Cognitive Robotics

01. Introduction

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Acknowledgment

- These slides have been created by Wolfram Burgard, Dieter Fox, Cyrill Stachniss and Maren Bennewitz

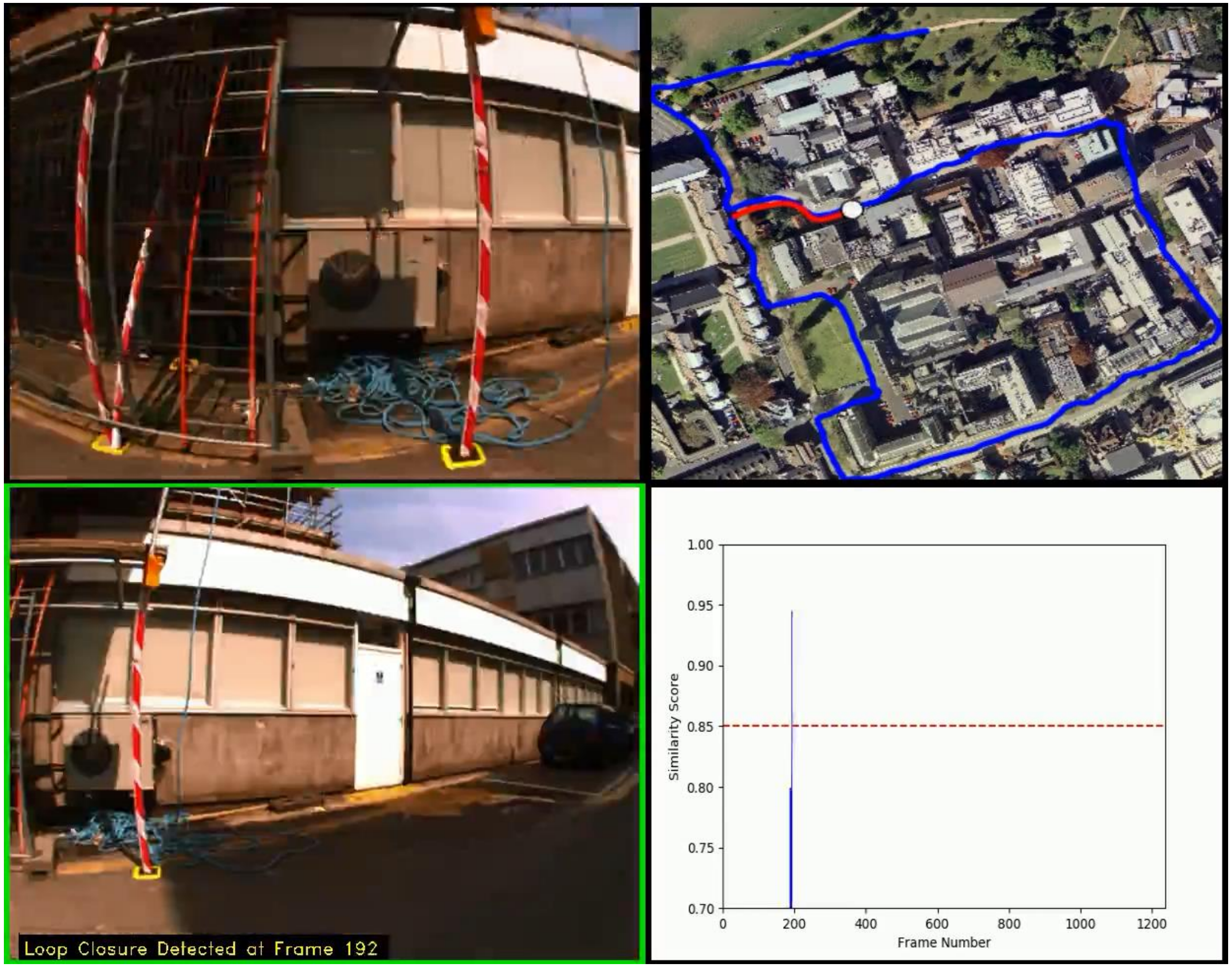
Little bit about me

- Current Affiliation:
  - Cairo University, Faculty of Engineering (Computer Engineering Dept.)

