Enhancing NHL Salary Evaluation through Dimensionality Reduction

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Case Studies

In [1]:
```
import common
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [2]:
```
original_df = common.load_dataset(preprocess=False)

df = common.preprocess_dataset(original_df)

# Split features and label
X_data, y_data = common.split_dataset(df)
```

Brendan Gallagher

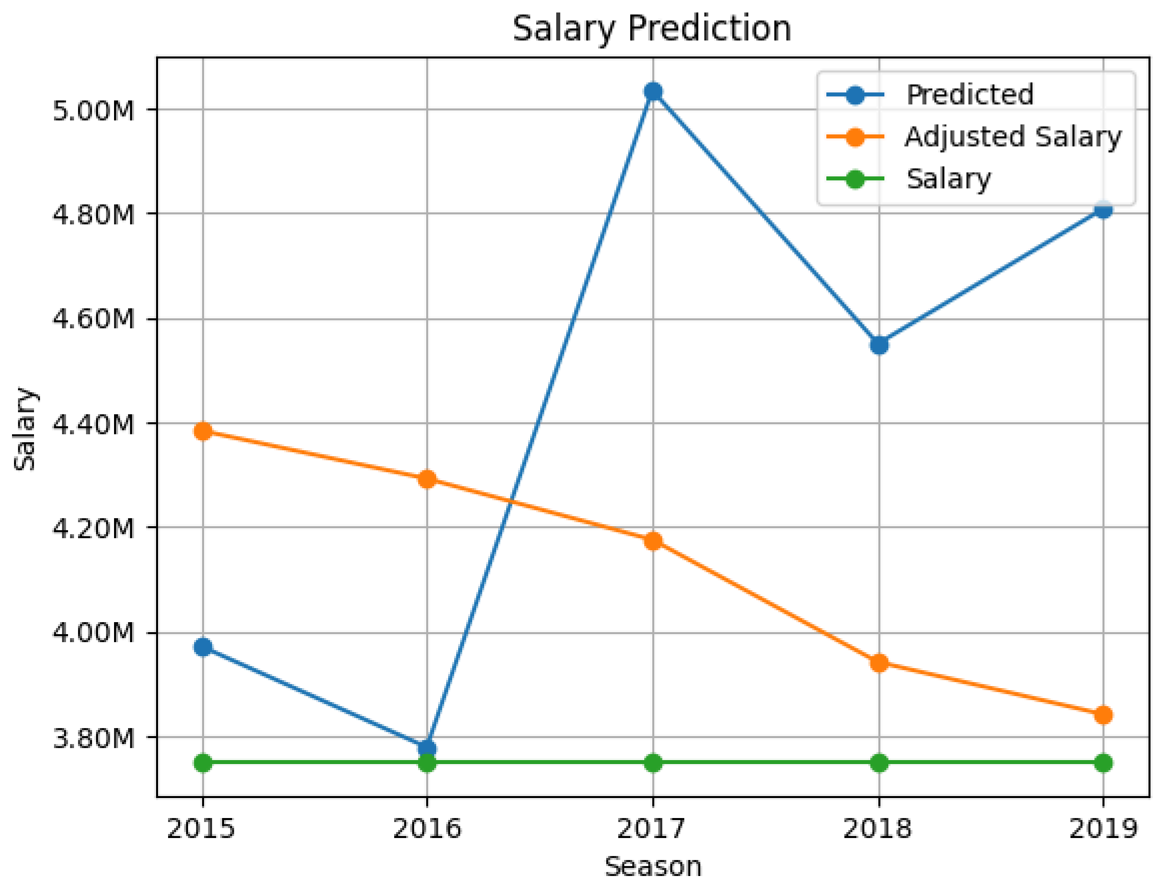
term: 6yrs
cap hit: $3.75M
seasons: 2015-2021

In [3]:
```
player_seasons = original_df[(original_df["name"] == "Brendan Gallagher") &
                             (original_df["season"] >= 2015) &
                             (original_df["season"] <= 2020)]

# Separate player seasons from X_data by using the indexes from player_seasons
X_player = X_data.loc[player_seasons.index].to_numpy()
y_player = y_data.loc[player_seasons.index].to_numpy()

X_train = X_data.drop(player_seasons.index).to_numpy()
y_train = y_data.drop(player_seasons.index).to_numpy()

# Standardize the data
X_train, X_player = common.standard_scaler(X_train, X_player)

# Train the models
results_df, predictions = common.train_and_evaluate(X_train, y_train, X_playe
r, y_player)
results_df
```

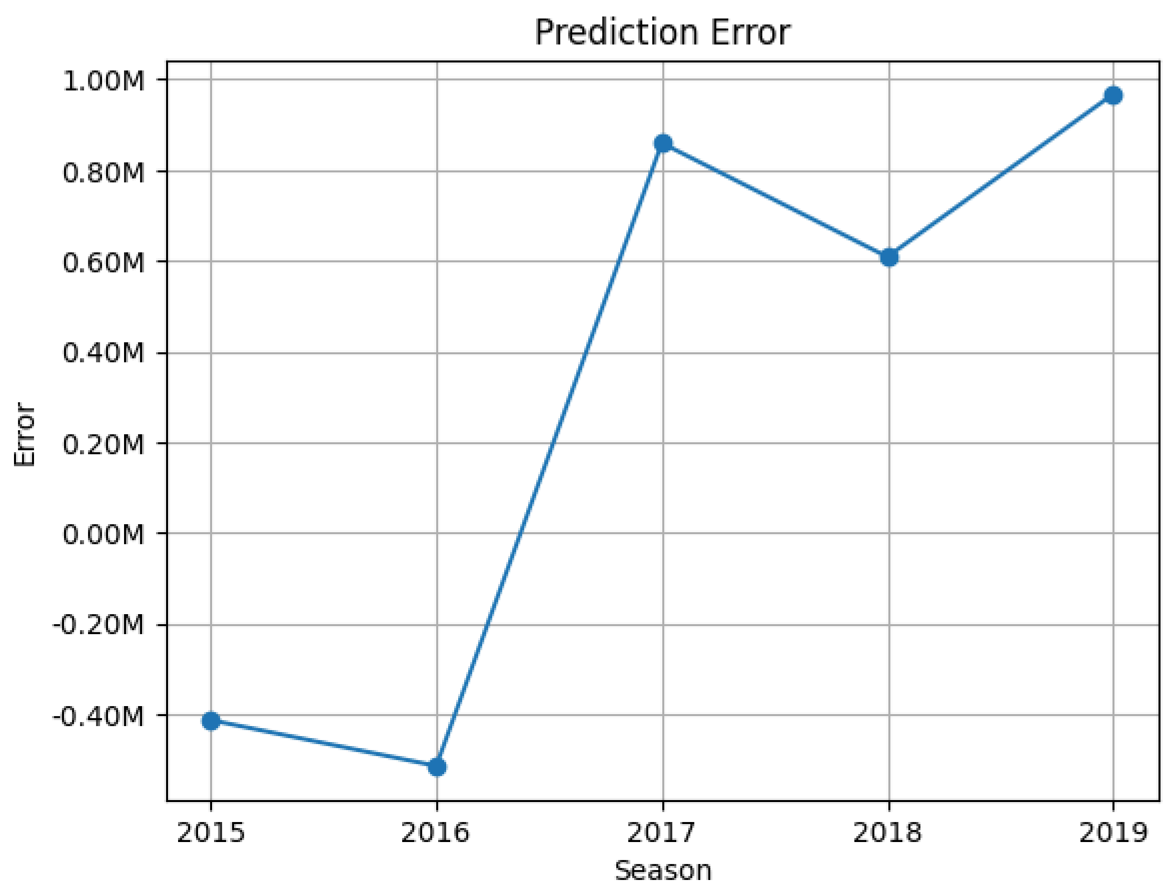
Out[3]:

	R2	MAE	Top-100 MAE	Top-50 MAE	SMAPE	Train time (sec)
Model						
Linear Regression	-23.0005	931,713	931,713	931,713	0.2494	0.50
Random Forest	-35.4415	1,090,176	1,090,176	1,090,176	0.2297	8.12
Support Vector	-10.7066	672,323	672,323	672,323	0.1559	6.61
K-Nearest Neighbors	-22.4009	836,157	836,157	836,157	0.1797	0.03

In [4]:
```python
# Use SVM prediction as the base model
salary_evaluation = predictions[2]
seasons = player_seasons["season"].astype(str)
adjusted_salary = player_seasons["adjustedSalary"]
salary = player_seasons["salary"]

# Plot the results
plt.plot(seasons, salary_evaluation, label="Predicted", marker="o")
plt.plot(seasons, adjusted_salary, label="Adjusted Salary", marker="o")
plt.plot(seasons, salary, label="Salary", marker="o")
plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
plt.xlabel("Season")
plt.ylabel("Salary")
plt.title("Salary Prediction")
plt.legend()
plt.grid()
plt.show()

# Plot the error by season
error = salary_evaluation - adjusted_salary
plt.plot(seasons, error, marker="o")
plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
plt.xlabel("Season")
plt.ylabel("Error")
plt.title("Prediction Error")
plt.grid()
plt.show()
```



Salary Prediction
Predicted
Adjusted Salary
Salary
5.00M
4.80M
4.60M
4.40M
4.20M
4.00M
3.80M
Salary
2015
2016
2017
2018
2019
Season



Prediction Error
1.00M
0.80M
0.60M
0.40M
0.20M
0.00M
-0.20M
-0.40M
Error
2015
2016
2017
2018
2019
Season

Zach Hyman

term: 6yrs
cap hit: $3.75M
seasons: 2017-2020

term: 7yrs
cap hit: $5.50M
seasons: 2021-2028

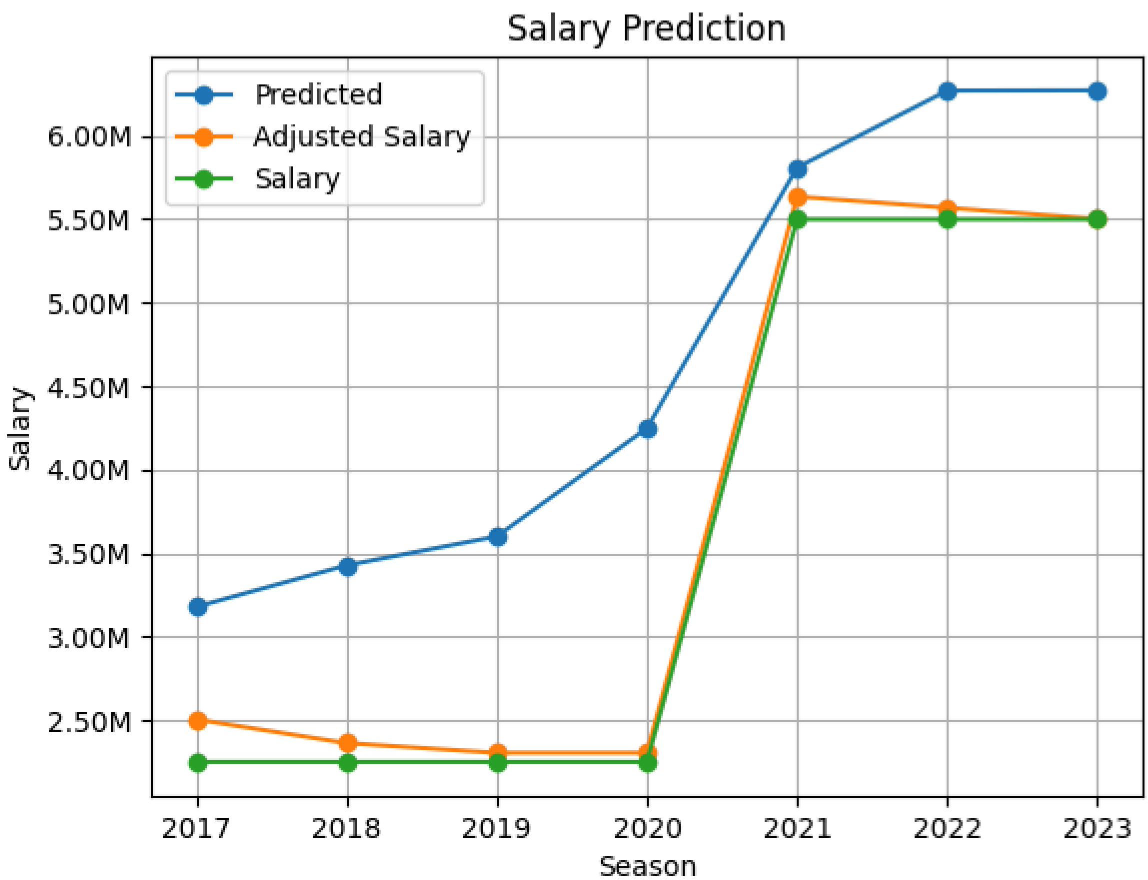
Baseline

In [5]:
```
player_seasons = original_df[(original_df["name"] == "Zach Hyman") &
                             (original_df["season"] >= 2017) &
                             (original_df["season"] <= 2023)]

# Separate player seasons from X_data by using the indexes from player_seasons
X_player = X_data.loc[player_seasons.index].to_numpy()
y_player = y_data.loc[player_seasons.index].to_numpy()

X_train = X_data.drop(player_seasons.index).to_numpy()
y_train = y_data.drop(player_seasons.index).to_numpy()

# Standardize the data
X_train, X_player = common.standard_scaler(X_train, X_player)

# Train the models
results_df, predictions = common.train_and_evaluate(X_train, y_train, X_playe
r, y_player)
results_df
```

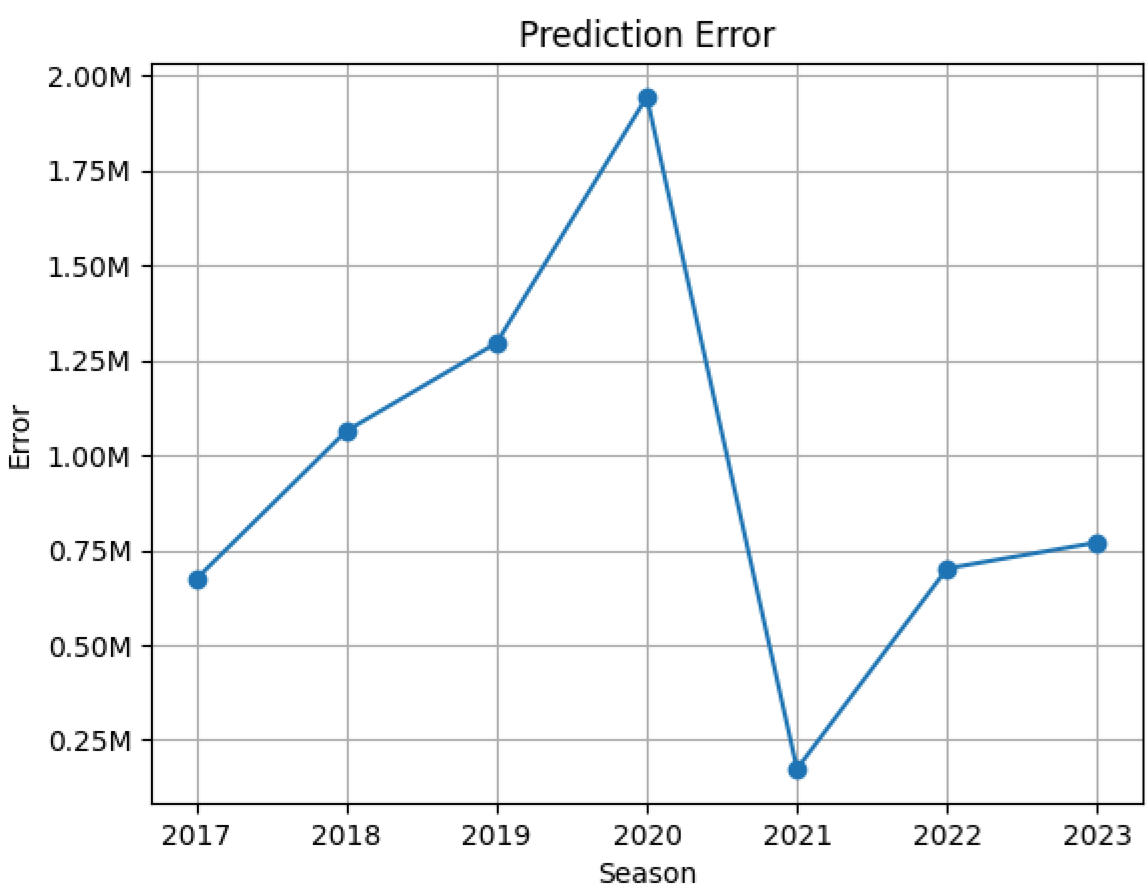
Out[5]:

Model	R2	MAE	Top-100 MAE	Top-50 MAE	SMAPE	Train time (sec)
Linear Regression	0.0976	1,276,427	1,276,427	1,276,427	0.3206	1.29
Random Forest	-0.6810	1,813,310	1,813,310	1,813,310	0.4139	7.99
Support Vector	0.5366	945,722	945,722	945,722	0.2737	7.33
K-Nearest Neighbors	-0.2359	1,458,428	1,458,428	1,458,428	0.3331	0.03

In [6]:
```python
# Use SVM prediction as the base model
salary_evaluation = predictions[2]
seasons = player_seasons["season"].astype(str)
adjusted_salary = player_seasons["adjustedSalary"]
salary = player_seasons["salary"]

