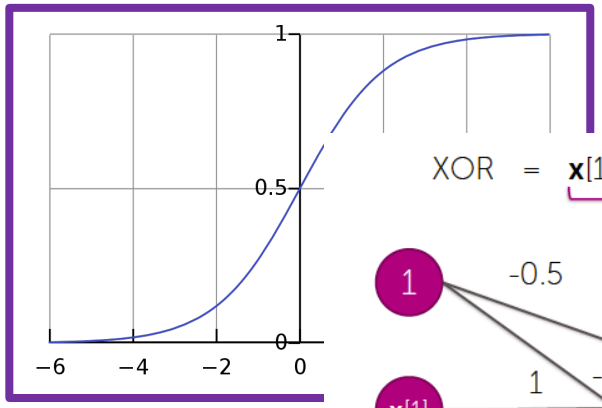
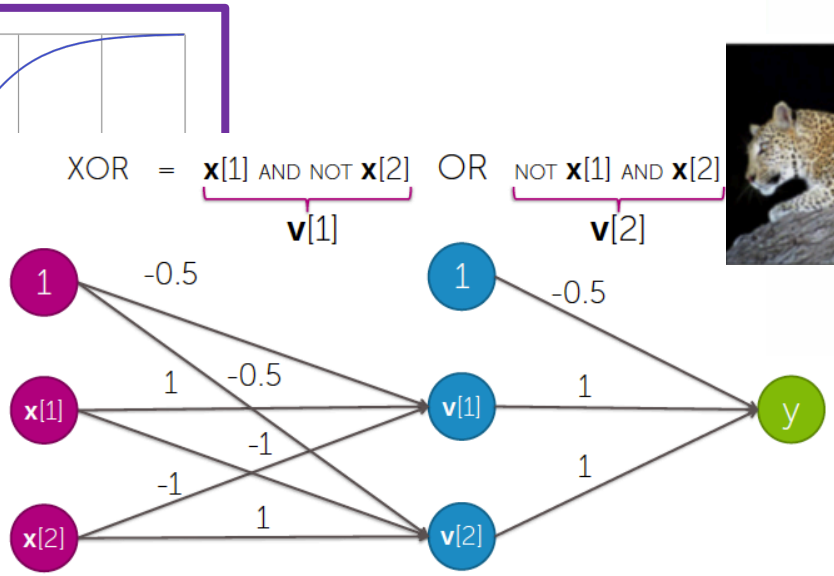
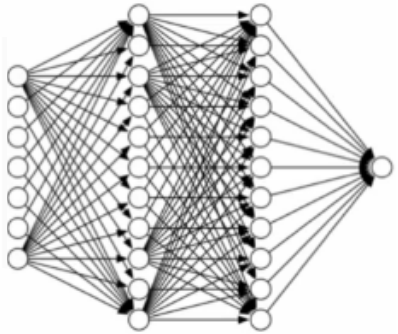
Tufts COMP 135: Introduction to Machine Learning

https://www.cs.tufts.edu/comp/135/2019s/

Neural Networks







Many slides attributable to:
Erik Sudderth (UCI), Emily Fox (UW),
Finale Doshi-Velez (Harvard)
James, Witten, Hastie, Tibshirani (ISL/ESL books)

Prof. Mike Hughes

Objectives Today: Neural Networks day 10

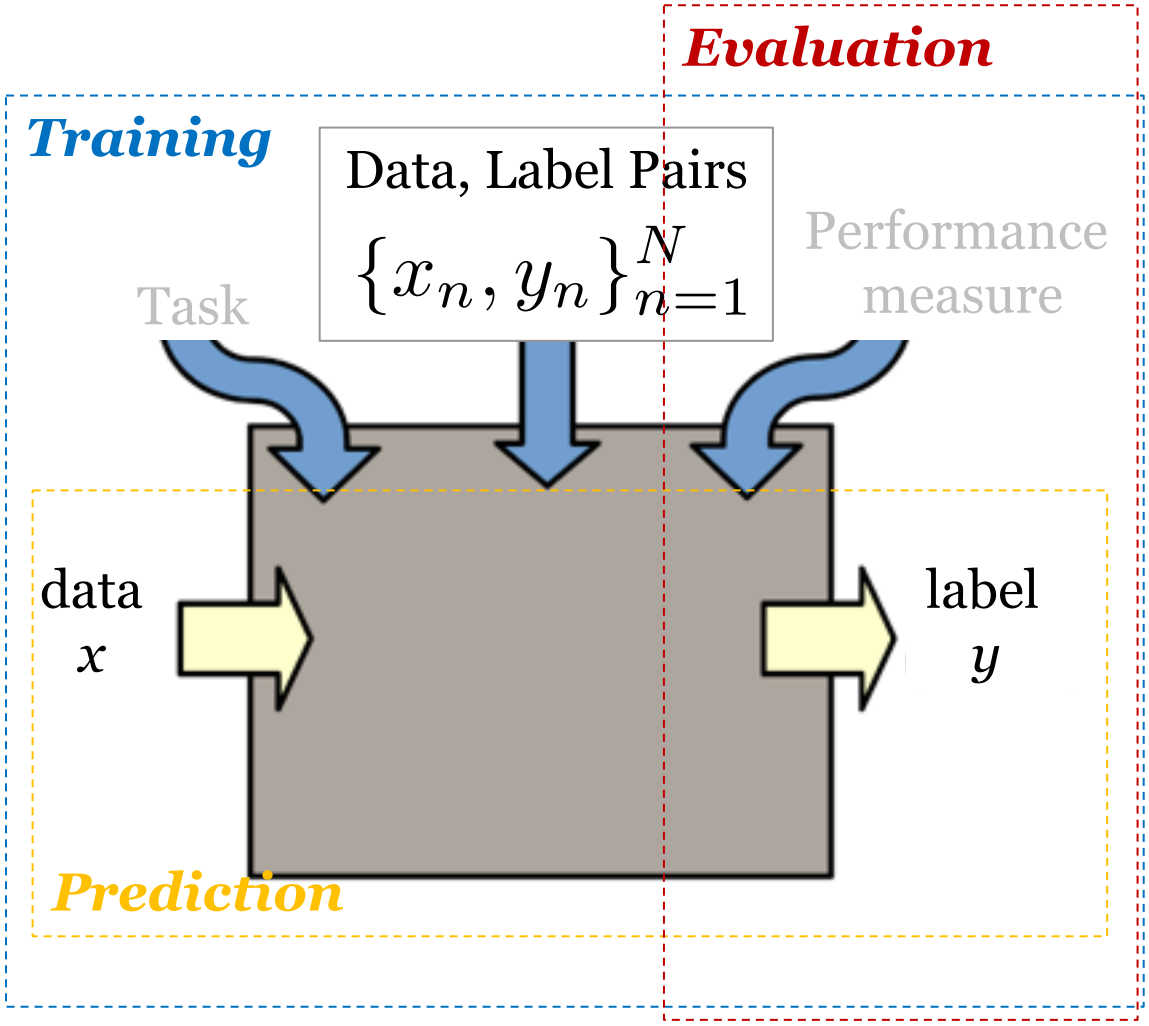
- How to **learn** feature representations
  - Feed-forward neural nets
    - Single neuron = linear function + activation
    - Multi-layer perceptrons (MLPs)
  - Universal approximation
- The Rise of Deep Learning:
  - Success stories on Images and Language

What will we learn?

Supervised Learning

Unsupervised Learning

Reinforcement Learning



Task: Binary Classification

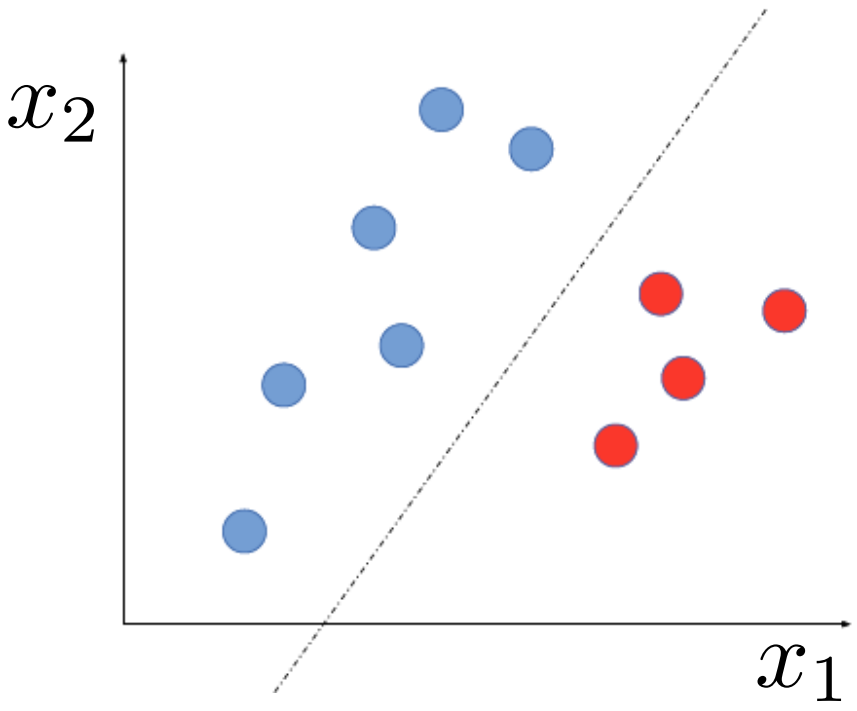
Supervised Learning

binary classification

Unsupervised Learning

Reinforcement Learning

y is a binary variable (red or blue)

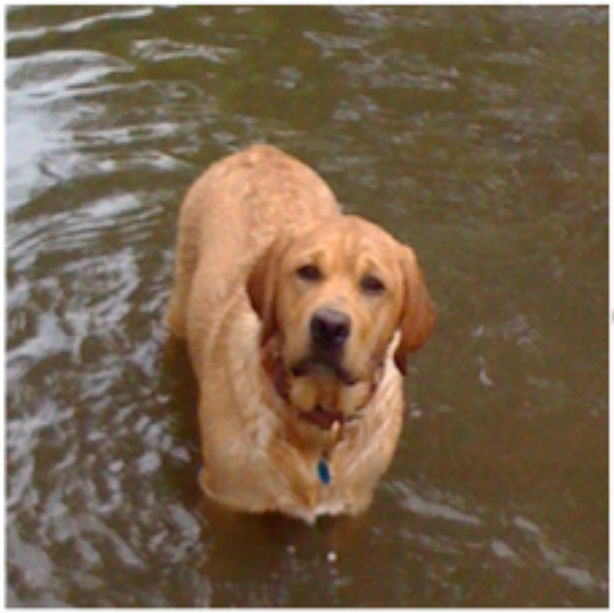


Example: Hotdog or Not

https://www.theverge.com/tldr/2017/5/14/15639784/hbo-silicon-valley-not-hotdog-app-download

Text Sentiment Classification

Image Classification



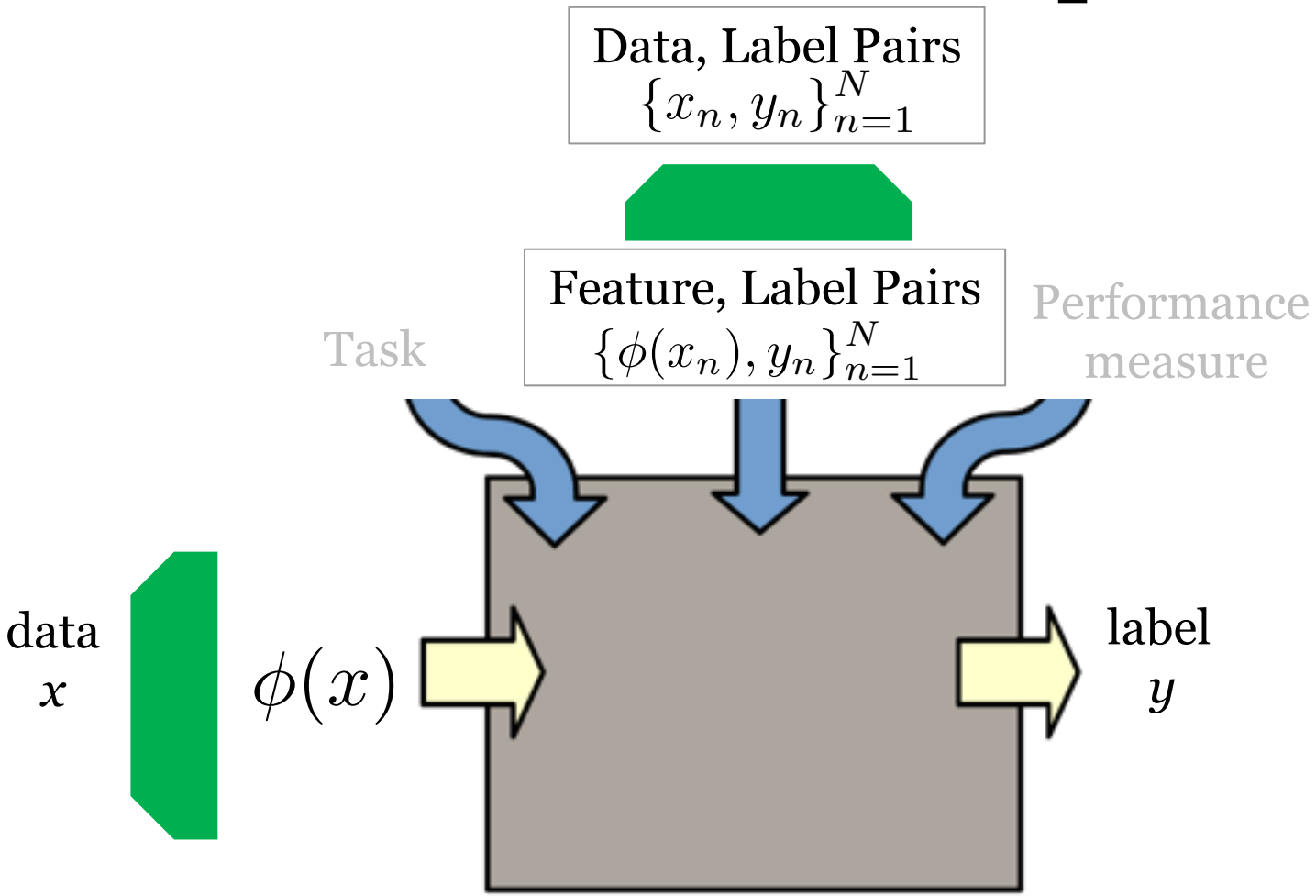
Input: x

Image pixels

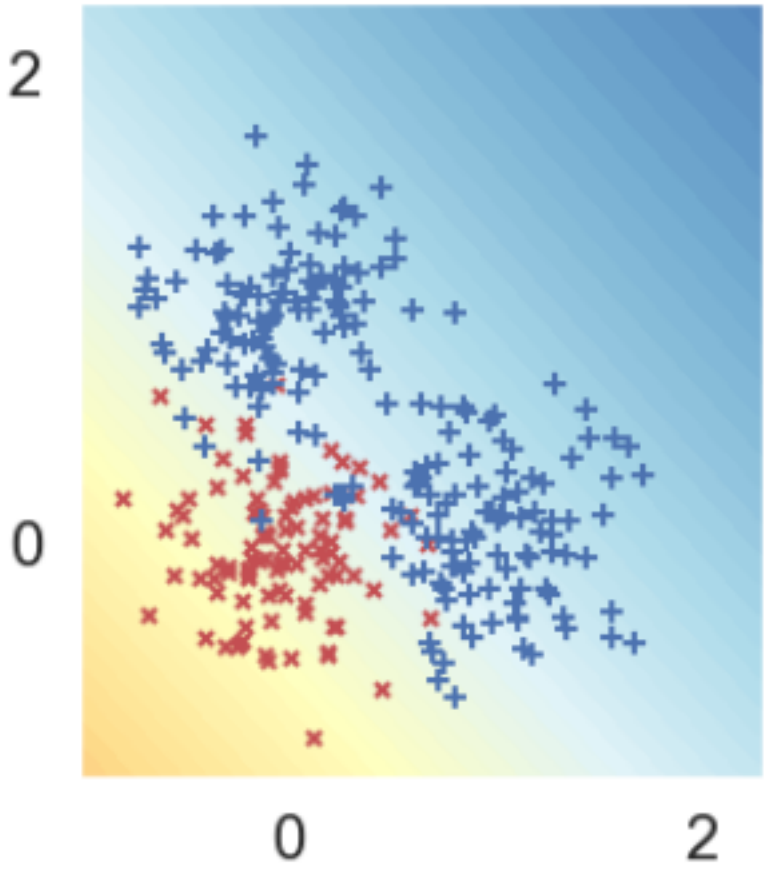
Output: y

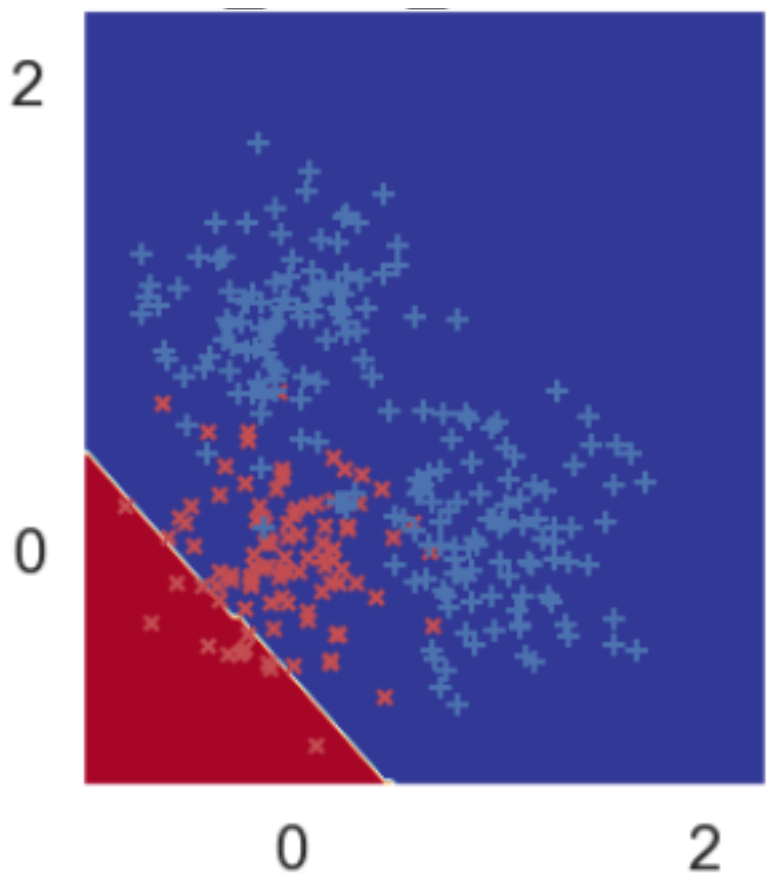
Predicted object

Feature Transform Pipeline

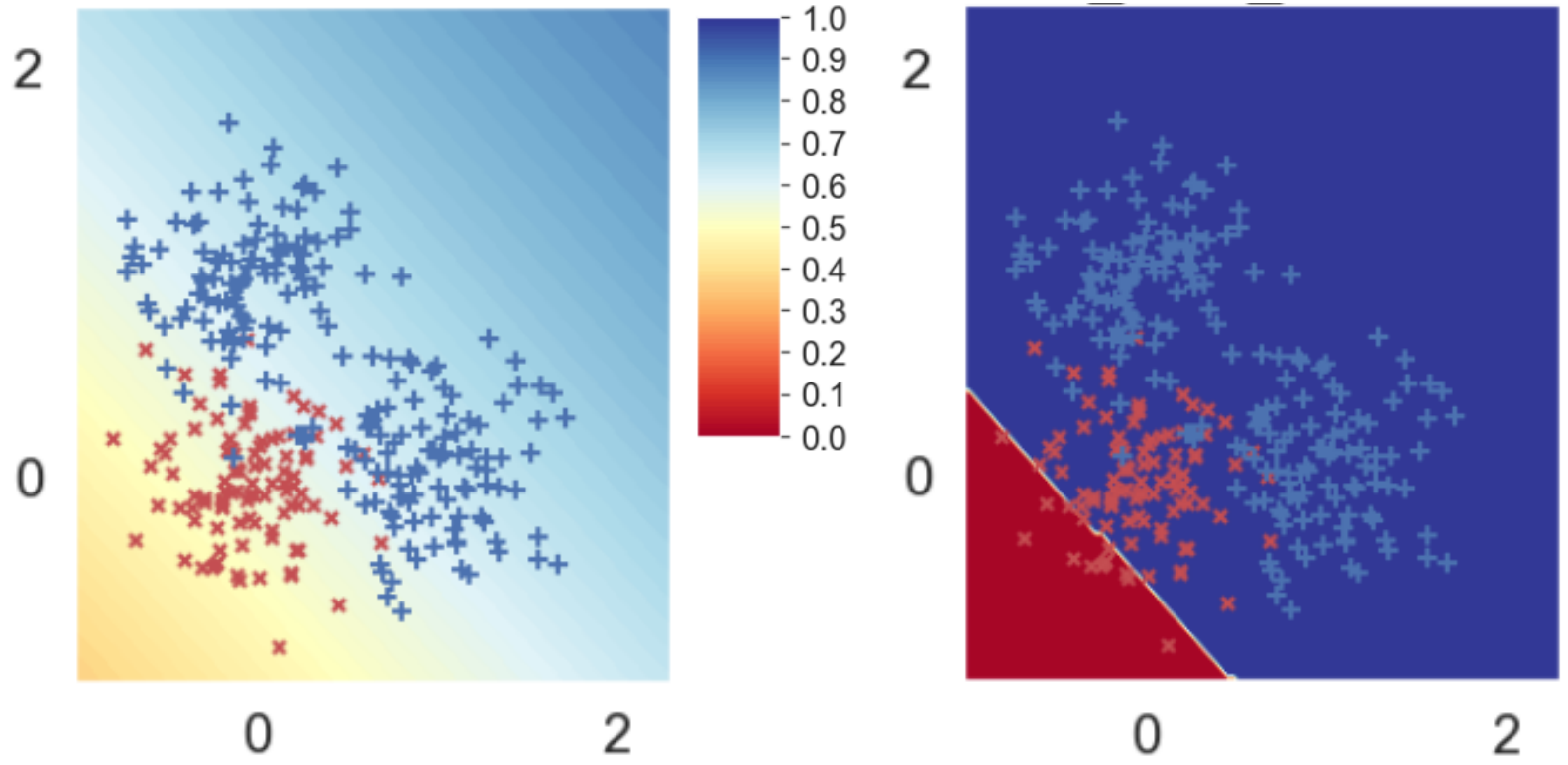


Predicted Probas vs Binary Labels



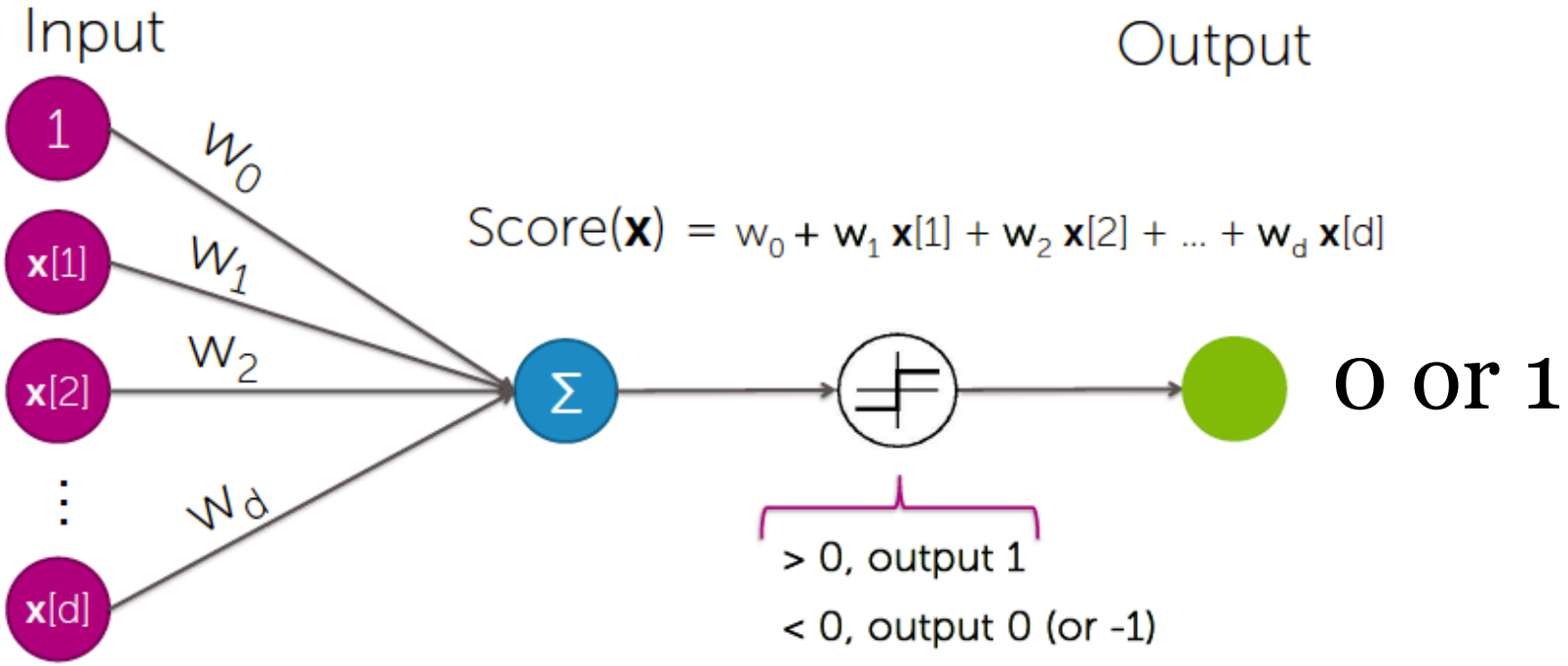


Decision Boundary is **Linear**



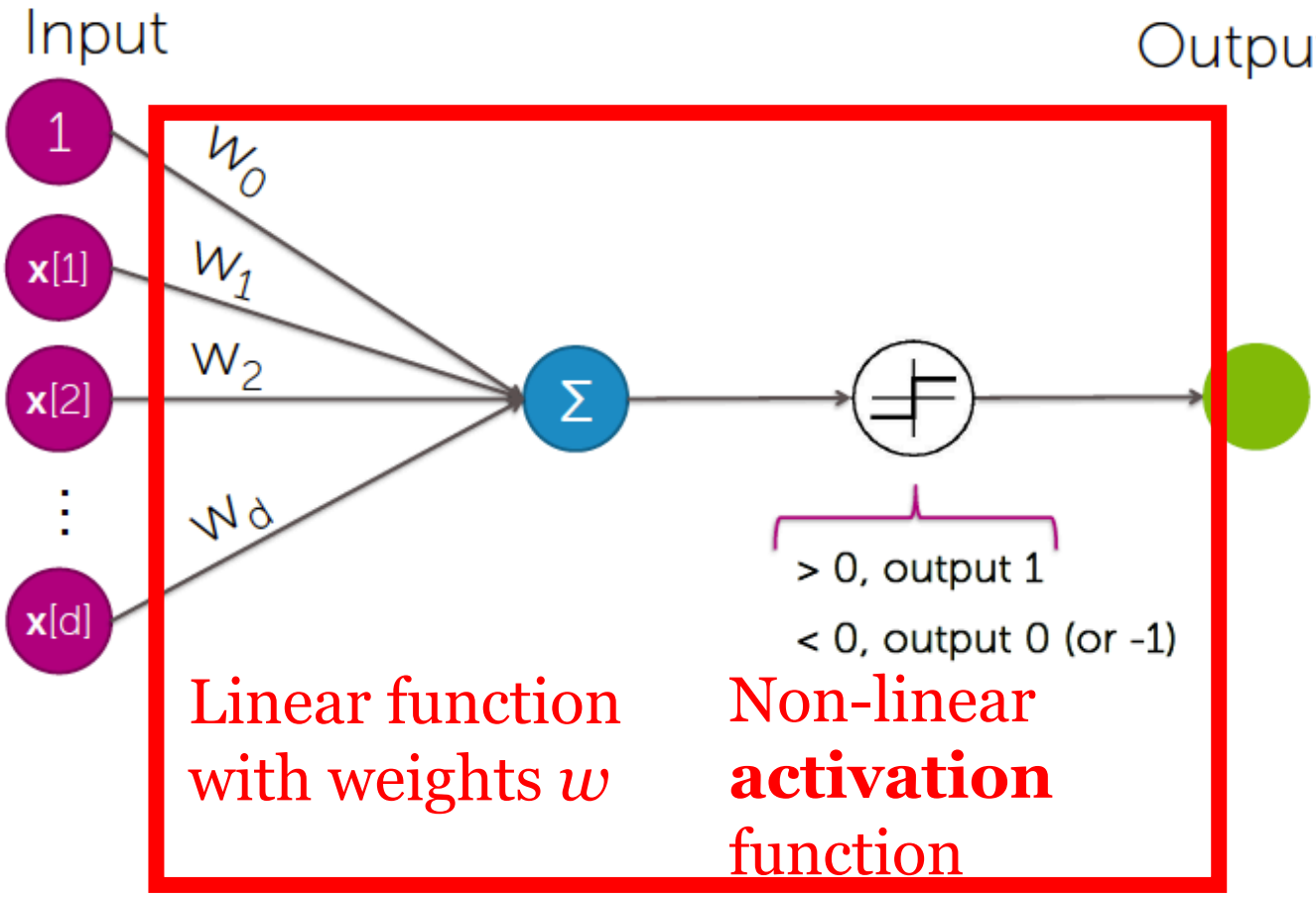
$$\{x \in \mathbb{R}^2 : \sigma(w^T \tilde{x}) = 0.5\} \longleftrightarrow \{x \in \mathbb{R}^2 : w^T \tilde{x} = 0\}$$

Logistic Regr. Network Diagram



Credit: Emily Fox (UW)
https://courses.cs.washington.edu/courses/cse416/18sp/slides/

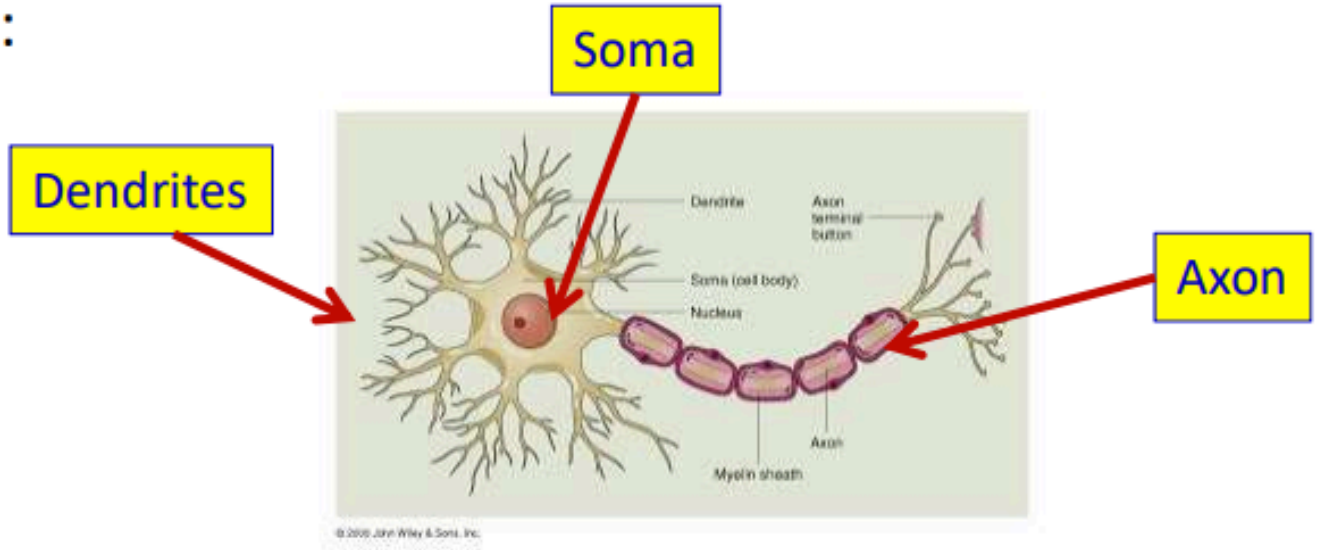
A "Neuron" or "Perceptron" Unit



Credit: Emily Fox (UW)

“Inspired” by brain biology

A neuron:



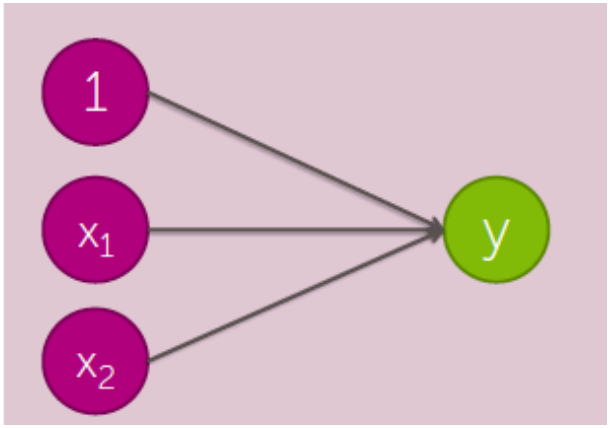
Signals come in through the dendrites into the Soma

A signal goes out via the axon to other neurons

- Only one axon per neuron

Slide Credit: Bhiksha Raj (CMU)

Challenge: Find w for these functions

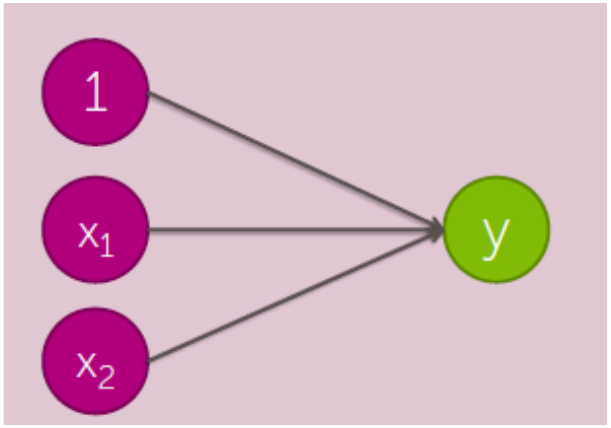


x_1 OR x_2		
x_1	x_2	y
0	0	0
0	1	1
1	0	1
1	1	1

x_1 AND x_2		
x_1	x_2	y
0	0	0
0	1	0
1	0	0
1	1	1

Credit: Emily Fox (UW)

Challenge: Find w for these functions



x_1 OR x_2

x_1	x_2	y
0	0	0
0	1	1
1	0	1
1	1	1

$-0.5 + \mathbf{x}[1] + \mathbf{x}[2]$

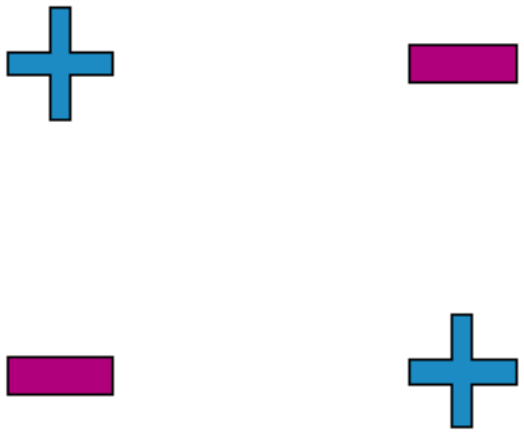
x_1 AND x_2

x_1	x_2	y
0	0	0
0	1	0
1	0	0
1	1	1

$-1.5 + \mathbf{x}[1] + \mathbf{x}[2]$

Credit: Emily Fox (UW)

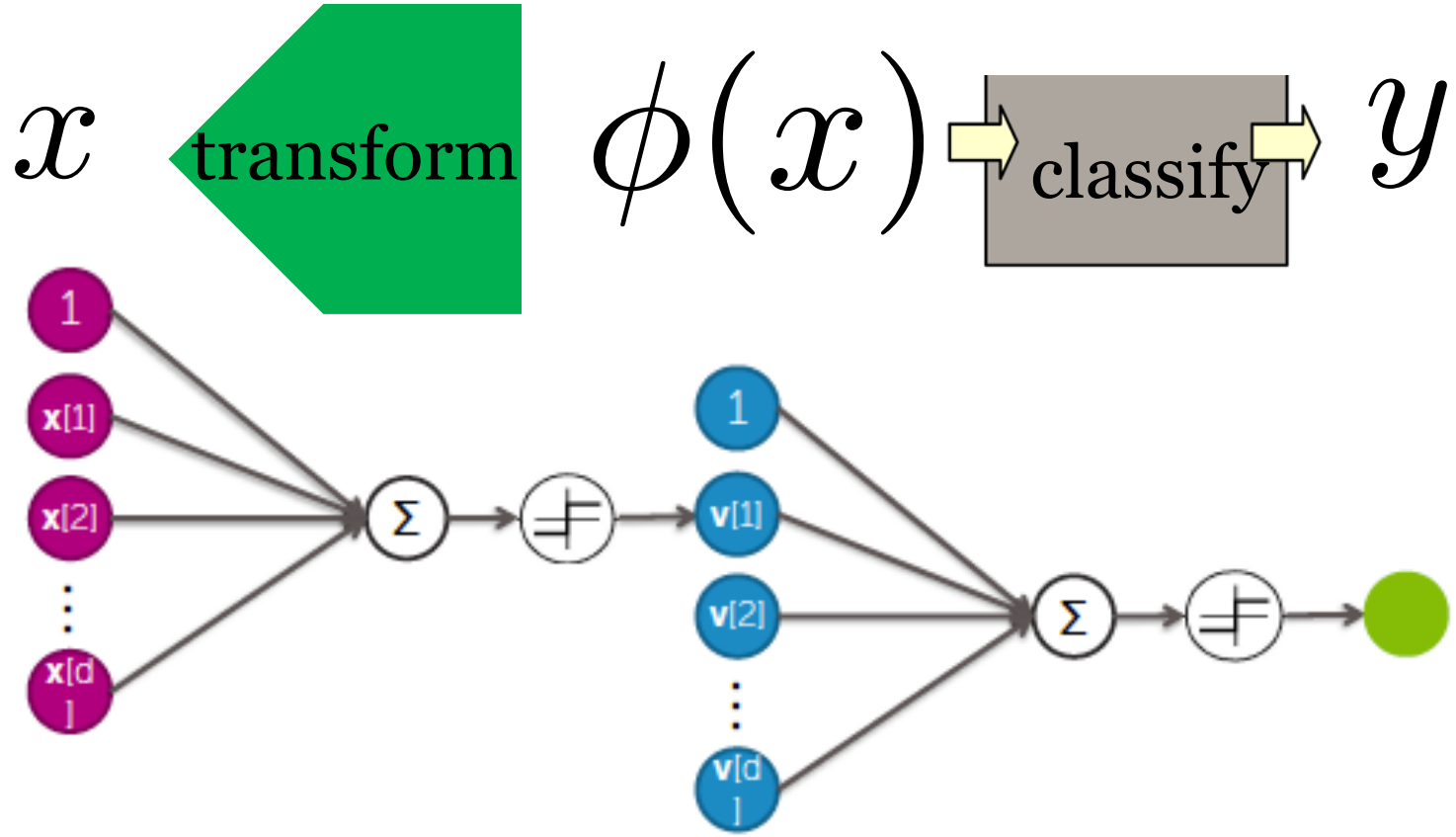
What we can't do with linear decision boundary classifiers



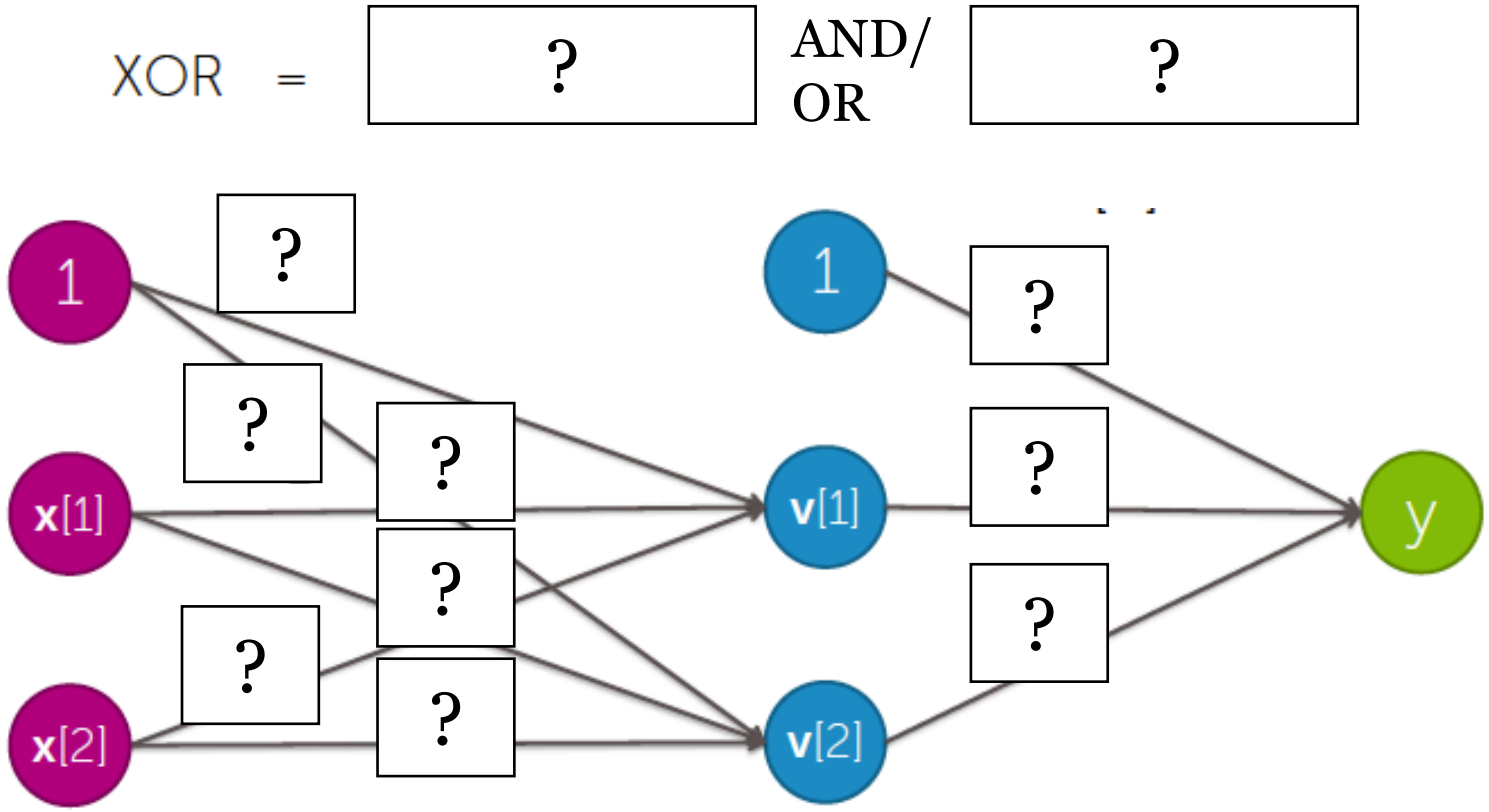
x_1	x_2	y
0	0	0
0	1	1
1	0	1
1	1	0

XOR = **x**[1] AND NOT **x**[2] OR NOT **x**[1] AND **x**[2]

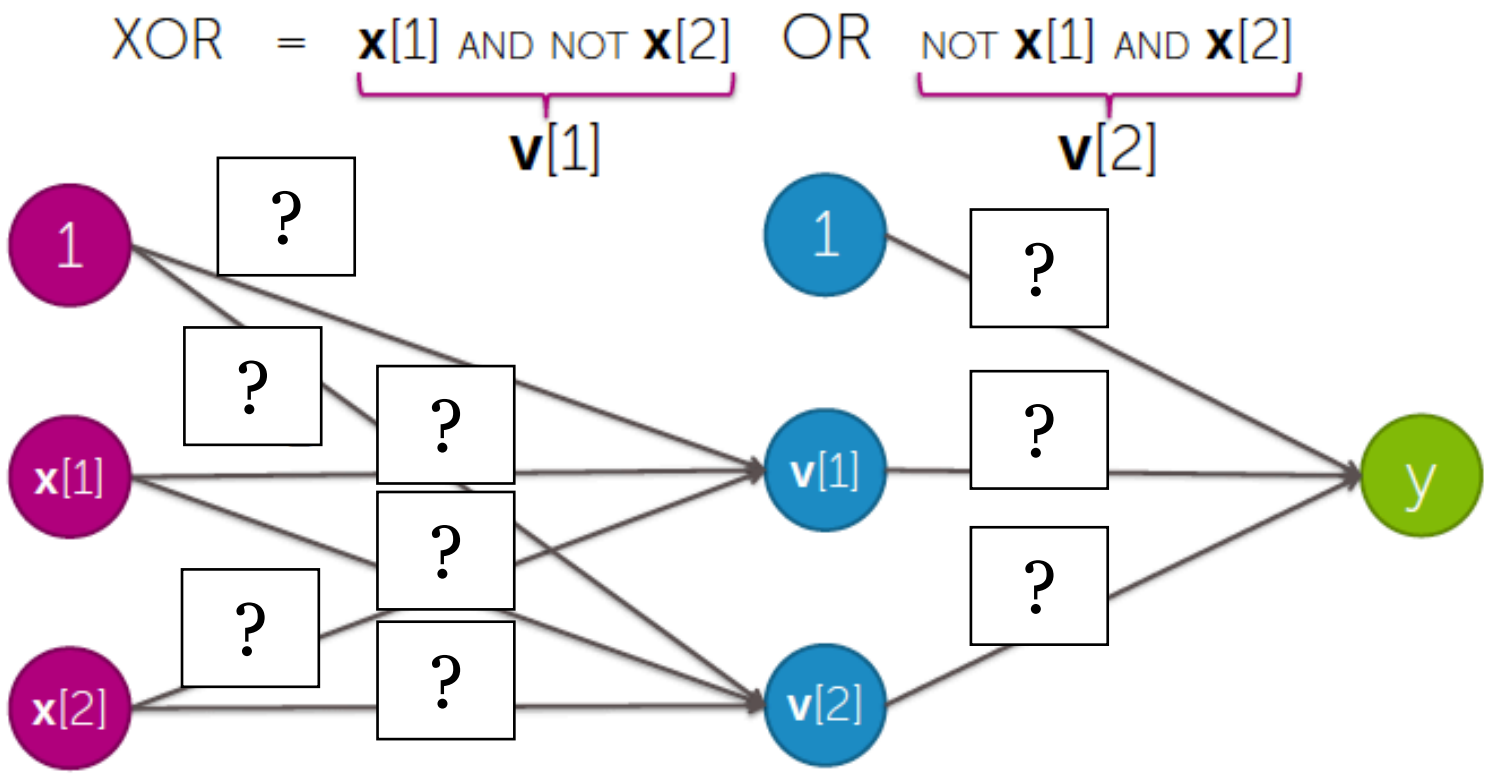
Idea:
Compose Neurons together!



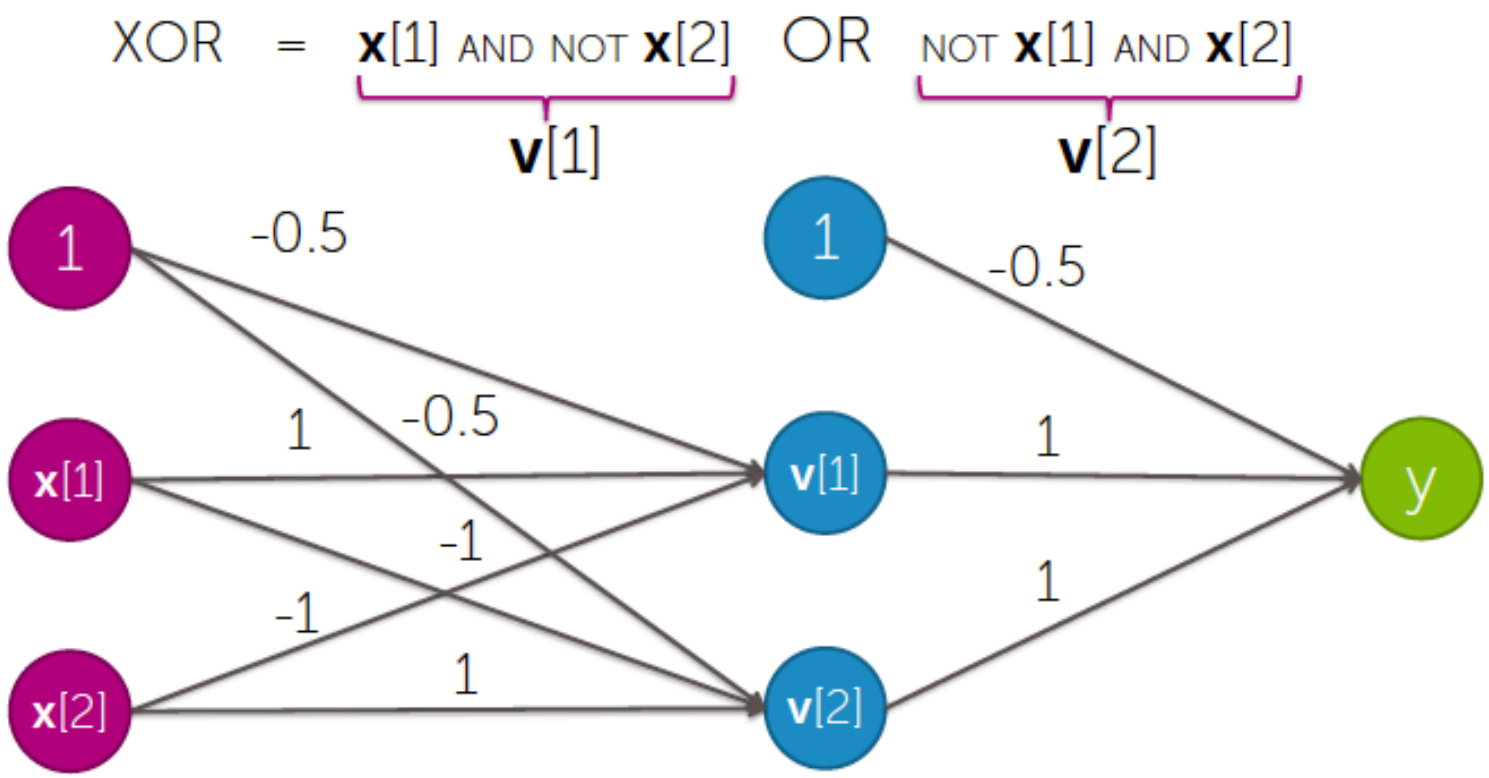
Can you find w to solve XOR?



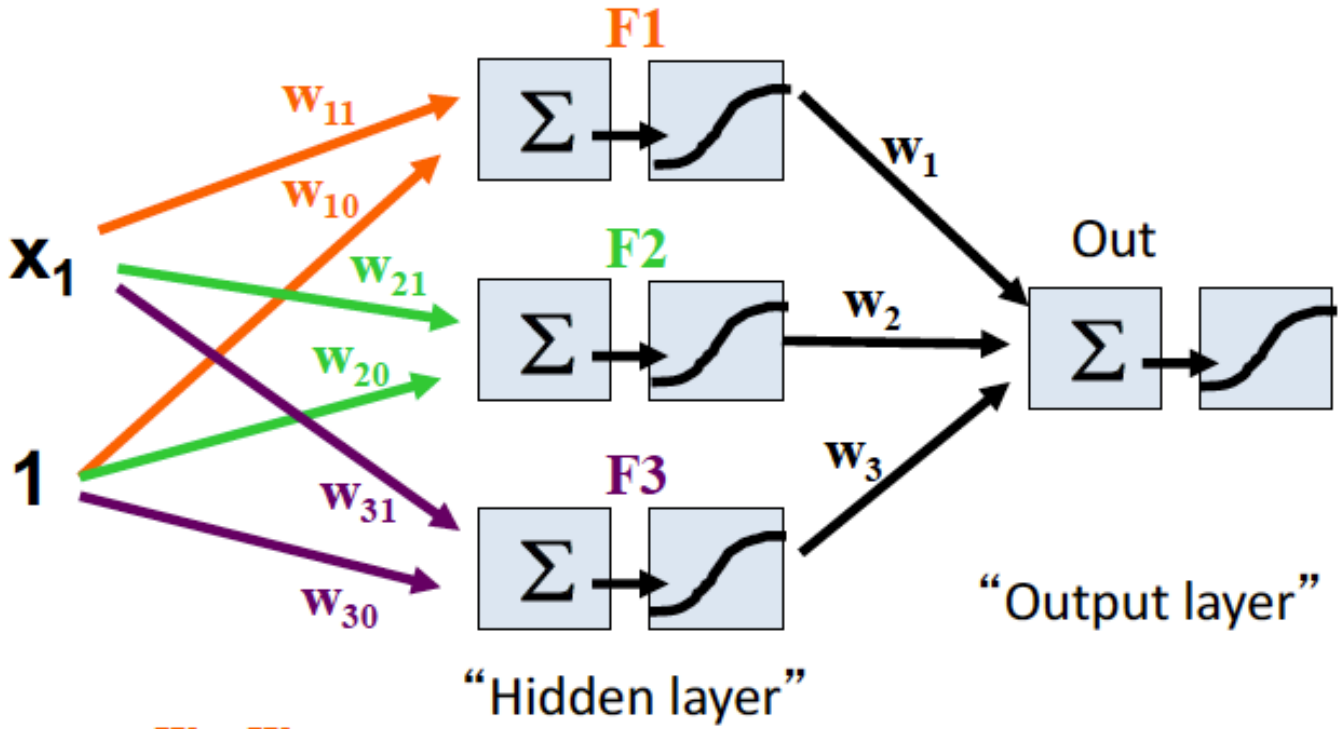
Can you find w to solve XOR?



Can you find w to solve XOR?



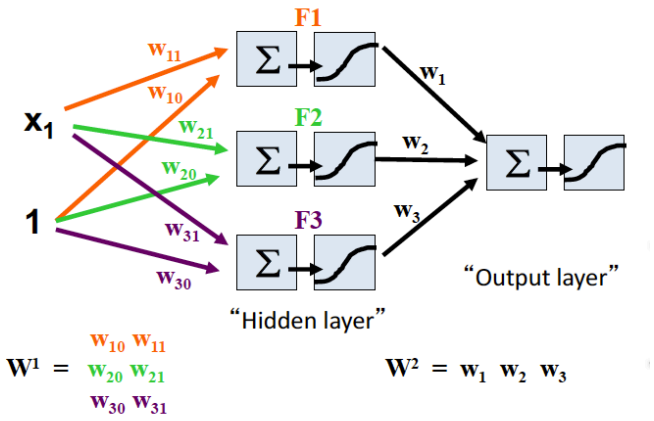
1D Input + 3 hidden units



$$W^1 = \begin{matrix} w_{10} & w_{11} \\ w_{20} & w_{21} \\ w_{30} & w_{31} \end{matrix}$$

$$W^2 = w_1 \; w_2 \; w_3$$

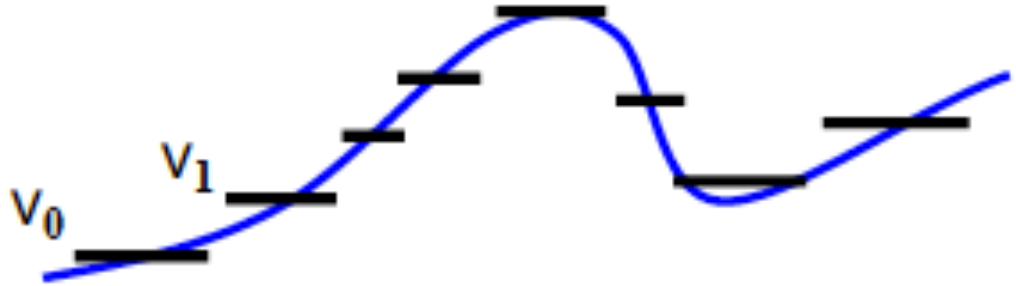
1D Input + 3 hidden units



Example functions
(before final threshold)

Intuition: Piece-wise step function
Partitioning input space into regions

MLPs can approximate any functions with enough hidden units!



Universal approximation theorem

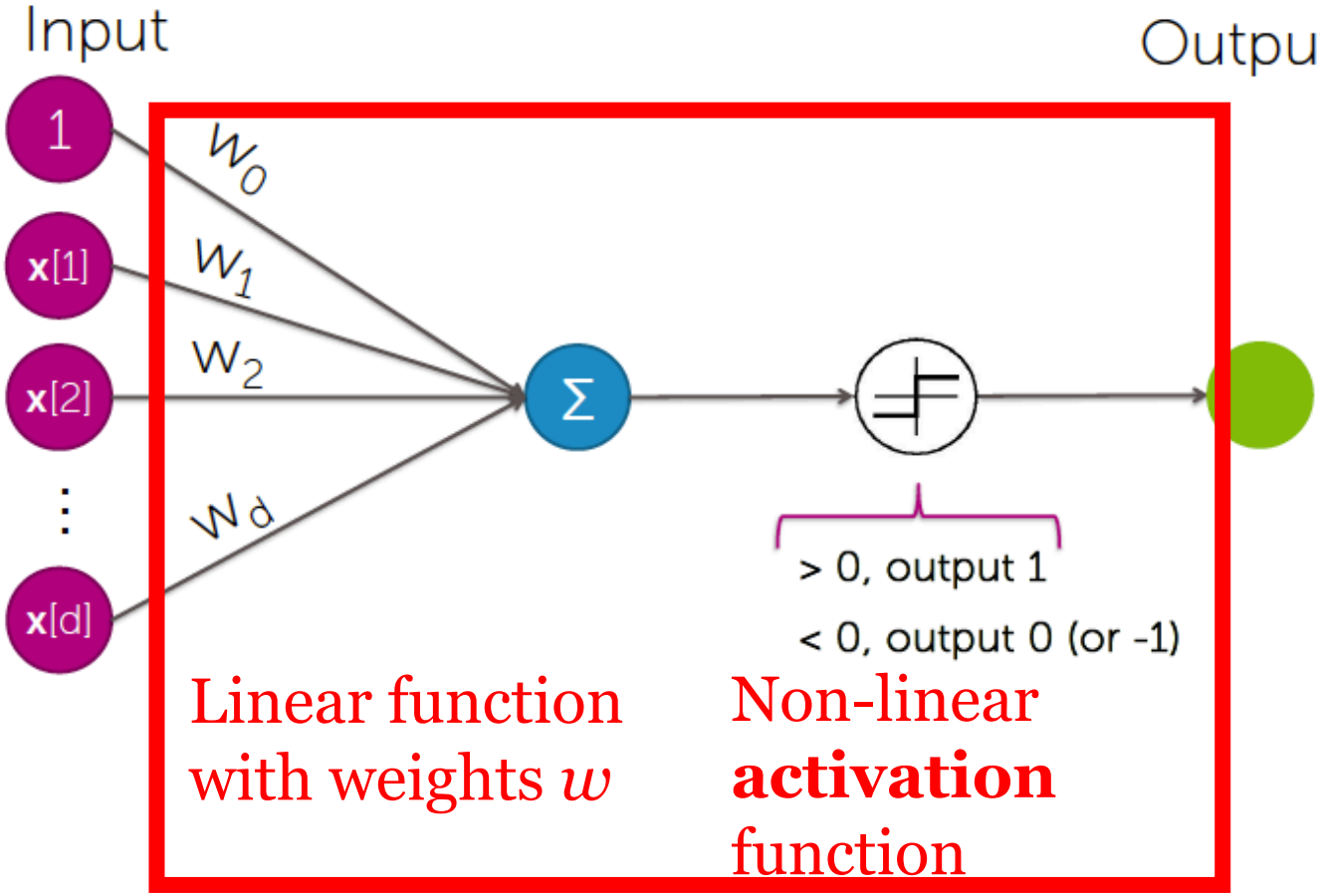
From Wikipedia, the free encyclopedia

In the mathematical theory of artificial neural networks, the **universal approximation theorem** states[1] that a feed-forward network with a single hidden layer containing a finite number of neurons can approximate continuous functions on compact subsets of $\mathbf{R}^n$, under mild assumptions on the activation function. The theorem thus states that simple neural networks can *represent* a wide variety of interesting functions when given appropriate parameters; however, it does not touch upon the algorithmic learnability of those parameters.

One of the first versions of the theorem was proved by George Cybenko in 1989 for sigmoid activation functions.[2]

Neuron Design

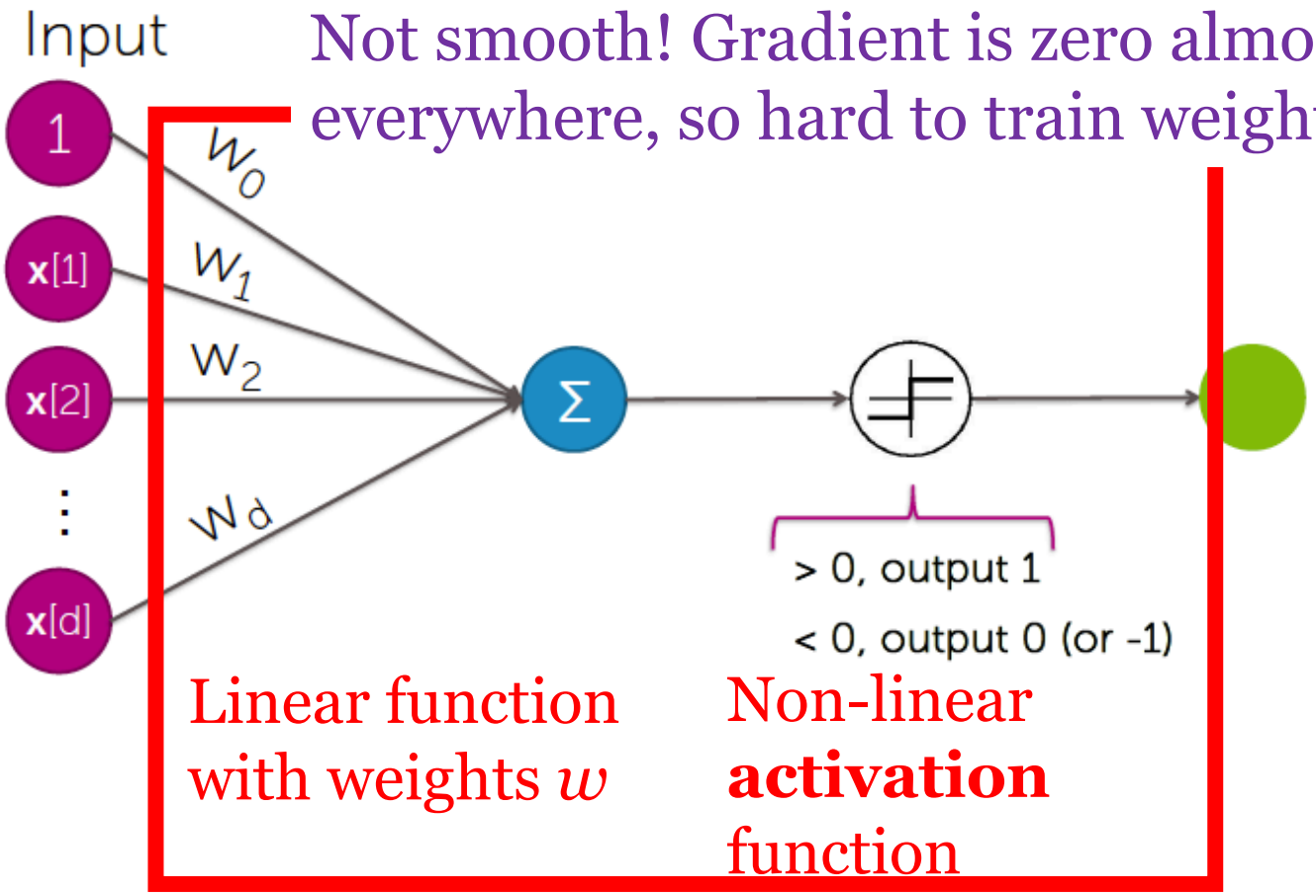
What's wrong with hard step activation function?



Credit: Emily Fox (UW)

Neuron Design

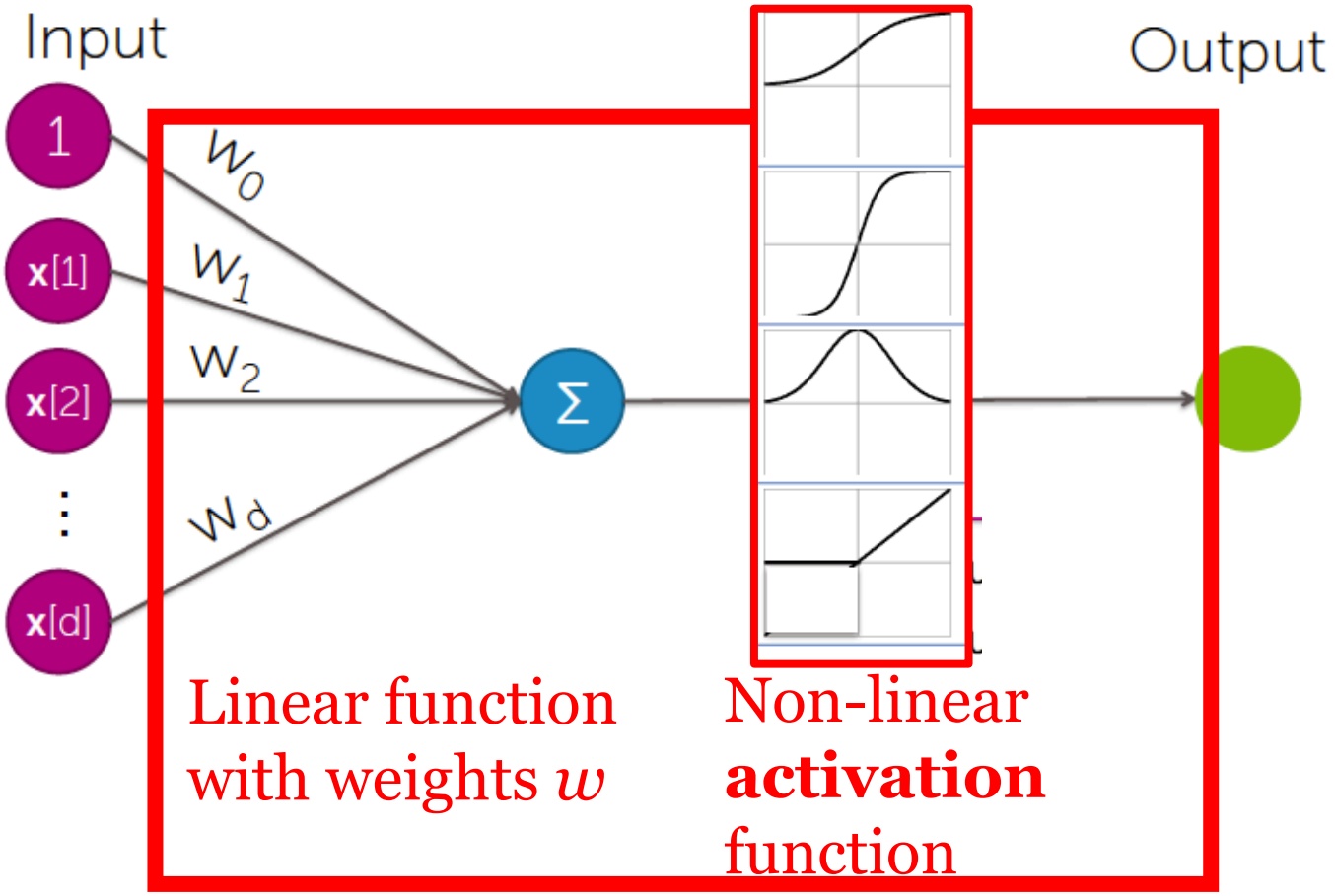
What's wrong with hard step activation function?



Not smooth! Gradient is zero almost everywhere, so hard to train weights!

Credit: Emily Fox (UW)

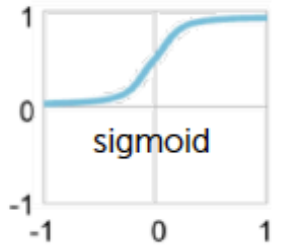
Which Activation Function?

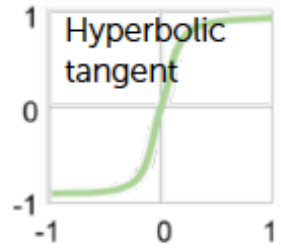


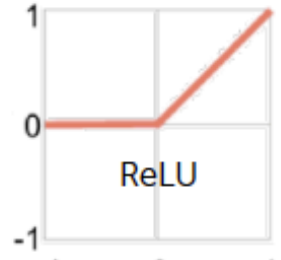
Credit: Emily Fox (UW)

Activation Functions Advice

- Sigmoid
  - Historically popular, but (mostly) fallen out of favor $\sigma(z) = \frac{1}{1+\exp(-z)}$
    - Neuron's activation saturates (weights get very large → gradients get small)
    - Not zero-centered → other issues in the gradient steps
  - When put on the output layer, called "softmax" because interpreted as class probability (soft assignment)
- Hyperbolic tangent g(x) = tanh(x)
  - Saturates like sigmoid unit, but zero-centered $\sigma(z) = \frac{1-\exp(-2z)}{1+\exp(-2z)}$
- Rectified linear unit (ReLU) $g(x) = x^+ = \max(0,x)$
  - Most popular choice these days
  - Fragile during training and neurons can "die off"... be careful about learning rates
  - "Noisy" or "leaky" variants $\sigma(z) = \max(0, z)$
- Softplus g(x) = log(1+exp(x))
  - Smooth approximation to rectifier activation



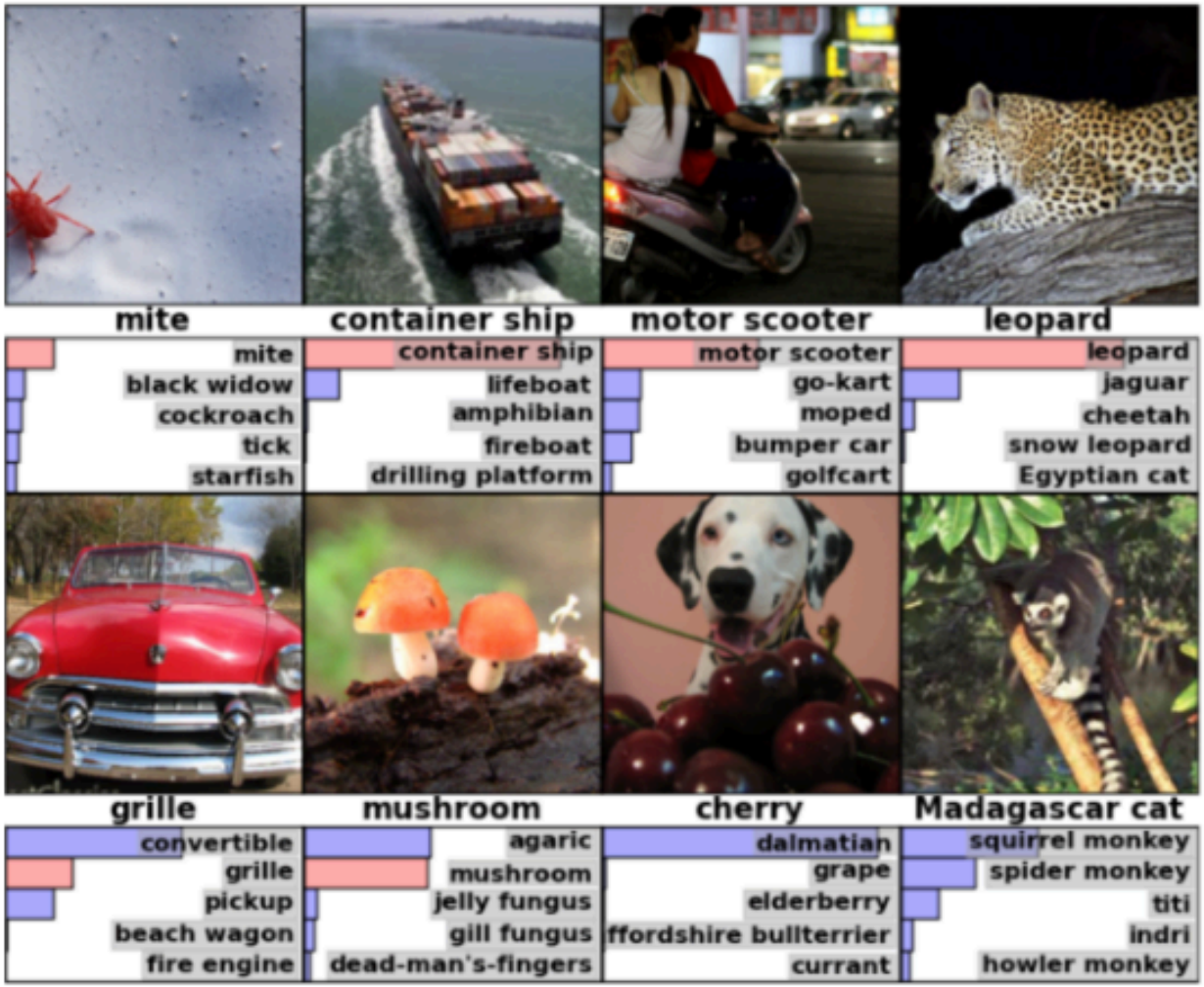




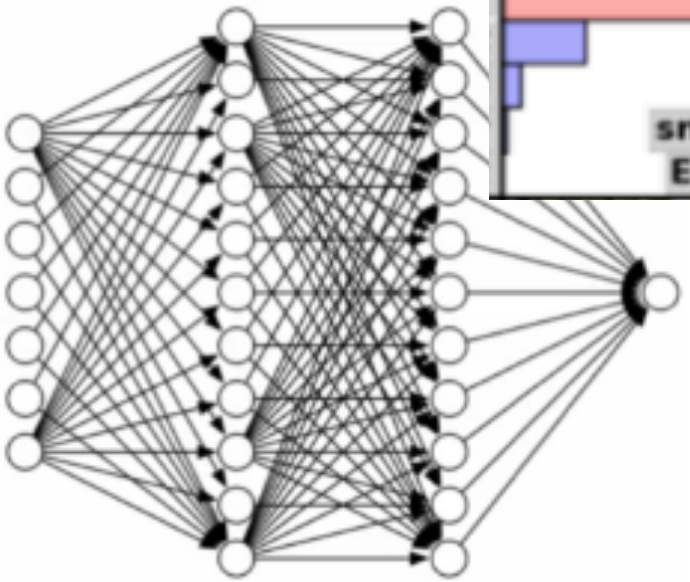
Credit: *Emily Fox (UW)*

Exciting Applications: Computer Vision

Object Recognition from Images



Deep Neural Networks for Object Recognition

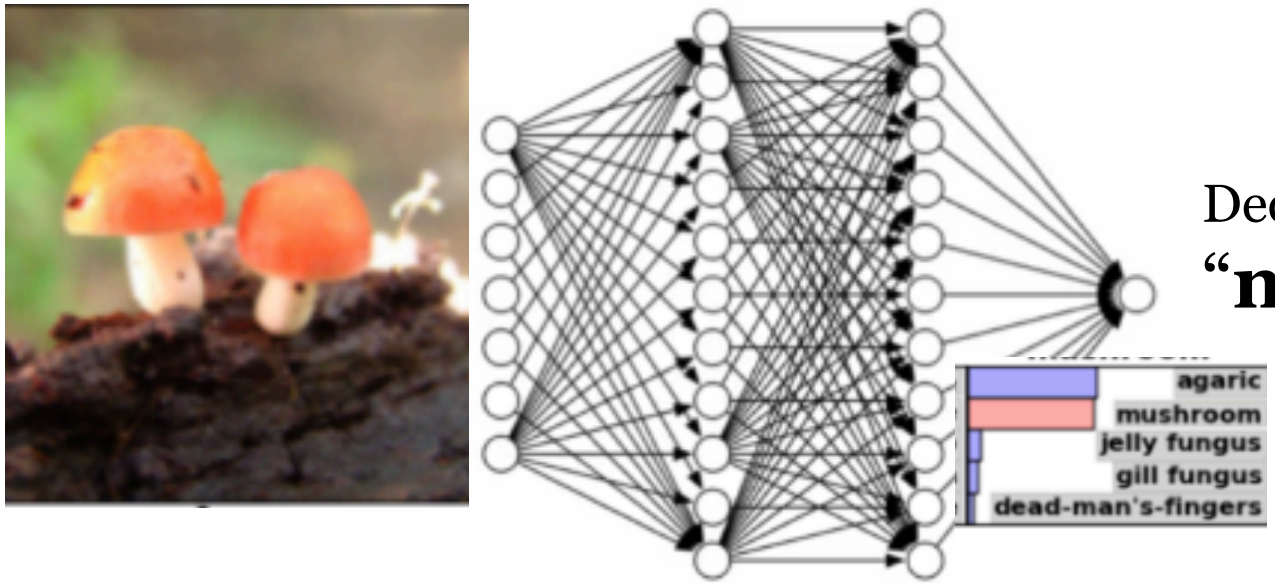


Scores for each possible object category

Decision:
"leopard"

Deep Neural Networks for Object Recognition

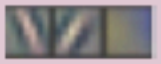
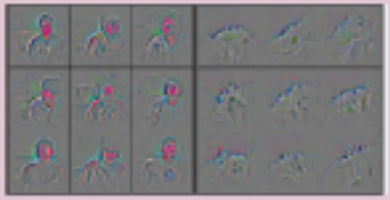
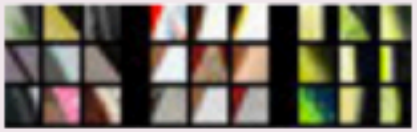
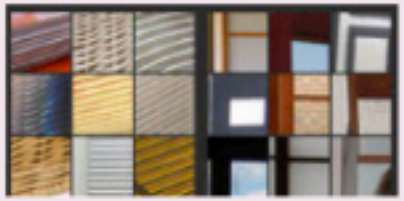
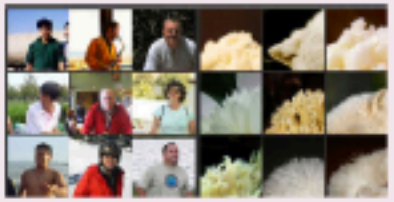
Scores for each possible object category



Decision:
"**mushroom**"

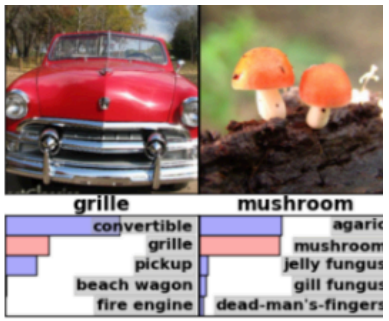
Each Layer Extracts "Higher Level" Features

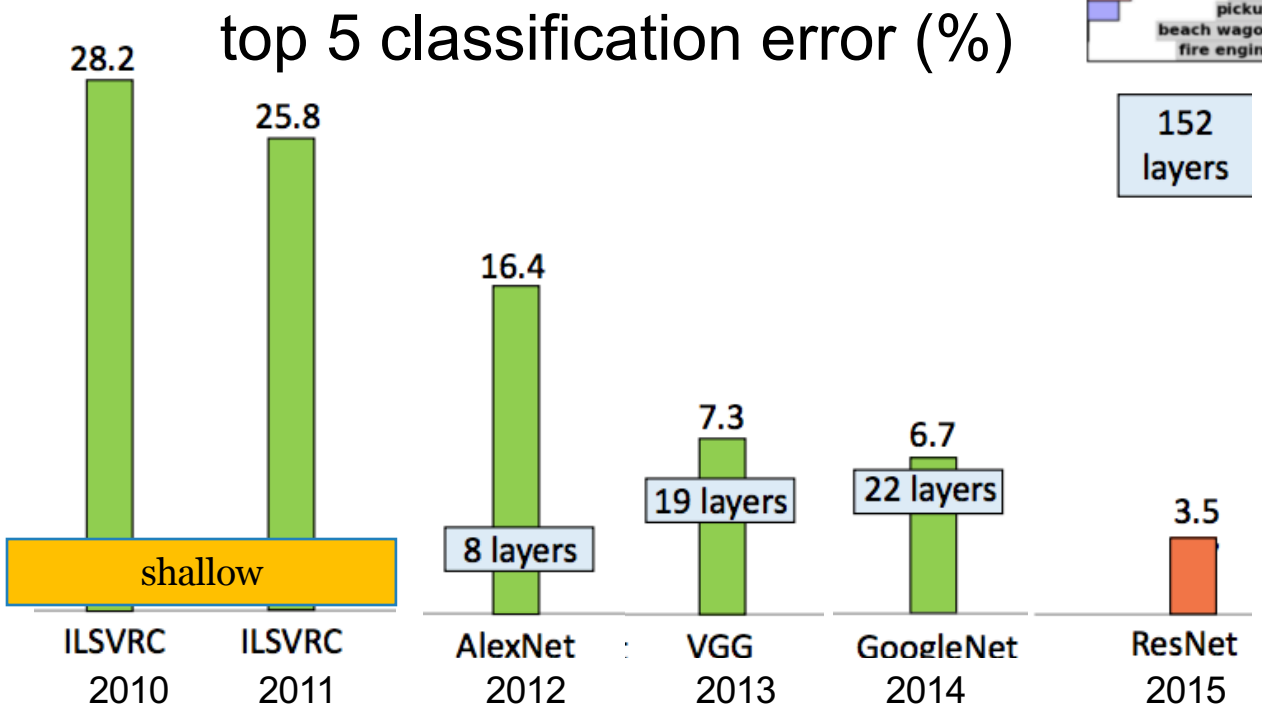
Layer 1 → Layer 2 → Layer 3 →

Example detectors learned			
Example interest points detected			

More layers = less error!

ImageNet challenge
1000 categories, 1.2 million images in training set



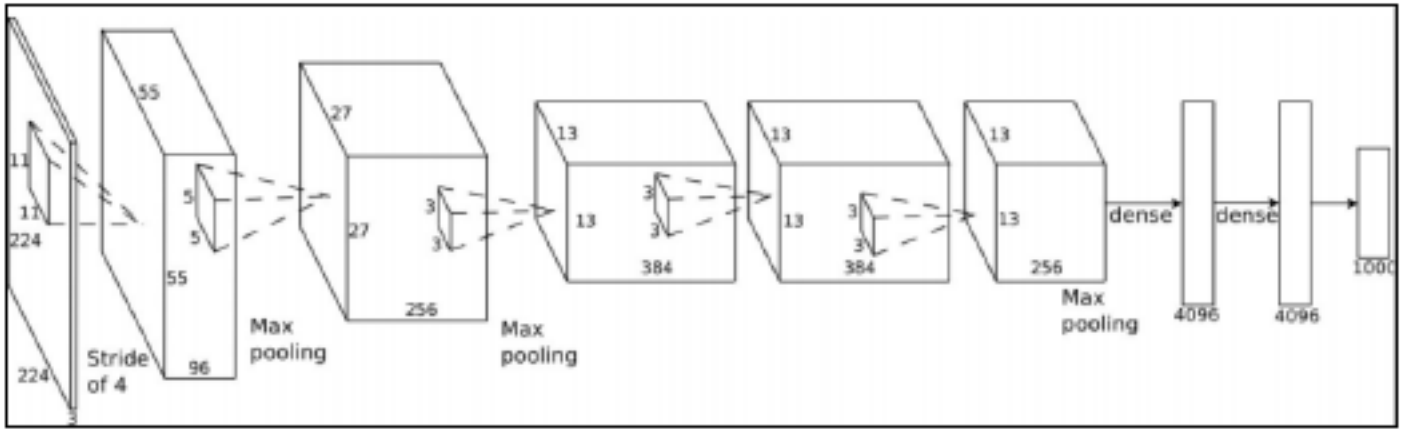


Credit: KDD Tutorial by Sun, Xiao, & Choi: http://dl4health.org/
Figure idea originally from He et. al., CVPR 2016

2012 ImageNet Challenge Winner

8 layers, 60M parameters [Krizhevsky et al. '12]

AlexNet



Achieving these amazing results required:

- New learning algorithms
- GPU implementation

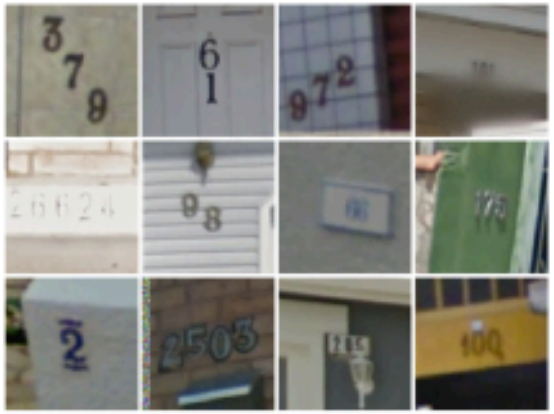
State of the art Results

German traffic sign recognition benchmark

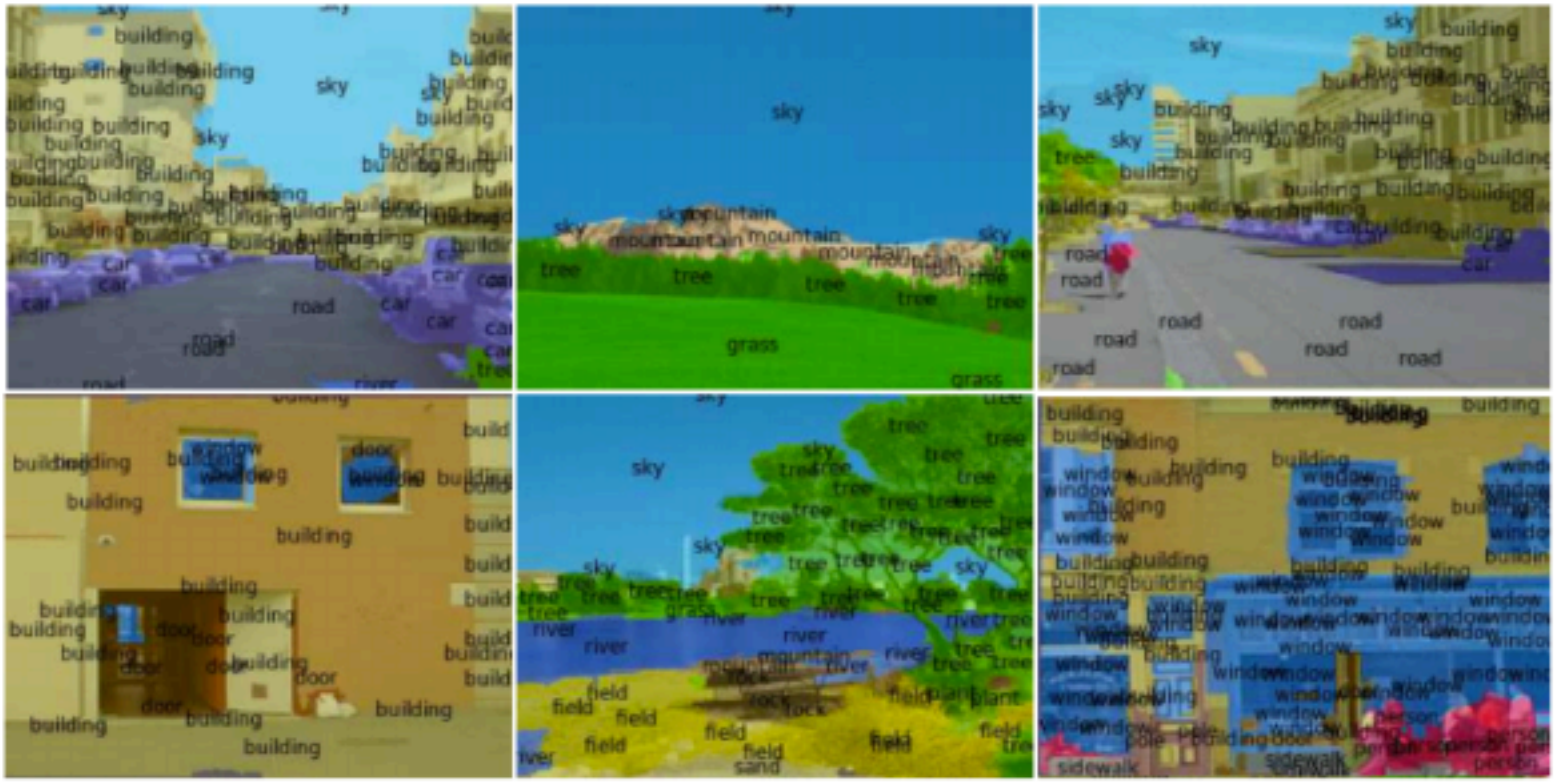
- 99.5% accuracy (IDSIA team)

House number recognition

- 97.8% accuracy per character [Goodfellow et al. '13]

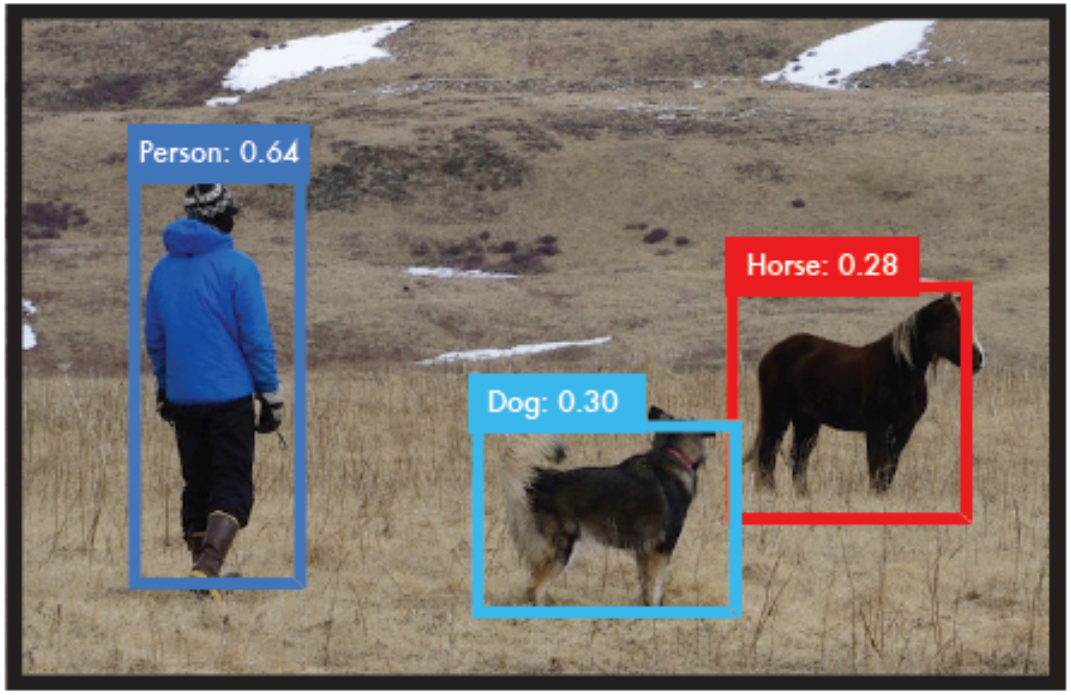


Semantic Segmentation



[Farabet et al. '13]

Object Detection



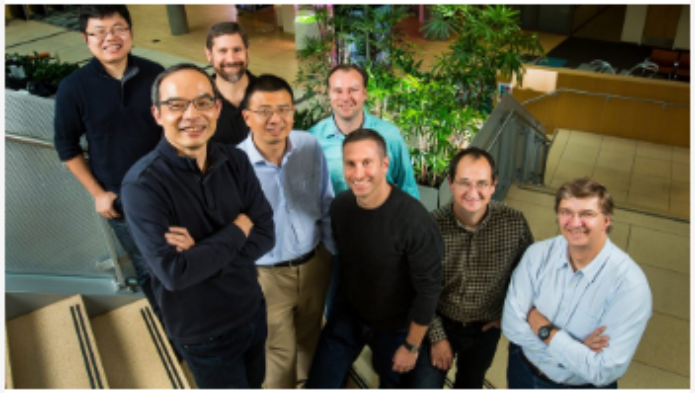
Redmon et al. 2015
http://pjreddie.com/yolo/

Exciting Applications:
Natural Language
(Spoken and Written)

Reaching Human Performance in Speech-to-Text

Historic Achievement: Microsoft researchers reach human parity in conversational speech recognition

October 18, 2016 | Allison Linn



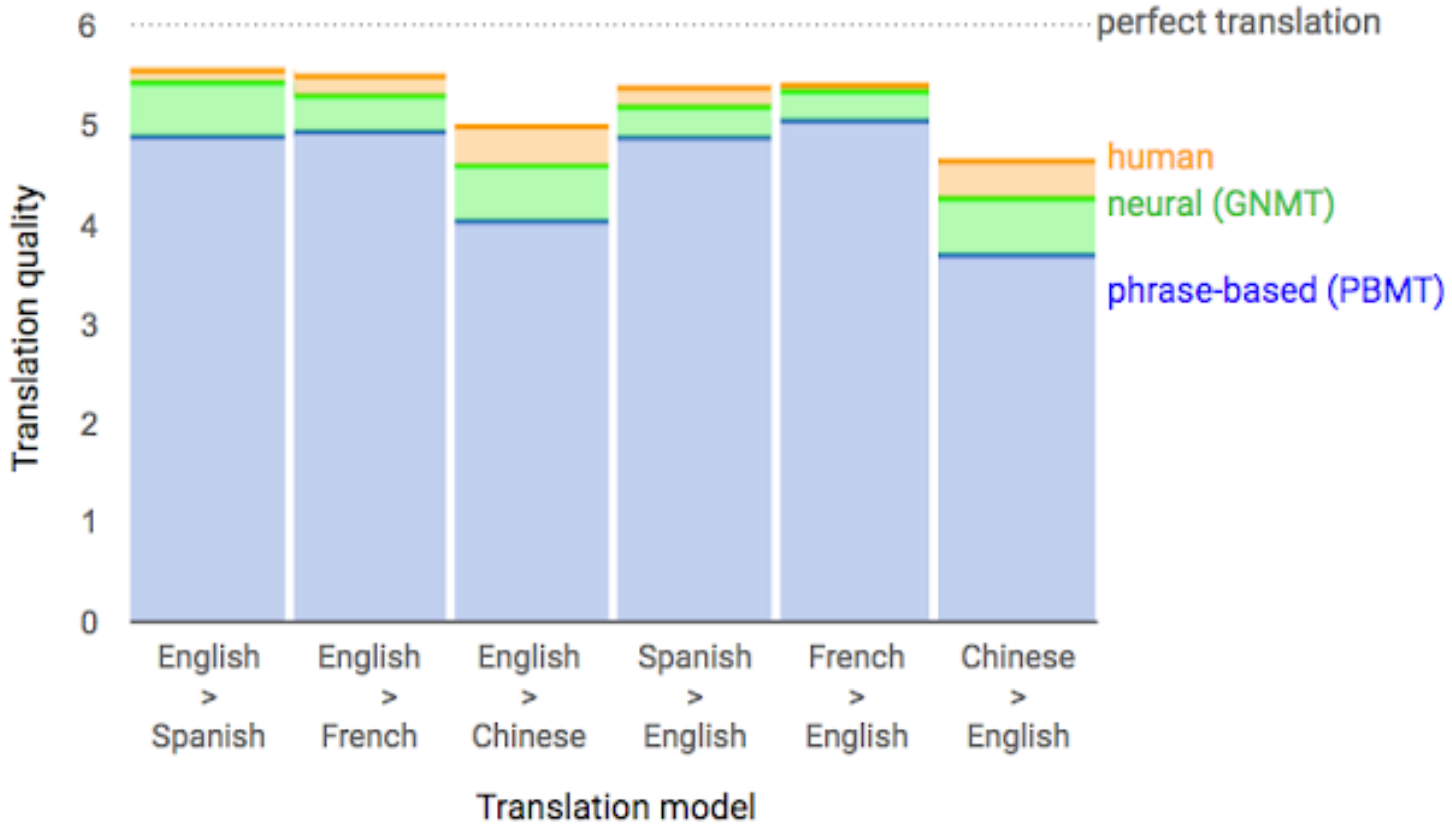
Microsoft | The AI Blog

https://arxiv.org/pdf/1610.05256.pdf

In a paper published Monday, a team of researchers and engineers in Microsoft Artificial Intelligence and Research reported a speech recognition system that makes the same or fewer errors than professional transcriptionists. The researchers reported a word error rate (WER) of 5.9 percent, down from the 6.3 percent WER the team reported just last month.

To reach the human parity milestone, the team used Microsoft Cognitive Toolkit, a homegrown system for deep learning that the research team has made available on GitHub via an open source license.

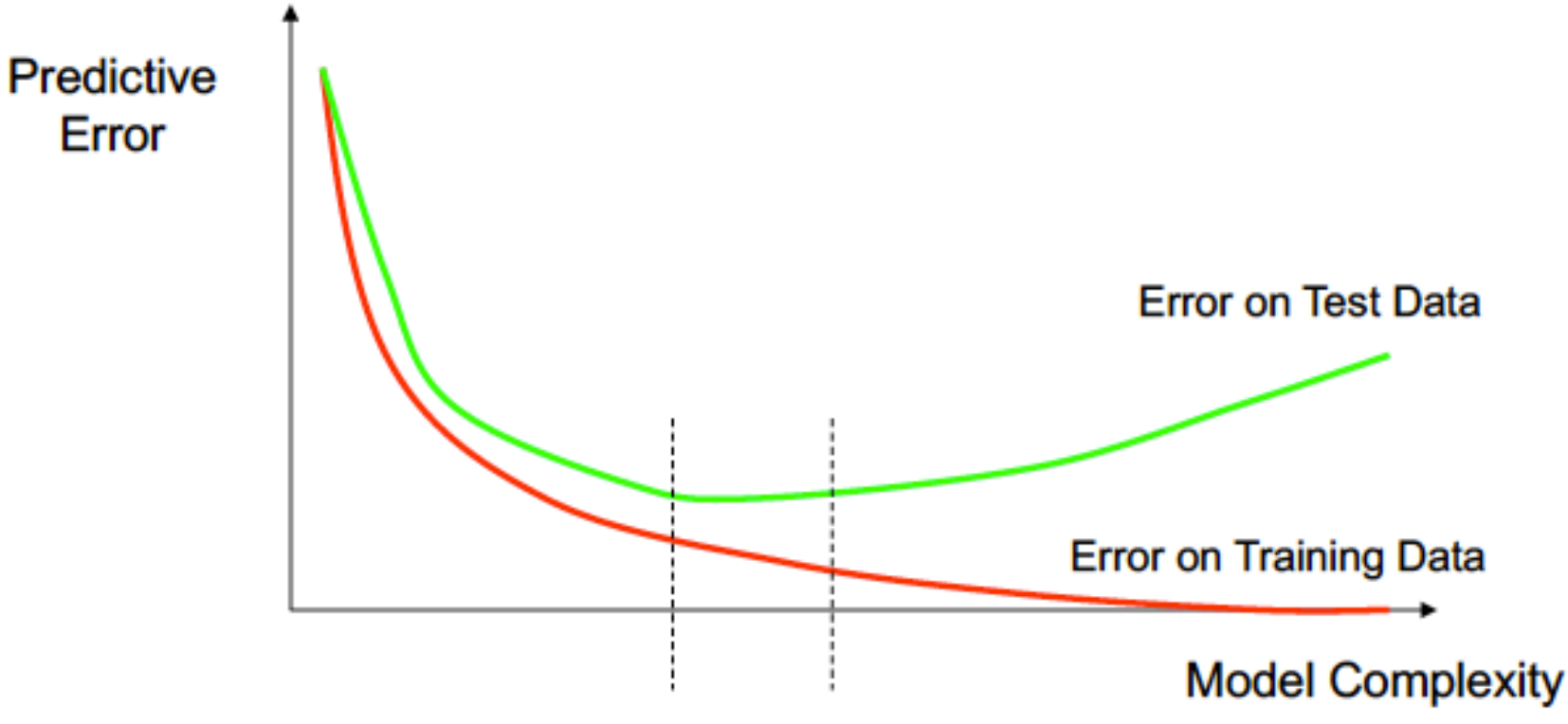
Gains in Translation Quality



https://ai.googleblog.com/2016/09/a-neural-network-for-machine.html

Any Disadvantages?

Deep Neural Networks can overfit!



1 layer
Few units / layer
Underfitting

Many layers
Many units / layer
Overfitting

Ways to avoid overfitting

- More training data!
- L2 / L1 penalties on weights
- More tricks (next week) ….
  - Early stopping
  - Dropout
  - Data augmentation

Objectives Today: Neural Networks Unit 1/2

- How to **learn** feature representations
  - Feed-forward neural nets
    - Single neuron = linear function + activation
    - Multi-layer perceptrons (MLPs)
  - Universal approximation
- The Rise of Deep Learning:
  - Success stories on Images and Language