WORKSHOP MACHINE LEARNING

Dania International Days

13 – 15 March 2024

Andy Louwyck

Vives University of applied sciences – Association KU Leuven – Kortrijk, Belgium





Andy Louwyck

andy.louwyck@vives.be

- Doctor & Master of Science: Geology
- Associate Degree: IT & Programming
- Micro Degree: Al & Data Science

2024	Voluntary	/ Post-Doctoral	Researcher	(Ghent University)
				(- : : - : : - : : : : - : - ; , ,

- 2023 ... IT Architect (Flanders Environment Agency)
- 2020 ... Lecturer AI (Vives University of Applied Sciences)
- 2020 2022 **Research Associate AI** (Vives University of Applied Sciences)
- 2009 2020 Groundwater Modeler & Data Expert (Flanders Environment Agency)
- 2007 2008 Project Engineer Water Management (International Marine & Dredging Consultants)
- 2006 **Science Teacher** (HH Ninove Secondary School)
- 2001 2005 PhD Fellow Hydrogeology (Ghent University)









Dania International Days 2024 Workshop Machine Learning

MACHINE LEARNING: OVERVIEW





Data

"We are drowning in data but starving for knowledge"
[Naisbitt, 1982]

- A lot of data is gathered, but never used
- It is easier to generate data than to analyze data

→ MACHINE LEARNING

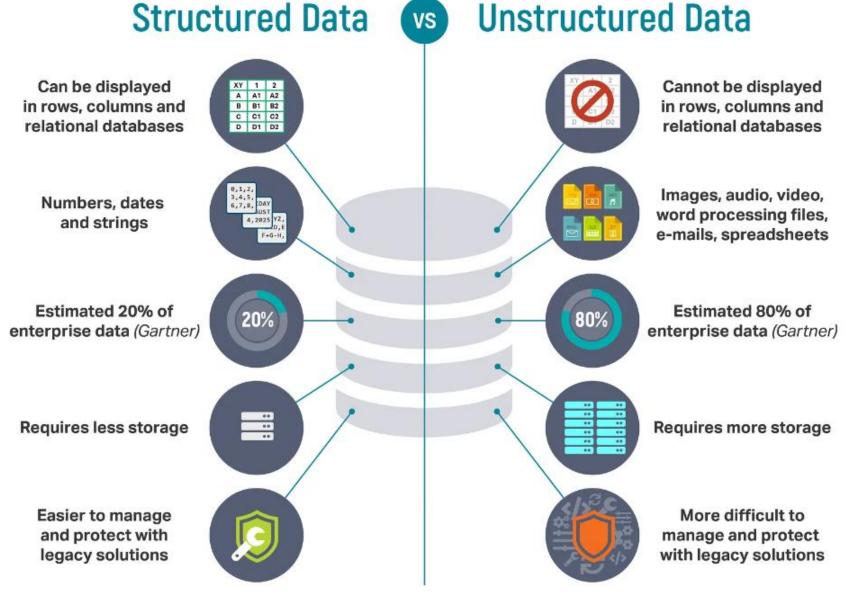


THE INTERNET IN 2023 EVERY MINUTE



Created by: eDiscovery Today & LTMG









Machine Learning & Artificial Intelligence

Artificial Intelligence (AI):

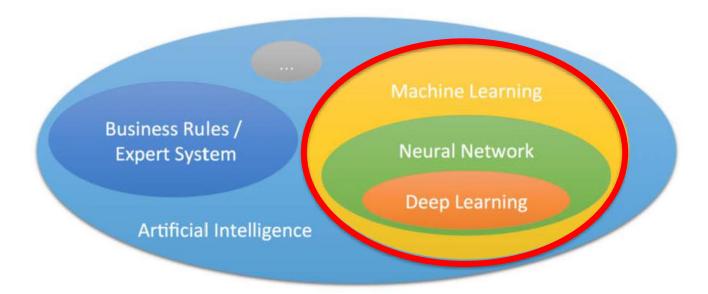
"The set of all tasks in which a computer can make decisions."

Machine Learning (ML):

"The set of all tasks in which a computer can make decisions based on data."

Deep Learning (DL):

"The field of machine learning that uses certain objects called neural networks."

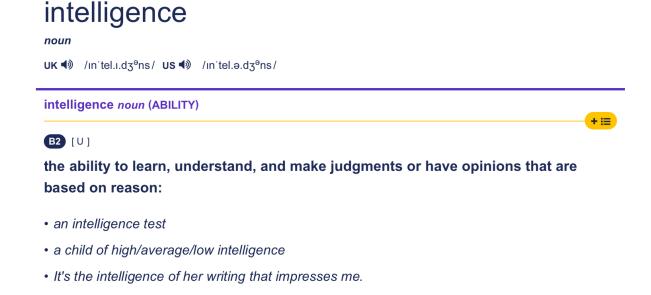






Machine Learning

Core domain of AI, concerned with automatic learning



 A computer is said to be able to <u>learn</u> if its performance in solving some task <u>improves with its experience</u>





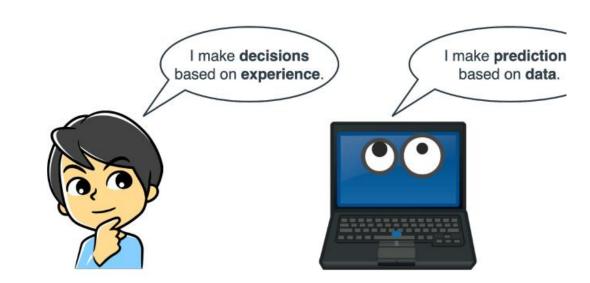
Machine Learning

Example: buying a new car

- How do we make decisions?
 - by logical reasoning
 - by relying on previous experiences (either our own or those of others)
- For a computer: **experiences = data**

"Machine learning is common sense, except done by a computer"



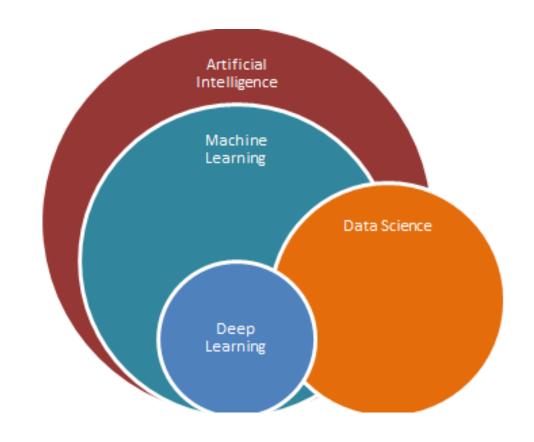




Machine Learning ≠ Data Science

In practice:

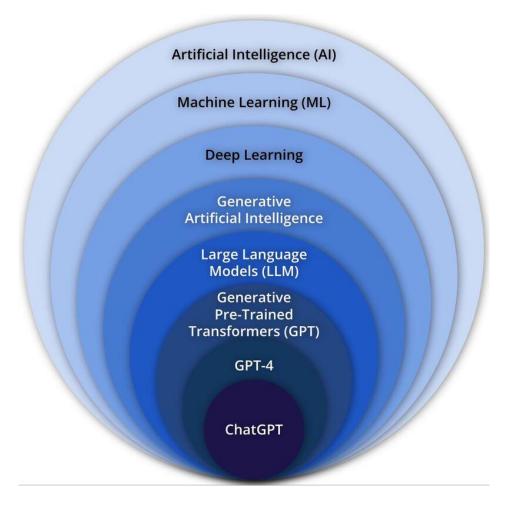
- ML team: delivers software
- DS team: provides new insights







What about ChatGPT?