# Plot the results
plt.plot(seasons, salary_evaluation, label="Predicted", marker="o")
plt.plot(seasons, adjusted_salary, label="Adjusted Salary", marker="o")
plt.plot(seasons, salary, label="Salary", marker="o")
plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
plt.xlabel("Season")
plt.ylabel("Salary")
plt.title("Salary Prediction")
plt.legend()
plt.grid()
plt.show()

# Plot the error by season
error = salary_evaluation - adjusted_salary
plt.plot(seasons, error, marker="o")
plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
plt.xlabel("Season")
plt.ylabel("Error")
plt.title("Prediction Error")
plt.grid()
plt.show()
```



Salary Prediction
Predicted
Adjusted Salary
Salary
6.00M
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M
Salary
2017
2018
2019
2020
2021
2022
2023
Season



Prediction Error
2.00M
1.75M
1.50M
1.25M
1.00M
0.75M
0.50M
0.25M
Error
2017
2018
2019
2020
2021
2022
2023
Season

PCA

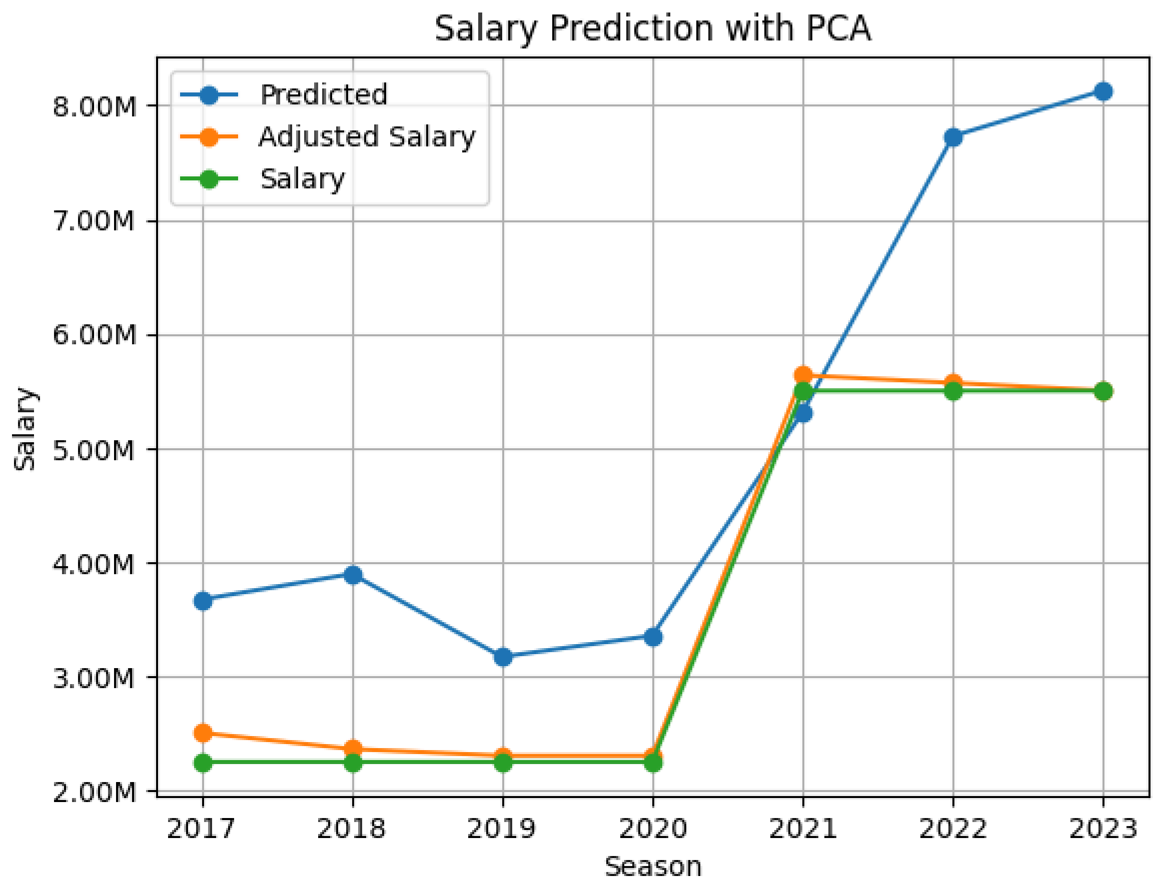
In [7]:
```
X = X_train.copy()
n_samples, n_features = X.shape

# Center the data (subtract the mean of each feature)
X_centered = X - np.mean(X, axis=0)

# Singular Value Decomposition
U, S, Vt = np.linalg.svd(X_centered, full_matrices=False)

# Compute explained variance
explained_variance = (S**2) / (n_samples-1)
total_explained_variance = np.sum(explained_variance)
explained_variance_ratio = explained_variance / total_explained_variance

# Compute cumulative explained variance
cumsum = np.cumsum(explained_variance_ratio)
x_range = range(0, len(cumsum))

n_components = 3

# Transform data into principal component space
X_train_pca = np.dot(X_centered, Vt.T)
X_train_pca = X_train_pca[:, :n_components]

# Adjust the features for playering
X_player_centered = X_player - np.mean(X, axis=0)
X_player_pca = np.dot(X_player_centered, Vt.T)
X_player_pca = X_player_pca[:, :n_components]

# Train the models
results_pca_df, predictions_pca = common.train_and_evaluate(X_train_pca, y_tra
in, X_player_pca, y_player)
results_pca_df
```

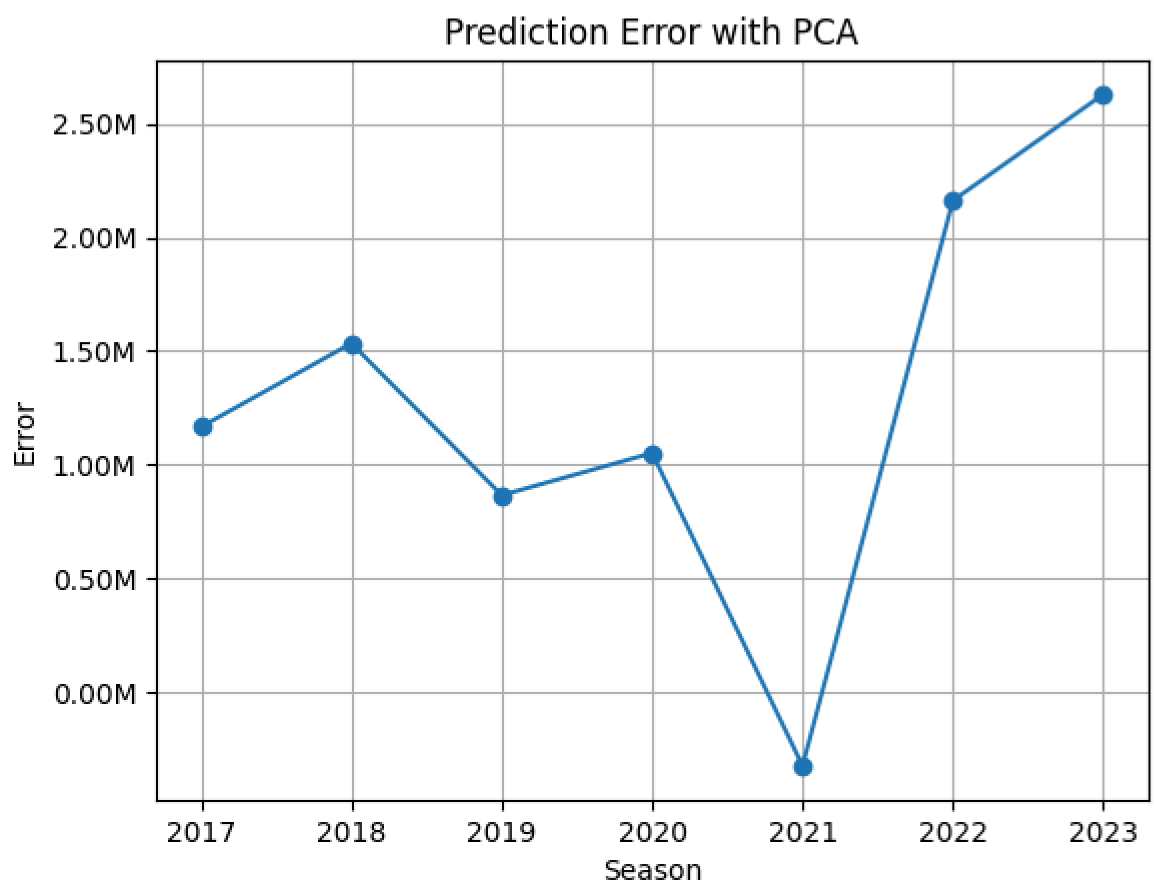
Out[7]:

Model	R2	MAE	Top-100 MAE	Top-50 MAE	SMAPE	Train time (sec)
Linear Regression	-0.1777	1,534,336	1,534,336	1,534,336	0.3691	0.00
Random Forest	-1.1858	1,828,733	1,828,733	1,828,733	0.3788	0.82
Support Vector	0.0191	1,390,071	1,390,071	1,390,071	0.3322	0.57
K-Nearest Neighbors	-0.8451	1,648,480	1,648,480	1,648,480	0.3330	0.00

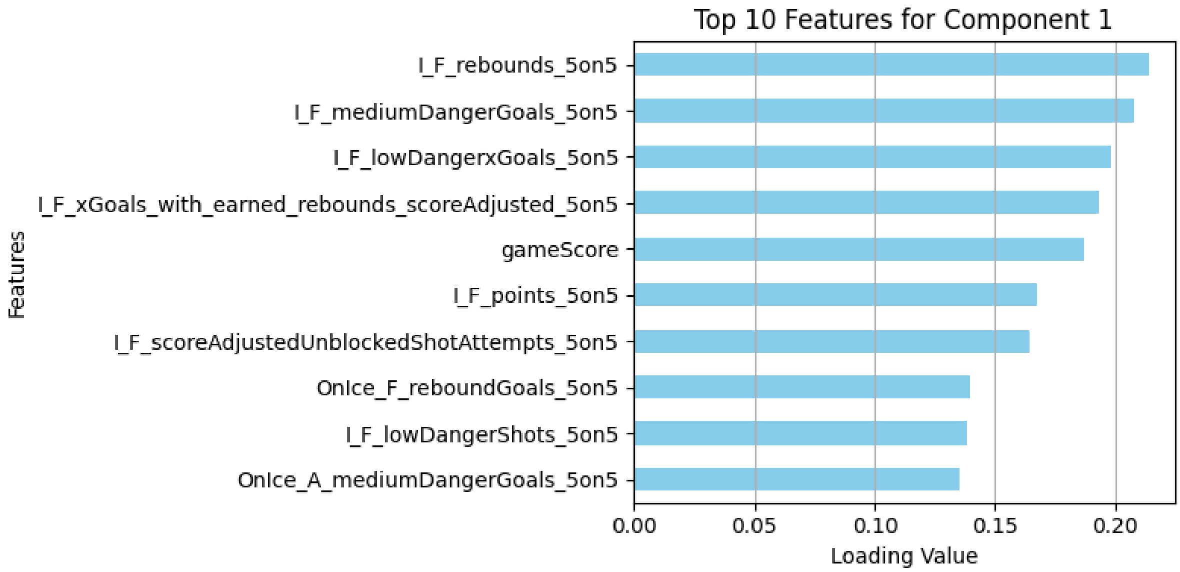
In [8]:

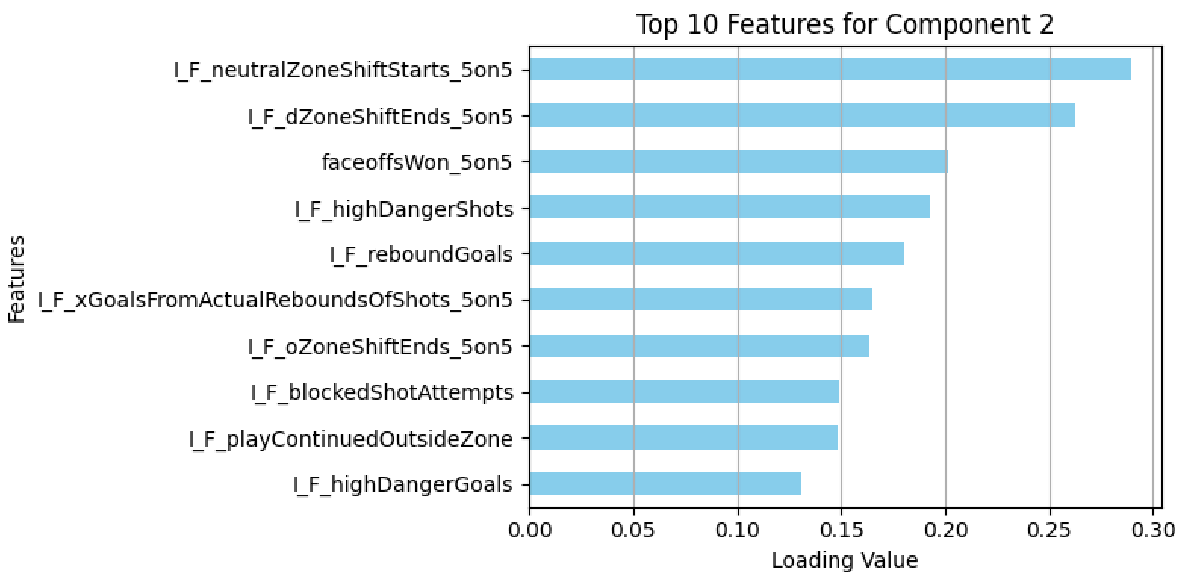
```
# Use SVM prediction as the base model
salary_evaluation = predictions_pca[2]
seasons = player_seasons["season"].astype(str)
adjusted_salary = player_seasons["adjustedSalary"]
salary = player_seasons["salary"]

# Plot the results
plt.plot(seasons, salary_evaluation, label="Predicted", marker="o")
plt.plot(seasons, adjusted_salary, label="Adjusted Salary", marker="o")
plt.plot(seasons, salary, label="Salary", marker="o")
plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
plt.xlabel("Season")
plt.ylabel("Salary")
plt.title("Salary Prediction with PCA")
plt.legend()
plt.grid()
plt.show()

# Plot the error by season
error = salary_evaluation - adjusted_salary
plt.plot(seasons, error, marker="o")
plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
plt.xlabel("Season")
plt.ylabel("Error")
plt.title("Prediction Error with PCA")
plt.grid()
plt.show()
```

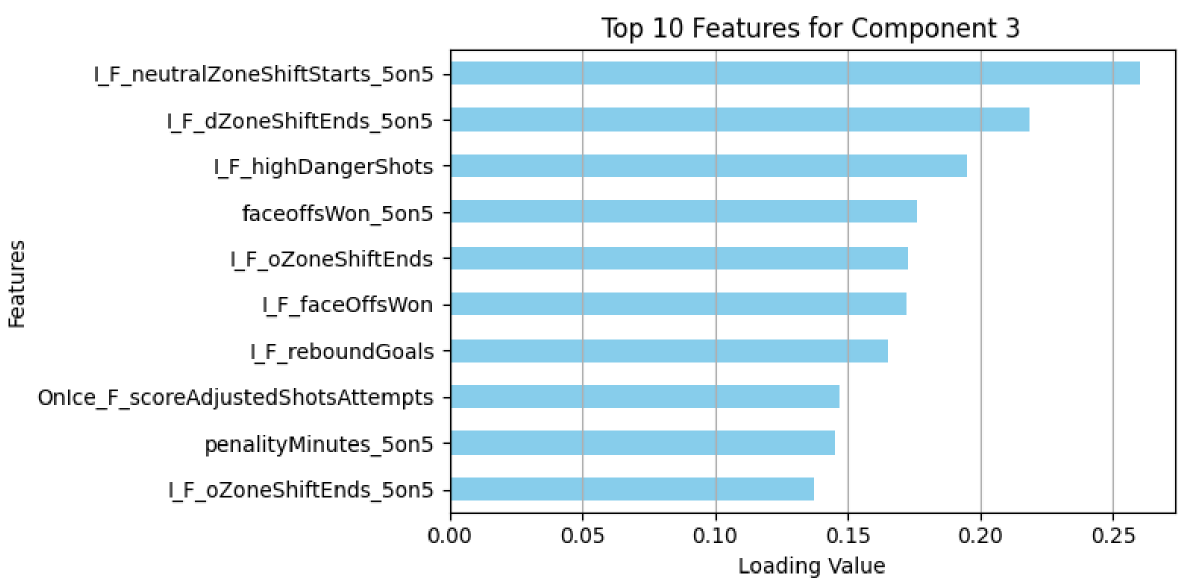

Salary Prediction with PCA
Predicted
Adjusted Salary
Salary
8.00M
7.00M
6.00M
5.00M
4.00M
3.00M
2.00M
Salary
2017
2018
2019
2020
2021
2022
2023
Season


Prediction Error with PCA
2.50M
2.00M
1.50M
1.00M
0.50M
0.00M
Error
2017
2018
2019
2020
2021
2022
2023
Season

In [9]:
```
n_top_features = 10

loadings_df = pd.DataFrame(Vt, index=X_data.columns)

for comp in range(n_components):
    plt.figure(figsize=(8, 4))
    # Sort features by absolute loading values for the current component
    top_features = loadings_df.iloc[:, comp].abs().nlargest(n_top_features)

    # Plot
    top_features.sort_values().plot(kind='barh', color='skyblue')
    plt.title(f"Top {n_top_features} Features for Component {comp + 1}")
    plt.xlabel("Loading Value")
    plt.ylabel("Features")
    plt.grid(axis='x')
    plt.tight_layout()
    plt.show()
```

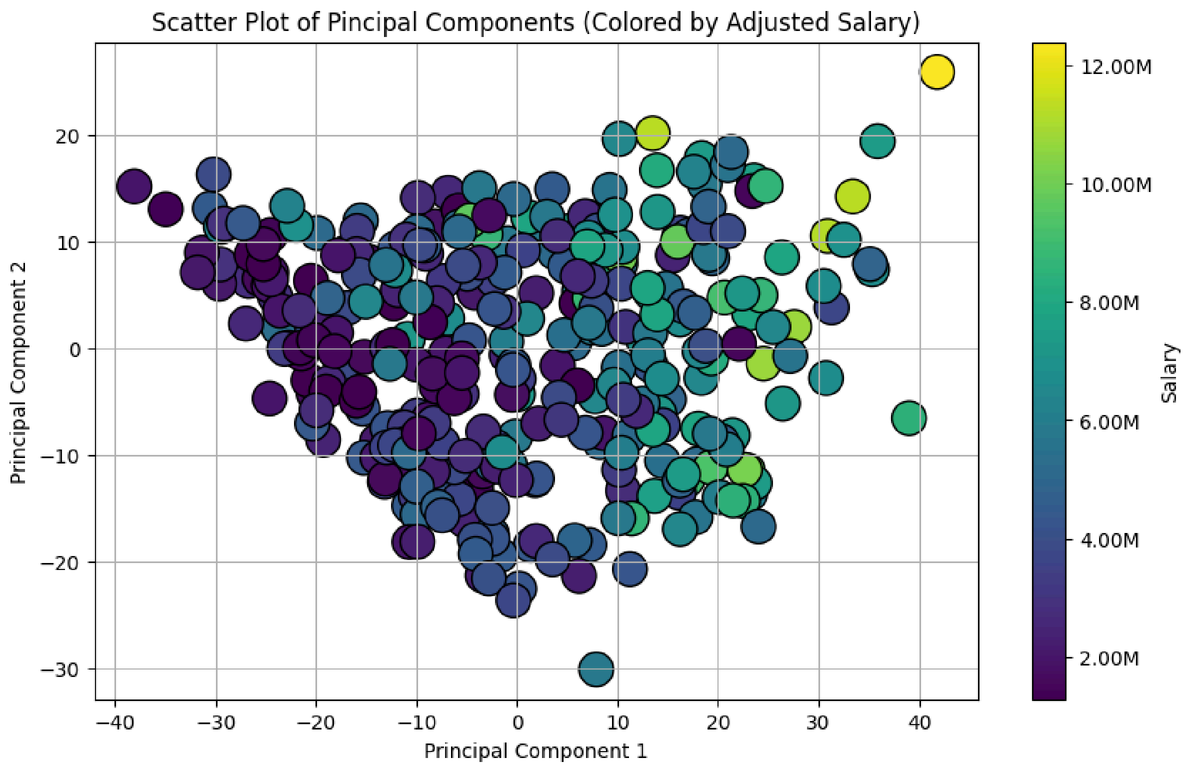

Top 10 Features for Component 1
I_F_rebounds_5on5
I_F_mediumDangerGoals_5on5
I_F_lowDangerxGoals_5on5
I_F_xGoals_with_earned_rebounds_scoreAdjusted_5on5
gameScore
I_F_points_5on5
I_F_scoreAdjustedUnblockedShotAttempts_5on5
OnIce_F_reboundGoals_5on5
I_F_lowDangerShots_5on5
OnIce_A_mediumDangerGoals_5on5
Features
0.00
0.05
0.10
0.15
0.20
Loading Value

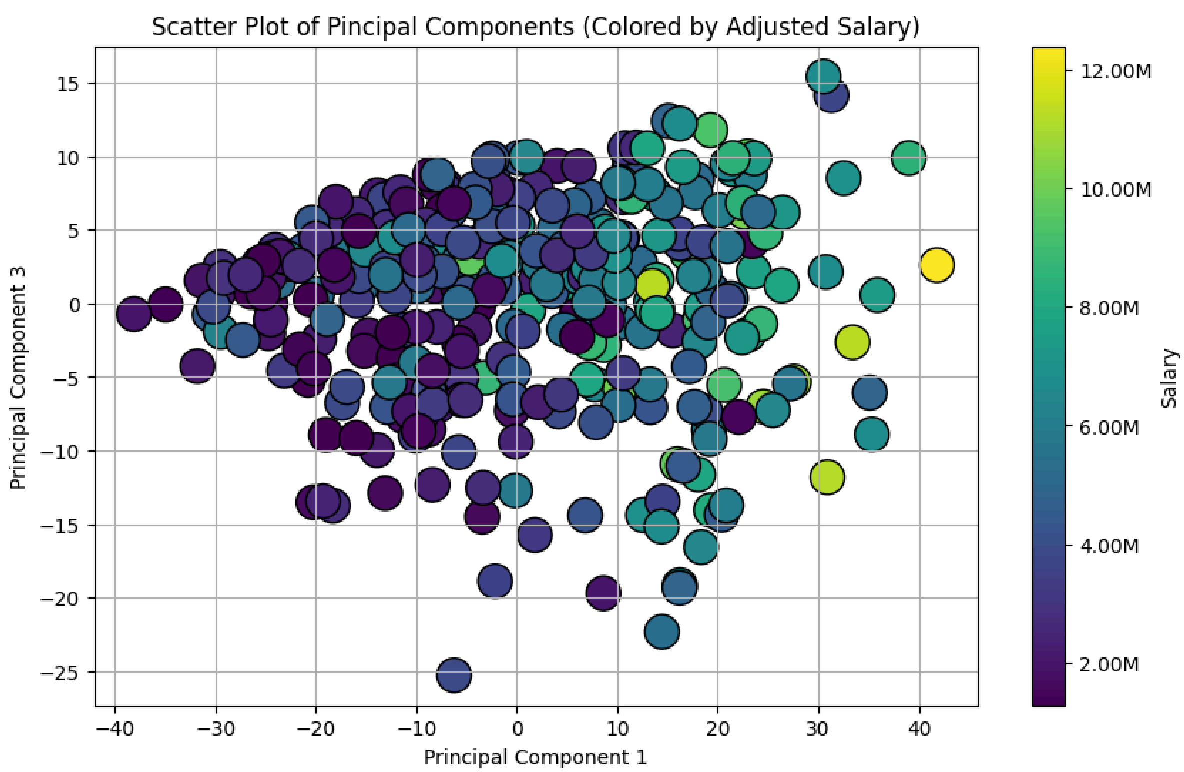

Top 10 Features for Component 2
I_F_neutralZoneShiftStarts_5on5
I_F_dZoneShiftEnds_5on5
faceoffsWon_5on5
I_F_highDangerShots
I_F_reboundGoals
I_F_xGoalsFromActualReboundsOfShots_5on5
I_F_oZoneShiftEnds_5on5
I_F_blockedShotAttempts
I_F_playContinuedOutsideZone
I_F_highDangerGoals
Features
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Loading Value

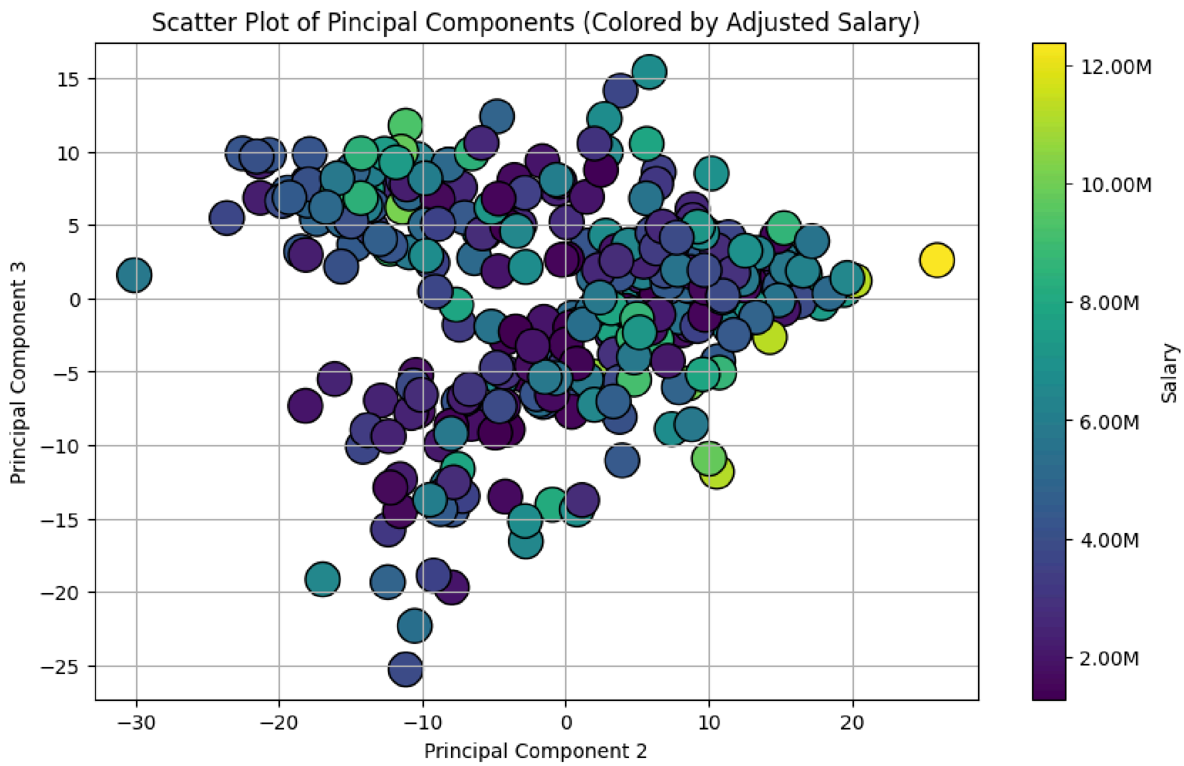

Top 10 Features for Component 3
I_F_neutralZoneShiftStarts_5on5
I_F_dZoneShiftEnds_5on5
I_F_highDangerShots
faceoffsWon_5on5
I_F_oZoneShiftEnds
I_F_faceOffsWon
I_F_reboundGoals
OnIce_F_scoreAdjustedShotsAttempts
penalityMinutes_5on5
I_F_oZoneShiftEnds_5on5
Features
0.00
0.05
0.10
0.15
0.20
0.25
Loading Value

In [10]:
```
def density_plot(df, c1=1, c2=2):
    plt.figure(figsize=(10, 6))
    scatter = plt.scatter(
        df[f"PC{c1}"], df[f"PC{c2}"],
        c=df["Salary"], cmap="viridis", edgecolor="k", s=300
    )
    colorbar = plt.colorbar(scatter, label="Salary")
    colorbar.ax.yaxis.set_major_formatter(common.get_mformatter(2))
    plt.xlabel(f"Principal Component {c1}")
    plt.ylabel(f"Principal Component {c2}")
    plt.title("Scatter Plot of Pincipal Components (Colored by Adjusted Salar
y)")
    plt.grid()
    plt.show()

def plot_component(df, c=1):
    plt.figure(figsize=(10, 6))
    plt.scatter(df[f"PC{c}"], df["Salary"], s=100)
    plt.xlabel(f"Principal Component {c}")
    plt.ylabel("Salary")
    plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
    plt.title(f"Principal Component {c} vs Salary")
    plt.grid()
    plt.show()
```

In [11]:
```
train_df = pd.DataFrame(X_train_pca, columns=[f"PC{i+1}" for i in range(n_comp
onents)])
train_df["Season"] = X_data["season"].astype(str)  # Add season info
train_df["Salary"] = y_data.drop(player_seasons.index)  # Add salary info

# Select only 2013 season
train_df = train_df[train_df["Season"] == "2013"]

density_plot(train_df, c1=1, c2=2)
density_plot(train_df, c1=1, c2=3)
density_plot(train_df, c1=2, c2=3)
```

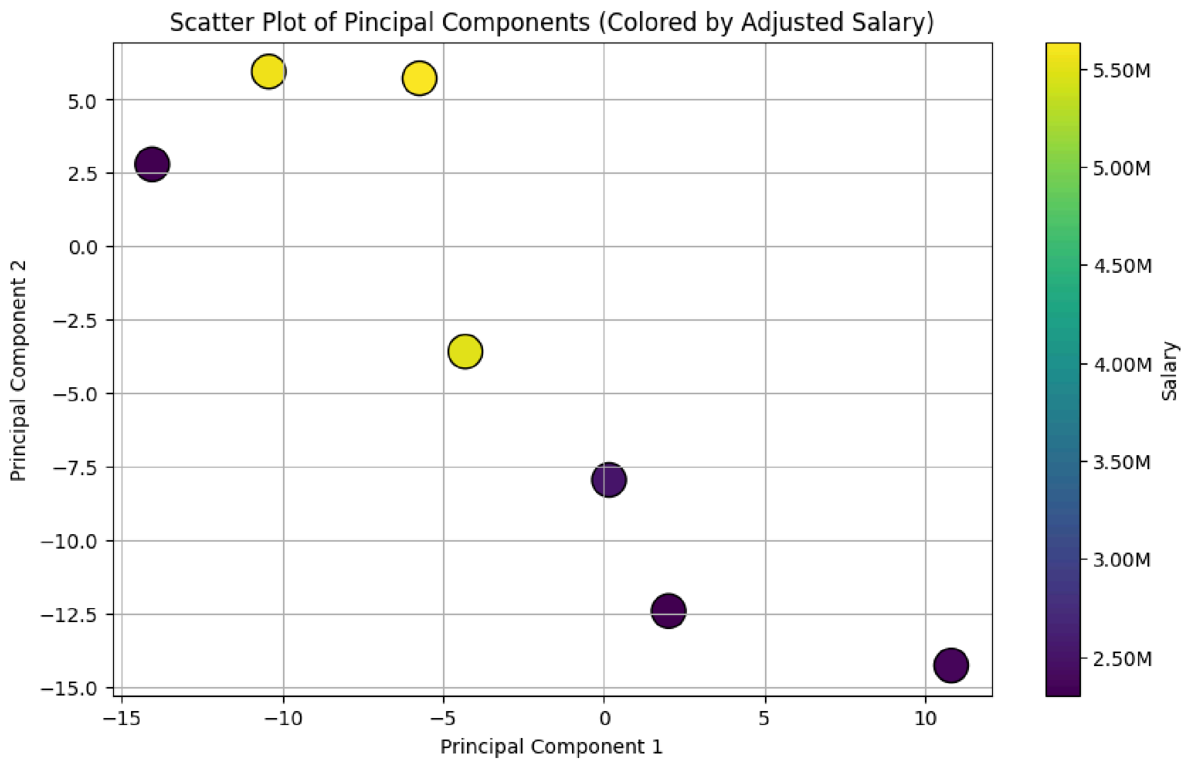

Scatter Plot of Pincipal Components (Colored by Adjusted Salary)
Principal Component 2
Principal Component 1
Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M

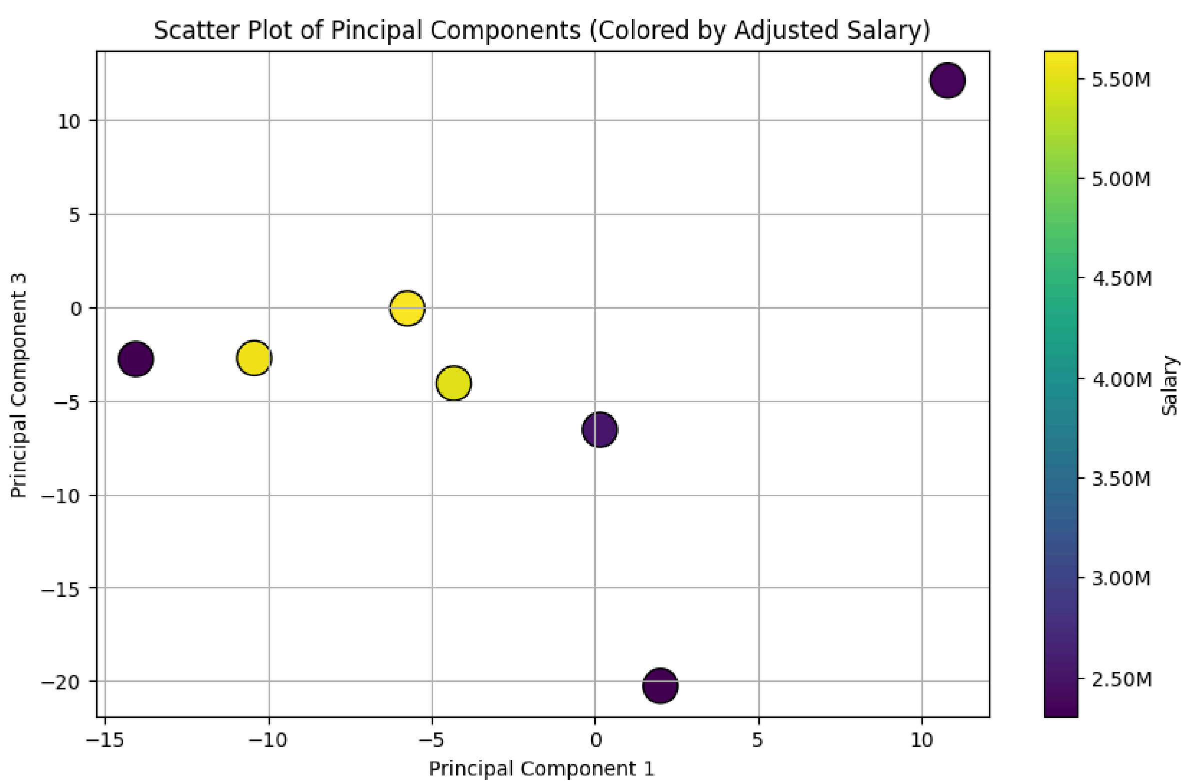

Scatter Plot of Pincipal Components (Colored by Adjusted Salary)
Principal Component 3
Principal Component 1
Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M

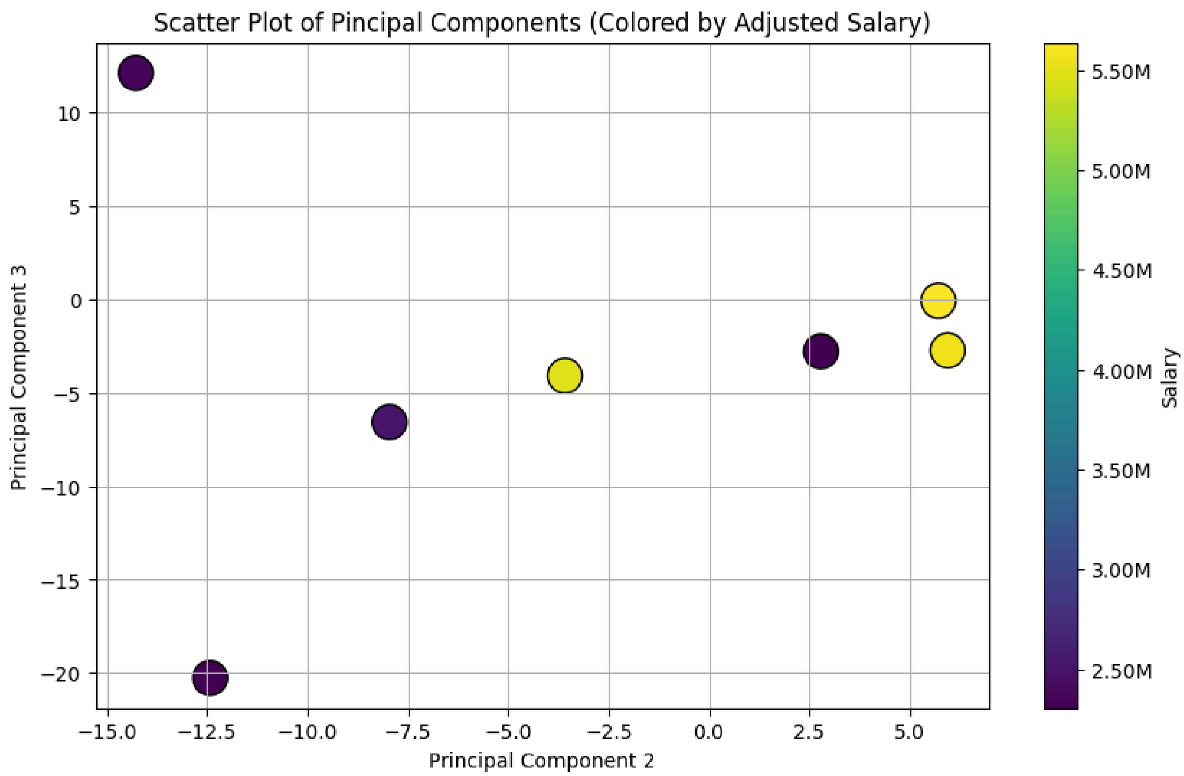


Scatter Plot of Pincipal Components (Colored by Adjusted Salary)
Principal Component 3
Principal Component 2
15
10
5
0
−5
−10
−15
−20
−25
−30
−20
−10
0
10
20
Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M

In [12]:
```
player_df = pd.DataFrame(X_train_pca, columns=[f"PC{i+1}" for i in range(n_com
ponents)])
player_df["Season"] = player_seasons["season"].astype(str)
player_df["Salary"] = player_seasons["adjustedSalary"]

density_plot(player_df, c1=1, c2=2)
density_plot(player_df, c1=1, c2=3)
density_plot(player_df, c1=2, c2=3)
```

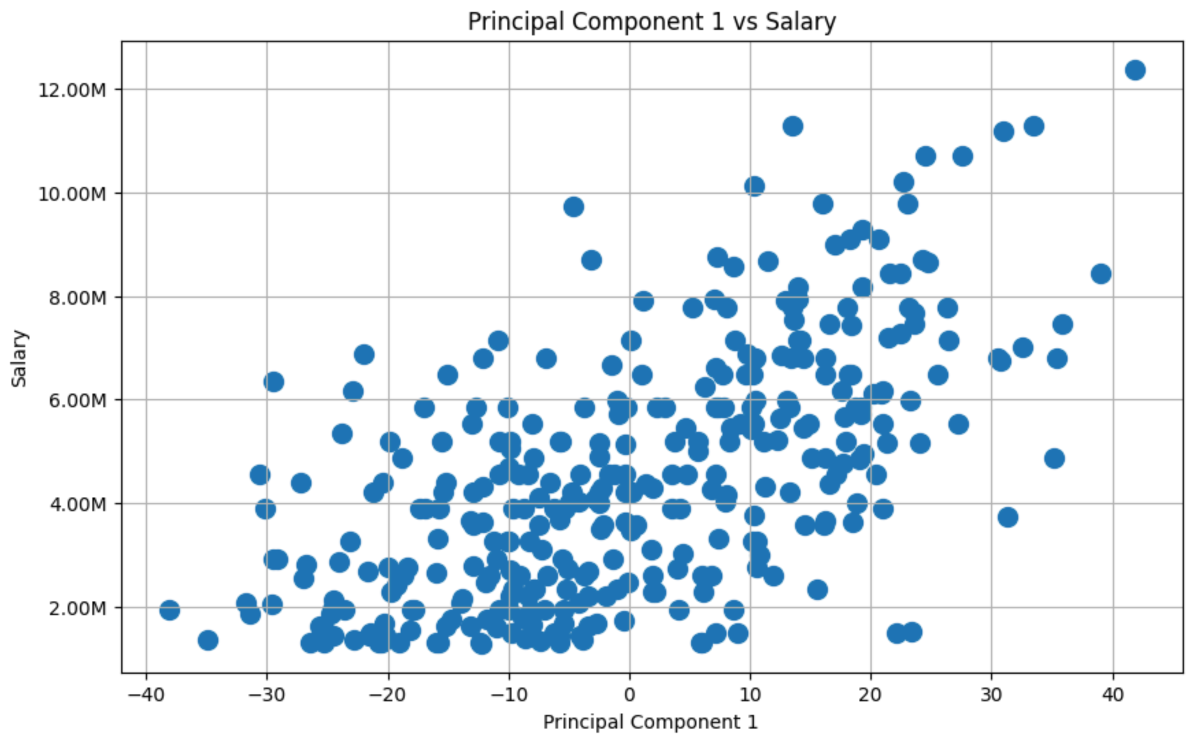

Scatter Plot of Pincipal Components (Colored by Adjusted Salary)
Principal Component 1
Principal Component 2
Salary
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M

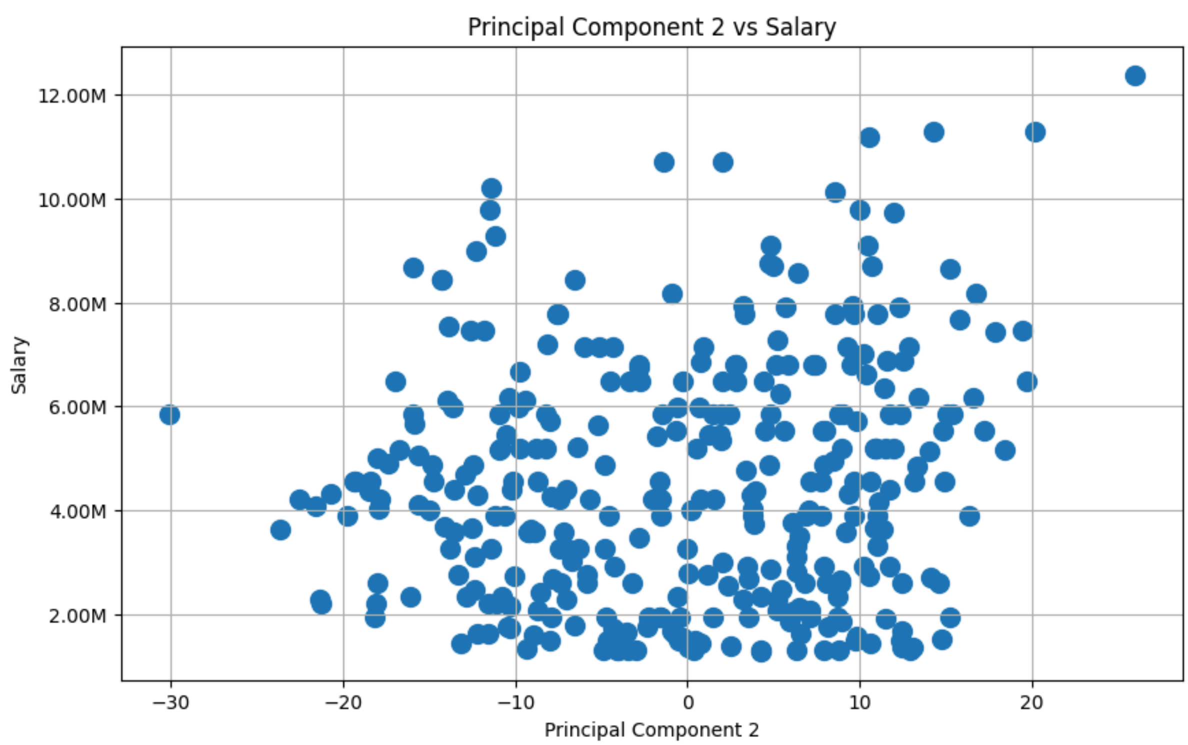

Scatter Plot of Pincipal Components (Colored by Adjusted Salary)
Principal Component 1
Principal Component 3
Salary
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M

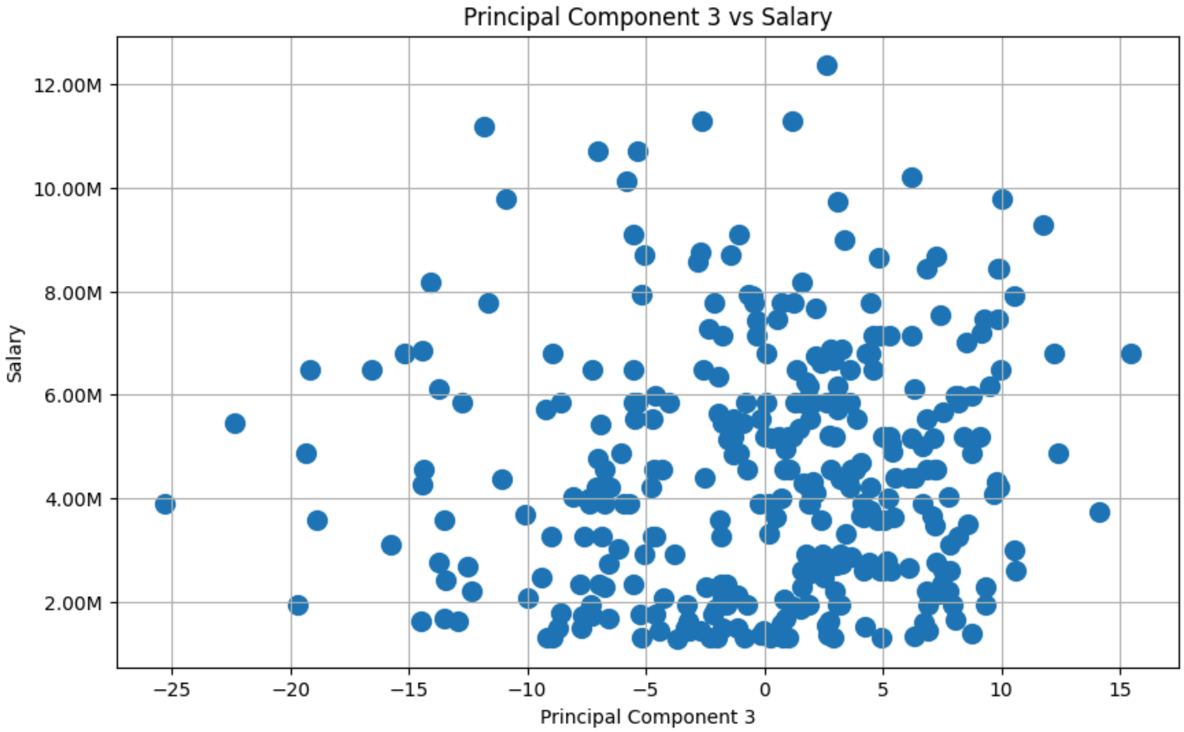


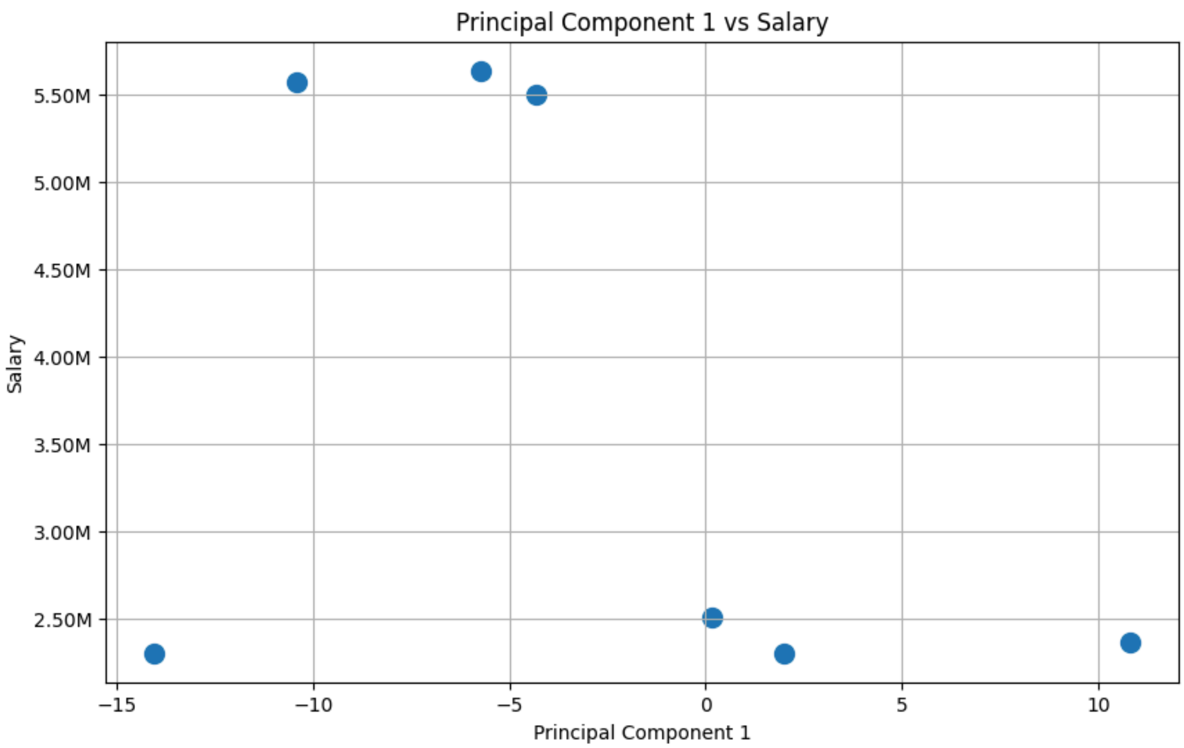
Scatter Plot of Pincipal Components (Colored by Adjusted Salary)
Principal Component 3
Principal Component 2
Salary
10
5
0
−5
−10
−15
−20
−15.0
−12.5
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M

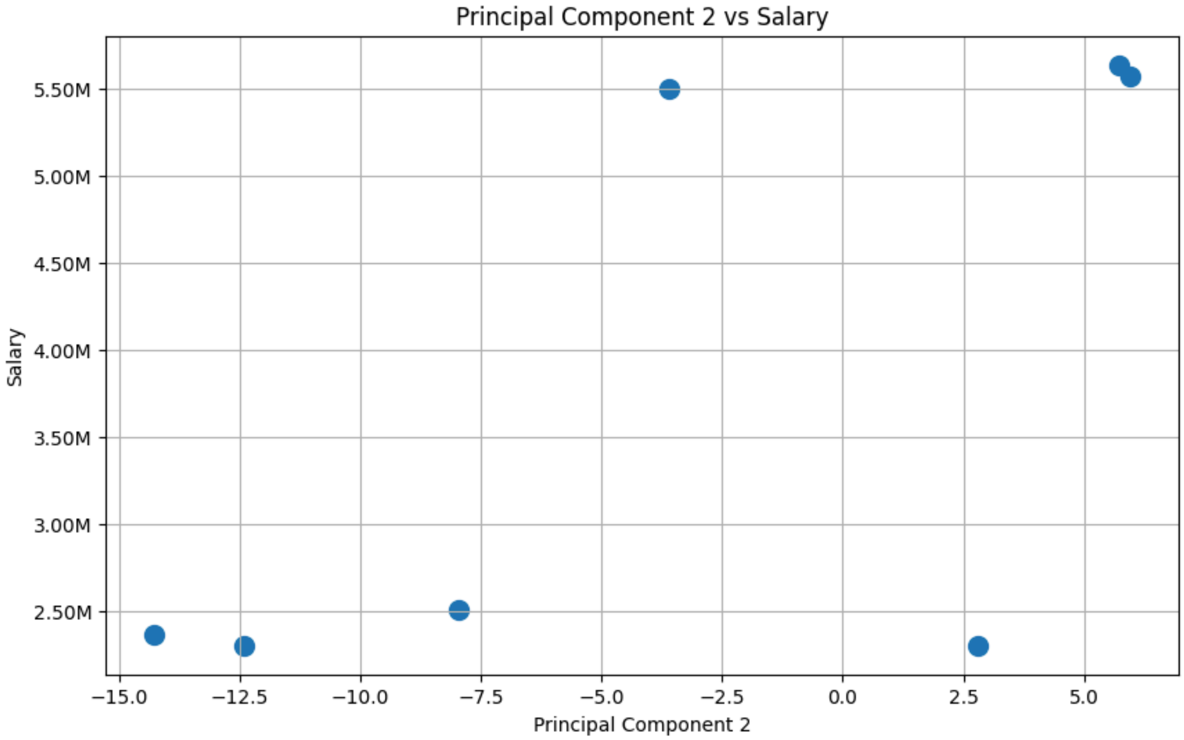
In [13]:
```
plot_component(train_df, c=1)
plot_component(train_df, c=2)
plot_component(train_df, c=3)

