DATA ANALYSIS

A complete Data Analysis workflow in Python and scikit-learn

A ready-to-run code including preprocessing, parameters tuning and model running and evaluation.

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In this short tutorial I illustrate a complete data analysis process which exploits the `scikit-learn` Python library. The process includes

- model selection with parameters tuning
- model evaluation

The code of this tutorial can be downloaded from my Github Repository.

Load Dataset

Firstly, I load the dataset through the Python `pandas` library. I exploit the `heart.csv` dataset, provided by the Kaggle repository.

```
import pandas as pd

df = pd.read_csv('source/heart.csv')
df.head()
```

	age	sex	cp	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	caa	thall	output
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

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I calculate the number of records and the number of columns in the dataset:

```
df.shape
```

which gives the following output:

```
(303, 14)
```

Features selection

```
features = []
for column in df.columns:
    if column != 'output':
        features.append(column)
X = df[features]
Y = df['output']
```

In order to select the minimum set of input features, I calculate the Pearson correlation coefficient among features, through `corr()` function, provided by a `pandas dataframe`.

	age	sex	cp	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	caa	thall
age	1.000000	-0.098447	-0.068653	0.279351	0.213678	0.121308	-0.116211	-0.398522	0.096801	0.210013	-0.168814	0.276326	0.068001
sex	-0.098447	1.000000	-0.049353	-0.056769	-0.197912	0.045032	-0.058196	-0.044020	0.141664	0.096093	-0.030711	0.118261	0.210041
cp	-0.068653	-0.049353	1.000000	0.047608	-0.076904	0.094444	0.044421	0.295762	-0.394280	-0.149230	0.119717	-0.181053	-0.161736
trtbps	0.279351	-0.056769	0.047608	1.000000	0.123174	0.177531	-0.114103	-0.046698	0.067616	0.193216	-0.121475	0.101389	0.062210
chol	0.213678	-0.197912	-0.076904	0.123174	1.000000	0.013294	-0.151040	-0.009940	0.067023	0.053952	-0.004038	0.070511	0.098803
fbs	0.121308	0.045032	0.094444	0.177531	0.013294	1.000000	-0.084189	-0.008567	0.025665	0.005747	-0.059894	0.137979	-0.032019
restecg	-0.116211	-0.058196	0.044421	-0.114103	-0.151040	-0.084189	1.000000	0.044123	-0.070733	-0.058770	0.093045	-0.072042	-0.011981
thalachh	-0.398522	-0.044020	0.295762	-0.046698	-0.009940	-0.008567	0.044123	1.000000	-0.378812	-0.344187	0.386784	-0.213177	-0.096439
exng	0.096801	0.141664	-0.394280	0.067616	0.067023	0.025665	-0.070733	-0.378812	1.000000	0.288223	-0.257748	0.115739	0.206754
oldpeak	0.210013	0.096093	-0.149230	0.193216	0.053952	0.005747	-0.058770	-0.344187	0.288223	1.000000	-0.577537	0.222682	0.210244
slp	-0.168814	-0.030711	0.119717	-0.121475	-0.004038	-0.059894	0.093045	0.386784	-0.257748	-0.577537	1.000000	-0.080155	-0.104764
caa	0.276326	0.118261	-0.181053	0.101389	0.070511	0.137979	-0.072042	-0.213177	0.115739	0.222682	-0.080155	1.000000	0.151832
thall	0.068001	0.210041	-0.161736	0.062210	0.098803	-0.032019	-0.011981	-0.096439	0.206754	0.210244	-0.104764	0.151832	1.000000

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I note that all the features have a low correlation, thus I can keep all of them as input features.

Data Normalization

Data Normalization scales all the features in the same interval. I exploit the `MinMaxScaler()` provided by the `scikit-learn` library. I dealt with Data Normalization in `scikit-learn` in my previous article, while I this article I described the general process of Data Normalization without `scikit-learn`.

```
X.describe()
```

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min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.000000	0.000000	0.000000	0.0
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.000000	1.000000	0.000000	2.0
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.800000	1.000000	0.000000	2.0
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.600000	2.000000	1.000000	3.0
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.200000	2.000000	4.000000	3.0

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Looking at the minimum and maximum value for each feature, I note that there are many features out the range [0,1], thus I need to scale them.

For each input feature I calculate the `MinMaxScaler()` and I store the result in the same `X` column. The `MinMaxScaler()` must be fitted firstly through the `fit()` function and then can be applied for a transformation through the `transform()` function. Note that I must reshape every feature in the format (-1,1) in order to be passed as input parameter of the scaler. For example, `Reshape(-1,1)` transforms the array `[0,1,2,3,5]` into `[[0],[1],[2],[3],[5]]`.

```
from sklearn.preprocessing import MinMaxScaler

for column in X.columns:
    feature = np.array(X[column]).reshape(-1,1)
    scaler = MinMaxScaler()
    scaler.fit(feature)
    feature_scaled = scaler.transform(feature)
    X[column] = feature_scaled.reshape(1,-1)[0]
```

Split the dataset in Training and Test

Now I split the dataset into two parts: training and testset. The test set size is 20% of the whole dataset. I exploit the `scikit-learn` function `train_test_split()`. I will use the training set to train the model and the testset to test the performance of the model.

```
import numpy as np
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split( X, Y,
test_size=0.20, random_state=42)
```

