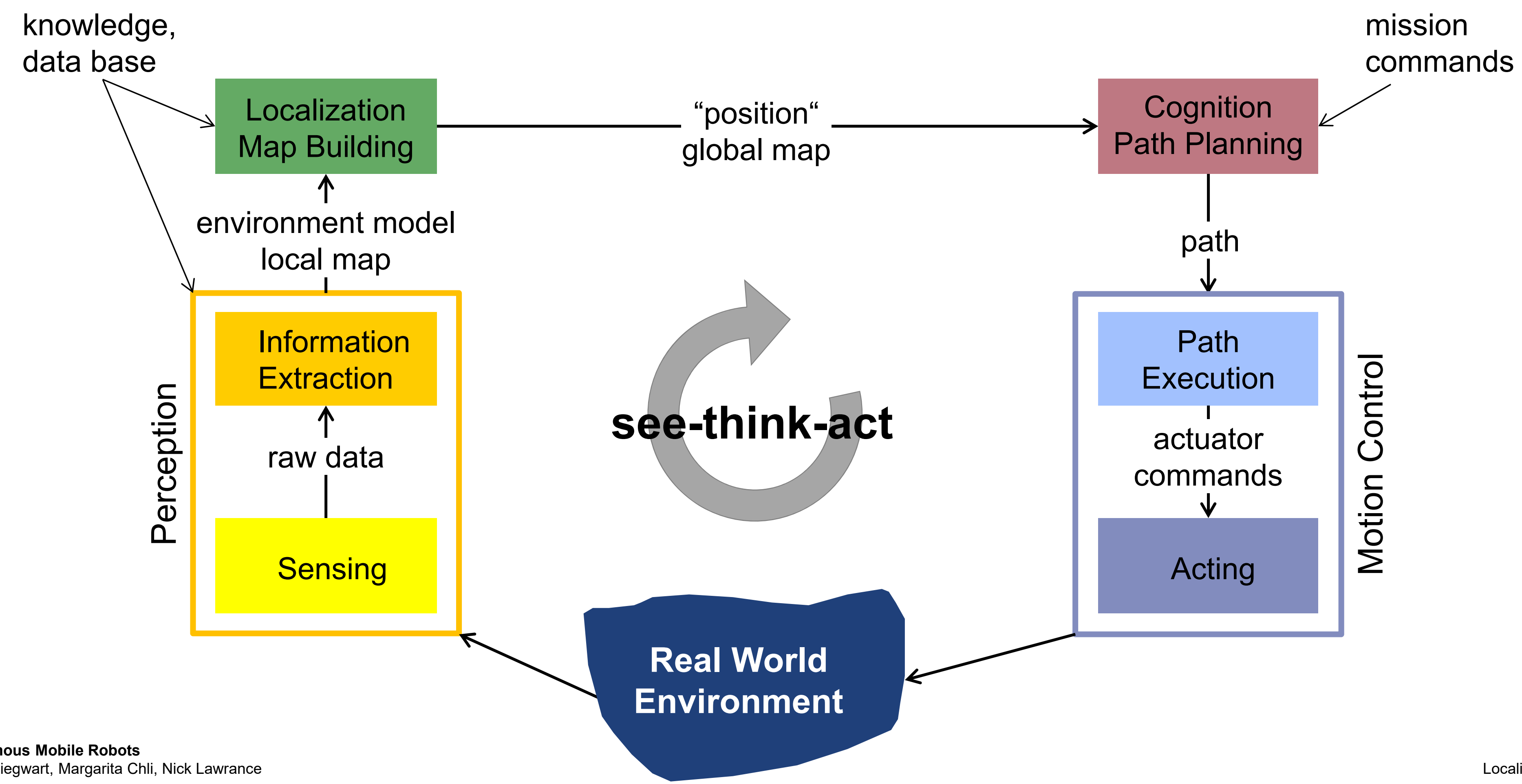
Spring 2019

Localization II

Roland Siegwart, Margarita Chli, Nick Lawrance

Autonomous mobile robot | the see-think-act cycle

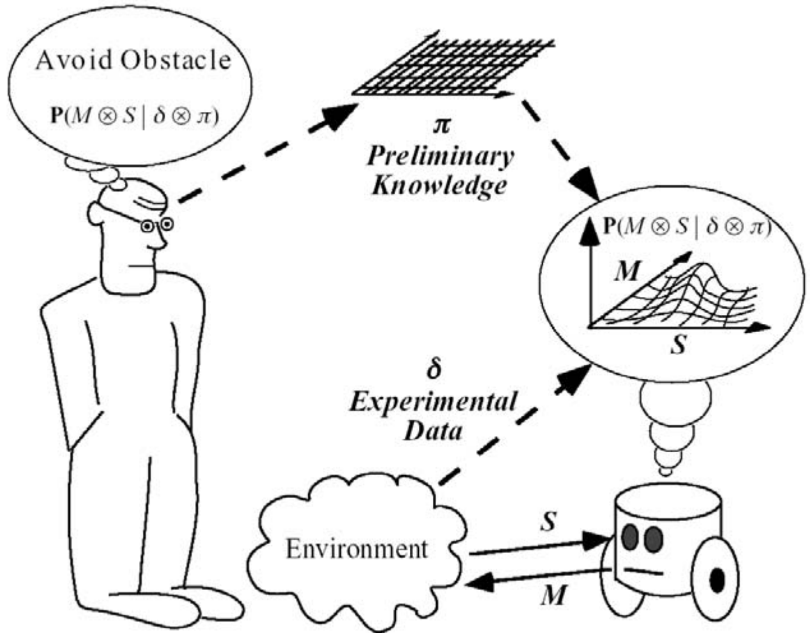


Probabilistic Reasoning (e.g. Bayesian)

- Reasoning in the presence of uncertainties and incomplete information
- Combining preliminary information and models with learning from experimental data

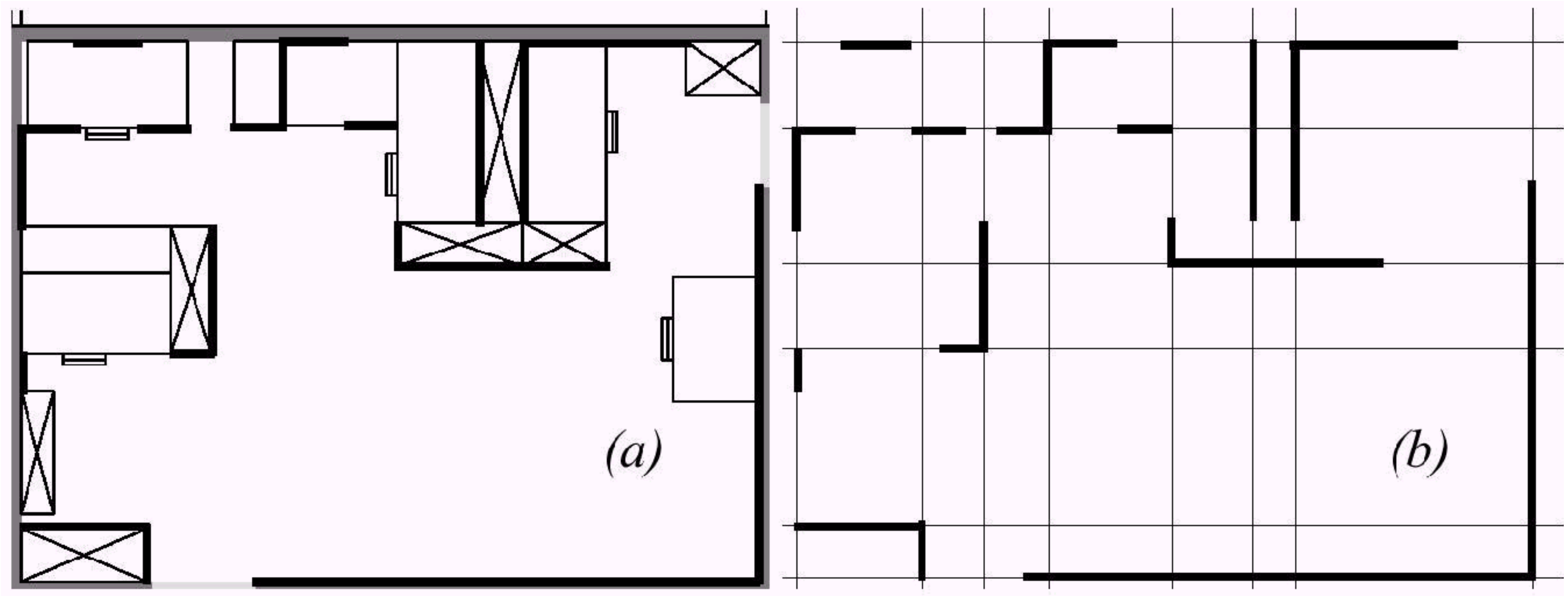
$$p(x|y) = \frac{p(y|x)p(x)}{p(y)}$$

"optimization"



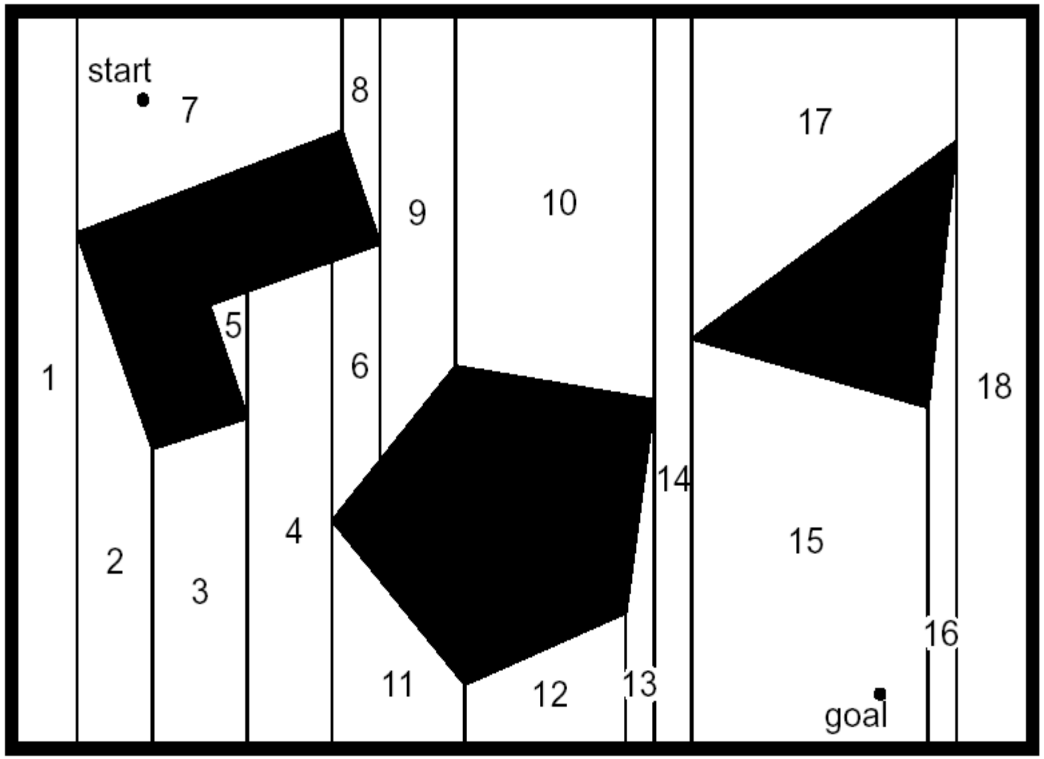
Map Representation | *Continuous Line-Based*

a) Architecture map
b) Representation with set of finite or infinite lines



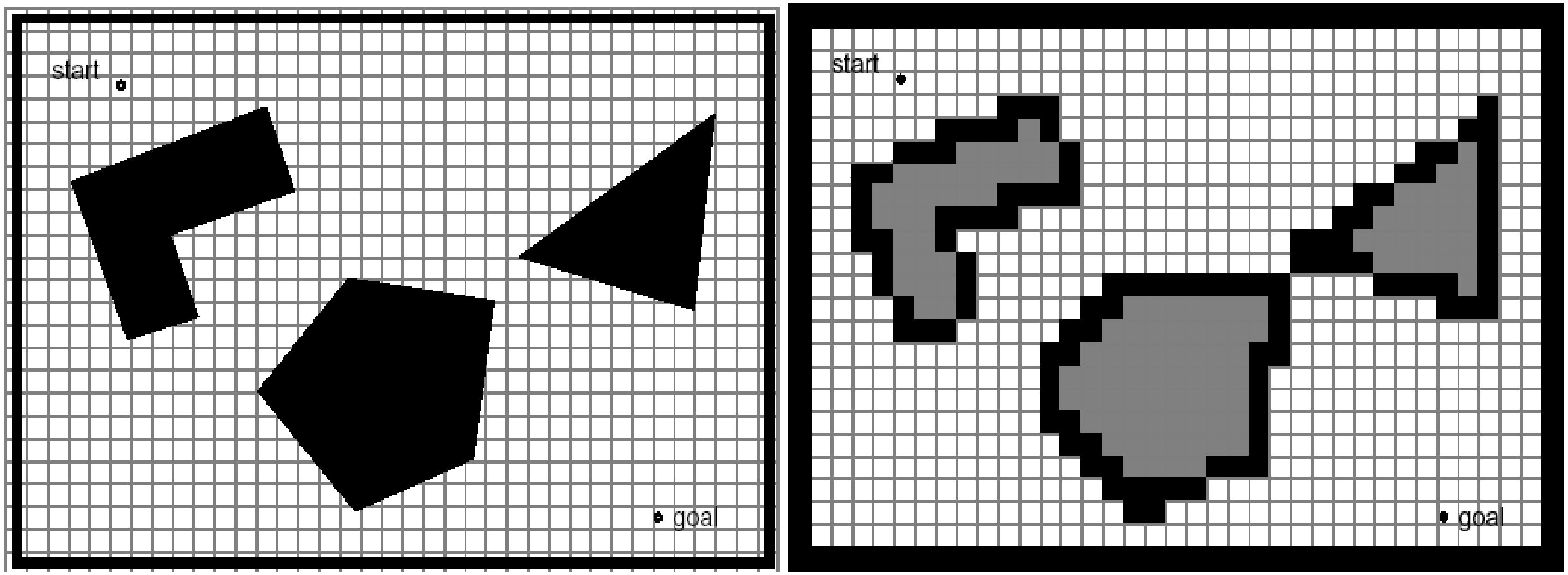
Map Representation | *Exact cell decomposition*

- Exact cell decomposition - Polygons



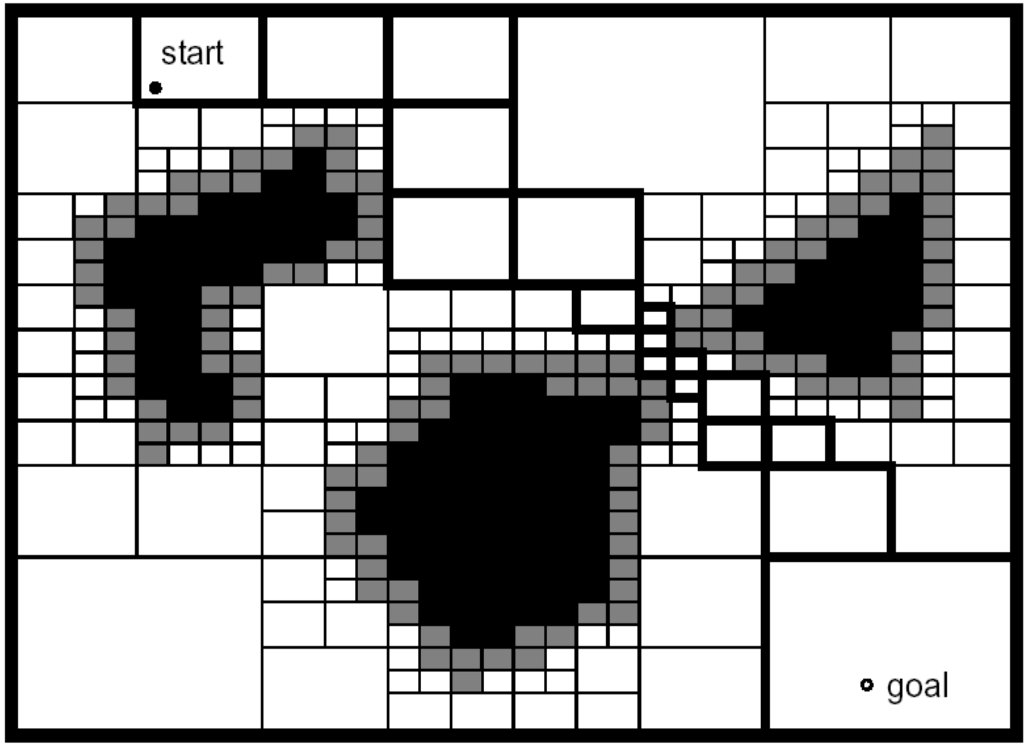
Map Representation | *Approximate cell decomposition*

- Fixed cell decomposition (occupancy grid)
    - Narrow passages disappear



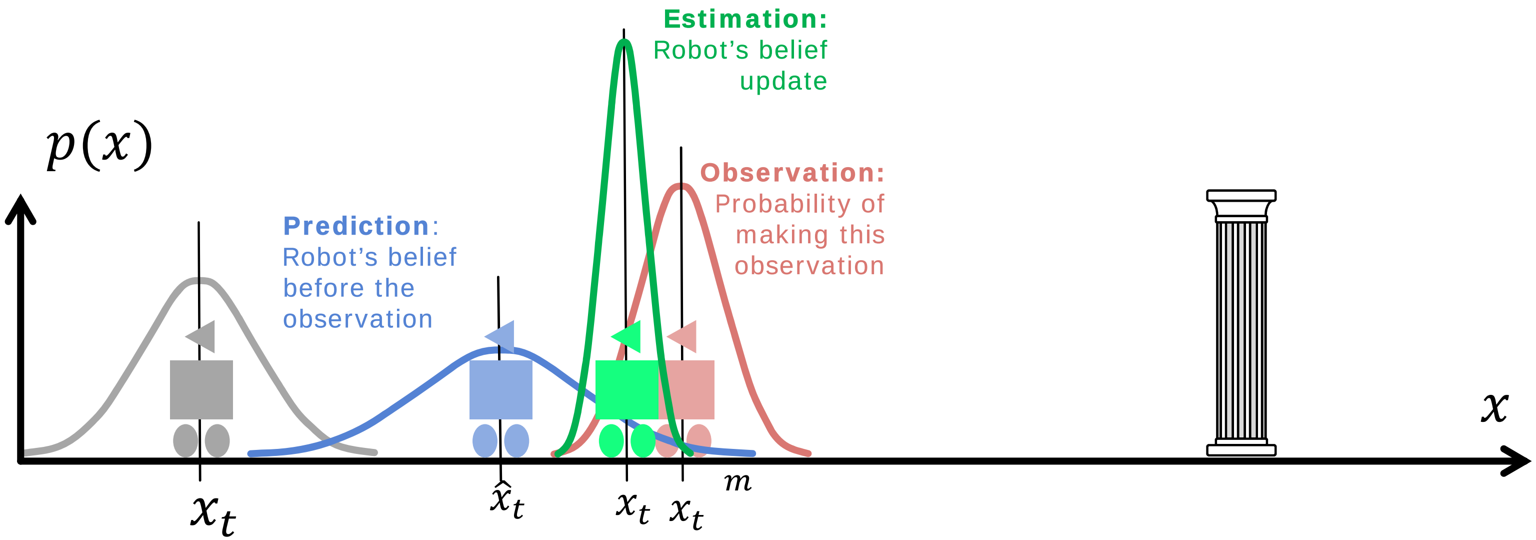
Map Representation | *Adaptive cell decomposition*

- Fixed cell decomposition
  - Narrow passages disappear



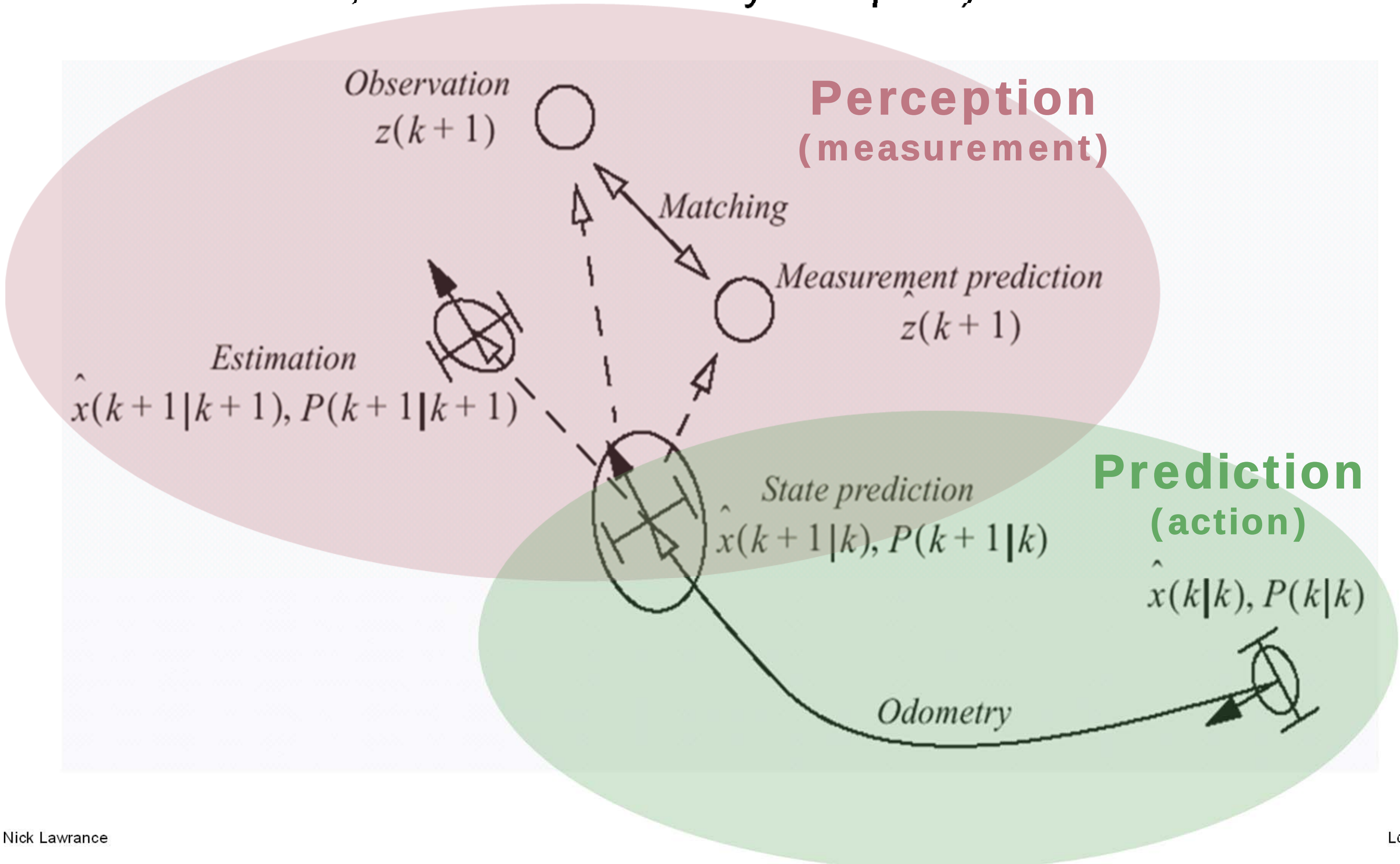
Kalman Filter Localization | in summery

1. **Prediction (ACT)** based on previous estimate and odometry
2. **Observation (SEE)** with on-board sensors
3. **Measurement prediction** based on prediction and map
4. **Matching** of observation and map
5. **Estimation** → position update (posteriori position)

