



CS249r – 2019 Nuts and Bolts



What are the prerequisites for CS 249r?

1. CS 141 and/or basic computer architecture and digital design
2. CS 61/161 and/or a basic systems programming experience
3. CS 124 and/or a basic algorithms experience

We hope to have a diverse class and assume few students will have full exposure to the full breadth of topics we will cover. As such, we intend to provide some background on all of the topics. That said, students may find it helpful if they also have some background in some of the algorithms employed in autonomous systems from classes such as CS 181/182 or AM 121. Please contact the instructor or teaching fellow if you are interested in taking the course but are unsure about whether the background you have is suitable.

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Wed, Sep 11	Motivation	Lecture	Intro to Robotics (Planning and Control)	
Mon, Sep 16		Lecture	Intro to Domain Specific Architectures	
Wed, Sep 18	Sample Presentations	Research Paper(s)	Example Research Paper Presentations	
Mon, Sep 23	Domain Specific Accelerators	Research Paper(s)	Domain Specific Accelerators	
Wed, Sep 25		Research Paper(s)	Domain Specific Accelerators	
Mon, Sep 30	ML Motivation	Guest Lecture	Reinforcement Learning 101	Tentative
Wed, Oct 2		Guest Lecture	Deep Reinforcement Learning 101	Tentative
Mon, Oct 7		No Class	Columbus Day	
Wed, Oct 9	E2E Control	Research Paper(s)	E2E Control	
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Wed, Oct 30		Research Paper(s)	Perception / Mapping	
Mon, Nov 4		Research Paper(s)	Perception / Mapping	
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Mon, Nov 11	Planning / Control	Research Paper(s)	Planning / Control	
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Class on 9/11 will be video taped (but not posted anywhere) as I am doing a Bok Center teaching review. We will have a “no camera” section as well.

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We are also going to have a day of sample presentations to provide a guide for the types of presentations we hope you will give on your research papers throughout the semester and on your final projects

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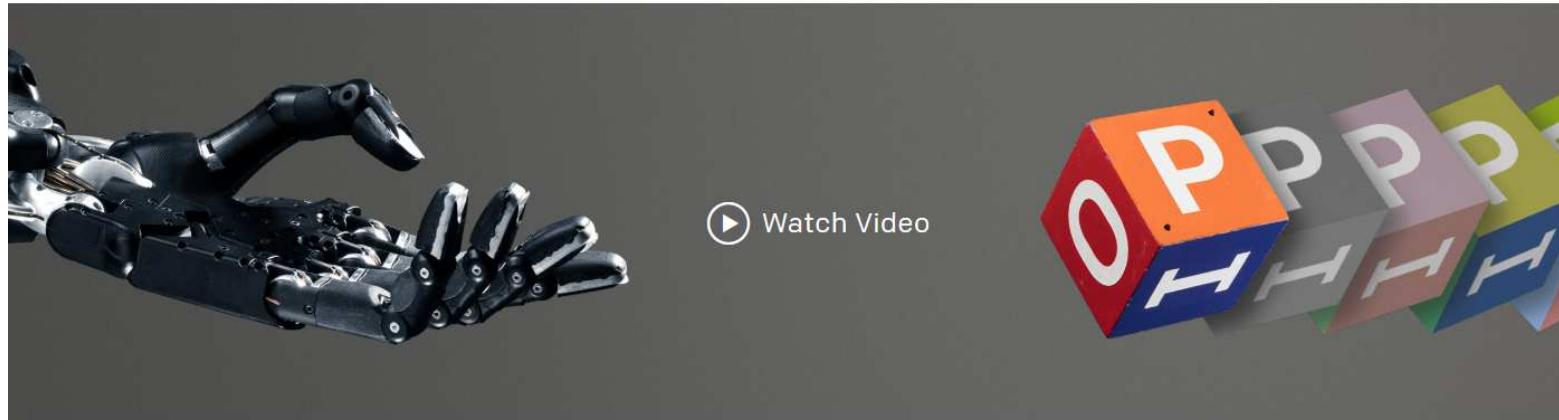
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So how is CS249r actually going to run?

JULY 30, 2018 • 9 MINUTE READ

Learning Dexterity

We've trained a human-like robot hand to manipulate physical objects with unprecedented dexterity.

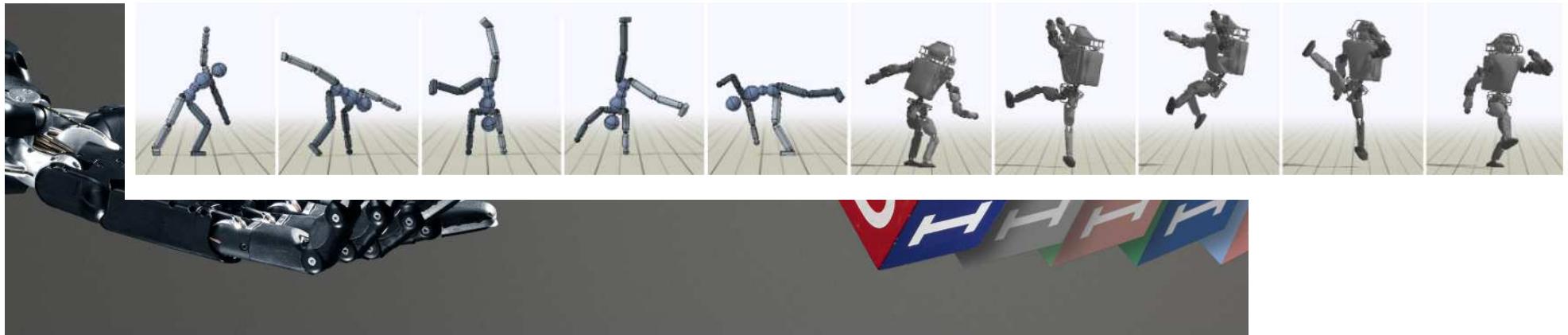


So how is CS249r actually going to run?

DeepMimic: Example-Guided Deep Reinforcement Learning of Physics-Based Character Skills

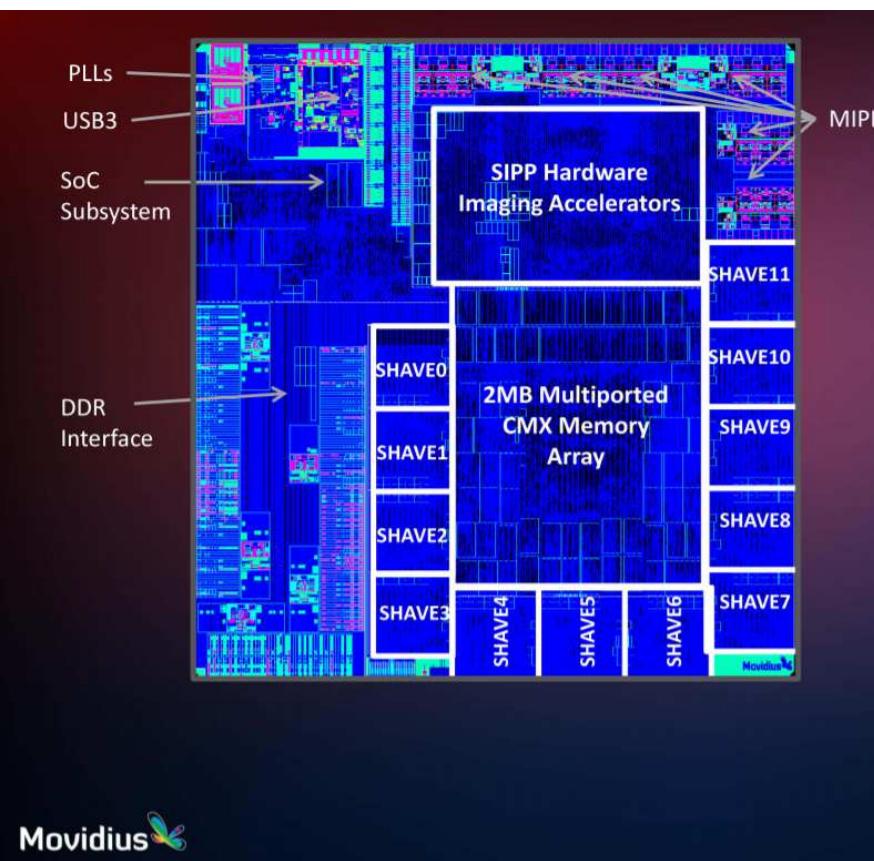
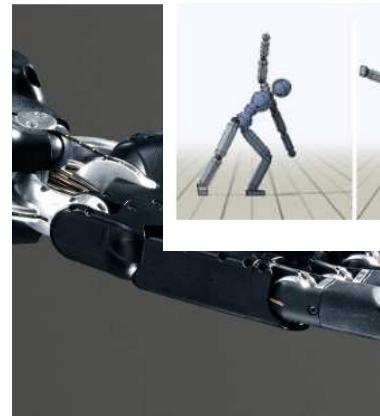
Transactions on Graphics (Proc. ACM SIGGRAPH 2018)

Xue Bin Peng(1) Pieter Abbeel(1) Sergey Levine(1) Michiel van de Panne(2)
(1)University of California, Berkeley (2)University of British Columbia



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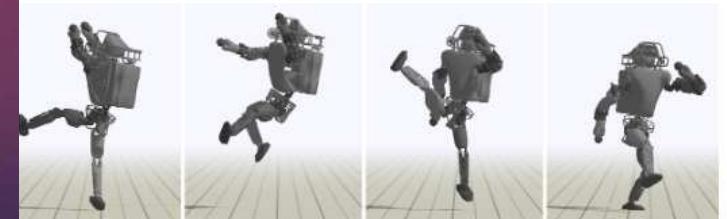
DeepMind



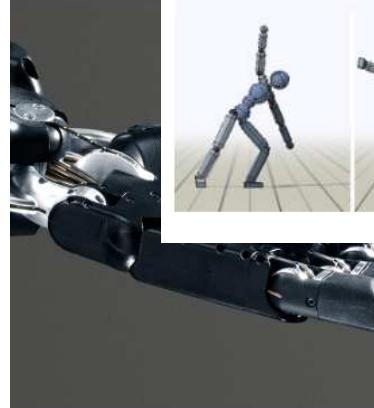
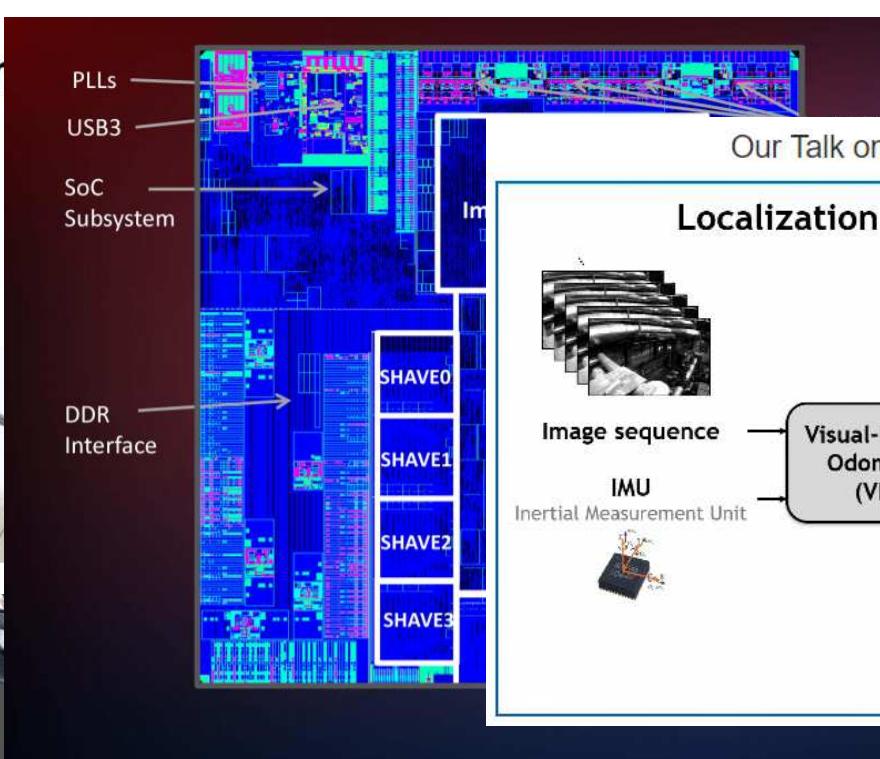
Learning of Physics-Based

ICRAH 2018)

Michiel van de Panne(2)
of British Columbia



So how is CS249r actually going to run?

DeepMind  

PLLs
USB3
SoC Subsystem
DDR Interface
SHAVE0
SHAVE1
SHAVE2
SHAVE3

Navigation Learning of Physics-Based Agents
Our Talk on Navion at Hot Chips-30

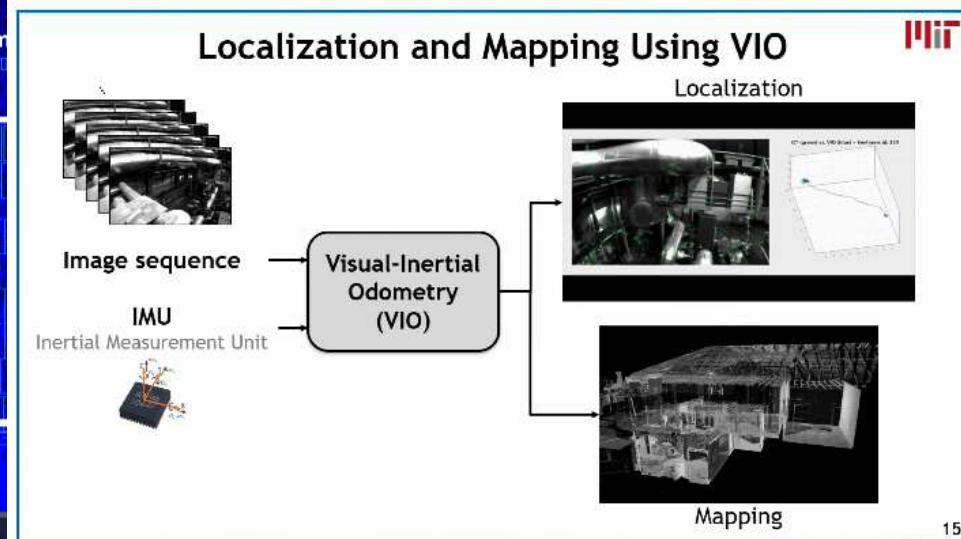
Localization and Mapping Using VIO 
Localization
Mapping

Image sequence
IMU
Inertial Measurement Unit

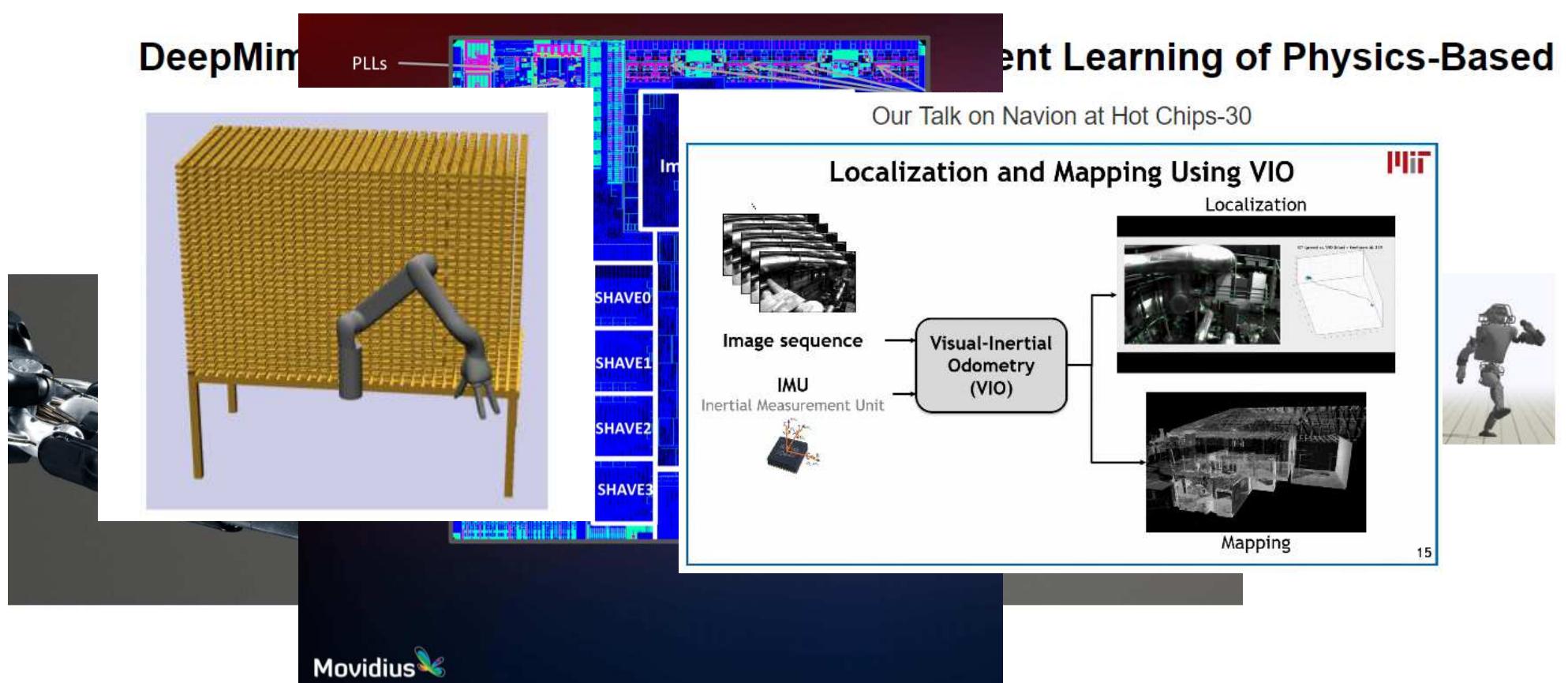
Visual-Inertial Odometry (VIO)

15

Movidius 



So how is CS249r actually going to run?



So how is CS249r actually going to run?



Figure 4: Testing setup and example output images. Left: Oval dirt test track where all test data was taken. Center: Photo of vehicle during testing. Right: Neural network input, top down output, and image plane output.

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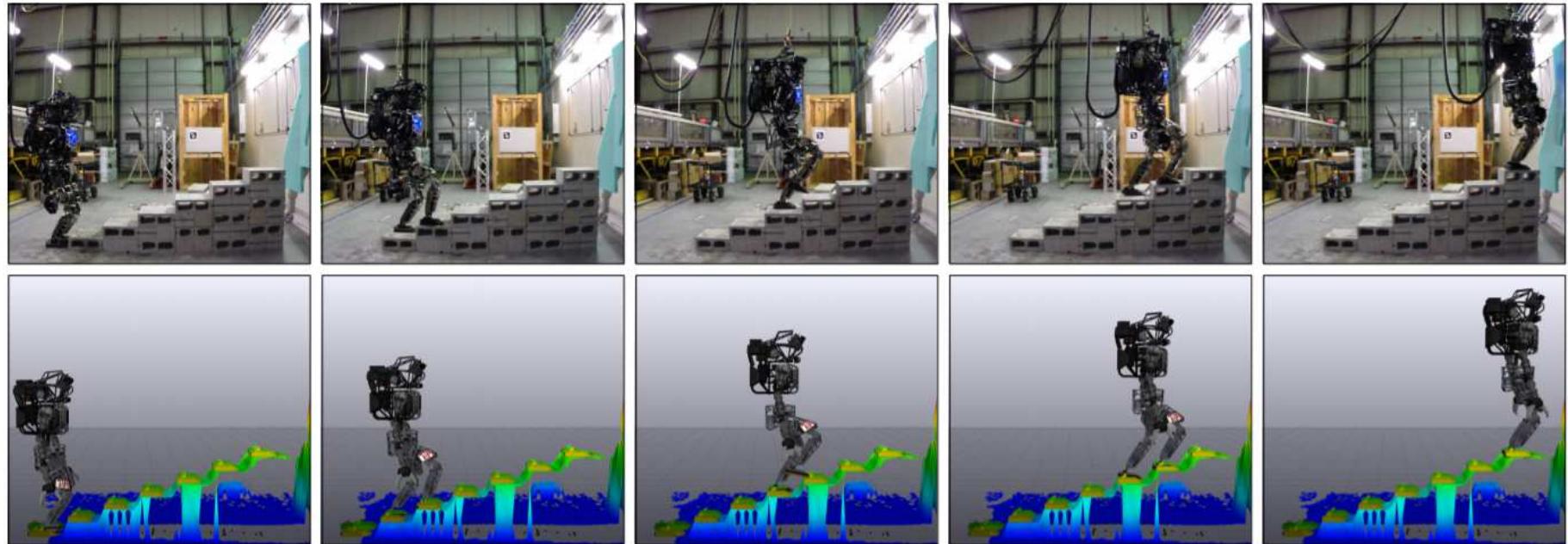


Fig. 12 Atlas walking continuously up six cinder block steps using LIDAR-based state estimation in a closed loop with the walking controller. Top: images of the robot climbing the stack of cinder blocks in our laboratory. Bottom: the state estimate rendering in our user interface.

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We will simulate the conference review process in the middle of the term to give students insight into how papers are judged and thus accepted or rejected

We will discuss the reviews of an accepted paper during the example paper presentations

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Finally we wrap up the semester with a lot of time to work on and then present final projects.

Note the mid semester project proposal due date!

How do you get an A in CS 249r?

1. Paper Reviews – 20%
 2. Paper Presentation – 20%
 3. Class Participation – 10%
 4. Final Project – 50%
-

Paper Reviews – 20%

Goals:

1. To develop the skill of reading papers and quickly taking away the big picture ideas.

Assignments:

1. Submit a short “review” on each research paper read during the course (and submit the review 36 hours BEFORE the class in which it is presented)
-

Paper Reviews – 20%

We will use HOTCRP (the standard submission system from Computer Architecture Conferences)

Goals:

1. To develop the skill of reading papers and quickly taking away the big picture ideas.

Assignments:

1. Submit a short “review” on each research paper read during the course (and submit the review 36 hours BEFORE the class in which it is presented)
-

Paper Reviews – 20%

Goals:

1. To develop the skill of reading papers and quickly taking away the big picture ideas.
2. **Crowdsource a best practice guide on writing papers**

Assignments:

1. Submit a short “review” on each research paper read during the course (and submit the review 36 hours BEFORE the class in which it is presented)
-

Paper Presentation(s) – 20%

Goals:

1. To develop the skill of understanding a paper in detail
2. Practice presenting a (conference) paper to audience and teaching a concept to a class

Assignments:

1. Give at least one 18 minute presentation on a research paper followed by 10 minutes of Q&A (and meet with the course staff a week prior to your presentation)
-

Paper Presentation(s) – 20%

Goals:

1. To develop the skill of understanding a paper in detail
2. Practice presenting a (conference) paper to audience and teaching a concept to a class

Assignments:

1. Give at least one 18 minute presentation on a research paper followed by 10 minutes of Q&A (and meet with the course staff a week prior to your presentation)

- **~5 minutes of setup** (What is the problem? Why is it important? What are the key challenges?)
- **~5 minutes of contribution** (What did the author(s) do? Why was it novel?)
- **~8 minutes of context** (What work did it build on /how does it compare?)

Class Participation – 10%

Goals:

1. Practice absorbing a (conference) paper presentation
2. To give feedback to presenters

Assignments:

1. Be an active participant in class
 2. Submit anonymous feedback on each presentation
-

Final Project – 50%

Goals:

1. Practice being a graduate student:
 - a) Coming up with a research idea
 - b) Workshopping the idea with others / advisors
 - c) Collaboratively conducting the research
 - d) Writing up a (conference) paper in Latex
 - e) Giving a presentation on the paper

Assignments:

1. Work in teams of 2-3 students to submit a project proposal midway through the semester and a final project report at the end of the semester as well as presenting that research to the class
-

Final Project – 50%

Goals:

1. Practice being a graduate student:
 - a) Coming up with a research idea
 - b) Workshopping the idea with others / advisors
 - c) Collaboratively conducting the research
 - d) Writing up a (conference) paper in Latex
 - e) Giving a presentation on the paper

We would love to find a way to incorporate your research into your final project

Assignments:

1. Work in teams of 2-3 students to submit a project proposal midway through the semester and a final project report at the end of the semester as well as presenting that research to the class
-

Any questions?

Quick survey of all of you

Undergrads vs Grads

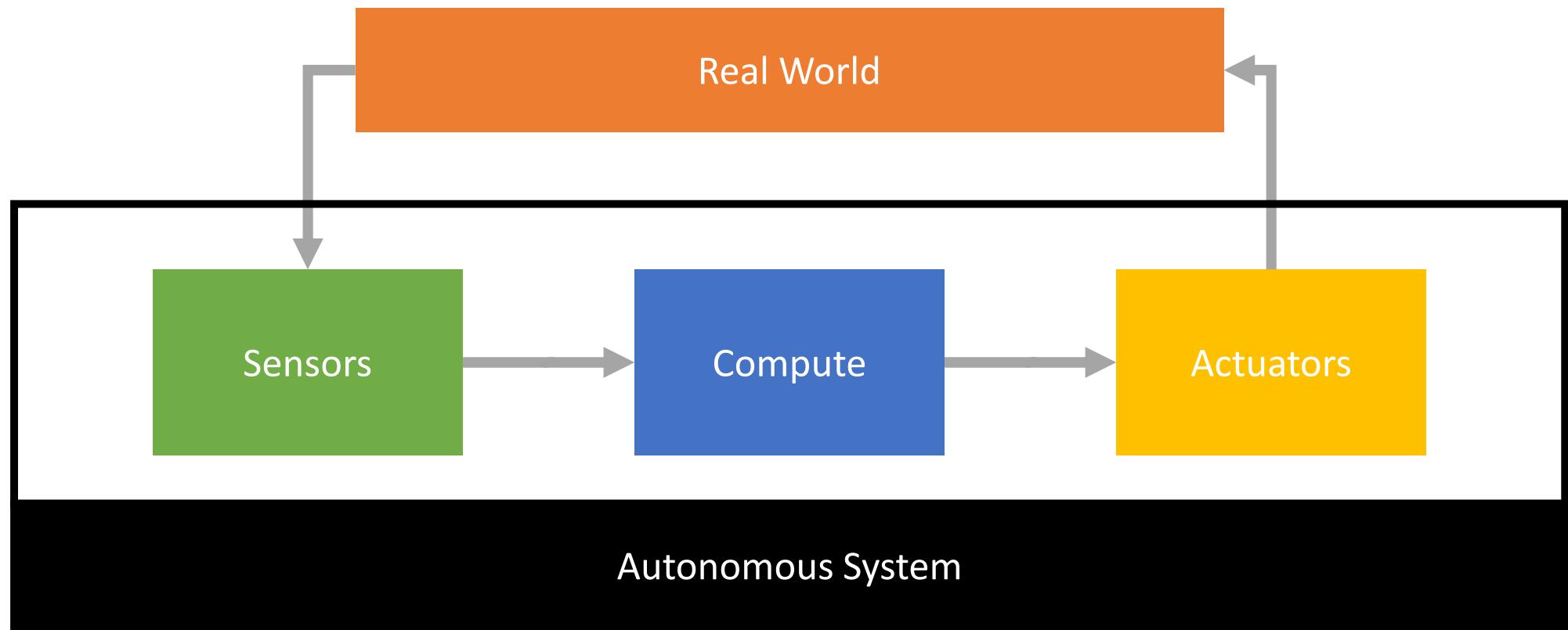
Definitely vs Maybe Enrolling

Architecture vs. Robotics / Autonomous Systems vs. Neither

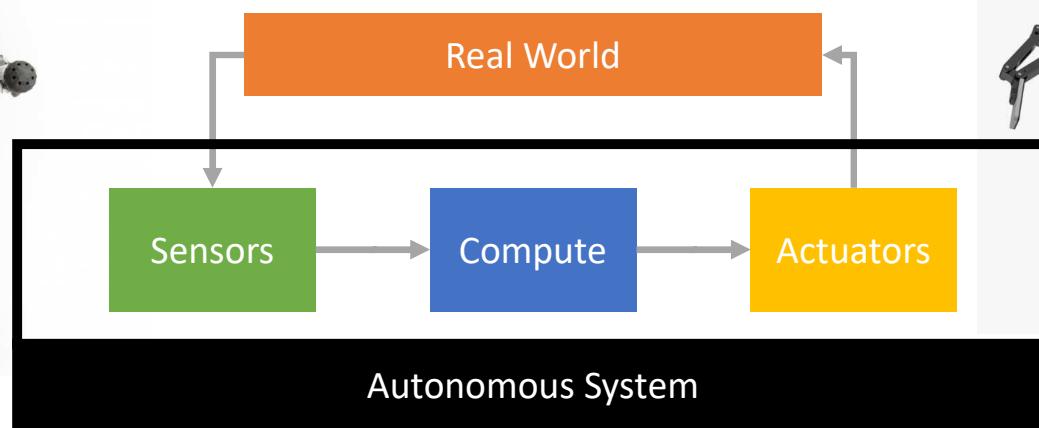


Ok so lets dive into a little material for next week!

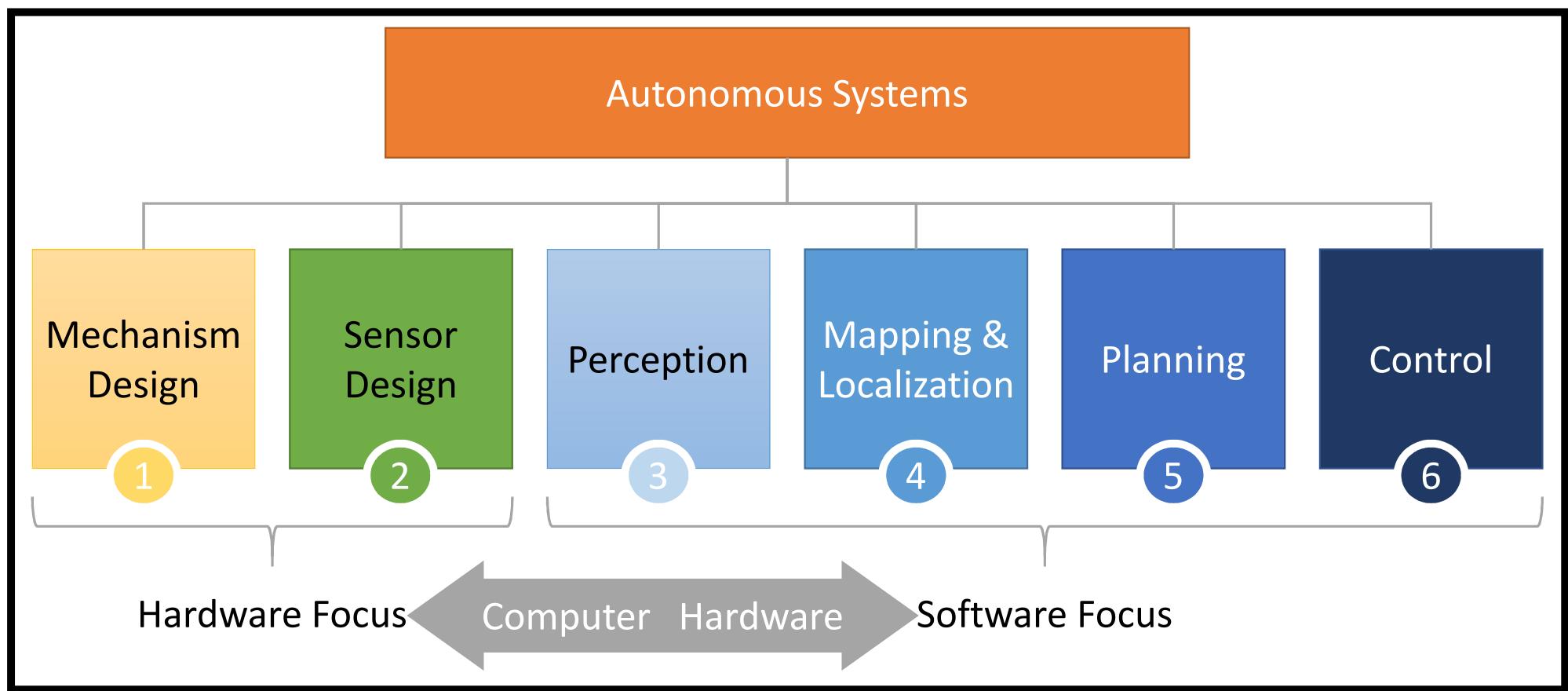
What do we mean by an Autonomous System?



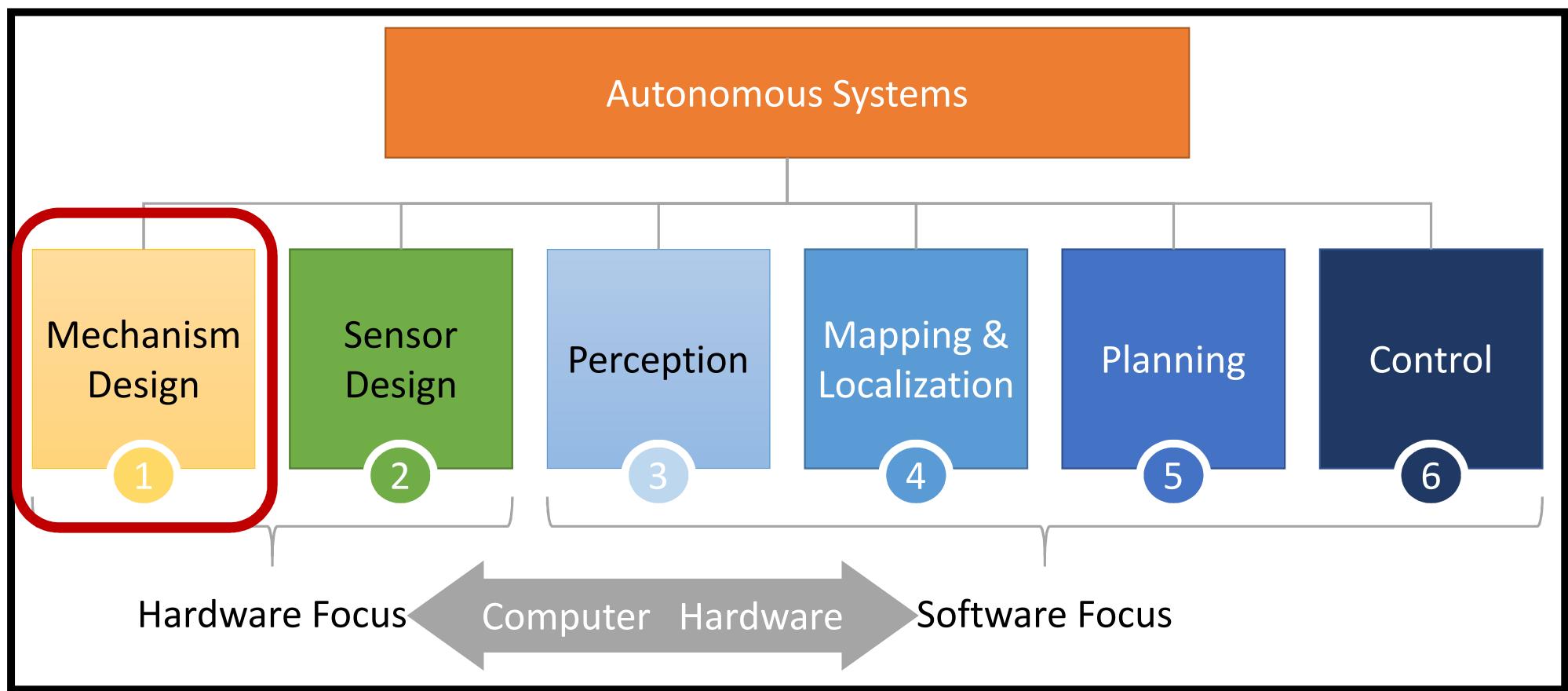
What do we mean by an Autonomous System?



Autonomous Systems / Robotics is a BIG space



Autonomous Systems / Robotics is a BIG space



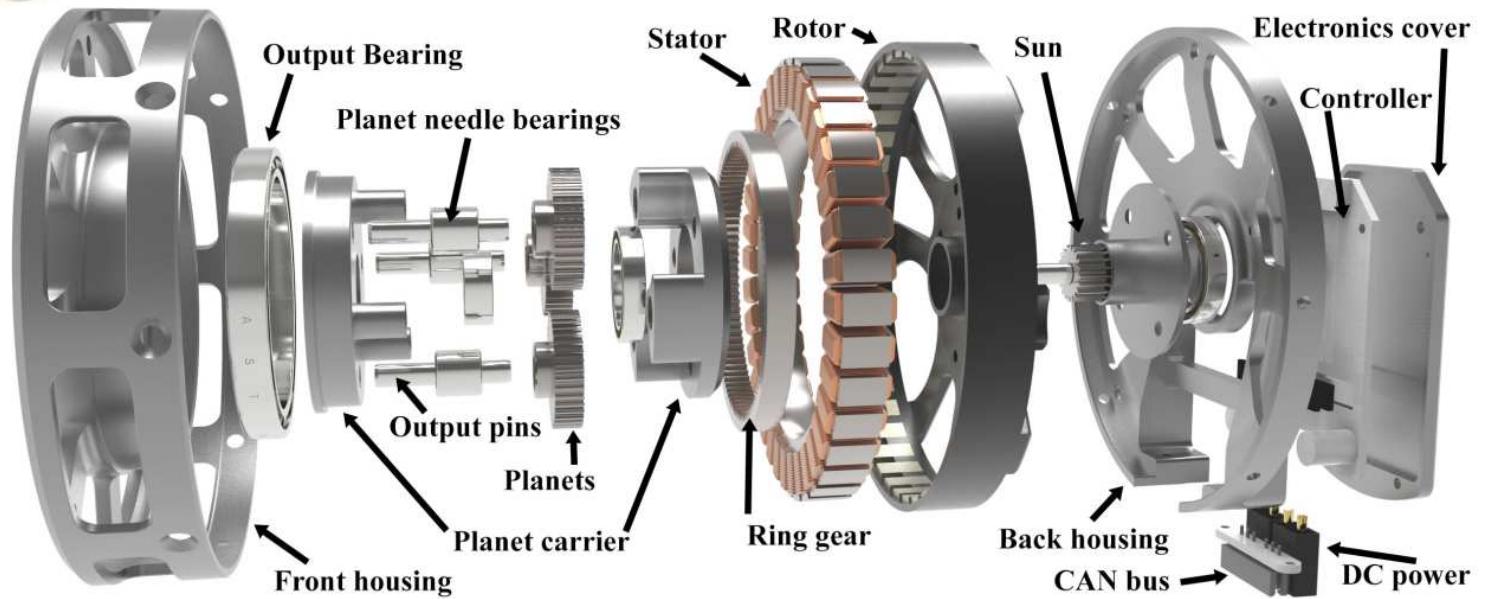
1

Mechanism designers create new robots and actuators



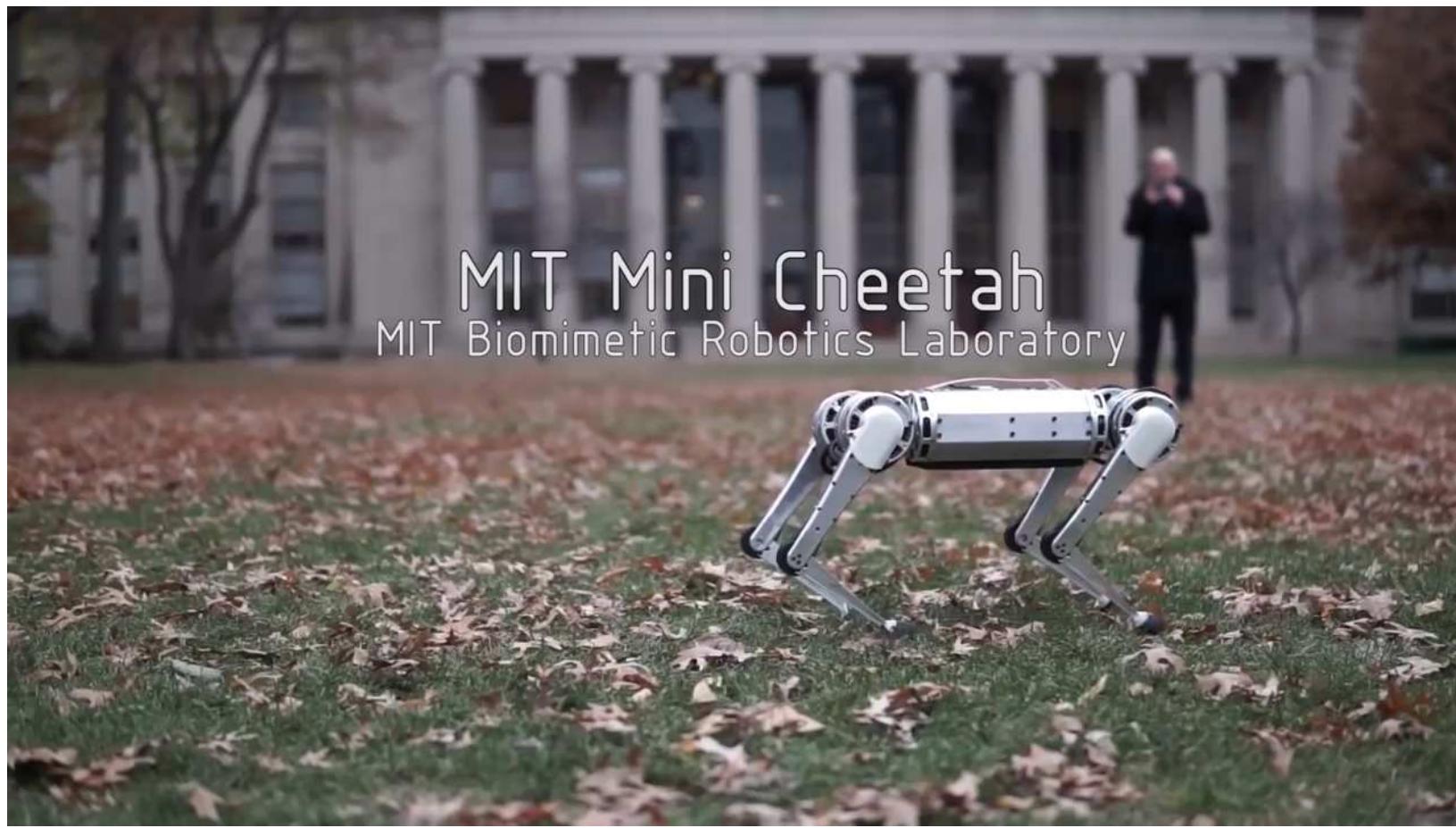
Fig. 4: The modular actuator used in the Mini Cheetah. Motor, planetary gear set, and control electronics are all built-in.

Fig. 5: Exploded view of the actuator.



1

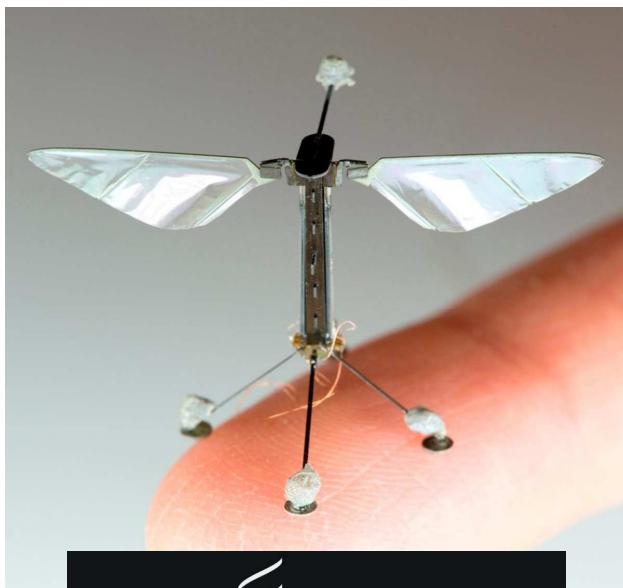
Mechanism designers create new robots and actuators



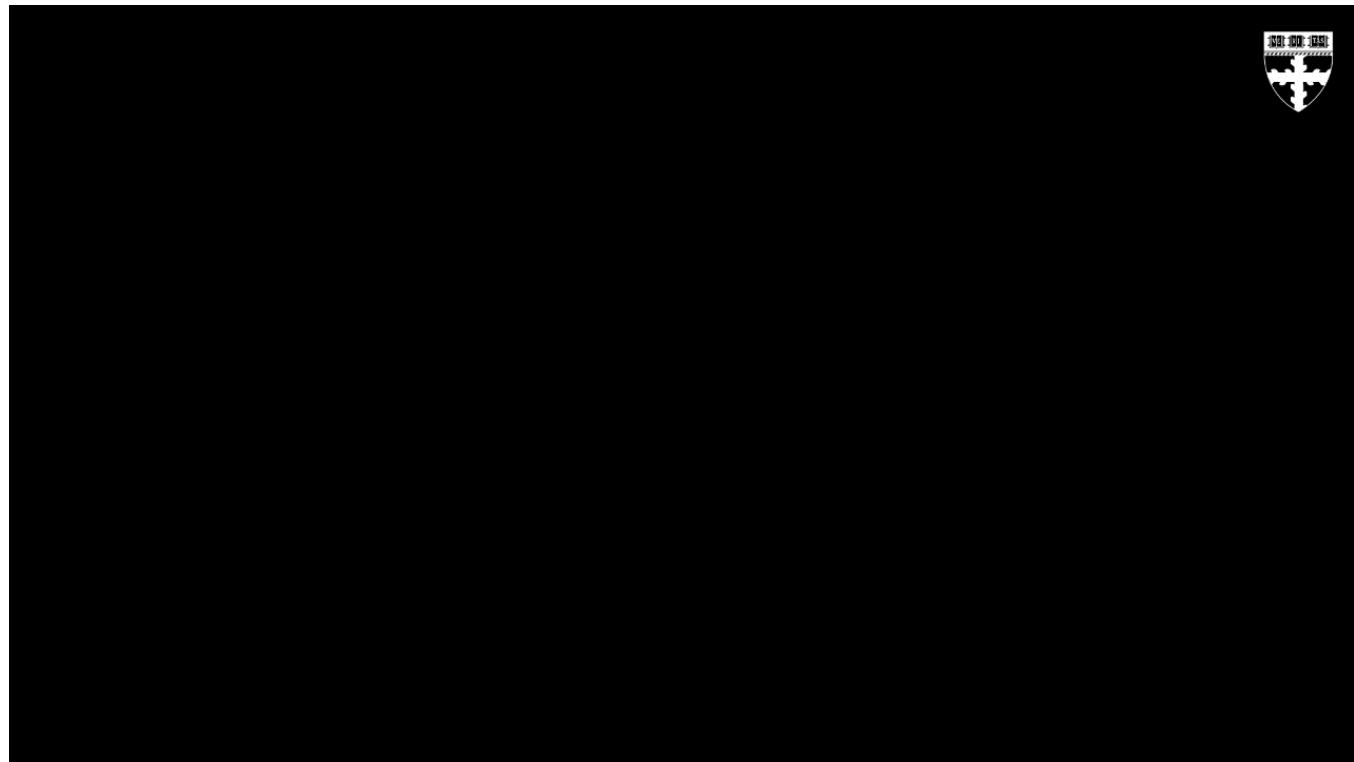
MIT 2.74

1

Mechanism designers create new robots and actuators



WYSS  INSTITUTE

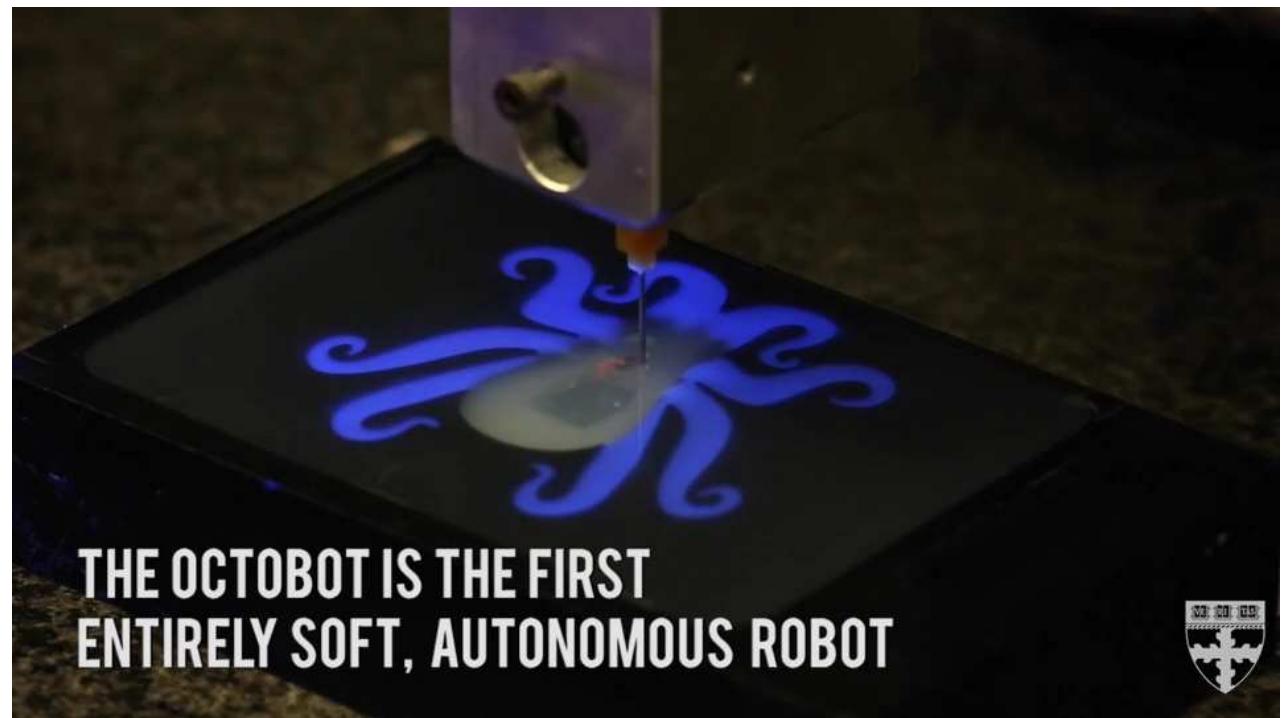


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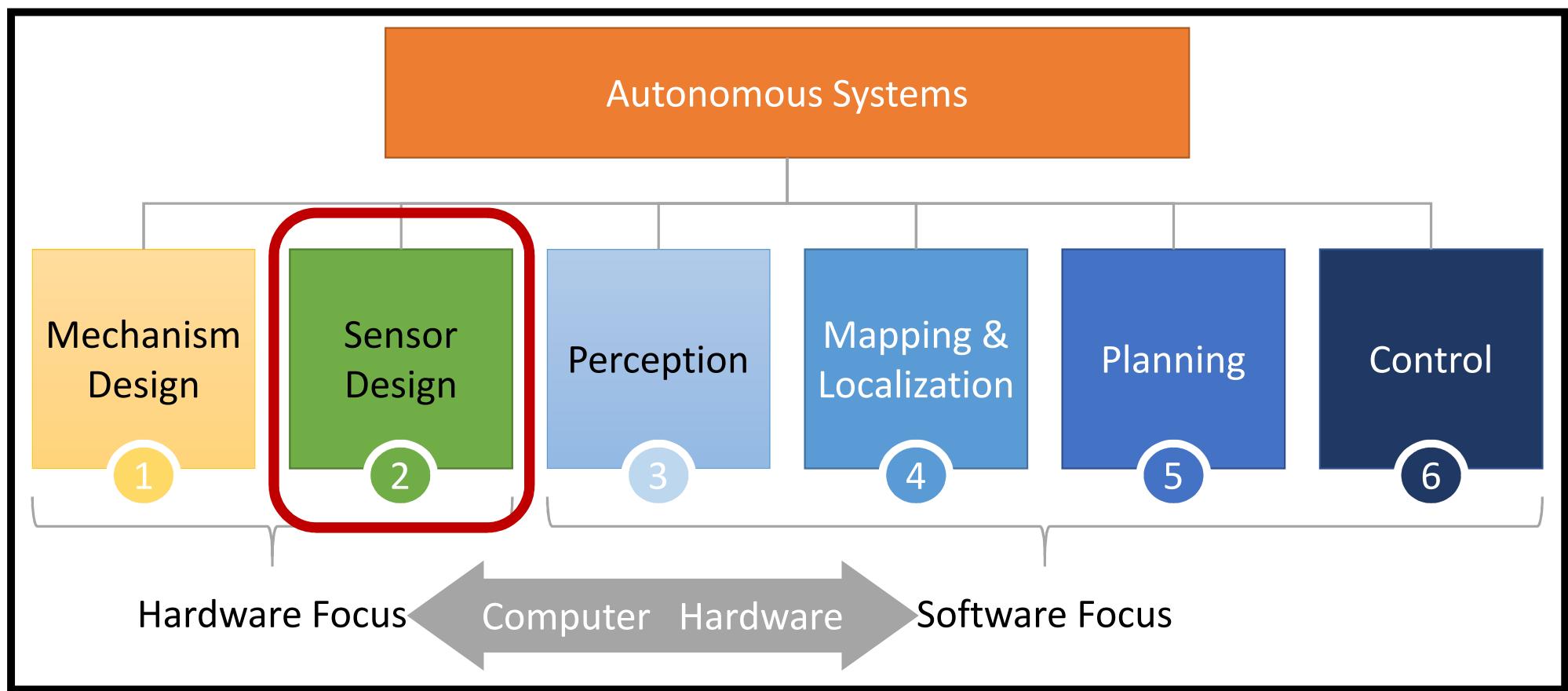
Mechanism designers create new robots and actuators



WYSS INSTITUTE



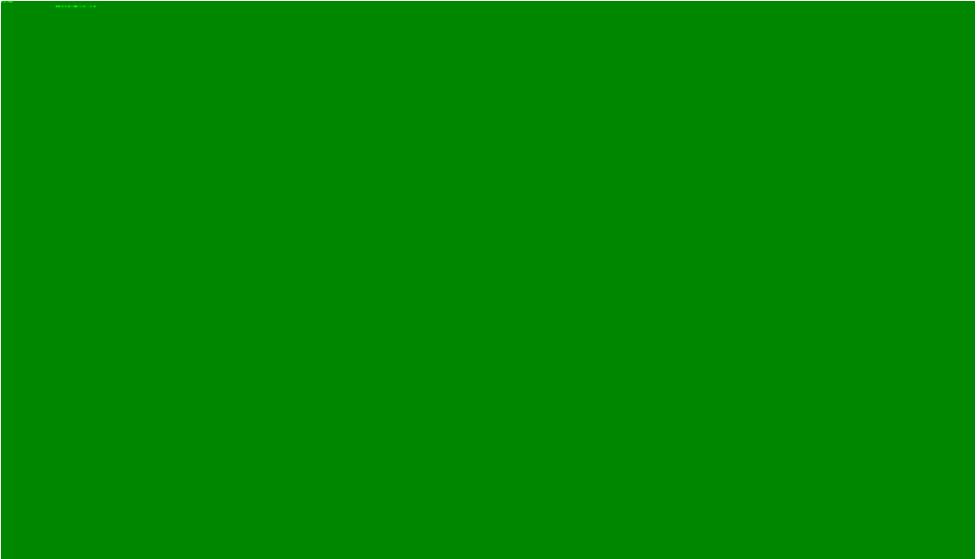
Autonomous Systems / Robotics is a BIG space



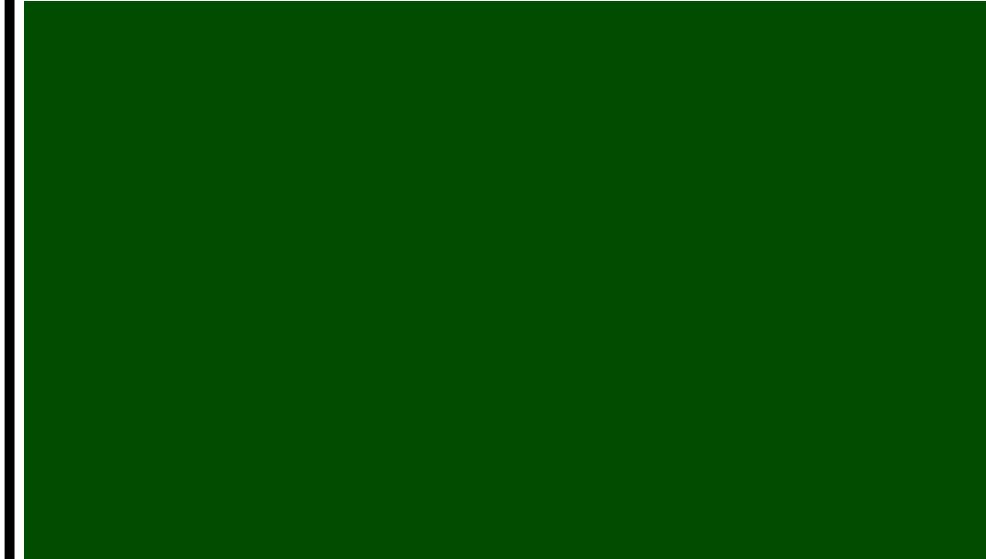
2

Sensor designers try to find new ways to collect data about the world around the autonomous system

MEMs IMUs / Gyroscopes



Motor Encoders



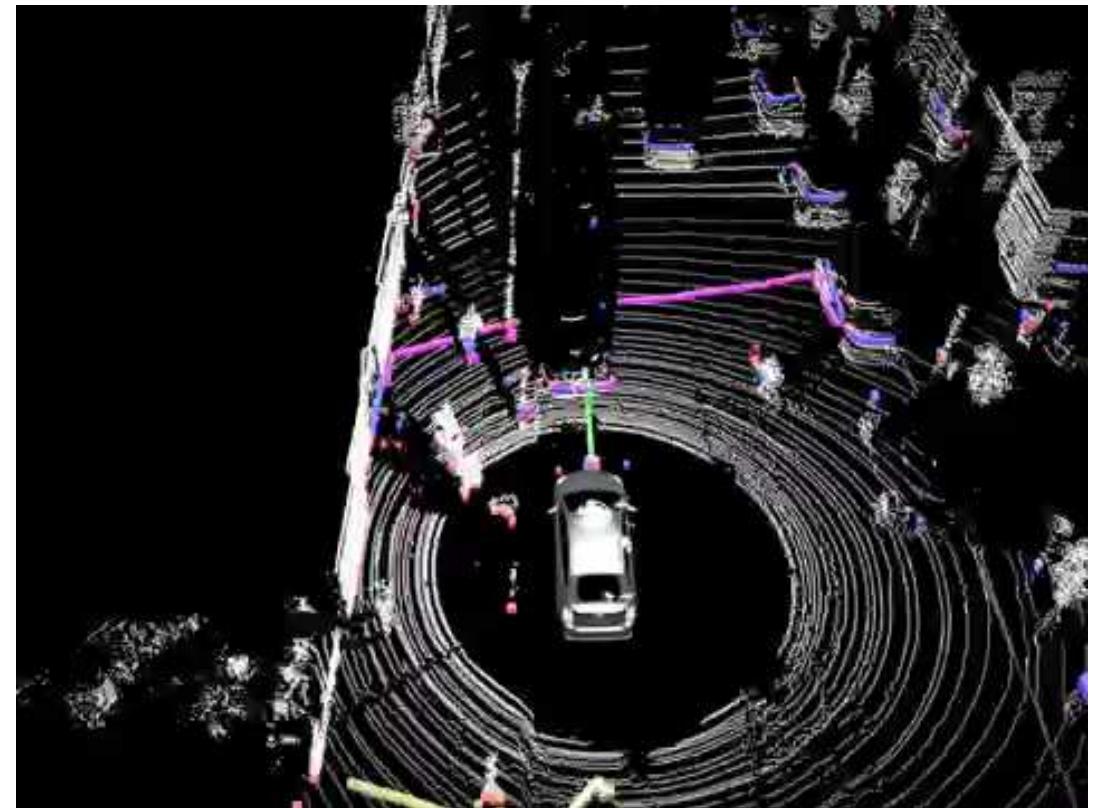
2

Sensor designers try to find new ways to collect data about the world around the autonomous system

Structured Light (e.g., LIDAR)



(and other Structured Waves e.g., Sonar, RADAR, etc.)



2

Sensor designers try to find new ways to collect data about the world around the autonomous system

Unstructured Light (aka Cameras)



2

Sensor designers try to find new ways to collect data about the world around the autonomous system

Unstructured Light (aka Cameras)

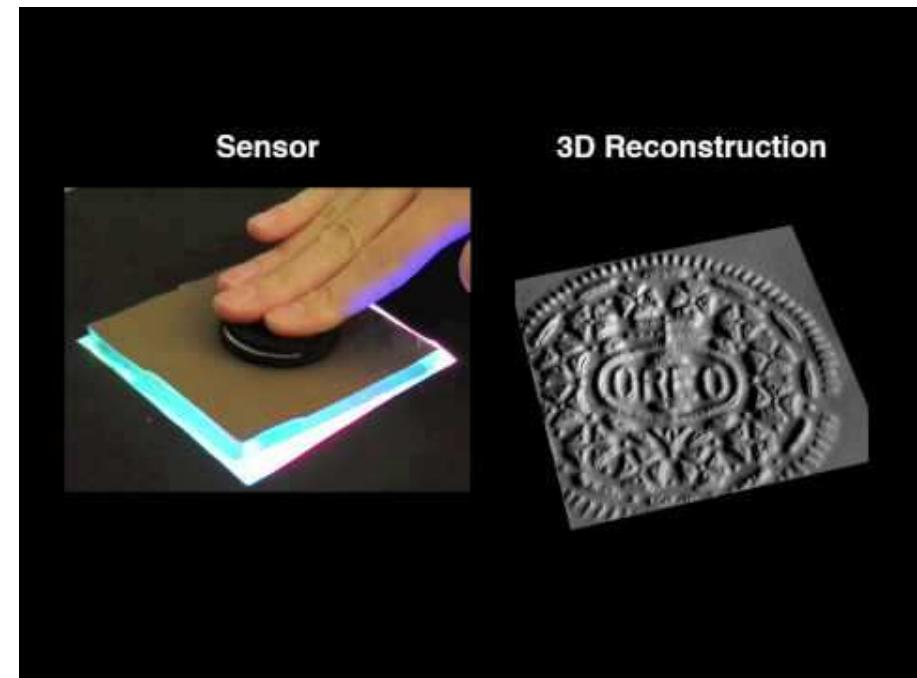
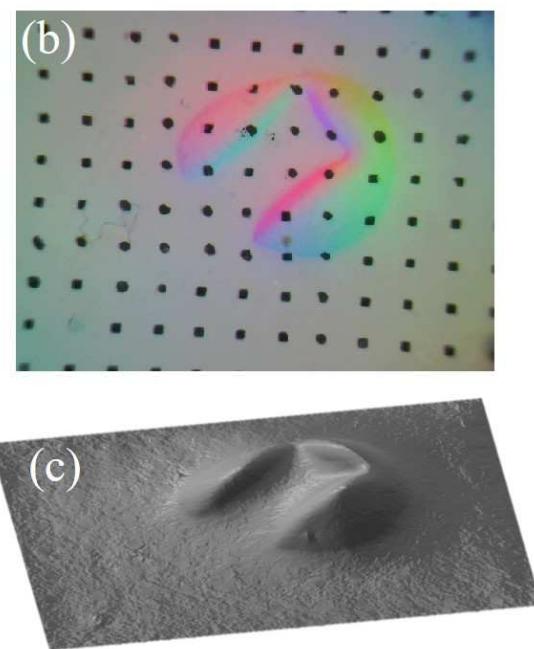
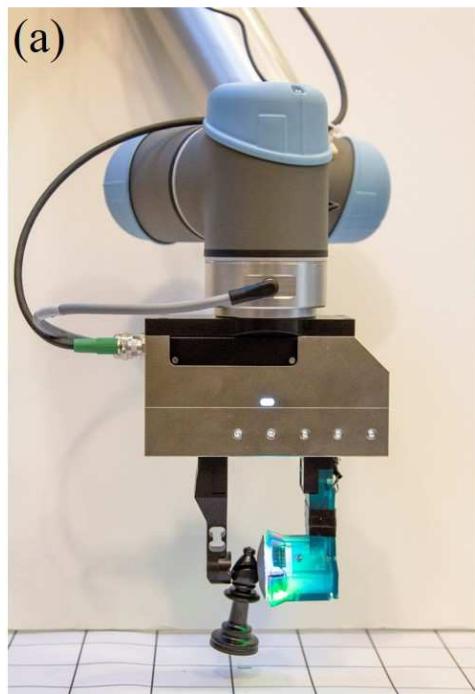


Computer
Vision
(we'll talk
about this
later)

Usable
Data

2

Sensor designers try to find new ways to collect data about the world around the autonomous system



<http://www.gelsight.com/>

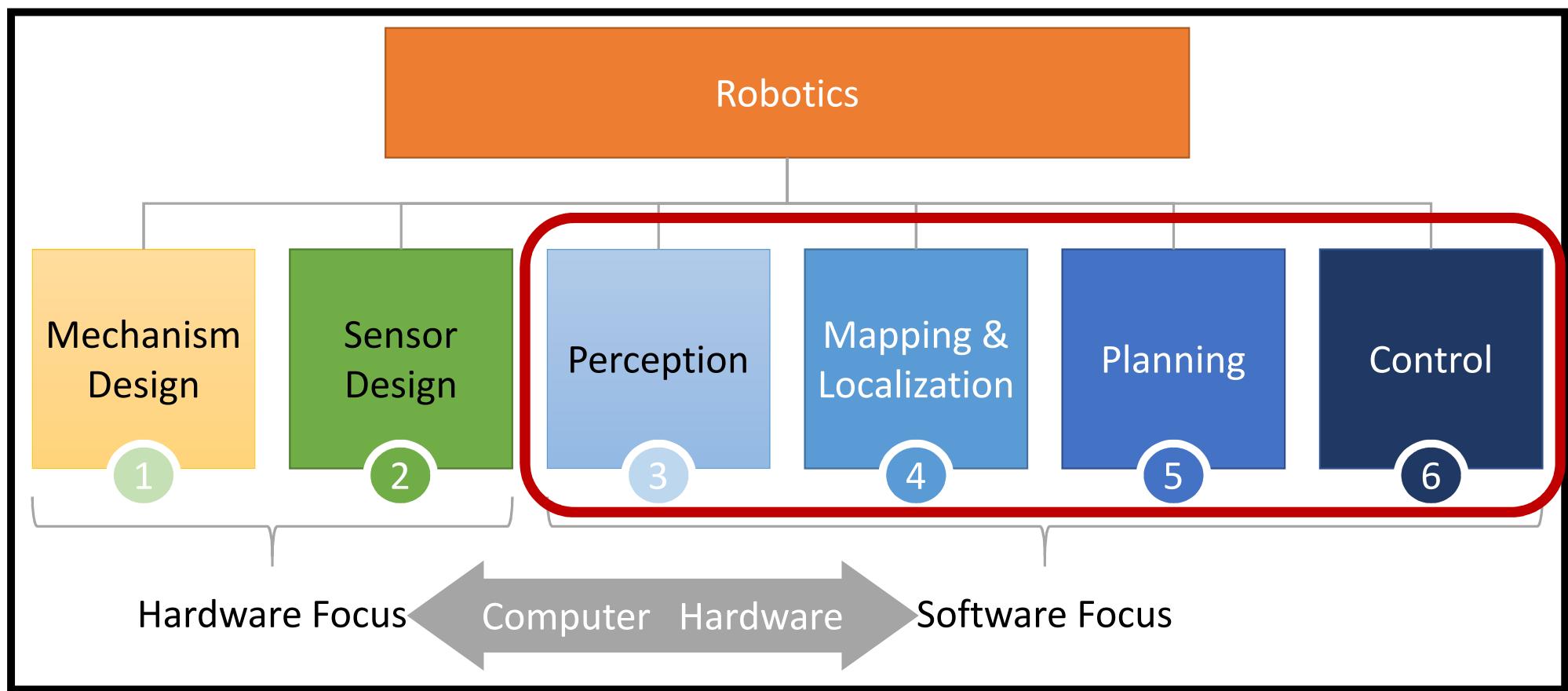
1 2

Key Takeaways:

1. Different kinds of systems will have different power, weight, and performance budgets for computer hardware and requirements for control algorithms
 2. Understanding the sensors on your system will help you understand at what rate you can get information and the bandwidth of the information you will need to process
 3. Different kinds of sensors will require different amounts of onboard compute to process the information
-

Our topic for next week – Compute!

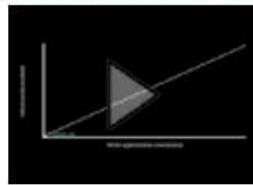
Autonomous Systems / Robotics is a BIG space



Your homework for next week 1/2

Pre-Reads for Intro to Robotics (Perception and Mapping)

[Chris Urmson: How a driverless car sees the road ↗](#)



[Meet Spot, the robot dog that can run, hop and open doors | Marc Raibert ↗](#)



Your homework for next week 2/2

Pre-Reads for Intro to Robotics (Planning and Control)

Computer Architecture to Close the Loop in Real-time Optimization:

<https://ieeexplore.ieee.org/document/7402937> ↗

The Architectural Implications of Autonomous Driving: Constraints and

Acceleration: <https://web.eecs.umich.edu/~shihclin/papers/AutonomousCar-ASPLOS18.pdf> ↗ ↘

A Summary of Team MIT's Approach to the Virtual Robotics Challenge:

https://agile.seas.harvard.edu/files/agile/files/vrc_entry.pdf



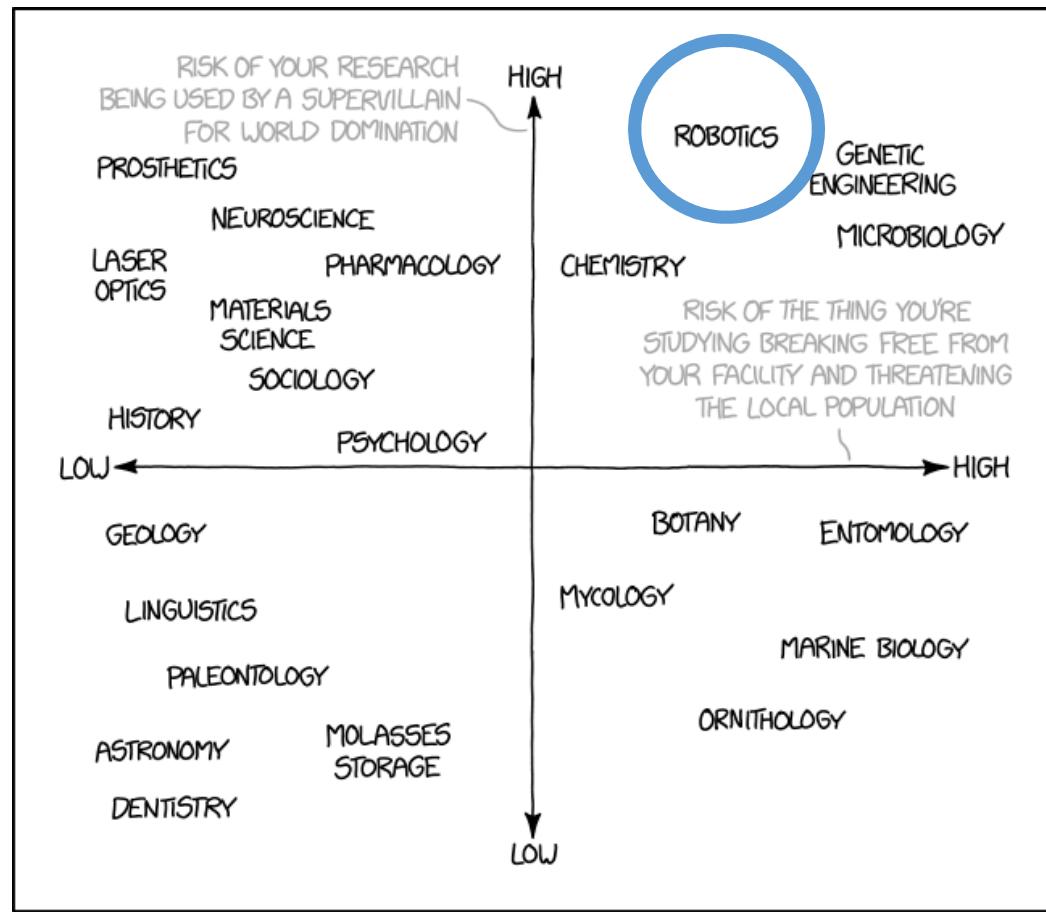
And finally some fun robot videos



6:16:34 05/06/2015

CS 249r: Special Topics in Edge Computing

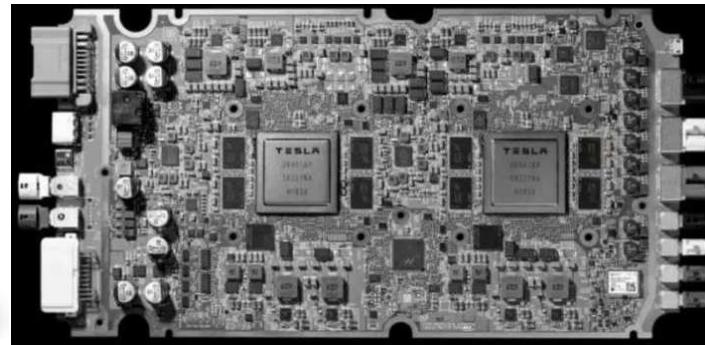
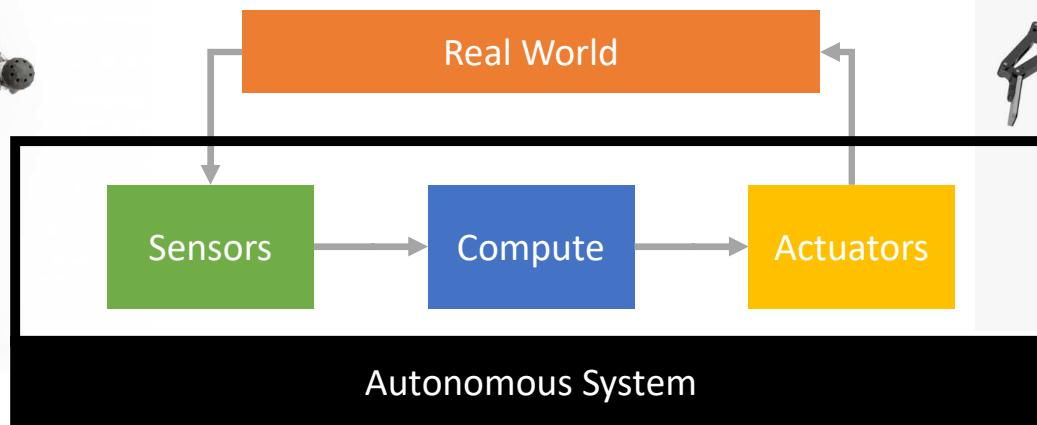
Intro to Autonomous Systems / Robotics Part 1



Brian Plancher
Fall 2019



What do we mean by an Autonomous System?



So how is CS249r actually going to run?

Date	Module	Class Type	Topic	Notes
Wed, Sep 4	Introduction	Lecture	Course Introduction, Overview, and Nuts and Bolts	
Mon, Sep 9		Lecture	Intro to Robotics (Perception and Mapping)	
Wed, Sep 11	Motivation	Lecture	Intro to Robotics (Planning and Control)	
Mon, Sep 16		Lecture	Intro to Domain Specific Architectures	
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Background Lectures

Reading / Presenting Papers

Final Project

So how is CS249r actually going to run?

FYI the exact dates of the first couple weeks are moving around a little bit

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Final Project

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-

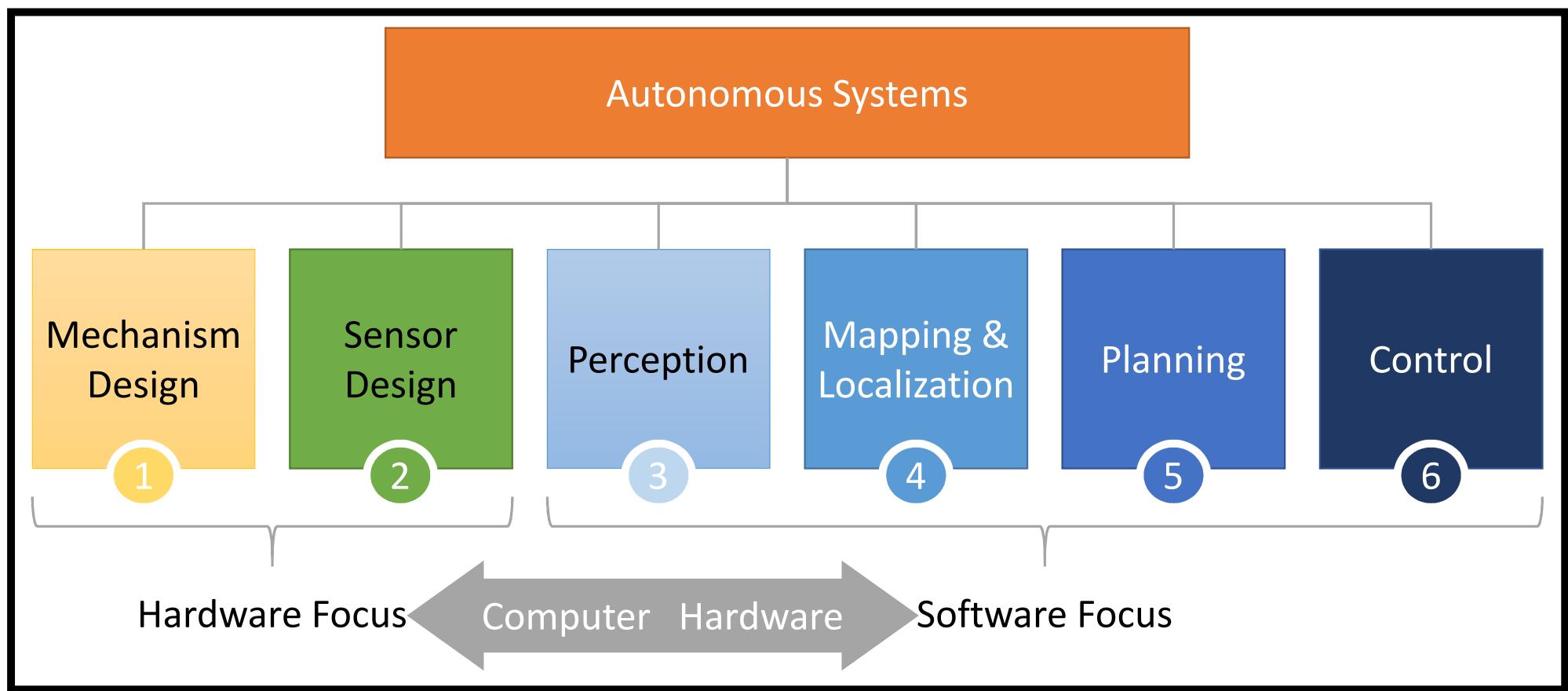
What are the prerequisites for CS 249r?

1. CS 141 and/or basic computer architecture and digital design
2. CS 61/161 and/or a basic systems programming experience
3. CS 124 and/or a basic algorithms experience

We hope to have a diverse class and assume few students will have full exposure to the full breadth of topics we will cover. As such, we intend to provide some background on all of the topics. That said, students may find it helpful if they also have some background in some of the algorithms employed in autonomous systems from classes such as CS 181/182 or AM 121. Please contact the instructor or teaching fellow if you are interested in taking the course but are unsure about whether the background you have is suitable.

Any quick nuts and bolts questions?

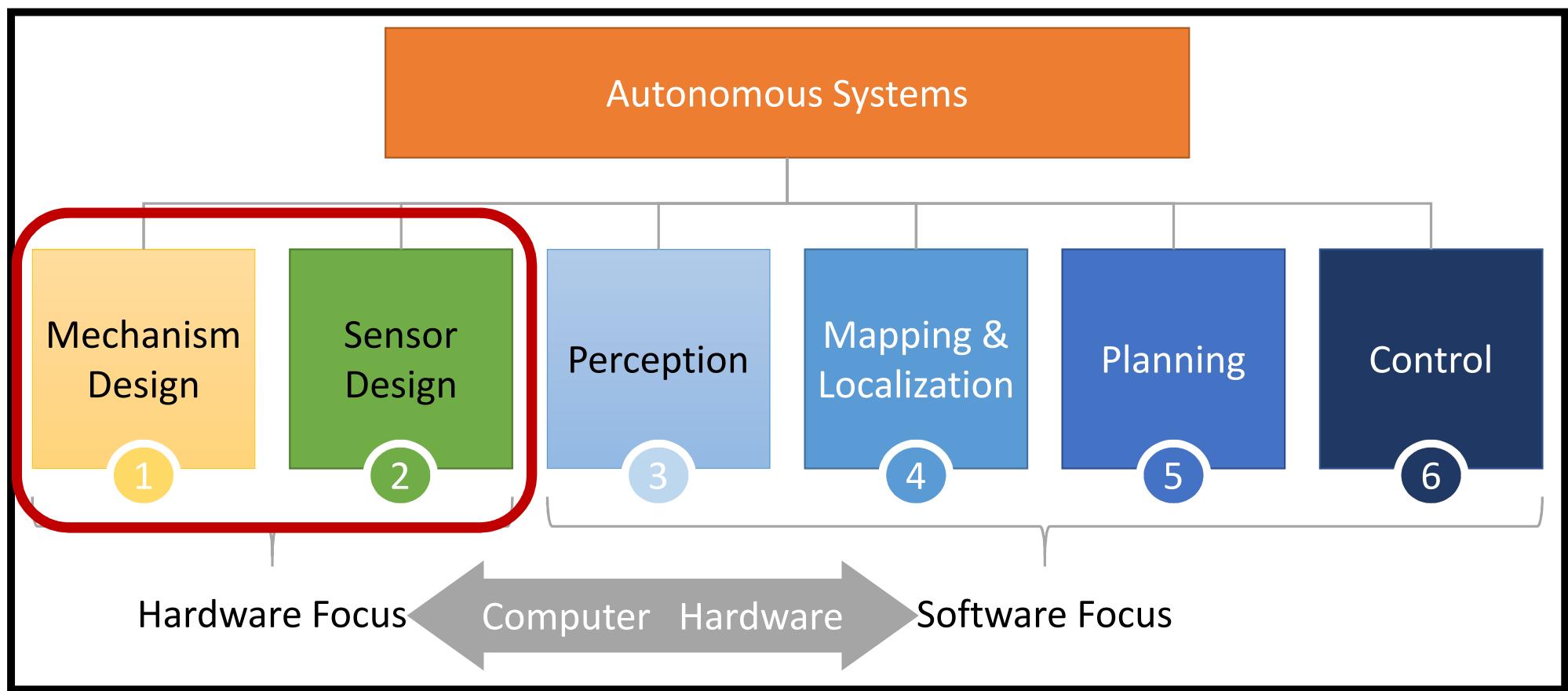
Autonomous Systems / Robotics is a BIG space



The goal for the next couple of lectures is to develop a **high level** understanding of:

1. What is an autonomous system
 2. Key **problems** for autonomous systems
 3. Some of the most important (classes of) **algorithms** in robotics
 4. The **model based** vs. **model free** tradeoff
 5. The **online** vs **offline** tradeoff
 6. The **no free lunch** theorem and the need for **approximations**
 7. How **computer systems / architecture** design has and can play a role in improving autonomous systems
-

Autonomous Systems / Robotics is a BIG space



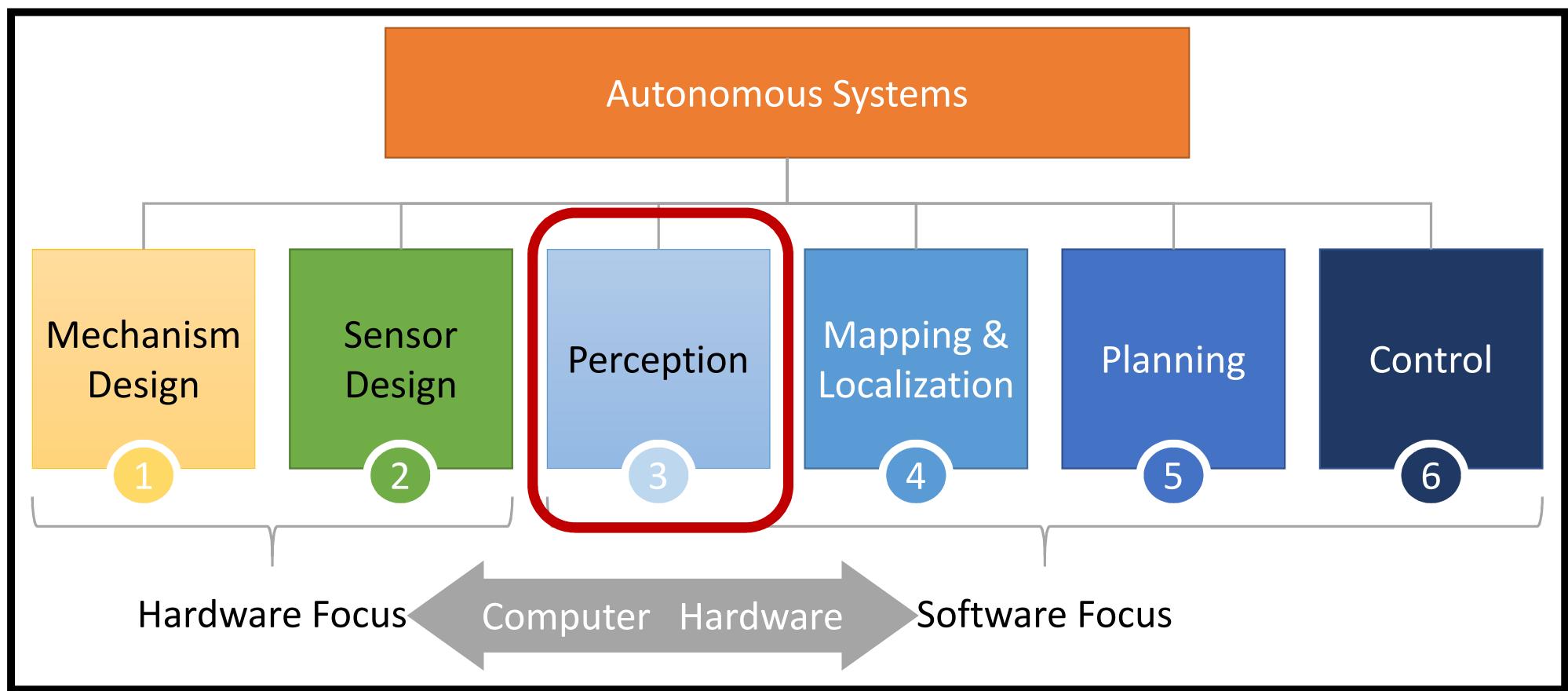
1 2

Key Takeaways:



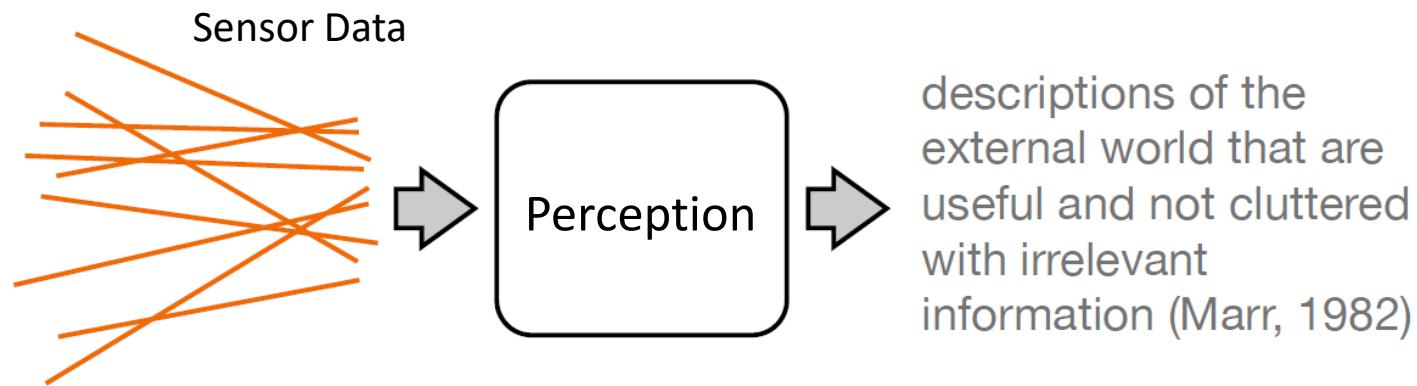
1. When designing algorithms for robots you need to understand the physical capabilities of the robot and you (potentially) need to understand how to model its physical behaviors
 2. Different kinds of systems will have different power, weight, and performance budgets for computer hardware
-

Autonomous Systems / Robotics is a BIG space



3

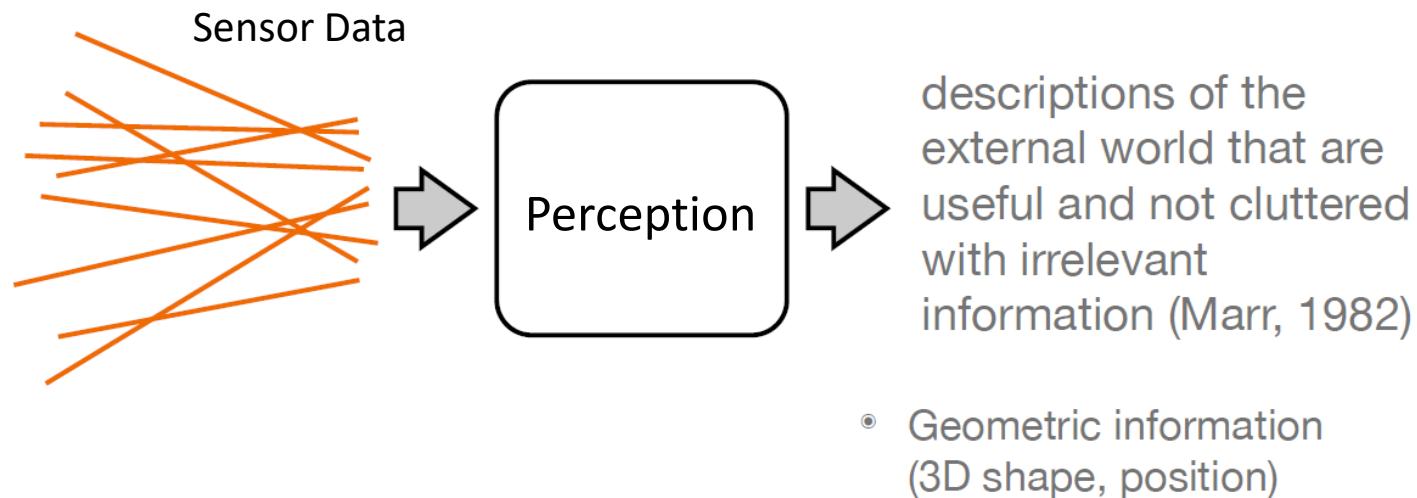
Perception is the processing of sensor data to understand the world around the robot



Slide Credit: Todd Zickler CS 283

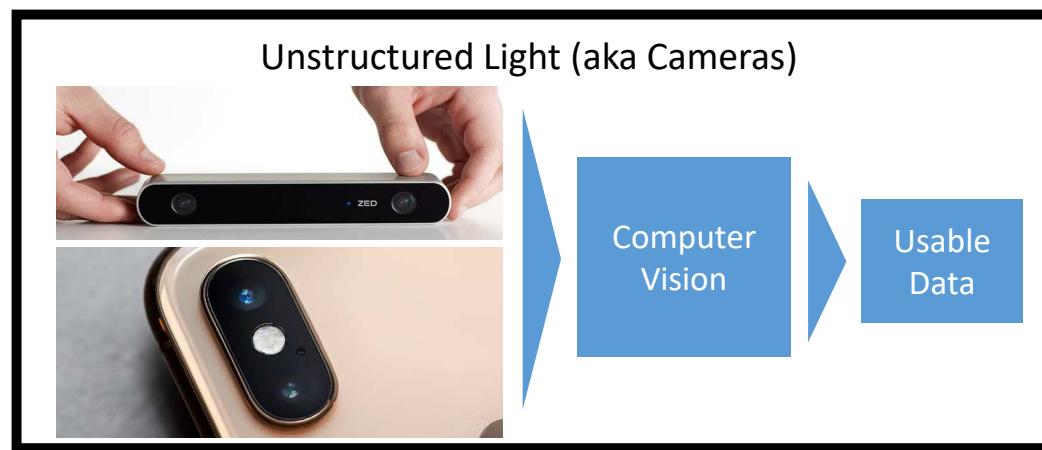
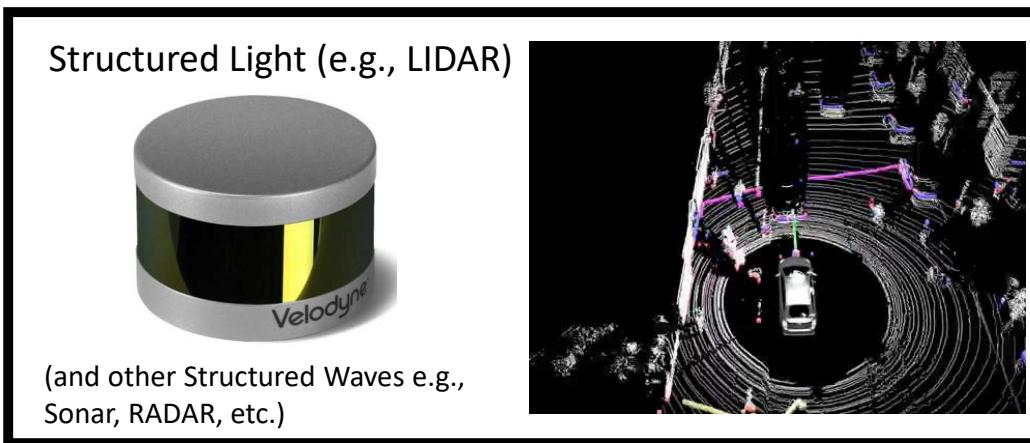
3

Perception is the processing of sensor data to understand the world around the robot



3

We can compute the depth to objects by using geometry and physics



3

We can compute the depth to objects by using geometry and physics



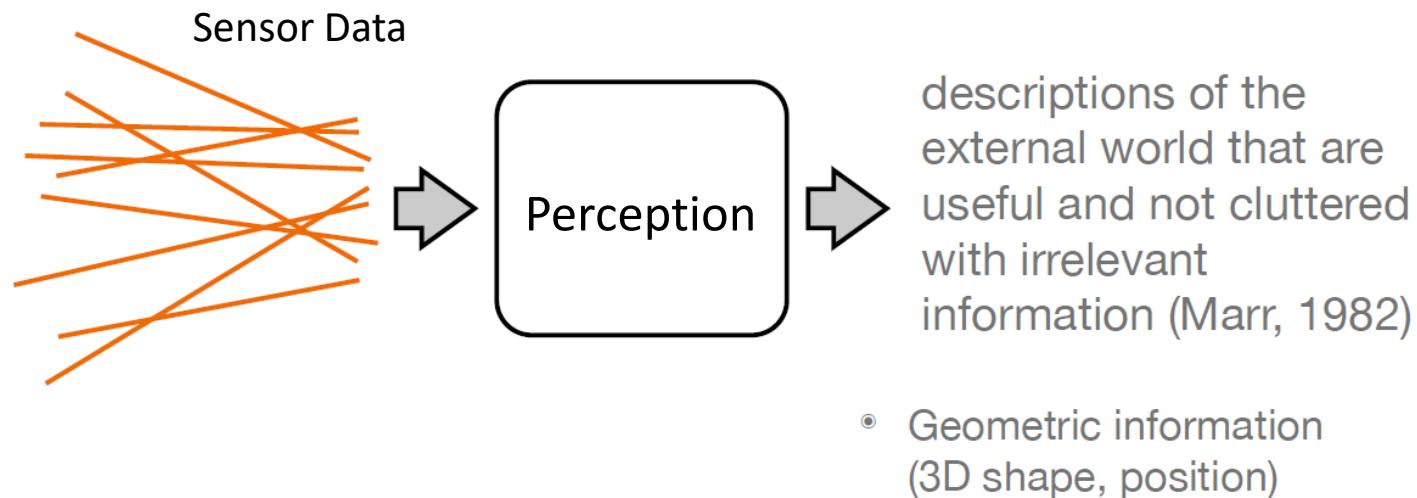
3

Stereo depth is such an important problem that Intel has designed a custom chip!



