

# Ensemble Techniques And Its Types Assignment - 4

March 12, 2024

#

Question 1

**0.1 Question 1 : You are working on machine learning project where you have containing numerical and categorical features. You have identified that some features are highly correlated and there are missing values in some of the columns. You want to build a pipeline that automates feature engineering process and handles missing values.**

**0.1.1 Design a Pipeline that includes following steps:**

- Use an automated method to identify important features of dataset
- Use a numerical pipeline that includes following steps:
  - Impute missing values in numeric columns with mean
  - Scale the numerical columns using standardisation
- Create a categorical pipeline that includes following steps:
  - Impute missing values in categorical columns with most frequent data
  - One Hot Encode the categorical columns
- Combine the numerical and categorical pipelines using a ColumnTransformer
- Use Random Forest Classifier to build final model
- Evaluate accuracy of model on the test dataset

**0.2 ### Note : Your Solution should include code snippets for each step of pipeline and a brief explanation of each step. You should also provide an interpretation of results and suggest possible improvements for pipeline**

**0.3 Answer :**

**0.3.1 Used Employee Attrition dataset for performing above tasks**

Dataset link : <https://www.kaggle.com/datasets/pavansubhasht/ibm-hr-analytics-attrition-dataset/>

Uncover the factors that lead to employee attrition and explore important questions such as ‘show me a breakdown of distance from home by job role and attrition’ or ‘compare average monthly income by education and attrition’.

### 0.3.2 Read the dataset

```
[1]: import pandas as pd
df = pd.read_csv('Attrition.csv')
df.head()
```

```
[1]:   Age Attrition   BusinessTravel   DailyRate   Department \
0   41      Yes   Travel_Rarely     1102      Sales
1   49      No   Travel_Frequently     279  Research & Development
2   37      Yes   Travel_Rarely     1373  Research & Development
3   33      No   Travel_Frequently     1392  Research & Development
4   27      No   Travel_Rarely     591   Research & Development

   DistanceFromHome   Education   EducationField   EmployeeCount   EmployeeNumber \
0                1           2   Life Sciences             1           1
1                8           1   Life Sciences             1           2
2                2           2         Other             1           4
3                3           4   Life Sciences             1           5
4                2           1         Medical             1           7

   ... RelationshipSatisfaction   StandardHours   StockOptionLevel \
0   ...                1                80                0
1   ...                4                80                1
2   ...                2                80                0
3   ...                3                80                0
4   ...                4                80                1

   TotalWorkingYears   TrainingTimesLastYear   WorkLifeBalance   YearsAtCompany \
0                8                0                1                6
1               10                3                3               10
2                7                3                3                0
3                8                3                3                8
4                6                3                3                2

   YearsInCurrentRole   YearsSinceLastPromotion   YearsWithCurrManager
0                4                0                5
1                7                1                7
2                0                0                0
3                7                3                0
4                2                2                2
```

[5 rows x 35 columns]

```
[2]: df.shape
```

```
[2]: (1470, 35)
```

```
[3]: # Checking dataset info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Age                                   1470 non-null   int64
1   Attrition                           1470 non-null   object
2   BusinessTravel                       1470 non-null   object
3   DailyRate                           1470 non-null   int64
4   Department                           1470 non-null   object
5   DistanceFromHome                    1470 non-null   int64
6   Education                           1470 non-null   int64
7   EducationField                       1470 non-null   object
8   EmployeeCount                       1470 non-null   int64
9   EmployeeNumber                      1470 non-null   int64
10  EnvironmentSatisfaction              1470 non-null   int64
11  Gender                              1470 non-null   object
12  HourlyRate                          1470 non-null   int64
13  JobInvolvement                      1470 non-null   int64
14  JobLevel                            1470 non-null   int64
15  JobRole                             1470 non-null   object
16  JobSatisfaction                     1470 non-null   int64
17  MaritalStatus                       1470 non-null   object
18  MonthlyIncome                       1470 non-null   int64
19  MonthlyRate                         1470 non-null   int64
20  NumCompaniesWorked                  1470 non-null   int64
21  Over18                              1470 non-null   object
22  OverTime                            1470 non-null   object
23  PercentSalaryHike                   1470 non-null   int64
24  PerformanceRating                   1470 non-null   int64
25  RelationshipSatisfaction             1470 non-null   int64
26  StandardHours                       1470 non-null   int64
27  StockOptionLevel                    1470 non-null   int64
28  TotalWorkingYears                   1470 non-null   int64
29  TrainingTimesLastYear               1470 non-null   int64
30  WorkLifeBalance                     1470 non-null   int64
31  YearsAtCompany                      1470 non-null   int64
32  YearsInCurrentRole                  1470 non-null   int64
33  YearsSinceLastPromotion              1470 non-null   int64
34  YearsWithCurrManager                 1470 non-null   int64
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

```
[4]: # Checking missing values in dataset
df.isnull().sum()
```

```
[4]: Age                                0
Attrition                             0
BusinessTravel                        0
DailyRate                            0
Department                           0
DistanceFromHome                     0
Education                             0
EducationField                        0
EmployeeCount                         0
EmployeeNumber                       0
EnvironmentSatisfaction               0
Gender                                0
HourlyRate                            0
JobInvolvement                       0
JobLevel                             0
JobRole                              0
JobSatisfaction                      0
MaritalStatus                        0
MonthlyIncome                        0
MonthlyRate                          0
NumCompaniesWorked                   0
Over18                               0
OverTime                             0
PercentSalaryHike                    0
PerformanceRating                    0
RelationshipSatisfaction              0
StandardHours                        0
StockOptionLevel                     0
TotalWorkingYears                    0
TrainingTimesLastYear                0
WorkLifeBalance                      0
YearsAtCompany                       0
YearsInCurrentRole                   0
YearsSinceLastPromotion               0
YearsWithCurrManager                 0
dtype: int64
```

### 0.3.3 No Missing values found in dataset

### 0.3.4 Seperate X and Y

```
[5]: X = df.drop(labels=['Attrition'],axis=1)
Y = df[['Attrition']]
```

```
[6]: Y.head()
```

```
[6]: Attrition
0      Yes
1      No
2      Yes
3      No
4      No
```

```
[7]: y_mapper = {'Yes':1,'No':0}
Y = Y.replace(y_mapper)
Y.head()
```

```
[7]: Attrition
0      1
1      0
2      1
3      0
4      0
```

```
[8]: cat_cols = list(X.select_dtypes(include='object').columns)
num_cols = list(X.select_dtypes(exclude='object').columns)
```

```
[9]: cat_cols
```

```
[9]: ['BusinessTravel',
      'Department',
      'EducationField',
      'Gender',
      'JobRole',
      'MaritalStatus',
      'Over18',
      'OverTime']
```

```
[10]: num_cols
```

```
[10]: ['Age',
      'DailyRate',
      'DistanceFromHome',
      'Education',
      'EmployeeCount',
      'EmployeeNumber',
      'EnvironmentSatisfaction',
      'HourlyRate',
      'JobInvolvement',
      'JobLevel',
      'JobSatisfaction',
```

```
'MonthlyIncome',
'MonthlyRate',
'NumCompaniesWorked',
'PercentSalaryHike',
'PerformanceRating',
'RelationshipSatisfaction',
'StandardHours',
'StockOptionLevel',
'TotalWorkingYears',
'TrainingTimesLastYear',
'WorkLifeBalance',
'YearsAtCompany',
'YearsInCurrentRole',
'YearsSinceLastPromotion',
'YearsWithCurrManager']
```

```
[11]: len(num_cols)
```

```
[11]: 26
```

### 0.3.5 Feature selection for numerical columns

```
[12]: from warnings import filterwarnings
filterwarnings('ignore')
```

```
[13]: from sklearn.feature_selection import SelectKBest, f_classif
X_num = X[num_cols]
k_best_numerical = SelectKBest(f_classif,k=10)
k_best_numerical.fit_transform(X_num,Y)
selected_num_features = list(X_num.columns[k_best_numerical.get_support()])
selected_num_features
```

```
[13]: ['Age',
'JobInvolvement',
'JobLevel',
'JobSatisfaction',
'MonthlyIncome',
'StockOptionLevel',
'TotalWorkingYears',
'YearsAtCompany',
'YearsInCurrentRole',
'YearsWithCurrManager']
```

### 0.3.6 Feature Selection for categorical variables

```
[14]: from sklearn.feature_selection import SelectKBest, chi2
X_cat = X[cat_cols]
from sklearn.preprocessing import OrdinalEncoder
oe = OrdinalEncoder()
X_cat_encoded = pd.DataFrame(oe.fit_transform(X_cat), columns=oe.
    ↳ get_feature_names_out())
k_best_categorical = SelectKBest(chi2, k=5)
k_best_categorical.fit_transform(X_cat_encoded, Y)
selected_cat_features = list(X_cat_encoded.columns[k_best_categorical.
    ↳ get_support()])
selected_cat_features
```

```
[14]: ['Department', 'EducationField', 'JobRole', 'MaritalStatus', 'OverTime']
```

```
[15]: selected_features = selected_num_features + selected_cat_features
selected_features
```

```
[15]: ['Age',
      'JobInvolvement',
      'JobLevel',
      'JobSatisfaction',
      'MonthlyIncome',
      'StockOptionLevel',
      'TotalWorkingYears',
      'YearsAtCompany',
      'YearsInCurrentRole',
      'YearsWithCurrManager',
      'Department',
      'EducationField',
      'JobRole',
      'MaritalStatus',
      'OverTime']
```

```
[16]: X_selected = X[selected_features]
X_selected.head()
```

```
[16]:
```

	Age	JobInvolvement	JobLevel	JobSatisfaction	MonthlyIncome	\
0	41	3	2	4	5993	
1	49	2	2	2	5130	
2	37	2	1	3	2090	
3	33	3	1	3	2909	
4	27	3	1	2	3468	

	StockOptionLevel	TotalWorkingYears	YearsAtCompany	YearsInCurrentRole	\
0	0	8	6	4	

1	1	10	10	7
2	0	7	0	0
3	0	8	8	7
4	1	6	2	2

	YearsWithCurrManager	Department	EducationField	\
0	5	Sales	Life Sciences	
1	7	Research & Development	Life Sciences	
2	0	Research & Development	Other	
3	0	Research & Development	Life Sciences	
4	2	Research & Development	Medical	

	JobRole	MaritalStatus	OverTime
0	Sales Executive	Single	Yes
1	Research Scientist	Married	No
2	Laboratory Technician	Single	Yes
3	Research Scientist	Married	Yes
4	Laboratory Technician	Married	No

```
[17]: X_selected.shape
```

```
[17]: (1470, 15)
```

### 0.3.7 Feature Selection is completed

### 0.3.8 Train Test Split of data

```
[18]: from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(X_selected,Y,test_size=0.
↪2,random_state=42,stratify=Y)
```

```
[19]: xtrain.shape
```

```
[19]: (1176, 15)
```

```
[20]: xtest.shape
```

```
[20]: (294, 15)
```

```
[21]: ytrain.value_counts()
```

```
[21]: Attrition
0      986
1      190
dtype: int64
```

```
[22]: ytest.value_counts()
```



```
[22]: Attrition
      0          247
      1          47
      dtype: int64
```

### 0.3.9 Creating numeric and categorical pipeline

```
[23]: from sklearn.impute import SimpleImputer
      from sklearn.pipeline import Pipeline
      from sklearn.preprocessing import OneHotEncoder, StandardScaler

      # Numeric Pipeline creation
      num_pipeline = Pipeline(steps=[('imputer', SimpleImputer(strategy='mean')),
                                     ('scaler', StandardScaler())])

      # Categorical Pipeline creation
      cat_pipeline = Pipeline(steps=[('imputer', SimpleImputer(strategy='most_frequent')),
                                     ('one_hot_encoder', OneHotEncoder()),
                                     ('scaler', StandardScaler(with_mean=False))])
```

### 0.3.10 ColumnTransformer to combine numeric and Categorical pipelines

```
[24]: selected_num_features
```

```
[24]: ['Age',
      'JobInvolvement',
      'JobLevel',
      'JobSatisfaction',
      'MonthlyIncome',
      'StockOptionLevel',
      'TotalWorkingYears',
      'YearsAtCompany',
      'YearsInCurrentRole',
      'YearsWithCurrManager']
```

```
[25]: selected_cat_features
```

```
[25]: ['Department', 'EducationField', 'JobRole', 'MaritalStatus', 'OverTime']
```

```
[26]: from sklearn.compose import ColumnTransformer
      preprocessor = ColumnTransformer([('num_pipeline', num_pipeline, selected_num_features),
                                     ('cat_pipeline', cat_pipeline, selected_cat_features)])
```

### 0.3.11 Transform the dataset with ColumnTransformer

```
[27]: xtrain_transformed = pd.DataFrame(preprocessor.  
    ↪fit_transform(xtrain), columns=preprocessor.get_feature_names_out())  
xtest_transformed = pd.DataFrame(preprocessor.  
    ↪transform(xtest), columns=preprocessor.get_feature_names_out())
```

```
[28]: preprocessor.get_feature_names_out()
```

```
[28]: array(['num_pipeline__Age', 'num_pipeline__JobInvolvement',  
    'num_pipeline__JobLevel', 'num_pipeline__JobSatisfaction',  
    'num_pipeline__MonthlyIncome', 'num_pipeline__StockOptionLevel',  
    'num_pipeline__TotalWorkingYears', 'num_pipeline__YearsAtCompany',  
    'num_pipeline__YearsInCurrentRole',  
    'num_pipeline__YearsWithCurrManager',  
    'cat_pipeline__Department_Human Resources',  
    'cat_pipeline__Department_Research & Development',  
    'cat_pipeline__Department_Sales',  
    'cat_pipeline__EducationField_Human Resources',  
    'cat_pipeline__EducationField_Life Sciences',  
    'cat_pipeline__EducationField_Marketing',  
    'cat_pipeline__EducationField_Medical',  
    'cat_pipeline__EducationField_Other',  
    'cat_pipeline__EducationField_Technical Degree',  
    'cat_pipeline__JobRole_Healthcare Representative',  
    'cat_pipeline__JobRole_Human Resources',  
    'cat_pipeline__JobRole_Laboratory Technician',  
    'cat_pipeline__JobRole_Manager',  
    'cat_pipeline__JobRole_Manufacturing Director',  
    'cat_pipeline__JobRole_Research Director',  
    'cat_pipeline__JobRole_Research Scientist',  
    'cat_pipeline__JobRole_Sales Executive',  
    'cat_pipeline__JobRole_Sales Representative',  
    'cat_pipeline__MaritalStatus_Divorced',  
    'cat_pipeline__MaritalStatus_Married',  
    'cat_pipeline__MaritalStatus_Single', 'cat_pipeline__OverTime_No',  
    'cat_pipeline__OverTime_Yes'], dtype=object)
```

```
[29]: xtrain_transformed.head()
```

```
[29]:   num_pipeline__Age  num_pipeline__JobInvolvement  num_pipeline__JobLevel  \  
0          1.090194          1.795282          1.762189  \  
1         -1.634828          0.373564         -0.986265  \  
2          0.981193          0.373564          1.762189  \  
3         -1.307825          0.373564         -0.986265  \  
4          0.654191          0.373564         -0.070114
```

	num_pipeline__JobSatisfaction	num_pipeline__MonthlyIncome	\
0	-0.647997	2.026752	
1	1.153526	-0.864408	
2	0.252765	2.347706	
3	0.252765	-0.956202	
4	0.252765	-0.185956	

	num_pipeline__StockOptionLevel	num_pipeline__TotalWorkingYears	\
0	2.613100	2.261482	
1	0.247430	-1.072675	
2	0.247430	1.492061	
3	-0.935405	-0.559727	
4	0.247430	-0.175017	

	num_pipeline__YearsAtCompany	num_pipeline__YearsInCurrentRole	\
0	-0.665706	-0.625365	
1	-0.830071	-0.905635	
2	0.813578	1.336527	
3	-0.008246	-0.064824	
4	0.156119	0.775986	

	num_pipeline__YearsWithCurrManager	...	\
0	-0.616406	...	
1	-0.897047	...	
2	1.348076	...	
3	0.506155	...	
4	0.786795	...	

	cat_pipeline__JobRole_Manufacturing Director	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	

	cat_pipeline__JobRole_Research Director	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	

	cat_pipeline__JobRole_Research Scientist	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	

```

4                                0.0

cat_pipeline__JobRole_Sales Executive \
0                                0.0
1                                0.0
2                                0.0
3                                0.0
4                                0.0

cat_pipeline__JobRole_Sales Representative \
0                                0.000000
1                                0.000000
2                                0.000000
3                                4.544641
4                                0.000000

cat_pipeline__MaritalStatus_Divorced cat_pipeline__MaritalStatus_Married \
0                                2.399905                                0.000000
1                                0.000000                                2.006697
2                                0.000000                                2.006697
3                                0.000000                                2.006697
4                                2.399905                                0.000000

cat_pipeline__MaritalStatus_Single cat_pipeline__OverTime_No \
0                                0.0                                2.205793
1                                0.0                                2.205793
2                                0.0                                2.205793
3                                0.0                                2.205793
4                                0.0                                0.000000

cat_pipeline__OverTime_Yes
0                                0.000000
1                                0.000000
2                                0.000000
3                                0.000000
4                                2.205793

```

[5 rows x 33 columns]

```
[30]: xtest_transformed.head()
```

```

[30]: num_pipeline__Age num_pipeline__JobInvolvement num_pipeline__JobLevel \
0          -1.416826          0.373564          -0.986265
1           0.763191          1.795282          -0.986265
2          -0.653820         -1.048155           0.846038
3           0.763191          1.795282           2.678340
4          -0.108815         -1.048155          -0.986265

```

	num_pipeline__JobSatisfaction	num_pipeline__MonthlyIncome	\
0	-0.647997	-0.969745	
1	1.153526	-0.974474	
2	1.153526	1.077650	
3	-1.548758	2.718533	
4	0.252765	-0.678457	

	num_pipeline__StockOptionLevel	num_pipeline__TotalWorkingYears	\
0	0.247430	-1.329148	
1	0.247430	-0.175017	
2	0.247430	-0.175017	
3	1.430265	1.876772	
4	0.247430	-1.200911	

	num_pipeline__YearsAtCompany	num_pipeline__YearsInCurrentRole	\
0	-0.994436	-1.185905	
1	0.484849	0.215446	
2	-0.336976	-0.064824	
3	2.950322	1.336527	
4	-0.994436	-1.185905	

	num_pipeline__YearsWithCurrManager	...	\
0	-1.177687	...	
1	0.786795	...	
2	-0.897047	...	
3	2.470637	...	
4	-1.177687	...	

	cat_pipeline__JobRole_Manufacturing Director	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	

	cat_pipeline__JobRole_Research Director	\
0	0.0	
1	0.0	
2	0.0	
3	0.0	
4	0.0	

	cat_pipeline__JobRole_Research Scientist	\
0	0.000000	
1	2.564289	
2	0.000000	

```

3          0.000000
4          2.564289

cat_pipeline__JobRole_Sales Executive \
0          0.0
1          0.0
2          0.0
3          0.0
4          0.0

cat_pipeline__JobRole_Sales Representative \
0          4.544641
1          0.000000
2          0.000000
3          0.000000
4          0.000000

cat_pipeline__MaritalStatus_Divorced  cat_pipeline__MaritalStatus_Married \
0          0.000000          2.006697
1          0.000000          2.006697
2          2.399905          0.000000
3          2.399905          0.000000
4          0.000000          2.006697

cat_pipeline__MaritalStatus_Single  cat_pipeline__OverTime_No \
0          0.0          2.205793
1          0.0          2.205793
2          0.0          2.205793
3          0.0          2.205793
4          0.0          0.000000

cat_pipeline__OverTime_Yes
0          0.000000
1          0.000000
2          0.000000
3          0.000000
4          2.205793

[5 rows x 33 columns]

```

### 0.3.12 Training Random Forest

```
[31]: from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(n_estimators=100,max_depth=8,random_state=21)
rfc.fit(xtrain_transformed,ytrain)
```

```
[31]: RandomForestClassifier(max_depth=8, random_state=21)
```

```
[32]: from sklearn.model_selection import cross_val_score, StratifiedKFold
skf = StratifiedKFold(n_splits=5, shuffle=True)
scores =
    ↪ cross_val_score(rfc,xtrain_transformed,ytrain,cv=skf,scoring='accuracy')
scores
```

```
[32]: array([0.84322034, 0.84255319, 0.85957447, 0.86382979, 0.86808511])
```

```
[33]: import numpy as np
np.mean(scores)
```

```
[33]: 0.855452578434908
```

### 0.3.13 Hyperparameter Tuning

```
[34]: parameters = {
    'n_estimators': [10,50,100,200,300,400],
    'max_depth': [4,5,6,7,8,9,10],
    'min_samples_leaf': [2,3,4,5,6],
    'min_samples_split': [2,5,10]
}
```

```
[35]: from sklearn.model_selection import RandomizedSearchCV
rscv = RandomizedSearchCV(RandomForestClassifier(),
                           param_distributions=parameters,
                           cv=skf,
                           n_iter=50,
                           scoring='accuracy',
                           verbose=3)
```

```
[36]: rscv.fit(xtrain_transformed,ytrain)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
[CV 1/5] END max_depth=10, min_samples_leaf=5, min_samples_split=10,
n_estimators=300;; score=0.852 total time= 0.4s
[CV 2/5] END max_depth=10, min_samples_leaf=5, min_samples_split=10,
n_estimators=300;; score=0.864 total time= 0.4s
[CV 3/5] END max_depth=10, min_samples_leaf=5, min_samples_split=10,
n_estimators=300;; score=0.851 total time= 0.4s
[CV 4/5] END max_depth=10, min_samples_leaf=5, min_samples_split=10,
n_estimators=300;; score=0.860 total time= 0.4s
[CV 5/5] END max_depth=10, min_samples_leaf=5, min_samples_split=10,
n_estimators=300;; score=0.860 total time= 0.5s
[CV 1/5] END max_depth=8, min_samples_leaf=6, min_samples_split=10,
n_estimators=200;; score=0.864 total time= 0.3s
[CV 2/5] END max_depth=8, min_samples_leaf=6, min_samples_split=10,
n_estimators=200;; score=0.860 total time= 0.3s
```

[CV 3/5] END max\_depth=8, min\_samples\_leaf=6, min\_samples\_split=10,  
 n\_estimators=200;; score=0.855 total time= 0.3s  
 [CV 4/5] END max\_depth=8, min\_samples\_leaf=6, min\_samples\_split=10,  
 n\_estimators=200;; score=0.860 total time= 0.3s  
 [CV 5/5] END max\_depth=8, min\_samples\_leaf=6, min\_samples\_split=10,  
 n\_estimators=200;; score=0.860 total time= 0.2s  
 [CV 1/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=50;; score=0.864 total time= 0.0s  
 [CV 2/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=50;; score=0.860 total time= 0.0s  
 [CV 3/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=50;; score=0.851 total time= 0.0s  
 [CV 4/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=50;; score=0.847 total time= 0.0s  
 [CV 5/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=50;; score=0.860 total time= 0.0s  
 [CV 1/5] END max\_depth=6, min\_samples\_leaf=6, min\_samples\_split=2,  
 n\_estimators=10;; score=0.869 total time= 0.0s  
 [CV 2/5] END max\_depth=6, min\_samples\_leaf=6, min\_samples\_split=2,  
 n\_estimators=10;; score=0.855 total time= 0.0s  
 [CV 3/5] END max\_depth=6, min\_samples\_leaf=6, min\_samples\_split=2,  
 n\_estimators=10;; score=0.851 total time= 0.0s  
 [CV 4/5] END max\_depth=6, min\_samples\_leaf=6, min\_samples\_split=2,  
 n\_estimators=10;; score=0.860 total time= 0.0s  
 [CV 5/5] END max\_depth=6, min\_samples\_leaf=6, min\_samples\_split=2,  
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 [CV 1/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=2,  
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 [CV 2/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=200;; score=0.860 total time= 0.2s  
 [CV 3/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=200;; score=0.855 total time= 0.3s  
 [CV 4/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=200;; score=0.843 total time= 0.2s  
 [CV 5/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=200;; score=0.860 total time= 0.2s  
 [CV 1/5] END max\_depth=10, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=300;; score=0.869 total time= 0.4s  
 [CV 2/5] END max\_depth=10, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=300;; score=0.860 total time= 0.4s  
 [CV 3/5] END max\_depth=10, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=300;; score=0.851 total time= 0.5s  
 [CV 4/5] END max\_depth=10, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=300;; score=0.851 total time= 0.4s  
 [CV 5/5] END max\_depth=10, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=300;; score=0.864 total time= 0.5s  
 [CV 1/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=300;; score=0.864 total time= 0.4s



[CV 2/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=5,  
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 [CV 3/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=5,  
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 [CV 4/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=300;; score=0.851 total time= 0.4s  
 [CV 5/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=5,  
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 [CV 2/5] END max\_depth=9, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=100;; score=0.864 total time= 0.1s  
 [CV 3/5] END max\_depth=9, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=100;; score=0.855 total time= 0.1s  
 [CV 4/5] END max\_depth=9, min\_samples\_leaf=3, min\_samples\_split=2,  
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 [CV 5/5] END max\_depth=9, min\_samples\_leaf=3, min\_samples\_split=2,  
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 [CV 2/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
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 [CV 3/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
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 [CV 4/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=200;; score=0.851 total time= 0.3s  
 [CV 5/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=200;; score=0.860 total time= 0.3s  
 [CV 1/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=10,  
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 [CV 3/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=10,  
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 [CV 4/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=10,  
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 [CV 5/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=10,  
 n\_estimators=100;; score=0.860 total time= 0.1s  
 [CV 1/5] END max\_depth=9, min\_samples\_leaf=5, min\_samples\_split=2,  
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 [CV 2/5] END max\_depth=9, min\_samples\_leaf=5, min\_samples\_split=2,  
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 [CV 3/5] END max\_depth=9, min\_samples\_leaf=5, min\_samples\_split=2,  
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 [CV 4/5] END max\_depth=9, min\_samples\_leaf=5, min\_samples\_split=2,  
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 [CV 5/5] END max\_depth=9, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=50;; score=0.860 total time= 0.0s

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 [CV 2/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=10,  
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 [CV 3/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=10,  
 n\_estimators=100;; score=0.855 total time= 0.1s  
 [CV 4/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=10,  
 n\_estimators=100;; score=0.855 total time= 0.1s  
 [CV 5/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=10,  
 n\_estimators=100;; score=0.864 total time= 0.1s  
 [CV 1/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=2,  
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 [CV 2/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=2,  
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 [CV 3/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=2,  
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 [CV 4/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=2,  
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 [CV 5/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=2,  
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 [CV 1/5] END max\_depth=10, min\_samples\_leaf=3, min\_samples\_split=2,  
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 [CV 2/5] END max\_depth=10, min\_samples\_leaf=3, min\_samples\_split=2,  
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 [CV 3/5] END max\_depth=10, min\_samples\_leaf=3, min\_samples\_split=2,  
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 [CV 4/5] END max\_depth=10, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=300;; score=0.855 total time= 0.5s  
 [CV 5/5] END max\_depth=10, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=300;; score=0.860 total time= 0.5s  
 [CV 1/5] END max\_depth=7, min\_samples\_leaf=3, min\_samples\_split=2,  
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 [CV 2/5] END max\_depth=7, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=200;; score=0.855 total time= 0.2s  
 [CV 3/5] END max\_depth=7, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=200;; score=0.847 total time= 0.2s  
 [CV 4/5] END max\_depth=7, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=200;; score=0.860 total time= 0.3s  
 [CV 5/5] END max\_depth=7, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=200;; score=0.864 total time= 0.3s  
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 [CV 3/5] END max\_depth=9, min\_samples\_leaf=2, min\_samples\_split=10,  
 n\_estimators=50;; score=0.847 total time= 0.0s  
 [CV 4/5] END max\_depth=9, min\_samples\_leaf=2, min\_samples\_split=10,  
 n\_estimators=50;; score=0.851 total time= 0.0s

[CV 5/5] END max\_depth=9, min\_samples\_leaf=2, min\_samples\_split=10,  
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 [CV 2/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=2,  
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 [CV 3/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=50;; score=0.855 total time= 0.0s  
 [CV 4/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=50;; score=0.847 total time= 0.0s  
 [CV 5/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=50;; score=0.864 total time= 0.0s  
 [CV 1/5] END max\_depth=7, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=200;; score=0.860 total time= 0.3s  
 [CV 2/5] END max\_depth=7, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=200;; score=0.864 total time= 0.2s  
 [CV 3/5] END max\_depth=7, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=200;; score=0.855 total time= 0.2s  
 [CV 4/5] END max\_depth=7, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=200;; score=0.851 total time= 0.3s  
 [CV 5/5] END max\_depth=7, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=200;; score=0.860 total time= 0.3s  
 [CV 1/5] END max\_depth=6, min\_samples\_leaf=4, min\_samples\_split=10,  
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 [CV 2/5] END max\_depth=6, min\_samples\_leaf=4, min\_samples\_split=10,  
 n\_estimators=300;; score=0.860 total time= 0.4s  
 [CV 3/5] END max\_depth=6, min\_samples\_leaf=4, min\_samples\_split=10,  
 n\_estimators=300;; score=0.855 total time= 0.4s  
 [CV 4/5] END max\_depth=6, min\_samples\_leaf=4, min\_samples\_split=10,  
 n\_estimators=300;; score=0.847 total time= 0.4s  
 [CV 5/5] END max\_depth=6, min\_samples\_leaf=4, min\_samples\_split=10,  
 n\_estimators=300;; score=0.864 total time= 0.4s  
 [CV 1/5] END max\_depth=10, min\_samples\_leaf=3, min\_samples\_split=10,  
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 [CV 2/5] END max\_depth=10, min\_samples\_leaf=3, min\_samples\_split=10,  
 n\_estimators=100;; score=0.860 total time= 0.1s  
 [CV 3/5] END max\_depth=10, min\_samples\_leaf=3, min\_samples\_split=10,  
 n\_estimators=100;; score=0.851 total time= 0.1s  
 [CV 4/5] END max\_depth=10, min\_samples\_leaf=3, min\_samples\_split=10,  
 n\_estimators=100;; score=0.860 total time= 0.1s  
 [CV 5/5] END max\_depth=10, min\_samples\_leaf=3, min\_samples\_split=10,  
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 [CV 2/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=5,  
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 [CV 3/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=5,  
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[CV 4/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=5,  
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 [CV 5/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=5,  
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 [CV 1/5] END max\_depth=9, min\_samples\_leaf=3, min\_samples\_split=5,  
 n\_estimators=10;; score=0.869 total time= 0.0s  
 [CV 2/5] END max\_depth=9, min\_samples\_leaf=3, min\_samples\_split=5,  
 n\_estimators=10;; score=0.855 total time= 0.0s  
 [CV 3/5] END max\_depth=9, min\_samples\_leaf=3, min\_samples\_split=5,  
 n\_estimators=10;; score=0.847 total time= 0.0s  
 [CV 4/5] END max\_depth=9, min\_samples\_leaf=3, min\_samples\_split=5,  
 n\_estimators=10;; score=0.847 total time= 0.0s  
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 [CV 1/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=5,  
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 [CV 2/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=300;; score=0.855 total time= 0.4s  
 [CV 3/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=5,  
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 [CV 4/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=300;; score=0.851 total time= 0.4s  
 [CV 5/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=5,  
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 [CV 1/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=2,  
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 [CV 2/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=2,  
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 [CV 3/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=2,  
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 [CV 4/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=2,  
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 [CV 5/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=2,  
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 [CV 2/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=10,  
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[CV 3/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=10,  
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 [CV 5/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=10,  
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 [CV 1/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=10,  
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 [CV 4/5] END max\_depth=4, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=10;; score=0.843 total time= 0.0s  
 [CV 5/5] END max\_depth=4, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=10;; score=0.860 total time= 0.0s  
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 [CV 2/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=5,  
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 [CV 3/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=50;; score=0.851 total time= 0.0s  
 [CV 4/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=50;; score=0.855 total time= 0.0s  
 [CV 5/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=50;; score=0.860 total time= 0.0s  
 [CV 1/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=400;; score=0.869 total time= 0.5s

[CV 2/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=2,  
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 [CV 3/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=2,  
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 [CV 4/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=2,  
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 [CV 5/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=2,  
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 n\_estimators=100;; score=0.855 total time= 0.1s  
 [CV 5/5] END max\_depth=7, min\_samples\_leaf=5, min\_samples\_split=10,  
 n\_estimators=100;; score=0.860 total time= 0.1s  
 [CV 1/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=100;; score=0.877 total time= 0.1s  
 [CV 2/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=100;; score=0.855 total time= 0.1s  
 [CV 3/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=100;; score=0.855 total time= 0.1s  
 [CV 4/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=100;; score=0.851 total time= 0.1s  
 [CV 5/5] END max\_depth=5, min\_samples\_leaf=2, min\_samples\_split=5,  
 n\_estimators=100;; score=0.855 total time= 0.1s  
 [CV 1/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=100;; score=0.856 total time= 0.1s  
 [CV 2/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=100;; score=0.860 total time= 0.1s  
 [CV 3/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=100;; score=0.851 total time= 0.1s  
 [CV 4/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=100;; score=0.851 total time= 0.1s  
 [CV 5/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=100;; score=0.864 total time= 0.1s  
 [CV 1/5] END max\_depth=4, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=100;; score=0.864 total time= 0.0s  
 [CV 2/5] END max\_depth=4, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=100;; score=0.860 total time= 0.0s  
 [CV 3/5] END max\_depth=4, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=100;; score=0.855 total time= 0.1s  
 [CV 4/5] END max\_depth=4, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=100;; score=0.855 total time= 0.0s  
 [CV 5/5] END max\_depth=4, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=100;; score=0.855 total time= 0.1s

[CV 1/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=10,  
 n\_estimators=200;; score=0.864 total time= 0.2s  
 [CV 2/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=10,  
 n\_estimators=200;; score=0.860 total time= 0.2s  
 [CV 3/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=10,  
 n\_estimators=200;; score=0.851 total time= 0.2s  
 [CV 4/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=10,  
 n\_estimators=200;; score=0.847 total time= 0.2s  
 [CV 5/5] END max\_depth=4, min\_samples\_leaf=3, min\_samples\_split=10,  
 n\_estimators=200;; score=0.855 total time= 0.2s  
 [CV 1/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=2,  
 n\_estimators=10;; score=0.873 total time= 0.0s  
 [CV 2/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=2,  
 n\_estimators=10;; score=0.855 total time= 0.0s  
 [CV 3/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=2,  
 n\_estimators=10;; score=0.860 total time= 0.0s  
 [CV 4/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=2,  
 n\_estimators=10;; score=0.834 total time= 0.0s  
 [CV 5/5] END max\_depth=9, min\_samples\_leaf=4, min\_samples\_split=2,  
 n\_estimators=10;; score=0.855 total time= 0.0s  
 [CV 1/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=10,  
 n\_estimators=200;; score=0.856 total time= 0.2s  
 [CV 2/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=10,  
 n\_estimators=200;; score=0.864 total time= 0.2s  
 [CV 3/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=10,  
 n\_estimators=200;; score=0.855 total time= 0.2s  
 [CV 4/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=10,  
 n\_estimators=200;; score=0.851 total time= 0.2s  
 [CV 5/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=10,  
 n\_estimators=200;; score=0.855 total time= 0.2s  
 [CV 1/5] END max\_depth=10, min\_samples\_leaf=4, min\_samples\_split=2,  
 n\_estimators=400;; score=0.856 total time= 0.6s  
 [CV 2/5] END max\_depth=10, min\_samples\_leaf=4, min\_samples\_split=2,  
 n\_estimators=400;; score=0.864 total time= 0.6s  
 [CV 3/5] END max\_depth=10, min\_samples\_leaf=4, min\_samples\_split=2,  
 n\_estimators=400;; score=0.851 total time= 0.6s  
 [CV 4/5] END max\_depth=10, min\_samples\_leaf=4, min\_samples\_split=2,  
 n\_estimators=400;; score=0.855 total time= 0.6s  
 [CV 5/5] END max\_depth=10, min\_samples\_leaf=4, min\_samples\_split=2,  
 n\_estimators=400;; score=0.864 total time= 0.6s  
 [CV 1/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=2,  
 n\_estimators=10;; score=0.852 total time= 0.0s  
 [CV 2/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=2,  
 n\_estimators=10;; score=0.851 total time= 0.0s  
 [CV 3/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=2,  
 n\_estimators=10;; score=0.855 total time= 0.0s  
 [CV 4/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=2,  
 n\_estimators=10;; score=0.834 total time= 0.0s

[CV 5/5] END max\_depth=6, min\_samples\_leaf=2, min\_samples\_split=2,  
 n\_estimators=10;; score=0.872 total time= 0.0s  
 [CV 1/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=400;; score=0.856 total time= 0.6s  
 [CV 2/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=400;; score=0.864 total time= 0.6s  
 [CV 3/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=400;; score=0.855 total time= 0.6s  
 [CV 4/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=400;; score=0.855 total time= 0.6s  
 [CV 5/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=400;; score=0.860 total time= 0.6s  
 [CV 1/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=10;; score=0.856 total time= 0.0s  
 [CV 2/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=10;; score=0.868 total time= 0.0s  
 [CV 3/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=10;; score=0.855 total time= 0.0s  
 [CV 4/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=10;; score=0.864 total time= 0.0s  
 [CV 5/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=10;; score=0.855 total time= 0.0s  
 [CV 1/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=50;; score=0.873 total time= 0.0s  
 [CV 2/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=50;; score=0.855 total time= 0.0s  
 [CV 3/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=50;; score=0.855 total time= 0.0s  
 [CV 4/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=50;; score=0.860 total time= 0.0s  
 [CV 5/5] END max\_depth=8, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=50;; score=0.860 total time= 0.0s  
 [CV 1/5] END max\_depth=5, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=200;; score=0.856 total time= 0.2s  
 [CV 2/5] END max\_depth=5, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=200;; score=0.864 total time= 0.2s  
 [CV 3/5] END max\_depth=5, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=200;; score=0.855 total time= 0.2s  
 [CV 4/5] END max\_depth=5, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=200;; score=0.851 total time= 0.2s  
 [CV 5/5] END max\_depth=5, min\_samples\_leaf=3, min\_samples\_split=2,  
 n\_estimators=200;; score=0.864 total time= 0.2s  
 [CV 1/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=10;; score=0.864 total time= 0.0s  
 [CV 2/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=10;; score=0.864 total time= 0.0s  
 [CV 3/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=10;; score=0.855 total time= 0.0s



[CV 4/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=10;; score=0.847 total time= 0.0s  
 [CV 5/5] END max\_depth=6, min\_samples\_leaf=5, min\_samples\_split=2,  
 n\_estimators=10;; score=0.868 total time= 0.0s  
 [CV 1/5] END max\_depth=4, min\_samples\_leaf=6, min\_samples\_split=10,  
 n\_estimators=10;; score=0.869 total time= 0.0s  
 [CV 2/5] END max\_depth=4, min\_samples\_leaf=6, min\_samples\_split=10,  
 n\_estimators=10;; score=0.847 total time= 0.0s  
 [CV 3/5] END max\_depth=4, min\_samples\_leaf=6, min\_samples\_split=10,  
 n\_estimators=10;; score=0.851 total time= 0.0s  
 [CV 4/5] END max\_depth=4, min\_samples\_leaf=6, min\_samples\_split=10,  
 n\_estimators=10;; score=0.843 total time= 0.0s  
 [CV 5/5] END max\_depth=4, min\_samples\_leaf=6, min\_samples\_split=10,  
 n\_estimators=10;; score=0.860 total time= 0.0s  
 [CV 1/5] END max\_depth=5, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=10;; score=0.852 total time= 0.0s  
 [CV 2/5] END max\_depth=5, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=10;; score=0.847 total time= 0.0s  
 [CV 3/5] END max\_depth=5, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=10;; score=0.834 total time= 0.0s  
 [CV 4/5] END max\_depth=5, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=10;; score=0.843 total time= 0.0s  
 [CV 5/5] END max\_depth=5, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=10;; score=0.855 total time= 0.0s  
 [CV 1/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=10;; score=0.860 total time= 0.0s  
 [CV 2/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=10;; score=0.864 total time= 0.0s  
 [CV 3/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=10;; score=0.855 total time= 0.0s  
 [CV 4/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=10;; score=0.847 total time= 0.0s  
 [CV 5/5] END max\_depth=5, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=10;; score=0.855 total time= 0.0s  
 [CV 1/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=100;; score=0.860 total time= 0.1s  
 [CV 2/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=100;; score=0.860 total time= 0.1s  
 [CV 3/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=100;; score=0.860 total time= 0.1s  
 [CV 4/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=100;; score=0.855 total time= 0.1s  
 [CV 5/5] END max\_depth=8, min\_samples\_leaf=5, min\_samples\_split=5,  
 n\_estimators=100;; score=0.864 total time= 0.1s  
 [CV 1/5] END max\_depth=6, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=100;; score=0.873 total time= 0.1s  
 [CV 2/5] END max\_depth=6, min\_samples\_leaf=4, min\_samples\_split=5,  
 n\_estimators=100;; score=0.864 total time= 0.1s

```
[36]: RandomizedSearchCV(cv=StratifiedKFold(n_splits=5, random_state=None,
shuffle=True),
estimator=RandomForestClassifier(), n_iter=50,
param_distributions={'max_depth': [4, 5, 6, 7, 8, 9, 10],
'min_samples_leaf': [2, 3, 4, 5, 6],
'min_samples_split': [2, 5, 10],
'n_estimators': [10, 50, 100, 200, 300,
400]}),
scoring='accuracy', verbose=3)
```

```
[37]: {'n_estimators': 100,
      'min_samples_split': 2,
      'min_samples_leaf': 3,
      'max_depth': 9}
```

```
[38]: 0.8630869094843131
```

```
[39]: RandomForestClassifier(max_depth=9, min_samples_leaf=3)
```

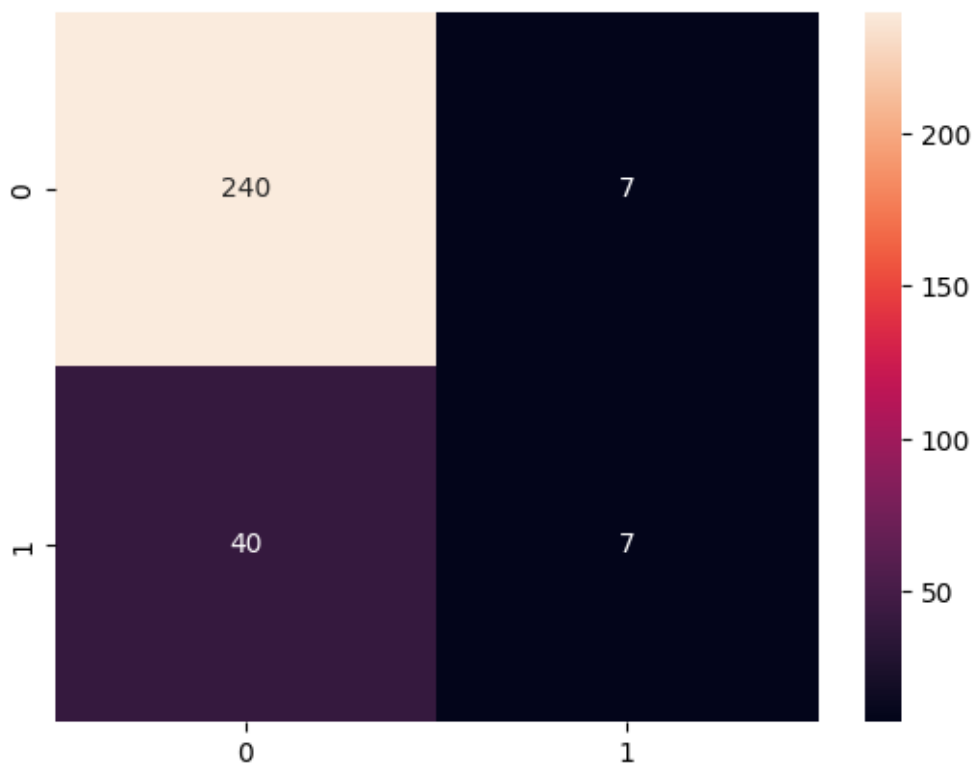
```
[40]: ypred_test = best_rfc.predict(xtest_transformed)
      ypred_test
```

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```
0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0], dtype=int64)
```

```
[41]: from sklearn.metrics import confusion_matrix
import seaborn as sns
cf = confusion_matrix(ytest, ypred_test)
sns.heatmap(cf,annot=True,fmt='d')
```

[41]: <Axes: >



```
[42]: from sklearn.metrics import accuracy_score
acc = accuracy_score(ytest, ypred_test)
print(f'Accuracy on testing data is {acc:.4f}')
```

Accuracy on testing data is 0.8401

### 0.3.15 Insights

1. Above model has accuracy of 0.8503 on testing data
2. However above data has imbalance data on target

3. To deal with imbalanced techniques such as SMOTE (Synthetic Minority Oversampling TEchnique)
4. Feature selection can also be avoided in above data and performance should be checked with all features as well

#

Question 2

**0.4 ## Question 2 : Build a pipeline that includes random forest classifier and a logistic regression classifier , and then voting classifier to combine their predictions. Train the pipeline on iris dataset and evaluate its accuracy**

**0.5 Answer :**

**0.5.1 Load Iris Dataset**

```
[43]: from sklearn.datasets import load_iris  
X,Y = load_iris(return_X_y=True)
```

```
[44]: X.shape
```

```
[44]: (150, 4)
```

```
[45]: Y.shape
```

```
[45]: (150,)
```

**0.5.2 Train Test Split**

```
[46]: from sklearn.model_selection import train_test_split  
xtrain, xtest, ytrain, ytest = train_test_split(X,Y,test_size=0.  
↪3,random_state=42)
```

```
[47]: xtrain.shape
```

```
[47]: (105, 4)
```

```
[48]: xtest.shape
```

```
[48]: (45, 4)
```

**0.5.3 Standard Scaling**

```
[49]: from sklearn.preprocessing import StandardScaler  
scaler = StandardScaler()  
xtrain = scaler.fit_transform(xtrain)  
xtest = scaler.transform(xtest)
```

#### 0.5.4 Create pipeline

```
[58]: from sklearn.pipeline import Pipeline
      from sklearn.ensemble import RandomForestClassifier
      from sklearn.linear_model import LogisticRegression
      from sklearn.ensemble import VotingClassifier
      from sklearn.preprocessing import StandardScaler

      # Defining Base models
      rfc = RandomForestClassifier(n_estimators=100,max_depth=4)
      lr = LogisticRegression(C=1.0)

      # Voting Classifier Pipeline
      vc = VotingClassifier(estimators=[('rfc',rfc),
                                       ('lr',lr)],
                           voting='soft')
```

```
[59]: vc.fit(xtrain,ytrain)
```

```
[59]: VotingClassifier(estimators=[('rfc', RandomForestClassifier(max_depth=4)),
                                   ('lr', LogisticRegression())],
                       voting='soft')
```

#### 0.5.5 Predicting the test results

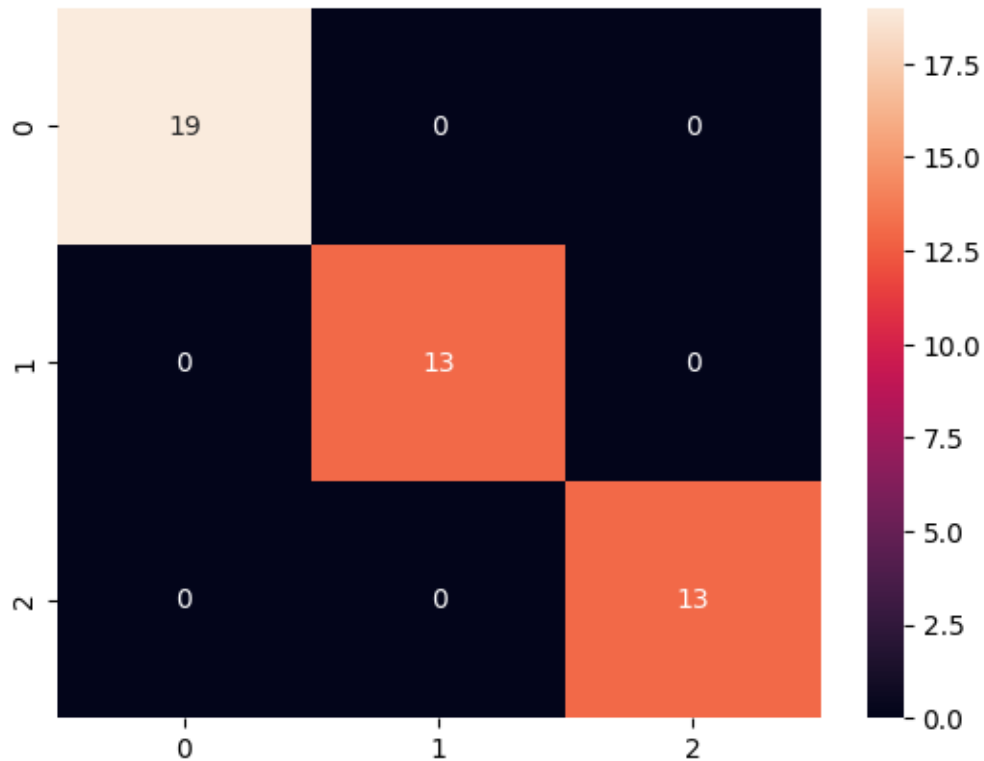
```
[61]: ypred_test = vc.predict(xtest)
      ypred_test
```

```
[61]: array([1, 0, 2, 1, 1, 0, 1, 2, 1, 1, 2, 0, 0, 0, 0, 1, 2, 1, 1, 2, 0, 2,
           0, 2, 2, 2, 2, 2, 0, 0, 0, 0, 1, 0, 0, 2, 1, 0, 0, 0, 2, 1, 1, 0,
           0])
```

#### 0.5.6 Evaluating the model on test data

```
[62]: from sklearn.metrics import confusion_matrix
      import seaborn as sns
      cf = confusion_matrix(ytest,ypred_test)
      sns.heatmap(cf,annot=True,fmt='d')
```

```
[62]: <Axes: >
```



```
[63]: # Classification Report
from sklearn.metrics import classification_report
print(classification_report(ytest,ypred_test))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	1.00	1.00	13
2	1.00	1.00	1.00	13
accuracy			1.00	45
macro avg	1.00	1.00	1.00	45
weighted avg	1.00	1.00	1.00	45

```
[64]: # Accuracy Score
from sklearn.metrics import accuracy_score
acc = accuracy_score(ytest,ypred_test)
print(f'Accuracy on Final Voting Classifier model is {acc*100:.2f}%')
```

Accuracy on Final Voting Classifier model is 100.00%