

# Week6\_5\_Bagging\_randomForest\_classifier

May 13, 2021

Bagging and Random Forest

Bagging

Import Libraries

\*Bootstrap Aggregation (Bagging)

\*An ensemble method is a technique that combines the predictions from multiple machine learning algorithms together to make more accurate predictions than any individual model.

\*Bagging constructs n classification trees using bootstrap sampling of the training data and then combines their predictions to produce a final meta-prediction.

\*Reduces variance of individual model in the ensemble

```
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn import preprocessing
from scipy.stats import pearsonr

import warnings
warnings.filterwarnings('ignore')
```

Import dataset

```
[2]: # data = pd.read_csv('/home/jayanthikishore/Downloads/ML_classwork/
↳DT_RF_Ensemble/indian_liver_patient.csv')
data = pd.read_csv('/Users/preethamvignesh/Downloads/ML_classwork/
↳DT_RF_Ensemble/indian_liver_patient.csv')

data.head()
```

```
[2]:   Age  Gender  Total_Bilirubin  Direct_Bilirubin  Alkaline_Phosphotase  \
0   65  Female             0.7              0.1             187
1   62   Male            10.9              5.5             699
2   62   Male             7.3              4.1             490
3   58   Male             1.0              0.4             182
```

4	72	Male	3.9	2.0	195
---	----	------	-----	-----	-----

	Alamine_Aminotransferase	Aspartate_Aminotransferase	Total_Protiens	\
0	16	18	6.8	
1	64	100	7.5	
2	60	68	7.0	
3	14	20	6.8	
4	27	59	7.3	

	Albumin	Albumin_and_Globulin_Ratio	Dataset
0	3.3	0.90	1
1	3.2	0.74	1
2	3.3	0.89	1
3	3.4	1.00	1
4	2.4	0.40	1

Features in dataset

```
[3]: data.columns
```

```
[3]: Index(['Age', 'Gender', 'Total_Bilirubin', 'Direct_Bilirubin',
          'Alkaline_Phosphotase', 'Alamine_Aminotransferase',
          'Aspartate_Aminotransferase', 'Total_Protiens', 'Albumin',
          'Albumin_and_Globulin_Ratio', 'Dataset'],
          dtype='object')
```

Data type

```
[4]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 583 entries, 0 to 582
Data columns (total 11 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Age                                    583 non-null    int64
1   Gender                                583 non-null    object
2   Total_Bilirubin                       583 non-null    float64
3   Direct_Bilirubin                      583 non-null    float64
4   Alkaline_Phosphotase                  583 non-null    int64
5   Alamine_Aminotransferase              583 non-null    int64
6   Aspartate_Aminotransferase            583 non-null    int64
7   Total_Protiens                        583 non-null    float64
8   Albumin                               583 non-null    float64
9   Albumin_and_Globulin_Ratio            579 non-null    float64
10  Dataset                               583 non-null    int64
dtypes: float64(5), int64(5), object(1)
memory usage: 50.2+ KB
```

