assignment-3

April 15, 2024

1 Name: Sourabh Barala

2 Course: M.Sc. Data Science

3 Year: 1st

4 Reg. No.: 23MSD7044

5 Subject: Machine Learning and its Applications

6

7

8

9

10

11

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier,␣
 ↪AdaBoostClassifier, GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
```

```
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
import xgboost as xgb
from sklearn.model_selection import KFold, cross_val_score
```

[2]:
```
titanic=pd.read_csv('archive/tested.csv')
```

[3]:
```
titanic.head(5)
```

[3]:
```
   PassengerId  Survived  Pclass  \
0          892         0       3
1          893         1       3
2          894         0       2
3          895         0       3
4          896         1       3

                                          Name     Sex   Age  SibSp  Parch  \
0                              Kelly, Mr. James    male  34.5      0      0
1              Wilkes, Mrs. James (Ellen Needs)  female  47.0      1      0
2                     Myles, Mr. Thomas Francis    male  62.0      0      0
3                              Wirz, Mr. Albert    male  27.0      0      0
4  Hirvonen, Mrs. Alexander (Helga E Lindqvist)  female  22.0      1      1

    Ticket     Fare Cabin Embarked
0   330911   7.8292   NaN        Q
1   363272   7.0000   NaN        S
2   240276   9.6875   NaN        Q
3   315154   8.6625   NaN        S
4  3101298  12.2875   NaN        S
