Multi-Approximate-Keyword Routing Query

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Outline

1. Introduction and Motivation
2. Preliminary
3. Exact solutions
4. Approximate solutions
5. Experiments
6. Related Work and Concluding Remarks

Introduction and motivation

- Approximate keyword search is important:
  - GIS data has errors and uncertainty with it.
  - GIS data is keeping evolving, routinely data cleaning and data integration is expensive
  - People may make mistakes in query input (typos)

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  - map service.
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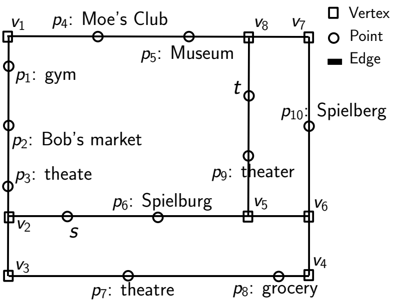
- Shortest path search has many applications:
  - map service.
  - strategic planning of resources
- Our work: Multi-Approximate-Keyword Routing (MAKR) query.
  - A combination of shortest path search and approximate keyword search
  - Given a source and destination pair (s, t) and a query keyword set ψ on a road network, the goal is to find the shortest path that passes through at least one matching object per keyword.

Multi-Approximate-Keyword Routing (MAKR) query



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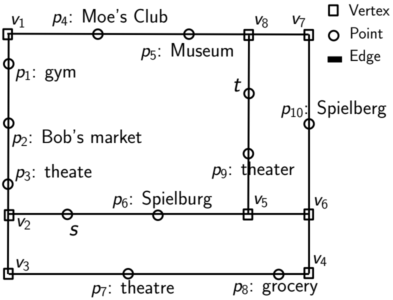

Approximate string similarity:
edit distance $\epsilon(\delta_1, \delta_2) = \tau$.

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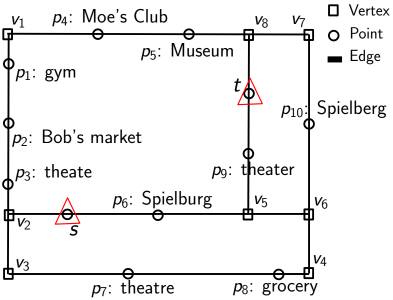

Example: $s, t, \psi = \{(\delta_1 = \text{theater}, \tau_1 = 2), (\delta_2 = \text{Spielber}$

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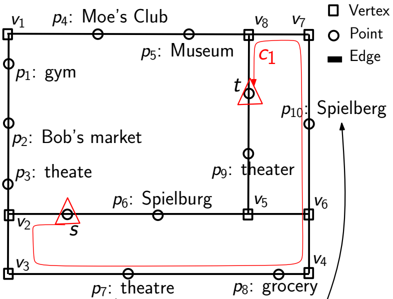

$\epsilon(\delta_1, p_7.\delta) = 2$ $\quad$ $\epsilon(\delta_2, p_{10}.\delta) =$

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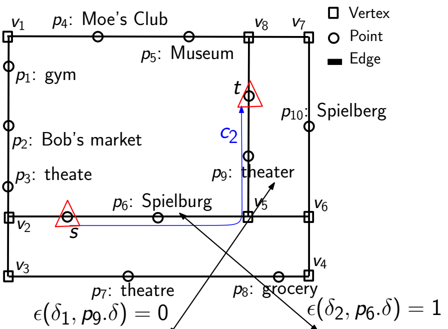

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path length: $d(c_2) < d(c_1)$

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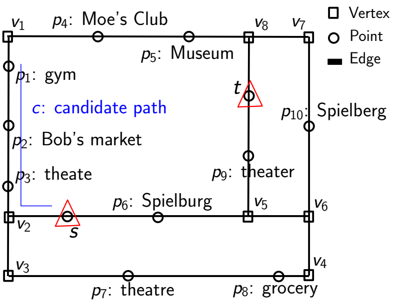

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$\psi(c) = \{\delta_1 = \mathit{theater}\}$

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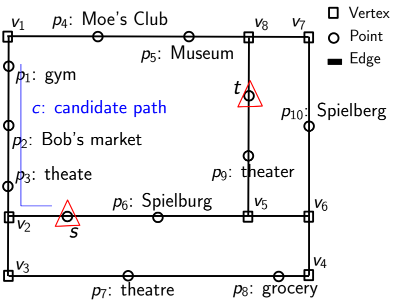

