

Deep Learning

Concepts and Its Applications

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CITE
College of Innovative
Technology and Engineering

About Me

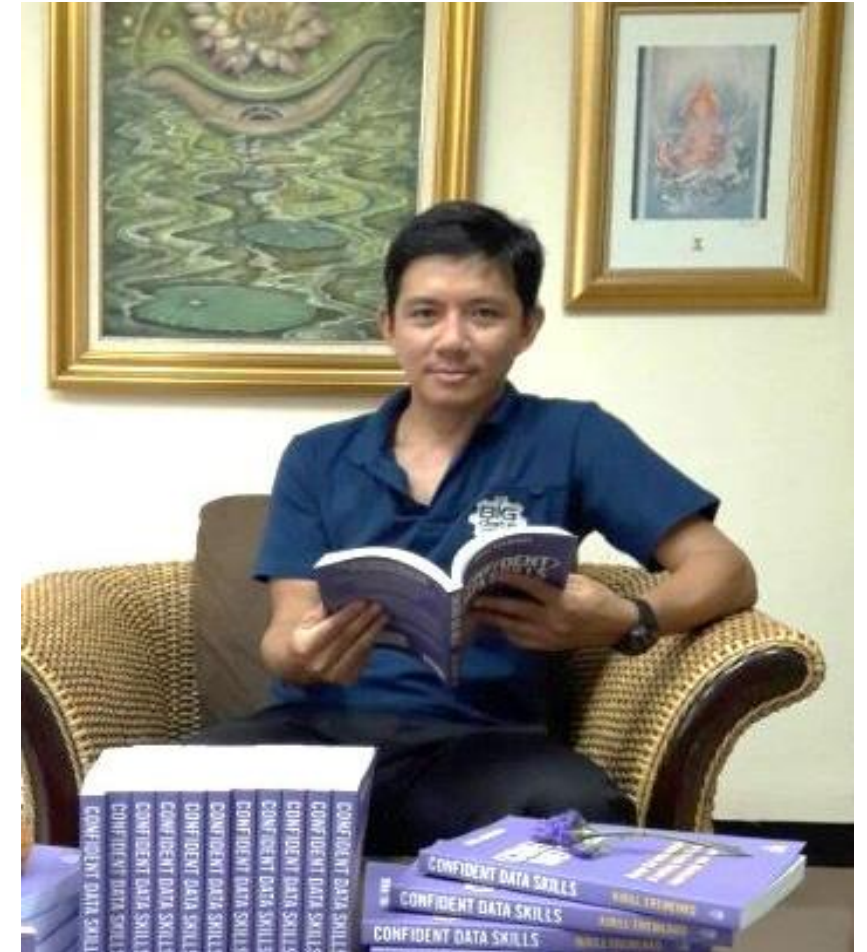
Name: Thanapat Kangkachit

ธนภัทร ช้างคะจิตร

Work: Lecturer at Big Data Engineering,
CITE, DPU since 2017

Education:

- Ph.D. in Computer Engineering,
Kasetsart University
- M.Eng. in Computer Engineering,
Kasetsart University
- B.Eng. in Computer Engineering,
Kasetsart University



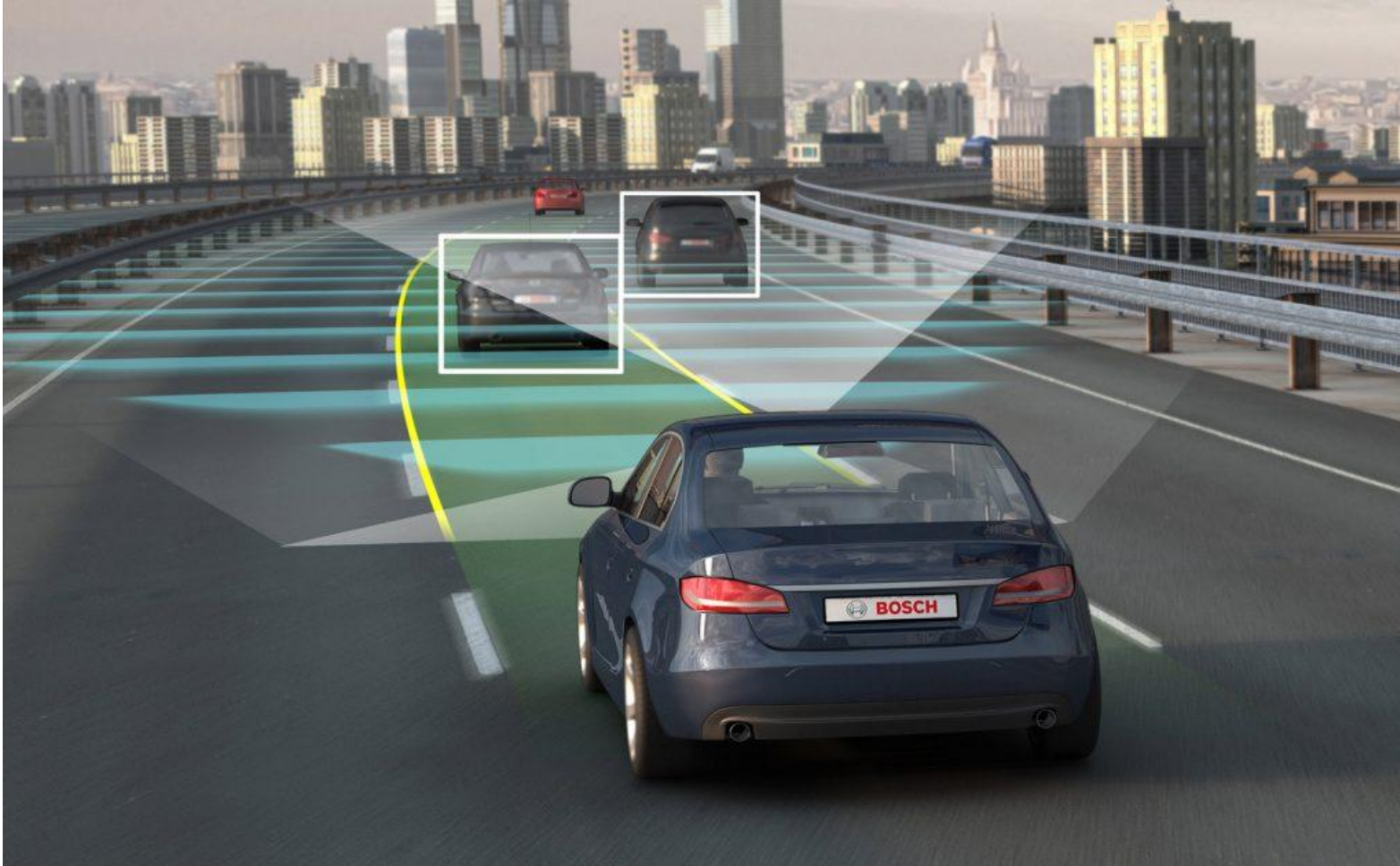
Agenda

- 🔍 01 – What is AI, Machine Learning and Deep Learning?
- 🔍 02 – Applications of Deep Learning
- 🔍 03 – Getting Start with Deep Learning

Google DeepMind [2016]



Self-Driving Cars



Real-time Face Recognition [2018]

Short-range Face Capturing / Recognition

SENSETIME 商汤科技

实时监控 历史记录 数据地图 以图搜图 名单管理 系统设置

Admin

08-13-2015 16:19:37

Face Capturing Success

发现重点人物

15:24:26 扶梯 抓拍人脸 93.2% 黑名单 郭军 440981197808063831

男 36岁 男 23岁

黑名单 46% 46% 45%

李刚 22 李承成 22 张忻 25 张崇璋 23

15:23:40 扶梯 抓拍人脸 93.1% 黑名单 张广彬 440981197808063831

男 35岁 男 23岁

黑名单 47% 46% 45%

郭军 23 张吉 22 张崇璋 23 李承成 22

人脸抓拍

抓拍统计 今日: 23976 张 本月: 25085 张 更多

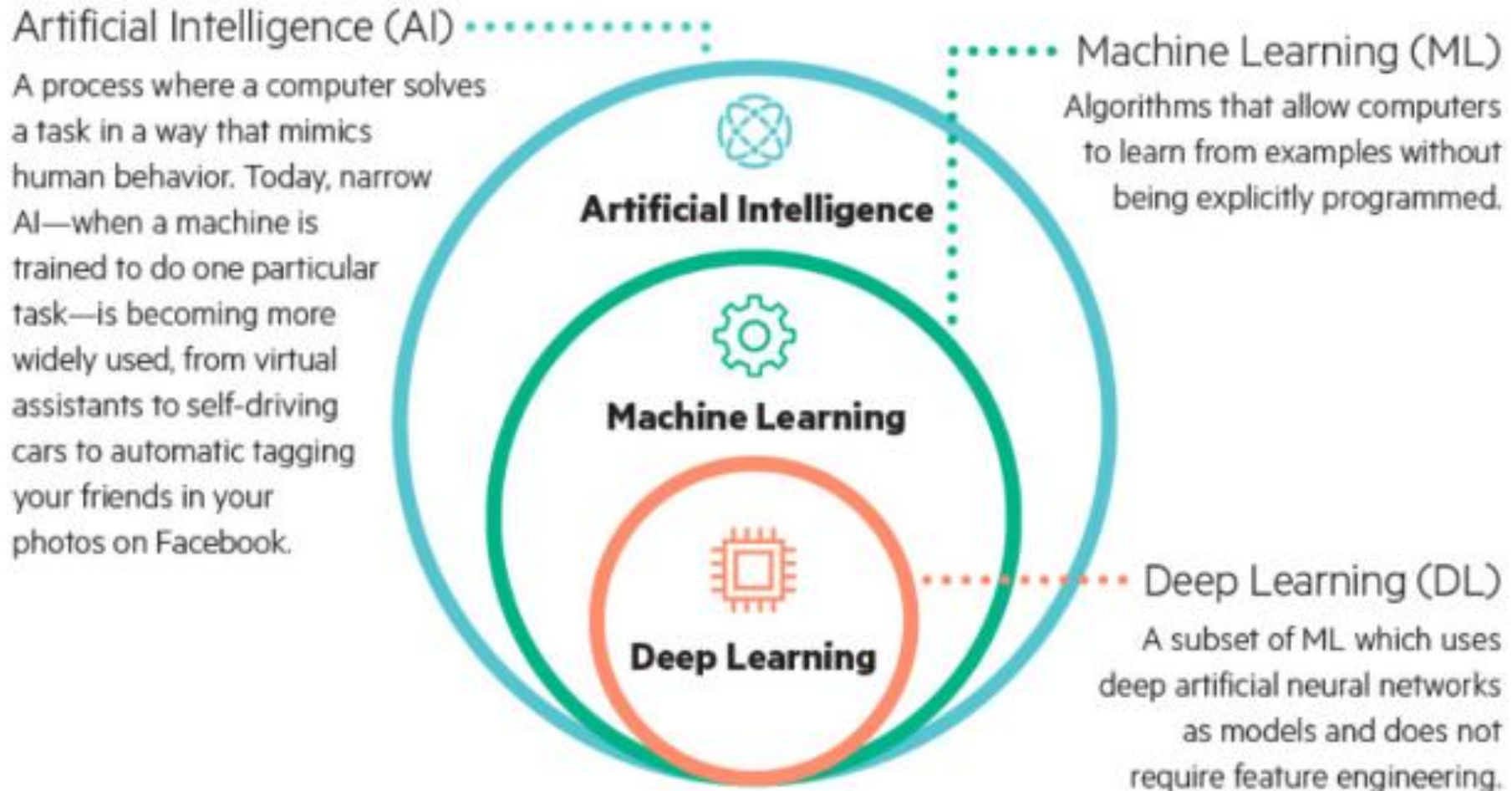
01

WHAT IS AI, MACHINE LEARNING AND DEEP LEARNING?



What Makes a Machine Intelligent?

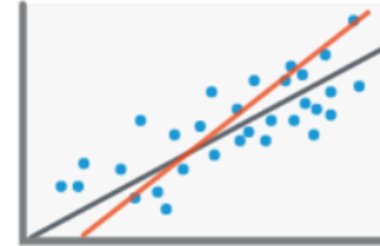
While AI is the headliner, there are actually subsets of the technology which can be applied to solving human problems in different ways.



Machine Learning: Problem Types



Classification
(supervised – predictive)



Regression
(supervised – predictive)

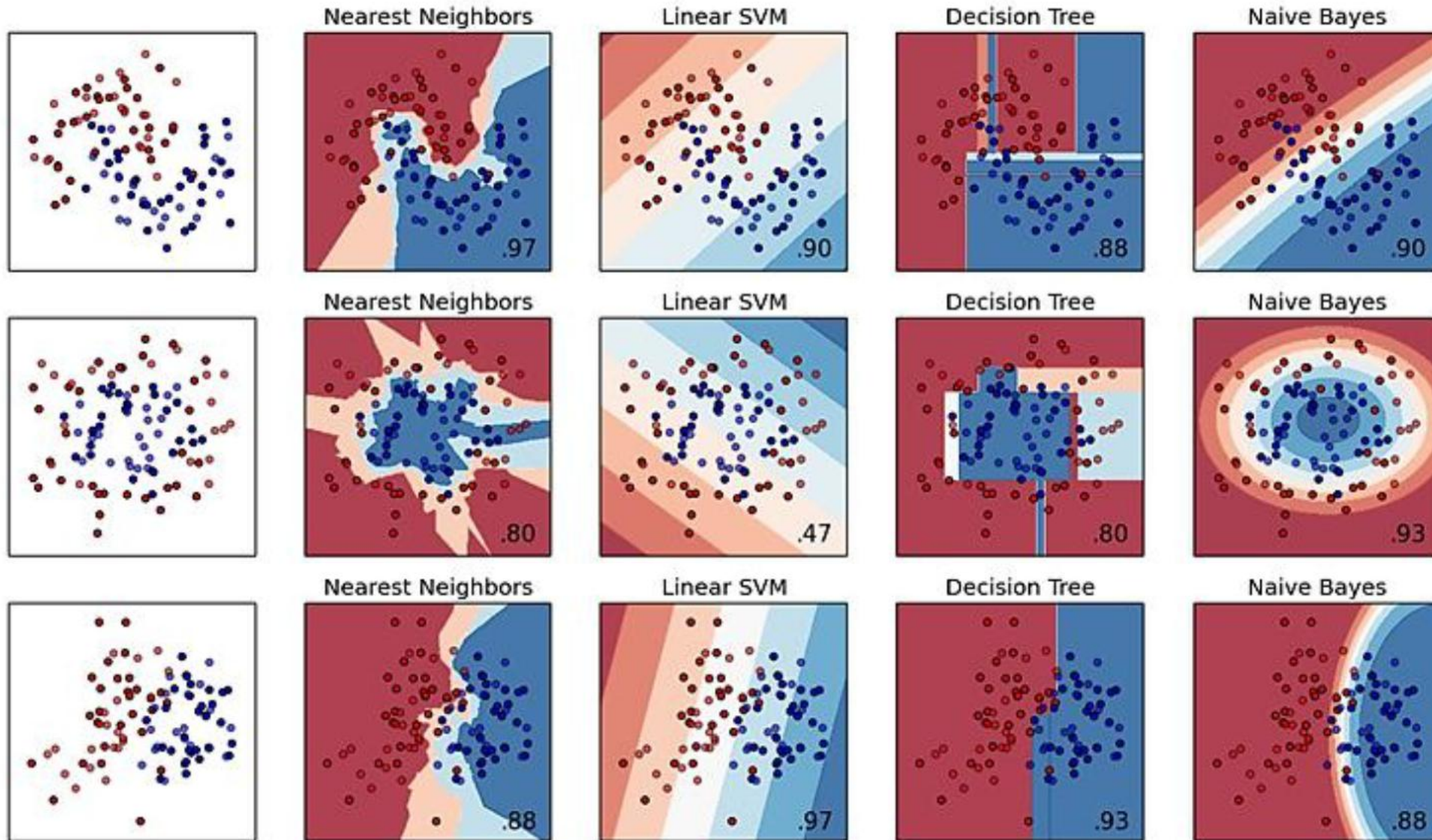


Clustering
(unsupervised – descriptive)



