Fast Obstacle k-Nearest Neighbour Query on Navigation Mesh

Final Presentation

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Supervisors: David Taniar, Daniel Harabor

Outline

1 Introduction

2 Related works

3 Challenges

4 New Framework

5 My research

6 Experiments

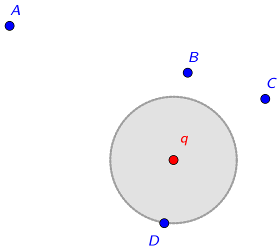
7 Conclusion and future work

8 End

Traditional k-Nearest Neighbor

k-Nearest Neighbor:

- Given:



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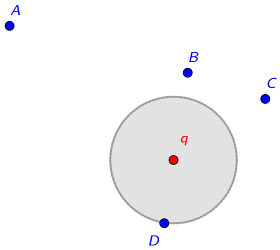

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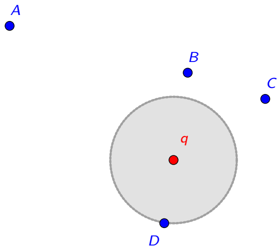

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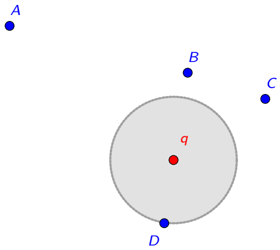

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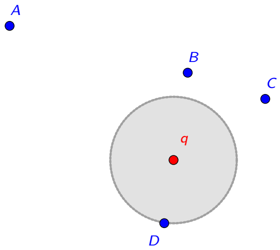

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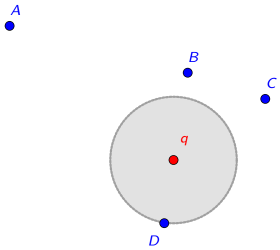
- the circle indicates that D is the nearest neighbor of q



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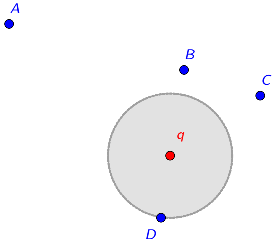

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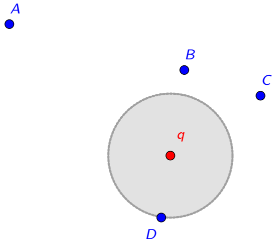

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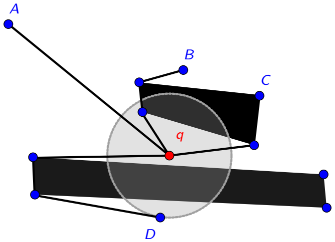
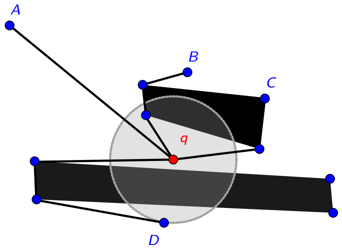


Application Scenario

In an industrial warehouse,
q is a robot.
It's interested in the closest storage locations,
but it can not cross obstacles



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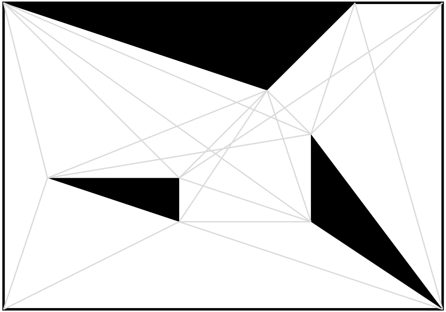
How to compute Obstacle Distance

- Existing works rely on *visibility graph* (VG)
  - any pair of visible points has an edge
- Run shortest path algorithm on *VG* (e.g. *Dijkstra*)
- Number of edge: up to $O(V^2)$

(*V*: the number of vertex)



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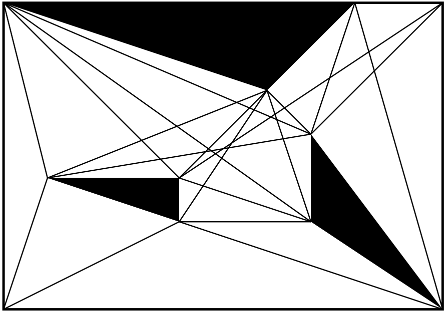

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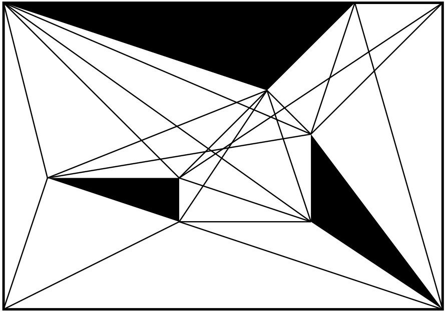

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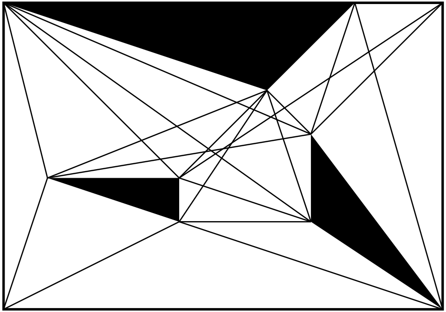

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- Motivation: only consider query related area
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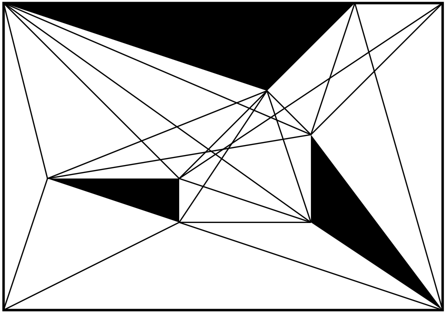

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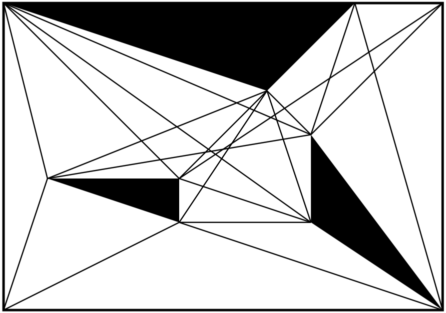

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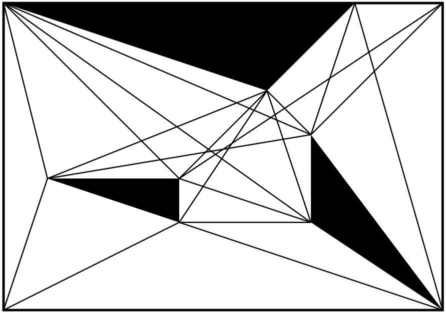

Obstacle Distance Computation: *LVG*

- Given: q, t
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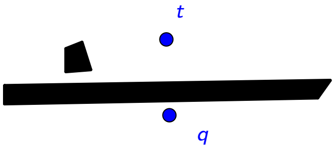

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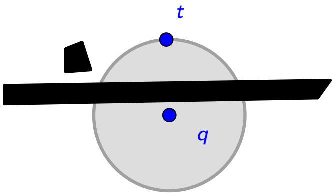

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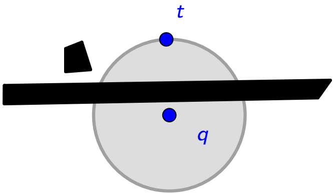

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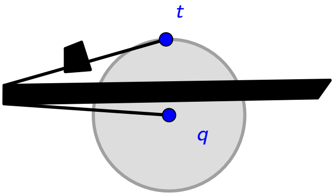

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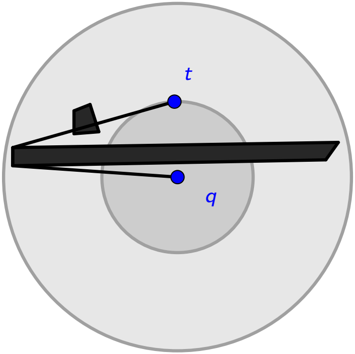

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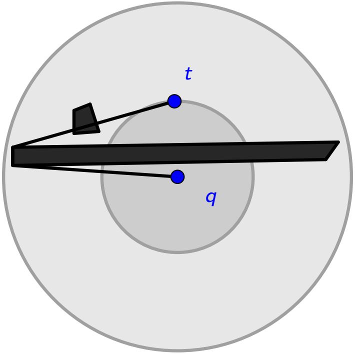

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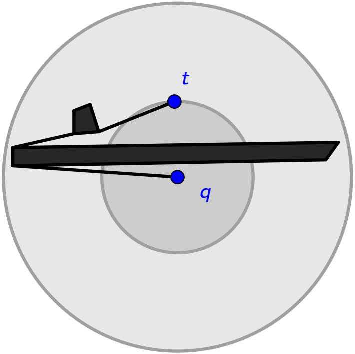

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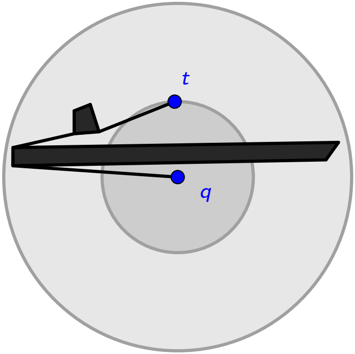

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- However ...

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It has some disadvantages:

- Costly online visibility checking
- An incremental construction can easily reach to $O(V^2)$ edges
- Duplicated effort:
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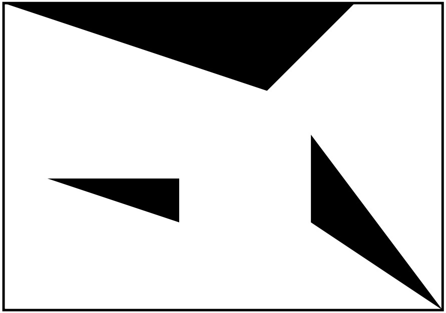

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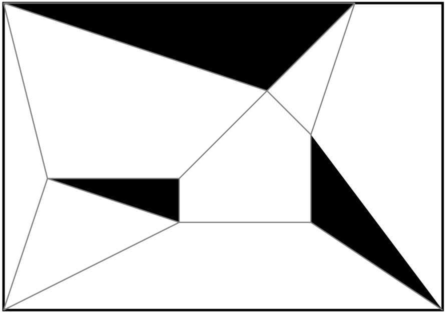
- traversable space => convex polygons



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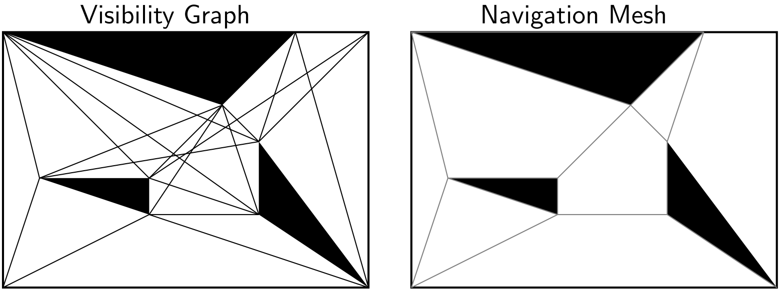

