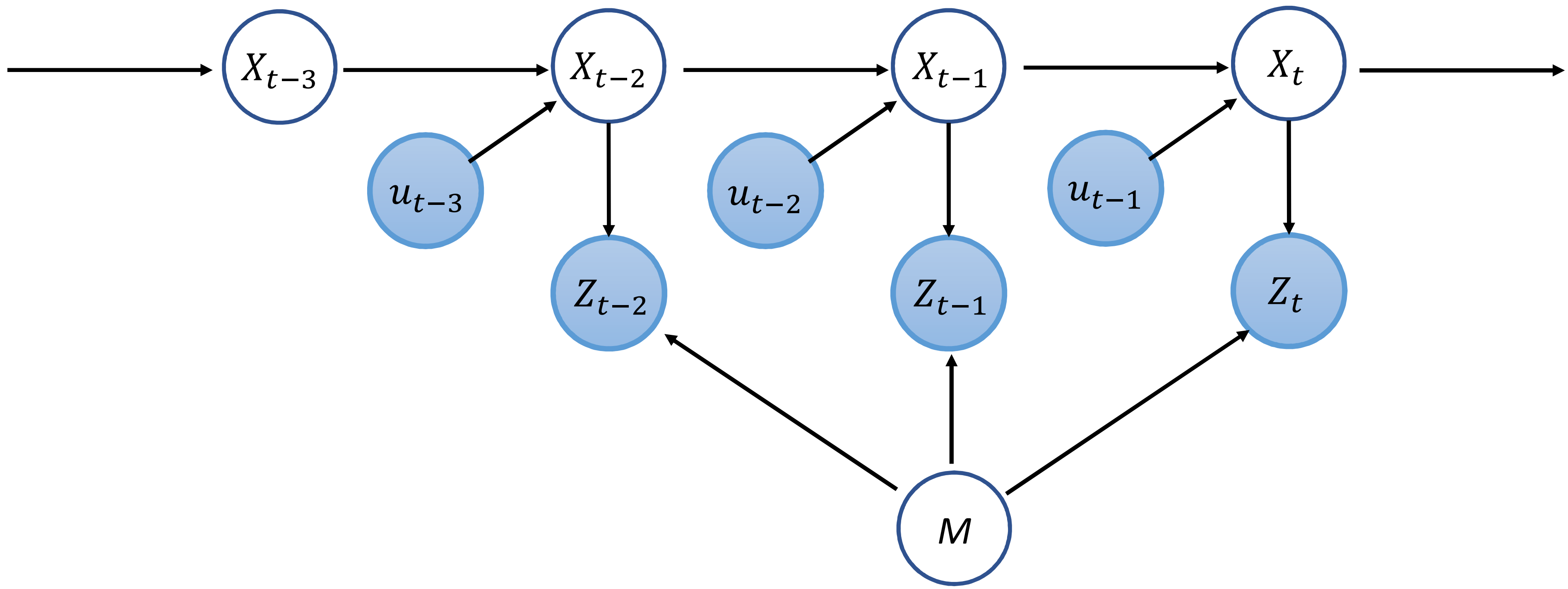
EECE 5550: Mobile Robotics



Lecture 11: Mapping

Recap

Last week: Bayesian networks and the Bayes Filter

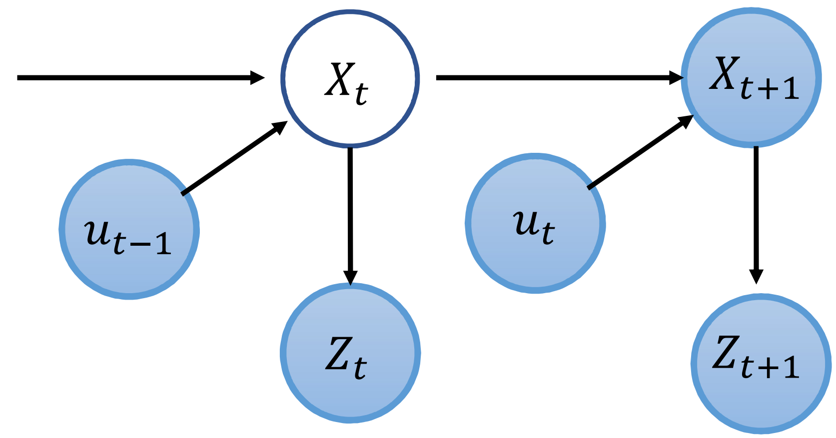
Bayes Filter: For t = 1, 2 … repeat the following operations:

- **Predict** belief for current state X_t given previous control u_{t-1}:

$$p(X_t|u_{0:t-1}, Z_{1:t-1}) = \int p(X_t|X_{t-1}, u_{t-1}) \cdot p(X_{t-1}|u_{0:t-2}, Z_{1:t-1})\ dX_{t-1}$$

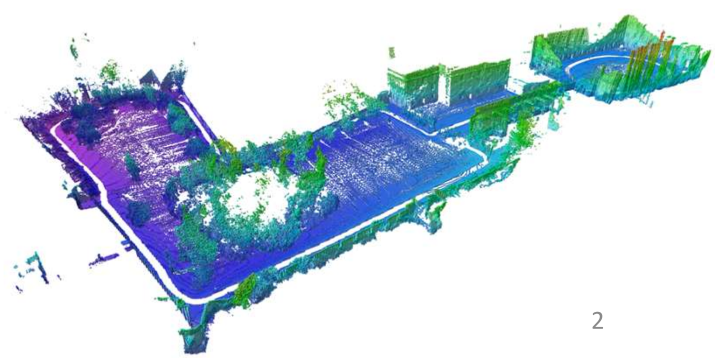
- **Update** belief after incorporating measurement Z_t at current state X_t:

$$p(X_t|u_{0:t-1}, Z_{1:t}) = \frac{p(Z_t|X_t)p(X_t|u_{0:t-1}, Z_{1:t-1})}{\int p(Z_t|X_t)p(X_t|u_{0:t-1}, Z_{1:t-1})\ dX_t}$$



Next two weeks: Mapping and localization!

1. Mapping
2. Localization
3. The Big One: Simultaneous localization and mapping (SLAM)

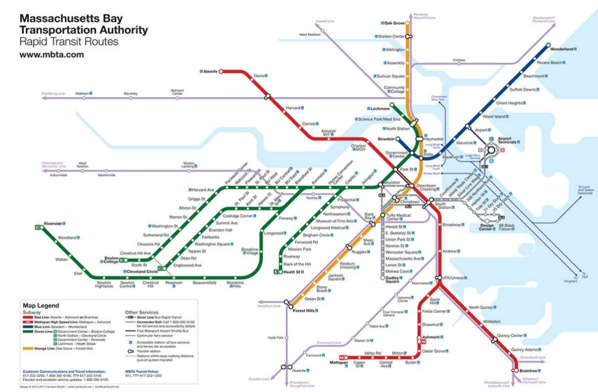


What is a “map”?

Simple answer: A *map* is a simply a *model* of an environment.

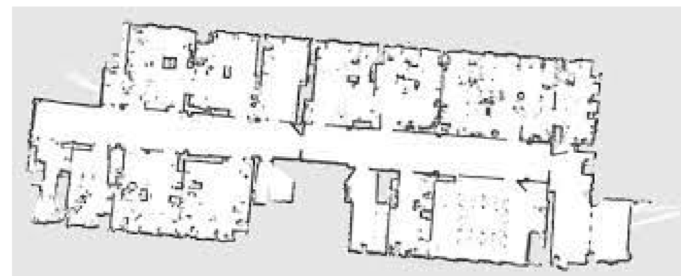
Less simple questions:

- What *properties* of the environment should a map capture?
- How should these properties be *represented* in the map?



