

AI FOR EVERYONE

Presented to: American Indian Science and Engineering Society Presenter: Meghana Rao, Intel Corporation 25th March, 2020

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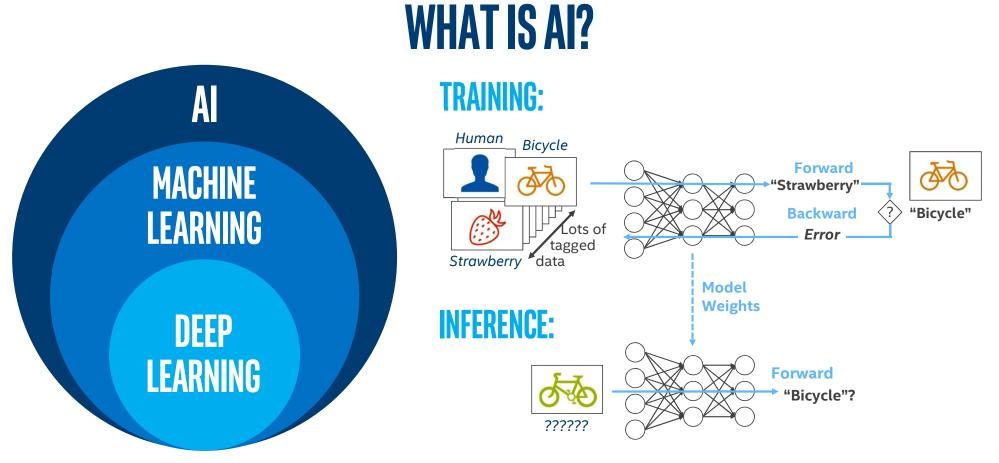


AGENDA

- Introduction to Artificial Intelligence
- Al in the past and present day
- Intel and AI
- Al Journey
- Introduction to Machine Learning
- Introduction to Deep Learning
- Challenges in solving problems through AI
- Community Support
- QnA



INTRODUCTION TO AI



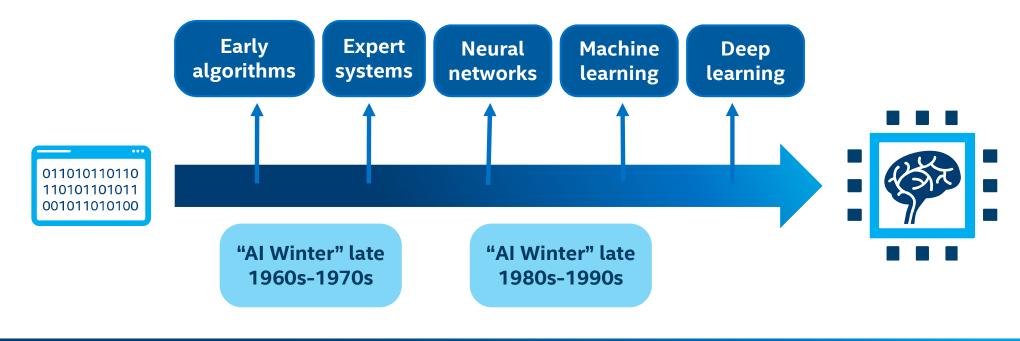
Many different approaches to AI

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HISTORY AND REASONS FOR CURRENT MOMENTUM

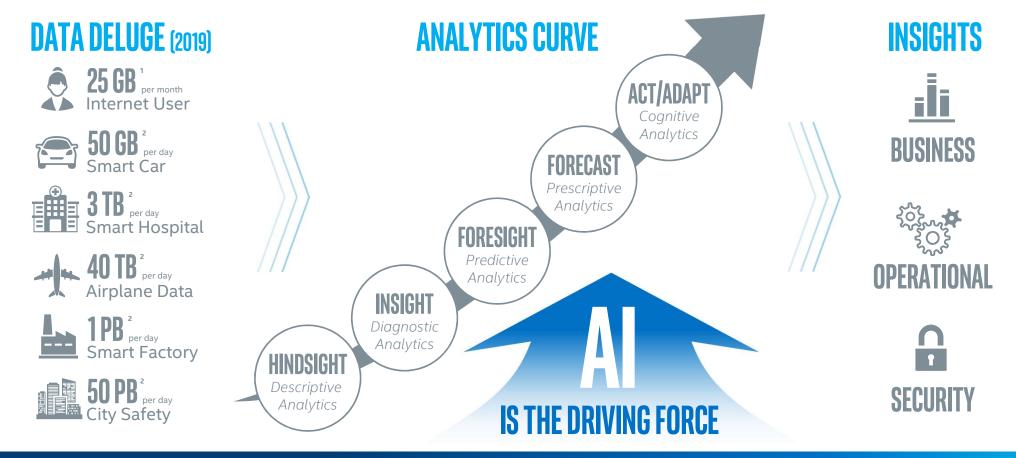
HISTORY OF AI

AI has experienced several hype cycles, where it has oscillated between periods of excitement and disappointment.



