Planning Problems for Social Robots

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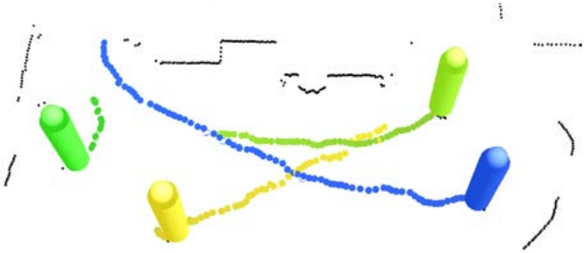
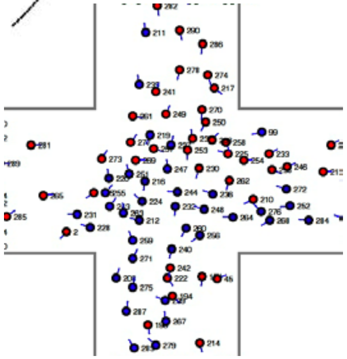
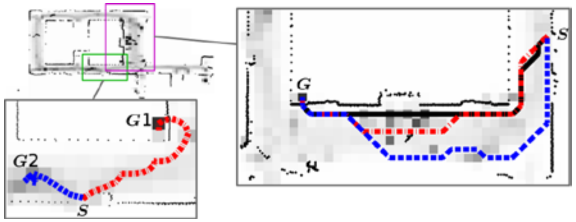
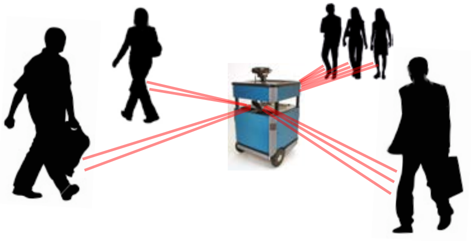
Motivations

- Socially compatible robots
  - Blend into human activities
- Understand social spaces
  - Learn patterns of activities
- Human-aware planning
  - Look for people around
  - Minimize hindrance to people



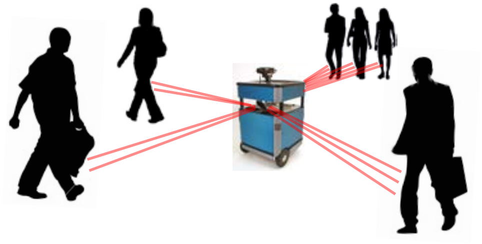






Learning Activity Patterns

- Learn spatio-temporal patterns of human activities
- Answer questions like:
  - How probable is an activity performed at a certain time and space?
  - How long do I need to wait for an activity to happen?
  - What is the path that maximize the probability of encountering a certain activity?



Spatial Affordance Map

- Poisson process
  - Non-homogeneous spatial Poisson process with rate function $\lambda(\vec{x}, t)$
- Assumption
  - Function approximators are too slow
  - Piecewise homogeneous in space and time

X

¸ (x̶; t) ' ¸ ij ¿ 1ij ¿ (x̶; t)

(i ;j)2 X ;¿2 T

- Learning
  - Using Bayesian learning
  - Gamma distributed

    ¸ » ¡ (¸ ; ®; ¯)
  - Poisson parameter obtained via expectation

b ¸ Bayesian = E[¸] = ®

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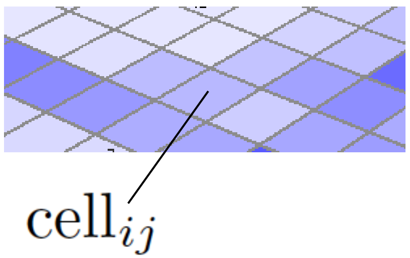
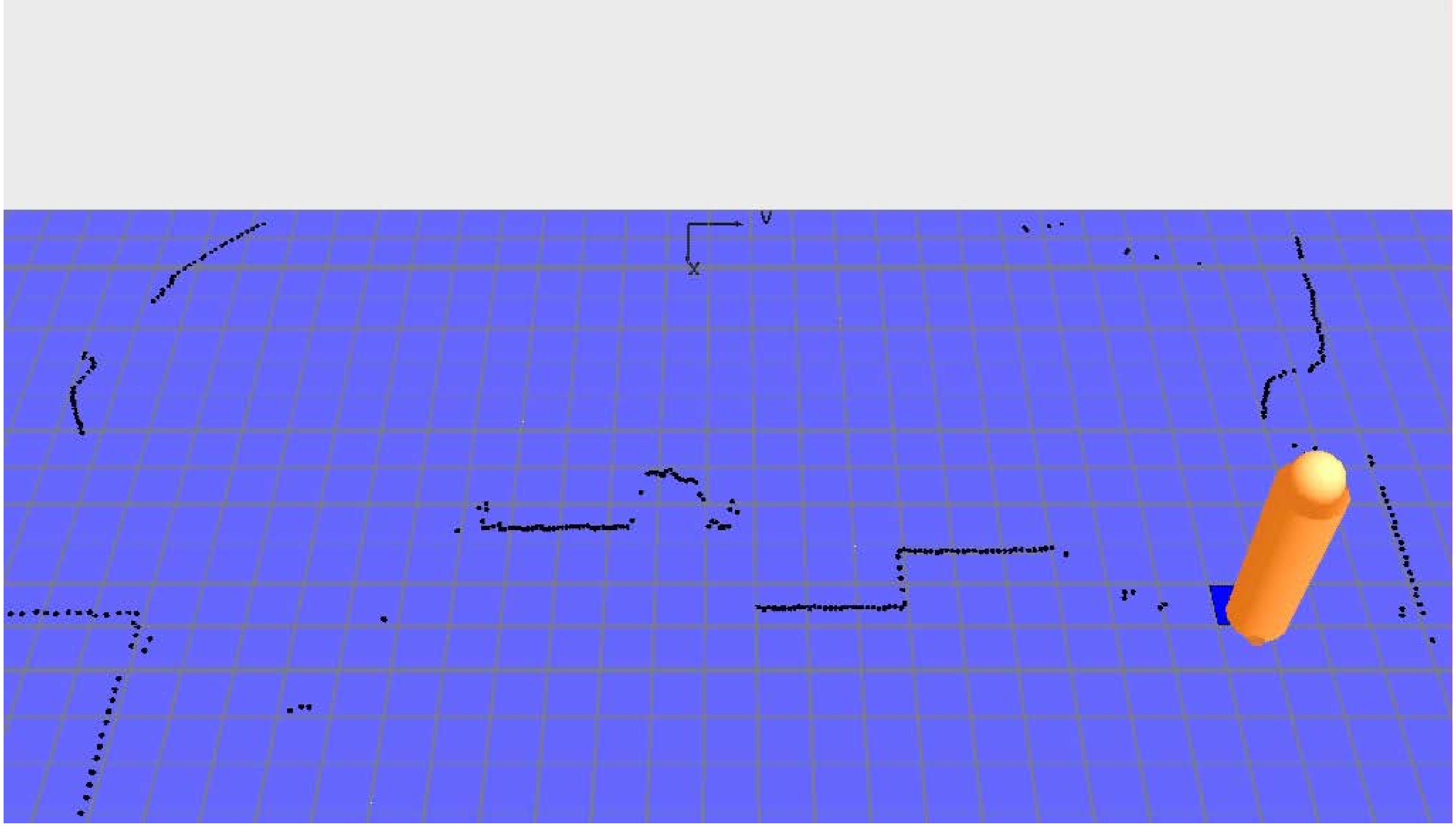


