



# 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, Natural 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

Natural Language Processing, text classification; web search, spam, email filtering



# CLASSIFICATION

-> Label the image

Person

Motorcyclist

Bike

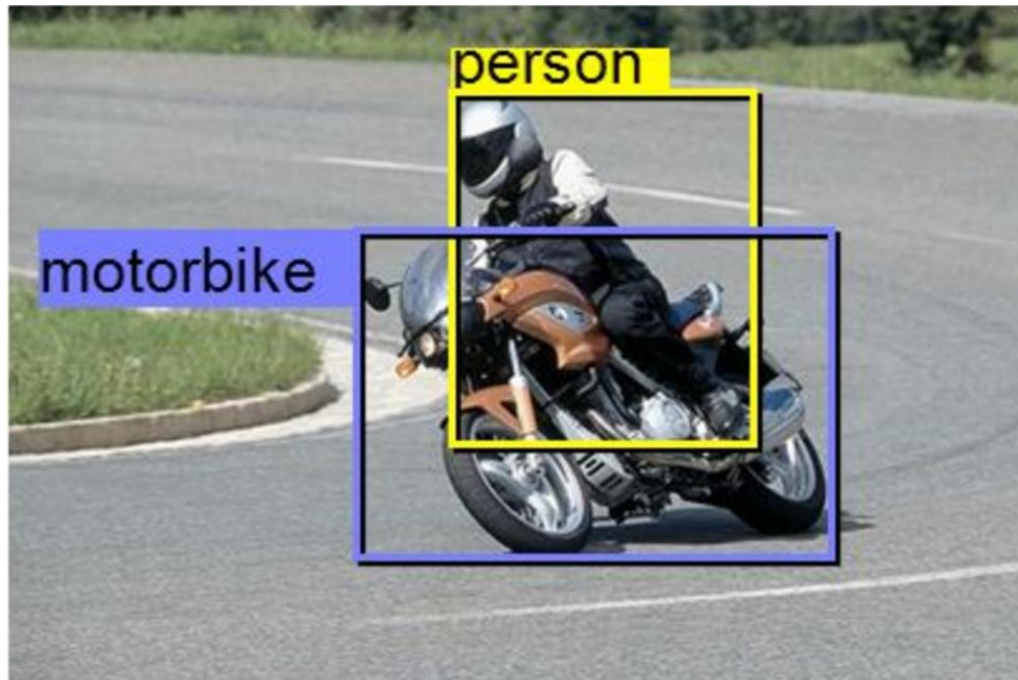


<https://people.eecs.berkeley.edu/~jhoffman/talks/llda-baylearn2014.pdf>



# DETECTION

-> Detect and label



<https://people.eecs.berkeley.edu/~jhoffman/talks/llda-baylearn2014.pdf>

# SEMANTIC SEGMENTATION

-> Label every pixel



<https://people.eecs.berkeley.edu/~jhoffman/talks/lsta-baylearn2014.pdf>

# NATURAL LANGUAGE OBJECT RETRIEVAL

a scene with three people query='man far right'



query='left guy'



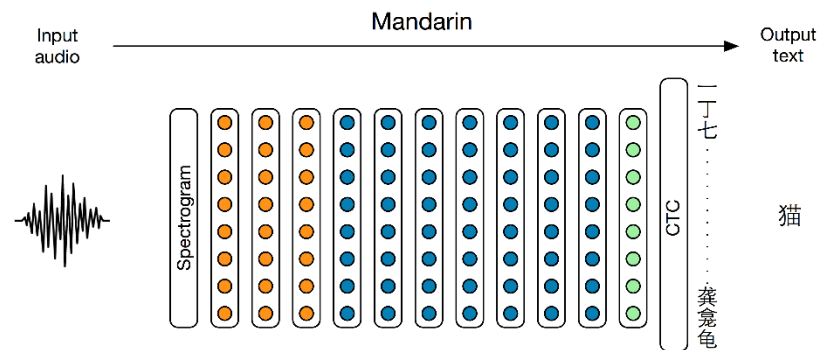
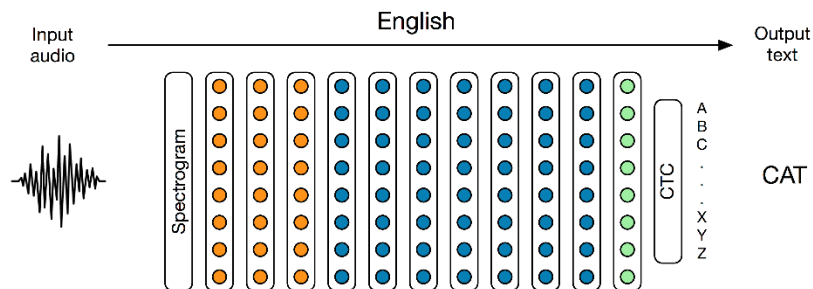
query='cyclist'



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



# SPEECH RECOGNITION



- Convolution Layer
- Recurrent Layer
- Fully Connected Layer



# IMAGE / VIDEO CAPTIONING

**Describes without errors**



**A person riding a motorcycle on a dirt road.**

**Describes with minor errors**



**Two dogs play in the grass.**

**Somewhat related to the image**



**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.**



**ARTIFICIAL  
INTELLIGENCE**



**STUDENT DEVELOPER PROGRAM**



# NEURAL NETWORKS



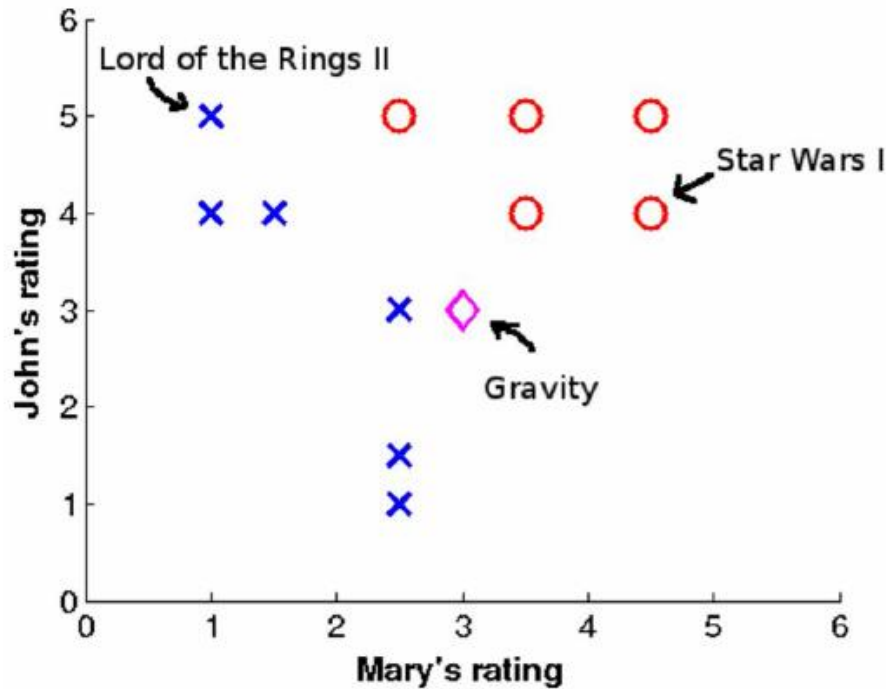
Will Nancy like Gravity?

