
Sensor networks

Exposure analysis

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What's coming up

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Everyday utility

Exposure

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What I will try:

- ❑ Introduction to sensor networks.
- ❑ Exposure problem.
- ❑ Algorithms for finding minimal exposure path in a network.

Philippe: Adaptive sampling.

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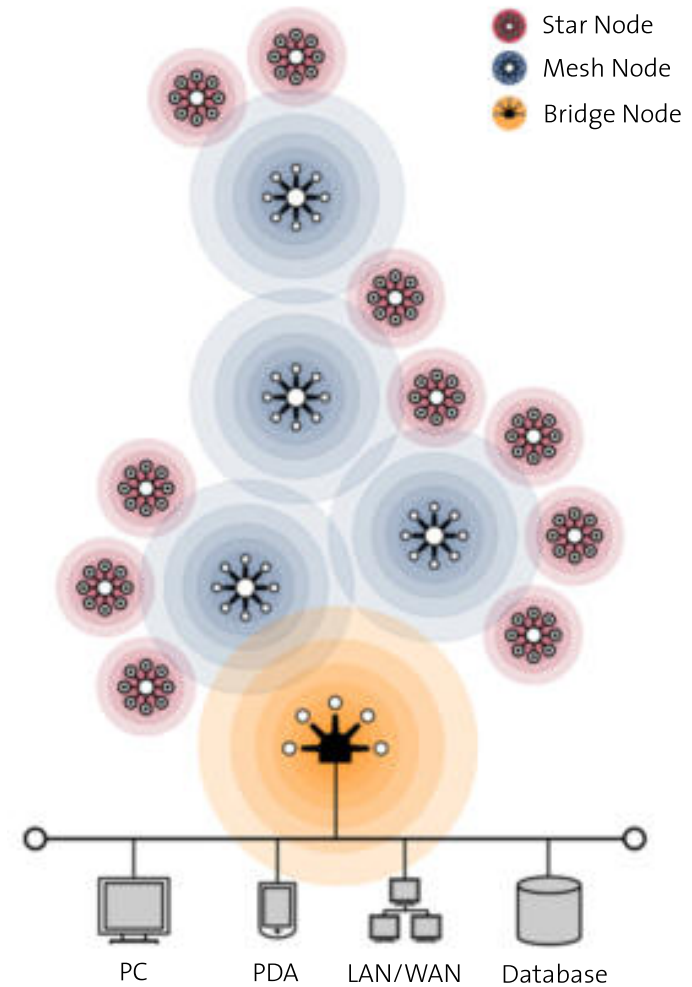
Sensor networks

Conclusion

- ❑ No fixed infrastructure.
- ❑ Fragile - flexible.
- ❑ Low computing power.
- ❑ Low battery life.
- ❑ Cheap.
- ❑ [Distributed.](#)

Revolutions:

- ❑ Connection to the internet.
- ❑ MEMS sensors.



Location discovery

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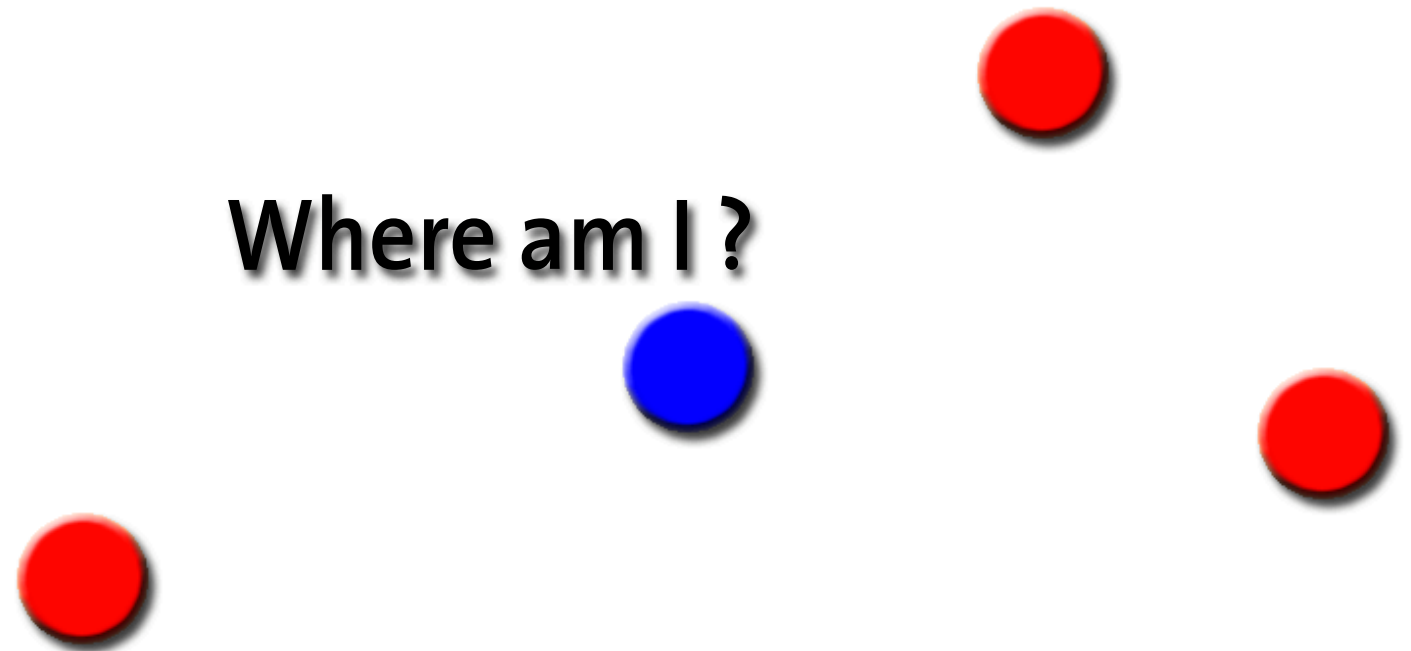
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- ❑ Deterministic placement.
- ❑ GPS.
- ❑ Trilateration.

Where am I ?



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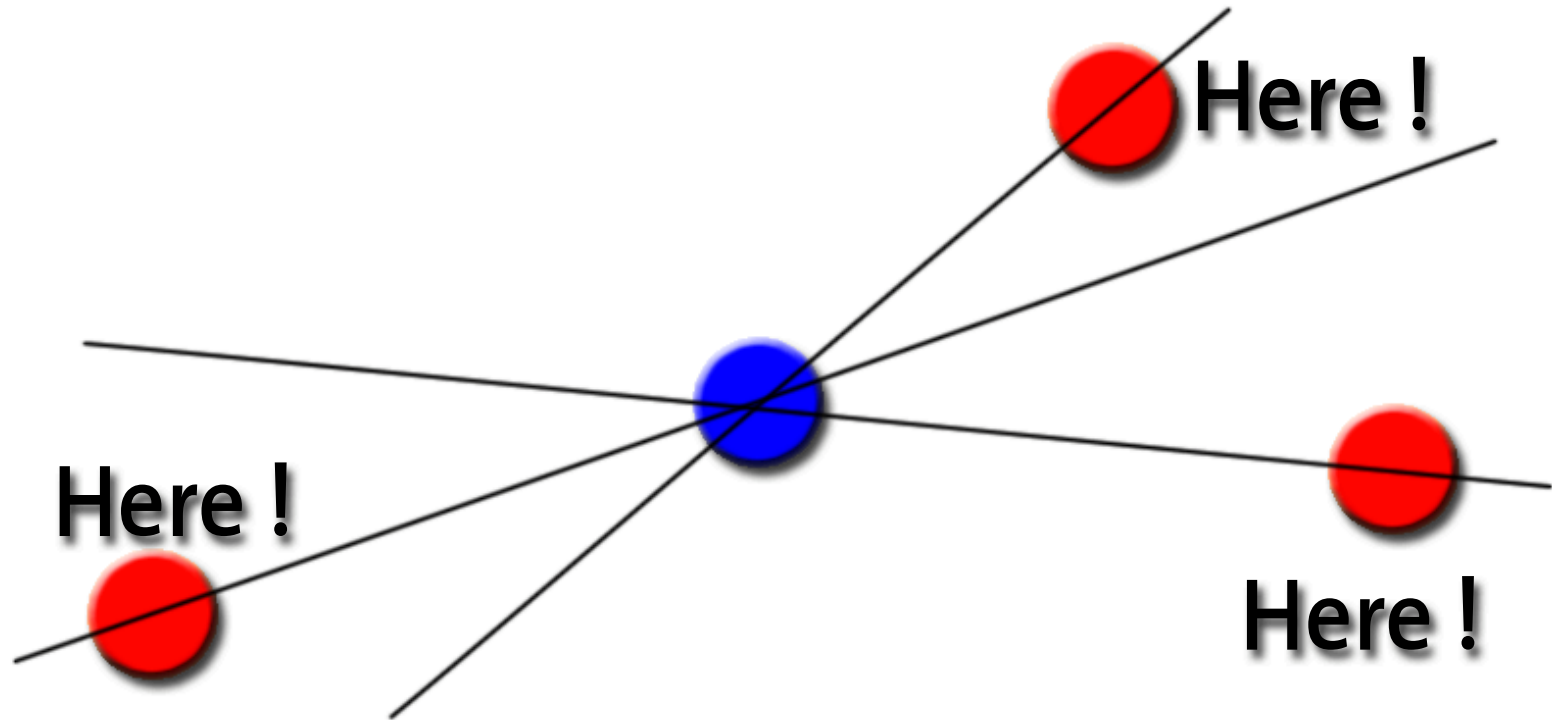
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- ❑ Deterministic placement.
- ❑ GPS.
- ❑ [Trilateration.](#)



Everyday utility

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Real life examples:

- ❑ Monitoring (enviromental, ...)
- ❑ Robotics.
- ❑ Industrial automation.
- ❑ Military applications (smart dust).
- ❑ Surveillance (mother-in-law detection, ...)