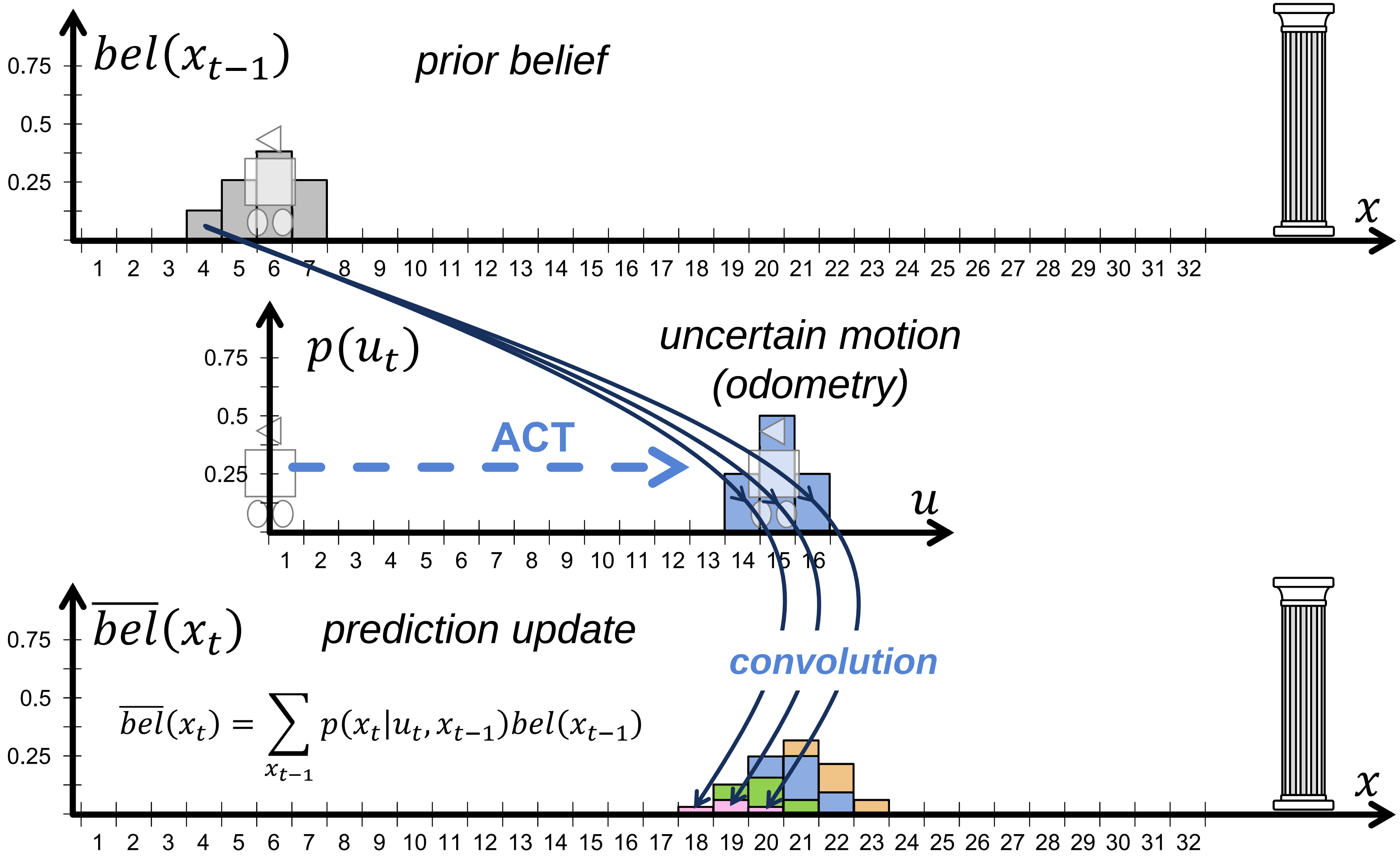


Localization: Probabilistic Position Estimation

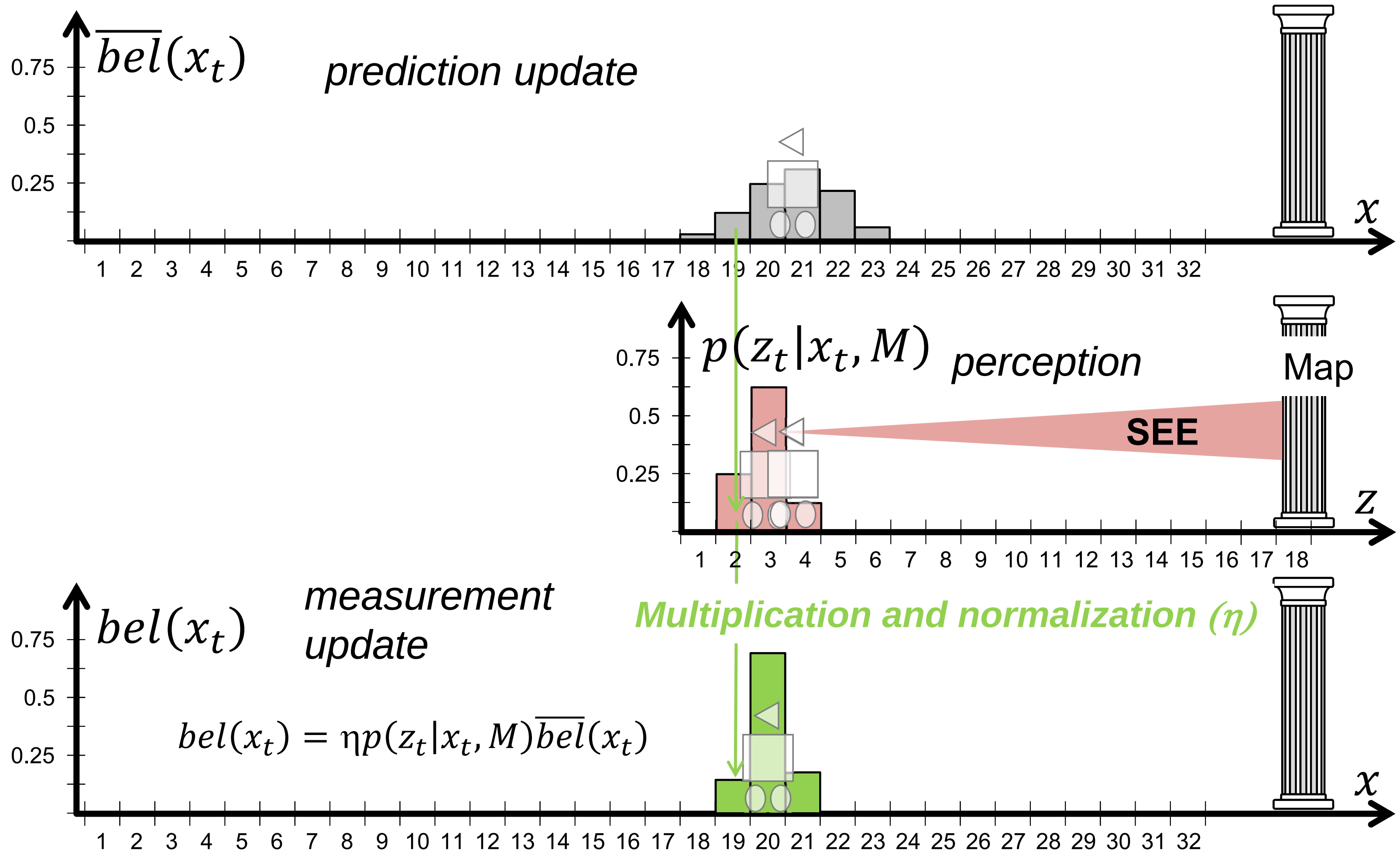
(Kalman Filter: continuous, recursive and very compact)



ACT | using motion model and its uncertainties



SEE | estimation of position based on perception and map



ACT and SEE - Markov localization

For all x_t do

$\overline{bel}(x_t) = \sum_{x_{t-1}} p(x_t|u_t, x_{t-1})bel(x_{t-1})$ (prediction update)

$bel(x_t) = \eta p(z_t|x_t, M)\overline{bel}(x_t)$ (measurement update)

endfor

Return $bel(x_t)$

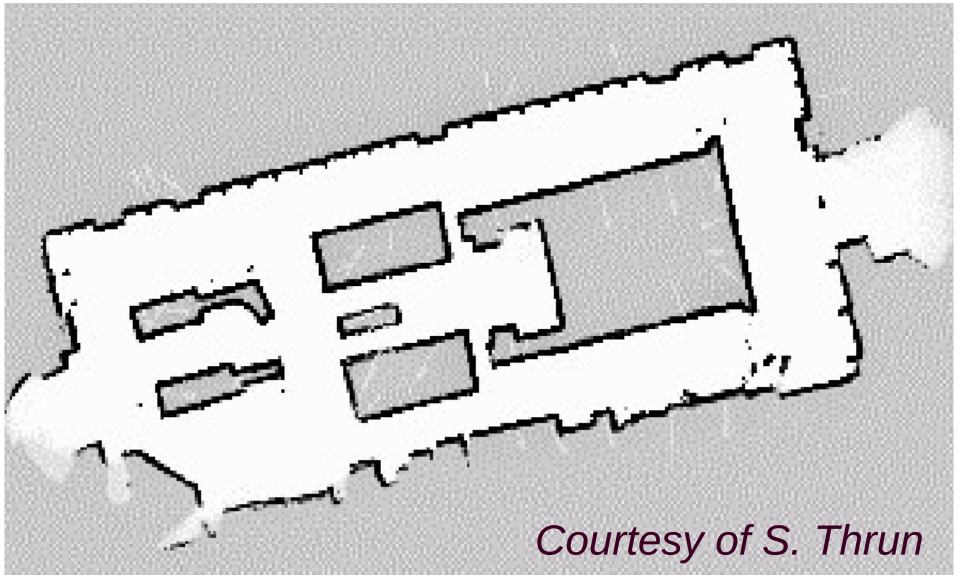
- ***Markov assumption***: Formally, this means that the output is a function x_t only of the robot's previous state x_t and its most recent actions (odometry) u_t and perception z_t.

Kalman Filter Localization

Markov versus Kalman localization

Markov	Kalman
PROS ▪ localization starting from any unknown position ▪ recovers from ambiguous situation	**PROS** ▪ Tracks the robot and is inherently very precise and efficient
CONS ▪ However, to update the probability of all positions within the whole state space at any time requires a discrete representation of the space (grid). The required memory and calculation power can thus become very important if a fine grid is used.	**CONS** ▪ If the uncertainty of the robot becomes to large (e.g. collision with an object) the Kalman filter will fail and the position is definitively lost

Map Representation | *Approximate cell decomposition*

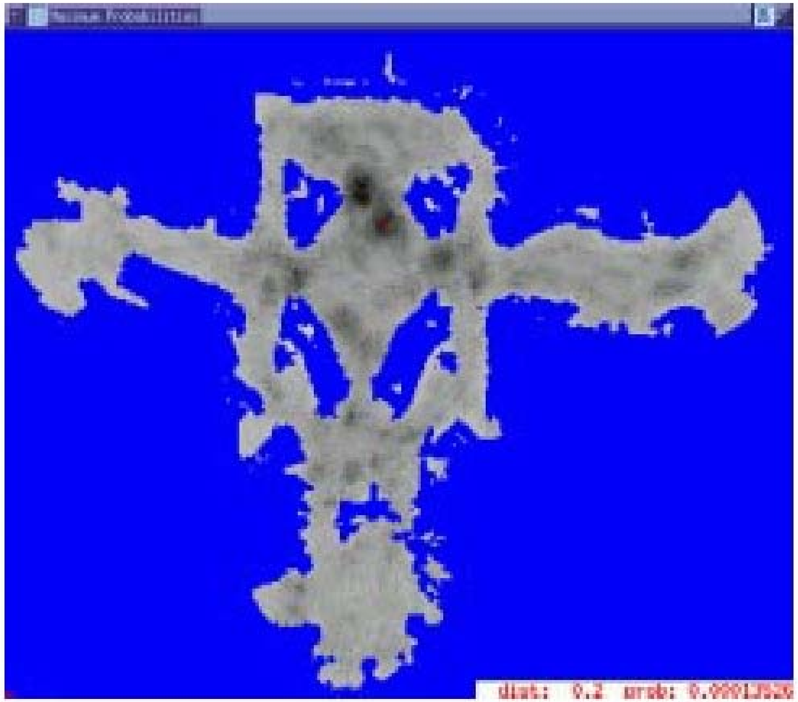


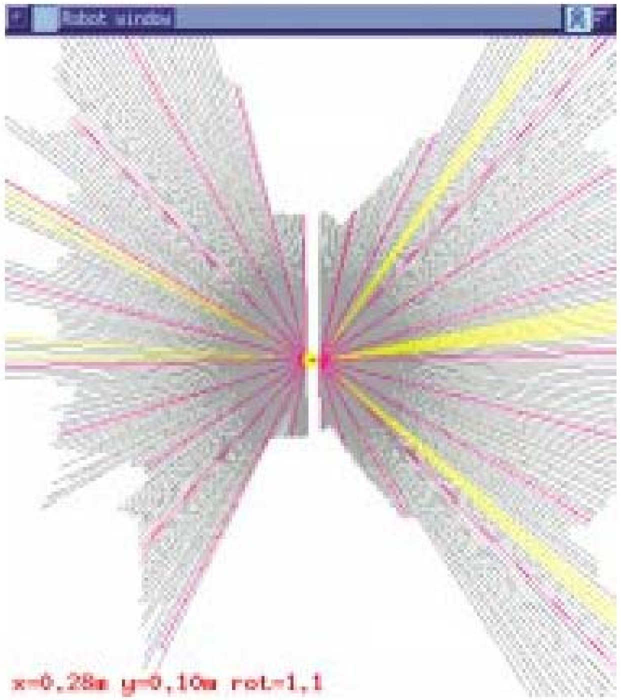
- Occupancy grid example
  - 0 indicates that the cell has not been hit by any ranging measurements (free space)
  - 1 indicates that the cell has been hit one or multiple times by ranging measurements (occupied space)
  - Can change over time (e.g. dynamic obstacles)

Markov Localization
Case Study – Grid Map

Courtesy of W. Burgard

- Example 2: Museum
  - Laser scan 1

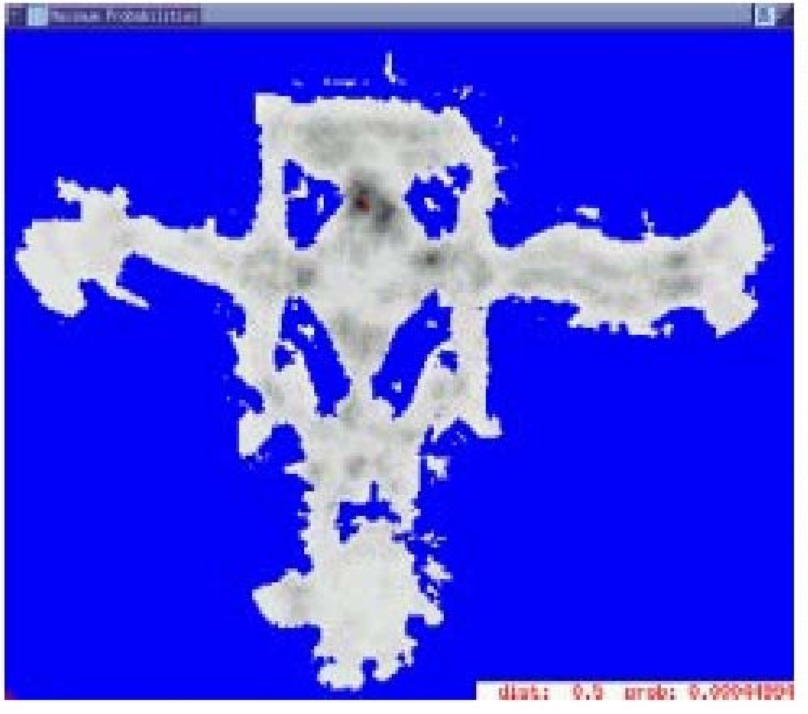


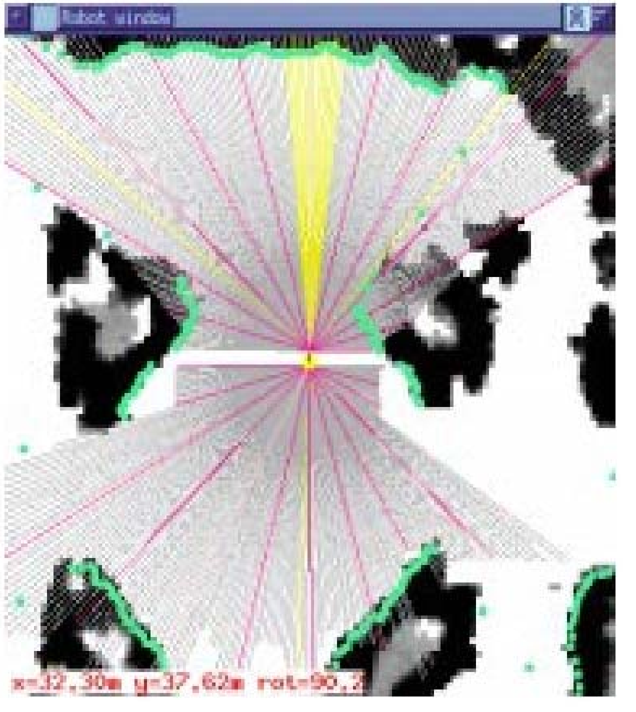


Markov Localization
Case Study – Grid Map

Courtesy of W. Burgard

- Example 2: Museum
  - Laser scan 2

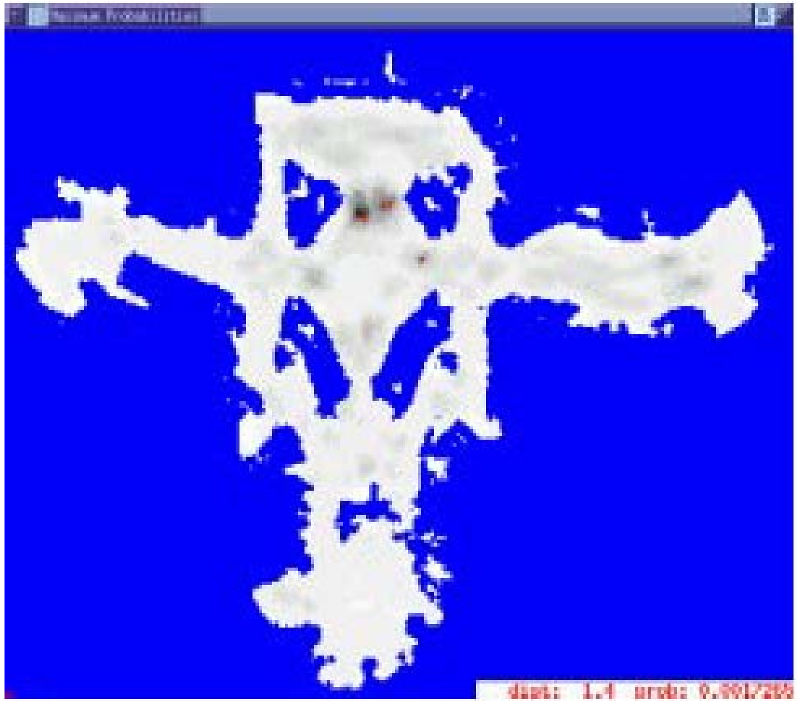


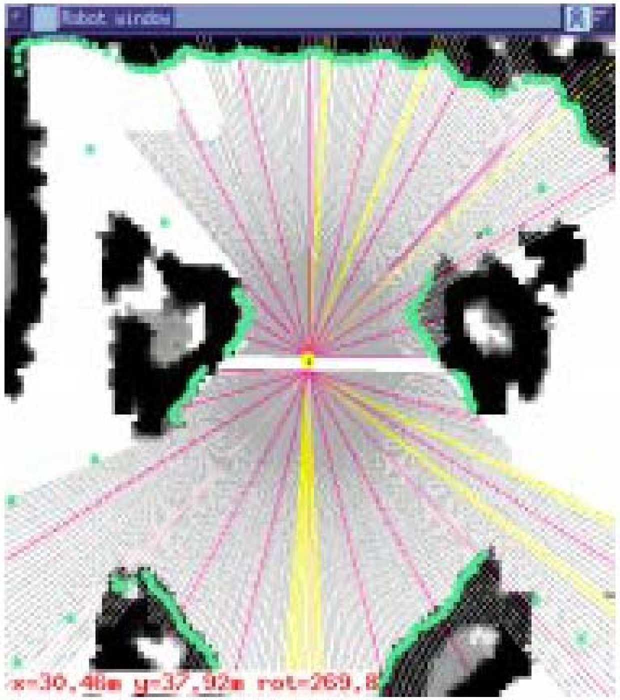


Markov Localization
Case Study – Grid Map

Courtesy of W. Burgard

- Example 2: Museum
  - Laser scan 3

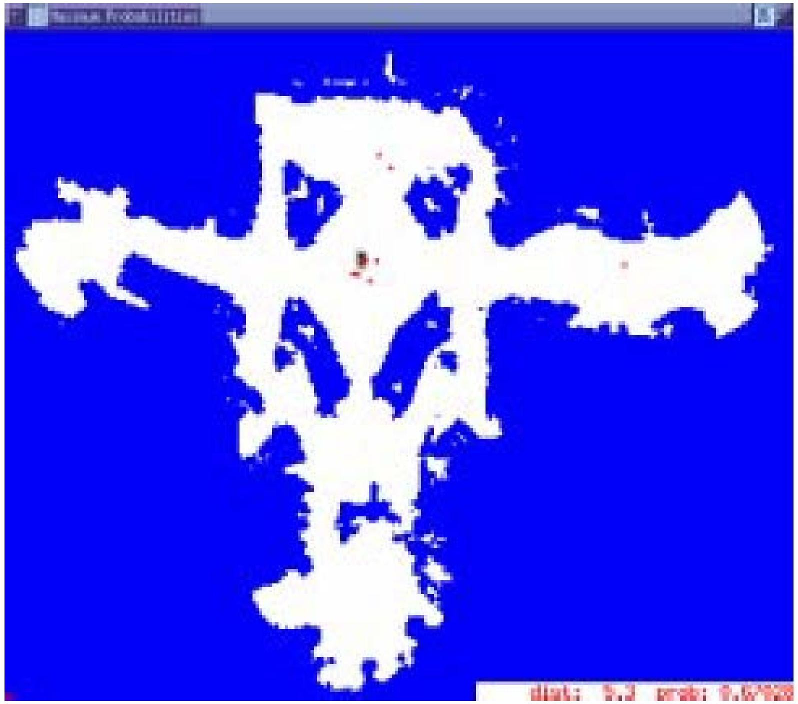


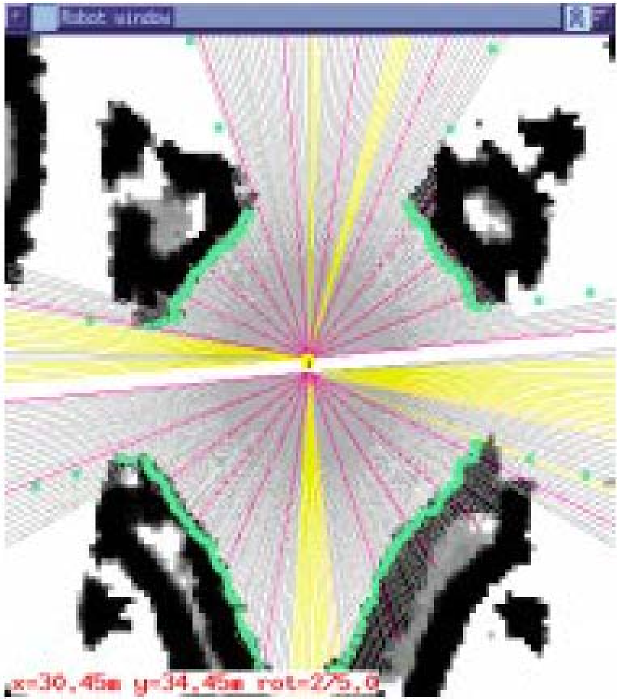


Markov Localization
Case Study – Grid Map

Courtesy of
W. Burgard

- Example 2: Museum
  - Laser scan 13

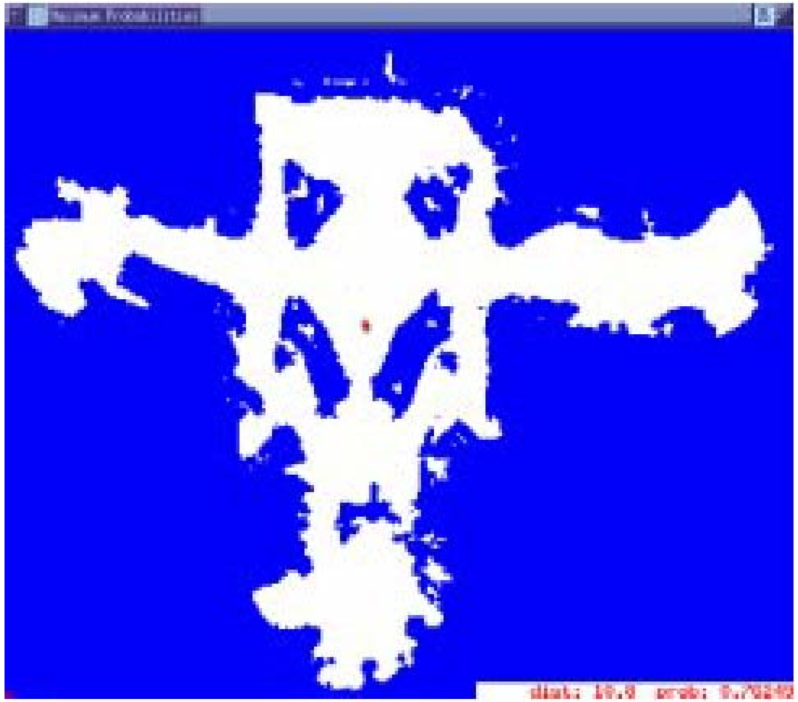


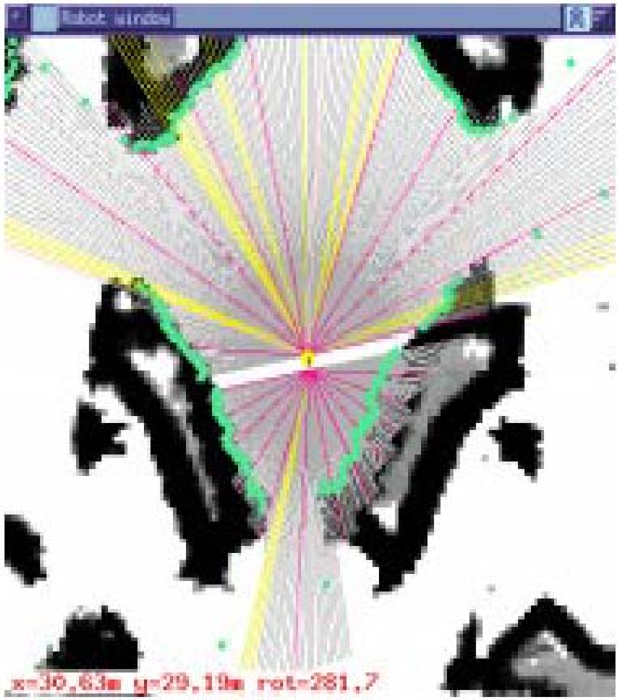


Markov Localization
Case Study – Grid Map

Courtesy of
W. Burgard

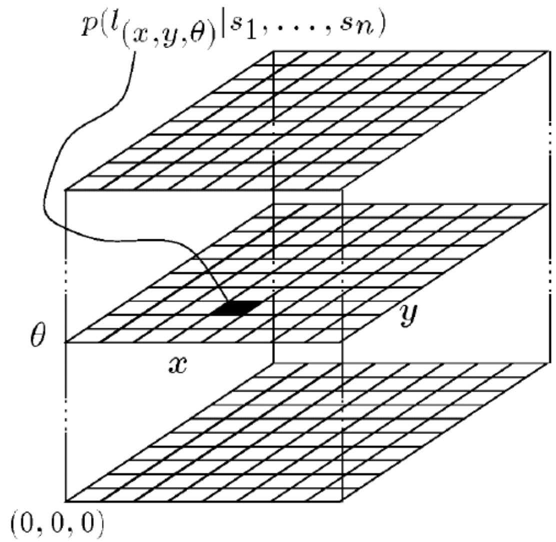
- Example 2: Museum
  - Laser scan 21



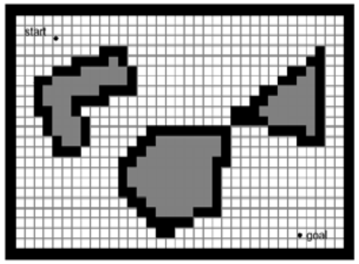


Drawbacks of Markov localization

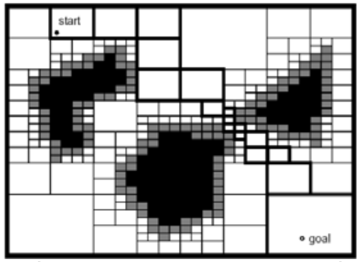
- Planar motion case
  - is a three-dimensional grid-map array
  - cell size must be chosen carefully.
- During each prediction and measurement steps
  - all the cells are updated
  - the computation can become too heavy for real-time operations.
- Example
  - 30x30 m environment;
    cell size of 0.1 m x 0.1 m x 1 deg
    → 300 x 300 x 360 = 32.4 million cells!
    → Important processing power needed
    → Large memory requirement



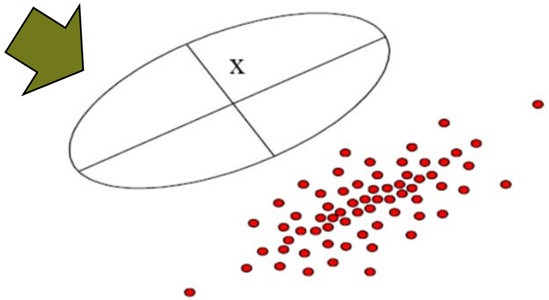
Drawbacks of Markov localization



- Reducing complexity
  - Various approached have been proposed for reducing complexity
    - One possible solution would be to increase the cell size at the expense of localization accuracy.
    - Another solution is to use an adaptive cell decomposition instead of a fixed cell decomposition.



- Randomized Sampling / Particle Filter
  - The main goal is to reduce the number of states that are updated in each step
  - Approximated belief state by representing only a 'representative' subset of all states (possible locations)
  - E.g update only 10% of all possible locations
  - The sampling process is typically weighted, e.g. put more samples around the local peaks in the probability density function
  - However, you have to ensure some less likely locations are still tracked, otherwise the robot might get lost

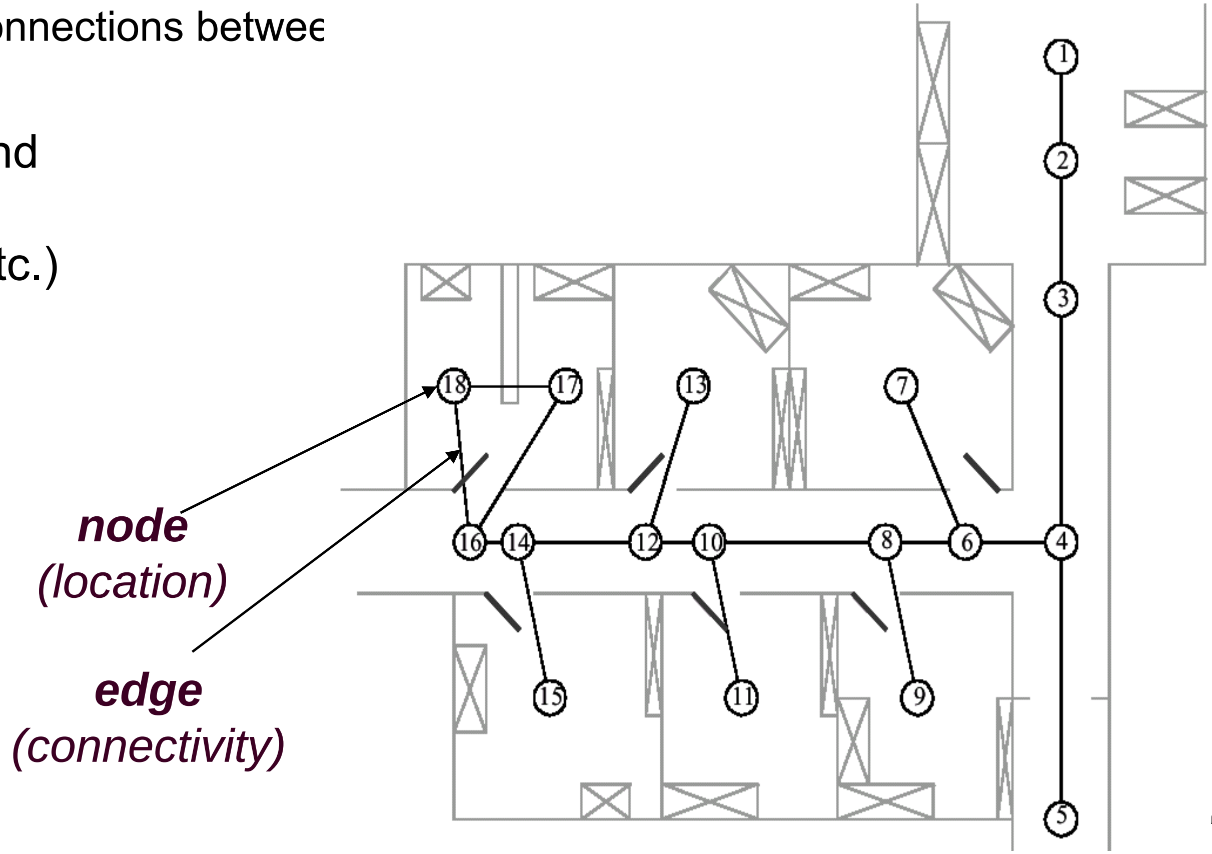


probability distribution (ellipse) as particle set (red dots)