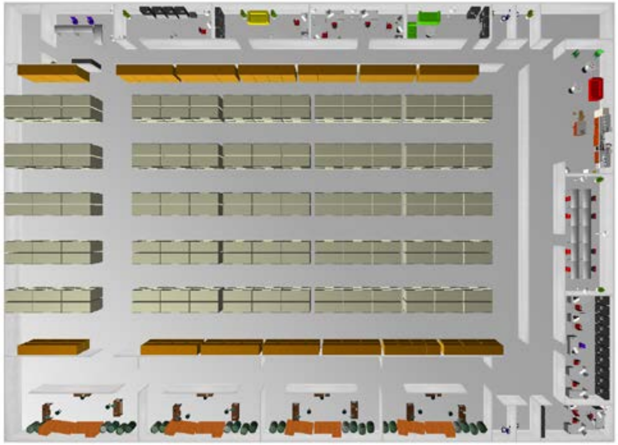
Learning Example



People Simulator

- Real data is hard to collect
- Simulator with 3-layer agent architecture
- Three simulated environments
- Activities learned from questionnaires

Office


Warehouse

House

Maximum Encounter Planning

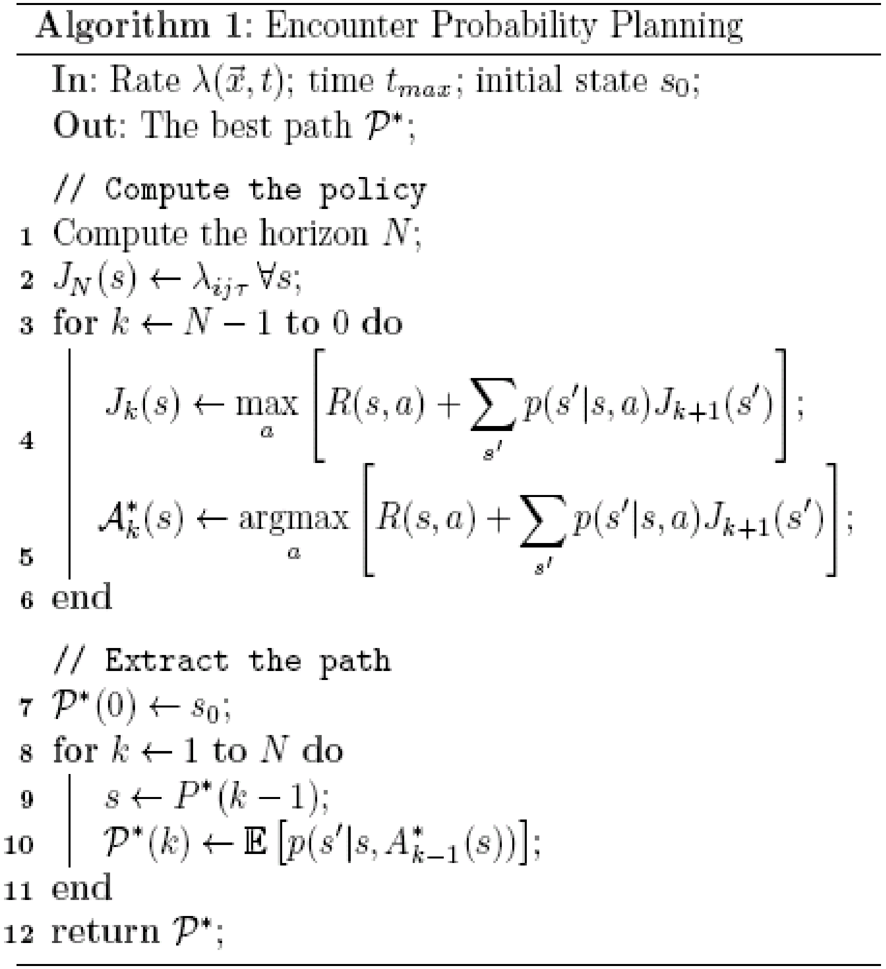
- Plan paths that maximize the probability of encountering people, giving a deadline