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



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

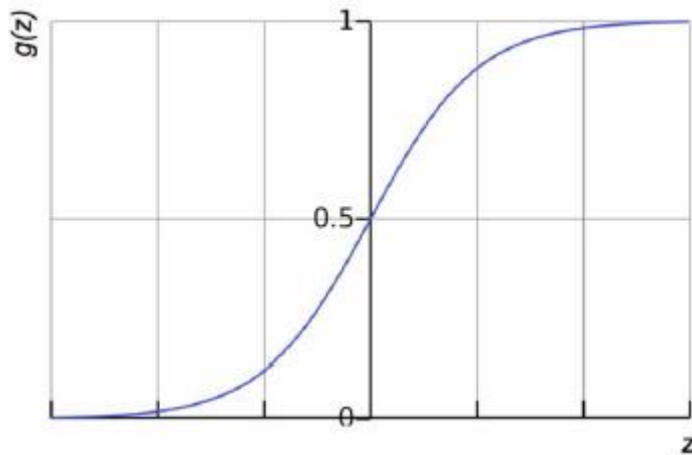
# ACTIVATION FUNCTION

This function has a problem. Its values are unbounded.  
We want its output to be in the range of 0 and 1.

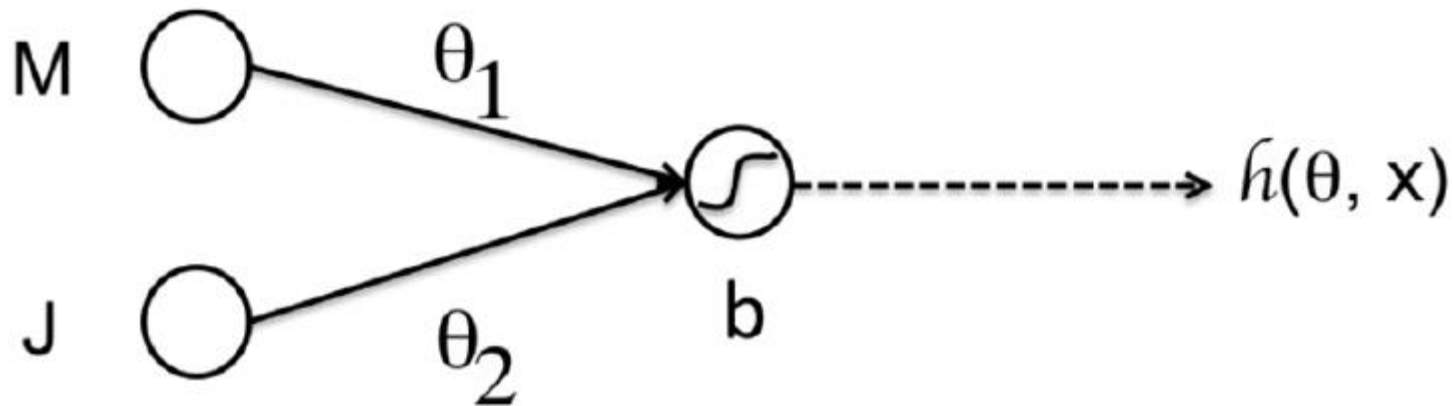
$$h_{\theta,b} = g(\theta^T x + b),$$

where  $g(z)$  is sigmoid function.

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



## ANOTHER WAY OF REPRESENTING THE MODEL





# LEARN FROM DATA

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

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

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

...

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



# COST FUNCTION

To find values of  $\theta$  and  $b$  we can minimize the following *cost function*:

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

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

# BACKPROPOGATION

TODO!

# STOCHASTIC GRADIENT DESCENT

Use Stochastic Gradient Descent (SGD):

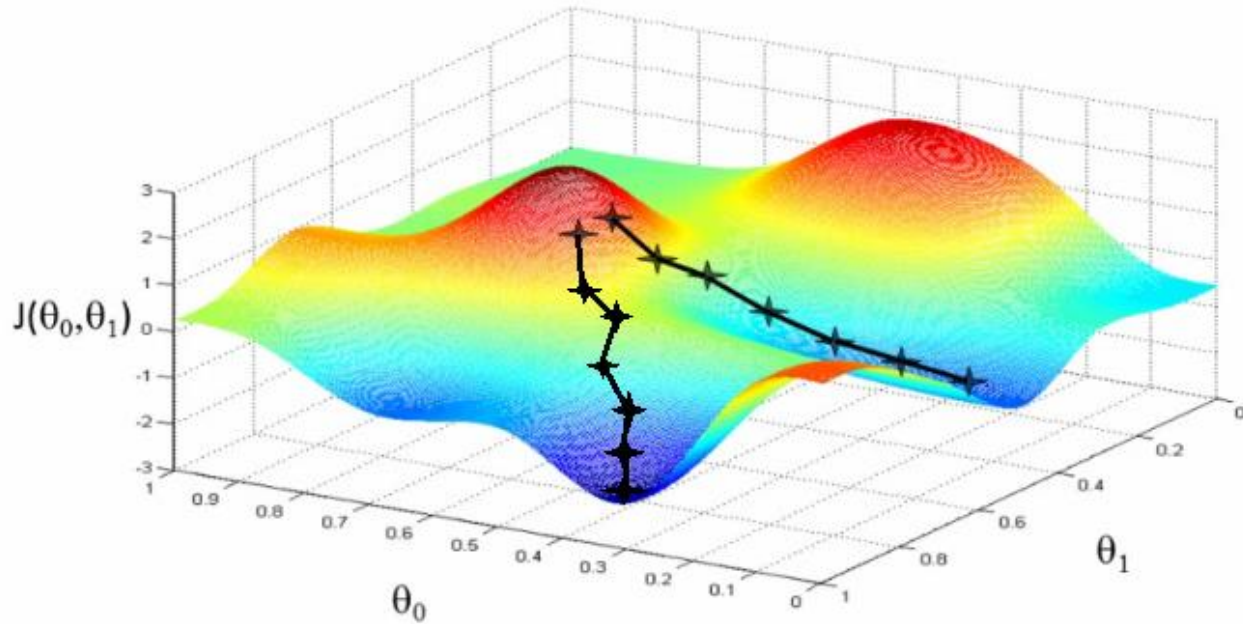
$$\theta_1 = \theta_1 - \alpha \Delta \theta_1$$

$$\theta_2 = \theta_2 - \alpha \Delta \theta_2$$

$$b = b - \alpha \Delta b$$



# STOCHASTIC GRADIENT DESCENT



# STEPS

1. Initialize the parameters  $\theta$  and  $b$  at random
2. Pick a random example  $\{x^{(i)}, y^{(i)}\}$
3. Compute the partial derivatives of  $\theta_1, \theta_2, b$
4. Update parameters using:

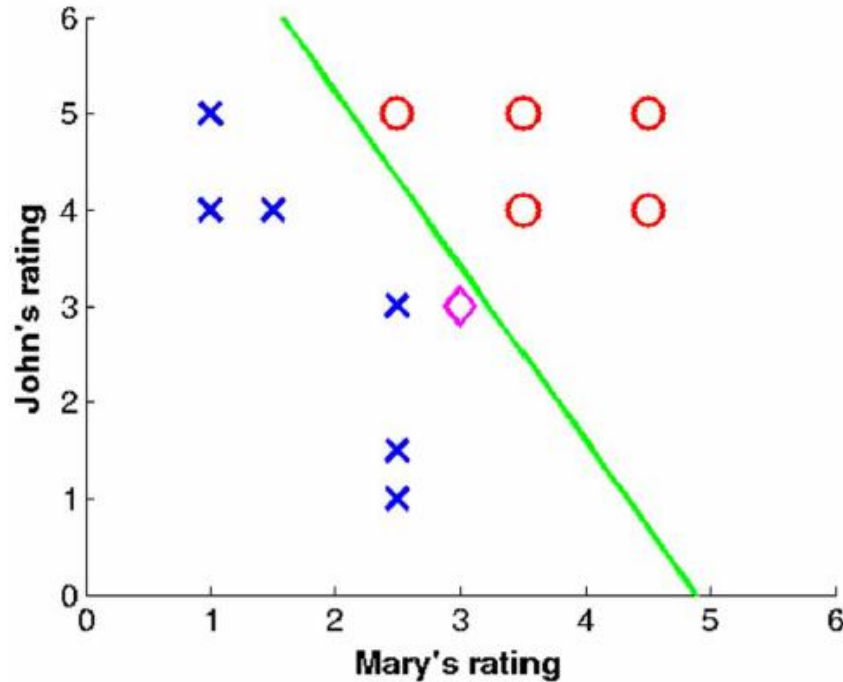
$$\theta_1 = \theta_1 - \alpha \Delta \theta_1$$

$$\theta_2 = \theta_2 - \alpha \Delta \theta_2$$

$$b = b - \alpha \Delta b$$

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

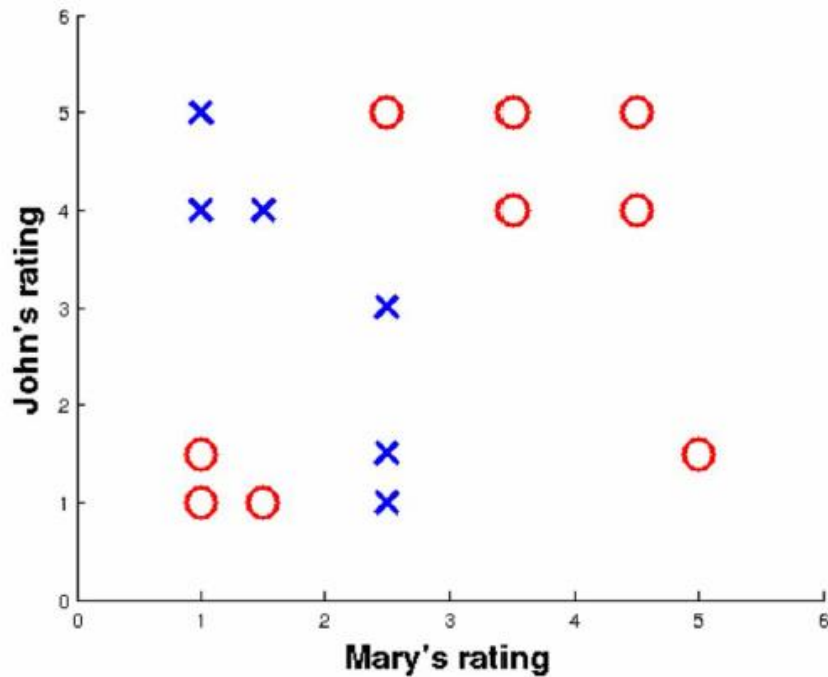
# NETFLIX



Gravity movie is slightly on the "don't watch" side.

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

# NETFLIX

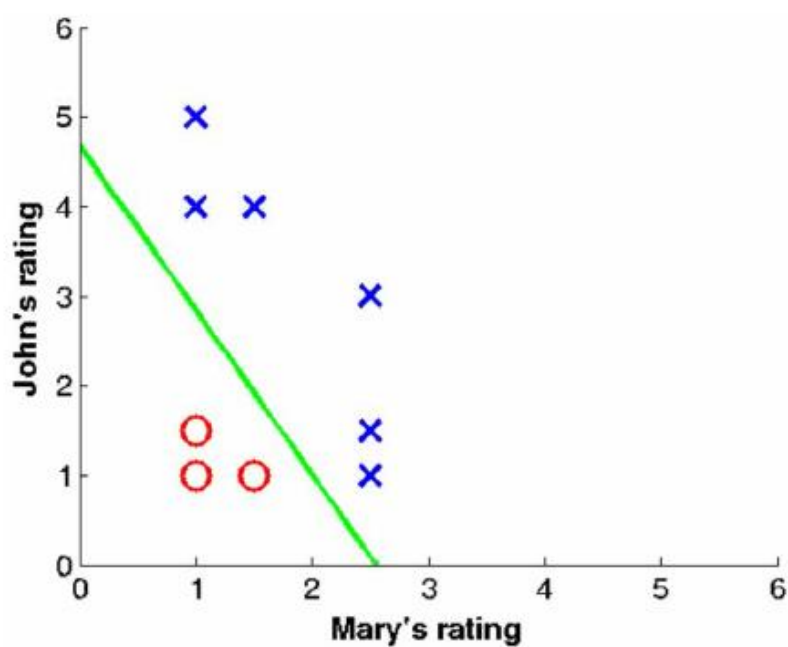
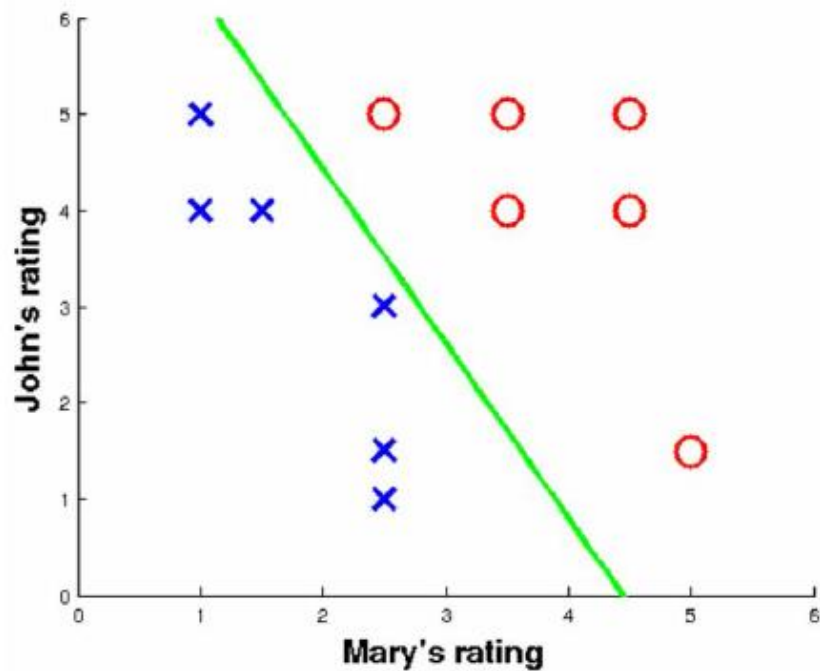