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WHY AI NOW? ACCESS TO DATA



Source: http://www.cisco.com/c/en/us/solutions/service-provider/vni-network-traffic-forecast/infographic.html
 Source: https://www.cisco.com/c/dam/m/en_us/service-provider/ciscoknowledgenetwork/files/547_11_10-15-DocumentsCisco_GCI_Deck_2014-2019_for_CKN_10NOV2015_.pdf



AI TRANSFORMATION ACROSS INDUSTRIES



CONSUMER

Smart Assistants Chatbots Search Personalization Augmented Reality Robots



HEALTH

Enhanced

Diagnostics

Drug

Discovery

Patient Care

Research

Sensory

Aids

Algorithmic Trading Fraud Detection Research Personal Finance Risk Mitigation

FINANCE



RETAIL

Support Experience Marketing Merchandising Loyalty Supply Chain Security



GOVERNMENT

Defense Data Insights Safety & Security Resident Engagement Smarter

Cities



ENERGY

Oil & Gas Exploration Smart Grid Operational Improvement Conservation



TRANSPORT



Factory

Automation

Predictive

Maintenance

Precision

Agriculture

Field

Automation



INDUSTRIAL

Advertising Education Gaming Professional & IT Services Telco/Media Sports

OTHER

Source: Intel forecast



ACCESS TO HARDWARE

END POINT

EDGE



User-touch end point devices with lower power requirements such as laptops, tablets, smart home devices, drones



Small scale data centers, small business IT infrastructure, to few on-premise server racks and workstations Large scale data centers such as public cloud or comms service providers, gov't and academia, large enterprise IT

All products, computer systems, dates, and figures are preliminary based on current expectations, and are subject to change without notice.



