descisionTree_hw_baseball_CMPE188

March 13, 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.

[43]:
```
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 LinearRegression
from sklearn.feature_selection import RFE
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
from sklearn.metrics import precision_recall_curve
from sklearn.model_selection import train_test_split
```

[44]:
```
# 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
X, y = make_classification(n_samples=1000, n_features=20, n_classes=2,
                           random_state=42)
```

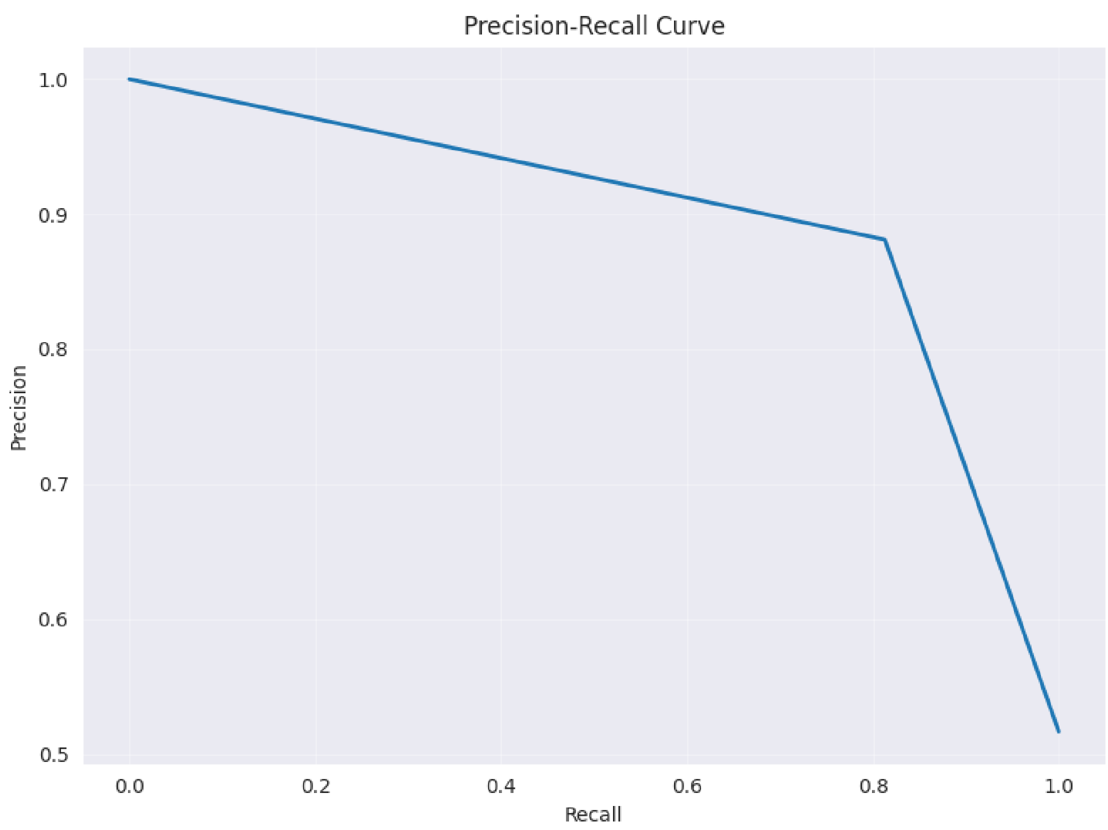
```python
# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
 ↪random_state=42)

# 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.

[45]:
```
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
```

[46]:
```
# 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
```

[47]:

```
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
```

[47]:

```
   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
```

[48]:
```
# 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"))
```

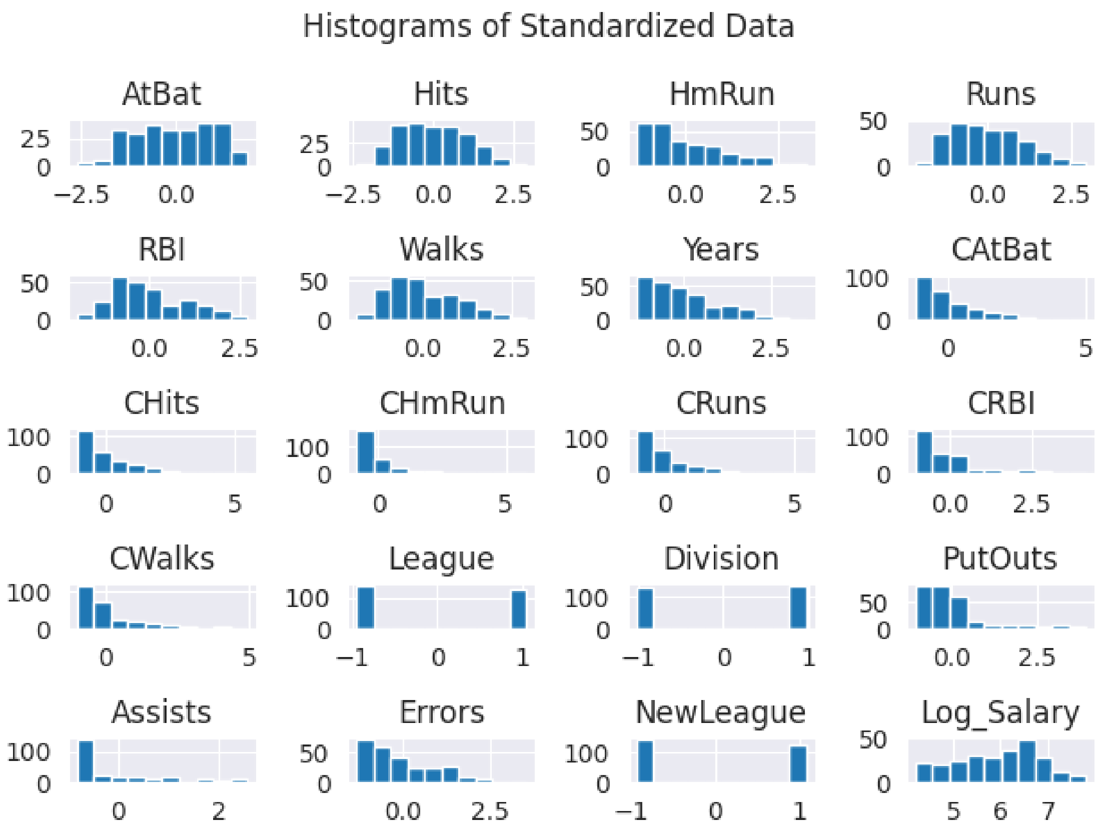
[49]:
```
set_option('display.width', 150)
set_option('display.precision', 1)
print('Standardized Data')
print(data_stand.describe())
```

```
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
```

[50]:
```
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).

[51]:
```
plt.figure() # new plot
#plt.tight_layout()
```

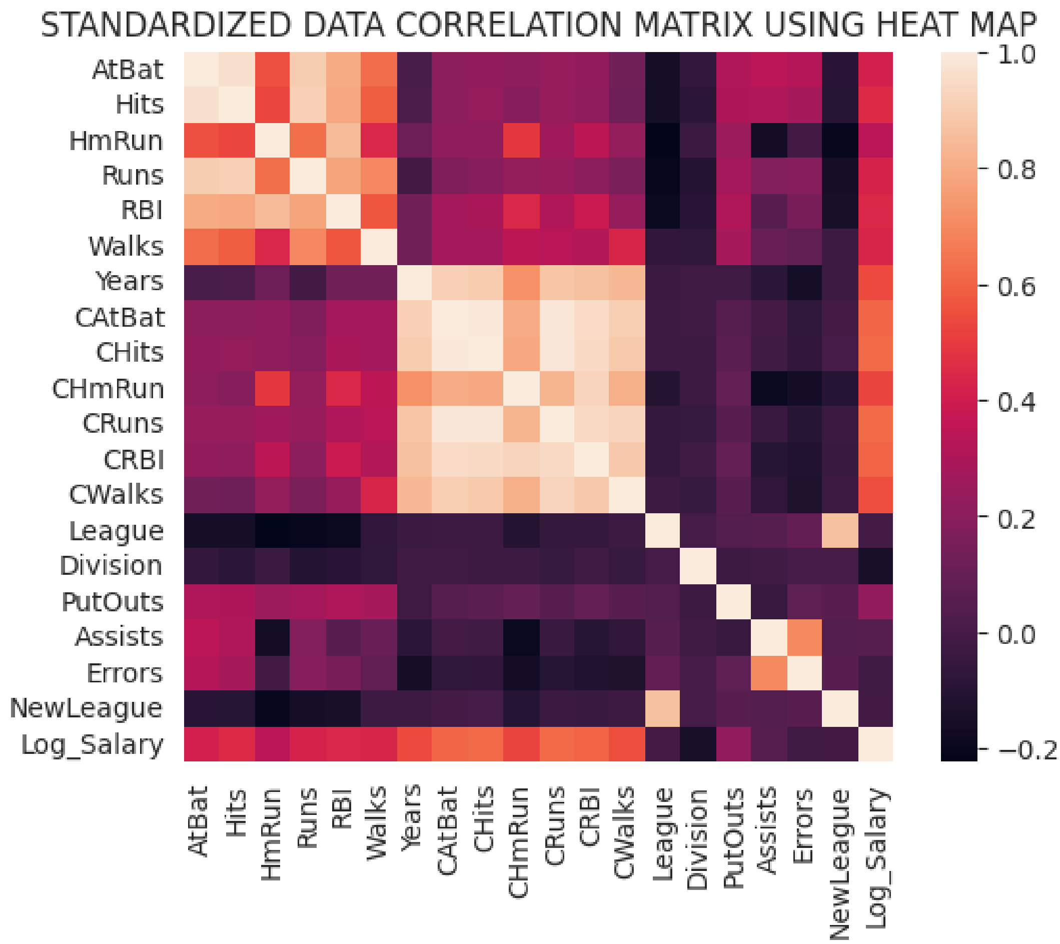
```
corMat = data_stand_with_salary.corr(method='pearson')
print(corMat)
## plot correlation matrix as a heat map
sns.heatmap(corMat, square=True)
plt.yticks(rotation=0)
plt.xticks(rotation=90)
plt.title(f"STANDARDIZED DATA CORRELATION MATRIX USING HEAT MAP")
plt.show()

## 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)
plt.show()
```

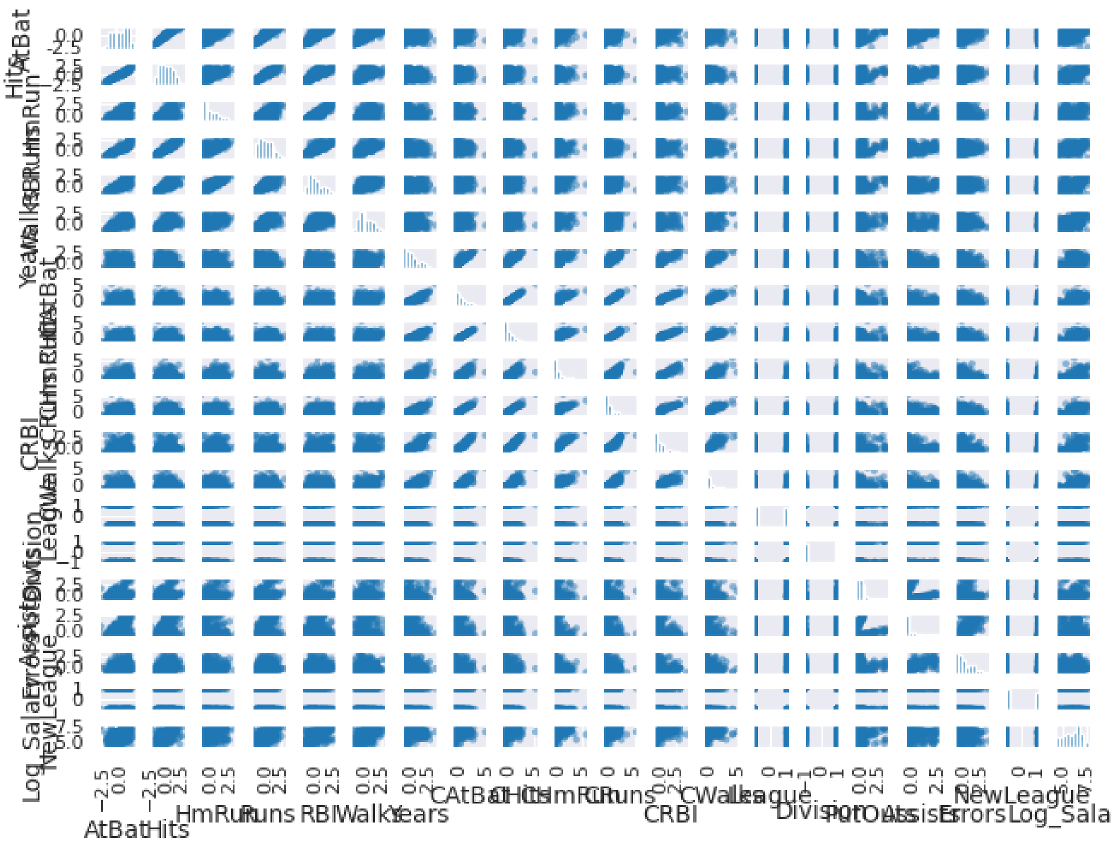
```
             AtBat     Hits    HmRun     Runs      RBI    Walks    Years  \
CAtBat    CHits   CHmRun    CRuns     CRBI   CWalks   League  Division  \
AtBat      1.0e+00  9.6e-01  5.6e-01  9.0e-01  8.0e-01  6.2e-01  1.3e-02
2.1e-01  2.3e-01  2.1e-01  2.4e-01  2.2e-01  1.3e-01 -1.5e-01  -5.6e-02
Hits       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>
```

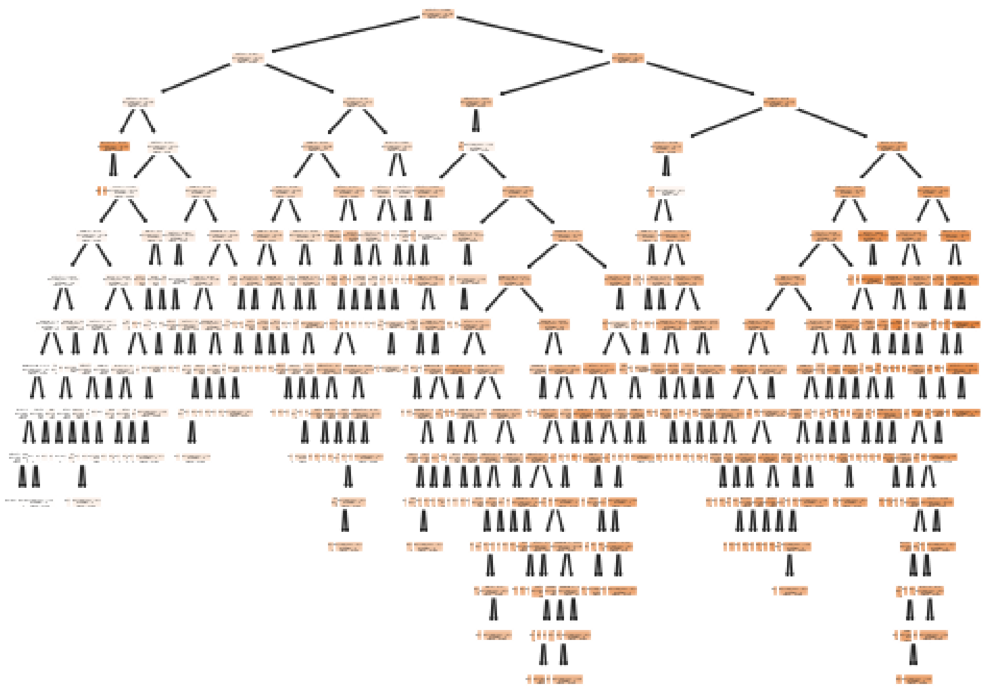


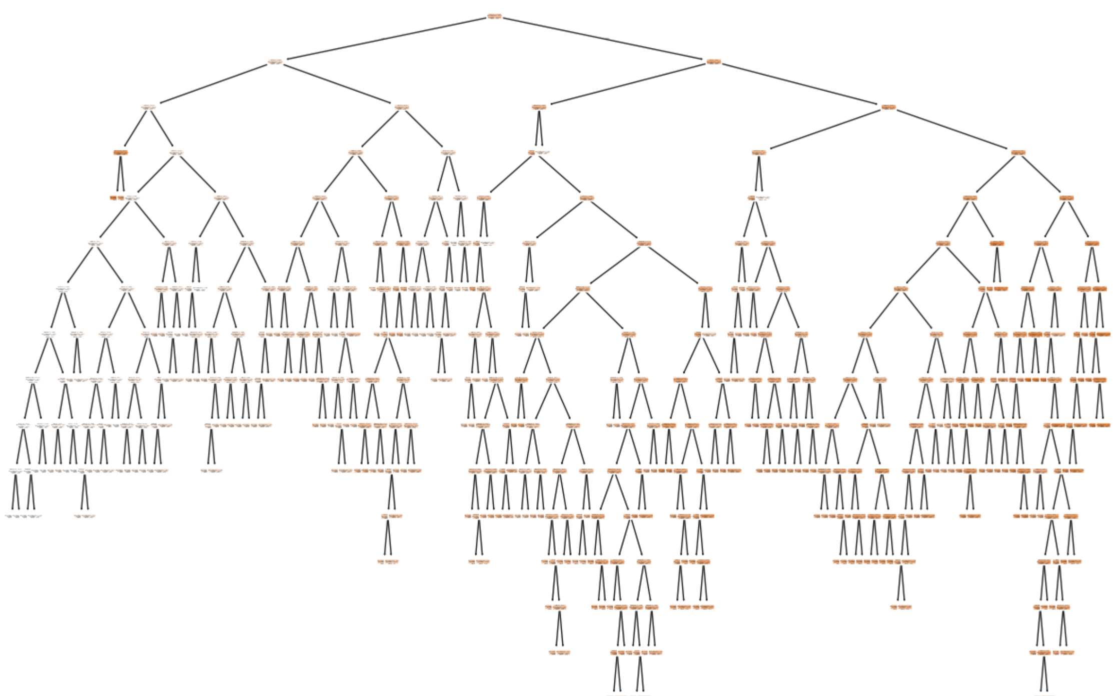
Features with high correlation to Log_Salary: CHits, CRuns, CAtBat, CRBI, CWalks, Years

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.

[52]:
```
model = DecisionTreeRegressor()
model.fit(data_stand, Y1)
# print image of the tree
from sklearn.tree import plot_tree
feature_names = data_stand.columns if hasattr(data_stand, 'columns') else None
plot_tree(model, filled=True, feature_names=feature_names)
# More customized tree plot
plt.figure(figsize=(15, 10))  # Set figure size
plot_tree(model,
          filled=True,
          feature_names=feature_names,
          precision=2,  # Number of decimal places
          proportion=True,  # Show proportions instead of counts
```

```
            rounded=True)  # Rounded node corners
plt.show()
```





5. How many levels does the default decision tree have based on the six features (tree depth)?
   The tree with 6 features has 15 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.