Nancy likes some of the movies both Mary and John rated poorly.

How can I have a linear decision boundary separate these?

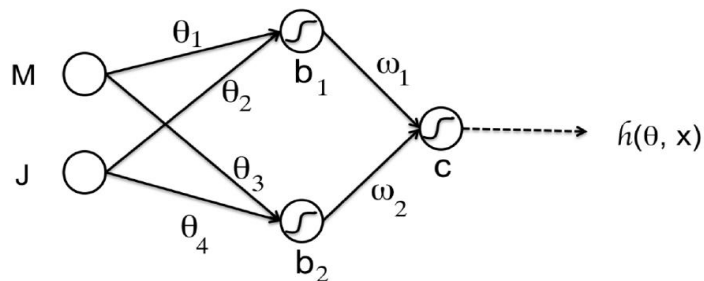


# NETFLIX

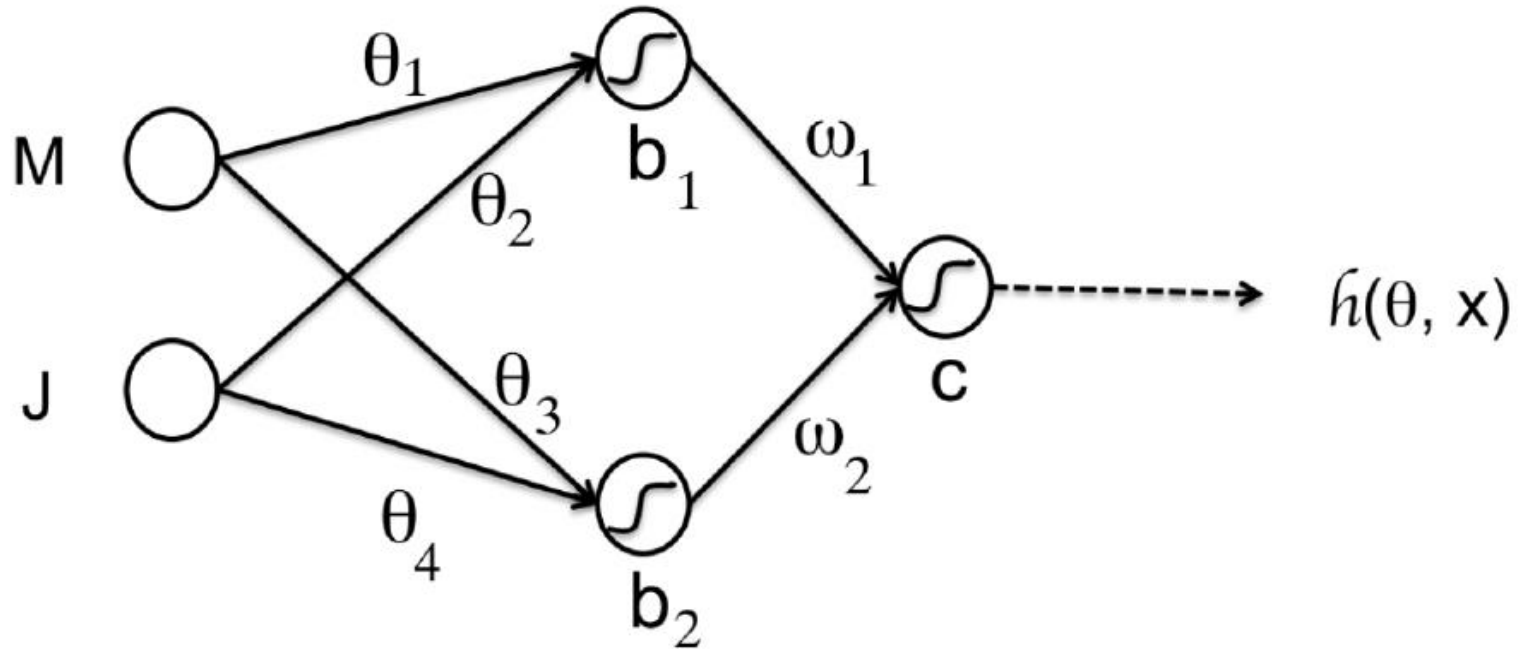




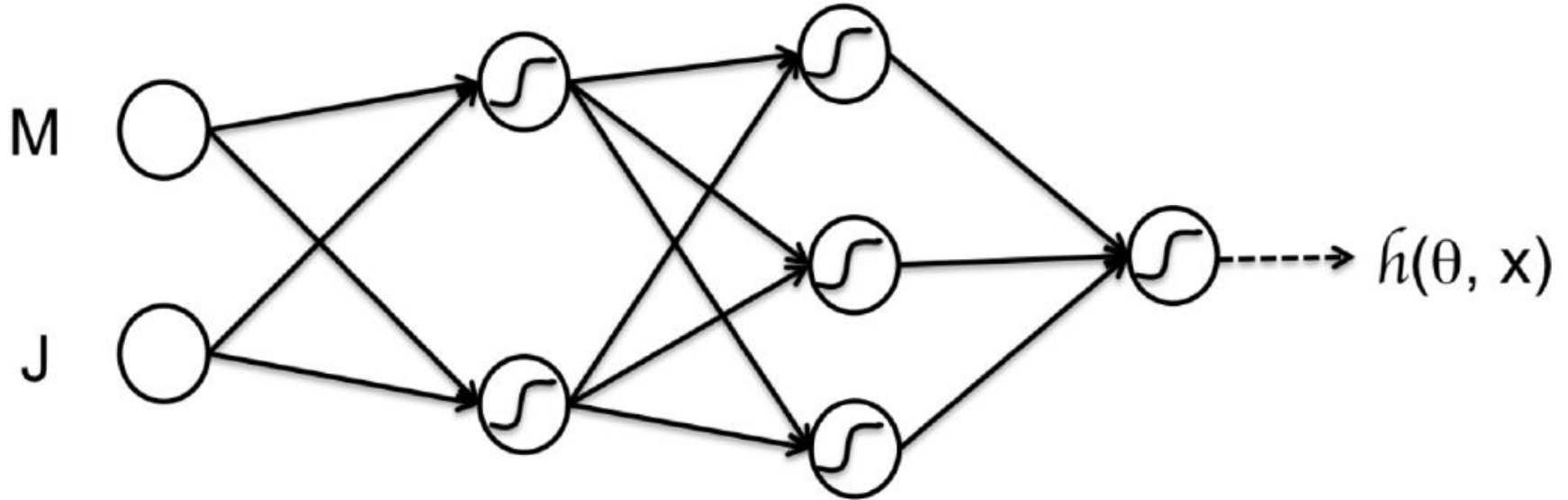
Movie	Output by decision function $h_1$	Output by decision function $h_2$	Does Nancy like?
Lord of the Rings 2	$h_1(x^{(1)})$	$h_2(x^{(1)})$	No
...	...	...	...
Star Wars 1	$h_1(x^{(n)})$	$h_2(x^{(n)})$	Yes
Gravity	$h_1(x^{(n+1)})$	$h_2(x^{(n+1)})$	?



