descisionTree_hw_baseball_CMPE188

March 16, 2025

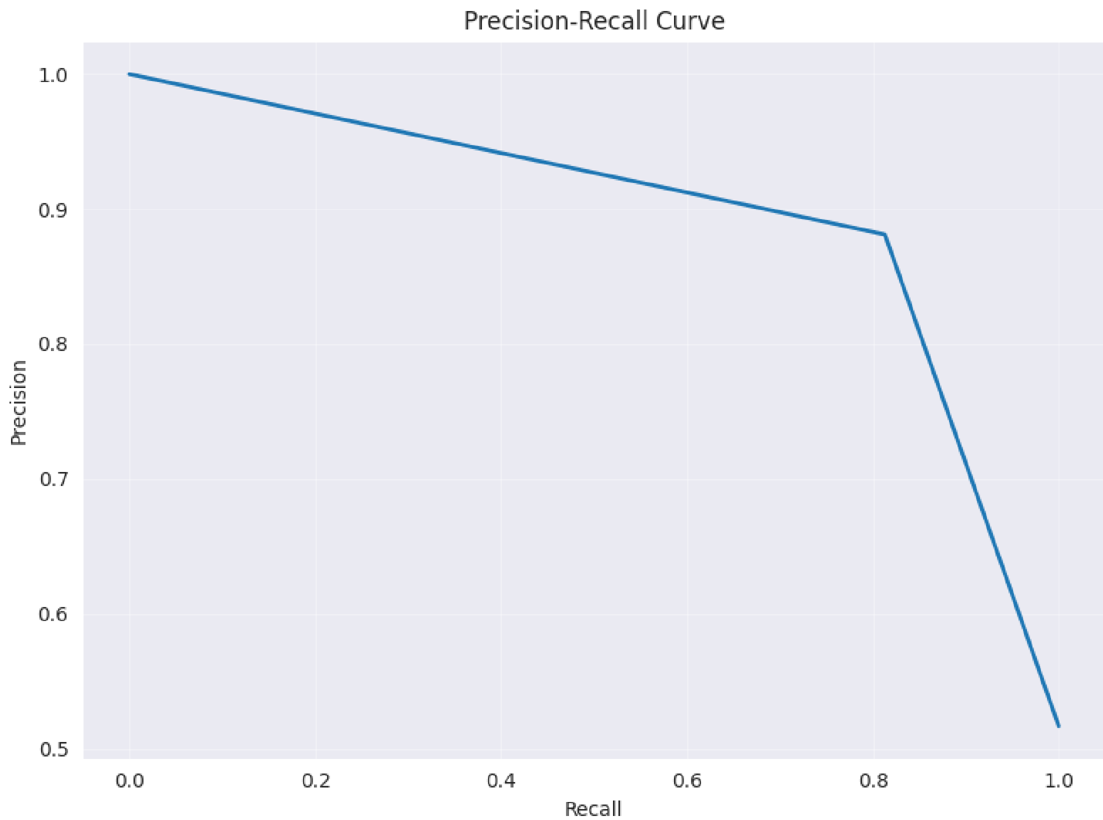
1. What are the definitions of precision and recall? Explain why there is a tradeoff between the two? You can use graphs or any other tools to answer this question.

Precision: Ratio of correctly predicted positive observations to the total. TP / (TP + FP). Measures how many of the items predicted as positive are actually positive. Focuses on minimizing false positives. Recall: Ratio of correctly predicted positive observations to all actual positives. TP / (TP + FN). Measures how many of the actual positives were predicted as positive. Focuses on minimizing false negatives. Tradeoff: Exists because improving one typically comes at the expense of the other. If we increase the classification threshold, we increase precision but decrease recall. If we decrease the threshold, we increase recall but decrease precision. This is because the model becomes more conservative with higher thresholds, leading to fewer false positives but more false negatives. Lower thresholds lead to more false positives but fewer false negatives.

[25]:
```
import pandas as pd
from pandas import set_option
from pandas import read_csv
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import Normalizer, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
from sklearn.model_selection import KFold, cross_val_score
from numpy import set_printoptions, log, argmax
import seaborn as sns
from pandas.plotting import scatter_matrix
import statsmodels.api as sm
import matplotlib.pyplot as plt
from sklearn.datasets import make_classification
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor,␣
 ↪plot_tree
from sklearn.metrics import precision_recall_curve, mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_classification
```

[26]:
```
# Sources: https://stackoverflow.com/questions/60865028/
 ↪sklearn-precision-recall-curve-and-threshold
#          https://scikit-learn.org/stable/modules/generated/sklearn.metrics.
 ↪precision_recall_curve.html
#          https://www.geeksforgeeks.org/precision-recall-curve-ml/
# Create a synthetic dataset
```

```python
X, y = make_classification(n_samples=1000, n_features=20, n_classes=2,
                           random_state=42)

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

# Train a logistic regression model
model = DecisionTreeClassifier()
model.fit(X_train, y_train)

# Get predicted probabilities
y_scores = model.predict_proba(X_test)[:, 1]

# Calculate precision and recall for different thresholds
precision, recall, thresholds = precision_recall_curve(y_test, y_scores)

# Create the precision-recall curve
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, linewidth=2)
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```



2. What is the definition of F1 score and how do you interpret a high F1 score? F1 is a performance metric for classification models that models precision and recall into a single value by the harmonic mean. F1 = 2 * (precision * recall) / (precision + recall). It balances the tradeoff between precision and recall, providing a single score that summarizes the model's performance. A high F1 score (closer to 1) indicates that the model has high precision and recall, meaning that it correctly identifies most of the positive samples while minimizing false positives.

[27]:
```
filename = 'Baseball_salary.csv'
data = read_csv(filename)
set_printoptions(precision=3)
data.head(5)
print(data.isnull().sum())
```

```
Unnamed: 0     0
AtBat          0
Hits           0
HmRun          0
Runs           0
RBI            0
Walks          0
Years          0
```

```
CAtBat         0
CHits          0
CHmRun         0
CRuns          0
CRBI           0
CWalks         0
League         0
Division       0
PutOuts        0
Assists        0
Errors         0
Salary        59
NewLeague      0
dtype: int64
```

[28]:

```
# Clean the data by dropping rows with null salary
data = data.dropna(subset=['Salary'])
print(data.isnull().sum())
```

```
Unnamed: 0    0
AtBat         0
Hits          0
HmRun         0
Runs          0
RBI           0
Walks         0
Years         0
CAtBat        0
CHits         0
CHmRun        0
CRuns         0
CRBI          0
CWalks        0
League        0
Division      0
PutOuts       0
Assists       0
Errors        0
Salary        0
NewLeague     0
dtype: int64
```

[29]:

```
label_encoder = LabelEncoder()
data['League'] = label_encoder.fit_transform(data['League'])
print(data['League'].value_counts())
data['Division'] = label_encoder.fit_transform(data['Division'])
print(data['Division'].value_counts())
data['NewLeague'] = label_encoder.fit_transform(data['NewLeague'])
```

```
print(data['NewLeague'].value_counts())

data['Log_Salary'] = log(data['Salary'])
array = data.values
Y1 = data['Log_Salary']
X1 = data.drop(columns=['Salary', 'Log_Salary', 'Unnamed: 0'], axis=1)
X1names = X1.columns
X1.head(5)
```

```
League
0    139
1    124
Name: count, dtype: int64
Division
1    134
0    129
Name: count, dtype: int64
NewLeague
0    141
1    122
Name: count, dtype: int64
```

[29]:

```
   AtBat  Hits  HmRun  Runs  RBI  Walks  Years  CAtBat  CHits  CHmRun  CRuns
 CRBI  CWalks  League  Division  PutOuts  Assists  Errors  NewLeague
 1    315    81      7    24   38     39     14    3449    835      69    321
 414     375       1         1      632       43       10           1
 2    479   130     18    66   72     76      3    1624    457      63    224
 266     263       0         1      880       82       14           0
 3    496   141     20    65   78     37     11    5628   1575     225    828
 838     354       1         0      200       11        3           1
 4    321    87     10    39   42     30      2     396    101      12     48
 46       33      1         0      805       40        4           1
 5    594   169      4    74   51     35     11    4408   1133      19    501
 336     194       0         1      282      421       25           0
```

[30]:

```
# Standardize
data_stand = X1.copy()
stand_scaler = StandardScaler().fit(data_stand)
data_stand = stand_scaler.transform(data_stand)
# add output to standardized data
data_stand = pd.DataFrame(data_stand, columns=X1names, index=X1.index)
X1_stand = data_stand.copy()
data_objects = ((data_stand, 'data_stand'), (data, "data_raw"))
```

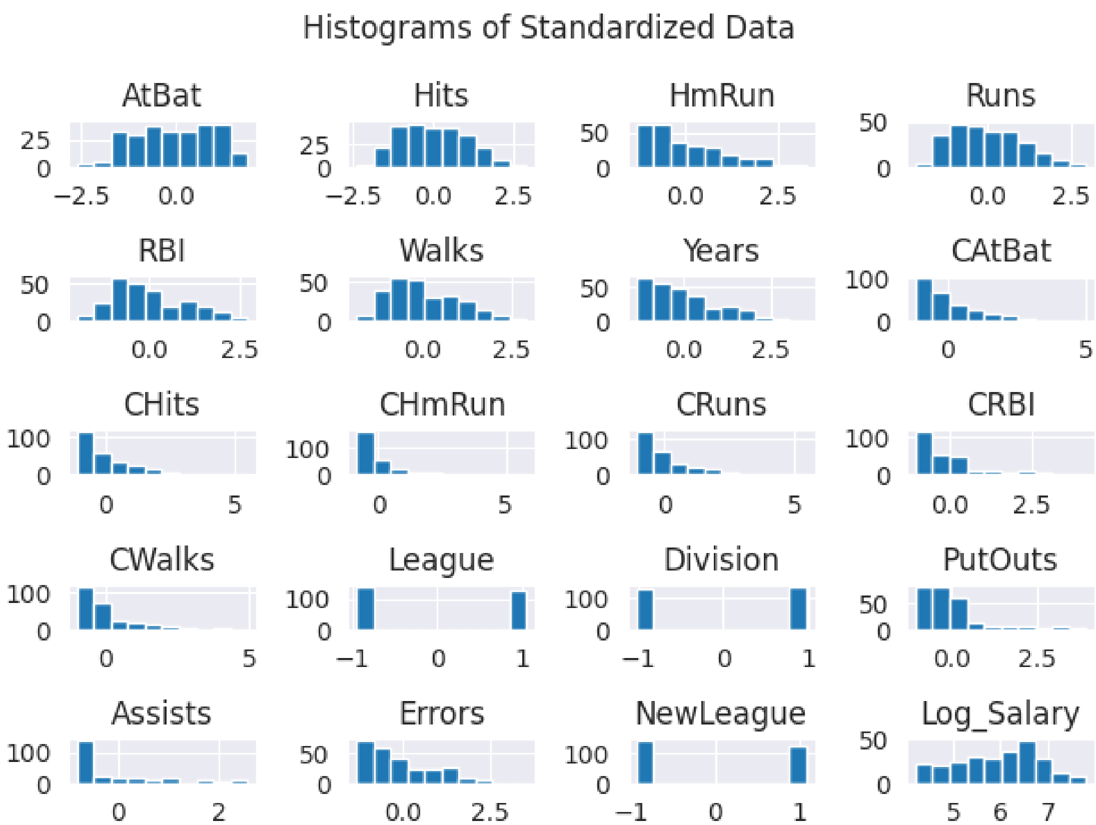
[31]:

```
set_option('display.width', 150)
set_option('display.precision', 1)
print('Standardized Data')
print(data_stand.describe())
```

```
Standardized Data
          AtBat     Hits    HmRun     Runs      RBI    Walks    Years   CAtBat
CHits   CHmRun    CRuns     CRBI   CWalks   League  Division  \
count  2.6e+02  2.6e+02  2.6e+02  2.6e+02  2.6e+02  2.6e+02  2.6e+02  2.6e+02
2.6e+02  2.6e+02  2.6e+02  2.6e+02  2.6e+02  2.6e+02   2.6e+02
mean   1.0e-17  5.7e-17  3.4e-17 -5.1e-17  1.2e-16  1.7e-18 -5.4e-17  6.1e-17
6.8e-17  5.4e-17  3.4e-17  4.1e-17  1.1e-16 -1.4e-17  -1.1e-16
std    1.0e+00  1.0e+00  1.0e+00  1.0e+00  1.0e+00  1.0e+00  1.0e+00  1.0e+00
1.0e+00  1.0e+00  1.0e+00  1.0e+00  1.0e+00  1.0e+00   1.0e+00
min   -2.6e+00 -2.4e+00 -1.3e+00 -2.1e+00 -2.0e+00 -1.9e+00 -1.3e+00 -1.2e+00
-1.1e+00 -8.4e-01 -1.1e+00 -1.0e+00 -9.8e-01 -9.4e-01  -1.0e+00
25%   -8.2e-01 -8.1e-01 -7.6e-01 -8.3e-01 -8.3e-01 -8.4e-01 -6.9e-01 -8.0e-01
-7.9e-01 -6.6e-01 -7.7e-01 -7.3e-01 -7.2e-01 -9.4e-01  -1.0e+00
50%    6.4e-02 -1.1e-01 -3.0e-01 -1.1e-01 -1.7e-01 -1.9e-01 -2.7e-01 -3.2e-01
-3.2e-01 -3.6e-01 -3.4e-01 -3.1e-01 -3.3e-01 -9.4e-01   9.8e-01
75%    8.3e-01  7.5e-01  7.3e-01  7.2e-01  7.6e-01  7.3e-01  5.6e-01  5.4e-01
5.1e-01  2.8e-01  4.1e-01  2.9e-01  2.6e-01  1.1e+00   9.8e-01
max    1.9e+00  2.9e+00  3.2e+00  3.0e+00  2.7e+00  2.9e+00  3.5e+00  5.0e+00
5.5e+00  5.8e+00  5.5e+00  4.1e+00  5.0e+00  1.1e+00   9.8e-01

