List of Twin Clusters: a Data Structure for Similarity Joins in Metric Spaces

Rodrigo Paredes

Departamento de Ciencias de la Computación
UNIVERSIDAD DE CHILE

Nora Reyes

Universidad Nacional
de San Luis

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Introduction

- We focus on a particular case of the ***similarity join*** **primitive:**
  - Given two sets $A = \{a_1,a_2,\ldots,a_{|A|}\} \subseteq X$ and $B = \{b_1,b_2 \ldots,b_{|B|}\} \subseteq X$

$$A \bowtie_r B = \{(a_i,b_j),\ a_i \in A,\ b_j \in B,\ d(a_i,b_j) \leq r\}$$

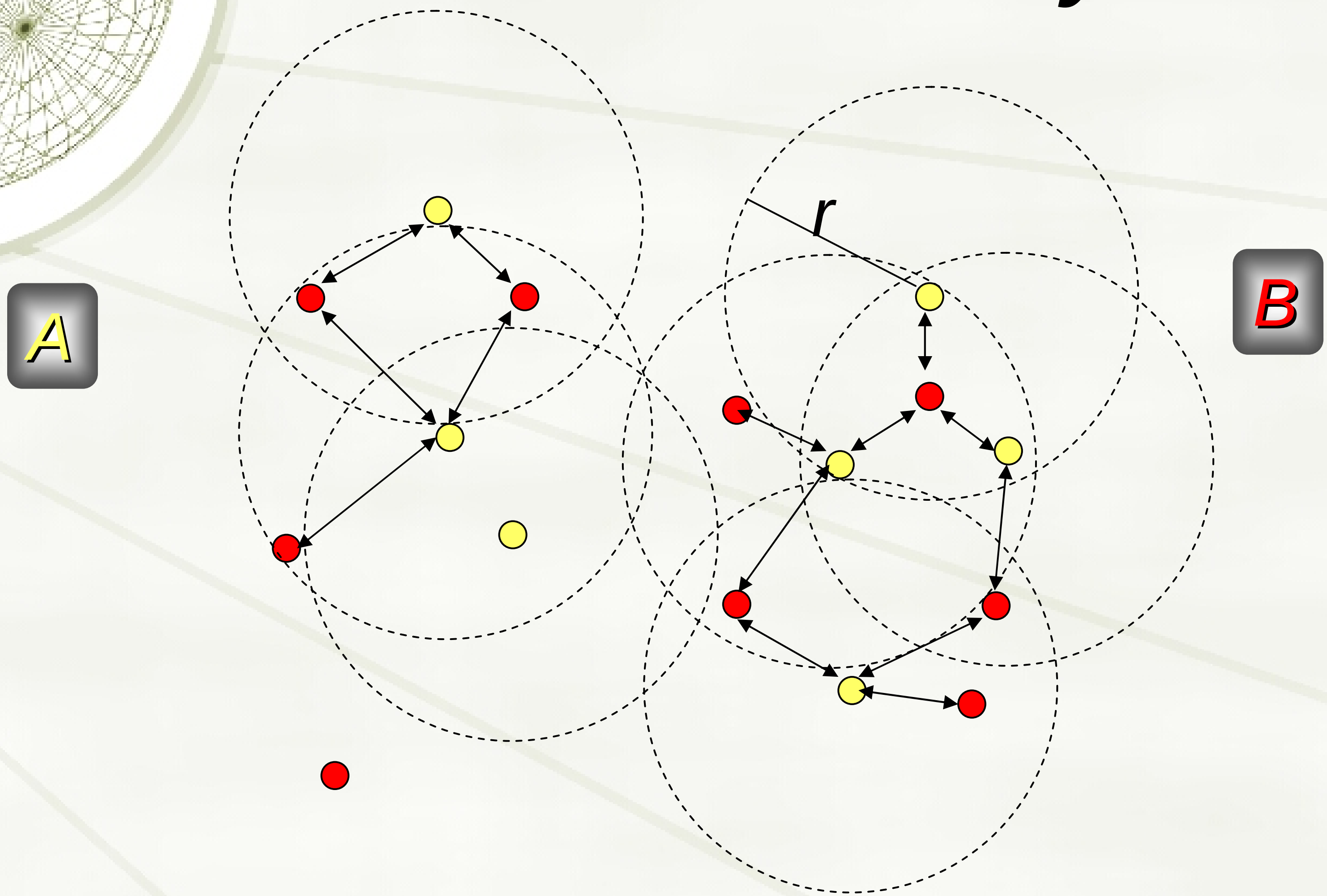
- **Find all the object pairs at distance at most *r*** (if $A=B$, is called ***similarity self join***).

Introduction

- Some applications: data mining, data cleaning, and data integration.

- This version of similarity join translates into solving several range queries.