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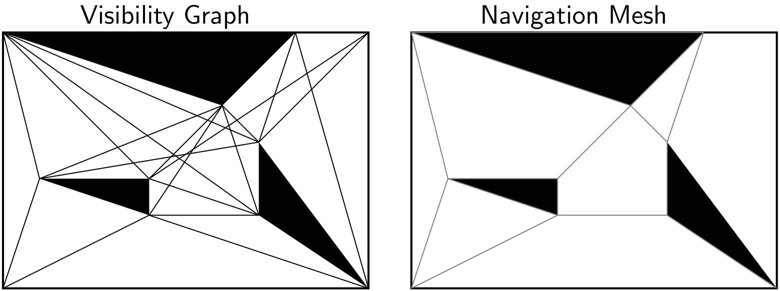
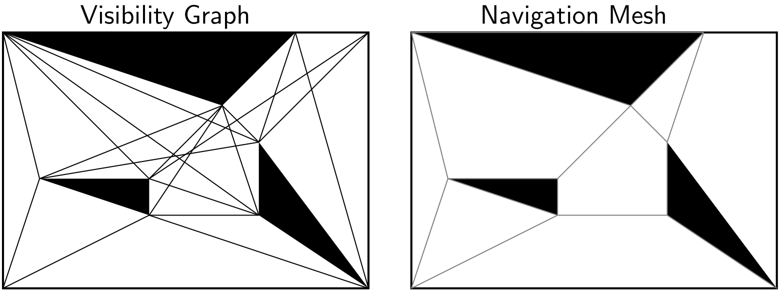


We can easily preprocess the entire map!

Advantage



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- But a recent work in 2017: *Polyanya*
  - fast, optimal, flexible
  - a new direction for Obstacle kNN query

What's the *Polyanya*?

- Given:
  - a map with polygonal obstacles
  - q: query point
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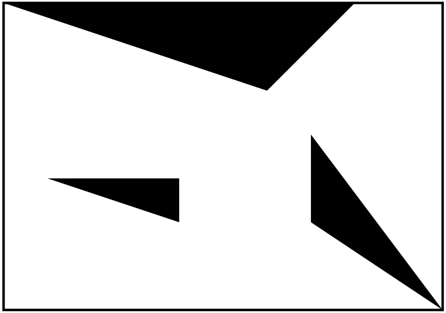
  - a precomputed navigation mesh
  - convex polygon: all inside points are visible
- find the shortest path along meshes



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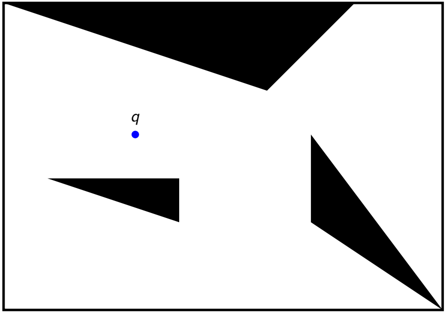

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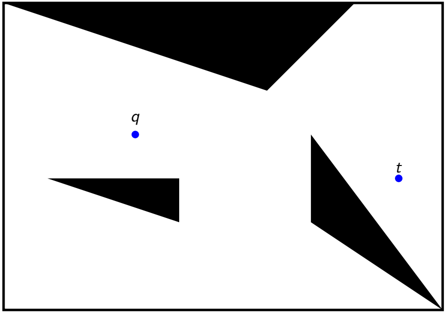

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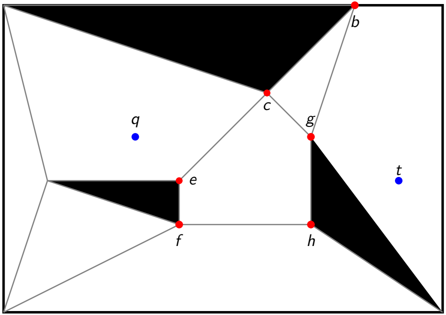

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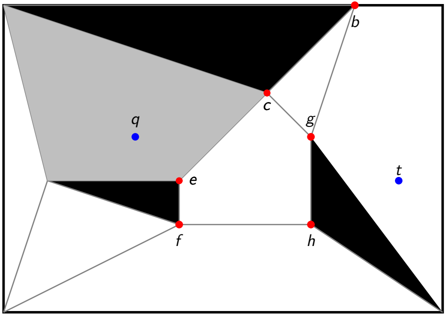

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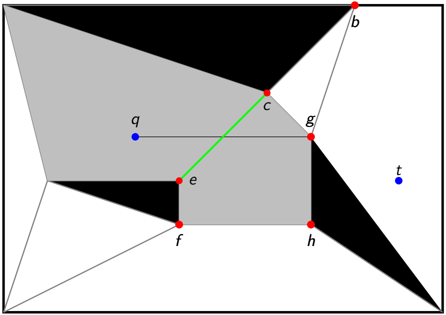

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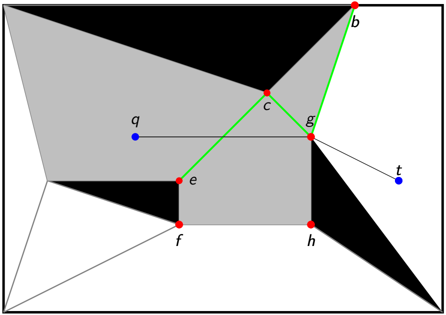

Polyanya: Overview

Polyanya is an *A** like algorithm, it has three components

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2. Successors
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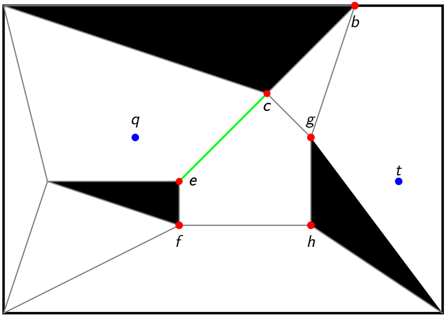
- all points $\in I$: visible from r



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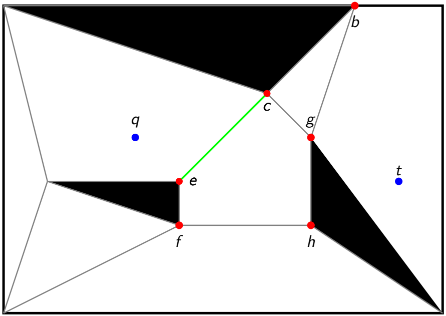

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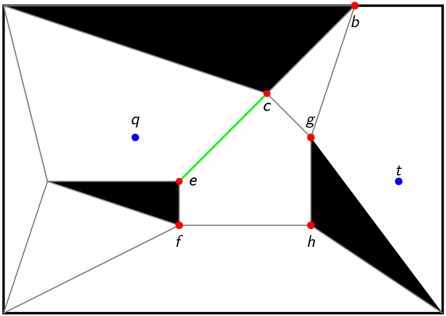

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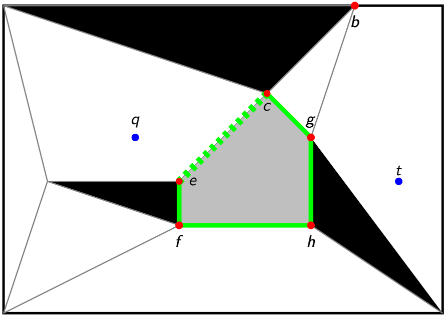

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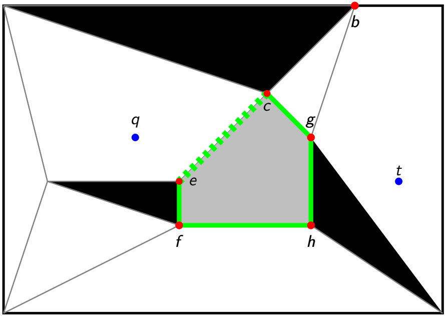
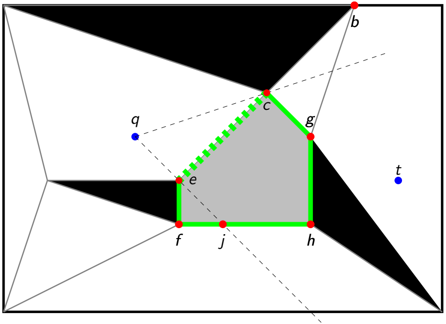


Polyanya: Successors

- Observable successors
  - root: parent's root
- Non-observable successors
  - root: an end point of I



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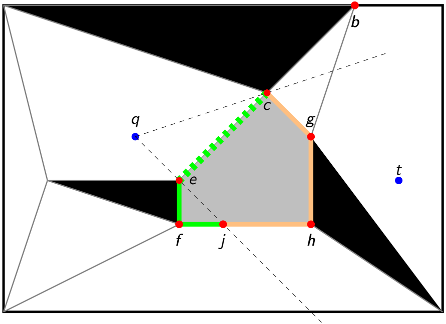

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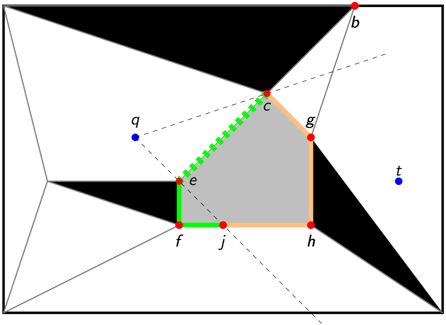

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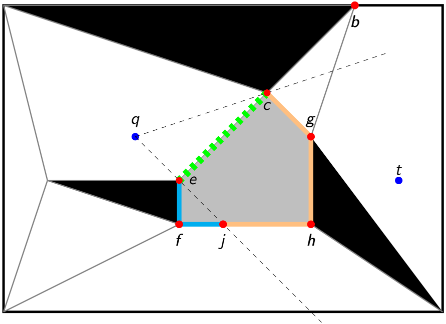
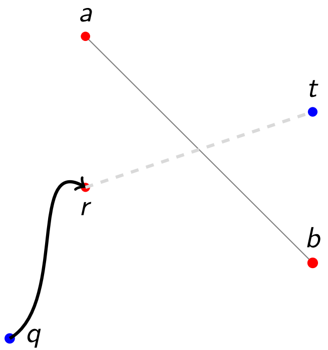


Polyanya: Evaluation Function

Evaluation function of a search node (r, I) has:

- *g-value*: $|shortestPath(q, r)|$ (certain)
- *h-value*: r to t cross I (underestimation)
- *f-value*: $g\text{-}value + h\text{-}value$ (underestimation of $|shortestPath(q, t|)$



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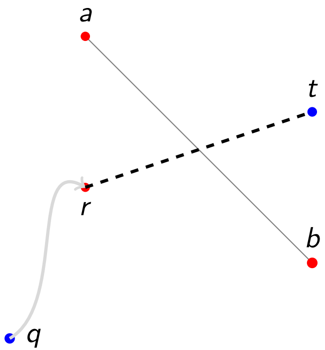

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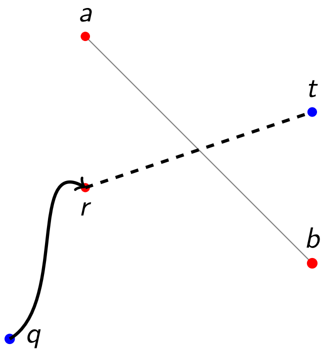
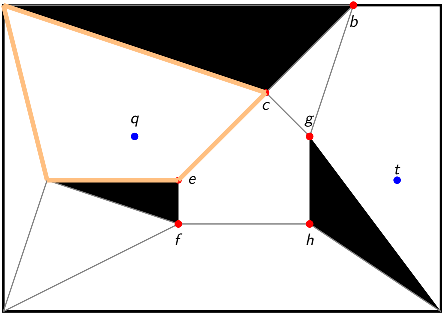


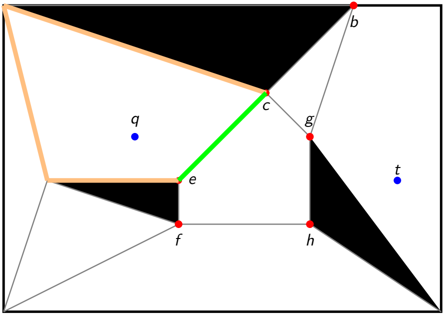
Polyanya: Example

Initial Search Nodes are edges of mesh that contains the q.



