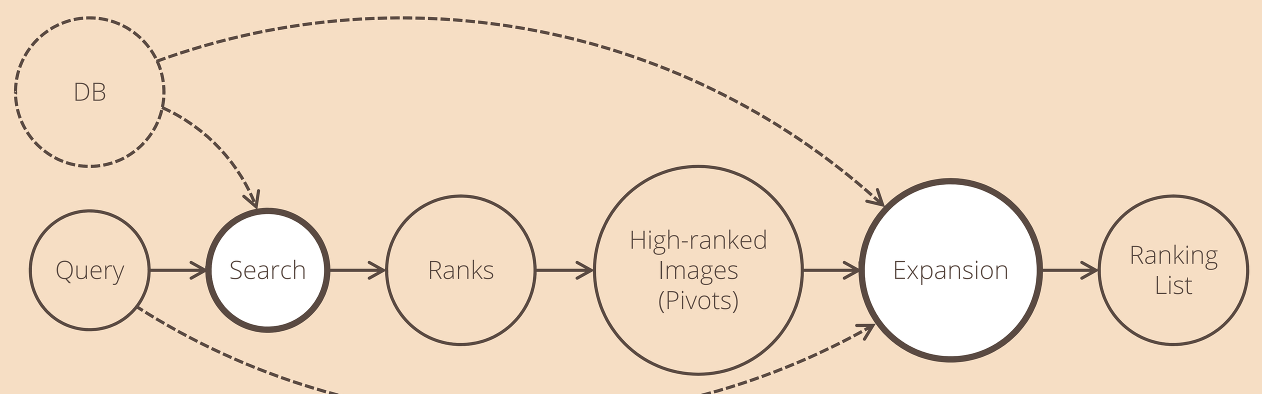
Xiaomeng Wu, Go Irie, Kaoru Hiramatsu, and Kunio Kashino

NTT Communication Science Laboratories, NTT Corporation, Japan

INTRODUCTION

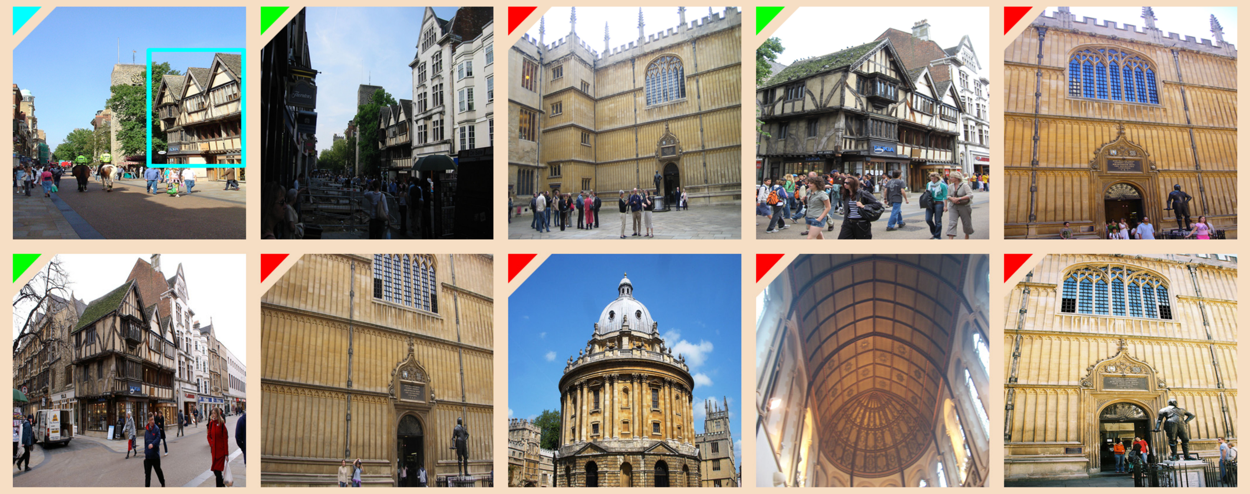
IMAGE RETRIEVAL WITH QUERY EXPANSION

- Assume that most high-ranked images, referred to as pivots, are true positives
- Reissue pivots as an expanded query to improve the coverage of visual aspects