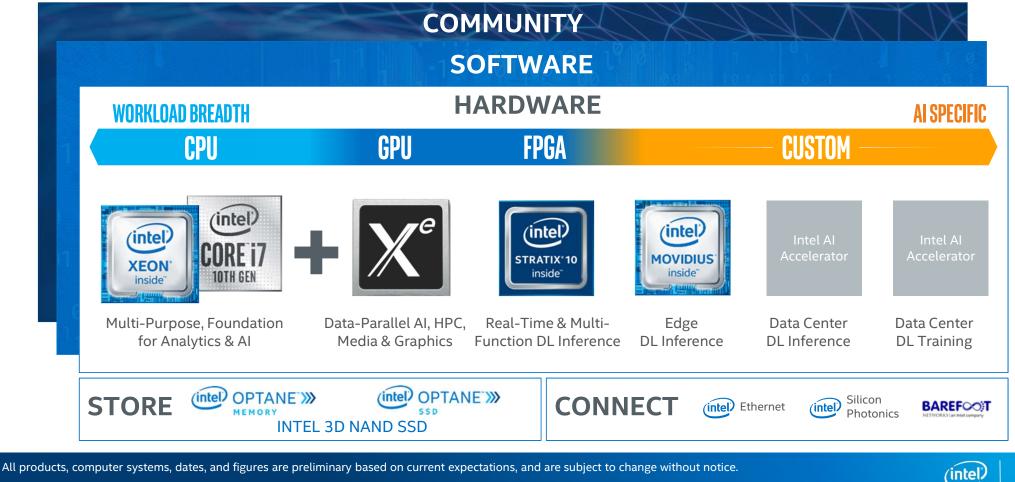


DATA CENTER



INTEL AI PORTFOLIO

ONE INTEL ANALYTICS & AI PRODUCTS



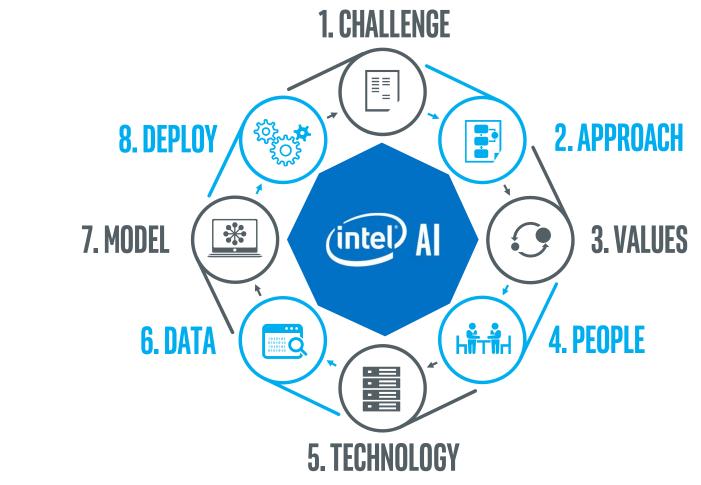
INTEL AI SOFTWARE AI = ML + DL + MT

		MACHINE LEARNING	DEEP LEARNING		MANAGEMENT TOOLS	
	DEVELOPER TOOLS App Developers SW Platform Developer		ModelZoo OpenVINO		Containers	
	TOPOLOGIES & MODELS Data Scientist FRAMEWORKS Data Scientist	 Intel Distribution for Python (SKlearn, Pandas) MILib and Mahout on Spark 	TensorFlow ○ PyTorch ママンマンマンマンマンマンマンマンマンマンマンマンマンマンマンマンマンマンマ	DL Tools NN Distiller, NLP Architect, RL Coach, CVAT	N A U T A kubernetes Kubeflow Deep Learning Reference	Architect & DevOps
	GRAPH ML Performance Engineer KERNEL	 Intel Data Analytics Acceleration Library (Intel DAAL) Intel Math Kernel Library (Intel MKL) 	 nGraph PlaidML Intel Machine Learning Scaling Library (Intel MLSL) Deep Learning Boost Intel[®] Deep Neural Network Library (DNNL) 		Stack Data Analytics Reference Stack	
Red font prod	ML Performance Engineer CPU CPU CPU CPU CPU CPU CPU FPGA					M

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AI JOURNEY



THE AI

JOURNEY

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MACHINE LEARNING

MACHINES LEARN IN TWO WAYS Supervised Learning & Unsupervised Learning



SUPERVISED LEARNING

We train the model. We feed the model with correct answers. Model Learns and finally predicts.

We feed the model with "ground truth".

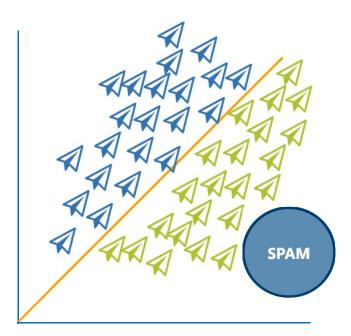


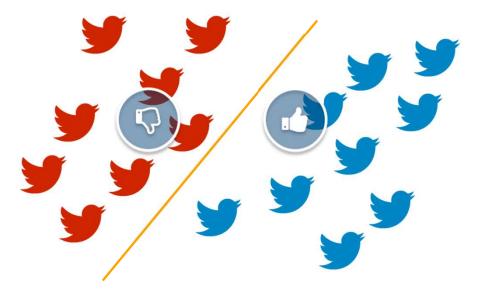
EXAMPLES OF SUPERVISED LEARNING - CLASSIFICATION

Predict a **label** for an entity with a given set of features.











EVALUATION METRIC

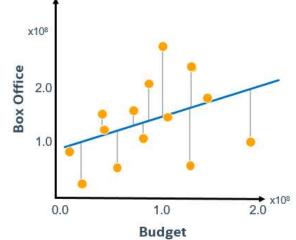
There are many metrics available* to measure performance, such as:

- Accuracy: how well predictions match true values.
- Mean Squared Error: average square distance between prediction and true value.

$$\min_{\beta_0,\beta_1} \frac{1}{m} \sum_{i=1}^{m} \left(\left(\beta_0 + \beta_1 x_{obs}^{(i)} \right) - y_{obs}^{(i)} \right)^2$$



Accuracy target



*The wrong metric can be misleading or not capture the real problem.

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UNSUPERVISED LEARNING

Data is given to the model. Right answers are not provided to the model. The model makes sense of the data given to it.

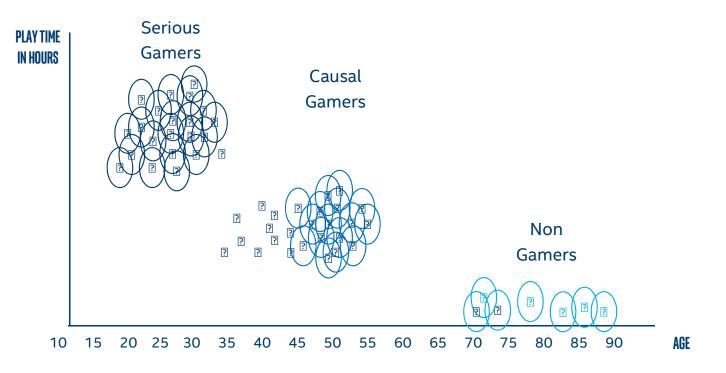
Can teach you something you were probably not aware of in the given dataset.



