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MACHINE LEARNING

COMP8220

01 – Introduction

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Teaching Staff

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- Career path

- Research interests
  - Scalable and secure machine learning
  - Big data privacy and cyber security

Unit Scheduling

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Machine Learning

Part I: Conventional machine learning techniques for regression, classification, and clustering

Part II: Deep learning models

Lecture Outline

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- What is Machine Learning?
- Types of Machine Learning Systems
- Main Challenges
- Machine Learning in Python

Lecture Outline

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- What is Machine Learning?
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What is Machine Learning?

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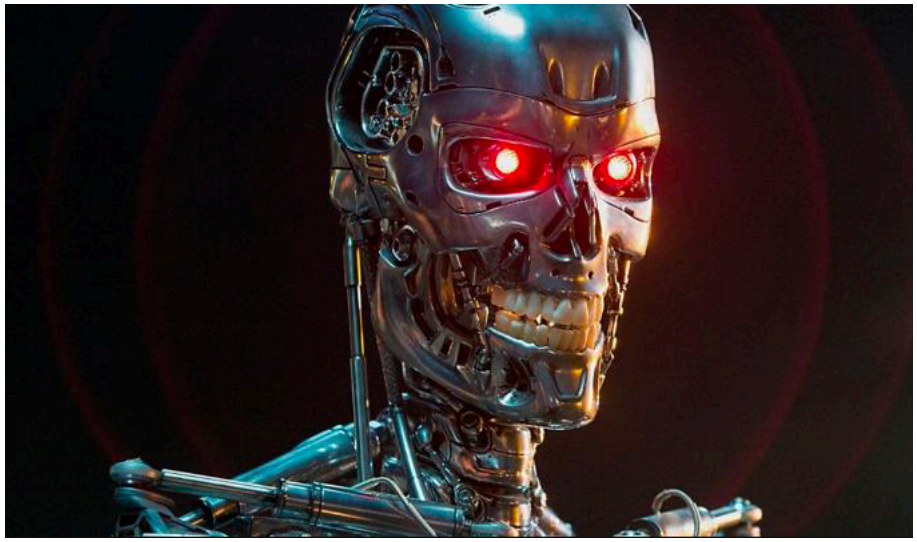

What is your first impression?

State-of-the-art Applications

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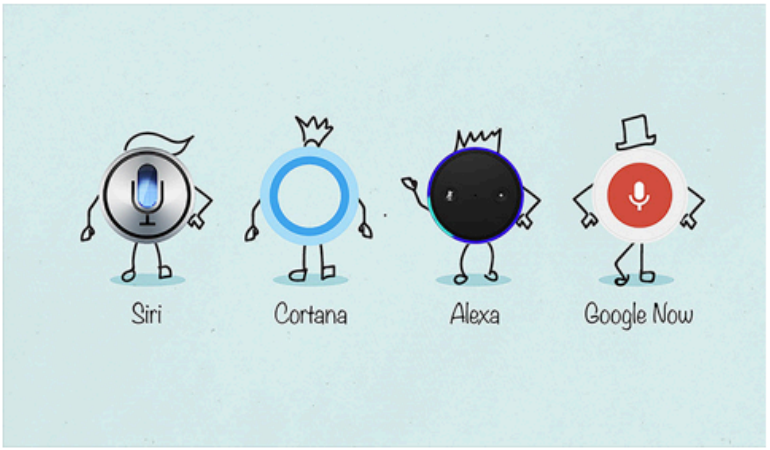
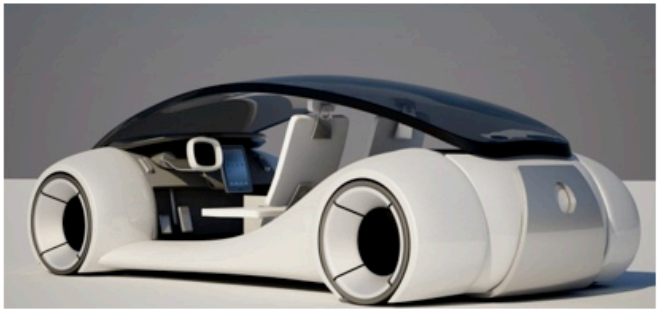
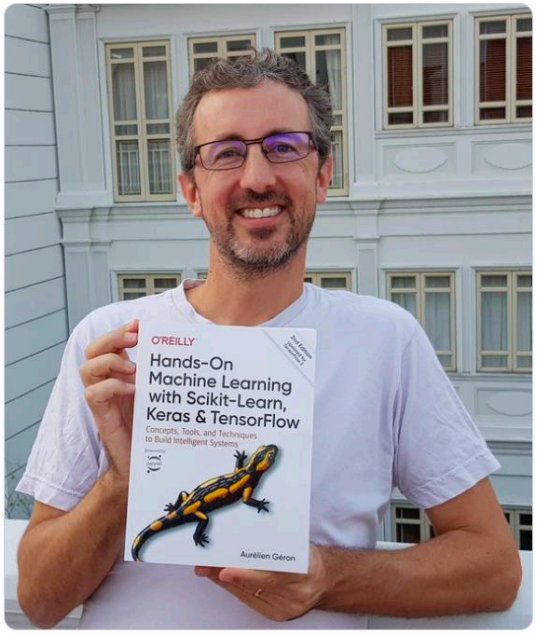
AlphaGo

Google DeepMind





Machine Learning Definition



Machine Learning is the science of programming computers so that they can learn from data.

(Aurélien Géron, 2019)

Machine Learning Definition

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Machine Learning is the field of study that gives computers the ability to learn without being explicitly programmed.

(Arthur Samuel, 1959)

Machine Learning Definition

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A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.

(Tom Mitchell, 1997)