Balancing

number of records in each output class.

```
y_train.value_counts()
```

which gives the following output:

```
1    133
0    109
```

The output classes are not balanced, thus I can balance it. I can exploit the `imblearn` library, to perform balancing. I try both oversampling the minority class and undersampling the majority class. More details related to the Imbalanced Learn library can be found here. Firstly, I perform over sampling through the `RandomOverSampler()`. I create the model and then I fit with the training set. The `fit_resample()` function returns the balanced training set.

```
from imblearn.over_sampling import RandomOverSampler
over_sampler = RandomOverSampler(random_state=42)
X_bal_over, y_bal_over = over_sampler.fit_resample(X_train, y_train)
```

I calculate the number of records in each class through the `value_counts()` function and I note that now the dataset is balanced.

```
y_bal_over.value_counts()
```

which gives the following output:

```
1    133
0    133
```

Secondly, I perform under sampling through the `RandomUnderSampler()` model.

```
under_sampler = RandomUnderSampler(random_state=42)
X_bal_under, y_bal_under = under_sampler.fit_resample(X_train,
y_train)
```

Model Selection and Training

Now, I'm ready to train the model. I choose a `KNeighborsClassifier` and firstly I train it with imbalanced data. I exploit the `fit()` function to train the model and then the `predict_proba()` function to predict the values of the test set.

```
from sklearn.neighbors import KNeighborsClassifier

model = KNeighborsClassifier(n_neighbors=3)
model.fit(X_train, y_train)
y_score = model.predict_proba(X_test)
```

I calculate the performance of the model. In particular, I calculate the `roc_curve()` and the `precision_recall()` and then I plot them. I exploit the `scikitplot` library to plot curves.

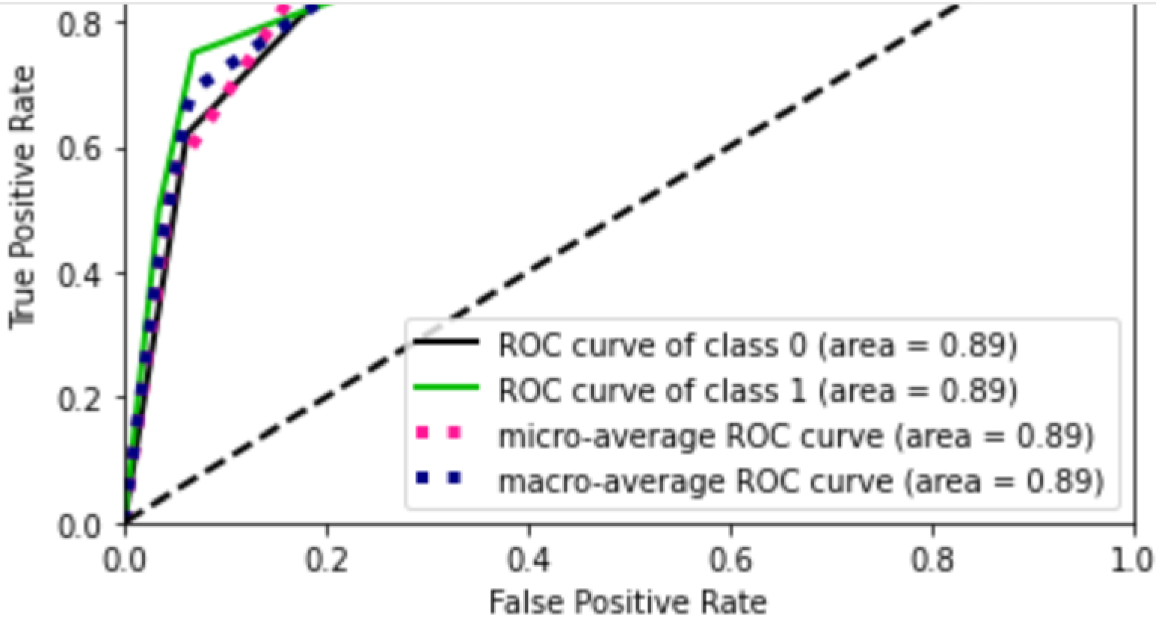
From the plot I note that there is a roc curve for each class. With respect to the precision recall curve, the class 1 works better than class 0, probably because it is represented by a greater number of samples.

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve
from scikitplot.metrics import plot_roc,auc
from scikitplot.metrics import plot_precision_recall

fpr0, tpr0, thresholds = roc_curve(y_test, y_score[:, 1])

# Plot metrics
plot_roc(y_test, y_score)
plt.show()

plot_precision_recall(y_test, y_score)
plt.show()
```



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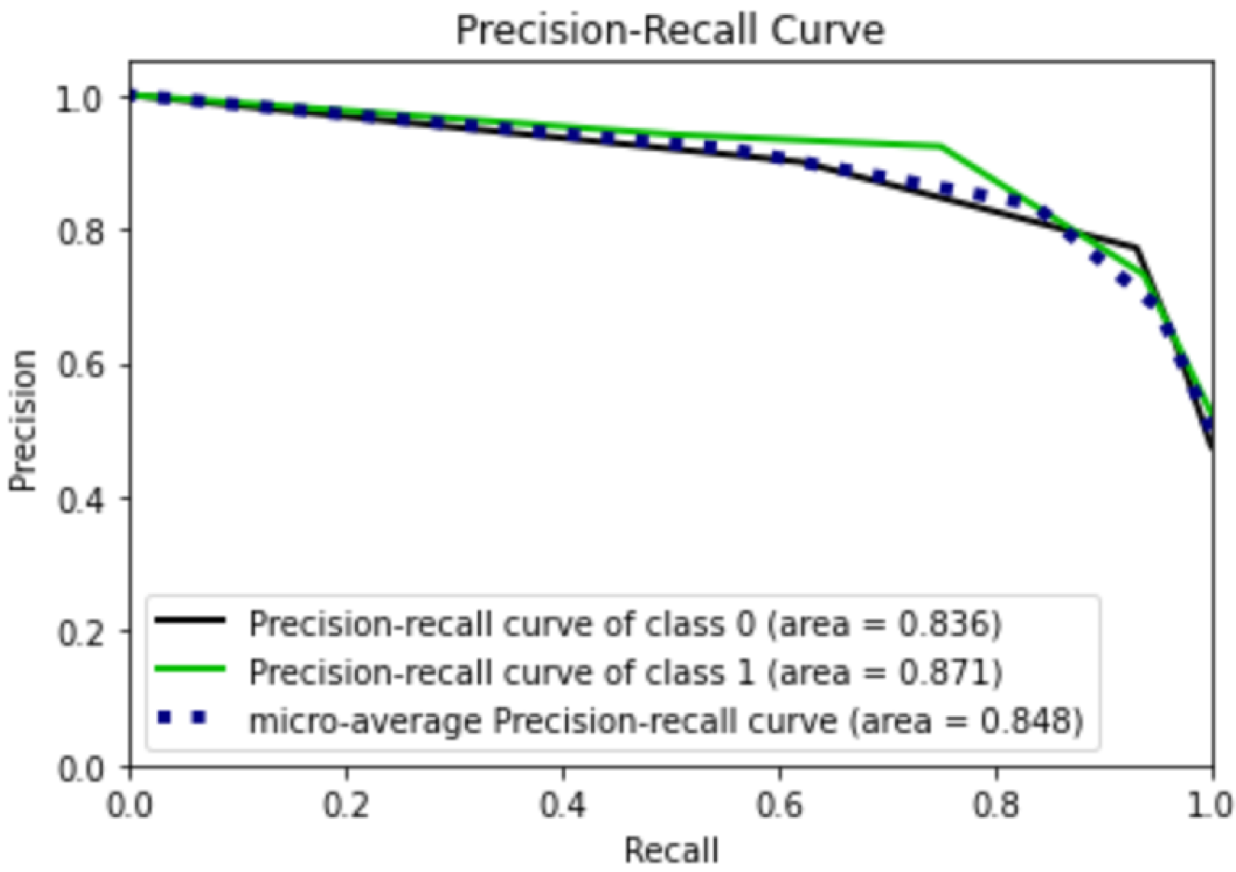

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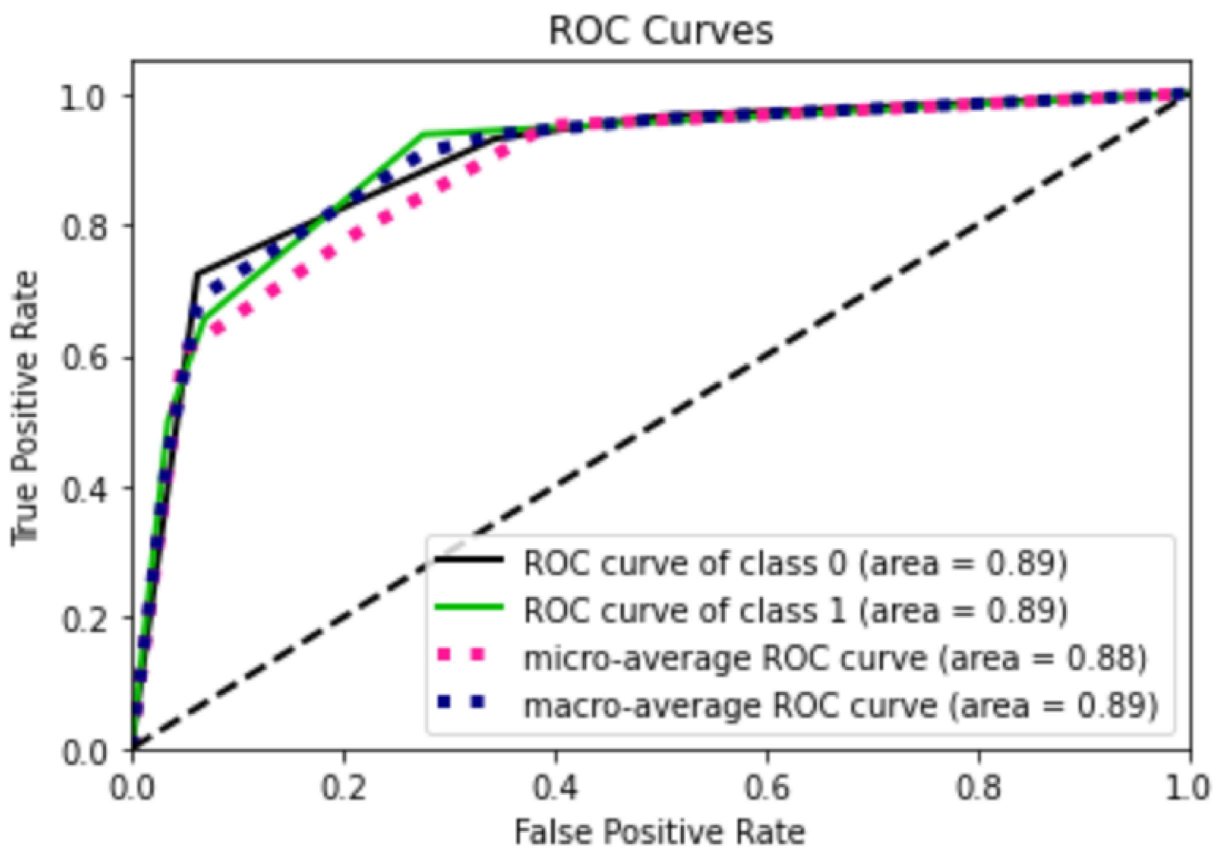
```
model = KNeighborsClassifier(n_neighbors=3)
model.fit(X_bal_over, y_bal_over)
y_score = model.predict_proba(X_test)
fpr0, tpr0, thresholds = roc_curve(y_test, y_score[:, 1])