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$|\psi| = \kappa$, when $\psi(c) = \psi$, c becomes a qualified path

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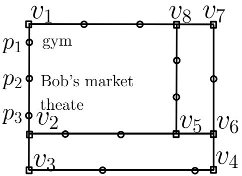
Data structure: Disk-based storage of the road network



$$d(v_1, v_2) = 6$$
$$d(v_1, v_8) = 8$$
$$d(v_1, p_1) = 1$$
$$d(v_1, p_2) = 3$$
$$d(v_1, p_3) = 5$$

v_i: network vertex.

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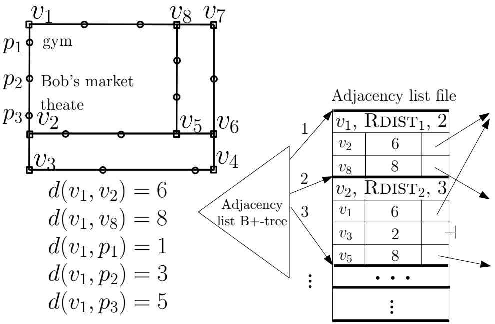

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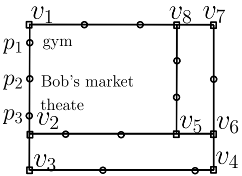

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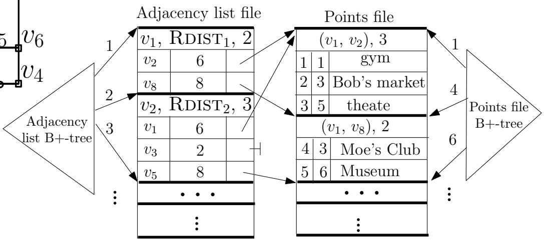

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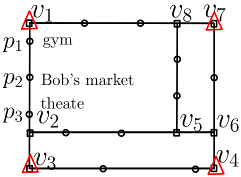
- [sl97]: CCAM: A connectivity-clustered access method for networks and network computations. In IEEE TKDE, 1997.



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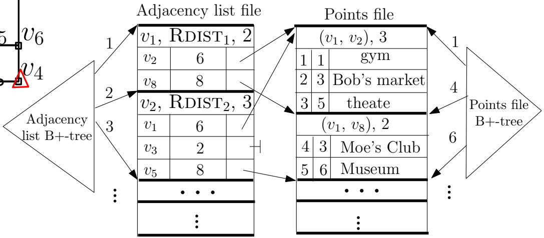

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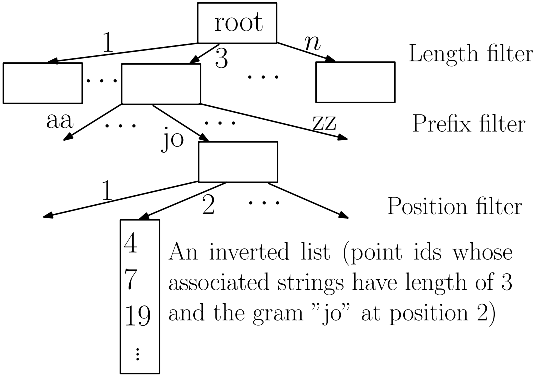
- [gh05]: Computing the shortest path: A* search meets graph theory. In SODA, 2005.

Data structure: FilterTree for Approximate Keywords-Matching



- [lll08]: Efficient merging and filtering algorithms for approximate string searches. In ICDE, 2008.

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- Intuition: **PER–P**ath **E**xpansion and **R**efinement.

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$$Q : s, t, \psi = \{(ab, 1), (cd, 1), (ef, 1)\}$$

For each keyword $w \in \psi - \psi(c)$, add a point p from $P(w)$ into current shortest candidate path, s.t. $\forall p \in P(w), \epsilon(p.\delta, w) \leq \tau_w$, to minimize the impact to $d(c)$

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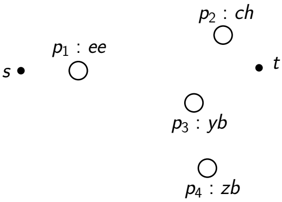

