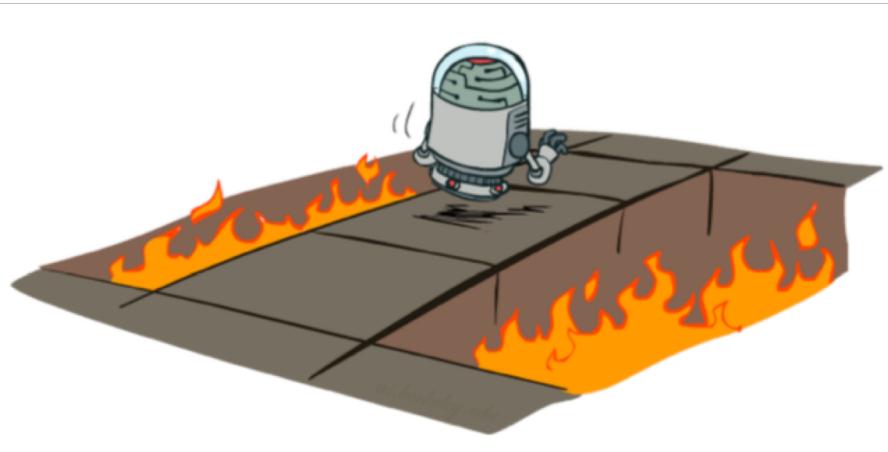


CS 1501: Intro to Robotics

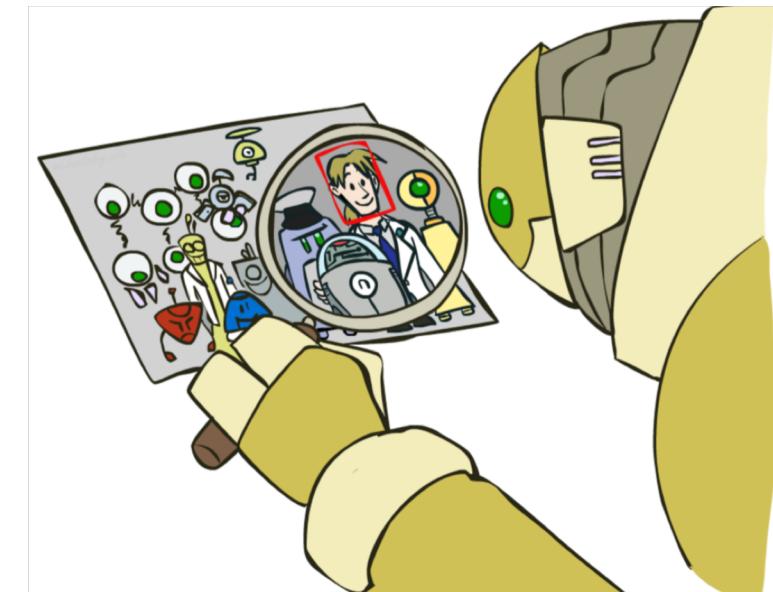
Autonomy, AI, and Applications



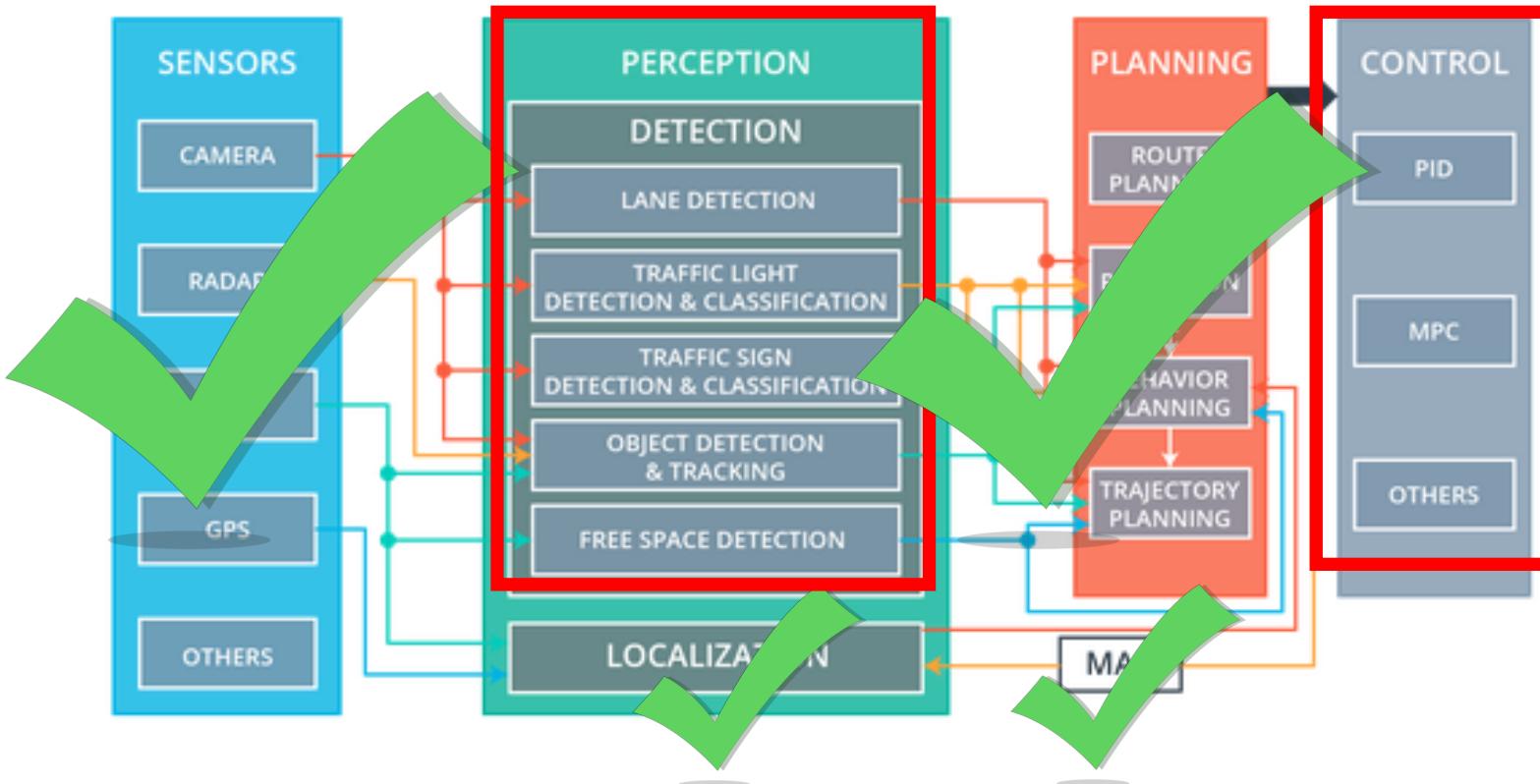
Motion Control II,
Perception

Rohan Raval

Monday 1-1:50pm, MEC 213



Roadmap: See-Think-Act

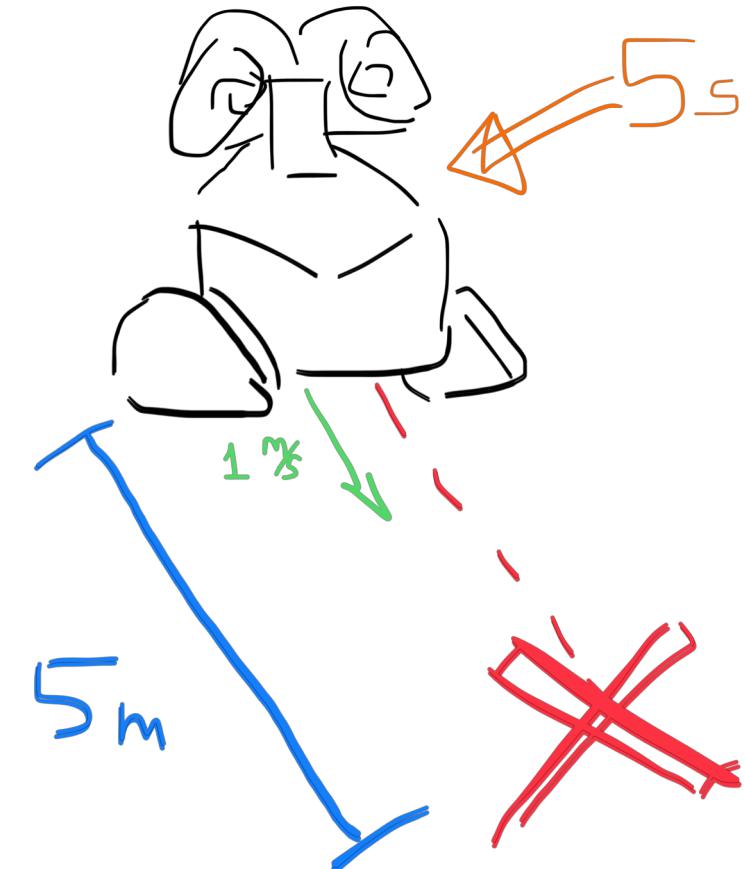
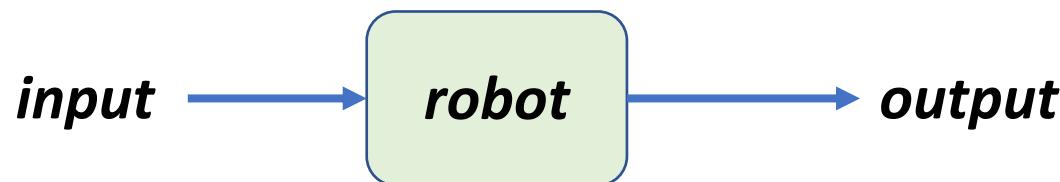


Recap: Control Theory

Task: We want our Robot to go to the Goal (red X)

Open-Loop Control

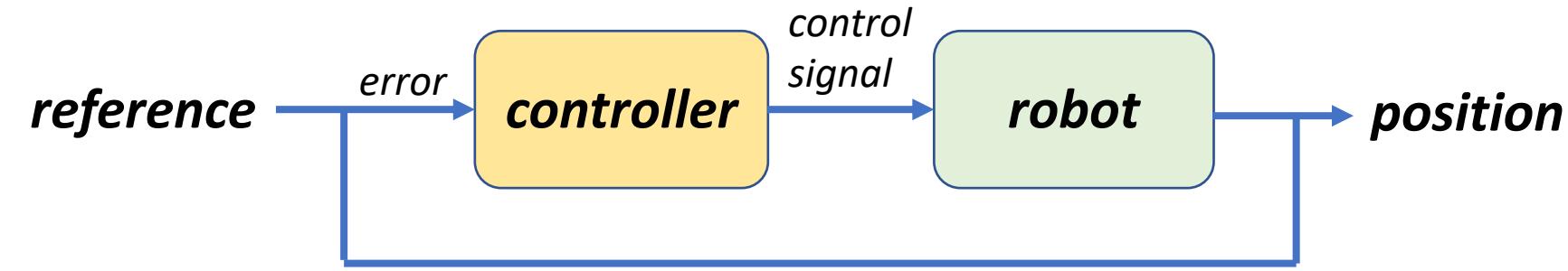
- Calculate distance and direction from Robot to Goal (5m forward)
- Given Robot's max speed (1 m/s)...
- Tell Robot to go 5 seconds in forward direction to reach goal
- Amount of time robot drives is not "adjusted"/corrected based on actual position of robot



Recap: Control Theory

Closed-Loop (Feedback) Control