Checking the NaN values

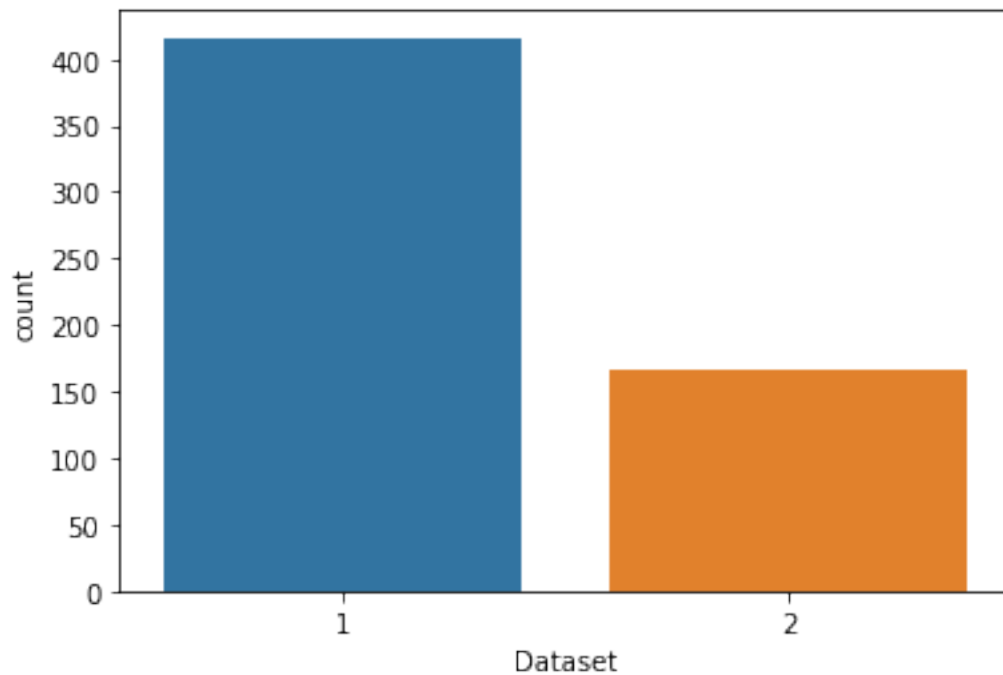
```
[5]: data.isnull().sum()
```

```
[5]: Age                0
     Gender              0
     Total_Bilirubin     0
     Direct_Bilirubin    0
     Alkaline_Phosphotase 0
     Alamine_Aminotransferase 0
     Aspartate_Aminotransferase 0
     Total_Protiens      0
     Albumin             0
     Albumin_and_Globulin_Ratio 4
     Dataset             0
     dtype: int64
```

Exploratory data Analysis (EDA)

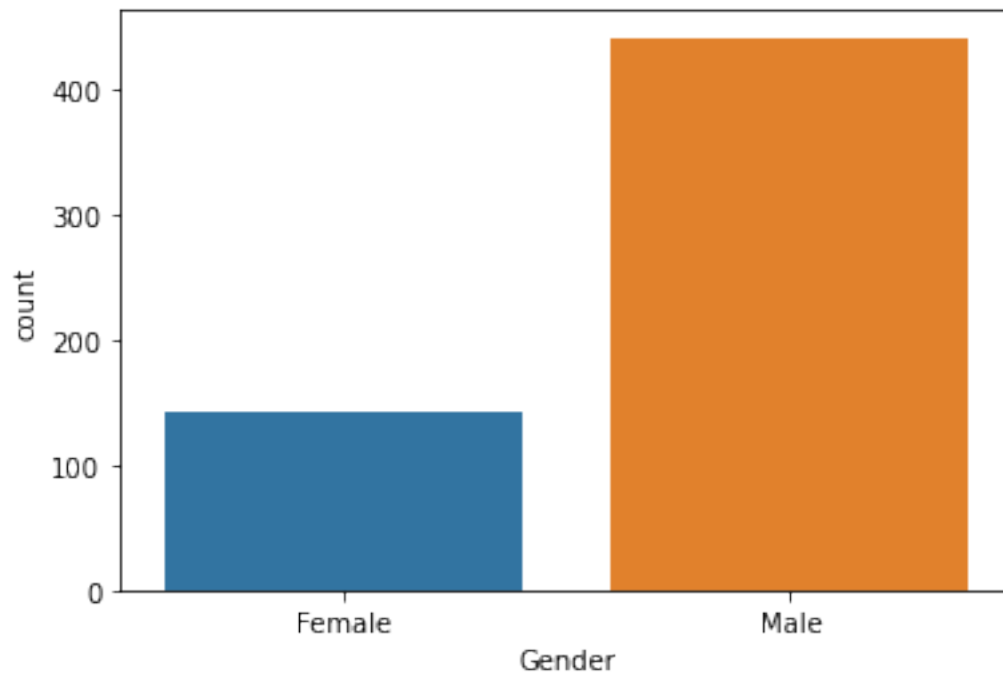
```
[6]: sns.countplot(data = data, x = "Dataset", label = "Count")
```

```
[6]: <AxesSubplot:xlabel='Dataset', ylabel='count'>
```



```
[7]: sns.countplot(data = data, x = "Gender", label = "Count")
```

```
[7]: <AxesSubplot:xlabel='Gender', ylabel='count'>
```