L

$\{s, p_1, t\}$
$\{s, p_3, t\}$
$\{s, p_2, t\}$

IO efficient priority queue of candidate paths: initialized with c's tha each covers a dinstinct, single $w \in \psi$

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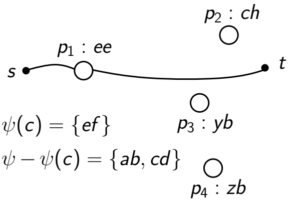

$\psi(c) = \{ef\}$

$\psi - \psi(c) = \{ab, cd\}$

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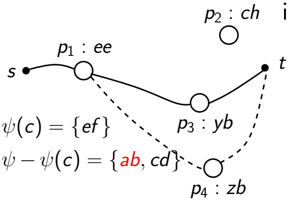

insert sp_1p_3t to L

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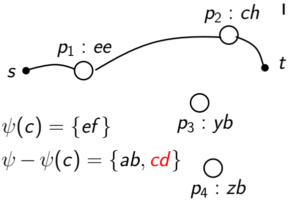

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Exact solution overview

- Improvement.
  - use Landmarks to estimate distances when finding points;
  - modify and then combine with FilterTree to find $p \in P(w)$ incrementally;
  - refine $d(c)$ when c becomes a qualified path.
    - two methods to refine $d(c)$: PER-full and PER-partial

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- Problem with the exact solution:
  Theorem 1: The MAKR problem is NP-hard.

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  Theorem 1: The MAKR problem is NP-hard.
- Approximate solutions:
  - The local minimum path algorithms: A_{LMP1} and A_{LMP2}.
  - The global minimum path algorithm: A_{GMP}.

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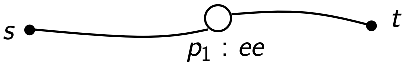

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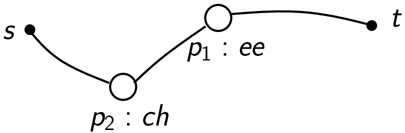

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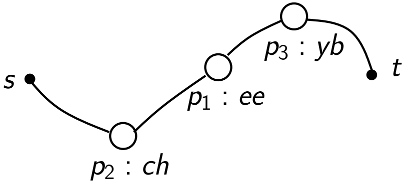

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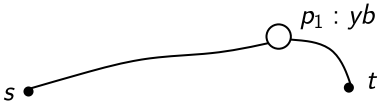

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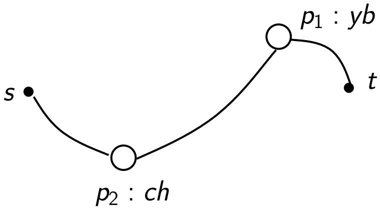

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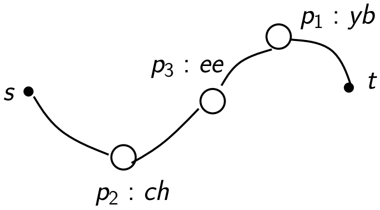

The minimum distance algorithm: A_{GMP}

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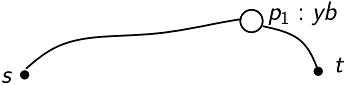

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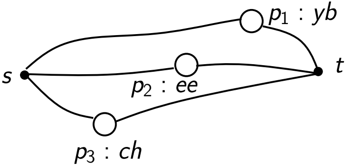

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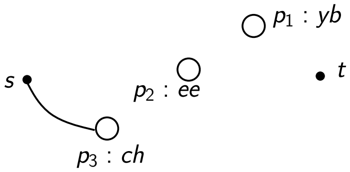

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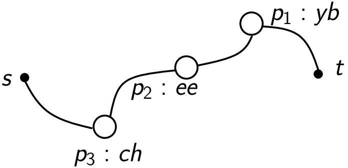

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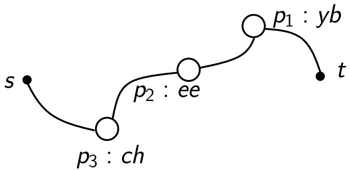


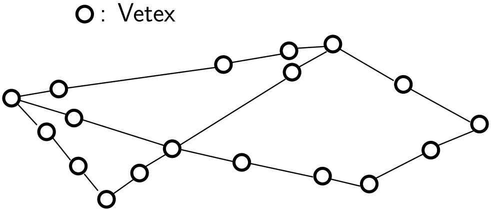
- Theorem 2: The A_{GMP} algorithm gives a κ-approximate path. This bound is tight.