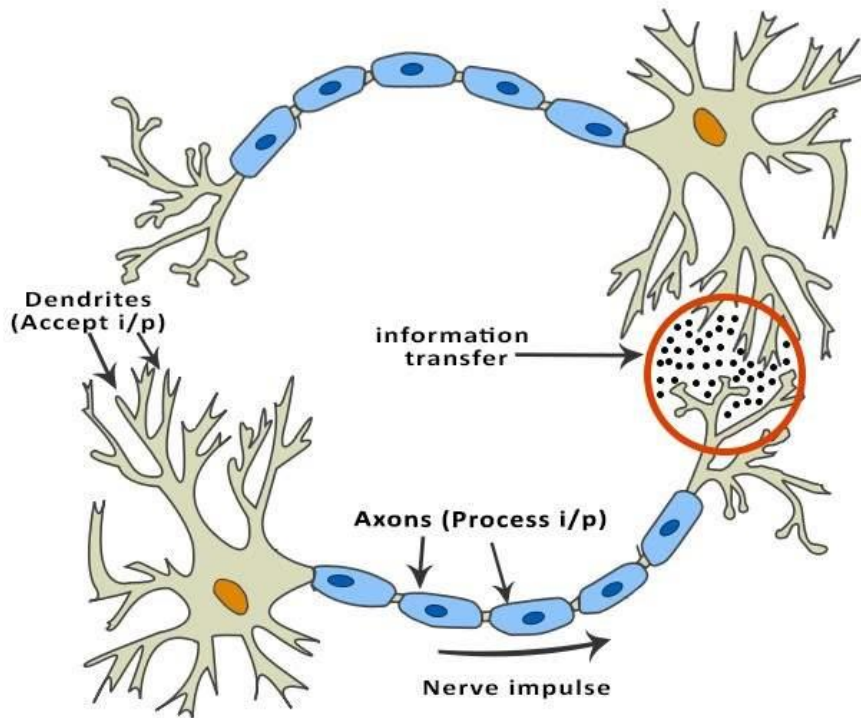
# THIS IS THE NEURAL NETWORK



# A DEEPER NEURAL NETWORK

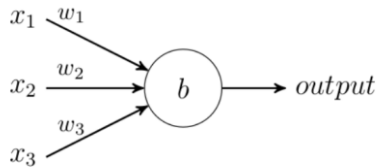


# INSPIRED BY HUMAN BRAIN



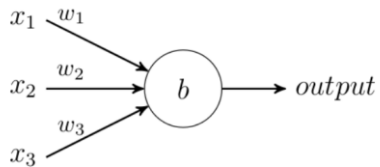
# DEEP LEARNING: BASIC STRUCTURE

## BASIC SINGLE NEURON

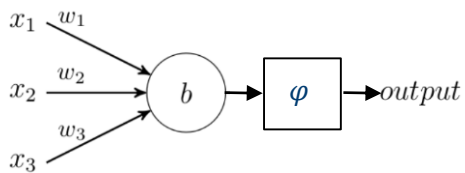


# DEEP LEARNING: BASIC STRUCTURE

## BASIC SINGLE NEURON



## SINGLE NEURON WITH ACTIVATION

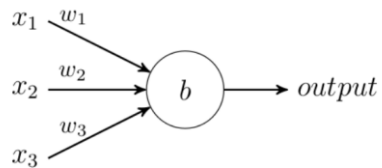


$\varphi$  → Activation function



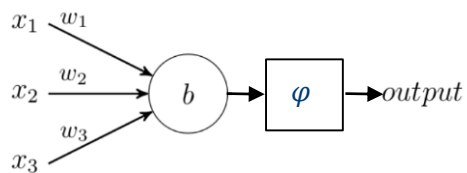
# DEEP LEARNING: BASIC STRUCTURE

## BASIC SINGLE NEURON



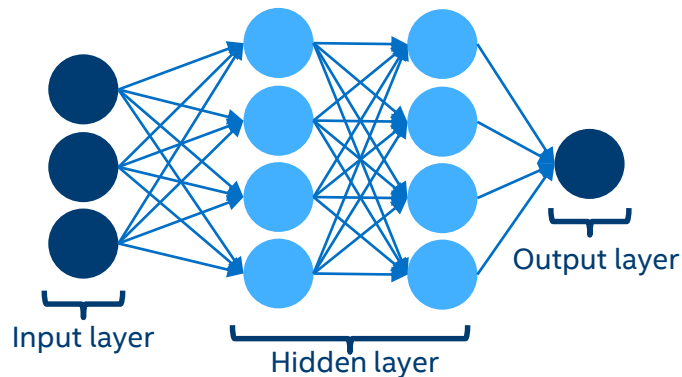
$$u_n = \sum_{j=1}^m w_{nj} x_j$$

## SINGLE NEURON WITH ACTIVATION



$\varphi$  → Activation function

## BASIC STRUCTURE WITH TWO HIDDEN LAYERS







# SUMMARY

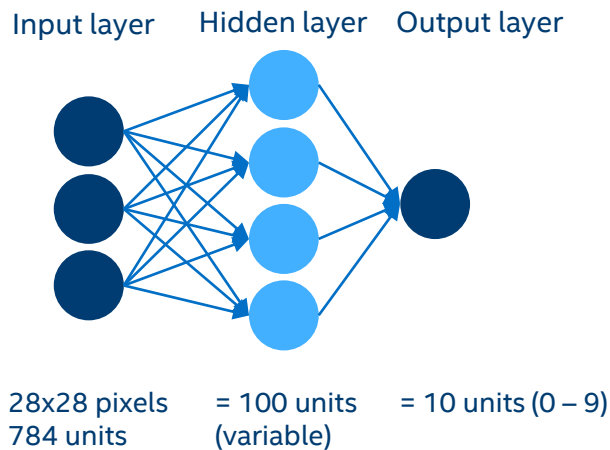
# KEYWORDS

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

# HANDWRITING EXAMPLE



MNIST DATASET  
