Query Expansion for Visual Search

using Data Mining Approach

Ph.D. Defense Presentation

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Note on major requirements from the previous presentation

Presentation

1. Discussing about weakness and limitation of the research. (done)
2. In which cases the method fails (done)
   - Evidences showing good/bad results.
3. Conducting experiments on larger datasets. (done)
   - MVS dataset/Instance search dataset

Thesis

1. Intensive literature review. (done)
2. Finishing thesis. (almost done)

Overview

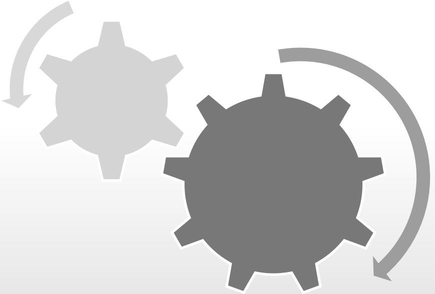
1. Introduction

- Motivation
- Baseline problem

2. Contributions list

- Visual word mining
- Spatial verification
- Automatic parameter tuning

3. Proposed methods



4. Experimental results

- Overall
- Robustness
- Time consumption

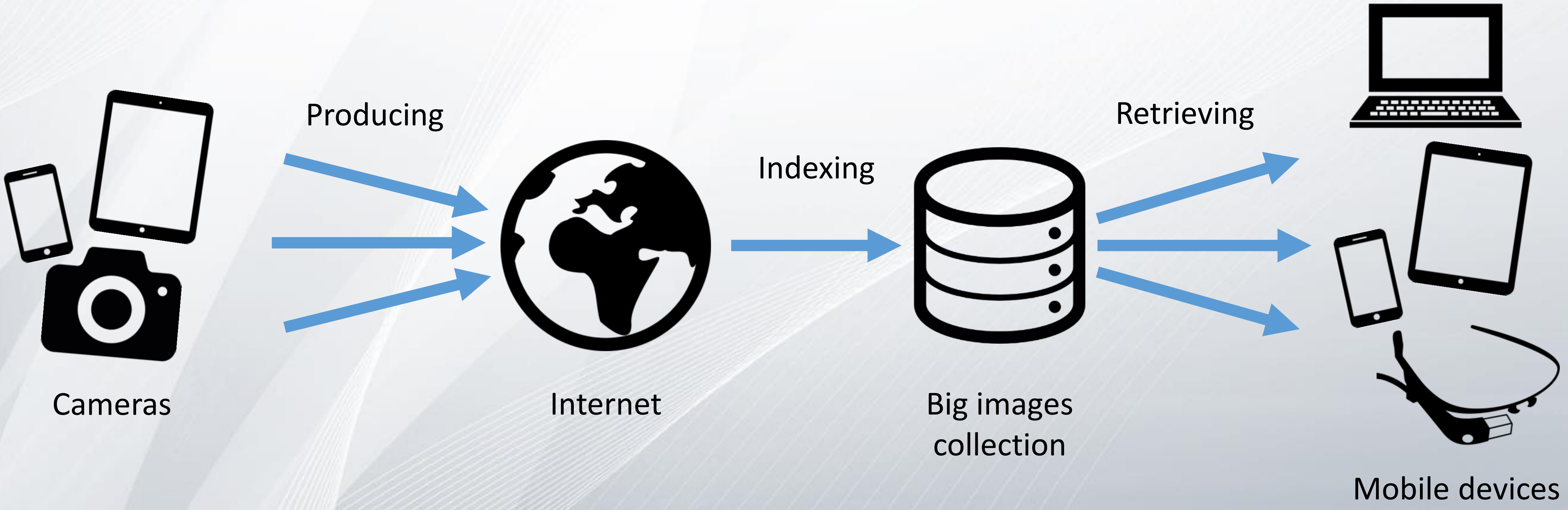
5. Conclusion

- Research achievements
- Pros and Cons
- Limitation

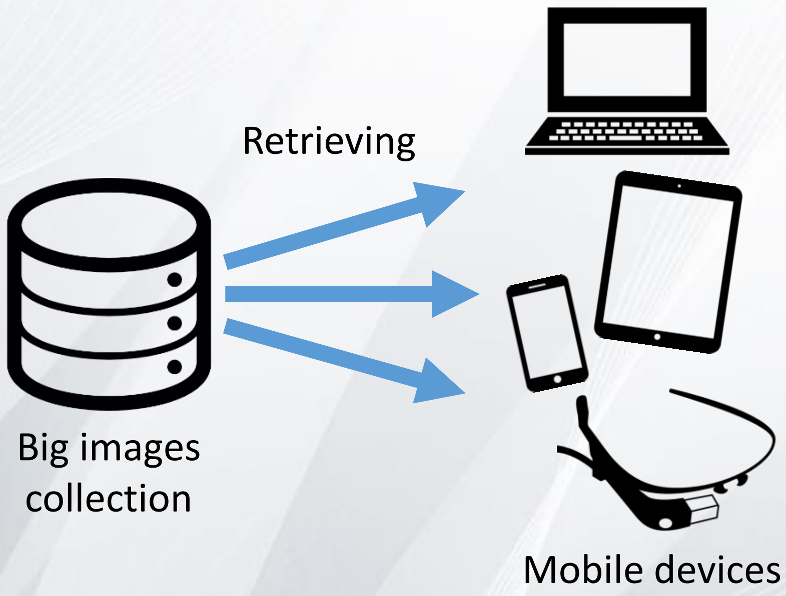
6. Future work

- Speed up
- Binary feature

1. Introduction



1.1 Motivation



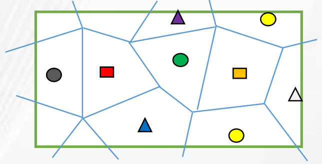
- Big images collection.
- Querying on-the-fly with mobile devices.
- Accuracy issue.

- ***State-of-the-art approaches***
  - Bag-of-visual-word (**BoVW**)
  - Average query expansion (**AQE**)

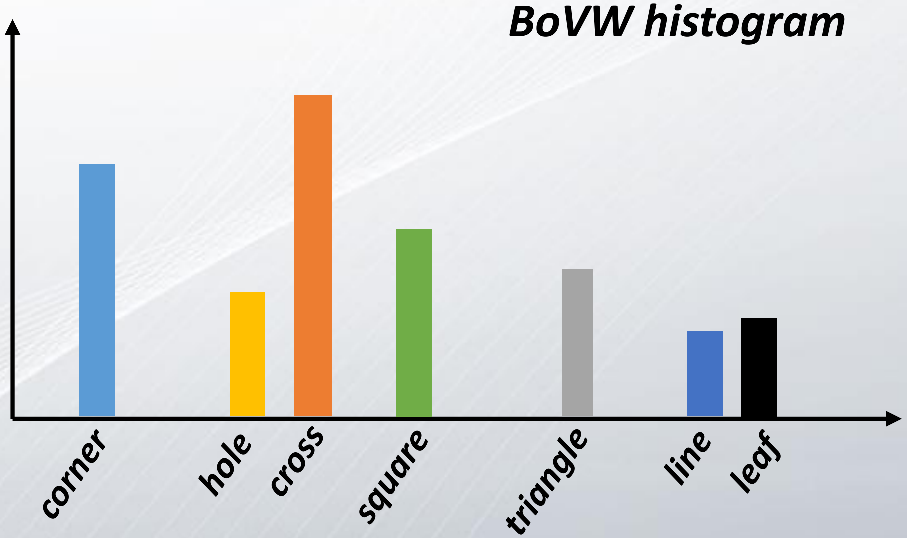
1.1.1 Bag-of-Visual-Word (BoVW)[1] (1)

- Image representation using BoVW technique.

Image Query



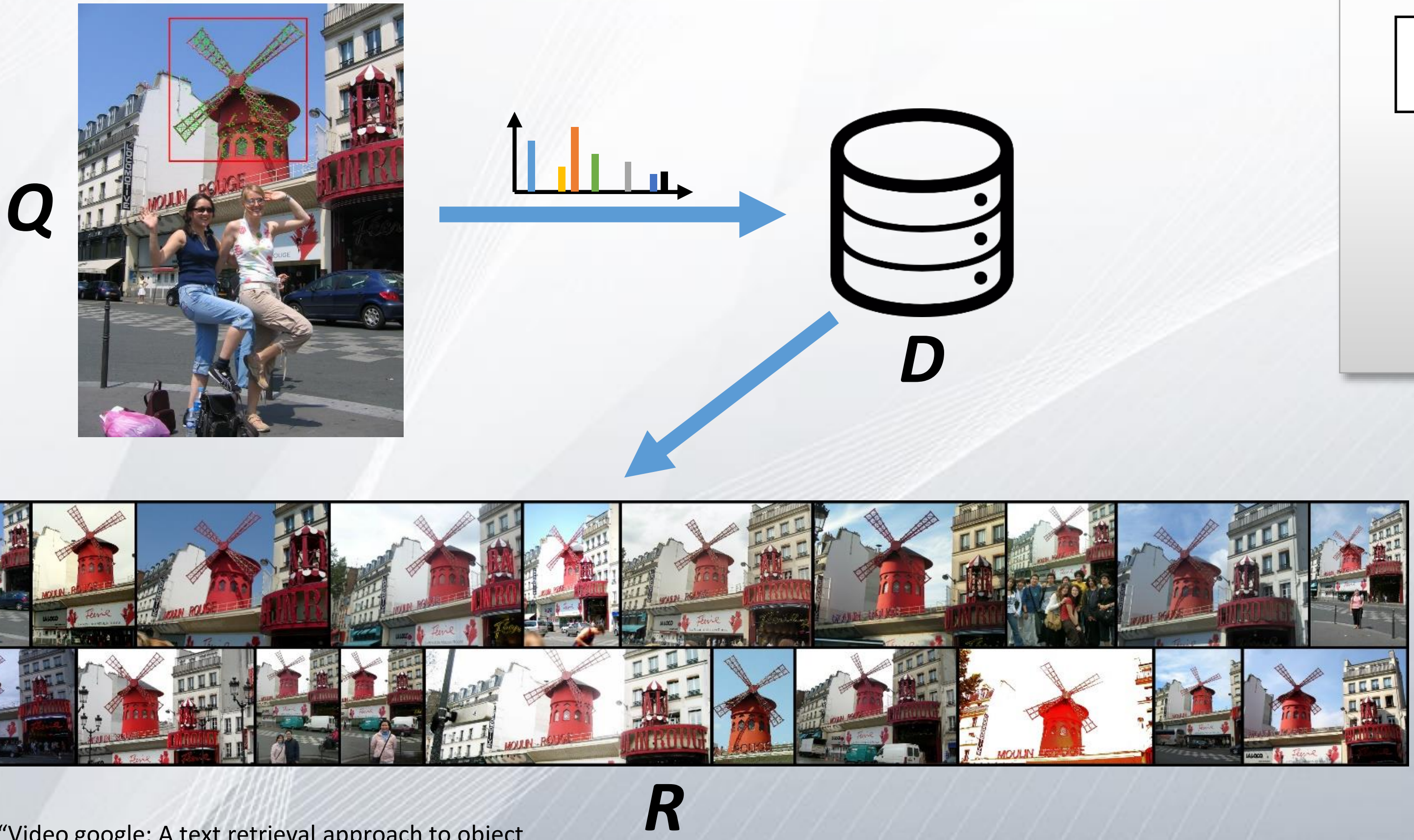
a. Feature extraction, SIFT [2,3]
b. Clustering, AKM [4]
c. Quantization, ANN [5]

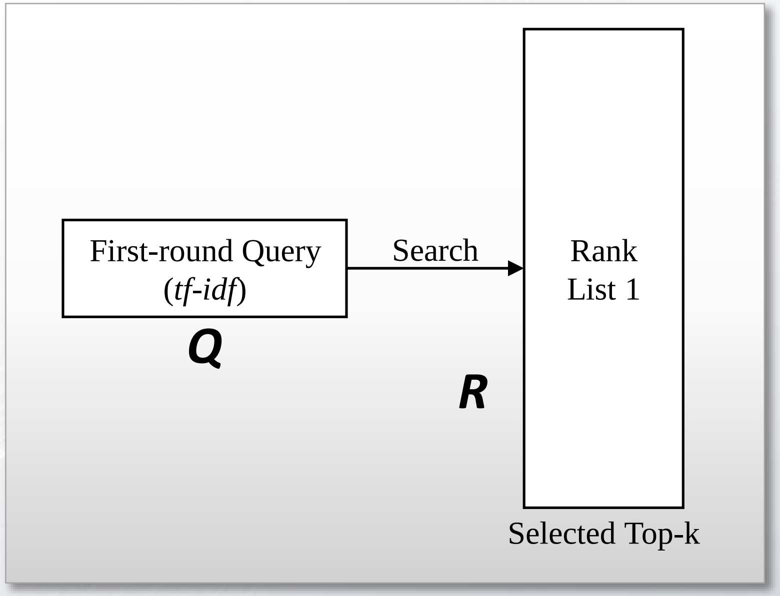


Ref:
[1] J. Sivic and A. Zisserman, “Video google: A text retrieval approach to object matching in videos,” ICCV, pp.1470–1477, 2003.
[2] Michal Perdoch Ondrej Chum, J. M., Efficient Representation of Local Geometry for Large Scale Object Retrieval, *CVPR,* 2009, 9-16
[3] Lowe, D. G., Distinctive Image Features from Scale-Invariant Keypoints, *International Journal of Computer Vision,* 2004, 91-110
[4] Muja, M. & Lowe, D. G., Fast Approximate Nearest Neighbors with Automatic Algorithm Configuration, *VISAPP,* 2009, 331-340
[5] Philbin, J.; Chum, O.; Isard, M.; Sivic, J. & Zisserman, A., Object retrieval with large vocabularies and fast spatial matching, *CVPR,* 2007, 1-8

1.1.1 Bag-of-Visual-Word (BoVW)[1] (2)

- Object-based image retrieval by ***BoVW***





BoVW architecture diagram

Q = Query image
D = Database images
R = Retrieved images

Ref:
[1] J. Sivic and A. Zisserman, “Video google: A text retrieval approach to object matching in videos,” ICCV, pp.1470–1477, 2003.

1.1.1.1 Similarity Calculation

$$sim(\boldsymbol{Q}, I) = 1 - \left\| \frac{\boldsymbol{Q}}{\|\boldsymbol{Q}\|_1} - \frac{I}{\|I\|_1} \right\|_1$$

$$\boldsymbol{R} = \{I_b \in D | I_b \text{ contains object appeared on } \boldsymbol{Q}\}$$

Q = Query image
D = Database images
R = Retrieved images
I = Reference image

1.1.1.2 BoVW problem

Q

Search

R

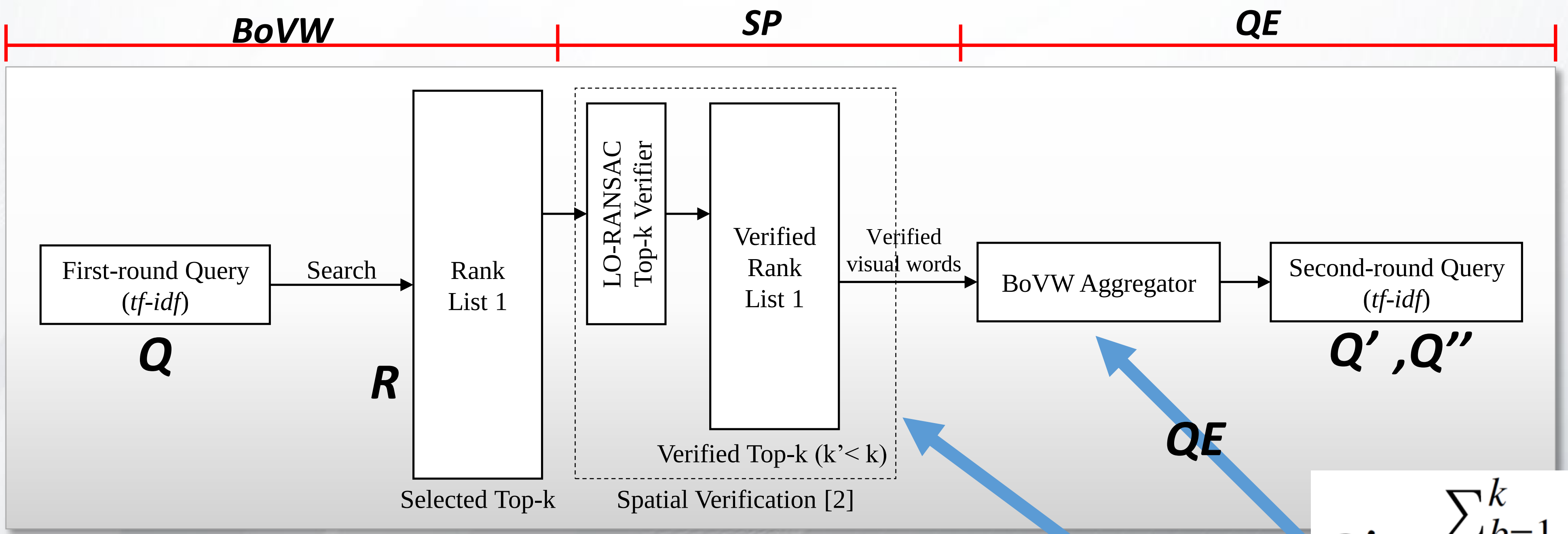
(kin mugi)

≠

(ka wa ru)

Partially matched
of an object / visual words
on the **irrelevant image**.

1.1.2 Average Query Expansion (AQE)[1]



AQE architecture diagram

$$Q' = \frac{\sum_{b=1}^{k} \boldsymbol{R}_b}{k}$$

$$Q'' = \frac{Q + \sum_{b=1}^{k'} \boldsymbol{R}_b}{k' + 1}$$

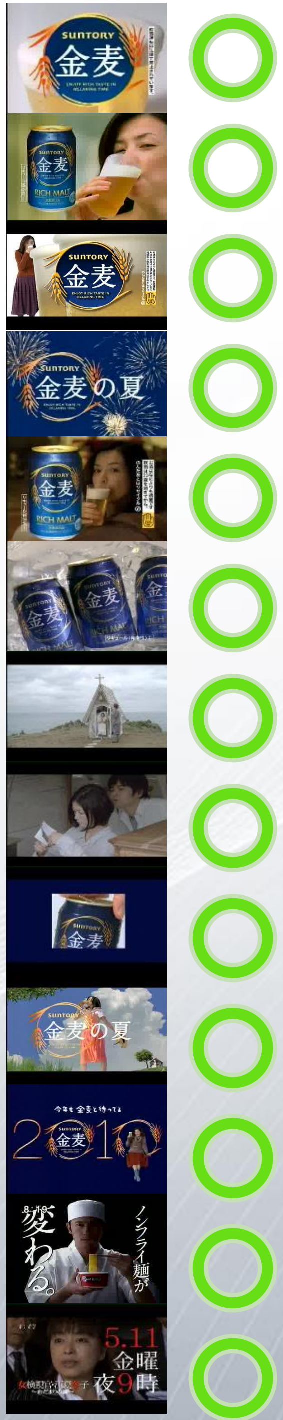
k = Selected top images
k' = Verified images
k' < k

Ref:
[1] O. Chum, J. Philbin, J. Sivic, M. Isard, and A. Zisserman, “Total recall: Automatic query expansion with a generative feature model for object retrieval.,” ICCV, pp.1–8, 2007.
[2] K. Lebeda, J. Matas, and O. Chum, “Fixing the locally optimized RANSAC,” BMVC, pp.1–11, 2012.