plot_component(player_df, c=1)
plot_component(player_df, c=2)
plot_component(player_df, c=3)
```

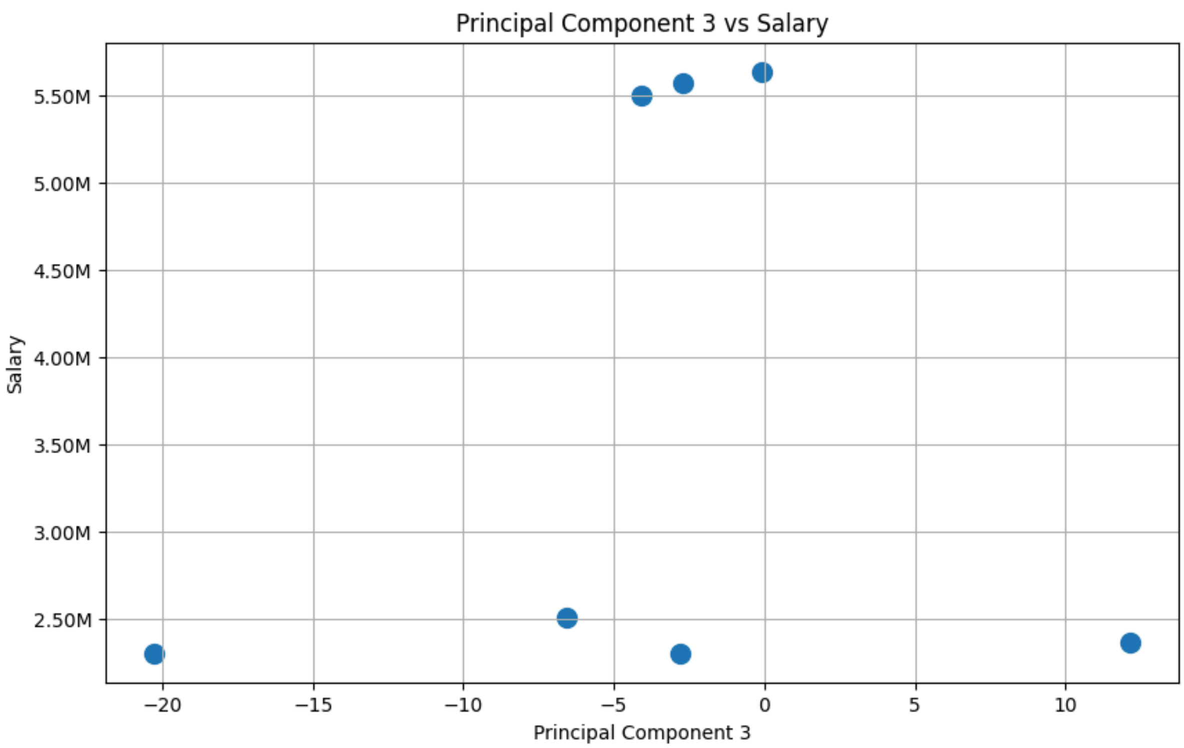

Principal Component 1 vs Salary
Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M
−40
−30
−20
−10
0
10
20
30
40
Principal Component 1


Principal Component 2 vs Salary
Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M
−30
−20
−10
0
10
20
Principal Component 2


Principal Component 3 vs Salary
Salary
Principal Component 3
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M
−25
−20
−15
−10
−5
0
5
10
15


Principal Component 1 vs Salary
Salary
Principal Component 1
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M
−15
−10
−5
0
5
10


Principal Component 2 vs Salary
Salary
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M
−15.0
−12.5
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
Principal Component 2


Principal Component 3 vs Salary
Salary
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M
−20
−15
−10
−5
0
5
10
Principal Component 3

PLS

In [14]:
```
def PLS(n_components):
    X = X_train.astype(np.float64)
    n_samples, n_features = X.shape

    # Reshape y to column vector of floats
    y = y_train.reshape(-1, 1).astype(np.float64)

    # Initialize matrices full of zeros
    T = np.zeros((n_samples, n_components))     # Components
    W = np.zeros((n_features, n_components))    # Weights
    P = np.zeros((n_features, n_components))    # Loadings for X
    Q = np.zeros(n_components)                  # Loadings for y

    for i in range(n_components):
        # Compute weights w that maximize covariance between X and y
        w = X.T @ y
        w /= np.linalg.norm(w)  # Normalize to unit length

        # Project X onto w to find t
        t = X @ w

        tk = (t.T @ t)

        # Compute loadings p
        p = (X.T @ t) / tk

        # Compute loadings q
        q = (y.T @ t) / tk
        q = q.item()  # Convert to scalar

        # Deflate X and y
        X -= t @ p.T
        y -= q * t

        # Store results
        T[:, i] = t.ravel()
        P[:, i] = p.ravel()
        W[:, i] = w.ravel()
        Q[i] = q

    return T, W, P, Q
```

In [15]:

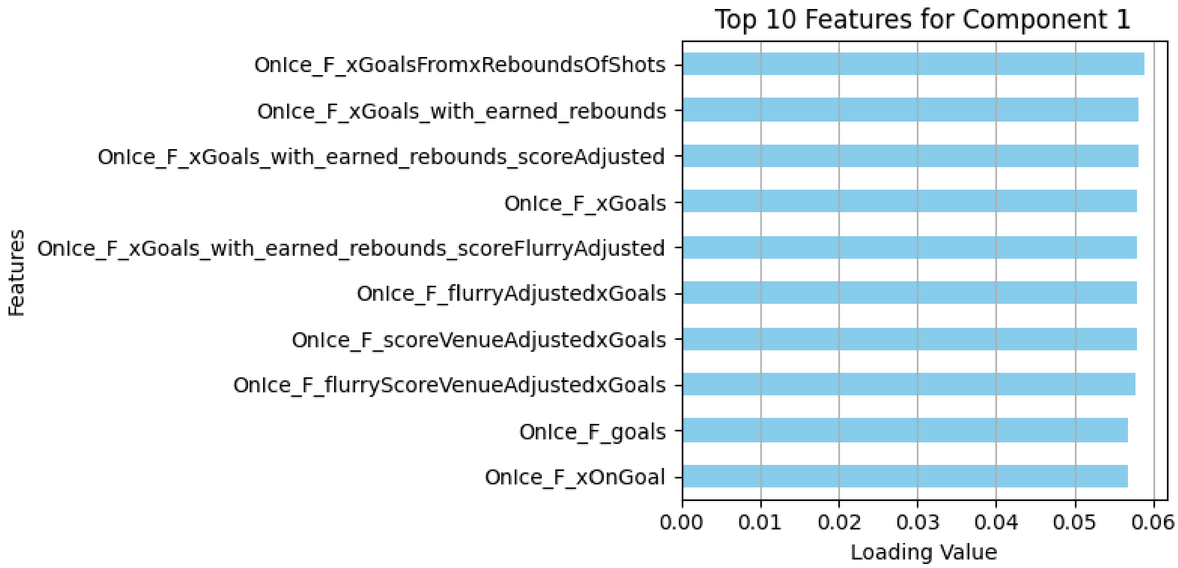
```
X = X_train.copy()
n_samples, n_features = X.shape

n_components = 3

# Perform PLS and apply to the data
T, W, P, Q = PLS(n_components)

X_train_pls = X_train @ W
X_player_pls = X_player @ W

# Train the models
results_pls_df, predictions_pls = common.train_and_evaluate(X_train_pls, y_tra
in, X_player_pls, y_player)
results_pls_df
```

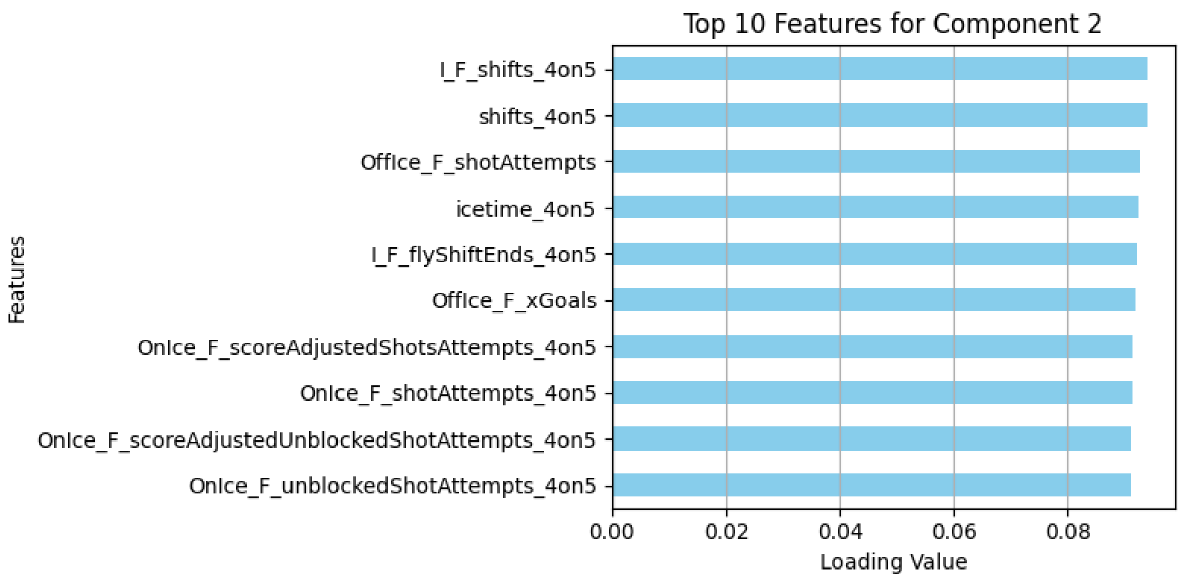
Out[15]:

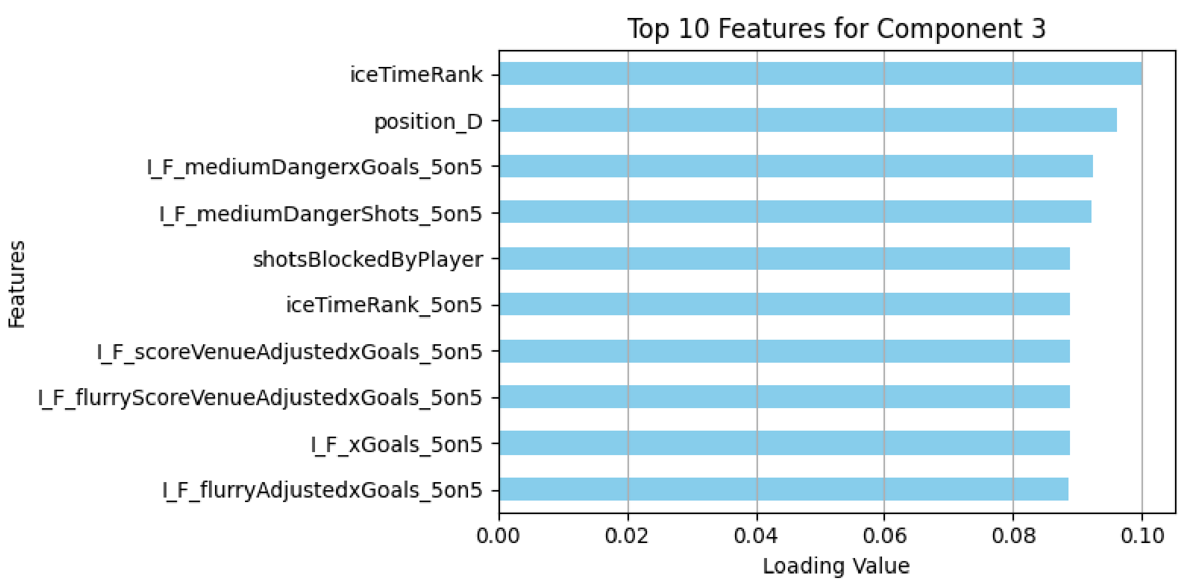
Model	R2	MAE	Top-100 MAE	Top-50 MAE	SMAPE	Train time (sec)
Linear Regression	0.4663	1,056,753	1,056,753	1,056,753	0.2781	0.00
Random Forest	-0.3950	1,622,787	1,622,787	1,622,787	0.3589	0.71
Support Vector	0.5480	979,214	979,214	979,214	0.2601	0.56
K-Nearest Neighbors	0.1857	1,280,001	1,280,001	1,280,001	0.3098	0.00

In [16]:

```python
n_top_features = 10

loadings_df = pd.DataFrame(P, index=X_data.columns)

for comp in range(n_components):
    plt.figure(figsize=(8, 4))
    # Sort features by absolute loading values for the current component
    top_features = loadings_df.iloc[:, comp].abs().nlargest(n_top_features)

    # Plot
    top_features.sort_values().plot(kind='barh', color='skyblue')
    plt.title(f"Top {n_top_features} Features for Component {comp + 1}")
    plt.xlabel("Loading Value")
    plt.ylabel("Features")
    plt.grid(axis='x')
    plt.tight_layout()
    plt.show()
```

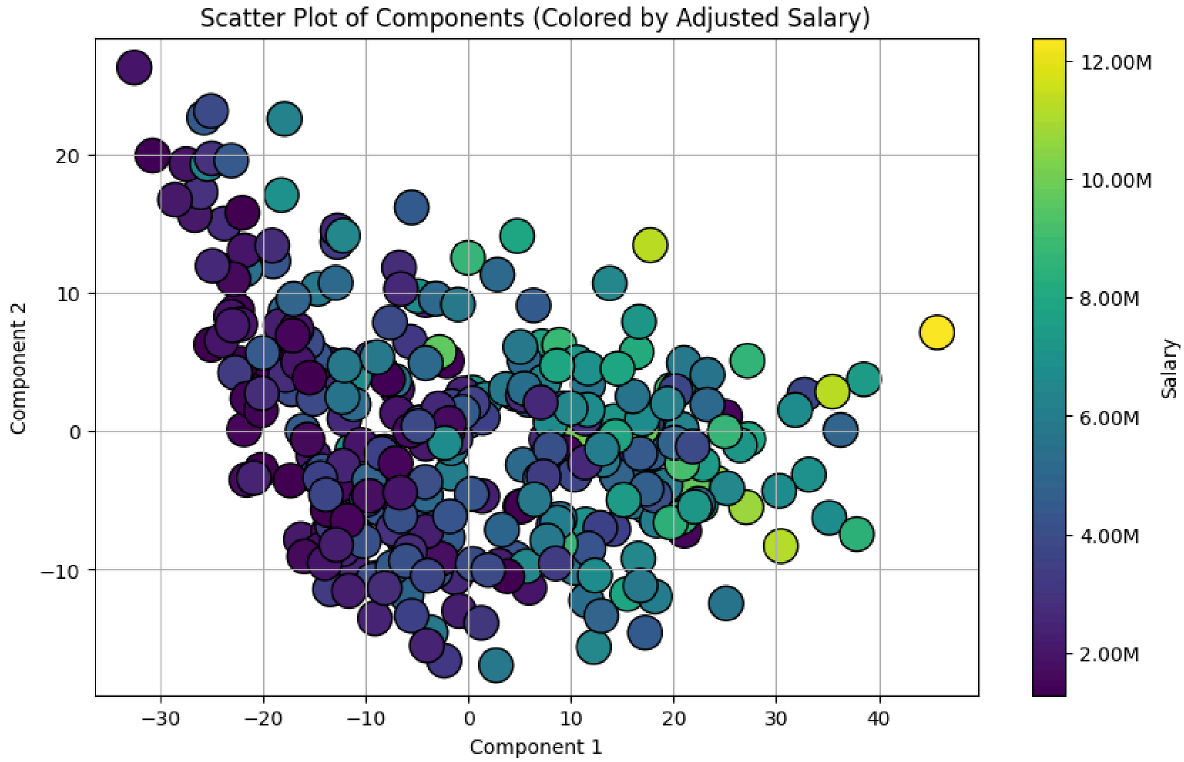

Top 10 Features for Component 1
OnIce_F_xGoalsFromxReboundsOfShots
OnIce_F_xGoals_with_earned_rebounds
OnIce_F_xGoals_with_earned_rebounds_scoreAdjusted
OnIce_F_xGoals
OnIce_F_xGoals_with_earned_rebounds_scoreFlurryAdjusted
OnIce_F_flurryAdjustedxGoals
OnIce_F_scoreVenueAdjustedxGoals
OnIce_F_flurryScoreVenueAdjustedxGoals
OnIce_F_goals
OnIce_F_xOnGoal
Features
0.00
0.01
0.02
0.03
0.04
0.05
0.06
Loading Value

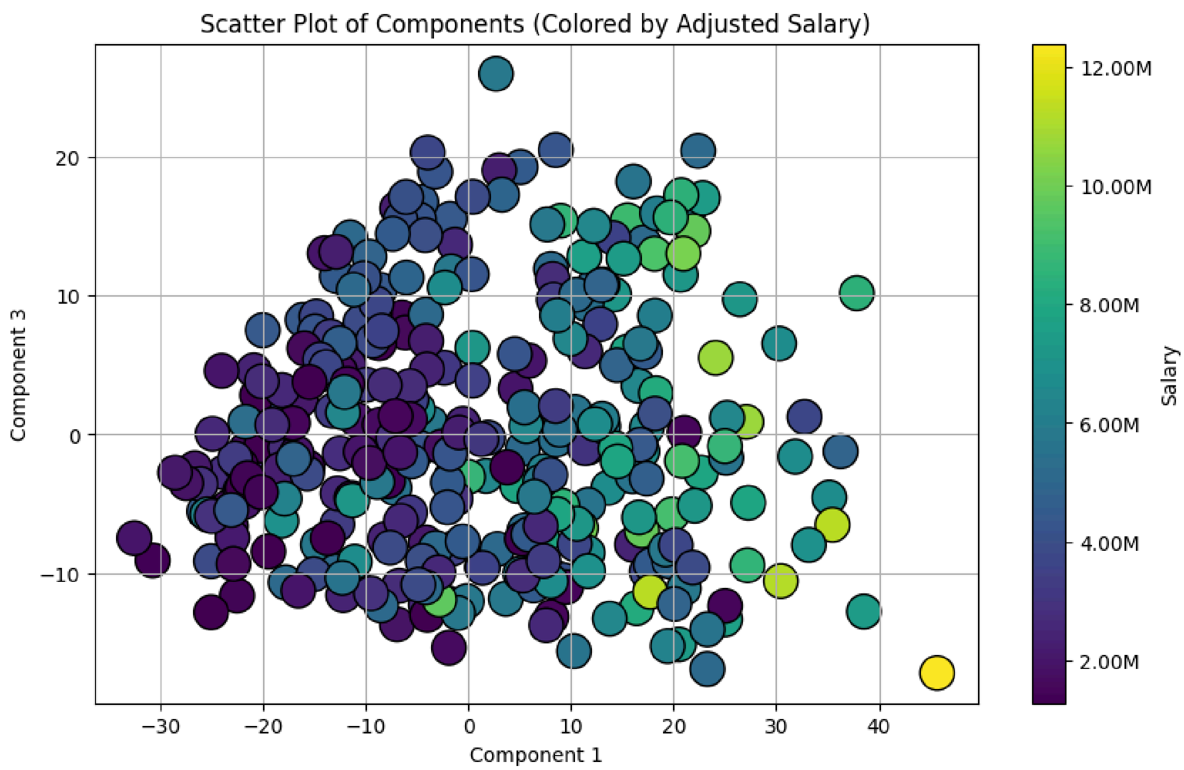

Top 10 Features for Component 2
I_F_shifts_4on5
shifts_4on5
OffIce_F_shotAttempts
icetime_4on5
I_F_flyShiftEnds_4on5
OffIce_F_xGoals
OnIce_F_scoreAdjustedShotsAttempts_4on5
OnIce_F_shotAttempts_4on5
OnIce_F_scoreAdjustedUnblockedShotAttempts_4on5
OnIce_F_unblockedShotAttempts_4on5
Features
0.00
0.02
0.04
0.06
0.08
Loading Value

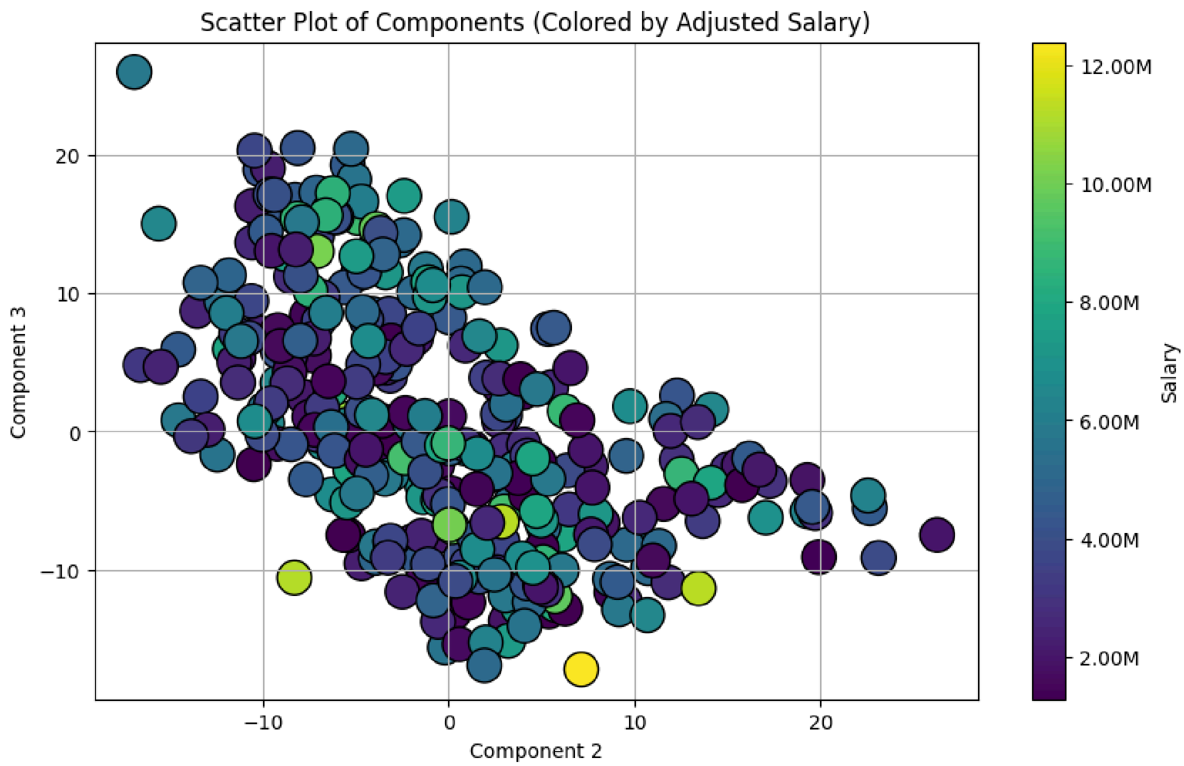

Top 10 Features for Component 3
iceTimeRank
position_D
I_F_mediumDangerxGoals_5on5
I_F_mediumDangerShots_5on5
shotsBlockedByPlayer
iceTimeRank_5on5
I_F_scoreVenueAdjustedxGoals_5on5
I_F_flurryScoreVenueAdjustedxGoals_5on5
I_F_xGoals_5on5
I_F_flurryAdjustedxGoals_5on5
Features
0.00
0.02
0.04
0.06
0.08
0.10
Loading Value

In [17]:
```
def density_plot(df, c1=1, c2=2):
    plt.figure(figsize=(10, 6))
    scatter = plt.scatter(
        df[f"PC{c1}"], df[f"PC{c2}"],
        c=df["Salary"], cmap="viridis", edgecolor="k", s=300
    )
    colorbar = plt.colorbar(scatter, label="Salary")
    colorbar.ax.yaxis.set_major_formatter(common.get_mformatter(2))
    plt.xlabel(f"Component {c1}")
    plt.ylabel(f"Component {c2}")
    plt.title("Scatter Plot of Components (Colored by Adjusted Salary)")
    plt.grid()
    plt.show()

def plot_component(df, c=1):
    plt.figure(figsize=(10, 6))
    plt.scatter(df[f"PC{c}"], df["Salary"], s=100)
    plt.xlabel(f"Component {c}")
    plt.ylabel("Salary")
    plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
    plt.title(f"Component {c} vs Salary")
    plt.grid()
    plt.show()
```

In [18]:
```
train_df = pd.DataFrame(X_train_pls, columns=[f"PC{i+1}" for i in range(n_comp
onents)])
train_df["Season"] = X_data["season"].astype(str)  # Add season info
train_df["Salary"] = y_data.drop(player_seasons.index)  # Add salary info

# Select only 2023 season
train_df = train_df[train_df["Season"] == "2013"]

density_plot(train_df, c1=1, c2=2)
density_plot(train_df, c1=1, c2=3)
density_plot(train_df, c1=2, c2=3)
```


Scatter Plot of Components (Colored by Adjusted Salary)
Component 2
Component 1
Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M
20
10
0
−10
−30
−20
−10
0
10
20
30
40

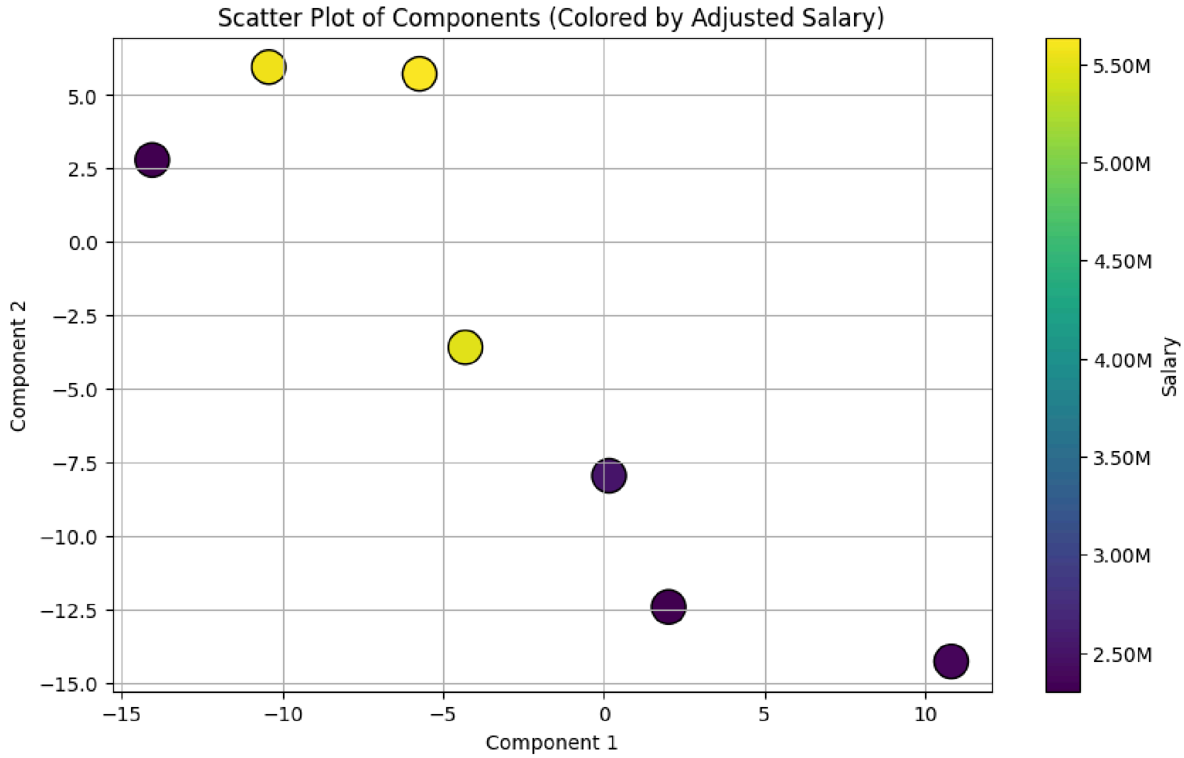

Scatter Plot of Components (Colored by Adjusted Salary)
Component 3
Component 1
Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M
20
10
0
−10
−30
−20
−10
0
10
20
30
40

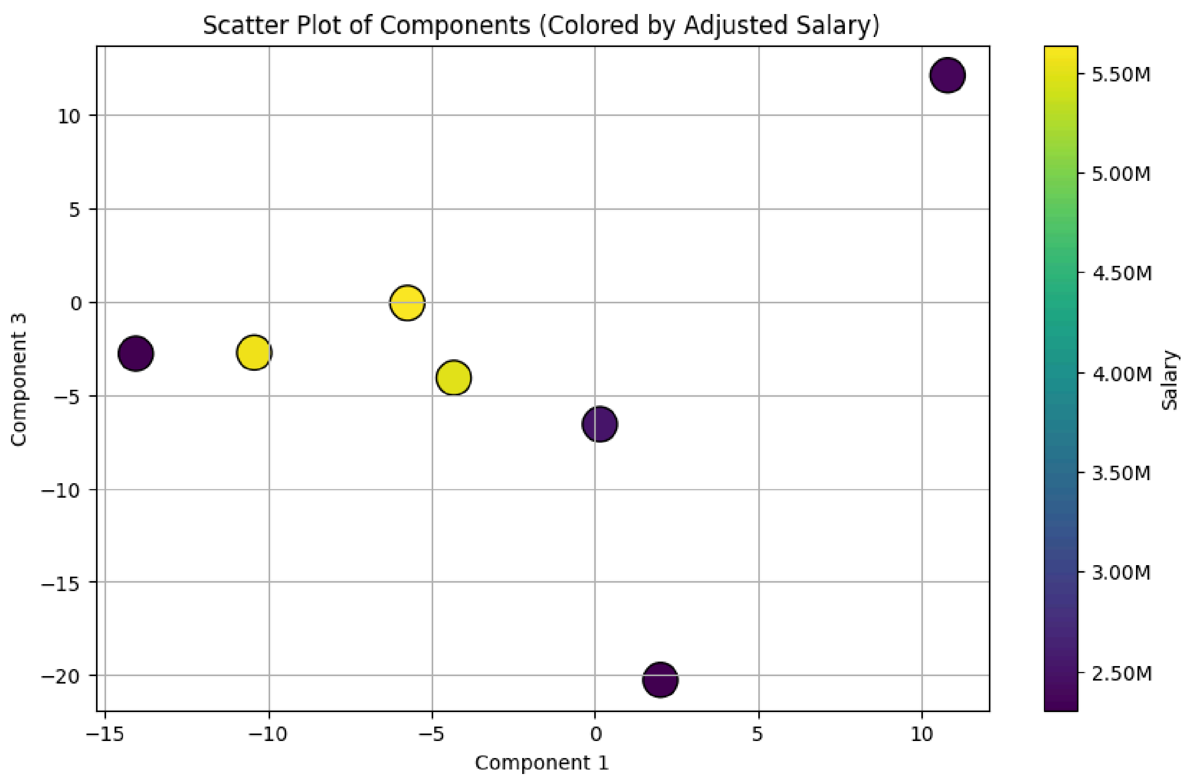


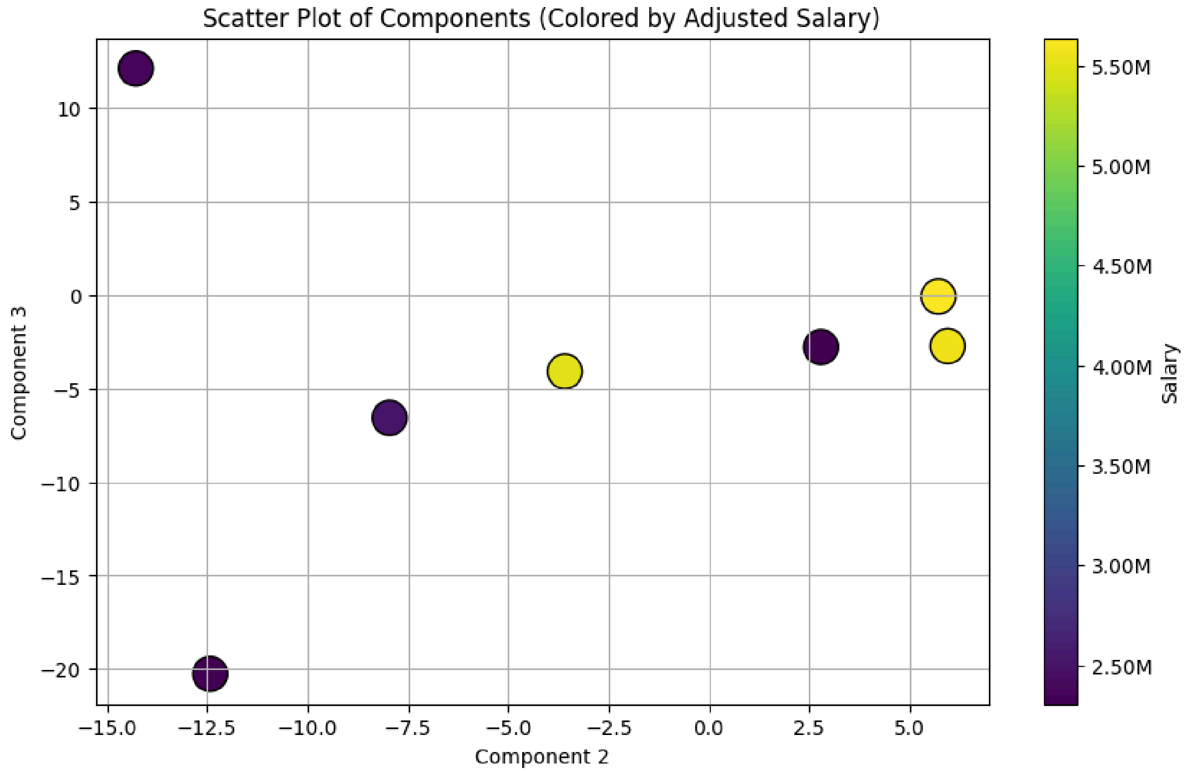
Scatter Plot of Components (Colored by Adjusted Salary)
Component 3
Component 2
20
10
0
−10
−10
0
10
20
Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M

In [19]:

```
player_df = pd.DataFrame(X_train_pca, columns=[f"PC{i+1}" for i in range(n_com
ponents)])
player_df["Season"] = player_seasons["season"].astype(str)
player_df["Salary"] = player_seasons["adjustedSalary"]

density_plot(player_df, c1=1, c2=2)
density_plot(player_df, c1=1, c2=3)
density_plot(player_df, c1=2, c2=3)
```


Scatter Plot of Components (Colored by Adjusted Salary)
Component 2
Component 1
Salary
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0
−12.5
−15.0
−15
−10
−5
0
5
10
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M


Scatter Plot of Components (Colored by Adjusted Salary)
Component 3
Component 1
Salary
10
5
0
−5
−10
−15
−20
−15
−10
−5
0
5
10
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M

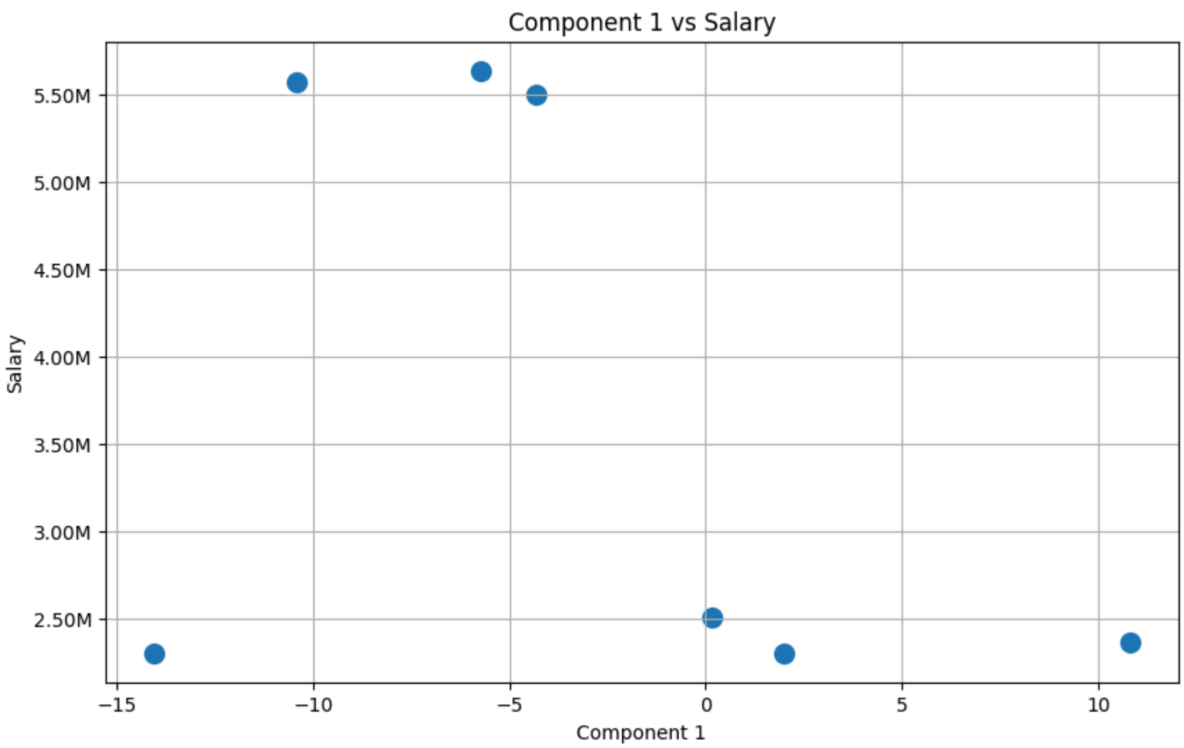

Scatter Plot of Components (Colored by Adjusted Salary)
Component 3
10
5
0
−5
−10
−15
−20
−15.0
−12.5
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
Component 2
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M
Salary

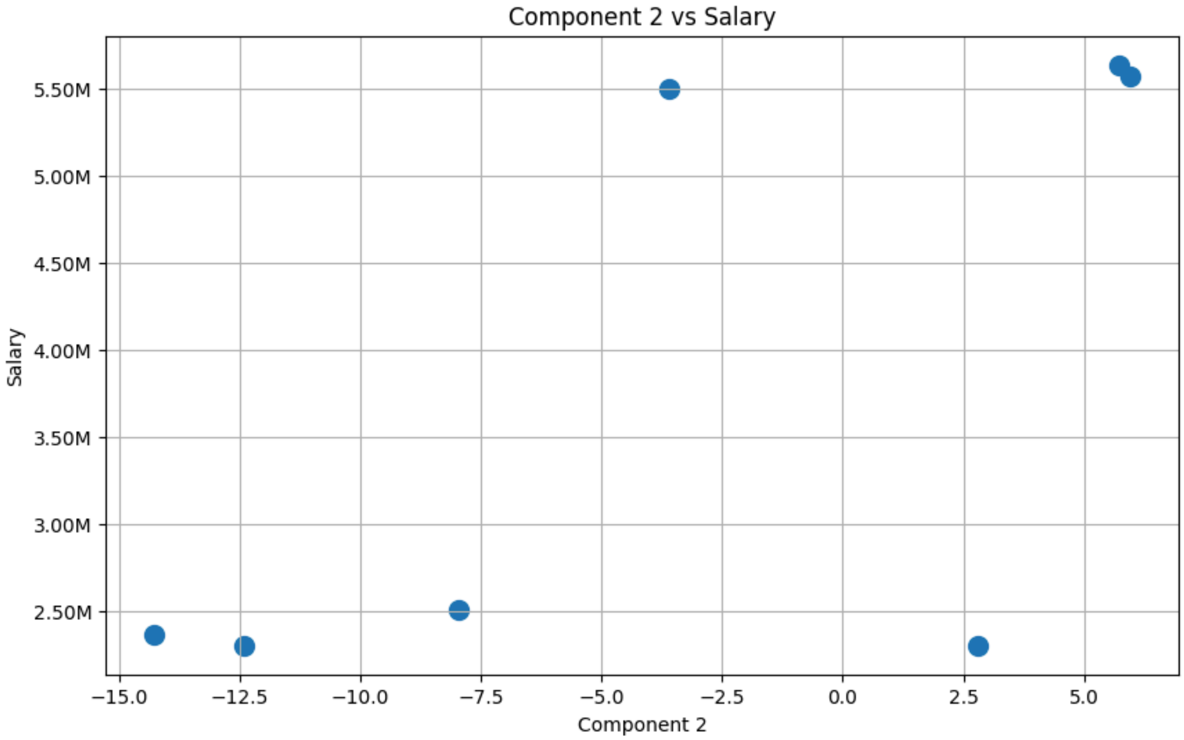
In [20]:
```
plot_component(train_df, c=1)
plot_component(train_df, c=2)
plot_component(train_df, c=3)

plot_component(player_df, c=1)
plot_component(player_df, c=2)
plot_component(player_df, c=3)
```

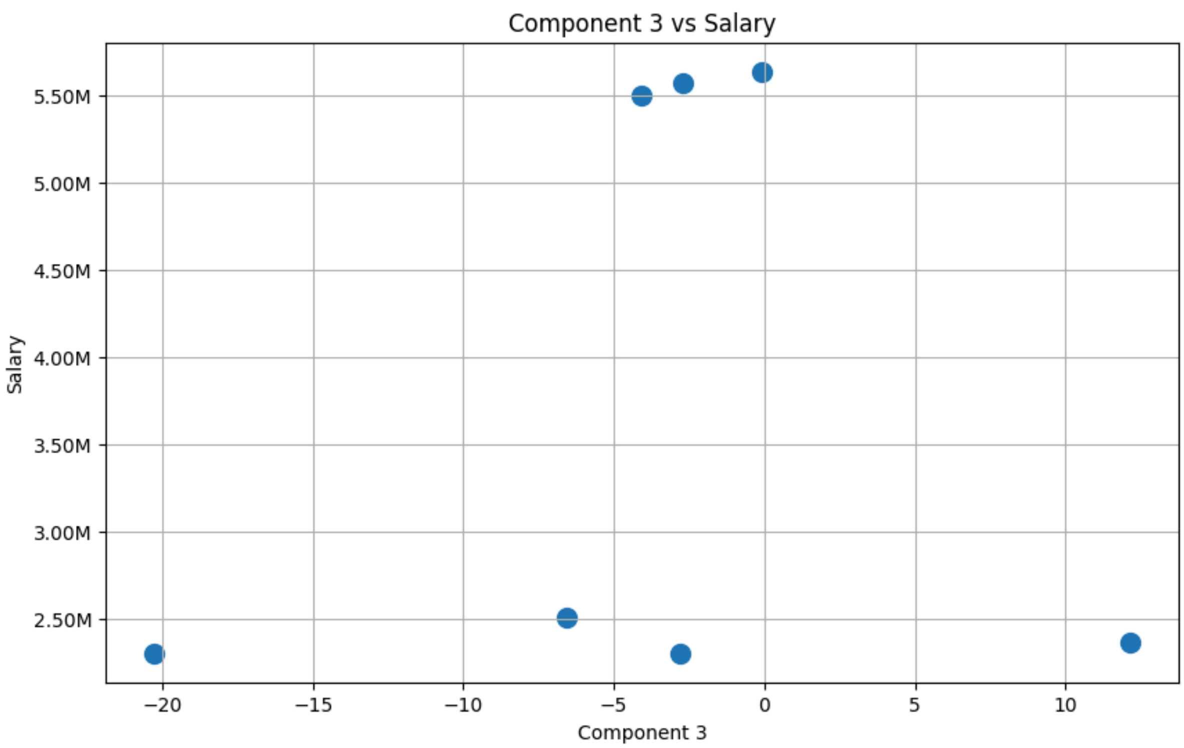

Component 1 vs Salary
Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M
−30
−20
−10
0
10
20
30
40
Component 1


Component 2 vs Salary
Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M
−10
0
10
20
Component 2


Component 3 vs Salary
12.00M
10.00M
8.00M
6.00M
4.00M
2.00M
Salary
−10
0
10
20
Component 3

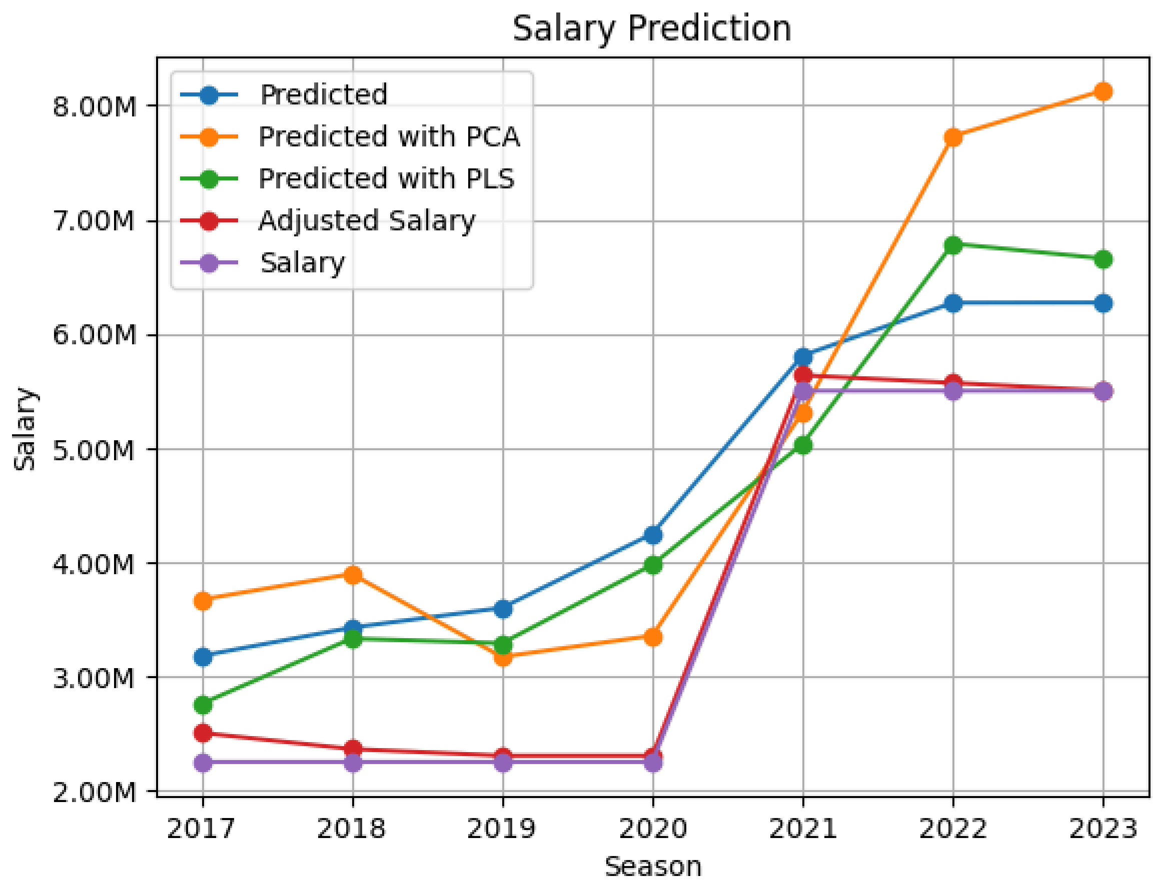

Component 1 vs Salary
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M
Salary
−15
−10
−5
0
5
10
Component 1

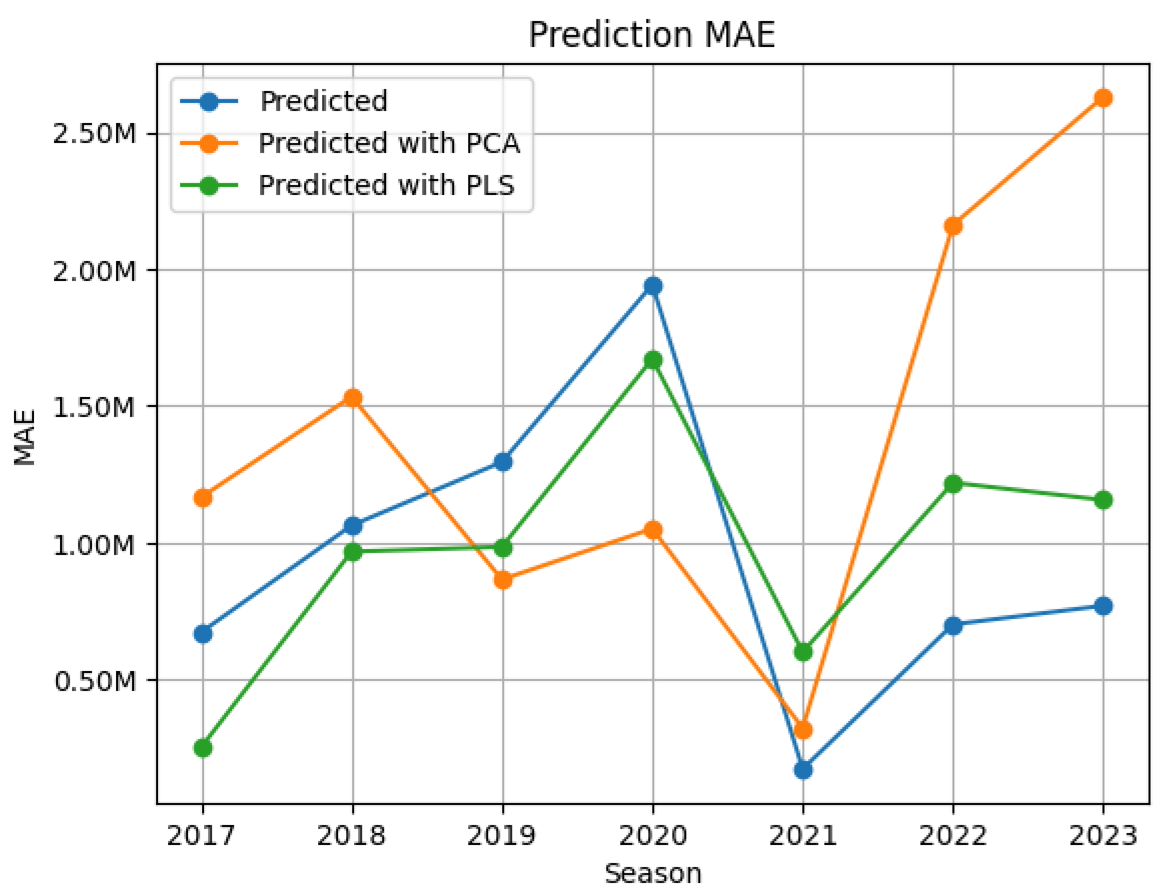

Component 2 vs Salary
Salary
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M
−15.0
−12.5
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
Component 2


Component 3 vs Salary
Salary
5.50M
5.00M
4.50M
4.00M
3.50M
3.00M
2.50M
−20
−15
−10
−5
0
5
10
Component 3

In [21]:

```
# Use SVM prediction as the base model
salary_evaluation = predictions[2]
salary_evaluation_PCA = predictions_pca[2]
salary_evaluation_PLS = predictions_pls[2]
seasons = player_seasons["season"].astype(str)
adjusted_salary = player_seasons["adjustedSalary"]
salary = player_seasons["salary"]

# Plot the results
plt.plot(seasons, salary_evaluation, label="Predicted", marker="o")
plt.plot(seasons, salary_evaluation_PCA, label="Predicted with PCA", marker
="o")
plt.plot(seasons, salary_evaluation_PLS, label="Predicted with PLS", marker
="o")
plt.plot(seasons, adjusted_salary, label="Adjusted Salary", marker="o")
plt.plot(seasons, salary, label="Salary", marker="o")
plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
plt.xlabel("Season")
plt.ylabel("Salary")
plt.title("Salary Prediction")
plt.legend()
plt.grid()
plt.show()

# Plot the error by season
error = salary_evaluation - adjusted_salary
error_PCA = salary_evaluation_PCA - adjusted_salary
error_PLS = salary_evaluation_PLS - adjusted_salary
plt.plot(seasons, error.abs(), label="Predicted", marker="o")
plt.plot(seasons, error_PCA.abs(), label="Predicted with PCA", marker="o")
plt.plot(seasons, error_PLS.abs(), label="Predicted with PLS", marker="o")
plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
plt.xlabel("Season")
plt.ylabel("MAE")
plt.title("Prediction MAE")
plt.legend()
plt.grid()
plt.show()
```


Salary Prediction
Predicted
Predicted with PCA
Predicted with PLS
Adjusted Salary
Salary
Salary
8.00M
7.00M
6.00M
5.00M
4.00M
3.00M
2.00M
2017
2018
2019
2020
2021
2022
2023
Season


Prediction MAE
Predicted
Predicted with PCA
Predicted with PLS
MAE
2.50M
2.00M
1.50M
1.00M
0.50M
2017
2018
2019
2020
2021
2022
2023
Season

Sidney Crosby

term: 12yrs
cap hit: $8.70M
seasons: 2013-2024

In [22]:
```
player_seasons = original_df[(original_df["name"] == "Sidney Crosby")]

# Separate player seasons from X_data by using the indexes from player_seasons
X_player = X_data.loc[player_seasons.index].to_numpy()
y_player = y_data.loc[player_seasons.index].to_numpy()

X_train = X_data.drop(player_seasons.index).to_numpy()
y_train = y_data.drop(player_seasons.index).to_numpy()

# Standardize the data
X_train, X_player = common.standard_scaler(X_train, X_player)

# Train the models
results_df, predictions = common.train_and_evaluate(X_train, y_train, X_playe
r, y_player)
results_df
```

Out[22]:

Model	R2	MAE	Top-100 MAE	Top-50 MAE	SMAPE	Train time (sec)
Linear Regression	-3.5726	1,470,148	1,470,148	1,470,148	0.1546	1.66
Random Forest	-5.8071	1,912,158	1,912,158	1,912,158	0.2208	8.76
Support Vector	-2.4039	1,275,435	1,275,435	1,275,435	0.1409	7.08
K-Nearest Neighbors	-6.5853	1,976,926	1,976,926	1,976,926	0.2299	0.02

In [23]:

```
X = X_train.copy()
n_samples, n_features = X.shape

# Center the data (subtract the mean of each feature)
X_centered = X - np.mean(X, axis=0)

# Singular Value Decomposition
U, S, Vt = np.linalg.svd(X_centered, full_matrices=False)

# Compute explained variance
explained_variance = (S**2) / (n_samples-1)
total_explained_variance = np.sum(explained_variance)
explained_variance_ratio = explained_variance / total_explained_variance

# Compute cumulative explained variance
cumsum = np.cumsum(explained_variance_ratio)
x_range = range(0, len(cumsum))

n_components = 3

# Transform data into principal component space
X_train_pca = np.dot(X_centered, Vt.T)
X_train_pca = X_train_pca[:, :n_components]

# Adjust the features for player
X_player_centered = X_player - np.mean(X, axis=0)
X_player_pca = np.dot(X_player_centered, Vt.T)
X_player_pca = X_player_pca[:, :n_components]

# Train the models
results_pca_df, predictions_pca = common.train_and_evaluate(X_train_pca, y_tra
in, X_player_pca, y_player)
results_pca_df
```

Out[23]:

Model	R2	MAE	Top-100 MAE	Top-50 MAE	SMAPE	Train time (sec)
Linear Regression	-9.3717	2,316,999	2,316,999	2,316,999	0.2840	0.00
Random Forest	-10.1698	2,440,196	2,440,196	2,440,196	0.2976	0.87
Support Vector	-10.2135	2,404,476	2,404,476	2,404,476	0.2976	0.48
K-Nearest Neighbors	-10.1510	2,303,808	2,303,808	2,303,808	0.2850	0.02

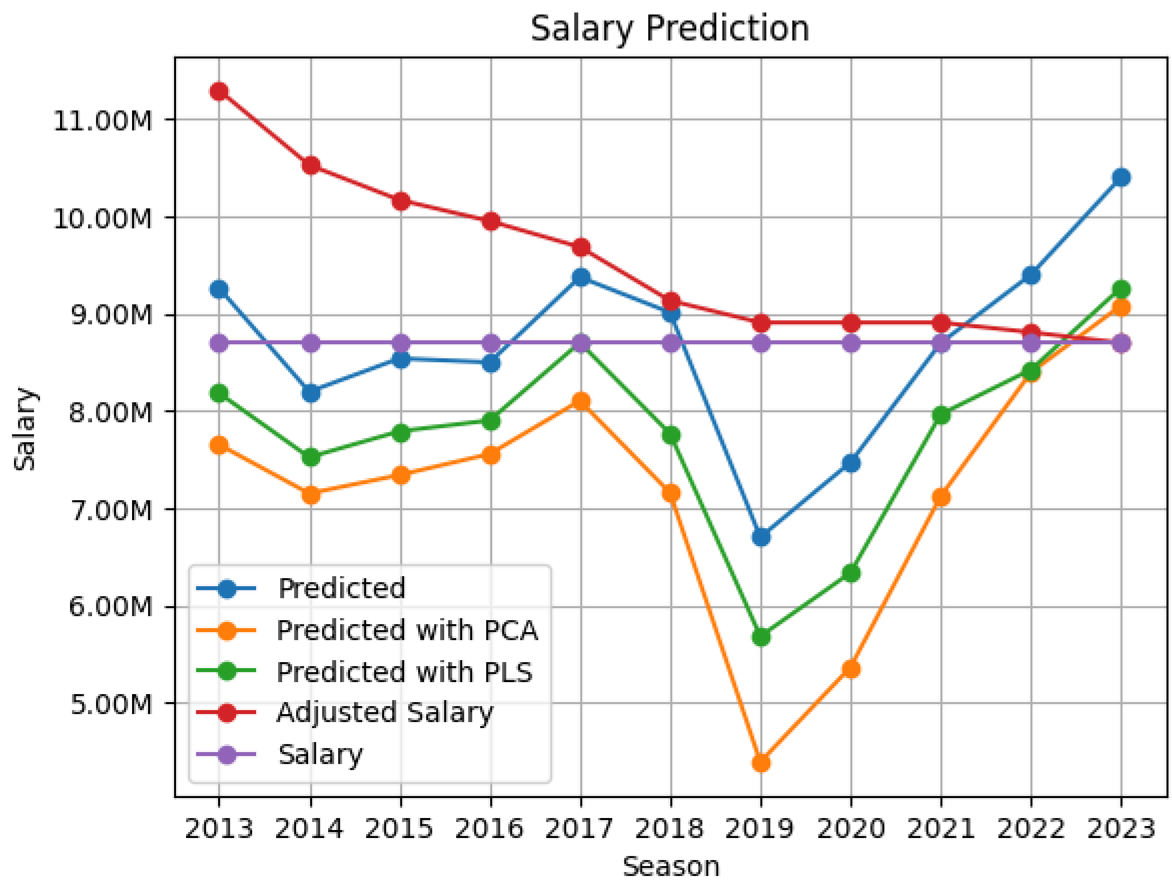
In [24]:
```python
X = X_train.copy()
n_samples, n_features = X.shape

n_components = 3

# Perform PLS and apply to the data
T, W, P, Q = PLS(n_components)

X_train_pls = X_train @ W
X_player_pls = X_player @ W

# Train the models
results_pls_df, predictions_pls = common.train_and_evaluate(X_train_pls, y_tra
in, X_player_pls, y_player)
results_pls_df
```

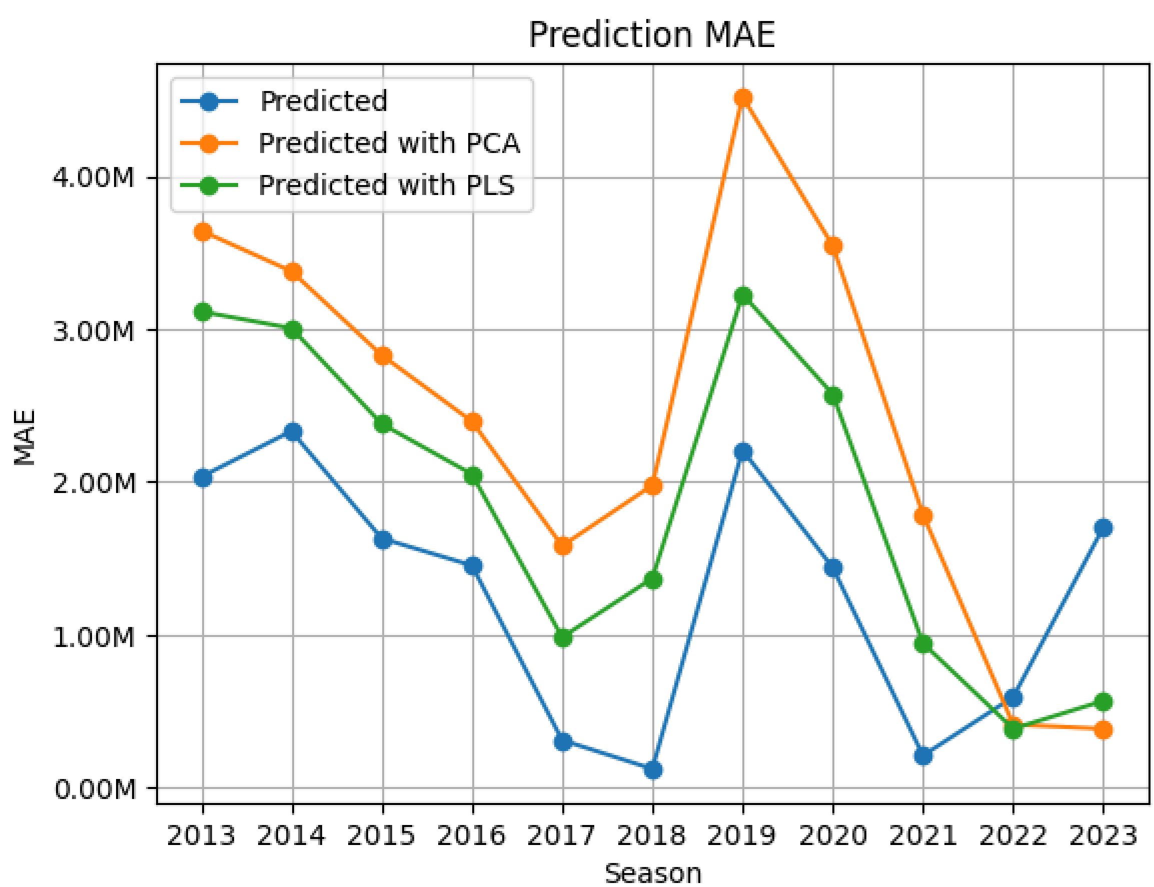
Out[24]:

Model	R2	MAE	Top-100 MAE	Top-50 MAE	SMAPE	Train time (sec)
Linear Regression	-5.3028	1,792,367	1,792,367	1,792,367	0.2084	0.00
Random Forest	-3.5646	1,477,570	1,477,570	1,477,570	0.1664	0.88
Support Vector	-5.8704	1,872,298	1,872,298	1,872,298	0.2196	0.63
K-Nearest Neighbors	-2.7305	1,386,503	1,386,503	1,386,503	0.1548	0.02

In [25]:

```python
# Use SVM prediction as the base model
salary_evaluation = predictions[2]
salary_evaluation_PCA = predictions_pca[2]
salary_evaluation_PLS = predictions_pls[2]
seasons = player_seasons["season"].astype(str)
adjusted_salary = player_seasons["adjustedSalary"]
salary = player_seasons["salary"]

# Plot the results
plt.plot(seasons, salary_evaluation, label="Predicted", marker="o")
plt.plot(seasons, salary_evaluation_PCA, label="Predicted with PCA", marker
="o")
plt.plot(seasons, salary_evaluation_PLS, label="Predicted with PLS", marker
="o")
plt.plot(seasons, adjusted_salary, label="Adjusted Salary", marker="o")
plt.plot(seasons, salary, label="Salary", marker="o")
plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
plt.xlabel("Season")
plt.ylabel("Salary")
plt.title("Salary Prediction")
plt.legend()
plt.grid()
plt.show()

# Plot the error by season
error = salary_evaluation - adjusted_salary
error_PCA = salary_evaluation_PCA - adjusted_salary
error_PLS = salary_evaluation_PLS - adjusted_salary
plt.plot(seasons, error.abs(), label="Predicted", marker="o")
plt.plot(seasons, error_PCA.abs(), label="Predicted with PCA", marker="o")
plt.plot(seasons, error_PLS.abs(), label="Predicted with PLS", marker="o")
plt.gca().yaxis.set_major_formatter(common.get_mformatter(2))
plt.xlabel("Season")
plt.ylabel("MAE")
plt.title("Prediction MAE")
plt.legend()
plt.grid()
plt.show()
```


Salary Prediction
11.00M
10.00M
9.00M
8.00M
7.00M
6.00M
5.00M
Salary
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Season
Predicted
Predicted with PCA
Predicted with PLS
Adjusted Salary
Salary


Prediction MAE
4.00M
3.00M
2.00M
1.00M
0.00M
MAE
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Season
Predicted
Predicted with PCA
Predicted with PLS