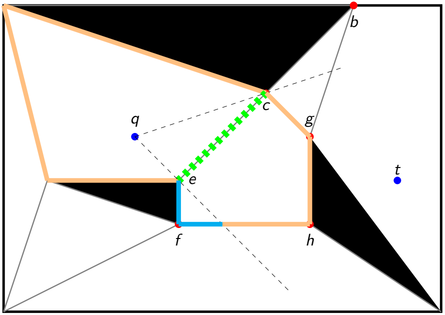
Polyanya: Example

Search Node $(q, [e, c])$ has the best estimation, so popped out



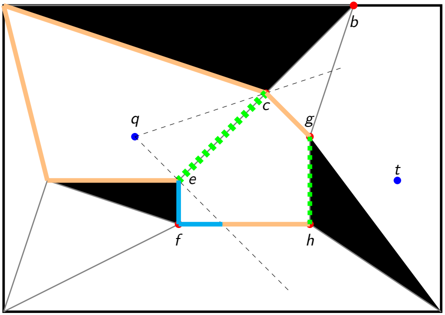
Polyanya: Example

Expand successors in adjacent mesh.



Polyanya: Example

Pop $(q, [g, h])$,
adjacent to obstacle,
so we discard it.



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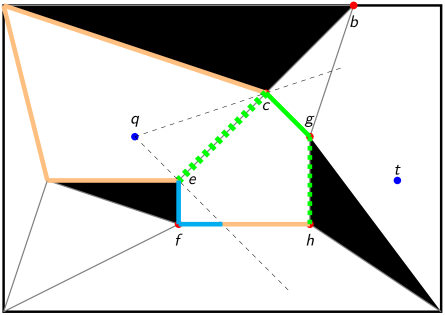

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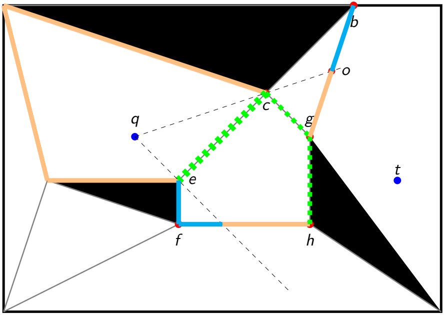
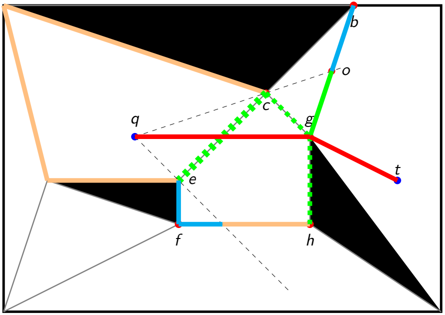


Polyanya: Example

Pop $(q, [g, o])$,
the adjacent mesh contains t.
We've found the shortest path!



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My Research

- *Polyanya* only work for single pair shortest path
- My research:
  - multi-targets search based on framework of *Polyanya*
  - with good scalability

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Proposed algorithm 1: brute-force *Polyanya*

A naive solution is calling *Polyanya* for each target:

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for t in targets:
  polyanya.run(q, t)
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- Drawback: inefficient when targets many.

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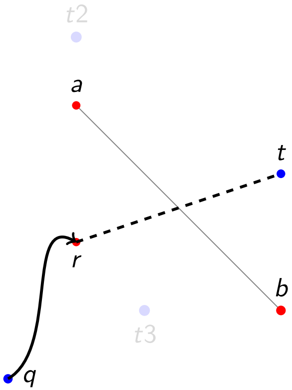
- When there are multiple targets...
  - *h-value* shouldn't affected by a specific target
- How about remove t from *h-value*?



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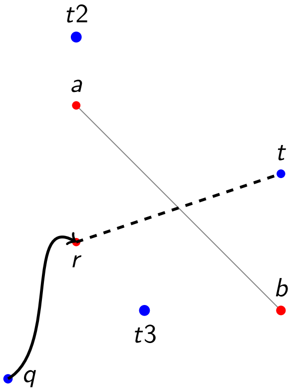

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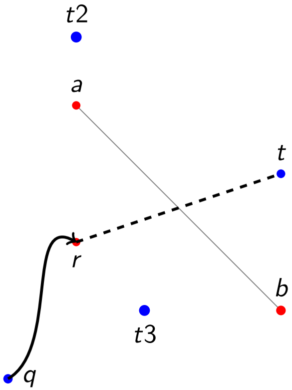

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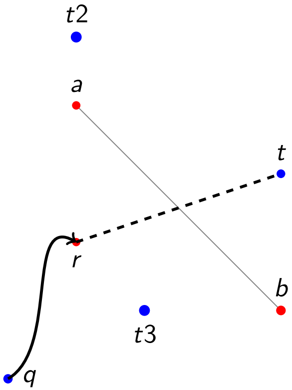

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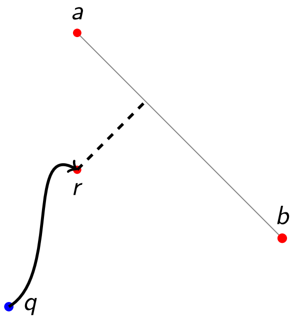

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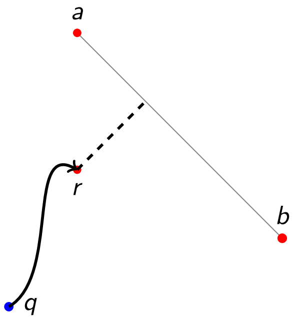

