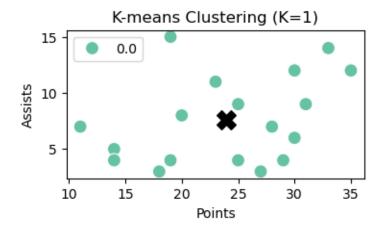
kmeans_clustering

October 16, 2024

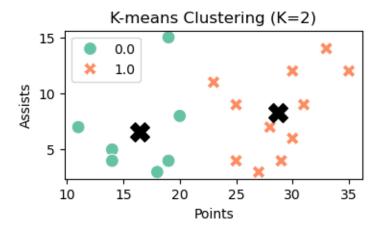
```
[11]: import numpy as np
      import pandas as pd
      import matplotlib.pyplot as plt
      import seaborn as sns
      df = pd.read_csv("baseball.csv")
      def euclidean_distance(point, centroid):
          return np.sqrt(np.sum((point - centroid) ** 2))
      def manhattan_distance(point, centroid):
          return np.sum(np.abs(point - centroid))
      def minkowski_distance(point, centroid, p=3):
          return np.power(np.sum(np.abs(point - centroid) ** p), 1/p)
      def k_means_clustering(data, k, distance_metric):
          centroids = data.sample(n=k).to_numpy()
          clusters = np.zeros(data.shape[0])
          sse = []
          while True:
              for i in range(len(data)):
                  if distance_metric == 'euclidean':
                      distances = [euclidean_distance(data.iloc[i], centroid) for_
       ⇔centroid in centroids]
                  elif distance_metric == 'manhattan':
                      distances = [manhattan_distance(data.iloc[i], centroid) for_
       ⇔centroid in centroids]
                  elif distance_metric == 'minkowski':
                      distances = [minkowski distance(data.iloc[i], centroid) for___
       ⇔centroid in centroids]
                  clusters[i] = np.argmin(distances)
              total_sse = 0
              for i in range(k):
```

```
points_in_cluster = data[clusters == i]
            if not points_in_cluster.empty:
                centroid = points_in_cluster.mean().to_numpy()
                total_sse += np.sum((points_in_cluster - centroid) ** 2)
        sse.append(total_sse)
        new_centroids = []
        for i in range(k):
            points_in_cluster = data[clusters == i]
            new_centroid = points_in_cluster.mean().to_numpy() if not_
 apoints_in_cluster.empty else centroids[i]
            new_centroids.append(new_centroid)
        new_centroids = np.array(new_centroids)
        if np.array_equal(new_centroids, centroids):
            break
        centroids = new_centroids
    return clusters, centroids, sse
def plot_clusters(data, clusters, centroids, k):
    plt.figure(figsize=(4, 2))
    sns.scatterplot(data=data, x='Points', y='Assists', hue=clusters, __
 →palette='Set2', style=clusters, s=100)
    plt.scatter(centroids[:, 0], centroids[:, 1], color='black', marker='X', u
 ⇔s=200, label='Centroids')
    plt.title(f'K-means Clustering (K={k})')
    plt.xlabel('Points')
    plt.ylabel('Assists')
    plt.show()
sse_results = []
for k in range(1, 5):
    clusters, centroids, sse = k_means_clustering(df, k, 'euclidean')
    sse_results.append(sse)
    plot_clusters(df, clusters, centroids, k)
sse_totals = [sse[-1] for sse in sse_results]
plt.figure(figsize=(8, 6))
plt.plot(range(1, 5), sse_totals, marker='o')
plt.title('K vs SSE')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Sum of Squared Errors (SSE)')
```

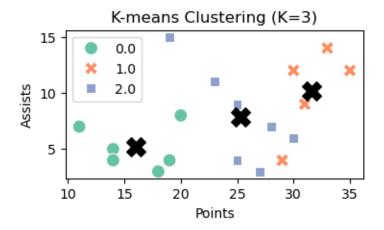
return reduction(axis=axis, out=out, **passkwargs)



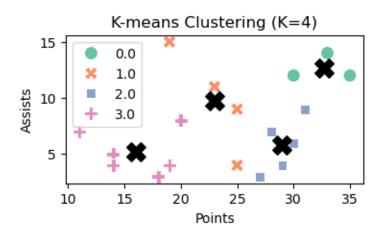
/usr/lib/python3/dist-packages/numpy/core/fromnumeric.py:86: FutureWarning: The behavior of DataFrame.sum with axis=None is deprecated, in a future version this will reduce over both axes and return a scalar. To retain the old behavior, pass axis=0 (or do not pass axis)