28x28 Pixels



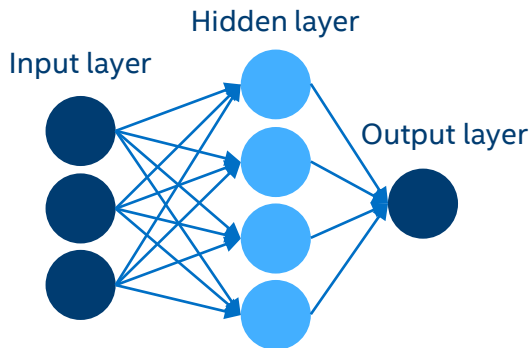
## TOTAL PARAMETERS

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

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

# TRAINING

3



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

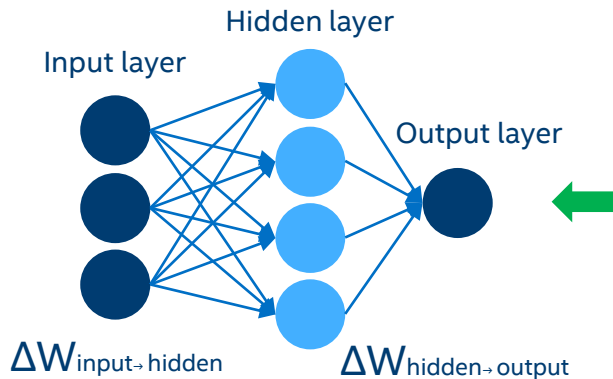
Output    Ground Truth

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 =  
 $C(\text{output, truth})$

# TRAINING: BACKPROPAGATION

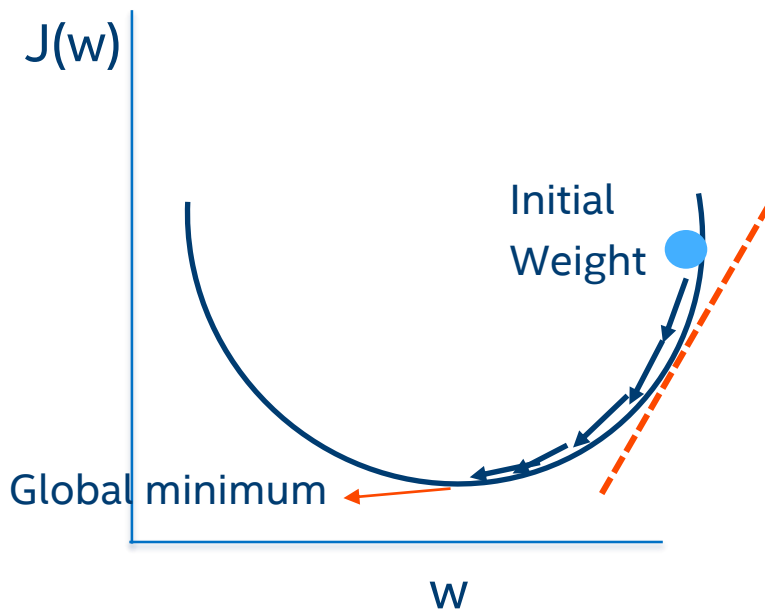
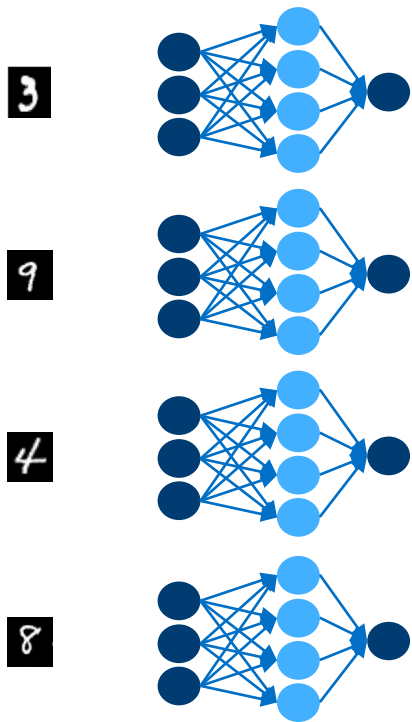
3



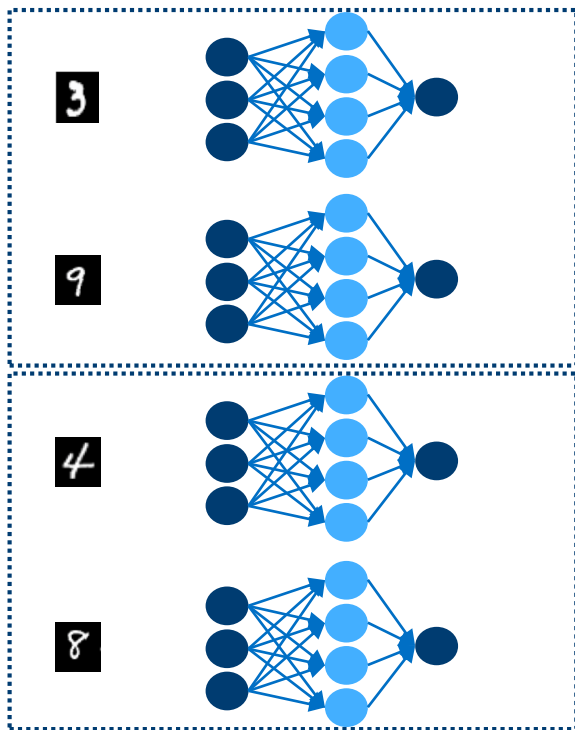
Cost function =  
 $C(\text{output}, \text{truth})$



# TRAINING: STOCHASTIC GRADIENT DESCENT



# TRAINING: STOCHASTIC GRADIENT DESCENT



INTEL® DEEP LEARNING SDK EXAMPLE:

Learning rate: 0.01

Batch size: 54

Epochs: 10



# 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\*

## DEEP LEARNING

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



CNN,  
RNN,  
RBM..

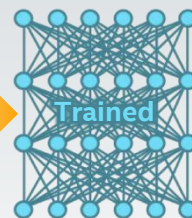
Step 1: Training



Hours to Days  
in Cloud

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

New Data



Step 2:



Real-Time  
at Edge/Cloud

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

\*Note: not all classic machine learning functions require training



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INTELLIGENCE



STUDENT DEVELOPER PROGRAM

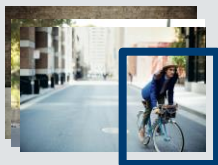


# DEEP LEARNING STEPS

## STEP 1: TRAINING

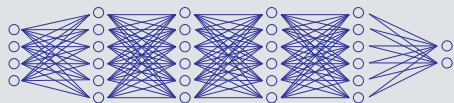
(In Data Center – Over Hours/Days/Weeks)

Lots of labeled  
input data



Person

Create “Deep  
neural net” math  
model



Trained  
Model

Output:  
Trained Model

## STEP 2: INFERENCE

(End point or Data Center - Instantaneous)

New input from  
camera and  
sensors



Trained neural  
network model



97% person  
2% traffic  
light

Output:  
Classification



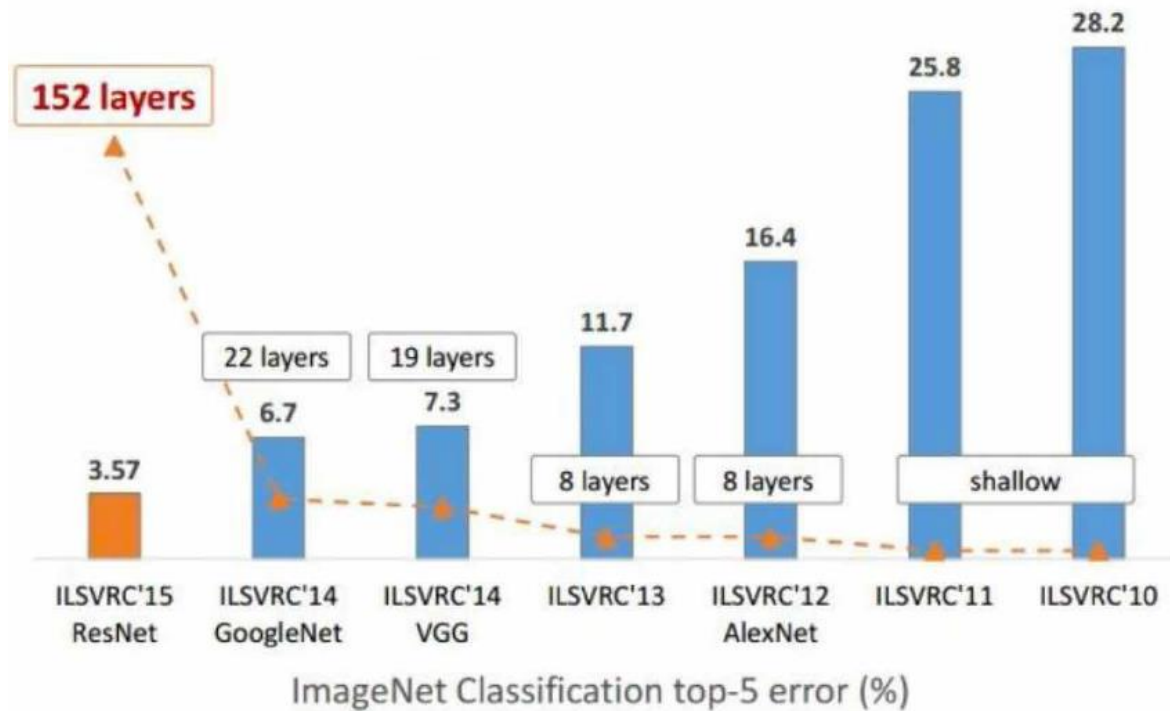


# CONVOLUTIONAL NEURAL NETWORKS (CNN)

# TODO



# Evolution of Depth





# RECURRENT NEURAL NETWORKS (RNN)

# TODO





# GENERATIVE ADVERSARIAL NETWORKS (GAN)

# TODO

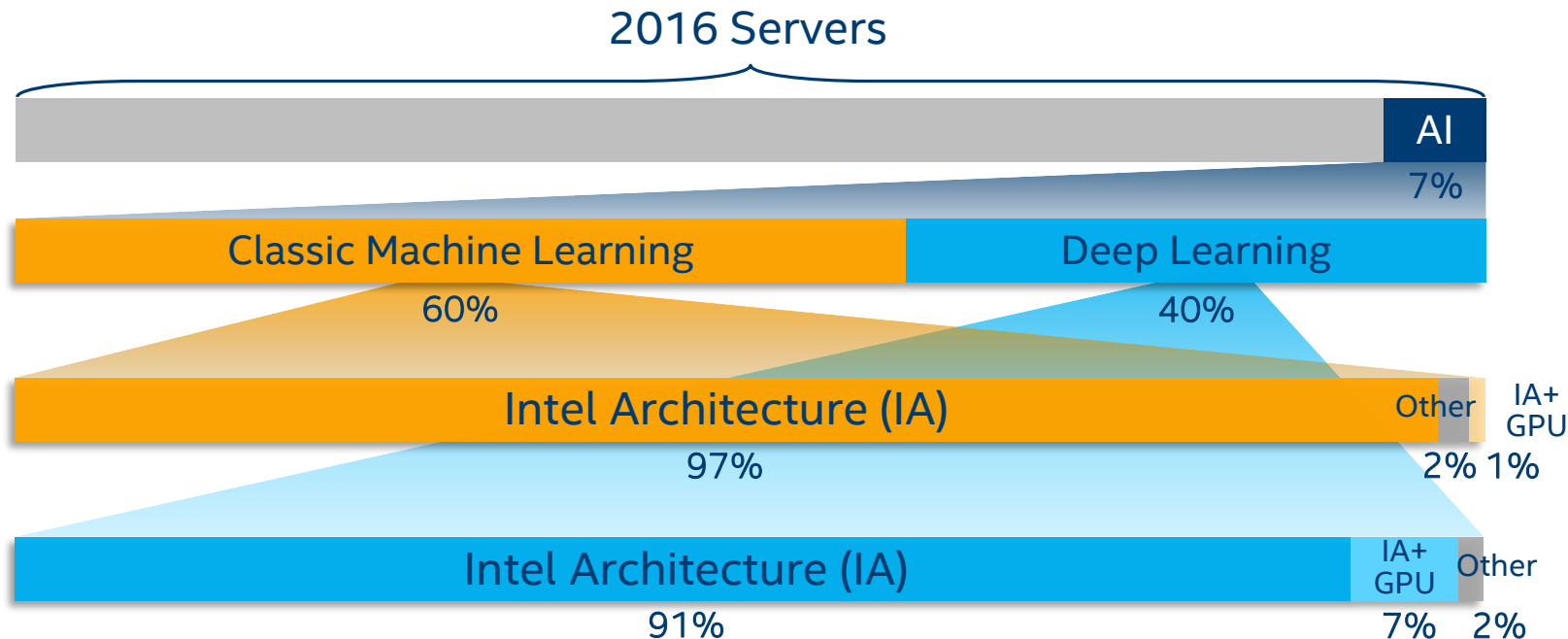






**INTEL<sup>®</sup> AI PORTFOLIO**

# AI IS THE FASTEST GROWING DATA CENTER WORKLOAD



# INTEL<sup>®</sup> NERVANA<sup>™</sup> AI ACADEMY

Hone Your Skills and Build the Future of AI



Benefit from expert-led trainings, hands-on workshops, exclusive remote access, and more.

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[software.intel.com/ai/academy](https://software.intel.com/ai/academy)

# INTEL AI PORTFOLIO

## EXPERIENCES



## TOOLS



Intel® Deep Learning SDK

Intel® Computer Vision SDK

Movidius Neural Compute Stick

saffron  
TECHNOLOGY  
an intel company

## FRAMEWORKS



theano



Caffe

E2E Tool

## LIBRARIES



Intel Dist  
Intel® DAAL

Intel® Nervana™ Graph\*

Intel® MKL MKL-DNN Intel® MLSL

Movidius  
MvTensor  
Library

Associative  
Memory Base

## HARDWARE



Compute



Memory & Storage



Networking



Visual Intelligence

UNLEASH  
FULL  
POTENTIAL

\*Coming 2017



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# LIBRARIES, FRAMEWORKS & TOOLS

## Intel® Math Kernel Library



## Intel® Data Analytics Acceleration Library (DAAL)



### 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
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### 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
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### 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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Find out more at <http://software.intel.com/ai>

# INTEL DISTRIBUTION FOR PYTHON

Advancing Python Performance Closer to Native Speeds



For developers using the most popular and fastest growing programming language for AI

## Easy, Out-of-the-box Access to High Performance Python

- Prebuilt, optimized for numerical computing, data analytics, HPC
- Drop in replacement for your existing Python (no code changes required)

## Drive Performance with Multiple Optimization Techniques

- Accelerated NumPy/SciPy/Scikit-Learn with Intel® MKL
- Data analytics with pyDAAL, enhanced thread scheduling with TBB, Jupyter\* Notebook interface, Numba, Cython
- Scale easily with optimized MPI4Py and Jupyter notebooks

## Faster Access to Latest Optimizations for Intel Architecture

- Distribution and individual optimized packages available through conda and Anaconda Cloud
- Optimizations upstreamed back to main Python trunk

[software.intel.com/intel-distribution-for-python](https://software.intel.com/intel-distribution-for-python)



# INTEL<sup>®</sup> MKL-DNN

## 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<sup>®</sup> MKL library.

BETA Now  
Available!

[github.com/01org/mkl-dnn](https://github.com/01org/mkl-dnn)

Direct 2D  
Convolution

Local response  
normalization  
(LRN)

Rectified linear unit  
neuron activation  
(ReLU)

Maximum  
pooling

Inner product



# INTEL® MACHINE LEARNING SCALING LIBRARY (MLSL)

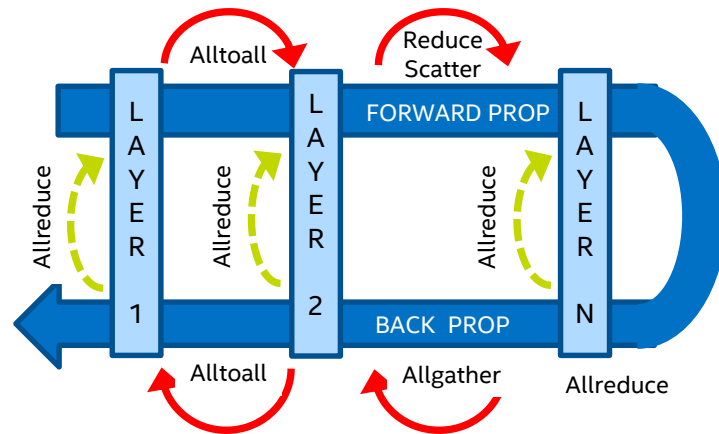
## Scaling Deep Learning to 32 Nodes and Beyond

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

BETA Now Available!

### Deep learning abstraction of message-passing implementation

- Built on top of MPI; allows other communication libraries to be used as well
- Optimized to drive scalability of communication patterns
- Works across various interconnects: Intel® Omni-Path Architecture, InfiniBand, and Ethernet
- Common API to support Deep Learning frameworks (Caffe, Theano, Torch etc.)



[github.com/01org/MLSL/releases](https://github.com/01org/MLSL/releases)





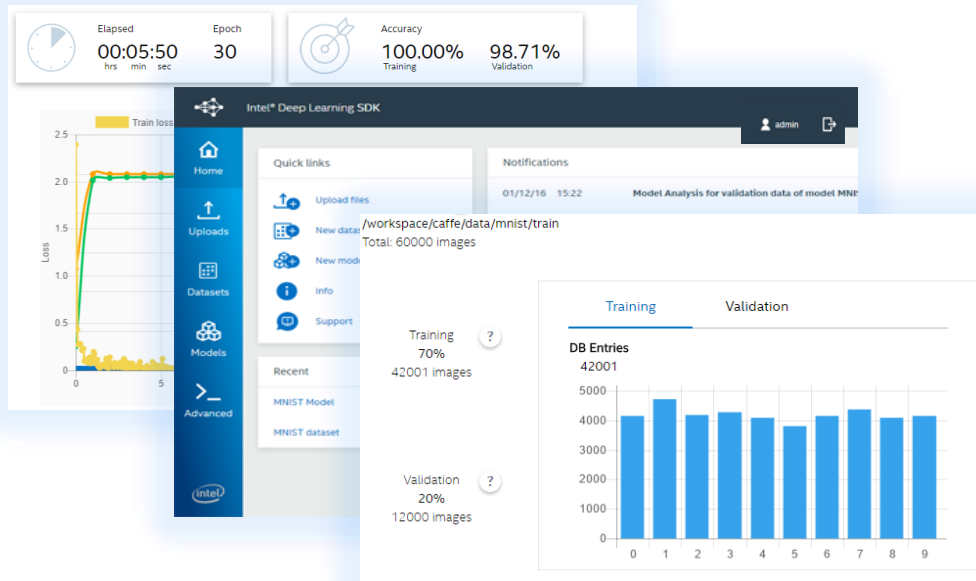
# INTEL® DEEP LEARNING SDK

## Accelerate Deep Learning Development



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



[software.intel.com/deep-learning-sdk](https://software.intel.com/deep-learning-sdk)



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# WHAT NEXT?



**Q&A**



Software

# STUDENT DEVELOPER PROGRAM