Interval heuristic: drawback

- *interval heuristic* causes redundant expansions
- especially in sparse targets scenario
- e.g.: query is "nearest storage locations where capacity >= 100".
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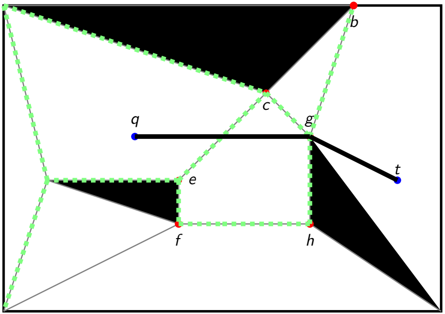

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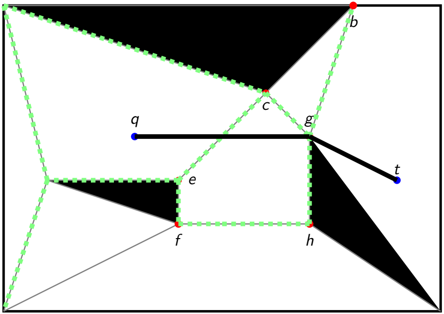

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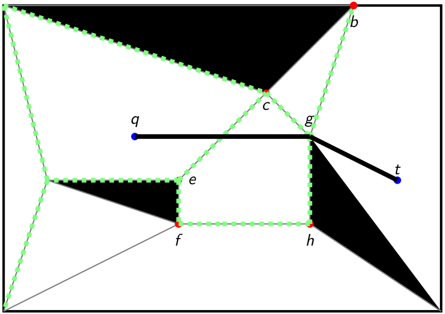

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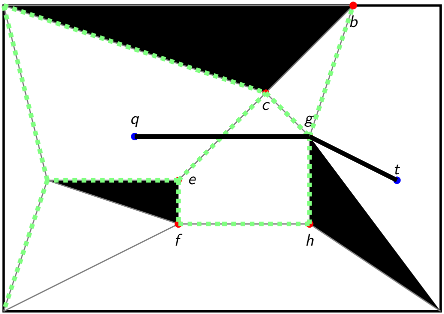

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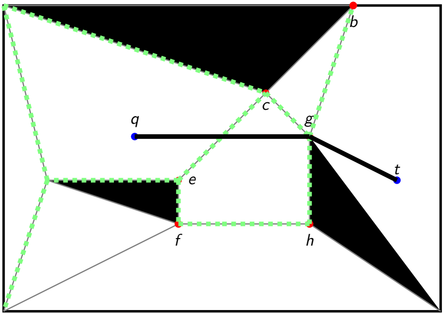

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Let me introduce the detail of *h-value* in *Polyanya*,
$h_p(node, t)$ equals:

- Case 1: $d_e(r, t_1)$
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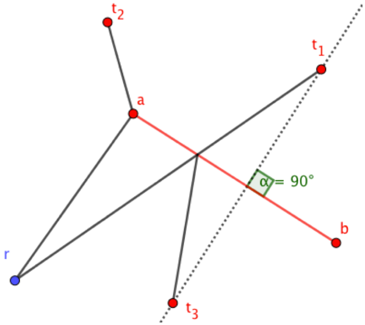
- Case 3: when r and t_3 at same side, compute mirror point of t_3, and go to Case 1 or Case 2



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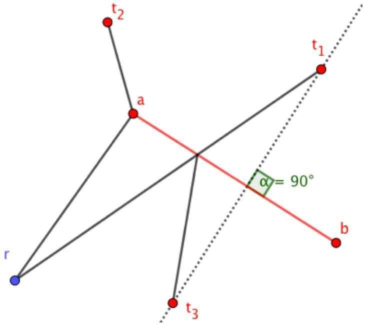

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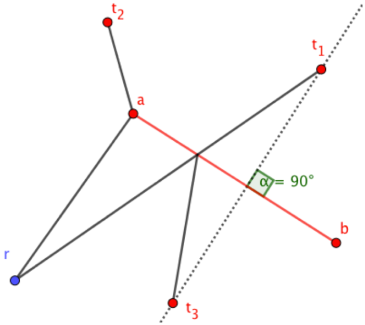

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How to find the closest target for a search node?

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- Let $NN_e(area, p)$: traditional nearest neighbor of p in $area$.

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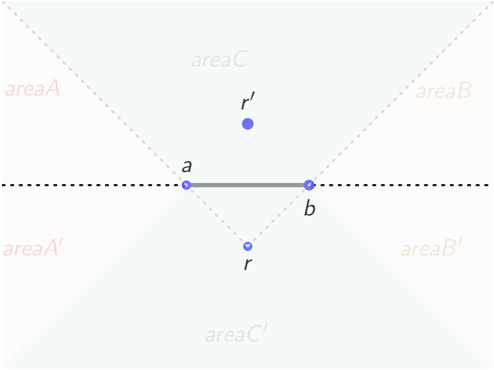

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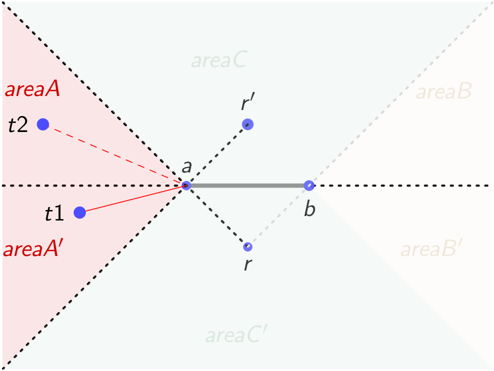

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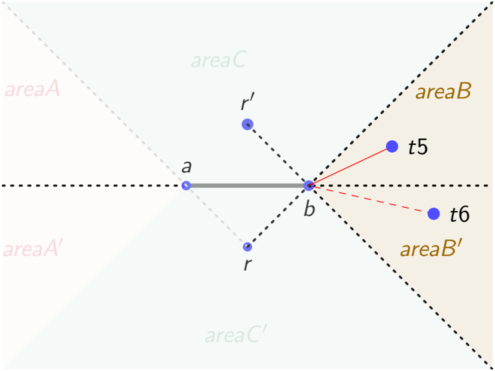