       PutOuts  Assists   Errors  NewLeague
count  2.6e+02    263.0  2.6e+02    2.6e+02
mean   7.4e-17      0.0  1.0e-16    1.4e-17
std    1.0e+00      1.0  1.0e+00    1.0e+00
min   -1.0e+00     -0.8 -1.3e+00   -9.3e-01
25%   -6.3e-01     -0.8 -8.5e-01   -9.3e-01
50%   -2.4e-01     -0.5 -2.4e-01   -9.3e-01
75%    1.1e-01      0.5  6.7e-01    1.1e+00
max    3.9e+00      2.6  3.5e+00    1.1e+00
```

[32]:

```python
data_stand_with_salary = data_stand.copy()
data_stand_with_salary['Log_Salary'] = Y1
data_stand_with_salary.hist()
plt.suptitle(f"Histograms of Standardized Data")
plt.tight_layout()
plt.show()
```



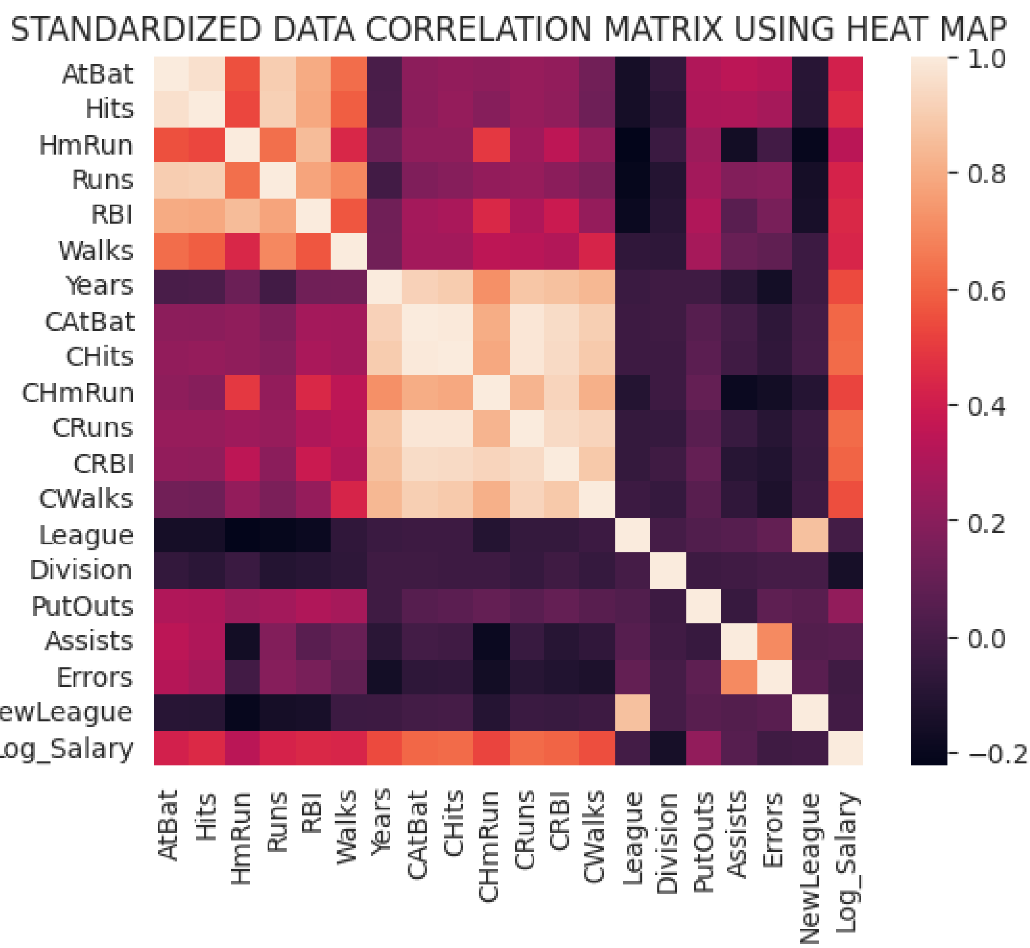
3. Use the baseball salary dataset and the exploratory data analysis to determine visually which are the candidate features for the model. Use the log(salary) as your output and pick six features as input for your data (use the exploratory analysis as a basis for the choice of input features).

[33]:
```
plt.figure() # new plot
#plt.tight_layout()
corMat = data_stand_with_salary.corr(method='pearson')
print(corMat)
## plot correlation matrix as a heat map
sns.heatmap(corMat, square=True)
plt.yticks(rotation=0)
plt.xticks(rotation=90)
plt.title(f"STANDARDIZED DATA CORRELATION MATRIX USING HEAT MAP")
plt.show()

## scatter plot of all data
plt.figure()
# # The output overlaps itself, resize it to display better (w padding)
scatter_matrix(data_stand_with_salary)
plt.tight_layout(pad=0.1)
```

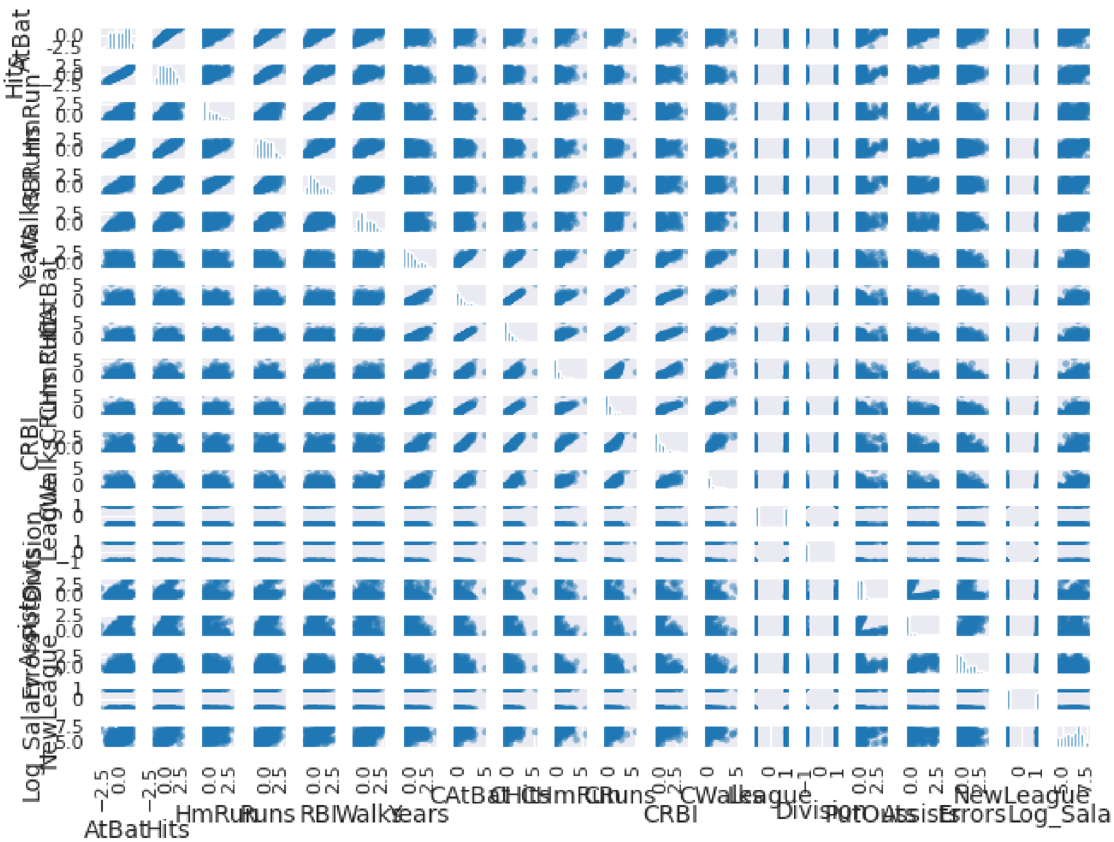
```python
plt.show()
```

```
              AtBat     Hits    HmRun      Runs       RBI    Walks    Years  
CAtBat    CHits   CHmRun    CRuns      CRBI   CWalks   League  Division  \
AtBat       1.0e+00  9.6e-01  5.6e-01  9.0e-01  8.0e-01  6.2e-01  1.3e-02
2.1e-01  2.3e-01  2.1e-01  2.4e-01  2.2e-01  1.3e-01 -1.5e-01  -5.6e-02
Hits        9.6e-01  1.0e+00  5.3e-01  9.1e-01  7.9e-01  5.9e-01  1.9e-02
2.1e-01  2.4e-01  1.9e-01  2.4e-01  2.2e-01  1.2e-01 -1.5e-01  -8.3e-02
HmRun       5.6e-01  5.3e-01  1.0e+00  6.3e-01  8.5e-01  4.4e-01  1.1e-01
2.2e-01  2.2e-01  4.9e-01  2.6e-01  3.5e-01  2.3e-01 -2.2e-01  -3.5e-02
Runs        9.0e-01  9.1e-01  6.3e-01  1.0e+00  7.8e-01  7.0e-01 -1.2e-02
1.7e-01  1.9e-01  2.3e-01  2.4e-01  2.0e-01  1.6e-01 -2.1e-01  -1.1e-01
RBI         8.0e-01  7.9e-01  8.5e-01  7.8e-01  1.0e+00  5.7e-01  1.3e-01
2.8e-01  2.9e-01  4.4e-01  3.1e-01  3.9e-01  2.3e-01 -1.9e-01  -9.0e-02
Walks       6.2e-01  5.9e-01  4.4e-01  7.0e-01  5.7e-01  1.0e+00  1.3e-01
2.7e-01  2.7e-01  3.5e-01  3.3e-01  3.1e-01  4.3e-01 -6.6e-02  -7.3e-02
Years       1.3e-02  1.9e-02  1.1e-01 -1.2e-02  1.3e-01  1.3e-01  1.0e+00
9.2e-01  9.0e-01  7.2e-01  8.8e-01  8.6e-01  8.4e-01 -3.3e-02  -2.0e-02
CAtBat      2.1e-01  2.1e-01  2.2e-01  1.7e-01  2.8e-01  2.7e-01  9.2e-01
1.0e+00  1.0e+00  8.0e-01  9.8e-01  9.5e-01  9.1e-01 -2.4e-02  -1.9e-02
CHits       2.3e-01  2.4e-01  2.2e-01  1.9e-01  2.9e-01  2.7e-01  9.0e-01
1.0e+00  1.0e+00  7.9e-01  9.8e-01  9.5e-01  8.9e-01 -2.3e-02  -2.4e-02
CHmRun      2.1e-01  1.9e-01  4.9e-01  2.3e-01  4.4e-01  3.5e-01  7.2e-01
8.0e-01  7.9e-01  1.0e+00  8.3e-01  9.3e-01  8.1e-01 -1.1e-01  -2.7e-02
CRuns       2.4e-01  2.4e-01  2.6e-01  2.4e-01  3.1e-01  3.3e-01  8.8e-01
9.8e-01  9.8e-01  8.3e-01  1.0e+00  9.5e-01  9.3e-01 -5.4e-02  -4.7e-02
CRBI        2.2e-01  2.2e-01  3.5e-01  2.0e-01  3.9e-01  3.1e-01  8.6e-01
9.5e-01  9.5e-01  9.3e-01  9.5e-01  1.0e+00  8.9e-01 -5.1e-02  -2.2e-02
CWalks      1.3e-01  1.2e-01  2.3e-01  1.6e-01  2.3e-01  4.3e-01  8.4e-01
9.1e-01  8.9e-01  8.1e-01  9.3e-01  8.9e-01  1.0e+00 -2.9e-02  -5.0e-02
League     -1.5e-01 -1.5e-01 -2.2e-01 -2.1e-01 -1.9e-01 -6.6e-02 -3.3e-02
-2.4e-02 -2.3e-02 -1.1e-01 -5.4e-02 -5.1e-02 -2.9e-02  1.0e+00  -2.7e-03
Division   -5.6e-02 -8.3e-02 -3.5e-02 -1.1e-01 -9.0e-02 -7.3e-02 -2.0e-02
-1.9e-02 -2.4e-02 -2.7e-02 -4.7e-02 -2.2e-02 -5.0e-02 -2.7e-03   1.0e+00
PutOuts     3.1e-01  3.0e-01  2.5e-01  2.7e-01  3.1e-01  2.8e-01 -2.0e-02
5.3e-02  6.7e-02  9.4e-02  5.9e-02  9.5e-02  5.8e-02  4.0e-02  -2.5e-02
Assists     3.4e-01  3.0e-01 -1.6e-01  1.8e-01  6.3e-02  1.0e-01 -8.5e-02
-7.9e-03 -1.3e-02 -1.9e-01 -3.9e-02 -9.7e-02 -6.6e-02  5.2e-02  -1.7e-02
Errors      3.3e-01  2.8e-01 -9.7e-03  1.9e-01  1.5e-01  8.2e-02 -1.6e-01
-7.0e-02 -6.8e-02 -1.7e-01 -9.4e-02 -1.2e-01 -1.3e-01  9.2e-02  -5.6e-04
NewLeague  -9.0e-02 -9.5e-02 -2.0e-01 -1.5e-01 -1.4e-01 -2.8e-02 -2.4e-02
-4.3e-03  8.9e-04 -1.0e-01 -3.5e-02 -3.7e-02 -2.6e-02  8.6e-01  -2.4e-03
Log_Salary  4.1e-01  4.5e-01  3.4e-01  4.3e-01  4.4e-01  4.3e-01  5.4e-01
6.1e-01  6.2e-01  5.2e-01  6.2e-01  6.0e-01  5.5e-01 -6.4e-03  -1.5e-01

