Part 1 -Static Data Analysis

Read Sub Demographic Data

```
from pyspark.sql.types import *
from pyspark import SparkContext
from pyspark.sql import SparkSession
from pyspark.sql.types import ArrayType, DoubleType, FloatType
from pyspark.sql.functions import udf
import pyspark.sql.functions as F
from pyspark.ml import Pipeline
from pyspark.ml.linalg import Vectors, VectorUDT, DenseVector,Vector
from pyspark.ml.feature import StringIndexer, OneHotEncoder, VectorAssembler, MaxAbsScaler,PCA
import matplotlib.pyplot as plt
from pyspark.ml.clustering import KMeans
from pyspark.sql.window import Window

spark = SparkSession.builder.appName("my project 2")\
    .config("spark.kryoserializer.buffer.max", "512m")\
    .config('spark.jars.packages', 'org.apache.spark:spark-sql-kafka-0-10_2.12:3.2.0')\
        .getOrCreate()
sc = spark.sparkContext
```

```
for_students_demo_path = "/mnt/ddscoursedatastorage/ro/fwm-stb-data/proj_B_demographic"
demographic_df = spark.read.parquet(for_students_demo_path)
display(demographic_df)
```

household_id	household_size	num_adults	num_generations	marital_status	race_code	dwelling_type	home
85	2	1	2	B	W	S	O
2073	1	1	2	M	H	S	O
2523	7	6	3	M	W	S	O
2717	3	2	2	S	W	S	O
3364	2	2	2	M	W	S	O
4046	4	3	3	M	W	S	O
4303	1	1	1	S	W	S	O
4559	3	2	2	S	W	S	O
5277	3	2	2	M	W	S	R

Read Static viewing data from Kafka

```
kafka_server = "kafka96224.eastus.cloudapp.azure.com:29092"
topic='viewstatic'
OFFSETS_PER_TRIGGER = 50000
SCHEMA = "device_id STRING, event_date STRING, event_time STRING, station_num STRING, prog_code STRING, household_id LONG"

static_df = spark.read\
                  .format("kafka")\
                  .option("kafka.bootstrap.servers", kafka_server)\
                  .option("subscribe", topic)\
                  .option("startingOffsets", "earliest")\
                  .option("failOnDataLoss",False)\
                  .load()

static_view_data = static_df.select(F.from_csv(F.decode("value", "US-ASCII"), schema=SCHEMA).alias("value")).select("value.*").na.drop()
display(static_view_data)
```

device_id	event_date	event_time	station_num	prog_code	household_id
000000033449	20150114	000000	59444	MV000963020000	1496400
000000033633	20150114	000000	16374	EP018001900333	1477911
0000000792ce	20150114	000000	60179	EP018001900333	1464390
00000007a06a	20150114	000000	19746	SH000299490000	1491604
00000007a196	20150114	000000	61812	EP002654380201	1468157

Feature Extraction

```
# GPT assistance
# create a df with the categorical columns vector
cat_cols = ['marital_status', 'race_code', 'dwelling_type', 'home_owner_status', 'gender_individual']
dem_cat_df = demographic_df.select('household_id',*cat_cols)
# Initialize a VectorAssembler with empty inputCols and the outputCol as "combined_features"
assembler = VectorAssembler(inputCols=[], outputCol="combined_categorical_features")
for col in cat_cols:
    # Apply StringIndexer to index the categorical column
    indexer = StringIndexer(inputCol=col, outputCol=col + "_Index")
    # Apply OneHotEncoder to one-hot encode the indexed column
    encoder = OneHotEncoder(inputCols=[col + "_Index"], outputCols=["encoded_" + col])
    # Add the encoded column to the inputCols of the VectorAssembler
    assembler.setInputCols(assembler.getInputCols() + ["encoded_" + col])
    # Create a pipeline with StringIndexer and OneHotEncoder
    pipeline = Pipeline(stages=[indexer, encoder])
    # Fit the pipeline to the DataFrame and transform the DataFrame
    dem_cat_df = pipeline.fit(dem_cat_df).transform(dem_cat_df)
# Apply the VectorAssembler to concatenate all the encoded columns into a single column
dem_cat_df = assembler.transform(dem_cat_df).select("household_id","combined_categorical_features")
```

```
# create a df with the categorical columns vector
demographic_df = demographic_df.withColumn('education_highest', F.col('education_highest').cast('double'))
numerical_cols = ['household_size', 'num_adults', 'num_generations', 'length_residence', 'home_market_value', 'net_worth', 'education_highest']

dem_numerical_df = demographic_df.select('household_id',*numerical_cols)
assembler = VectorAssembler(inputCols=numerical_cols, outputCol="features")
dem_numerical_df = assembler.transform(dem_numerical_df)
# Create an instance of MinMaxScaler
scaler = MaxAbsScaler(inputCol="features", outputCol="combined_numerical_features")
# Fit the scaler to the DataFrame and transform
dem_numerical_df = scaler.fit(dem_numerical_df).transform(dem_numerical_df).select("household_id","combined_numerical_features")
```

```
# GPT assistance
# Join the DataFrames and select the household_id column along with the struct arrays
df = dem_numerical_df.join(dem_cat_df, "household_id")

# Define UDF to convert UDT to a compatible type
udf_convert_udt = udf(lambda x: x.toArray().tolist(), ArrayType(DoubleType()))

# Convert UDT columns to compatible type
df = df.withColumn("converted_categorical_features", udf_convert_udt(F.col("combined_categorical_features")))
df = df.withColumn("converted_numerical_features", udf_convert_udt(F.col("combined_numerical_features")))

# Concatenate the struct arrays using the concat function
df = df.withColumn("concatenated_vector", F.concat(F.col("converted_numerical_features"),F.col("converted_categorical_features")))

# Define UDF to convert the concatenated array to a dense vector
udf_array_to_vector = F.udf(lambda arr: Vectors.dense(arr), VectorUDT())

# Convert the concatenated array to a dense vector
df = df.withColumn("features", udf_array_to_vector(F.col("concatenated_vector")))
# select and display
feature_vec_df=df.select("household_id", "features")
feature_vec_df.show(7, truncate=False)
```

```
+------------+--------------------------------------------------------------------------------------------------------------
|household_id|features
+------------+--------------------------------------------------------------------------------------------------------------
|85          |[0.2222222222222222,0.16666666666666666,0.6666666666666666,1.0,0.125,0.05,0.25,0.0,0.0,0.0,1.0,0.0,0.0,1.0,1.0,0.0]
|2073        |[0.1111111111111111,0.16666666666666666,0.6666666666666666,1.0,0.15,0.1,0.25,1.0,0.0,0.0,0.0,0.0,1.0,1.0,1.0,0.0]
|2523        |[0.7777777777777777,1.0,1.0,1.0,0.1,0.1,0.5,1.0,0.0,0.0,1.0,0.0,0.0,1.0,1.0,1.0]
```

```
|2717        |[0.3333333333333333,0.3333333333333333,0.6666666666666666,0.7333333333333333,0.125,0.2,0.75,0.0,1.0,0.0,1.0,0.0,0.0,1.0,1.0,
|3364        |[0.2222222222222222,0.3333333333333333,0.6666666666666666,1.0,0.1,0.1,0.25,1.0,0.0,0.0,1.0,0.0,0.0,1.0,1.0,1.0]
|4046        |[0.4444444444444444,0.5,1.0,0.4,0.075,0.05,0.25,1.0,0.0,0.0,1.0,0.0,0.0,1.0,1.0,0.0]
|4303        |[0.1111111111111111,0.16666666666666666,0.3333333333333333,1.0,0.15,0.2,0.25,0.0,1.0,0.0,1.0,0.0,0.0,1.0,1.0,1.0]
+------------+-------------------------------------------------------------------------------------------------------------------------
only showing top 7 rows
```

Visual Analysis

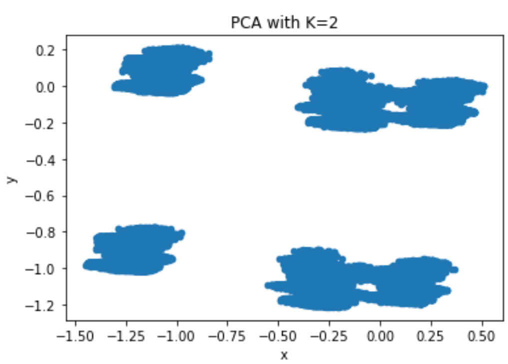
```
pca = PCA(k=2, inputCol="features", outputCol="pca_features")
model = pca.fit(feature_vec_df)
feature_vec_df = model.transform(feature_vec_df)\
                        .withColumn("pca_features", udf_convert_udt(F.col("pca_features")))
```

```
PCA_feature_vec_df= feature_vec_df.select('household_id','pca_features')
PCA_feature_vec_df.show(7,truncate=False)
```

```
+------------+--------------------------------------------+
|household_id|pca_features                                |
+------------+--------------------------------------------+
|85          |[-0.35625542326615856, -0.11097025338253685]|
|2073        |[-1.0925316168664254, 0.12397733233143077]  |
|2523        |[-1.4149098090986307, -0.970179836670209]   |
|2717        |[0.06329368821084108, -1.158369672110097]   |
|3364        |[-1.2929454215296108, -0.9714139901152655]  |
|4046        |[-1.1192228102668804, -0.006375350365083842]|
|4303        |[0.07476265653874331, -1.1529793790408365]  |
+------------+--------------------------------------------+
only showing top 7 rows
```

```
# Select the individual elements within the struct array
Coordinates = PCA_feature_vec_df.select(F.col("pca_features")[0].alias("x"), F.col("pca_features")[1].alias("y"))\
                                    .toPandas()\

# Plot the scatter plot using Pandas
Coordinates.plot.scatter(x="x", y="y")
plt.title('PCA with K=2')
# Display the plot
plt.show()
```