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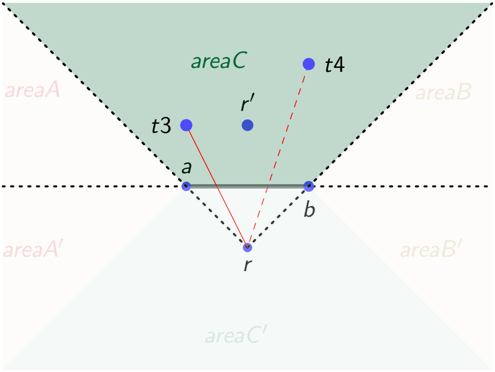

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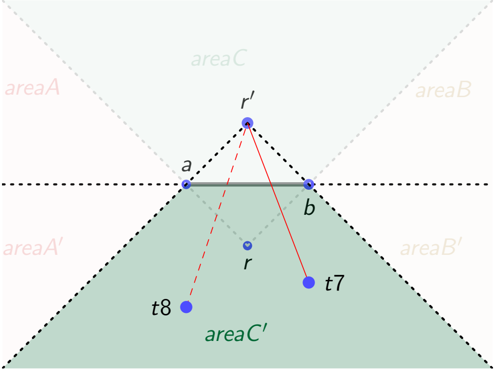

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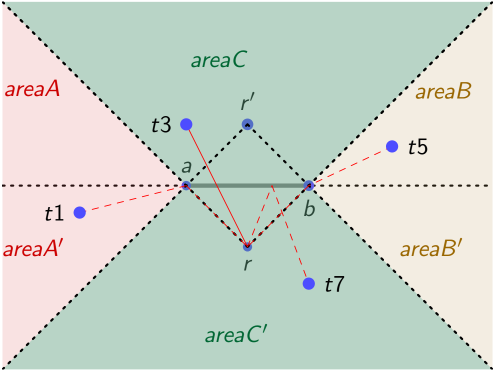

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- For each successor, assign the closest target to it
- Correctness:

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Non-decreasing property: Whenever the closest target of a search node changes, the h-value never decrease.

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- So we are looking for further refinements...

Proposed algorithm 3: target heuristic refinements

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In expansion, instead of finding a new target, successors can inherit the closest target from their parent if the *h-value* doesn't change.

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In this case, it is impossible to find a target with less h-value.

Proposed algorithm 3: target heuristic refinements

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Once t be retrieved, we must reassign another target to those search nodes who are regarding t as their closest target

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Lazy reassignment doesn't change relative expansion order.

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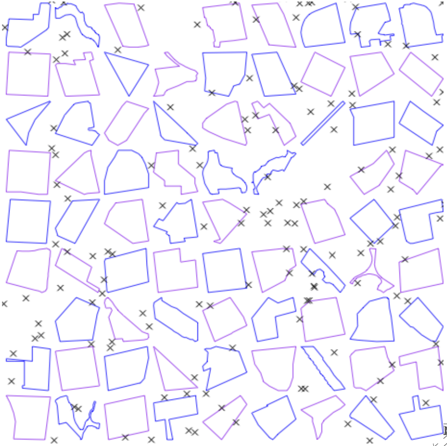
Dataset in *Zhang, EDBT 2004*: no longer available, so we generate new benchmark problems:

- All parks (≈ 9000) in Australia from *OpenStreetMap*
- Use them as polygonal obstacles



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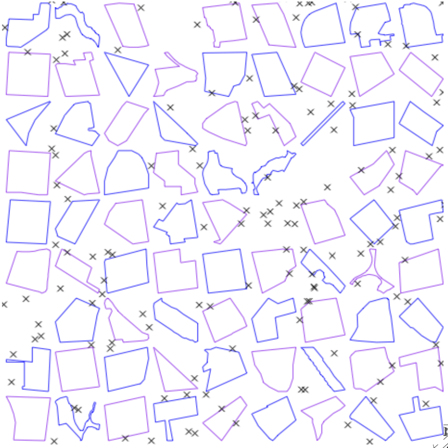

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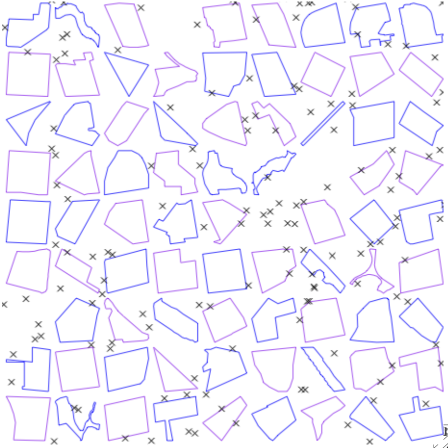

Competitors

There are two types of test case:

- Dense targets: $|T| \approx |O|, |O| \approx 9000$
- Sparse targets: $|T| <= 10, |O| \approx 9000$

In dense targets experiments, we compare between:

- *LVG* (from *Zhang, EDBT 2004*)
- Interval heuristic
- Target heuristic

In sparse targets experiments, we compare between:

- burte-force Polyanya
- Interval heuristic
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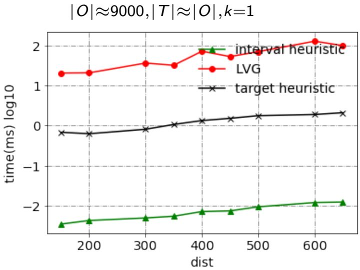
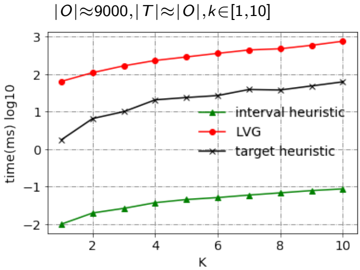
Dense targets

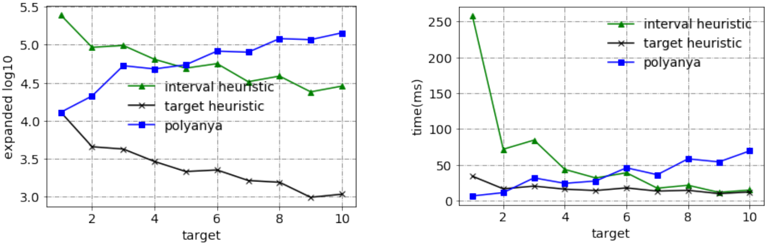




- *Interval heuristic* is three order of magnitude faster than *LVG*, in all aspects.

