

Performance indices

Classification



Confusion matrix

		Predicted Values	
		Class 1	Class 0
Actual Values	Class 1	True Positive	False Negative
	Class 0	False Positive	True Negative

Confusion matrix

		Predicted Values	
		Class 1	Class 0
Actual Values	Class 1	True Positive	False Negative
	Class 0	False Positive	True Negative

Objective of any classification task:
reaching highest rates of true values

		True value	
		Sick	Not sick
Prediction	Sick	True Sick 78 True positive	False Sick 11 False positive
	Not sick	False Not sick 3 False Negative	True Not sick 99 True Negative

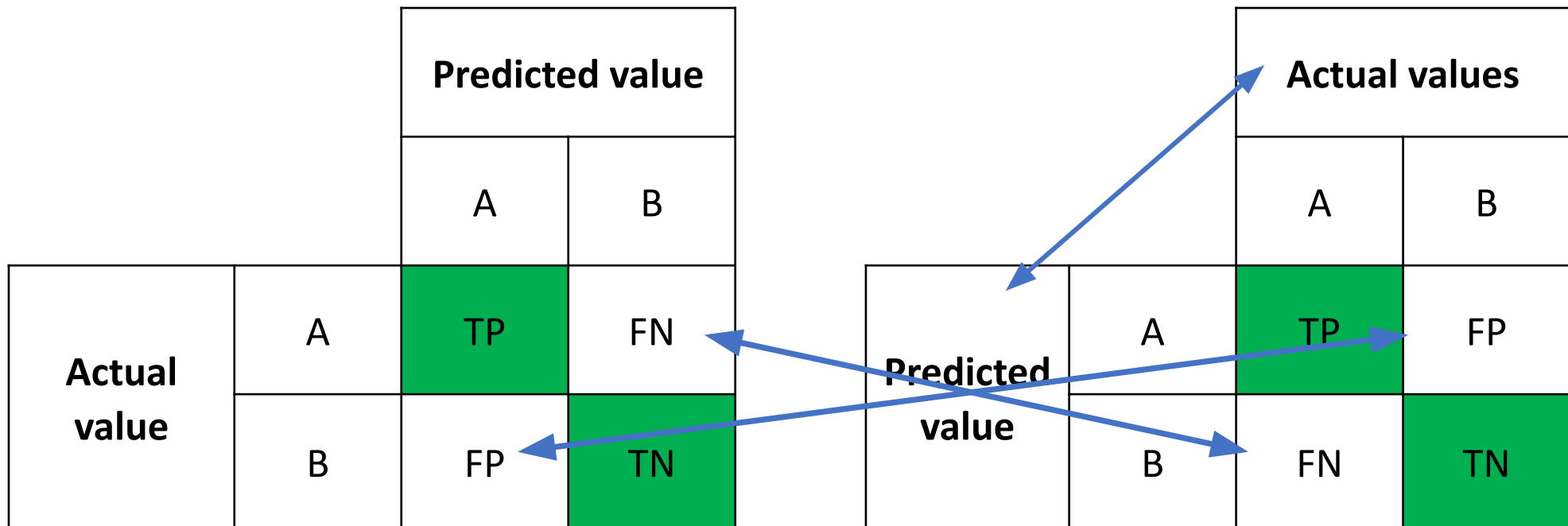
		True value			
		Car	Boat	Plane	Train
Prediction	Car	98 ✓	0 ✗	0 ✗	1 ✗
	Boat	0 ✗	85 ✓	0 ✗	3 ✗
	Plane	0 ✗	0 ✗	72 ✓	4 ✗
	Train	4 ✗	0 ✗	1 ✗	60 ✓

False
Negative

False
Positive

True

- Confusion !!!



By default presentation in scikit-learn
(e.g. for confusion matrix, classification
report)

Accuracy

- Percentage of good prediction

		Predicted value	
		Immune	No Imm.
Actual value	Immune	45	15
	No Imm.	13	27

Covid

In a sample of 100 observations

- 60, naturally immune

- 40, no immunization

Good predictions

$$Accuracy = \frac{TP + TN}{Total} = \frac{45 + 27}{100} = 0,72$$

Accuracy !!! not good indicator if strongly unbalanced classes

- No skill model predict that everyone is immune

		Predicted value		
		Immune	No Imm.	
Actual value	Immune	95	0	In a sample of 100 observations - 95, naturally immune - 5, no immunization
	No Imm.	5	0	

Good predictions

$$Accuracy = \frac{TP + TN}{Total} = \frac{95 + 0}{100} = 0,95$$

Accuracy !!! not good indicator if strongly unbalanced classes

- No skill model predict that no one is immune

		Predicted value	
		Immune	No Imm.
Actual value	Immune	0	95
	No Imm.	0	5

Covid

In a sample of 100 observations

- 95, naturally immune

- 5, no immunization

Good predictions

$$Accuracy = \frac{TP + TN}{Total} = \frac{0 + 5}{100} = 0,05$$

Precision

$$Precision = \frac{TP}{TP + FP} \rightarrow \text{Penalize optimistic models (i.e. those with high FP rate)}$$

- Ratio true positives (TP) on all predicted positives (TP + FP)

		Predicted value		
		Immune	No Imm.	
Actual value	Immune	45	15	In a sample of 100 observations - 60, naturally immune - 40, no immunization
	No Imm.	13	27	

Good predictions

$$Precision = \frac{TP}{TP + FP} = \frac{45}{45 + 13} = 0,78$$

Recall

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

→ Penalize pessimistic models
(i.e. those with high FN rate)

- Ratio true positives (TP) on all real/actual positives (TP + FN)

		Predicted value	
		Immune	No Imm.
Actual value	Immune	45	15
	No Imm.	13	27

Covid

In a sample of 100 observations

- 60, naturally immune

- 40, no immunization

Good predictions

$$Recall = \frac{TP}{TP + FP} = \frac{45}{45 + 15} = 0,75$$

Accuracy, precision, recall

Pessimistic model			
		Predicted values	
		Imm.	No i.
Actual values	Imm	35	25
	No i.	2	38

Accuracy 0.73

Precision 0.95

Most predicted positives are TP (few FP)

Recall 0.58

Many actual positives not correctly predicted (many FN)

Perfect model			
		Predicted values	
		Imm	No i.
Actual values	Imm	60	0
	No i.	0	40

Accuracy 1.00

Precision 1.00

Recall 1.00

Optimistic model			
		Predicted values	
		Imm	No i.
Actual values	Imm	58	2
	No i.	25	15

Accuracy 0.73

Precision 0.69

Many predicted positives are not TP (many FP)

Recall 0.97

Most actual positives correctly predicted (few FN)

Actual positives

Predicted positives

F1-score

- Harmonic mean of precision and recall

- Harmonic mean

- Reciprocal of the arithmetic mean of the reciprocals of the given set of observations

- Used for averaging rates/ratios (respect proportionality links)

- Ex : calculate the average speed of a round trip when the speed of the outbound trip is not the same as the return trip

$$\frac{n}{\sum_{i=1}^n \frac{1}{x_i}}$$

F1-score

- Harmonic mean of precision and recall

$$F1score = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} = \frac{2}{\frac{precision + recall}{precision * recall}} = 2 * \frac{precision * recall}{precision + recall}$$

$$F1score = \frac{2}{\frac{1}{\frac{TP}{TP + FP}} + \frac{1}{\frac{TP}{TP + FN}}} = \frac{2}{\frac{TP + FP + TP + FN}{TP}} = \frac{2 * TP}{2 * TP + FP + FN} \rightarrow \text{ratio/\# of FP and FN}$$

respected in the harmonic mean calculation

Penalize optimistic and pessimistic models in the exact same way

F1-score

		Predicted value	
		Immune	No imm.
Actual value	Immune	45	15
	No imm.	13	27

$$Precision = \frac{TP}{TP + FP} = \frac{45}{45 + 13} = 0,78$$

$$Recall = \frac{TP}{TP + FN} = \frac{45}{45 + 15} = 0,75$$

$$F1score = 2 * \frac{precision + recall}{precision * recall} = 2 * \frac{0.78 * 0.75}{0.78 + 0.75} = 2 * \frac{0.585}{1,53} = 0,76$$

$$F1score = \frac{2 * TP}{2 * TP + FP + FN} = \frac{2 * 45}{2 * 45 + 13 + 15} = \frac{90}{118} = 0.76$$

Accuracy, Precision, Recall & F1-Score

Pessimistic model			
		Predicted values	
		Imm.	No I.
Actual values	Imm.	35	25
	No I.	2	38

Perfect model			
		Predicted values	
		Imm.	No I.
Actual values	Imm.	60	0
	No I.	0	40

Optimistic model			
		Predicted values	
		Imm.	No I.
Actual values	Imm.	58	2
	No I.	25	15

Accuracy 0.73

Precision 0.95

Recall 0.58

F1-Score 0,72

Accuracy 1.00

Precision 1.00

Recall 1.00

F1-Score 1.00

Accuracy 0.73

Precision 0.69

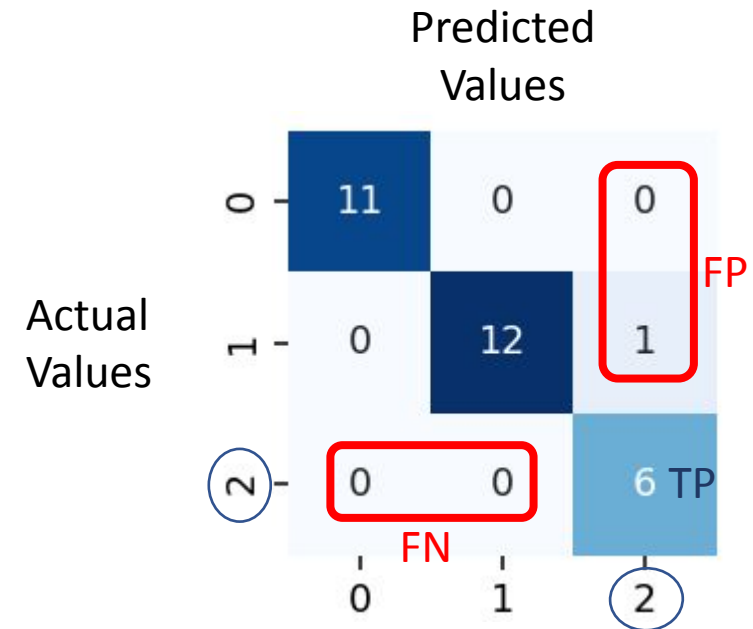
Recall 0.97

F1-Score 0,81

Multiclass classification

```
from sklearn.metrics import confusion_matrix

conf_matrix = confusion_matrix(y_test, y_pred)
fig = plt.figure(figsize=(2,2))
sns.heatmap(conf_matrix, annot=True, cmap="Blues", cbar=False)
```



```
print(classification_report(y_test, y_pred, target_names=iris_data.target_names))
```

	precision	recall	f1-score	support
setosa	1.00	1.00	1.00	11
versicolor	1.00	0.92	0.96	13
virginica	0.86	1.00	0.92	6
accuracy	Simple mean		0.97	30
macro avg	0.95	0.97	0.96	30
weighted avg	0.97	0.97	0.97	30

Mean weighted by cells size

cells size