

Robot Mapping

Introduction to Robot Mapping

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What is Robot Mapping?

- **Robot** – a device, that moves through the environment
- **Mapping** – modeling the environment

Related Terms

State
Estimation

Localization

Mapping

SLAM

Navigation

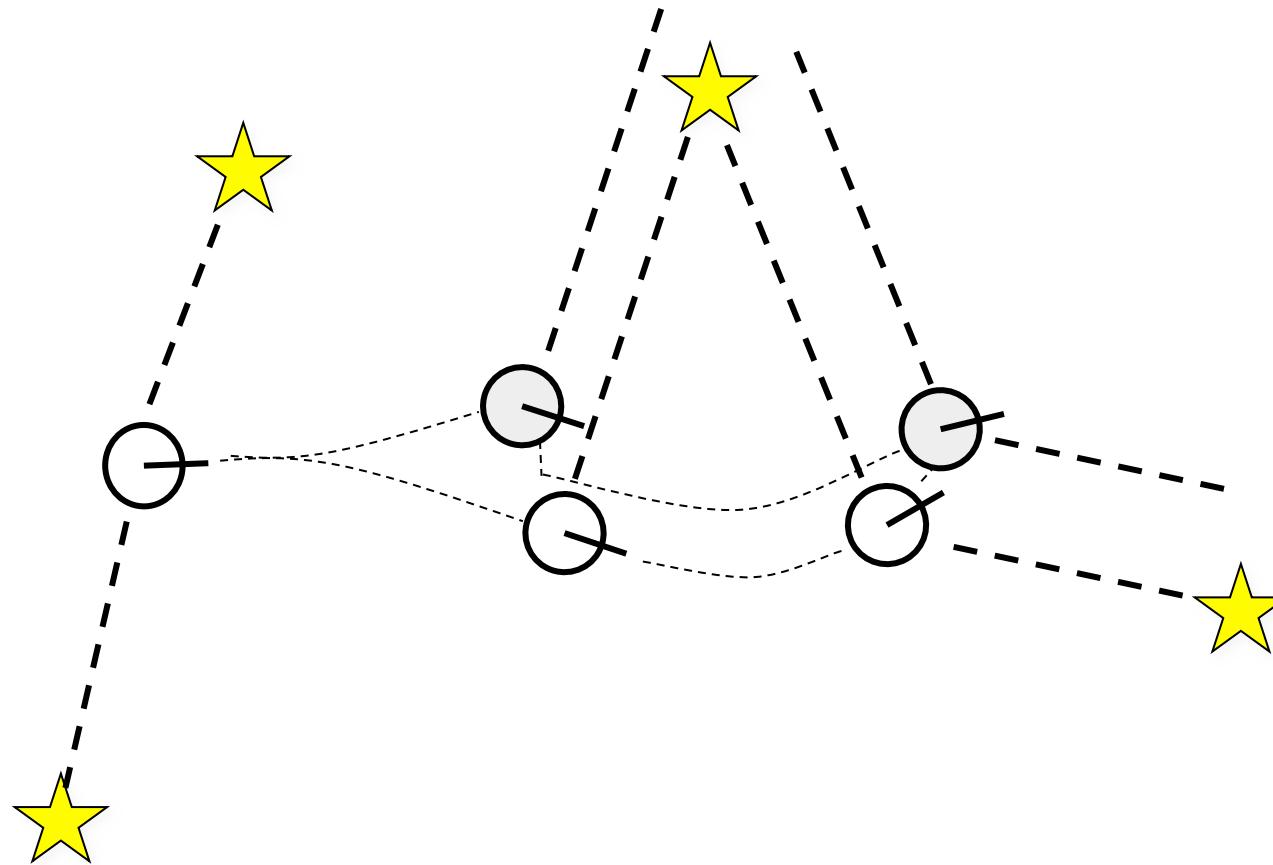
Motion
Planning

What is SLAM?

- Computing the robot's poses and the map of the environment at the same time
- **Localization:** estimating the robot's location
- **Mapping:** building a map
- **SLAM:** building a map and localizing the robot simultaneously

