Clustering_models

May 8, 2023

0.1 Dataset Download

[ ]:
```
#put kaggle.json file in the Files (/content/)
!pip install pyspark
!pip install kaggle
!pip install tqdm
!mkdir ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
!kaggle datasets download -d yelp-dataset/yelp-dataset
!unzip yelp-dataset.zip
```

```
--2023-05-08 18:52:12--  https://github.com/kabirthakur/Data-
Science/blob/main/kaggle.json
Resolving github.com (github.com)… 192.30.255.113
Connecting to github.com (github.com)|192.30.255.113|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: unspecified [text/html]
Saving to: ‘kaggle.json.1’

kaggle.json.1           [ <=>                ] 143.92K  --.-KB/s    in 0.02s

2023-05-08 18:52:12 (6.59 MB/s) - ‘kaggle.json.1’ saved [147369]

Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting pyspark
  Downloading pyspark-3.4.0.tar.gz (310.8 MB)
                           310.8/310.8
MB 4.6 MB/s eta 0:00:00
  Preparing metadata (setup.py) … done
Requirement already satisfied: py4j==0.10.9.7 in /usr/local/lib/python3.10/dist-
packages (from pyspark) (0.10.9.7)
Building wheels for collected packages: pyspark
  Building wheel for pyspark (setup.py) … done
  Created wheel for pyspark: filename=pyspark-3.4.0-py2.py3-none-any.whl
size=311317145
sha256=f721f8841436ccd64797a9a2180a56a04b8d4d12013a45edb5c4ed3f6c19801c
```

```
  Stored in directory: /root/.cache/pip/wheels/7b/1b/4b/3363a1d04368e7ff0d408e57
ff57966fcdf00583774e761327
Successfully built pyspark
Installing collected packages: pyspark
Successfully installed pyspark-3.4.0
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: kaggle in /usr/local/lib/python3.10/dist-packages
(1.5.13)
Requirement already satisfied: certifi in /usr/local/lib/python3.10/dist-
packages (from kaggle) (2022.12.7)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-
packages (from kaggle) (1.26.15)
Requirement already satisfied: python-dateutil in
/usr/local/lib/python3.10/dist-packages (from kaggle) (2.8.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(from kaggle) (4.65.0)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from kaggle) (2.27.1)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.10/dist-
packages (from kaggle) (1.16.0)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.10/dist-
packages (from kaggle) (8.0.1)
Requirement already satisfied: text-unidecode>=1.3 in
/usr/local/lib/python3.10/dist-packages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: charset-normalizer~=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from requests->kaggle) (2.0.12)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests->kaggle) (3.4)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(4.65.0)
Downloading yelp-dataset.zip to /content
100% 4.06G/4.07G [00:50<00:00, 33.9MB/s]
100% 4.07G/4.07G [00:50<00:00, 86.8MB/s]
Archive:  yelp-dataset.zip
  inflating: Dataset_User_Agreement.pdf
  inflating: yelp_academic_dataset_business.json
  inflating: yelp_academic_dataset_checkin.json
  inflating: yelp_academic_dataset_review.json
  inflating: yelp_academic_dataset_tip.json
  inflating: yelp_academic_dataset_user.json
```

0.2 Libraries

[ ]:
```
import re
import pyspark
import numpy as np
import pandas as pd
import seaborn as sns
from tqdm import tqdm, trange
import matplotlib.pyplot as plt
from pyspark.ml import Pipeline
from pyspark.sql import SparkSession
from pyspark.ml.linalg import Vectors
from pyspark.sql import functions as f
from pyspark.ml.clustering import KMeans
from pyspark.sql.types import FloatType, DoubleType
from pyspark.ml.feature import StringIndexer, VectorAssembler
from pyspark.ml.evaluation import RegressionEvaluator, ClusteringEvaluator
from pyspark.sql.functions import col, count, split, explode, when, lit, sum
from pyspark.sql.functions import array, struct, sort_array, array_min, expr,␣
 ↪desc
```

0.3 Create SparkSession and Import Data

[ ]:
```
spark = SparkSession.builder \
    .appName("Yelp") \
    .config("spark.executor.memory", "4g") \
    .config("spark.driver.memory", "4g") \
    .config("spark.driver.maxResultSize", "2g") \
    .getOrCreate()

# businesses dataframe
business_df = spark.read.json("yelp_academic_dataset_business.json")

# users dataframe
user_df = spark.read.json("yelp_academic_dataset_user.json")

# reviews dataframe
review_df = spark.read.json("yelp_academic_dataset_review.json")
```

[ ]:
```
#renaming columns for clarity
business_df = business_df.withColumnRenamed("stars", "business_stars")
review_df = review_df.withColumnRenamed("stars", "review_stars")
```

0.4 Data cleaning and Feature engineering

Business Dataframe

```
[ ]: restaurants_df = business_df.filter(col("categories").contains("Restaurants"))
     restaurants_df = restaurants_df.filter(col("state").contains("PA"))
     restaurants_df = restaurants_df.filter(col("is_open").contains("1"))
     # Choosing Restaurants in Penssylvania that are open (Based on EDA)
```

We are only looking at the categories column and will be using most categories as features of out model. The following code takes the categories and pivots them and gives f

```
[ ]: categories_splitted = restaurants_df.select("business_id",␣
      ↪split(col("categories"), ", ").alias("categories_array"))
     categories_exploded = categories_splitted.select("business_id",␣
      ↪explode(col("categories_array")).alias("category"))
     distinct_categories = categories_exploded.select("category").distinct().rdd.
      ↪flatMap(lambda x: x).collect()

     for category in tqdm(distinct_categories):
         categories_exploded = categories_exploded.withColumn(category,␣
      ↪when(col("category") == category, 1).otherwise(0))
```

```
100%|      | 449/449 [02:20<00:00,  3.20it/s]
```

```
[ ]: new_column_names=categories_exploded.columns
     categories_pivoted = categories_exploded.groupBy("business_id").sum()
```

```
[ ]: columns=categories_pivoted.columns
     features=columns[1:]
     sums = categories_pivoted.agg(*[f.sum(f.col(c)).alias(c) for c in␣
      ↪tqdm(features)]).collect()[0].asDict()
     selected_columns = [c for c in sums if sums[c] > 10]

     # Including the 'business_id' column in the selected columns
     selected_columns.insert(0, columns[0])

     result_df = categories_pivoted.select([f.col(c) for c in selected_columns])
     result_df=result_df.drop('sum(Restaurants)','sum(Food)')
```

```
100%|      | 449/449 [00:01<00:00, 263.65it/s]
```

```
[ ]: def rename_columns(df):
         """
         Renames columns in a PySpark DataFrame based on the column name in the␣
      ↪format 'sum(col)'.
         """
         columns = df.columns
         pattern = re.compile(r'sum\((.*?)\)')

         for column in tqdm(columns):
             match = pattern.search(column)
```

```
        if match:
            new_column = match.group(1)
            df = df.withColumnRenamed(column, new_column)

    return df
```

[ ]:
```
business_features = rename_columns(result_df)
```

```
100%|      | 156/156 [01:23<00:00,  1.86it/s]
```

[ ]:
```
business_features.count(),len(result_df.columns)
```

[ ]:
```
(8069, 156)
```

Users Dataframe

[ ]:
```
filtered_reviews_df = review_df.select(f.col('business_id'),f.col('user_id'),)
joined_df = filtered_reviews_df.join(business_features, 'business_id', 'inner')
joined_df = joined_df.drop(f.col("business_id"))
summed_df = joined_df.groupBy("user_id").sum()
user_features=rename_columns(summed_df)
```

```
100%|      | 156/156 [01:41<00:00,  1.54it/s]
```

[ ]:
```
user_features.count(),len(user_features.columns)
```

[ ]:
```
(269462, 156)
```

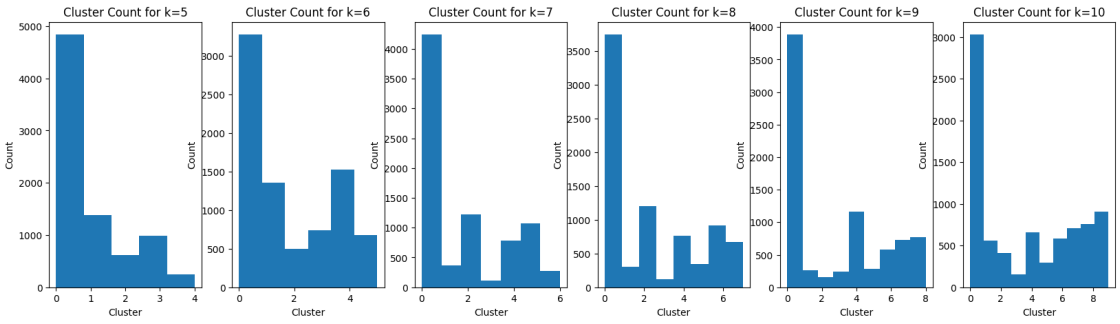
0.4.1 KMeans Analysis

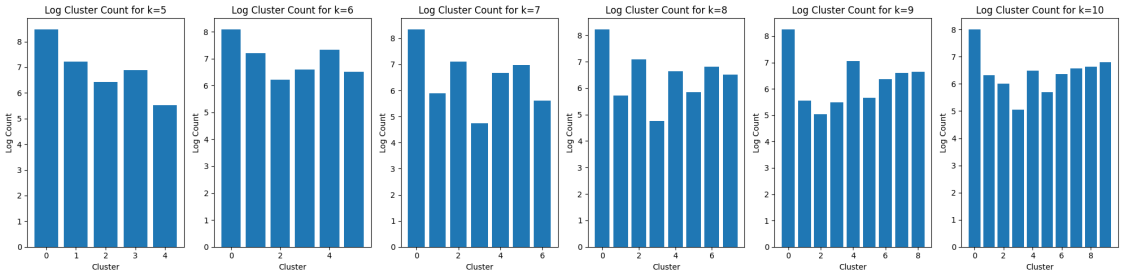
[ ]:
```
def kmeans_pipeline(data, input_cols, k_range=(5, 11), seed=42):
    assembler = VectorAssembler(inputCols=input_cols, outputCol="features")
    feature_df = assembler.transform(data)

    inertia_values = []
    silhouette_scores = []
    fig, axs = plt.subplots(1, len(range(*k_range)), figsize=(20, 5))
    fig2, axs2 = plt.subplots(1, len(range(*k_range)), figsize=(20, 5))
    for i,k in enumerate(trange(*k_range)):
        kmeans = KMeans(k=k, featuresCol='features', seed=seed)
        kmeans_model = kmeans.fit(feature_df)
        transformed_df = kmeans_model.transform(feature_df)

        axs[i].hist(transformed_df.select('prediction').rdd.flatMap(lambda x:␣
 ↪x).collect(), bins=k)
        axs[i].set_title(f'Cluster Count for k={k}')
        axs[i].set_xlabel('Cluster')
        axs[i].set_ylabel('Count')
```

```
        counts = transformed_df.select('prediction').groupBy('prediction').
↪count().orderBy('prediction').rdd.map(lambda x: x[1]).collect()
        log_counts = np.log(counts)

        axs2[i].bar(range(k), log_counts)
        axs2[i].set_title(f'Log Cluster Count for k={k}')
        axs2[i].set_xlabel('Cluster')
        axs2[i].set_ylabel('Log Count')

        evaluator = ClusteringEvaluator()
        silhouette_score = evaluator.evaluate(transformed_df)
        silhouette_scores.append(silhouette_score)

        center_points = kmeans_model.clusterCenters()
        squared_distances = transformed_df.rdd.map(
            lambda x: float(x['features'].
↪squared_distance(center_points[x['prediction']]))
        )
        inertia_values.append(squared_distances.sum())

        # print(f'Finished k={k}')
    plt.tight_layout()

    return inertia_values, silhouette_scores, fig, fig2
```

