In [ ]:

```
# Hitters Cluster Analysis

# Libraries
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
```

In [ ]:

```
# Reading in Data
hitters = pd.read_csv('Hitters.csv')
hitters.head()
```

Out[ ]:

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

In [ ]:

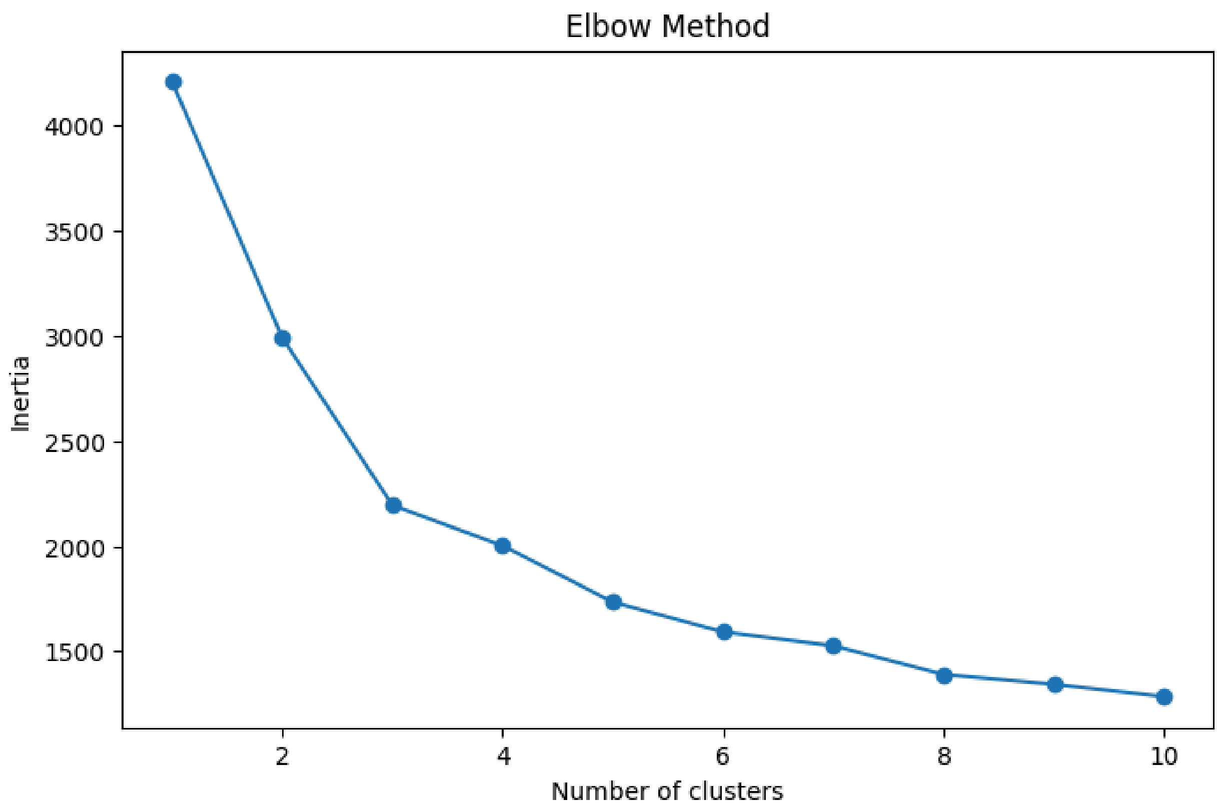
```
# Feature Selection - Removed categorical variables and Salary
X = hitters.drop(columns = ['Salary', 'League', 'Division', 'NewLeague']).dropna()

# Standardization
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [ ]:

```
# Elbow Method for Optimal Number of Clusters (K)
inertia = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

# Elbow method plot
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), inertia, marker='o')
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.show()
#k=3, 4, or 5 seem like good options, there stops being a drastic change around k=3
```



In [ ]:
```
# Silhouette Score to determine number of clusters
scores = []
for k in range(2, 10):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init='auto')
    labels = kmeans.fit_predict(X_scaled)
    score = silhouette_score(X_scaled, labels)
    scores.append((k, score))

print(scores)
#K=3 is best for cluster amount, it has the highest silhouette score while keeping the
```

