TTIC 31170:
Planning, Learning, and Estimation for Robotics and Artificial Intelligence
(aka Robot Learning and Estimation)

Spring 2020

Matthew Walter
TTI-Chicago

Lecture 1: Introduction, Graphical Models

Course logistics

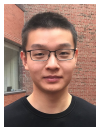
- **Lectures**: Tuesdays & Thursdays 2:40pm–4:00pm CDT
  - The current plan is to live-stream lectures using Zoom
  - Lectures will be recorded and made available for offline viewing
- **Webpage**:
  - http://canvas.uchicago.edu

Course logistics: Staff

Instructor: Matthew Walter
- mwalter@ttic.edu
- Office Hours: TBD (via Zoom)

Guest Instructor: Bradly Stadie
- bstadie@ttic.edu

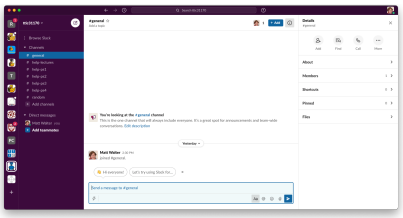
TA: Shengjie Lin
- slin@ttic.edu
- Office Hours: TBD (via Zoom)



Course logistics: Zoom

- We will use Zoom for lectures and office hours
  - **Meeting ID**: 958-8820-0752
  - **Password**: 31170
  - https://uchicago.zoom.us/j/95888200752
  - See Canvas for more information on joining meetings
- I strongly encourage you to regularly interact with one another via Zoom (or similar)

Course logistics: Slack



- http://ttic31170.slack.com
- Dedicated channels to discuss lectures and problem sets
- See Canvas for information on how to get an account

Course logistics: Grading

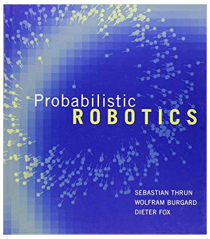
- **Grading**

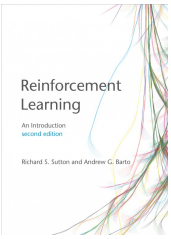
Problem Sets	50%
Midterm Exam	25%
Final Project	25%

- **Problem Sets** (4):
  - Written (or typeset) and programming assignments
  - Submitted via Canvas/Gradescope
  - **Late budget**: Each student has a budget of 3 late days
  - **Late policy**: 10% off per day, no credit beyond 3 days
  - Discussion encouraged, but individual submissions

Course logistics: Readings

- Required:
  - Thrun, Burgard, & Fox, *Probabilistic Robotics*, 2005
  - Sutton & Barto, *Reinforcement Learning: An Introduction*, 1998





Course logistics: Schedule

Lecture	Date	Topic	Out/Due
1	**March 30**	**Course Introduction, Graphical Models Review**	
2	April 1	Graphical Models Review (continued)	PS1 Out
3	April 6	Recursive Bayesian Estimation	
4	April 8	Recursive Bayesian Estimation	
5	April 13	Kalman Filters	
6	April 15	Nonparametric Filters	PS1 Due/PS2 Out
7	April 20	Simultaneous Localization and Mapping	
8	April 22	Simultaneous Localization and Mapping (continued)	
9	April 27	Multi-Arm Bandits	
10	April 29	Markov Decision Processes	PS2 Due/PS3 Out
11	May 4	Linear Quadratic Regulators	
12	May 6	Midterm Exam	
13	May 11	Reinforcement Learning: Model-based Learning	
14	May 13	Reinforcement Learning: Model-free Learning	PS3 Due/PS4 Out
15	May 18	Reinforcement Learning: Function Approximation	
16	May 20	Reinforcement Learning: Function Approximation	
17	May 25	Reinforcement Learning: Policy Gradient Methods	
18	May 27	Inverse Reinforcement Learning	PS4 Due
19	June 1	No Class: College Reading Period	
20	June 3		
21/22	June 11/13	Final Exam	

Autonomy in the presence of certainty

Autonomy in the presence of certainty

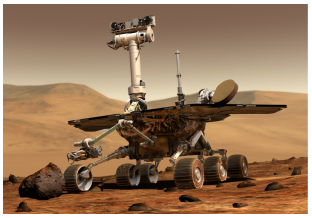
Unimate (1959)

