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# 1 Machine Learning Evaluation Metrics

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## 1.2 This lab is part of the project adlabs.

### 1.2.1 See <https://github.com/augustodamasceno/adlabs/>

## 1.3 ADlabs Licenses

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## 1.4 Libraries

```
[1]: # Numpy
import numpy as np
# Pyplot is a state-based interface to matplotlib. It provides a MATLAB-like
    ↪ way of plotting.
import matplotlib.pyplot as plt
# Display plots that are the output of running code cells
%matplotlib inline
# Pandas
import pandas as pd
# Train and Test Subsets
from sklearn.model_selection import train_test_split
# Breast Cancer Wisconsin Dataset from Scikit-Learn Toy datasets
from sklearn.datasets import load_breast_cancer
# MLP Classifier
from sklearn.neural_network import MLPClassifier
# Accuracy Metric
from sklearn.metrics import accuracy_score
# Precision Metric
from sklearn.metrics import precision_score
# Recall Metric
```

```

from sklearn.metrics import recall_score
# F1 Metric
from sklearn.metrics import f1_score
# Confusion Matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
# Cross-validation Metric
from sklearn.model_selection import cross_val_score

```

## 1.5 Breast Cancer Wisconsin Dataset

Data Set Characteristics:

Number of Instances:	569
Number of Attributes:	30 numeric, predictive attributes and the class
Attribute Information:	<ul style="list-style-type: none"> <li>• radius (mean of distances from center to points on the perimeter)</li> <li>• texture (standard deviation of gray-scale values)</li> <li>• perimeter</li> <li>• area</li> <li>• smoothness (local variation in radius lengths)</li> <li>• compactness (perimeter<sup>2</sup> / area - 1.0)</li> <li>• concavity (severity of concave portions of the contour)</li> <li>• concave points (number of concave portions of the contour)</li> <li>• symmetry</li> <li>• fractal dimension ("coastline approximation" - 1)</li> </ul> <p>The mean, standard error, and "worst" or largest (mean of the three worst/largest values) of these features were computed for each image, resulting in 30 features. For instance, field 0 is Mean Radius, field 10 is Radius SE, field 20 is Worst Radius.</p> <ul style="list-style-type: none"> <li>• class: <ul style="list-style-type: none"> <li>◦ WDBC-Malignant</li> <li>◦ WDBC-Benign</li> </ul> </li> </ul>

```
[2]: data = load_breast_cancer()
```

```

[3]: # X = data.data
# y = data.target
X, y = load_breast_cancer(return_X_y=True)

```

```

[4]: print('Features:\n')
for feature in data.feature_names:
    print('\t', feature)

```

Features:

```

mean radius
mean texture
mean perimeter
mean area
mean smoothness

```

```
mean compactness
mean concavity
mean concave points
mean symmetry
mean fractal dimension
radius error
texture error
perimeter error
area error
smoothness error
compactness error
concavity error
concave points error
symmetry error
fractal dimension error
worst radius
worst texture
worst perimeter
worst area
worst smoothness
worst compactness
worst concavity
worst concave points
worst symmetry
worst fractal dimension
```

```
[5]: print('Targets:\n\t', data.target_names)
```

```
Targets:
      ['malignant' 'benign']
```

```
[6]: # print(data.DESCR)
```

## 1.6 Training and Test Subsets

```
[7]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
      ↪3, shuffle=True, random_state=None)
```

```
[8]: X_train.shape
```

```
[8]: (398, 30)
```

```
[9]: X_test.shape
```

```
[9]: (171, 30)
```

```
[10]: y_train.shape
```

```
[10]: (398,)
```

```
[11]: y_test.shape
```

```
[11]: (171,)
```

## 1.7 Model Training

```
[12]: clf = MLPClassifier(random_state=None, max_iter=50*X_train.shape[0]).  
      ↪fit(X_train, y_train)
```

## 1.8 Model Prediction

```
[13]: y_pred = clf.predict(X_test)
```

## 1.9 Model Evaluation with Accuracy

### 1.10 “All correct predictions”

$$\frac{TP+TN}{TP+FP+TN+FN}$$

```
[14]: accuracy_score(y_test, y_pred)
```

```
[14]: 0.9707602339181286
```

## 1.11 Model Evaluation with Precision

### 1.12 “It’s really true when it says so.”

$$\frac{TP}{TP+FP}$$

```
[15]: precision_score(y_test, y_pred, average='binary')
```

```
[15]: 0.9557522123893806
```

## 1.13 Model Evaluation with Recall

### 1.14 “How much predicts positive compare to all real positives.”

$$\frac{TP}{TP+FN}$$

```
[16]: recall_score(y_test, y_pred, average='binary')
```

```
[16]: 1.0
```

### 1.15 Model Evaluation with Specificity

1.16 “How much predicts negative compare to all real negatives.”

$$\frac{TN}{TN+FP}$$

```
[17]: tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
      specificity = tn / (tn+fp)
      specificity
```

```
[17]: 0.9206349206349206
```

### 1.17 Model Evaluation with F1

1.18 “Harmonic mean of precision and recall.”

$$\frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

```
[18]: f1_score(y_test, y_pred, average='binary')
```

```
[18]: 0.9773755656108597
```

### 1.19 Model Evaluation with Confusion Matrix

```
[19]: # Code from this cell in reference 15.

np.set_printoptions(precision=2)
class_names = data.target_names

titles_options = [
    ("Confusion matrix, without normalization", None),
    ("Normalized confusion matrix", "true"),
]
for title, normalize in titles_options:
    disp = ConfusionMatrixDisplay.from_estimator(
        clf,
        X_test,
        y_test,
        display_labels=class_names,
        cmap=plt.cm.Blues,
        normalize=normalize,
    )
    disp.ax_.set_title(title)

    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
    print("tn={}\nfp={}\nfn={}\ntp={}\n".format(tn, fp, fn, tp))
    print(title)
    print(disp.confusion_matrix)
```

```
plt.show()
```

```
tn=58  
fp=5  
fn=0  
tp=108
```

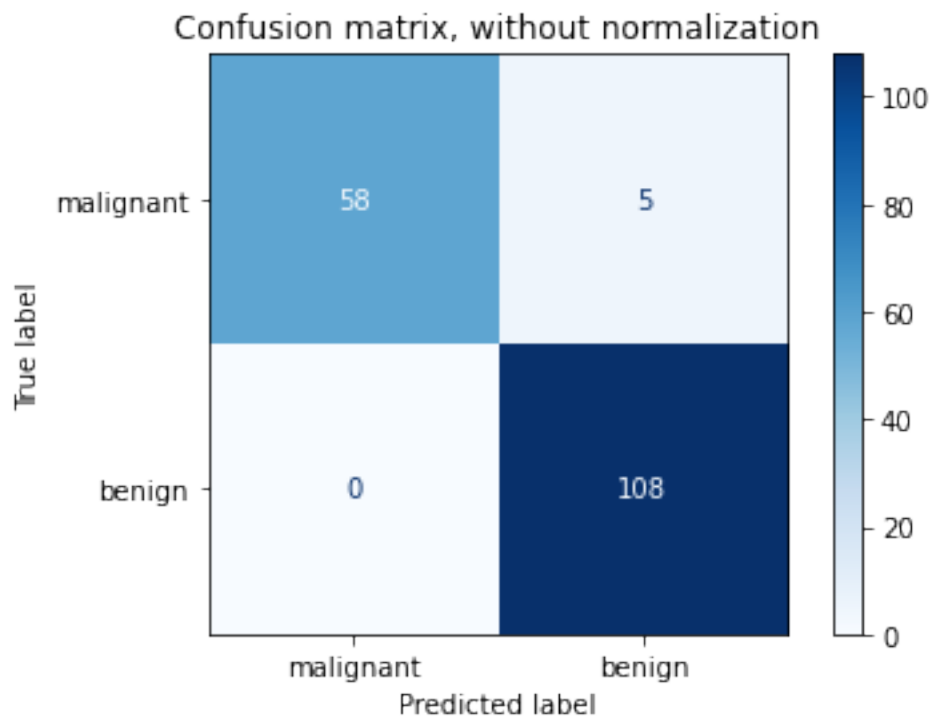
Confusion matrix, without normalization

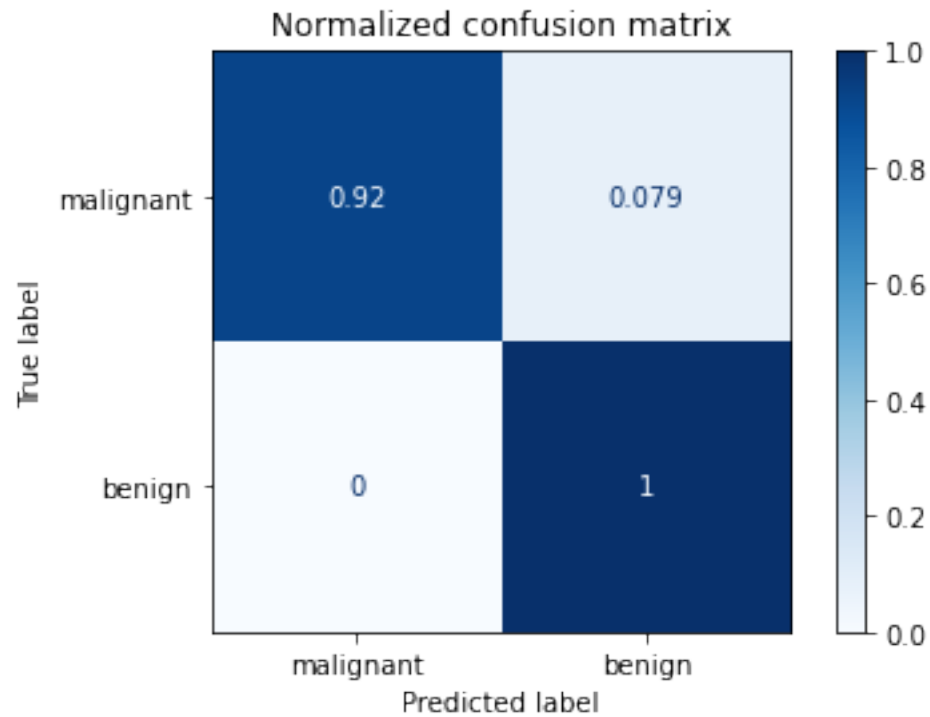
```
[[ 58   5]  
 [  0 108]]
```

```
tn=58  
fp=5  
fn=0  
tp=108
```