3

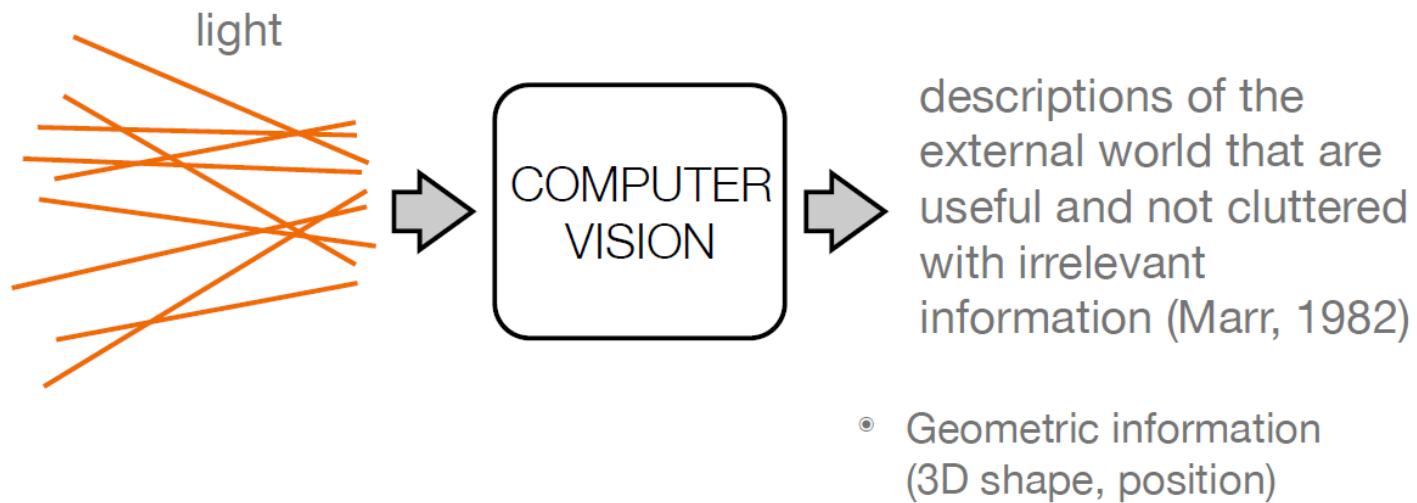
Perception is the processing of sensor data to understand the world around the robot



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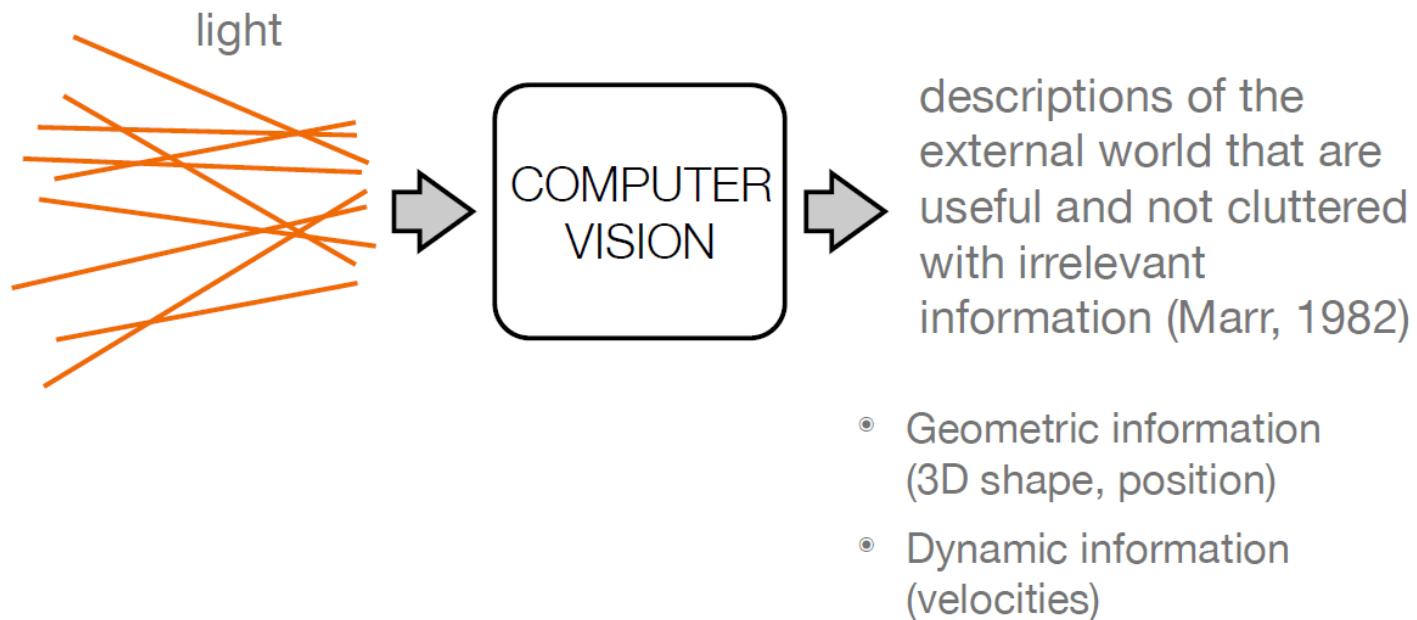
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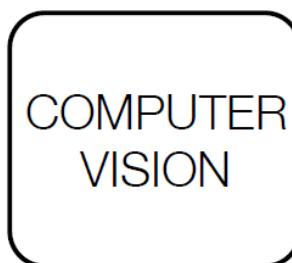
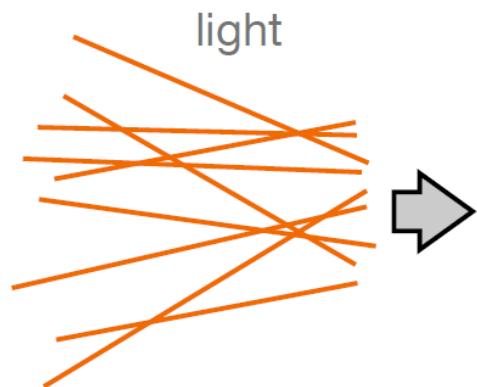
Perception is the processing of sensor data to understand the world around the robot



Slide Credit: Todd Zickler CS 283

3

Perception is the processing of sensor data to understand the world around the robot



descriptions of the external world that are useful and not cluttered with irrelevant information (Marr, 1982)

- Geometric information (3D shape, position)
- Dynamic information (velocities)
- Semantic information (object, scene categories)

Slide Credit: Todd Zickler CS 283

3

Computer Vision is a hard problem

3

Computer Vision is a hard problem

What color(s) are this shirt and these pants?



Slide Credit: Hamilton Chong

3

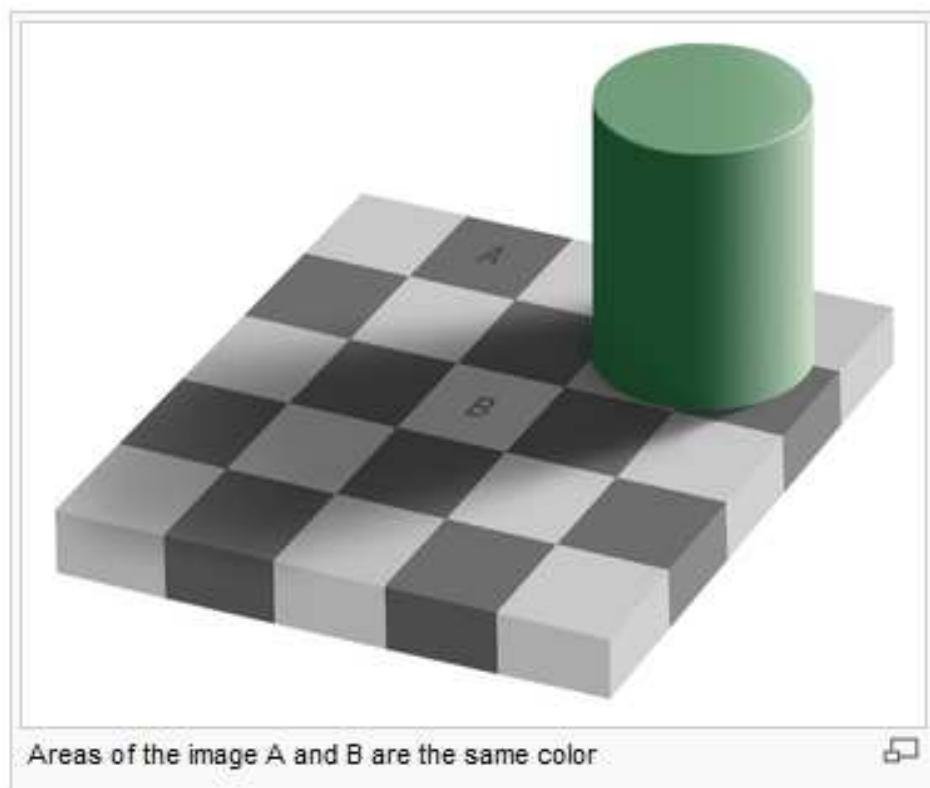
Computer Vision is a hard problem



Slide Credit: Hamilton Chong

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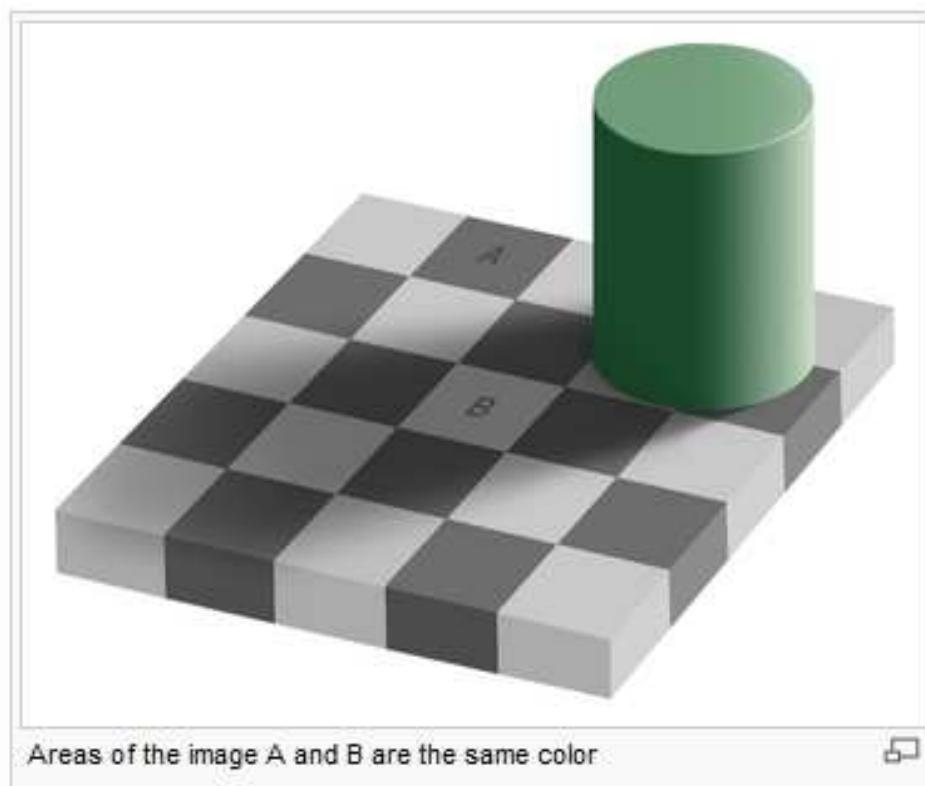
Computer Vision is a hard problem



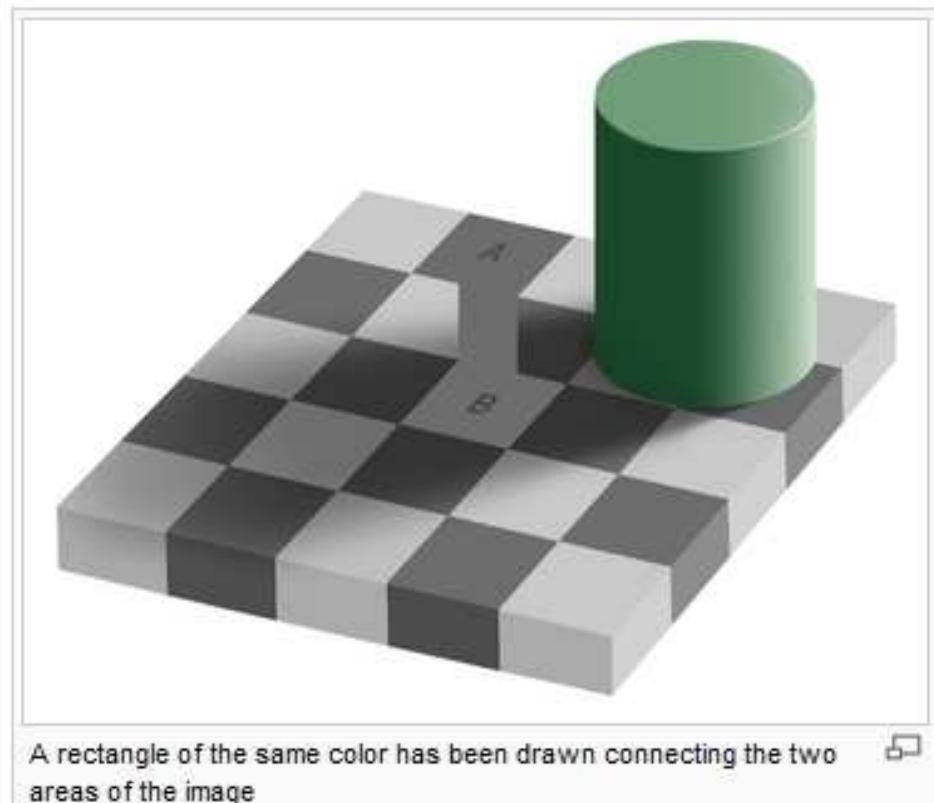
Adelson 1995

3

Computer Vision is a hard problem



Areas of the image A and B are the same color



A rectangle of the same color has been drawn connecting the two areas of the image



Adelson 1995

3

Computer Vision is a hard problem

Sinha et al.: Face Recognition by Humans: Nineteen Results Researchers Should Know About



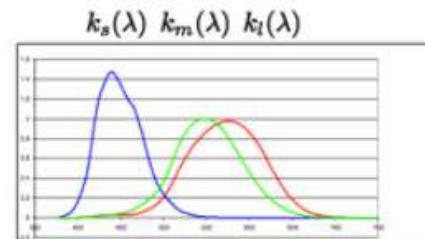
3

Computer Vision is a hard problem

Retinal color

$$\mathbf{c}(\ell(\lambda)) = (c_s, c_m, c_l)$$

$$c_s = \int k_s(\lambda) \ell(\lambda) d\lambda$$

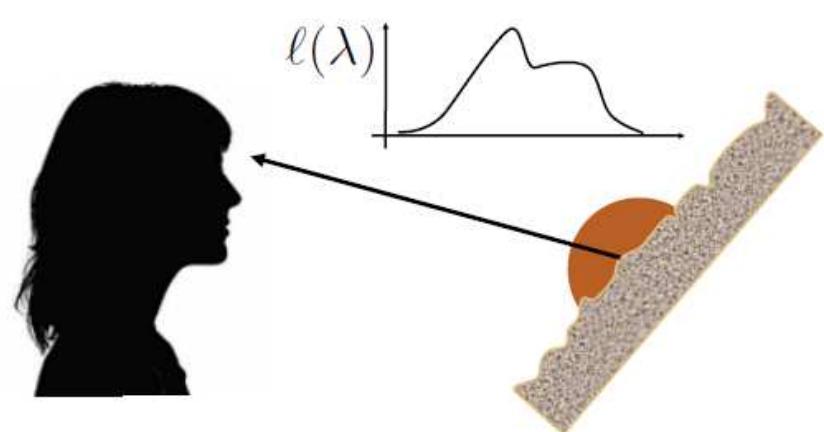


LMS sensitivity functions

Perceived color

Object color

Color names



Slide Credit: Todd Zickler CS 283

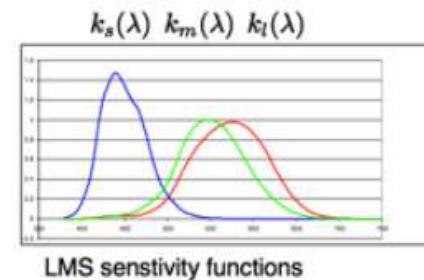
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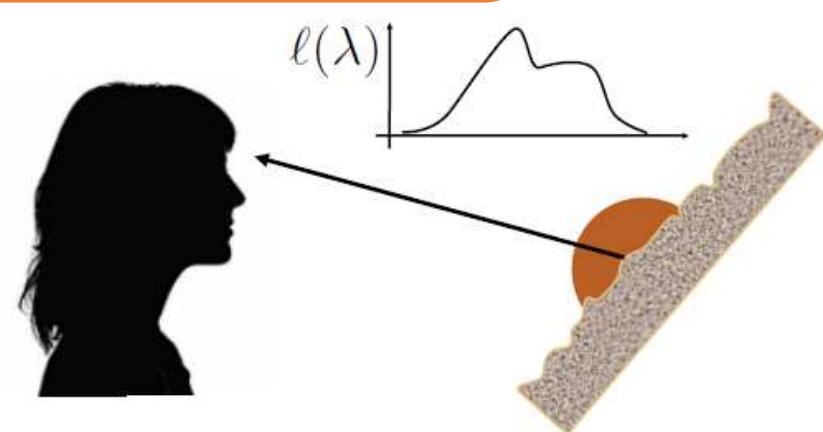


So how can we represent this with an algorithm?

Perceived color

Object color

Color names



Slide Credit: Todd Zickler CS 283

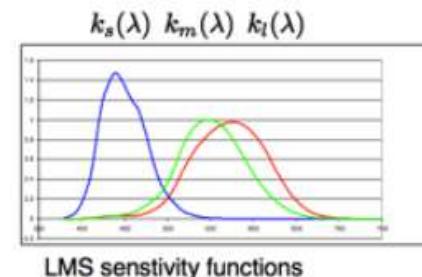
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Computer Vision is a hard problem

Retinal color

$$\mathbf{c}(\ell(\lambda)) = (c_s, c_m, c_l)$$

$$c_s = \int k_s(\lambda) \ell(\lambda) d\lambda$$



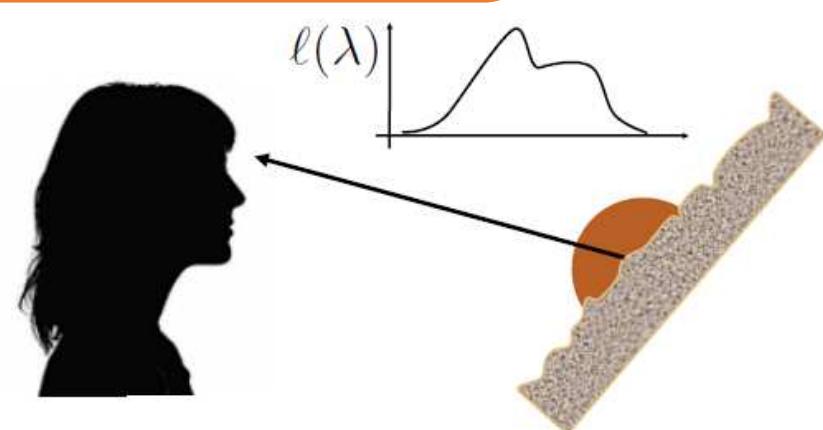
So how can we represent this with an algorithm?

Perceived color

Object color

Color names

Well lets start by building up some intuition for how to find an edge!

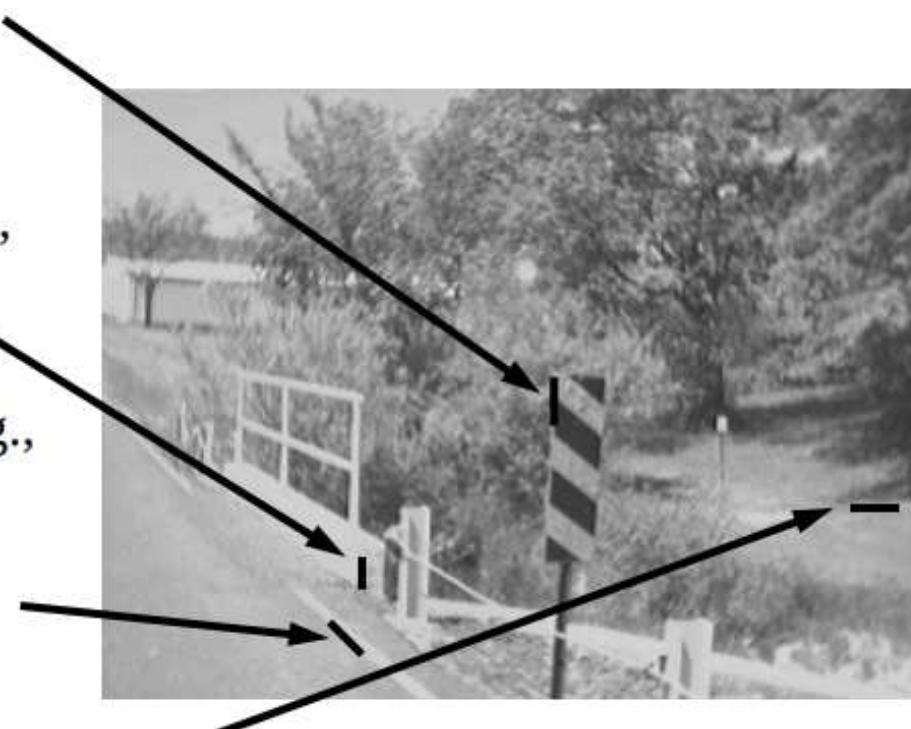


Slide Credit: Todd Zickler CS 283

3

Edges are where discontinuities occur in images

- Depth discontinuity
- Surface orientation discontinuity
- Reflectance discontinuity (i.e., change in surface material properties)
- Illumination discontinuity (e.g., shadow)

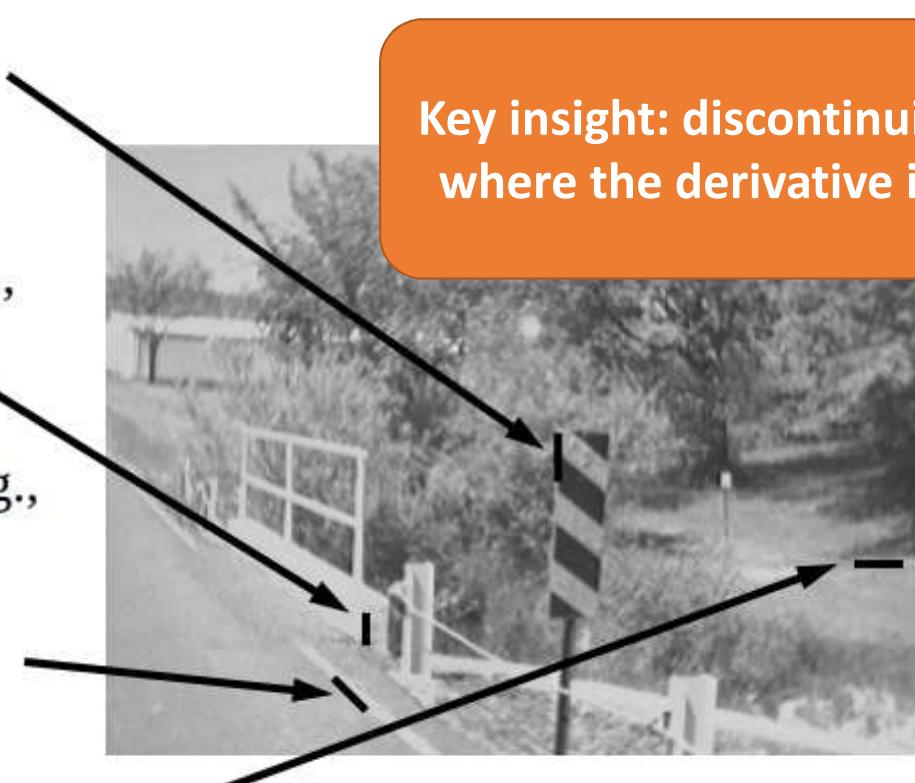


Slide credit: Christopher Rasmussen

3

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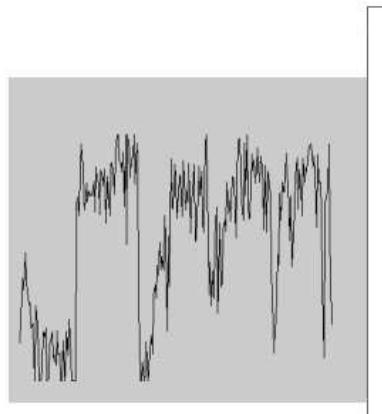
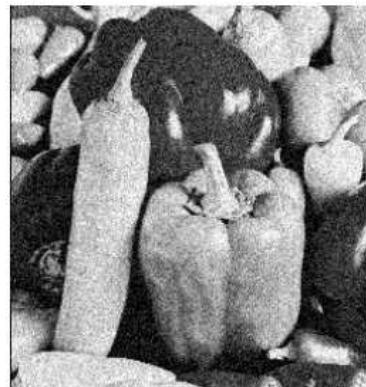


Key insight: discontinuities are where the derivative is high!

Slide credit: Christopher Rasmussen

3

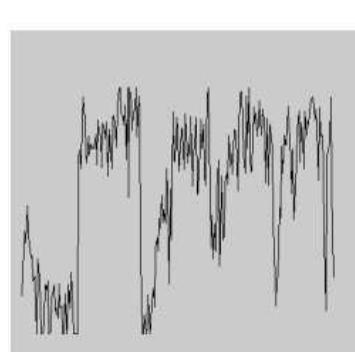
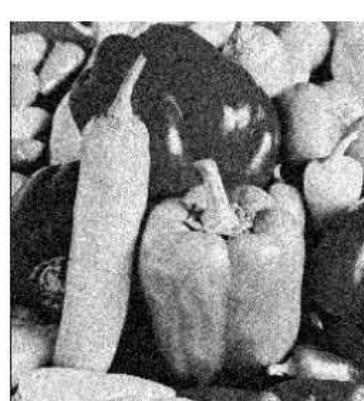
Noise will corrupt our derivative computation



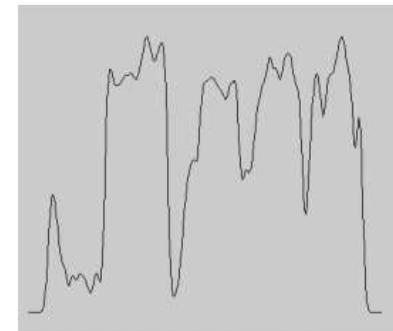
No smoothing

3

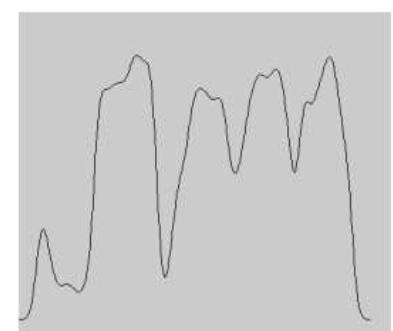
“Spatially local averaging” reduces noise



No smoothing



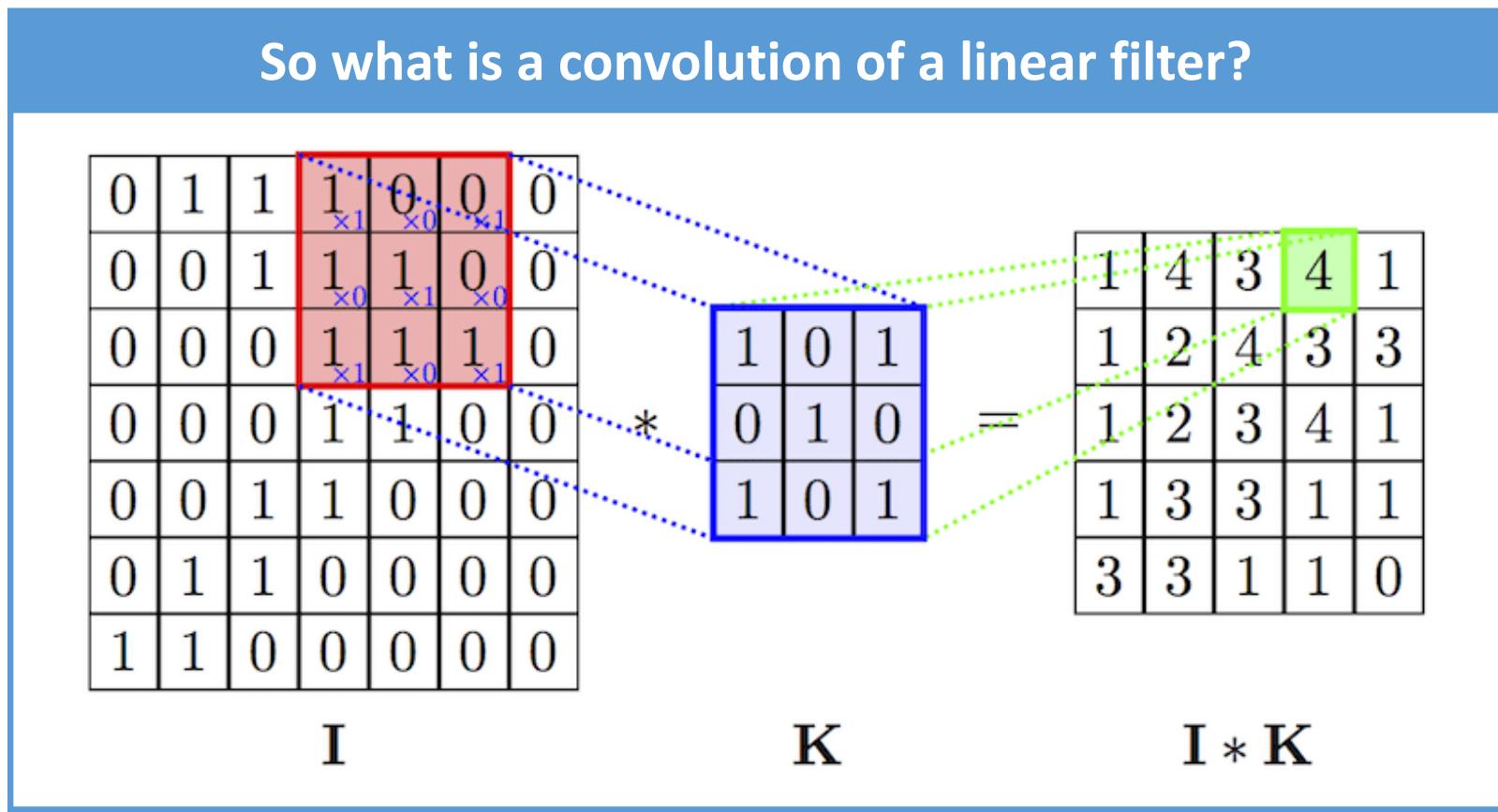
$\sigma = 2$



$\sigma = 4$

3

The traditional Computer Vision approach is through convolution of linear filters



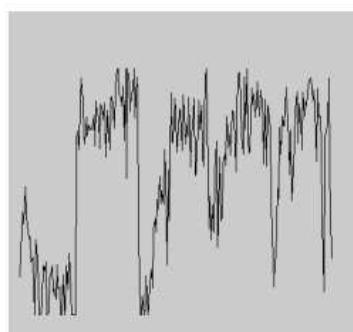
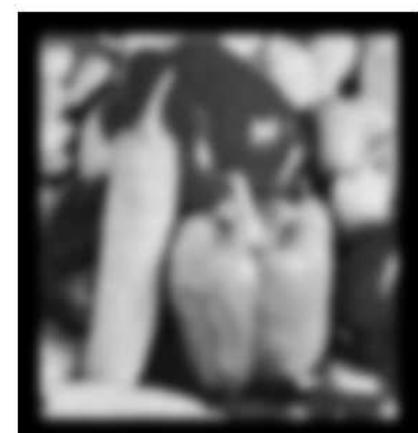
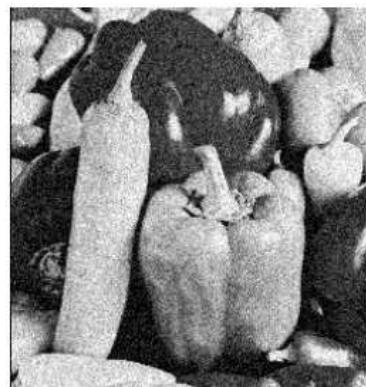
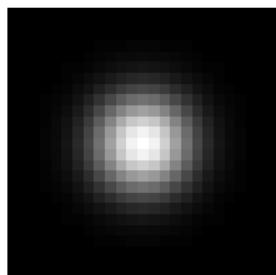
3

“Spatially local averaging” reduces noise

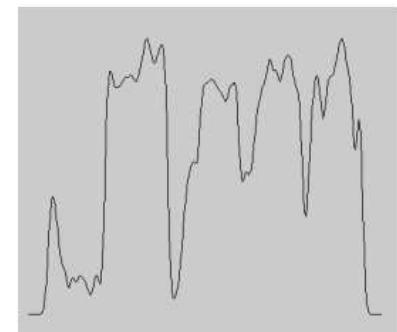
$$G_\sigma = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

0.003	0.013	0.022	0.013	0.003
0.013	0.059	0.097	0.059	0.013
0.022	0.097	0.159	0.097	0.022
0.013	0.059	0.097	0.059	0.013
0.003	0.013	0.022	0.013	0.003

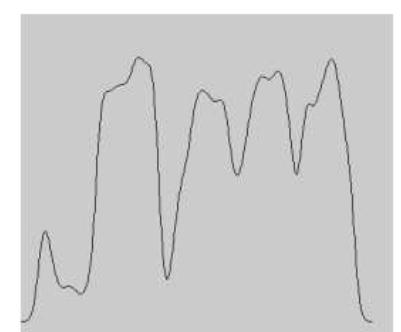
$5 \times 5, \sigma = 1$



No smoothing



$\sigma = 2$



$\sigma = 4$

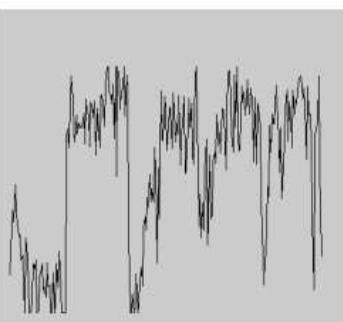
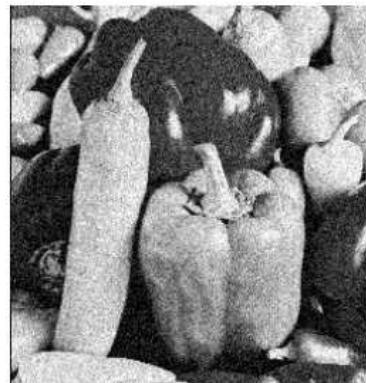
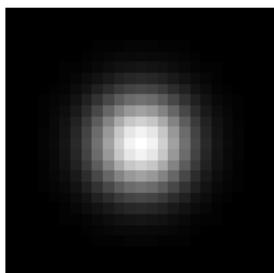
3

“Spatially local averaging” reduces noise

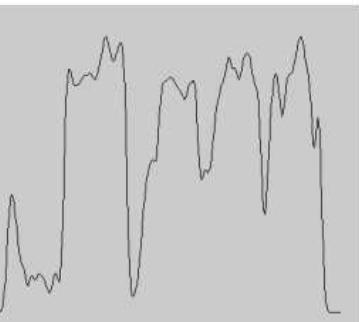
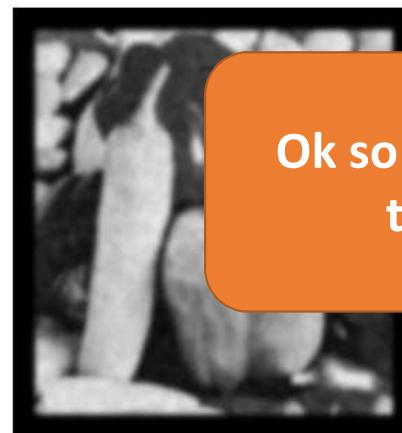
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0.022	0.097	0.159	0.097	0.022
0.013	0.059	0.097	0.059	0.013
0.003	0.013	0.022	0.013	0.003

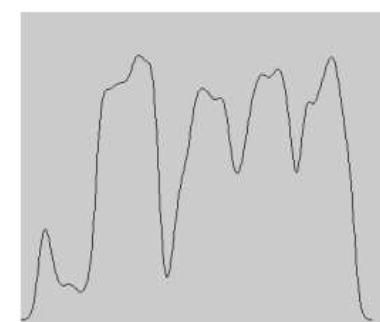
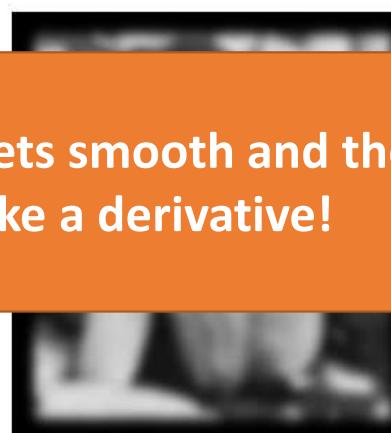
$5 \times 5, \sigma = 1$



No smoothing



$\sigma = 2$



$\sigma = 4$

Ok so lets smooth and then take a derivative!

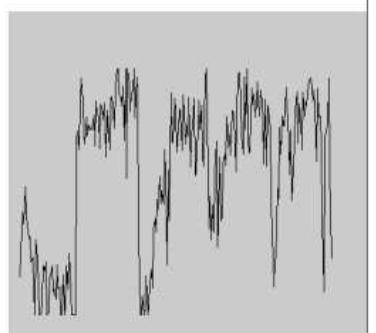
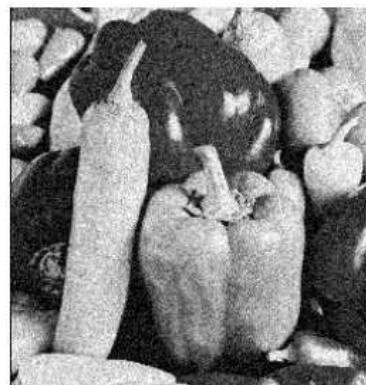
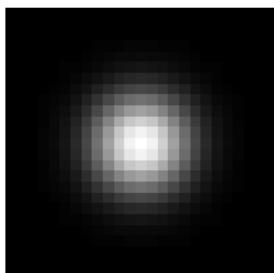
3

“Spatially local averaging” reduces noise

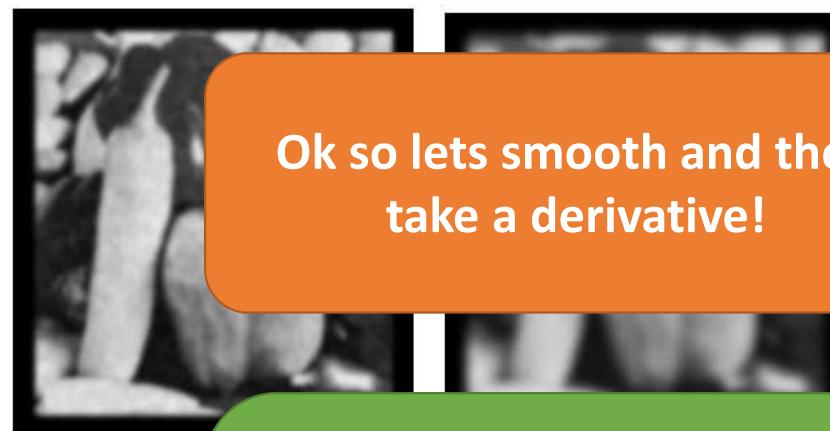
$$G_\sigma = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

0.003	0.013	0.022	0.013	0.003
0.013	0.059	0.097	0.059	0.013
0.022	0.097	0.159	0.097	0.022
0.013	0.059	0.097	0.059	0.013
0.003	0.013	0.022	0.013	0.003

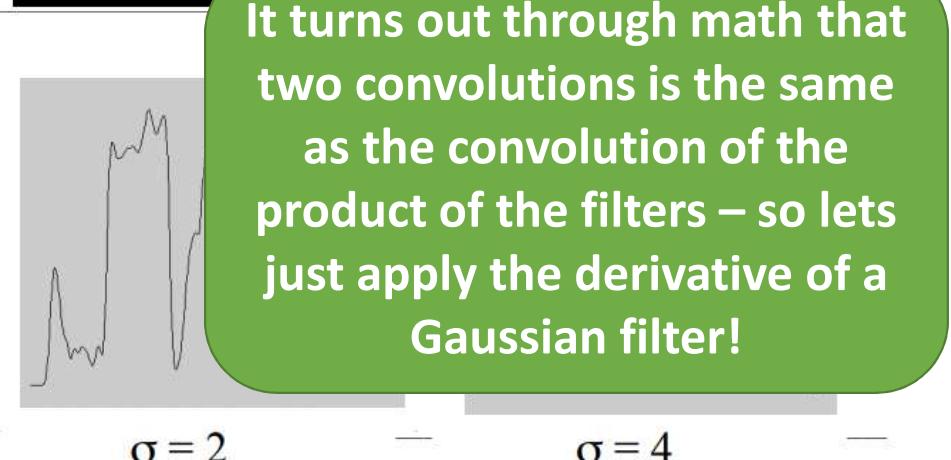
$5 \times 5, \sigma = 1$



No smoothing



Ok so lets smooth and then take a derivative!



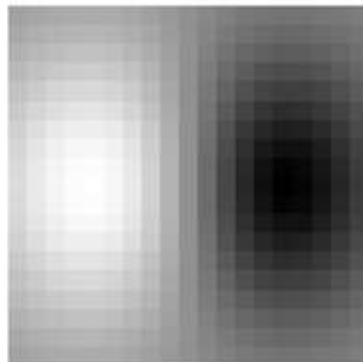
It turns out through math that two convolutions is the same as the convolution of the product of the filters – so lets just apply the derivative of a Gaussian filter!

3

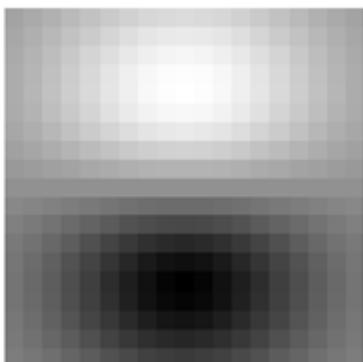
Derivatives increase noise so we can find edges using a derivative of Gaussian Filter

Applying the first derivative of Gaussian

$$\frac{d}{dx}$$



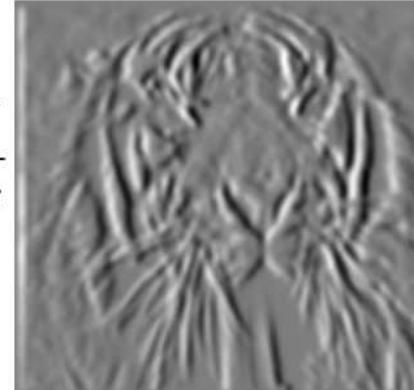
$$\frac{d}{dy}$$



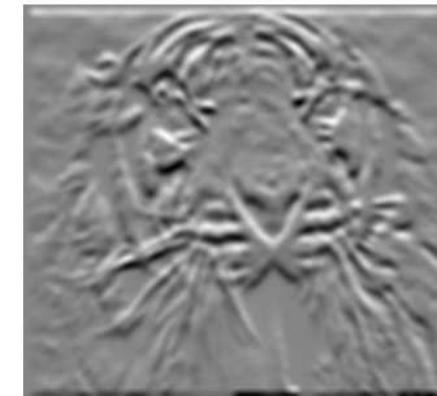
I



$$\frac{\partial I}{\partial x}$$



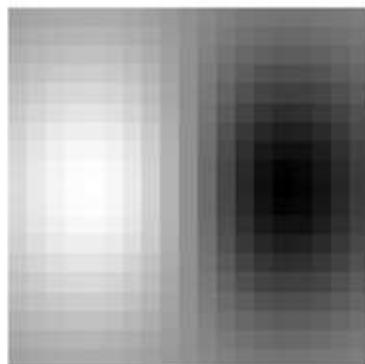
$$\frac{\partial I}{\partial y}$$



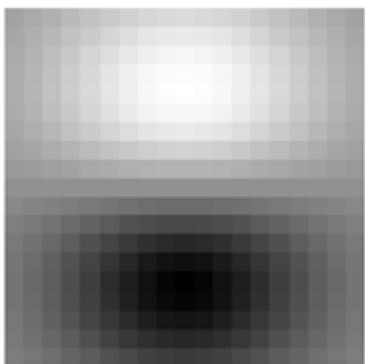
3

Derivatives increase noise so we can find edges using a derivative of Gaussian Filter

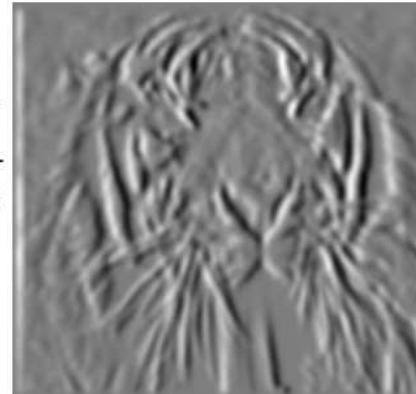
$$\frac{d}{dx}$$



$$\frac{d}{dy}$$

 I

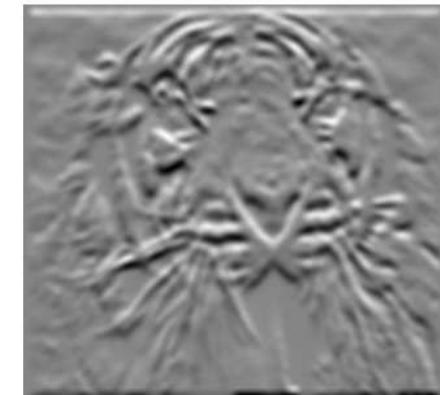
$$\frac{\partial I}{\partial x}$$



Applying the first derivative of Gaussian

**But not all edges are
vertical or horizontal
what can we do?**

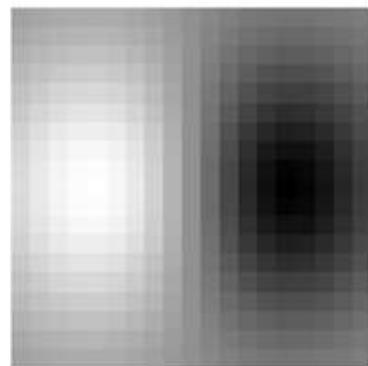
$$\frac{\partial I}{\partial y}$$



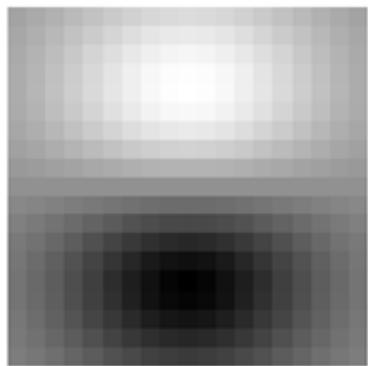
3

Derivatives increase noise so we can find edges using a derivative of Gaussian Filter

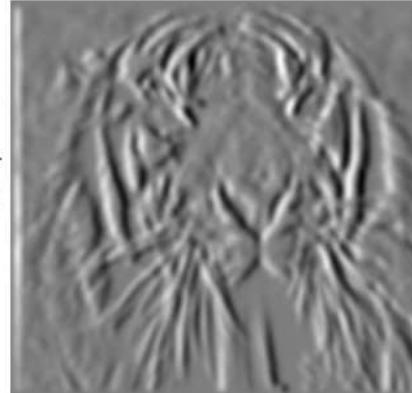
$$\frac{d}{dx}$$



$$\frac{d}{dy}$$

 I 

$$\frac{\partial I}{\partial x}$$

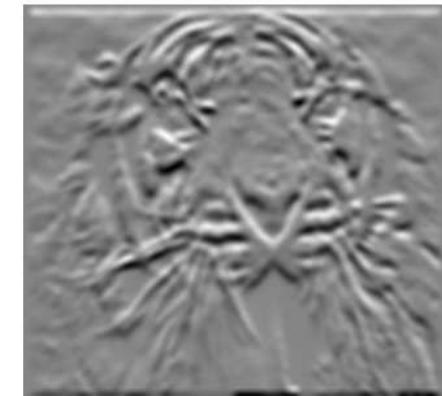


Applying the first derivative of Gaussian



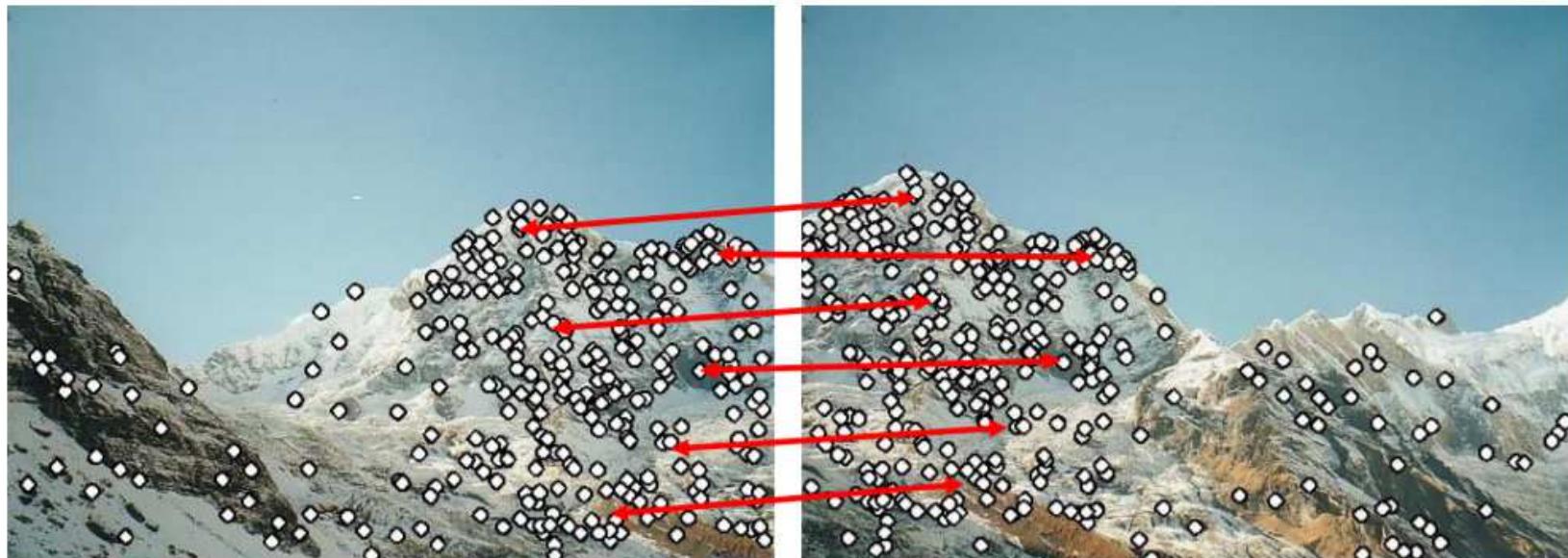
$$|\nabla I| = \sqrt{\frac{\partial I^2}{\partial x} + \frac{\partial I^2}{\partial y}}$$

$$\frac{\partial I}{\partial y}$$



3

Various filters can be used to extract features to e.g., stitch panoramas



Step 1: extract features

Step 2: match features

3

Various filters can be used to extract features to e.g.,
stitch panoramas



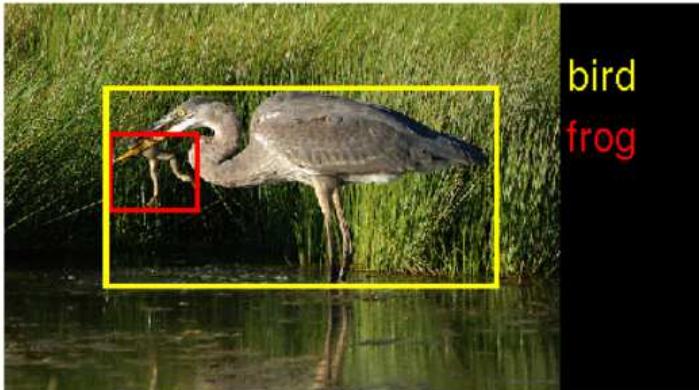
Step 1: extract features

Step 2: match features

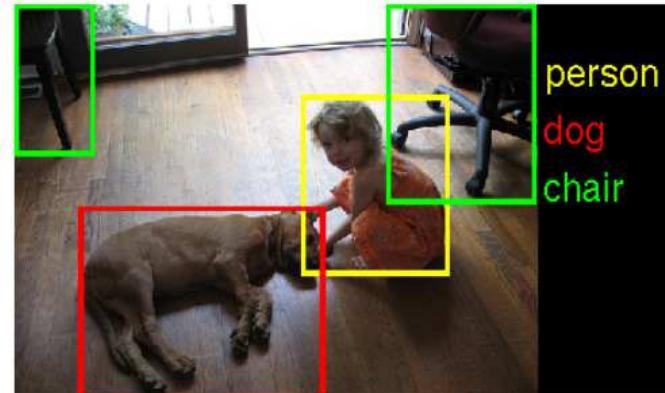
Step 3: align images

3

But what features should we use for object recognition?



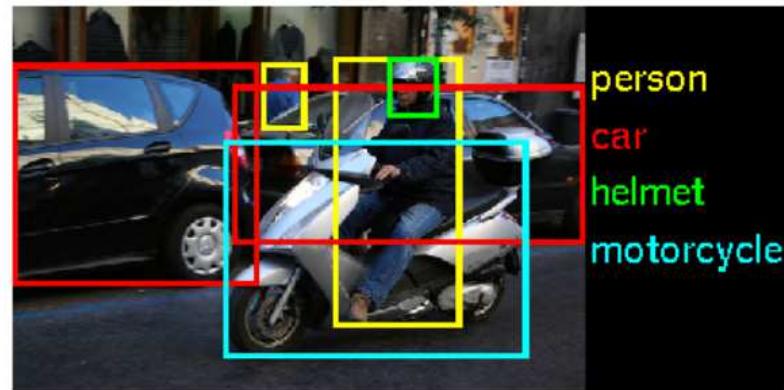
bird
frog



person
dog
chair



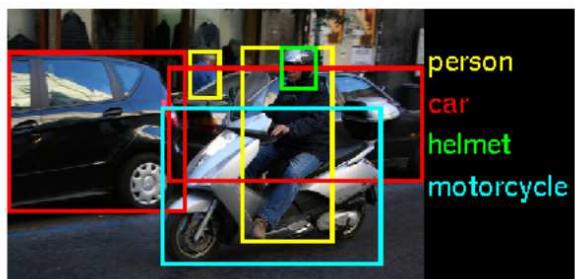
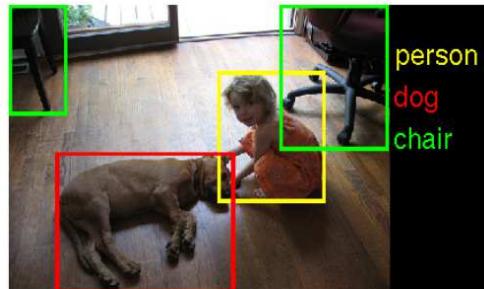
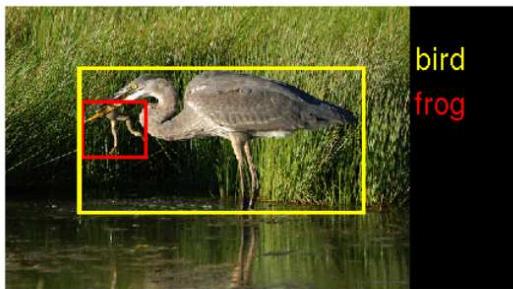
person
hammer
flower pot
power drill



person
car
helmet
motorcycle

3

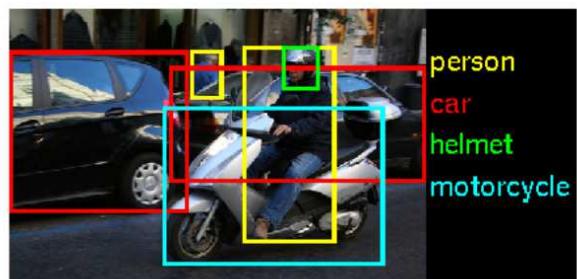
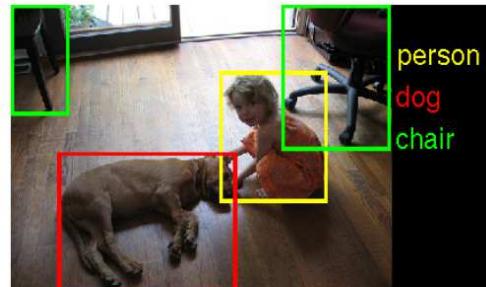
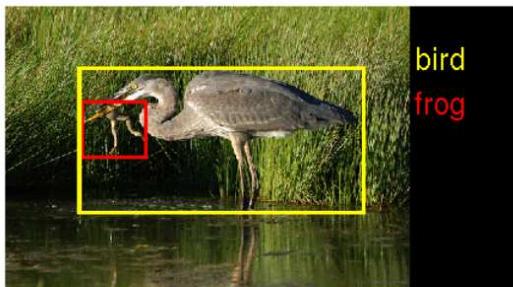
The ImageNet Challenge



The ImageNet Challenge provided 1.2 million examples of 1,000 **labeled** items and challenged algorithms to learn from the data and then was tested on another 100,000 images

3

The ImageNet Challenge

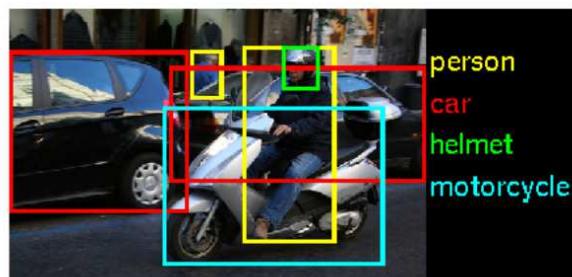
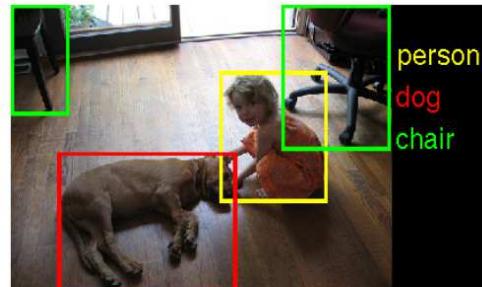
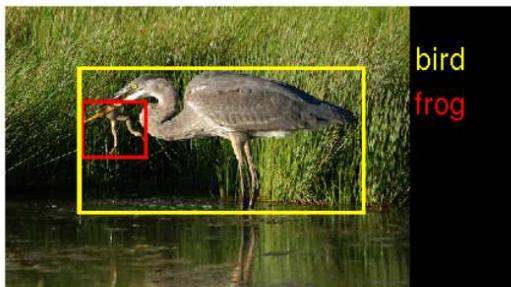


In 2010 teams had
75-50% error

In 2011 teams had
75-25% error

3

The ImageNet Challenge

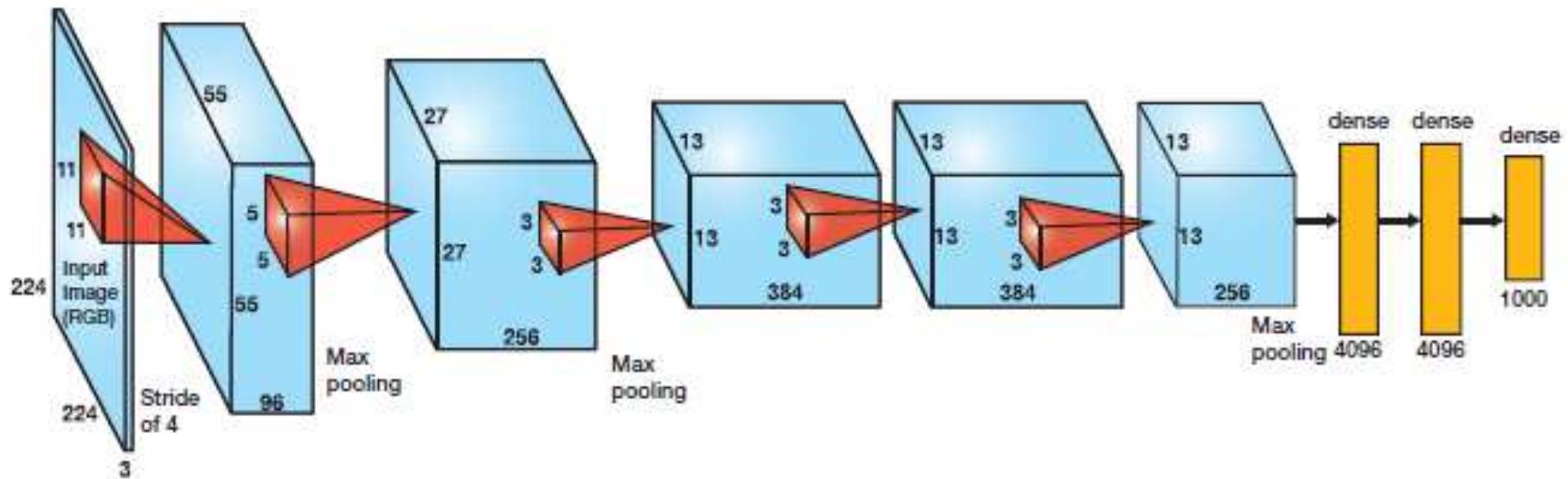


In 2012 still no team had less than 25% error barrier except **AlexNet at 15%**

3

Deep learning automates the design, selection and extraction of features, with amazing results

AlexNet: the first widely successful application of deep learning

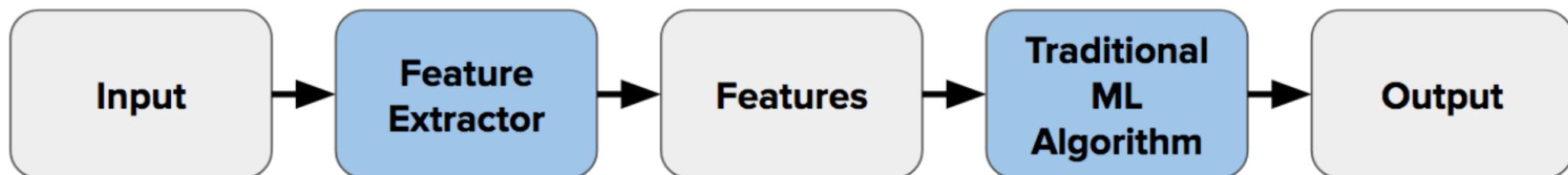


<https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf>

<https://cv-tricks.com/cnn/understand-resnet-alexnet-vgg-inception/>

3

Deep learning automates the design, selection and extraction of features, with amazing results



Traditional Computer Vision Flow

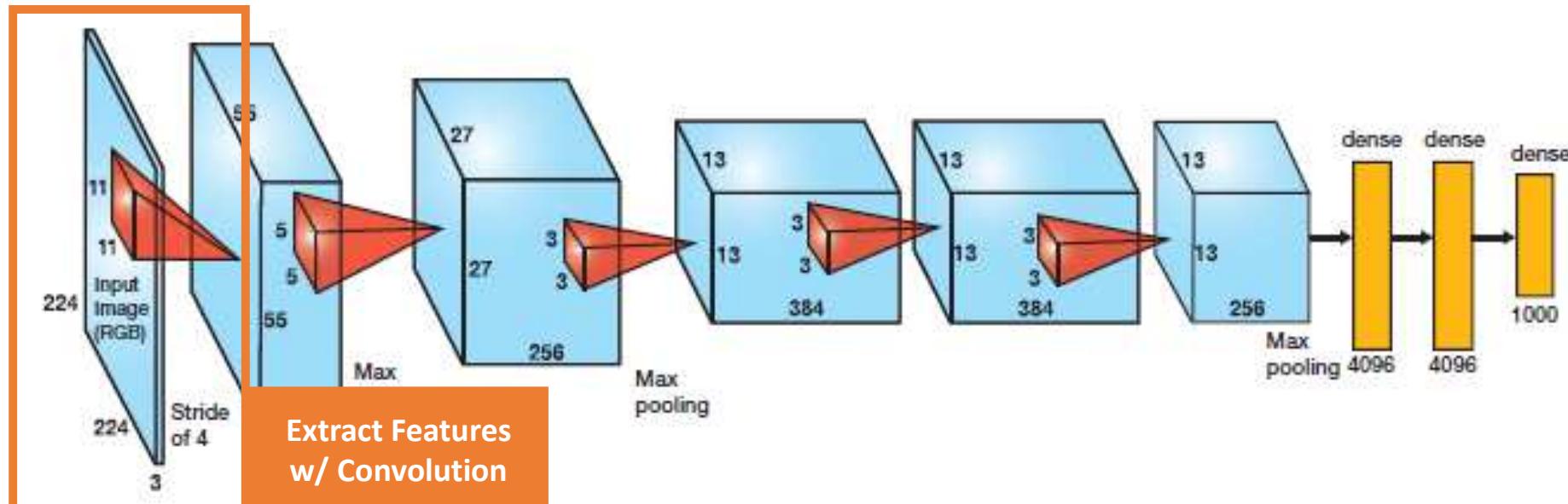


Deep Learning Flow

3

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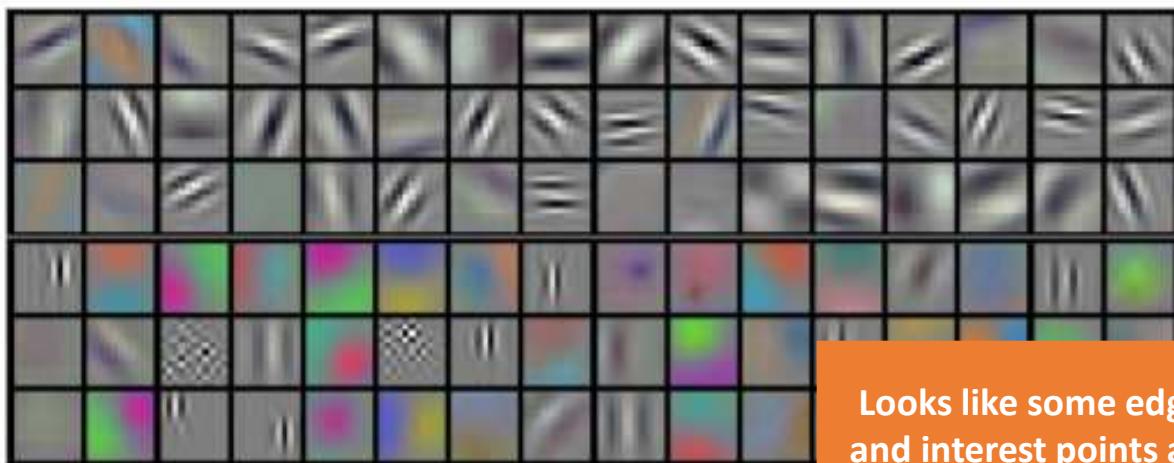
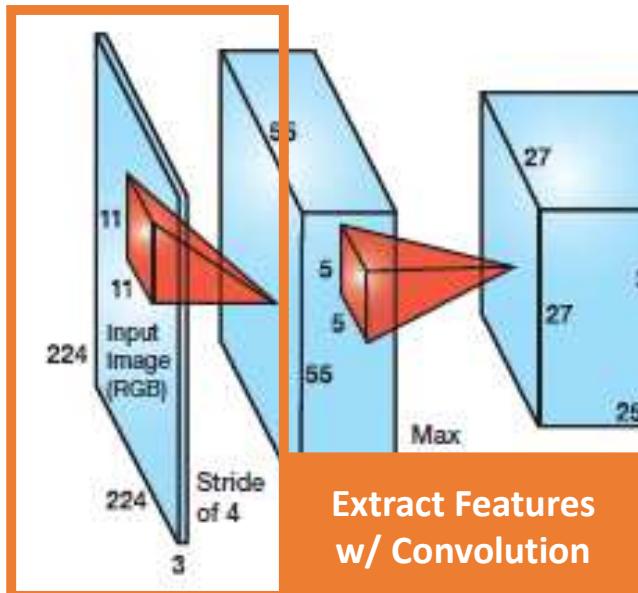
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Deep learning automates the design, selection and extraction of features , with amazing results

AlexNet: the first widely successful application of deep learning



Looks like some edges
and interest points and
important color patterns

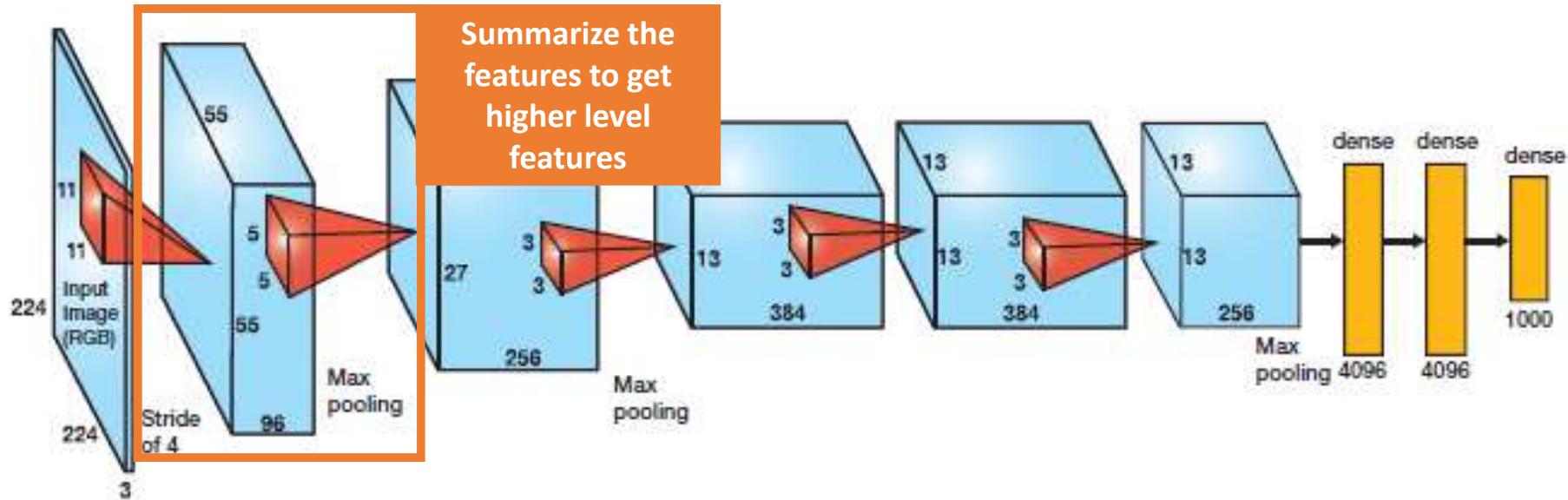
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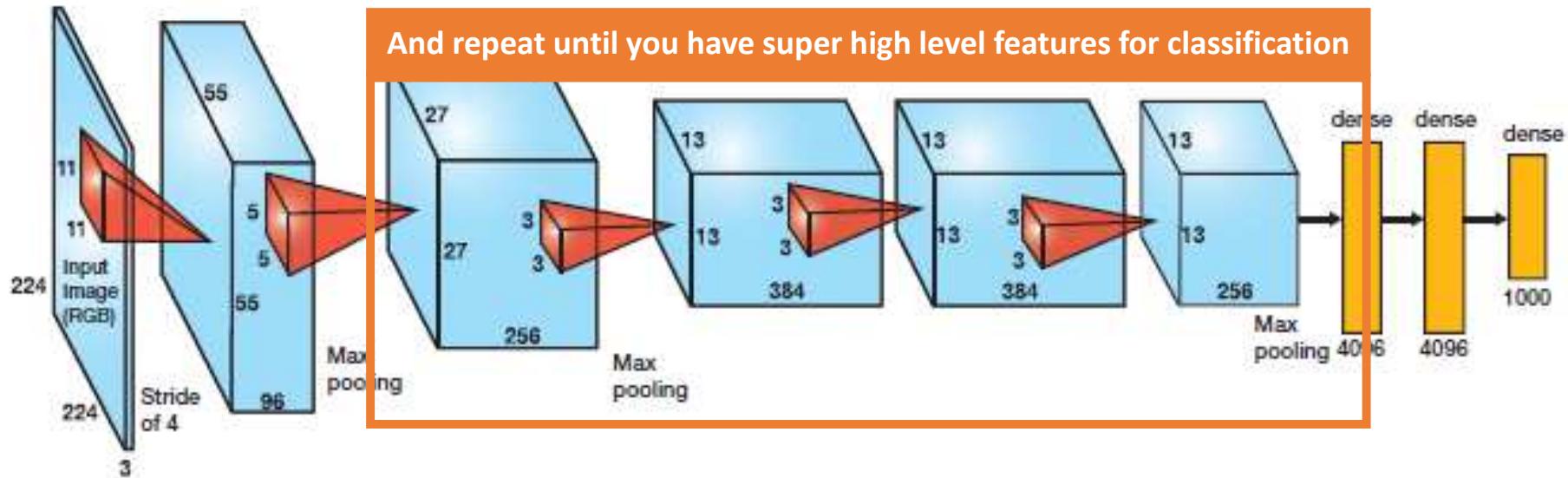
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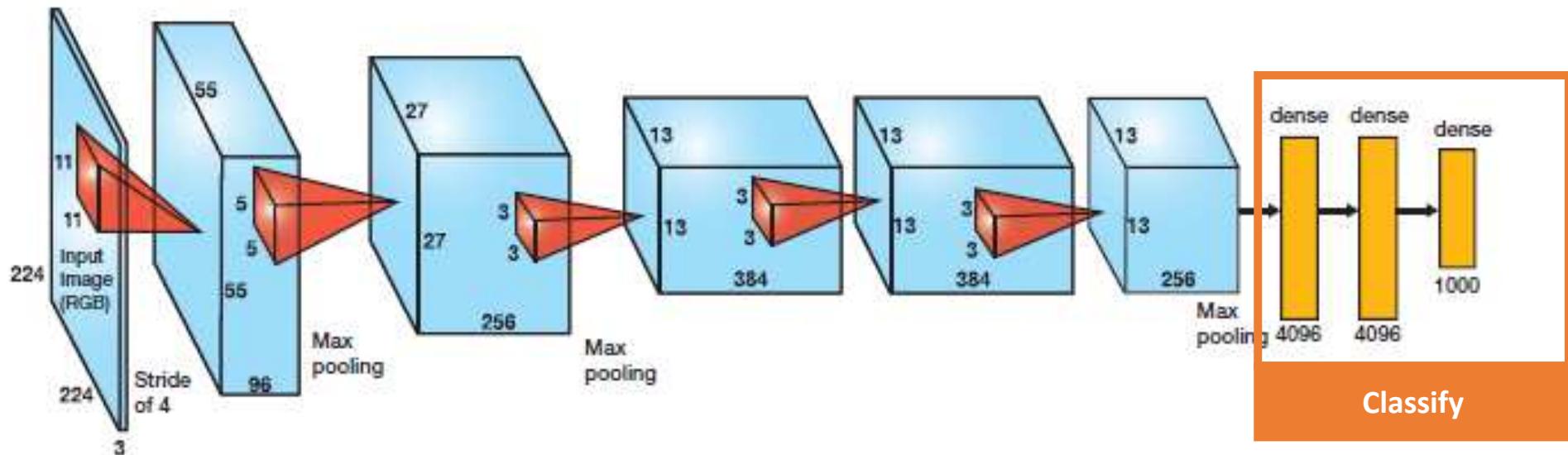
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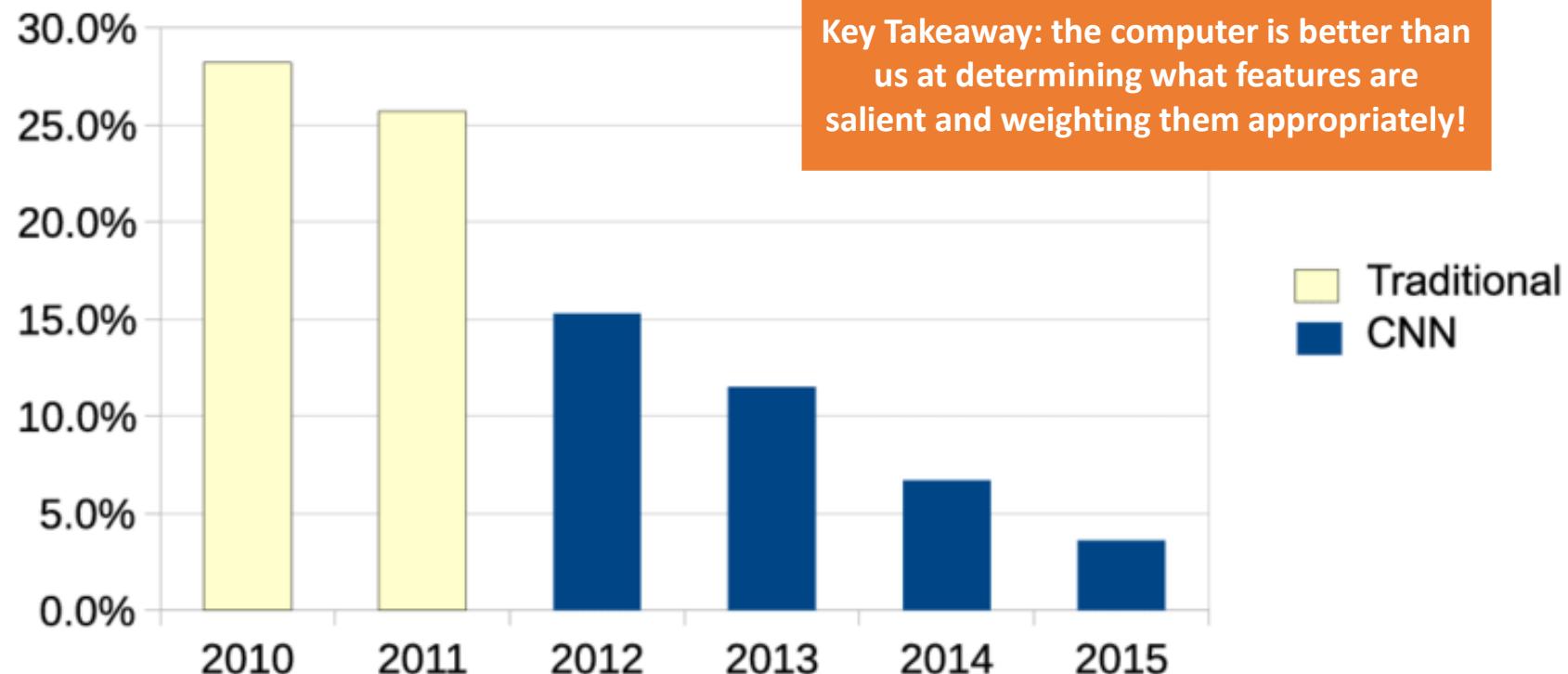


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3

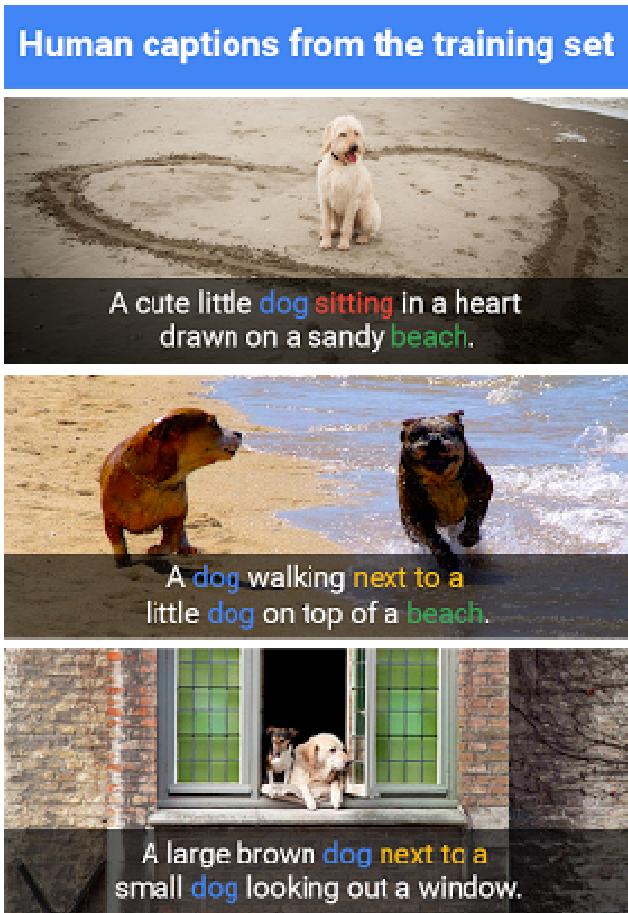
Deep learning automates the design, selection and extraction of features, with amazing results



https://www.researchgate.net/figure/Historical-top5-error-rate-of-the-annual-winner-of-the-ImageNet-image-classification_fig7_303992986

3

Google can now even automatically caption images!



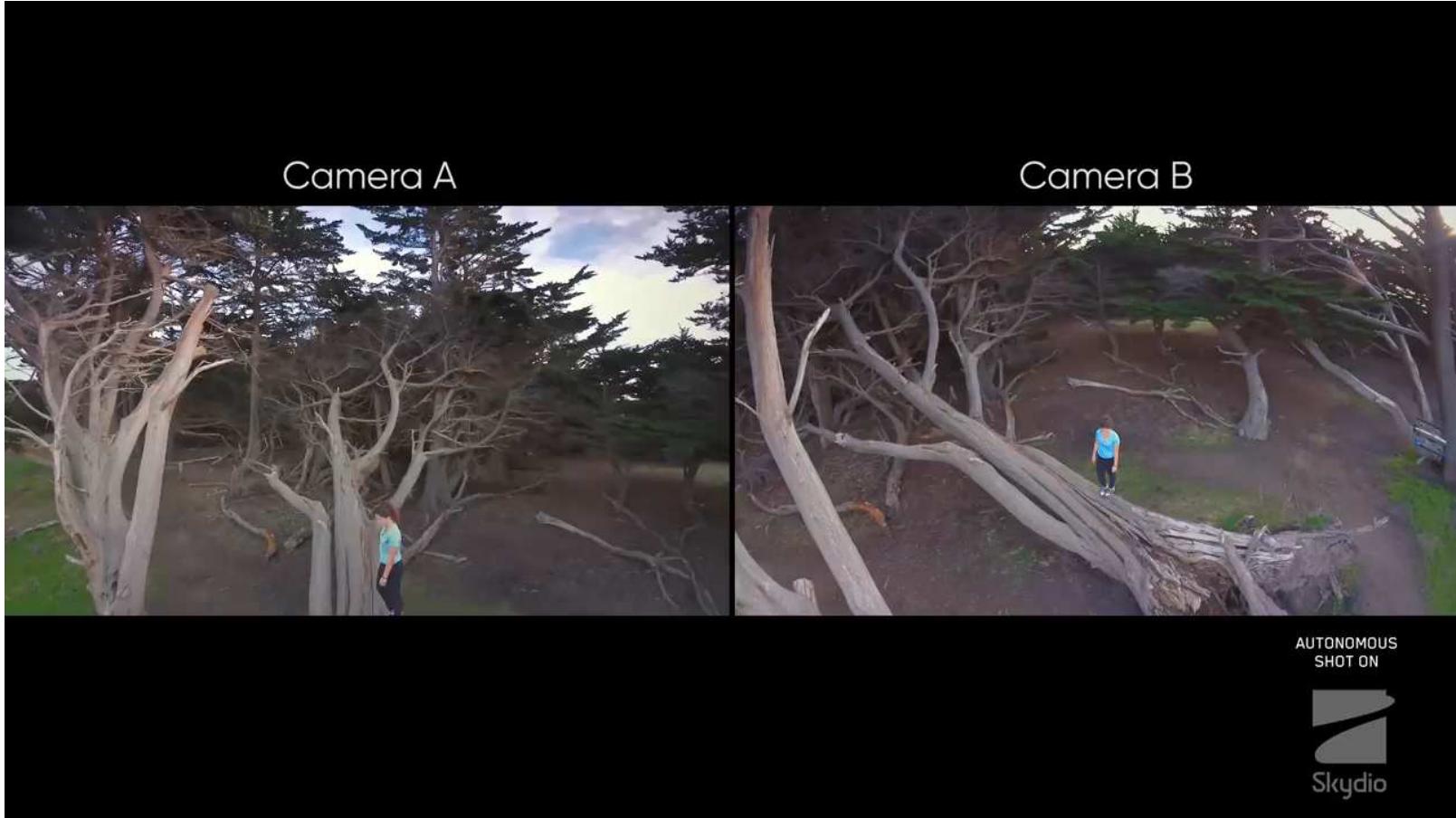
3

- The latest and greatest detectors can now find thousands of images in real-time
-



3

And can be used to track objects in real time



3

What might be the downside to using NNs?



