

Workshop AI: CNN, NLP, and deployment





Nele Custers

nele.custers@pxl.be

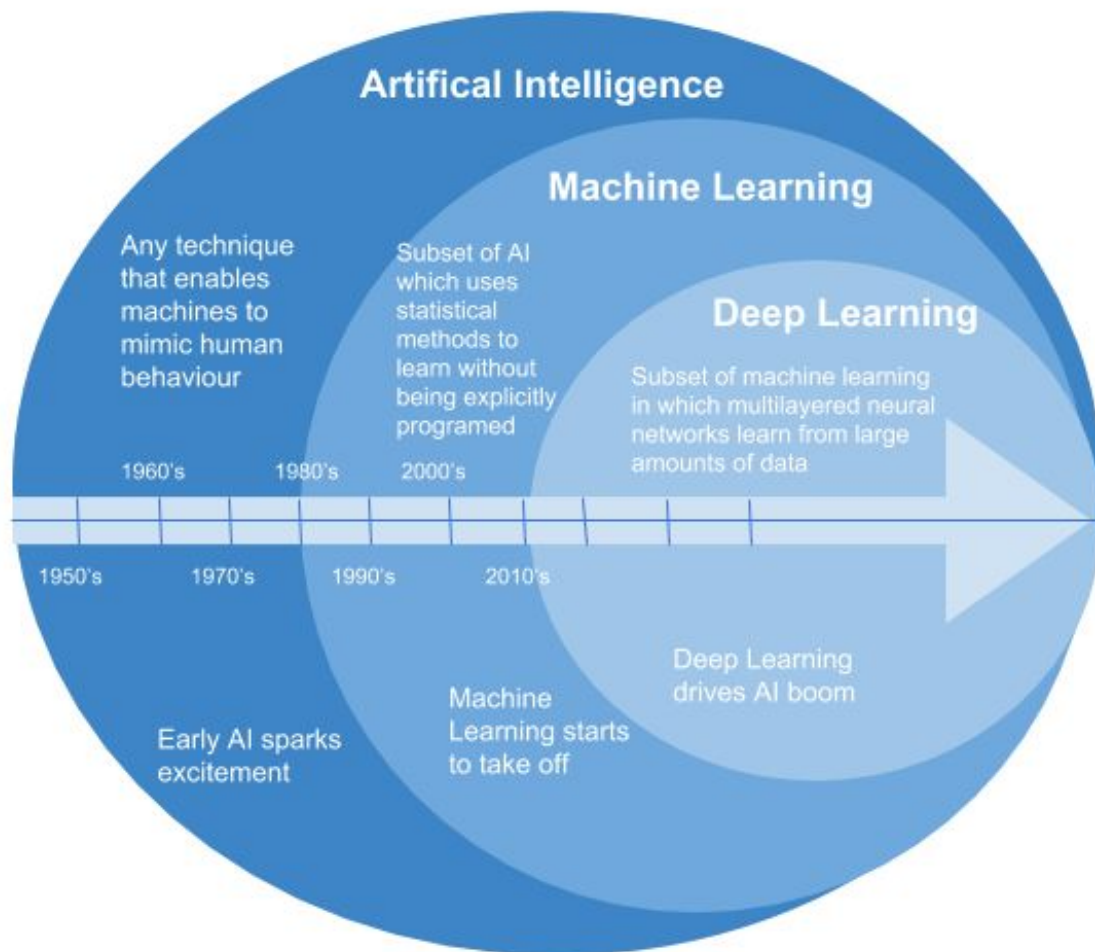
Teaching:

- Programming in Python, Java, and Neural Networks.

Educational Background:

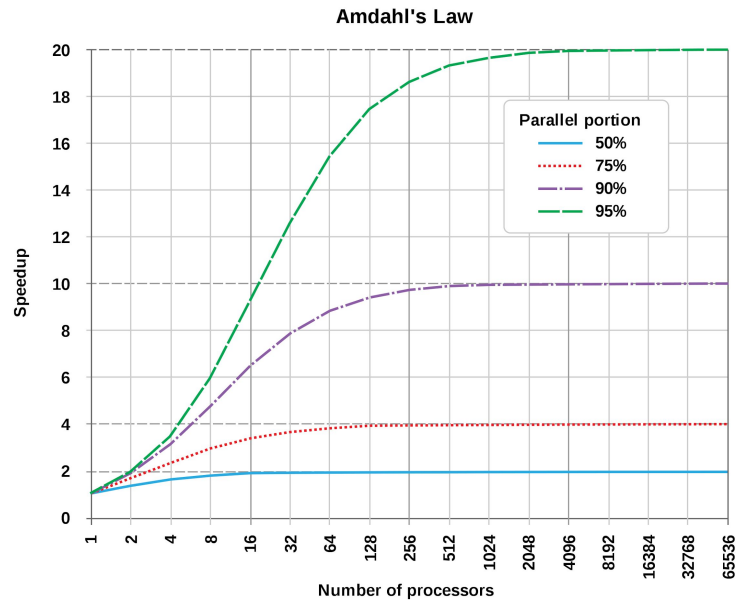
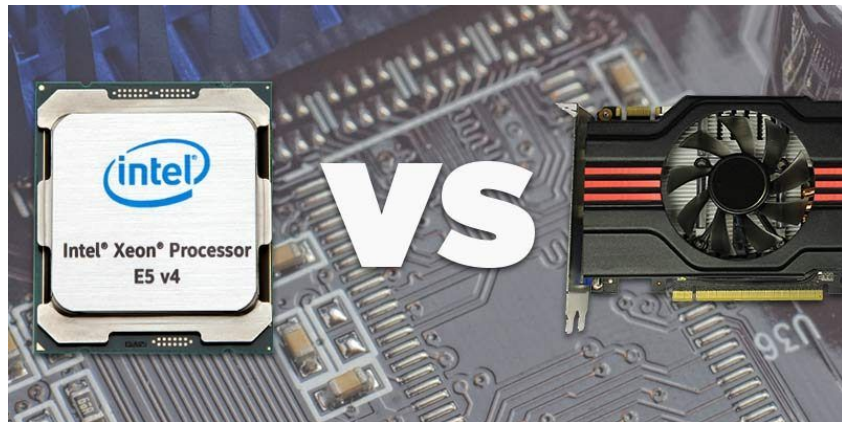
- Degree in Informatics
- Worked as a Java Consultant





Base conditions for AI

GPU



Base conditions for AI

Storage
Big Data

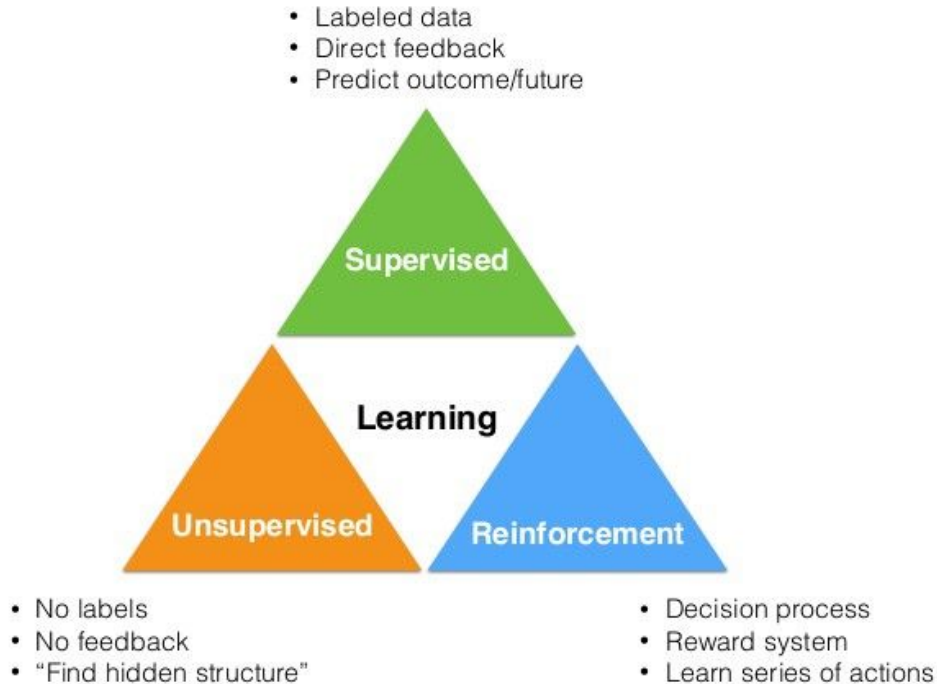


Base conditions for AI

Base algorithms in the
cloud



Machine learning algorithms



ML problems



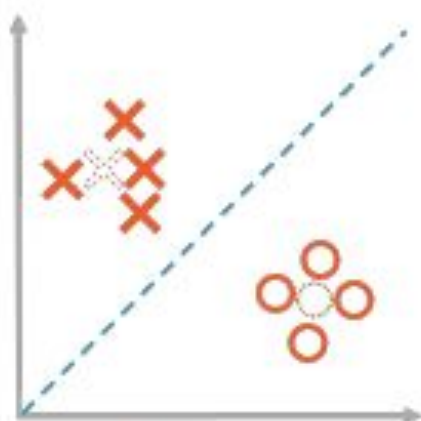
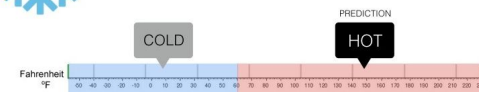
Regression

What is the temperature going to be tomorrow?

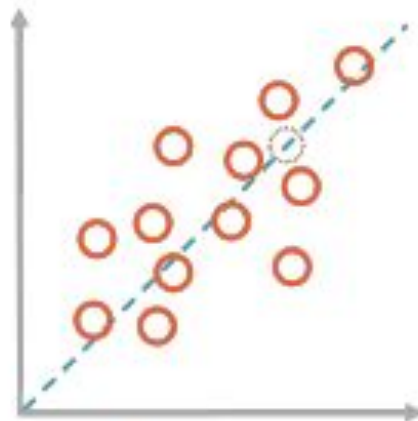


Classification

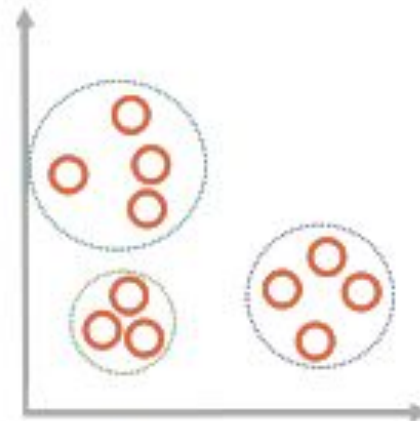
Will it be Cold or Hot tomorrow?



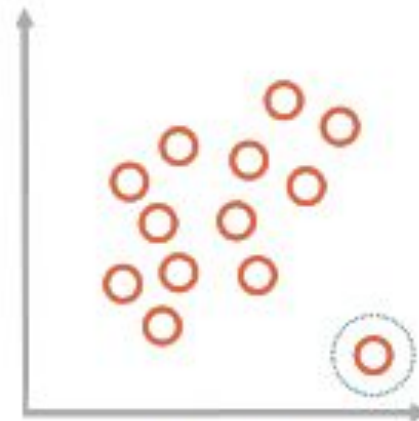
Classification



Regression

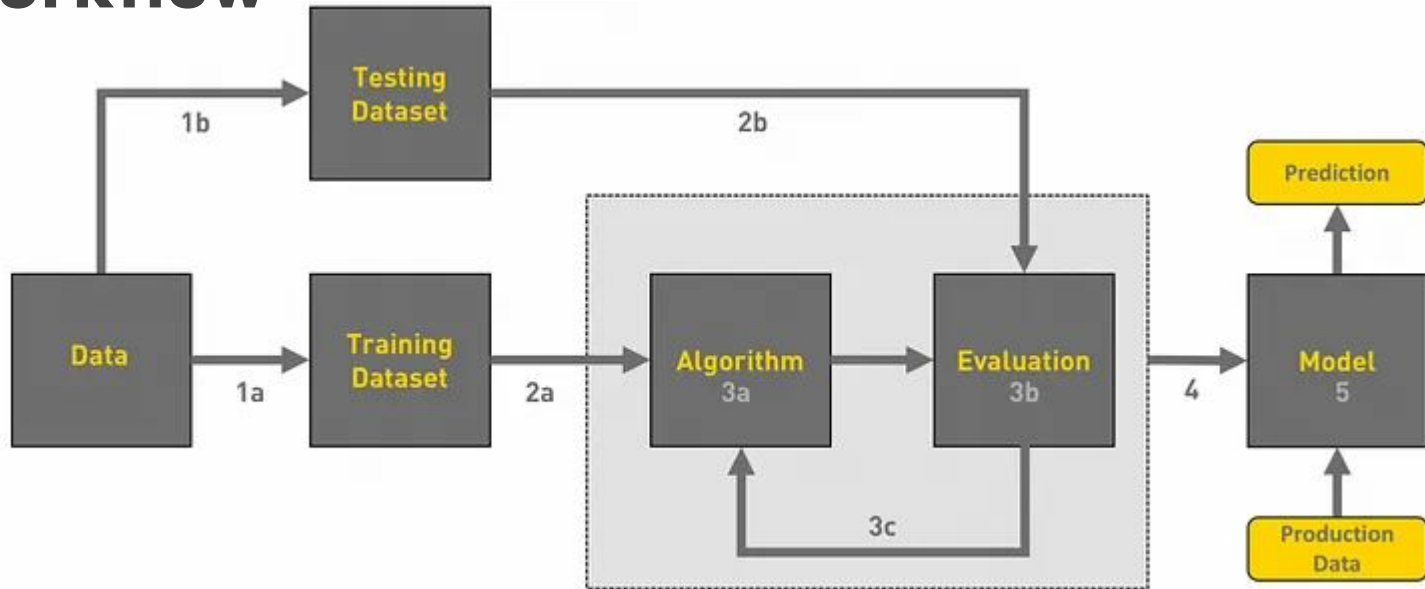


Clustering



Anomaly
detection

ML workflow



Training data

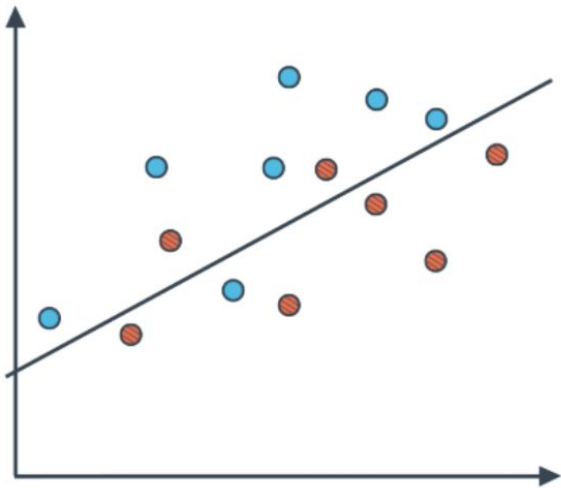


Year	Breakthroughs in AI	Datasets (First Available)	Algorithms (First Proposed)
1994	Human-level spontaneous speech recognition	Spoken Wall Street Journal articles and other texts (1991)	Hidden Markov Model (1984)
1997	IBM Deep Blue defeated Garry Kasparov	700,000 Grandmaster chess games, aka "The Extended Book" (1991)	Negascout planning algorithm (1983)
2005	Google's Arabic- and Chinese-to-English translation	1.8 trillion tokens from Google Web and News pages (collected in 2005)	Statistical machine translation algorithm (1988)
2011	IBM Watson became the world Jeopardy! champion	8.6 million documents from Wikipedia, Wiktionary, Wikiquote, and Project Gutenberg (updated in 2010)	Mixture-of-Experts algorithm (1991)
2014	Google's GoogLeNet object classification at near-human performance	ImageNet corpus of 1.5 million labeled images and 1,000 object categories (2010)	Convolution neural network algorithm (1989)
2015	Google's Deepmind achieved human parity in playing 29 Atari games by learning general control from video	Arcade Learning Environment dataset of over 50 Atari games (2013)	Q-learning algorithm (1992)
Average No. of Years to Breakthrough:		3 years	18 years