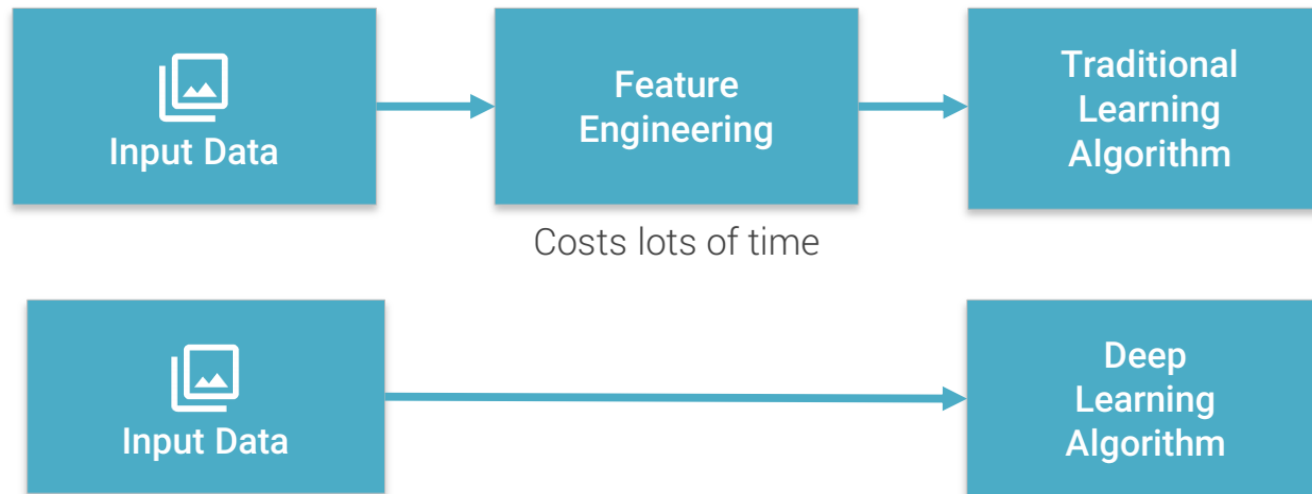
Anomaly Detection
(unsupervised – descriptive)

Machine Learning: Classification Algorithms



What is Deep Learning?

- A subset of **machine learning** field
- Uses **deep artificial neural networks** as models
- Does not require feature engineering



Hype or Reality?



I have worked all my life in Machine Learning, and I've never seen one algorithm knock over benchmarks like Deep Learning

– Andrew Ng (Stanford & Baidu)



Deep Learning is an algorithm which has no theoretical limitations of what it can learn; the more data you give and the more computational time you provide, the better it is – Geoffrey Hinton (Google)

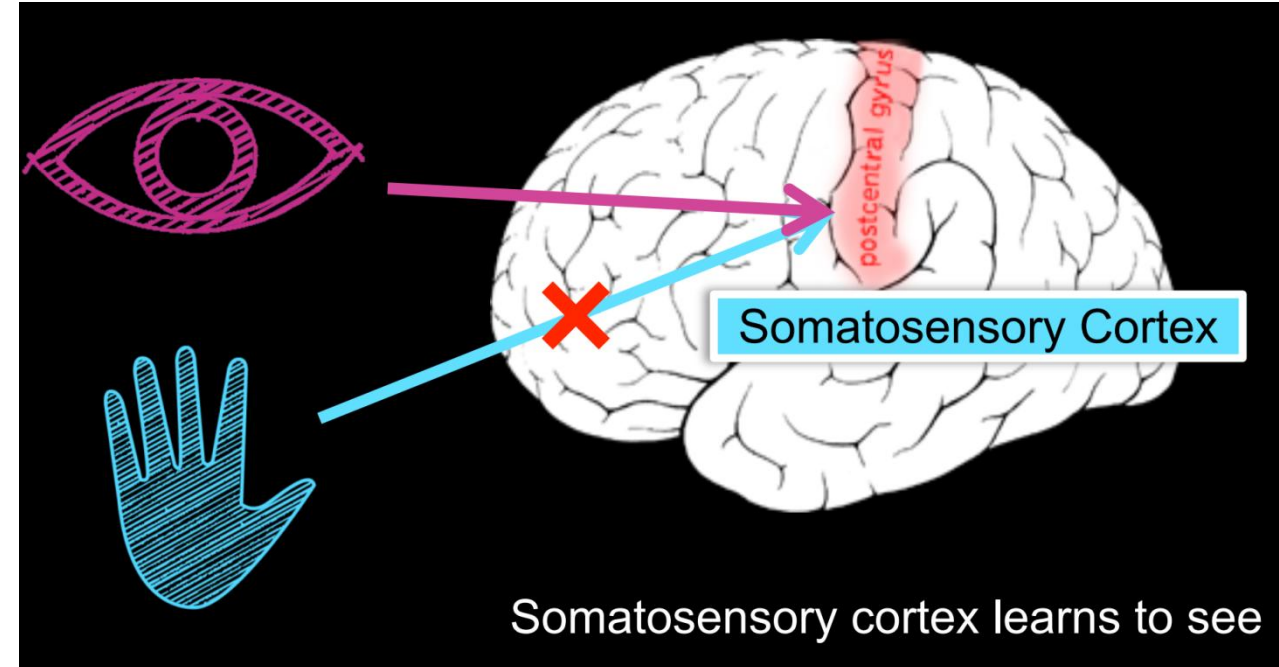
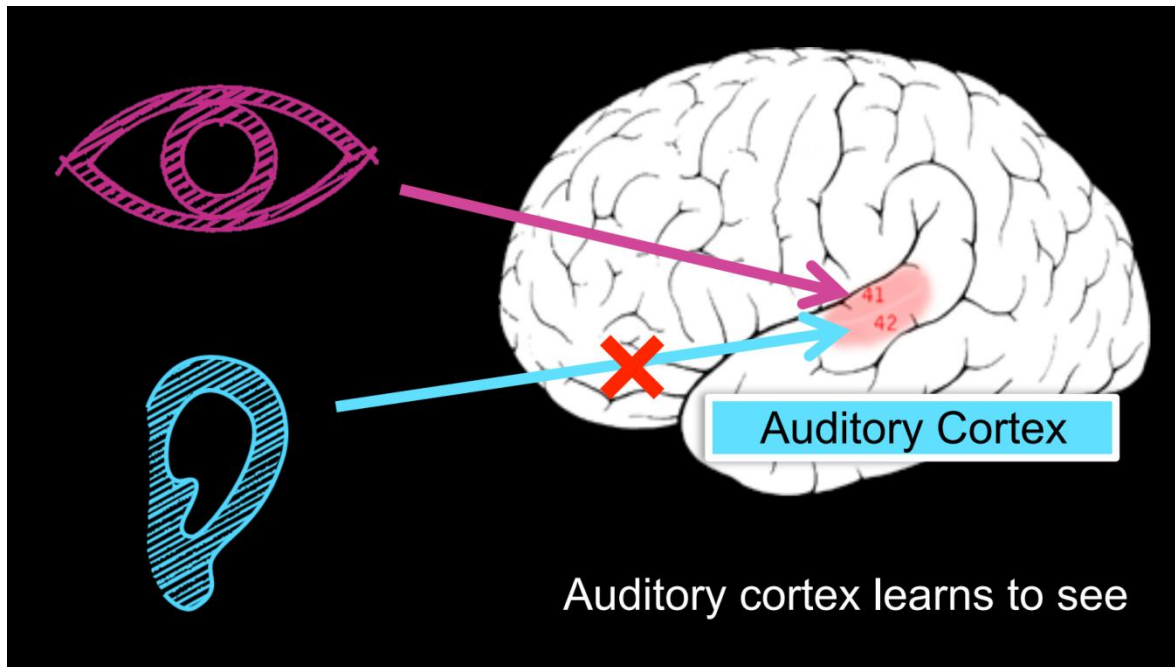


Human-level artificial intelligence has the potential to help humanity thrive more than any invention that has come before it – Dileep George (Co-Founder Vicarious)

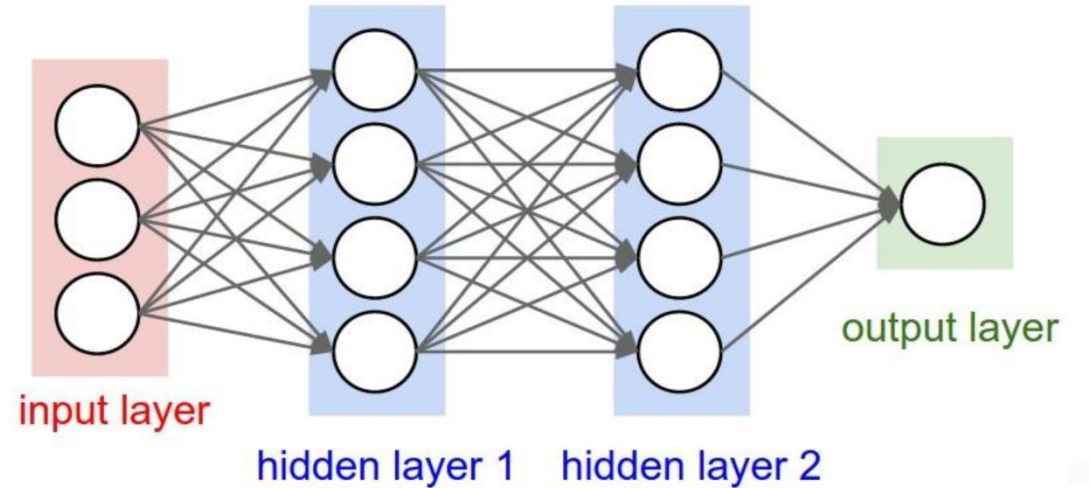
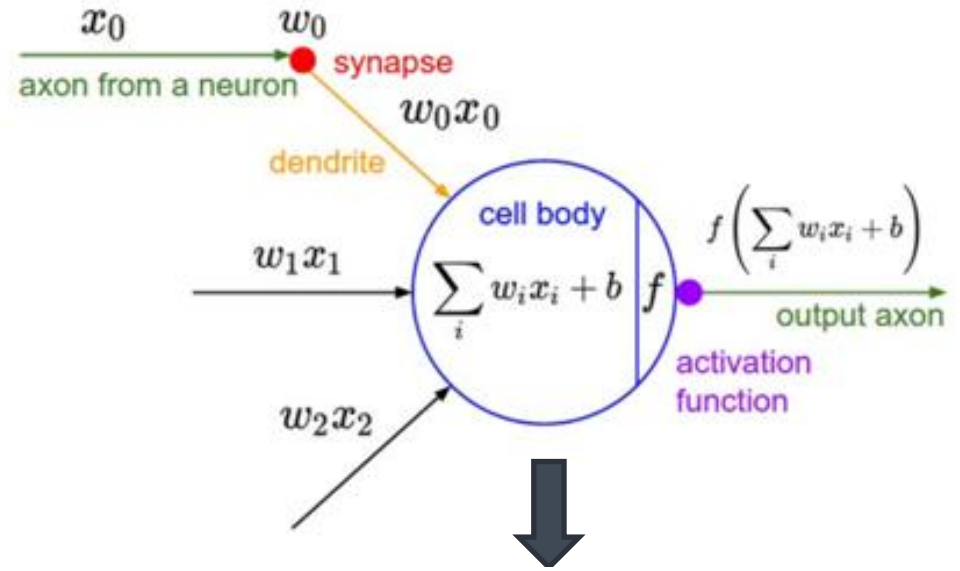
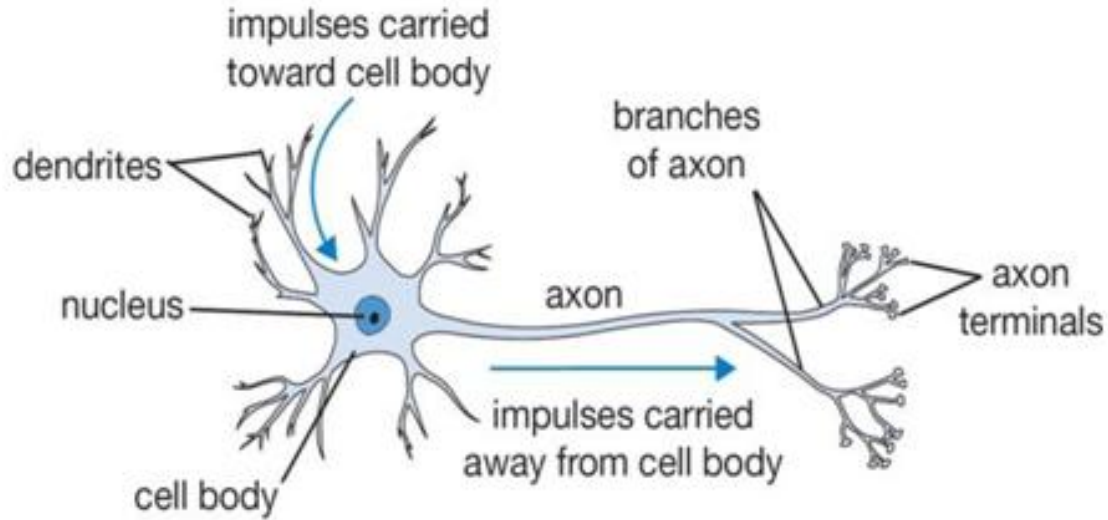


For a very long time it will be a complementary tool that human scientists and human experts can use to help them with the things that humans are not naturally good – Demis Hassabis (Co-Founder DeepMind)