Clustering

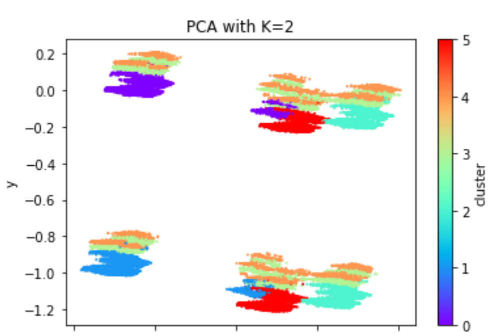
```
#
num_features = len(feature_vec_df.select("features").first()[0])
clustering_df = feature_vec_df.withColumn("features", udf_convert_udt(F.col("features")))
clustering_df = clustering_df.select(
    F.col('household_id'),
    *[F.col("features")[i].alias(f"x{i}") for i in range(num_features)]
)
cols=[f"x{i}" for i in range(num_features)]
assembler = VectorAssembler(inputCols=cols,outputCol='features_for_cluster')
clustering_df = assembler.transform(clustering_df)
for col in cols:
    clustering_df=clustering_df.drop(col).cache()


# kmeans_df = PCA_feature_vec_df.select(F.col('household_id'),F.col("pca_features")[0].alias("x"), F.col("pca_features")[1].alias("y"))
# assembler = VectorAssembler(inputCols=['x','y'],outputCol='features')
# kmeans_df = assembler.transform(kmeans_df).drop('x','y').cache()
kmeans = KMeans(k=6, featuresCol='features_for_cluster', predictionCol='cluster', seed=3)
# Fit the KMeans model to the input data
model = kmeans.fit(clustering_df)
predictions = model.transform(clustering_df)
cluster_centers =  model.clusterCenters()
# Define the UDF to map cluster ID to centroid coordinates
centroid_udf = udf(lambda cluster: cluster_centers[cluster].tolist(), ArrayType(FloatType()))
# Add a new column 'centroid_coordinates' using the UDF
predictions = predictions.withColumn('centroid_coordinates', centroid_udf('cluster'))
distance_udf = udf(lambda features, centroid_coordinates: \
                   float(Vectors.squared_distance(features, centroid_coordinates)),
                   FloatType())
predictions = predictions.withColumn('distance', \
    distance_udf(F.col('features_for_cluster'), F.col('centroid_coordinates'))).drop('centroid_coordinates')

# Show the resulting DataFrame
predictions.show(7,truncate=False)
```

```
+------------+------------------------------------------------------------------------------------------------------------
|household_id|features_for_cluster
+------------+------------------------------------------------------------------------------------------------------------
|85          |[0.2222222222222222,0.16666666666666666,0.6666666666666666,1.0,0.125,0.05,0.25,0.0,0.0,0.0,1.0,0.0,0.0,1.0,1.0,0.0]
|2073        |[0.1111111111111111,0.16666666666666666,0.6666666666666666,1.0,0.15,0.1,0.25,1.0,0.0,0.0,0.0,0.0,1.0,1.0,1.0,0.0]
|2523        |[0.7777777777777777,1.0,1.0,1.0,0.1,0.1,0.5,1.0,0.0,0.0,1.0,0.0,0.0,1.0,1.0,1.0]
|2717        |[0.3333333333333333,0.3333333333333333,0.6666666666666666,0.7333333333333333,0.125,0.2,0.75,0.0,1.0,0.0,1.0,0.0,0.0,1.0,1.0,
|3364        |[0.2222222222222222,0.3333333333333333,0.6666666666666666,1.0,0.1,0.1,0.25,1.0,0.0,0.0,1.0,0.0,0.0,1.0,1.0,1.0]
|4046        |[0.4444444444444444,0.5,1.0,0.4,0.075,0.05,0.25,1.0,0.0,0.0,1.0,0.0,0.0,1.0,1.0,0.0]
|4303        |[0.1111111111111111,0.16666666666666666,0.3333333333333333,1.0,0.15,0.2,0.25,0.0,1.0,0.0,1.0,0.0,0.0,1.0,1.0,1.0]
+------------+------------------------------------------------------------------------------------------------------------
only showing top 7 rows
```

```
pred_clusters = predictions.select("household_id","cluster")
k_plots =  PCA_feature_vec_df.join(pred_clusters, on='household_id')\
                          .select(F.col("pca_features")[0].alias("x"), F.col("pca_features")[1].alias("y"),'cluster')\
                          .toPandas()
# k_plots = predictions.withColumn("features", udf_convert_udt(F.col("features")))\
#              .select(F.col('household_id'),F.col("features")[0].alias("x"), F.col("features")[1].alias("y"),F.col('cluster'))
k_plots.plot.scatter(x="x", y="y",s=1,c='cluster',cmap='rainbow')
plt.title('PCA with K=2')
# Display the plot
plt.show()
```



Dividing households into subsets

```
window_spec = Window.partitionBy("cluster").orderBy(F.col("distance").asc())
ranked_df = predictions.withColumn("rank", F.row_number().over(window_spec))
third_subset = ranked_df.filter(F.col('rank')%3==0)
seventeenth_subset = ranked_df.filter(F.col('rank')%17==0)
ranked_df.write.mode('overwrite').parquet('ranked_df.parquet')
third_subset.write.mode('overwrite').parquet('third_subset.parquet')
seventeenth_subset.write.mode('overwrite').parquet('seventeenth_subset.parquet')
```

household_id	features_for_cluster	cluster	distance	rank
8972	Map(vectorType -> dense, length -> 16, values -> List(0.3333333333333333, 0.3333333333333333, 0.6666666666666666, 0.7333333333333333, 0.15, 0.2, 0.25, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0, 1.0, 1.0, 1.0))	1	0.034352075	17
3939052	Map(vectorType -> dense, length -> 16, values -> List(0.3333333333333333, 0.3333333333333333, 0.6666666666666666, 0.8, 0.125, 0.2, 0.25, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0, 1.0, 1.0, 1.0))	1	0.035196282	34
2814052	Map(vectorType -> dense, length -> 16, values -> List(0.3333333333333333, 0.3333333333333333, 0.6666666666666666, 0.7333333333333333, 0.2, 0.2, 0.25, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0, 1.0, 1.0, 1.0))	1	0.035979014	51
1465901	Map(vectorType -> dense, length -> 16, values -> List(0.3333333333333333, 0.3333333333333333, 0.6666666666666666, 0.7333333333333333, 0.1, 0.2, 0.25, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0, 1.0, 1.0, 1.0))	1	0.037725136	68
3802857	Map(vectorType -> dense, length -> 16, values -> List(0.3333333333333333, 0.3333333333333333, 0.6666666666666666, 0.8, 0.225, 0.2, 0.25, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0, 1.0, 1.0, 1.0))	1	0.038450163	85
2828482	Map(vectorType -> dense, length -> 16, values -> List(0.3333333333333333, 0.5, 0.6666666666666666, 0.8, 0.175, 0.2, 0.25, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0, 1.0, 1.0, 1.0))	1	0.038707823	102