- Example: Coffee delivery robot
  - Deliver coffee fast
  - Coffee must be still hot (deadline)
  - People may move

Maximum Encounter Planning

- Finite horizon MDP
  - State: cell in the map
  - Action: move to next cell
  - Reward: Poisson rate
  - Horizon: the deadline

- Challenges
  - Horizon reduced in time
  - Time variance of reward



Algorithm 1: Encounter Probability Planning

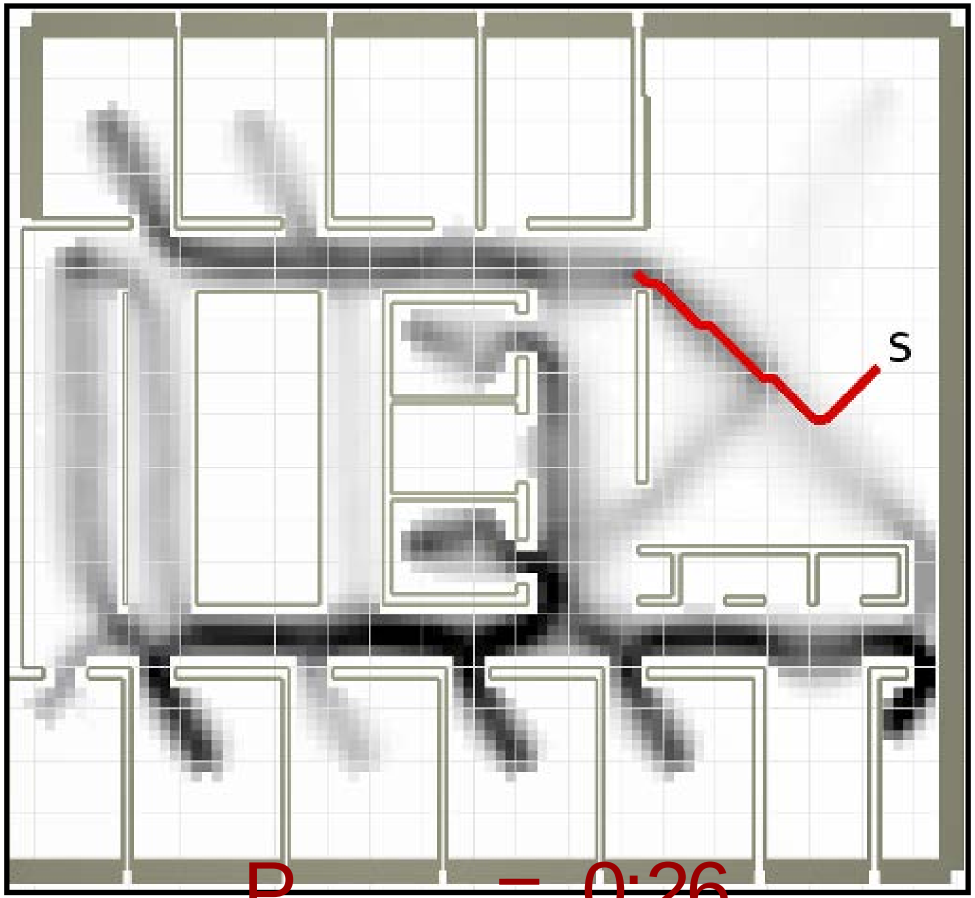
```
In: Rate $\lambda(\vec{x}, t)$; time $t_{max}$; initial state $s_0$;
Out: The best path $\mathcal{P}^*$;
// Compute the policy
Compute the horizon $N$;
$J_N(s) \leftarrow \lambda_{ij\tau}\ \forall s$;
for $k \leftarrow N-1$ to $0$ do
    $J_k(s) \leftarrow \max_a \left[ R(s,a) + \sum_{s'} p(s'|s,a) J_{k+1}(s') \right]$;
    $A^*_k(s) \leftarrow \operatorname{argmax}_a \left[ R(s,a) + \sum_{s'} p(s'|s,a) J_{k+1}(s') \right]$;
end
// Extract the path
$\mathcal{P}^*(0) \leftarrow s_0$;
for $k \leftarrow 1$ to $N$ do
    $s \leftarrow P^*(k-1)$;
    $\mathcal{P}^*(k) \leftarrow \mathbb{E}\left[p(s'|s, A^*_{k-1}(s))\right]$;
end
return $\mathcal{P}^*$;
```

Planning heuristics

- MDP is too complex for real time planning
- O(N^3) time complexity
  - Too slow
- O(N^3) space complexity
  - Memory swap for limited resource robots

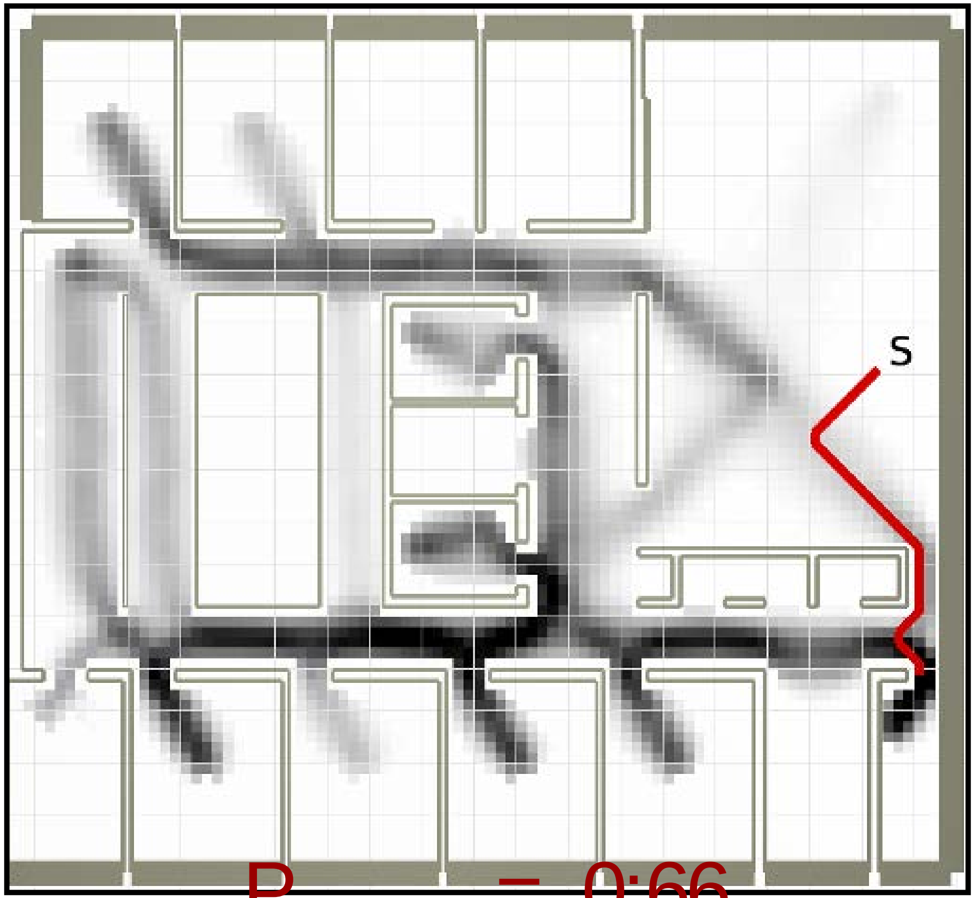
- MDP behavior
  - Go towards the sink if deadline is enough
  - Use a longer but more probable path
- Heuristics
  - Relax action stochasticity
  - A* towards the local sink
  - A* towards the global sink