Autonomy in the presence of certainty

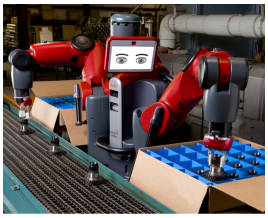
Unimate (1959)

Autonomous Benthic Explorer (WHOI)

Talos (MIT)



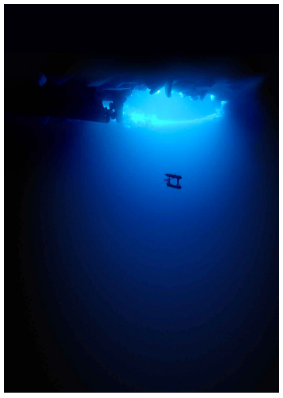
Mars Exploration Rover (NASA/JPL)



Baxter (Rethink Robotics)

Atlas
(BDI/Google)

Mapping sea ice



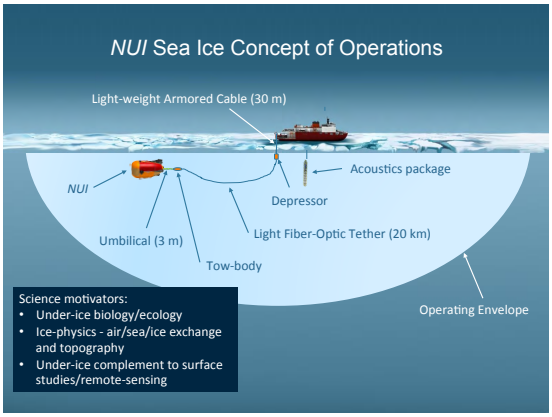
Seabed Jaguar AUV (WHOI)

Mapping sea ice

Nereid Under Ice (NUI) (Courtesy: WHOI)

Mapping sea ice

Mapping sea ice

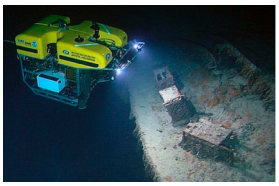


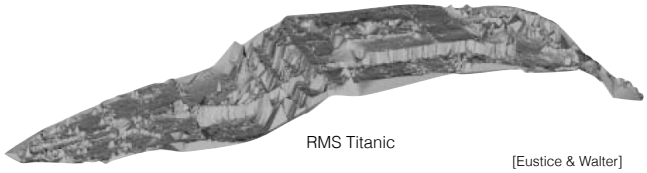
Mapping sea ice

Mapping sea ice

Nereid Under Ice (NUI) (Courtesy: WHOI)

Mapping the RMS Titanic

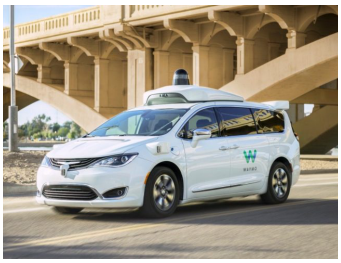




RMS Titanic

[Eustice & Walter]

Self-driving cars



Waymo (Google)

Talos (MIT)

Self-driving cars

Google NISSAN BOSCH BMW VOLVO TOYOTA DELPHI GM Audi MOBILEYE NVIDIA Mercedes-Benz Ford

Capabilities of AVs: Estimation

(Courtesy: Google)

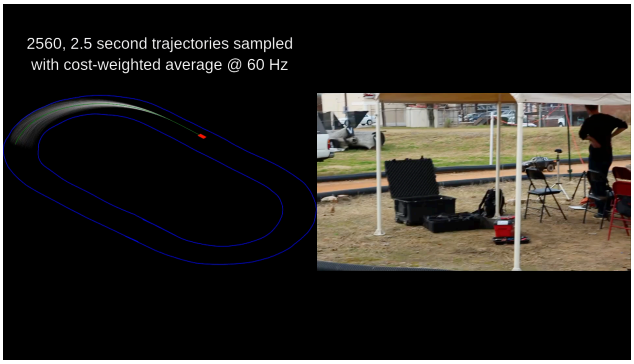
Capabilities of AVs: Estimation

(Courtesy: Google)