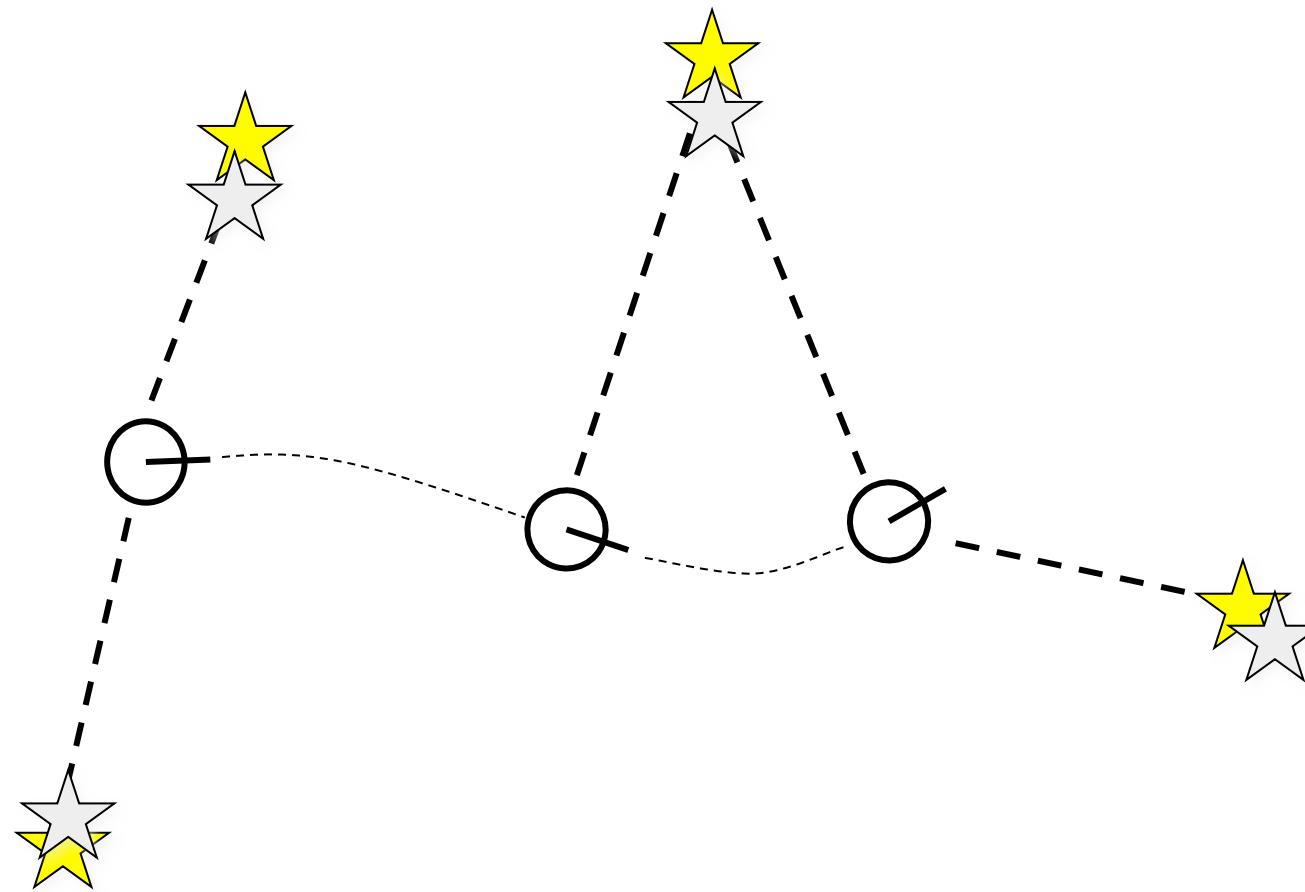
Localization Example

- Estimate the robot's poses given landmarks



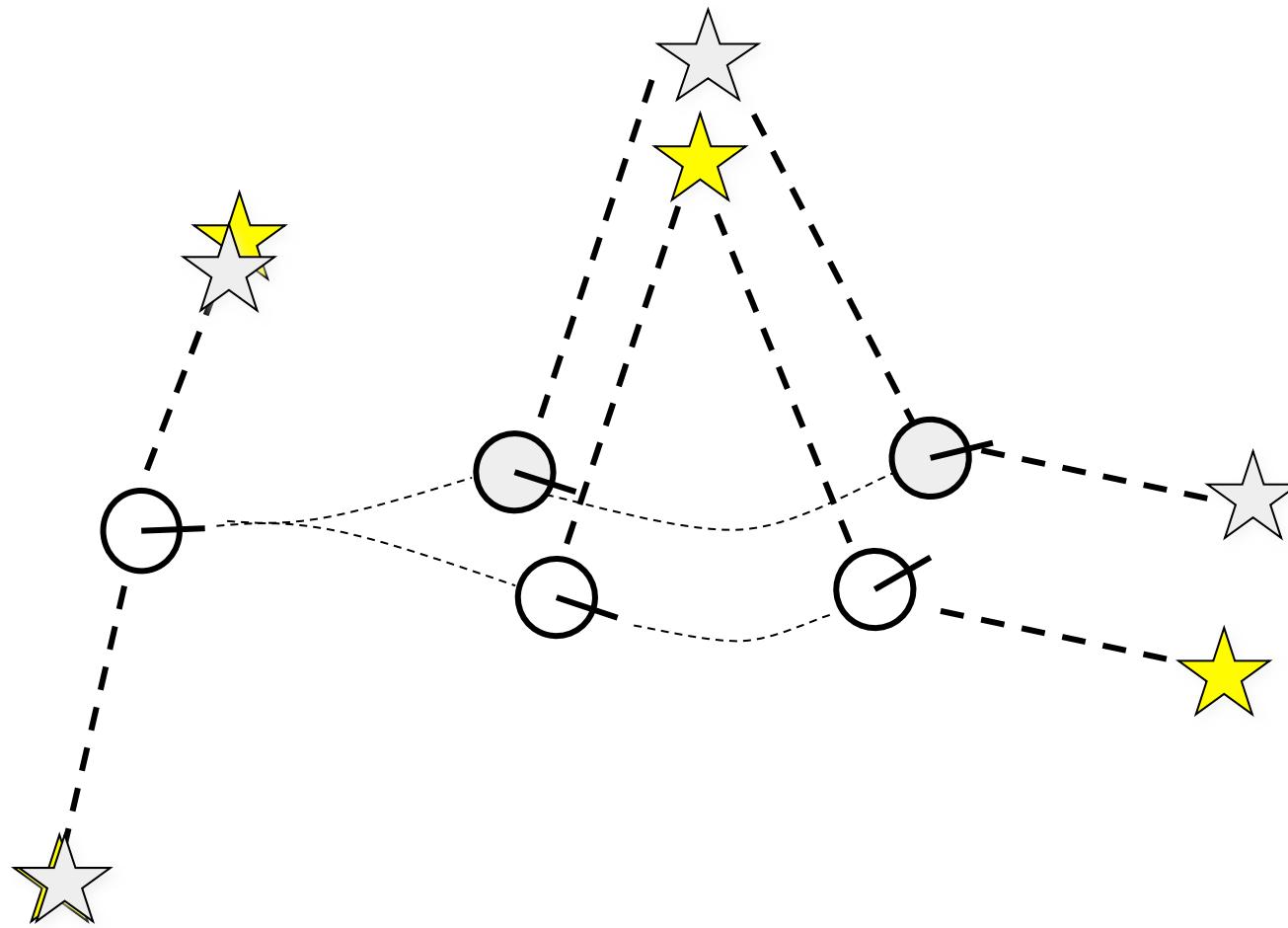
Mapping Example

- Estimate the landmarks given the robot's poses



SLAM Example

- Estimate the robot's poses and the landmarks at the same time



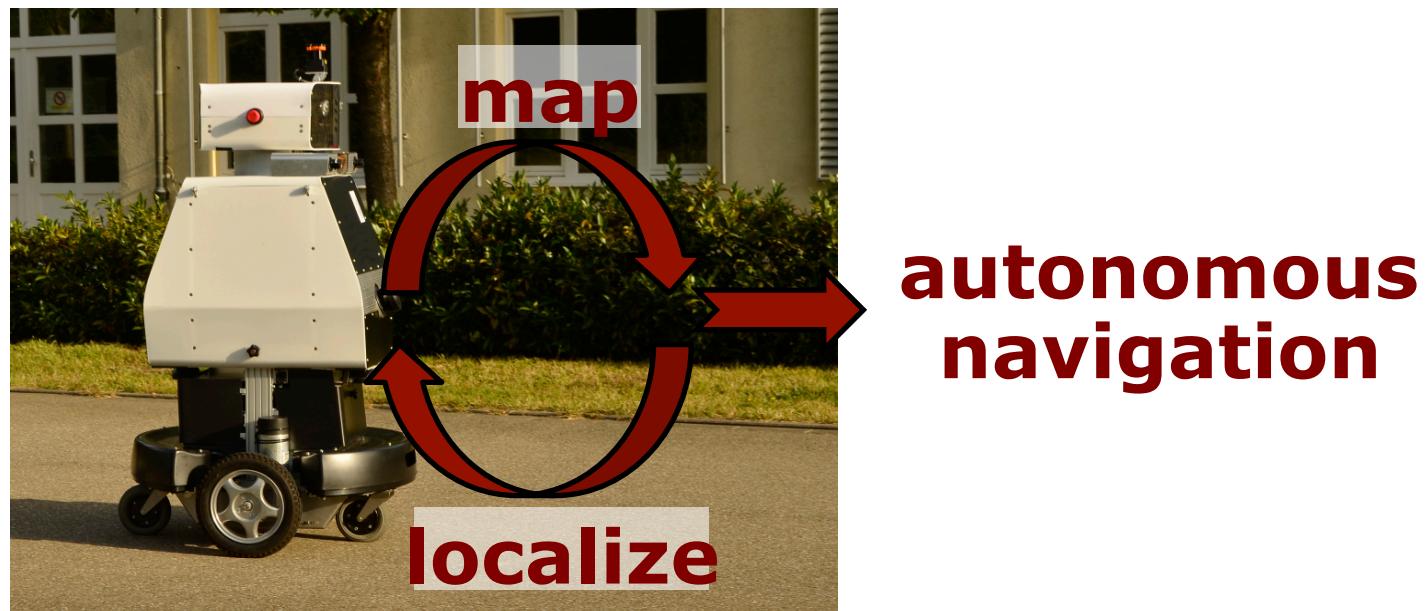
The SLAM Problem

- SLAM is a **chicken-or-egg** problem:
 - a map is needed for localization and
 - a pose estimate is needed for mapping



SLAM is Relevant

- It is considered a fundamental problem for truly autonomous robots
- SLAM is the basis for most navigation systems



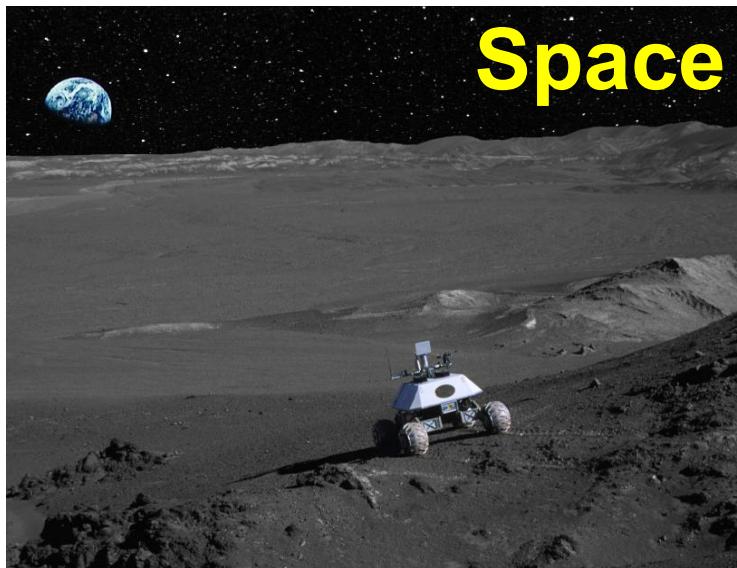
SLAM Applications

- SLAM is central to a range of indoor, outdoor, air and underwater applications for both manned and autonomous vehicles.

