Karlsruhe Institute of Technology

Candidate Sets for Alternative Routes in Road Networks

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`http://algo2.iti.kit.edu/AlgorithmenII.php`

Institute of Theoretical Informatics - Algorithmics II

Motivation

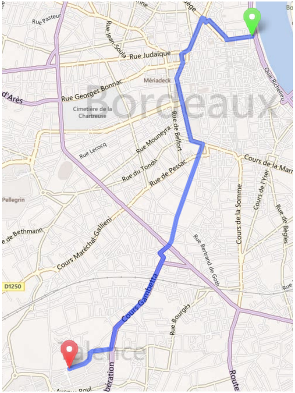
Advanced Route Planning

PAST: finding shortest paths

- "race" in algorithm engineering
  (new algorithms, engineering existing ones)
- sub-microsecond query times, preprocessing in minutes

PRESENT: more complex tasks

- time-dependent / stochastic routing
- dynamic / multi-modal settings
- alternative routes



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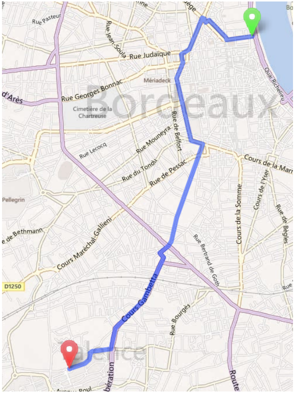

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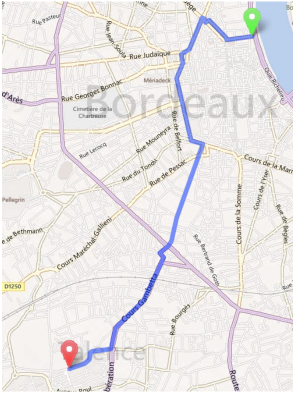
Advanced Route Planning

Why even consider alternative routes?

- attractive from a business point of view
  - easy way to provide options
    (users have diverse preferences, let them decide)
  - overcome shortcomings in model and data
    (shortest path might not be best in reality!)

- interesting from a scientific viewpoint
  - building block (traffic models, stochastic routing)
  - NP-hard aspects (alternative graphs)



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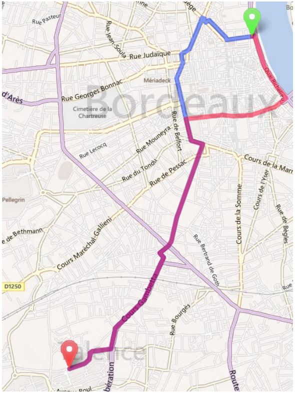

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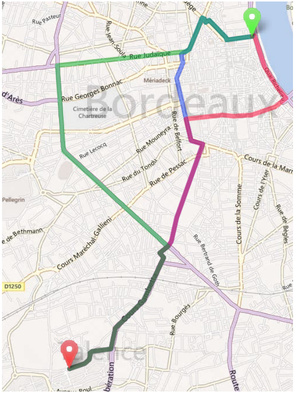

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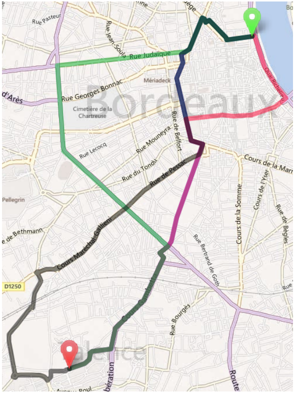

Alternative Routes

What has been done before?

Alternative Route Graphs in Road Networks

[Bader et al. 11]

- penalty method
- constructing alternative graphs
  (open how to extract single alternatives)
- slow, difficult to tune properly

Alternative Routes in Road Networks

[Abraham et al. 10a]

- via nodes (Choice Routing)
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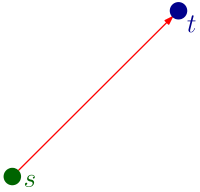

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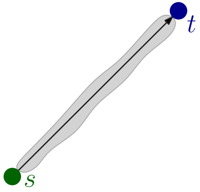

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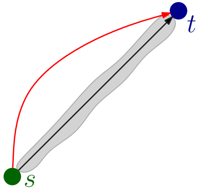

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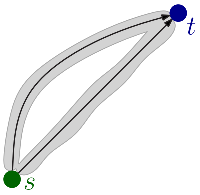

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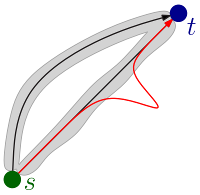

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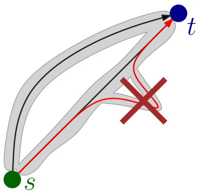

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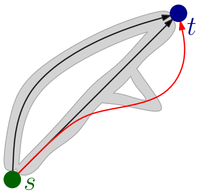

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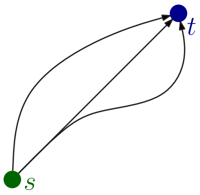

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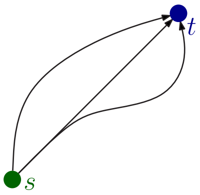

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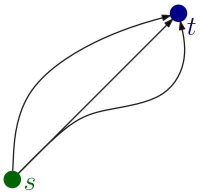

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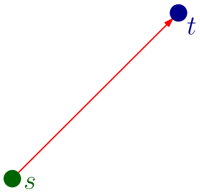

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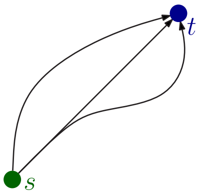

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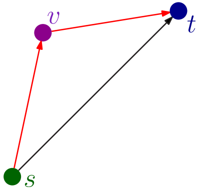

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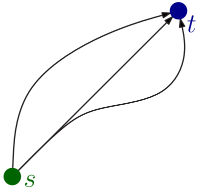

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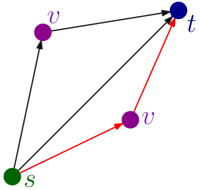

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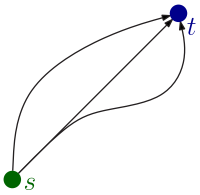

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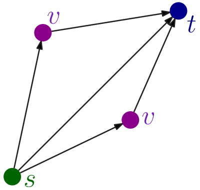


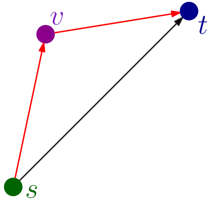
Modeling

[Abraham et al. 10a]

How do you define a good alternative?

basic model

- *road network*: graph $G(V, E)$, edge weights $w : E \to \mathbb{R}_0^+$
- *alternative*: concatenation of two shortest paths $\langle s..v \rangle$, $\langle v..t \rangle$



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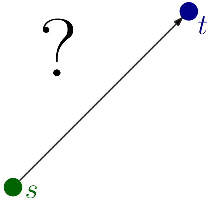

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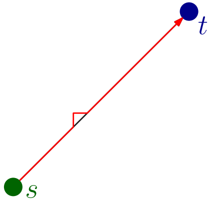

