

## Robot brains: AI and Machine Learning

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CMU 15-110  
April 13, 2018



## The Sense-Think-Act Paradigm

- Analogous to functions!
- A **function** takes **inputs** and yields **outputs**
- A robot **thinks** about **sensory** inputs and **acts** on its environment in some way
- The most important principle of AI and Robotics is...?

## You are now a robot in 15-110

- Why not? Humans study biology. Beep boop.
- You **hate** pop quiz days. Do you think there will be one today?
- Are you 100% sure about that?
- ...are you *really* 100% sure? [O \_ O"]

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Part 1: It's all about

## PROBABILITY



## A simple approach first!

- Assume there will only ever be one quiz per day!
- Let's say you've had **16 quizzes** so far...
- ...and there have been **50 classes**...
- ...and because you are a good robot, you have come to all of them.
- The probability of a quiz today is 32%, or 16/50!

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## Maybe we can find a hint...

- Prof. Cortina likes to have a bottle of water during lectures, but...
  - ...sometimes he doesn't bring one if there is a quiz
  - ...and sometimes he just forgets
- He doesn't have any water today! Does that mean there's probably a quiz?

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## Important notation

- H – Hypothesis
- E – Evidence
- $P(H)$  – Probability of H
  - Also called the **prior**
- $P(H|E)$  – Probability of H given observation E
  - Also called the **posterior**

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## We want to know $P(H|E)$

- H = 'having a quiz'  
 $P(H) = 0.32$ 
  - because we've had 16 quizzes in 50 classes
- E = 'doesn't have a water bottle'  
 $P(E) = 0.2$ 
  - You've noticed the professor is four times more likely to have water with him than not
- E | H = 'doesn't have a water bottle given a quiz occurs'  
 $P(E|H) = 0.5$ 
  - In the last 16 quizzes, the professor has only had water 8 times

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## Bayesian Inference!

- $P(H|E) = P(E | H) * P(H) / P(E)$

Bayes' Theorem tells us the probability of an event H conditional on observation E.

We just need to know  $P(H)$ ,  $P(E)$ , and  $P(E|H)$

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## Bayesian Inference!

$$P(H) = 0.32$$

$$P(E) = 0.2$$

$$P(E|H) = 0.5$$

$$P(H|E) = 0.5 * 0.32 / 0.2 \quad \text{Hope you studied!}$$
$$= 0.8 \quad (80\% \text{ chance})$$

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## Update as we get new data!

**If no water and a quiz happened**

$P(H)$  increases

$P(E)$  increases

$P(E|H)$  increases

**If no water and no quiz**

$P(H)$  decreases

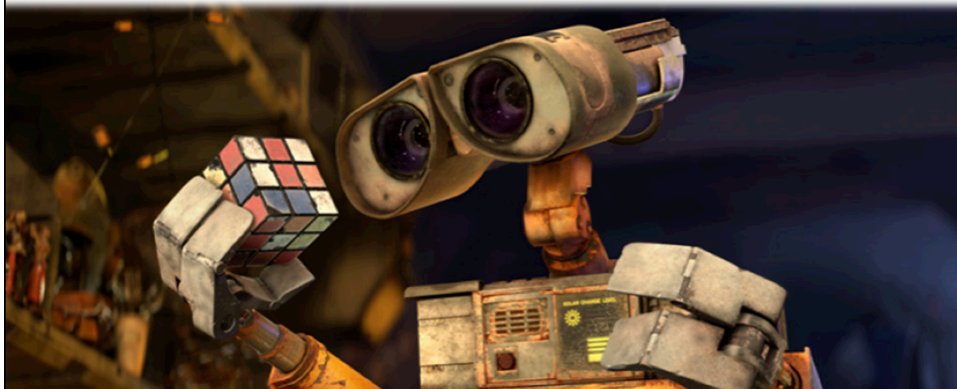
$P(E)$  increases

$P(E|H)$  stays the same

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## And now we're smarter robots!

We observed some data, made a prediction, and incorporated the result into our model for next time



## More info...

- There are some flaws...
  - You can't predict an event you haven't seen
  - Small datasets and rare events can yield poor performance
- Training sets can help
- Typical Bayesian applications are similar but more complex
  - Observations and outcomes may not be binary
  - Multiple sources of evidence, i.e. sensors

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## Other examples in the real world

- Predictive text, i.e. on phones
- Simple games, i.e. rock, paper, scissors
- Spam filters and text classification

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Part 2: How do robots “see?”