QE

Q

R



All images
will be averaged

Q’

k = Total images

AQE

Q

R

inlier = 10

inlier = 7

inlier = 8

inlier = 7

inlier = 6

inlier = 14

inlier = 0

inlier = 0

inlier = 0

inlier = 2

inlier = 3

inlier = 1

inlier = 2

Only ***verified images*** and ***inlied visual words*** will be averaged

Q''

k' = verified images

National University SOKENDAI The Graduate University for Advanced Studies

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RANSAC spatial verification between images

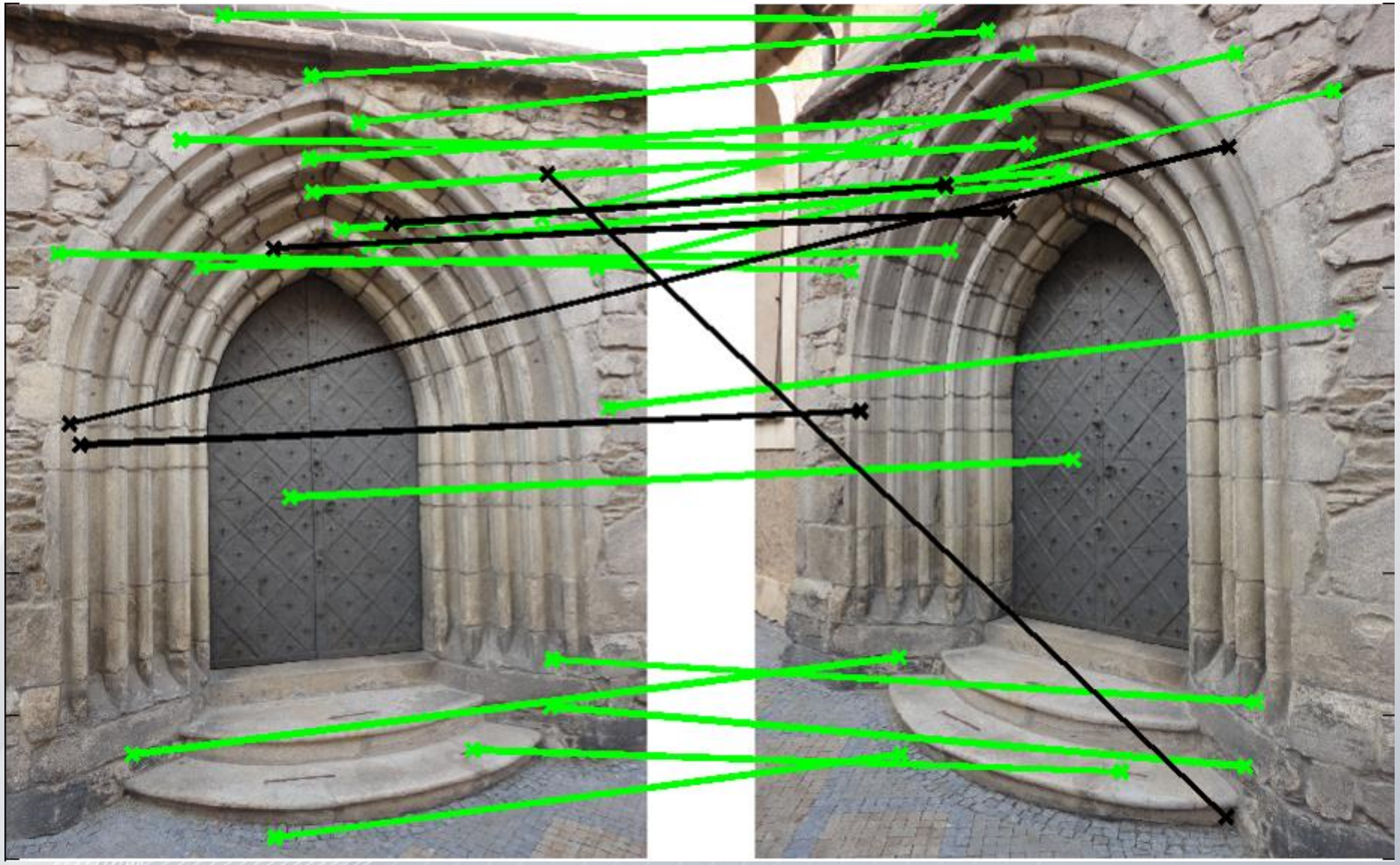


Image reference: https://cyber.felk.cvut.cz/theses/detail.phtml?id=360

1.1.2.1 AQE problem (inlier threshold = 4)

Normal query

1-to-M

inlier = 10 ○
inlier = 7 ○
inlier = 8 ○
inlier = 7 ○
inlier = 6 ○
inlier = 14 ○

⋮

Bad condition query

1-to-M

inlier = 4 ○
inlier = 3 ✕
inlier = 2 ✕
inlier = 2 ✕
inlier = 2 ✕
inlier = 10 ○

⋮

Too many relevant images were rejected

Self-correspondences without query over-dependency?

Query Bootstrapping!!!

1.1.2.2 Query conditions

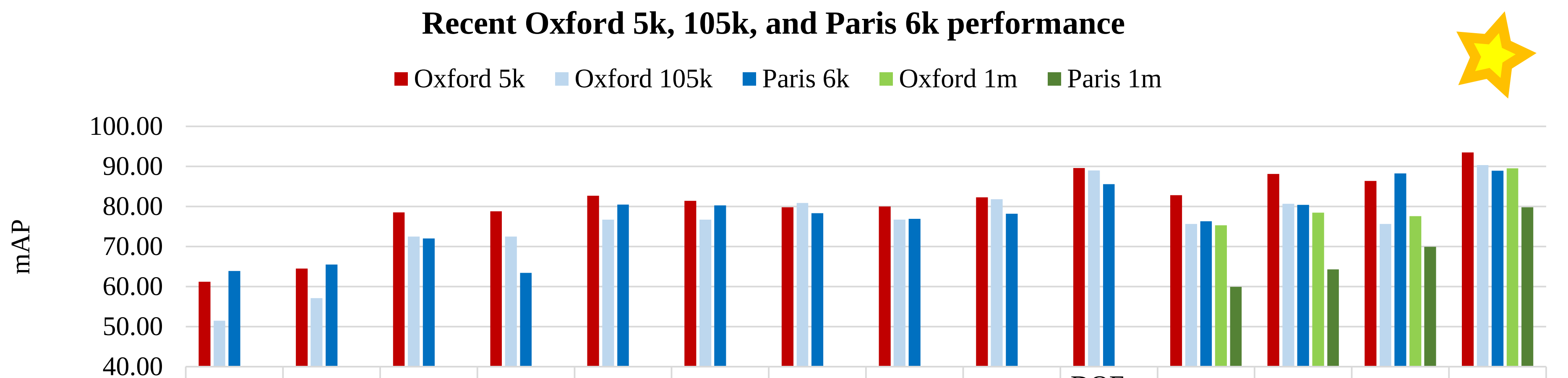
On-the-fly image retrieval..

***Good query** may not be as expected.*

1.2 Research objective

- This research aims to **relax** the **over-dependency** on query verification.
  - By finding the ***consistency among highly ranked images***, instead.
- We evaluate our methods on several standard datasets.
  - Oxford building **5k**, **105k**.
  - Paris landmark **6k**.
  - Extended distractor with **MIR Flickr 1M** for (**Oxford 1m** and **Paris 1m**)
- Robustness on several query degradation cases.

Where we are?



	BoVW [1]	Spatial verification [1]	AQE [2]	Local geometry [3]	Total recall II [4]	Hello neighbors [5]	DQE [6]	AQE [7]	DQE + Boosting [7]	DQE + Boosting (group) [7]	BoVW [Our]	AQE [Our]	QB [Our]	QB + SP [Our]
Oxford 5k	61.20	64.50	78.50	78.80	82.70	81.40	79.80	80.00	82.30	89.60	82.84	88.12	86.41	93.49
Oxford 105k	51.50	57.10	72.50	72.50	76.70	76.70	80.90	76.70	81.80	89.00	75.66	80.71	75.67	90.36
Paris 6k	63.90	65.50	72.00	63.40	80.50	80.30	78.30	76.90	78.20	85.60	76.33	80.44	88.28	88.96
Oxford 1m											75.28	78.48	77.56	89.52
Paris 1m											59.95	64.32	69.94	79.81

2007-------------------2009--2011----------2012---2014-----------------------------------**2015**------------ つづく

Ref:
[1] J. Philbin, O. Chum, M. Isard, J. Sivic, and A. Zisserman. Object retrieval with large vocabularies and fast spatial matching. In CVPR, 2007.
[2] O. Chum, J. Philbin, J. Sivic, M. Isard, and A. Zisserman. Total recall: Automatic query expansion with a generative feature model for object retrieval. In ICCV, 2007.
[3] M. Perdoch, O. Chum, and J. Matas. Efficient representation of local geometry for large scale object retrieval. In CVPR, 2009.
[4] O. Chum, A. Mikulik, M. Perdoch, and J. Matas. Total recall II: Query expansion revisited. In CVPR, 2011.
[5] D. Qin, S. Gammeter, L. Bossard, T. Quack, and L. J. V. Gool. Hello neighbor: Accurate object retrieval with k-reciprocal nearest neighbors. In CVPR. IEEE Computer Society, 2011.
[6] R. Arandjelovic. Three things everyone should know to improve object retrieval. In CVPR, 2012.
[7] C. Yanzhi, L. Xi, D. Anthony, and H. Anton van den. Boosting object retrieval with group queries. In SPS, 2014.

Result overview

- Overall accuracy improvement
  Normal query **+ 10-14% (best)**
- Higher robustness to low quality queries
  Low resolution / Small object / Blur **+ ~26% (best)**
  Noisy **+ ~19-26% (best)**

SUCCESS

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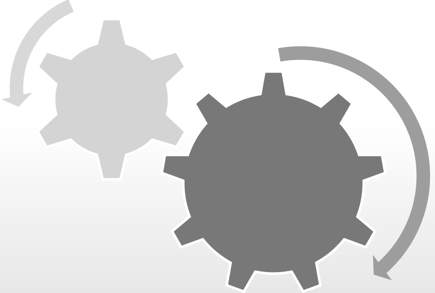

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2. Contributions list

1. We proposed a “**Query Bootstrapping (QB)**” as a visual mining for query expansion
   - To discover object consistency among highly ranked images by using Frequent Itemset Mining (FIM)
   - Relaxed a strong constraint between a query image and first-round retrieved list.
   - Gained higher robustness on low quality query.
2. We proposed an “**Adaptive Support (ASUP)**” tuning algorithm for FIM.
   - To automatically provide an optimal support value (important parameter for FIM).
   - Locally optimize support value for each query, for the best performance of each query.
3. We integrated a **LO-RANSAC spatial verification (SP)** based method to QB (**QB + SP**).
   - To verify correspondences between a query and retrieved images.
   - Give a chance for FIM to find correct co-occurrence patterns through the whole of verified images.
     - Less constraint than AQE
4. We proposed an “**Adaptive Inlier Threshold (ADINT)**” for LO-RANSAC
   - To find an inlier threshold automatically.
   - Good for QB + SP.

Average improvement over the state-of-the-arts

	BoVW	***AQE***
Q4-2013	**+3%**	**-1%**
Q1-2014	**+5%**	**+1%**
Q4-2014	**+12%**	**+7%**
Q1-2015	**+14%**	**+9%**

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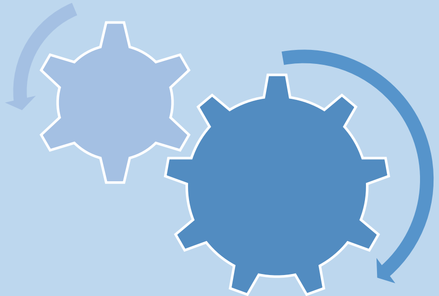

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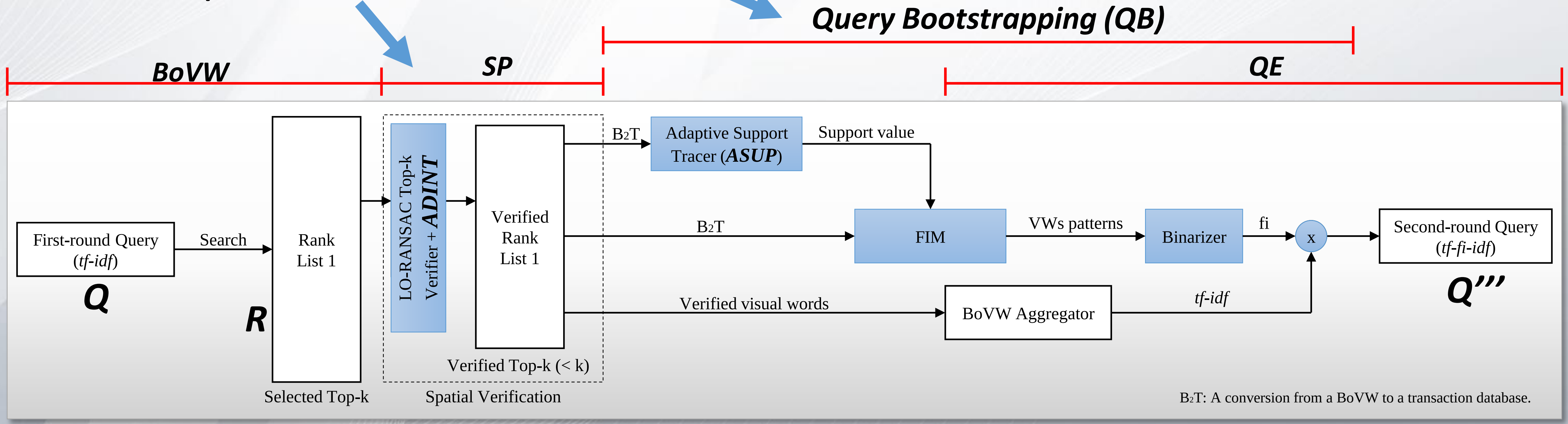
3. Proposed methods

1. Visual word mining
2. Spatial verification

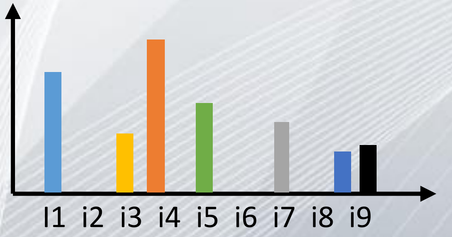


QB / QB + SP architecture diagram

Intro - Frequent Itemset mining (FIM)

T

Img. I_k	Trans. t_k
I_1	$t_1 = \{i_1, i_2, i_4, i_6\}$
I_2	$t_2 = \{i_2, i_5, i_8\}$
I_3	$t_3 = \{i_2, i_3, i_9\}$
I_4	$t_4 = \{i_1, i_2, i_4, i_7\}$
I_5	$t_5 = \{i_2, i_3, i_8\}$



FIM

Pattern	*support*
$\{i_2\}$	60%
$\{i_3\}$	40%
$\{i_8\}$	40%
$\{i_1, i_4\}$	40%
$\{i_3, i_8\}$	20%
$\{i_1, i_4, i_7\}$	20%
$\{i_2, i_3, i_9\}$	20%
$\{i_2, i_5, i_8\}$	20%
$\{i_1, i_2, i_4, i_6\}$	20%

P

Related works that applied FIM

- Video mining [1]
  - Mining visual word motions into groups.
- Visual phrase mining [2]
  - Finding visual phrase lexicon.
  - Separating object out of background.
- Mining multiple queries [3]
  - Mining query patterns to better focus of targeted object.
- Mining for re-ranking and classification [4]
  - Voting image score by counting FIM patterns.

Our work closed to

[3] FIM for multiple images.

- But we are on the **result side.**

[4] FIM on result images.

- But we feed **back result** as AQE.

Non of them work directly on

FIM for Query expansion!

Ref:
[1] T. Quack, V. Ferrari, and L.J.V. Gool, "Video mining with frequent itemset configurations.," FIMI, pp.360–369, 2006.
[2] J. Yuan, Y. Wu, and M. Yang, "Discovery of collocation patterns: from visual words to visual phrases," CVPR, pp.1–8, 2007.
[3] B. Fernando and T. Tuytelaars, "Mining multiple queries for image retrieval: On-the-fly learning of an object-specific mid-level representation," ICCV, pp.2544–2551, 2013.
[7] W. Voravuthikunchai, B. Cr´emilleux, and F. Jurie, "Image re-ranking based on statistics of frequent patterns," ICMR, pp.129–136, 2014.

3.1 Contribution 1 - QB

- Mining co-occurrence visual words among highly ranked images.
  - **FIM** returns frequent patterns (***fi***).
- Constructing a new query (***Q'''***)
  - We regard ***fi*** is a representative form of the occurrences of visual words.
  - Considering a new term ***fi*** into a standard BoVW term (***tf-idf***)
  - Named as ***tf-fi-idf (or fi*** x ***tf-idf)***

R

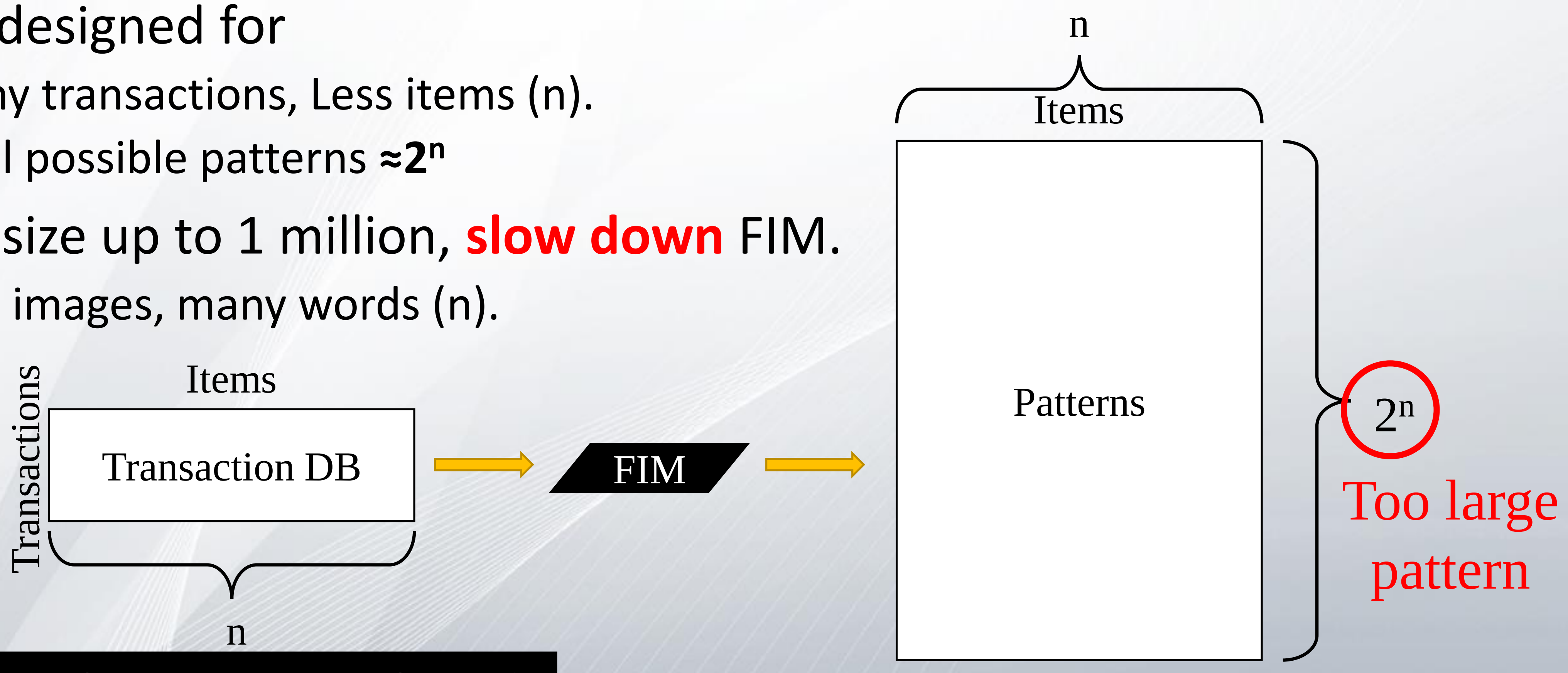
FIM

Q'''

Back-projected visualization

3.1 QB problem 1 (1)

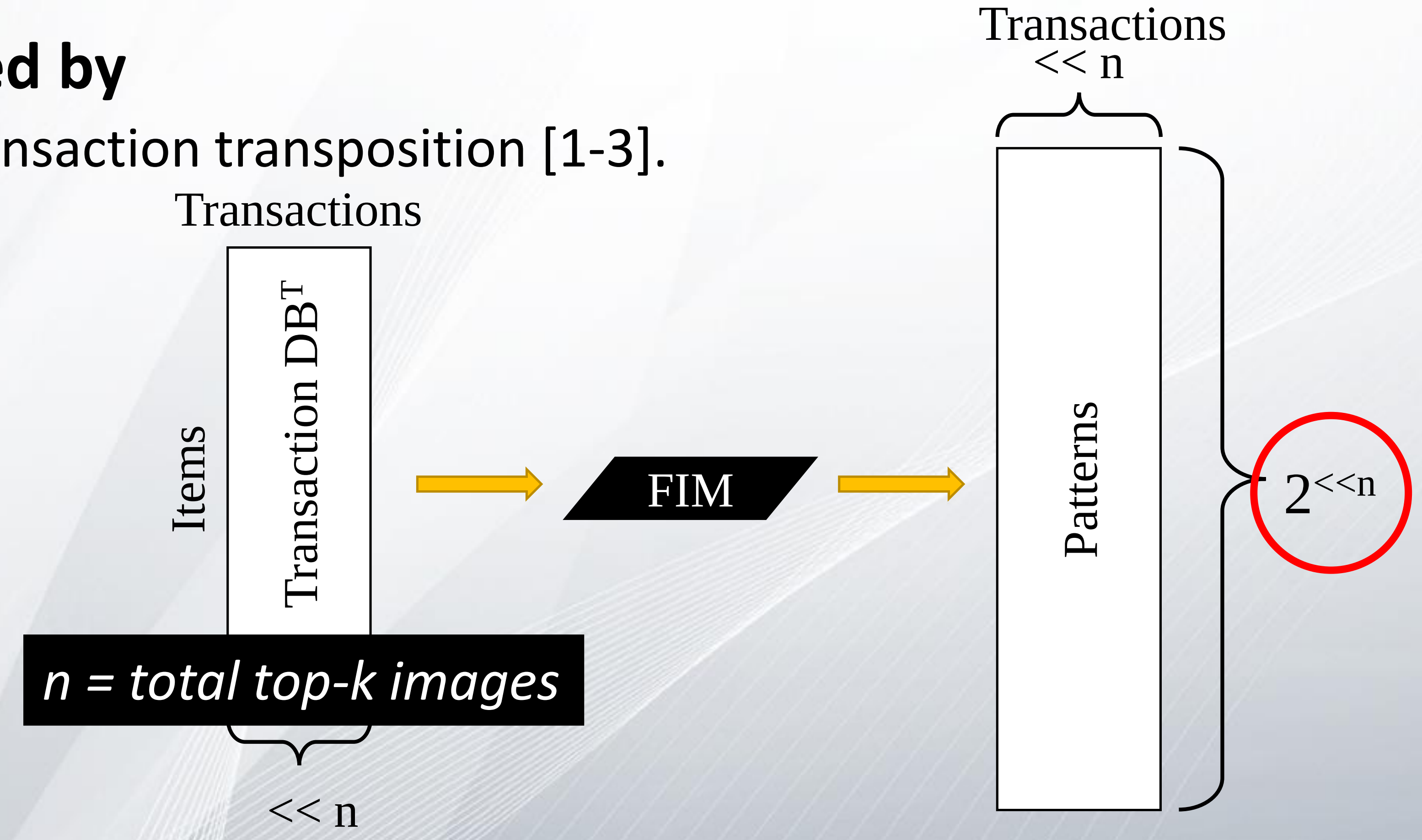
- FIM is designed for
  - Many transactions, Less items (n).
  - Total possible patterns **≈2^n**
- BoVW size up to 1 million, **slow down** FIM.
  - Less images, many words (n).