Examples:

- At home: vacuum cleaner, lawn mower
- Air: surveillance with unmanned air vehicles
- Underwater: reef monitoring
- Underground: exploration of mines
- Space: terrain mapping for localization

SLAM Applications



Courtesy of Evolution Robotics, H. Durrant-Whyte, NASA, S. Thrun

SLAM Showcase – Mint

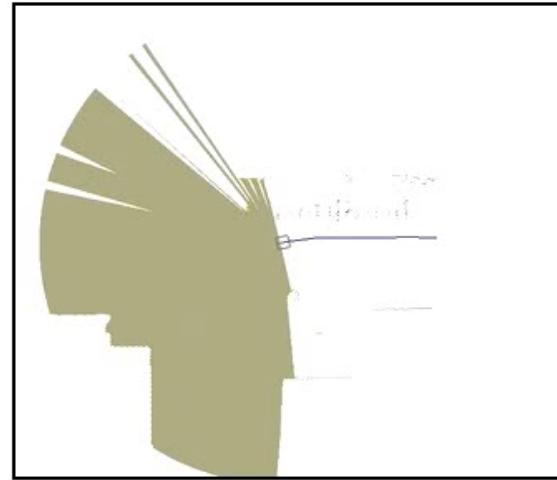


Courtesy of Evolution Robotics (now iRobot)

SLAM Showcase – EUROPA



Mapping Freiburg CS Campus



Definition of the SLAM Problem

Given

- The robot's controls

$$u_{1:T} = \{u_1, u_2, u_3 \dots, u_T\}$$

- Observations

$$z_{1:T} = \{z_1, z_2, z_3 \dots, z_T\}$$

Wanted

- Map of the environment

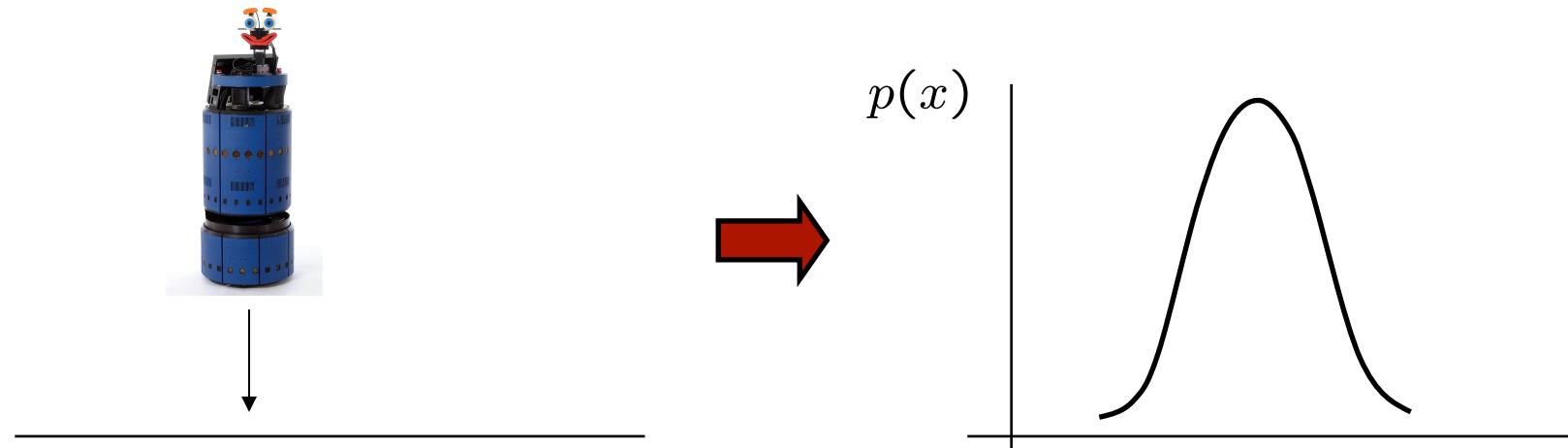
$$m$$

- Path of the robot

$$x_{0:T} = \{x_0, x_1, x_2 \dots, x_T\}$$

Probabilistic Approaches

- Uncertainty in the robot's motions and observations
- Use the probability theory to explicitly represent the uncertainty



“The robot is
exactly here”

“The robot is
somewhere here”