saving our work, for convenience

```
ranked_df = spark.read.parquet('/ranked_df.parquet')
third_subset = spark.read.parquet('/third_subset.parquet')
seventeenth_subset = spark.read.parquet('/seventeenth_subset.parquet')
```

Cluster’s Viewing Analysis

Q1+Q2

```
seventeenth_joined=(seventeenth_subset.select("household_id","cluster")).join(static_view_data, on="household_id", how="inner")
seventeenth_joined.write.mode('overwrite').parquet('seventeenth_joined.parquet')
```

```
third_joined=(third_subset.select("household_id","cluster")).join(static_view_data, on="household_id", how="inner")
third_joined.write.mode('overwrite').parquet('third_joined.parquet')
```

```
ranked_df_joined=(ranked_df.select("household_id","cluster")).join(static_view_data, on="household_id", how="inner")
ranked_df_joined.write.mode('overwrite').parquet('ranked_df_joined.parquet')
```

```
ranked_df_joined = spark.read.parquet('/ranked_df_joined.parquet')
third_joined = spark.read.parquet('/third_joined.parquet')
seventeenth_joined = spark.read.parquet('/seventeenth_joined.parquet')
```

Getting the popularity ratings for all, 3rd's and 17th's

```
window_spec=Window.partitionBy("cluster")
window_spec2=Window.partitionBy("cluster").orderBy(F.desc('popularity_rating'))
views_per_station17=seventeenth_joined.groupBy("cluster",'station_num').agg(F.count("*").alias("views_per_station"))
pop_rating_17 = views_per_station17.withColumn('views_per_cluster', F.sum("views_per_station").over(window_spec))\
                                .withColumn('popularity_rating', F.lit(100)*F.col('views_per_station')/F.col('views_per_cluster'))\
                                    .select('cluster','station_num', 'popularity_rating')\
                                        .withColumn('rank',  F.row_number().over(window_spec2))
display(pop_rating_17)
```

cluster	station_num	popularity_rating	rank
0	16374	1.632555334846765	1
0	14902	1.6228007945516458	2
0	60179	1.5358967082860386	3
0	11221	1.306221623155505	4

```
window_spec = Window.partitionBy("cluster")
window_spec2=Window.partitionBy("cluster").orderBy(F.desc('popularity_rating'))
views_per_station_third = third_joined.groupBy("cluster", "station_num").agg(F.count("*").alias("count_over_cluster"))
pop_rating_third = views_per_station_third.withColumn('views_per_cluster', F.sum('count_over_cluster').over(window_spec)) \
                                        .withColumn('popularity_rating', (F.col('count_over_cluster') / F.col('views_per_cluster')) * 100) \
                                             .select('cluster', 'station_num', 'popularity_rating')\
                                                    .withColumn('rank',  F.row_number().over(window_spec2))
display(pop_rating_third)
```

cluster	station_num	popularity_rating	rank
0	60179	1.731533905085839	1
0	16374	1.5867196840859514	2
0	14902	1.1988244492648243	3
0	14771	1.1747901562837508	4
0	32645	1.1007097722218333	5
0	11207	1.0996449617733048	6
0	49788	1.059942743621025	7
0	11221	1.023130725257608	8
0	12131	0.9876877488994424	9
0	11187	0.9654788452587033	10

```
window_spec=Window.partitionBy("cluster")
window_spec2=Window.partitionBy("cluster").orderBy(F.desc('popularity_rating'))
views_per_station_all=ranked_df_joined.groupBy("cluster",'station_num').agg(F.count("*").alias("views_per_station"))
pop_rating_all = views_per_station_all.withColumn('views_per_cluster', F.sum("views_per_station").over(window_spec))\
                                .withColumn('popularity_rating', 100*F.col('views_per_station')/F.col('views_per_cluster'))\
                                    .select('cluster','station_num', 'popularity_rating')\
                                        .withColumn('rank',  F.row_number().over(window_spec2))
display(pop_rating_all)
```

cluster	station_num	popularity_rating	rank
0	16374	1.6600458595129426	1
0	60179	1.567870106925949	2
0	14771	1.212142286975919	3
0	11207	1.1617466474703049	4
0	14902	1.157542685781371	5
0	49788	1.0761103908438752	6
0	32645	1.0468383613061139	7
0	11221	1.0282059878946663	8
0	12131	1.007705187065915	9
0	11187	0.9650946617990672	10

```
7
```

```
Out[57]: 7
```

