Deep Learning Mini Lecture

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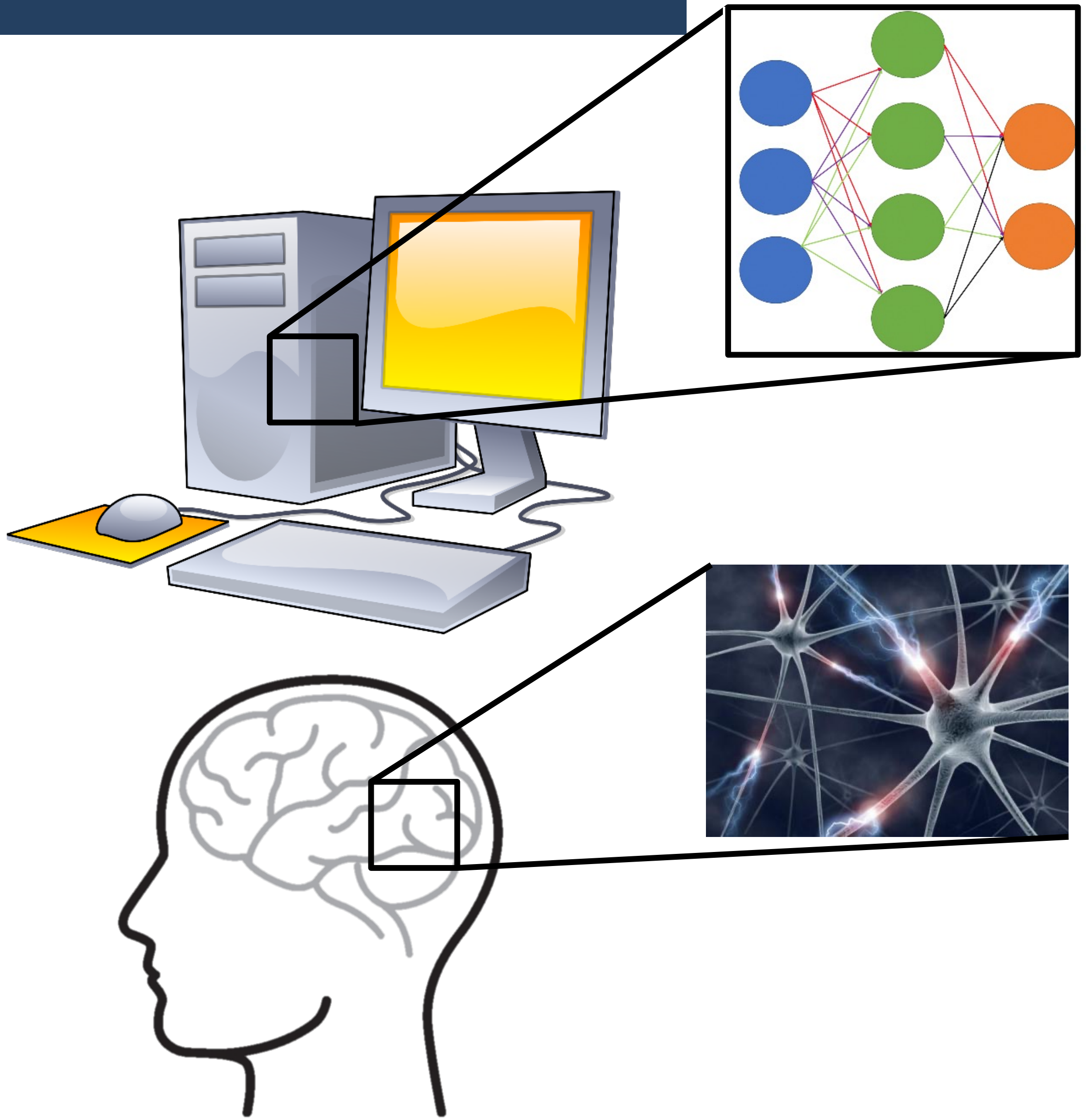
OUTLINE

- Introduction
- Deep Learning Hierarchy
- Unsupervised Learning
- Supervised Learning
- Reinforcement Learning
- Conclusion
- References

INTRODUCTION

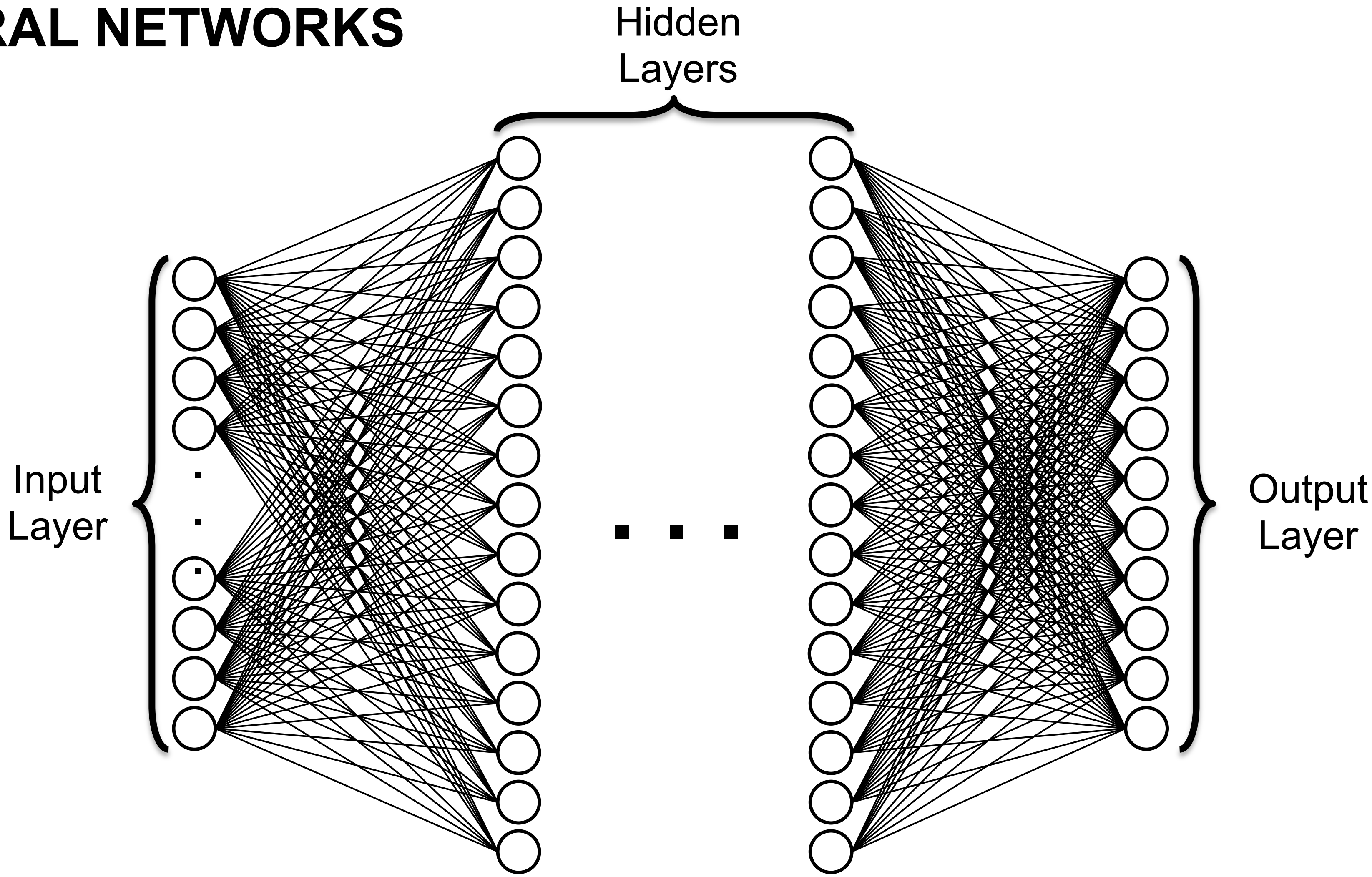
- Computer learning via a hierarchy of concepts
  - Each layer of the hierarchy represents a more abstract concept for the computer
  - “Deep” refers to the number of hierarchy layers

- Generally consist of a Neural Network
  - Biological analog of a Neural Network is the human brain
  - “Deep” refers to the number of hidden layers of the Neural Network



INTRODUCTION

DEEP NEURAL NETWORKS



INTRODUCTION

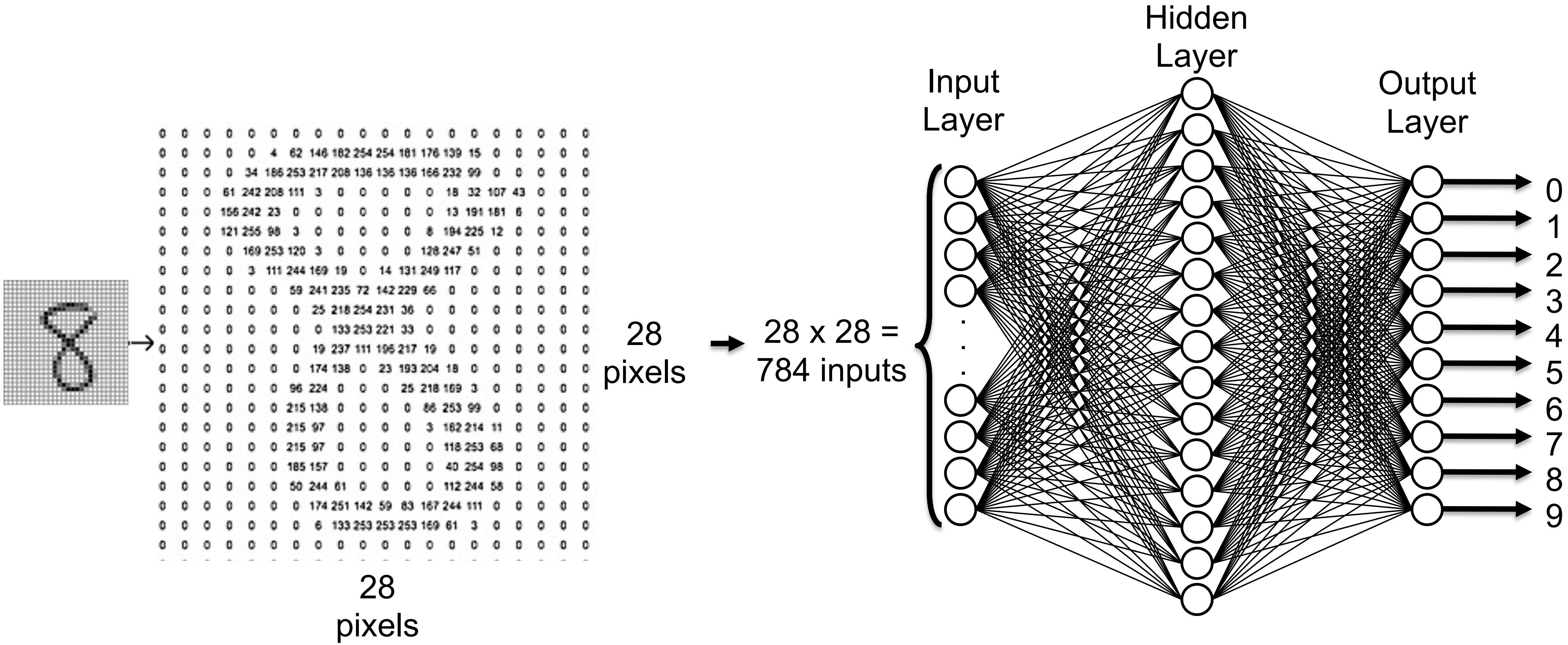
EXAMPLE: HANDWRITTEN DIGIT RECOGNITION

- **GOAL:** to creating and train a Neural Network to distinguish handwritten digits
- Digits are input as 28 x 28 pixel greyscale images
- System is trained using many sets of labeled training data (Supervised Learning)

Courtesy of Neural Networks and Deep Learning
By Michael Nielsen

INTRODUCTION

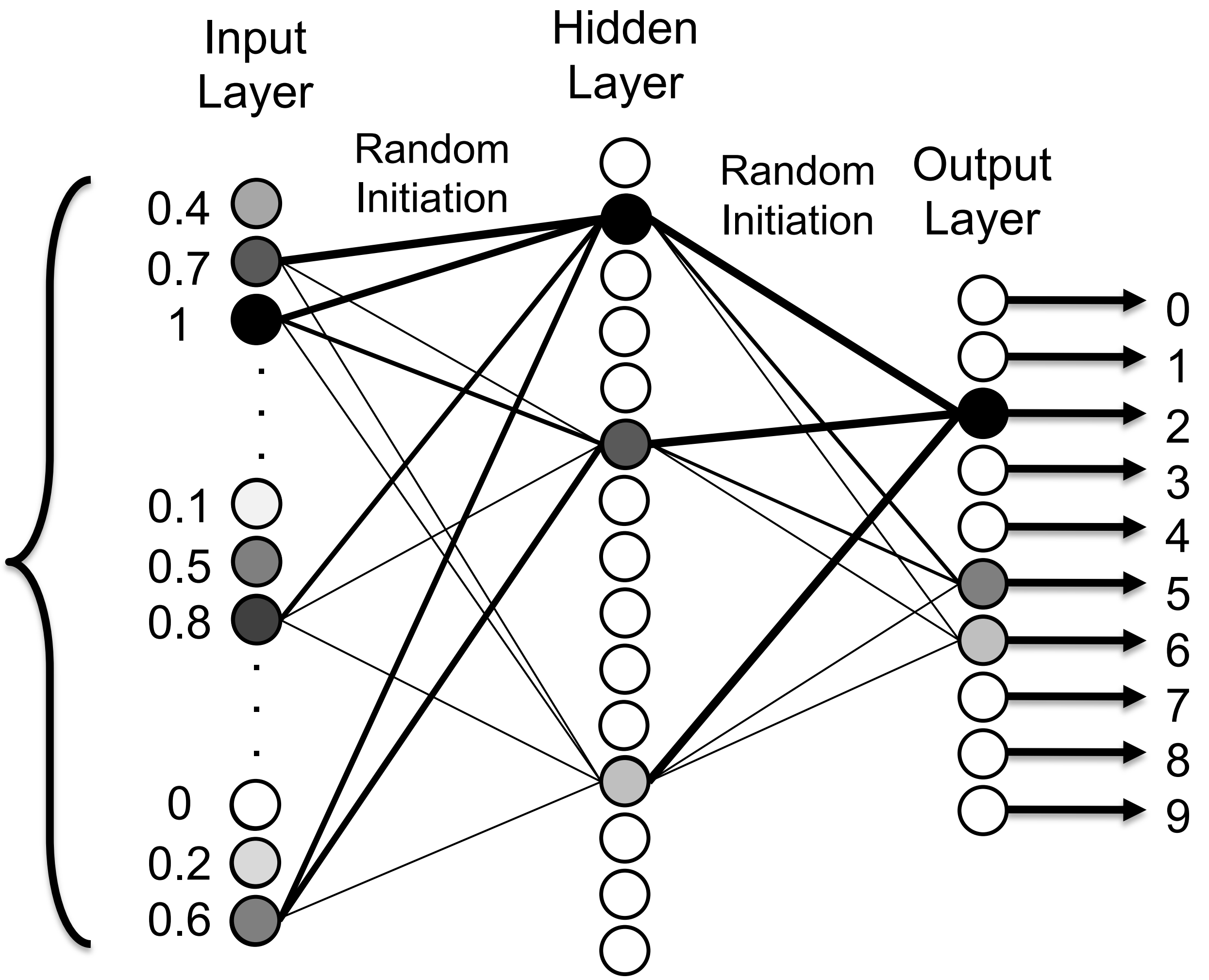
EXAMPLE: HANDWRITTEN DIGIT RECOGNITION



INTRODUCTION

EXAMPLE: HANDWRITTEN DIGIT RECOGNITION

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	4	62	146	182	254	254	181	176	139	15	0	0	0	0	0
0	0	0	0	34	186	253	217	208	136	136	136	166	232	99	0	0	0	0	0
0	0	0	61	242	208	111	3	0	0	0	0	0	18	32	107	43	0	0	0
0	0	0	156	242	23	0	0	0	0	0	0	0	13	191	181	6	0	0	0
0	0	0	121	255	98	3	0	0	0	0	0	8	194	225	12	0	0	0	0
0	0	0	0	169	253	120	3	0	0	0	0	128	247	51	0	0	0	0	0
0	0	0	0	3	111	244	169	19	0	14	131	249	117	0	0	0	0	0	0
0	0	0	0	0	0	59	241	235	72	142	229	66	0	0	0	0	0	0	0
0	0	0	0	0	0	0	25	218	254	231	36	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	133	253	221	33	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	19	237	111	196	217	19	0	0	0	0	0	0	0
0	0	0	0	0	0	0	174	138	0	23	193	204	18	0	0	0	0	0	0
0	0	0	0	0	0	96	224	0	0	0	25	218	169	3	0	0	0	0	0
0	0	0	0	0	0	215	138	0	0	0	0	86	253	99	0	0	0	0	0
0	0	0	0	0	0	215	97	0	0	0	0	3	162	214	11	0	0	0	0
0	0	0	0	0	0	215	97	0	0	0	0	0	118	253	68	0	0	0	0
0	0	0	0	0	0	185	157	0	0	0	0	0	40	254	98	0	0	0	0
0	0	0	0	0	0	50	244	61	0	0	0	0	112	244	58	0	0	0	0
0	0	0	0	0	0	0	174	251	142	59	83	167	244	111	0	0	0	0	0
0	0	0	0	0	0	0	6	133	253	253	253	169	61	3	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0



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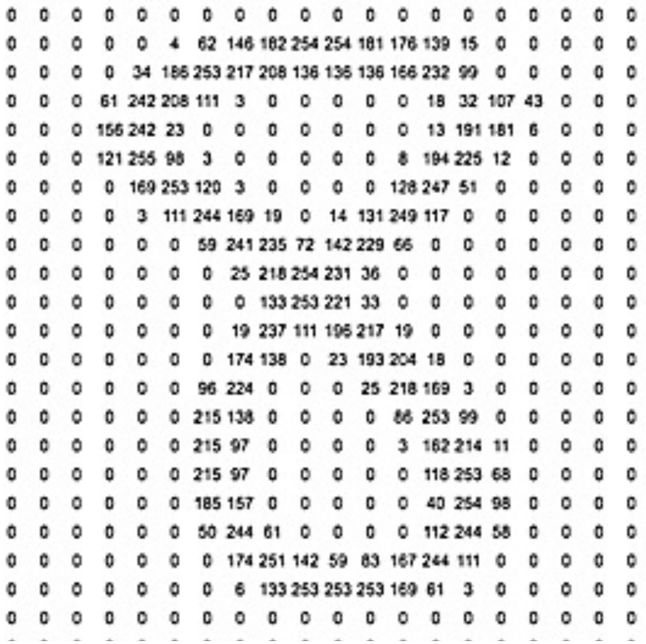
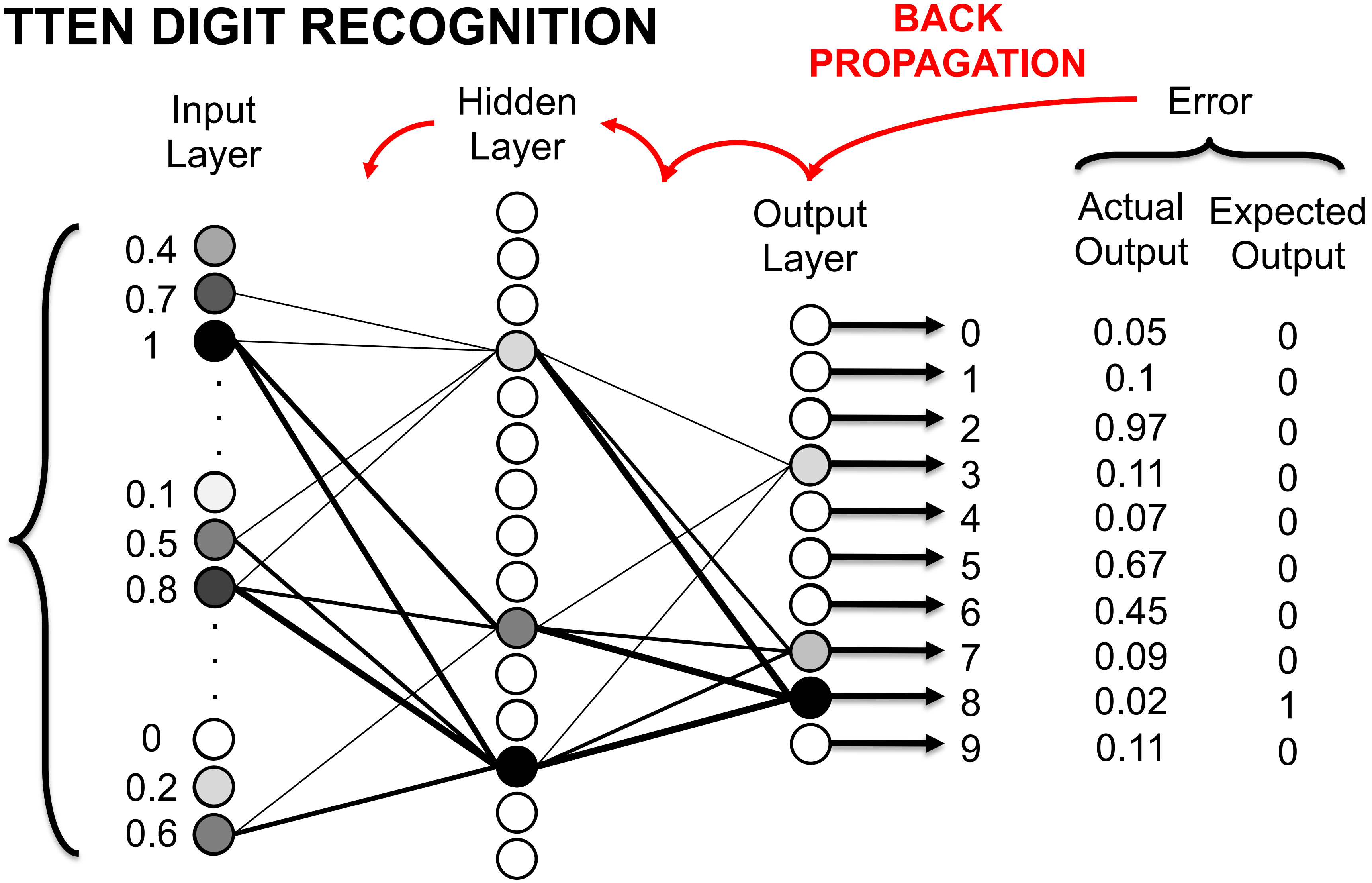
INCORRECT!