Sparse targets: fix $k = 1$

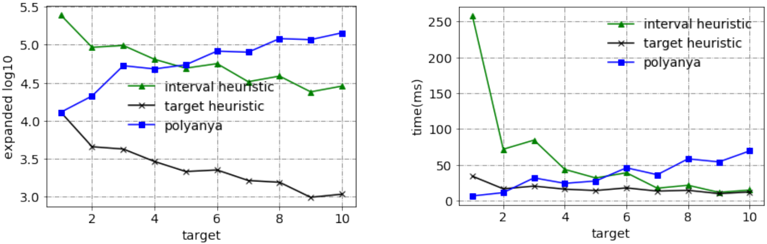
$|O| \approx 9000, |T| \in [1, 10]$



- *Target heuristic* always has smaller search space. (left)
- It gradually lose such advantage when $|T|$ increase. (right)
- Reason: the costly heuristic function.

Sparse targets: fix $k = 1$

$|O| \approx 9000, |T| \in [1, 10]$



- *Target heuristic* always has smaller search space. (left)
- It gradually lose such advantage when $|T|$ increase. (right)
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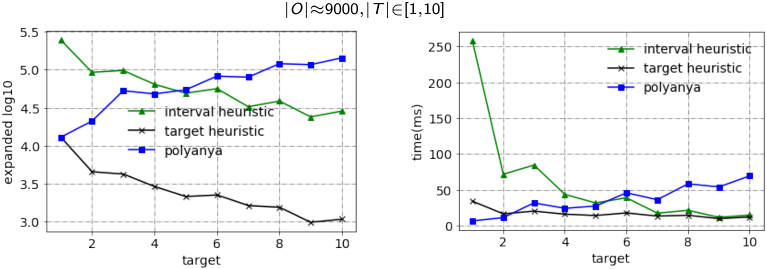

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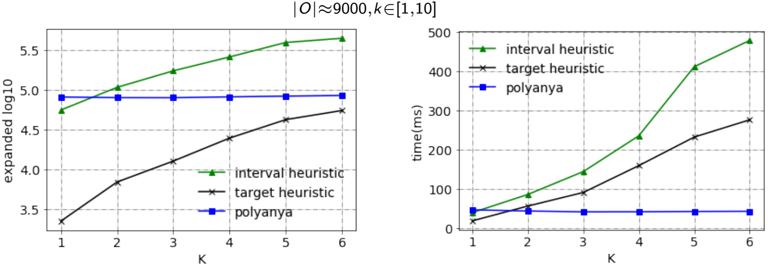

- *Target heuristic* always has small search space. (left)
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- It's outperformed by *brute-force Polyanya* when $k >= 2$. (right)
- Reason: lazy reassignment becomes more frequent.

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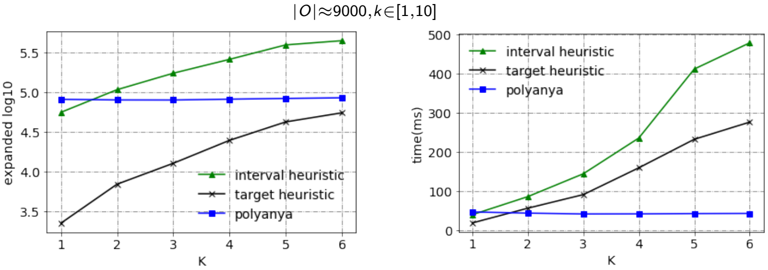

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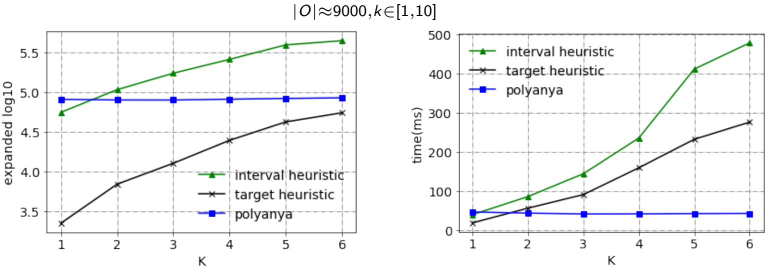

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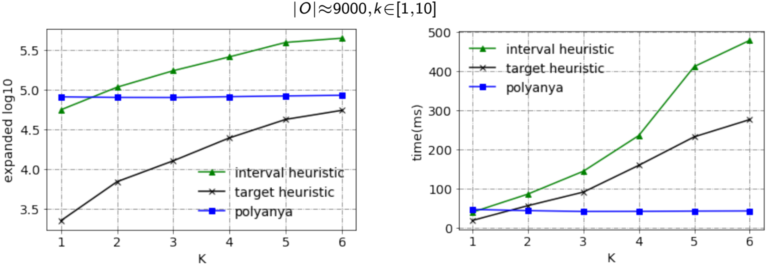

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2 Related works

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4 New Framework

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7 Conclusion and future work

8 End

Conclusion

- Proposed algorithms outperform *LVG* in all cases
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Future works 1: improve other query processing

- Proposed algorithms can be used to speed up other types of spatial query which need to compute obstacle distance, e.g. *Obstacle Reverse Nearest Neighbor*.

Future works 2: improve *target heuristic*

- *Target heuristic* cost $\approx 80\%$ of total run time in *R-tree* query.
- Improve it by combining four queries into one, or using more suitable datastructure.

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Q & A

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Thank you!