The problem

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Simple example

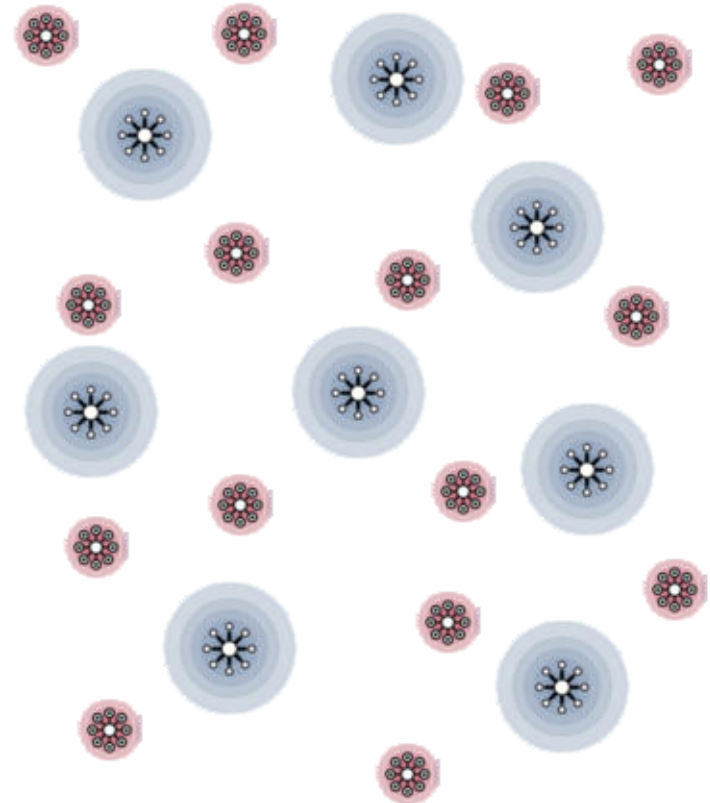
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Let's say we have deployed a sensor network.

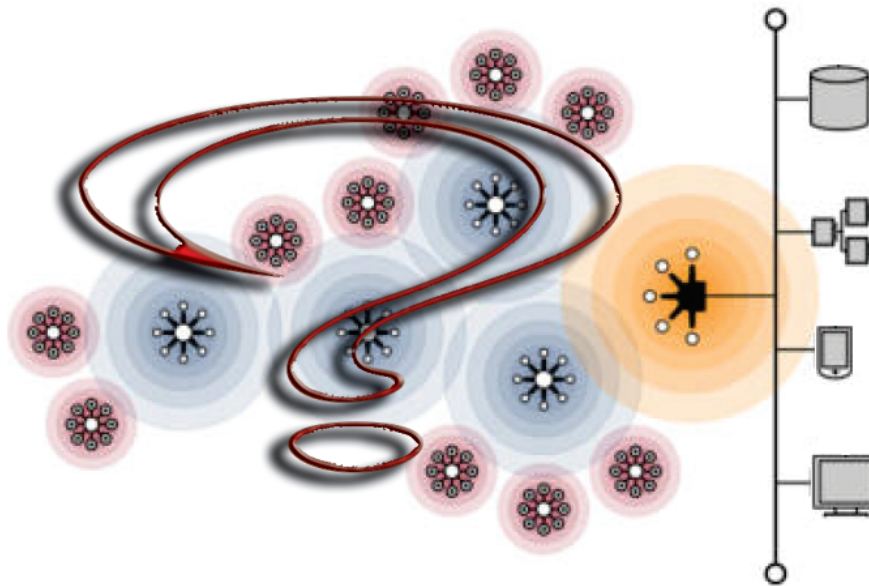
- ❑ How **good** is it?
- ❑ Efficient correction?
 - adding least sensors
 - getting best result

Exposure helps us answer such questions.



Why?

Exposure is directly related to coverage in that it is an integral **measure** of how well the sensor network can **observe** an object, moving on an **arbitrary path**, over a period of **time**.



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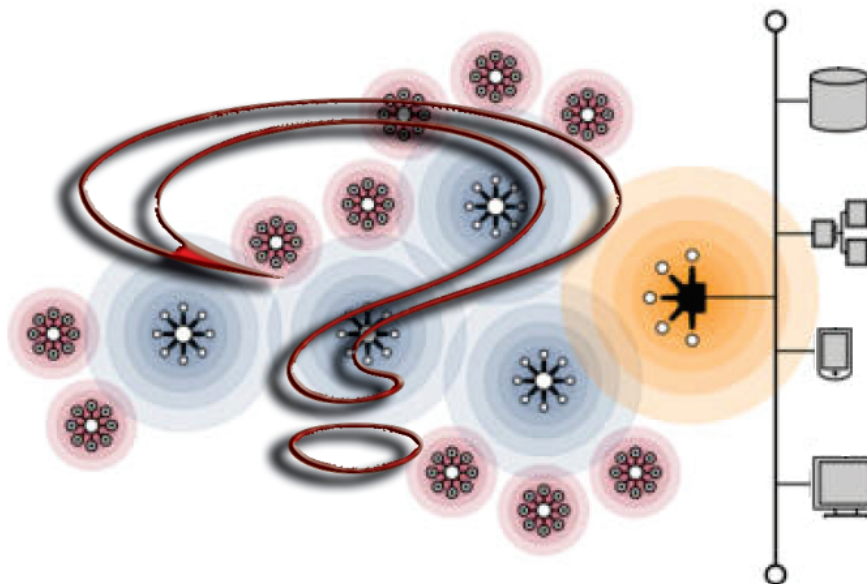
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The **minimal** exposure path provides valuable information about the **worst case** exposure-based coverage in sensor networks.



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Intuition:
if sensors can sense you then stay away!

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Intuition:

if sensors can sense you then stay away!

In 2D, the Voronoi diagram of a set of discrete sites (points) partitions the plane into a set of [convex polygons](#) such that all points inside a polygon are closest to [only one](#) site.

Voronoi diagram

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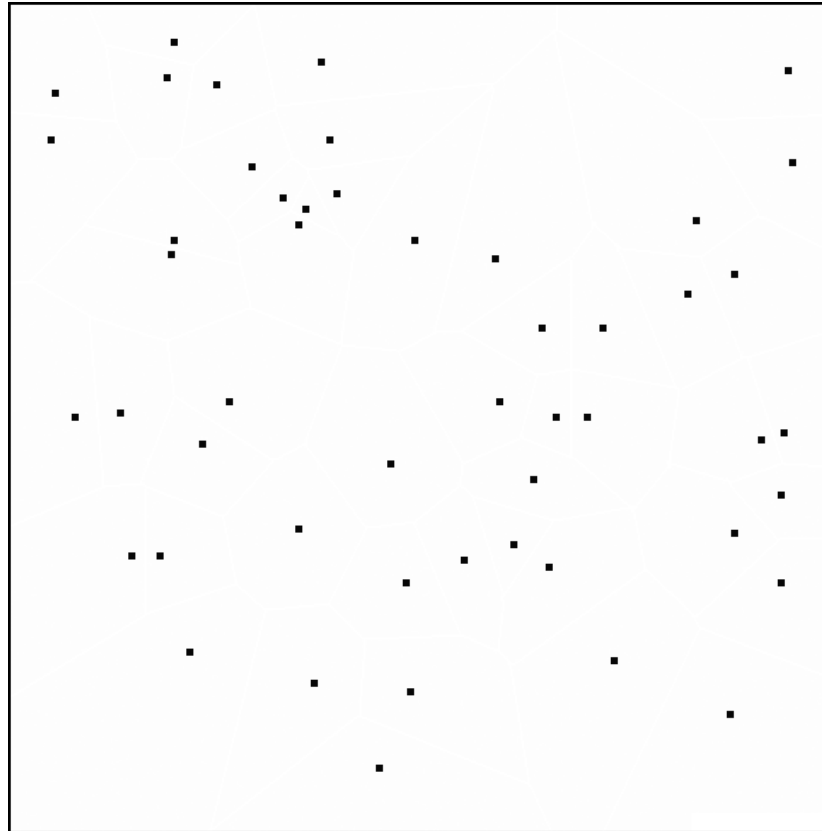
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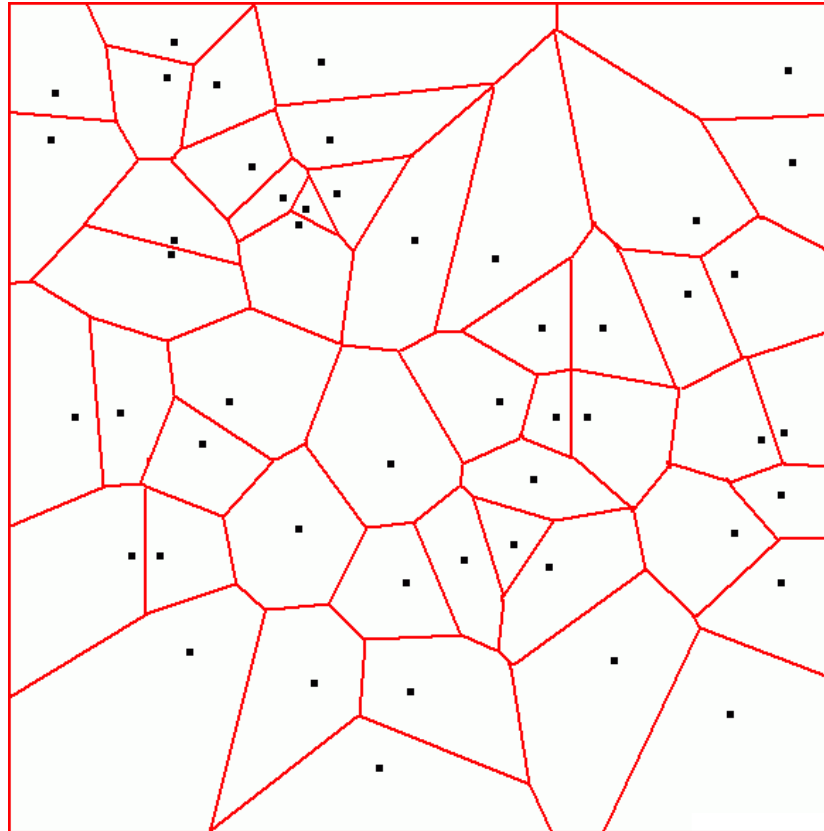
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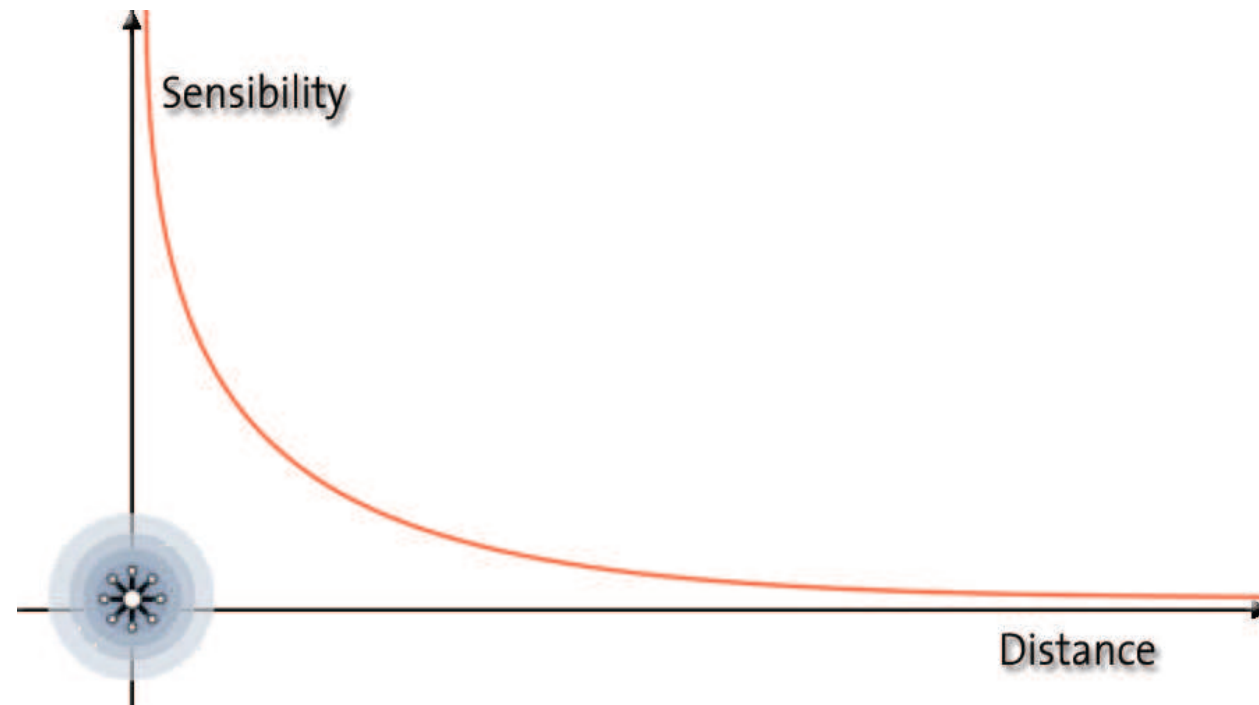
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Definition:

$$S(s, p) = \frac{\lambda}{[d(s, p)]^k}$$

- ❑ Point p
- ❑ Sensor s
- ❑ $d(s, p)$ Euclidean distance
- ❑ λ and k sensor parameters



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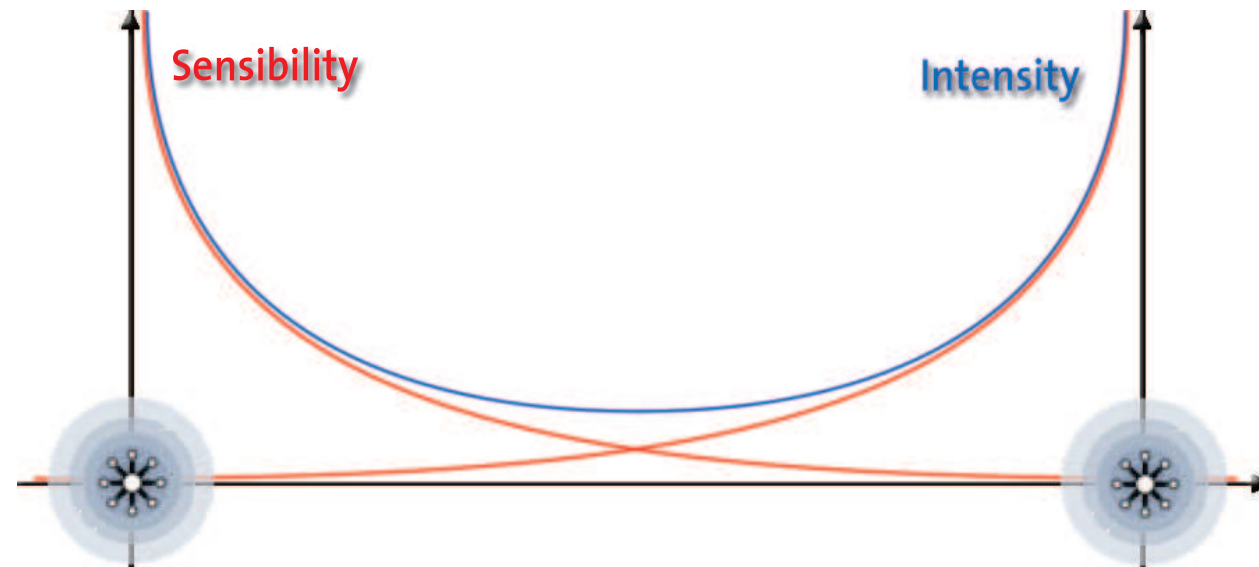
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Definition: All-Sensor Field Intensity $I_A(F, p)$ for a point p in the field F is defined as the effective sensing measures at point p from all sensors in F .

$$I_A(F, p) = \sum_{i=1}^n S(s_i, p)$$



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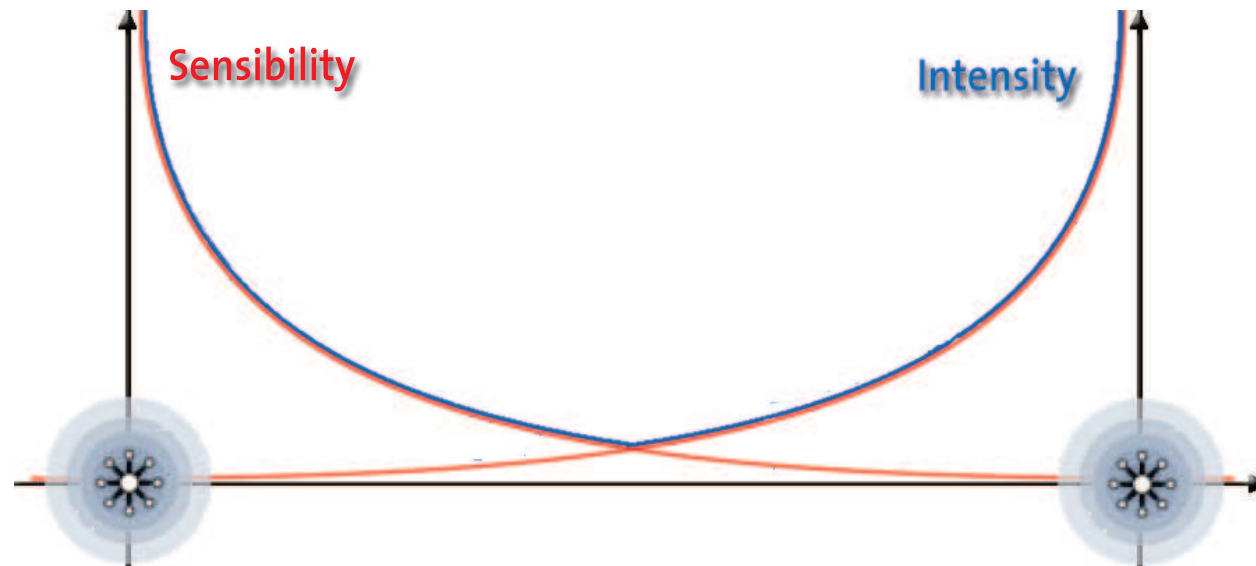
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Definition: Closest-Sensor Field Intensity $I_C(F, p)$ for a point p in the field F is defined as the sensing measure at point p from the closest sensor in F , i.e. the sensor that has the **smallest Euclidean distance** from point p .

$$I_C(F, p) = S(s_{min}, p)$$



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Definition: The **exposure** for an object in the sensor field during the **interval** $[t1, t2]$ along the **path** $p(t)$ is defined as

$$E(p(t), t1, t2) = \int_{t1}^{t2} I(F, p(t)) \left| \frac{dp(t)}{dt} \right| dp$$

where the sensor field intensity $I(F, p(t))$ can either be $I_A(F, p(t))$ or $I_C(F, p(t))$ and $\left| \frac{dp(t)}{dt} \right|$ is the element of arc length.

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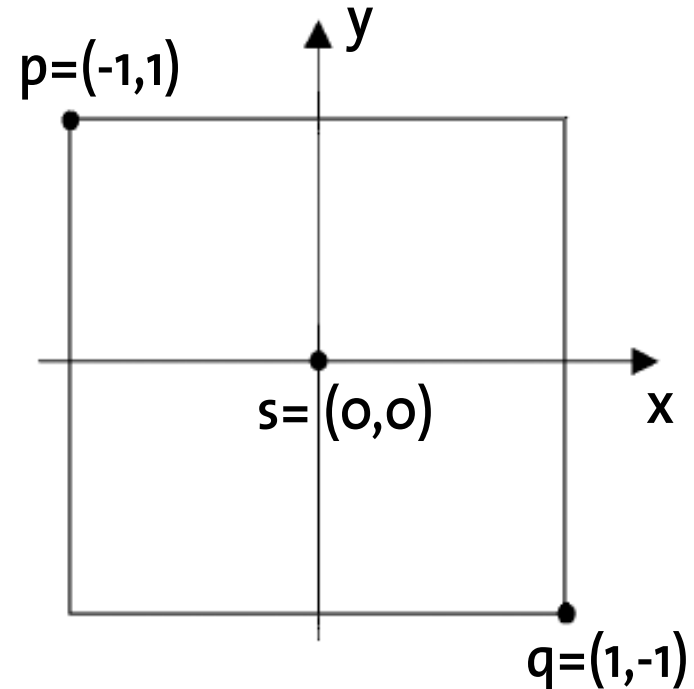
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How *simple* is the Exposure?

What is the **minimal** exposure path from p to q ?

Let us test if the **Voronoi** diagram approach is **sufficient**.



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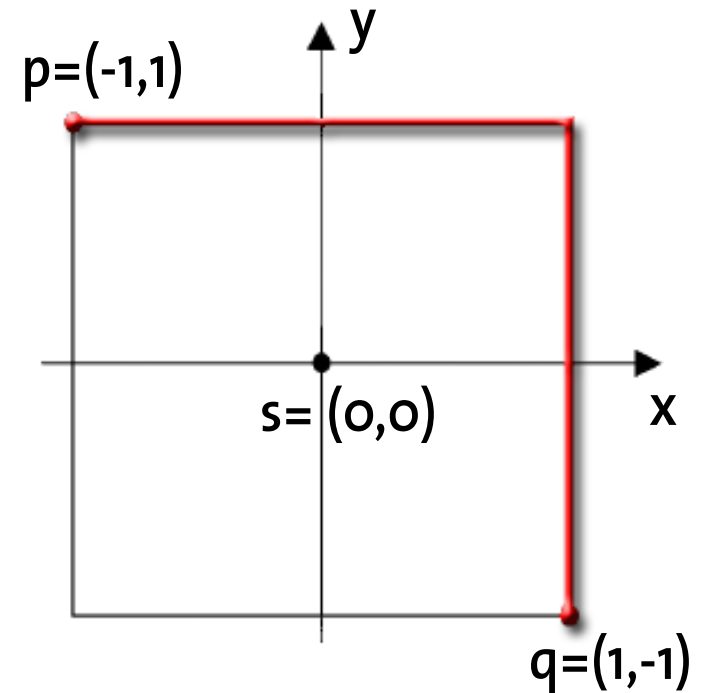
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The Voronoi diagram approach would suggest sticking to the **edges** of the graph.



