

Practical Activity 9 Classification using ensemble models

September 19, 2023

1 Practical Activity 9

1.1 Classification using Random Forest Ensemble

This notebook is an exercise for developing a Random Forest classifier for predicting the types of wine. We apply the concepts discussed in Week 9. We walk through RF Classifier in this practical. Note: this activity is unmarked. It develops your skills for predictive model development using Ensemble approaches.

1.2 Task

Our aim is to build a classification model to predict types of wine. We will be using the wine dataset which contains 178 observations and 13 variables: Alcohol, Malic acid, Ash, Alcalinity of ash, Magnesium, Total phenols, Flavanoids, Nonflavanoid phenols, Proanthocyanins, Color intensity, Hue, OD280/OD315 of diluted wines, Proline; and the Outcome - class_0, class_1 and class_2. The dataset is available at https://scikit-learn.org/stable/modules/generated/sklearn.datasets.load_wine.html#sklearn.datasets.load_wine

1.3 Evaluation Metric

We will evaluate the performance of the model using precision, recall and F1 score. See https://en.wikipedia.org/wiki/Precision_and_recall for more details.

1.3.1 Step 1 - Load libraries

```
[29]: import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

from sklearn.datasets import load_wine
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
```

1.3.2 Step 2 - Load data

```
[17]: # Load data
data = load_wine()
# Transform the data to dataframe format
df = pd.DataFrame(data=np.c_[data['data'], data['target']],
                  columns= data['feature_names'] + ['target'])
# Transform the outcome to categorical
df['target'] = df.target.astype('str')
df.head()
```

```
[17]:   alcohol  malic_acid  ash  alcalinity_of_ash  magnesium  total_phenols  \
0    14.23      1.71  2.43             15.6      127.0           2.80
1    13.20      1.78  2.14             11.2      100.0           2.65
2    13.16      2.36  2.67             18.6      101.0           2.80
3    14.37      1.95  2.50             16.8      113.0           3.85
4    13.24      2.59  2.87             21.0      118.0           2.80

   flavanoids  nonflavanoid_phenols  proanthocyanins  color_intensity  hue  \
0         3.06                0.28             2.29             5.64  1.04
1         2.76                0.26             1.28             4.38  1.05
2         3.24                0.30             2.81             5.68  1.03
3         3.49                0.24             2.18             7.80  0.86
4         2.69                0.39             1.82             4.32  1.04

   od280/od315_of_diluted_wines  proline  target
0                3.92      1065.0      0.0
1                3.40      1050.0      0.0
2                3.17      1185.0      0.0
3                3.45      1480.0      0.0
4                2.93       735.0      0.0
```

```
[18]: # Shape
df.shape
```

```
[18]: (178, 14)
```

```
[19]: # Statistical summary
df.describe()
```

```
[19]:   alcohol  malic_acid  ash  alcalinity_of_ash  magnesium  \
count  178.000000  178.000000  178.000000      178.000000  178.000000
mean    13.000618    2.336348    2.366517      19.494944    99.741573
std     0.811827    1.117146    0.274344     3.339564    14.282484
min    11.030000    0.740000    1.360000    10.600000    70.000000
25%    12.362500    1.602500    2.210000    17.200000    88.000000
50%    13.050000    1.865000    2.360000    19.500000    98.000000
75%    13.677500    3.082500    2.557500    21.500000   107.000000
```

max	14.830000	5.800000	3.230000	30.000000	162.000000
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	total_phenols	flavanoids	nonflavanoid_phenols	proanthocyanins	\
count	178.000000	178.000000	178.000000	178.000000	
mean	2.295112	2.029270	0.361854	1.590899	
std	0.625851	0.998859	0.124453	0.572359	
min	0.980000	0.340000	0.130000	0.410000	
25%	1.742500	1.205000	0.270000	1.250000	
50%	2.355000	2.135000	0.340000	1.555000	
75%	2.800000	2.875000	0.437500	1.950000	
max	3.880000	5.080000	0.660000	3.580000	

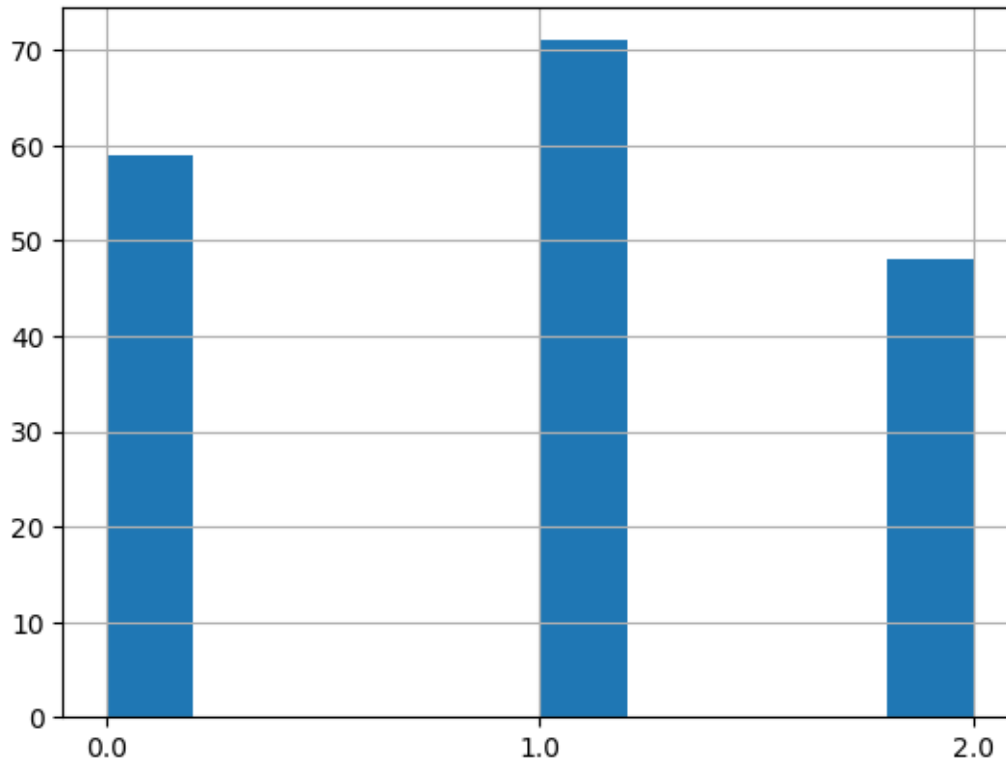
	color_intensity	hue	od280/od315_of_diluted_wines	proline
count	178.000000	178.000000	178.000000	178.000000
mean	5.058090	0.957449	2.611685	746.893258
std	2.318286	0.228572	0.709990	314.907474
min	1.280000	0.480000	1.270000	278.000000
25%	3.220000	0.782500	1.937500	500.500000
50%	4.690000	0.965000	2.780000	673.500000
75%	6.200000	1.120000	3.170000	985.000000
max	13.000000	1.710000	4.000000	1680.000000

```
[20]: # Info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 14 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   alcohol                               178 non-null    float64
1   malic_acid                            178 non-null    float64
2   ash                                   178 non-null    float64
3   alcalinity_of_ash                     178 non-null    float64
4   magnesium                             178 non-null    float64
5   total_phenols                         178 non-null    float64
6   flavanoids                            178 non-null    float64
7   nonflavanoid_phenols                  178 non-null    float64
8   proanthocyanins                       178 non-null    float64
9   color_intensity                       178 non-null    float64
10  hue                                   178 non-null    float64
11  od280/od315_of_diluted_wines          178 non-null    float64
12  proline                               178 non-null    float64
13  target                                178 non-null    object
dtypes: float64(13), object(1)
memory usage: 18.8+ KB
```

```
[23]: df.target.hist()
```

[23]: <AxesSubplot:>



The above shows that the target variable is quite balanced.

1.3.3 Step 3 - Create train and test data

```
[26]: # Split
train, test = train_test_split(df, test_size = 0.3, stratify = df['target'])

X_train = train.drop('target', axis=1)
y_train = train['target']

X_test = test.drop('target', axis = 1)
y_test = test['target']

# shapes
X_train.shape, X_test.shape
```

[26]: ((124, 13), (54, 13))

1.3.4 Step 4 - Build the random forest model

In this step, we will build the random forest model using sklearn, see <https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html> for details.

```
[28]: # build model
      clf = RandomForestClassifier(max_depth=5, random_state=0)
      # fit to data
      clf.fit(X_train, y_train)

      clf
```

```
[28]: RandomForestClassifier(max_depth=5, random_state=0)
```

1.3.5 Step 5 - Evaluate the performance

```
[30]: # prediction on train
      pred_train = clf.predict(X_train)

      target_names = ['class 0', 'class 1', 'class 2']
      print(classification_report(y_train, pred_train, target_names=target_names))
```

	precision	recall	f1-score	support
class 0	1.00	1.00	1.00	41
class 1	1.00	1.00	1.00	50
class 2	1.00	1.00	1.00	33
accuracy			1.00	124
macro avg	1.00	1.00	1.00	124
weighted avg	1.00	1.00	1.00	124

The F1 score on train data is 1.00.

```
[32]: # prediction on test
      pred_test = clf.predict(X_test)

      target_names = ['class 0', 'class 1', 'class 2']
      print(classification_report(y_test, pred_test, target_names=target_names))
```

	precision	recall	f1-score	support
class 0	1.00	0.89	0.94	18
class 1	0.90	0.90	0.90	21
class 2	0.88	1.00	0.94	15
accuracy			0.93	54
macro avg	0.93	0.93	0.93	54

weighted avg	0.93	0.93	0.93	54
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The F1 score on test data is 0.93.

2 Task

Try to find the best set of parameters for the random forest model. Try to build another ensemble approaches, using different ensemble set of models, e.g. the combination of LR and SVM.