

Day 10: Advanced Model Evaluation

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Null Accuracy

>>> 0.709677419355

Null Accuracy

```
from sklearn.dummy import DummyClassifier
dumb_model = DummyClassifier(strategy='most_frequent')
dumb_model.fit(X_train, y_train)
y_dumb_class = dumb_model.predict(X_test)
metrics.accuracy_score(y_test, y_dumb_class)
```



Null Accuracy

```
from yellowbrick import ClassBalance
visualizer = ClassBalance(dumb_model, classes=[0,1])
visualizer.fit(X_train, y_train)
visualizer.score(X_test, y_test)
g = visualizer.poof()
Class Balance
Class Balance
Class Balance
```





Performance Measures

- Sensitivity/true positive rate(TPR)/recall: What fraction of the "abnormal" samples in unseen data did we correctly predict?
- Specificity/true negative rate(TNR): What fraction of "normal" samples in unseen data did we correctly predict?
- Precision/positive predictive value(PPV) How frequently is our model correct when it predicts "abnormal" on new data?
- Negative predictive value (NPV): How frequently is our model correct when it predicts
 "normal" on new data?
- Accuracy (ACC): How frequently is our model correct on all new data, regardless of class?
- F1 score (F1): The harmonic mean of precision and recall:



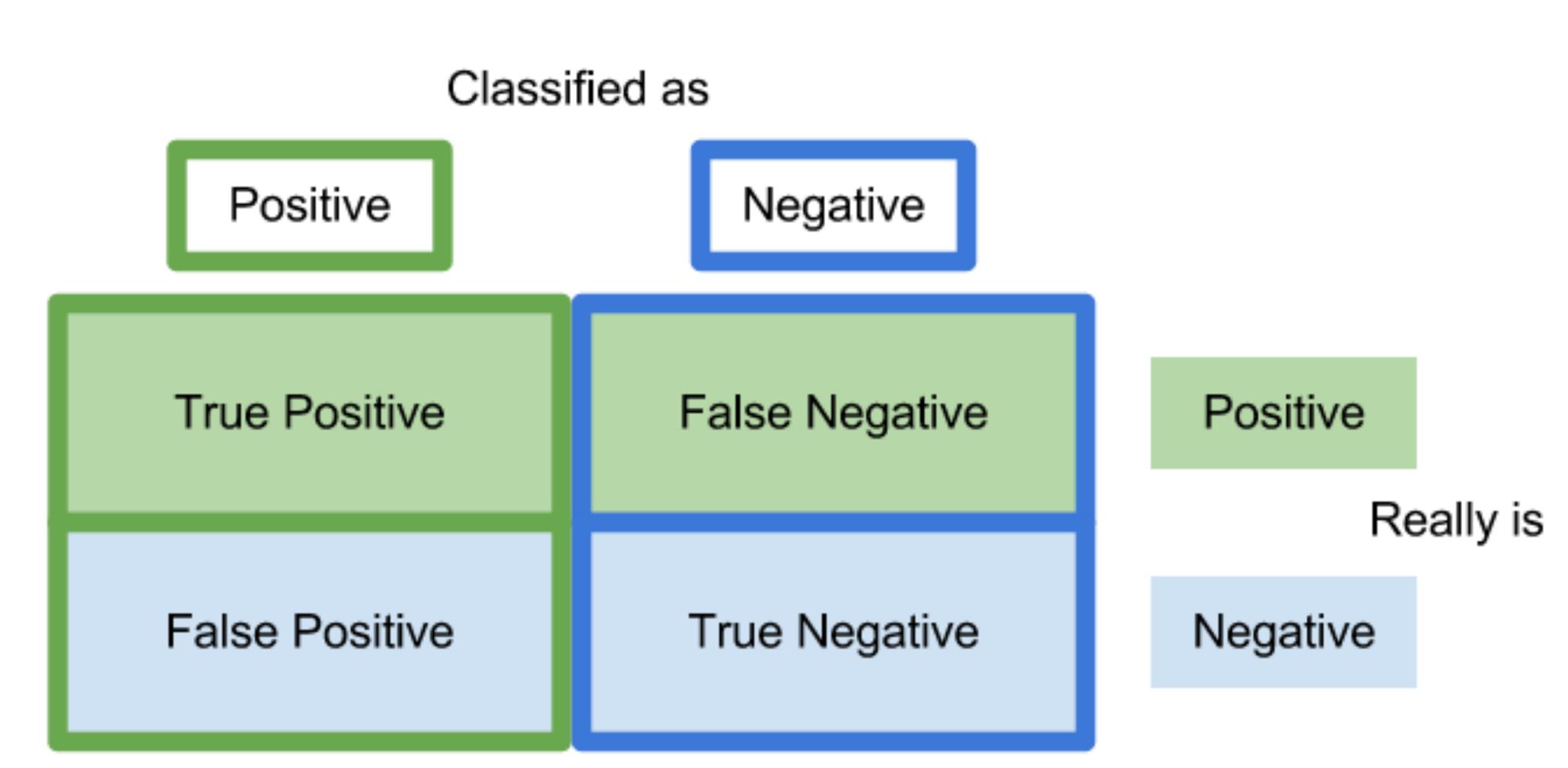
Performance Measures

metrics.classification_report(y_test,y_test_pred)

Classification Report:

	precision	recall	f1-score	support
0	0.78	0.78	0.78	27
1	0.91	0.91	0.91	66
avg / total	0.87	0.87	0.87	93

