

100



معالجة اللغات الطبيعية

Natural Language Processing(NLP)

تطبيق عملي

إختبار و تقييم النموذج – (خوارزمية تعلم الآله)

Model Evaluation(2)

Model Evaluation Metrics

SMS SPAM Filtering

Model Evaluation Metrics

- ▶ **Evaluation metrics** explain the performance of a model. An important aspect of evaluation metrics is their capability to discriminate among model results.
- ▶ Model evaluation metrics are required to **quantify model performance**.
- ▶ Ideally, the estimated performance of a model **tells us how well it performs on unseen data**.
- ▶ It's important to **understand the context** before choosing a metric because each machine learning model tries to solve a problem with a different objective using a different dataset(**Different evaluation metrics are used for different kinds of problems**)
- ▶ The choice of evaluation metrics **depends on a given machine learning task** (such as classification, regression, ranking, clustering, topic modeling..etc)
- ▶ There are several evaluation metrics, like **confusion matrix, Log Loss, Gini Coefficient AUC-ROC curve, etc.** in our model will talk only about :
 - ▶ **Classification Accuracy**
 - ▶ **Confusion matrix**

Classification Accuracy

- ▶ **Classification accuracy** is simply the rate of correct classifications, (ratio of **correct predictions** to **total predictions made**)
- ▶ Classification accuracy = **correct predictions / total predictions * 100**
- ▶ The main problem with classification accuracy is that it **hides the detail you need to better understand** the performance of your classification model. There are two examples where you are most likely to encounter this problem:
 1. When the data does not have an even number of classes. (**Imbalanced data set**)
 2. When your data **has more than 2 classes**.
- ▶ Classification accuracy is a **great place to start**, but often encounters problems in practice.

Metrics Beyond Accuracy -Confusion Matrix

- ▶ Classification accuracy alone **can be misleading** if you have an **unequal number** of observations in each class or if you have more than two classes in your dataset.
- ▶ A confusion matrix provides **a more detailed breakdown of correct and incorrect** classifications for each class.
- ▶ Calculating a confusion matrix can give you a better **idea/ insightful picture** of what your classification model **is getting right and what types of errors it is making**, (which classes are being predicted correctly and incorrectly)

| | | Actual Value | |
|-----------------|----------|------------------------|------------------------|
| | | Positive | Negative |
| Predicted Value | Positive | TP (True Positive) | FP (False Positive) |
| | Negative | FN (False Negative) | TN (True Negative) |

- True Positive (TP) : Observation is positive, and is predicted to be positive.
- False Negative (FN) : Observation is positive, but is predicted negative.
- True Negative (TN) : Observation is negative, and is predicted to be negative.
- False Positive (FP) : Observation is negative, but is predicted positive.

Metrics Beyond Accuracy -Confusion Matrix

1. **Accuracy** : the ratio of **correct** predictions to **total** predictions made.

► $\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FN} + \text{FP})$

2. **Precision**: the ratio between the **True Positives** and **all the Positives**.

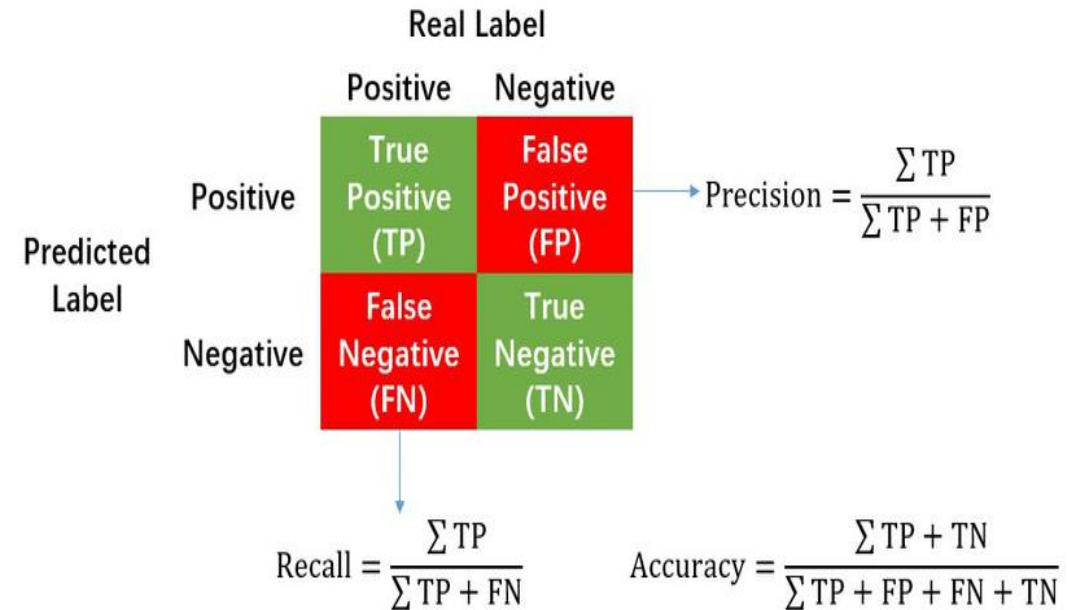
► For our problem statement, *If the spam filter says this email is spam, what's the probability that it's spam*

► $\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$

3. **Recall**: the measure of our model **correctly identifying True Positives**.

► The all SMSs are **Spam** ,recall tells us how many we correctly identified as **Spam**

► $\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$



Confusion Matrix

- ▶ Number of test SMSs : ', $TP+TN+FP+FN$)= $10+77+8+5$ = **100**
- ▶ Number of actual SPAM SMSs : ', $TP+FN$)= $10+8$ = **18**
- ▶ Number of actual HAM SMSs: : ', $TN+FP$)= $8+77$ = **85**
- ▶ Number of predicted SMSs as SPAM: ', $TP+FP$) = $10+5$ = **15**
- ▶ Number of predicted SMSs as HAM : ', $FN+TN$) =**85**
- ▶ The number along the diagonal **Green Box** tell us how many of the samples **were correctly classified**
- ▶ The number **Not** on the diagonal **Red Box** tell us how many of the samples **were messed up**
- ▶ Accuracy=($TP+TN$)/($TP+TN+FN+FP$)= $87/100$ = **0.87**
- ▶ Precision = $TP / (TP + FP)$ = $10/15$ = **0.667**
- ▶ Recall = $TP / (TP + FN)$ = $10/18$ = **0.556**

| Sample 100 | | Actual | |
|------------|------|---------|---------|
| | | Spam | Ham |
| Predicted | Spam | TP (10) | FP (5) |
| | Ham | FN(8) | TN (77) |

- **10 Spam SMSs** → model successfully classified it as spam
- **77 Ham SMSs**→ model successfully classified it as ham
- **8 Spam SMSs** → model misclassified it by saying those are ham and should send them to the inbox
- **5 Ham SMSs**→ model misclassified it by saying those are Spam and should send them to the Junk

Confusion Matrix

- **Accuracy:** Overall, how often does the classifier predict right?
 $(TP+TN)/Total = (10+77)/100 = 87\%$
- **Misclassification Rate (Error Rate):** Overall, how often is it wrong?
 $(FP+FN)/Total = (5+8)/100 = 13\%$
This is the equivalent of 1 minus Accuracy.
- **Prevalence:** How often does the "yes" event occur in the sample?
 $Actual\ Yes/Total = 18/100 = 18\%$
- **True Positive Rate:** Events that were correctly predicted by the model as "occurred = Yes."
 $TP/ actual\ yes = 10/18 = 56\%$ ("**Recall**" or "**Sensitivity**")

| Sample 100 | | Actual | |
|------------|------|---------|---------|
| | | Spam | Ham |
| Predicted | Spam | TP (10) | FP (5) |
| | Ham | FN(8) | TN (77) |

- **10 Spam SMSs** → model successfully classified it as spam
- **77 Ham SMSs** → model successfully classified it as spam
- **8 Spam SMSs** → model misclassified it by saying those are ham and should send them to the inbox
- **5 Ham SMSs** → model misclassified it by saying those are Spam and should send them to the Junk

Confusion Matrix

- **Specificity:** When an event was actually predicated as "no," and it was actually a "no."
 $TN / \text{actual no} = 77 / 82 = 94\%$
- **False Positive Rate:** Events that were predicted as "occurred = Yes," but in reality, it was "not occurred = No."
 $FP / \text{actual no} = 5 / 82 = 6\%$
- This is the equivalent of 1 minus **Specificity**.
- **Precision:** When an event is predicted "yes," how often it is correct?
 $TP / \text{predicted yes} = 10 / 15 = 67\%$

| Sample 100 | | Actual | |
|------------|------|---------|---------|
| | | Spam | Ham |
| Predicted | Spam | TP (10) | FP (5) |
| | Ham | FN(8) | TN (77) |

- **10 Spam SMSs** → model successfully classified it as spam
- **77 Ham SMSs** → model successfully classified it as spam
- **8 Spam SMSs** → model misclassified it by saying those are ham and should send them to the inbox
- **5 Ham SMSs** → model misclassified it by saying those are Spam and should send them to the Junk



Thank You