

# Re-CoSKQ: Towards POIs Recommendation Using Collective Spatial Keyword Queries

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## Introduction and goals

- ☐ Interest of recommender systems in mobile computing scenarios
- ☐ The location is a key spatial attribute:
  - Can techniques from the field of spatial databases help?
  - → Explore the potential use of
     Collective Spatial Keyword
     Querying (CoSKQ)

# **Proposal: Re-CoSKQ for the recommendation of POIs**

- ☐ Semantic coverage of the query keywords (no exact match req.)
- ☐ Minimize the cost:
  - Distance to get to the POIs
  - Similarity between the query and the descriptions of items

$$U = \{u_1, ..., u_n\} \rightarrow \text{users}$$

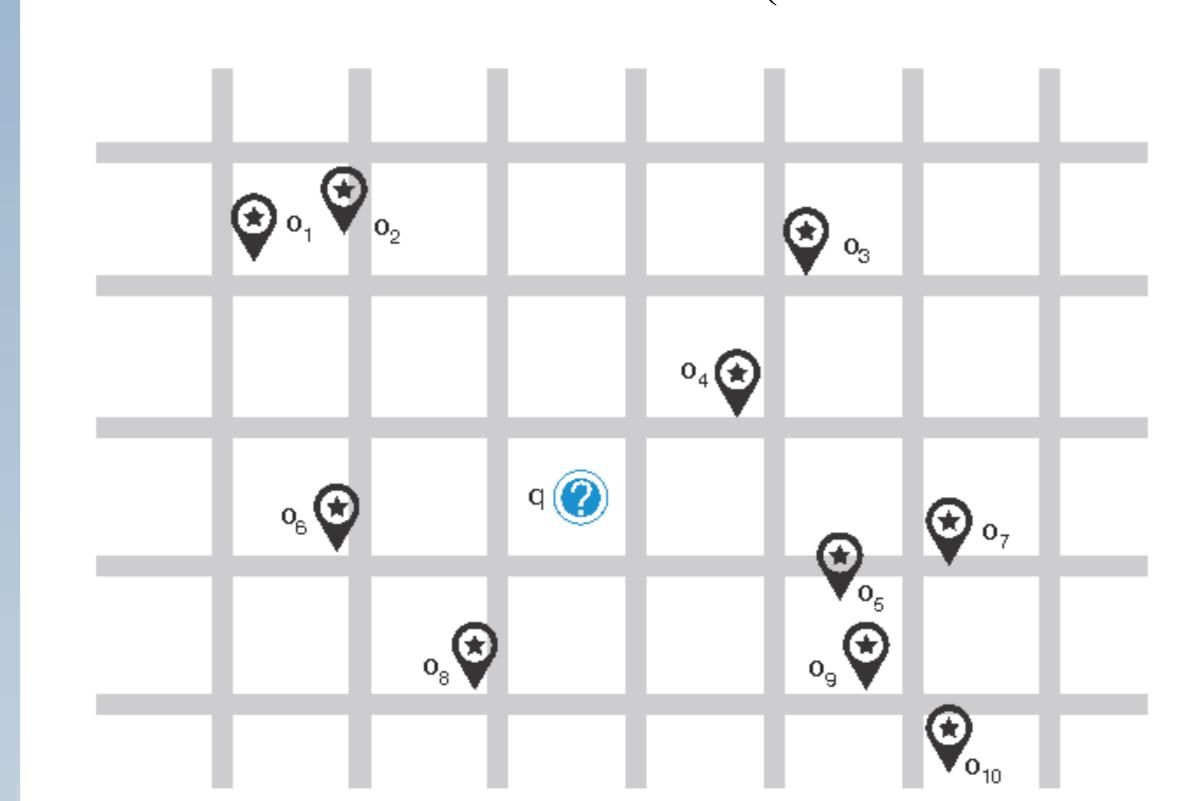
$$O = \{o_1, ..., o_m\} \rightarrow \text{POIs}$$