In the Probabilistic World

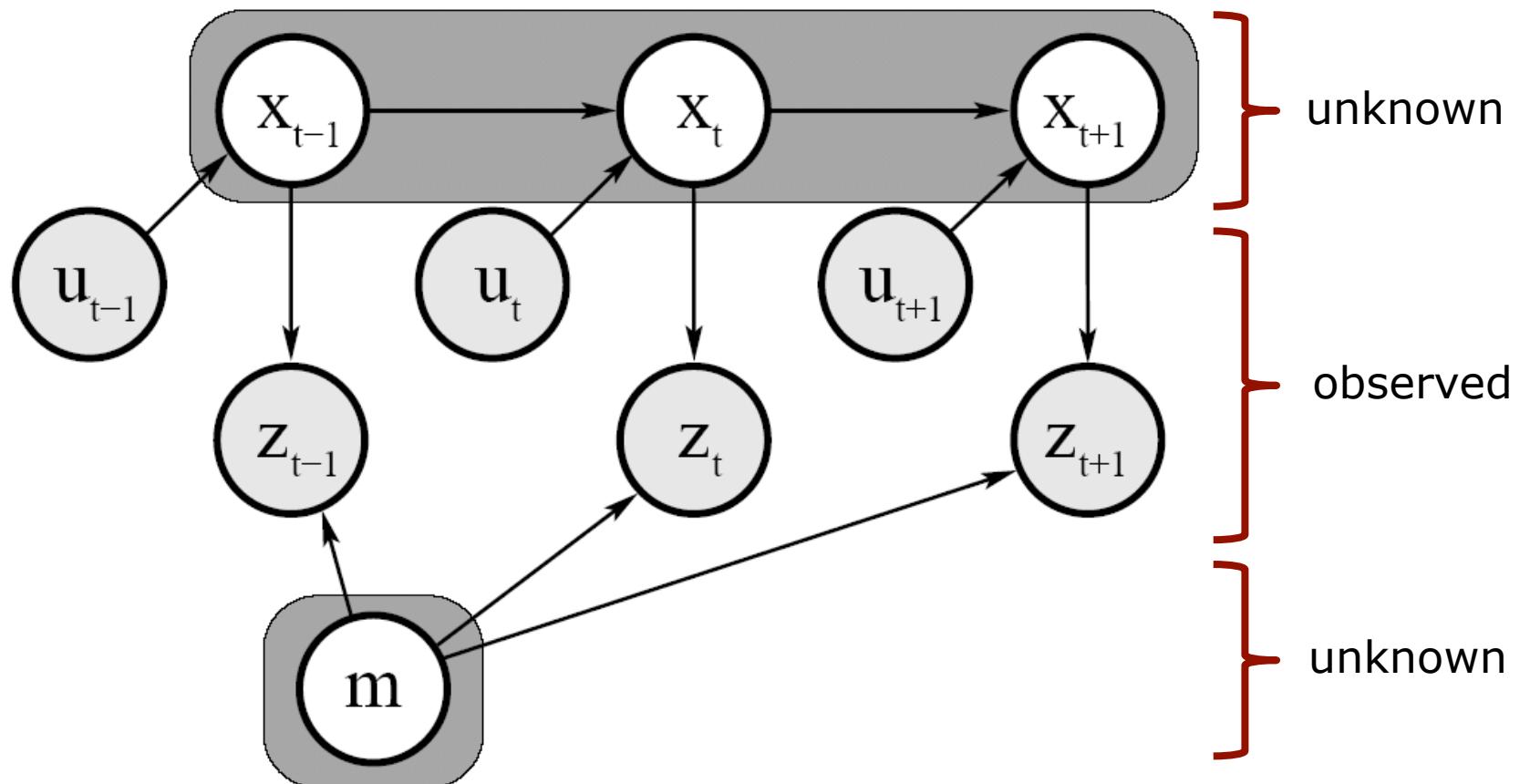
Estimate the robot's path and the map

$$p(x_{0:T}, m \mid z_{1:T}, u_{1:T})$$

distribution path map given observations controls

```
graph TD; A[p(x_{0:T}, m | z_{1:T}, u_{1:T})] --> B[distribution]; A --> C[path]; A --> D[map]; A --> E[given]; A --> F[observations]; A --> G[controls]
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Graphical Model



$$p(x_{0:T}, m \mid z_{1:T}, u_{1:T})$$

Full SLAM vs. Online SLAM

- Full SLAM estimates the entire path

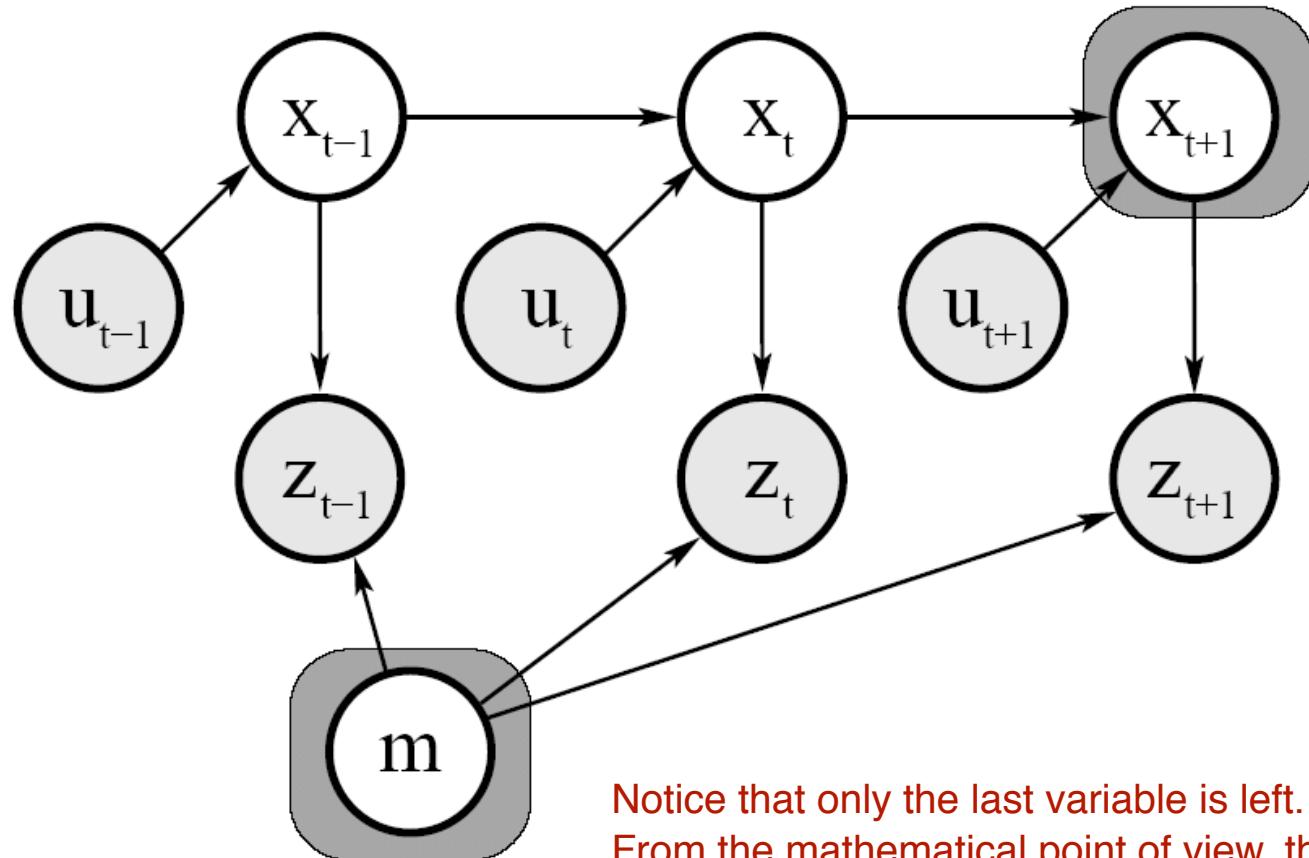
$$p(x_{0:T}, m \mid z_{1:T}, u_{1:T})$$

- Online SLAM seeks to recover only the most recent pose

Don't want to collect all the information and then build a map. I want to do it online, right now.

$$p(x_t, m \mid z_{1:t}, u_{1:t})$$

Graphical Model of Online SLAM



$$p(x_{t+1}, m \mid z_{1:t+1}, u_{1:t+1})$$

Online SLAM

- Online SLAM means marginalizing out the previous poses

$$p(x_t, m \mid z_{1:t}, u_{1:t}) =$$

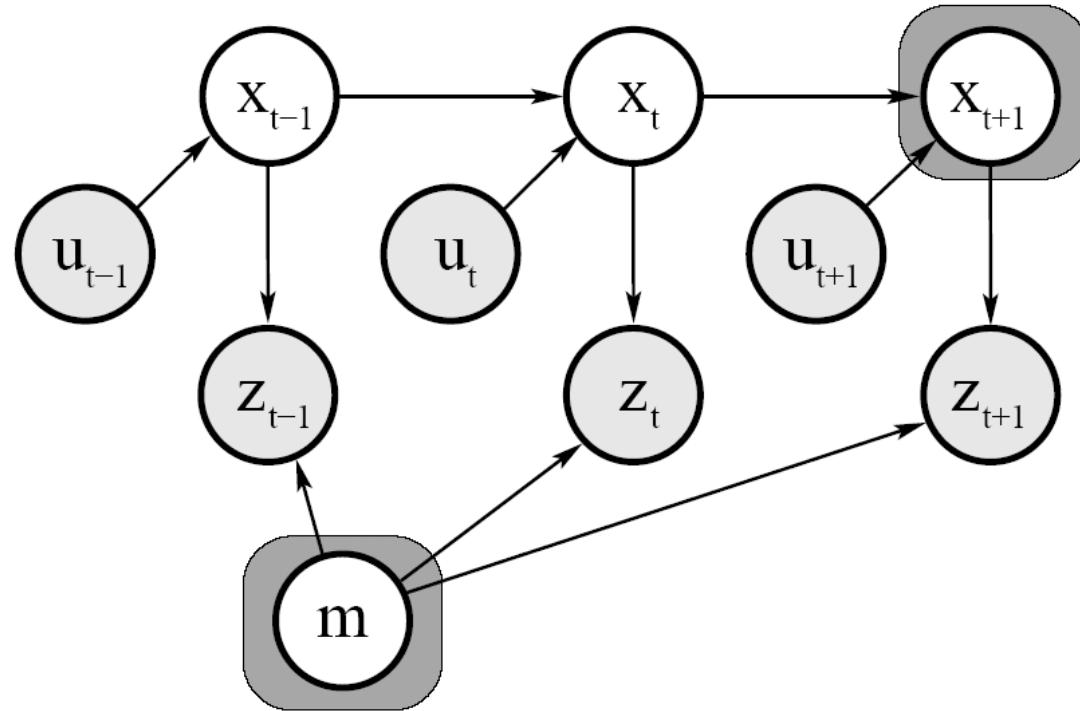
$$\int_{x_0} \dots \int_{x_{t-1}} p(x_{0:t}, m \mid z_{1:t}, u_{1:t}) dx_{t-1} \dots dx_0$$

Works for other joint distributions
 $P(A) = \text{integral over all } B \text{ of } (P(A,B) dB)$

To estimate the position at time t, we need the integral of all the possible locations of x_0 , all the possible locations of x_1, x_2, \dots , of the full SLAM posterior.

- Integrals are typically solved recursively, one at at time

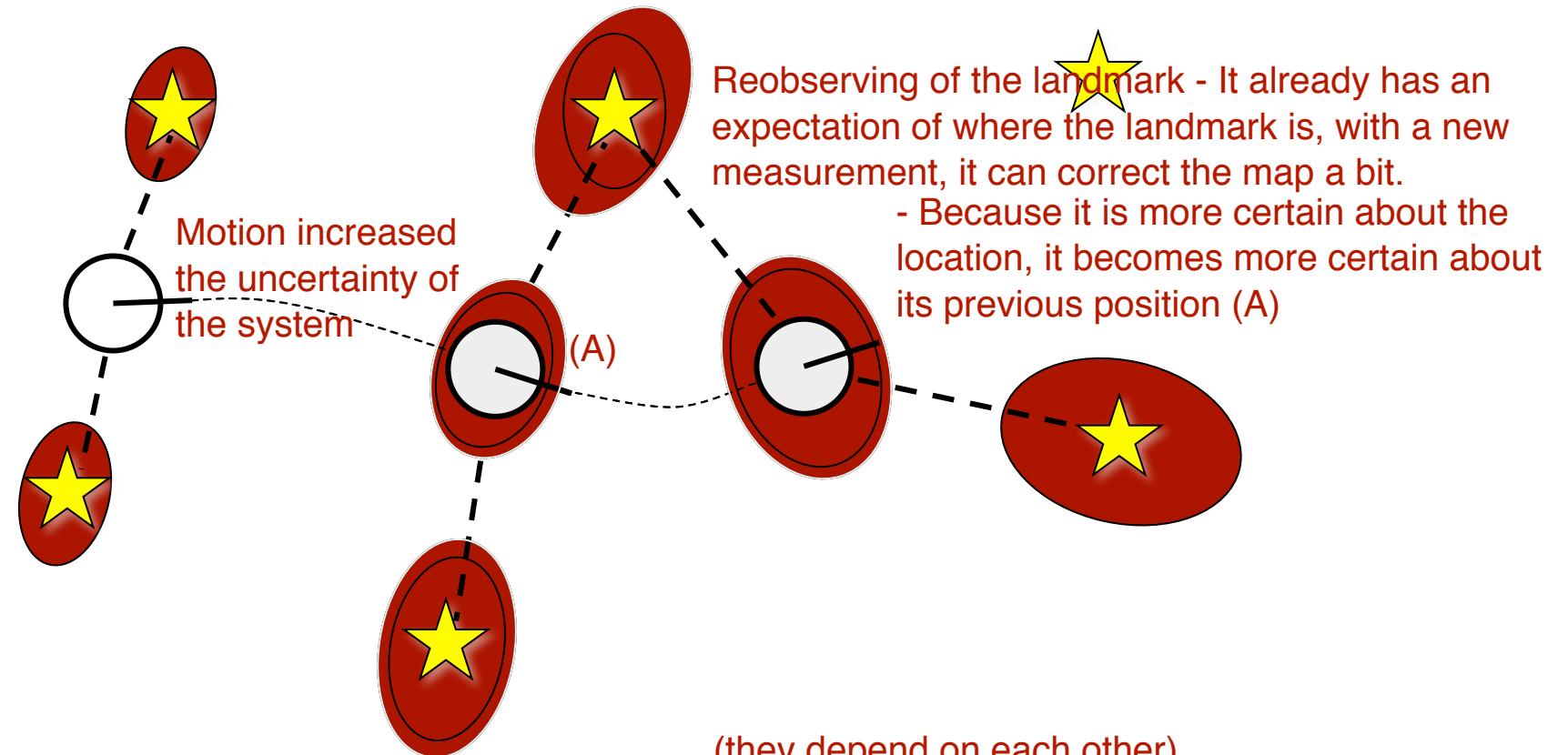
Graphical Model of Online SLAM



$$p(x_{t+1}, m \mid z_{1:t+1}, u_{1:t+1}) = \\ \int_{x_0} \dots \int_{x_t} p(x_{0:t+1}, m \mid z_{1:t+1}, u_{1:t+1}) dx_t \dots dx_0$$

Why is SLAM a Hard Problem?

1. Robot path and map are both **unknown**

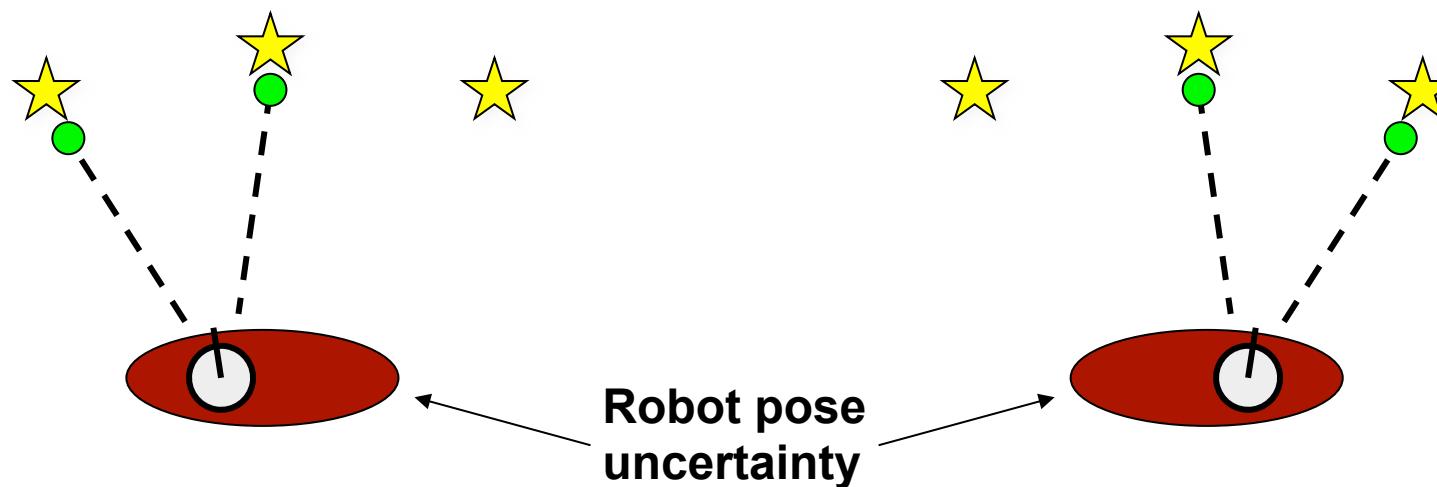


2. Map and pose estimates correlated

Why is SLAM a Hard Problem?

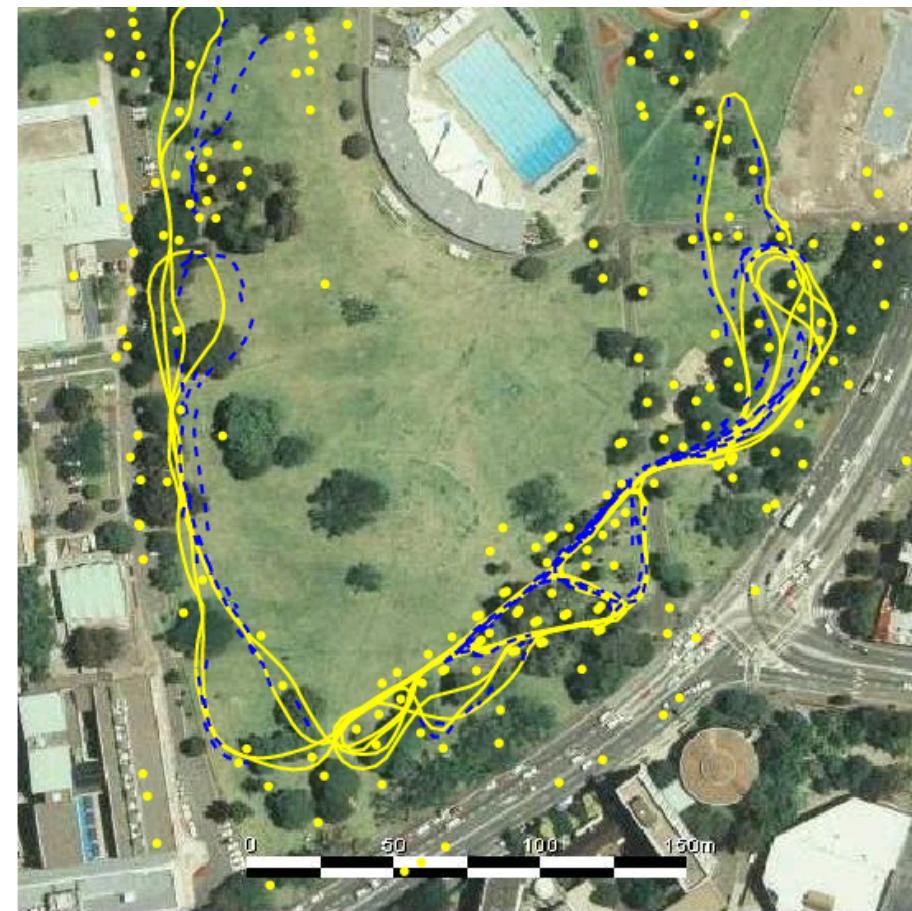
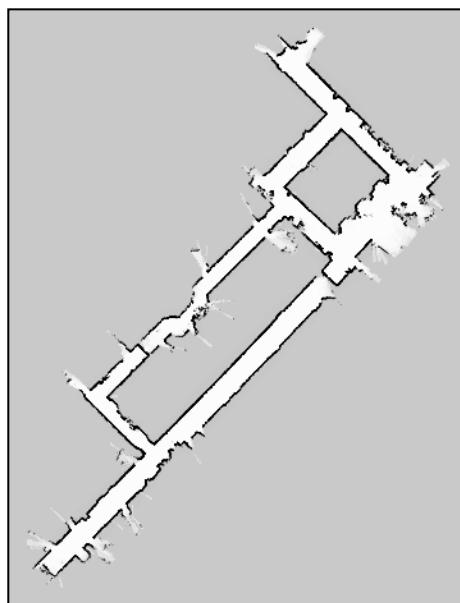
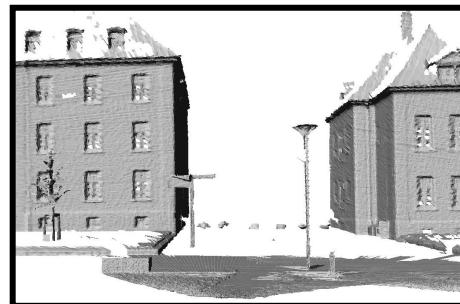
- The **mapping between observations and the map is unknown**
- Picking **wrong** data associations can have **catastrophic** consequences (divergence)

Need to relate what the robot has seen with what it has seen before



Taxonomy of the SLAM Problem

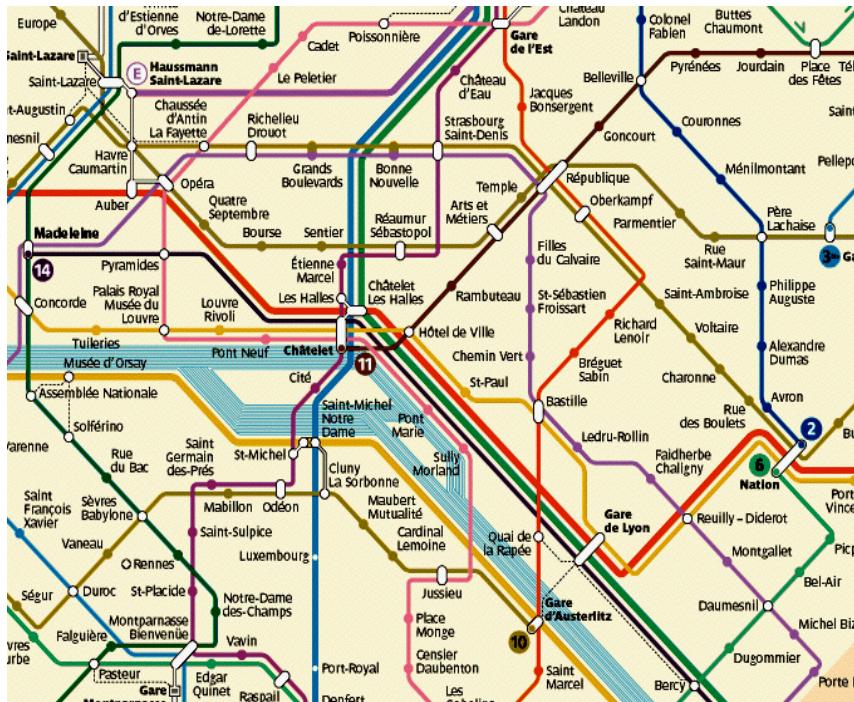
Volumetric vs. feature-based SLAM



Courtesy by E. Nebot

Taxonomy of the SLAM Problem

Topologic vs. geometric maps



Not to scale. Just hold instructions to get from A to B.

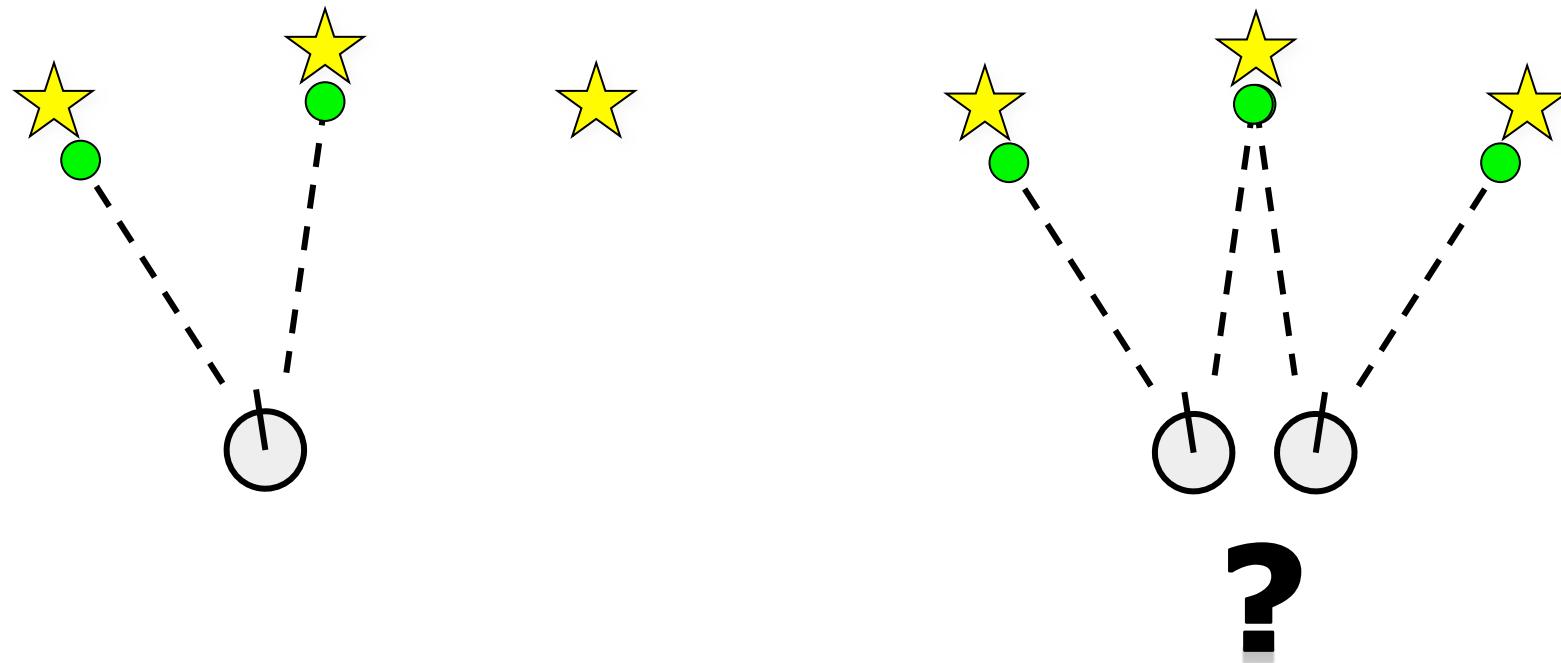
- Might be easier to do A* search etc



More popular

Taxonomy of the SLAM Problem

Known vs. unknown correspondence



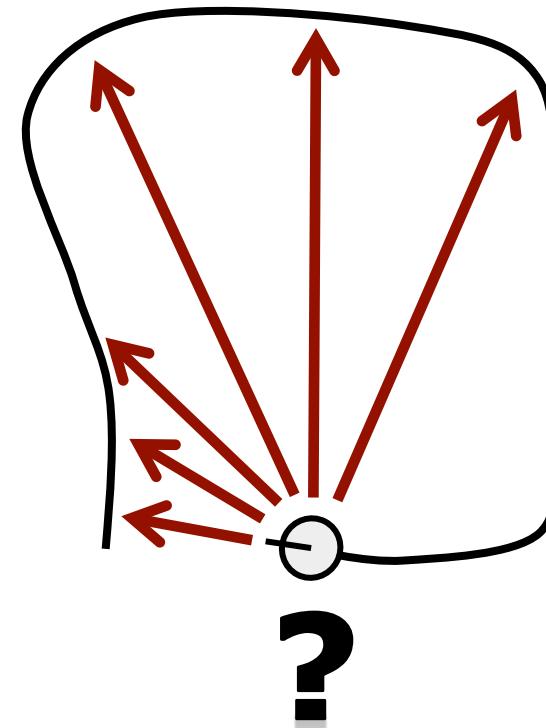
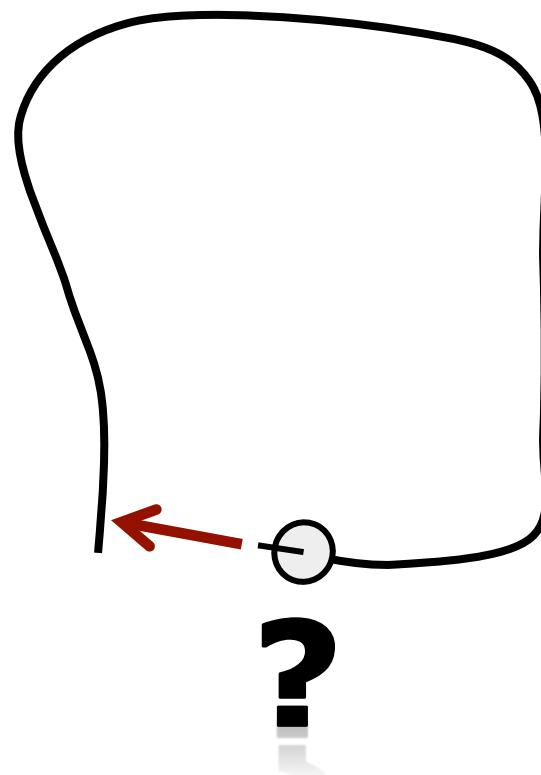
Taxonomy of the SLAM Problem

Static vs. dynamic environments



Taxonomy of the SLAM Problem

Small vs. large uncertainty



Taxonomy of the SLAM Problem

Active vs. passive SLAM

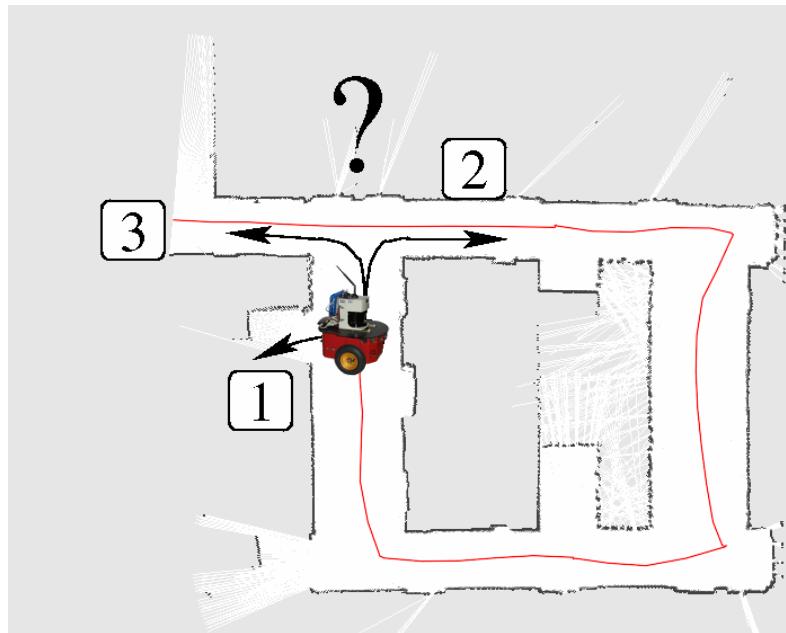


Image courtesy by Petter Duvander

Taxonomy of the SLAM Problem

Any-time and any-space SLAM

You only have this amount of time, what is the best estimate that you can get?

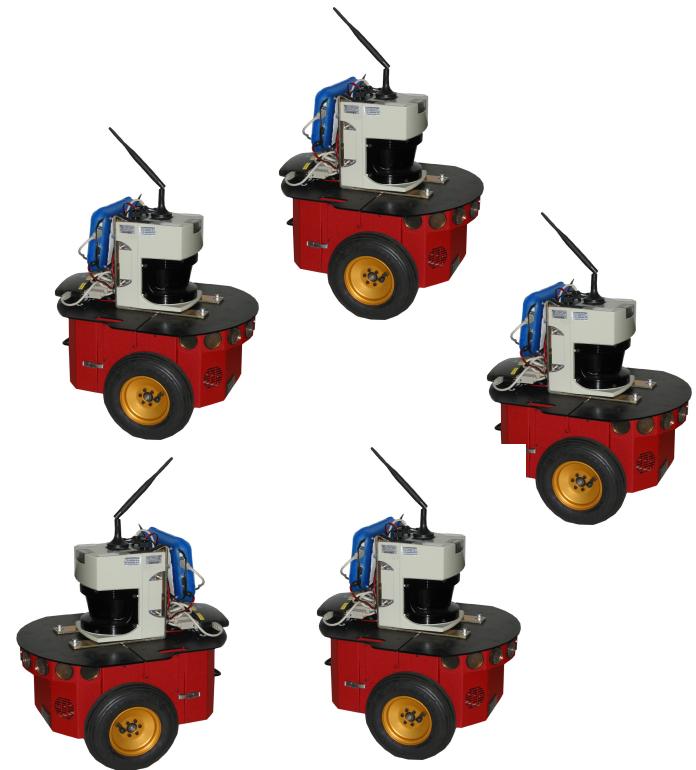
You have limited memory, what are the things that you should remember and the things that you should forget?



Taxonomy of the SLAM Problem

Single-robot vs. multi-robot SLAM

Distinction was clearer many years ago but not so much now.



Approaches to SLAM

- Large variety of different SLAM approaches have been proposed
- Most robotics conferences dedicate multiple tracks to SLAM
- The majority of techniques uses probabilistic concepts
- History of SLAM dates back to the mid-eighties
- Related problems in geodesy and photogrammetry

SLAM History by Durrant-Whyte

- 1985/86: Smith et al. and Durrant-Whyte describe geometric uncertainty and relationships between features or landmarks
- 1986: Discussions at ICRA on how to solve the SLAM problem followed by the key paper by Smith, Self and Cheeseman
- 1990-95: Kalman-filter based approaches
- 1995: SLAM acronym coined at ISRR'95
- 1995-1999: Convergence proofs & first demonstrations of real systems
- 2000: Wide interest in SLAM started

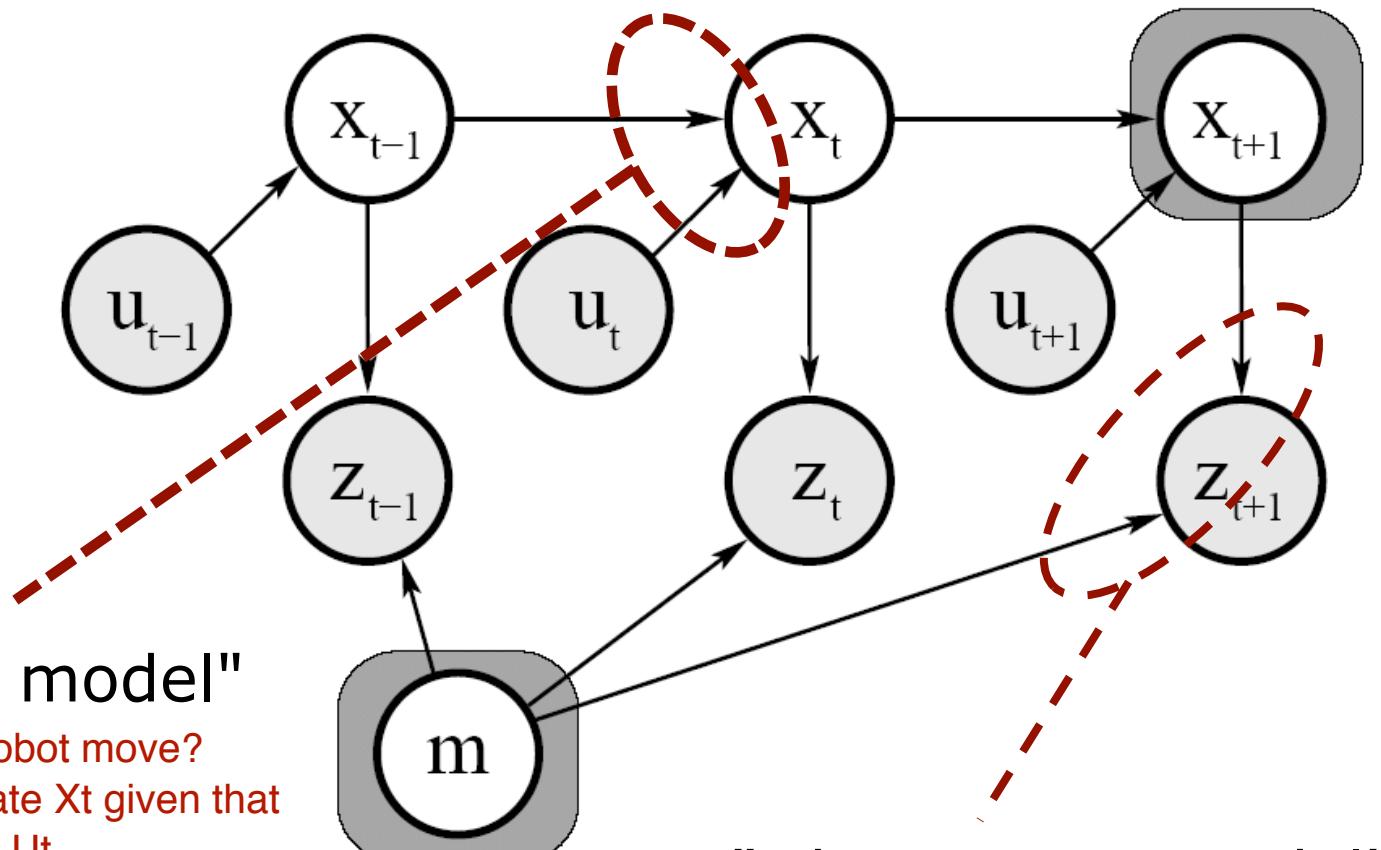
Three Main Paradigms

Kalman
filter

Particle
filter

Graph-
based

Motion and Observation Model



"Motion model"

How does the robot move?
How do I estimate X_t given that
I know X_{t-1} and U_t

"Observation model"

How should I interpret my observation?

Motion Model

- The motion model describes the relative motion of the robot

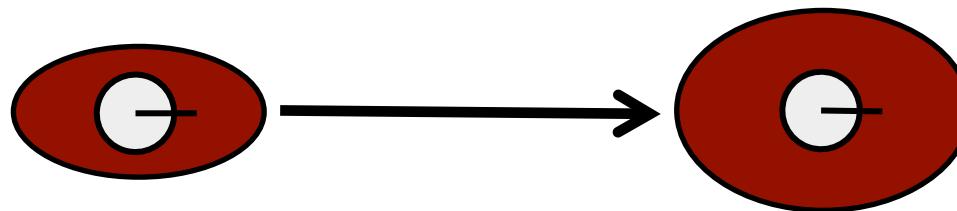
$$p(x_t \mid x_{t-1}, u_t)$$

distribution new pose given old pose control

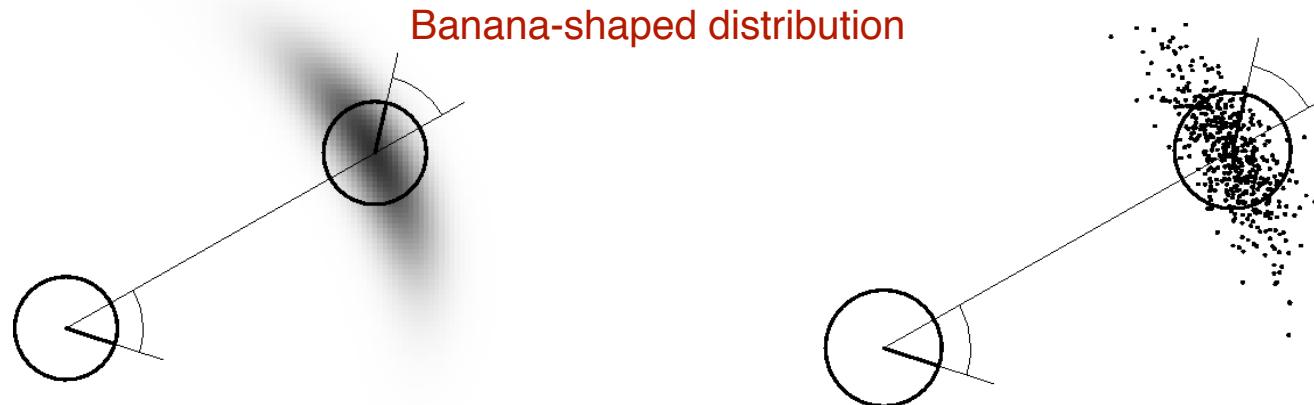
The diagram illustrates the components of a motion model probability distribution. At the top is the mathematical expression $p(x_t \mid x_{t-1}, u_t)$. Below it, five labels are arranged horizontally: "distribution", "new pose", "given", "old pose", and "control". Red arrows point from each label to its corresponding term in the expression: "distribution" points to x_t , "new pose" points to x_{t-1} , "given" points to the vertical bar separating the two arguments, "old pose" points to u_t , and "control" points to the comma separating the arguments.

Motion Model Examples

- Gaussian model



- Non-Gaussian model



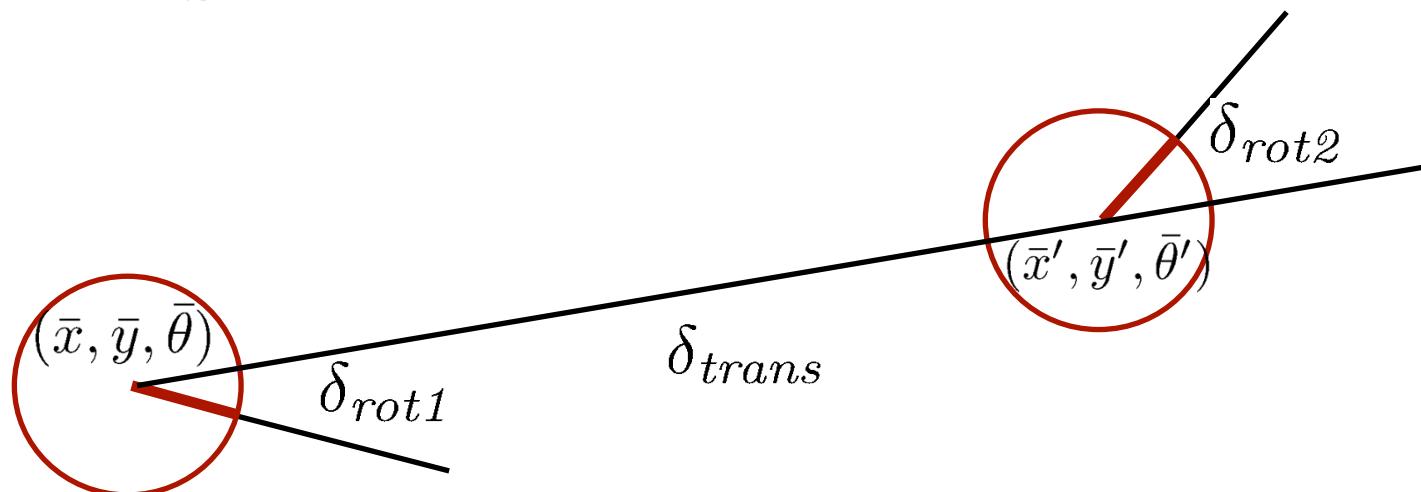
Standard Odometry Model

- Robot moves from $(\bar{x}, \bar{y}, \bar{\theta})$ to $(\bar{x}', \bar{y}', \bar{\theta}')$
- Odometry information $u = (\delta_{rot1}, \delta_{trans}, \delta_{rot2})$

$$\delta_{trans} = \sqrt{(\bar{x}' - \bar{x})^2 + (\bar{y}' - \bar{y})^2}$$