```
[(2, 0.2736891147512909), (3, 0.27624556979855547), (4, 0.2602841804472285), (5, 0.27
4232459531468), (6, 0.21675845823250642), (7, 0.22093483036605935), (8, 0.21480243860
503043), (9, 0.20172996412256916)]
```

In [ ]:
```
# K-means with K=3
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(X_scaled)

# Added clusters as attribute
hitters['Cluster'] = kmeans.labels_
```

In [21]:
```
# Interpreting Clusters
#Numeric Columns
feature_cols = [c for c in hitters.columns if c not in ['Salary','League','Division','

#Feature means
cluster_means = hitters.groupby('Cluster')[feature_cols].mean().round(1)
display(cluster_means)
```

Cluster	AtBat	Hits	HmRun	Runs	RBI	Walks	Years	CAtBat	CHits	CHmRun	CRuns	CRBI	CW
0	427.8	113.8	16.3	59.2	64.8	52.6	14.7	6663.4	1843.6	214.1	945.8	933.6	7
1	274.4	69.6	6.3	33.6	31.4	26.1	5.8	1466.9	379.8	28.5	181.3	156.1	1
2	525.2	144.3	15.1	74.4	66.3	51.6	5.7	2201.1	603.7	50.4	300.9	256.6	1

In [ ]:

```
# Average salary of each cluster
salary_means = hitters.groupby('Cluster')['Salary'].mean().round(0)
print(salary_means)

#Salary differences even though not used to create cluster - forms naturally
#Cluster 0: Veterans - high totals, high years of experience, highest salaries
#Cluster 1: Younger or Role Players - less atbats and hits (low playing time), low car
#Cluster 2: Regulars - higher career totals than cluster 2 - same experience average b
```

```
Cluster
0    929.0
1    299.0
2    613.0
Name: Salary, dtype: float64
```

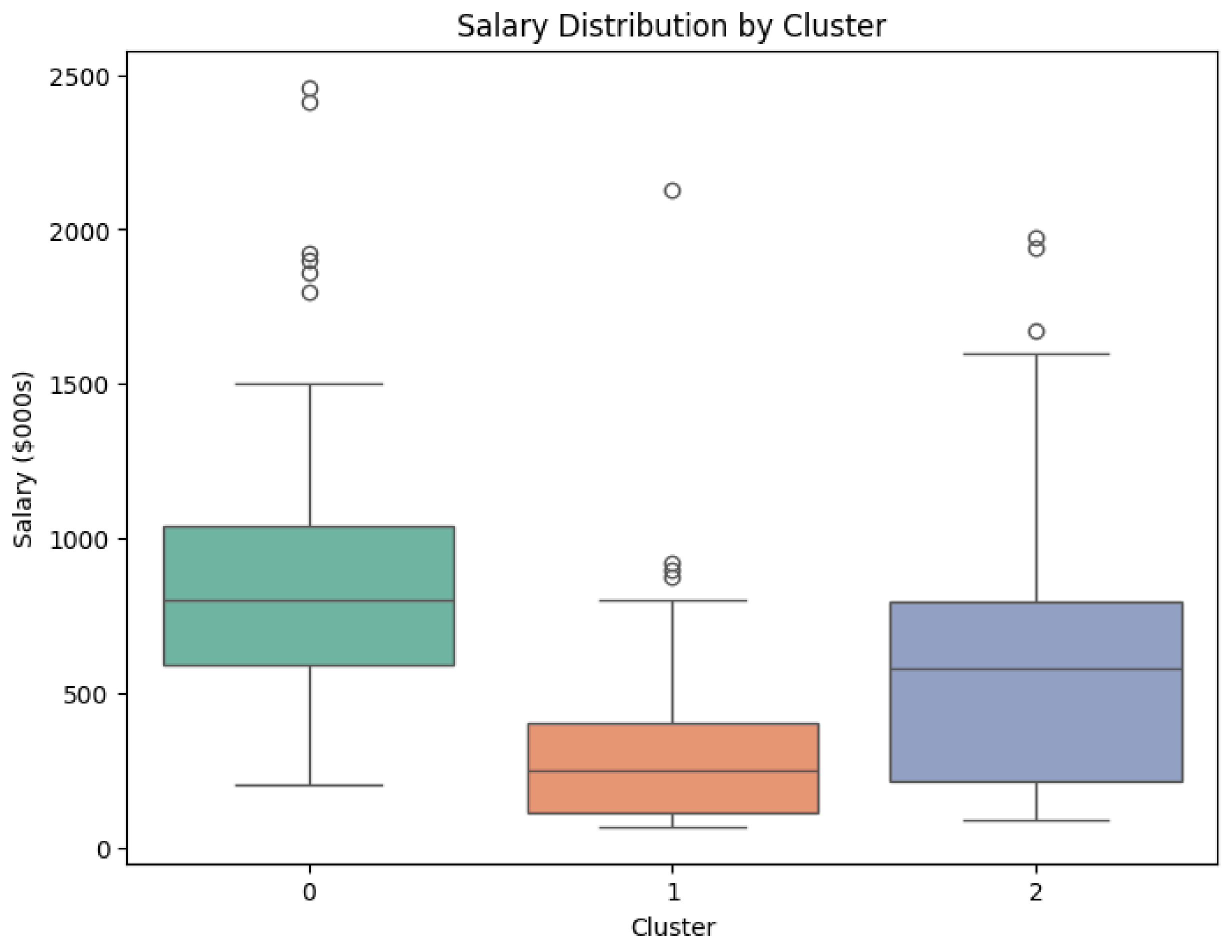
In [ ]:

```
# Salary distribution by cluster plot
plt.figure(figsize=(8,6))
sns.boxplot(x="Cluster", y="Salary", data=hitters, palette= 'Set2')
plt.title("Salary Distribution by Cluster")
plt.ylabel("Salary ($000s)")
plt.xlabel("Cluster")
plt.show()
```

```
C:\Users\amina\AppData\Local\Temp\ipykernel_22640\2366997697.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.
0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(x="Cluster", y="Salary", data=hitters, palette= 'Set2')
```



In [ ]:

```
# Years vs Hits plot
plt.figure(figsize=(8,6))
sns.scatterplot(
    x="Years", y="Hits",
    hue="Cluster", palette="Set1",
    data=hitters, s=70, alpha=0.8
)
plt.title("Years of Experience vs. Hits by Cluster")
plt.xlabel("Years in MLB")
plt.ylabel("Hits (Season)")
plt.legend(title="Cluster")
plt.show()
```

In [ ]:
```
# PCA analysis
pca = PCA()
pca.fit(X_scaled)

explained_variance = pca.explained_variance_ratio_
cumulative = np.cumsum(explained_variance)
print(cumulative)
#PC3 best option- explains 81.8% of variation
#Will use PC1 vs PC2 for modeling - these explain 71% of variation
```

```
[0.45311913 0.70998464 0.81798318 0.87238195 0.91596762 0.94799095
 0.96372127 0.97528009 0.98355667 0.98967987 0.99351456 0.99695435
 0.99871587 0.99961897 0.99992487 1.        ]
```

In [ ]:
```
# Determining what features most make up PC1 and PC2

#Feature columns
feature_cols = [c for c in hitters.columns if c not in ['Salary','League','Division','

#PCA loadings
loadings = pd.DataFrame(
    pca.components_.T,
    columns=[f'PC{i+1}' for i in range(len(pca.components_))],
    index=feature_cols
)

#Features sorted by importance
print("Top features for PC1:")
print(loadings['PC1'].sort_values(key=abs, ascending=False).head(5))
```

```python
print("\nTop features for PC2:")
print(loadings['PC2'].sort_values(key=abs, ascending=False).head(5))
```

```
Top features for PC1:
CRBI      0.342675
CRuns     0.340501
CHits     0.333577
CAtBat    0.333319
CHmRun    0.320087
Name: PC1, dtype: float64

Top features for PC2:
AtBat    0.391118
Hits     0.383922
Runs     0.381179
RBI      0.318169
Years   -0.259716
Name: PC2, dtype: float64
```

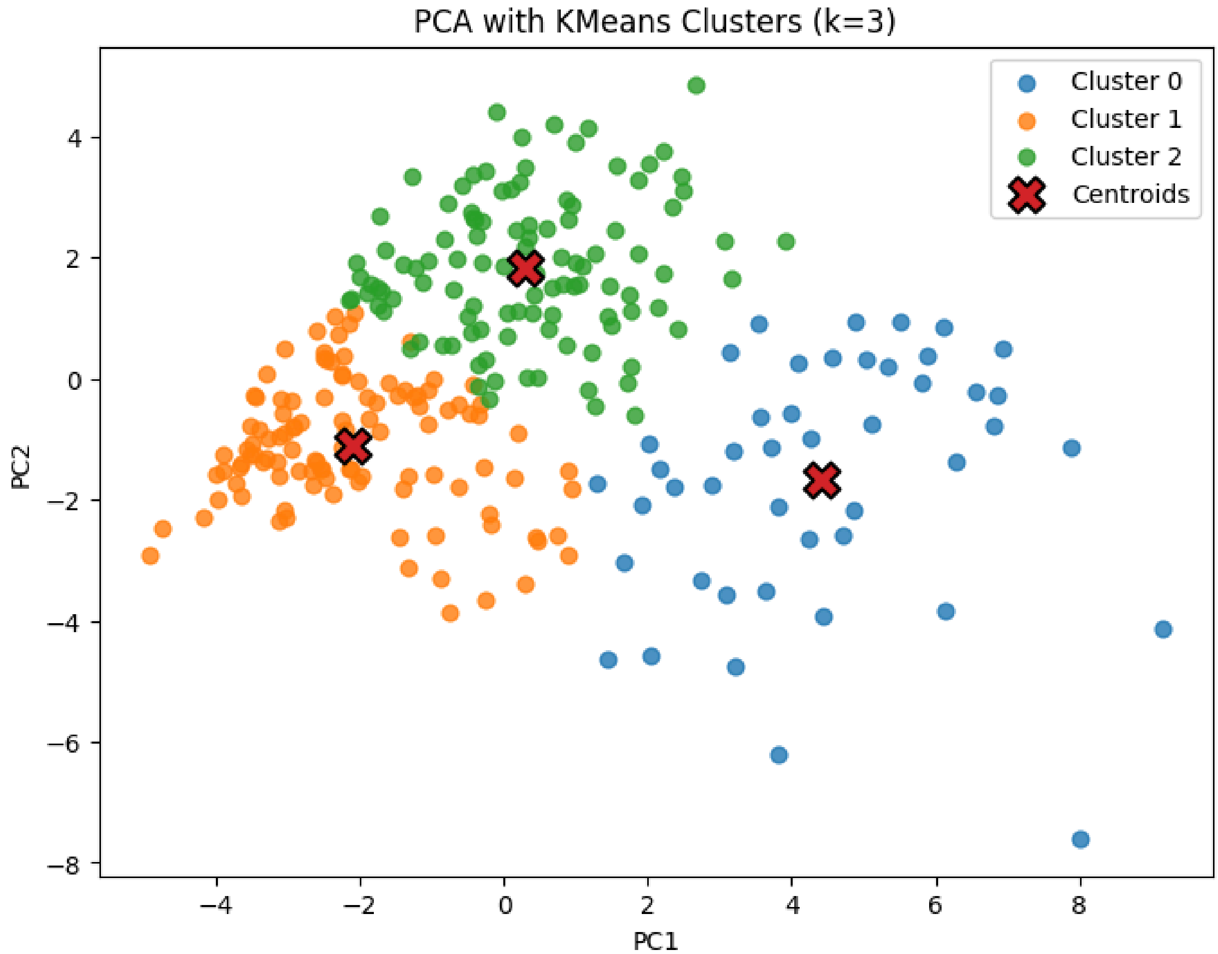
In [ ]:

```python
# PCA cluster graph
pca = PCA(n_components=2, random_state=42)
Xp = pca.fit_transform(X_scaled)

plt.figure(figsize=(8,6))
for c in np.unique(hitters['Cluster']):
    idx = hitters['Cluster'] == c
    plt.scatter(Xp[idx, 0], Xp[idx, 1], s=40, alpha=0.8, label=f'Cluster {c}')

#Cluster centroids
centroids_pca = pca.transform(kmeans.cluster_centers_)
plt.scatter(centroids_pca[:,0], centroids_pca[:,1], s=200, marker='X',
            edgecolor='black', linewidth=1.5, label='Centroids')

plt.title('PCA with KMeans Clusters (k=3)')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend()
plt.show()
```


PCA with KMeans Clusters (k=3)
Cluster 0
Cluster 1
Cluster 2
Centroids
PC2
4
2
0
−2
−4
−6
−8
PC1
−4
−2
0
2
4
6
8