Shameless plug

Current edX Course: Self-Driving Cars with Duckietown
https://www.edx.org/course/self-driving-cars-with-duckietown

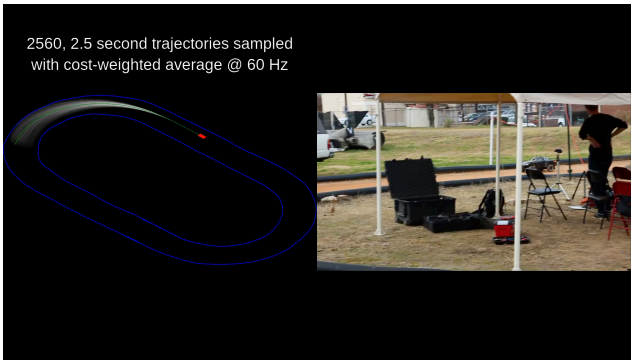
High-speed off-road driving



Autorally (Courtesy: Boots et al.)

Topics: Model predictive control, stochastic optimal control, Bayesian filtering

High-speed off-road driving



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Topics: Model predictive control, stochastic optimal control, Bayesian filtering

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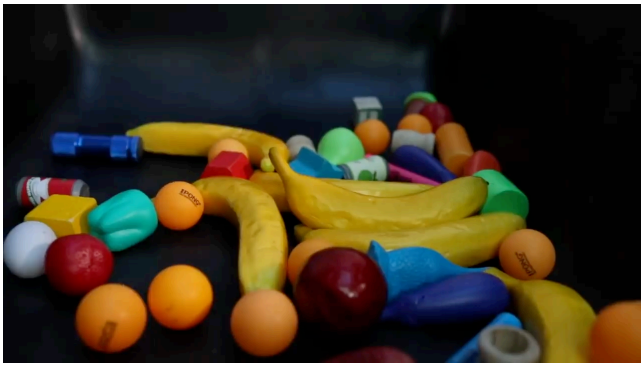
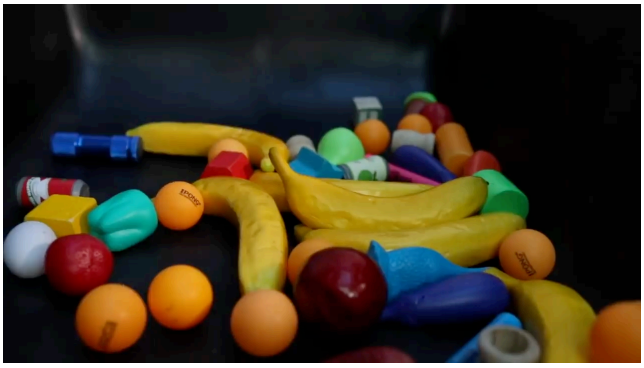
Residual control: Learning to throw



[Zeng, Song, Lee, Rodriguez, and Funkhouser]

Topics: Optimal control, residual learning, reinforcement learning

Residual control: Learning to throw



[Zeng, Song, Lee, Rodriguez, and Funkhouser]

Topics: Optimal control, residual learning, reinforcement learning

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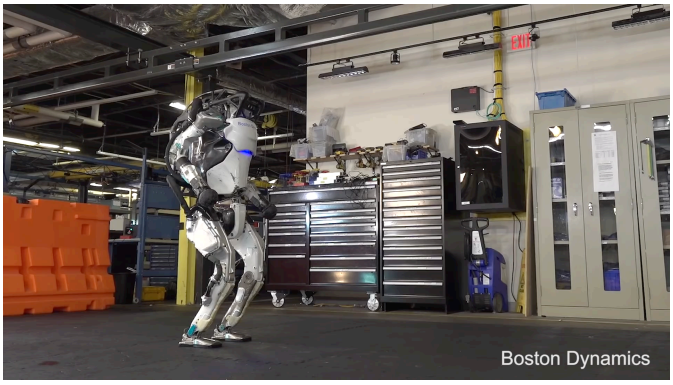
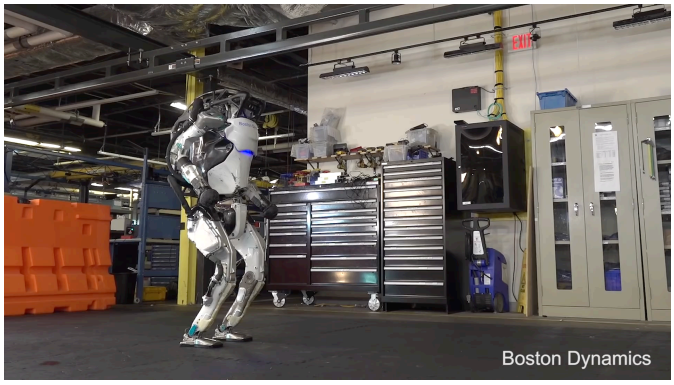
Highly agile locomotion



