Experiment_6_data_mining

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1 Data Mining and machine Learning

2 Experiment 6

2.1 12 February

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4.1 Performance measures: Cross validation

4.1.1 Q1. Today we will try to perform cross validation to check how well the model generalizes to a unseen data. We will see how to implement K fold cross validation and stratified K fold cross validation.

[36]:
```
## Loading the necessary libraries
import numpy as np
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split, KFold,cross_val_score
```

[18]:
```
## Loading the dataset

df = pd.read_csv(r"C:\Users\Batch1\Documents\Downloads\TK\12_feb\liver_patient.
↪csv")
df
```

[18]:
```
     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
..   …     …                …                 …                     …
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  liver_disease
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
..       …                         …            …
578      1.6                        0.37              0
579      3.2                        1.10              1
580      3.2                        1.00              1
581      3.4                        1.00              1
582      4.4                        1.50              0

[583 rows x 11 columns]
```

[19]:
```
df.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  583 non-null    float64
 10  liver_disease               583 non-null    int64
dtypes: float64(5), int64(5), object(1)
memory usage: 50.2+ KB
```

4.1.2 Dropping the unnecessary Age and Gender column

```
[20]: df.drop(['Age','Gender'],axis=1,inplace = True)
```

4.1.3 Perform Min-Max scaling

```
[21]: from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X = scaler.fit_transform(df)
```

```
[25]: X
```

```
[25]: array([[0.00402145, 0.        , 0.06057645, …, 0.52173913, 0.24      ,
         1.        ],
        [0.14075067, 0.2755102 , 0.31069858, …, 0.5       , 0.176     ,
         1.        ],
        [0.0924933 , 0.20408163, 0.20859795, …, 0.52173913, 0.236     ,
         1.        ],
        …,
        [0.00536193, 0.00510204, 0.0889106 , …, 0.5       , 0.28      ,
         1.        ],
        [0.01206434, 0.02040816, 0.05911089, …, 0.54347826, 0.28      ,
         1.        ],
        [0.0080429 , 0.01020408, 0.07474353, …, 0.76086957, 0.48      ,
         0.        ]])
```

```
[26]: x = X[:,:-1]
y = X[:,-1]
```

4.1.4 Do the train test split of the data with test size 20%

```
[32]: x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=.
  ↪2,random_state=42)
```

4.1.5 Fit the LogisticRegression model to the this training data.

```
[35]: model = LogisticRegression()
model.fit(x_train,y_train)
y_pred = model.predict(x_test)
```

```
## Print the accuracy which is also a performance measure as far as a␣
↪classification problem is concerned with.
print(f"The accuracy of the model is:
↪{round(accuracy_score(y_test,y_pred)*100,3)} %")
```

```
The accuracy of the model is:74.359 %
```

4.1.6 Now import Kfold and cross val score functions from the available modules for performing Kfold cross validation.

4.1.7 Now you can create a new object of the class LogisticRegression as logisticR

[39]:
```
logisticR = LogisticRegression()

## now let us perform the KFold class to split the data into 5 folds.
kfold_validation = KFold(n_splits = 5, shuffle = True, random_state=42)
```

4.1.8 Now we will use cross val score function to perform the 5 fold cross validation and print the accuracy scores in each case.

[42]:
```
result = cross_val_score(logisticR,x_train,y_train,scoring = 'accuracy',cv =␣
↪kfold_validation)

print("Cross validation accuracy scores:", result)
print(f"Mean accuracy: {np.mean(result)*100}%")
```

```
Cross validation accuracy scores: [0.74468085 0.77419355 0.62365591 0.65591398
0.7311828 ]
Mean accuracy: 70.59254175245938%
```

4.1.9 Now we can try how we can implement StratifiedKFold cross validation

[44]:
```
from sklearn.model_selection import StratifiedKFold

skf = StratifiedKFold(n_splits=5,shuffle=True,random_state=42)
scores = cross_val_score(logisticR,x_train,y_train,scoring = "accuracy",cv =␣
↪skf)

print("Stratified Cross validation scores:",scores)
print(f"Mean accuracy: {scores.mean()*100}%")
```

```
Stratified Cross validation scores: [0.70212766 0.70967742 0.70967742 0.70967742
0.69892473]
Mean accuracy: 70.60169297643561%
```

4.2 Performance measures: Confusion matrix, Precision, Recall, F1 score

4.3 Q2. Now fit the logistic regression model for the liver patient data without performing cross validation with a train test split of 80:20.

[46]:
```
model_new = LogisticRegression()
model_new.fit(x_train,y_train)
y_pred_new = model_new.predict(x_test)
## Print the accuracy which is also a performance measure as far as a␣
↪classification problem is concerned with.
print(f"The accuracy of the model is:
↪{round(accuracy_score(y_test,y_pred_new)*100,3)} %")
```

```
The accuracy of the model is:74.359 %
```

4.3.1 we can also print the confusion matrix, precision and recall

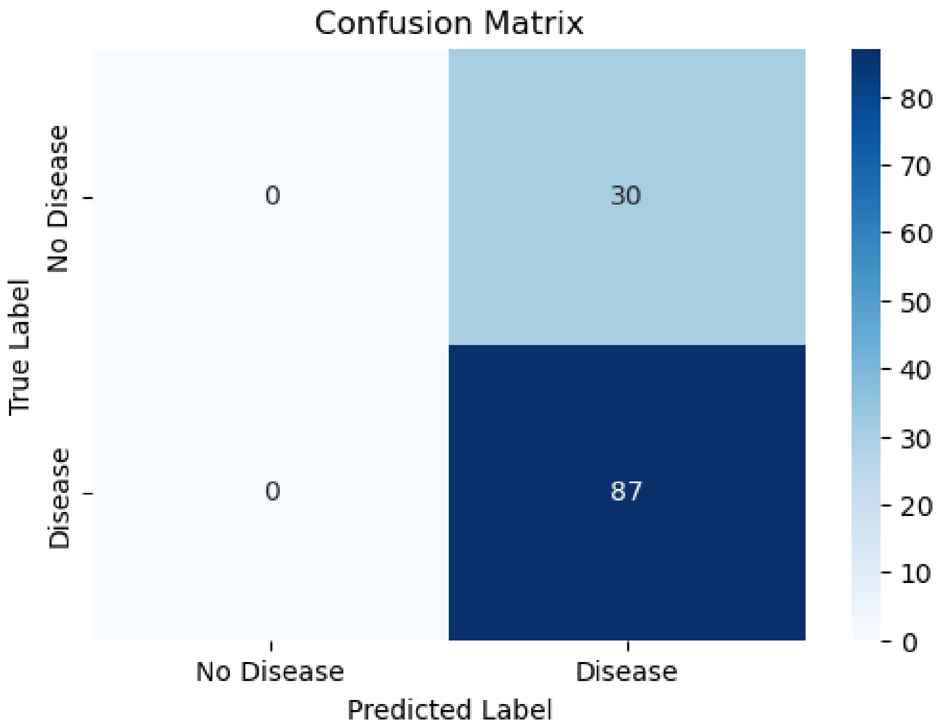
[47]:
```
from sklearn.metrics import confusion_matrix, precision_score,␣
↪recall_score,f1_score,ConfusionMatrixDisplay

cm = confusion_matrix(y_test,y_pred_new)
print("Confusion matrix:\n",cm)

precision = precision_score(y_test,y_pred_new)
recall = recall_score(y_test,y_pred_new)
f1 = f1_score(y_test,y_pred_new)

print("Precision:",precision)
print("Recall:",recall)
print("F1 score:",f1)
```

```
Confusion matrix:
 [[ 0 30]
 [ 0 87]]
Precision: 0.7435897435897436
Recall: 1.0
F1 score: 0.8529411764705882
```

4.3.2 The same confusion matrix if we want can be printed in a more better manner using the below code.

[52]:
```
# Plot confusion matrix using seaborn heatmap import seaborn as sns
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["No␣
↪Disease","Disease"], yticklabels=["No Disease", "Disease"])
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
```

```
plt.title("Confusion Matrix")
plt.show()
```



4.4 Deicsion trees: Regression and classification

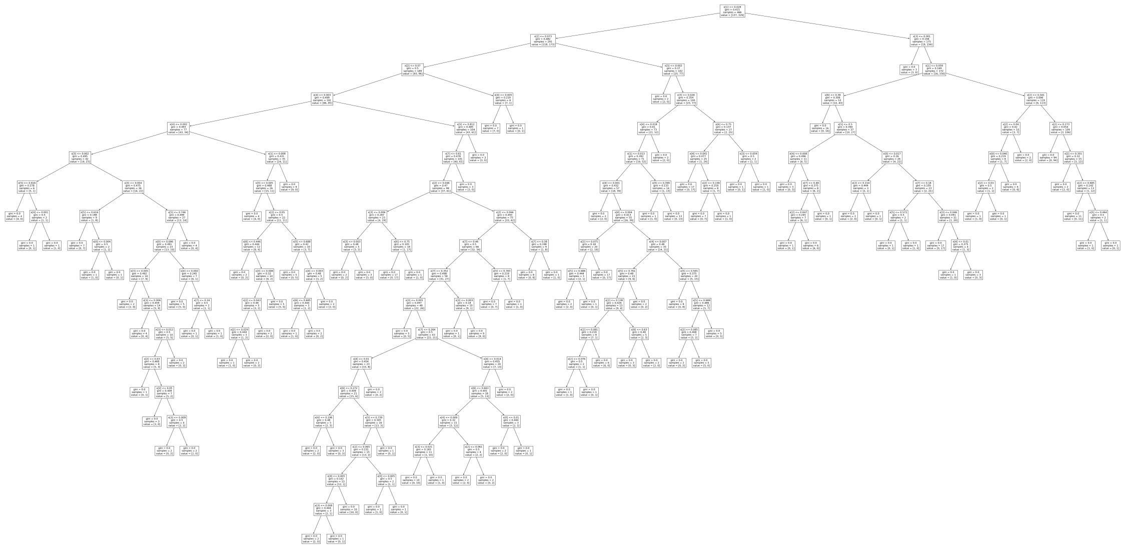
4.4.1 Let's try to fit a decision tree for a classification problem and view the same and see how the predictions can be made using the same.

[54]:
```
from sklearn.tree import DecisionTreeClassifier

model_dc = DecisionTreeClassifier()
model_dc.fit(x_train,y_train)
prediction1 = model_dc.predict(x_test)
print(f"Accuracy score:{accuracy_score(y_test,prediction1)*100}%")
```

```
Accuracy score:70.08547008547008%
```

4.4.2 We can print and check the Decision tree.

[59]:
```
from sklearn.tree import plot_tree
plt.figure(figsize=(100,50),dpi = 150)
plot_tree(model_dc)
plt.show()
```



4.5 Compare the accuracy of logistic regression model and decision tree model you have fitted.

[60]:
```
print(f"Accuracy of Logistic Regression model:
    {accuracy_score(y_test,y_pred_new)*100}%")
print(f"Accuracy of Decision Tree model:
    {accuracy_score(y_test,prediction1)*100}%")
```

```
Accuracy of Logistic Regression model:74.35897435897436%
Accuracy of Decision Tree model:70.08547008547008%
```

4.6 Now use the Book1.csv file we used in multiple regression fitting in Labsheet 3.

[61]:
```
df = pd.read_csv(r"C:\Users\Batch1\Documents\Downloads\TK\12_feb\Book1.csv")
df
```

[61]:

	price	area	bedrooms	bathrooms	stories	parking	furnishingstatus
0	13300000	7420	4	2	3	2	furnished
1	12250000	8960	4	4	4	3	furnished
2	12250000	9960	3	2	2	2	semi-furnished
3	12215000	7500	4	2	2	3	furnished
4	11410000	7420	4	1	2	2	furnished
..	…	…	…	…	…	…	…
244	4550000	5320	3	1	2	0	semi-furnished
245	4550000	5360	3	1	2	2	unfurnished
246	4550000	3520	3	1	1	0	semi-furnished
247	4550000	8400	4	1	4	3	unfurnished
248	4543000	4100	2	2	1	0	semi-furnished

```
[249 rows x 7 columns]
```

4.6.1 Do the necessary preprocessing of the data and train test split of the data and fit a multiple regression model and compute the error.

[62]:
```python
df['furnishingstatus'].value_counts()
```

[62]:
```
furnishingstatus
semi-furnished    118
furnished          81
unfurnished        50
Name: count, dtype: int64
```

[65]:
```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
encoded = le.fit_transform(df['furnishingstatus'])
df.drop(['furnishingstatus'],axis = 1)
df['furnishingstatus'] = encoded
df
```

[65]:

	price	area	bedrooms	bathrooms	stories	parking	furnishingstatus
0	13300000	7420	4	2	3	2	0
1	12250000	8960	4	4	4	3	0
2	12250000	9960	3	2	2	2	1
3	12215000	7500	4	2	2	3	0
4	11410000	7420	4	1	2	2	0
..	…	…	…	…	…	…	…
244	4550000	5320	3	1	2	0	1
245	4550000	5360	3	1	2	2	2
246	4550000	3520	3	1	1	0	1
247	4550000	8400	4	1	4	3	2
248	4543000	4100	2	2	1	0	1

```
[249 rows x 7 columns]
```

[68]:
```python
scaler = MinMaxScaler()
X = scaler.fit_transform(df)
```

[69]:
```python
x = X[:,1:]
y = X[:,0]
```

4.6.2 Train test split

[78]:
```python
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.
↪2,random_state=42)
```

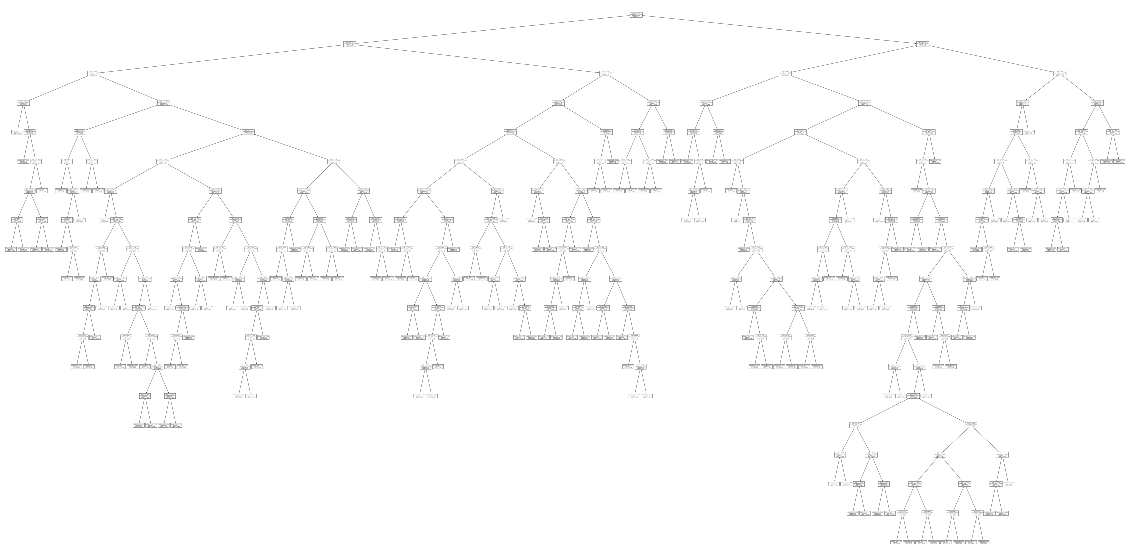
4.7 Now use the DecisionTreeRegressor class to fit a decision tree model and check the decision tree and errors

[79]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error,r2_score
model_dr = DecisionTreeRegressor()
model_dr.fit(x_train,y_train)
y_pred = model_dr.predict(x_test)
print("Mean squared error:",mean_squared_error(y_test,y_pred))
print("R2 score:",r2_score(y_test,y_pred))
```

```
Mean squared error: 0.08041115309191495
R2 score: -1.4174264960281975
```

4.8 Now plot the decision tree as done in the classifier case above.

[80]:
```
from sklearn.tree import plot_tree
plt.figure(figsize=(100,50),dpi = 150)
plot_tree(model_dr)
plt.show()
```



4.9 Checking the result using Multiple linear regression model

[81]:
```
from sklearn.linear_model import LinearRegression
multi_model = LinearRegression()
multi_model.fit(x_train,y_train)
y_pred2 = multi_model.predict(x_test)

print("Mean squared error:",mean_squared_error(y_test,y_pred2))
```

```
print("R2 score:",r2_score(y_test,y_pred2))
```

```
Mean squared error: 0.022324532863058973
R2 score: 0.3288503499891078
```

4.10 Further also compare the errors you received in both the case and print and compare them.

[84]:
```
print("Mean squared error(Decision Tree Regressor):
↪",mean_squared_error(y_test,y_pred))
print("Mean squared error(Multiple linear regression):
↪",mean_squared_error(y_test,y_pred2))
```

```
Mean squared error(Decision Tree Regressor): 0.08041115309191495
Mean squared error(Multiple linear regression): 0.022324532863058973
```

4.11 Using cross validation and hyper parameter tuning in Decision Tree

[92]:
```
import pandas as pd
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
data = pd.read_csv(r'C:
↪\Users\Batch1\Documents\Downloads\TK\12_feb\liver_patient.csv')
data.drop('Gender', axis=1, inplace=True)
scaler = MinMaxScaler()
x = scaler.fit_transform(data)
X = x[:, 0:9]
Y = x[:, 9]
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,␣
↪random_state=42)
param_grid = {
 'max_depth': [1,3, 5,6,8, 10],
 'min_samples_leaf': [1, 5, 10, 20]
}
dt_model = DecisionTreeClassifier(random_state=42)
grid_search = GridSearchCV(estimator=dt_model, param_grid=param_grid, cv=5,␣
↪scoring='accuracy', n_jobs=-1)
grid_search.fit(X_train, Y_train)
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_
Y_pred = best_model.predict(X_test)
accuracy = accuracy_score(Y_test, Y_pred)
print("Best Parameters:", best_params)
print("Best Cross-validation Accuracy:", grid_search.best_score_)
```

```
print("Test Accuracy:", accuracy)
```

```
Best Parameters: {'max_depth': 1, 'min_samples_leaf': 1}
Best Cross-validation Accuracy: 0.7060169297643561
Test Accuracy: 0.7435897435897436
```