DANGER OF QUERY DRIFT

False positives among pivots make the inference of the expanded query diverge from the object of interest



QUERY EXPANSION WITH FEATURE SELECTION

- Discard noisy image features from pivots by imposing similarity and frequency constraints [Tolias'14] or spatial consistency constraints (spatial verification) [Chum'07][Tolias'14][Shen'14][Wu'18]
- Limited to specific image representations

IMAGE RETRIEVAL WITH DIFFUSION [Kontschieder'09][Yang'09][Donoser'13][Iscen'17]

- Diffuse image similarities through an image graph defined on all database images
- Require large-scale matrix manipulations
- Suffer from the presence of false positives in the image graph
- Implicitly assume that images of different object classes are uniformly distributed in a descriptor space

CONTRIBUTIONS

INCORPORATION OF DIFFUSION INTO QUERY EXPANSION

- A more efficient solution for diffusion
- More robust as regards false positives in the image graph

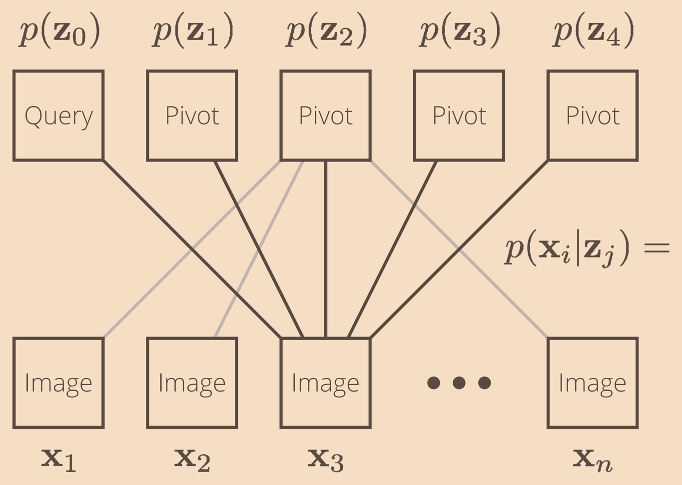
PROPOSAL OF MUTUAL RANK GRAPH

Account for varying local densities of different object classes in the descriptor space

QUERY EXPANSION WITH DIFFUSION

QUERY EXPANSION AS MARGINALIZATION

The probability of a database image being relevant to the query is estimated by marginalizing over the distribution of pivots

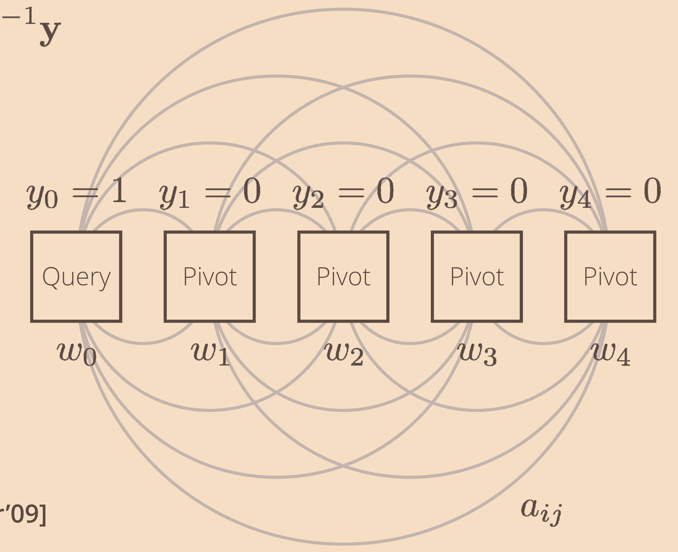


$$p(\mathbf{x}_i|\mathbf{z}_j) = \frac{s(\mathbf{x}_i, \mathbf{z}_j)}{\sum_{i'=1}^{n} s(\mathbf{x}_{i'}, \mathbf{z}_j)}$$

$$p(\mathbf{x}_i) = \sum_{j=0}^{m} p(\mathbf{x}_i, \mathbf{z}_j) = \sum_{j=0}^{m} p(\mathbf{x}_i|\mathbf{z}_j)p(\mathbf{z}_j)$$

LEARNING PIVOT DISTRIBUTION WITH DIFFUSION [Zhou'03]

$$\mathbf{w}^\star = \arg\min_{\mathbf{w}} \left(\frac{1}{2} \sum_{i,j=0}^{m} a_{ij} \left(\frac{w_i}{d_i} - \frac{w_j}{d_j} \right)^2 + \mu \sum_{j=0}^{m} \frac{(w_j - y_j)^2}{d_j} \right)$$
$$= \beta(\mathbf{I} - \alpha \mathbf{A}\mathbf{D}^{-1})^{-1}\mathbf{y}$$



KNN GRAPH [Kontschieder'09]

MUTUAL RANK GRAPH

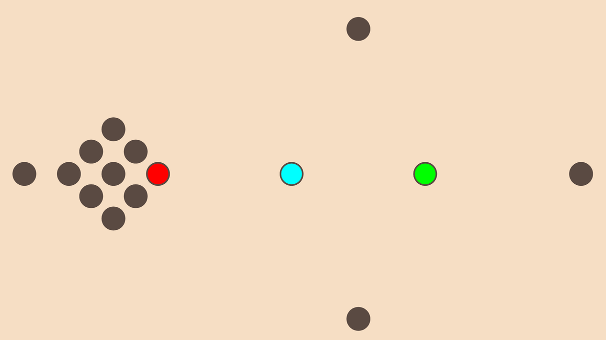
PREVIOUS AFFINITY DEFINITIONS

Assume that data of different classes are distributed according to the same scale

$$s(\mathbf{z}_i, \mathbf{z}_j) = \exp\left(\frac{-\|\mathbf{z}_i - \mathbf{z}_j\|_2^2}{\sigma^2} \right)$$

TOY EXAMPLE

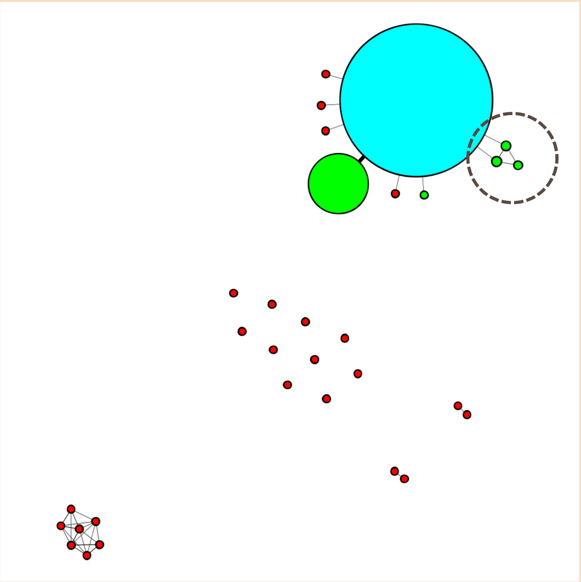
Previous studies treat the red and green points equally in terms of their affinities with the blue point



$$s(\mathbf{q}, \mathbf{z}_j) = s(\mathbf{q}, \mathbf{z}_i)$$

EXAMPLE OF AFFINITY GRAPH (ASMK*)

The pivots surrounded by the dashed circle were underrated after diffusion due to their small query similarities