INTRODUCTION

EXAMPLE: HANDWRITTEN DIGIT RECOGNITION

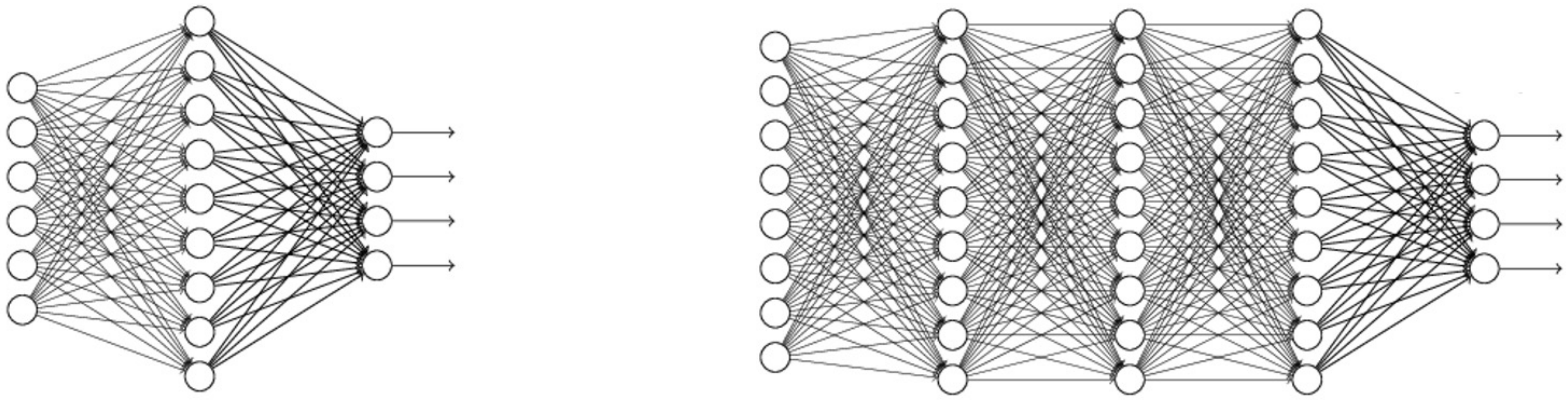




INTRODUCTION

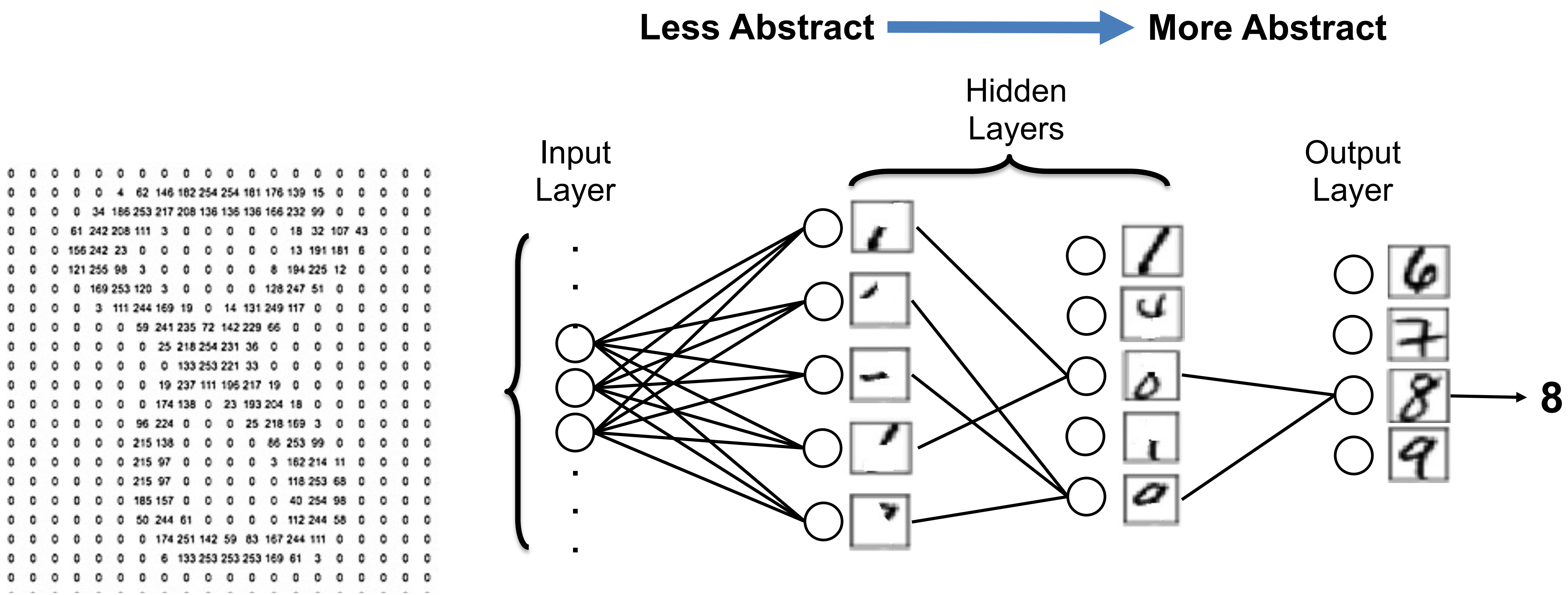
SHALLOW vs DEEP LEARNING

- The previous example was a case of “Shallow” learning, as the Neural Network consisted of only a single hidden layer.
- As more layers are added, the computer is able to understand and classify more abstract concepts.
- Deep Learning provides better performance with increasing depth, but at the cost of greater learning and computational time.

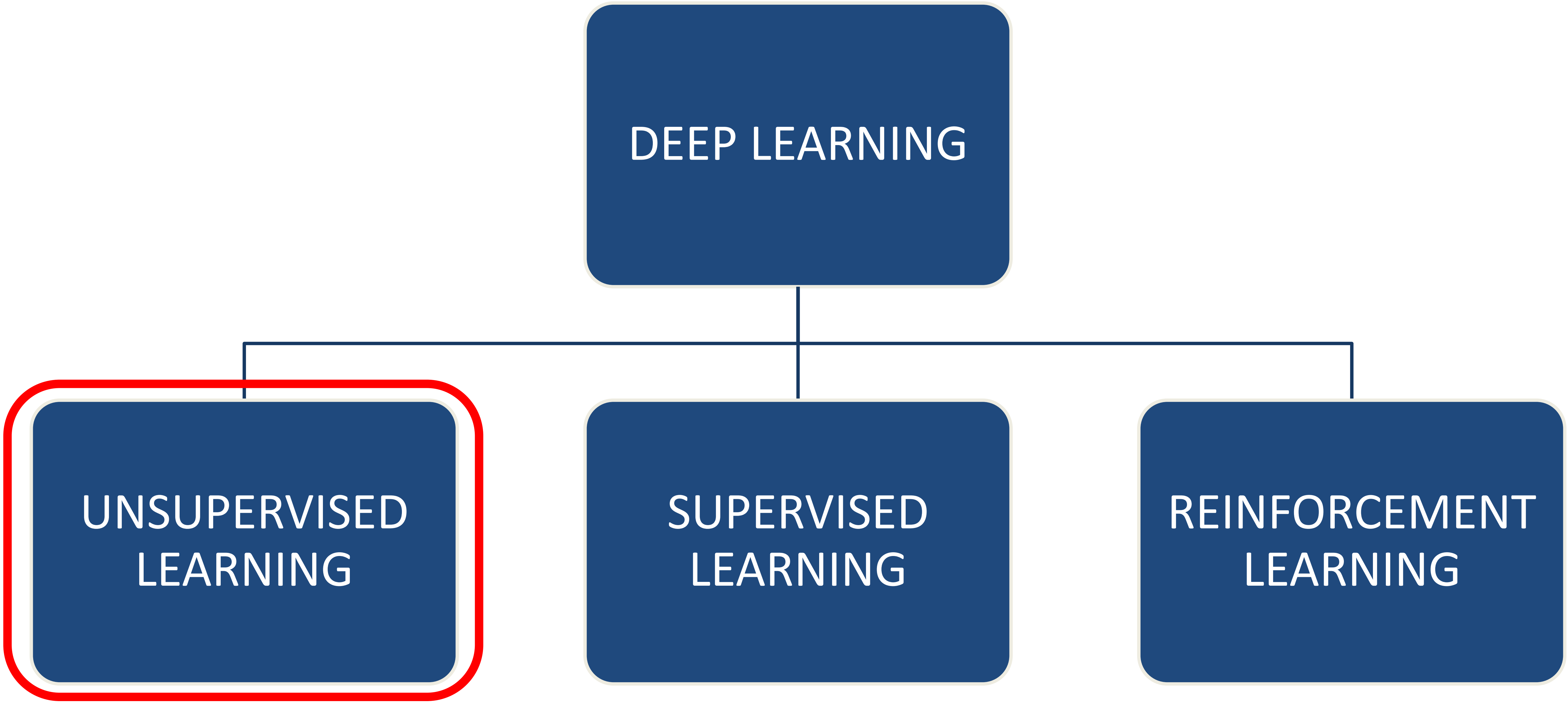


INTRODUCTION

SHALLOW vs DEEP LEARNING

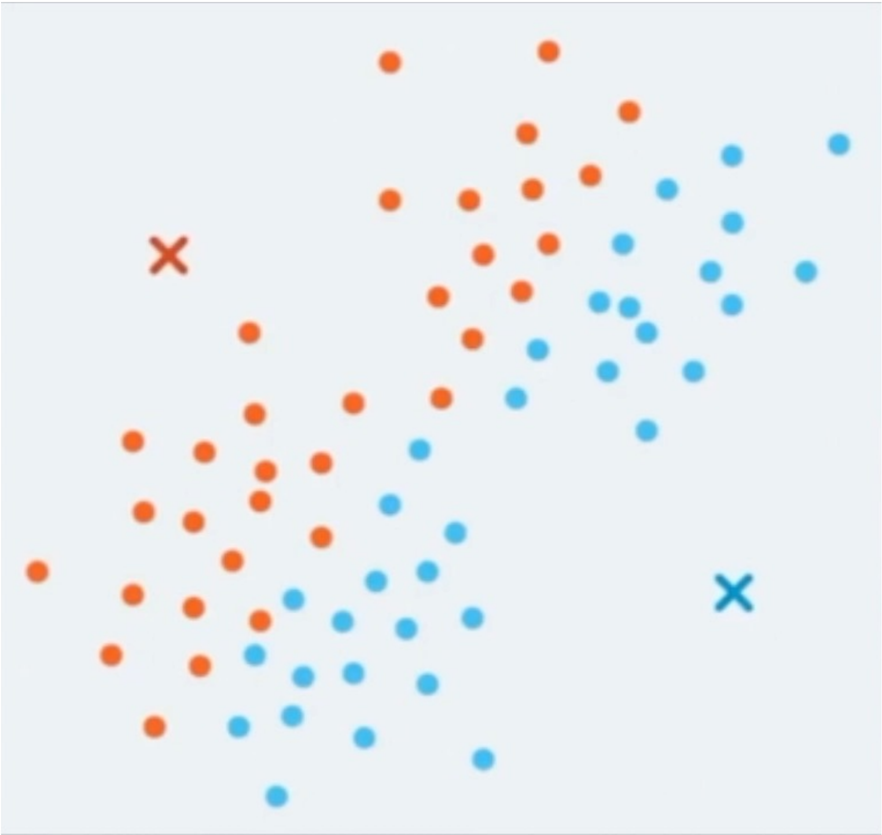


TOPICS OF DEEP LEARNING



UNSUPERVISED LEARNING

- Method to train a Neural Network with little human interaction
- Unlabelled data fed to network for interpretation
  - No meta-data (Dates, Location Tags etc.)
- Derive patterns and correlations from the data without any labels
- "This image of a furry thing looks like these other furry things"

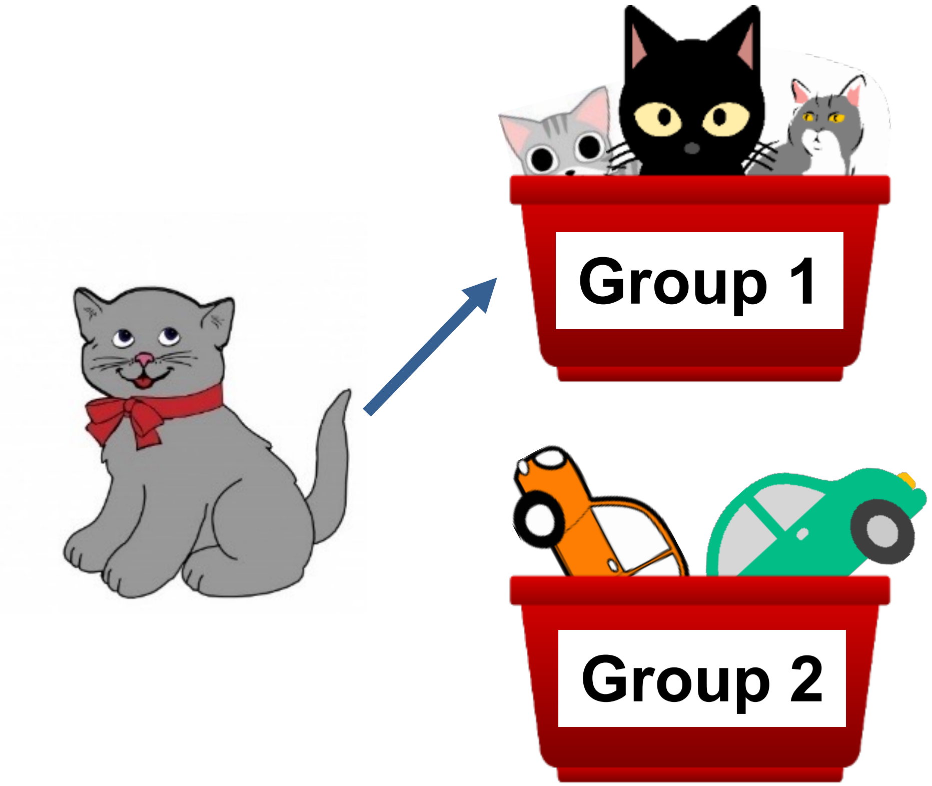


Courtesy of Toptal

UNSUPERVISED LEARNING

PURPOSE

- Able to make decisions from recognized patterns
- Define the problem with an unknown solution
  - Sorting photos based on image context rather than meta data
- Benefits:
  - Less man hours to label and track data
  - Solutions found with no predetermined connections
    - Driving a silver car leads to cancer
    - Investing on a Tuesday has less returns
  - Elimination of human biasing



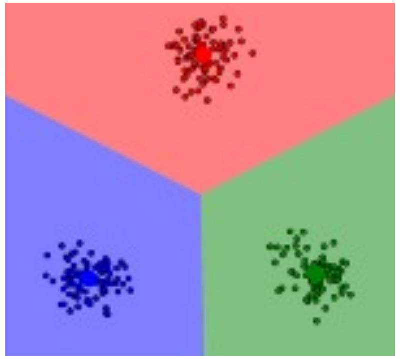
UNSUPERVISED LEARNING

METHODS

- Clustering (Grouping Data)

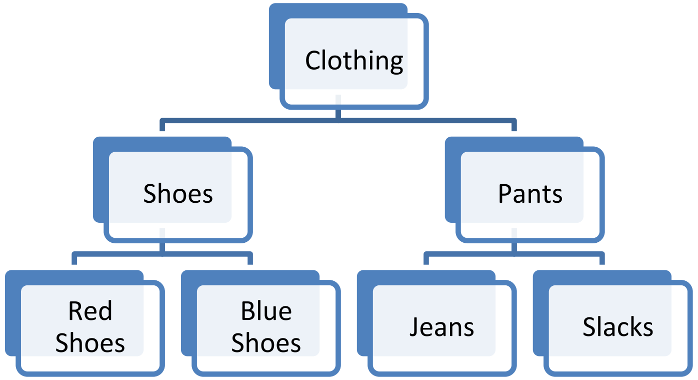
K-means clustering

- K-number of clusters (Groups) created
- Centroids of clusters denoted where close data points are added to the k_{th} cluster



Hierarchical clustering

- Clusters are grouped together creating a hierarchy
- E.g. Refine your search in online shopping



- Reducing Dimensions
  - Compressing data while keeping features
  - Compressed data easily compared

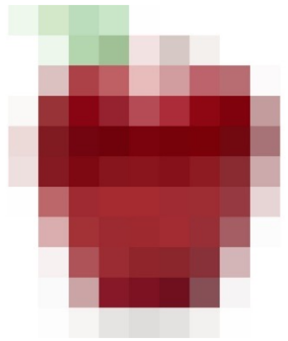
Effective w/ Deep Learning

Images Courtesy of Medium.com

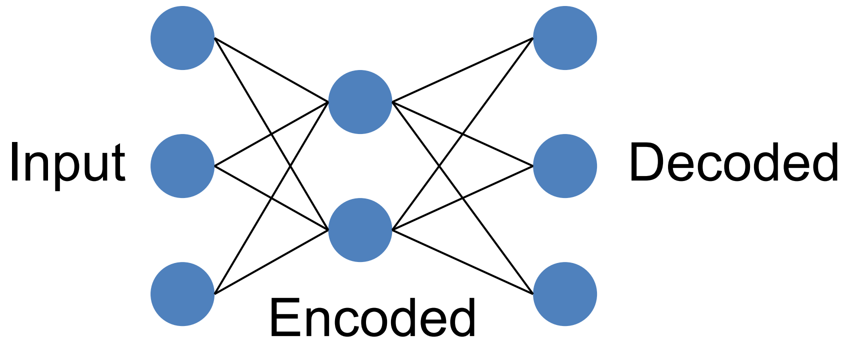
UNSUPERVISED LEARNING

AUTOENCODERS

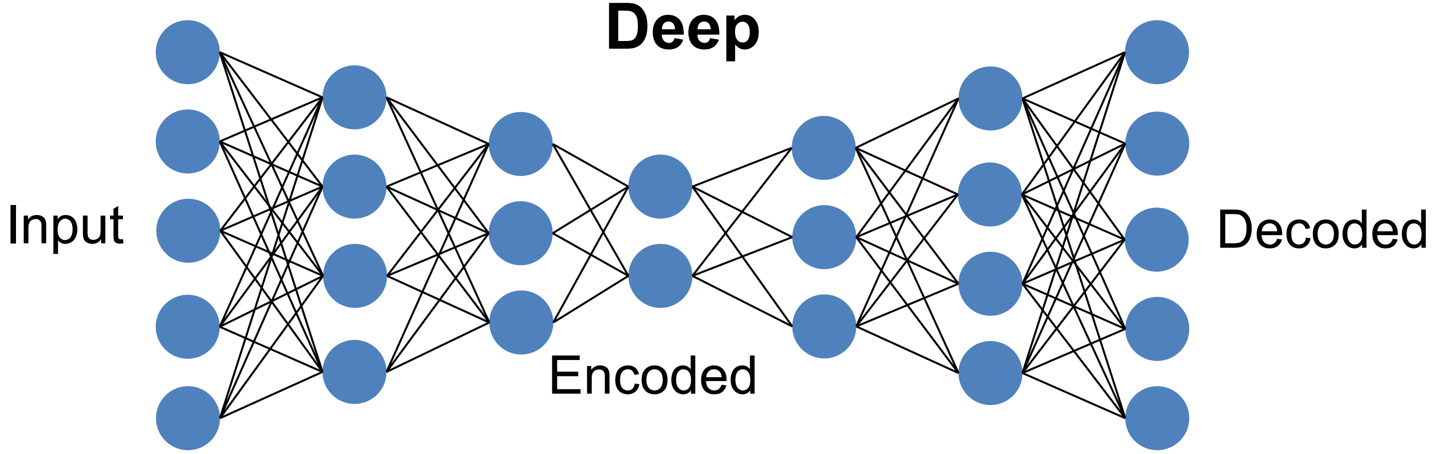
- Taking large data and outputting a smaller size for comparison
  - Attributes of a 784 pixel image condensed to a 30 unit vector
- Performed by symmetrical neural network structure
  - Output is trained to generate the same as the input
  - Center layer represents the compressed feature vector
  - Network can be shallow or deep



Shallow



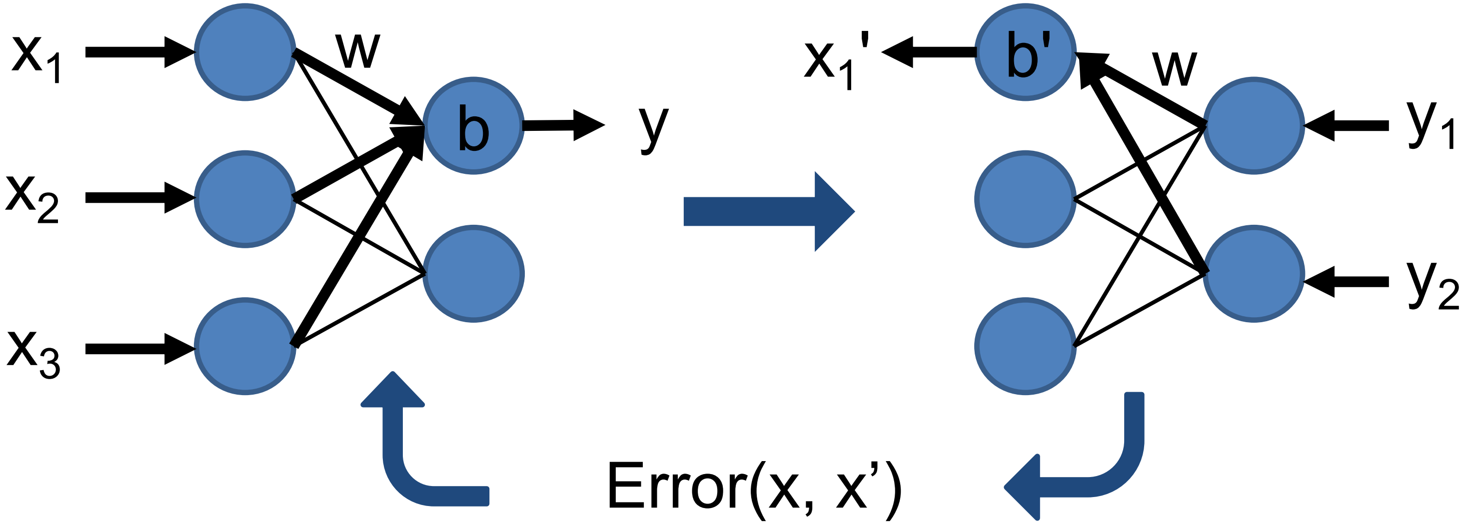
Deep



UNSUPERVISED LEARNING

RESTRICTED BOLTZMANN MACHINE (RBM)

- Construction
  - Two Layer (Visible and Hidden)
  - “Restricted”
- Forward and backward passes train the weights in unsupervised manor
  - Outputs from the forward pass become inputs on the backward pass
  - New outputs from the backward pass are compared to initial inputs

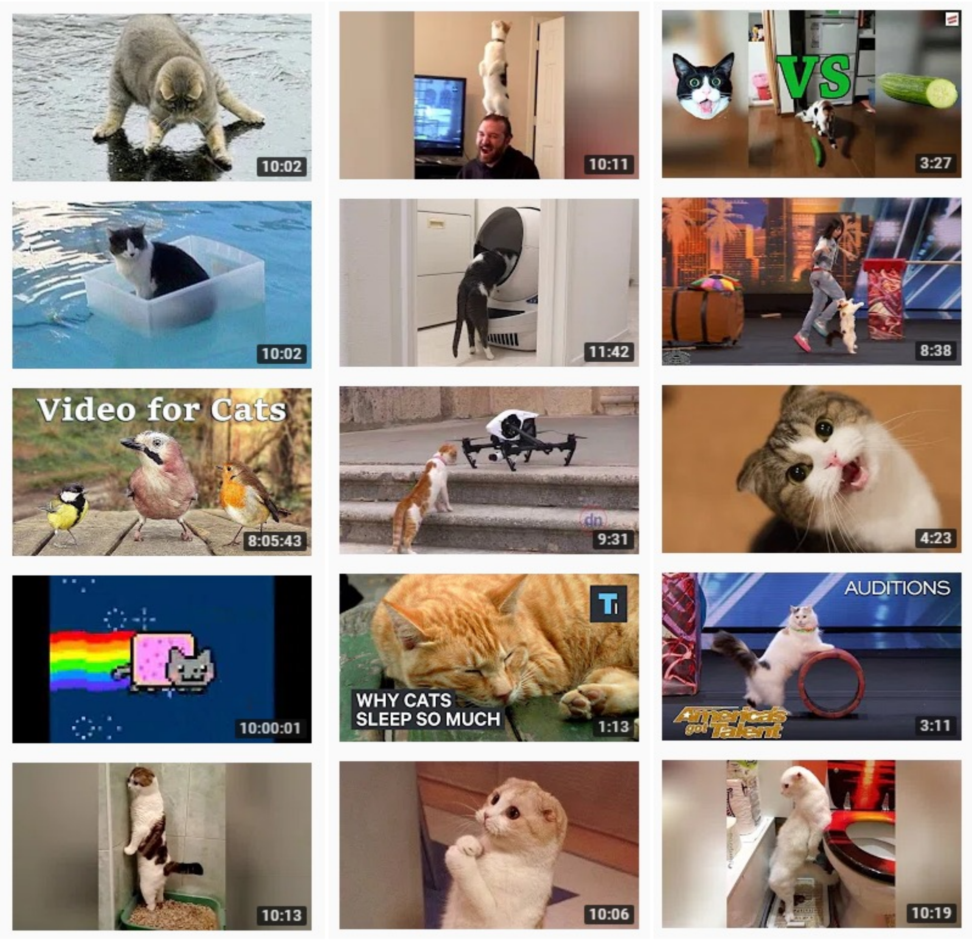


UNSUPERVISED LEARNING

GOOGLE'S CAT VIDEO FINDER

- Data Set
  - Unlabeled images from YouTube
- Network
  - 1 Billion connections
  - 9 Layer Autoencoder

  Deep Belief Network
- Output
  - Found Specific Neuron Related to Cat Faces
  - Captured "Complex Invariances"
    - Related to human capability
    - AKA Understanding the "important things" in pictures



Courtesy of Youtube

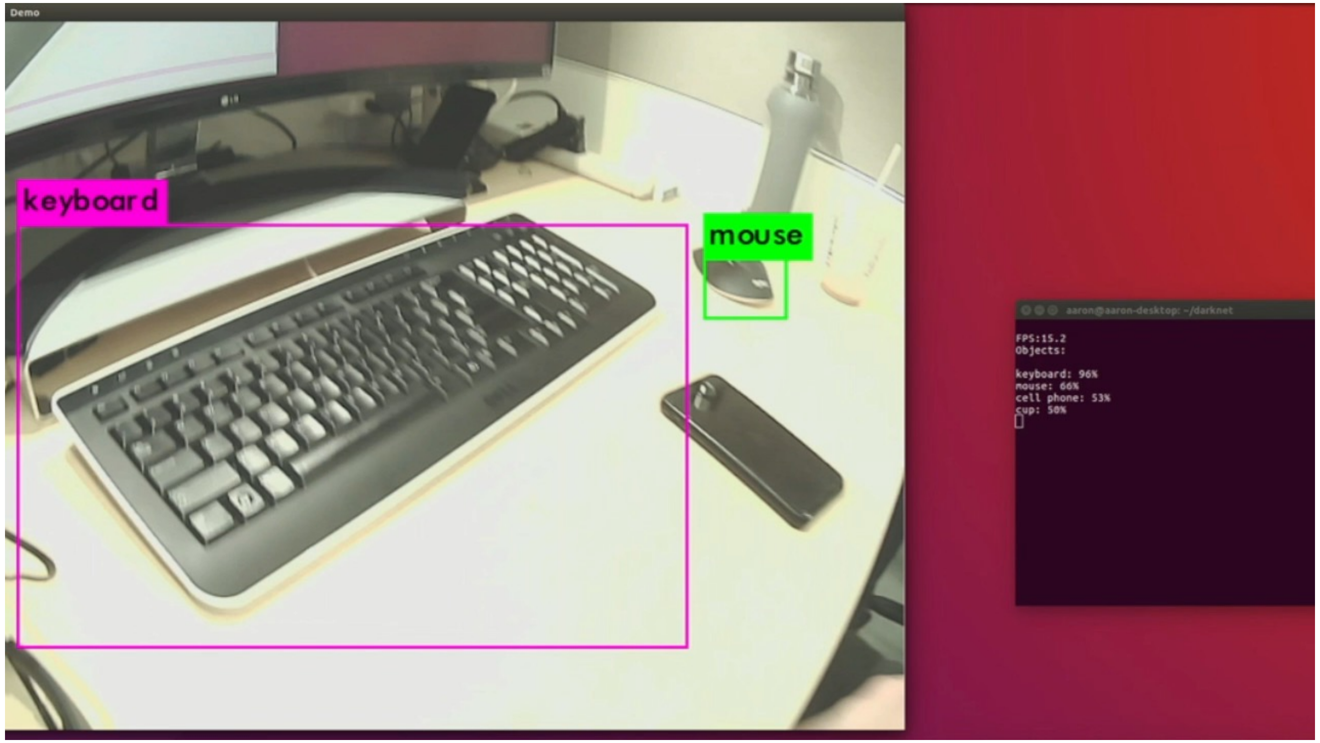
TOPICS OF DEEP LEARNING

- DEEP LEARNING
  - UNSUPERVISED LEARNING
  - SUPERVISED LEARNING
  - REINFORCEMENT LEARNING

SUPERVISED LEARNING

Supervised learning is useful for building a classifier of LABELLED DATA

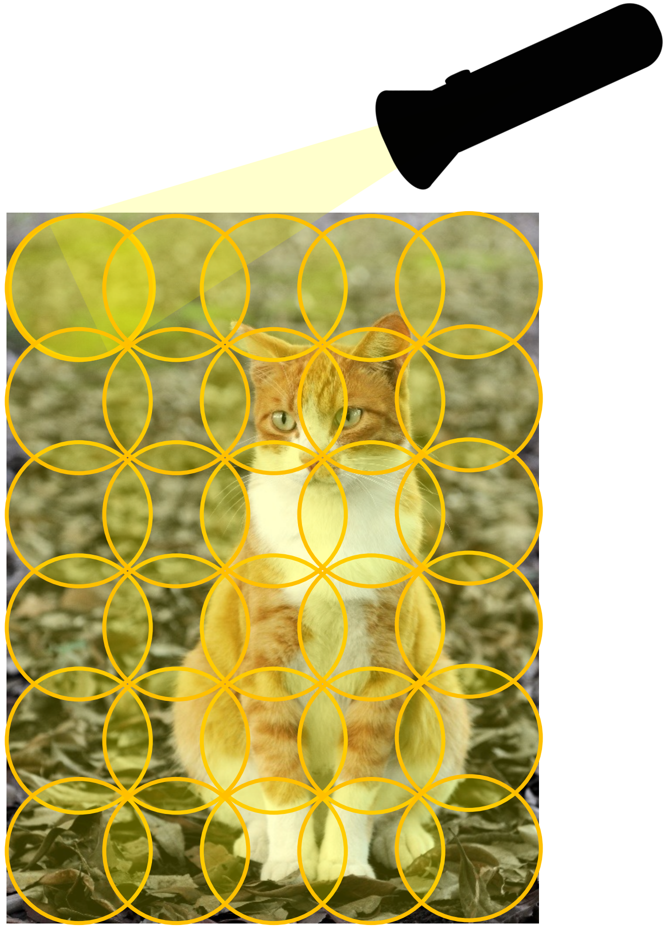
- Text Processing
  - Recursive Neural Tensor Network
  - Recurrent Network
- Image Recognition
  - Deep Belief Network
  - Convolutional Neural Network
- Object Recognition
  - Recursive Neural Tensor Network
  - Convolutional Neural Network
- Speech Recognition
  - Recurrent Network



Live YOLO V3 Demo on NVIDIA GTX 1060

SUPERVISED LEARNING

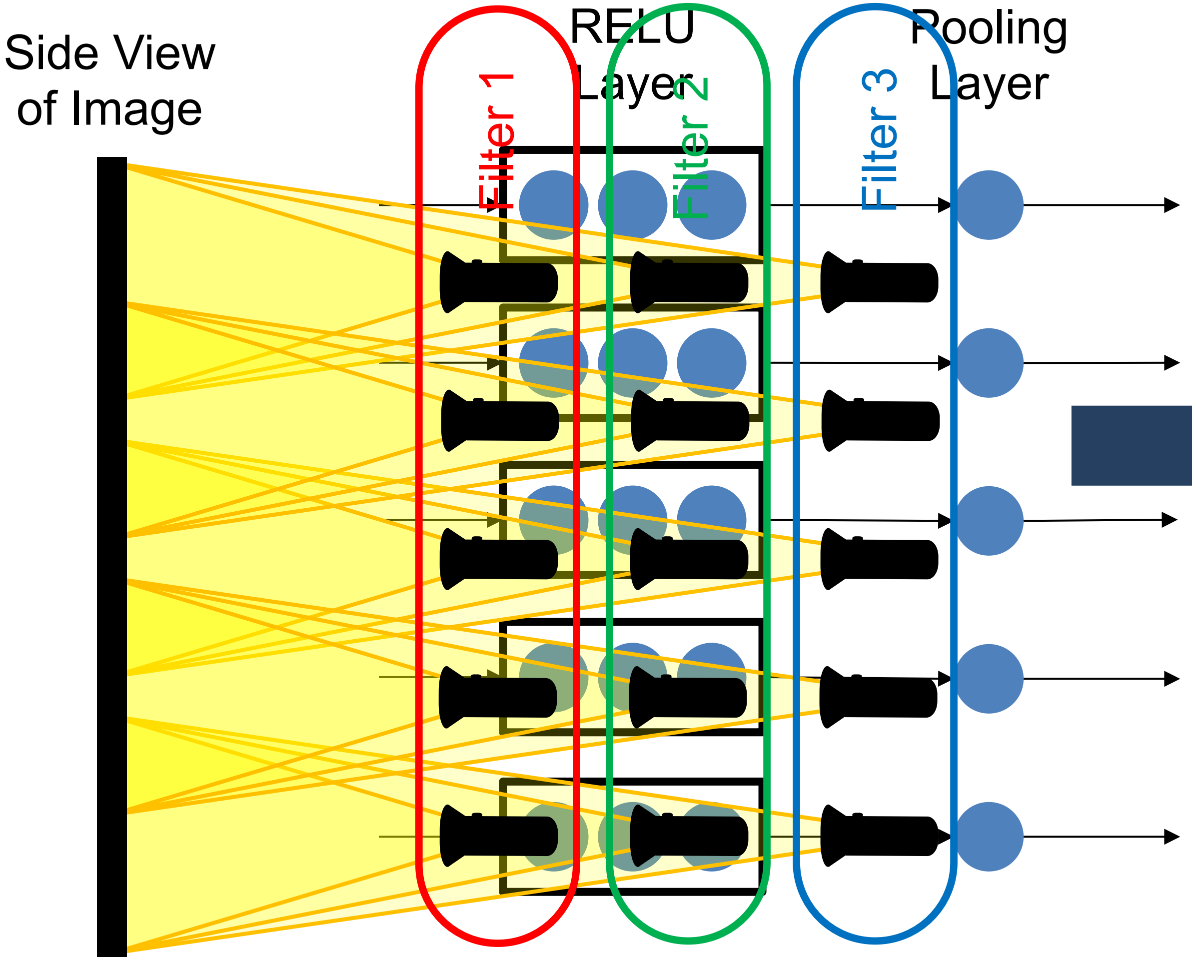
FLASHLIGH EXAMPLE



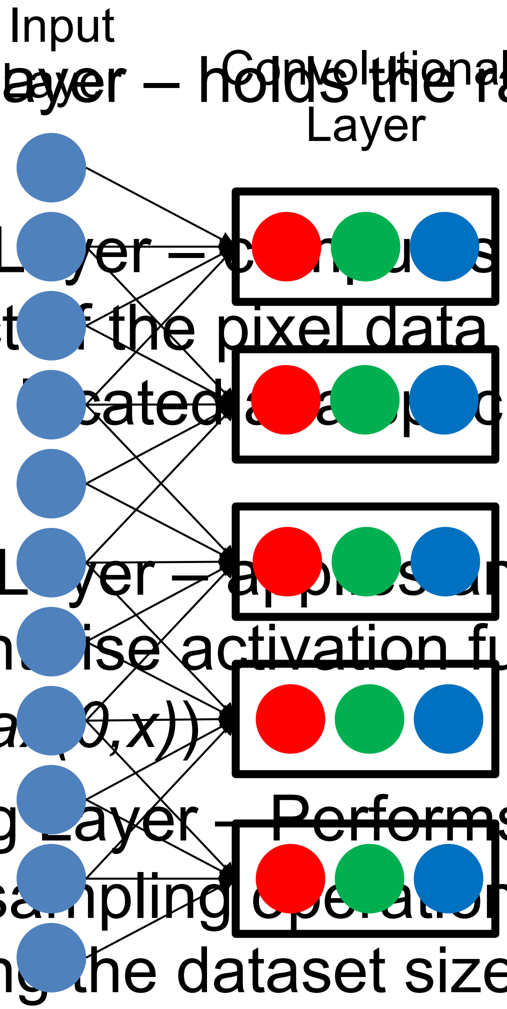
- The flashlight “slides” (convolves) along the image pixel by pixel, leaving behind a spot of light
- Each spot of light, called a filter, seeks out a specific pattern at that specific location in the image
- Since each filter can only look for one specific pattern, multiple filters must be used at each location on the image.

SUPERVISED LEARNING

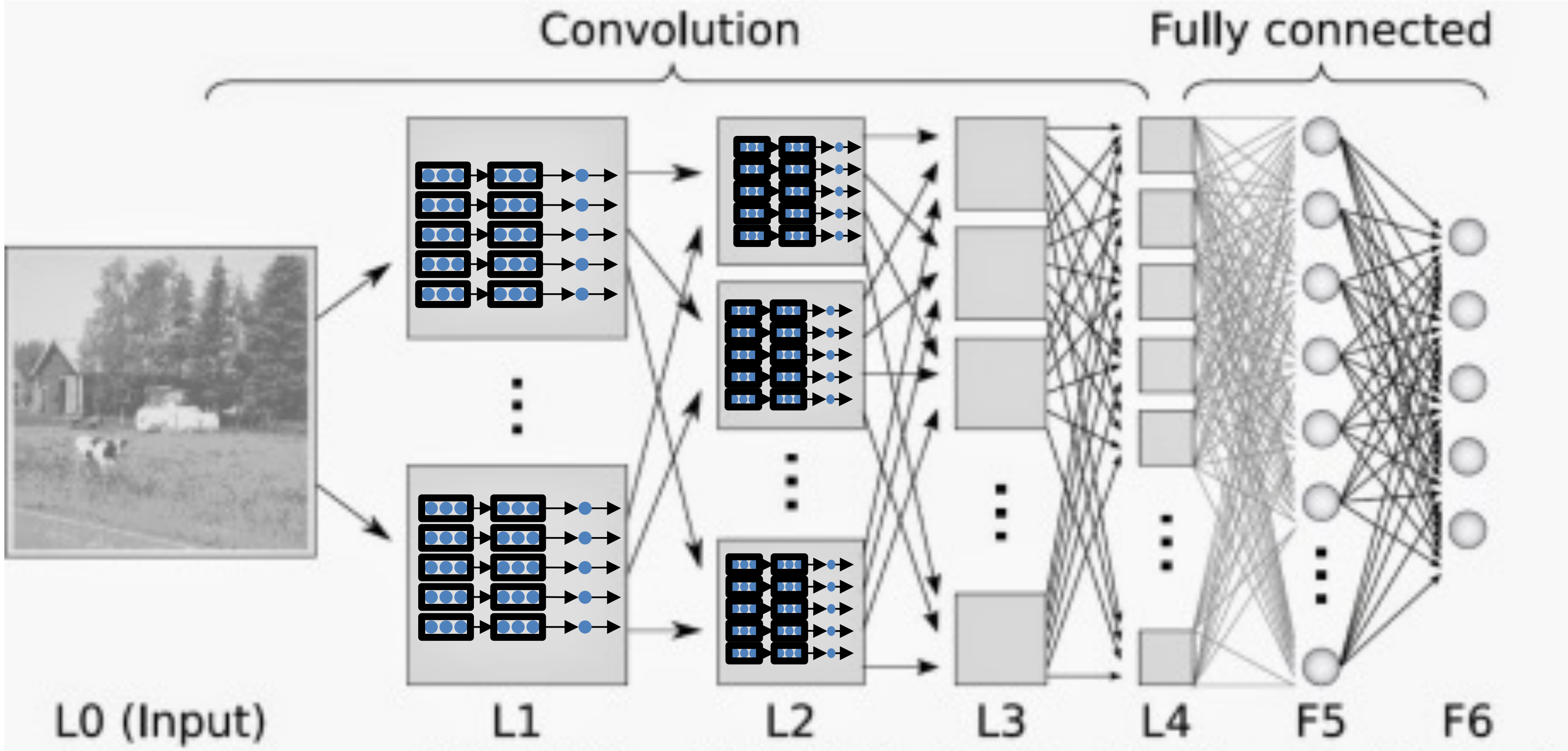
FLASHLIGH EXAMPLE (Cont.)



- Input Layer – holds the raw pixel data
- Conv. Layer – computes the dot product of the pixel data and the filter(s) located at a specific region
- RELU Layer – applies an element wise activation function (i.e. *max(0,x)*)
- Pooling Layer – Performs a down sampling operation, reducing the dataset size



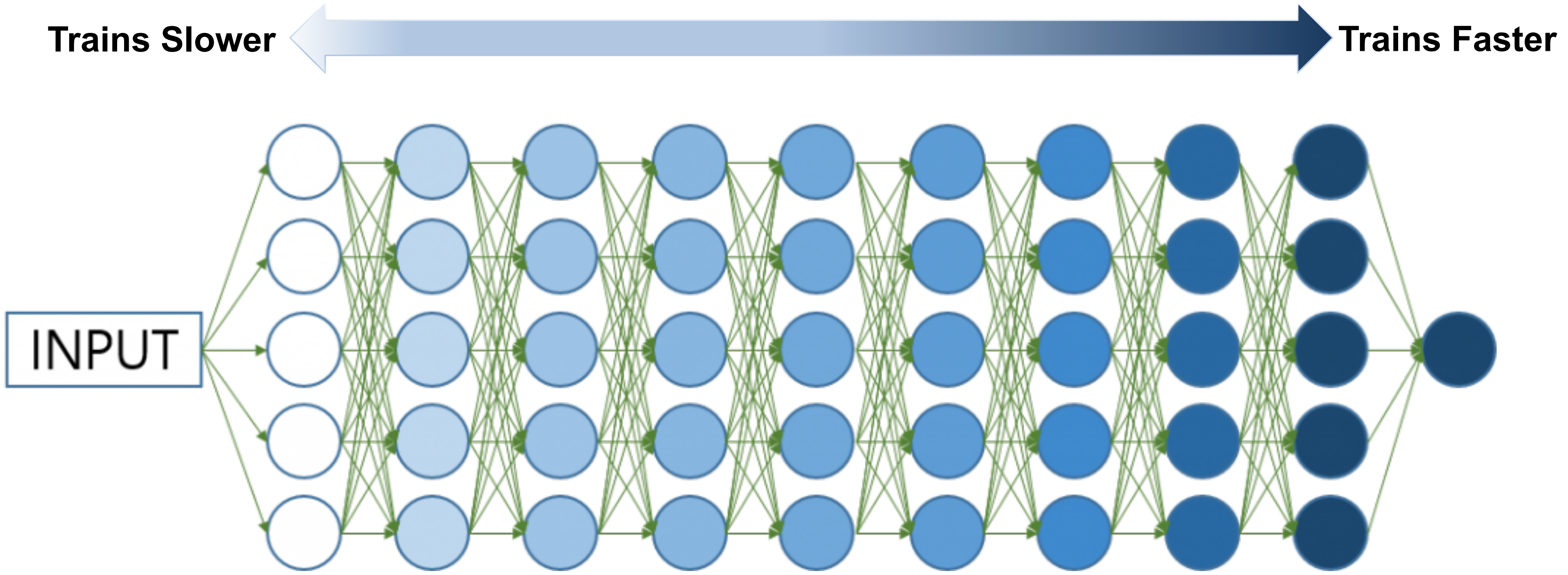
SUPERVISED LEARNING



SUPERVISED LEARNING

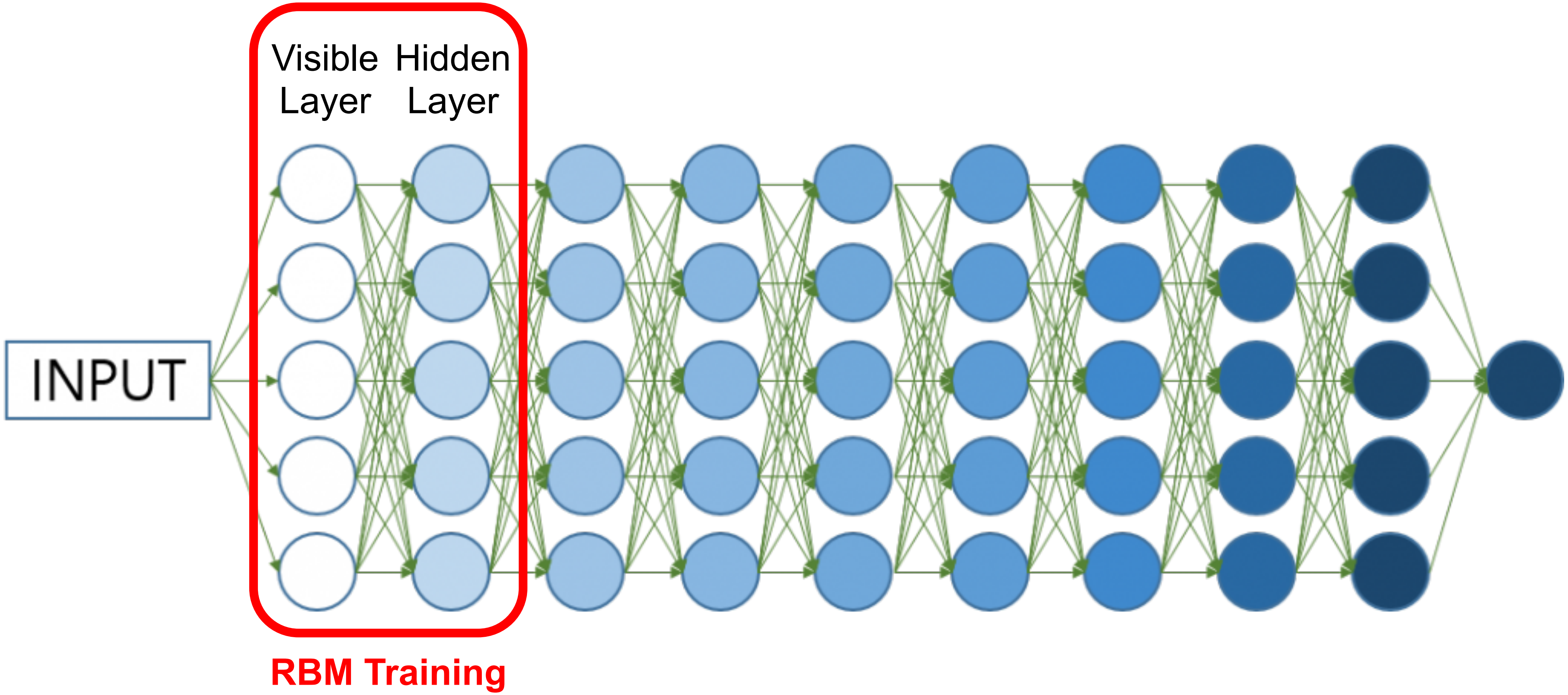
CHALLENGES

- Requires Large Set of Training Data (10’s of millions)
- The Fundamental Issue: Vanishing Gradient



SUPERVISED LEARNING

- Geoffrey Hinton of UofT proposed a solution in 2006
  - Utilizes Restricted Boltzmann Machine which trains two layers at a time

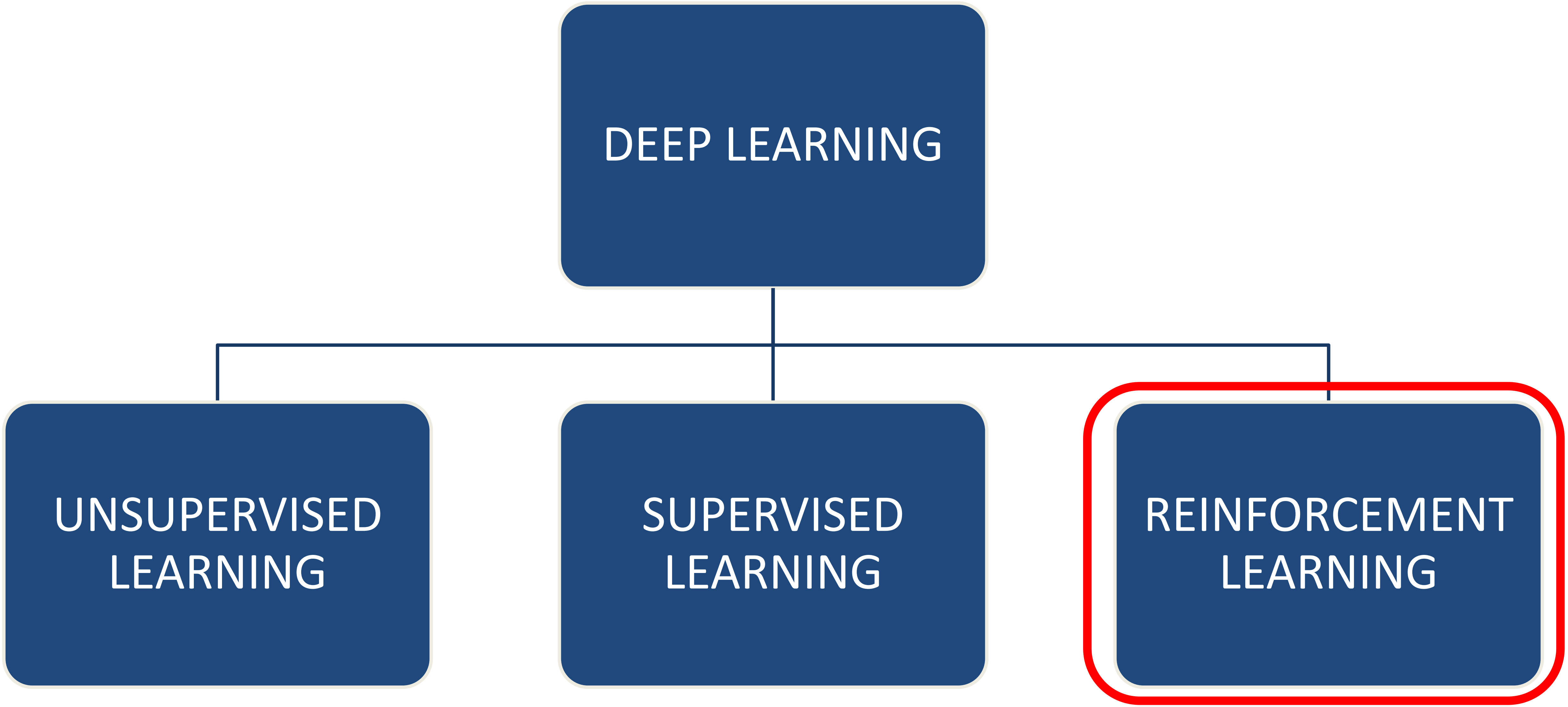


SUPERVISED LEARNING

HISTORY OF PROGRESS

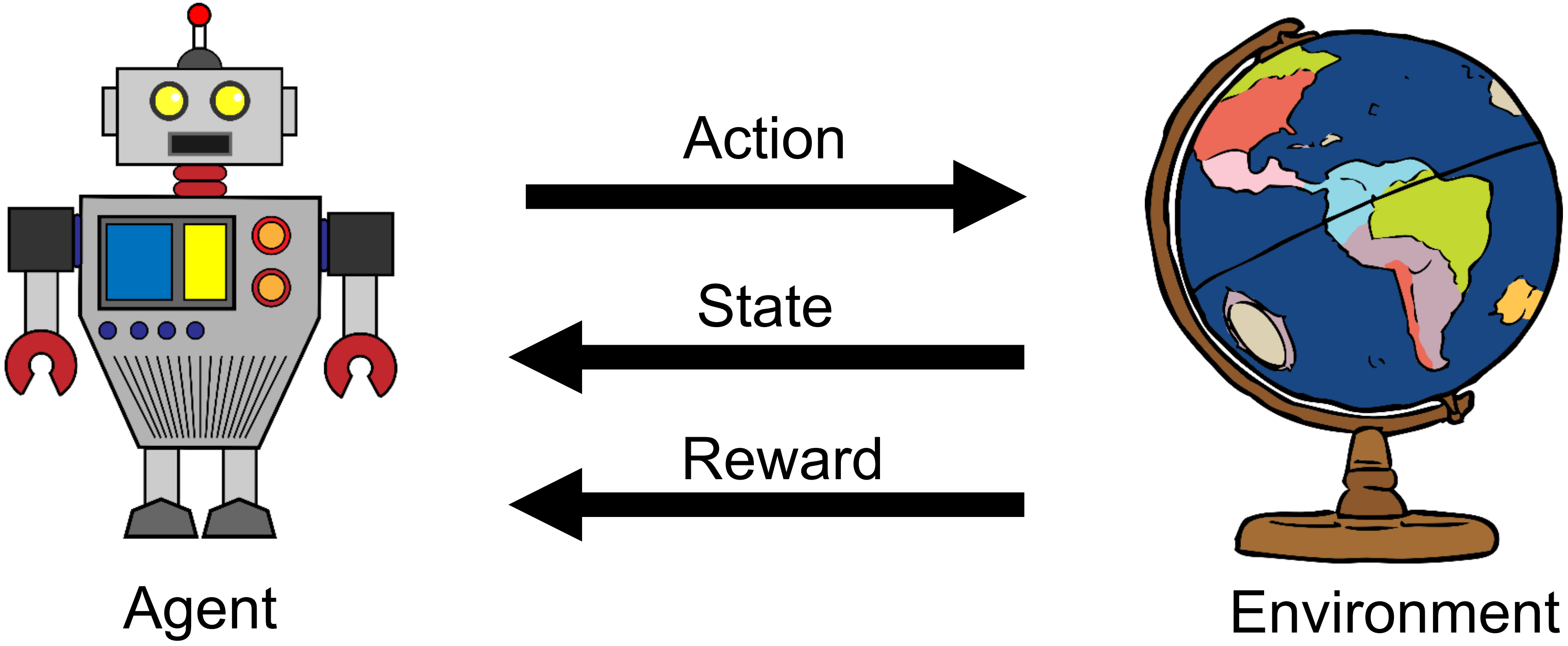
- 2012 – AlexNet
  - CNN surpasses traditional image processing methods to win the 2012 ImageNet Large-Scale Visual Recognition Challenge
  - Reduced error from previous **26.2% to 15.4%** with CNN
- 2013 – ZF Net
  - Error reduced to only 11.2%
  - Trained with only 1.3 million datasets opposed to 15 million with AlexNet
- 2015 – Microsoft ResNet
  - Error further reduced to **3.6%** to surpass **humans (generally 5-10%)**
  - “Ultra Deep” CNN architecture consisting of 152 layers

TOPICS OF DEEP LEARNING



REINFORCEMENT LEARNING

- The goal is to learn sequences of actions that will lead an agent towards its goal
- There are rewards for right decisions and penalties for wrong decisions
- Feedback is delayed, not instantaneous
- 2 Types of Rewards: Shaped Reward vs Sparse Reward



REINFORCEMENT LEARNING

Policy Gradients

Focuses on directly inferring a policy that maximizes the reward on a specific environment

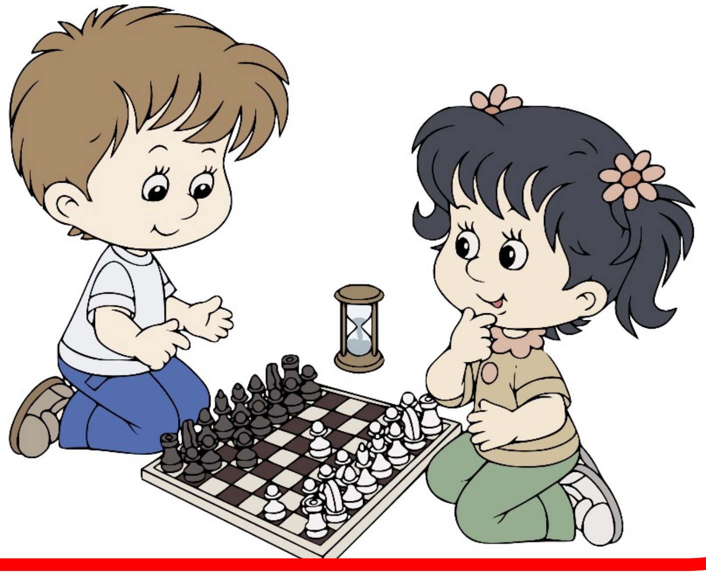
Agent would plan to move in a way that achieve certain well known position

VS

Q Learning

Tries to quantify the value of every state-action pair

Agent would assign a value to every position and select the move that score higher



Q LEARNING

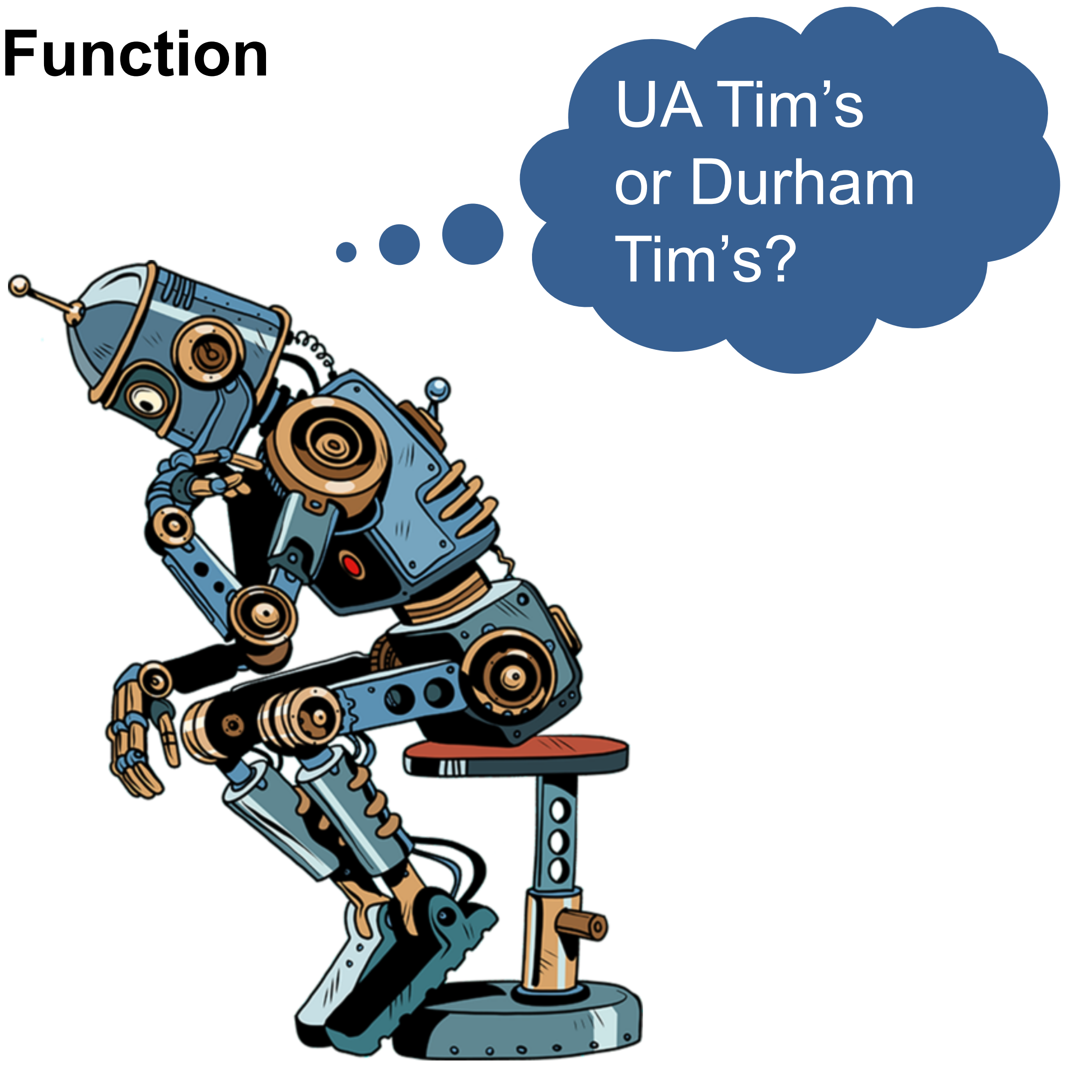
The goal of Q Learning is to approximate a Q Function and use it to infer the optimal policy

Q Function: Quantify state-action pairs

$$Q(s,a) = r + \gamma max_{a'} Q(s', a')$$

Key Vocabulary

- State: an immediate situation
- Action: an action
- Reward: the feedback
- Discount Factor: dampen future rewards



DEEP REINFORCEMENT LEARNING

ATARI BREAKOUT: AN EXAMPLE

- Supervised Learning
  - a good human gamer play for a couple of hours, then create a data set where all the frames are logged as well as the response the gamer is outputting
    - Feed this data in to the NN to train it to replicate the actions of a human gamer

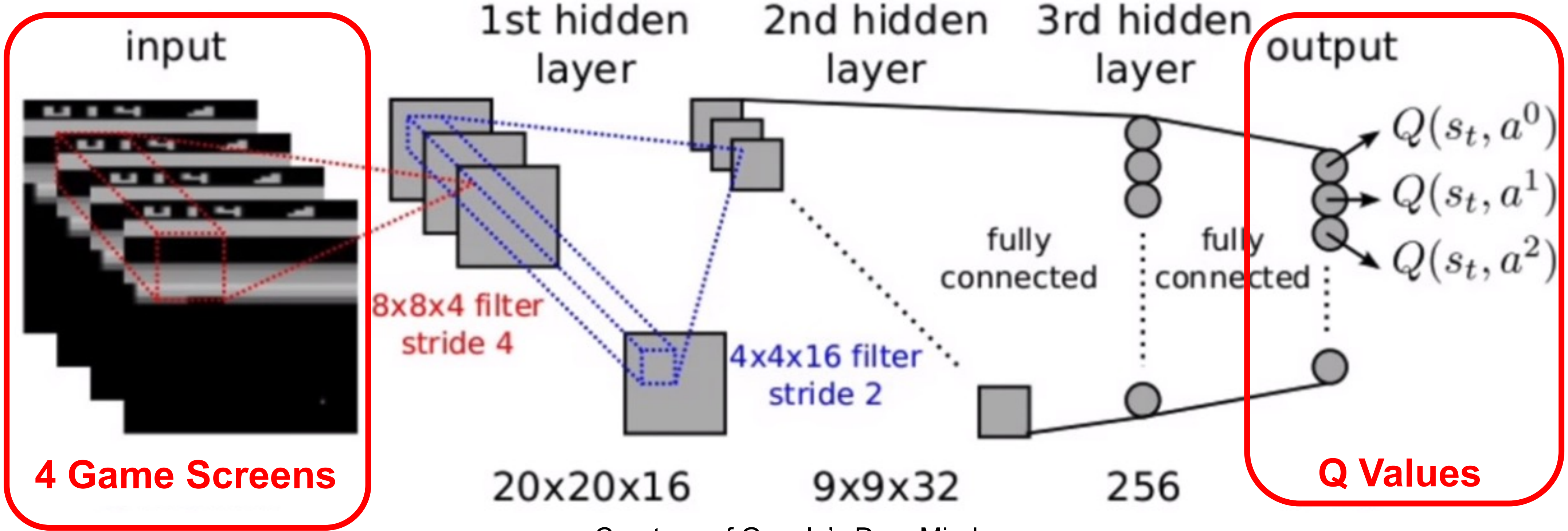
- Reinforcement Learning
  - Q Learning would define states such as location of paddle, location/direction of ball and presence of brick as states
  - The Q-table will be too large with many pixel combinations that doesn't occur

Atari Breakout

DEEP REINFORCEMENT LEARNING

DEEP Q NETWORK

- Can represent our Q-Function with a NN that use game screens and outputs the corresponding Q-Value for the next best action
- 3 Convolutional Layers and 2 fully connected layers



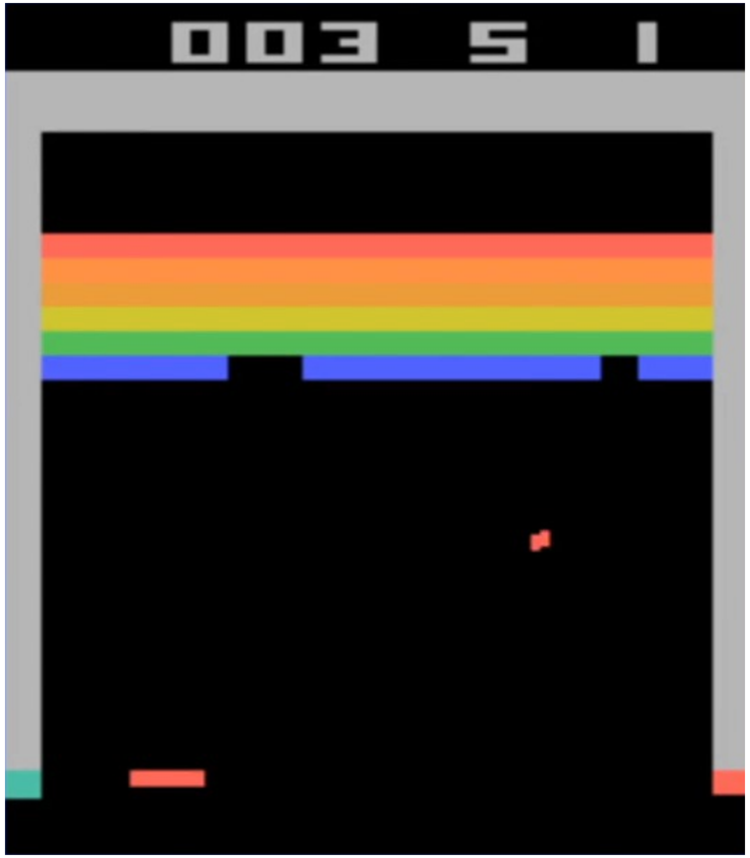
Courtesy of Google's DeepMind

DEEP REINFORCEMENT LEARNING

ATARI BREAKOUT

10 minutes of training

120 minutes of training



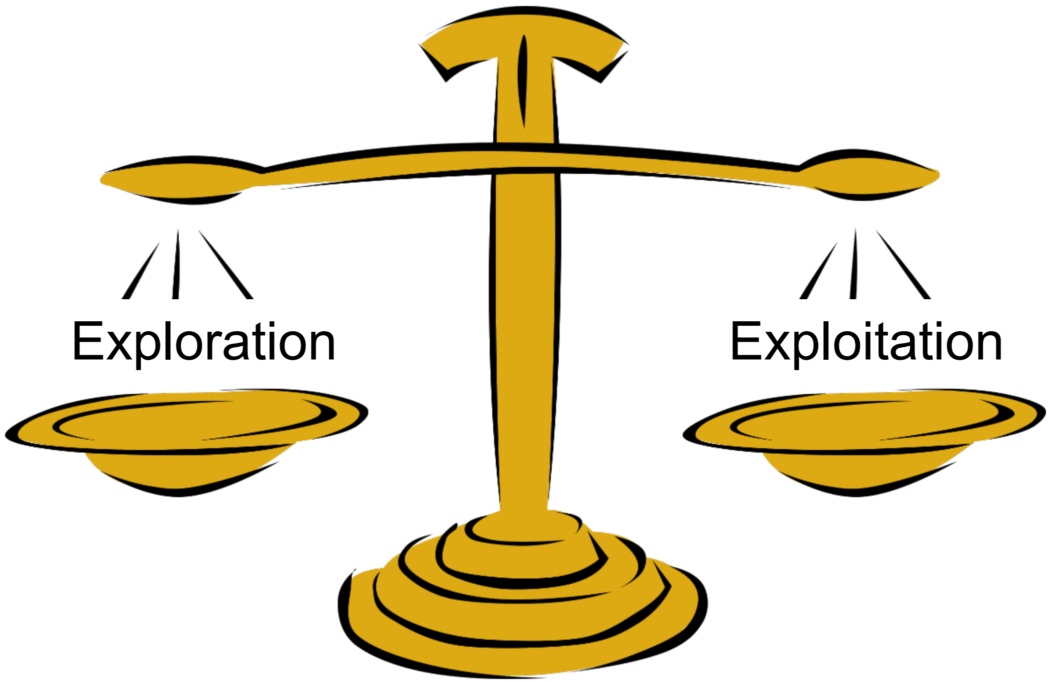
240 minutes of training

Video Courtesy of Google's DeepMind

DEEP REINFORCEMENT LEARNING

CHALLENGES

Finding new ways to solve existing problems



Use existing knowledge to solve the problem

- As Q Function converges, it returns more consistent Q-values and the amount of exploration decreases
- Agent starts to settle with the first effective strategy it finds

DEEP REINFORCEMENT LEARNING

CHALLENGES

- Takes days to learning something that humans may be able to pick up in a few minutes
- Often times, the problems you are trying to solve with DRL may be solved easier with other classical techniques
- Reward function design is difficult
  - Could lead to “reward hacking”

Video Courtesy of Jack Clark “Coast Runners 7”

CONCLUSION

- Unsupervised Learning
  - “That thing is like this other thing”
  - Learn similarities without names
- Supervised Learning
  - “That thing is a double bacon cheese burger”
  - Learn correlations between data and labels
  - Fundamental Problem: Vanishing Gradient
- Reinforcement Learning
  - “Eat that thing because it tastes good and will keep you alive longer”
  - Actions based on short/long term rewards – trial and error
  - Highest potential to achieve Artificial General Intelligence

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THE END

THANK YOU

QUESTIONS?