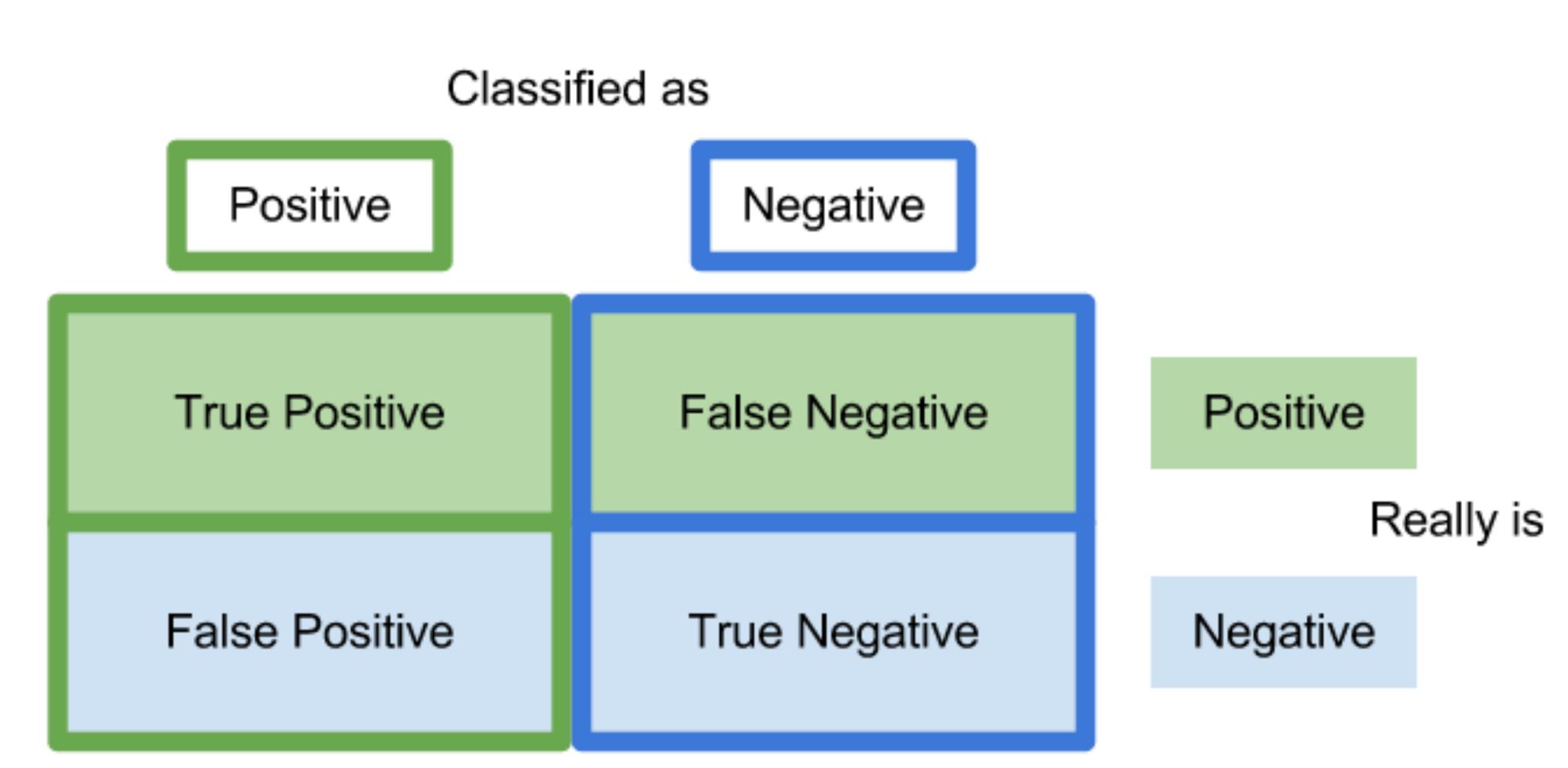






- predict 0 (normal), actual 0 (normal) called a correct rejection/true negative
- predict 0 (normal), actual 1 (abnormal) <-- this is an error called a miss/false negative
- predict 1 (abnormal), actual 0 (normal) <-- this is an error called a false alarm/ false positive
- predict 1 (abnormal), actual 1 (abnormal) called a hit/true positive





```
target = [1,0,0,1,1,1,1,1,1,0,0,0,0,0,0,0,0]
target_pred = [0,1,1,0,0,1,1,1,1,0,0,0,0,0,0,0]
print(metrics.confusion_matrix(target, target_pred))
```

Predicted target

True positive	False Negative (Type II error)
False Positive (Type I error)	True negative



Accuracy

accuracy = metrics.accuracy_score(target, target_pred)

True positive	False Negative (Type II error)
False Positive (Type I error)	True negative

Predicted target

Accuracy = (TP + TN)/ N Quiz: Calculate by hand!



Accuracy

accuracy = metrics.accuracy_score(target, target_pred)

