![](_page_0_Picture_0.jpeg)

# Machine Learning with Python

# Introduction to ML (Part2)

Dr. Aeshah Alsughayyir

Collage of Computer Science and Engineering

Taibah University

2021-2022

# Introduction to Machine Learning (Part 2)

- Machine Learning Definition
- Where is Machine Learning in Computer Science?
- Applications of Machine Learning

- Approaches to Machine Learning
- Learning Process (workflow)

## Motivation Example

![](_page_2_Figure_1.jpeg)

Song ID	Intensity	Tempo	Output (Like/Dislike)
1	Soaring	Fast	Like
2	Soaring	Medium	Like
3	Soaring	Fast	Like
9	Light	Relaxed	Dislike
10	Light	Relaxed	Dislike
11	Light	Relaxed	Dislike

# Approaches to Machine Learning

### (1) Supervised learning

Data is labeled and comes in pairs (input, output)=( $\mathbf{x}$ , y). We need to find a mapping  $f(\mathbf{x}) = y$ 

- If y is a discrete label: classification
- If y is a number: regression

### (2) Unsupervised learning

Data comes without labels. We need to find regularities in the data.

- clustering
- novelty/outlier detection
- dimensionality reduction

### (3) Reinforcement learning

Learning an optimal strategy based on trials with a delayed credit.

![](_page_3_Figure_12.jpeg)

# Approaches to Machine Learning (Supervised)

• Classification example:

predicting if the input image contains a **Duck** 

![](_page_4_Figure_3.jpeg)

# Approaches to Machine Learning (Supervised)

- Regression example:
  - predicting urban heat island (UHI)

https://www.sciencedirect.com/science/article/pii/S0048969717322738

![](_page_5_Figure_4.jpeg)

# Approaches to Machine Learning (Supervised)

#### Classification vs. Regression:

Classification	Regression			
<ul> <li>Classification is the task of predicting a</li></ul>	<ul> <li>Regression is the task of predicting a</li></ul>			
discrete class label	continuous quantity			
<ul> <li>In a classification problem data is labelled</li></ul>	<ul> <li>A regression problem requires the prediction</li></ul>			
into one of two or more classes	of a quantity			
<ul> <li>A classification problem with two classes is</li></ul>	<ul> <li>A regression problem with multiple input</li></ul>			
called binary, more than two classes is called	variables is called a multivariate regression			
a multi-class classification	problem			
<ul> <li>Classifying an email as spam or non-spam is</li></ul>	<ul> <li>Predicting the price of a stock over a period</li></ul>			
an example of a classification problem	of time is a regression problem			

# Approaches to Machine Learning (Unsupervised)

• Clustering example:

![](_page_7_Figure_2.jpeg)

#### Put these people in different clustering

![](_page_7_Figure_4.jpeg)

#### □ Which are the keys?

- Define what's similar
- Group similar things in different clusters
  - Size of the clusters?
- Which type of clustering do I want?
  - Hierarchical clustering?
  - Partition-based clustering?

- *Hierarchical clustering* does not require any input parameters, while *partitional clustering* algorithms require the number of clusters (k) to start running.
- *Hierarchical clustering* returns a much more meaningful and subjective division of clusters, but *partitional clustering* results in exactly k clusters.

## Classification vs. clustering

- <u>Classification</u> and <u>clustering</u> are two methods of *pattern identification used in machine learning*.
- Although both techniques have certain similarities, the difference lies in the fact that classification uses predefined "classes" (the data labels) in which objects are assigned, while clustering identifies similarities between objects, which it groups according to those characteristics in common and which differentiate them from other groups of objects. These groups are known as "clusters".

![](_page_8_Picture_3.jpeg)

## Approaches to Machine Learning (semi-supervised)

![](_page_9_Figure_1.jpeg)

# Approaches to Machine Learning (Reinforcement)

- Basic idea:
  - Receive feedback in the form of rewards
  - Agent's utility is defined by the reward function
  - Must learn to act so as to maximize expected rewards

![](_page_10_Figure_5.jpeg)

![](_page_10_Figure_6.jpeg)

# Approaches to Machine Learning (Reinforcement)

• Reinforcement example:

MARIO HORLD 00×0 ? ?

supper Mario

## Approaches to Machine Learning (Examples)

#### *Identifying the post-code from handwritten digits on an envelope*

- $\checkmark$  Here the input is a scan of the handwriting, and the desired output is the actual digits in the post code.
- $\checkmark$  To create a dataset for building a ML model, you need to collect many envelopes.
- ✓ Then you can read the post codes yourself and store the digits as your desired outcomes.

#### Segmenting customers into groups with similar preferences

- ✓ Given a set of customer records, you might want to identify which customers are similar, and whether there are groups of customers with similar preferences.
- ✓ For a shopping site, these might be "parents," "bookworms," or "gamers."
- ✓ Because you don't know in advance what these groups might be, or even how many there are, you have no known outputs.

![](_page_12_Picture_9.jpeg)

Supervised

Unsupervised

# Summary

### Supervised Learning

Labeled Data Direct Feedback Classification and Regression

### Semi-supervised Learning

### Unsupervised Learning

Unlabeled Data No Feedback Clustering & Dimensionality Reduction

### Reinforcement Learning

Labeled and Unlabeled Data Some Feedback Classification and Regression Reward Based Learning Direct Feedback Learn series of actions

## **Any Question?**

Dr. Aeshah Alsughayyir

### Learning Process (Workflow)

![](_page_14_Figure_1.jpeg)

![](_page_15_Figure_0.jpeg)

### > Data Acquisition:

- One of the most important part in the ML process is understanding the data you are working with and how it relates to the task you want to solve.
- ✓ Defining the potential usefulness and accuracy of your project with the quality of the data you collect.
- Having a single dataset can be from one source or aggregated from several sources.
  - Downloading open-source data sets
  - Internet of Things sensors
  - Assorted files, logs, or media.

## Data Acquisition (cont.):

- Often it is helpful to think of your data as a table.
- Each data point that you want to reason about (e.g., each transaction) is a row, and each property that describes that data point (e.g., Transaction Date, Customer ID or the Quantity) is a column.

Trans. ID	Transaction Date	Customer ID	Product ID	Shipping Address	Quantity	Unit Price (Rp)	Shipping and Other Expenses (Rp)	Nett Income (Rp)
1	1/12/2017	CUST 01	X1	Self pickup	5	250,000	0	1,250,000
2	1/14/2017	CUST 02	X2	Jakarta	100	35,000	175,000	3,325,000
3	1/14/2017	CUST 02	X3	Self pickup	100	42,000	0	4,200,000
4	1/14/2017	CUST 02	X4	Self pickup	100	33,000	0	3,300,000
5	1/18/2017	CUST 03	X5	Tangerang	30	194,500	115,000	5,720,000
295	5/30/2018	CUST 51	X80	Jakarta	1	125,000	25,000	100,000

Each entity or row here is known as a *sample* (or data point) in machine learning, while the columns—the properties that describe these entities—are called *features*.

![](_page_17_Figure_0.jpeg)

### > Data Preprocessing (and Feature Engineering)

- Pre-processing involves cleaning, verifying, and formatting data into a usable dataset.
- If you are aggregating data from several sources, you need to make sure that:
  - data formats match, data is equally reliable, and remove any potential duplicates.
- No ML algorithm will be able to make a prediction on data for which it has no information (e.g., if the only feature that you have for a patient is their last name ).