EXAMPLE OF UNSUPERVISED LEARNING - CLUSTERING

Group entities with similar features

MARKET SEGMENTATION





ADDITIONAL MACHINE LEARNING EXAMPLES





Movie Recommendation

Fraud Detection

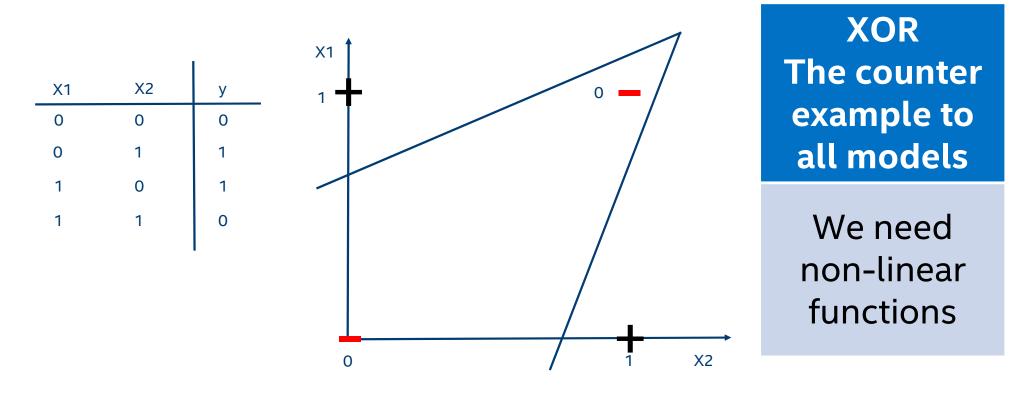
Recommending Similar news articles



Other brand names can be claimed as the property of others

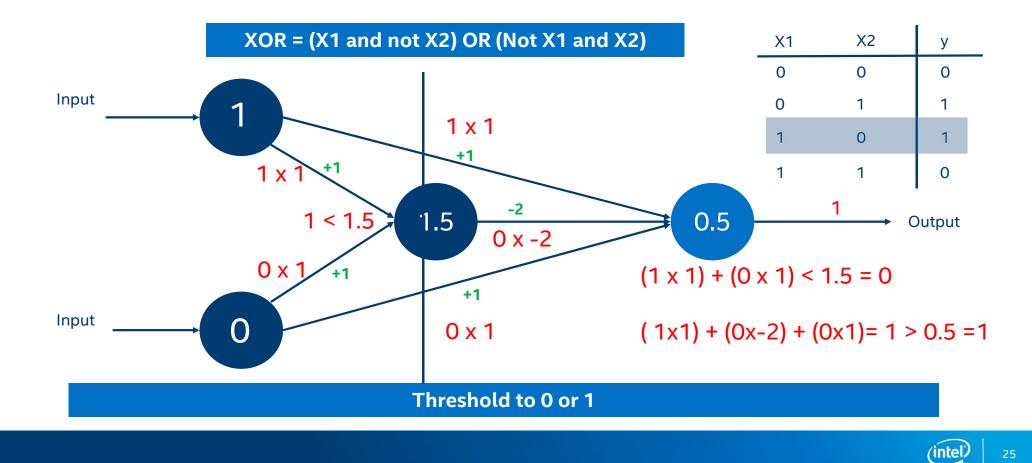


WHAT IS THE LIMITATION WITH LINEAR CLASSIFIERS?



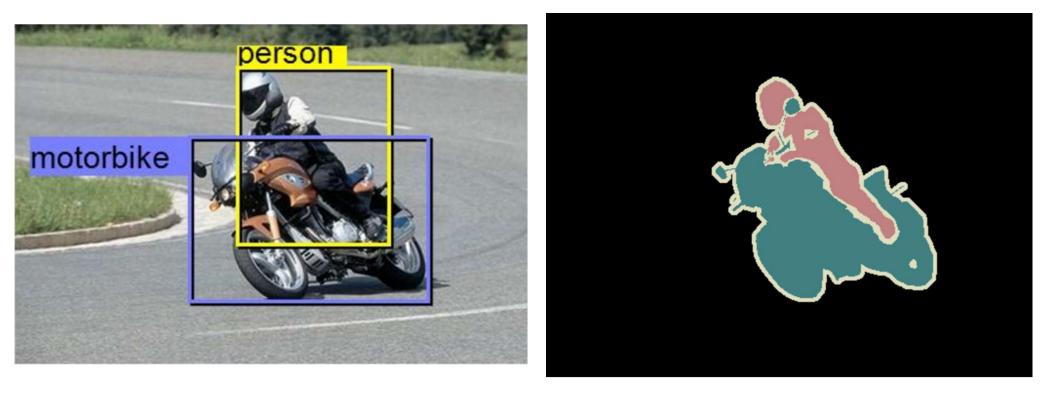


WE NEED LAYERS USUALLY LOTS WITH NON-LINEAR TRANSFORMATIONS



DEEP LEARNING

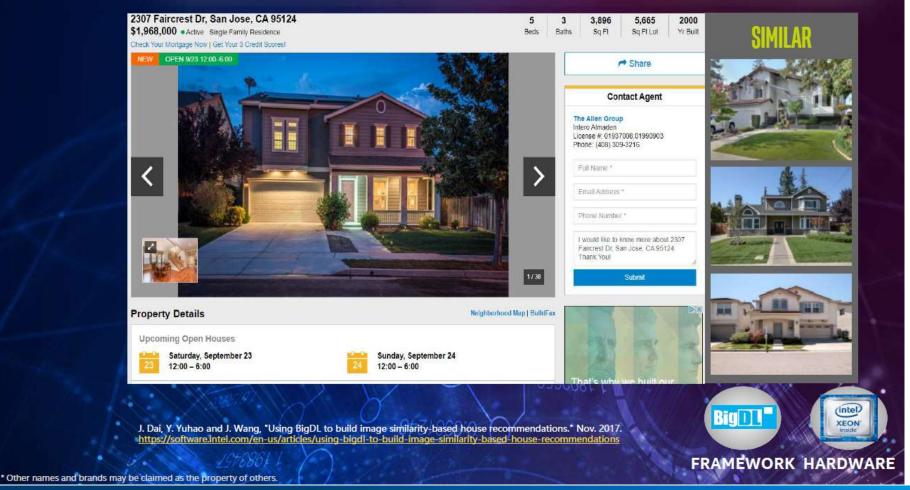
CLASSIFICATION / DETECTION / SEMANTIC SEGMENTATION



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

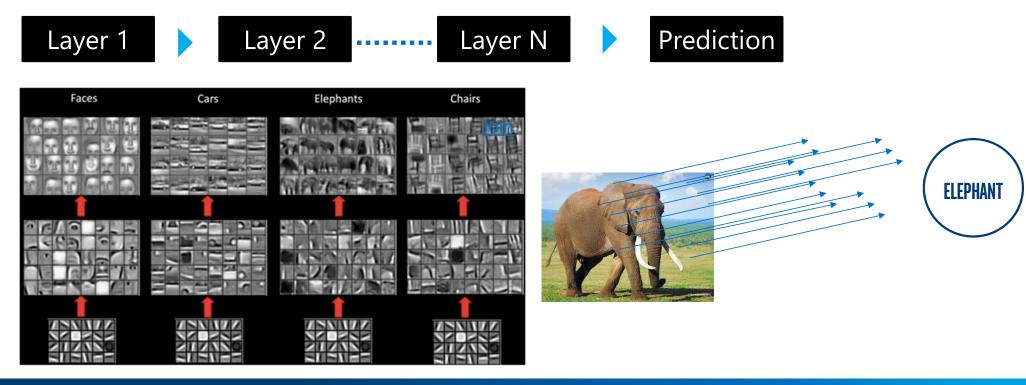
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HOME BUYING ASSISTANT: 10 CPU NODES



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HOW DO DEEP LEARNING NETWORKS LEARN? EACH LAYER LEARNS Something



Zeiler & Fergus '13

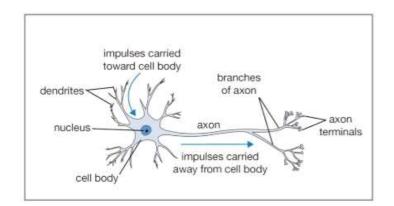


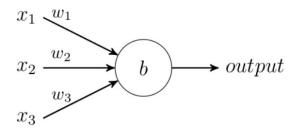
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HOW CAN I BUILD A NEURAL NETWORK?

