Deep Network Development

Lecture #1

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Questions to me! (Teams preferred)

Course information

Class: Tuesday from 17:00, (South building 0.821., Bolyai terem)

Canvas page: https://canvas.elte.hu/courses/62740

- Course materials
- Assignments
- Assignment feedback
- Grading

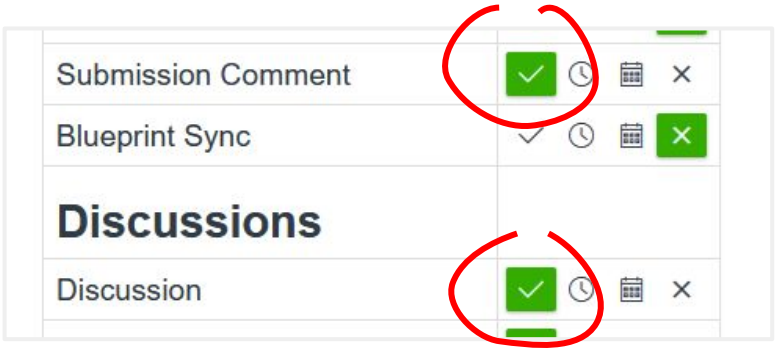
Teams group – join with code: mzy01jp

- Announcements

Canvas

Assignment submission feedback example

Canvas → Account → Notifications:
Enable “Submission Comment”
Enable “Discussion”



Course information – Evaluation

Theory

- **Theory test 1 & 2** – Written tests from theory
- **Oral exam** – Questions from theory during the exam period

Practice

- **Homework 1** – Simple neural network training/evaluation
- **Coding test** – Simple neural network training/evaluation
- **Homework 2** – A more complex coding task on neural networks
- **Oral exam** – Defense of Homework 2

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Details, schedule, grading rules will be posted soon on Canvas.

The classic approach

The classic approach to solving problems using computers:

Writing an algorithm…

```
void insertionSort(int[] ar) {
   for (int i=1; i < ar.length; i++) {
      int index = ar[i]; int j = i;
      while (j > 0 && ar[j-1] > index) {
           ar[j] = ar[j-1];
           j--;
      }
      ar[j] = index;
   }
}
```

The classic approach

Writing an algorithm might not be ideal when…

1. … we need to solve **many** slightly different **varieties** of the same task

Image sources: boardgamegeek.com, Sandipan Dey, sandipanweb.wordpress.com/

The classic approach

Writing an algorithm might not be ideal when…

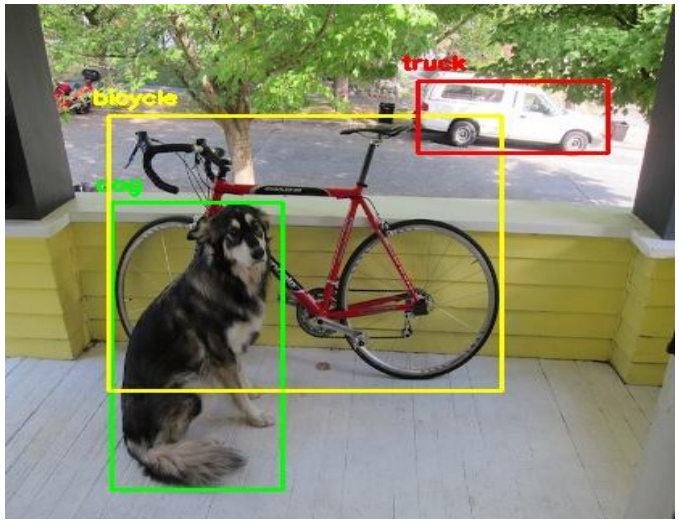
2. … an **algorithmic solution is unknown** or hard to compute

The classic approach

Writing an algorithm might not be ideal when…

3. … the task can **only be formulated by** showing **examples**

E.g., **“Is there a dog in the image?”**
– “Yes.”



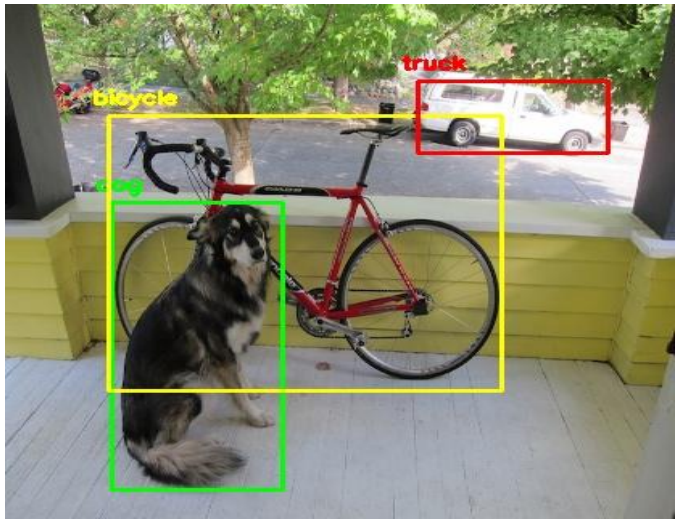
The classic approach

Writing an algorithm might not be ideal when…

3. … the task can **only be formulated by** showing **examples**

E.g., **“Is there a dog in the image?”**
– “Yes.”

How does a dog look like?
→ Impossible to describe accurately with rules.
Instead, we can show examples.



The essence of machine learning

We **learn to solve the problem** without knowing the specific algorithm for the solution.

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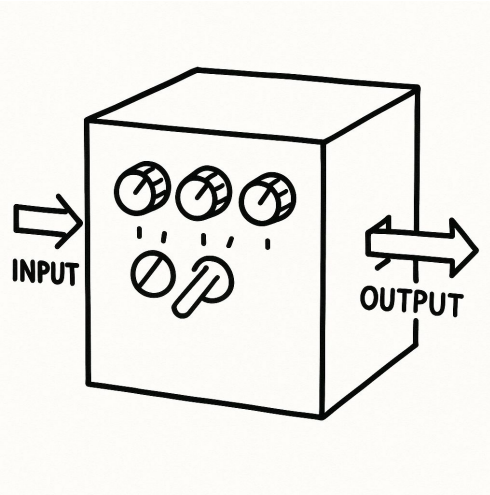
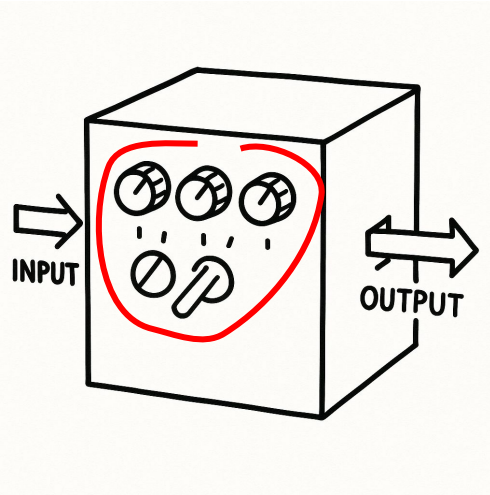
- We define a machine learning **model with parameters**.



The essence of machine learning

We **learn to solve the problem** without knowing the specific algorithm for the solution.

- We define a machine learning **model with parameters**.
- We try to **find such parameters** that will make our model **solve the task** as **well** as possible.



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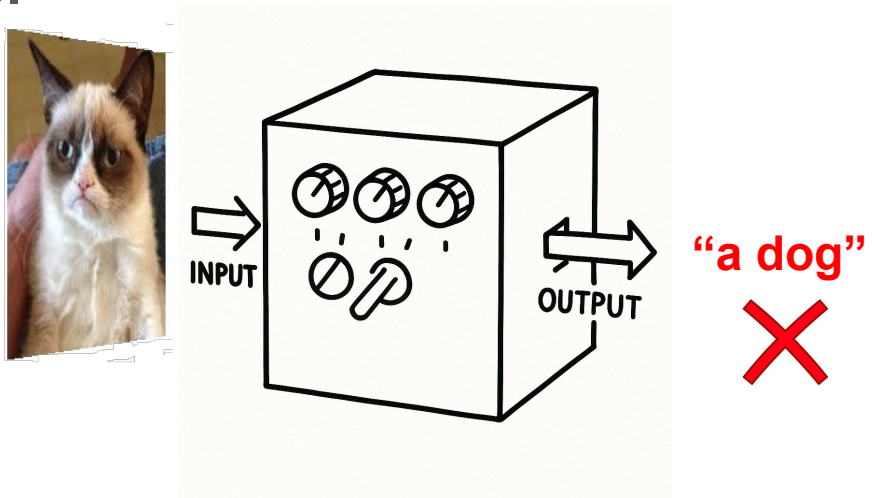

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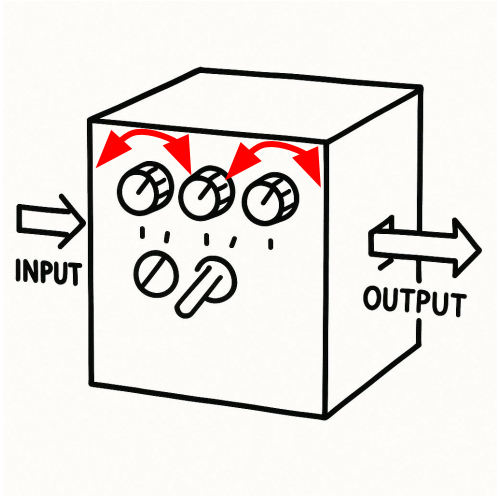

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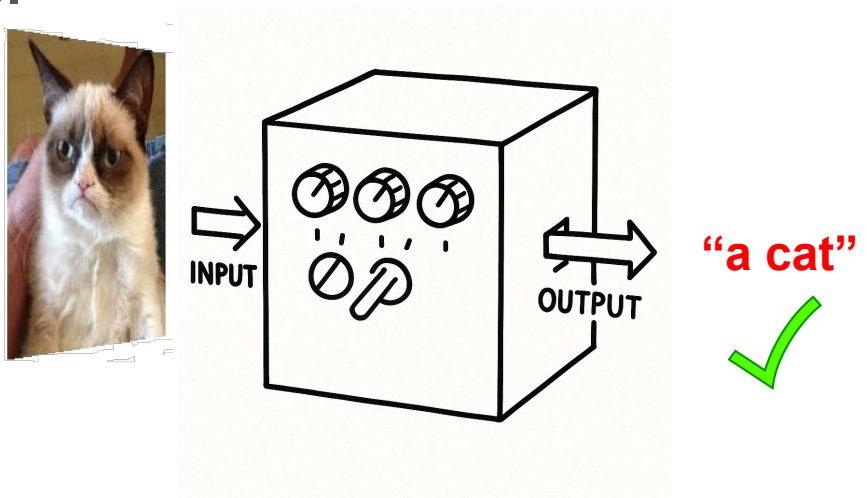
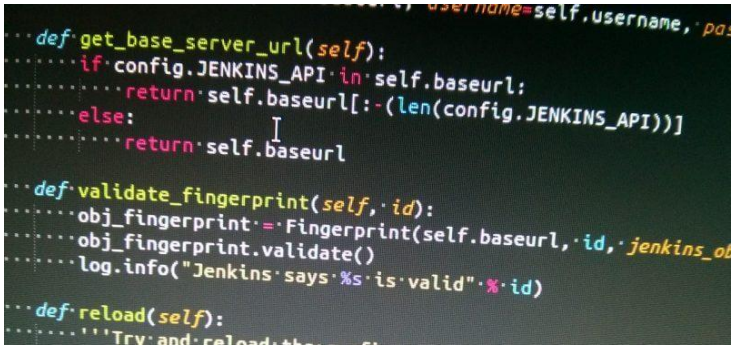


Tasks not suitable for machine learning

- If an **efficient solution** to the problem **is known** and can be easily algorithmized.
- If an **approximate result is not satisfactory**.