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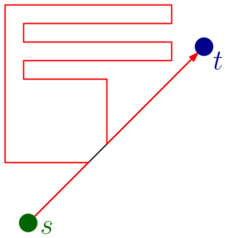

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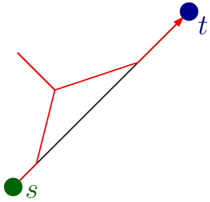

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criteria for a good alternative

- not too much longer (stretch ϵ)
- sufficiently different (overlap γ)
- reasonable (α-locally optimal)

$\rightarrow$ define *quantitative quality measure* $f(\alpha, \gamma, \epsilon)$ for alternatives
(only accept alternatives as viable, if single criteria are good enough)

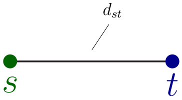
Alternatives Routes

[Abraham et al. 10a]

How do you find them?

basic approach (X-BDV)

- based on bidirectional search (Dijkstra's algorithm)
  → grow search spaces from *s* and *t*
- meeting nodes in search spaces are *candidate via nodes*
  → rank and check if alternative is viable



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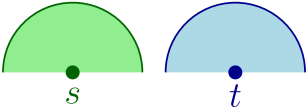

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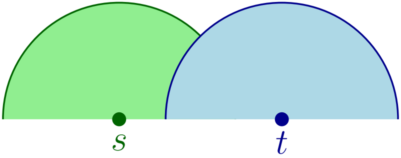

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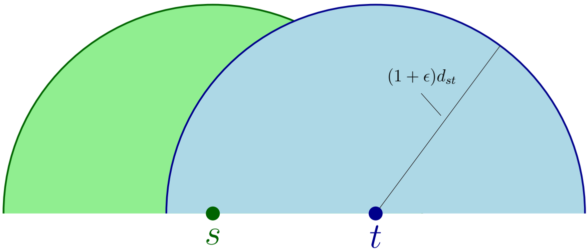

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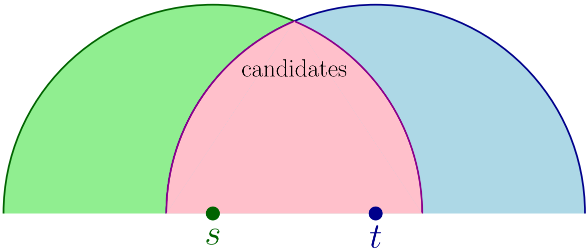

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How do you find them, quicker?

[Abraham et al. 10a]

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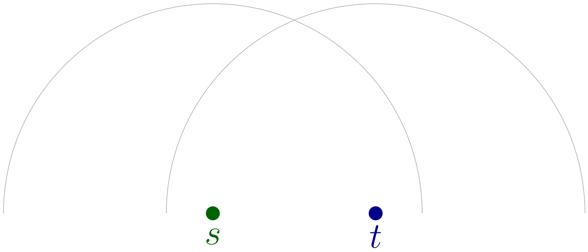

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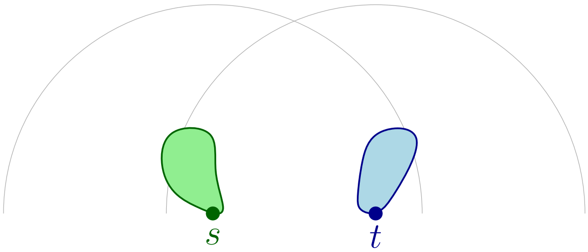

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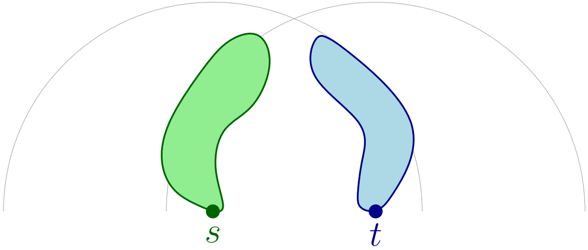

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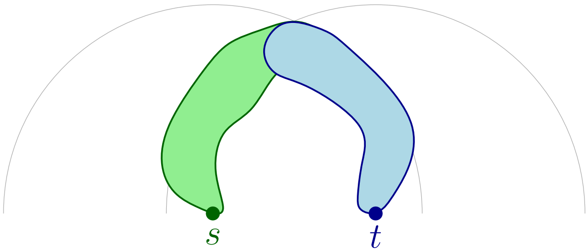

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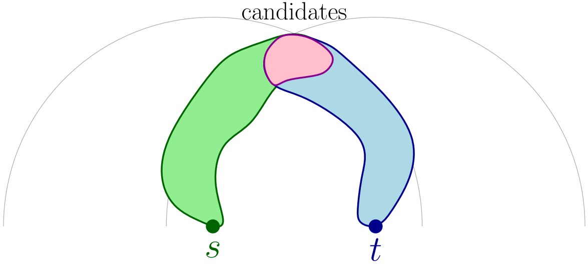

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What can we improve?

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  - full search space exploration
  - evaluation of candidates
- store all via nodes?

  $\rightarrow$ quadratic overhead in number of nodes...

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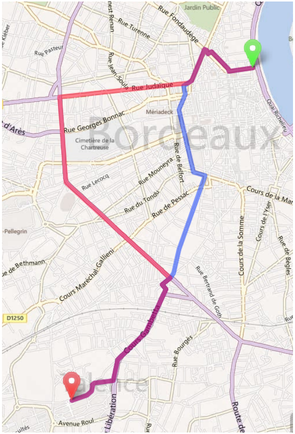
  $\longrightarrow$ quadratic overhead in number of nodes. . . you don't want to do that!

Optimization Potential

Can we still find a more substantial improvement?



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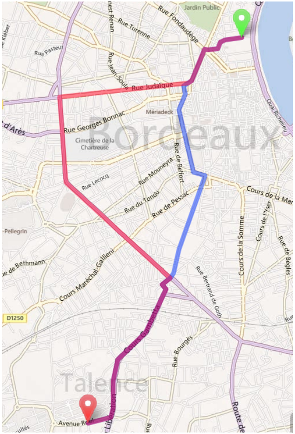

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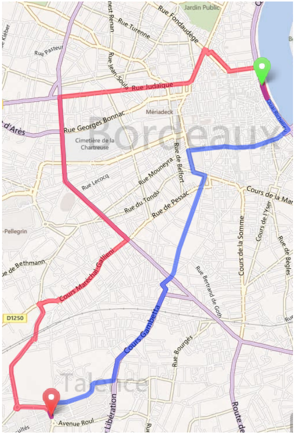

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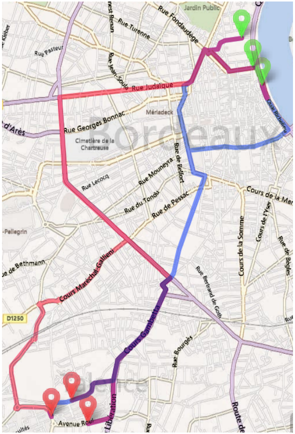
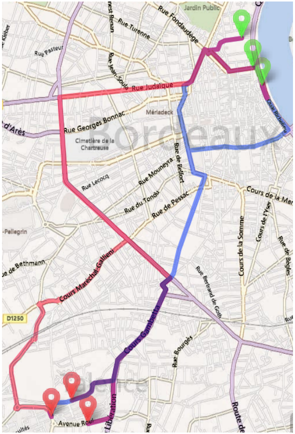


