course:

Searching the Web (NDBI038)

Searching the Web and Multimedia Databases (BI-VWM)

lecture 11:

Similarity queries and multi-modal search

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Today's lecture outline

- fundamentals
- similarity queries
  - similarity ordering, range, kNN, kRNN queries
  - similarity joins, self-joins, (k) closest pairs
- multi-modal search
  - early fusion
    - multi-metric model
  - late fusion
    - skyline operator
    - top-k operator
    - re-ranking
    - query languages

Fundamentals

- similarity search = a content-based retrieval concept
- formalized model
  - **feature extraction** procedure $\mathbf{e: X \rightarrow U}$
    - transforming a multimedia object from database universe **X** into a descriptor of descriptor universe **U**
      - the original database $\mathbf{D \subset X}$,
      - the descriptor database $\mathbf{S \subset U}$
  - **distance (dissimilarity) function** $\mathbf{\delta: U \times U \rightarrow R}$
    - i.e., close means similar
  - similarity queries: query-by-example paradigm
    - similarity query defined by its **type**, an **example** object **q** and an **extent** of the query
    - returns **ranked query result**, consisting of descriptors based on their closeness to **q**

Similarity queries

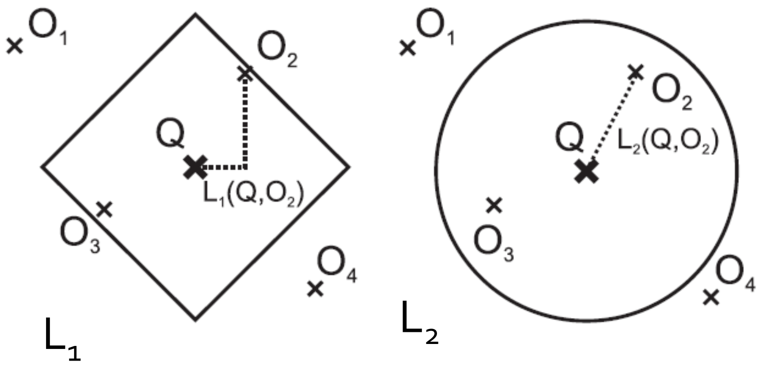
- similarity ordering
  - given a query object $\mathbf{q} \in \mathbf{U}$ and the descriptor universe $\mathbf{U}$,

  - SimOrder: $\mathbf{U} \rightarrow \mathbf{S}^{|S|}$,
    where $\forall \mathbf{i} \in (1, |\mathbf{S}|)$: $\delta(\mathbf{q}, \text{SimOrder}(\mathbf{q})[i]) \leq \delta(\mathbf{q}, \text{SimOrder}(\mathbf{q})[i+1])$
    - informally, SimOrder is the database **S** ordered desc. by distance of their elements to **q**

  - SimOrder is the basic concept when defining a similarity query
  - just an abstraction (i.e., SimOrder is not fully materialized when querying)

Similarity queries

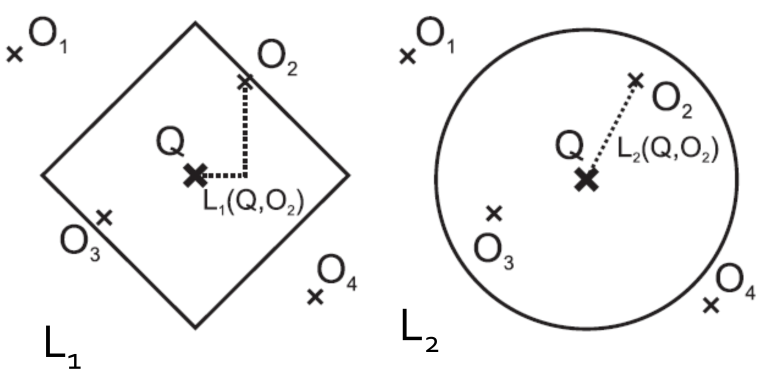
- range query
  - given a distance radius **r** (dissimilarity threshold), a range query returns all database descriptors the distances of which to **q** is no more than **r**
    - i.e., a prefix **P** ⊂ SimOrder(**q**), such that **x**∈**P**, δ(**q**, **x**) ≤ **r**
    - shortly, (**q**, **r**) = {**x**∈**S** | δ(**q**, x) ≤ **r**}
  - a "ball "in the distance space
    - just visualization, as geometry is meaningful only in vector spaces
    - delimits a region (subset) in **S**