“Goodness of a model” - Confusion Matrix

Confusion Matrix Summary



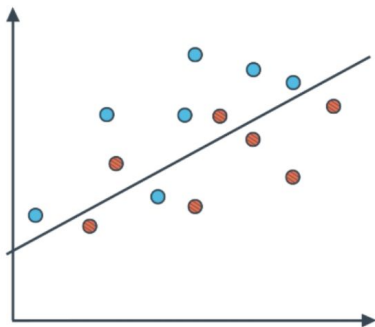
	Guessed Positive	Guessed Negative
Positive	True Positives	False Negatives
Negative	False Positives	True Negatives

Blue Points — labelled positive; Red Points — labelled negative



“Goodness of a model” - Confusion Matrix

Confusion Matrix Summary



Blue Points — labelled positive; Red Points — labelled negative

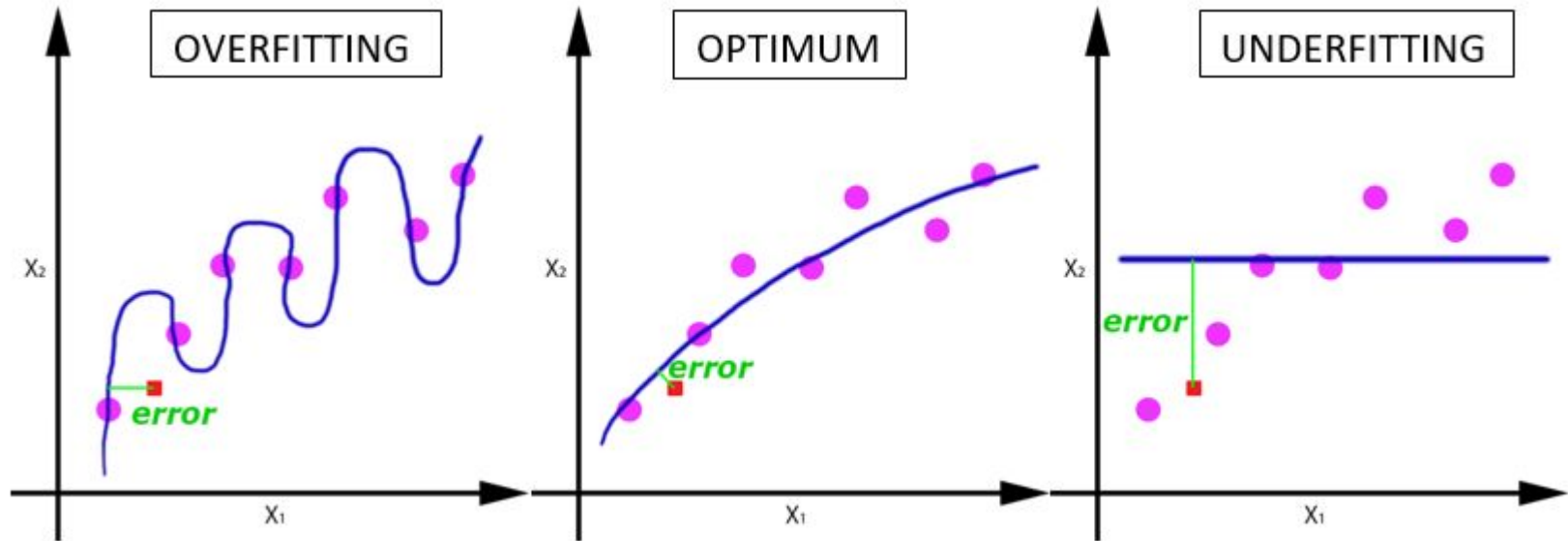
	Guessed Positive	Guessed Negative
Positive	True Positives	False Negatives
Negative	False Positives	True Negatives

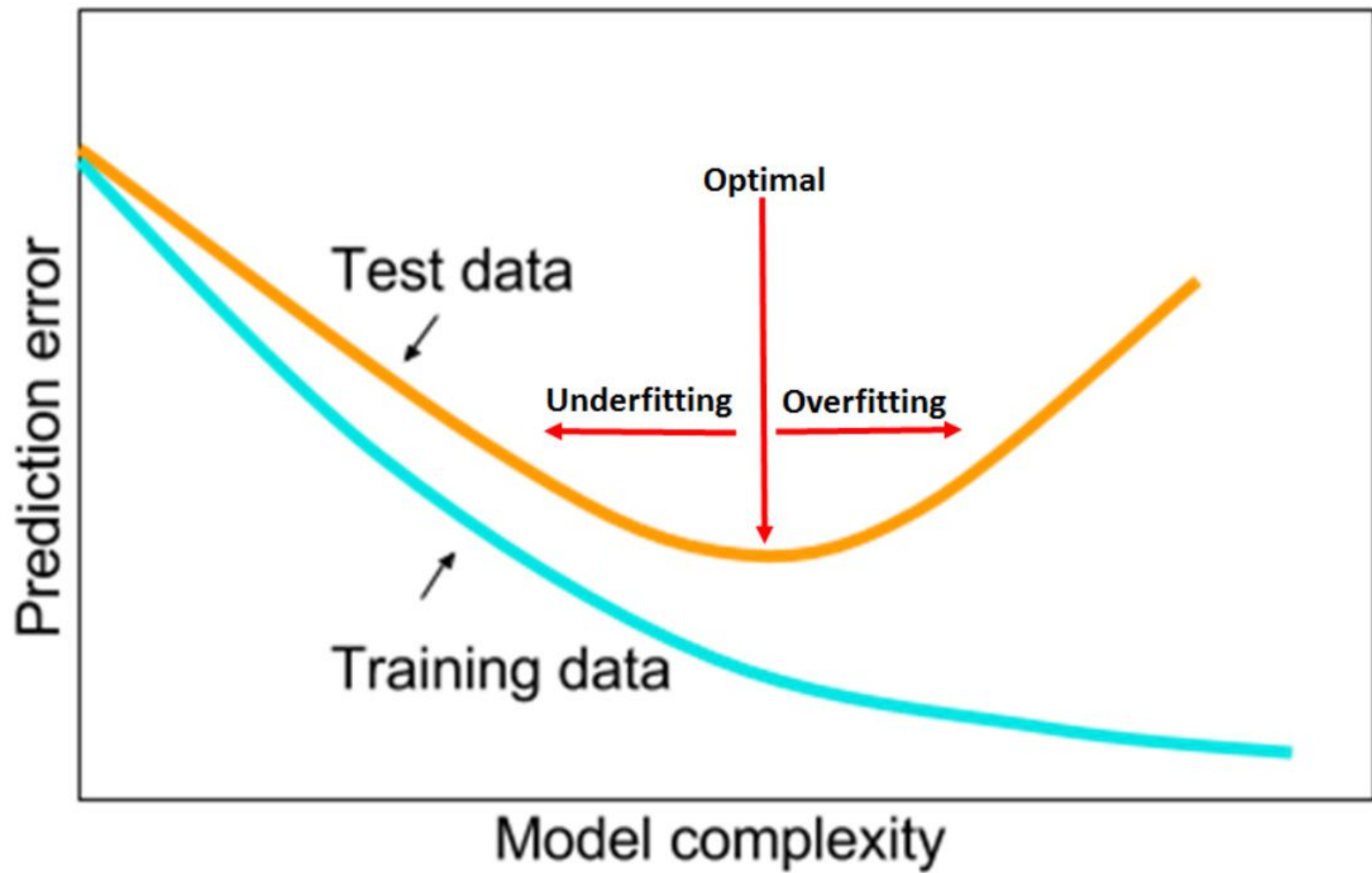
$$\text{accuracy} = (\text{True Positives} + \text{True Negatives}) / \text{Total Points}$$

$$\text{precision} = \text{True Positives} / (\text{True Positives} + \text{False Positives})$$

$$\text{recall} = \text{True Positives} / (\text{True Positives} + \text{False Negatives})$$

Bias and variance





Bias-Variance Dilemma and No. of Features

high bias

pays little attention to data
oversimplified

high error on training set
(low r^2 , large SSE)

high variance

pays too much attention to data
(does not generalize well)

overfits

much higher error on test set
than on training set

Bias all around...



Confirmation bias

- Confirmation bias is a phenomenon wherein data scientists or analysts tend to lean towards data that is in alignment with their beliefs, views, and opinions.

Availability heuristic

- Availability heuristic refers to the way in which data scientists make inferences only based on readily available data or recent information, and hold the belief that immediate data is relevant data.

Simpson's paradox

- In analytics, a pattern when analyzed in individual groups showcases the dominance of a particular trend. However, when these patterns are viewed cumulatively, the results are completely opposite. This is known as Simpson's paradox.

Non-normality

- In non-normality, analysts who are sifting through aggregated data sometimes assume the existence of a bell curve, when in actuality, the data has certain errors and faults that is nowhere near the curve of the bell.

Overfitting and underfitting

- Overfitting refers to an overly complex model in which a large number of parameters are assessed and added to the data model.
- Underfitting is when data analysts try to fit nonlinear data into a linear data model.

Coded bias (trailer):
<https://www.youtube.com/watch?v=jZI55PsfZJQ>

Terminology

Epoch :

An Epoch represent one iteration over the entire dataset.



Batch :

We cannot pass the entire dataset into the Neural Network at once. So, we divide the dataset into number of batches.



Iteration :

If we have 1000 images as Data and a batch size of 20, then an Epoch should run $1000/20 = 50$ iteration.



The typically mini-batch sizes are 64, 128, 256 or 512.

And, in the end, make sure the minibatch fits in the CPU/GPU.

Datasets

<https://www.kaggle.com/datasets/grassknoted/asl-alphabet>

<https://www.kaggle.com/competitions/asl-signs>

http://facundoq.github.io/guides/sign_language_datasets/slr

<https://www.kaggle.com/datasets/datamunge/sign-language-mnist>

<https://www.youtube.com/watch?v=a99p> +

<https://github.com/kinivi/hand-gesture-recognition-mediapipe>

Computer vision and NLP

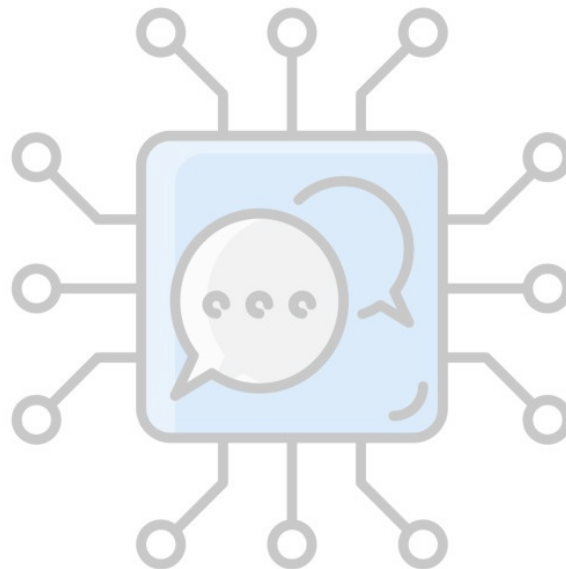
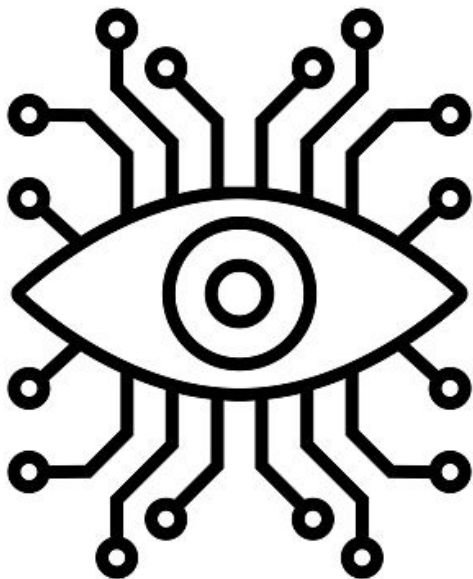
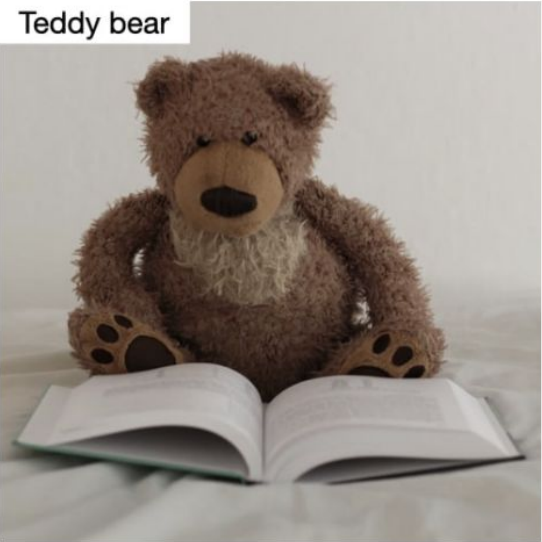
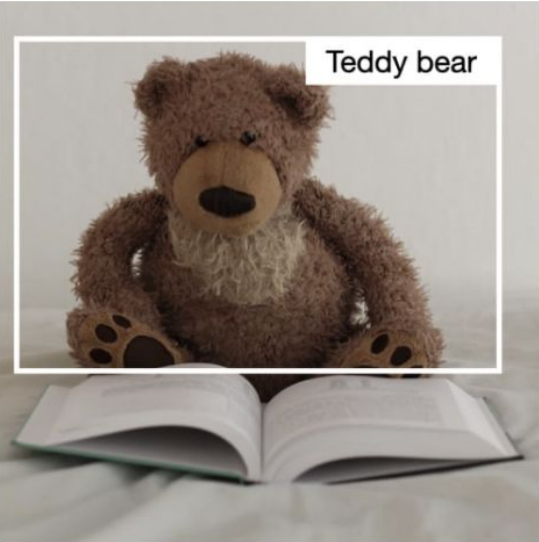
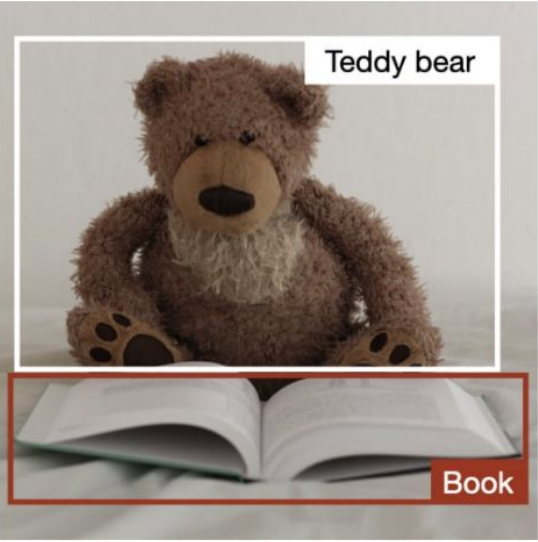
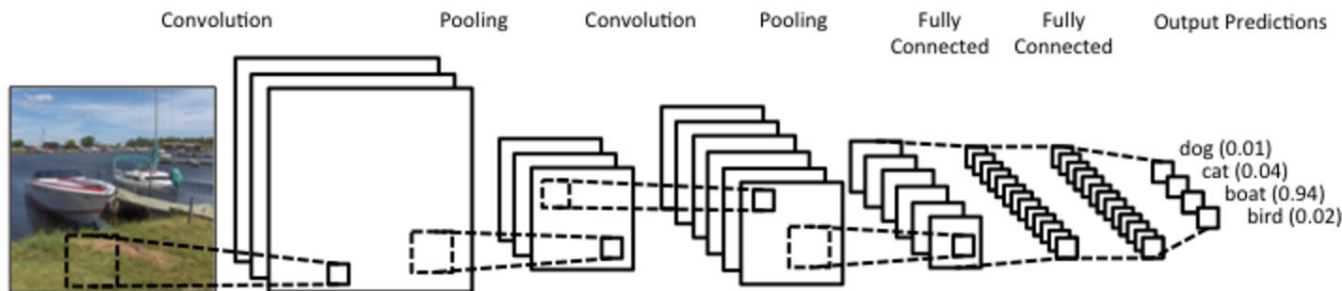


Image classification	Classification w. localization	Detection
<p data-bbox="102 123 258 153">Teddy bear</p> 	<p data-bbox="1020 161 1176 192">Teddy bear</p> 	<p data-bbox="1628 161 1785 192">Teddy bear</p>  <p data-bbox="1746 587 1823 618">Book</p>
<ul data-bbox="85 790 600 882" style="list-style-type: none"> • Classifies a picture • Predicts probability of object 	<ul data-bbox="689 764 1217 908" style="list-style-type: none"> • Detects an object in a picture • Predicts probability of object and where it is located 	<ul data-bbox="1296 707 1823 965" style="list-style-type: none"> • Detects up to several objects in a picture • Predicts probabilities of objects and where they are located
Traditional CNN	Simplified YOLO, R-CNN	YOLO, R-CNN

Convolutional Neural Network

Convolutional networks for images, speech, and time series

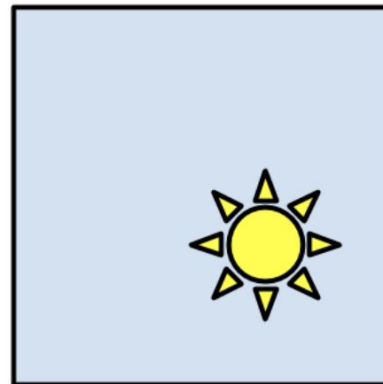
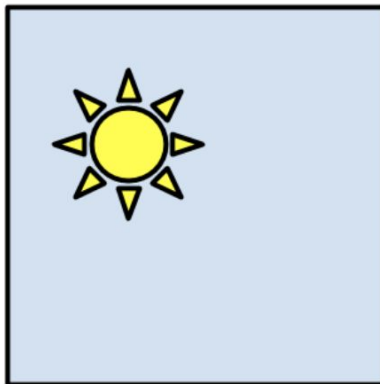
Yann LeCun & Yoshua Bengio (1995)



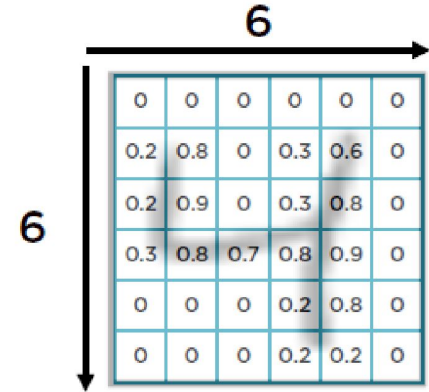
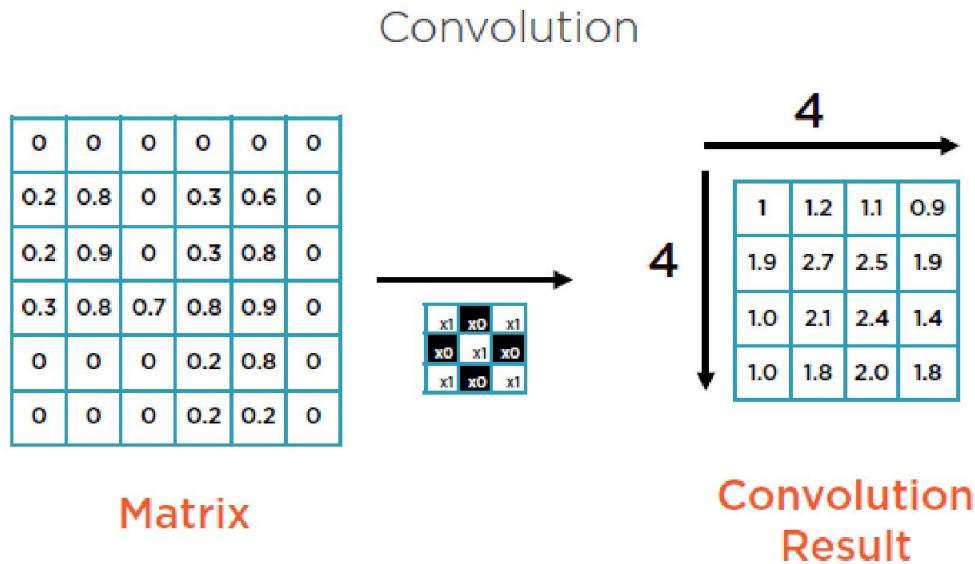
Motivation CNNs

Reason 1: Images are big

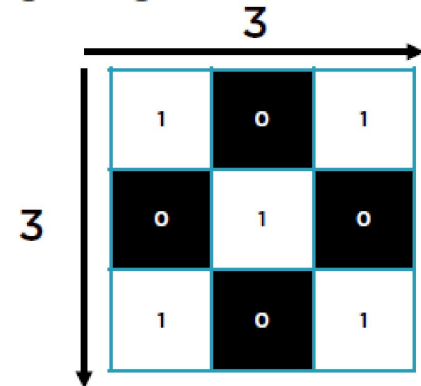
Reason 2: Positions can change



What is a convolution?




= 36 pixels



Kernel

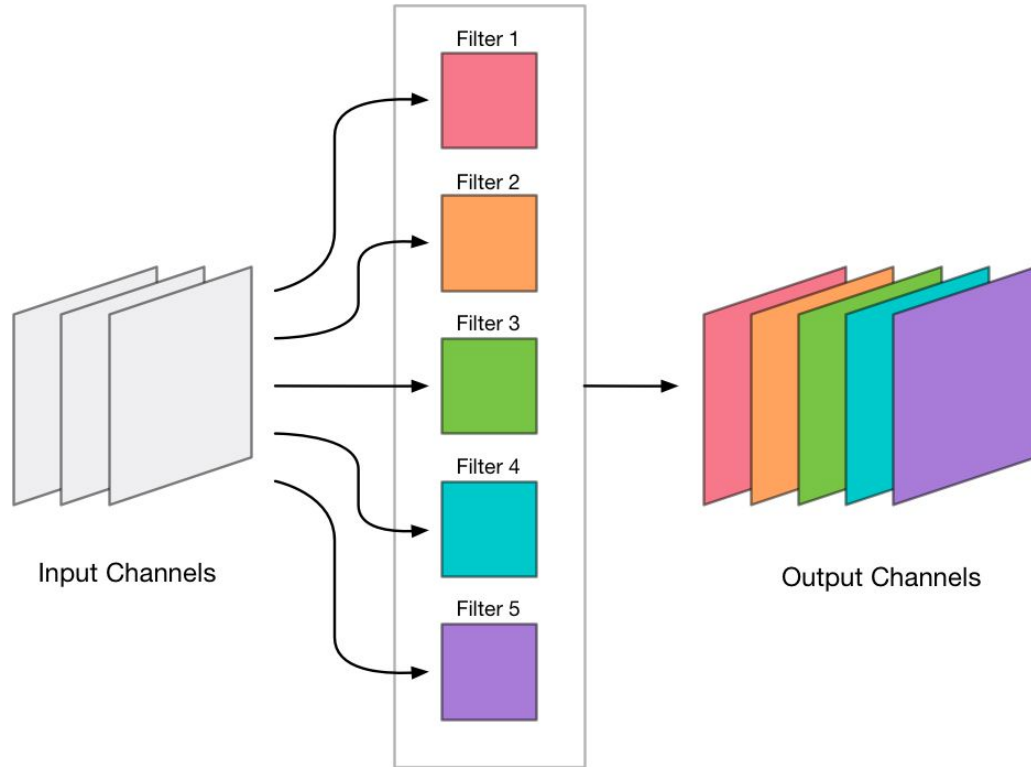
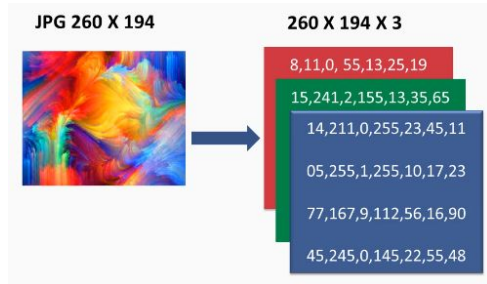
Kernels

Try out at:
<https://setosa.io/ev/image-kernels/>

Operation	Kernel ω	Image result $g(x,y)$
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	

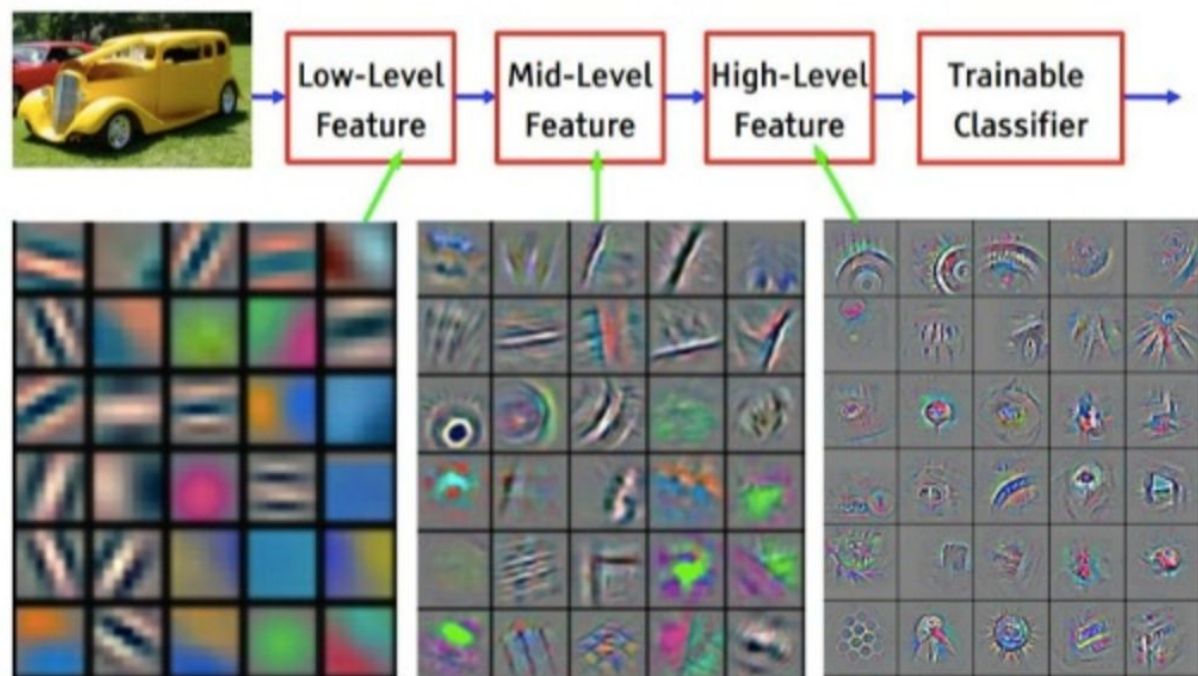
[https://en.wikipedia.org/wiki/Kernel_\(image_processing\)](https://en.wikipedia.org/wiki/Kernel_(image_processing))

Filters



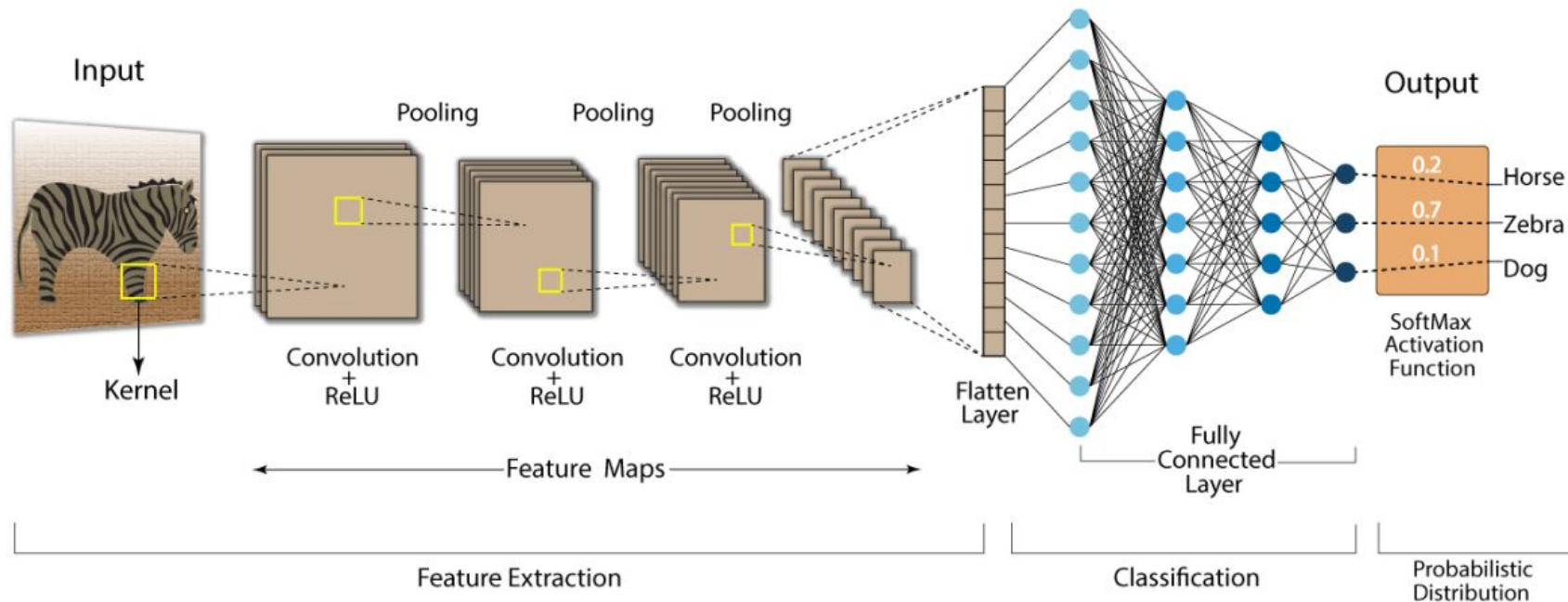
CNN doesn't only learn one filter, it learns multiple filters. In fact, it even learns multiple filters in each layer! Every filter learns a specific pattern, or feature.

Convolutional Neural Network



Activation functions

Convolution Neural Network (CNN)



Pooling

Max Pooling

29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2
pool size

100	184
12	45

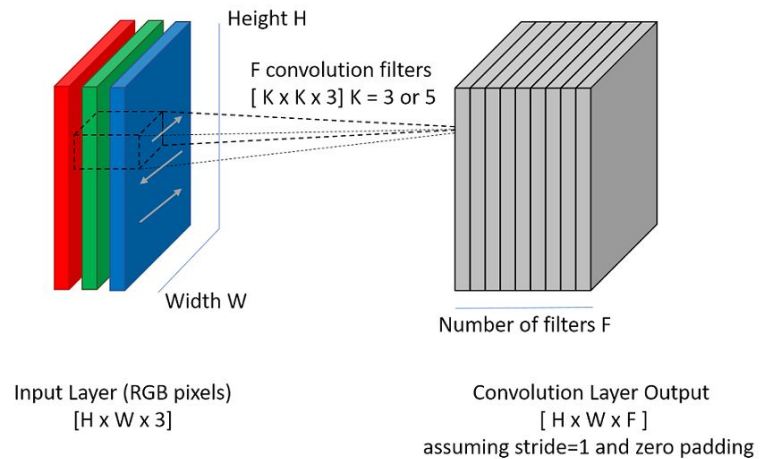
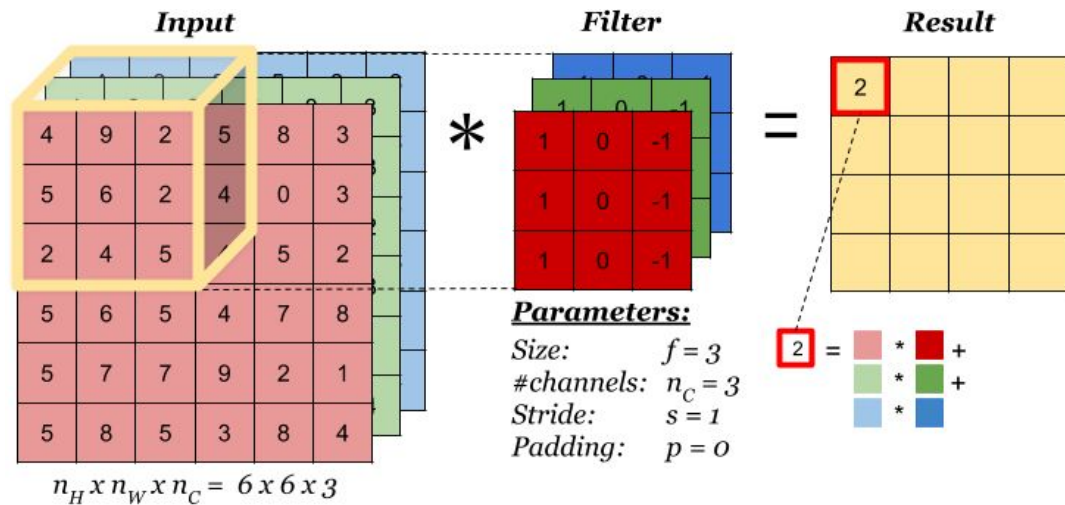
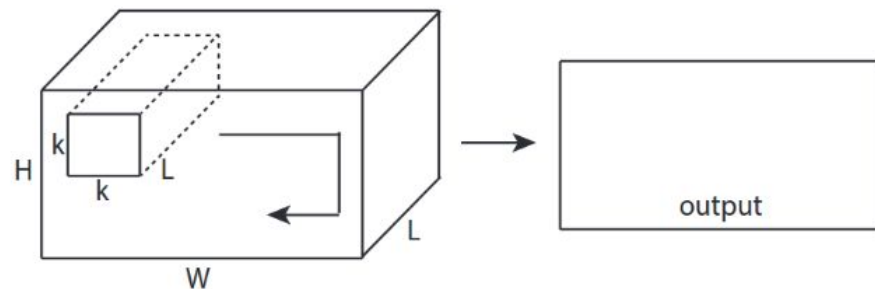
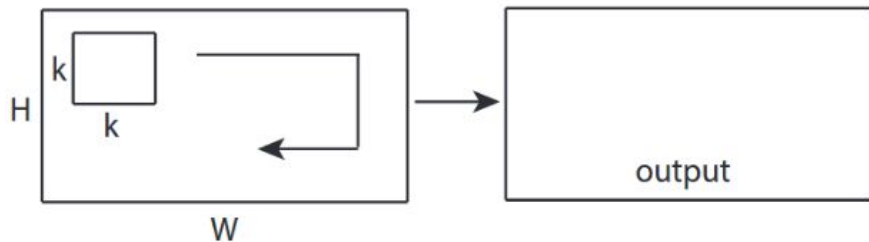
Average Pooling

31	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

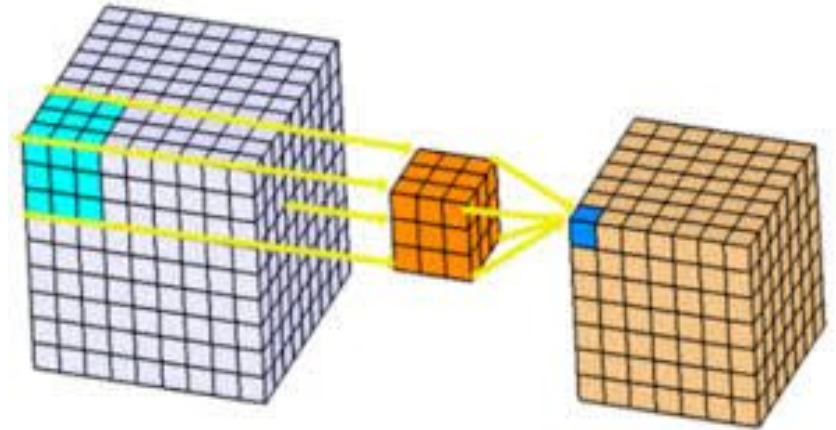
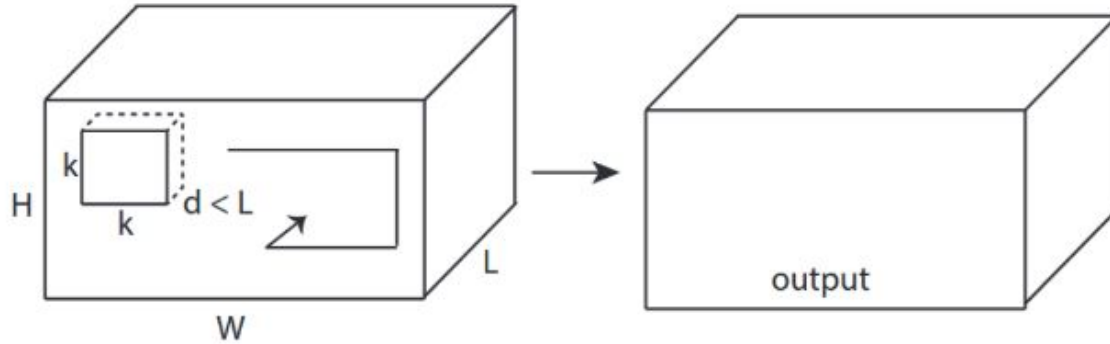
2 x 2
pool size

36	80
12	15

2D Convolution (images)

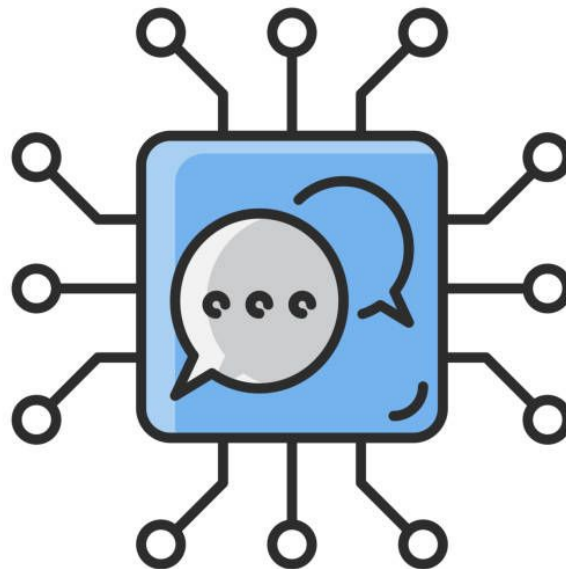
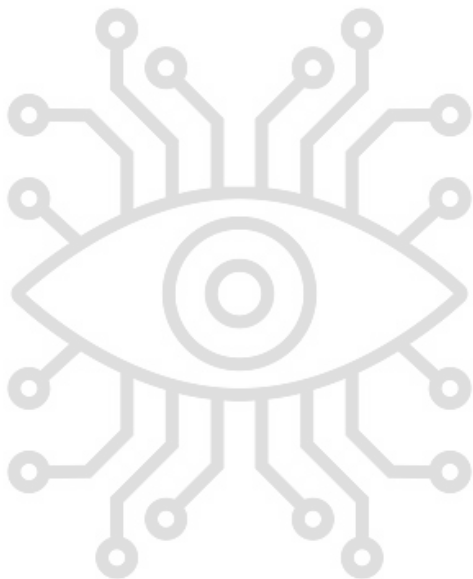


3D Convolutions (e.g. movies)





Computer vision and NLP





Language model

A language model in NLP is a model that computes probability of a sentence(sequence of words) or the probability of a next word in a sequence.

- Sentimental Analysis
- Question-Answering
- Summarization
- Machine Translation

$$P(w_5 | w_1, w_2, w_3, w_4)$$

Word embeddings

Vocabulary:
Man, woman, boy,
girl, prince,
princess, queen,
king, monarch



	1	2	3	4	5	6	7	8	9
man	1	0	0	0	0	0	0	0	0
woman	0	1	0	0	0	0	0	0	0
boy	0	0	1	0	0	0	0	0	0
girl	0	0	0	1	0	0	0	0	0
prince	0	0	0	0	1	0	0	0	0
princess	0	0	0	0	0	1	0	0	0
queen	0	0	0	0	0	0	1	0	0
king	0	0	0	0	0	0	0	1	0
monarch	0	0	0	0	0	0	0	0	1

Each word gets
a 1x9 vector
representation

Try to build a lower dimensional embedding

Vocabulary:
Man, woman, boy,
girl, prince,
princess, queen,
king, monarch



	Femininity	Youth	Royalty
Man	0	0	0
Woman	1	0	0
Boy	0	1	0
Girl	1	1	0
Prince	0	1	1
Princess	1	1	1
Queen	1	0	1
King	0	0	1
Monarch	0.5	0.5	1

Each word gets a
1x3 vector

Similar words...
similar vectors

Models for NLP

output distribution

$$\hat{y} = \text{softmax}(Uh + b_2) \in \mathbb{R}^{|V|}$$

hidden layer

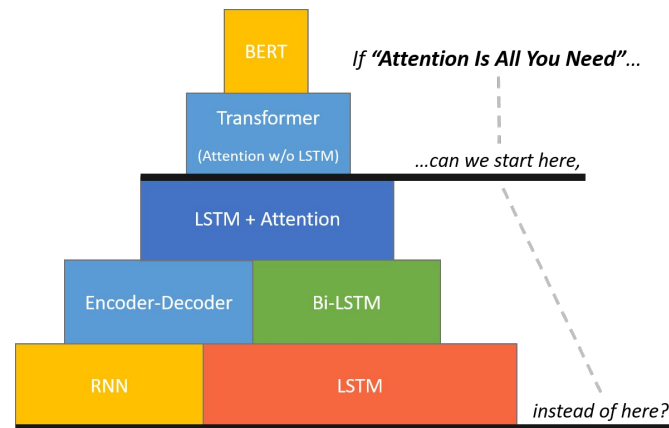
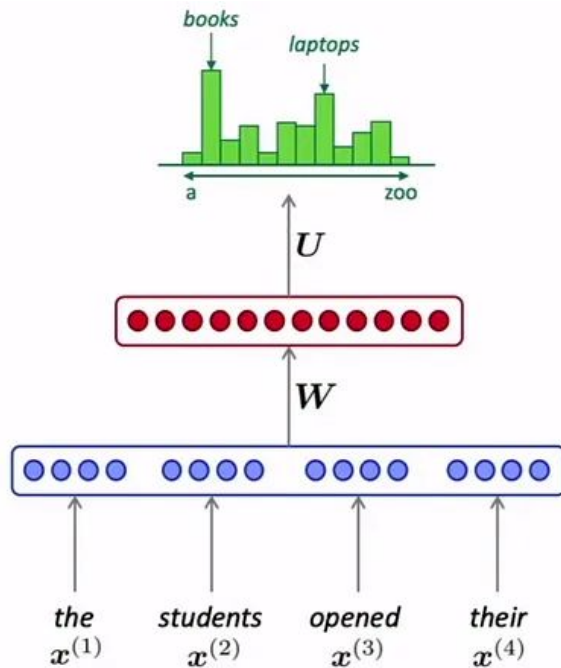
$$h = f(We + b_1)$$

concatenated word embeddings

$$e = [e^{(1)}; e^{(2)}; e^{(3)}; e^{(4)}]$$

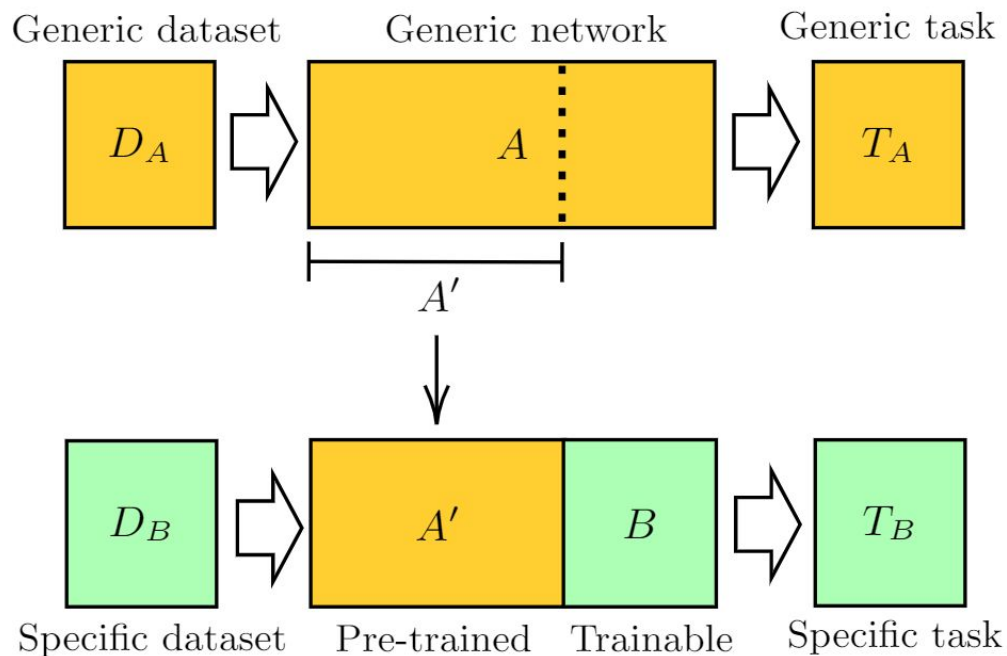
words / one-hot vectors

$$x^{(1)}, x^{(2)}, x^{(3)}, x^{(4)}$$

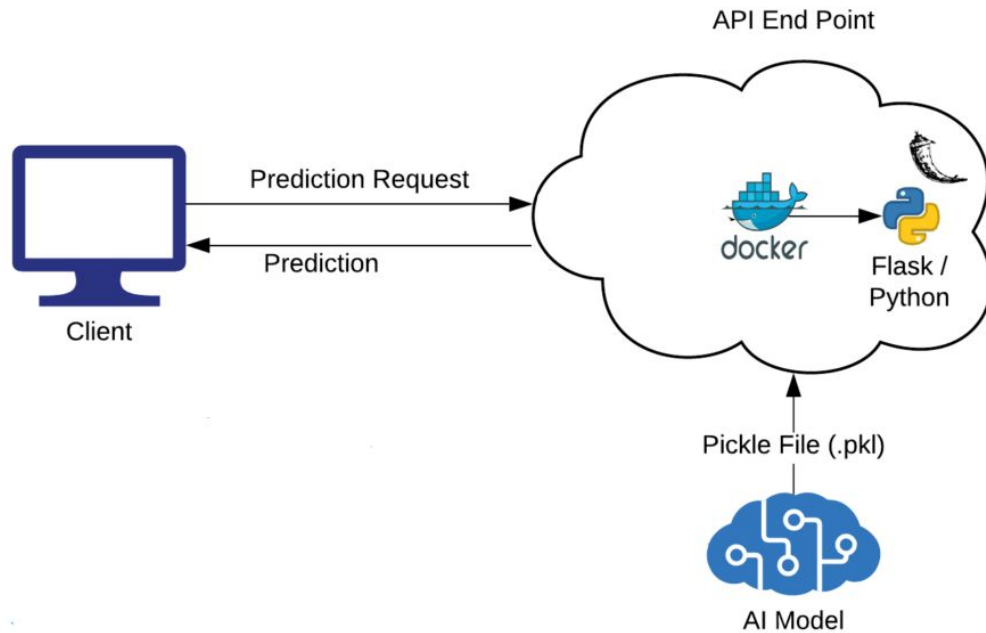




Transfer learning



Deploying







Additional resources

<https://wandb.ai/site/experiment-tracking>

https://youtube.com/playlist?list=PLam9sigHPGwOBuH4_4fr-XvDbe5uneaf6

<https://segment-anything.com/>