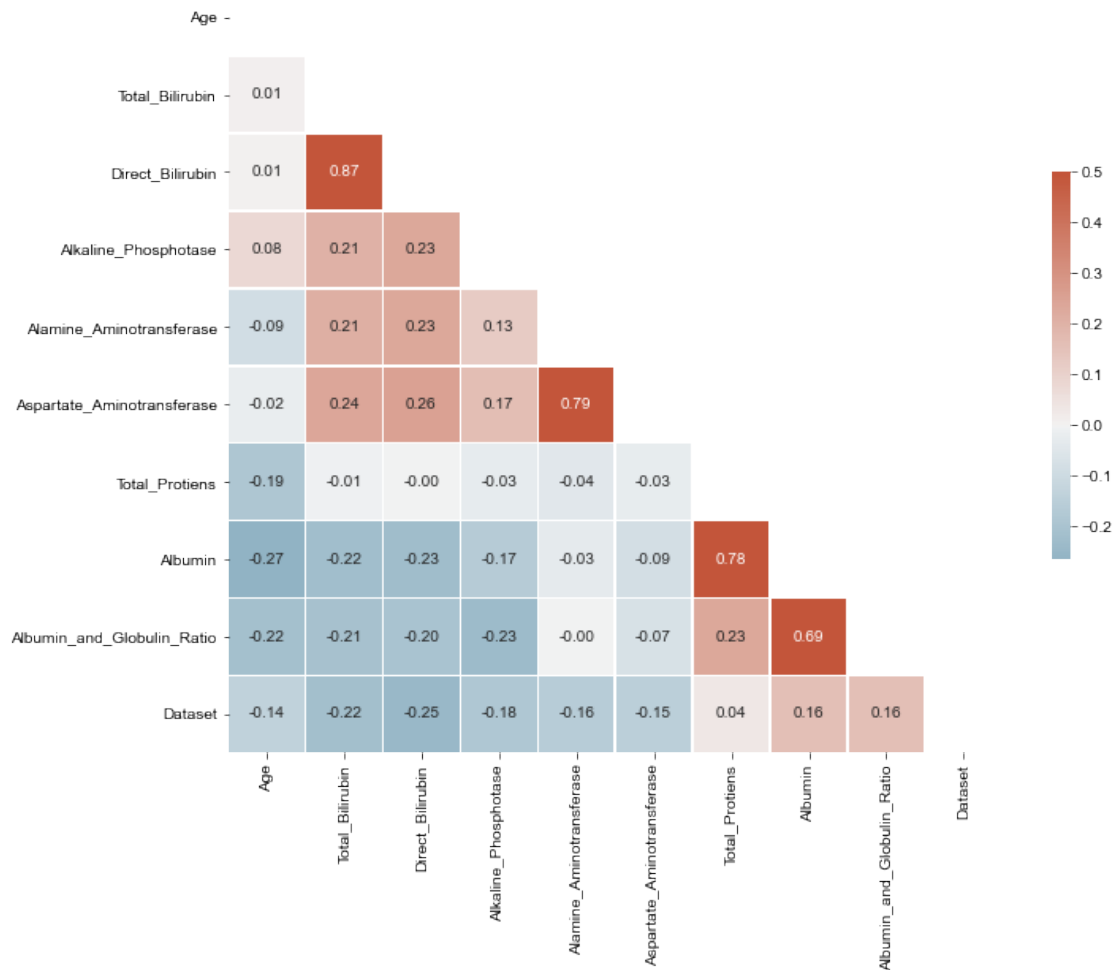
### Correlation Analysis

```
[8]: from string import ascii_letters
corr = data.corr()
# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.5, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5},
            annot=True, fmt='.2f')
sns.set(font_scale=1.1)
```