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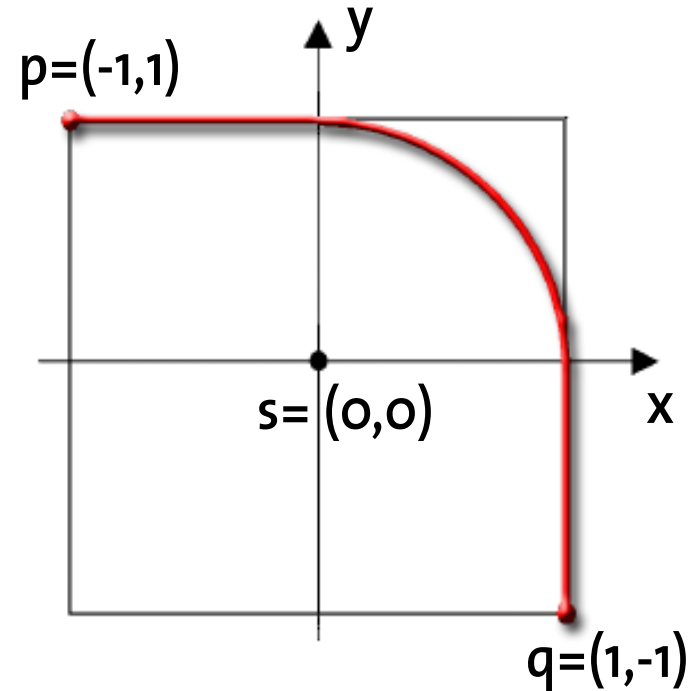
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- ❑ step closer to sensor
- BUT
- ❑ reduced sensing time
- ❑ reduced path length
- ❑ **overall exposure reduced**



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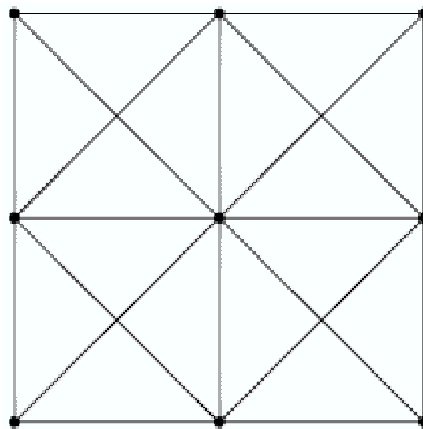
Greedy

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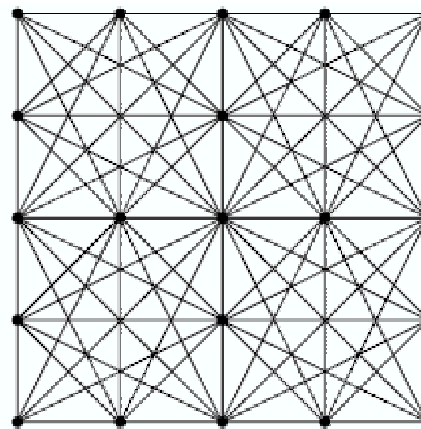
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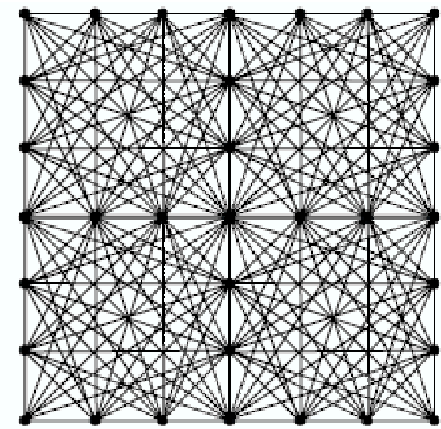
- ❑ [Generate grid.](#)
- ❑ Transform grid into edge-weighted graph.
- ❑ Find minimal exposure path using Dijkstra's Single-Source-Shortest-Path algorithm.



$n=2, m=1$



$n=2, m=2$



$n=2, m=3$

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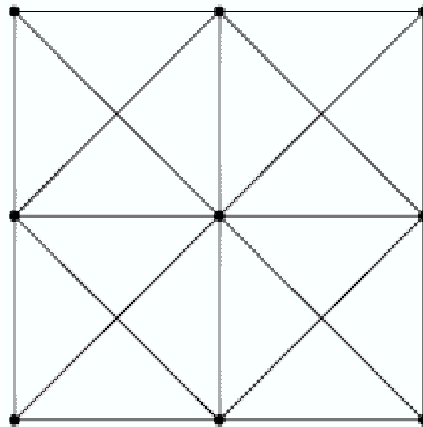
Greedy

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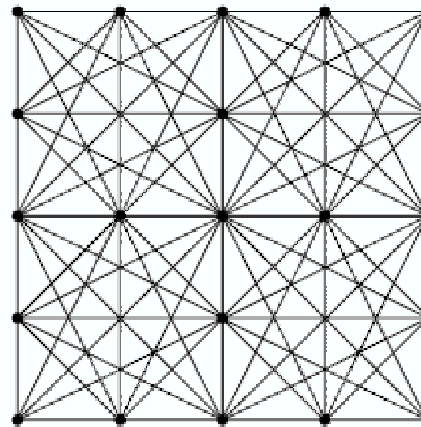
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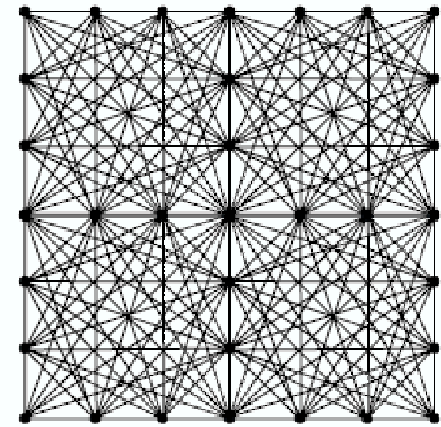
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$n=2, m=1$



$n=2, m=2$



$n=2, m=3$

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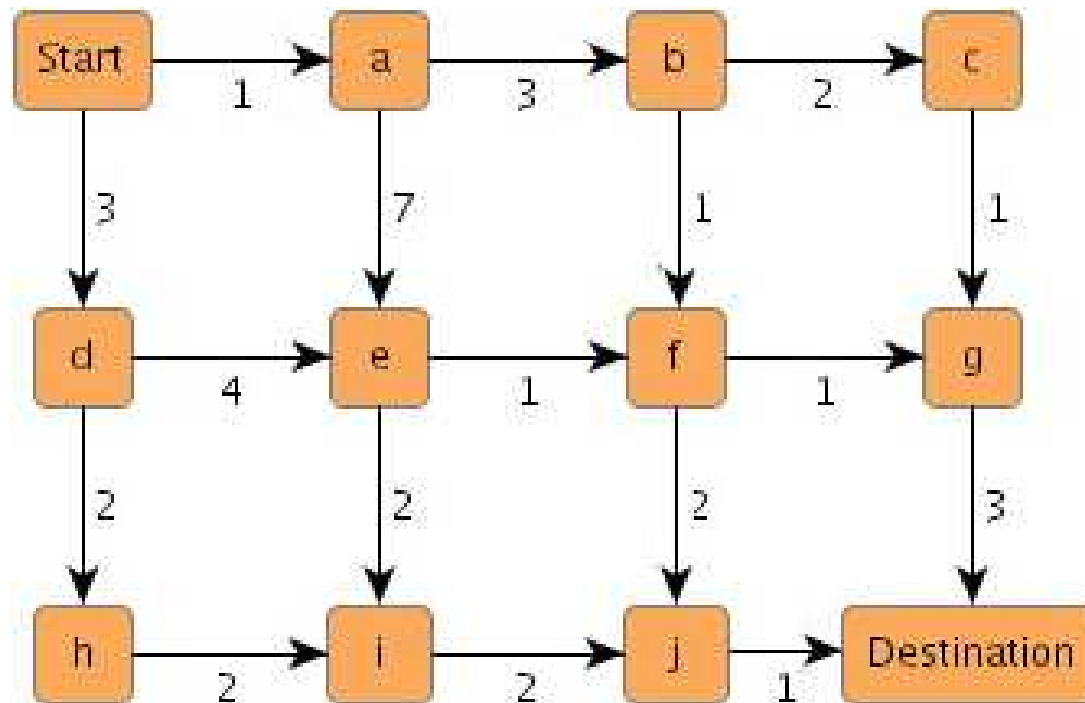
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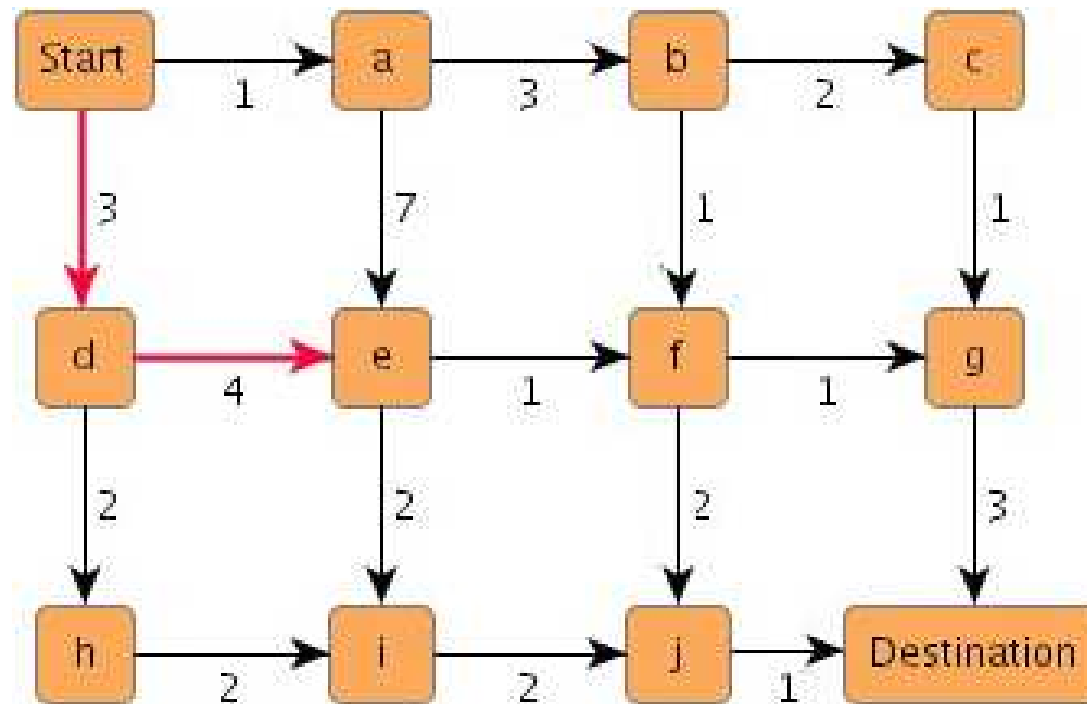
Conclusion

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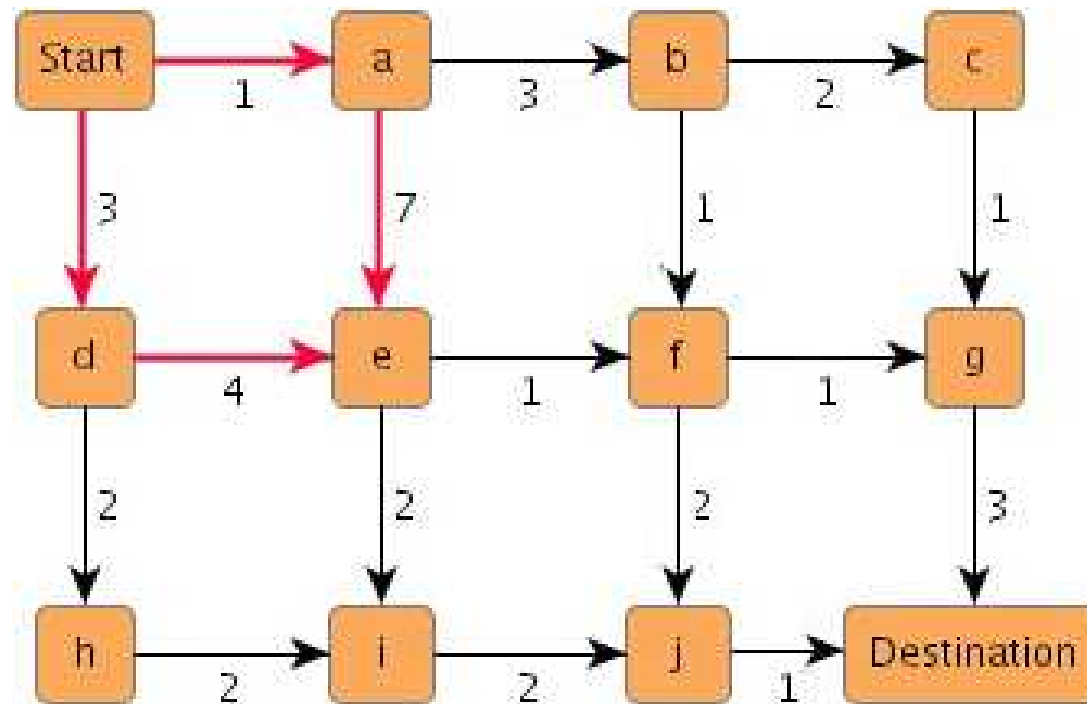
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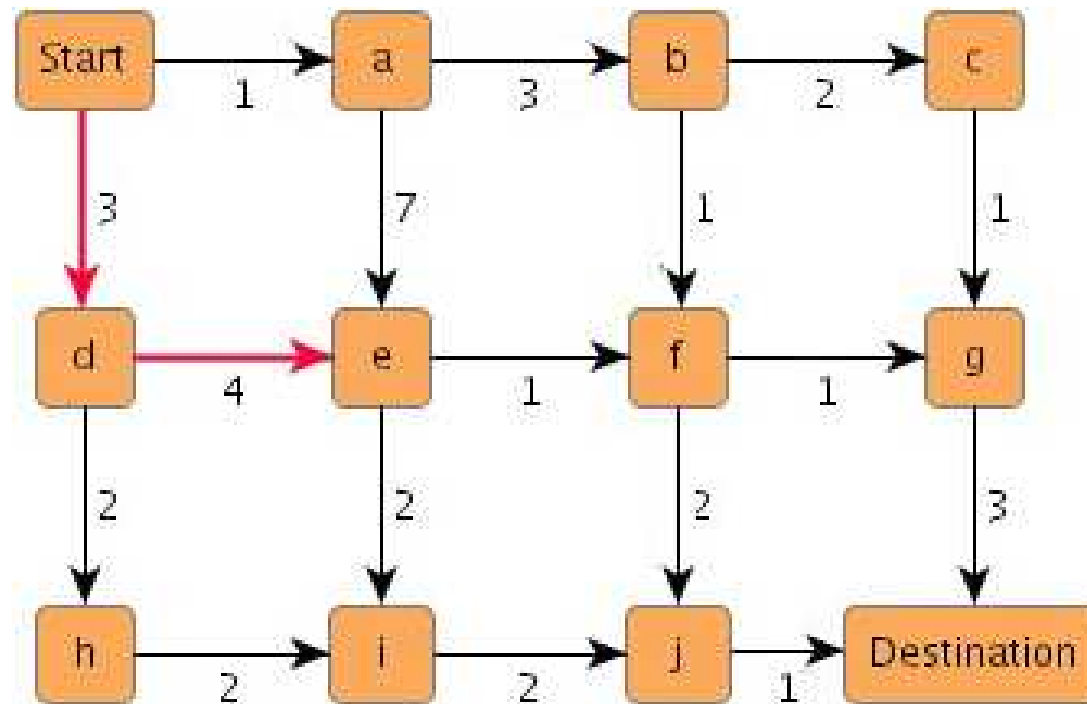
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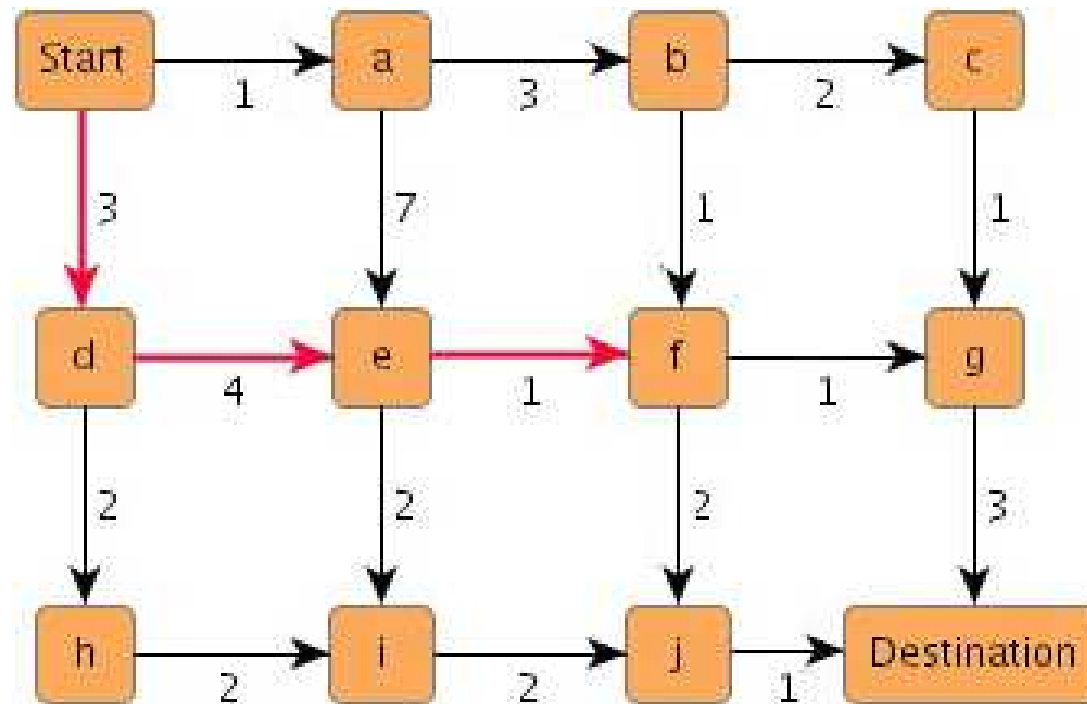
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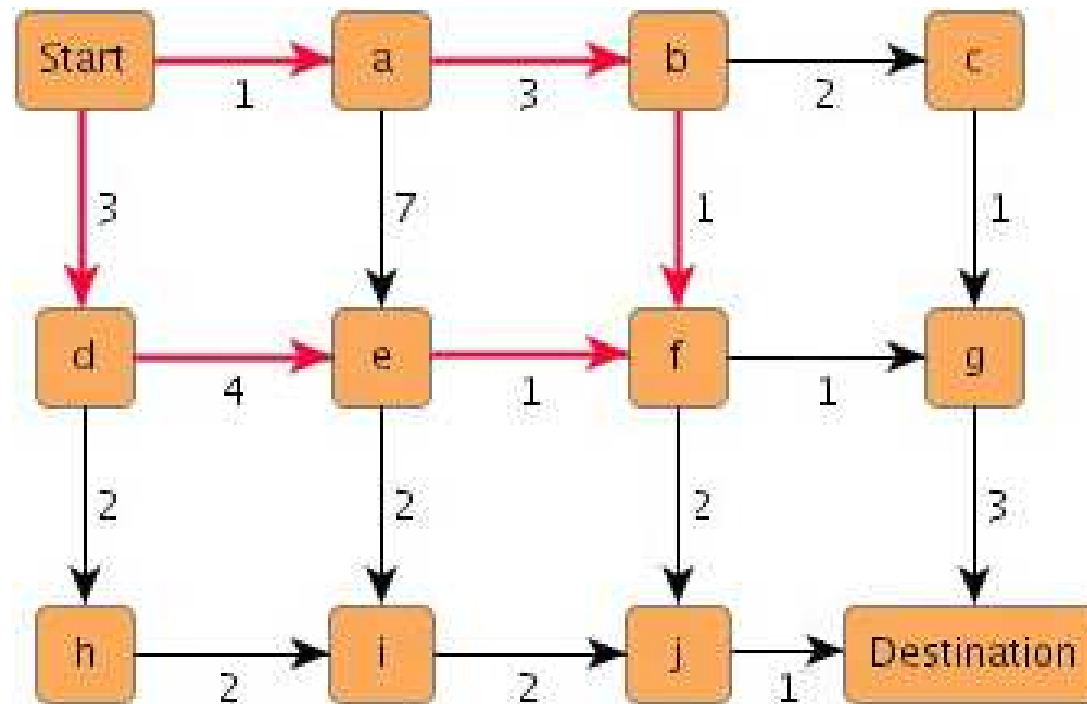
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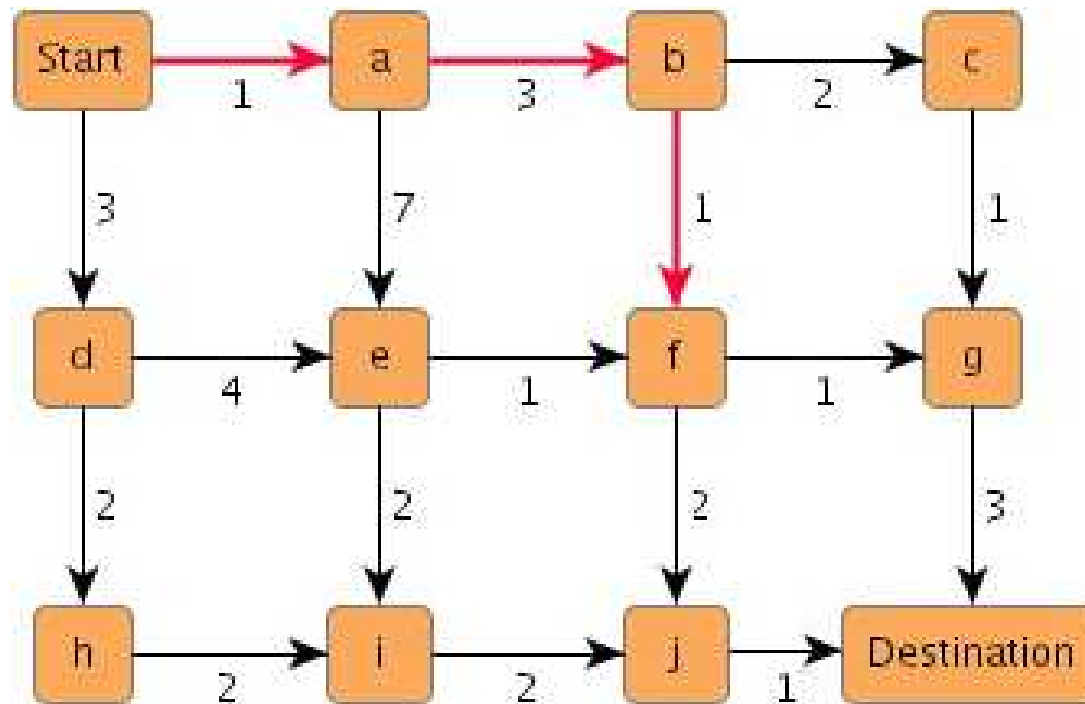
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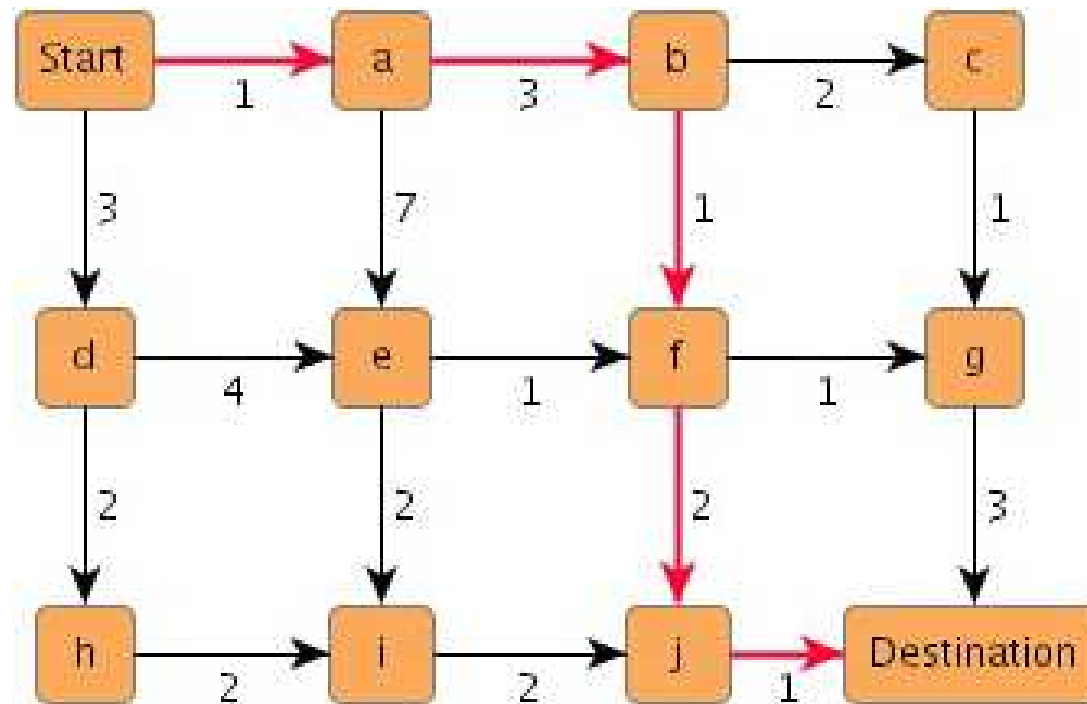
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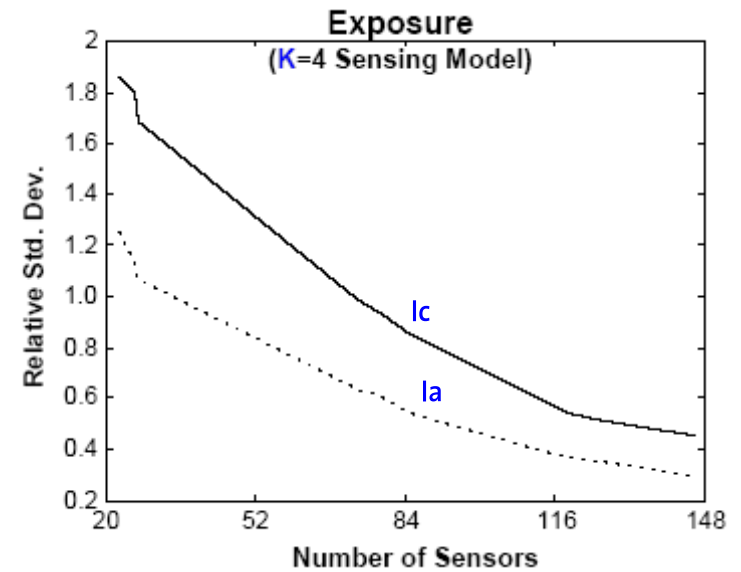
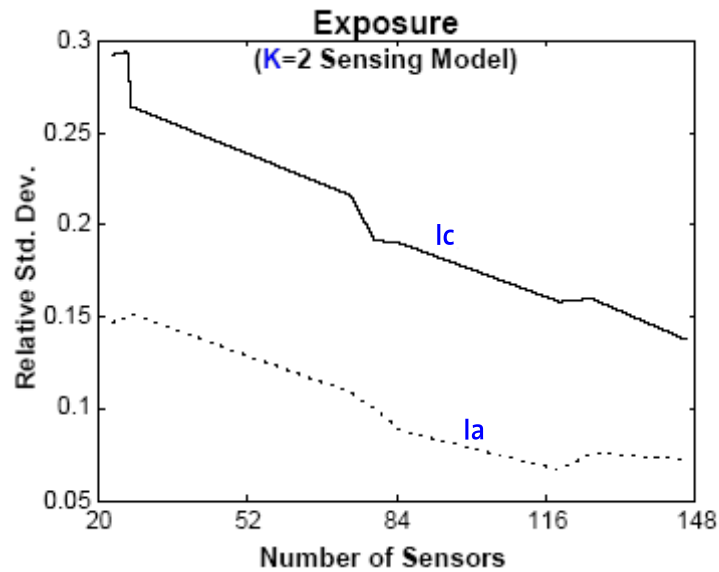
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$$S(s, p) = \frac{\lambda}{[d(s, p)]^k}$$