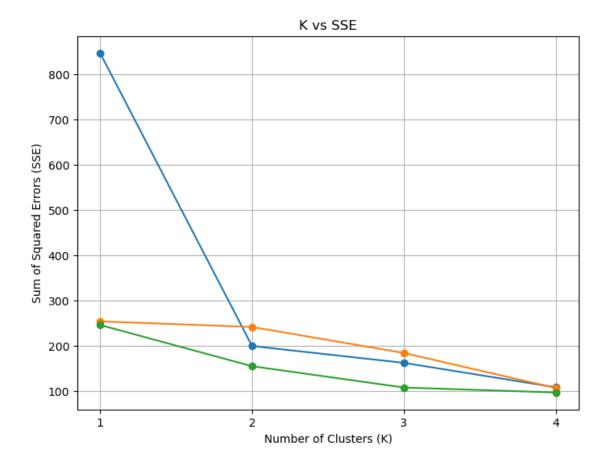


return reduction(axis=axis, out=out, **passkwargs)



/usr/lib/python3/dist-packages/numpy/core/fromnumeric.py:86: FutureWarning: The behavior of DataFrame.sum with axis=None is deprecated, in a future version this will reduce over both axes and return a scalar. To retain the old behavior, pass axis=0 (or do not pass axis)





Optimal K is: 3

```
[10]: import numpy as np
  import pandas as pd
  import matplotlib.pyplot as plt
  import seaborn as sns

df = pd.read_csv("baseball.csv")

def euclidean_distance(point, centroid):
    return np.sqrt(np.sum((point - centroid) ** 2))

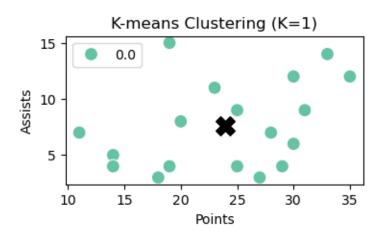
def manhattan_distance(point, centroid):
    return np.sum(np.abs(point - centroid))

def minkowski_distance(point, centroid, p=3):
    return np.power(np.sum(np.abs(point - centroid) ** p), 1/p)

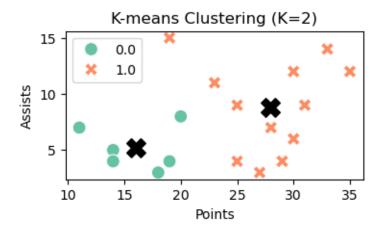
def k_means_clustering(data, k, distance_metric):
    centroids = data.sample(n=k).to_numpy()
```

```
clusters = np.zeros(data.shape[0])
    sse = []
    while True:
        for i in range(len(data)):
            if distance_metric == 'euclidean':
                distances = [euclidean_distance(data.iloc[i], centroid) for_
 ⇔centroid in centroids]
            elif distance_metric == 'manhattan':
                distances = [manhattan_distance(data.iloc[i], centroid) for_
 ⇒centroid in centroids]
            elif distance_metric == 'minkowski':
                distances = [minkowski_distance(data.iloc[i], centroid) for_
 ⇔centroid in centroids]
            clusters[i] = np.argmin(distances)
        total_sse = 0
        for i in range(k):
            points_in_cluster = data[clusters == i]
            if not points_in_cluster.empty:
                centroid = points_in_cluster.mean().to_numpy()
                total sse += np.sum((points in cluster - centroid) ** 2)
        sse.append(total_sse)
        new centroids = []
        for i in range(k):
            points_in_cluster = data[clusters == i]
            new_centroid = points_in_cluster.mean().to_numpy() if not_
 →points_in_cluster.empty else centroids[i]
            new_centroids.append(new_centroid)
        new_centroids = np.array(new_centroids)
        if np.array_equal(new_centroids, centroids):
            break
        centroids = new_centroids
    return clusters, centroids, sse
def plot_clusters(data, clusters, centroids, k):
    plt.figure(figsize=(4, 2))
    sns.scatterplot(data=data, x='Points', y='Assists', hue=clusters,_
 →palette='Set2', style=clusters, s=100)
    plt.scatter(centroids[:, 0], centroids[:, 1], color='black', marker='X', u
 ⇔s=200, label='Centroids')
```

```
plt.title(f'K-means Clustering (K={k})')
    plt.xlabel('Points')
    plt.ylabel('Assists')
    plt.show()
sse_results = []
for k in range(1, 5):
    clusters, centroids, sse = k_means_clustering(df, k, 'manhattan')
    sse_results.append(sse)
    plot_clusters(df, clusters, centroids, k)
sse_totals = [sse[-1] for sse in sse_results]
plt.figure(figsize=(8, 6))
plt.plot(range(1, 5), sse_totals, marker='o')
plt.title('K vs SSE')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Sum of Squared Errors (SSE)')
plt.xticks(range(1, 5))
plt.grid()
plt.show()
optimal_k = np.argmin(np.diff(sse_totals, 2)) + 2 # +2 because we start from_
 ∽K=1
print(f'Optimal K is: {optimal_k}')
```