The “one learning algorithm” hypothesis

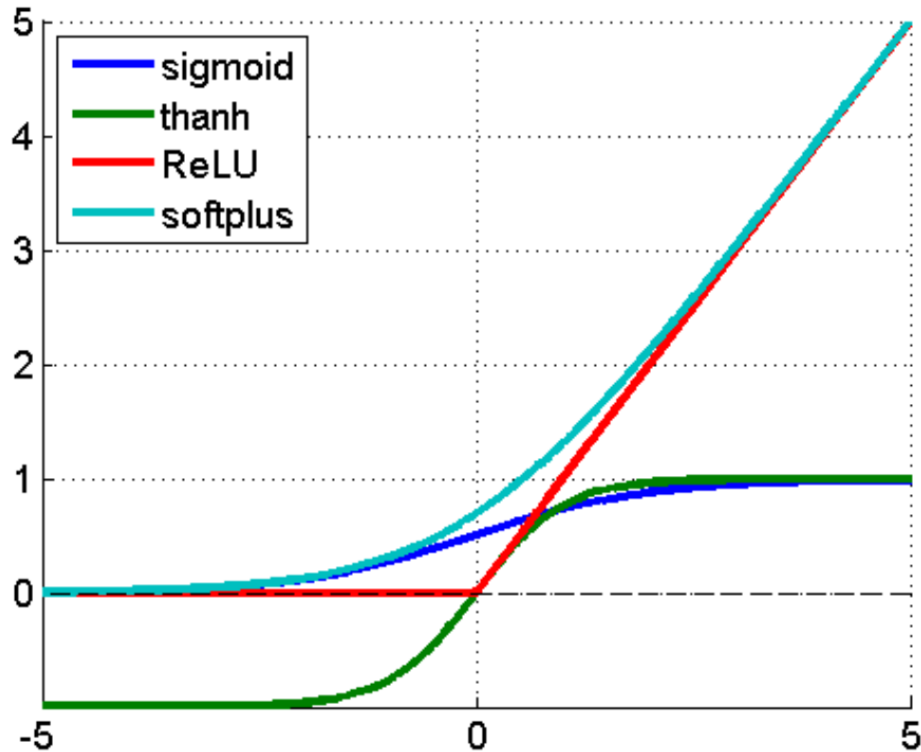
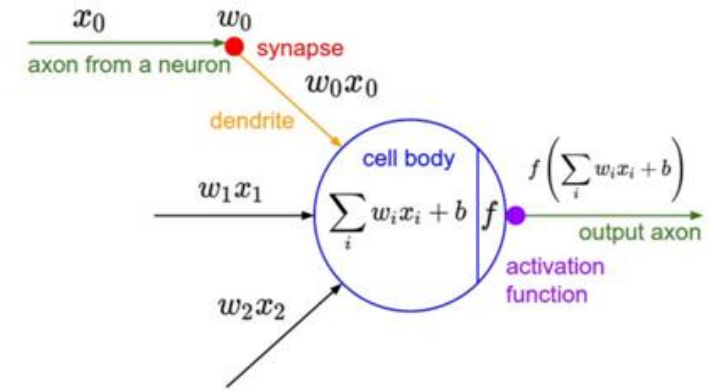


Neurons in the Brain VS Artificial Neurons



Artificial Neural Networks

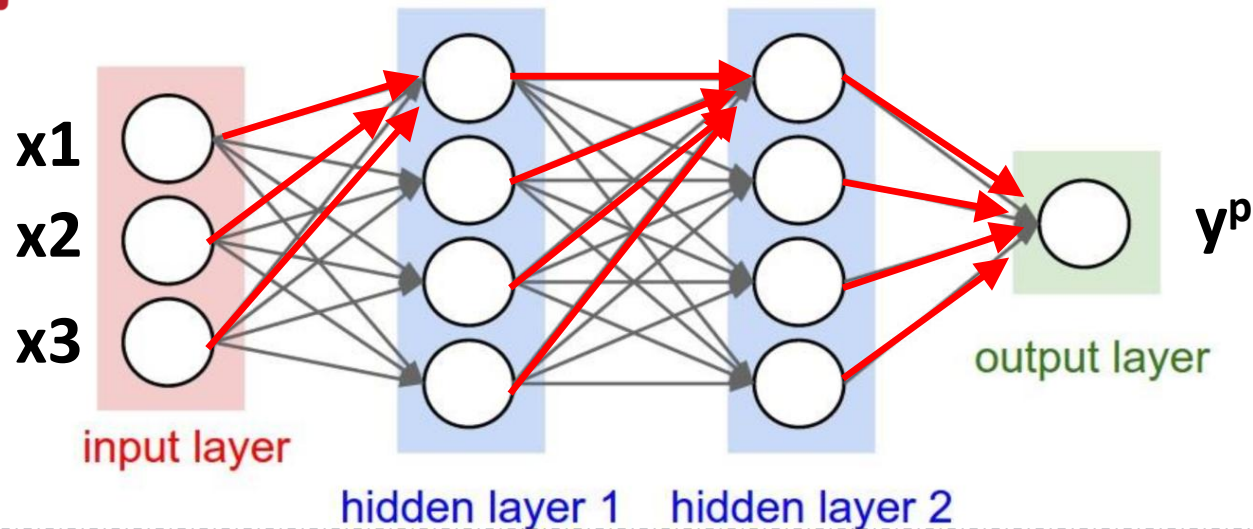
Non-linear Activation Function



ReLU, $\max(0, x)$

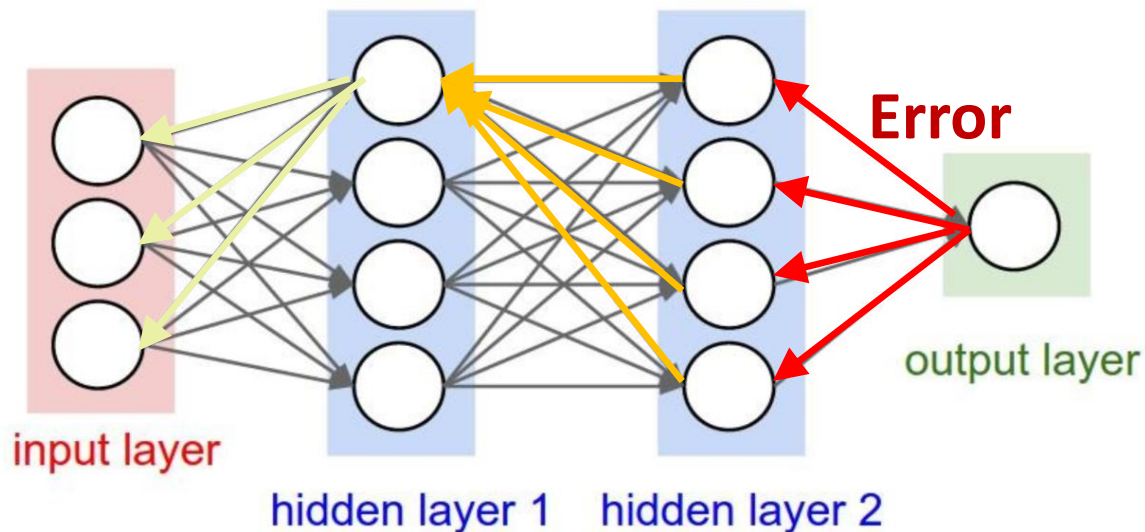
- used by **most deep networks**
- much faster training time
- prevent **gradient vanishing** problem

Artificial Neural Networks: The Training Process



Forward Propagation

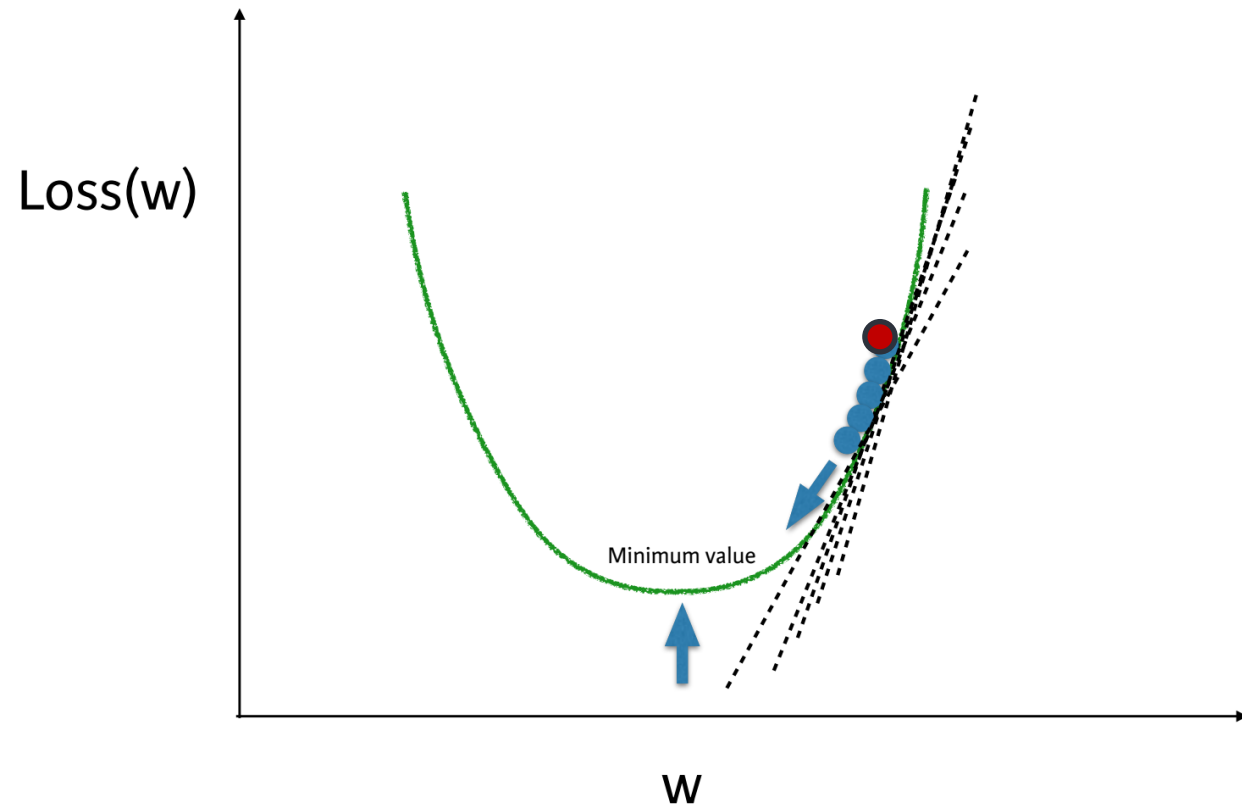
- Sample labeled data (x_1, x_2, x_3, Y)
- Forward** it through the network to get **predictions (y^p)**



Backward Propagation

- Compute the **Error ($Y - y^p$)**
- Update the connection weight using **gradient descent**

Gradient Descent



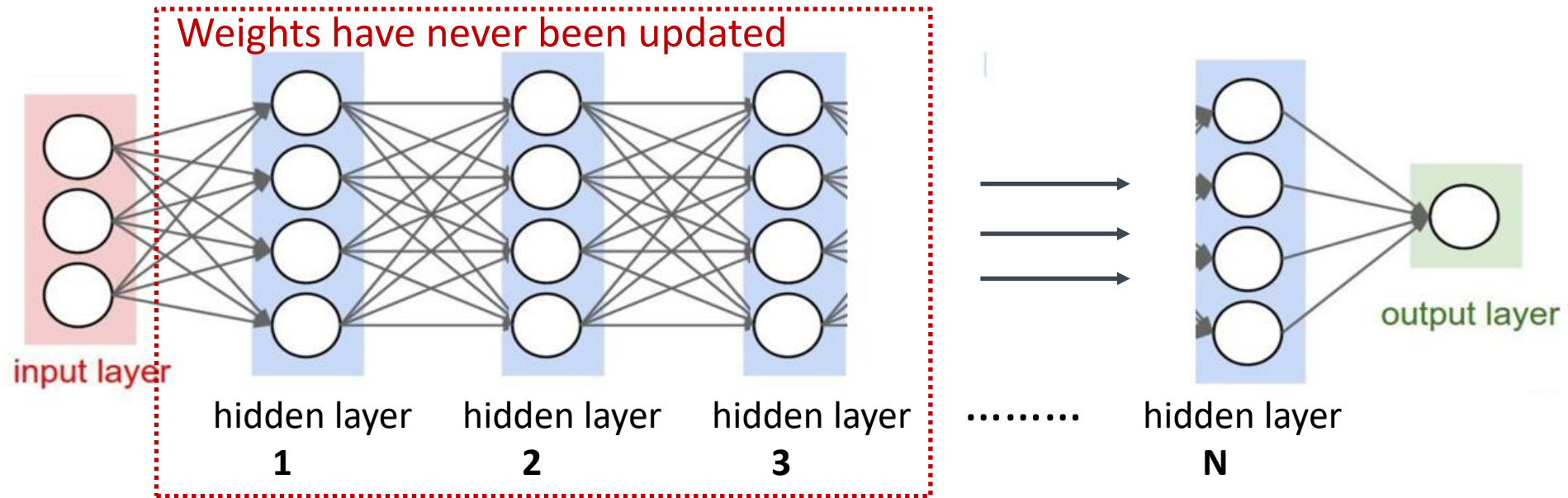
Imagine you are in a **pitch dark field** and want to find the **lowest point**

- **Feel the ground** to see how it slopes
- Take a **small step downhill** (learning rate)
- **Repeat until** it is **uphill** in every direction

Update each weight (w)

$$w_{\text{new}} = w - (\text{learning rate} * \text{slope})$$

Vanishing Gradient in Deep Networks



- Connection **weights** of the **first** couple hidden layers have **never** been **updated**.
 - Unfortunately, they are **random weights**.
- In 2006, **Geoff Hinton et. al.** showed how a many-layered neural networks could be effectively **pre-trained one layer at a time**, treating each layer in turn as an unsupervised **restricted Boltzmann machine**, then fine-tuning it using supervised backpropagation.

A brief History of ANNs



1958 Perceptron

1974 Backpropagation

Convolution Neural Networks for Handwritten Recognition
1998

Google Brain Project on 16k Cores
2012



1969
Perceptron criticized



1995
SVM reigns

2006
Restricted Boltzmann Machine

2012
AlexNet wins ImageNet
IMAGENET

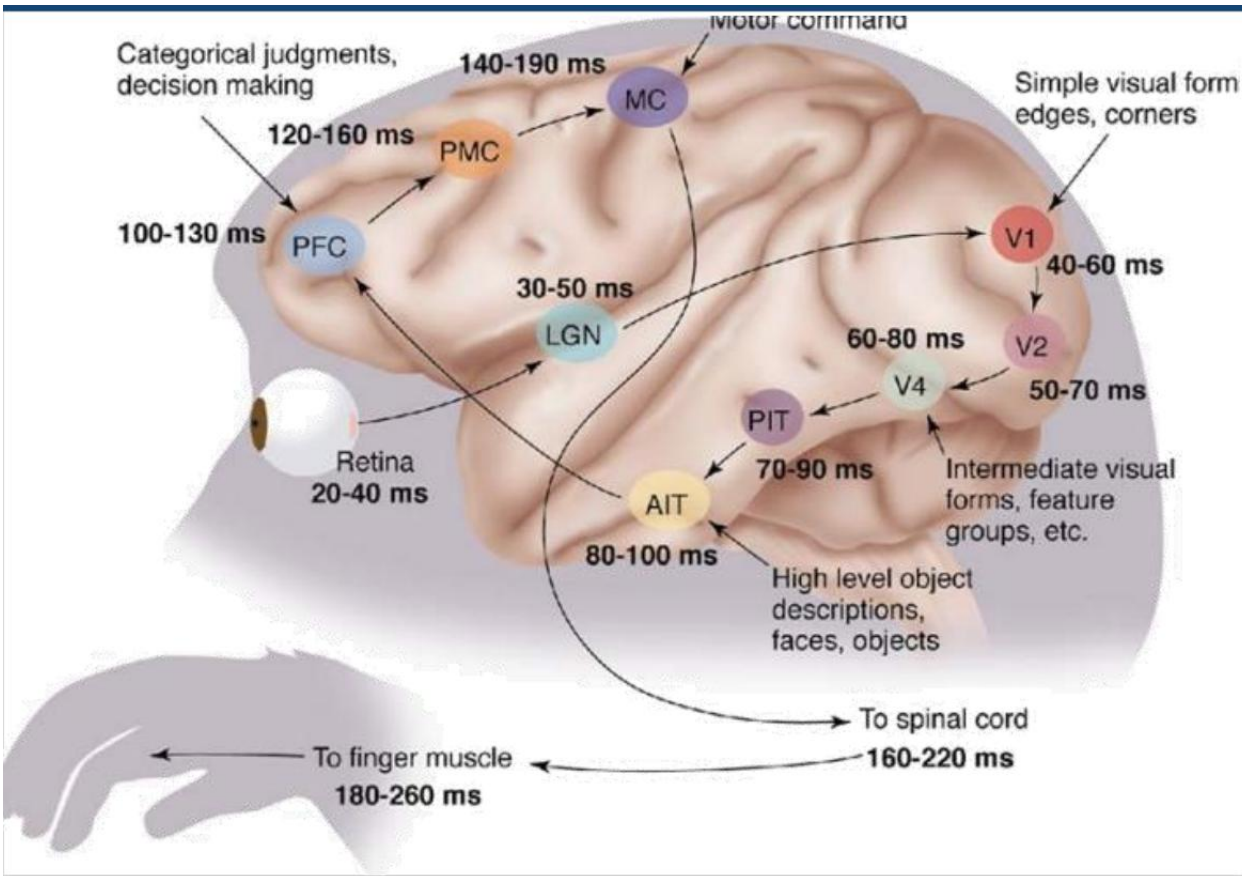
Inspired by the Visual Cortex Brain

In the visual cortex:

- The **first** hierarchy of neurons (**V1**) are sensitive to **specific edges, corners**.
- The brain regions **further down** the visual pipeline (**PIT, AIT**) are sensitive to more **complex structure** such as faces, objects.

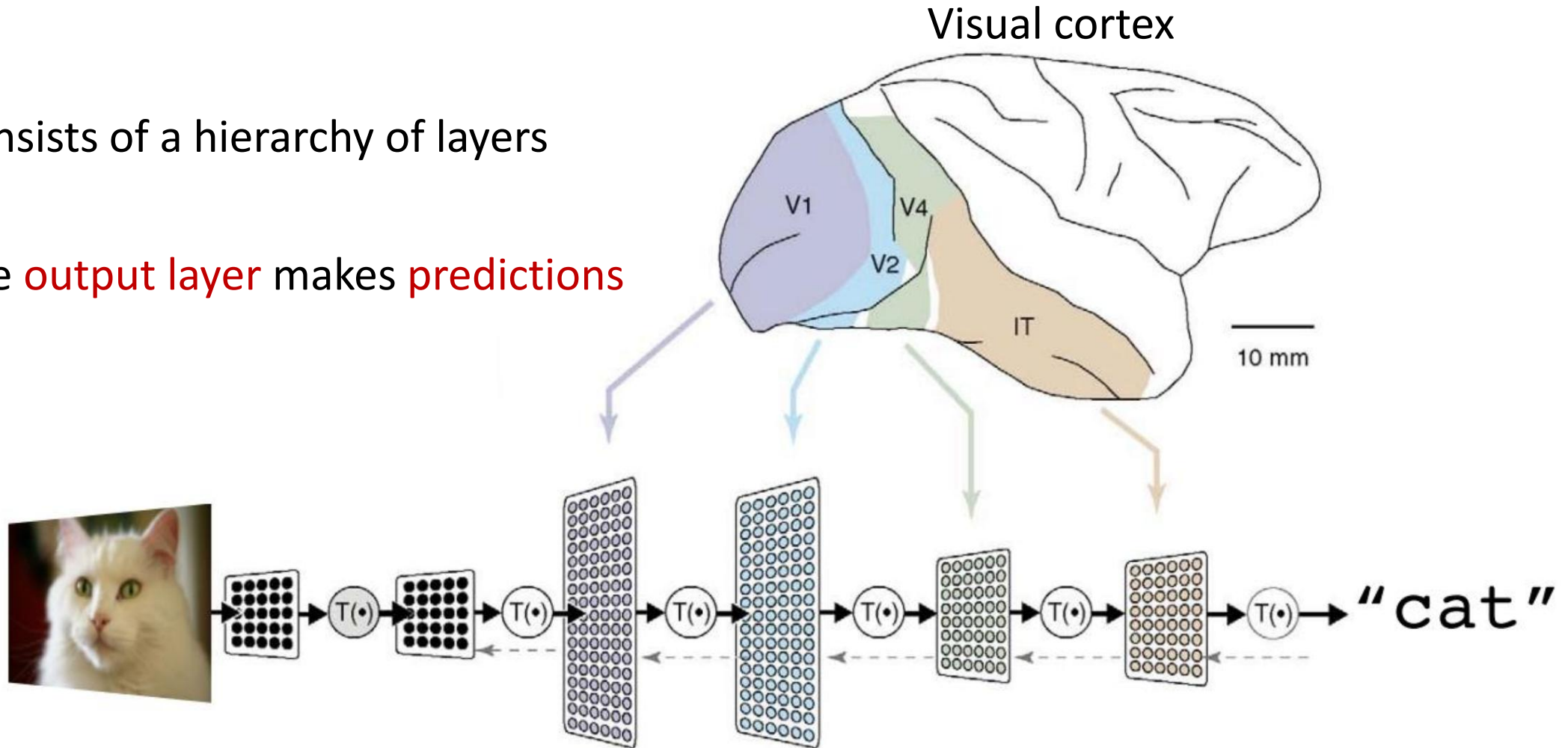
=> **Convolutional Neural Networks (CNNs)**

[Yann Lecun, 1998]



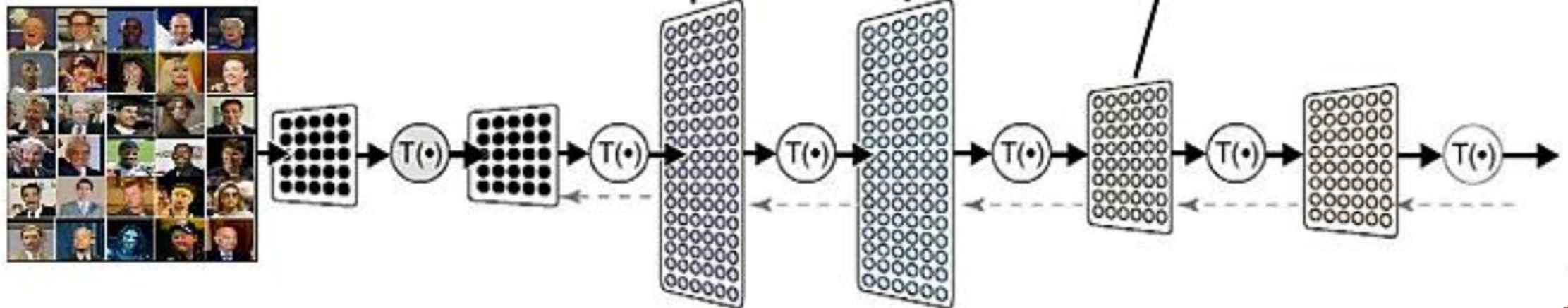
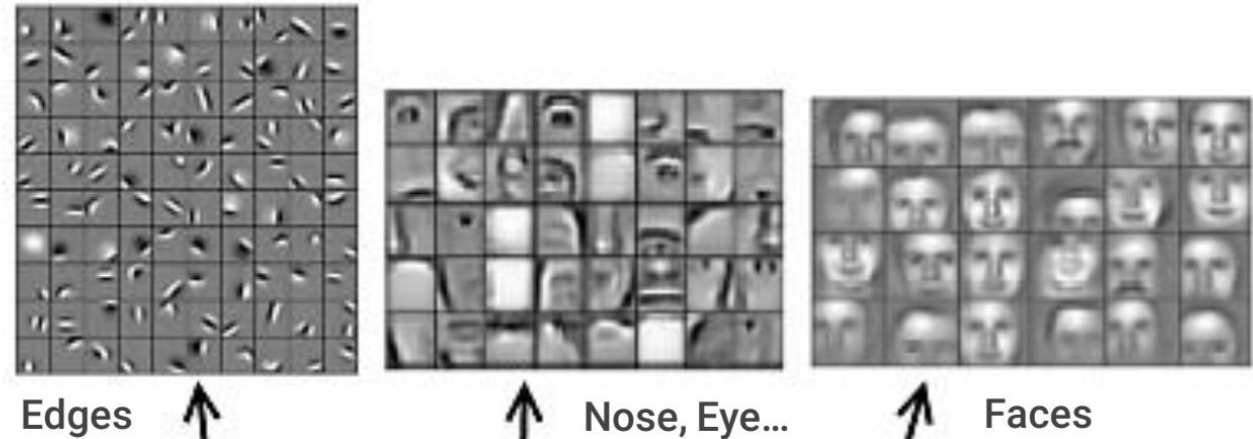
CNNs Architecture

- Consists of a hierarchy of layers
- The **output layer** makes **predictions**

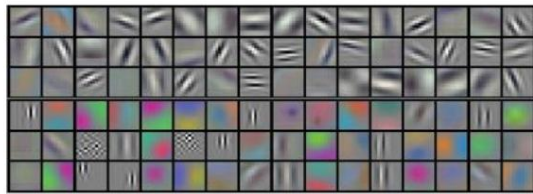
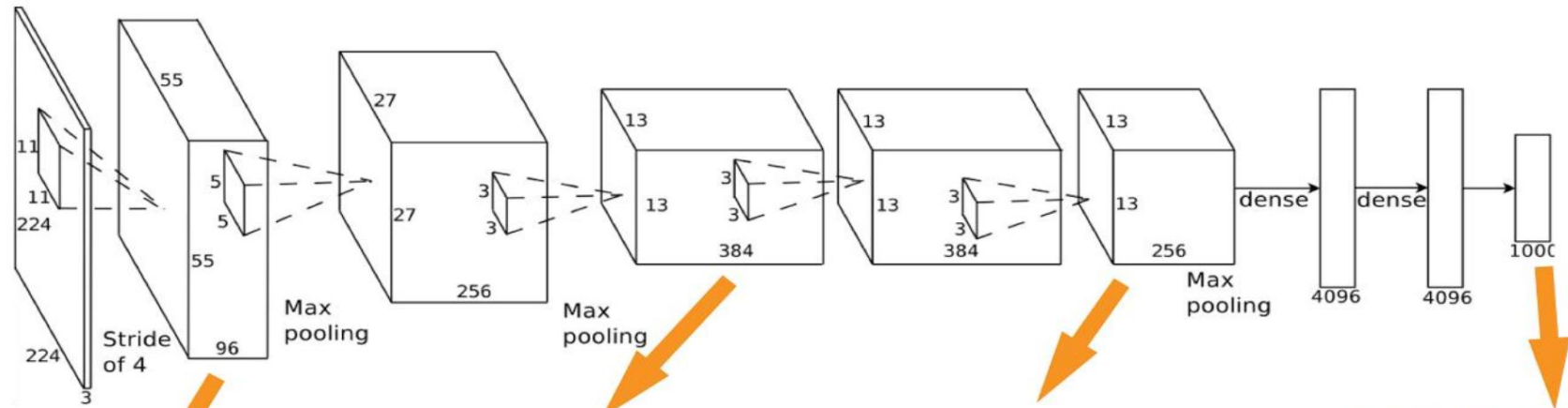


CNNs Architecture

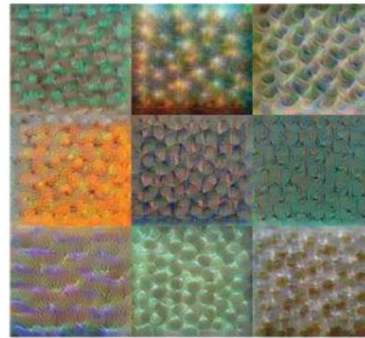
- Each layer transforms input data into **more abstract representation** (e.g. edge -> nose-> face).
- The **output layer** combines those features to make **predictions**.



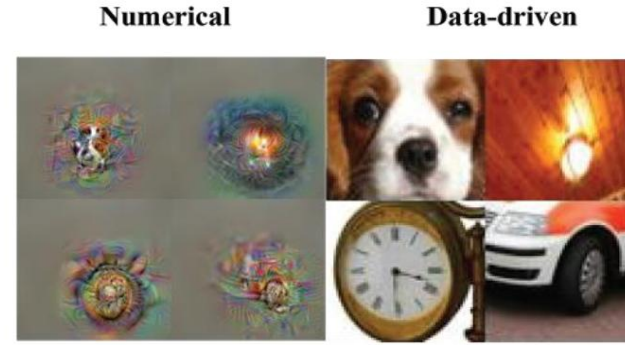
CNNs:



Conv 1: Edge+Blob



Conv 3: Texture



Conv 5: Object Parts



Fc8: Object Classes

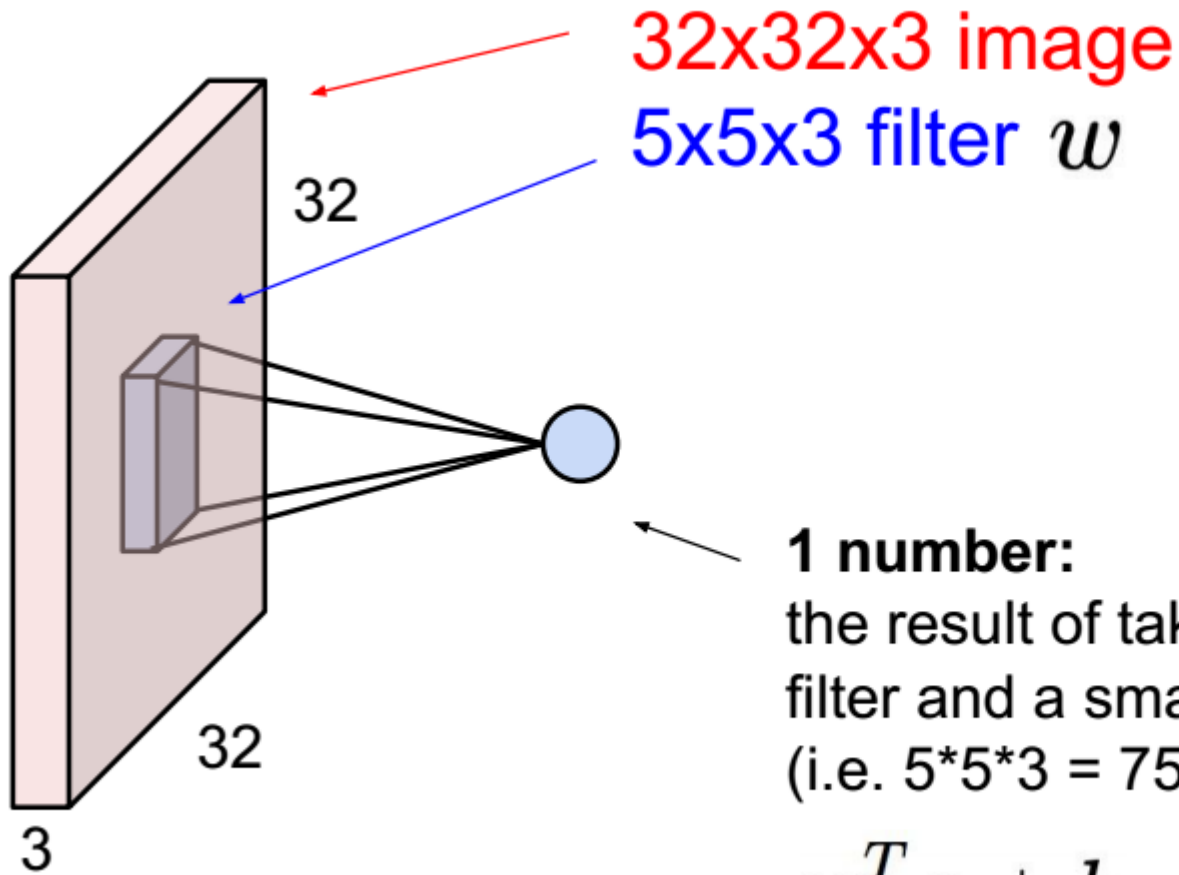
Convolutional Layer

- Is a **feature detector**
- Learn to **filter out** not needed info using **kernels**