- What if the robot doesn't reach the goal?
 - Environmental factors (drift, ground, etc.)
 - Systematic biases (Steering wheels misaligned)
- Need to convey to robot that we are “off-track”, and adjust accordingly
- Compare reference trajectory to current position = error
- Now just try to minimize that error!
- Controller = converts error into a command (control signal u) to be sent to robot



Recap: PID Controller

$$u(t) = k_P e(t) + k_I \int_0^t e(\tau) d\tau + k_D \frac{de(t)}{dt}$$

Video: [Controlling Self Driving Cars](#)

Recap: PID Controller

$$u(t) = k_P e(t) + k_I \int_0^t e(\tau) d\tau + k_D \frac{de(t)}{dt}$$

What does Proportional (k_P) do?

- “*Present*”: Contributes to stability, medium-rate responsiveness

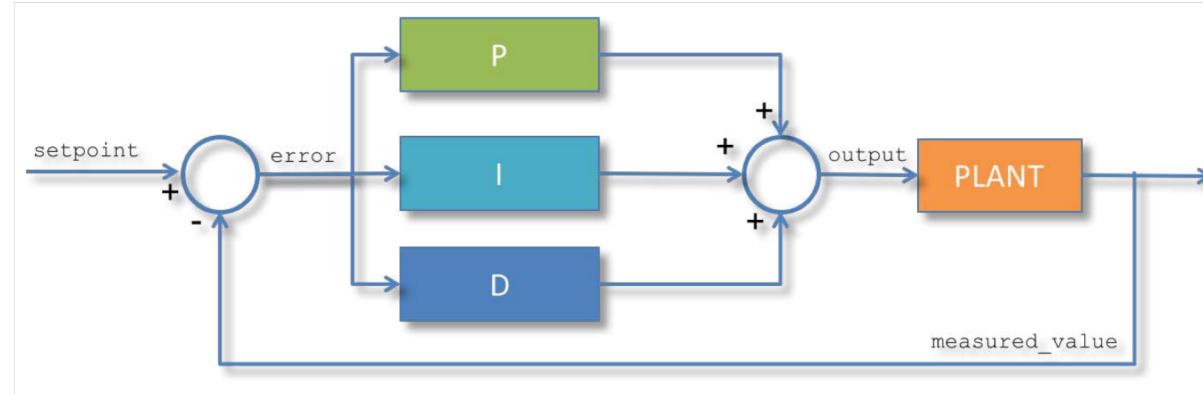
What does Integral (k_I) do?

