Scheduling and Motion Planning for Wireless Sensors and Mobile Networks

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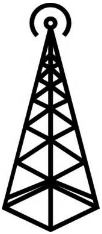
Research Interest and Projects

Computational Geometry, Algorithm Design and Analysis, Wireless Networks, Social Networks

- Geometric Methods for Network Analysis.
- Location and Trajectory Privacy.
- Social Influence and Contagions
- Scheduling Algorithms.

Scheduling Wireless Devices





Considerations:

- Efficiency – energy, storage, bandwidth.
- Performance – coverage, detection, connectivity.

Constraint dimensions:

- Spatial – visibility, proximity.
- Temporal – mobility.

Two Application Scenarios

How to schedule and allocate resources in spatial and temporal domains?

- Smart building: optimize energy usage, improve safety & security.

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How to schedule and allocate resources in spatial and temporal domains?

- Smart building: optimize energy usage, improve safety & security.
- Mobile networks: assign mobile nodes to collect data from sensors with storage capacities.

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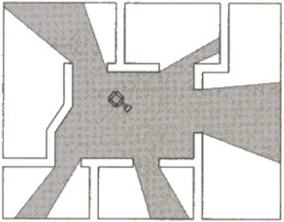

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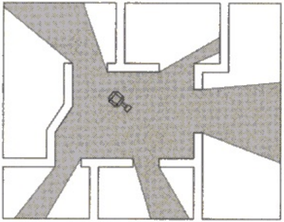

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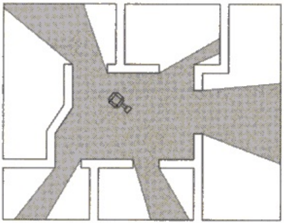

- If sensors are turned on all the time: Art Gallery Problem;
- Sensors are not turned on all the time: Duty Cycle Scheduling.

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- At each time slot at most k cameras are turned on.
- Minimize the maximum or average *dark duration*.
- Or, meet specific target coverage frequency requirements.

Scheduling for Minimizing Dark Duration

Given n camera nodes and m target nodes, the set of targets covered by sensors g_i is $P(g_i)$, suppose at any slot only k sensors are turned on, how to schedule sensors such that no target stays 'in dark' for too long.

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S :	g_1	g_2	g_3	g_2	g_1	g_2	g_3	g_2	$\cdots$
	p_1				p_1				
	p_2	p_2		p_2	p_2	p_2		p_2	
		p_3		p_3		p_3		p_3	
			p_4				p_4		

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$$\min \sum_{p \in D} w(p) \cdot T(p)$$

where $w(p)$ is a weight parameter.

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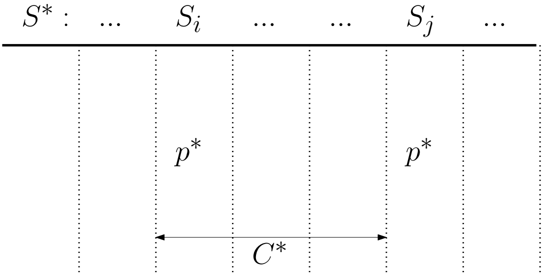

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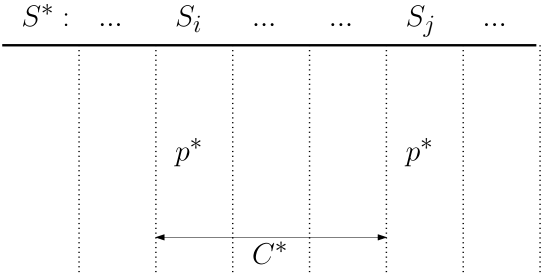

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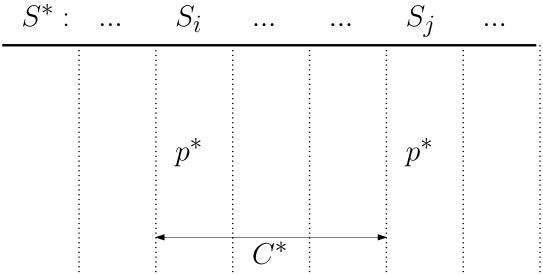

Assume $C^* < \lceil n/k \rceil$ realized by $p^* \in D$.
Then at least one guard g does not appear during the interval of length C^* as shown below.
$\rightarrow$ the point that is only guarded by g has dark duration $> C^*$.

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Min Max problem is tailored towards worst case & sensitive to outliers.

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Example:

- Three guards g_1, g_2, g_3 and six targets $p_1, p_2, p_3, p_4, p_5, p_6$.

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- Targets with higher importance have higher weights.

Algorithms for Min Average Dark Duration Scheduling

Challenge:

- Which sensor to repeat, and how many times?
- How to schedule them?

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Find the optimal one π^* that minimizes the min average dark duration.

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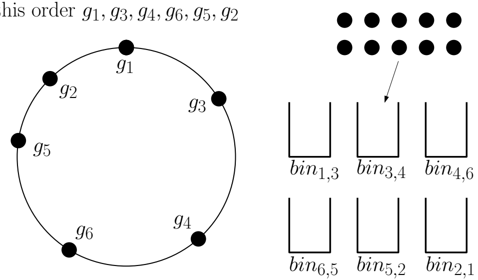
$G(p) \subseteq V$, $|V| = 16$ $\qquad$ $\ell = |G(p)|$ bins

$G(p) = \{g_1, g_2, g_3, g_4, g_5, g_6\}$ $\qquad$ $m = |G \setminus G(p)|$ balls

Assume $G(p)$ appears in the permutation with this order $g_1, g_3, g_4, g_6, g_5, g_2$



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- Throw m balls randomly into ℓ bins, how many balls do we have in the largest bin?
- Compared to the optimal (uniform), the ratio is $\alpha = O(1)$ if $k \geq \log n / \log \log n$, and $\alpha = O(\log n / \log \log n)$ otherwise.

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B is a convex function of $f(g)$ – we can minimize the right hand side!

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This algorithm gives $(2+\varepsilon)\alpha$ approximation in expectation, $\alpha = O(1)$ if $k \geq \log n / \log \log n$, and $\alpha = O(\log n / \log \log n)$ otherwise.

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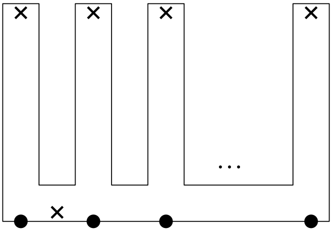

Bottom target must be covered every slot while each of the top target must be covered every m slots.

Min Energy Scheduling with Target Coverage Frequency

Use set multi-cover & randomization. Details skipped.

- $O(\log n + \log m)$ approximation.
- Geometric setting: better approximation.

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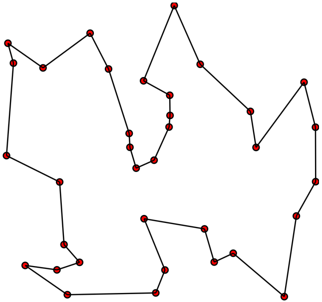

Additional constraints: data rate/node capacity, time-window.

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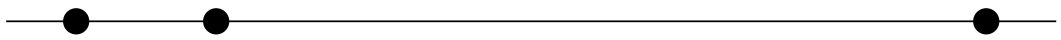

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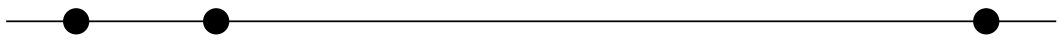

- Theorem: The optimal solution is a zig-zag tour on an interval.
- Run Dynamic Programming in $O(n^2)$ time.

Data Collection Problem

With Sensors	Single mule	k-mule	No Data Loss
on a Line	in P	$\frac{1}{3}$	exact
on a Tree	pseudo-poly	$\frac{1}{3}(1 - 1/e^{\frac{1}{2+\varepsilon}})$	12
General Metric	$1/6 - \varepsilon$		
Euclidean	$1/3 - \varepsilon$	$\frac{1}{3}(1 - 1/e^{1-\varepsilon})$	
Diff Capacities	$O(\frac{1}{m})$		$O(m)$

Table: $m \leq \log(\frac{c_{max}}{c_{min}})$ where c_{max} is the largest capacity and c_{min} is the smallest capacity. For the results in the first four rows, we assume that the sensor capacities are all the same. ε is any positive constant.

Example: Single Mule, Capacity c, Euclidean Setting

Algorithm:

- Find a path of length $c/2$ w/ max # R of nodes.
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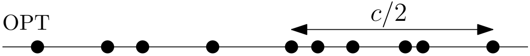

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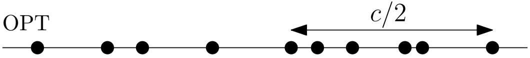
Proof: OPT $R^* \leq 3R$.

- Find in the OPT tour the interval of length $c/2$ with max data collection rate (which is at least R^*).



- The interval has at most R *distinct* nodes.
- Total data collected from any sensor is c (on the first visit) and $c/2$ after each $c/2$ interval. Data rate is at most $3R$.

Conclusion

- Classical problems revisited.
- Worst-case performance guarantees.
- Optimization and scheduling are a crucial part of the machine intelligence era.

Acknowledgement

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- Gui Citovsky, Jie Gao, Joseph Mitchell, Jiemin Zeng, Exact and Approximation Algorithms for Data Mule Scheduling in a Sensor Network, ALGOSENSORS 2015.
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- Questions and comments?