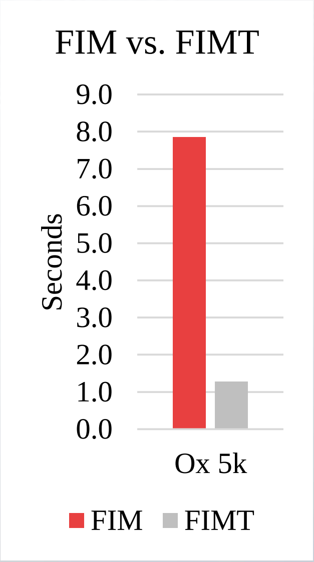


n = total non-zero visual words

3.1 QB problem 1 (2)

- **Helped by**
  - Transaction transposition [1-3].

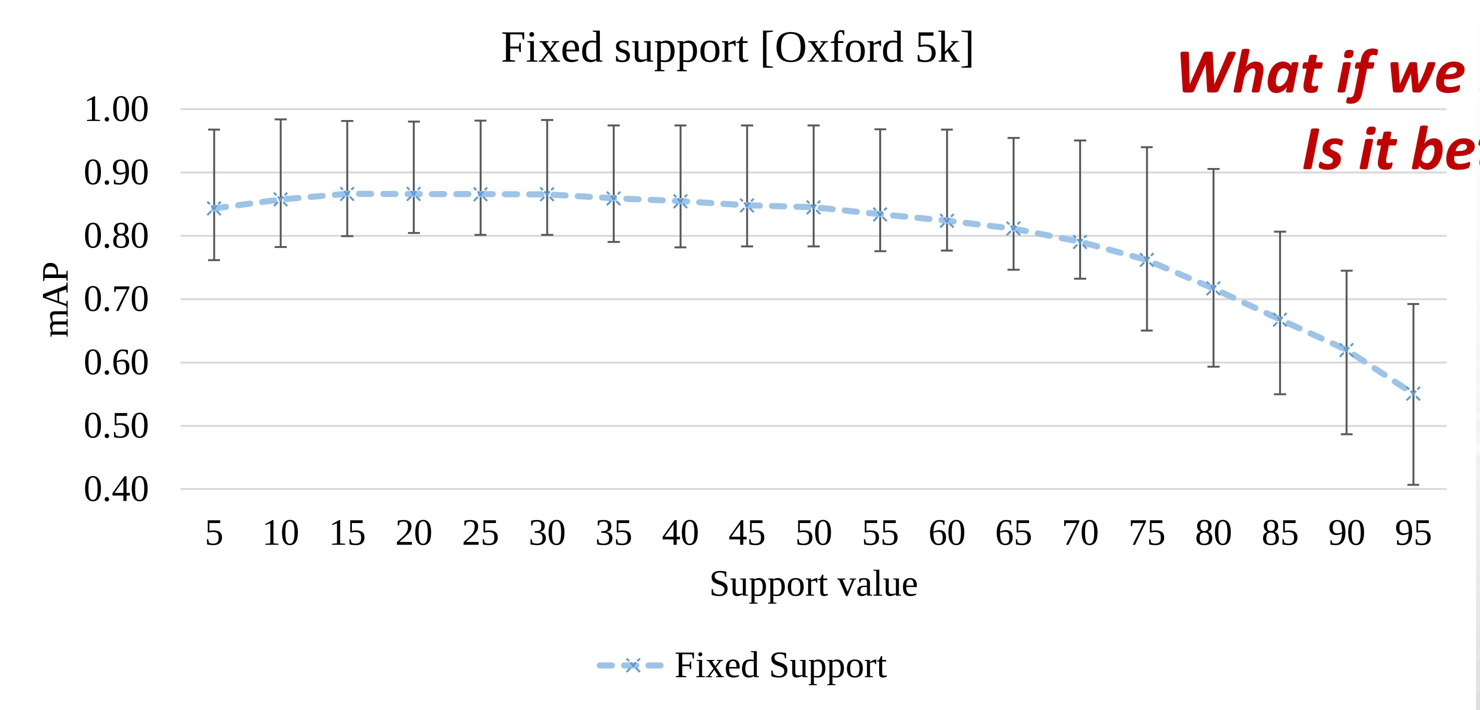




Faster!!

Ref:
[1] F. Rioult, J.F. Boulicaut, B. Cr´emilleux, and J. Besson, “Using transposition for pattern discovery from microarray data,” DMKD, pp.73–79, 2003.
[2] F. Rioult, “Mining strong emerging patterns in wide sage data,” 2004.
[3] F. Domenach and M. Koda, “Mining association rules using lattice theory (6th workshop on stochastic numerics),” 2004.

3.1 QB problem 2



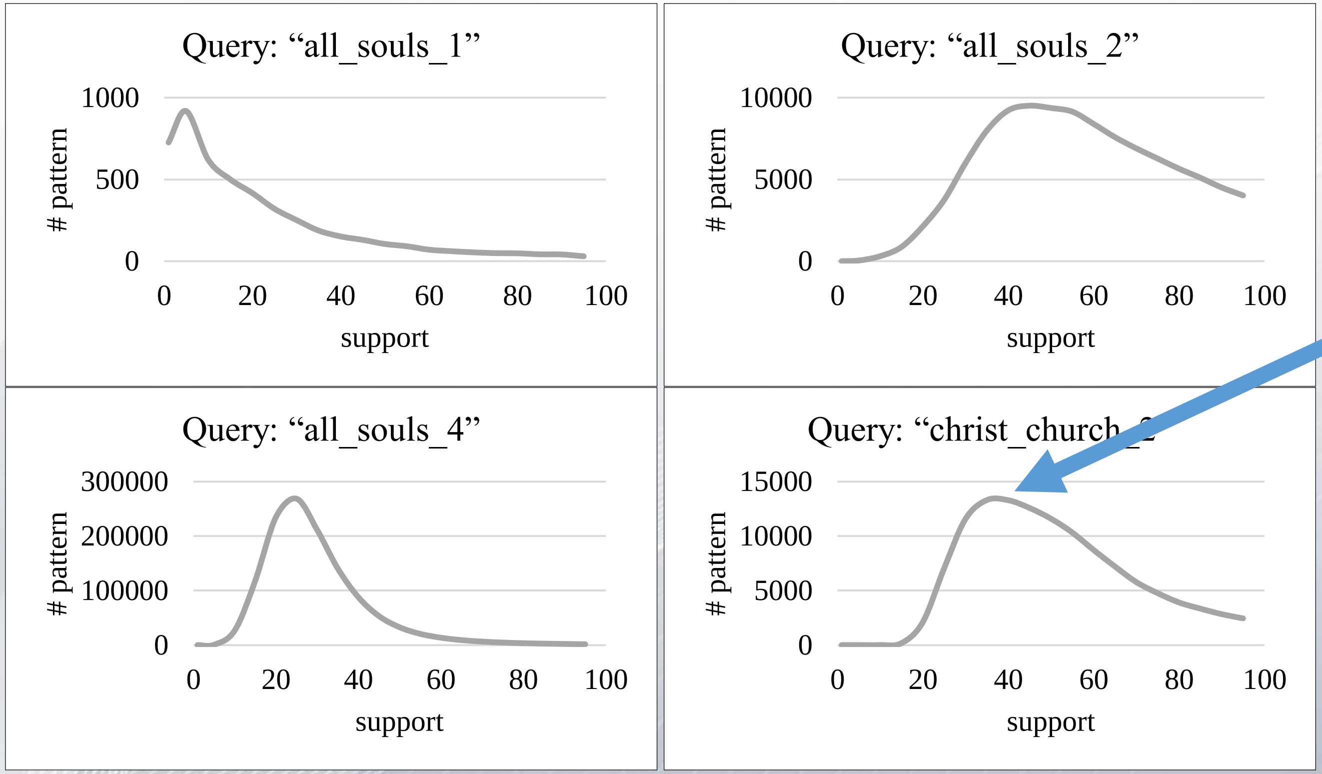
Fixed support value and its performance

What if we set support individually?
Is it better to set it locally?

- How much support value is appropriate?
  - Too low support give too much patterns.
  - Too high support might give nothing.

3.2 Contribution 2 - ASUP

- **Adaptive Support** tuning algorithm for ***individual query***.



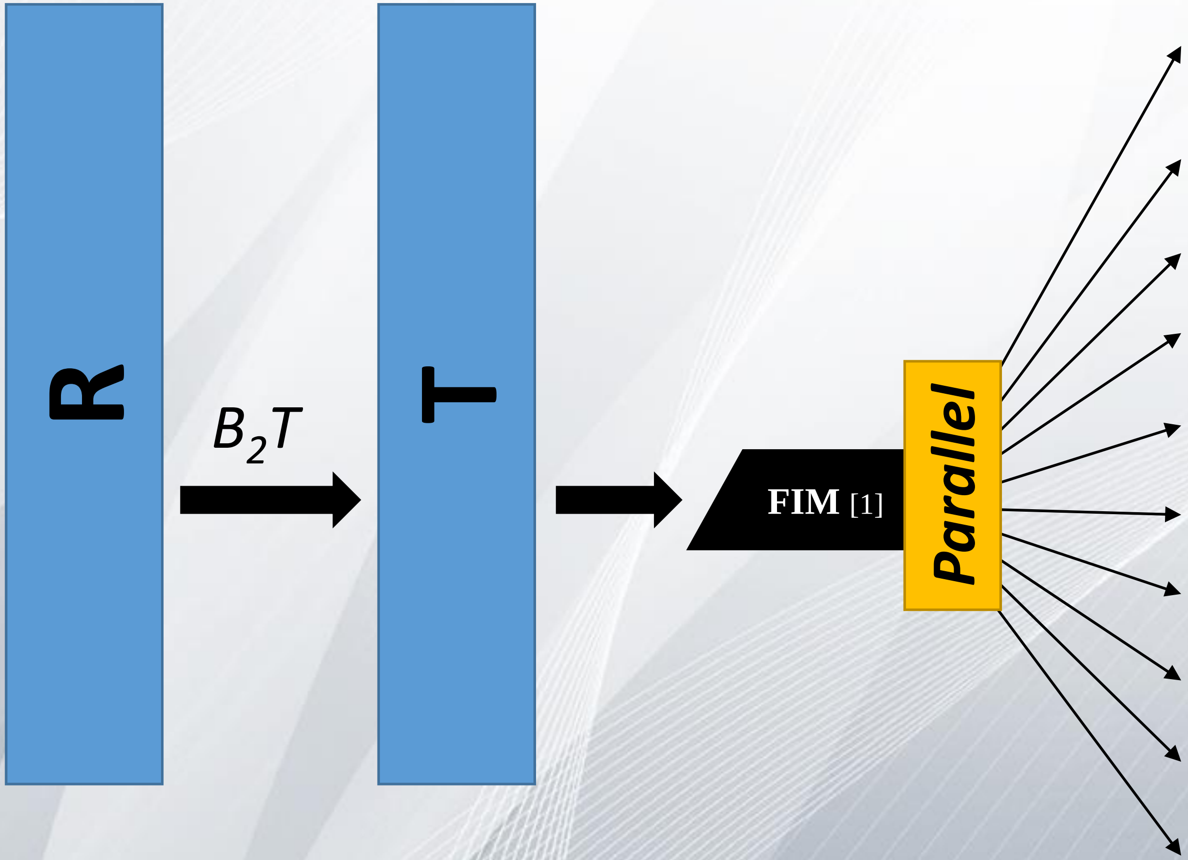
Pattern amount at each specific support range

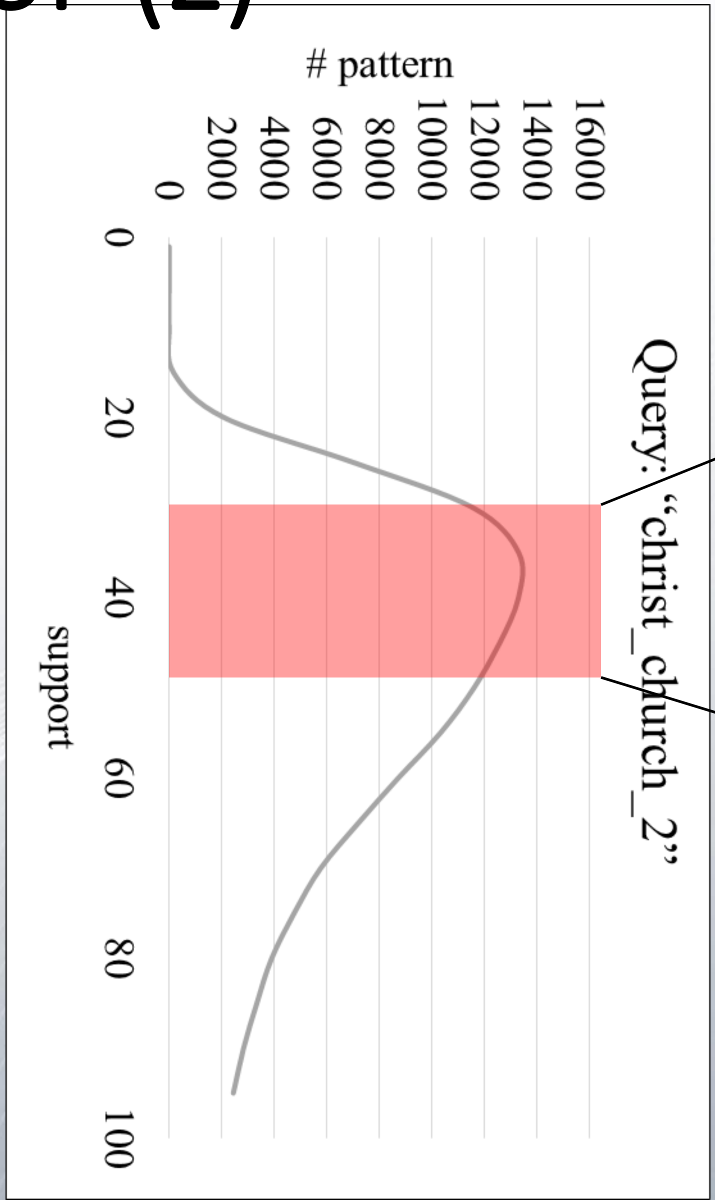
As we observed..

The optimal support is at the highest frequent patterns.

3.2 Contribution 2 – ASUP (2)

- ASUP algorithm





Optimal!!

minsup = 30

maxsup = 50

Ref:
[1] Uno, T.; Asai, T.; Uchida, Y. & Arimura, H., LCM: An Efficient Algorithm for Enumerating Closed Patterns in Transaction Databases, *FIMI,* 2003, *3245*, 16-31

3.2 ASUP problem (1)

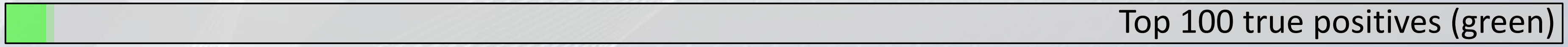
- BoVW result (***R***) may be dominated by irrelevant images.

Q

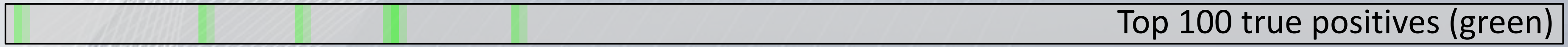
Top 10 images example.

The rest of images are mostly a branches and a tree →

Round1 *R* (BoVW)

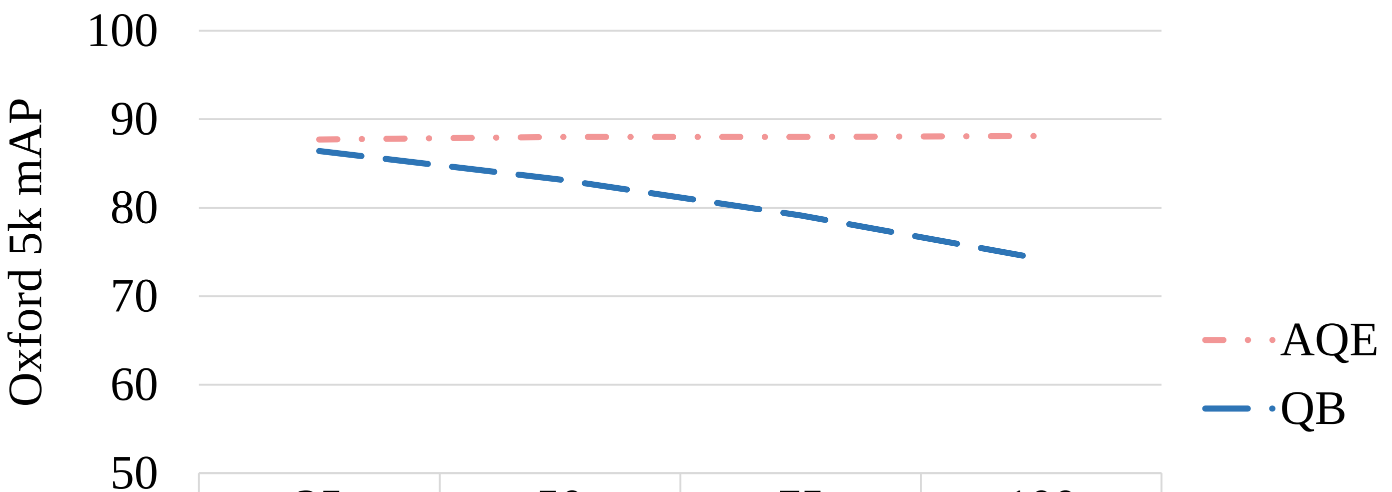


Round2 *R* (QB)



3.2 ASUP problem (2)

- The performance is decreasing
  when the number of **top-k** is increasing.



	25	50	75	100
AQE	87.73	88.01	87.99	88.11
QB	86.41	83.20	79.12	74.23

top-k

3.3 Contribution 3 - QB + SP (1)

- Spatial verification is back
  - Properly for QB.
  - To give hints of verify ***images***.
  - Mining will be more focused.

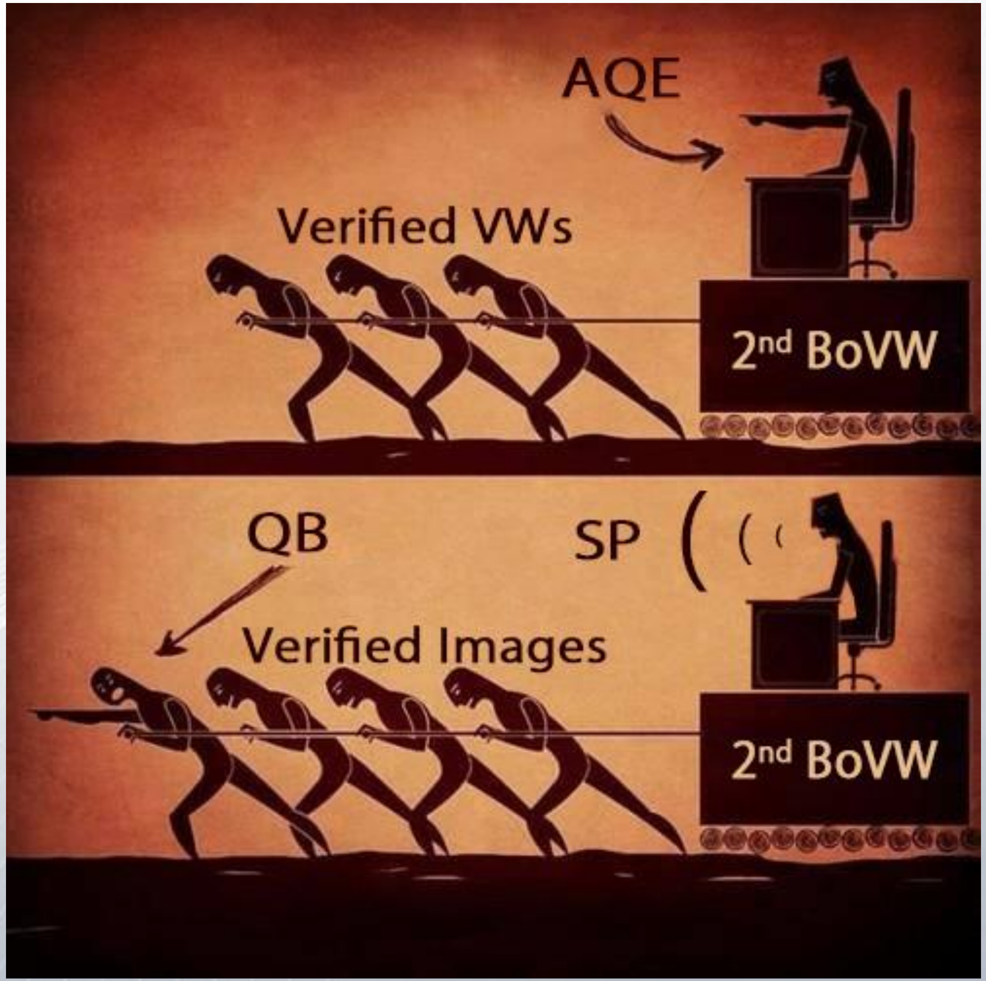


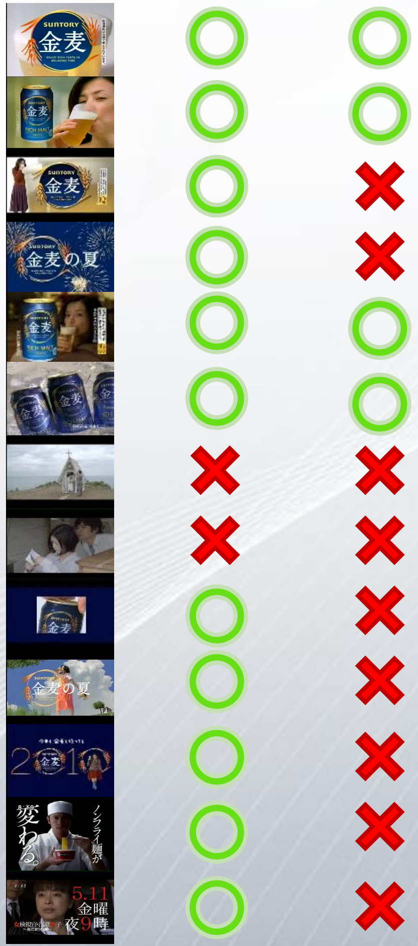
Image reference: Modified from an Internet meme comparing between Boss vs. Leader

3.3 Contribution 3 - QB + SP (2)

Q

R

Low threshold *High threshold*



Accepting relevant images is fine!