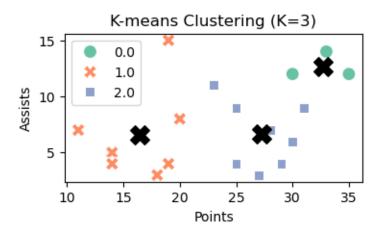


return reduction(axis=axis, out=out, **passkwargs)

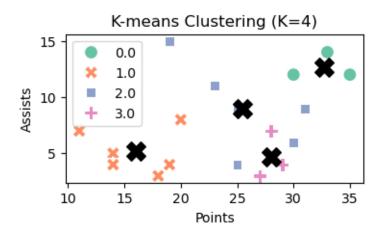


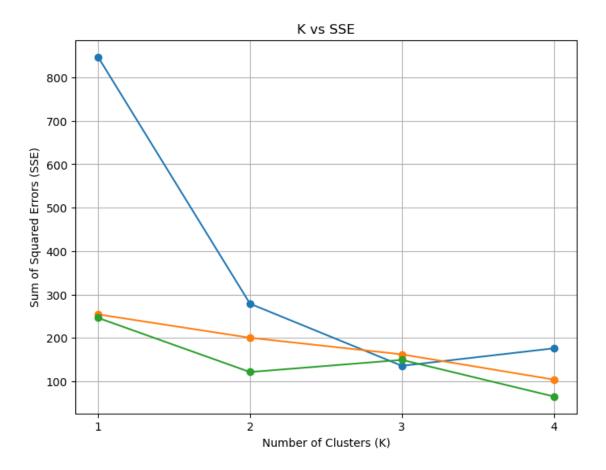
/usr/lib/python3/dist-packages/numpy/core/fromnumeric.py:86: FutureWarning: The behavior of DataFrame.sum with axis=None is deprecated, in a future version this will reduce over both axes and return a scalar. To retain the old behavior, pass axis=0 (or do not pass axis)

return reduction(axis=axis, out=out, **passkwargs)



/usr/lib/python3/dist-packages/numpy/core/fromnumeric.py:86: FutureWarning: The behavior of DataFrame.sum with axis=None is deprecated, in a future version this will reduce over both axes and return a scalar. To retain the old behavior, pass axis=0 (or do not pass axis)





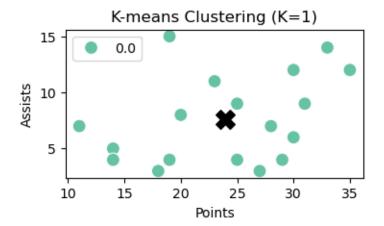
Optimal K is: 4

[8]: import numpy as np import pandas as pd

```
import matplotlib.pyplot as plt
import seaborn as sns
df = pd.read_csv("baseball.csv")
def euclidean_distance(point, centroid):
    return np.sqrt(np.sum((point - centroid) ** 2))
def manhattan distance(point, centroid):
    return np.sum(np.abs(point - centroid))
def minkowski_distance(point, centroid, p=3):
    return np.power(np.sum(np.abs(point - centroid) ** p), 1/p)
def k_means_clustering(data, k, distance_metric):
    centroids = data.sample(n=k).to_numpy()
    clusters = np.zeros(data.shape[0])
    sse = []
    while True:
        for i in range(len(data)):
            if distance metric == 'euclidean':
                distances = [euclidean_distance(data.iloc[i], centroid) for___
 ⇔centroid in centroids]
            elif distance_metric == 'manhattan':
                distances = [manhattan_distance(data.iloc[i], centroid) for__
 ⇔centroid in centroids]
            elif distance_metric == 'minkowski':
                distances = [minkowski_distance(data.iloc[i], centroid) for_
 ocentroid in centroids
            clusters[i] = np.argmin(distances)
        total_sse = 0
        for i in range(k):
            points_in_cluster = data[clusters == i]
            if not points_in_cluster.empty:
                centroid = points_in_cluster.mean().to_numpy()
                total_sse += np.sum((points_in_cluster - centroid) ** 2)
        sse.append(total_sse)
        new_centroids = []
        for i in range(k):
            points_in_cluster = data[clusters == i]
            new_centroid = points_in_cluster.mean().to_numpy() if not__
 →points_in_cluster.empty else centroids[i]
```