3

For one, NNs can be tricked by adversarial markings



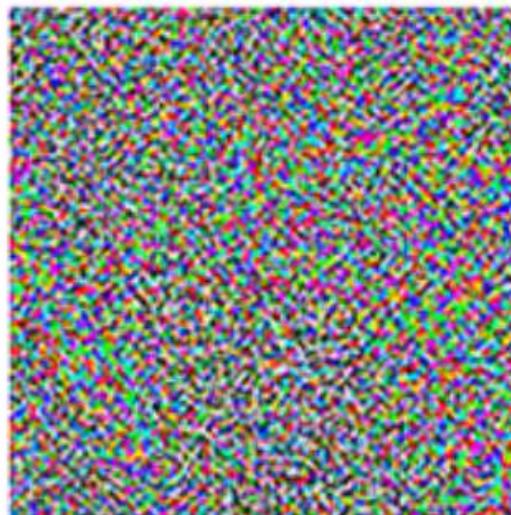
3

For one, NNs can be tricked by adversarial markings

Ackerman "Hacking the Brain With Adversarial Images"



$+ \epsilon$



=



"panda"

57.7% confidence

"gibbon"

99.3% confidence

3

For one, NNs can be tricked by adversarial markings

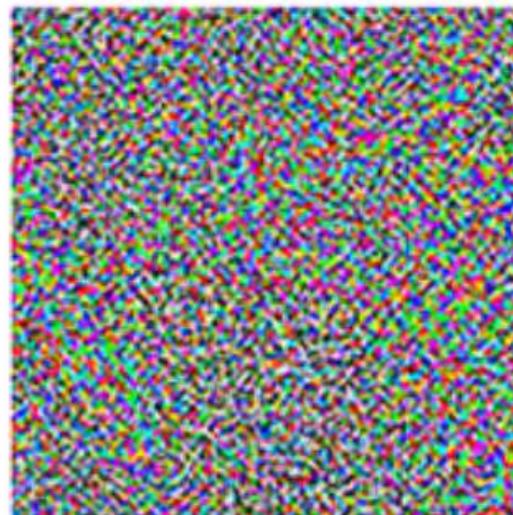
Ackerman "Hacking the Brain With Adversarial Images"



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57.7% confidence

$+ \epsilon$



=



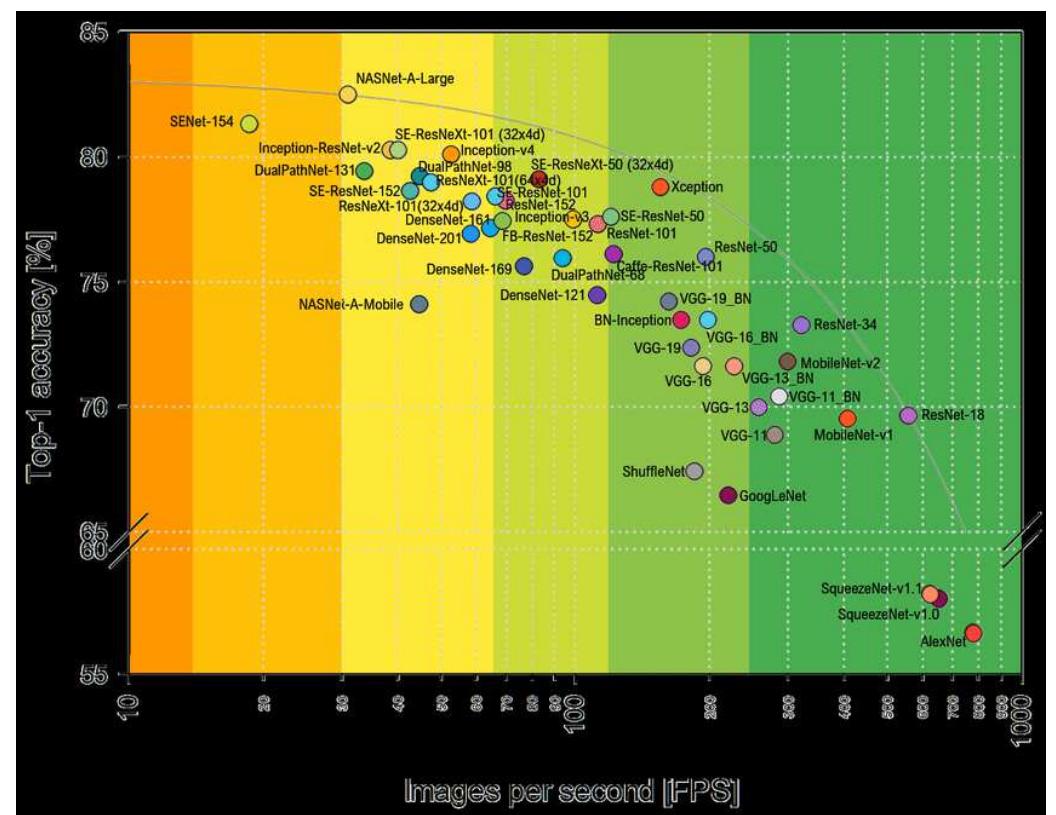
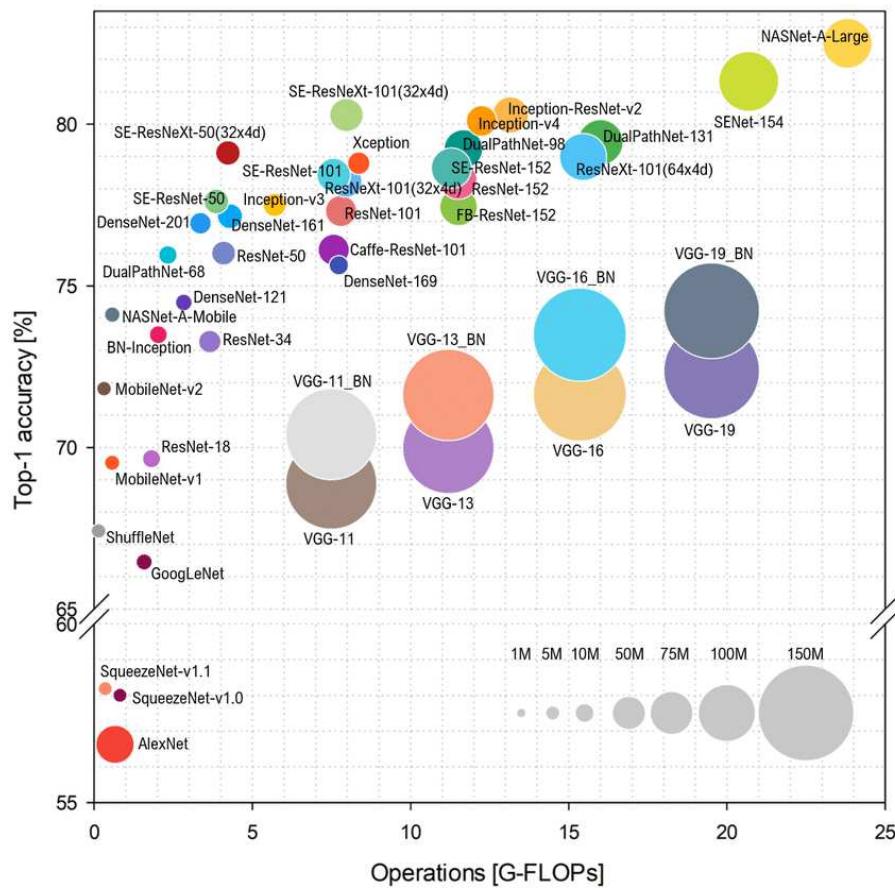
"gibbon"

99.3% confidence

There is **no model** of
the world semantically
just mathematically

3

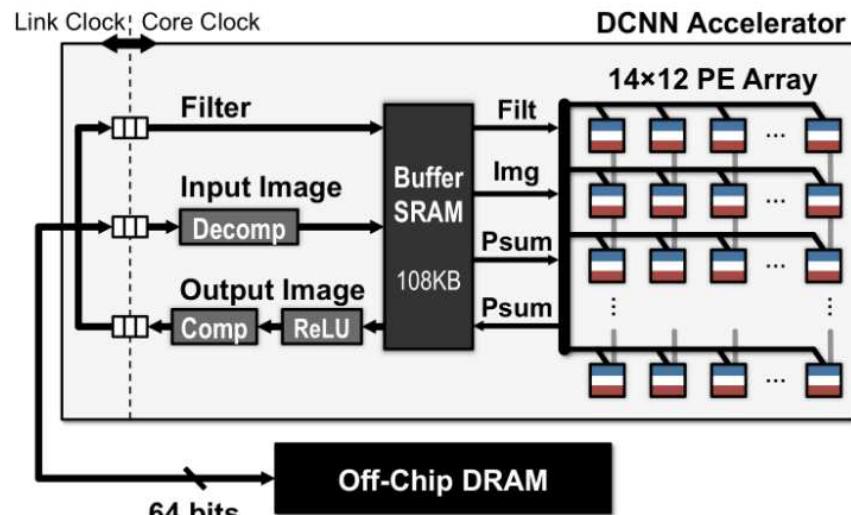
Second, (good) NN models are (often) large and expensive to train and compute



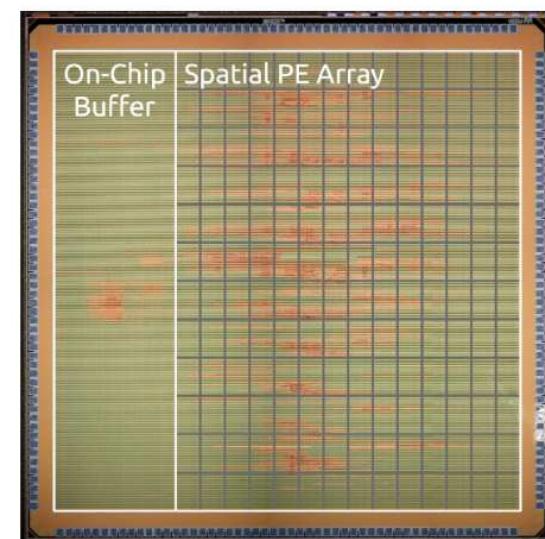
[Bianco et. al. Benchmark Analysis of Representative Deep Neural Network Architectures]

3

For this reason NNs (often) need accelerators to run online (and this is a very active area of research)



Eyeriss Architecture



Die Photo

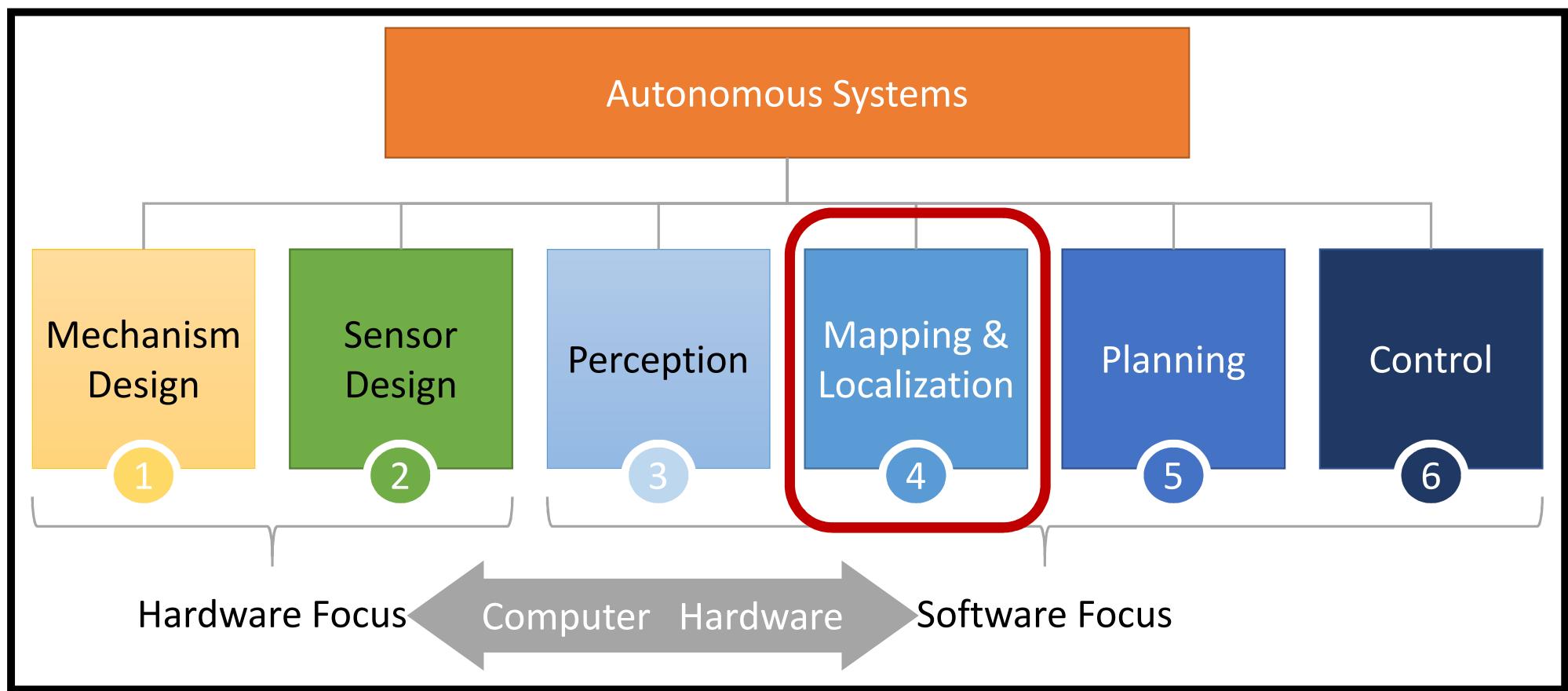
Can run in real time (35fps) at a 10X energy reduction over a mobile GPU (TX2?)!

3

Key Takeaways:

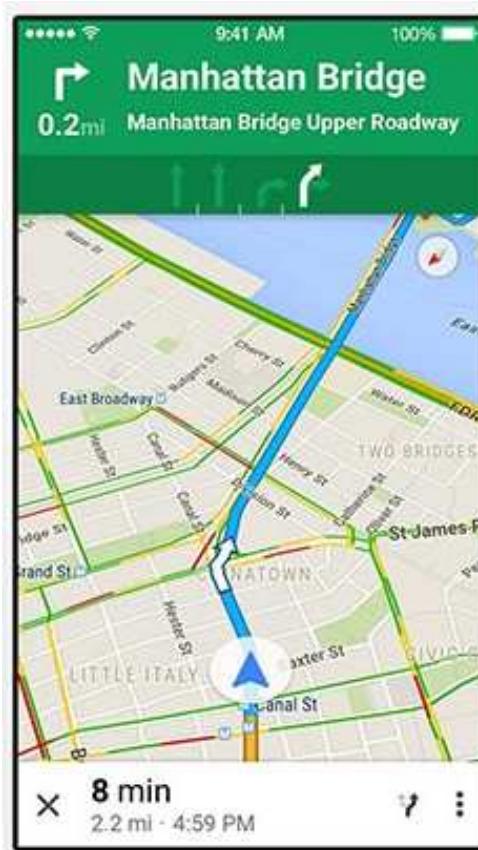
1. As of today it seems like **CNNs** that automate the design and summary of salient features via convolution are the way to go
 - But/and will need specialized NN running on **specialized accelerator chips** to get them small enough to fit on small power constrained autonomous systems (e.g., small drones)
 - And we will need to find ways to **secure them against attacks!**
 2. Also, other more targeted problems such as **Stereo Depth** seem to need accelerators!
-

Autonomous Systems / Robotics is a BIG space



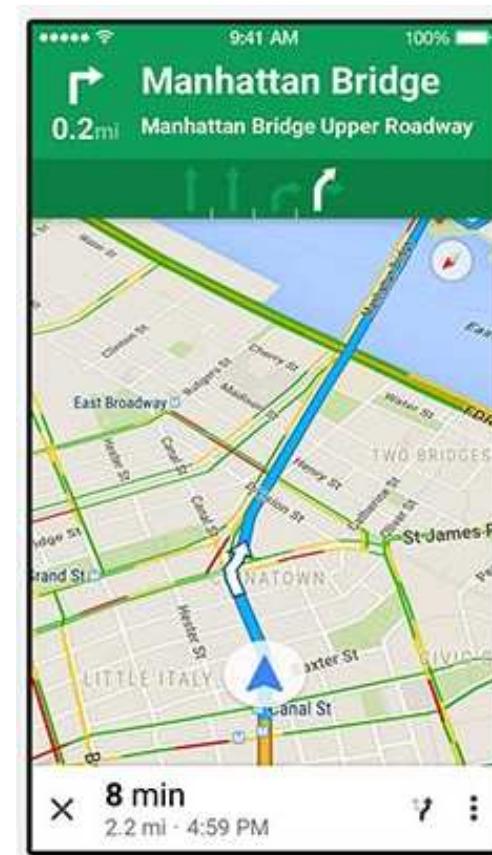
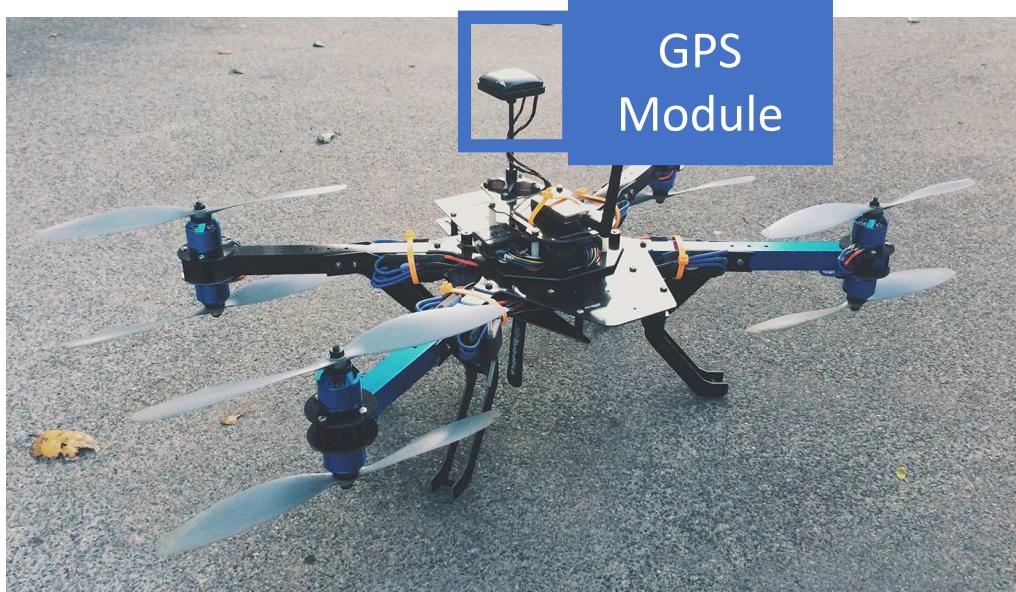
4

Mapping & Localization is the process of using perception information to understand where a robot is in the world



4

GPS provides a good idea of where a robot is globally...



4

... but isn't very accurate locally and requires a map

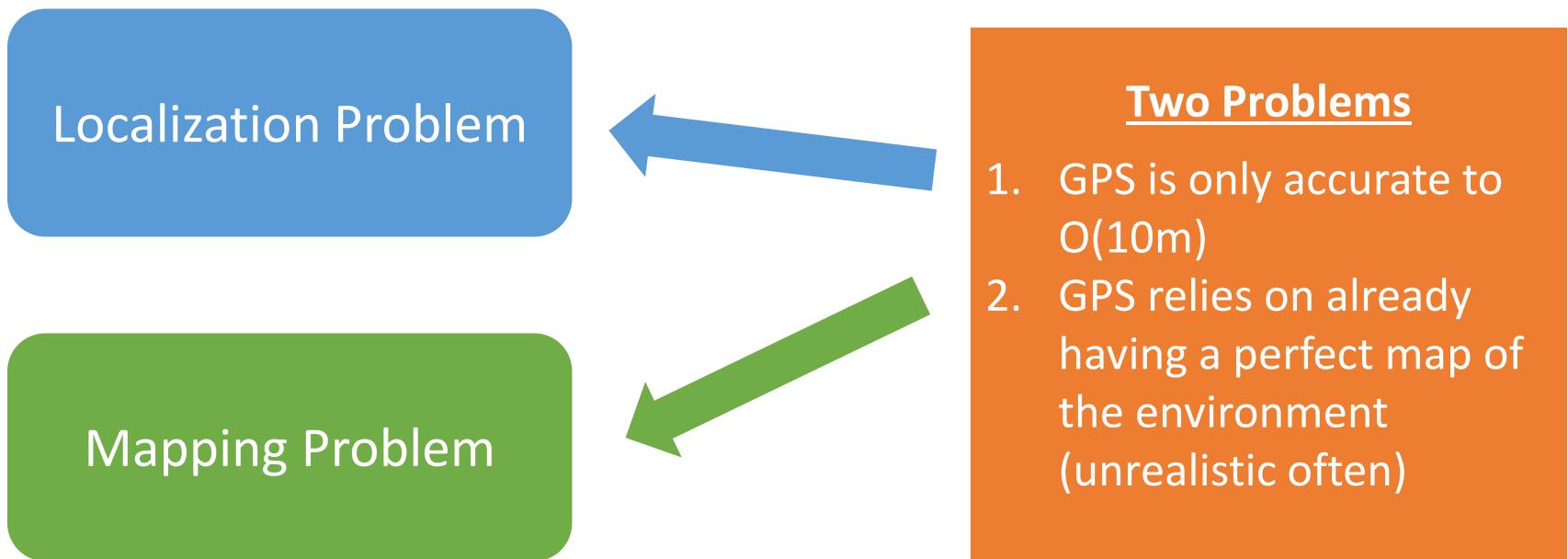


Two Problems

1. GPS is only accurate to $O(10m)$
2. GPS relies on already having a perfect map of the environment (unrealistic often)

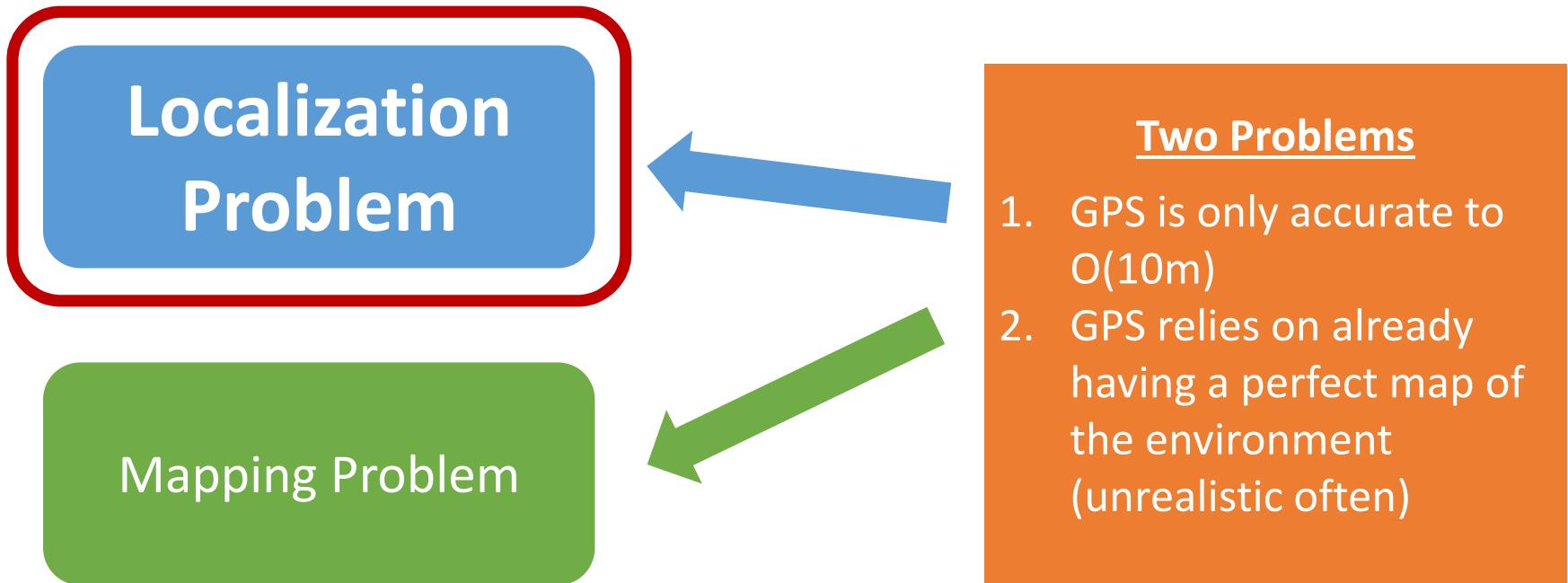
4

... but isn't very accurate locally and requires a map



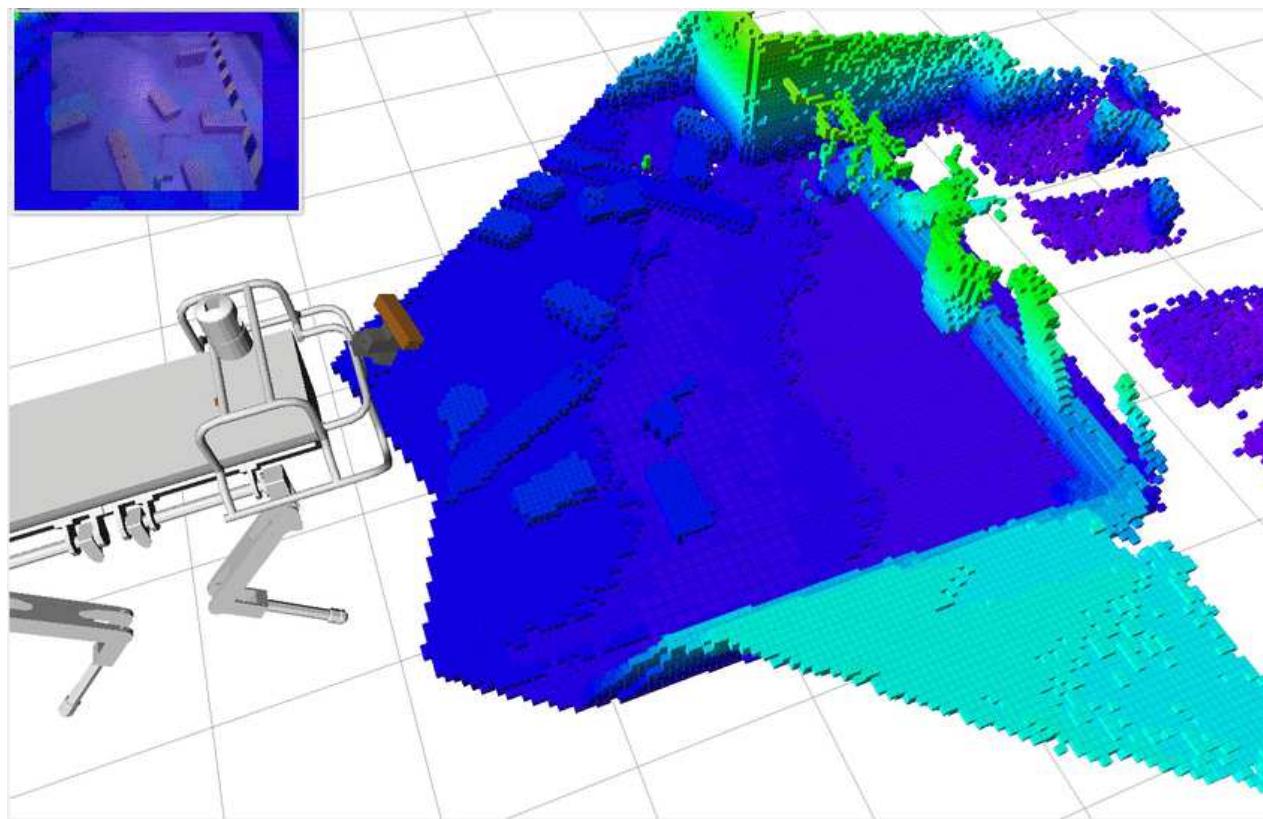
4

... but isn't very accurate locally and requires a map



4

We can use cameras and other sensors to measure the local environment but these sensors are also noisy



4

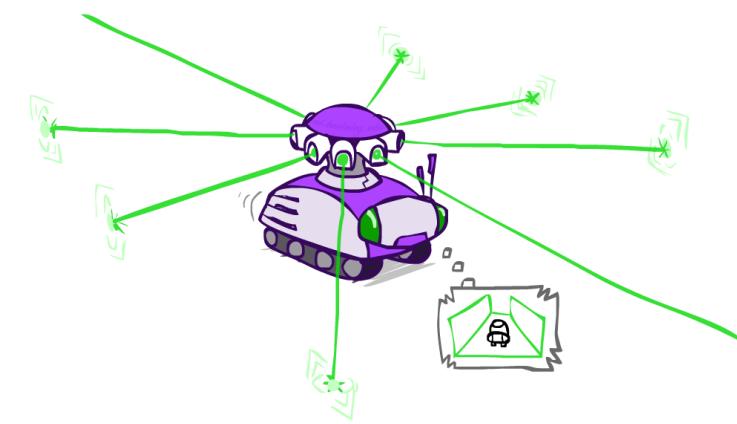
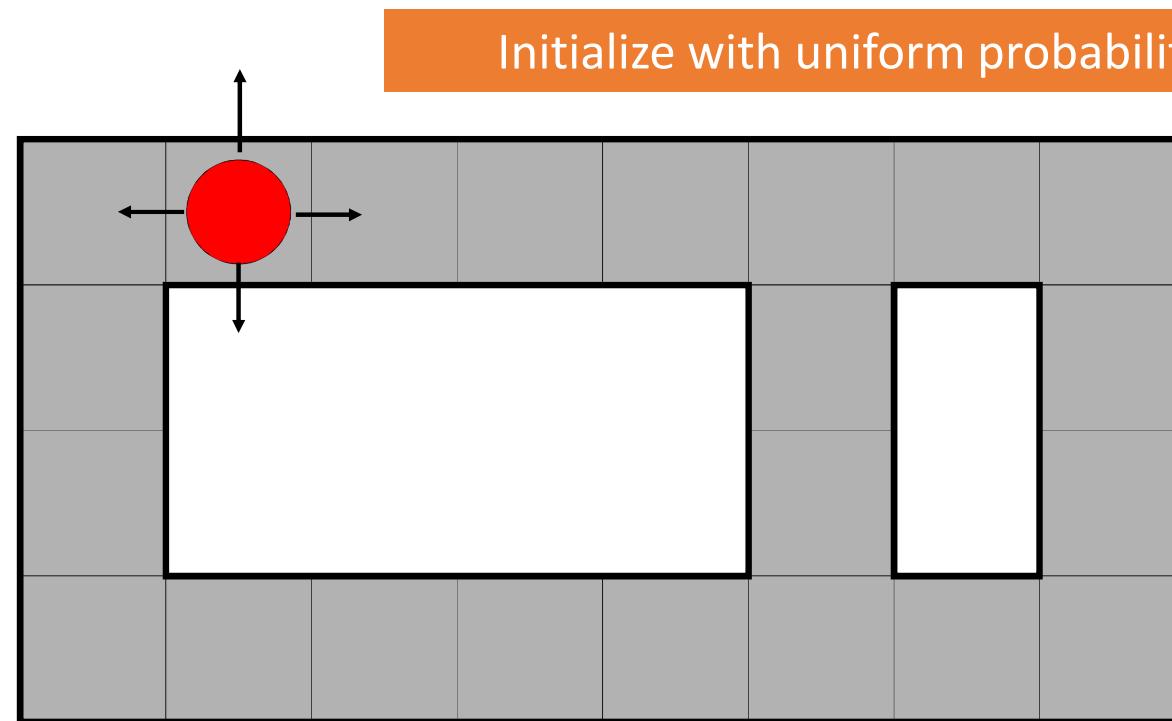
So what can we do?

Track the **Belief State** B_t

$$B_t = p(x_t = X | \text{Past States and Sensor Info})$$

4

Let's look at a concrete example of this in action



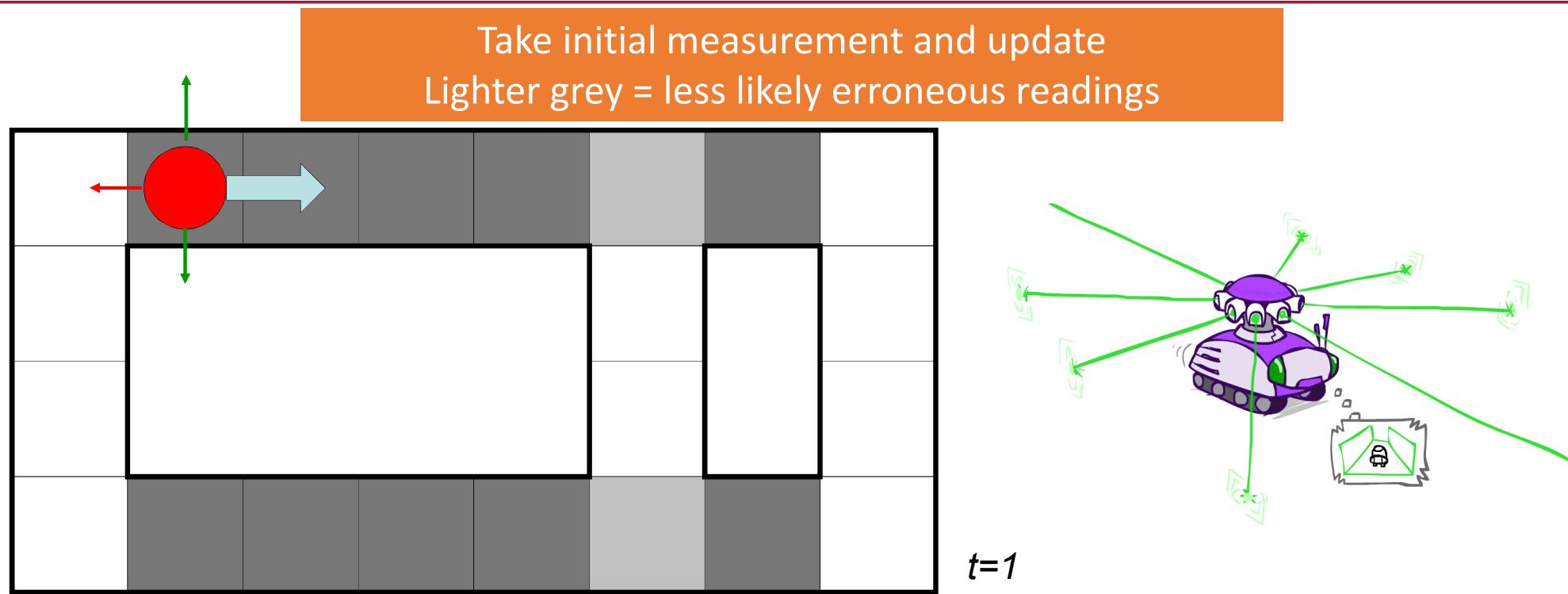
$t=0$

Probabilities
0 1

Example from Michael Pfeiffer

4

Let's look at a concrete example of this in action

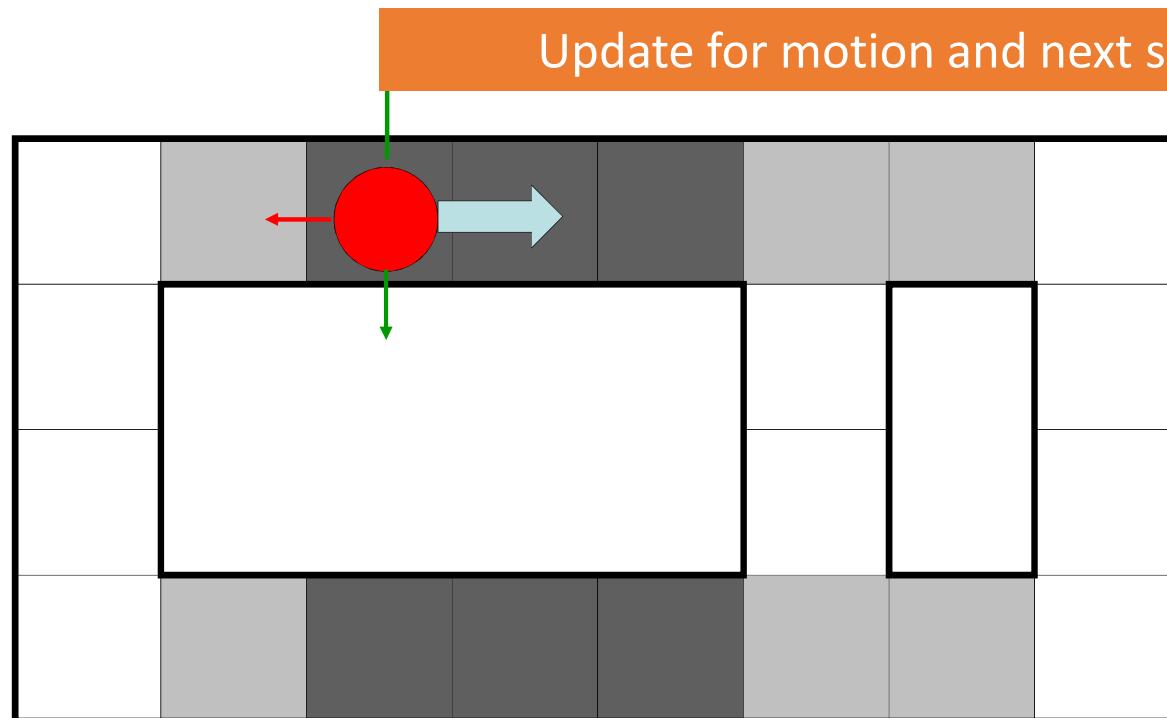


Probabilities

Example from Michael Pfeiffer

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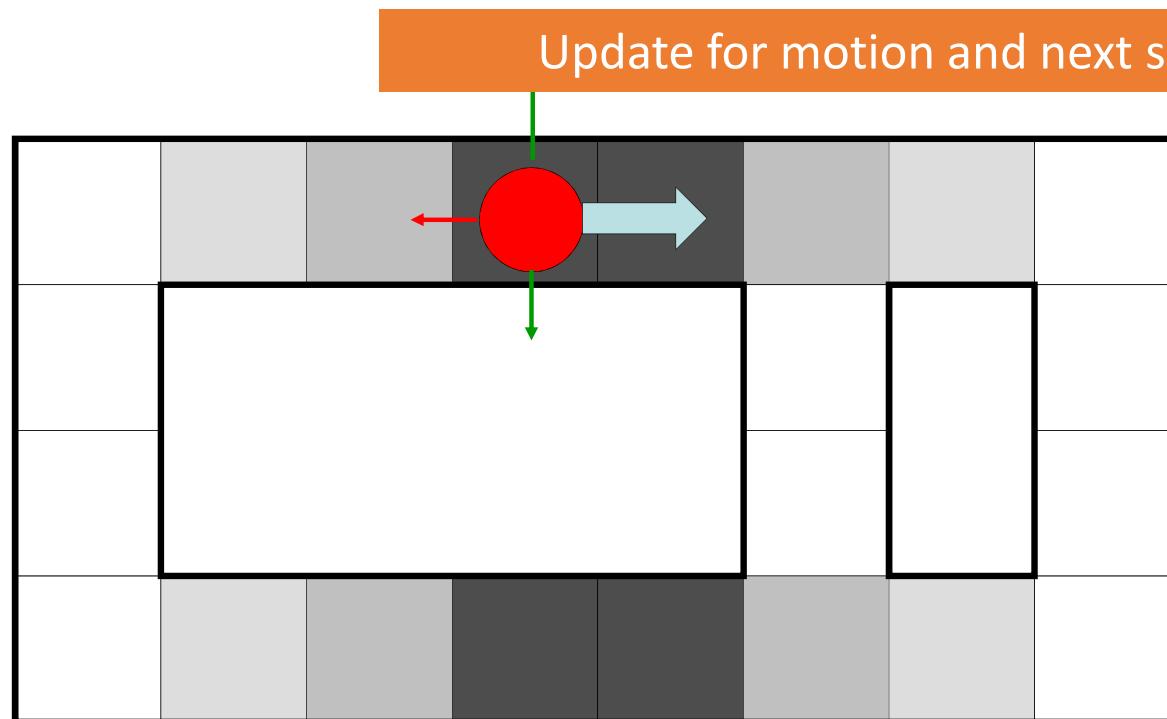


Probabilities 0 1

Example from Michael Pfeiffer

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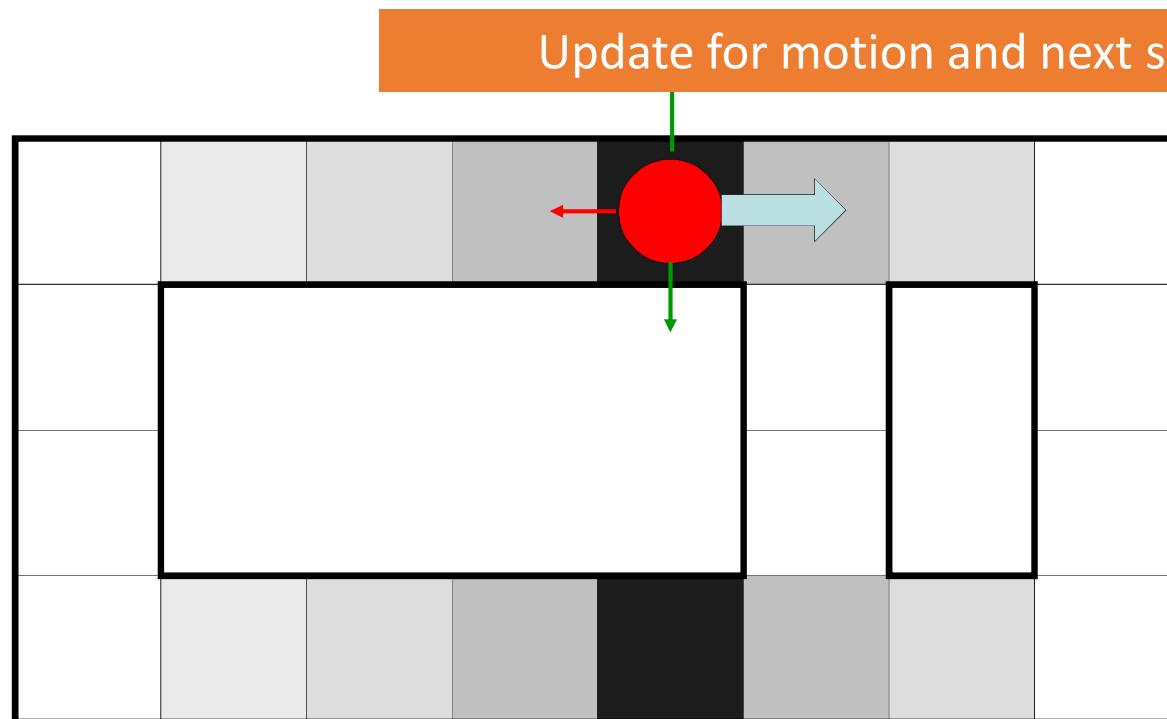


Probabilities

Example from Michael Pfeiffer

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Let's look at a concrete example of this in action



Probabilities

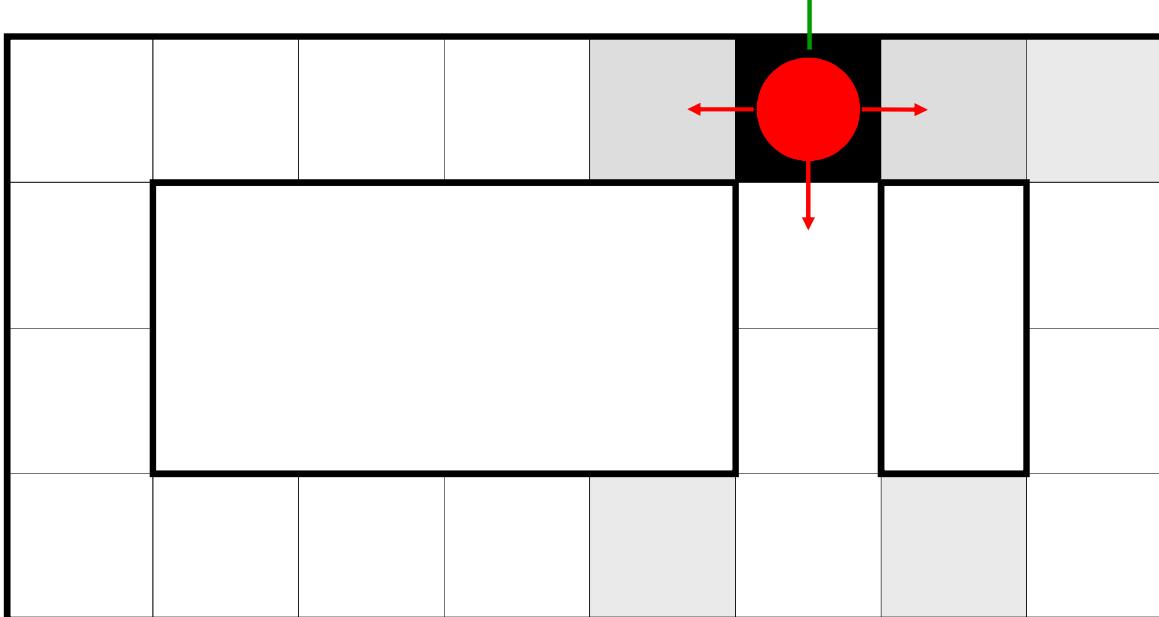
0 1

Example from Michael Pfeiffer

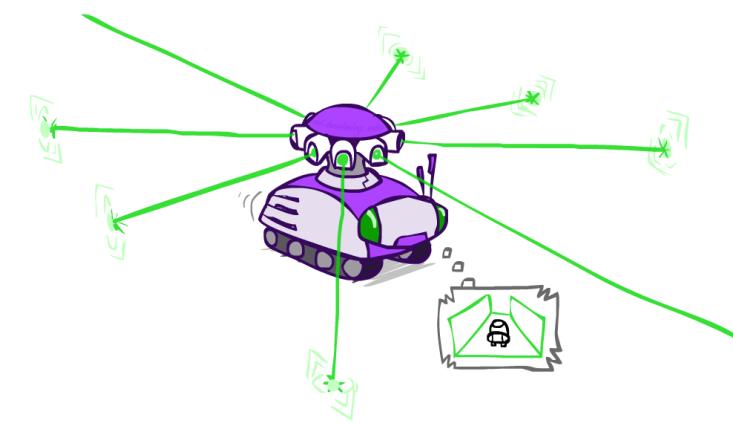
4

Let's look at a concrete example of this in action

Converge after motion and next sensor reading



$t=5$



Probabilities

Example from Michael Pfeiffer

4

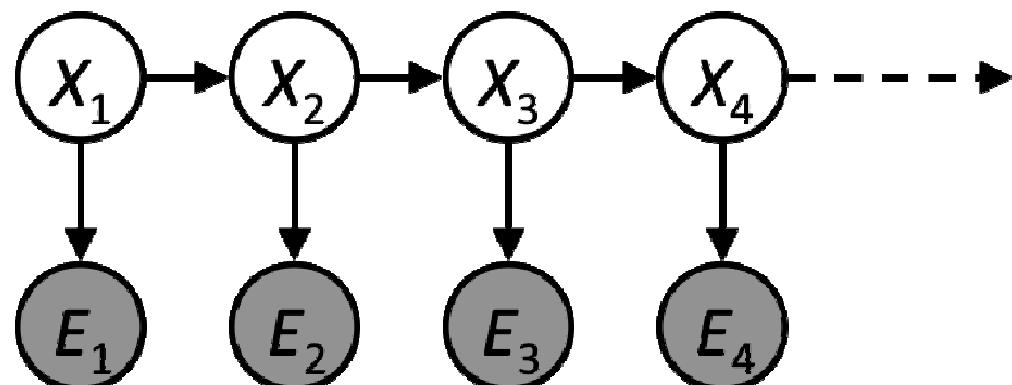
One approach is to model the probability of being in a given state with a Hidden Markov Model

Track the **Belief State** B_t

$$B_t = p(X_t | X_o, E_o \dots E_{t-1})$$

Hidden Markov Model (HMM)

States X update in time but we only observe the effects E

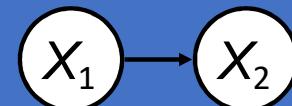


Report the **mean** of the **Belief State** (which is a probability distribution) as our current best estimate of the state

4

The Kalman Filter updates the belief state (a probability distribution) for the passage of time and for evidence

Time Update



$$P(x_{t+1}|x_0, e_1 \dots e_t) = \int P(x_t|x_0, e_1 \dots e_t) * P(x_{t+1}|x_t)$$

Based on a model of physics usually

Evidence Update



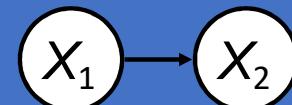
$$P(x_{t+1}|x_0, e_1 \dots e_{t+1}) \propto \int P(x_{t+1}|x_0, e_1 \dots e_t) * P(e_{t+1}|x_{t+1})$$

Based on a model of the sensor data usually

4

The Kalman Filter updates the belief state (a probability distribution) for the passage of time and for evidence

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Evidence Update



$$P(x_{t+1}|x_0, e_1 \dots e_{t+1}) \propto \int P(x_{t+1}|x_0, e_1 \dots e_t) * P(e_{t+1}|x_{t+1})$$

Based on a model of

There are a variety of ways to compute this (and we'll highlight 4)

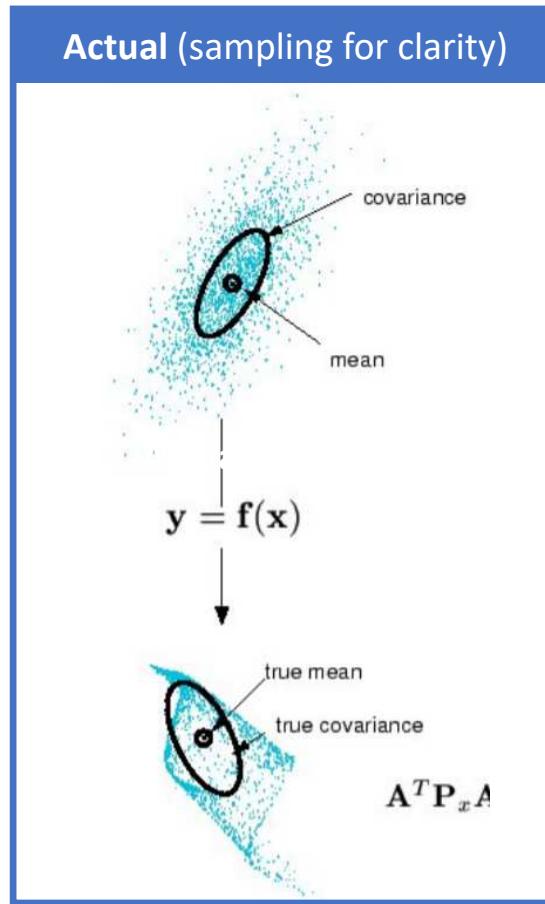
usually

4

There are four popular ways to compute this in practice

van der Merwe and Wan (2001)

1. Pass the full belief PDF through **nonlinear** equations for the motion update (physics) and the sensor update

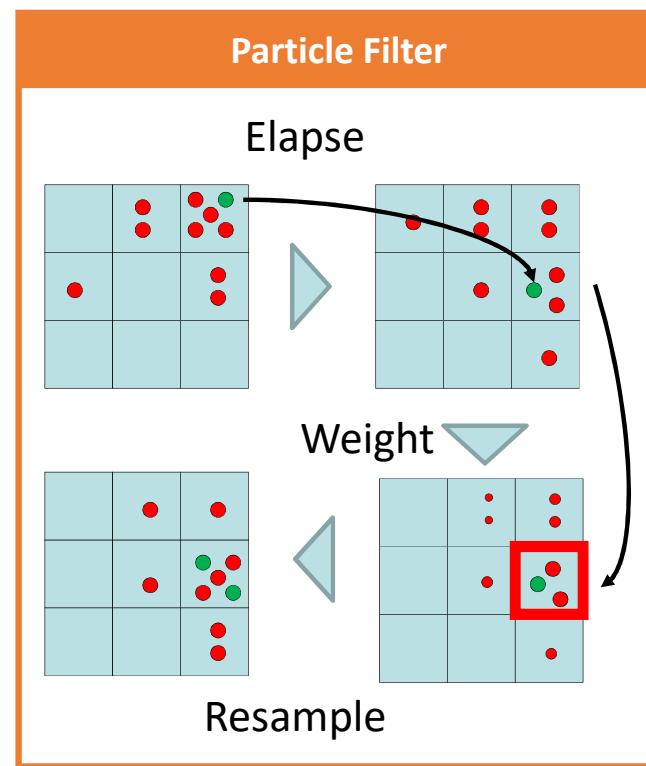


Most accurate but computationally very expensive (often intractable)

There are four popular ways to compute this in practice

Berkely AI Material and Scott Kuindersma

2. Pass many samples through the nonlinear equations for the motion update (physics) and the sensor update and use the samples as a discrete approximation of the probability distribution

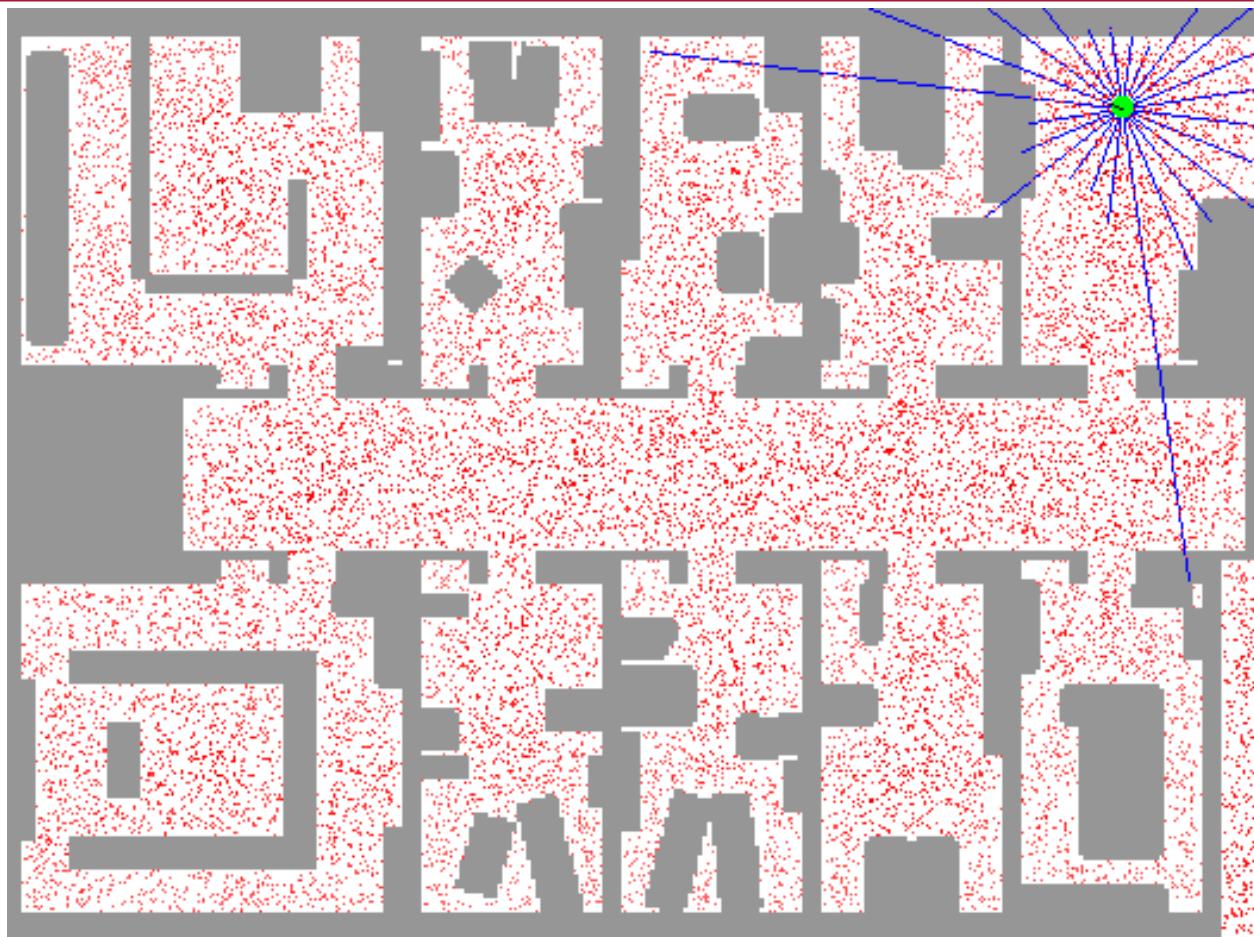


Can be very accurate but also computationally expensive (lots of particles)

4

There are four popular ways to compute this in practice

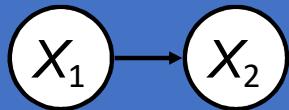
Dieter Fox



4

There are four popular ways to compute this in practice

What if we
don't want to
sample?

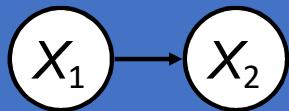


$$P(x_{t+1}|x_0, e_1 \dots e_t) = \int P(x_t|x_0, e_1 \dots e_t) * P(x_{t+1}|x_t)$$

4

There are four popular ways to compute this in practice

Lets do some
math for a
minute



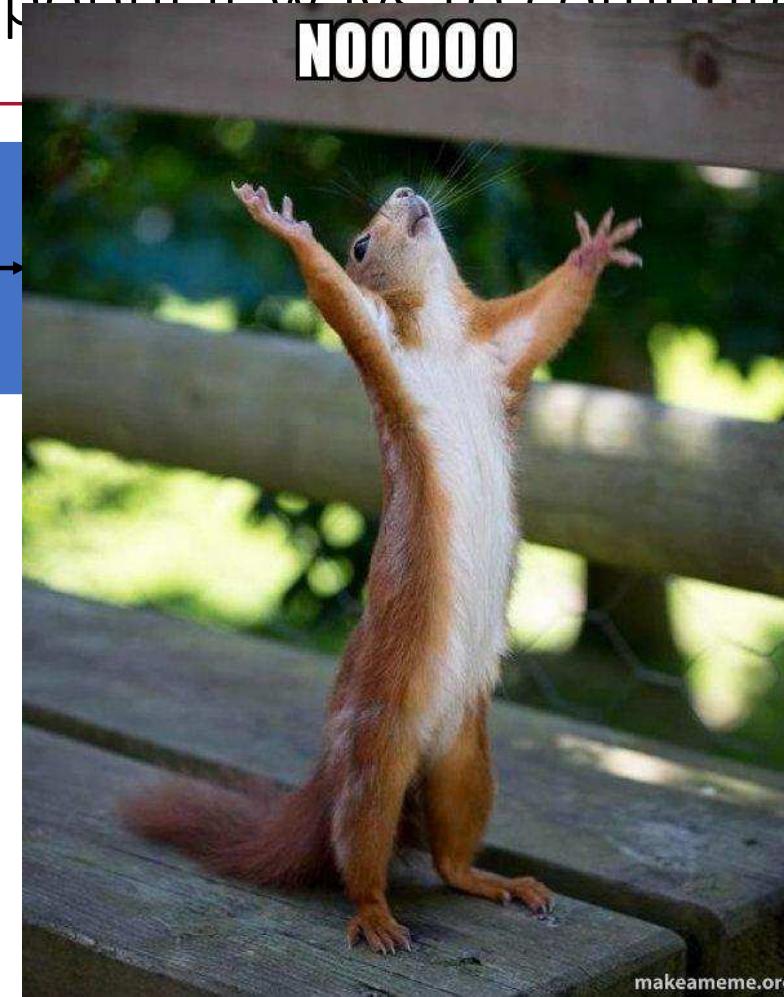
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4

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X_1



$P(x_t | x_0, e_1 \dots e_t) * P(x_{t+1} | x_t)$

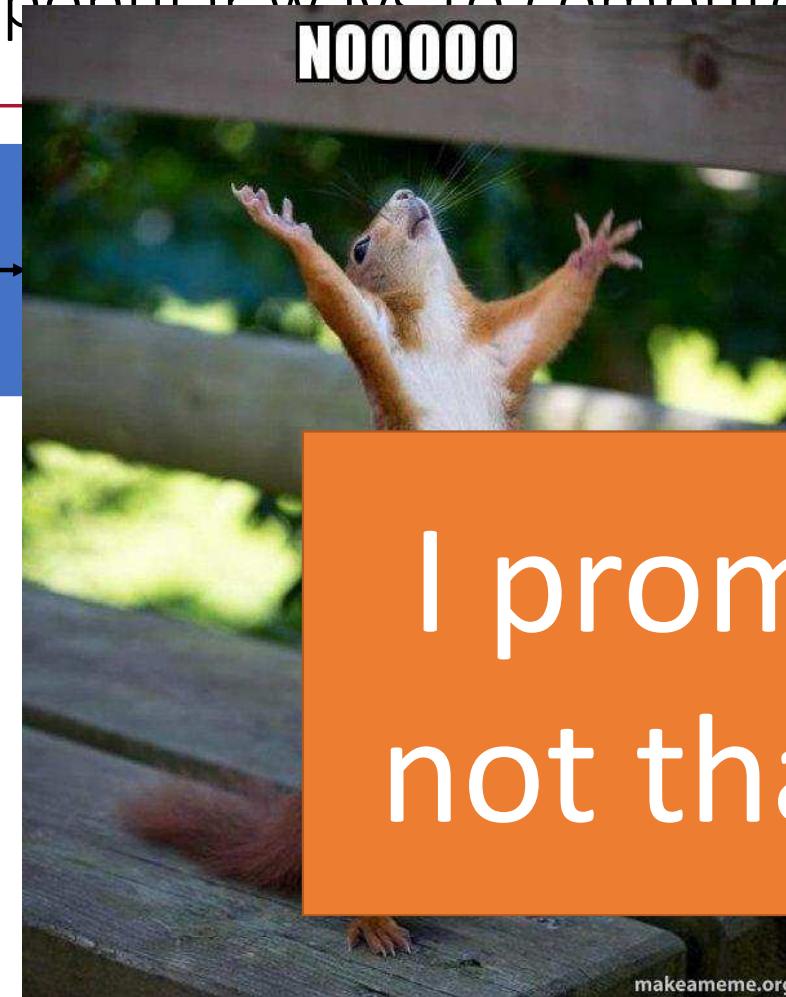
makeameme.org

4

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$P(x_t | x_0, e_1 \dots e_t) * P(x_{t+1} | x_t)$

makeameme.org

4

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$x_0, e_1 \dots e_t) * P(x_{t+1}|x_t)$

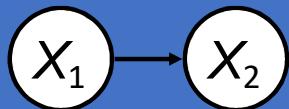
rise its
t bad!

4

There are four popular ways to compute this in practice

http://www.cs.columbia.edu/~liulp/pdf/linear_normal_dist.pdf

Lets do some
math for a
minute



$$P(x_{t+1}|x_0, e_1 \dots e_t) = \int P(x_t|x_0, e_1 \dots e_t) * P(x_{t+1}|x_t)$$

Suppose $\mathbf{x} \sim \mathcal{N}(\mu_x, \Sigma_x)$ and $\mathbf{y} = A\mathbf{x} + \mathbf{b}$, where $\mathbf{b} \sim \mathcal{N}(0, \Sigma_b)$.

$$\mu_y = E[\mathbf{y}] = E[A\mathbf{x} + \mathbf{b}] = AE[\mathbf{x}] + E[\mathbf{b}] = A\mu_x,$$

$$\Sigma_y = \text{Var}(A\mathbf{x} + \mathbf{b}) = \text{Var}(A\mathbf{x}) + \text{Var}(\mathbf{b}) = A\Sigma_x A^T + \Sigma_b,$$

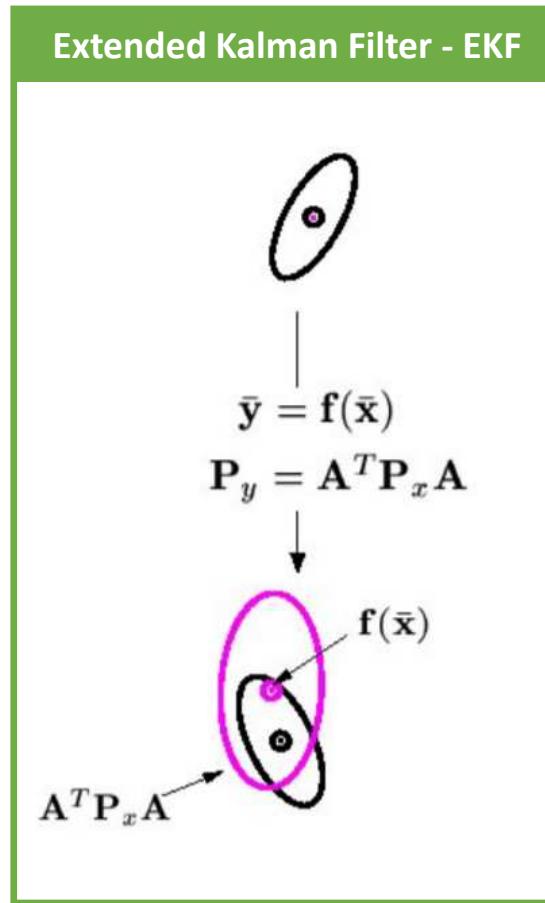
Well if we represent the transition from one state to the next by a linear equation (just linearize physics) and represent $P(x)$ as Gaussian then we can just use this simple linear transformation to do all of the math super fast!

4

There are four popular ways to compute this in practice

van der Merwe and Wan (2001)

3. Assume the belief PDF is **Gaussian** and pass it through **linearized** equations for the motion update (physics) and the sensor update



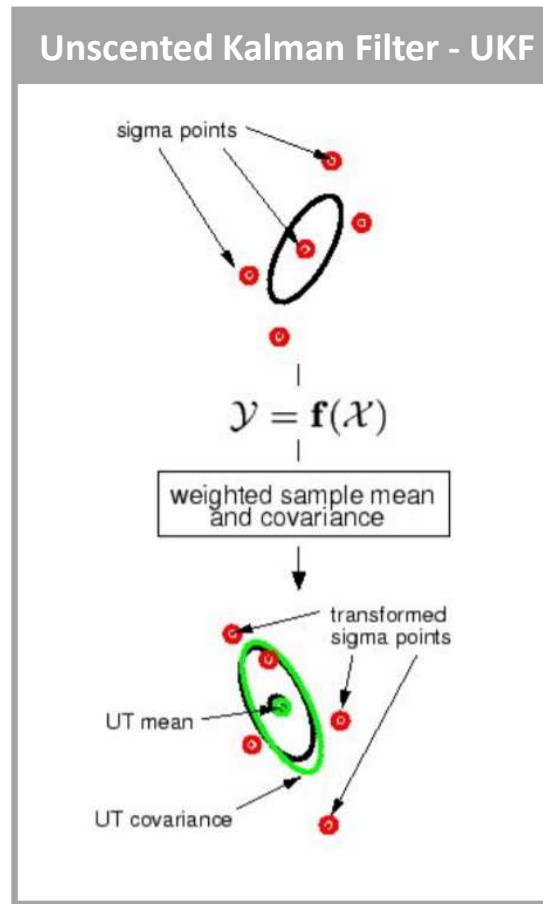
Simplest and least accurate as assumes Gaussian + linear

4

There are four popular ways to compute this in practice

van der Merwe and Wan (2001)

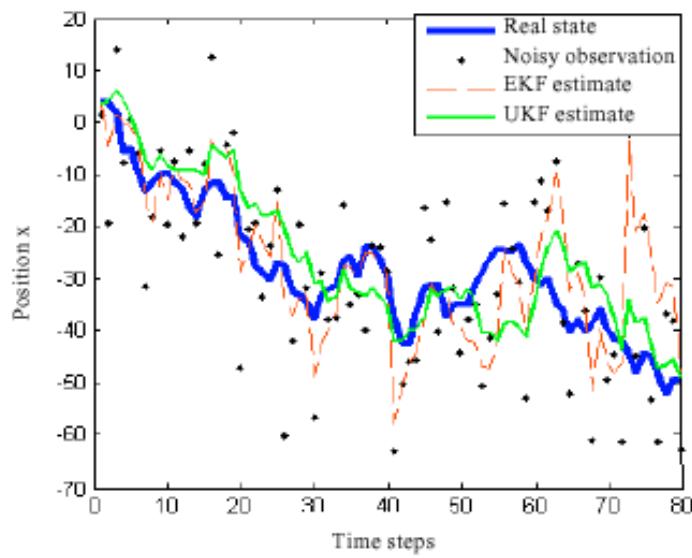
4. Assume the belief PDF is **Gaussian** and **pass limited samples** through the **nonlinear** equations for the motion update (physics) and the sensor update and reconstruct the Gaussian on the other side



Moderately accurate
but assumes Gaussian

4

There are four popular ways to compute this in practice



Hassanzadeh and Fallah 2008

4

There are four popular ways to compute this in practice

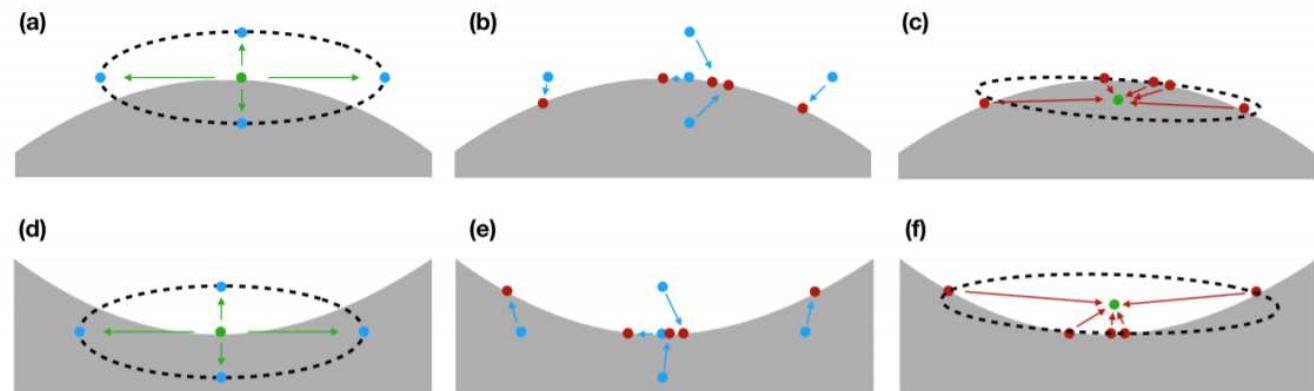
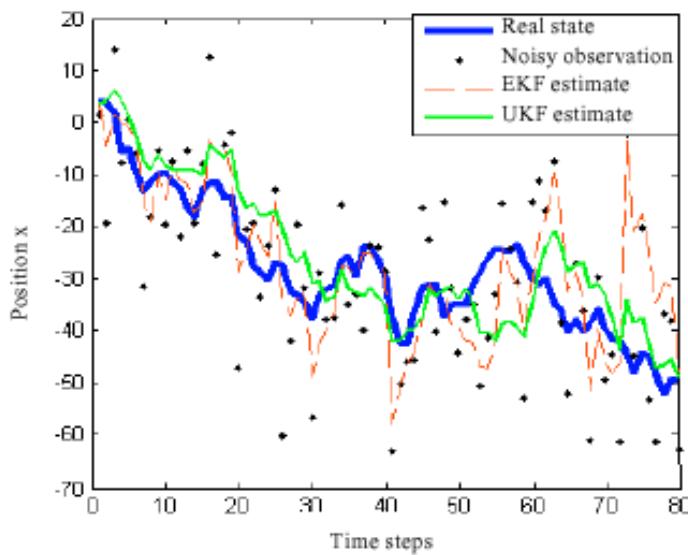


Fig. 1: Two illustrations of fundamental problems associated with the UKF in the presence of the inequalities associated with contact. When sample points are generated (a and d) samples are either infeasible or have different contact modes than the mean estimate. In the first sequence (a-c) the resulting estimate (c) is infeasible even though all of the samples are feasible. In the second sequence (d-f) the resulting estimate (f) is feasible, but has a contact mode that is different from any of the individual sample points. In our experience this is the more common behavior, biasing the estimate away from the contact manifold.

4

There are four popular ways to compute this in practice

Modeling is helpful to reduce computation but No Free Lunch!

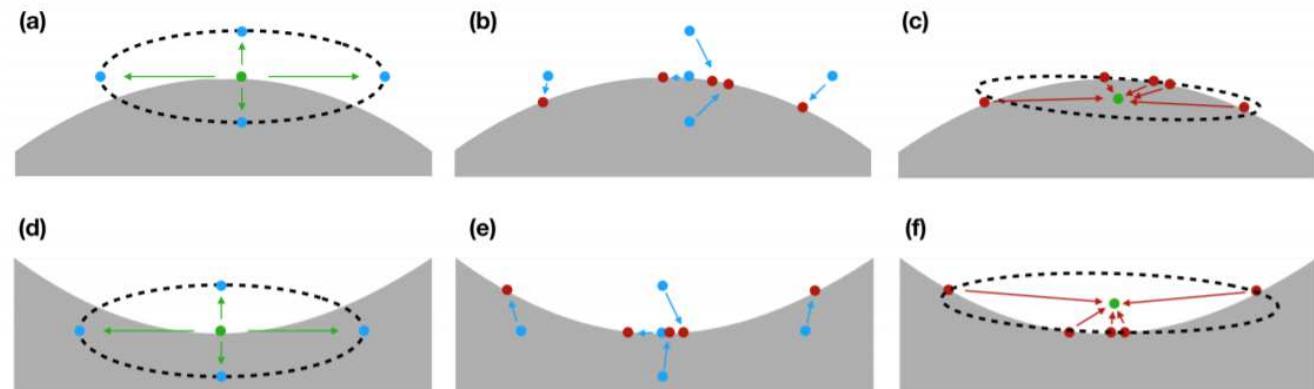
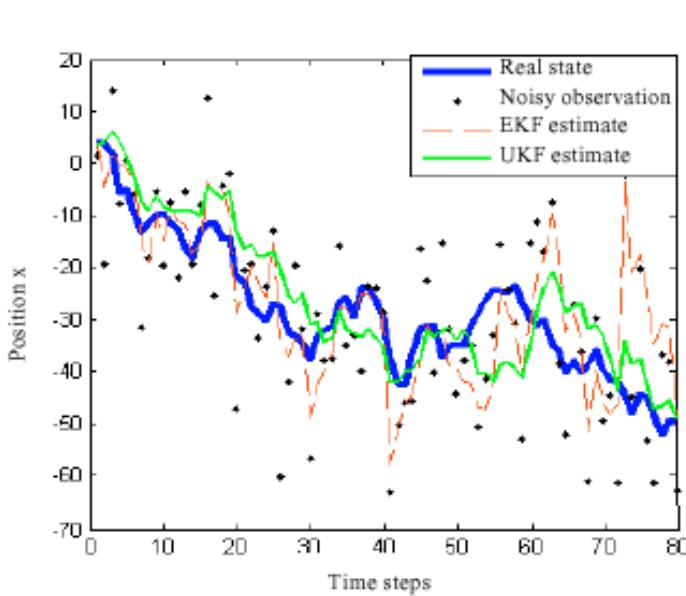


Fig. 1: Two illustrations of fundamental problems associated with the UKF in the presence of the inequalities associated with contact. When sample points are generated (a and d) samples are either infeasible or have different contact modes than the mean estimate. In the first sequence (a-c) the resulting estimate (c) is infeasible even though all of the samples are feasible. In the second sequence (d-f) the resulting estimate (f) is feasible, but has a contact mode that is different from any of the individual sample points. In our experience this is the more common behavior, biasing the estimate away from the contact manifold.

4

There are four popular ways to compute this in practice

1. Pass the full belief PDF through **nonlinear** equations for the motion update (physics) and the sensor update

Most accurate but computationally very expensive (often intractable)

2. Pass **many samples** through the **nonlinear** equations for the motion update (physics) and the sensor update and use the samples as a discrete approximation of the probability distribution

Can be very accurate but can also be computationally expensive (**Particle Filter**)

4

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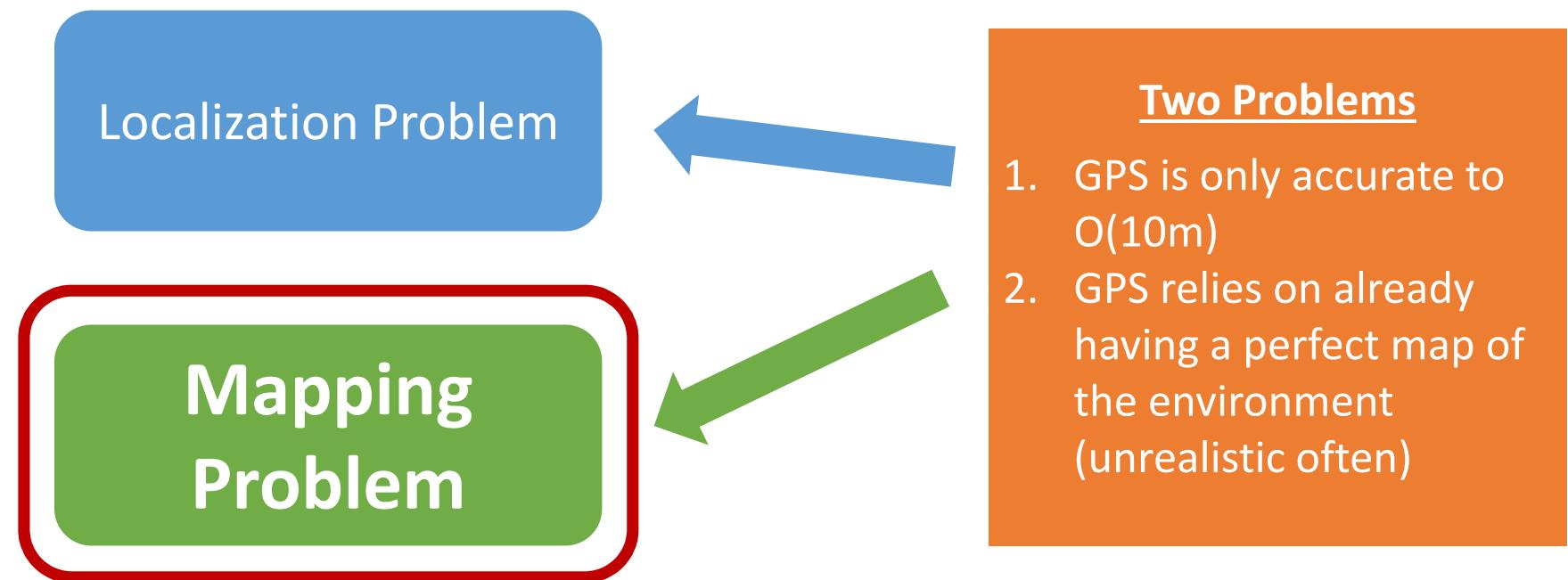
Simplest and least accurate as assumes linear (**Extended Kalman Filter - EKF**)

4. Assume the belief PDF is **Gaussian** and **pass limited samples** through the **nonlinear** equations for the motion update (physics) and the sensor update and reconstruct the Gaussian on the other side

Moderately accurate but assumes Gaussian (**Unscented Kalman Filter - UKF**)

4

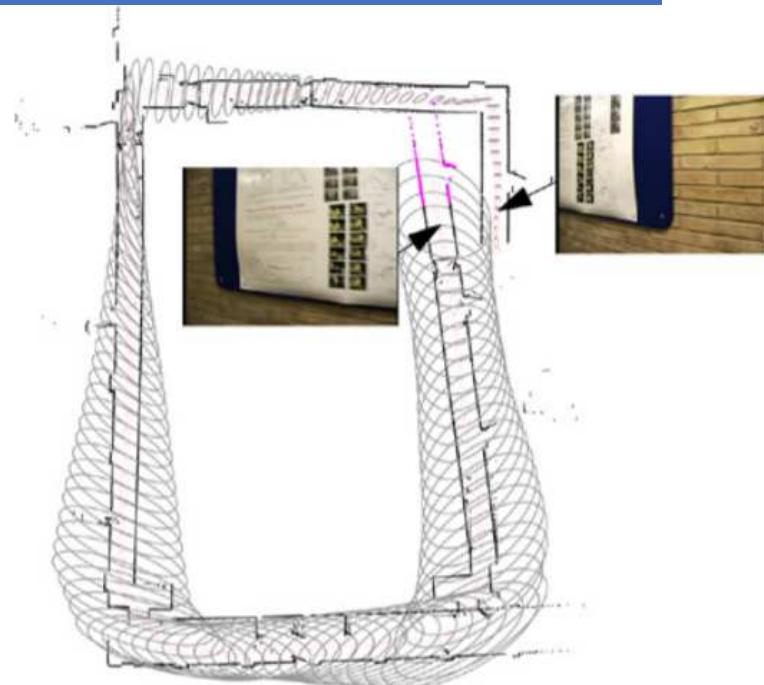
But what if we don't have a map of the environment?



4

But what if we don't have a map of the environment? Enter Simultaneous Localization and Mapping (SLAM)

Essentially just additionally tracking the belief of **landmarks** in the environment (walls, buildings, trees, etc.)



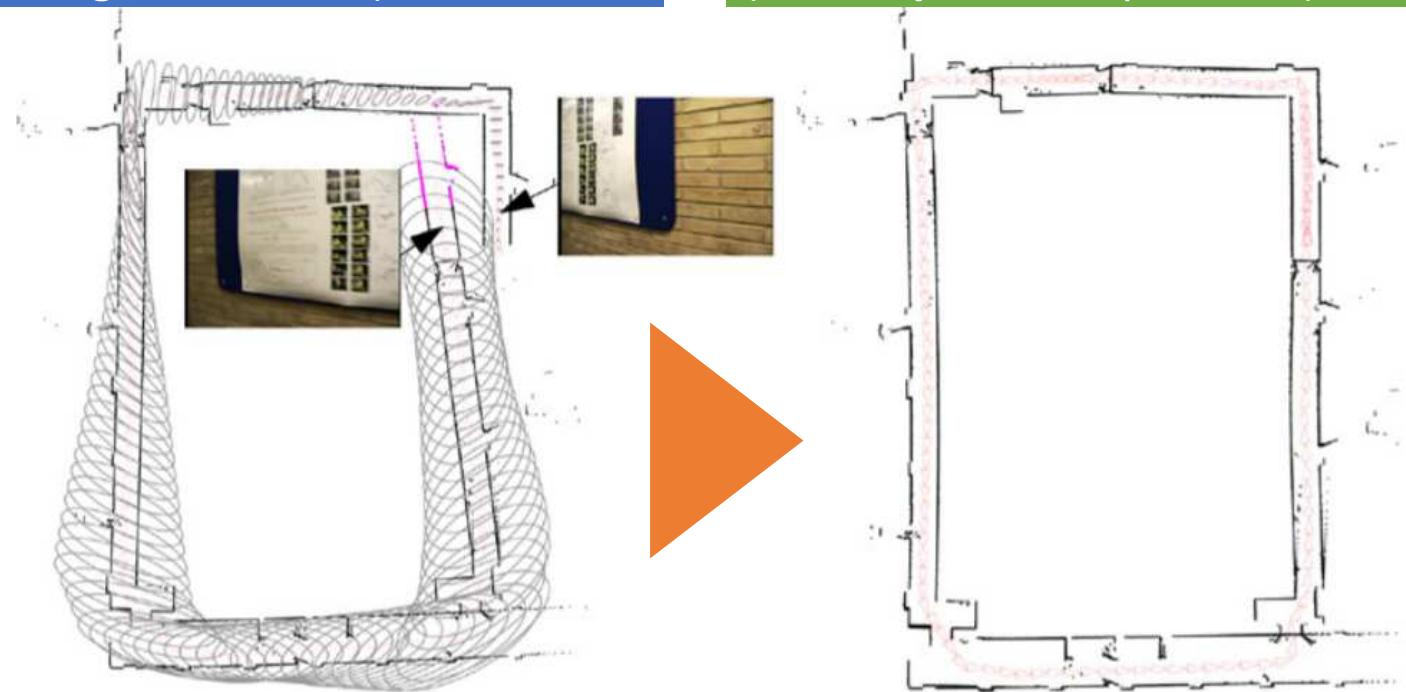
Ho and Newman 2006

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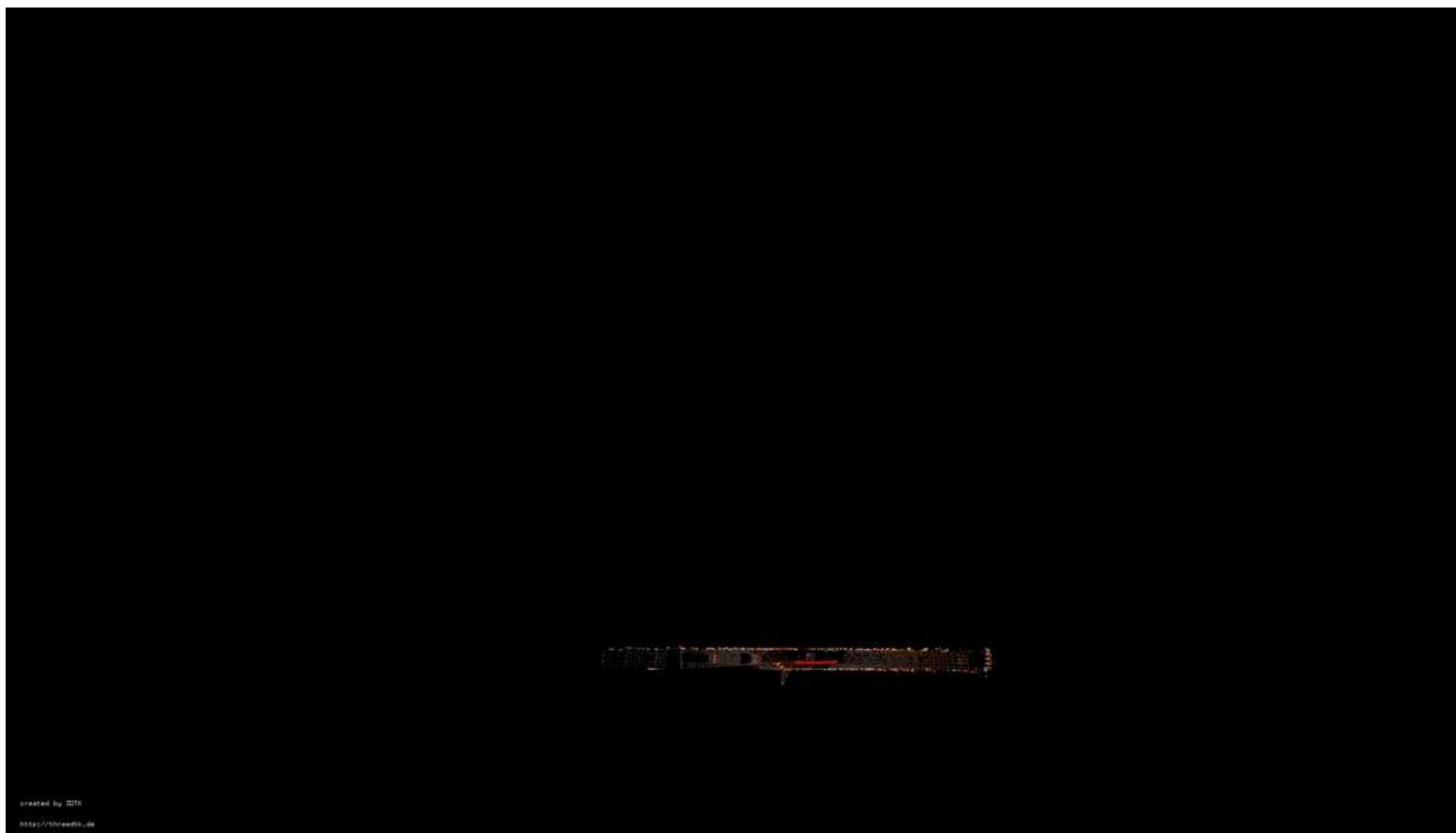
The real hard part is figuring out when you have been somewhere before as measurements drift (the **loop closure** problem)



Ho and Newman 2006

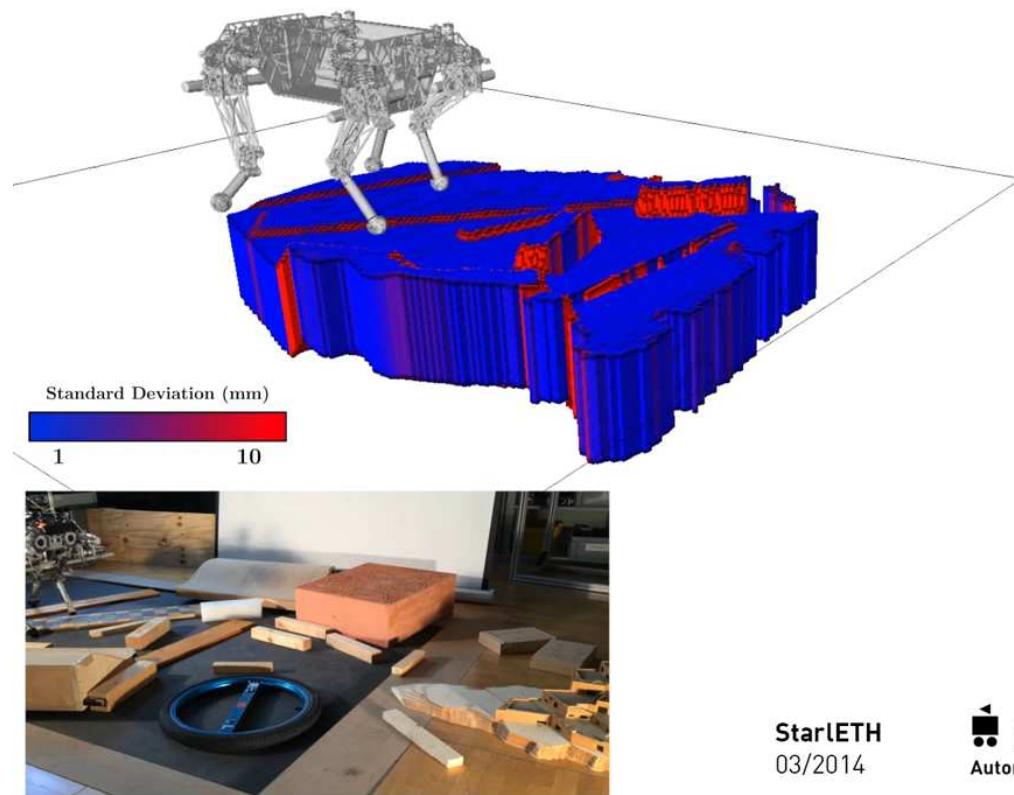
4

SLAM with Loop Closure



4

Mapping can even be done in 3D!



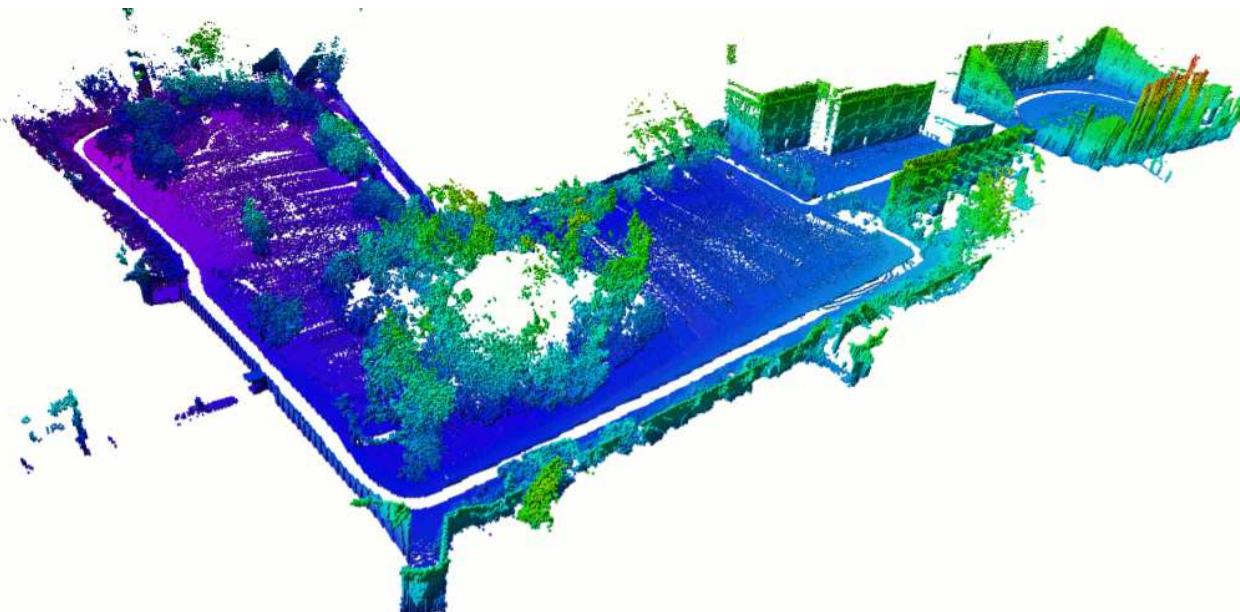
StarlETH
03/2014



ETH zürich

4

- However building (and even storing) maps leads to a huge memory problem especially on small mobile systems
-

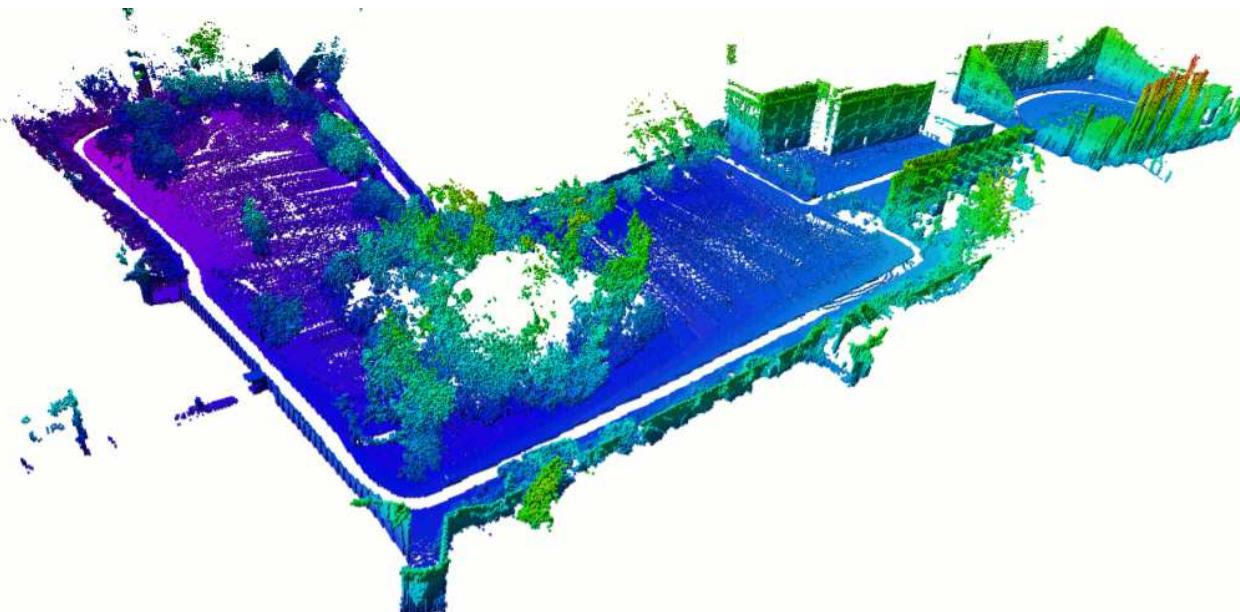


3D grid at 10cm resolution was
5058.76 MB (over 5 GB)

“Octomap” Hornung et. al. 2012

4

- However building (and even storing) maps leads to a huge memory problem especially on small mobile systems
-



3D grid at 10cm resolution was
5058.76 MB (over 5 GB)

Oct-tree w/ Maximum Likelihood metric was able to compress that to 230.33 MB

“Octomap” Hornung et. al. 2012

4

However building (and even storing) maps leads to a huge memory problem especially on small mobile systems

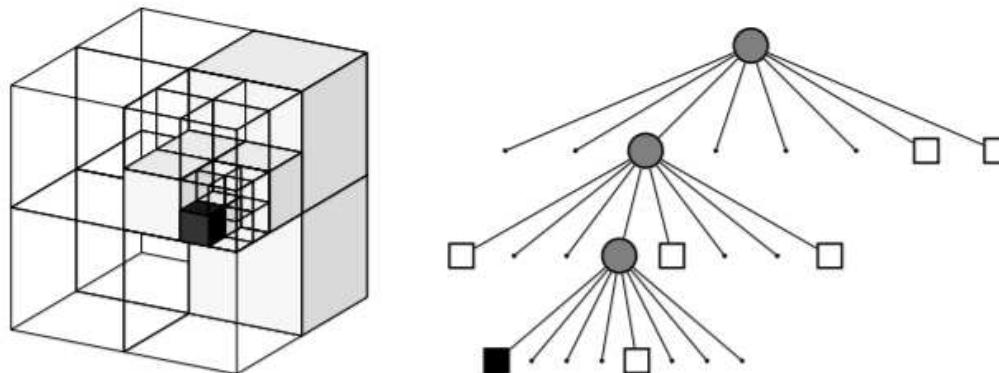


Fig. 2 Example of an octree storing free (shaded white) and occupied (black) cells. The volumetric model is shown on the left and the corresponding tree representation on the right.

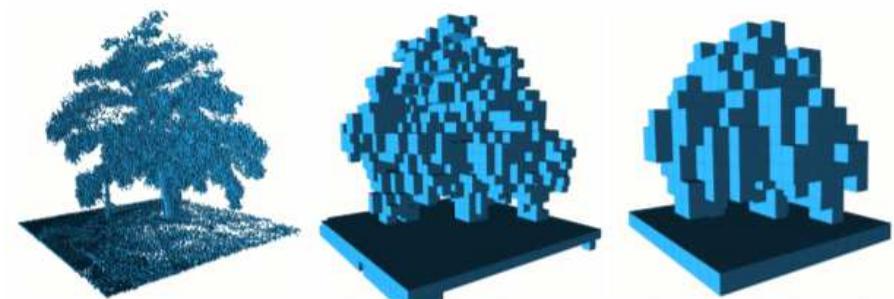


Fig. 3 By limiting the depth of a query, multiple resolutions of the same map can be obtained at any time. Occupied voxels are displayed in resolutions 0.08 m, 0.64 , and 1.28 m.