# Plot metrics
plot_roc(y_test, y_score)
plt.show()

plot_precision_recall(y_test, y_score)
plt.show()
```



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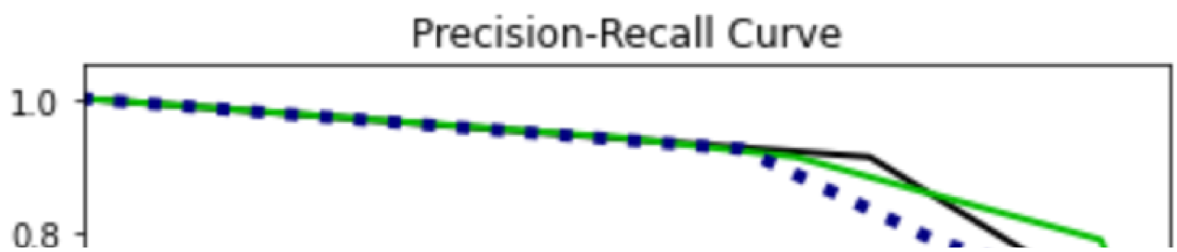

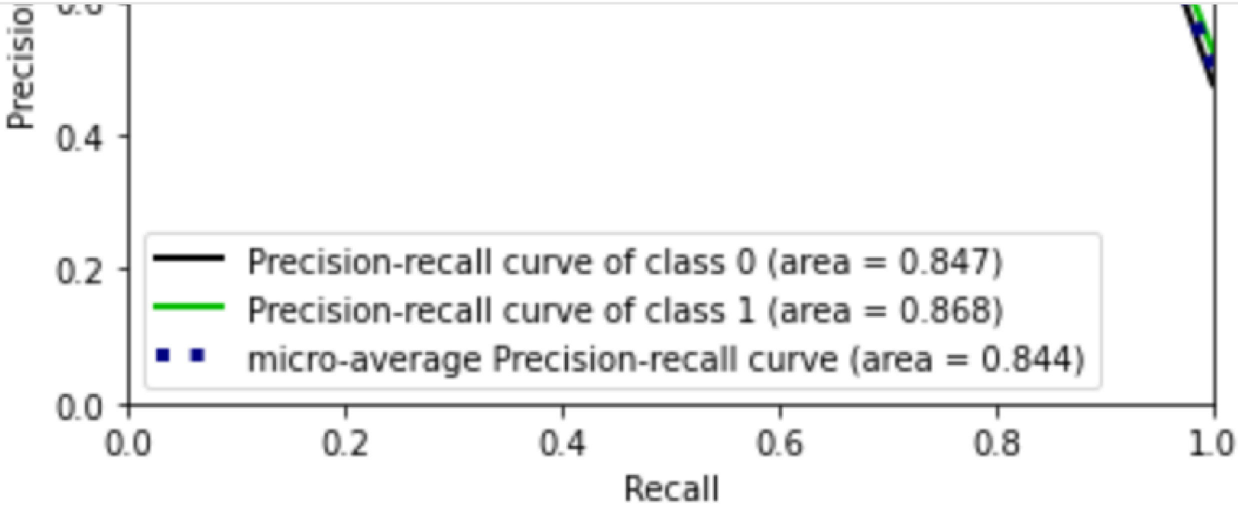

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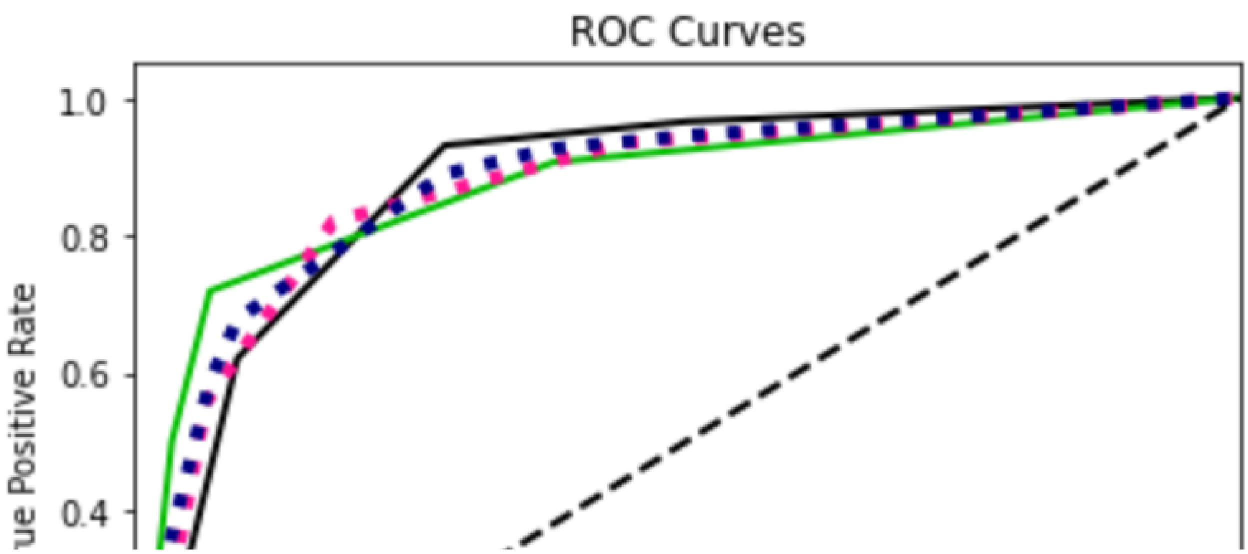
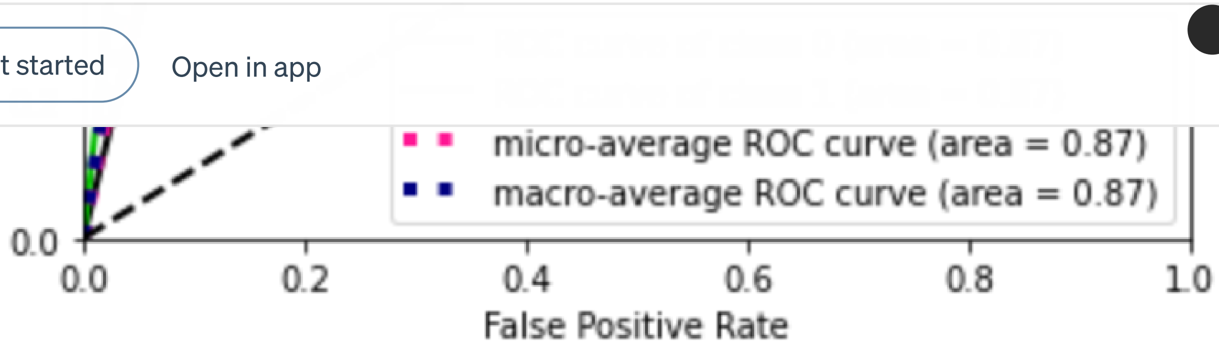
Finally, I train the model through under sampled data and I note a general deterioration of the performance.