- “*Past*”: Accumulates steady-state (past) errors
- Tracking and disturbance/bias rejection, slow-rate responsiveness

What does Derivative (k_D) do?

- “*Future*”: Anticipates errors based on rate of change
- Corrects Fast-rate responsiveness, sensitive to noise

Recap: PID Controller



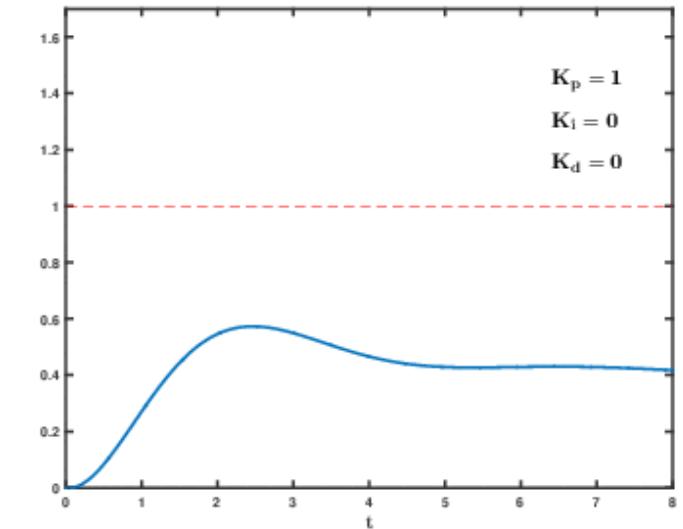
Pseudo-code:

```
previous_error = 0
integral = 0
start:
    error = setpoint - measured_value
    integral = integral + error*dt
    derivative = (error - previous_error)/dt
    output = Kp*error + Ki*integral + Kd*derivative
    previous_error = error
    wait(dt)
    goto start
```

Recap: Tuning a PID

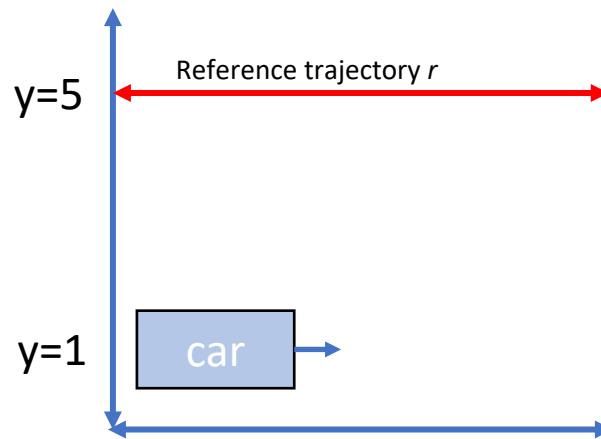
$$u(t) = k_P e(t) + k_I \int_0^t e(\tau) d\tau + k_D \frac{de(t)}{dt}$$

- Steps to tune your k_p , k_i and k_d parameters:
 - Start with k_p and increase until oscillations appear
 - Then move to k_i to reduce error
 - Finally move k_d to reduce oscillations
 - Go back to k_p and change until almost no oscillations (just a little overshoot)



PID Controller: Exercise

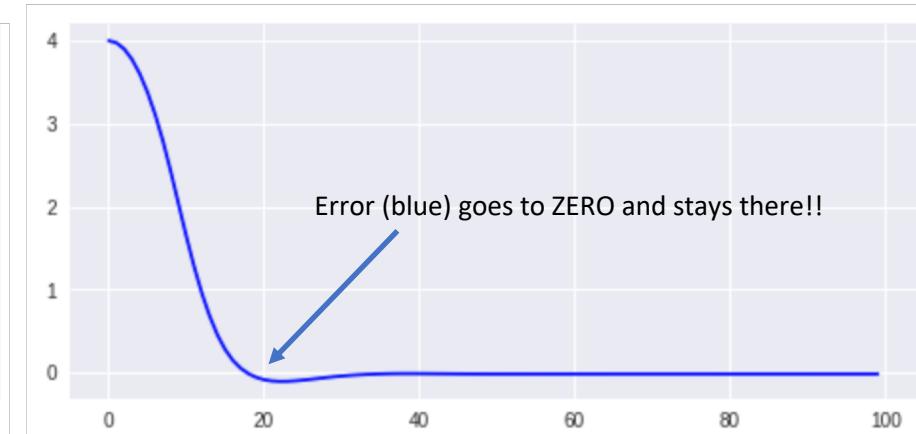
- Task:
 - Car starts at $y=1$
 - We want to follow a trajectory of $y=5$ (for all x)
 - So we need to steer car from $y=1$ to $y=5$, using a PID controller, & keep it there
 - Controller is on the *steering angle* (not velocity, like the previous slides!)
 - Fill in the code here: bit.ly/cs1501-pid



Depiction of task

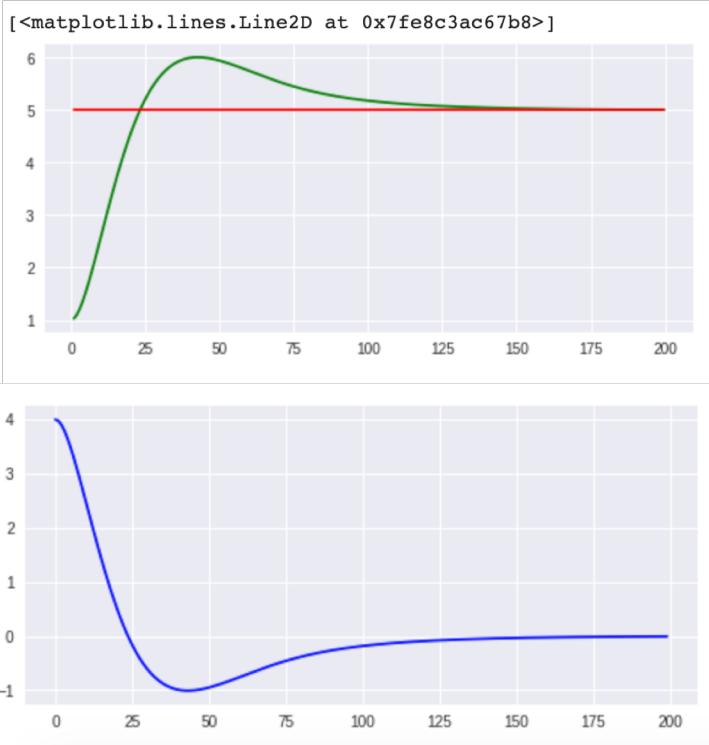


What we want to do



What we want the *error* graph to look like

PID Controller: Exercise Solution



`k_p = 0.2`
`k_i = 0.004`
`k_d = 3.0`

```
def run(robot, k_p, k_i, k_d, n=100, speed=1.0, dt=1.0):  
    x_trajectory = []  
    y_trajectory = []  
    errors = []  
  
    prev_e = 0  
    integral_e = 0  
  
    for i in range(n):  
  
        # error  
        e = ref - robot.y  
  
        # integral term  
        integral_e += e * dt  
  
        # derivative term  
        diff_e = (e - prev_e) / dt  
        prev_e = e  
  
        # control input u (PID)  
        steer_angle = (k_p * e) + (k_d * diff_e) + (k_i * integral_e)  
  
        robot.move(steer_angle, speed)  
  
        x_trajectory.append(robot.x)  
        y_trajectory.append(robot.y)  
        errors.append(e)  
  
    return x_trajectory, y_trajectory, errors
```

Perception

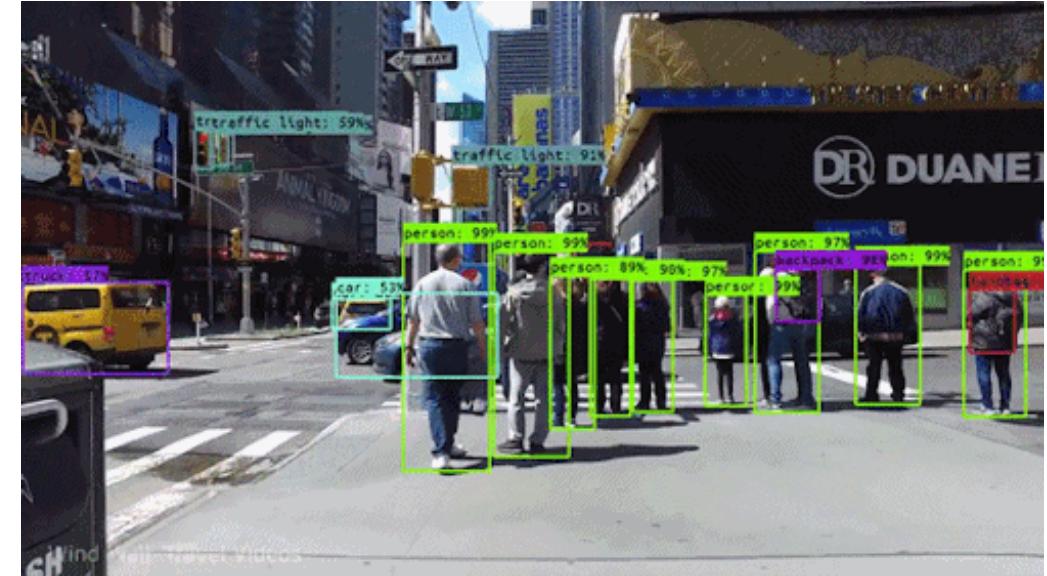
Perception = How can a robot “see”?

What does “see”-ing mean for a robot?

- Camera Images (stereo)
- LiDAR Point Clouds

Why would a robot want to “see”?

- Detect Pedestrians
- Stop Signs
- Traffic Lights
- Maps...



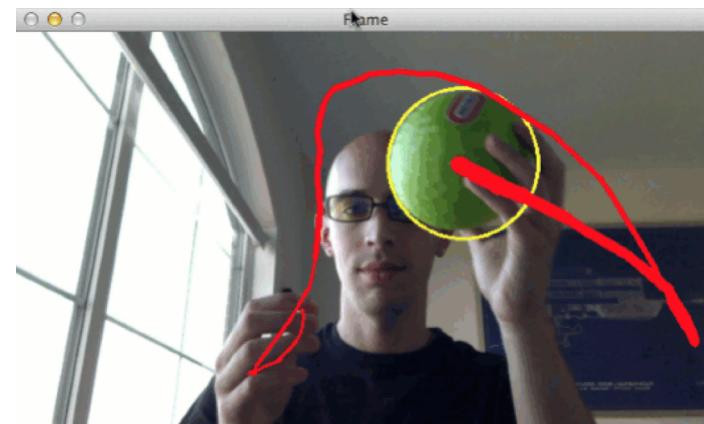
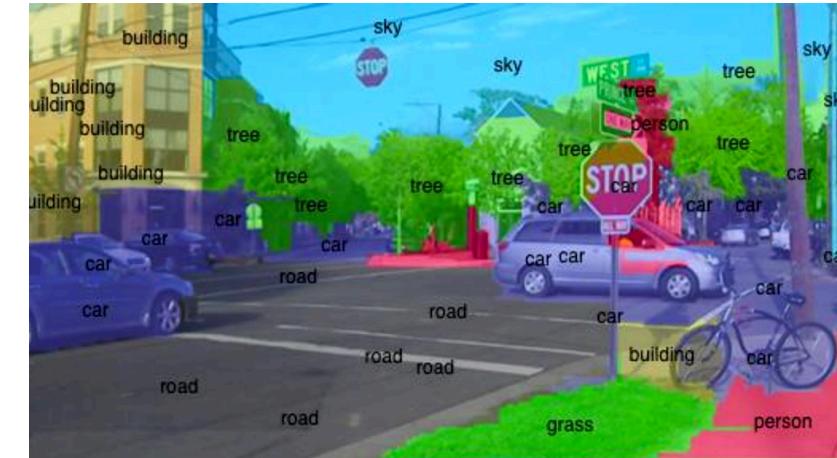
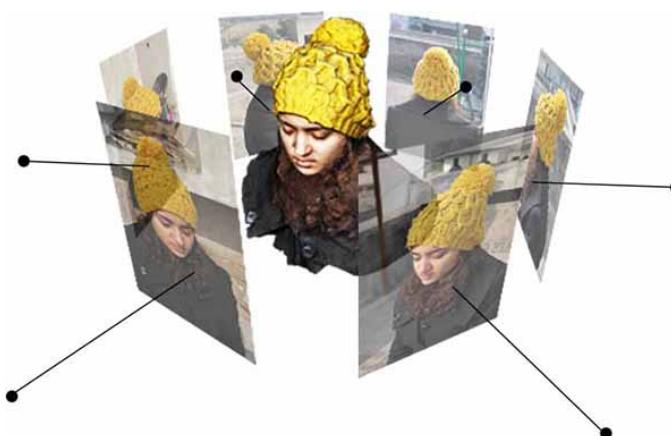
Computer Vision

Computer Vision = how can a computer make sense of images/videos?

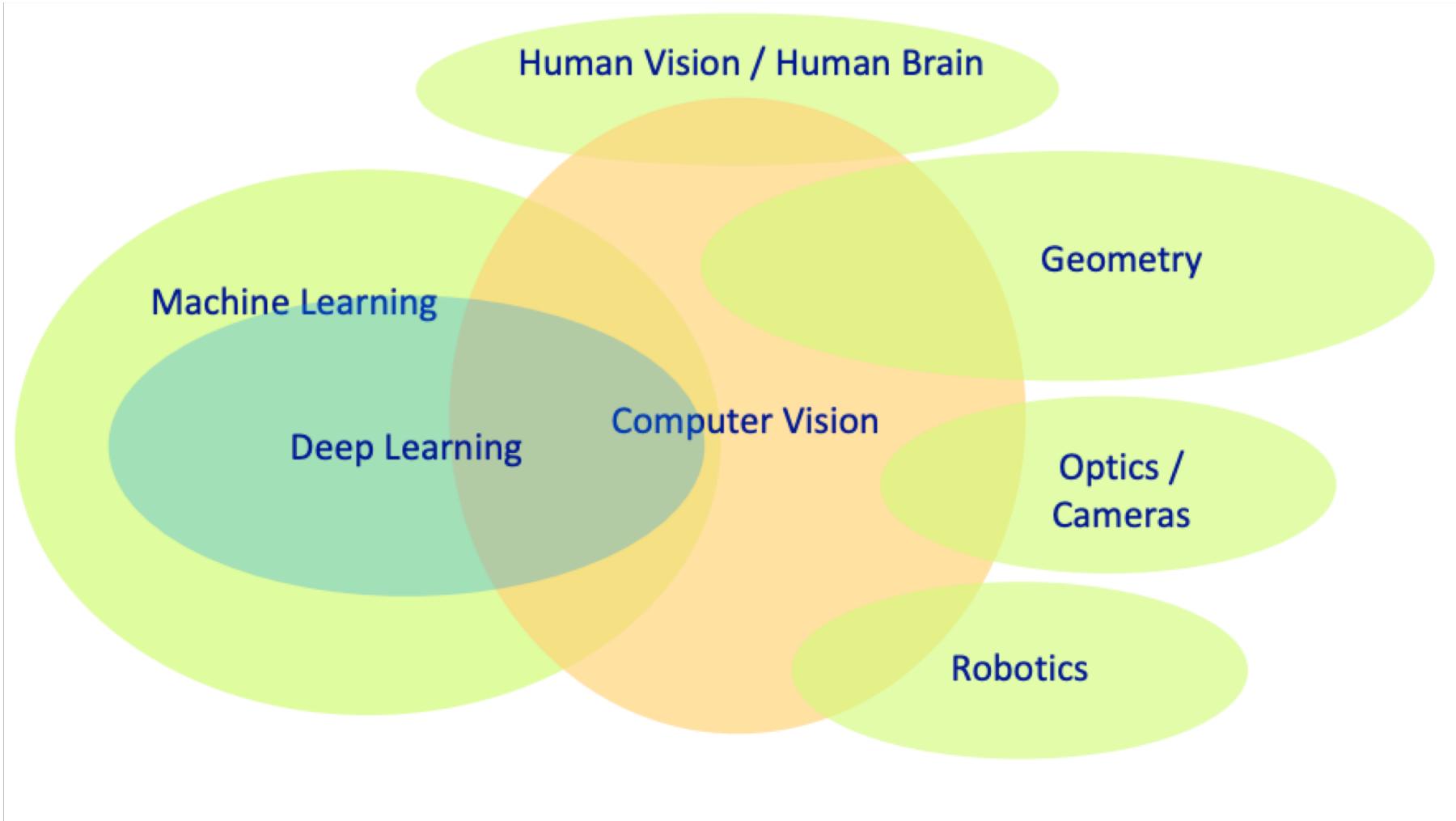
- Image → Knowledge

Purpose:

- Classification
- Object Detection
- 3D Reconstruction
- Pose Estimation
- Video Tracking
- So much more...!

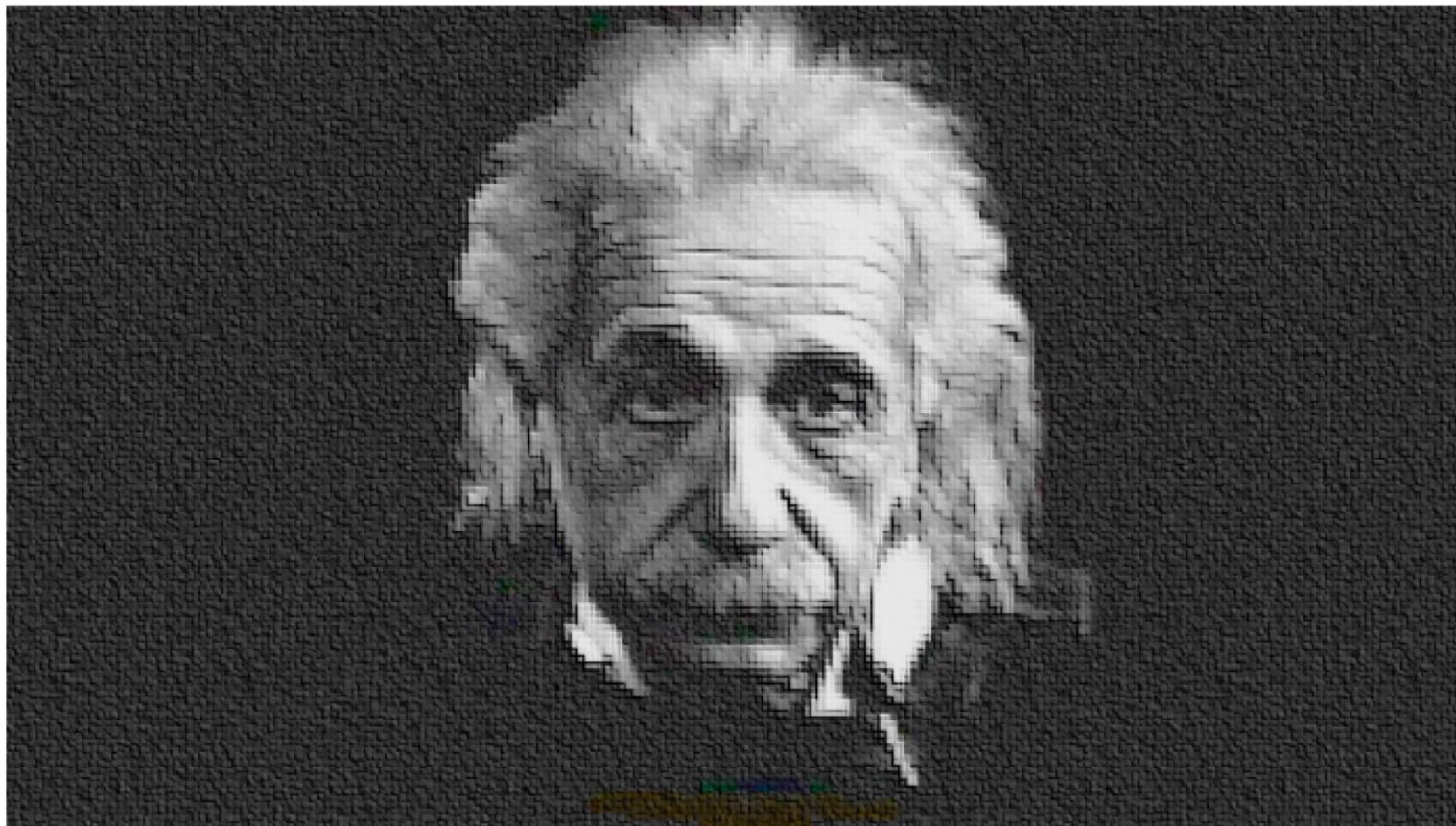


Computer Vision is a Big Field



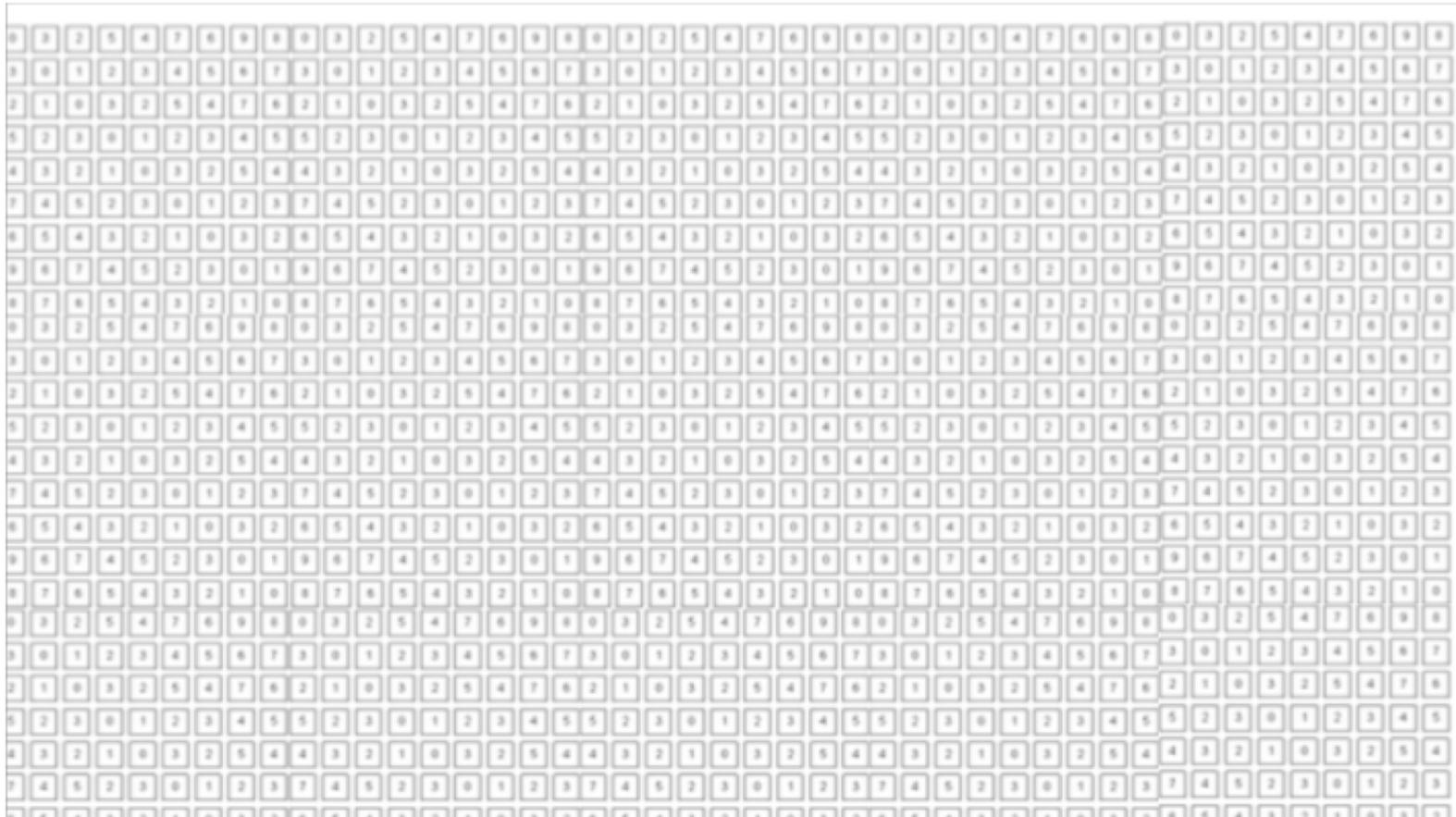
Computer Vision is Hard!

This is an image to us:



Computer Vision is Hard!

This is an image to a computer:



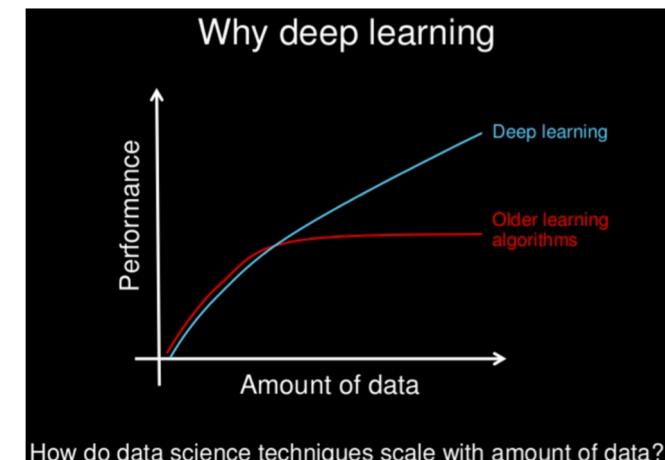
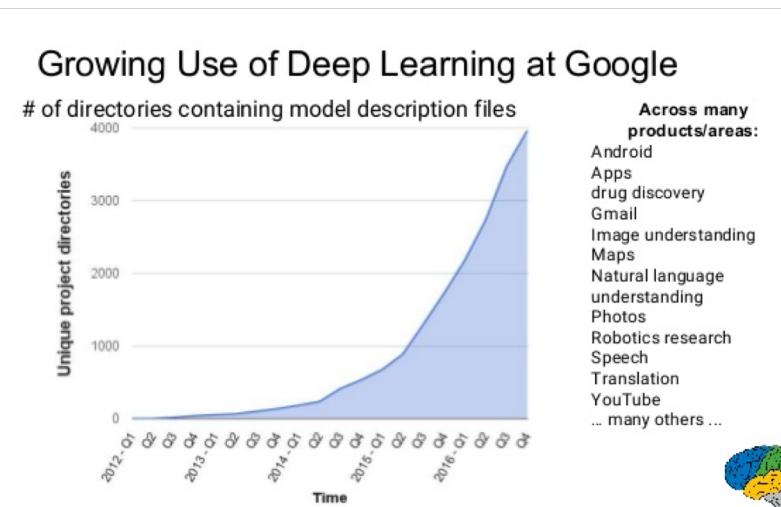
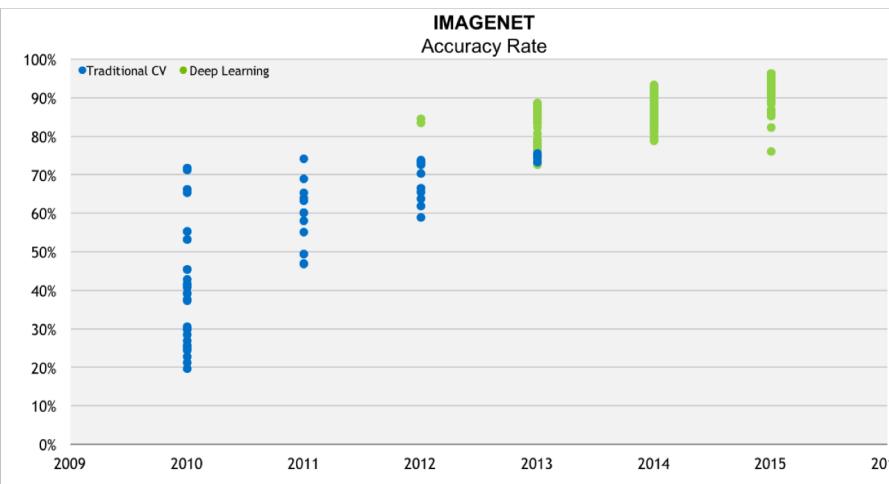
Types of Computer Vision

Two Main Types of Computer Vision:

- Pre-ML (Classical)
- Post-ML (Deep Learning)

The adoption of Deep Learning (~2012) accelerated Computer Vision

<https://twitter.com/olivercameron/status/1111671064600301568>



Classical Computer Vision

One big problem is Edge Detection!

- We want to detect all the edges in an image



Classical Computer Vision

Idea: “convolution” – apply a “kernel” on the image

- Image is a matrix (pixels)
- Kernel is a matrix
- Convolve them!

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Image matrix

1	0	1
0	1	0
1	0	1

Convolution filter

=

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved Feature

Classical Computer Vision

Sobel Operator: uses unique kernels to highlight edges in image

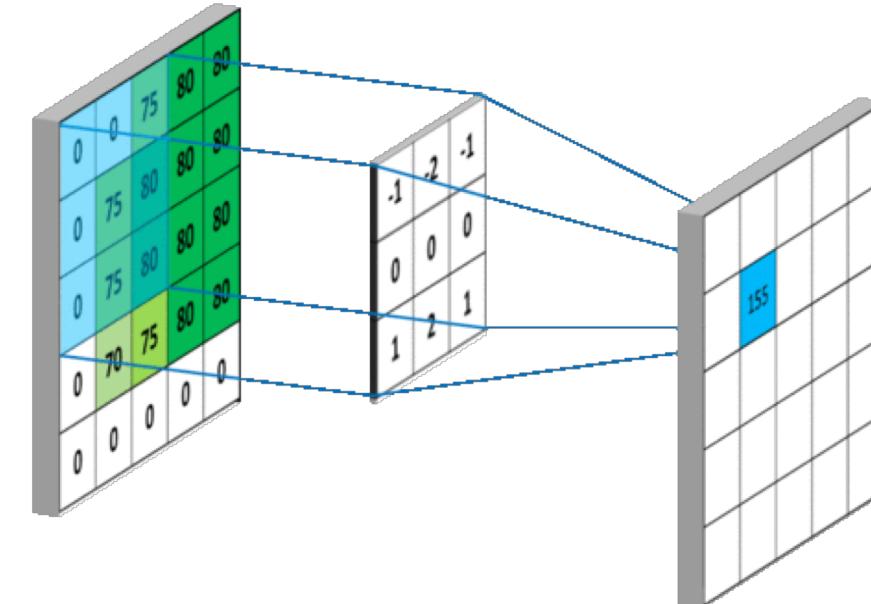
- Horizontal Edges
- Vertical Edges

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy



Classical Computer Vision

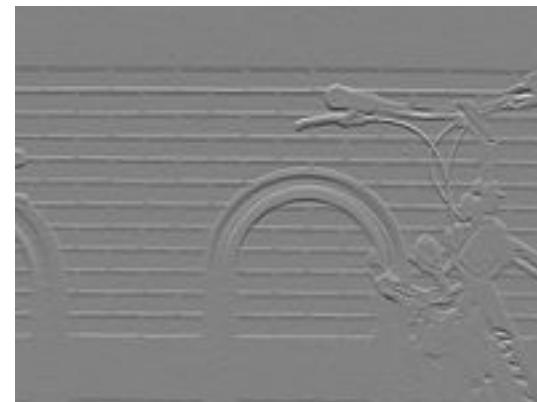
Sobel Operator: uses unique kernels to highlight edges in image



image



Sobel Vertical gradient



Sobel Horizontal gradient



Sobel combined

Deep Learning

What is a Neural Network?

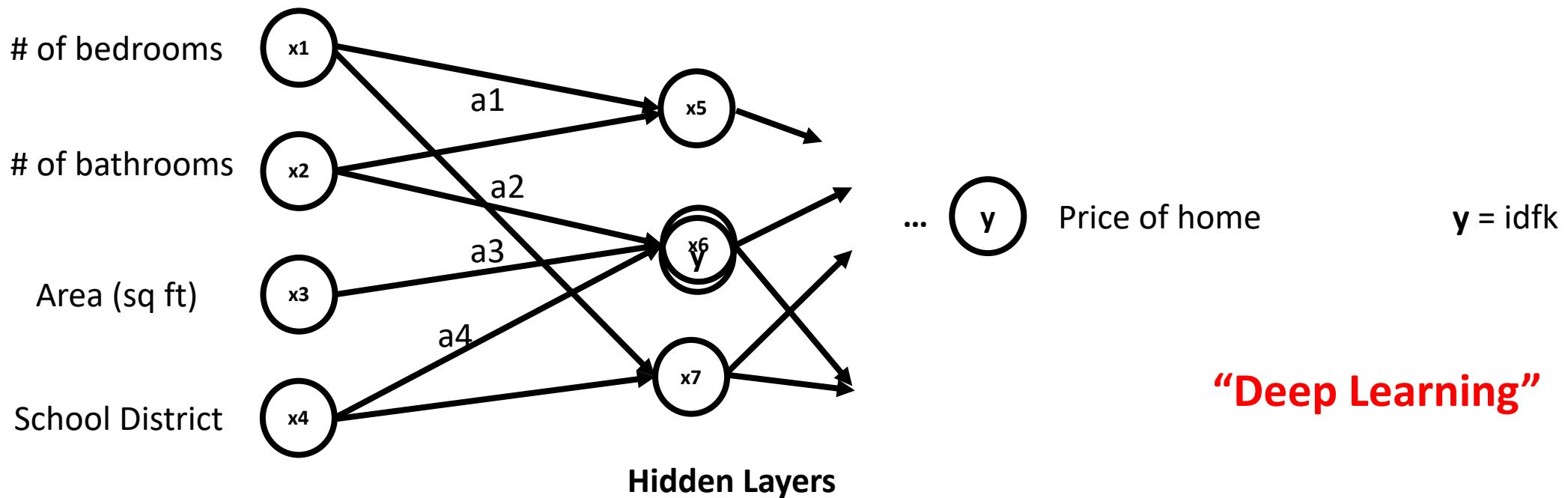
Example: We are trying to predict the price of a house:



Deep Learning

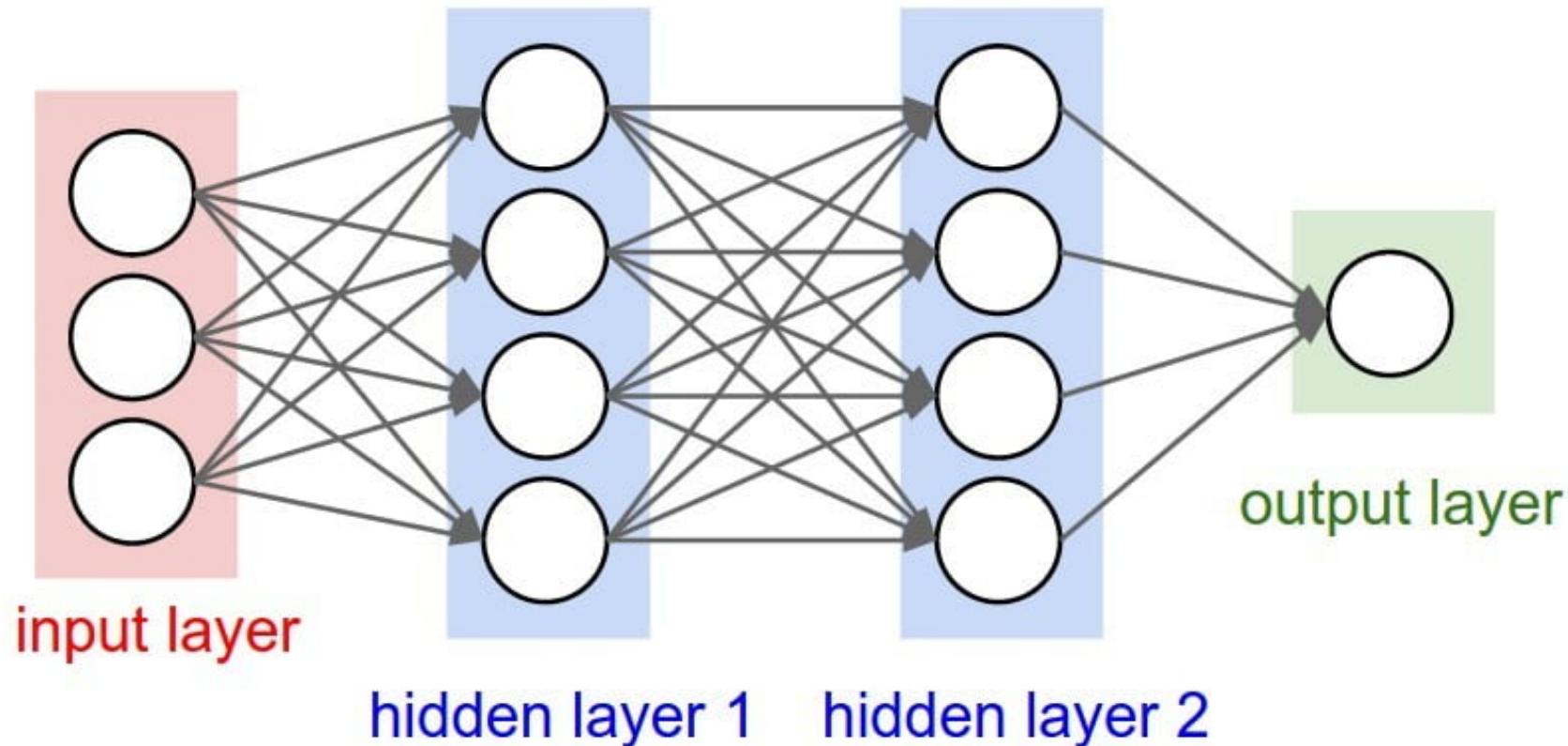
What is a Neural Network?

Example: We are trying to predict the price of a house:



Deep Learning

What is a Neural Network?



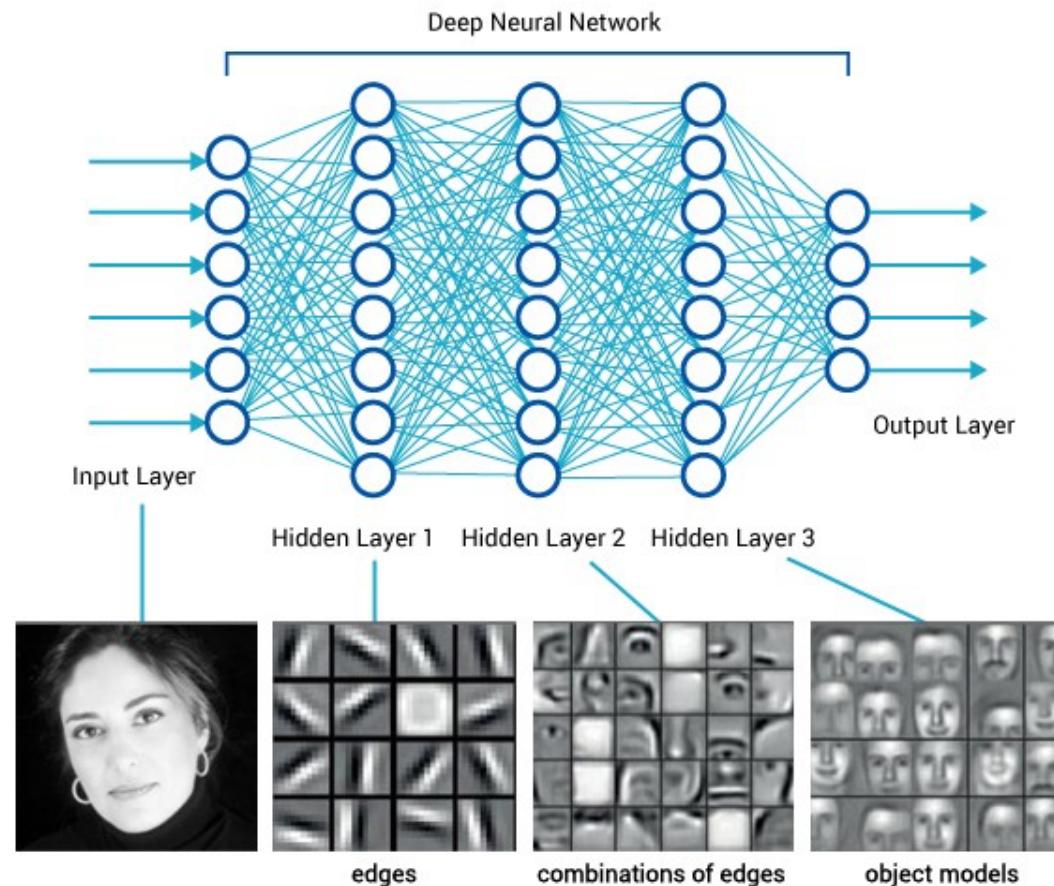
Deep Learning

What does this have to do with Computer Vision?



Deep Learning

What does this have to do with Computer Vision?



Deep Learning

Convolutional Neural Networks (CNNs)