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

Similarity queries

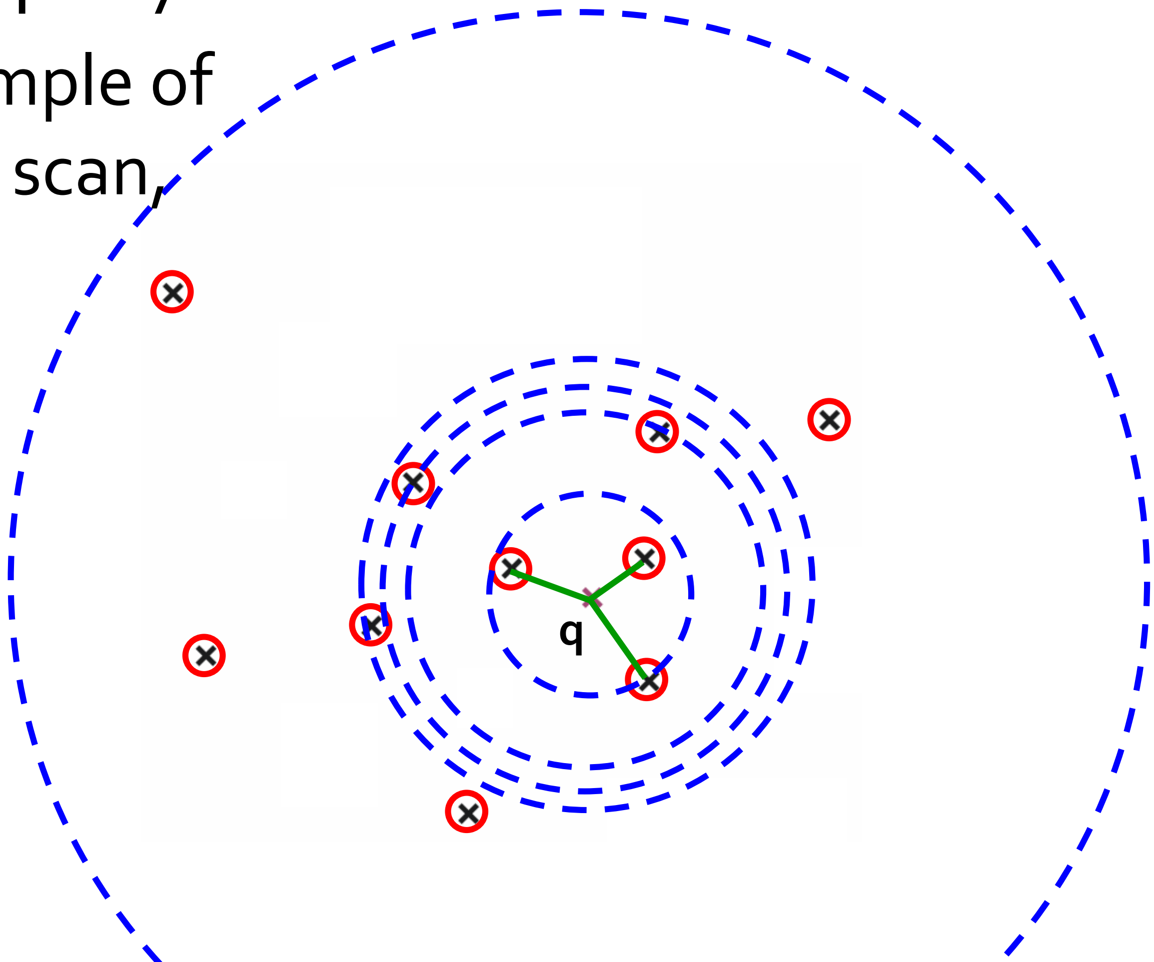
- k nearest neighbor (kNN) query
  - given a number of desired descriptors k,
    a kNN query returns k database descriptors closest to **q**
    - i.e., a prefix **P** $\subset$ SimOrder(**q**), such that **|P| = k**
    - shortly, (**q**, **k**) = {**C** | **C**$\subseteq$**S**, |**C**|=**k**, $\forall$**x**$\in$**C**, **y**$\in$**S**-**C**$\Rightarrow$ δ(**q**,**x**) ≤ δ(**q**,**y**) }
    - ties are solved arbitrarily
      (**k**th and (**k**+1)th NN could be
      the same close to **q**)
  - also "ball "in the distance space
    - but the query radius
      is not known in advance
    - delimits a region (subset) in **S**