\*Two category columns: Age and Dataset(y value). In the Dataset 1 mean ill and 2 means healthy. Albumin\_and\_Globulin\_Ratio has missing values.

```
[9]: #Convert the Dataset columns into strings.
data['Dataset'].replace({1:'ill',2:'healthy'}, inplace=True)
# converts all string columns into category
data["Dataset"] = data["Dataset"].astype("category")
data["Gender"] = data["Gender"].astype("category")
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 583 entries, 0 to 582
Data columns (total 11 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Age                    583 non-null    int64
1   Gender                 583 non-null    category
```

```

2   Total_Bilirubin          583 non-null   float64
3   Direct_Bilirubin         583 non-null   float64
4   Alkaline_Phosphotase     583 non-null   int64
5   Alamine_Aminotransferase 583 non-null   int64
6   Aspartate_Aminotransferase 583 non-null   int64
7   Total_Protiens           583 non-null   float64
8   Albumin                  583 non-null   float64
9   Albumin_and_Globulin_Ratio 579 non-null   float64
10  Dataset                  583 non-null   category

```

dtypes: category(2), float64(5), int64(4)

memory usage: 42.4 KB

Label encoder

```

[10]: #label encoder
le = preprocessing.LabelEncoder()
le.fit(data['Gender'])
data['Gender_Encoded'] = le.transform(data['Gender'])

```

```

[11]: data.tail()

```

```

[11]:      Age  Gender  Total_Bilirubin  Direct_Bilirubin  Alkaline_Phosphotase  \
578   60   Male             0.5             0.1             500
579   40   Male             0.6             0.1             98
580   52   Male             0.8             0.2            245
581   31   Male             1.3             0.5            184
582   38   Male             1.0             0.3            216

      Alamine_Aminotransferase  Aspartate_Aminotransferase  Total_Protiens  \
578                        20                        34             5.9
579                        35                        31             6.0
580                        48                        49             6.4
581                        29                        32             6.8
582                        21                        24             7.3

      Albumin  Albumin_and_Globulin_Ratio  Dataset  Gender_Encoded
578        1.6                0.37  healthy         1
579        3.2                1.10    ill         1
580        3.2                1.00    ill         1
581        3.4                1.00    ill         1
582        4.4                1.50  healthy         1

```

Liver disease patients information

```

[12]: # Counting the number of patients
LD, NLD = data['Dataset'].value_counts()
print('Number of patients diagnosed with liver disease: ',LD)
print('Number of patients not diagnosed with liver disease: ',NLD)

```

```
Number of patients diagnosed with liver disease: 416
Number of patients not diagnosed with liver disease: 167
Ill patients in the dataset are 71.35506003430532 percent of the total
```

```
[13]: import scipy
from scipy.cluster import hierarchy as hc
# Redundant Features
corr = np.round(scipy.stats.spearmanr(data).correlation, 4)
corr_condensed = hc.distance.squareform(1-corr)
z = hc.linkage(corr_condensed, method='average')
fig = plt.figure(figsize=(16,10))
dendrogram = hc.dendrogram(z, labels=data.columns, orientation='left',
    ↪ leaf_font_size=16)
plt.show()
```



```
[15]: data
```

7

2	62	Male	7.3	4.1	490
3	58	Male	1.0	0.4	182
4	72	Male	3.9	2.0	195
..	...	...	...	...	...
578	60	Male	0.5	0.1	500
579	40	Male	0.6	0.1	98
580	52	Male	0.8	0.2	245
581	31	Male	1.3	0.5	184
582	38	Male	1.0	0.3	216