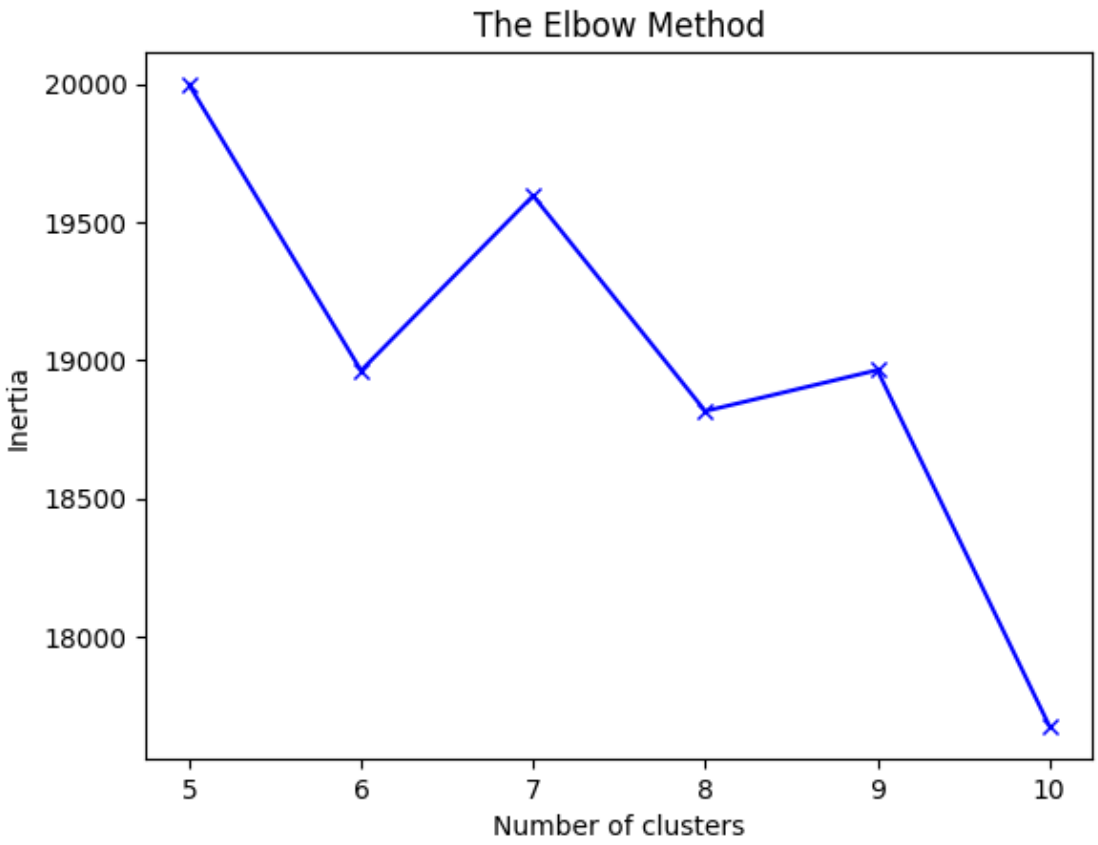
[ ]:
```
business_cols = business_features.columns[1:]

# Running the pipeline takes about 10 minutes
inertia_values_business, silhouette_scores_business,fig_plots,fig_logplots =␣
↪kmeans_pipeline(business_features, business_cols)
```

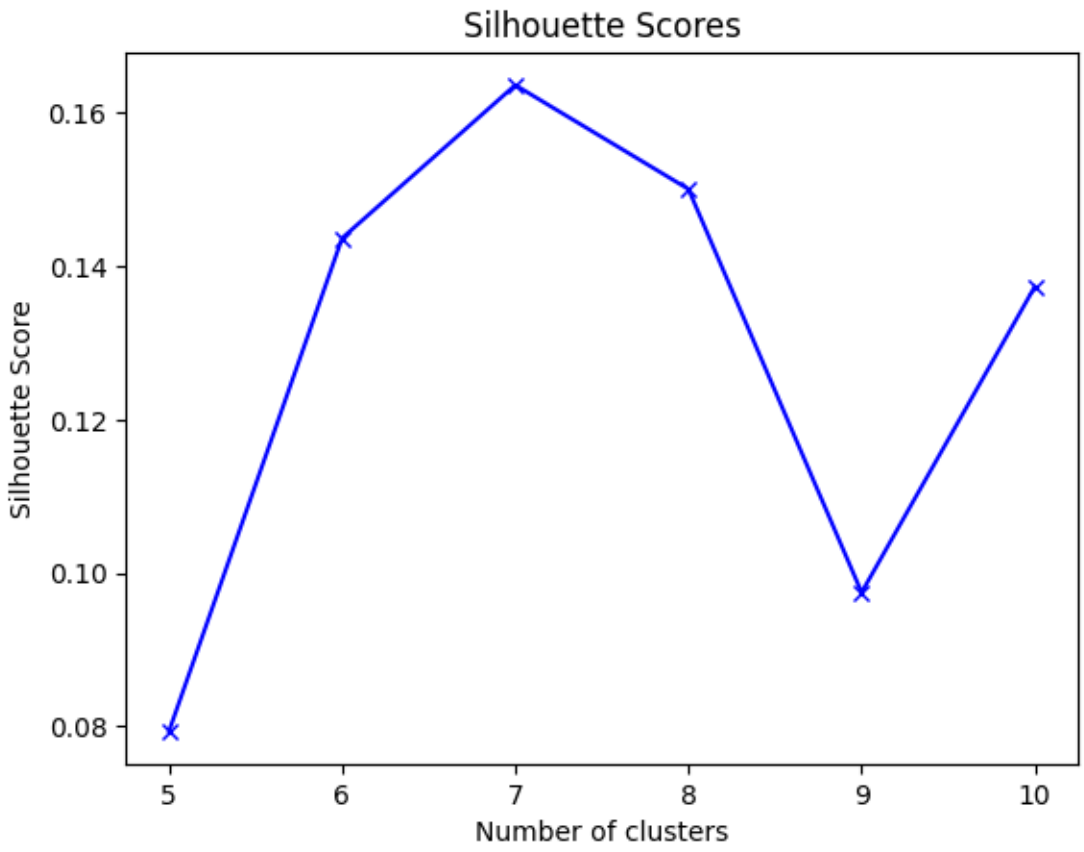
```
100%|      | 6/6 [07:14<00:00, 72.47s/it]
```





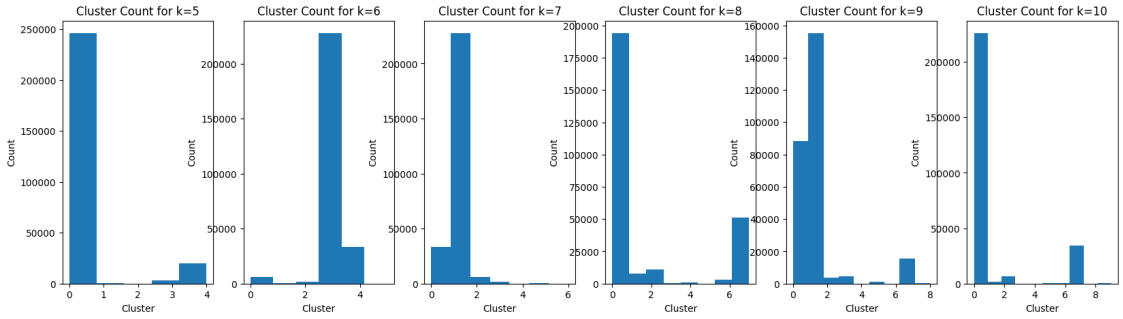
[ ]:
```
cluster_range=range(5,11)

plt.plot(cluster_range, inertia_values_business, 'bx-')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.title('The Elbow Method')
plt.show()

plt.plot(cluster_range, silhouette_scores_business, 'bx-')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Scores')
plt.show()
```

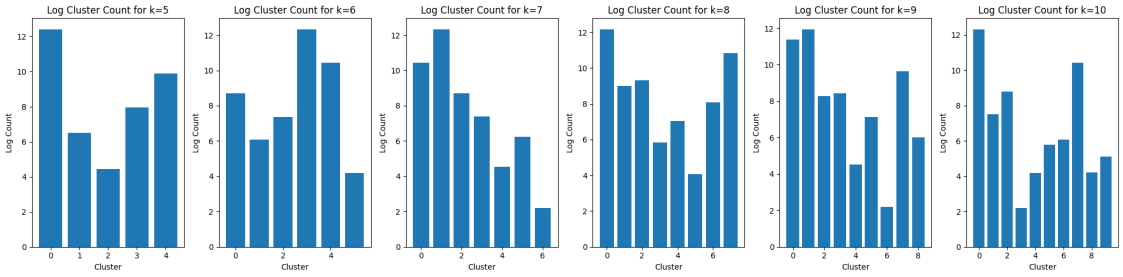

The Elbow Method
20000
19500
19000
18500
18000
Inertia
5
6
7
8
9
10
Number of clusters



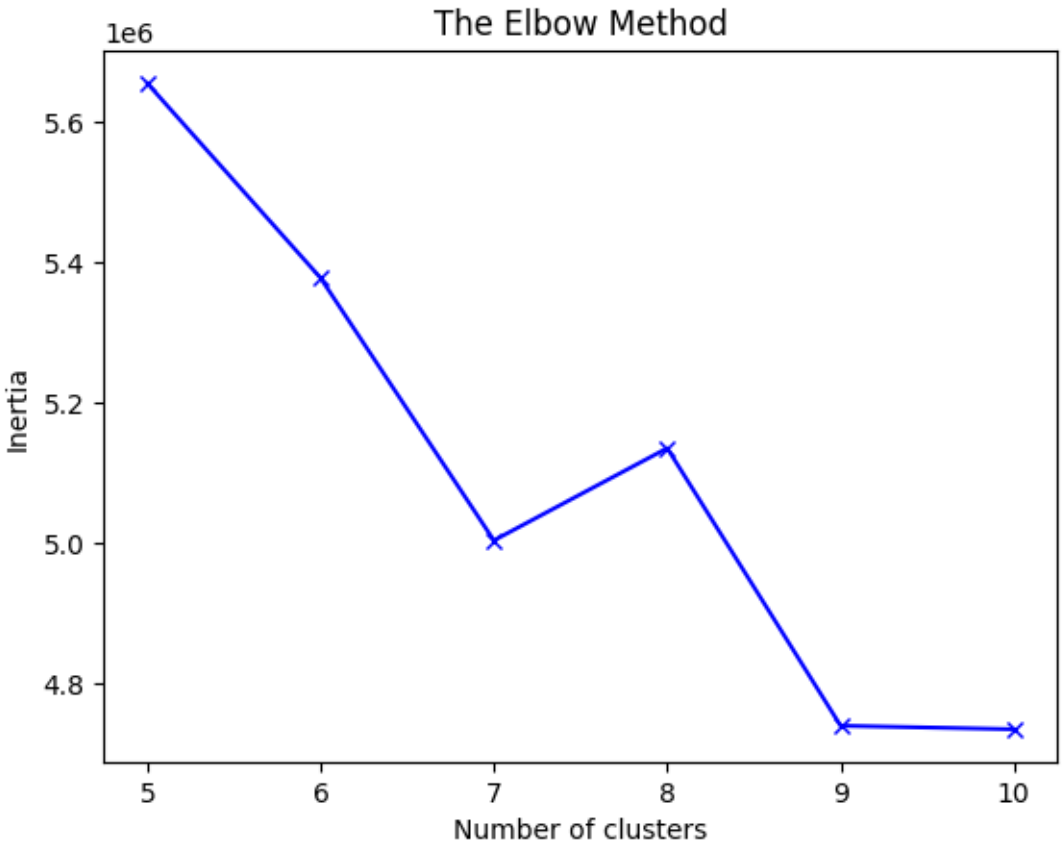
[ ]:
```
user_cols = user_features.columns[1:]

# Run the pipeline takes about 1 hr 20 minutes. Got to have patience
inertia_values_user, silhouette_scores_user, fig_plots_user, fig_logplots_user␣
↪= kmeans_pipeline(user_features, user_cols)
```

```
100%|      | 6/6 [1:00:02<00:00, 600.44s/it]
```





[ ]:
```
plt.plot(cluster_range, inertia_values_user, 'bx-')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.title('The Elbow Method')
plt.show()
plt.plot(cluster_range, silhouette_scores_user, 'bx-')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Scores')
plt.show()
```

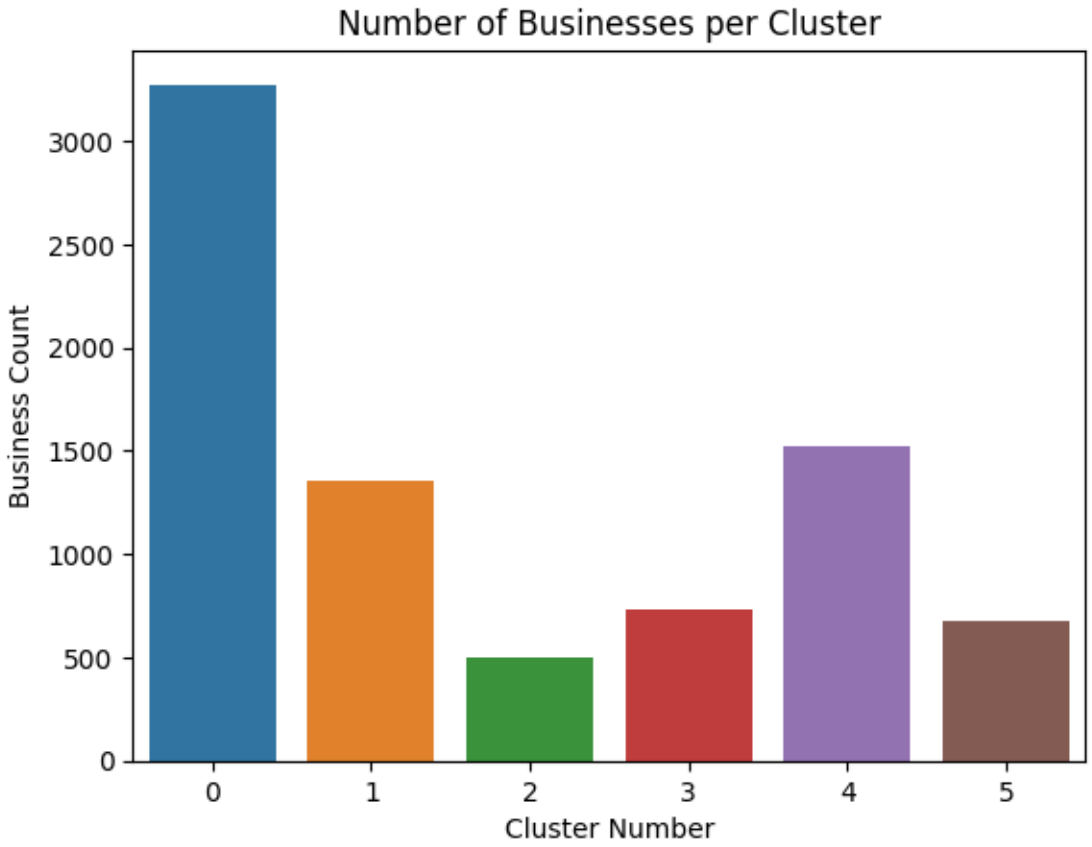


0.4.2 K-Means Final Models

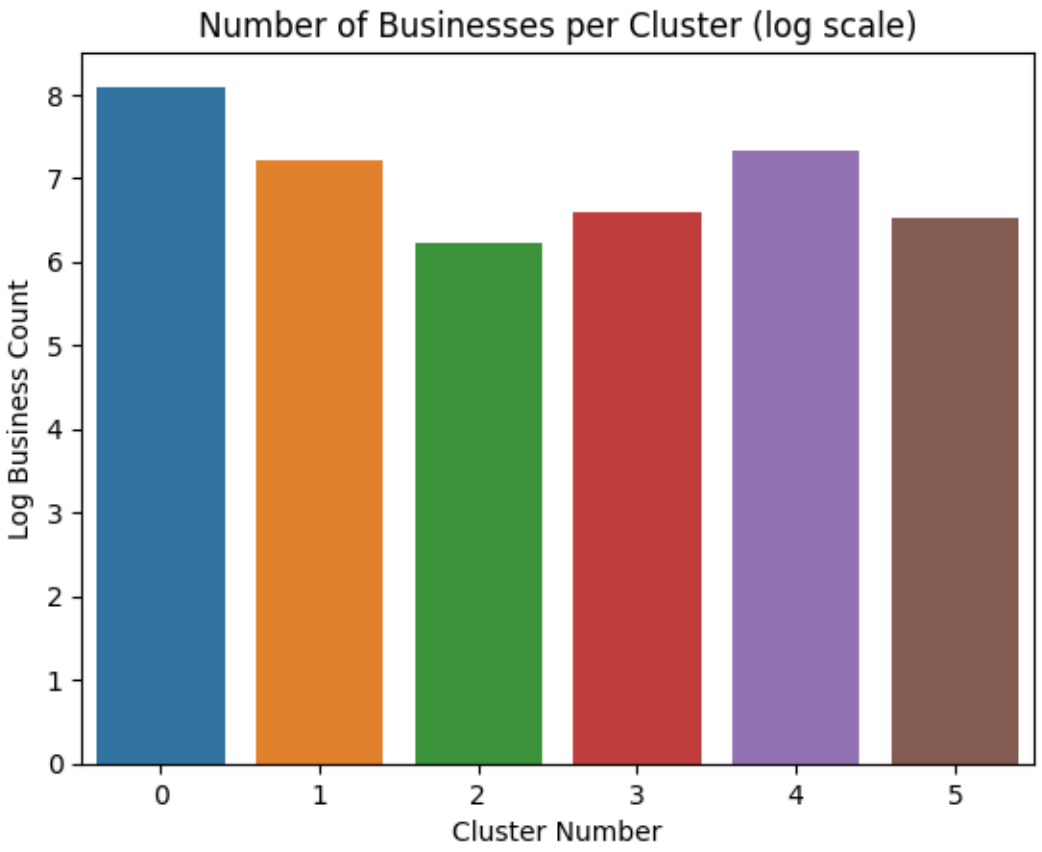
0.4.3 Final Model For Businesses

[ ]:
```
assembler = VectorAssembler(inputCols=business_cols, outputCol='features')

kmeans = KMeans(k=6, featuresCol='features', seed=42)

pipeline = Pipeline(stages=[assembler, kmeans])

model_business = pipeline.fit(business_features)

kmeans_business = model_business.stages[-1]

business_centroids = kmeans_business.clusterCenters()

predictions_business = model_business.transform(business_features)
```

[ ]:
```
cluster_counts_business = predictions_business.groupBy("prediction").
 ↪agg(count("business_id").alias("business_count"))
sns.barplot(x="prediction", y="business_count", data=cluster_counts_business.
 ↪toPandas())
plt.title("Number of Businesses per Cluster")
plt.xlabel("Cluster Number")
plt.ylabel("Business Count")
plt.show()
```



[ ]:
```
cluster_counts_business = predictions_business.groupBy("prediction").
 ↪agg(count("business_id").alias("business_count"))
data_business = cluster_counts_business.toPandas()
sns.barplot(x="prediction", y=np.log(data_business["business_count"]),␣
 ↪data=data_business)
plt.title("Number of Businesses per Cluster (log scale)")
plt.xlabel("Cluster Number")
plt.ylabel("Log Business Count")
plt.show()
```



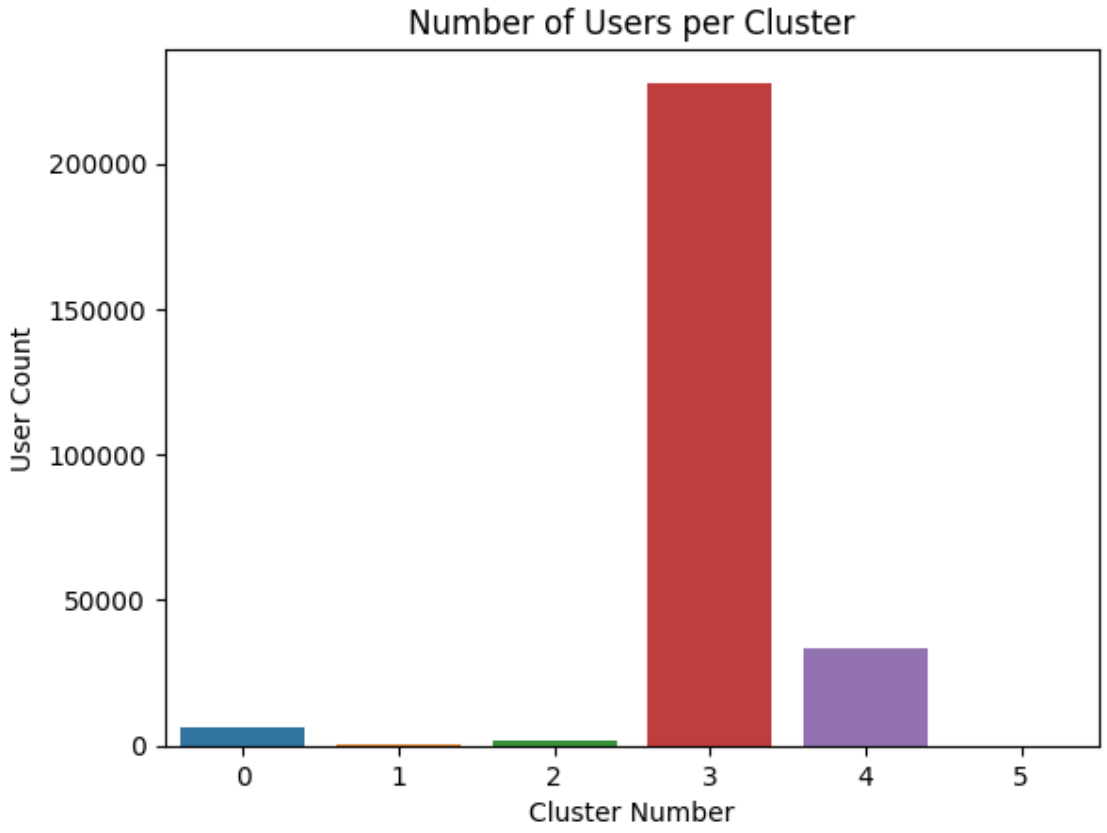
[ ]:
```
# Group by 'prediction' column and count the number of elements in each group
cluster_counts_businesses = predictions_business.groupBy("prediction").count()

# Sort the result by the 'prediction' column and display the counts
cluster_counts_businesses.sort("prediction").show()
```

```
+----------+-----+
|prediction|count|
+----------+-----+
|         0| 3274|
|         1| 1354|
|         2|  502|
|         3|  736|
|         4| 1525|
|         5|  678|
+----------+-----+
```