```
model = KNeighborsClassifier(n_neighbors=3)
model.fit(X_bal_under, y_bal_under)
y_score = model.predict_proba(X_test)
fpr0, tpr0, thresholds = roc_curve(y_test, y_score[:, 1])

# Plot metrics
plot_roc(y_test, y_score)
plt.show()

plot_precision_recall(y_test, y_score)
plt.show()
```





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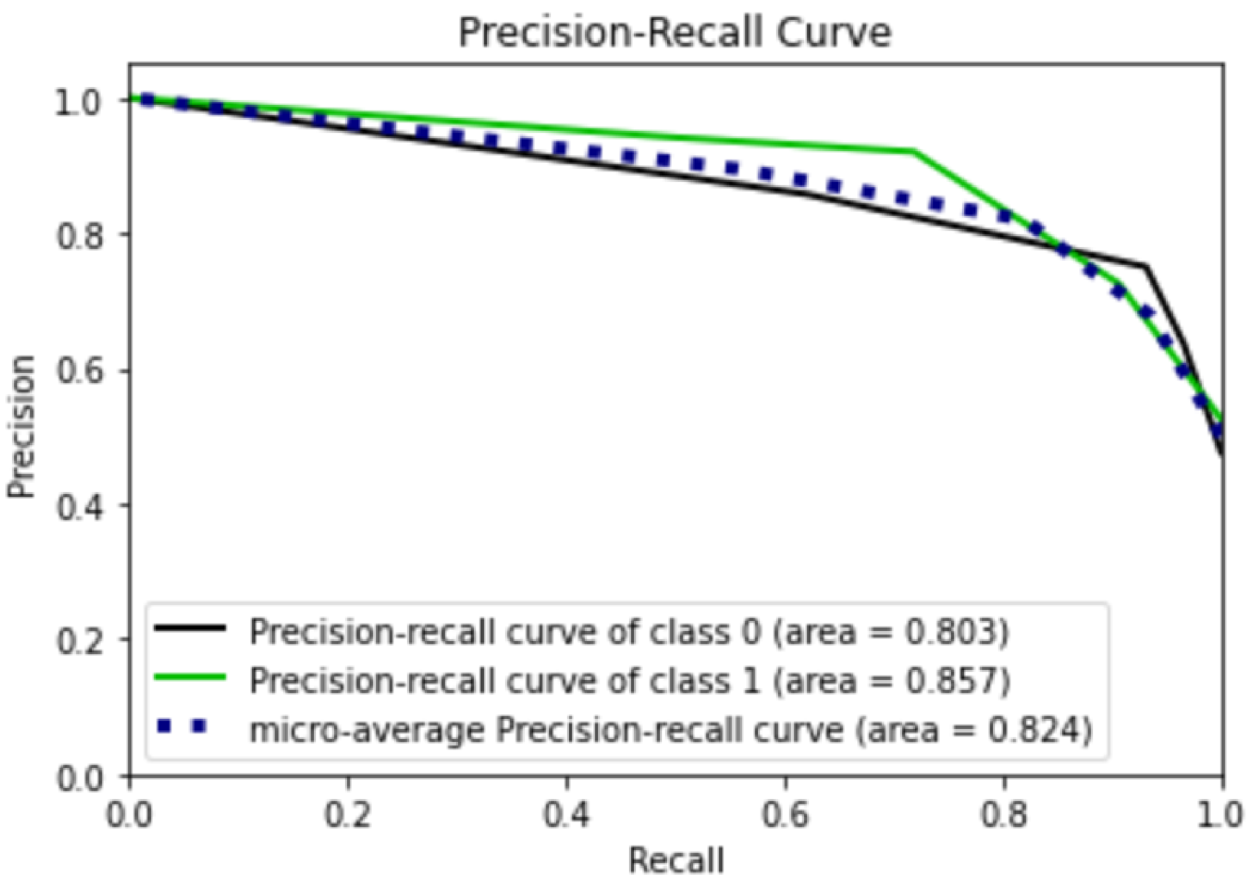

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Parameters Tuning

In the last part of this tutorial, I try to improve the performance of the model by searching for best parameters for my model. I exploit the `GridSearchCV` mechanism provided by the `scikit-learn` library. I select a range of values for each parameter to be tested and I put them in the `param_grid` variable. I create a `GridSearchCV()` object, I fit with the training set and then I retrieve the best estimator, contained in the `best_estimator_` variable.