Challenges in approximate solutions

- Challenges in all approximate methods:
  - how to find $p \in P(w)$ incrementally for each type of objective function (instead of finding $P(w)$ all at once and iterate through points in $P(w)$ one by one)?
  - how to avoid exact distance computation as much as possible?

Improvement on approximate solutions by network partitioning

- Voronoi-diagram-like partition (by Erwig and Hagen's algorithm).



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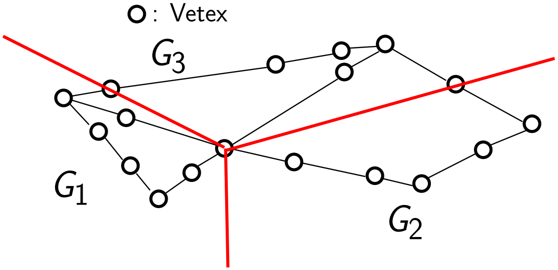

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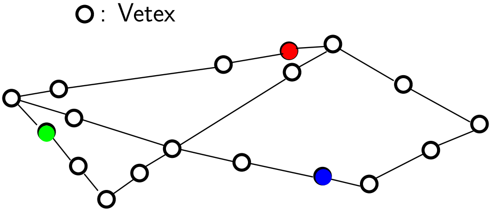

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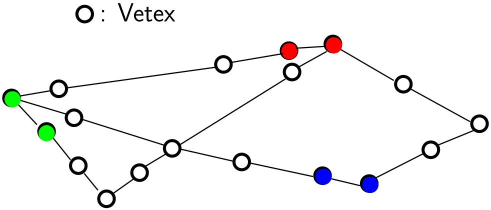

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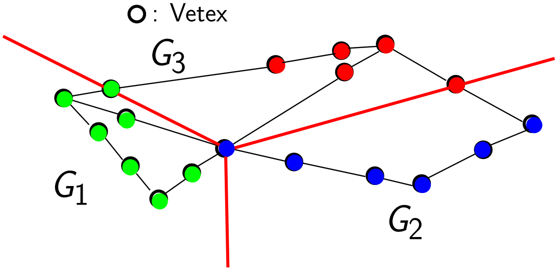

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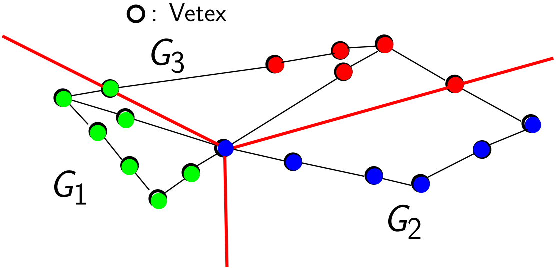

$d^-(p, G_i)$: lower bound distance from p to the boundary of G_i, computed using the landmarks.

$$d^-(s, G_i) + d^-(G_i, t) \leq d^-(s, p) + d^-(p, t), \forall p \in G_i.$$

Extensions

- Top-k MAKR query:
  - Exact methods.
  - Approximate methods.

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- Data sets:
  - road networks from the *Digital Chart of the World Server*:
    City of Oldenburg (OL,6105 vertices, 7029 edges)
    California(CA,21048 vertices, 21693 edges)
    North America (NA,175813 vertices, 179179 edges)
  - building locations in OL, CA and NA from the *OpenStreetMap* project.

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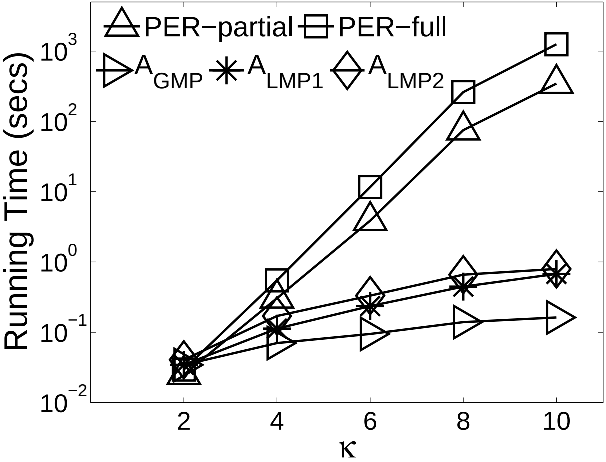
  - building locations in OL, CA and NA from the *OpenStreetMap* project.
- The default experimental parameters:

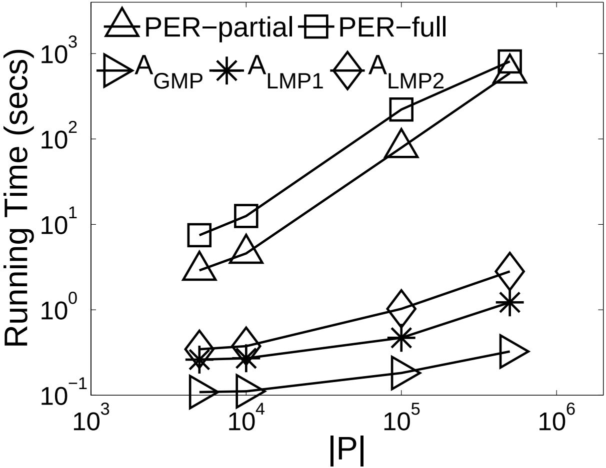
Symbol	Definition	Default Value
$\|P\|$	number of points for exact solution	$10,000$
$\|P\|$	number of points for approximate solution	$1,000,000$
κ	number of query strings	6
τ	edit distance threshold	2
	road network	CA

Query time:



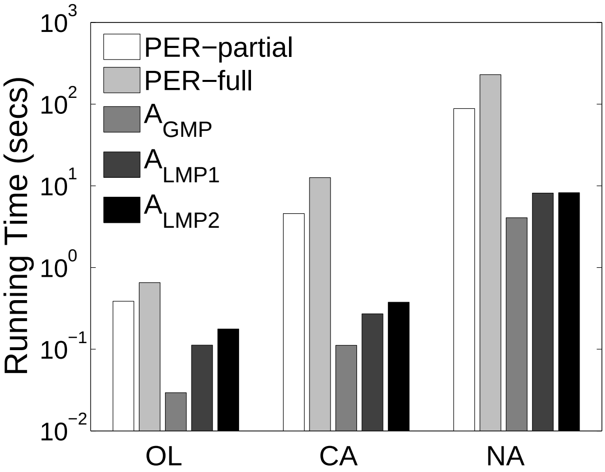
$|P| = 10,000$

Query time:



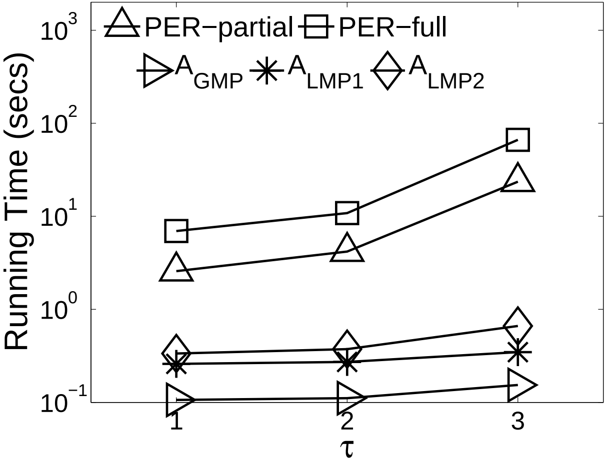
$|P| = 10,000$

Query time:



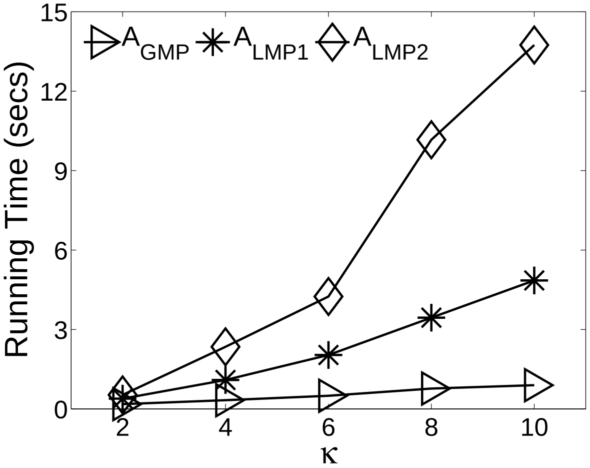
$|P| = 10,000$

Query time:

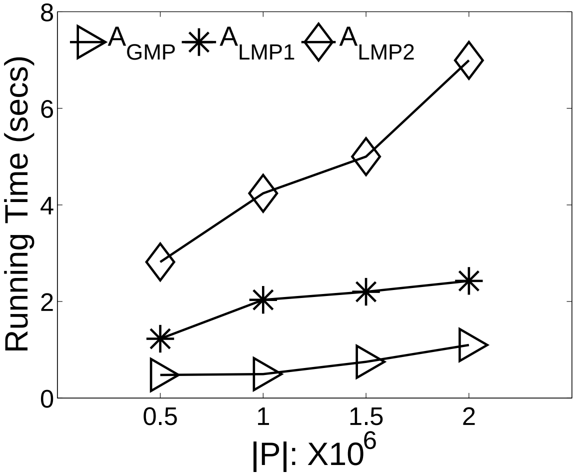


$|P| = 10,000$

Scalability of approximate solutions:

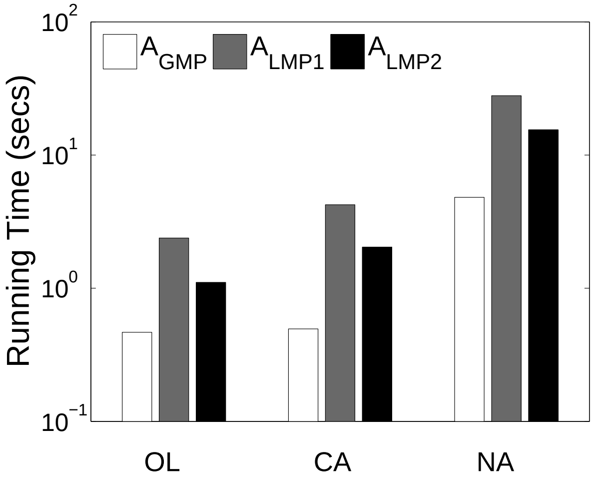


$|P| = 1,000,000$



$|P| = 1,000,000$

Scalability of approximate solutions:



$|P| = 1,000,000$

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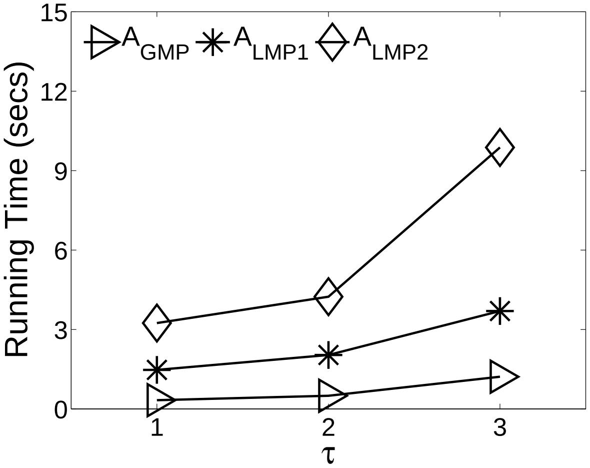
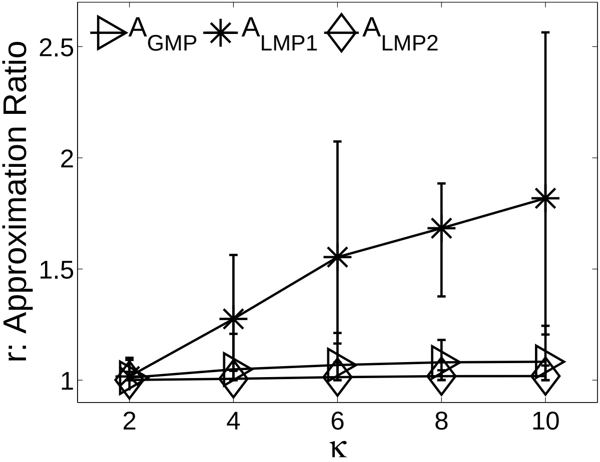
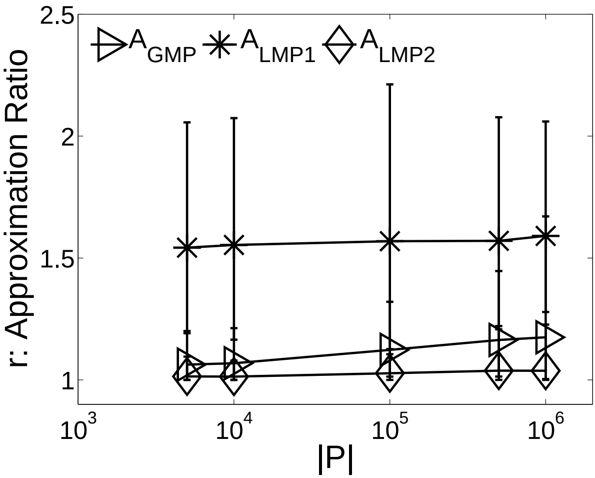


