

# metrics\_classification

May 29, 2021

## 1 Classification

This notebook aims at giving an overview of the classification metrics that can be used to evaluate the predictive model statistical performance. We can recall that in a classification setting, the vector `target` is categorical rather than continuous.

We will load the blood transfusion dataset.

```
[1]: import pandas as pd

blood_transfusion = pd.read_csv("../datasets/blood_transfusion.csv")
data = blood_transfusion.drop(columns="Class")
target = blood_transfusion["Class"]
```

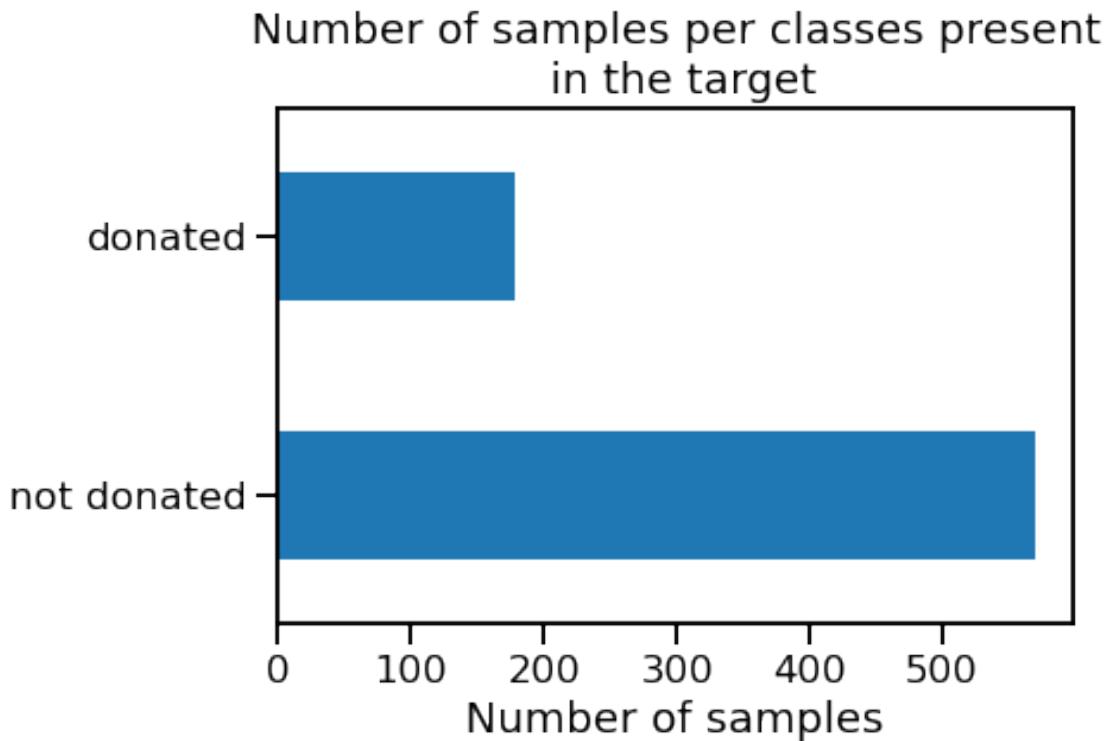
Note

If you want a deeper overview regarding this dataset, you can refer to the Appendix - Datasets description section at the end of this MOOC.

Let's start by checking the classes present in the target vector `target`.

```
[2]: import matplotlib.pyplot as plt

target.value_counts().plot.barh()
plt.xlabel("Number of samples")
_ = plt.title("Number of samples per classes present\n in the target")
```



We can see that the vector `target` contains two classes corresponding to whether a subject gave blood. We will use a logistic regression classifier to predict this outcome.

To focus on the metrics presentation, we will only use a single split instead of cross-validation.

```
[3]: from sklearn.model_selection import train_test_split

data_train, data_test, target_train, target_test = train_test_split(
    data, target, shuffle=True, random_state=0, test_size=0.5)
```

We will use a logistic regression classifier as a base model. We will train the model on the train set, and later use the test set to compute the different classification metric.

```
[4]: from sklearn.linear_model import LogisticRegression

classifier = LogisticRegression()
classifier.fit(data_train, target_train)
```

```
[4]: LogisticRegression()
```

## 1.1 Classifier predictions

Before we go into details regarding the metrics, we will recall what type of predictions a classifier can provide.

For this reason, we will create a synthetic sample for a new potential donor: he/she donated blood twice in the past (1000 c.c. each time). The last time was 6 months ago, and the first time goes back to 20 months ago.

```
[5]: new_donor = [[6, 2, 1000, 20]]
```

We can get the class predicted by the classifier by calling the method `predict`.

```
[6]: classifier.predict(new_donor)
```

```
[6]: array(['not donated'], dtype=object)
```

With this information, our classifier predicts that this synthetic subject is more likely to not donate blood again.

However, we cannot check whether the prediction is correct (we do not know the true target value). That's the purpose of the testing set. First, we predict whether a subject will give blood with the help of the trained classifier.

```
[7]: target_predicted = classifier.predict(data_test)  
target_predicted[:5]
```

```
[7]: array(['not donated', 'not donated', 'not donated', 'not donated',  
         'donated'], dtype=object)
```

## 1.2 Accuracy as a baseline

Now that we have these predictions, we can compare them with the true predictions (sometimes called ground-truth) which we did not use until now.

```
[8]: target_test == target_predicted
```

```
[8]: 258      True  
 521     False  
 14      False  
 31      False  
 505      True  
 ...  
 665      True  
 100     False  
 422      True  
 615      True  
 743      True  
Name: Class, Length: 374, dtype: bool
```

In the comparison above, a `True` value means that the value predicted by our classifier is identical to the real value, while a `False` means that our classifier made a mistake. One way of getting an overall rate representing the statistical performance of our classifier would be to compute how many times our classifier was right and divide it by the number of samples in our set.

```
[9]: import numpy as np  
  
np.mean(target_test == target_predicted)
```

```
[9]: 0.7780748663101604
```

This measure is called the accuracy. Here, our classifier is 78% accurate at classifying if a subject will give blood. scikit-learn provides a function that computes this metric in the module `sklearn.metrics`.

```
[10]: from sklearn.metrics import accuracy_score  
  
accuracy = accuracy_score(target_test, target_predicted)  
print(f"Accuracy: {accuracy:.3f}")
```

```
Accuracy: 0.778
```

LogisticRegression also has a method named `score` (part of the standard scikit-learn API), which computes the accuracy score.

```
[11]: classifier.score(data_test, target_test)
```

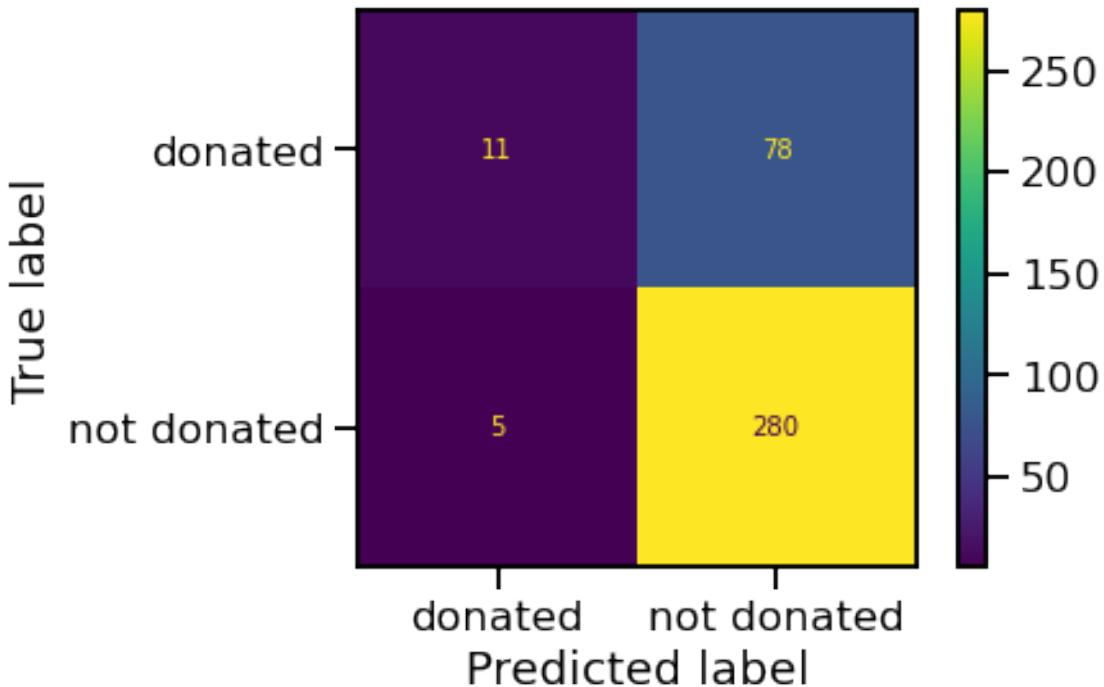
```
[11]: 0.7780748663101604
```

### 1.3 Confusion matrix and derived metrics

The comparison that we did above and the accuracy that we calculated did not take into account the type of error our classifier was making. Accuracy is an aggregate of the errors made by the classifier. We may be interested in finer granularity - to know independently what the error is for each of the two following cases:

- we predicted that a person will give blood but she/he did not;
- we predicted that a person will not give blood but she/he did.

```
[12]: from sklearn.metrics import plot_confusion_matrix  
  
_ = plot_confusion_matrix(classifier, data_test, target_test)
```



The in-diagonal numbers are related to predictions that were correct while off-diagonal numbers are related to incorrect predictions (misclassifications). We now know the four types of correct and erroneous predictions:

- the top left corner are true positives (TP) and corresponds to people who gave blood and were predicted as such by the classifier;
- the bottom right corner are true negatives (TN) and correspond to people who did not give blood and were predicted as such by the classifier;
- the top right corner are false negatives (FN) and correspond to people who gave blood but were predicted to not have given blood;
- the bottom left corner are false positives (FP) and correspond to people who did not give blood but were predicted to have given blood.

Once we have split this information, we can compute metrics to highlight the statistical performance of our classifier in a particular setting. For instance, we could be interested in the fraction of people who really gave blood when the classifier predicted so or the fraction of people predicted to have given blood out of the total population that actually did so.

The former metric, known as the precision, is defined as  $TP / (TP + FP)$  and represents how likely the person actually gave blood when the classifier predicted that they did. The latter, known as the recall, defined as  $TP / (TP + FN)$  and assesses how well the classifier is able to correctly identify people who did give blood. We could, similarly to accuracy, manually compute these values, however scikit-learn provides functions to compute these statistics.

```
[13]: from sklearn.metrics import precision_score, recall_score
```

```

precision = precision_score(target_test, target_predicted, pos_label="donated")
recall = recall_score(target_test, target_predicted, pos_label="donated")

print(f"Precision score: {precision:.3f}")
print(f"Recall score: {recall:.3f}")

```

Precision score: 0.688

Recall score: 0.124

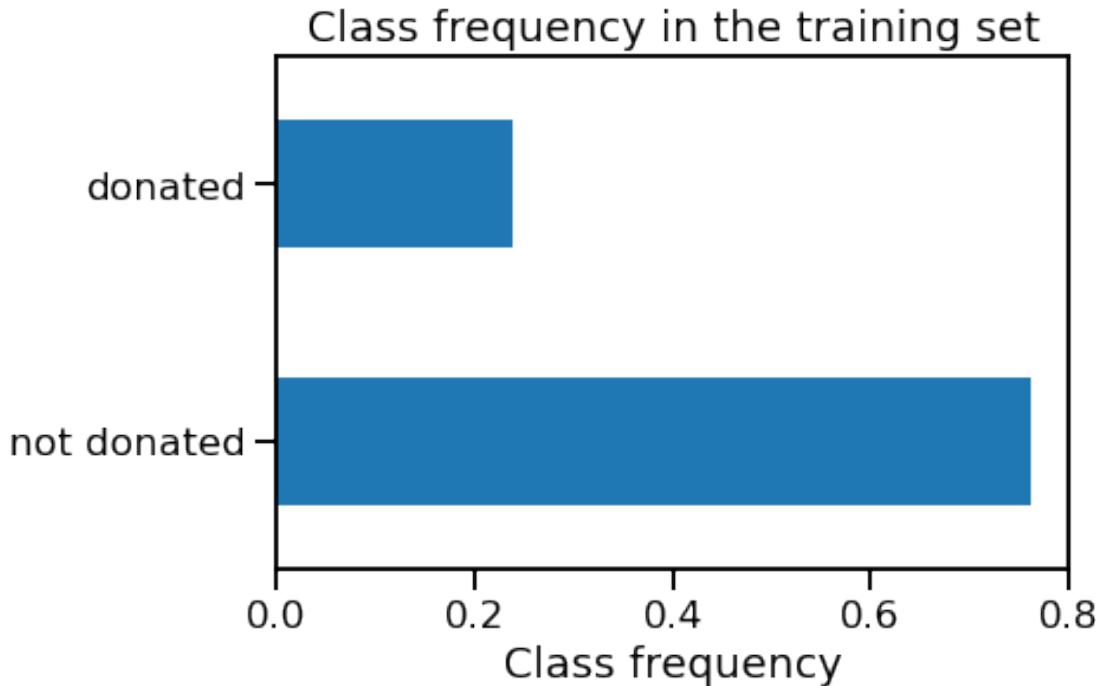
These results are in line with what was seen in the confusion matrix. Looking at the left column, more than half of the “donated” predictions were correct, leading to a precision above 0.5. However, our classifier mislabeled a lot of people who gave blood as “not donated”, leading to a very low recall of around 0.1.

#### 1.4 The issue of class imbalance

At this stage, we could ask ourselves a reasonable question. While the accuracy did not look bad (i.e. 77%), the recall score is relatively low (i.e. 12%).

As we mentioned, precision and recall only focus on samples predicted to be positive, while accuracy takes both into account. In addition, we did not look at the ratio of classes (labels). We could check this ratio in the training set.

```
[14]: target_train.value_counts(normalize=True).plot.barh()
plt.xlabel("Class frequency")
_ = plt.title("Class frequency in the training set")
```



We observe that the positive class, 'donated', comprises only 24% of the samples. The good accuracy of our classifier is then linked to its ability to correctly predict the negative class 'not donated' which may or may not be relevant, depending on the application. We can illustrate the issue using a dummy classifier as a baseline.

```
[15]: from sklearn.dummy import DummyClassifier

dummy_classifier = DummyClassifier(strategy="most_frequent")
dummy_classifier.fit(data_train, target_train)
print(f"Accuracy of the dummy classifier: "
      f"{dummy_classifier.score(data_test, target_test):.3f}")
```

Accuracy of the dummy classifier: 0.762

With the dummy classifier, which always predicts the negative class 'not donated', we obtain an accuracy score of 76%. Therefore, it means that this classifier, without learning anything from the data `data`, is capable of predicting as accurately as our logistic regression model.

The problem illustrated above is also known as the class imbalance problem. When the classes are imbalanced, accuracy should not be used. In this case, one should either use the precision and recall as presented above or the balanced accuracy score instead of accuracy.

```
[16]: from sklearn.metrics import balanced_accuracy_score

balanced_accuracy = balanced_accuracy_score(target_test, target_predicted)
print(f"Balanced accuracy: {balanced_accuracy:.3f}")
```

Balanced accuracy: 0.553

The balanced accuracy is equivalent to accuracy in the context of balanced classes. It is defined as the average recall obtained on each class.

## 1.5 Evaluation and different probability thresholds

All statistics that we presented up to now rely on `classifier.predict` which outputs the most likely label. We haven't made use of the probability associated with this prediction, which gives the confidence of the classifier in this prediction. By default, the prediction of a classifier corresponds to a threshold of 0.5 probability in a binary classification problem. We can quickly check this relationship with the classifier that we trained.

```
[17]: target_proba_predicted = pd.DataFrame(classifier.predict_proba(data_test),
                                             columns=classifier.classes_)

target_proba_predicted[:5]
```

```
[17]:    donated  not donated
0   0.271820    0.728180
1   0.451764    0.548236
2   0.445211    0.554789
3   0.441577    0.558423
4   0.870583    0.129417
```

```
[18]: target_predicted = classifier.predict(data_test)
target_predicted[:5]
```

```
[18]: array(['not donated', 'not donated', 'not donated', 'not donated',
'donated'], dtype=object)
```

Since probabilities sum to 1 we can get the class with the highest probability without using the threshold 0.5.

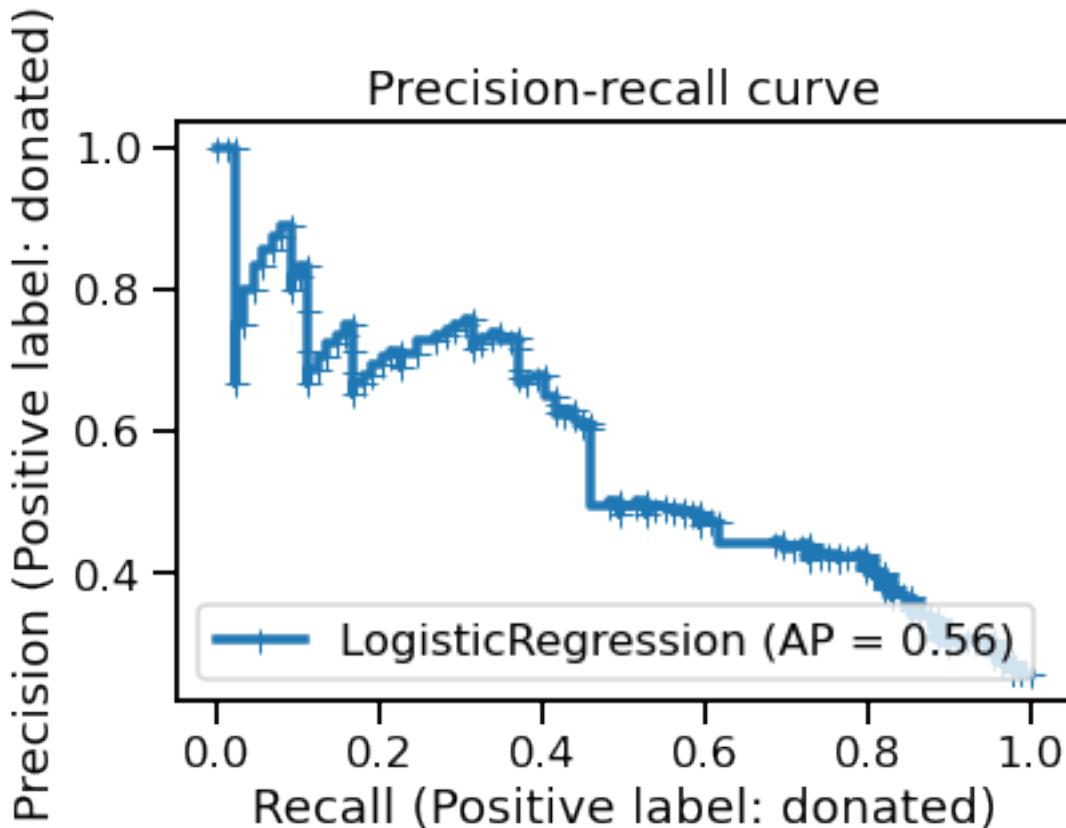
```
[19]: equivalence_pred_proba = (
    target_proba_predicted.argmax(axis=1).to_numpy() == target_predicted)
np.all(equivalence_pred_proba)
```

```
[19]: True
```

The default decision threshold (0.5) might not be the best threshold that leads to optimal statistical performance of our classifier. In this case, one can vary the decision threshold, and therefore the underlying prediction, and compute the same statistics presented earlier. Usually, the two metrics recall and precision are computed and plotted on a graph. Each metric plotted on a graph axis and each point on the graph corresponds to a specific decision threshold. Let's start by computing the precision-recall curve.

```
[20]: from sklearn.metrics import plot_precision_recall_curve

disp = plot_precision_recall_curve(
    classifier, data_test, target_test, pos_label='donated',
    marker="+"
)
_ = disp.ax_.set_title("Precision-recall curve")
```



### Tip

Scikit-learn will return a display containing all plotting element. Notably, displays will expose a matplotlib axis, named `ax_`, that can be used to add new element on the axis. You can refer to the documentation to have more information regarding the visualizations in scikit-learn