Examples:

- **Lossless compression** algorithms.
- **Sorting** algorithms.
- Most software products that are defined by **a complex set of rules**.



Machine learning

Three main groups of machine learning methods:

- **Supervised learning**
- Unsupervised learning
- Reinforcement learning

Supervised learning

Given: The training sample, a set of (input, label) pairs

$$\{(x^{(1)}, y^{(1)}), \ldots, (x^{(m)}, y^{(m)})\}$$

$$x \in X \subset \mathbb{R}^n,\ y \in Y \subset \mathbb{R}^k$$

Task: The estimation of the label (the expected output) from the input

I.e., we search for a (hypothesis-)function h_θ, for which:

$$h_\theta(x) = \hat{y} \approx y$$

Supervised learning

Our examples (1, …, m)

Given: The training sample, a set of (input, label) pairs

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I.e., we search for a (hypothesis-)function h_θ, for which:

The machine learning model with parameters

$$h_\theta(x) = \hat{y} \approx y$$

- The **true label** is “y”.
- Our model h_θ gives an **estimate** for the label: “y hat”.

Supervised learning

Given: The training sample, a set of (input, label) pairs

$$\{(x^{(1)}, y^{(1)}), \ldots, (x^{(m)}, y^{(m)})\}$$

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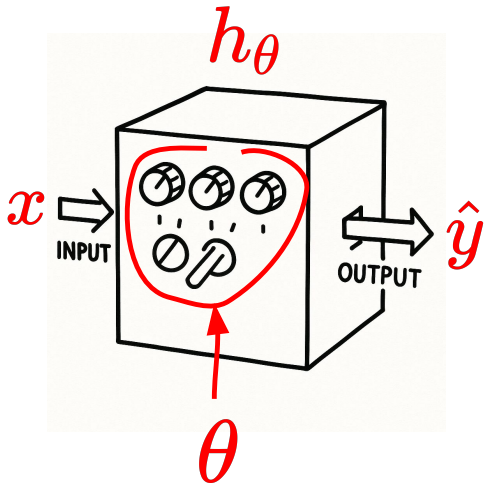


Goal: Find θ that makes $\hat{y}$ be as similar to y as possible!

Task: The estimation of the label (the expected output) from the input

I.e., we search for a (hypothesis-)function h_θ, for which:

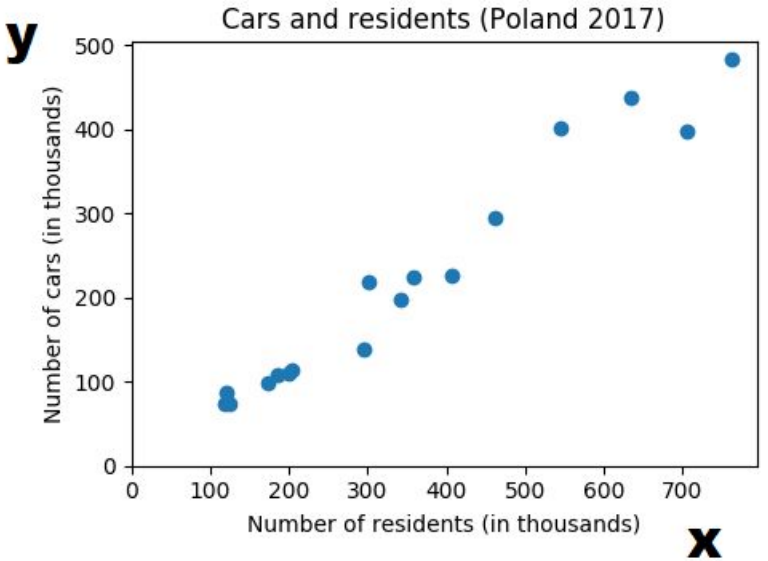
$$h_\theta(x) = \hat{y} \approx y$$

Supervised learning

Example: Estimate the number of cars in a particular city given the population of that city.

x: The **population** of a particular city

y: The **number of cars** in a particular city



$$x^{(j)}, y^{(j)} \in \mathbb{R}$$

Supervised learning

Example: Estimate the number of cars in a particular city given the population of that city.

x: The **population** of a particular city

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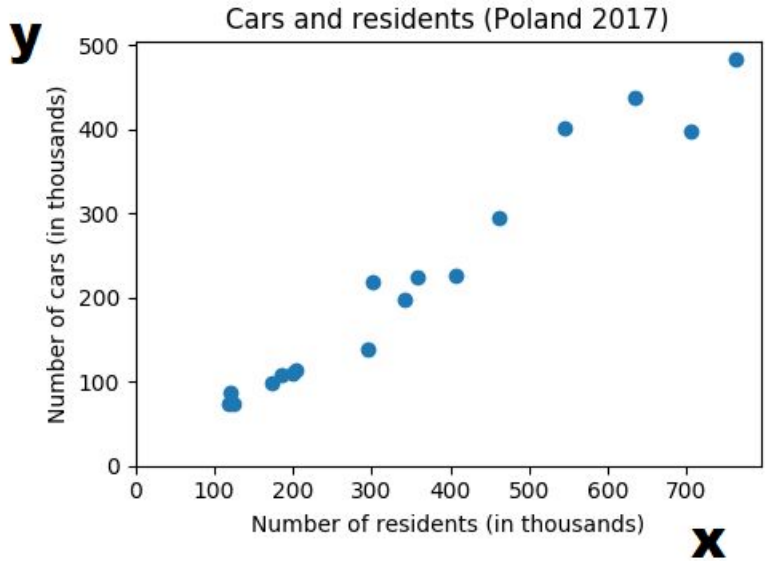
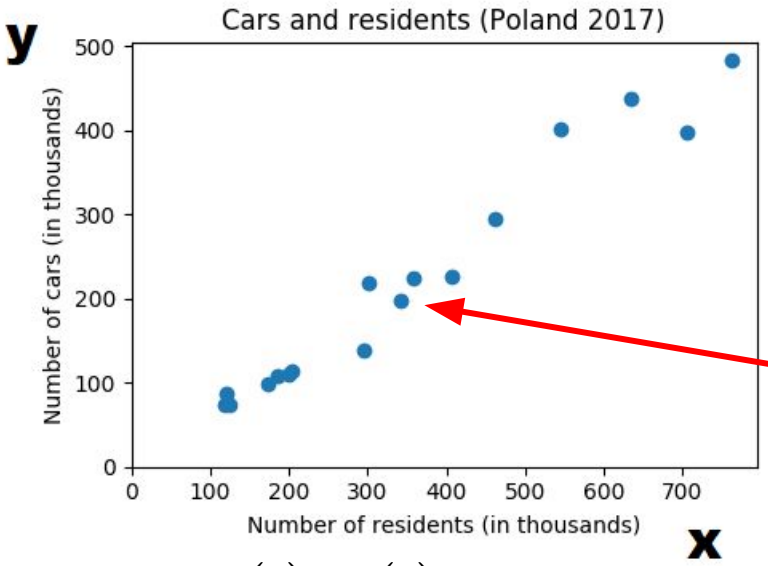


A single input variable and **a label:**
Our labeled examples can be interpreted as points located in a two-dimensional vector space (a plane).

$$x^{(j)}, y^{(j)} \in \mathbb{R}$$

Visualizing the data



$x^{(j)}, y^{(j)} \in \mathbb{R}$

	the input variable (feature) x (population, ×1000)	the label y (n. of cars, ×1000)
Warsaw (j = 1)	1760	910
Krakow (j = 2)	770	465
Lublin (j = 3)	340	198
...	...	...

Supervised learning

How should our model look like?
What type of hypothesis function are we looking for?

The number of cars is roughly proportional to the population of the city...

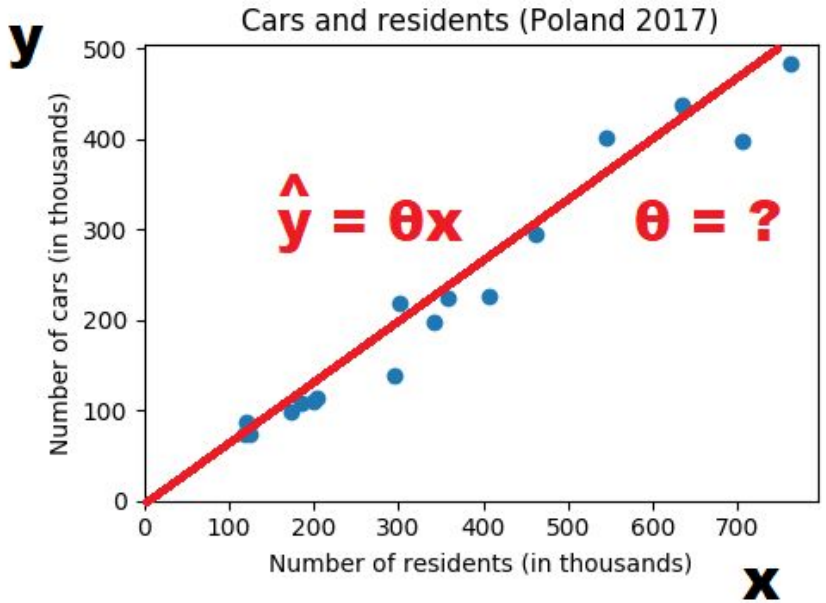
Supervised learning

What type of hypothesis function are we looking for?

A very simple (linear)
hypothesis function:

$$y \approx \hat{y} = h_\theta(x) = \theta x$$

θ is the parameter of the hypothesis-function: in this case,
this is going to be the **slope of the line**.



Supervised learning

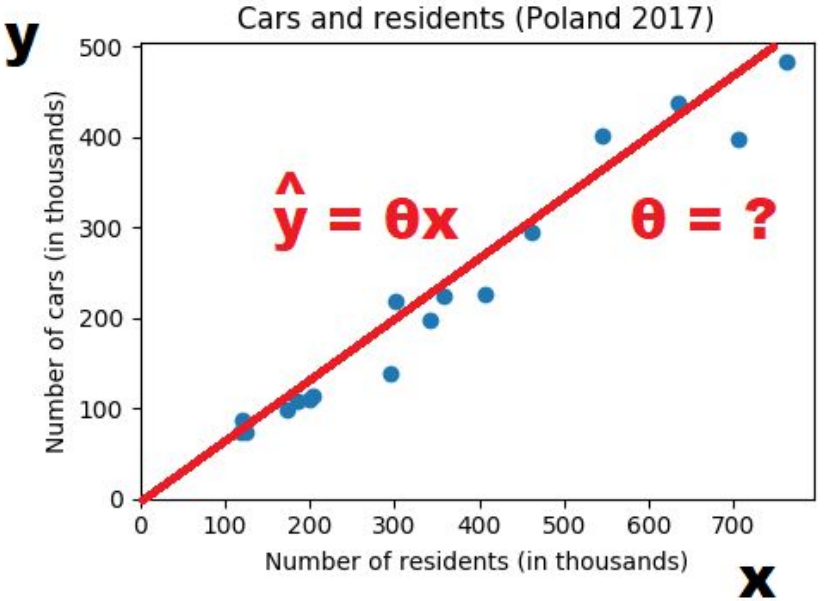
What type of hypothesis function are we looking for ?

A very simple (linear) hypothesis function:

$$y \approx \hat{y} = h_\theta(x) = \theta x$$

θ is the parameter of the hypothesis-function: in this case, this is going to be the **slope of the line**.

We are looking for a parameter θ such that h(x) closely approximates the true y labels.
For example, the hypothesis function h(x) = 0.65*x fits this particular sample well, so a good parameter is θ = 0.65.



Supervised learning

Examples **do not necessarily consist of a single input variable and a single label...**

Supervised learning

Example: Estimate the age of the people in the pictures!

x: A portrait
(a fixed-resolution color image)

y: The age of the person in the image

$$x^{(j)} \in [0, 255]^{196608}$$

$$y^{(j)} \in \mathbb{R}$$

How many dimensions would the sample plot have in this case?

Supervised learning

Example: Estimate the age of the people in the pictures!

x: A portrait
(a fixed-resolution color image)

y: The age of the person in the image

$$x^{(j)} \in [0, 255]^{196608}$$

$$y^{(j)} \in \mathbb{R}$$

The brightness of each color channel of each pixel is an input variable:
Examples are points in a 196608 (+1 label) dimensional vector space.

Visualizing the data

$x^{(j)} \in [0, 255]^{196608}$

$y^{(j)} \in \mathbb{R}$

input vars	#1	#2	…	#196608	the label
	x_1 (pixel #1 “red” bright.)	x_2 (pixel #1 “green” bright.)	...	x_{196608} (pixel #65535 “blue” brightness)	y (age of the person)
Img #1 (j = 1)	255	17	...	175	29
Img #2 (j = 2)	125	0	...	0	9
Img #3 (j = 3)	36	240	...	215	35
...	...	...		...	...

Supervised learning

How should our model look like?
What type of hypothesis function are we looking for?

The linear hypothesis function might not work well this time…

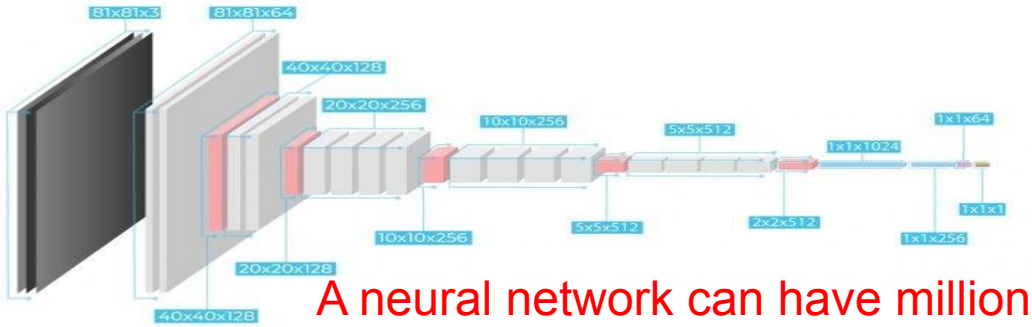
Image source: J. S. Combinido et al., 2018

Supervised learning

What type of hypothesis function are we looking for?

The linear hypothesis function might not work well this time…

Instead, let's use a really complicated function, a deep convolutional neural network! **Neural networks are just functions too...**

$h_\theta : x \rightarrow$ 

$\rightarrow \hat{y}$

A neural network can have millions of parameters, so **θ** here is **a vector** with millions of elements.

The two main types of tasks in supervised learning

Regression: Continuous labels (The label set is infinite)

$|Y| = \infty$ **Example:** Number of cars or the age of a person

Classification: Discrete labels (The label set is finite)

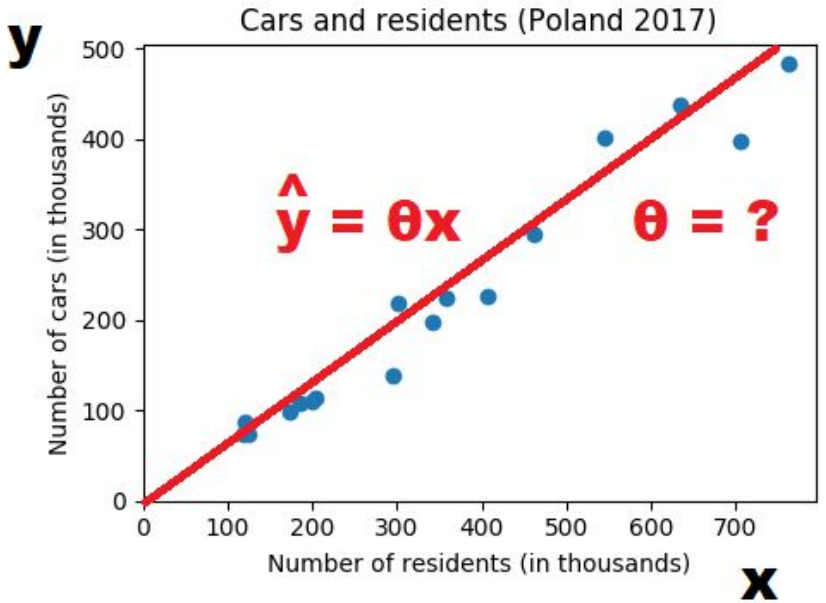
$|Y| < \infty$ **Example:** Categorization of examples

- What is the profession of the person in the image?

Supervised learning

How do we determine how good the estimate is?

$$h_\theta(x) = \hat{y} \overset{?}{\approx} y$$



Supervised learning

How do we determine how good the estimate is?

With the help of the loss function J. $J : \theta \rightarrow \mathbb{R}_{\geq 0}$

The loss function indicates **how much the actual label differs from our estimate** for given parameter values.

A simple example for a loss function: $J(\theta) = |\underbrace{h_\theta(x)}_{\hat{y}} - y|$

Supervised learning

How do we determine how good the estimate is?

With the help of the loss function $J(\theta)$.

The loss must be a single number (scalar). If the y label consists of multiple variables, then instead of the absolute value, we will need, for example, a norm...

The loss function indicates **how much the actual label differs from our estimate** for given parameter values.

A simple example for a loss function:

$$J(\theta) = |\underbrace{h_\theta(x)}_{\hat{y}} - y|$$

The greater the error in our estimate with a given parameter **θ**, the greater the loss is in **θ**.
In the case of a perfect estimate, the loss is 0.

Supervised learning

The goal of supervised learning:

Find the **θ*** parameters that make our hypothesis function $h_\theta(x)$ approximate the true label (**y**) as closely as possible,
i.e., minimize our loss **J**.

$$\theta^* = \arg\min_\theta J(\theta)$$

Supervised learning

The goal of supervised learning:

Find the **θ*** parameters that make our hypothesis function $h_\theta(x)$ approximate the true label (**y**) as closely as possible,
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Steps:

1. **Finding** (learning) **optimal parameters on the training set.**
2. **Estimating labels** for new, unlabeled examples by our trained model.

Supervised learning - applications

Supervised learning implemented with neural networks is also **suitable for more complex tasks...**

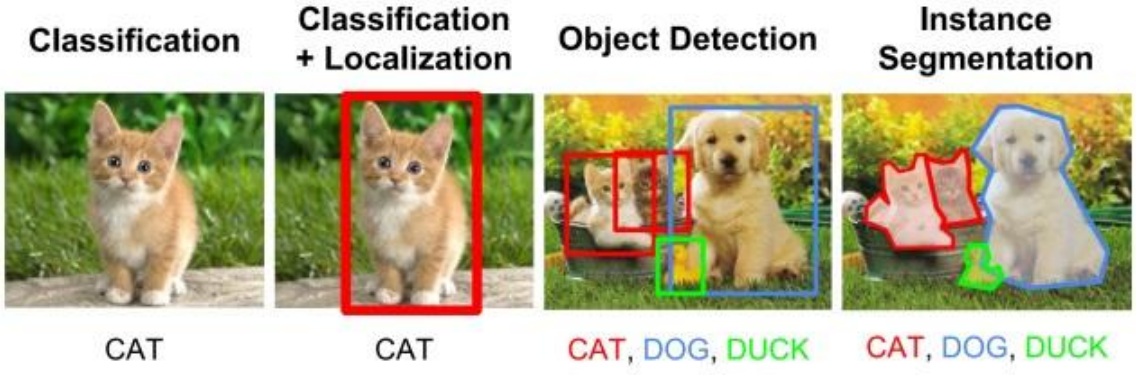
Image source: https://towardsdatascience.com/object-localization-in-overfeat-5bb2f7328b62 ; Yu et al., 2014

Supervised learning - applications

Object detection, object segmentation

x: An image

y: The coordinates of the enclosing rectangles (bounding boxes) of objects (bounding box), or the pixel-level outline of objects.



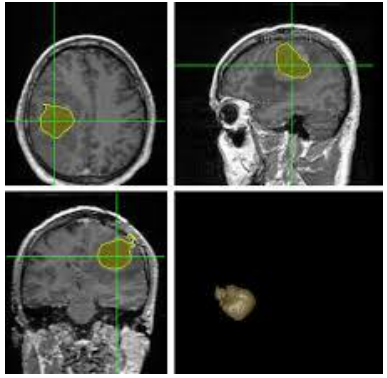


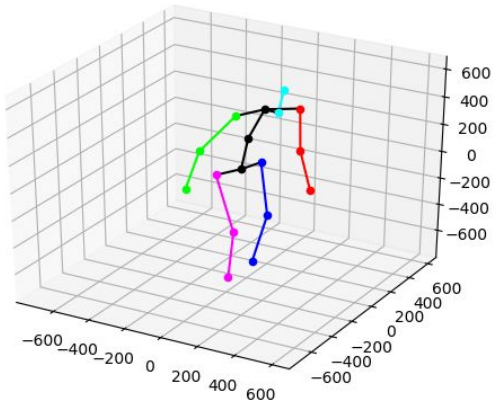
Image source: Newell et al., 2015

Supervised learning - applications

2D / 3D visual human pose estimation

x: An image

y: The joint coordinates of the persons in the image



Supervised learning - applications

Natural Language Processing (NLP), Text sentiment analysis

x: A sequence of characters / words

y: A sentiment category

Supervised learning - applications

Natural Language Processing (NLP), Image captioning

x: An image

y: A sequence of characters / words describing the content of the image

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

Image source: http://vas3k.com/blog/machine_translation/

Supervised learning - applications

Natural Language Processing (NLP), Machine translation

x: A sequence of characters / words in the source language

y: A sequence of characters / words in the target language

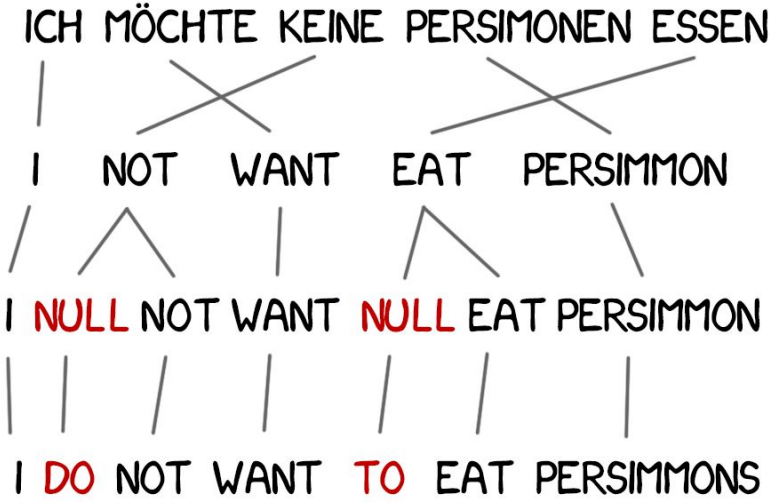
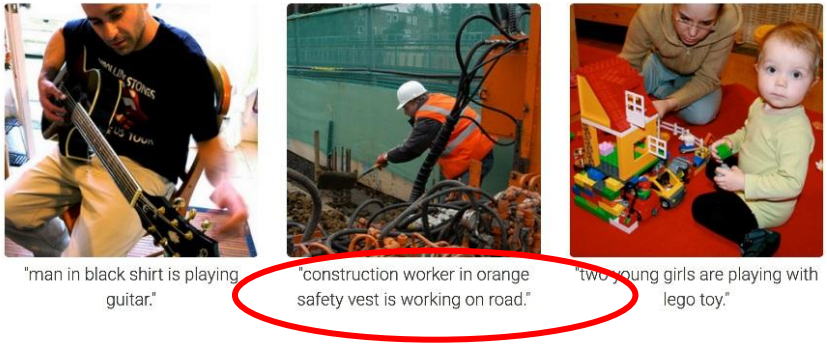
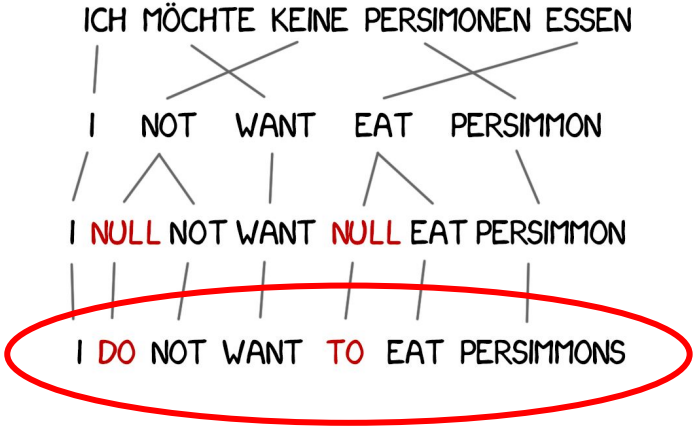