Optimization Potential

Can we still find a more substantial improvement?

observation

- alternatives between regions share a lot



Optimization Potential

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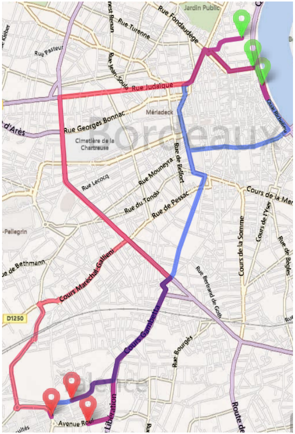
- alternatives between regions share a lot

- well-known fact for shortest paths

  → shortest paths entering/leaving a region are covered by small number of nodes [Abraham et al. 10b]



Optimization Potential

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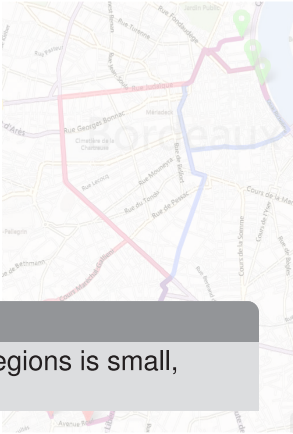

combined assumption

If the number of shortest paths between two regions is small, so is the number of viable alternatives.

→ they can be covered by few nodes

Optimization Potential

Can we still find a more substantial improvement? Yes we can!

Karlsruhe Institute of Technology

How to profit from this assumption?

- graph partitioning
  $\longrightarrow$ group nodes with similar shortest path characteristics
  (and alternative route characteristics)

- for each pair of regions store a *via node candidate set*
  $\longrightarrow$ nodes that cover (good) alternatives between this region pair
  $\longrightarrow$ only evaluate these candidates
  (search space exploration no longer needed)

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$\longrightarrow$ **single-level approach**
(preprocessing, query)

Query

How to find an alternative between s and t?

- look up respective via node candidate set $C(R_s, R_t)$
- check if path $\langle s..v..t \rangle$ is a viable alternative, $v \in C(R_s, R_t)$
  $\longrightarrow$ stop as soon as one is found (greedy)
  $\longrightarrow$ iterate over all candidates to find best alternative (full processing)
  (optimization: sort via node candidates in order of importance)

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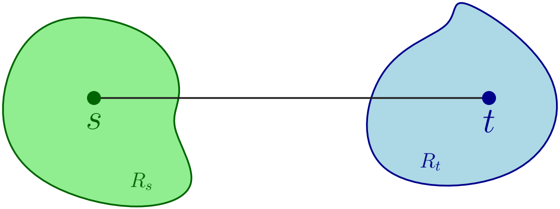

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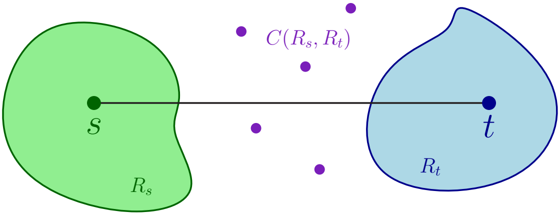

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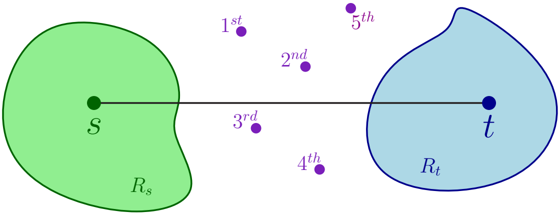

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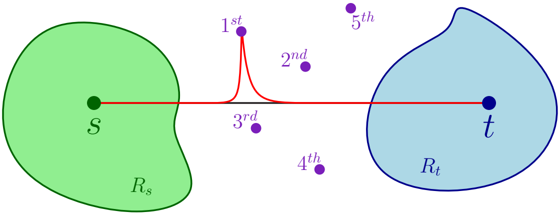

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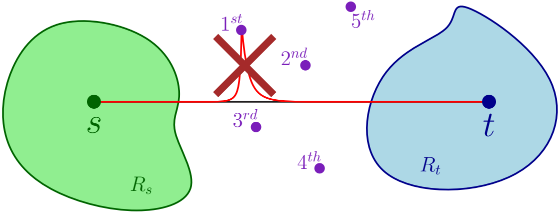

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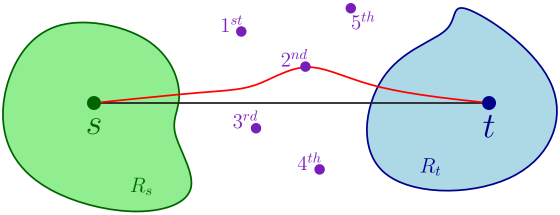

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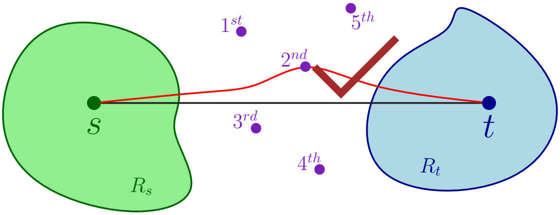

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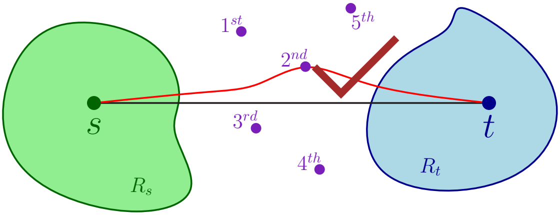
$\longrightarrow$ checking candidates much faster than search space exploration



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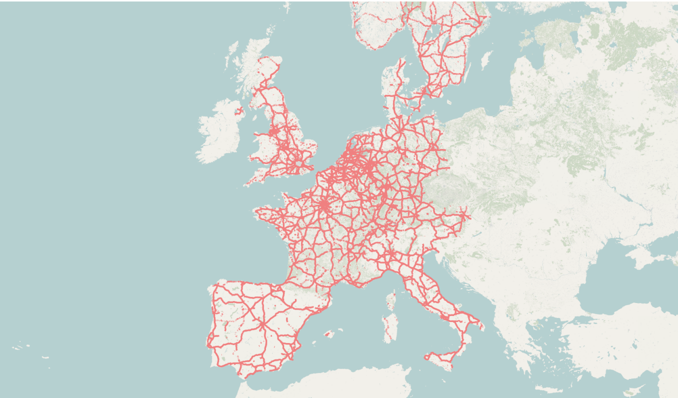