Problem

How much inlier threshold should be set?

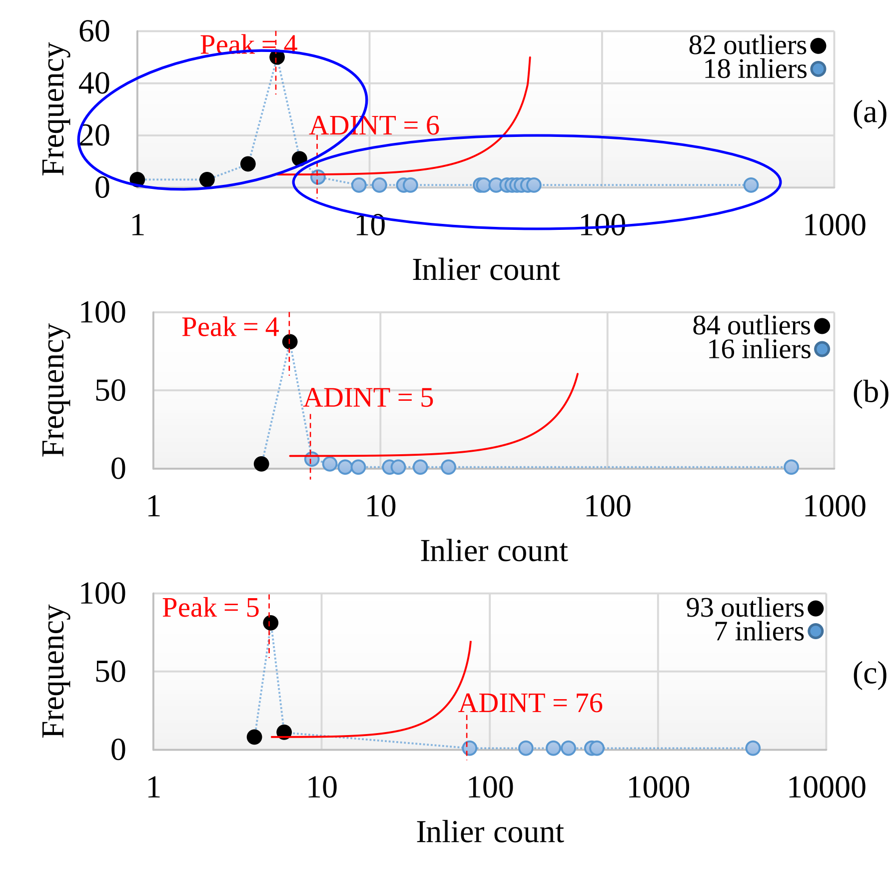
- Too low filtering nothing.
- Too high filtering everything.

Accepting irrelevant images leads high noise to FIM!

3.4 Contribution 4 – ADINT (1)

- Adaptive Inlier Threshold (ADINT) algorithm
  1. Feed top-k to LO-RANSAC
  2. Constructing the inlier count histogram.
  3. Select a pivot on a peak.
  4. Sweeping clockwise from a pivot with a radius of 0.9 (ADINT ratio)
  5. The first point that cut histogram will be an Adaptive Inlier Threshold.

Inlier count histogram
Horizontal axis
Inlier count value provided by LO-RANSAC.
Vertical axis
Total number of images.

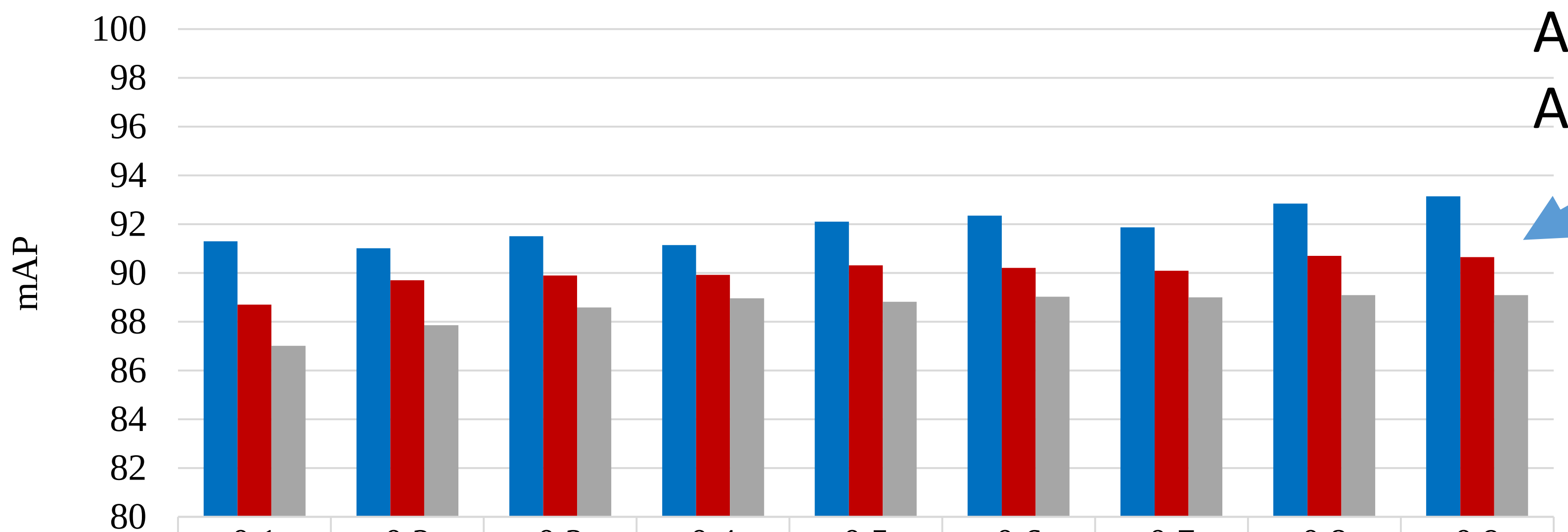


Inlier count histogram

3.4 Contribution 4 – ADINT (2)

- Why ADINT ratio = 0.9?

ADINT ratio ~0.9
Always gives the best ADINT performance



	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Ox5k	91.29	91.01	91.51	91.14	92.10	92.35	91.87	92.84	93.14
Ox105k	88.70	89.70	89.89	89.92	90.32	90.21	90.09	90.70	90.65
Paris6k	87.02	87.86	88.58	88.96	88.82	89.02	89.00	89.09	89.08

Adaptive Inlier Threshold (ADINT)

Ox5k Ox105k Paris6k

3.4 Contribution 4 – ADINT (3)

- **ADINT** thresholding result

ADINT thresholding result

Color code	
(blue)	Inlier count from LO-RANSAC
(red)	ADINT threshold
(orange)	Automated selected relevant images
(gray)	Ground truth

Overview

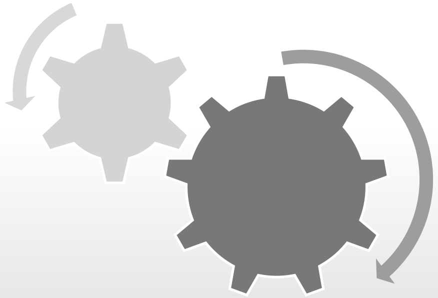
1. Introduction

- Motivation
- Baseline problem

2. Contributions list

- Visual word mining
- Spatial verification
- Automatic parameter tuning

3. Proposed methods



4. Experimental results

- Overall
- Robustness
- Time consumption

5. Conclusion

- Research achievements
- Pros and Cons
- Limitation

6. Future work

- Speed up
- Binary feature

4. Experimental results (1)

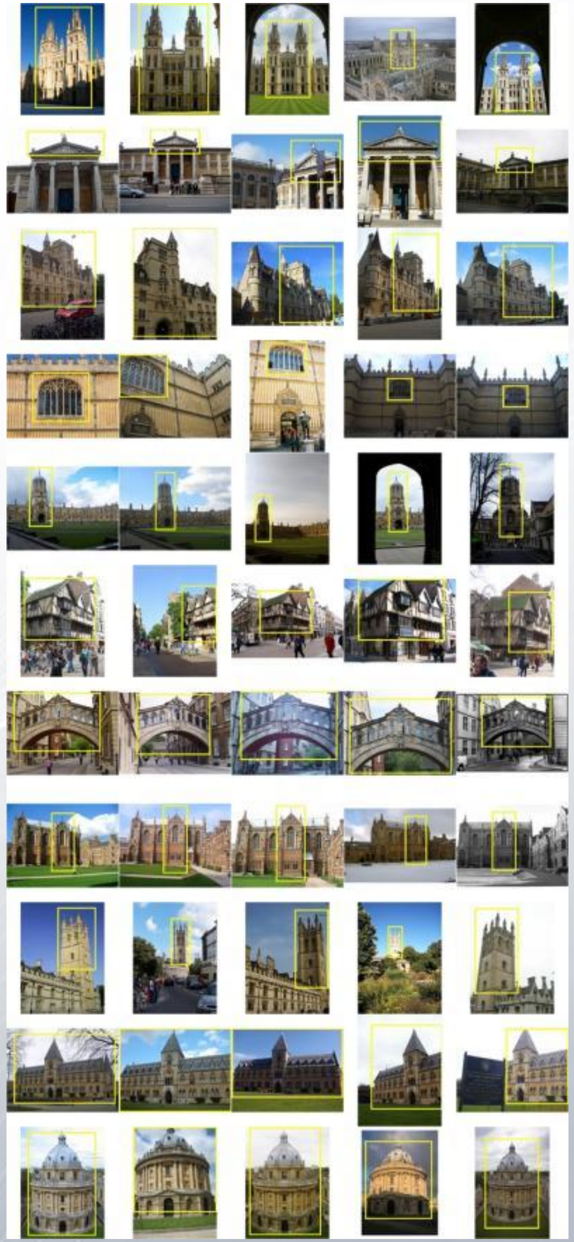
- **Standard dataset**
  - Oxford building 5k and 105k.
  - Paris 6k.
  - Total 55 queries on each dataset.
    - 11 landmarks and locations (topic).
    - 5 different views on each topic.
- **Extra 1 million distractor dataset images**
  - MIR Flickr 1m to make Oxford building 1m and Paris 1m.
- **Evaluation protocol**
  - We use mean average precision (mAP) as an evaluation matric.
  - And ground truth files obtained from the dataset provider.

Ref:
Oxford dataset: http://www.robots.ox.ac.uk/~vgg/data/oxbuildings/
Paris dataset: http://www.robots.ox.ac.uk/~vgg/data/parisbuildings/
MIRFlickr1M dataset: http://press.liacs.nl/mirflickr/mirdownload.html

4. Experimental results (2)

- Dataset examples

Paris landmarks

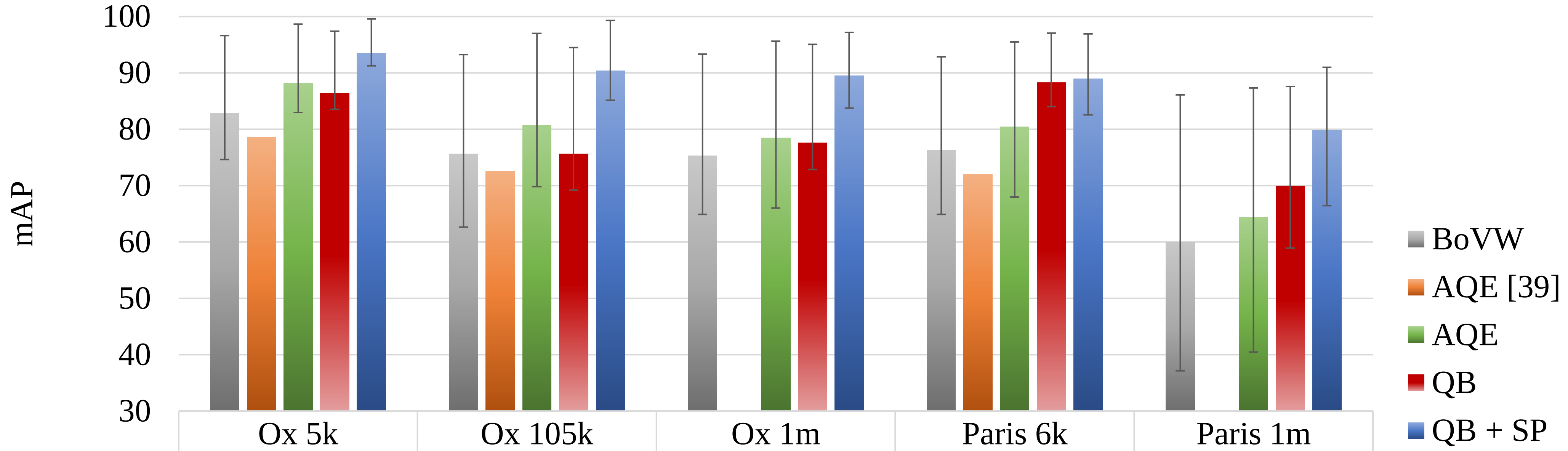


Oxford buildings

4. Experimental results (3)

1. Overall retrieval performance
2. Contributions comparison
3. Impact of Top-k retrieval images
4. Automatic parameter evaluation
5. Impact of varies quality query
6. Time consumption

4.1 Overall retrieval performance



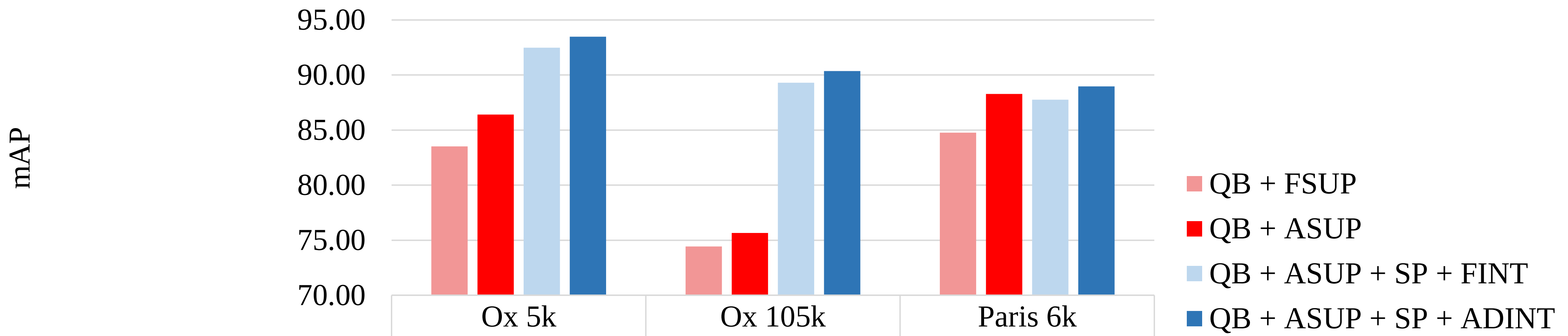
	Ox 5k	Ox 105k	Ox 1m	Paris 6k	Paris 1m
BoVW	82.84	75.66	75.28	76.33	59.95
AQE [39]	78.50	72.50		72.00	
AQE	88.12	80.71	78.48	80.44	64.32
QB	86.41	75.67	77.56	88.28	69.94
QB + SP	93.49	90.36	89.52	88.96	79.81

mAP for each method and dataset

Ref:
[39] O. Chum, A. Mikulik, M. Perdoch, and J. Matas, “Total recall II: Query expansion revisited,” CVPR, pp.889–896, 2011.

4.2 Contributions comparison

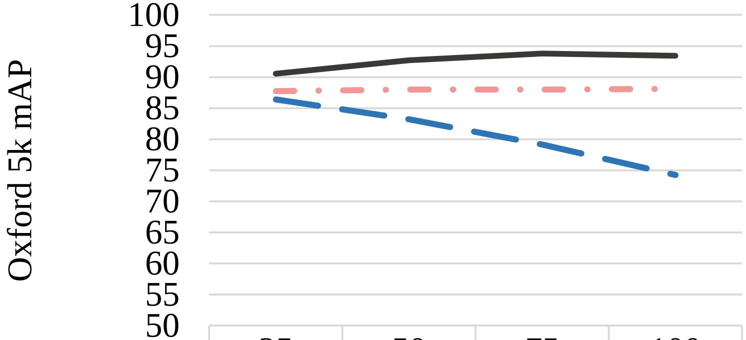
- Notation of our proposed methods
  - QB = (QB + ASUP)
  - QB + SP = (QB + ASUP) + (SP + ADINT)



	Ox 5k	Ox 105k	Paris 6k
QB + FSUP	83.52	74.43	84.77
QB + ASUP	86.41	75.67	88.28
QB + ASUP + SP + FINT	92.48	89.31	87.76
QB + ASUP + SP + ADINT	93.49	90.36	88.96

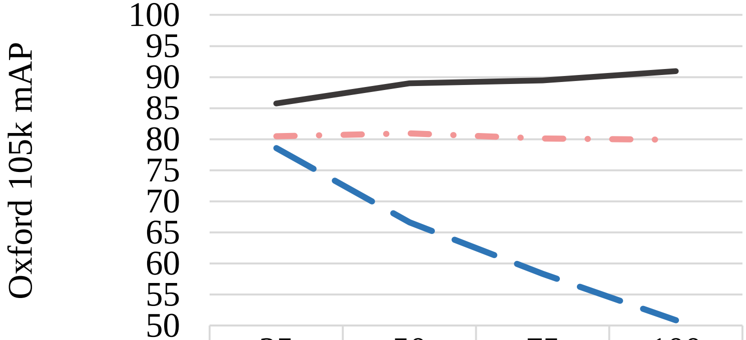
The performance comparison between our contributions

4.3 Impact of Top-k relevant images



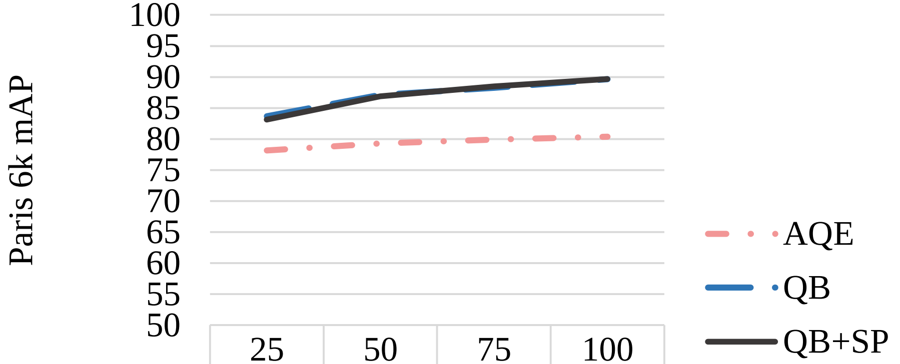
	25	50	75	100
AQE	87.73	88.01	87.99	88.11
QB	86.41	83.20	79.12	74.23
QB+SP	90.54	92.71	93.81	93.43

top-k



	25	50	75	100
AQE	80.50	80.92	80.13	79.93
QB	78.55	66.62	58.32	50.87
QB+SP	85.77	88.98	89.47	90.95

top-k



	25	50	75	100
AQE	78.16	79.31	79.89	80.38
QB	83.66	87.13	88.28	89.62
QB+SP	83.14	86.89	88.47	89.67

top-k

mAP vs. total number of retrieved images

Result:

- Higher top-k is good for spatial verification based methods.
  - Some relevant images can be found in lower ranked images.
  - AQE, QB + SP
- Higher top-k is bad for greedy methods.
  - Too many irrelevant images were added during aggregation.
  - QE, QB

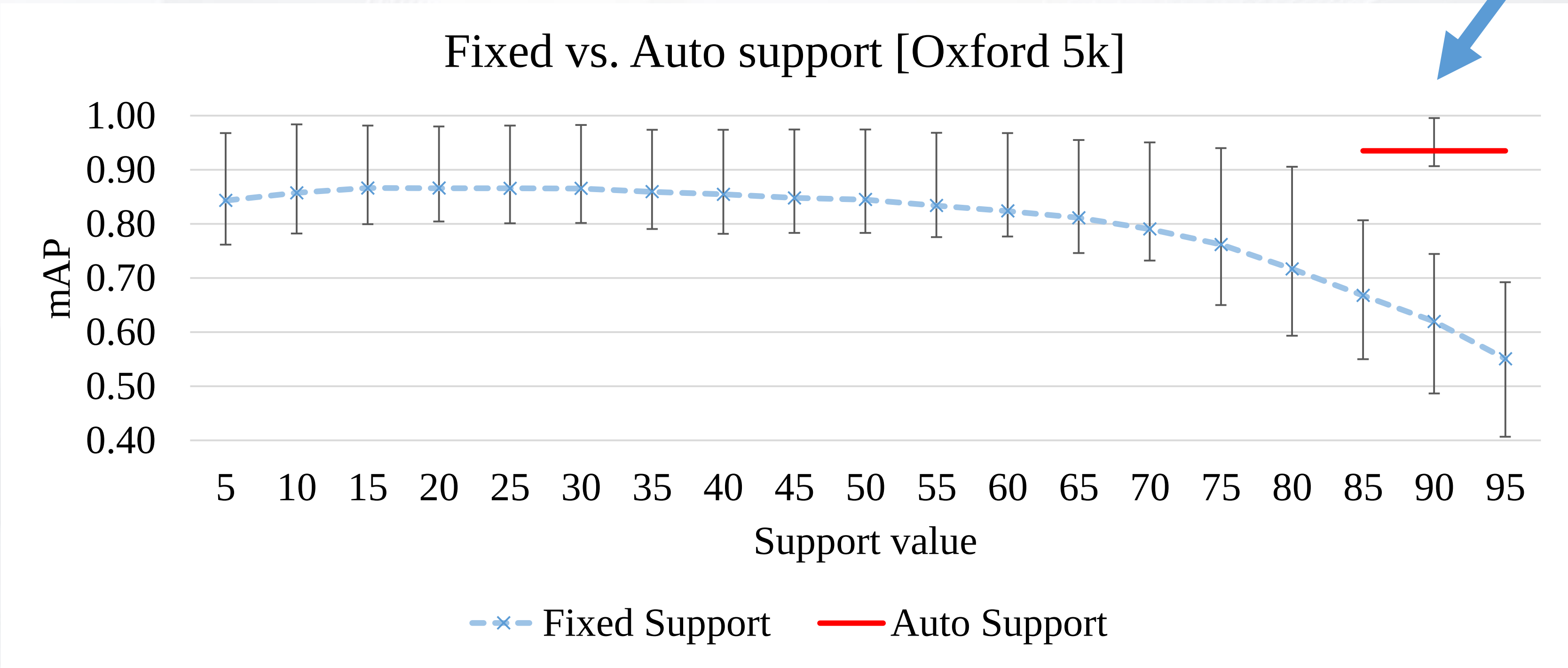
Why QE/QB did not fail on Paris6k?