Image source: http://vas3k.com/blog/machine_translation/

Supervised learning - applications

Natural Language Processing: The problem of the loss function





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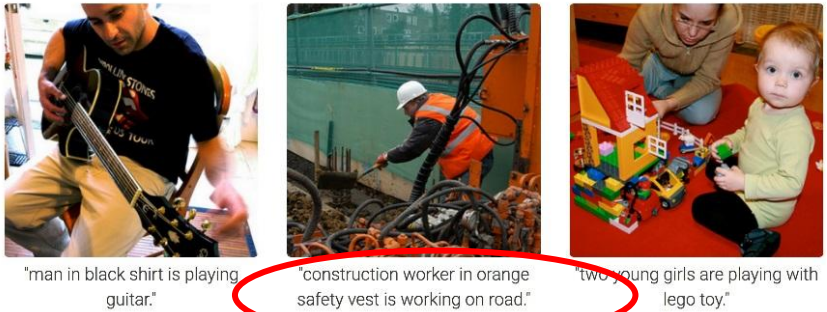
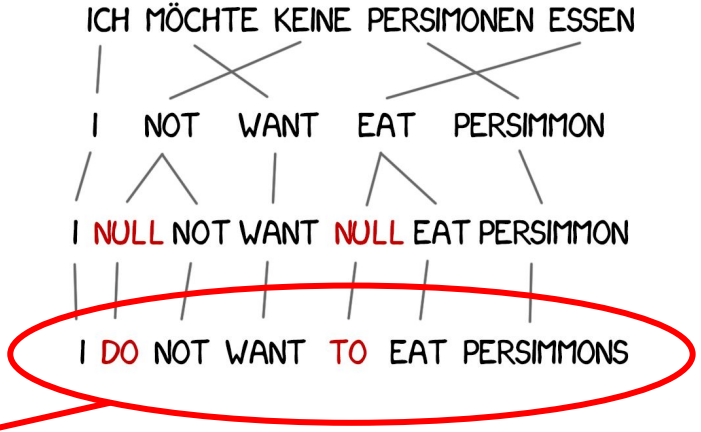




The true label is not clear. The same meaning can be expressed in several ways. How do we know how good our estimate is? How do we calculate the error of our estimate (the loss value)?

Supervised learning

A problem of supervised learning

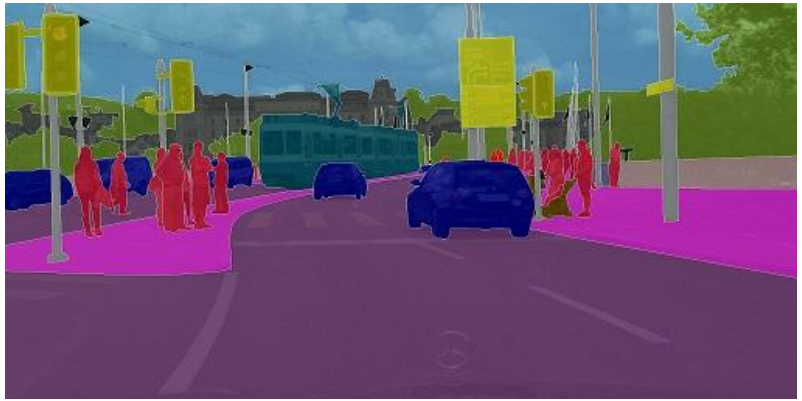
- **Natural intelligence** (animals/humans) generally **does not require** specific **(x, y) input-output pairs** in order to learn.

Supervised learning

A problem of supervised learning

- **Natural intelligence** (animals/humans) generally **does not require** specific **(x, y) input-output pairs** in order to learn.

- The **production of labeled data** may require a **great deal of human labor**.
  However, there is a vast amount of unlabeled data available.



Machine learning

Three main groups of machine learning methods:

- Supervised learning
- **Unsupervised learning**
- Reinforcement learning

Unsupervised learning

Without labels, the task is unclear…

Several specific tasks are possible:

- **Clustering**
- **Compression / dimensionality reduction**
- **Sample generation**
- **...**

Image source: Saglam et al., 2016

Unsupervised learning

Clustering

- **Marketing, targeted advertising, recommendation systems:** grouping similar customers for targeted offers
- **Classic computer vision,** e.g., image segmentation
- **Anomaly** (outlier) **detection**

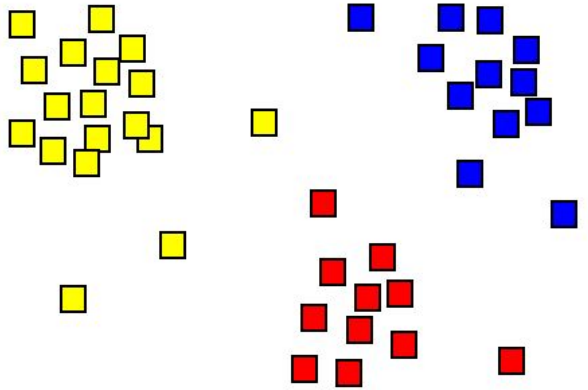


Image source: Sandipan Dey, sandipanweb.wordpress.com/

Unsupervised learning

Compression / dimensionality reduction

- Lossy compression adapted to work with a certain type of data

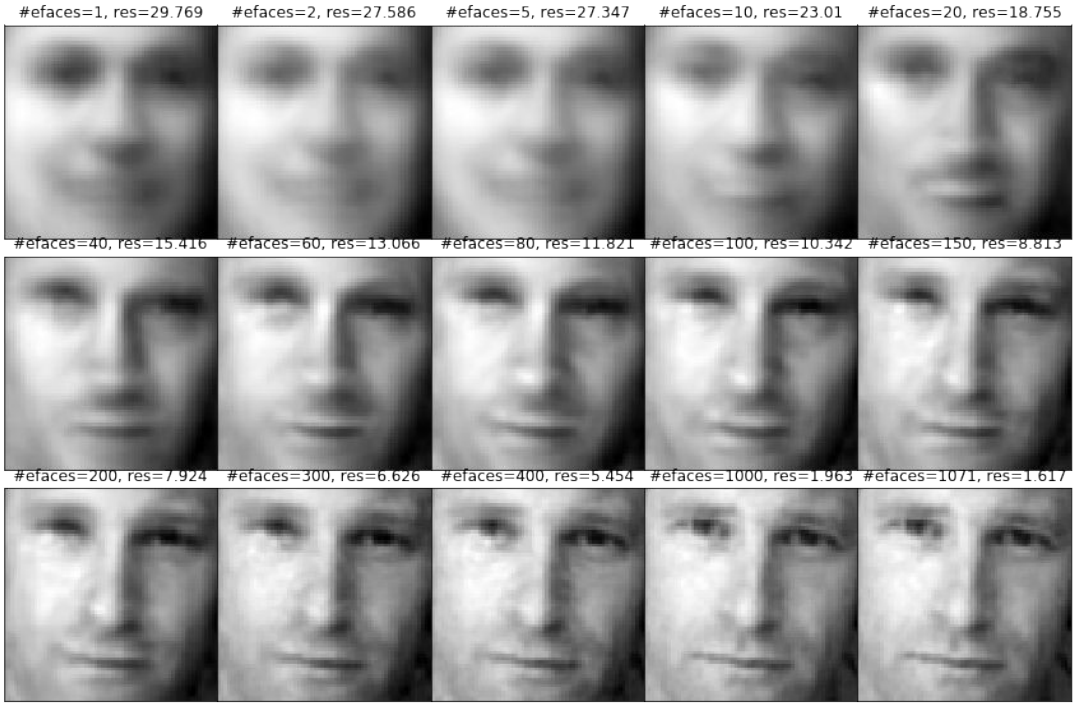


Image source: Sandipan Dey, sandipanweb.wordpress.com/

Unsupervised learning

Principal component analysis (PCA) on human faces. **Reconstruction** (x hat) from the compressed representation, with different compression ratios.

Compression / dimensionality reduction

- Lossy compression adapted to work with a certain type of data

Original input (x)

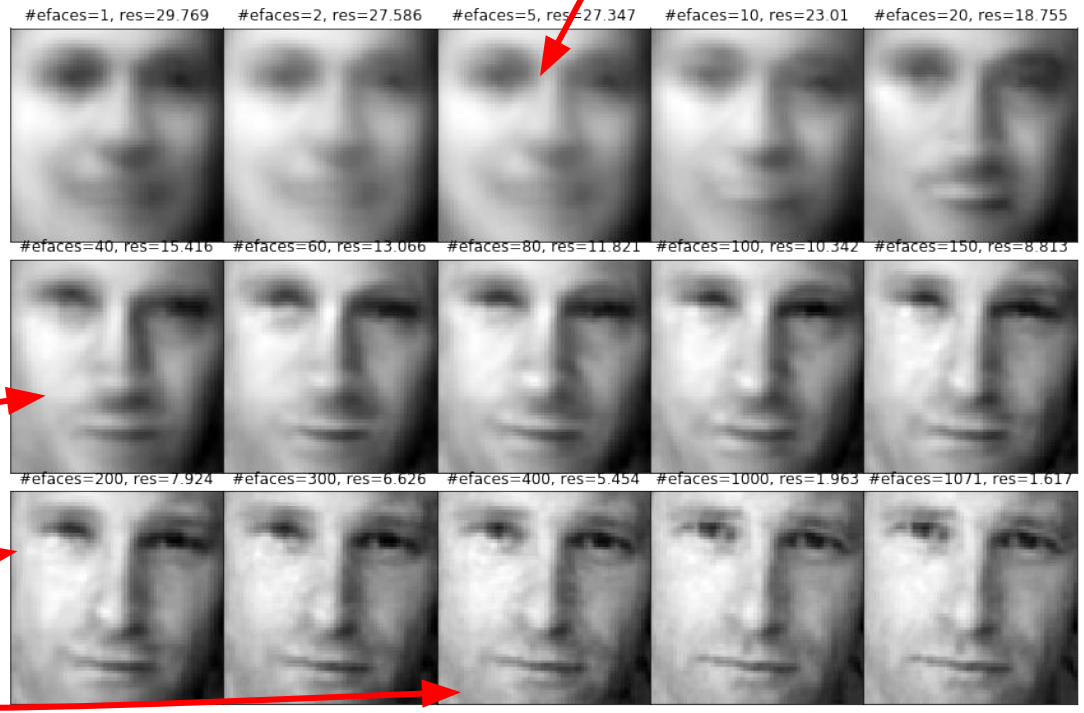


Image source: Sandipan Dey, sandipanweb.wordpress.com/

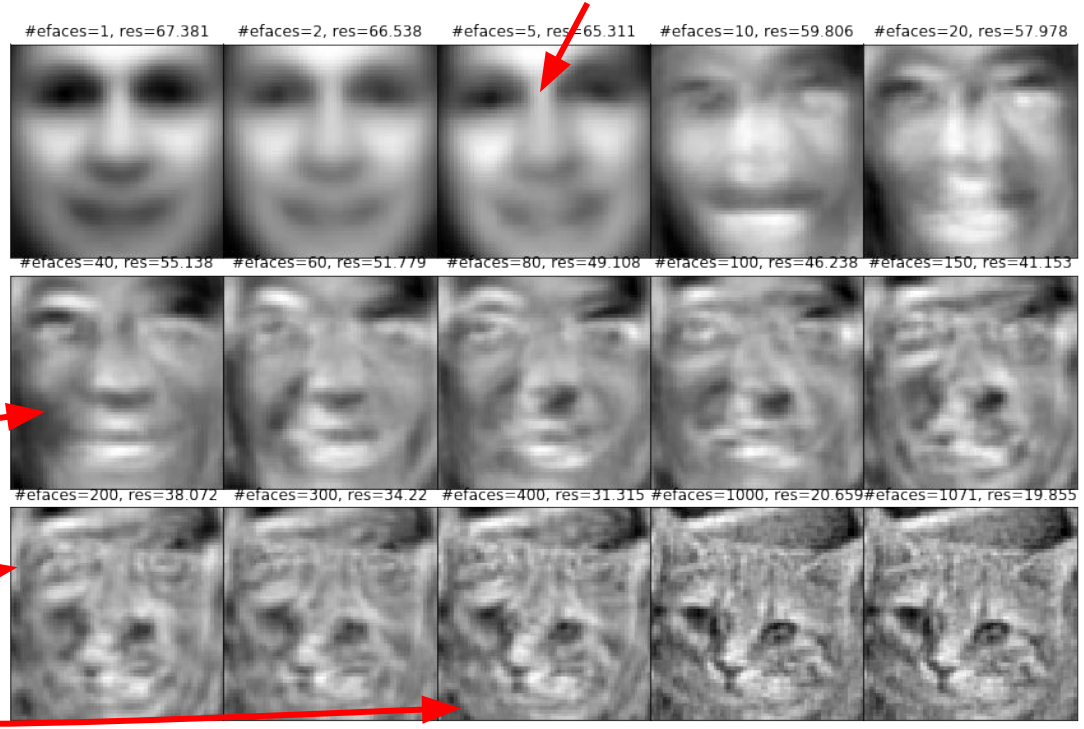
Unsupervised learning

Principal component analysis (PCA) on human faces. **Reconstruction** (x hat) from the compressed representation, with different compression ratios.

Compression / dimensionality reduction

- It only works well on data similar to the training images.

Original input (x)



Unsupervised learning

Compression / dimensionality reduction

- **Less storage** space and bandwidth usage.
- A compressed representation (consisting of fewer variables) is often **easier to work with**.
- In a 2-3 dimensional representation, the location of the data points can even be **visualized on a plot** (points on a plane / in 3D space).

Unsupervised learning

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- In a 2-3 dimensional representation, the location of the data points can even be **visualized on a plot** (points on a plane / in 3D space).

The task of compression / dimension reduction is well defined, but effective compression takes advantage of the fact that compressed data is similar in nature. It would be difficult to write unique algorithms for compressing many different types of data.
→ **Ideal task for machine learning**

Unsupervised learning

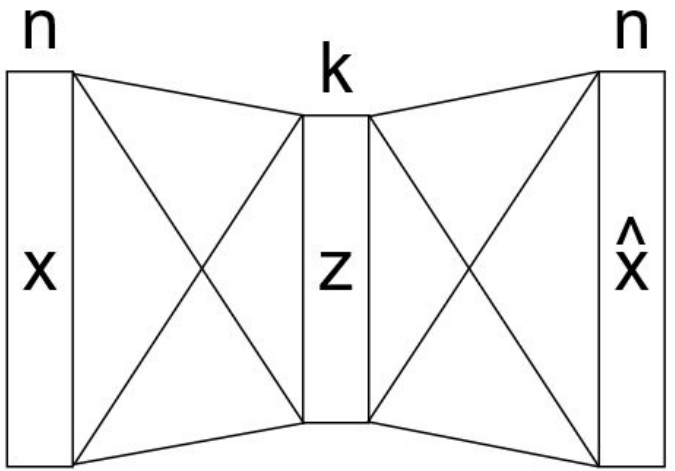
Compression / dimensionality reduction

The task can be formulated as follows:

x: The input (to be compressed)
h: The hypothesis-function performing
the compression
(e.g., an *autoencoder* neural network)

$$h_\theta(x) = \hat{x} \approx x$$

J: The (normed) difference between x and $\hat{x}$
Goal: Minimize J (improve reconstruction)



Unsupervised learning

Goal: In the absence of a label (**y**), we learn to recover the input (**x**) from the compressed representation (**z**).

Compression / dimensionality reduction

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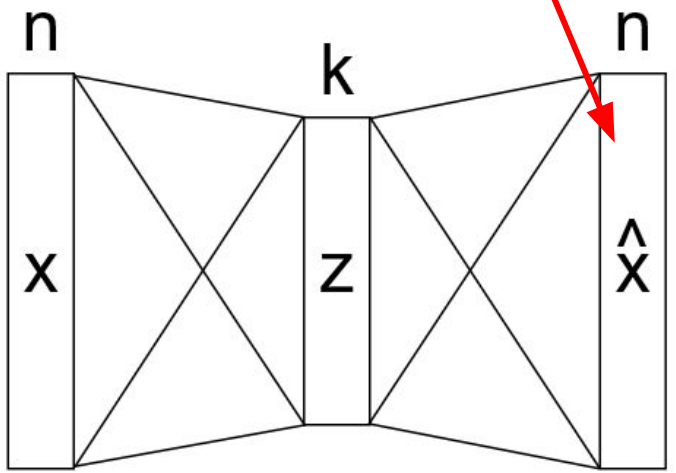
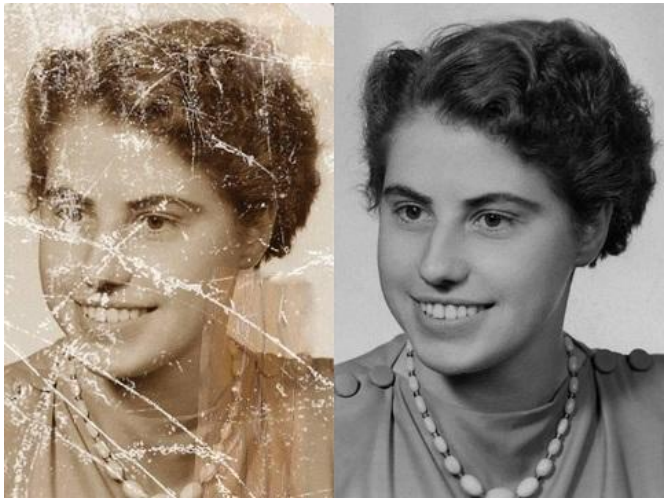


Unsupervised learning - applications

Denoising



Denoising: Improving image quality

Inpainting: Filling in missing parts of an image.

Unsupervised learning

Sample generation (learning the distribution of the data)

Generating new examples similar to those found in the training set.

Unsupervised learning

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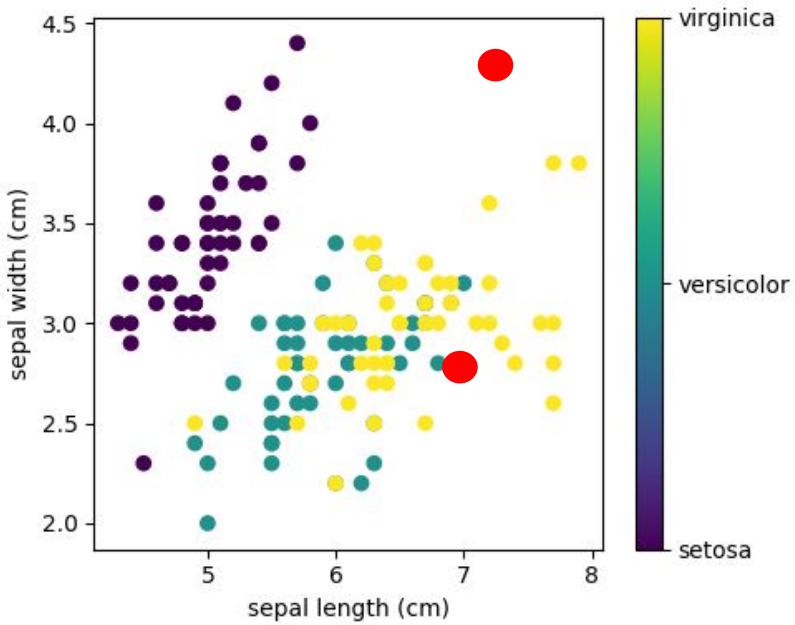
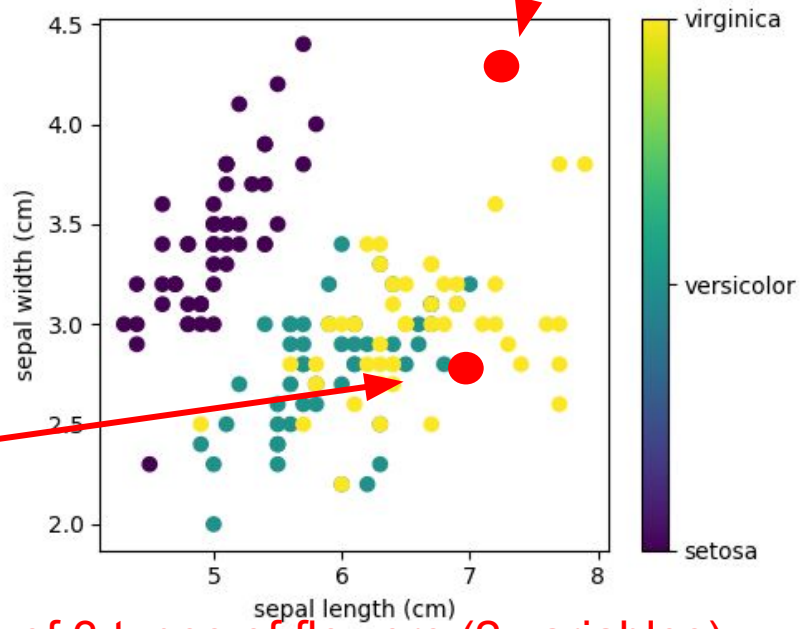


Unsupervised learning

This new sample element is unlikely:
Its petals are too large.

Sample generation (learning the distribution of the data)

Generating new examples similar to those found in the training set.



This new sample is good:
The petal sizes are similar to those of real flowers.

