Chapter 5 Classification:

A predictive modeling problem that involves assigning a class label to each observation

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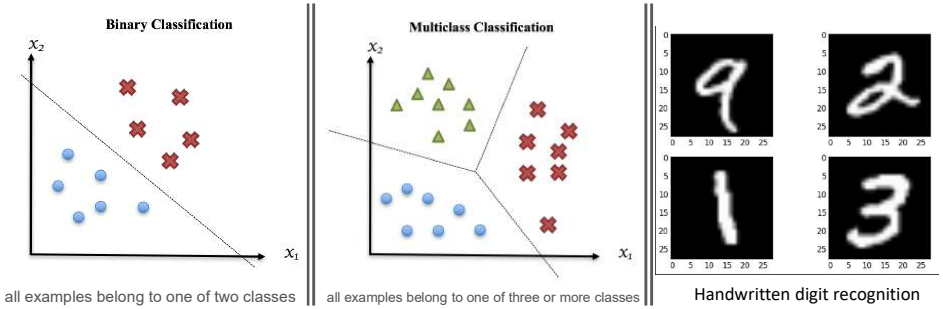


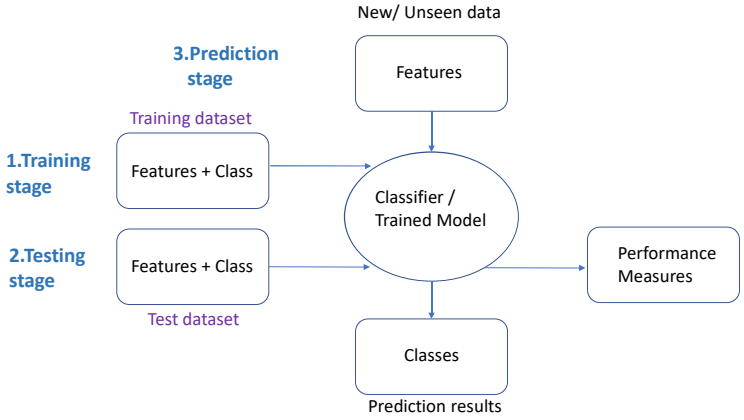
all examples belong to one of two classes

all examples belong to one of three or more classes

Handwritten digit recognition

Types of Classification

Classification (Supervised Learning)



Dataset

- ชุดข้อมูลสอน (training dataset) ใช้ในขั้นตอนการเรียนรู้เพื่อสร้างโมเดลผลลัพธ์
- ชุดข้อมูลทดสอบ (test dataset) ใช้ทดสอบโมเดลผลลัพธ์เพื่อวัดสมรรถนะ (performance) หรือ ความเป็นทั่วไป (generalization) ในการใช้โมเดลนั้นกับข้อมูลใหม่หรือข้อมูลทั่วไป
- ชุดข้อมูลตรวจความสมเหตุสมผล (validation dataset) ใช้ปรับแต่งสมรรถนะ (performance) ของโมเดล เช่น ค่าพารามิเตอร์ที่ใช้ในการเรียนรู้ หรือนำทาง (gauge) เพื่อหลีกเลี่ยง overfit

Model Assessment

- **Accuracy =**

- **Accuracy =**

Model Assessment : k-fold Cross-validation

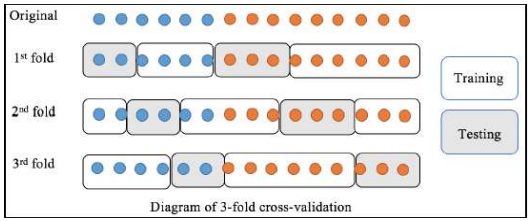


Diagram of 3-fold cross-validation

Confusion Matrix: Performance of Classifier

Actual Class \ Predicted Class	Positive	Negative	
Positive	True Positive (TP)	False Negative (FN) **Type II Error**	**Sensitivity** (Recall) $\frac{TP}{(TP+FN)}$
Negative	False Positive (FP) **Type I Error**	True Negative (TN)	**Specificity** $\frac{TN}{(TN+FP)}$
	Precision $\frac{TP}{(TP+FP)}$	**Negative Predictive Value** $\frac{TN}{(TN+FN)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$

TP = positive class correctly identified as positive

FN = positive class incorrectly identified as negative

FP = negative class incorrectly identified as positive

TN = negative class correctly identified as negative

Accuracy

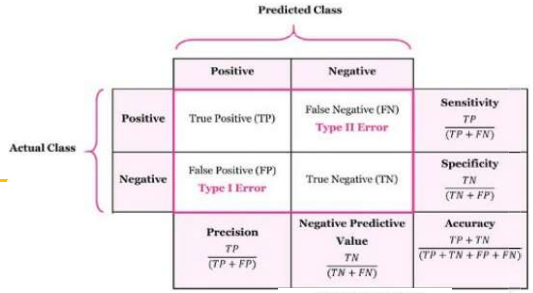
- How good the model is at guessing the correct labels or ground truths.