Pooling Layers

- compute max or average value of a particular feature over a region
- Downsizing input images

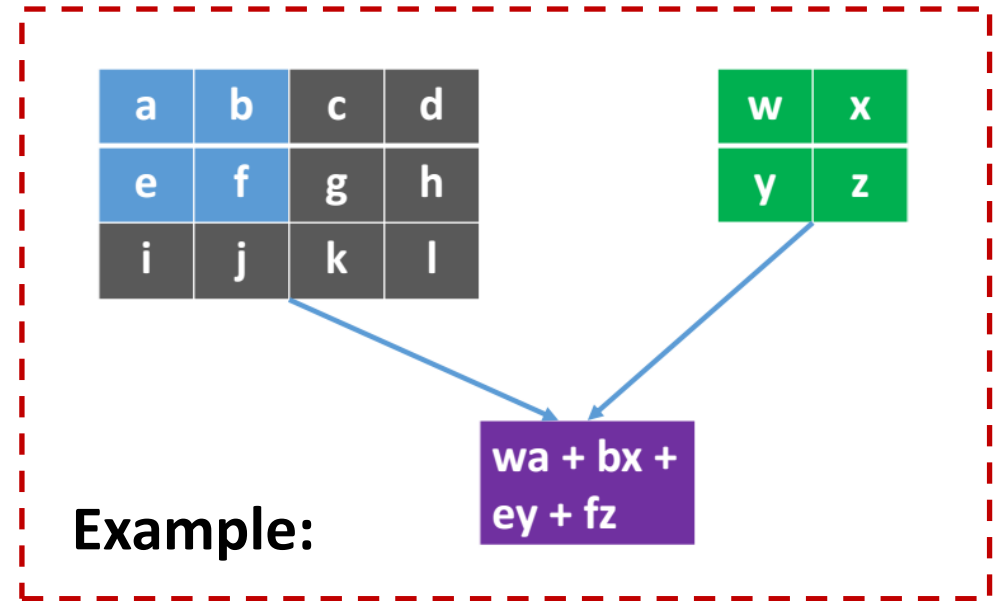
Convolutional Layer



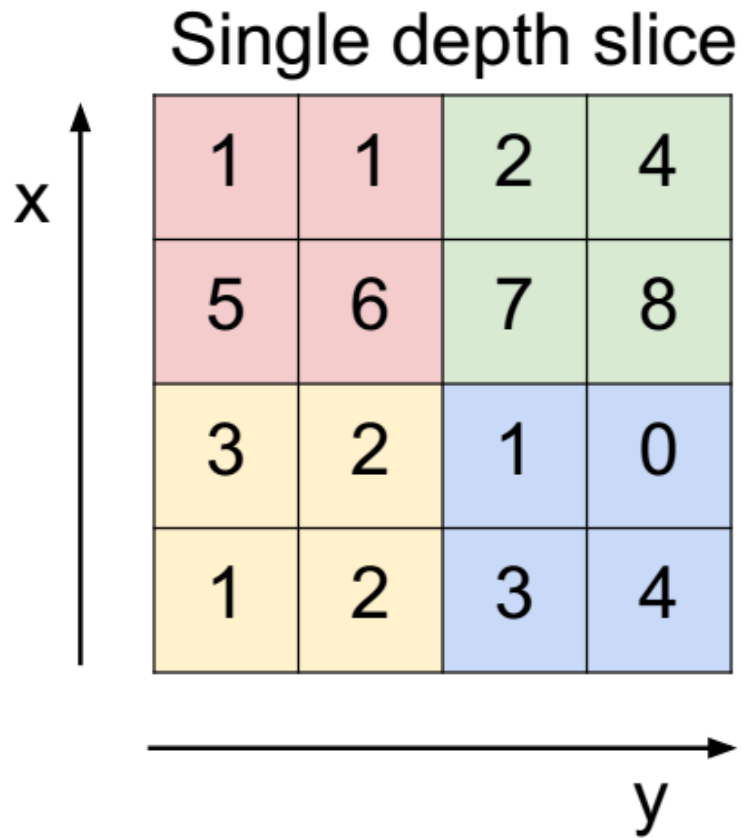
1 number:

the result of taking a dot product between the filter and a small 5x5x3 chunk of the image (i.e. $5 \cdot 5 \cdot 3 = 75$ -dimensional dot product + bias)

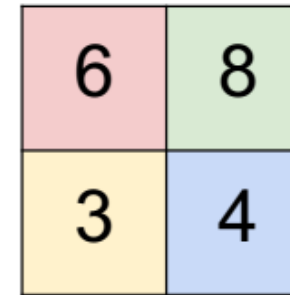
$$w^T x + b$$



Pooling Layer

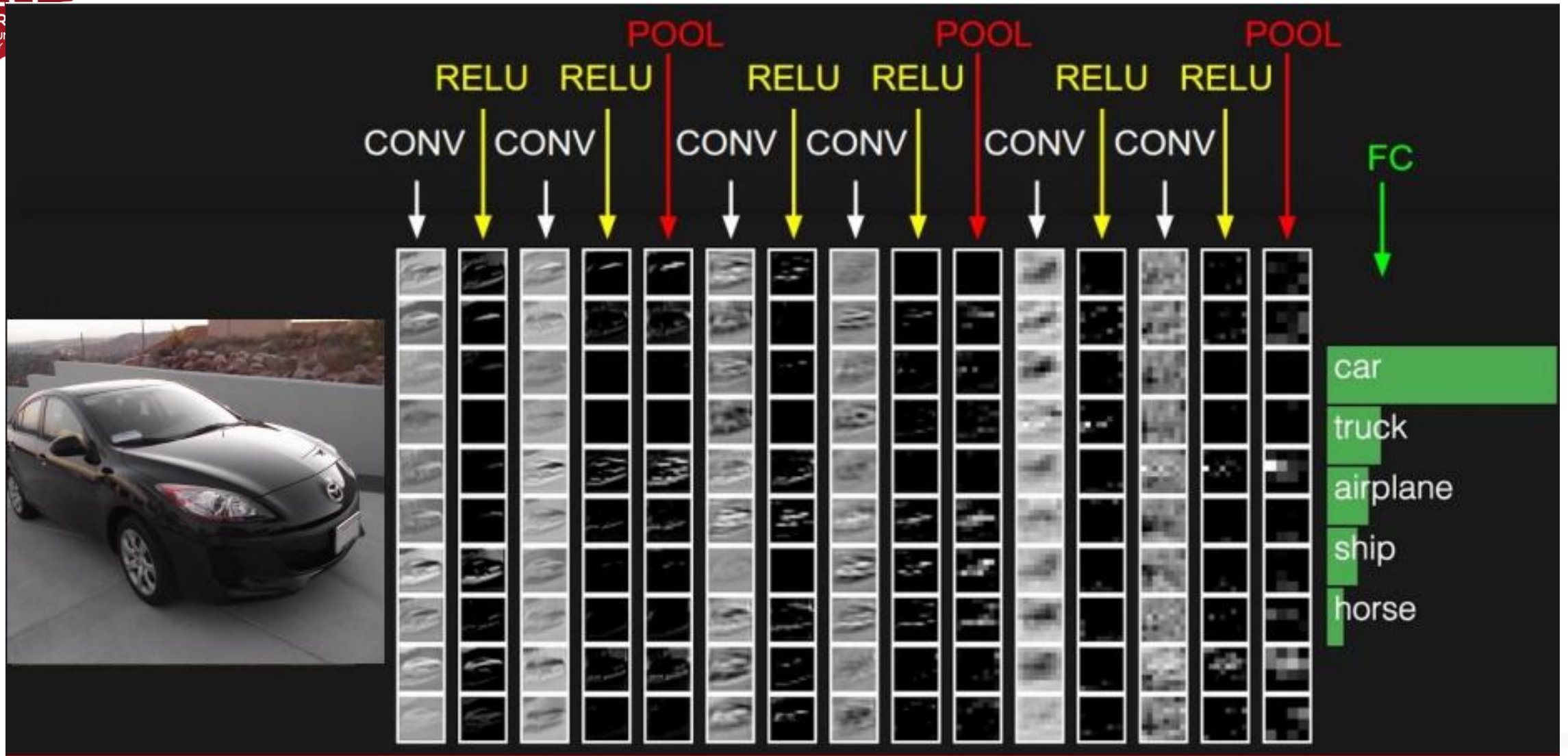


max pool with 2x2 filters
and stride 2



- Preserve the features
- Account for possible textures or distortions
- Reduce the feature size
- Prevent overfitting

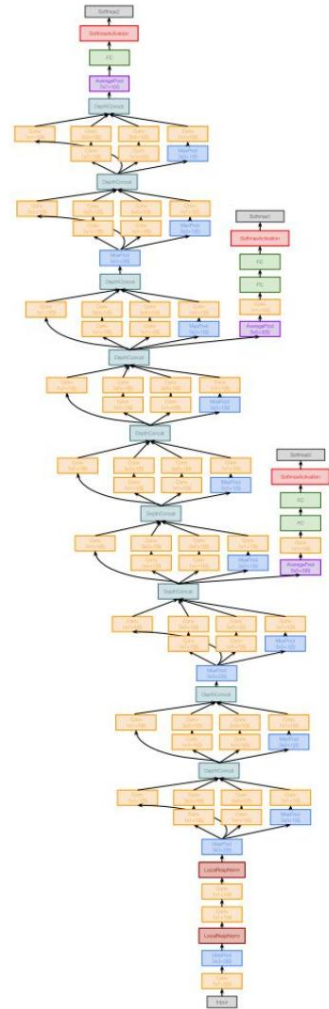
Typical CNNs Architecture:



CNNs Architecture:



VGG16 VGG19



GoogLeNet

Revolution of Depth

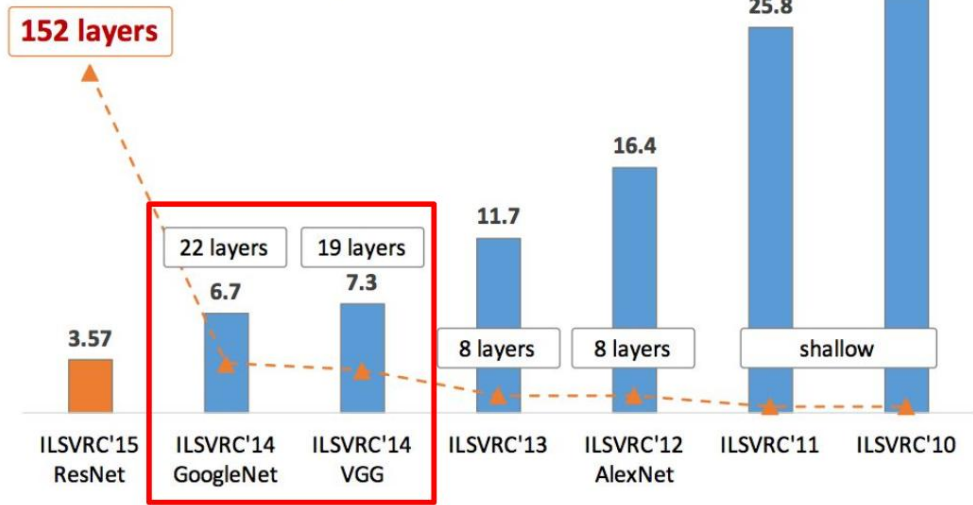


Figure copyright Kaiming He, 2016. Reproduced with permission.