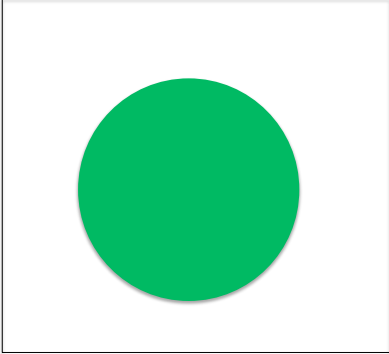
# COMPUTER VISION



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Jibo image: PCMag

The image shows a white and black Jibo robot head, which is a small, spherical robot with a large black circular opening on its front. The robot is positioned on the right side of the slide. The text 'Part 2: How do robots “see?”' is located to the left of the robot, and 'COMPUTER VISION' is written in large, bold, black letters below it. In the bottom right corner, there is a small number '15' and the text 'Jibo image: PCMag'.

## Which pixels are “Ball?”



16

The image shows a green circle centered on a white background, enclosed within a black square border. The text 'Which pixels are “Ball?”' is positioned above the circle. In the bottom right corner, there is a small number '16'.



### Which pixels are “Ball?”

```
00000000000000000000000000000000
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```

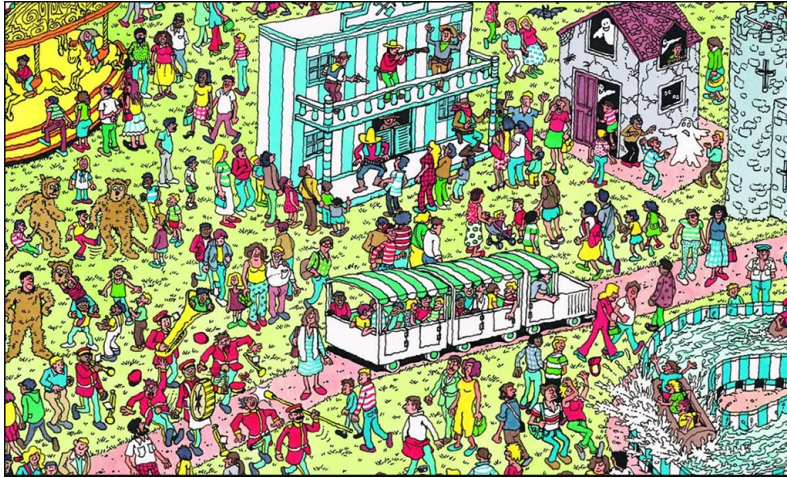
Remember, images can be lists of lists!  
Or with color... lists of lists of lists ad nauseum...

### Which pixels are “Ball?”



<https://en.wikipedia.org/wiki/Ball>

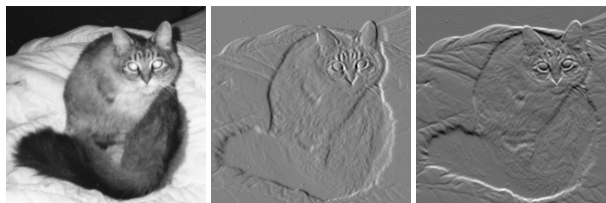
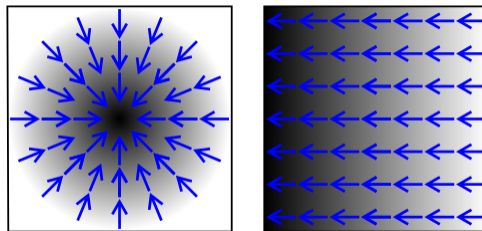
## Where's Wally?!



<https://www.theguardian.com/technology/2015/feb/06/wheres-wally-where-waldo-machine-learning-algorithm>

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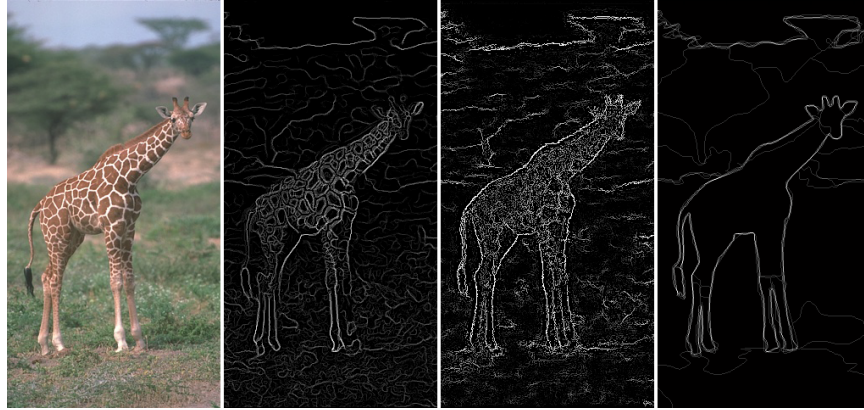
## More information than just color! Gradients, for example:



[https://en.wikipedia.org/wiki/Image\\_gradient](https://en.wikipedia.org/wiki/Image_gradient)

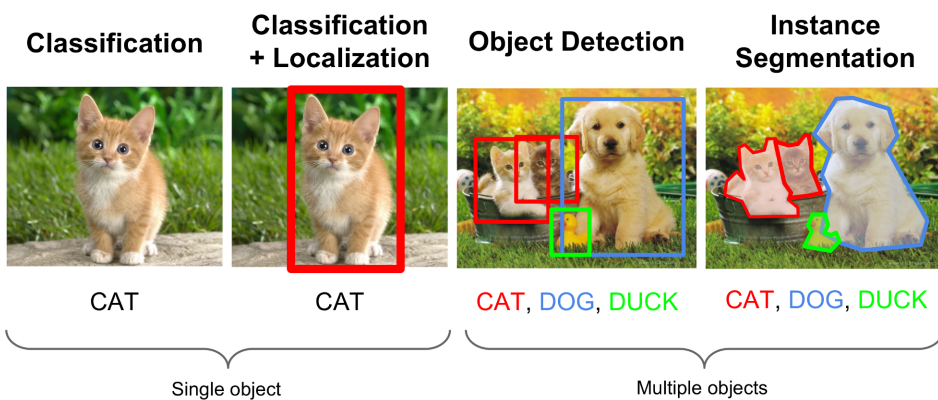
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## Edge detection



<http://cs.brown.edu/courses/cs143/2013/proj5/>

## Computer vision tasks use probability!



From <http://cs224d.stanford.edu/index.html>

Part 3: Where am I? Where am I going?

## ROBOT MOTION



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Cosmo image: Apple.com

## A robot in an empty parking lot

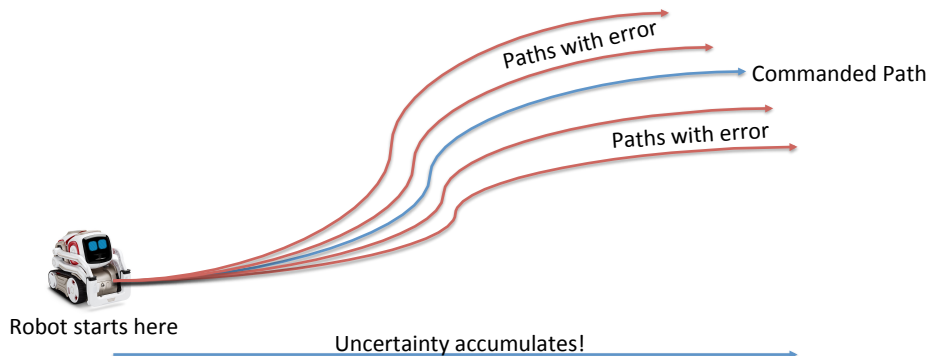
- I want my robot to drive in a square
  - Drive forward  $y$  seconds
  - Turn left  $x$  seconds
  - Repeat three times\*
- Will I actually get a square?
- Try drawing a big square with your eyes closed!



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## Uncertainty in motion

- Motion model: Given a command to move a certain way, where *might* the robot end up?



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## Uncertainty in sensing

- Sensor model: Given a reading from one of our sensors, how likely is it to be accurate?
- Mapping: Use sensor data to model the environment
- Localization: Given the sensor model and motion model and a **map**, where is the robot most likely to be?

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# Artificial Intelligence in a Nutshell

Sense – Think – Act

Machine learning is applied probability

Models are imperfect; always model uncertainty

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