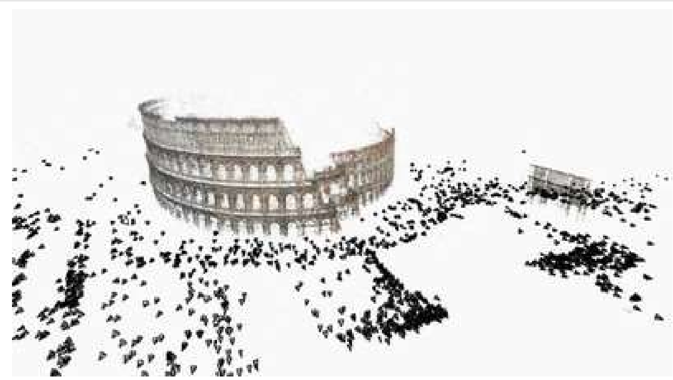
Examples:

- **Connectivity/traversability:** Topological maps (graph)
  Good for: Route planning



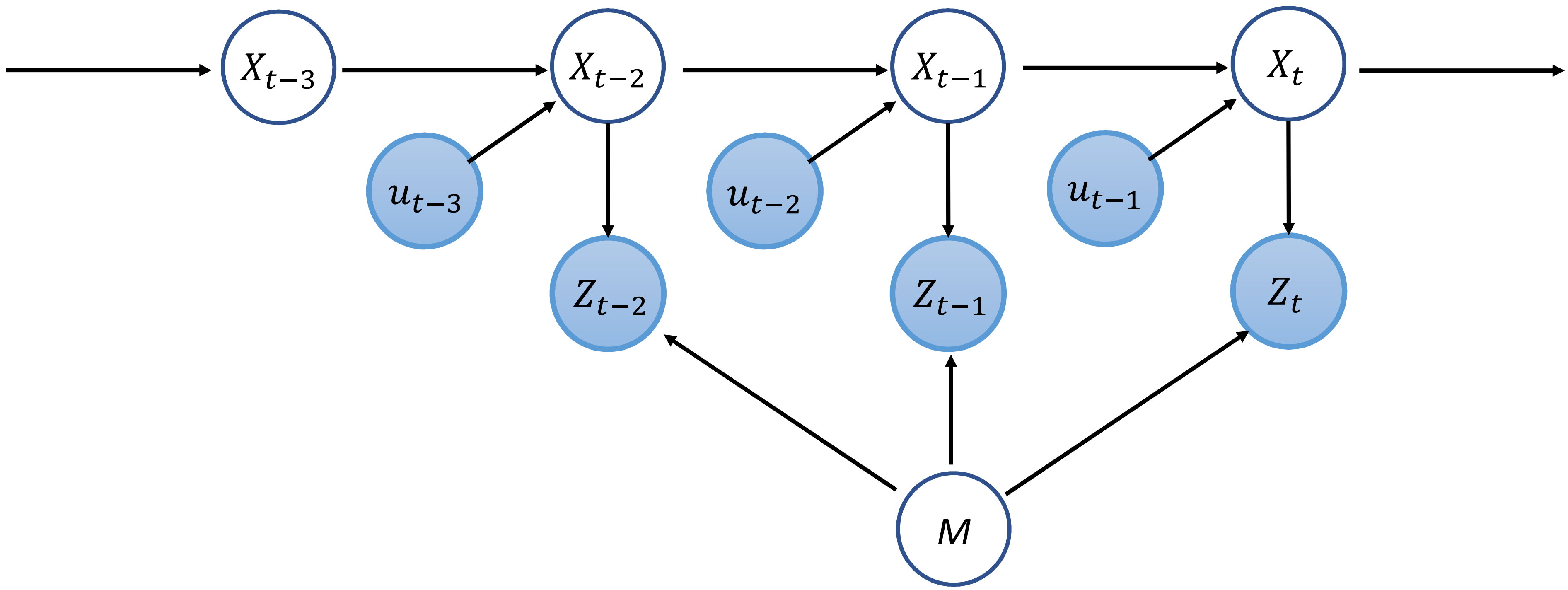
- **Free and occupied space:** Occupancy grids / voxels
- Good for: 2D / 3D navigation

- **Appearance:** Visual maps (keyframes)
  Good for: Visual reconstruction, place recognition



- **Objects & affordances:** Semantic maps, scene graphs, etc.
  Good for: high-level autonomy, environmental interaction

The Mapping Problem as a Bayesian Network

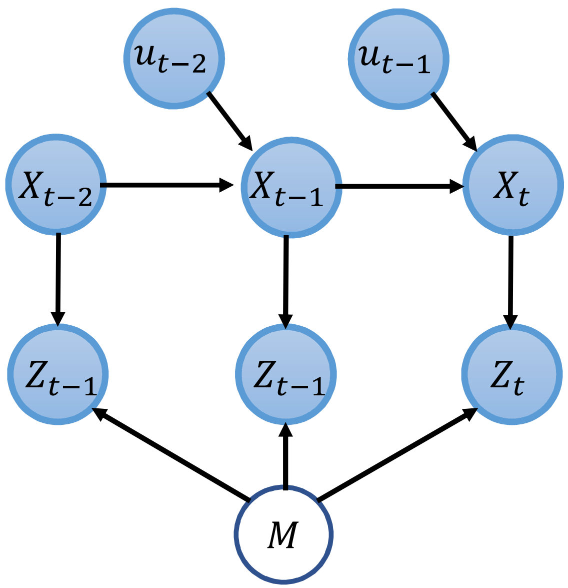


Two fundamental problems in robotic perception

Mapping

Given: Robot poses $x_{0:t}$, measurements $z_{1:t}$

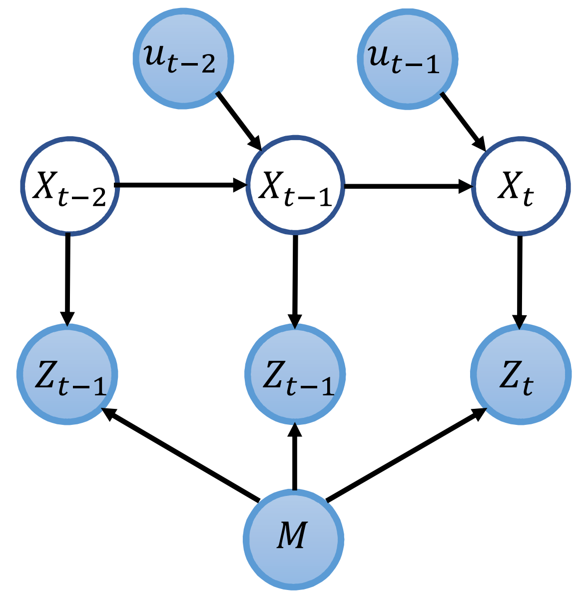
Estimate: Belief $p(m|x_{0:t}, z_{1:t})$ over the map *M*



Localization

Given: Map *m***,** measurements $z_{1:t}$

Estimate: Belief $p(x_t| \, m, z_{1:t})$ over the robot pose

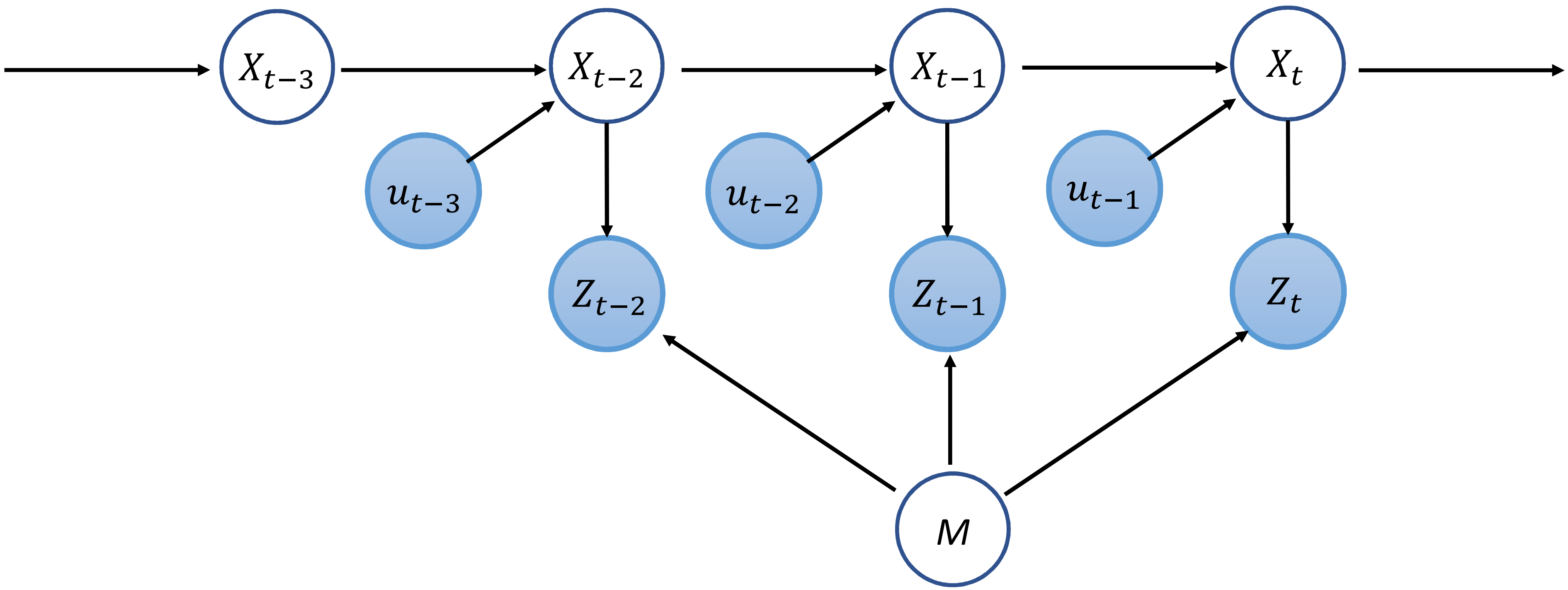


Key observation: Given *either* poses $x_{0:t}$ *or* map *m*, we can efficiently recover the other via *recursive Bayesian estimation* (Bayes Filter)

Simultaneous Localization and Mapping (SLAM)

Given: Prior $p(x_0)$ for initial pose x_0, sequence of motor commands $u_{0:t-1}$, observations $z_{1:t}$

Estimate: Joint posterior $p(x_{0:t}, m \,|u_{0:t-1}, z_{1:t})$ over robot poses $x_{0:t}$ and map m given $u_{0:t-1}$ and $z_{1:t}$

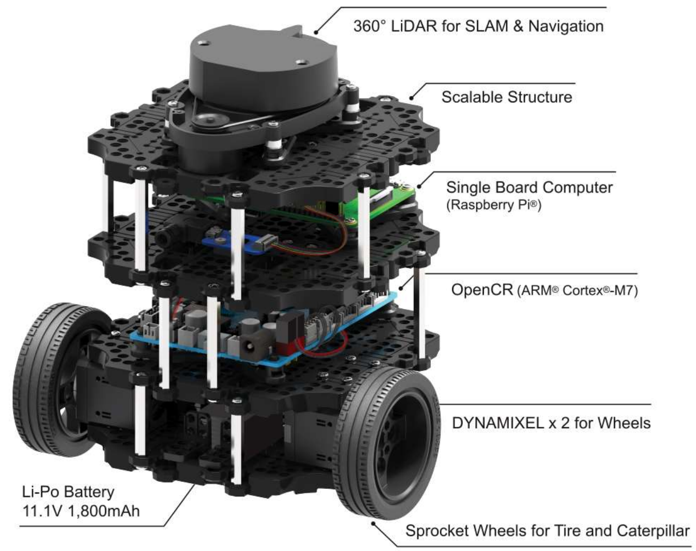


Key point: This coupled problem is *much* harder than either mapping or localization alone

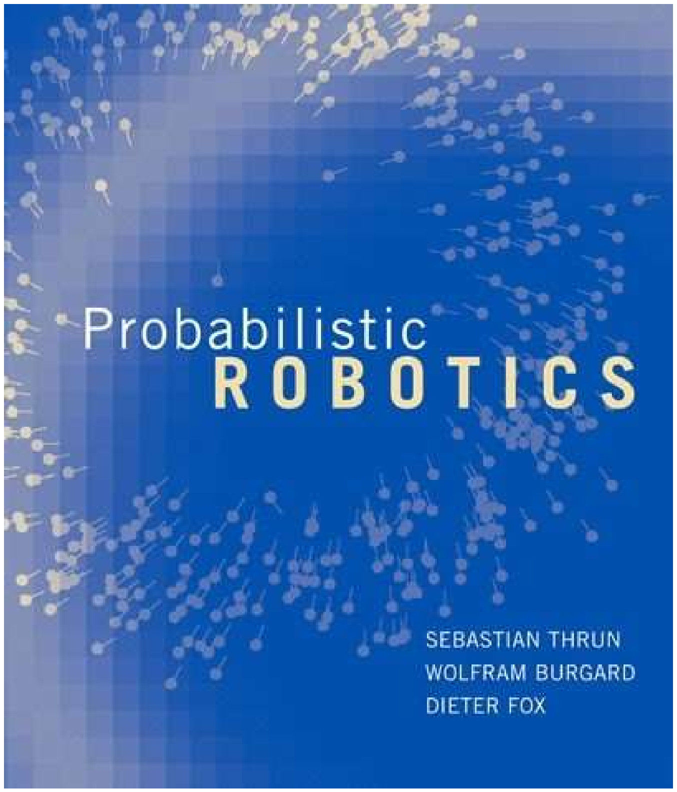
Plan of the day

Today we will consider the specific problem of 2D occupancy mapping using beam sensors, as a prelude to/subcomponent of *full SLAM* (next week!)

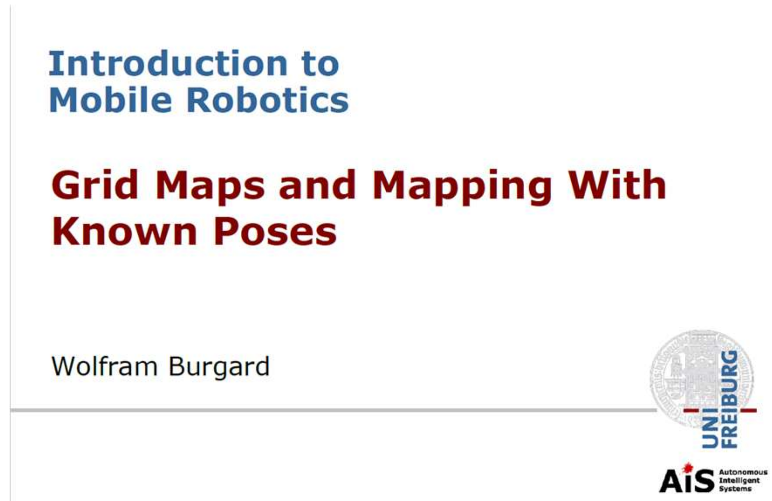
- Probabilistic occupancy grid maps
- Recursive Bayesian estimation for occupancy mapping with known poses
- (Inverse) sensor models for beam sensors



References



Chapter 9 of “Probabilistic Robotics”



Wolfram Burgard’s lecture “Grid Maps and Mapping with Known Poses”