Example: Spam Filtering

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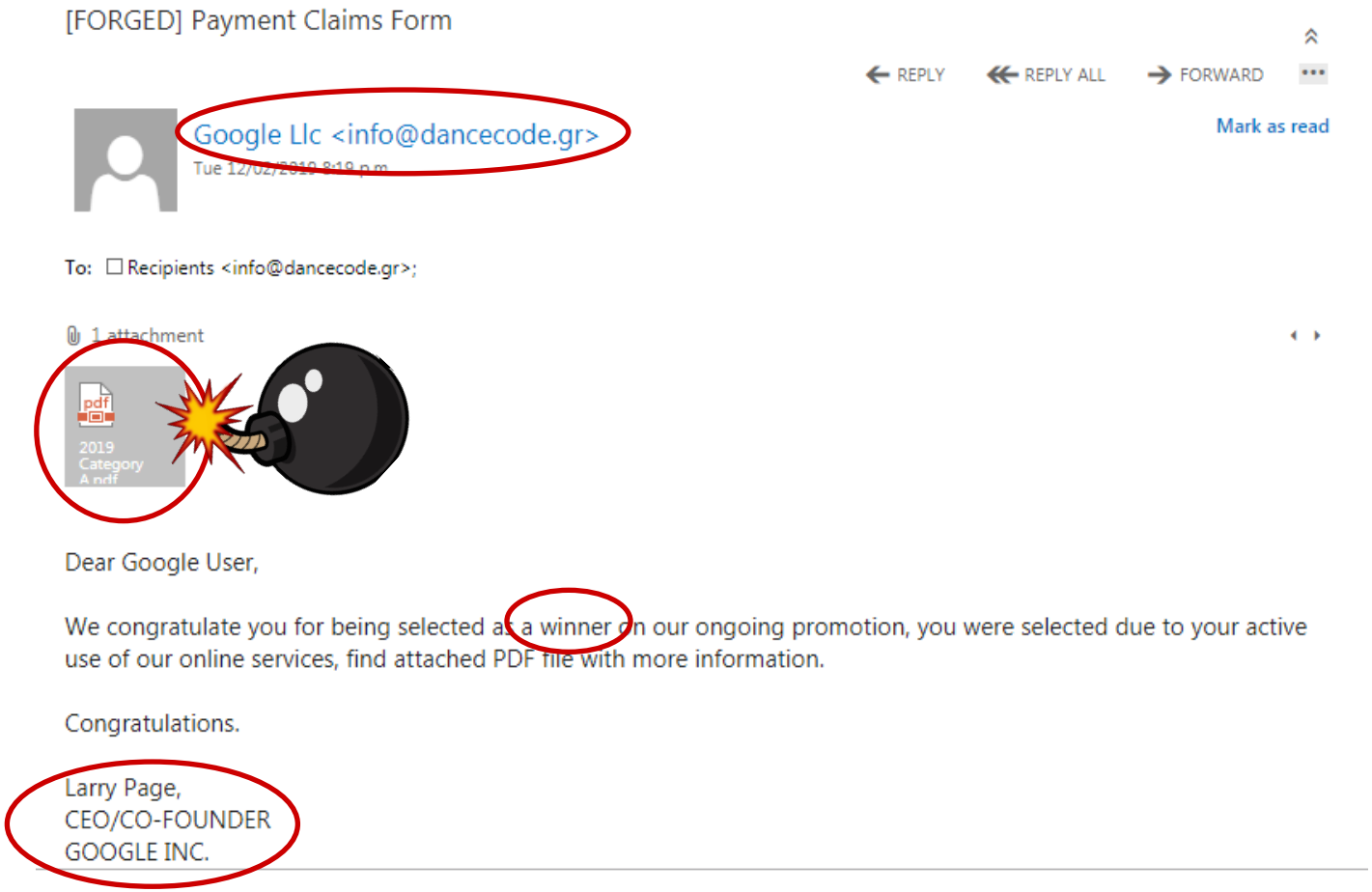
- Task: Given an email, a spam filter must classify the email as bad (spam) or as good (ham)



Example: Spam Filtering

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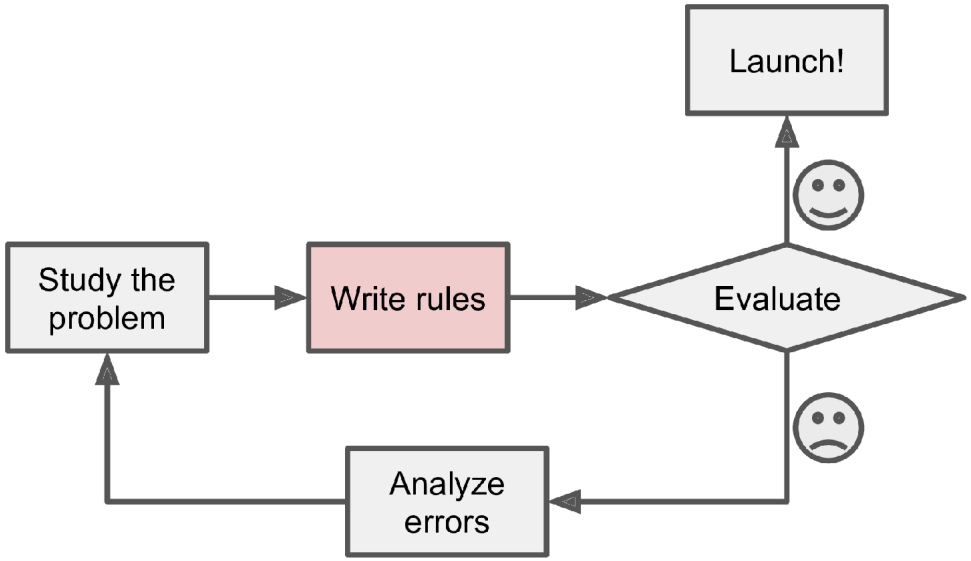
- Traditional way: hand-crafted rules
  - E.g., if it contains 'winner', then classified as a spam



- Limitations
  - Need to memorize many complex rules to detect patterns
  - Spam creators often change their tactics over time

Example: Spam Filtering

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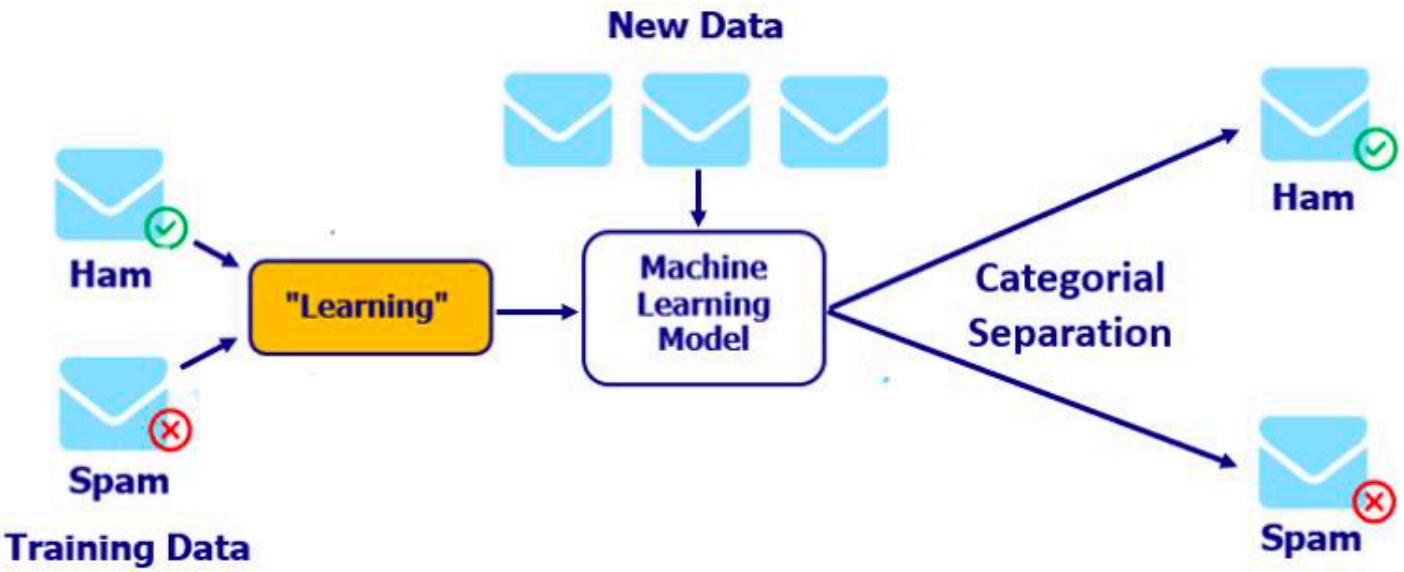
- A spam filter based on machine learning can automatically learn which words and phrases are good predictors for spam using term frequency
- Architecture



Example: Spam Filtering

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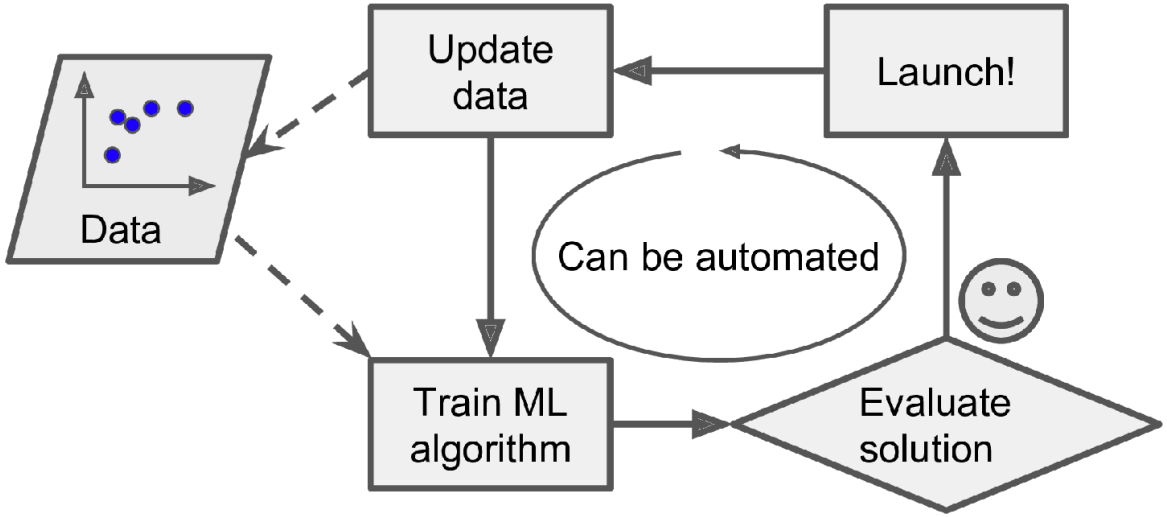
- Machine learning based detection
  - It requires: examples of regular emails and spam emails



- Three learning aspects
  - T: to separate spam from regular emails
  - E: both regular and spam emails
  - P: can be defined, e.g., ratio of correctly classified emails

What if No Learning?

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- Experience (email data):

ID	'winner'	'payment'	'attachment'	spam
1	yes	yes	no	yes
2	yes	no	yes	yes
3	no	yes	yes	no

- Task: to predict if an email is a spam or not
- Performance: accuracy
- No learning: to randomly guess for a future email
  - Accuracy: 50%
- A simple learning: predict a future email with 'yes'
  - Accuracy: 66.7% > 50%

Learning vs Memorizing

Sees:

So, what really matters in learning is the capability of generalization from experience for unseen instances

Learning vs Memorizing

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- When do we use machine learning?
  - Human expertise does not exist (navigating on Mars)
  - Humans are unable to explain their expertise (speech recognition; face recognition; driving)
  - Complex problems for which no good solution exists
  - Solution changes in time (routing on a computer network; browsing history; driving)
- When do we **not** use machine learning?
  - Calculating payroll
  - Sorting a list of words
  - Monitoring CPU usage
  - Querying a database

Machine Learning Ingredients

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- Data: experience (E) is embedded in the form of data
  - E.g., email text (raw data)
- Learning models: the task (T) we need to specify
  - Regression, classification, or clustering?
  - High-level abstraction learned from observations
- Learning algorithm: the computer program
  - E.g., decision trees, Naïve Bayes classifier, stochastic gradient descent, maximum likelihood estimation, etc.
- Testing and evaluation: check if the performance (P) has been improved
  - E.g., k-folder cross validation

Two Stages of Machine Learning

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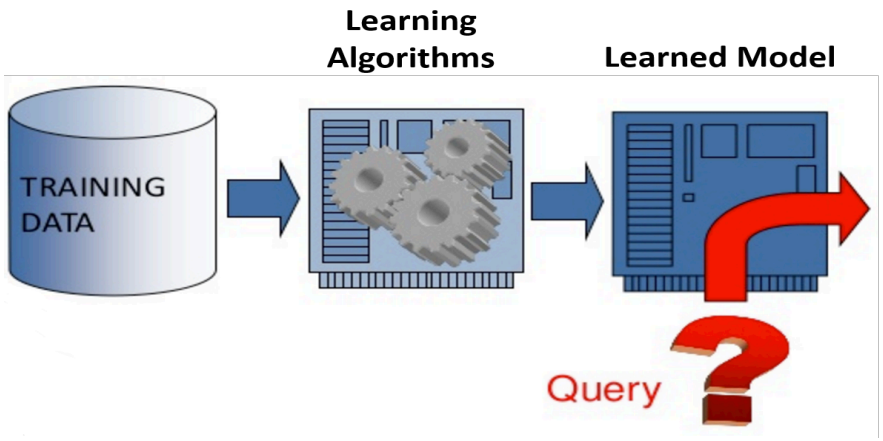
- Training stage
  - Training: to generate a model from observed data
- Testing stage
  - Testing: to use the learned model to predict unseen data



E.g., does a patient with coughing, running nose and fever suffer from COVID-19 or flu?

Data

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- **Data set** D: a set of observed data instances
  - $D = \{d_1, d_2, \cdots, d_{|D|}\}$
  - Many types: numerical vectors, an image, a graph, …
  - Assumption: i.i.d. (independent & identical distributed)
    - Instances in D follow a (unknown) distribution, from which each instance is independently sampled
- **Training data**: data used in the training stage
- **Testing data**: data used in the testing stage
- **Validation data**: used to select learning models
  - Part of a training data

Data

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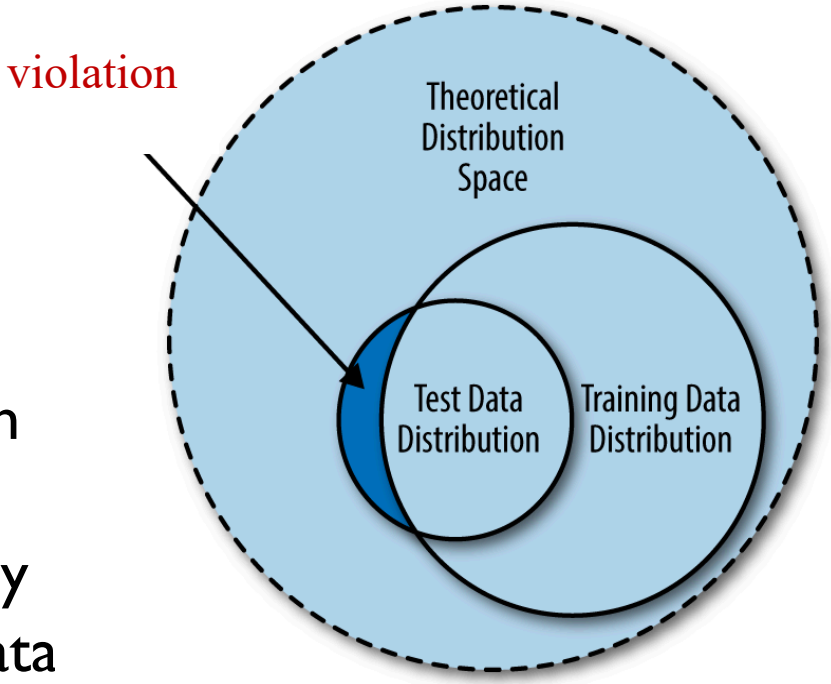
- Assumption: the distribution of training examples is identical to the distribution of test examples (including future unseen examples)
  - In practice, this is often violated to certain degree
  - Strong violations will clearly result in poor performance
  - To achieve good accuracy on the test data, training examples must be sufficiently representative of the test data



Data

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- Label/target of data
  - The interesting attribute(s) for prediction
  - Further, $d_i \equiv \langle x_i, y_i \rangle$
  - **Supervised learning models**
    - **Regression**: y is continuous
    - **Classification**: y is discrete (binary or multi-class)
- No explicit label/target information
  - Then, $d_i \equiv \langle x_i, \cdot \rangle$
  - **Unsupervised learning models**
    - **Clustering**
- **Semi-supervised learning** (labeling is often costly)

Model

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- **Model**: a map from input space to output space
  - i.e., $f : \mathcal{X} \to \mathcal{Y}$
  - An infinite number of such maps
  - Input space: space spanned by feature attributes
  - Output space: space spanned by label/target attributes
- **Hypothesis space** H: space of all possible maps
  - Functional space: $\mathcal{H} \equiv \{f \mid \mathcal{X} \to \mathcal{Y}\}$
- **Ground truth**: underlying true mechanisms of generating the observed data
  - But never known in reality
  - The purpose of learning: approximate the ground truth

Parameter Space

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- What do we really learn from data for a model?
  - Hypothesis space is usually pre-specified in terms of problem domains
  - Different models are determined by parameters
  - Let θ denote the parameter vector, we have

$$\mathcal{H} \equiv \{f \mid y = f_\theta(x)\}$$

- Parameter space
  - Can be real value spaces, e.g., $\mathbb{R}^n$
  - Structure of a model (more implicit), e.g., tree or graph structures, as well as partitions of the input space

Lecture Outline

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- What is Machine Learning?
- Types of Machine Learning Systems
- Main Challenges
- Machine Learning in Python

AI, ML, and DL

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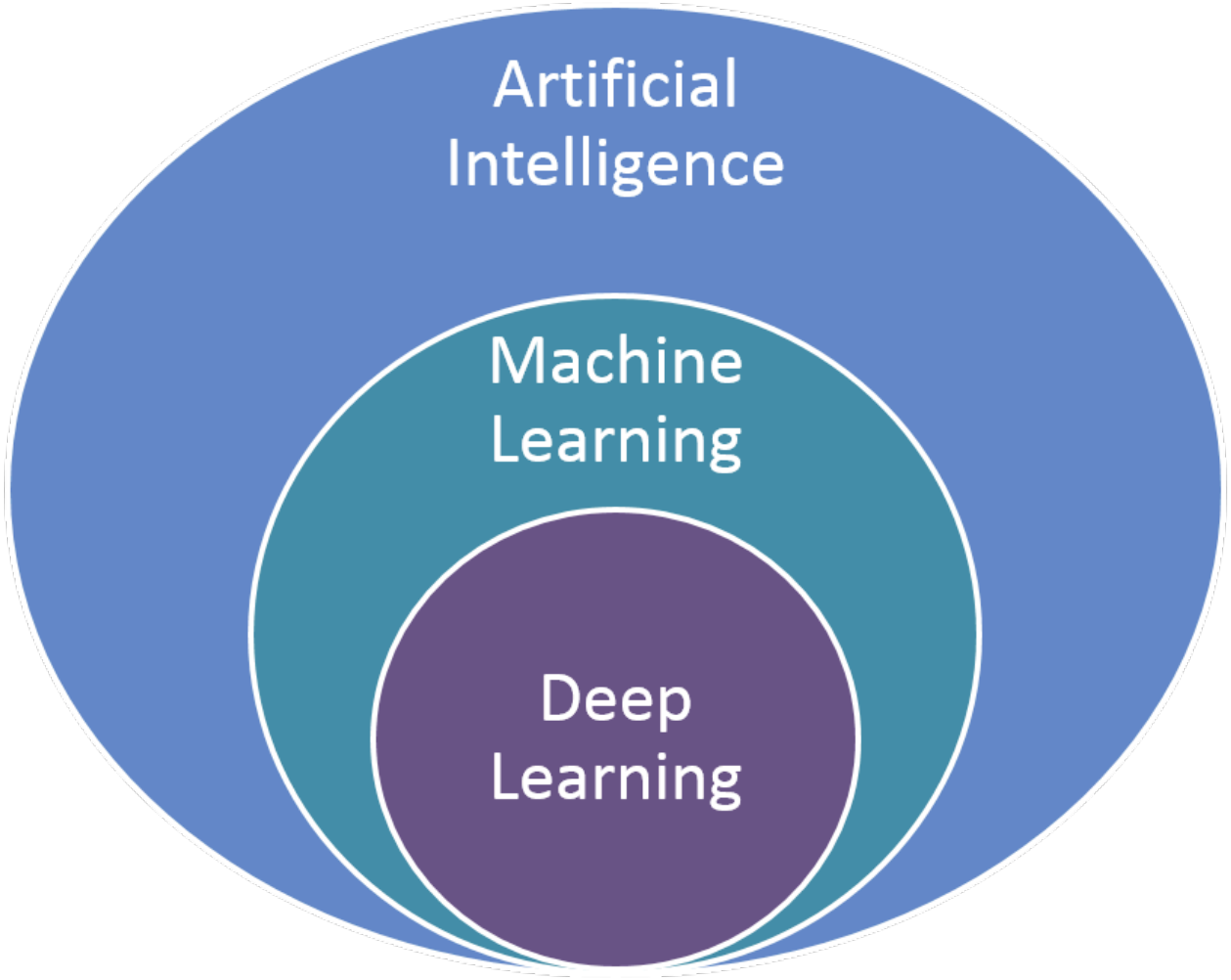

AI, ML, and DL

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- 1950s Deductive reasoning stage
  - Formal logic, e.g., proof of mathematic theorems
- 1970s Knowledge engineering stage
  - Knowledge representation, e.g., expert systems
- 1980s Machine learning stage
  - Symbolism: based on symbols, e.g., first-order logic-based learning
  - Statistical learning: applying probability theory and statistics, e.g., co-locating diaper and beer
  - Connectionism: reverse engineering brain mechanism for artificial neural nets
    - Black-box model with low interpretability

Types of ML Systems

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- One can classify ML systems along the following questions:
- Are they trained with or without human supervision?
  - => supervised versus unsupervised learning
- Can they learn incrementally or not?
  - => batch versus online learning
- Do they measure the similarity between data points or do they detect patterns and build a predictive model?
  - => instance-based versus model-based learning

Supervised vs Unsupervised

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- Supervised learning, e.g.,
  - Linear Regression, Logistic Regression
  - Support Vector Machines (SVMs)
  - Neural Networks
- Unsupervised learning, e.g.,
  - K-Means for clustering
  - PCA for dimension reduction
  - Apriori for association rule learning
- Semi-supervised learning
- Reinforcement learning

Supervised Learning

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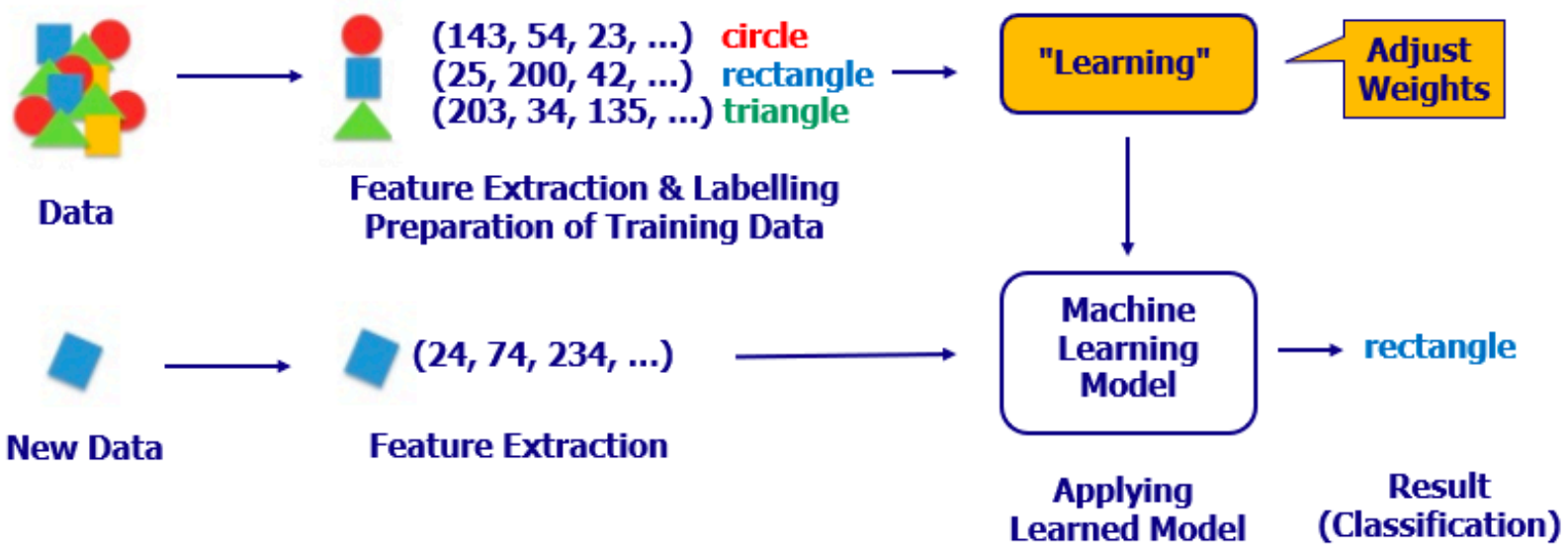
- Training data is labelled with expected solutions



- Tasks: classification and regression

Unsupervised Learning

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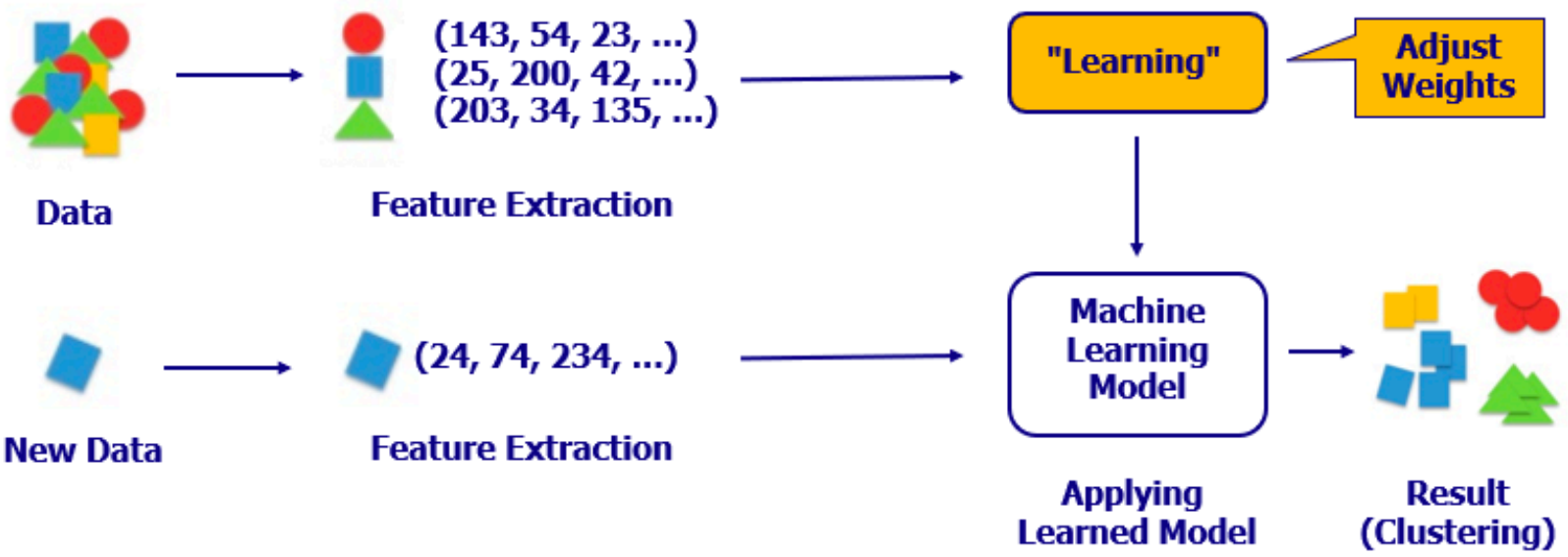
- Training data is NOT labelled with expected solutions