Map Representation | *Topological map*

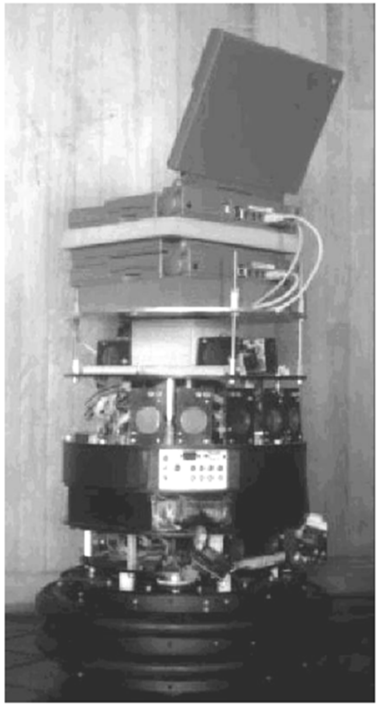
- A topological map represents the environment as a graph with nodes and edges.
  - Nodes correspond to spaces
  - Edge correspond to physical connections betwee

- Topological maps lack scale and distances, but topological relationships (e.g., left, right, etc.) are maintained



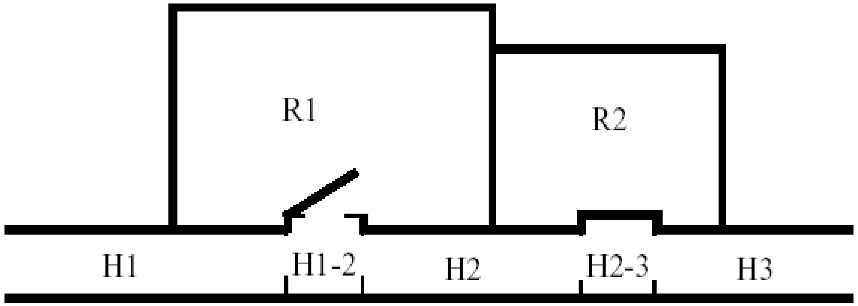
Markov Localization: *Case Study - Topological Map (1)*

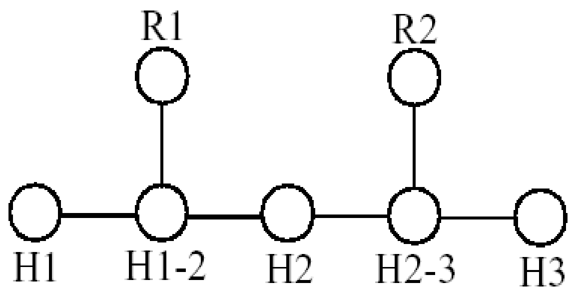
- The Dervish Robot
- Topological Localization



Markov Localization: *Case Study - Topological Map (2)*

- Topological map of office-type environment





	Wall	Closed door	Open door	Open hallway	Foyer
Nothing detected	0.70	0.40	0.05	0.001	0.30
Closed door detected	0.30	0.60	0	0	0.05
Open door detected	0	0	0.90	0.10	0.15
Open hallway detected	0	0	0.001	0.90	0.50

Markov Localization: *Case Study - Topological Map (3)*

- Update of believe state for position *n* given the percept-pair *i*

  - $p(n|i)$: new likelihoo
    $$p(n|i) = p(i|n)p(n)$$
  - $p(n)$: current believe state
  - $p(i|n)$: probability of seeing *i* in *n* (see table)

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Open hallway detected	0	0	0.001	0.90	0.50

- No action update !
  - However, the robot is moving and therefore we can apply a combination of action and perception update

    $$p(n_t|i_t) = \int p(n_t|n'_{t-i}, i_t)p(n'_{t-i})dn'_{t-i}$$

  - *t-i* is used inste ... n *n'* and *n* is very depending on the specific topolog

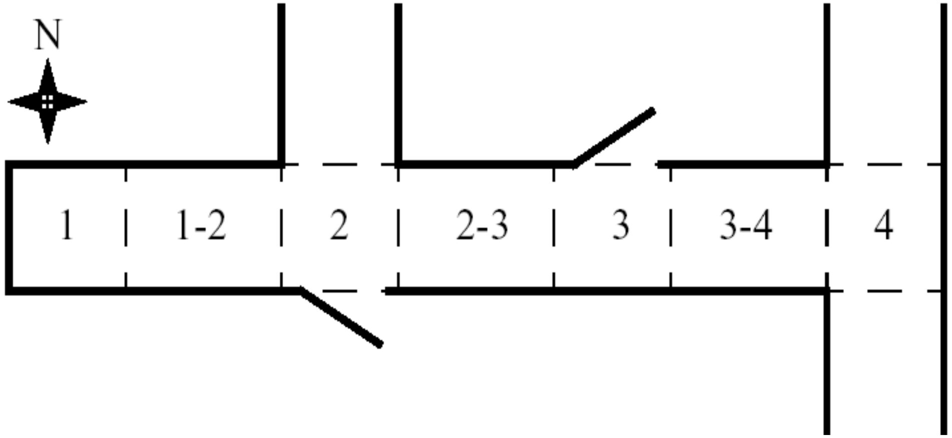
Markov Localization: *Case Study - Topological Map (4)*

- The calculation

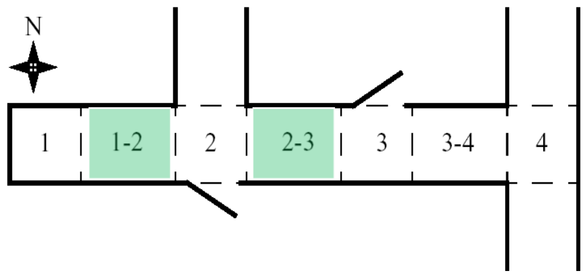
$$p(n_t | n'_{t-i}, i_t)$$

is realized by multiplying the **probability of generating perceptual event *i* at position *n*** by the **probability of having failed to generate perceptual event *s* at all nodes between *n'* and *n***.

$$p(n_t | n'_{t-i}, i_t) = p(i_t, n_t) \cdot p(\varnothing, n_{t-1}) \cdot p(\varnothing, n_{t-2}) \cdot \ldots \cdot p(\varnothing, n_{t-i+1})$$



Markov Localization: *Case Study - Topological Map (5)*



- Example calculation
  - Assume that the robot has two nonzero belief states
    - p*(1-2)* = 1.0 ; p*(2-3)* = 0.2*

    and that it is facing east with certainty
  - **Perceptual event**: open hallway on its left and open door on its right
  - State *2-3* will progress potentially to *3*, *3-4* or *4*.
  - State *3* and *3-4* can be eliminated because the likelihood of detecting an open door is zero.
  - The likelihood of reaching state *4* is the product of the initial likelihood p*(2-3)*= **0.2**, (a) the likelihood of detecting anything at node *3* and the likelihood of detecting a hallway on the left and a door on the right at node *4* and (b) the likelihood of detecting a hallway on the left and a door on the right at node *4*. (for simplicity we assume that the likelihood of detecting nothing at node *3-4* is *1.0*)
  - (a) occurs only if Dervish fails to detect the door on its left at node ***3*** (either closed or open), **[0.6 · 0.4 +(1-0.6) · 0.05]** and correctly detects nothing on its right, **0.7**.
  - (b) occurs if Dervish correctly identifies the open hallway on its left at node 4, **0.90**, and mistakes the right hallway for an open door, **0.10**.
  - This leads to:
    - **0.2** · **[0.6 · 0.4 + 0.4 · 0.05]** · **0.7** · **[0.9 · 0.1]** → p(4) = 0.003.
    - Similar calculation for progress from 1-2 → **p(2) = 0.3.**

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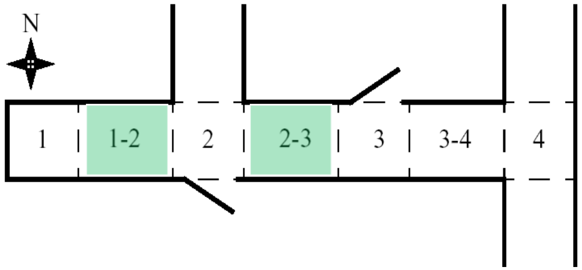
Markov Localization: *Case Study - Topological Map (5)*



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