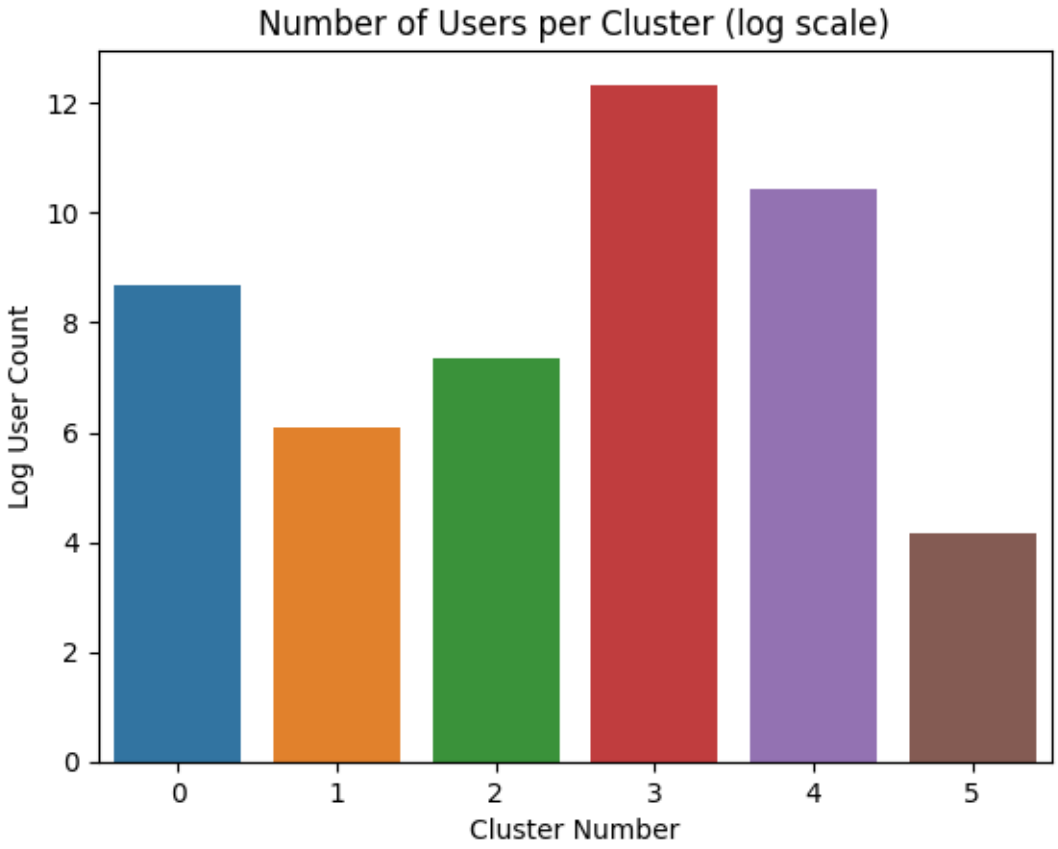
0.4.4 Final Model for Users

[ ]:
```
assembler = VectorAssembler(inputCols=user_cols, outputCol='features')

kmeans = kmeans = KMeans(k=6, featuresCol='features', seed=42)

pipeline = Pipeline(stages=[assembler, kmeans])

model_user = pipeline.fit(user_features)

kmeans_user = model_business.stages[-1]

user_centroids = kmeans_user.clusterCenters()

predictions_user = model_user.transform(user_features)
```

[ ]:
```
cluster_counts_user = predictions_user.groupBy("prediction").
 ↪agg(count("user_id").alias("user_count"))
sns.barplot(x="prediction", y="user_count", data=cluster_counts_user.toPandas())
plt.title("Number of Users per Cluster")
plt.xlabel("Cluster Number")
plt.ylabel("User Count")
plt.show()
```



[ ]:
```
cluster_counts_user = predictions_user.groupBy("prediction").
  ↪agg(count("user_id").alias("user_count"))
data_user=cluster_counts_user.toPandas()
sns.barplot(x="prediction", y=np.log(data_user["user_count"]),data=data_user)
plt.title("Number of Users per Cluster (log scale)")
plt.xlabel("Cluster Number")
plt.ylabel("Log User Count")
plt.show()
```



[ ]:
```
# Group by 'prediction' column and count the number of elements in each group
cluster_counts_users = predictions_user.groupBy("prediction").count()

# Sort the result by the 'prediction' column and display the counts
cluster_counts_users.sort("prediction").show()
```

```
+----------+------+
|prediction| count|
```

```
+----------+------+
|         0|  5992|
|         1|   441|
|         2|  1583|
|         3|227874|
|         4| 33507|
|         5|    65|
+----------+------+
```

0.4.5 Dataframe for similar businesses by euclidean distance from centroid

[ ]:
```
def split_clusters(dataframe, cluster_column):
    """
    Splits a DataFrame into separate DataFrames based on unique values in the␣
 ↪specified column.
    """

    unique_clusters = dataframe.select(cluster_column).distinct().collect()
    unique_clusters = [row[cluster_column] for row in unique_clusters]
    cluster_dataframes = {}

    for cluster in unique_clusters:
        cluster_df = dataframe.filter(col(cluster_column) == cluster)
        cluster_dataframes[f"cluster_{cluster}"] = cluster_df

    return cluster_dataframes
```

[ ]:
```
def sort_clusters_by_distance(cluster_dataframes, cluster_centroids):
    """
    Sorts each PySpark DataFrame in the given dictionary of cluster DataFrames
    by the Euclidean distance between each data point and the centroid of its␣
 ↪cluster.
    """

    def euclidean_distance(vector, array):
        return float(np.linalg.norm(np.array(vector) - np.array(array)))

    euclidean_distance_udf = f.udf(euclidean_distance, DoubleType())
    cluster_label=0

    for cluster_name, cluster_df in tqdm(cluster_dataframes.items()):
        cluster_df = cluster_df.withColumn(
            "distance_to_centroid",
            euclidean_distance_udf(f.col("features"), f.array([f.lit(c) for c␣
 ↪in cluster_centroids[cluster_label]]))
        )
```

```
        # Sort the DF by the Euclidean distance
        cluster_df = cluster_df.sort("distance_to_centroid", ascending=True)

        cluster_dataframes[cluster_name] = cluster_df
        cluster_label+=1
    return cluster_dataframes
```

[ ]:
```
def recommendations(dfs):
    dfs_pd = {}
    if dfs['cluster_0'].columns[0]=="business_id":
        col_name='business_id'
    else:
        col_name='user_id'
    for cluster, df in tqdm(dfs.items()):
        df_pd = df.toPandas()
        df_pd=df_pd.sort_values('distance_to_centroid')
        df_pd["recommendations"] = None
        for i in range(len(df_pd)):
            if i == 0:
                df_pd.at[i, "recommendations"] = [df_pd.loc[1, col_name], df_pd.
 ↪loc[2, col_name]]
            elif i == 1:
                df_pd.at[i, "recommendations"] = [df_pd.loc[0, col_name], df_pd.
 ↪loc[2, col_name]]
            elif i == len(df_pd) - 1:
                df_pd.at[i, "recommendations"] = [df_pd.loc[i-1, col_name],␣
 ↪df_pd.loc[i-2, col_name]]
            elif i == len(df_pd) - 2:
                df_pd.at[i, "recommendations"] = [df_pd.loc[i+1, col_name],␣
 ↪df_pd.loc[i-1, col_name]]
            else:
                df_pd.at[i, "recommendations"] = [df_pd.loc[i-1, col_name],␣
 ↪df_pd.loc[i+1, col_name]]

        df_spark = spark.createDataFrame(df_pd)
        dfs_pd[cluster] = df_spark
    return dfs_pd
```

[ ]:
```
def merge_cluster_dataframes(dic):
    merged = []
    for i in range(len(dic)):
        businesses = dic[f"cluster_{i}"].withColumn("Cluster", lit(i))
        merged.append(businesses)

    elements_all = merged[0]
    for i in range(1, len(merged)):
```

```
        elements_all = elements_all.union(merged[i])

    return elements_all
```

1. predictions_business is the transformed model dataframe. I split the data by the clusters to make the computation easier.
2. The split_clusters function splits the clusters into a dictionary where the key is the cluster and the value is the dataframe object of each cluster. This is the object that we will be using thoughout. The split cluster function is genralised and works for both user and business data with the prediction column.

[ ]:
```
business_rec=predictions_business.select("business_id",'features','prediction')
dict_businesses = split_clusters(business_rec, "prediction")
user_rec=predictions_user.select("user_id",'features','prediction')
dict_user = split_clusters(user_rec, "prediction")
```

3. The sort_clusters_by_distance function takes in the dictionary we created and the array of centroids from the k-means model and calculated euclidean distance from centroid to each point. The dataframe is then sorted by distance.

NOTE : A lot of points are on similar distances

[ ]:
```
dict_businesses=sort_clusters_by_distance(dict_businesses,business_centroids)
dict_user=sort_clusters_by_distance(dict_user,user_centroids)
```

```
100%|      | 6/6 [00:18<00:00,  3.09s/it]
100%|      | 6/6 [00:22<00:00,  3.77s/it]
```

4. The recommendations function takes the dictionary and transforms each dataframe to a pandas object. This is done to iterate over the data as we wanted to assign recommendations based on how far each user is from the centroid based on distance. This function ensures that the data is sorted by distance and then assigns two recommendations to each id, specifically the one above it and the one below it in the progression. Same dictionary is returned with a recommendation column.

[ ]:
```
dict_businesses=recommendations(dict_businesses)
dict_user=recommendations(dict_user)
```

```
100%|      | 6/6 [01:28<00:00, 14.71s/it]
100%|      | 6/6 [17:11<00:00, 171.94s/it]
```

5. Finally the dictionary is merged together

[ ]:
```
business_recommendations=merge_cluster_dataframes(dict_businesses)
user_recommendations=merge_cluster_dataframes(dict_user)
```

Business recommendation dataframe contains the names of two similar businesses as recommendations for each unique business

[ ]:
```
business_recommendations.select('business_id','recommendations').
  ↪show(truncate=False) # Here the recommendations are other businesses
```

```
+----------------------+--------------------------------------------------+
|business_id           |recommendations                                   |
+----------------------+--------------------------------------------------+
|ziFtaIQdzQfFL79iLTq_zQ|[_snyGj46oghIWXSDcrxq1A, zNi8ceY3sLBXZoTUstjrvg]|
|_snyGj46oghIWXSDcrxq1A|[ziFtaIQdzQfFL79iLTq_zQ, zNi8ceY3sLBXZoTUstjrvg]|
|zNi8ceY3sLBXZoTUstjrvg|[_snyGj46oghIWXSDcrxq1A, zWQWjJ0270yqp_KignAmkg]|
|zWQWjJ0270yqp_KignAmkg|[zNi8ceY3sLBXZoTUstjrvg, jREUbQSPxCd3lS0AouzTzg]|
|jREUbQSPxCd3lS0AouzTzg|[zWQWjJ0270yqp_KignAmkg, 6zXBmEBGqFVwTcPqmGStfw]|
|6zXBmEBGqFVwTcPqmGStfw|[jREUbQSPxCd3lS0AouzTzg, kmKHBCTec-e6H4aK7fD8Ag]|
|kmKHBCTec-e6H4aK7fD8Ag|[6zXBmEBGqFVwTcPqmGStfw, Sk1WdGuaCNQlQZ_u_JE0Ew]|
|Sk1WdGuaCNQlQZ_u_JE0Ew|[kmKHBCTec-e6H4aK7fD8Ag, NxB8M1wnJQ5xoXDiUgqmIg]|
|NxB8M1wnJQ5xoXDiUgqmIg|[Sk1WdGuaCNQlQZ_u_JE0Ew, OAs42PSxiaPS25sO8Vtfiw]|
|YinVjl_e8croGmeUK8hRkA|[egFo1PkGkKM-lPli61raiA, Rx6d8NSWTdOt9Nd8QWjfZw]|
|Rx6d8NSWTdOt9Nd8QWjfZw|[YinVjl_e8croGmeUK8hRkA, OddKlB5d2KQpIP2rJt89ow]|
|yvpwN5321mM3x8G2ZiEZmw|[OddKlB5d2KQpIP2rJt89ow, -PkchovDBosOtZx4XLatVw]|
|-PkchovDBosOtZx4XLatVw|[yvpwN5321mM3x8G2ZiEZmw, J8UPVO_FTALzvJ0tlMdr8w]|
|t5T6NYFsOqnYl0NETDgj7g|[4IvQU16RBKuLtpgx8yLqmQ, r9sFTXBUGSYB7orbyYOPLw]|
|4zQV6v8TwEYMwI9Ekdf19g|[J8UPVO_FTALzvJ0tlMdr8w, mEMcdzVzuSX34TXRKG83iA]|
|mEMcdzVzuSX34TXRKG83iA|[4zQV6v8TwEYMwI9Ekdf19g, 4IvQU16RBKuLtpgx8yLqmQ]|
|4IvQU16RBKuLtpgx8yLqmQ|[mEMcdzVzuSX34TXRKG83iA, t5T6NYFsOqnYl0NETDgj7g]|
|egFo1PkGkKM-lPli61raiA|[ZynowAYBV6-mBBJb7dWN8w, YinVjl_e8croGmeUK8hRkA]|
|J8UPVO_FTALzvJ0tlMdr8w|[-PkchovDBosOtZx4XLatVw, 4zQV6v8TwEYMwI9Ekdf19g]|
|ZynowAYBV6-mBBJb7dWN8w|[v1UZ0rYgVr_WEfLsK82VPA, egFo1PkGkKM-lPli61raiA]|
+----------------------+--------------------------------------------------+
only showing top 20 rows
```

User recommendation dataframe contains the names of two similar users as recommendations for each unique user. While getting the recommendation from user cluster we use the top rated businesses visited by the similar user.

[ ]:
```
user_recommendations.select('user_id','recommendations').show(truncate=False)␣
  ↪#Here the recommendations are other users
```

```
+----------------------+--------------------------------------------------+
|user_id               |recommendations                                   |
+----------------------+--------------------------------------------------+
|pRAG05KXr_mZY0gzKAwAPw|[75--7VO10mTfrvV3yCGuHg, huayr-WjhExgJPIZcRhZIQ]|
|75--7VO10mTfrvV3yCGuHg|[pRAG05KXr_mZY0gzKAwAPw, huayr-WjhExgJPIZcRhZIQ]|
|huayr-WjhExgJPIZcRhZIQ|[75--7VO10mTfrvV3yCGuHg, NmC36b6gUGg-kcvm7BiqHg]|
|NmC36b6gUGg-kcvm7BiqHg|[huayr-WjhExgJPIZcRhZIQ, H9x_8vghL3a7Gp6OckLhZQ]|
|H9x_8vghL3a7Gp6OckLhZQ|[NmC36b6gUGg-kcvm7BiqHg, -_x2LGJj_YKxJcM-P2Kvkg]|
|-_x2LGJj_YKxJcM-P2Kvkg|[H9x_8vghL3a7Gp6OckLhZQ, YDjpFw_K46BW9Wf9c8izzA]|
|YDjpFw_K46BW9Wf9c8izzA|[-_x2LGJj_YKxJcM-P2Kvkg, C9xi-33ob-hlRXF7uuIuCQ]|
|C9xi-33ob-hlRXF7uuIuCQ|[YDjpFw_K46BW9Wf9c8izzA, iJpgy47yC8tpwy7_6G3tpA]|
|iJpgy47yC8tpwy7_6G3tpA|[C9xi-33ob-hlRXF7uuIuCQ, XhGCAPGI_GEzeV7v-s9RBQ]|
|XhGCAPGI_GEzeV7v-s9RBQ|[iJpgy47yC8tpwy7_6G3tpA, CgNkIOILQowcP3mQaVpX7Q]|
|CgNkIOILQowcP3mQaVpX7Q|[XhGCAPGI_GEzeV7v-s9RBQ, U8MXIhRf3WjkAT5TAw8c-w]|
|U8MXIhRf3WjkAT5TAw8c-w|[CgNkIOILQowcP3mQaVpX7Q, rUfxQ6rZRwemZe11MD-O0g]|
```

```
|rUfxQ6rZRwemZe11MD-OOg|[U8MXIhRf3WjkAT5TAw8c-w, -Yni53KuteKxm3JbabyYgQ]|
|-Yni53KuteKxm3JbabyYgQ|[rUfxQ6rZRwemZe11MD-OOg, l4iQ8z7Q6PFatFx_UUMpCw]|
|l4iQ8z7Q6PFatFx_UUMpCw|[-Yni53KuteKxm3JbabyYgQ, 2r9omWlNODtsofY6pKVGhw]|
|2r9omWlNODtsofY6pKVGhw|[l4iQ8z7Q6PFatFx_UUMpCw, FoMY7RWU7454wkYZDZ3vGA]|
|FoMY7RWU7454wkYZDZ3vGA|[2r9omWlNODtsofY6pKVGhw, cGoBqXzBUeUJLmEu7DMArg]|
|cGoBqXzBUeUJLmEu7DMArg|[FoMY7RWU7454wkYZDZ3vGA, xWYcCL8sBOKhGkXCG1qBdQ]|
|xWYcCL8sBOKhGkXCG1qBdQ|[cGoBqXzBUeUJLmEu7DMArg, au7FVtivg_OKZmkvhmSAhQ]|
|au7FVtivg_OKZmkvhmSAhQ|[xWYcCL8sBOKhGkXCG1qBdQ, 1XP3HQHiSFZlzmlNOZzspw]|
+----------------------+--------------------------------------------------+
only showing top 20 rows
```

6. A visit score is calculated for all restaurants. For each person we calculated an avg score that they gave to the restaurants they visited and that is in the visit_score dataframe. This is done by joining the restaurant table to the review table.

[ ]:
```
from pyspark.sql.functions import avg
b_mod = business_df.filter(col("categories").contains("Restaurants"))
b_mod = restaurants_df.filter(col("state").contains("PA"))
b_mod = restaurants_df.filter(col("is_open").contains("1"))
visit_score = review_df.groupBy('user_id', 'business_id').
 ↪agg(avg('review_stars').alias('avg_review_stars'))
visit_score = b_mod.join(visit_score, on="business_id", how="inner")
visit_score=visit_score.select('business_id','user_id','avg_review_stars')
```

7. This information about each restaurant and the respective avg rating given to them by the user is added to the row for each user_id. This is saved in visits_df

[ ]:
```
from pyspark.sql.functions import collect_list, struct, desc, sort_array

# assuming your dataframe is called 'new_df'
user_business_df = visit_score.select('user_id', struct('business_id',␣
 ↪'avg_review_stars').alias('business_review'))
grouped_df = user_business_df.groupBy('user_id').
 ↪agg(collect_list('business_review').alias('businesses'))
visits_df = grouped_df.select('user_id', sort_array('businesses', asc=False).
 ↪alias('businesses'))
```

1 Recommendation Engine

1. Get recommendations from business clustering model

[ ]:
```
def business_cluster_rec(user_id, visits_df, business_recommendations):
    # Find the top 3 businesses for each user
    top_3_businesses = visits_df.filter(col("user_id") == user_id) \
                                .select(col("user_id"),␣
 ↪explode(col("businesses")).alias("businesses"))
    expanded_df = top_3_businesses \
```

```
        .withColumn("business_id", col("businesses.business_id")) \
        .withColumn("score", col("businesses.avg_review_stars")) \
        .drop("businesses")
    expanded_df.filter(col("score") >= 3)

    result_df = expanded_df.join(business_recommendations, on="business_id",␣
↪how="inner") \
                           .select("user_id", "business_id", "score",␣
↪"recommendations")
    result_df=result_df.select("user_id",'recommendations')
    combined_df = result_df.select('user_id', explode(col('recommendations')).
↪alias('recommendations'))

    return combined_df
```

2. Get recommendations from user clustering model

```
[ ]: def user_cluster_rec(user_id, visits_df, user_recommendations,␣
↪business_recommendations):
    similar_users=user_recommendations.filter(col("user_id") == user_id) \
                                      .select(col("user_id"),␣
↪explode(col("recommendations")).alias("recommendations"))
    recommendations_list = similar_users.select("recommendations").rdd.
↪flatMap(lambda x: x).collect()
    results = []
    for recommendation in recommendations_list:
        result_df = business_cluster_rec(recommendation, visits_df,␣
↪business_recommendations)
        results.append(result_df)
    combined_df = results[0]
    for i in range(1, len(results)):
        combined_df = combined_df.union(results[i])
    combined_df = combined_df.drop('user_id')
    combined_df = combined_df.withColumn('user_id', lit(user_id))
    #combined_df = combined_df.select('user_id',␣
↪explode(col('recommendations')).alias('recommendations'))
    combined_df=combined_df.select('user_id', 'recommendations')
    return combined_df
```

3. Merge recommendations and fetch names

```
[ ]: def merge_recommendations(u_cluster_recs, b_cluster_recs, user_df, business_df):
    u_cluster_recs = u_cluster_recs.withColumn("cluster_type", lit("u"))

    b_cluster_recs = b_cluster_recs.withColumn("cluster_type", lit("b"))

    combined_recs = u_cluster_recs.union(b_cluster_recs)
```

```
    combined_recs = combined_recs.join(user_df, on="user_id", how="inner") \
                                 .select("user_id", "name",␣
 ↪"recommendations",'cluster_type') \
                                 .withColumnRenamed("name", "name_user")
    combined_recs = combined_recs.join(business_df, col("recommendations") ==␣
 ↪col("business_id"), "inner") \
                                 .select("user_id", "name_user", "recommendations",␣
 ↪"name",'cluster_type') \
                                 .withColumnRenamed("name", "name_restaurant")
    combined_recs = combined_recs.
 ↪select('name_user',"name_restaurant",'cluster_type')
    return combined_recs
```

1.0.1 Recommendations for User Desirae

[ ]:
```
user_id='6O4seIFz_buDGYXCOIT03A'
b_cluster_recs=business_cluster_rec(user_id,visits_df, business_recommendations)
u_cluster_recs=user_cluster_rec(user_id, visits_df, user_recommendations,␣
 ↪business_recommendations)
final=merge_recommendations(u_cluster_recs, b_cluster_recs, user_df,␣
 ↪business_df)
final.show(truncate=False)
```

```
+---------+----------------------+------------+
|name_user|name_restaurant       |cluster_type|
+---------+----------------------+------------+
|Desirae  |Charley's Grilled Subs |u           |
|Desirae  |FreshWorks of Levittown|u           |
|Desirae  |Walt's Steak Shop      |u           |
|Desirae  |Charley's Grilled Subs |u           |
|Desirae  |FreshWorks of Levittown|b           |
|Desirae  |La Casa Del Sandwich   |b           |
+---------+----------------------+------------+
```

Restaurants previously visited by Desirae

[ ]:
```
business_ids = review_df.filter(col("user_id") == "6O4seIFz_buDGYXCOIT03A") \
                        .select("business_id") \
                        .distinct()
business_names = business_ids.join(business_df, on="business_id", how="inner") \
                             .select(col("business_id"), col("name"))

business_names.select('name').show()
```

```
+--------------------+
|                name|
```

```
+--------------------+
|Cosmos Fine Nail …|
|          Jeans Cafe|
+--------------------+
```

Cluster number for Desirae

[ ]:
```
#Desirae
filtered_df = predictions_user.filter(col('user_id') ==␣
 ↪'6O4seIFz_buDGYXCOIT03A')

prediction_value = filtered_df.select('prediction').collect()[0][0]

print(prediction_value)
```

```
3
```

1.0.2 Recommendations for User Aaron

[ ]:
```
user_id='A3DrdXmkNb1I6x-lSbj96g'
b_cluster_recs=business_cluster_rec(user_id,visits_df, business_recommendations)
u_cluster_recs=user_cluster_rec(user_id, visits_df, user_recommendations,␣
 ↪business_recommendations)
final=merge_recommendations(u_cluster_recs, b_cluster_recs, user_df,␣
 ↪business_df)
final.show(truncate=False)
```

```
+---------+--------------------------------+------------+
|name_user|name_restaurant                 |cluster_type|
+---------+--------------------------------+------------+
|Aaron    |Tony Luke's                     |u           |
|Aaron    |Slack's Hoagie Shack            |u           |
|Aaron    |Pompei’s State Street Sandwiches|u           |
|Aaron    |Angelina's Panini Bar           |u           |
|Aaron    |Sam's Sub Shop                  |b           |
|Aaron    |Angelina's Panini Bar           |b           |
+---------+--------------------------------+------------+
```

Restaurants previously visited by Aaron

[ ]:
```
business_ids = review_df.filter(col("user_id") == "A3DrdXmkNb1I6x-lSbj96g") \
                        .select("business_id") \
                        .distinct()
business_names = business_ids.join(business_df, on="business_id", how="inner") \
                             .select(col("business_id"), col("name"))

business_names.select('name').show(truncate=False)
```

```
+-------------------------------+
|name                           |
+-------------------------------+
|Pompei's State Street Sandwiches|
+-------------------------------+
```

Cluster number for Aaron

[ ]:
```
filtered_df = predictions_user.filter(col('user_id') ==␣
  ↪'A3DrdXmkNb1I6x-lSbj96g')

prediction_value = filtered_df.select('prediction').collect()[0][0]

print(prediction_value)
```

3

This user has visited over 1000 restaurants

[ ]:
```
user_id='pou3BbKsIozfH50rxmnMew'
b_cluster_recs=business_cluster_rec(user_id,visits_df, business_recommendations)
u_cluster_recs=user_cluster_rec(user_id, visits_df, user_recommendations,␣
  ↪business_recommendations)
final=merge_recommendations(u_cluster_recs, b_cluster_recs, user_df,␣
  ↪business_df)
final.show(32,truncate=False)
```

```
+---------+-------------------------+------------+
|name_user|name_restaurant          |cluster_type|
+---------+-------------------------+------------+
|Brett    |QDOBA Mexican Eats       |u           |
|Brett    |QDOBA Mexican Eats       |u           |
|Brett    |Biryani City             |u           |
|Brett    |Miss Winnie's            |u           |
|Brett    |Rio Brazilan Steak Truck |u           |
|Brett    |Meat Wagon BBQ           |u           |
|Brett    |Concerto Fusion          |u           |
|Brett    |Tran's Chinese Food Cart |u           |
|Brett    |Sake Hana                |u           |
|Brett    |Kapow Kitchen            |u           |
|Brett    |Rebel Taco               |u           |
|Brett    |Buena Onda               |u           |
|Brett    |Bibou                    |u           |
|Brett    |Landolfi's Cafe & Deli   |u           |
|Brett    |Ummi Dee's burger bistro |u           |
|Brett    |WIBS                     |u           |
|Brett    |Delorenzo's Tomato Pies  |u           |
|Brett    |Diamante Pizzaria        |u           |
```

```
|Brett    |Keshet Kitchen           |u           |
|Brett    |Poke Bros                |u           |
|Brett    |Rocky's Pizza and Grille |u           |
|Brett    |Via Veneto Pizza         |u           |
|Brett    |A'Dello Vineyard & Winery|u           |
|Brett    |La Collina               |u           |
|Brett    |Restaurant Alba          |u           |
|Brett    |Avola Kitchen + Bar      |u           |
|Brett    |Panera Bread             |u           |
|Brett    |Mercer Cafe              |u           |
|Brett    |Stove and Tap            |u           |
|Brett    |IHOP                     |u           |
|Brett    |Forsythia                |u           |
|Brett    |WOOJUNG Sushi            |u           |
+---------+-------------------------+------------+
only showing top 32 rows
```

[ ]:
```
business_ids = review_df.filter(col("user_id") == "pou3BbKsIozfH50rxmnMew") \
                        .select("business_id") \
                        .distinct()
business_names = business_ids.join(business_df, on="business_id", how="inner") \
                             .select(col("business_id"), col("name"))

business_names.select('name').show(truncate=False)
```

```
+----------------------------------------+
|name                                    |
+----------------------------------------+
|The Independent                         |
|Monstah Lobstah                         |
|Endodontic Specialists                  |
|CC's Coffee House                       |
|Brady's BBQ                             |
|Tire Choice Auto Service Centers        |
|Zeko's Mediterranean Grill              |
|Los Comparres                           |
|Tryst Gastro Lounge                     |
|Reservations Bistro                     |
|Quality Foods Market                    |
|Brew D Licious                          |
|Ledo Pizza                              |
|Zoes Kitchen                            |
|Simply Delicious - Country Market & Deli|
|Mazzaro's Italian Market                |
|Icesmile                                |
|Glazer Children's Museum                |
|Angry Chair Brewing                     |
```

```
|Bandit Coffee Co.                        |
+-----------------------------------------+
only showing top 20 rows
```

[ ]:
```
col1 = business_names.select('name')
col2 = final.select("name_restaurant")
intersection = col1.intersect(col2)

intersection.show()
```

```
+-----------+
|       name|
+-----------+
|Kung Fu Tea|
|Shake Shack|
+-----------+
```

[ ]:
```
filtered_df = predictions_user.filter(col('user_id') ==␣
 ↪'pou3BbKsIozfH50rxmnMew')

prediction_value = filtered_df.select('prediction').collect()[0][0]

print(prediction_value)
```

```
4
```

Business cluster features

[ ]:
```
def get_cluster_features(a, predictions_business):

    joined_df = a.join(predictions_business, on=['business_id'], how='inner')

    selected_df = joined_df.select(predictions_business.columns).
 ↪drop('features','prediction')
    sums_df = selected_df.agg(*[sum(f.col(c)).alias(c) for c in selected_df.
 ↪columns])

    sorted_sums_df = sums_df.select('*').orderBy(desc(sums_df.columns[0])).
 ↪drop("business_id")

    b = sorted_sums_df.toPandas()
    cols = b.columns
    list_2 = b.iloc[0].tolist()

    data = {'Feature names': cols, 'frequency': list_2}
    df = pd.DataFrame(data)
```

```
    df = df.sort_values('frequency', ascending=False)

    return df
```

[ ]:
```
cluster_0=dict_businesses['cluster_0'].drop('features','prediction')
cluster_0_features = get_cluster_features(cluster_0, predictions_business)
cluster_0_features.head(20)
```

[ ]:

	Feature names	frequency
28	Chinese	595
59	Japanese	295
7	Mexican	281
123	Seafood	279
138	American (New	233
139	Asian Fusion	230
93	Sushi Bars	229
119	American (Traditional	226
65	Event Planning & Services	206
145	Specialty Food	201
84	Italian	195
12	Bakeries	195
136	Delis	178
80	Coffee & Tea	146
19	Thai	141
26	Indian	127
98	Caterers	126
52	Grocery	117
113	Desserts	114
101	Vegetarian	112

[ ]:
```
cluster_1=dict_businesses['cluster_1'].drop('features','prediction')
cluster_1_features = get_cluster_features(cluster_1, predictions_business)
cluster_1_features.head(20)
```

[ ]:

	Feature names	frequency
74	Pizza	1354
84	Italian	474
97	Sandwiches	324
75	Chicken Wings	122
61	Cheesesteaks	118
2	Salad	107
119	American (Traditional	94
73	Burgers	81
65	Event Planning & Services	72
98	Caterers	64
115	Food Delivery Services	61
123	Seafood	45

```
138              American (New         43
145            Specialty Food          35
68                  Fast Food          35
113                  Desserts          32
13                 Gluten-Free         29
117                Pasta Shops         25
136                      Delis         25
142             Mediterranean          21
```

[ ]:
```
cluster_2=dict_businesses['cluster_2'].drop('features','prediction')
cluster_2_features = get_cluster_features(cluster_2, predictions_business)
cluster_2_features.head(20)
```

[ ]:
```
                Feature names  frequency
48                  Nightlife        502
119      American (Traditional        502
143                       Bars        493
15                Sports Bars        156
138              American (New        135
144                       Pubs        125
73                     Burgers         73
65   Event Planning & Services         66
69               Cocktail Bars         60
123                    Seafood         58
55         Breakfast & Brunch          53
118                       Beer         50
132            Wine & Spirits         50
20       Venues & Event Spaces         49
3                     Beer Bar         47
97                  Sandwiches         41
16                  Gastropubs         41
74                       Pizza         38
60        Arts & Entertainment         37
134                Steakhouses         37
```

[ ]:
```
cluster_3=dict_businesses['cluster_3'].drop('features','prediction')
cluster_3_features = get_cluster_features(cluster_3, predictions_business)
cluster_3_features.head(20)
```

[ ]:
```
                Feature names  frequency
48                  Nightlife        736
143                       Bars        724
138              American (New        229
69               Cocktail Bars        142
144                       Pubs        128
84                     Italian        110
74                       Pizza         89
```

```
30                   Wine Bars         85
123                    Seafood         82
3                     Beer Bar         82
97                  Sandwiches         78
15                 Sports Bars         78
55          Breakfast & Brunch         75
132             Wine & Spirits         66
17                     Lounges         66
118                       Beer         66
7                      Mexican         62
65   Event Planning & Services         56
16                   Gastropubs         53
60        Arts & Entertainment         47
```

[ ]:
```
cluster_4=dict_businesses['cluster_4'].drop('features','prediction')
cluster_4_features = get_cluster_features(cluster_4, predictions_business)
cluster_4_features.head(20)
```

[ ]:
```
                Feature names  frequency
97                  Sandwiches        967
55          Breakfast & Brunch        736
80                Coffee & Tea        499
136                      Delis        278
95                       Cafes        259
119      American (Traditional        254
138              American (New        177
2                         Salad        174
50          Convenience Stores        157
12                    Bakeries        142
65   Event Planning & Services        124
56                      Bagels        114
98                    Caterers        106
67                      Diners        103
73                     Burgers        100
84                     Italian         94
113                   Desserts         85
61                Cheesesteaks         81
39      Juice Bars & Smoothies         81
94                        Soup         78
```

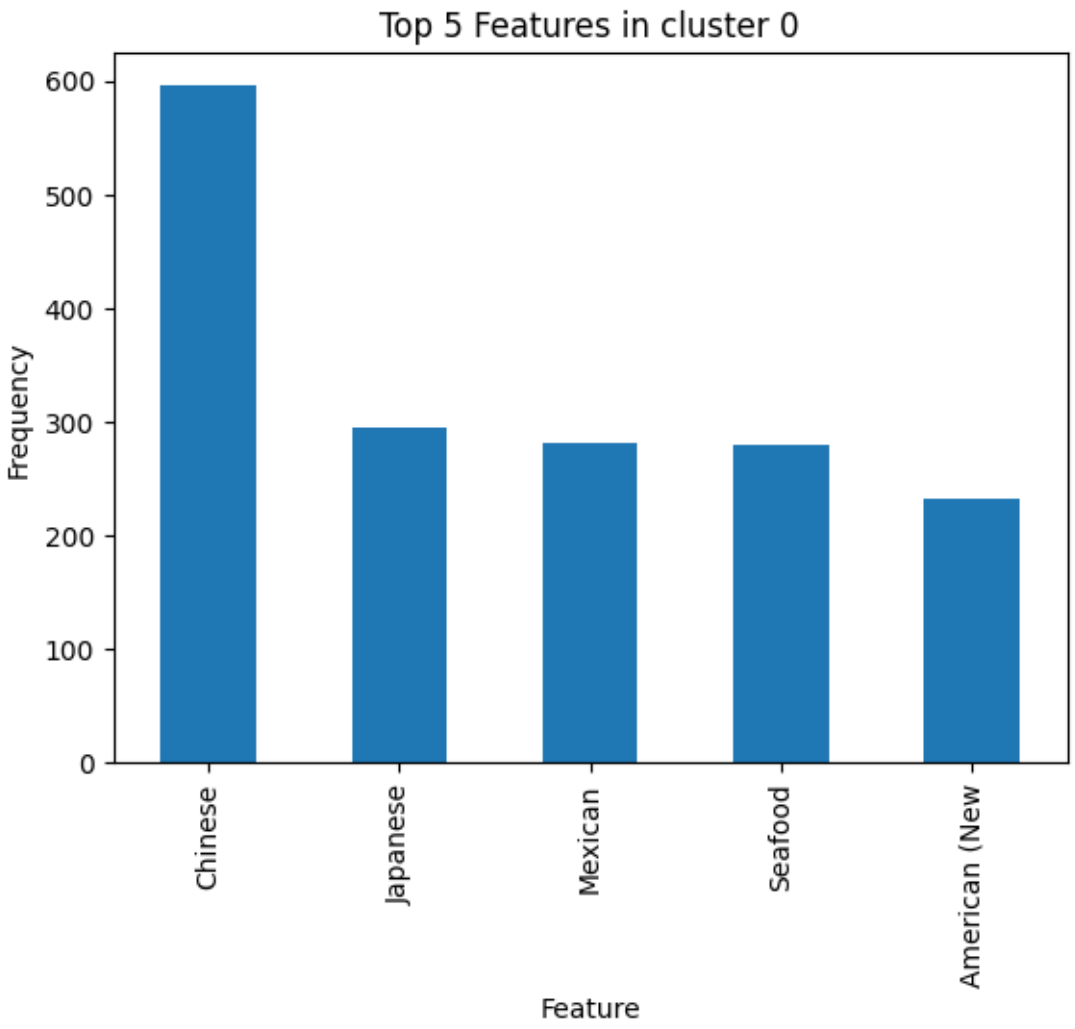
[ ]:
```
cluster_5=dict_businesses['cluster_5'].drop('features','prediction')
cluster_5_features = get_cluster_features(cluster_5, predictions_business)
cluster_5_features.head(20)
```

[ ]:
```
                Feature names  frequency
68                   Fast Food        615
73                     Burgers        369
```

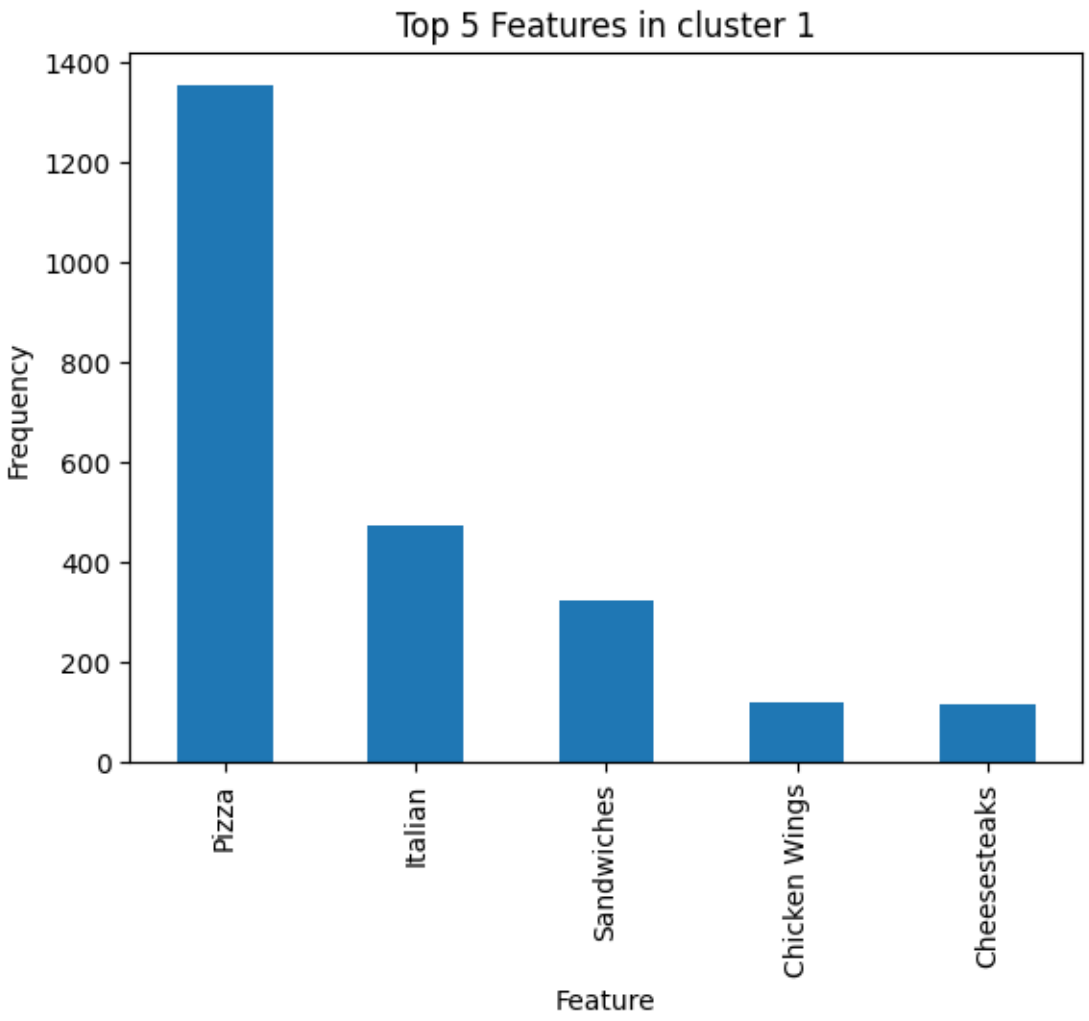
```
119      American (Traditional        120
80                 Coffee & Tea       111
7                       Mexican       100
75                Chicken Wings        89
105  Ice Cream & Frozen Yogurt         68
82                 Chicken Shop        67
97                   Sandwiches        62
65   Event Planning & Services         58
98                     Caterers        54
103                    Hot Dogs        46
55           Breakfast & Brunch        34
34                        Tacos        33
154                    Tex-Mex        30
2                        Salad        27
138               American (New        25
28                      Chinese        17
123                     Seafood        17
12                     Bakeries        15
```

[ ]:
```
def top_5_features_bar_graph(df,i):
    df_sorted = df.sort_values(by='frequency', ascending=False)

    top_5_features = df_sorted.head(5)

    ax = top_5_features.plot(x='Feature names', y='frequency', kind='bar',␣
 ↪legend=False)

    ax.set_title('Top 5 Features in cluster {}'.format(i))
    ax.set_xlabel('Feature')
    ax.set_ylabel('Frequency')

    return ax.get_figure()
```

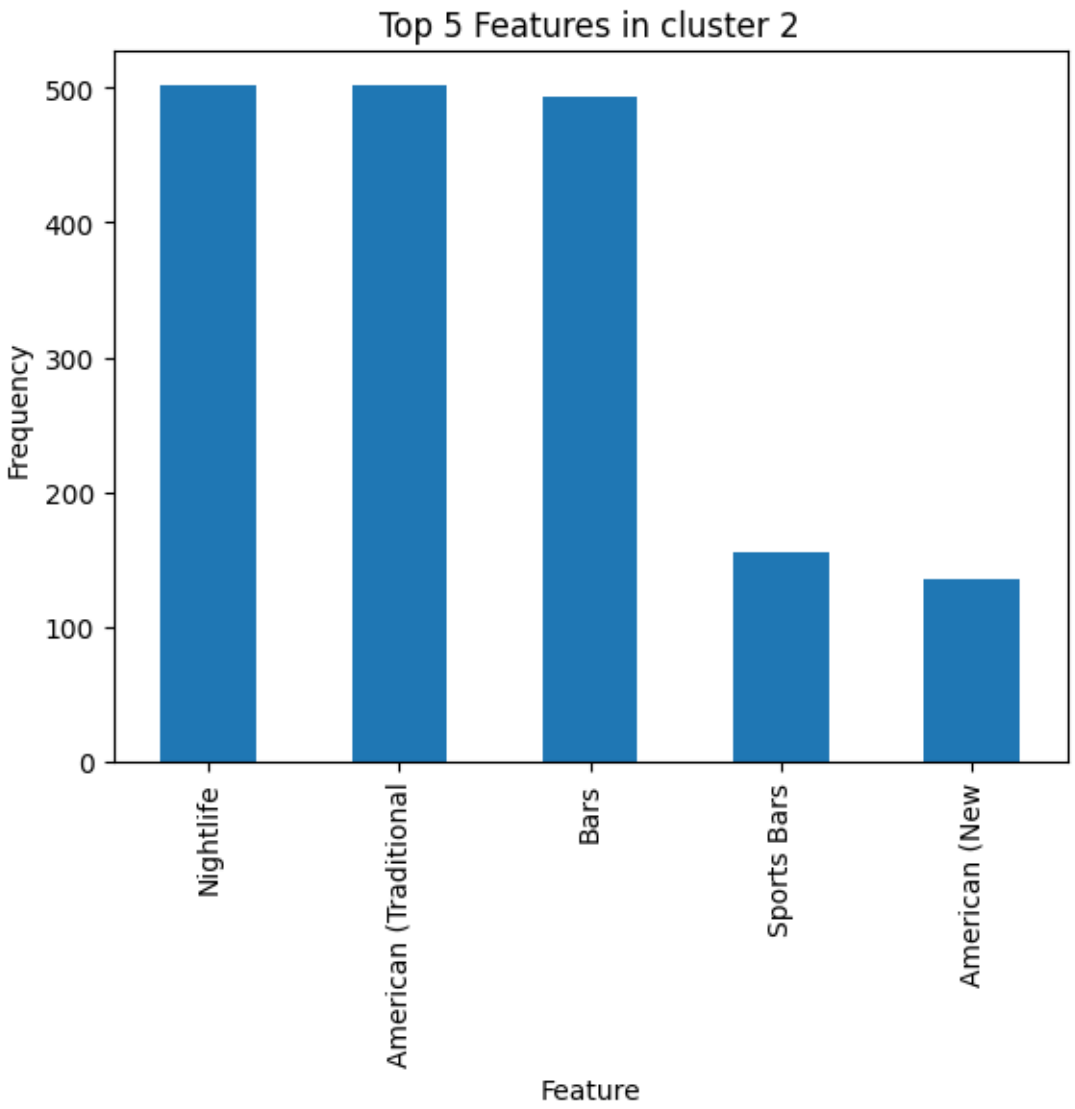
[ ]:
```
fig0=top_5_features_bar_graph(cluster_0_features,0)
```