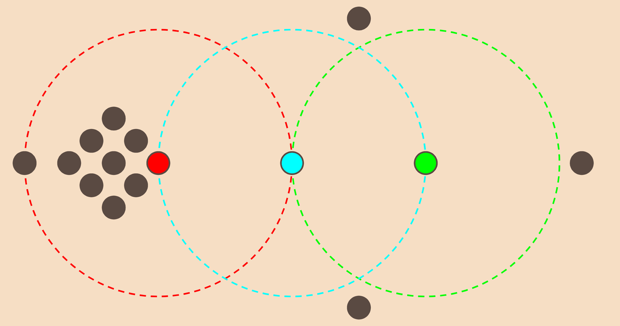
RECIPROCAL OF MUTUAL RANK

Give an advantage to the affinity of data with low densities in the descriptor space

$$s_b(\mathbf{z}_i, \mathbf{z}_j) = \left(\frac{[r(\mathbf{z}_j|\mathbf{z}_i)]^b + [r(\mathbf{z}_i|\mathbf{z}_j)]^b}{2} \right)^{-1/b}$$

TOY EXAMPLE

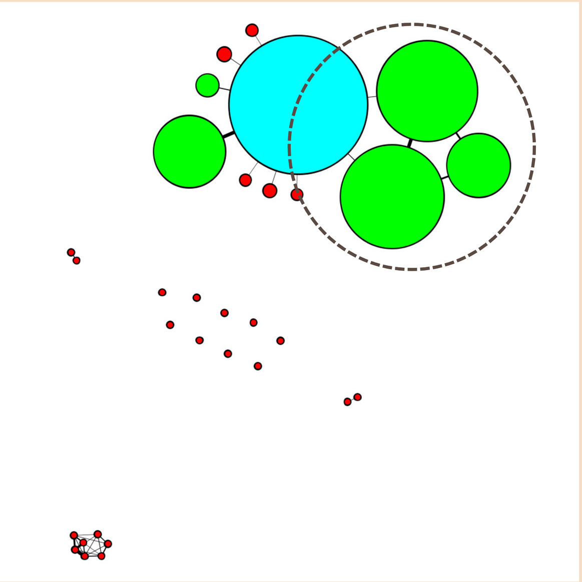
Our method emphasizes the green point more because it has a higher mutual rank with respect to the blue point



$$s_\infty(\mathbf{q}, \mathbf{z}_j) = \frac{1}{10} = 0.1 \text{ and } s_\infty(\mathbf{q}, \mathbf{z}_i) = 1$$

EXAMPLE OF MUTUAL RANK GRAPH

Our method took their low densities into account and greatly increased their learned probabilities



The query and the three pivots surrounded by the dashed circle in the graphs above.

EXPERIMENTS

PARAMETER INVESTIGATION

MAP COMPARISON WITH STATE OF THE ART USING HANDCRAFTED FEATURES

	QE	SP	#pivot	Oxford5K	Oxford105K	Paris6K
ASMK* [Tolias'13]	✗	✗	–	80.3	74.9	77.1
[Mikulik'13]	✓	✓	~ 50	84.9	79.5	82.4
[Qin'13]	✓	✗	~	85.0	81.6	<u>85.5</u>
ASMK*+SCSM [Shen'14]	✓	✗	100	85.0	82.0	84.4
i-ASMK*+HQE [Tolias'16]	✓	✗	100	86.9	<u>85.3</u>	85.1
HQE-SP [Tolias'14]	✓	✓	100	<u>88.0</u>	84.0	82.8
ASMK*+DP-LC-MR	✓	✗	25	88.8	87.1	85.6
ASMK*+DP-LC-MR	✓	✗	50	89.3	88.0	87.3
ASMK*+DP-LC-MR	✓	✗	100	**90.1**	**88.6**	**89.0**

QUALITATIVE RESULTS

Precision at the position where each instance is retrieved is shown under the corresponding image for ASMK* <u>without</u> and **with** our QE method

<u>0.4</u> → 100 <u>2.4</u> → 100 <u>2.7</u> → 99 <u>3.2</u> → 99.3 <u>2.5</u> → 98.5 <u>4.7</u> → 100