- Ph.D., University of Bonn, Germany

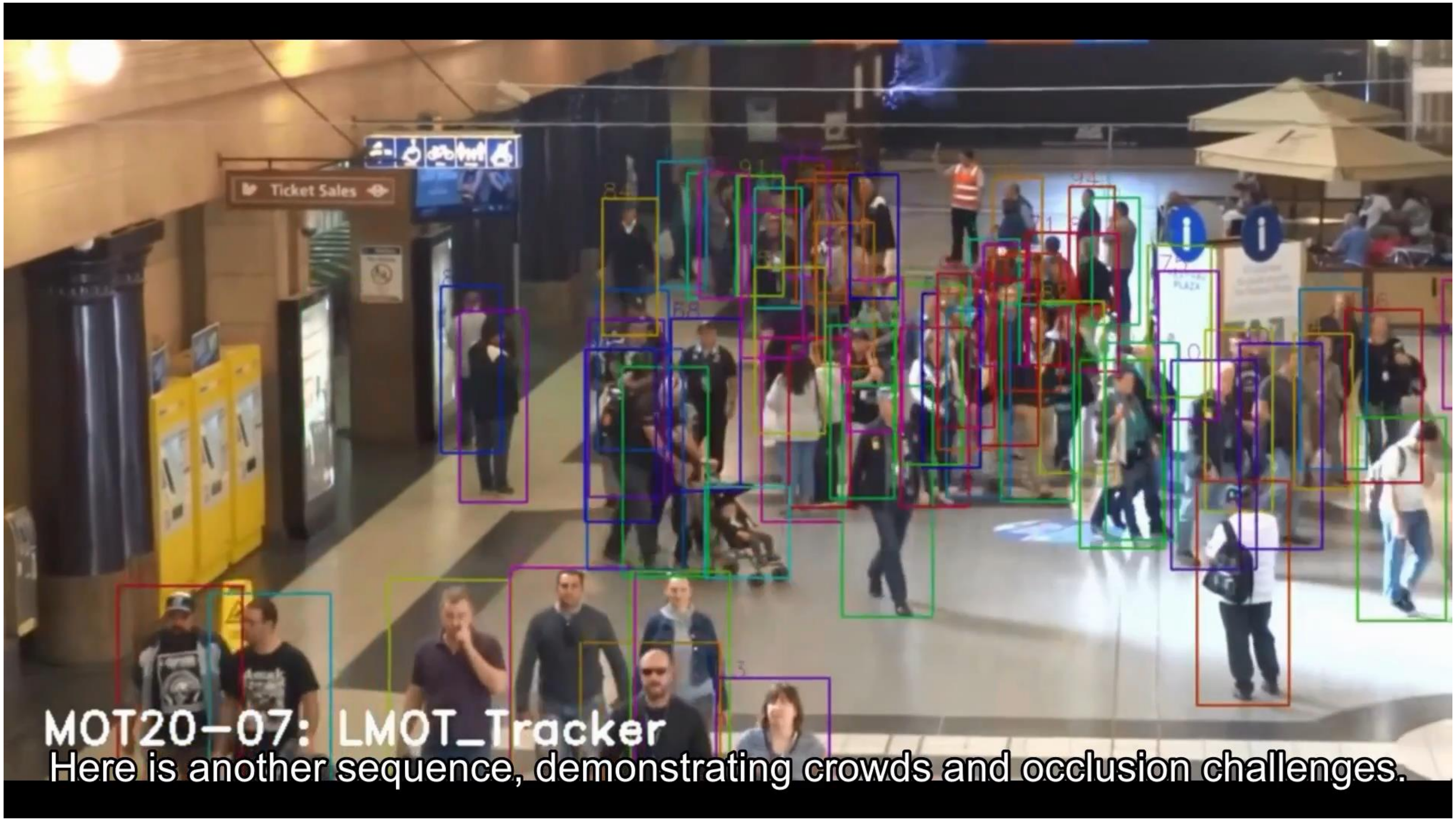
- Research Interests:
  - Deep learning
  - Navigation

Research Interests



[LoopNet: Where to Focus? Detecting Loop Closures in Dynamic Scenes]()
H. Osman, N. Darwish, and A. Bayoumi
In: IEEE Robotics and Automation Letters (RA-L), 2022, presented in ICRA 2022.

Research Interests



[LMOT: Efficient Light-Weight Detection and Tracking in Crowds]
R. Mostafa, H. Baraka, and A. Bayoumi
In: IEEE Access, 2022.

Administrivia

- Contacts:
  - abayoumi@cu.edu.eg
- Grading Policy:
  - Project: 20%
  - Assignments: 10%
  - Midterm: 10%
  - Final Exam: 60% (written & closed book exam)
- Slides: https://shorturl.at/hoGQ4

Administrivia

- Contacts:
  - abayoumi@cu.edu.eg
- Grading Policy:
  - Project: 15%
  - Assignments: 5%
  - Midterm: 10%
  - Final Exam: 70% (written & closed book exam)

Content of This Course

- Probabilities and Bayes
- The Kalman Filter
- The Extended Kalman Filter
- Probabilistic Motion Models
- Probabilistic Sensor Models
- Discrete Filters
- The Particle Filter, Monte Carlo Localization
- Mapping with Known Poses
- SLAM: Simultaneous Localization and Mapping
- SLAM: Landmark-based FastSLAM
- SLAM: Grid-based FastSLAM
- Path Planning and Collision Avoidance

Traditional Robotics

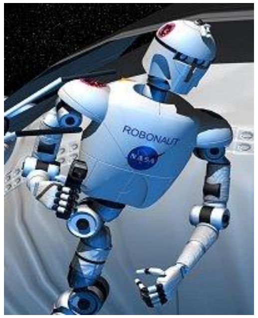
- Controlled environment
- Well understood
- Millions of robots in mass production
- Not covered in this lecture

New Application Domains

- Flexible automation
- Mining, agriculture,…
- Logistics
- Household
- Medicine
- Dangerous environments (Space, under water, nuclear power plants, …)
- Toys, entertainment







Cognitive Robotics

- Have cognitive functions normally associated with people or animals
- Interpret various kinds of sensor data
- Act purposefully and autonomously towards achieving goals
- Operate in dynamic real-life environments
- Exhibit a high degree of robustness in coping with unpredictable situations
- Key challenges
  - Systematic treatment of uncertainties
  - Perceiving the environmental state
  - Coordination of teams of collaborative robots in dynamic environments
  - ….