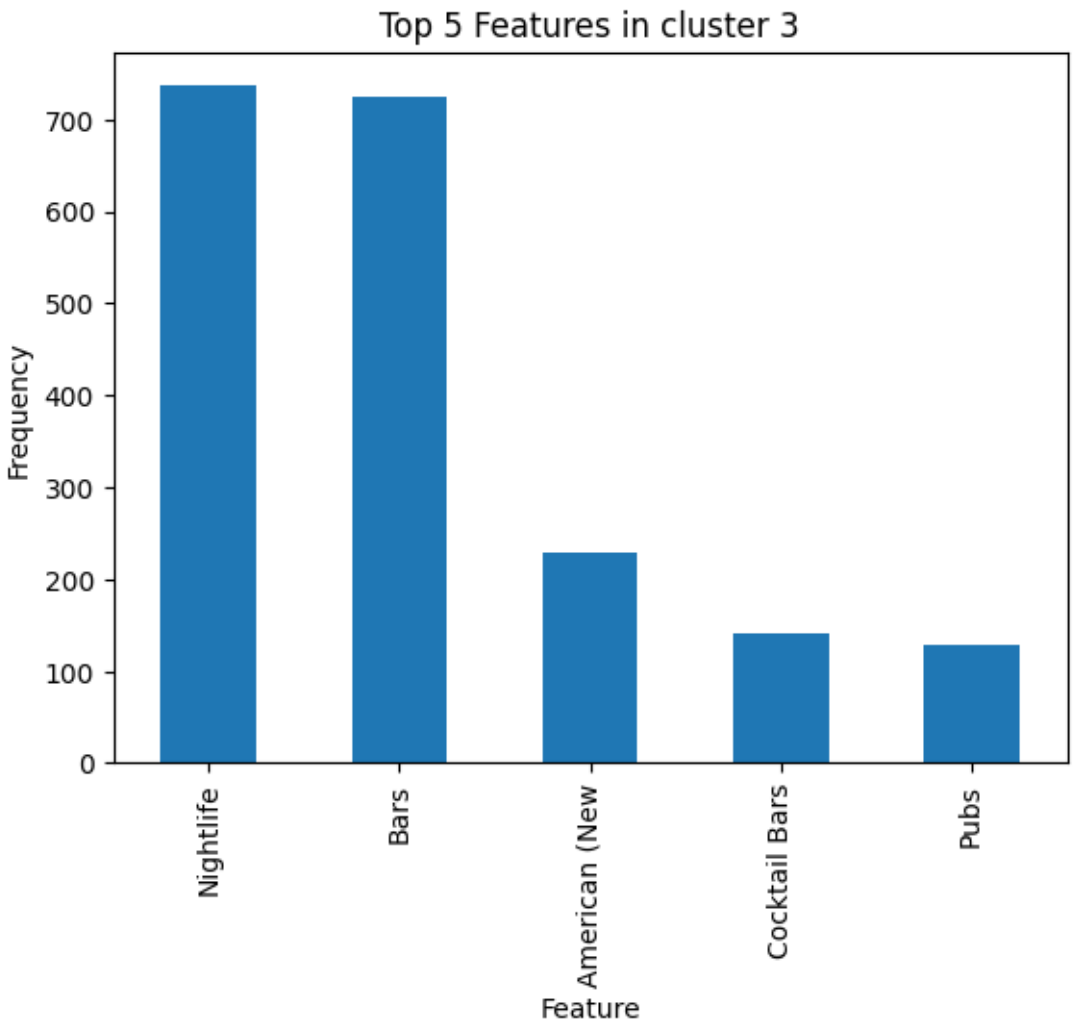
[ ]:
```
fig1=top_5_features_bar_graph(cluster_1_features,1)
```



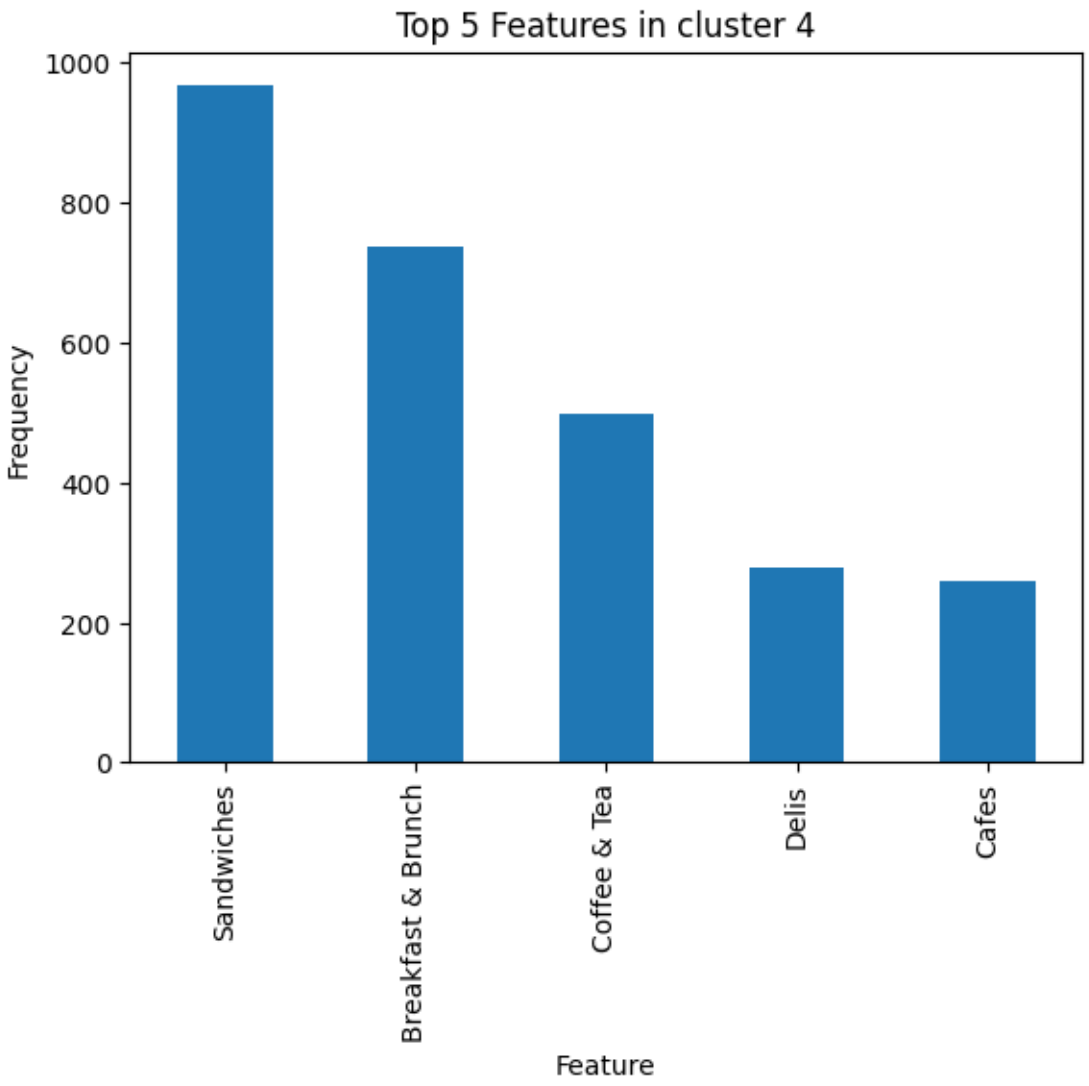
[ ]:
```
fig2=top_5_features_bar_graph(cluster_2_features,2)
```



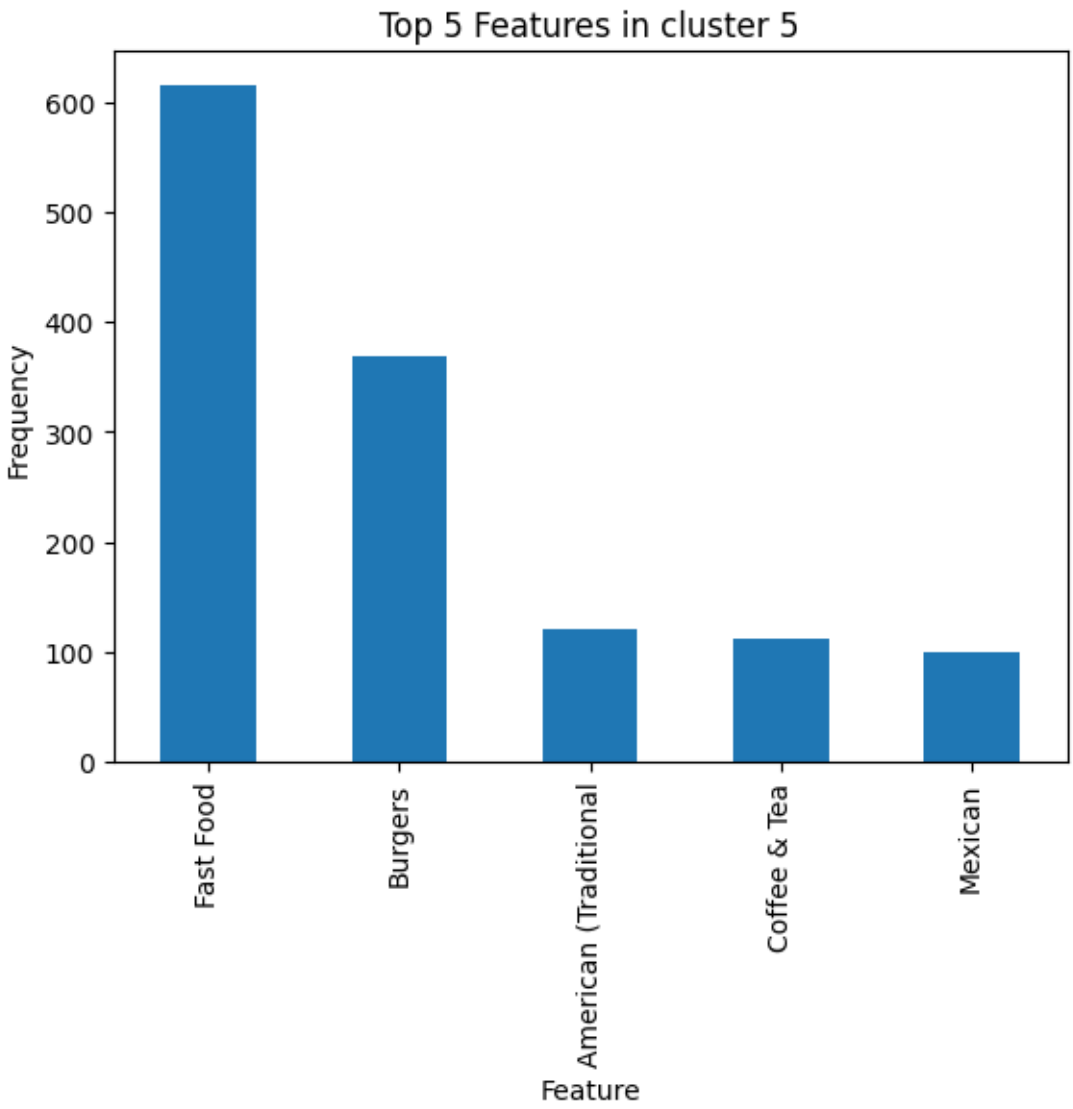
[ ]:
```
fig3=top_5_features_bar_graph(cluster_3_features,3)
```



[ ]:
```
fig4=top_5_features_bar_graph(cluster_4_features,4)
```



[ ]:
```
fig5=top_5_features_bar_graph(cluster_5_features,5)
```


Top 5 Features in cluster 5
Frequency
600
500
400
300
200
100
0
Fast Food
Burgers
American (Traditional
Coffee & Tea
Mexican
Feature