INTRODUCTION TO DEEP LEARNING

MUSTAFA ALDEMIR, INTEL TURKEY

WHAT IS DEEP LEARNING GOOD FOR

DEEP LEARNING: EXAMPLES

Images
Computer vision, Image classification, Traffic sign detection, Pedestrian detection, localization…

Sound
Speech recognition, Natual Language Processing, Translation, Content captioning, speaker identification

"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum."

Text
Natual Language Processing, text classification; web search, spam, email filtering

CLASSIFICATION

-> Label the image

Person

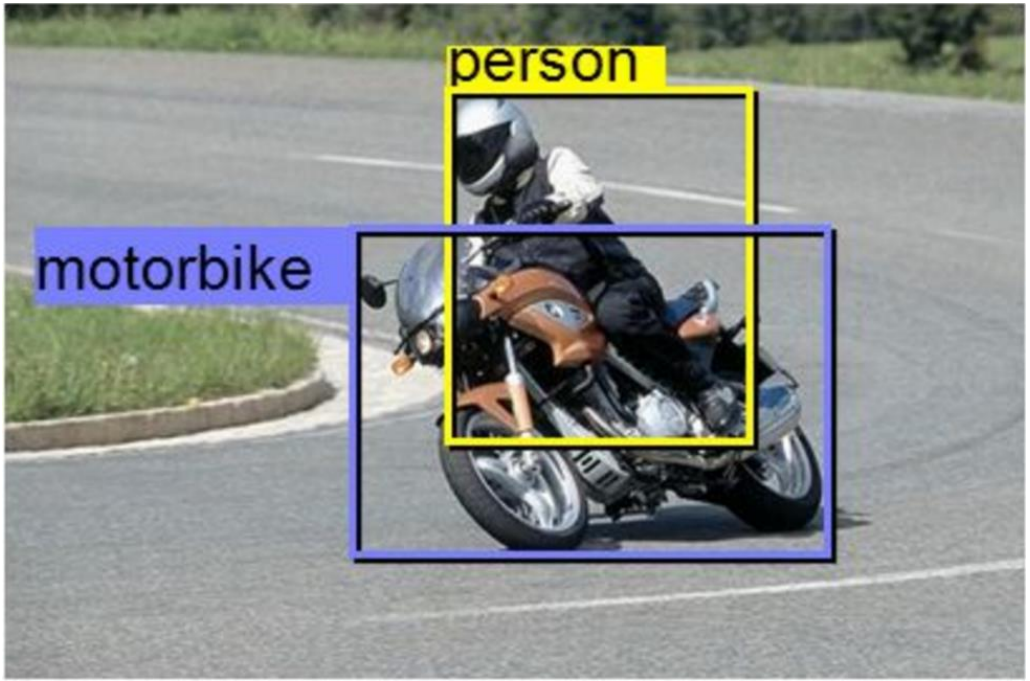
Motorcyclist

Bike

https://people.eecs.berkeley.edu/~jhoffman/talks/lsda-baylearn2014.pdf

DETECTION

-> Detect and label



https://people.eecs.berkeley.edu/~jhoffman/talks/lsda-baylearn2014.pdf

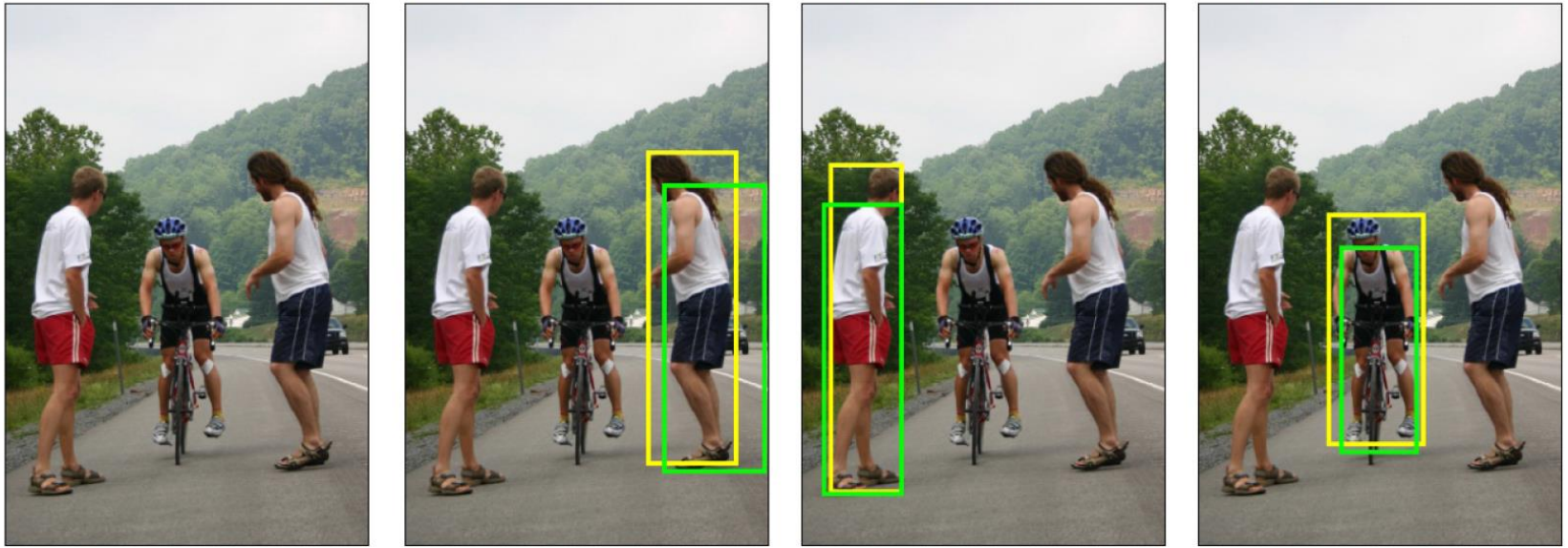
SEMANTIC SEGMENTATION

-> Label every pixel

https://people.eecs.berkeley.edu/~jhoffman/talks/lsda-baylearn2014.pdf

NATURAL LANGUAGE OBJECT RETRIEVAL

a scene with three people query='*man far right*' query='*left guy*' query='*cyclist*'



http://arxiv.org/pdf/1511.04164v3.pdf

SPEECH RECOGNITION

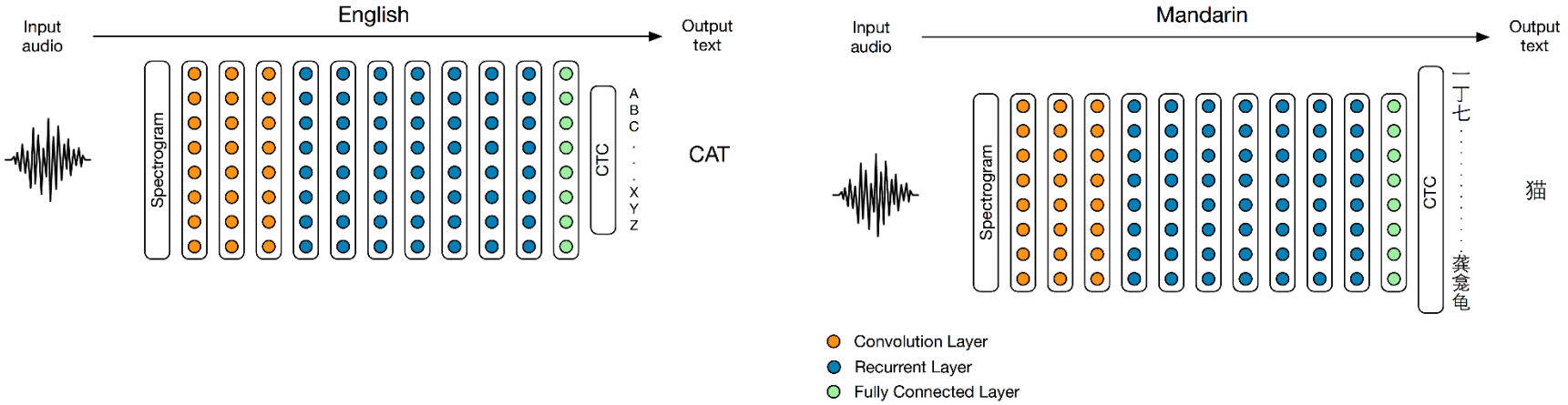
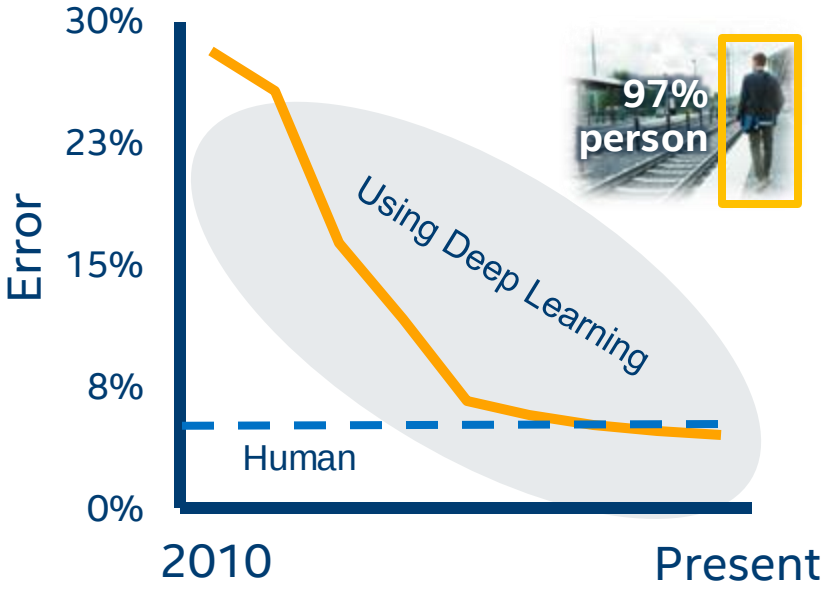


IMAGE / VIDEO CAPTIONING

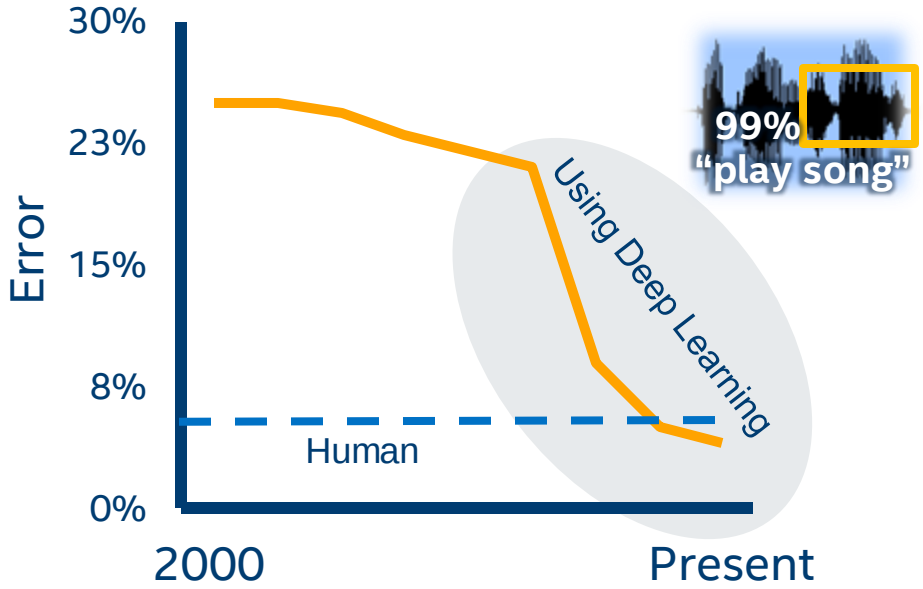
Describes without errors	Describes with minor errors	Somewhat related to the image
		
A person riding a motorcycle on a dirt road.	Two dogs play in the grass.	A skateboarder does a trick on a ramp.
		
A group of young people playing a game of frisbee.	Two hockey players are fighting over the puck.	A little girl in a pink hat is blowing bubbles.