Q3

Getting the popularity rating for all stations in the full data

```
gen_pop_views_per_station=static_view_data.dropDuplicates().select("station_num")
gen_pop_views_per_station = static_view_data.groupBy('station_num').agg(F.count('*').alias('views per station'))
all_views = gen_pop_views_per_station.agg(F.sum("views per station")).collect()[0][0]
gen_pop_rating = gen_pop_views_per_station.withColumn('gen pop station rating', 100*F.col('views per station')/F.lit(all_views))\
                                            .select('station_num','gen pop station rating')
```

```
gen_pop_views_per_station.show(5, truncate=False)
gen_pop_rating.write.mode('overwrite').parquet('gen_pop_rating.parquet')
```

```
+-----------+-----------------+
|station_num|views per station|
+-----------+-----------------+
|65348      |718              |
|14899      |11223            |
|18726      |110              |
|45540      |811              |
|12394      |4498             |
+-----------+-----------------+
only showing top 5 rows
```

Q4

Joining each subset df with the Gen-Pop df to get the diff-rank

```
gen_pop_rating = spark.read.parquet('/gen_pop_rating.parquet')
```

All - All Clusters

```
pop_rating_all_with_gen=pop_rating_all.join(gen_pop_rating, on="station_num", how="inner")
pop_rating_all_with_gen=pop_rating_all_with_gen.withColumn("diff_rank", F.col("popularity_rating")-F.col("gen pop station rating")).drop("popula
```

17th's - All Clusters

```
pop_rating_17_with_gen=pop_rating_17.join(gen_pop_rating, on="station_num", how="inner")
pop_rating_17_with_gen=pop_rating_17_with_gen.withColumn("diff_rank", F.col("popularity_rating")-F.col("gen pop station rating")).drop("populari
pop_rating_17_with_gen.show()
```

```
+-----------+-------+--------------------+
|station_num|cluster|           diff_rank|
+-----------+-------+--------------------+
|      17561|      0|-0.01014024842534...|
|      58623|      0|0.046221317774797044|
|      19548|      0|-0.02032718710020...|
|      11115|      0| 0.01952854285105822|
|      21722|      0|0.012879254591467864|
|      80740|      0|0.004272906657443113|
|      63138|      0|0.009076319766946027|
|      14752|      0|0.018816862108918645|
|      10002|      0|7.090097884506572E-4|
|      11309|      0|-7.73074495949684...|
|      10431|      0|-2.05455341267511...|
|      77361|      0|0.003700775879433...|
|      51464|      0|0.025943335961671452|
|      14753|      0|-0.01268082824369...|
|      82570|      0|-0.00540636433101...|
|      15090|      0|-0.01126354540117147|
|      12435|      0|0.004548320581218732|
|      21915|      0|-0.00760114207574...|
|      32569|      0|0.025769099448017238|
|      16376|      0|-0.01540067931603...|
+-----------+-------+--------------------+
only showing top 20 rows
```

3rd's - All Clusters

```
pop_rating_third_with_gen=pop_rating_third.join(gen_pop_rating, on="station_num", how="inner")
pop_rating_third_with_gen = pop_rating_third_with_gen.withColumn("diff_rank", F.col("popularity_rating")-F.col("gen pop station rating")).drop("
```

Displaying the top-7 highest ’diff rank’ stations per cluster

```
window_spec3=Window.partitionBy("cluster").orderBy(F.desc('diff_rank'))

top_7_diff_rank_17 = pop_rating_17_with_gen.withColumn("rank", F.row_number().over(window_spec3)) \
```

```
                                                         .filter(F.col("rank") <= 7)\
                                                             .withColumnRenamed("station_num","station_num_17th")\
                                                                 .withColumnRenamed("diff_rank","diff_rank_17th")
top_7_diff_rank_3 = pop_rating_third_with_gen.withColumn("rank", F.row_number().over(window_spec3)) \
                                                         .filter(F.col("rank") <= 7)\
                                                             .withColumnRenamed("station_num","station_num_3rd")\
                                                                 .withColumnRenamed("diff_rank","diff_rank_3rd")
top_7_diff_rank_All = pop_rating_all_with_gen.withColumn("rank", F.row_number().over(window_spec3)) \
                                                         .filter(F.col("rank") <= 7)\
                                                             .withColumnRenamed("station_num","station_num_all")\
                                                                 .withColumnRenamed("diff_rank","diff_rank_all")


joined_top_7 = top_7_diff_rank_All.join(top_7_diff_rank_17, on=["cluster","rank"], how="left")\
                                    .join(top_7_diff_rank_3, on=["cluster","rank"], how="left")
display(joined_top_7)
```

cluster	rank	station_num_all	diff_rank_all	station_num_17th	diff_rank_17th	station_num_3r
0	1	16374	0.15923312579402515	14902	0.5762356726443569	60179
0	2	60179	0.14842073350135188	11221	0.38810456264190385	74796
0	3	14902	0.1109775638740822	74796	0.3145780347246405	14902
0	4	11221	0.11008892738106513	11066	0.2611963244651673	61522
0	5	49788	0.10625692103643791	12131	0.20879228724084276	11221
0	6	61522	0.10264767102404004	12574	0.2032162580533473	31709
0	7	11069	0.08976342159548512	10335	0.19399937327147634	49788
1	1	60179	0.2722119018380882	60179	0.28318345927220134	60179
1	2	16374	0.16436943002324855	11150	0.23035366343074815	16374

Part 2 - Dynamic Data Analysis

Read Streaming viewing data from Kafka

```
topic = "viewstream"
streaming_df = spark.readStream\
                  .format("kafka")\
                  .option("kafka.bootstrap.servers", kafka_server)\
                  .option("subscribe", topic)\
                  .option("startingOffsets", "earliest")\
                  .option("failOnDataLoss",False)\
                  .option("maxOffsetsPerTrigger", OFFSETS_PER_TRIGGER )\
                  .load()\
                  .select(F.from_csv(F.decode("value", "US-ASCII"), schema=SCHEMA).alias("value")).select("value.*")


num_processed = 0
window_spec = Window.partitionBy("cluster")
window_spec2=Window.partitionBy("cluster").orderBy(F.desc('popularity_rating'))
window_spec3=Window.partitionBy("cluster").orderBy(F.desc('diff_rank'))
third_subset = spark.read.parquet('/third_subset.parquet').select('household_id','cluster')
def handle_batch(trigger_df, epoch_num):
    global num_processed
    print(f'$$$$$$$$$$$$$$$$---------{epoch_num}---------$$$$$$$$$$$$$$$$$$$$$$$')
    if num_processed == 5:
        query.stop()
        return

    batch_size = trigger_df.count()
    if batch_size == 0:
        print(f"NOTHING to process in epoch {epoch_num}")
        return

    num_processed += 1
    if num_processed != 1:
        prev_trigger = spark.read.parquet(f'/batch_{num_processed - 1}')
        acc_df = prev_trigger.union(trigger_df)
    else:
        acc_df = trigger_df
```

```
    acc_df.write.mode('overwrite').parquet(f'batch_{num_processed}')
    joined_batch = third_subset.join(acc_df, how='inner', on='household_id')

    views_per_station_third = joined_batch.groupBy("cluster", "station_num") \
        .agg(F.count("*").alias("count_over_cluster"))
    pop_rating_third = views_per_station_third.withColumn('views_per_cluster', F.sum('count_over_cluster').over(window_spec)) \
        .withColumn('popularity_rating', (F.col('count_over_cluster') / F.col('views_per_cluster')) * 100) \
        .select('cluster', 'station_num', 'popularity_rating')

    gen_pop_views_per_station = acc_df.groupBy('station_num').agg(F.count('*').alias('views_per_station'))
    gen_pop_N = gen_pop_views_per_station.agg(F.sum("views_per_station")).collect()[0][0]
    gen_pop_rating = gen_pop_views_per_station.withColumn('gen_pop_station_rating',
                                                          100 * F.col('views_per_station') / F.lit(gen_pop_N)) \
        .select('station_num', 'gen_pop_station_rating')
    pop_rating_third_with_gen=pop_rating_third.join(gen_pop_rating, on="station_num", how="inner")
    pop_rating_third_with_gen = pop_rating_third_with_gen.withColumn("diff_rank", F.col("popularity_rating")-F.col("gen_pop_station_rating")).dr
    top_7_diff_rank_3 = pop_rating_third_with_gen.withColumn("rank", F.row_number().over(window_spec3)) \
                                                            .filter(F.col("rank") <= 7)\
                                                                .withColumnRenamed("station_num","station")\
                                                                    .withColumnRenamed("diff_rank","diff_rank for third cluster")
    top_7_diff_rank_3.show(42)
```

As you can see our implementation is very naive and relies on accumulating the data and recalculating the scores each stream. we realize this is not feasible in the long run. However, in this case we're dealing with a relatively small amount of data, i.e a small amount of batches, so we chose the simple way of dealing with it. in case of a larger amount of batches, we would maintain a intemediate DataFrame that would help speed up the proccess for each batch.

```
query = streaming_df.writeStream\
                    .format('memory')\
                    .foreachBatch(handle_batch)\
                    .start()
```

Output for 5 triggers

```
$$$$$$$$$$$$$$$$---------0---------$$$$$$$$$$$$$$$$$$$$$$
+-------+-------+---------------------------+----+
|station|cluster|diff_rank for third cluster|rank|
+-------+-------+---------------------------+----+
|  32645|      0|         0.5663073526164712|   1|
|  11164|      0|          0.418875689997792|   2|
|  74796|      0|           0.35927710311327|   3|
|  10021|      0|        0.34231618458820934|   4|
|  14902|      0|        0.33247604327666147|   5|
|  60179|      0|        0.33151512475160083|   6|
|  11221|      0|        0.31047604327666145|   7|
|  32645|      1|         0.3422020444978955|   1|
|  56905|      1|        0.33798436560432965|   2|
|  19606|      1|         0.3308819402685909|   3|
|  57708|      1|        0.26349929845660464|   4|
|  11661|      1|        0.24670555221487273|   5|
|  58646|      1|          0.245852074564041|   6|
|  45507|      1|        0.23380797755061145|   7|
|  14771|      2|        0.35353958749168335|   1|
|  16615|      2|         0.3341383898868927|   2|
|  61522|      2|         0.3109367930805056|   3|
|  99995|      2|        0.30447238855622105|   4|
|  11865|      2|         0.3015355954757153|   5|
|  16409|      2|         0.2666027944111777|   6|
|  12131|      2|         0.2512707917498336|   7|
|  11118|      3|         1.8721290322580646|   1|
|  58574|      3|         1.4589354838709676|   2|
|  64490|      3|          0.872483870967742|   3|
|  10222|      3|         0.8552580645161291|   4|
|  21883|      3|         0.8248709677419355|   5|
|  59684|      3|         0.6908709677419356|   6|
|  65732|      3|         0.6580645161290323|   7|
|  10171|      4|         1.6332320217096334|   1|
|  14765|      4|         1.1799077340569877|   2|
|  35513|      4|         1.1168521031207599|   3|
|  70387|      4|         0.9808521031207599|   4|
|  11561|      4|         0.9311668928086838|   5|
|  12131|      4|         0.9160651289009496|   6|
```

```
|  44940|      4|        0.8973242876526457|   7|
|  51529|      5|        0.4568937329700271|   1|
|  10179|      5|       0.41481198910081707|   2|
|  16616|      5|        0.4079509536784741|   3|
|  64241|      5|        0.3854550408719346|   4|
|  58515|      5|       0.35193460490463213|   5|
|  21214|      5|        0.3459673024523161|   6|
|  57394|      5|       0.29095912806539503|   7|
+-------+-------+--------------------------+----+

$$$$$$$$$$$$$$$$$---------1---------$$$$$$$$$$$$$$$$$$$$$$$

+-------+-------+--------------------------+----+
|station|cluster|diff_rank for third cluster|rank|
+-------+-------+--------------------------+----+
|  32645|      0|        0.3870944282837323|   1|
|  10021|      0|       0.27774848959498777|   2|
|  16615|      0|        0.2465603043186395|   3|
|  11221|      0|       0.22899574848959492|   4|
|  14902|      0|        0.2283130454240322|   5|
|  60179|      0|       0.21658223316178127|   6|
|  58646|      0|       0.20458223316178126|   7|
|  11661|      1|        0.3249850905218318|   1|
|  11713|      1|        0.2454294704230806|   2|
|  36069|      1|       0.23083686707328877|   3|
|  60179|      1|        0.2294071062058285|   4|
|  10179|      1|        0.2283033207474101|   5|
|  20288|      1|       0.20744437990124887|   6|
|  57391|      1|        0.1956146771226644|   7|
|  10142|      2|        0.4672889561270801|   1|
|  16615|      2|       0.25376332156664994|   2|
|  10918|      2|       0.24666784333501435|   3|
|  16123|      2|        0.2420959825180703|   4|
|  10510|      2|       0.21381005210959828|   5|
|  10402|      2|       0.20861959993276186|   6|
|  10518|      2|       0.20685779122541603|   7|
|  19320|      3|        1.9479262493934983|   1|
|  11118|      3|        1.5562047549733138|   2|
|  51529|      3|        0.8561242115477924|   3|
|  58574|      3|        0.7440436681222707|   4|
|  10222|      3|        0.6678020378457059|   5|
|  10171|      3|        0.5216443474041728|   6|
|  44714|      3|        0.5107214944201844|   7|
|  10171|      4|        1.1746328469630136|   1|
|  35513|      4|        1.0305812690872072|   2|
|  14765|      4|         0.890976586359009|   3|
|  11367|      4|        0.8307828299966069|   4|
|  11207|      4|        0.7821109602986087|   5|
|  11561|      4|        0.7429172039362062|   6|
|  70387|      4|        0.7199172039362061|   7|
|  16616|      5|        0.3450229178311906|   1|
|  58623|      5|        0.3377143655673561|   2|
|  10145|      5|        0.3142001117942985|   3|
|  31042|      5|        0.3040229178311906|   4|
|  64490|      5|        0.2919200670765791|   5|
|  34432|      5|        0.2880229178311906|   6|
|  64241|      5|       0.28607434320849645|   7|
+-------+-------+--------------------------+----+

$$$$$$$$$$$$$$$$$---------2---------$$$$$$$$$$$$$$$$$$$$$$$
+-------+-------+--------------------------+----+
|station|cluster|diff_rank for third cluster|rank|
+-------+-------+--------------------------+----+
|  19320|      0|        0.3799091995221027|   1|
|  60179|      0|        0.2735507765830347|   2|
|  10021|      0|        0.2711278375149343|   3|
|  16615|      0|        0.2594050179211469|   4|
|  14902|      0|       0.25754360812425336|   5|
|  11221|      0|        0.2295244922341697|   6|
|  74796|      0|       0.18870728793309438|   7|
|  60179|      1|       0.32225142656483197|   1|
|  11661|      1|       0.26370889298569045|   2|
|  16374|      1|        0.2567790360811164|   3|
|  36069|      1|       0.24059257308401372|   4|
|  19606|      1|       0.20678166973926787|   5|
|  11713|      1|       0.19332876832587131|   6|
|  20288|      1|       0.17944833640593452|   7|
|  10142|      2|       0.31128825410994576|   1|
|  58646|      2|       0.29312817079520936|   2|
```

```
|  16615|      2|       0.28863036524585284|   3|
|  19630|      2|       0.21432894443204645|   4|
|  12131|      2|        0.2135059138585137|   5|