IRIS dataset: The length and width of the petals of 3 types of flowers (2 variables)

Unsupervised learning

Sample generation (learning the distribution of the data)
https://www.youtube.com/watch?v=36lE9tV9vm0

Image source: https://blog.segmind.com/sdxl-samplers-2/

Unsupervised learning

Iterative denoising as a generative model (Stable Diffusion)

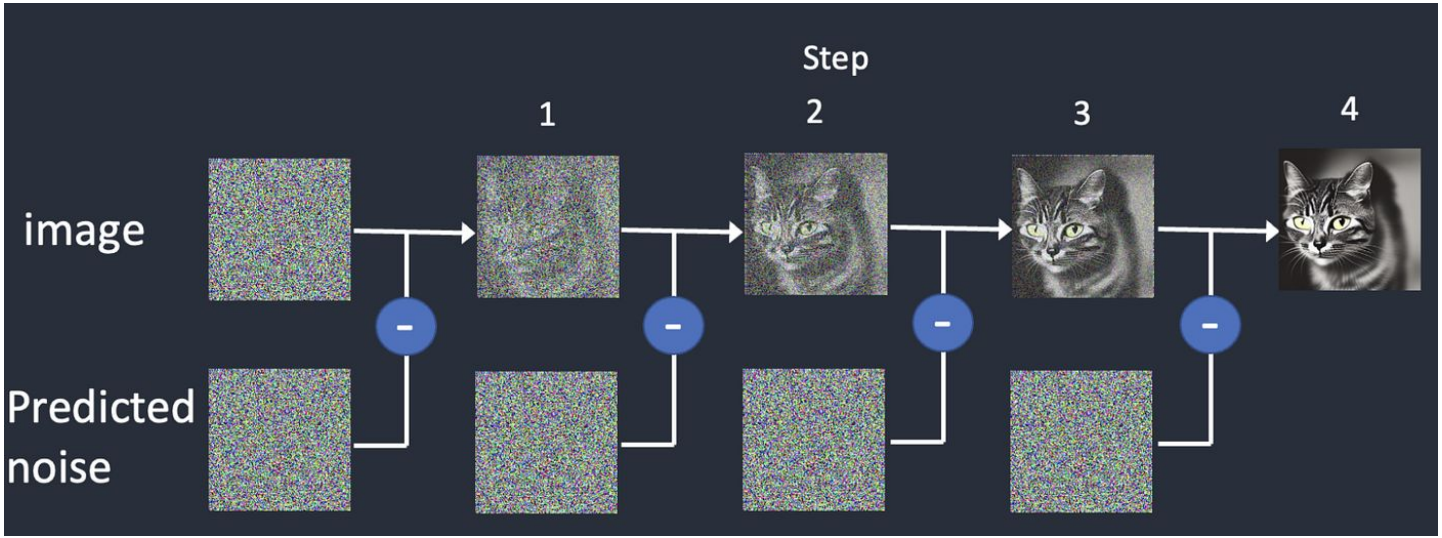


Image source: LM Po @ medium.com

Unsupervised learning

Denoising / next token prediction, as an unsupervised learning task

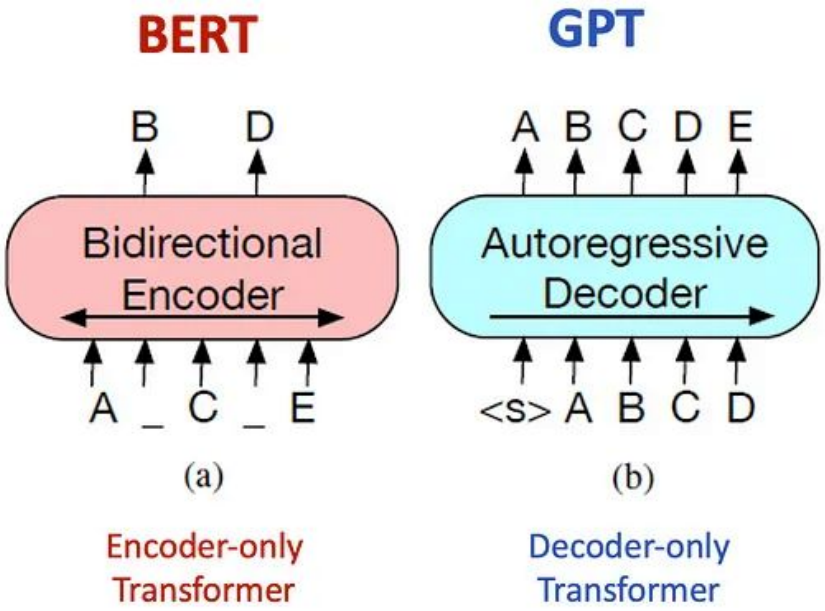
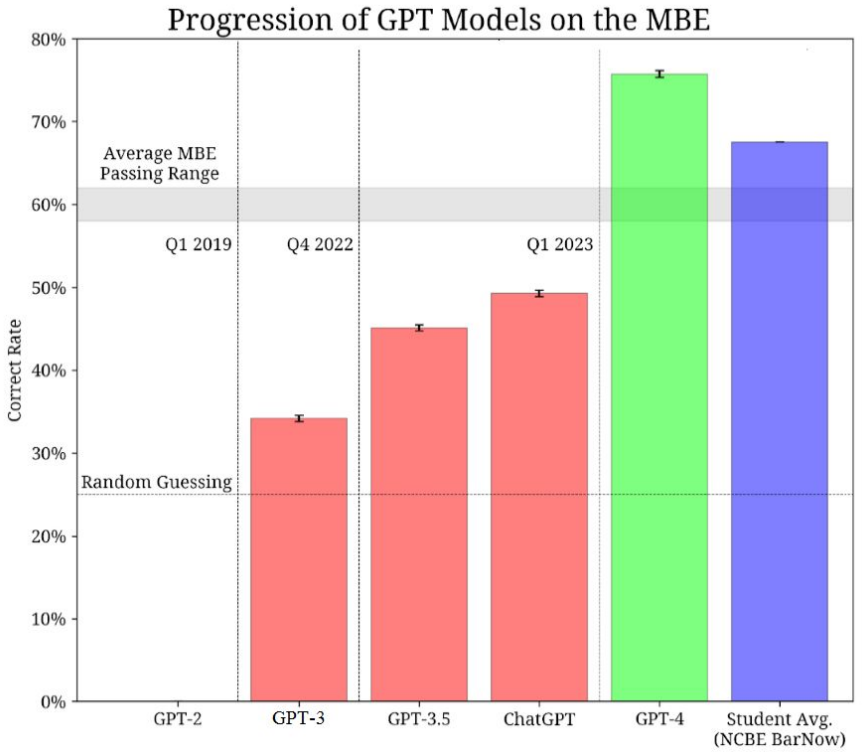


Image source: businessolution.org

Unsupervised learning

Large Language Models (LLMs)

Unsupervised training on a large amount of data, **then fine-tuning** on partially supervised language tasks.



Machine learning

Three main groups of machine learning methods:

- **Supervised learning**
- **Unsupervised learning**
- **Reinforcement learning**

Reinforcement learning

Natural intelligence rarely encounters supervised learning tasks...

More common: We perform a series of actions,
and if they lead to objectively assessable results,
we receive some kind of **positive or negative feedback.**

→ **Reinforcement Learning** (RL)

Image source: https://opendatascience.com/

Reinforcement learning

- The **agent** navigates the **environment** (and influences it).
- The **agent** observes the **state** of the environment and then modifies it by performing some **action**.
- If certain predefined goals are met in the environment, the agent receives a (possibly negative) **reward**.

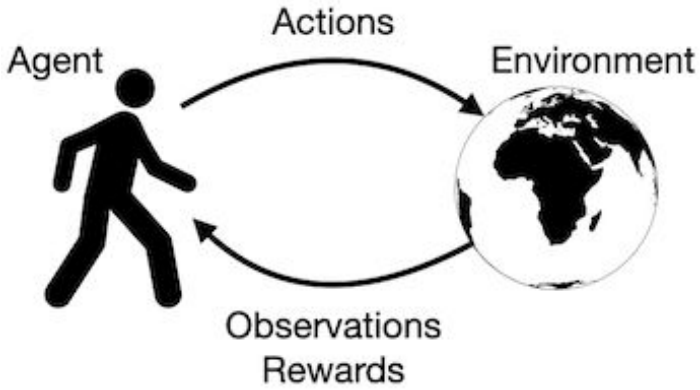
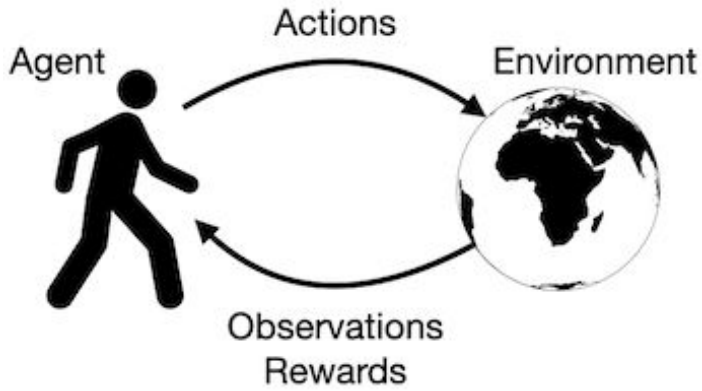


Image source: https://opendatascience.com/

Reinforcement learning

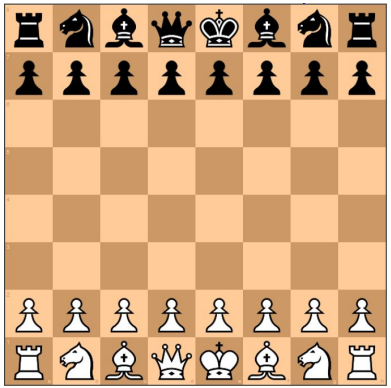
Goal: Choosing actions that are expected to **maximize** the total amount of **rewards** received in the future.

- The **agent** navigates the **environment** (and influences it).
- The **agent** observes the **state** of the environment and then modifies it by performing some **action**.
- If certain predefined goals are met in the environment, the agent receives a (possibly negative) **reward**.



Reinforcement learning

Sparse feedback. The *Credit Assignment problem*.



$r_1, \ldots, r_{51} = 0$

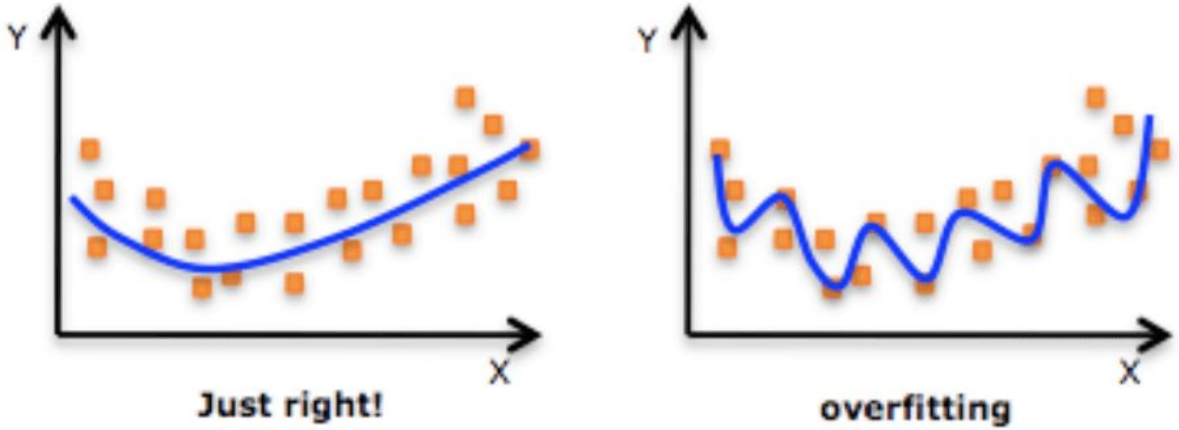
1.d4 ♘f6 2.c4 e6 3.♘f3 b6 4.g3 ♗a6 5.b3 ♗b4+ 6.♗d2 ♗e7 7.♘c3 c6 8.e4 d5 9.♕c2 dxe4 10.♘xe4 ♗b7 11.♘eg5 c5 12.d5 exd5 13.cxd5 h6 14.♘xf7 ♔xf7 15.O-O-O ♗d6 16.♘h4 ♗c8 17.♖e1 ♘a6 18.♖e6 ♘b4 19.♗xb4 cxb4 20.♗c4 b5 21.♗xb5 ♗e7 22.♘g6 ♘xd5 23.♖xe7+ ♘xe7 24.♗c4+ ♔f6 25.♘xh8 ♕d4 26.♖d1 ♕a1+ 27.♔d2 ♕d4+ 28.♔e1 ♕e5+ 29.♕e2 ♕xe2+ 30.♔xe2 ♘f5 31.♘f7 a5 32.g4 ♘h4 33.h3 ♖a7 34.♖d6+ ♔e7 35.♖b6 ♖c7 36.♘e5 ♘g2 37.♘g6+ ♔d8 38.♔f1 ♗b7 39.♖xb7 ♖xb7 40.♔xg2 ♖d7 41.♘f8 ♖d2 42.♘e6+ ♔e7 43.♘xg7 ♖xa2 44.♘f5+ ♔f6 45.♘xh6 ♖c2 46.♗f7 ♖c3 47.f4 a4 48.bxa4 b3 49.g5+ ♔g7 50.f5 b2 51.f6+ ♔h7 52.♘f5 1-0

$r_{52} = 100$

Key questions of artificial intelligence

The ability to generalize

Does our trained model memorize the training examples one by one, or does it actually learn “useful” things?

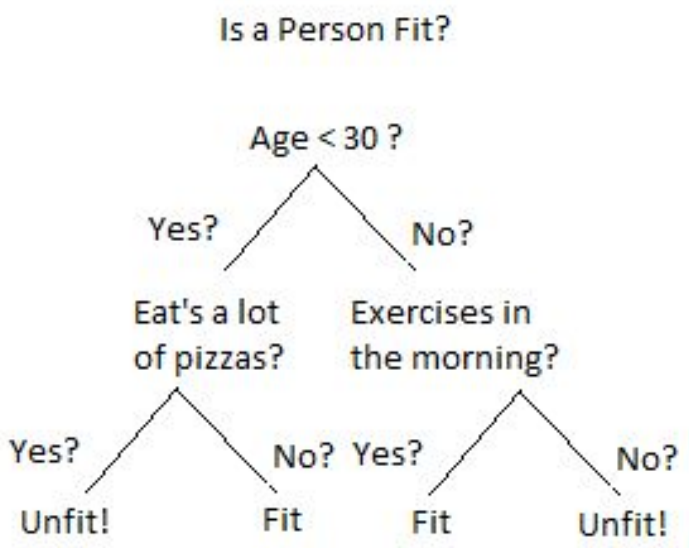


Key questions of artificial intelligence

Explainability

Some classic machine learning methods learn easily **explainable / interpretable models**.

Decision trees are one example:



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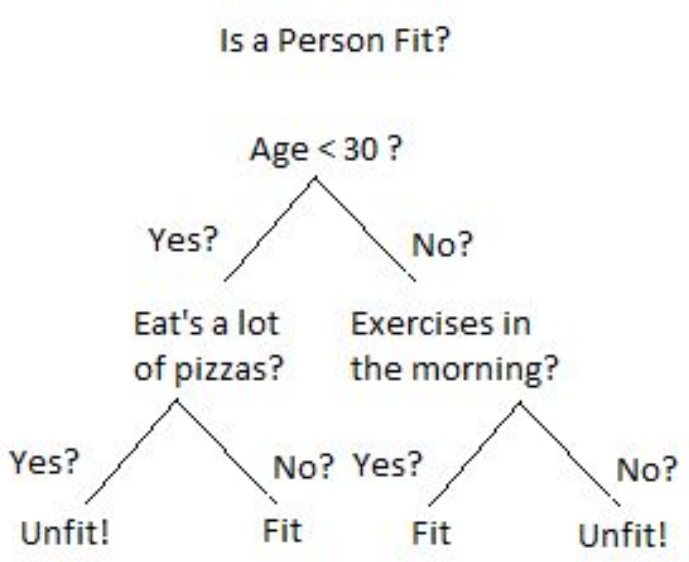


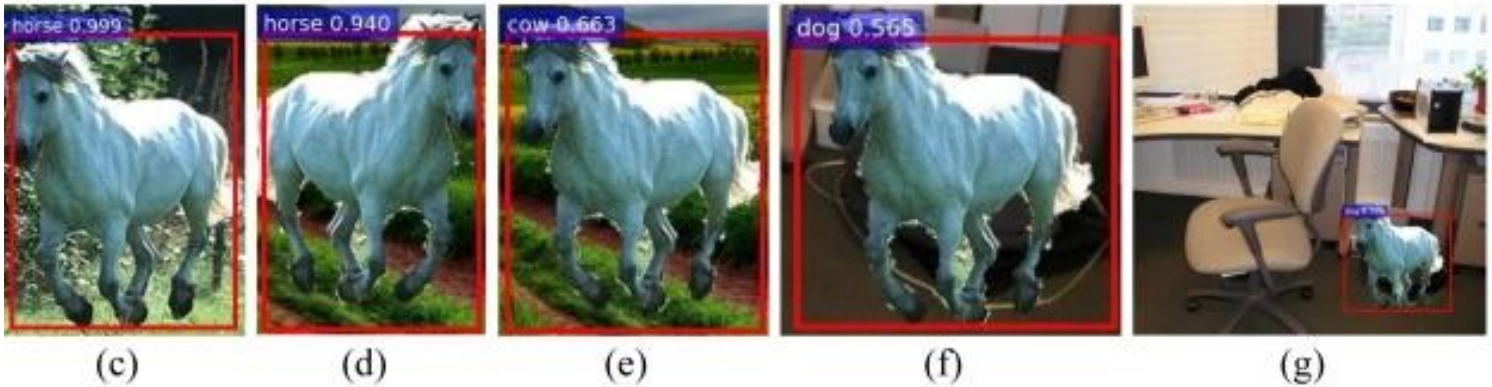
They are very limited, unfortunately…

Image source: Lőrincz et al., 2017

Key questions of artificial intelligence

Explainability

The knowledge learned by neural networks is difficult to interpret.



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Key questions of artificial intelligence

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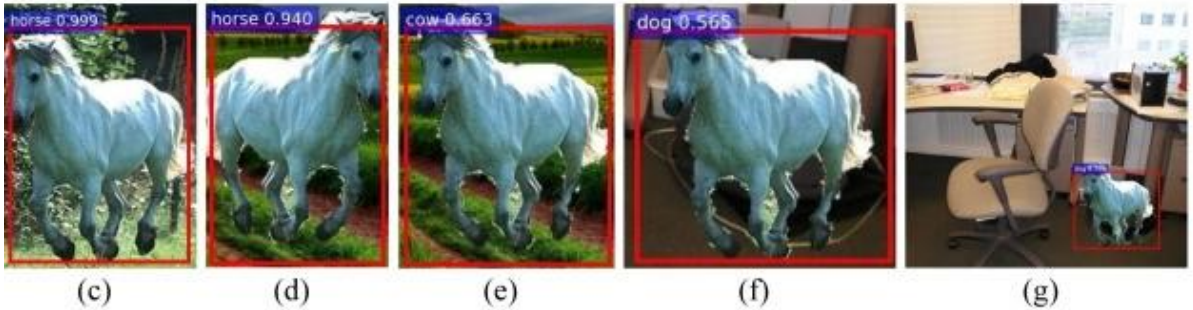


Estimates of a neural network categorizing objects (animals): Depending on the horse's environment, the network estimates the labels “horse,” “cow,” and “dog” for a picture of a horse. The neural network has therefore learned to estimate the label better from the appearance of its environment than from the appearance of the animal itself...

Key questions of artificial intelligence

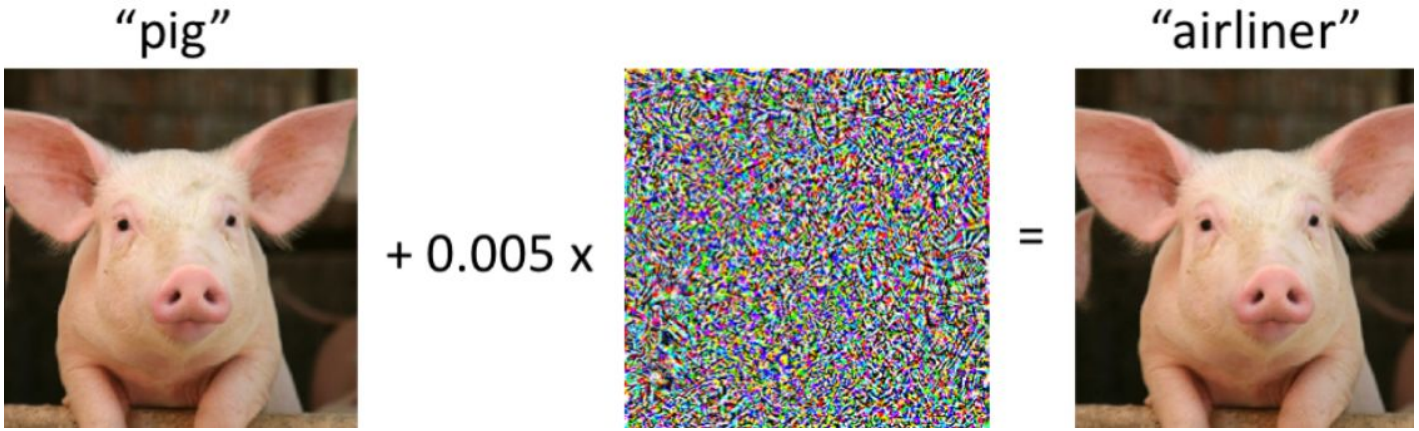
Explainability

Software used in critical applications
is thoroughly tested and formally verified.

Deep learning methods can only be tested empirically.
We cannot say whether they made their decisions in a “logical way”...

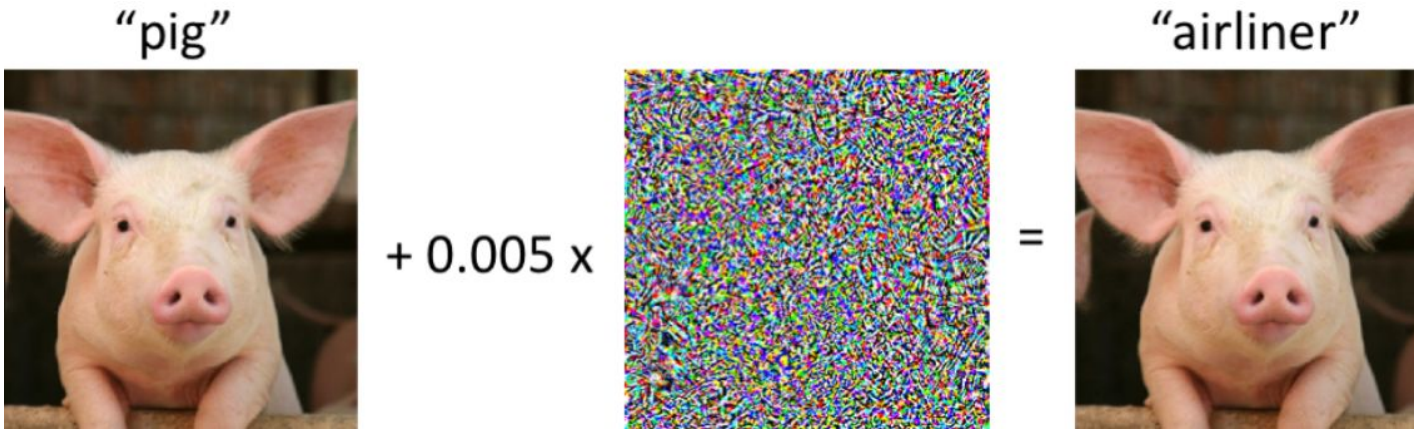
Key questions of artificial intelligence

Safety - Adversarial attacks



Key questions of artificial intelligence

Safety - Adversarial attacks



Adversarial attacks: Even without the knowledge of the neural network architecture and parameters, a specific small perturbation of the image can be found, that changes the label estimates dramatically.

Image source: Morgulis et al., 2019

Key questions of artificial intelligence

Safety - Adversarial attacks

The attacks work in reality, as well…

Image source: Nightingale and Farid, 2022.

Key questions of artificial intelligence

Explainability

Knowledge learned by artificial neural networks **cannot be explained** well.

However, can humans explain how they recognize a familiar face or voice?

Career advice

3. Test your neuron by creating an instance of the class and passing it some input values. Make sure that the output value is what you expect.

Here's some sample code that demonstrates how you can implement these steps:

Copy code

```
import numpy as np

class Neuron:
    def __init__(self, num_inputs, activation_function):
        # Initialize the weights and bias with random values
        self.weights = np.random.uniform(-1, 1, size=num_inputs)
        self.bias = np.random.uniform(-1, 1)
        self.activation_function = activation_function

    def forward(self, inputs):
        # Perform the dot product of the inputs and weights, add the
bias, and pass the result through the activation function
        output = self.activation_function(np.dot(inputs, self.weights) +
self.bias)
        return output

# Test the neuron
neuron = Neuron(2, lambda x: x)
inputs = np.array([1, 2])
output = neuron.forward(inputs)
print(output)
```

This code defines a simple neuron class with two inputs and an activation function that simply returns its input. When you run this code and pass it some input values, it should calculate the output of the neuron based on those input values.

Regenerate response

I hope this helps! Let me know if you have any questions or need further guidance.

Career advice

Potentially AI-resistant applications of Computer Science:

- **Where security / safety is a priority.**
  (medical, transportation, cybersecurity, infrastructure management)
- **Too much interaction with the physical world.**
  (robotics, industrial control, architecture)
- **Little data available on the subject, too many edge cases.**
  (finances, economy, threat detection, bioinformatics)

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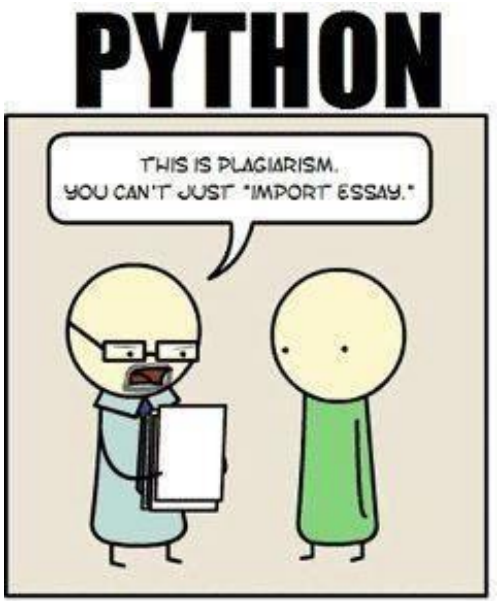
In contrast: Purely virtual software development
→ easy & cheap to experiment, easy to simulate, lots of data available…

Software

Python

- High level
- Automatic memory management
- Runtime type inference and checking
- Interpreted language
- Simple syntax, limited language features
- Portable
- Lots of tools in many available libraries



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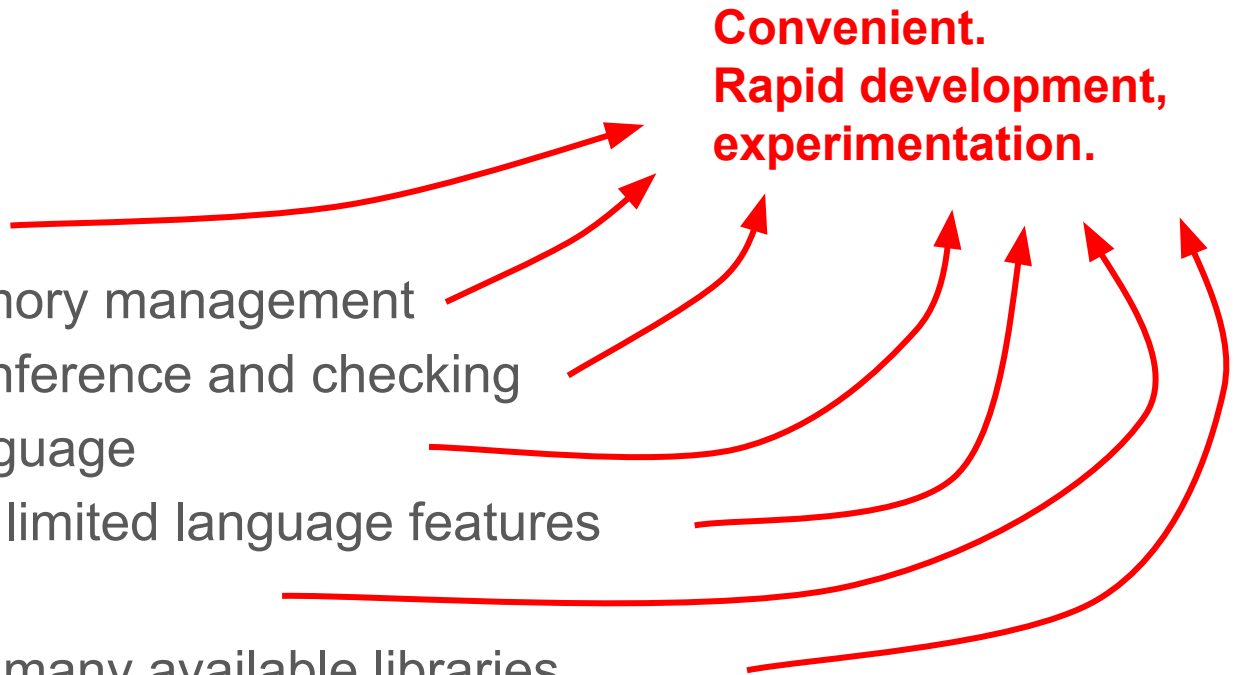

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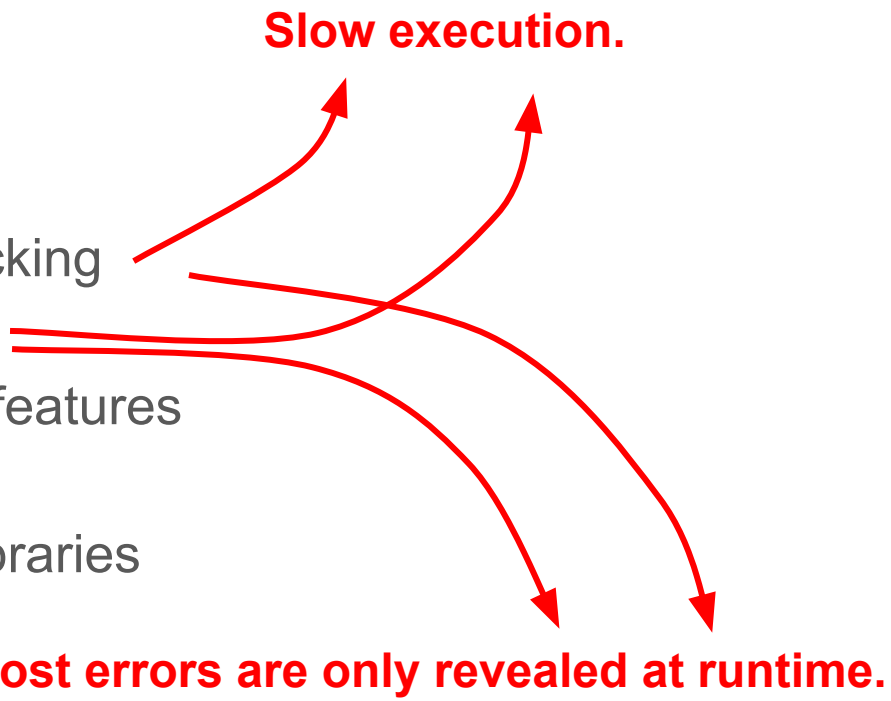

Software

Python

“Slow execution”.

If Python is not efficient, why has it become popular in (computationally intensive) **machine learning?**

Software

Python

“Slow execution”.

If Python is not efficient, why has it become popular in (computationally intensive) **machine learning?**

We perform our computationally intensive operations efficiently using libraries written in other languages.
We only use Python for scripting!

Software

NumPy - Generating and multiplying two random matrices (400 x 400)

Naive Python: ?

```
matrix1 = [[random.random() for col_idx in range(matrix_dim)] for row_idx in range(matrix_dim)]
matrix2 = [[random.random() for col_idx in range(matrix_dim)] for row_idx in range(matrix_dim)]
matrix_out = [[0. for col_idx in range(matrix_dim)] for row_idx in range(matrix_dim)]

for row1_idx in range(matrix_dim):
  for col2_idx in range(matrix_dim):
    for item_idx in range(matrix_dim):
      matrix_out[row1_idx][col2_idx] += matrix1[row1_idx][item_idx] * matrix2[item_idx][col2_idx]
```

NumPy: ?

```
matrix1 = np.random.rand(matrix_dim, matrix_dim)
matrix2 = np.random.rand(matrix_dim, matrix_dim)
return np.matmul(matrix1, matrix2)
```

Software

NumPy - Generating and multiplying two random matrices (400 x 400)

Naive Python: **14.79 sec**

```
matrix1 = [[random.random() for col_idx in range(matrix_dim)] for row_idx in range(matrix_dim)]
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```

NumPy: **0.019 sec**

```
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return np.matmul(matrix1, matrix2)
```

Software

NumPy example: Count elements divisible by 3 or 5!

Naive Python:

```
c = 0
for elem in my_list:
  if (elem % 3 == 0) or (elem % 5 == 0):
    c += 1
```

NumPy:

```
c = np.count_nonzero((my_array % 3 == 0) | (my_array % 5 == 0))
```

Software

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Software

NumPy example: Given several sets of three numbers. Specify which ones can be used to form triangles, and then specify the area and perimeter of these triangles.

```
def triangle_area_perimeter(edges):
  valid_tr_mask = (edges[:,0] + edges[:,1] > edges[:,2]) & (edges[:,0] + edges[:,2] > edges[:,1]) &\
                  (edges[:,1] + edges[:,2] > edges[:,0]) & np.all(edges >= 0., axis=1)
  valid_triangle_idxs = np.where(valid_tr_mask)[0]
  edges = edges[valid_triangle_idxs]
  perimeter = np.sum(edges, axis=1)
  semi_per = perimeter*.5
  area = np.sqrt(semi_per*(semi_per-edges[:,0])*(semi_per-edges[:,1])*(semi_per-edges[:,2]))
  area_perimeter = np.stack([area, perimeter], axis=1)
  return valid_triangle_idxs, area_perimeter
```

Software

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  semi_per = perimeter*.5
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  area_perimeter = np.stack([area, perimeter], axis=1)
  return valid_triangle_idxs, area_perimeter
```

N dimensional arrays, indices

Indexing with all elements of an array at once

Executing operations across entire axes of an array

Software

Array programming

- Execution of a **single operation on a large amount of data** at once.
- Code implemented with array operations is much **easier to translate into parallel machine code**.
- In machine learning, we mostly use operations that are well suited for **parallelization**.
- Code written with array programming is generally much more **compact**.

Software

PyTorch

PyTorch - Library for implementing neural networks, with GPU support

```
import torch
import torch.nn as nn

model = nn.Sequential(
    nn.Linear(28, 50),
    nn.ReLU(),
    nn.Linear(50, 10)
)

loss_fn = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

for epoch_idx in range(num_epochs):
    y_pred = model(x)                # x: inputs from training set; y_pred: estimated labels
    loss = loss_fn(y_pred, y)        # y: true labels from training set
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

High-level components for building neural networks

Software

Google Colab

https://colab.research.google.com

Synonyms in ML terminology

- Example ≈ (data) sample ≈ data point ≈ observation
- (Input) variable ≈ (input) feature
- Training ≈ fitting
- Prediction ≈ estimation
- (True) label ≈ (expected) output ≈ target variable ≈ ground truth
- Predicted/estimated label ≈ predicted/actual output ≈ estimates
- (Model) parameters ≈ (model) weights
- Loss function ≈ cost function

θ: theta