Generated Path Analysis



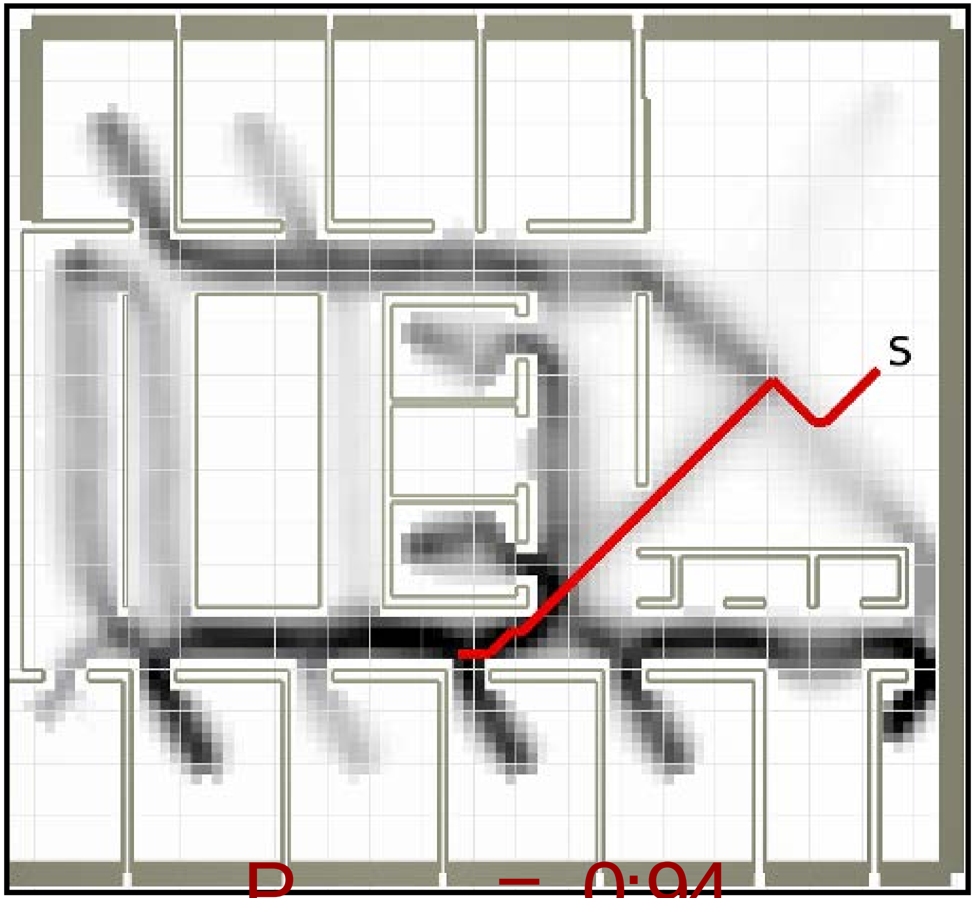
$P_{MDP} = 0:26$

Generated Path Analysis



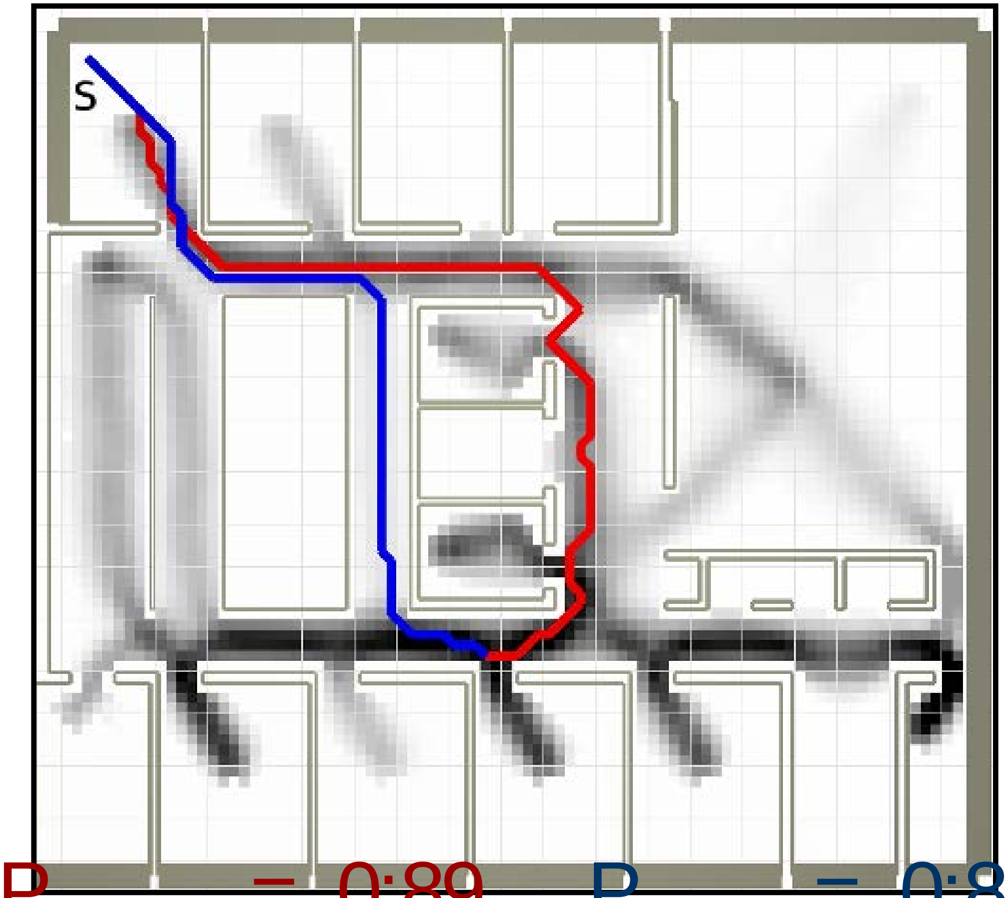
$P_{MDP} = 0:66$

Generated Path Analysis



$P_{MDP} = 0:94$

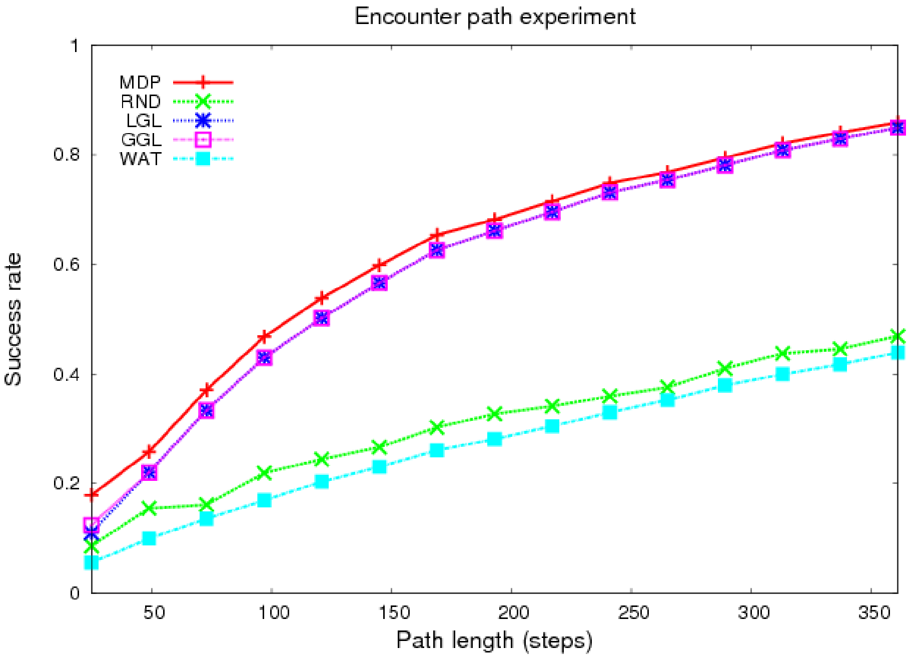
Generated Path Analysis



$P_{MDP} = 0:89$ $P_{LOC} = 0:83$

Encounter Planning Experiments

- Experiment setup
  - 10 simulation days
  - 1000 paths
  - Random starting location
  - Random starting time
- Metric used
  - Success rate with respect to the deadline
- Approaches
  - MDP
  - Local/global sink
  - Waiting
  - Random walk