MOTIVATION FOR NEURAL NETS

- Use biology as inspiration for mathematical model
- Get signals from previous neurons
- Generate signals (or not) according to inputs
- A neuron fires when it's output > threshold
- Pass signals on to next neurons
- By layering many neurons, can create complex model

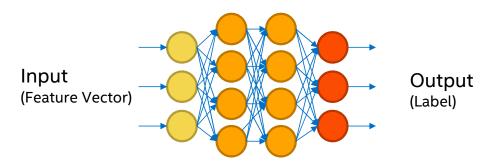






FULLY CONNECTED NEURAL NETWORK

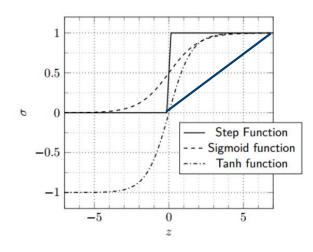
- Multiple layers of stacked neurons forming a network (topology)
- Each neuron is connected to every neuron in subsequent layers
- Network topologies are constantly evolving based on complexity of problems being solved by AI

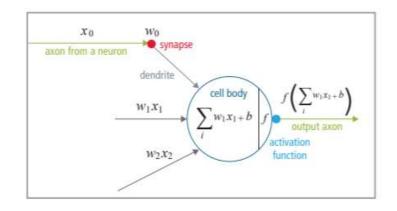




WHAT IS AN ACTIVATION FUNCTION?

- The output of a neuron could range from –infinity to + infinity
- How does it know when to fire?
- An activation function establishes a boundary for the output
- Many types of activation functions exist





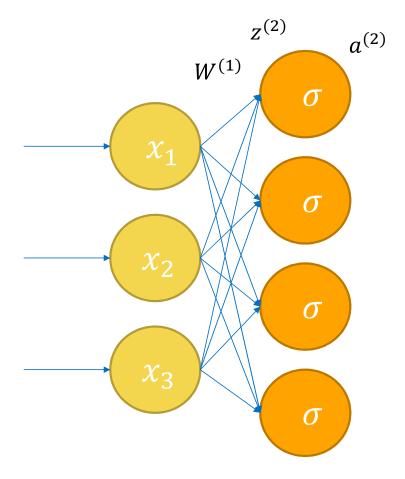
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MATRIX REPRESENTATION OF COMPUTATION

$$z^{(2)} = xW^{(1)}$$

 $a^{(2)} = \sigma(z^{(2)})$

 $W^{(1)}$ is a 3x4 matrix $z^{(2)}$ is a 4-vector $a^{(2)}$ is a 4-vector



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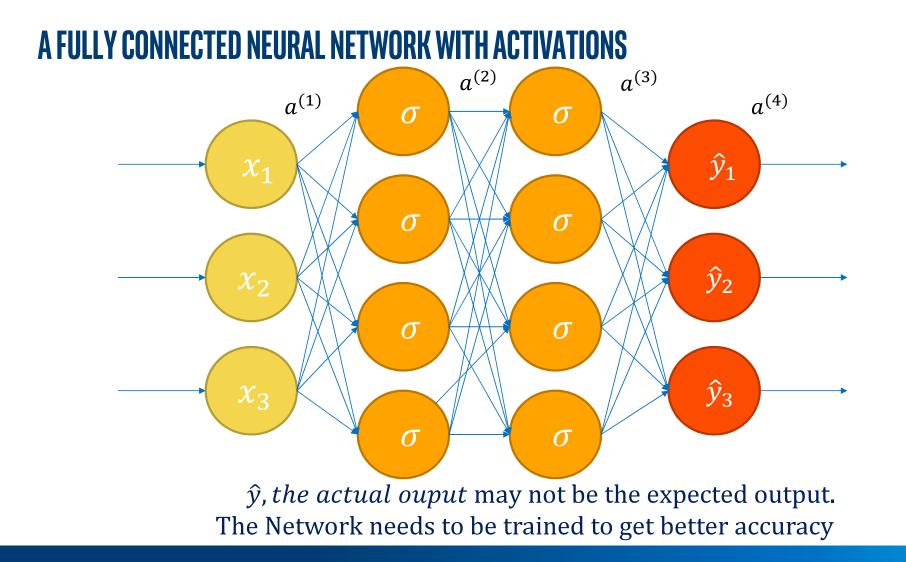
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CONTINUING THE COMPUTATION

For a single training instance (data point) Input: vector x (a row vector of length 3) Output: vector \hat{y} (a row vector of length 3)

 $z^{(2)} = xW^{(1)} \qquad a^{(2)} = \sigma(z^{(2)})$ $z^{(3)} = a^{(2)}W^{(2)} \qquad a^{(3)} = \sigma(z^{(3)})$ $z^{(4)} = a^{(3)}W^{(3)} \qquad \hat{y} = softmax(z^{(4)})$



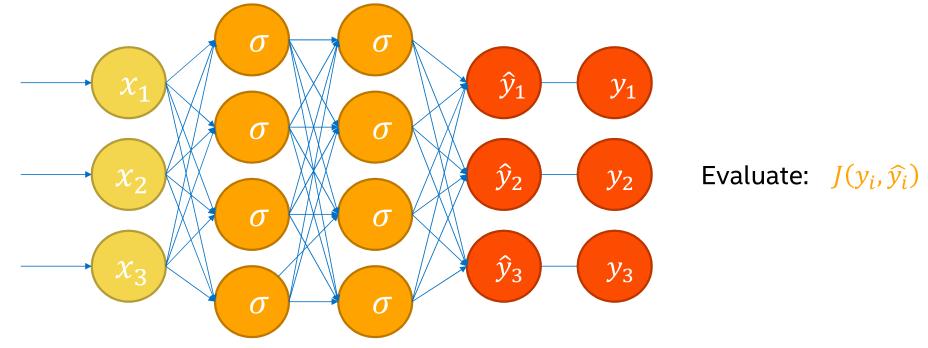


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HOW CAN I TRAIN A NEURAL NETWORK?

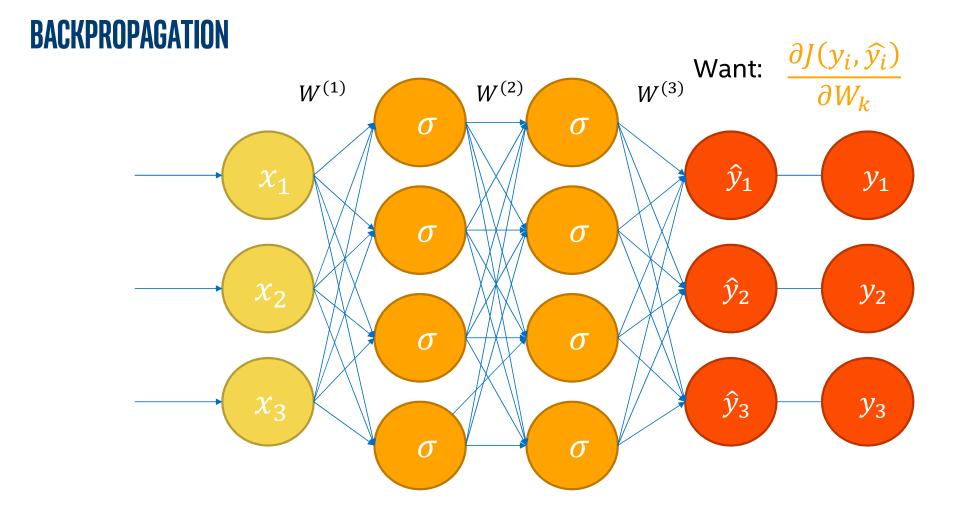
FORWARD PROPAGATION

• Calculate the Loss Function – compare the predictions to the ground truth



• How far the "actual output" is from "Ground Truth" determines how much more the network needs to learn to adjust it's output to minimize loss

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APPLY GRADIENTS TO EVERY WEIGHT IN THE NETWORK

$$\frac{\partial J}{\partial W^{(3)}} = (\hat{y} - y) \cdot a^{(3)}$$

~ -

$$\frac{\partial J}{\partial W^{(2)}} = (\hat{y} - y) \cdot W^{(3)} \cdot \sigma'(z^{(3)}) \cdot a^{(2)}$$

$$\frac{\partial J}{\partial W^{(1)}} = (\hat{y} - y) \cdot W^{(3)} \cdot \sigma'(z^{(3)}) \cdot W^{(2)} \cdot \sigma'(z^{(2)}) \cdot X$$

- Recall that: $\sigma'(z) = \sigma(z)(1 \sigma(z))$ (Sigmoid activation function)
- Though they appear complex, above are easy to compute!

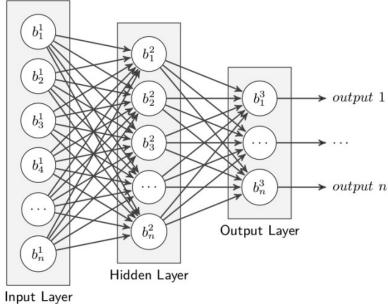


FULLY CONNECTED NEURAL NETWORK VS. Convoluted neural networks

FULLY CONNECTED NETWORK

More complicated problems can be solved by connecting multiple neurons together and using more complicated activation functions.

