

A Scalable Pattern Spotting System for Historical Documents

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Introduction: Pattern Spotting

- A lot of interest in historical document image management systems
- Indexing platform:
 - Word spotting

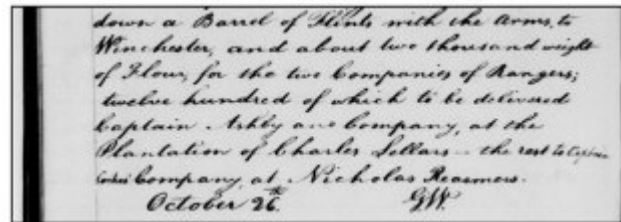
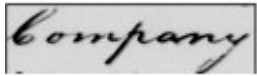


What about graphical object spotting ?
(pattern spotting)



Introduction: Pattern Spotting

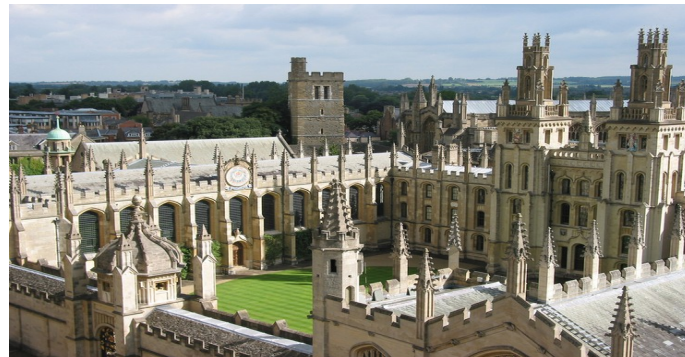
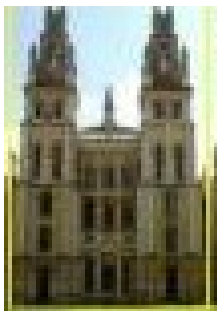
- Word spotting



- Pattern spotting



- (sub-)Image retrieval



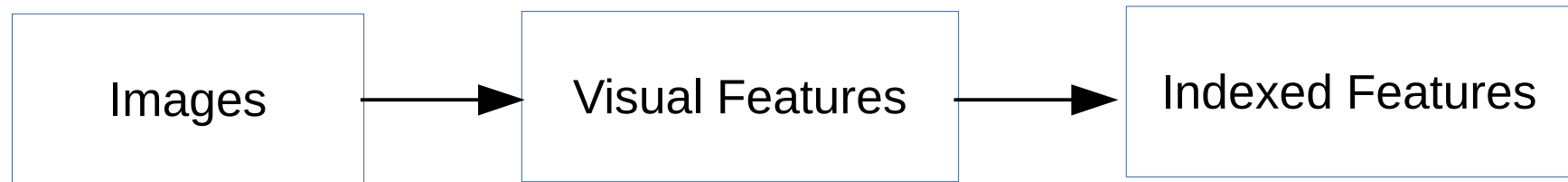
Key Factors:

- Prior knowledge
- Query size
- Image quality

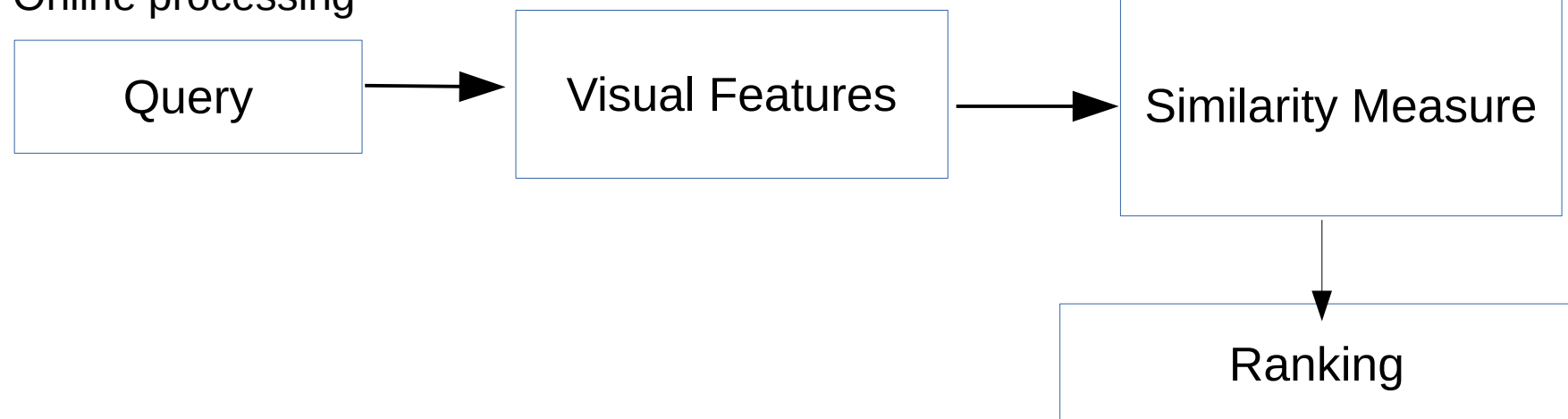
Introduction: Pattern Spotting

- Global Processing Chain

Offline processing



Online processing



Content

1. Introduction

2. Pattern Spotting System

- processing pipeline
- corpus preparation
- non-exhaustive search

3. Experimentation

4. Future works and perspective

Processing Pipeline

- Constraints:
 - The targeted patterns can appear everywhere
 - The query size is relatively small (20*20 pixels to 500*500 pixels) compared to the Image
- sliding windows is needed, but **not an exhaustive way**

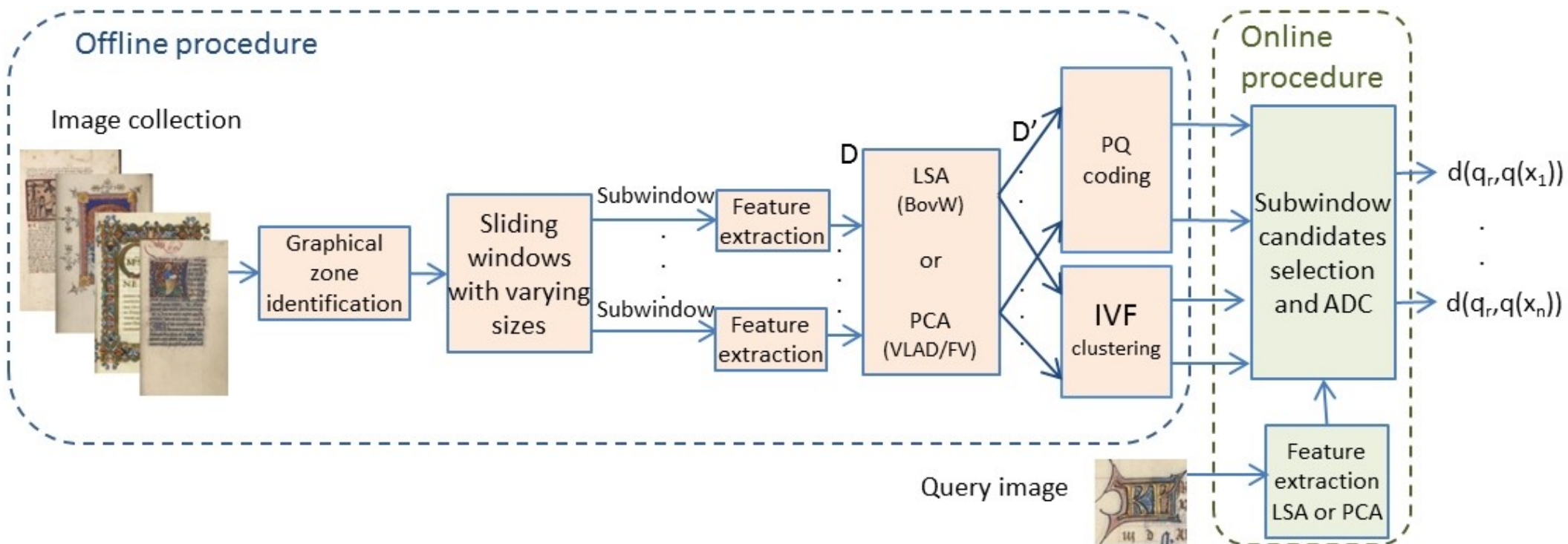


Processing Pipeline

Key ingredients:

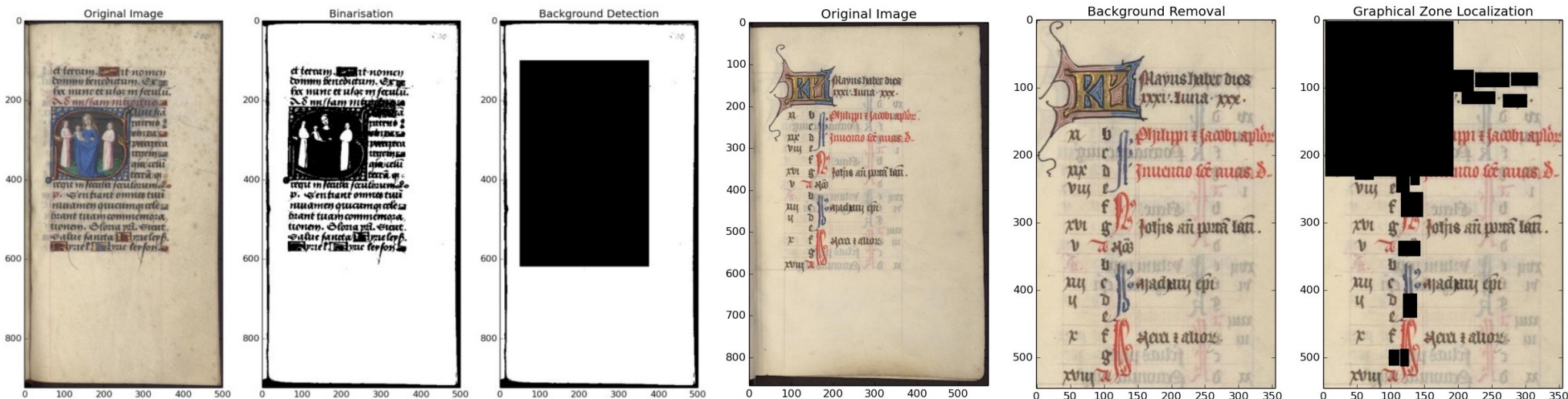
- background removal: gradient information
- graphical zone identification:
 - Scribo module (https://olena.lrde.epita.fr/demos/historical_document_layout_analysis.php)
- restricted sliding windows:
 - quantized sizes, {20, 40, 80, 160, 320} pixels
- Non-exhaustive search:
 - Inverted file structure + distance approximation
- feature compression
 - dimensionality reduction and product quantization

Processing Pipeline




Corpus Preparation: preprocessing

- Preprocessing:
 1. binarisation
 2. find the biggest region for which all the pixels to the border are white
 3. Extract graphical zones



Corpus Preparation: feature extraction

- Multi-scale sliding windows is used (20, 40, 80, 160, 320 pixels)
- Feature extraction:
 - dense sampling
 - bag of visual word + tf.idf
 - fisher vector [Sánchez et al., 2013]
 - vector locally aggregated descriptor (VLAD) [Jégou et al., 2012]

 Image classification with the fisher vector: Theory and practice, IJCV'13, Sánchez et al.

 Aggregating local descriptors into a compact image code, CVPR'12, Jégou et al.

Corpus Preparation: feature compression

- Dimensionality reduction
 - latent semantic indexing (LSI)
 - principle component analysis (PCA)
- Compression
 - Product quantization (PQ)
 - 1:32 compression ratio, $m=8$

32D feature vector:

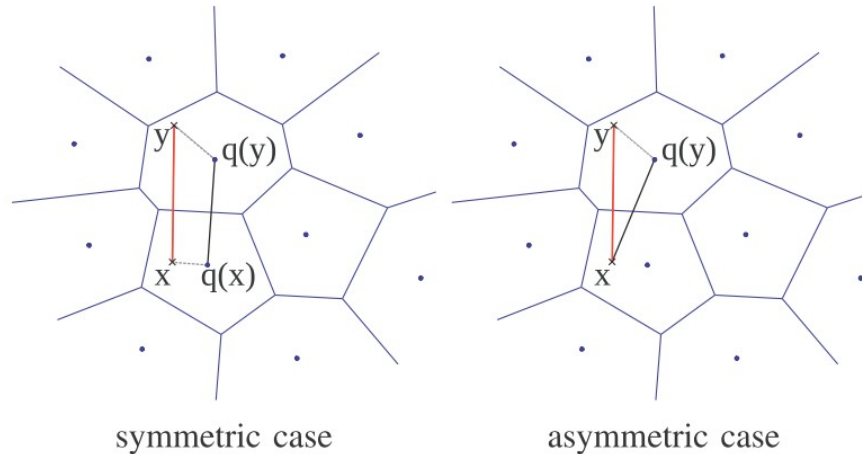


4D code words:



Non-exhaustive search

- Avoid exhaustive search
 - Inverted File Structure (IVF)
- Avoid exhaustive distance computation
 - Assymmetric distance computation (ADC)



- Distance measure: Cosine, Euclidean, Dot product

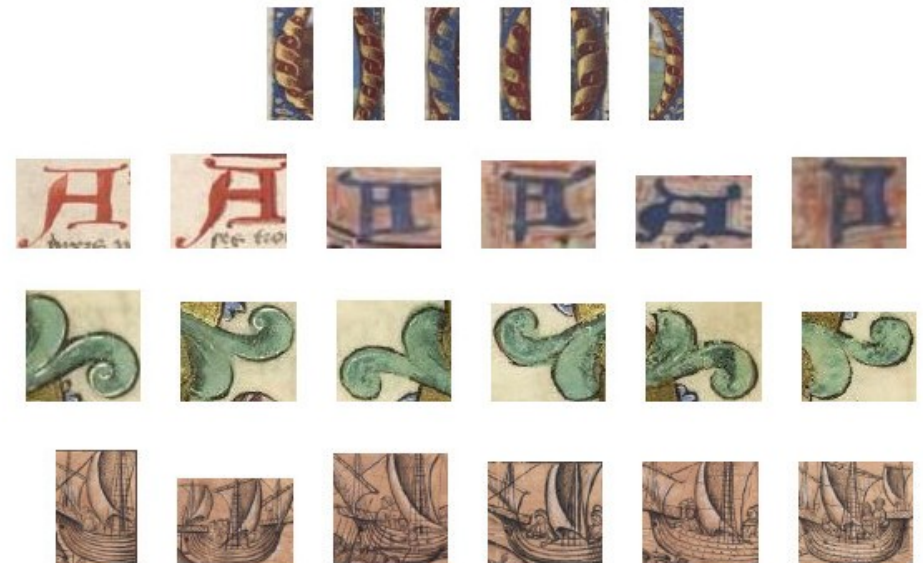
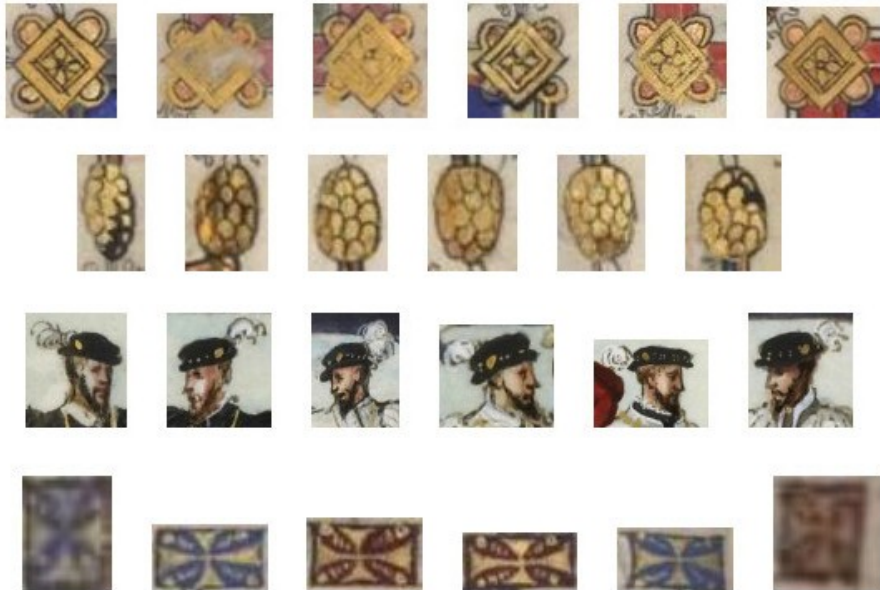
Experimentation: dataset

- DocExplore (<http://www.docexplore.eu/>) Dataset:
 - 1597 medieval manuscript images
 - maximum size: 1024 * 1024 pixels
 - 1097 queries with groundtruth annotations
 - varying size: 20*20 pixels to 500*500 pixels
 - performance is measured as mAP



Experimentation: dataset

- Illustration of variability of the queries



Experimentation: results

- Background removal Vs Graphical Zone Identification

| <i>Codebook size</i> | 500 | 1k | 5k | 10k | #subw. |
|----------------------|-------|-------|-------|-------|--------|
| Background removal | 0.189 | 0.190 | 0.186 | 0.171 | 14.5M |
| Scribo module | 0.195 | 0.204 | 0.212 | 0.212 | 2.1M |

- Feature used: BoVW

Experimentation: results

- A unified benchmarking: image representation and distance measures

| K | BoVW | | | K | VLAD | | | FV | | |
|-----|--------------|--------------|--------------|-----|--------------|--------------|--------------|--------------|-------|--------------|
| | Dot | Cos | Euc | | Dot | Cos | Euc | Dot | Cos | Euc |
| 500 | 0.195 | 0.195 | 0.195 | | | | | | | |
| 1k | 0.203 | 0.204 | 0.204 | 4 | 0.251 | 0.250 | 0.250 | 0.216 | 0.215 | 0.216 |
| 5k | 0.213 | 0.212 | 0.213 | 16 | 0.319 | 0.320 | 0.319 | 0.261 | 0.276 | 0.277 |
| 10k | 0.212 | 0.212 | 0.212 | 64 | 0.295 | 0.295 | 0.295 | 0.348 | 0.310 | 0.315 |

- Distances used: cosine, dot product and euclidean
- K stands for codebook size

Experimentation: results

- Scalable search: BoVW

| <i>codebook size</i> | D | D'=512 | | D'=256 | | D'=128 | |
|----------------------|-------|--------------|-------|--------|-------|--------|-------|
| | | Exh | N-Exh | Exh | N-Exh | Exh | N-Exh |
| 500 | 0.195 | - | - | 0.198 | 0.156 | 0.193 | 0.168 |
| 1k | 0.203 | 0.195 | 0.138 | 0.191 | 0.154 | 0.189 | 0.162 |
| 5k | 0.213 | 0.181 | 0.100 | 0.177 | 0.145 | 0.171 | 0.149 |
| 10k | 0.212 | 0.172 | 0.095 | 0.170 | 0.137 | 0.165 | 0.138 |

Exh and N-Exh stands for exhaustive search and non-exhaustive search (PQ+ADC+IVF) respectively. D and D' represents feature dimension and reduced dimension.

Experimentation: results

- Scalable search: VLAD

| <i>codebook size</i> | D | D'=512 | | D'=256 | | D'=128 | |
|----------------------|-------|--------------|-------|--------|-------|--------|-------|
| | | Exh | N-Exh | Exh | N-Exh | Exh | N-Exh |
| 4 | 0.251 | - | | 0.269 | 0.224 | 0.261 | 0.217 |
| 16 | 0.319 | 0.359 | 0.282 | 0.353 | 0.306 | 0.340 | 0.286 |
| 64 | 0.295 | 0.357 | 0.304 | 0.346 | 0.306 | 0.332 | 0.288 |

Exh and N-Exh stands for exhaustive search and non-exhaustive search (PQ+ADC+IVF) respectively. D and D' represents feature dimension and reduced dimension.

Experimentation: results

- Scalable search: Fisher Vector

| <i>codebook size</i> | D | D'=512 | | D'=256 | | D'=128 | |
|----------------------|-------|--------------|-------|--------|-------|--------|-------|
| | | Exh | N-Exh | Exh | N-Exh | Exh | N-Exh |
| 4 | 0.216 | - | | 0.243 | 0.186 | 0.240 | 0.190 |
| 16 | 0.261 | 0.287 | 0.242 | 0.283 | 0.242 | 0.275 | 0.229 |
| 64 | 0.348 | 0.374 | 0.342 | 0.364 | 0.330 | 0.350 | 0.302 |

Exh and N-Exh stands for exhaustive search and non-exhaustive search (PQ+ADC+IVF) respectively. D and D' represents feature dimension and reduced dimension.

Conclusion & future works

- A memory and computation efficient pattern spotting
 - 14.5M sub-windows Vs 2.1M sub-windows
 - Less than 1 second for a single query
- A unified benchmarking:
 - Features: BoVW, VLAD and Fisher Vector
 - Distances: Cosine, Dot product and Euclidean
- Future work:
 - A better localization or post processing (spatial reenforcement) framework
 - Color feature in combination with the existing pipeline

Thanks for your attention !

