Technische Universität Braunschweig

Deep Learning

Summer School – 25.08.2022

Dr. Pedro Achanccaray Diaz

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Outline

1. Introduction
   1) Deep Learning
   2) Machine Learning
   3) Artificial Neural Networks
   4) Computer Vision
   5) Remote Sensing
   6) Computer Vision tasks

2. Application: Automatic detection of system halls

3. Lab

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1.1. Deep Learning – Definition

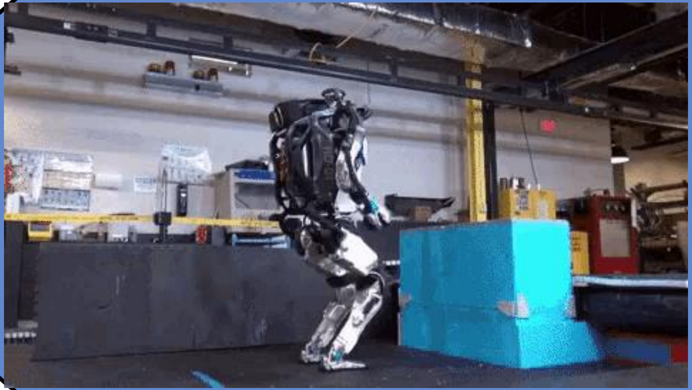
Artificial Intelligence (AI)

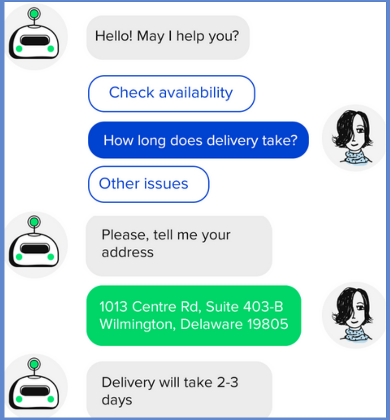
A technology with wich we can create intelligent systems that can simulate human intelligence.

- Weak / General AI

1.1. Deep Learning – Definition

Artificial Intelligence (AI)





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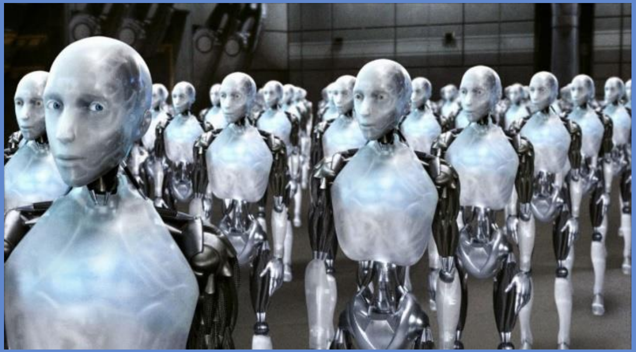

A technology with wich we can create intelligent systems that can simulate human intelligence.

- **Weak / General AI**
- **Strong AI (reasoning, judging, learning, communicating, awarenss, self-awareness)**

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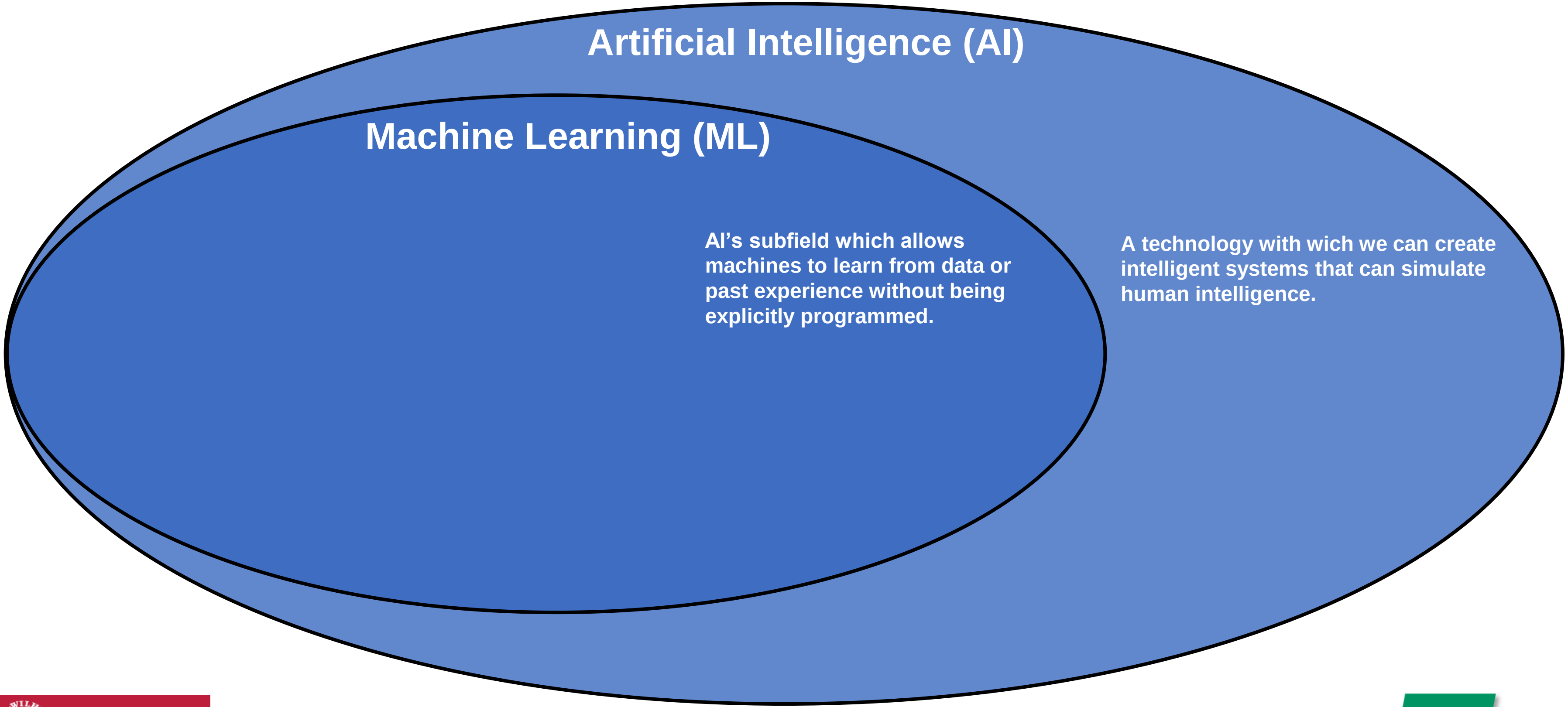

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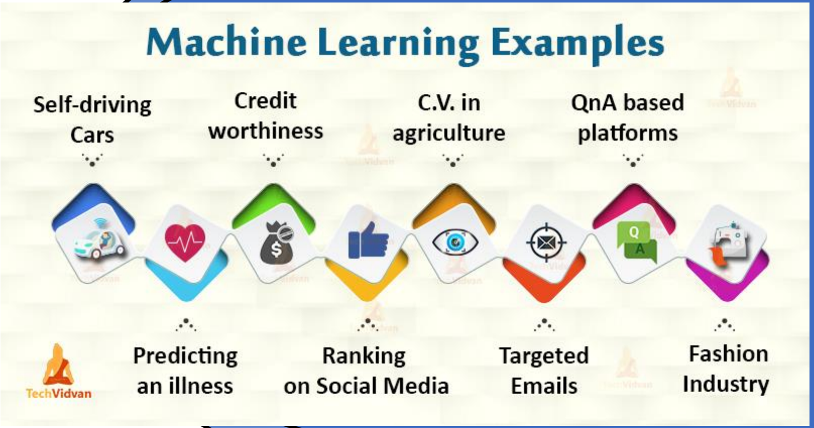
Machine Learning (ML)



AI's subfield which allows machines to learn from data or past experience without being explicitly programmed.

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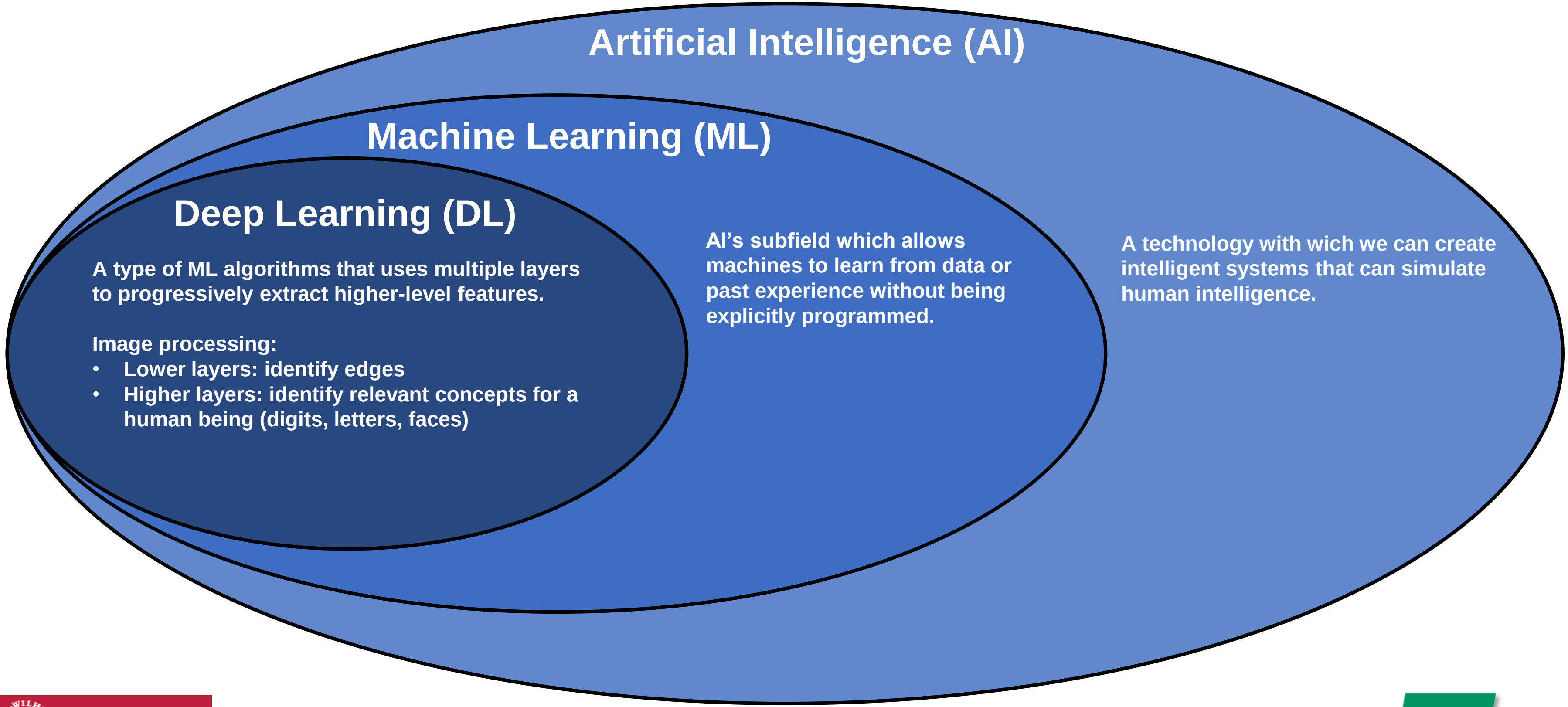

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Artificial Intelligence (AI)

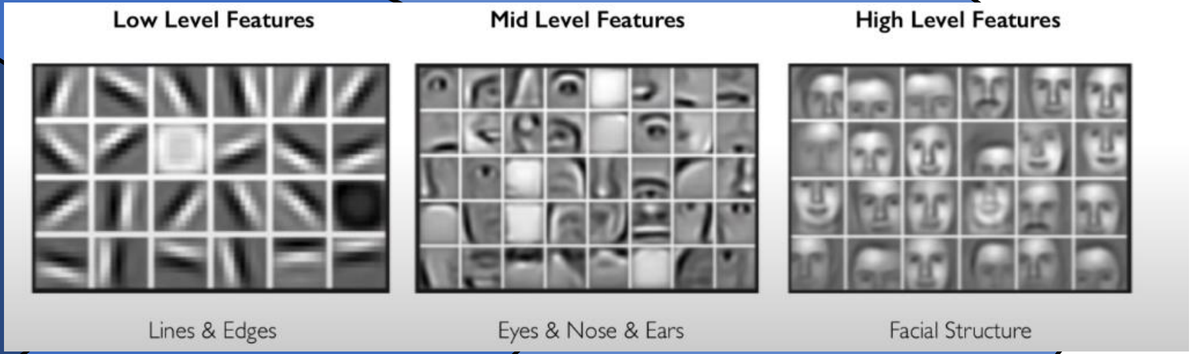
Machine Learning (ML)

Deep Learning (DL)

A type of ML algorithms that uses multiple layers to progressively extract higher-level features.

Image processing:

- Lower layers: identify edges
- Higher layers: identify relevant concepts for a human being (digits, letters, faces)



First layers → *Last layers*

1.1. Deep Learning – Applications

Autonomous driving

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Autonomous driving

Sentiment analysis

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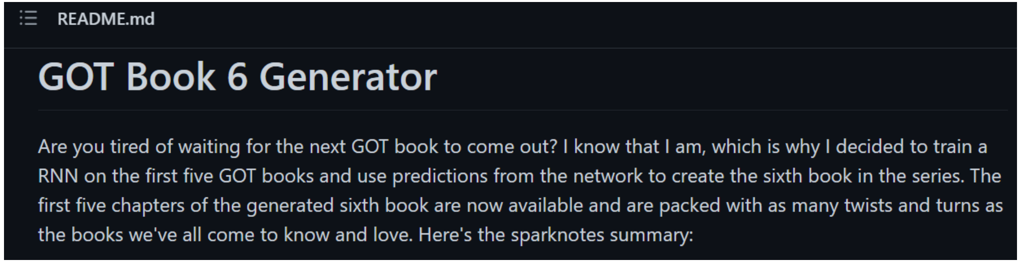
Sentiment analysis

Text synthesis



1.1. Deep Learning – Applications

Autonomous driving

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Text synthesis

README.md

GOT Book 6 Generator

Are you tired of waiting for the next GOT book to come out? I know that I am, which is why I decided to train a RNN on the first five GOT books and use predictions from the network to create the sixth book in the series. The first five chapters of the generated sixth book are now available and are packed with as many twists and turns as the books we've all come to know and love. Here's the sparknotes summary:

Automatic translation

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1.2. Machine Learning – Algorithms

Algorithms that can learn from ***data***.

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*"A computer program is said **to learn** from **experience E** with respect to some class of **tasks T**, and **performance measure D**, if **its performance on tasks T, as measured by D, improves with experience E**." – Mitchell, 1997.*

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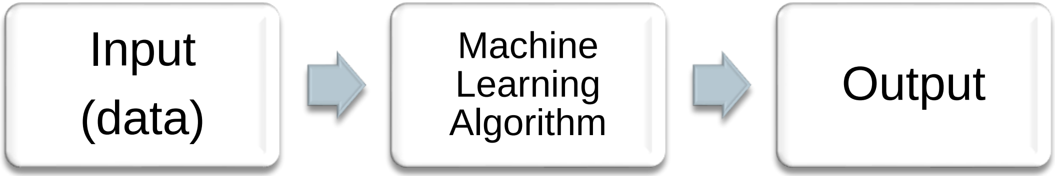

1.2. Machine Learning – Tasks *T*

Tasks are described in terms of how the machine learning system should ***process a sample***.

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A **sample** is a collection of ***features*** that have been ***quantitatively*** measured from some ***object*** or ***event***.