|  10510|      2|       0.21137960276723947|   6|
|  14767|      2|       0.19092806665178907|   7|
|  19320|      3|        1.8553516763477023|   1|
|  11118|      3|        1.2204877203709366|   2|
|  10222|      3|        0.8710557423825537|   3|
|  51529|      3|        0.8602977682665851|   4|
|  44714|      3|        0.7322922653622745|   5|
|  10171|      3|        0.6622064608172833|   6|
|  16288|      3|        0.5934338122898196|   7|
|  10171|      4|         1.362002800501142|   1|
|  70387|      4|        0.9541049450954382|   2|
|  12131|      4|        0.9329560026531064|   3|
|  35513|      4|        0.8370240990493036|   4|
|  11367|      4|        0.7549148795047534|   5|
|  11561|      4|        0.7210240990493035|   6|
|  11207|      4|        0.6546623922175547|   7|
|  58623|      5|       0.41523566407695156|   1|
|  64490|      5|        0.3755893451720311|   2|
|  16616|      5|       0.36693895671476134|   3|
|  10178|      5|       0.33759748427672964|   4|
|  34432|      5|         0.301605623381428|   5|
|  59684|      5|        0.2567621161672216|   6|
|  15591|      5|       0.24812800591934886|   7|
+-------+-------+--------------------------+----+

$$$$$$$$$$$$$$$$---------3---------$$$$$$$$$$$$$$$$$$$$$$$
+-------+-------+--------------------------+----+
|station|cluster|diff_rank for third cluster|rank|
+-------+-------+--------------------------+----+
|  19320|      0|       0.36988539000778903|   1|
|  60179|      0|       0.28408000445087356|   2|
|  11221|      0|        0.2685649827528652|   3|
|  14902|      0|       0.23705379993323683|   4|
|  10021|      0|        0.2358829420273728|   5|
|  74796|      0|       0.20975820629798603|   6|
|  16615|      0|       0.20671837098030477|   7|
|  60179|      1|       0.30413277075947476|   1|
|  36069|      1|        0.2869349378339242|   2|
|  16374|      1|        0.2503361711689218|   3|
|  20288|      1|        0.2220888051130973|   4|
|  11661|      1|       0.20663599141159433|   5|
|  11713|      1|       0.20560346032855648|   6|
|  19606|      1|        0.1881899186098767|   7|
|  16615|      2|        0.3567731162249731|   1|
|  58646|      2|        0.2526576804851708|   2|
|  12131|      2|       0.21550332308714792|   3|
|  10142|      2|       0.20227477776854674|   4|
|  57394|      2|        0.1783090471047603|   5|
|  11187|      2|        0.1709647337376422|   6|
|  10510|      2|       0.16457784331644093|   7|
|  19320|      3|        1.3211378555798685|   1|
|  11118|      3|        0.9979737417943108|   2|
|  10222|      3|        0.8634190371991246|   3|
|  51529|      3|        0.7536739606126914|   4|
|  44714|      3|        0.7119824945295404|   5|
|  10171|      3|        0.6992472647702406|   6|
|  16288|      3|        0.5916914660831509|   7|
|  10171|      4|        1.2440050093926114|   1|
|  70387|      4|         1.128089542892924|   2|
|  35513|      4|        0.9485763932373199|   3|
|  12131|      4|        0.8887874139010643|   4|
|  11207|      4|        0.7347808390732624|   5|
|  11367|      4|        0.6497980588603631|   6|
|  14765|      4|        0.6438850970569819|   7|
|  64490|      5|        0.3727543859649122|   1|
|  16616|      5|       0.36493859649122806|   2|
|  58623|      5|        0.3536052631578947|   3|
|  59684|      5|         0.324359649122807|   4|
|  10057|      5|       0.29118421052631577|   5|
|  10178|      5|        0.2739385964912281|   6|
|  34432|      5|       0.23958771929824557|   7|
+-------+-------+--------------------------+----+

$$$$$$$$$$$$$$$$---------4---------$$$$$$$$$$$$$$$$$$$$$$$
+-------+-------+--------------------------+----+
|station|cluster|diff_rank for third cluster|rank|
```

```
+-------+-------+--------------------------+----+
|  19320|      0|        0.3840301054223567|   1|
|  60179|      0|        0.3278386192785019|   2|
|  10021|      0|         0.276927165161692|   3|
|  14902|      0|        0.2748796227925805|   4|
|  74796|      0|        0.2557797251011965|   5|
|  11221|      0|       0.22047394688848354|   6|
|  16615|      0|        0.2155731862461635|   7|
|  60179|      1|        0.3235263835263835|   1|
|  16374|      1|        0.2823953667953667|   2|
|  36069|      1|       0.24643191763191763|   3|
|  11661|      1|       0.21793153153153155|   4|
|  20288|      1|       0.20790965250965254|   5|
|  19606|      1|       0.20615649935649932|   6|
|  16062|      1|        0.1867567567567568|   7|
|  16615|      2|        0.3394253944806286|   1|
|  12131|      2|        0.2542797555898745|   2|
|  11187|      2|       0.21693216947559268|   3|
|  42642|      2|       0.21160008057476665|   4|
|  58646|      2|       0.19698653058483861|   5|
|  58452|      2|       0.19184470556637345|   6|
|  16123|      2|       0.18336316390250457|   7|
|  11118|      3|        1.1786573164381184|   1|
|  19320|      3|        1.1054478042006597|   2|
|  10171|      3|        0.8935755597986459|   3|
|  10222|      3|        0.8573372678354453|   4|
|  44714|      3|        0.7786305849678875|   5|
|  51529|      3|        0.7376154139906267|   6|
|  59684|      3|        0.6636344384655442|   7|
|  70387|      4|        1.3340688845401174|   1|
|  10171|      4|        1.3061424657534242|   2|
|  35513|      4|         1.091170254403131|   3|
|  12131|      4|        0.9145925636007827|   4|
|  11207|      4|        0.6540031311154597|   5|
|  44940|      4|        0.6482880626223091|   6|
|  14765|      4|        0.6178755381604696|   7|
|  16616|      5|        0.4060841892347455|   1|
|  59684|      5|        0.3720285425328689|   2|
|  10057|      5|        0.3652563658838072|   3|
|  58623|      5|       0.32082854253286885|   4|
|  64490|      5|       0.31044697156983936|   5|
|  10178|      5|        0.2598608832453085|   6|
|  74796|      5|        0.2506052365434318|   7|
+-------+-------+--------------------------+----+
```