Metric Indexes based on Recursive Voronoi Partitioning

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http://disa.fi.muni.cz/

Outline of the Talk

1. Motivation: Efficiency of Similarity Search
2. Metric Data Partitioning
   - Fundamentals
   - Voronoi Partitioning
3. M-Index
   - Principles
   - Precise and Approximate Search
   - M-Index Related Pieces of Work
4. PPP-Codes
   - Data Encoding and Searching
   - Efficiency Evaluation
   - Visual Search Demo

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

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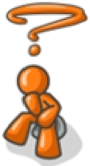

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- **effectiveness**: how to measure similarity of two "objects"
  - domain specific (photos, X-rays, voice, music, EEG, MTR. . .)

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- **effectiveness**: how to measure similarity of two "objects"
  - domain specific (photos, X-rays, voice, music, EEG, MTR...)
- **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)
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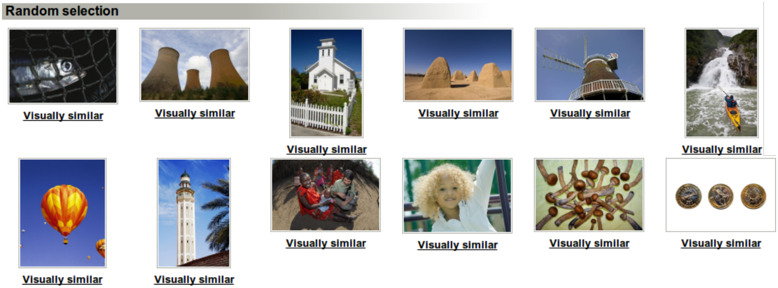

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Efficiency problem:

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

Distance-based Similarity Search

- generic similarity search
  - applicable to many domains
- data modeled 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 postulates of identity, symmetry, and triangle inequality

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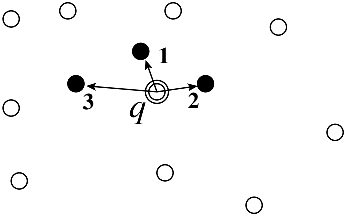

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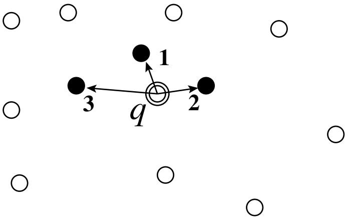
- dataset $\mathcal{X}$ may be very large
- function δ may be time consuming



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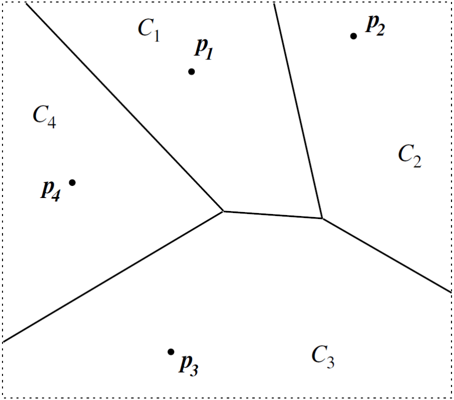
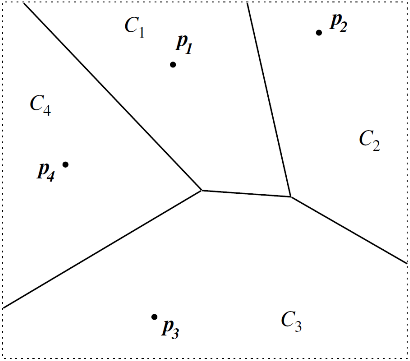


- Voronoi cell C_i = all objects for which pivot p_i is the closest

Recursive Voronoi Partitioning

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



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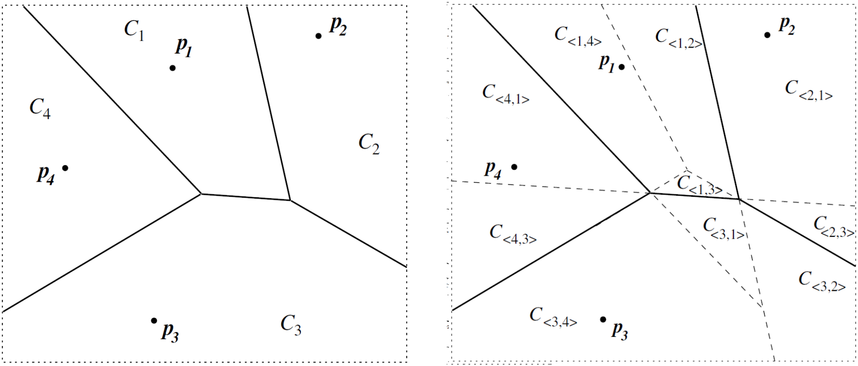

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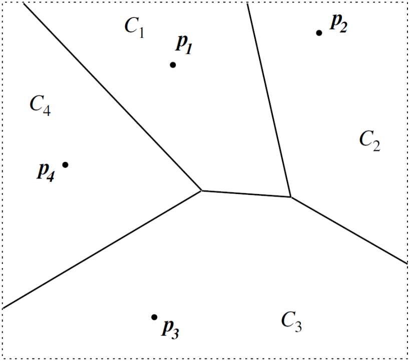

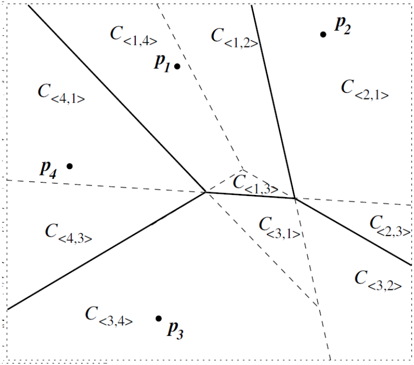

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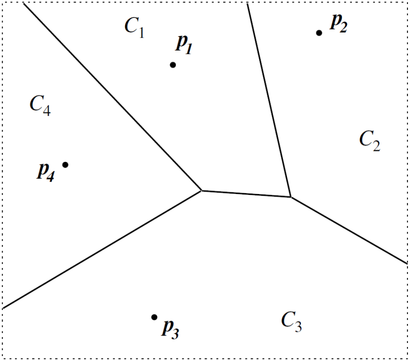

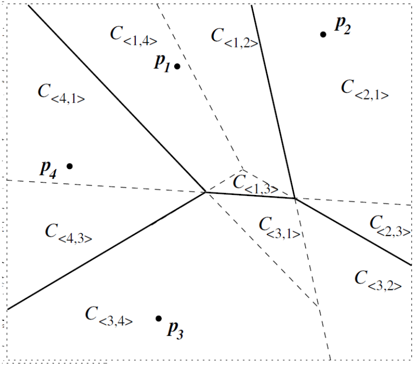

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- $C_{i,j}$ = objects for which p_i is the closest and p_j the second closest
    - this principle can be used l-times recursively up to level $l = n$

Pivot Permutations

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

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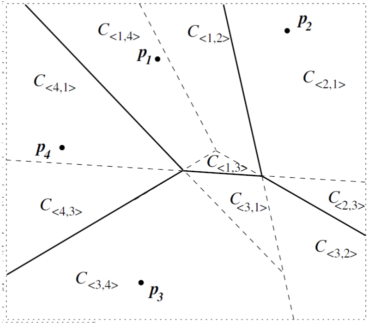
- Π_x is denoted as pivot permutation (PP) with respect to x.

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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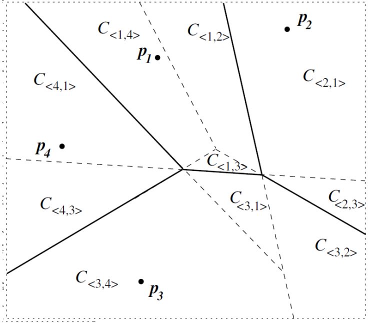

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- l-tuple $\langle i_1, \ldots, i_l \rangle$ is an l-prefix of pivot permutation Π_x
  - pivot permutation prefix (PPP)
  - terms "Voronoi cell" and "PPP" correspond to each other

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M-Index: basic properties

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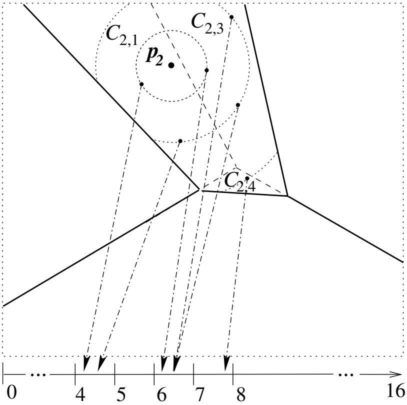
M-Index Mapping Function



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

integral part of the key

- identification of the cell

fractional part of the key

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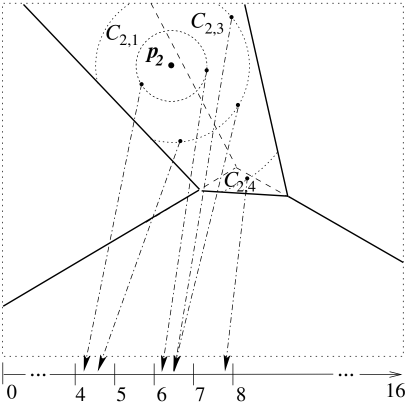

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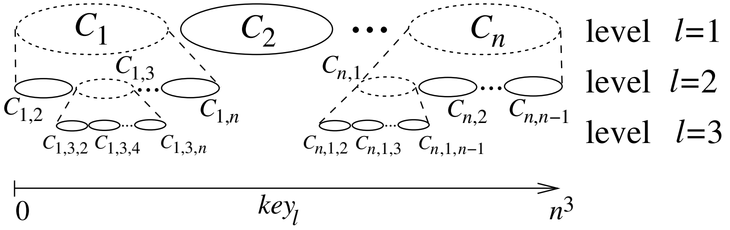
$$key_l(x) =$$

$$= \delta(p_{\Pi_x(1)}, x) + \sum_{i=1}^{l} (\Pi_x(i) - 1) \cdot n^{(l-i)}$$

domain of δ normalized to $[0, 1)$

size of the key_l domain: n^l

M-Index with Dynamic Level



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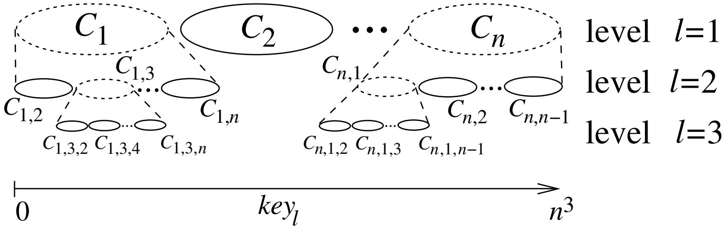

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- range-pivot distance constraint
  - each leaf cell $C_{i_1,\ldots,i_l}$ stores $r_{\min}$ and $r_{\max}$ as min and max of distances $\{\delta(x, p_{i_1}) | x \in C_{i_1,\ldots,i_l}\}$
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$$\delta(q, p_{i_1}) + r < r_{\min} \qquad \text{or} \qquad \delta(q, p_{i_1}) - r > r_{\max}$$

M-Index: Precise Range Query Evaluation (cont.)

- object-pivot distance constraint
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- pivot filtering
  - store distances $\delta(x, p_1), \ldots, \delta(x, p_n)$ together with each object x
  - skip computation of $\delta(q, x)$ at query time if

$$\max_{i \in \{1,\ldots,n\}} |\delta(q, p_i) - \delta(x, p_i)| > r$$

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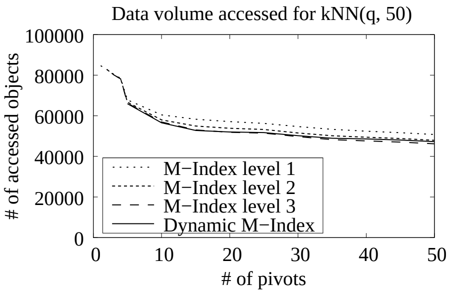

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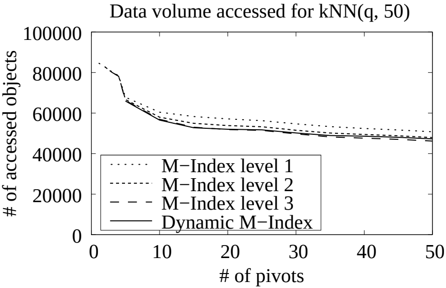
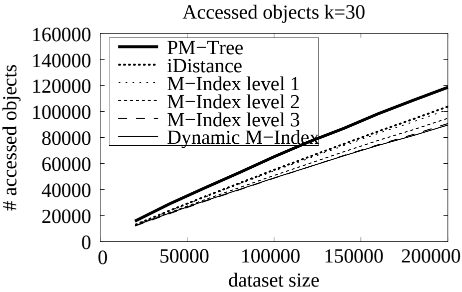
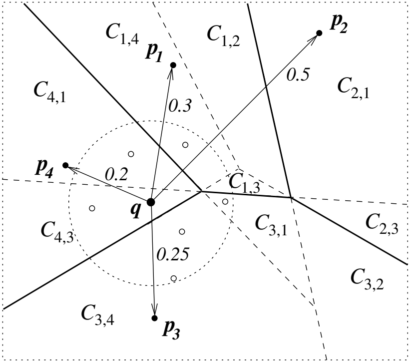




- dataset size: 100,000
- dynamic M-Index: $l_{\max} = 5$
- 20 pivots

Approximate Strategy for M-Index



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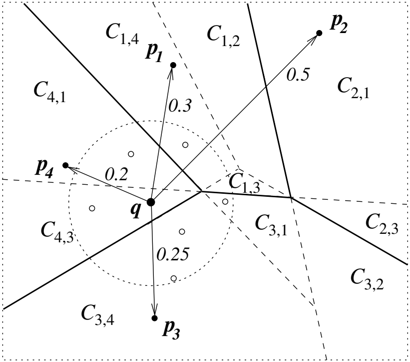

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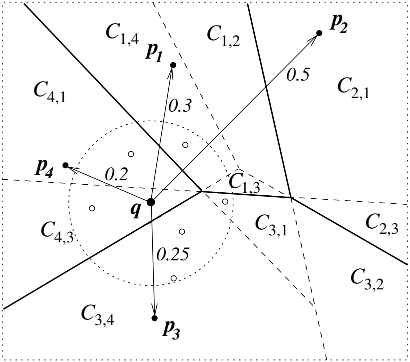

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- query q is represented by distances $\delta(q,p_1),\delta(q,p_2),\ldots,\delta(q,p_n)$

- each Voronoi cell is assigned a “penalty” with respect to q

$$penalty(C_{i_1,\ldots,i_l}) = \sum_{j=1}^{l} \max\left\{\delta(p_{i_j},q) - \delta(p_{\Pi_q(j)},q), 0\right\}$$

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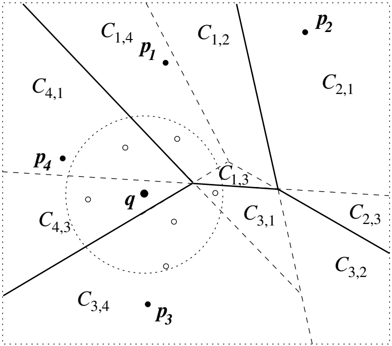

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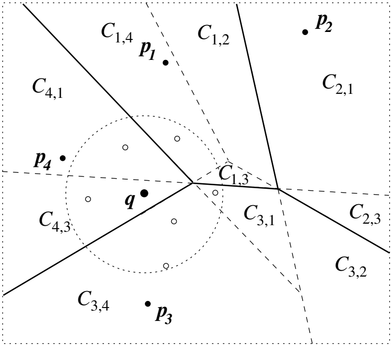

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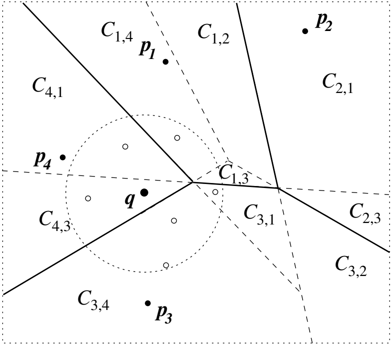
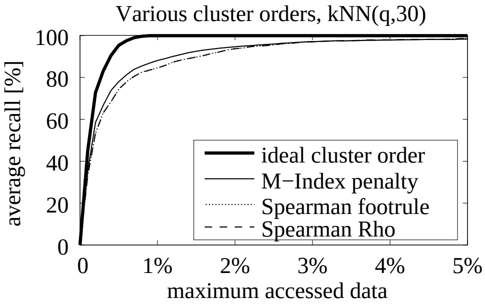
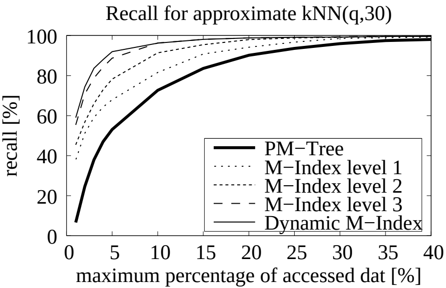




- using richer information for the query than for data is worth

M-Index Approximate Strategy: Brief Evaluation



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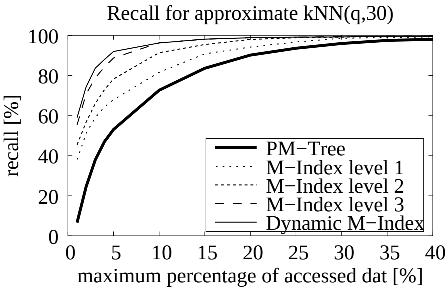

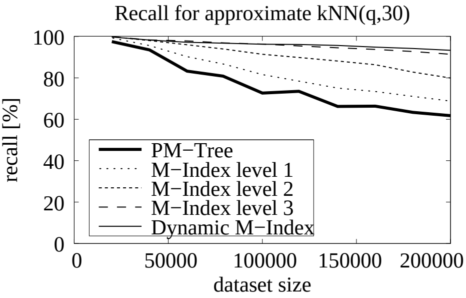

- dataset of 100,000 objects
- algorithm accesses 10,000 objects

M-Index Related Pieces of Work

- Distributed indexes: M-Chord (preliminary), distributed M-Index

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M-Index Related Pieces of Work

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- Multiple independent M-Indexes to improve the search (LSH style)

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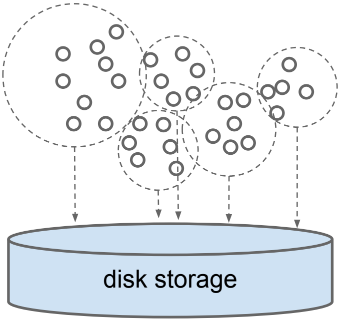
Standard Similarity Search Approach

standard approach to large-scale approximate search (e.g. M-Index):

- dataset $\mathcal{X}$ is partitioned and stored



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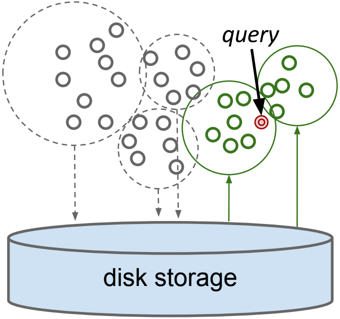

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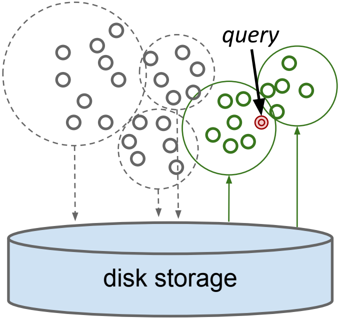

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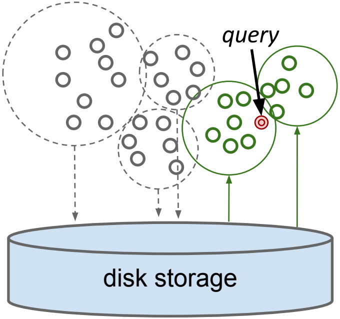

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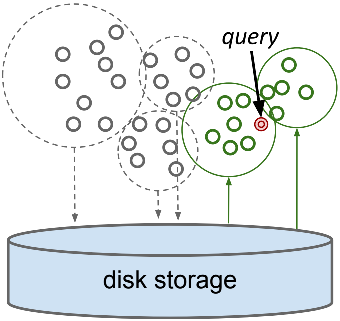
$\Longrightarrow$ accuracy of the candidate set is key



PPP-Codes in a Nutshell

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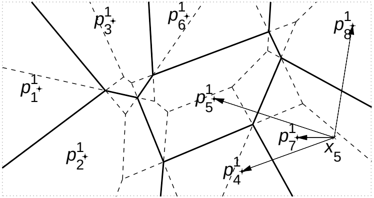
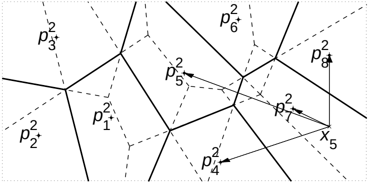
Best paper of DEXA 2014 Award.

Space Partitioning and Data Encoding

PPP-Codes define λ independent recursive Voronoi-like space partitionings





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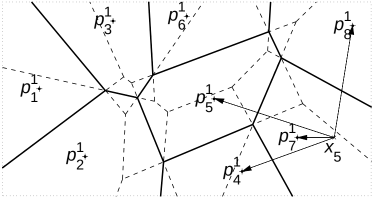
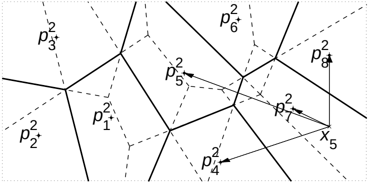




each data object $x \in \mathcal{X}$ is encoded by position in these diagrams

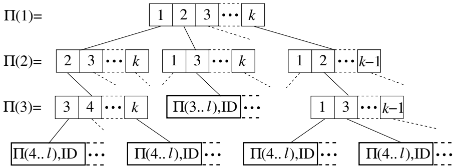
$$PPP\text{-}Code_l^{1..\lambda}(x) = \langle \Pi_x^1(1..l), \ldots, \Pi_x^\lambda(1..l) \rangle.$$

where $\Pi_x^j(1..l)$ is the l-prefix of the j-th pivot permutation of object x

PPP-Code Index

We build a trie-like structure for each pivot space

- the memory trie contains only the PPP-Codes and object IDs
- with a focus is on memory optimization



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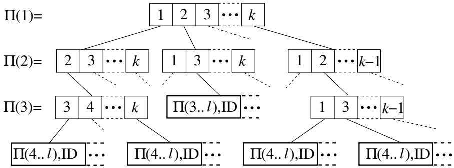

Given query q, Voronoi cells from each partitioning (trie) are ranked

- in a similar way as for M-Index
- result: λ independent candidate rankings of object IDs

Candidate set Identification

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$q \in \mathcal{D}$

$$\psi_q^1\colon\ \overbrace{\{\boldsymbol{x}\ y_1\, y_2\}}^{\text{objects with the rank '1'}}\ \overbrace{\{y_3\, y_4\, y_5\}}^{\text{rank '2'}}\ \overbrace{\{y_6\}}^{\text{rank '3'}}\ \ldots$$

$$\psi_q^2\colon\ \{y_3\, y_2\}\ \{y_1\, y_4\, y_6\, y_7\}\ \{\boldsymbol{x}\ y_8\}\ \ldots$$

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$$\psi_q^5\colon\ \{y_1\, y_2\}\ \{y_4\, y_5\}\ \{y_3\}\ \{\boldsymbol{x}\ y_7\}\ \ldots$$

Candidate set Identification

- λ rankings ψ_q^j of IDs are aggregated into the final ranking
- ranking of object x is **p**-percentile (e.g. median) of its λ ranks

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

$q \in \mathcal{D}$

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ψ_q^1: $\{\mathbf{x}\ y_1\ y_2\}$ $\{y_3\ y_4\ y_5\}$ $\{y_6\}$ ...
ψ_q^2: $\{y_3\ y_2\}$ $\{y_1\ y_4\ y_6\ y_7\}$ $\{\mathbf{x}\ y_8\}$ ...
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ψ_q^4: $\{y_1\ y_2\}$ $\{y_3\ y_4\ y_5\}$ $\{y_8\}$ $\{y_6\}$ ...
ψ_q^5: $\{y_1\ y_2\}$ $\{y_4\ y_5\}$ $\{y_3\}$ $\{\mathbf{x}\ y_7\}$ ...

$$\Psi_{0.5}(q, x) = percentile_{0.5}\{1, 1, \mathbf{3}, 4, ?\} = 3$$

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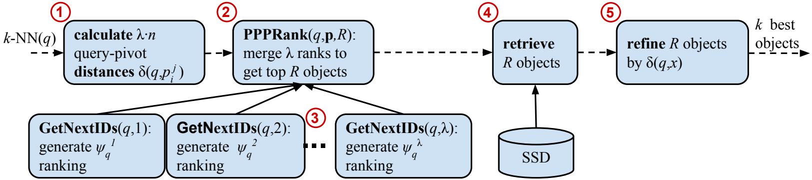
- the percentile-based aggregation increases probability that query-relevant objects are ranked higher than the distant ones

Overall schema of the PPP-Codes search algorithm



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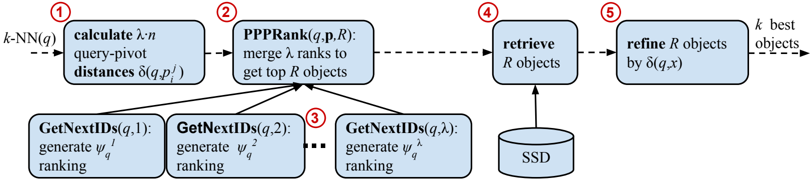

- individual steps run in separate threads
- requires a fast ID-object storage (SSD or distributed)

Evaluation 1: Accuracy of the Candidate Set

How many candidate objects are needed to achieve certain recall level

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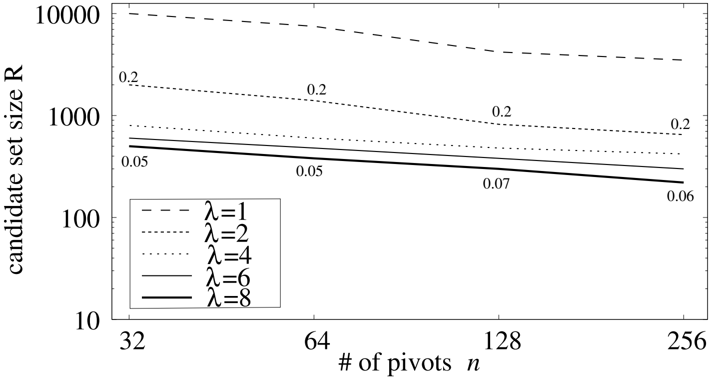

Candidate set size R necessary to achieve 80% of 1-NN recall

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

Evaluation 2: Overall Efficiency

candidate set size R vs. recall and time

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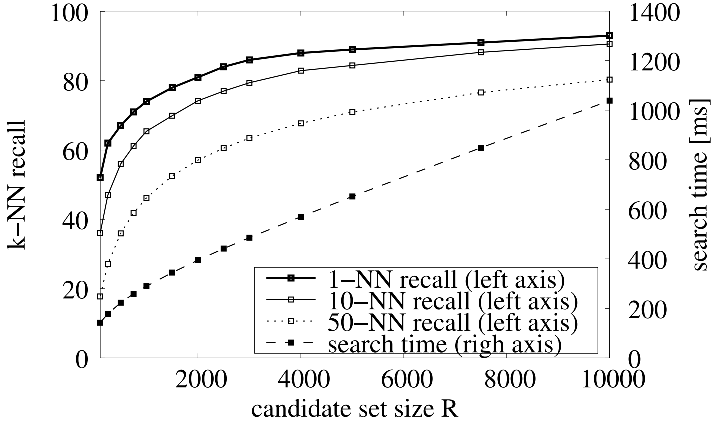

Recall and search time while increasing candidate set size R.

Settings: 100M CoPhIR dataset, $n = 512$, $l = 8$, $\lambda = 5$, $\mathbf{p} = 0.5$ (3rd rank out of 5)

PPP-Codes Conclusions

The results of the PPP-Codes evaluation show that

- even two pivot spaces help, more than five do not help much
- the candidate set is reduced by one–two orders of magnitude
- the rank & merge algorithm is complex but usually worth
  - for larger data objects and complex distance function

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Demonstration of image visual search

- 20 million images
- powerful visual descriptors from deep convolutional neural networks
  - 4096-dimensional vectors with L_2 distance
- PPP-Codes index (1 GB in memory, 124 GB on the SSD disk)
- *To be presented at SIGIR 2015*

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