[Courtesy: Boston Dynamics]

Topics: Optimal control, learning? (probably not here)

Highly agile locomotion



[Courtesy: Boston Dynamics]

Topics: Optimal control, learning? (probably not here)

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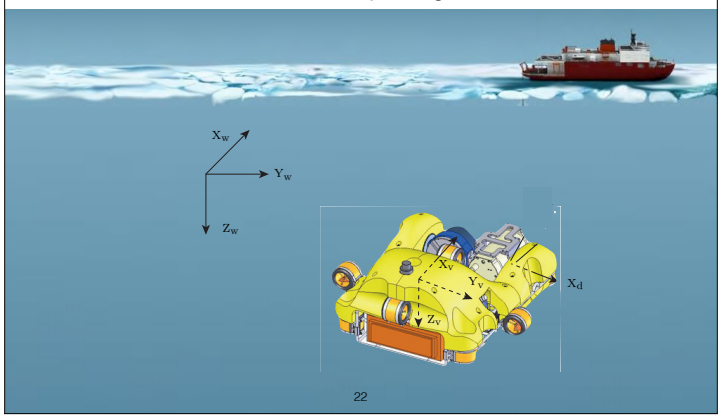
Why think probabilistically?

- State of the agent (robot) and world aren't known and measurements are noisy
  - Probability provides a framework to fuse observations
  - Result: Probability distribution over possible states
- The future is unknown: Stochastic dynamics prevent planning actions for deterministic outcomes
  - Probability provides a framework to reason in this setting
  - Result: Algorithms that select actions suited to stochastic dynamics and environments

Example: Underwater vehicles

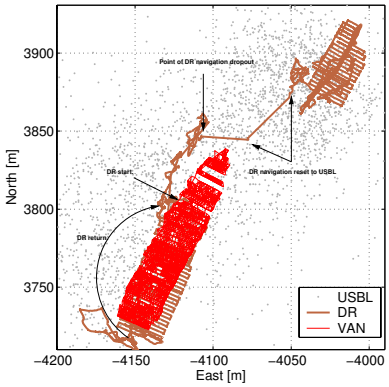
- State: Position, orientation, velocity, & angular rate



Example: underwater vehicles

- State: Position, orientation, velocity, & angular rate
- Sensors:
  - Inertial Navigation System (INS) (IMU+filter)
    - Heading ($\pm 0.1^\circ$ RMS w/ FOG)
    - Roll/pitch ($\pm 0.01^\circ$ RMS w/ FOG)
  - 3-axis magnetometer (sensitive to bias)
  - Doppler Velocity Log (DVL)
    - Linear velocity (± 5mm/s, only near seafloor)
  - Downward-facing camera
  - Sonar

Example: underwater vehicles



[Eustice, Singh, Leonard, & Walter]

Example: Mobile robot

- State: Position and heading
- Sensors:
  - Wheel encoders
    - Forward velocity
  - Laser range finder (LIDAR)
    - Distance and bearing to nearby obstacles
  - Camera
- Dynamics:
  - Unmodeled dynamics, wheel slippage

Example: Mobile robot

- State: F
- Sensor
  - Whe
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  - Cam
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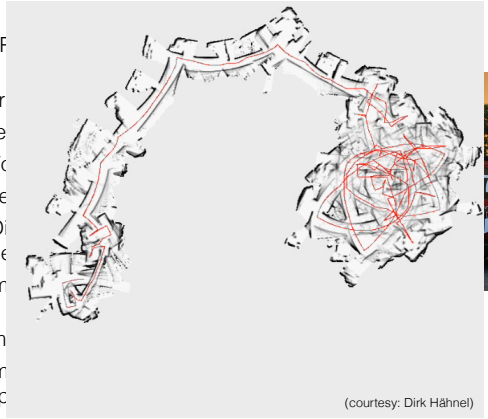


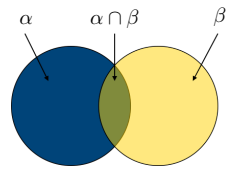
Probability review: Probability space

Probability space $(\Omega, \mathcal{S}, P)$ models a real-world process ("experiment") consisting of randomly occurring states

- Ω : An **outcome space** as the set of all possible outcomes
- $\mathcal{S} \subseteq 2^{\Omega}$: A set of **measureable events** to which we can assign a probability, where each event is a set containing zero or more outcomes
- $P : \mathcal{S} \to \mathbb{R}$: A **probability measure** that assigns probabilities to events

Probability review: Probability distributions

- A **probability distribution** $P : \mathcal{S} \to \mathbb{R}$ such that
  - $P(\alpha) \geq 0 \;\; \forall \alpha \in \mathcal{S}$
  - $P(\Omega) = 1$
  - If $\alpha, \beta \in \mathcal{S}$ and $(\alpha \cap \beta) = \emptyset$, then $P(\alpha \cup \beta) = P(\alpha) + P(\beta)$
- Axioms imply that $P(\emptyset) = 0$ and $P(\alpha \cup \beta) = P(\alpha) + P(\beta) - P(\alpha \cap \beta)$

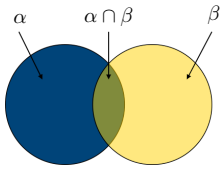


Chain rule

Let $\alpha_1, \ldots, \alpha_n \in \mathcal{S}$ be events such that $P(\alpha_i) > 0$

The joint distribution **factorizes** as

$$P(\alpha_1 \cap \alpha_2 \ldots \cap \alpha_n) = P(\alpha_1)P(\alpha_2 \,|\, \alpha_1) \cdots P(\alpha_n \,|\, \alpha_{n-1}, \ldots, \alpha_2, \alpha_1)$$



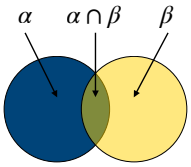
Bayes' Rule

Thomas Bayes*
(1701–1761)

Let $\alpha_1, \alpha_2 \in \mathcal{S}$ be events such that $P(\alpha_i) > 0$

$$P(\alpha \,|\, \beta)P(\beta) = P(\alpha \cap \beta) = P(\beta \,|\, \alpha)P(\alpha)$$

$$P(\alpha \,|\, \beta) = \frac{P(\alpha \cap \beta)}{P(\beta)} = \frac{P(\beta \,|\, \alpha)P(\alpha)}{P(\beta)}$$



*Likely not a portrait of Thomas Bayes, and in fact none may exist (https://www.york.ac.uk/depts/maths/histstat/bayespic.htm)

Random variables

- Events can be difficult to work with
  - We often group events by **attributes** (e.g., person by "age," "height," and "weight"), particularly numerical values
- A **random variable** $X : \Omega \to D$ is a measureable function that maps an outcome to a measureable space D
  - D may be discrete or continuous
  - Induces a partition on Ω of all outcomes: $\{w \in \Omega : X(w) = x\}$
- For a given $x \in D$, define the "probability that X instantiates as x (the **realization** of X)

$$P(X = x) = P(\{w \in \Omega : X(w) = x\})$$

Multivariate random variables

- We have a random *vector* rather than a random variable

$$\mathbf{X}(w) = \begin{bmatrix} X_1(w) & X_2(w) & \ldots & X_n(w) \end{bmatrix}$$

- $X_i = x_i$ is an event and the joint distribution is defined as

$$P(X_1 = x_1, \ldots, X_N = x_n) = P(X_1 = x_1 \cap \ldots \cap X_N = x_n)$$

- It is common to use shorthand

$$P(X_1 = x_1, \ldots, X_N = x_n) = P(x_1, \ldots, x_n)$$