$|P| = 1,000,000$

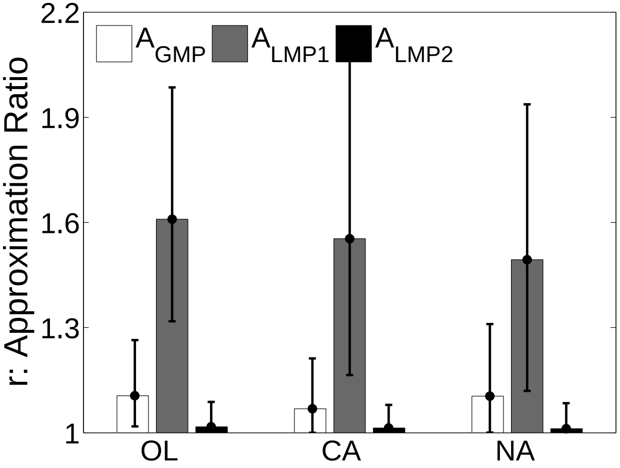
Approximation quality:



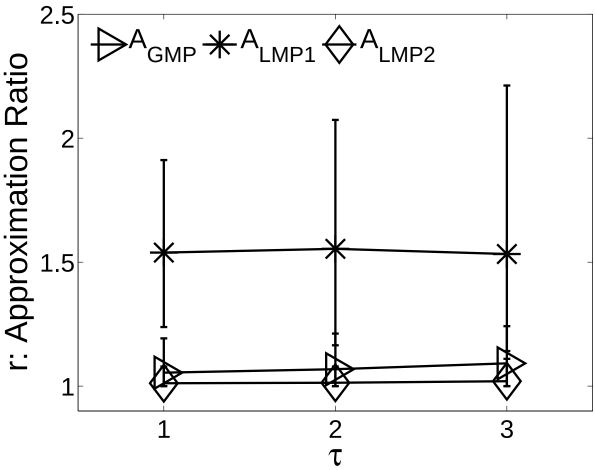
Approximation quality:



Approximation quality:



Approximation quality:

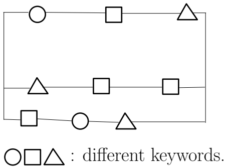


Outline

1. Introduction and Motivation
2. Preliminary
3. Exact solutions
4. Approximate solutions
5. Experiments
6. Related Work and Concluding Remarks

Related work

- The optimal sequenced route (OSR) query [sks07].



- [sks07]: The Optimal Sequenced Route Query. In VLDBJ, 2007.

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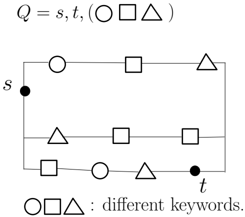

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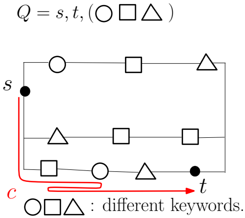

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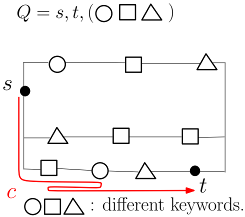
Related work

- The optimal sequenced route (OSR) query [sks07].
- Exact keyword query and only handles the query keywords sequentially.



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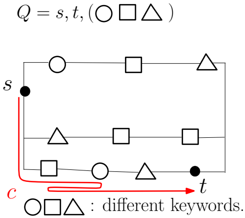
Related work

- The optimal sequenced route (OSR) query [sks07].
- Exact keyword query and only handles the query keywords sequentially.
- In MAKR queries, "categories" are dynamically decided only at the query time.



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Thank You

Q and A