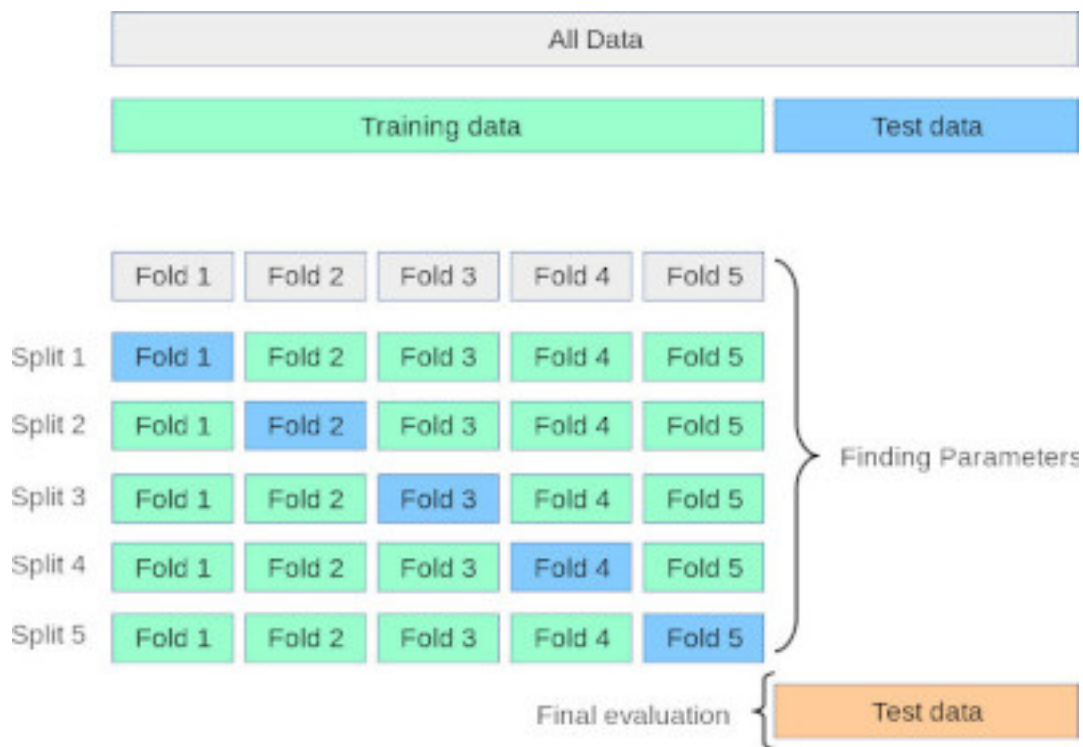
Normalized confusion matrix

```
[[0.92 0.08]  
 [0.   1.  ]]
```





## 1.20 Model Evaluation with Cross-validation



```
[20]: scores = cross_val_score(clf, X, y, cv=5)
      scores
```

```
[20]: array([0.95, 0.92, 0.95, 0.96, 0.92])
```

```
[21]: np.mean(scores)
```

```
[21]: 0.9384567613724576
```

```
[22]: np.std(scores)
```

```
[22]: 0.01484694607160666
```

## 2 References

- 1. [Python DOC](#)
- 2. [Numpy DOC](#)
- 3. [matplotlib.pyplot](#)
- 4. [ipython magic functions](#)
- 5. [Pandas DOC](#)
- 6. [Breast Cancer Wisconsin Dataset](#)
- 7. [sklearn.model\\_selection.train\\_test\\_split](#)
- 8. [sklearn.neural\\_network.MLPClassifier](#)
- 9. [sklearn.metrics.accuracy\\_score](#)
- 10. [sklearn.metrics.precision\\_score](#)
- 11. [sklearn.metrics.recall\\_score](#)
- 12. [sklearn.metrics.f1\\_score](#)
- 13. [Harmonic Mean](#)
- 14. [sklearn.metrics.confusion\\_matrix](#)
- 15. [https://scikit-learn.org/stable/auto\\_examples/model\\_selection/plot\\_confusion\\_matrix.html](https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html)
- 16. [Cross-validation](#)