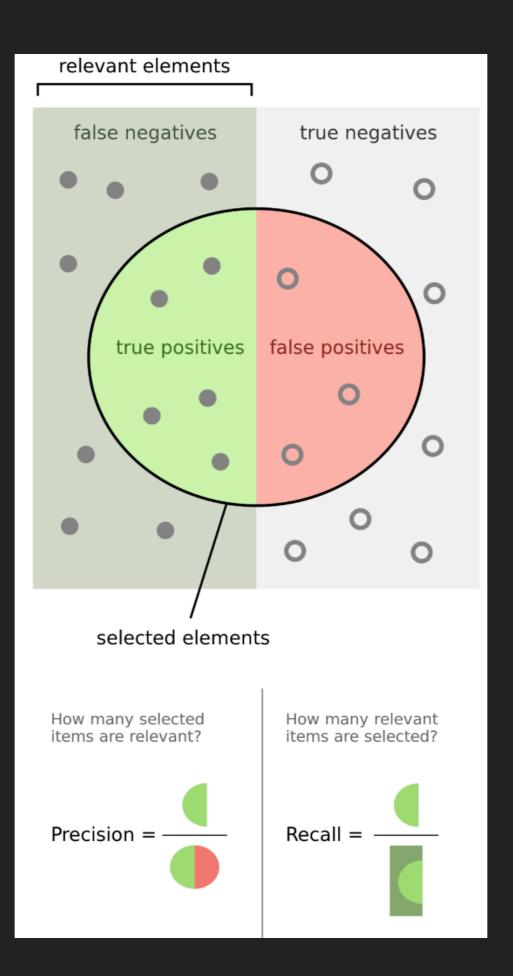
# **CLASSIFICATION**

# EVALUATION METRICS

# **CONFUSION MATRIX**

- A confusion matrix is a summary of prediction results on a classification problem
- The number of correct and incorrect predictions are summarized with count values and broken down by each class



## **True Positives(TP):**

• When we predict positive and the actual is positive

## **False Positives(FP):**

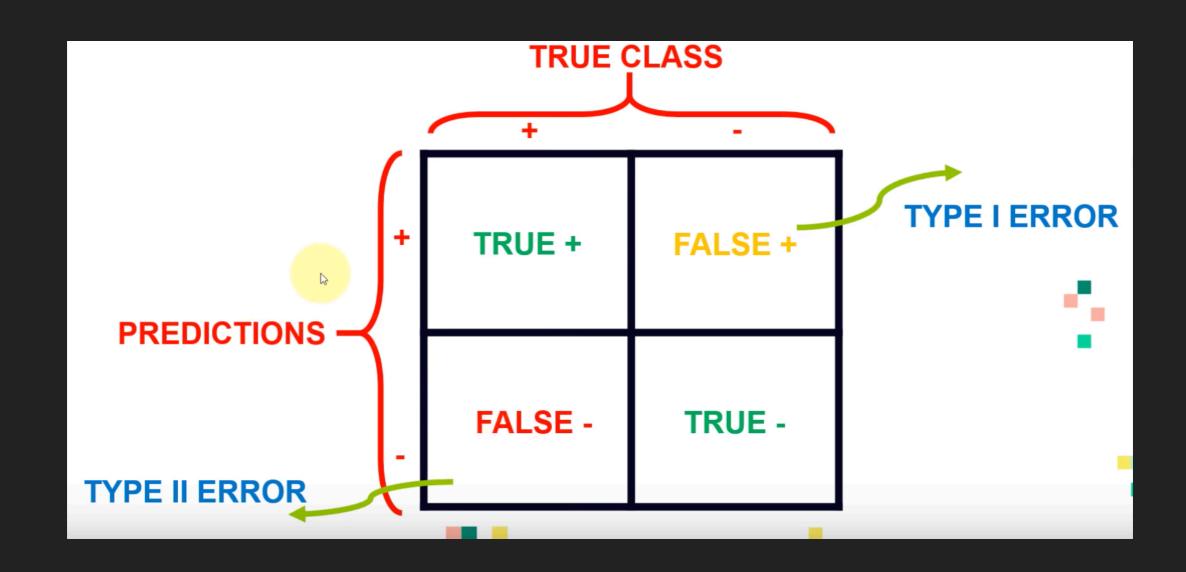
• When we predict that someone is positive and the actual is negative.

# **False Negatives(FN):**

• When we predict that someone is negative and the actual result from the blood test is positive.

# **True Negatives(TN):**

• When we predict that someone is negative and the actual result from the blood test is negative



# **Accuracy:**

Overall, how often is the classifier correct?

#### **Error Rate / Misclassification Rate:**

Overall, how often is it wrong?

All incorrect / total = (FP+FN) / TP+FP+TN+FN

# **Specificity** (True Negative Rate):

- When it's actually no, how often does it predict no?
- Equivalent to 1 minus False Positive Rate

True negatives/ all negatives (actual no ) = TN / TN+FP

# **Sensitivity or Recall** (True Positive Rate):

• When the class was actually positive, how often does it predict positive?

True positives/all positives (actual yes) = TP / TP+FN

# **Precision:**

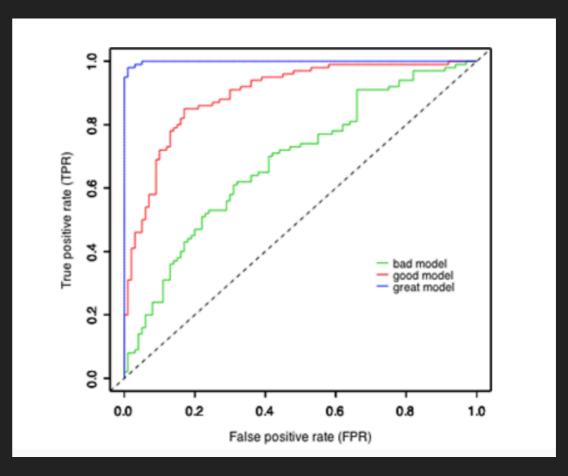
When model predicted positive class, how often it correct?

True positives / predicted positives = TP / TP+FP

# Other metrics

# **ROC - AUC score**

- AUC score is that if you randomly choose a positive case and a negative case, the probability that the positive case outranks the negative case according to the classifier
- The value can range from 0 to 1. However AUC score of a random classifier for balanced data is 0.5



#### F1 Score:

This is a weighted average of the true positive rate (recall) and precision

# Kappa:

Cohen's kappa statistic is a very good measure that can handle very well both multi-class and imbalanced class problems

A measure of how well the classifier performed as compared to how well it would have performed simply by chance

$$\kappa \equiv rac{p_o - p_e}{1 - p_e} = 1 - rac{1 - p_o}{1 - p_e}$$

where,

Po is the relative observed agreement

Pe is the hypothetical probability of chance agreement

• Calculation:

		В	
		Yes	No
A	Yes	a	b
	No	С	d

- Po = a+d/a+b+c+d
- $\bullet$  P yes = a+b / a+b+c+d
- $\bullet$ P no = c+d / a+b+c+d
- Pe = P yes + P no

Python: sklearn.metrics.cohen\_kappa\_score