“Octomap” Hornung et. al. 2012

4

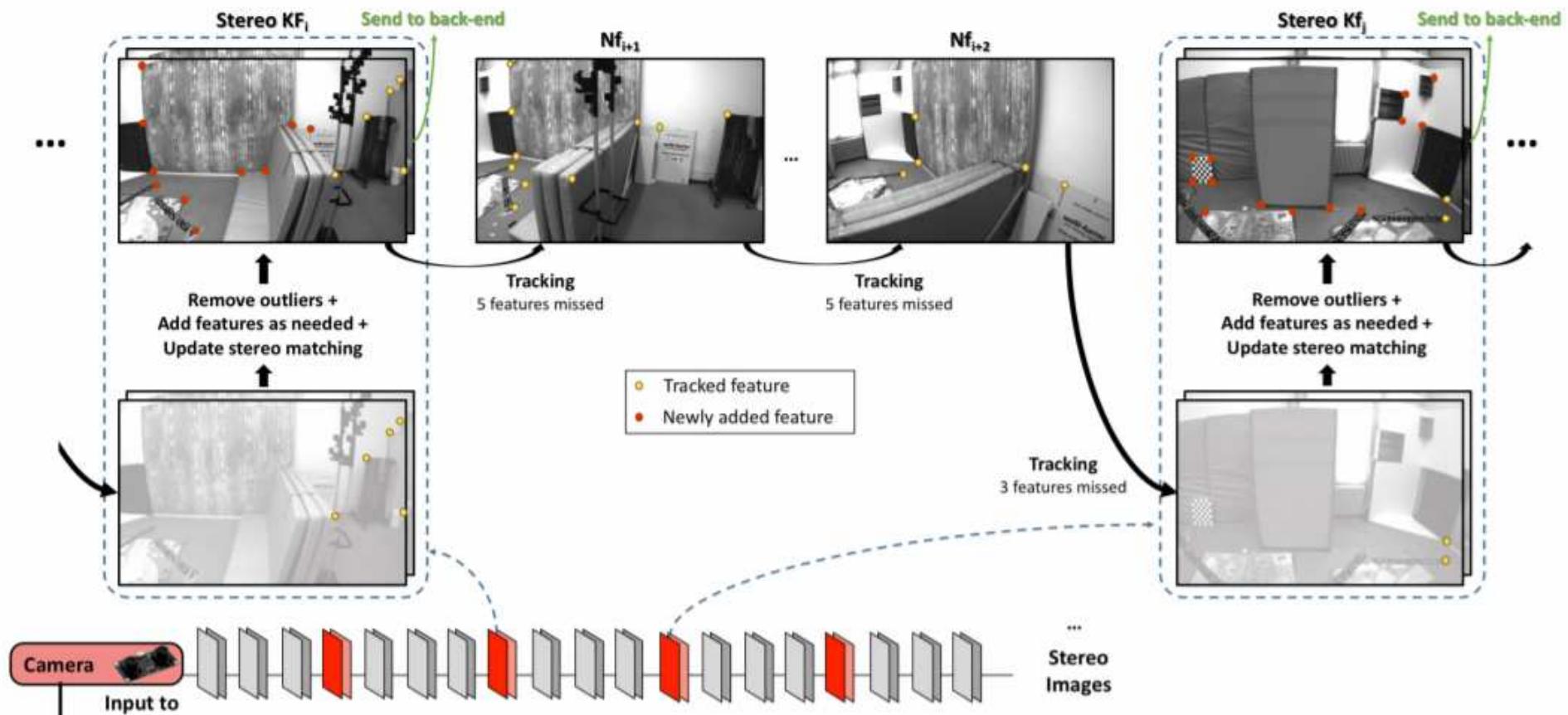
But how would we run localization online in a drone that is too small to carry fancy sensors?



Any ideas?

4

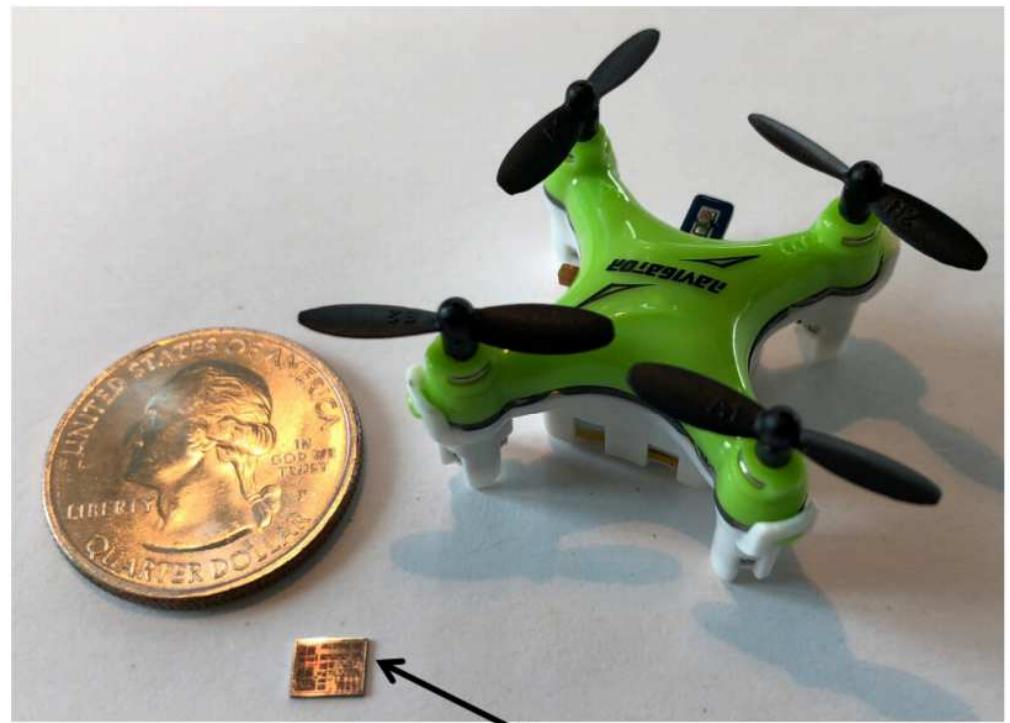
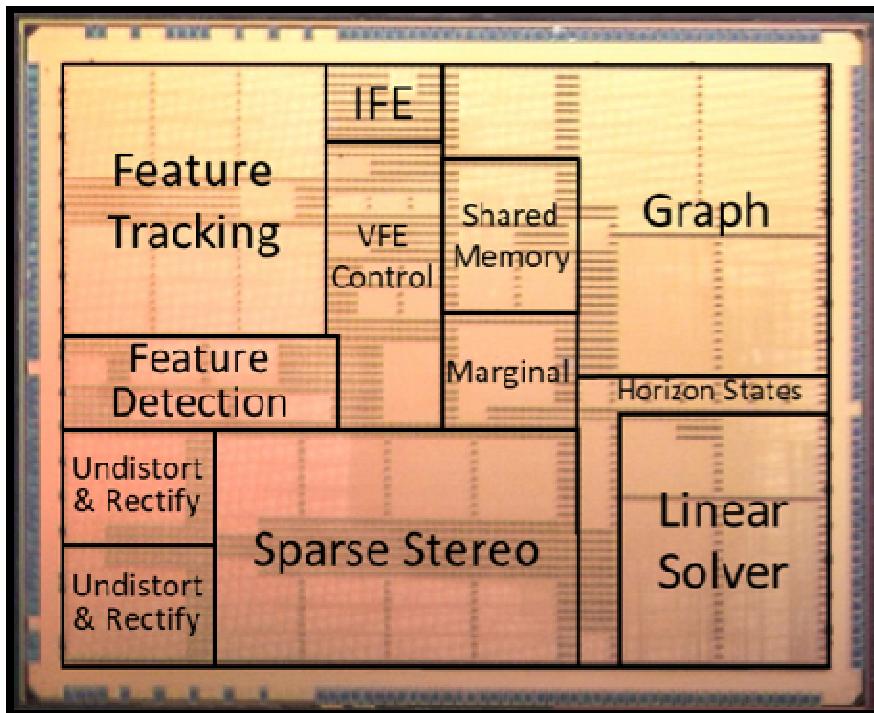
You can estimate the velocity of an object through matching interest points (Visual Odometry)...



4

...and then build a custom chip to fit it onboard!

<http://navion.mit.edu>



Key Takeaways:

1. The [Kalman/Particle Filter](#) uses probability to solve the localization problem but [modeling and/or approximations](#) are needed for it to run efficiently online
 2. Mapping quickly becomes a [memory storage problem](#)
 3. Constrained form factors (aka [tiny drones](#)) will need [novel accelerators](#) to allow for autonomy
-

Your homework for next class

Pre-Reads for Intro to Robotics (Planning and Control)

 Published

 Edit

Computer Architecture to Close the Loop in Real-time Optimization:

<https://ieeexplore.ieee.org/document/7402937> ↗

The Architectural Implications of Autonomous Driving: Constraints and

Acceleration: <https://web.eecs.umich.edu/~shihclin/papers/AutonomousCar-ASPLOS18.pdf> ↗ ↘

A Summary of Team MIT's Approach to the Virtual Robotics Challenge:

https://agile.seas.harvard.edu/files/agile/files/vrc_entry.pdf

Your homework for next class

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A Summary of Team MIT's Approach to the Virtual Robotics Challenge:
https://agile.seas.harvard.edu/files/agile/files/vrc_entry.pdf

We have posted a tentative paper list to Canvas (along with PDFs and links)

Start to think about which papers you want as we will be allocating them in a week or two!

If you have an idea for a paper not on the list please run it by us and we may be willing to swap it in!

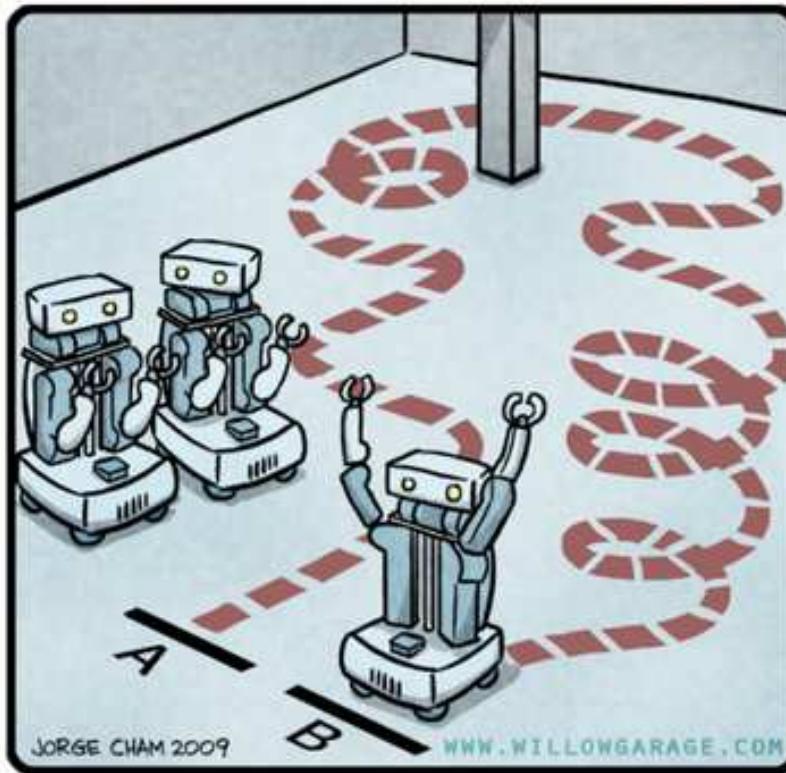
I'd love any Feedback!

<http://bit.ly/CS249-Feedback-L1>



CS 249r: Special Topics in Edge Computing

Intro to Autonomous Systems / Robotics Part 2



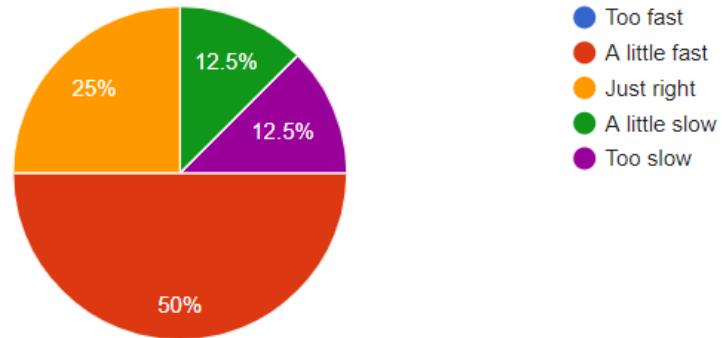
"HIS PATH-PLANNING MAY BE
SUB-OPTIMAL, BUT IT'S GOT FLAIR."

Brian Plancher
Fall 2019

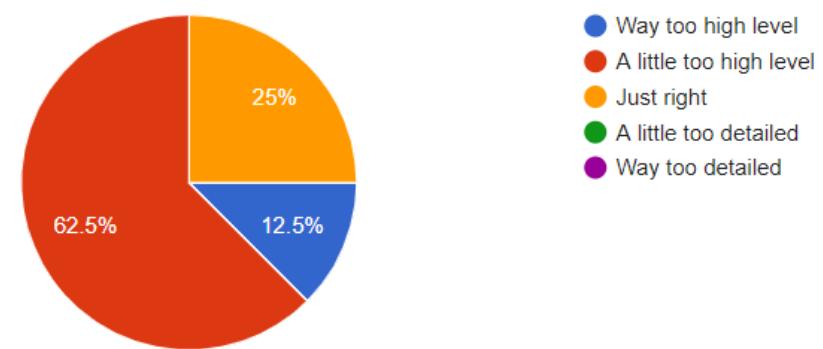


Feedback from last class

How was the pace of class today?



How was the depth of the content covered today?

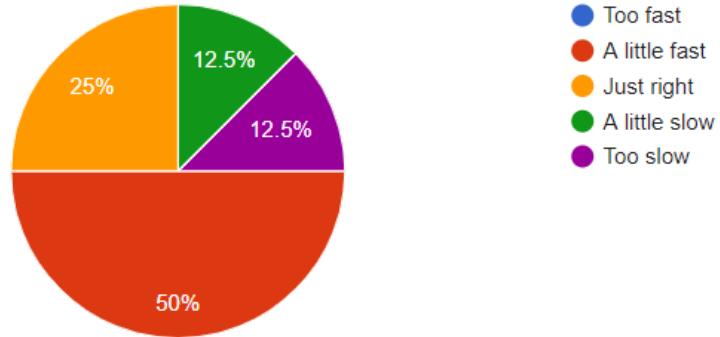


1. Pace is a tad fast
2. Get more technical/depth

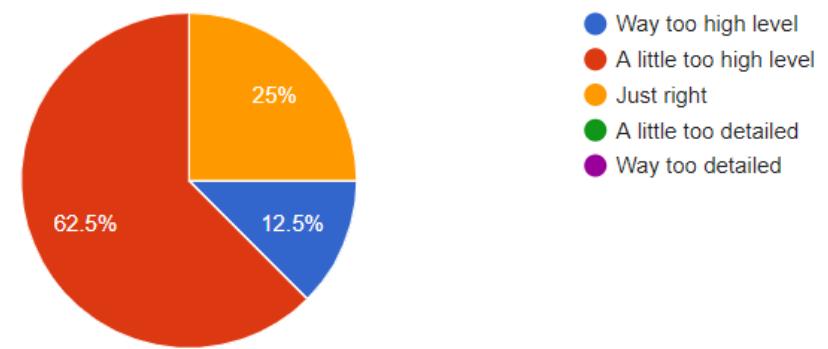
Feedback from last class

Also thanks for the open ended feedback!

How was the pace of class today?



How was the depth of the content covered today?



1. Pace is a tad fast
2. Get more technical/depth

Your homework for next class

Pre-Reads for Intro to Domain Specific Architectures

Is dark silicon useful? Harnessing the four horsemen of the coming dark apocalypse: <https://ieeexplore.ieee.org/document/6241647> ↗

Turing Lecture: A New Golden Age for Computer Architecture:
<https://californiaconsultants.org/wp-content/uploads/2018/04/CNSV-1806-Patterson.pdf> ↗ (watch the lecture its great!)



We have posted a tentative paper list to Canvas (along with PDFs and links)

Start to think about which papers you want – I will send a link to vote for preferences in a week or so!

If you have an idea for a paper not on the list please run it by us and we may be willing to swap it in!

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We're going to use **HOTCRP** (linked on Canvas and <https://www.eecs.harvard.edu/cs249r/>) for these for Monday – you will get an email from **Glenn Holloway** with a Password to access the site. (I am giving him the full roster as of today)

Your homework for next class

Click on a paper to access that paper's page

The screenshot shows the homepage of the CS 249 conference management system. At the top left is a pink header bar with the text "CS 249". On the right, the user is logged in as "brian_plancher@g.harvard.edu" with links for "Profile", "Help", and "Sign out". Below the login, there is a search bar with dropdown options "Search: (All)" and "in Active papers" followed by a "Search" button. To the right of the search bar is a "(All)" button and a "Search" button. On the left side, under "Recent activity", there is a link to "Start new paper (No deadline)". Below this, a red box highlights two recent submissions:

- #1 Is Dark Silicon Useful? Harnessing the Four Horsemen of the Coming Dark Silicon Apocalypse Submitted
- #2 A New Golden Age for Computer Architecture: WATCH THE VIDEO LINKED ON SLIDE 1 Submitted

On the right side, there is a sidebar titled "Administration" with links to "Settings", "Users", "Assignments", "Mail", and "Action log". Another sidebar titled "Conference information" has a link to "Program committee". At the bottom right of the page is a small "HotCRP v2.100" watermark.

Your homework for next class

The screenshot shows a web interface for a conference submission system. At the top, it says "CS 249r Home" and "brian_plancher@g.harvard.edu". Below that, the title of the submission is "#1 Is Dark Silicon Useful? Harnessing the Four Horsemen of the Coming Dark Silicon Apocalypse". The main content area shows the submission details: "Submitted" (10 Sep 2019 2:37:22am EDT), "Abstract" (N/A), and "Authors" (+ Hidden for blind review). A note says "You have used administrator privileges to view and edit reviews for this paper. (Unprivileged view)". Below this, it says "You are an author of this paper." and has two buttons: "Write review" (highlighted with a red box) and "Add comment". At the bottom, there's a "+ Add Comment" button and a "HotCRP v2.100" footer.

Then click “Write review” to open up the form to submit a “review”

Your homework for next class

Are you a(n):

What is your field of expertise?

If you were scoring this paper for a conference how would you rank its overall merit?

What was the main contribution of this paper?

What did you find confusing about this paper?

What did you like about the writing?

What did you dislike about the writing?

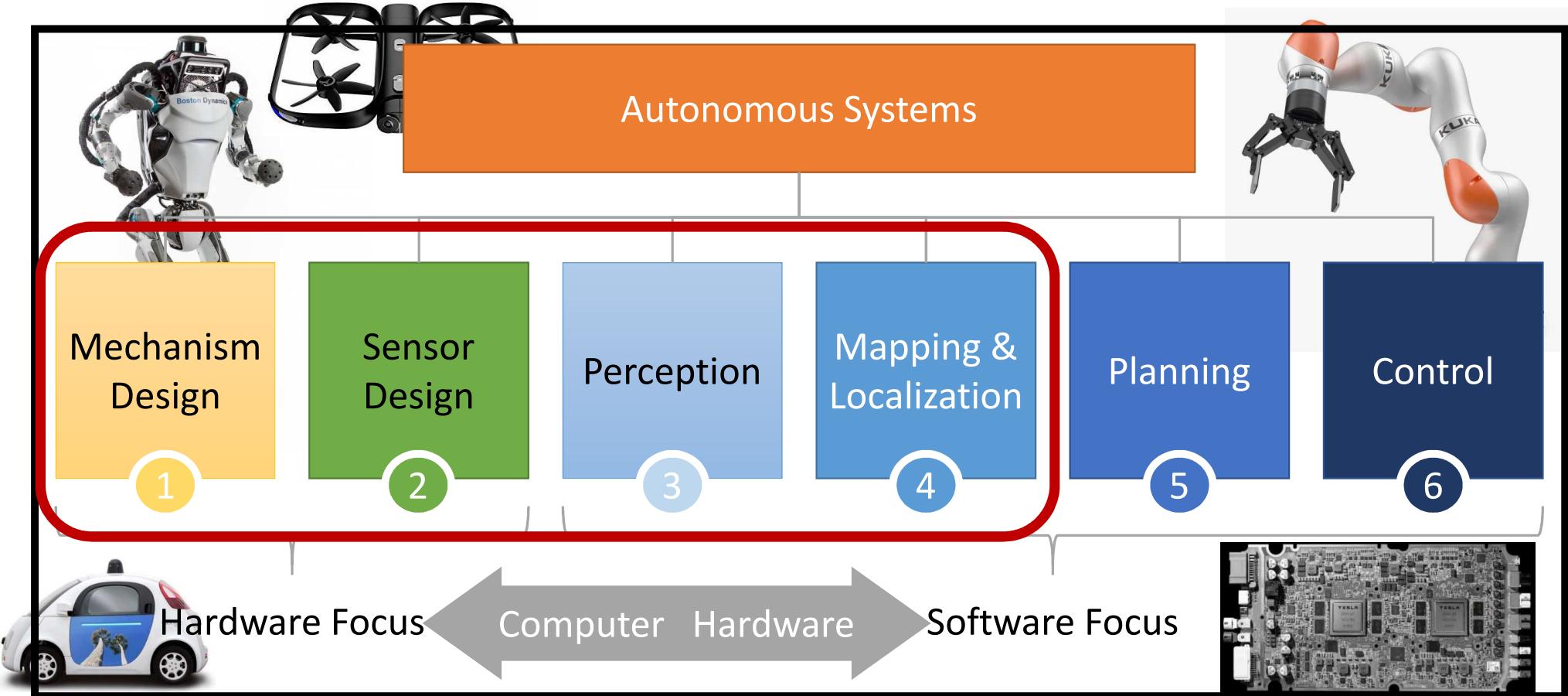
Any other comments?

Then just fill it
out and submit
and you'll be
good to go!

The goal for the next couple of lectures is to develop a **high level** understanding of:

1. What is an autonomous system
 2. Key **problems** for autonomous systems
 3. Some of the most important (classes of) **algorithms** in robotics
 4. The **model based** vs. **model free** tradeoff
 5. The **online** vs **offline** tradeoff
 6. The **no free lunch** theorem and the need for **approximations**
 7. How **computer systems / architecture** design has and can play a role in improving autonomous systems
-

Autonomous Systems / Robotics is a BIG space



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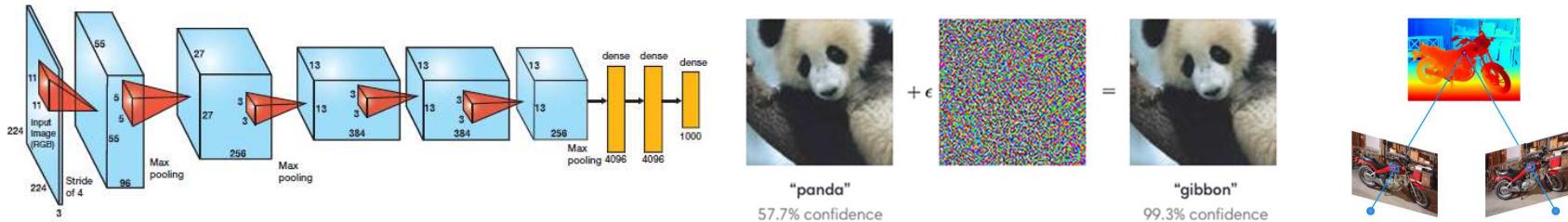
Key Takeaways:



1. When designing algorithms for robots you need to understand the physical capabilities of the robot and you (potentially) need to understand how to model its physical behaviors
 2. Different kinds of systems will have different power, weight, and performance budgets for computer hardware
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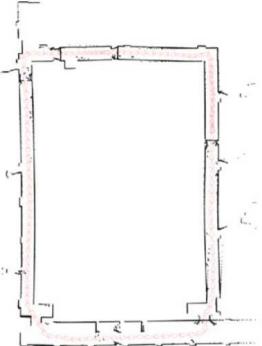
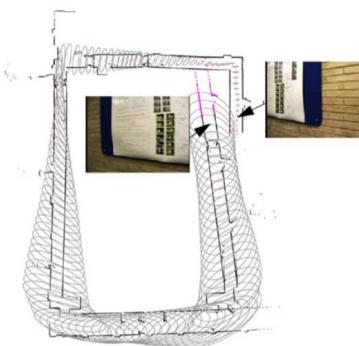
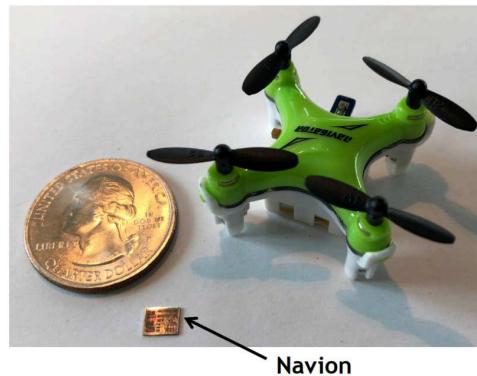
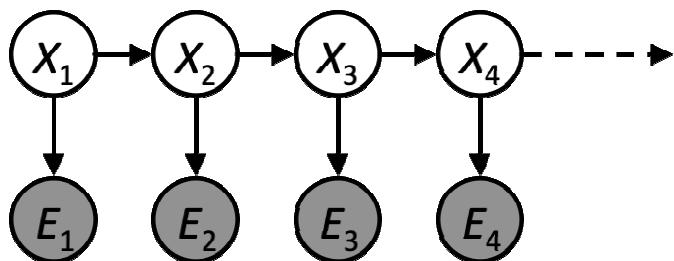
Key Takeaways:



1. As of today it seems like **CNNs** that automate the design and summary of salient features via convolution are the way to go
 - But/and will need specialized NN running on **specialized accelerator chips** to get them small enough to fit on small power constrained autonomous systems (e.g., small drones)
 - And we will need to find ways to **secure them against attacks!**
2. Also, other more targeted problems such as **Stereo Depth** seem to need accelerators!

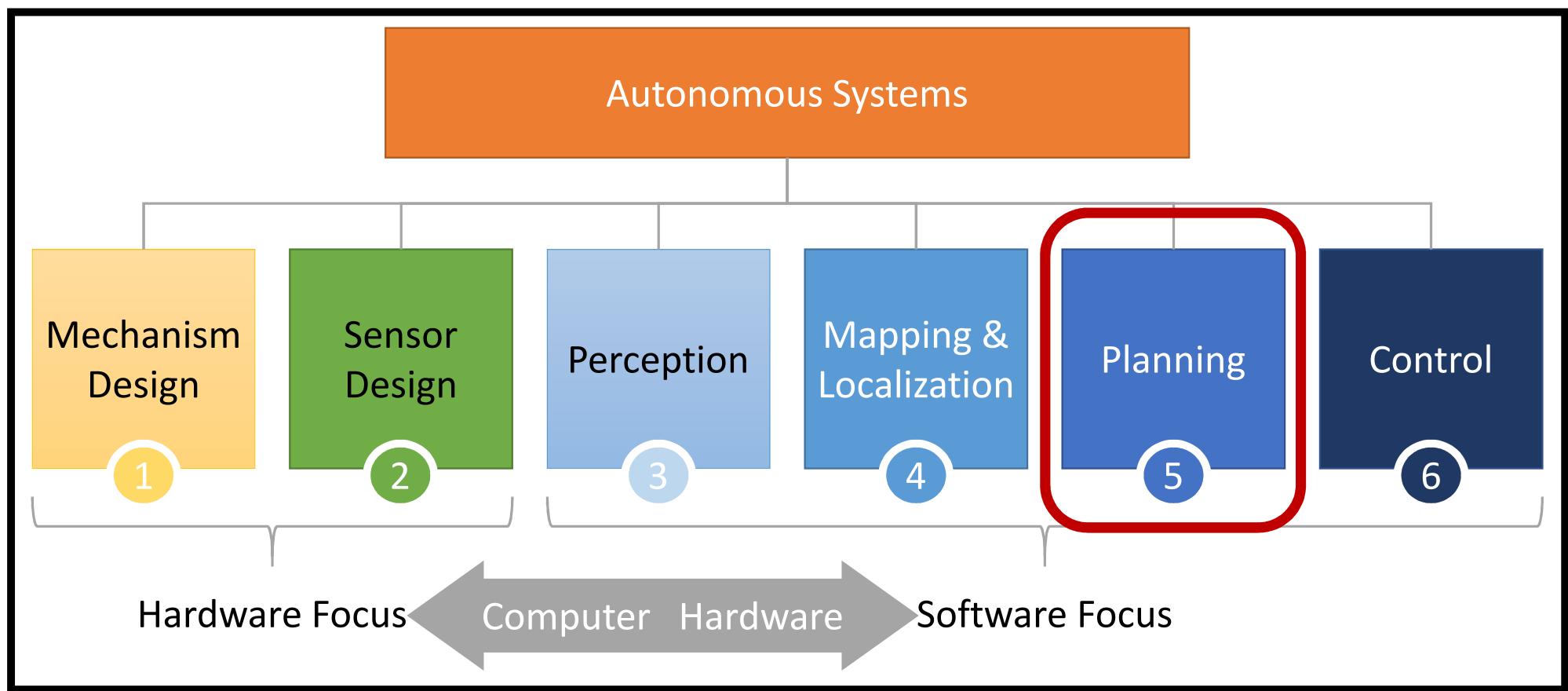
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Key Takeaways:



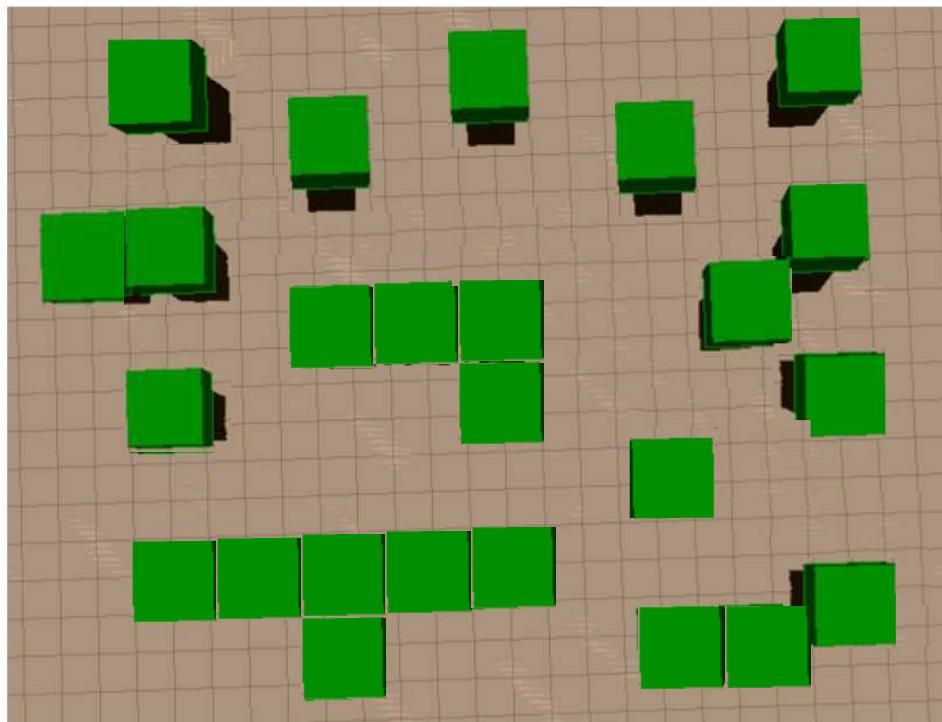
1. The **Kalman/Particle Filter** uses probability to solve the localization problem but **modeling and/or approximations** are needed for it to run efficiently online
2. Mapping quickly becomes a **memory storage problem**
3. Constrained form factors (aka **tiny drones**) will need **novel accelerators** to allow for autonomy

Autonomous Systems / Robotics is a BIG space



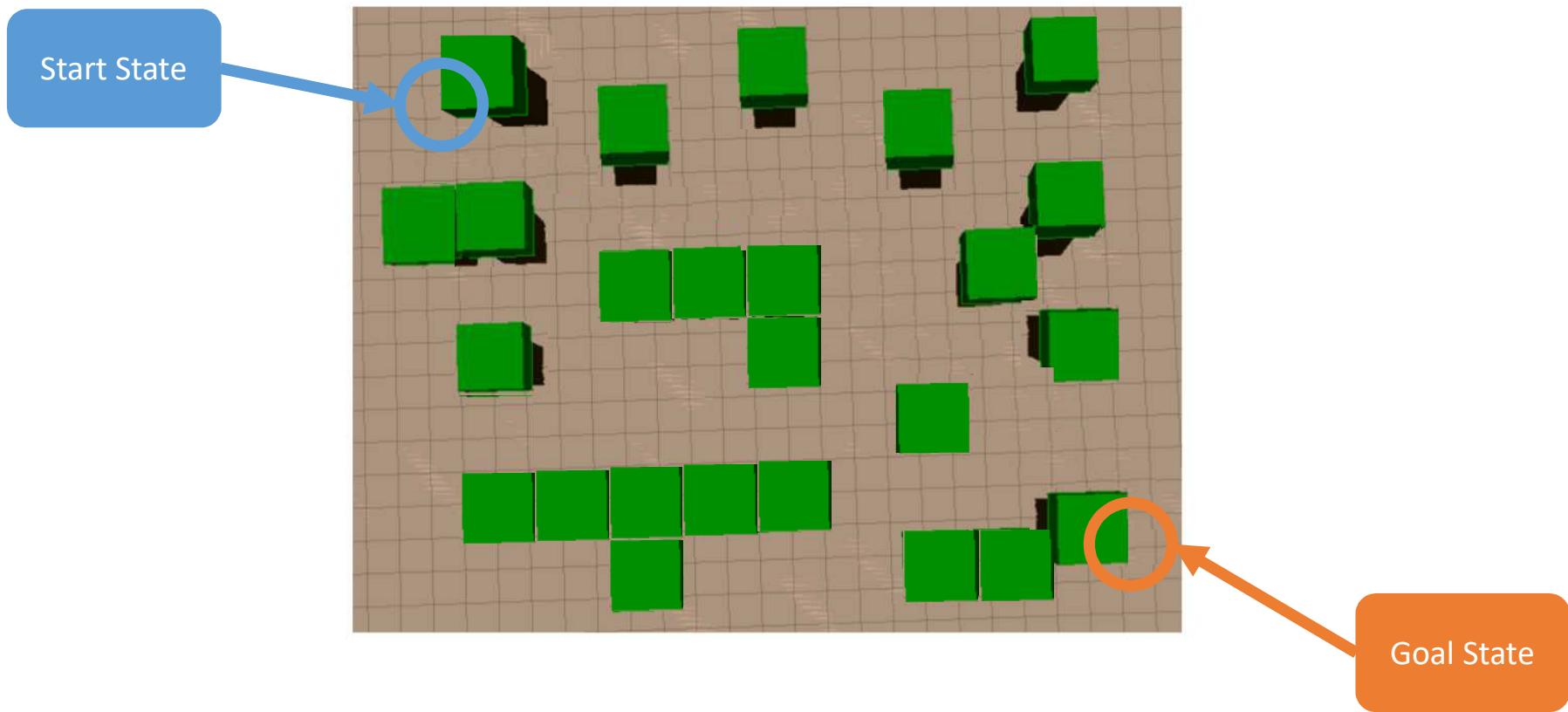
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Planning is the process of computing an action plan for a robot based on the previously computed map



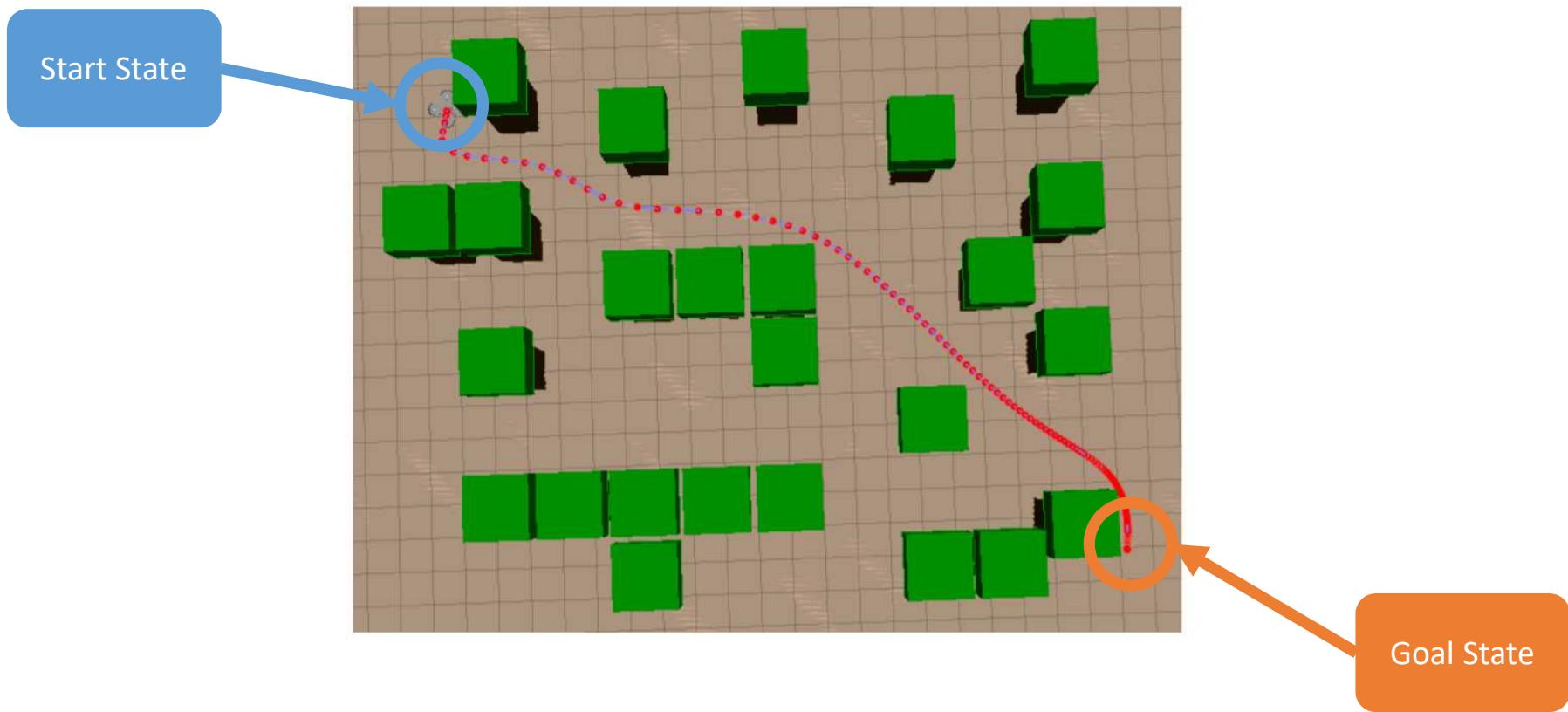
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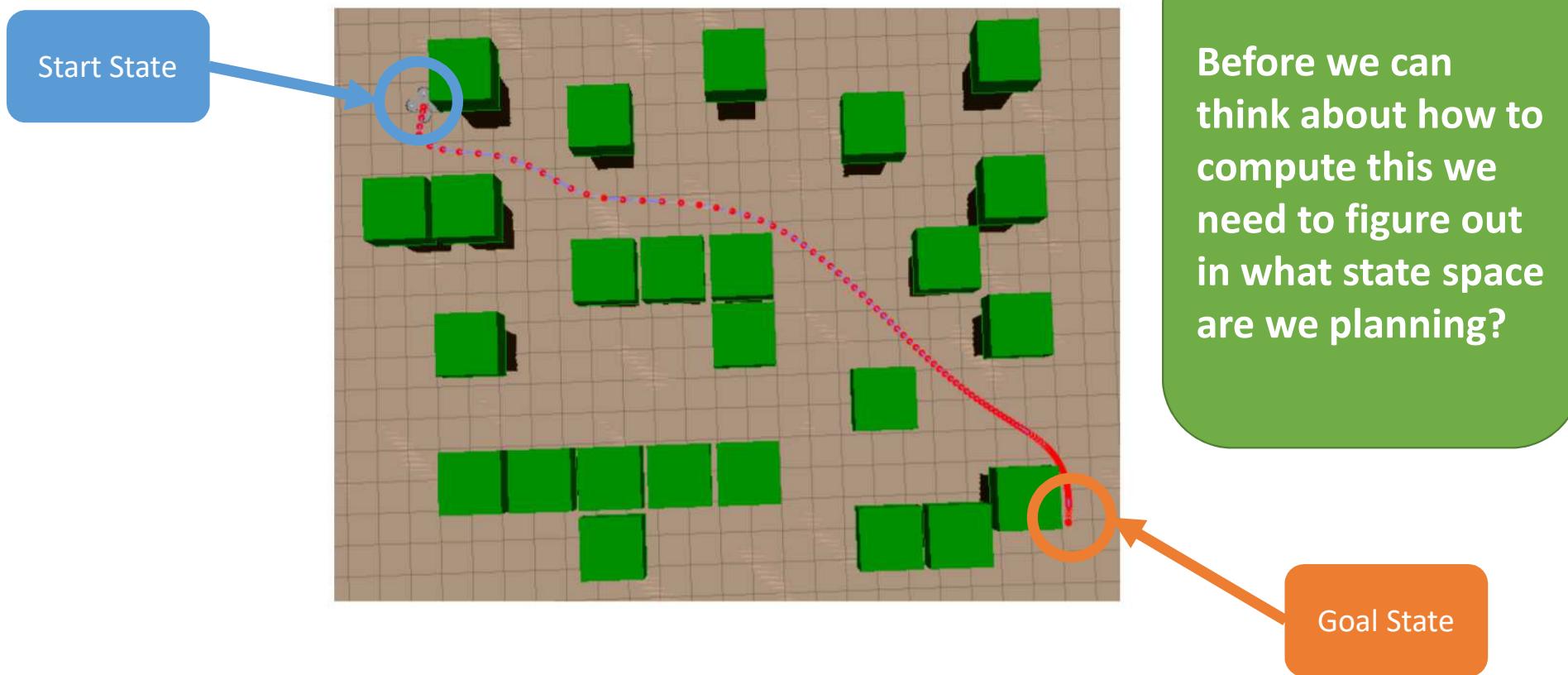
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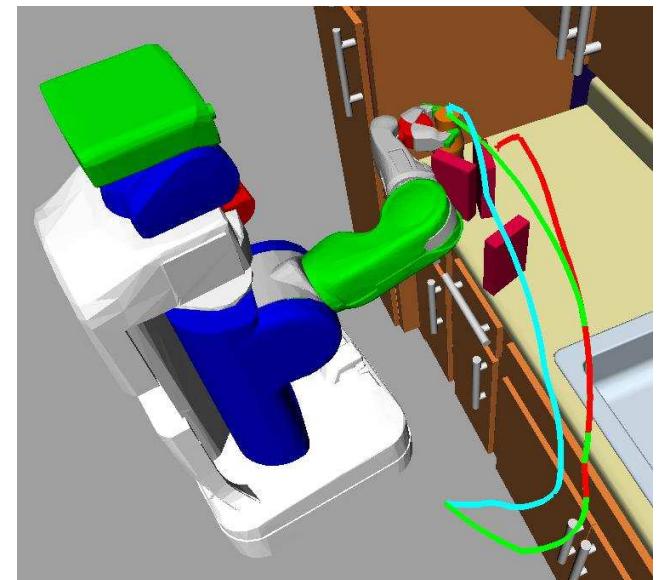
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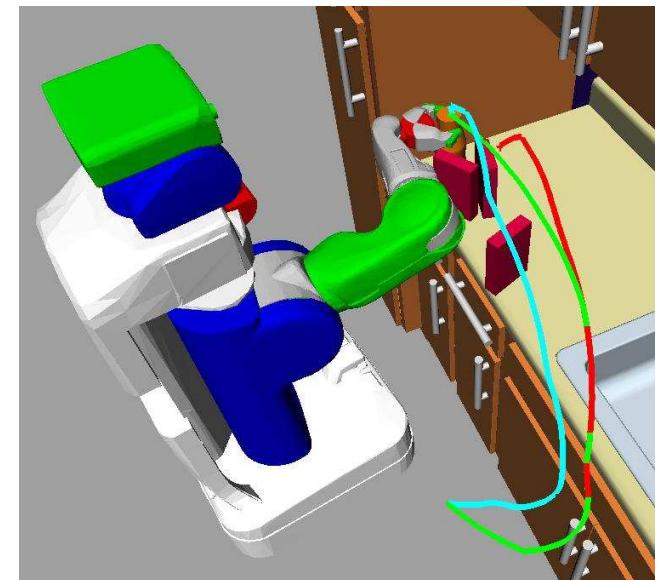
5 Spaces and Transformations (aka where are we planning?)

- **Task space**: the 6D workspace of the robot
 - E.g., the **pose** ($x,y,z,\text{roll},\text{pitch},\text{yaw}$) of the robot's hand or an object



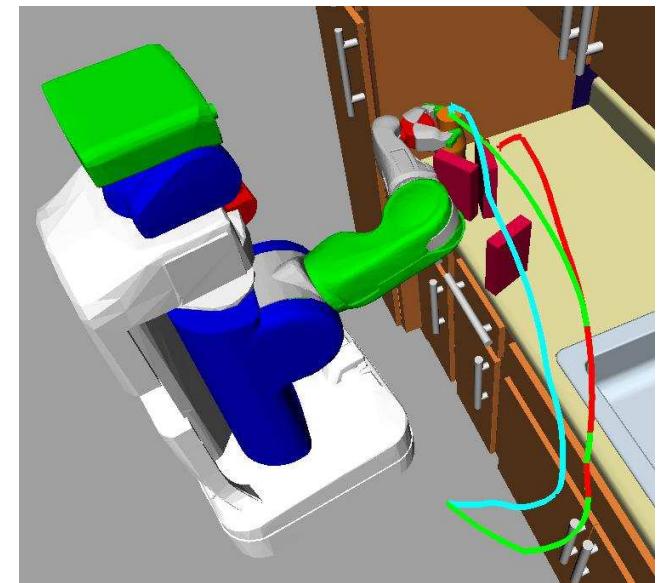
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 - Vector $q \in \mathbb{R}^n$



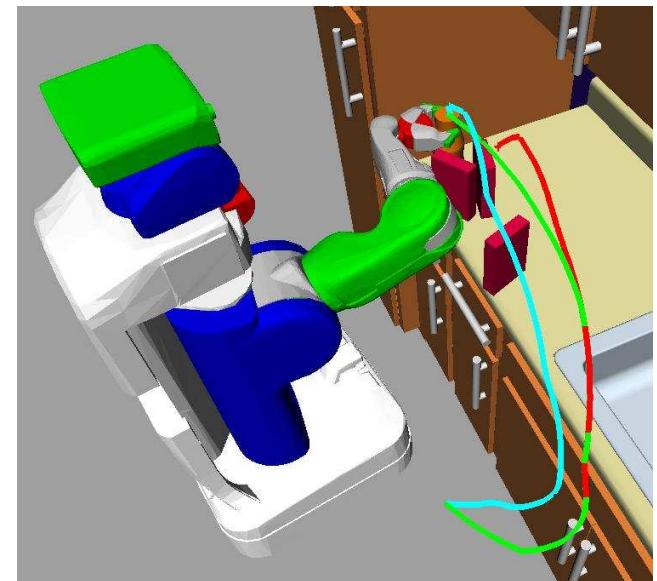
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 - **Inverse kinematics**: maps task space poses to configuration space
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5 Spaces and Transformations (aka where are we planning?)

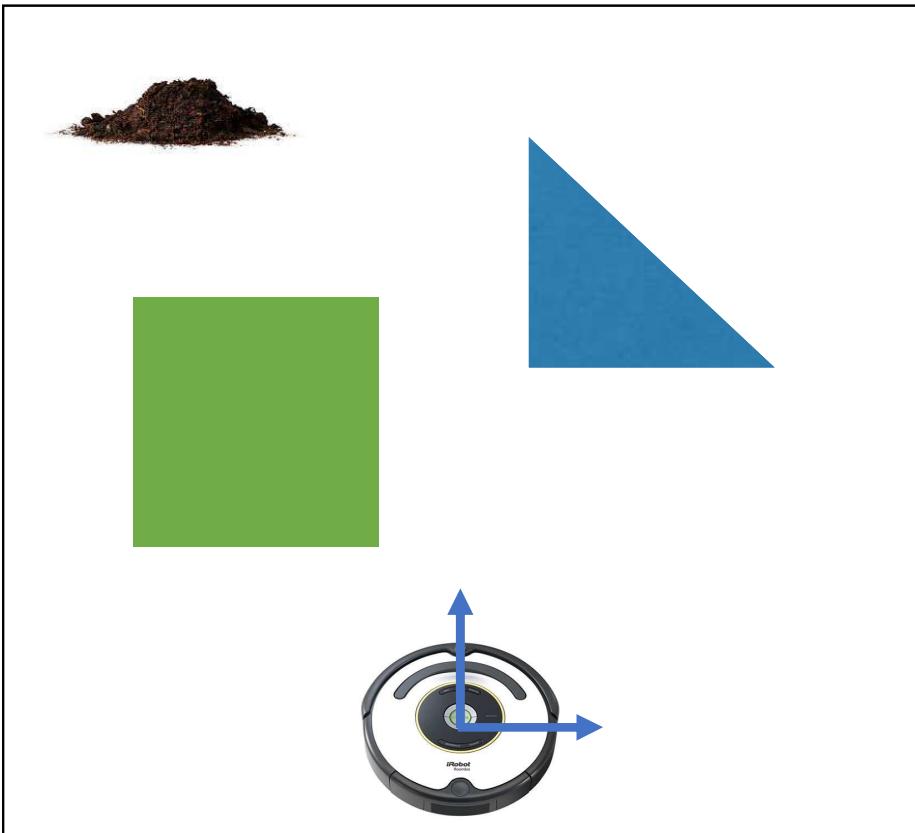
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Q: Are forward and inverse kinematics 1 to 1 operations?

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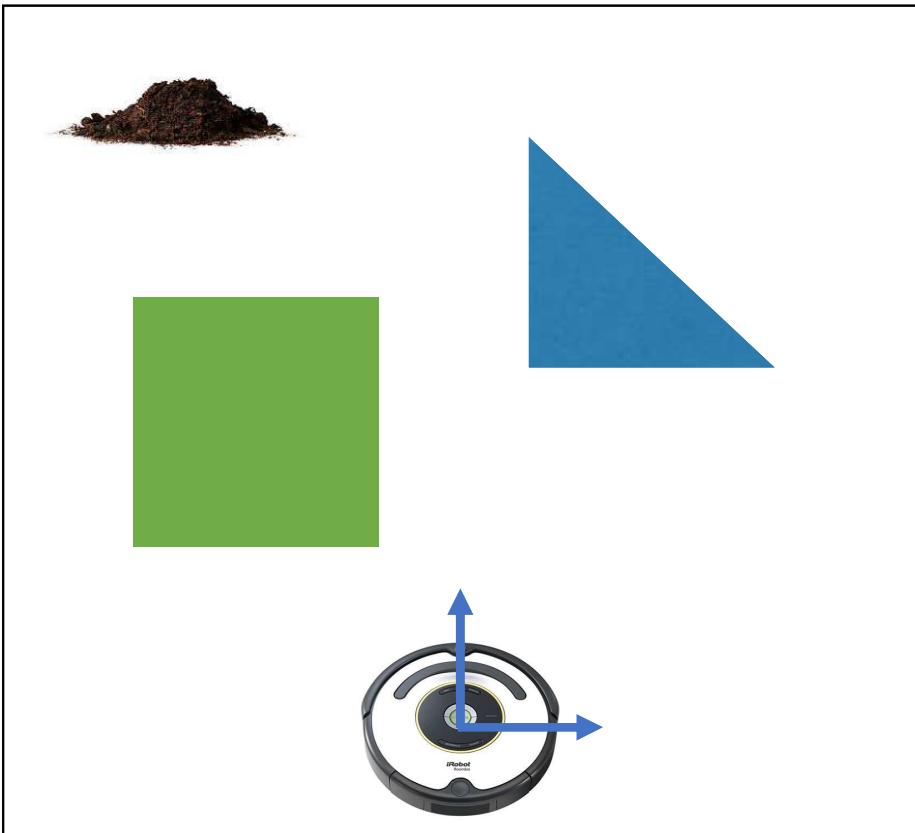
Configuration Space



Q1: What is the configuration space state for this omnidirectional robot?

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Configuration Space

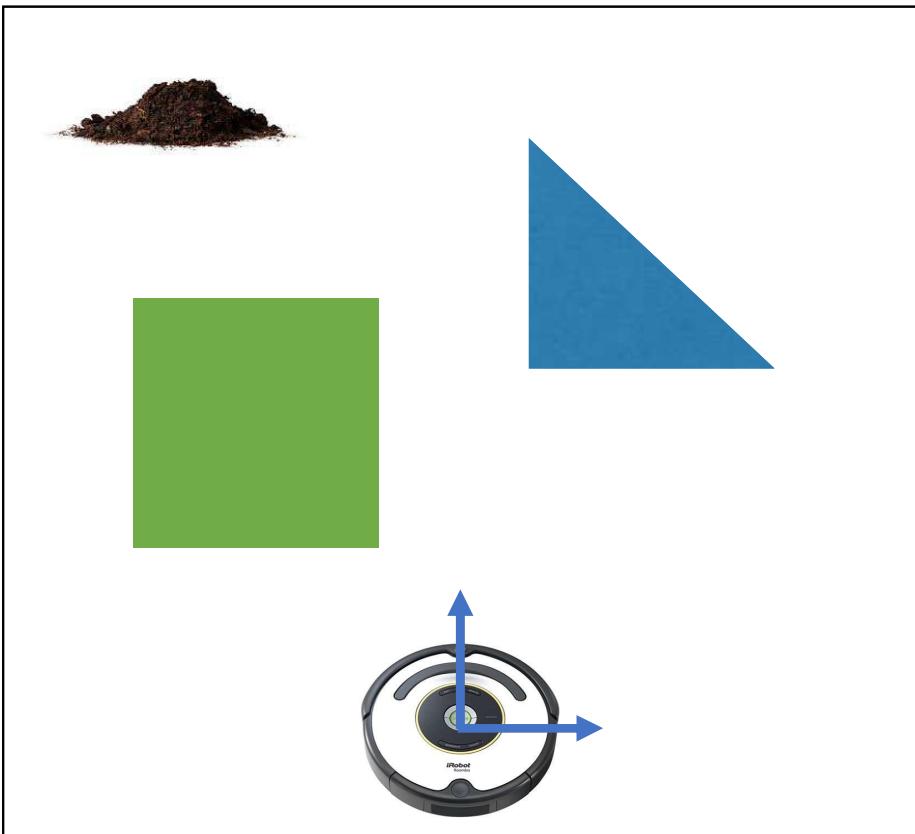


Q1: What is the configuration space state for this omnidirectional robot?

A1: (x,y) position of the center of the robot

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Configuration Space

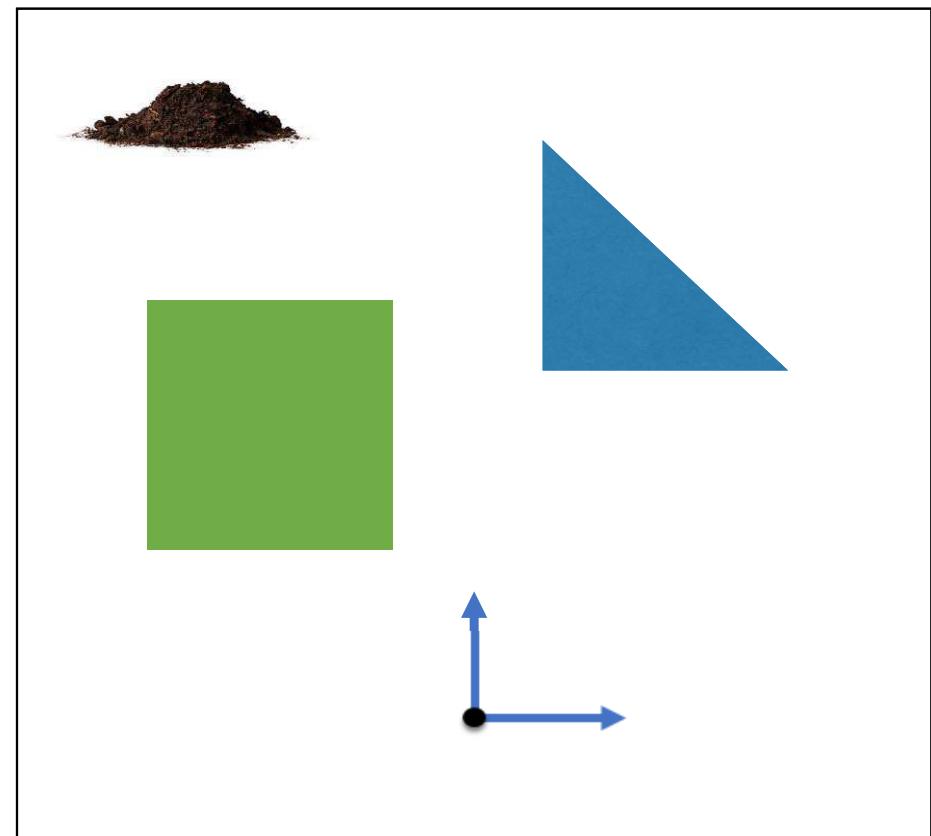
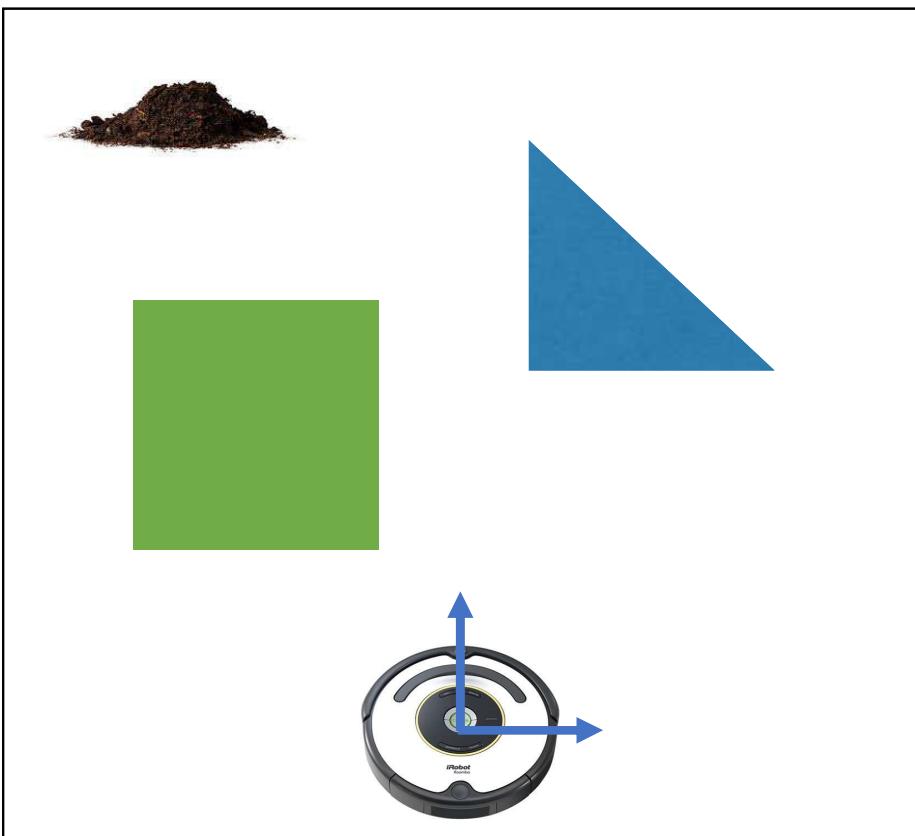


Q2: How can we map this robot's world into configuration space?

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Configuration Space

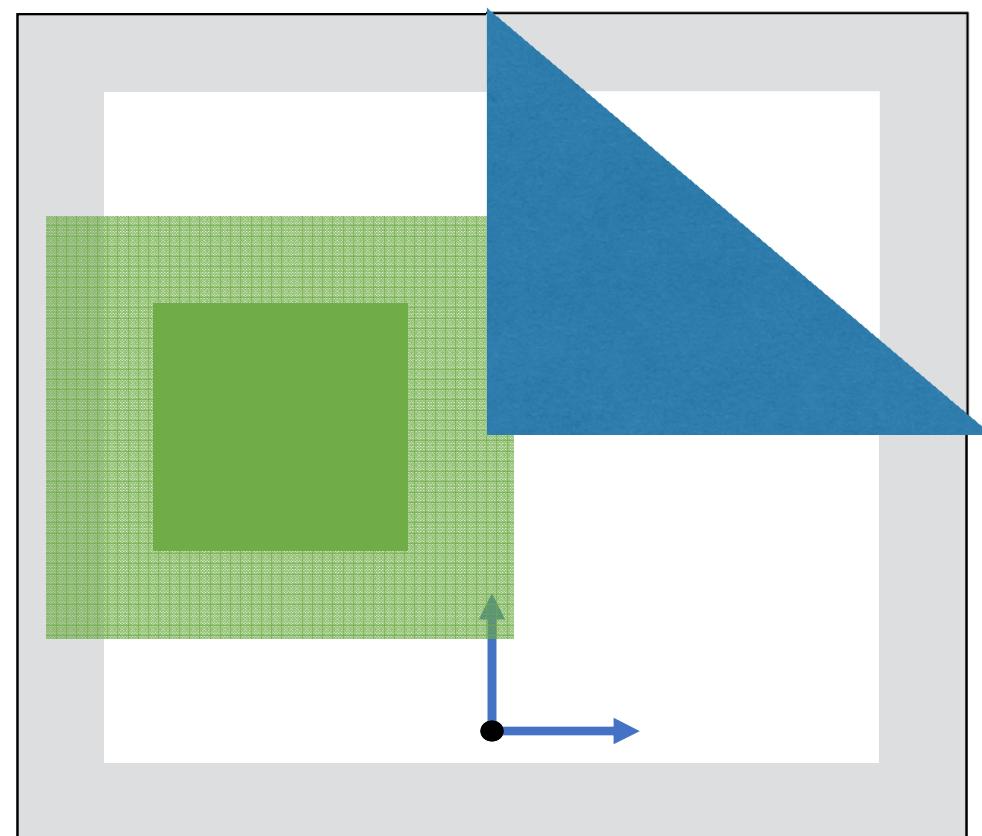
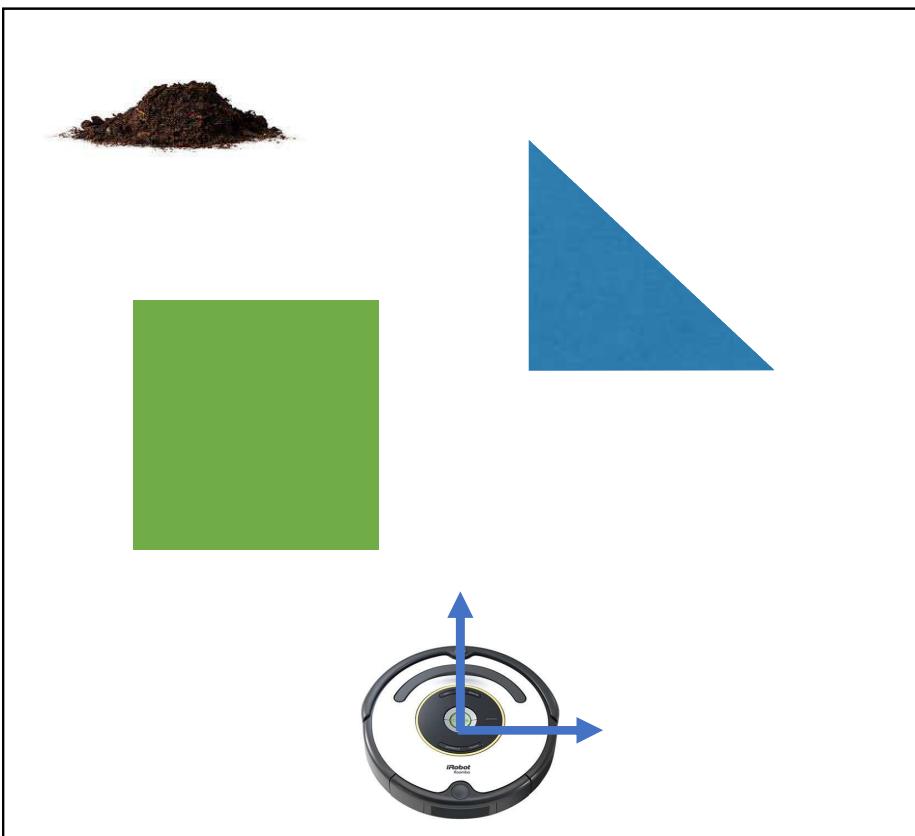
Well we want the robot to become a single (x,y) point



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Configuration Space

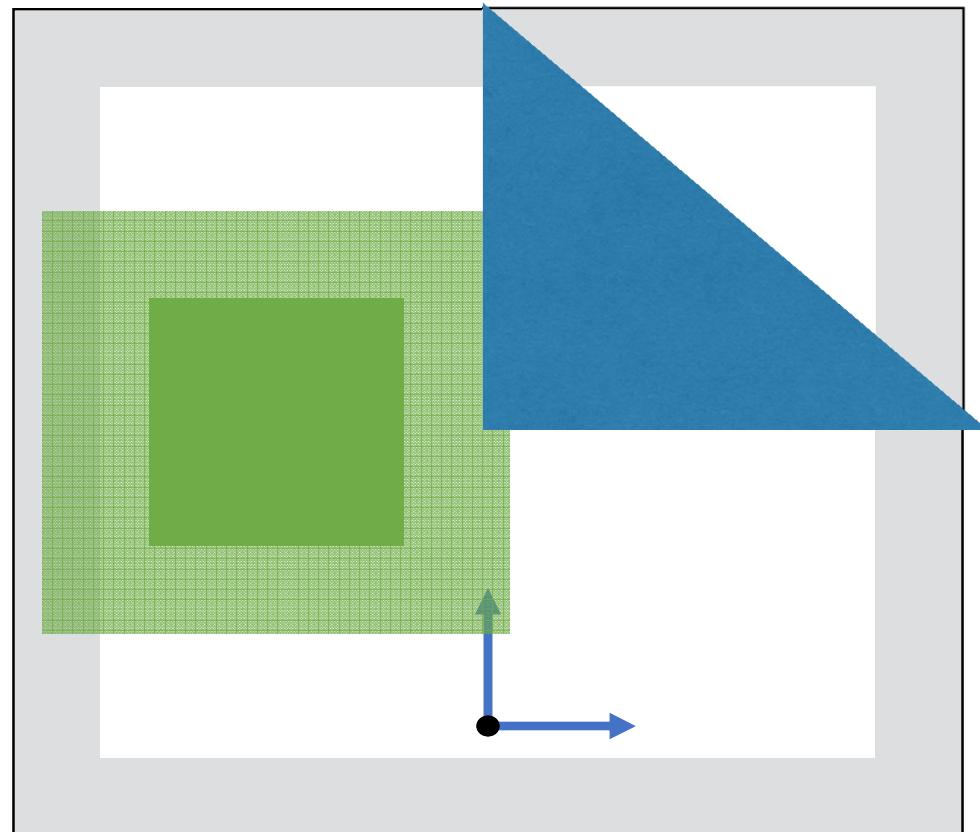
So we need to inflate the obstacles accordingly



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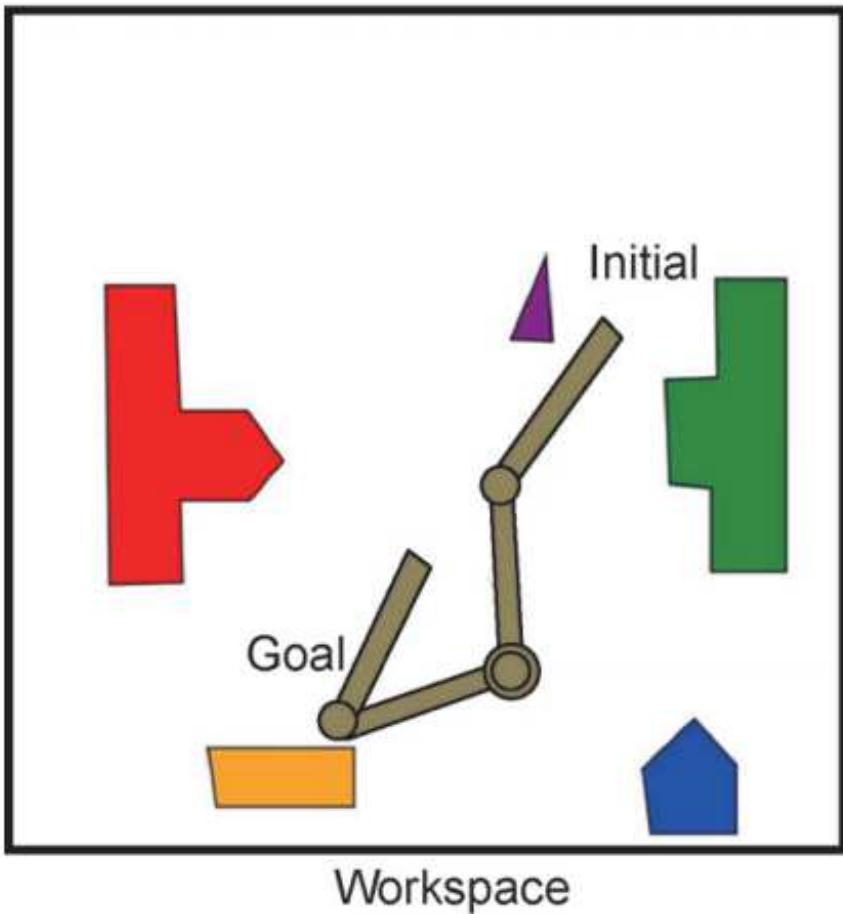
Configuration Space

- **Insight:** mapping task space obstacles and goals into configuration space allows us to **plan a path for a single point** instead of worrying about a full robot



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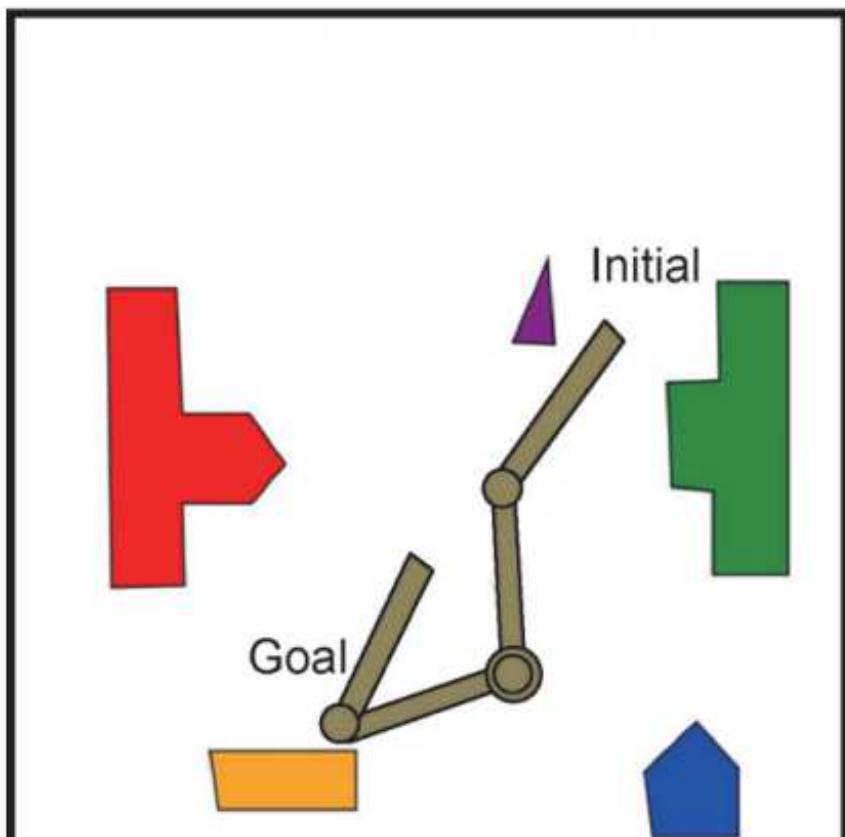
Configuration Space



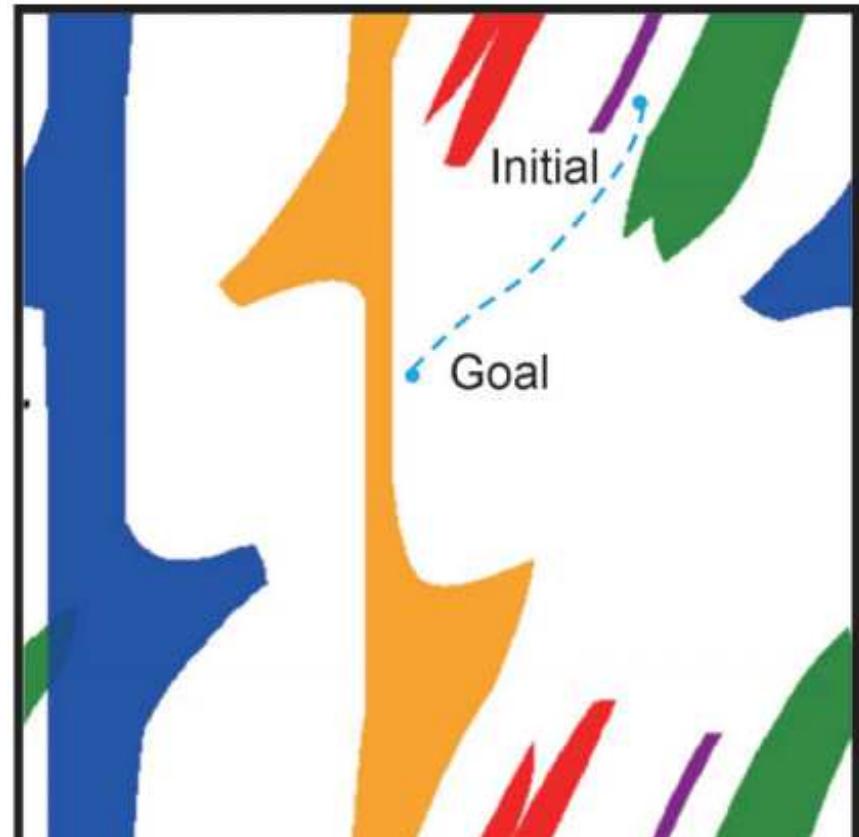
How can we map this robot and its world into configuration space?

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Configuration Space



Workspace



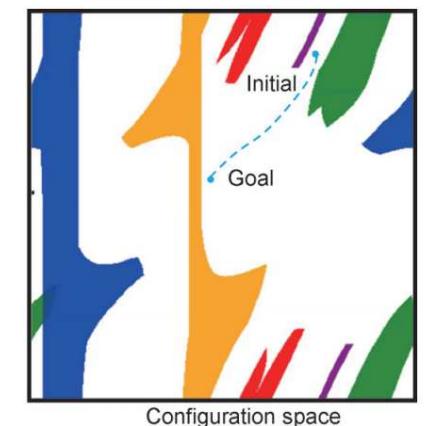
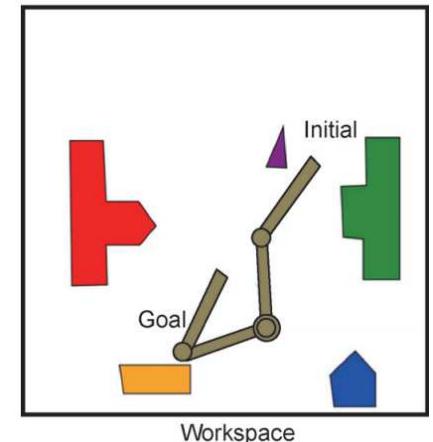
Configuration space

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How to use configuration space in practice

If we map the obstacles into configuration space we can check whether the configuration point, q , is in an obstacle and we have a **unique plan** for the robot

- **Problem:** mapping obstacles into configuration space is hard



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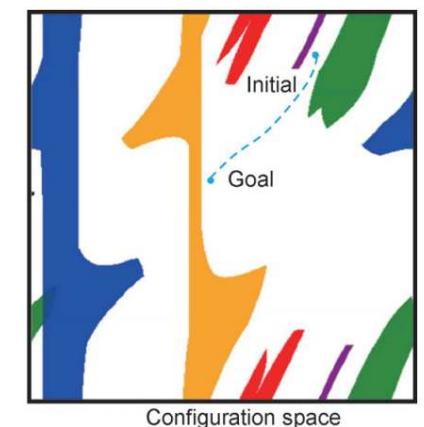
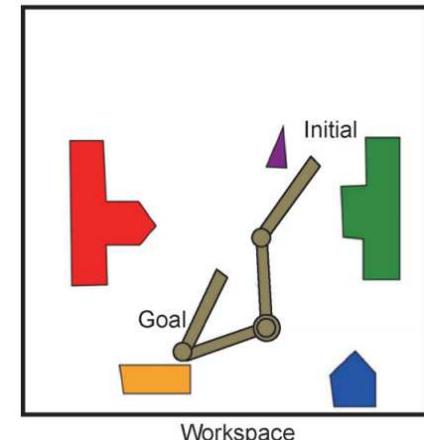
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Better approach: **use forward kinematics** to check task space obstacle collisions!

Treat the collision checker as a black box function evaluator!



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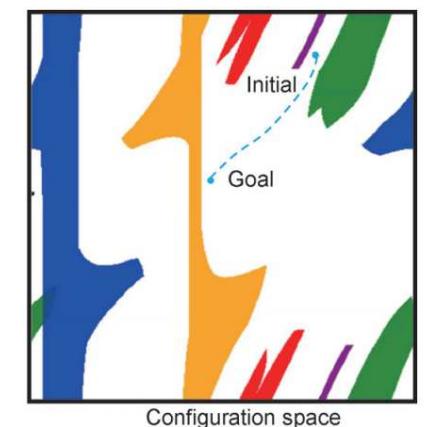
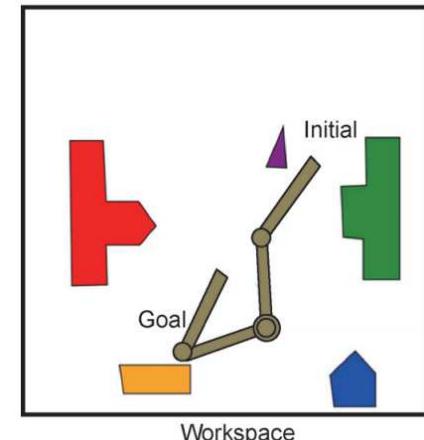
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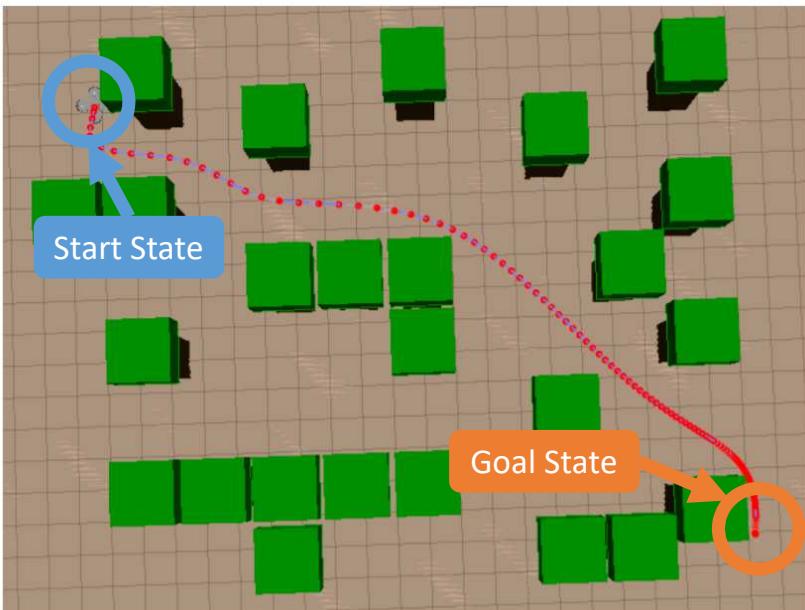
Better approach: **use forward kinematics** to check task space obstacle collisions!

- **No free lunch** – Now each collision check requires full kinematics and not a simple lookup



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Planning in Configuration Space

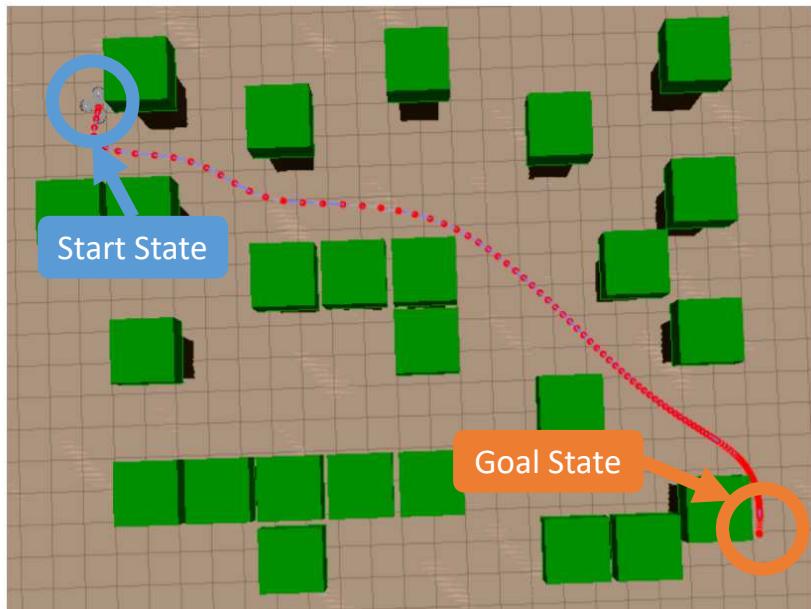


Goal: Find shortest collision-free path from start to goal

States: configurations $q \in \mathcal{R}^6$ **Actions:** Δq **Transition:** $q' \leftarrow q + \Delta q$

5

Planning in Configuration Space



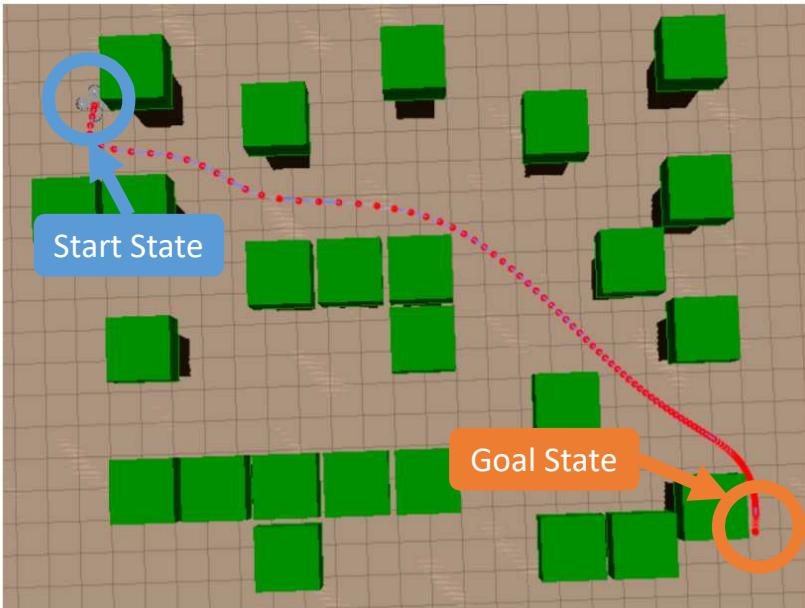
$$q \in \mathcal{R}^6: (x, y, z, \theta, \phi, \varphi)$$

Goal: Find shortest collision-free path from start to goal

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Planning in Configuration Space



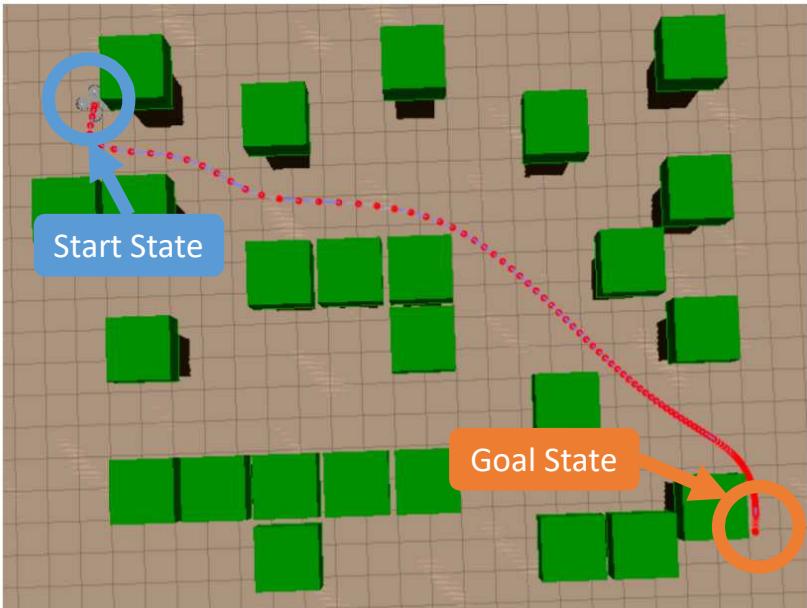
One approach is to *discretize* the statespace (grid it) and use graph search (think A* which is known fast)

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Planning in Configuration Space



One approach is to *discretize* the statespace (grid it) and use graph search (think A* which is known fast)

Unfortunately if we use say 100 discrete steps in each direction we get:

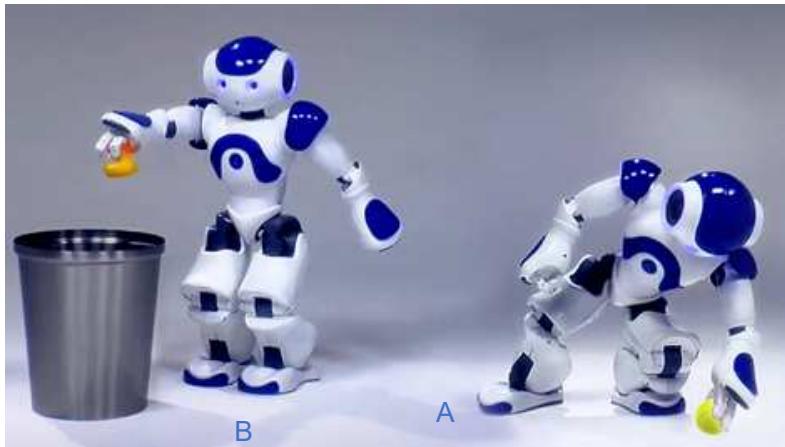
$$|S| = 100^6$$

Goal: Find shortest collision-free path from start to goal

States: configurations $q \in \mathcal{R}^6$ **Actions:** Δq **Transition:** $q' \leftarrow q + \Delta q$

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Planning in Configuration Space



Goal: Find shortest collision-free path from

States: configurations $q \in \mathcal{R}^{20}$

Actions: Δ

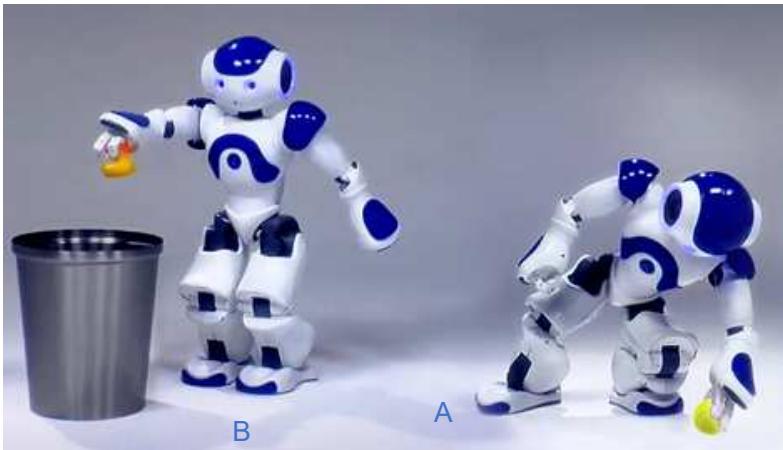
One approach is to *discretize* the statespace (grid it) and use graph search (think A* which is known fast)

Unfortunately if we use say 100 discrete steps in each direction we get:

(2 ankles + 2 knees + 2 hips + 2 shoulders + 2 elbows + 4 fingers + pose of com) = ~ 20 variables

5

Planning in Configuration Space



One approach is to *discretize* the statespace (grid it) and use graph search (think A* which is known fast)

Unfortunately if we use say 100 discrete steps in each direction we get:

$$|S| = 100^{20}$$

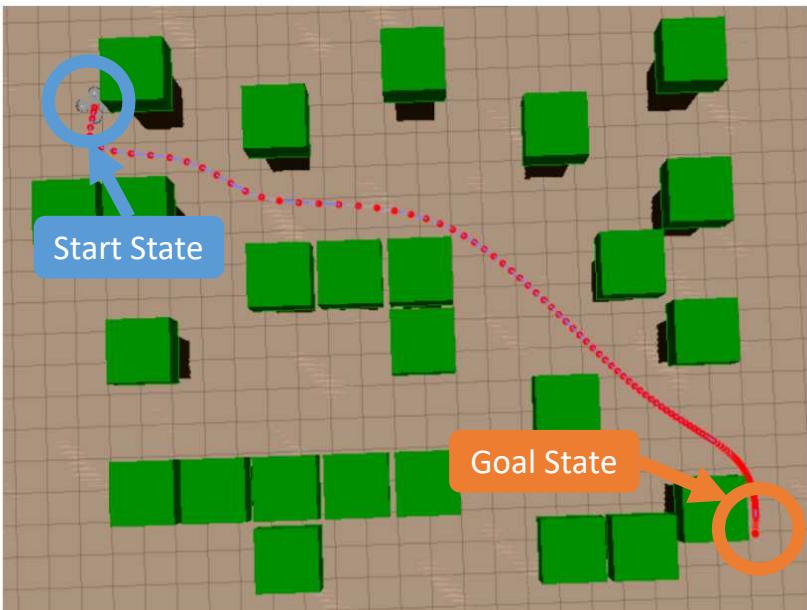
Curse of Dimensionality!

Goal: Find shortest collision-free path from start to goal

States: configurations $q \in \mathcal{R}^{20}$ **Actions:** Δq **Transition:** $q' \leftarrow q + \Delta q$

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Planning in Configuration Space



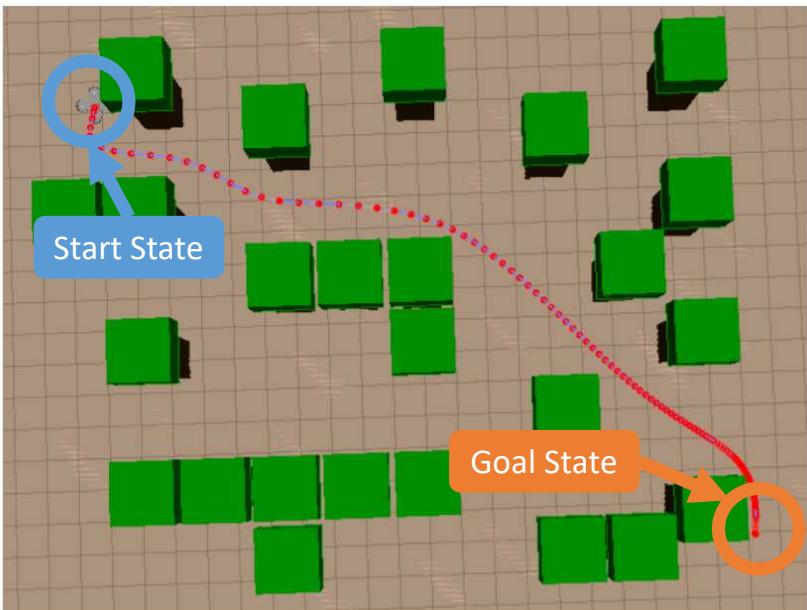
So if we can't explicitly form the graph and search the configuration space what can we do?