            PutOuts  Assists   Errors  NewLeague  Log_Salary
AtBat       3.1e-01  3.4e-01  3.3e-01   -9.0e-02     4.1e-01
Hits        3.0e-01  3.0e-01  2.8e-01   -9.5e-02     4.5e-01
```

HmRun	2.5e-01	-1.6e-01	-9.7e-03	-2.0e-01	3.4e-01
Runs	2.7e-01	1.8e-01	1.9e-01	-1.5e-01	4.3e-01
RBI	3.1e-01	6.3e-02	1.5e-01	-1.4e-01	4.4e-01
Walks	2.8e-01	1.0e-01	8.2e-02	-2.8e-02	4.3e-01
Years	-2.0e-02	-8.5e-02	-1.6e-01	-2.4e-02	5.4e-01
CAtBat	5.3e-02	-7.9e-03	-7.0e-02	-4.3e-03	6.1e-01
CHits	6.7e-02	-1.3e-02	-6.8e-02	8.9e-04	6.2e-01
CHmRun	9.4e-02	-1.9e-01	-1.7e-01	-1.0e-01	5.2e-01
CRuns	5.9e-02	-3.9e-02	-9.4e-02	-3.5e-02	6.2e-01
CRBI	9.5e-02	-9.7e-02	-1.2e-01	-3.7e-02	6.0e-01
CWalks	5.8e-02	-6.6e-02	-1.3e-01	-2.6e-02	5.5e-01
League	4.0e-02	5.2e-02	9.2e-02	8.6e-01	-6.4e-03
Division	-2.5e-02	-1.7e-02	-5.6e-04	-2.4e-03	-1.5e-01
PutOuts	1.0e+00	-4.3e-02	7.5e-02	5.5e-02	2.2e-01
Assists	-4.3e-02	1.0e+00	7.0e-01	4.4e-02	5.0e-02
Errors	7.5e-02	7.0e-01	1.0e+00	6.3e-02	-2.1e-02
NewLeague	5.5e-02	4.4e-02	6.3e-02	1.0e+00	-1.0e-02
Log_Salary	2.2e-01	5.0e-02	-2.1e-02	-1.0e-02	1.0e+00



<Figure size 640x480 with 0 Axes>

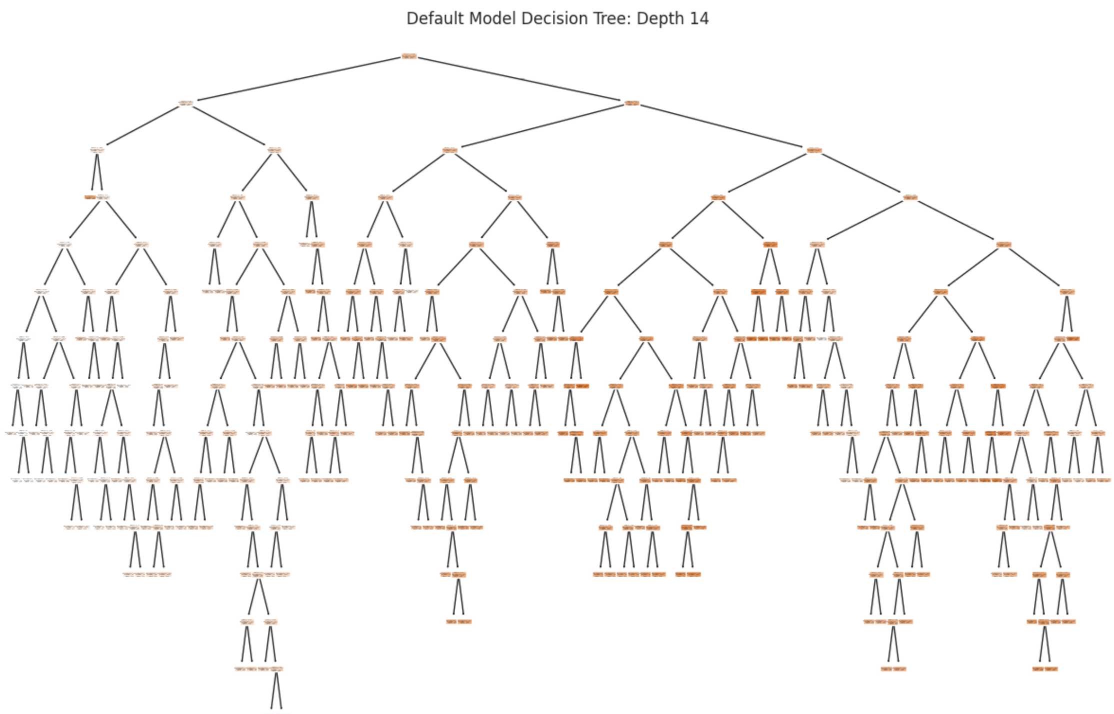


Features with high correlation to Log_Salary: CHits, CRuns, CAtBat, CRBI, CWalks, Years

4. Develop a regression decision tree model for the dataset base on default setting of the regressor, (i.e. use DecisionTreeRegressor() without any input. Check out the documentation for DecisionTreeRegressor() in Scikit learn library). You can save the image of the decision tree by right clicking on the console and save image/copy image and paste it into a paint or any other graphic package and save it as a .png file so you can look at it.

[34]:
```
selected_feature_names = ['CHits', 'CRuns', 'CAtBat', 'CRBI', 'CWalks', 'Years']
X1_selected = data_stand[selected_feature_names]
X_train, X_test, y_train, y_test = train_test_split(X1_selected, Y1,␣
↪test_size=0.3)
default_model = DecisionTreeRegressor()
default_model.fit(X_train, y_train)
feature_names = X1_selected.columns if hasattr(X1_selected, 'columns') else None
plt.figure(figsize=(12, 8))
plot_tree(default_model, filled=True,
          feature_names=selected_feature_names,
```

```
           precision=2, proportion=True)
plt.title(f"Default Model Decision Tree: Depth {default_model.get_depth()}")
plt.tight_layout()
plt.show()
```



[35]:
```
default_predict = default_model.predict(X_test)
default_mse = mean_squared_error(y_test, default_predict)
print(f"MSE of default tree: {default_mse:.4f}")
```

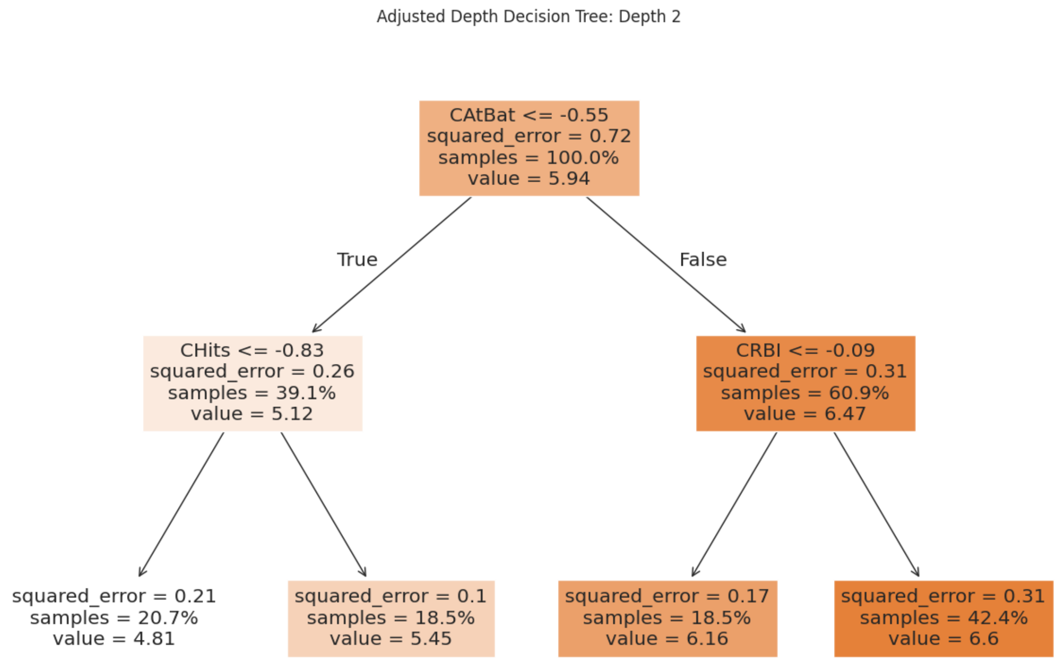
```
MSE of default tree: 0.2756
```

5. How many levels does the default decision tree have based on the six features (tree depth)? The tree with 6 features has 14 levels, indicating an overfit model. The tree is too large to display in full here, but the image can be saved as a .png file for further examination.

6. Run the system again with a depth of 2 and compare the performance measures in the two cases. Explain the difference in the context of performance measure as it relates to variance/bias trade off.

[36]:
```
depth_2_model = DecisionTreeRegressor(max_depth=2)
depth_2_model.fit(X_train, y_train)
feature_names = X1_selected.columns if hasattr(X1_selected, 'columns') else None
plt.figure(figsize=(12, 8))
plot_tree(depth_2_model, filled=True,
```

```
          feature_names=selected_feature_names,
          precision=2, proportion=True)
plt.title(f"Adjusted Depth Decision Tree: Depth {depth_2_model.get_depth()}")
plt.tight_layout()
plt.show()
```



[37]:
```
depth_2_predict = depth_2_model.predict(X_test)
depth_2_mse = mean_squared_error(y_test, depth_2_predict)
print(f"MSE of depth of 2 tree: {depth_2_mse:.4f}")
```

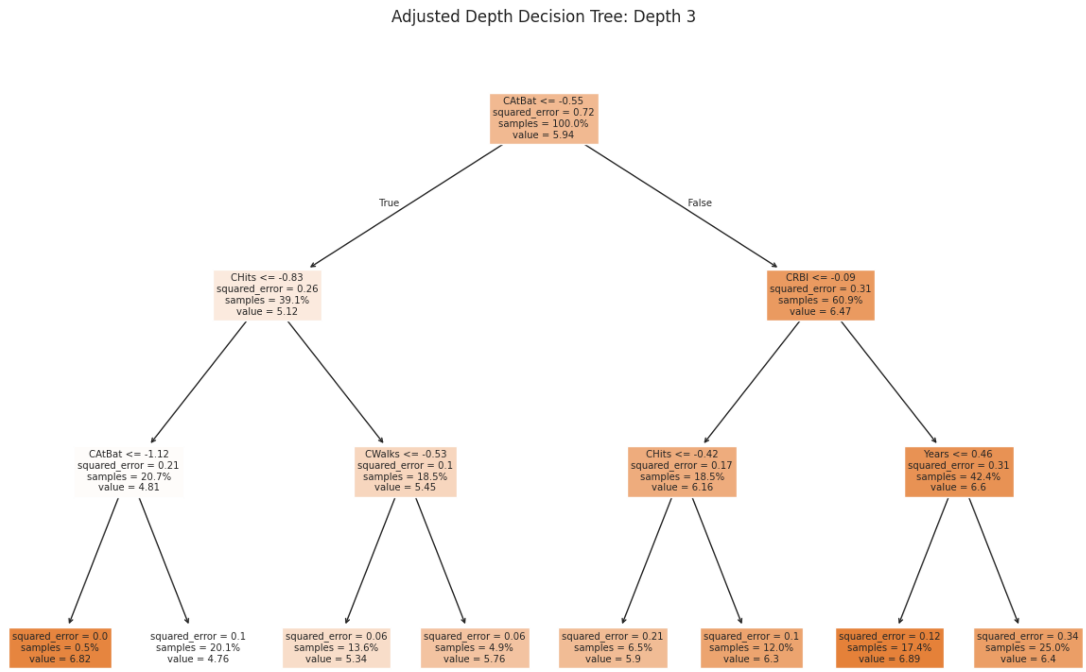
```
MSE of depth of 2 tree: 0.3662
```

The default model has the maximum amount of features (depth of 14). This makes the model highly overfitted and has a lower MSE_test. It fits the training data very well, hence not being able to generalize and make predictions if a new and unexposed dataset is given to it. The tree with depth of 2 has less features and a lower variance, better for generalization.

7. Try the code a third time with a depth of 3 and make the same comparison as in step 6.

[38]:
```
depth_3_model = DecisionTreeRegressor(max_depth=3)
depth_3_model.fit(X_train, y_train)
feature_names = X1_selected.columns if hasattr(X1_selected, 'columns') else None
plt.figure(figsize=(12, 8))
plot_tree(depth_3_model, filled=True,
```

```
         feature_names=selected_feature_names,
         precision=2, proportion=True)
plt.title(f"Adjusted Depth Decision Tree: Depth {depth_3_model.get_depth()}")
plt.tight_layout()
plt.show()
```



[39]:
```
depth_3_predict = depth_3_model.predict(X_test)
depth_3_mse = mean_squared_error(y_test, depth_3_predict)
print(f"MSE of depth of 3 tree: {depth_3_mse:.4f}")
```

```
MSE of depth of 3 tree: 0.2790
```

The tree with depth of 3 yields a slightly lower MSE_test than the depth of 2, but is still higher than the default model. This is an expected outcome as the progression shows movement toward the optimal complexity in the bias-variance tradeoff. Depth of 3 may be the most optimal number of features, yielding similar error but way less complexity.

8. If you were to optimize this system using the tree depth (max_depth) as the hyper-parameter what would be your suggestion? Use the depth of 3 as it is half as deep/complex but has a similar MSE. This allows for better predicting while maintaining accuracy.

9. Use the bank note authentication dataset as given in the sample code to build a classification tree

[40]:

```
filename = 'bill_authentication.csv'
data = read_csv(filename)
set_printoptions(precision=3)
data.head(5)
print(data.isnull().sum())
```

```
Variance    0
Skewness    0
Curtosis    0
Entropy     0
Class       0
dtype: int64
```

[41]:

```
Y1 = data['Class']
array = data.values
X1 = data.drop(columns='Class', axis=1)
X1names = X1.columns
X1.head(5)
```

[41]:

	Variance	Skewness	Curtosis	Entropy
0	3.6	8.7	-2.8	-0.4
1	4.5	8.2	-2.5	-1.5
2	3.9	-2.6	1.9	0.1
3	3.5	9.5	-4.0	-3.6
4	0.3	-4.5	4.6	-1.0

[42]:

```
# Standardize
data_stand = X1.copy()
stand_scaler = StandardScaler().fit(data_stand)
data_stand = stand_scaler.transform(data_stand)
# add output to standardized data
data_stand = pd.DataFrame(data_stand, columns=X1names, index=X1.index)
X1_stand = data_stand.copy()
data_objects = ((data_stand, 'data_stand'), (data, "data_raw"))
```

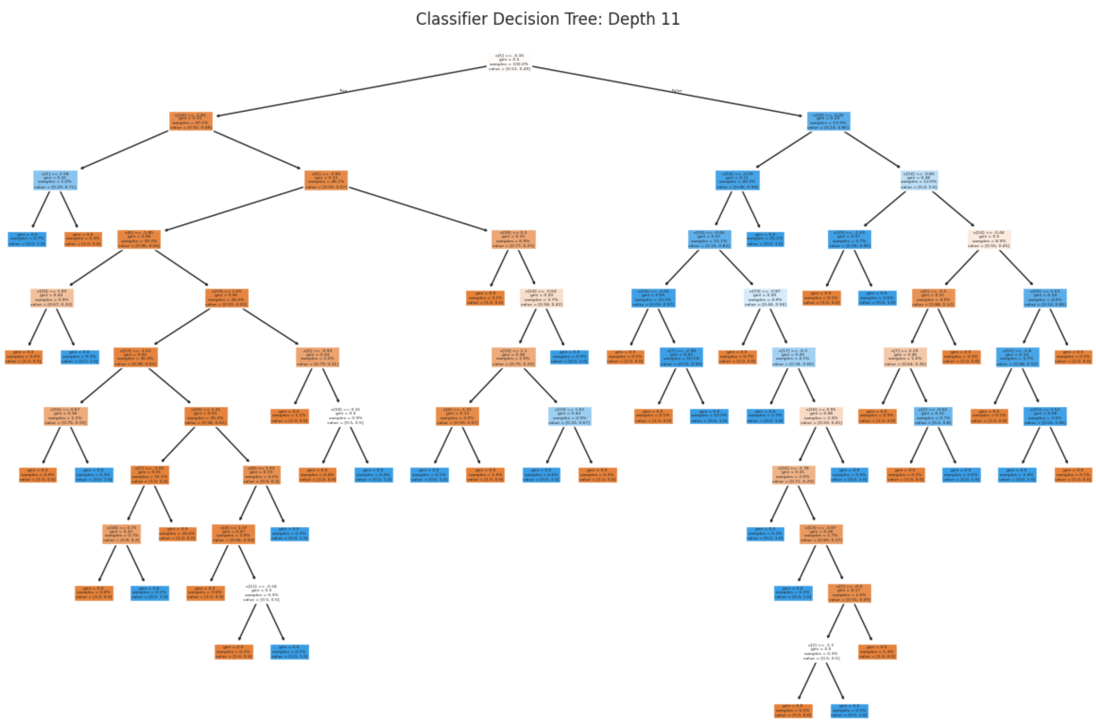
[43]:

```
set_option('display.width', 150)
set_option('display.precision', 1)
print('Standardized Data')
print(data_stand.describe())
```

```
Standardized Data
       Variance  Skewness  Curtosis  Entropy
count   1.4e+03   1.4e+03   1.4e+03  1.4e+03
mean    0.0e+00   4.1e-17   1.0e-17 -4.9e-17
std     1.0e+00   1.0e+00   1.0e+00  1.0e+00
min    -2.6e+00  -2.7e+00  -1.6e+00 -3.5e+00
25%    -7.8e-01  -6.2e-01  -6.9e-01 -5.8e-01
50%     2.2e-02   6.8e-02  -1.8e-01  2.9e-01
```

```
75%      8.4e-01   8.3e-01   4.1e-01   7.6e-01
max      2.2e+00   1.9e+00   3.8e+00   1.7e+00
```

[44]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=42)
classifier_model = DecisionTreeClassifier()
feature_names = X_train.columns if hasattr(X_train, 'columns') else None
classifier_model.fit(X_train, y_train)
plt.figure(figsize=(12, 8))
plot_tree(classifier_model, filled=True,
          feature_names=feature_names,
          precision=2, proportion=True)
plt.title(f"Classifier Decision Tree: Depth {classifier_model.get_depth()}")
plt.tight_layout()
plt.show()
```

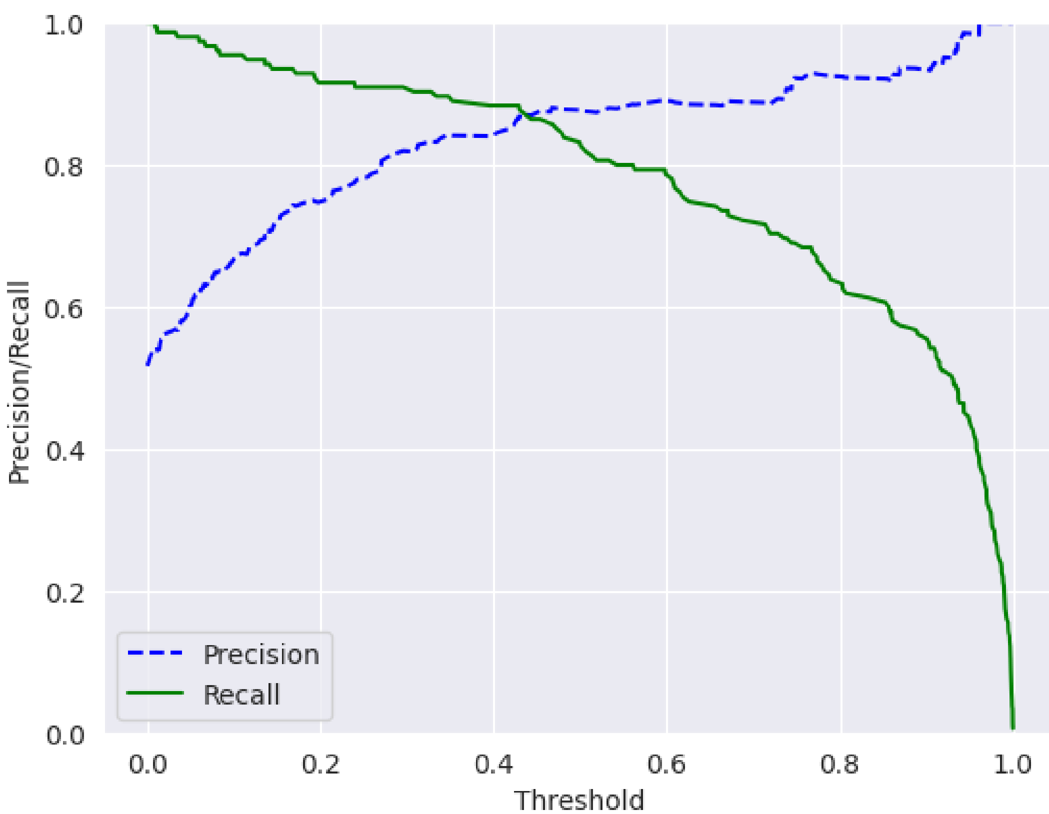


10. Use the sample code given on Canvas to plot the recall/precision curve for authentication dataset.

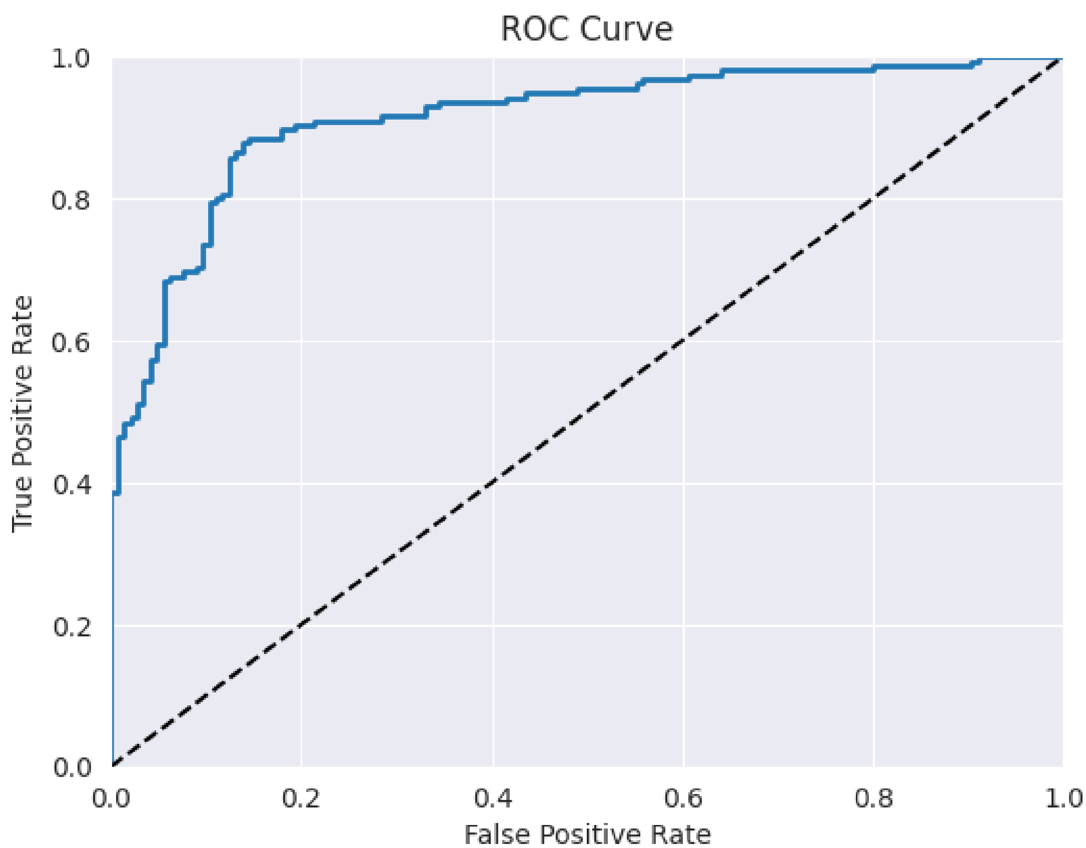
[45]:
```
num_folds = 10
kfold = KFold(n_splits=10, random_state=7, shuffle=True)

# use logistic regression model
model = LogisticRegression()
```

```python
# calculate the results
results = cross_val_score(model, data_stand, Y1, cv=kfold)
print(results.mean())
logit = model.fit(X_train,y_train)
y_scores =logit.predict_proba(X_test)
precisions, recalls, thresholds = precision_recall_curve(y_test, y_scores[:,1])

# Finally, you can plot precision and recall as functions of the threshold␣
↪value using
# Matplotlib
def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
    plt.plot(thresholds, precisions[:-1], "b--", label="Precision")
    plt.plot(thresholds, recalls[:-1], "g-", label="Recall")
    plt.xlabel("Threshold")
    plt.legend(loc="lower left")
    plt.ylim([0, 1])
    plt.ylabel("Precision/Recall")
plot_precision_recall_vs_threshold(precisions, recalls, thresholds)
plt.show()
```

0.981053633767058



[46]:
```
from sklearn.metrics import roc_curve
fpr, tpr, thresholds2 = roc_curve(y_test, y_scores[:,1])
# plot roc_curve
def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title("ROC Curve")
plt.figure()
plot_roc_curve(fpr, tpr)
plt.show()
```



11. Based on step 10 choose a suitable threshold to achieve a high precision. Would this strategy work in every case? It seems with a high enough threshold you can achieve a good precision, is this method a good approach to optimizing your classifier?

A good threshold would be ~0.45 as it balances precision and recall. Choosing a threshold of 0.8 will give higher precision (~0.1 increase) but at a great detriment to recall. This type of strategy will likely not work in every case. For example, precision might be the highest need in cybersecurity, but recall might be more important in healthcare. It depends on the context and the goals of the model. Optimizing just on precision is similar to optimizing just on variance. There's a tradeoff and there is no one universal way to approach optimization for a classifier.