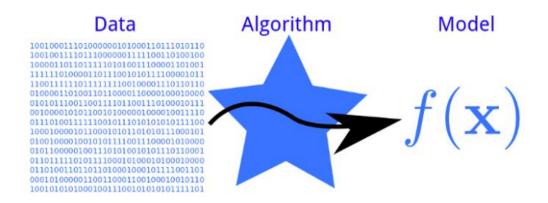






Algorithm vs Model

- Model: A set of rules that represent our data and can be used to make predictions.
- Algoritme: A procedure, or a set of steps, used to build a model.

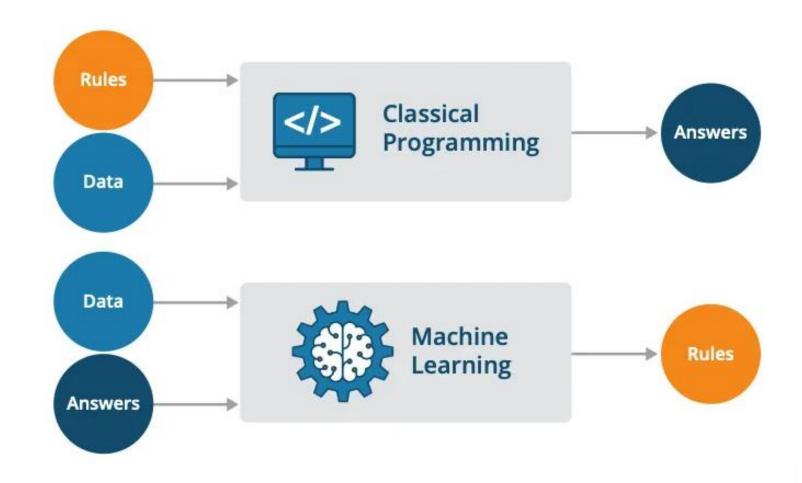


"An algorithm is run on data to create a model"





Machine Learning vs Classical Programming







Thermostat example







Traditional approach

- The rule is given:
 - "If temperature is smaller than 17°C, then heating is on, otherwise it's off"
- The algorithm implements the rule
- No data required to derive the rule!

The heating is off!

```
threshold = 17
temperature = float(input("What is the temperature?\n"))  # data
heating = 'on' if temperature < threshold else 'off'  # rule
print(f'The heating is {heating}!')  # answer

What is the temperature?
18</pre>
```





Machine learning

The rule is not known and must be derived from data!

```
import pandas as pd
temperature = [17.1, 15.6, 23.1, 19.8, 12.9, 20.3, 14.7, 16.2] # data
heating = ['off', 'on', 'off', 'on', 'off', 'on', 'on'] # answers
table = pd.DataFrame(dict(temperature=temperature, heating=heating))
```

temperature heating

•		
0	17.1	off
1	15.6	on
2	23.1	off
3	19.8	off
4	12.9	on
5	20.3	off
6	14.7	on
7	16.2	on

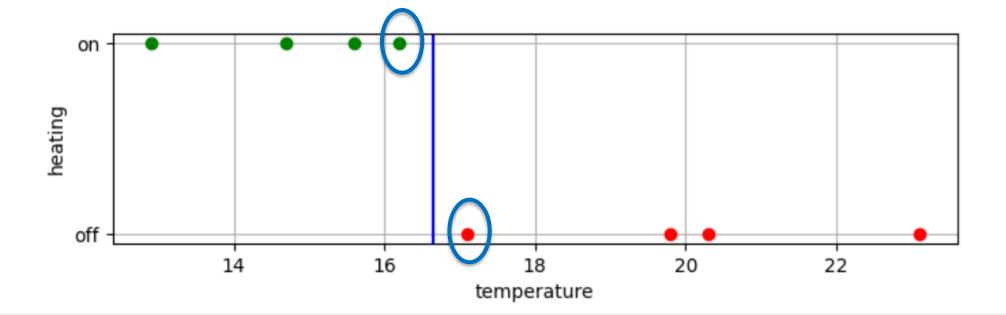




Naive algorithm

```
max_temperature_on = table[table.heating=='on']['temperature'].max()
min_temperature_off = table[table.heating=='off']['temperature'].min()
threshold = (max_temperature_on + min_temperature_off) / 2
print(f'maximum temperature if heating is on: {max_temperature_on}°C')
print(f'minimum temperature if heating is off: {min_temperature_off}°C')
print(f'threshold is {threshold}°C')
```

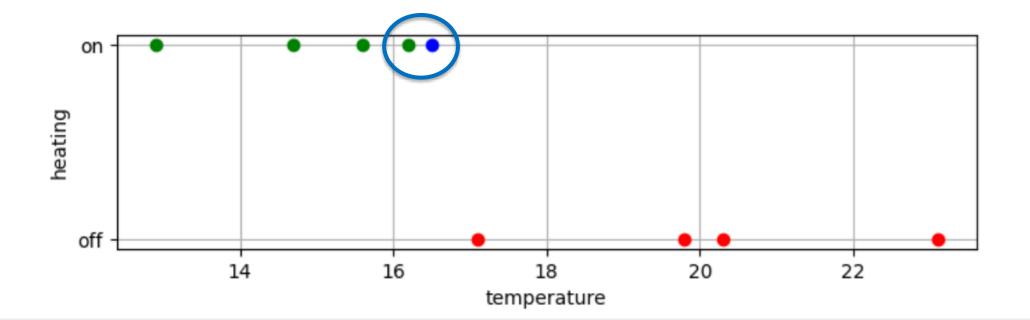
maximum temperature if heating is on: 16.2°C minimum temperature if heating is off: 17.1°C threshold is 16.65°C



Nearest neighbor

```
temperature = float(input("What is the temperature?\n"))  # input temperature
abs_difference = (temperature - table.temperature).abs()  # absolute difference
heating = table.heating.iloc[abs_difference.argmin()]  # label of nearest neighbor
print(f'The heating is {heating}!')  # answer
```

What is the temperature? 16.5 The heating is on!