Because of the number of true positive images.
Paris6k has avg.~163 (51-289) positive images.
Oxford has avg.~51 (6-221) positive images.

4.4.1 Adaptive support (ASUP)

- Experiment for FIM based methods (run with QB + SP)
- Comparison of
  - mAP of a **fixed minimum support** of 5 to 95
  - and **adaptive support** (ASUP)

-- Best performance –
Achieved by ***ASUP***,
which also has much lower variances.



4.4.2 Adaptive inlier threshold (ADINT)

- Experiment for **AQE, QB + SP**
- Comparison on mAP of
  - **Fixed inlier threshold** (FINT) of 3, 5, 7, 9, 11 and
  - **Adaptive inlier threshold** (ADINT) or **A**

$\boxed{\Delta(\text{min}, \mathbf{A})}$ is

how much **ADINT** better than a minimum of FINT.

$\boxed{\Delta(\text{max}, \mathbf{A})}$ is

how much **ADINT** better than a maximum of FINT.

Inlier Threshold	AQE (mAP %)			QB + SP (mAP %)		
	Ox5k	Ox105k	Paris6k	Ox5k	Ox105k	Paris6k
3	88.11	79.69	80.44	74.39	50.95	89.66
5	88.60	80.72	80.13	85.47	68.44	89.32
7	87.87	81.86	79.19	92.48	89.31	87.76
9	87.32	81.15	78.87	91.64	88.28	86.62
11	87.13	80.85	78.70	90.77	87.56	85.88
A	**87.88**	**81.85**	**78.70**	**93.49**	**90.36**	**88.96**
Δ(min, **A**)	0.75	2.16	0.00	19.10	39.41	3.08
Δ(max, **A**)	-0.72	-0.01	-1.74	1.01	1.05	-0.70

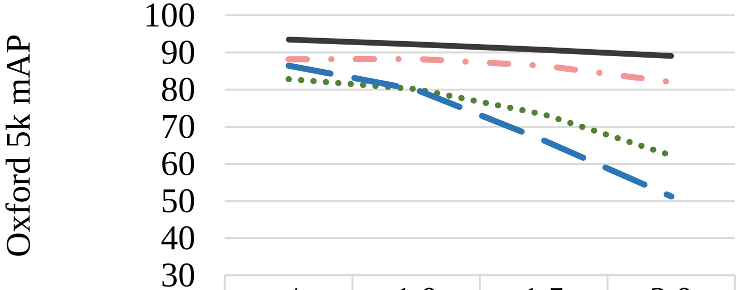
ADINT vs. FINT performance

Result:

- ADINT better than FINT in most cases of QB + SP.
- ADINT does not improve much on AQE, but at least it's automated!!

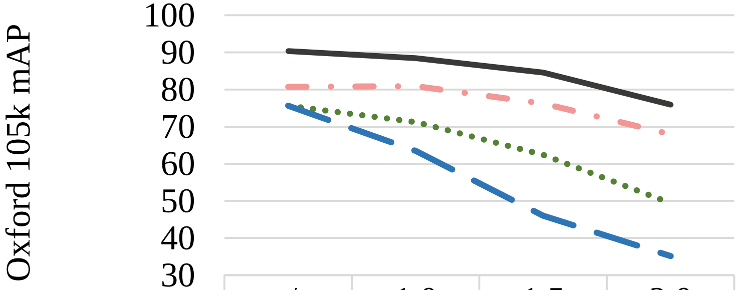
4.5 Impact of a noisy query

Sample query image with noise @sigma = 2.0



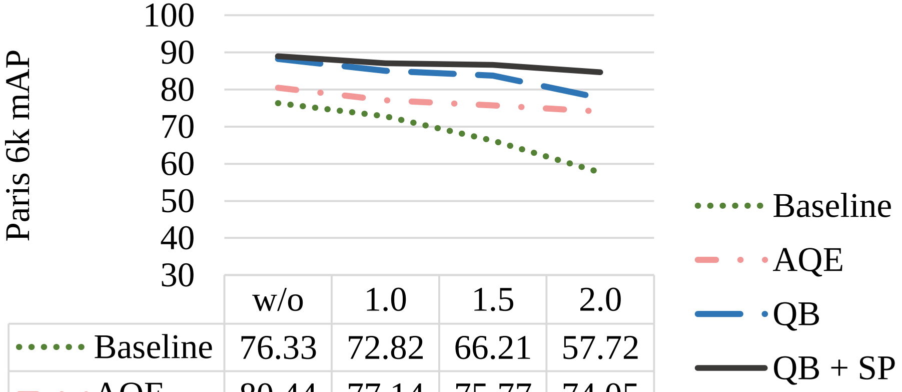
	w/o	1.0	1.5	2.0
Baseline	82.84	80.17	73.32	62.28
AQE	88.12	88.24	86.43	82.02
QB	86.41	79.94	66.29	51.18
QB + SP	93.49	92.15	90.71	89.03

Gaussian sigma (σ)



	w/o	1.0	1.5	2.0
Baseline	75.66	71.25	62.45	49.36
AQE	80.71	80.92	76.25	67.92
QB	75.67	63.49	46.02	35.18
QB + SP	90.36	88.48	84.60	75.92

Gaussian sigma (σ)



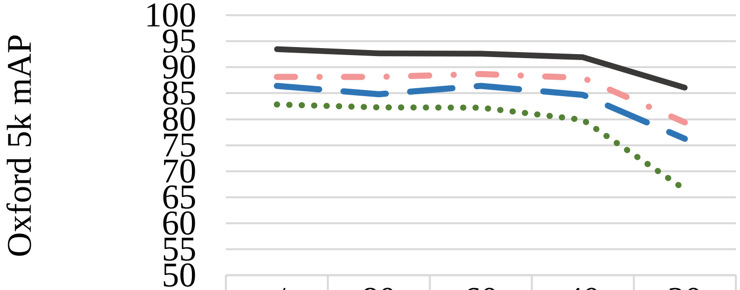
	w/o	1.0	1.5	2.0
Baseline	76.33	72.82	66.21	57.72
AQE	80.44	77.14	75.77	74.05
QB	88.28	85.01	83.77	77.70
QB + SP	88.96	87.11	86.61	84.64

Gaussian sigma (σ)

mAP vs. noise level

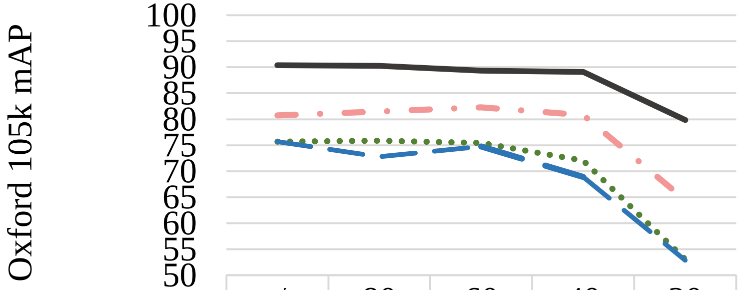
4.5 Impact of a low resolution query

Sample query image with scale of 20% of original



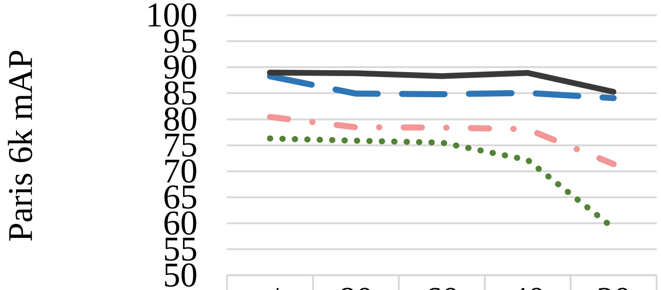
	w/o	80	60	40	20
Baseline	82.84	82.29	82.25	79.89	66.47
AQE	88.12	88.14	88.70	87.93	79.37
QB	86.41	84.78	86.39	84.69	76.22
QB + SP	93.49	92.68	92.58	91.92	86.07

Query scale (%)



	w/o	80	60	40	20
Baseline	75.66	75.85	75.45	72.04	53.07
AQE	80.71	81.51	82.28	80.80	64.46
QB	75.67	72.77	74.74	68.93	52.86
QB + SP	90.36	90.28	89.31	89.12	79.82

Query scale (%)



	w/o	80	60	40	20
Baseline	76.33	75.90	75.47	72.17	59.05
AQE	80.44	78.46	78.38	78.09	71.40
QB	88.28	84.91	84.81	85.04	84.05
QB + SP	88.96	88.84	88.31	88.93	85.29

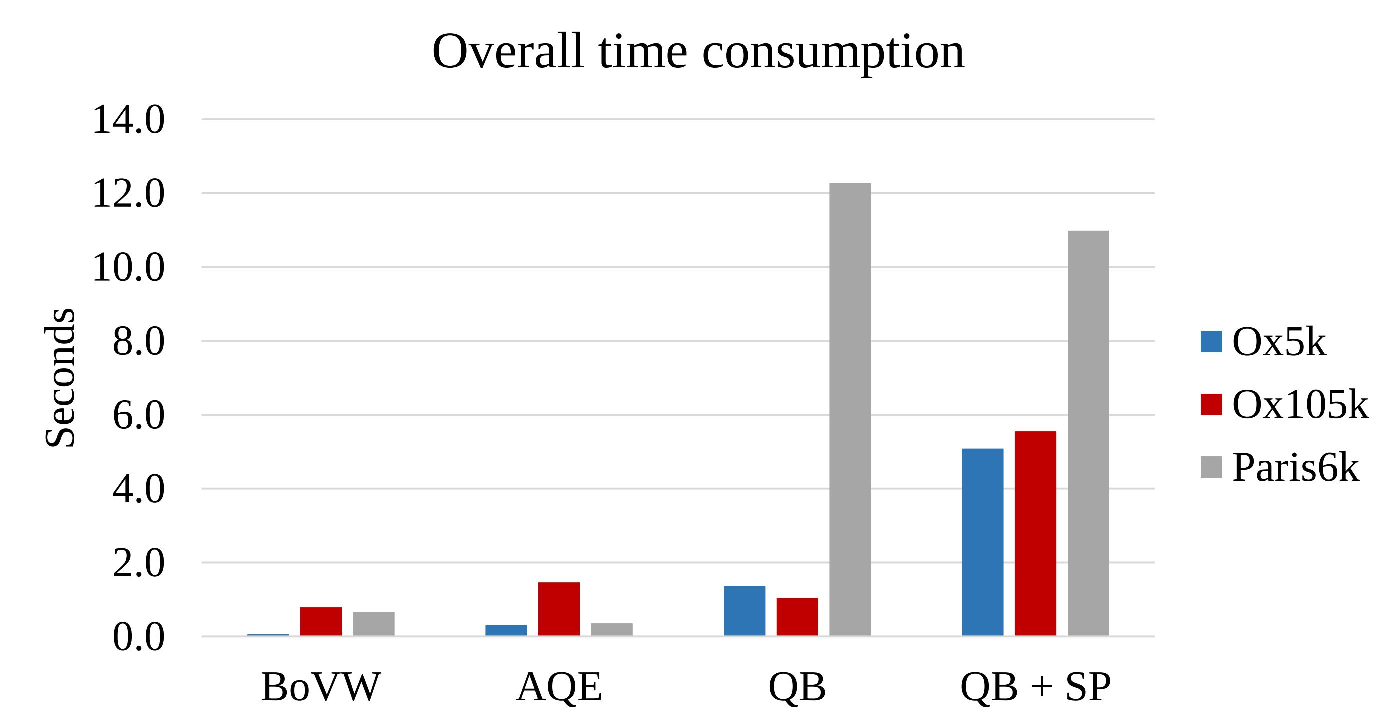
Query scale (%)

Baseline
AQE
QB
QB + SP

mAP vs. image scale

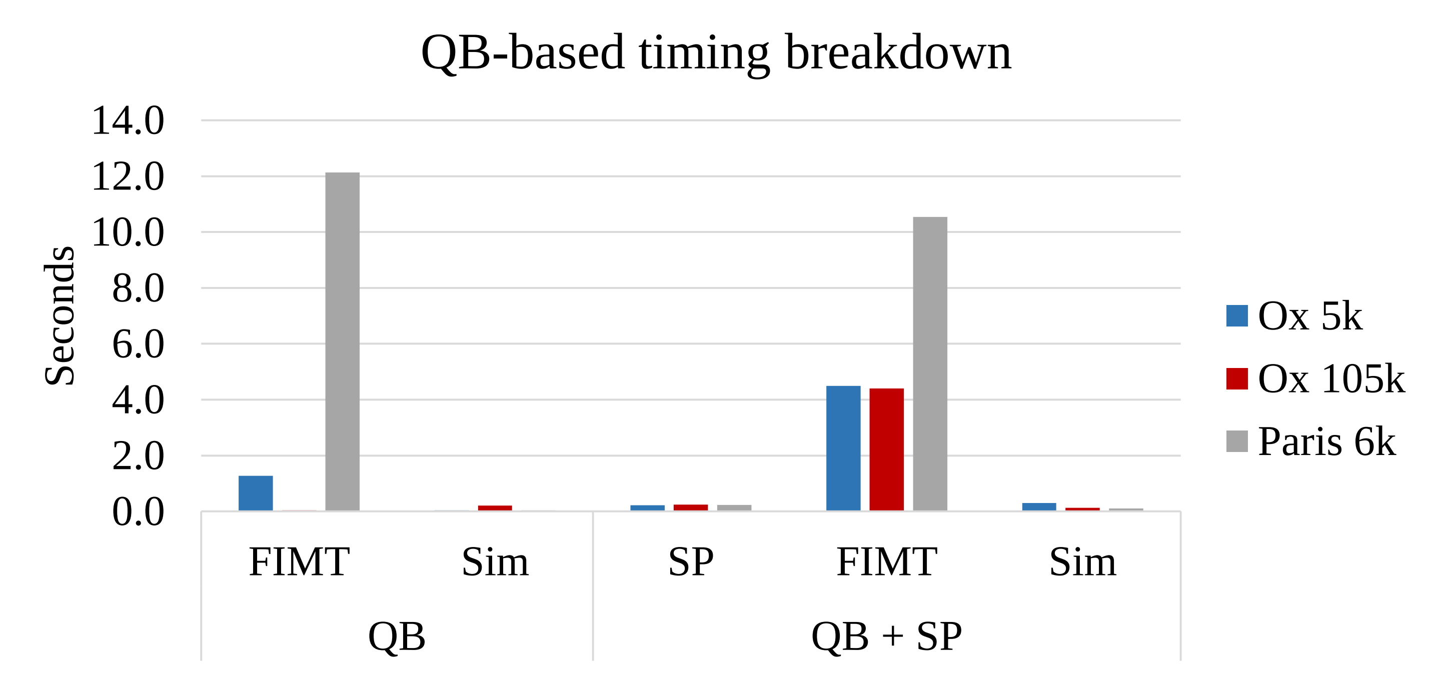
4.6 Time consumption

- **Overall time consumption**
  - Fast with BoVW, and AQE
  - Slow with QB, and QB + SP

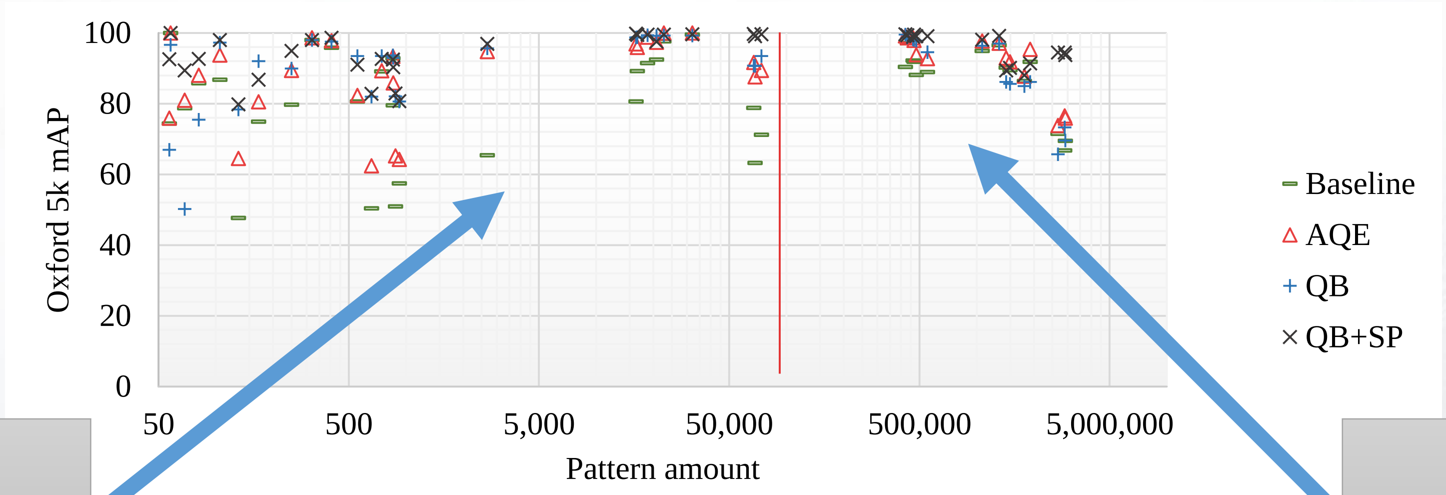


4.6 Time consumption - breakdown

- FIM-based methods are **QB** and **QB + SP**
- **Result:**
  - FIM is the most slowest part, why?



4.6.1 Colossal pattern[1]



Lower number of pattern
BoVW not really good
our QB + SP gives it *big improvement*
Query class: **Easy** (to be improved)

Higher number of pattern
BoVW already good
our QB + SP gives a *small improvement*
Query class: **Hard** (to be improved)

	Type	#Topics	BoVW	QB				QB+SP			
				FIM^T(s)	Precision(%)			FIM^T(s)	Precision(%)		
			mAP(%)		mAP(%)	SD(±%)	mAP+(%)		mAP(%)	SD(±%)	mAP+(%)
Ox 5k	Easy	40	81.26	0.075	85.51	21.02	4.25	0.166	92.69	14.25	**11.43**
	Hard	15	87.06	4.471	88.79	10.97	1.72	16.037	95.64	4.07	**8.58**
Ox 105k	Easy	40	73.94	0.011	73.99	29.94	0.05	0.066	90.77	15.95	**16.83**
	Hard	15	80.24	0.109	80.13	13.81	-0.11	15.949	89.28	9.19	**9.04**
Paris 6k	Easy	25	71.09	0.922	86.53	9.23	**15.44**	0.363	86.17	9.39	15.08
	Hard	30	80.69	21.475	89.74	15.37	9.05	19.030	91.28	12.28	**10.59**

QB + SP improve "**Easy**" query very well.
And FIMT time usage on "**Easy**" is not much.

Ref:
[1] F. Zhu, X. Yan, J. Han, P.S. Yu, and H. Cheng, "Mining colossal frequent patterns by core pattern fusion," ICDE, pp.706–715, 2007.

4.7 Result

(a) Query (b) BoVW results.

(c) AQE results.

(d) QB + SP results.

BoVW
Baseline

AQE
More relevant
to query ROI

QB + SP
Relevant to
each others

4.7 Result

BoVW
Baseline

AQE
More relevant
to query ROI

QB + SP
Relevant to
each others

Overview

1. Introduction

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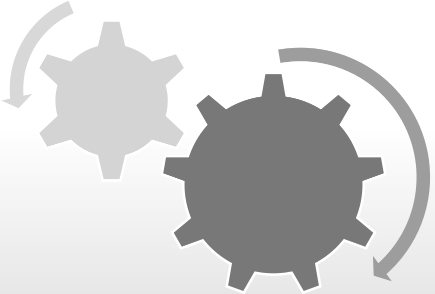
- Baseline problem

2. Contributions list

- Visual word mining
- Spatial verification
- Automatic parameter tuning

3. Proposed methods



4. Experimental results

- Overall
- Robustness
- Time consumption

5. Conclusion

- Research achievements
- Pros and Cons
- Limitation

6. Future work

- Speed up
- Binary feature

5. Conclusion

- ***We proposed***
  - "Query Bootstrapping (QB)" as visual mining technique for query expansion.
  - The way to integrate "Spatial Verification (SP)" for such mining.
- ***The important parameters are automatically determined.***
  - Adaptive support (ASUP) for FIM.
  - Adaptive inlier threshold (ADINT) for LO-RANSAC.
- ***Achievements***
  - Our methods reach the highest performance on all datasets.
  - Very high robustness on difficult cases of query quality are proved.

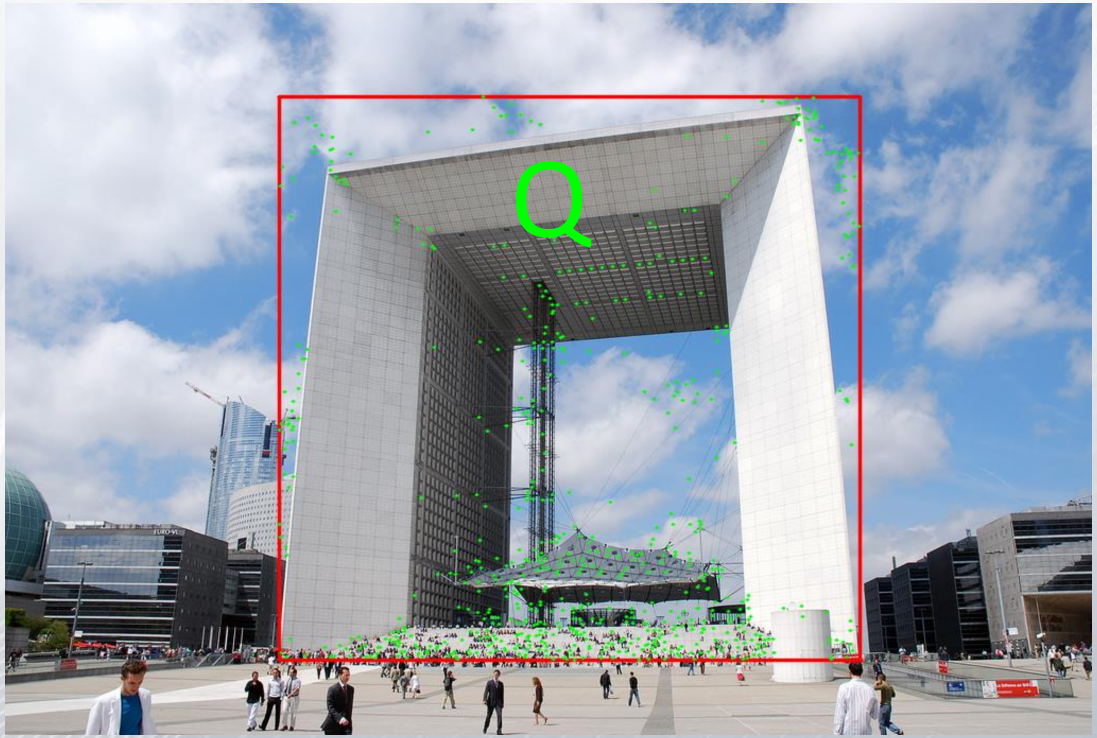
5.1 Benefits of using QB

- ***To help understand more on the target object and its context.***
  - Context can also be learned.
  - Hidden visual words from other view angles can be learned.
- ***QB can be used to reject irrelevant visual words.***
  - Object occlusions.
  - Misleading visual words.
  - Not useful visual words, not clearly related to the object.

5.1.1 Context discovery example (1)

Notation:
Query = Q =
Context = C =

- Query topic: defense_2

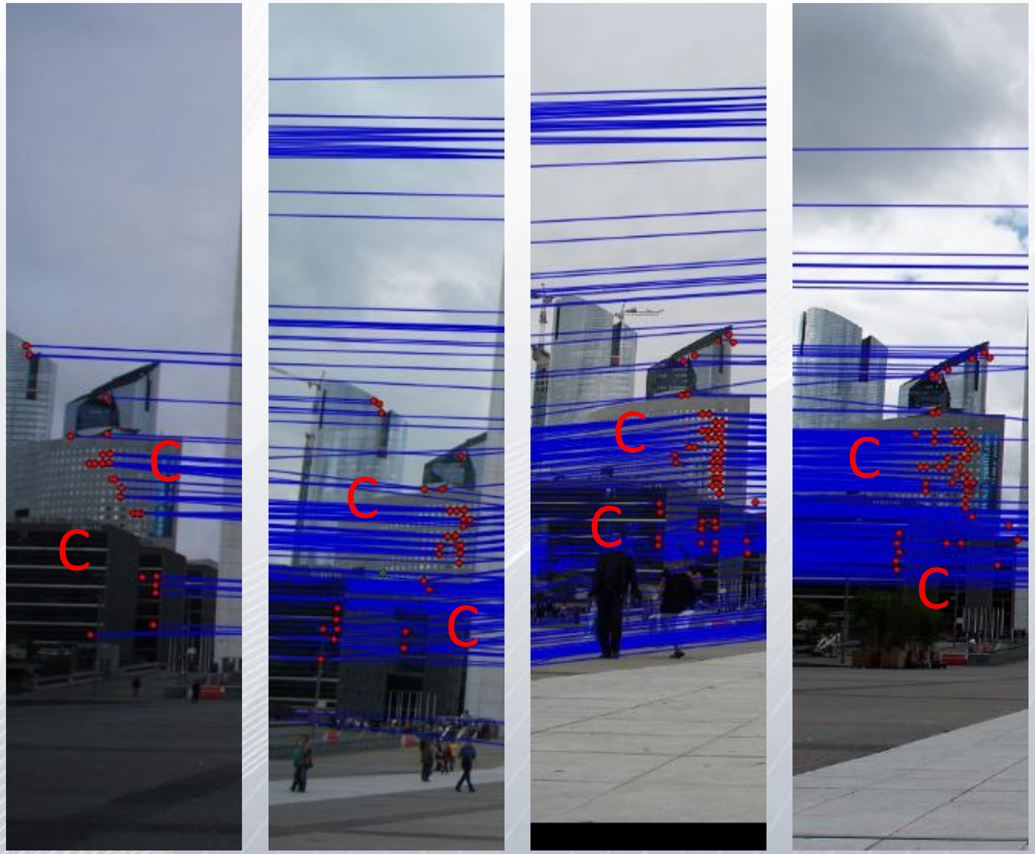


5.1.1 Context discovery example (2)

- Co-occurrences between top-1 and top-2

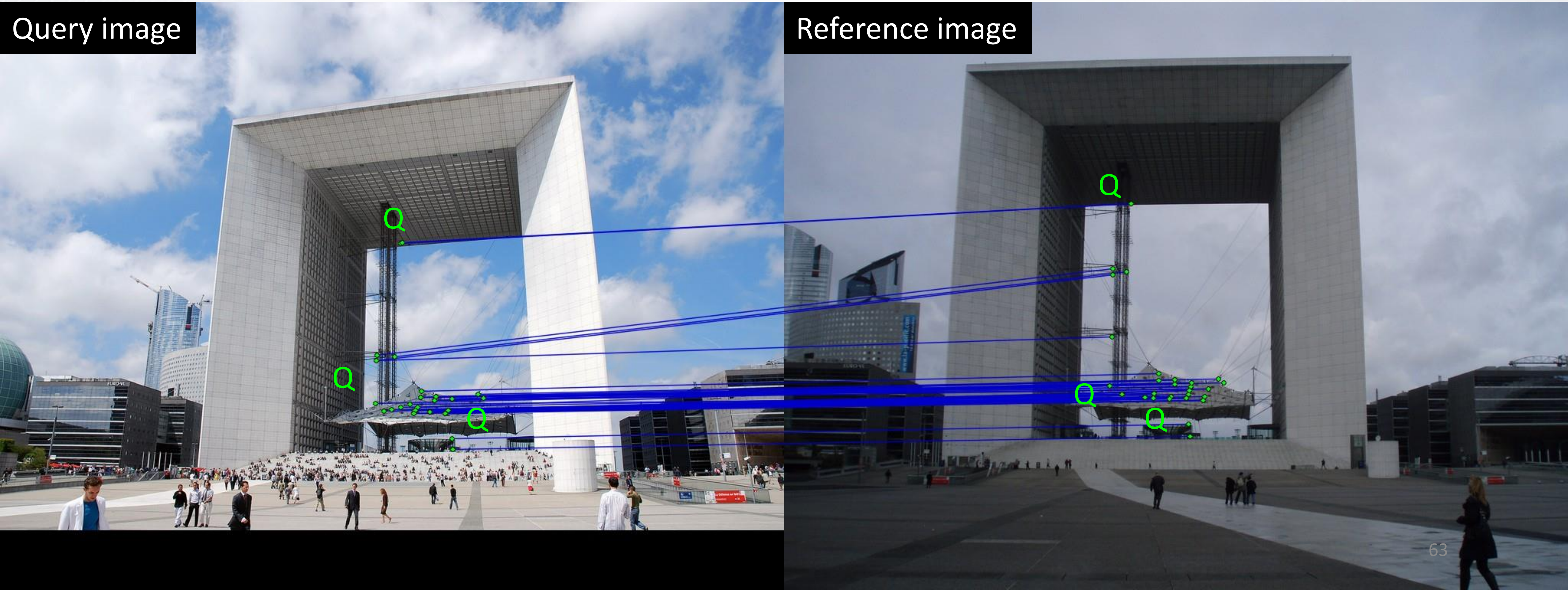
5.1.1 Context discovery example (3)

- Learned object contexts that help describing a target object.



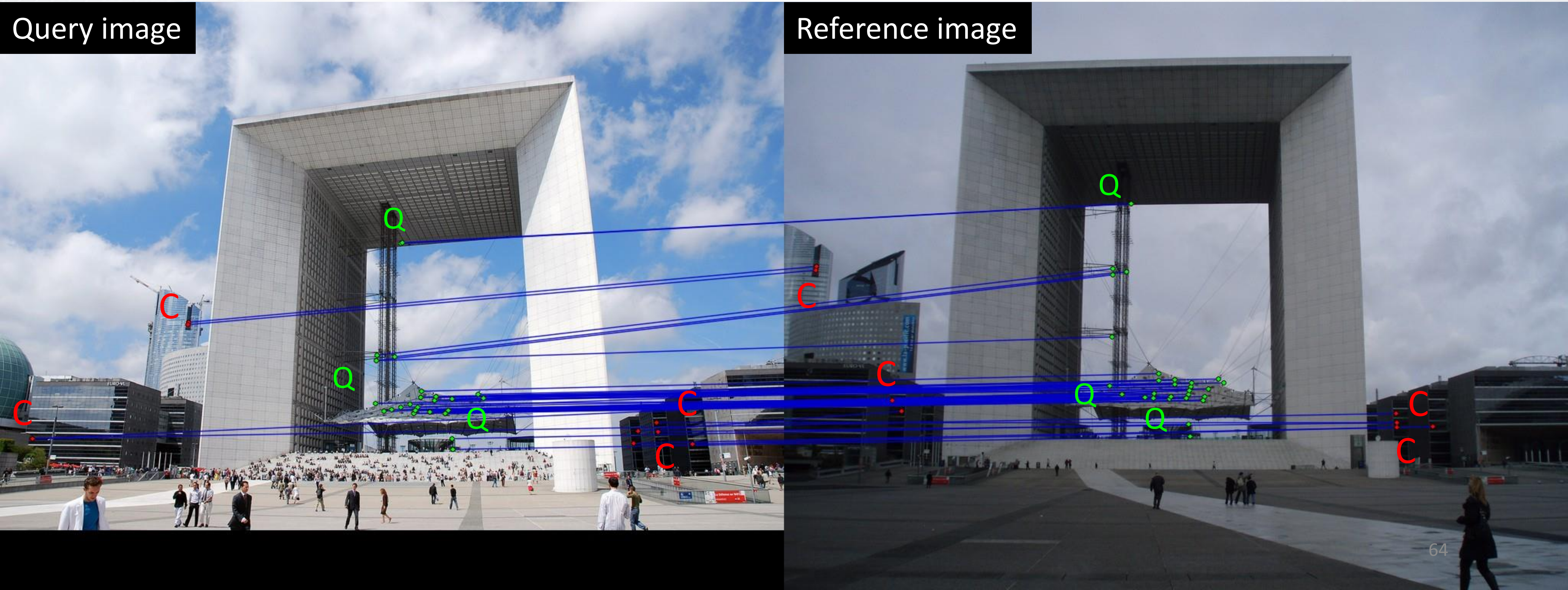
5.1.1 Context discovery example (4)

- ***AQE*** result of “defense_2” on Paris 1M, AP = **27.04%**



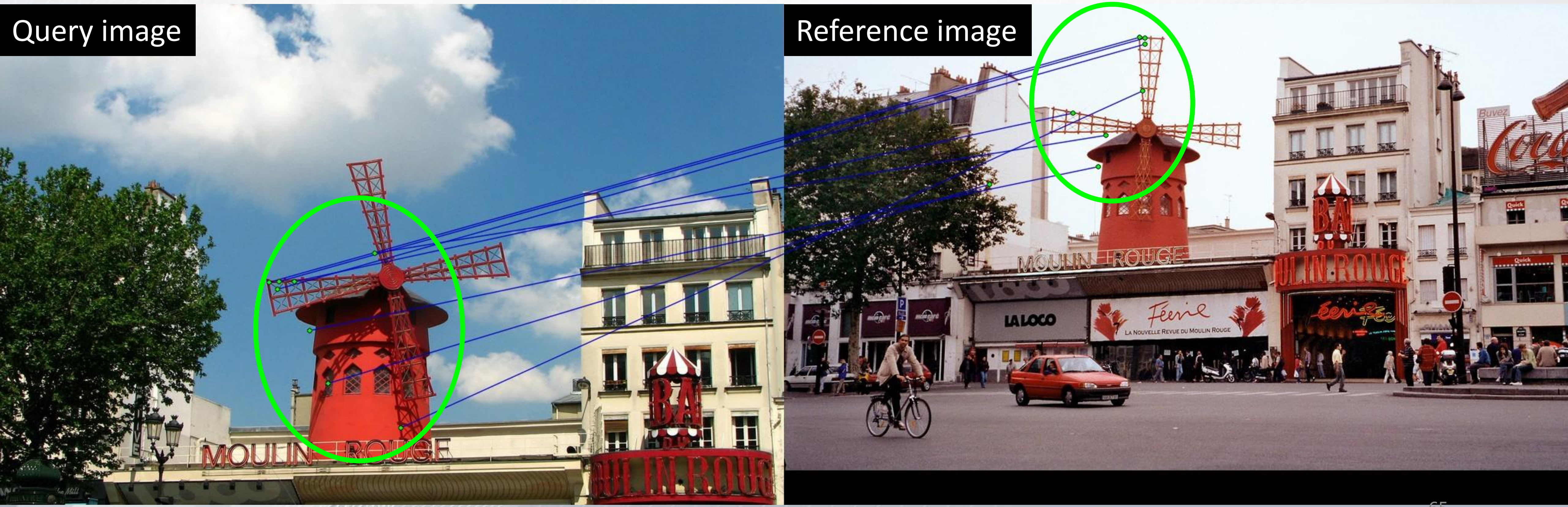
5.1.1 Context discovery example (5)

- ***QB*** result of "defense_2" on Paris 1M, AP = **71.35%**



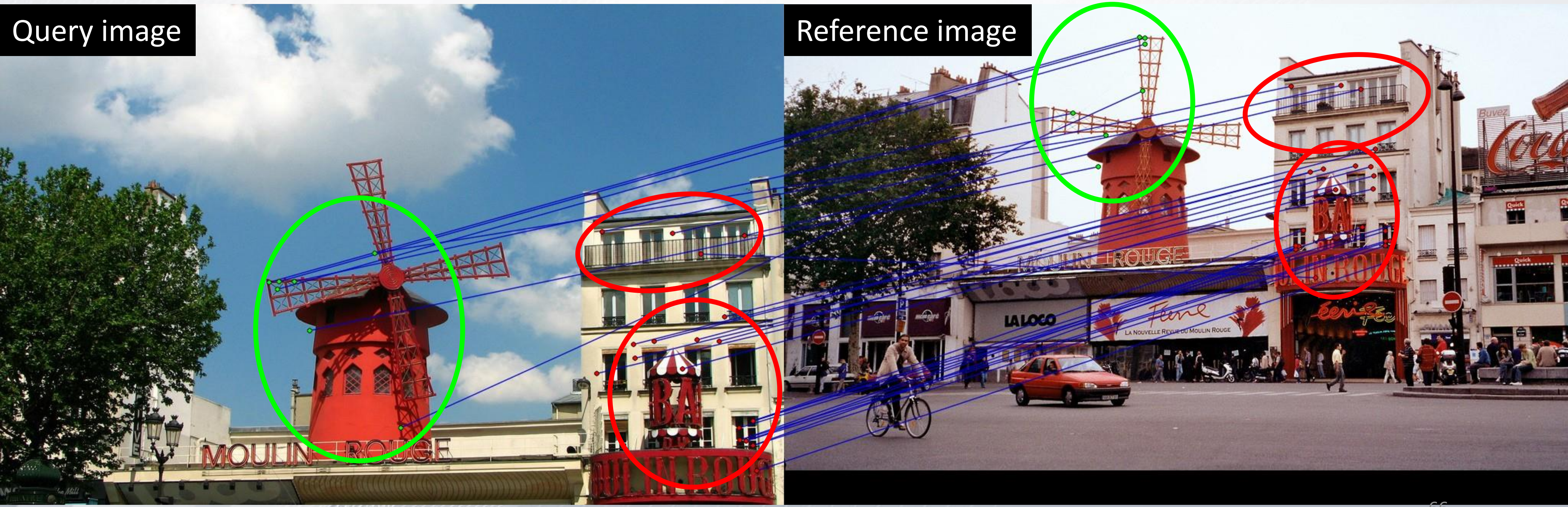
5.1.1 Context discovery example (6)

- ***AQE*** result of "moulinrouge_1" on Paris 1M, AP = **28.86%**



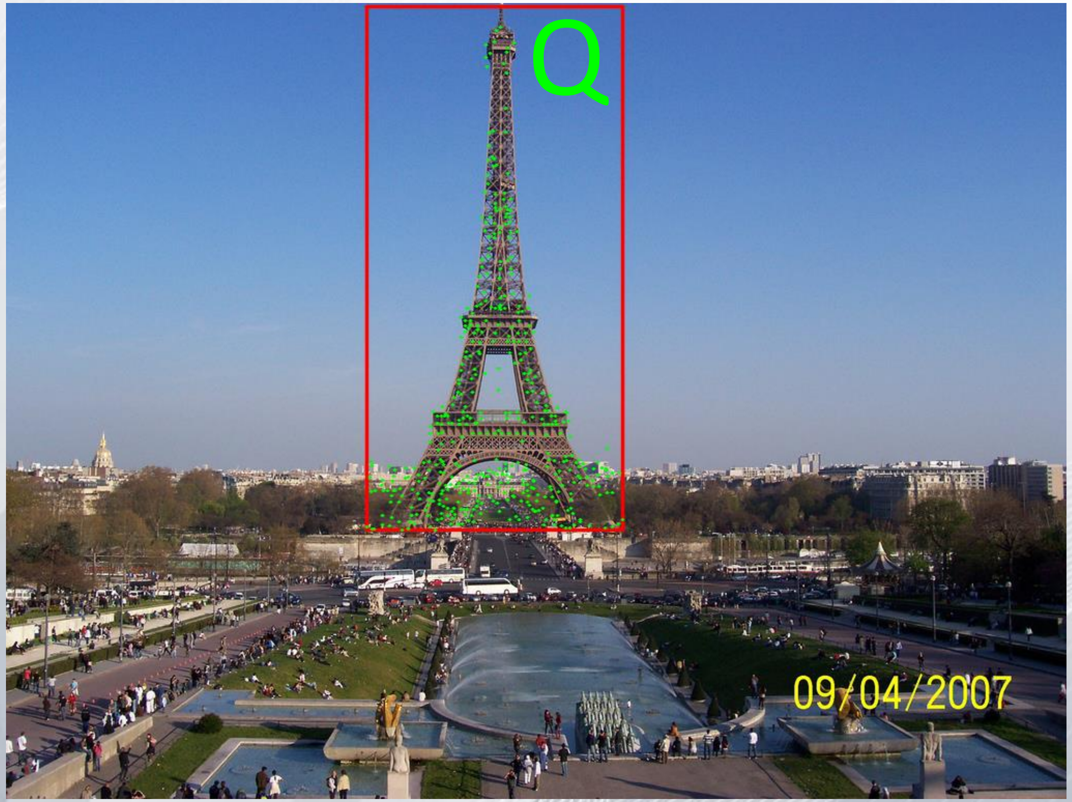
5.1.1 Context discovery example (7)

- ***QB*** result of “moulinrouge_1” on Paris 1M, AP = **83.52%**

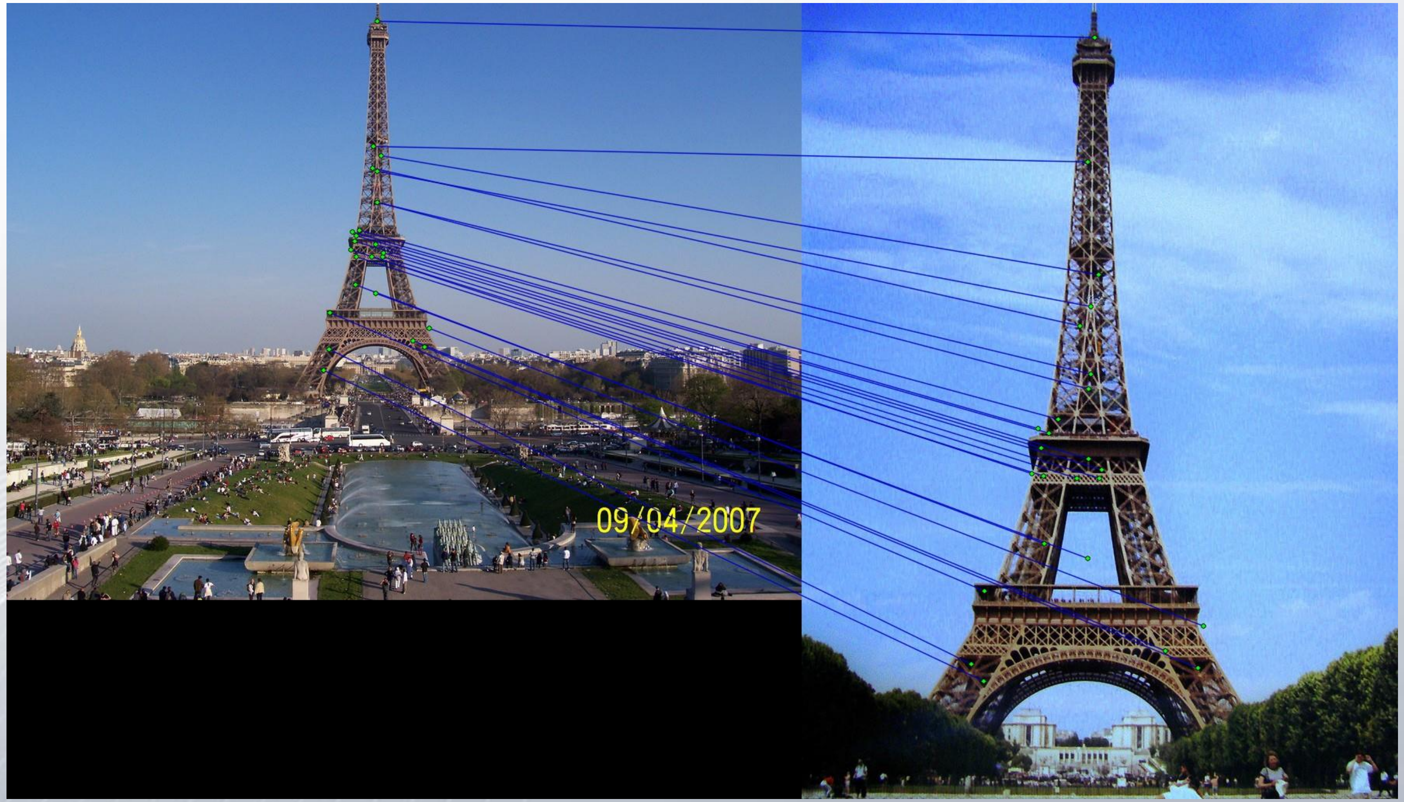


5.1.2 Hidden visual words discovery (1)

- One query image may have limited visual contents



Query topic: eiffel_3

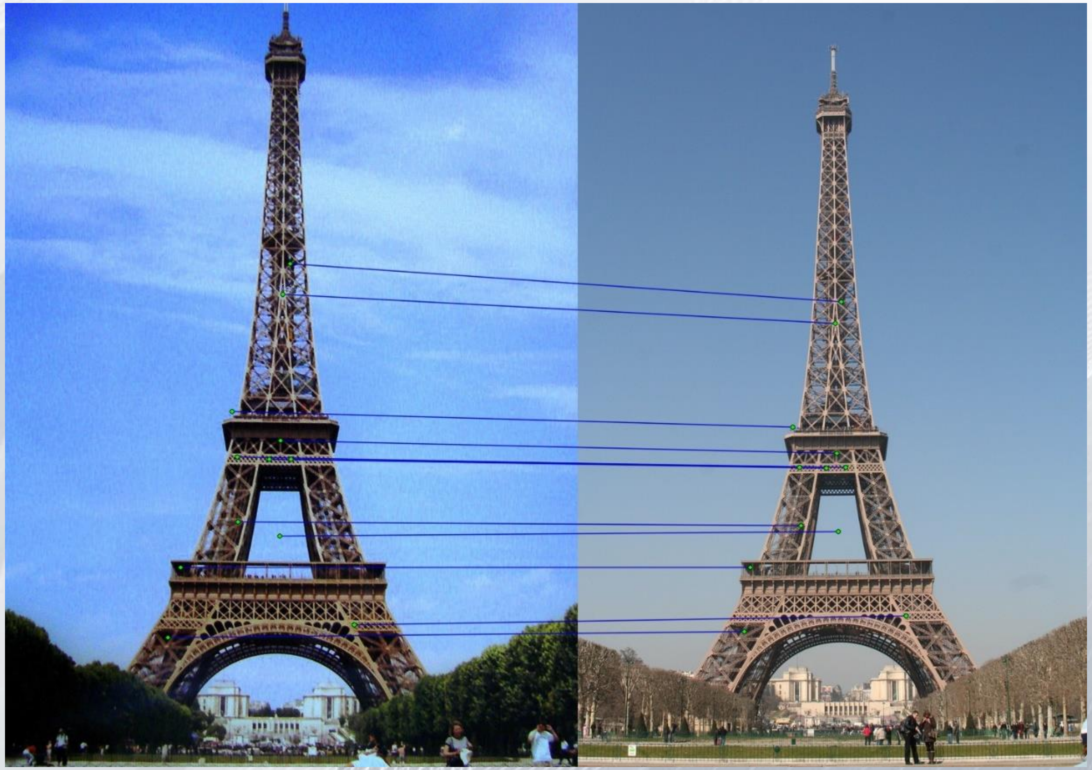


Matching result can be a few

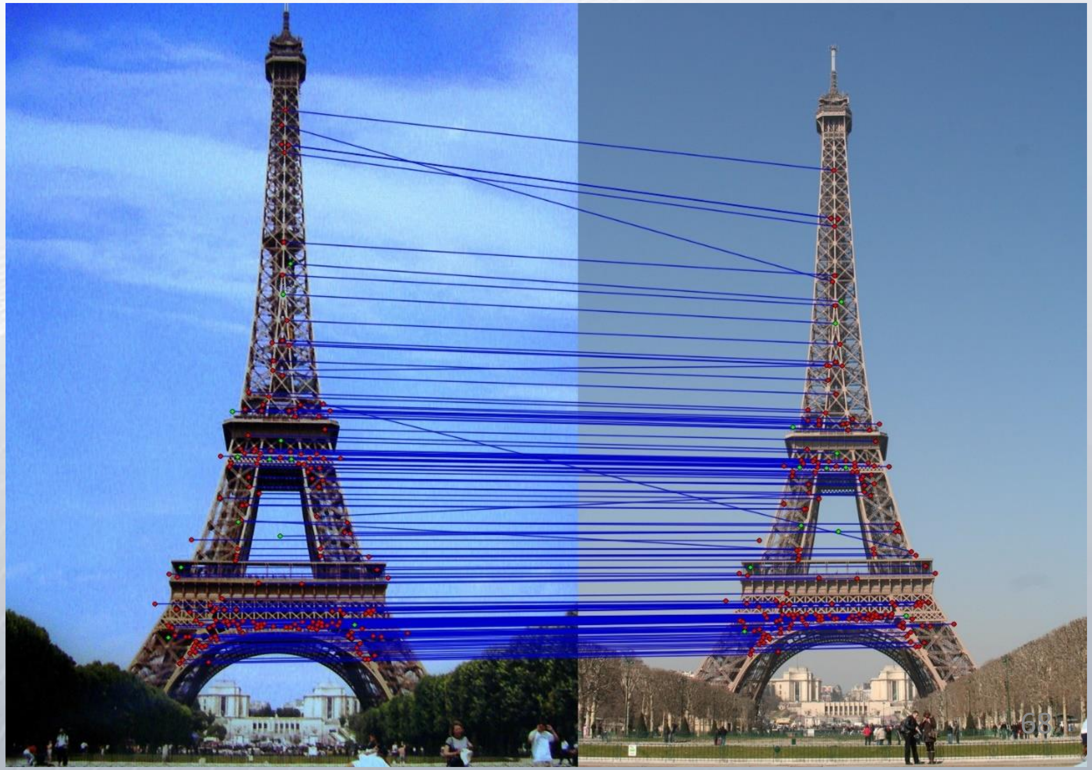
5.1.2 Hidden visual words discovery (2)

- ***QB*** finds hidden visual words within the target object
  - Using relevance images.

AQE

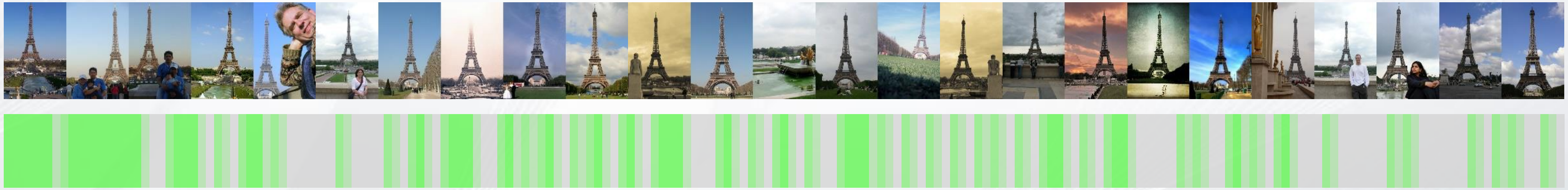


QB

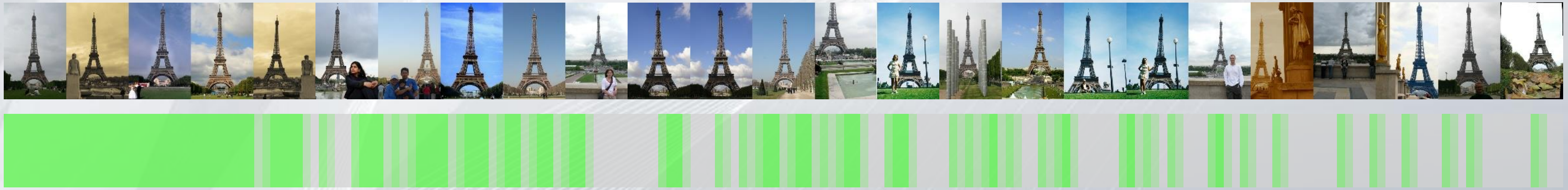


5.1.2 Hidden visual words discovery (3)

- ***AQE*** Result (AP 23.67%)

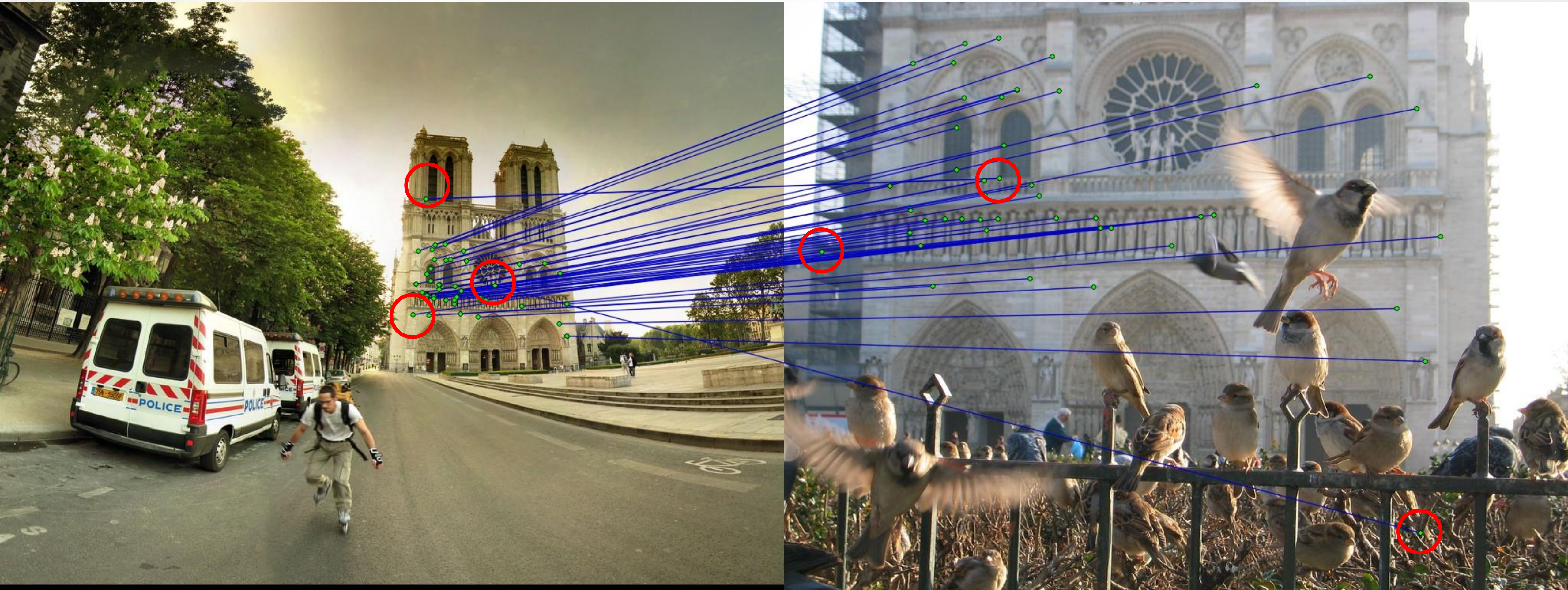


- ***QB*** Result (AP 44.77%)



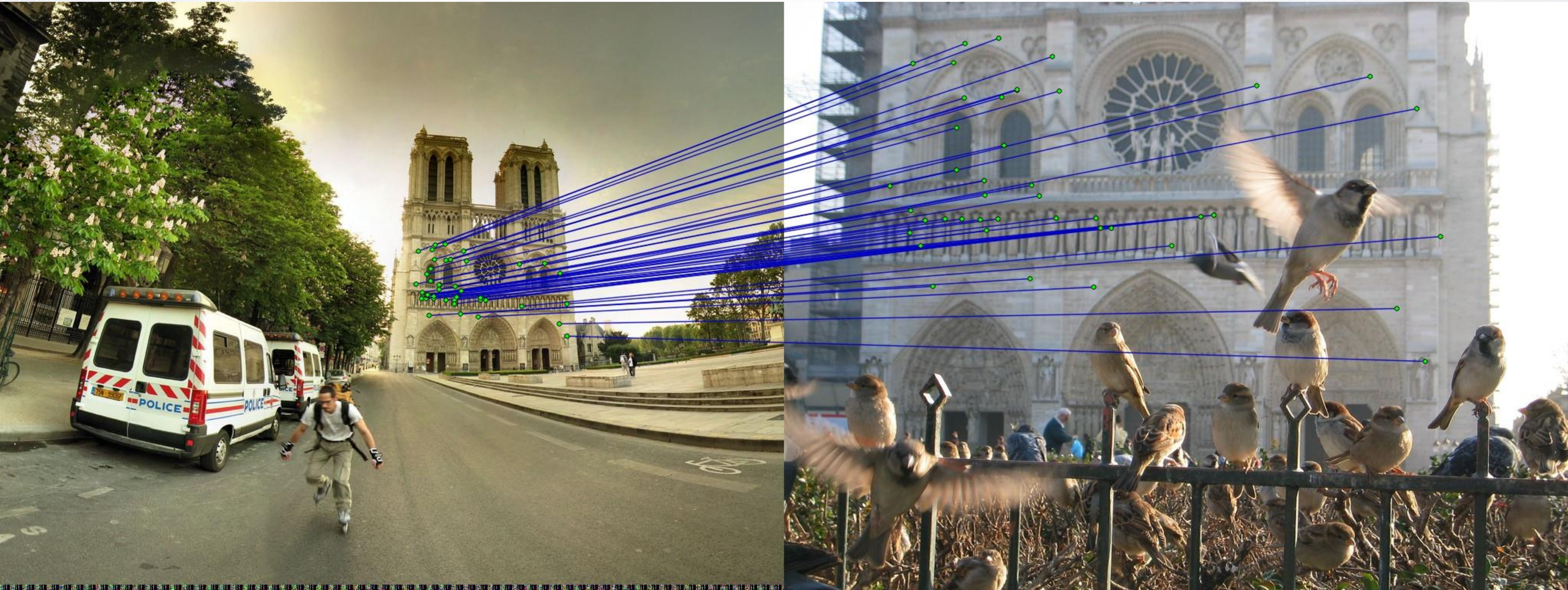
5.1.3 Irrelevant visual word identification (1)

- Misleading visual words in ***AQE*** matching.



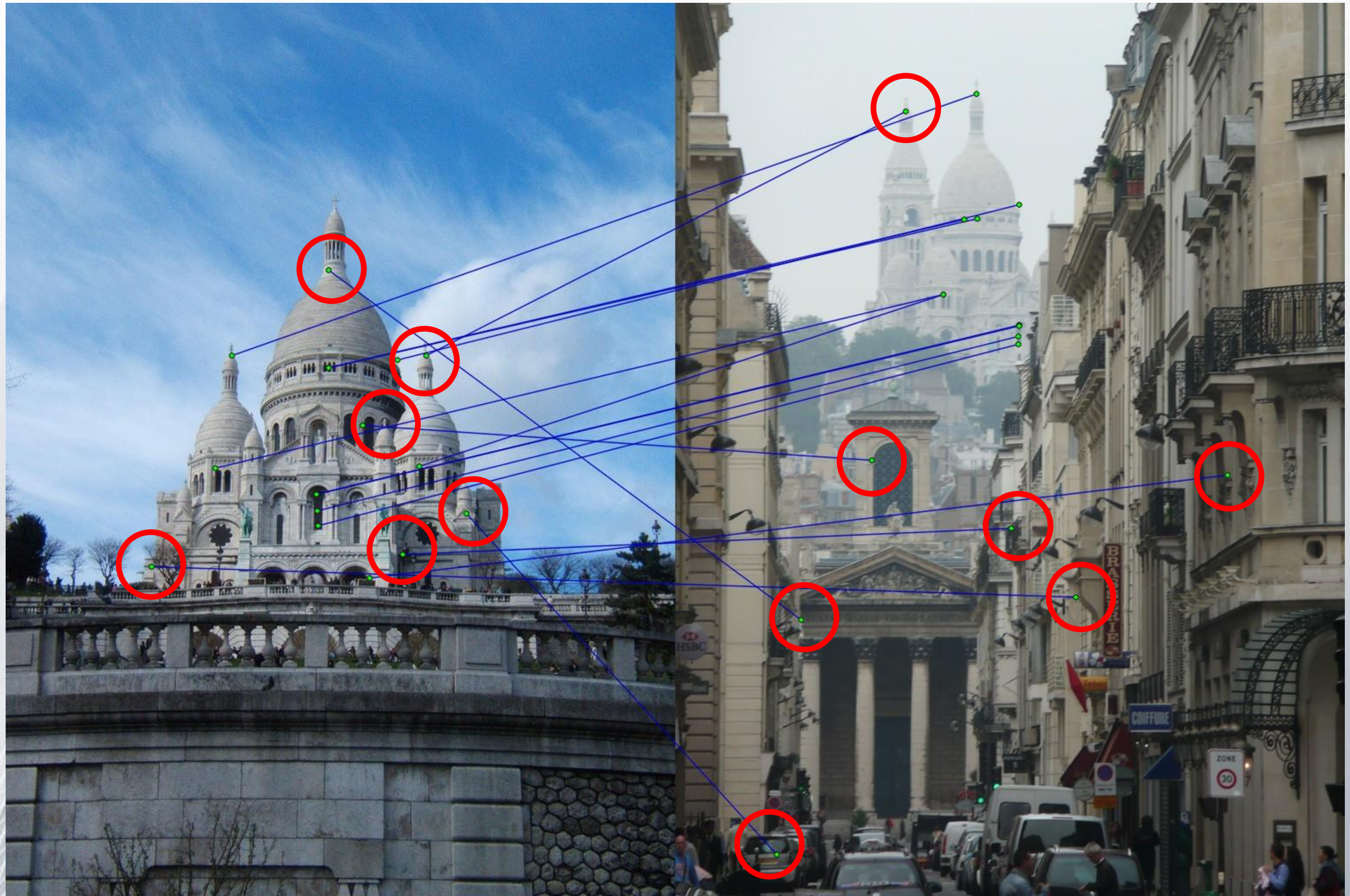
5.1.3 Irrelevant visual word identification (2)

- ***QB*** can identify and reject those visual words.



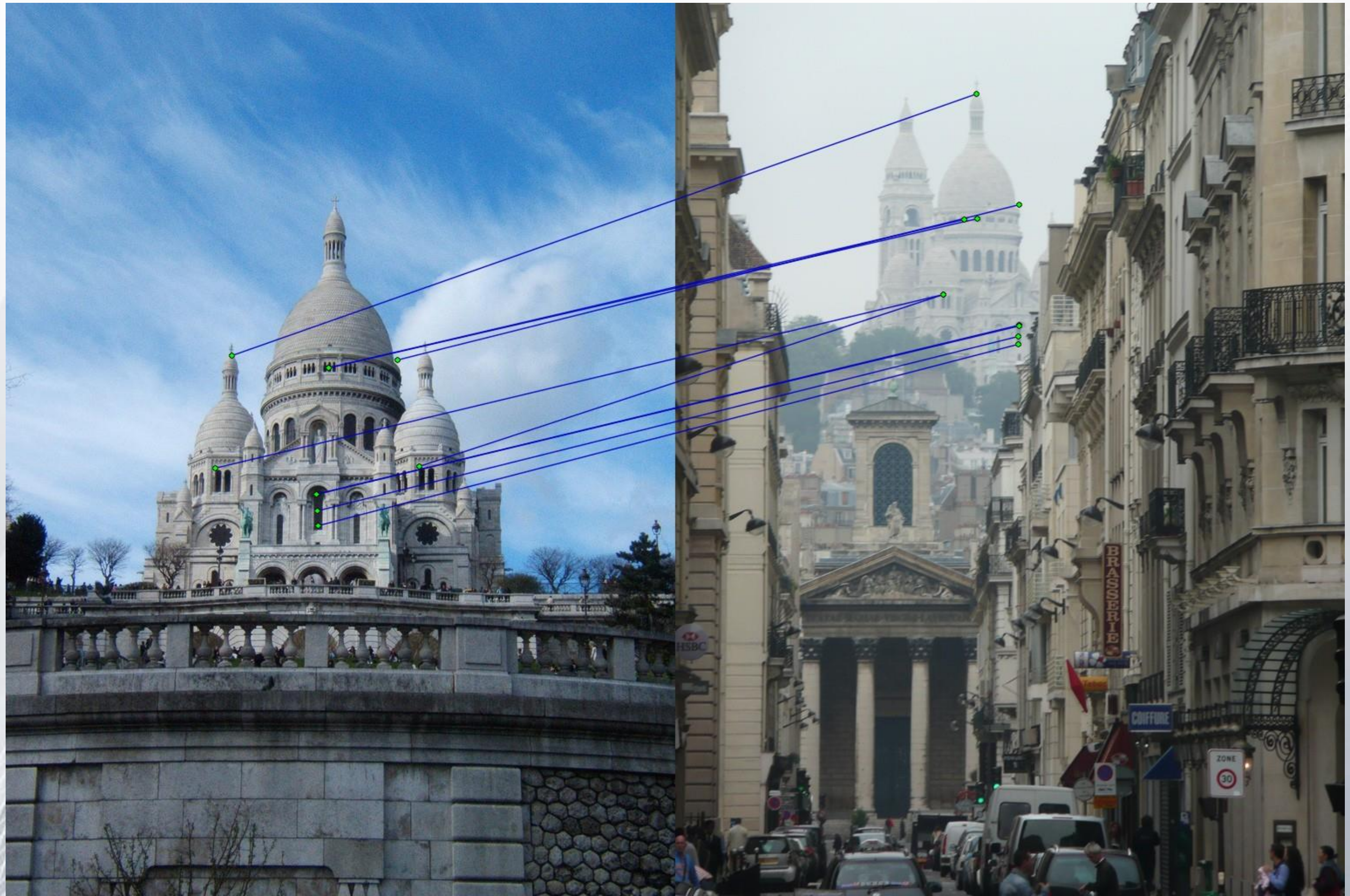
5.1.3 Irrelevant visual word identification (3)

- Misleading visual words in ***AQE*** matching.



5.1.3 Irrelevant visual word identification (4)

- ***QB*** can identify and reject those visual words.

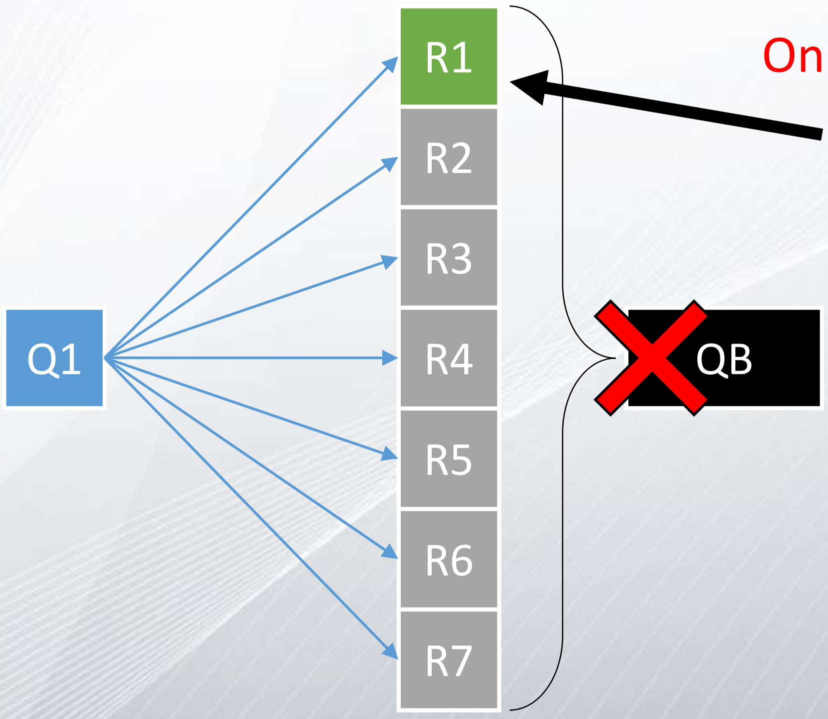


5.2 QB limitations

- Experiments with the other datasets
  - Mobile visual search
  - Instance Search
- Target dataset characteristics
- Weakness summarization

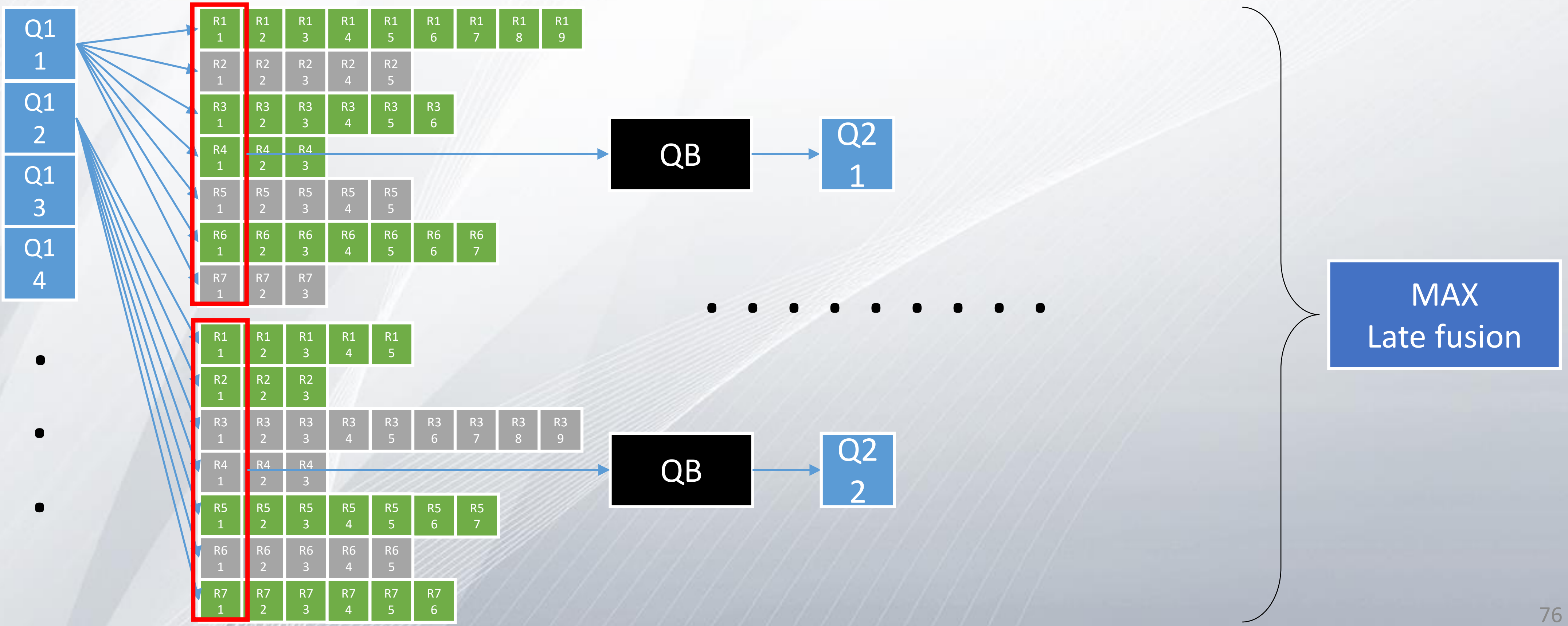
5.2.1 Experiments with the other datasets (1)

- **Stanford Mobile Visual Search**
  - Book covers
  - Business cards
  - CD covers
  - DVD covers
  - Landmarks
  - Museum paintings
  - Prints
  - Video frames



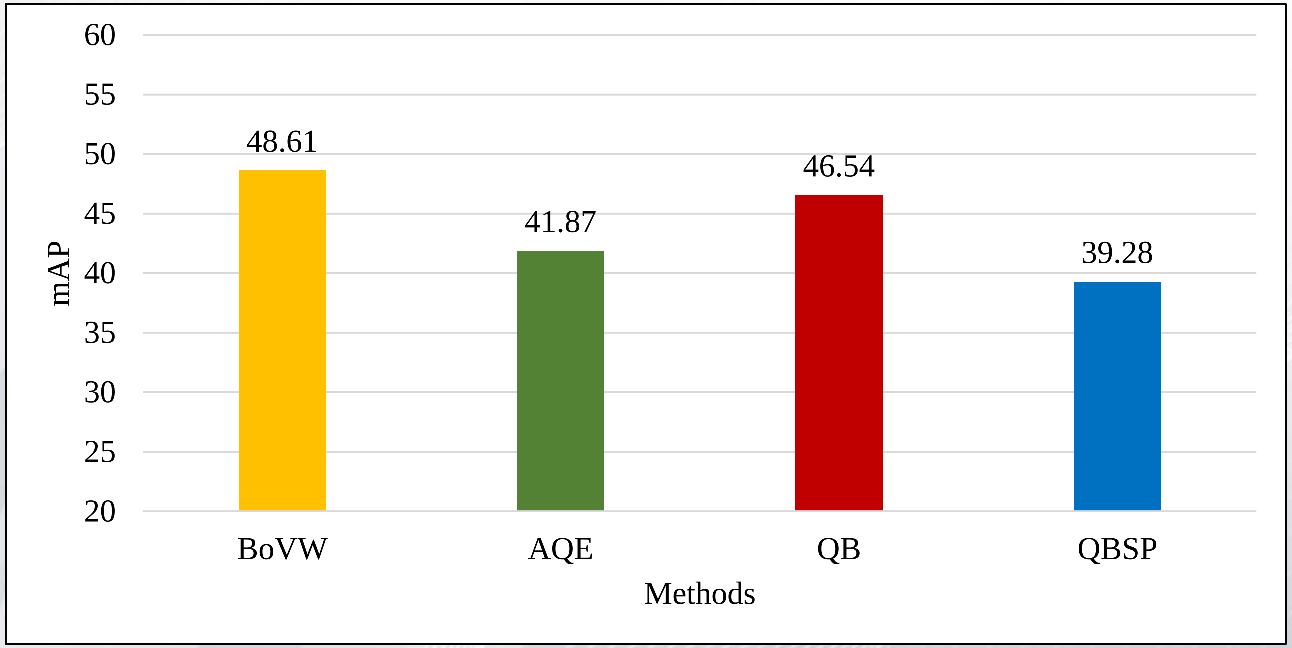
5.2.1 Experiments with the other datasets (2)

- **Instance Search 2011, 2013**

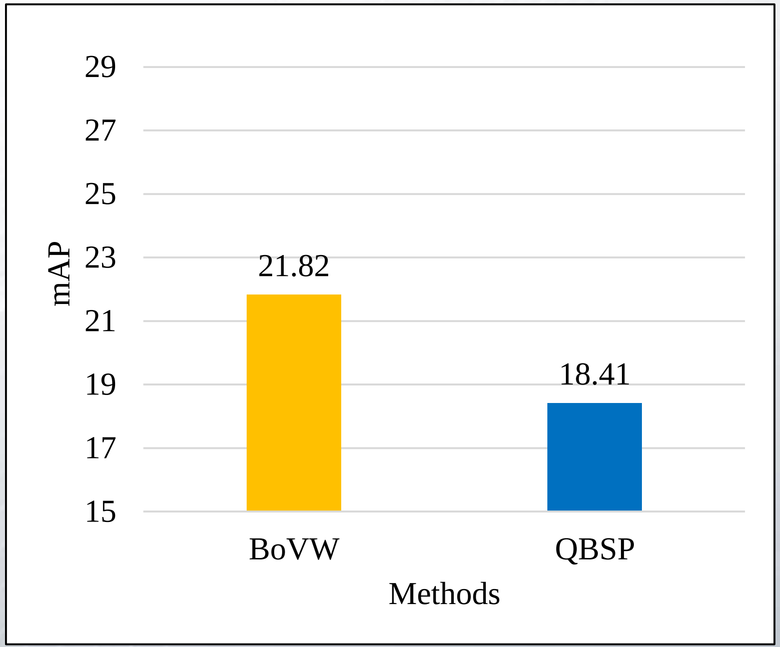


5.2.1 Experiments with the other datasets (3)

- Instance Search performance evaluation



Instance Search 2011



Instance Search 2013

5.2.1 Experiments with the other datasets (4)

- QB works well with some query e.g. “9028”

  - BoVW – Result consisted with several big enough airplanes. (AP = **52.14**%)

  - QBSP – Mining pattern focused on an airplane (AP = **80.98**%)

5.2.1 Experiments with the other datasets (5)

- QB works well with some query e.g. “9029”
  - BoVW – This room (AP = **51.26**%)

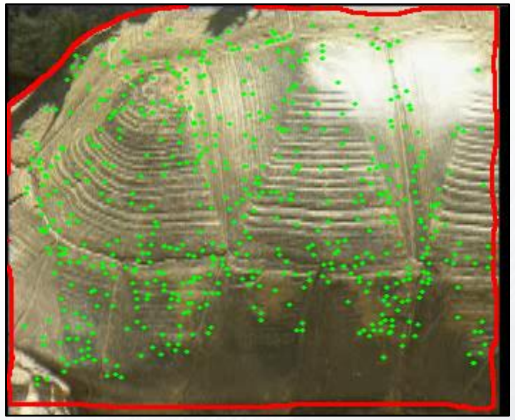
  - QBSP – This room (AP = **64.12**%)

5.2.1 Experiments with the other datasets (6)

- QB works well with some query e.g. "9037"
  - BoVW – A back balloon (AP = **40.07**%)

  - QBSP – A back balloon helped by in front balloon (AP = **47.61**%)

5.2.1 Experiments with the other datasets (7)



- QB **do not works** in the most cases e.g.
  - BoVW – A back balloon (AP = **18.72**%)

  - QBSP – A back balloon helped by in front balloon (AP = **3.85**%)

5.2.2 Target dataset characteristics

- QB will work perfectly when
  - Original BoVW provides **good enough result**,
    then QB will boost its performance.
  - QB help improving the performance by **using context**,
    e.g. Finding an **object that does not move**, or **finding a landmark**.

5.2.3 Weakness

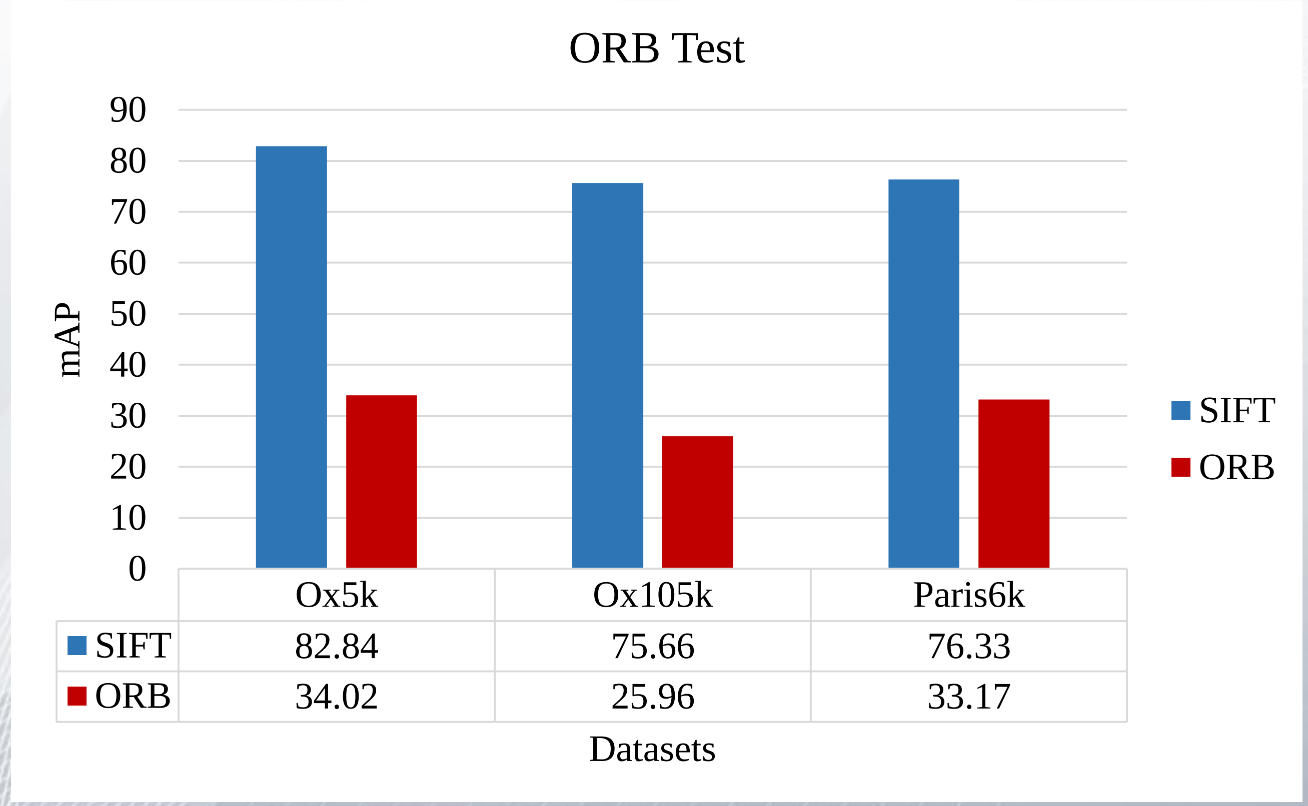
- QB will not work if
  - Only one true positive is provided,
    so no more consistency can be discovered, e.g. MVS dataset.
  - To search for a deformable object,
    e.g. Cloth, animal, texture less object, etc.
    (mostly are the characteristic of INS dataset)
- Results of QB are narrow
  - QB try to find thing that similar to each others out of the relevancies.

6. Future work

- ***This research can be extended***
  - Detect the ***possibility of colossal pattern.***
  - Let ***AQE handle*** the task of "***Hard***" query.
  - Result to ***reduce overall time*** consumption taken by our QB.

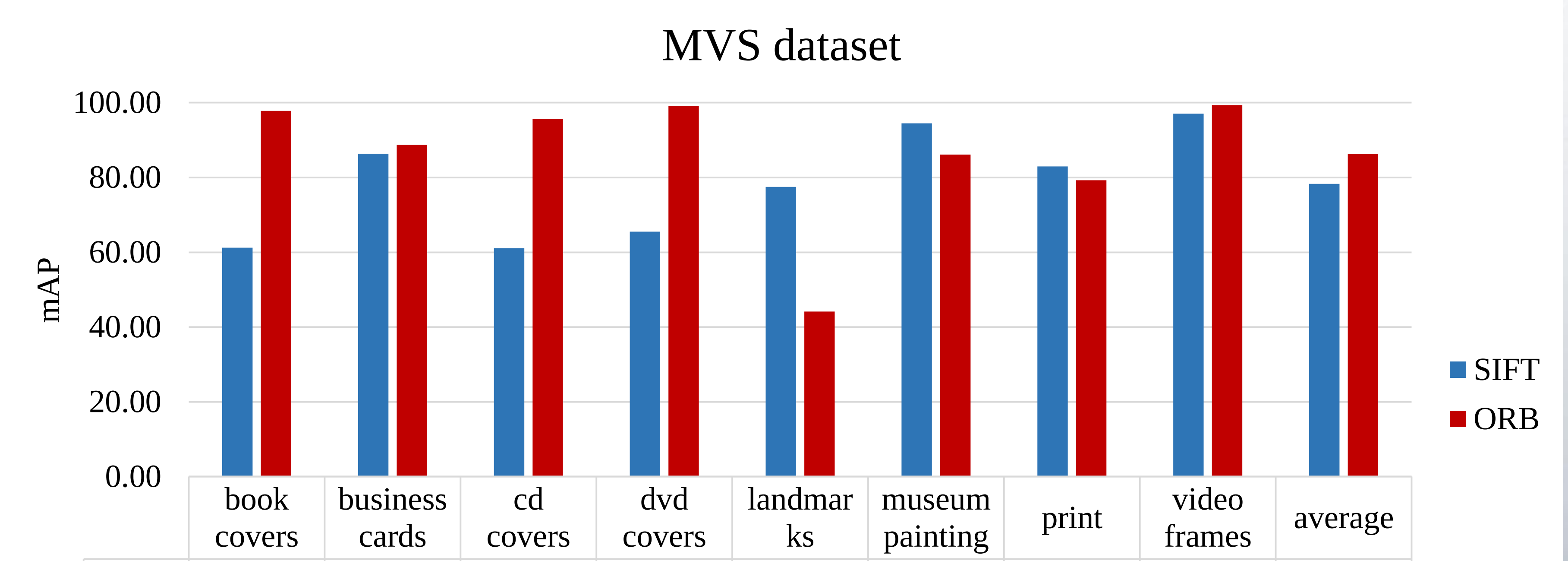
6. Future work

- We also did experiments on binary feature.
  - ORB feature



6. Future work

- ORB experiments on MVS dataset



	book covers	business cards	cd covers	dvd covers	landmarks	museum painting	print	video frames	average
SIFT	61.21	86.33	61.10	65.51	77.52	94.50	82.99	97.08	78.28
ORB	97.79	88.74	95.61	99.08	44.15	86.17	79.29	99.35	86.27

ORB wins! ***SIFT wins!*** ***Par***

Overview and Q/A

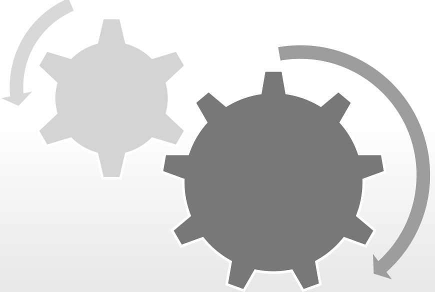
1. Introduction

- Motivation
- Baseline problem

2. Contributions list

- Visual word mining
- Spatial verification
- Automatic parameter tuning

3. Proposed methods



4. Experimental results

- Overall
- Robustness
- Time consumption

5. Conclusion

- Research achievements
- Pros and Cons

6. Future work

- Speed up
- Binary feature