True positive	False Negative (Type II error)
False Positive (Type I error)	True negative

Accuracy =
$$(TP + TN)/N$$

= $(7+4)/16$
= 0.6875



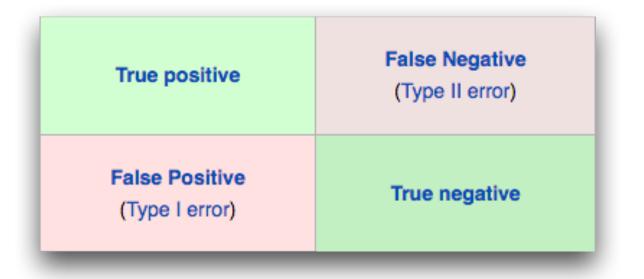


Column-wise!





precision_class = metrics.precision_score(target, target_pred, average = None)
precision_avg = metrics.precision_score(target, target_pred, average = 'binary')



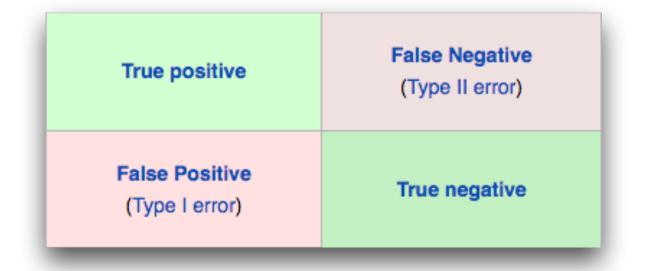
Predicted target

Precision = TP/ (TP + FP)
Quiz: Calculate precision by
hand for both classes!





precision_class = metrics.precision_score(target, target_pred, average = None)
precision_avg = metrics.precision_score(target, target_pred, average = 'binary')



Predicted target

Precision = TP/ (TP + FP)
Prec_Class0 =
$$7/(7+3) = 0.7$$

Prec_Class1 = $4/(4+2) = 0.666$





Accurate Precise Not Accurate Precise Accurate Not Precise Not Accurate Not Precise











Recall



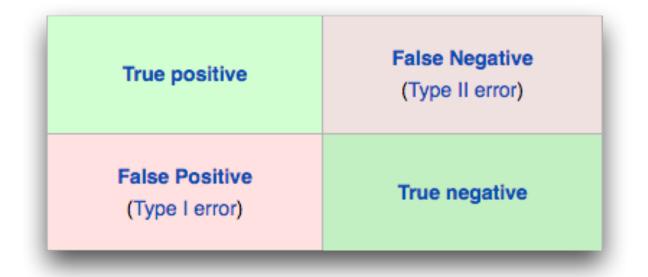
Row-wise!