- E.g., a clustering algorithm can detect groups of similar objects

Semi-supervised Learning

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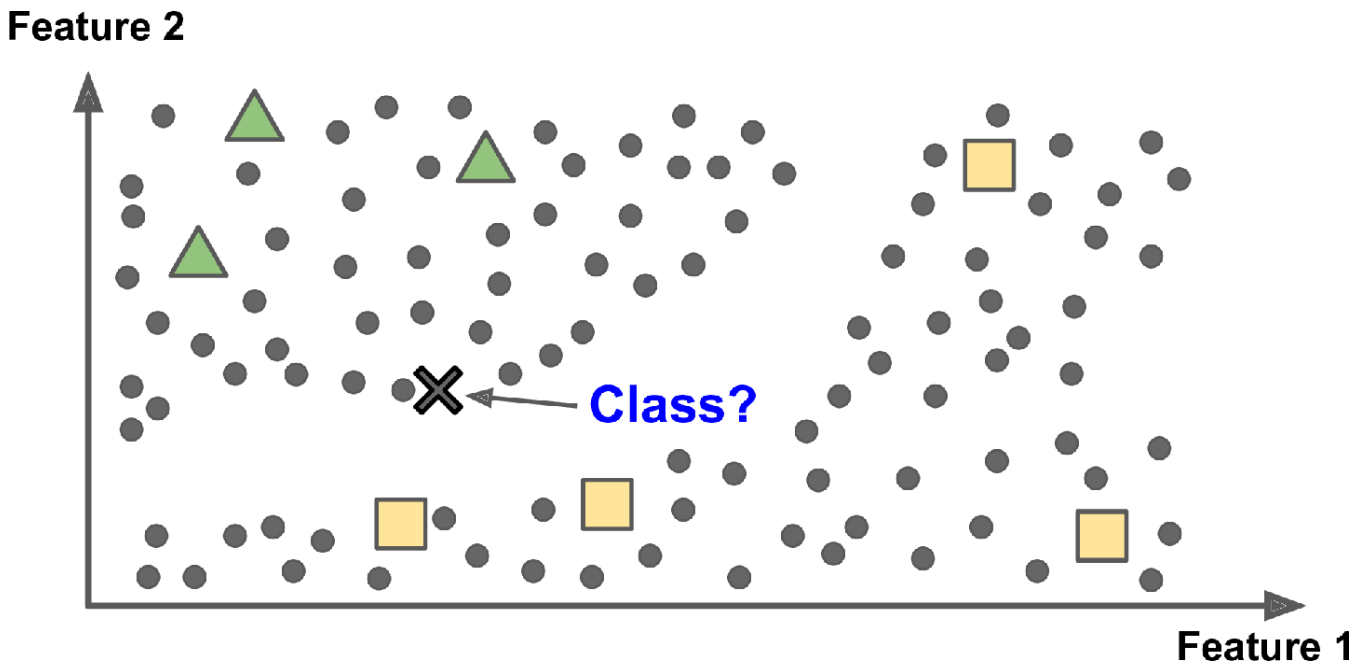
- Semi-supervised learning uses
  - A small amount of labelled data and
  - A large amount of unlabelled data



Example: Pseudo-Labelling

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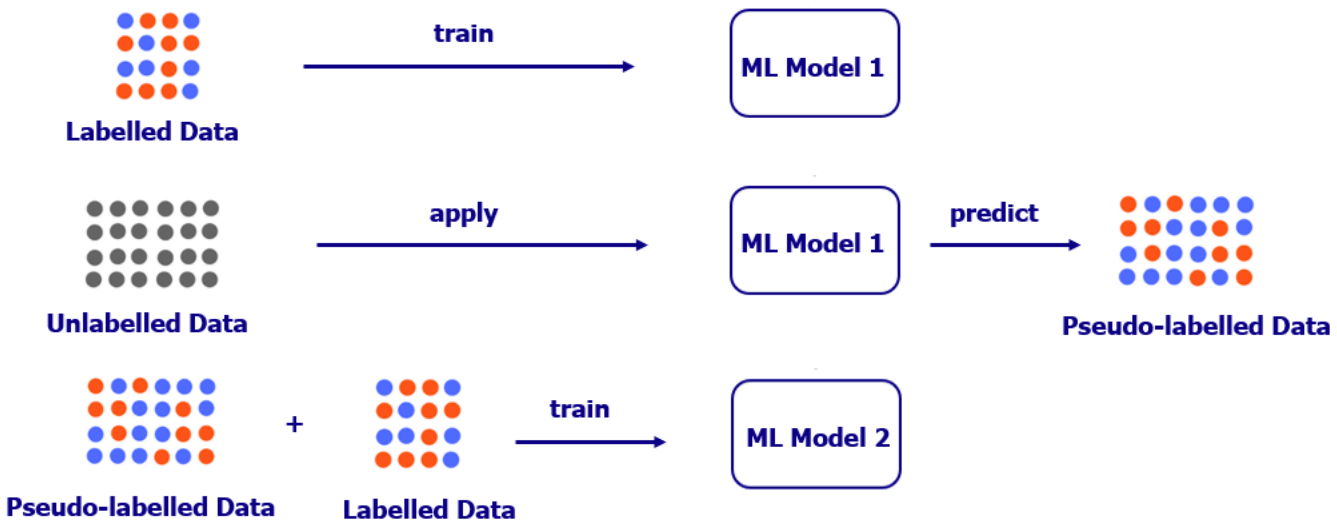
- One important technique is pseudo-labelling
  - Pseudo labels are predicated using a first model trained on the labelled data
  - Pseudo labelled data and labelled data are then used to train a second model
  - Second model is then used for predictions on test data



Reinforcement Learning

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- The aim of reinforcement learning is to train an agent via trial and error for a task in an unknown environment
  - E.g. AlphaGo

- The agent receives observations and rewards from the environment and sends actions to the environment
- The agent consists of a policy and a learning algorithm:
  - The policy defines what action the agent should choose
  - The learning algorithm continuously updates the policy parameters to maximize the cumulative reward

Reinforcement Learning

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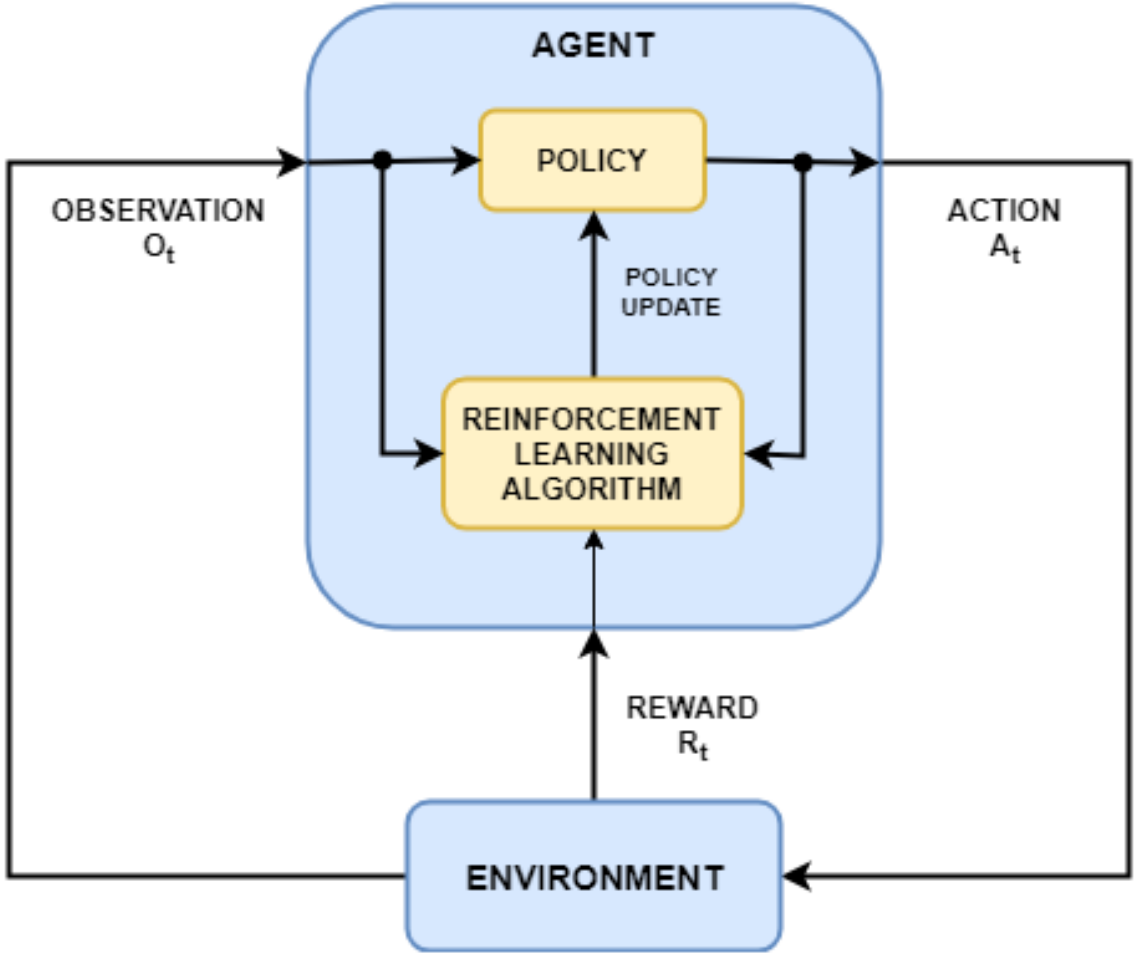

Batch versus Online Learning

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- Can learn incrementally from a stream of data or not?
- Batch learning
  - System is not capable of learning incrementally
  - System must be trained using all available data
  - Note that re-training using the full dataset may be time consuming and may require a lot of computing resources
- Online learning
  - System is capable of learning incrementally
  - System can be trained by feeding data sequentially in small groups of data (mini batches) or as individual instances
  - Can deal with datasets that cannot fit into memory

Instance-based vs Model-based

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- One can classify ML systems by how they generalize
  - Most ML tasks are about making predictions
  - Given a number of training examples, the system needs to generalize to new instances it has never seen before
- Two main approaches to generalization
  - Instance-based learning: compares new instances with instances seen in the training data, stored in memory
    - E.g, k nearest neighbors algorithm
  - Model-based learning: uses features in the training data to predict the target variable
    - E.g., linear regression models: A linear regression model predicts the target variable as a weighted sum of the feature inputs

Lecture Outline

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- What is Machine Learning?
- Types of Machine Learning Systems
- Main Challenges
- Machine Learning in Python

Main Challenges

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- Basically two things can go wrong in a ML project:

1. Bad Data

"Garbage in, garbage out"

Your analysis is as good as your data.

2. Bad Algorithms

Bad Data

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- Insufficient quantity of training data
  - Humans can classify using few examples
  - Simple ML problems require thousands of examples
  - Complex problems like image and speech recognition require millions of examples
- Nonrepresentative training data
  - Violation of the i.i.d. assumption
  - In order to generalize well, data needs to be representative
  - Too small sample sizes lead to sampling noise
  - Flawed sampling methods lead to sampling bias

Bad Data

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- Poor quality data
  - Underlying patterns are difficult to detect if training data is full of errors, outliers and noise
  - Good idea to clean up training data (manually)
  - Remove clear outliers and fix errors
  - Many ways to deal with missing features
- Irrelevant features
  - Training data needs enough relevant features
  - Irrelevant features make too much noise
  - Some ML models are sensitive to irrelevant features
  - Feature engineering is concerned with the selection, of a set of good features

Bad Algorithm

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- Underfitting the data
  - Occurs when the model is too simple to learn the underlying structure of data
  - E.g., linear models are prone to underfit; reality is more complex than the model

- Possible solutions:
  - Select a more powerful model with more parameters
  - Feed better features to the learning algorithm
  - Reduce the constraints on the model
    - E.g. reduce the number of hyperparameters

Bad Algorithm

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- Overfitting training data
  - Overfitting means that the model performs well on the training data, but does not generalize well
  - Overfitting happens when the model is too complex to the amount and noise of training data

- Possible solutions:
  - Simplify the model; select one with fewer parameters
  - Gather more training data
  - Reduce the noise in the training data
  - Constrain the model
    - Regularization

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Machine Learning in Python

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- We use Python's Anaconda distribution: https://www.anaconda.com/distribution/
- Enables data scientists to
  - Perform data science and machine learning on various operating systems
  - Develop and train models for example with Scikit-Learn and TensorFlow
  - Analyze data for example with NumPy and Pandas
  - Visualize results for example with MatplotLib
  - Manage libraries and dependencies
  - Include Jupyter Notebook for interactive data anlysis

Scikit-Learn

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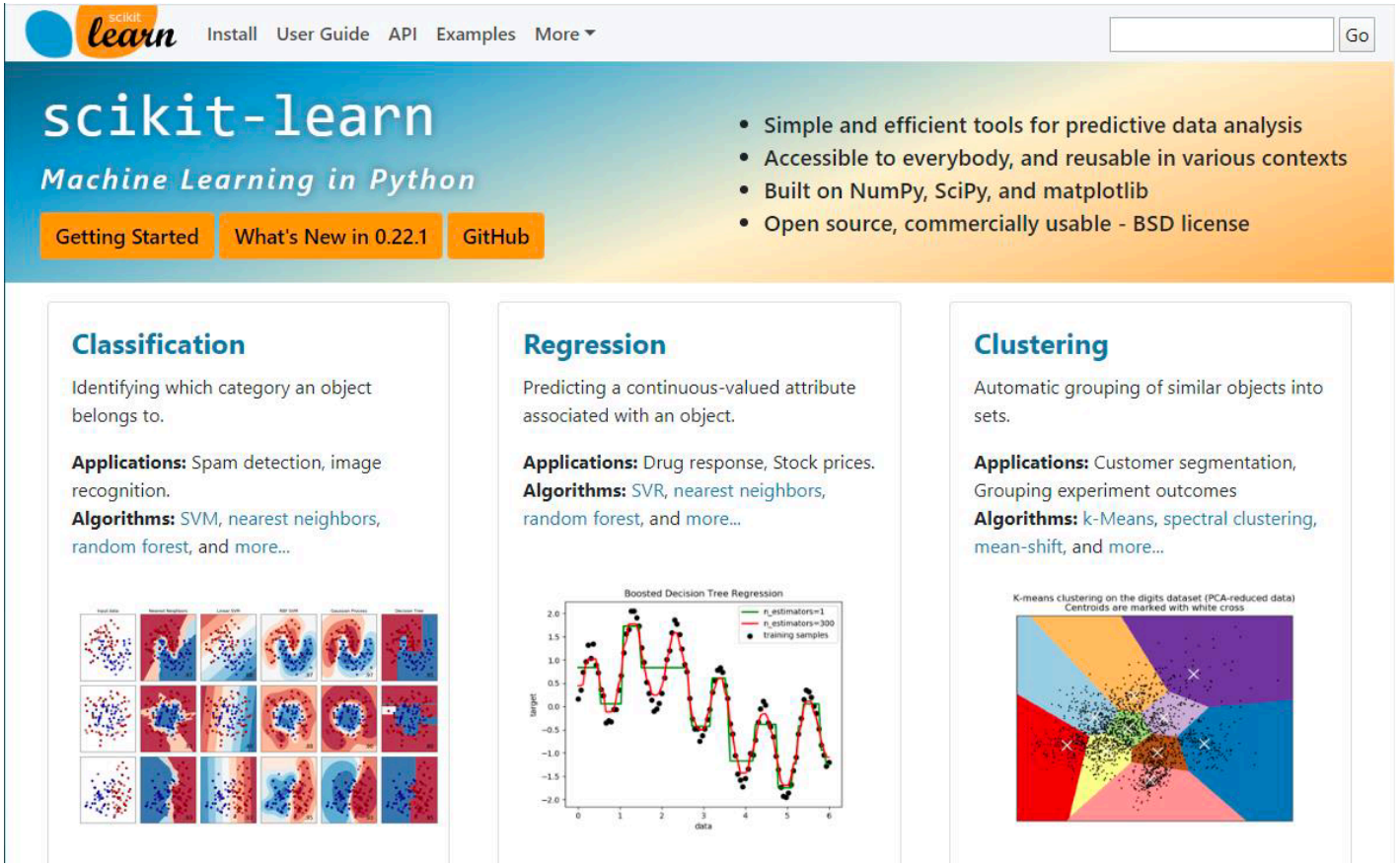
- https://scikit-learn.org/stable/



Scikit-Learn: Libraries

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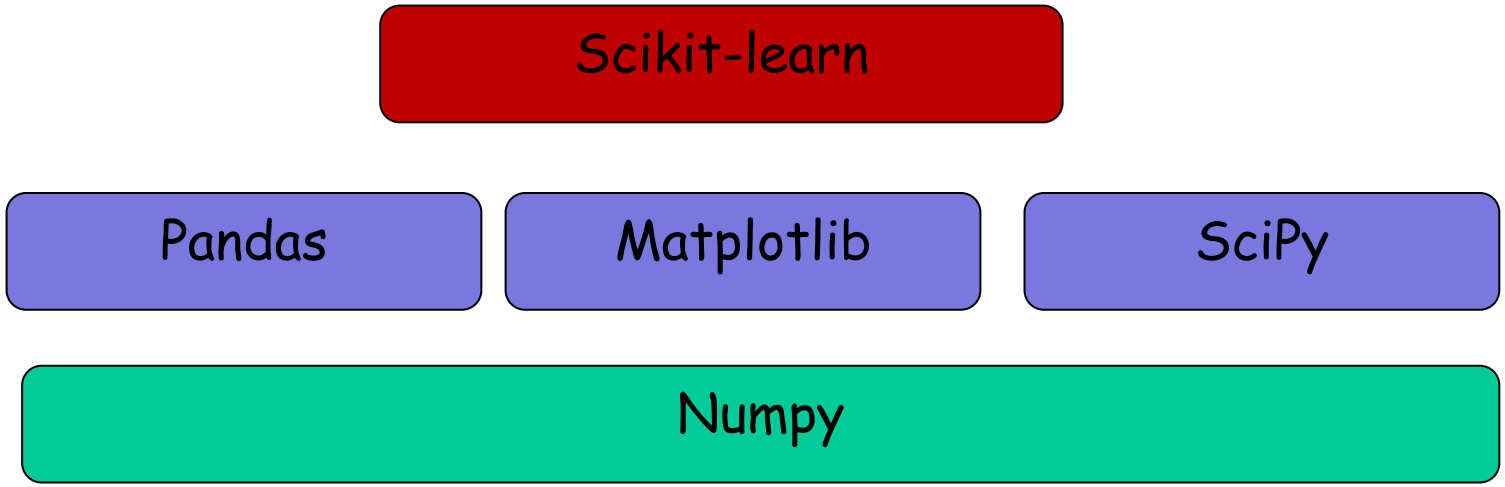

Scikit-Learn: Libraries

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- NumPy:
  - Written in C and adds support for large, multi-dimensional arrays and matrices
  - Provides mathematical functions to operate on these arrays

- Pandas:
  - Offers data structures and operations for manipulating numerical tables and time series
  - Provides in memory 2d table object called Dataframe
  - Like a spreadsheet with column names and row labels

Scikit-Learn: Libraries

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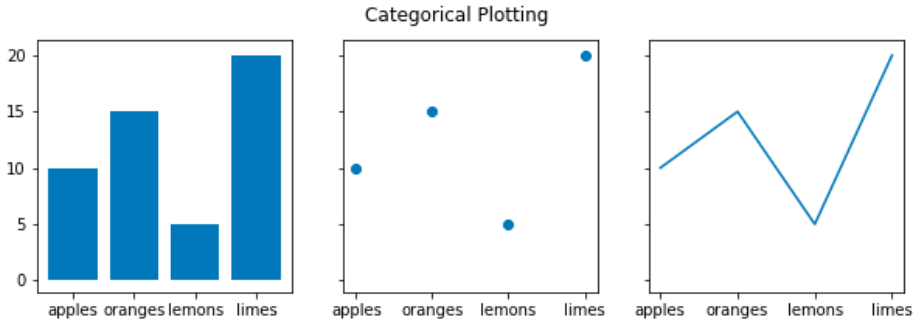
- Matplotlib:
  - A plotting library,
  - Generate plots, histograms, bar charts, error charts, etc.



- SciPy:
  - Provides many user friendly and efficient numerical routines for integration, interpolation, optimization, linear algebra, and statistics
  - Uses NumPy arrays as the basic data structure

Take-Home Messages

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- Machine Learning is the science of programming computers so that they can learn from data.
- Supervised learning uses labelled training data; unsupervised learning does not.
- Online learning learn on the fly, batch learning not.
- Instance-based learning measures the similarity between instances, while model-based learning generates a model from training data to make predications.
- Scikit-learn is a machine learning library in Python built on NumPy, Pandas, SciPy, and Matplotlib.