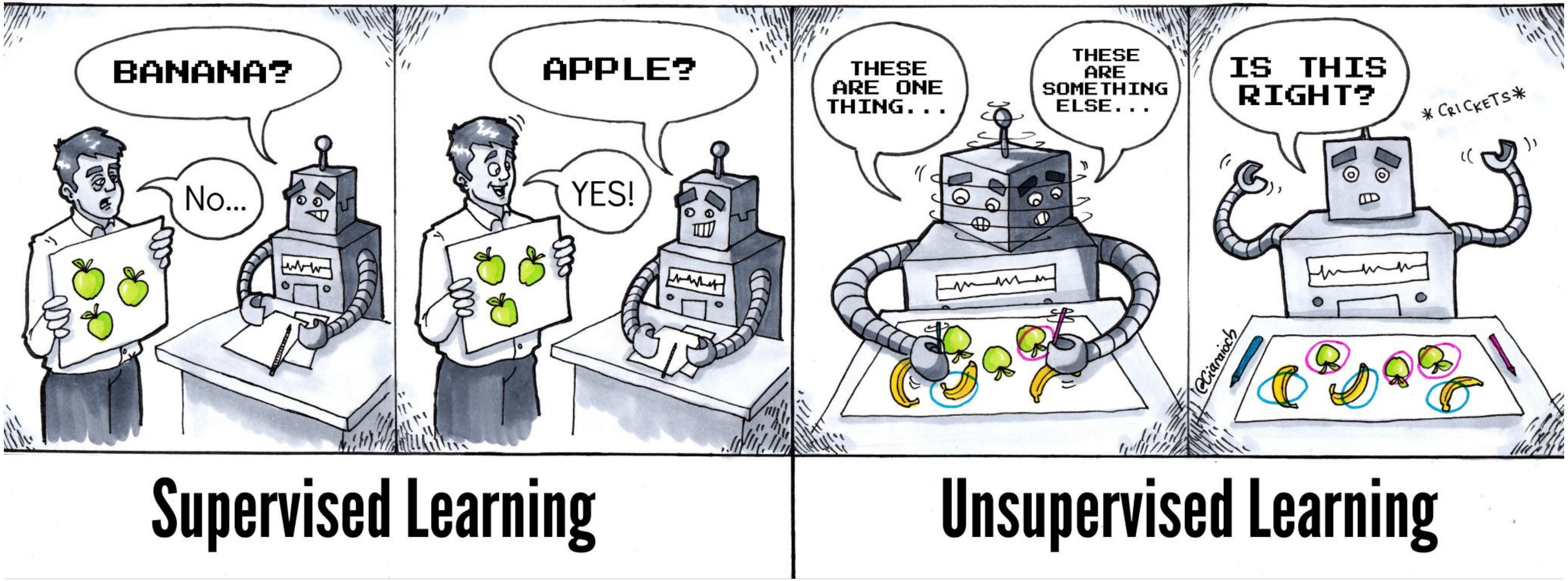
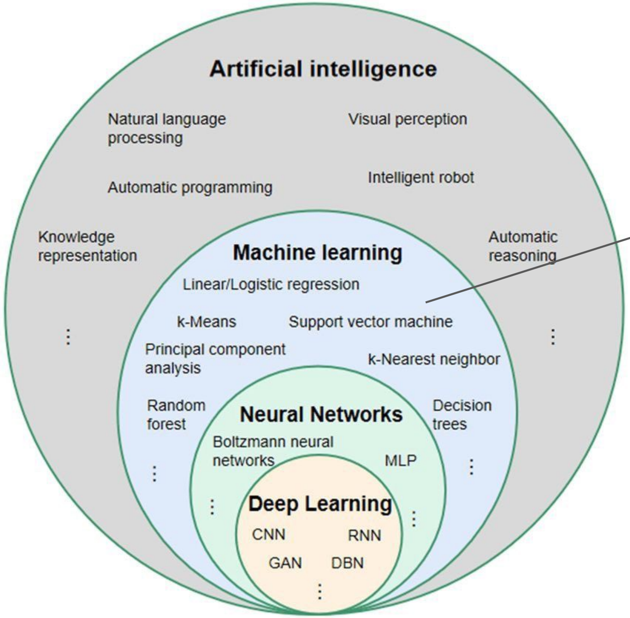
Machines that Learn

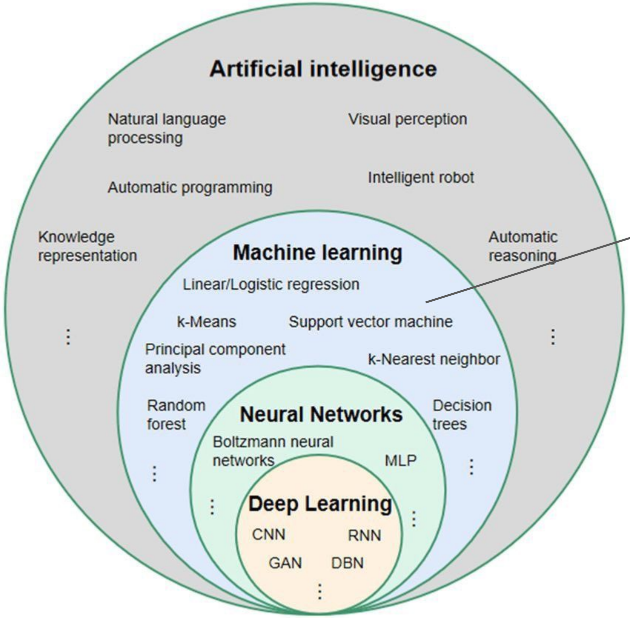


Recap



Supervised Learning
Unsupervised Learning
Reinforcement Learning

Recap

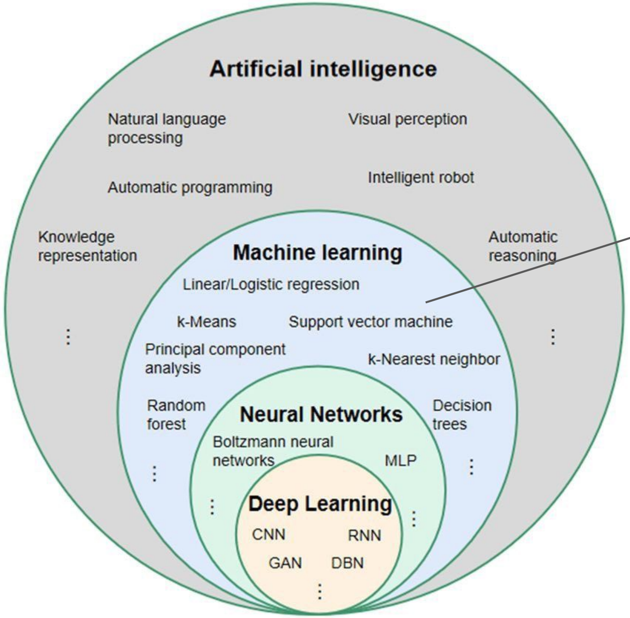


Supervised Learning
- Self-Supervised Learning
- Few-shot Learning
- Zero-shot Learning
- Transfer Learning

Unsupervised Learning
Reinforcement Learning

Federated Learning

Recap



Supervised Learning

- Self-Supervised Learning
- Few-shot Learning
- Zero-shot Learning
- Transfer Learning

Unsupervised Learning

Reinforcement Learning

Federated Learning

Recap

Supervised Learning

$f(x) = y$

Recap

Supervised Learning

$f(x) = y$

input target

Recap

Supervised Learning

$f(x) = y$

input target

Machine learning algorithm i.e logistic classification, logistic regression, naive bayes, etc…

Recap

Supervised Learning

Tries to match the prediction to the targets

We have the targets

$f(x) = y$

input

target

Machine learning algorithm i.e logistic classification, logistic regression, naive bayes, etc…

Recap

Supervised Learning

f(x) = y

Getting this

P.s we don't always have labels readily available

Making sure the data is good

Finding the most suitable algorithm and training it

Recap

Supervised Learning

$f(x) = y$

Getting this

Evaluate if the result makes sense and is relevant for the given use-case

Making sure the data is good

Finding the most suitable algorithm and training it

Supervised Learning

This class will be about

- Being empiricists
- **(more)**Exploratory Data Analysis (EDA)
- Feature Engineering **(more data wrangling)**
- Training Models
- Evaluation

Supervised Learning

If machines can learn by themselves, just give it data.
Shouldn’t it be easy ?

Supervised Learning

If machines can learn by themselves, just give it data.
Shouldn't it be easy ?

Supervised Learning

How do we separate good from garbage ?

Supervised Learning

How do we separate good from garbage ?
How do we know if it smells ?

https://ideogram.ai/

Supervised Learning

How do we separate good from garbage ?
How do we know if it smells ?

Exploratory data analysis, explore correlation and quickly build baseline models

Supervised Learning

How do we separate good from garbage ?
How do we know if it smells ?

Things to aim for when working on a dataset:

- Complete
- Consistent
- Relevant
- Representative
- Accurate

Supervised Learning

How do we separate good from garbage ?
How do we know if it smells ?

Things to aim for when working on a dataset:

- Complete - Ensure all necessary data points are included and address missing data appropriately.
- Consistent - Maintain uniform formats and values throughout the dataset to avoid contradictions.
- Relevant - Include only data directly aligned with your analysis goals or application needs
- Representative - Ensure the dataset accurately reflects the population or phenomenon being studied.
- Accurate - Verify data correctness to minimize errors or misleading insights

Supervised Learning

How do we separate good from garbage ?
How do we know if it smells ?

Things to aim for when working on a dataset:

- Complete
- Consistent
- Relevant
- Representative
- Accurate

Red flags

- Too many empties or NaN
- Outliers
- Biases
- Noisy Data
- Weird things

Supervised Learning

Data $\longrightarrow$ Features

Supervised Learning

Feature Engineering

Data $\longrightarrow$ Features

- Categorical Encoding
- Handle Missing Values
- Feature Scaling
- Creating new features

Supervised Learning

Feature Engineering

Data → Features

- Categorical Encoding
  - one-hot encoding
  - multi-hot encoding

Supervised Learning

Feature Engineering

Data → Features

- Categorical Encoding
  - one-hot encoding
  - multi-hot encoding

Some ways to do it:

- df.get_dummies
- sklearn one hot encoder
- sklearn multi hot encoding

Supervised Learning

Feature Engineering

Data $\longrightarrow$ Features

- Handle Missing Values

Supervised Learning

Feature Engineering

Data → Features

- Handle Missing Values
  - Drop
  - Imputation (Mean, Median, Mode)
  - Forward Fill and Backward Fill
  - Random Values

Top 4 Techniques for Handling Missing Values in Machine Learning

Supervised Learning

Feature Engineering

Data → Features

- Feature Scaling
  - Normalization
  - Standardization

Supervised Learning

Feature Engineering

Data $\longrightarrow$ Features

- Creating new features based on existing data

Supervised Learning

Cool ?

Supervised Learning

Supervised Learning

Data understood.
Features created.
Now it's time to train.

Supervised Learning

Linear Regression
Logistic Regression

Supervised Learning

Linear Regression
Logistic Regression
Naive-Bayes
KNN (k-nearest neighbors)
SVM (Support Vector Machines)

Supervised Learning

Naive-Bayes

Naive Bayes is a **probabilistic** machine learning algorithm based on **Bayes' Theorem**, which calculates the **probability** of a class given a set of features. It assumes that all features are independent (the "naive" assumption), which simplifies computation but may not hold true in all real-world cases. Despite this limitation, it is highly effective for **text classification** and **spam filtering** because it works well with **high-dimensional data** and **provides fast predictions**.

Reference: Sklearn Naive Bayes

Supervised Learning

Naive-Bayes

Naive Bayes is a **probabilistic** machine learning algorithm based on **Bayes' Theorem**, which calculates the **probability** of a class given a set of features. It assumes that all features are independent (the "naive" assumption), which simplifies computation but may not hold true in all real-world cases. Despite this limitation, it is highly effective for **text classification** and **spam filtering** because it works well with **high-dimensional data** and **provides fast predictions**.

Reference: [Sklearn Naive Bayes]

Challenge: Try to implement this algorithm from scratch

Supervised Learning

K-Nearest Neighbors (KNN)

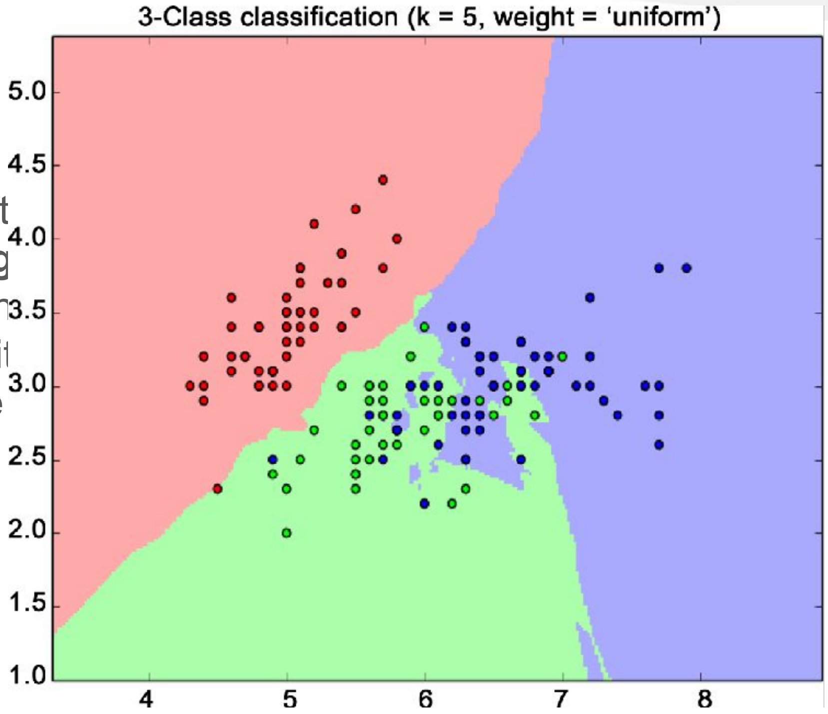
KNN is a simple, instance-based algorithm that **predicts the class** of a data point by **considering the classes of its k closest neighbors in the feature space**. The "closeness" is typically determined using distance metrics like **Euclidean distance**. KNN is intuitive and non-parametric, meaning it makes no assumptions about the underlying data distribution, but it can **become computationally expensive as the dataset grows**.

Reference: Sklearn KNN

Supervised Learning

K-Nearest Neighbors (KNN)

KNN is a simple, instance-based algorithm that
considering the classes of its k closest neig
"closeness" is typically determined using distan
KNN is intuitive and non-parametric, meaning it
underlying data distribution, but it can **become**
dataset grows.



Reference: [Sklearn KNN]

Supervised Learning

Support Vector Machines (SVM)

SVM is a powerful algorithm used for **classification** and **regression** tasks. It works by finding a **hyperplane that best separates data points** of different classes in a **high-dimensional space**. SVM focuses on maximizing the margin between the classes, making it robust to outliers and well-suited for both linear and non-linear data (with the help of kernel functions). **It is especially effective for datasets with clear margins of separation.**

Reference: Sklearn SVM

Let's do some feature engineering

More EDA
Feature Engineering
More training

Let's do some feature engineering

More EDA
Feature Engineering
More training

Supervised Learning

Remember when I said we need to be empiricists ?

And act like scientists.

We need to create hypothesis and properly evaluate them.

Supervised Learning

Data = Train + Testing
Testing = Validation + Testing
Data = Train + Validation + Testing

Supervised Learning

Data = Train + Testing
Testing = **Validation** + Testing
Data = Train + **Validation** + Testing

Validation - used during development to validate hyperparameters (like max_iter of logistic regression)

* more on this on the next class

Supervised Learning

Data = Train + Testing
Testing = Validation + Testing
Data = Train + Validation + Testing

Sidenote:
In real world use-cases data is not stagnant.
Any ML models need to be constantly re-evaluated and more often than not re-trained.

Supervised Learning

Hypothesis
We can learn a reasonable enough valid correlation between X and Y

Testing
How close did we get ?
Is it close enough ?

Supervised Learning

Testing results are only considered correct if there are no biases* during training or evaluation - i.e no **data leakage**

*data leakage is just one possible bias, we also can have selection bias, sampling bias among others

[Understanding Bias in Machine Learning Models - Arize AI]

Supervised Learning

Testing results are only considered correct if there are no biases during training or evaluation - i.e no **data leakage**

This means that testing data, *ideally* is locked away.

Supervised Learning

Testing results are only considered correct if there are no biases during training or evaluation - i.e no **data leakage**

This means that testing data, *ideally* is locked away.

Which means that certain **transformations** must be done **only after splitting the data** e.g Normalization, Standardization, TF-IDF,...

Supervised Learning

Hypothesis
We can learn a reasonable enough valid correlation between X and Y

Testing
How close did we get ?
Is it close enough ?

Supervised Learning

Evaluation is looking closely at the right metrics.

Let's go back to titanic and store sales.

Supervised Learning

Hypothesis
We can learn a reasonable enough valid correlation between X and Y

Testing
How close did we get ?
Is it close enough ?

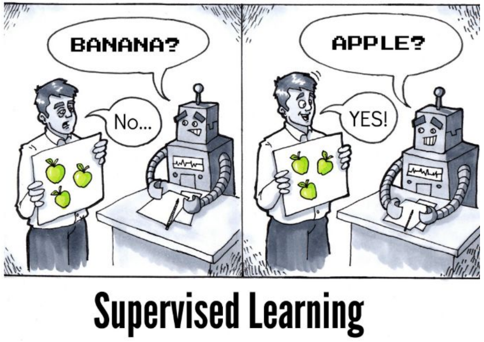
Supervised Learning

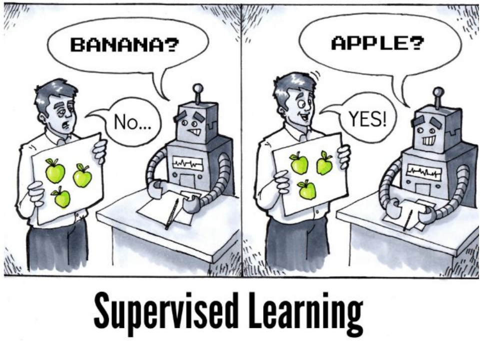
Building blocks

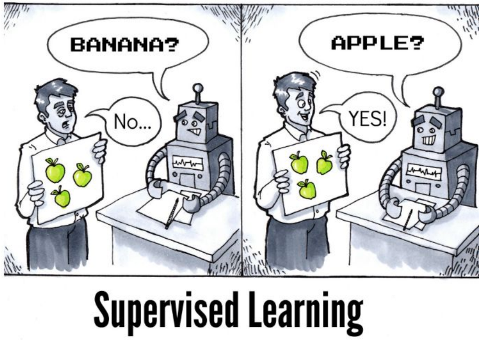
- Pipeline — scikit-learn 1.5.2 documentation
- sklearn.datasets — scikit-learn 1.5.2 documentation
- sklearn.preprocessing — scikit-learn 1.5.2 documentation

Machines that Learn

More on the next class







Hyperparameter Search
Cross-Validation