} Informed

} Uninformed

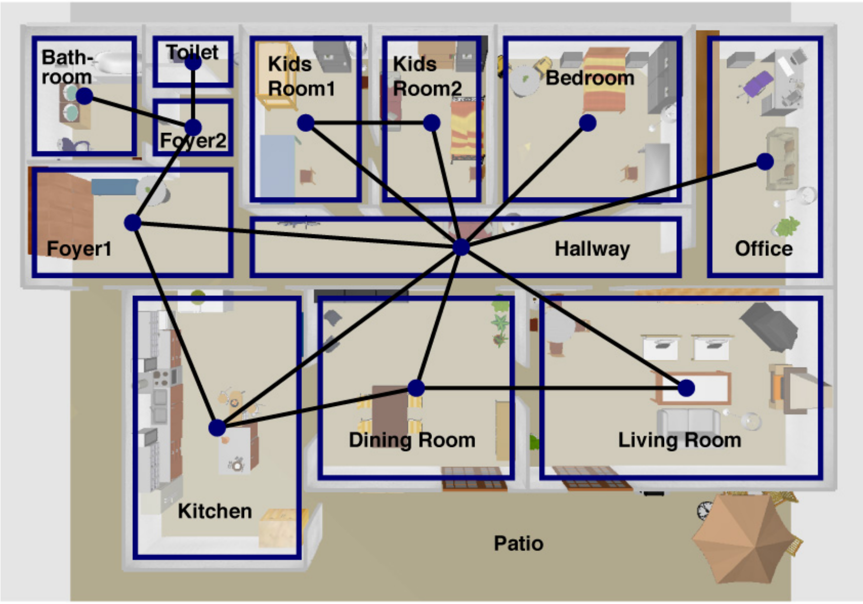
Minimum Interference Coverage

- Plan paths that cover the entire space, minimizing the interference with humans

- Example: Autonomous vacuum cleaner
  - Cleans the whole house
  - Cleans room when people are not there
  - Uses the routes with the minimum traffic

Minimum Interference Coverage

- Time-dependent TSP
  - Nodes: rooms
  - Edges: doorways
  - Costs: Poisson rates

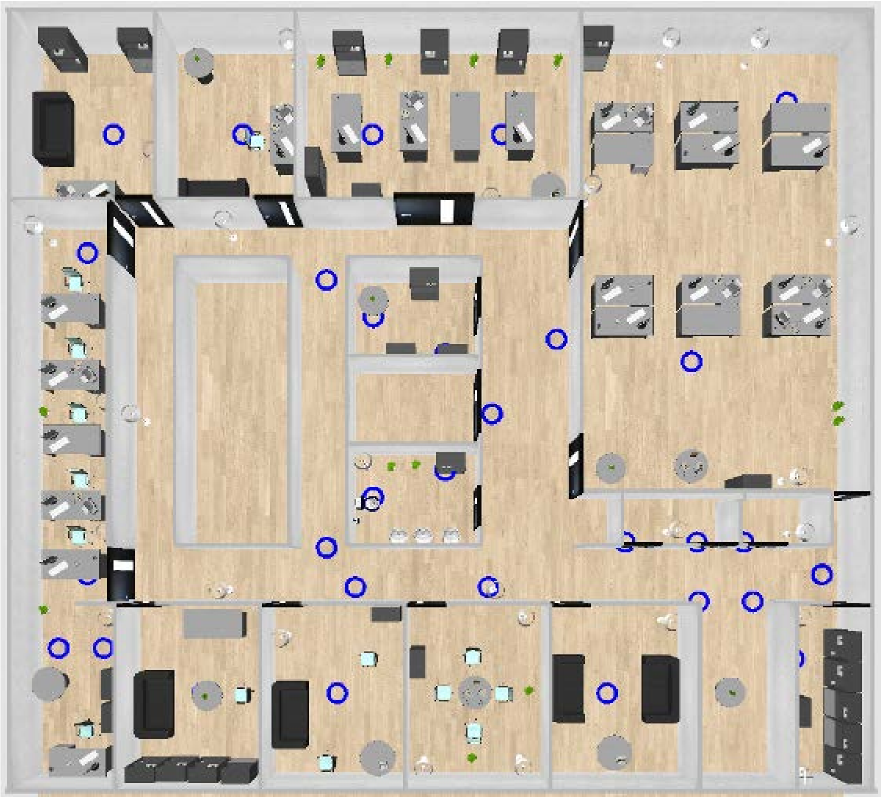


- Challenges and properties
  - Sparseness: TSP is usually fully connected
  - Asymmetry: presence of node costs
  - Time dependence: Poisson rates vary over time

Minimum Interference Coverage

Algorithm: ATDTSP

- Generate the room graph
- Complete the graph (Floyd-Warshall)
- Solve the TSP (dynamic programming)