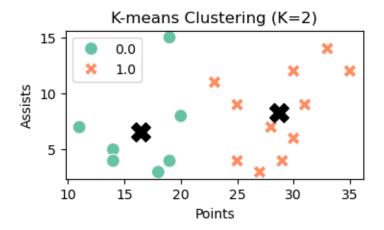
```
new_centroids.append(new_centroid)
        new_centroids = np.array(new_centroids)
        if np.array_equal(new_centroids, centroids):
            break
        centroids = new_centroids
    return clusters, centroids, sse
def plot_clusters(data, clusters, centroids, k):
    plt.figure(figsize=(4, 2))
    sns.scatterplot(data=data, x='Points', y='Assists', hue=clusters,
 →palette='Set2', style=clusters, s=100)
    plt.scatter(centroids[:, 0], centroids[:, 1], color='black', marker='X', __
 ⇒s=200, label='Centroids')
    plt.title(f'K-means Clustering (K={k})')
    plt.xlabel('Points')
    plt.ylabel('Assists')
    plt.show()
sse_results = []
for k in range(1, 5):
    clusters, centroids, sse = k_means_clustering(df, k, 'minkowski')
    sse_results.append(sse)
    plot clusters(df, clusters, centroids, k)
sse_totals = [sse[-1] for sse in sse_results]
plt.figure(figsize=(8, 6))
plt.plot(range(1, 5), sse_totals, marker='o')
plt.title('K vs SSE')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Sum of Squared Errors (SSE)')
plt.xticks(range(1, 5))
plt.grid()
plt.show()
optimal_k = np.argmin(np.diff(sse_totals, 2)) + 2 # +2 because we start from
print(f'Optimal K is: {optimal_k}')
```

return reduction(axis=axis, out=out, **passkwargs)

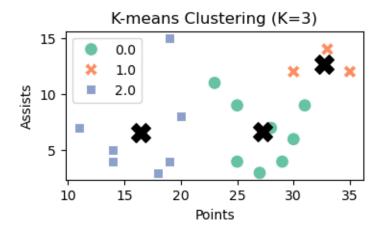


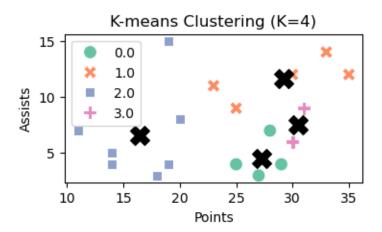
/usr/lib/python3/dist-packages/numpy/core/fromnumeric.py:86: FutureWarning: The behavior of DataFrame.sum with axis=None is deprecated, in a future version this will reduce over both axes and return a scalar. To retain the old behavior, pass axis=0 (or do not pass axis)

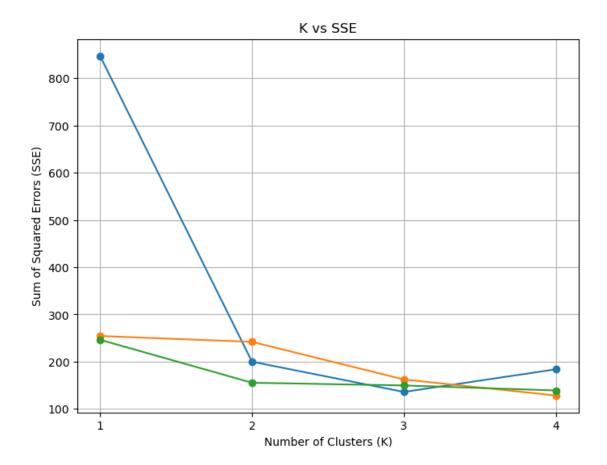
return reduction(axis=axis, out=out, **passkwargs)



/usr/lib/python3/dist-packages/numpy/core/fromnumeric.py:86: FutureWarning: The behavior of DataFrame.sum with axis=None is deprecated, in a future version this will reduce over both axes and return a scalar. To retain the old behavior, pass axis=0 (or do not pass axis)







Optimal K is: 3

[]: