```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.naive_bayes import GaussianNB
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score
from sklearn.impute import KNNImputer
from scipy.stats import kurtosis, skew
from scipy.stats import chi2_contingency, ttest_ind, f_oneway
from sklearn.preprocessing import LabelEncoder
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report
from sklearn.decomposition import PCA
from scipy import stats
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold, cross_val_score
from sklearn.tree import DecisionTreeClassifier
```

```
df=pd.read_csv('SalaryPrediction.csv')
```

```
df.head()
```

	Wage	Age	Club	League	Nation	Position	Apps	Caps
0	46,427,000	23	PSG	Ligue 1 Uber Eats	FRA	Forward	190	57
1	42,125,000	30	PSG	Ligue 1 Uber Eats	BRA	Midfilder	324	119
2	34,821,000	35	PSG	Ligue 1 Uber Eats	ARG	Forward	585	162
3	19,959,000	31	R. Madrid	La Liga	BEL	Forward	443	120
4	19,500,000	31	Man UFC	Premier League	ESP	Goalkeeper	480	45

```
df.tail()
```

	Wage	Age	Club	League	Nation	Position	Apps	Caps
3902	3,400	19	Vigo	La Liga	ESP	Defender	0	0
3903	3,200	18	Famalicao	Primiera Liga	BRA	Goalkeeper	0	0
3904	2,900	18	Vigo	La Liga	ESP	Forward	0	0
3905	2,700	18	Vigo	La Liga	ESP	Defender	0	0
3906	1,400	18	Vigo	La Liga	ESP	Defender	0	0

```
df.sample()
```

	Wage	Age	Club	League	Nation	Position	Apps	Caps
610	2,600,000	22	Brentford	Premier League	DEN	Midfilder	136	16

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3907 entries, 0 to 3906
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   Wage      3907 non-null   object
 1   Age       3907 non-null   int64 
 2   Club      3907 non-null   object
 3   League    3907 non-null   object
 4   Nation    3907 non-null   object
 5   Position  3907 non-null   object
 6   Apps      3907 non-null   int64 
 7   Caps      3907 non-null   int64 
```

```
dtypes: int64(3), object(5)
memory usage: 244.3+ KB
```

```
df.dtypes
```

```
Wage        object
Age          int64
Club        object
League      object
Nation      object
Position    object
Apps         int64
Caps         int64
dtype: object
```

```
df.shape
```

```
(3907, 8)
```

```
df.columns
```

```
Index(['Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'], dtype='object')
```

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Age	3907.0	24.120553	4.935638	18.0	20.0	24.0	28.0	41.0
Apps	3907.0	140.057077	131.694425	0.0	15.0	115.0	224.5	715.0
Caps	3907.0	8.926542	20.518234	0.0	0.0	0.0	6.0	180.0

```
df.isnull().sum()
```

```
Wage        0
Age         0
Club        0
League      0
Nation      0
Position    0
Apps        0
Caps        0
dtype: int64
```

```
df.dropna()
```

	Wage	Age	Club	League	Nation	Position	Apps	Caps
0	46,427,000	23	PSG	Ligue 1 Uber Eats	FRA	Forward	190	57
1	42,125,000	30	PSG	Ligue 1 Uber Eats	BRA	Midfilder	324	119
2	34,821,000	35	PSG	Ligue 1 Uber Eats	ARG	Forward	585	162
3	19,959,000	31	R. Madrid	La Liga	BEL	Forward	443	120
4	19,500,000	31	Man UFC	Premier League	ESP	Goalkeeper	480	45
...	...	...	...	...	...	...	...	...
3902	3,400	19	Vigo	La Liga	ESP	Defender	0	0
3903	3,200	18	Famalicao	Primiera Liga	BRA	Goalkeeper	0	0
3904	2,900	18	Vigo	La Liga	ESP	Forward	0	0
3905	2,700	18	Vigo	La Liga	ESP	Defender	0	0
3906	1,400	18	Vigo	La Liga	ESP	Defender	0	0

3907 rows × 8 columns

```
df.isnull().sum()
```

```
Wage        0
Age         0
Club        0
League      0
```

```
Nation      0
Position    0
Apps        0
Caps        0
dtype: int64
```

```
df.isna().any(axis=0)
```

```
Wage        False
Age         False
Club        False
League      False
Nation      False
Position    False
Apps        False
Caps        False
dtype: bool
```

```
df.isnull().sum()
```

```
Wage        0
Age         0
Club        0
League      0
Nation      0
Position    0
Apps        0
Caps        0
dtype: int64
```

```
df['Wage'].fillna('Unknown', inplace=True)
df['Age'].fillna('Unknown', inplace=True)
df['Club'].fillna('Unknown', inplace=True)
df['League'].fillna('Unknown', inplace=True)
df['Nation'].fillna('Unknown', inplace=True)
df['Position'].fillna('Unknown', inplace=True)
df['Apps'].fillna('Unknown', inplace=True)
df['Caps'].fillna('Unknown', inplace=True)
df.isnull().sum()
```

```
Wage        0
Age         0
Club        0
League      0
Nation      0
Position    0
Apps        0
Caps        0
dtype: int64
```

```
df.duplicated()
```

```
0       False
1       False
2       False
3       False
4       False
        ...
3902    False
3903    False
3904    False
3905    False
3906    False
Length: 3907, dtype: bool
```

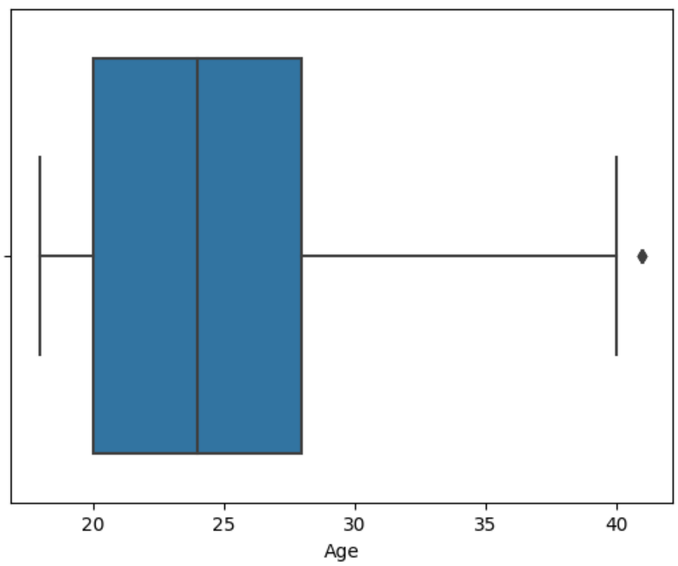
```
df[df.duplicated()]
```

	Wage	Age	Club	League	Nation	Position	Apps	Caps
1488	780,000	18	Chelsea	Premier League	ENG	Midfilder	0	0
2372	182,000	18	Chelsea	Premier League	ENG	Defender	0	0
2433	163,000	18	LOSC	Ligue 1 Uber Eats	CMR	Midfilder	2	0
2476	156,000	18	Man City	Premier League	ENG	Midfilder	0	0
2584	130,000	18	Liverpool	Premier League	ENG	Forward	0	0
...	...	...	...	...	...	...	...	...
3868	13,000	18	A. Madrid	La Liga	ESP	Midfilder	0	0
3869	13,000	18	A. Madrid	La Liga	ESP	Defender	0	0
3875	13,000	18	Sevilla	La Liga	ESP	Defender	0	0
3878	13,000	18	Valencia	La Liga	ESP	Defender	0	0
3879	13,000	18	A. Bilbao	La Liga	ESP	Defender	0	0

65 rows × 8 columns

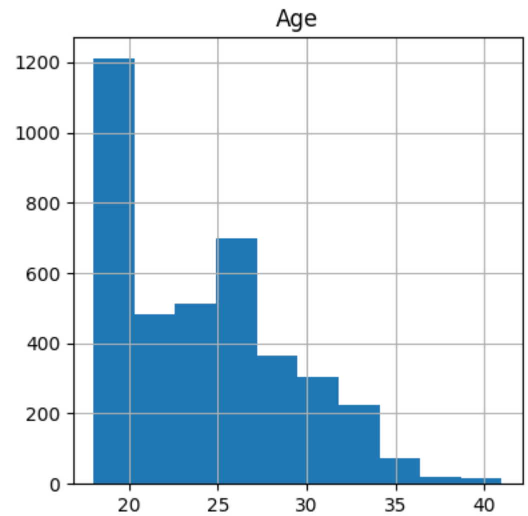
Data Visualization and Missing Values Treament

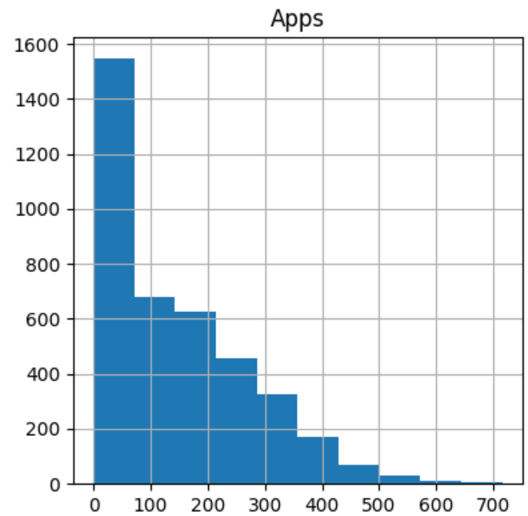
```
sns.boxplot(x='Age', data=df)
plt.show()
```

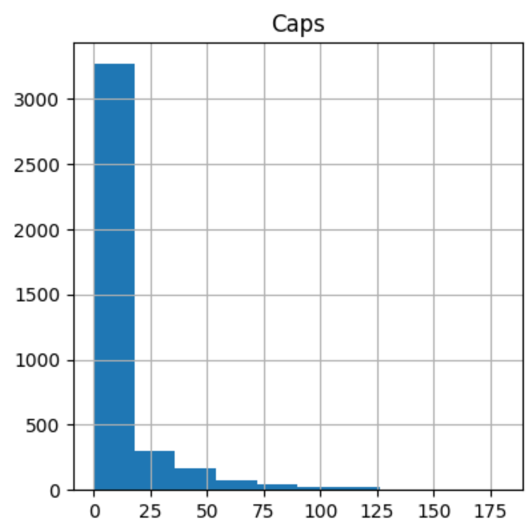



```
df.hist(figsize=(10,10))
```

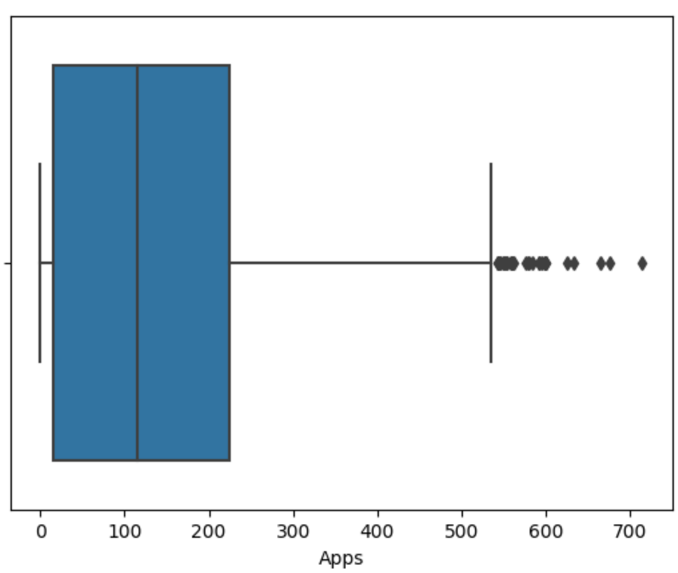
```
array([[<Axes: title={'center': 'Age'}>,
        <Axes: title={'center': 'Apps'}>],
       [<Axes: title={'center': 'Caps'}>, <Axes: >]], dtype=object)
```



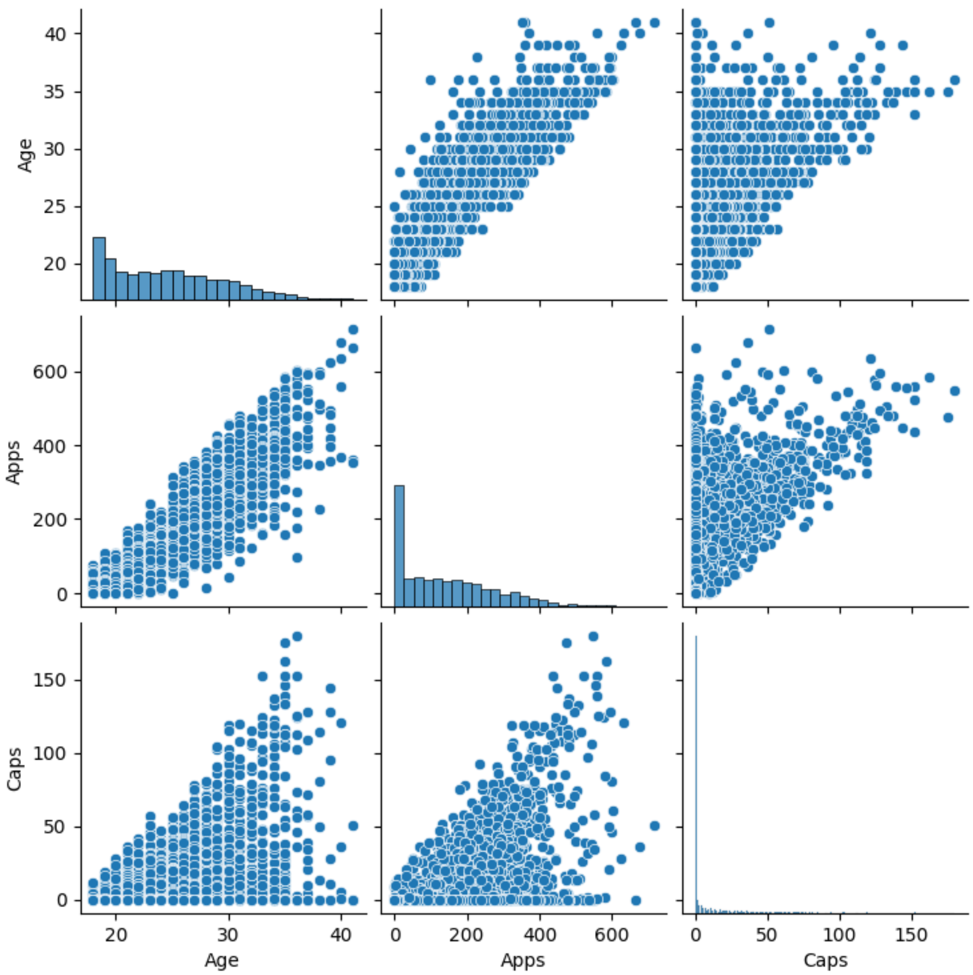





```
sns.boxplot(x='Apps', data=df)
plt.show()
```



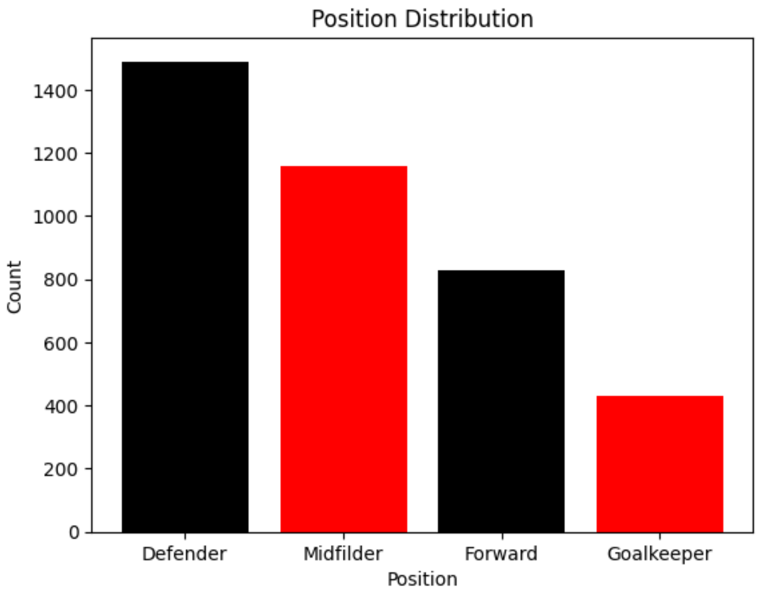
```
import seaborn as sns
import matplotlib.pyplot as plt

scatter_columns = ['Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps']
sns.pairplot(df[scatter_columns])
plt.show()
```



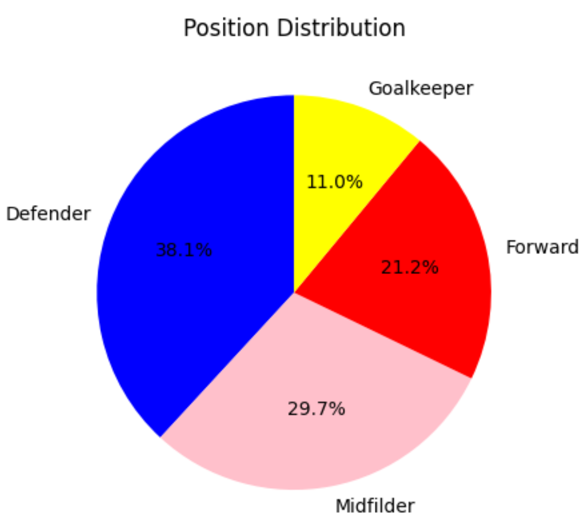

```
df.Position.value_counts()
```

```
Defender      1490
Midfilder     1160
Forward        827
Goalkeeper     430
Name: Position, dtype: int64
```

```
import matplotlib.pyplot as plt

position_counts = df['Position'].value_counts()
colors = ['black', 'red']

plt.bar(position_counts.index, position_counts.values, color=colors)
plt.xlabel('Position')
plt.ylabel('Count')
plt.title('Position Distribution')
plt.show()
```




```
import matplotlib.pyplot as plt

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
gender_counts = df['Position'].value_counts()
colors = ['blue', 'pink','Red','Yellow']

plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%', startangle=90, colors=colors)

# Adding a title
plt.title('Position Distribution')

# Show the plot
plt.show()
```



Binning process

```
import numpy as np
import pandas as pd
```

```
import numpy as np
import pandas as pd

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
num_bins = int(np.sqrt(len(df)))
columns_to_bin = ['Apps', 'Caps']

# Equal-width binning using pd.qcut for non-numeric columns
for column in columns_to_bin:
    bin_edges = np.linspace(df[column].min(), df[column].max(), num_bins + 1)
    bin_labels = [f'Bin{i}' for i in range(1, num_bins + 1)]
    df[f'{column}_bins'] = pd.cut(df[column], bins=bin_edges, labels=bin_labels, duplicates='drop')

result_columns = [col for column in columns_to_bin for col in [column, f'{column}_bins']]

# Resetting index and filtering the first 15 rows
df_reset = df[result_columns + ['Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps']].reset_index(drop=True)
df_filtered = df_reset.head(15)

print(df_filtered)
print(num_bins)
```

```
    Apps Apps_bins  Caps Caps_bins        Wage  Age       Club  \
0    190     Bin17    57     Bin20  46,427,000   23        PSG
1    324     Bin29   119     Bin41  42,125,000   30        PSG
2    585     Bin51   162     Bin56  34,821,000   35        PSG
3    443     Bin39   120     Bin42  19,959,000   31  R. Madrid
4    480     Bin42    45     Bin16  19,500,000   31    Man UFC
5    371     Bin33    94     Bin33  18,810,000   30  R. Madrid
6    427     Bin38   102     Bin36  18,200,000   29      Inter
7    367     Bin32    85     Bin30  18,200,000   30  Liverpool
8    326     Bin29    77     Bin27  18,200,000   27    Chelsea
9    287     Bin25    86     Bin30  18,200,000   29    Man UFC
10   399     Bin35    91     Bin32  17,680,000   31   Man City
11   159     Bin14    21      Bin8  17,680,000   22   Man City
12   433     Bin38   105     Bin37  16,121,000   32  R. Madrid
13   368     Bin32    50     Bin18  15,965,000   29  A. Madrid
14   347     Bin31    61     Bin22  15,600,000   31    Chelsea

               League Nation    Position  Apps  Caps
0   Ligue 1 Uber Eats    FRA     Forward   190    57
1   Ligue 1 Uber Eats    BRA   Midfilder   324   119
2   Ligue 1 Uber Eats    ARG     Forward   585   162
3             La Liga    BEL     Forward   443   120
4      Premier League    ESP  Goalkeeper   480    45
5             La Liga    AUT    Defender   371    94
6             Serie A    BEL     Forward   427   102
7      Premier League    EGY     Forward   367    85
8      Premier League    ENG   Midfilder   326    77
9      Premier League    FRA    Defender   287    86
10     Premier League    BEL   Midfilder   399    91
11     Premier League    NOR     Forward   159    21
12            La Liga    GER   Midfilder   433   105
13            La Liga    SVN  Goalkeeper   368    50
14     Premier League    SEN    Defender   347    61
62
```

```
import pandas as pd
from scipy.stats import skew, kurtosis

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Apps', 'Caps'
numerical_columns = ['Wage', 'Age', 'Apps', 'Caps']
categorical_columns = ['Club', 'League', 'Nation', 'Position']

# Convert numerical columns to numeric (handling errors)
df[numerical_columns] = df[numerical_columns].apply(pd.to_numeric, errors='coerce')

numerical_statistics = pd.DataFrame({
    'Column': numerical_columns,
    'Min': df[numerical_columns].min(),
    'Max': df[numerical_columns].max(),
    'Mean': df[numerical_columns].mean(),
    'Variance': df[numerical_columns].var(),
    'Standard Deviation': df[numerical_columns].std(),
    'Skewness': skew(df[numerical_columns]),
    'Kurtosis': kurtosis(df[numerical_columns])
})

categorical_value_counts = pd.DataFrame({
    'Column': categorical_columns,
    'Value Counts': df[categorical_columns].apply(lambda x: x.value_counts().to_dict())
})

print("Numerical Statistics:")
print(numerical_statistics)
print("\nCategorical Value Counts:")
print(categorical_value_counts)
```

```
Numerical Statistics:
     Column   Min    Max        Mean      Variance  Standard Deviation  \
Wage   Wage   NaN    NaN         NaN           NaN                 NaN
Age     Age  18.0   41.0   24.120553     24.360527            4.935638
Apps   Apps   0.0  715.0  140.057077  17343.421473          131.694425
Caps   Caps   0.0  180.0    8.926542    420.997931           20.518234

      Skewness   Kurtosis
Wage       NaN        NaN
Age   0.569030  -0.460465
Apps  0.854847   0.166011
Caps  3.418042  14.239202

Categorical Value Counts:
            Column                                       Value Counts
Club          Club  {'MRT': 64, 'BRG': 61, 'VIZ': 57, 'Chelsea': 5...
League      League  {'Premier League': 875, 'Primiera Liga': 747, ...
Nation      Nation  {'ESP': 452, 'POR': 428, 'ENG': 410, 'FRA': 35...
Position  Position  {'Defender': 1490, 'Midfilder': 1160, 'Forward...
```

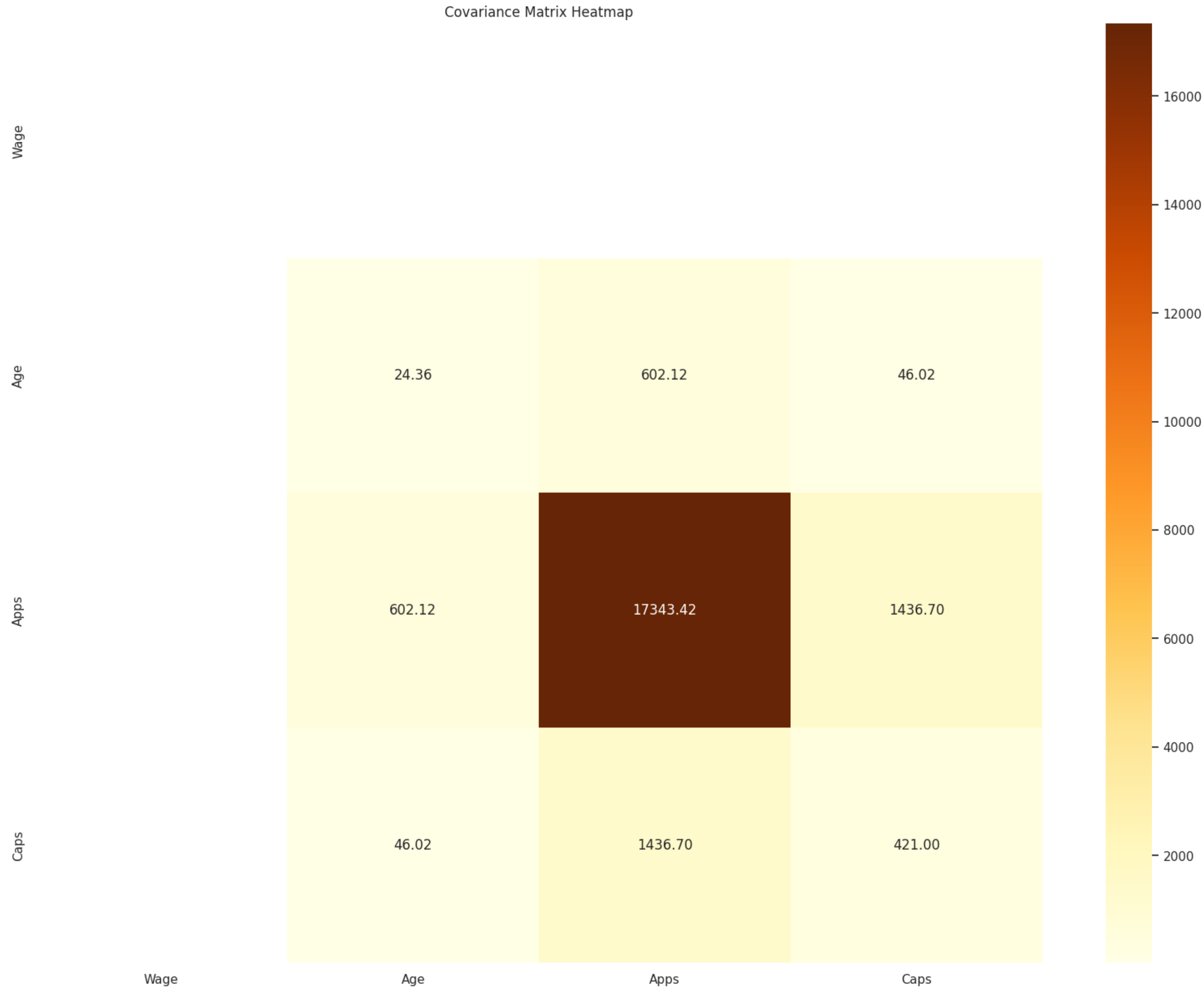
Covariance Matrix

```
import pandas as pd
# Assuming your dataset is named 'df' and has columns: 'Name', 'Gender', 'Count', 'Probability' numerical_columns = ['Count', 'Probability'
covariance_matrix = df[numerical_columns].cov()
print("Covariance Matrix:")
print(covariance_matrix)
```

```
Covariance Matrix:
      Wage         Age          Apps         Caps
Wage   NaN         NaN           NaN          NaN
Age    NaN   24.360527    602.115749    46.023451
Apps   NaN  602.115749  17343.421473  1436.704399
Caps   NaN   46.023451   1436.704399   420.997931
```

Covariance Matrix Heat Map

```
plt.figure(figsize=(20, 15))
sns.set(style="white") # Set background style
sns.heatmap(covariance_matrix, annot=True, cmap="YlOrBr", fmt=".2f",xticklabels=numerical_columns, yticklabels=numerical_columns)
plt.title("Covariance Matrix Heatmap")
plt.show()
```



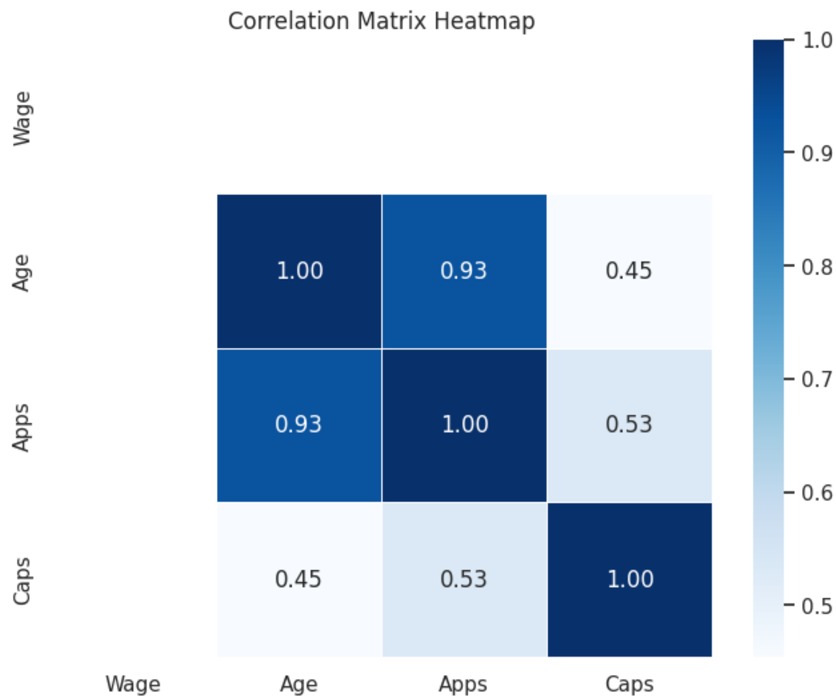
Correlation Matrix

```
correlation_matrix = df[numerical_columns].corr()
print(correlation_matrix)
```

```
      Wage       Age      Apps      Caps
Wage   NaN       NaN       NaN       NaN
Age    NaN  1.000000  0.926338  0.454460
Apps   NaN  0.926338  1.000000  0.531692
Caps   NaN  0.454460  0.531692  1.000000
```

Correlation Matrix Heatmap

```
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='Blues', fmt=".2f", linewidths=.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



Chi Square Test

```
import pandas as pd
from scipy.stats import chi2_contingency

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
categorical_columns = ['Club', 'League']
contingency_table = pd.crosstab(df[categorical_columns[0]], df[categorical_columns[1]])

chi2, p, dof, expected = chi2_contingency(contingency_table)

print("Chi-Square Statistics:", chi2)
print("P-value:", p)
print("Degrees of Freedom:", dof)
print("Expected Frequencies:")
print(pd.DataFrame(expected, index=contingency_table.index, columns=contingency_table.columns))
```

```
Chi-Square Statistics: 19535.0
P-value: 0.0
Degrees of Freedom: 575
Expected Frequencies:
League         Bundesliga   La Liga  Ligue 1 Uber Eats  Premier League  \
Club
1. FC Koln       4.704633  5.017149           3.919120        7.390581
A. Bilbao        3.849245  4.104940           3.206552        6.046839
A. Madrid        4.847197  5.169184           4.037881        7.614538
AC Ajaccio       3.849245  4.104940           3.206552        6.046839
AJ Auxerre       3.564116  3.800870           2.969030        5.598925
...                   ...       ...                ...             ...
VfL Wolfsburg    4.847197  5.169184           4.037881        7.614538
Vigo             4.989762  5.321218           4.156642        7.838495
Villarreal       3.849245  4.104940           3.206552        6.046839
West Ham         5.274891  5.625288           4.394164        8.286409
Wolves           6.700537  7.145636           5.581776       10.525979

League         Primiera Liga   Serie A
Club
1. FC Koln          6.309445  5.659073
A. Bilbao           5.162273  4.630151
A. Madrid           6.500640  5.830561
AC Ajaccio          5.162273  4.630151
AJ Auxerre          4.779882  4.287177
...                      ...       ...
VfL Wolfsburg       6.500640  5.830561
Vigo                6.691835  6.002048
Villarreal          5.162273  4.630151
West Ham            7.074226  6.345022
Wolves              8.986179  8.059893
```

```
[116 rows x 6 columns]
```

Z-Test

```
import numpy as np
import pandas as pd
from scipy import stats

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
sample_size = 100
df_sample = df['Wage'].sample(sample_size)

population_mean = df['Wage'].mean()
population_std = df['Wage'].std()
sample_mean = df_sample.mean()

alpha = 0.05
z_score = (sample_mean - population_mean) / (population_std / np.sqrt(sample_size))
print("Z-Score:", z_score)

z_critical = stats.norm.ppf(1 - alpha)
print("Critical Z-Score:", z_critical)

if z_score > z_critical:
    print("Reject H0")
else:
    print("Fail to Reject H0")
```

```
Z-Score: nan
Critical Z-Score: 1.6448536269514722
Fail to Reject H0
```

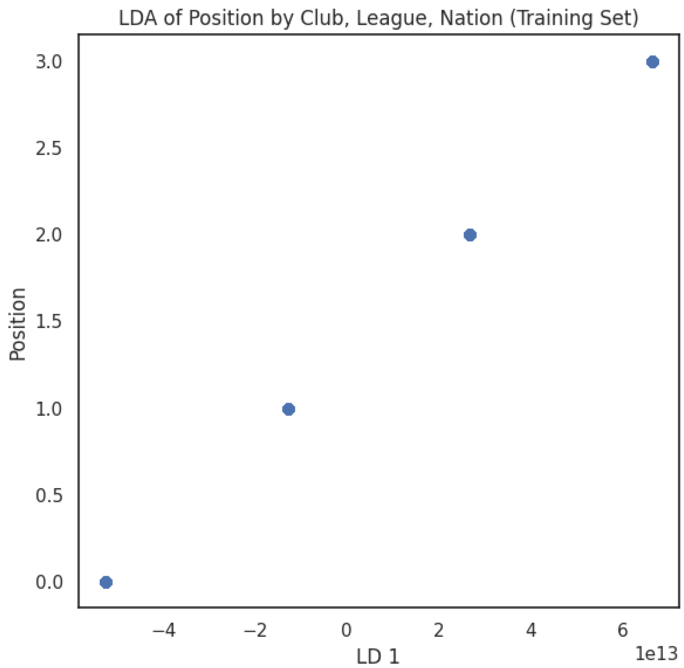
ANOVA

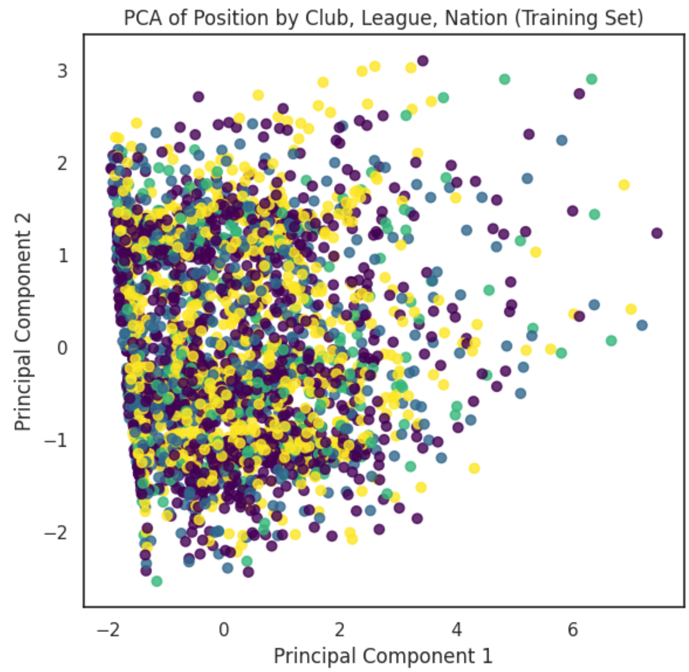
```
from scipy.stats import f_oneway

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
anova_result = f_oneway(
    df['Wage'][df['Position'] == 'Goalkeeper'],
    df['Wage'][df['Position'] == 'Defender'],
    df['Wage'][df['Position'] == 'Midfilder'],
    df['Wage'][df['Position'] == 'Forward']
)

print("\nANOVA Result")
print("F-statistic:", anova_result.statistic)
print("P-value:", anova_result.pvalue)
```

```
ANOVA Result
F-statistic: nan
P-value: nan
```

Feature reduction LDA and PCA

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.decomposition import PCA
from sklearn.impute import SimpleImputer  # Import SimpleImputer
import matplotlib.pyplot as plt

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
label_encoder = LabelEncoder()
categorical_columns = ['Club', 'League', 'Nation', 'Position']
for column in categorical_columns:
    df[column + '_encoded'] = label_encoder.fit_transform(df[column])

# Select relevant columns
columns_of_interest = ['Club_encoded', 'League_encoded', 'Nation_encoded', 'Position_encoded', 'Wage', 'Age', 'Apps', 'Caps']
features = df[columns_of_interest]
target = df['Position_encoded']  # Assuming 'Position' is the target variable for demonstration

# Impute missing values
imputer = SimpleImputer(strategy='mean')
features_imputed = imputer.fit_transform(features)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features_imputed, target, test_size=0.2, random_state=42)

# Standardize the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Applying LDA
lda = LinearDiscriminantAnalysis(n_components=1)
X_train_lda = lda.fit_transform(X_train_scaled, y_train)
X_test_lda = lda.transform(X_test_scaled)

# Applying PCA
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_scaled)
X_test_pca = pca.transform(X_test_scaled)

# Plotting LDA results
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.scatter(X_train_lda, y_train, alpha=0.8)
plt.title('LDA of Position by Club, League, Nation (Training Set)')
plt.xlabel('LD 1')
plt.ylabel('Position')

# Plotting PCA results
plt.subplot(1, 2, 2)
plt.scatter(X_train_pca[:, 0], X_train_pca[:, 1], c=y_train, cmap='viridis', alpha=0.8)
plt.title('PCA of Position by Club, League, Nation (Training Set)')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')

plt.tight_layout()
plt.show()
```





Naive Bayes

```
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.preprocessing import LabelEncoder
```

```
label_encoder = LabelEncoder()
```

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.impute import SimpleImputer  # Import SimpleImputer

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
label_encoder = LabelEncoder()
categorical_columns = ['Club', 'League', 'Nation', 'Position']
for column in categorical_columns:
    df[column + '_encoded'] = label_encoder.fit_transform(df[column])

features = df[['Club_encoded', 'League_encoded', 'Nation_encoded', 'Position_encoded', 'Wage', 'Age', 'Apps', 'Caps']]
target = df['Position_encoded']  # Assuming 'Position' is the target variable for demonstration

# Impute missing values
imputer = SimpleImputer(strategy='mean')
features_imputed = imputer.fit_transform(features)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features_imputed, target, test_size=0.2, random_state=42)

# Train Gaussian Naive Bayes model
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = nb_model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

print(f'Accuracy: {accuracy}')
print('Confusion Matrix:')
print(conf_matrix)
print('Classification Report:')
print(classification_rep)
```

```
Accuracy: 1.0
Confusion Matrix:
[[292   0   0   0]
 [  0 174   0   0]
 [  0   0  95   0]
 [  0   0   0 221]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       292
           1       1.00      1.00      1.00       174
           2       1.00      1.00      1.00        95
           3       1.00      1.00      1.00       221

    accuracy                           1.00       782
   macro avg       1.00      1.00      1.00       782
weighted avg       1.00      1.00      1.00       782
```

```
pip install pgmpy
```

```
Collecting pgmpy
  Downloading pgmpy-0.1.24-py3-none-any.whl (2.0 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.0/2.0 MB 6.3 MB/s eta 0:00:00
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from pgmpy) (3.2.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from pgmpy) (1.23.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from pgmpy) (1.11.4)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (from pgmpy) (1.2.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from pgmpy) (1.5.3)
Requirement already satisfied: pyparsing in /usr/local/lib/python3.10/dist-packages (from pgmpy) (3.1.1)
Requirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages (from pgmpy) (2.1.0+cu121)
Requirement already satisfied: statsmodels in /usr/local/lib/python3.10/dist-packages (from pgmpy) (0.14.1)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from pgmpy) (4.66.1)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from pgmpy) (1.3.2)
Requirement already satisfied: opt-einsum in /usr/local/lib/python3.10/dist-packages (from pgmpy) (3.3.0)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas->pgmpy) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas->pgmpy) (2023.3.post1)
```

```
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->pgmpy) (3.2.0)
Requirement already satisfied: patsy>=0.5.4 in /usr/local/lib/python3.10/dist-packages (from statsmodels->pgmpy) (0.5.4)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels->pgmpy) (23.2)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from torch->pgmpy) (3.13.1)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.10/dist-packages (from torch->pgmpy) (4.5.0)
Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages (from torch->pgmpy) (1.12)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from torch->pgmpy) (3.1.2)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (from torch->pgmpy) (2023.6.0)
Requirement already satisfied: triton==2.1.0 in /usr/local/lib/python3.10/dist-packages (from torch->pgmpy) (2.1.0)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.4->statsmodels->pgmpy) (1.16.0)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->torch->pgmpy) (2.1.3)
Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.10/dist-packages (from sympy->torch->pgmpy) (1.3.0)
Installing collected packages: pgmpy
Successfully installed pgmpy-0.1.24
```

```python
unique_wage_values = df['Wage'].unique()
unique_club_values = df['Club'].unique()

# Choose valid values
valid_wage = unique_wage_values[0]  # Replace with a valid value
valid_club = unique_club_values[0]  # Replace with a valid value

# Example of querying the probabilities
valid_value = 23  # Replace with a valid value in your dataset
try:
    prob_age_given_wage_club = age_given_wage_club.loc[(valid_wage, valid_club), valid_value]
    print(f"Probability of Age being {valid_value} given Wage='{valid_wage}' and Club='{valid_club}': {prob_age_given_wage_club}")
except KeyError:
    print(f"Combination not found in the dataset: Wage='{valid_wage}', Club='{valid_club}', Age={valid_value}")
```

```
Combination not found in the dataset: Wage='nan', Club='PSG', Age=23
```

Decision Tree (Entropy, and error estimation)

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, mean_squared_error, precision_score, recall_score, f1_score
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
label_encoder = LabelEncoder()
categorical_columns = ['Club', 'League', 'Nation', 'Position']
for column in categorical_columns:
    df[column + '_encoded'] = label_encoder.fit_transform(df[column])

# Select relevant columns
columns_of_interest = ['Wage', 'Age', 'Club_encoded', 'League_encoded', 'Nation_encoded', 'Position_encoded', 'Apps', 'Caps']
features = df[columns_of_interest]
target = df['Age']  # Change the target variable to 'Age'

# Handle missing values in features
imputer_features = SimpleImputer(strategy='mean')
features_imputed = imputer_features.fit_transform(features)

# Handle missing values in the target variable
target = df['Age']  # Change the target variable to 'Age'
target_imputed = target.replace(0, np.nan)  # Replace 0 values with NaN for imputation
imputer_target = SimpleImputer(strategy='mean')
target_imputed = imputer_target.fit_transform(target_imputed.values.reshape(-1, 1)).ravel()

# Replace NaN values with 0 in the target variable
target_imputed = np.nan_to_num(target_imputed, nan=0)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features_imputed, target_imputed, test_size=0.2, random_state=42)

# Train Decision Tree Classifier
dt = DecisionTreeClassifier(criterion='entropy', ccp_alpha=0.015)
dt.fit(X_train, y_train)

# Make predictions on the test set
dt_predictions = dt.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, dt_predictions)
mse = mean_squared_error(y_test, dt_predictions)
precision = precision_score(y_test, dt_predictions, average='macro')
recall = recall_score(y_test, dt_predictions, average='macro')
f1 = f1_score(y_test, dt_predictions, average='macro')

# Print metrics
print("Accuracy:", accuracy)
print("Mean Squared Error:", mse)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

```
Accuracy: 0.989769820971867
Mean Squared Error: 0.09335038363171355
Precision: 0.7678571428571429
Recall: 0.7916666666666666
F1 Score: 0.775
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is ill-defined and b
  _warn_prf(average, modifier, msg_start, len(result))
```

K-NN (Different distances)

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
label_encoder = LabelEncoder()
categorical_columns = ['Club', 'League', 'Nation', 'Position']
for column in categorical_columns:
    df[column + '_encoded'] = label_encoder.fit_transform(df[column])

# Select relevant columns
columns_of_interest = ['Wage', 'Age', 'Club_encoded', 'League_encoded', 'Nation_encoded', 'Position_encoded', 'Apps', 'Caps']
features = df[columns_of_interest]
target = df['Age']  # Change the target variable to 'Age'

# Handle missing values in features
imputer = SimpleImputer(strategy='mean')
features_imputed = imputer.fit_transform(features)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features_imputed, target, test_size=0.2, random_state=42)

# Initialize KNN classifier with k=3 (you can adjust k as needed)
knn_classifier = KNeighborsClassifier(n_neighbors=3)

# Train the classifier
knn_classifier.fit(X_train, y_train)

# Make predictions on the test set
knn_predictions = knn_classifier.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, knn_predictions)
classification_rep = classification_report(y_test, knn_predictions)

# Print metrics
print("Accuracy:", accuracy)
print("Classification Report:")
print(classification_rep)
```

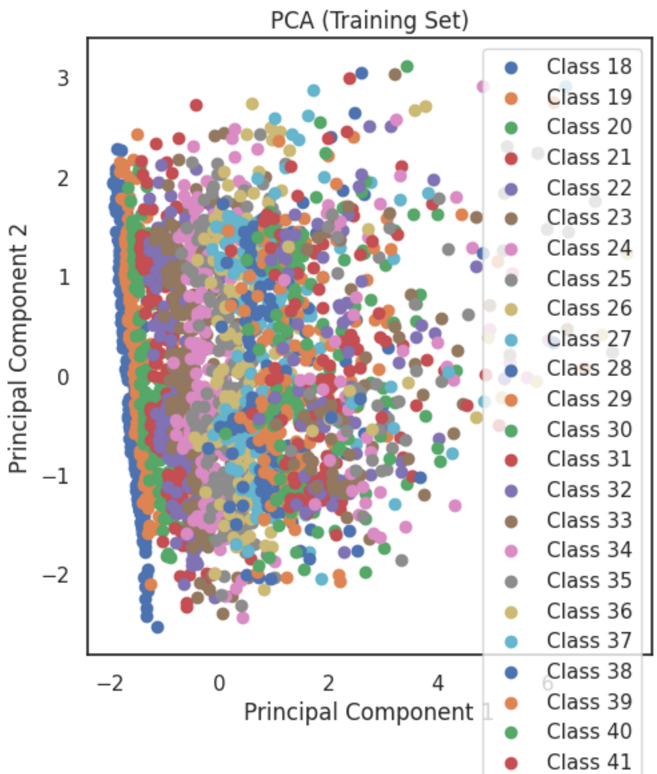
```
Accuracy: 0.29028132992327366
Classification Report:
              precision    recall  f1-score   support

          18       0.70      0.81      0.75       116
          19       0.46      0.60      0.52        68
          20       0.22      0.20      0.21        54
          21       0.26      0.17      0.21        53
          22       0.13      0.19      0.15        42
          23       0.22      0.19      0.20        52
          24       0.22      0.29      0.25        45
          25       0.11      0.12      0.12        56
          26       0.09      0.09      0.09        45
          27       0.11      0.13      0.12        39
          28       0.15      0.13      0.14        39
          29       0.16      0.12      0.14        41
          30       0.04      0.03      0.04        31
          31       0.17      0.15      0.16        27
          32       0.36      0.22      0.28        18
          33       0.50      0.12      0.20        16
          34       0.25      0.14      0.18        14
          35       0.33      0.17      0.22        12
          36       0.00      0.00      0.00         6
          37       0.00      0.00      0.00         3
          38       0.00      0.00      0.00         1
          39       0.00      0.00      0.00         1
          40       0.00      0.00      0.00         2
          41       0.00      0.00      0.00         1

    accuracy                           0.29       782
   macro avg       0.19      0.16      0.17       782
weighted avg       0.28      0.29      0.28       782

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
```

```
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
  _warn_prf(average, modifier, msg_start, len(result))
```

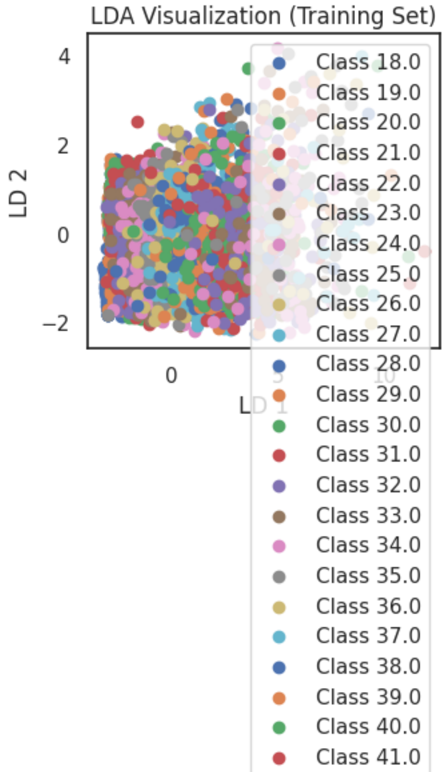
PCA

```
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
for label in np.unique(y_train):
 plt.scatter(X_train_pca[y_train == label, 0], X_train_pca[y_train == label, 1], label=f'Class {label}')
plt.title('PCA (Training Set)')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f9de66f4430>
```



```
import matplotlib.pyplot as plt
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer
import numpy as np

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
label_encoder = LabelEncoder()
categorical_columns = ['Club', 'League', 'Nation', 'Position']
for column in categorical_columns:
    df[column + '_encoded'] = label_encoder.fit_transform(df[column])

# Select relevant columns
columns_of_interest = ['Wage', 'Age', 'Club_encoded', 'League_encoded', 'Nation_encoded', 'Position_encoded', 'Apps', 'Caps']
features = df[columns_of_interest]
target = df['Age']  # Change the target variable to 'Wage' or any other column as needed

# Handle missing values in features
imputer_features = SimpleImputer(strategy='mean')
features_imputed = imputer_features.fit_transform(features)

# Handle missing values in the target variable
target = df['Age']  # Assuming 'Wage' is the target variable
target_imputed = target.replace(0, np.nan)  # Replace 0 values with NaN for imputation
imputer_target = SimpleImputer(strategy='mean')
target_imputed = imputer_target.fit_transform(target_imputed.values.reshape(-1, 1)).ravel()

# Replace NaN values with 0 in the target variable
target_imputed = np.nan_to_num(target_imputed, nan=0)

# Check the number of features and classes in your dataset
n_features = features_imputed.shape[1]
n_classes = len(np.unique(target_imputed))

# Set n_components to the minimum of available features and classes - 1
n_components = min(n_features, n_classes - 1) if min(n_features, n_classes - 1) > 0 else None

# Assuming X_train_lda is the result of LDA transformation on your training set
lda = LinearDiscriminantAnalysis(n_components=n_components)
X_train_lda = lda.fit_transform(features_imputed, target_imputed)

# Visualize LDA results
plt.subplot(1, 2, 2)

# Check if there is more than one component for visualization
if n_components and n_components > 1:
    for label in np.unique(target_imputed):
        plt.scatter(X_train_lda[target_imputed == label, 0], X_train_lda[target_imputed == label, 1], label=f'Class {label}')

    plt.title('LDA Visualization (Training Set)')
    plt.xlabel('LD 1')
    plt.ylabel('LD 2')
    plt.legend()
    plt.tight_layout()
    plt.show()
else:
    print("Only one component available. Unable to visualize in 2D.")
```



Model evaluations

K-NN (different distances) & data splitting

```
import warnings
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_absolute_error
from sklearn.preprocessing import LabelEncoder

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
label_encoder = LabelEncoder()
categorical_columns = ['Club', 'League', 'Nation', 'Position']

for column in categorical_columns:
    df[column + '_encoded'] = label_encoder.fit_transform(df[column])

X = df[['Wage', 'Club_encoded', 'League_encoded', 'Nation_encoded', 'Position_encoded', 'Apps', 'Caps']]
y = df['Age']  # 'Age' as the target variable

warnings.filterwarnings("ignore")

# Impute missing values in X
imputer = SimpleImputer(strategy='mean')
X_imputed = imputer.fit_transform(X)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_imputed, y, test_size=0.2, random_state=42)

# Define K-NN regressor with different distance metrics
k_values = [3, 5, 7]
distance_metrics = ['euclidean', 'manhattan', 'chebyshev']

for k in k_values:
    for metric in distance_metrics:
        # Train K-NN regressor
        knn = KNeighborsRegressor(n_neighbors=k, metric=metric)
        knn.fit(X_train, y_train)

        # Predict on the test set
        y_pred = knn.predict(X_test)

        # Calculate mean absolute error
        mae = mean_absolute_error(y_test, y_pred)
        print(f"K = {k}, Distance Metric = {metric}: Mean Absolute Error = {mae:.4f}")
```

```
K = 3, Distance Metric = euclidean: Mean Absolute Error = 1.4390
K = 3, Distance Metric = manhattan: Mean Absolute Error = 1.4467
K = 3, Distance Metric = chebyshev: Mean Absolute Error = 1.4267
K = 5, Distance Metric = euclidean: Mean Absolute Error = 1.3959
K = 5, Distance Metric = manhattan: Mean Absolute Error = 1.3821
K = 5, Distance Metric = chebyshev: Mean Absolute Error = 1.3808
K = 7, Distance Metric = euclidean: Mean Absolute Error = 1.3692
K = 7, Distance Metric = manhattan: Mean Absolute Error = 1.3732
K = 7, Distance Metric = chebyshev: Mean Absolute Error = 1.3646
```

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor
import numpy as np

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
label_encoder = LabelEncoder()
categorical_columns = ['Club', 'League', 'Nation', 'Position']
for column in categorical_columns:
    df[column + '_encoded'] = label_encoder.fit_transform(df[column])

X = df[['Wage', 'Club_encoded', 'League_encoded', 'Nation_encoded', 'Position_encoded', 'Apps', 'Caps']]
y = df['Age']  # 'Age' as the target variable

# Impute missing values in X
imputer = SimpleImputer(strategy='mean')
X_imputed = imputer.fit_transform(X)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_imputed, y, test_size=0.2, random_state=42)

# Define K-NN regressor with different distance metrics
k_values = [3, 5, 7]
distance_metrics = ['euclidean', 'manhattan', 'chebyshev']

for k in k_values:
    for metric in distance_metrics:
        # Train K-NN regressor
        knn = KNeighborsRegressor(n_neighbors=k, metric=metric)
        knn.fit(X_train, y_train)

        # Predict on the test set
        y_pred = knn.predict(X_test)

        # Calculate regression metrics
        mae = mean_absolute_error(y_test, y_pred)
        mse = mean_squared_error(y_test, y_pred)
        r2 = r2_score(y_test, y_pred)

        print(f"K = {k}, Distance Metric = {metric}:")
        print(f"Mean Absolute Error: {mae:.4f}")
        print(f"Mean Squared Error: {mse:.4f}")
        print(f"R-squared: {r2:.4f}")
        print("------------")
```

```
K = 3, Distance Metric = euclidean:
Mean Absolute Error: 1.4390
Mean Squared Error: 4.0523
R-squared: 0.8412
------------
K = 3, Distance Metric = manhattan:
Mean Absolute Error: 1.4467
Mean Squared Error: 4.1122
R-squared: 0.8388
------------
K = 3, Distance Metric = chebyshev:
Mean Absolute Error: 1.4267
Mean Squared Error: 3.8728
R-squared: 0.8482
------------
K = 5, Distance Metric = euclidean:
Mean Absolute Error: 1.3959
Mean Squared Error: 3.6762
R-squared: 0.8559
------------
K = 5, Distance Metric = manhattan:
Mean Absolute Error: 1.3821
Mean Squared Error: 3.6407
R-squared: 0.8573
------------
K = 5, Distance Metric = chebyshev:
Mean Absolute Error: 1.3808
Mean Squared Error: 3.6197
R-squared: 0.8581
------------
K = 7, Distance Metric = euclidean:
Mean Absolute Error: 1.3692
```

```
Mean Squared Error: 3.5210
R-squared: 0.8620
------------
K = 7, Distance Metric = manhattan:
Mean Absolute Error: 1.3732
Mean Squared Error: 3.6208
R-squared: 0.8581
------------
K = 7, Distance Metric = chebyshev:
Mean Absolute Error: 1.3646
Mean Squared Error: 3.5475
R-squared: 0.8610
------------
```

k-fold cross validation and average accuracy

```
from sklearn.impute import SimpleImputer

# Assuming your dataset is named 'df' and has columns: 'Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Caps'
# Define X and y
X = df[['Wage', 'Age', 'Club_encoded', 'League_encoded', 'Nation_encoded', 'Position_encoded', 'Apps', 'Caps']]
y = df['Age']  # Replace 'Target_Column' with your actual target column

# Impute missing values in X
imputer = SimpleImputer(strategy='mean')
X_imputed = imputer.fit_transform(X)

# Initialize KFold and Decision Tree Classifier
kf = KFold(n_splits=5, shuffle=True, random_state=42)
model = DecisionTreeClassifier(random_state=42)
fold = 1
accuracies = []

# Perform K-fold cross-validation
for train_index, test_index in kf.split(X_imputed):  # Use X_imputed instead of X
    X_train, X_test = X_imputed[train_index], X_imputed[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    accuracies.append(accuracy)
    print(f"Fold {fold} Accuracy: {accuracy}")
    fold += 1

# Calculate average accuracy
avg_accuracy = sum(accuracies) / len(accuracies)
print(f"\nAverage Accuracy: {avg_accuracy}")
```

```
Fold 1 Accuracy: 0.9987212276214834
Fold 2 Accuracy: 1.0
Fold 3 Accuracy: 1.0
Fold 4 Accuracy: 1.0
Fold 5 Accuracy: 1.0

Average Accuracy: 0.9997442455242966
```

```
# Calculate evaluation metrics
conf_matrix = confusion_matrix(y_test, y_pred)
accuracy = accuracy_score(y_test, y_pred)
error_rate = 1 - accuracy

# Precision, Recall, and F1 Score for multiclass classification
precision = precision_score(y_test, y_pred, average='weighted')  # You can use 'micro', 'macro', or 'weighted'
recall = recall_score(y_test, y_pred, average='weighted')  # You can use 'micro', 'macro', or 'weighted'
f1 = f1_score(y_test, y_pred, average='weighted')  # You can use 'micro', 'macro', or 'weighted'

# Display results
print("Confusion Matrix:")
print(conf_matrix)
print("\nAccuracy:", accuracy)
print("Error Rate:", error_rate)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)

plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix, annot=True, cmap='Blues', fmt='g')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
# Plot evaluation metrics
metrics = ['Accuracy', 'Error Rate', 'Precision', 'Recall', 'F1 Score']
values = [accuracy, error_rate, precision, recall, f1]
plt.figure(figsize=(6, 4))
plt.bar(metrics, values, color=['blue', 'red', 'green', 'orange', 'purple'])
plt.title('Evaluation Metrics')
plt.ylabel('Score')
plt.xticks(rotation=45)
```

```
   0   0   0   0   0]
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   0   0   0   0   0]
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   0   0   0   0   0]
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   0   0   0   0   0]
 [ 0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  12   0
   0   0   0   0   0]
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   0   0   0   0   0]
 [ 0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   4   0   0   0   0]
 [ 0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   3   0   0   0]
 [ 0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   4   0   0]
 [ 0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   2   0]
 [ 0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   1]]

Accuracy: 1.0
Error Rate: 0.0
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
```