Similarity Joins

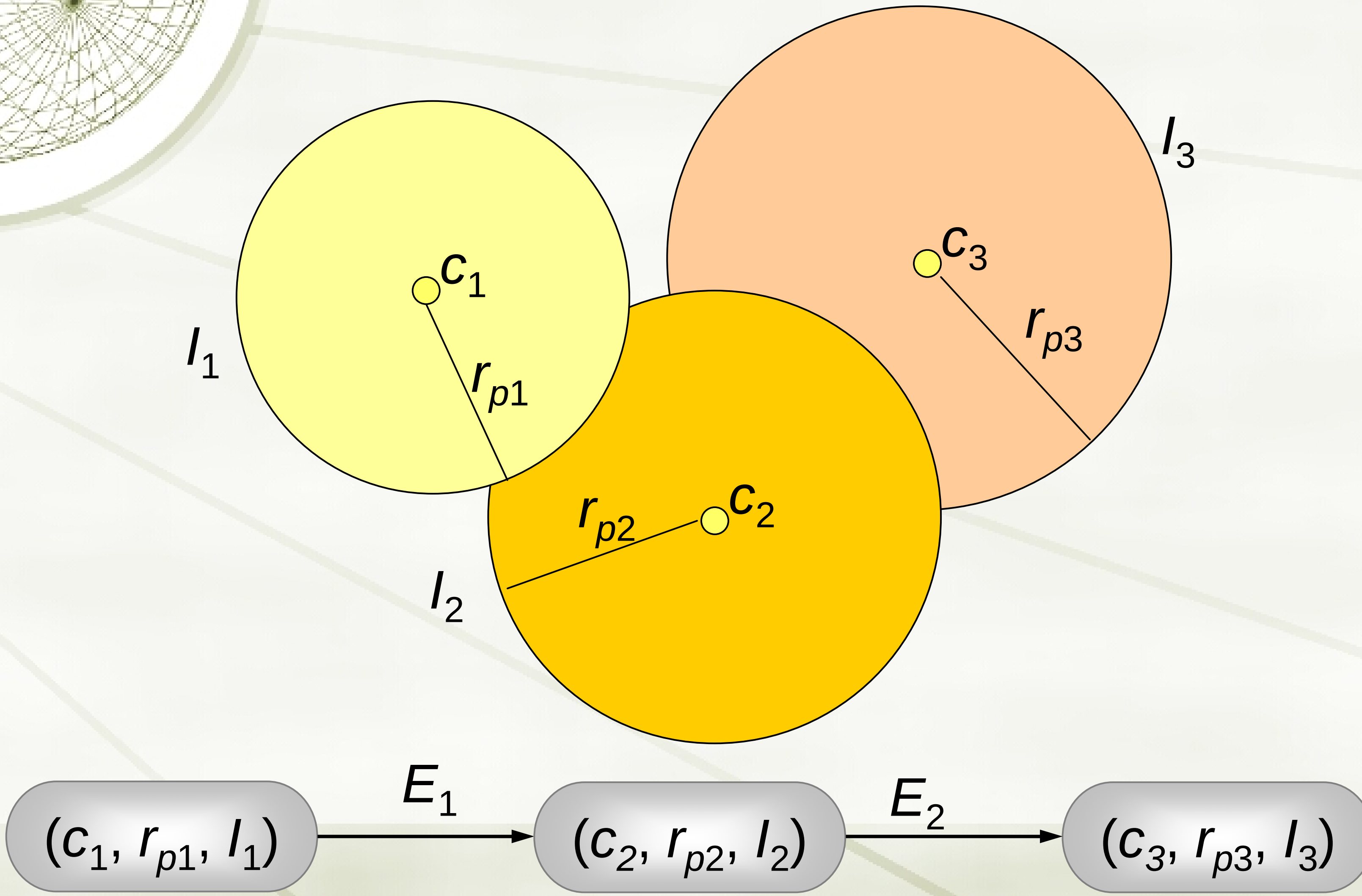


Range queries with threshold *r* for all element *in A*

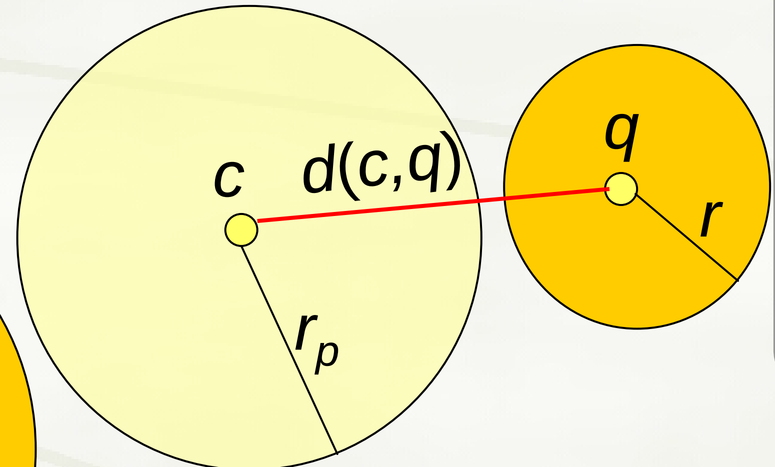
List of Clusters (LC)

- The LC splits the space into zones.
- Each zone has a center c and stores both its radius r_p and the bucket I of internal objects.
- The center ball $(c,r_p) = \{x \in X, d(c, x) \leq r_p\}$.

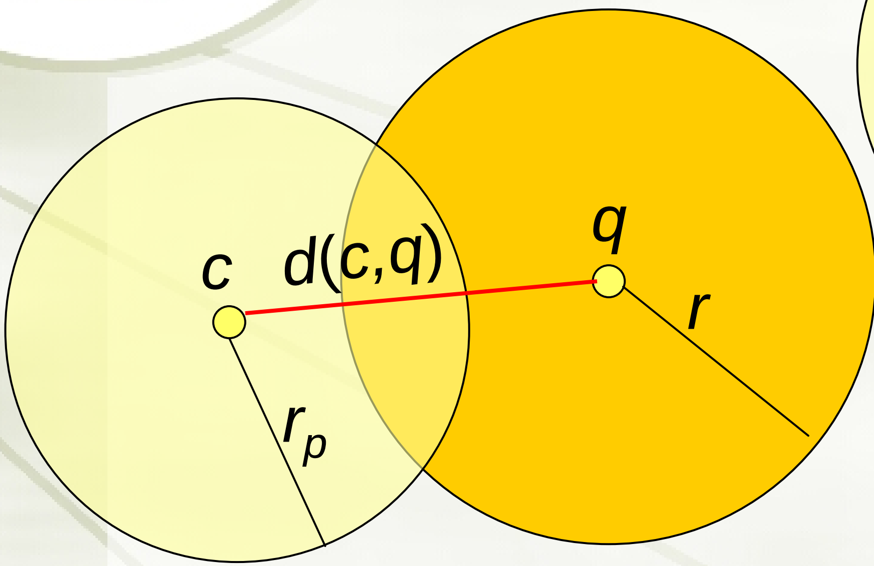
List of Clusters (LC)



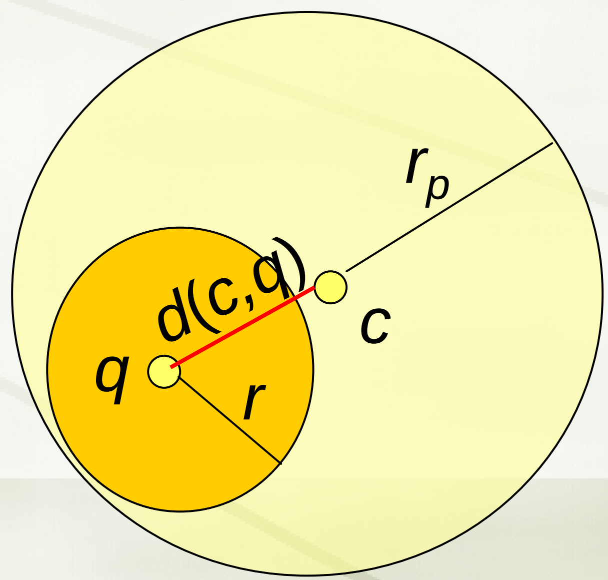
LC: solving queries



We do not search in *I*, but we continue searching in *E.*



We search exhaustively in *I*, and continue searching in *E.*



We search exhaustively in *I*, but we **do not** continue searching in *E.*

Similarity Joins

- Given $A,B \subseteq X$, the naive approach to compute the similarity join uses $|A|\cdot|B|$ distance computation.

- This is usually called the ***Nested Loop***.

- A natural approach consists in indexing one or both sets independently, and then solving range queries for the involved elements.

List of Twin Clusters (LTC)

- We propose to index both sets jointly: solving the similarity join by indexing the datasets *A* and *B* in a single data structure.

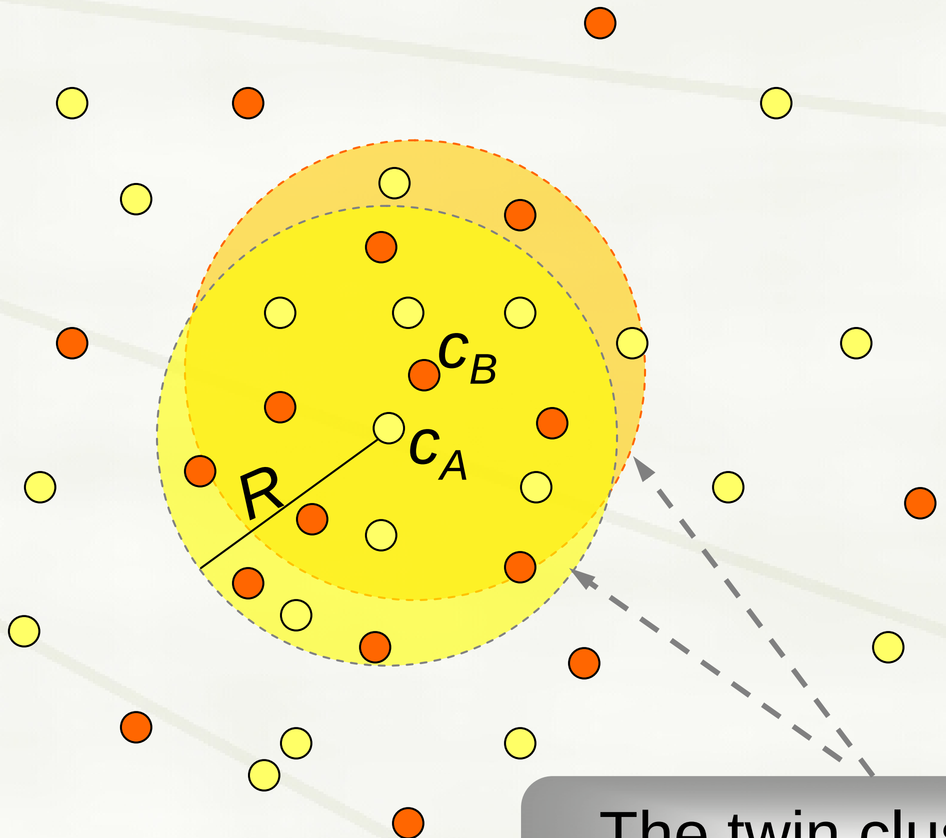
- We do not perform distance computations between objects of the same set.

- The LTC is based on the *List of Clusters*.

List of Twin Clusters (LTC)

- We have chosen to use clusters with fixed radius.
- LTC considers a list of overlapping clusters, which we call ***twin clusters.***
- Most of relevant objects would belong to the twin cluster of the object we are considering.

List of Twin Clusters (LTC)



The twin clusters with centers c_A and c_B

List of Twin Clusters (LTC)

- We solve range queries for objects from one set retrieving relevant objects from the other.

- We suppose:
  - We are computing range queries for elements in A,
  - $|A| \geq |B|$.

Range Queries with LTC

- We have to process three kinds of objects: cluster centers, regular objects (inside clusters), and non-indexed objects (the rest).

- We use the ***triangle inequality*** and all the ***distances in the index*** (the list of twin clusters, the distances among centers, and the distances to closest and furthest centers) to ***avoid distance computations***.

Computing the LTC-join

- Given the datasets *A* and *B*, and a radius *R*, we compute the LTC index.

- Then, with the join threshold *r* we actually compute range queries:
  - cluster centers: previous clusters of the list.
  - regular objects: the list and distances among centers.
  - non-indexed objects: distances among centers and distances to closest and furthest centers.

Experimental Evaluation

- We compare our proposal against:
  - The *Nested loop*.
  - The simple join algorithm having a LC built for one database: LC-join.
  - Indexing both databases with LC with a join algorithm that uses all the information from the indices to improve the join cost: LC2-join.

Experimental Evaluation

- Three different pairs of real world databases from two metric spaces:
  - Face images: 1,016 761-dimensional feature vectors from a face image database.
  - Strings: a dictionary of words.
    - A subset of English words with a subset of Spanish words.
    - The same English subset with a subset of the vocabulary of terms from a document collection.

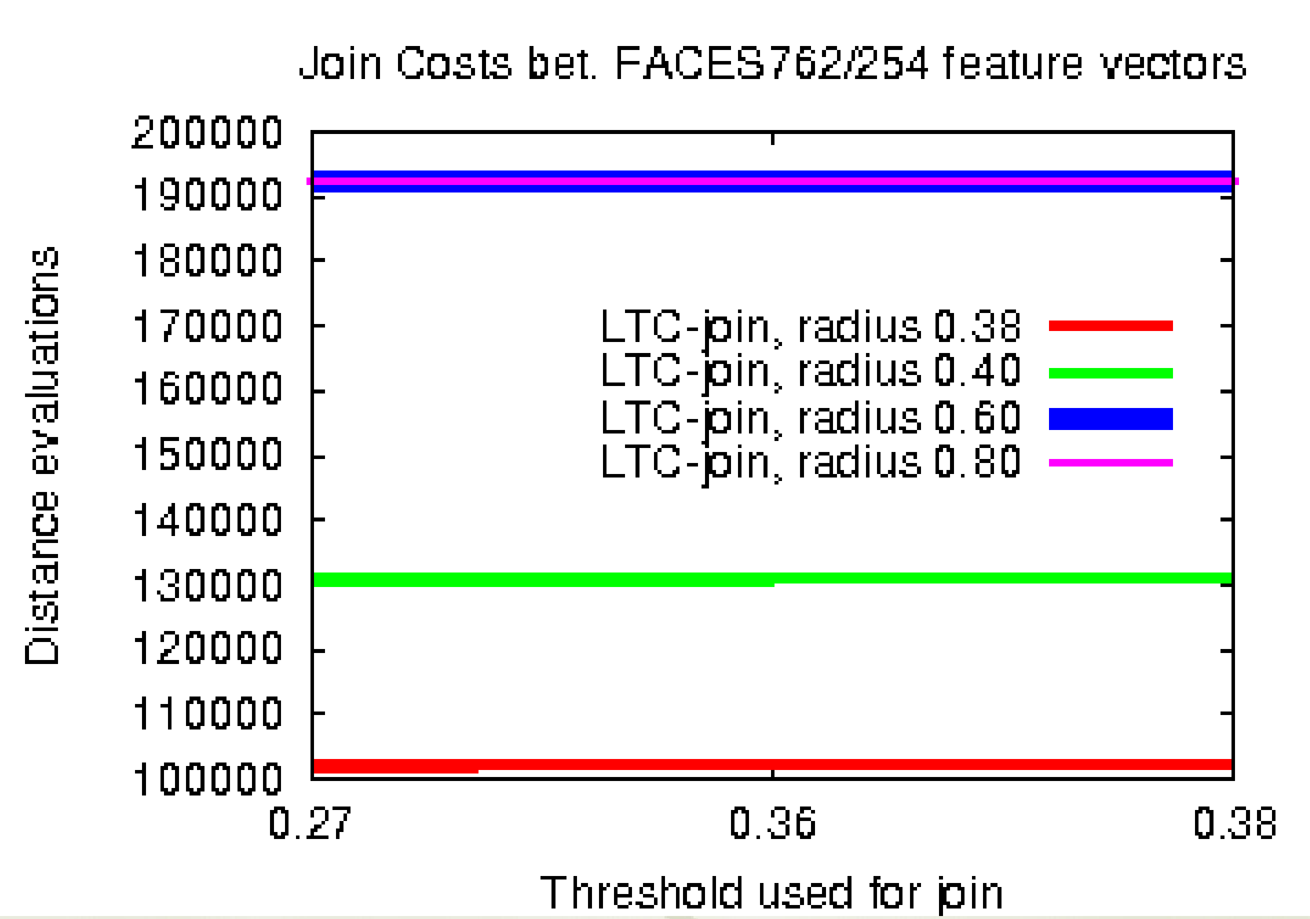
Experimental Evaluation

- We need to fix the radius before building the LC and LTC.

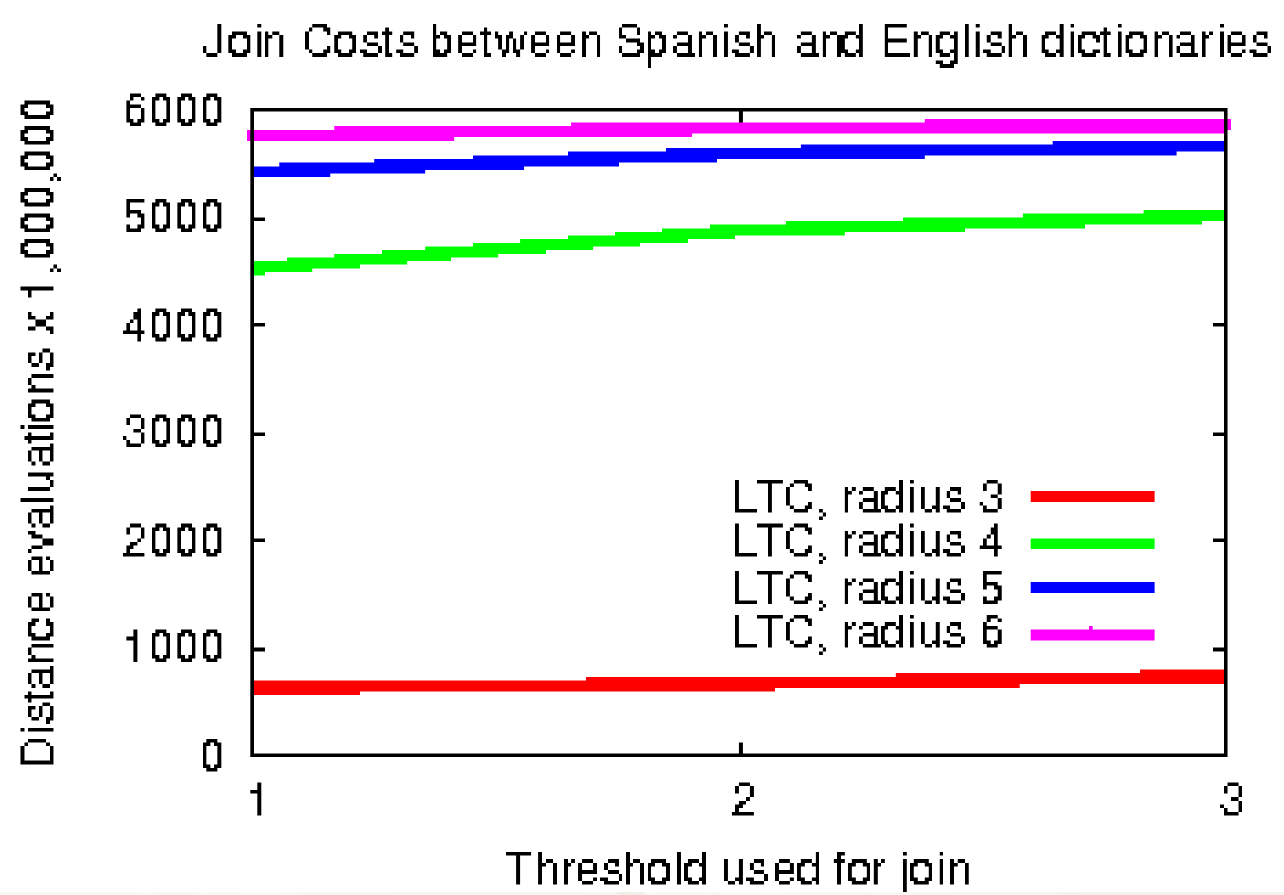
- We choose the radius *R* which obtains better join cost for each alternative.

- *R* should be greater than or equal to the largest r used in the similarity join: $A \bowtie_r B$

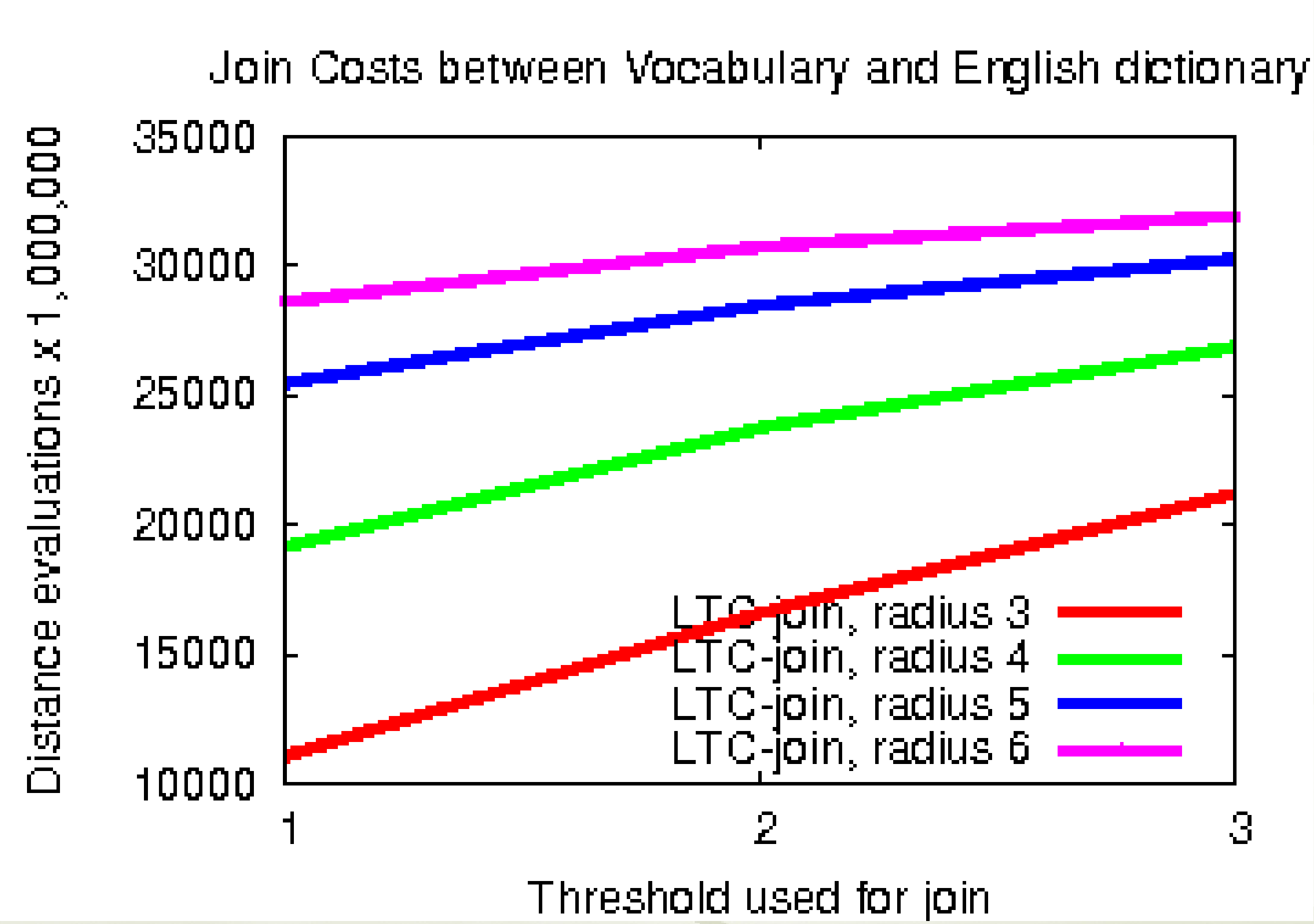
Experimental Evaluation



Experimental Evaluation



Experimental Evaluation

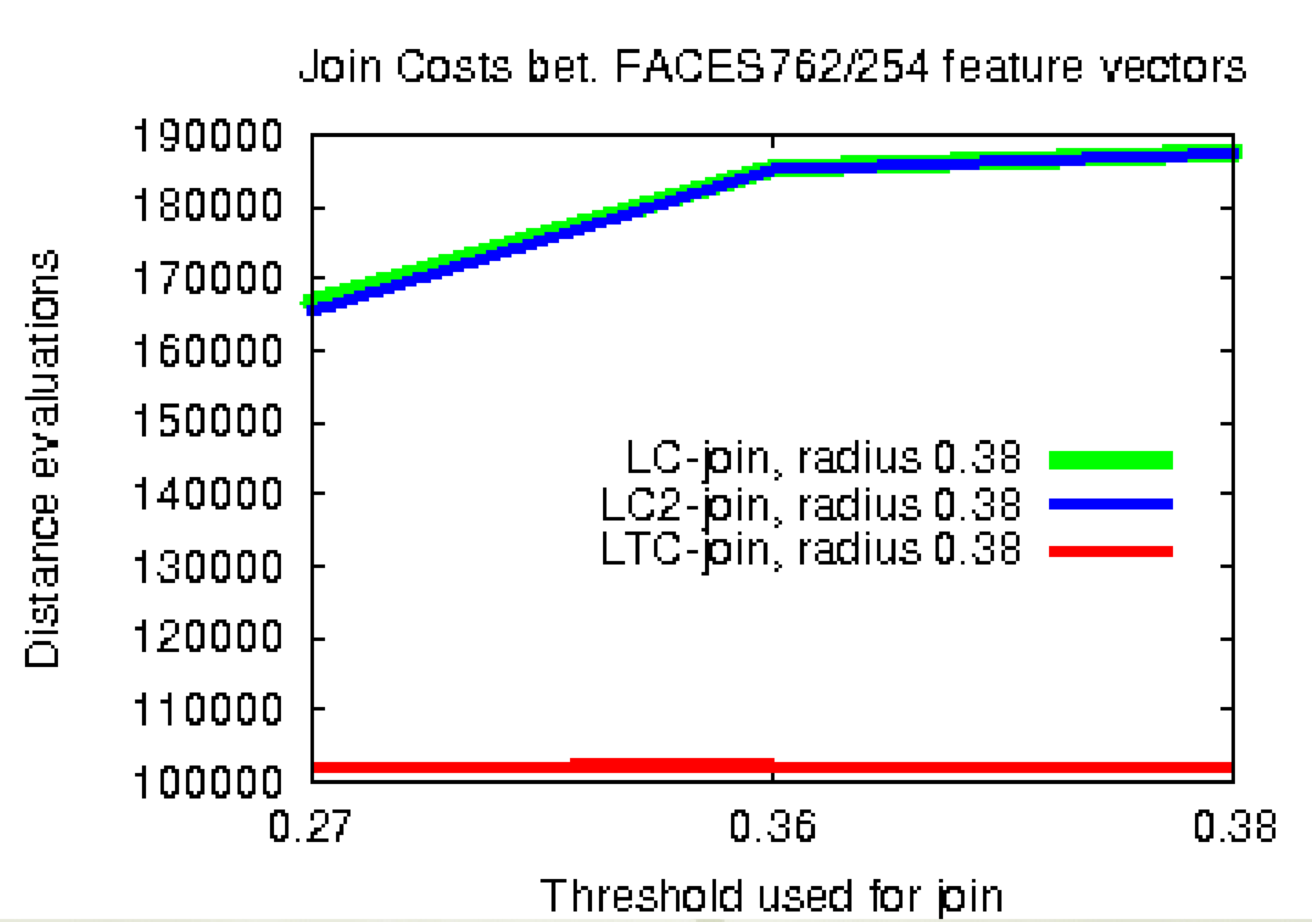


Experimental Evaluation

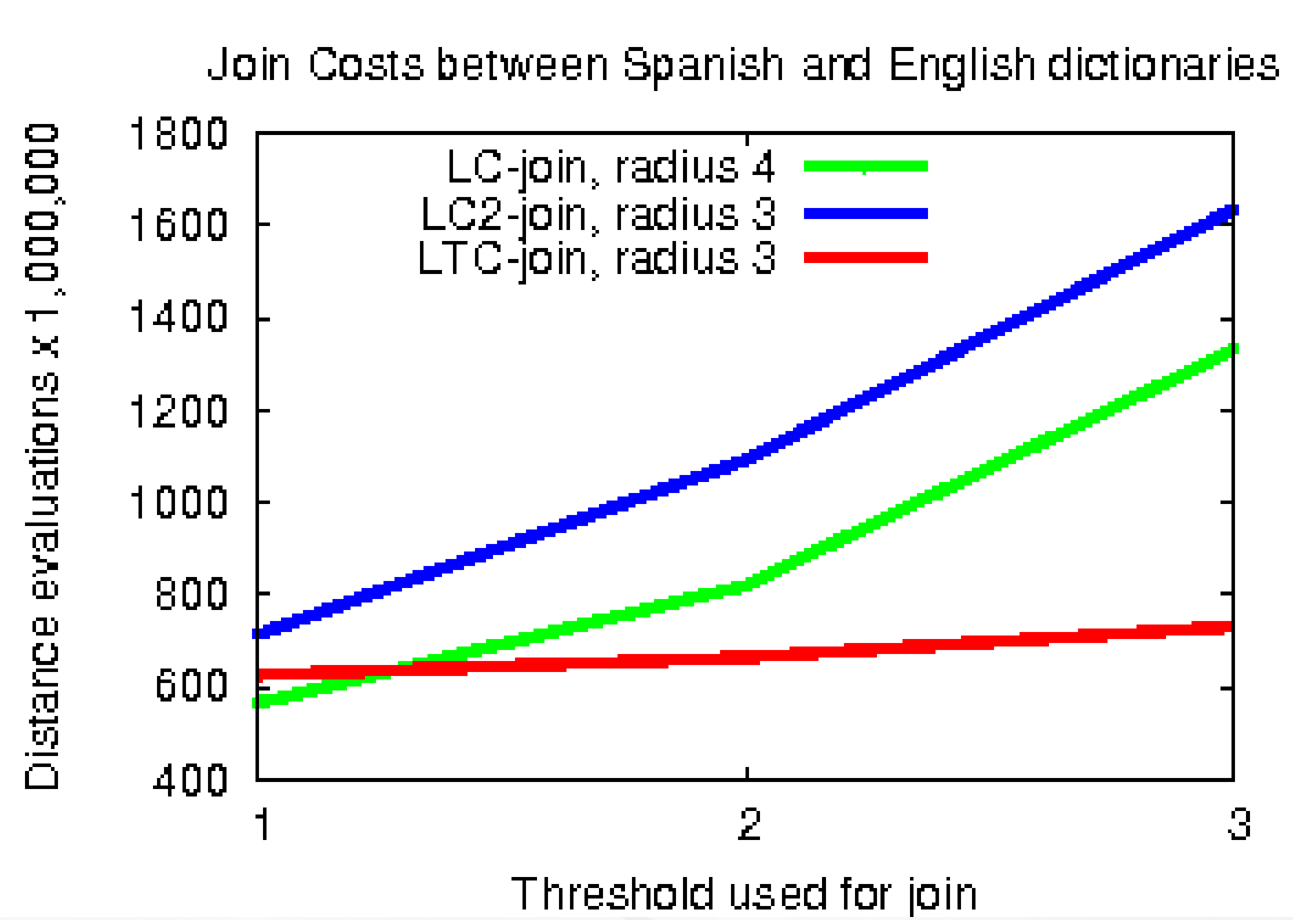
- The better results are obtained with the building radius *R* closest to the greatest value of *r* considered.

- The construction costs of the LTC and the LC over one of the databases are similar.

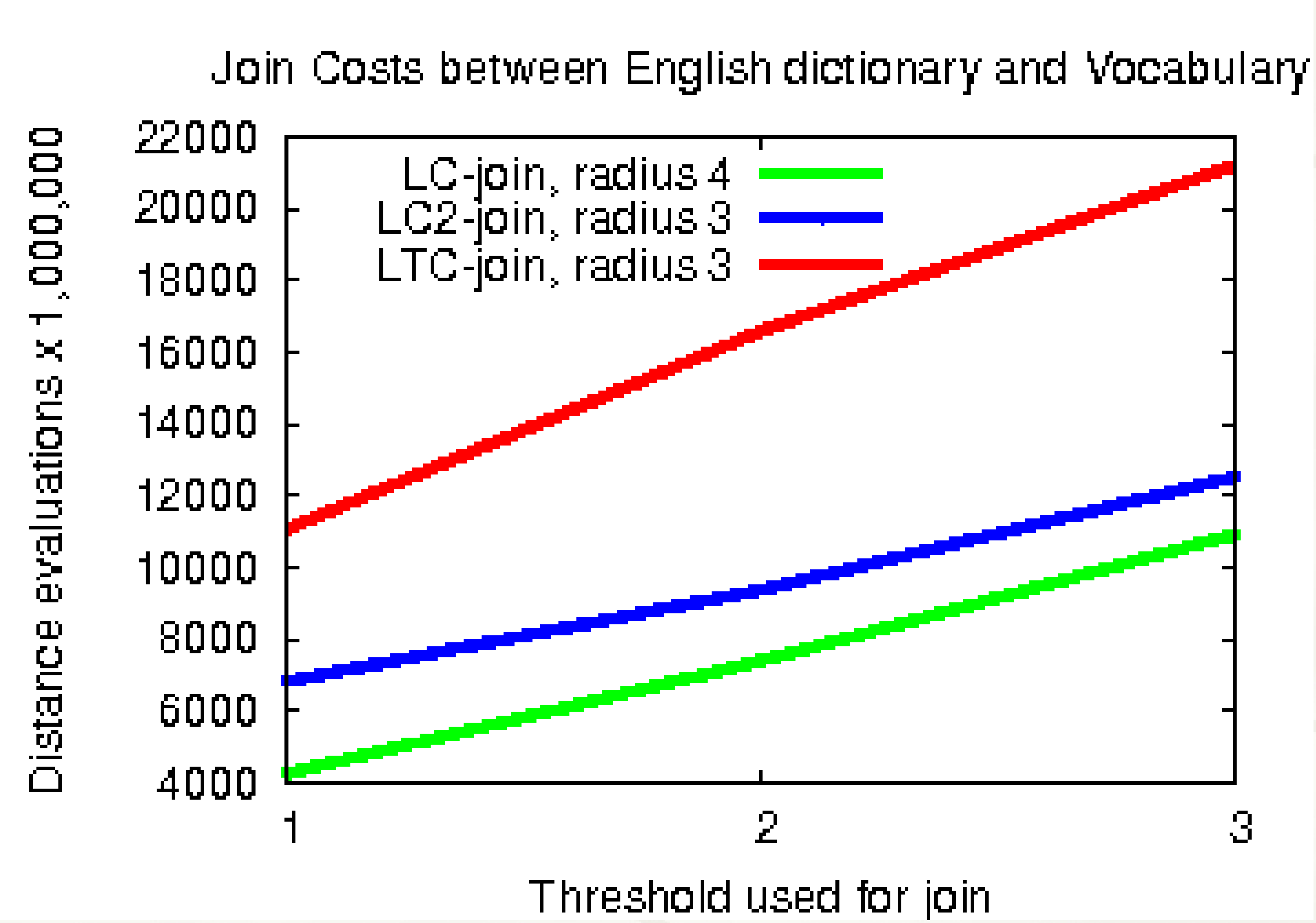
Experimental Evaluation



Experimental Evaluation



Experimental Evaluation



Experimental Evaluation

- The LTC-join outperforms largely the LC-join and LC2-join in two of the database pairs.
- For the other pair LTC largely improves over nested loop, but LC and LC2 beat us.
- This non-intuitive behavior can be explained by taking into account the amount of non-indexed elements.

Conclusions

- We show a new approach, LTC-join, for similarity join by indexing both datasets jointly.
- Our results show speedups over LC-join and LC2-join.
- LTC index stands out as a practical and efficient data structure to solve a particular case of similarity join.

Work in Progress

- The similarity self join.
- Improve the LTC by exploiting internal distances.
- The center selection.
- A version of the LTC similar to the recursive list of clusters.
- Researching on alternatives to manage the non-indexed objects.