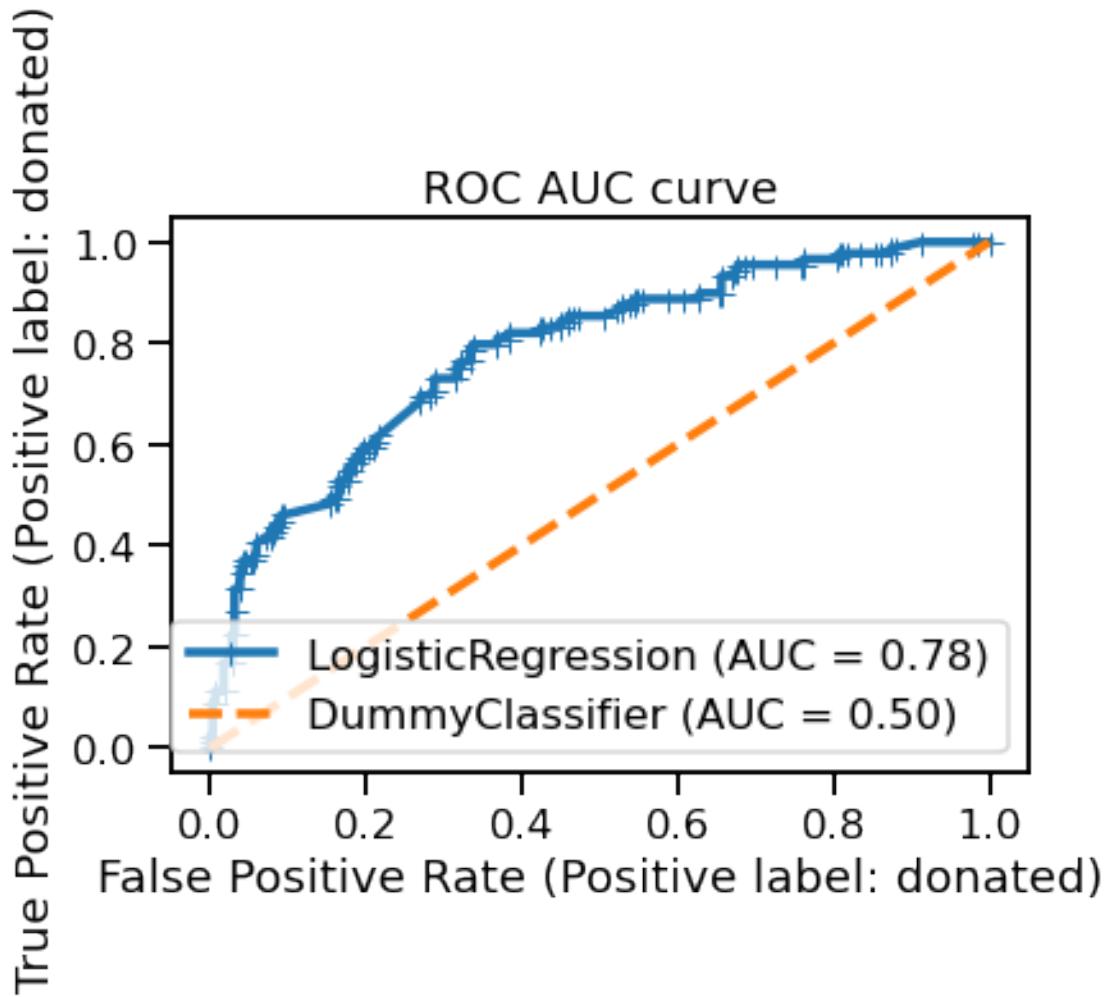
On this curve, each blue cross corresponds to a level of probability which we used as a decision threshold. We can see that, by varying this decision threshold, we get different precision vs. recall values.

A perfect classifier would have a precision of 1 for all recall values. A metric characterizing the curve is linked to the area under the curve (AUC) and is named average precision (AP). With an ideal classifier, the average precision would be 1.

The precision and recall metric focuses on the positive class, however, one might be interested in the compromise between accurately discriminating the positive class and accurately discriminating the negative classes. The statistics used for this are sensitivity and specificity. Sensitivity is just another name for recall. However, specificity measures the proportion of correctly classified samples in the negative class defined as:  $TN / (TN + FP)$ . Similar to the precision-recall curve, sensitivity and specificity are generally plotted as a curve called the receiver operating characteristic (ROC) curve. Below is such a curve:

```
[21]: from sklearn.metrics import plot_roc_curve

disp = plot_roc_curve(
    classifier, data_test, target_test, pos_label='donated',
    marker="+")
disp = plot_roc_curve(
    dummy_classifier, data_test, target_test, pos_label='donated',
    color="tab:orange", linestyle="--", ax=disp.ax_)
_ = disp.ax_.set_title("ROC AUC curve")
```



This curve was built using the same principle as the precision-recall curve: we vary the probability threshold for determining “hard” prediction and compute the metrics. As with the precision-recall curve, we can compute the area under the ROC (ROC-AUC) to characterize the statistical performance of our classifier. However, it is important to observe that the lower bound of the ROC-AUC is 0.5. Indeed, we show the statistical performance of a dummy classifier (the orange dashed line) to show that even the worst statistical performance obtained will be above this line.