#### Feature engineering or *feature extraction*

- It is the process of using domain knowledge to extract features (characteristics, properties, attributes) from raw data.
- The question of how to represent your data best for a particular application is known as Feature Engineering.
- A feature is a property shared by independent units on which analysis or prediction is to be done.
  - It is represented by a <u>column</u> in dataset, and known as <u>dimension</u>
  - It can be *categorical features (discrete features)* and *continuous feature*

### Data Preprocessing (and Feature Engineering) cont.

• Continuous is an analog of <u>Regression</u>,,, and Categorical is an analog of <u>Classification</u>,,,

#### > Example:

					Features						
Outlook	Temperature	Humidity	Windy	Play		itout (I	abole	4			
sunny	85	85	false	no		atput (L	abels	• /			
sunny	80	90	true	no							
overcast	83	78	false	yes		No	Outlook	Tomporaturo	Unmidity	Windy	Dla
rain	70	96	false	yes		NO.	Outlook	remperature	Hummuny	windy	Flay
rain	68	80	false	yes		1	Sunny	Hot	High	False	No
rain	65	70	true	no		2	Sunny	Hot	High	True	No
overcast	64	65	true	yes		3	Overcast	Hot	High	False	Yes
sunny	72	95	false	no		4	Rain	Mild	High	False	Yes
sunny	69	70	false	yes		-	Rain	Cool	Normal	Falce	Vec
rain	75	80	false	yes		5	Rain D.:	COOI	Normal	Taise	100
sunny	75	70	true	yes		0	Rain	Cool	Normal	True	NO
overcast	72	90	true	yes		7	Overcast	Cool	Normal	True	Yes
overcast	81	75	false	yes		8	Sunny	Mild	High	False	No
rain	71	80	true	no	J	9	Sunny	Cool	Normal	False	Yes
						10	Rain	Mild	Normal	False	Yes
						11	Sunny	Mild	Normal	True	Yes

Overcast Mild

Overcast Hot

Rain

Mild

12

13

14

High

High

Normal

True

True

False Yes

Yes

No

### Data Preprocessing (and Feature Engineering) cont.

• Having the right representation of the data is often crucial for supervised or unsupervised learning to succeed.

### Note:

- Representing your data in the right way can have a bigger influence on the performance of a <u>supervised model</u> than <u>the exact parameters you choose</u>.
- How you represent your features can have an enormous effect on the performance of machine learning models.

### Data Preprocessing (and Feature Engineering) cont.

- This phase involves breaking processed data into two (or three) datasets—training, validating, and testing:
- <u>Training set</u>—used to initially train the algorithm and teach it how to process information. This set defines model classifications through parameters.
- <u>Validation set</u>—used to estimate the accuracy of the model. This dataset is used to finetune model parameters.
- <u>Testing set</u>—used to assess the accuracy and performance of the models. This set is meant to expose any issues or mistrainings in the model.

![](_page_21_Figure_0.jpeg)

### Model Training

Once you have datasets, you are ready to train your model.

• This involves feeding your training set to your algorithm so that it can learn appropriate parameters and features used in classification.

**Training** is the process of feeding an ML algorithm with data to help identify and learn good values for all attributes involved.

- There are several types of ML models, of which the most common ones are supervised and unsupervised ones.
- <u>Once training is complete</u>, you can <u>then refine the model</u> using your validation dataset.
  - This may involve *modifying* or *discarding variables* and includes a process of tweaking model-specific settings (hyperparameters) <u>until an acceptable accuracy level is reached</u>.
    - $\checkmark$  <u>Consistent training</u> can significantly improve the prediction rate of the ML model.
    - $\checkmark$  <u>The weights of the model must be initialized randomly.</u>
    - $\checkmark$  This way <u>the algorithm will learn to adjust the weights accordingly</u>.

# Model Training (cont.)

### Supervised learning: Training and prediction

- **Training** is the process of making the system able to learn.
- **Training set** and **testing set** come from the same distribution

![](_page_22_Figure_4.jpeg)

# Model Training (cont.)

### Supervised learning: Training and prediction (cont.)

![](_page_23_Figure_2.jpeg)

# Model Training (cont.)

### Supervised learning: Training and prediction (cont.)

- A <u>supervised model</u> first needs to be trained on labelled data, and after that the model can be used for prediction (*classification or regression*) on previously unseen data.
- Each data instance is represented as a vector of features x, where each feature encodes one aspect of the input (*e.g., height, weight, income, ...*).
- Feature extractor generates the feature vector x for each data instance (this step is identical for both training and prediction).
- During training, the model is fed with data instances x and their labels y, i.e., the pairs (x,y).
- Once the model is trained, it will be used for prediction.
- During prediction, the model will take only data instances x as input, and in turn generates y as output.

![](_page_25_Figure_0.jpeg)

### Model Evaluation and Tuning

- The *training dataset* used to fit (train) the model and, also, can be further split into a *training set* and a *validation set*.
- This subset of the training dataset, called the *validation set*, can be used to get an early estimate of the skill (accuracy) of the model.
- "The model is fit on the training set, and <u>the fitted model is</u> used to predict the responses for the observations in the validation set. The resulting validation set error rate provides an estimate of the test error rate." (Gareth James, et al., 2013)
  - typically assessed using Mean Square Error MSE in the case of a quantitative response.

![](_page_25_Figure_6.jpeg)

The set of parameters that are selected based on their influence on the model architecture are called *hyperparameters*.

- The process of identifying the hyperparameters by tuning the model is called parameter tuning.
- The parameters for correlation should be clearly defined in a way *the point of diminishing returns* for validation is as close to 100% accuracy as possible.

# Model Evaluation and Tuning (cont.):

- Finally, after an acceptable set of hyperparameters is found and your model accuracy is optimized you can test your model.
- Testing uses your test dataset and is meant to verify that your models are using accurate features.
- Based on the feedback you receive you may return to training the model to improve accuracy, adjust output settings, or deploy the model as needed.

![](_page_27_Figure_0.jpeg)

### Model Deployment

**Deployment** is the process of integrating a ML model into an existing production environment where it can take in an input and return an output. So, its predictions are available to users or other systems.

There are <u>various approaches</u> to deploy a ML model:

- **One-off** : Trained once or ad-hoc when its needed.
- Batch training: Continuously up-to-date version of the model / good with model that used on a consistent basis.
- **Real-time prediction**: When a prompt prediction is required/ using Online ML model: *stochastic gradient descent*.

![](_page_28_Picture_0.jpeg)

Basic workflow for training a supervised machine learning model:
No matter what ML algorithm you use the basic process is the same

- For The project of predicting home prices:
  - Collect data for houses sold in one area for a year.

### Step 1: Get Data

bedrooms	size	stories	sale_price
5	3800 sq. ft.	2	\$400,000
4	2200 sq. ft.	1	\$150,000
2	1150 sq. ft.	1	\$300,000

### **Step 2: Clean and Preprocess Data**

bedrooms	size	stories	sale_price
5	3800	2	400000
4	2200	1	150000
2	1150	1	300000

## Example (cont.)

### Step 3: Shuffle the Data

bedrooms	size	stories	sale_price
2	1150	1	150000
4	2200	1	300000
5	3800	2	400000

So, the ML algorithm doesn't pick up a pattern that isn't really there! Because the data in certain order.

### Step 4: Split into Training/Test Data

Usually with 70% of rows in the data for training the model, and 30% for testing

	bedrooms	size	stories	sale_price
Training Data	2	1150	1	150000
	4	2200	1	300000

TIDI	bedrooms	size	stories	sale_price
lest Data	5	3800	2	400000

# Example (cont.)

### Step 5: Set Model Hyperparameters

![](_page_30_Figure_2.jpeg)

Each ML algorithm has a few parameters we have to set. These parameters will control things like <u>how fast the model should learn data</u> and <u>how complex of a pattern to look for .</u>

### **Step 6: Train the Model**

![](_page_30_Figure_5.jpeg)

## Example (cont.)

### Step 7: Evaluate the Model

![](_page_31_Figure_2.jpeg)

We need to check the accuracy of the model against the test data set.. This proves if the model works well on new data or if it only works on the training data.

### Step 8: Use the Model

![](_page_31_Figure_5.jpeg)

# Summary

![](_page_32_Figure_1.jpeg)