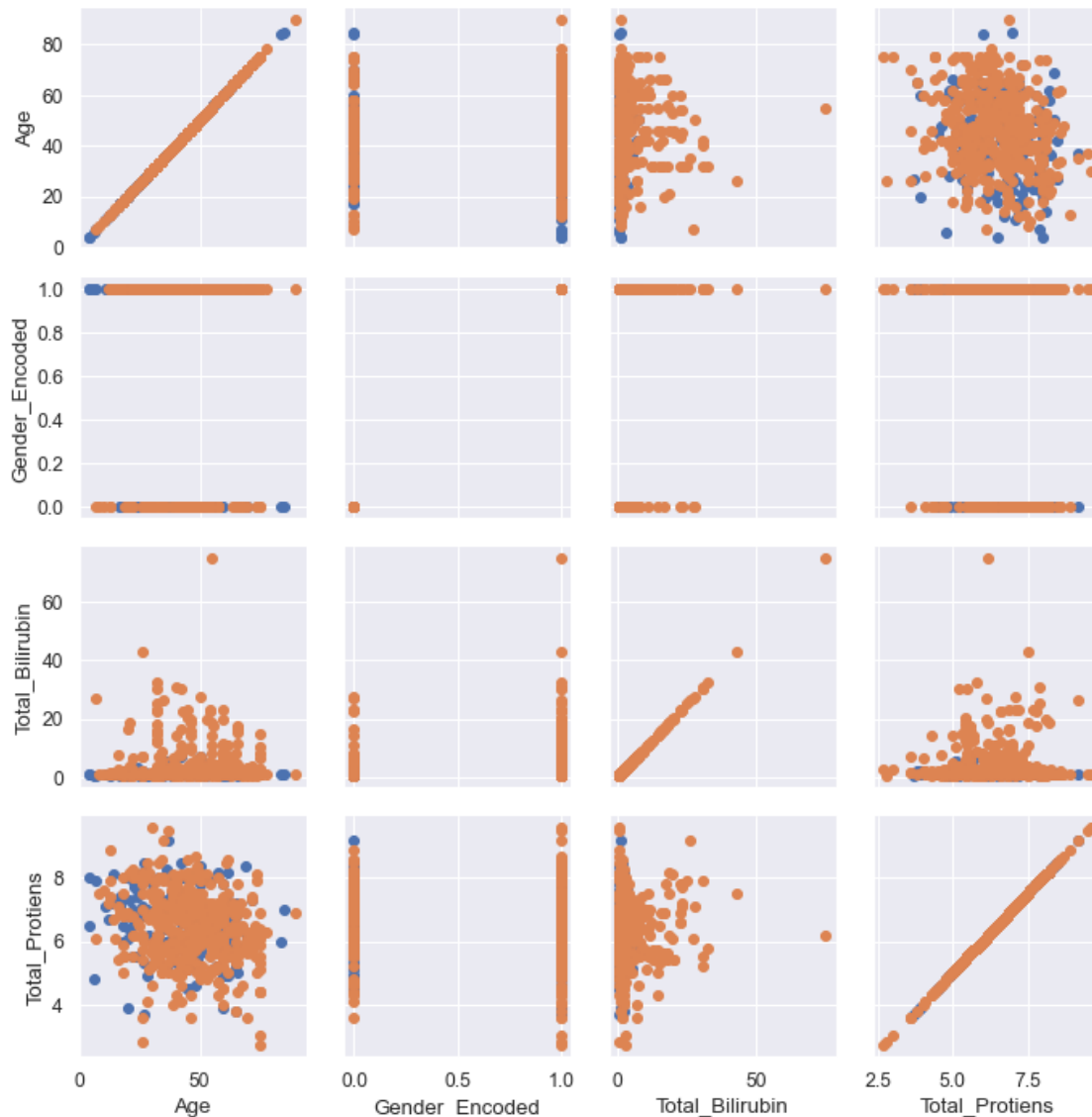
	Alamine_Aminotransferase	Aspartate_Aminotransferase	Total_Protiens	\
0	16	18	6.8	
1	64	100	7.5	
2	60	68	7.0	
3	14	20	6.8	
4	27	59	7.3	
..	...	...	...	
578	20	34	5.9	
579	35	31	6.0	
580	48	49	6.4	
581	29	32	6.8	
582	21	24	7.3	