Representation of a **sample**:

$$\boldsymbol{x} \in \mathbb{R}^n, \boldsymbol{x} = [x_1, x_2, \ldots, x_n], x_i \Rightarrow \textit{feature, attribute, characteristic}$$

1.2. Machine Learning – Tasks *T*

- Classification
- Regression
- Automatic translation
- Sampling and synthesis
- …

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- **Classification**
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Specify which of the k categories a sample belongs to.

$$\mathrm{y} = f(\boldsymbol{x})$$

output, categories identified by a numerical code

input
$\boldsymbol{x} = [x_1, x_2, \dots, x_n]$

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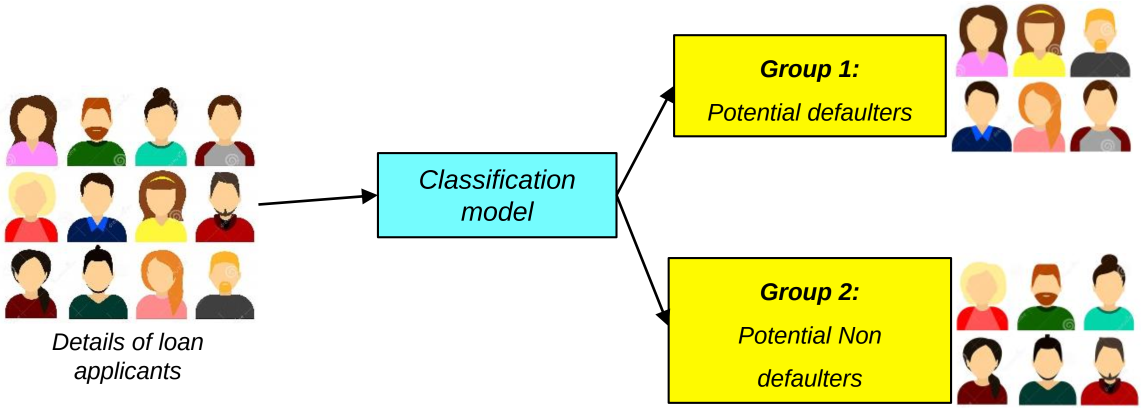

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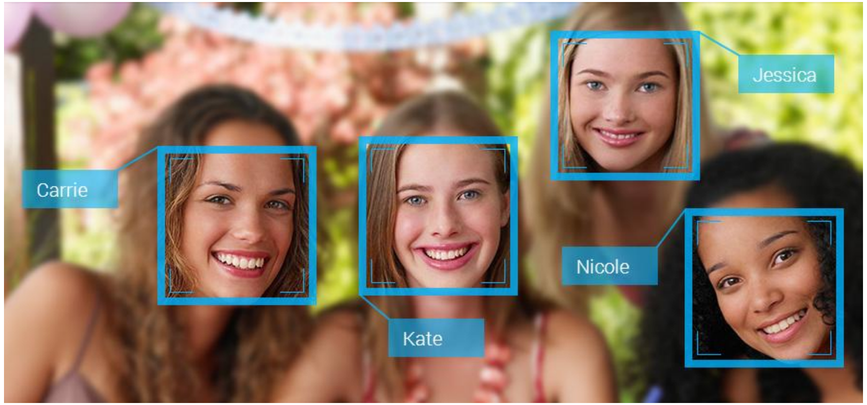

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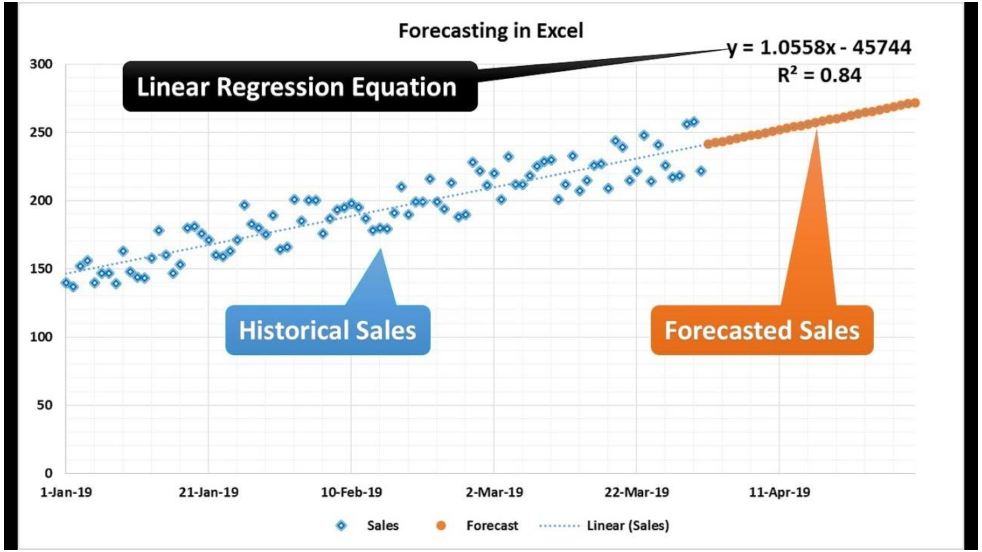

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Input: a sequence of symbols in some language
Output: a sequence of symbols in another language

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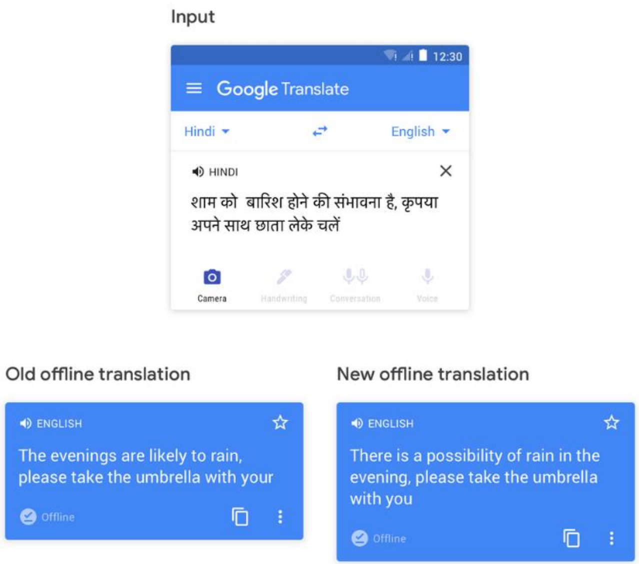

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Generate new samples that are similar to those of the training data.

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https://www.thispersondoesnotexist.com/

1.2. Machine Learning – Performance measure *D*

The ***performance measure D*** is specific to the ***task T***.

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The ***performance measure*** $\boldsymbol{D}$ is specific to the ***task*** $\boldsymbol{T}$.

Task: **classification**, ***accuracy*** is usually measured

- Proportion of samples for which the model produces the correct output.
- ***Error rate:*** proportion of samples for which the model produces an incorrect output.

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- Unsupervised learning

- Supervised learning

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- **Unsupervised learning**

  Learns from samples represented by features

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Recommender systems

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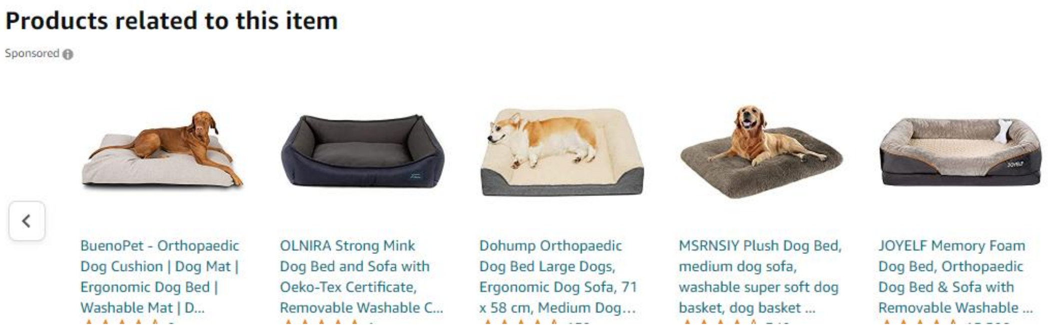

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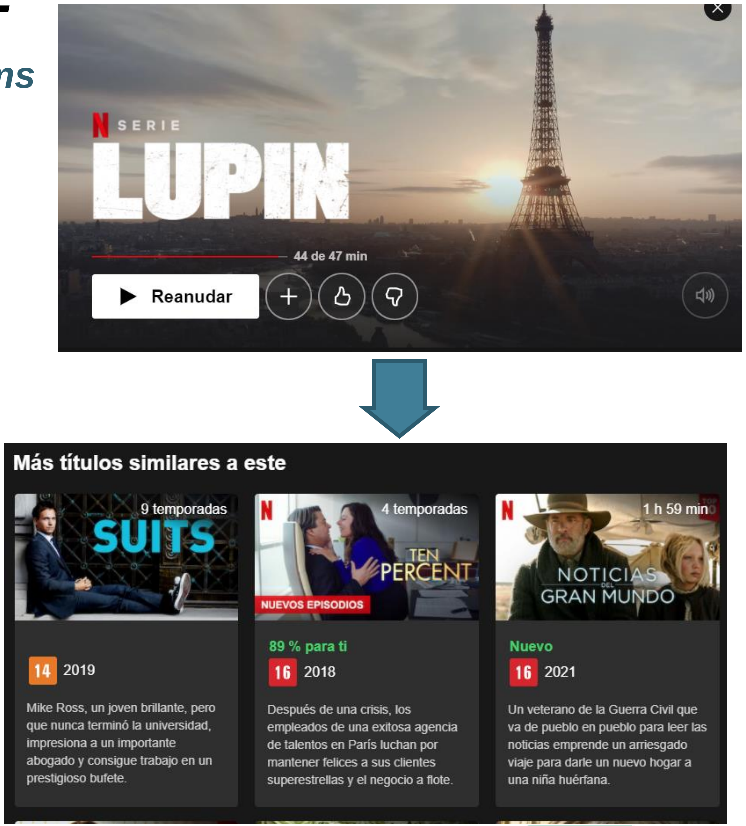

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1.2. Machine Learning – Experience *E*

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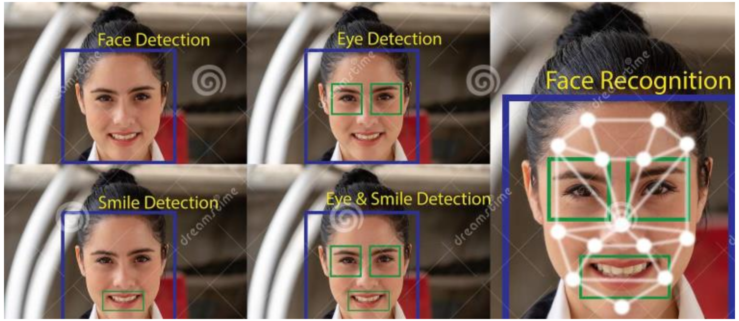
  Learns from samples represented by features and labels

1.2. Machine Learning – Experience *E*

Face recognition



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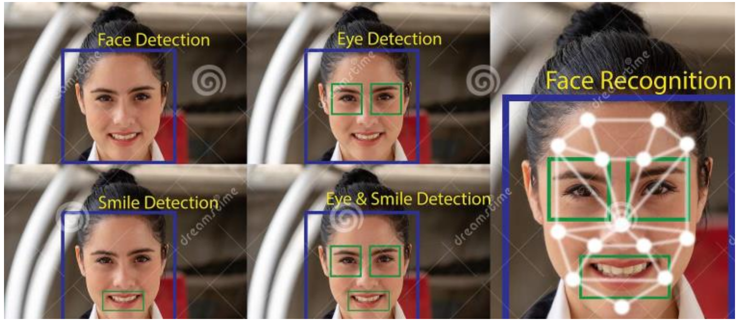

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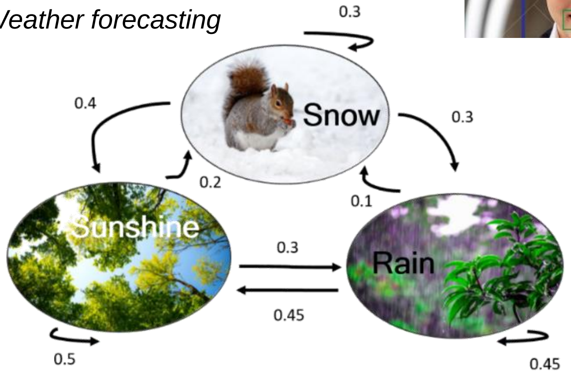
Weather forecasting



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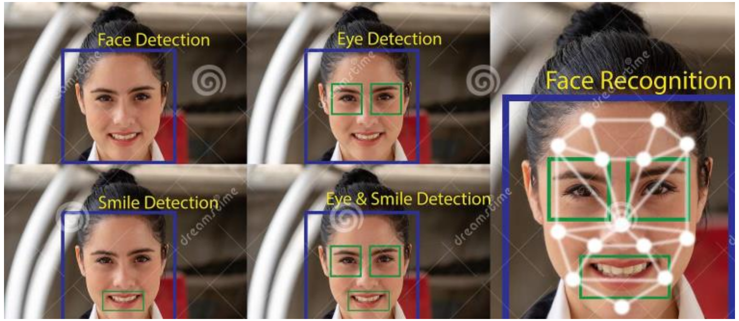

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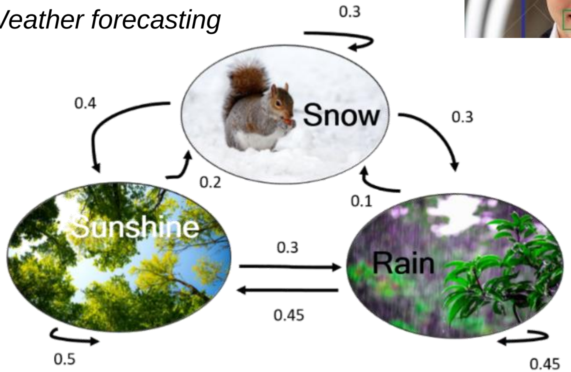

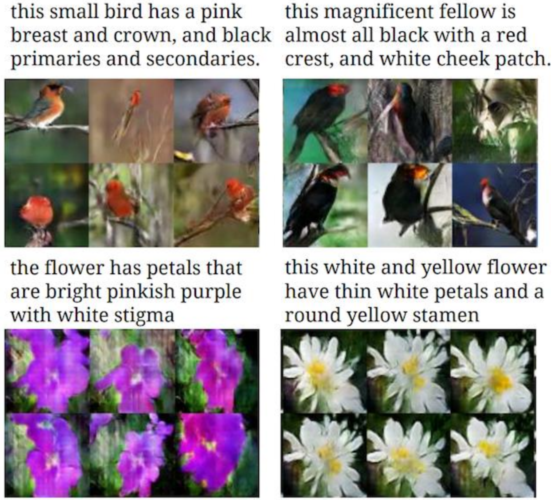

Text-to-Image translation

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1.3. Artificial Neural Networks

Watanabe, S., Sakamoto, J., & Wakita, M. (1995). ***Pigeons' discrimination of paintings by Monet and Picasso.*** *Journal of the experimental analysis of behavior, 63(2), 165-174.*

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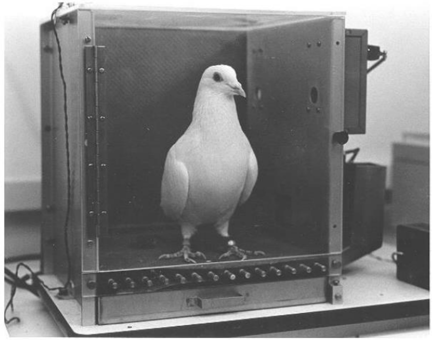

Experiment:

- Pigeon in a ***Skinner box***.

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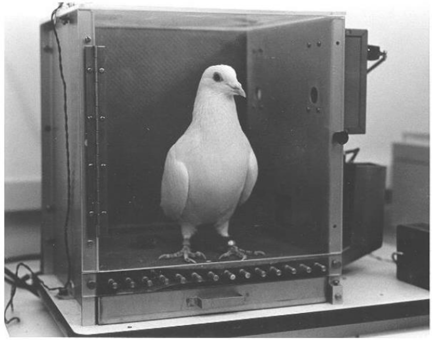

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"Three musicians masks" - Picasso

"Pathway in Monet's Garden at Giverny" – C. Monet

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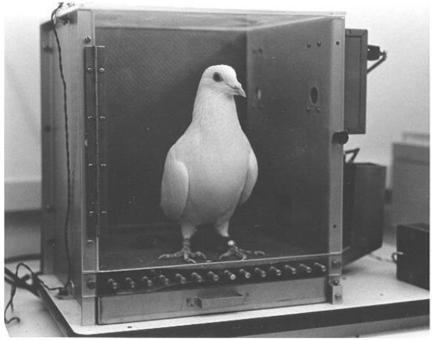

Experiment:

- Pigeon in a ***Skinner box***.
- ***Paintings*** by two artists are presented: ***Monet*** and ***Picasso***.
- The pigeon ***receives a reward*** if it presses the button when ***Picasso paintings*** are presented.

"Three musicians masks" - Picasso

"Pathway in Monet's Garden at Giverny" – C. Monet

1.3. Artificial Neural Networks

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- The pigeons ***did not memorize*** the paintings.
- They can ***extract*** and ***recognize*** patterns => ***style***.
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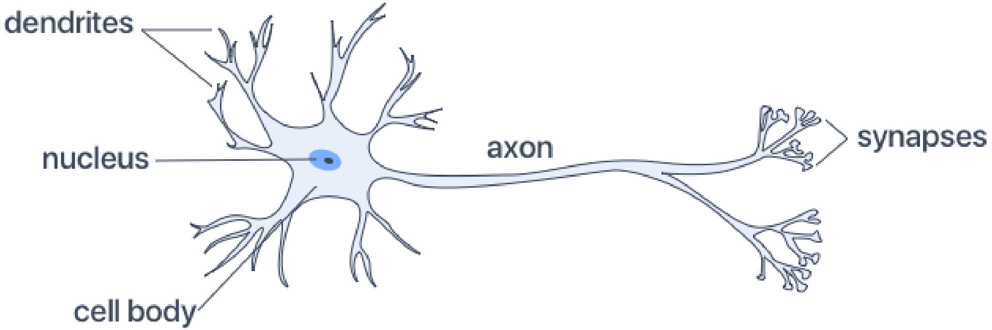
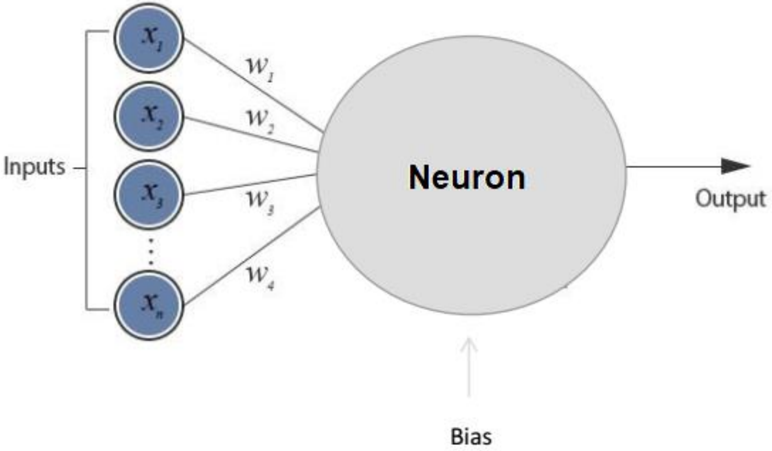
- Capacity of ***Neural Networks*** (biological and artificial)!

1.3. Artificial Neural Networks

Biological neuron



Artificial neuron



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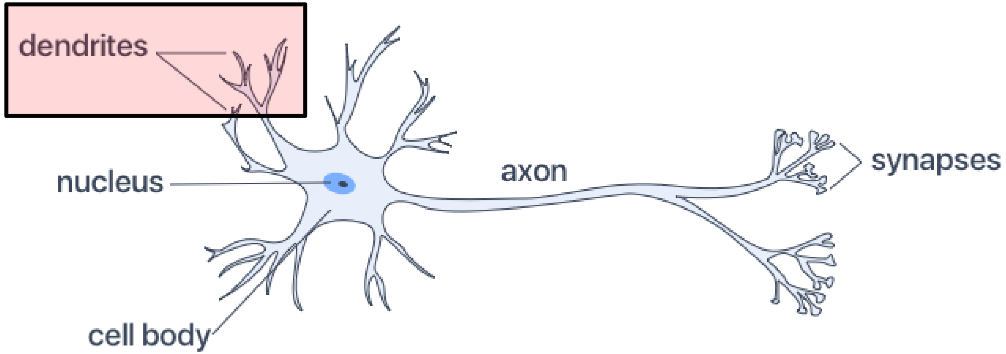

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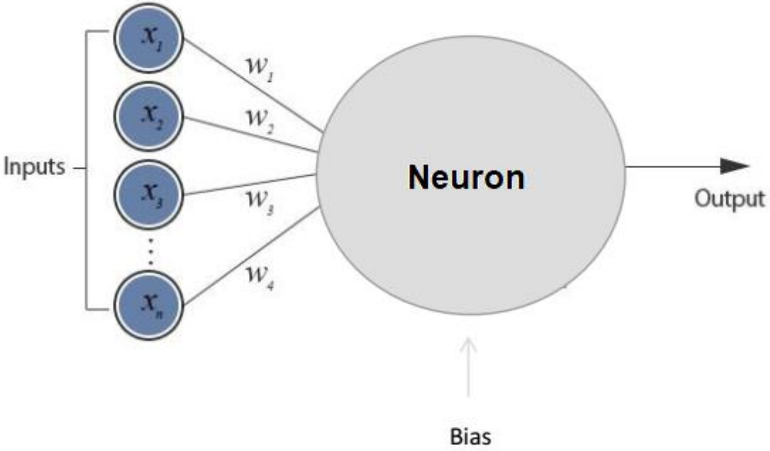

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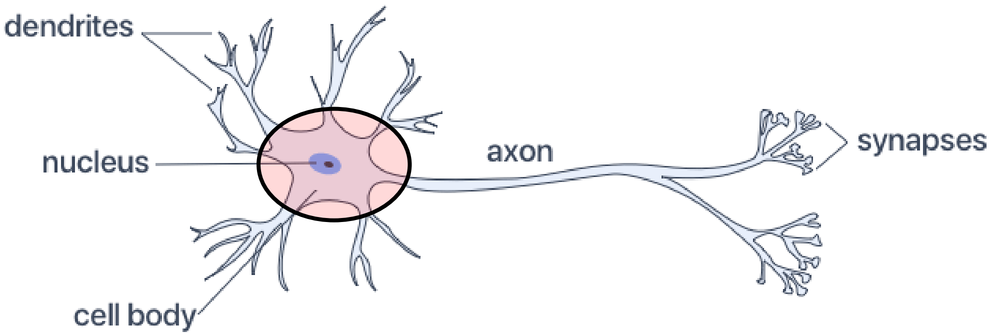

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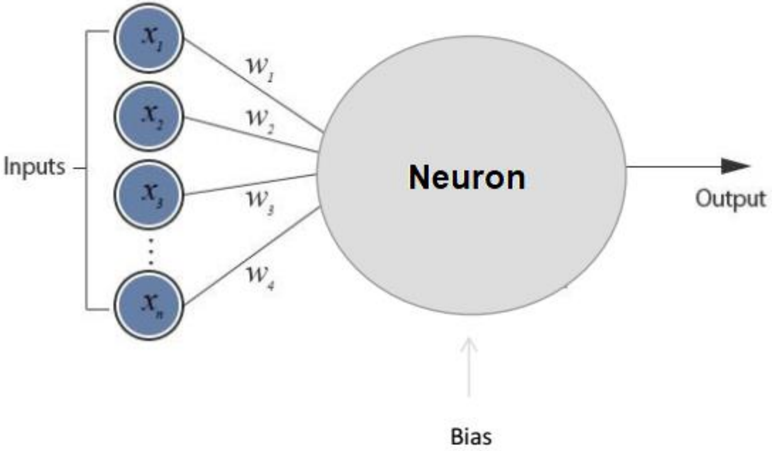

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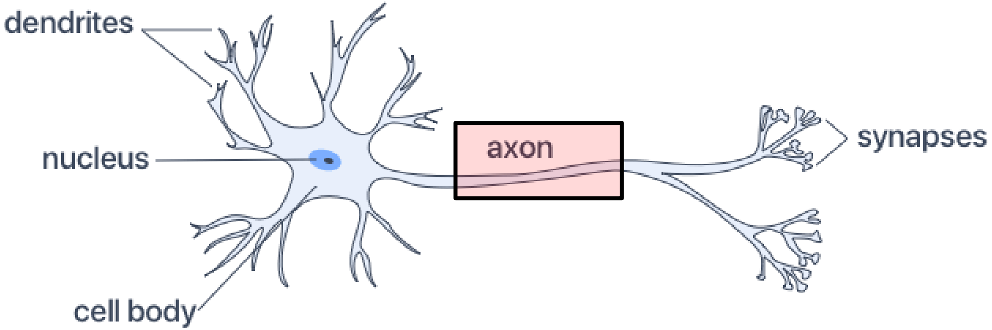

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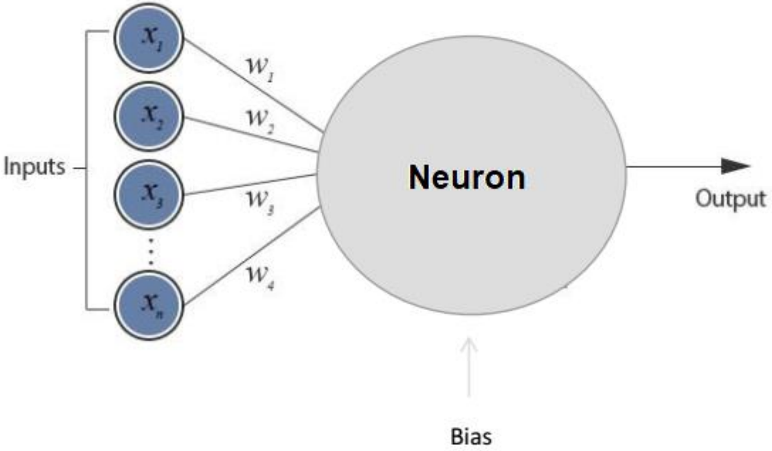

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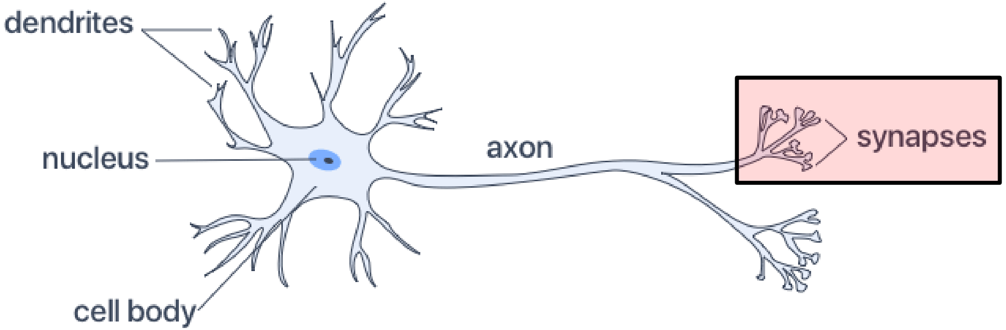

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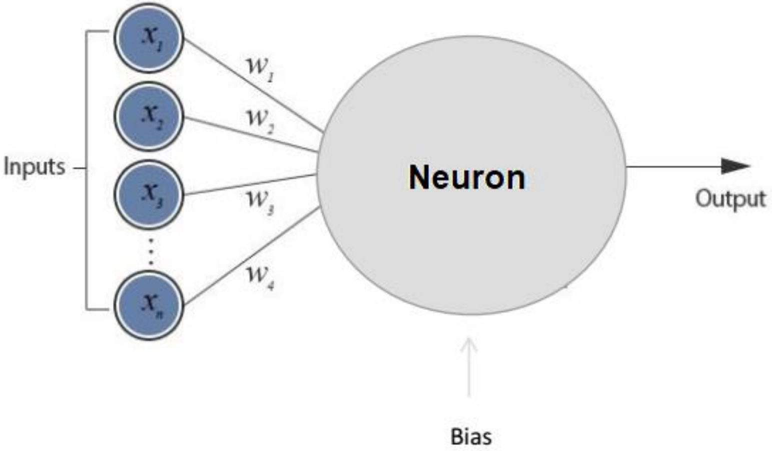

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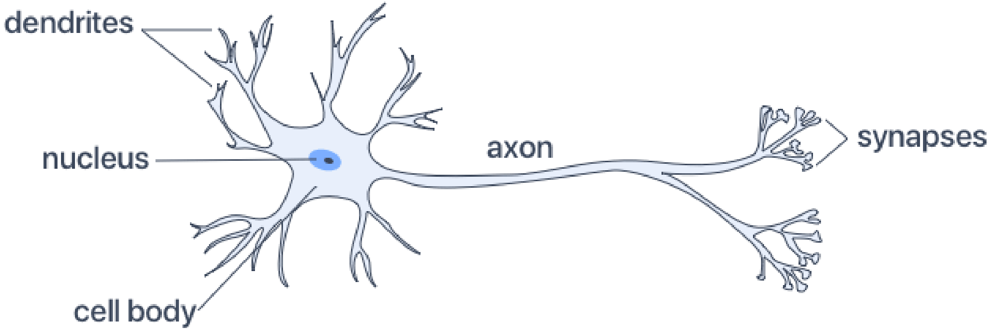

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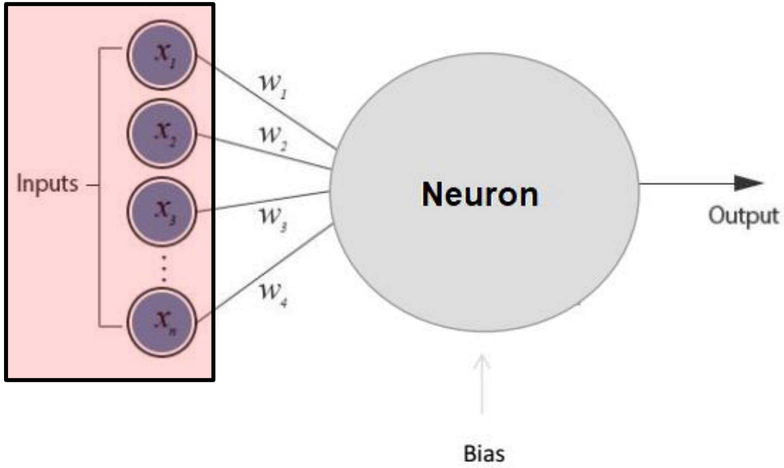

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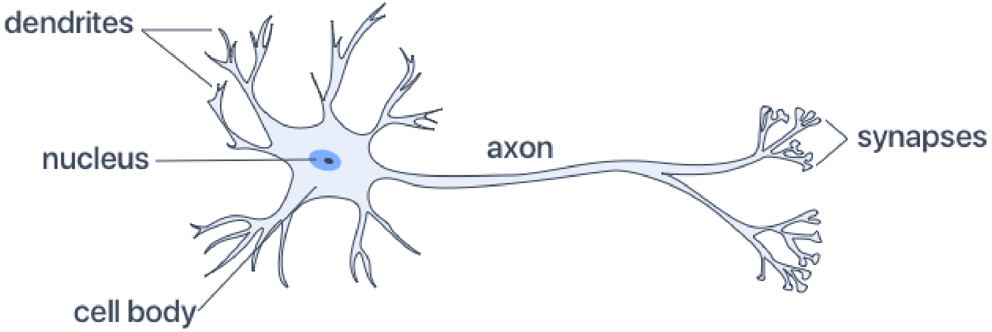

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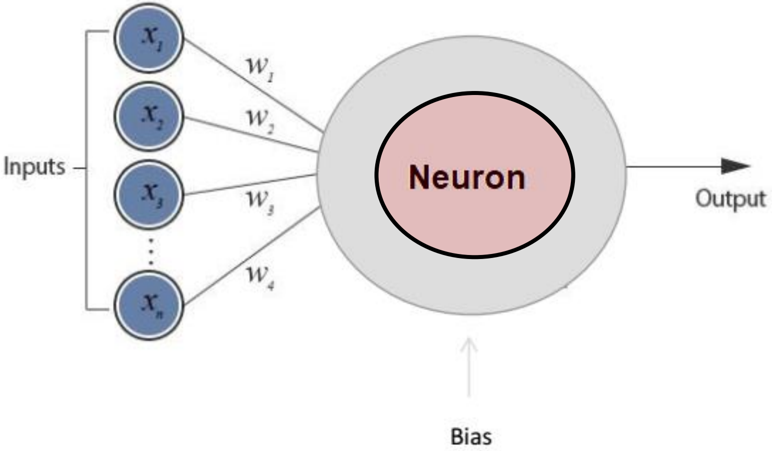

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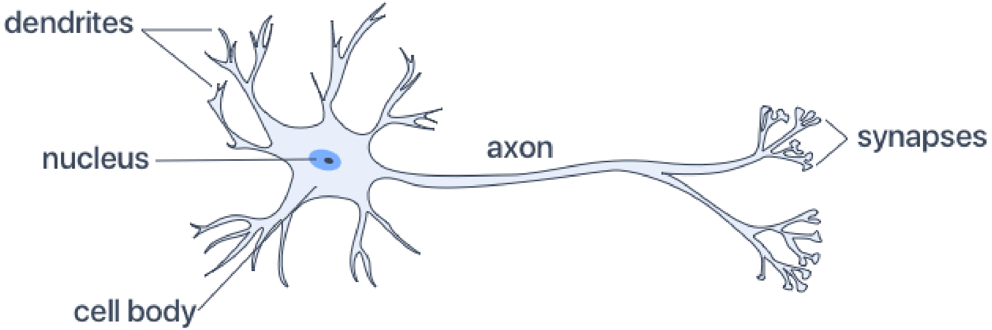

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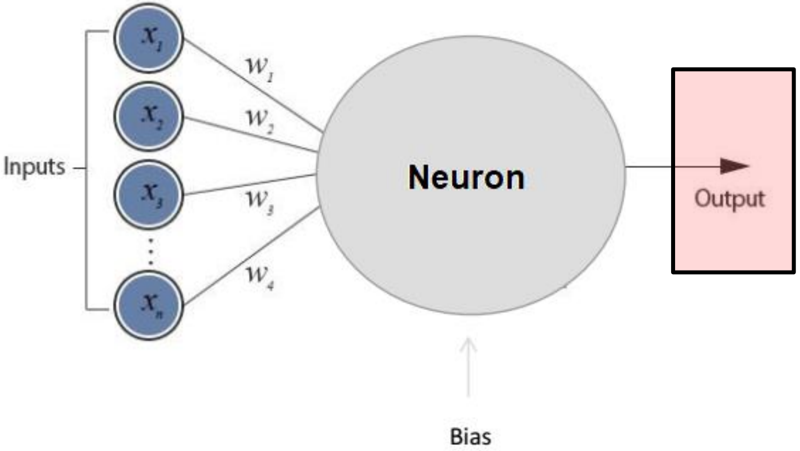

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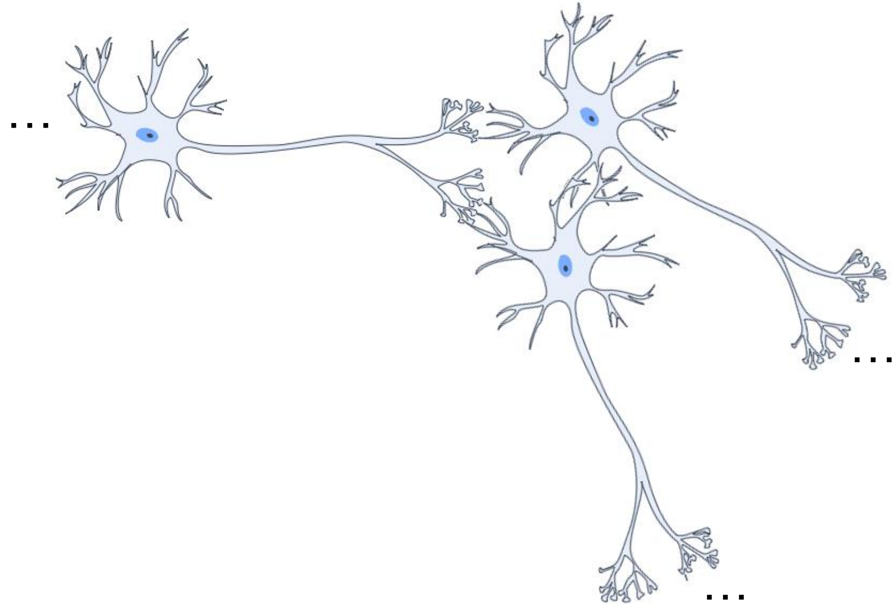

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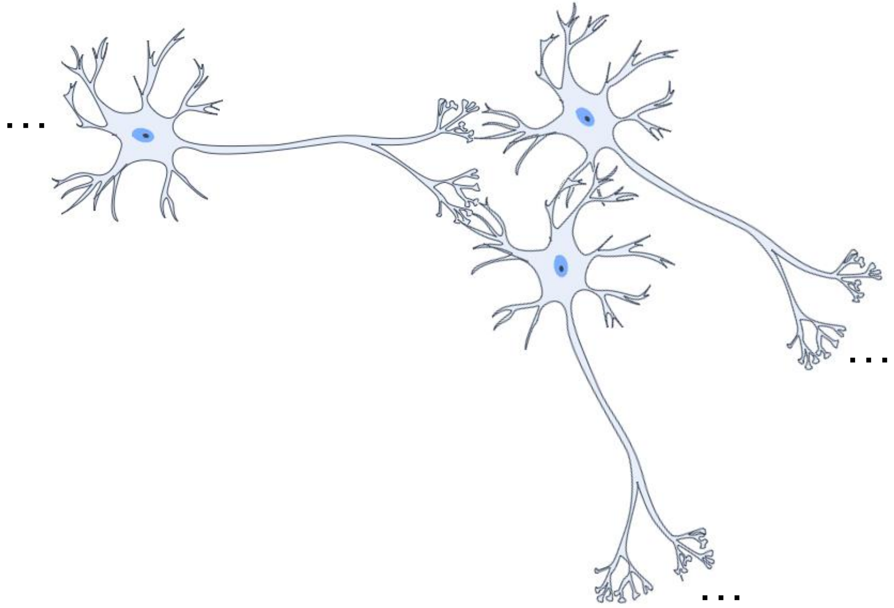
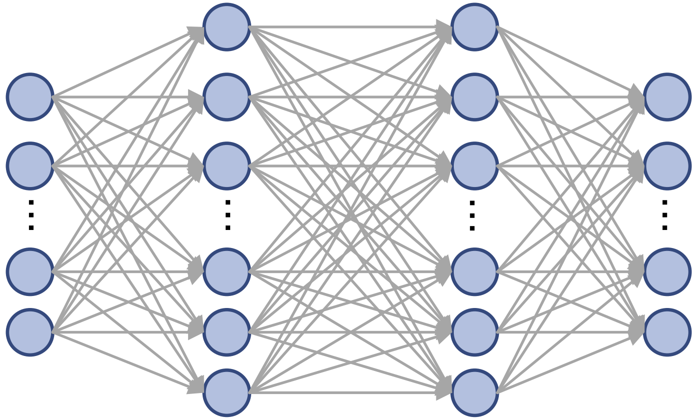


Artificial neural network



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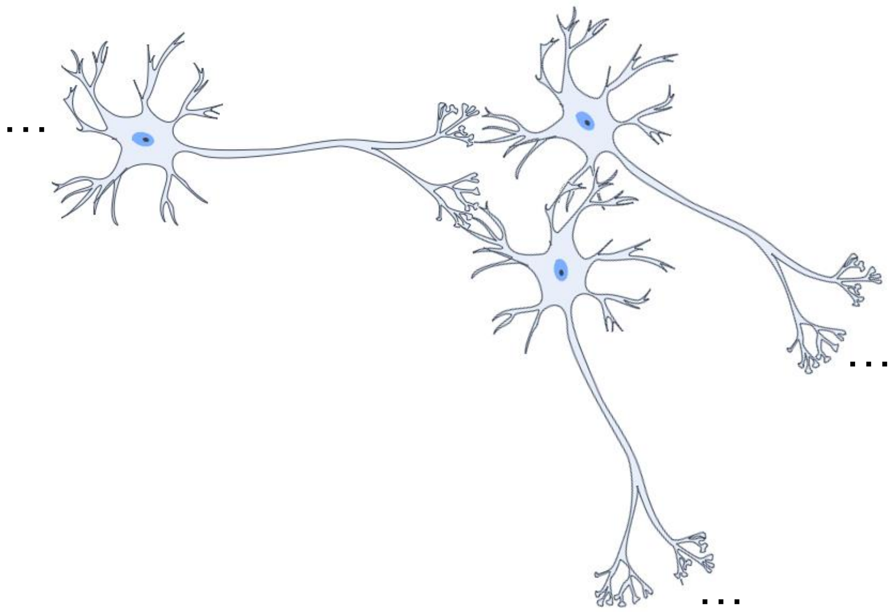
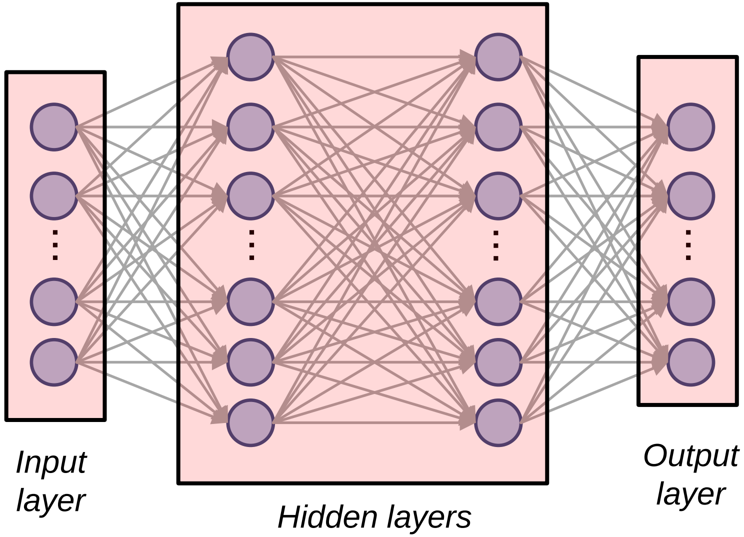
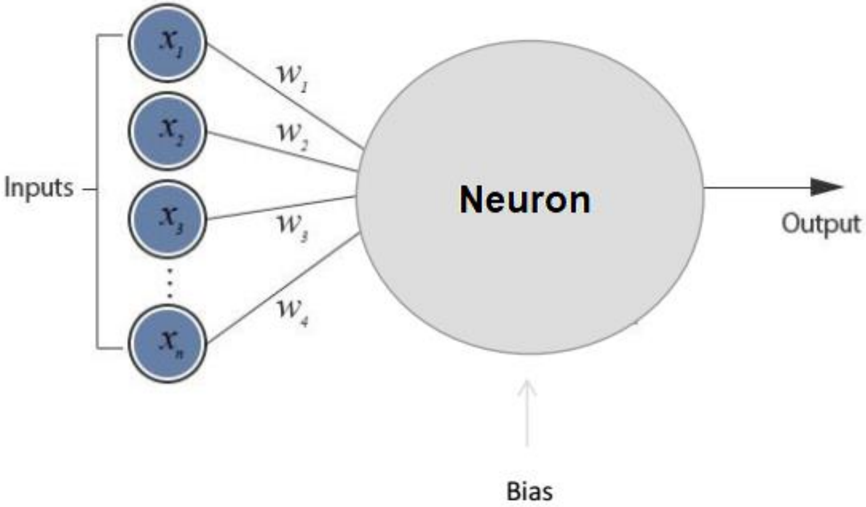


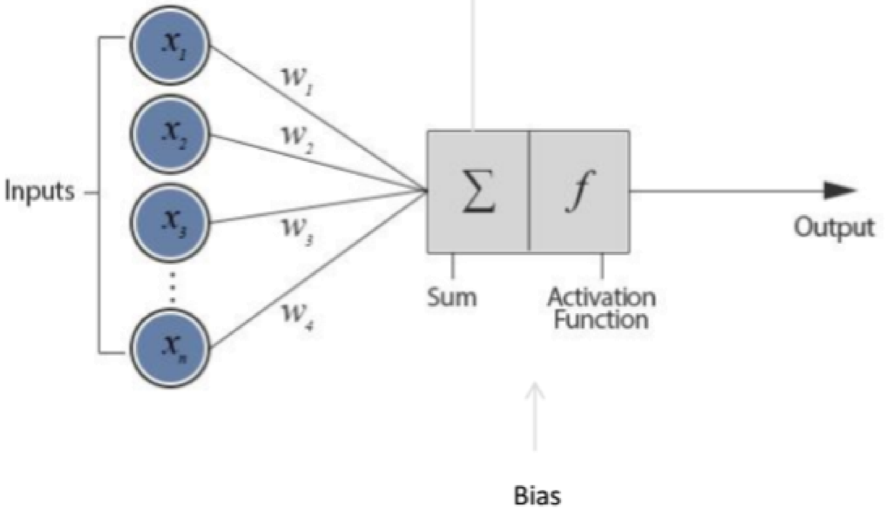
Artificial neural network



1.3. Artificial Neural Networks



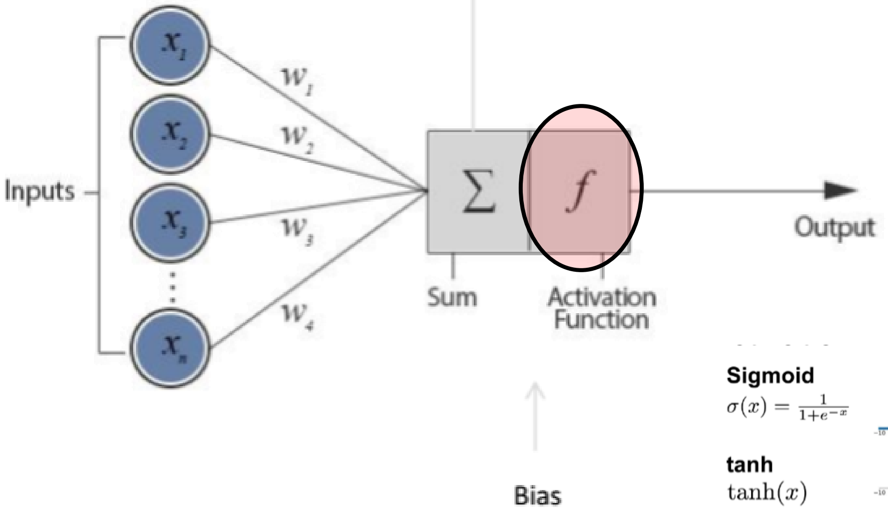
1.3. Artificial Neural Networks



$$u_k = \sum_{j=1}^{m} w_{kj} x_j$$

$$y_k = \varphi(u_k + b_k)$$

1.3. Artificial Neural Networks



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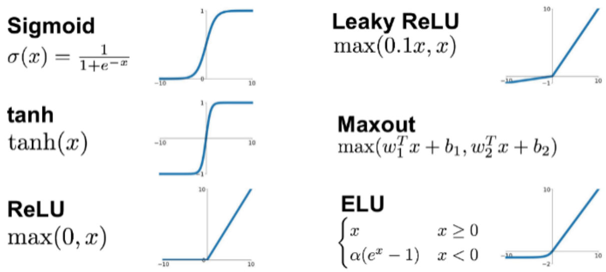
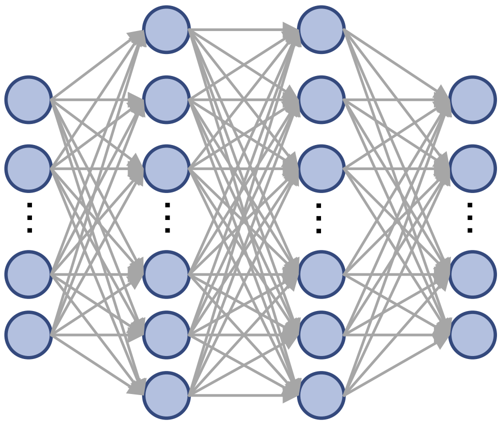


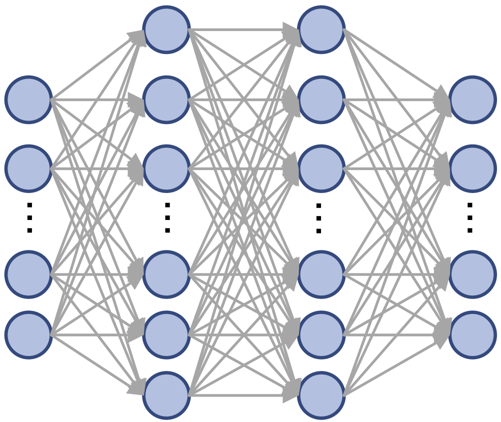
1.3. Neural Networks and Deep Learning

Neural Network

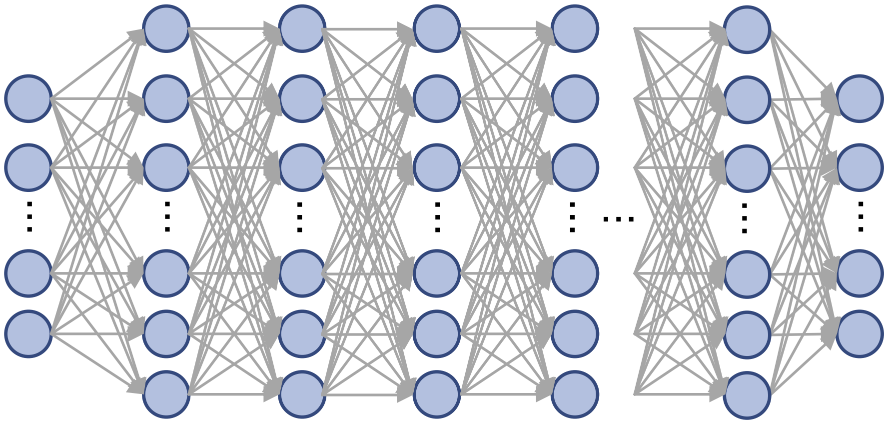


1.3. Neural Networks and Deep Learning

Neural Network



Deep Learning Neural Network



Outline

1. **Introduction**
   1) Deep Learning
   2) Machine Learning
   3) Artificial Neural Networks
   4) **Computer Vision**
   5) Remote Sensing
   6) Computer Vision tasks

2. Application: Automatic detection of system halls

3. Lab

1.4. Computer Vision

Computer Vision

*how computers can **understand** digital images or videos and **extract information***

1.4. Computer Vision

Computer Vision

*how computers can **understand** digital images or videos and **extract information***

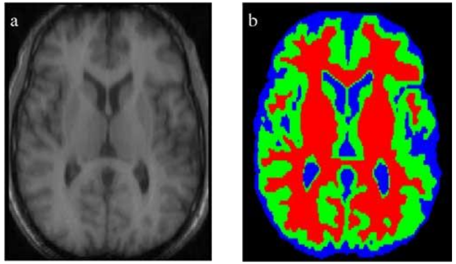
Autonomous driving [Source]

Autonomous driving [Source]

1.4. Computer Vision

Computer Vision

how computers can ***understand*** *digital images or videos and* ***extract information***



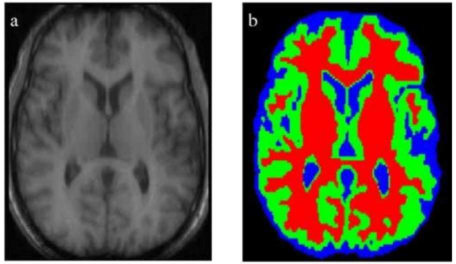
Abnormalities identification [Source]

1.4. Computer Vision

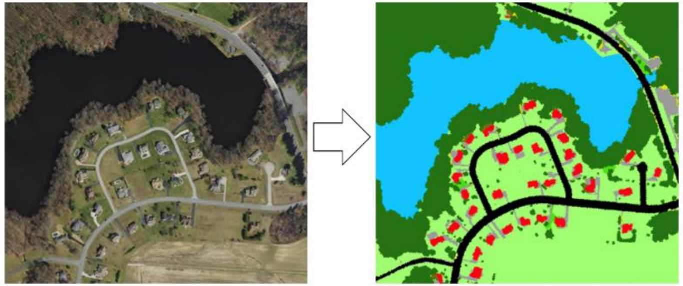
Autonomous driving [Source]

Computer Vision

how computers can ***understand*** *digital images or videos and* ***extract information***



Abnormalities identification [Source]



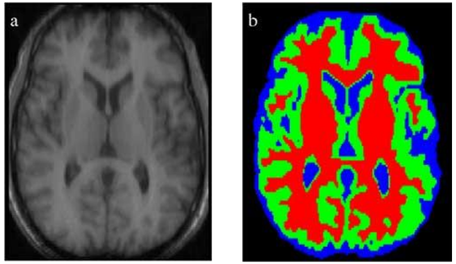
Land Use, Land Cover | Road extraction [Source]

1.4. Computer Vision

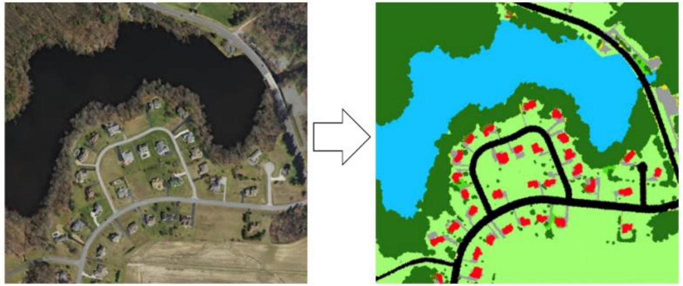
Computer Vision

*how computers can **understand** digital images or videos and **extract information***

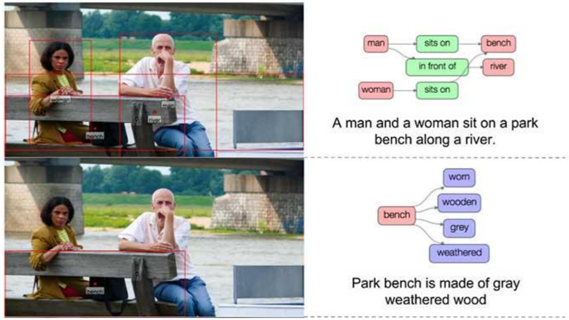
Autonomous driving [Source]



Abnormalities identification [Source]



Land Use, Land Cover | Road extraction [Source]



Scene understanding | Visual Question and Answer (VQA) [Source]

Outline

1.5. Remote Sensing

Remote Sensing

acquisition of information *about an object or phenomenon* ***without making physical contact*** *with it*

1.5. Remote Sensing

Digital Cameras [Source]

Remote Sensing

acquisition of information about an object or phenomenon without making physical contact with it

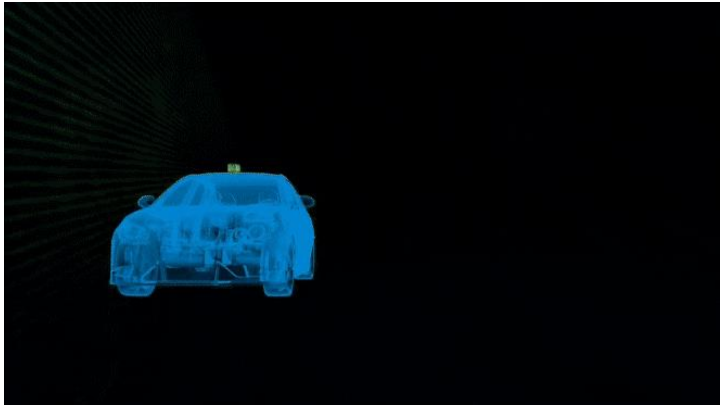
1.5. Remote Sensing

Digital Cameras [Source]

Remote Sensing

acquisition of information *about an object or phenomenon* ***without making physical contact*** *with it*

Lidar [Source]



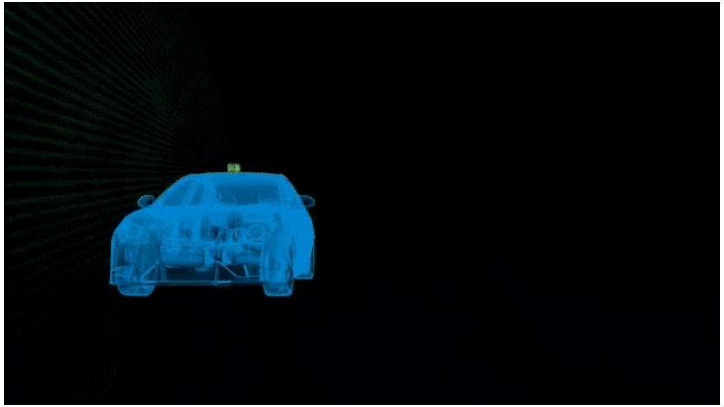
1.5. Remote Sensing

Remote Sensing

acquisition of information *about an object or phenomenon* ***without making physical contact*** *with it*

Digital Cameras [Source]

Lidar [Source]



Satellites [Source]

Outline

1. **Introduction**
   1) Deep Learning
   2) Machine Learning
   3) Artificial Neural Networks
   4) Computer Vision
   5) Remote Sensing
   6) **Computer Vision tasks**

2. Application: Automatic detection of system halls

3. Lab

1.6. Computer Vision tasks

1.6. Computer Vision tasks

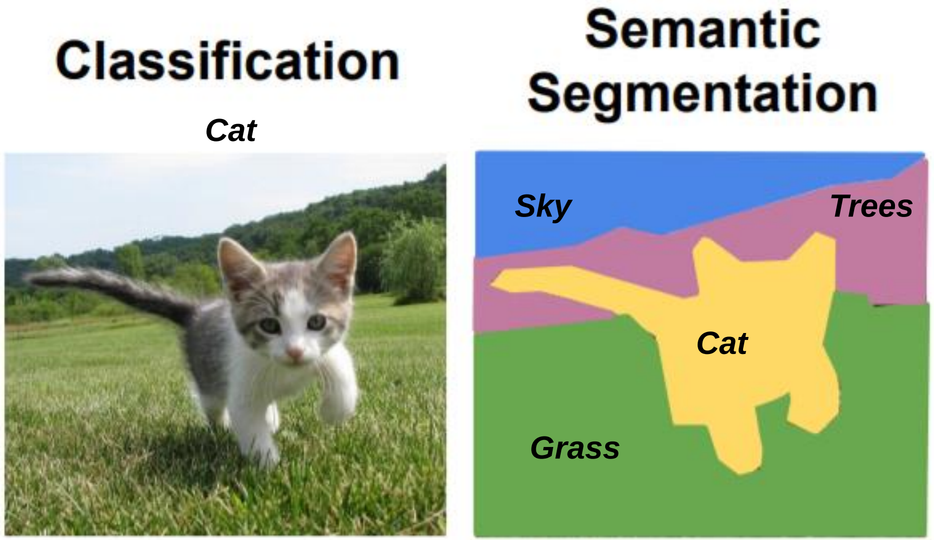
Classification

Cat

http://cs231n.stanford.edu/slides/2020/le

“assign a label to the whole image”

1.6. Computer Vision tasks

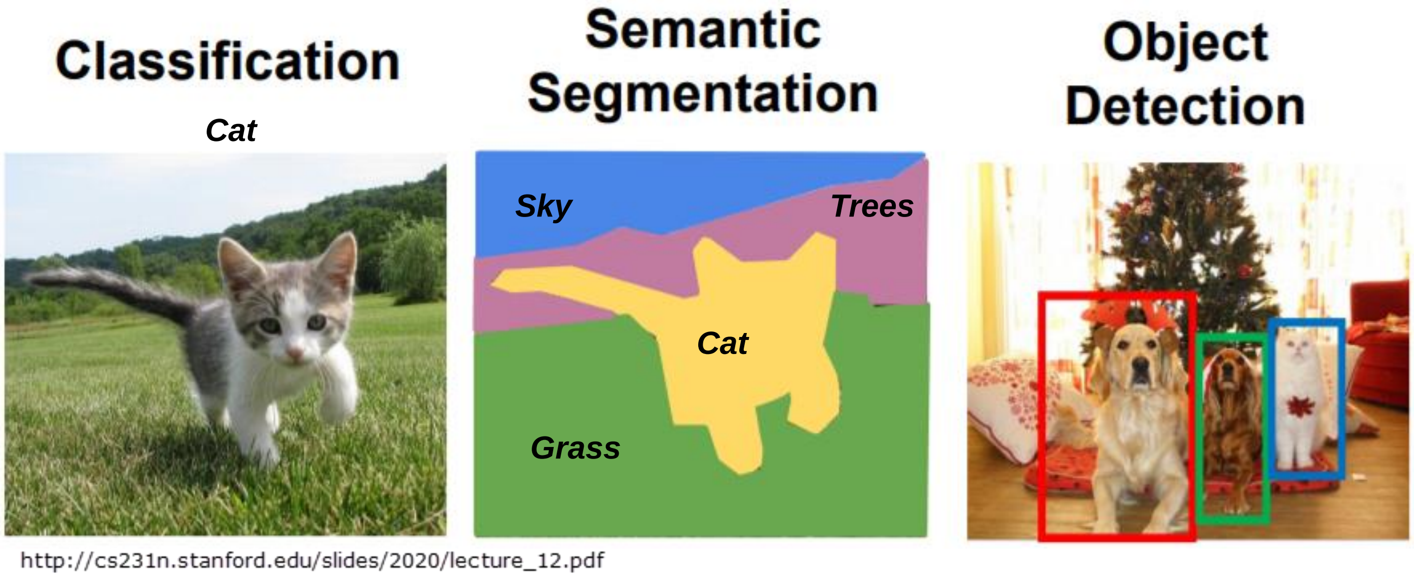


http://cs231n.stanford.edu/slides/2020/lecture_12.pdf

“assign a label to the whole image”

“assign a label to each pixel in the image”

1.6. Computer Vision tasks



“assign a label to the whole image”	*“assign a label to each pixel in the image”*	*“find where an object is in the image”*

1.6. Computer Vision tasks (remote sensing)

Classification

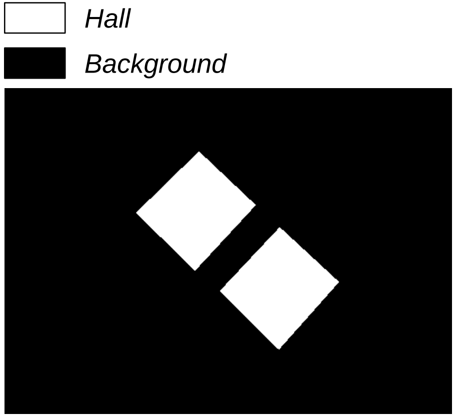
“assign a label to the whole image”

1.6. Computer Vision tasks (remote sensing)

Classification

Semantic Segmentation

"assign a label to the whole image"



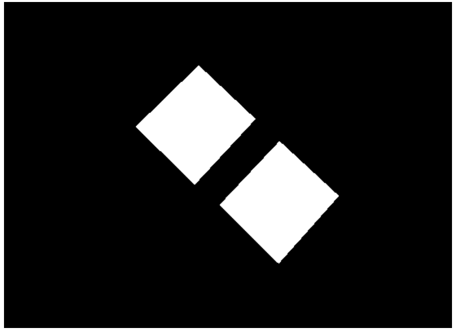
"assign a label to each pixel in the image"

1.6. Computer Vision tasks (remote sensing)

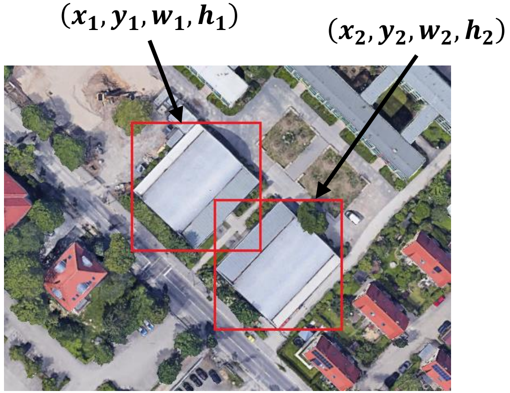
Classification	Semantic Segmentation	Object Detection (Regression)

“assign a label to the whole image”

Hall
Background



“assign a label to each pixel in the image”



“find where an object is in the image”

Outline

2. Application

Mass Monument Industrial Hall?

Classification of steel construction system halls of the High Modernism period and their attribution for an automated airborne image-based acquisition

P. Achanccaray · M. Gerke · L. Wesche · S. Hoyer · K. Thiele · U. Knufinke · C. Krafczyk

DFG Deutsche Forschungsgemeinschaft

SPP 2255 KULTURERBE KONSTRUKTION

Niedersächsisches Landesamt für Denkmalpflege

igp

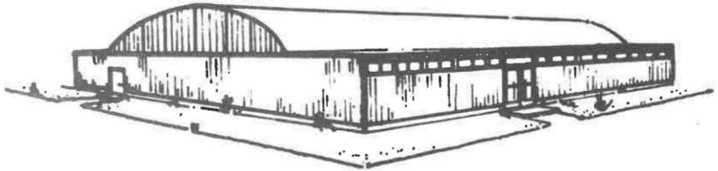
bt

Site: https://kulturerbe-konstruktion.de/spp-2255-teilprojekt/massenphaenomen-gewerbehalle-c3/

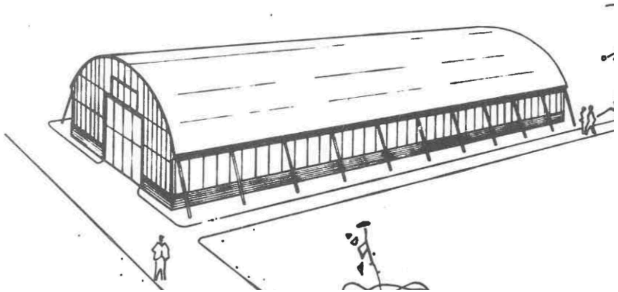
2. Industrial Halls – Types

- Turnhalle – KT 60 L
- Bogenhalle – Ruhland
- Other types

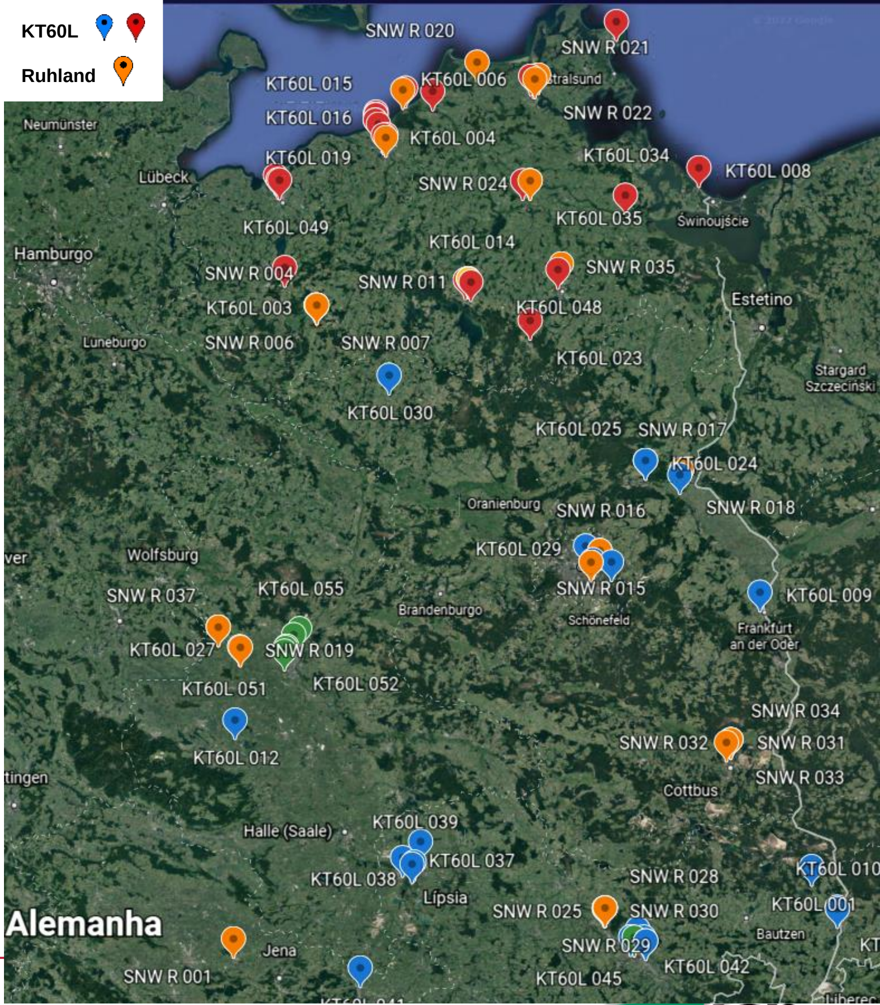
Turnhalle – KT 60 L



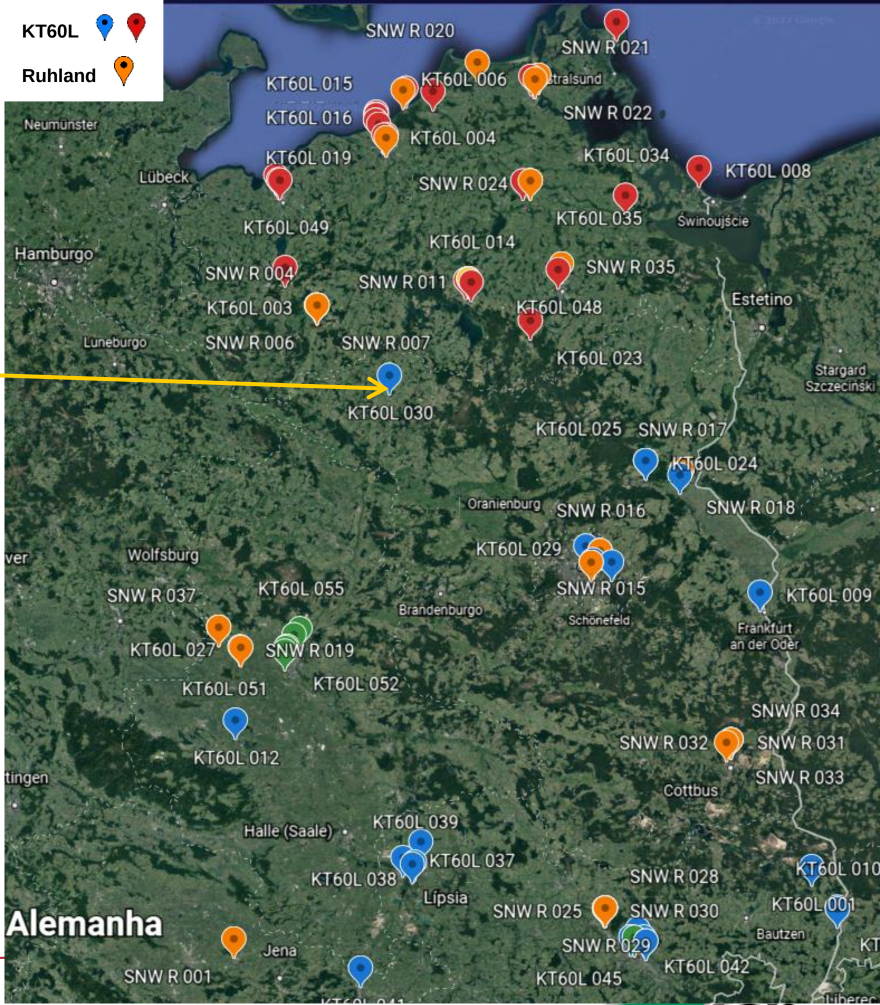
Bogenhalle – Ruhland



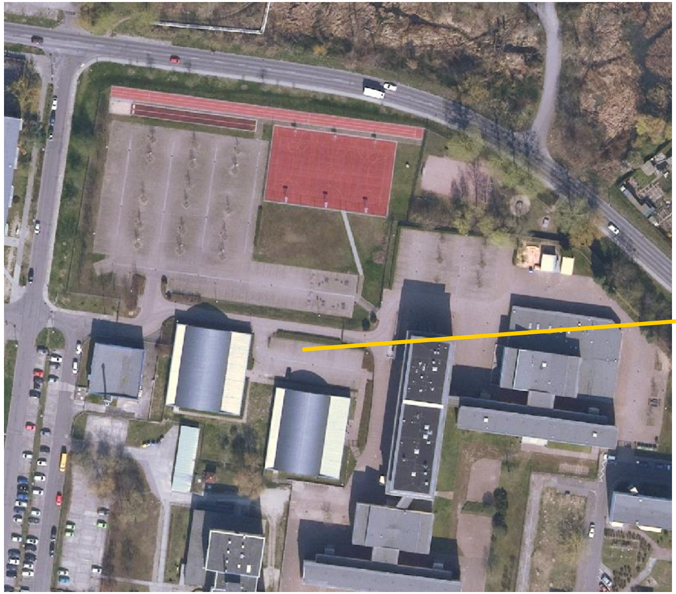
2. Industrial Halls – Locations

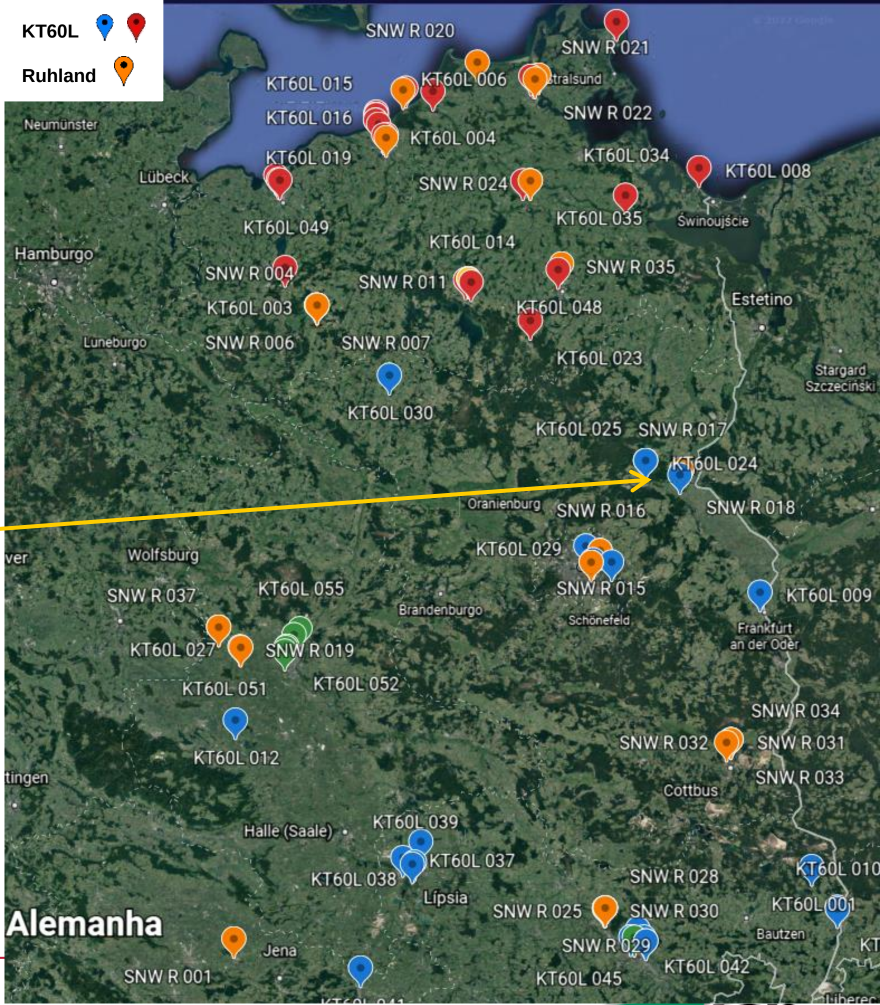


2. Industrial Halls – Samples



2. Industrial Halls – Samples

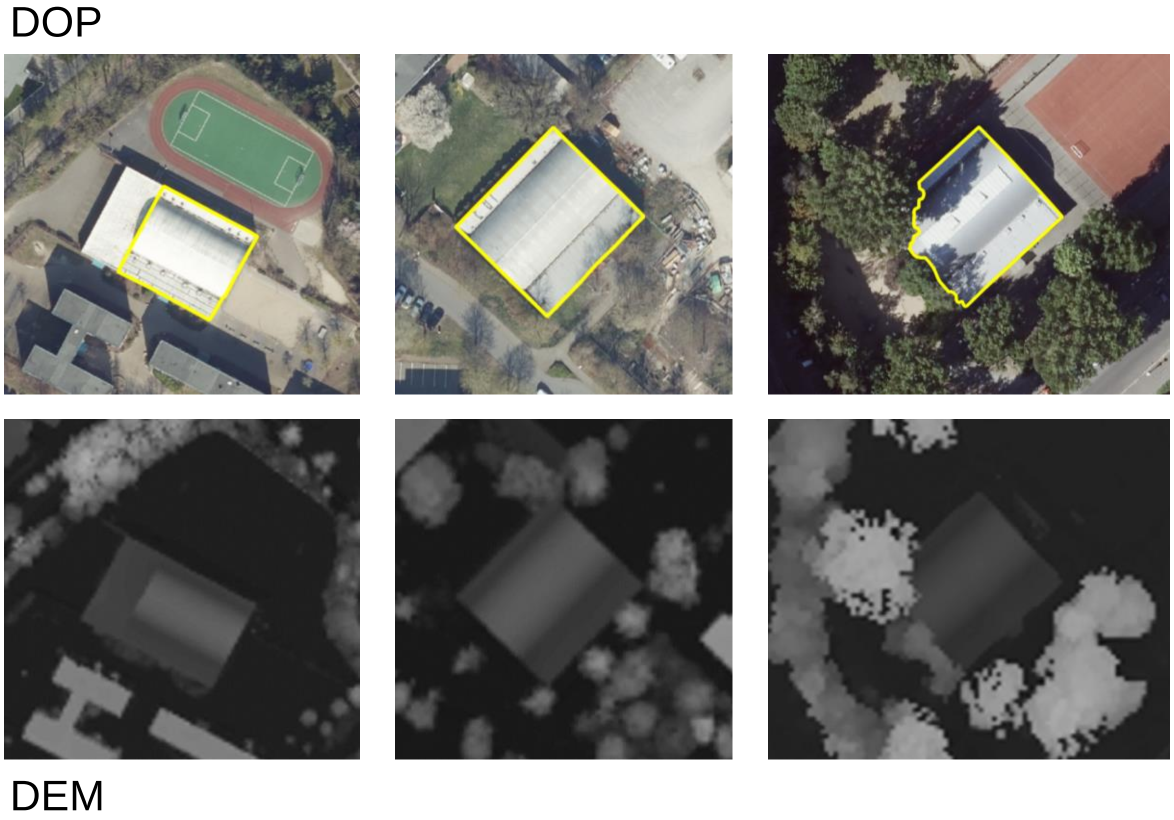




2. Dataset

Images:
- Digital Orthophotos – DOP *(appearance, texture)*
- Digital Elevation Model – DEM *(height)*
- 20 cm spatial resolution

Labels:
- Supervised learning
- Manually delineated



3. Task

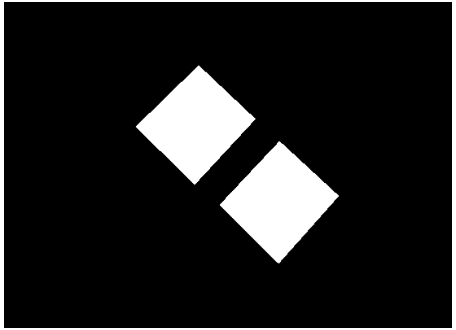
Classification

"assign a label to the whole image"

Semantic Segmentation

Hall

Background

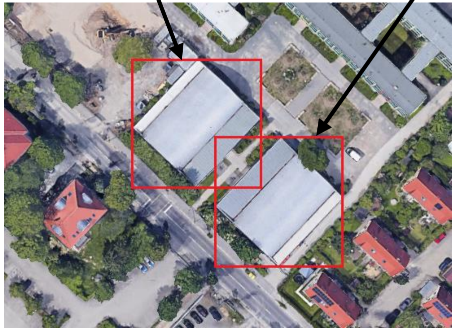


"assign a label to each pixel in the image"

Object Detection

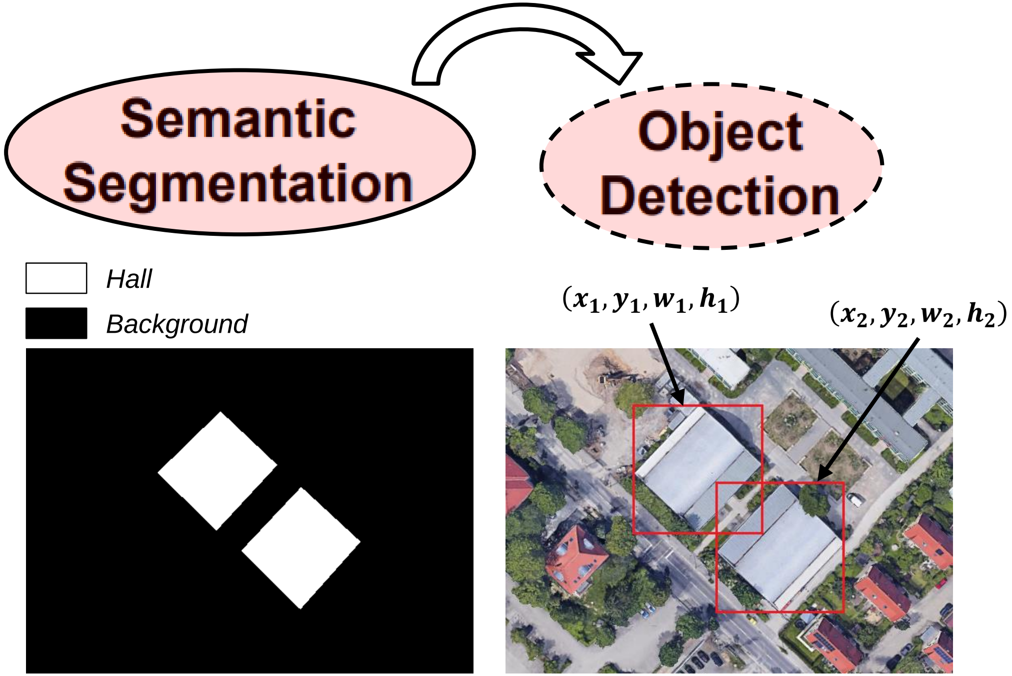
(x_1, y_1, w_1, h_1)

(x_2, y_2, w_2, h_2)



"find where an object is in the image"

3. Task



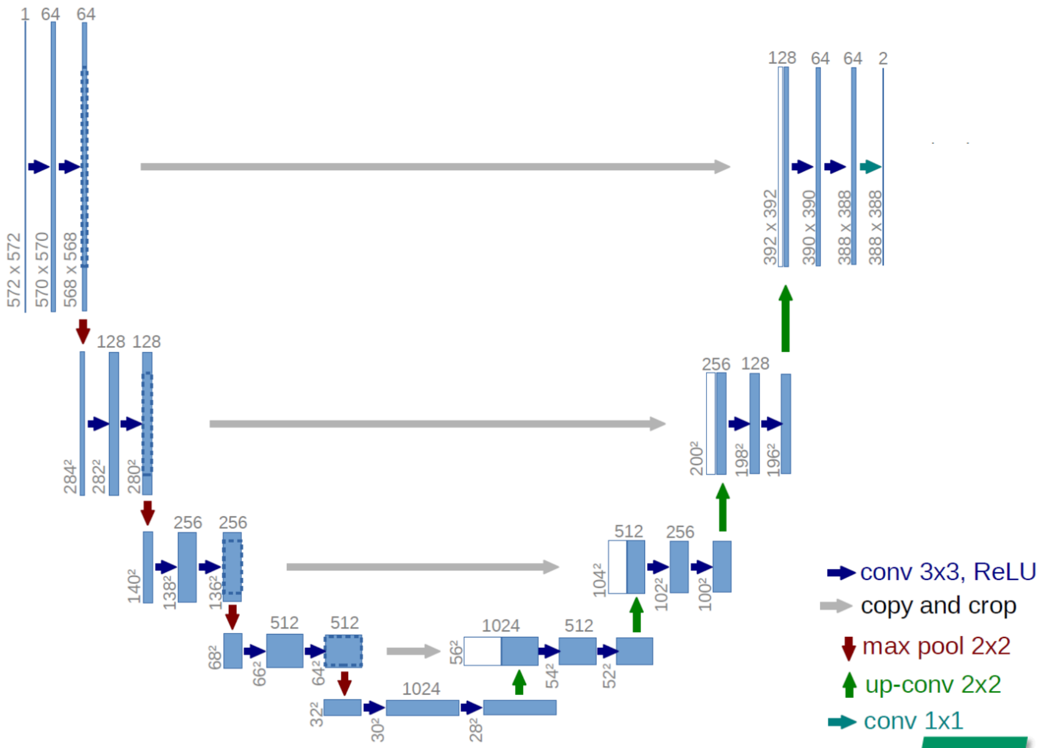
“assign a label to each pixel in the image”

“find where an object is in the image”

Source: Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. https://doi.org/10.1007/978-3-319-24574-4_28

4. Deep Learning model

Model: U-Net



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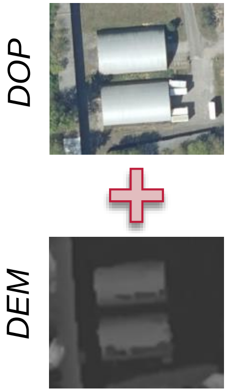
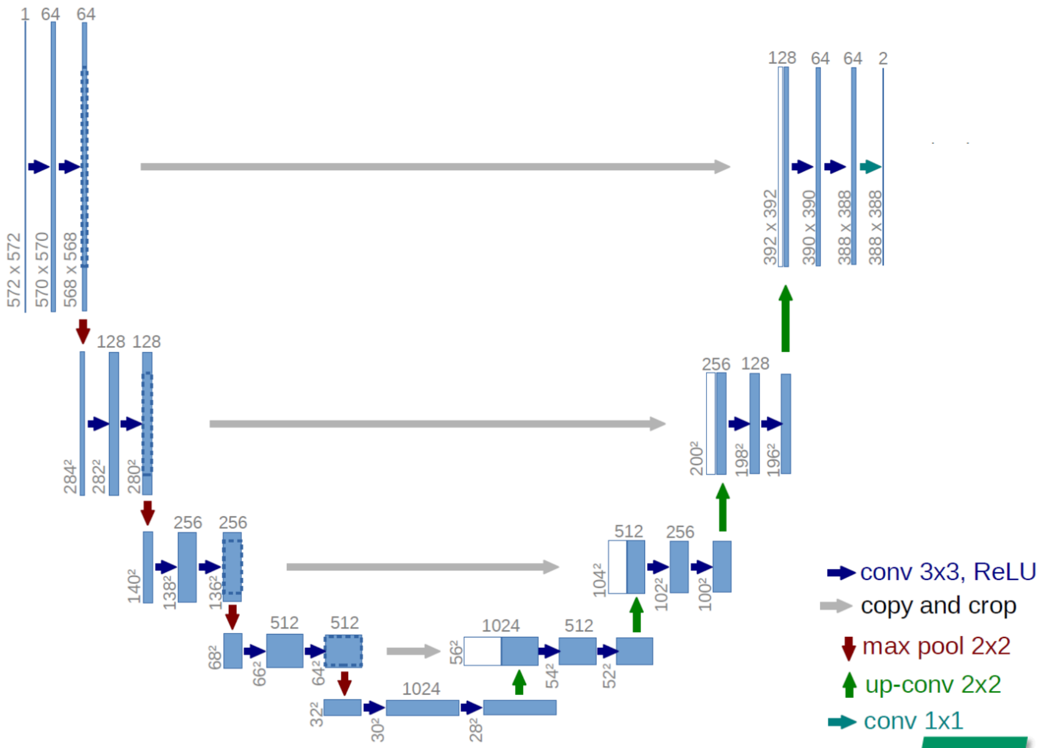
4. Deep Learning model

Model: U-Net





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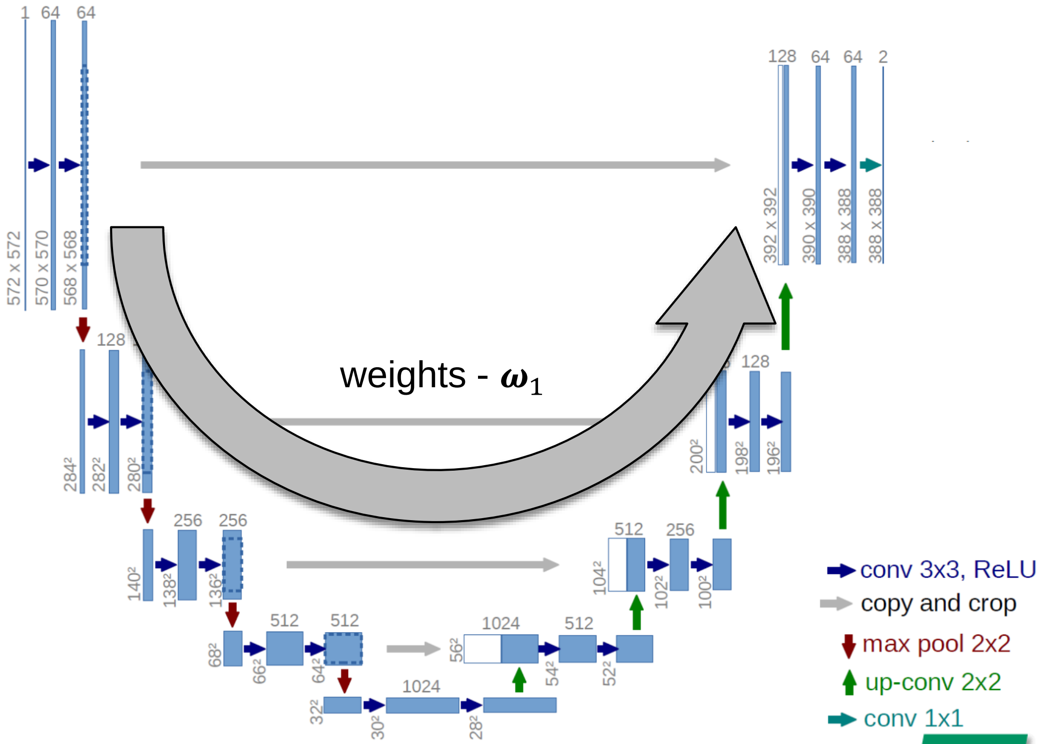
4. Deep Learning model

Model: U-Net

DOP

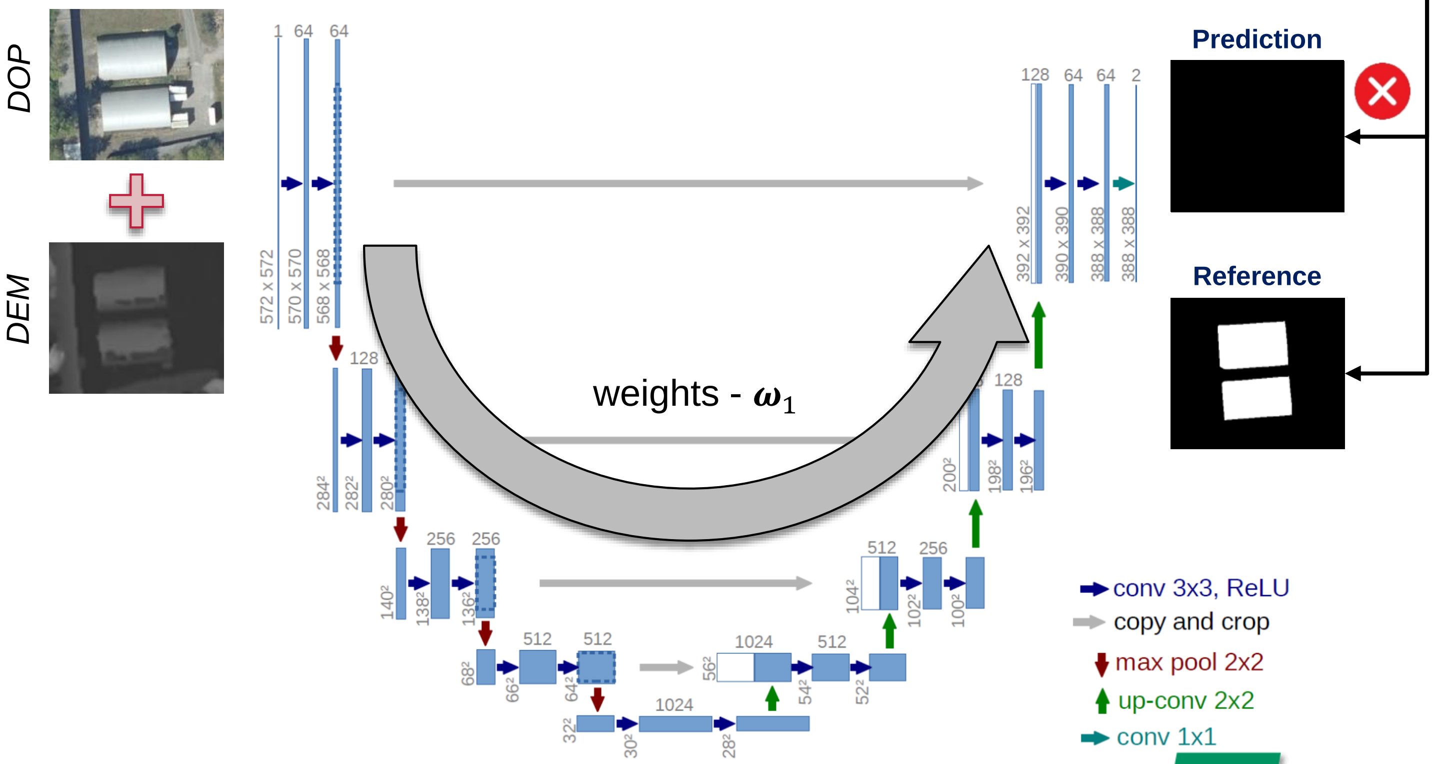
DEM



Source: Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. https://doi.org/10.1007/978-3-319-24574-4_28

4. Deep Learning model

Model: U-Net



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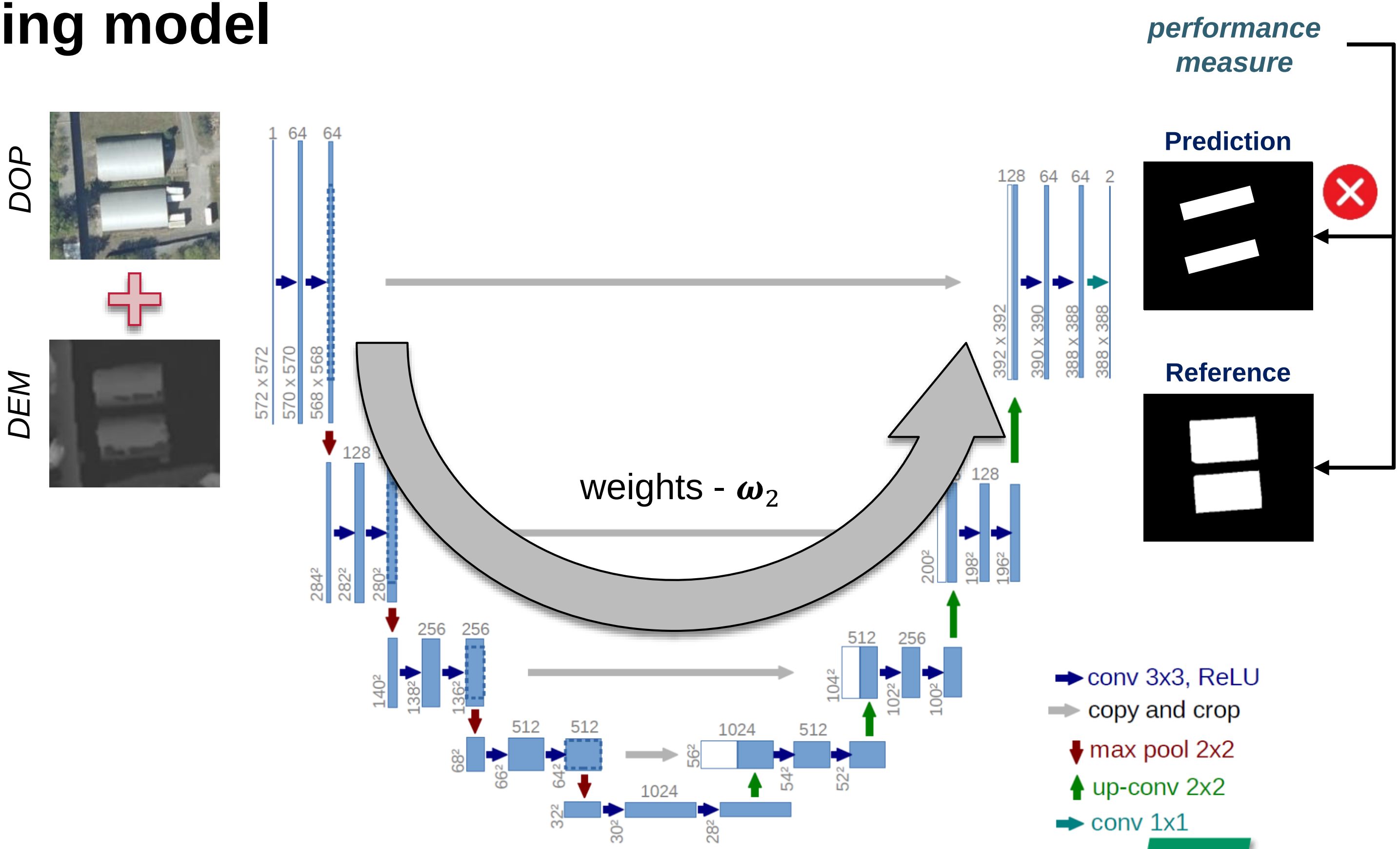
4. Deep Learning model

Model: U-Net



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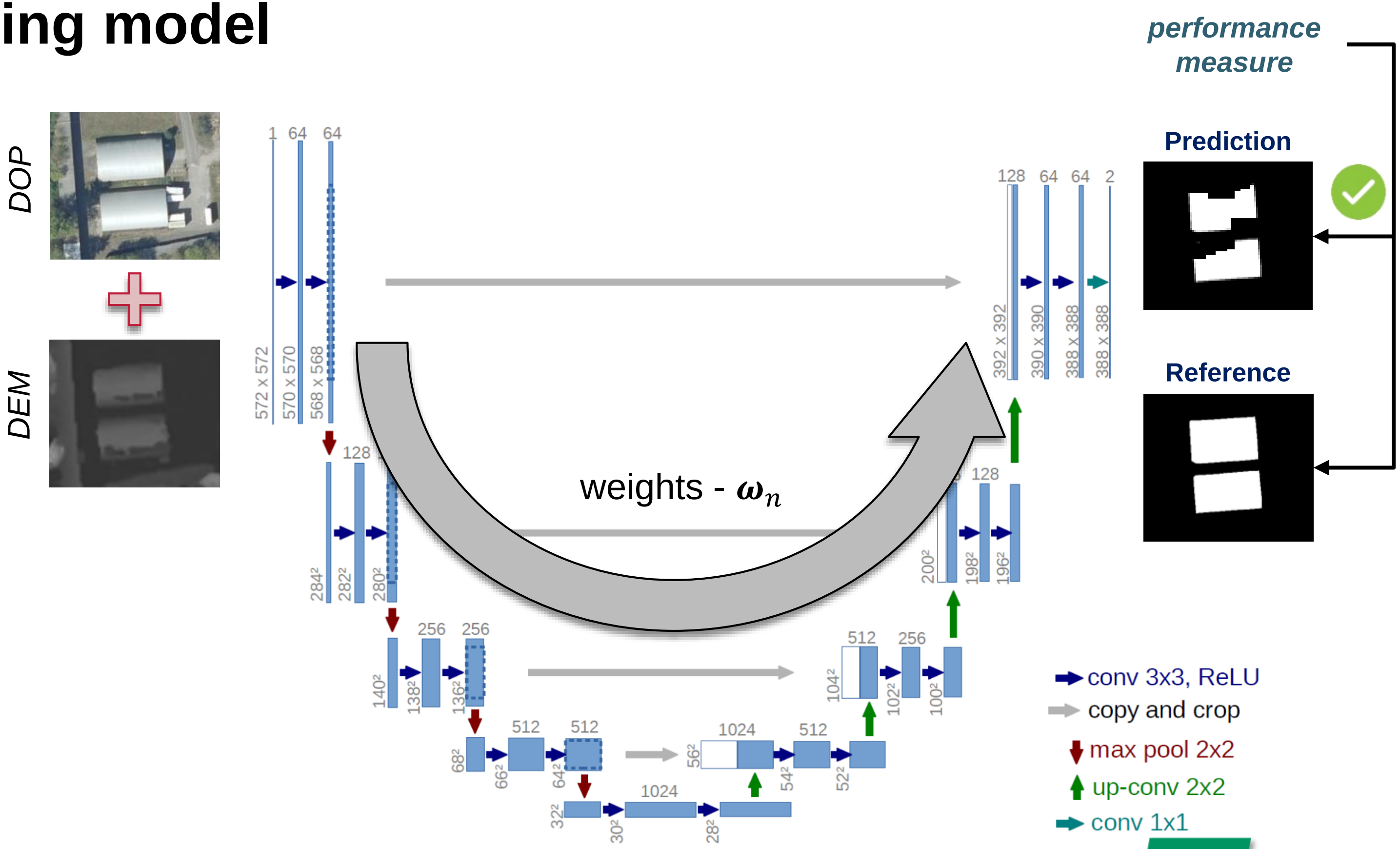
4. Deep Learning model

Model: U-Net



5. Results

Detection rate

(not use during training, we know if there are halls or not)

System halls – Testing		
Detected	Missed	False positives
25	1	2

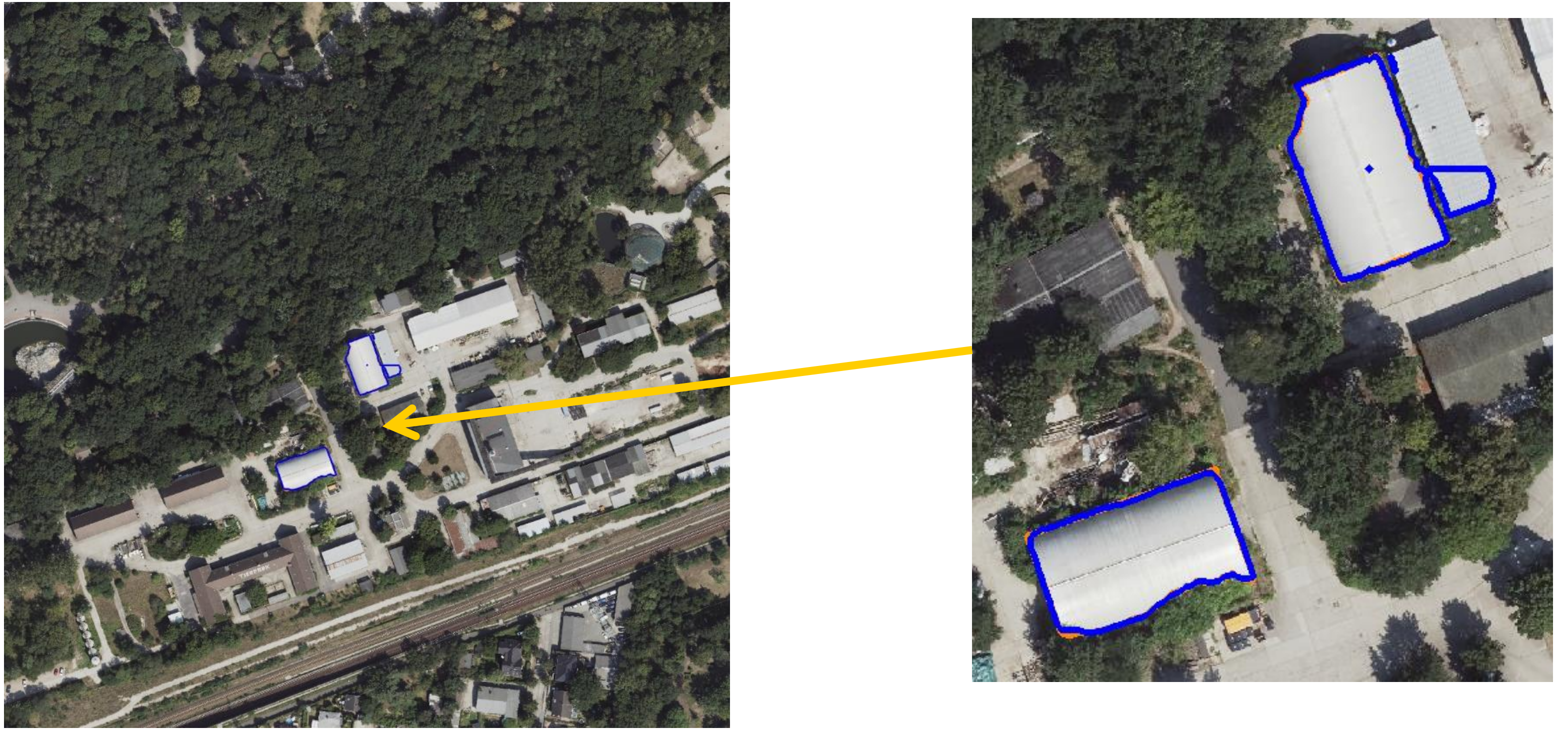
(not use during training, we do not know if there are halls or not)

System halls – Blind testing	
Detected	False positive
2	4

5. Results – Testing

0.4 km x 0.4 km	Processing time: ~6 s

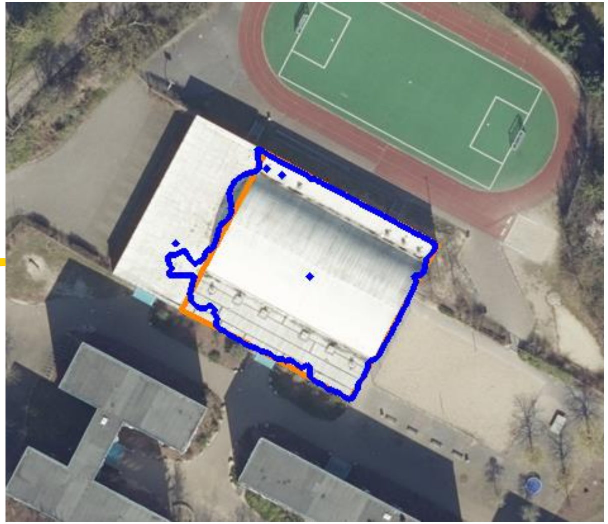
Reference (orange)
Prediction (blue)



5. Results – Testing

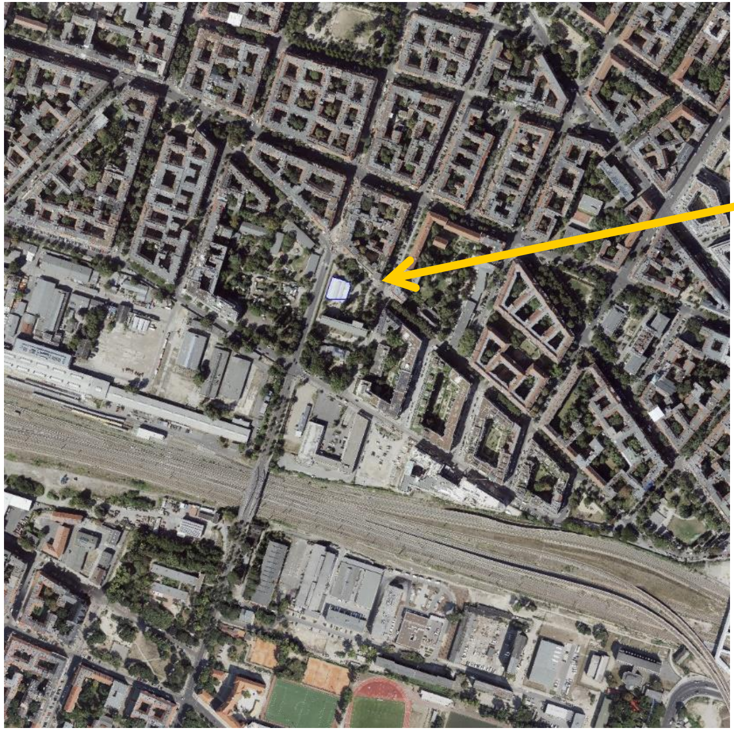
0.4 km x 0.4 km	Processing time: ~6 s

Reference (orange)
Prediction (blue)



5. Results – Blind Testing

1 km x 1 km	Processing time: ~24 s



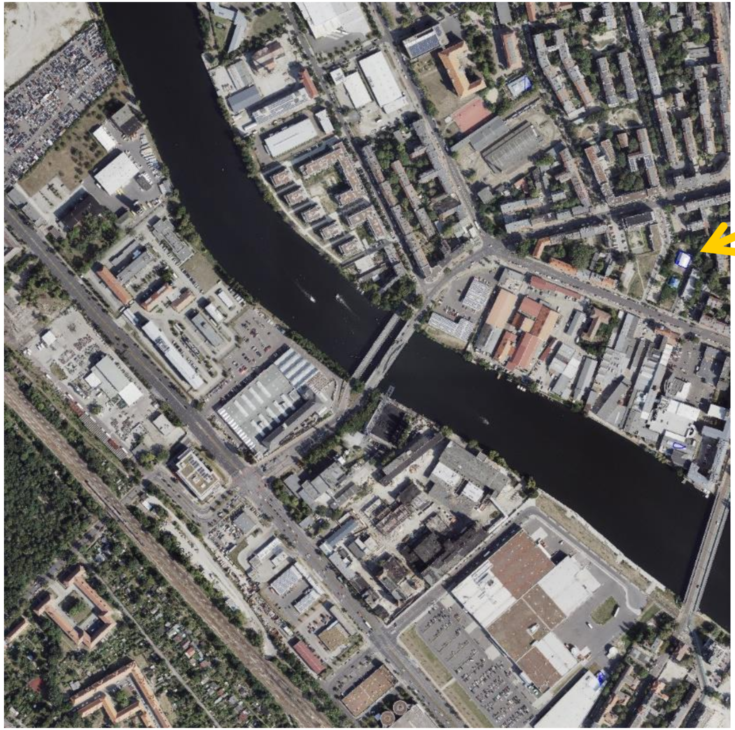
Prediction (**blue**)

Google Earth

New detection

5. Results – Blind Testing

1 km x 1 km	Processing time: ~24 s



Prediction (**blue**)

Google Earth

False Positive

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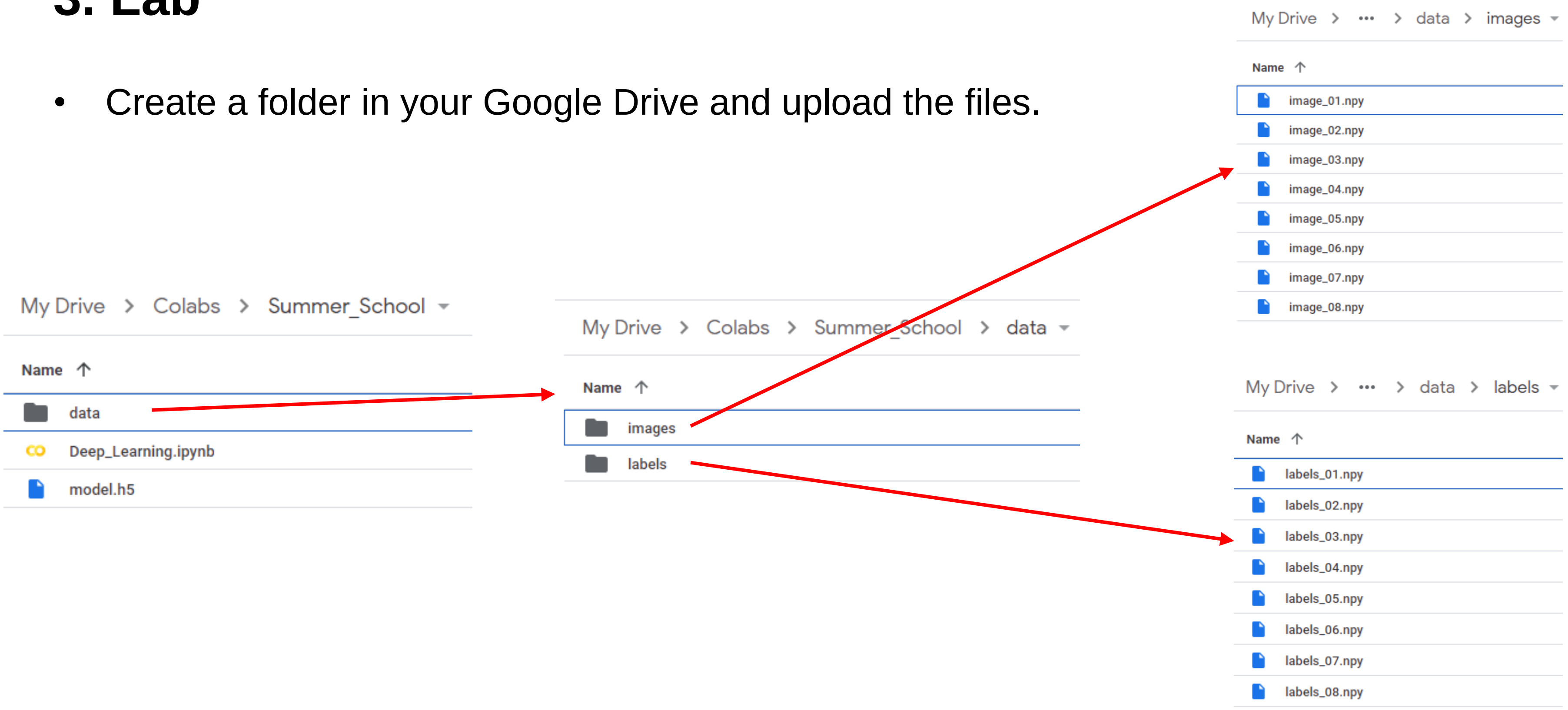
3. **Lab**

3. Lab

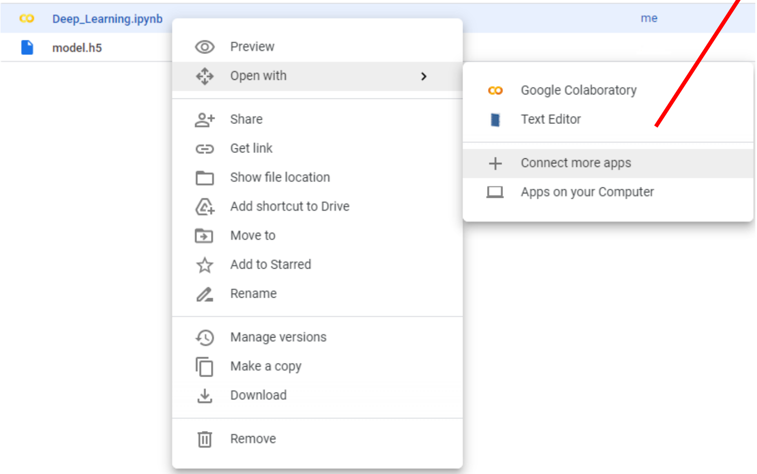
- Create a folder in your Google Drive and upload the files.



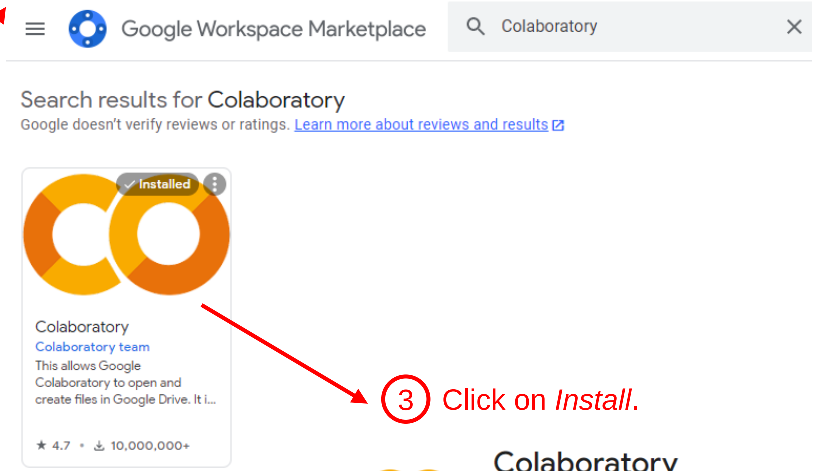
3. Lab

- Google Colaboratory

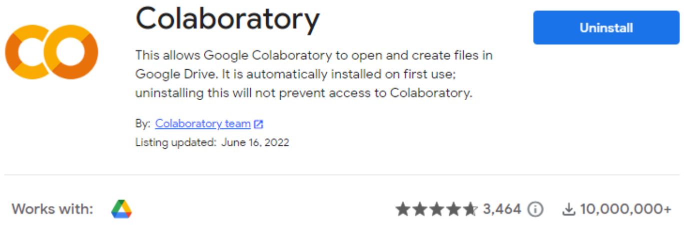
① Right click on the *Deep_Learning.ipynb* file. Go to *Open with => Connect more apps*.



② Search for *Colaboratory* app and select it.



③ Click on *Install*.



3. Lab

- Google Colaboratory

4 Right click on the *Deep_Learning.ipynb* file. Go to *Open with => Google Colaboratory*.