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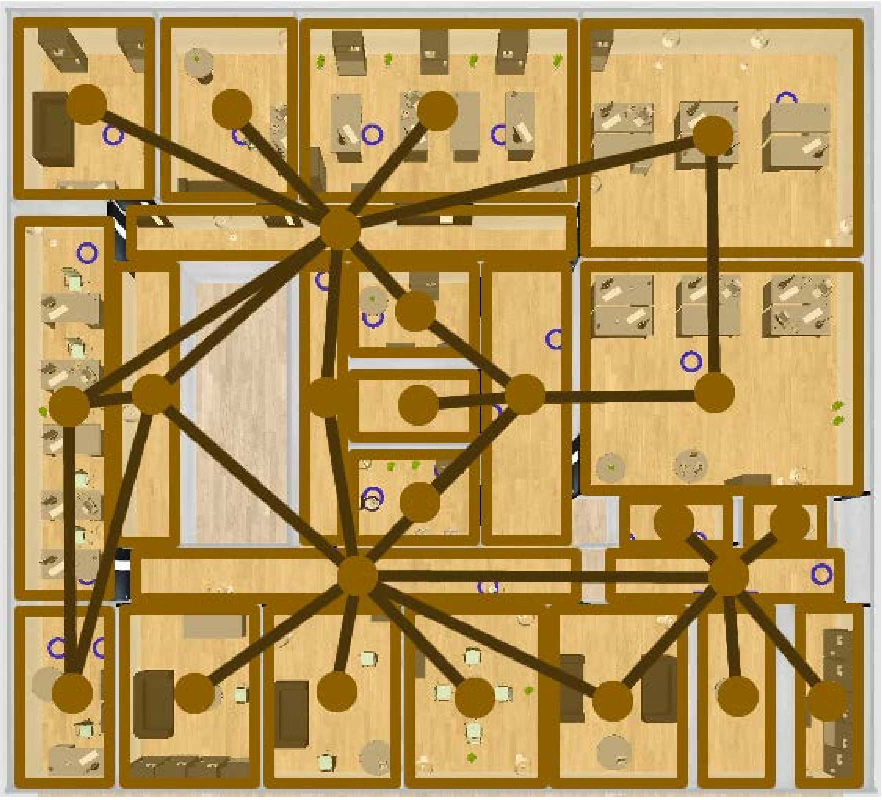

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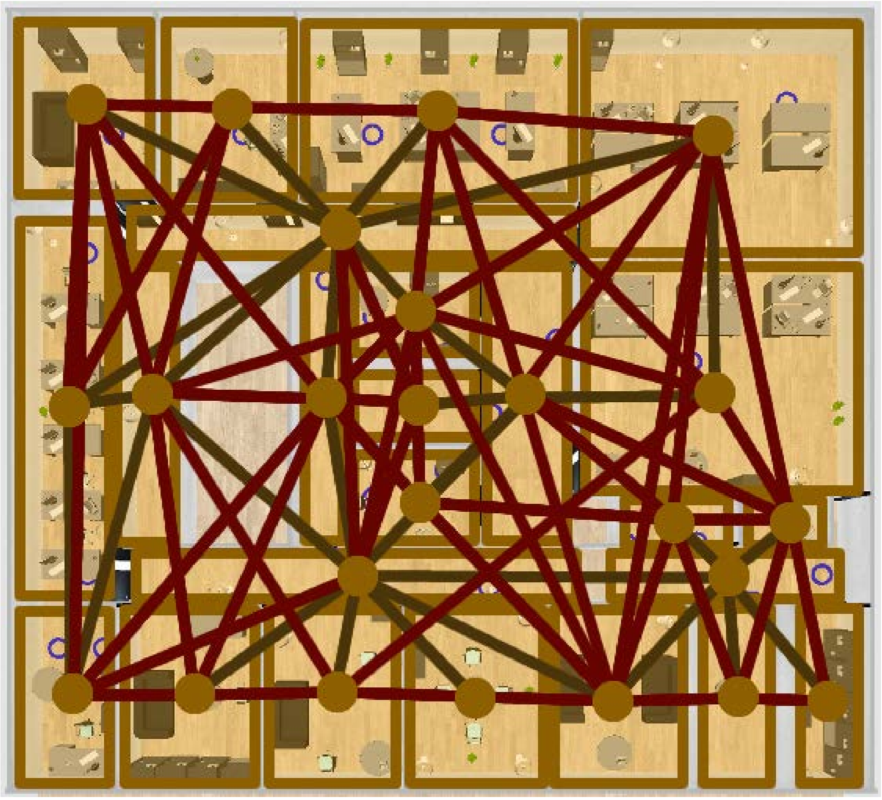

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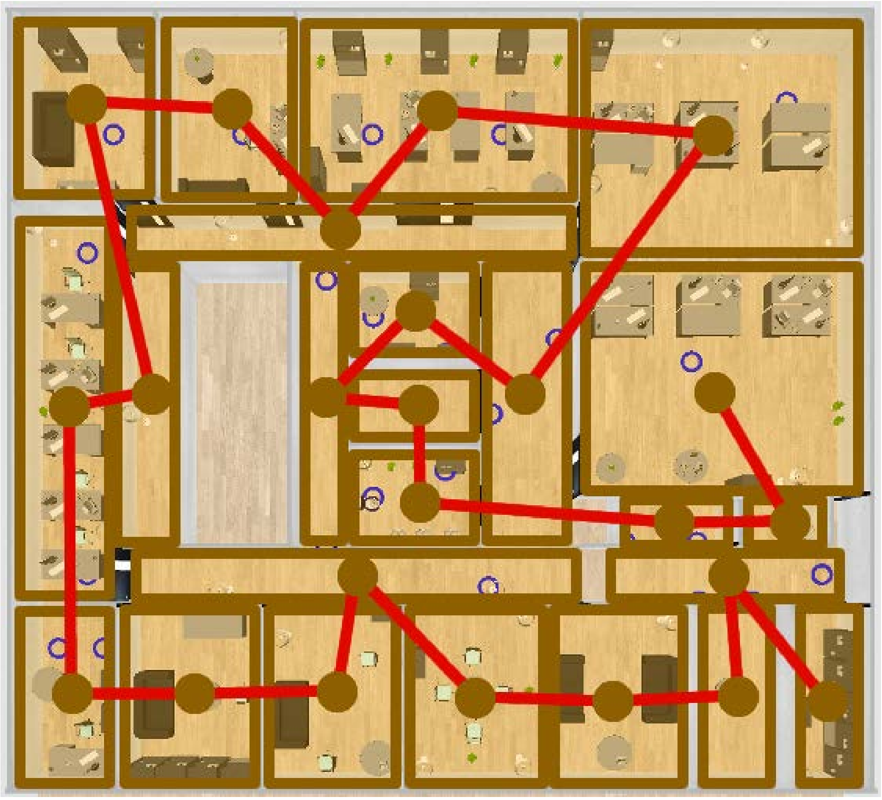
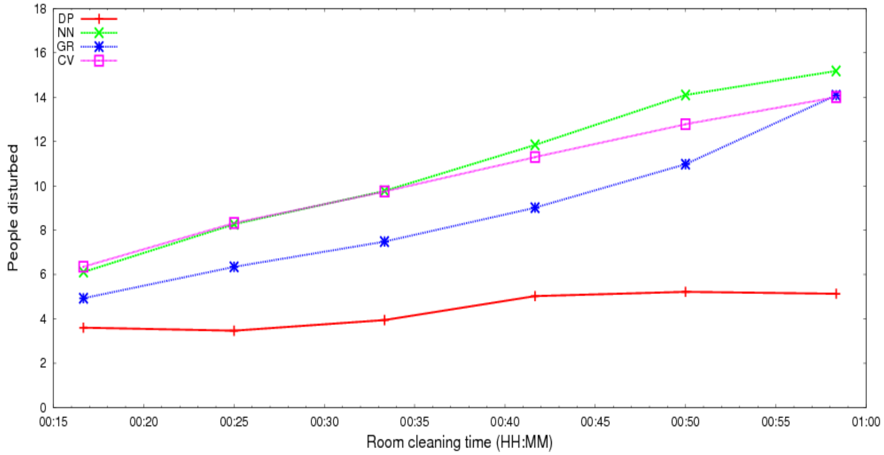
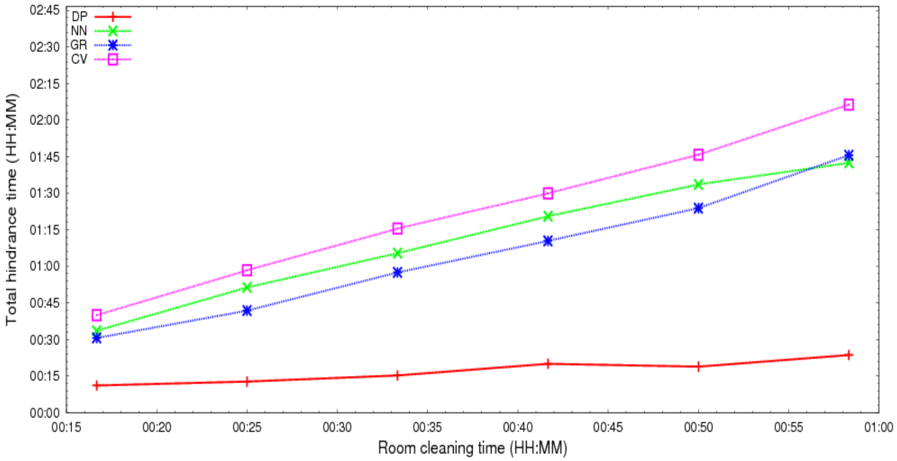


Preliminary results

- Experiment setup
  - 10 simulation days
  - 1000 paths
  - Random starting location
  - Random starting time
  - Coverage/transit times
- Metric used
  - Interference time
  - People interfered
- Approaches
  - Dynamic programming
  - Greedy/NN heuristic
  - General TSP



# People



Time

Complexity and Heuristics

- Dynamic programming too expensive
  - $O(N2^N)$ in time
  - $O(2^N)$ in space
- Graph completion also expensive
  - Floyd-Warshall for every time step $O(N^4)$

- Heuristics
  - Greedy $O(N^2 \log^2 N)$
  - Nearest neighbor $O(N^2)$
  - Good search heuristic for asymmetric problems?
- TSP: good formulation?
  - No sparseness
  - Complex reduction
- Alternatives?
  - Symbolic planning?
  - Temporal planning?

Conclusions

- Novel planning problems for social robots
  - Maximum encounter probability
  - Minimum interference coverage

- Learn and reason about human activities
  - Spatial affordance map

- Simulator engine of populated environments
  - Three realistic scenarios
  - Code available soon (mail me!)

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