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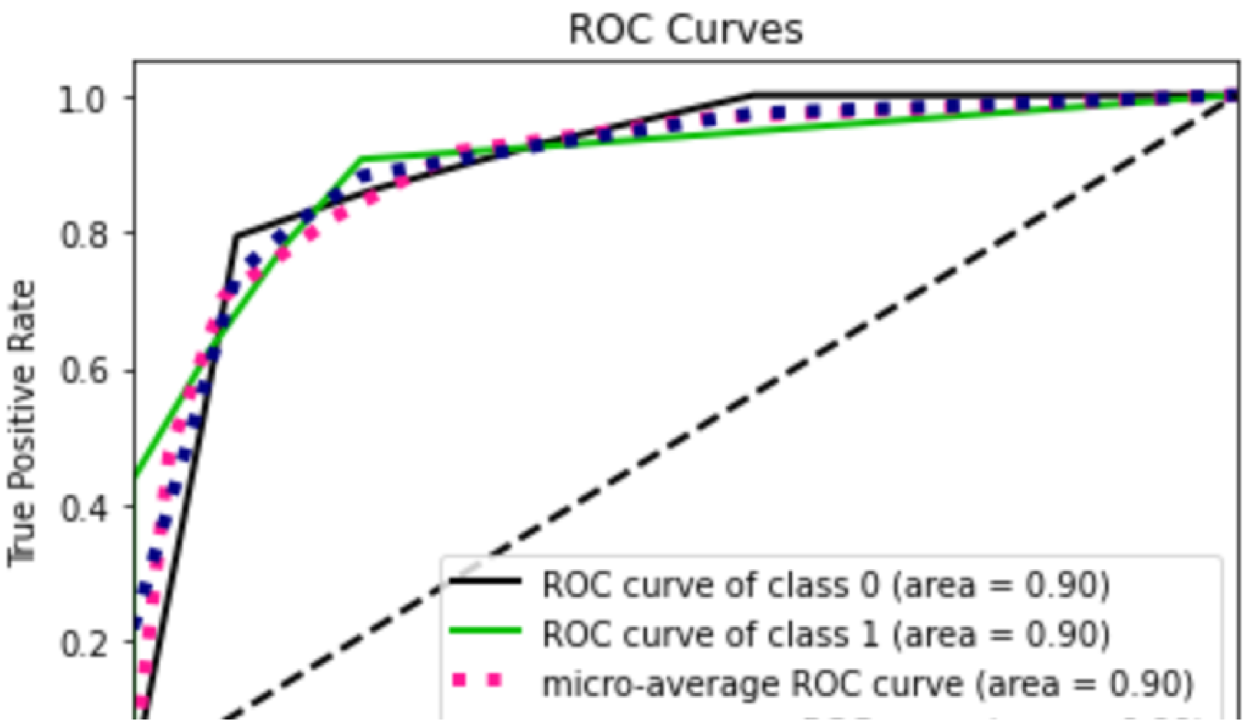
```
model = KNeighborsClassifier()

param_grid = {
   'n_neighbors': np.arange(2,8),
   'algorithm' : ['auto', 'ball_tree', 'kd_tree', 'brute'],
    'metric' : ['euclidean','manhattan','chebyshev','minkowski']
}

grid = GridSearchCV(model, param_grid = param_grid)
grid.fit(X_train, y_train)

best_estimator = grid.best_estimator_
```

I exploit the best estimator as model for my predictions and I calculate the performance of the algorithm.

```
best_estimator.fit(X_train, y_train)
y_score = best_estimator.predict_proba(X_test)
fpr0, tpr0, thresholds = roc_curve(y_test, y_score[:, 1])

# Plot metrics
plot_roc(y_test, y_score)
plt.show()

plot_precision_recall(y_test, y_score)
plt.show()
```



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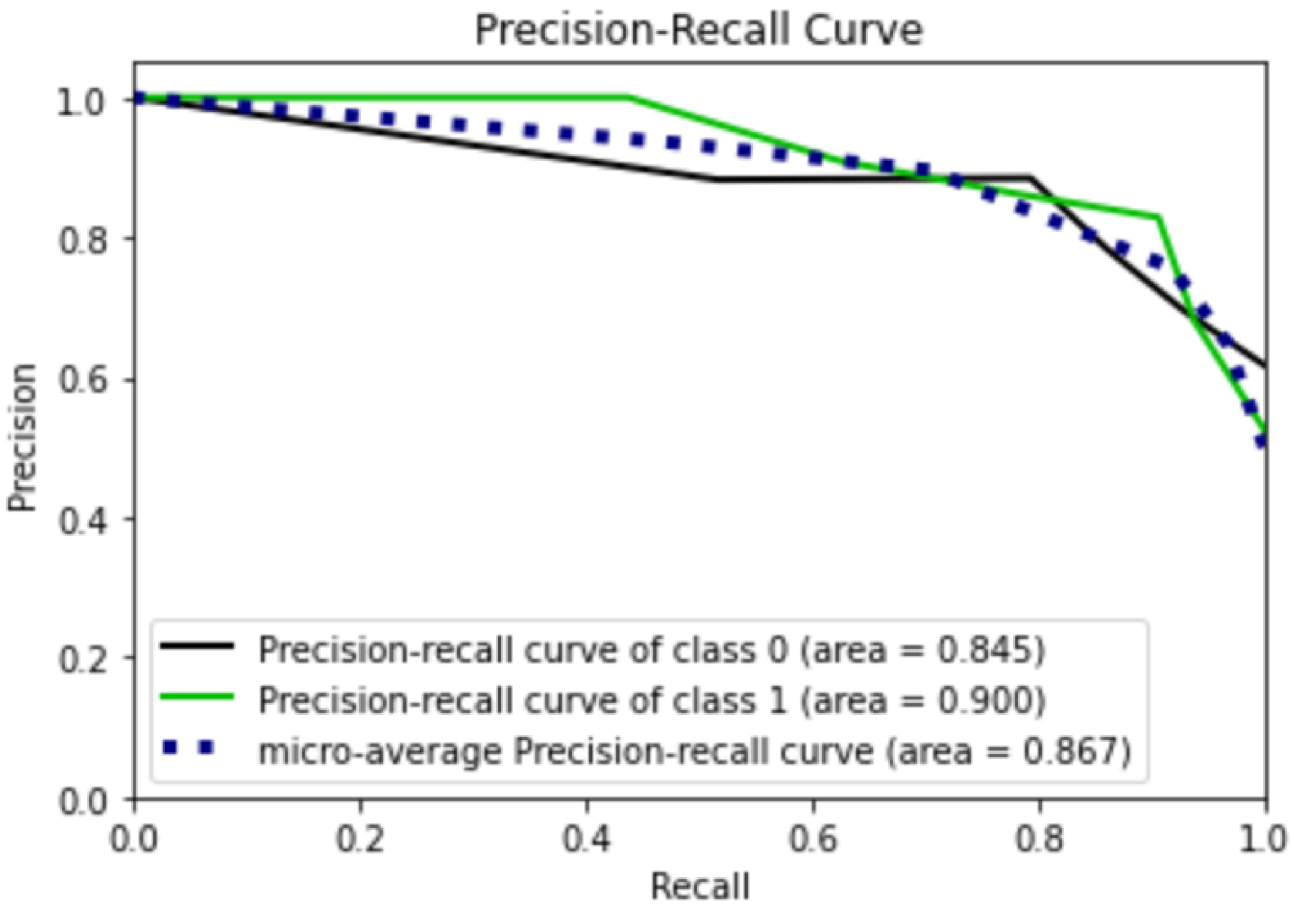

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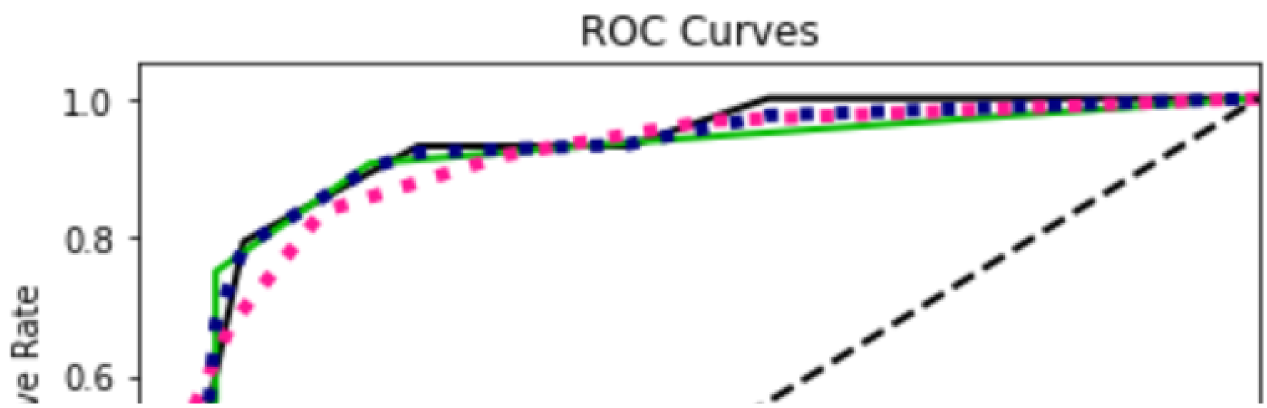
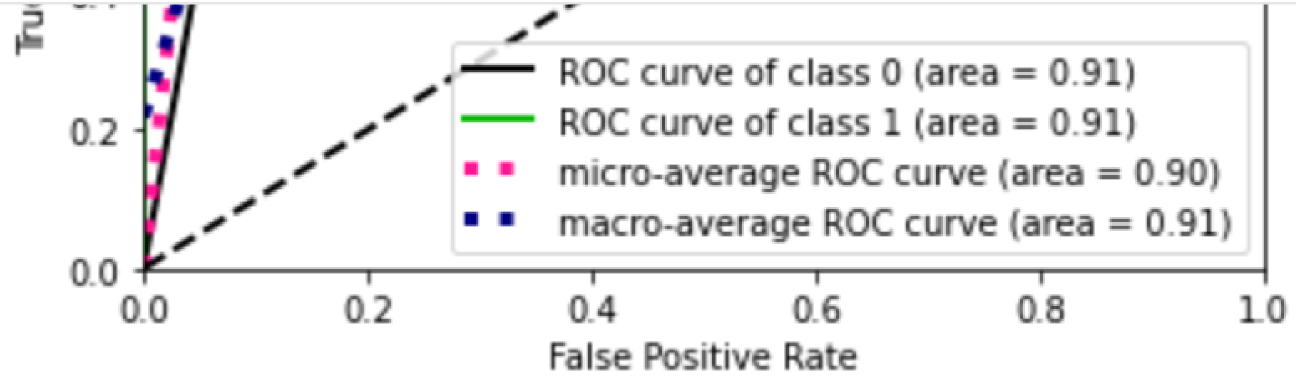
I note that the roc curve has improved. I try now with the over sampled training set. I omit the code because it is the same as before. In this case I obtain the best performance.





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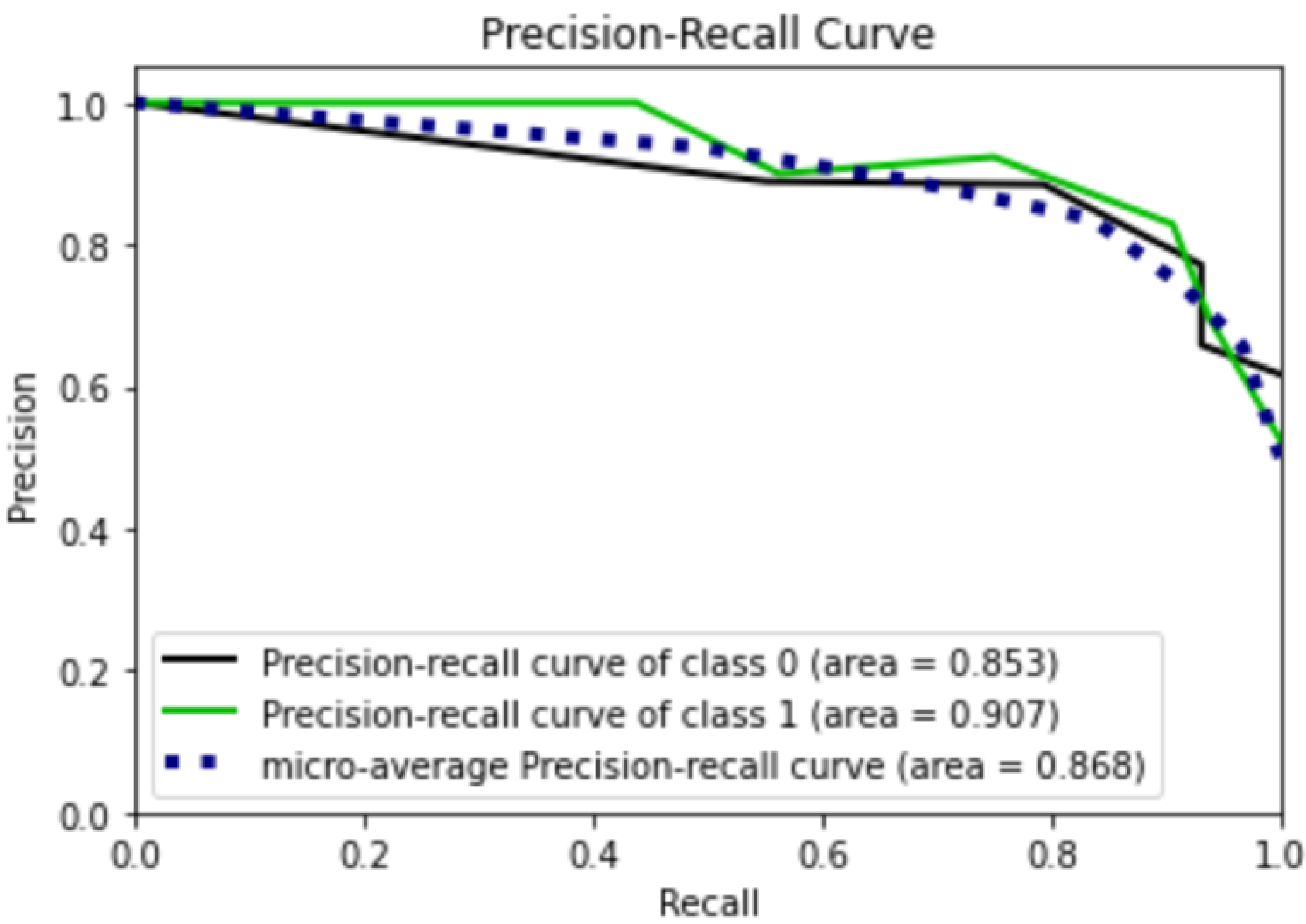

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Summary

In this tutorial I have illustrated the full workflow to build a good model for data analysis. The workflow includes:

- data preprocessing, with features selection and balancing

- model evaluation, through the ROC curve and the Precision Recall curve.

In this tutorial I have not dealt with Outliers Detection. If you want to learn something about this aspect, you can give a look to my previous article.

If you wanted to be updated on my research and other activities, you can follow me on Twitter, Youtube and and Github.

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