Goal: Find shortest collision-free path from start to goal

States: configurations $q \in \mathcal{R}^6$ **Actions:** Δq **Transition:** $q' \leftarrow q + \Delta q$

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Planning in Configuration Space



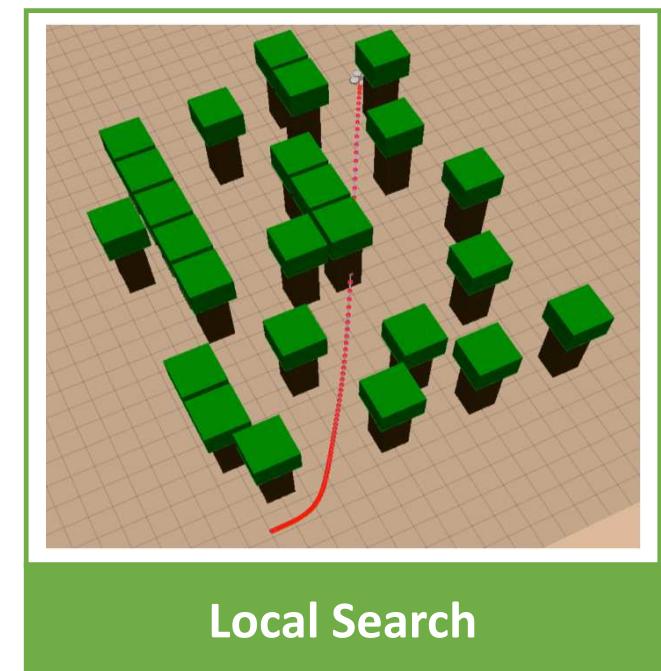
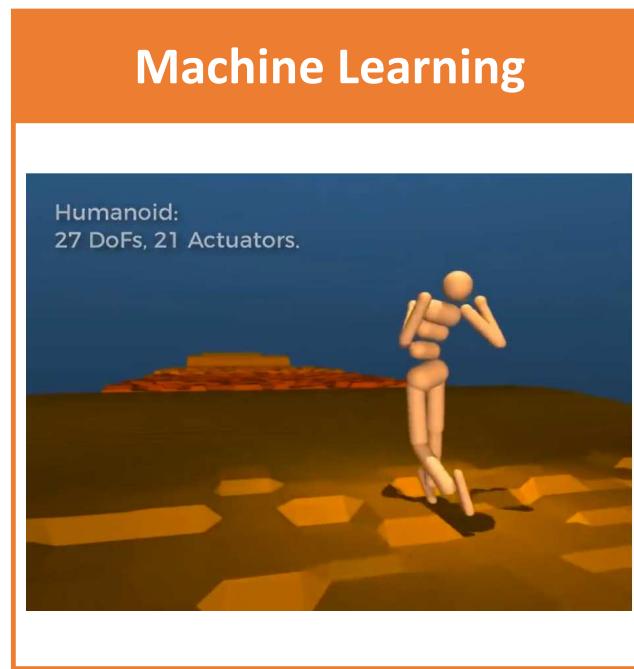
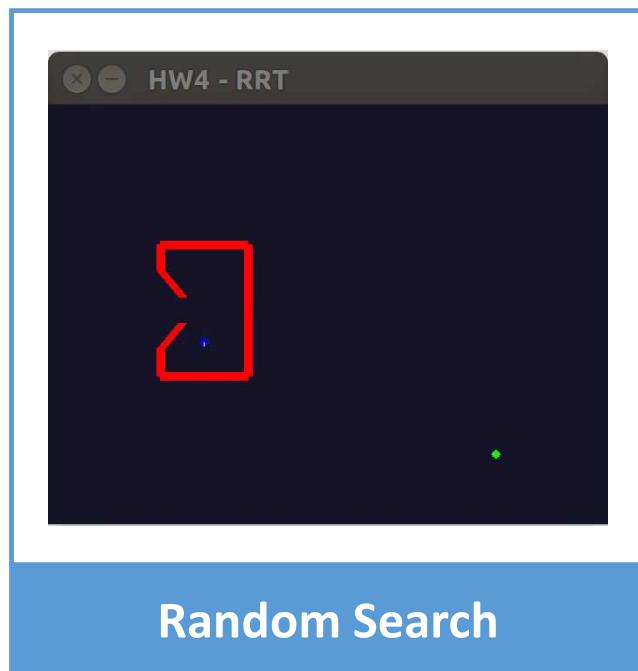
What if we **incrementally build up a path** toward the goal?

Goal: Find shortest collision-free path from start to goal

States: configurations $q \in \mathcal{R}^6$ **Actions:** Δq **Transition:** $q' \leftarrow q + \Delta q$

5

Planning in Configuration Space



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Rapidly Exploring Random Trees (RRTs)

One of the most famous robot motion planning algorithms is **Rapidly Exploring Random Trees (RRTs)** [Lavalle & Kuffner]

The main idea is to **use randomness** to **rapidly explore** an entire state space to find a path from a given start location to the goal.



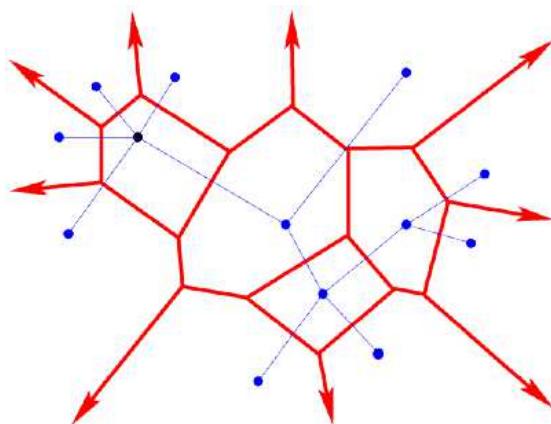
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Randomness encourages exploration

Key idea: uniform random sampling in configuration space is actually a heuristic that encourages exploration!

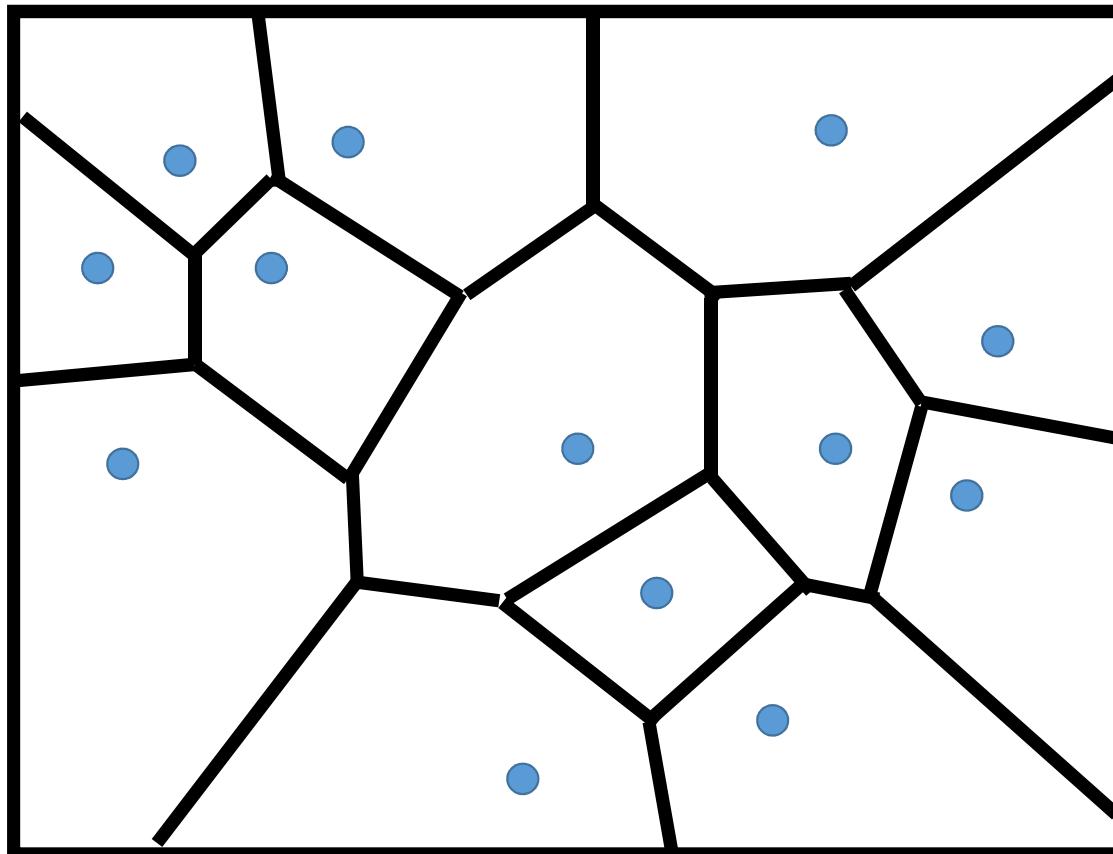
To see this we use **Voronoi regions**

Def: Voronoi region is the set of points in space that are closest to a particular node in the tree:



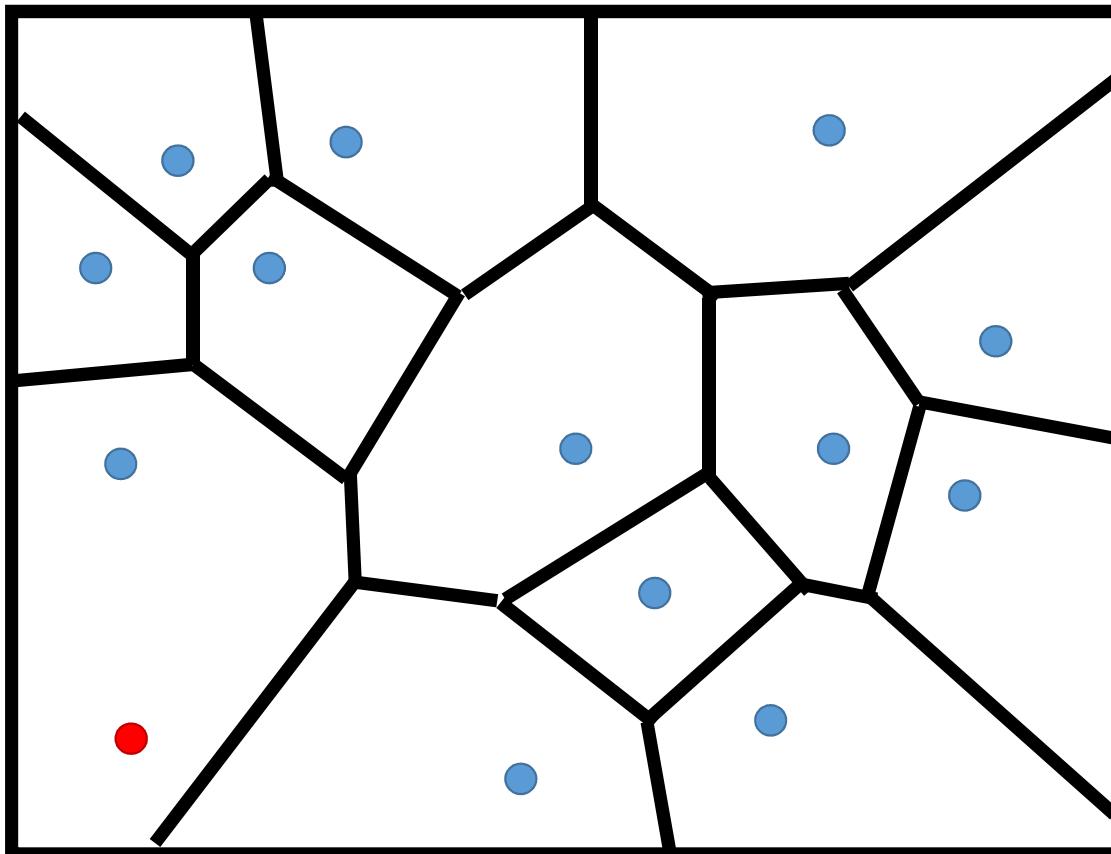
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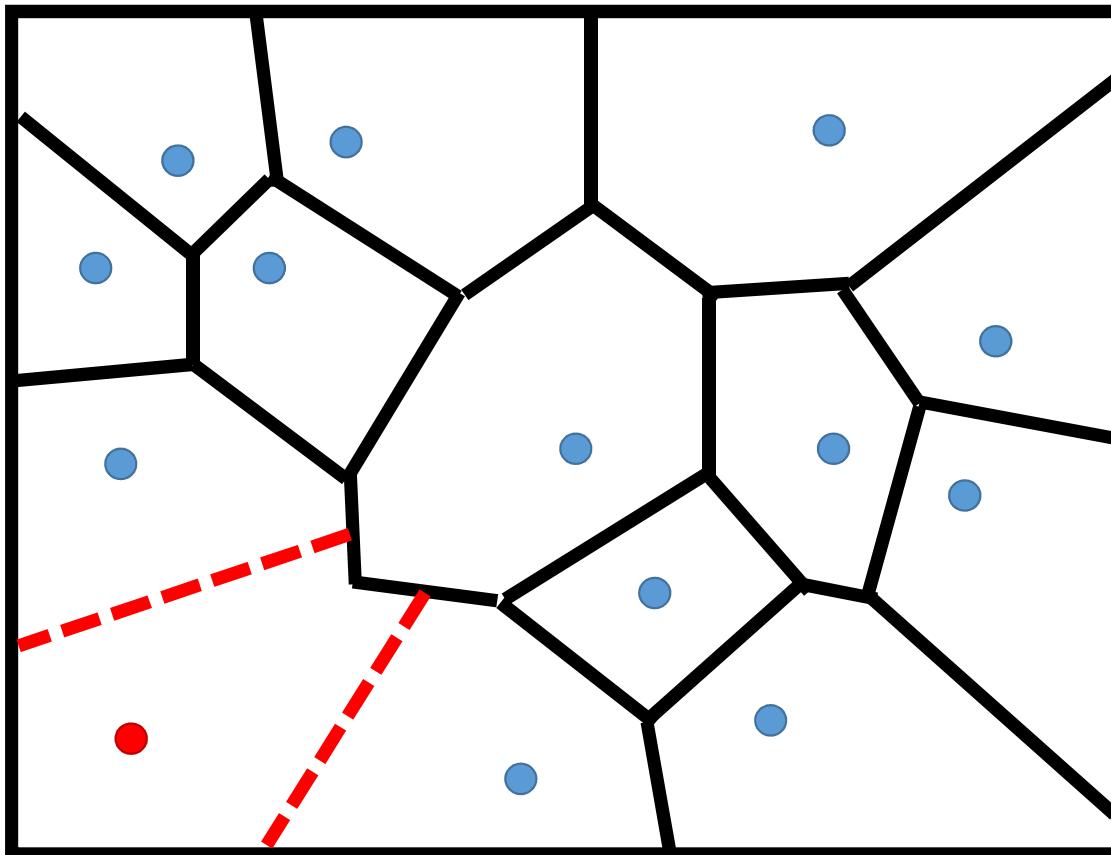
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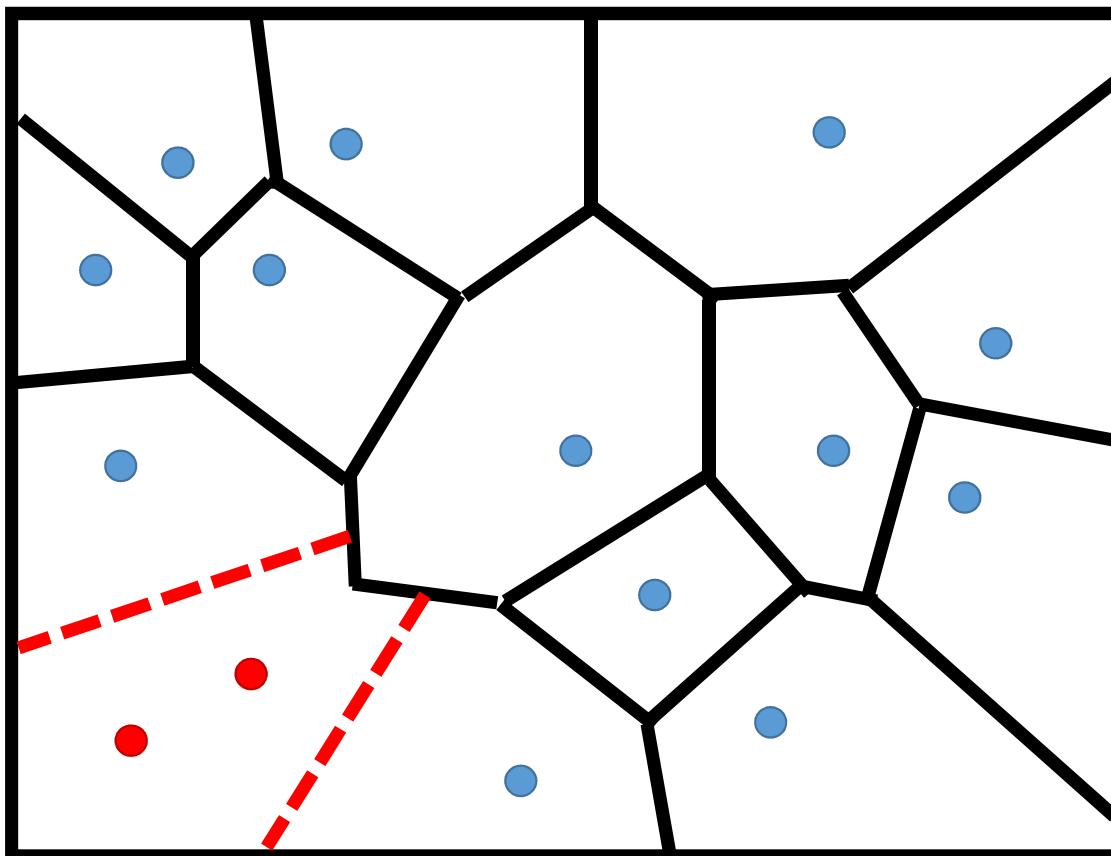
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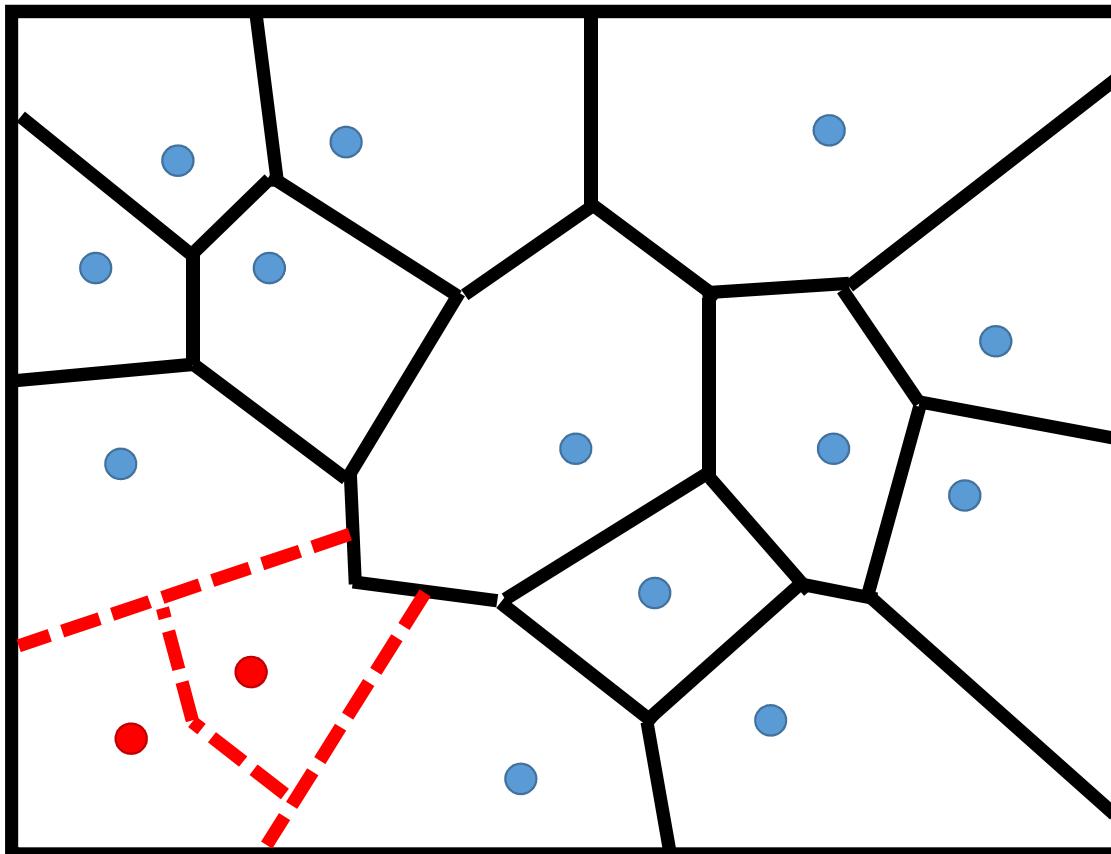
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Randomness encourages exploration



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Randomness encourages exploration



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Rapidly Exploring Random Trees (RRTs)

Algorithm (input: s_0 , s_{goal} , initial state tree T)

- Sample states $s \in S = R^n$ until s is collision-free
- Find closest state $s_c \in T$
- Extend s_c toward s
- Add resulting state s' to T
- Repeat until T contains a path from s_0 to s_{goal}

● s_{goal}



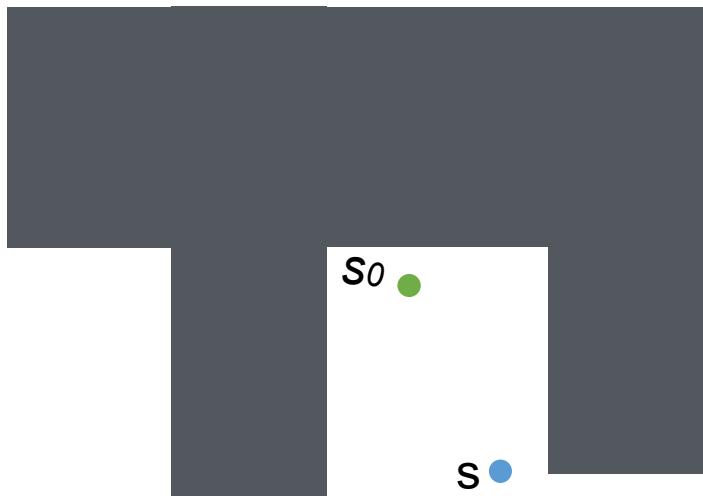
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Rapidly Exploring Random Trees (RRTs)

Algorithm (input: s_0, s_{goal} , initial state tree T)

- Sample states $s \in S = \mathbb{R}^n$ until s is collision-free
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● s_{goal}



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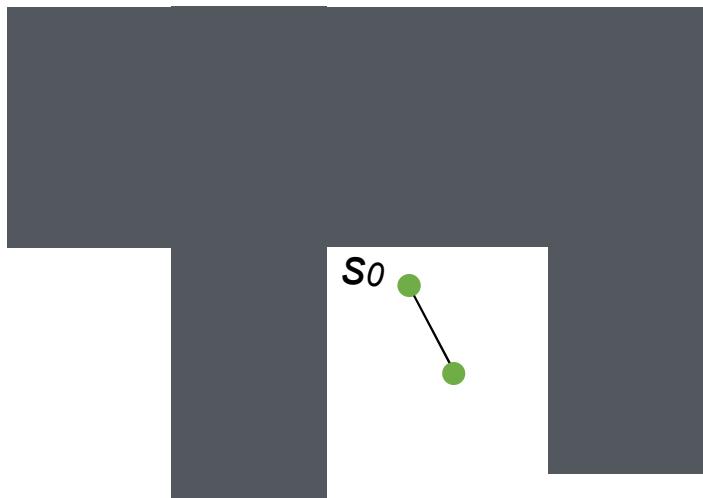
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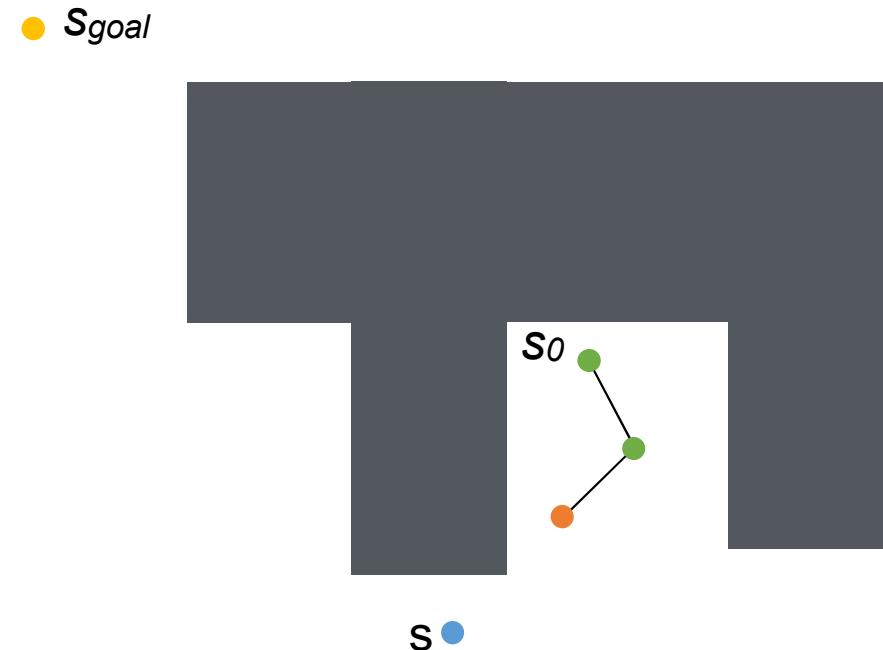


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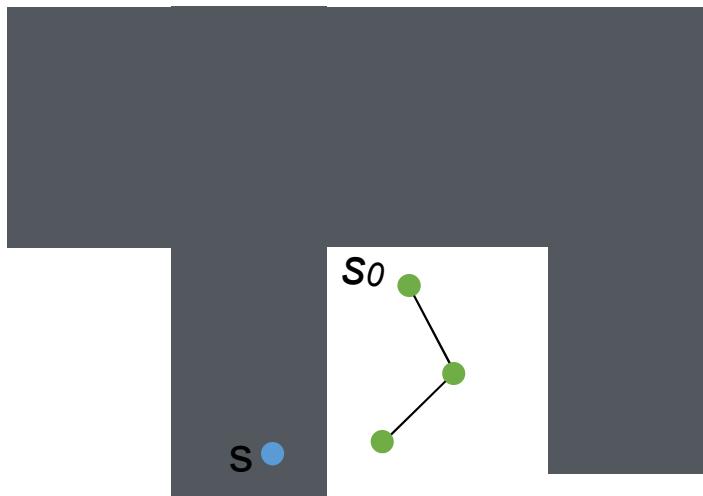
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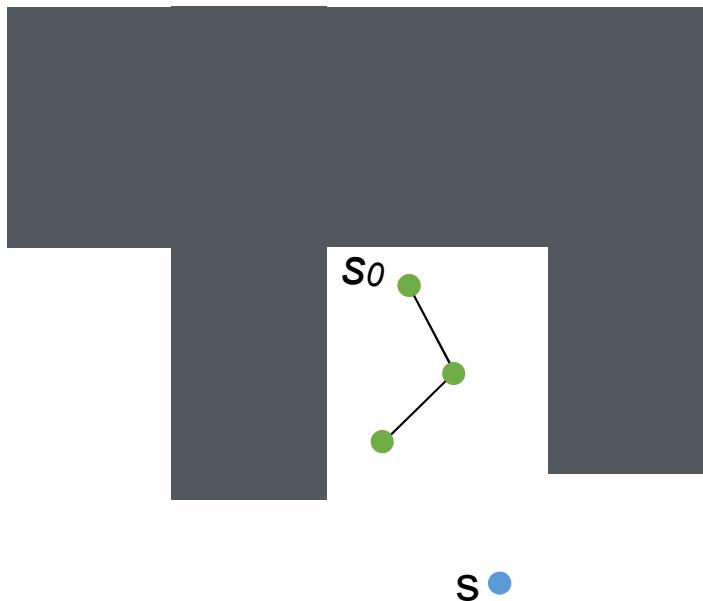
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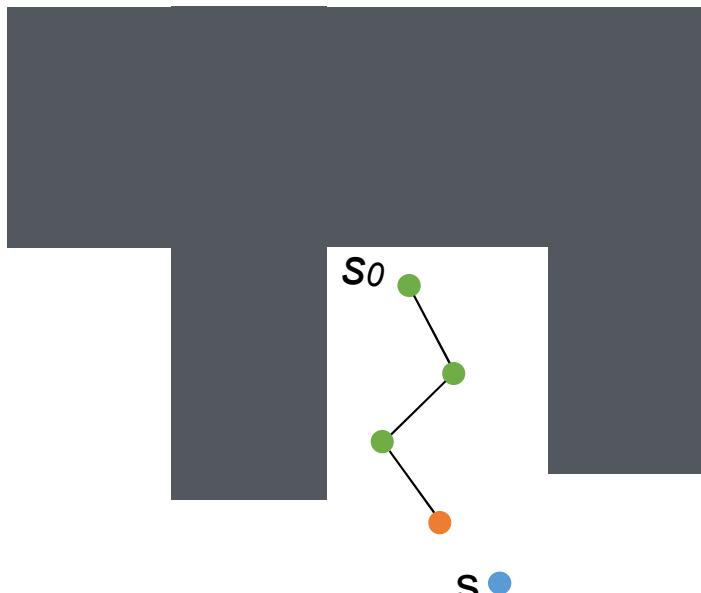
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s

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s ●

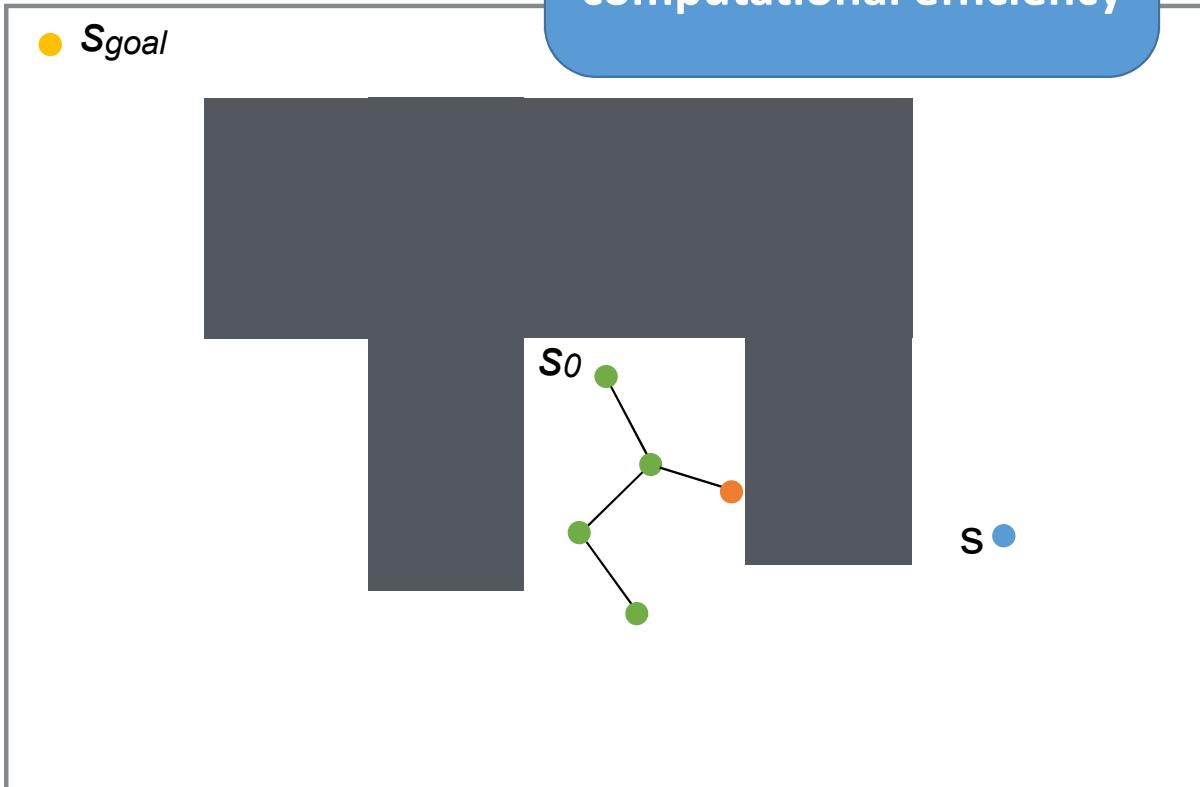
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Rapidly Exploring Random Trees (RRTs)

Extend distance trades off sample vs. computational efficiency

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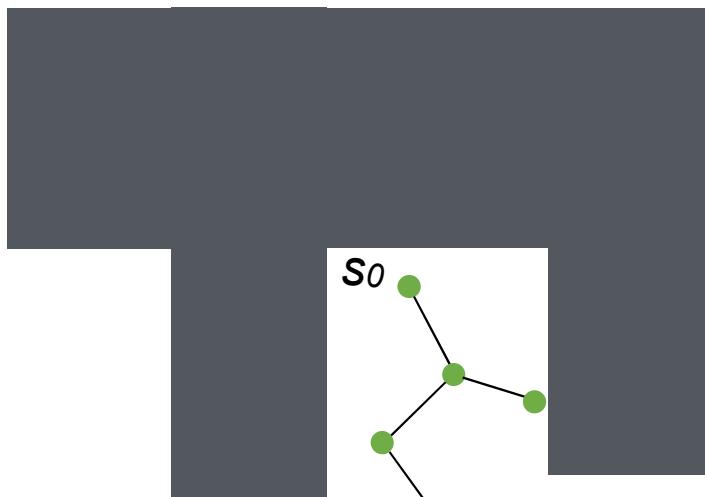
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s

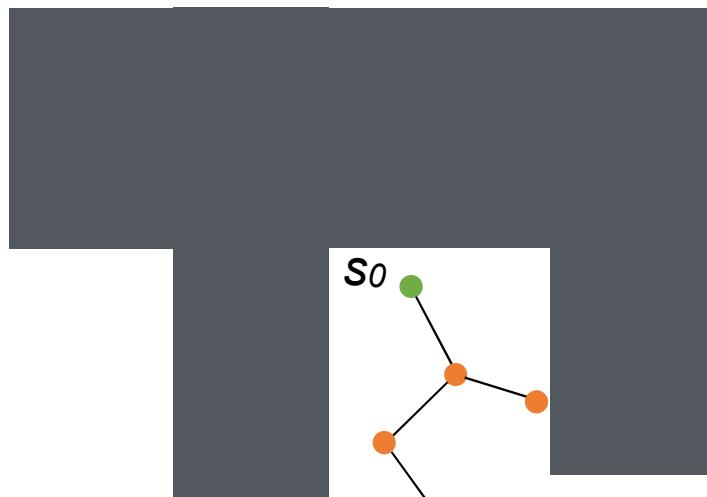
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s

It will always find a solution because it is **probabilistically complete**

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Rapidly Exploring Random Trees (RRTs)



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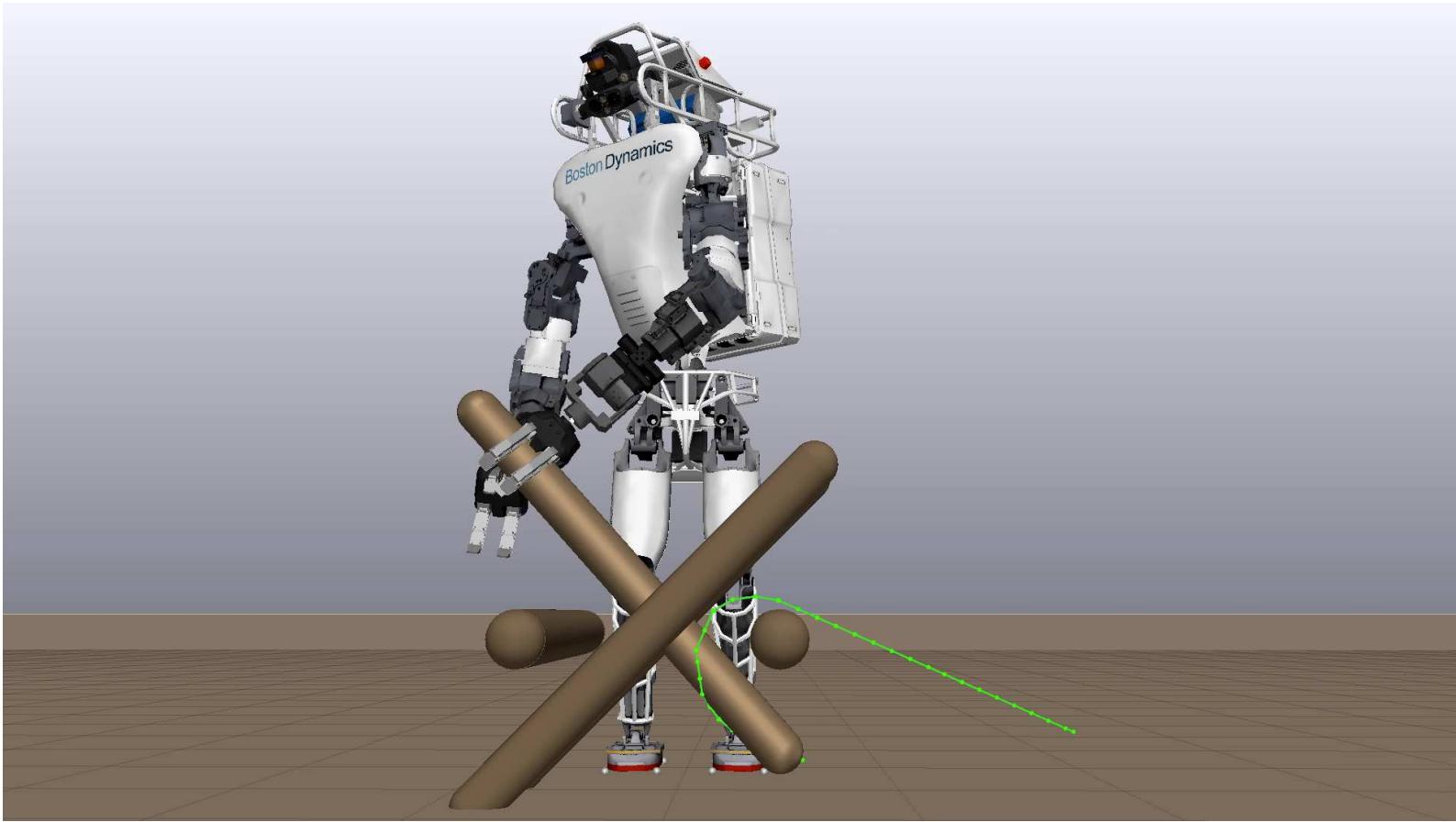
Rapidly Exploring Random Trees (RRTs)



Biased
sampling
can help!

5

RRTs often works really well in practice



5

RRTs often works really well in practice

204 J. Leonard et al.

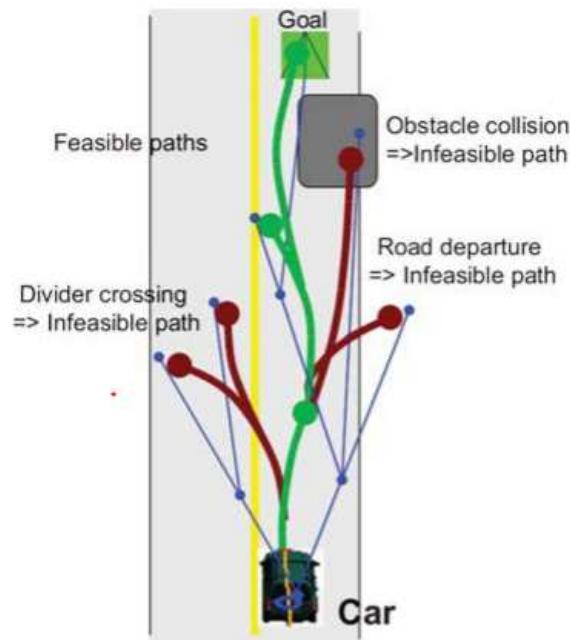


Fig. 22. Illustration of RRT Motion planning. Each leaf of the tree represents a stopping location. The motion control points (in blue) are translated into a predicted path. The predicted paths are checked for drivability (shown in green and red).

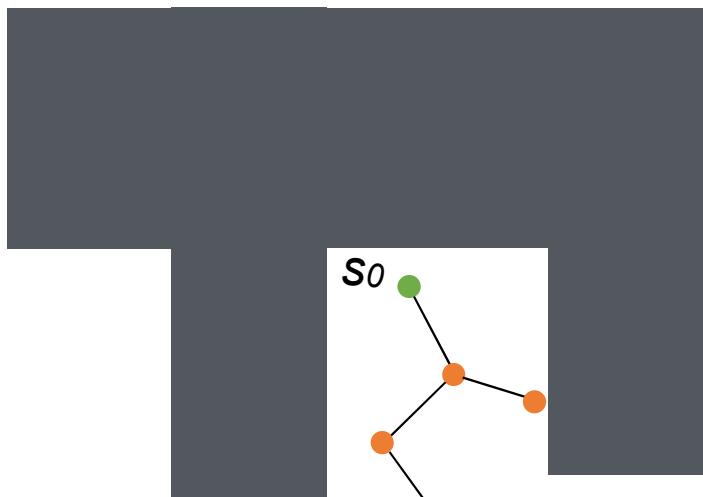
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Questions about the RRT algorithm?

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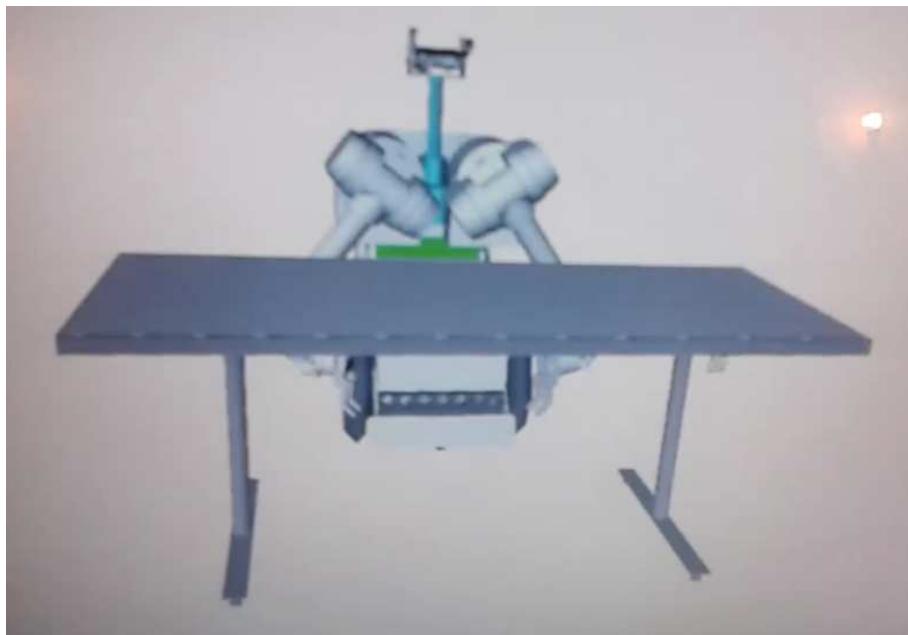
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s

5

But we can get some WEIRD outputs...



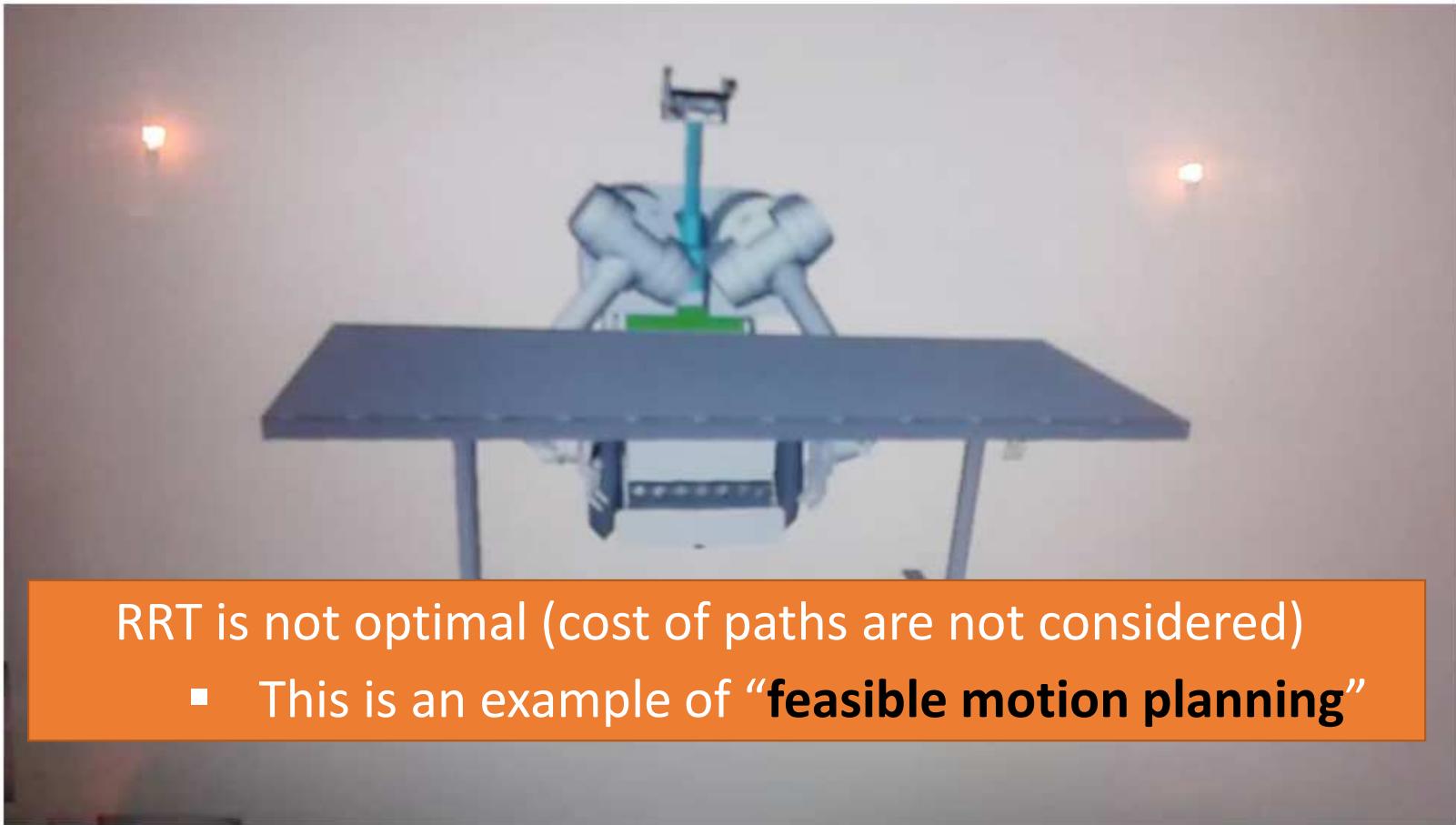
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RRT is not optimal (cost of paths are not considered)

- This is an example of “**feasible motion planning**”

5

We solve this problem with RRT*

The big trick:

- incrementally “**re-wiring**” the tree to keep locally optimal paths

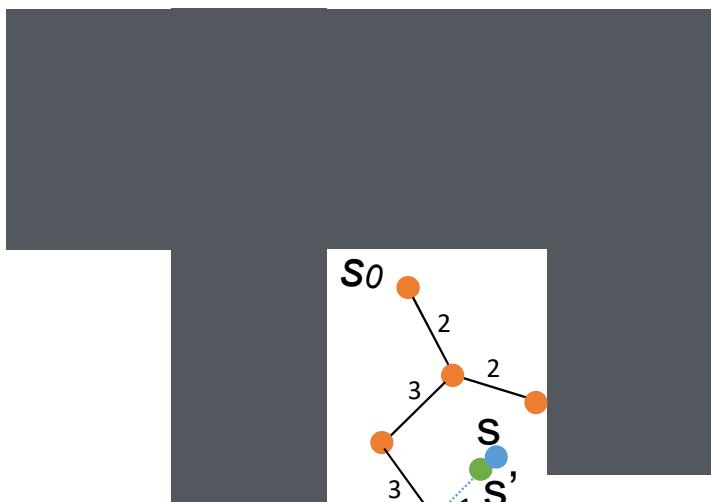
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RRT* (input: s_0, s_{goal} , initial state tree T)

- Sample states $s \in S = R^{15}$ until s is collision-free (often goal directed)
- Find closest state $s_c \in T$
- Extend s_c toward s resulting in state s'
- Find all $s_{near} \subseteq T$ within a distance d to s'
- Find $s_{min} \in s_{near}$, that has the lowest *path cost* to $s_0 \rightarrow s_{min} \rightarrow s'$
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- Check path cost through s' to all states in $s \in s_{near}$, if any are lower than existing path cost to s , then “rewire” tree to include edge $s' \rightarrow s$
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• s_{goal}



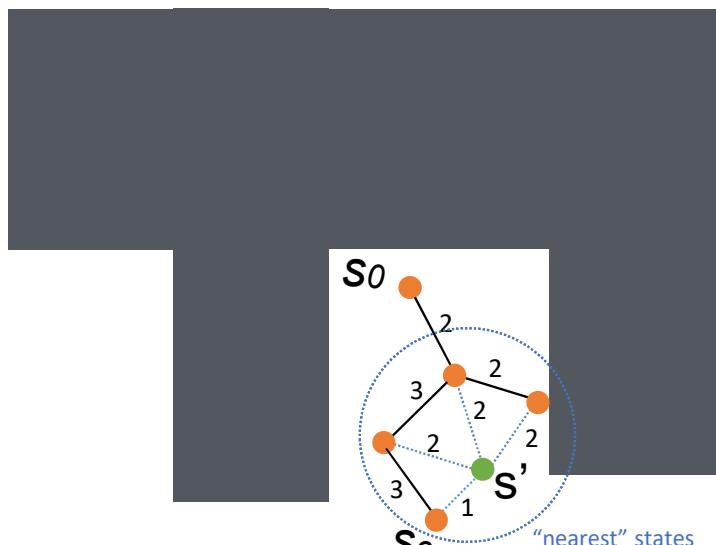
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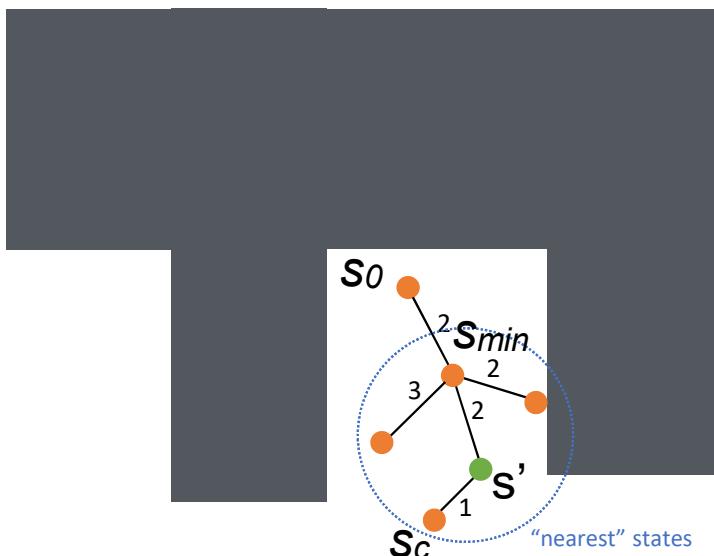
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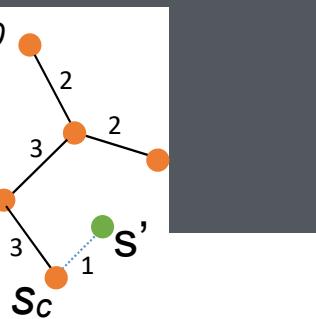
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We solve this problem with RRT*

● s_{goal}

RRT

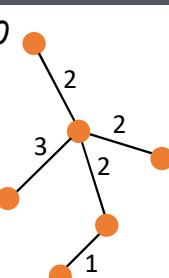
s_0



● s_{goal}

RRT*

s_0

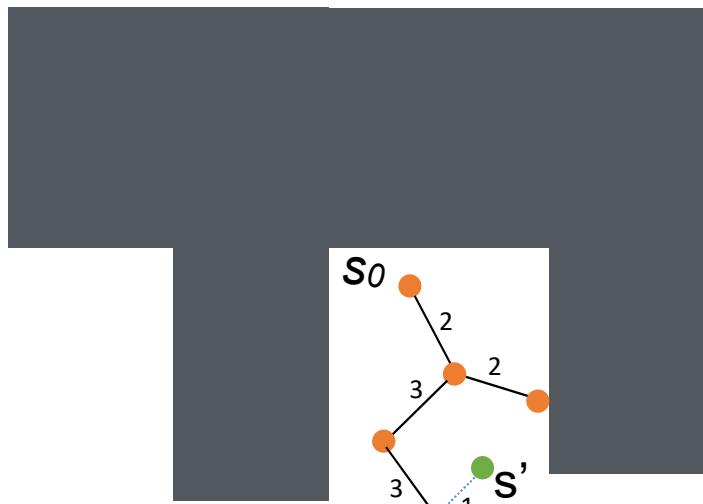


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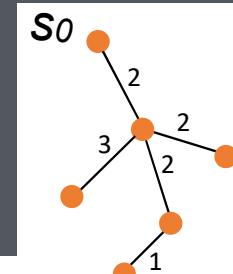
We solve this problem with RRT*

Nearest radius size is another sample vs. computational efficiency decision!

● s_{goal}



● s_{goal}



RRT*

[Karaman & Fazzoli Sampling-based Algorithms for Optimal Motion Planning]

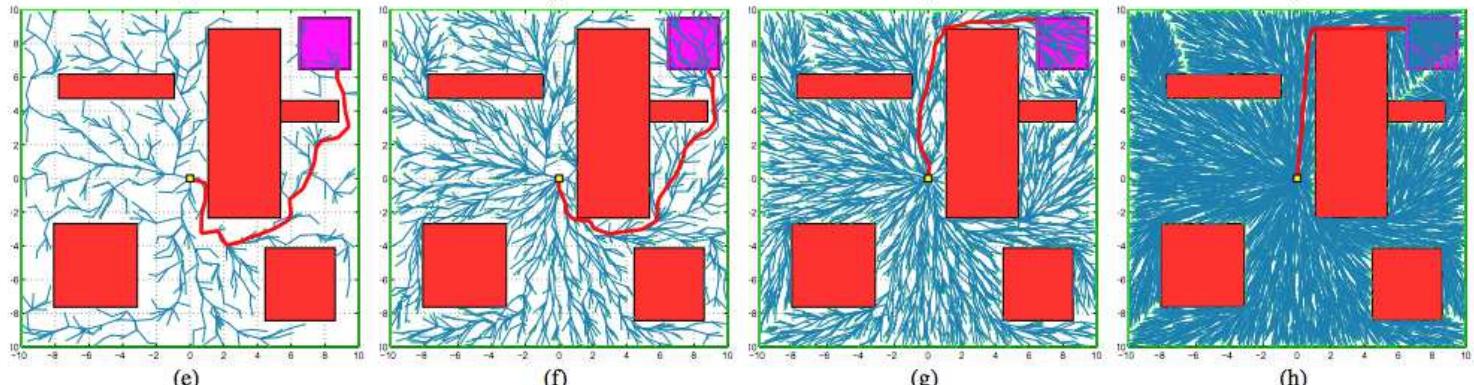
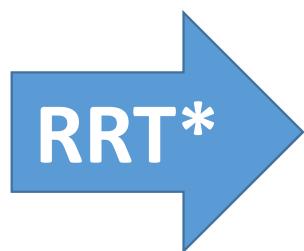
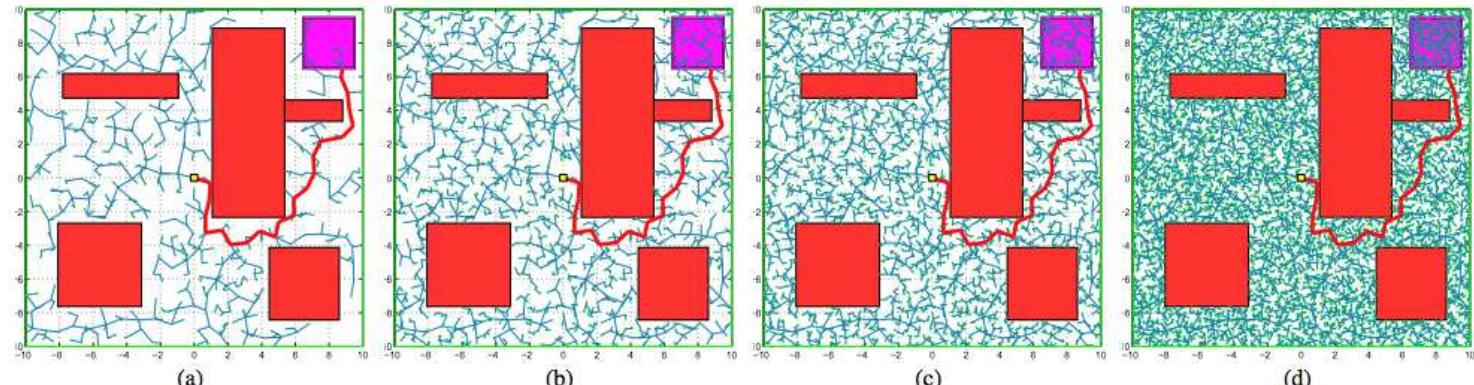
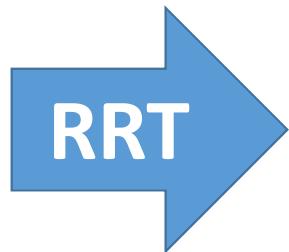


Fig. 1. A Comparison of the RRT* and RRT algorithms on a simulation example. The tree maintained by the RRT algorithm is shown in (a)-(d) in different stages, whereas that maintained by the RRT* algorithm is shown in (e)-(h). The tree snapshots (a), (e) are at 1000 iterations, (b), (f) at 2500 iterations, (c), (g) at 5000 iterations, and (d), (h) at 15,000 iterations. The goal regions are shown in magenta. The best paths that reach the target are highlighted with red.

5

So what have we learned so far?

1. Robot planning usually involves thinking about both **task and configuration spaces**
2. For many real problems, **collision checking** can be expensive
3. **RRT**: a powerful algorithm based on a very simple idea!
 - **Probabilistically complete**: If there's a solution it will find it eventually (but can still be slow for some problems)!
 - BUT RRT is not optimal (cost of paths are not considered)
 - This is an example of “**feasible motion planning**”
 - **RRT*** fixes that by incrementally rewiring the tree

5

To RRT or not to RRT that is the question!

1. Why might RRTs not be the best algorithmic choice for a robot that repeatedly does the same task?
 2. How might you adapt RRT to fix this issue?
-

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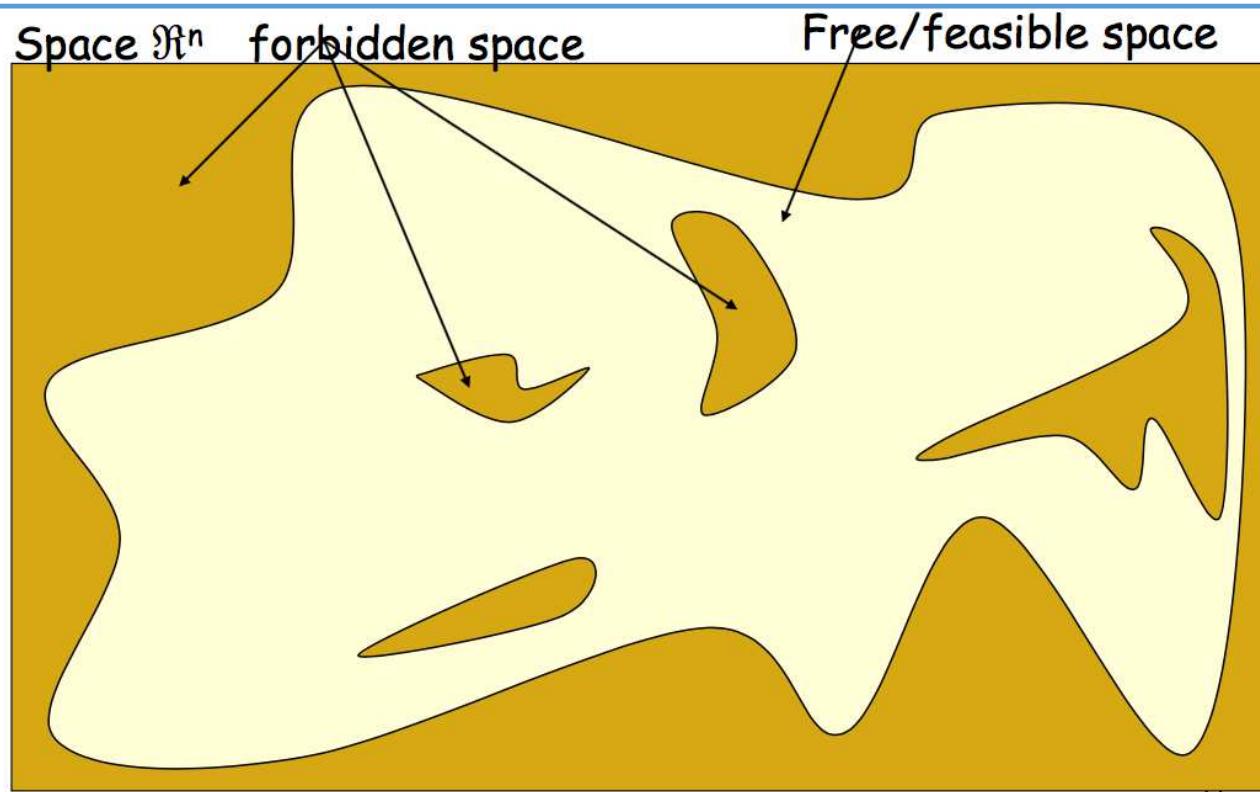
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This “**multi-query**” approach is called **Probabilistic Roadmaps (PRMs)**

5

- Probabilistic Roadmaps (PRMs) leverage an offline and an online computation phase
-

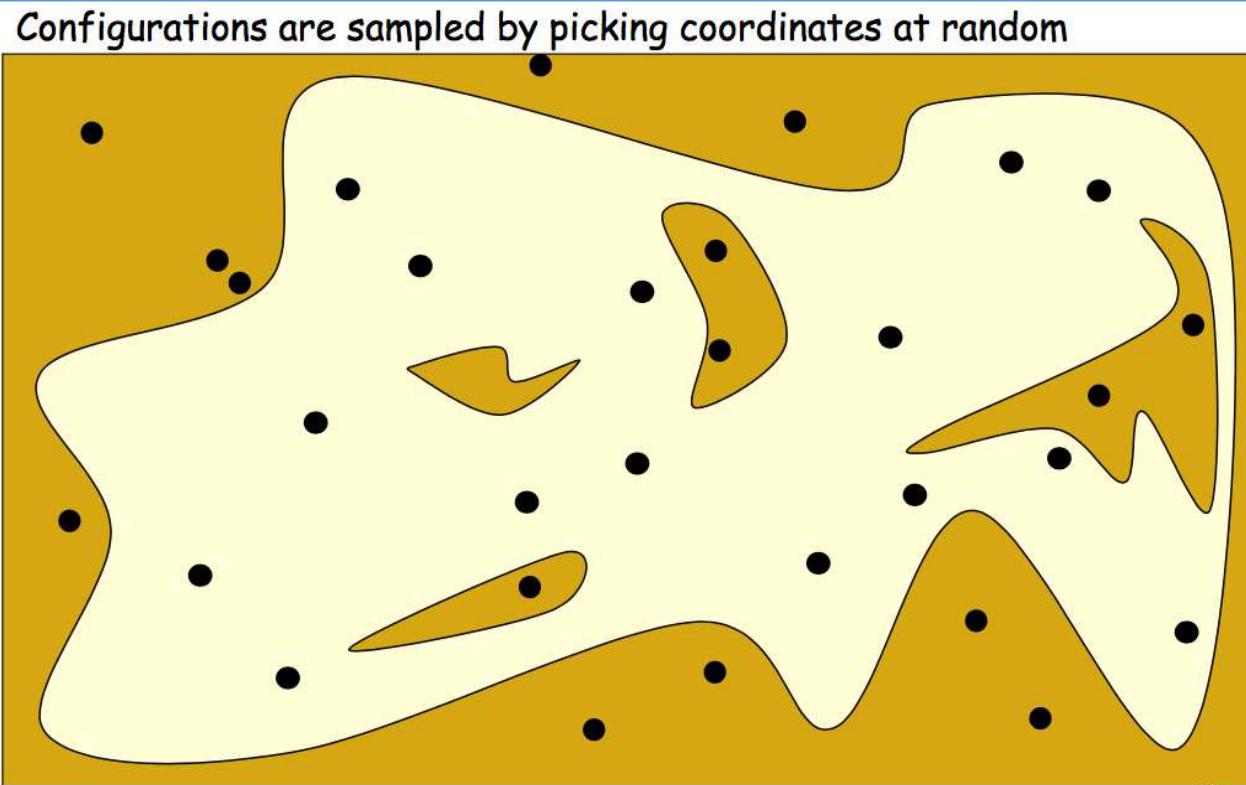
Step 1: Offline build a random graph \mathbf{G} that covers the state space



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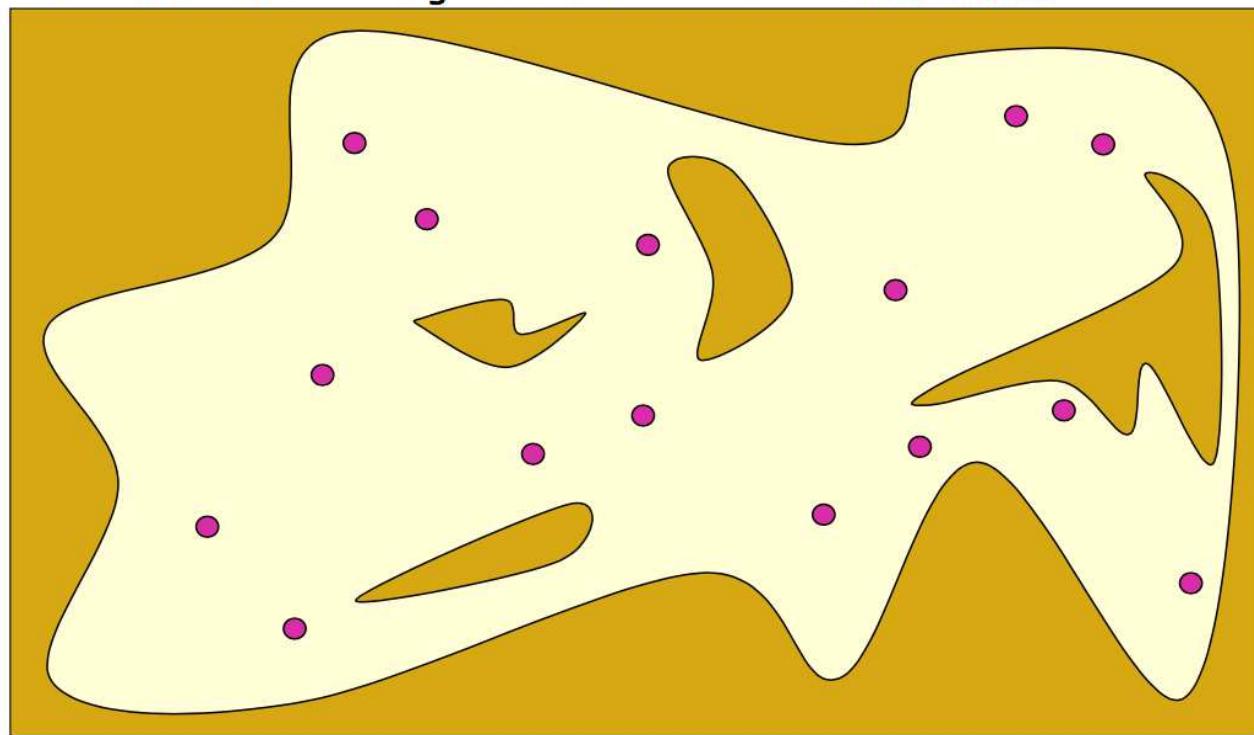


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The collision-free configurations are retained as **milestones**

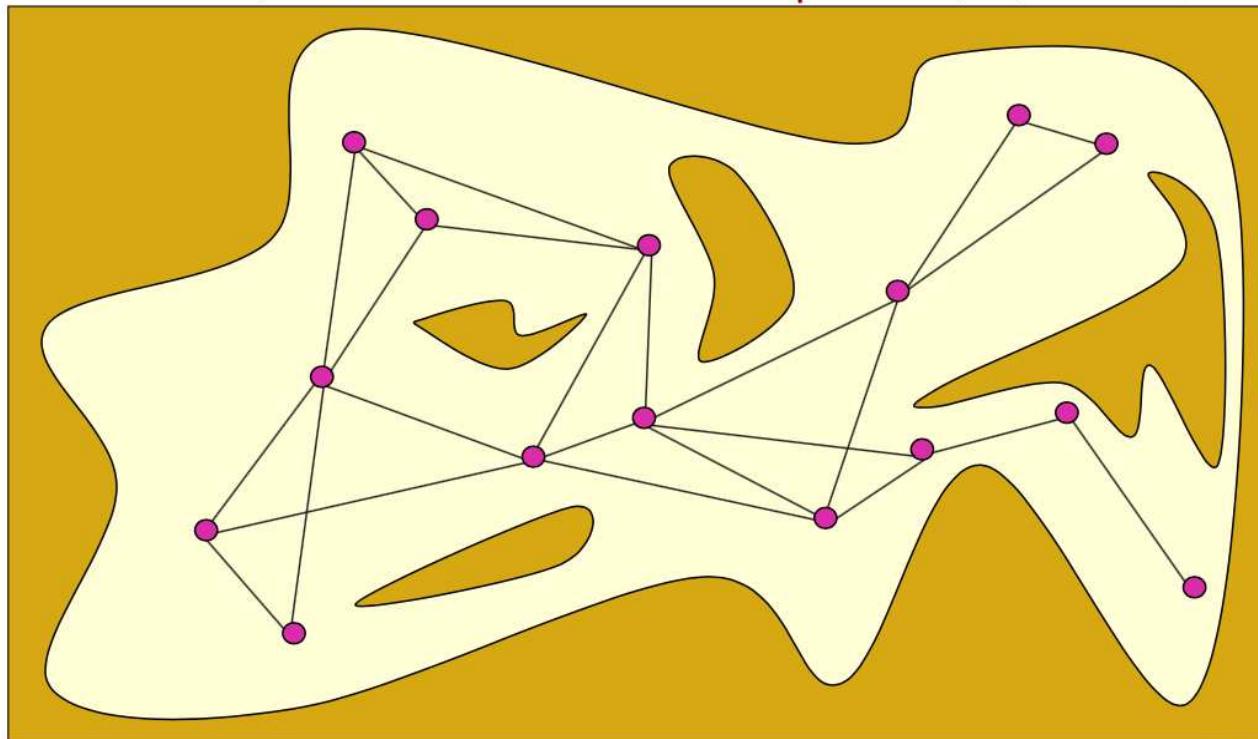


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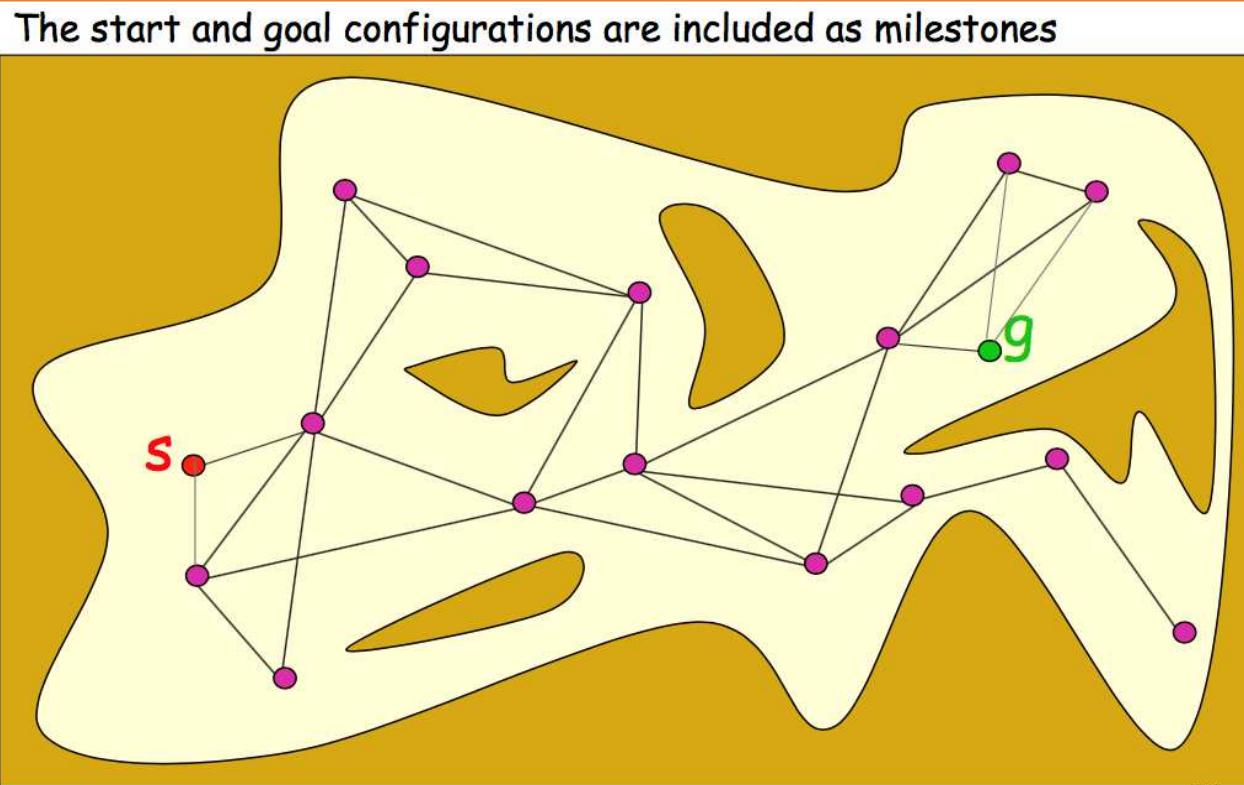
The collision-free links are retained as **local paths** to form the PRM



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- Probabilistic Roadmaps (PRMs) leverage an offline and an online computation phase
-

Step 2: Online connect the start and goal nodes and run graph search

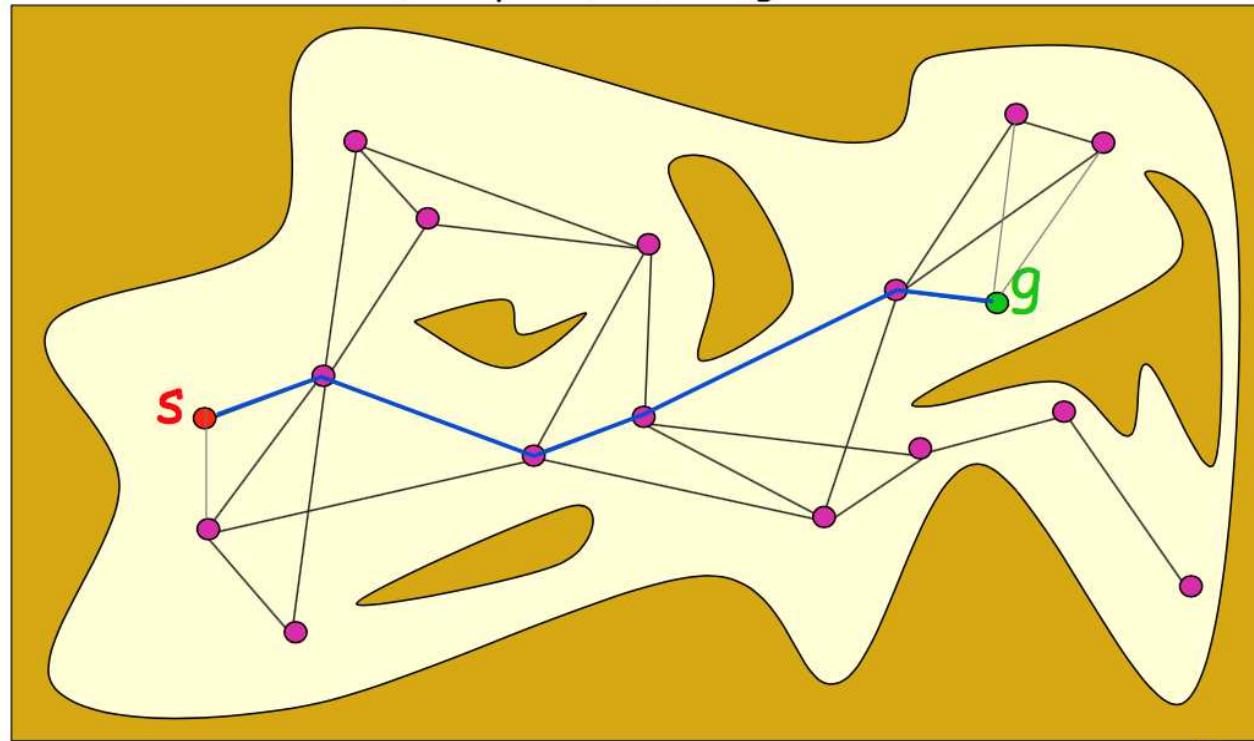


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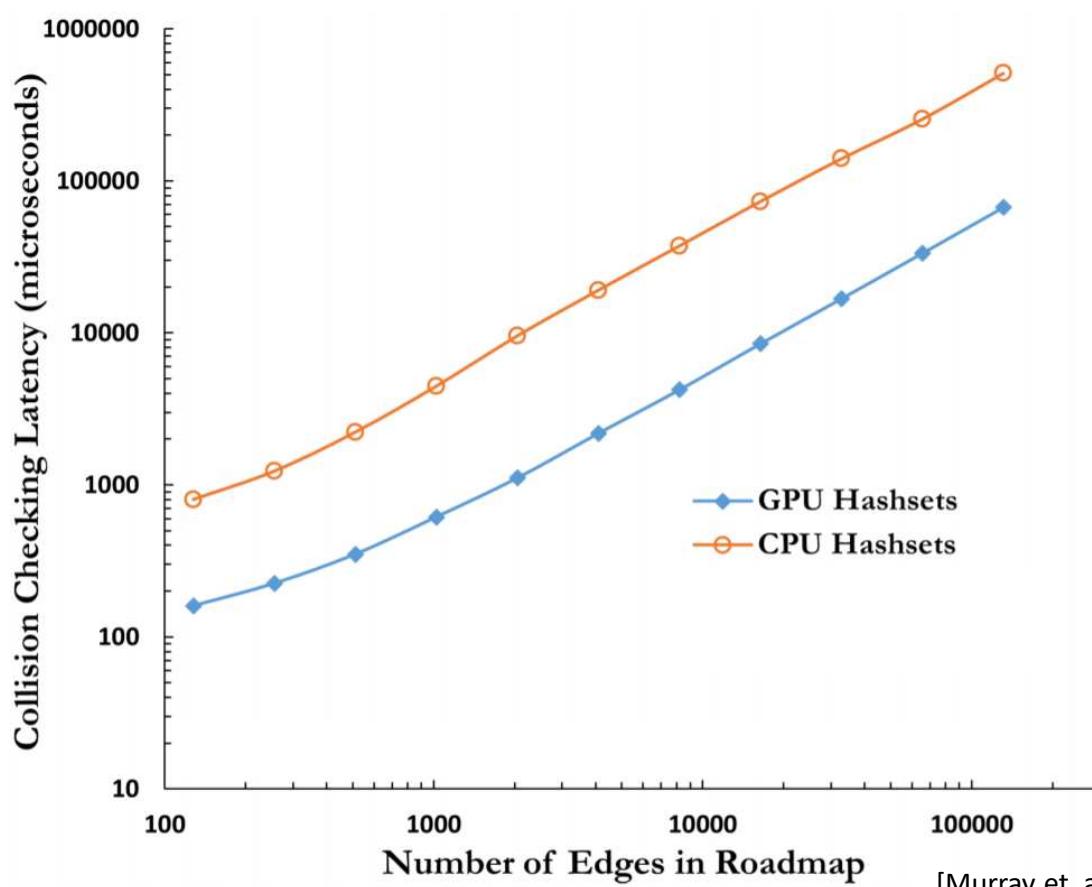
Step 2: Online connect the start and goal nodes and run graph search

The PRM is searched for a path from s to g



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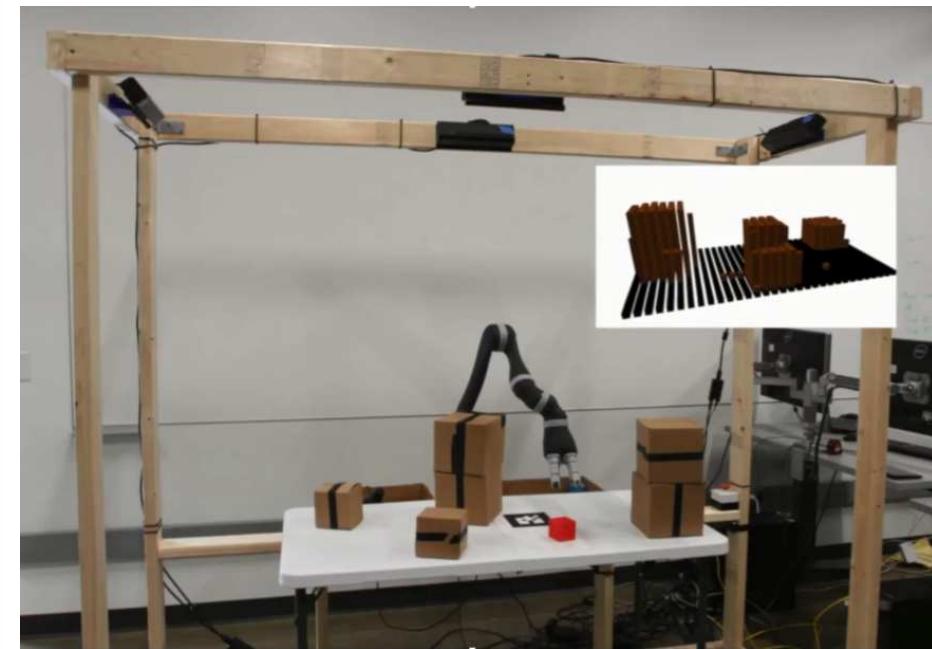
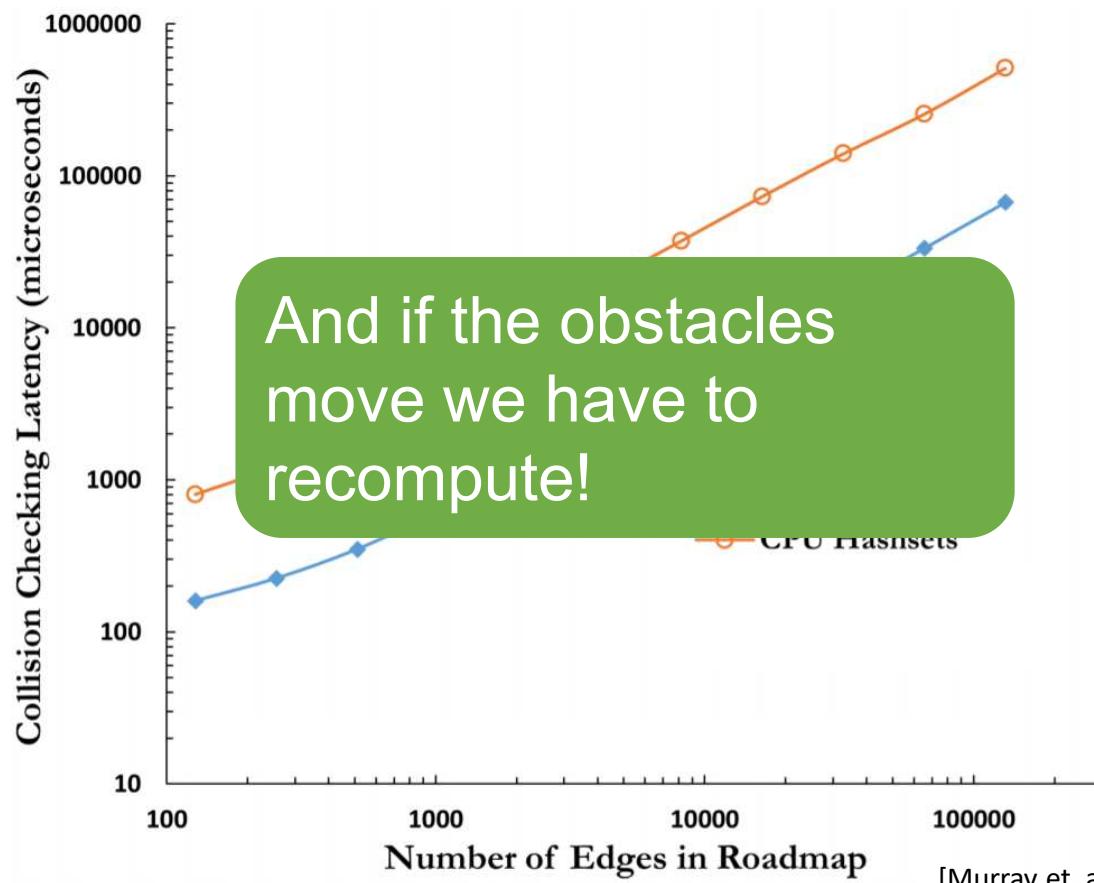
Collision detection for each connecting path in the construction of the PRM can be very expensive



[Murray et. al. The Microarchitecture of a Real-Time Robot Motion Planning Accelerator]

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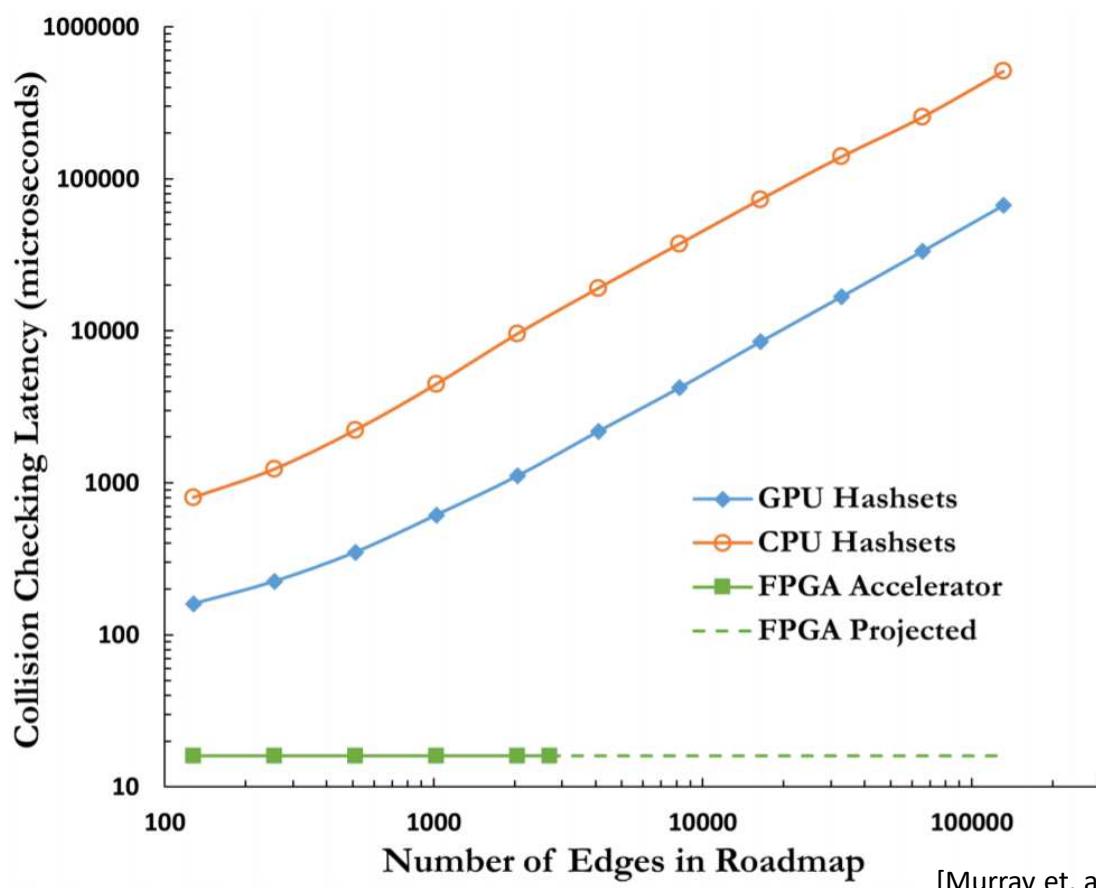
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Custom hardware can lead to near-instantaneous collision checking!



Robot Motion Planning on a Chip

Sean Murray, Will Floyd-Jones, Ying
Qi, Dan Sorin, George Konidaris



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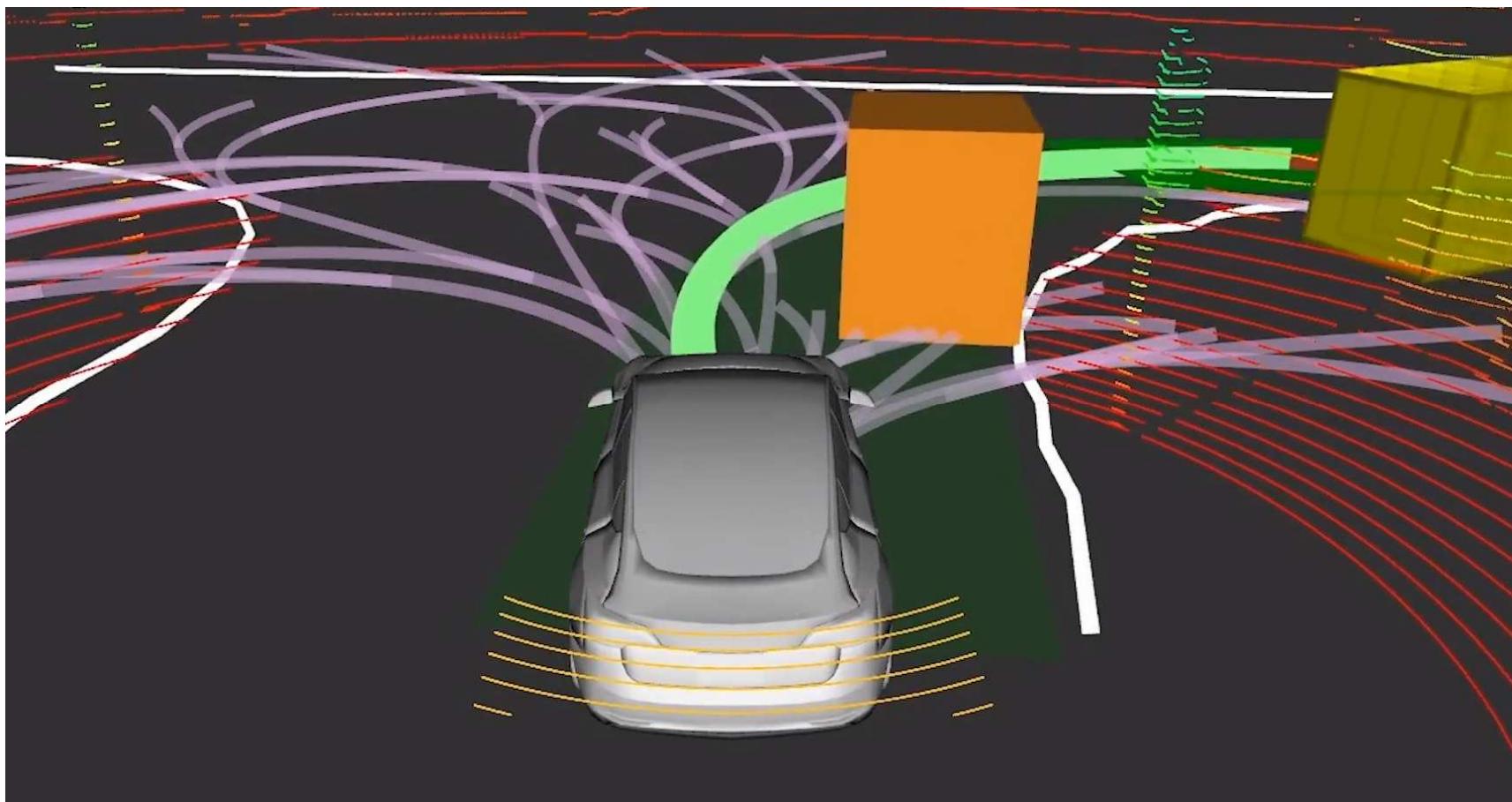
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Realtime Robotics



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Ok so why can't robots use these awesome **kinematic** planning algorithms all the time and be better at life?!?