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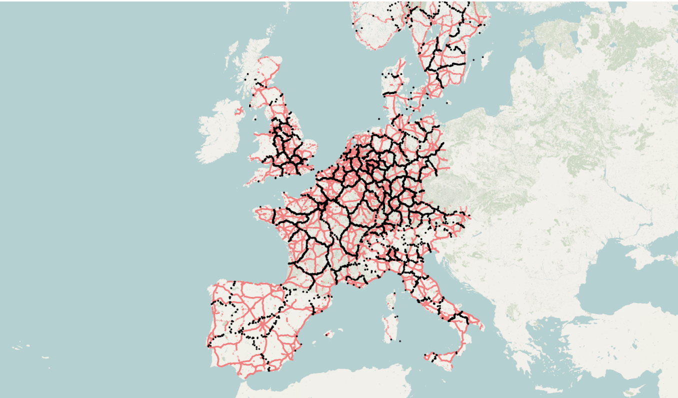

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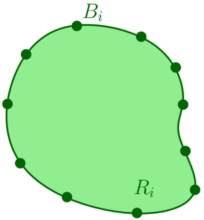

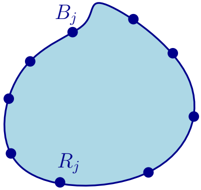

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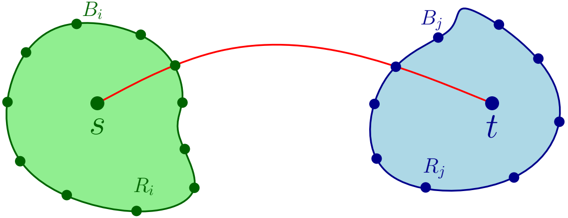

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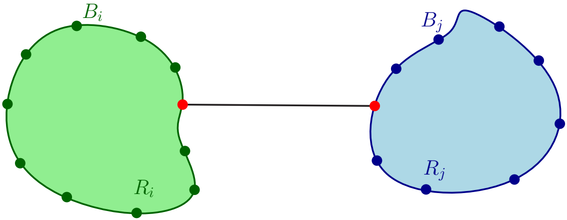

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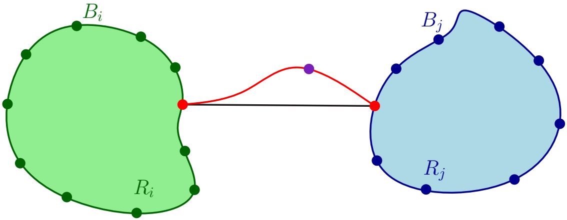

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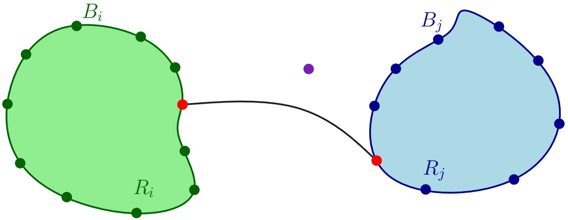

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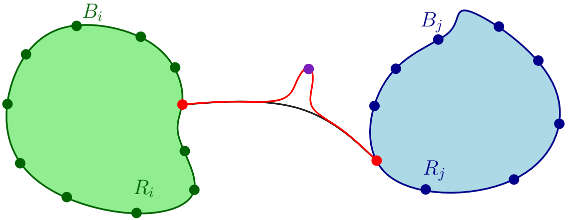

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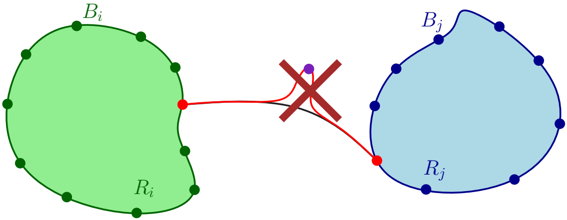

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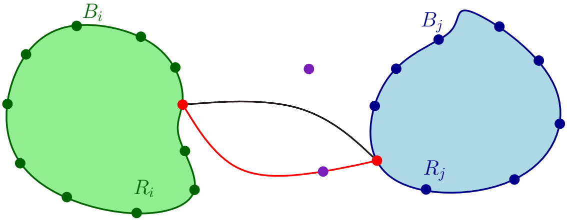

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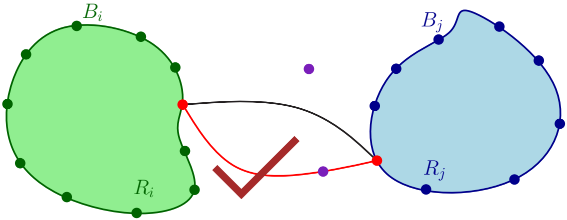

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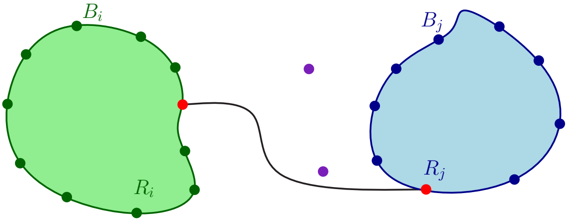

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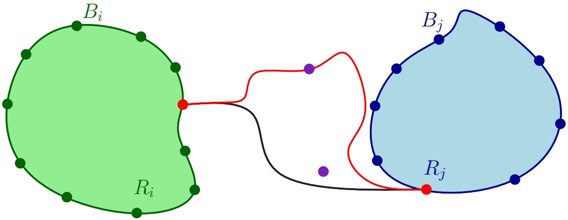

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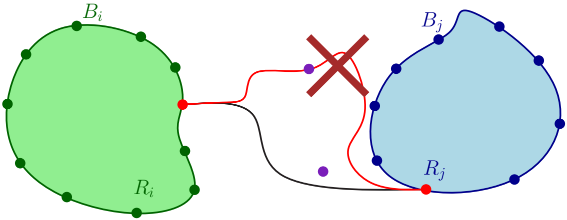

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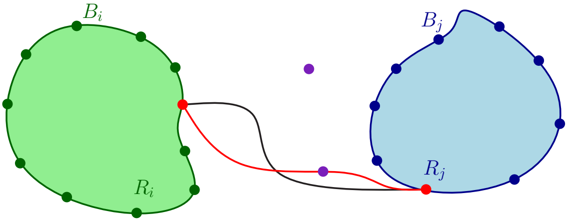

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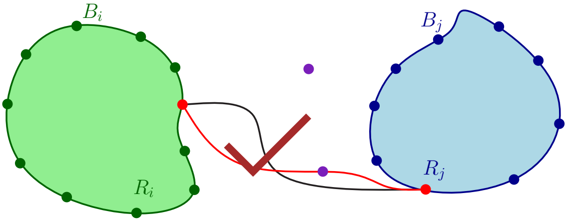

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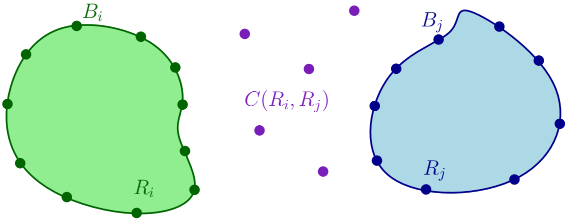

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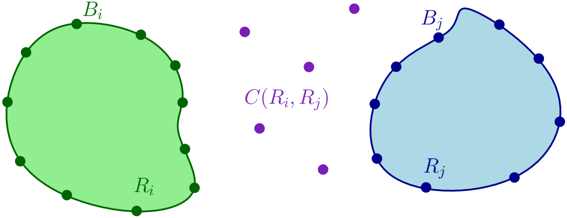
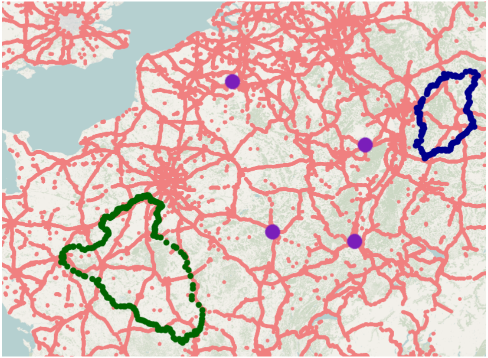
$\rightarrow$ quadratic overhead, but in number of regions ($\sim$ linear in number of nodes)



One problem remains...

What can we do about it?

- via sets of neighboring regions are *very* large
  $\longrightarrow$ longer query times, higher space consumption



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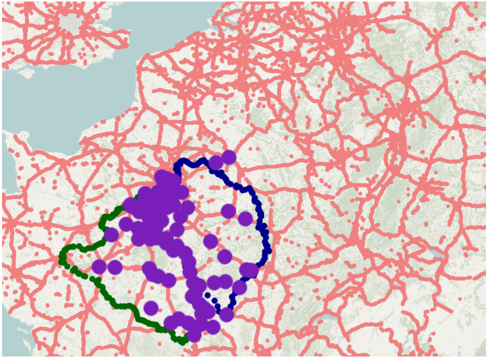

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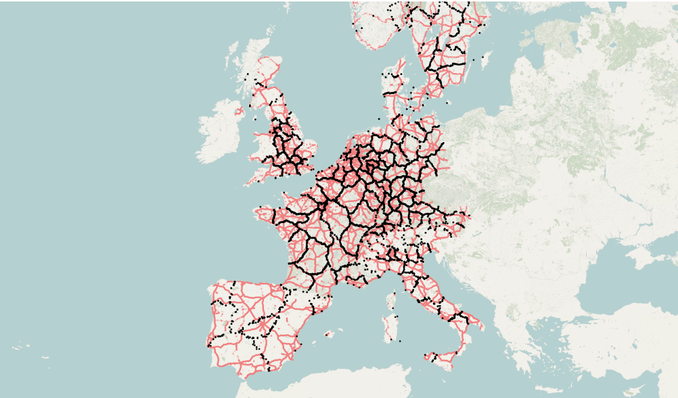
possible solutions

- fallback to baseline algorithm (X-CHASEV)
  (for neighboring regions / within one region)
- multi-level approach
  (additional overhead)

Multi-level approach

How does it work?

- additional finer graph partitioning (1024 regions, Buffoon)
  - finer regions respect original course regions



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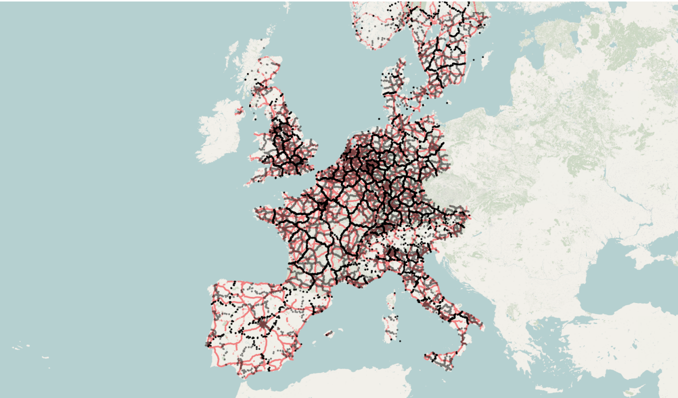

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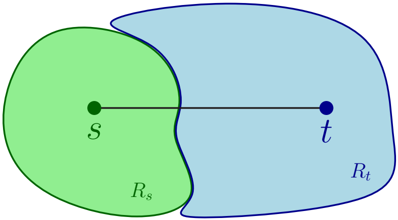

Multi-level approach

How does it work?

- additional finer graph partitioning (1024 regions, Buffoon)
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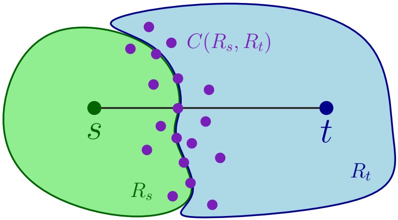

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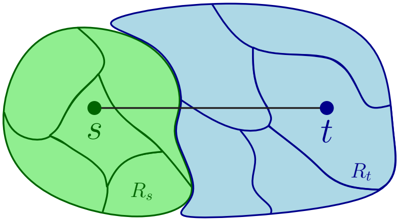

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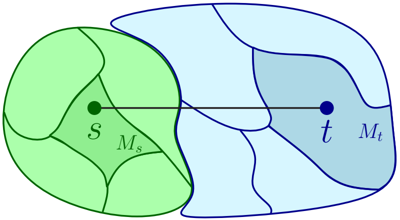

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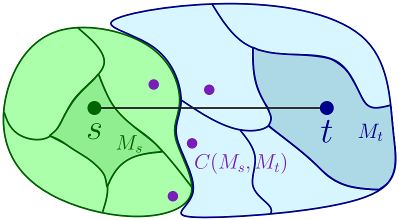

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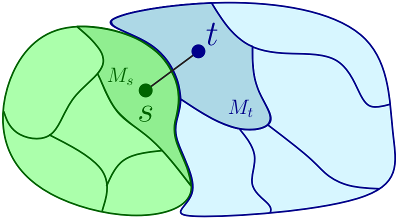

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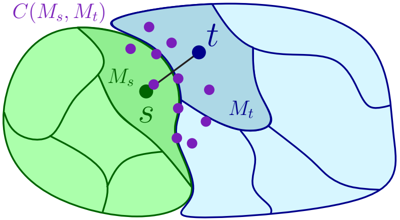

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Preprocessing performance

				candidate sets					
				p=1		p=2		p=3	
relaxed	preprocessing	time [h]	size [kiB]	empty [%]	avg. size	empty [%]	avg. size	empty [%]	avg. size
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✓	single-level	2.3	1 742	1.4	6.7	3.0	10.2	10.8	11.5
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- via node candidate sets are sparse (even better on connected regions)
  $\longrightarrow$ small memory overhead
  $\longrightarrow$ less than 10 MByte (good for caching)
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(relaxed variant of baseline algorithm with higher success rates but additional overhead)

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X-BDV	11.5s	94.5	-	12.2s	80.6	-	13.3s	59.5	-
X-CHV	1.2	75.5	-	1.7	40.2	-	2.3	14.2	-
X-CHASEV	0.5	75.5	-	0.7	40.2	-	1.0	14.2	-
single-level	0.1	80.7	1.9	0.3	50.8	2.8	0.4	24.8	3.8
multi-level	0.1	81.2	2.0	0.3	51.2	2.9	0.4	25.0	3.8

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- alternatives in sub-milliseconds
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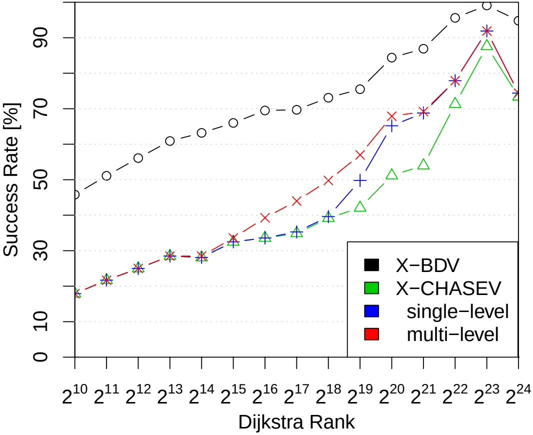
Results

Local queries (first alternative)

- success rates compared to shortest path lengths
- highest improvement for mid-range queries
  (avg. region sizes: 2^{15}, 2^{18})



(relaxed variant ≈ 5% below X-BDV)

Online Setting

Application I

Properties

- learn via node candidate sets from stream of queries
- applicable to legacy system (that implements some baseline algorithm)
- only partitioning required in advance

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Properties

- learn via node candidate sets from stream of queries
- applicable to legacy system (that implements some baseline algorithm)
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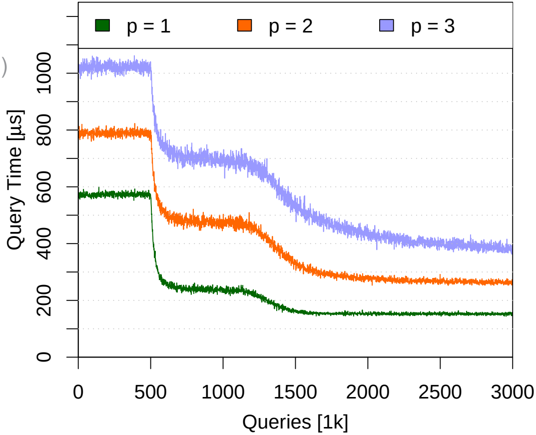
Algorithm

- start with empty via node candidate sets
- apply our *single-level approach*
  (check if existing candidate yields viable alternative)
- if no alternative is found
  - apply baseline algorithm (X-CHASEV)
  - if alternative is found: store its via node
- stop using baseline algorithm after some threshold is reached
  (except for neighboring regions / within one region)

Online Setting

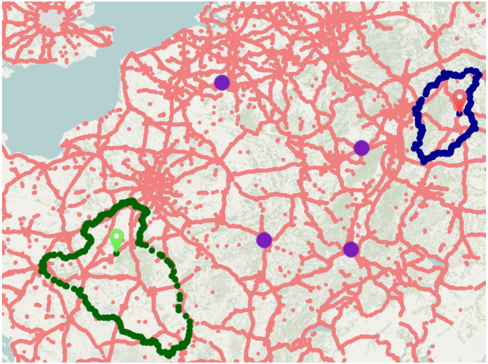
Simulation results

- baseline algorithm for first 500k queries (no learning)
- rapid fall in query times as our algorithm is applied (learning phase ≈ 100k queries)
- second decline when thresholds are reached (50 queries for each region pair)



Alternative Graphs
Application II

Properties
- fast to compute, little overhead
- two variants (with and without additional preprocessing)



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- combination of shortest paths
- *base method*
  - s to t
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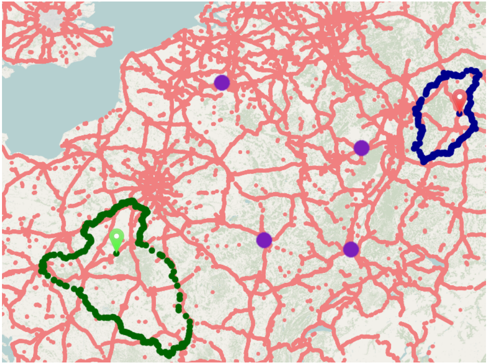

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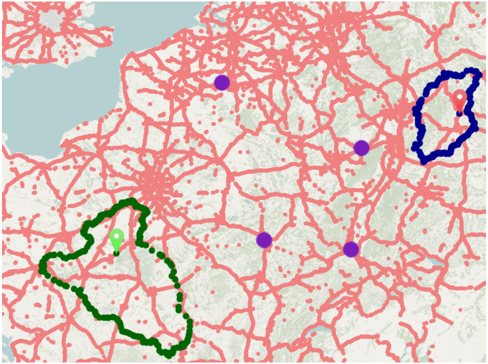

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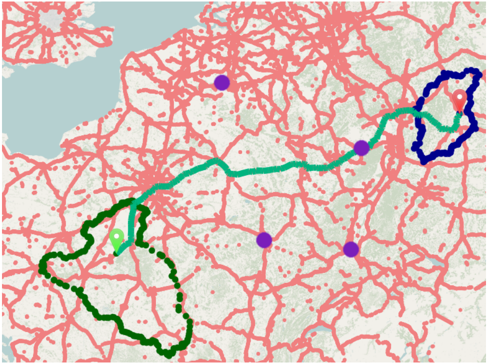

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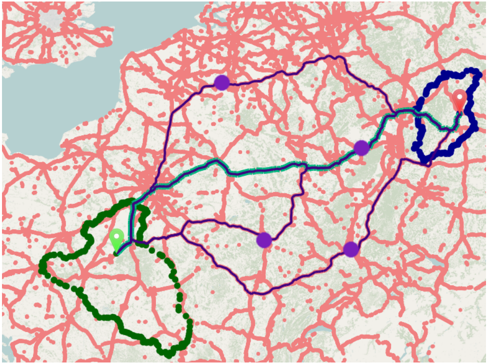

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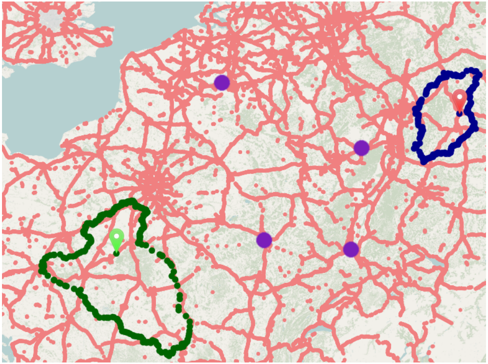

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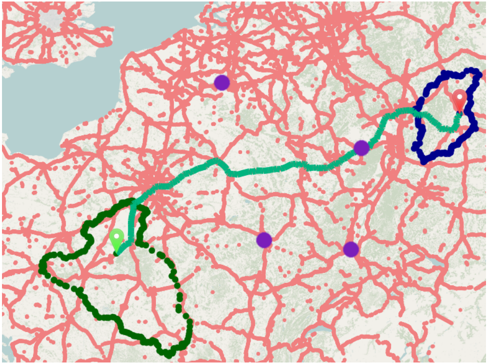

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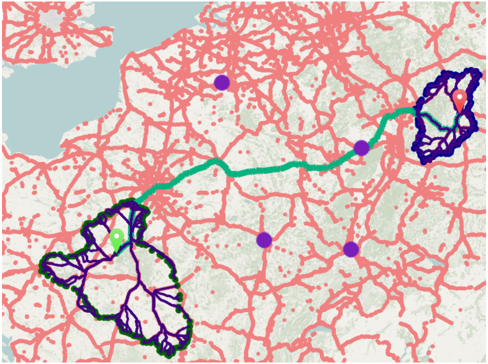

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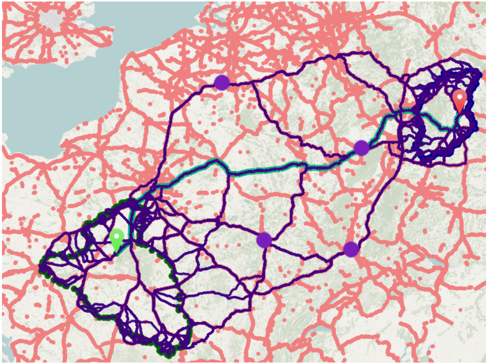

Conclusion

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Summary

- improvement in query times (one order of magnitude)
- lowered quality gap to X-BDV (25% and more)
- negligible memory footprint (less than 10 MByte)
- applications (online setting, alternative graphs)

Outlook

- theoretical foundations (using highway dimension)
- alternatives with more via nodes (similar to transit node routing)

Thank you for your attention!

Time for questions!

References

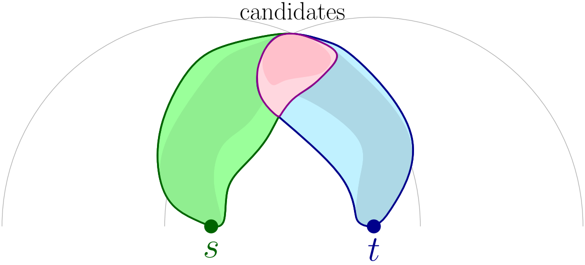
- [Abraham et al. 10a]
  Alternative Routes in Road Networks
- [Abraham et al. 10b]
  Highway Dimension, Shortest Paths and Provably Efficient Algorithms
- [Bader et al. 11]
  Alternative Route Graphs in Road Networks

Alternatives Routes

How do you find them, quicker and more often?

relaxed Contraction Hierarchies

- artificially increase search space (allow descent up to *x* levels)
  → improves success rate
- adjustable trade-off: speed vs. success rate



Results

Query performance (relaxed CH)

algorithm	p=1 time [ms]	p=1 success rate[%]	p=1 avg. tested	p=2 time [ms]	p=2 success rate[%]	p=2 avg. tested	p=3 time [ms]	p=3 success rate[%]	p=3 avg. tested
X-BDV	11.5s	94.5	-	12.2s	80.6	-	13.3s	59.5	-
X-CHV	3.4	88.5	-	4.3	64.7	-	5.3	38.0	-
X-CHASEV	2.7	88.5	-	3.2	64.7	-	3.8	38.0	-
single-level	0.2	90.0	2.2	0.4	70.2	3.8	0.6	44.0	5.6
multi-level	0.1	90.0	2.3	0.3	70.4	4.0	0.5	44.2	5.8

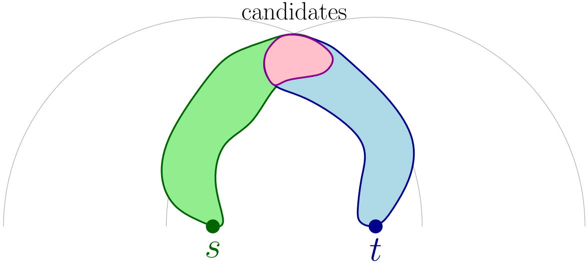
(Intel Core i7-920 (2.66 GHz), 12 GiB main memory, single core)

- alternatives in sub-milliseconds
  → *more than* one order of magnitude faster than X-CHV
- higher success rates
  → relative gap to X-BDV reduced by more than 25%

Results
Query performance

Why does *single-level*/*multi-level* improve success rates?

- via node candidates derived from alternatives between border nodes
  $\longrightarrow$ combination of search spaces of all border nodes
  $\longrightarrow$ larger overlap
  $\longrightarrow$ more chances to encounter viable via nodes



Results

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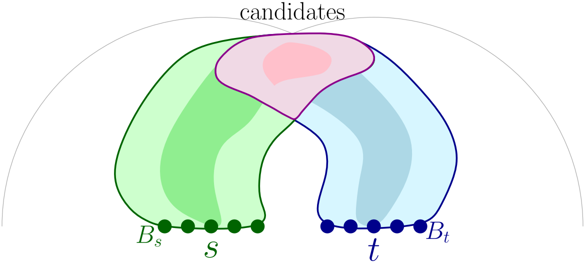
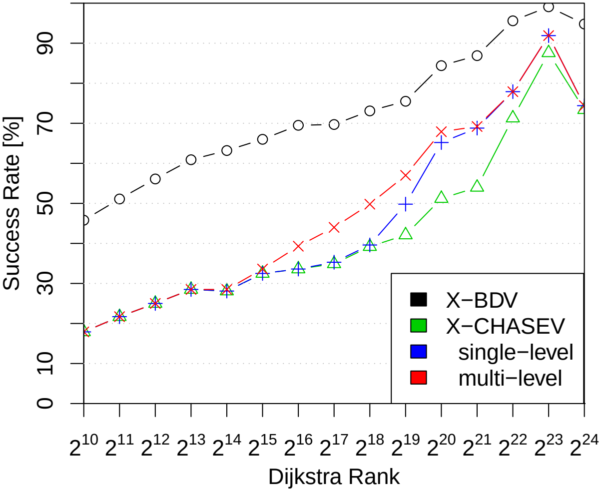


Results

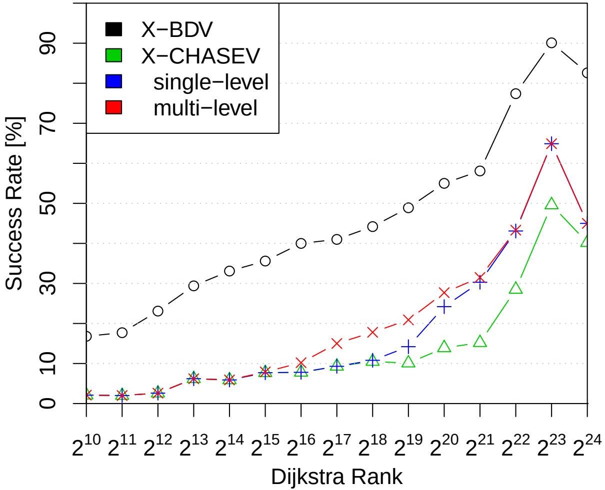
Local queries (basic CH)
first alternative