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

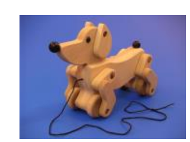
Similarity queries

- kNN query
  - example of seq. scan, k=3



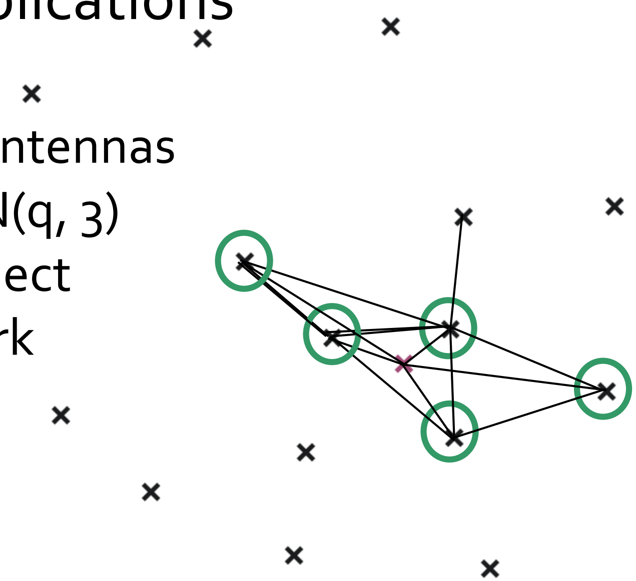
Similarity queries

- range vs. kNN queries
  - **range query** appropriate when
    - end-user is able to specify **r**, i.e., knows the semantics of the model
    - e.g., edit distance on strings,
      counting the smallest number of character edits to transform s_1 into s_2
      range query ('drier', 2) = {driver, d_iver, _river, drive_}
    - 100% recall is guaranteed (because of user's confidence on **r**)
  - **kNN query** appropriate when
    - user cannot specify **r**, i.e., does not know the semantics of the model
    - majority of cases

4NN, q=  ⇨  0.2  0.3  0.5  0.6  0.7

Similarity queries

- *k* reverse nearest neighbors (kRNN)
  - not very frequent, but interesting query type
  - for a query descriptor **q**, *k*RNN returns all descriptors x_i from the database for which $\mathbf{q} \in \text{kNN}(x_i, k)$
  - identifies the closest distinct neighborhood around **q**
- mostly used in spatial databases applications
  - e.g., in a GIS application,
    let the descriptors be positions of GSM antennas
    (**q** is a planned one), if the result of kRNN(q, 3)
    is large enough, **q** is needed to interconnect
    the other antennas into a reliable network
- could be used as similarity query
  - e.g., for identification of redundancy



Similarity operators

- database operator = an operation on the database with result
- query vs. operator
  - query – the query expression/example is a parameter
    - small subset of the database is expected as a result
    - repeated queries of the same type on a static database makes sense (query expression is changing)
  - operator – often defined as non-parameterized operation
    - repeated processing of non-parameterized operator on a static database leads to the same result
    - only dynamic databases expected to run non-parameterized operators repeatedly
    - the answer is often large (more a database transformation than query)

Similarity operators

- similarity join
  - joining descriptors of database A with descriptors of database B, based on a similarity-query predicate
    - range or kNN query predicate
  - if A=B, we talk about similarity self-join
  - self-joins are suitable for near-duplicates detection

Similarity operators

- *k* closest pairs
  - based on the distance function δ, select the *k* pairs $\langle x, y \rangle \in A \times B$, that have the smallest distance $\delta(x, y)$
  - repeated usage makes sense for different combinations of A and B, dynamic or streamed databases, where the closest pairs have to be continuously updated

Multi-modal search

- description of objects/queries by multiple modalities (models, examples, interfaces, etc.)
  - often reduced to multi-modal query-by-example
  - e.g., keywords+image, multiple images, image+audio+relational, etc.
- early fusion (in similarity search)
  - all modalities aggregated in single similarity model
  - single descriptor per object (1:1 problem, one query/index)
- late fusion
  - each modality represented (and queried, indexed) individually
  - hence, 1:N problem, where fusion step is needed

Early fusion

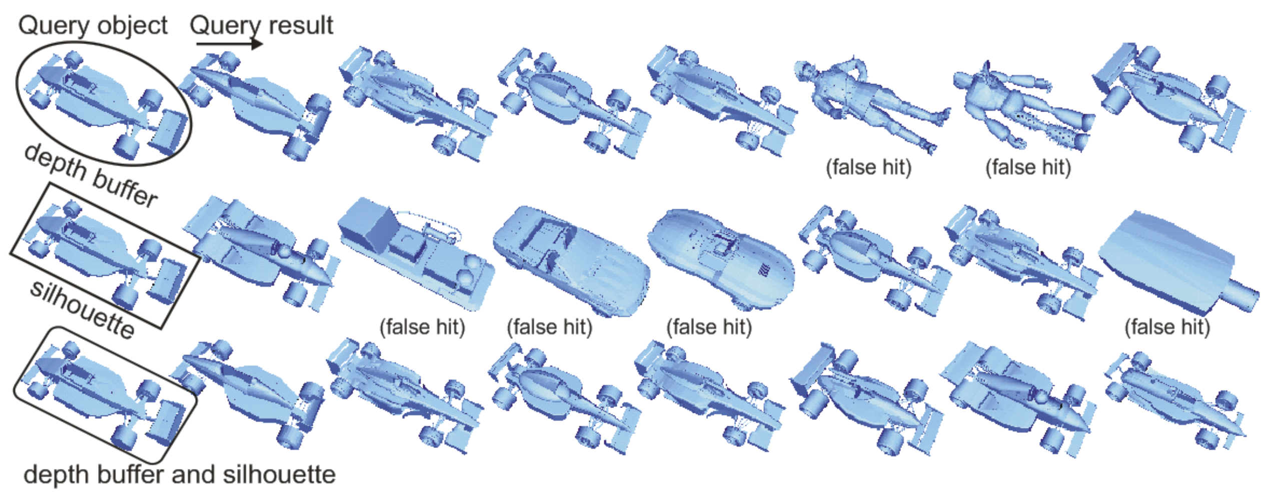
- partial similarity models aggregated
- e.g., multi-metric approach
  - provides flexible (parameterized) similarity in single model
  - descriptor composed from multiple sub-descriptors
  - each sub-descriptor its own similarity model (metric space)
  - for each query object different contribution of particular sub-descriptor needed
  - multi-metric
    - linear combination of distances on sub-descriptors
    - vector of weights W defined at query time

$$\mathbb{W} = \langle w_i \rangle$$

$$\Delta_{\mathbb{W}}(O_1, O_2) = \sum_{i=1}^{m} w_i \cdot \delta_i(O_1, O_2)$$

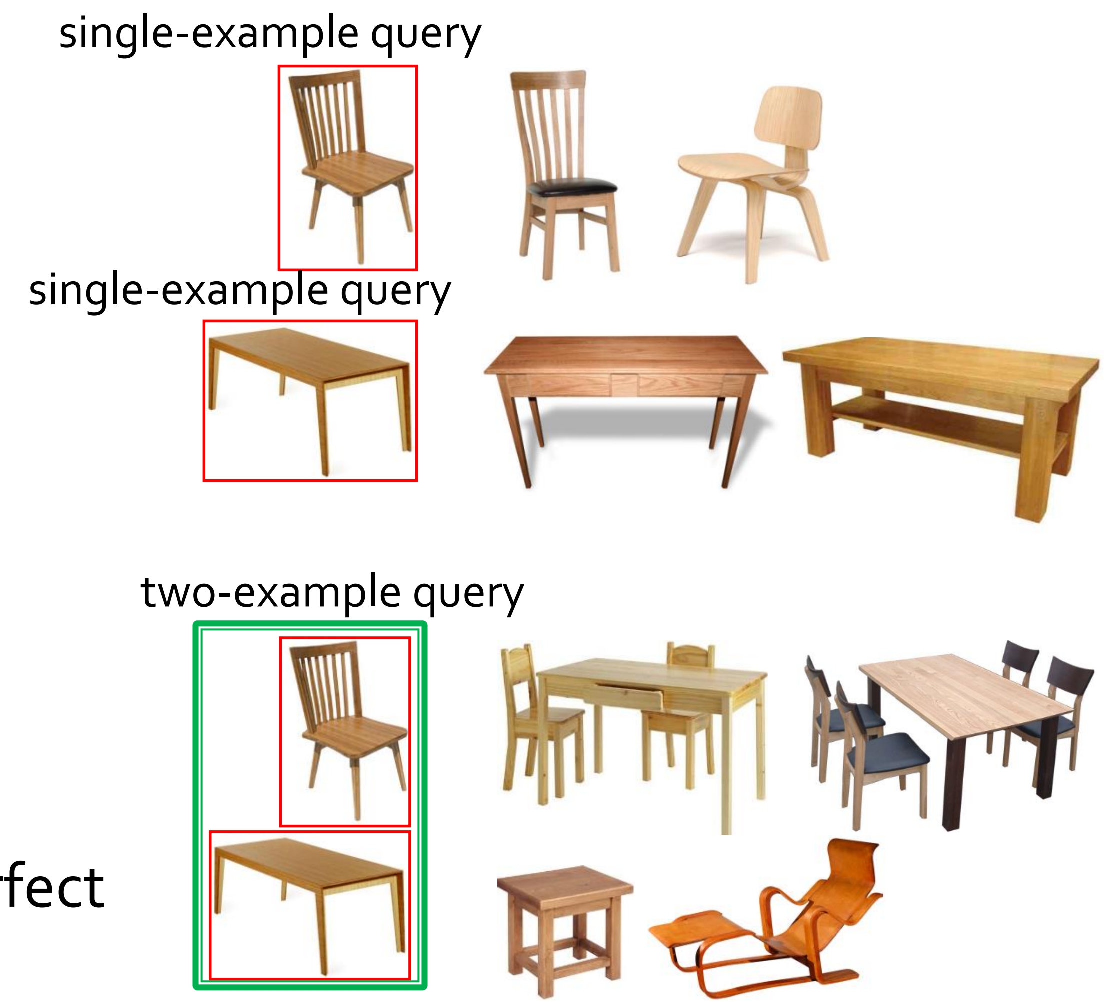
Early fusion – multi-metric model

- multi-metric model consisting of
  - depth buffer feature descriptor + distance δ_1
  - silhouette feature descriptor + distance δ_2
- single multi-metric index
- results for query model "formula"; W set at query time as
  - $w_1 = 1, w_2 = 0$
  - $w_1 = 0, w_2 = 1$
  - $w_1 = 0.5, w_2 = 0.5$



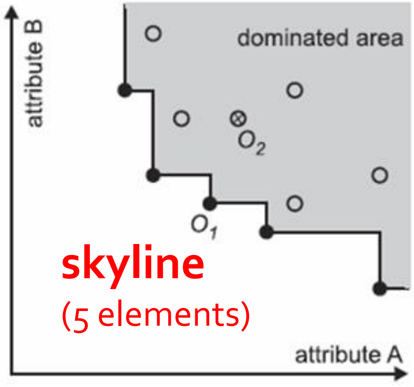
Late fusion – skyline operator

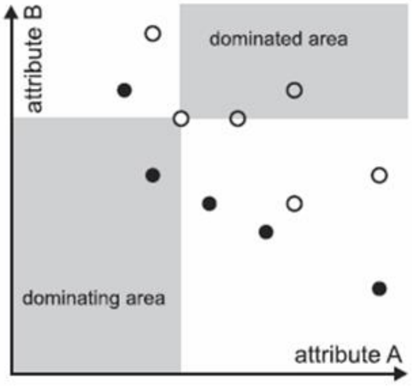
- single-example queries often not sufficient
  - user is not able to find perfect example
- multi-example queries
  - aggregating queries/operators
  - multiple not-so-perfect examples



Late fusion – skyline operator

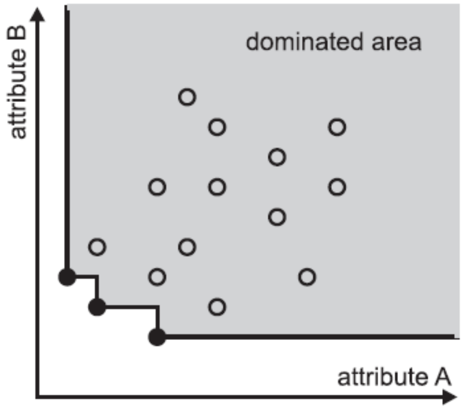
- traditional skyline operator (also Pareto set)
  - database **S** modeled in several ordered domains (attributes)
  - skyline = subset of elements from **S** that are not dominated by other elements
    - element is not dominated if there does not exist another element that is better in all the attributes (let's better = lower value)
  - why the term "skyline"?
    - when connected by vertical and horizontal lines, the set looks like skyline of a city
  - application
    - e.g., market basket,
      consider database of hotels
      with attributes
      price and
      distance to airport



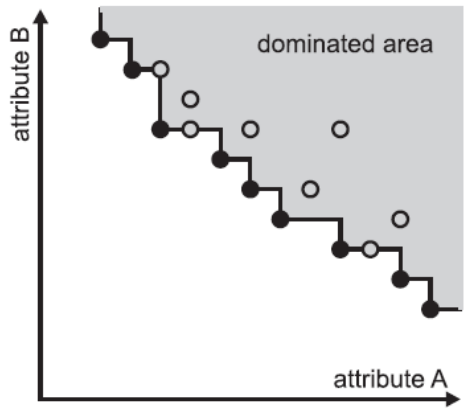


Late fusion – skyline operator

- problems
  - skyline is not limited in size
    - correlated data lead to very small skyline (a)
    - anti-correlated data lead to very large skyline (b)
  - there is not ranking/ordering inside
  - i.e., problems similar to the Boolean model
- often too large skyline
  - manufacturers/distributors create additional unique attributes to put their products on the skyline
    - e.g., my hotel is the closest one to a winery ☺



(a)



(b)

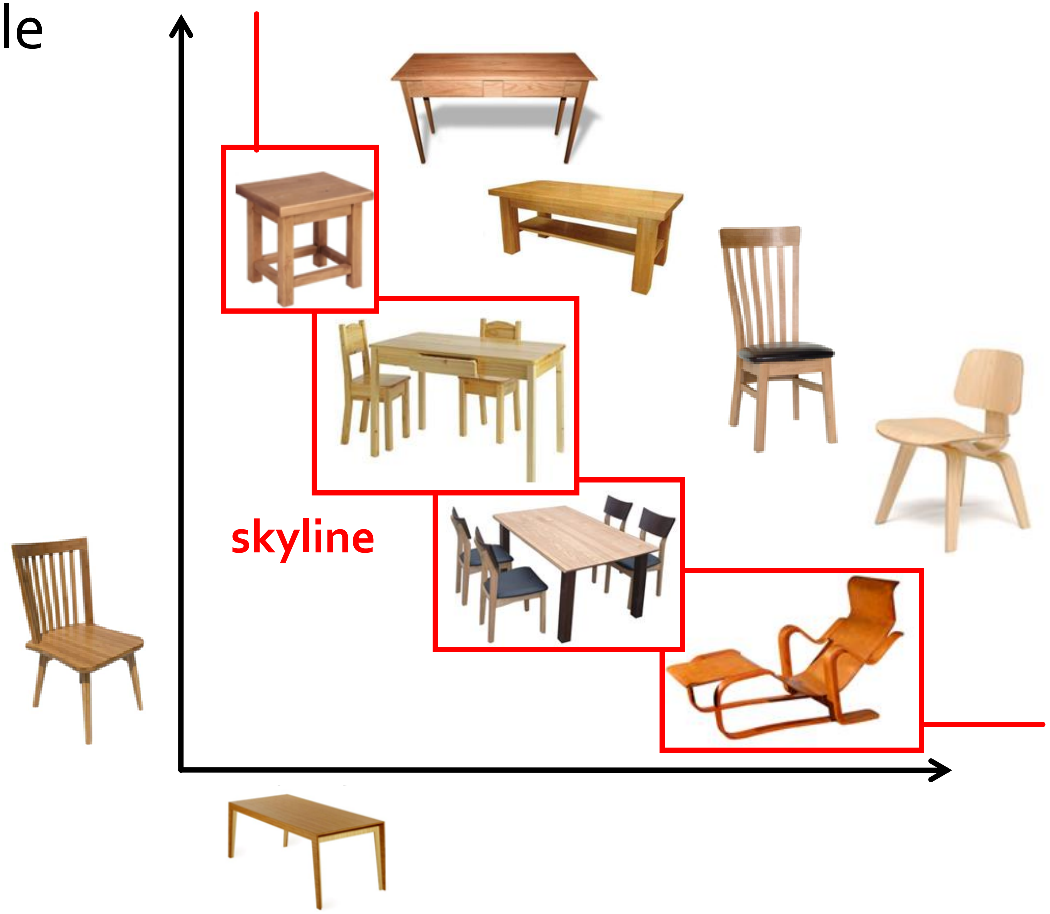
Late fusion – skyline operator

- let the “attributes” be interpreted as similarity orderings with respect to multiple query examples

- the skyline operator then becomes a **multi-example similarity query**
  - a particular skyline is a set of descriptors that are compromises with respect to the query examples
  - dynamic schema (attributes)
    - the coordinate system is established for each query separately
    - cannot be implemented by traditional skyline operator

Late fusion – skyline operator

- example of two-example similarity skyline query



Late fusion – top-k operator

- motivation
  - consider a single database of multimedia objects (or web pages)
  - consider several (similarity) models that can be used to rank the database – search result fusion
    - similarity query, the similarity ordering, respectively
    - other rankings, e.g., PageRank
  - for example, database of web pages including images
    - ranking #1 = vector model of inf. retrieval (cosine sim. of web page text)
    - ranking #2 = similarity of images of the web pages (e.g., MPEG7 and L1)
    - ranking #3 = the PageRank of the web pages
  - thus, we need an aggregation procedure to create one final ranking based on the partial rankings – the **top-k operator**

Late fusion – top-k operator

- top-k operator
  - real-valued ordered attributes $A_1,\ldots,A_m$
    - in our case, let the attributes be **different rankings of the same objects**
    - for now let's better value = higher value (but could be defined inversely)
  - aggregation function $f: A_1 \times \ldots \times A_m \rightarrow R$
    - let f be monotonic, i.e., if $x > y$, then $f(\ldots, x, \ldots) > f(\ldots, y, \ldots)$
    - e.g., Min, Max, Avg
  - the top-k operator evaluates the aggregation function on all the objects' partial ranks and returns *k* objects with the highest aggregate ranks
    - could be done sequentially, but how to do that efficiently?
    - Fagin and Threshold algorithm (already discussed in Lecture 5)

Late fusion – re-ranking

- multi-phase querying (dependent aggregation)
  - applying different similarity model on part of the previous ranking
  - when single similarity is too complex to model