DEEP LEARNING BREAKTHROUGHS

IMAGE RECOGNITION



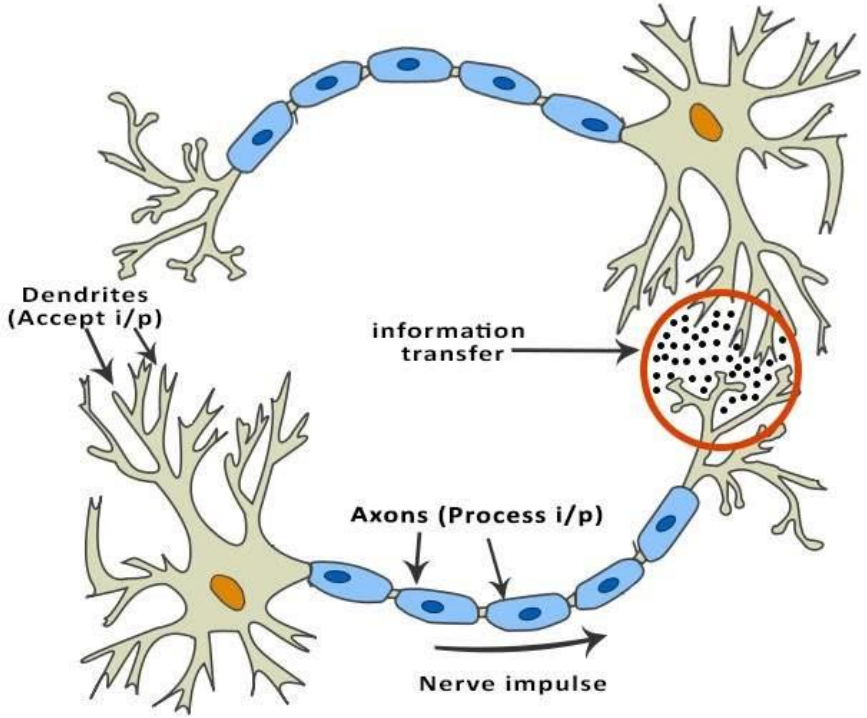
SPEECH RECOGNITION



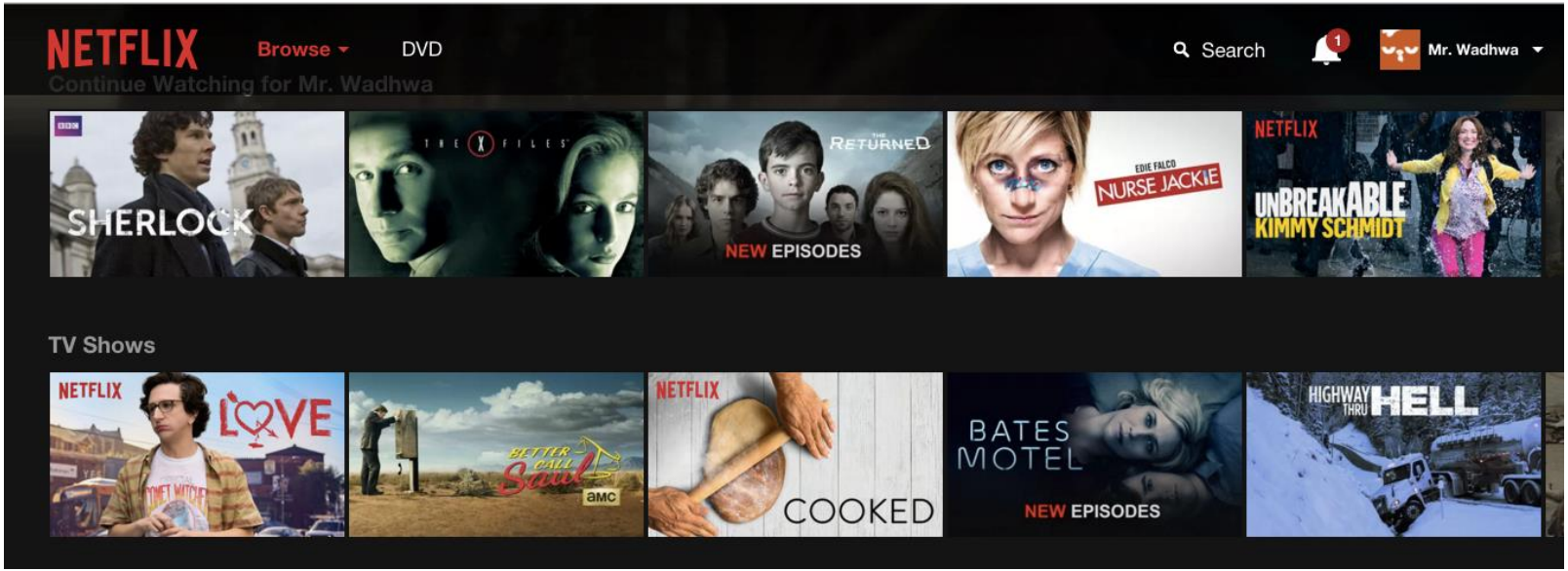
These and more are enabling new & improved applications

NEURAL NETWORKS

INSPIRED BY HUMAN BRAIN



CASE STUDY: RECOMMENDATION SYSTEMS

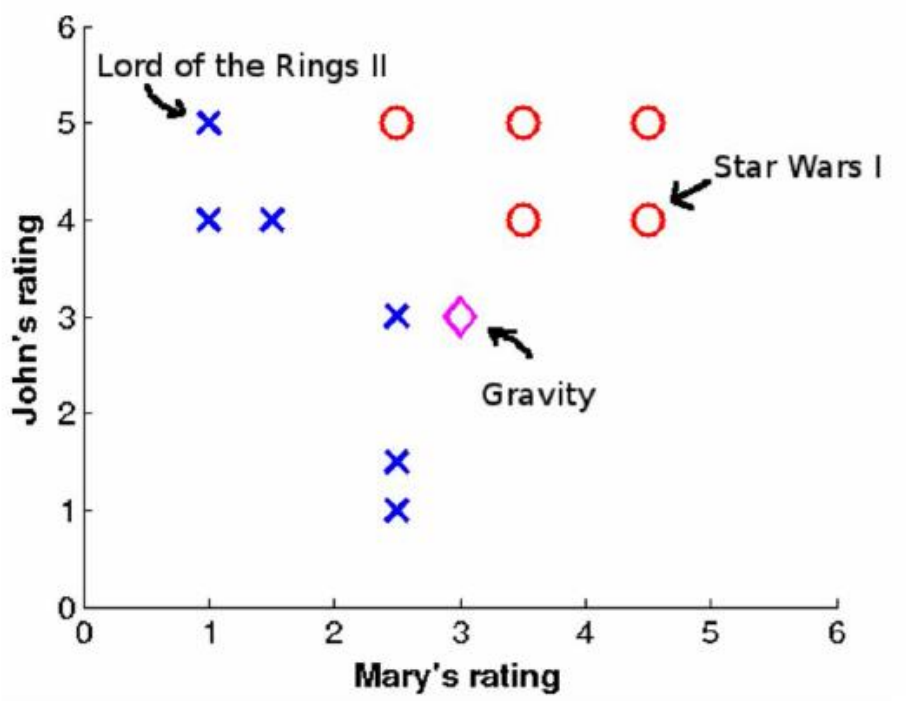


Will Nancy like Gravity?

Let's ask close friends Mary and John, who already watched it and rated between 1-5.

Movie	Mary's Rating	John's Rating	Does Nancy like?
Lord of the Rings 2	1	5	No
…	…	…	…
Star Wars 1	4.5	4	Yes
Gravity	3	3	?

NETFLIX


Lord of the Rings II
Star Wars I
Gravity
John's rating
Mary's rating
0
1
2
3
4
5
6

A decision function can be as simple as weighted linear combination of friends:

$$h_{\theta,b} = \theta_1 x_1 + \theta_2 x_2 + b$$

$$h_{\theta,b} = \theta^T x + b$$

- Labels: “I like it” -> 1 “I don’t like it” -> 0
- Inputs: Mary’s rating, John’s rating

ACTIVATION FUNCTION

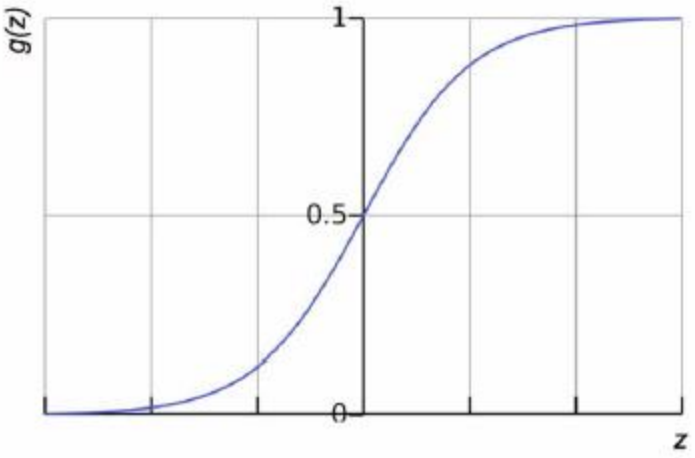
This function has a problem. Its values are unbounded.

We want its output to be in the range of 0 and 1.

$$h_{\theta,b} = g(\theta^T x + b),$$

where $g(z)$ is sigmoid function.

$$g(z) = \frac{1}{1 + exp(-z)}$$



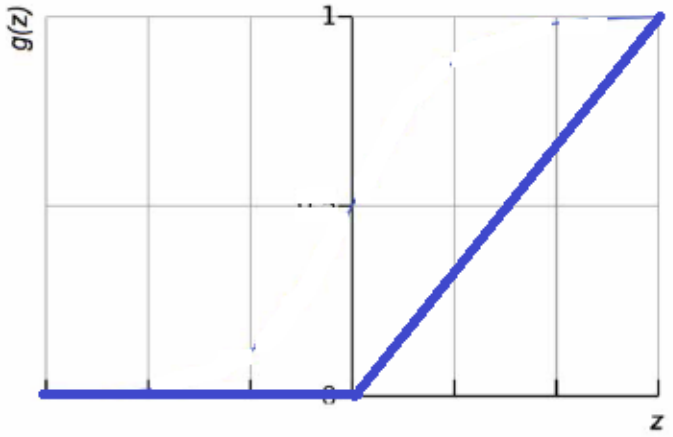
ACTIVATION FUNCTION

This function has a problem. Its values are unbounded.

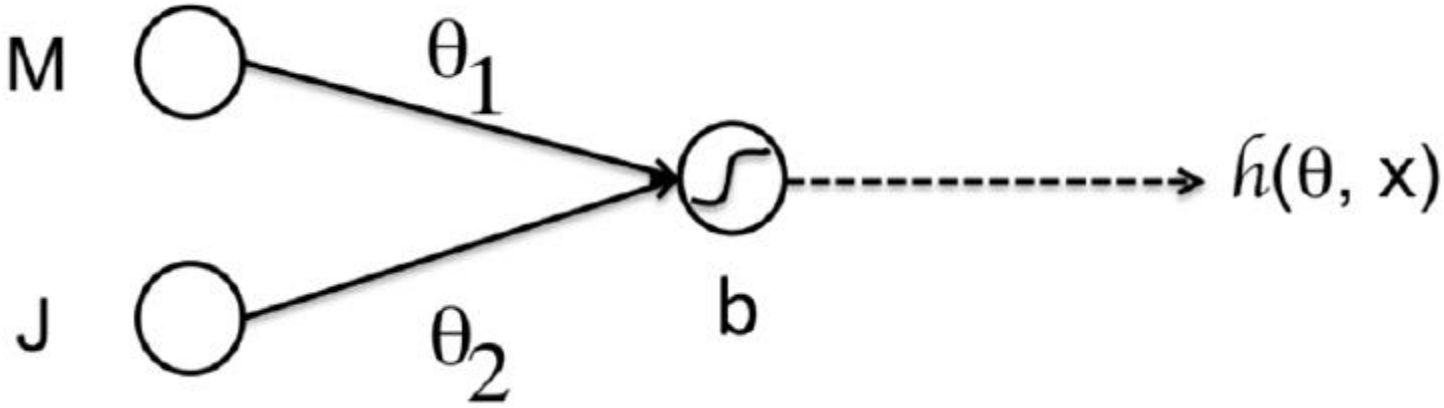
We want its output to be in the range of 0 and 1.

ReLU (Rectified Linear Unit)

$f(x) = \max(0,x)$



ANOTHER WAY OF REPRESENTING THE MODEL



LEARN FROM DATA

We will use the past data to learn θ, b to approximate y. In particular, we want to obtain θ, b such that:

$h_{\theta,b}(x^{(1)}) \approx y^{(1)}$ where $x^{(1)}$ is my friend's ratings for 1st movie.

$h_{\theta,b}(x^{(2)}) \approx y^{(2)}$ where $x^{(2)}$ is my friend's ratings for 2nd movie.

...

$h_{\theta,b}(x^{(m)}) \approx y^{(m)}$ where $x^{(m)}$ is my friend's ratings for mth movie.

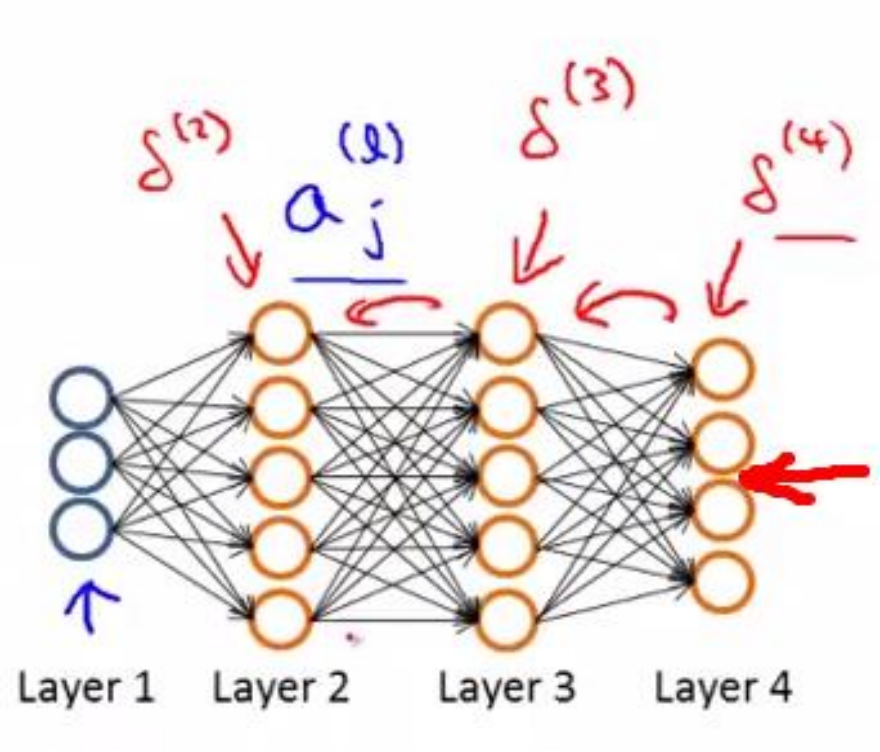
COST FUNCTION

To find values of θ and b we can minimize the following *cost function*:

$$J(\theta, b) = \left(h_{\theta,b}\left(x^{(1)}\right) - y^{(1)}\right)^2 + \left(h_{\theta,b}\left(x^{(2)}\right) - y^{(2)}\right)^2 + \ \ldots + \left(h_{\theta,b}\left(x^{(m)}\right) - y^{(m)}\right)^2$$

$$J(\theta, b) = \sum_{i=1}^{m} \left(h_{\theta,b}\left(x^{(i)}\right) - y^{(i)}\right)^2$$

BACKPROPOGATION

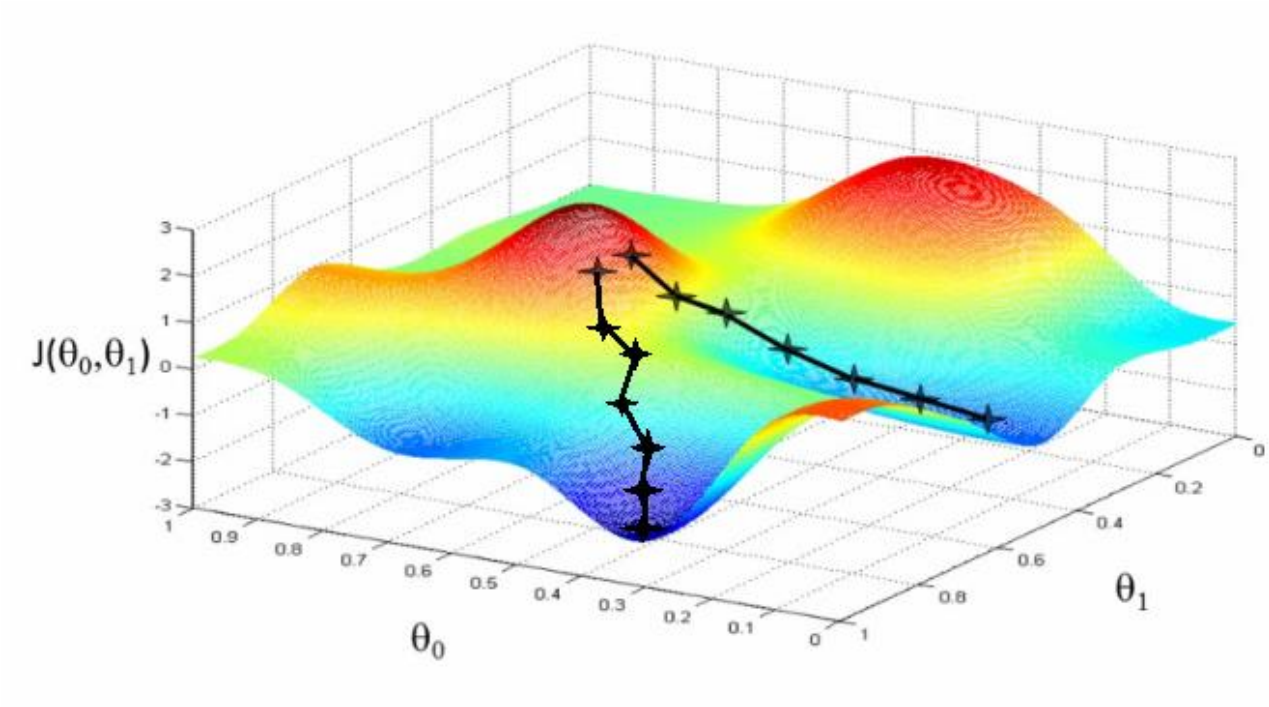


STOCHASTIC GRADIENT DESCENT

Use Stochastic Gradient Descent (SGD):

$$\theta_1 = \theta_1 - \alpha\Delta\theta_1$$
$$\theta_2 = \theta_2 - \alpha\Delta\theta_2$$
$$b = b - \alpha\Delta b$$