Tour Guide Robot Minerva (CMU + Univ. Bonn, 1998)

Autonomous Vacuum Cleaners

new improved version with mapping capabilities
and better cleaning strategies

Autonomous Lawn Mowers

not many cognitive capabilities required

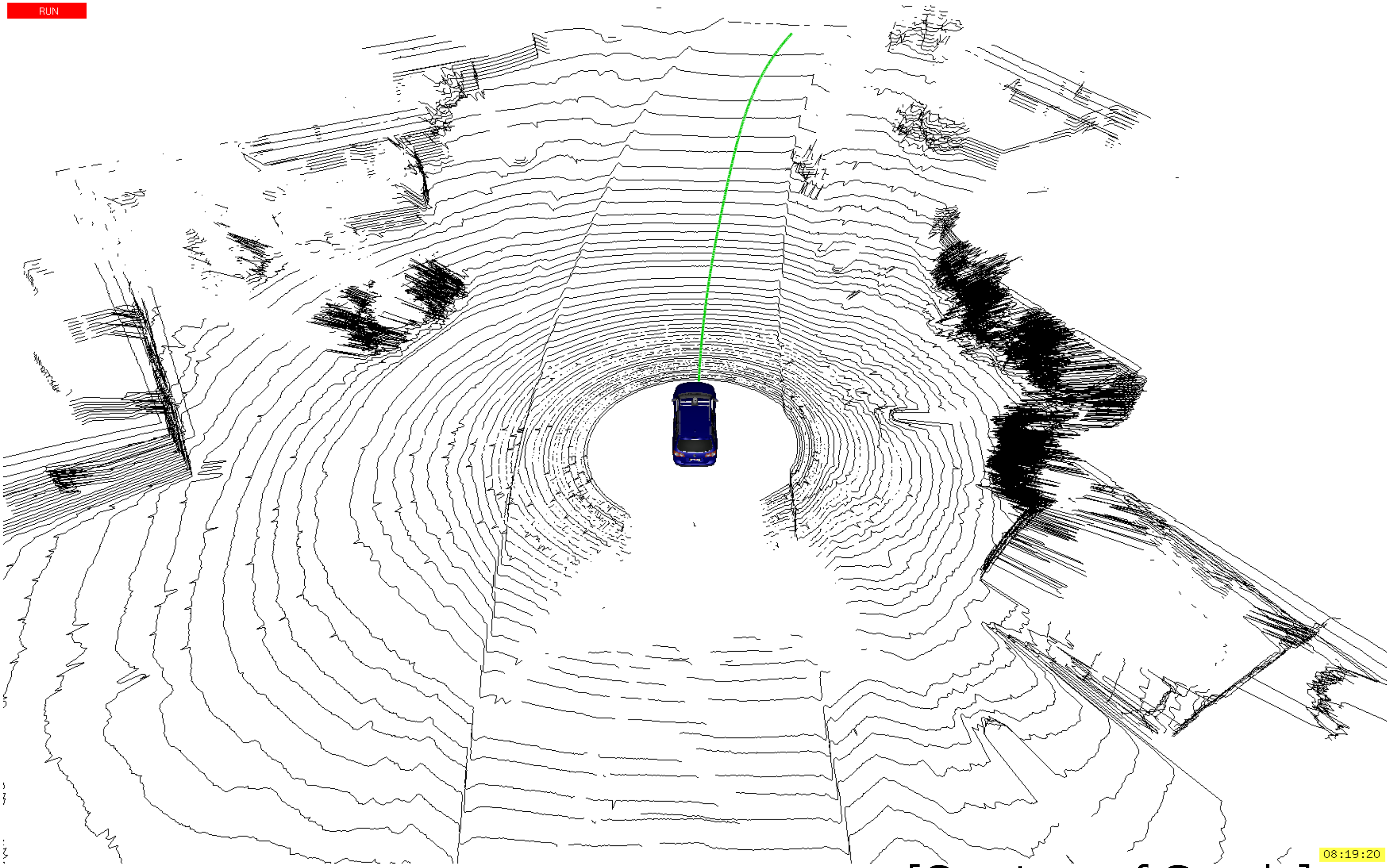
DARPA Grand Challenge 2005

[Courtesy of Sebastian Thrun]