Some issues

- Real-life datasets are typically much larger:
 - more data points
 - more variables
- Real-life datasets may contain outliers and/or errors
- Therefore we need more robust algorithms
 - that use more than 1 or 2 samples only
 - that quantify and minimize the errors
- Examples:
 - Logistic regression: separates all data points instead of 2
 - K Nearest Neighbors: considers K nearest data points instead of 1





Dania International Days 2024 Workshop Machine Learning

MACHINE LEARNING: APPLICATIONS & TASKS

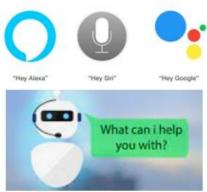




Machine Learning Applications

- Spam filters
- Recommender systems
- Personalized shopping
- Voice assistants
- Self-driving cars
- Search engines
- Chatbots
- Fraud prevention
- Face recognition
- Medical imaging
- Robotics
- Route planning
- Sales forecasting











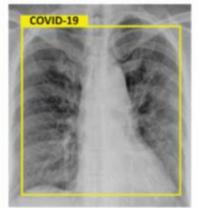














Machine Learning Tasks

- Classification
 Regression
 Forecasting
 Prediction
 Anomaly detection
 Association rule mining
 Clustering
- supervised learning
- = A to B mapping
- = Input to output mapping
- = learning from (input, output) pairs

unsupervised learning

= learning from data without output





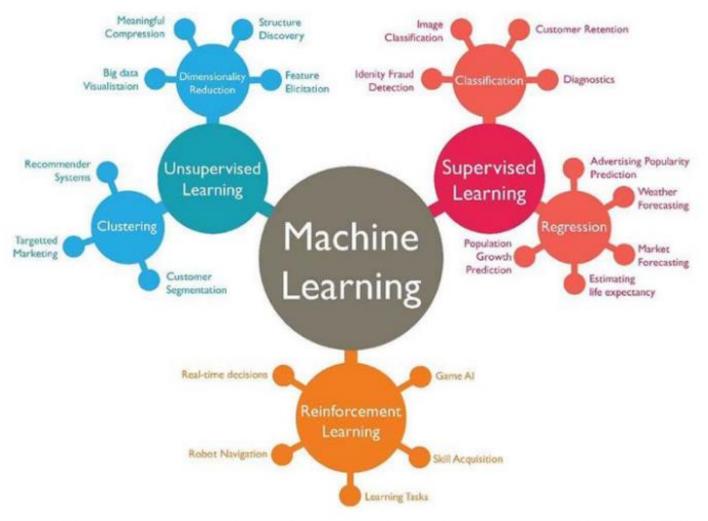
Supervised Learning

Input (A)	Output (B)	Application
email	spam? (0/1)	spam filtering
audio	text transcript	speech recognition
English	Chinese	machine translation
ad, user info	click? (0/1)	online advertising
image, radar info	position of other cars	self-driving car
image of phone	defect? (0/1)	visual inspection





The Big Three

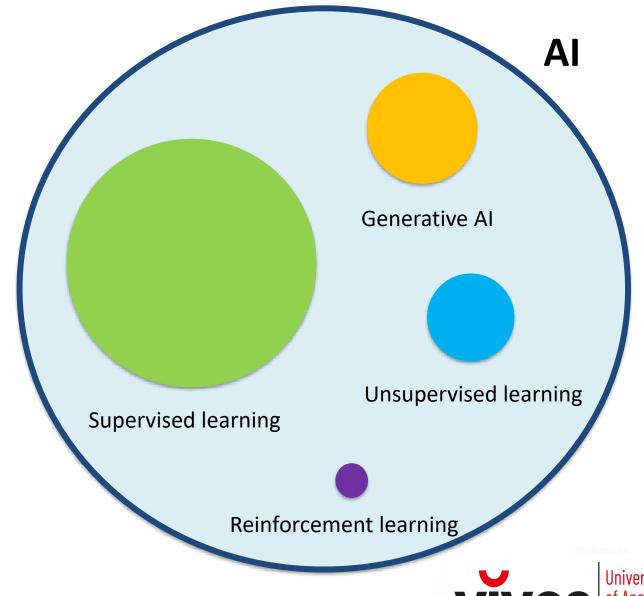






What about GenAl?

- Supervised learning
 - = learning from <u>labeled</u> data
- Unsupervised learning
 - = learning from <u>unlabeled</u> data
- Reinforcement learning
 - = learning from rewards
- Generative Al
 - = generating new data







Supervised vs Unsupervised

- Labeled data: data with label
 - → **SUPERVISED** LEARNING
- Unlabeled data: data without label
 - → UNSUPERVISED LEARNING





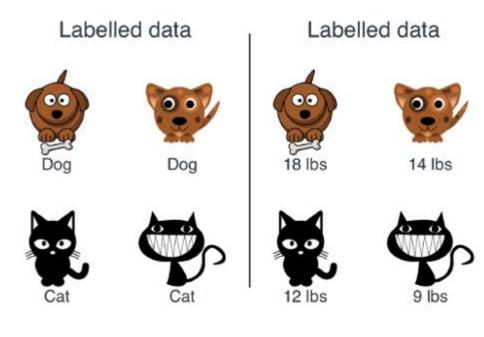


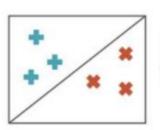




Classification vs Regression

- Categorical target → Classification
- Numerical target → Regression





CLASSIFICATION

Sorting items into categories



REGRESSION Identifying real values (dollars, weight, etc.)



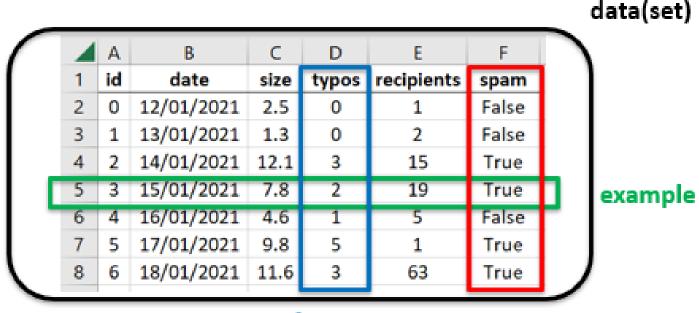
DANIA ACADEMY

Numerical



Structured Data

- Data = information (= table)
- **Example** = sample = instance = data point (= table row/record)
- Feature = independent variable (= table column/attribute)
- Target = labels = dependent variable = feature we want to predict







Dania International Days 2024 Workshop Machine Learning

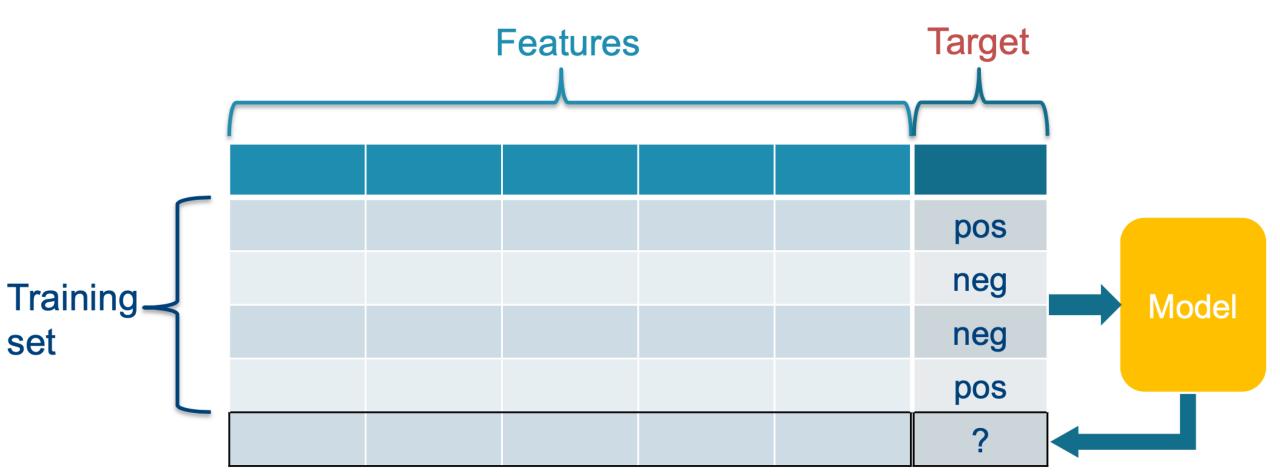
MACHINE LEARNING: SUPERVISED LEARNING





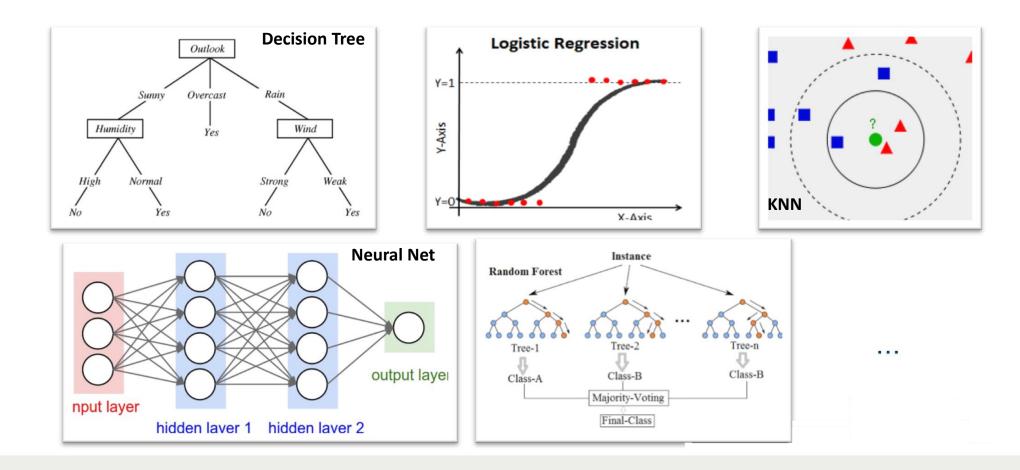
Supervised Learning

<u>Task</u>: learn a model to predict a target for new data instances,
 based on a training set of data instances for which the target is known



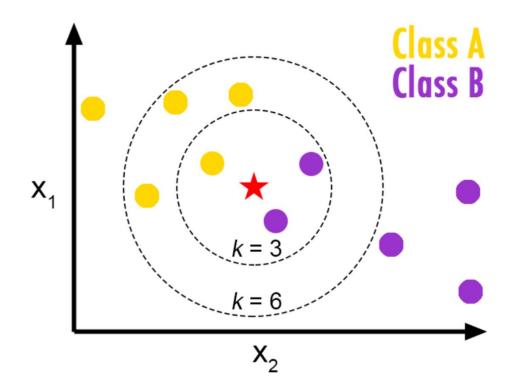
Supervised Learning Algorithms

- There exist plenty of supervised learning algorithms
- No free lunch: there is no algorithm that works best for every problem



K Nearest Neighbors (KNN)

- Classification (regression is also possible)
- Requires no training (= lazy learning, as opposed to eager learning)
- Main task: find suitable distance function (Euclidean, Manhattan, ...)

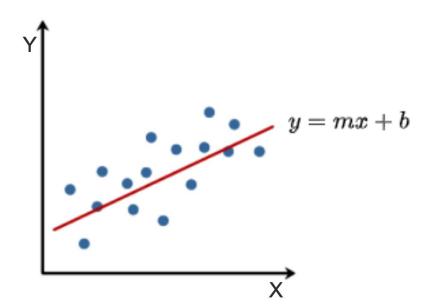






Simple Linear Regression

- Regression for numeric targets
- 1 independent variable (feature x) and 1 dependent variable (target y)
- Main task: estimate parameters m and b, such that predictions (red line) and targets (blue dots) are as close as possible (= best-fitting straight line)

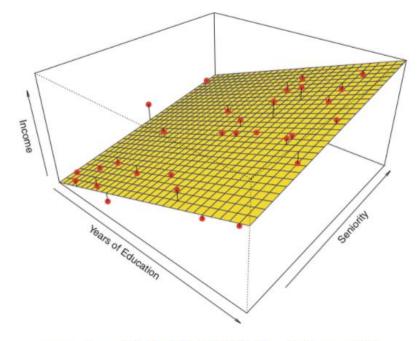




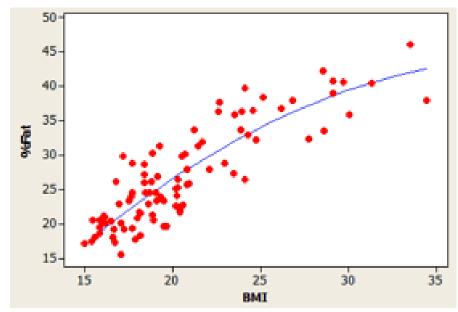


Linear & Nonlinear Regression

- Linear Regression 2 features and 1 target (left)
- Nonlinear regression 1 feature and 1 target (right)



Source: James et al. Introduction to Statistical Learning (Springer 2013)



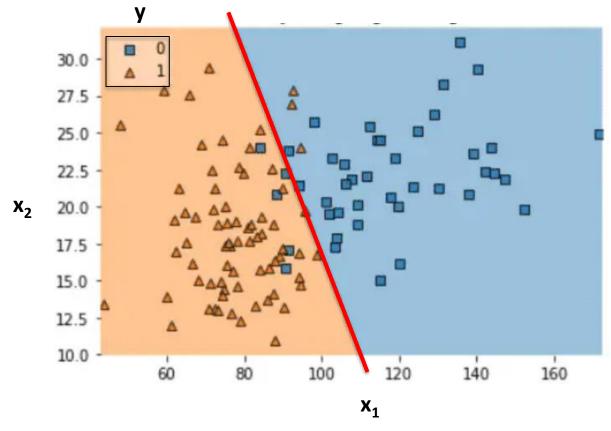
Source: the minitab blog





Logistic Regression

- Regression for binary targets
- Features x_i and target y
- Main task: find a separating straight line
 = binary classification
- N dimensions: separating hyperplane



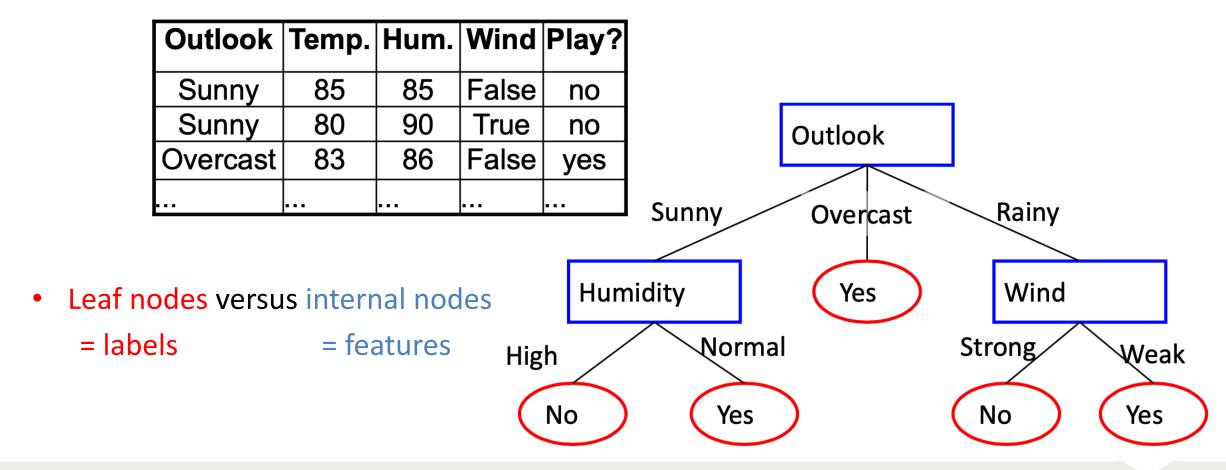
source: https://www.jcchouinard.com/logistic-regression/





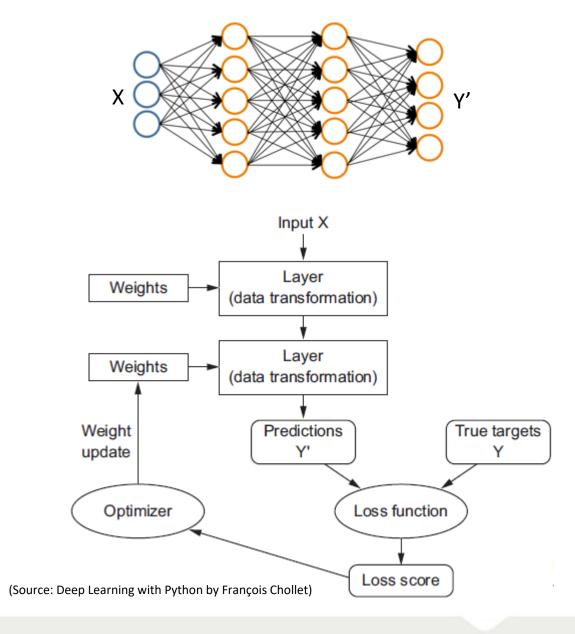
Decision Tree

- Classification (regression is also possible)
- Example: Play tennis or not? (depending on weather conditions)



Artificial Neural Network

- Regression or classification
- Features X and targets Y
- Loss: function quantifying differences between targets Y and predictions Y'
- Main task: find optimal weights that minimize the loss



Thermostat example



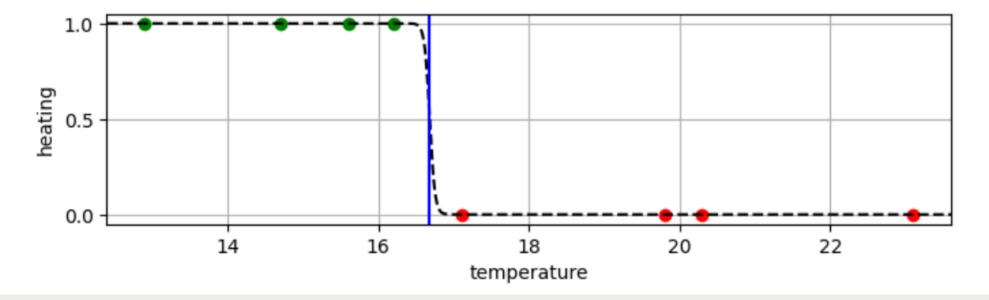




Logistic Regression

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression(penalty=None) # instantiate
model.fit(table[['temperature']].values, table.heating=='on') # fit data
threshold = -model.intercept_.item() / model.coef_.item() # determine threshold
print(f'threshold is {threshold}°C')
model.predict([[17]]).item() # predict label for new temperature value
```

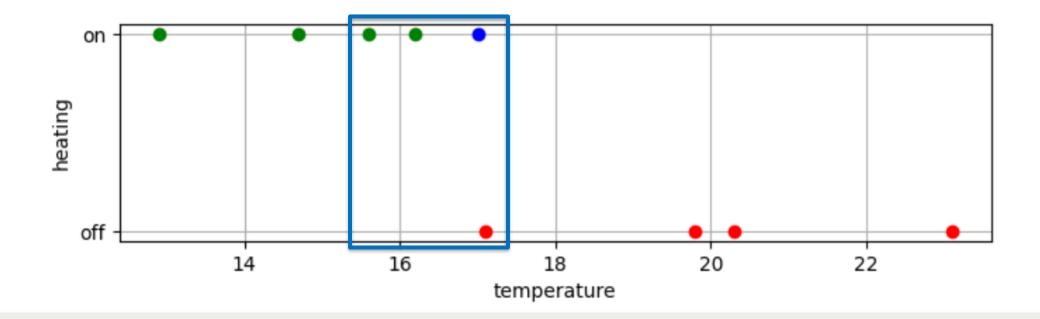
threshold is 16.681991552397978°C False



K Nearest Neighbors

```
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier(n_neighbors=3) # instantiate with K = 3
model.fit(table[['temperature']].values, table.heating=='on') # fit data
model.predict([[17.0]]).item() # predict label for new temperature value
```

True



Dania International Days 2024 Workshop Machine Learning

MACHINE LEARNING: UNSUPERVISED LEARNING





Unsupervised Learning

- Data are not labeled
- Often used during data preprocessing
- I have no idea what you gave me, but I can tell you these two on the left are different from the two in the right.

 Unsupervised learning model
- Clustering: grouping data based on similarities
- <u>Dimensionality reduction</u>: reducing the number of features while retaining as much meaningful information as possible
- Matrix factorization: decomposing the data in order to discover latent features





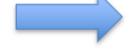
Clustering

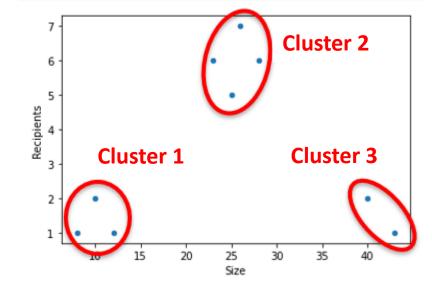
Applications:

- Genetics: grouping species based on similarities
- Medical imaging: partitioning images based on tissue structures
- Market segmentation: clustering customers based on demographics, income, etc.
- Mails:

No labels!

E-mail	Size	Recipients
1	8	1
2	12	1
3	43	1
4	10	2
5	40	2
6	25	5
7	23	6
8	28	6
9	26	7



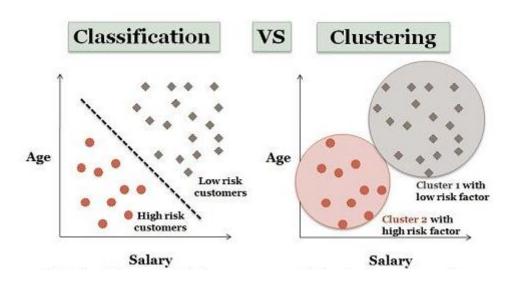


mails.csv

Clustering vs Classification

- Classification: labeled data → classes already exist
- **Clustering**: unlabeled data → classes don't exist yet

customer	age	salary	risk
0	23	1500	high
1	51	2500	low
2	42	3100	low
3	36	1900	high
4	67	2100	low



age	salary	risk
23	1500	?
51	2500	?
42	3100	?
36	1900	?
67	2100	?
	23 51 42 36	51 2500 42 3100 36 1900

(source: https://techdifferences.com/difference-between-classification-and-clustering.html)





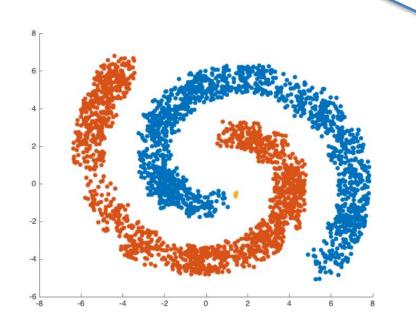
Clustering Algorithms

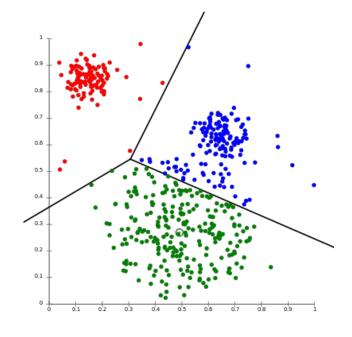
K-means clustering

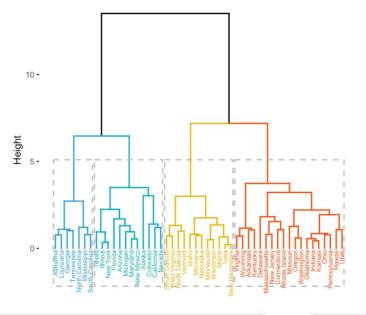
https://youtu.be/nXY6PxAaOk0

- Hierarchical clustering (dendrogram)
- Gaussian mixture models
- DBSCAN

•

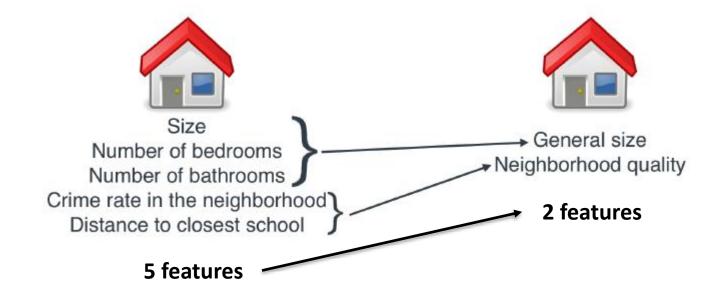






Dimensionality Reduction

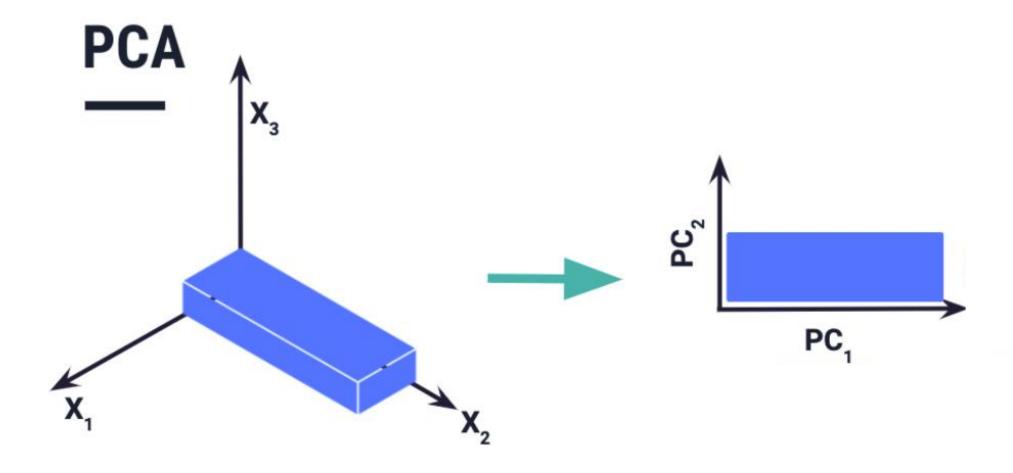
- Number of dimensions = number of features
- Reducing the number of features







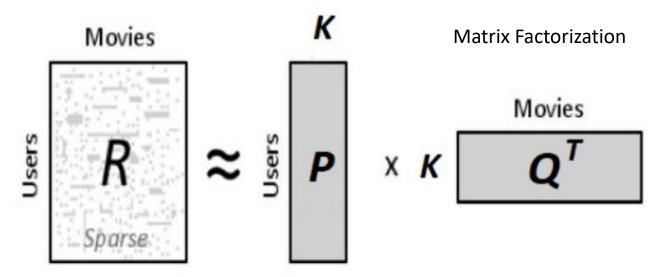
Example: Principal Component Analysis

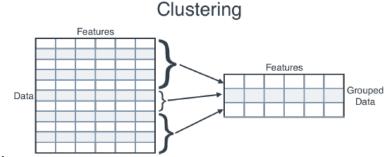


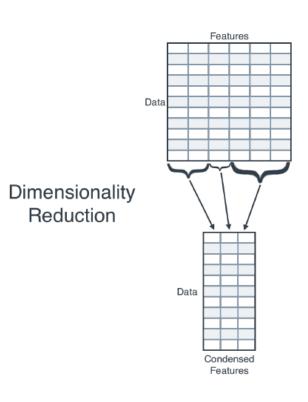
(source: https://knowledge.dataiku.com/latest/ml-analytics/statistics/concept-principal-component-analysis-pca.html)

Matrix Factorization

- Clustering: reducing samples (= rows)
- Dimensionality Reduction: reducing features (= columns)
- Matrix Factorization: reducing both rows and columns







(source: https://www.kaggle.com/code/residentmario/notes-on-matrix-factorization-machines)

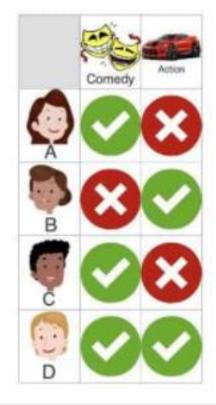
Example: Recommender Systems

Matrix Factorization

	M1	M2	МЗ	M4	M5
Comedy	3	1	1	3	1
Action	1	2	4	1	3



https://youtu.be/ZspR5PZemcs



	M1	M2	МЗ	M4	M5
	3	1	1	3	1
	1	2	4	1	3
9	3	1	1	3	1
	4	3	5	4	4

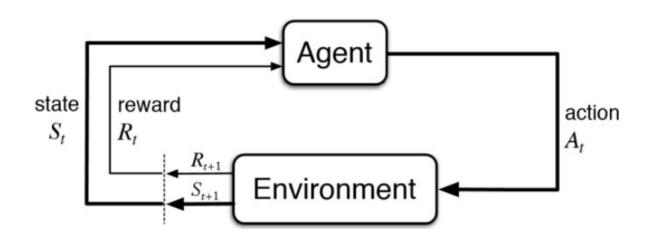
Dania International Days 2024 Workshop Machine Learning

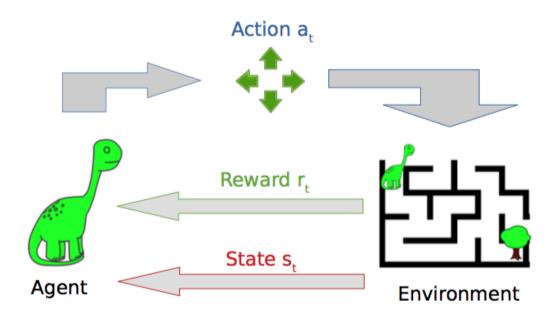
MACHINE LEARNING: REINFORCEMENT LEARNING





Reinforcement Learning





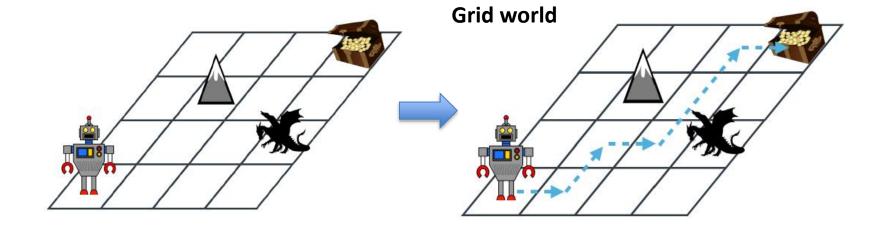
(source: https://towardsdatascience.com/reinforcement-learning-101-e24b50e1d292)





Applications

- Robotics
- Self-driving cars
- Games
- •



AlphaGo en AlphaZero

https://deepmind.google/technologies/alphago/ AlphaGo - the movie





Dania International Days 2024 Workshop Machine Learning

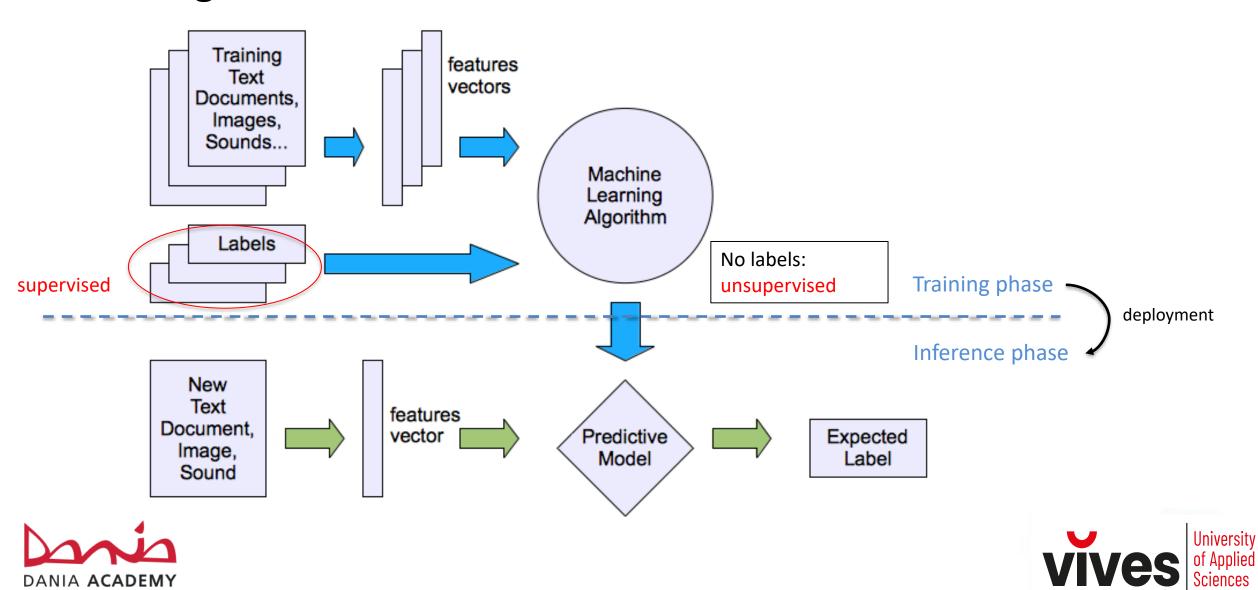
MACHINE LEARNING: TRAINING AND EVALUATION



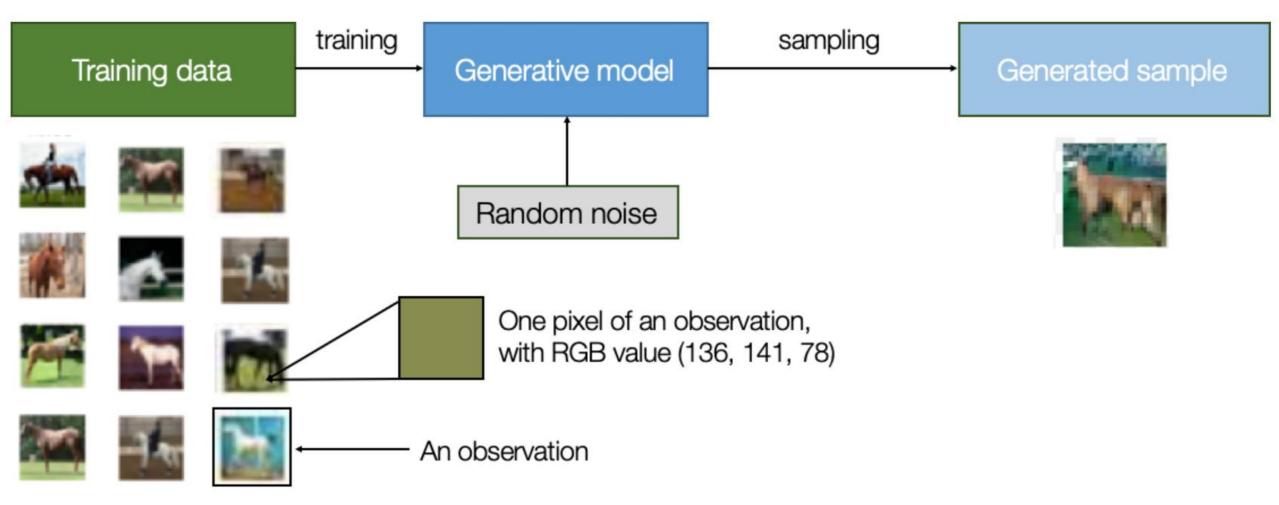


Training vs Inference

DANIA ACADEMY



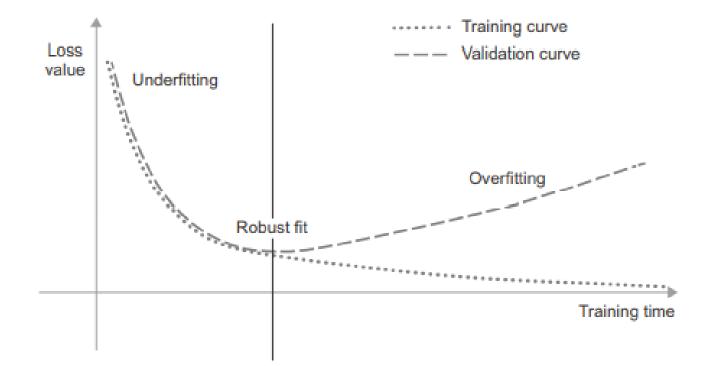
What about GenAI? Training vs Sampling



https://www.oreilly.com/library/view/generative-deep-learning/9781492041931/ch01.html

Optimization vs Generalization

- Optimization: fitting the data as best as possible during training
- Generalization: good model performance on new data during inference







Underfitting vs Overfitting

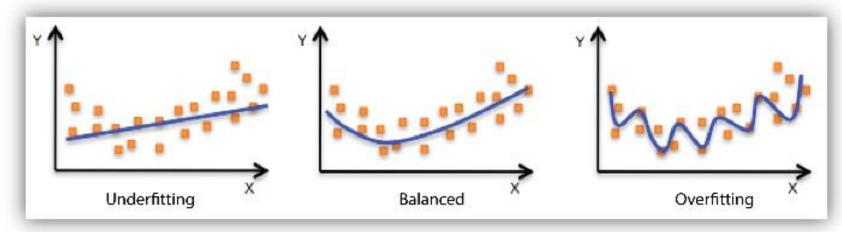
• <u>Underfitting:</u> model is too simple

Overfitting:

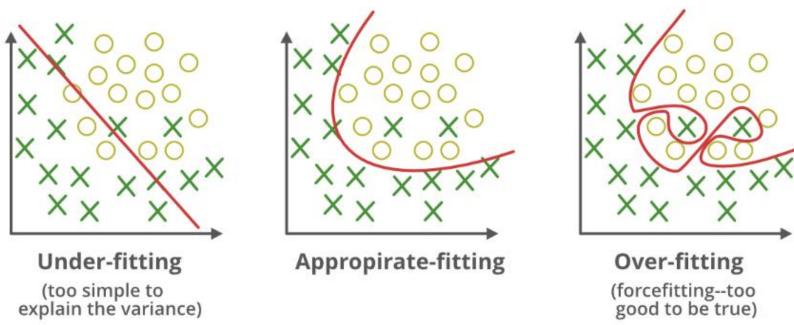
model is too specific

Causes:

- Noise
- Uncertainty
- Rare features
- **—** ..



(source: https://towardsdatascience.com/underfitting-and-overfitting-in-machine-learning-and-how-to-deal-with-it-6 fe 4a 8a 49 db f)



(source: https://www.geeksforgeeks.org/underfitting-and-overfitting-in-machine-learning)

Training, Validating and Testing

Splitting the dataset:

• training:

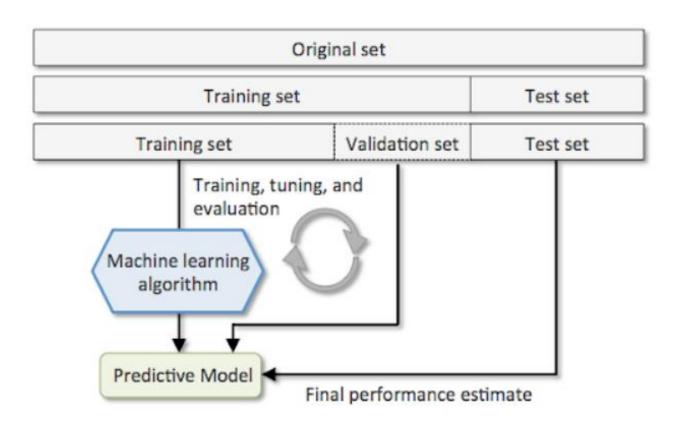
- deriving the optimal model parameters
- by the machine learning algorithm

validating:

- finding the optimal model configuration
- fine-tuning the hyperparameters
- to overcome overfitting
- by the machine learning engineer

testing:

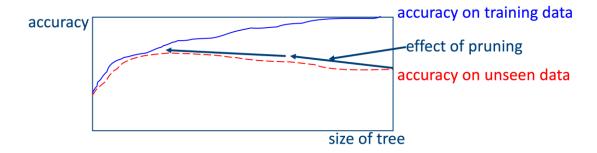
- final evaluation
- by the machine learning engineer



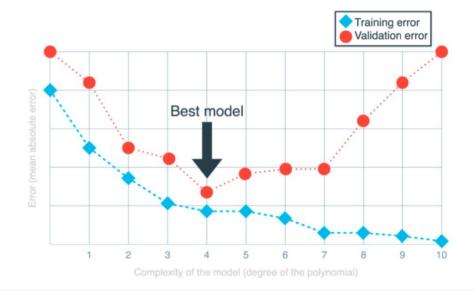
(source: https://vitalflux.com/hold-out-method-for-training-machine-learning-model)

Training vs Validation Performance

Decision Trees

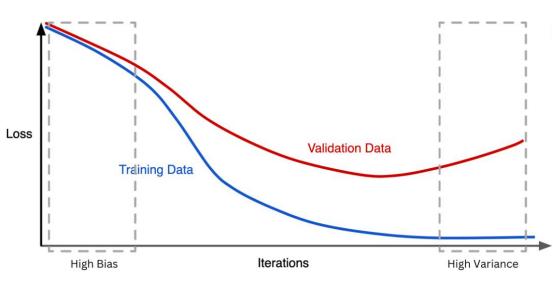


Polynomial Regression





Artificial Neural Networks



(source: https://www.dataquest.io/blog/regularization-in-machine-learning)

Model Evaluation

Loss functions:

- Compare predictions and true target values
- Minimized by machine learning <u>algorithms</u> to obtain the best fit of the data
- Should be mathematically convenient

Evaluation metrics:

- Also compare predictions and true target values
- Used by machine learning <u>engineers</u> to evaluate the model performance
- Easier to interpret by humans





Common Loss Functions and Metrics

Task	Loss	Metric
Regression	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)
	= mean of the squared differences between predictions and targets	= square root of MSE
	Mean Absolute Error (MAE)	Coefficient of Determination (R2)
	= mean of the absolute differences between predictions and targets	= number between 0 and 1 expressing the goodness of fit where 1 indicates a perfect fit
Classification	Cross-Entropy or Log Loss	Accuracy
	quantifies the difference between the predicted probabilities and the true labels	= the number of correct predictions divided by the total number of samples





Machine Learning Workflow







Sources

- Many slides are based on the book "Grokking Machine Learning" by Luis G Serrano (2021)
- Other slides are inspired by the book "Deep Learning with Python (2nd edition)" by François Chollet (2021)
- Some slides are adopted from the presentation on machine learning that was part of the course "Introduction to Artificial Intelligence" taught by Dr. Stefaan Haspeslagh at the Vives University of Applied Sciences during the academic year 2019-2020
- A few slides are taken from lectures given by Prof. Dr. Celine Vens and Prof. Dr. Hendrik Blockeel (Computer Sciences, KUL)
- Information was also obtained from Andrew Ng's online course "AI for Everyone": https://www.deeplearning.ai/courses/ai-for-everyone/
- Other sources are mentioned on the slides.