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  418 non-null    int64
 1   Survived     418 non-null    int64
 2   Pclass       418 non-null    int64
 3   Name         418 non-null    object
 4   Sex          418 non-null    object
 5   Age          332 non-null    float64
 6   SibSp        418 non-null    int64
 7   Parch        418 non-null    int64
 8   Ticket       418 non-null    object
 9   Fare         417 non-null    float64
```

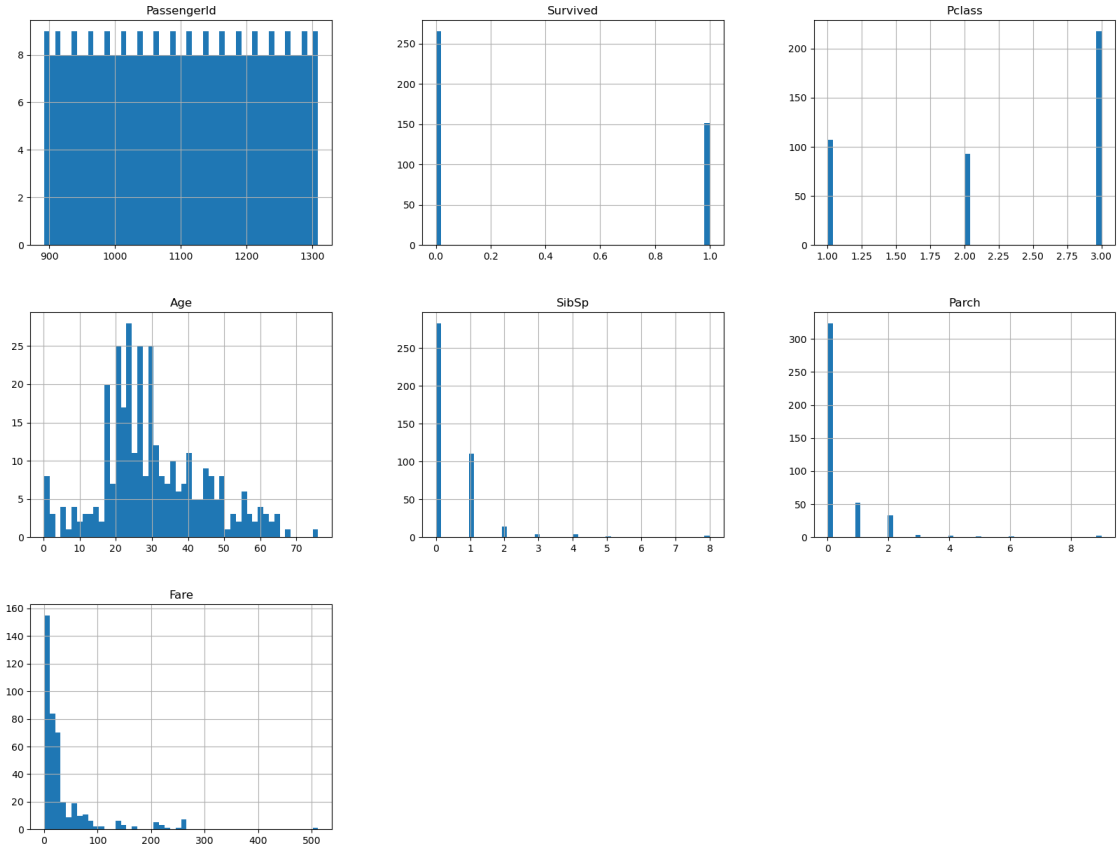
```
 10  Cabin        91 non-null     object
 11  Embarked     418 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 39.3+ KB
```

[5]:
```
titanic.describe()
```

[5]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	418.000000	418.000000	418.000000	332.000000	418.000000	418.000000	417.000000
mean	1100.500000	0.363636	2.265550	30.272590	0.447368	0.392344	35.627188
std	120.810458	0.481622	0.841838	14.181209	0.896760	0.981429	55.907576
min	892.000000	0.000000	1.000000	0.170000	0.000000	0.000000	0.000000
25%	996.250000	0.000000	1.000000	21.000000	0.000000	0.000000	7.895800
50%	1100.500000	0.000000	3.000000	27.000000	0.000000	0.000000	14.454200
75%	1204.750000	1.000000	3.000000	39.000000	1.000000	0.000000	31.500000
max	1309.000000	1.000000	3.000000	76.000000	8.000000	9.000000	512.329200

[6]:
```
titanic.hist(bins=50,figsize=(20,15))
plt.show()
```



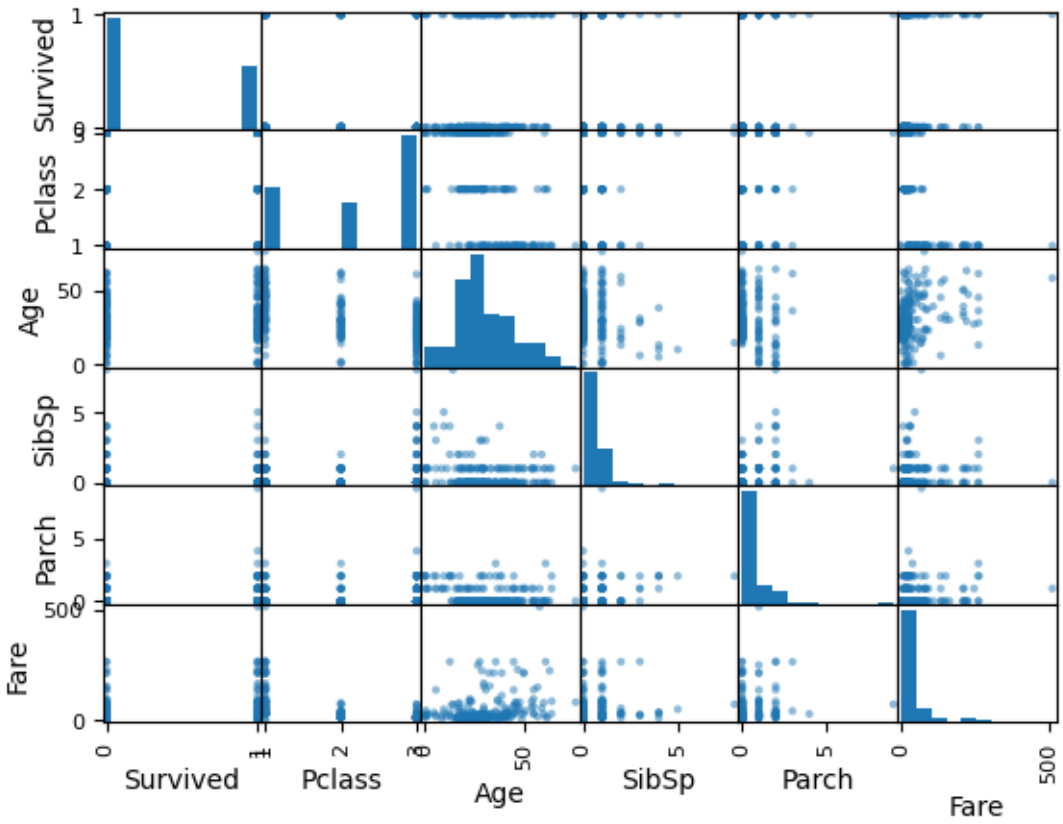
[7]:
```
train_set,test_set=train_test_split(titanic,random_state=100,test_size=0.
↪3,stratify=titanic['Survived'])

titanic=train_set.copy()
```

[8]:
```
numeric_cols=['Survived','Pclass','Age','SibSp','Parch','Fare']
```

[9]:
```
titanic[numeric_cols].corr()['Survived']
```

[9]:
```
Survived    1.000000
Pclass     -0.108371
Age         0.054808
SibSp       0.052525
Parch       0.213548
Fare        0.204776
Name: Survived, dtype: float64
```

[10]:
```
pd.plotting.scatter_matrix(titanic[numeric_cols])
plt.show()
```



[11]:
```
labels,category=pd.factorize(titanic['Embarked'])
labels2,category2=pd.factorize(titanic['Sex'])
labels3,category3=pd.factorize(titanic['Cabin'])
```

[ ]:
```

```

[12]:
```
titanic['embarked_num']=labels
titanic['Sex_num']=labels2
titanic['cabin_num']=labels3
```

[13]:
```
numeric_cols.extend(['embarked_num','Sex_num','cabin_num'])
```

[14]:
```
titanic[numeric_cols].corr()
```

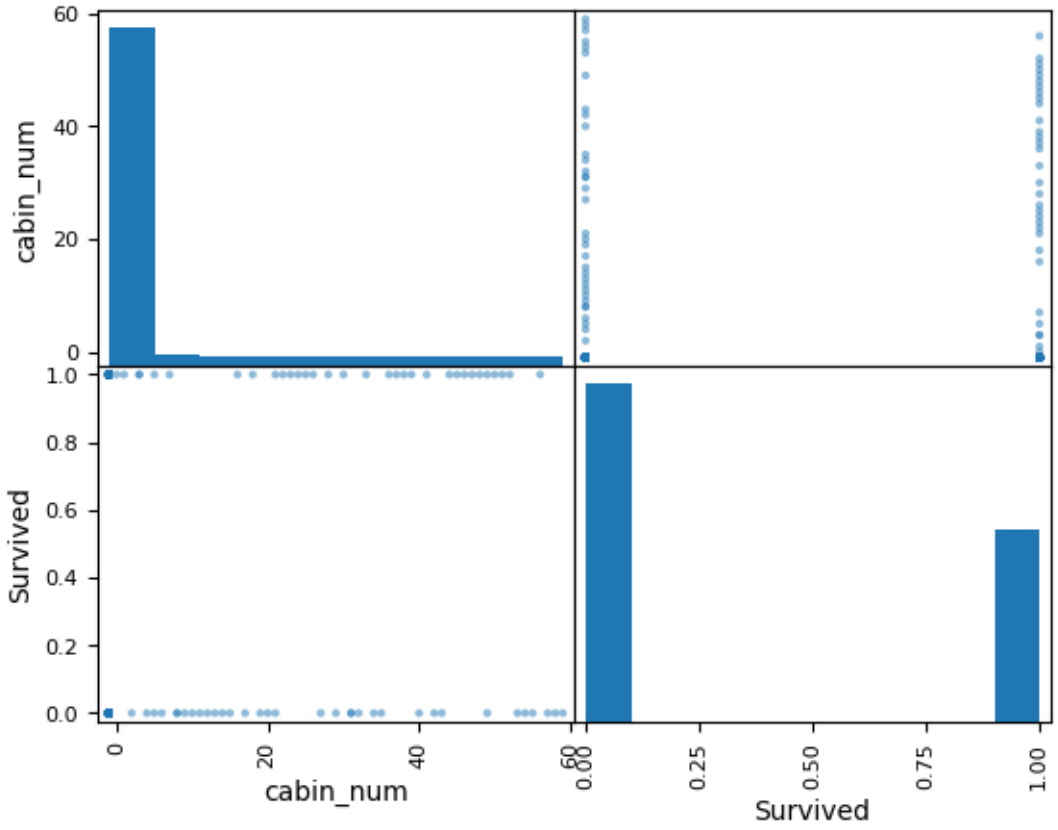
[14]:

	Survived	Pclass	Age	SibSp	Parch	Fare
Survived	1.000000	-0.108371	0.054808	0.052525	0.213548	0.204776
Pclass	-0.108371	1.000000	-0.545526	0.028740	0.037316	-0.569527
Age	0.054808	-0.545526	1.000000	-0.133935	-0.167283	0.308094
SibSp	0.052525	0.028740	-0.133935	1.000000	0.356761	0.140274
Parch	0.213548	0.037316	-0.167283	0.356761	1.000000	0.191723

```
Fare          0.204776 -0.569527  0.308094  0.140274  0.191723  1.000000
embarked_num  0.139645  0.043861  0.131046 -0.106346 -0.108267  0.055062
Sex_num       1.000000 -0.108371  0.054808  0.052525  0.213548  0.204776
cabin_num     0.137130 -0.604828  0.390074  0.059850  0.086654  0.583569
```

```
              embarked_num   Sex_num  cabin_num
Survived          0.139645  1.000000   0.137130
Pclass            0.043861 -0.108371  -0.604828
Age               0.131046  0.054808   0.390074
SibSp            -0.106346  0.052525   0.059850
Parch            -0.108267  0.213548   0.086654
Fare              0.055062  0.204776   0.583569
embarked_num      1.000000  0.139645   0.027665
Sex_num           0.139645  1.000000   0.137130
cabin_num         0.027665  0.137130   1.000000
```

[15]:
```
pd.plotting.scatter_matrix(titanic[['cabin_num','Survived']])
plt.show()
```



[16]:
```
train_para=train_set.
 ↪drop(['PassengerId','Name','Ticket','Survived','Cabin'],axis=1)  #␣
 ↪parameters for training
train_label=train_set['Survived']              # labels for training
```

[ ]:
```
```

[17]:
```
train_para.isnull().sum()
```

[17]:
```
Pclass       0
Sex          0
Age         61
SibSp        0
Parch        0
Fare         1
Embarked     0
dtype: int64
```

[18]:
```
train_para.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 292 entries, 192 to 315
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Pclass    292 non-null    int64
 1   Sex       292 non-null    object
 2   Age       231 non-null    float64
 3   SibSp     292 non-null    int64
 4   Parch     292 non-null    int64
 5   Fare      291 non-null    float64
 6   Embarked  292 non-null    object
dtypes: float64(2), int64(3), object(2)
memory usage: 18.2+ KB
```

[19]:
```
from sklearn.base import BaseEstimator, TransformerMixin
class CleanNumericData(BaseEstimator, TransformerMixin):
    def __init__(self,method='median',fill_value=0):
        self.method=method
        self.fill_value=fill_value

    def give_numeric_cols(self,data):
        col_names=[data.columns[i] for i in range(len(data.dtypes)) if (data.
 ↪dtypes[i]==int or data.dtypes[i]==float)]
        return col_names

    def fit(self,data):
```

```
        return self

    def transform(self,data):
        imputer=SimpleImputer(strategy=self.method)
        num_cols=self.give_numeric_cols(data)
        X=imputer.fit_transform(data[num_cols])
        X_df=pd.DataFrame(X,columns=num_cols,index=data.index)
        return X_df


def ApplyOneHotEncoding(data):
    cato_cols=['Sex','Embarked']
    cat_encoder=OneHotEncoder()
    encoded=cat_encoder.fit_transform(data[cato_cols])
    encoded_df=pd.DataFrame(encoded.
 ↪toarray(),columns=['female','male','embarked_C','embarked_Q','embarked_S'],index=data.
 ↪index)
    encoded_df=encoded_df.drop('male',axis=1)
    return encoded_df


num_pipline = Pipeline([
    ('cleaner',CleanNumericData()),
    ('standard_scaler',StandardScaler())
])

full_pipeline=ColumnTransformer([
    ('num',num_pipline,['Pclass','Age','SibSp','Parch','Fare']),
    ('cat',OneHotEncoder(),['Sex','Embarked']),
])
```

[20]:
```
temp=train_para.copy()
```

[21]:
```
temp2=full_pipeline.fit_transform(temp)
```

[22]:
```
transformed_train_para=pd.DataFrame(temp2,columns=['Pclass','Age', 'SibSp',␣
 ↪'Parch',␣
 ↪'Fare','Female','Male','Embarked_c','Embarked_S','Embarked_q'],index=temp.
 ↪index)
```

[23]:
```
transformed_train_para
```

[23]:

	Pclass	Age	SibSp	Parch	Fare	Female	Male	\
192	0.890640	-1.444960	0.636853	0.748420	-0.384944	0.0	1.0	
134	0.890640	1.023488	-0.476686	-0.426519	-0.494953	0.0	1.0	
317	-0.275579	-0.857234	-0.476686	-0.426519	-0.451573	0.0	1.0	
135	0.890640	-0.465417	-0.476686	-0.426519	-0.495646	0.0	1.0	

```
72   0.890640 -0.073600 -0.476686 -0.426519 -0.494466     1.0   0.0
..        …        …        …        …        …      …    …
181 -1.441799  0.553308  0.636853  0.748420  0.758729     0.0   1.0
283  0.890640 -1.640869  0.636853  0.748420 -0.372520     1.0   0.0
390 -1.441799 -0.543780 -0.476686 -0.426519  0.930995     0.0   1.0
137 -0.275579 -0.308690 -0.476686 -0.426519 -0.409930     0.0   1.0
315  0.890640 -1.013961 -0.476686 -0.426519 -0.497660     1.0   0.0

     Embarked_c  Embarked_S  Embarked_q
192         0.0         0.0         1.0
134         0.0         0.0         1.0
317         0.0         0.0         1.0
135         0.0         0.0         1.0
72          0.0         0.0         1.0
..          …         …         …
181         1.0         0.0         0.0
283         1.0         0.0         0.0
390         0.0         0.0         1.0
137         0.0         0.0         1.0
315         0.0         1.0         0.0

[292 rows x 10 columns]
```

[24]:
```
test_param=test_set.drop('Survived',axis=1)
test_labels=test_set['Survived']
```

[25]:
```
temp=test_param.copy()
```

[26]:
```
temp2=full_pipeline.fit_transform(temp)
```

[27]:
```
transformed_test_para=pd.DataFrame(temp2,columns=['Pclass','Age', 'SibSp',␣
↪'Parch',␣
↪'Fare','Female','Male','Embarked_c','Embarked_S','Embarked_q'],index=temp.
↪index)
```

[28]:
```
transformed_test_para
```

[28]:
```
      Pclass       Age     SibSp     Parch      Fare  Female  Male  \
131 -1.67332  1.900885 -0.553748 -0.375548 -0.053824     0.0   1.0
45   0.83666 -0.348615 -0.553748 -0.375548 -0.521055     0.0   1.0
348 -0.41833 -0.428954 -0.553748 -0.375548 -0.394454     0.0   1.0
118 -1.67332  0.535117 -0.553748 -0.375548  1.007620     0.0   1.0
173  0.83666 -0.268276 -0.553748 -0.375548 -0.536856     0.0   1.0
..       …        …        …        …        …      …    …
364 -1.67332 -0.348615  0.571611 -0.375548  0.557987     1.0   0.0
322 -0.41833 -0.268276 -0.553748 -0.375548 -0.405808     0.0   1.0
1    0.83666  1.418849  0.571611 -0.375548 -0.542061     1.0   0.0
```

```
120 -0.41833 -1.393026 -0.553748 -0.375548 -0.343360     1.0   0.0
406 -0.41833 -0.509294  0.571611 -0.375548 -0.462580     0.0   1.0

     Embarked_c  Embarked_S  Embarked_q
131         1.0         0.0         0.0
45          0.0         0.0         1.0
348         0.0         0.0         1.0
118         1.0         0.0         0.0
173         1.0         0.0         0.0
..          …           …           …
364         1.0         0.0         0.0
322         0.0         0.0         1.0
1           0.0         0.0         1.0
120         0.0         0.0         1.0
406         0.0         0.0         1.0

[126 rows x 10 columns]
```

[29]:
```
ds_tree=DecisionTreeClassifier(max_depth=1)
kfold=KFold(n_splits=5,random_state=100,shuffle=True)
score=cross_val_score(estimator=ds_tree,X=transformed_train_para,y=train_label,cv=kfold)
```

11.1 Random Forest

[30]:
```
rnd_clf=RandomForestClassifier(n_estimators=500,max_leaf_nodes=16,n_jobs=-1)
```

[31]:
```
rnd_clf.fit(transformed_train_para,train_label)
```

[31]:
```
RandomForestClassifier(max_leaf_nodes=16, n_estimators=500, n_jobs=-1)
```

[32]:
```
rnd_clf_pred=rnd_clf.predict(transformed_test_para)
```

11.2 Bagging

[33]:
```
bag_clf=BaggingClassifier(DecisionTreeClassifier(splitter='random',max_leaf_nodes=16),n_estima
↪0,bootstrap=True,n_jobs=-1)
```

[34]:
```
bag_clf.fit(transformed_train_para,train_label)
```

[34]:
```
BaggingClassifier(estimator=DecisionTreeClassifier(max_leaf_nodes=16,
                                                   splitter='random'),
                  n_estimators=500, n_jobs=-1)
```

[35]:
```
bag_clf_pred=bag_clf.predict(transformed_test_para)
```

11.3 AdaBoost

[36]:
```
ada_clf=AdaBoostClassifier(DecisionTreeClassifier(max_depth=1),n_estimators=200,algorithm='SAM
↪R',learning_rate=0.5)
```

[37]:
```
ada_clf.fit(transformed_train_para,train_label)
```

[37]:
```
AdaBoostClassifier(estimator=DecisionTreeClassifier(max_depth=1),
                   learning_rate=0.5, n_estimators=200)
```

[38]:
```
ada_clf_pred=ada_clf.predict(transformed_test_para)
```

11.4 Gradient boosting

[39]:
```
gb_clf=GradientBoostingClassifier(max_depth=2,n_estimators=3,learning_rate=1.0)
```

[40]:
```
gb_clf.fit(transformed_train_para,train_label)
```

[40]:
```
GradientBoostingClassifier(learning_rate=1.0, max_depth=2, n_estimators=3)
```

[41]:
```
gb_clf_pred=gb_clf.predict(transformed_test_para)
```

11.5 XGBoost

[42]:
```
xgb_model=xgb.XGBClassifier()
```

[43]:
```
xgb_model.fit(transformed_train_para,train_label)
```

[43]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, …)
```

[44]:
```
xgb_pred=xgb_model.predict(transformed_test_para)
xgb_pred
```

[44]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1,
       1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1,
       0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0,
```

```
       0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0])
```

11.6 Blending

[45]:
```
class blending_ensemble:
    def __init__(self,meta_model,models):
        self.meta_model=meta_model
        self.models=models
        self.data=None
        self.labels=None
        self.tst_size=None


    def get_meta_train_data(self):
        train_meta=[]
        from sklearn.model_selection import train_test_split
        train_para, val_para ,train_labels, val_labels=train_test_split(self.
 ↪data,self.labels,test_size=self.tst_size,stratify=self.labels)
        for model in models:
            model.fit(train_para,train_labels)
            preds=model.predict(val_para)
            preds=preds.reshape(len(preds),1)
            train_meta.append(preds)

        train_meta=np.hstack(train_meta)

        return (train_meta,val_labels)

    def get_meta_test_data(self,predict_data):
        test_meta=[]
        for model in models:

            preds=model.predict(predict_data)
            preds=preds.reshape(len(preds),1)
            test_meta.append(preds)
        test_meta=np.hstack(test_meta)
        return test_meta

    def fit(self,train_data,train_labels,test_size):
        self.data=train_data
        self.labels=train_labels
        self.tst_size=test_size

        meta_train_data,meta_train_labels=self.get_meta_train_data()
        # print(meta_train_data)
        self.meta_model.fit(meta_train_data,meta_train_labels)
```

```
    def predict(self,predict_data):

        meta_test_data=self.get_meta_test_data(predict_data)
        # print(meta_test_data)
        return self.meta_model.predict(meta_test_data)
```

[46]:
```
models=[DecisionTreeClassifier(),KNeighborsClassifier(),LogisticRegression(),SVC(probability=T

bl_en=blending_ensemble(meta_model=LogisticRegression(),models=models)
```

[47]:
```
bl_en.fit(transformed_train_para,train_label,test_size=0.3)
```

[48]:
```
bl_pred=bl_en.predict(transformed_test_para)
```

11.7 Stacking

[49]:
```
class stacking_ensemble:
    def __init__(self,models,meta_model):
        self.data=None
        self.models=models
        self.meta_model=meta_model
        self.labels=None
        self.number_of_folds=None


    def get_folds(self):
        start=0
        fold_size=len(self.data)//self.number_of_folds
        folds=[]
        for j in range(self.number_of_folds):
            if j==(self.number_of_folds-1):
                # print(start,start+fold_size)
                hold_out=self.data[start:]
                hold_out_labels=self.labels[start:]

                train_on=self.data[:start]
                train_on_labels=self.labels[:start]

            else:

                hold_out=self.data[start:(start+fold_size)]
                hold_out_labels=self.labels[start:(start+fold_size)]

                train_on=np.concatenate(( self.data[:start] , self.
↪data[(start+fold_size):] ) ,axis=0)
```

```
                train_on_labels=np.concatenate(( self.labels[:start] , self.
 ↪labels[(start+fold_size):] ), axis=0)

            start+=fold_size

            folds.append((train_on,train_on_labels,hold_out,hold_out_labels))

        return folds

    def get_meta_train_data(self):
        train_meta=[]

        folds=self.get_folds()
        train_meta_labels=np.array([])

#         getting labels for validation set, this will be used in␣
 ↪stacking_ensemble class
        for i in folds:
            train_meta_labels=np.concatenate((train_meta_labels,i[3]),axis=0)


#         multiple models
        if type(self.models)==list:

            for model in models:

                pred=np.array([])
                pred=pred.reshape(len(pred),1)

                for i in folds:
#                       train base model
                    model.fit(i[0],i[1])
#                       predict for validation set
                    curr_pred=model.predict(i[2])

                    curr_pred=curr_pred.reshape(len(curr_pred),1)
                    pred=np.concatenate((pred,curr_pred),axis=0)

                train_meta.append(pred)
            train_meta=np.hstack(train_meta)

#         single model
        else:
            print('y')
            pred=np.array([])
            pred=pred.reshape(len(pred),1)
            for i in folds:
```

```
            self.models.fit(i[0],i[1])
            curr_pred=self.models.predict(i[2])
            curr_pred=curr_pred.reshape(len(curr_pred),1)
            pred=np.concatenate((pred,curr_pred),axis=0)
        train_meta.append(pred)


    return (train_meta,train_meta_labels)


def get_meta_test_data(self,predict_data):
    test_meta=[]


    if type(self.models)==list:

        pred=np.array([])
        pred=pred.reshape(len(pred),1)

        for model in models:

            curr_pred=model.predict(predict_data)
            curr_pred=curr_pred.reshape(len(curr_pred),1)

            test_meta.append(curr_pred)

        test_meta=np.hstack(test_meta)

    # single model
    else:

        pred=np.array([])
        pred=pred.reshape(len(pred),1)
        curr_pred=models.predict(predict_data)
        curr_pred=curr_pred.reshape(len(curr_pred),1)

        test_meta.append(curr_pred)


    return test_meta


def fit(self,data,labels,number_of_folds=5):

    self.data=np.array(data)
    self.labels=np.array(labels)
    self.number_of_folds=number_of_folds
```

```
        meta_train_data,meta_train_labels=self.get_meta_train_data()
        # print(meta_train_data)
        self.meta_model.fit(meta_train_data,meta_train_labels)

    def predict(self,predict_data):
        # temp=kfold(data=predict_data, labels=labels,␣
↪models=base_layer_models, number_of_folds=number_of_folds)
        predict_data=np.array(predict_data)
        meta_test_data=self.get_meta_test_data(predict_data)
        # print(meta_test_data)
        return self.meta_model.predict(meta_test_data)
```

[50]:
```
models=[DecisionTreeClassifier(),KNeighborsClassifier(),LogisticRegression(),SVC(probability=T
stk=stacking_ensemble(meta_model=LogisticRegression(),models=models)
```

[51]:
```
stk.fit(data=transformed_train_para,labels=train_label,number_of_folds=10)
```

[52]:
```
stk_pred=stk.predict(transformed_test_para)
```

[53]:
```
from sklearn.metrics import recall_score,accuracy_score,precision_score,f1_score
```

11.8 Accuracy

[54]:
```
print(f'bagging: {accuracy_score(y_true=test_labels, y_pred=bag_clf_pred)}')
print(f'gradient boosting: {accuracy_score(y_true=test_labels,␣
↪y_pred=gb_clf_pred)}')
print(f'AdaBoosting: {accuracy_score(y_true=test_labels, y_pred=ada_clf_pred)}')
print(f'xgboosting: {accuracy_score(y_true=test_labels, y_pred=xgb_pred)}')
print(f'blending: {accuracy_score(y_true=test_labels, y_pred=bl_pred)}')
print(f'stacking: {accuracy_score(y_true=test_labels, y_pred=stk_pred)}')
```

```
bagging: 1.0
gradient boosting: 1.0
AdaBoosting: 1.0
xgboosting: 1.0
blending: 1.0
stacking: 1.0
```

11.9 precision

[55]:
```
print(f'bagging: {precision_score(y_true=test_labels, y_pred=bag_clf_pred)}')
print(f'gradient boosting: {precision_score(y_true=test_labels,␣
↪y_pred=gb_clf_pred)}')
print(f'AdaBoosting: {precision_score(y_true=test_labels,␣
↪y_pred=ada_clf_pred)}')
print(f'xgboosting: {precision_score(y_true=test_labels, y_pred=xgb_pred)}')
```

```
print(f'blending: {precision_score(y_true=test_labels, y_pred=bl_pred)}')
print(f'stacking: {precision_score(y_true=test_labels, y_pred=stk_pred)}')
```

```
bagging: 1.0
gradient boosting: 1.0
AdaBoosting: 1.0
xgboosting: 1.0
blending: 1.0
stacking: 1.0
```

11.10 Recall

[56]:
```
print(f'bagging: {recall_score(y_true=test_labels, y_pred=bag_clf_pred)}')
print(f'gradient boosting: {recall_score(y_true=test_labels,␣
 ↪y_pred=gb_clf_pred)}')
print(f'AdaBoosting: {recall_score(y_true=test_labels, y_pred=ada_clf_pred)}')
print(f'xgboosting: {recall_score(y_true=test_labels, y_pred=xgb_pred)}')
print(f'blending: {recall_score(y_true=test_labels, y_pred=bl_pred)}')
print(f'stacking: {recall_score(y_true=test_labels, y_pred=stk_pred)}')
```

```
bagging: 1.0
gradient boosting: 1.0
AdaBoosting: 1.0
xgboosting: 1.0
blending: 1.0
stacking: 1.0
```

12 F1

[57]:
```
print(f'bagging: {f1_score(y_true=test_labels, y_pred=bag_clf_pred)}')
print(f'gradient boosting: {f1_score(y_true=test_labels, y_pred=gb_clf_pred)}')
print(f'AdaBoosting: {f1_score(y_true=test_labels, y_pred=ada_clf_pred)}')
print(f'xgboosting: {f1_score(y_true=test_labels, y_pred=xgb_pred)}')
print(f'blending: {f1_score(y_true=test_labels, y_pred=bl_pred)}')
print(f'stacking: {f1_score(y_true=test_labels, y_pred=stk_pred)}')
```

```
bagging: 1.0
gradient boosting: 1.0
AdaBoosting: 1.0
xgboosting: 1.0
blending: 1.0
stacking: 1.0
```

12.1 Kfold Cross Validation

[62]:
```
scores=cross_val_score(rnd_clf,transformed_train_para,train_label,
                       scoring='neg_mean_squared_error',cv=5)
scores=np.sqrt(-scores)
```

[63]:
```
scores
```

[63]:
```
array([0., 0., 0., 0., 0.])
```

[ ]:
```

```

12.2 Hold-out validation

[69]:
```
from sklearn.metrics import mean_squared_error
```

[65]:
```
X_train, X_test, y_train,␣
↪y_test=train_test_split(transformed_train_para,train_label,test_size=0.3)
```

[67]:
```
rnd_clf.fit(X_train,y_train)
```

[67]:
```
RandomForestClassifier(max_leaf_nodes=16, n_estimators=500, n_jobs=-1)
```

[68]:
```
pred=rnd_clf.predict(X_test)
```

[70]:
```
mean_squared_error(y_true=y_test,y_pred=pred)
```

[70]:
```
0.0
```

[ ]:
```

```