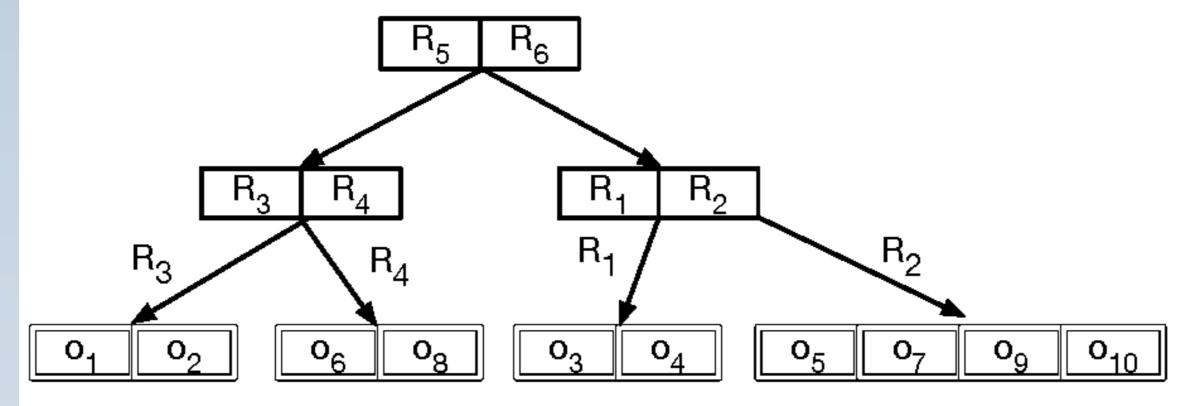
$$o_i.\kappa = \{k_1, ..., k_j\} \rightarrow \text{keywords}$$

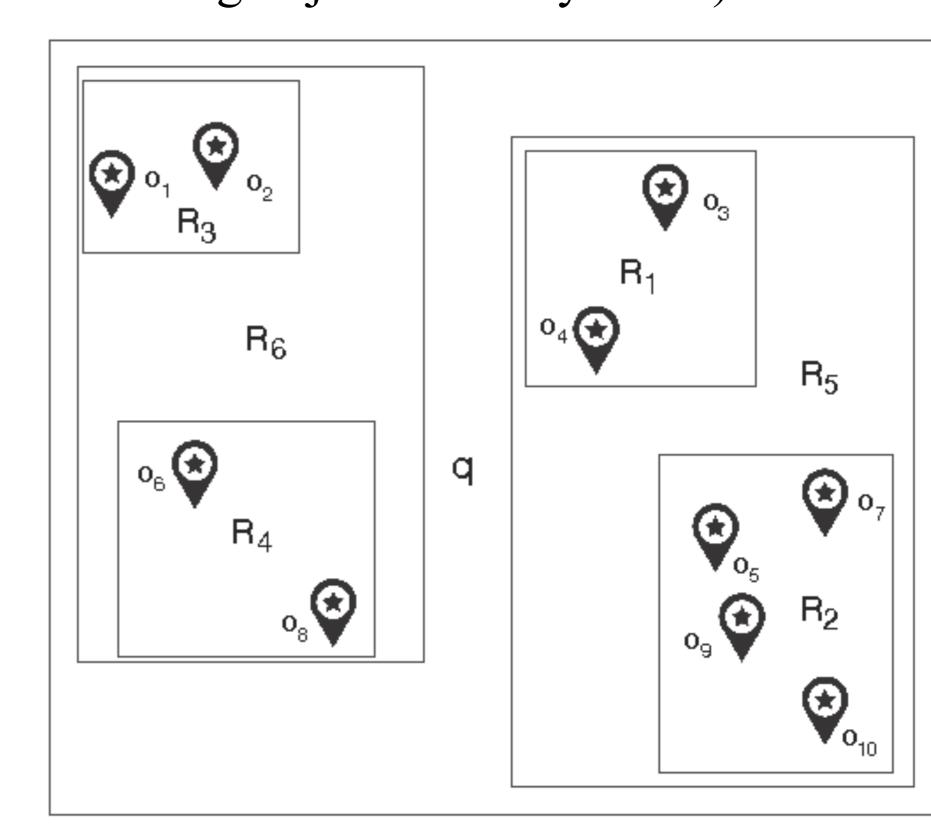
$$\text{describing POI } o_i \in O$$

## Collective Spatial Keyword Querying (CoSKQ)

- ☐ Technique from the spatial databases field
- ☐ Goal: retrieve a group of spatial objects that collectively match the user preferences given:
  - Specific locations (of the user and also of the objects)
  - A set of keywords
- ☐ Use of IR-tree data structures (balanced trees that allow indexing objects and keywords)







#### Internal node:

- pointers to the child nodes
- a Minimum Bounding Rectangle (MBR) covering its subtree
- the set of all keywords in the subtree

#### Leaf node:

- items o (POI objects) in the node
- a bounding rectangle for each o
- a pointer to an inverted file with the keywords that describe each POI

#### **Examples of distance functions**

- □ Location distance:
- Euclidean
- L1-Norm / Manhattan
- Geodesic distance (shortest path)
- ☐ Term distance:
- Similarity based on concept closeness (relatedness)

$$sim(k_1, k_2) = 1 - \frac{sp(k_1, k_2)}{2D}$$

Similarity based on closeness and concept depth

$$sim(k_1,k_2) = \begin{cases} e^{-\alpha l} \frac{e^{\beta h} - e^{-\beta h}}{e^{\beta h} + e^{-\beta h}} & if \quad k_1 \neq k_2 \\ 1 & otherwise \end{cases}$$
• I: shortest path
• d:depth of the least common subsumer
•  $\alpha, \beta > 0$ : weights

#### **Evaluation proposal**

- Define a representative set of queries
- Annotate a dataset of POIs with predefined categories based on the keywords → ground truth → precision, recall, ... + performance and tuning
- Also interesting: user-centered evaluation, DataGenCARS

# Acknowledgments

- Government of Aragon (Group Reference T35\_17D, COSMOS group) and cofunded with Feder 2014-2020 "Construyendo Europa desde Aragón".
- Project TIN2016-78011-C4-3-R (AEI/FEDER, UE).

# **Examples of cost functions**

$$cost(q, \mathbb{O}') = \alpha \cdot \max_{o \in \mathbb{O}'} \left[ dist(q.\lambda, o.\lambda) \right] + \beta \cdot \max_{o_1, o_2 \in \mathbb{O}'} \left[ dist(o_1, o_2) \right] \\ + \omega \cdot \max_{k_1 \in q.\kappa, k_2 \in \cup_{o \in \mathbb{O}'} o.\kappa} \left[ dist(k_1, k_2) \right]$$
  $\leftarrow$  TYPE 1 – COMB

$$cost(q, \mathbb{O}') = \max \left\{ \alpha \cdot \max_{o \in \mathbb{O}'} \left[ dist(q.\lambda, o.\lambda) \right], \beta \cdot \max_{o_1, o_2 \in \mathbb{O}'} \left[ dist(o_1, o_2) \right], \right.$$

$$\left. \omega \cdot \max_{k_1 \in q.\kappa, k_2 \in \cup_{o \in \mathbb{O}'} o.\kappa} \left[ dist(k_1, k_2) \right] \right\}$$

$$\leftarrow \text{TYPE 2 - MAX}$$

$$\begin{split} cost(q,\mathbb{O}') = & \left[ \left( \alpha \cdot \left( \sum_{o \in \mathbb{O}'} (dist(q.\lambda,o.\lambda))^{\phi_1} \right)^{\frac{1}{\phi_1}} \right)^{\phi_2} \right. \\ & + \left( \beta \cdot \max_{o_1,o_2 \in \mathbb{O}'} dist(o_1,o_2) \right)^{\phi_2} \\ & + \left( \omega \cdot \max_{k_1 \in q.\kappa, k_2 \in \cup_{o \in \mathbb{O}'} o.\kappa} dist(k_1,k_2) \right)^{\phi_2} \right]^{\frac{1}{\phi_2}} \end{split}$$

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