- Organized into layers of neurons.
- Each neuron is connected to every neuron in the previous layer.
- Each layer transforms the output of the previous layer and then passes it on to the next.
- Every connection has a separate weight



http://svail.github.io/mandarin/



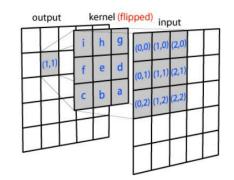
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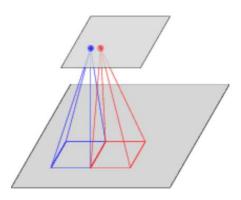
CONVOLUTIONAL NEURAL NETWORK

CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional neural networks reduce the required computation and are good for detecting features.

- Each neuron is connected to a small set of nearby neurons in the previous layer
- The same set of weights are used for each neuron
- Ideal for spatial feature recognition, Ex: Image recognition
- Cheaper on resources due to fewer connections





http://svail.github.io/mandarin/



CNN FOR RECOGNIZING DIGITS

CNN FOR DIGIT RECOGNITION

PROC. OF THE IEEE, NOVEMBER 1998

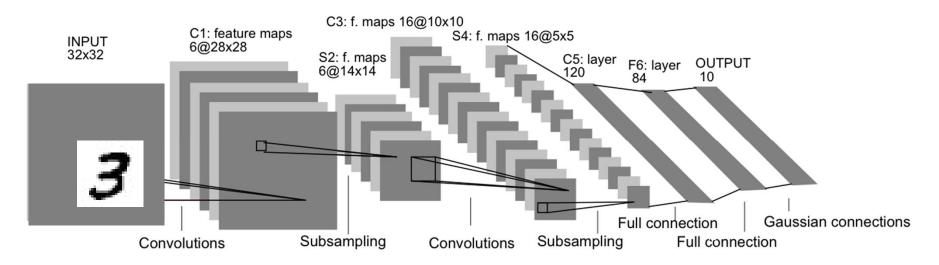


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

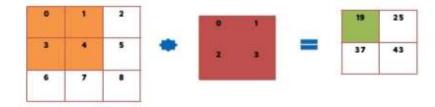


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Source: http://cs231n.github.io/

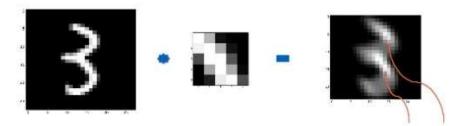
IDENTIFYING FEATURES

Convolution



 Each element in the output is the result of a dot product between two vectors





Detected the pattern!



CHALLENGES

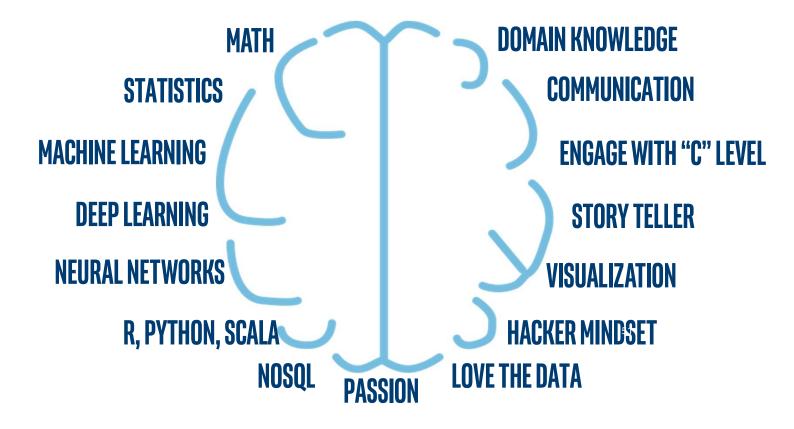
CHALLENGES

- Availability of data
 - Data Sources
 - Data Shapes
 - Amount of Data
 - Data Preprocessing
 - Labelling the data
- Reducing possibilities for overfitting and under-fitting
- Human error in data labelling
- Human Bias



HOW CAN YOU LEARN MORE?

DATA SCIENTIST SKILL SET





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Get smarter using online tutorials, webinars, student kits and support forums

Educate others using available course materials, hands-on labs, and more



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Showcase your innovation at industry & academic events and online via the Intel AI community forum

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RESOURCES

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

• Intel[®] AI Student Kits

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