Results

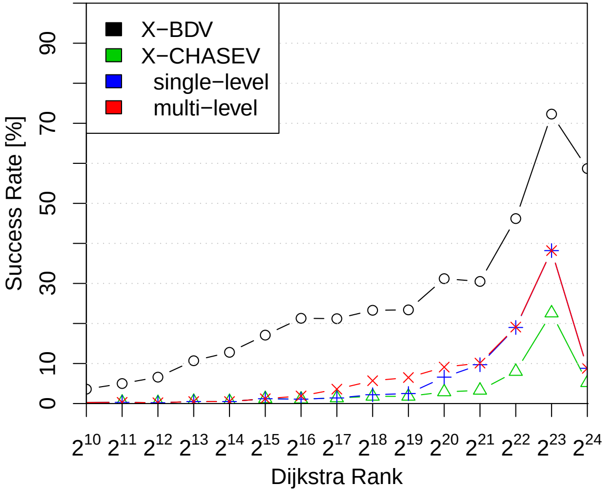
Local queries (basic CH)

second alternative



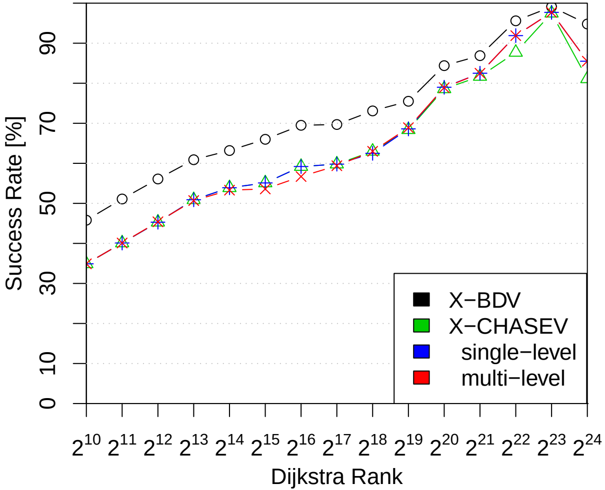
Results

Local queries (basic CH)
third alternative



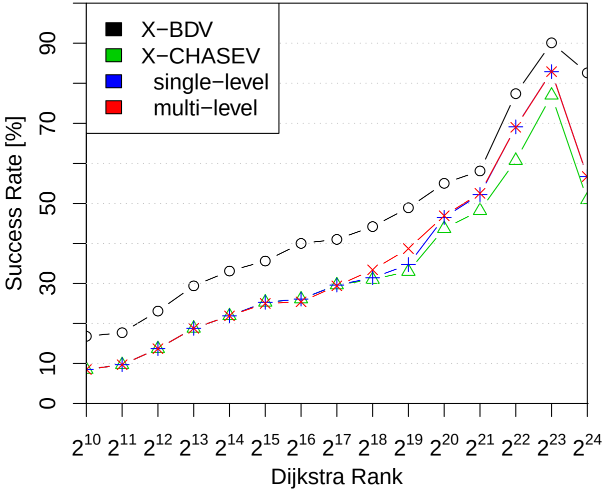
Results

Local queries (relaxed CH)
first alternative



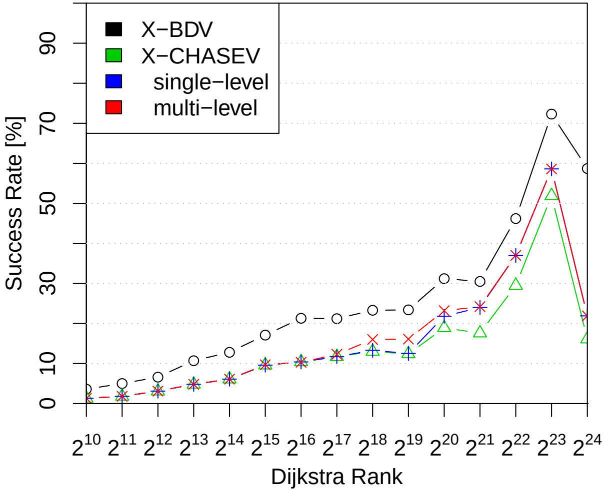
Results

Local queries (relaxed CH) second alternative



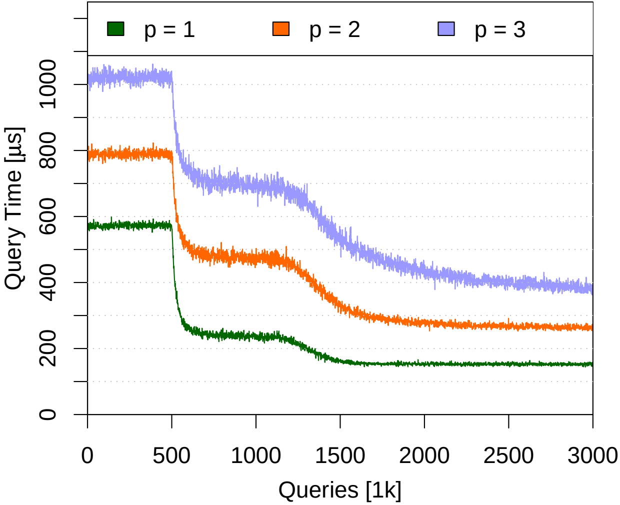
Results

Local queries (relaxed CH)
third alternative



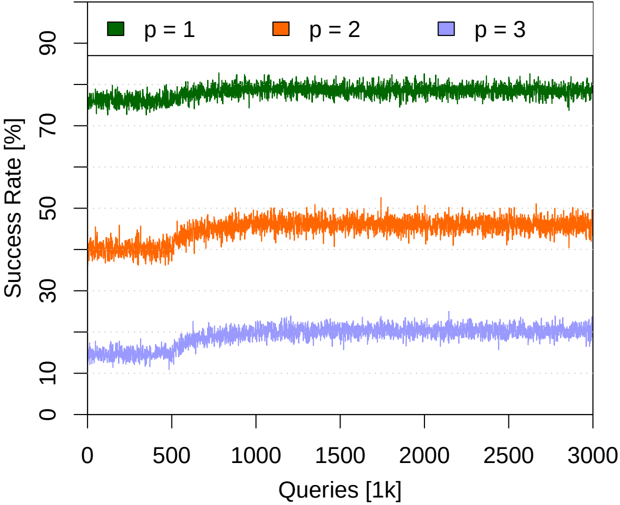
Online Setting

Simulation results (basic CH)



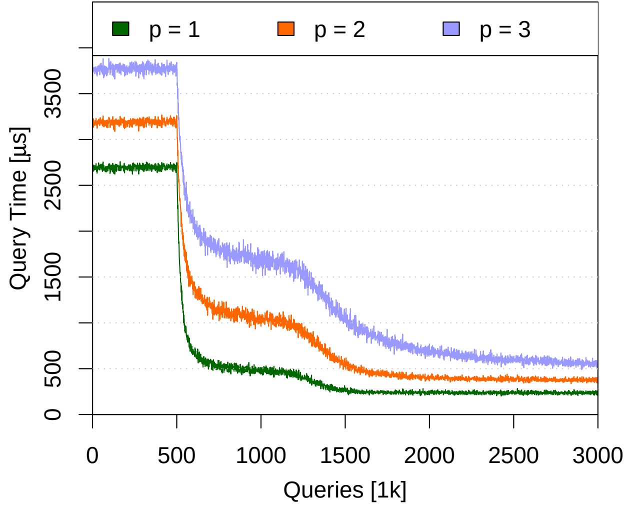
Online Setting

Simulation results (basic CH)



Online Setting

Simulation results (relaxed CH)



Online Setting

Simulation results (relaxed CH)