STOCHASTIC GRADIENT DESCENT



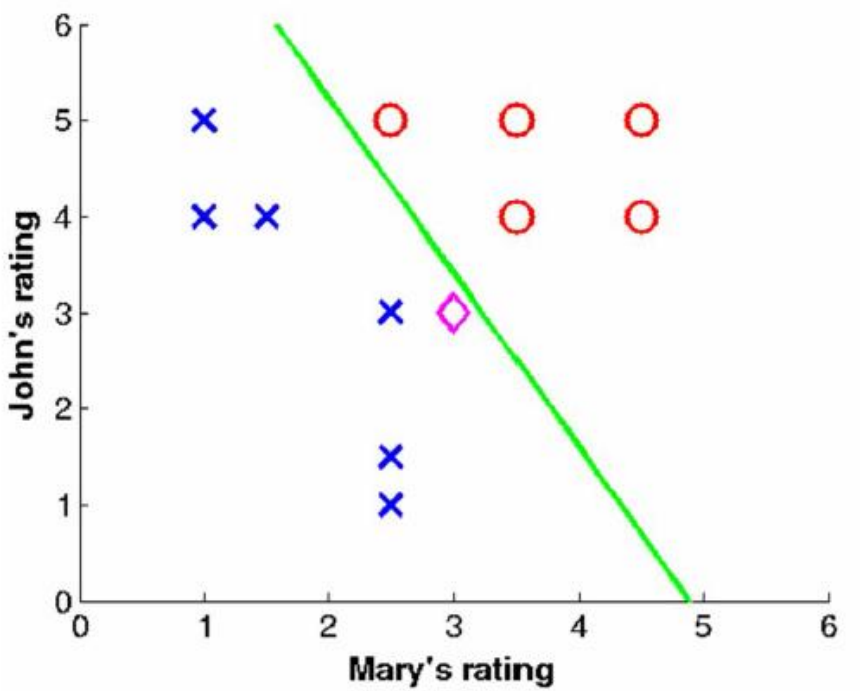
STEPS

1. Initialize the parameters θ and b at random
2. Pick a random example $\{x^{(i)}, y^{(i)}\}$
3. Compute the partial derivatives of θ_1, θ_2, b
4. Update parameters using:

$$\theta_1 = \theta_1 - \alpha\Delta\theta_1$$
$$\theta_2 = \theta_2 - \alpha\Delta\theta_2$$
$$b = b - \alpha\Delta b$$

Stop it when parameters don't change much, or after a certain number of iterations.

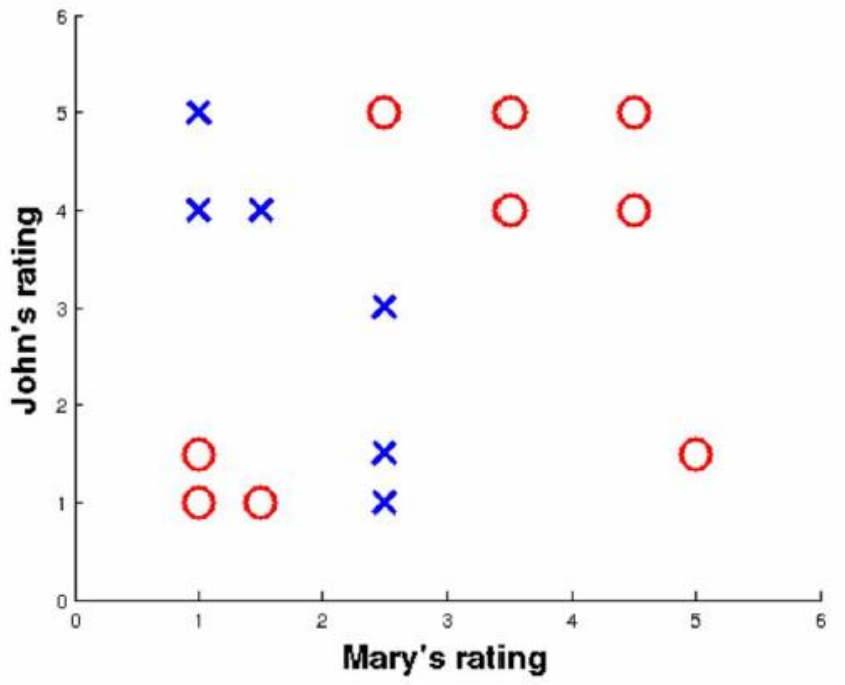
NETFLIX



Gravity movie is slightly on the “don’t watch” side.

With this data set, it seems like ”not watching it” makes more sense.

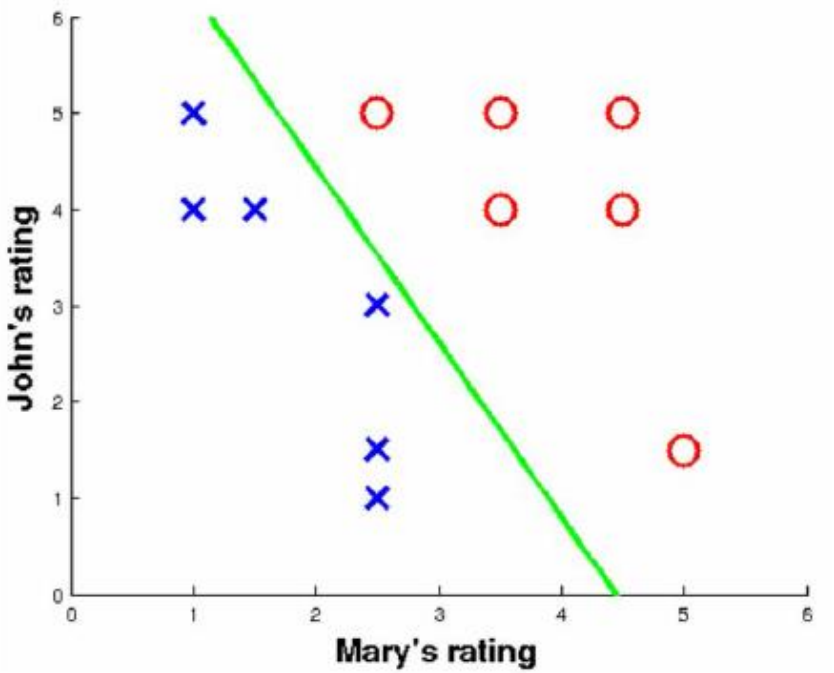
NETFLIX

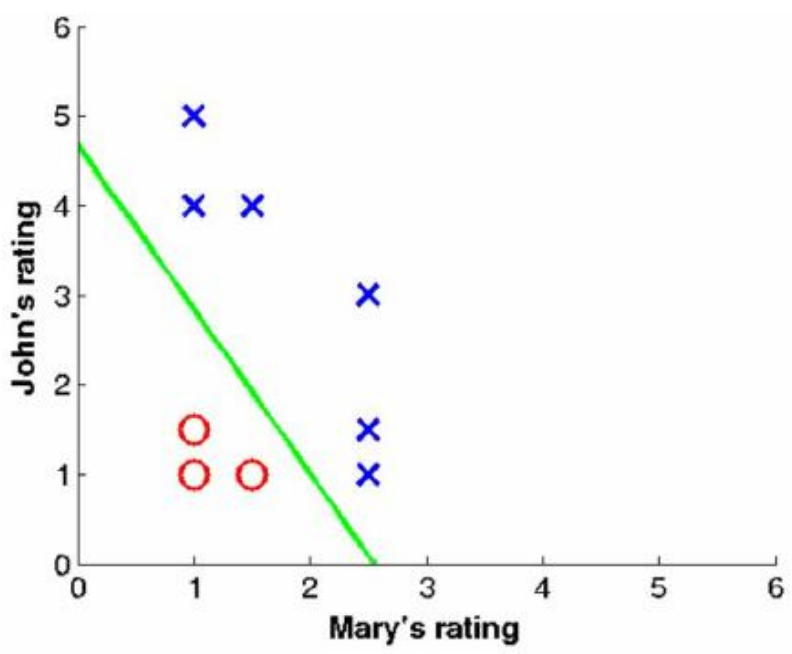


Nancy likes some of the movies both Mary and John rated poorly.

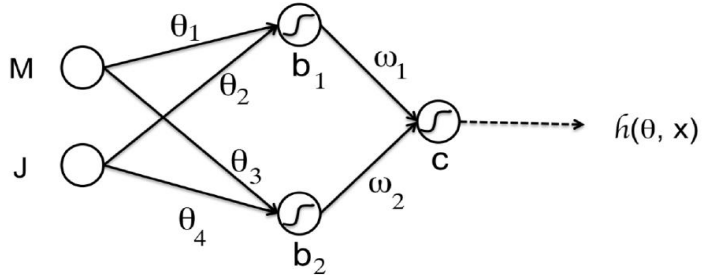
How can I have a linear decision boundary separate these?

NETFLIX

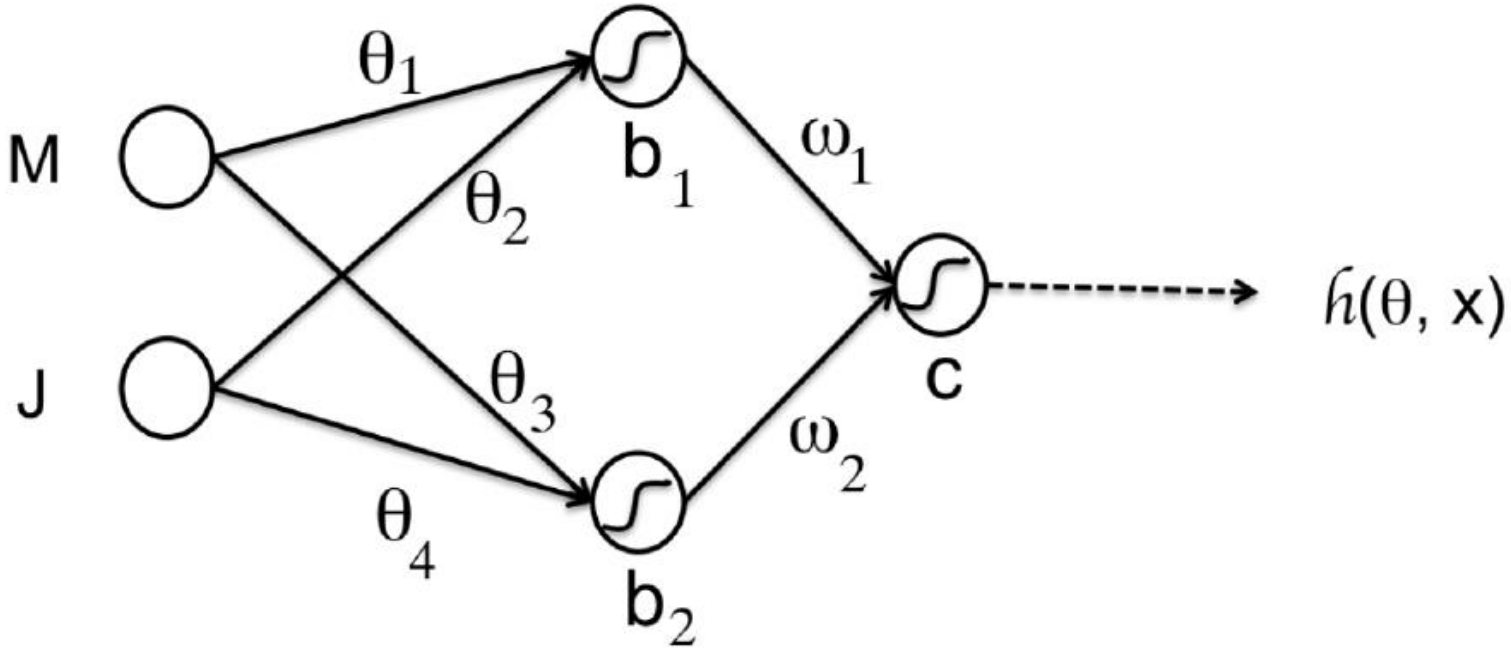

John's rating
Mary's rating
0
1
2
3
4
5
6


John's rating
Mary's rating
0
1
2
3
4
5
6

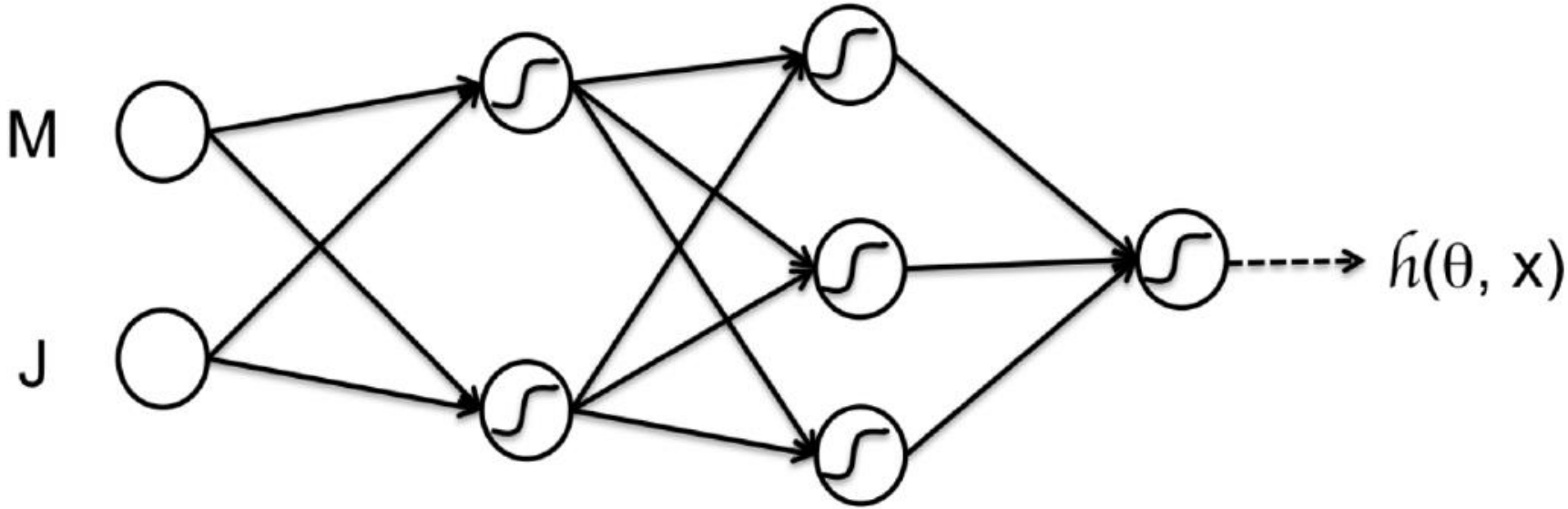
Movie	Output by decision function *h1*	Output by decision function *h2*	Does Nancy like?
Lord of the Rings 2	$h_1(x^{(1)})$	$h_2(x^{(1)})$	No
…	…	…	…
Star Wars 1	$h_1(x^{(n)})$	$h_2(x^{(n)})$	Yes
Gravity	$h_1(x^{(n+1)})$	$h_2(x^{(n+1)})$	?



THIS IS THE NEURAL NETWORK

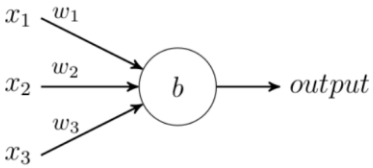


A DEEPER NEURAL NETWORK



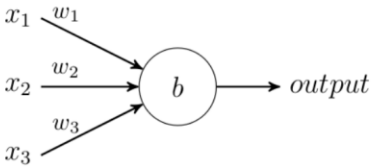
DEEP LEARNING: BASIC STRUCTURE

BASIC SINGLE NEURON



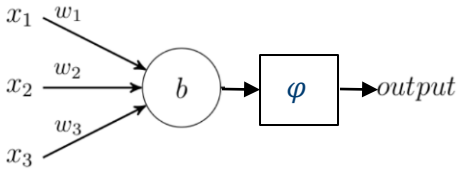
DEEP LEARNING: BASIC STRUCTURE

BASIC SINGLE NEURON



$$u_n = \sum_{j=1}^{m} w_{nj} x_j$$

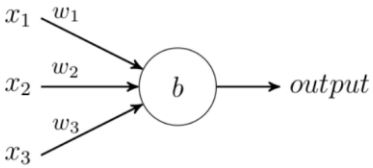
SINGLE NEURON WITH ACTIVATION



φ → Activation function

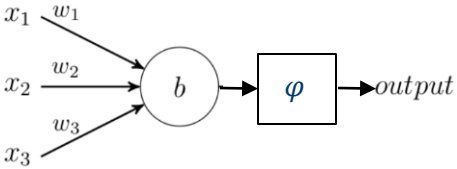
DEEP LEARNING: BASIC STRUCTURE

BASIC SINGLE NEURON



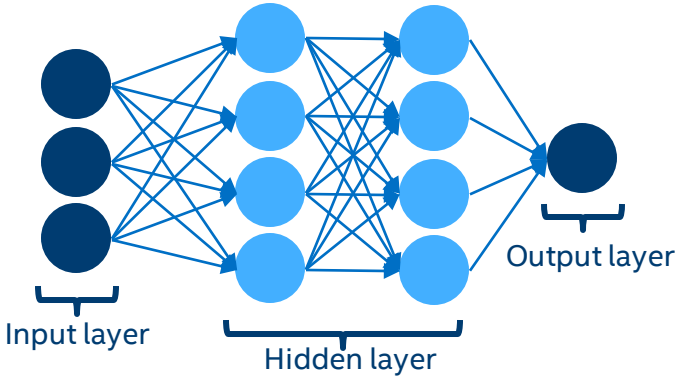
$$u_n = \sum_{j=1}^{m} w_{nj} x_j$$

SINGLE NEURON WITH ACTIVATION



φ → Activation function

BASIC STRUCTURE WITH TWO HIDDEN LAYERS



KEYWORDS

- Training / Testing percentage
- Overfitting – Underfitting
- Topology
- Training Algorithms
- Learning Rate
- Batch Size

CLASSICAL MACHINE LEARNING VS DEEP LEARNING

CLASSIC ML

Using optimized functions or algorithms to extract insights from data

Training Data*

Algorithms
- Random Forest
- Support Vector Machines
- Regression
- Naïve Bayes
- Hidden Markov
- K-Means Clustering
- Ensemble Methods
- More...

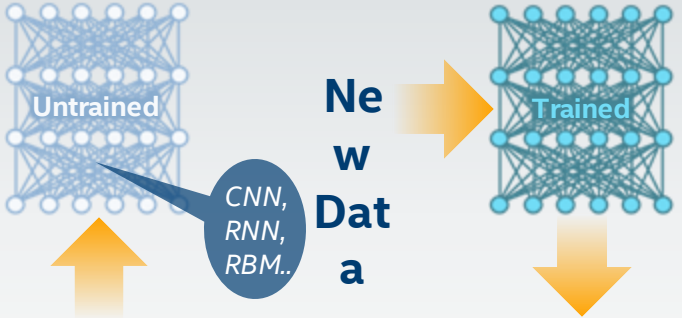
Inference, Clustering, or Classification

New Data*

*Note: not all classic machine learning functions require training

DEEP LEARNING

Using massive labeled data sets to train deep (neural) graphs that can make inferences about new data



Step 1: Training

Hours to Days in Cloud

Use massive labeled dataset (e.g. 10M tagged images) to iteratively adjust weighting of neural network connections

Step 2: Inference

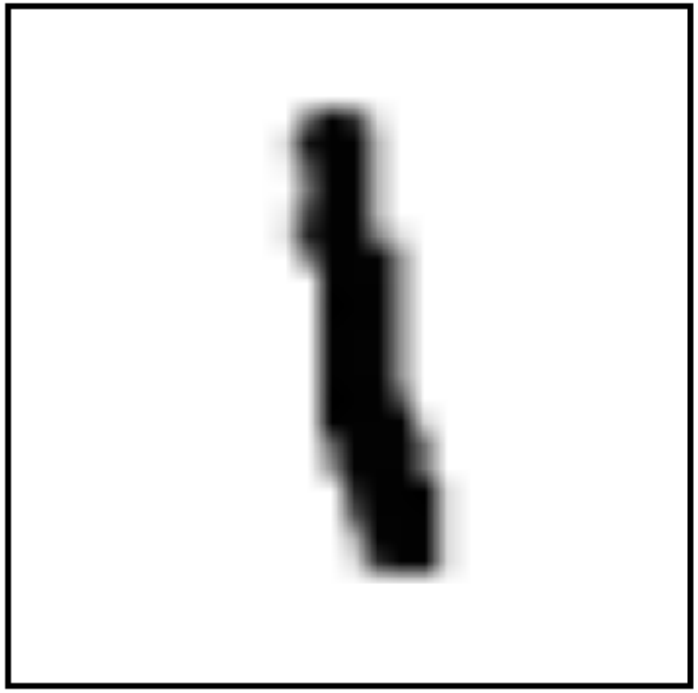
Real-Time at Edge/Cloud

Form inference about new input data (e.g. a photo) using trained neural network

NAIVE APPROACH

USE CASE: HANDWRITTEN DIGITS (MNIST)

USE CASE: HANDWRITTEN DIGITS (MNIST)

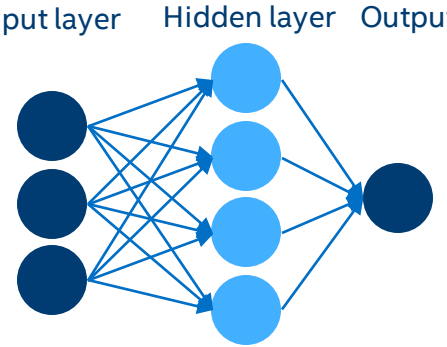


$\approx$

$$\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .6 & .8 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .7 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .7 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .5 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .7 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & .9 & 1 & .1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & .3 & 1 & .1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}$$

USE CASE: HANDWRITTEN DIGITS (MNIST)

MNIST DATASET
28x28 Pixels



= 28x28 pixels
= 784 units

= 100 units
(variable)

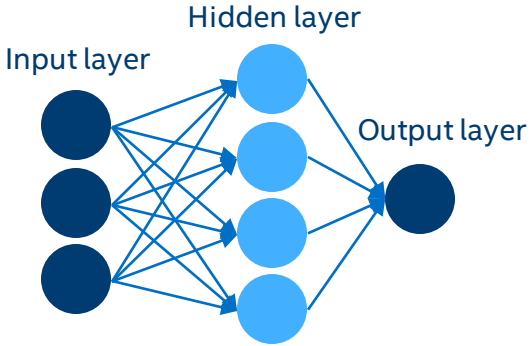
= 10 units (0 – 9)

TOTAL PARAMETERS

$W_{\text{input} \rightarrow \text{hidden}}$	784 x 100
b_{hidden}	100
$W_{\text{hidden} \rightarrow \text{output}}$	100 x 10
B_{output}	10

$$u_n = \sum_{j=1}^{m} w_{nj} x_j$$

TRAINING

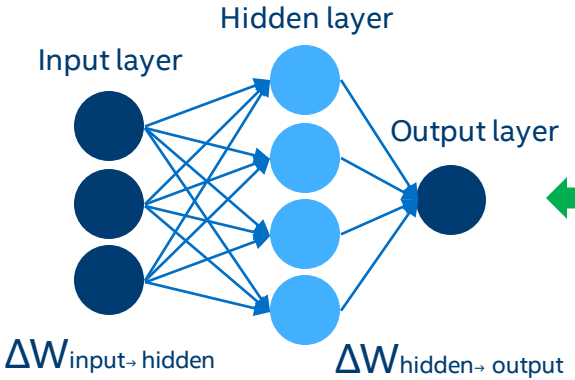


1) Initialize weights
2) Forward pass
3) Calculate cost
4) Backward pass
5) Update weights

Output	Ground Truth
0.2	0.0
0.0	0.0
0.5	1
0.0	0.0
0.1	0.0
0.4	0.0
0.2	0.0
0.0	0.0
0.1	0.0
0.0	0.0

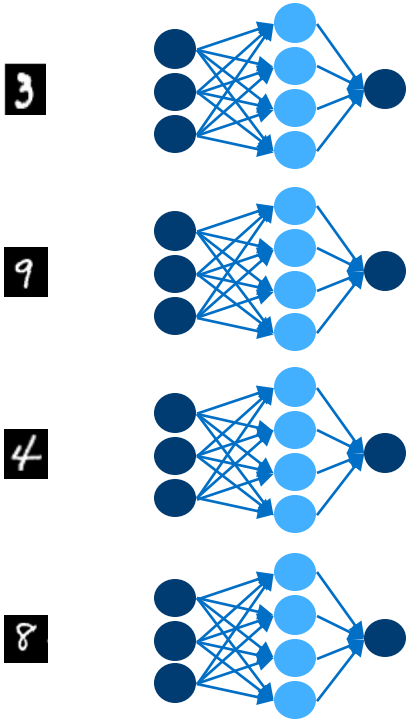
Cost function =
C(output, truth)

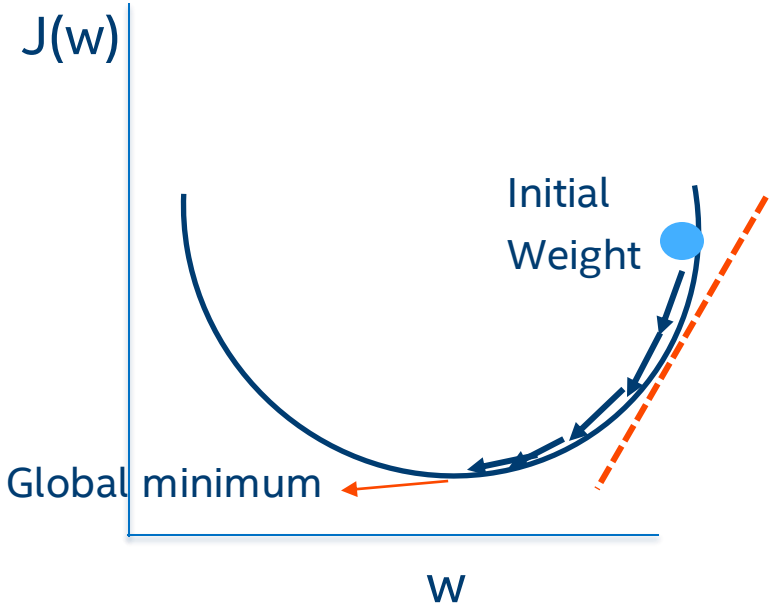
TRAINING: BACKPROPAGATION



Cost function =
C(output, truth)

TRAINING: STOCHASTIC GRADIENT DESCENT





HANDS-ON WORK

Case Study: MNIST by Softmax Regression

USE CASE: HANDWRITTEN DIGITS (MNIST)

Softmax Regression

iPython notebook:

https://github.com/mstfldmr/IntelAIWorkshop/blob/master/SoftmaxRegression.ipynb

CONVOLUTIONAL NEURAL NETWORKS (CNN)

Convolutional Neural Networks (CNN)

Essentially neural networks that use convolution in place of general matrix multiplication in at least one of their layers.

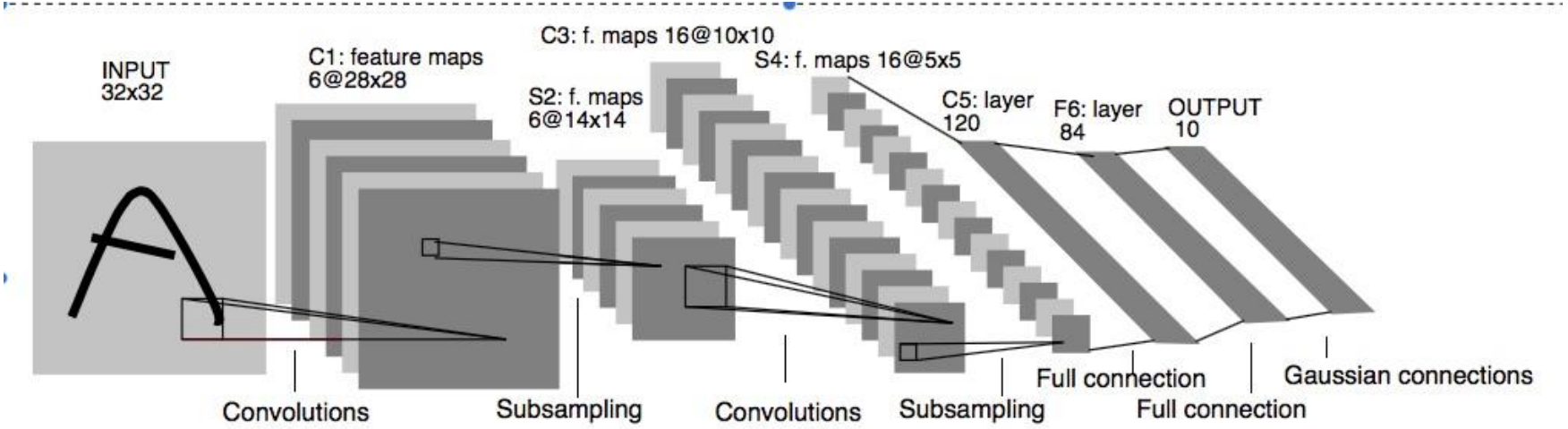
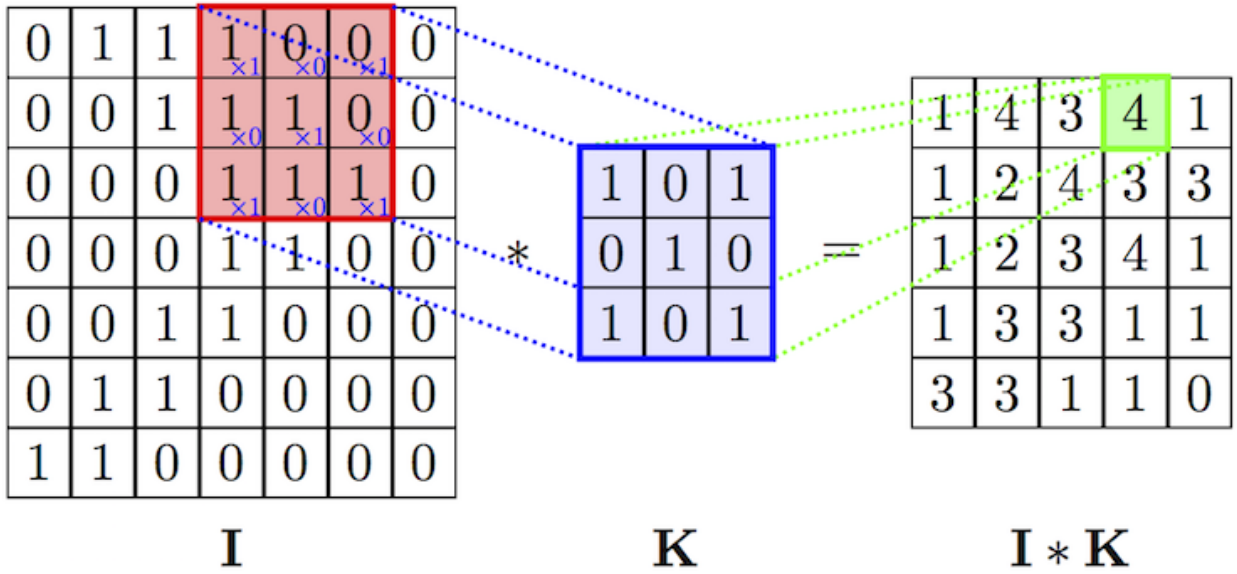


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

CONVOLUTION



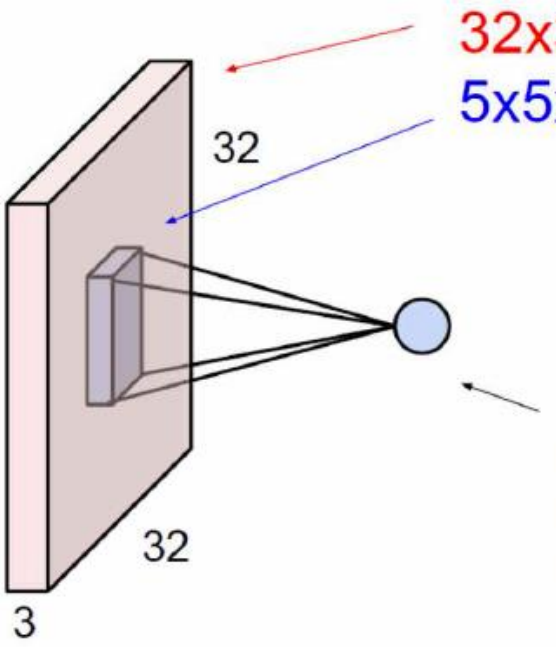
CONVOLUTION

$*$

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

CONVOLUTION

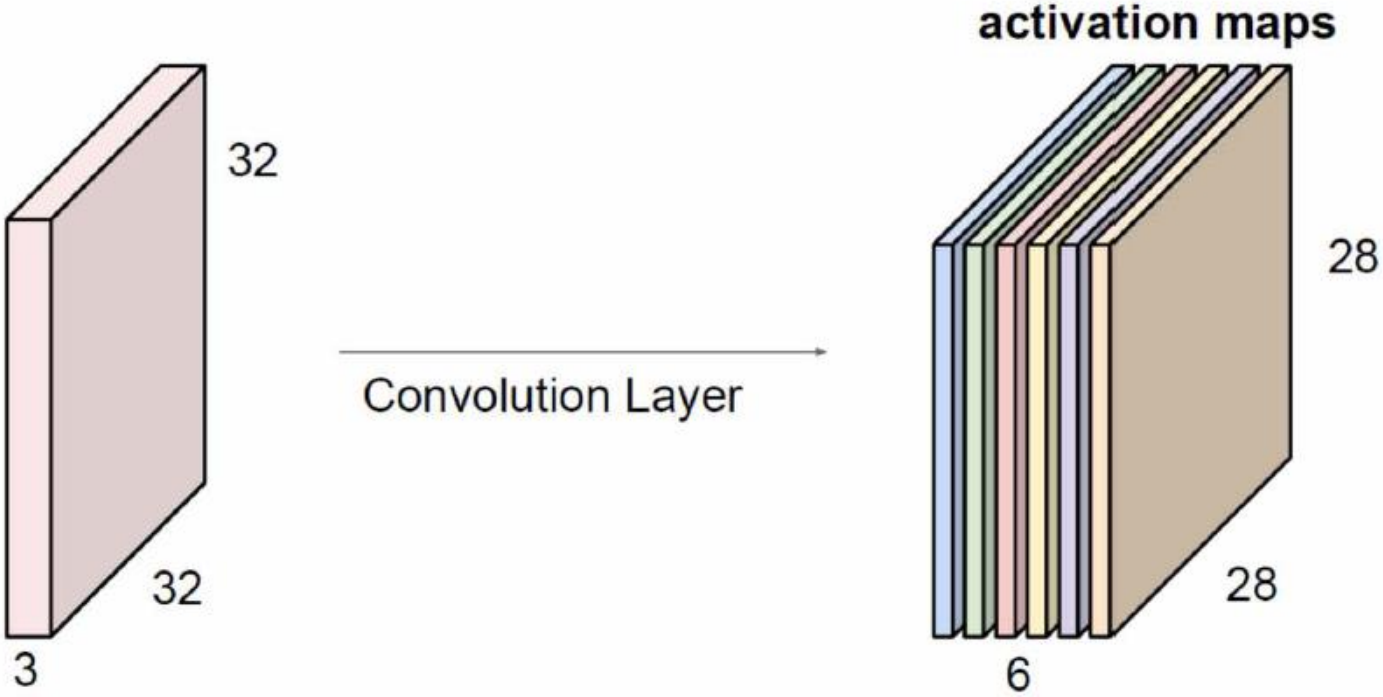
Convolution Layer



1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias

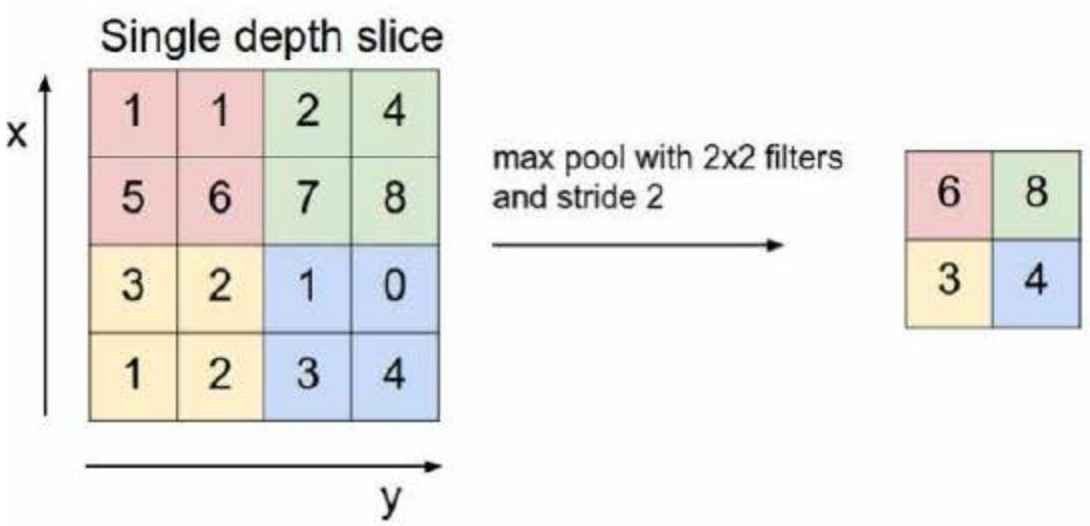
$$w^T x + b$$

Convolution Layer

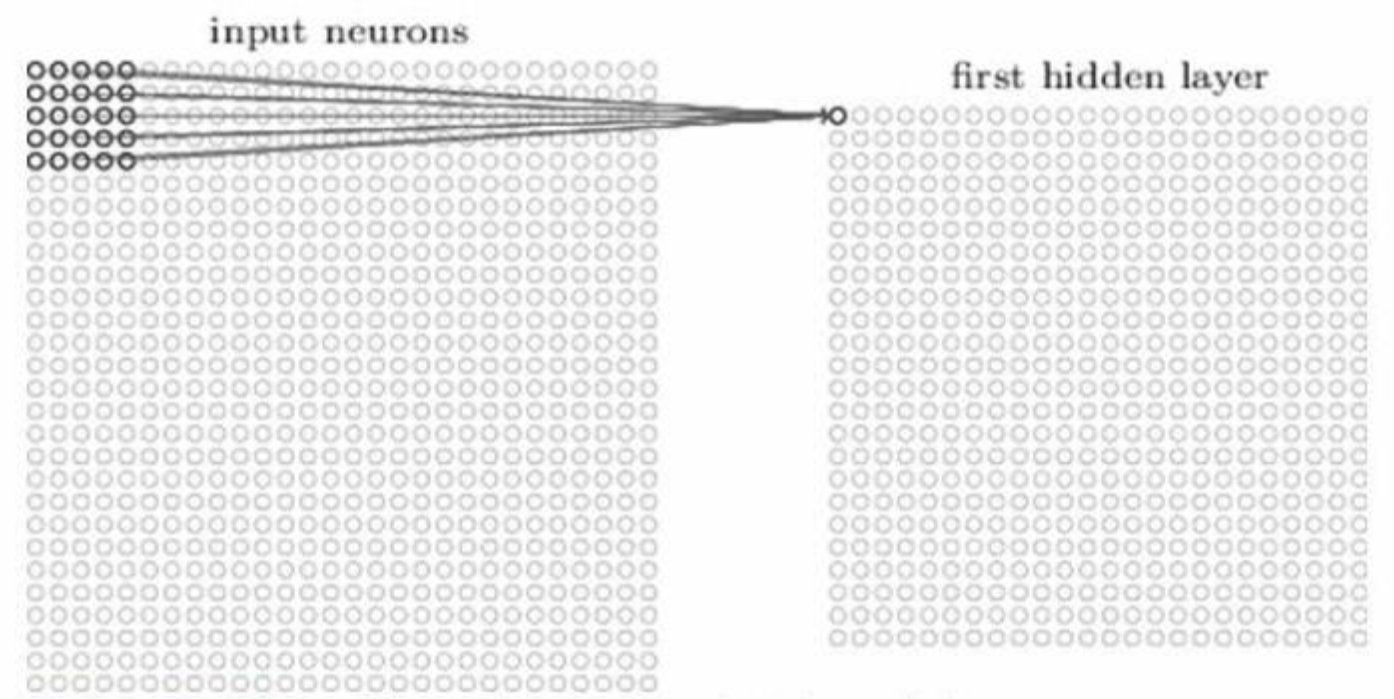


We stack these up to get a “new image” of size 28x28x6!

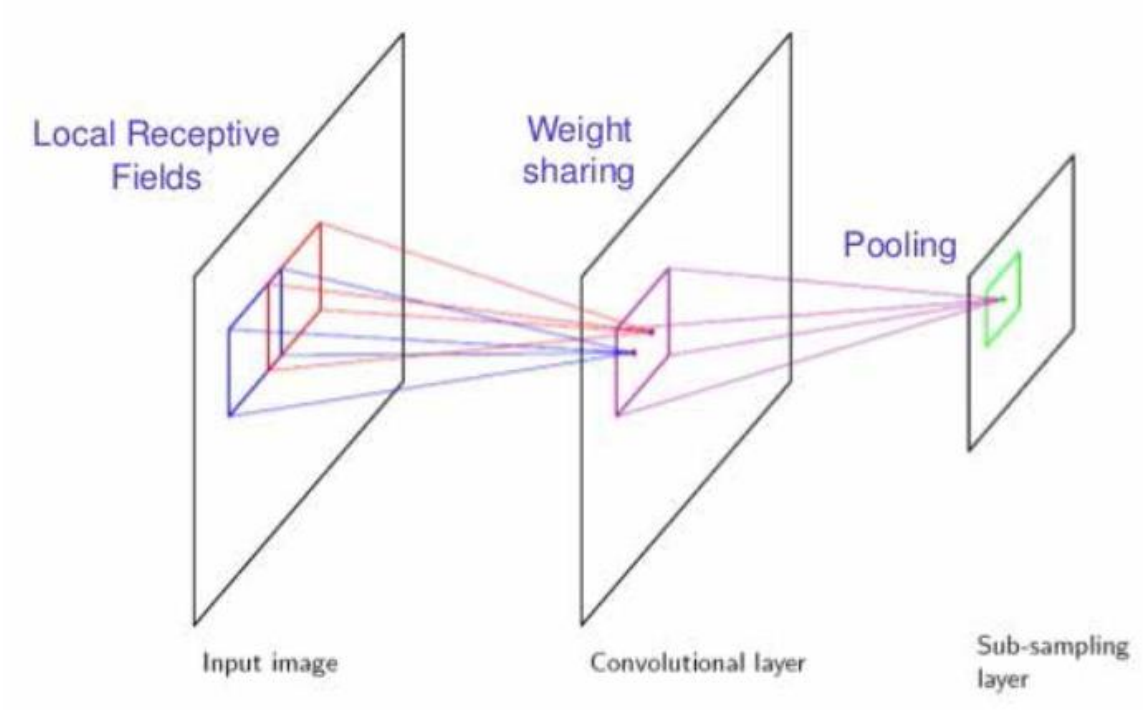
Max Pooling


Single depth slice
x
y
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2x2 filters
and stride 2
6 8
3 4

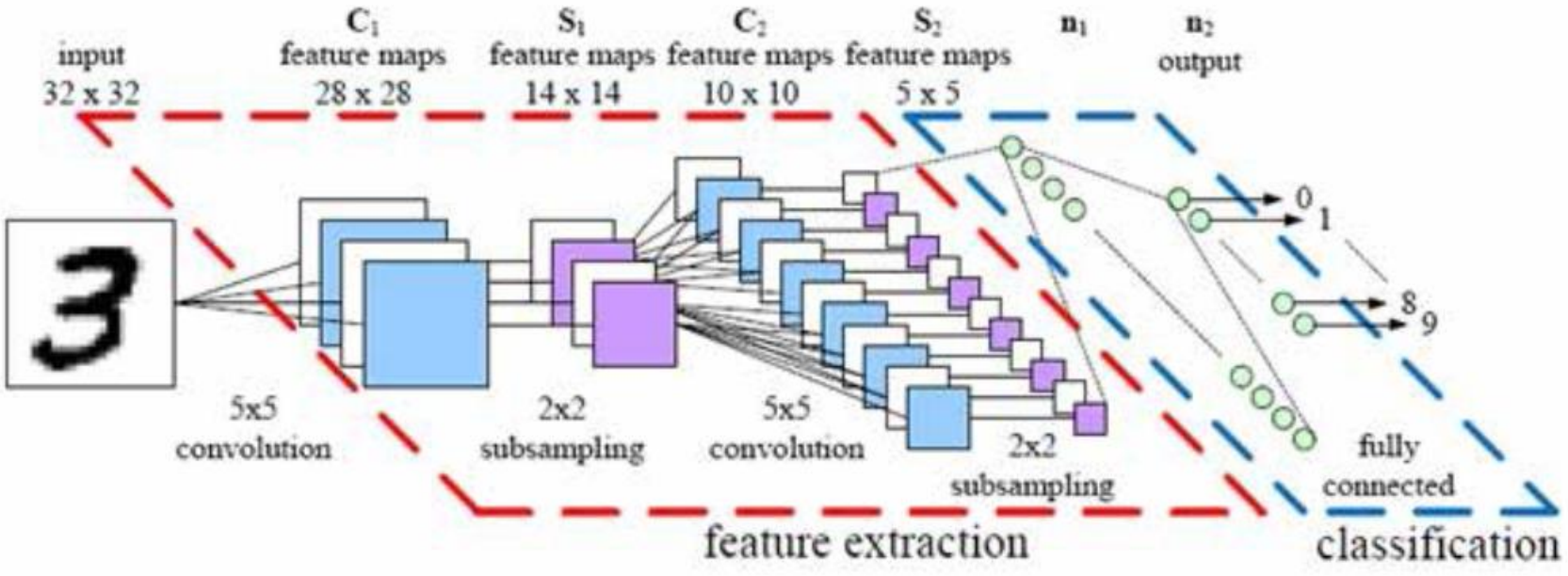
Simplification 1: Local Receptive Fields



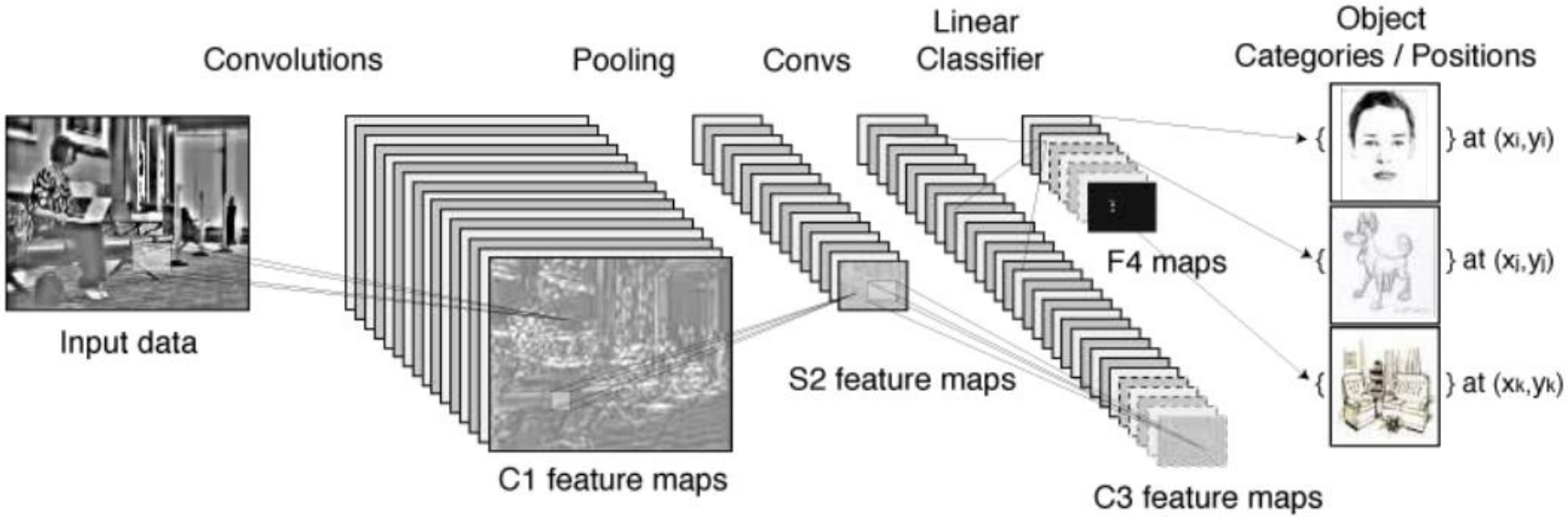
Simplification 2: Shared Weights



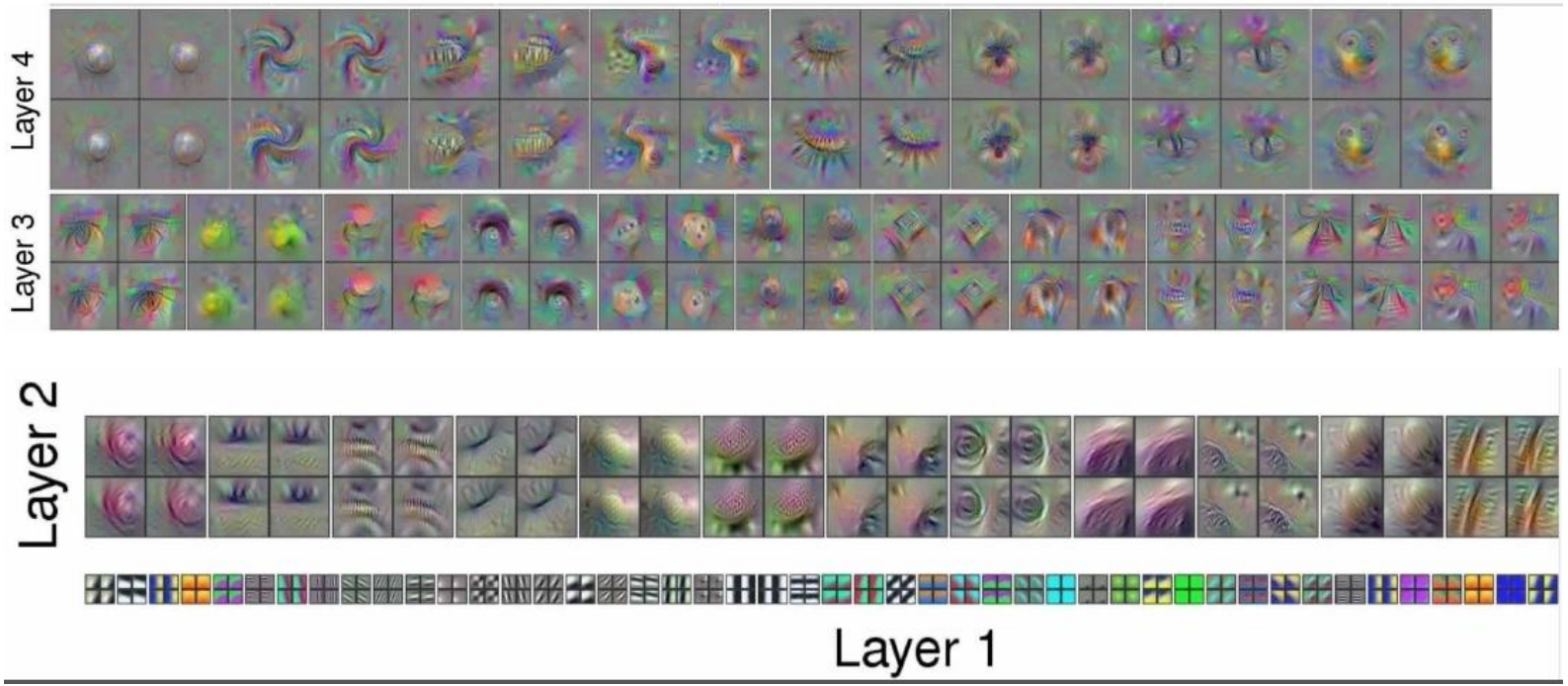
CNN Pipeline



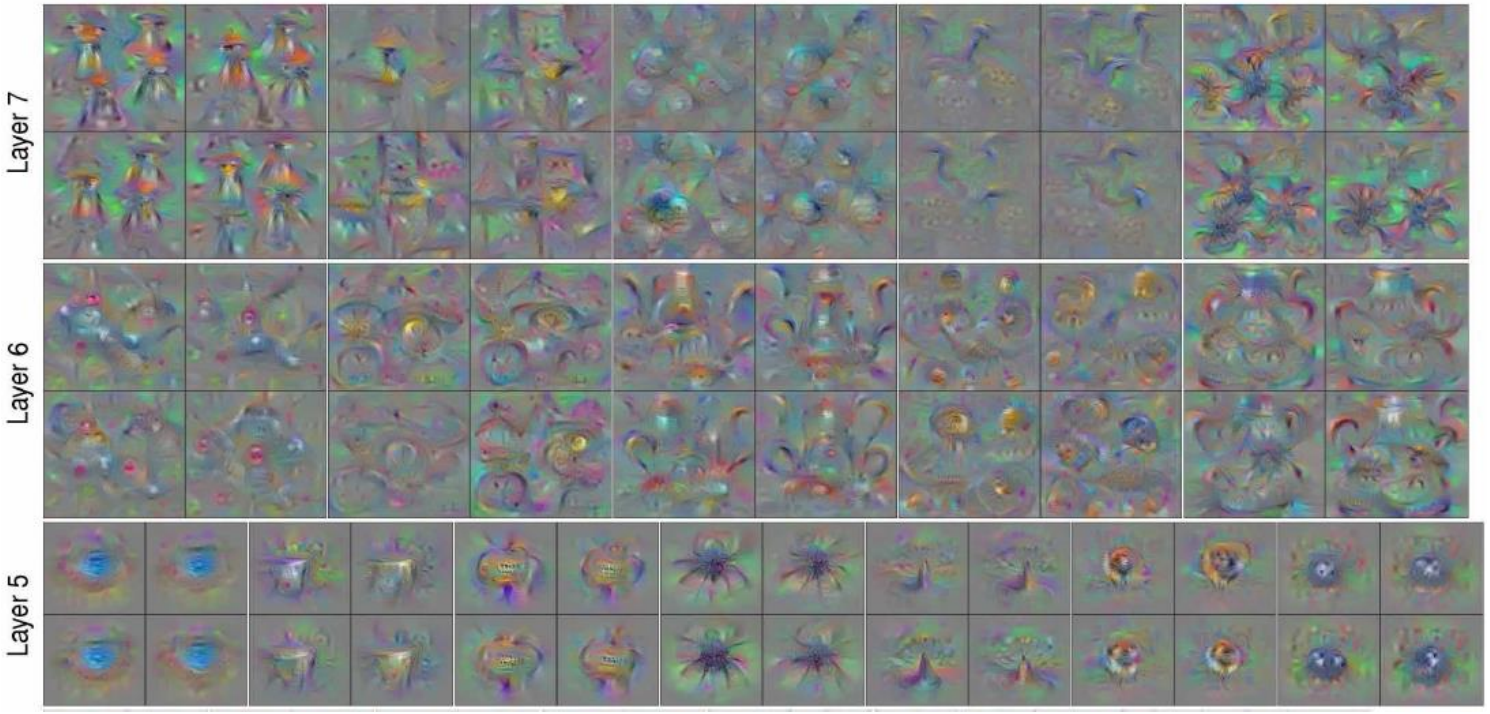
Example CNN Pipeline for Object Detection



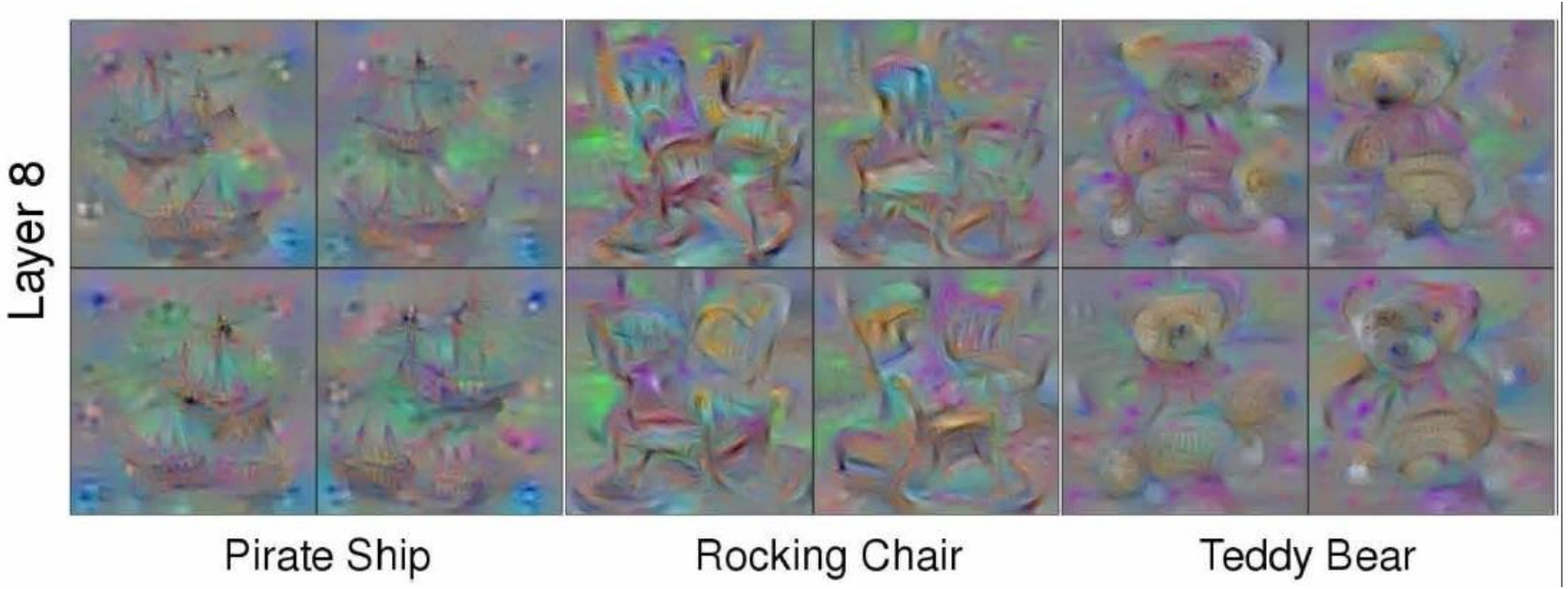
Visualizing Neurons



Visualizing Neurons



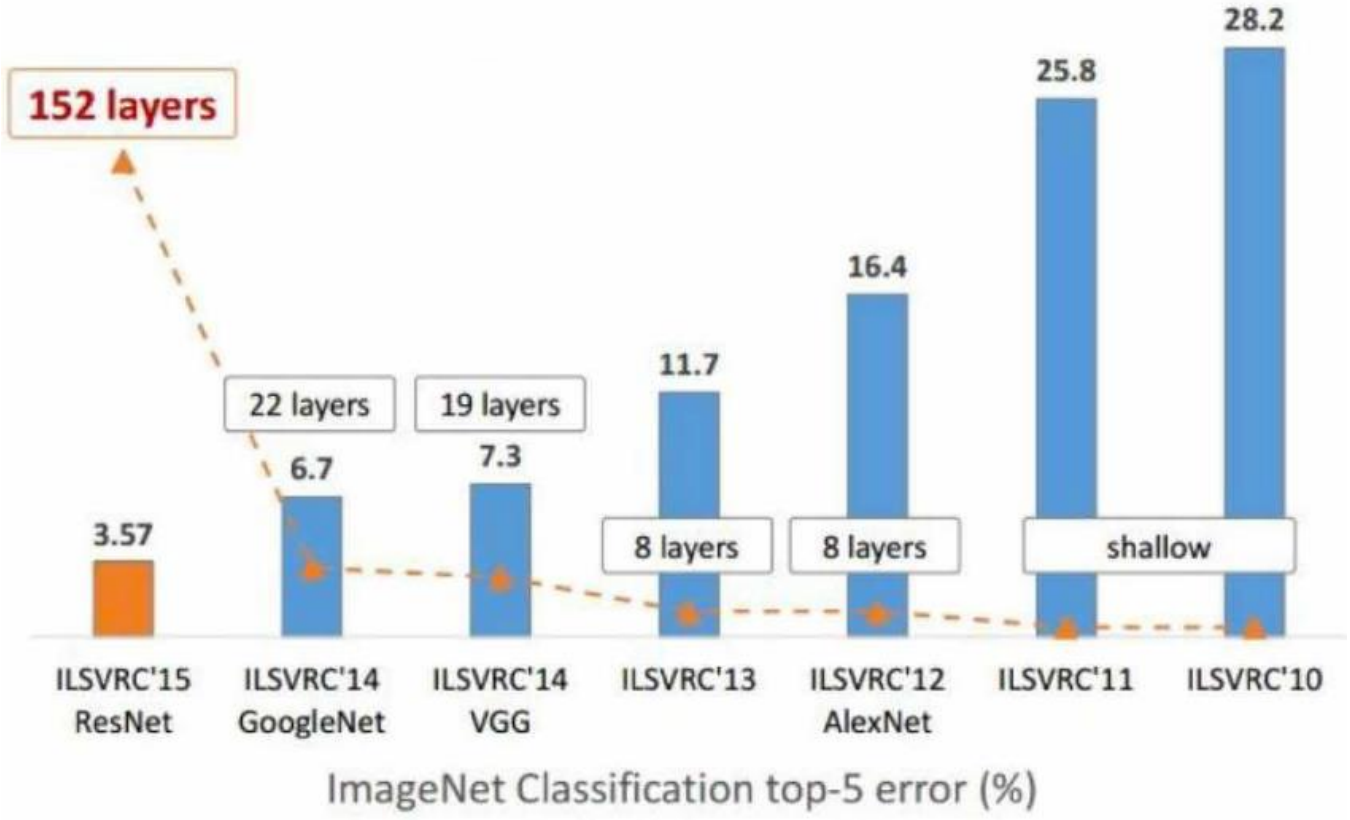
Visualizing Neurons



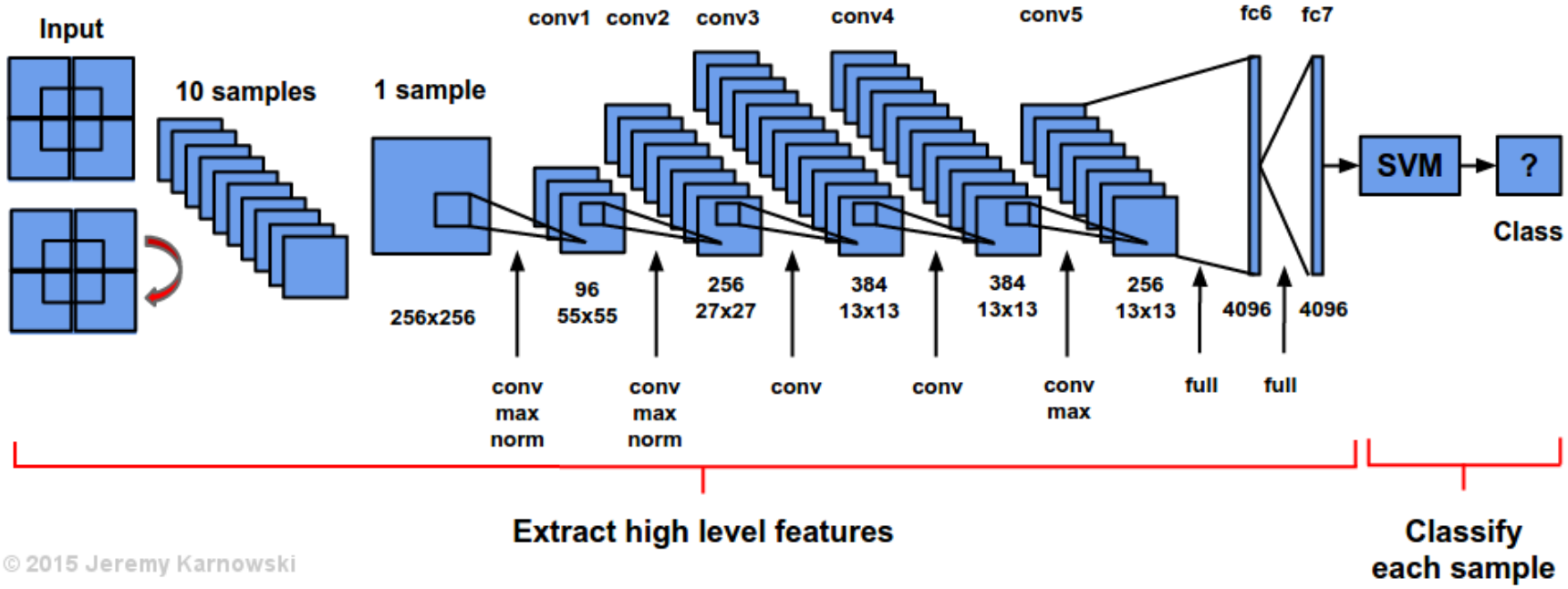
ImageNet Large Scale Visual Recognition Competition (ILSVRC)

- ~1M images
- 1K object categories in the training set
- Task: What is the object in the image?
- Classify the image into one of 1000 categories
- Evaluation
  - Is one of the best 5 guesses is correct?
  - Human performance is around 5.1% error.

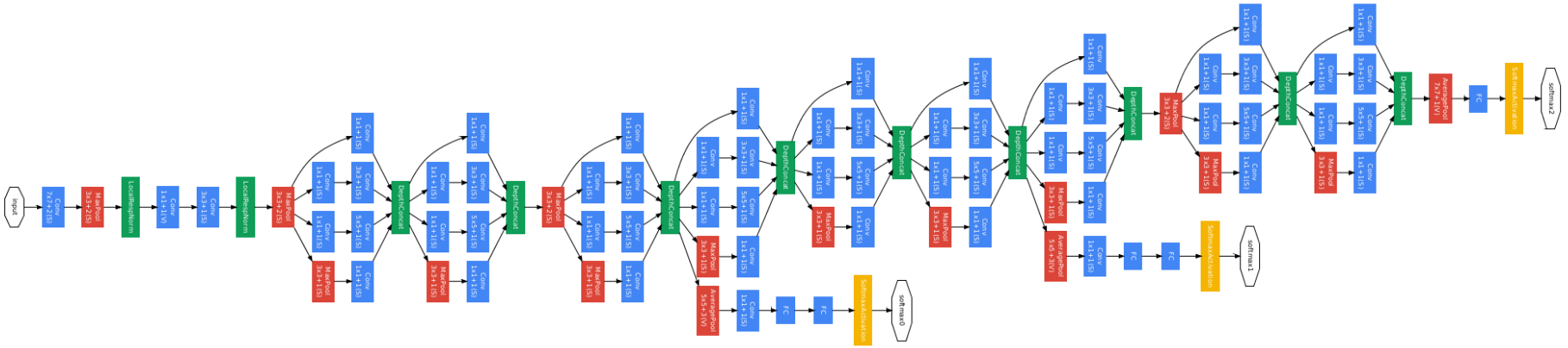
Evolution of Depth



AlexNet (2012)



GoogleNet (2014)



ResNet (2015)

http://josephpcohen.com/w/visualizing-cnn-architectures-side-by-side-with-mxnet/

HANDS-ON WORK

Case Study: MNIST by Convolutional Neural Networks

USE CASE: HANDWRITTEN DIGITS (MNIST)

Convolutional Neural Networks

iPython notebook:

https://github.com/mstfldmr/IntelAIWorkshop/blob/master/ConvolutionalNeuralNetwork.ipynb

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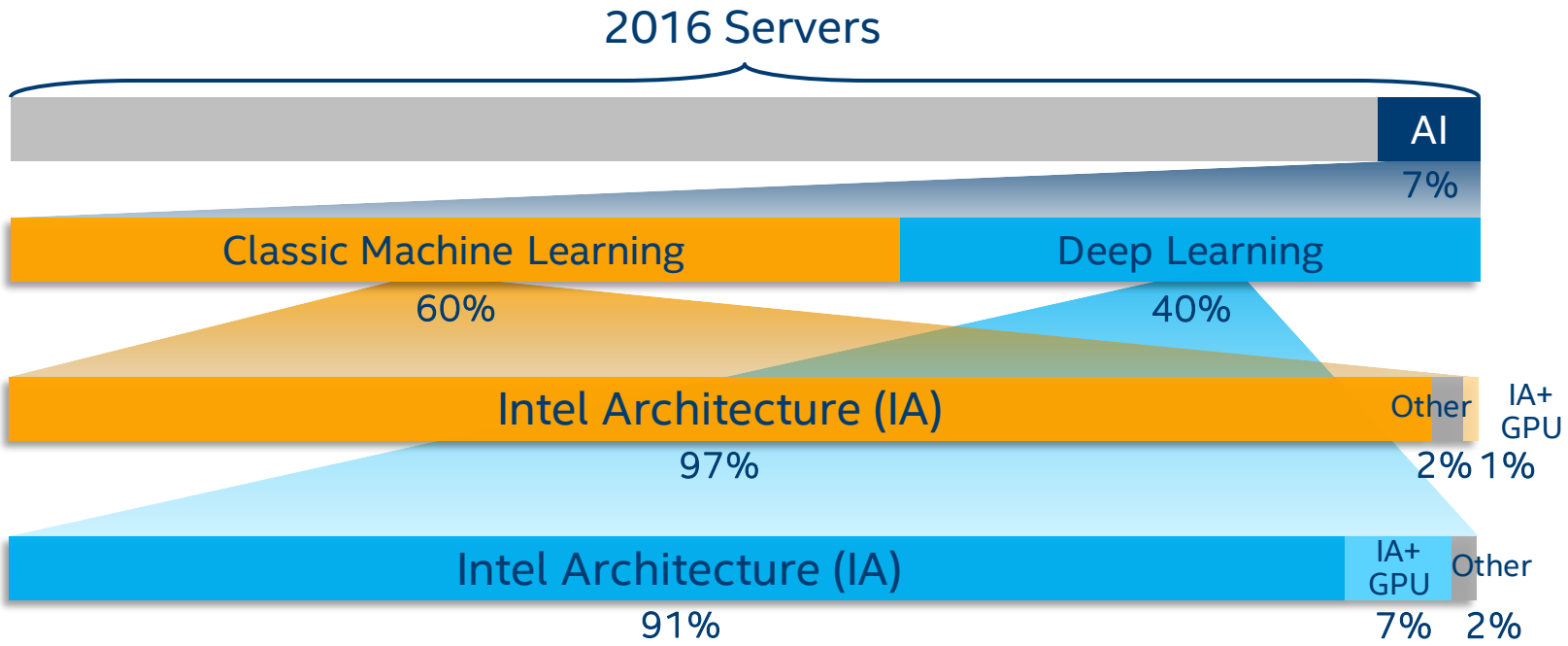
AI IS THE FASTEST GROWING DATA CENTER WORKLOAD



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saffron TECHNOLOGY an intel company

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TensorFlow

mxnet

theano

neon

torch

Caffe

E2E Tool

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Intel® Nervana™ Graph*

Intel® MKL MKL-DNN Intel® MLSL

Movidius MvTensor Library

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Compute: Intel Atom, Quark, Core i7, Xeon, Xeon Phi, Arria 10, Lake Crest*

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Networking

Visual Intelligence: RealSense Technology, Movidius

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LIBRARIES, FRAMEWORKS & TOOLS

	Intel® Math Kernel Library Intel® MKL	MKL-DNN	Intel® MLSL	Intel® Data Analytics Acceleration Library (DAAL)	Intel® Distribution	Open Source Frameworks	Intel Deep Learning SDK	Intel® Computer Vision SDK
High Level Overview	Computation primitives; high performance math primitives granting low level of control	Computation primitives; free open source DNN functions for high-velocity integration with deep learning frameworks	Communication primitives; building blocks to scale deep learning framework performance over a cluster	Broad data analytics acceleration object oriented library supporting distributed ML at the algorithm level	Most popular and fastest growing language for machine learning	Toolkits driven by academia and industry for training machine learning algorithms	Accelerate deep learning model design, training and deployment	Toolkit to develop & deploying vision-oriented solutions that harness the full performance of Intel CPUs and SOC accelerators
Primary Audience	Consumed by developers of higher level libraries and Applications	Consumed by developers of the next generation of deep learning frameworks	Deep learning framework developers and optimizers	Wider Data Analytics and ML audience, Algorithm level development for all stages of data analytics	Application Developers and Data Scientists	Machine Learning App Developers, Researchers and Data Scientists.	Application Developers and Data Scientists	Developers who create vision-oriented solutions
Example Usage	Framework developers call matrix multiplication, convolution functions	New framework with functions developers call for max CPU performance	Framework developer calls functions to distribute Caffe training compute across an Intel® Xeon Phi™ cluster	Call distributed alternating least squares algorithm for a recommendation system	Call scikit-learn k-means function for credit card fraud detection	Script and train a convolution neural network for image recognition	Deep Learning training and model creation, with optimization for deployment on constrained end device	Use deep learning to do pedestrian detection

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software.intel.com/intel-distribution-for-python

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Math Kernel Library for Deep Neural Networks

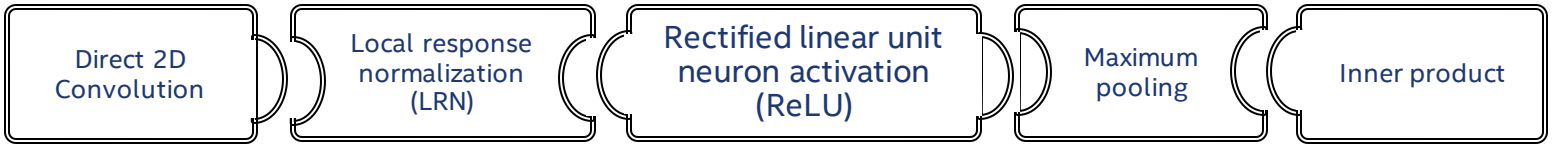
For developers of deep learning frameworks featuring optimized performance on Intel hardware

Distribution Details

- Open Source
- Apache 2.0 License
- Common DNN APIs across all Intel hardware.
- Rapid release cycles, iterated with the DL community, to best support industry framework integration.
- Highly vectorized & threaded for maximal performance, based on the popular Intel® MKL library.

BETA Now Available!

github.com/01org/mkl-dnn



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Scaling Deep Learning to 32 Nodes and Beyond

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For maximum deep learning scale-out performance on Intel® architecture

Deep learning abstraction of message-passing implementation

- Built on top of MPI; allows other communication libraries to be used as well
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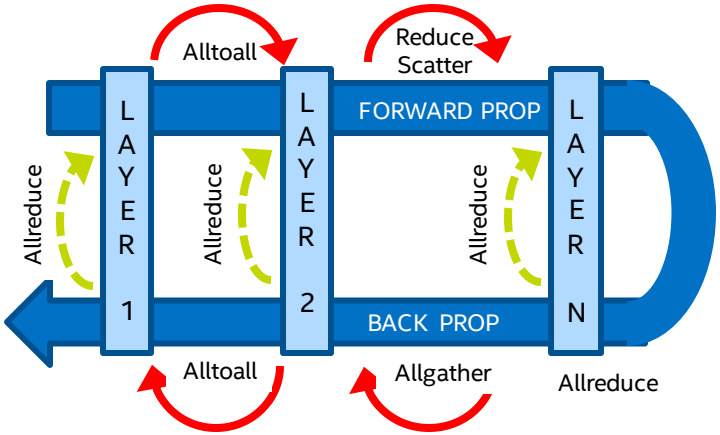


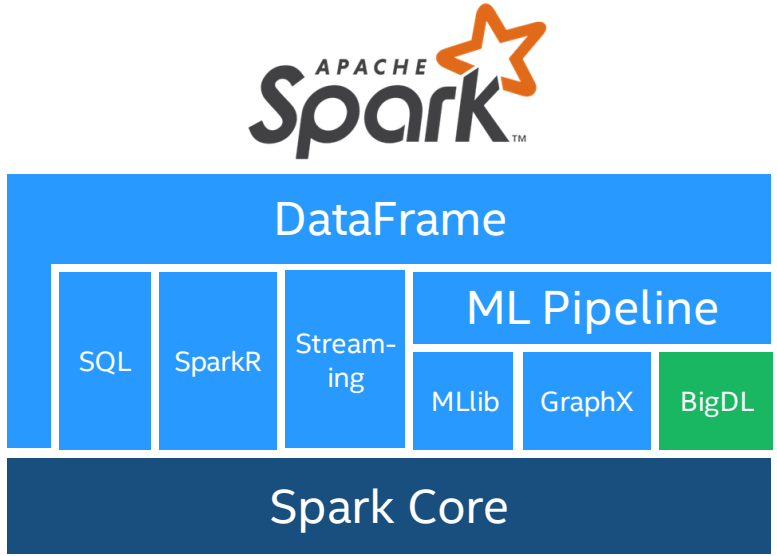
github.com/01org/MLSL/releases

BIGDL

Bringing Deep Learning to Big Data

For developers looking to run deep learning on Hadoop/Spark due to familiarity or analytics use

- **Open Sourced** Deep Learning Library for Apache Spark*
- **Make Deep learning more Accessible** to Big data users and data scientists.
- **Feature Parity** with popular DL frameworks like Caffe, Torch, Tensorflow etc.
- **Easy Customer and Developer Experience**
  - Run Deep learning Applications as Standard Spark programs;
  - Run on top of existing Spark/Hadoop clusters (No Cluster change)
- **High Performance** powered by Intel MKL and Multi-threaded programming.
- **Efficient Scale out** leveraging Spark architecture.



github.com/intel-analytics/BigDL

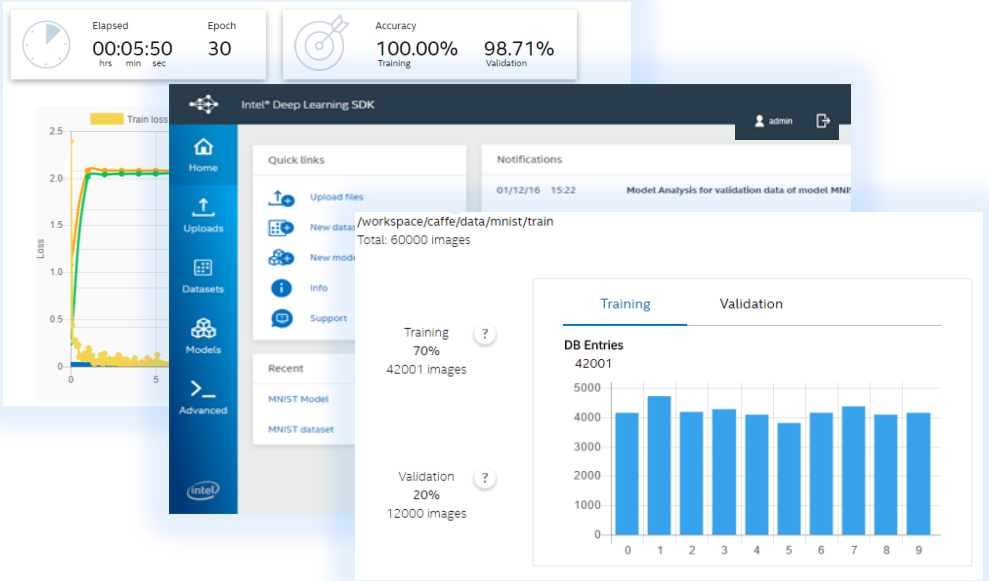
INTEL® DEEP LEARNING SDK

Accelerate Deep Learning Development

BETA Available Now

For developers looking to accelerate deep learning model design, training & deployment

- **FREE** for data scientists and software developers to develop, train & deploy deep learning
- **Simplify installation** of Intel optimized frameworks and libraries
- **Increase productivity** through simple and highly-visual interface
- **Enhance deployment** through model compression and normalization
- **Facilitate integration** with full software stack via inference engine



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NEXT STEPS...

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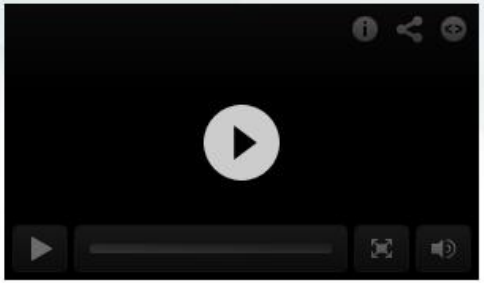
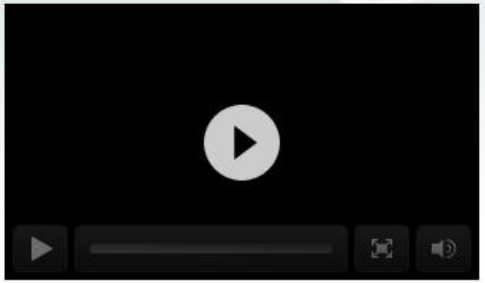


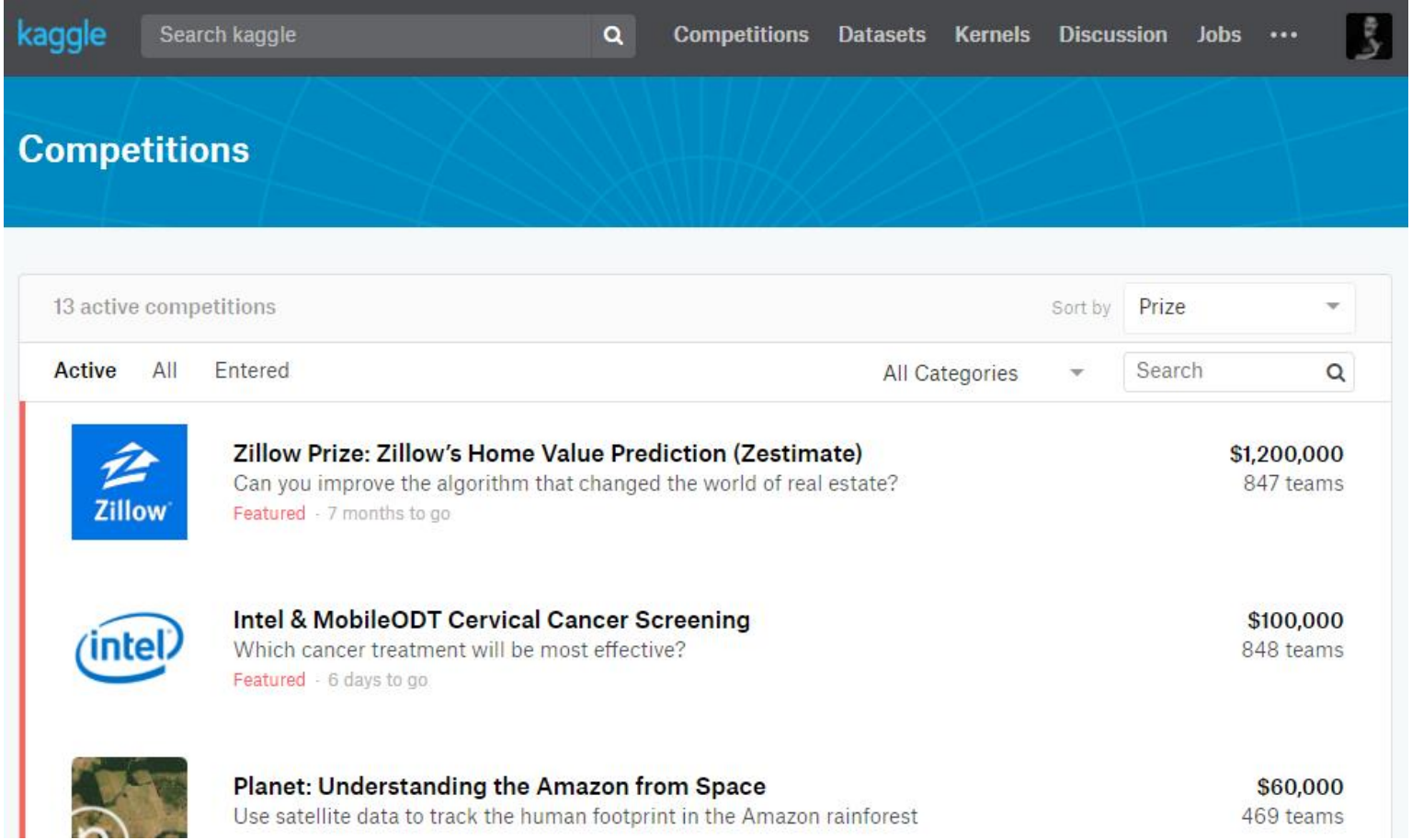
Deep Learning 101

In this webinar, we describe various deep learning uses and highlight those in which



Deep Learning 102: Neural Networks, Cost Functions, and More

https://software.intel.com/ai/academy



https://www.kaggle.com

İsmail Arı Bilgisayar Bilimleri ve Mühendisliği Bilimsel Eğitim Etkinliği
31 Temmuz - 4 Ağustos 2017 Boğaziçi Üniversitesi, İstanbul
https://cmpe.boun.edu.tr/ismail/2017/index.html

Bozkırda Yapay Öğrenme Yaz Okulu 2017
21-24 Ağustos 2017, Beytepe, Ankara
https://byoyo2017.vision.cs.hacettepe.edu.tr/

Q&A

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