	Albumin	Albumin_and_Globulin_Ratio	Dataset	Gender_Encoded
0	3.3	0.90	ill	0
1	3.2	0.74	ill	1
2	3.3	0.89	ill	1
3	3.4	1.00	ill	1
4	2.4	0.40	ill	1
..	...	...	...	...
578	1.6	0.37	healthy	1
579	3.2	1.10	ill	1
580	3.2	1.00	ill	1
581	3.4	1.00	ill	1
582	4.4	1.50	healthy	1

[583 rows x 12 columns]

```
[16]: g = sns.PairGrid(data, hue = "Dataset",
→vars=['Age', 'Gender_Encoded', 'Total_Bilirubin', 'Total_Protiens'])
g.map(plt.scatter)
plt.show()
```





Split train and test datasets

```
[17]: # machine learning - supervised
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import accuracy_score

[18]: X = data[['Age', 'Total_Bilirubin', 'Direct_Bilirubin', 'Alkaline_Phosphotase',
            'Alamine_Aminotransferase', 'Aspartate_Aminotransferase',
            ↪ 'Total_Protiens',
            'Albumin', 'Albumin_and_Globulin_Ratio', 'Gender_Encoded']]
y = data[['Dataset']]
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
↳stratify=y)
print(X_train.shape,X_test.shape)
```

(408, 10) (175, 10)

Random Forest Classifier

```
[19]: #Random Forest
rf = RandomForestClassifier(n_estimators=25, random_state=0)
rf.fit(X_train, y_train)
rf_predicted = rf.predict(X_test)

random_forest_score      = round(rf.score(X_train, y_train) * 100, 2)
random_forest_score_test = round(rf.score(X_test, y_test) * 100, 2)

print('Random Forest Score: ', random_forest_score)
print('Random Forest Test Score: ', random_forest_score_test)
print('Accuracy: ', (accuracy_score(y_test,rf_predicted)) *100,4)

# g = sns.heatmap(confusion_matrix(y_test,rf_predicted), annot=True, fmt="d")
```

Random Forest Score: 99.75

Random Forest Test Score: 72.0

Accuracy: 72.0 4

```
[20]: print('\nClassification report: \n', classification_report(y_test,rf_predicted))
```

Classification report:

	precision	recall	f1-score	support
healthy	0.52	0.34	0.41	50
ill	0.77	0.87	0.82	125
accuracy			0.72	175
macro avg	0.64	0.61	0.61	175
weighted avg	0.70	0.72	0.70	175

```
[21]: from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score

y_pred = rf.predict(X_test)
con_res = confusion_matrix(y_test,rf_predicted)
# con_res = metrics.confusion_matrix(y_test,y_pred, labels=[0, 1])
```

```
print("Confusion matrix:")
print(confusion_matrix(y_test,y_pred))
print("Accuracy: {:.2f}%".format(accuracy_score(y_test, y_pred)*100))
```

Confusion matrix:

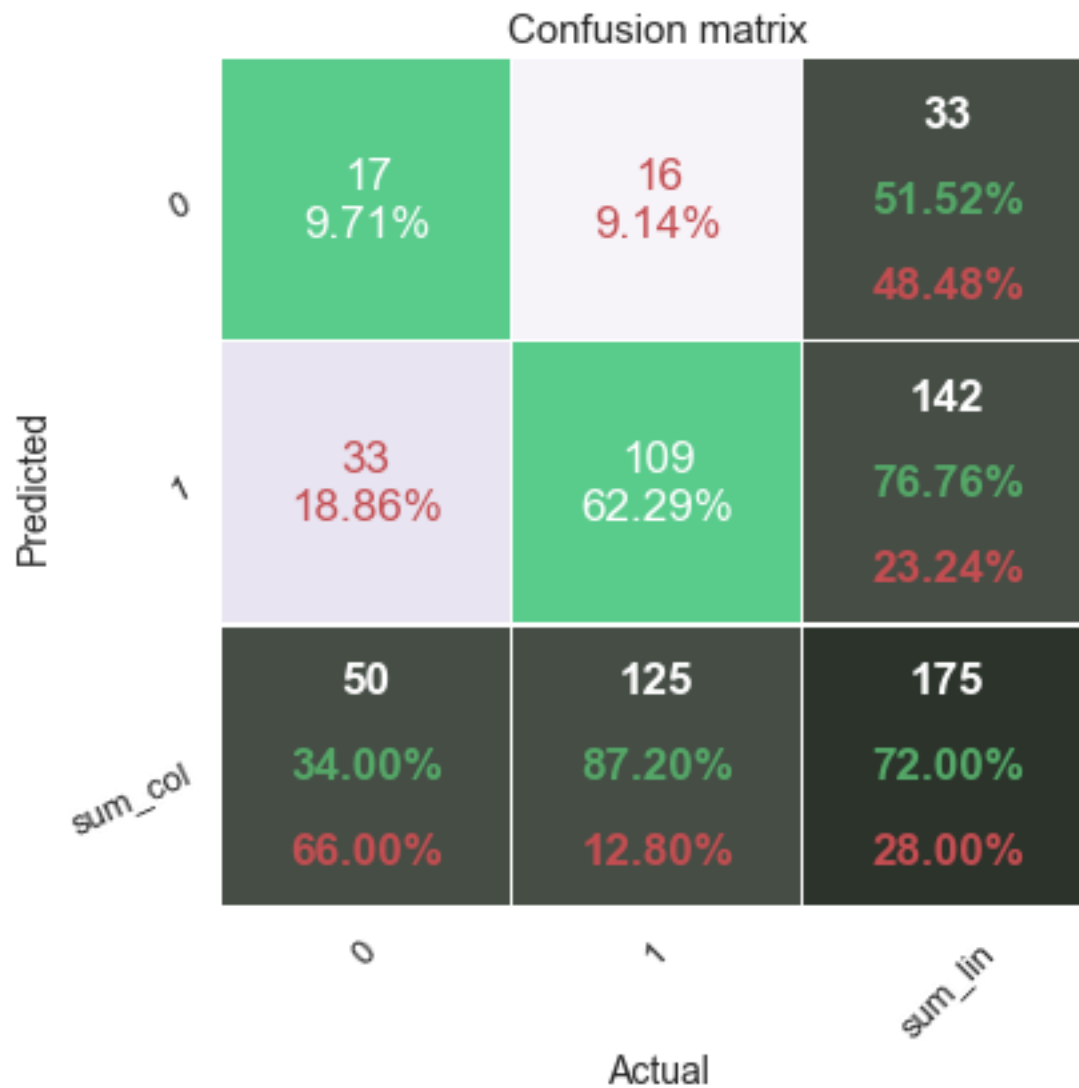
```
[[ 17  33]
```

```
 [ 16 109]]
```

Accuracy: 72.00%

```
[22]: # %run -i '/home/jayanthikishore/Desktop/Analysis/Work/ML_EIT/
      ↪confusion_matrix_different_ways1.py'
%run -i '/Users/preethamvignesh/Desktop/Work/ML_EIT/
      ↪confusion_matrix_different_ways1.py'

df_confmatrx = pd.DataFrame(con_res, range(2),range(2))
df_confmatrx
cmap = 'PuRd'
confusion_matrix_dfrntway(df_confmatrx, cmap=cmap,fz=17)
```



[ ]: