Introduction to Similarity Search in Multimedia Databases

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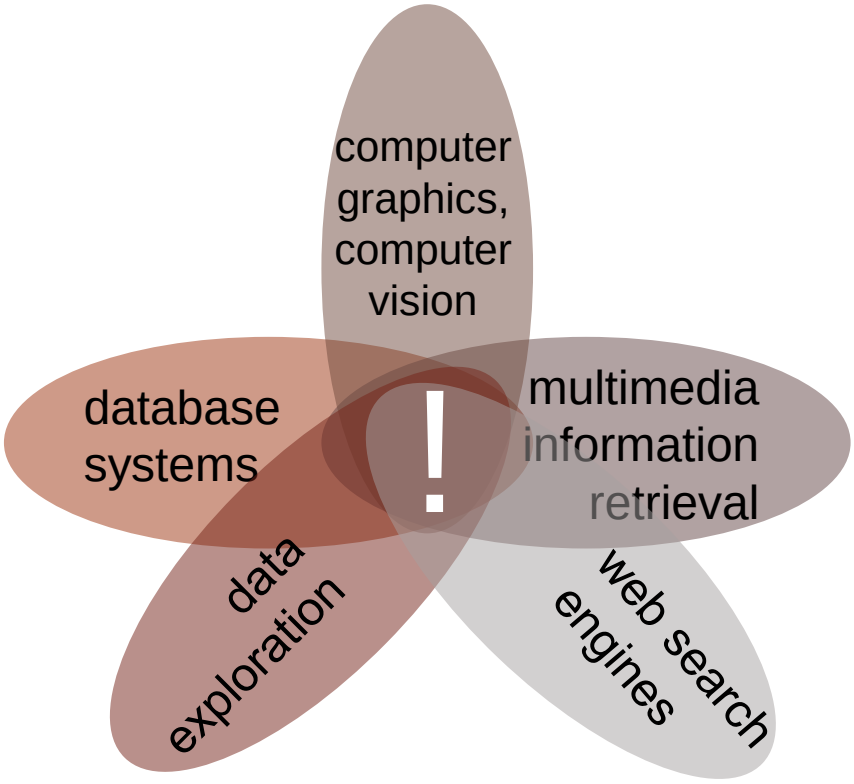
The context of the research topic

Similarity Search in Multimedia Databases



Talk outline

- motivation
- context vs. content-based search
- similarity search
- examples of applications in various domains
  - images
  - shapes
  - audio
- metric indexing for fast search

Multimedia content on the Web

- more than 95% (99.9%?) of web space is considered to store multimedia content
  - 100 billions of photographs are expected to be taken every year

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- factors
  - high-speed internet, increasing computational power
  - cheap digital devices
    - cameras, camcoders, all-in-one devices (PDA, smartphones)
    - everyone is producer of multimedia
  - human activities move to internet in a large extent
    - social networks (FaceBook, Twitter, MySpace)
    - industry (e-banking, e-commerce, e-services)

What is multimedia content?

- **multi–media** = more than one type of **digital media**
- traditional interpretation
  - **image, audio**, **video** content

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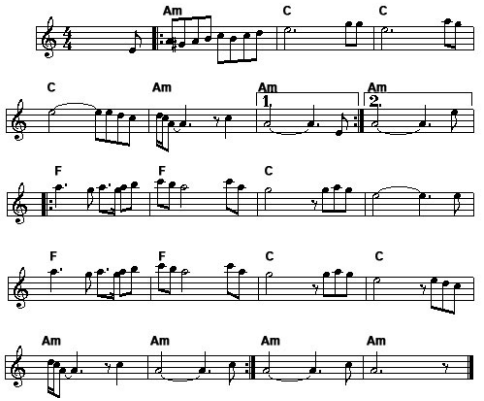
- extended interpretation of multimedia
  - any media type with **unstructured content**
  - mostly **“digitized nature”**
    - sensory data
  - also “**human-processed”** data
    - text, XML, geometry & illustration, application (flash), etc.

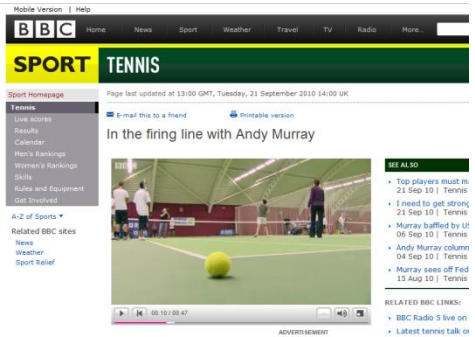
Producers of multimedia data

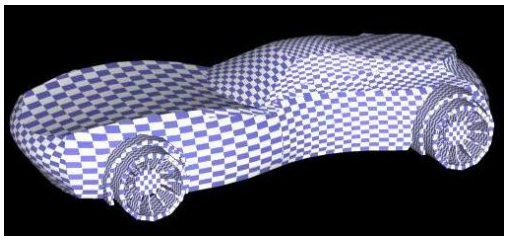
- individuals
  - recording whatever using phones, PDAs, cameras

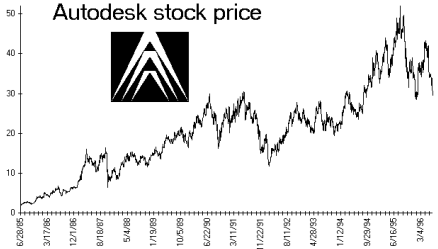
Producers of multimedia data

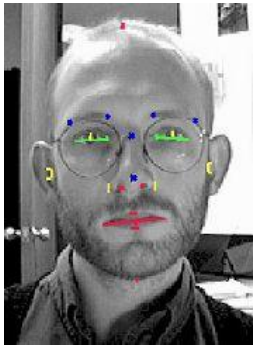
- industry
  - entertainment
  - financial
  - internet news media
  - manufacturing
  - biometrics

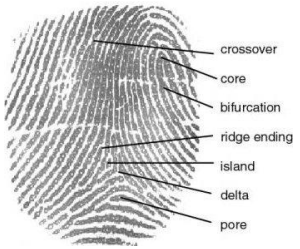


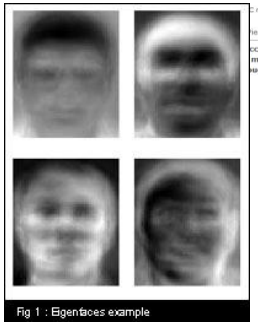


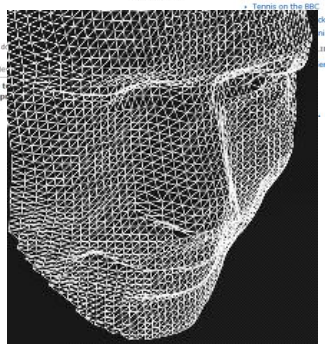












Producers of multimedia data

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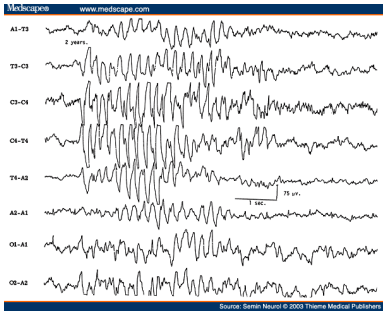
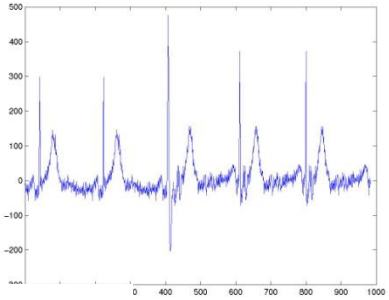
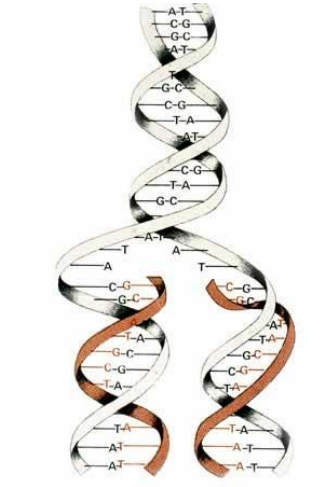
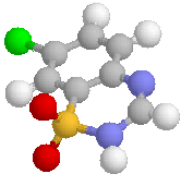
  - medicine
  - material engineering
  - biochemistry









Context and content

- context – description/annotation/neighborhood of content
  - high-level semantics (e.g., image of a ship)
  - keywords/tags, full-text, URL, categorization
    - mostly human-annotated
    - some can be automated
      - e.g., Google images and the embedding web page
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- content – the actual data content
  - raw content (e.g., color pixels, audio wave)

Content and context

Example:
a photograph hosted at Flickr
found by keyword query “vacation”

raw content

manual annotation

automated annotation

Text-based search pros and cons

- **pros**
  - text/keyword annotation allows to implement semantically high-level queries
    - high-level keyword query vs. high-level keyword annotation
  - easy to implement a fulltext index
    - the same as web search engine, i.e., Boolean or vector model
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  - context-based search will be a powerful concept in the future due to the omnipresent social networks
- **cons**
  - requires human labor
    - Ask yourselves,

      how many of your photos from vacations did you keyworded? ☺
  - highly subjective (two persons keyword differently)
  - incomplete (some possibly relevant content is not keyworded)

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- full-text databases
  - loose structure – plain sequence of words
  - strong semantics – query and text share the model
- **multimedia databases**
  - **loose structure**
    – digitized signal (e.g., pixels)
  - **loose semantics**
    – how to query based on pixels?

Content-based similarity search

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- multimedia content has loose structure + semantics,
  - these have to be **revealed** (or **interpreted**) by establishing a content-based similarity search model
  - condensing the raw content into a higher-level information
    - analogy to text search, as to the extreme case, i.e., a few-byte information (e.g., “sunset”) vs. 5MB of mess (a lot of pixels)

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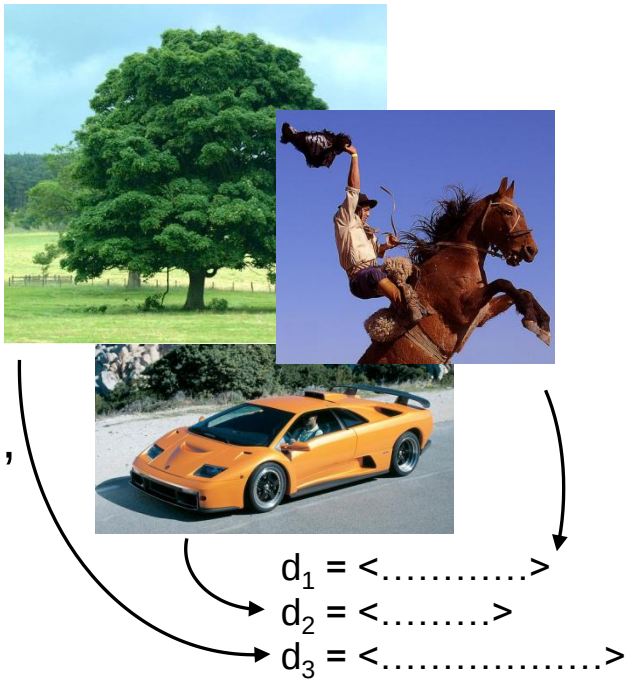
    - we obtain a structured database, however, unlike relational databases, the descriptor structure is **hidden** to the end user



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  - **feature extraction** procedure
    - definition and production of concise **structured descriptors**
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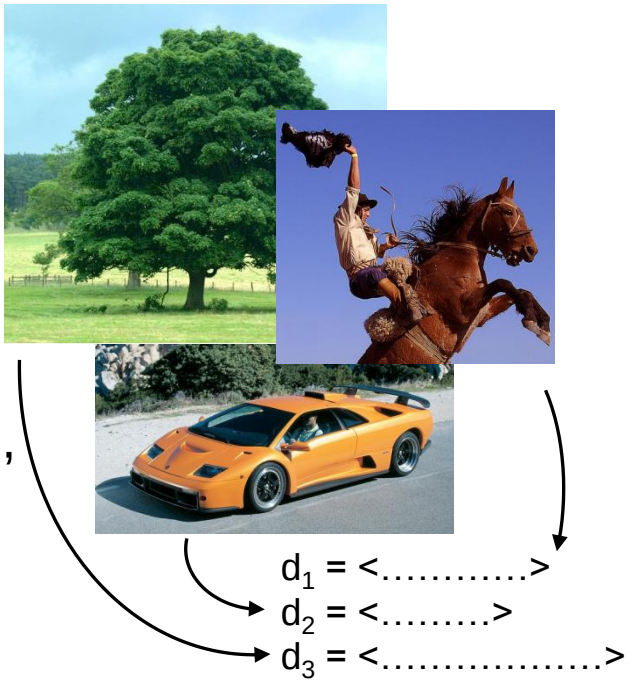
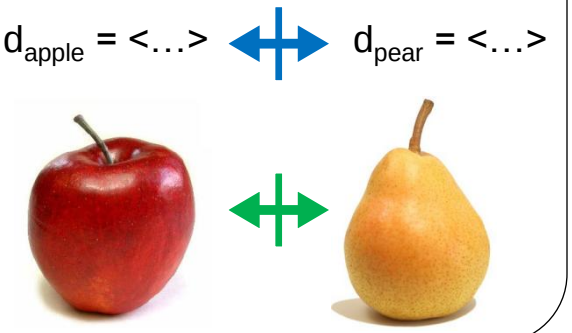
  - **similarity** function
    - suitable function for **comparison** of the descriptors
    - should mimic the **semantic** similarity of the original multimedia objects





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  - for querying we can only utilize the model tools, i.e.,
    - feature extraction procedure
    - similarity measure
  - **query-by-example concept**
    - a multimedia object is obtained, its descriptor **q** is extracted
    - using the similarity function,
      q is compared to all descriptors in the database
    - which results in ordering of the most similar ones to **q**
      - **range query** – returned objects above a similarity threshold
      - **k nearest neighbors** (kNN) query – the **k** most similar ones

Content-based similarity search

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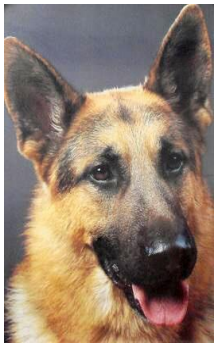

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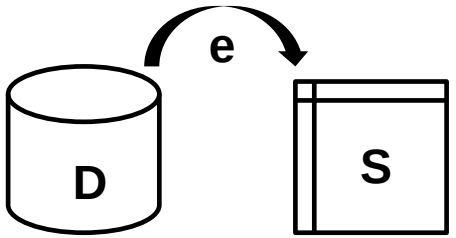
range query (q, 0.5) or 3NN query

Content-based similarity search

- in summary, we have the following formalized model
  - feature extraction procedure **e: X → U**
    - transforming a multimedia object from database universe **X** into a descriptor in descriptor universe **U**
      - the original database **D ⊂ X**,
      - the descriptor database **S ⊂ U**



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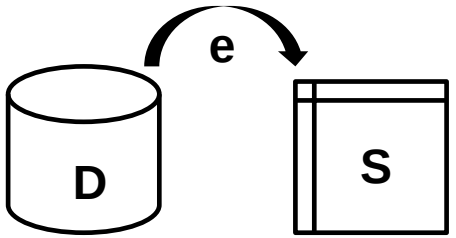

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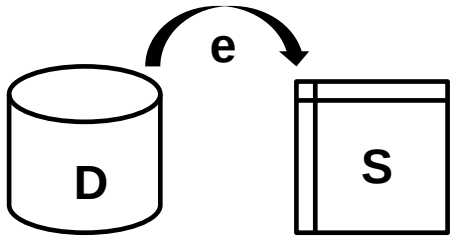

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    - better a dissimilarity (distance), i.e., **close means similar**
  - query-by-example types
    - range query $(\mathbf{q}, \mathbf{r}) = \{x \in S \mid \delta(\mathbf{q}, x) \leq \mathbf{r}\}$
    - **k** nearest neighbor query (**k**NN)

$$(\mathbf{q}, \mathbf{k}) = \{C \mid C \subseteq S, |C| = \mathbf{k}, \forall x \in C, y \in S\text{-}C \Rightarrow \delta(\mathbf{q},x) \leq \delta(\mathbf{q},y)\}$$

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  2) **combining low-level features** to obtain an **expressive** yet **concise** descriptor
     - competence of data exploration, multimedia retrieval
- MPEG7, standard ISO/IEC 15938 (launched in 1998)
  - definitions of visual, audio and motion descriptors
  - selection of some successful content-based descriptors

Feature extraction

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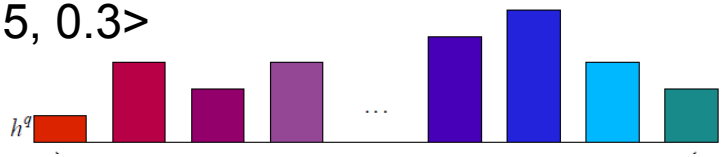
  - **vector** (for feature histograms)

    e.g.,

    x = <0.1, 0.4, 0.3, 0.4, …, 0.6, 0.7, 0.5, 0.3>



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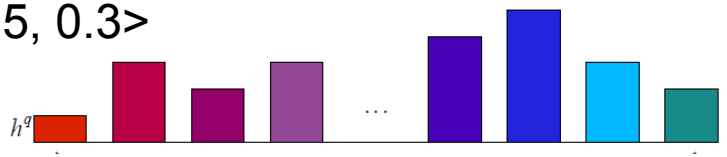

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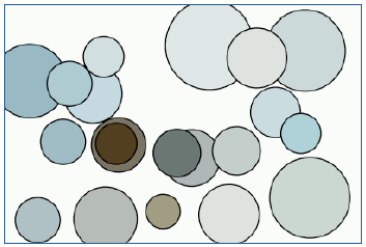

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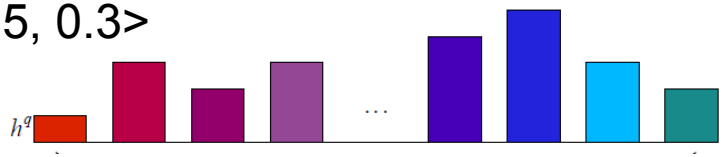

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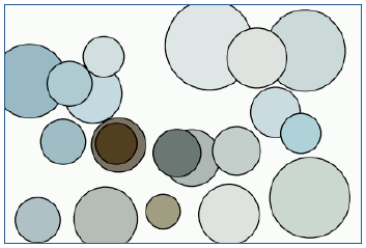
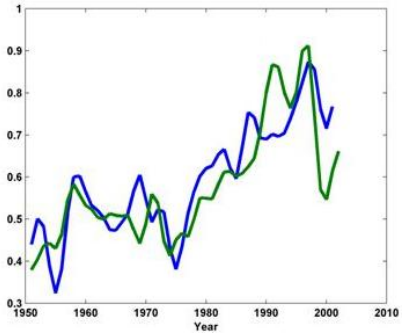


  - **ordered set** (for time series, sequences, strings)

    e.g.,

    x = <t_1, t_2, …, t_k>



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      - Minkowski L_n distances (independent dimensions)

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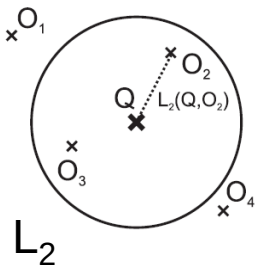

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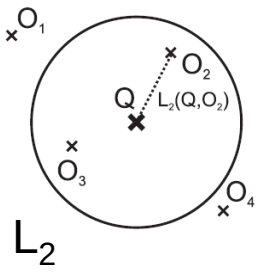
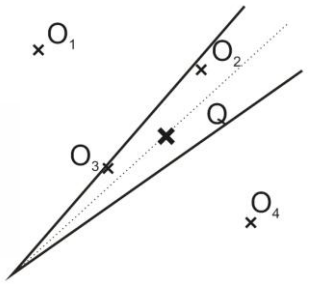


      - cosine distance (angle matters)

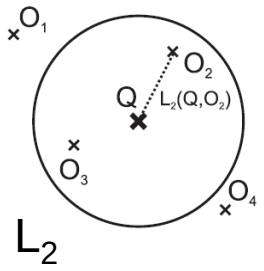
$$\mathrm{SIM}_{cos}(v_1, v_2) = \frac{\sum_{i=1}^{D} v_1[i] v_2[i]}{\sqrt{\sum_{i=1}^{D} v_1[i]^2 \cdot \sum_{i=1}^{D} v_2[i]^2}}$$



Modeling similarity

- how to obtain a **suitable similarity function** for comparing descriptors?
  - depends on the descriptor structure, and the semantics of low-level features
  - based on descriptor structure, we can use, among others
    - **vectorial distances** (for general vectors, histograms)
      - Minkowski L_n distances (independent dimensions)

$$L_p(v_1, v_2) = \left(\sum_{i=1}^{D} |v_1[i] - v_2[i]|^p\right)^{\frac{1}{p}} \qquad (p \geq 1)$$



L_2

      - cosine distance (angle matters)

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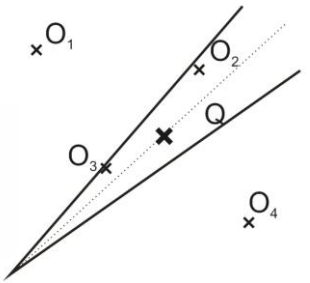
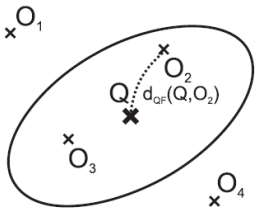


      - quadratic form distance (histograms)

$$d_{QF}(v_1, v_2) = \sqrt{(v_1 - v_2) M (v_1 - v_2)^T}$$



Modeling similarity

- **adaptive distances** (signatures, gen. sets)

Modeling similarity

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  - signature quadratic form distance

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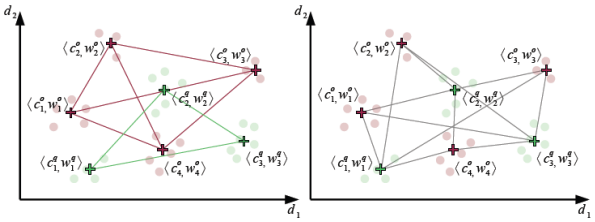

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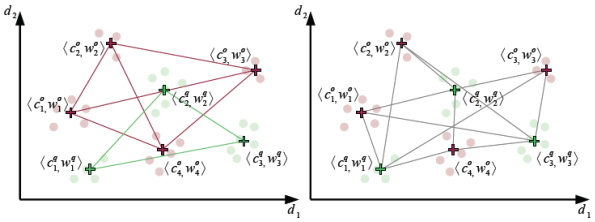

  - earth mover's distance

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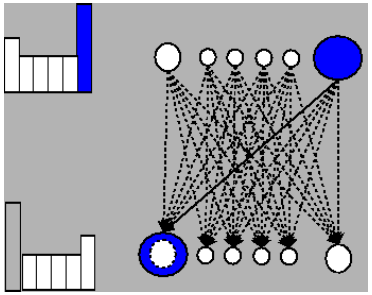

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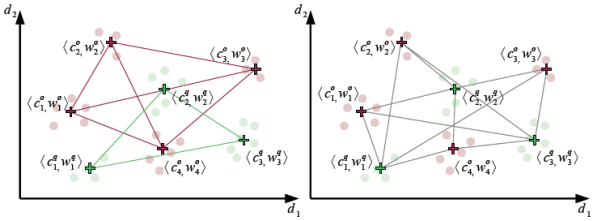

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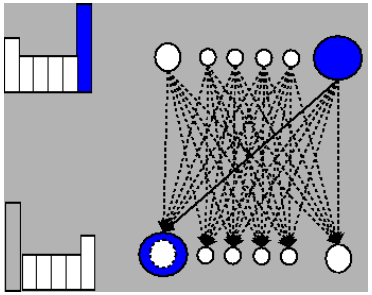

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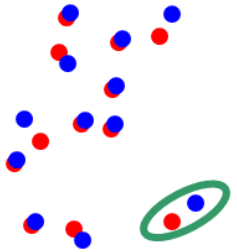

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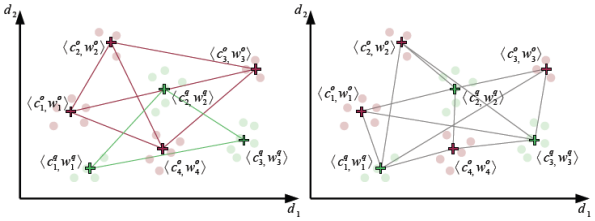

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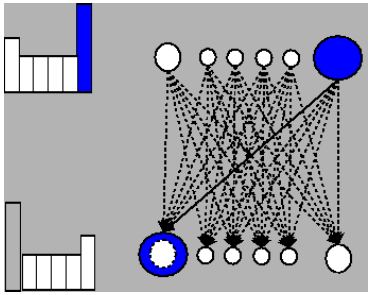

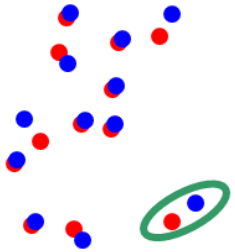

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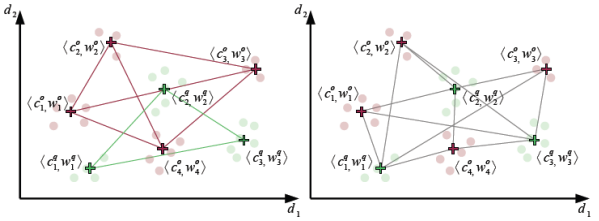

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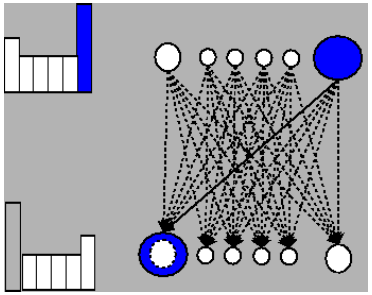

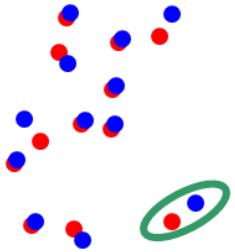

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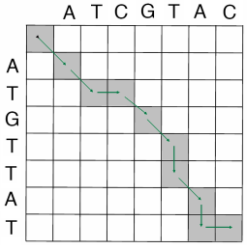

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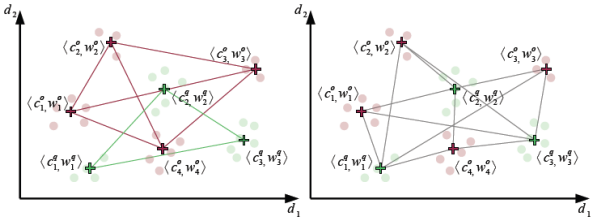

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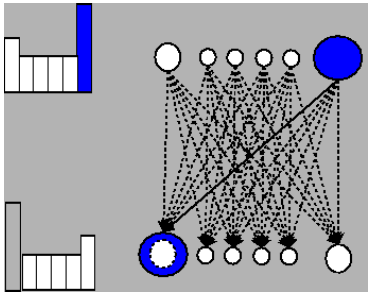

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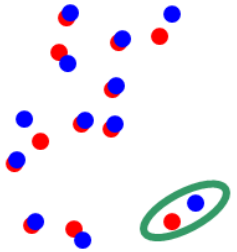

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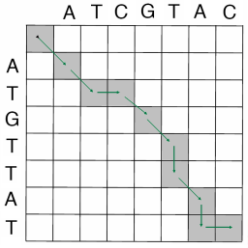
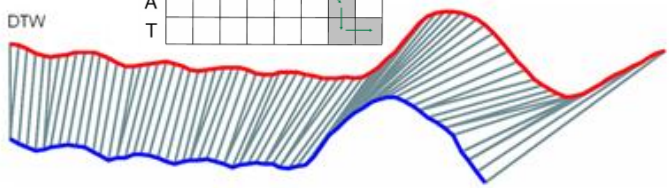


  - dynamic time warping distance

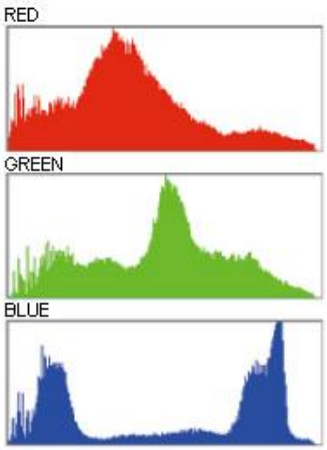
$$\delta_{DTW}(x,y) = \min_W \left\{ \sqrt{\sum_{k=1}^{t} w_k} \right\}$$

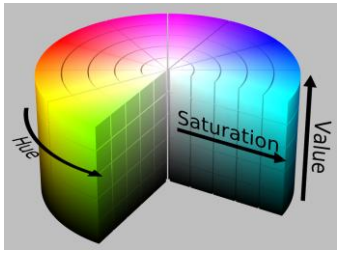


Applications

- image retrieval using **global features**, e.g.,

Applications





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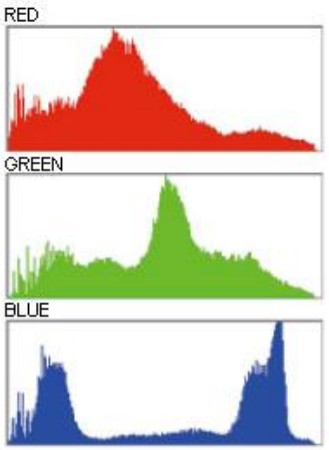

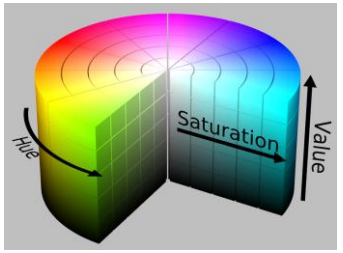

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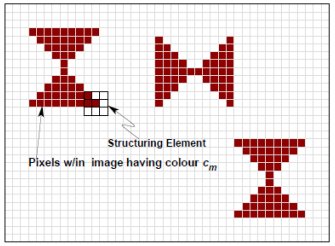
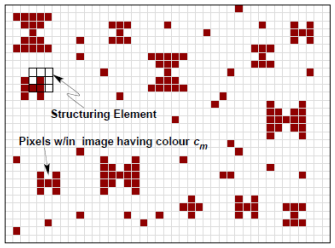
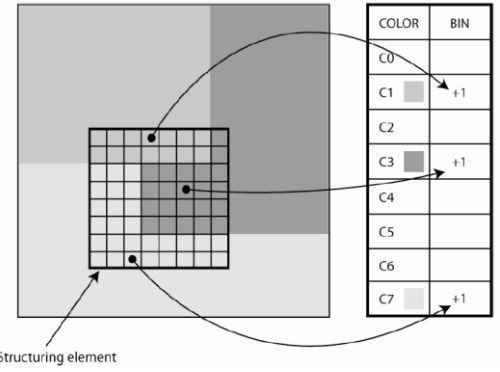
  - **Color structure** (MPEG7)
    - specific color histogram that includes local information
    - moving structuring element (grid), adding its content to histogram (the descriptor) after each movement
    - L_1 distance used



high color structure



low color structure



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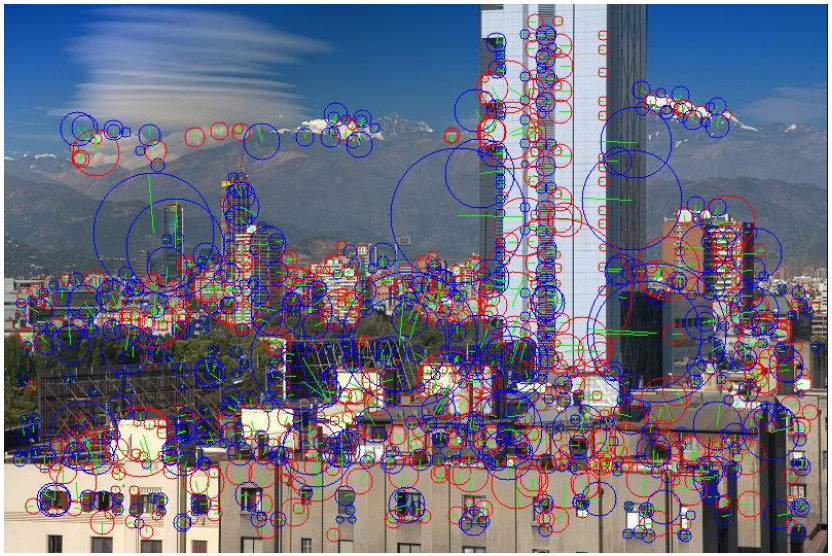
view at Santiago, 1174 interest points (SURF)



- image retrieval using **local features**, e.g.,
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    - interest points/blobs
    - local SIFT feature vector = 128D vector consisting of gradient orientation histograms around an interest point
    - image descriptor – signature
      - SIFT feature vectors are clustered
      - signature consists of weighted centroids

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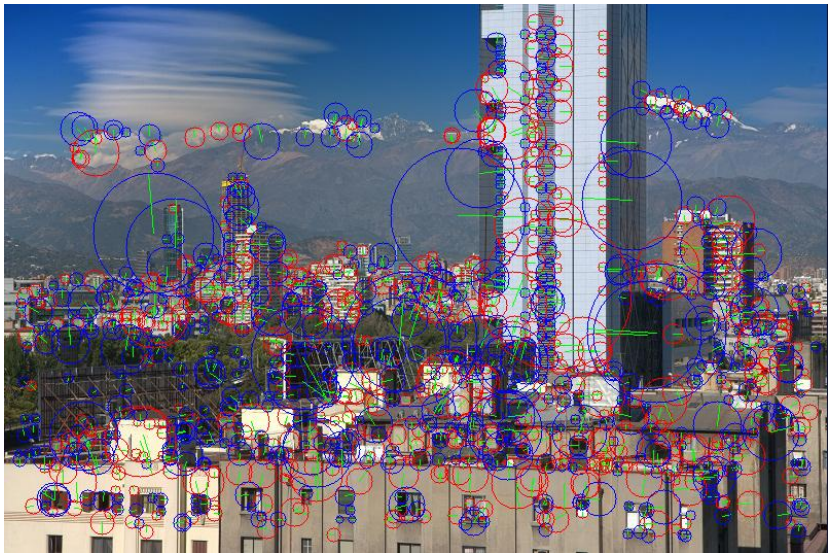

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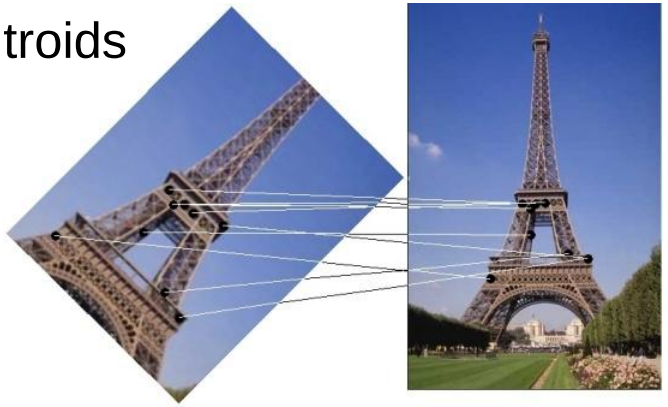
      - SIFT feature vectors are clustered
      - signature consists of weighted centroids
    - set distance
      - (signature) quadratic form dist.
      - Hausdorff distance
      - using an L_p ground distance for the SIFT features



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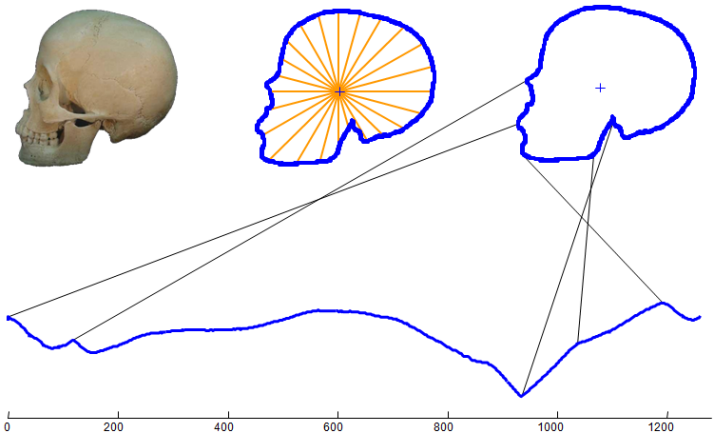

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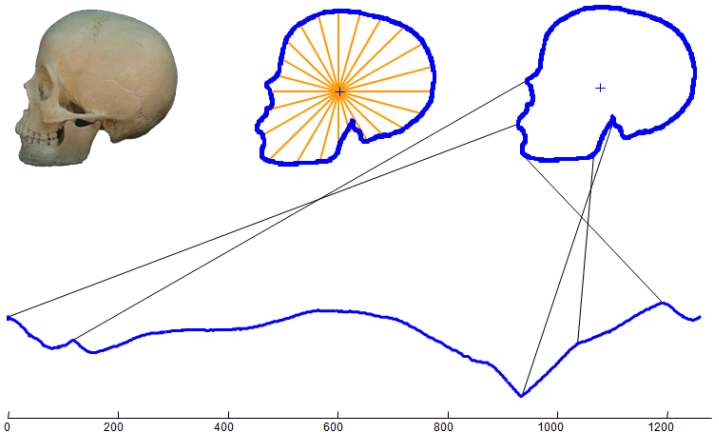
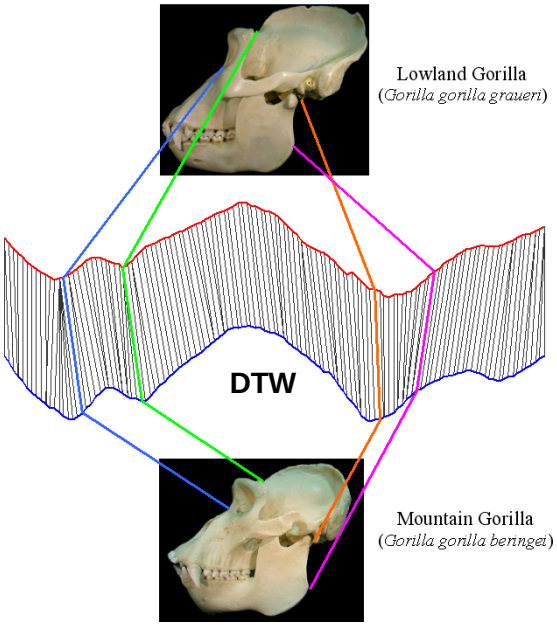
  - **dynamic time warping distance** (DTW) or





Applications

- shape retrieval using **time series**, e.g.,
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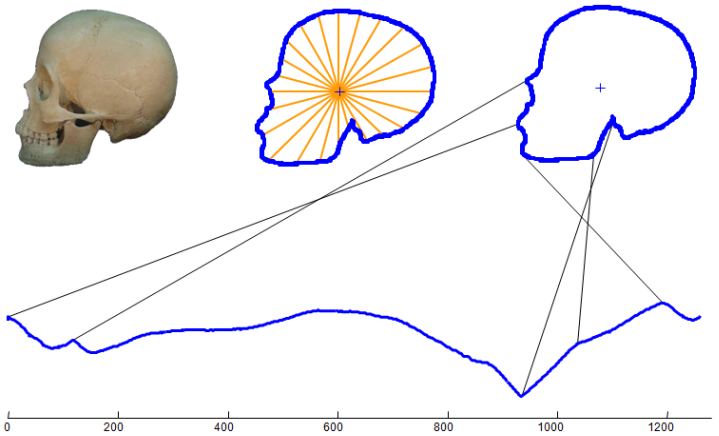
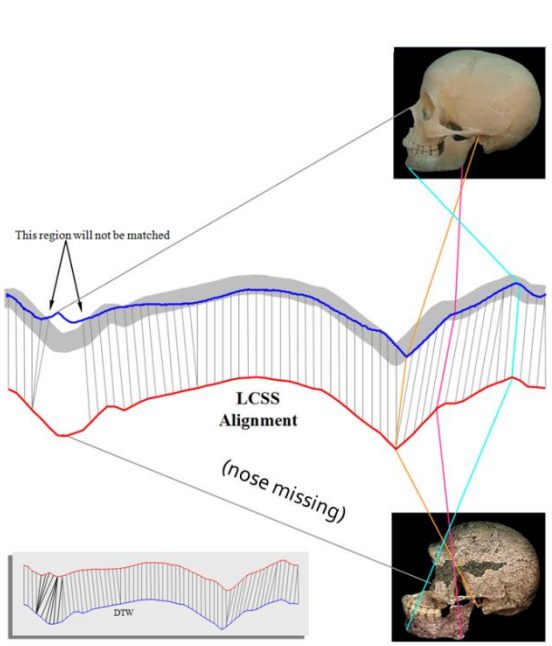
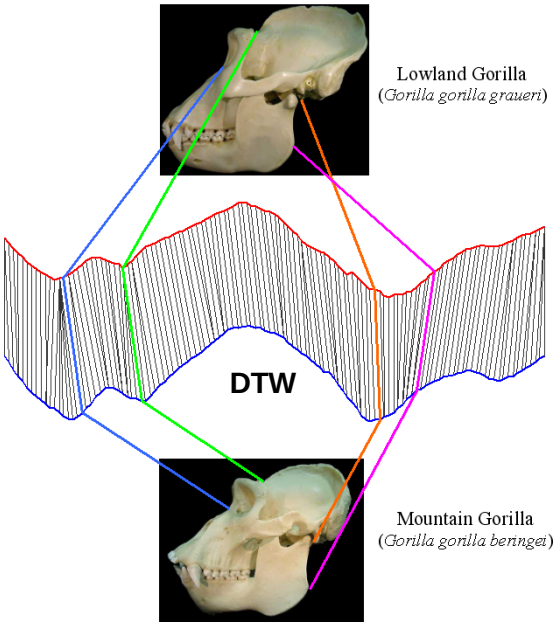
  - **dynamic time warping distance** (DTW) or **longest common subsequence** (LCSS)

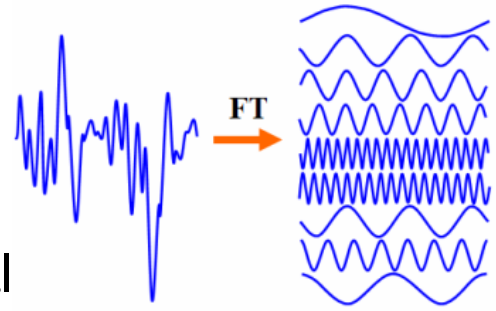






Applications

- audio retrieval using **waveform spectral information**
  - discrete Fourier transformation of the signal into the frequency domain – the power spectrum



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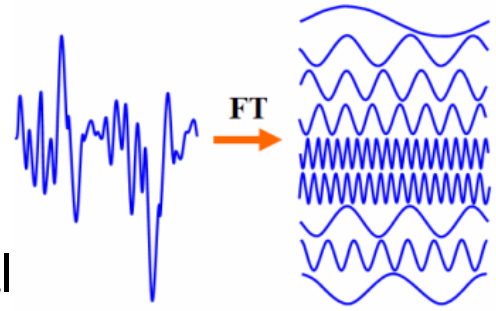

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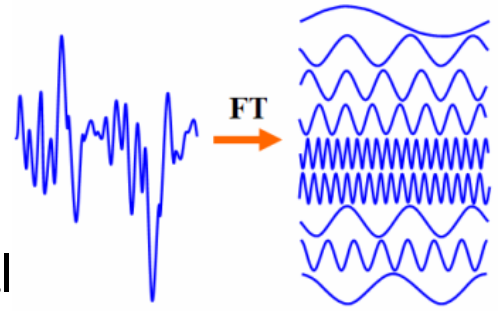

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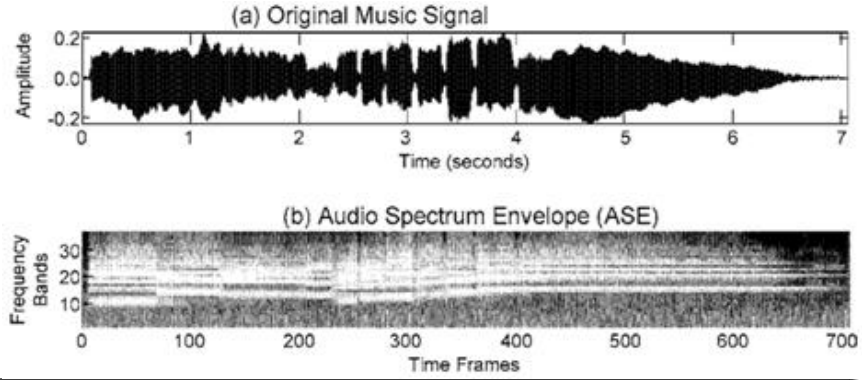
    - concatenation of local features into a spectrogram (the descriptor)
    - some distance for multidimensional time series



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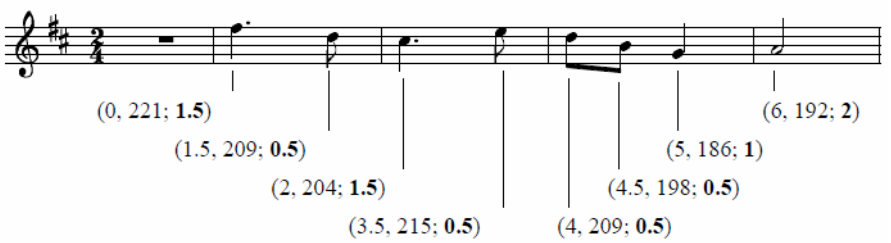

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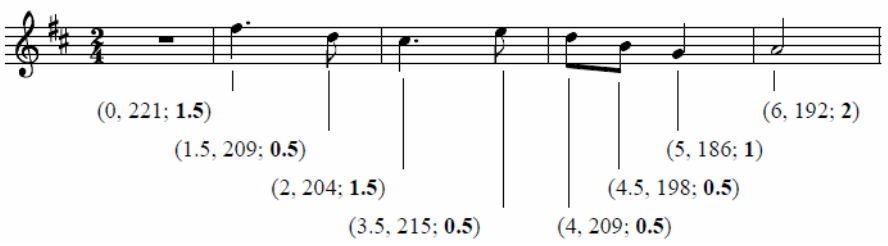

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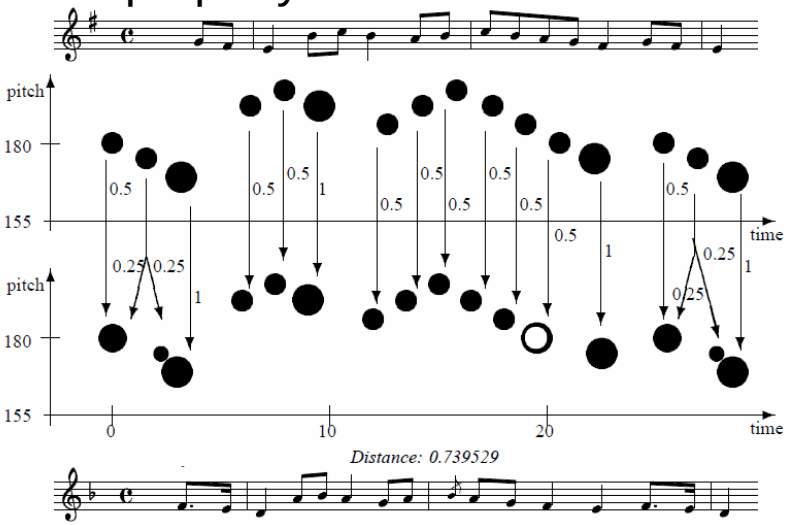
  - distance
    - Earth mover's distance
    - Proportional Transportation distance



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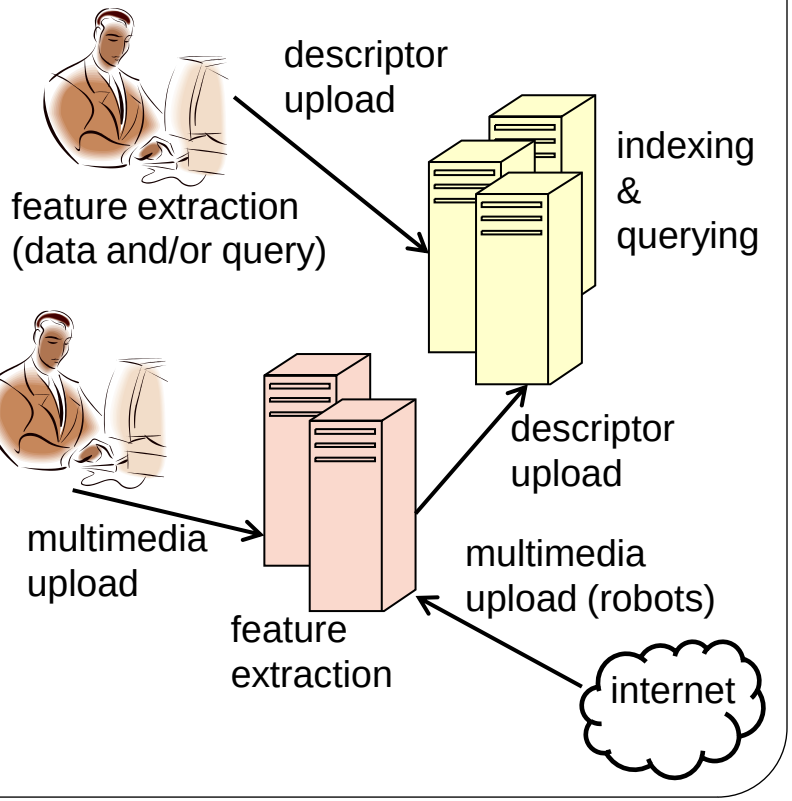
Performance of similarity search

- search engine subsystems
  - feature extraction – expensive, but
    - could be forwarded to the clients or to dedicated servers
      - both the data and the query (example)
    - well-parallelizable
      - just the multimedia object needed to extract descriptor, not the entire database
    - updates less frequent than querying



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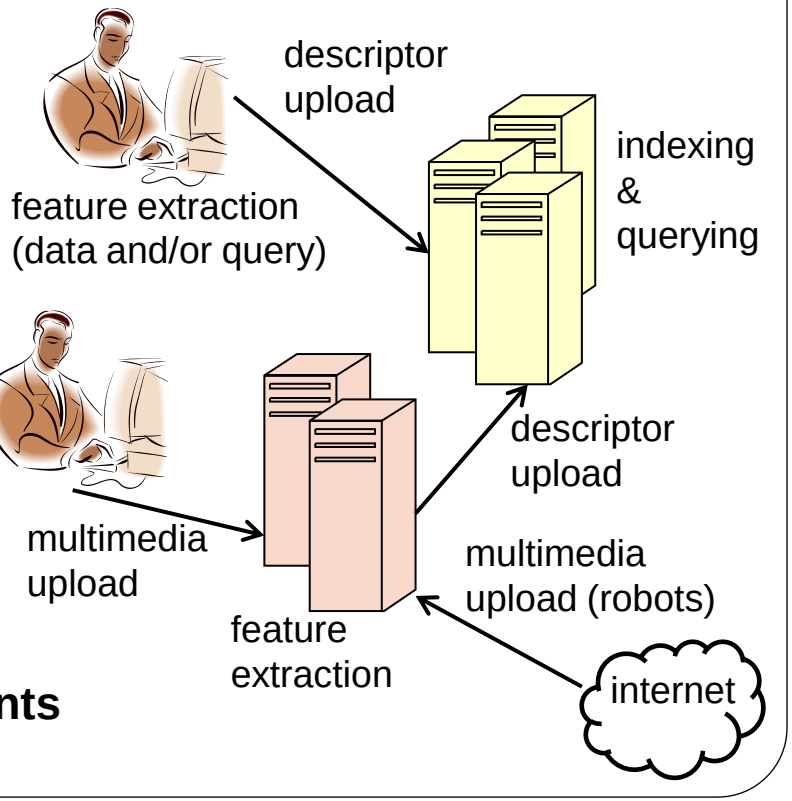
  - similarity indexing
    - the computational **complexity of distance function is crucial**
    - centralized or distributed index
      - **cannot be forwarded to the clients**



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- very expensive **$O(2^n)$**
  - (general) earth mover's distance (transportation problem, resp.)

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  - general, yet simple, model
    - metric postulates

$$\begin{aligned} \delta(x,y) &= 0 && \Leftrightarrow x = y && \text{reflexivity} \\ \delta(x,y) &> 0 && \Leftrightarrow x \neq y && \text{non-negativity} \\ \delta(x,y) &= \delta(y,x) && && \text{symmetry} \\ \delta(x,y) + \delta(y,z) &\geq \delta(x,z) && && \text{triangle inequality} \end{aligned}$$

  - allows to partition and prune the data space (triangle inequality), resulting in a **metric index**
  - the search is performed just in several partitions → **efficient search**

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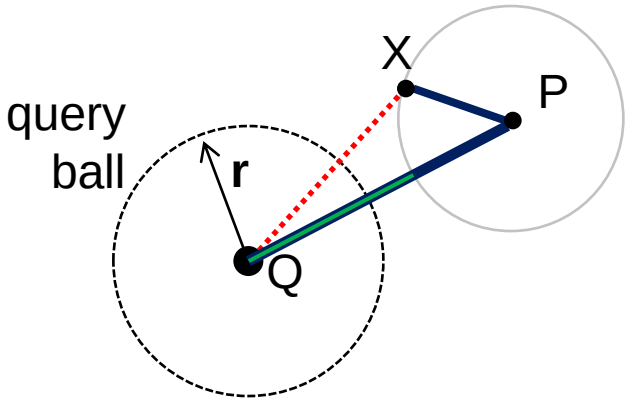

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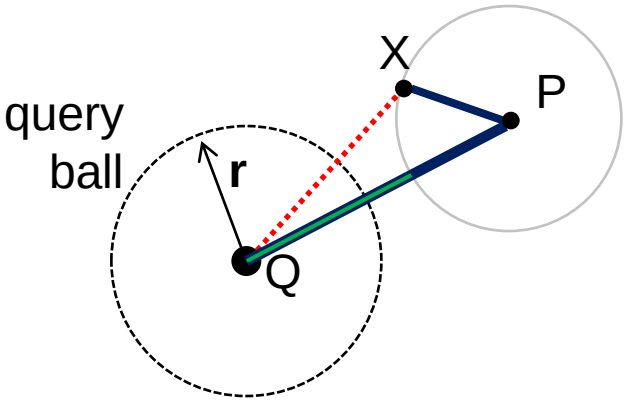

The task: check if **X** is inside query ball

- we know **δ(Q,P)**
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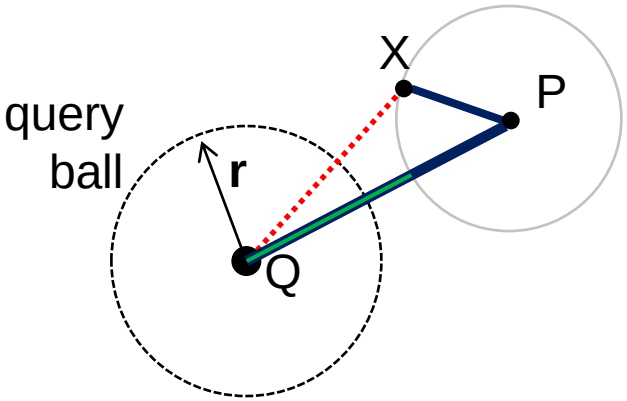

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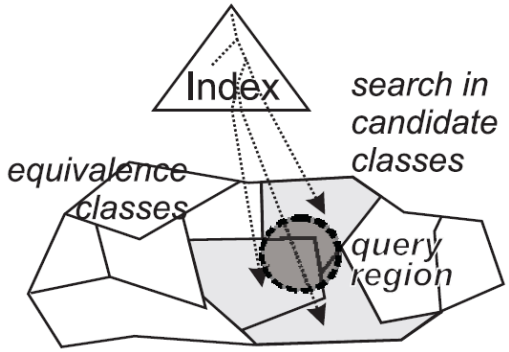
- this filtering is used in various forms by metric access methods, where **X** stands for a database object and **P** for a pivot object

Metric access methods (MAMs)

- indexes for **efficient similarity search in metric spaces**
  - just the distances are used for indexing (structure of universe **U** unknown)
  - database **S** is partitioned into equivalence classes
  - index construction usually takes between O(k**n**) to O($\mathbf{n}^2$)



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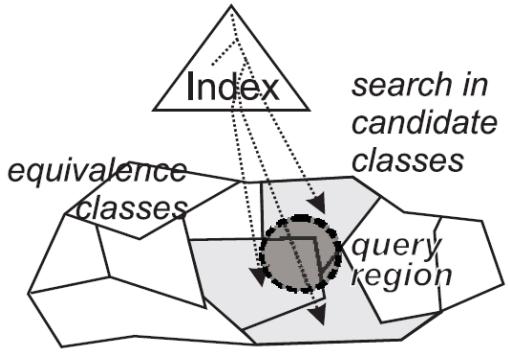
- using the **lower-bounding** filtering when searching
  - pruning some equivalence classes, the remaining classes are searched sequentially



Metric access methods (MAMs)

- various structural designs
  - flat pivot tables (LAESA)
  - trees
    - ball-partitioning (M-tree)
    - hyperplane-partitioning (e.g., GNAT)
  - hashed indexes (D-index)
  - combinations of the above (PM-tree, M-index)
  - index-free approach (D-file)

Pivot tables

- set of **m** pivots p_i
- mapping individual objects into pivot space by use of the **m** pivots – distance matrix
  - $v_i = [\delta(o_i, p_1), \delta(o_i, p_2), ..., \delta(o_i, p_m)]$
  - contractive: $L_{max}(v_i, v_j) \leq \delta(o_i, o_j)$
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	p_1	p_2
o_1	5	2.6
o_2	7.2	1.4
o_3	6.7	1.6
o_4	4.8	2.7
o_5	2.6	3.2
o_6	3.6	3.5
o_7	3.6	4.5
o_8	2.5	5.5

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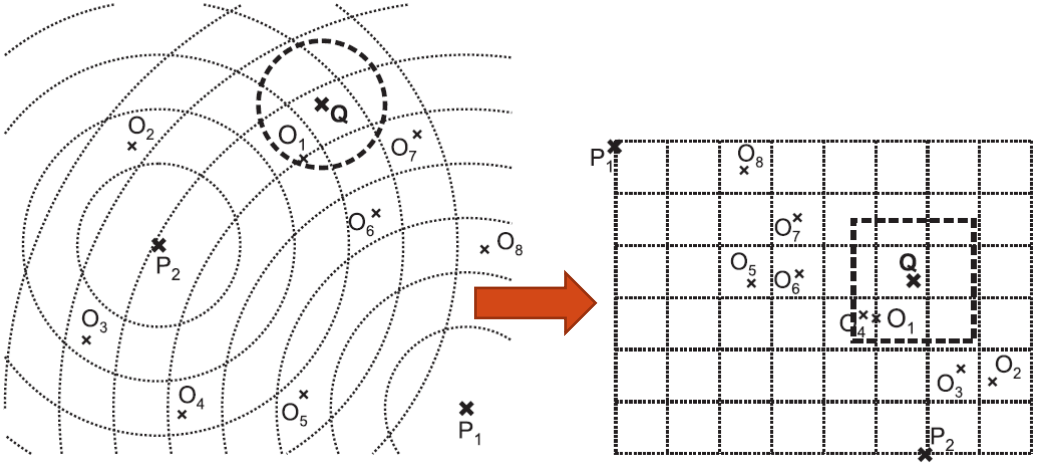

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- feature extraction and similarity models allow to focus on domain-specific semantics, which leads to more precise retrieval
- emerging phenomena
  will affect the research in the future
  - search aided by social networks (linked media)
  - more complex models, including non-metric similarities
  - powerful indexes for huge multimedia repositories

Thank you for attention!