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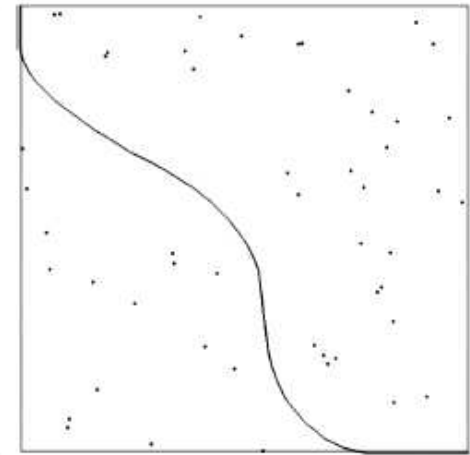
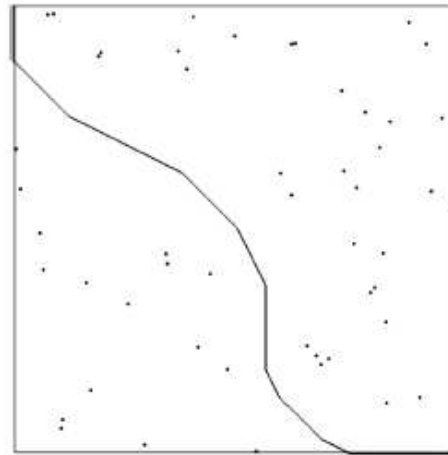
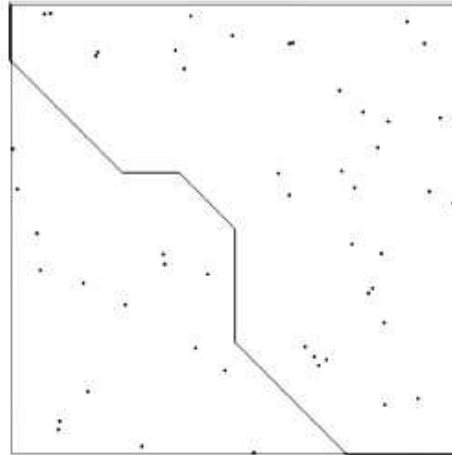
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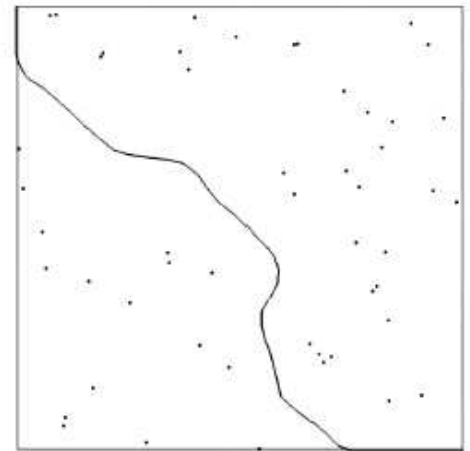
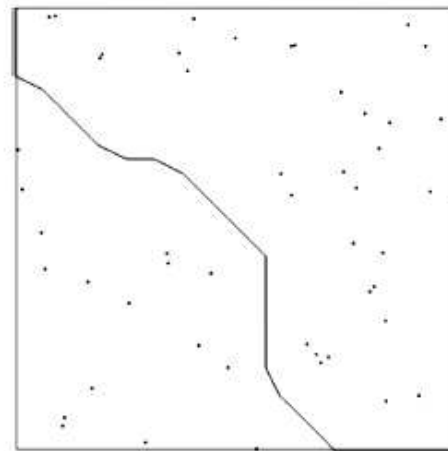
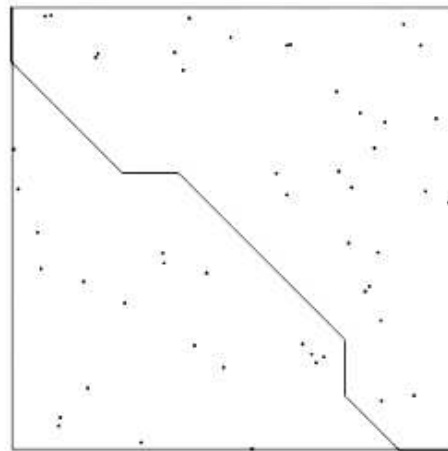
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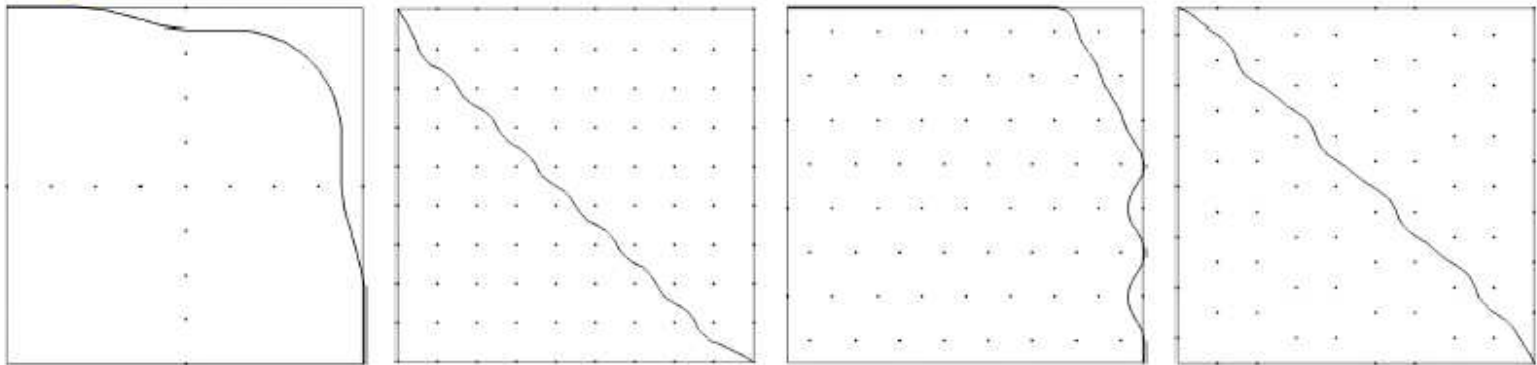
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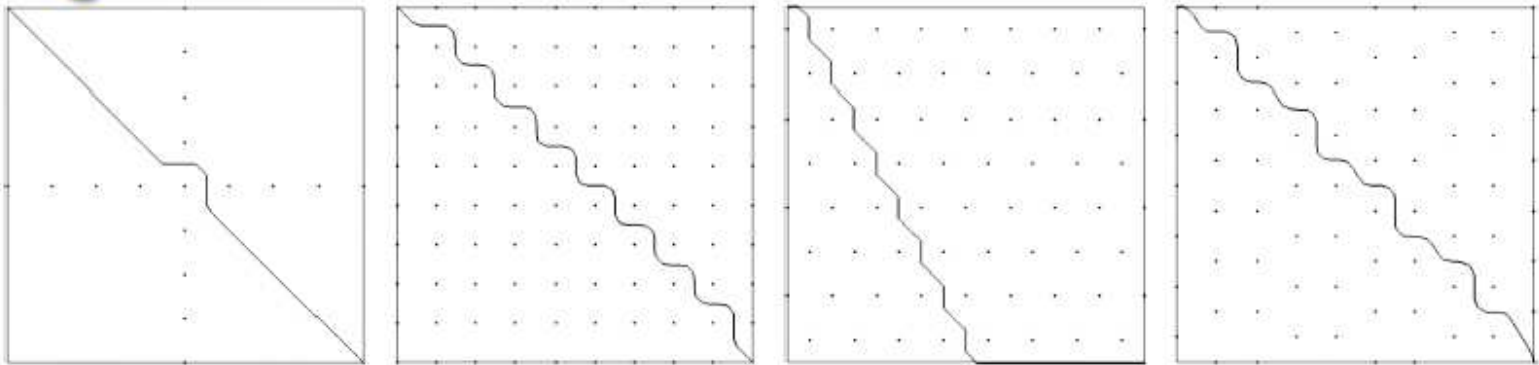
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Assumptions:

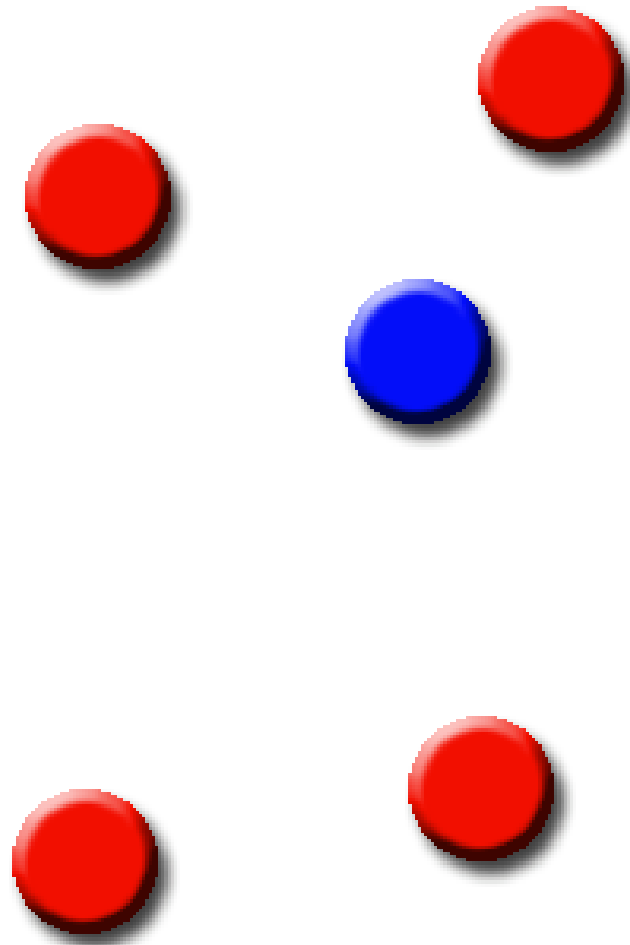
- ☐ Location knowledge.
- ☐ Neighbour knowledge.
- ☐ Can compute Voronoi cells.

Specialities:

- ☐ Minimal communication.
- ☐ Minimize power consumption.

VERSUS

- ☐ Response time.



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- ❑ Agent starts algorithm at point p.
- ❑ Sensor closest to p computes initial exposure profile (EP).
- ❑ Forwards exposures to neighbouring sensors.
- ❑ If update smaller:
 - compute new values
 - send updates to concerned sensors
 - update parent
- ❑ else
 - send abort back
- ❑ Backtrack for solution.

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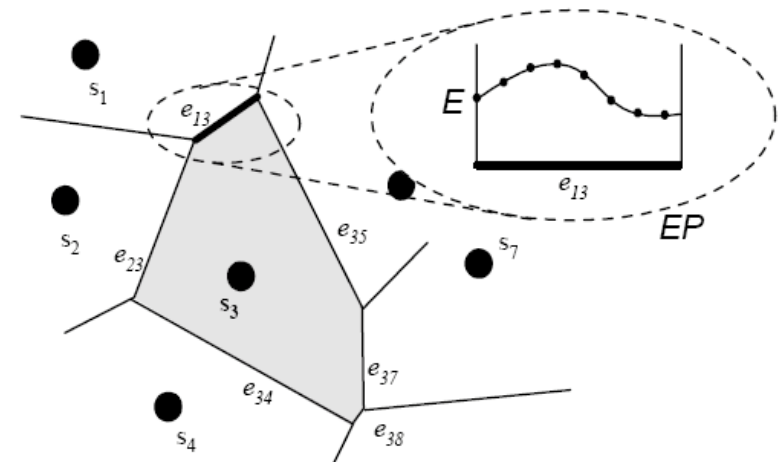
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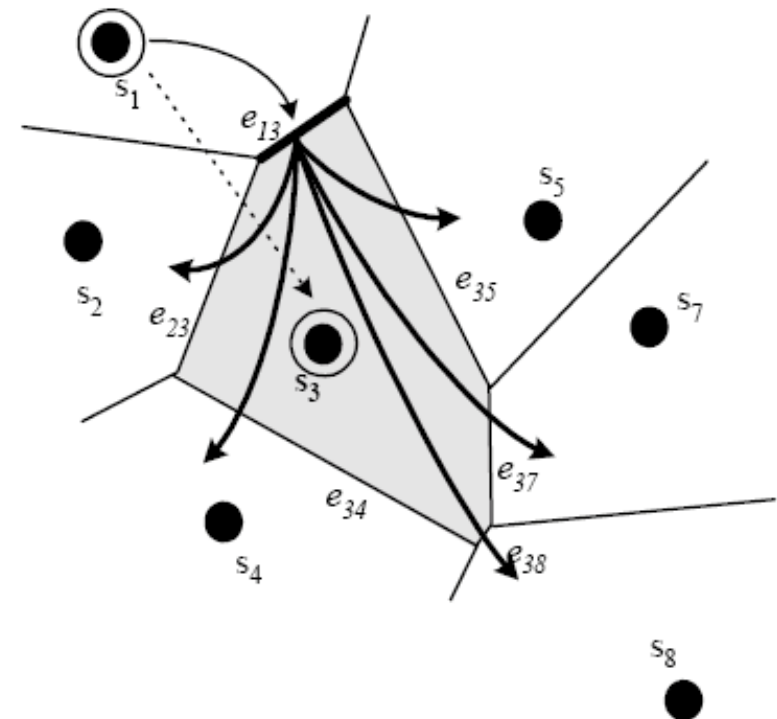
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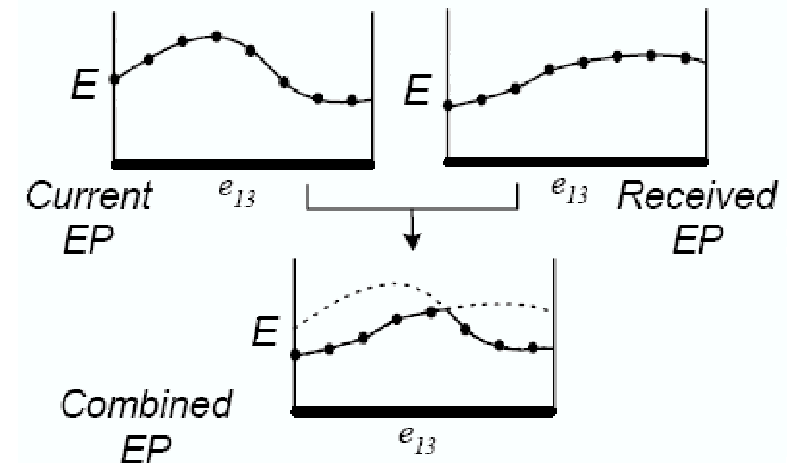
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A few examples