The Google Self-Driving Car

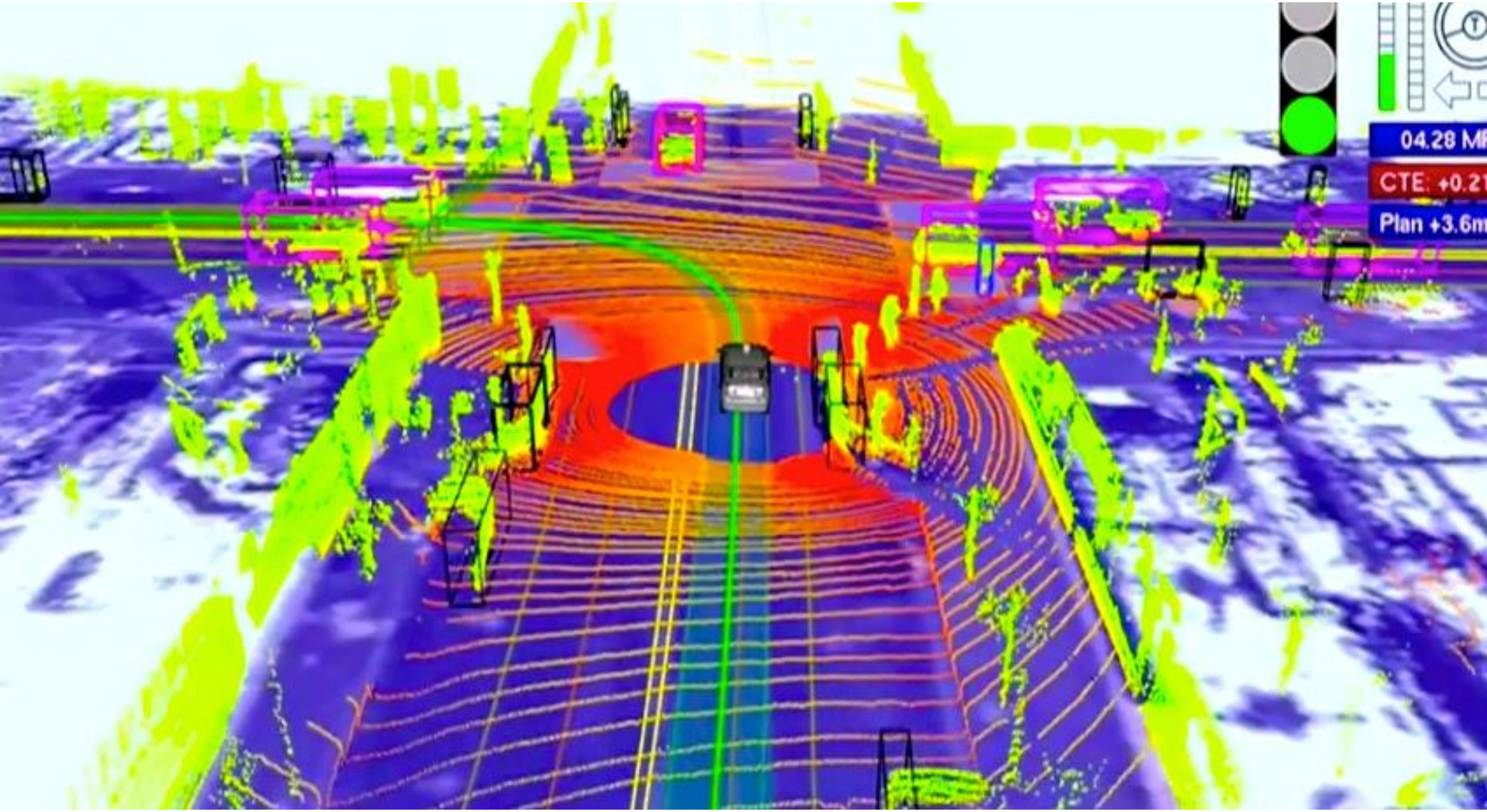
[Courtesy of Google]

The Google Self-Driving Car



[Courtesy of Google]

The Google Self-Driving Car



[Courtesy of Google]

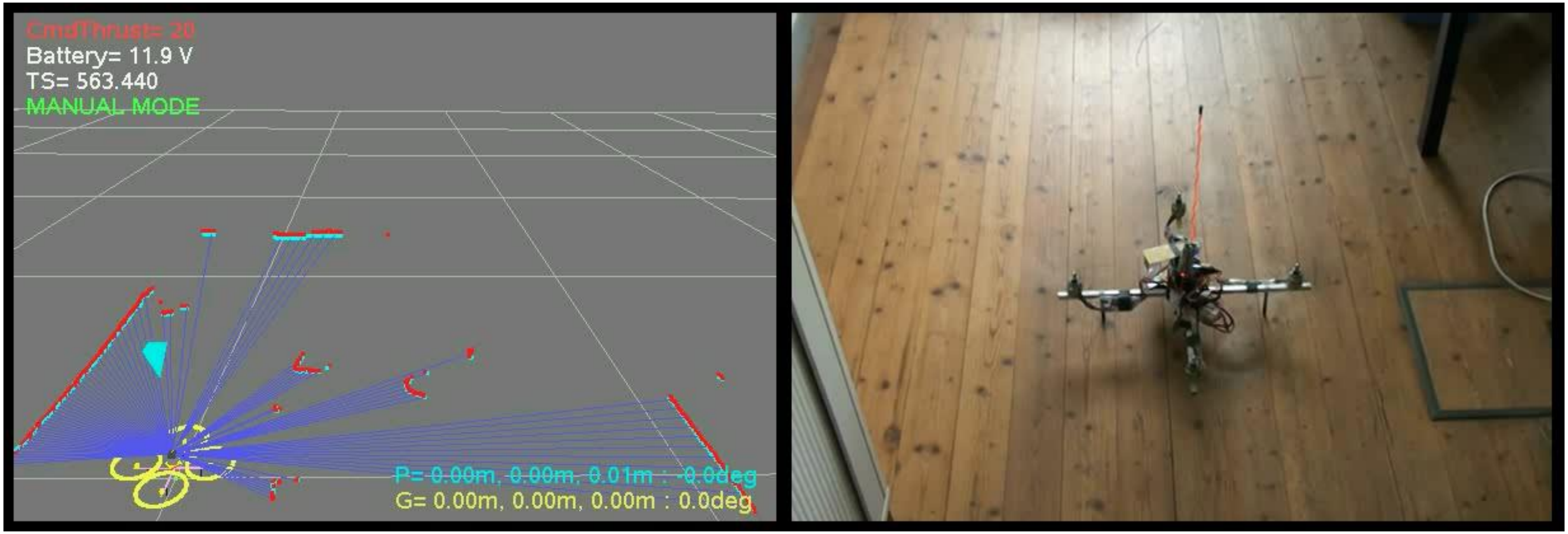
Driving in the Google Car

[Courtesy of Google]