02

APPLICATIONS OF DEEP LEARNING

***COMPUTER VISION**



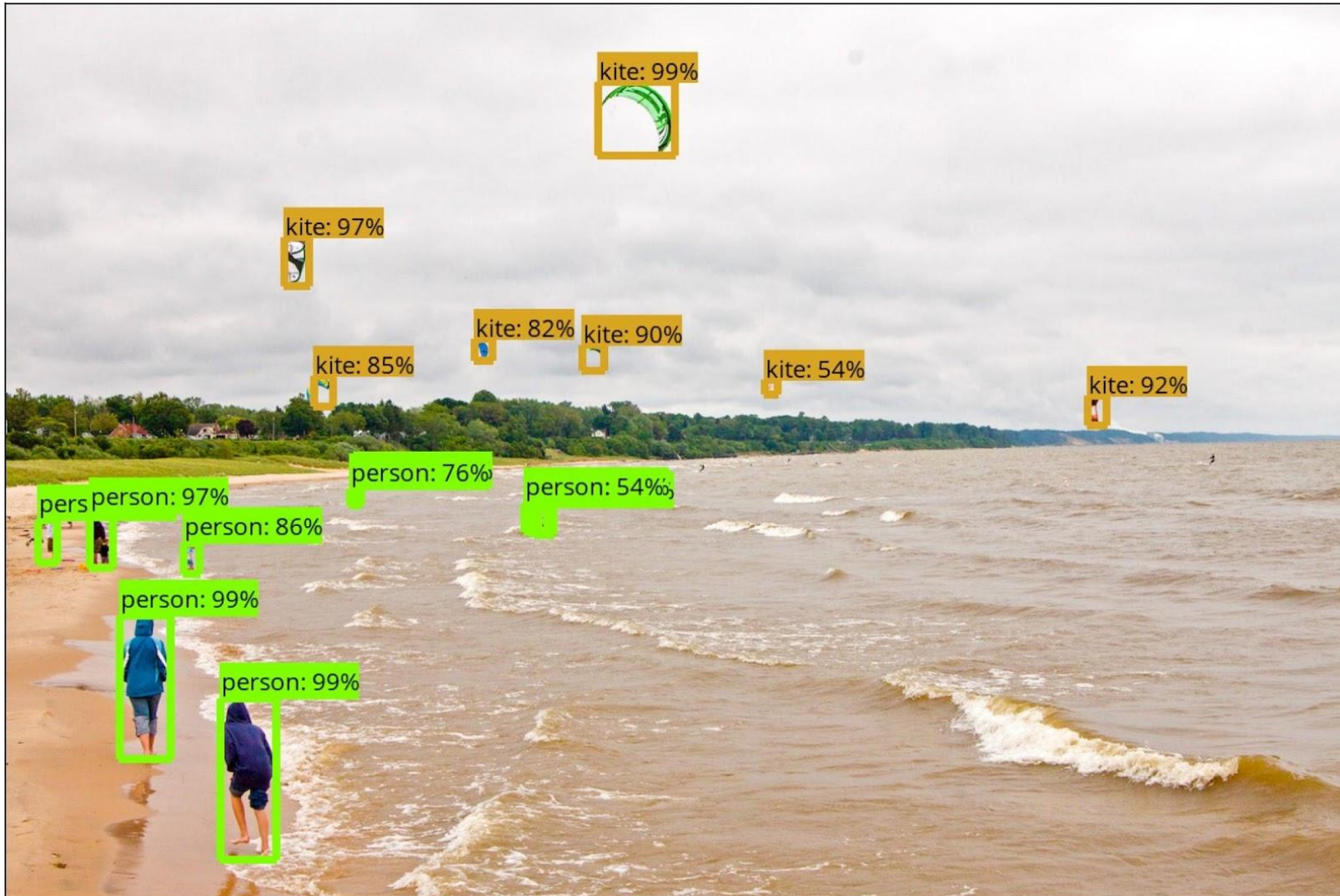
Object Classification



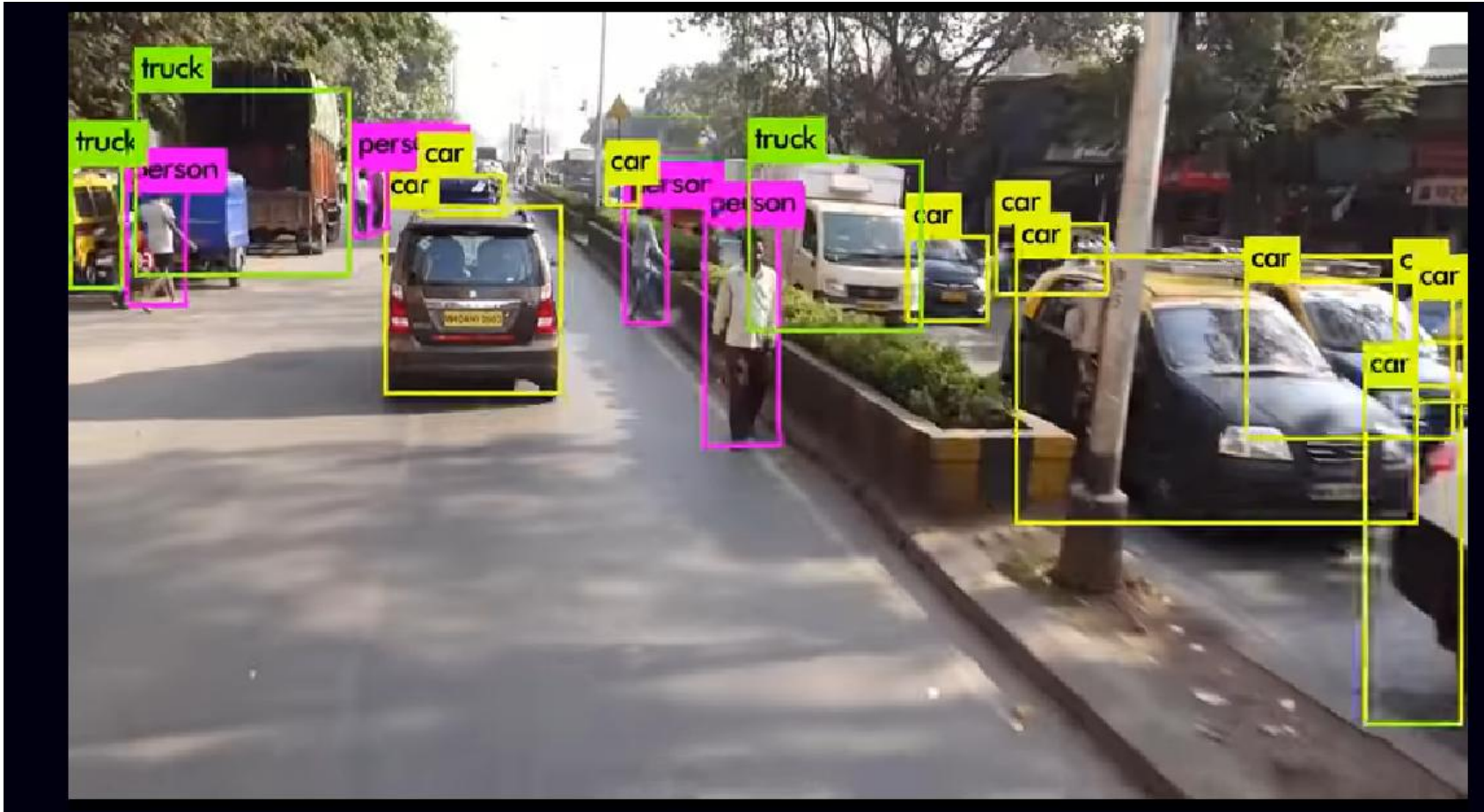
Image Retrieval



TensorFlow Object Detection API [2016]



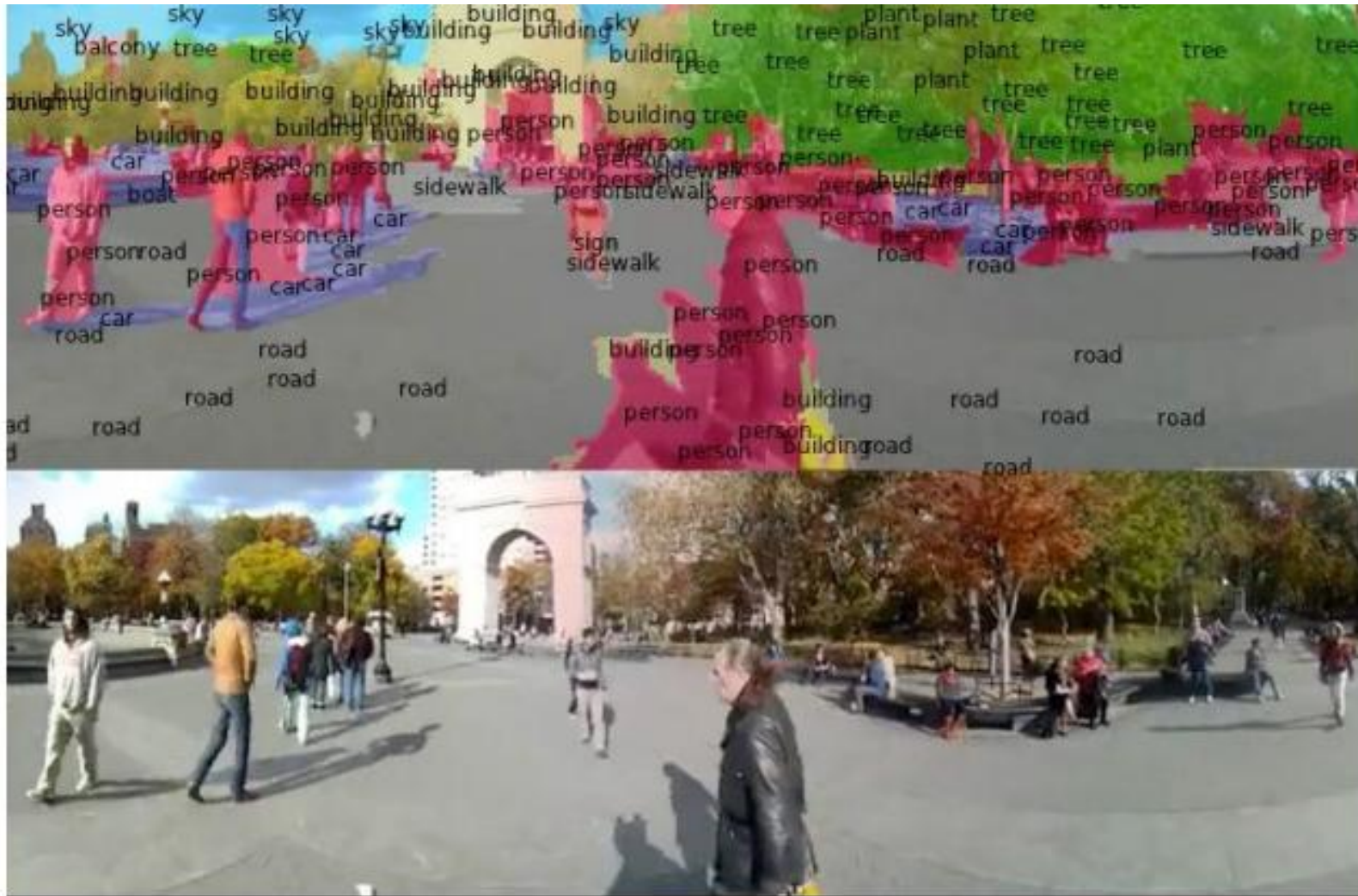
YOLOv3: Real-time Object Detection [2018]



YOLOv3-608

- mAP: 57.9
- FPS: 20

Image Segmentation



Figures copyright Clement Farabet, 2012.
Reproduced with permission.

[Farabet et al., 2012]

Mask R-CNN: Object Detection & Segmentation



- Facebook research
- 2017

Mask R-CNN: pose estimation & instance segmentation



My Research Topics:

Alcohol Brand Logos Classification

ICDAMT 2018 conference



- CNNs
- 4 Thai alcohol brands
vs Non-alcohol
- Accuracy: 89.16%

My Research Topics:

Facial Expressions Recognition

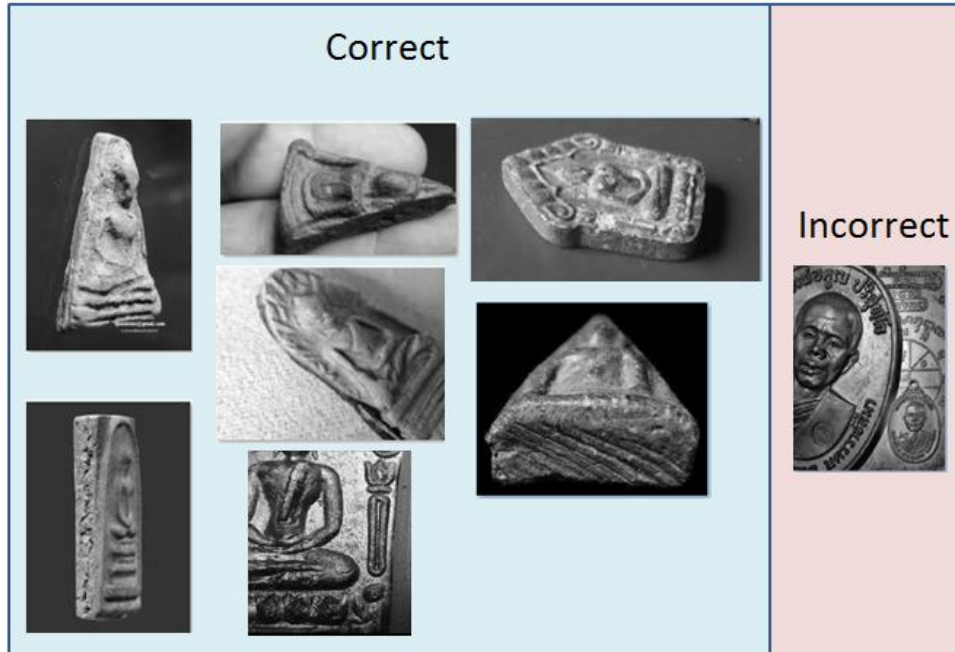
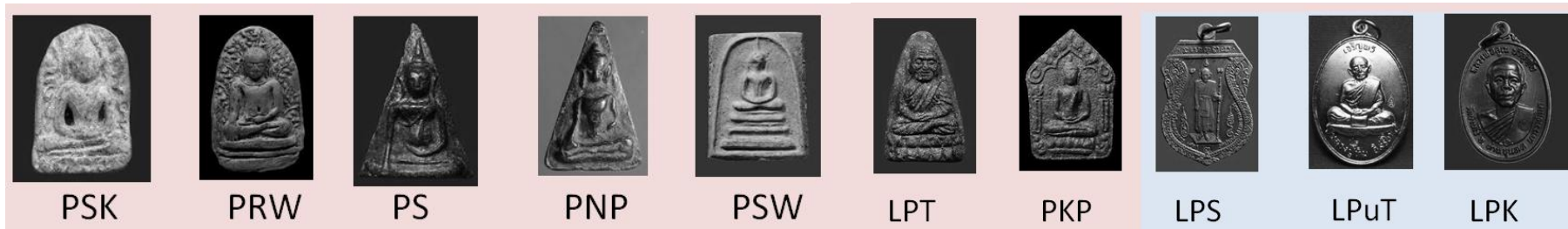


JCSSE 2018 conference

- XCEPTION
- 7 facial expressions
- Accuracy
 - Our model: **71.69%**
 - Human: **65-70%**

My Research Topics:

Buddha Amulets Classification



Submitted to KSE 2018 conf

- CNNs: 15 layers
- 34.5 M parameters
- 10 famous editions
- Accuracy: ~91%

02

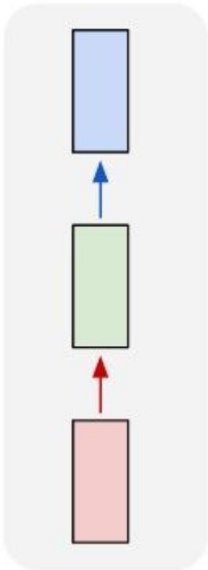
APPLICATIONS OF DEEP LEARNING

***SEQUENCE DATA, TIME SERIES**

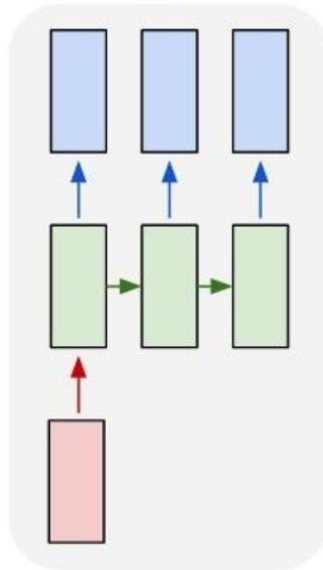


Recurrent Neural Networks (RNNs):

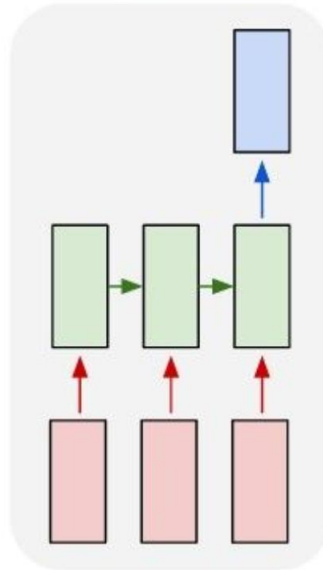
one to one



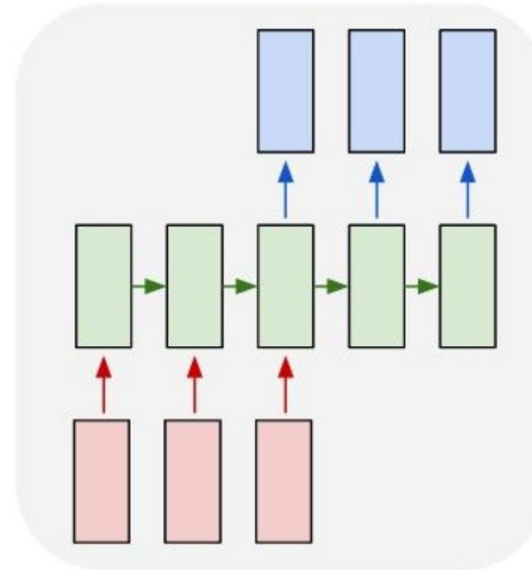
one to many



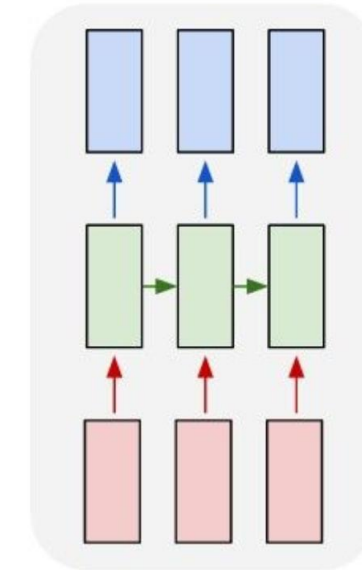
many to one



many to many



many to many



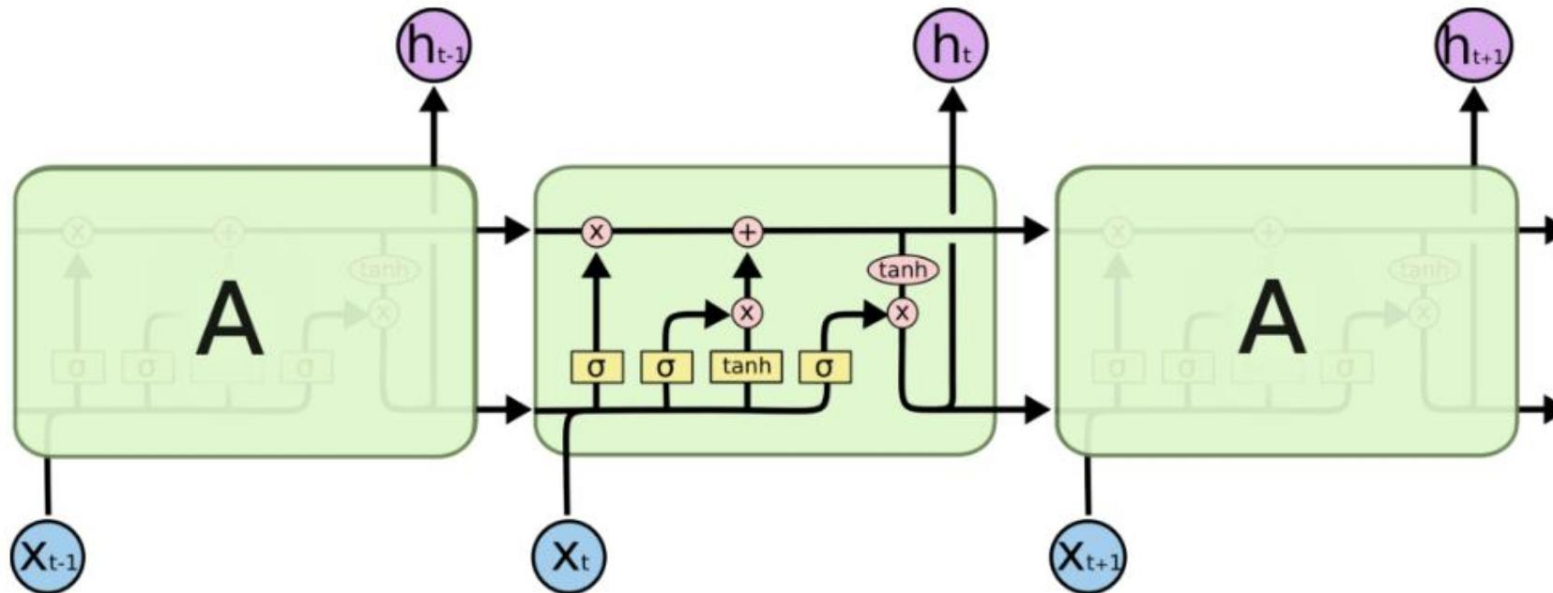
Output(s)

RNNs

Input(s)

- Learn algorithms to **map input sequences to output sequences** (flexible-sized vectors).
- The **output** vector's content are **influenced** by the **entirely of inputs**.

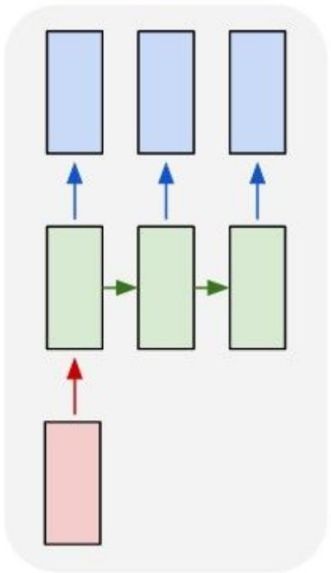
Long Short-Term Memory RNNs (LSTM)



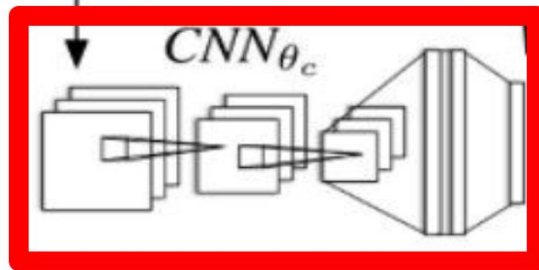
- LSTM contains **memory cells** with **read**, **write** and **reset** operations.
- The network can learn
 - **when** it should **remember data** =>Long term
 - **when** it should **throw it away (forget)** =>Short term

Image Captioning:

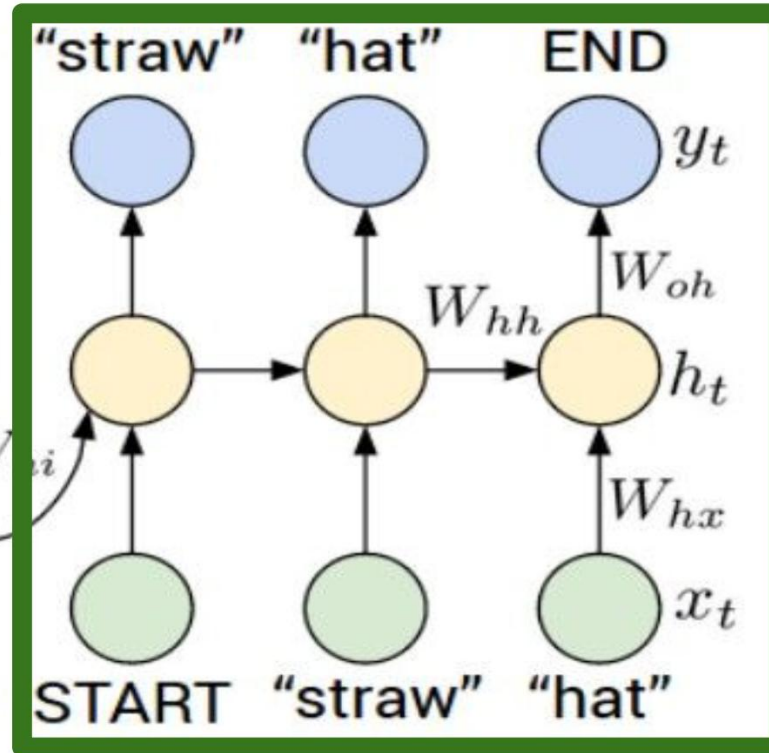
one to many



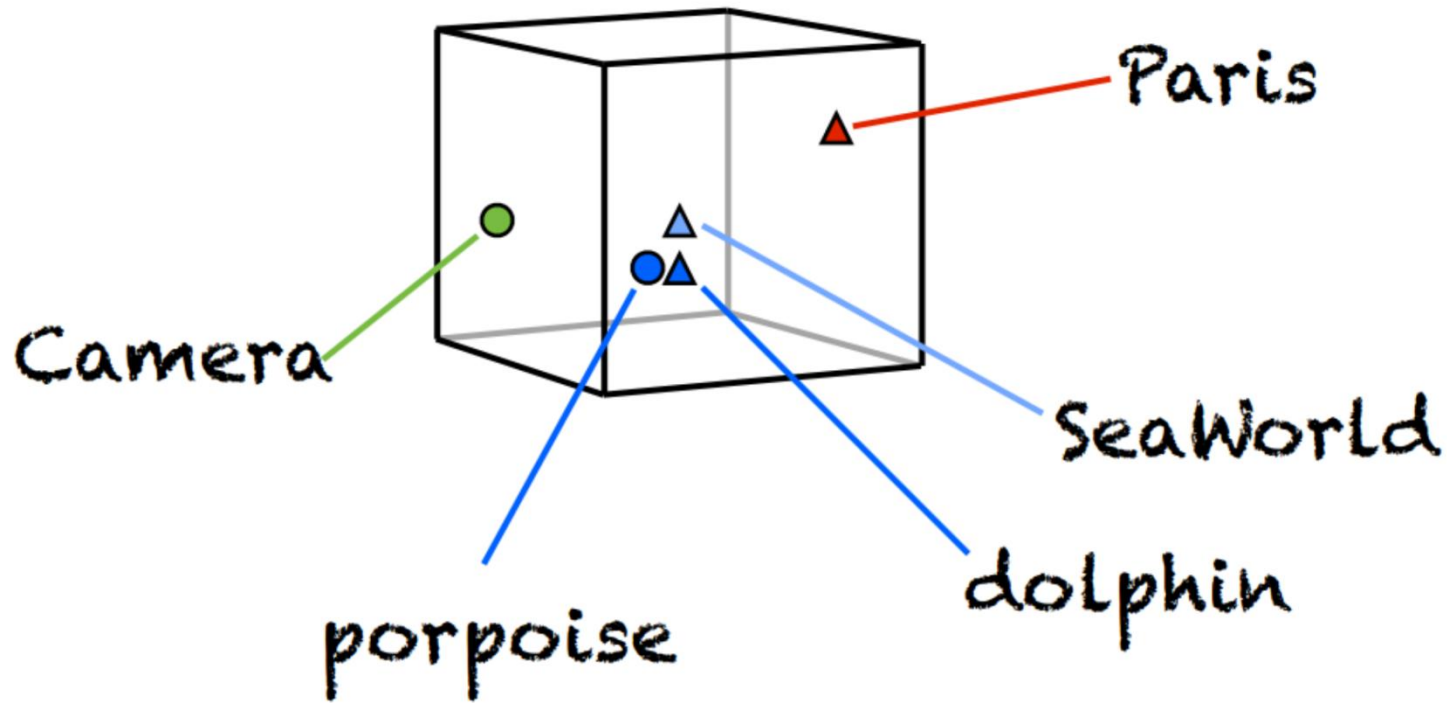
CNNs



RNNs

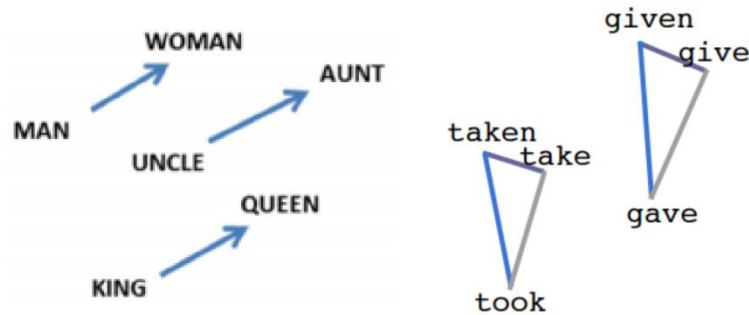
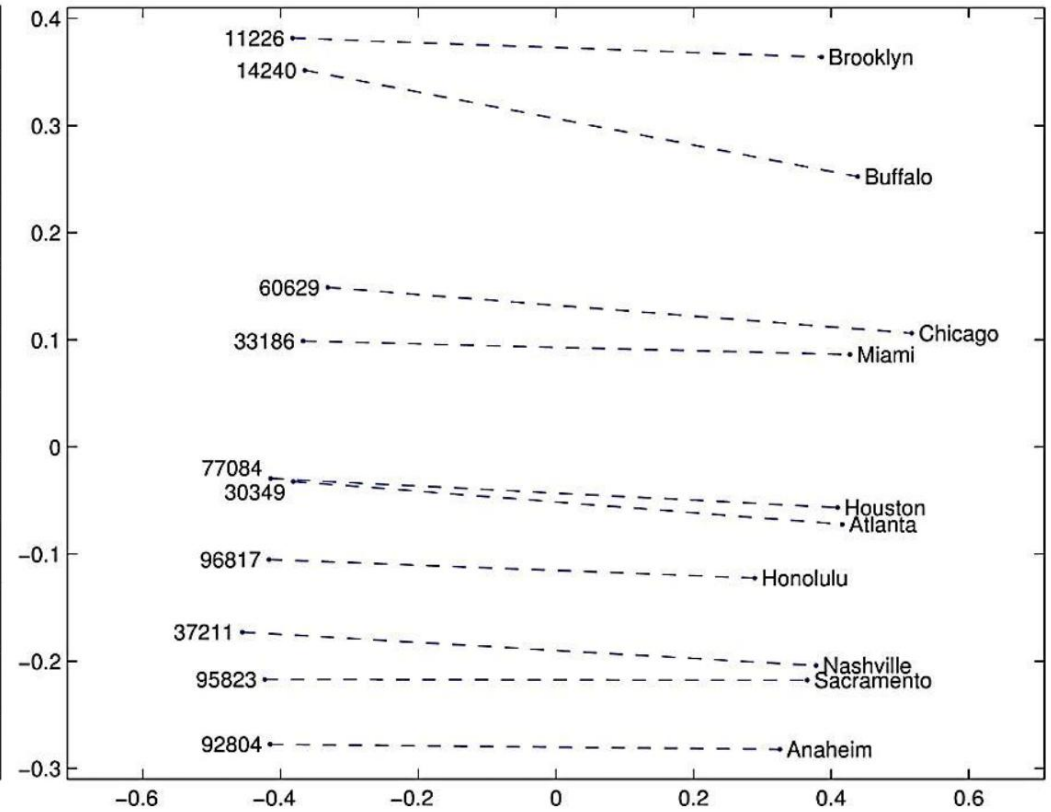
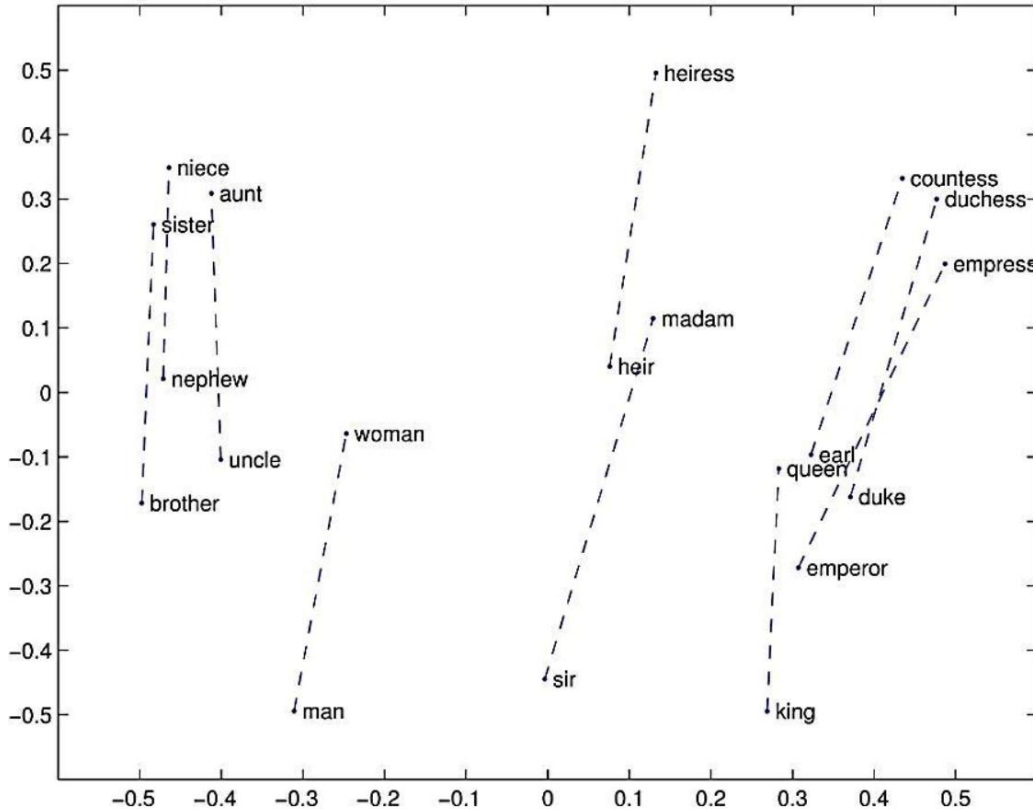


Natural Language Processing- Embeddings



- Turn **textual data (words, sentences, paragraphs)** into high dimension **vector** representation
- Can **group** them together with semantically data in **vectorspace**

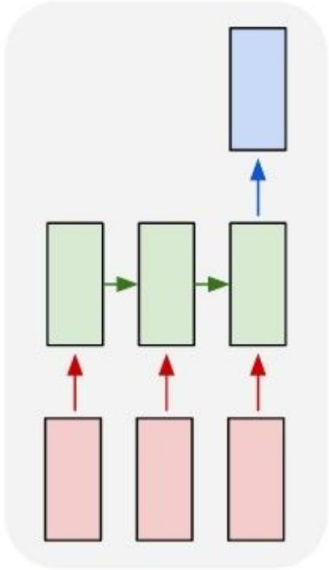
Word2Vec



$Woman - Man \approx Aunt - Uncle$
 $King - Male + Female \approx Queen$
 $Human - Animal \approx Ethics$

Sentiment Analysis:

many to one



Don't fly with @British_Airways.
They can't keep track of your
luggage.

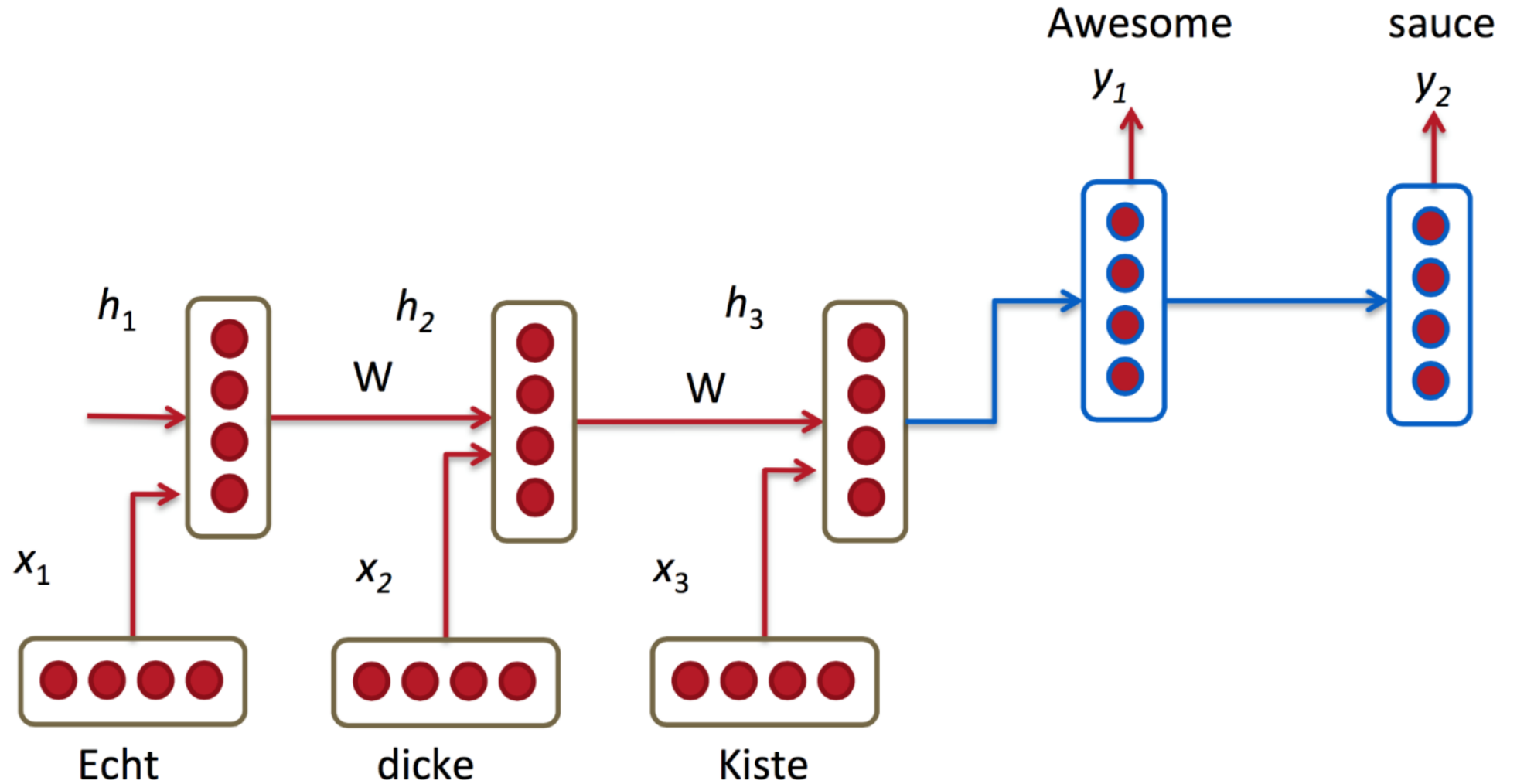
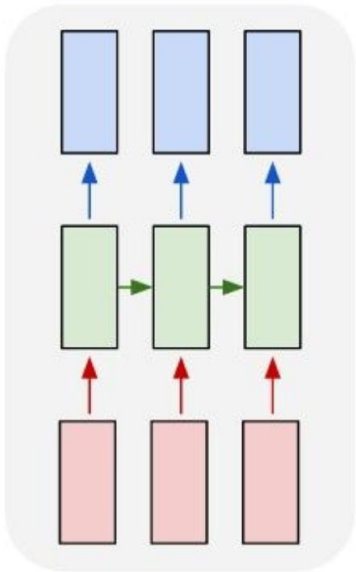


Happy Birthday to my best friend, the ♥ of
my life, my soul!!!! I love you beyond words!
[instagram.com/p/aTgfl-OS-a/](https://www.instagram.com/p/aTgfl-OS-a/)



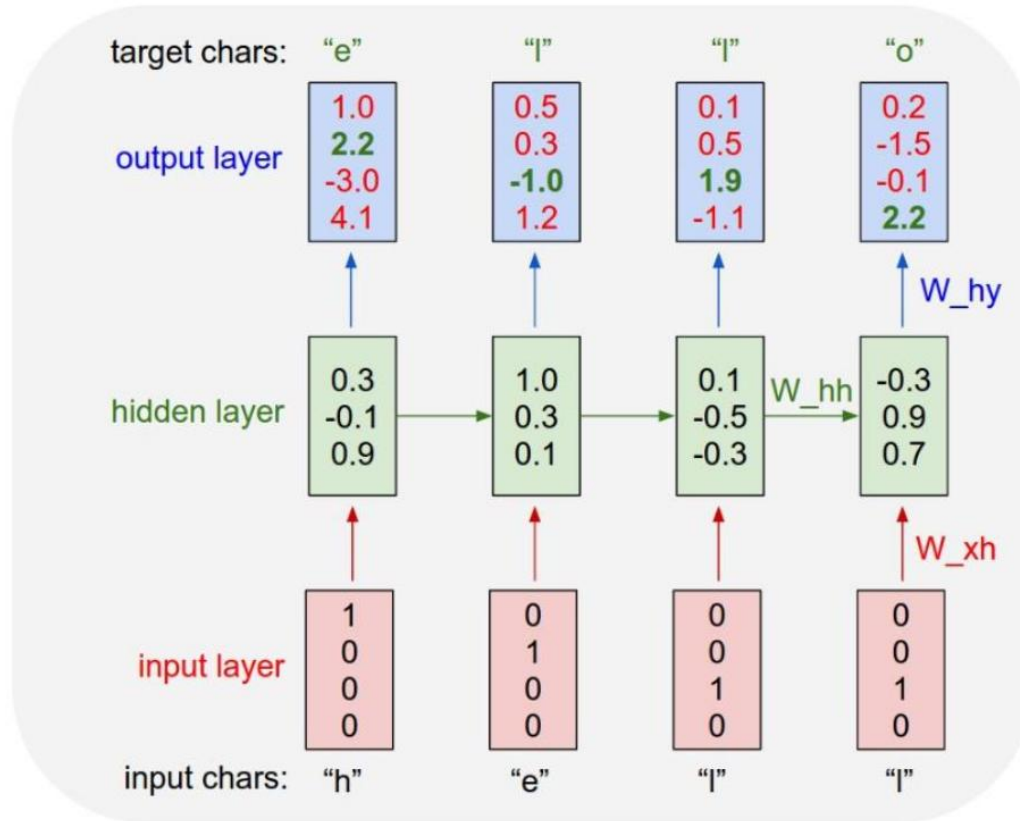
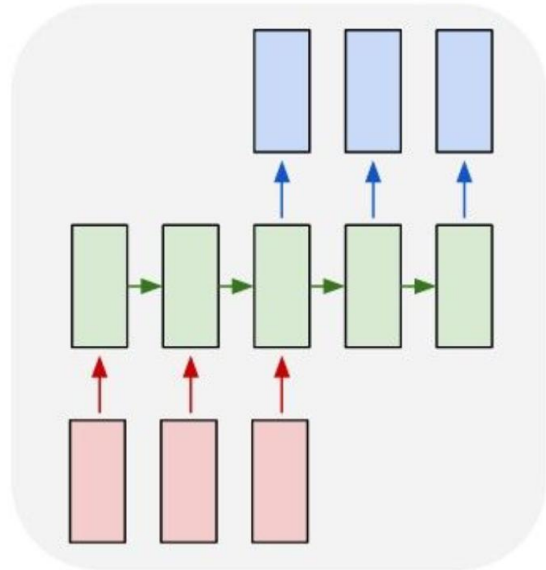
Machine Translation:

many to many



Generating Text:

many to many



Life Is About **The Weather!**
 Life Is About **The True Love Of Mr. Mom**
 Life Is About **Kids**
 Life Is About **An Eating Story**
 Life Is About **The Truth Now**

The meaning of life is
literary recognition

The meaning of life is
the tradition of the ancient human reproduction

Andrej Karpathy. "The Unreasonable Effectiveness of Recurrent Neural Networks." (2015).



Usage Requirements

- **Large** dataset with good quality (input-output mappings)
- Measurable and **describable** goals (define the cost)
- Enough **computing power** (AWS GPU Instance)
- Excels in tasks where the basic unit (pixel, word) has very little meaning in itself, but **the combination of such units has a useful meaning**

03

GET STARTED WITH DEEP LEARNING





Step 0: Pre-requisites

- **Basics of Math**

Resource : [“Math | Khan academy”](#)

Especially Calculus, Probability and Linear Algebra)

- **Basics of Python**

Resource: [“Intro to Computer Science”, edX course\)](#)

- **Basics of Statistics**

Resource: [“Intro to Stats”, Udacity course\)](#)

- **Basics of Machine Learning**

Resource: [“Intro to Machine Learning”, Udacity course](#)



Step 1: Setup Google CoLab

- **Google's free cloud service for AI developers**
 - improve your **Python** programming language coding skills
- Develop deep learning applications on the **GPU for free**
 - using popular libraries such as **Keras, TensorFlow, PyTorch, and OpenCV**
- Google CoLab Free GPU **Tutorial:**
<https://medium.com/deep-learning-turkey/google-colab-free-gpu-tutorial-e113627b9f5d>



Step 2: Basic Deep Learning

- **CS231n: Convolutional Neural Networks for Visual Recognition**

[<http://cs231n.stanford.edu/2017/syllabus.html>]

- Introduction to Neural Networks
- Loss Functions and Optimization
- CNNs, RNNs, LSTM

- **Popular Libraries:**

- **TensorFlow (using Keras => Recommended)**
- Caffe
- Torch



Step 3: Advanced Deep Learning

- **Deep Learning for Computer Vision**

Primer : [“DL for Computer Vision”](#) blog.

Project : [“Facial Keypoint Detection”](#) Tutorial

Required libraries : [Nolearn](#)

Associated Course : [“CS231n: Convolutional Neural Networks for Visual Recognition”](#)

- **Deep Learning for Natural Language**

ProcessingPrimer : [“Deep Learning, NLP, and Representations”](#) blog.

Project : “Deep Learning for Chatbots”: [“Part 1”](#), [“Part 2”](#)

Required library : [Tensorflow](#)

Associated Course : [“CS224d: Deep Learning for Natural Language Processing”](#)



Step 4: Setup your own Machine (optional)

- A good enough **GPU** (4+ GB), preferably **Nvidia**
- An **OK CPU** (e.g. Intel Core i3 is ok, Intel Pentium may not be OK)
- **16 GB of RAM** or depending upon the dataset.
- **Power supply** (+100 to 120 w)



Which GPU(s) to Get?

Best GPU overall (by a small margin): Titan Xp

Cost efficient but expensive: GTX 1080 Ti, GTX 1070, GTX 1080

Cost efficient and cheap: GTX 1060 (6GB)

I work with data sets > 250GB: GTX Titan X (Maxwell), NVIDIA Titan X Pascal, or NVIDIA Titan Xp

I have little money: GTX 1060 (6GB)

I have almost no money: GTX 1050 Ti (4GB)

I do Kaggle: GTX 1060 (6GB) for any “normal” competition, or GTX 1080 Ti for “deep learning competitions”

I am a competitive computer vision researcher: NVIDIA Titan Xp; do not upgrade from existing Titan X (Pascal or Maxwell)

I am a researcher: GTX 1080 Ti. In some cases, like natural language processing, a GTX 1070 or GTX 1080 might also be a solid choice — check the memory requirements of your current models

I want to build a GPU cluster: This is really complicated, you can get some ideas [here](#)

I started deep learning and I am serious about it: Start with a GTX 1060 (6GB). Depending of what area you choose next (startup, Kaggle, research, applied deep learning) sell your GTX 1060 and buy something more appropriate

I want to try deep learning, but I am not serious about it: GTX 1050 Ti (4 or 2GB)



Q & A

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References

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- [3] <https://www.youtube.com/watch?v=wMUmPumXtpw>
- [4] <https://www.slideshare.net/LuMa921/deep-learning-a-visual-introduction>
- [5] <https://www.datacamp.com/courses/deep-learning-in-python>
- [6] http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture5.pdf
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- [8] https://github.com/karolmajek/Mask_RCNN
- [9] <https://www.youtube.com/watch?v=KYNDzlcQMWA>
- [10] http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf
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