Distance-based Similarity Searching

and its Applications in Multimedia Retrieval with Deep Learning

David Novak

Laboratory of Data Intensive Systems and Applications (DISA)
Masaryk University, Brno, Czech Republic

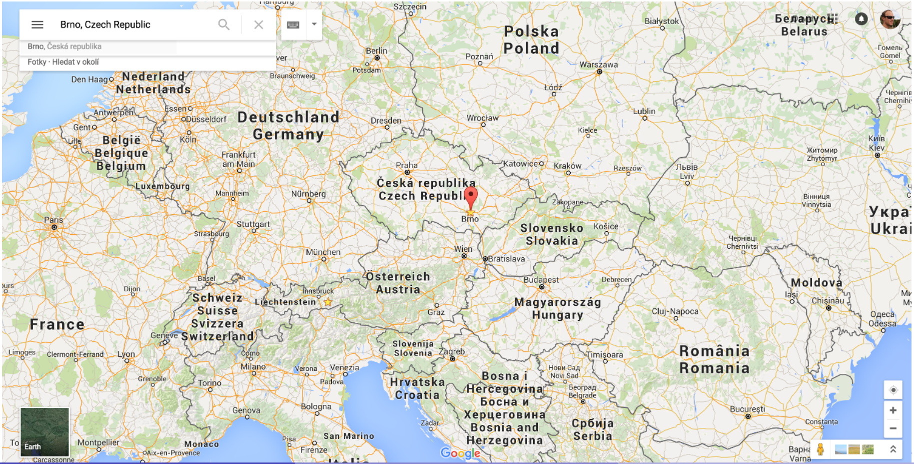
Fulbright scholar at CIIR, UMass, Amherst, MA, USA

CIIR Meeting, 21st September 2015

http://disa.fi.muni.cz/david-novak/

Where Do I Come From

Lab of Data Intensive Systems and Applications (DISA) http://disa.fi.muni.cz/
Faculty of Informatics, Masaryk University http://www.fi.muni.cz/
Brno, Czech Republic



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Faculty of Informatics, Masaryk University http://www.fi.muni.cz/
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- Head of DISA Lab: prof. Pavel Zezula
- Post-doc researches:
  - Michal Batko
  - Petra Budikova
  - Vlastislav Dohnal
  - David Novak
  - Jan Sedmidubsky
- PhD students:
  - current: 6
  - successful (over 12 years): 10
- undergraduates
- fields of interest: databases, Big Data processing, similarity searching, multimedia retrieval, biometrics

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- The similarity is key to human cognition, learning, memory…

[cognitive psychology]

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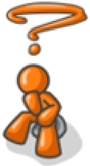

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- **effectiveness**: how to measure similarity of two "objects"
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- **effectiveness**: how to measure similarity of two "objects"
  - domain specific (data- and application-specific, context dependent, ...)
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- **efficiency**: how to realize similarity search fast
  - using a given data + similarity measure
  - on very large data collections

Efficiency: Motivation Example

Example of data:

- general images (photos)
- every image processed by a deep convolutional neural network
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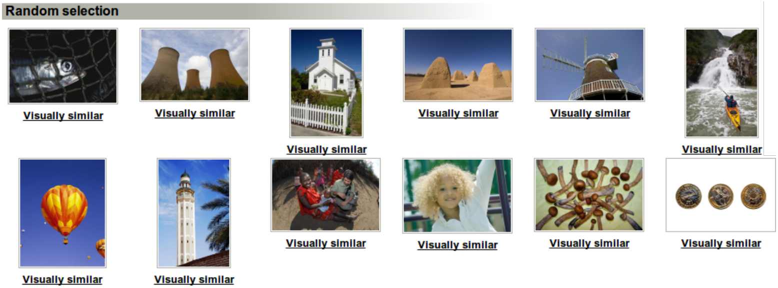

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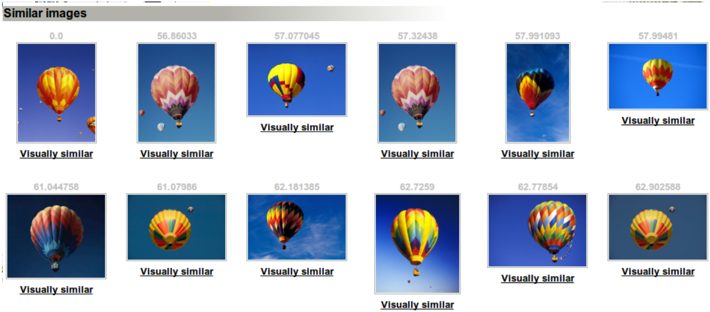

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Efficiency problem:

- 20 million of images with such descriptors
- each descriptor is a 4096-dimensional float vector (16 kB)
- ⇒ over 320 GB of data to be organized for similarity search
  - answer similarity queries online

Outline of the Talk

1. Motivation & Fundamentals
   - Similarity Search: Effectiveness and Efficiency
2. Indexing & Searching in Metric Spaces
   - Metric-based Model of Similarity
   - Overview and Principles
   - Voronoi Partitioning
3. Specific Similarity Indexes
   - M-Index
   - PPP-Codes
4. Deep Convolutional Neural Networks
   - and their applications in image recognition
5. Visual Search Demo

Metric-based Model of Similarity

- We model the data as metric space $(\mathcal{D}, \delta)$, where $\mathcal{D}$ is a *domain* of objects and δ is a total distance function $\delta : \mathcal{D} \times \mathcal{D} \longrightarrow \mathbb{R}_0^+$ satisfying the following postulates $\forall x, y, x \in \mathcal{D}$:
  - identity: $\delta(x, x) = 0$
  - symmetry: $\delta(x, y) = \delta(y, x)$
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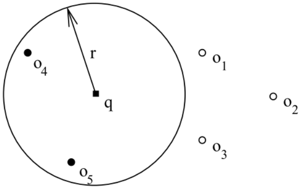
range query $R(q, r)$ returns all objects $x \in \mathcal{X}$ with $\delta(q, x) \leq r$



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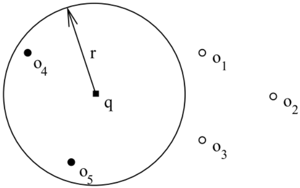
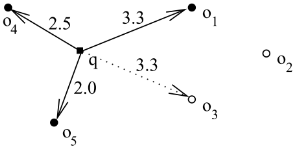


k-NN(q) query returns k objects $x \in \mathcal{X}$ with the smallest $\delta(q, x)$



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But the distance-based indexing is often able to capture intrinsic complexity of the similarity space

- ignoring unnecessary external "dimensions" of the data

Examples of Metric Spaces

Vector data:

- L_p metrics (Minkowski distances)
  - L_1 – Manhattan (city block) distance $$L_1(x,y) = \sum_{i=1}^{n} |x_i - y_i|$$
  - L_2 – Euclidean distance $$L_2(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$
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- Hamming distance (on vectors over a finite field, e.g. binary vectors)

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Other types of data:

- Earth mover's distance (for histograms)
- Tree Edit distance
- Signature Quadratic Form distance, etc.

Problem Formulation and Overview

Objective: Preprocess and organize collection of objects $\mathcal{X} \subseteq \mathcal{D}$ in such a way that similarity queries are processed efficiently

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- theoretical principles identified
- static and dynamic memory structures for precise similarity search
- efficient disk-oriented techniques
  - precise and approximate (not all objects from k-NN answer returned)
- distributed processing

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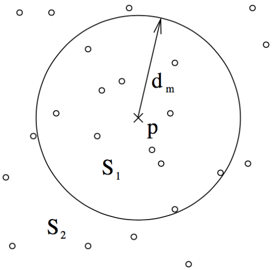

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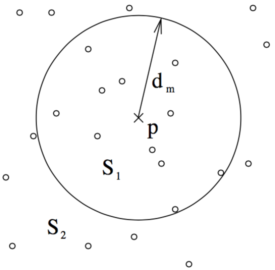

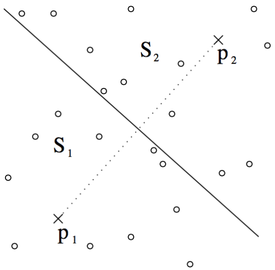

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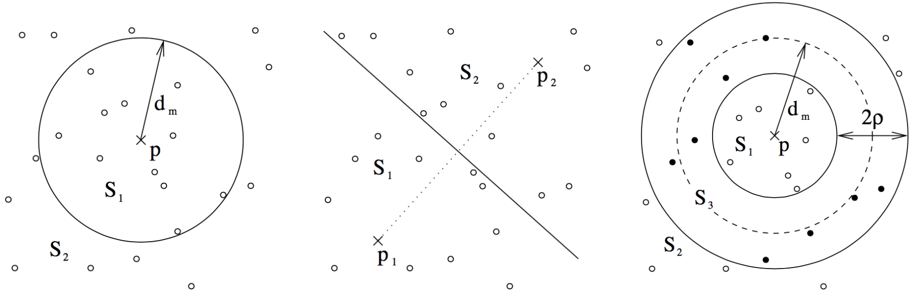

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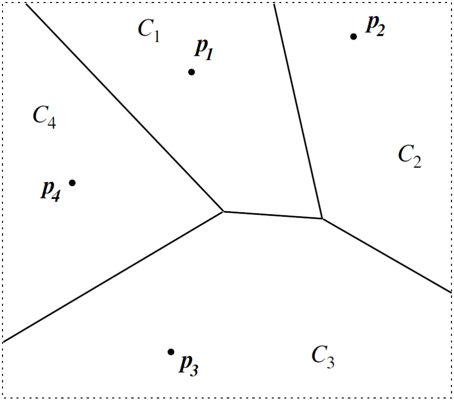
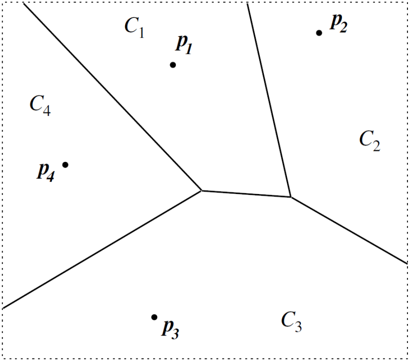


- Voronoi cell C_i = all objects for which pivot p_i is the closest

Recursive Voronoi Partitioning

- Let us use the same set of n pivots $p_1, \ldots, p_n$ recursively



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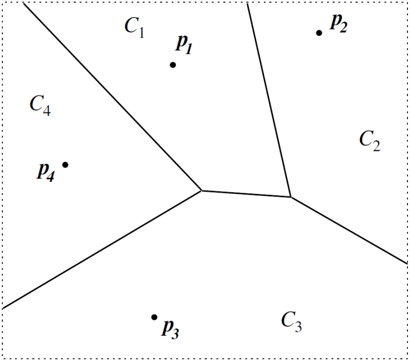

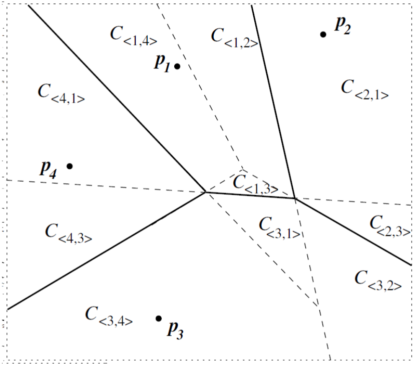

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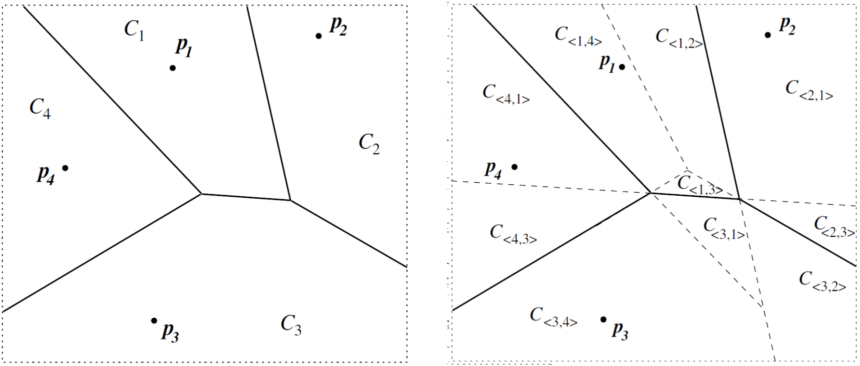

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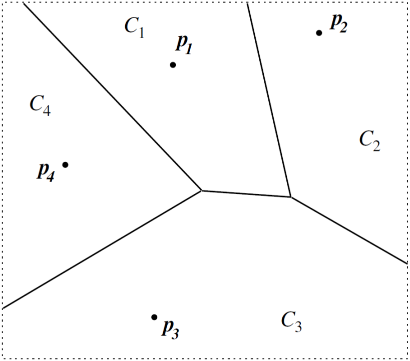

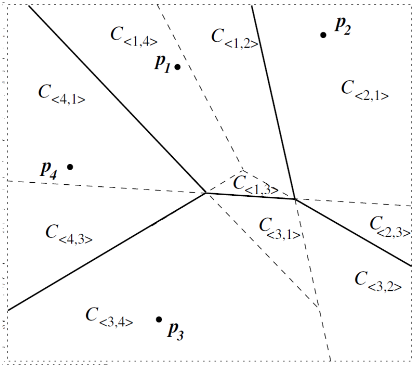

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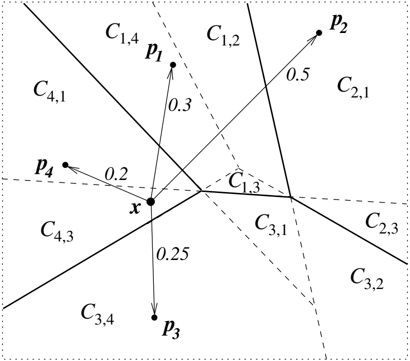
  - this principle can be used l-times recursively up to level $l = n$

Pivot Permutations

A different point of view: **(prefixes of) pivot permutations**

- Given object $x \in \mathcal{X}$, order the pivots according to distances $\delta(x, p_i)$



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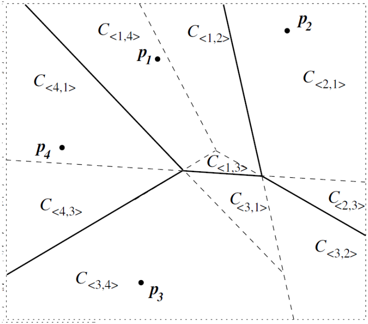
- Π_x is denoted as pivot permutation (PP) with respect to x.

Correspondence between Voronoi partitioning and PPs



- Recursive Voronoi partitioning to level l
- Cell $C_{\langle i_1,\dots,i_l \rangle}$ contains objects x for which

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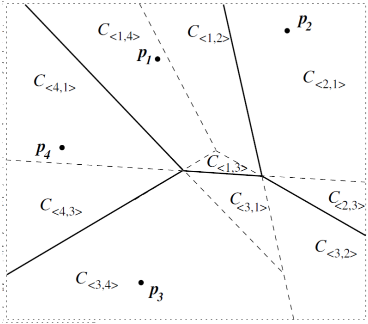

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- l-tuple $\langle i_1, \ldots, i_l\rangle$ is an l-prefix of pivot permutation Π_x
  - pivot permutation prefix (PPP)
  - there is one-to-one correspondence between "Voronoi cell" and "PPP"

M-Index Indexing Structure

Specific Voronoi-based indexes: M-Index, Distributed M-Index, PPP-Codes

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M-Index: basic properties

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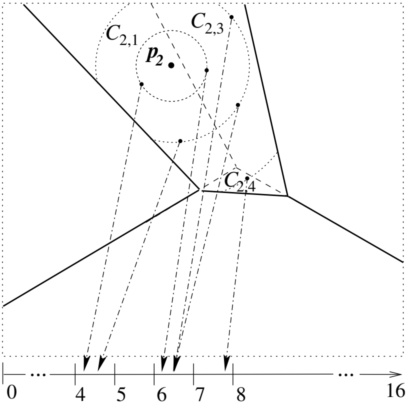
M-Index Mapping Function



example with $n = 4$ and $l = 2$

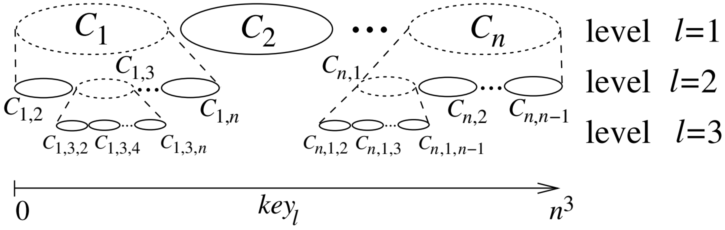
integral part of the key

- identification of the cell

fractional part of the key

- position within the cell
- distance from the closest pivot

M-Index with Dynamic Level



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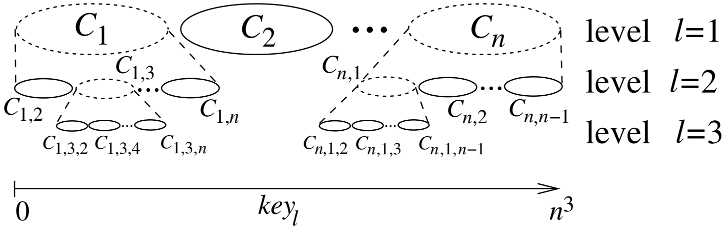

- partition only those cells that exceed certain capacity
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- a kind of dynamic hashing, similar to extensible hashing
- it is a locality sensitive hashing for generic distance spaces

M-Index: Precise Query Evaluation Strategy

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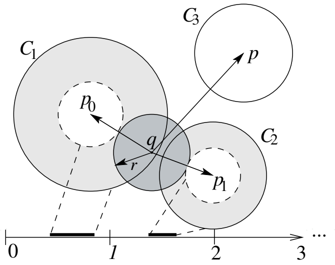

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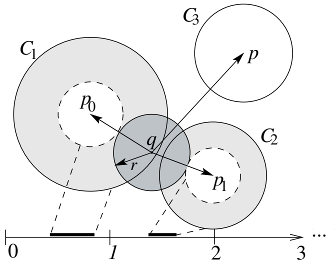

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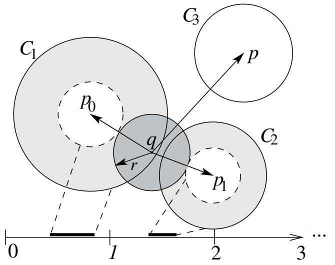

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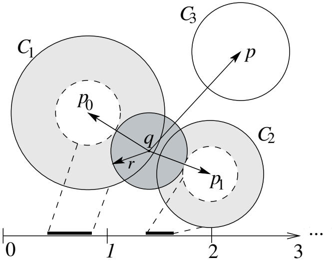
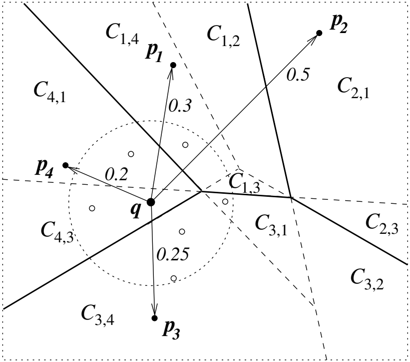


- the search must still access and refine about 30–50% of the data
  - for collections with high intrinsic dimensionality (dimensionality curse)
  - for $R(q, r)$ and k-NN queries with reasonable r and k

Approximate Strategy for M-Index



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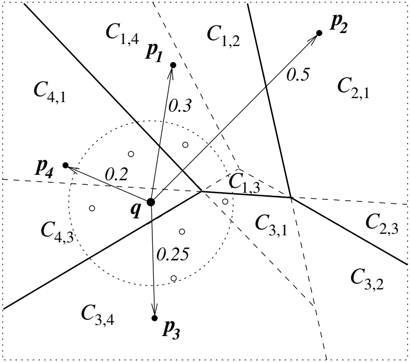

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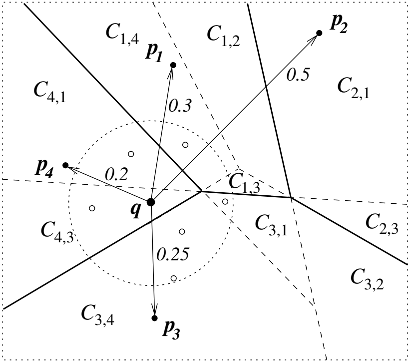

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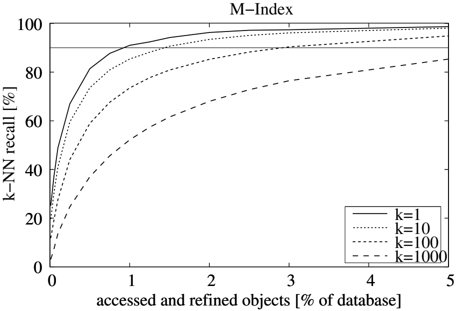
- measure quality of k-NN approximate search by recall = precision

$$recall(A) = \frac{|A \cap A^P|}{k} \cdot 100\%$$

M-Index Approximate Strategy: Brief Evaluation



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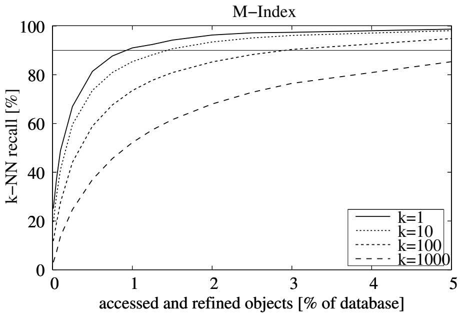

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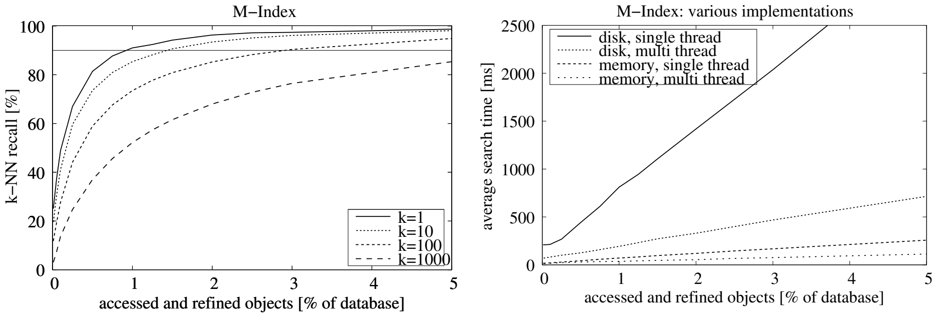

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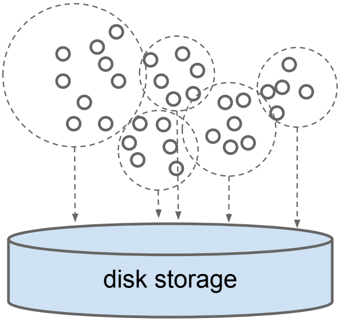

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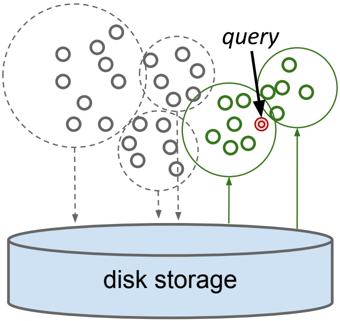

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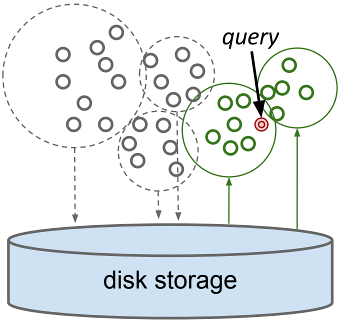

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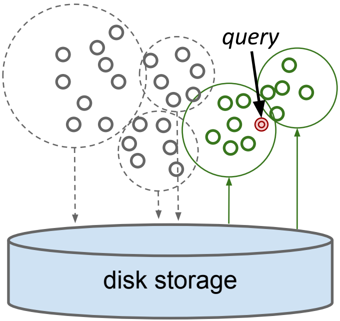
majority of the search costs:

- reading and refinement of S_C

$\Longrightarrow$ accuracy of the candidate set is key



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Novak, D. and Zezula, P. Rank Aggregation of Candidate Sets for Efficient Similarity Search. In Proceedings of 25th Inter. Conf. on Database and Expert Systems Applications (DEXA 2014)

Best paper of DEXA 2014 Award.

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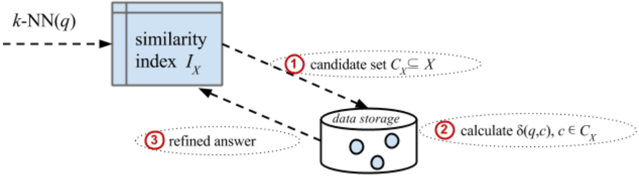

Candidate Aggregation Principle

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- λ candidate rankings ψ_q^j of object IDs to be aggregated

$q \in \mathcal{D}$

$$\psi_q^1\text{:}\ \overbrace{\{\boldsymbol{x}\ y_1\, y_2\}}^{\text{objects with the rank '1'}}\ \overbrace{\{y_3\, y_4\, y_5\}}^{\text{rank '2'}}\ \overbrace{\{y_6\}}^{\text{rank '3'}}\ \ldots$$
$$\psi_q^2\text{:}\ \{y_3\, y_2\}\ \{y_1\, y_4\, y_6\, y_7\}\ \{\boldsymbol{x}\ y_8\}\ \ldots$$
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- final rank of object x is **p**-percentile (e.g. median) of its λ ranks

$$\Psi_{\mathbf{p}}(q,x) = percentile_{\mathbf{p}}(\psi_q^1(x), \psi_q^2(x), \ldots, \psi_q^\lambda(x))$$

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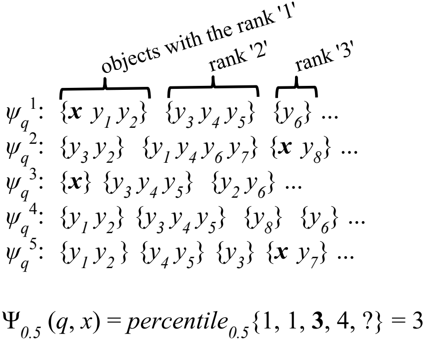

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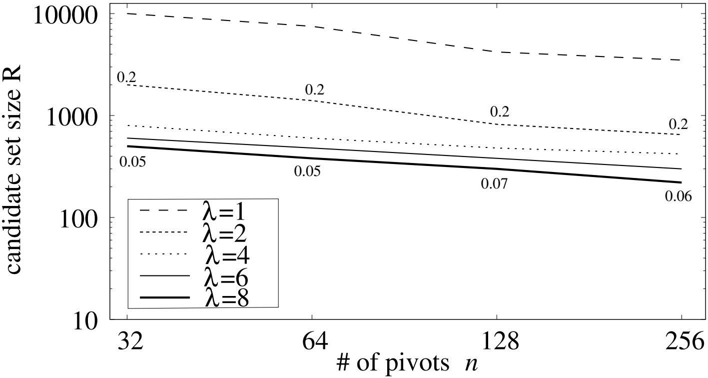
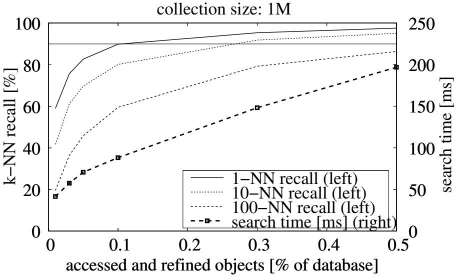


Candidate set size R necessary to achieve 80% of 1-NN recall

Settings: 1M CoPhIR dataset, $l = 8$ and $\mathbf{p} = 0.75$

Evaluation 2: Overall Efficiency



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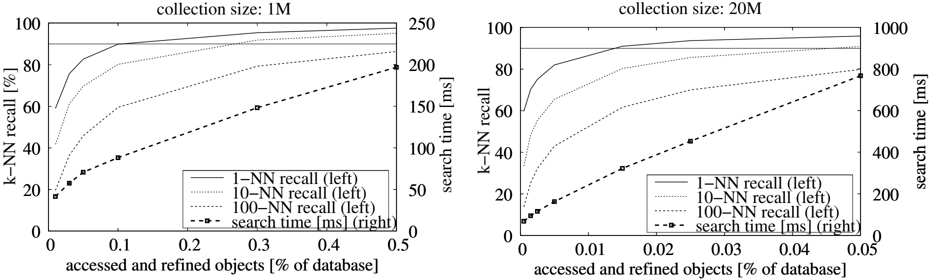

- 4096-dimensional float vectors with L_2 distance
- shrinking the candidate set size by one or two orders of magnitude
  - while preserving the answer quality
  - the larger the data collection, the lower the percentage

Deep Convolutional Neural Networks

▸ a separate Google docs presentation

Online Demonstration

Demonstration of large-scale image visual search

- 20 million images from a photo stock company
- features from deep convolutional neural networks
  - 4096-dimensional vectors with L_2 distance
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- PPP-Codes index (1 GB in memory, 124 GB on the SSD disk)

http://disa.fi.muni.cz/demos/profiset-decaf/

front-end temporarily running at

http://cybela12.fi.muni.cz:8888/demos/profiset-decaf/

Novak, D., Batko. M. and Zezula, P. (2015). Large-scale Image Retrieval using Neural Net Descriptors. Presented at SIGIR 2015.