Obelix Experiment: Uni Freiburg

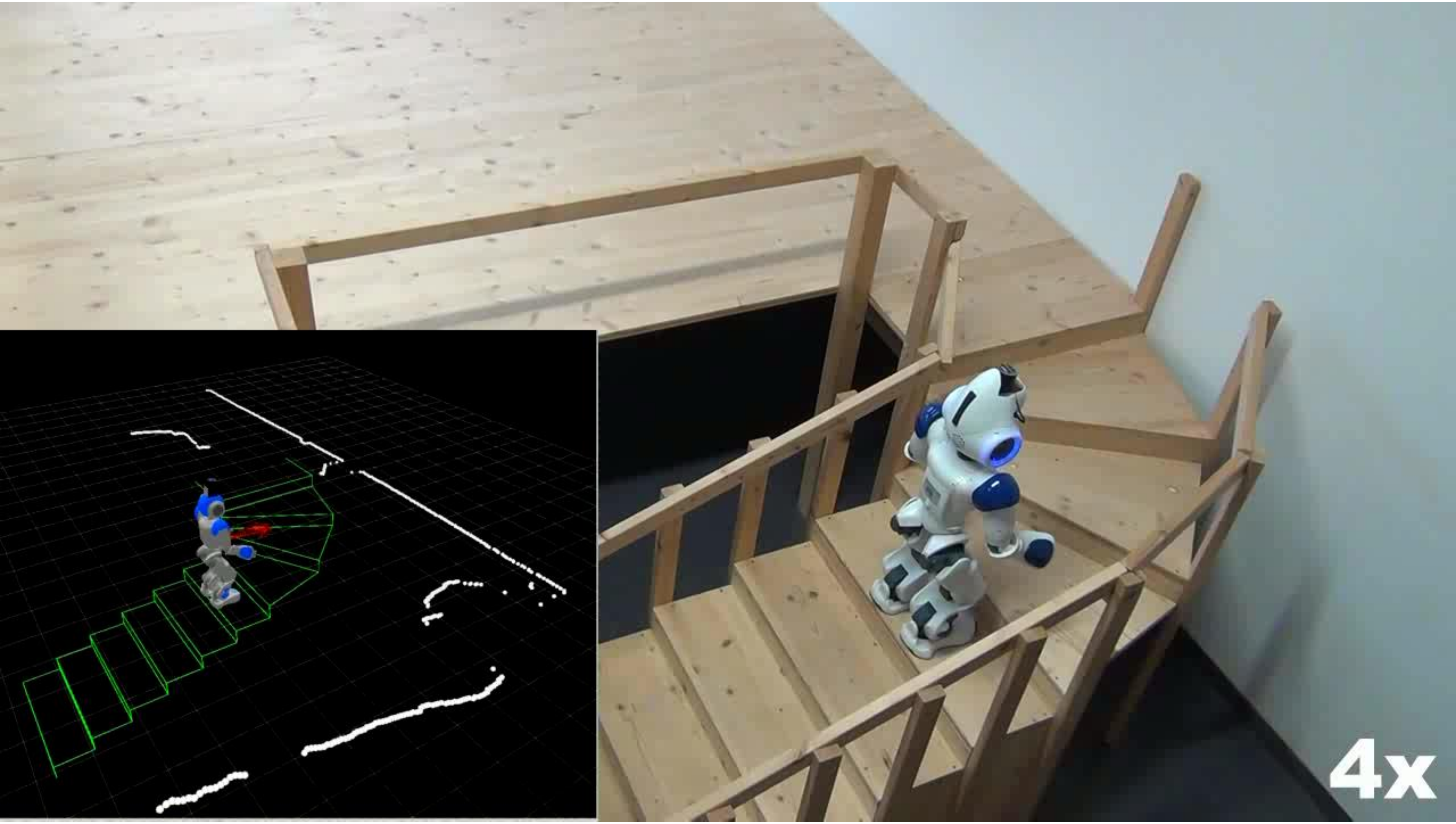
[Courtesy of AIS, Freiburg]

Autonomous Quadrotor Navigation



[Courtesy of AIS, Freiburg]

Stair Climbing (HRL)



Interaction, Object Grasping

[Courtesy of T. Asfour etl al.]

Towel Folding

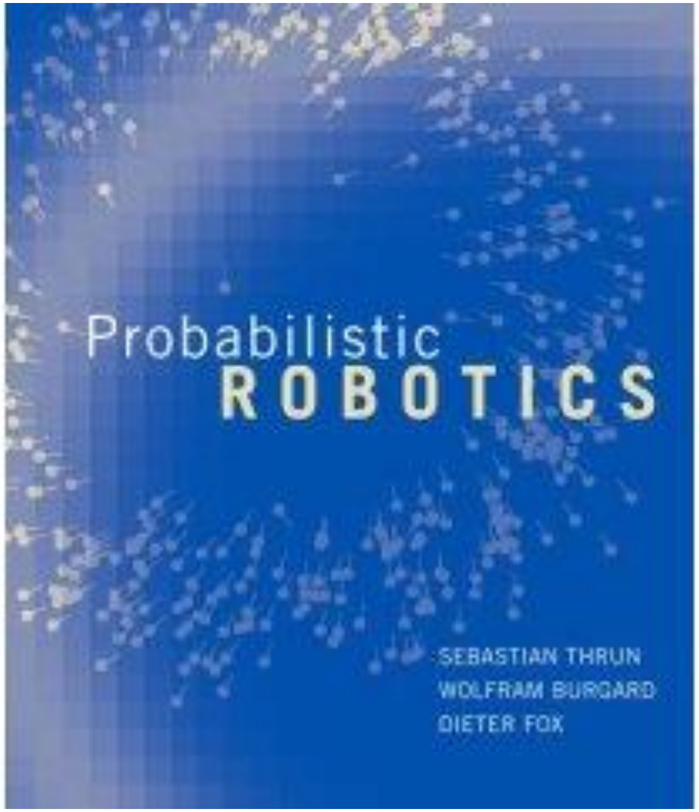
[Courtesy of P. Abbeel et al.]

Cognitive Robot Cosero
AIS Lab Uni Bonn (Sven Behnke)

- Manipulation tasks in domestic environments
- Human-robot interaction

Probabilistic Robotics

- Authors:
  - Sebastian Thrun
  - Wolfram Burgard
  - Dieter Fox
- MIT Press, 2005



http://www.probabilistic-robotics.org

Probabilistic Robotics
Key Idea

- **Explicit representation of uncertainty**
- Using the calculus of probability theory
- Perception = state estimation
- Action = utility optimization

Axioms of Probability Theory

- P*(A)* denotes the probability that proposition *A* is true

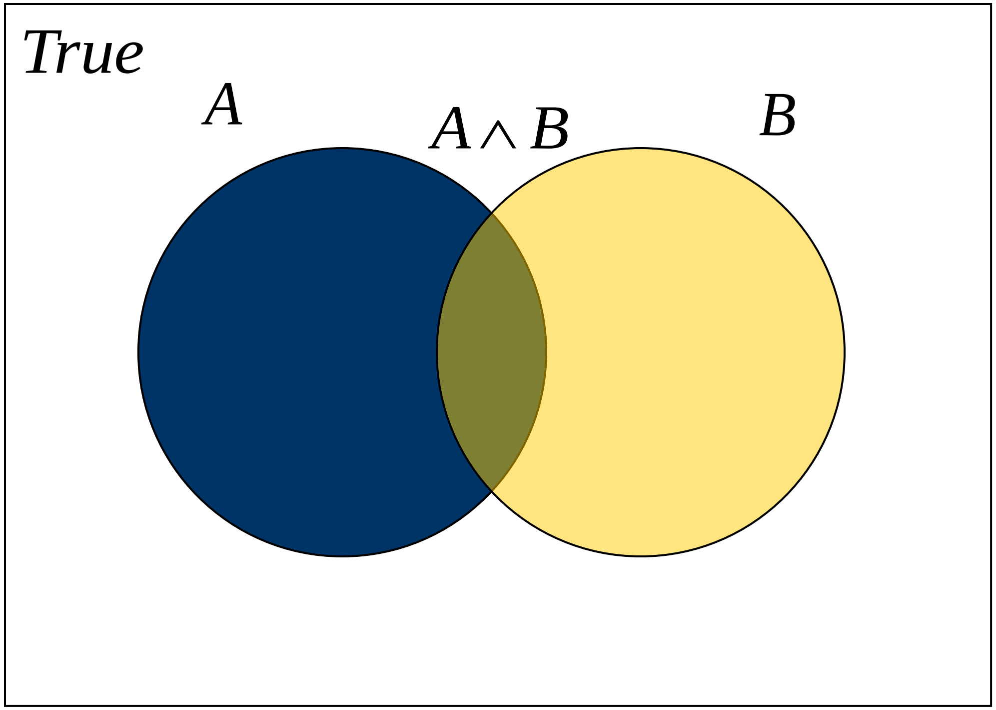
- $0 \pounds \mathrm{P}(A) \pounds 1$

- $\mathrm{P}(True) = 1 \qquad \mathrm{P}(False) = 0$

- $P(A \cup B) = P(A) + P(B) - P(A \cap B)$

A Closer Look at Axiom 3

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$



Using the Axioms

$$\begin{aligned}
P(A \cup \neg A) &= P(A) + P(\neg A) - P(A \cap \neg A) \\
P(True) &= P(A) + P(\neg A) - P(False) \\
1 &= P(A) + P(\neg A) - 0 \\
P(A) &= 1 - P(\neg A)
\end{aligned}$$