Local knowledge

Flooding

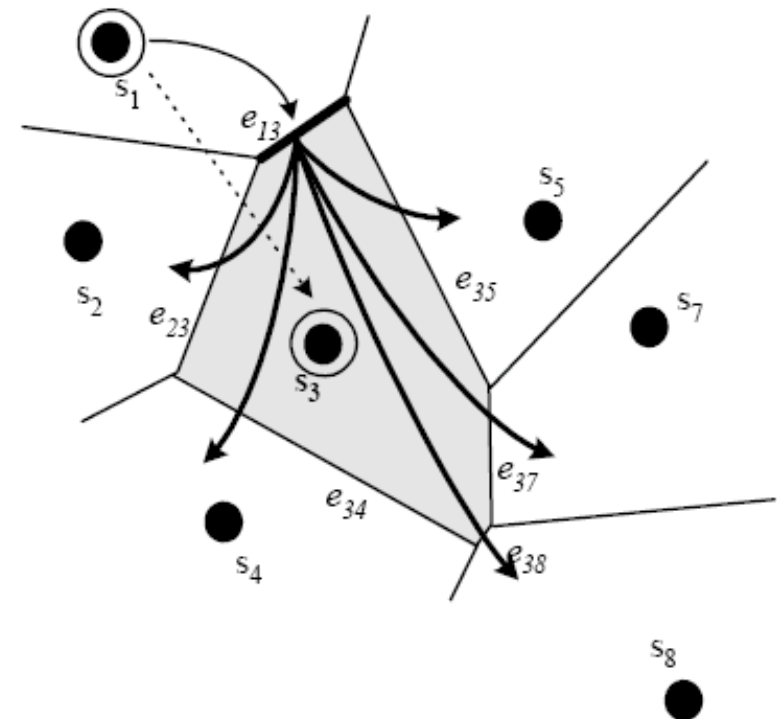
Greedy

More examples

More local algorithms?

Conclusion

- ❑ Agent starts algorithm at point p.
- ❑ Sensor closest to p computes initial exposure profile (EP).
- ❑ Forwards exposures to neighbouring sensors.
- ❑ If update smaller:
 - compute new values
 - **send updates to concerned sensors**
 - update parent
- ❑ else
 - send abort back
- ❑ Backtrack for solution.



Greedy

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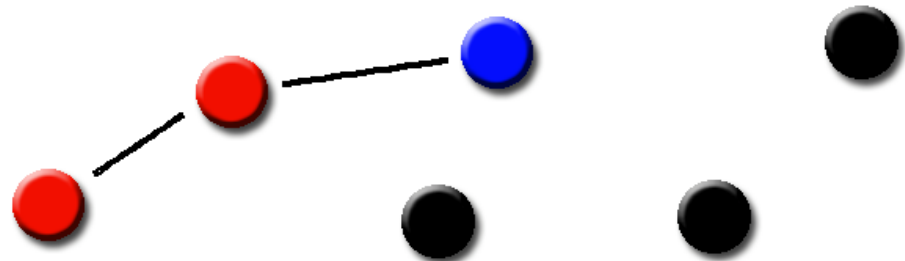
Greedy

More examples

More local algorithms?

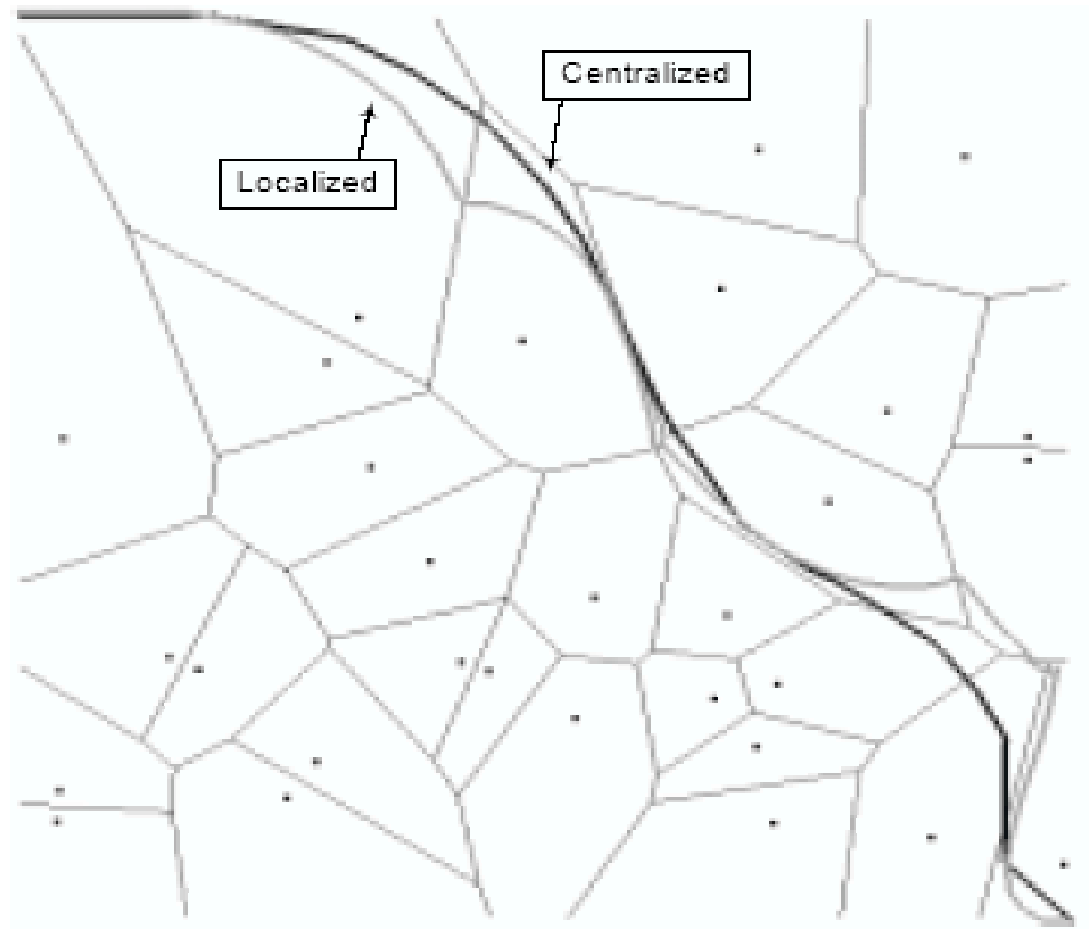
Conclusion

- ❑ Agent starts algorithm at point p.
- ❑ Sensor closest to p computes node exposures in Voronoi cell.
- ❑ Forward search message to sensor of most promising node.
- ❑ Sensor computes new path portion.
- ❑ Returns results.
- ❑ Maybe updates parent.
- ❑ Recompute most interesting node.



More examples

Flooding:



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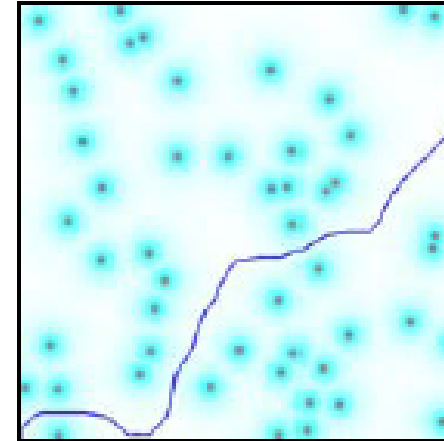
More local algorithms?

Conclusion

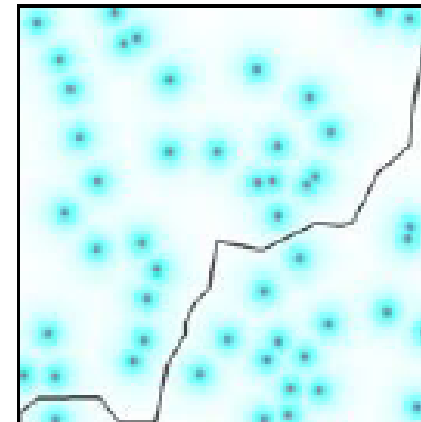
More examples

Greedy:

Centralized algorithm.



Localized algorithm.



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Conclusion

- ❑ Simulated annealing.
- ❑ Swarm approach.
- ❑ Simplex.
- ❑ Genetic algorithms.
- ❑ Random-restart hill climbing.
- ❑ ...



Recap

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[Recap](#)

My opinion

Sources

What we saw:

- ❑ Introduction to sensor networks (location discovery...)
- ❑ Introduction to exposure problem.
 - Voronoi diagram
 - mathematical models
- ❑ Algorithms for minimal exposure path.
 - centralized knowledge
 - localized knowledge

My opinion

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Sources

- ❑ [Interesting theme.](#)

BUT

- ❑ Very mathematical.

- ❑ Not as creative as I hoped.

- ❑ Algorithms much more interesting!

Sources

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[Sources](#)

- ❑ **Exposure In Wireless Ad-Hoc Sensor Networks**
Seapahn Meguerdichian
- ❑ **Coverage Problems in Wireless Ad-hoc Sensor Networks**
Seapahn Meguerdichian
- ❑ **Localized Algorithms In Wireless Ad-Hoc Networks: Location Discovery And Sensor Exposure**
Seapahn Meguerdichian
- ❑ **Minimal and Maximal Exposure Path Algorithms for Wireless Embedded Sensor Networks**
Giacomino Veltri
- ❑ **Sensor Deployment Strategy for Detection of Targets: Traversing a Region**
Thomas Clouqueur
- ❑ **Internet:** Wikipedia, Google, ...