$$\delta_{rot1} = \text{atan2}(\bar{y}' - \bar{y}, \bar{x}' - \bar{x}) - \bar{\theta}$$

$$\delta_{rot2} = \bar{\theta}' - \bar{\theta} - \delta_{rot1}$$



More on Motion Models

- Course: Introduction to Mobile Robotics, Chapter 6
- Thrun et al. “Probabilistic Robotics”, Chapter 5

Observation Model

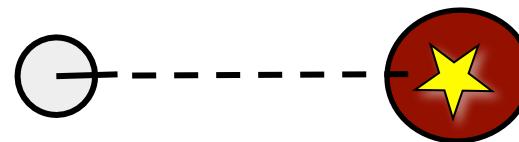
- The observation or sensor model relates measurements with the robot's pose

$$p(z_t | x_t)$$

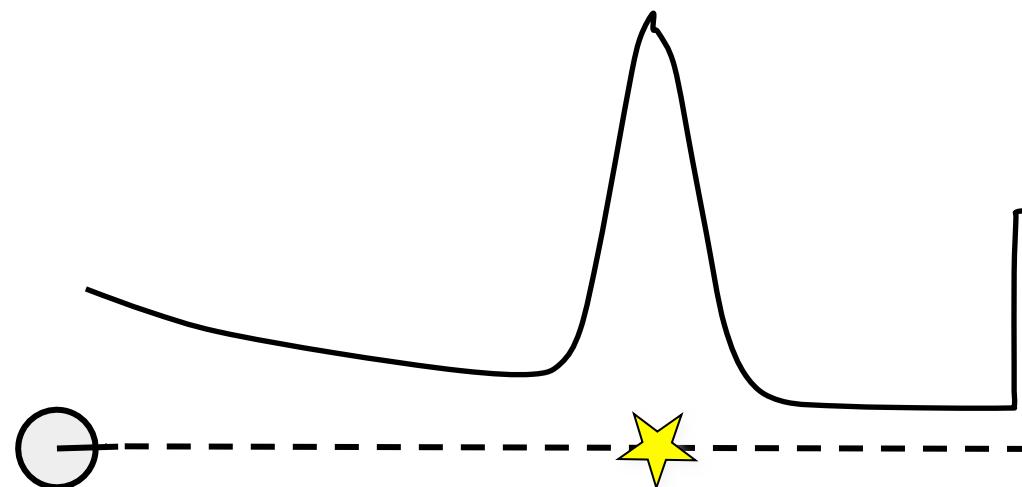
A diagram illustrating the components of the observation model. At the top is the mathematical expression $p(z_t | x_t)$. Below it, four red arrows point upwards from the words "distribution", "observation", "given", and "pose" to the corresponding terms in the expression.

Observation Model Examples

- Gaussian model



- Non-Gaussian model



More on Observation Models

- Course: Introduction to Mobile Robotics, Chapter 7
- Thrun et al. “Probabilistic Robotics”, Chapter 6

Summary

- Mapping is the task of modeling the environment
- Localization means estimating the robot's pose
- SLAM = simultaneous localization and mapping
- Full SLAM vs. Online SLAM
- Rich taxonomy of the SLAM problem

Literature

SLAM overview

- Springer “Handbook on Robotics”, Chapter on Simultaneous Localization and Mapping (subsection 1 & 2)

On motion and observation models

- Thrun et al. “Probabilistic Robotics”, Chapters 5 & 6
- Course: Introduction to Mobile Robotics, Chapters 6 & 7