- example
  - first ranking as 4NN – color layout
  - re-ranking as 3NN – shape

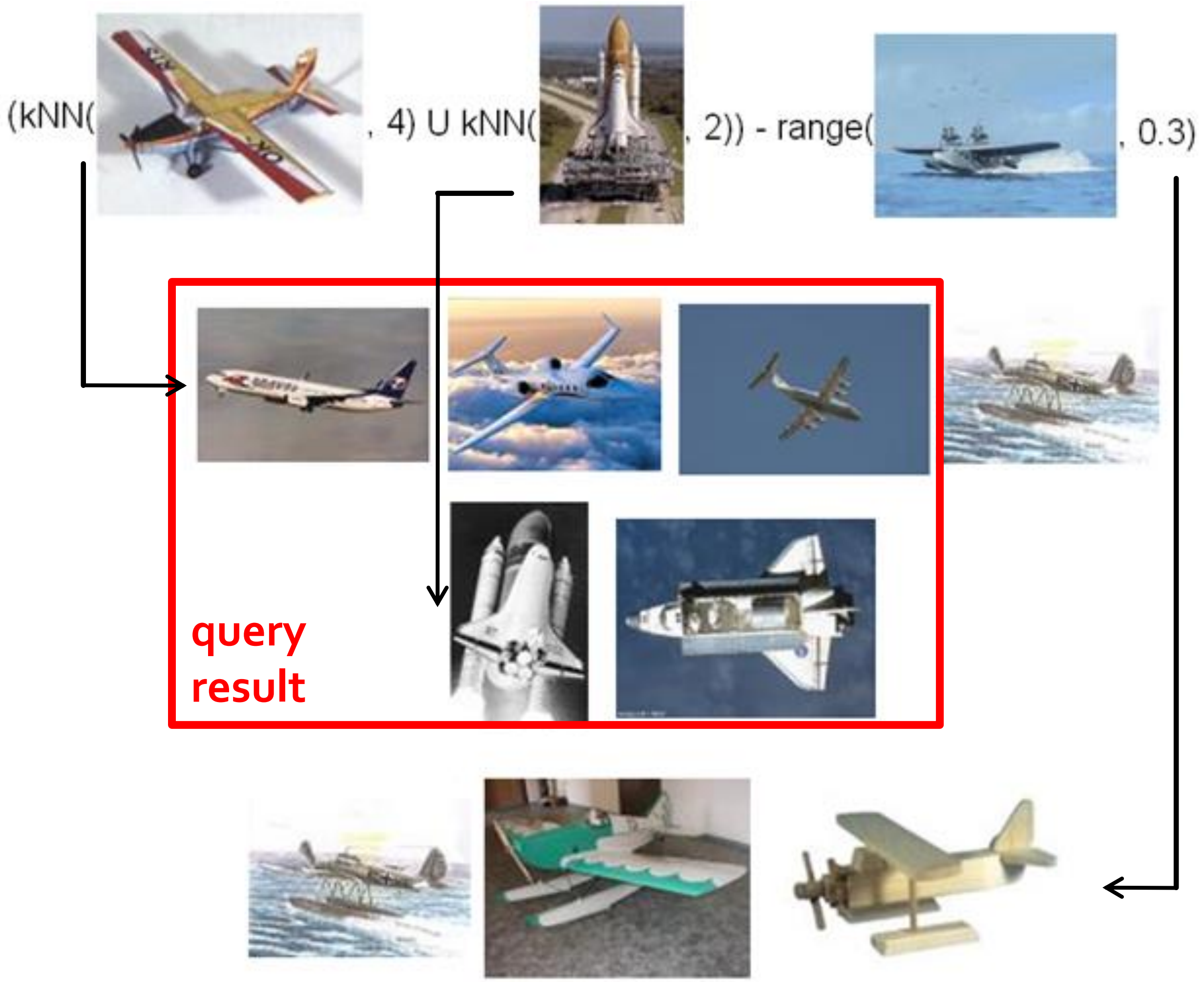
Late fusion – query languages

- similarity queries could serve as a basis for higher-level late-fusion query models

- query languages for similarity search
  - ad-hoc set-based expressions
  - extension of SQL
    - allows combination with structured attributes (relational modality)

Late fusion – query languages

- set operations with similarity queries



Late fusion – integration to SQL

- let a database of descriptors is stored in a BLOB-type attribute in a table of relational database
- new SQL predicates could enable relational databases to execute similarity queries
  - general SQL predicate
    - given an expression, the predicate condition is evaluated for all rows of a given table (or a join)
    - if the row passes the expression, the predicate is true
    - classic SQL predicate is, e.g., LIKE, ANY, IN, etc. in WHERE or HAVING
  - similarity predicates
    - range(example.MMattribute, table.MMattribute, r)
    - kNN(example.MMattribute, table.MMattribute, k)

Late fusion – integration to SQL

- simple queries

```
SELECT Id FROM BioData WHERE
    range(JohnSmith.Fingerprint, BioData.FingerPrint, 0.01)

SELECT Id FROM DNAData WHERE
    kNN(MickeyMouse.DNA, DNAData.DNA, 1)
```

Late fusion – integration to SQL

- join based on range query
  - range(A's descriptor, B's descriptor, query radius)
  - example in SQL

    SELECT Criminal.Id, Citizen.Id FROM Criminal
    SIMILARITY JOIN Citizen ON range(Criminal.FingerPrint,
    Citizen.FingerPrint, 0.01)
- join based on kNN query
  - kNN(A's descriptor, B's descriptor, k)
  - example in SQL

    SELECT Mammal.Id, Insect.Id FROM Mammal
    SIMILARITY JOIN Insect ON kNN(Mammal.DNA, Insect.DNA, 2)