Actual Class \ Predicted Class	Positive	Negative	
Positive	True Positive (TP)	False Negative (FN) **Type II Error**	**Sensitivity** $\frac{TP}{(TP+FN)}$
Negative	False Positive (FP) **Type I Error**	True Negative (TN)	**Specificity** $\frac{TN}{(TN+FP)}$
	Precision $\frac{TP}{(TP+FP)}$	**Negative Predictive Value** $\frac{TN}{(TN+FN)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$

ACCURACY

$$= \frac{\text{WHAT THE MODEL PREDICTED CORRECTLY}}{\text{EVERYTHING}}$$

Precision

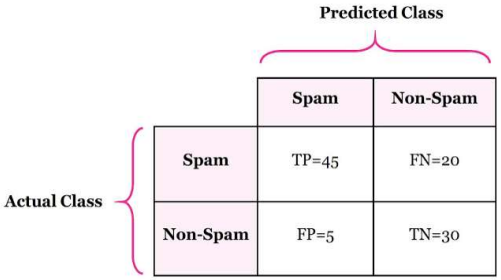


- Precision is the ratio of what the model predicted correctly to what the model predicted.
- There is one precision value for each category/ class.

PRECISION FOR 'WIN' = WHAT THE MODEL PREDICTED CORRECTLY AS 'WIN' / WHAT THE MODEL PREDICTED AS 'WIN'

PRECISION FOR 'LOSE' = WHAT THE MODEL PREDICTED CORRECTLY AS 'LOSE' / WHAT THE MODEL PREDICTED AS 'LOSE'

Confusion matrix of email classification (2)



- **Precision** shows correctness achieved in positive prediction.

Precision = 45/(45+5)= 90%

The 90% of examples are classified as spam are actually spam.

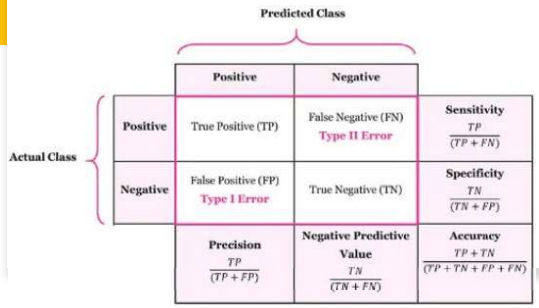
- **Accuracy** is proportion of the total number of predictions that are correct.

Accuracy = (45+30)/(45+20+5+30)

= 75%

The 75% of examples are correctly classified by the classifier.

https://manisha-sirsat.blogspot.com/2019/04/confusion-matrix.html

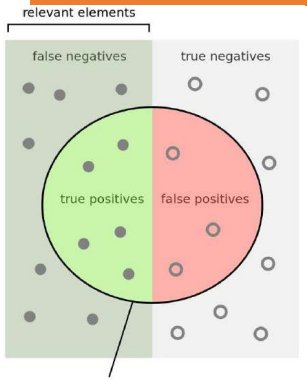


RECALL FOR 'BOMB' = WHAT THE MODEL PREDICTED CORRECTLY AS 'BOMB' / WHAT IS ACTUALLY 'BOMB'

Recall (Sensitivity)

- index of diagnostic accuracy, also called *true positive rate* → a highly sensitive test rarely overlooks an actual positive
- A 90 percent sensitivity means that 90 percent of the diseased people screened by the test will give a "true-positive" result and the remaining 10 percent a "false-negative" result
- the cost of missing a prediction is much higher than a wrong prediction.

Precision vs. Recall



How many selected items are relevant?

Precision = true positives / (true positives + false positives)

How many relevant items are selected?

Recall = true positives / (true positives + false negatives)

F1 score is a weighted average of the recall (sensitivity) and precision. F1 score might be good choice when you seek to balance between Precision and Recall.

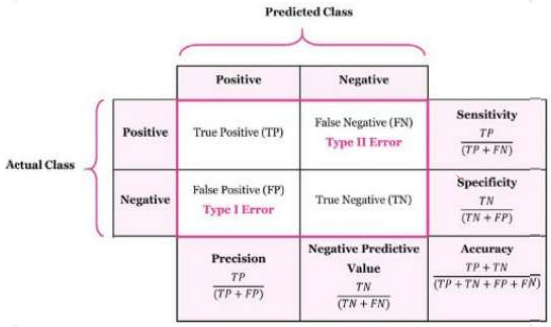
$$\text{F1 Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} = \frac{2TP}{2TP + FP + FN}$$

It helps to compute recall and precision in one equation so that the problem to distinguish the models with low recall and high precision or vice versa could be solved.

$$F\beta \text{ Score} = \frac{1+\beta^2}{\frac{1}{\text{Precision}} + \frac{\beta^2}{\text{Recall}}} = \frac{(1+\beta^2) \times \text{Precision} \times \text{Recall}}{(\beta^2 \times \text{Precision}) + \text{Recall}}$$

F1 Score

- F1 score ranges from 0-100%
- Higher F1 score → better classifier
- β denotes user-defined hyperparameter
- β > 0 always
- β > 1 favors Recall
- β < 1 favors Precision
- If consider recall as twice important as precision, set β=2.
- Standard F-score equivalent set β=1



Specificity

- ability of a test to identify correctly those without disease, also called *true negative rate*
- A 90 percent specificity means that 90 percent of the non-diseased persons will give a "true-negative" result, 10 percent of non-diseased people screened by the test will be wrongly classified as "diseased" when they are not.
- A highly specific test rarely registers a positive classification for anything that is not the target of testing.

Confusion matrix of email classification (1)

Actual Class \ Predicted Class	Spam	Non-Spam
Spam	TP=45	FN=20
Non-Spam	FP=5	TN=30

- **Sensitivity (Recall):** *True Positive Rate;* proportion of emails which are spam among all spam emails

Recall = 45/(45+20) = 69.23%

The 69.23% spam emails are correctly classified and excluded from all non-spam emails.

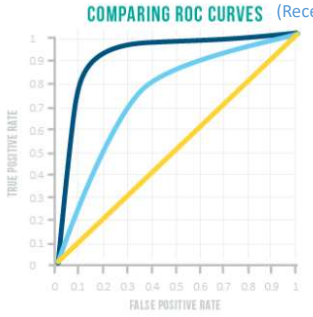
- **Specificity:** *True Negative Rate;* proportion of emails which are non-spam among all non-spam emails

Specificity = 30/(30+5) = 85.71%

The 85.71% non-spam emails are accurately classified and excluded from all spam emails.

https://manisha-sirsat.blogspot.com/2019/04/confusion-matrix.html

The TPR (sensitivity) is plotted against the FPR (1 - specificity) for given cut-off values to give a plot similar to the one below. Ideally a point around the shoulder of the curve is picked which both limits false positives whilst maximizing true positives.



AUC=1 (ideal model) ability to identify all TP while avoiding FP

AUC=0.5 (random guess) TPR and FPR would increase in parallel to one another

A test that gave a ROC curve such as the yellow line would be no better than random guessing, pale blue is good, but a test represented by the dark blue line would be excellent. It would make cutoff determination relatively simple and yield a high true positive rate at very low false positives rate – sensitive and specific.

Scaling Data: Before or After Train-Test Split?

DATA LEAKAGE

HAPPENS WHEN INFORMATION FROM OUTSIDE THE TRAINING DATASET IS USED TO CREATE A MODEL.

NEVER FIT YOUR SCALER TO THE TEST DATA

TREAT THE TEST DATA AS FUTURE, UNSEEN DATA

ALWAYS REMEMBER: SCALE BASED ON THE TRAINING SET, AND THEN APPLY THOSE TRANSFORMATIONS TO THE TEST SET TO MAINTAIN THE PURITY OF THE TEST ENVIRONMENT, I.E. THE SCALING OPERATION DOES NOT HAVE INFORMATION ABOUT THE DISTRIBUTION OF THE TEST SET.

https://medium.com/@megha.natarajan/scaling-data-before-or-after-train-test-split-35e9a9a7453f

Step by Step:

- **Split Your Data:** Divide your dataset into training and test sets, typically using a 70:30 or 80:20 ratio, ensuring each set is representative of the overall distribution.
- **Compute Scaling Parameters on the Training Set:** This includes the mean and standard deviation in standard scaling and the min/max values in min-max scaling.
- **Scale the Training Data:** Apply the scaling transformation to the training data.
- **Fit the Model:** Use the scaled training data to train your model.
- **Scale the Test Data:** Before making predictions, scale the test data using the same parameters computed from the training data.
- **Evaluate the Model:** Assess model performance using the scaled test data.

IMBALANCED CLASSIFICATION

Classification problem where there is an unequal distribution of classes in the training dataset.

The number of samples that belong to each class may be referred to as the class distribution.

Most imbalanced classification problems involve two classes: a negative case with the majority of examples and a positive case with a minority of examples.

For example, found every 1 fraud per 10,000 authentic transactions, i.e. the class distribution is highly unbalanced.

Many real-world classification problems have an imbalanced class distribution: fraud detection, spam detection, and churn prediction.

Imbalanced classifications pose a challenge for predictive modeling.

Poor predictive performance, specifically for the minority class considered more important, but more sensitive to classification errors.

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TECHNIQUES TO DEAL WITH A CLASS IMBALANCE

Oversampling

oversampling minority class

increase number of minority observations until reaching a balanced dataset

- Random oversampling- simply duplicate minority class observations, reducing variance of dataset, though
- Synthetic Minority Over-sampling TEchnique (SMOTE)
- Adaptive Synthetic (ADASYN)

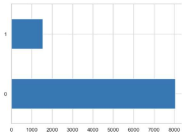
Undersampling

undersampling majority class

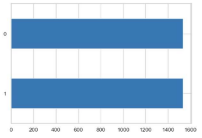
This could potentially result in removing key characteristics of the majority class.

- Random undersampling

Class 0 (8045 instances)
Class 1 (1533 instances)



Overall 3066 instances
Each class 1533 instances



- Near miss
- Tomeks links