



الجامعة السورية الخاصة
SYRIAN PRIVATE UNIVERSITY

المحاضرة الخامسة

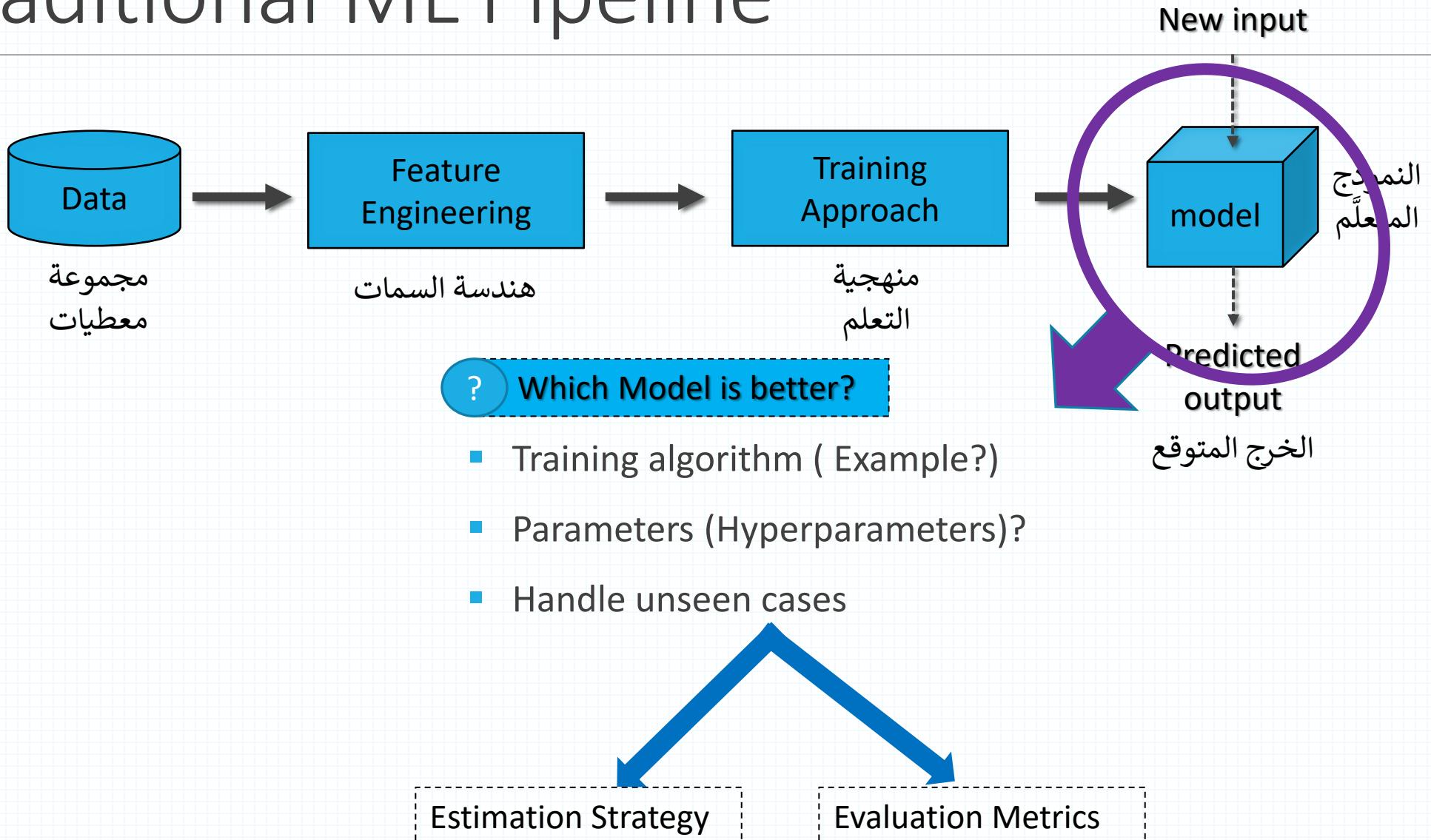
كلية الهندسة المعلوماتية

مقرر تعلم الآلة

معايير تقييم جودة النماذج المدربة

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Traditional ML Pipeline



Metrics

- It is extremely important to use quantitative metrics for evaluating a machine learning model.
- These metrics can be used to better evaluate and understand the model
- For classification: Accuracy/Precision/Recall/F1-score, ROC curves,...
- For regression: Mean Absolute Error (NMAE),...
- In this lecture, we will focus on classification tasks.

Accuracy

- Accuracy is a measure of how close a given set of guessing from our model are closed to their true value:

$$\text{Accuracy} = \frac{\# \text{ Correct classifications}}{\# \text{ All classifications}}$$

- If a classifier make 10 predictions and 8 of them are correct, the accuracy is 80%.

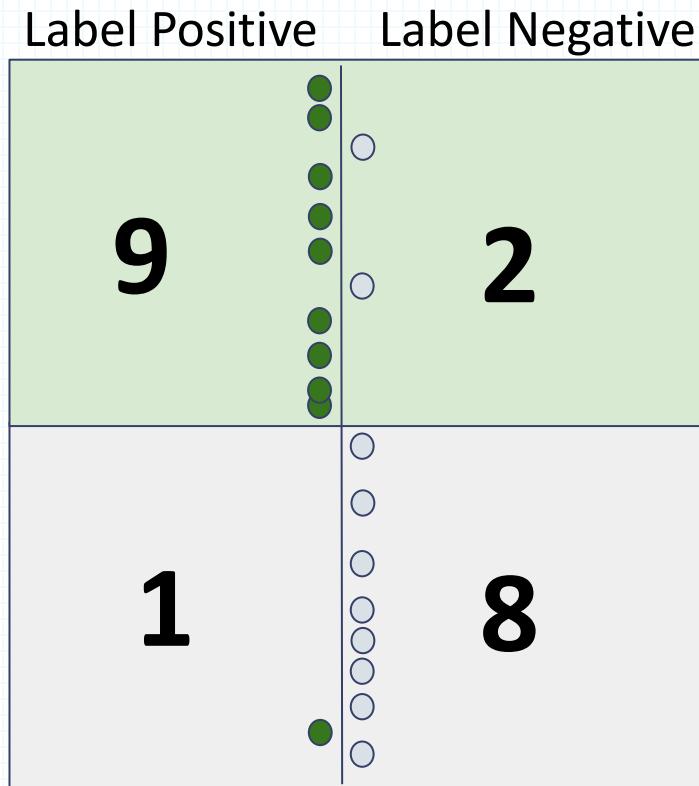
Confusion Matrix

- Confusion Matrix is a performance measurement for the machine learning classification problems where the output can be two or more classes. It is a table with combinations of predicted and actual values.
- **Example (Binary Classification)**
 - True Positive: We predicted positive and it's true.
 - True Negative: We predicted negative and it's true.
 - False Positive (Type 1 Error): We predicted positive and it's false.
 - False Negative (Type 2 Error): We predicted negative and it's false.

		Predicted Classes	
		Negative	Positive
Actual Classes	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

Example

Predict Negative Predict Positive



TP	TN	FP	FN	Acc
9	8	2	1	0.85

Limitation of Accuracy

- Consider a 2-class problem
 - Number of Class 0 examples = 9990
 - Number of Class 1 examples = 10
- If model predicts everything to be class 0, accuracy is $9990/10000 = 99.9\%$
- Accuracy is misleading because model does not detect any class 1 example
- Solution ☺
 - Use precision, recall, F1 measure, etc

Precision

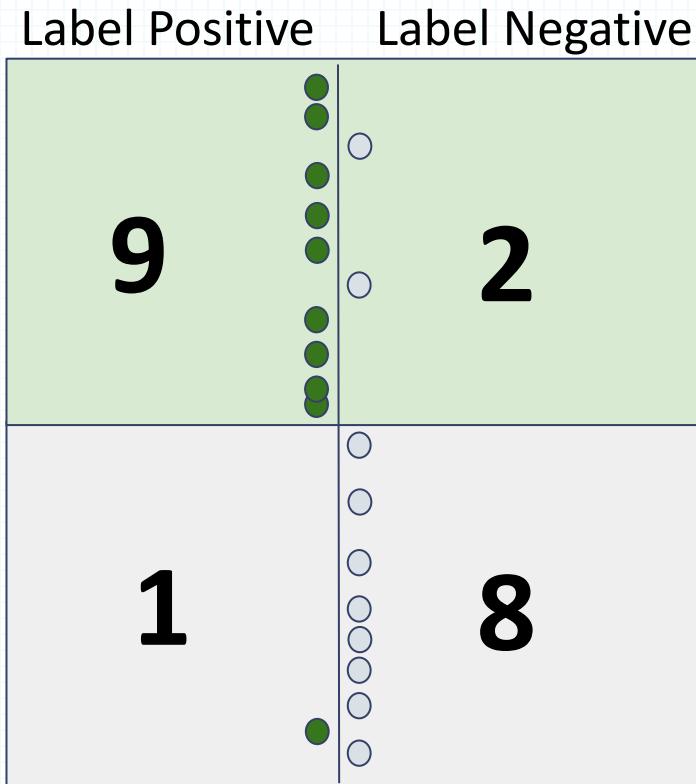
- Precision is defined as the ratio of **True Positives count to total True Positive count** made by the model.
- **Precision = $TP/(TP+FP)$**
- It explains how many of the correctly predicted cases actually turned out to be positive.
- Precision is useful in the cases where **False Positive is a higher concern** than False Negatives.
 - Ex: music or video recommendation systems

Recall

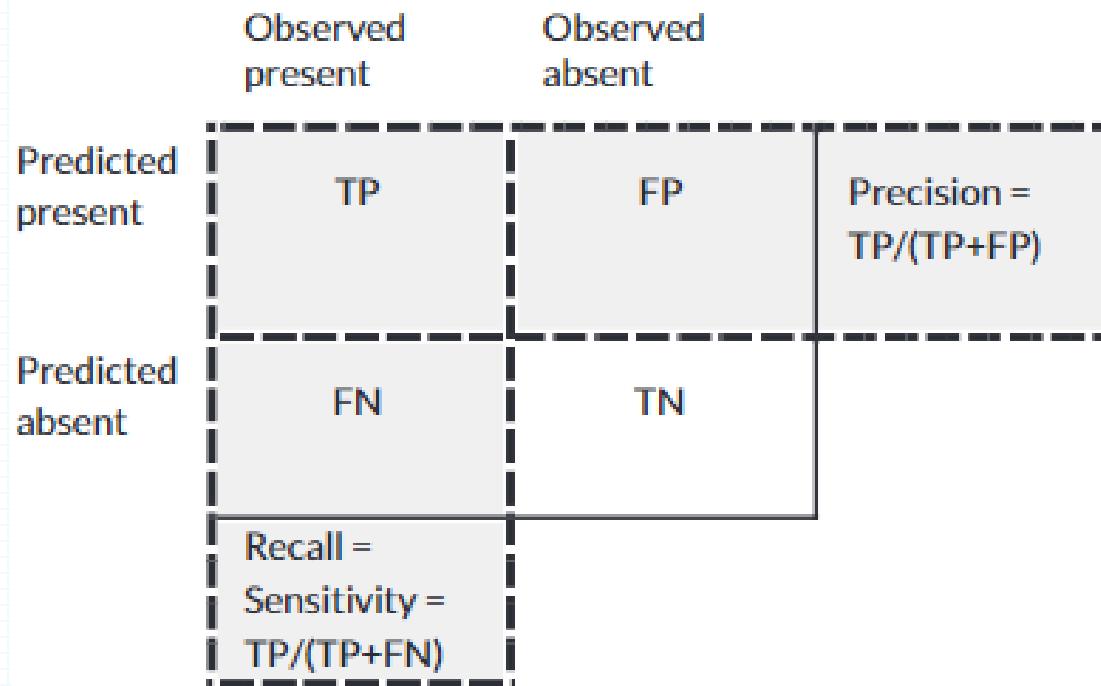
- Recall is defined as the ratio of **True Positives count to the total Actual Positive count**. It is also called “True Positive Rate”/ “sensitivity”.
- **Recall = $TP/(TP+FN)$**
- It explains how many of the actual positive cases we were able to predict correctly with our model.
- Recall is a useful metric in cases where **False Negative is of higher concern** than False Positive.
 - Ex: medical cases

Example

Predict Positive Predict Negative



TP	TN	FP	FN	Acc	P	R	F1
9	8	2	1	0.85	0.81	0.90	0.857



F1-score

- It is usually better to compare models by means of one number only.
- The F1-score can be used to combine precision and recall

	Precision(P)	Recall (R)	Average	F ₁ Score
Algorithm 1	0.5	0.4	0.45	0.444
Algorithm 2	0.7	0.1	0.4	0.175
Algorithm 3	0.02	1.0	0.51	0.0392

Algorithm 3 predict always 1

Average says not correctly that Algorithm 3 is the best

$$\text{Average} = \frac{P + R}{2}$$

$$F_1\text{score} = 2 \frac{PR}{P + R}$$

- $P = 0 \text{ or } R = 0 \Rightarrow F_1\text{score} = 0$
- $P = 1 \text{ and } R = 1 \Rightarrow F_1\text{score} = 1$

Multiclass Classifier

- Having m classes, confusion matrix is a table of size $m \times m$, where, element at (i, j) indicates the number of instances of class i but classified as class j.

Class	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
C ₁	52	10	7	0	0	1
C ₂	15	50	6	2	1	2
C ₃	5	6	6	0	0	0
C ₄	0	2	0	10	0	1
C ₅	0	1	0	0	7	1
C ₆	1	3	0	1	0	24

- What is the accuracy?

Multiclass Classifier

- Precision, Recall, and F1-score are calculated for each class.
 - A large confusion matrix of $m*m$ can be considered into $2*2$ matrix.

Class	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
C ₁	52	10	7	0	0	1
C ₂	15	50	6	2	1	2
C ₃	5	6	6	0	0	0
C ₄	0	2	0	10	0	1
C ₅	0	1	0	0	7	1
C ₆	1	3	0	1	0	24



C ₁	+	-
+	52	18
-	21	123

- Finally, we can merge overall scores (ex: using weighted average)
 - What is the overall F1-score in the previous example?