Recall

```
recall_class = metrics.recall_score(target, target_pred, average = None)
recall_avg = metrics.recall_score(target, target_pred, average = 'binary')
```



```
O [ [ 7 2 ] - [ 3 4 ] ] O 1
```

Predicted target

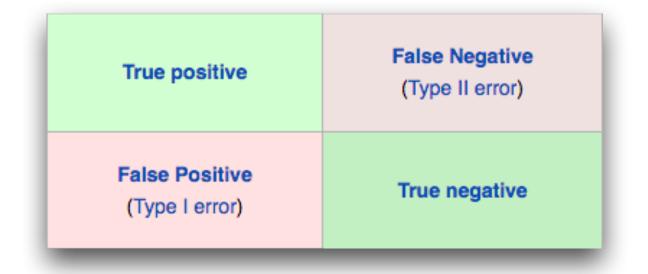
Recall = TP/ (TP + FN)
Quiz: Calculate recall by hand for both classes!





Recall

```
recall_class = metrics.recall_score(target, target_pred, average = None)
recall_avg = metrics.recall_score(target, target_pred, average = 'binary')
```



Recall = TP/ (TP + FN)
Rec_Class0 =
$$7/(7+2) = 0.777$$

Rec_Class1 = $4/(4+3) = 0.571$





Quiz: compute metrics for each class of 3-class confusion matrix

True positive	False Negative (Type II error)
False Positive (Type I error)	True negative

True targe

```
[ [ 7 2 5 ]
[ 3 4 2 ]
[ 0 1 4 ]
```

Predicted target

Accuracy = (Sum Diagonal)/ N

Precision = TP/ (TP + FP)

Recall = TP/(TP + FN)



Quiz: compute metrics for each class of 3-class confusion matrix

True positive	False Negative (Type II error)	
False Positive (Type I error)	True negative	

True targe

```
[ [ 7 2 5 ] 
 [ 3 4 2 ] 
 [ 0 1 4 ] ]
```

Predicted target

```
Accuracy = (7+4+4)/28 = 0.5357

Prec_Class2 = 4/(4+5+2) = 0.3636

Rec_Class2 = 4/(4+1+0) = 0.8
```

```
Precision: [ 0.7 0.57142857 0.36363636]
Recall: [ 0.5 0.4444444 0.8]
```



Where is the biggest crime scene?



Confusion matrices all with equal accuracy 0.6875!!!

How about precision and recall?

[[10 0] [[7 2] [[0 4] [5 1]] [3 4]] [1 11]]

A C



Where is the biggest crime scene?

Confusion matrices all with equal accuracy 0.6875!!! How about precision and recall?

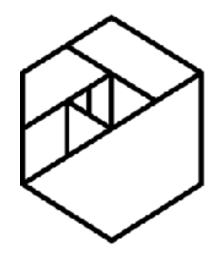
Precision: [0.7 1] Precision: [0.7 0.7] Precision: [0 0.7] Recall: [1 0.2]

Recall: [0.8 0.6]

Recall: [0 0.9]

[[10 0] [5 1] [3 4]]

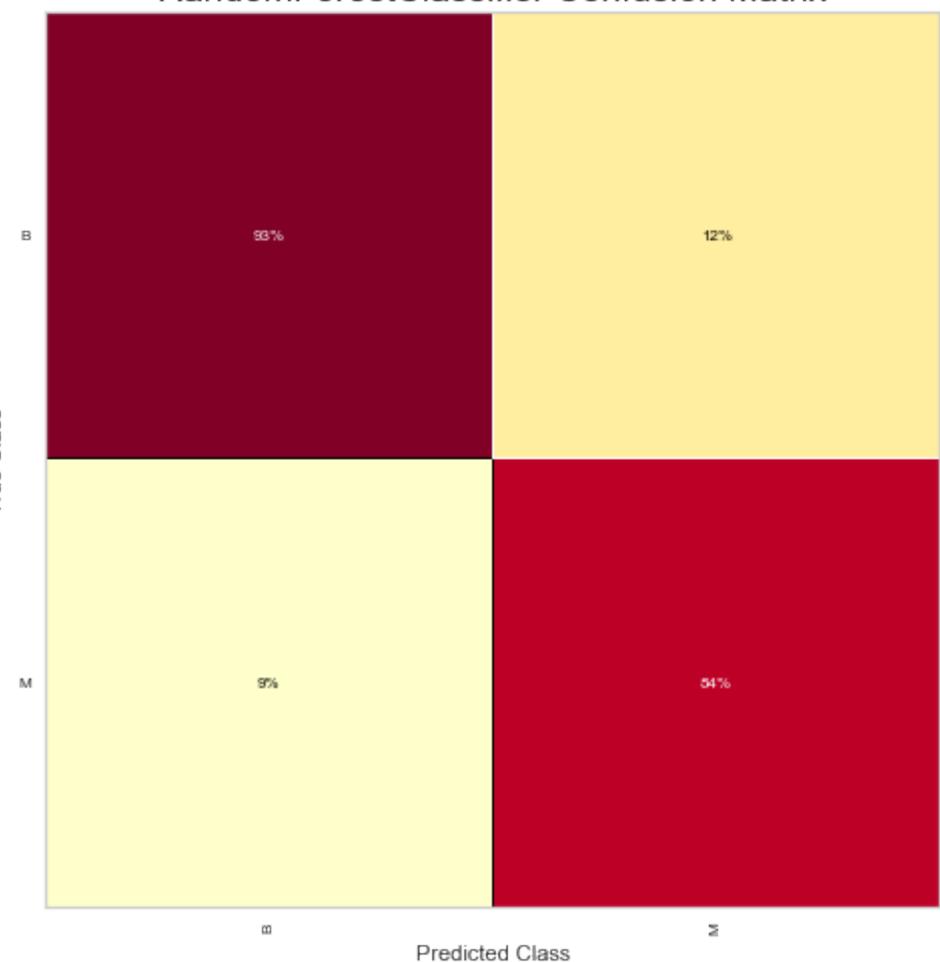


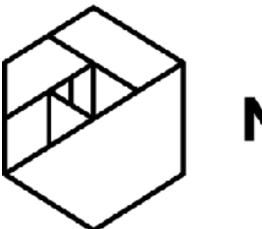


METIS

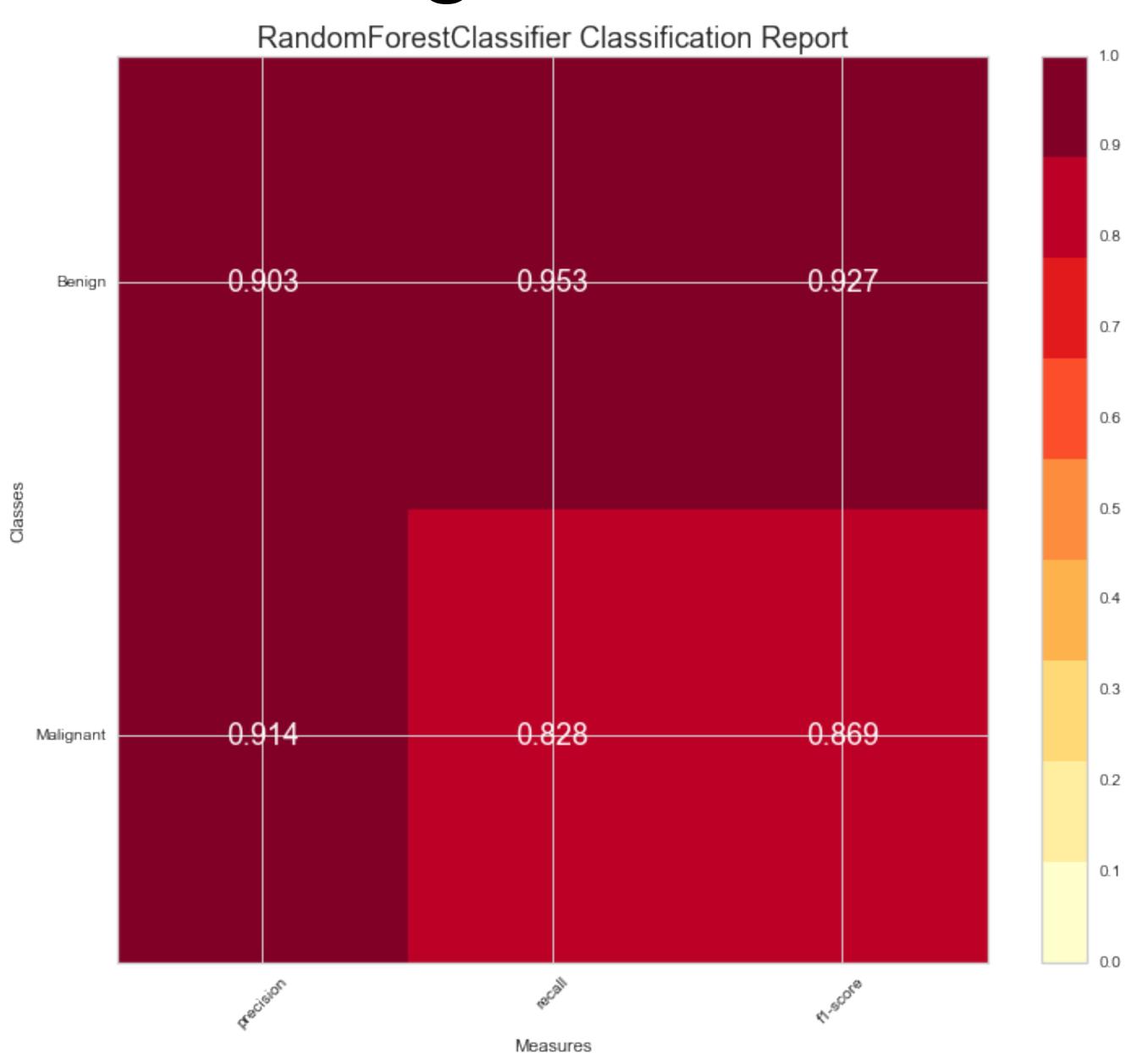
Visualizing the Confusion Matrix

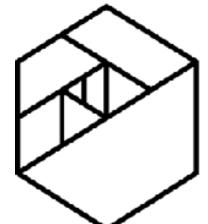




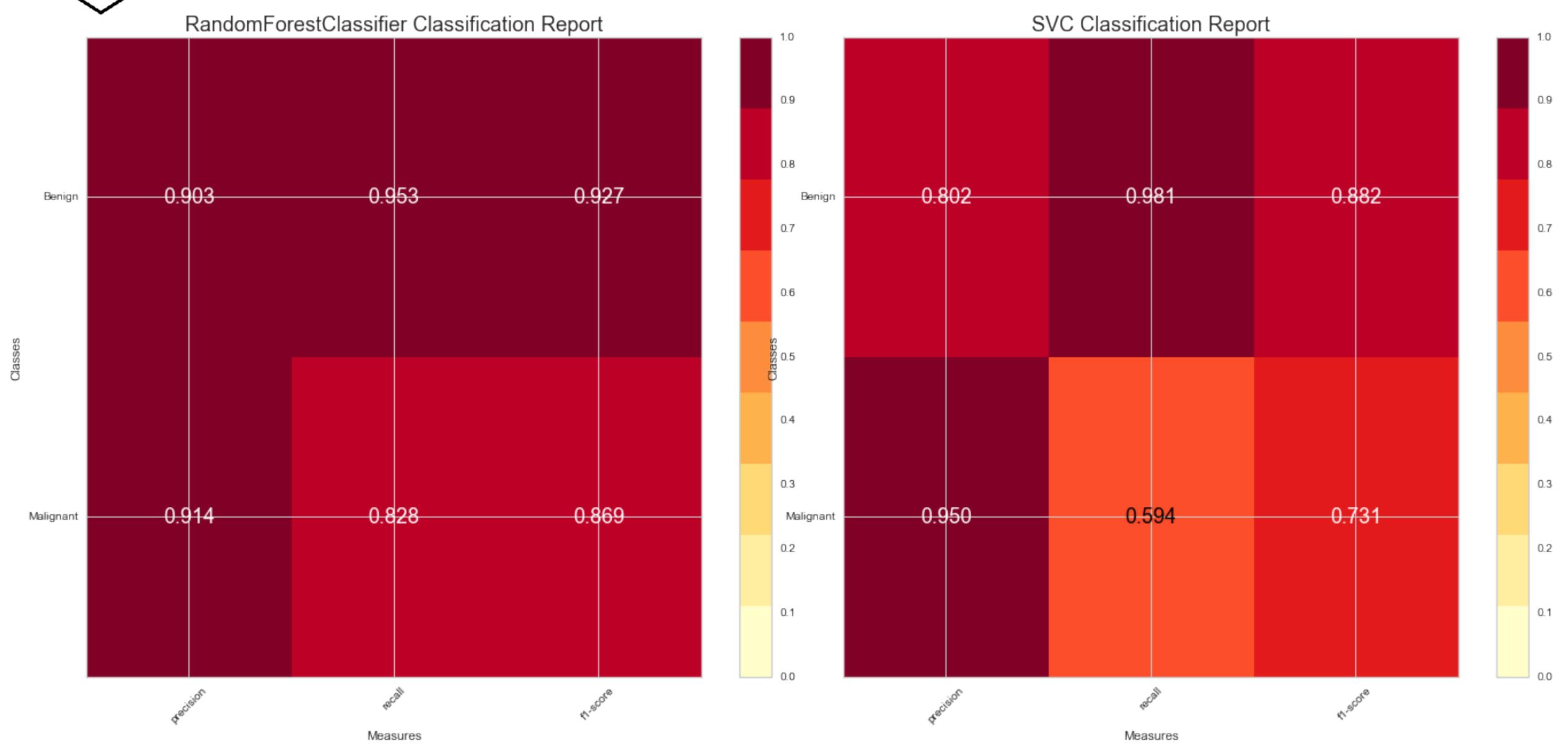


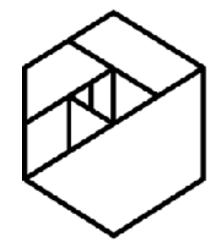
METIS Visualizing the Classification Report



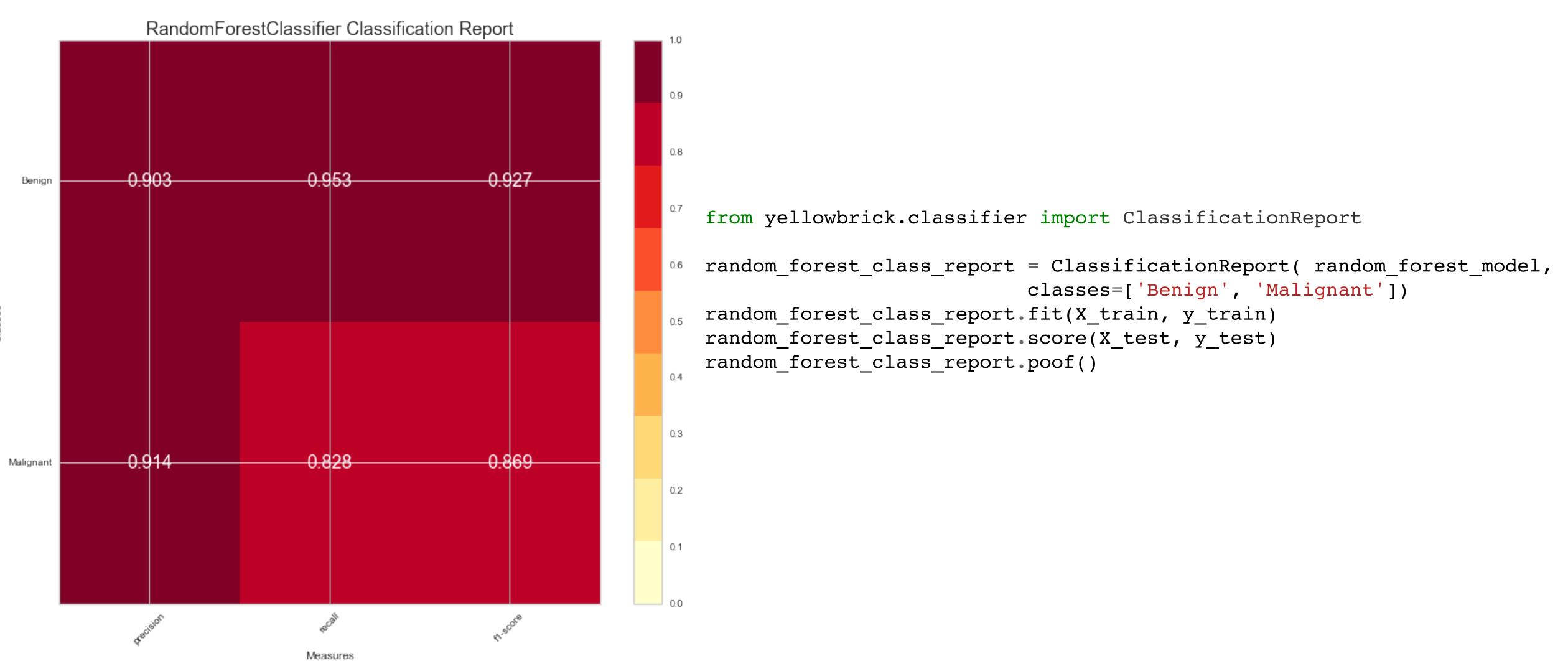


METIS Visualizing the Classification Report





METIS Visualizing the Classification Report





An Receiver Operating Characteristic (ROC) Curve is a graphical plot that illustrates the performance of a binary classifier system as its discrimination threshold is systematically varied.