Discrete Random Variables

- X denotes a random variable
- X can take on a countable number of values in $\{x_1, x_2, \ldots, x_n\}$
- $P(X=x_i)$ or $P(x_i)$ is the probability that the random variable X takes on value x_i
- $P(\cdot)$ is called probability mass function
- For example:

$$P(Room) = \langle 0.7, 0.2, 0.08, 0.02 \rangle$$

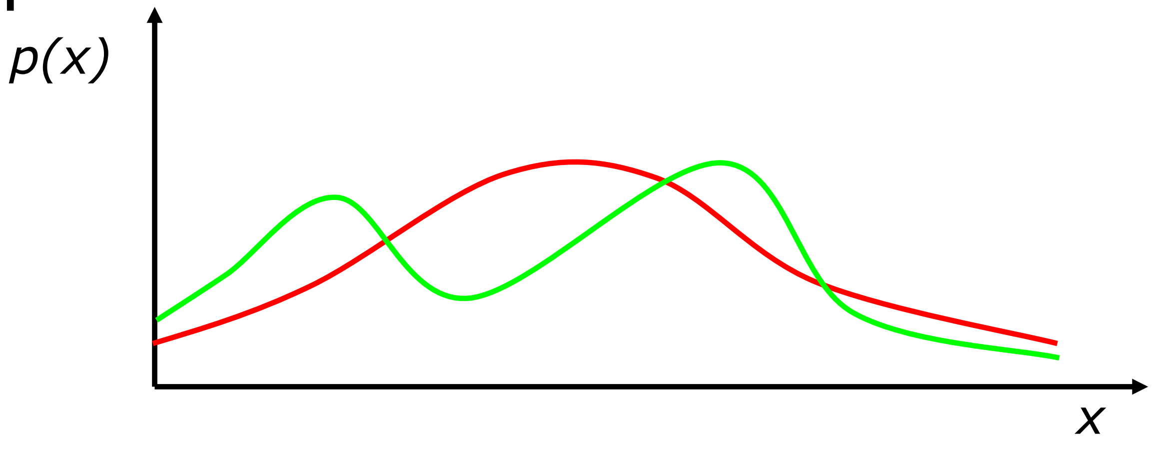
office, lecture hall, seminar room, kitchen

Continuous Random Variables

- X takes on values in the continuum
- $p(X=x)$ or $p(x)$ is a probability density function

$$P(x \in [a,b]) = \int_a^b p(x)dx$$

- For example:



The Probability Sums up to One

Discrete case

$$\sum_x P(x) = 1$$

Continuous case

$$\int p(x)dx = 1$$

Joint and Conditional Probability

- $P(X{=}x$ and $Y{=}y) = P(x,y)$
- If X and Y are independent then

$$P(x,y) = P(x)\,P(y)$$

- $P(x \mid y)$ is the probability of x given y

$$P(x \mid y) = P(x,y) \,/\, P(y) \quad \text{conditional probability}$$

$$P(x,y) \quad = P(x \mid y)\,P(y) \quad \text{product rule}$$

- If X and Y are independent then

$$P(x \mid y) = P(x)$$

Law of Total Probability

Discrete case

$$P(x) = \sum_y P(x \mid y) P(y)$$

Continuous case

$$p(x) = \int p(x \mid y)\, p(y)\, dy$$

Marginalization

Discrete case

$$P(x) = \sum_y P(x, y)$$

Continuous case

$$p(x) = \int p(x, y) dy$$

Bayes' Rule

$$P(x,y) = P(x \mid y)P(y) = P(y \mid x)P(x)$$

$$\Rightarrow$$

$$\boxed{P(x \mid y) = \frac{P(y \mid x)P(x)}{P(y)} = \frac{\text{likelihood} \cdot \text{prior}}{\text{evidence}}}$$

posterior

Normalization

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

$$= \eta \; P(y|x)P(x)$$

$$\eta = P(y)^{-1} = \frac{1}{\sum_z P(y|z)\,P(z)}$$

Algorithm:

$$\forall x : \text{aux}_{x|y} = P(y \mid x)P(x)$$

// compute
// unnormalized posterior

$$\eta = \frac{1}{\sum_x \text{aux}_{x|y}}$$

// compute
// normalization factor

$$\forall x : P(x \mid y) = \eta \, \text{aux}_{x|y}$$

// normalize posterior

Bayes' Rule with Background Knowledge

$$P(x \mid y, z) = \frac{P(y \mid x, z)\, P(x \mid z)}{P(y \mid z)}$$

Conditional Independence

$$P(x, y \mid z) = P(x \mid z) P(y \mid z)$$

Equivalent to $P(x \mid z) = P(x \mid z, y)$

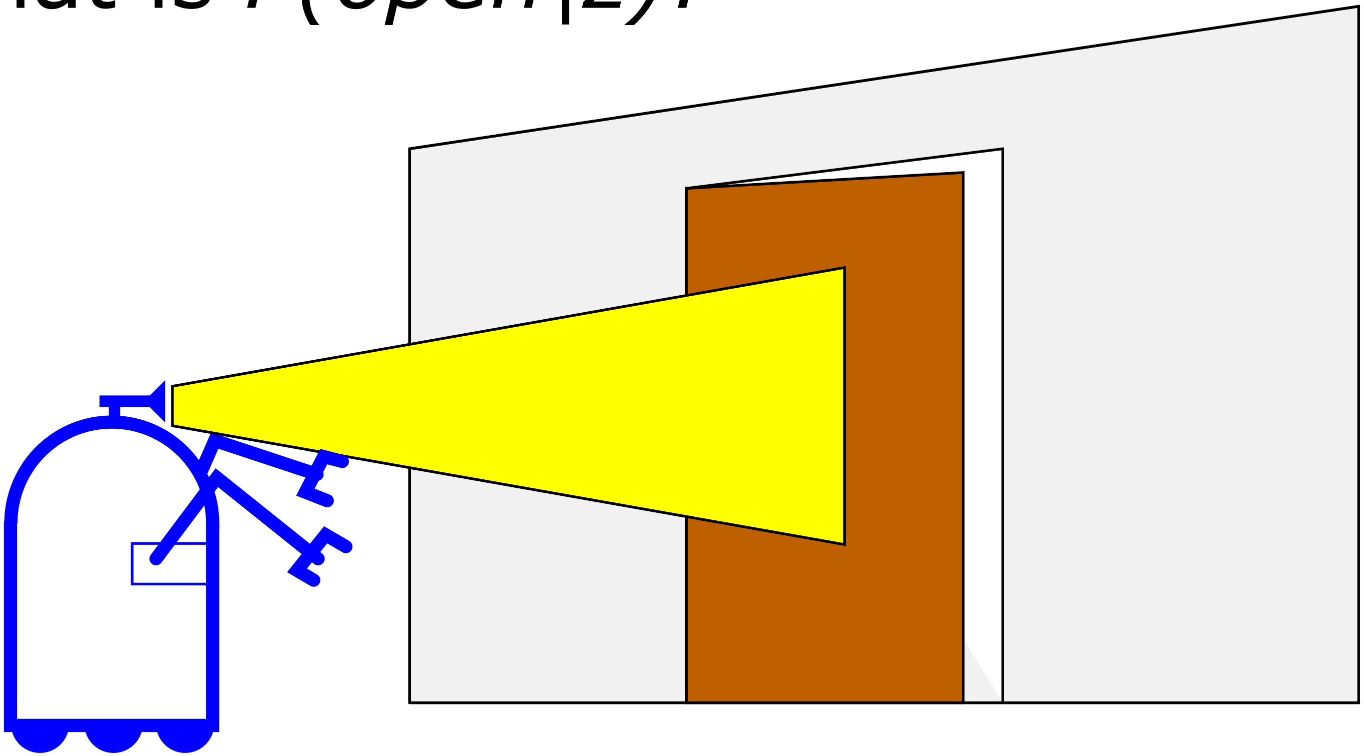
When z is known,
y does not tell us
anything about x

and $P(y \mid z) = P(y \mid z, x)$

When z is known,
x does not tell us
anything about y

Simple Example of State Estimation

- Suppose a robot obtains a measurement z
- What is $P(open|z)$?



Causal vs. Diagnostic Reasoning

- *P(open|z)* is diagnostic
- *P(z|open)* is causal
- Often causal knowledge is easier to obtain

count frequencies!

- Bayes' rule allows us to use causal knowledge:

$$P(open \mid z) = \frac{P(z \mid open)P(open)}{\underbrace{P(z)}}$$

Example

- $P(z|open) = 0.6$ $\quad\quad$ $P(z|\neg open) = 0.3$
- $P(open) = P(\neg open) = 0.5$

$$P(open \mid z) = \frac{P(z \mid open)P(open)}{P(z \mid open)\,p(open) + P(z \mid \neg open)\,p(\neg open)}$$

$$P(open \mid z) = \frac{0.6 \cdot 0.5}{0.6 \cdot 0.5 + 0.3 \cdot 0.5} = \frac{0.3}{0.3 + 0.15} = 0.67$$

- *z* increases the probability that the door is open

Combining Evidence

- Suppose our robot obtains another observation z_2
- How can we integrate this new information?
- More generally, how can we estimate $P(x \mid z_1, \ldots, z_n)$?

Recursive Bayesian Updating

$$P(x \mid z_1,\ldots,z_n) = \frac{P(z_n \mid x, z_1,\ldots,z_{n-1})\, P(x \mid z_1,\ldots,z_{n-1})}{P(z_n \mid z_1,\ldots,z_{n-1})}$$

Markov assumption:
Last measurement z_n is independent of previous measurements $z_1,\ldots,z_{n-1}$ if we know the state x

$$P(x \mid z_1,\ldots,z_n) = \frac{P(z_n \mid x)\, P(x \mid z_1,\ldots,z_{n-1})}{P(z_n \mid z_1,\ldots,z_{n-1})}$$

$$= \eta P(z_n \mid x)\, P(x \mid z_1,\ldots,z_{n-1})$$

$$= \eta_{1\ldots n} \left[\prod_{i=1\ldots n} P(z_i \mid x) \right] P(x)$$

Example: Second Measurement

lw fket da, hytl3lk nfs el equation el fo2.

$$P(open|z_2, z_1) = \frac{P(z_2|open)P(open|z_1)}{\underbrace{P(z_2|open)P(open|z_1) + P(z_2|\neg open)P(\neg open|z_1)}}$$

This is the normalization factor.

Summary

- Probabilities allow us to model uncertainties in a systematic way
- Bayes' rule allows us to compute probabilities that are hard to assess otherwise
- Under the Markov assumption, recursive Bayesian updating can be used to efficiently combine evidence

Acknowledgment

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