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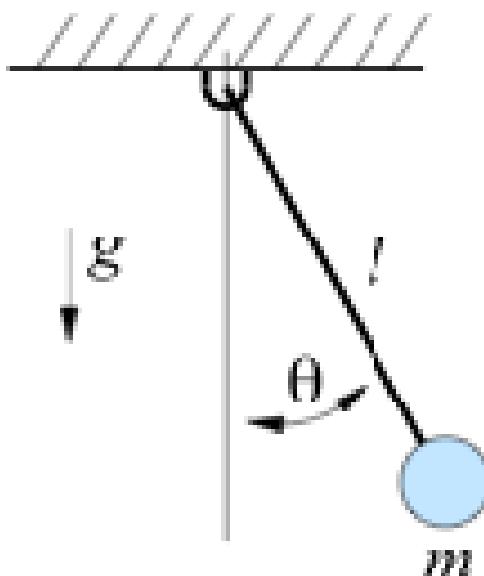
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Dynamics (aka Physics)

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The Simplest “Robot”

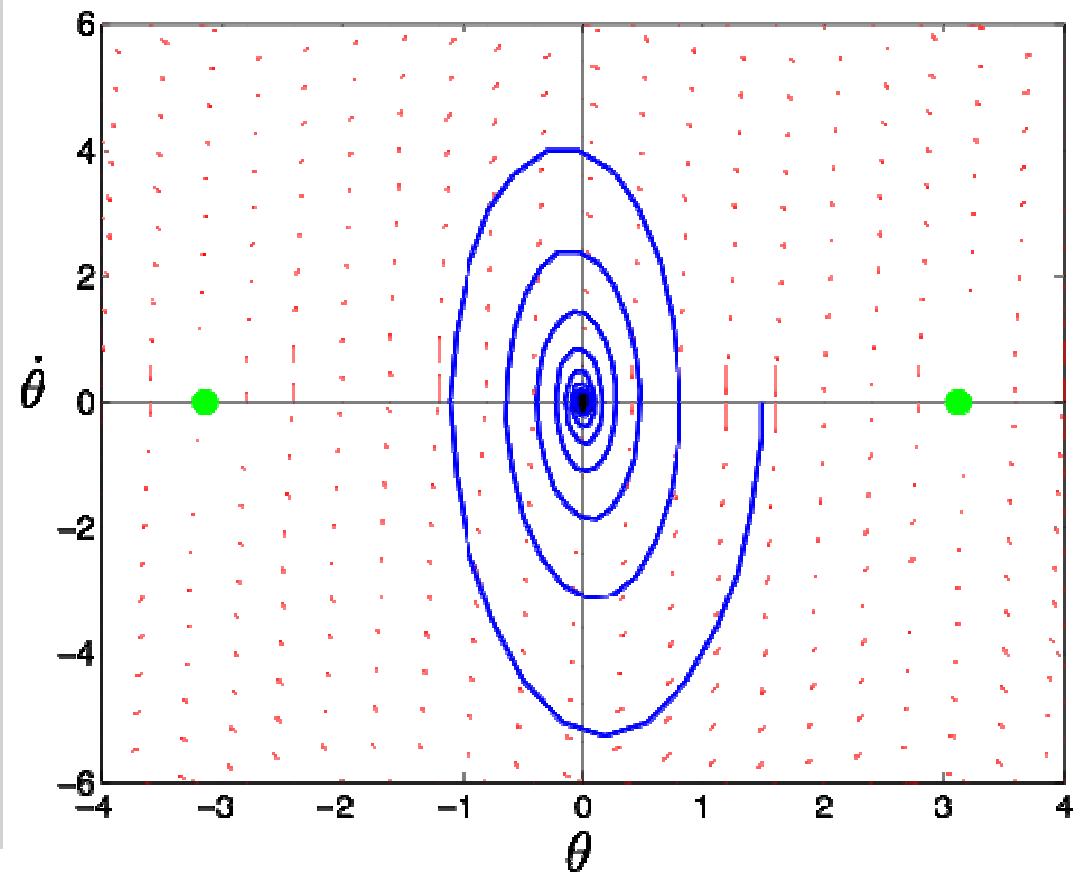
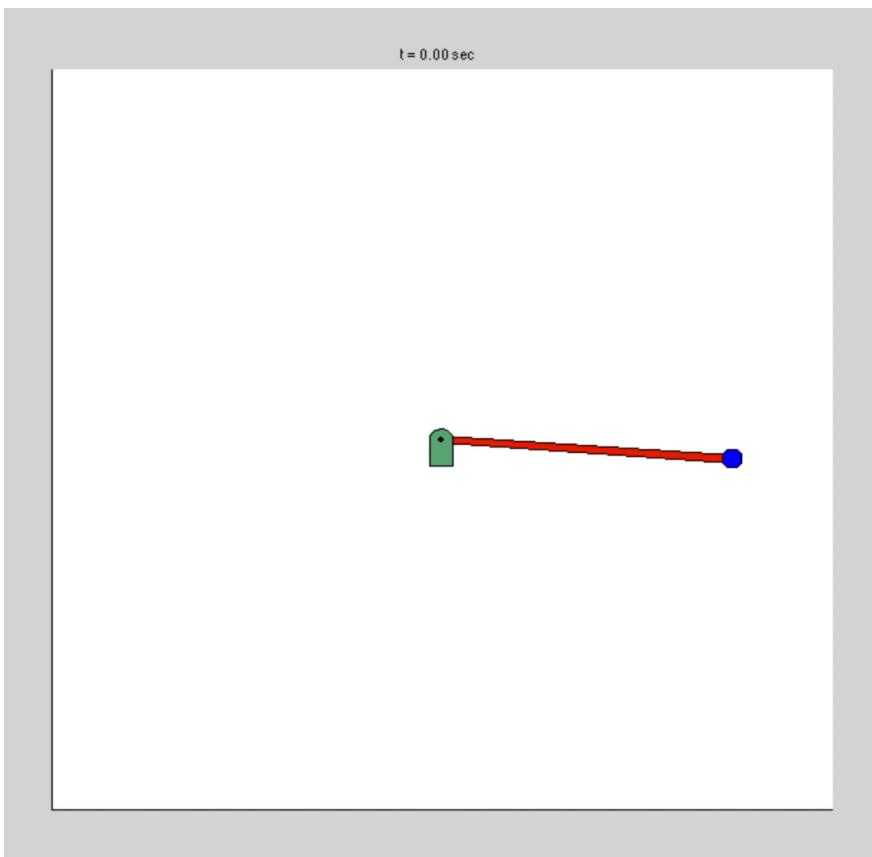


Dynamics (aka Physics)

- States: $s = \{\theta, \dot{\theta}\}$ aka angle and angular **velocity**
- Actions: $a = \tau$ aka torque at joint
- Transitions: $s' = f(s, a)$ aka physics

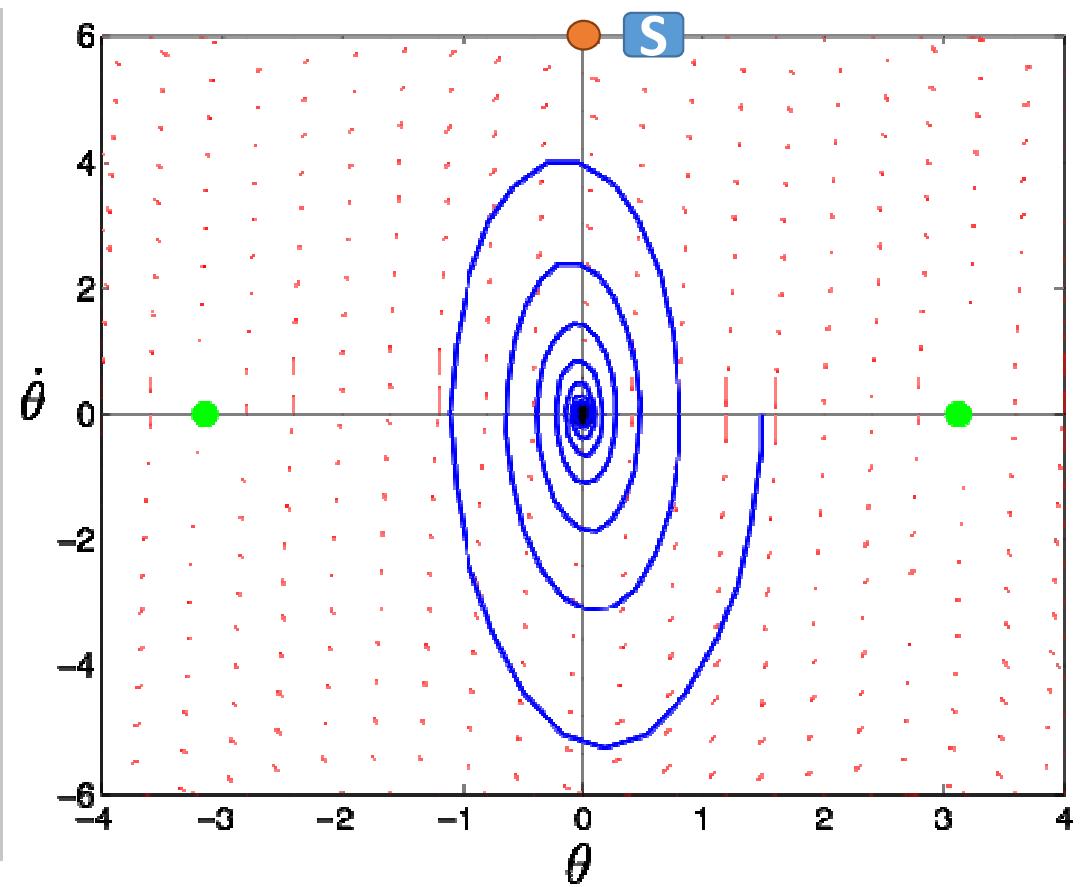
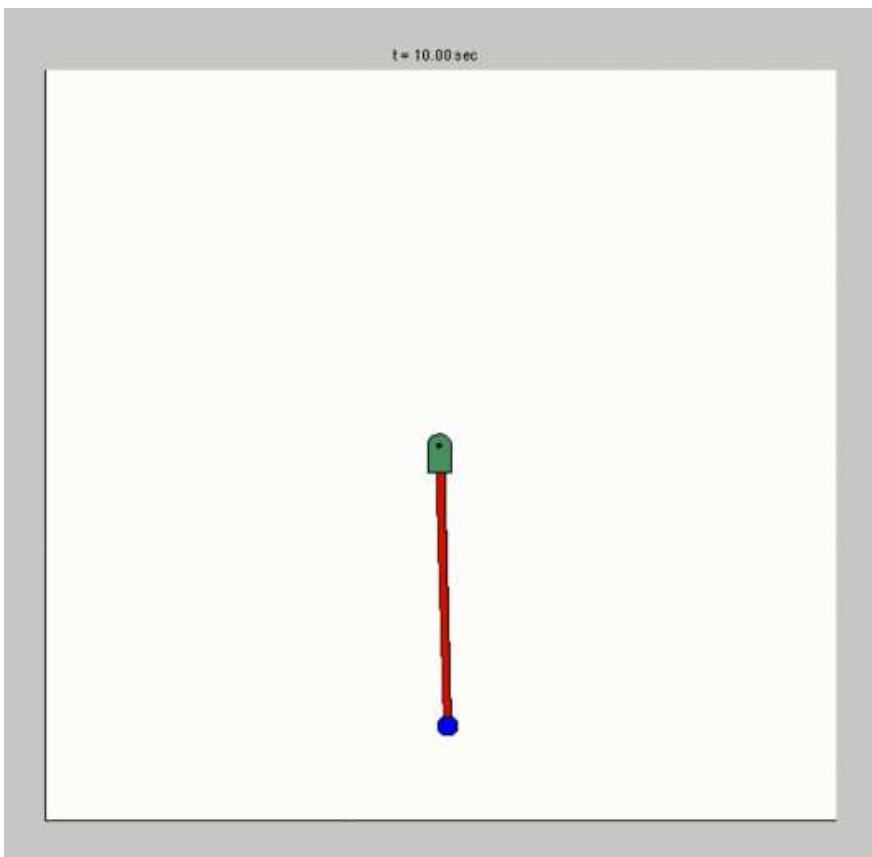
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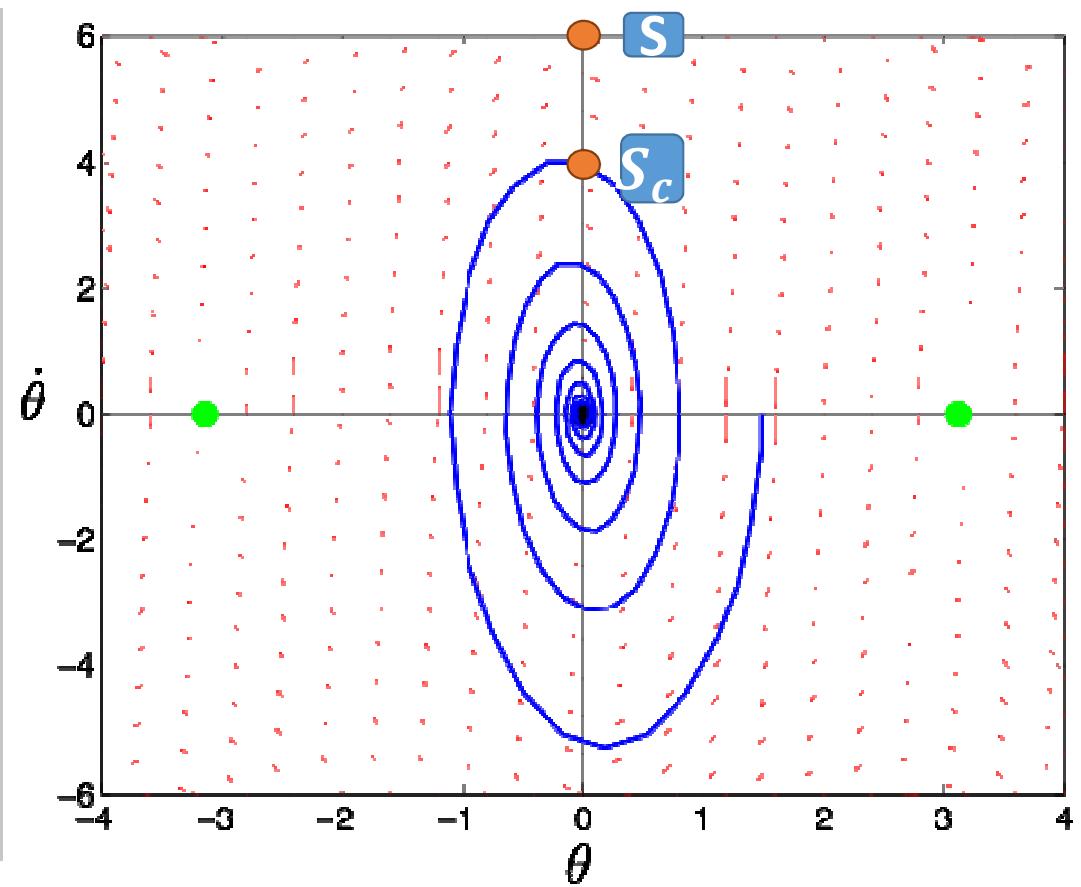
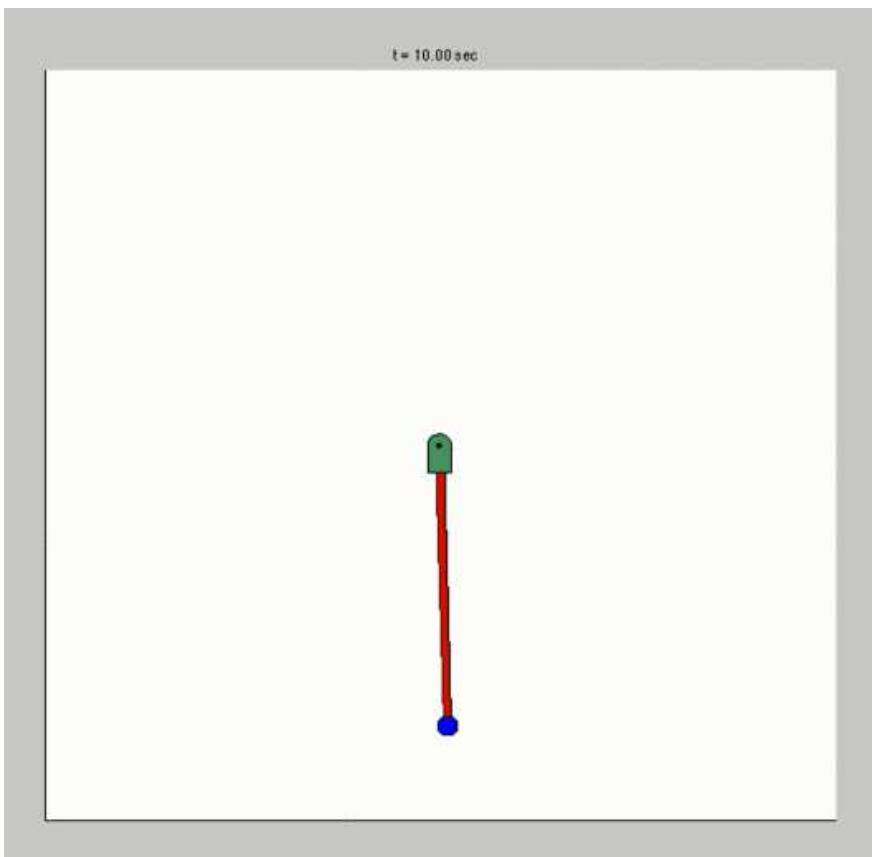
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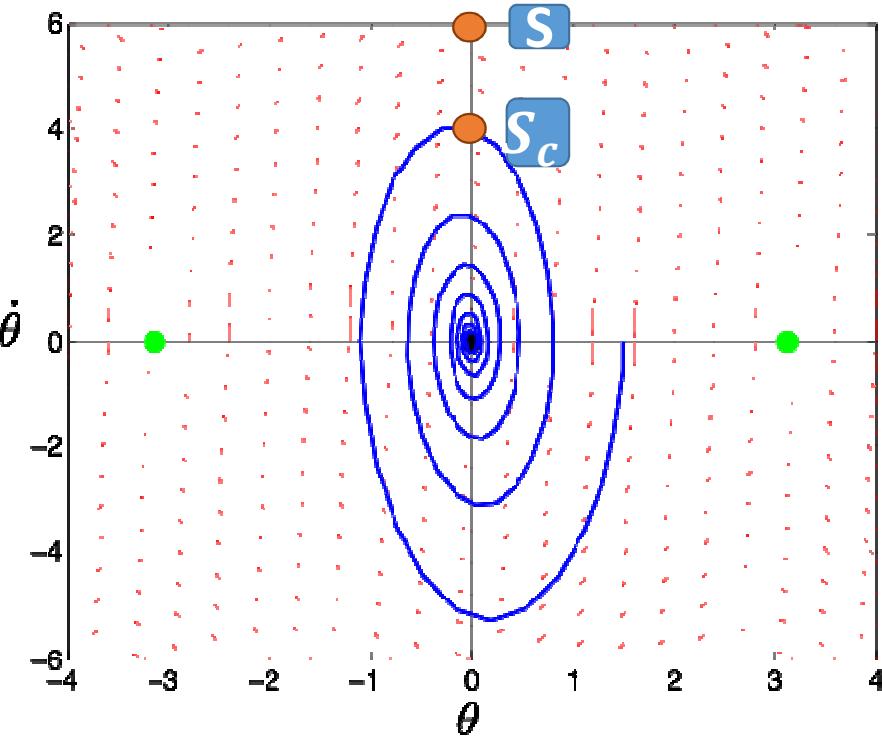
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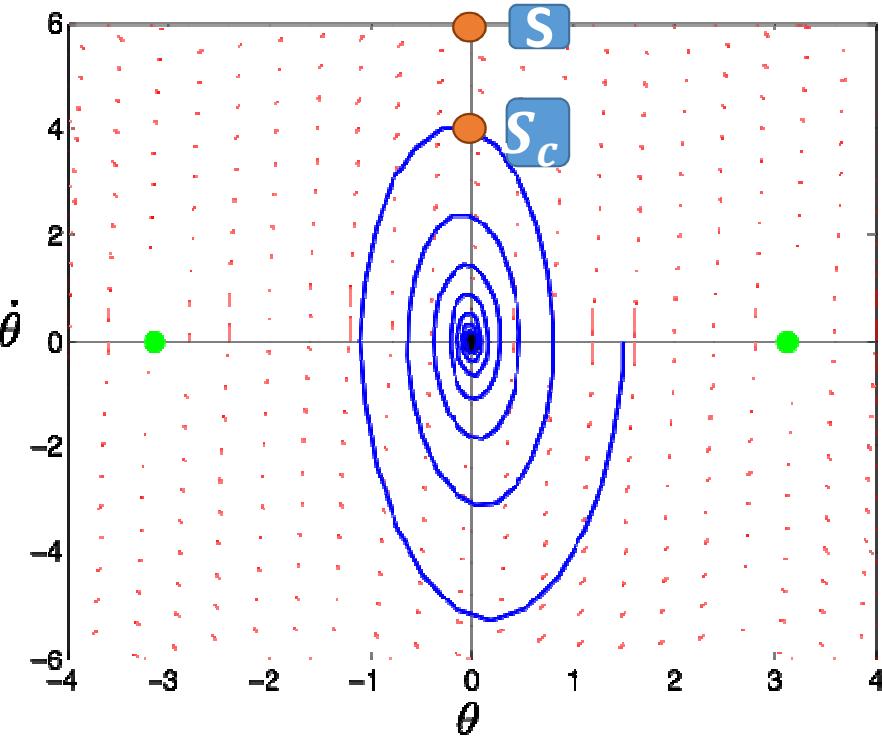
Challenges for Dynamic RRTs

The “extend” operation is complex!

- We need to solve a **boundary value problem** (find a path from s_c to s such that it follows the dynamics)
- Basically a “mini” planning problems

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Challenges for Dynamic RRTs

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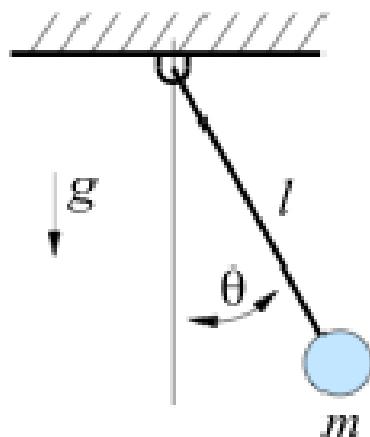
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- [REDACTED]

Q: Why don't we just try a discretization of possible actions instead of solving a boundary value problem?

5

Ok so why can't robots use these awesome **kinematic** planning algorithms all the time and be better at life?!?

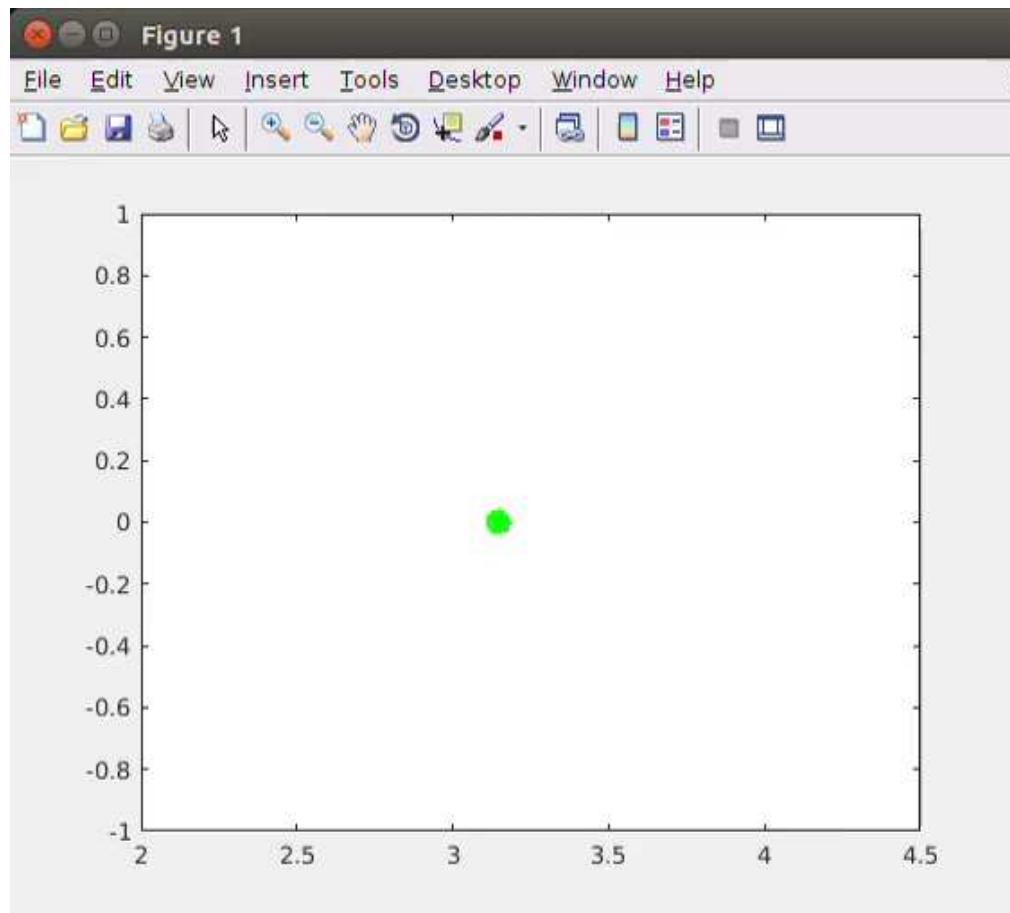


- **States:** $s = \{\theta, \dot{\theta}\}$ aka angle and angular velocity
- **Actions:** $a = \tau$ aka torque at joint
- **Transitions:** $s' = f(s, a)$ aka physics

Task: start from the **stable downward equilibrium $(0,0)$** and **swing up to the unstable upward equilibrium $(\pi,0)$**

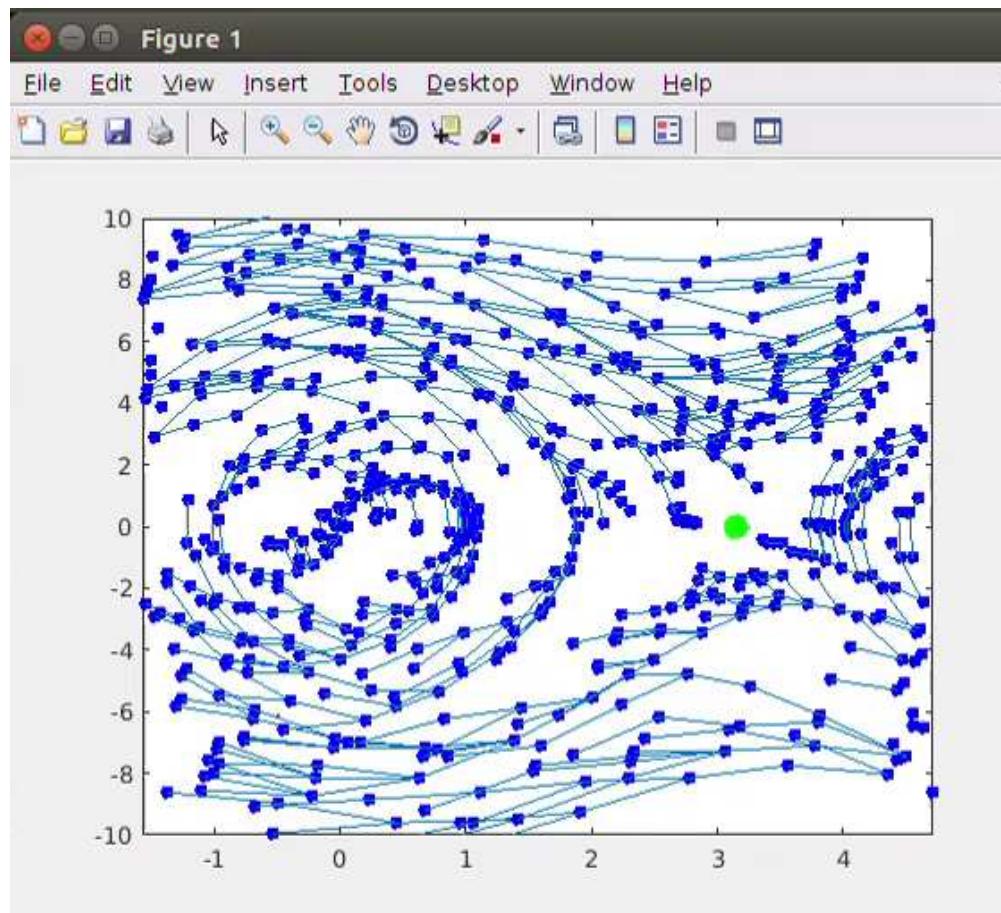
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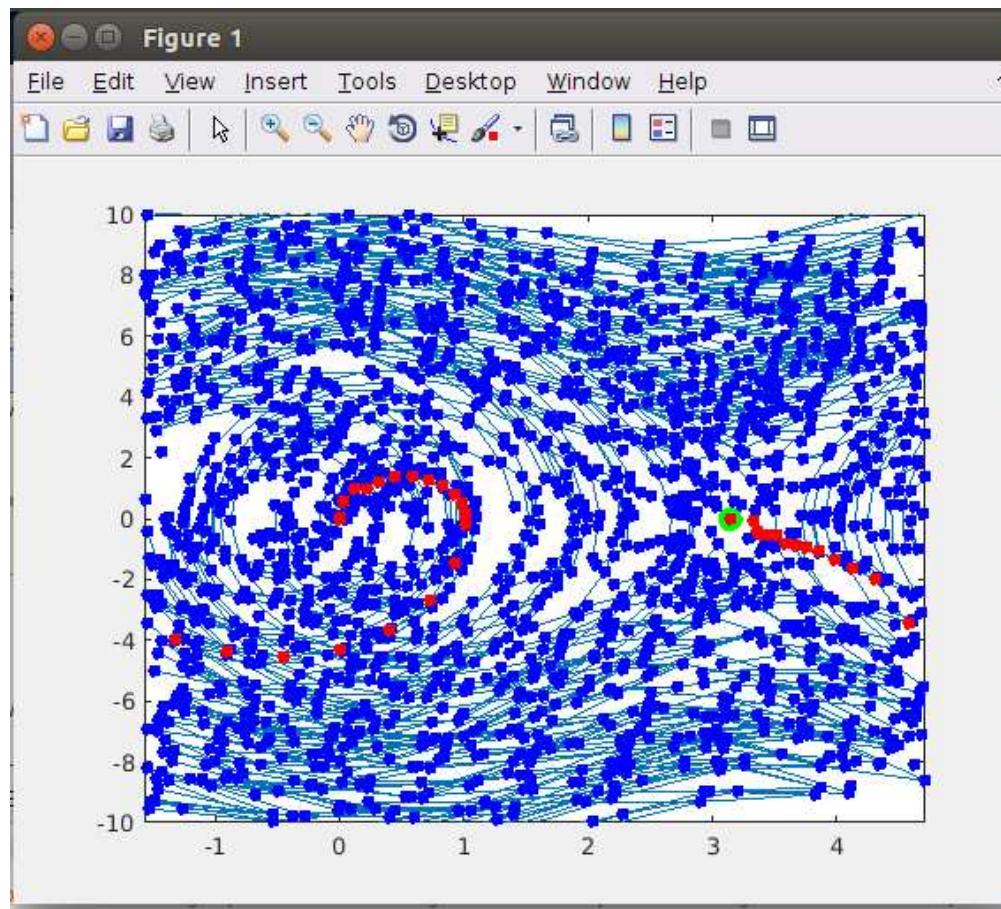
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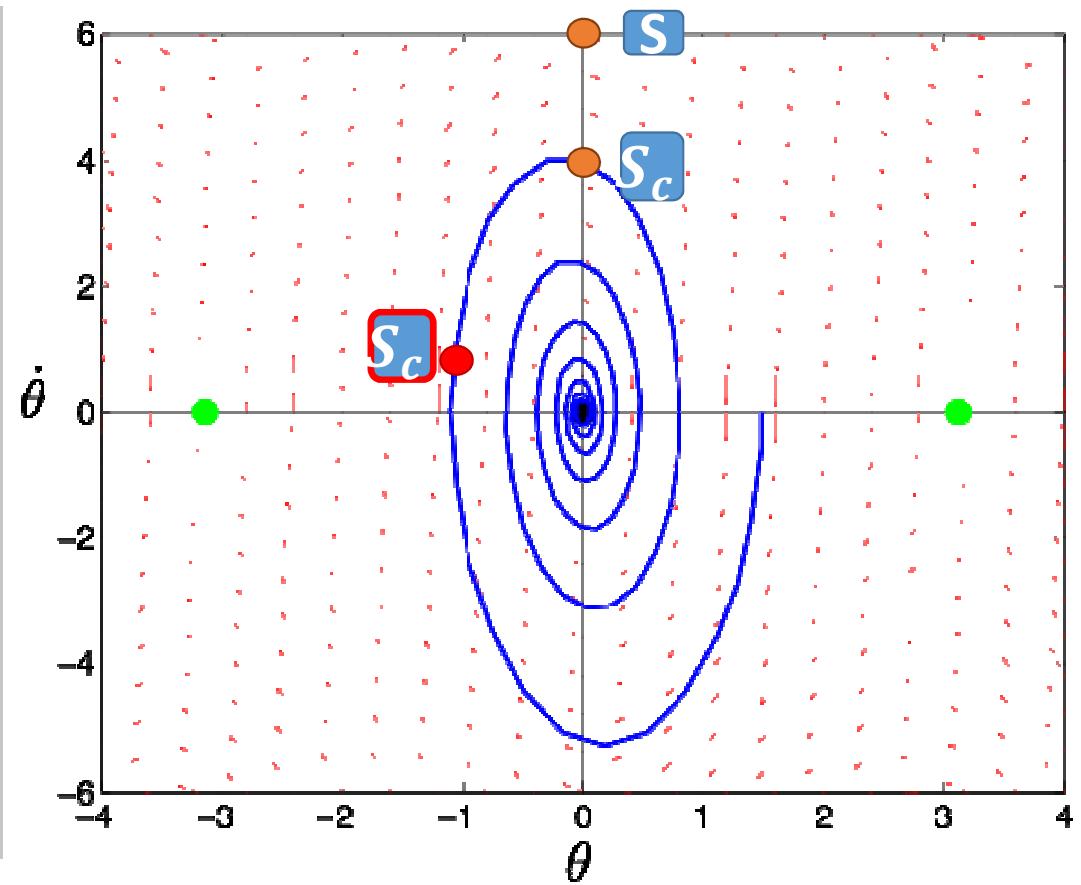
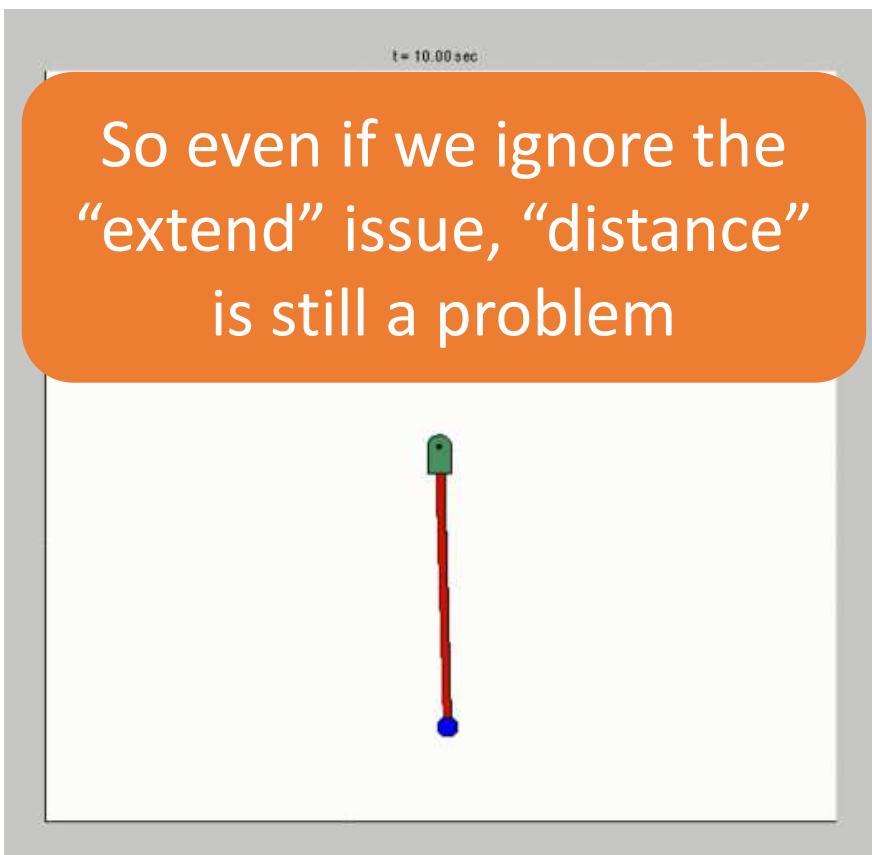
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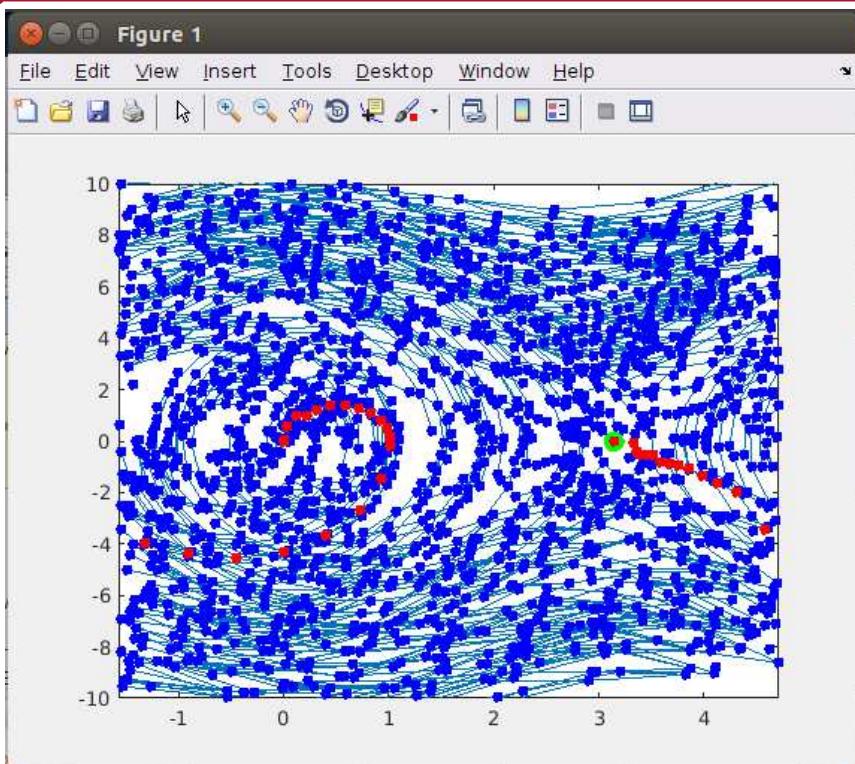
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Ok so why can't robots use these awesome **kinematic** planning algorithms all the time and be better at life?!?



5

Ok so why can't robots use these awesome **kinematic** planning algorithms all the time and be better at life?!?



Challenges for Dynamic RRTs

The “extend” operation is complex!

- We need to solve a **boundary value problem** (find a path from s_c to s such that it follows the dynamics)
- Basically a “mini” planning problems

What is the “closest state in the tree”

- The “**distance**” between states of dynamical systems is **not well-defined**

5

So what do we do?



5

So what do we do?

Give up and make
the computer solve
it for us?

5

So what do we do?

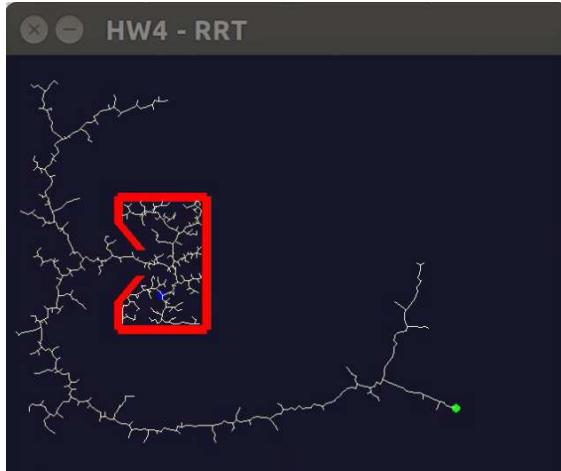
#Learning

#EfficientUseOfHumans

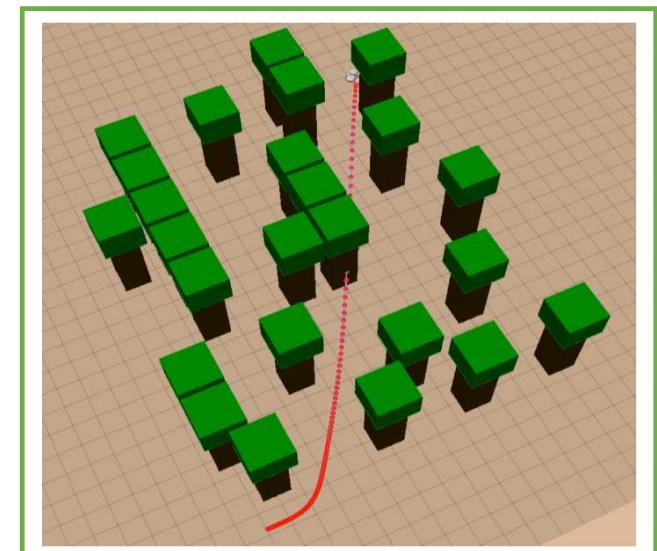
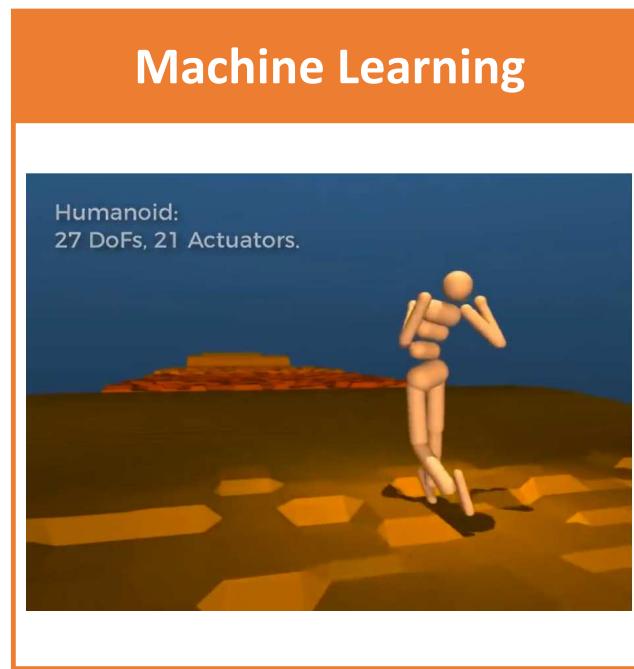
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Planning in Configuration Space



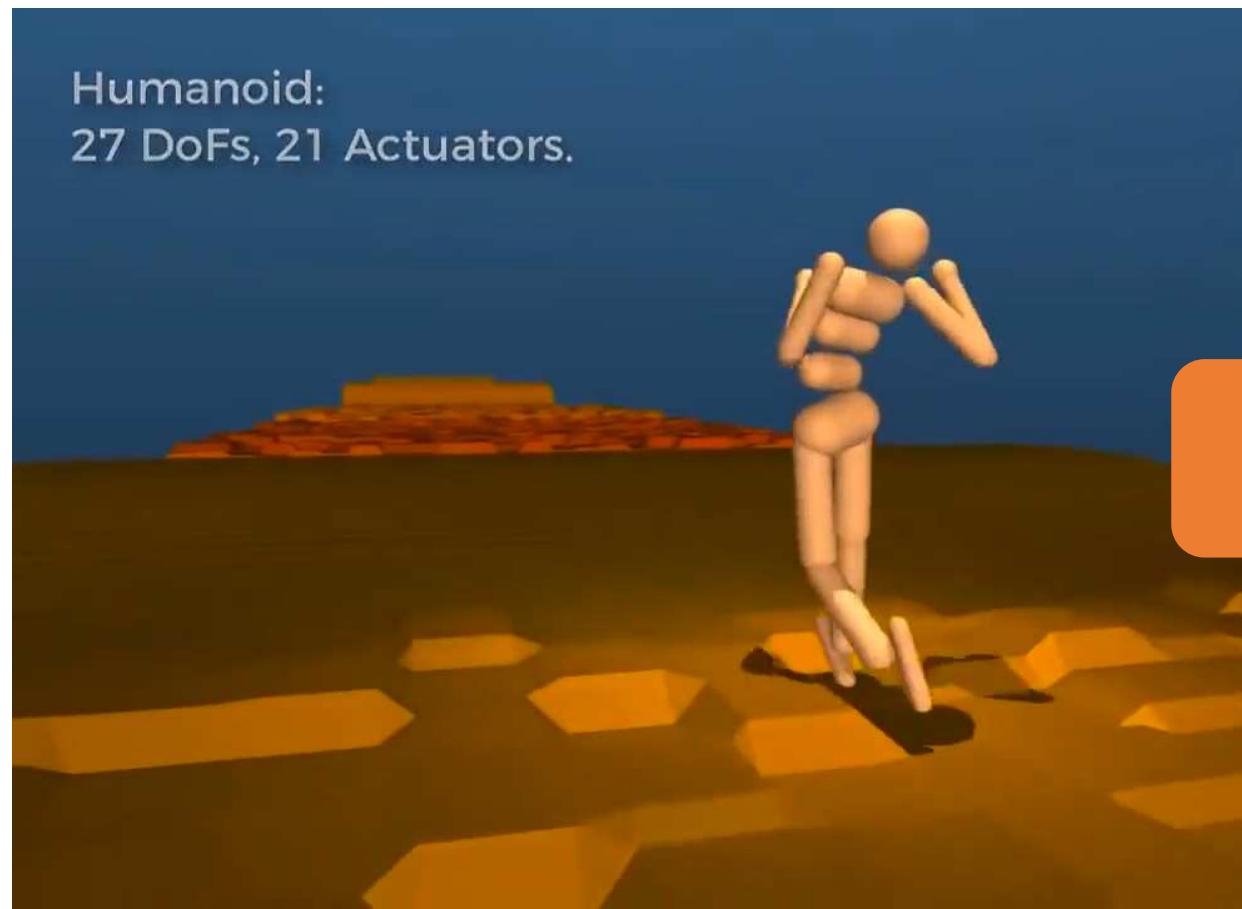
Random Search



Local Search

5

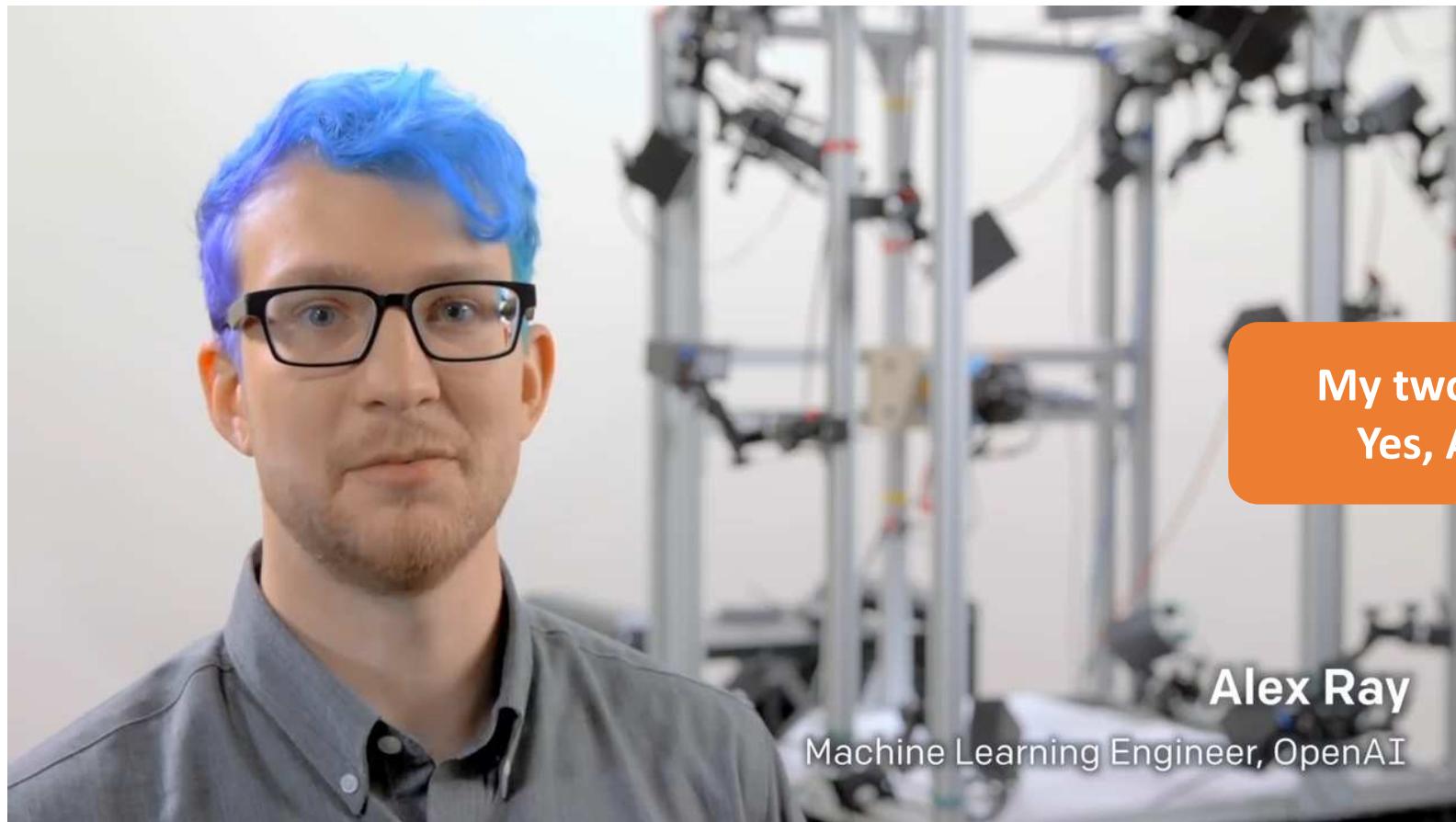
Guest Lecture in two weeks: Can I make the computer learn all of this for me automatically?



My two cents:
Yes, And...

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Guest Lecture in two weeks: Can I make the computer learn all of this for me automatically?

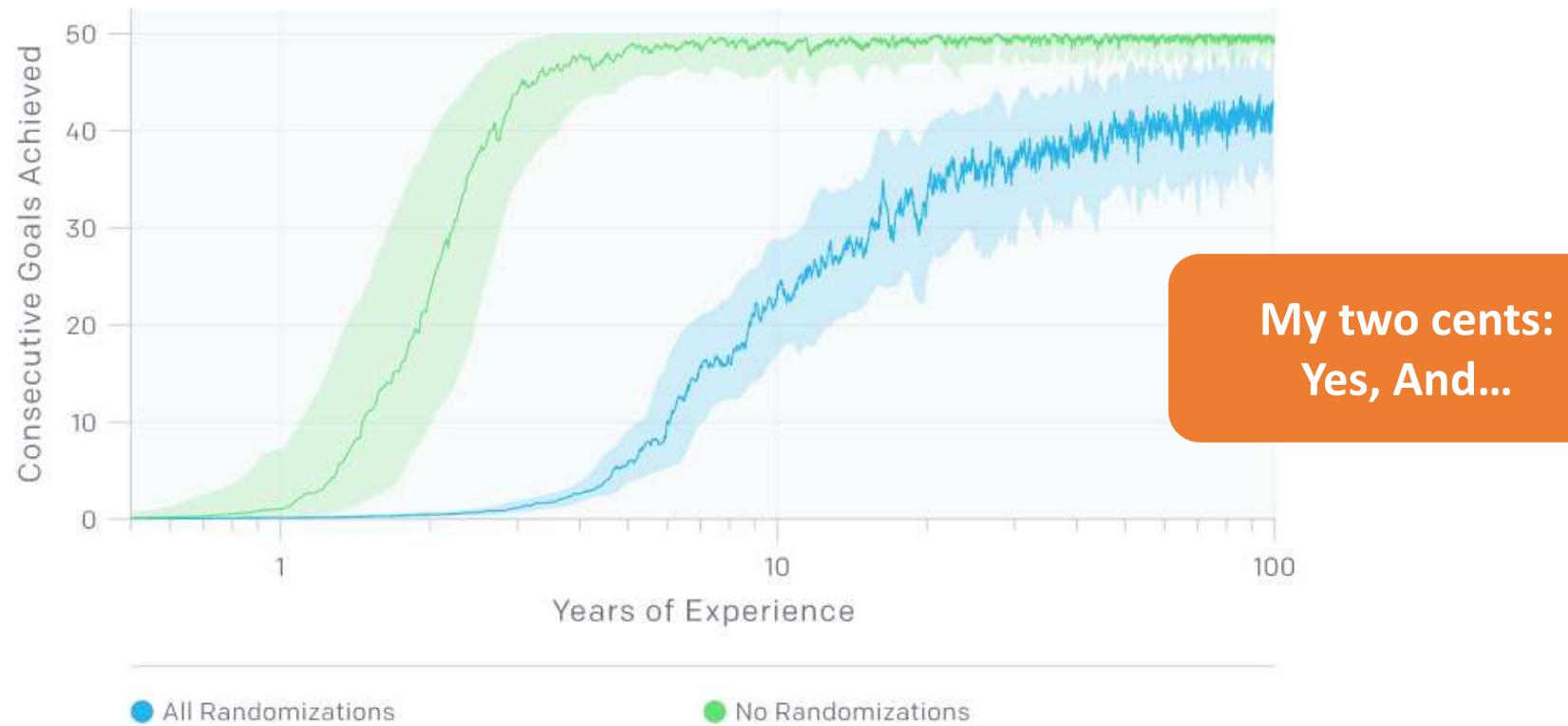


**My two cents:
Yes, And...**

Alex Ray
Machine Learning Engineer, OpenAI

5

Guest Lecture in two weeks: Can I make the computer [learn](#) all of this for me automatically?



5

So what else can we do?

•

5 So what else can we do?

Lots of math!



5 So what else can we do?

Lots of math!



5 So what else can we do?

Its actually not that
bad and the math
isn't actually that
scary I promise!



5

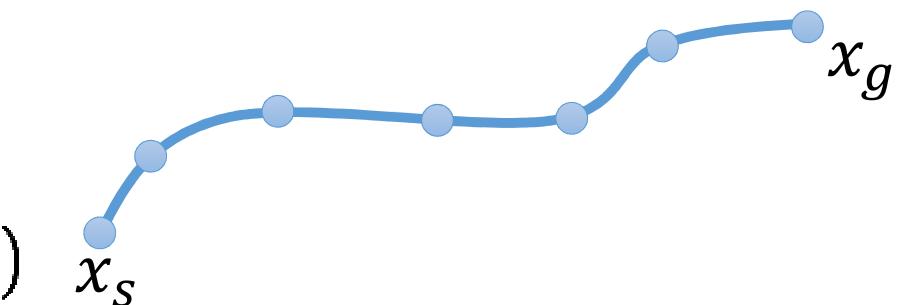
Optimization

We can write the planning problem down as an optimization problem!

$$\underset{s_0, a_0, \dots, s_N, a_N}{\text{minimize}} \sum_{k=0}^N c(s_k, a_k)$$

$$\text{subject to } s_{k+1} = f(s_k, a_k) \quad x_s$$

$$s_N = s_{\text{goal}}$$



5

Optimization

We can write the planning problem down as an optimization problem!

$$\underset{s_0, a_0, \dots, s_N, a_N}{\text{minimize}} \sum_{k=0}^N c(s_k, a_k)$$

Minimize a cost in each state
(e.g., energy used)

$$\text{subject to } s_{k+1} = f(s_k, a_k)$$

Obey physics

$$s_N = s_{\text{goal}}$$

Get to the goal

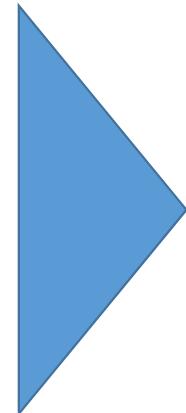
Optimization

We can use Bellman updates to solve this:

- We can start at the goal state and then work backwards computing the lowest cost actions to get to all states all the way back to the start state

$$\underset{s_0, a_0, \dots, s_N, a_N}{\text{minimize}} \sum_{k=0}^N c(s_k, a_k)$$

$$\begin{aligned} \text{subject to } s_{k+1} &= f(s_k, a_k) \\ s_N &= s_{\text{goal}} \end{aligned}$$



$$V_N(s_N) = c(s_N, a_N)$$

$$V_{N-1}(s) = \min_a c(s_{N-1}, a_{N-1}) + V_N(f(s_{N-1}, a_{N-1}))$$

This leads to the classic *Value Iteration* algorithm

Optimization

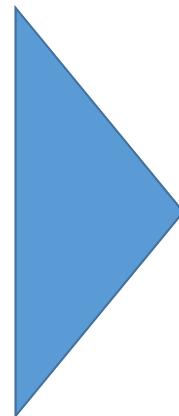
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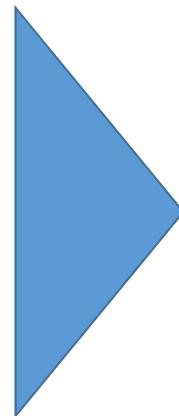
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Sadly again the complexity scales with $d^{|S| = |A|}$ and those can get **HUGE** fast! This is the “**curse of dimensionality**” again

Optimization

Lets lower our expectations!

#localOptima #efficientUseOfComputers

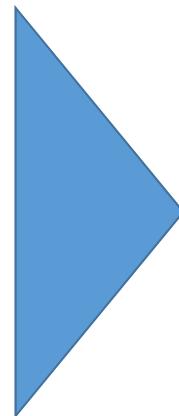
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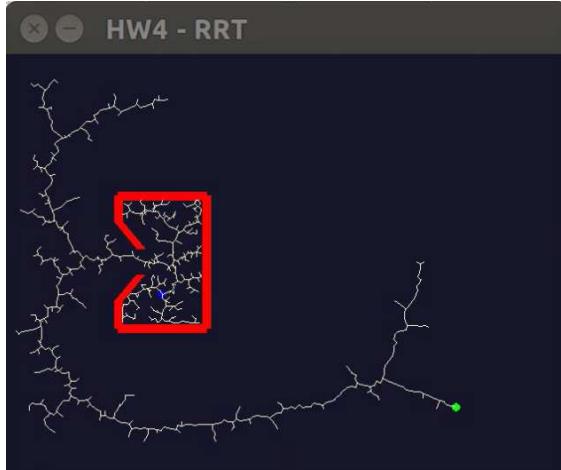
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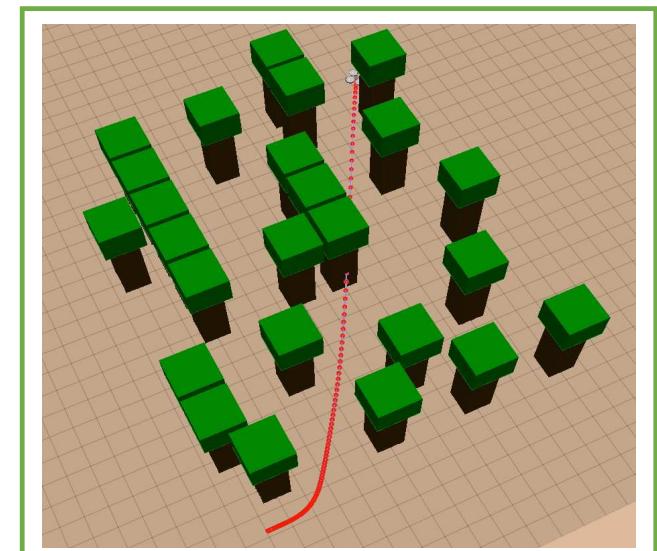
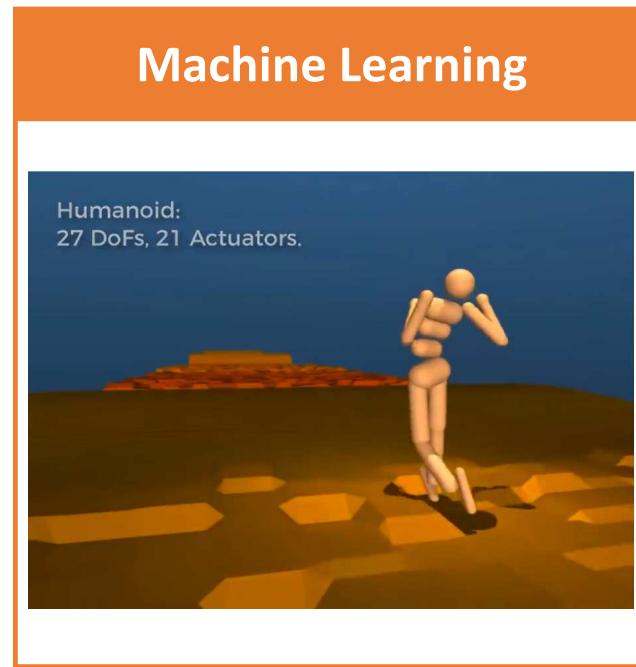
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Planning in Configuration Space



Random Search



Local Search

5 Trajectory Optimization

What if instead of finding a globally optimal path we search for a locally optimal path (off of some initial condition)?

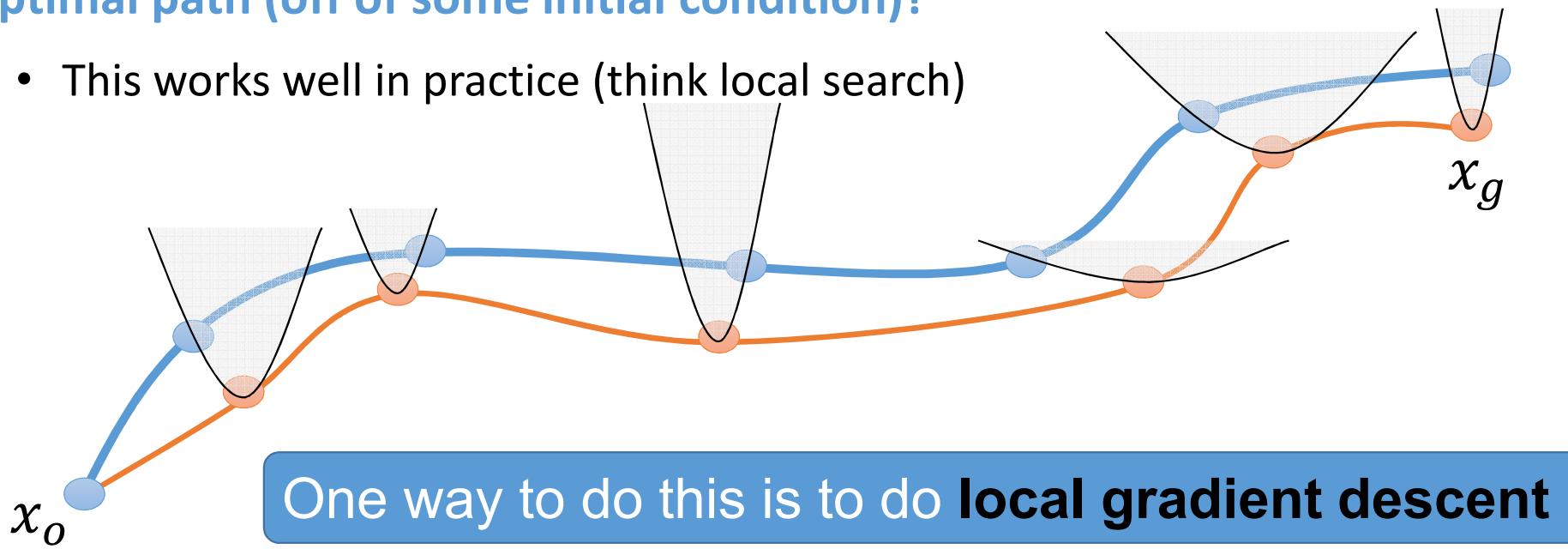
- This works well in practice (think local search)



5 Trajectory Optimization

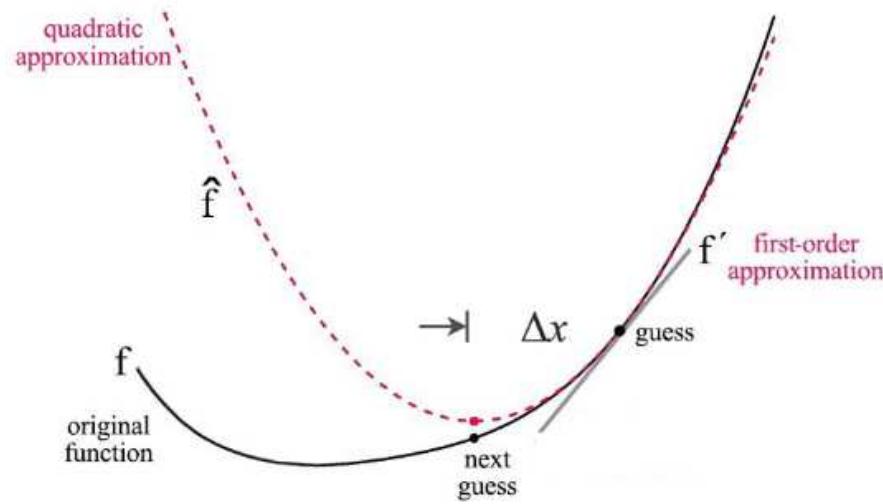
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5 Trajectory Optimization

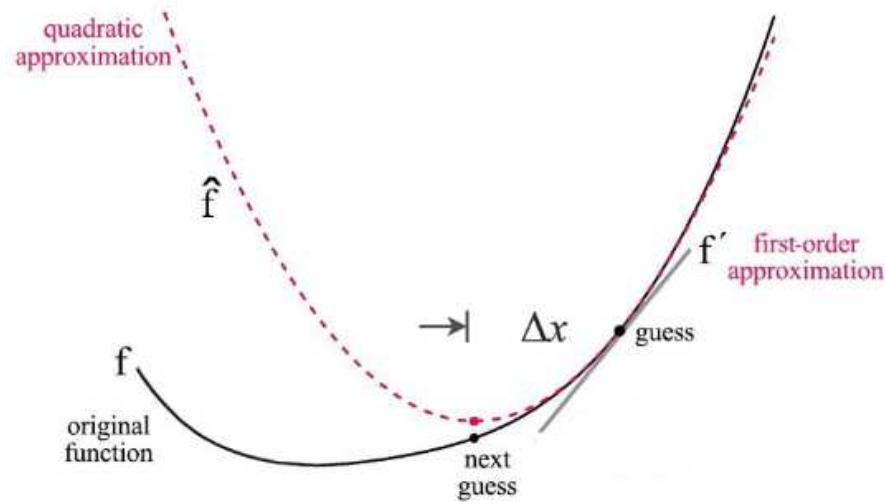
I'm drawing small quadratic bowls because most (if not all) of the practical algorithms make **linear and quadratic approximations** of the nonlinear functions allowing for efficient gradient descent



5 Trajectory Optimization

And convex optimization tells us how to descend to the minima of a quadratic function

I'm drawing small quadratic bowls because most (if not all) of the practical algorithms make **linear and quadratic approximations** of the nonlinear functions allowing for efficient gradient descent



5 Trajectory Optimization

There are also a whole host of algorithms one can use to solve these problems including:

- DDP, SQP, Interior-Point Methods, Trust-Region Methods, Stochastic Gradient Descent Methods, etc.

And you can use off-the-shelf solvers to solve these problems. Popular solvers include:

- SNOPT, IPOPT, NLOPT, fmincon (MATLAB), etc.
- **Most people use off the shelf solvers!**

5 Trajectory Optimization

So trajectory optimization solves everything right?

- Can handle full robot **dynamics**
- No need for distance metrics
- Can use **off the shelf solvers** reducing the coding burden
- Finds a **locally optimal** solution – no weird paths coming out!
 - Extra motions are “optimized away”

5 Trajectory Optimization

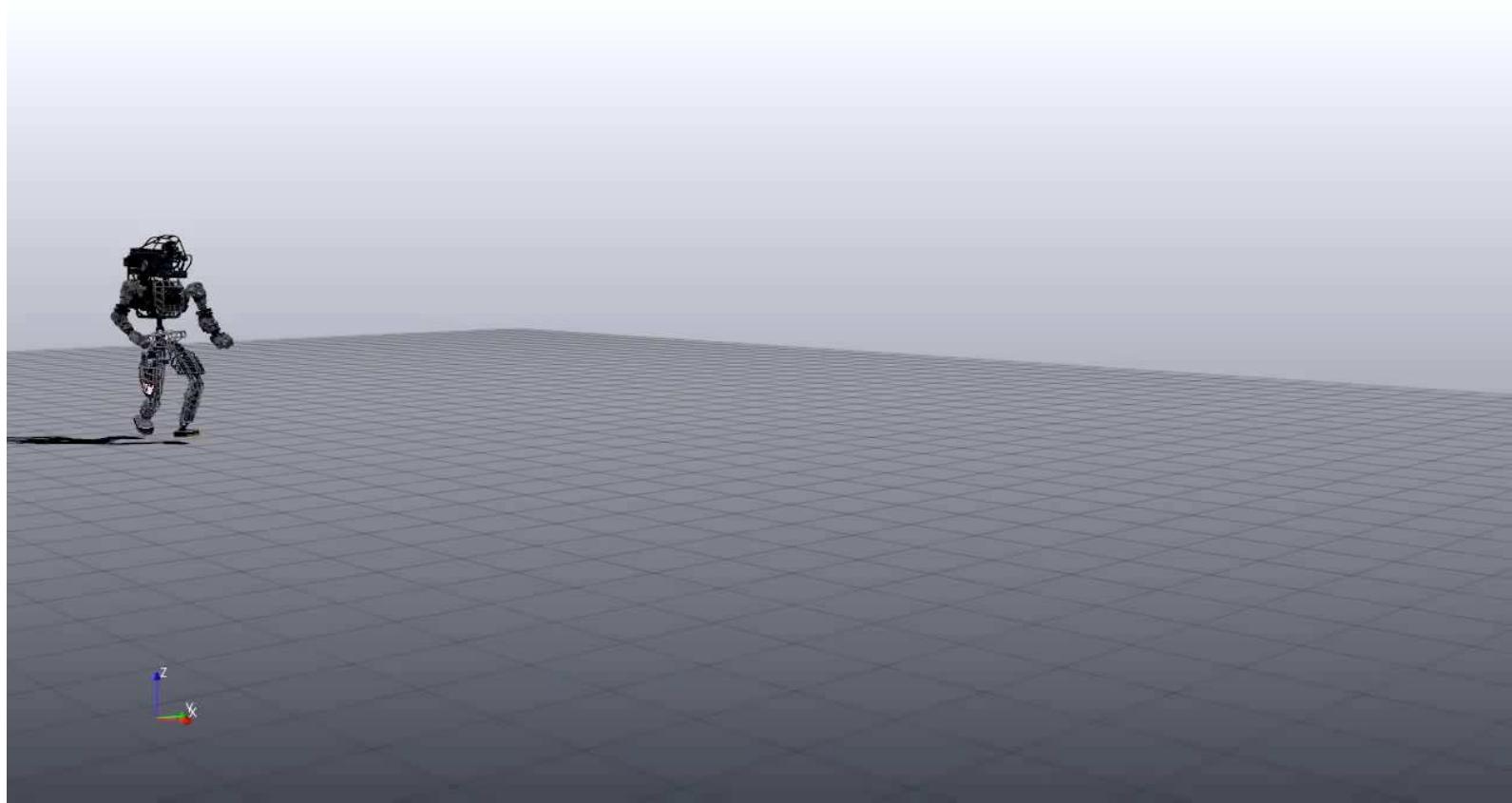
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And optimal motions often look bio-inspired as nature generally uses optimally efficient motions!

5

Atlas 1.0 Trajectory Optimization



5 Trajectory Optimization

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No free lunch strikes again!

But....

- **Not globally optimal** (will often get stuck in local minima)
- **Not even complete** (problems are often non-convex so it may not even find a feasible solution)
- **Also generally slow**

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Lets dive a little deeper into solvers!

5

There are two popular classes of solvers

Pros

Shooting Methods

(e.g., DDP, iLQR)

- Known fast

Cons

- Hard to add constraints (e.g., torque limits, obstacle avoidance)
- Generally people code it themselves

Direct Methods

(e.g., DIRTRAN using SQP or IP)

- Easy to add constraints (e.g., torque limits, obstacle avoidance)
- Easy to leverage **off the shelf solvers** (e.g., SNOPT, IPOPT)

- Considered slow

5

There are two popular classes of solvers

Pros

- K
- t
- C

Technical note: DDP reduces to a specific factorization of the **KKT matrix** solve in a direct method to exploit sparsity!

$$\begin{aligned} & \text{minimize} && (1/2)x^T Px + q^T x + r \\ & \text{subject to} && Ax = b \end{aligned}$$

$$\begin{bmatrix} P & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} x^* \\ \nu^* \end{bmatrix} = \begin{bmatrix} -q \\ b \end{bmatrix}$$

Cons

5

There are two popular classes of solvers

Pros

- Known fast

Cons

- Hard to add constraints (e.g., torque limits, obstacle avoidance)
- Generally people consider them slow

Shooting Methods
(e.g., DDP, iPiano)

I'll dig a little deeper / explain this more in 2 weeks when I present my research on parallel shooting methods

Direct Methods
(e.g., DIRTRAN using SQP or IP)

easy to add constraints (e.g., torque limits, obstacle avoidance)
easy to leverage **off the shelf solvers** (e.g., SNOPT, IPOPT)

5

There are two popular classes of solvers

Stephen Boyd and
Lieven Vandenberghe

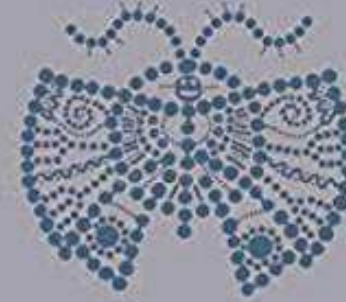
Convex Optimization

But/and these
are two great
textbooks if you
want to learn
more about the
math!

Springer Series in
Operations Research

Jorge Nocedal
Stephen J. Wright

Numerical
Optimization
Second Edition



Springer

Practical Challenges for Trajectory Optimization: Robustness

Manchester and Kuindersma 2017
Plancher and Kuindersma 2018

1. Solvers are (numerically) sensitive to:
 - Cost function designs and dynamic range
 - Regularization scheme

2. Solutions are sensitive to:
 - Initial state and input trajectories
 - Perturbations (solutions are often on constraint boundaries)

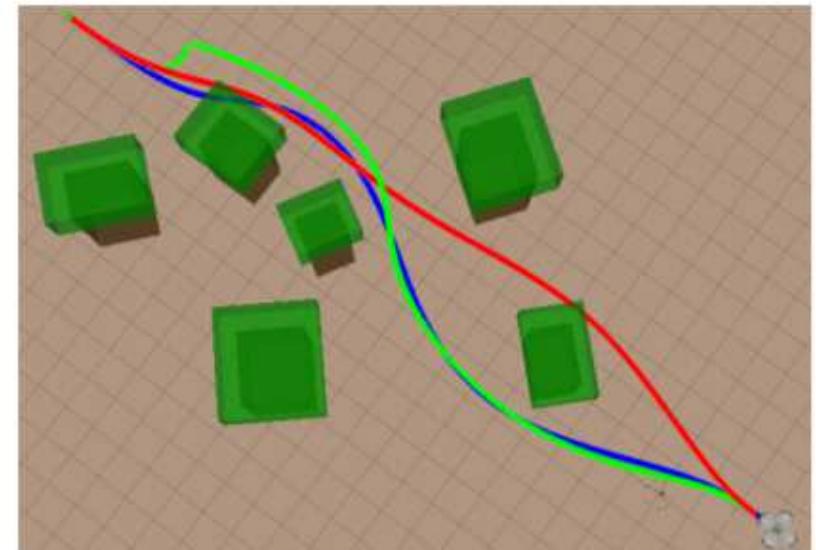
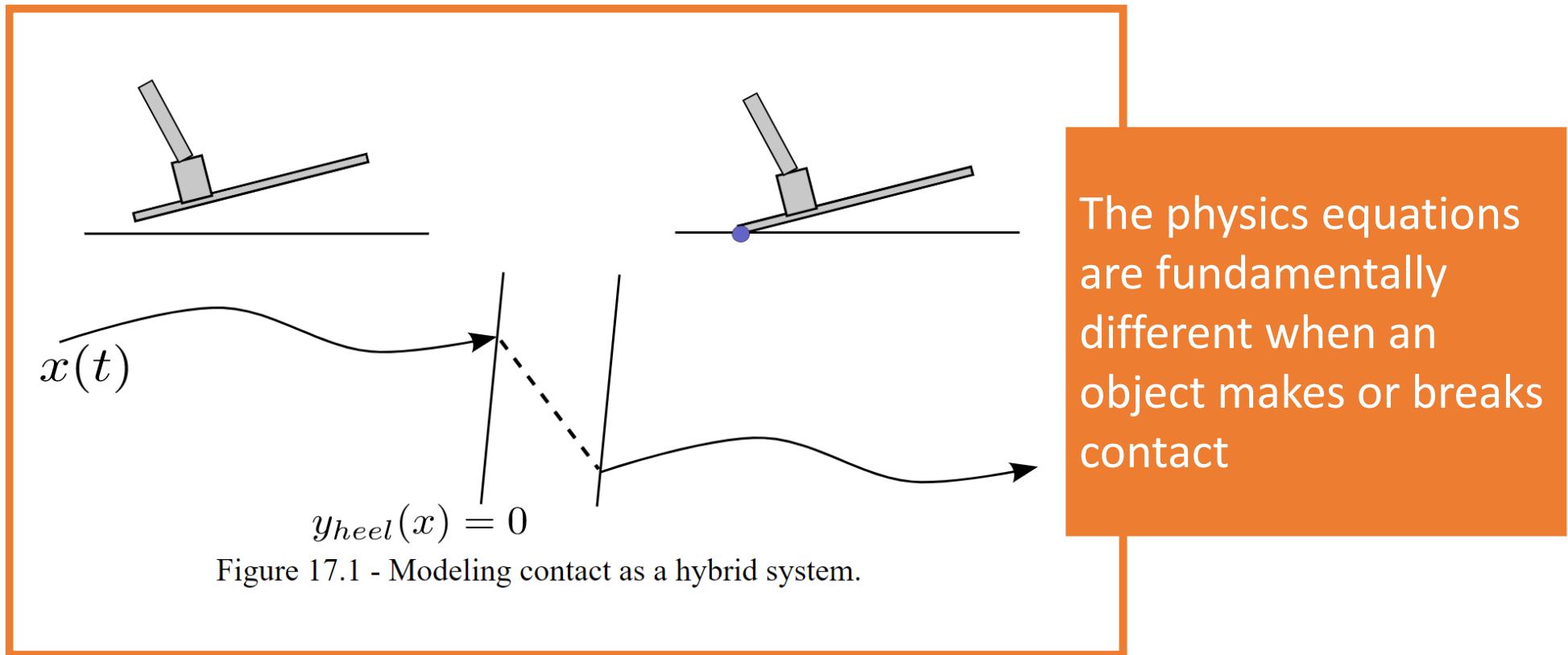


Fig. 4. DIRTRAN (red), DIRTREL-1 (blue), and DIRTREL-2 (green) quadrotor trajectories.

5

Practical Challenges for Trajectory Optimization: Contact

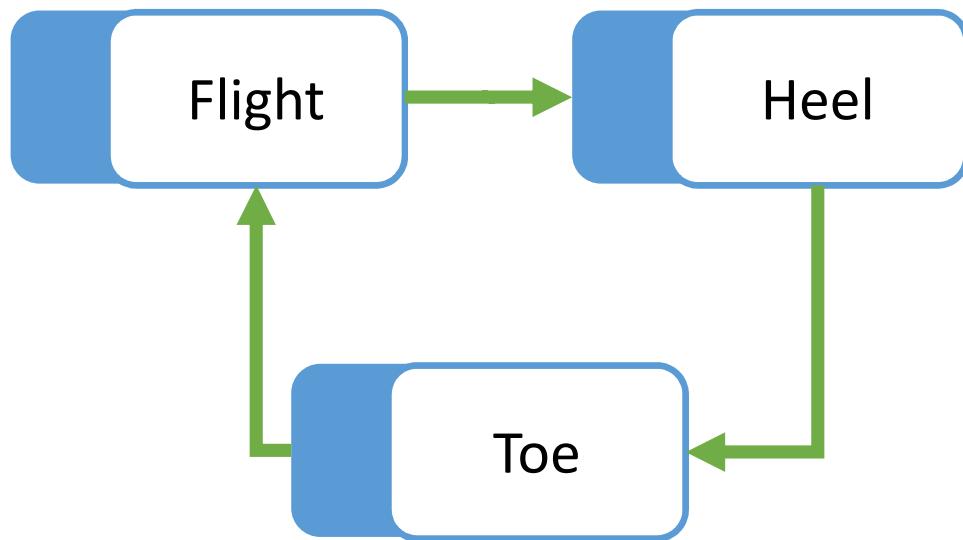
Tedrake Underactuated



5

Practical Challenges for Trajectory Optimization: Contact

Tedrake Underactuated



For walking these
hybrid modes form a
cyclic graph

If we **pre-specify** the
mode sequence and
timing we can use our
algorithms as before

5

Practical Challenges for Trajectory Optimization: Contact

Manchester and Kuindersma 2017

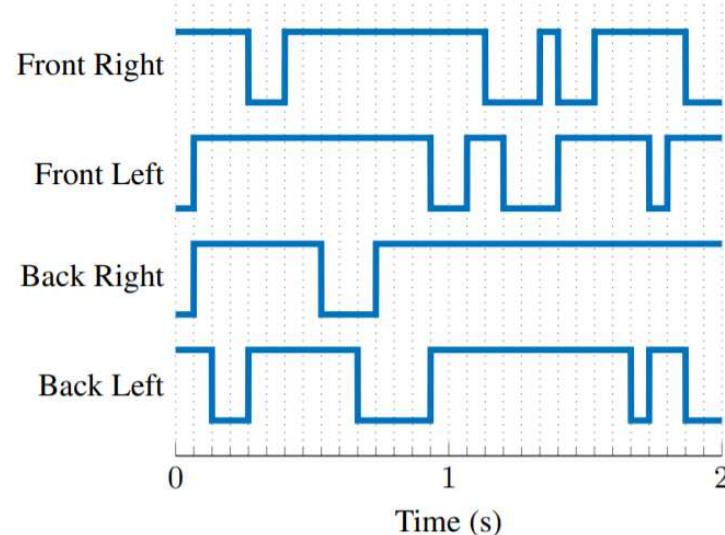
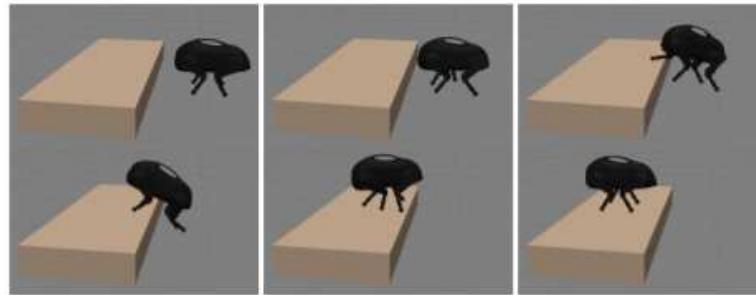


Figure 4. Contact mode sequence for each foot from LittleDog step-climbing example.



But for **complex actions** these modes start to become **hard to pre-specify**

5

Practical Challenges for Trajectory Optimization: Contact

Doshi, et. al. 2018

Contact-Implicit
Trajectory
Optimization
includes the
contact timings
and mode
transitions as
state variables

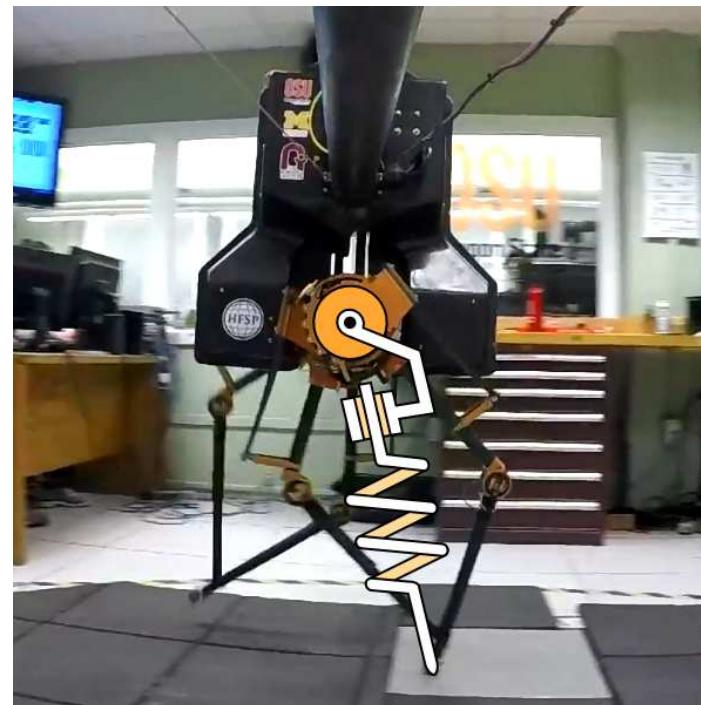
2Hz Gaits
(real-time)

But these approaches
are computationally
very expensive (read
offline) as the number
of modes explodes
combinatorically with
the number of contact
points (Mixed-Integer
Programming)!

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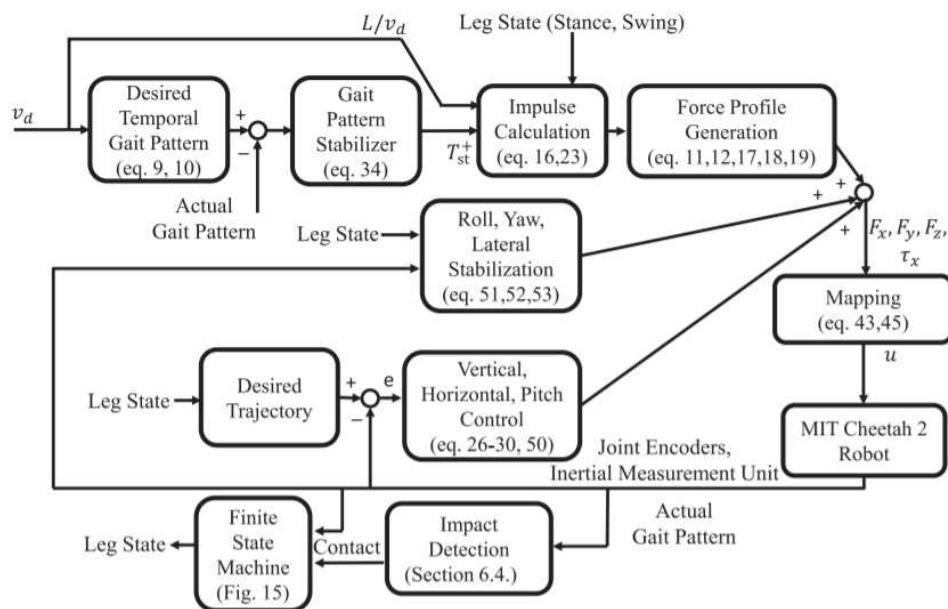
Practical Challenges for Trajectory Optimization: Contact

One approach to avoid solving these large hard problems is to solve the problem on **simpler models** of the system



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Practical Challenges for Trajectory Optimization: Contact

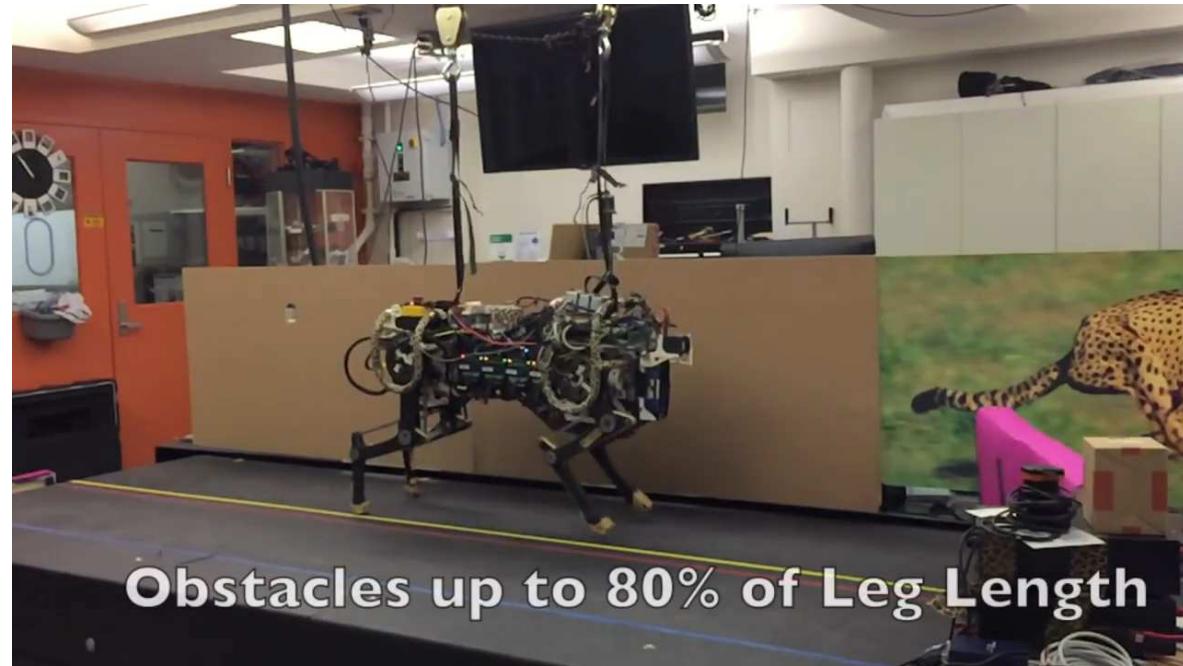


And then **combine solutions** to these **(conservative) simpler problems**

Fig. 11. Overall control system diagram.

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Practical Challenges for Trajectory Optimization: Contact



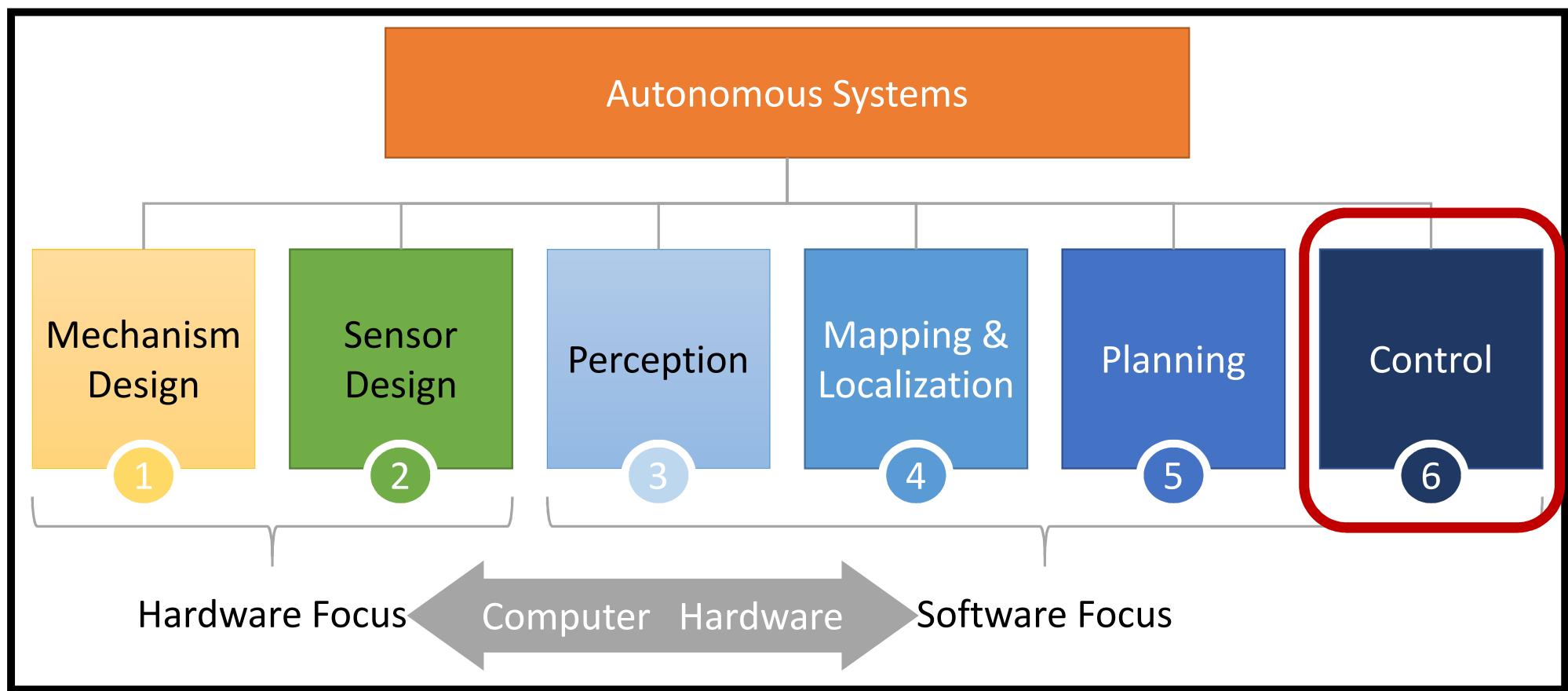
And then **combine solutions** to these (**conservative**) simpler problems

5

Key Takeaways:

1. Robot planning involves both **task and configuration spaces**
 2. For many real problems, **collision checking** can be expensive
 3. **Sample Based Planners** that leverage random search (**RRT/PRM**):
 - **Probabilistically complete** (but can still be slow sometimes)
 - **Single-query (RRT) vs. Multi-query (PRM)**
 - **Probabilistically optimal (RRT*)** but generally need smoothers
 4. **Trajectory Optimization** leverages local search to find **locally optimal** (generally smooth) solutions
 - Handles dynamics well but **not complete or robust**
 - Can use **off the shelf solvers** (SQP) but **generally slower** than a solver that **exploits sparsity** in the problem (DDP/iLQR)
 - **Contact is hard** and we (sometimes) use **simpler models** for tractability
-

Autonomous Systems / Robotics is a BIG space



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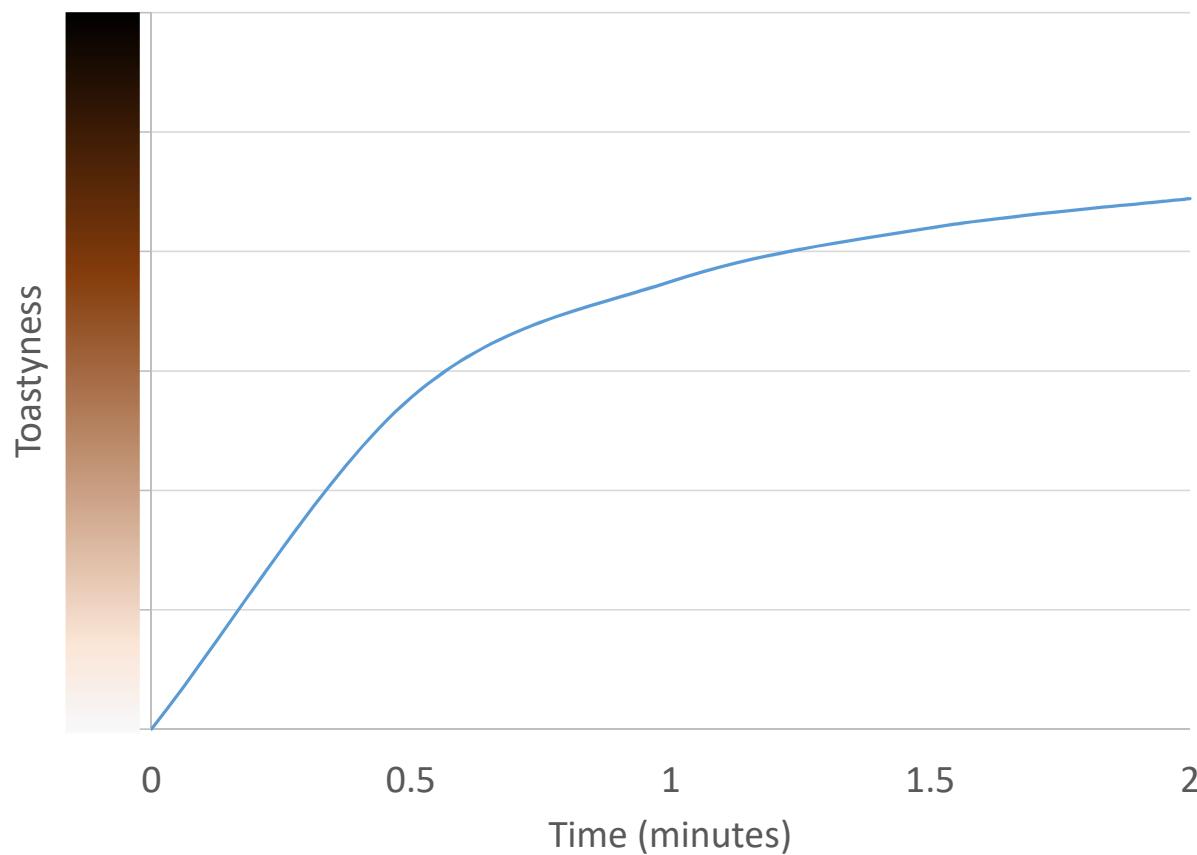
Control is the process of executing a plan in the real world

Well the simplest thing we could try would be to just execute the controls from our plan directly on the real system. This is called **Open-Loop Control!**

6

Open Loop Control

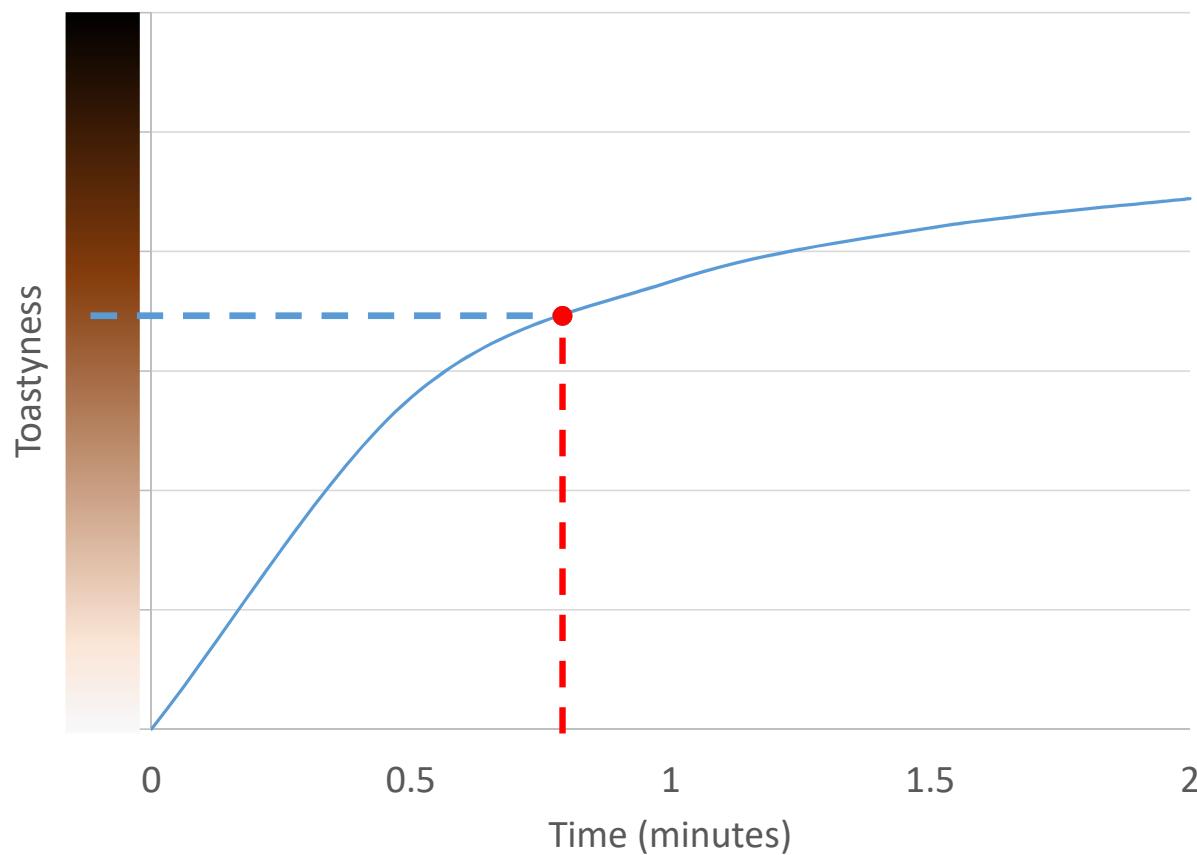
Adapted from MATLAB Control Toolbox



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Open Loop Control

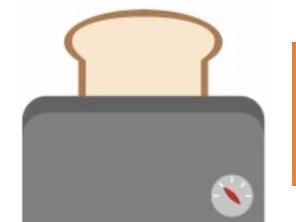
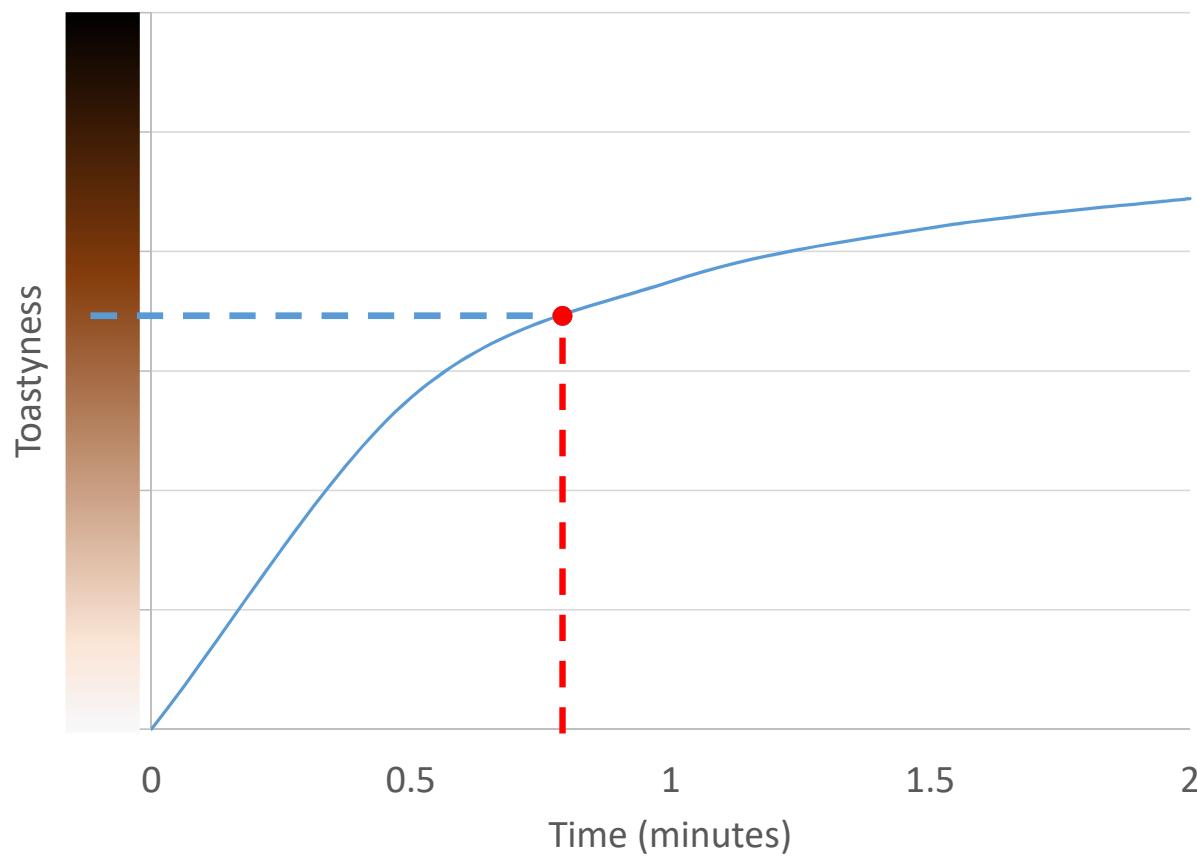
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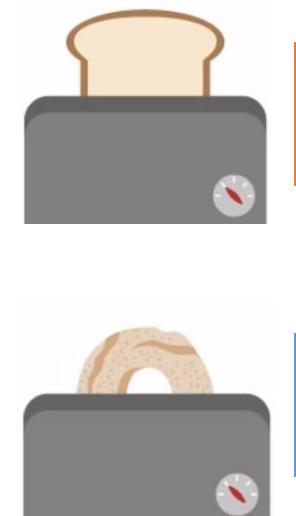
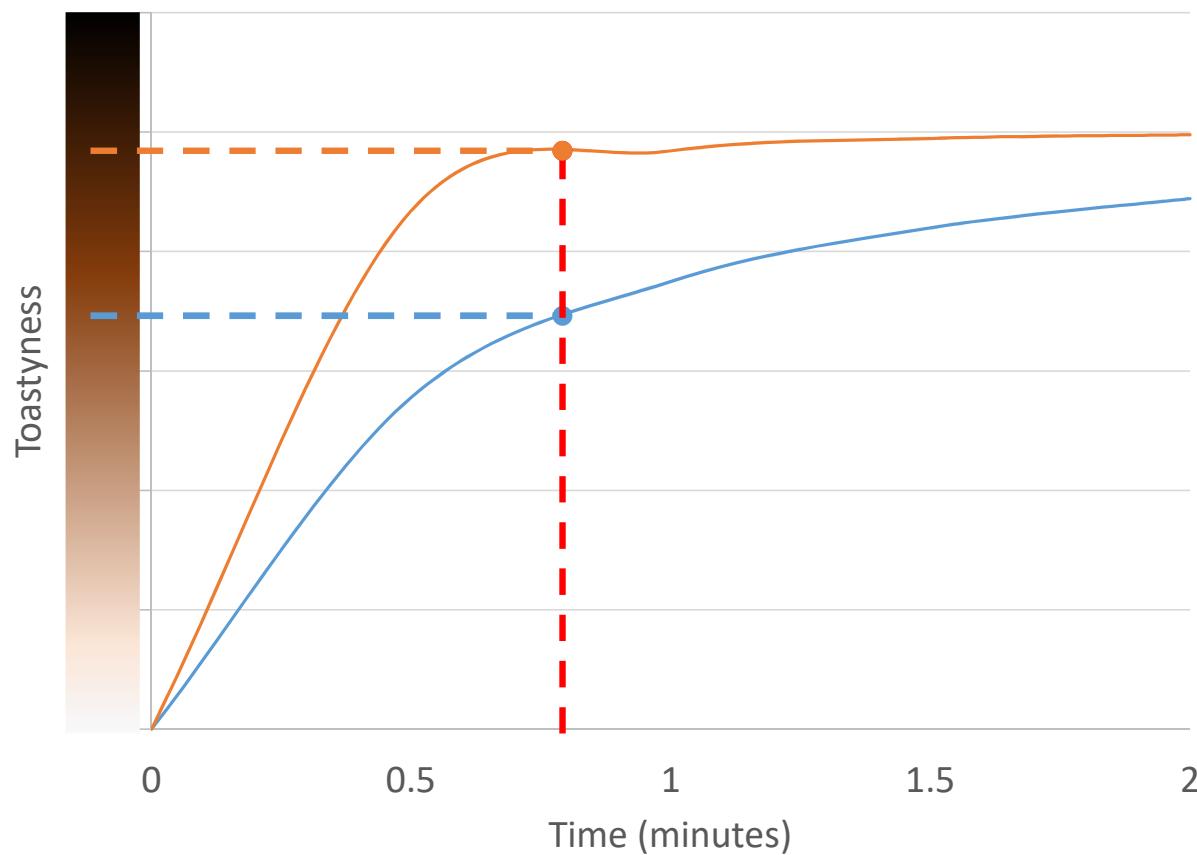
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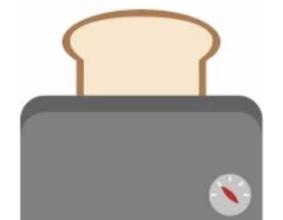
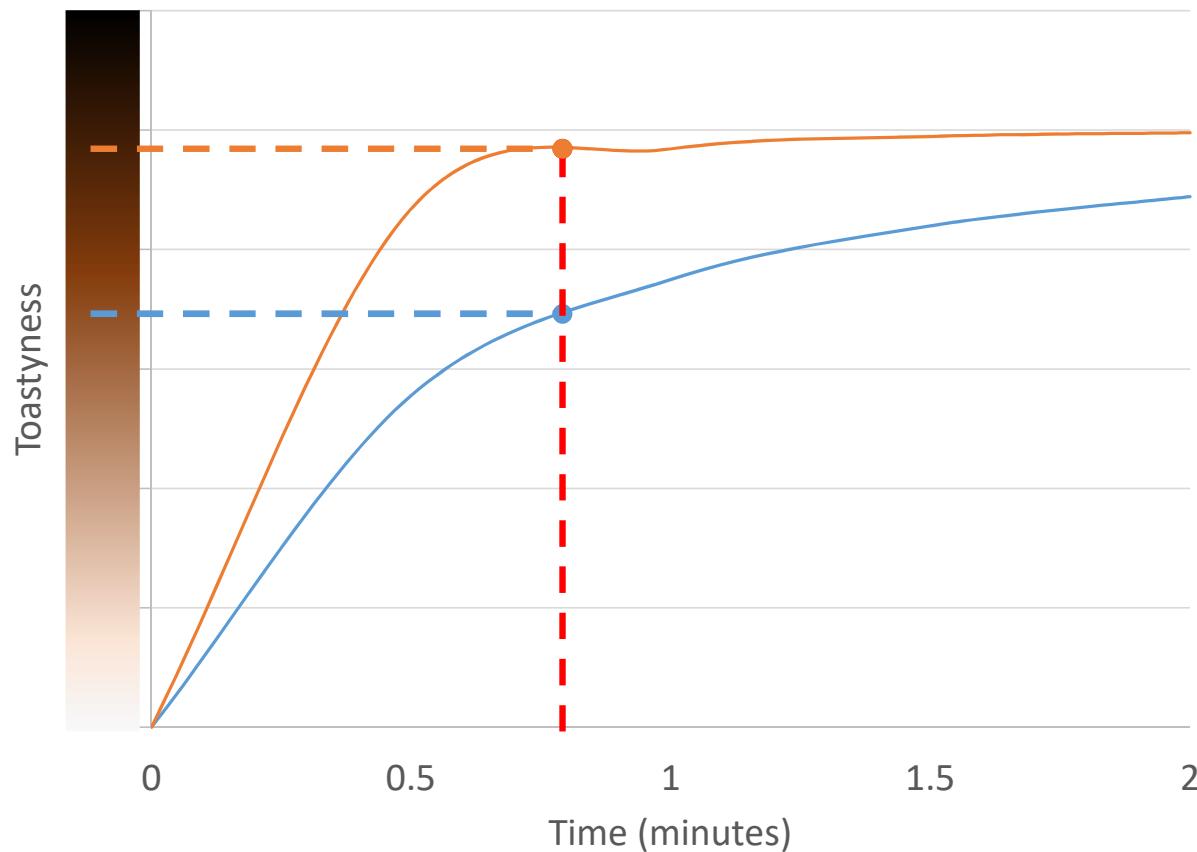
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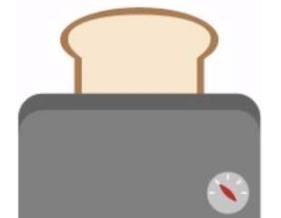
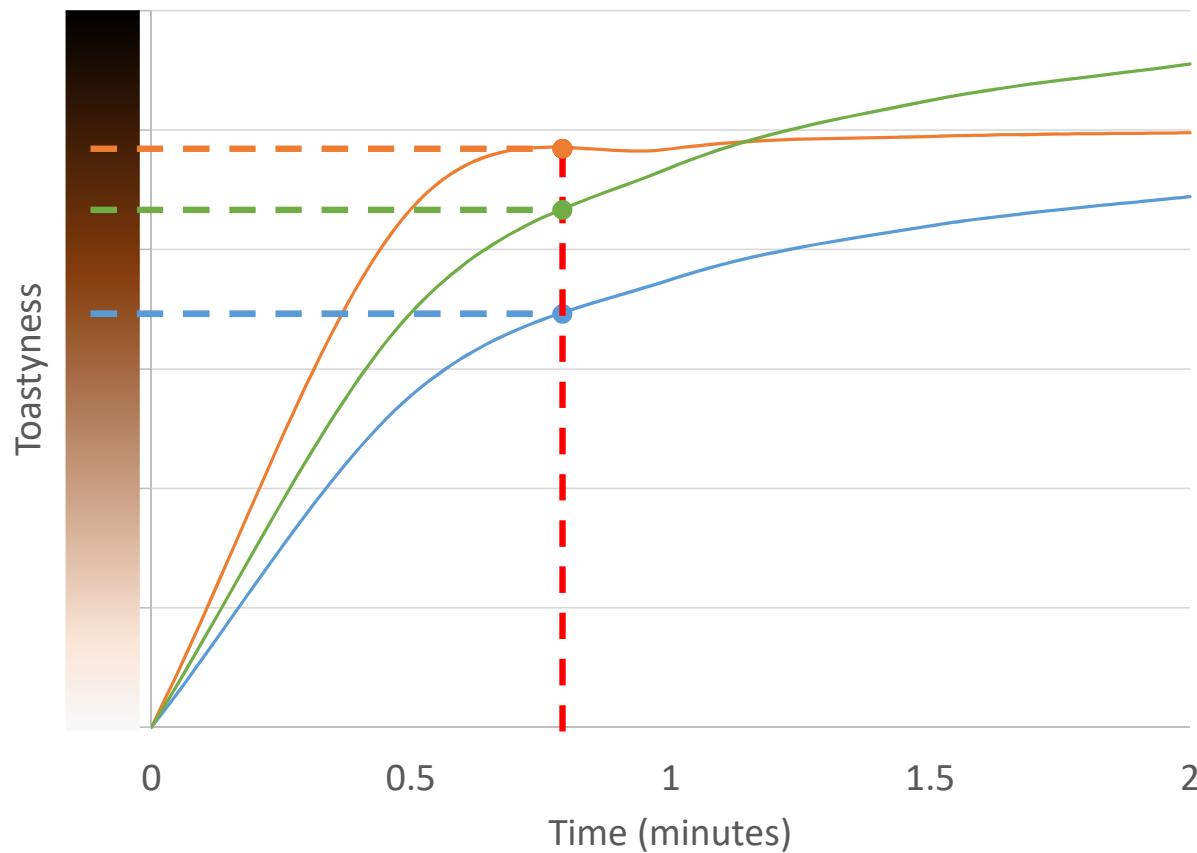
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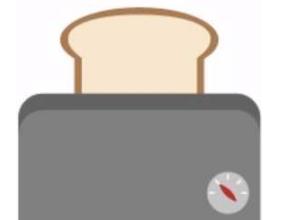
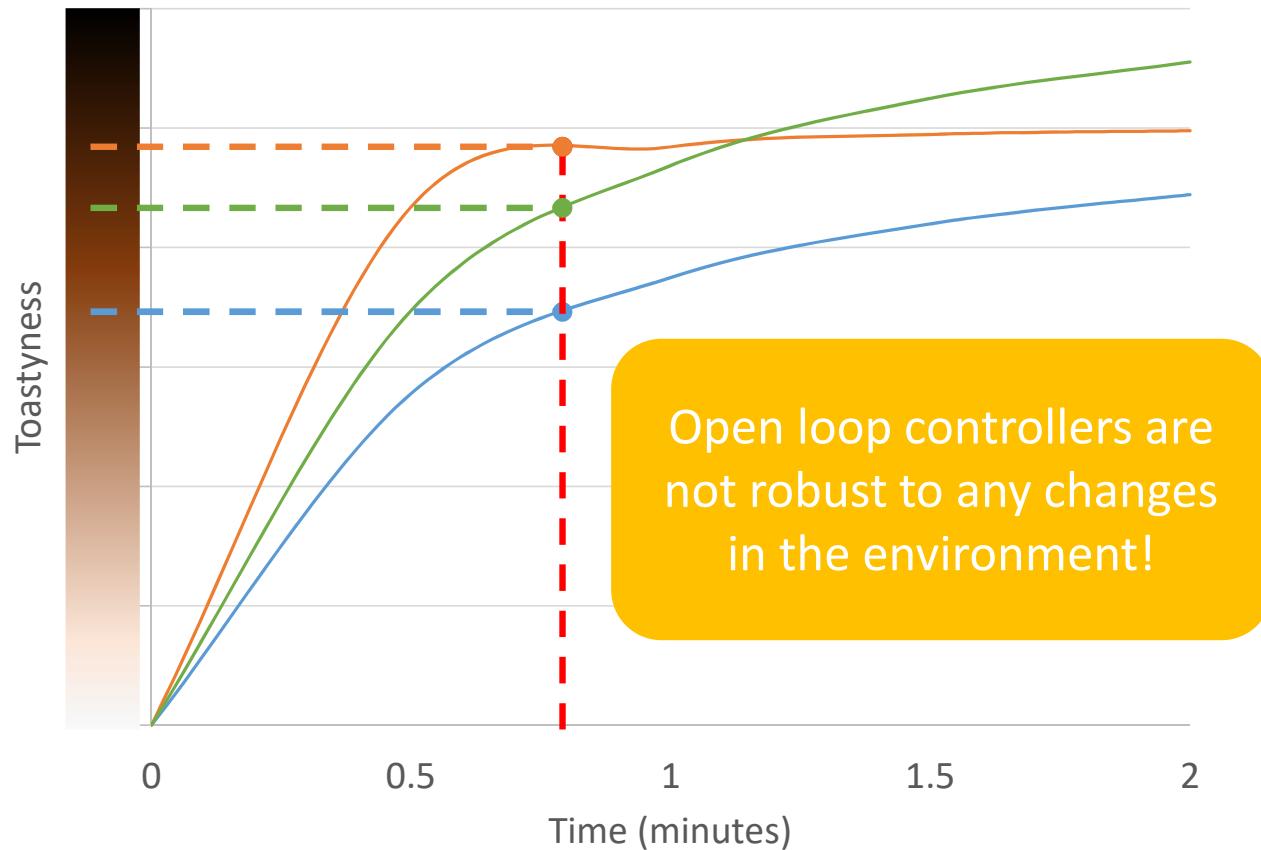
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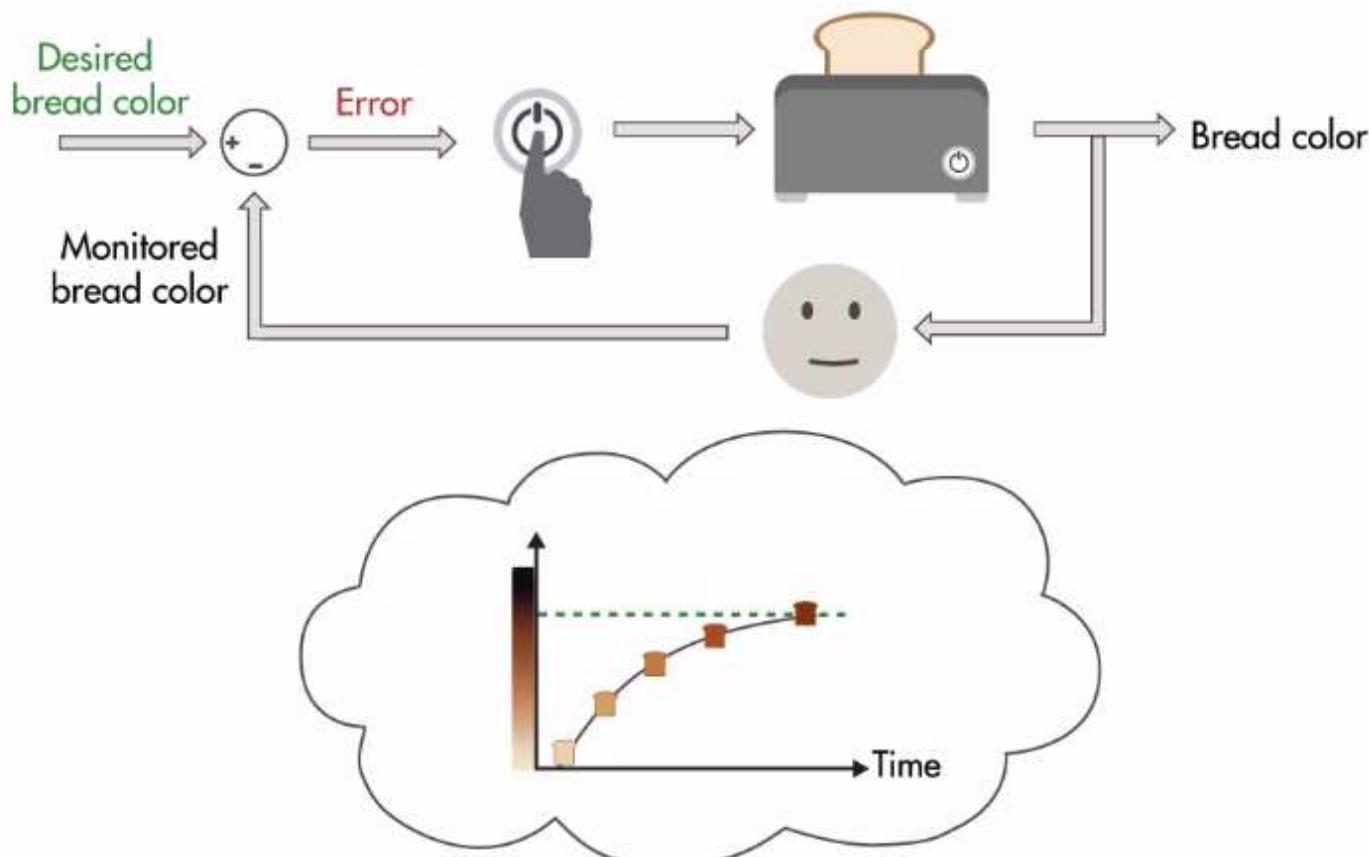
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Feedback (Closed Loop) Control

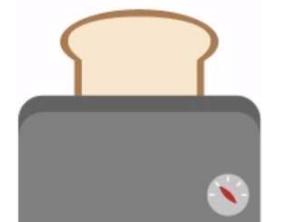
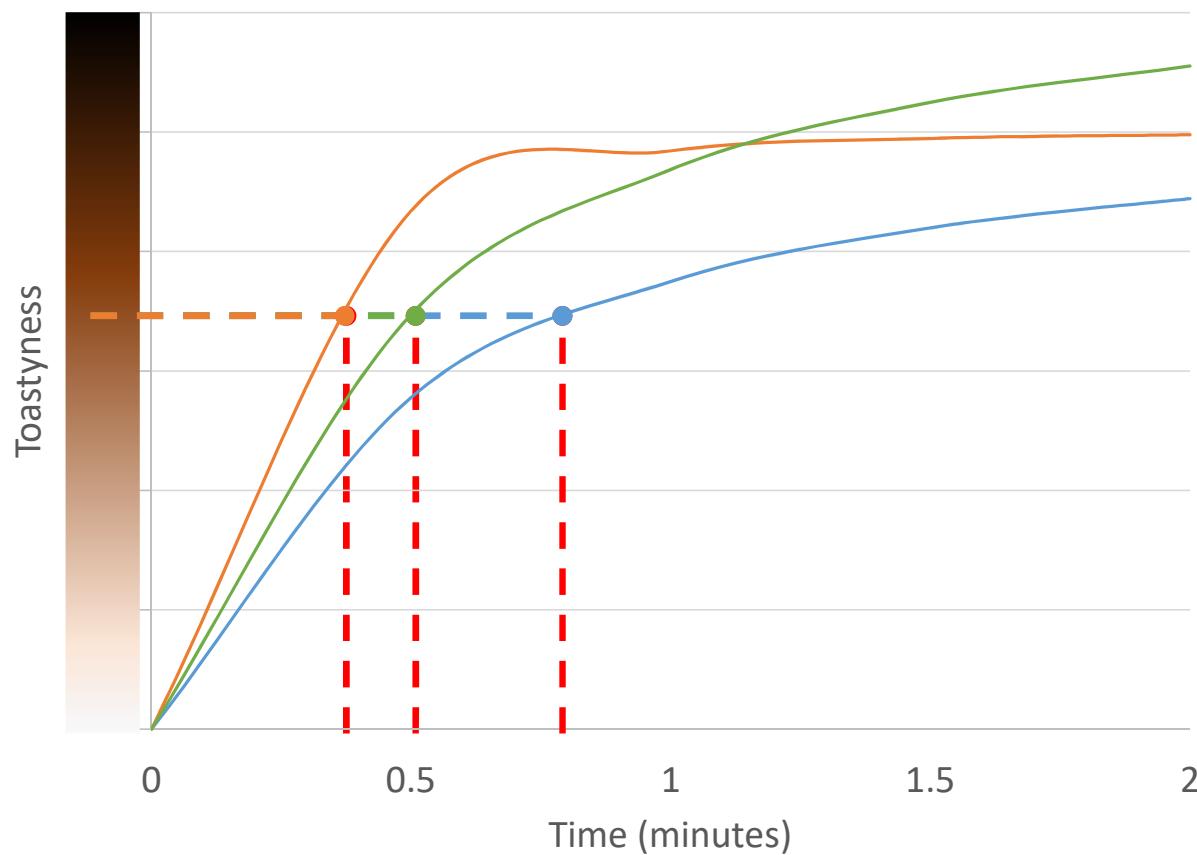
Adapted from MATLAB Control Toolbox



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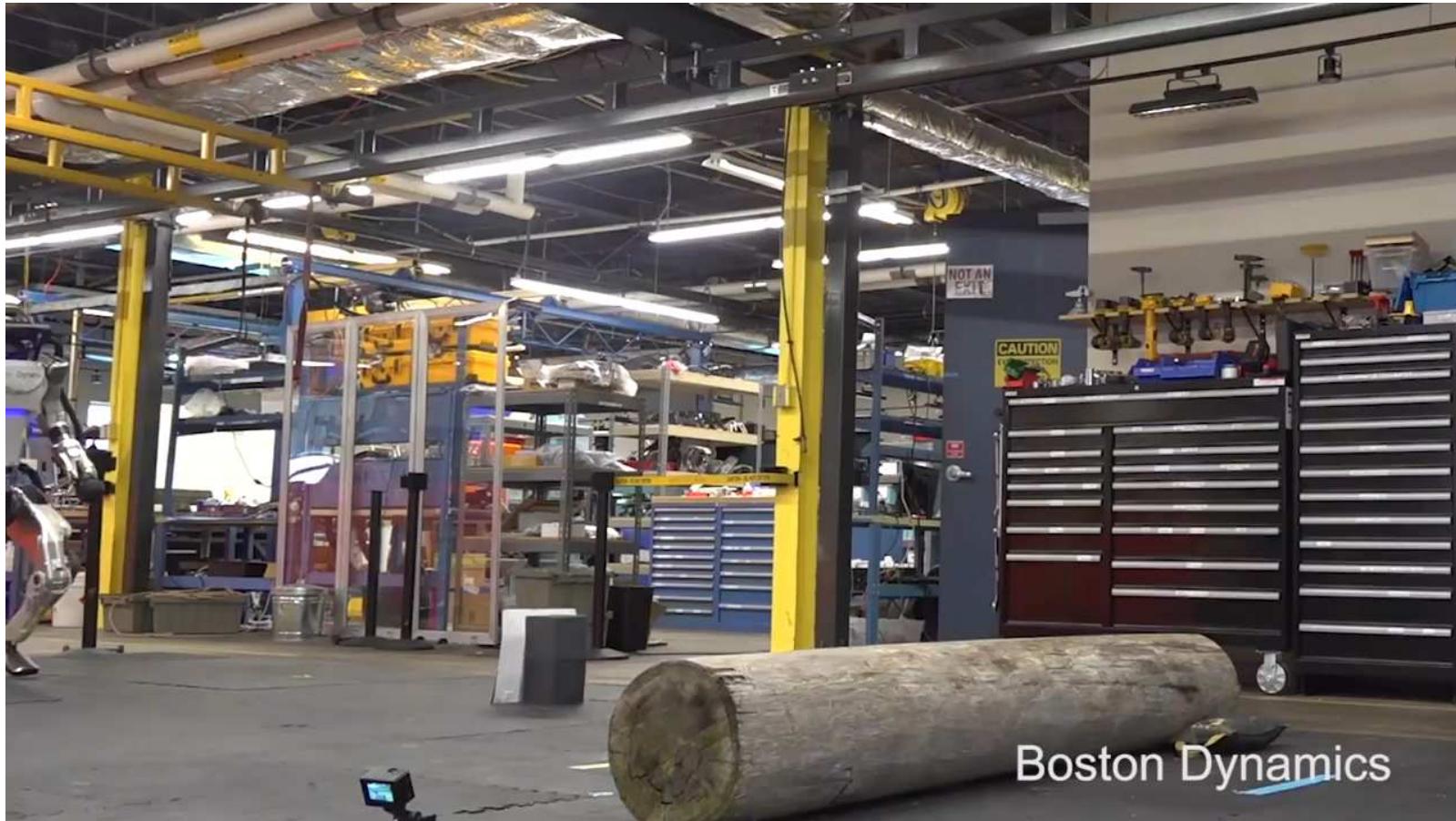
Feedback Control

Adapted from MATLAB Control Toolbox



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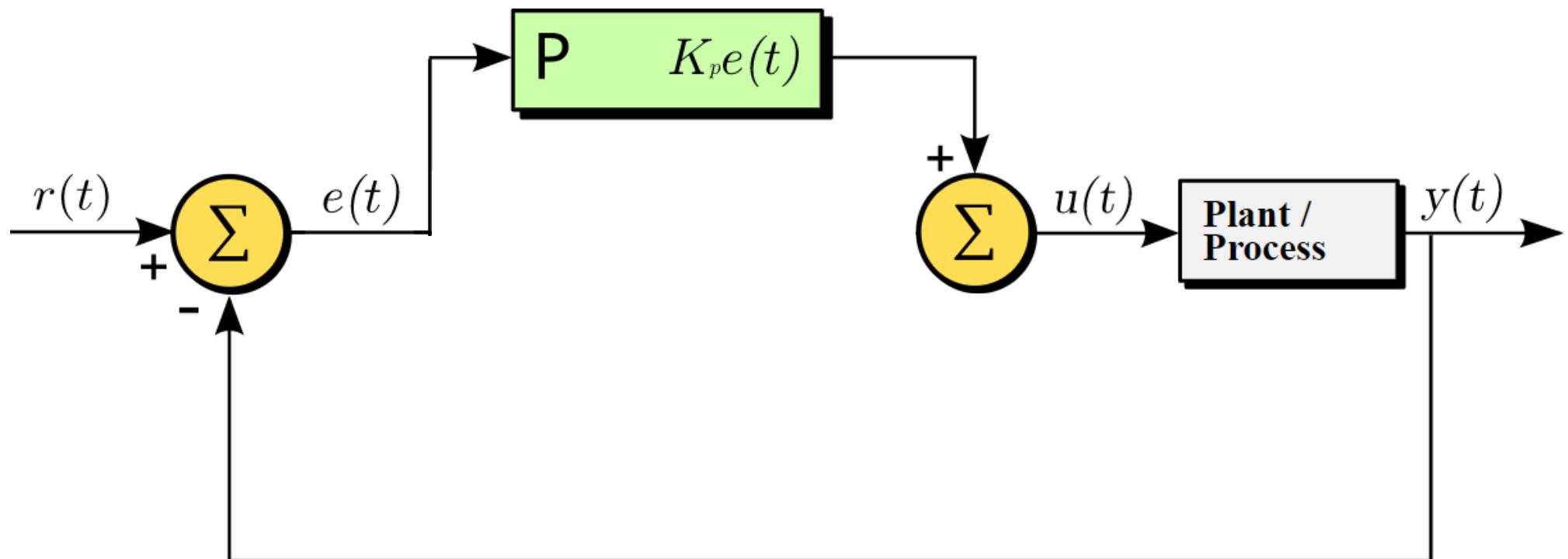
Feedback Control can lead to amazing performance!



6

So how do we do Feedback Control in practice?

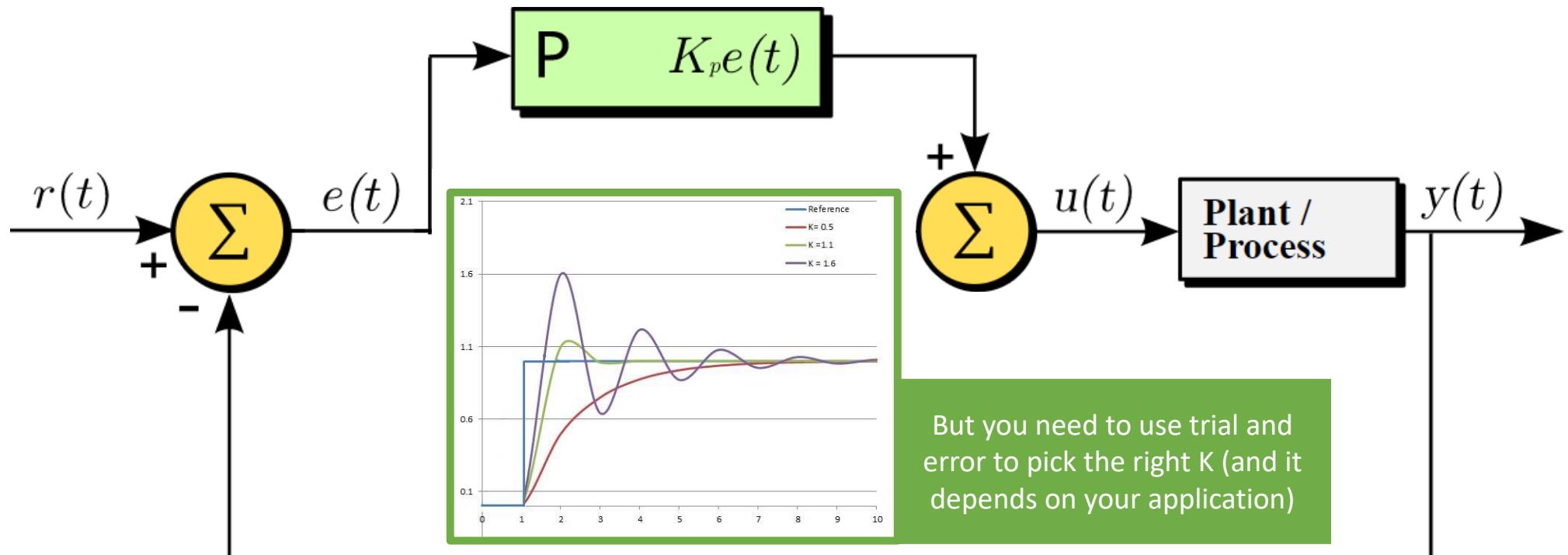
Adapted from Wikipedia



6

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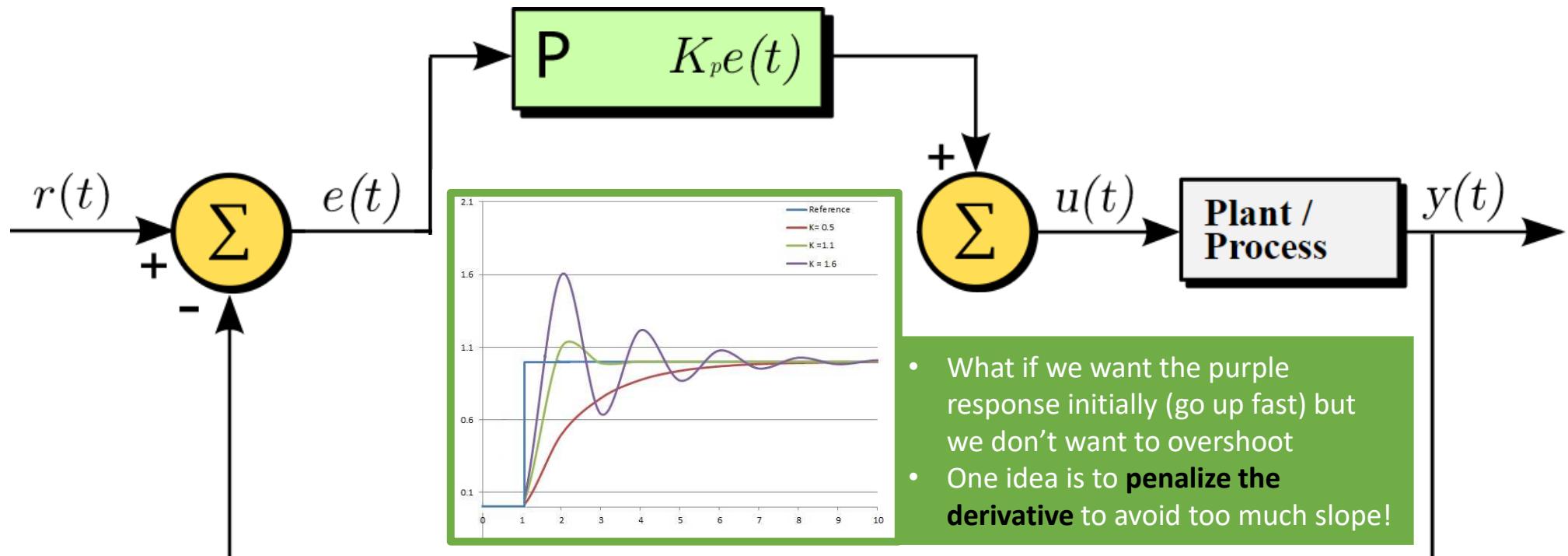
Adapted from Wikipedia



6

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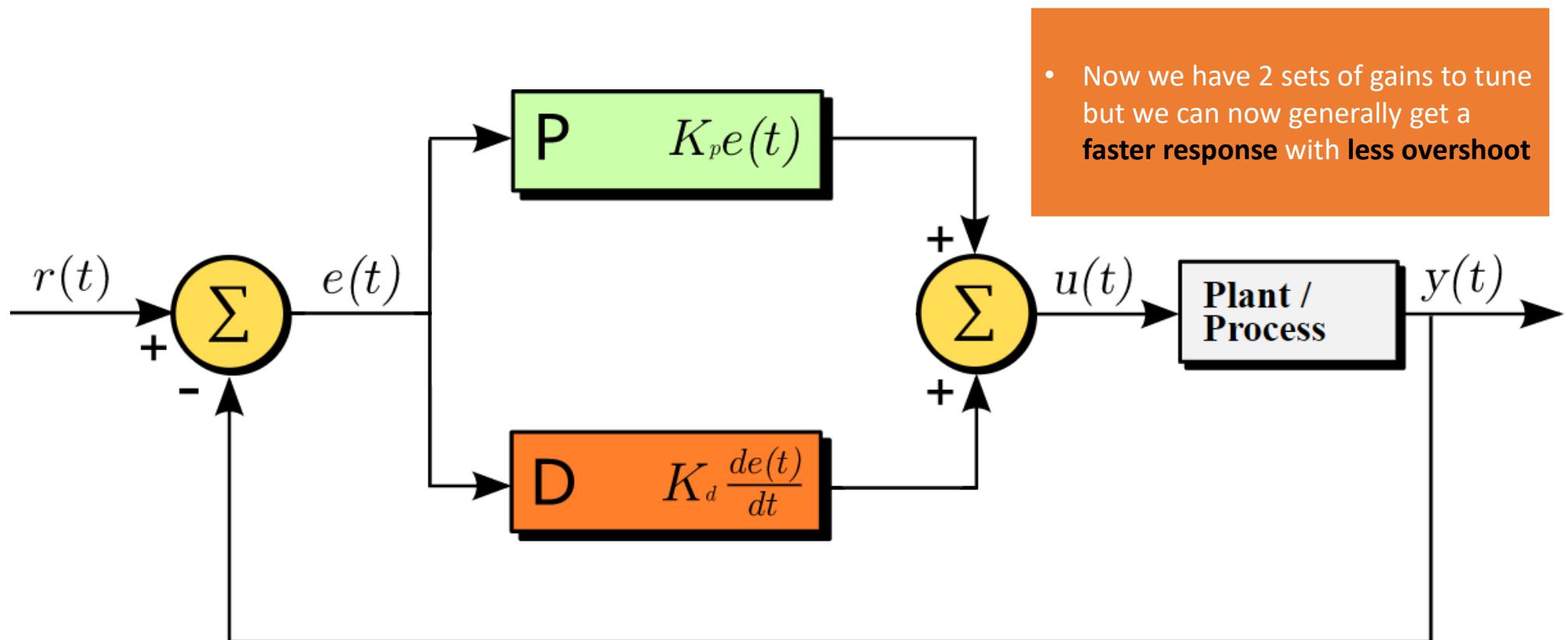
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6

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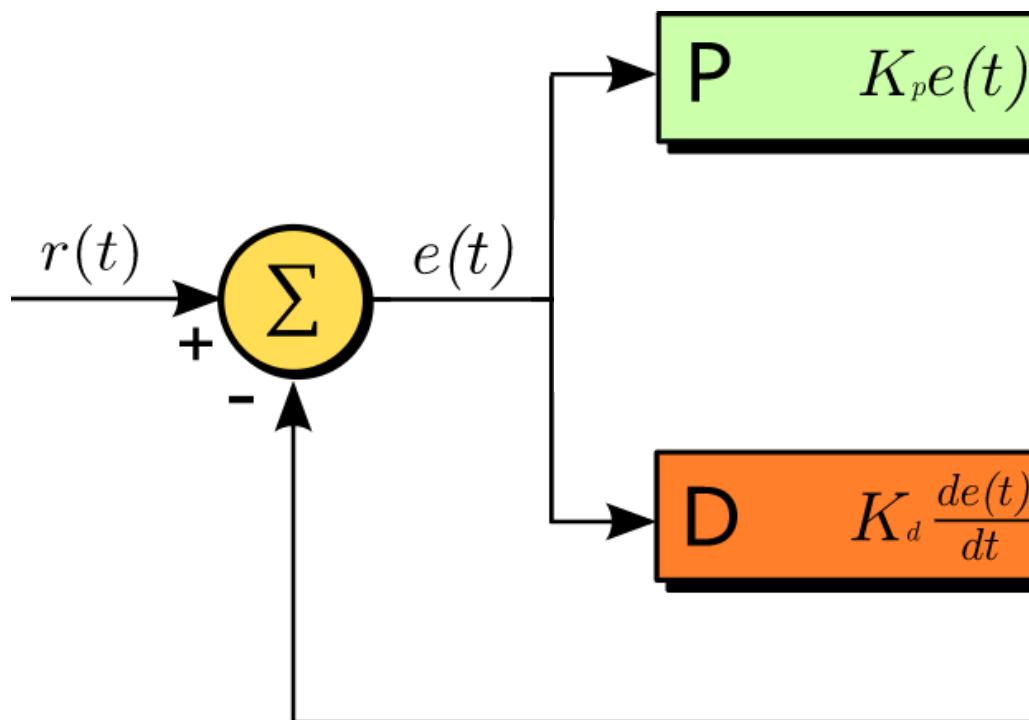
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So how do we do Feedback Control in practice?

Adapted from Wikipedia



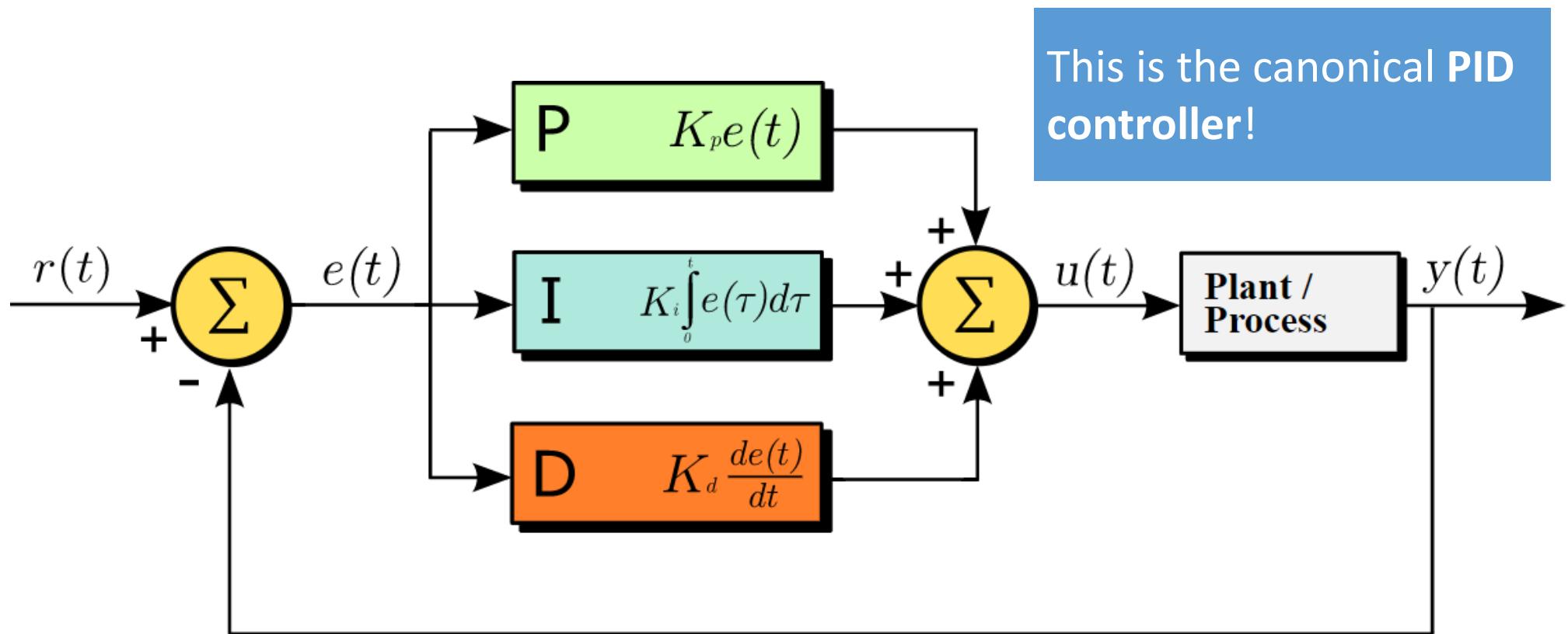
- But what if there is still an error at convergence (aka we want the graph to end at 1.1 exactly)



6

So how do we do Feedback Control in practice?

Adapted from Wikipedia



So how do we do Feedback Control in practice?

Adapted from Wikipedia

Ziegler–Nichols method

From Wikipedia, the free encyclopedia

Main article: PID controller

The **Ziegler–Nichols tuning method** is a heuristic method of tuning a PID controller. It was developed by John G. Ziegler and Nathaniel B. Nichols. It is performed by setting the I (integral) and D (derivative) gains to zero. The "P" (proportional) gain, K_p is then increased (from zero) until it reaches the **ultimate gain** K_u , at which the output of the control loop has stable and consistent oscillations. K_u and the oscillation period T_u are used to set the P, I, and D gains depending on the type of controller used:

Ziegler–Nichols method^[1]

Control Type	K_p	T_i	T_d	K_i	K_d
P	$0.5K_u$	–	–	–	–
PI	$0.45K_u$	$T_u/1.2$	–	$0.54K_u/T_u$	–
PD	$0.8K_u$	–	$T_u/8$	–	$K_u T_u/10$
classic PID ^[2]	$0.6K_u$	$T_u/2$	$T_u/8$	$1.2K_u/T_u$	$3K_u T_u/40$
Pessen Integral Rule ^[2]	$7K_u/10$	$2T_u/5$	$3T_u/20$	$1.75K_u/T_u$	$21K_u T_u/200$
some overshoot ^[2]	$K_u/3$	$T_u/2$	$T_u/3$	$0.666K_u/T_u$	$K_u T_u/9$
no overshoot ^[2]	$K_u/5$	$T_u/2$	$T_u/3$	$(2/5)K_u/T_u$	$K_u T_u/15$

Tuning PID gains is an art and there is a whole literature on a variety of methods to get particular types of response curves!

6

PID controllers work really well in practice



6

Tuning gains is hard and non-intuitive is there a better way?

6

Tuning gains is hard and non-intuitive is there a better way?

Of course there is or I wouldn't
need the transition slide!

6

The LQR Controller

What if instead of specifying gains we can specify a **cost function** we want to achieve...

6

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Maybe something like track the desired state but don't use too much energy to do it?

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The LQR Controller

What if instead of specifying gains we can specify a **cost function** we want to achieve...

Maybe something like track the desired state but don't use too much energy to do it?

Instead of tuning gains we can tune cost weights (Q, R) which are often more intuitive

$$L(x, u) = \underbrace{(x - x_g)^T Q (x - x_g)}_{\text{Deviation of the state from some goal state}} + \underbrace{u^T R u}_{\text{Effort (torque)}}$$

Deviation of the state from some goal state

Effort (torque)

6

The LQR Controller

It turns out if we minimize this quadratic cost over time with a linear model of the dynamics

$$\begin{aligned} \min_{x,u} \quad & \sum_{k=0}^N (x_k - x_g)^T Q (x_k - x_g) + u_k^T R u_k \\ \text{s.t. } \quad & x_{k+1} = Ax_k + Bu_k \end{aligned}$$



There is a closed form solution to the optimal feedback controller!
(Riccati Equation)

$$u_k = -K_k x_k$$

6

The LQR Controller

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s.t. $x_{k+1} = Ax_k + Bu_k$

This is used widely in practice!

There is a closed form solution to the optimal feedback controller!
(Riccati Equation)

$$u_k = -K_k x_k$$

6

We can also use LQR in RRT as a better metric of “distance” and the feedback controller as the best “extend”

Finite-horizon, discrete-time LQR [edit]

For a discrete-time linear system described by: ^[1]

$$x_{k+1} = Ax_k + Bu_k$$

with a performance index defined as:

$$J = x_N^T Q x_N + \sum_{k=0}^{N-1} (x_k^T Q x_k + u_k^T R u_k + 2x_k^T N u_k)$$

the optimal control sequence minimizing the performance index is given by:

$$u_k = -F_k x_k$$

where:

$$F_k = (R + B^T P_{k+1} B)^{-1} (B^T P_{k+1} A + N^T)$$

Feedback Controller for “Extend”

and P_k is found iteratively backwards in time by the dynamic Riccati equation:

$$P_{k-1} = A^T P_k A - (A^T P_k B + N) (R + B^T P_k B)^{-1} (B^T P_k A + N^T) + Q$$

Cost-to-Go as “Distance Metric”

from terminal condition $P_N = Q$. Note that u_N is not defined, since x is driven to its final state x_N by $Ax_{N-1} + Bu_{N-1}$.

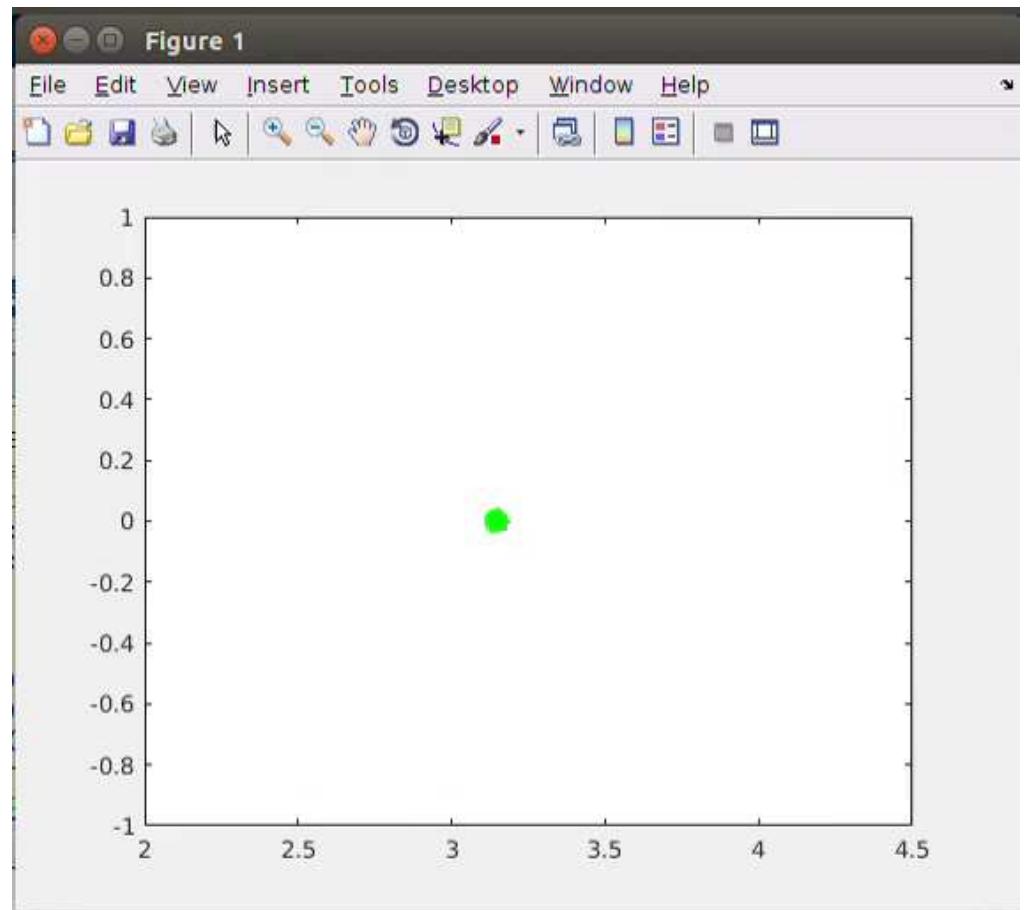
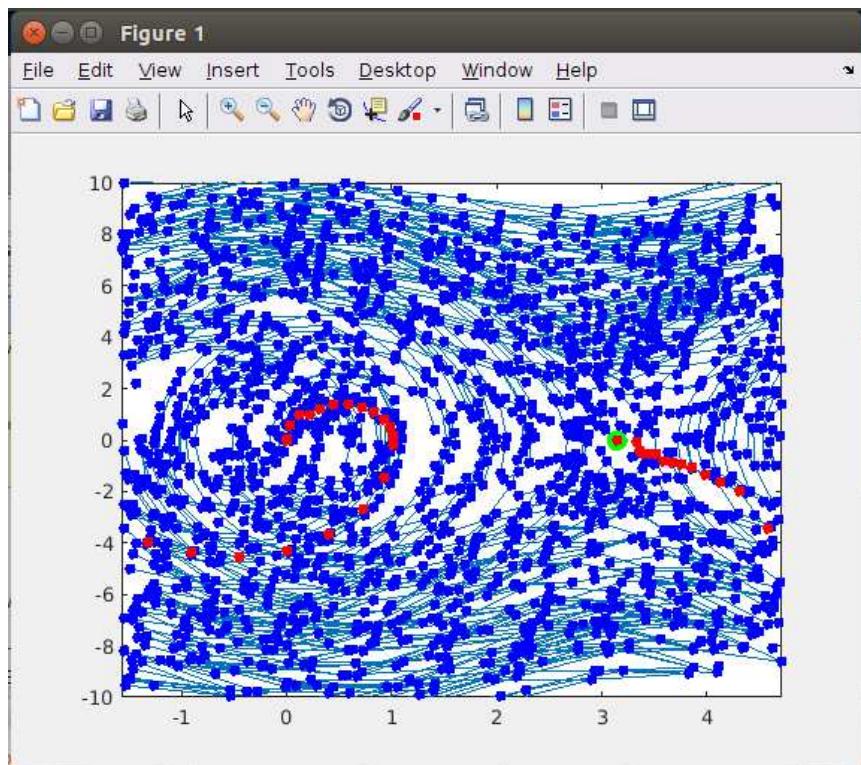
Bellman Updates

$$V_N(x_N) = c(x_N, u_N)$$

$$V_{k+1}(x) = \min_a c(x, u) + V_k(f(x, u))$$

6

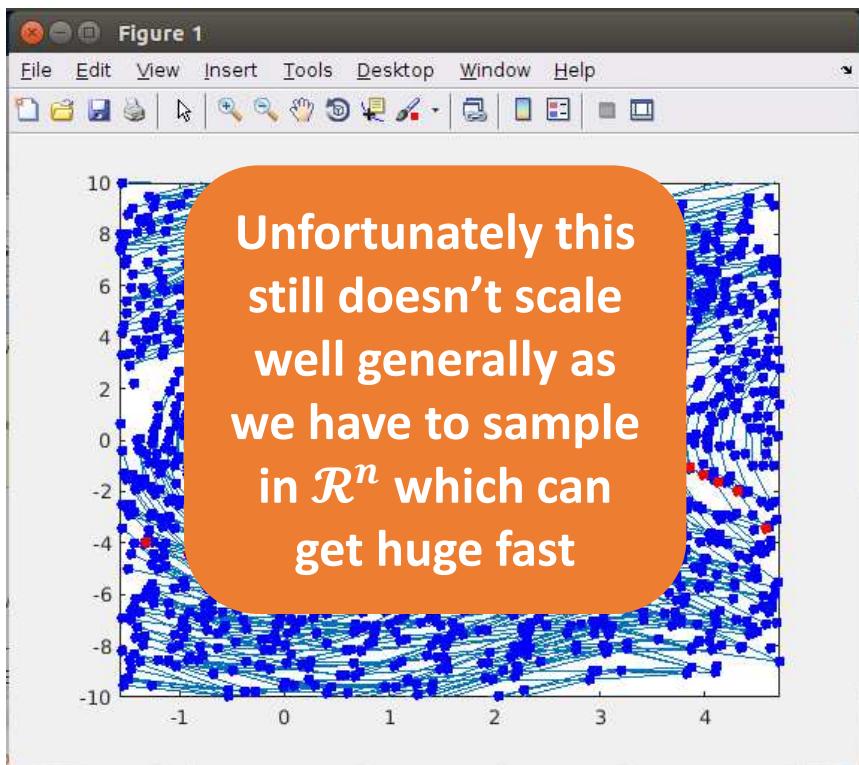
We can also use LQR in RRT as a better metric of “distance” and the feedback controller as the best “extend”



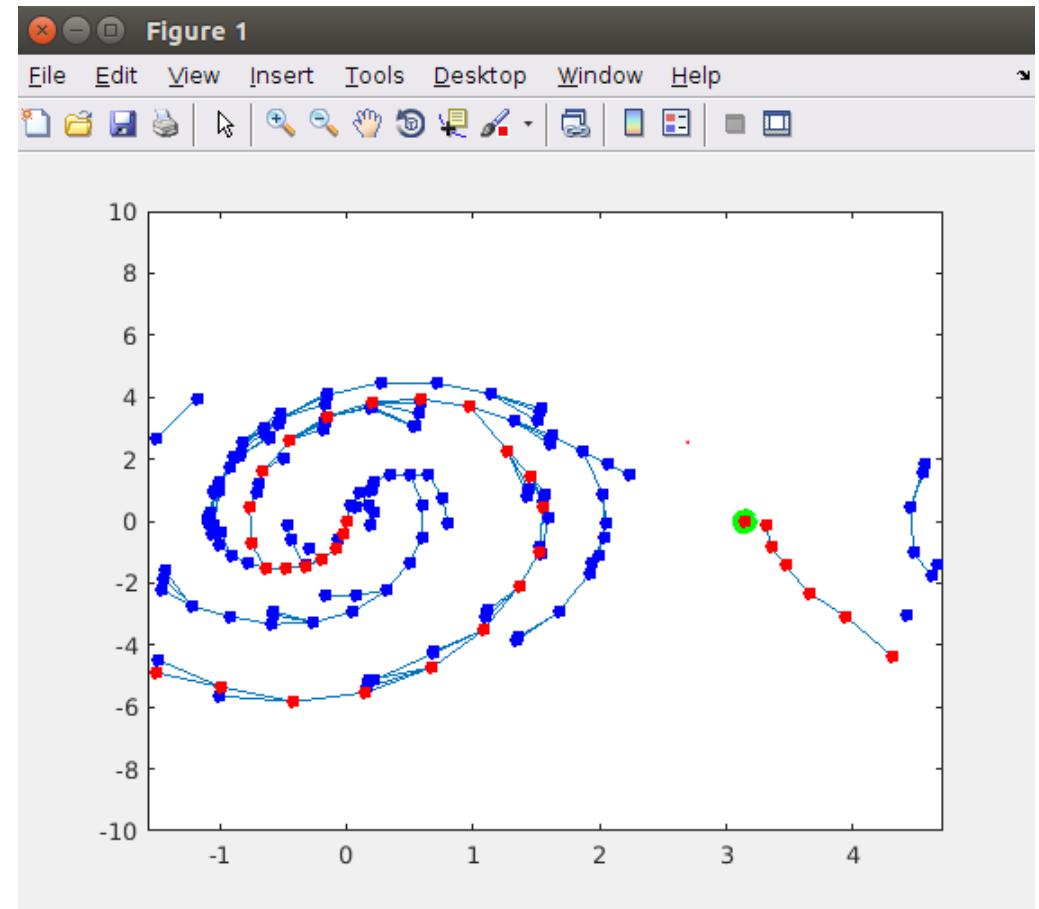
[Perez et. al. LQR-RRT*]

6

We can use LQR in RRT as a better metric of “distance” and the feedback controller as the best “extend”



[Perez et. al. LQR-RRT*]



6

So what have we learned so far?

1. Real world autonomous systems need to use **Feedback Control**
2. **PID** controllers are simple and effective but require **gain tuning**
3. **LQR** controllers allow for **cost function design** instead
4. PID and LQR require a plan to already exist and are simply **tracking controllers**

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6

So what have we learned so far?

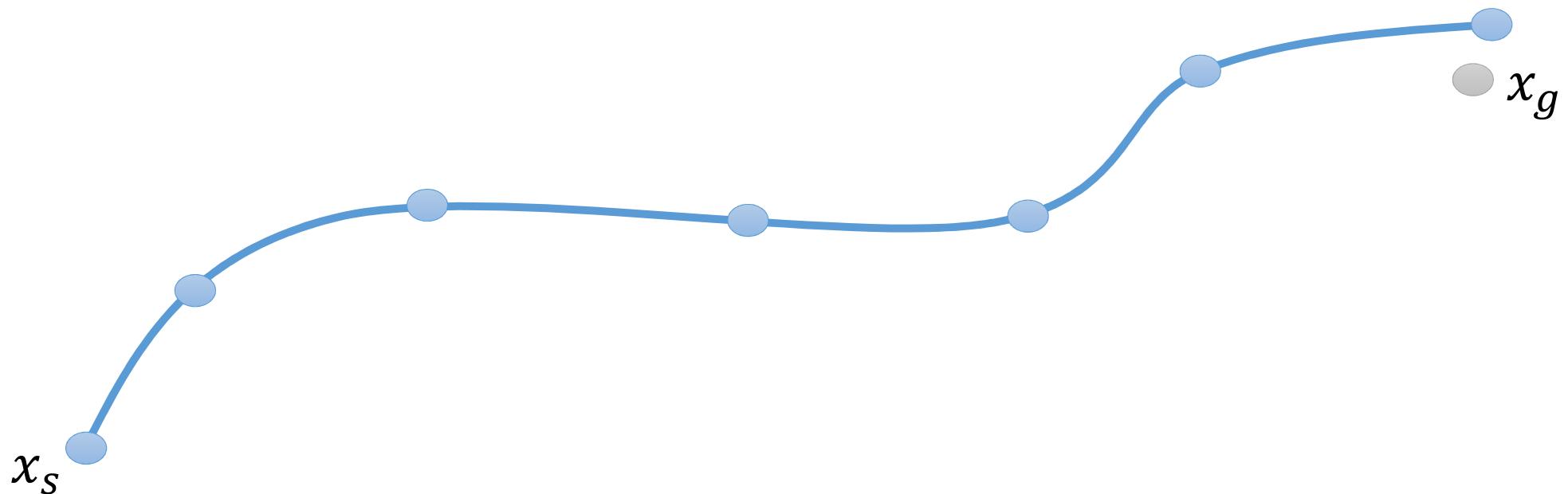
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- But what happens if we **deviate** so much from our original plan that it is **no longer valid**? How do we initiate **re-plans**?

This is an open unsolved problem!

6

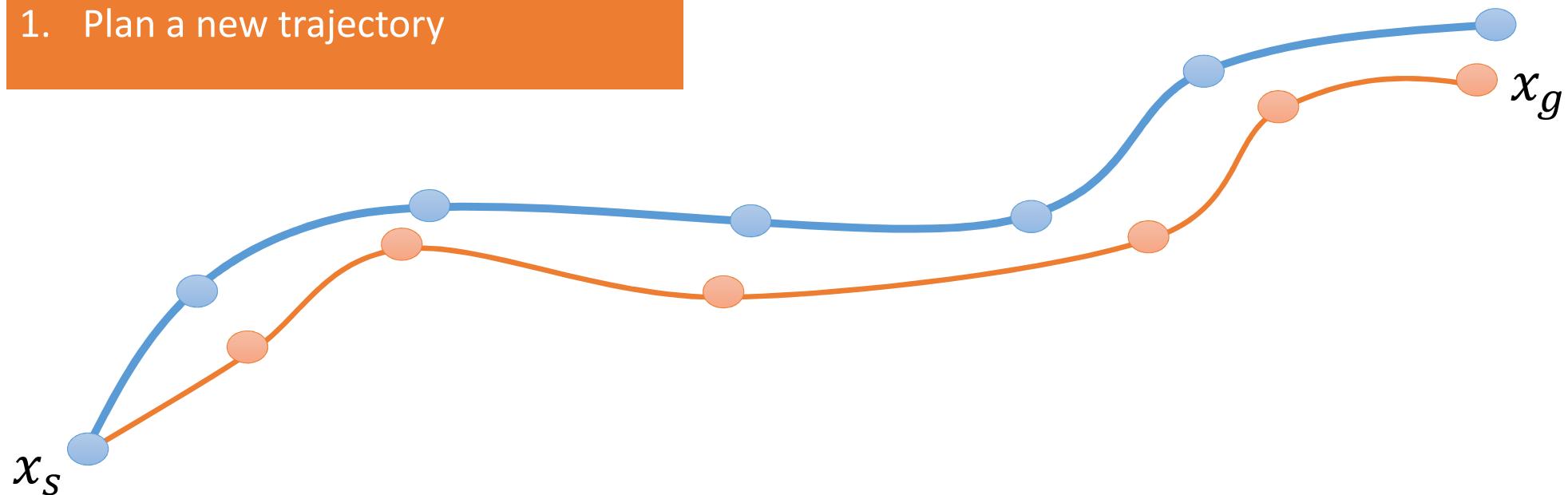
Model Predictive Control: re-planning fast enough that the plan becomes the controller!



6

Model Predictive Control: re-planning fast enough that the plan becomes the controller!

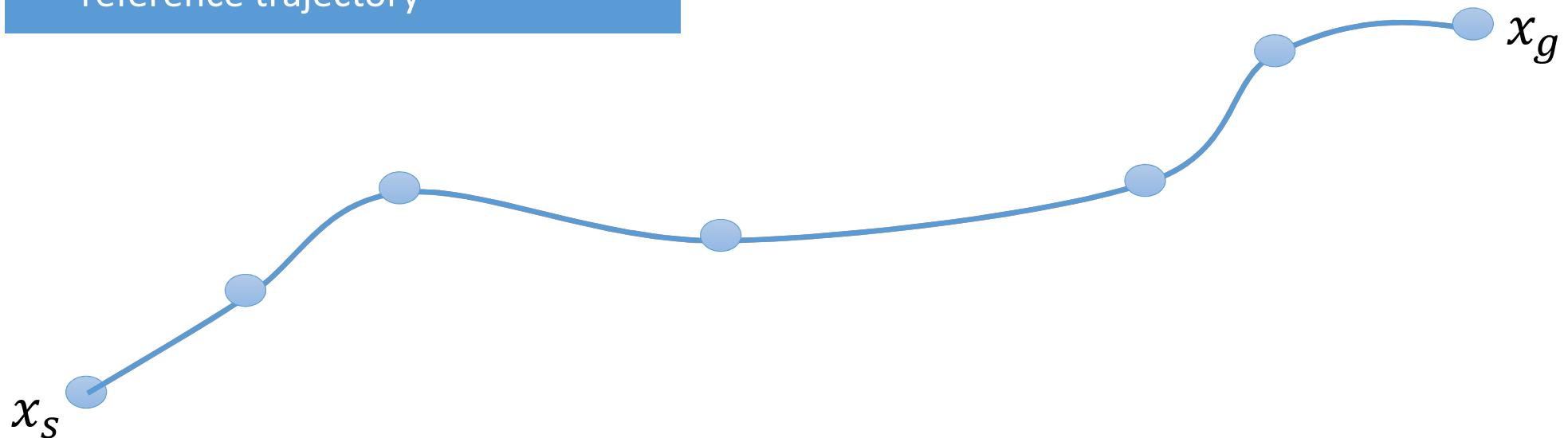
1. Plan a new trajectory



6

Model Predictive Control (MPC): re-planning fast enough that the plan becomes the controller!

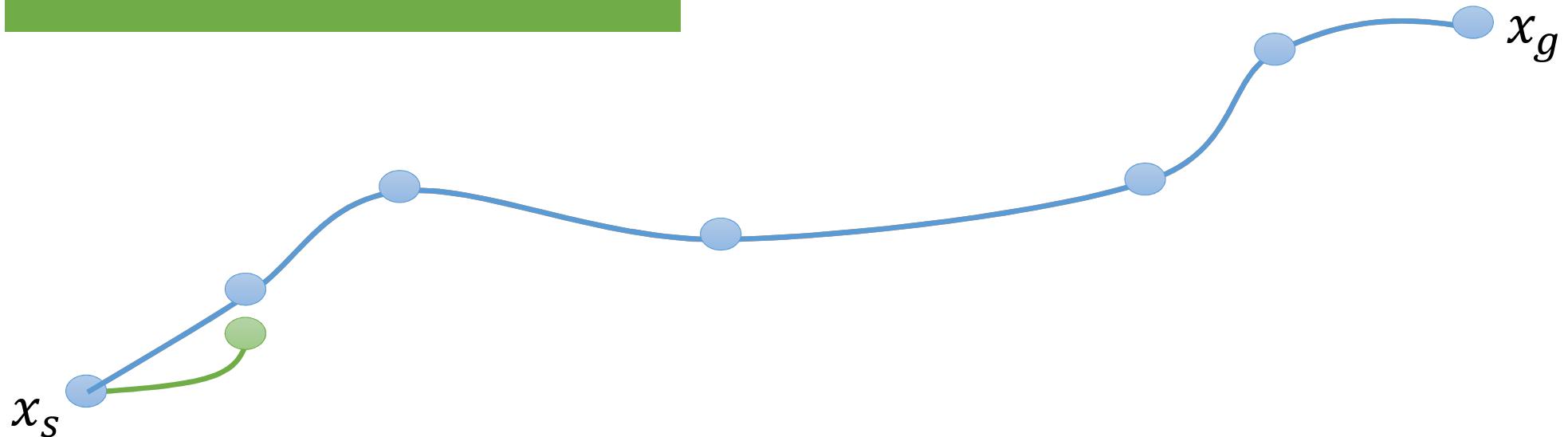
2. The new plan becomes the reference trajectory



6

Model Predictive Control (MPC): re-planning fast enough that the plan becomes the controller!

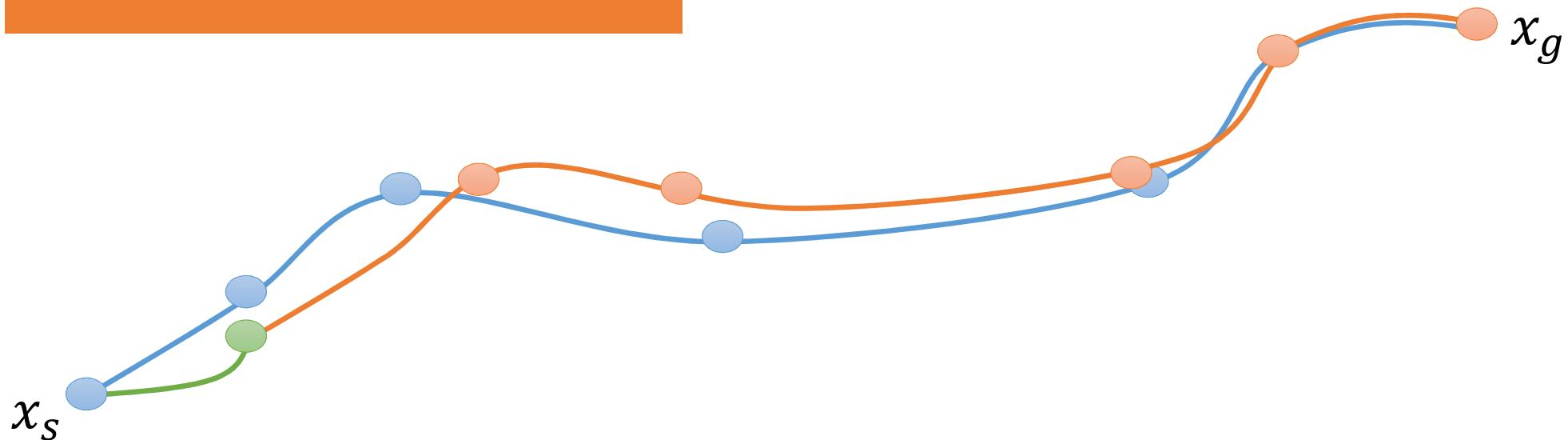
3. Execute the first step of the plan



6

Model Predictive Control (MPC): re-planning fast enough that the plan becomes the controller!

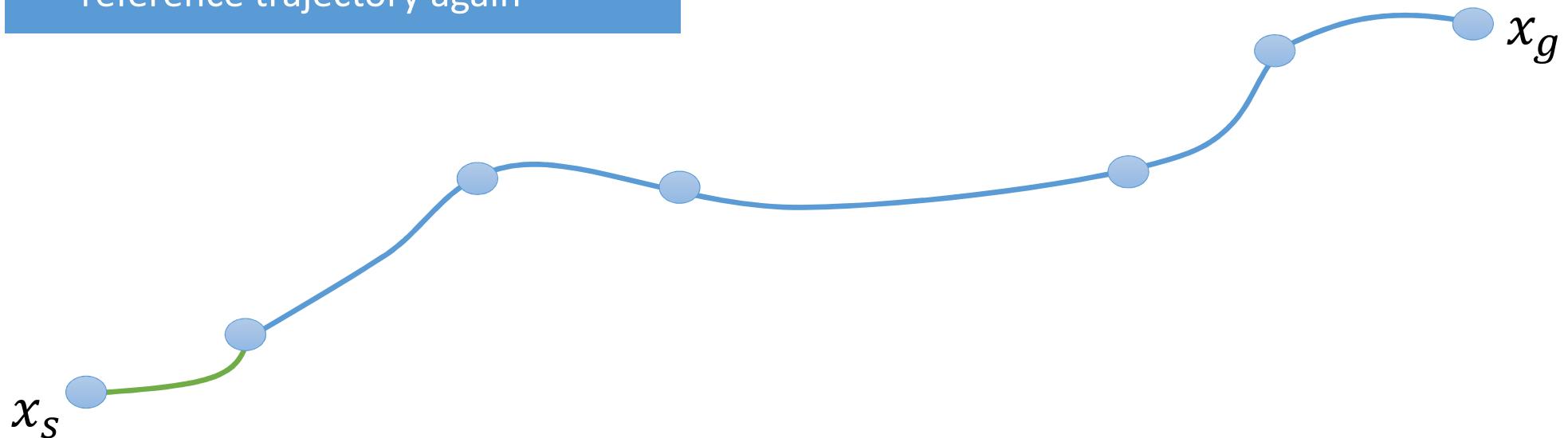
1. Re-plan based on that step



6

Model Predictive Control (MPC): re-planning fast enough that the plan becomes the controller!

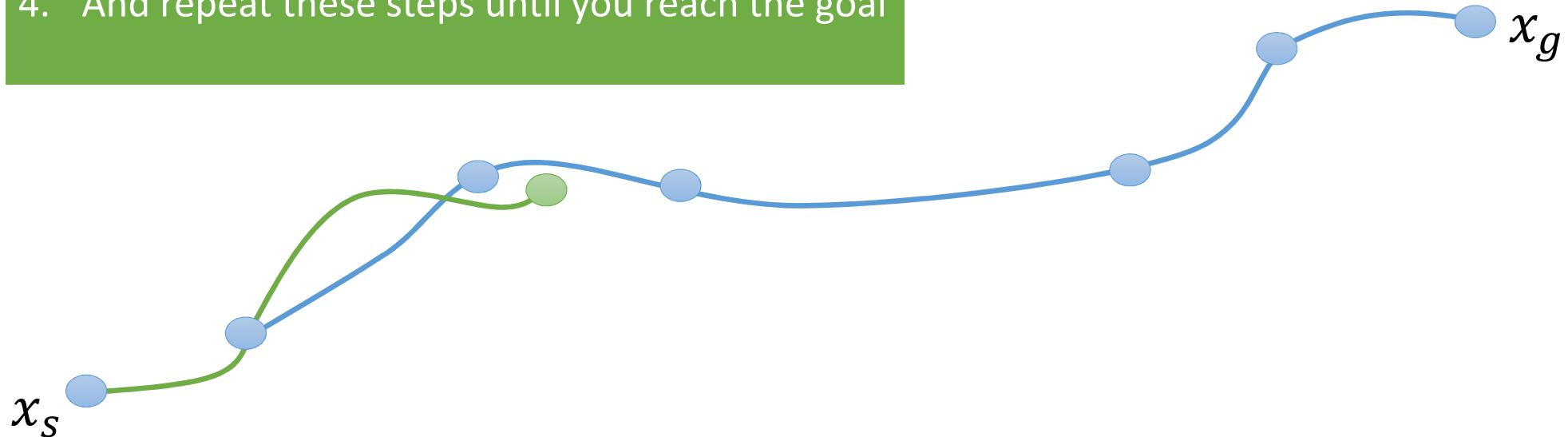
2. The new plan becomes the reference trajectory again



6

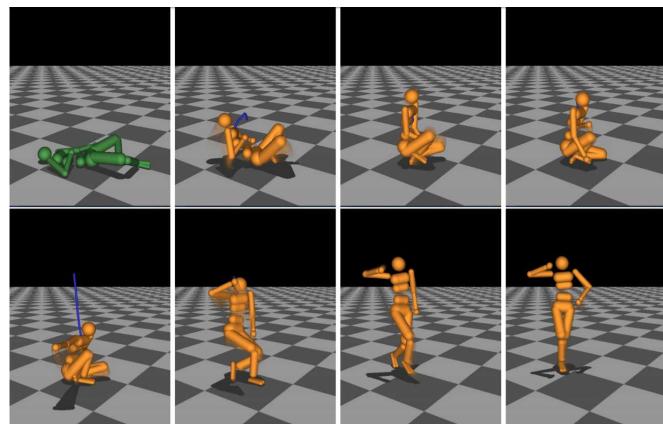
Model Predictive Control (MPC): re-planning fast enough that the plan becomes the controller!

- 3. Execute the first step of the new plan again
- 4. And repeat these steps until you reach the goal

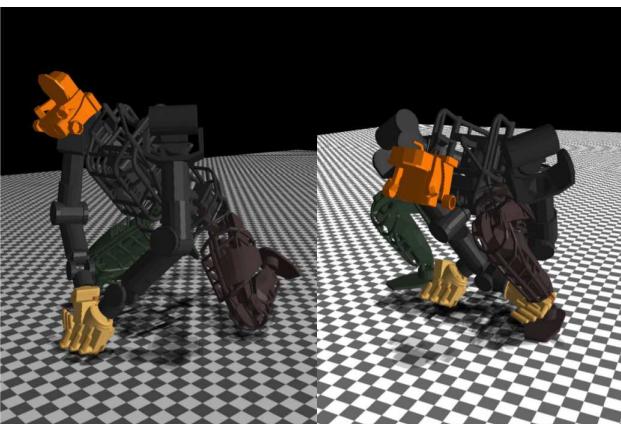


6

Recently MPC has been used in a variety of complex autonomous systems in simulation and on physical robots



[Tassa et. al. IROS 2012]



[Erez et. al. Humanoids 2013]



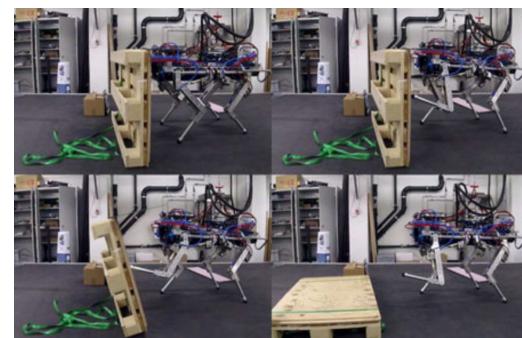
[Koenemann et. al. IROS 2015]



[Neunert et. al. ICRA 2016]



[Neunert et. al. Humanoids 2017]



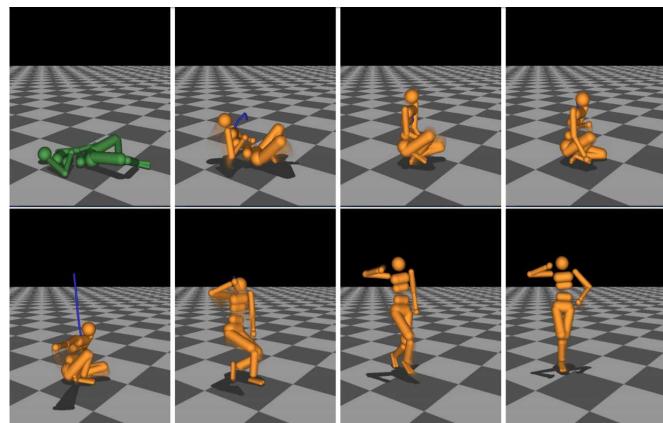
[Farshidian et. al. IEEE RAL 2017]



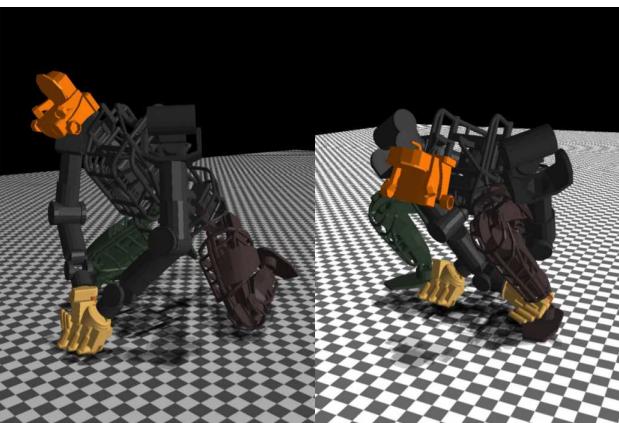
[Plancher et. al. WAFR 2018]
[Plancher et. al. ICRA 2019]

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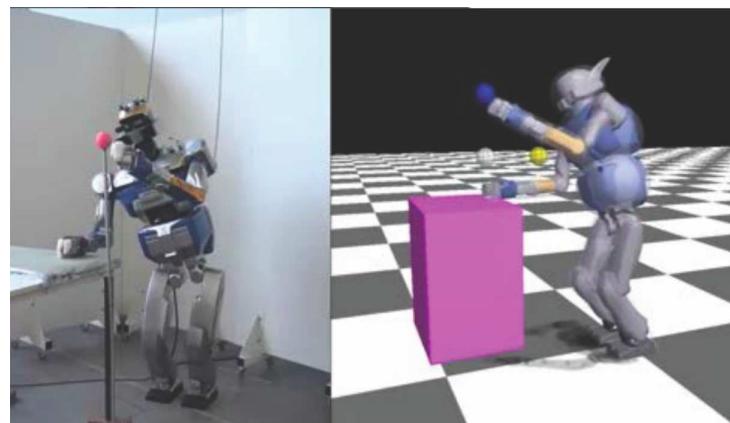
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I will go into far more detail on this when
I present my recent work during the
sample paper presentations!

[Neunert et. al. Humanoids 2017]

[Farshidian et. al. IEEE RAL 2017]



[Plancher et. al. WAFR 2018]

[Plancher et. al. ICRA 2019]

6

Practical Challenges for Control: Contact

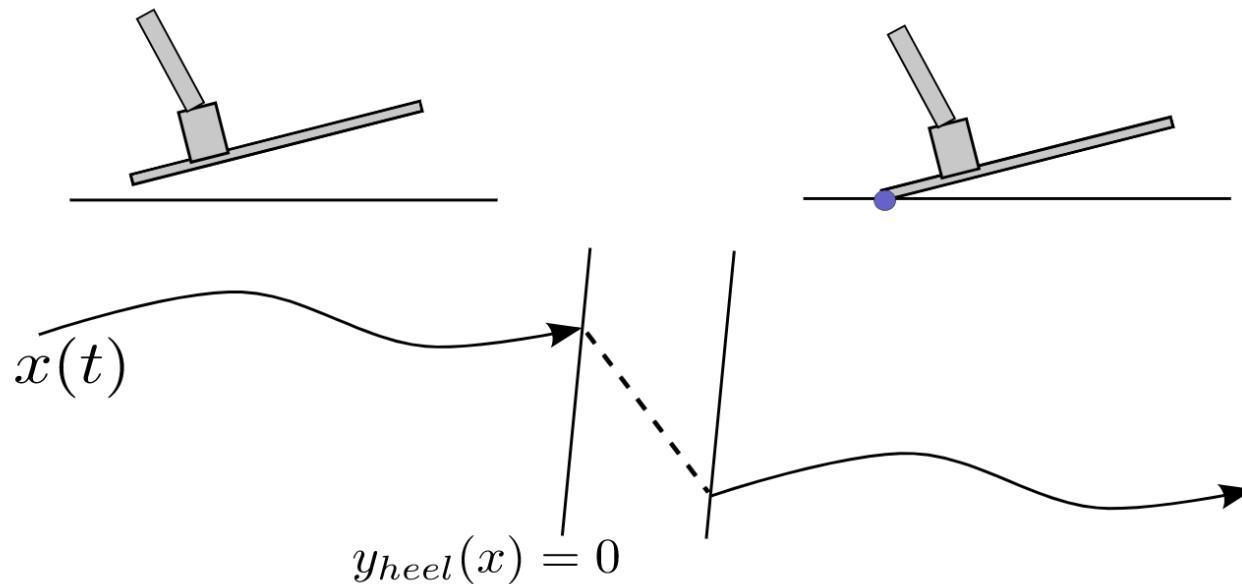


Figure 17.1 - Modeling contact as a hybrid system.

6

Practical Challenges for Control: Contact

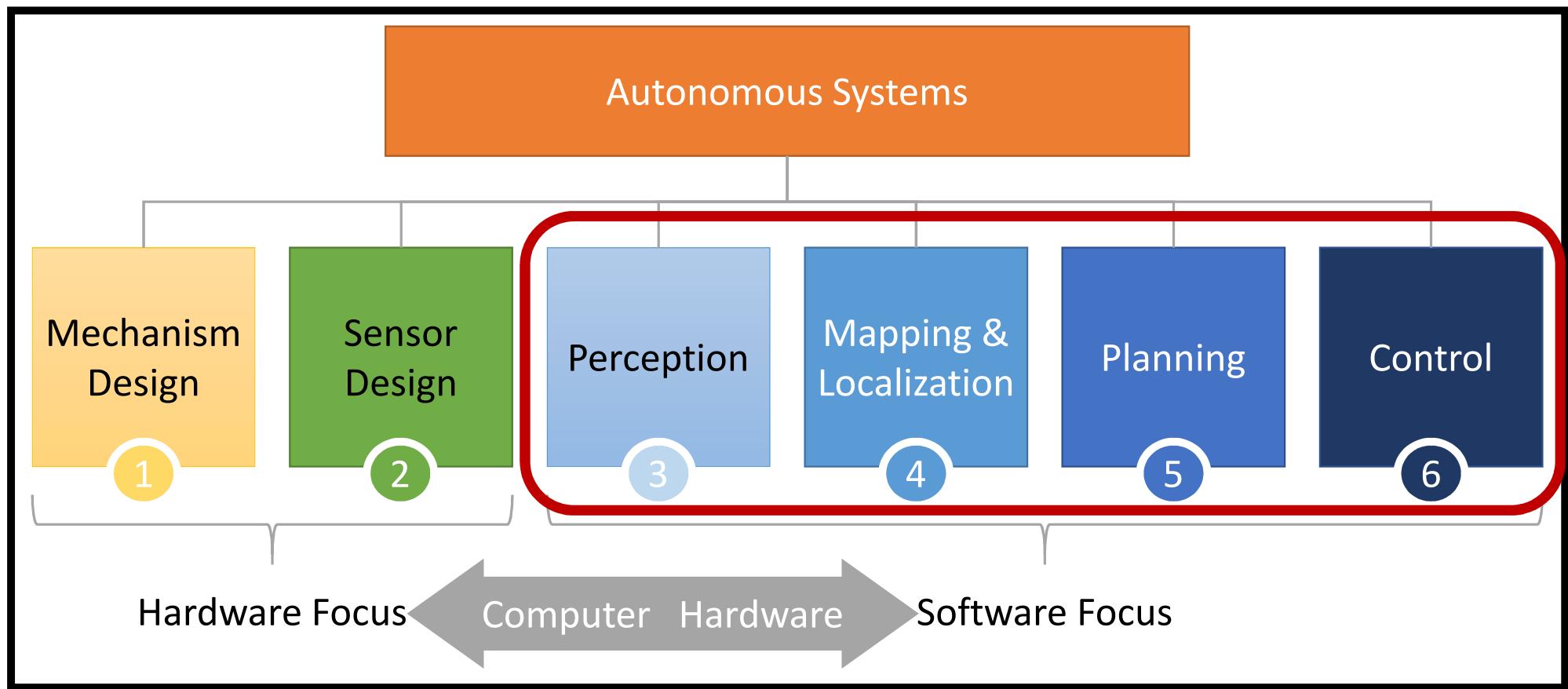


6

Key Takeaways:

1. Real world autonomous systems need to use **Feedback Control**
 2. **Tracking controllers** allow for simple control design and are quite effective in practice. Two common controllers are:
 1. PID with gain tuning
 2. LQR with cost function design
 3. Using **MPC** allows for the planner to be the controller which enables more **sophisticated control strategies**
 4. Contact is really hard!
-

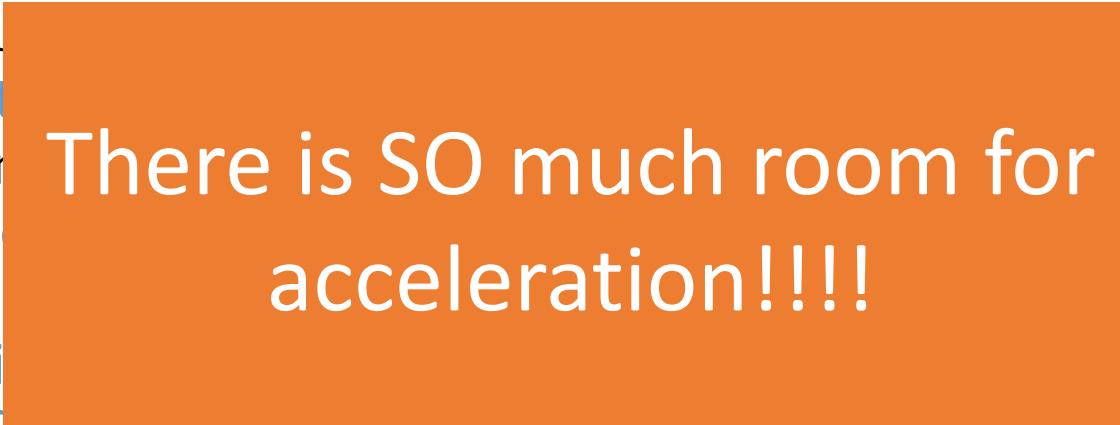
Autonomous Systems / Robotics is a BIG space



Key Takeaways:

1. NNs running on **accelerator chips** solve most perception problems
 2. The **Kalman/Particle Filter** uses probability to solve the localization problem but **modeling and/or approximations** are needed to run online
 3. Mapping quickly becomes a **memory storage problem**
 4. **Stereo Depth** and **Visual Odometry** also need acceleration to run online
 5. Robot planning involves both **task and configuration spaces**
 6. **Collision checking** can be expensive
 7. Sample Based Planners (**PRM, RRT, RRT***) leverage random search and are **probabilistically complete** but do not scale well to high dimensions
 8. Trajectory Optimization finds **locally optimal** paths but is **not complete or robust** and (often) solved with (slow) **off the shelf solvers**
 9. Tracking controllers (**PID, LQR**) work well in practice but **MPC** is a much more powerful (and computationally expensive) approach
 10. Contact is hard and we (sometimes) use **simpler models** for tractability
-

Key Takeaways:

1. NNs running on **accelerator chips** solve most perception problems
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 3. Mapping qu...
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 5. Robot planning is used to run online
 6. **Collision checks** are used to run online
 7. Sample Based Planning is used to search and plan in high dimensions
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 9. Tracking controllers (**PID, LQR**) work well in practice but **MPC** is a much more powerful (and computationally expensive) approach
 10. Contact is hard and we (sometimes) use **simpler models** for tractability
- 
- There is SO much room for acceleration!!!!

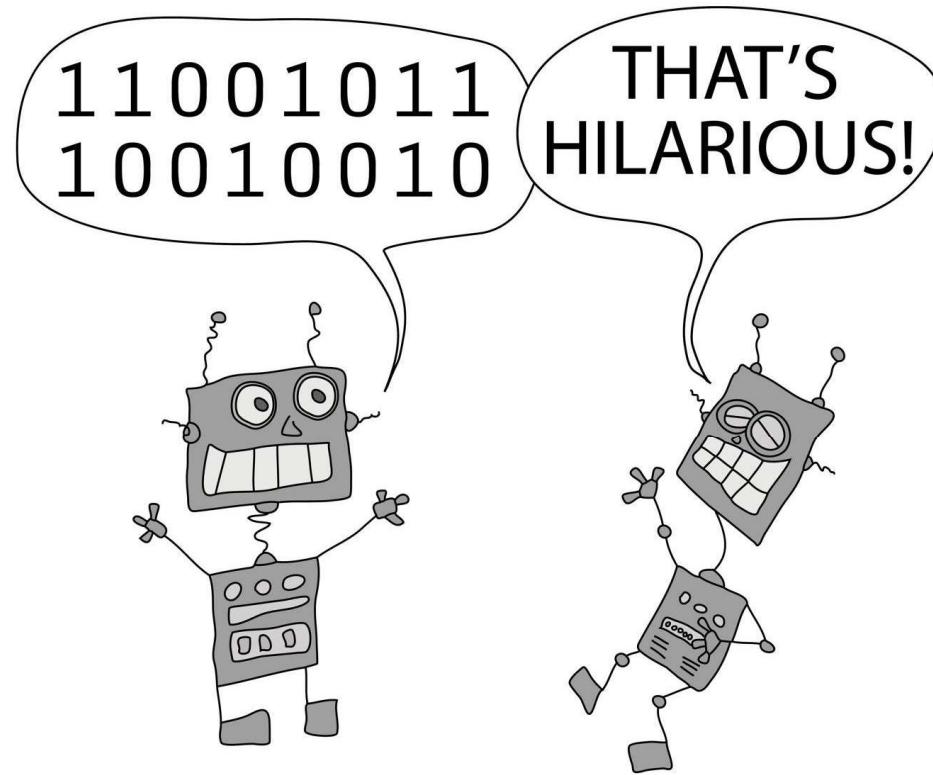
And that's everything!

<http://bit.ly/CS249-Feedback-L2>



CS 249r: Special Topics in Edge Computing

Intro to Autonomous Systems / Robotics Wrap-Up



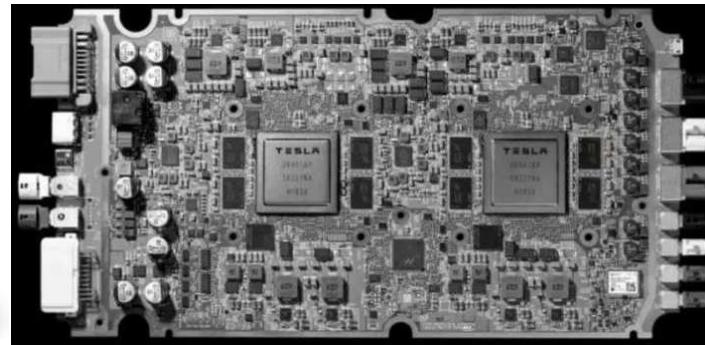
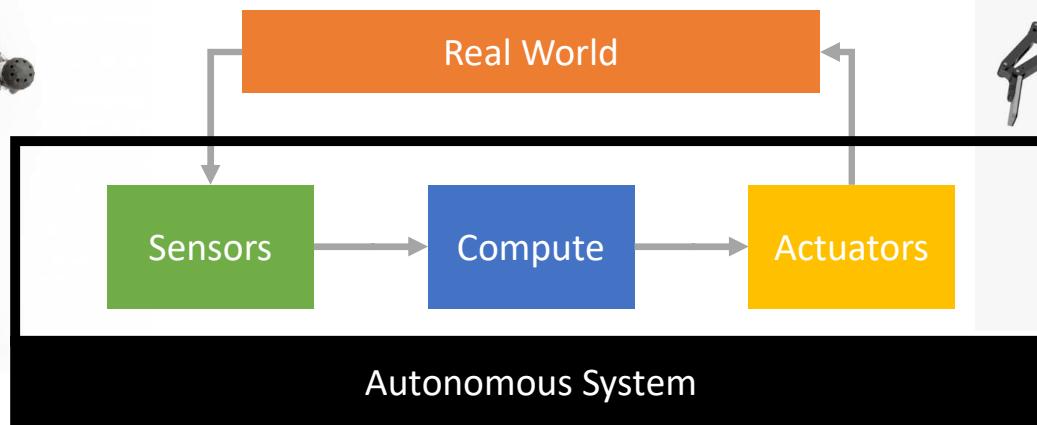
Brian Plancher
Fall 2019



The goal for the next couple of lectures is to develop a **high level** understanding of:

1. What is an autonomous system
 2. Key **problems** and **constraints** for autonomous systems
 3. Some of the most important (classes of) **algorithms** in robotics
 - A. The **model based** vs. **model free** tradeoff
 - B. The **online** vs **offline** tradeoff
 - C. The **no free lunch** theorem and the need for **approximations**
 4. How **computer systems / architecture** design has and can play a role in improving autonomous systems
-

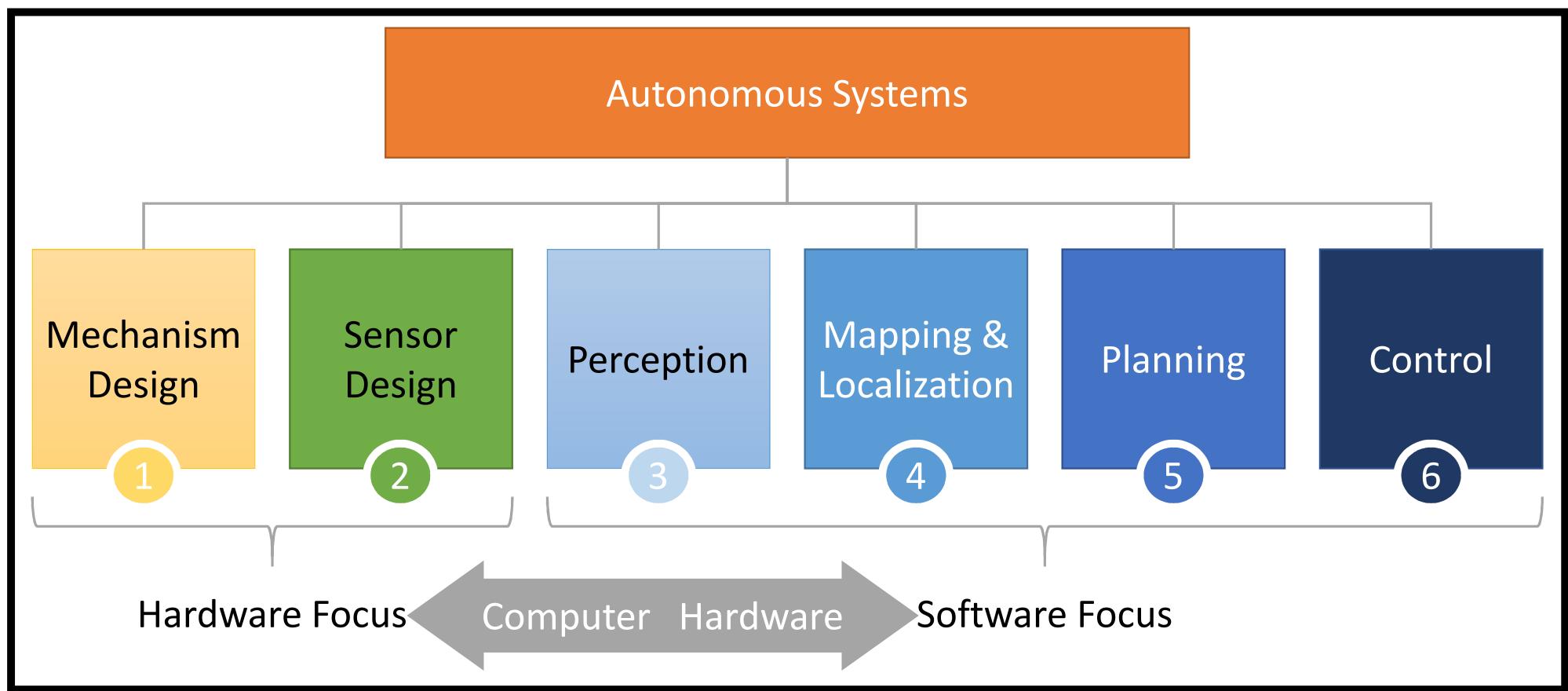
What do we mean by an Autonomous System?



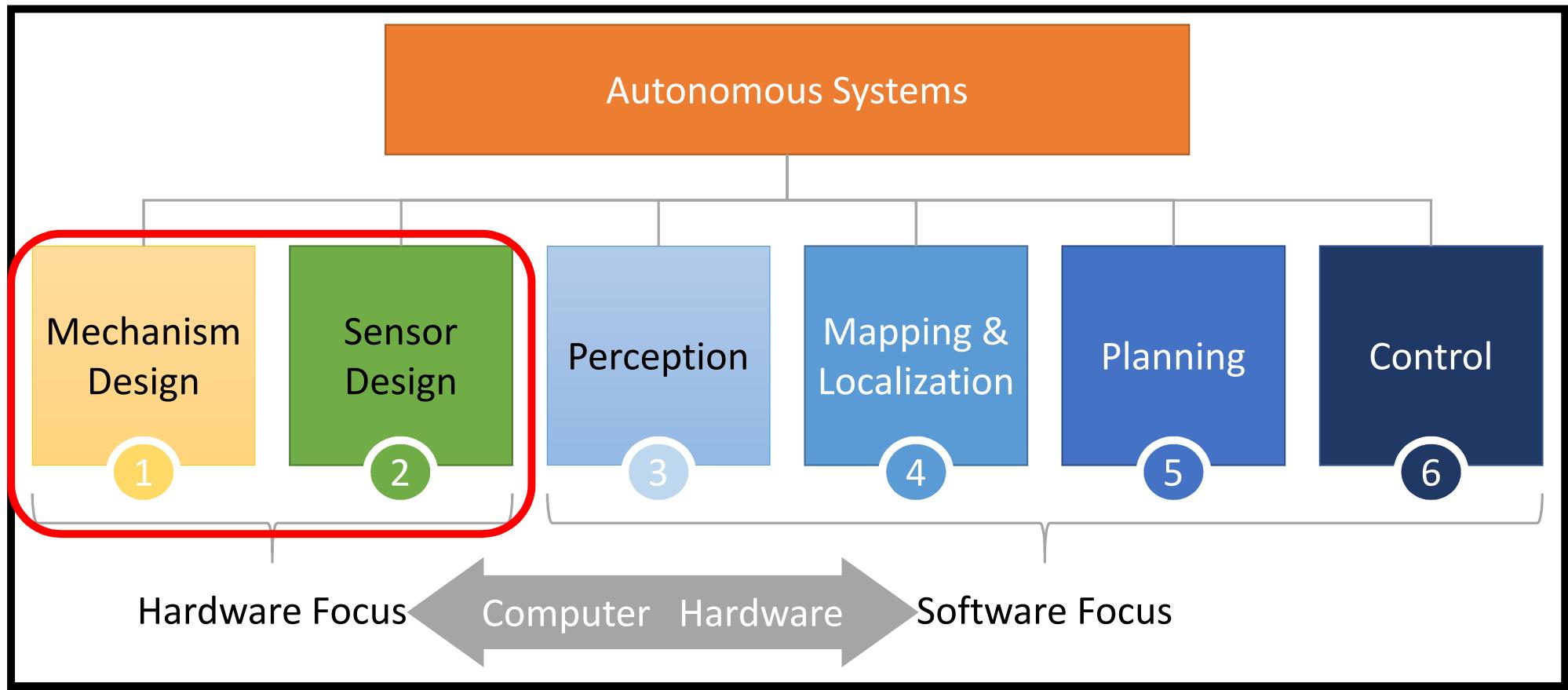
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Autonomous Systems / Robotics is a BIG space



Autonomous Systems / Robotics is a BIG space



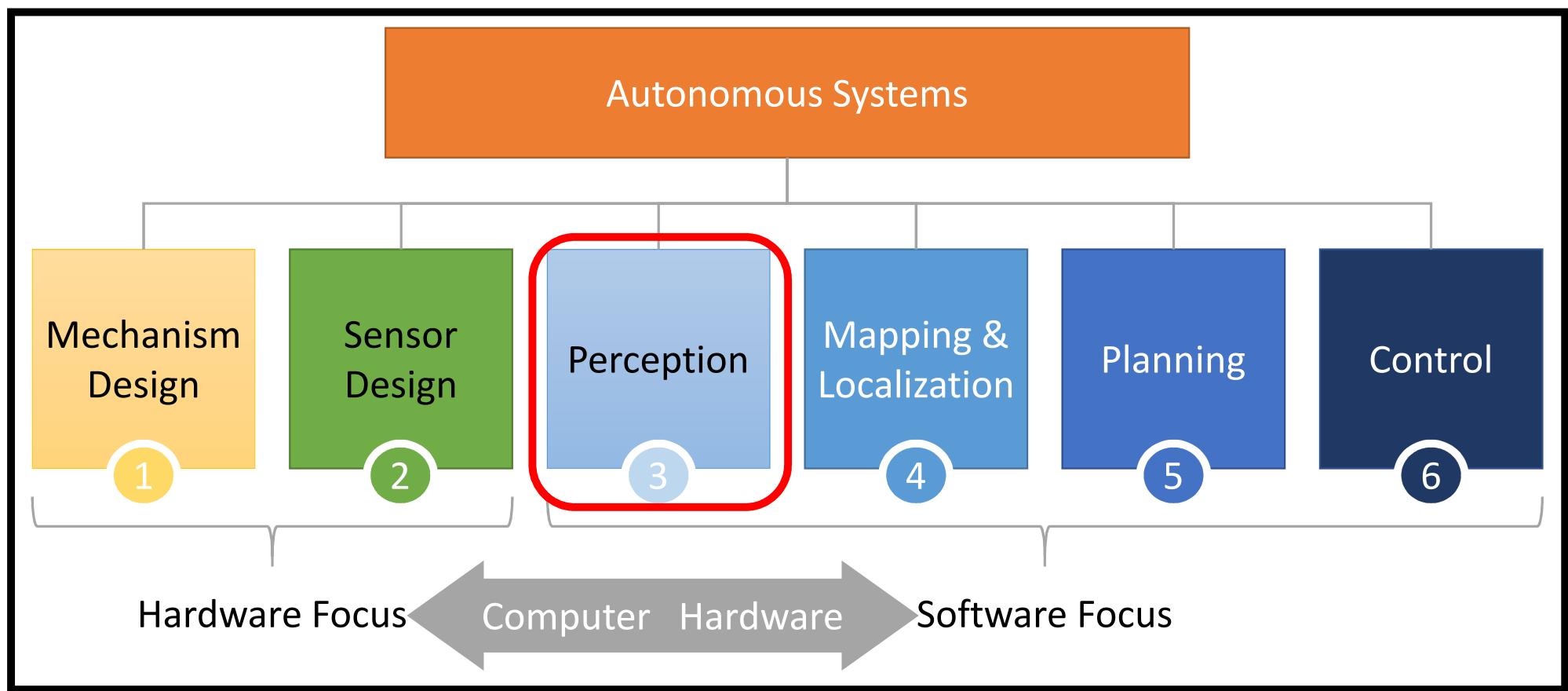
1 2

Key Takeaways:



1. When designing algorithms for robots you need to understand the physical capabilities of the robot and you (potentially) need to understand how to model its physical behaviors
 2. Different kinds of systems will have different power, weight, and performance budgets for computer hardware
-

Autonomous Systems / Robotics is a BIG space



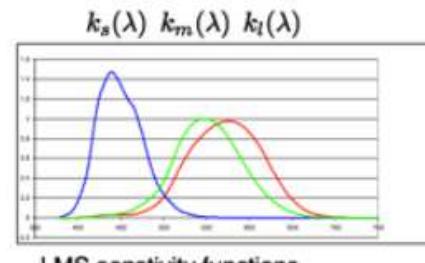
3

Computer Vision (and Perception in general) is hard

Retinal color

$$\mathbf{c}(\ell(\lambda)) = (c_s, c_m, c_l)$$

$$c_s = \int k_s(\lambda) \ell(\lambda) d\lambda$$

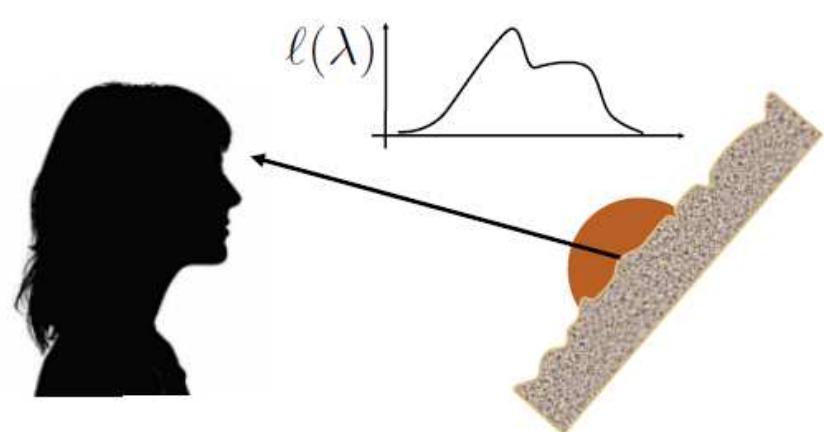


LMS sensitivity functions

Perceived color

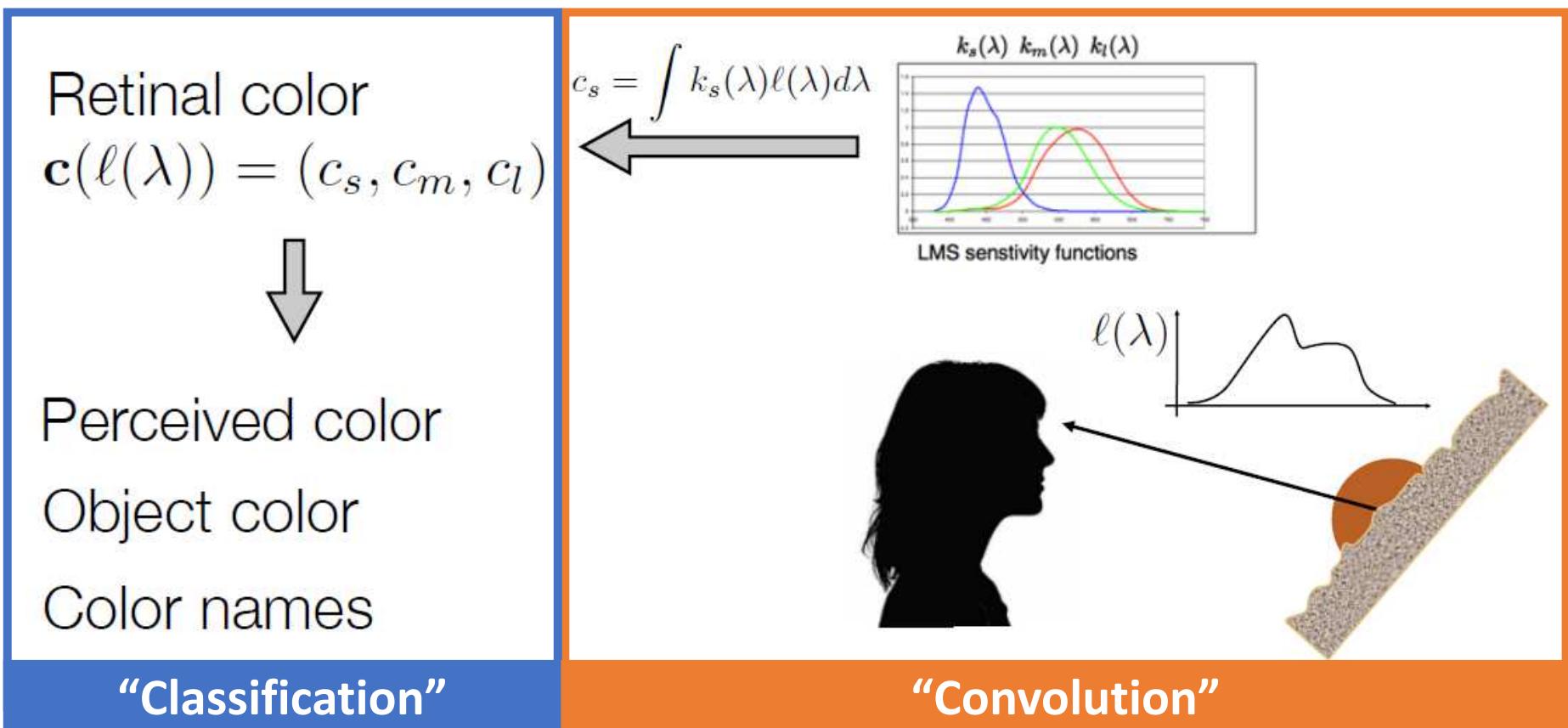
Object color

Color names



Slide Credit: Todd Zickler CS 283

CV/Perception is solved by modeling and approximating the classification of convolution



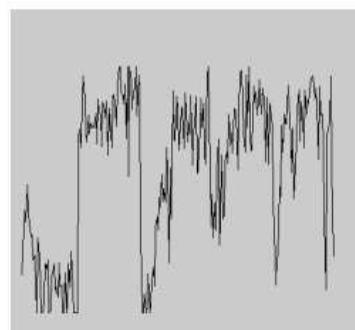
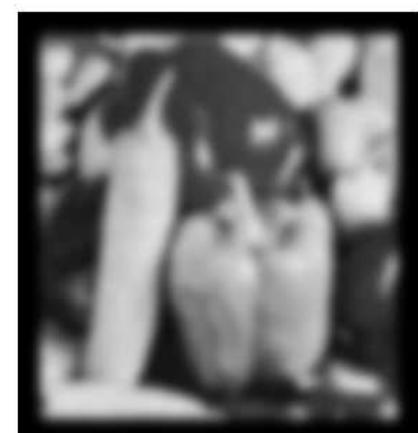
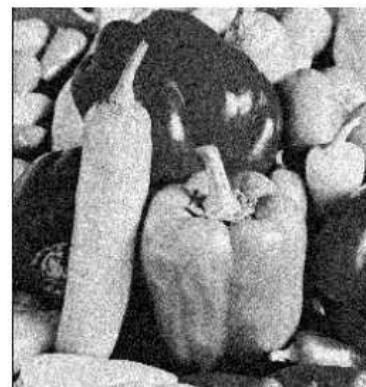
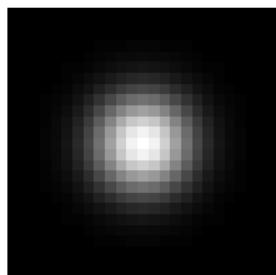
3

We approximate convolution using linear filters

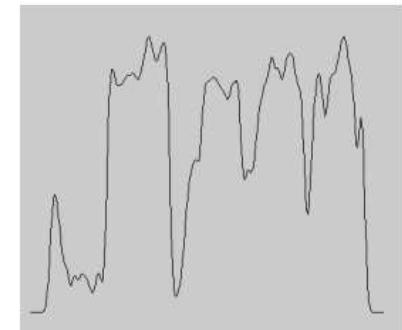
$$G_\sigma = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

0.003	0.013	0.022	0.013	0.003
0.013	0.059	0.097	0.059	0.013
0.022	0.097	0.159	0.097	0.022
0.013	0.059	0.097	0.059	0.013
0.003	0.013	0.022	0.013	0.003

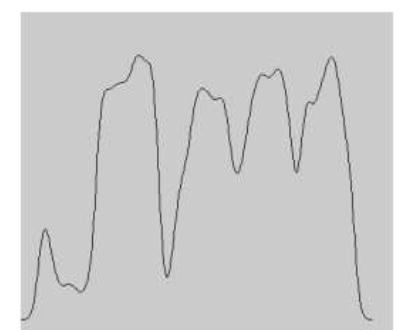
$5 \times 5, \sigma = 1$



No smoothing



$\sigma = 2$

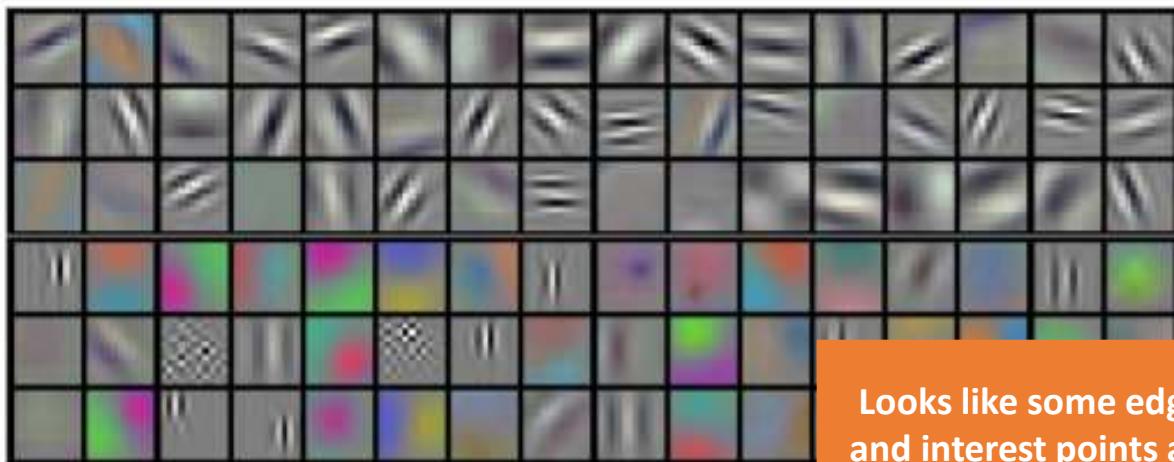
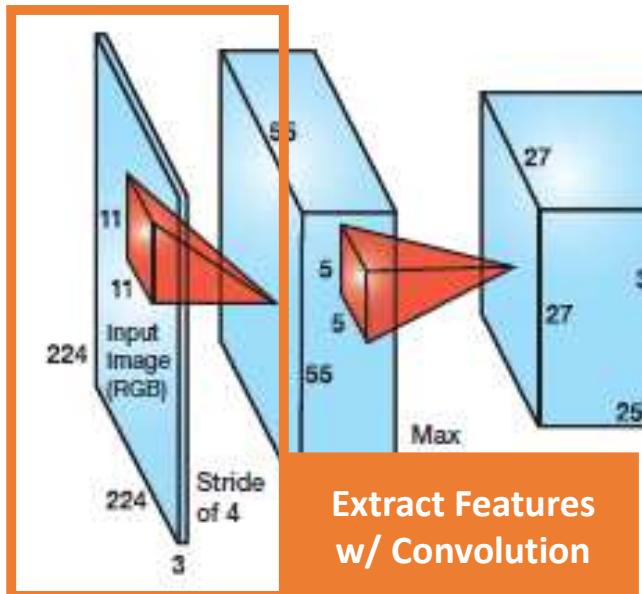


$\sigma = 4$

3

Deep learning automates the design of filters, and the selection/combination of features for classification

AlexNet: the first widely successful application of deep learning



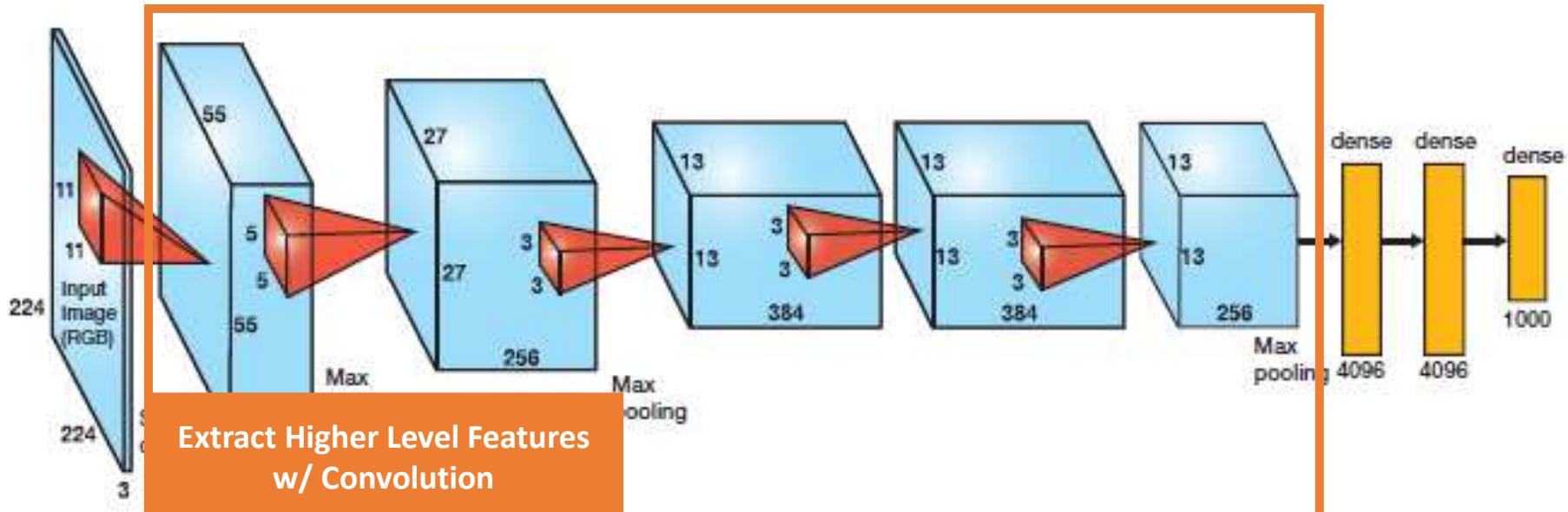
<https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf>

<https://cv-tricks.com/cnn/understand-resnet-alexnet-vgg-inception/>

3

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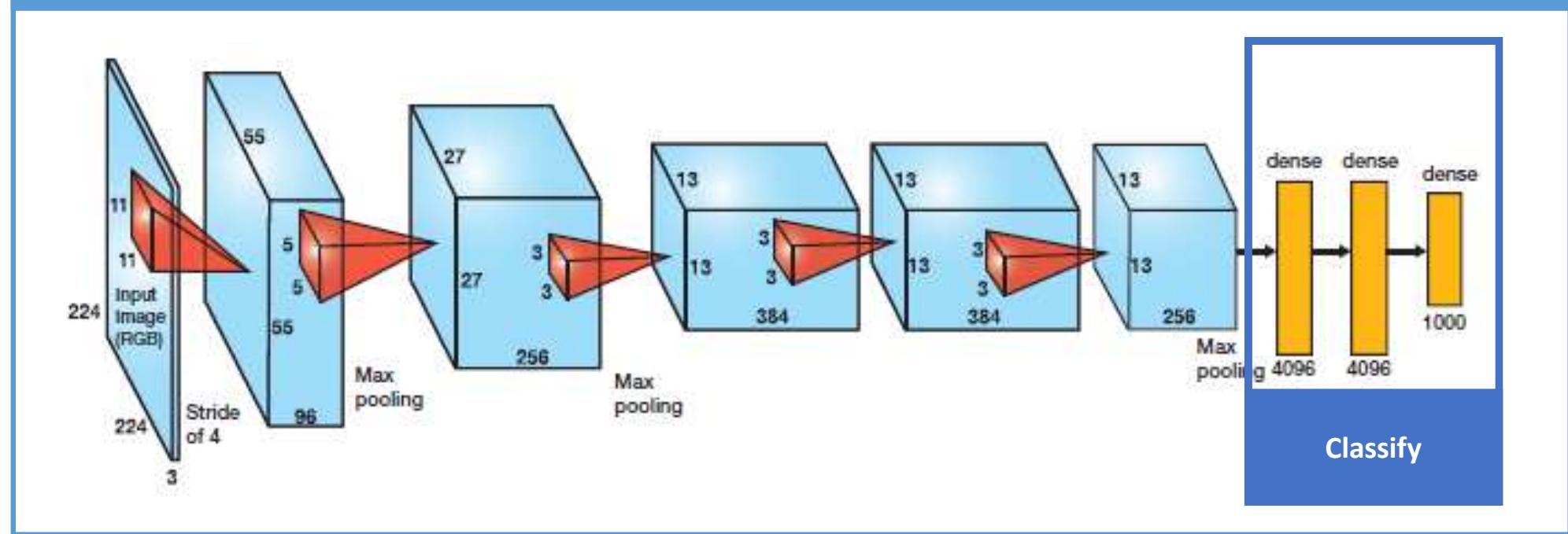
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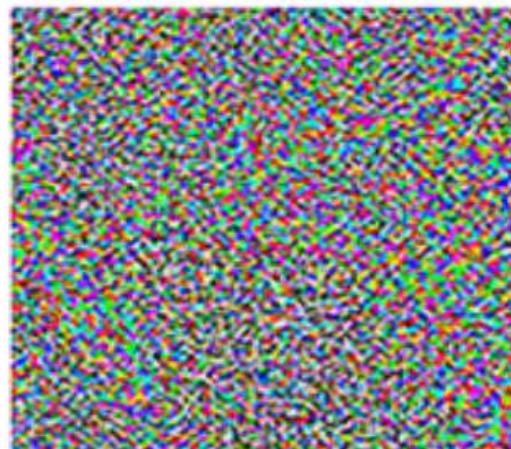
But watch our for adversarial attacks on the math!



“panda”

57.7% confidence

$+\epsilon$



=

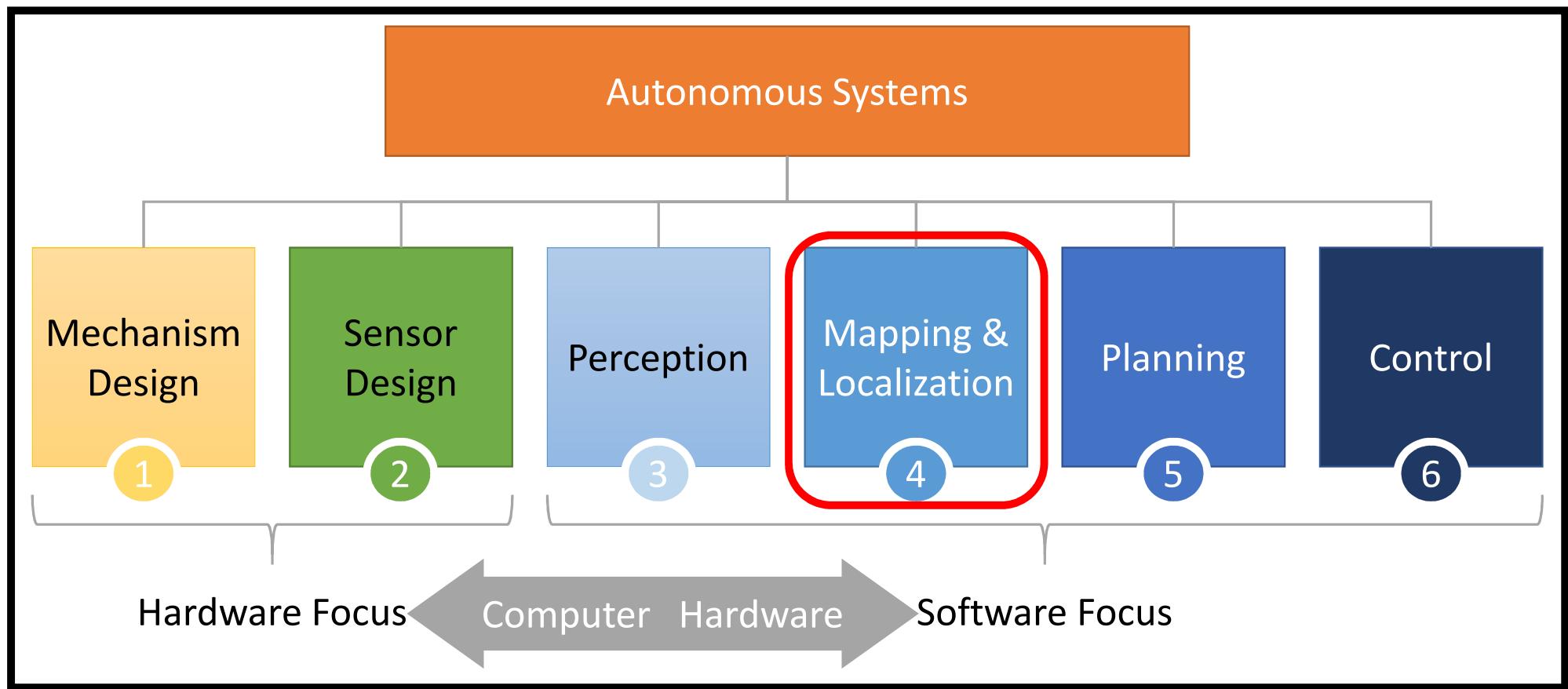


“gibbon”

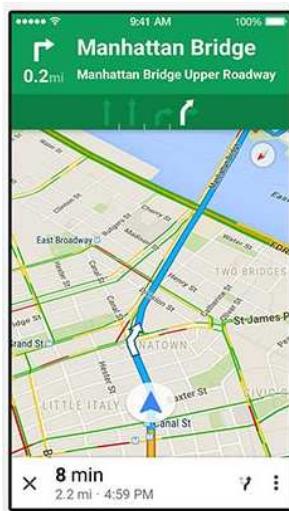
99.3% confidence

“No Free Lunch!”

Autonomous Systems / Robotics is a BIG space

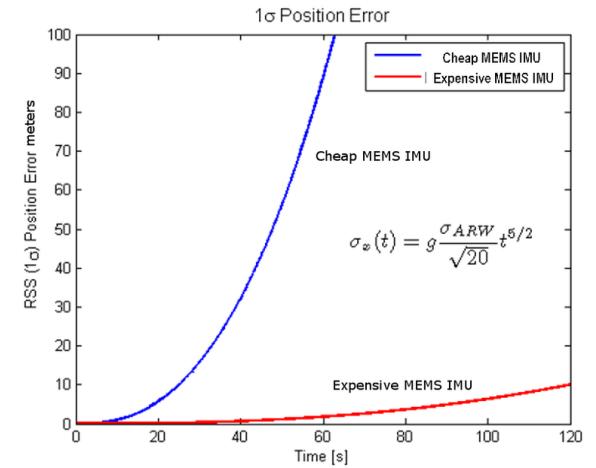
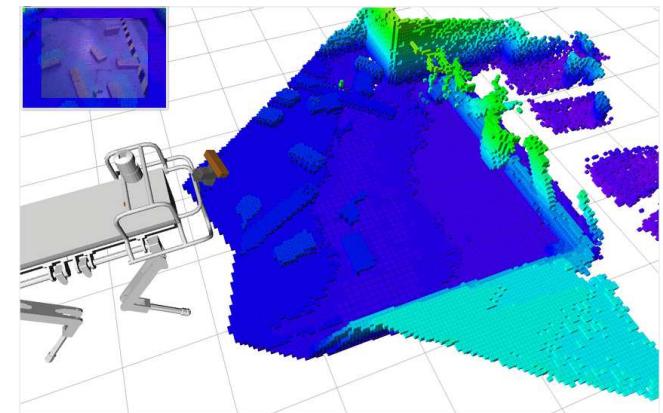


Mapping/Localization is hard



Three Problems

1. GPS is only accurate to $O(10m)$
2. GPS relies on already having a perfect map of the environment (unrealistic often)
3. Other sensor data is also quite noisy!



4

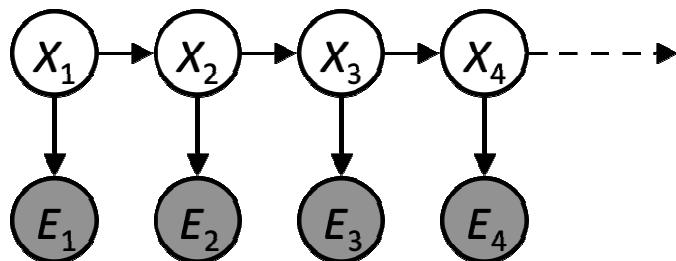
Mapping/Localization is solved by modeling the world as an HMM and using modeling and approximating to solve it

Track the **Belief State** B_t of the state and landmarks

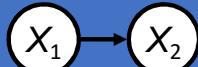
$$B_t = p(X_t | X_o, E_o \dots E_{t-1})$$

Hidden Markov Model (HMM)

States X update in time but we only observe the effects E



Time Update



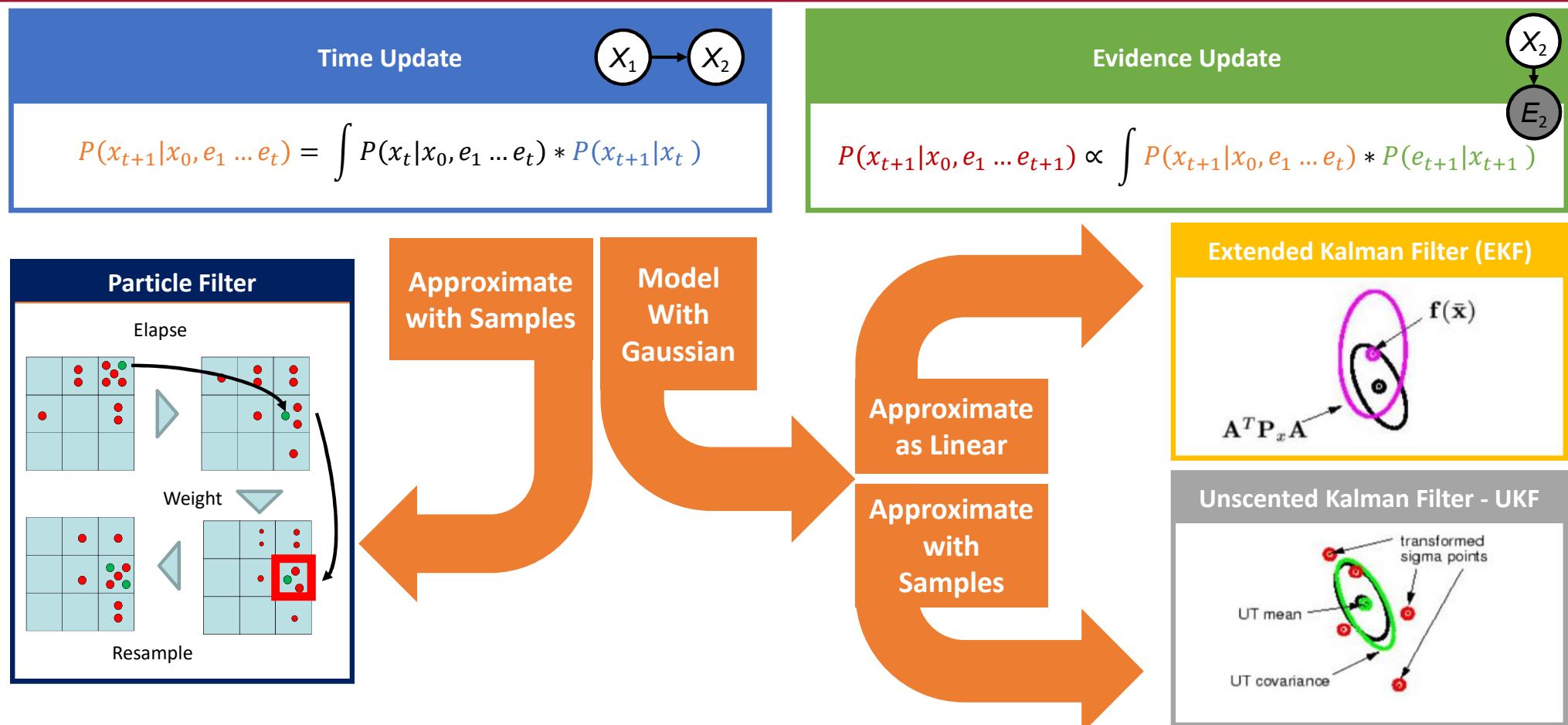
$$P(x_{t+1} | x_0, e_1 \dots e_t) = \int P(x_t | x_0, e_1 \dots e_t) * P(x_{t+1} | x_t)$$

Evidence Update

$$P(x_{t+1} | x_0, e_1 \dots e_{t+1}) \propto \int P(x_{t+1} | x_0, e_1 \dots e_t) * P(e_{t+1} | x_{t+1})$$

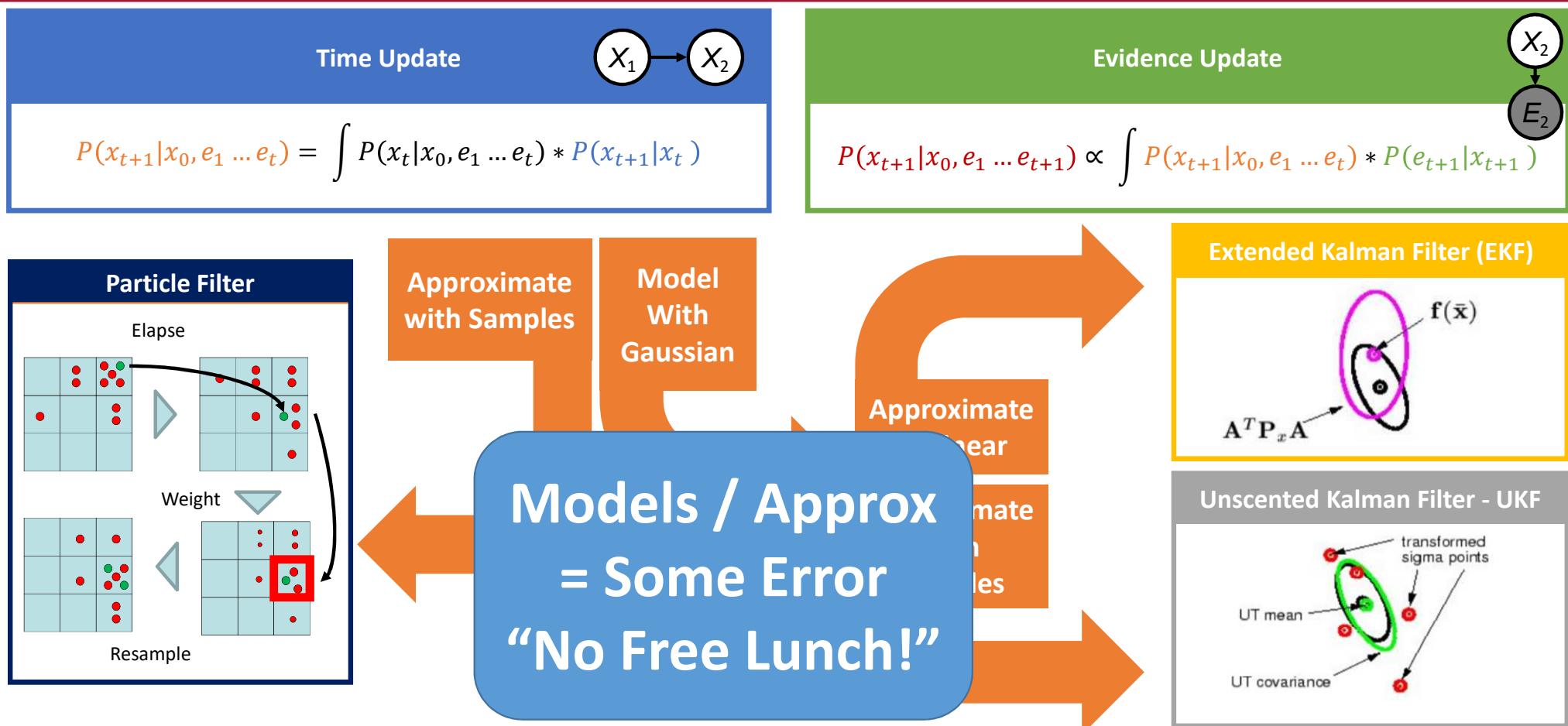
4

Mapping/Localization is solved by modeling the world as an HMM and using modeling and approximating to solve it



4

Mapping/Localization is solved by modeling the world as an HMM and using modeling and approximating to solve it



4

Also we need to approximate the resolution of our maps and store them intelligently to fit them in memory

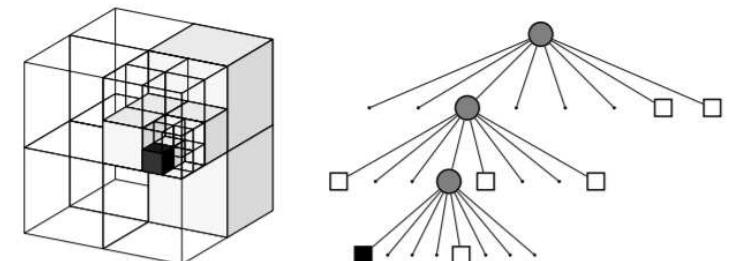
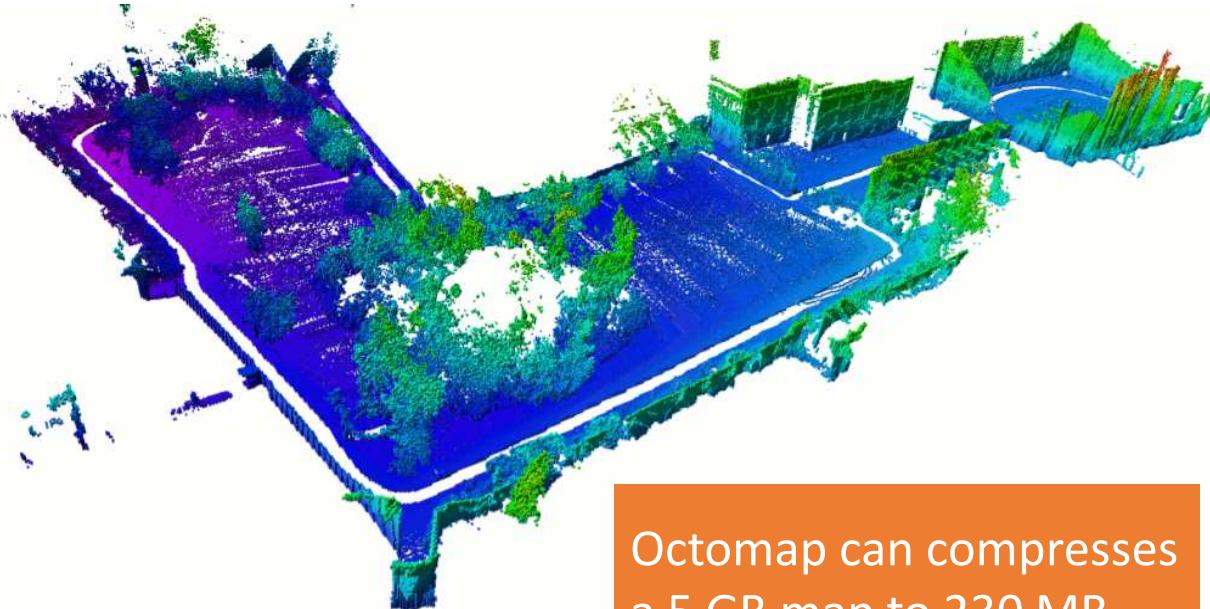


Fig. 2 Example of an octree storing free (shaded white) and occupied (black) cells. The volumetric model is shown on the left and the corresponding tree representation on the right.

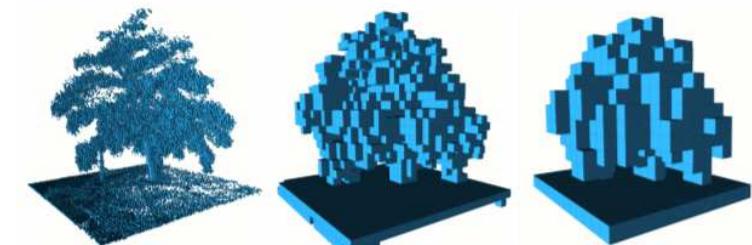
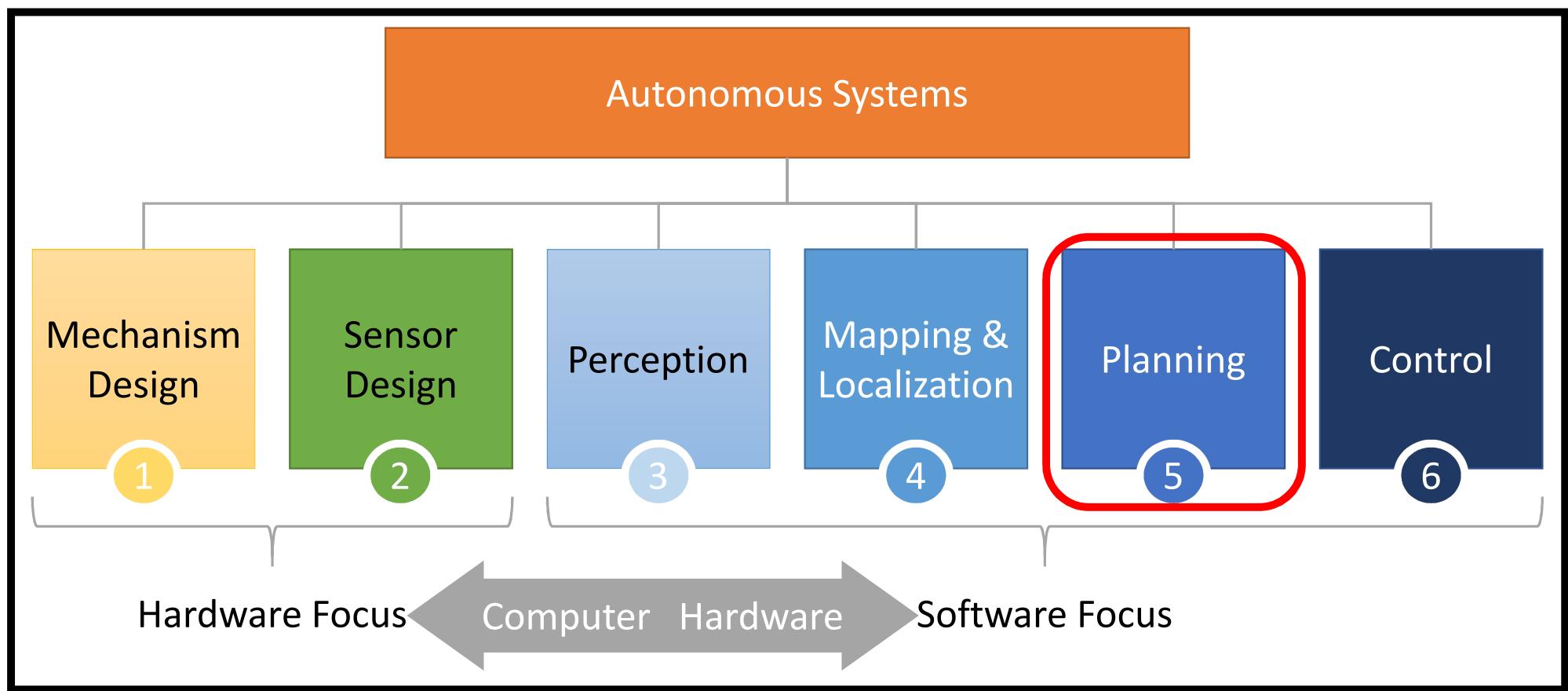


Fig. 3 By limiting the depth of a query, multiple resolutions of the same map can be obtained at any time. Occupied voxels are displayed in resolutions 0.08 m, 0.64 , and 1.28 m.

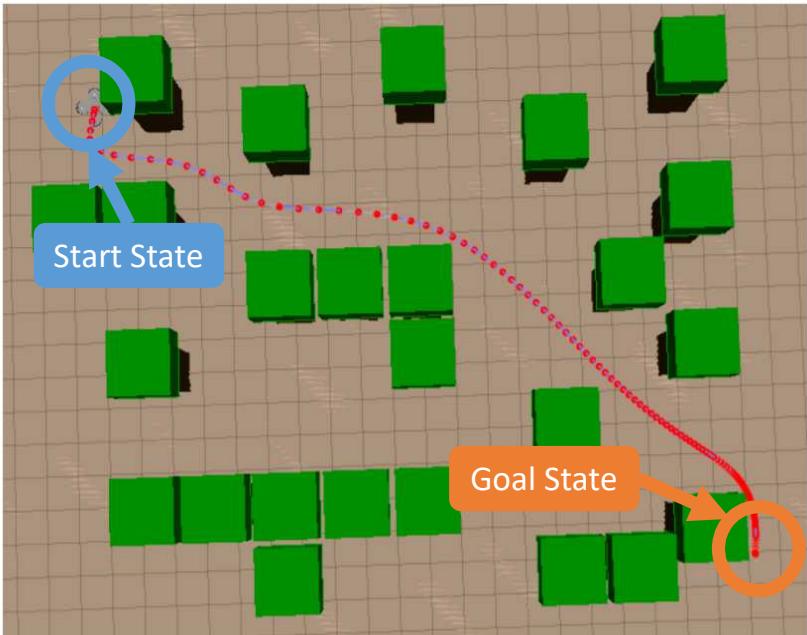
“Octomap” Hornung et. al. 2012

Autonomous Systems / Robotics is a BIG space



5

Planning (in Configuration Space) is hard



One approach is to ***discretize*** the statespace (grid it) and use graph search (A^* = fast)

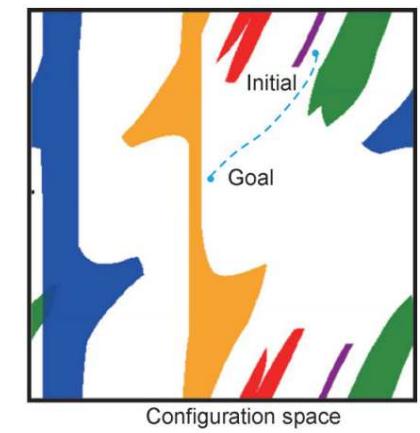
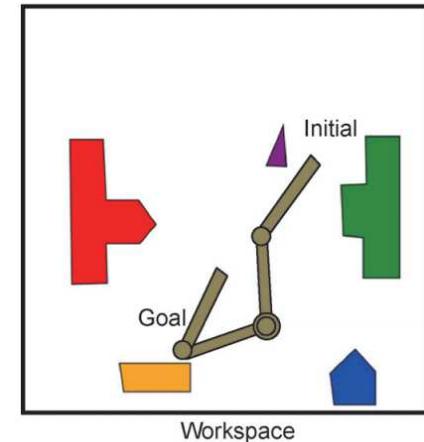
Another is to solve a global optimization problem:

$$\underset{s_0, a_0, \dots, s_N, a_N}{\text{minimize}} \sum_{k=0}^N c(s_k, a_k)$$

$$\text{subject to } s_{k+1} = f(s_k, a_k)$$

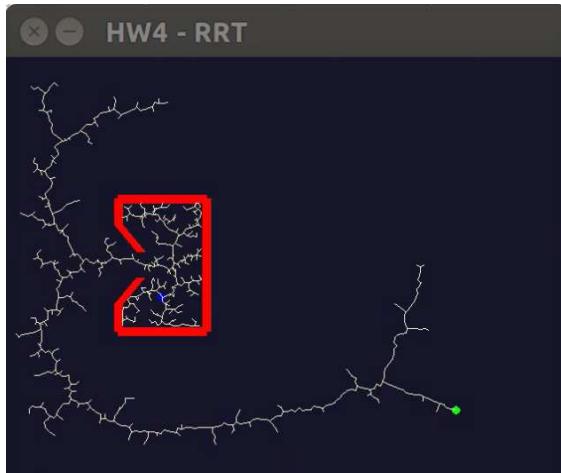
$$s_N = s_{\text{goal}}$$

Complexity scales with $d^{|S|=|A|}$: **Curse of Dimensionality**

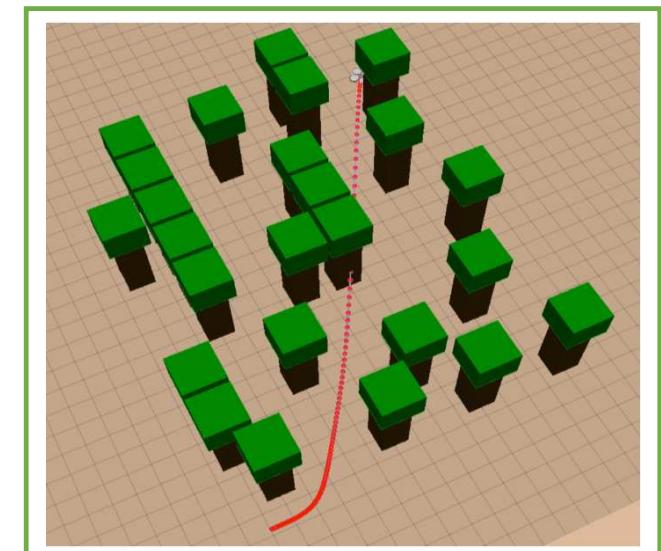
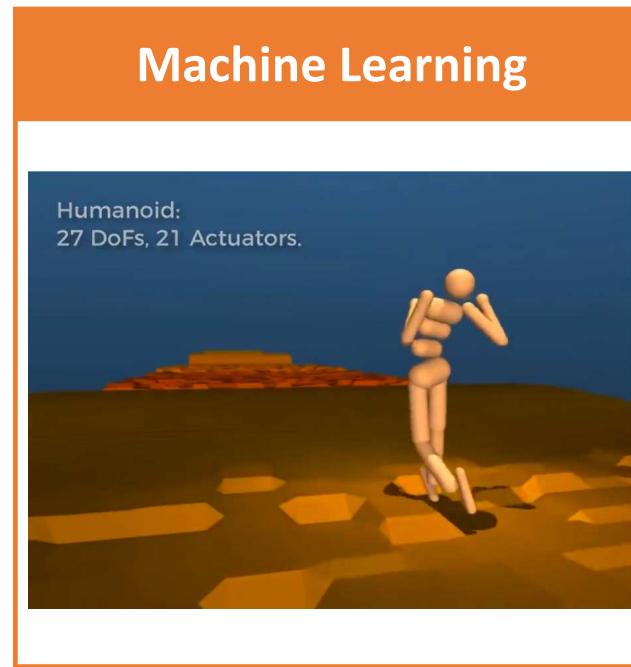


5

There are three main ways to approximately plan in Configuration Space



Random Search



Local Search

5

We can approximately plan locally optimal plans in Configuration Space in three ways

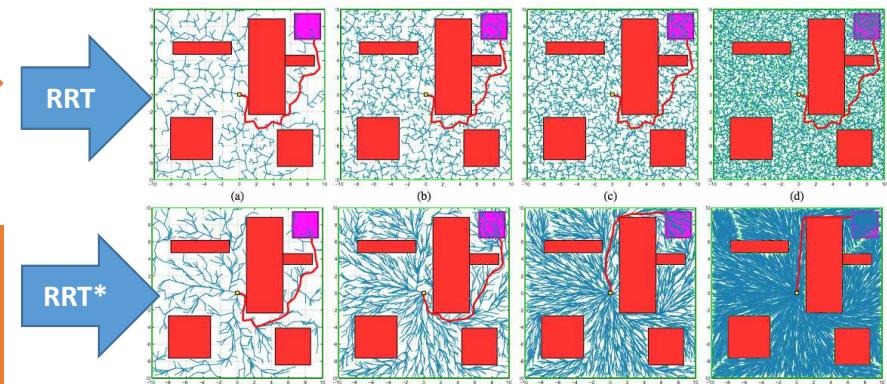
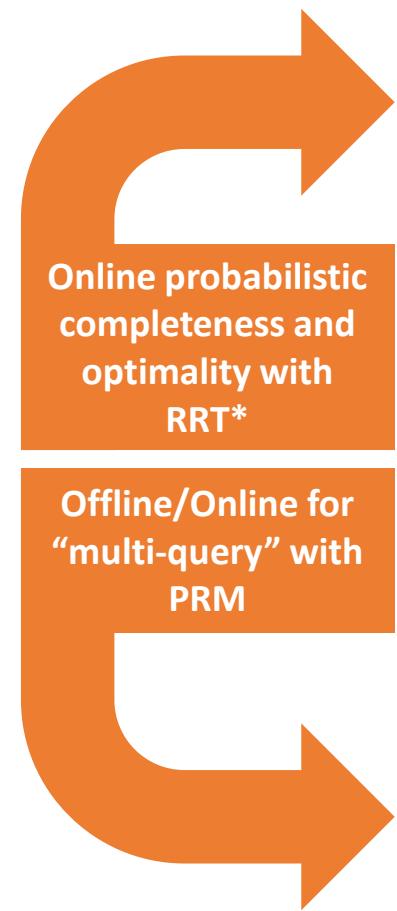
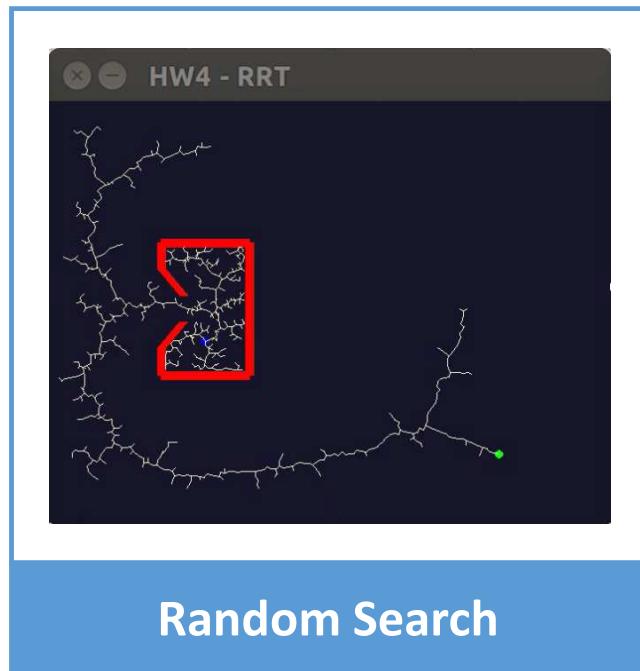
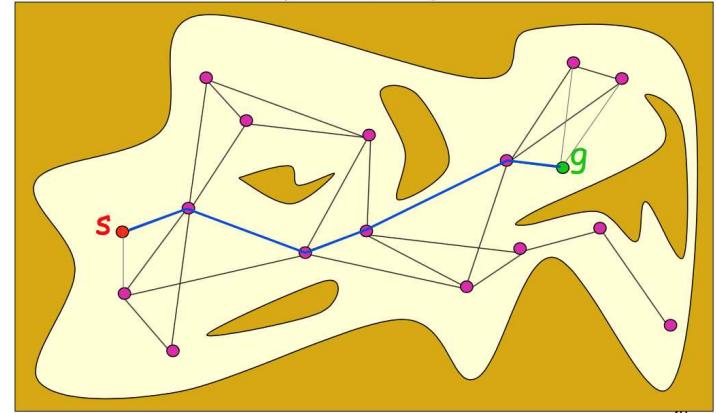


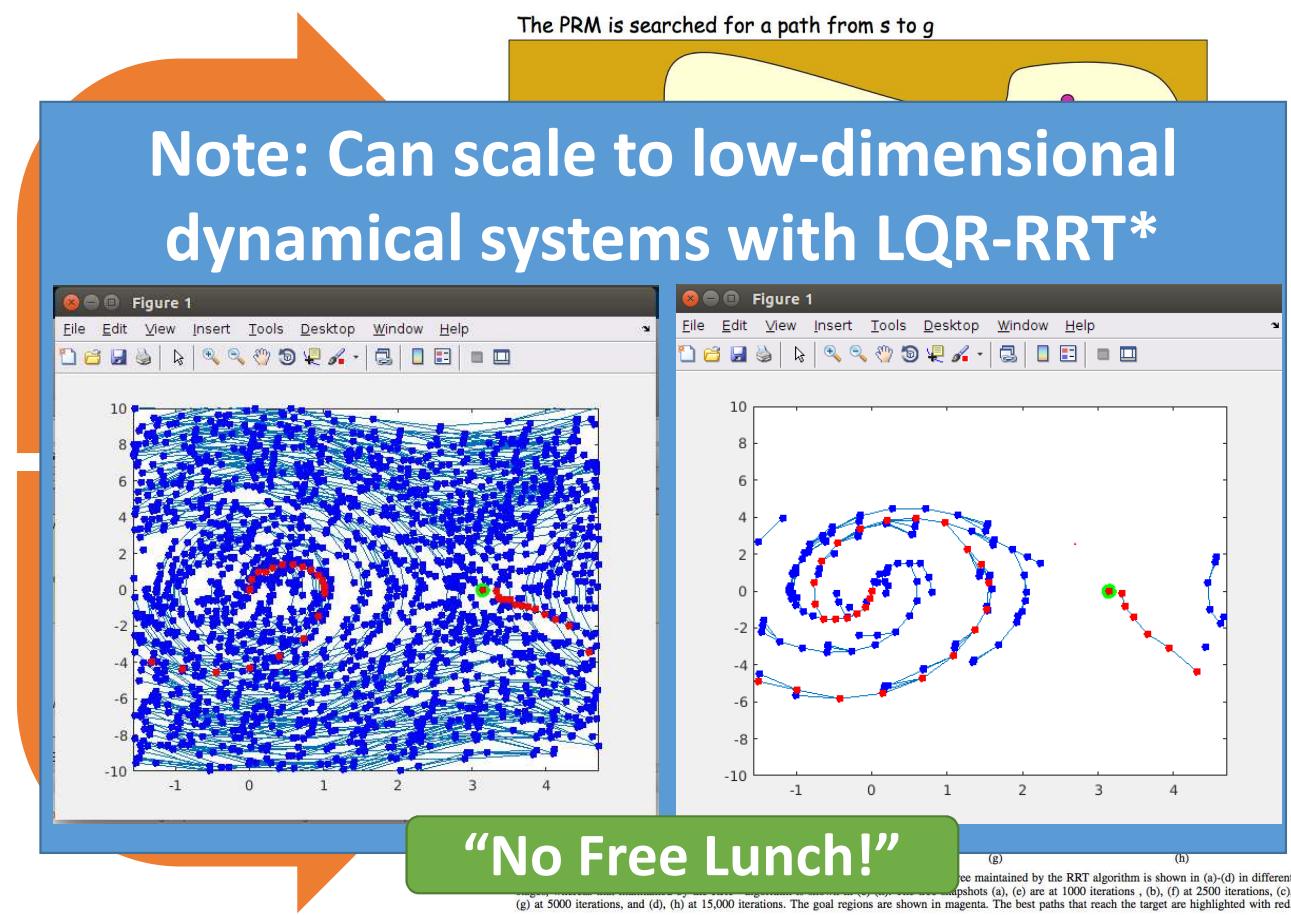
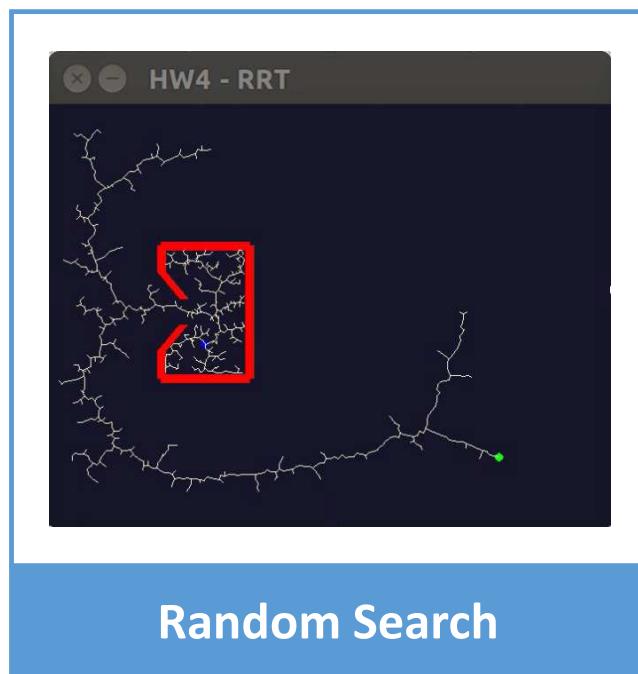
Fig. 1. A Comparison of the RRT* and RRT algorithms on a simulation example. The tree maintained by the RRT algorithm is shown in (a)-(d) in different stages, whereas that maintained by the RRT* algorithm is shown in (e)-(h). The tree snapshots (a), (c) are at 1000 iterations , (b), (f) at 2500 iterations, (c), (g) at 5000 iterations, and (d), (h) at 15,000 iterations. The goal regions are shown in magenta. The best paths that reach the target are highlighted with red.

The PRM is searched for a path from s to g



5

We can approximately plan locally optimal plans in Configuration Space in three ways



5

We can approximately plan locally optimal plans in Configuration Space in three ways

Machine Learning

Humanoid:
27 DoFs, 21 Actuators.



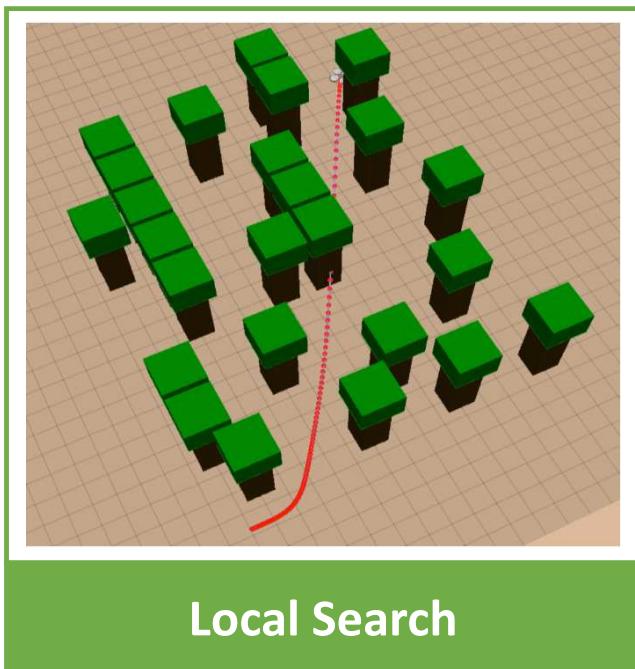
My two cents:
Yes, and no free
lunch!

Needs to re-lean
physics and suffers
from sample
complexity

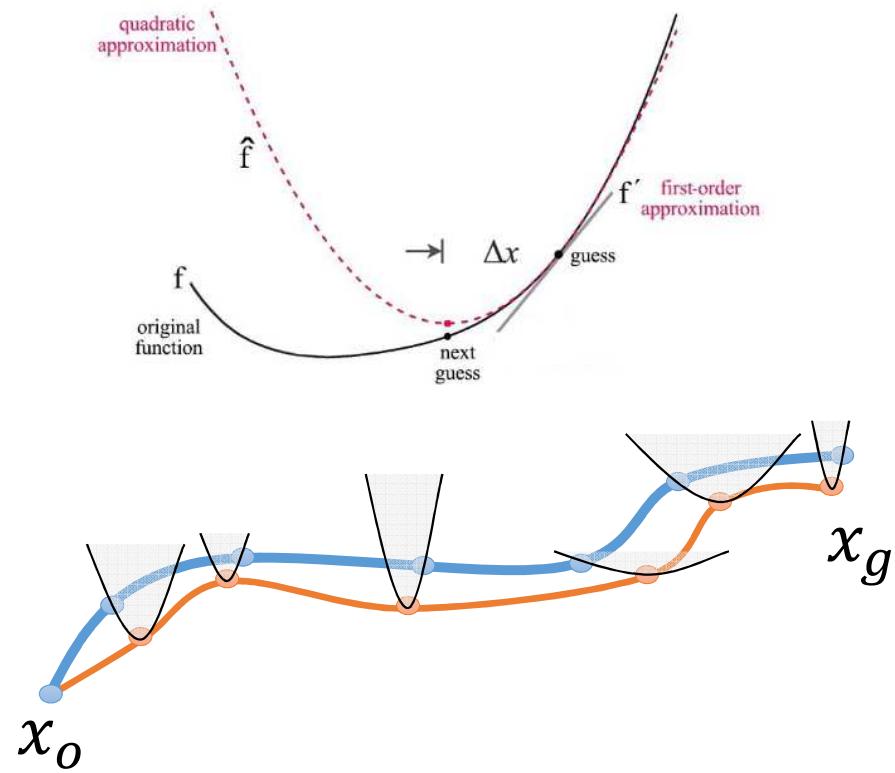
In two weeks more
on this!

5

We can approximately plan locally optimal plans in Configuration Space in three ways



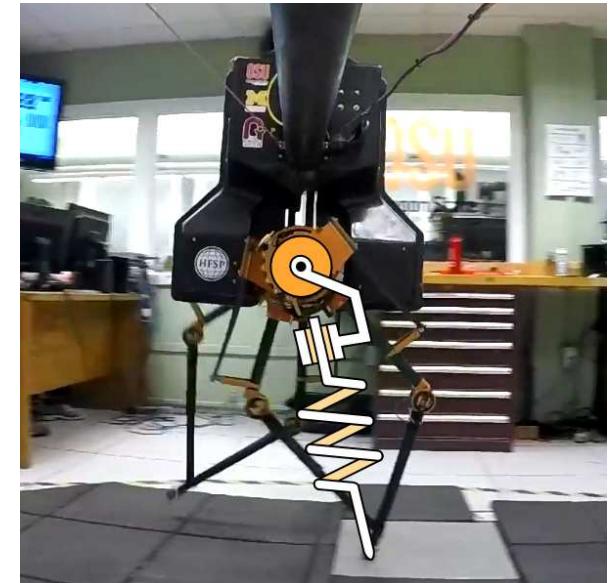
Solve math locally with linear & quadratic approximations



Practical Challenges for Trajectory Optimization: Not Complete, Not Robustness and Contact = No Free Lunch!

1. Not complete (aka no guaranteed solution) and often slow!
2. Solvers are numerically sensitive
3. Solutions are sensitive to initial trajectories and perturbations
4. The physics equations are fundamentally different when an object makes or breaks contact leading to a combinatorial explosion

One approach to avoid solving these large hard problems is to solve the problem by combining simpler models of the system although this leads to conservative behavior



5

Control is hard (even for the experts)

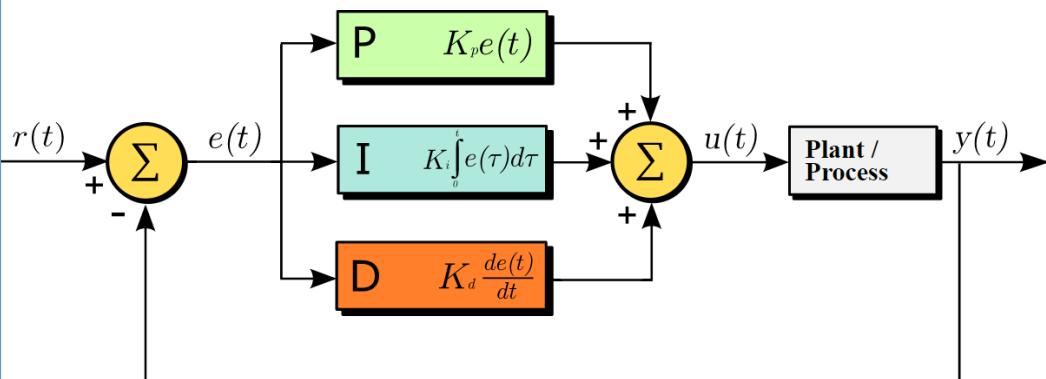


6

We use feedback tracking controllers to run our plans in the real world (and handle the differences encountered)

Model as linear combination of errors and approximate gains

This is the canonical PID controller!



LQR: Quadratic Cost with Linear Dynamics

$$\min_{x,u} \sum_{k=0}^N (x_k - x_g)^T Q (x_k - x_g) + u_k^T R u_k$$

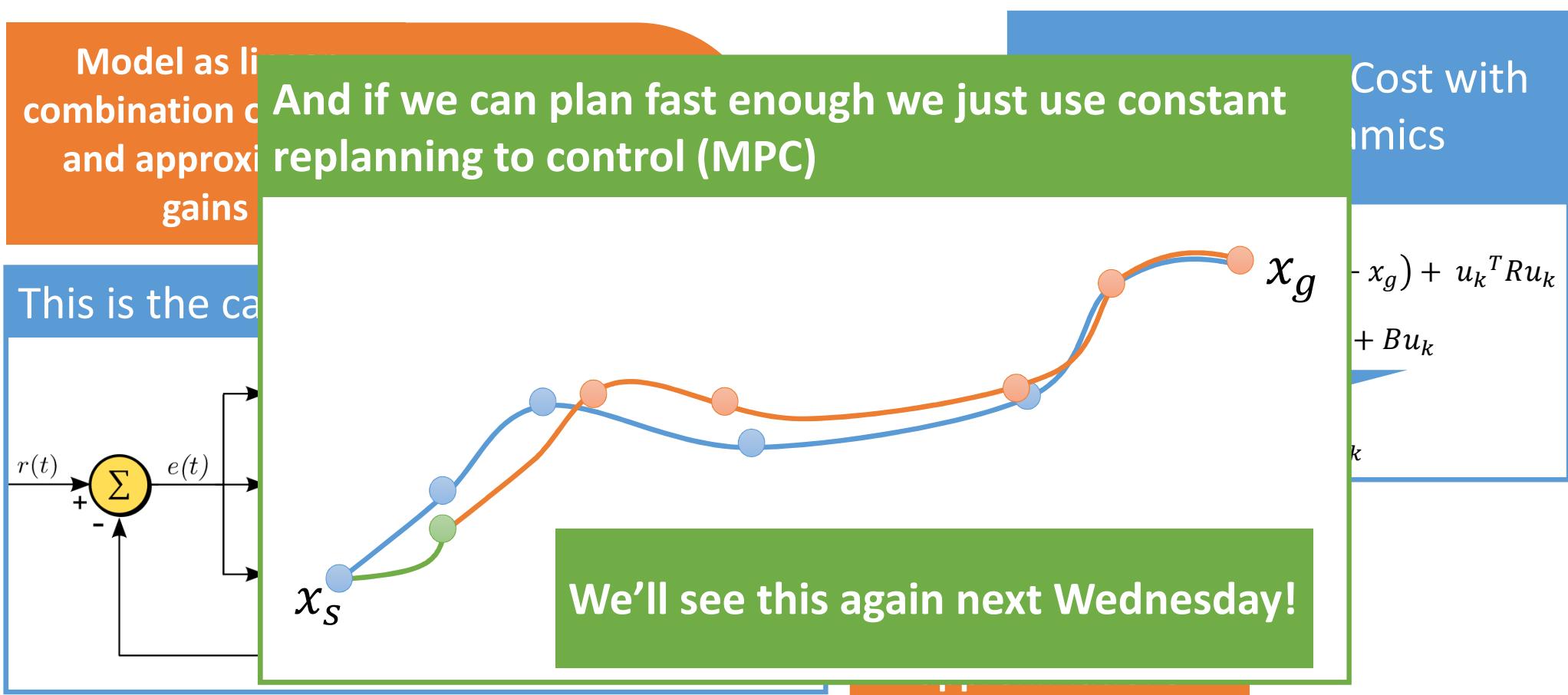
s.t. $x_{k+1} = Ax_k + Bu_k$

$$u_k = -K_k x_k$$

Solve math locally with linear & quadratic approximations

6

We use feedback tracking controllers to run our plans in the real world (and handle the differences encountered)



6

Practical Challenges for Control: Contact

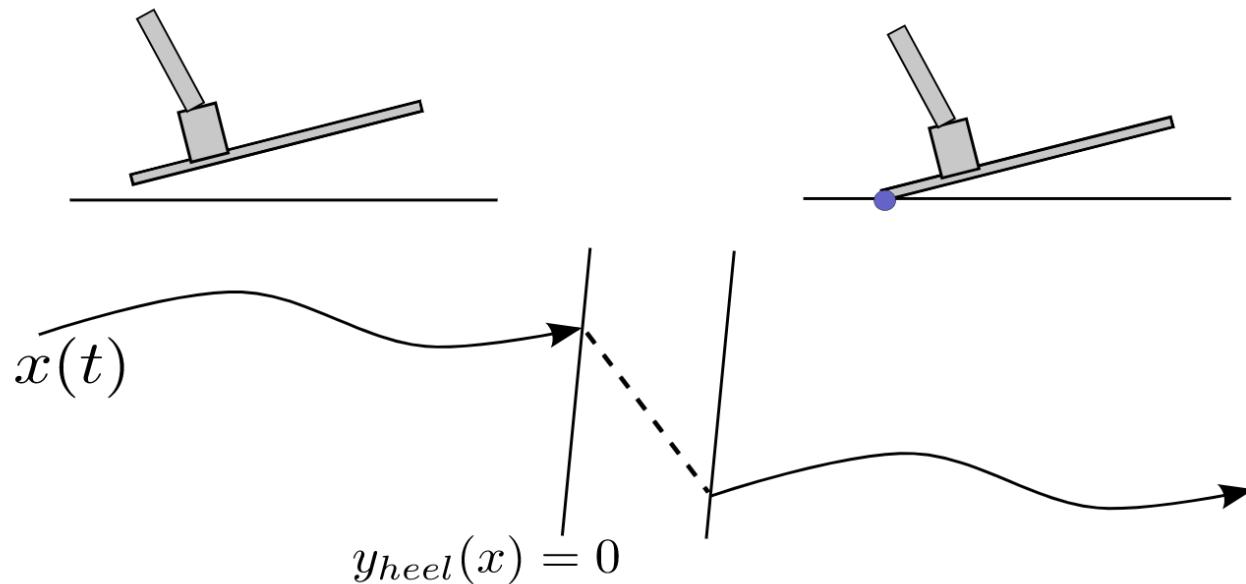


Figure 17.1 - Modeling contact as a hybrid system.

The goal for the next couple of lectures is to develop a **high level** understanding of:

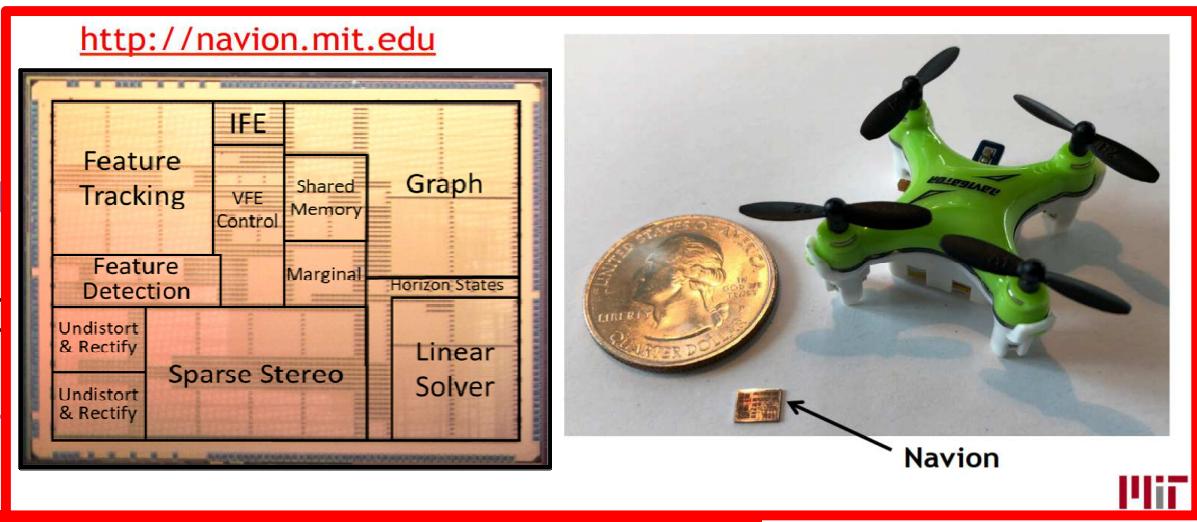
1. What is an autonomous system
2. Key **problems** and **constraints** for autonomous systems
3. Some of the most important (classes of) **algorithms** in robotics
 - A. The **model based** vs. **model free** tradeoff
 - B. The **online** vs **offline**
 - C. The **no free lunch** t

This is what we will explore
in all of the papers!

4. How **computer systems / architecture** design has and can play a role in improving autonomous systems
-

The goal for the next couple of lectures is to develop a **high level** understanding of:

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3. Some of the most important ones:
 - A. The **model based** vs. **data driven** approaches
 - B. The **online** vs **offline** approaches
 - C. The **no free lunch theorem** and **trade-offs**



This is what we will explore
in all of the papers!

4. How **computer systems / architecture** design has and can play a role in improving autonomous systems

Your homework – get on HOTCRP

Email **Glenn Holloway:**
holloway@eecs.harvard.edu

He will send you a password (username is that email address) after which I can assign you access to review papers