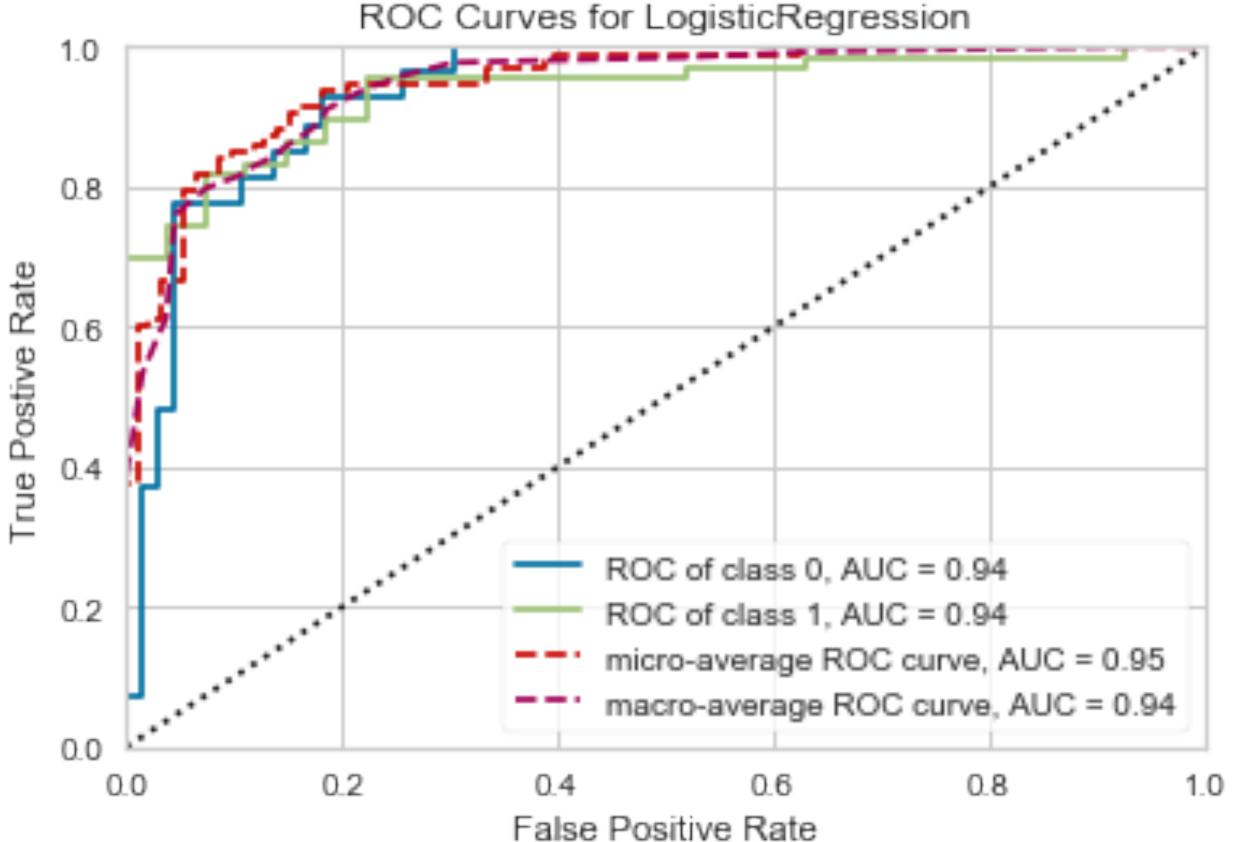
ROC Curves

	class_0	class_1	predicted	actual
0	0.06	0.94	1.0	1.0
1	0.38	0.62	1.0	0.0
2	0.08	0.92	1.0	1.0
3	0.08	0.92	1.0	1.0
4	0.22	0.78	1.0	1.0

ROC Curves

```
visualizer = ROCAUC(lr)
```

visualizer.fit(X_train, y_train)
visualizer.score(X_test, y_test)
g = visualizer.poof()



ROC Curves

```
metrics.roc_auc_score(y_test, y_preds)
```