Project 2 - Starter Notebook

Please make sure your solution is divided into multiple code cells, explained clearly and properly, and most importantly, pretty.

In [0]:
```
from pyspark.sql.types import *
from pyspark.sql.functions import *
import os,time
from pyspark.sql import SparkSession

spark = SparkSession.builder.appName("my_project_2").getOrCreate()
```

Read Sub Demographic data

In [0]:
```
demographic_df = spark.read\
    .parquet("dbfs:/FileStore/project_b_data/proj_B_demographic/")
demographic_df.printSchema()
display(demographic_df.limit(10))
```

```
root
 |-- household_id: long (nullable = true)
 |-- household_size: integer (nullable = true)
 |-- num_adults: integer (nullable = true)
 |-- num_generations: integer (nullable = true)
 |-- marital_status: string (nullable = true)
 |-- race_code: string (nullable = true)
 |-- dwelling_type: string (nullable = true)
 |-- home_owner_status: string (nullable = true)
 |-- length_residence: integer (nullable = true)
 |-- home_market_value: double (nullable = true)
 |-- net_worth: double (nullable = true)
 |-- gender_individual: string (nullable = true)
 |-- education_highest: string (nullable = true)
```

household_id	household_size	num_adults	num_generations	marital_status
85	2	1	2	B
2073	1	1	2	M
2523	7	6	3	M
2717	3	2	2	S
3364	2	2	2	M
4046	4	3	3	M
4303	1	1	1	S
4559	3	2	2	S
5277	3	2	2	M
5440	1	1	1	S

Read Static Viewing Data

In [0]:
```
schema = StructType([
    StructField("device_id", StringType(), True),
    StructField("event_date", StringType(), True),
    StructField("event_time", StringType(), True),
    StructField("station_num", IntegerType(), True),
    StructField("prog_code", StringType(), True),
    StructField("household_id", IntegerType(), True)
])

viewing_static_df = spark.read.schema(schema)\
    .option("header", True).csv("dbfs:/FileStore/project_b_data/viewing_stat

viewing_static_df.printSchema()
display(viewing_static_df.limit(10))
```

```
root
 |-- device_id: string (nullable = true)
 |-- event_date: string (nullable = true)
 |-- event_time: string (nullable = true)
 |-- station_num: integer (nullable = true)
 |-- prog_code: string (nullable = true)
 |-- household_id: integer (nullable = true)
```

device_id	event_date	event_time	station_num	prog_code	househ
001bd74cc8d1	20150120	181338	75523	EP000009110053	3
10ea5940d694	20150120	181338	11218	MV001054110000	3
44e08ed80c35	20150120	181338	11713	SH004464010000	
0000048de4f2	20150120	181338	65626	MV000506130000	3
0000059867a7	20150120	181338	58812	EP019199930005	3
000011ff9ba9	20150120	181338	18510	EP010855880111	3
00000254e5f6	20150120	181338	35513	EP000369550087	3
000002bd8a47	20150120	181338	10035	EP013413450102	2
000003c4c597	20150120	181338	59337	MV000744670000	2
00407bba00fe	20150120	181338	14771	EP015899250028	2

Static Data Analysis (65 points)

In [0]:

```
from pyspark.ml import Pipeline
from pyspark.ml.feature import VectorAssembler\
    , StringIndexer, OneHotEncoder, MinMaxScaler
```

Feature Extraction

In [0]:

```
from pyspark.sql.functions import col
from pyspark.sql.types import IntegerType, StringType, DoubleType

numerical_cols = ['household_size', 'num_adults', 'num_generations',\
     'length_residence', 'home_market_value', 'net_worth']
categorical_cols = ['marital_status', 'race_code', 'dwelling_type',\
     'home_owner_status', 'gender_individual', 'education_highest']

indexed_col = [c + "_index" for c in categorical_cols]
onehot_cols  = [c + "_onehot" for c in categorical_cols]

assembler_stage = VectorAssembler(inputCols=numerical_cols, \
    outputCol='num_features')
scaler_stage    = MinMaxScaler(inputCol='num_features', \
    outputCol='scaled_num_features')

# אינדוקס: skip כדי שלא יווצר דלי "invalid"
indexer = [StringIndexer(inputCol=c, outputCol=i, handleInvalid="skip")
           for c, i in zip(categorical_cols, indexed_col)]

# OHE: dropLast=True (ברירת מחדל) + error כדי לא להוסיף דלי נוסף
encoder = [OneHotEncoder(inputCol=i, outputCol=o, dropLast=True,\
     handleInvalid="error")
           for i, o in zip(indexed_col, onehot_cols)]

onehot_assembler = VectorAssembler(inputCols=onehot_cols,\
```

```
    outputCol='cat_features')
final_assembler  = VectorAssembler(inputCols=\
    ['scaled_num_features', 'cat_features'], outputCol='full_features')

stages = [assembler_stage, scaler_stage] + indexer +\
     encoder + [onehot_assembler, final_assembler]

pipeline = Pipeline(stages=stages)
model = pipeline.fit(demographic_df)
result_df = model.transform(demographic_df)

# הצג 7 שורות לפי הדרישה
display(result_df.select('household_id', 'full_features').limit(7))
```

```
Downloading artifacts:   0%|          | 0/150 [00:00<?, ?it/s]
Uploading artifacts:   0%|          | 0/4 [00:00<?, ?it/s]
🏃 View run efficient-panda-238 at: https://adb-385435138940782.2.azuredatab
ricks.net/ml/experiments/30648897007770/runs/4c28426973a44a2d814551dddfc973a
0
🧪 View experiment at: https://adb-385435138940782.2.azuredatabricks.net/ml/
experiments/30648897007770
```

household_id	full_features
85	Map(vectorType -> sparse, length -> 18, indices -> List(0, 2, 3, 4, 5, 9, 12, 13, 15), values -> List(0.125, 0.5, 1.0, 0.12412412412412413, 0.05, 1.0, 1.0, 1.0, 1.0))
2073	Map(vectorType -> sparse, length -> 18, indices -> List(2, 3, 4, 5, 6, 11, 12, 13, 15), values -> List(0.5, 1.0, 0.14914914914914915, 0.1, 1.0, 1.0, 1.0, 1.0, 1.0))
2523	Map(vectorType -> dense, length -> 18, values -> List(0.75, 1.0, 1.0, 1.0, 0.09909909909909911, 0.1, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0, 1.0, 1.0, 1.0, 0.0, 1.0, 0.0))
2717	Map(vectorType -> dense, length -> 18, values -> List(0.25, 0.2, 0.5, 0.7333333333333333, 0.12412412412412413, 0.2, 0.0, 1.0, 0.0, 1.0, 0.0, 0.0, 1.0, 1.0, 1.0, 0.0, 0.0, 1.0))
3364	Map(vectorType -> dense, length -> 18, values -> List(0.125, 0.2, 0.5, 1.0, 0.09909909909909911, 0.1, 1.0, 0.0, 0.0, 1.0, 0.0, 0.0, 1.0, 1.0,

In [0]:

```
import pyspark.sql.functions as sfn
from pyspark.ml.functions import vector_to_array as v2a

# 1) Pull the vector safely (no 'col' alias anywhere)
dbg = (result_df
       .select("full_features")
       .withColumn("features_array", v2a(sfn.col("full_features"))))

# Show actual length and values for one row
row = dbg.select("features_array").limit(1).collect()[0]["features_array"]
print("Actual vector length:", len(row))
print("Vector values:", row)

# 2) Expected length (manual; no max, no risky aliases)
numerical_cols = [
    'household_size','num_adults','num_generations',
```

```
    'length_residence','home_market_value','net_worth'
]
categorical_cols = [
    'marital_status','race_code','dwelling_type',
    'home_owner_status','gender_individual','education_highest'
]

num_len = len(numerical_cols)

# distinct counts
dcnts = []
for name in categorical_cols:
    dcnts.append((name, demographic_df.select(name).distinct().count()))

# one-hot width = (count-1) if count>1 else 0
cat_len = 0
for _, d in dcnts:
    d_minus_1 = d - 1
    if d_minus_1 > 0:
        cat_len += d_minus_1

print("Distinct counts per categorical:", dcnts)
print("Expected numerical part:", num_len)
print("Expected categorical one-hot part:", cat_len)
print("Expected total vector length:", num_len + cat_len)
```

```
Actual vector length: 18
Vector values: [0.125, 0.0, 0.5, 1.0, 0.12412412412412413, 0.05, 0.0, 0.0,
0.0, 1.0, 0.0, 0.0, 1.0, 1.0, 0.0, 1.0, 0.0, 0.0]
Distinct counts per categorical: [('marital_status', 4), ('race_code', 4),
('dwelling_type', 2), ('home_owner_status', 2), ('gender_individual', 2),
('education_highest', 4)]
Expected numerical part: 6
Expected categorical one-hot part: 12
Expected total vector length: 18
```

Visual Analysis

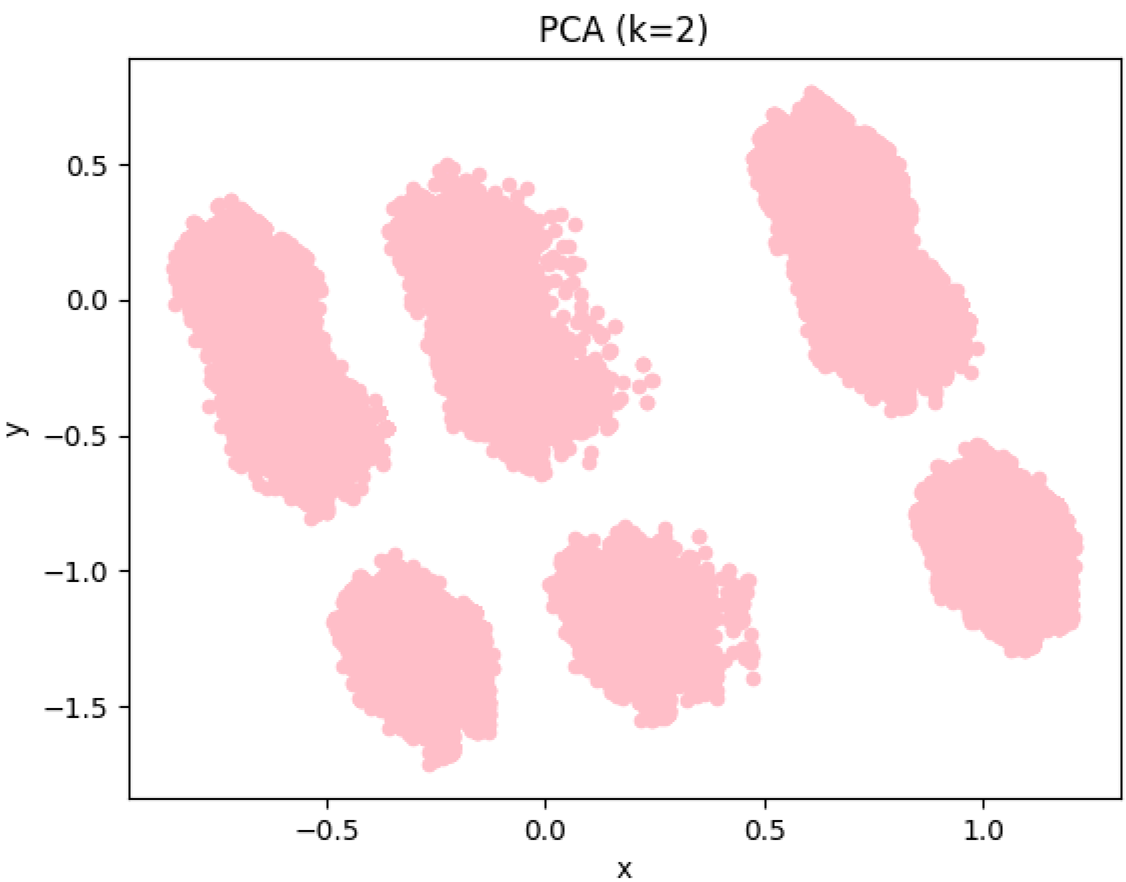
In [0]:
```
from pyspark.ml.feature import PCA
from pyspark.ml.functions import vector_to_array
from pyspark.sql import functions as F
```

In [0]:
```
# PCA על וקטור הפיצ'רים
pca = PCA(k=2, inputCol="full_features", outputCol="pca_features")
pca_model = pca.fit(result_df)
pca_result = pca_model.transform(result_df)

# הוצאת x,y ממערך ה-PCA
pca_result = (pca_result
              .withColumn("pca_arr", vector_to_array(F.col("pca_features")))
              .withColumn("x", F.col("pca_arr")[0])
              .withColumn("y", F.col("pca_arr")[1])
              .select("x", "y"))

# הצגת 7 שורות כפי שדרשו
```

```
display(pca_result.limit(7))

# סקאטר בפנדהס (אופציונלי)
pdf = pca_result.select("x","y").toPandas()
ax = pdf.plot(kind="scatter", x="x", y="y", color="pink", title="PCA (k=2)")
```

```
🏃 View run secretive-bird-812 at: https://adb-385435138940782.2.azuredatabricks.net/ml/experiments/30648897007770/runs/6cd0eab24f94476287cf5310320bdd57
🧪 View experiment at: https://adb-385435138940782.2.azuredatabricks.net/ml/experiments/30648897007770
```

x	y
0.7696161667682888	-0.14328450444325935
1.0470607429479757	-0.8077002155153579
-0.21564461720437628	-1.6496380625532248
-0.1472713333051469	-0.009878108533882997
1.0866265581511159	-1.0202633541472845
0.9640643076197327	-0.9501483206226211
0.6852258565823554	0.33186218098408143



Clustering

In [0]:

```python
from pyspark.ml.clustering import KMeans
from pyspark.ml.linalg import Vectors
from pyspark.ml.linalg import VectorUDT
from pyspark.sql.types import StructType, StructField, IntegerType
```

In [0]:

```python
from pyspark.ml.clustering import KMeans
from pyspark.ml.linalg import Vectors, VectorUDT
from pyspark.ml.functions import vector_to_array
from pyspark.sql import functions as F
from pyspark.sql.types import StructType, StructField, IntegerType

# Step 1: Rename the actual feature vector (full_features -> features)
result_data = result_df.withColumnRenamed("full_features", "features")

# Step 2: Train KMeans model (k=6, seed=3). Use predictionCol='cluster'
# 3 for clarity
km = KMeans(k=6, seed=3, featuresCol="features", predictionCol="cluster")
km_model = km.fit(result_data)
km_result = km_model.transform(result_data)  # adds 'cluster'

# Step 3: Convert cluster centers to Spark Vectors with schema
centers = [(i, Vectors.dense(vec)) for i, vec in enumerate(km_model\
    .clusterCenters())]
schema = StructType([
    StructField("cluster", IntegerType(), False),
    StructField("centroid", VectorUDT(), False)
])
center_df = spark.createDataFrame(centers, schema=schema)

# Step 4: Join cluster assignments with cluster centers (by 'cluster')
km_result = km_result.join(center_df, on="cluster", how="left")

# Step 5: Convert vectors to arrays for Spark SQL operations
km_result = (km_result
    .withColumn("features_array", vector_to_array(F.col("features")))
    .withColumn("centroid_array", vector_to_array(F.col("centroid"))))

# Step 6: Compute distance to centroid (Euclidean).
km_result = (km_result
    .withColumn("distance_sq",
                F.expr("aggregate(zip_with(features_array, centroid_array\
                    , (x, y) -> pow(x - y, 2)), 0D, (acc, z) -> acc + z)"))
    .withColumn("distance_to_centroid", F.sqrt(F.col("distance_sq")))
    .drop("features_array", "centroid_array", "distance_sq"))

# Step 7: Preview
km_result.printSchema()
display(km_result.select("household_id", "cluster", "distance_to_centroid")\
    .limit(7))
```

```
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Uploading artifacts:   0%|          | 0/4 [00:00<?, ?it/s]
```

```
🏃 View run luminous-donkey-969 at: https://adb-385435138940782.2.azuredatabricks.net/ml/experiments/30648897007770/runs/a20a2bc15fb3454da564df95d8cc3796
🧪 View experiment at: https://adb-385435138940782.2.azuredatabricks.net/ml/experiments/30648897007770
root
 |-- cluster: integer (nullable = false)
 |-- household_id: long (nullable = true)
 |-- household_size: integer (nullable = true)
 |-- num_adults: integer (nullable = true)
 |-- num_generations: integer (nullable = true)
 |-- marital_status: string (nullable = true)
 |-- race_code: string (nullable = true)
 |-- dwelling_type: string (nullable = true)
 |-- home_owner_status: string (nullable = true)
 |-- length_residence: integer (nullable = true)
 |-- home_market_value: double (nullable = true)
 |-- net_worth: double (nullable = true)
 |-- gender_individual: string (nullable = true)
 |-- education_highest: string (nullable = true)
 |-- num_features: vector (nullable = true)
 |-- scaled_num_features: vector (nullable = true)
 |-- marital_status_index: double (nullable = false)
 |-- race_code_index: double (nullable = false)
 |-- dwelling_type_index: double (nullable = false)
 |-- home_owner_status_index: double (nullable = false)
 |-- gender_individual_index: double (nullable = false)
 |-- education_highest_index: double (nullable = false)
 |-- marital_status_onehot: vector (nullable = true)
 |-- race_code_onehot: vector (nullable = true)
 |-- dwelling_type_onehot: vector (nullable = true)
 |-- home_owner_status_onehot: vector (nullable = true)
 |-- gender_individual_onehot: vector (nullable = true)
 |-- education_highest_onehot: vector (nullable = true)
 |-- cat_features: vector (nullable = true)
 |-- features: vector (nullable = true)
 |-- centroid: vector (nullable = true)
 |-- distance_to_centroid: double (nullable = true)
```

household_id	cluster	distance_to_centroid
85	1	0.9568649711438204
2073	2	0.8481485938466666
2523	0	1.3296410205779297
2717	1	1.4315091453110265
3364	5	0.58615854643112
4046	5	0.9358106506190059
4303	1	0.9705720982818974

Dividing households into subsets

In [0]:
```
from pyspark.sql.functions import col, expr, row_number
from pyspark.sql.window import Window
```

In [0]:
```
windowspec = Window.partitionBy("cluster").orderBy("distance_to_centroid")
assigned = km_result.withColumn("rank", row_number().over(windowspec))
full_subsets = {}
thirds_subsets = {}
seventeenths_subsets = {}
for i in range(6):
    full_subsets[i] = assigned.filter(col("cluster") == i)
    thirds_subsets[i] = full_subsets[i].filter(col("rank") % 3 == 0)
    seventeenths_subsets[i] = full_subsets[i].filter(col("rank") % 17 == 0)
for i in range(6):
    thirds_subsets[i] = thirds_subsets[i].cache()

display(full_subsets[4].select("household_id", "cluster", \
    "distance_to_centroid", "rank").orderBy("household_id").limit(20))

display(thirds_subsets[0].select("household_id", "rank", \
    "distance_to_centroid").orderBy("rank").limit(20))

display(seventeenths_subsets[0].select("household_id", "rank"\
    , "distance_to_centroid").orderBy("rank").limit(20))
```

household_id	cluster	distance_to_centroid	rank
828	4	1.0431279601805084	324
907	4	1.2070723215901578	4118
1000	4	1.0497595374377215	433
1043	4	1.033987174114564	179
1124	4	1.0828574619897031	1000
1143	4	1.3656220515631412	6828
1365	4	1.1175355527246138	1743
1480	4	1.1583557895242602	2956
1531	4	1.1795273576703513	3483
1628	4	1.1303754450258676	2308

household_id	rank	distance_to_centroid
3514686	3	0.7044092313106604
23167	6	0.7044092313106604
19916	9	0.7051120446118223
2164280	12	0.7053905341282163
2725436	15	0.7057182024603863
2410867	18	0.7065123836932489
2330934	21	0.7067903214482653
1969118	24	0.7067903214482653
3945526	27	0.7072564951095969
3240541	30	0.7072564951095969

household_id	rank	distance_to_centroid
1942214	17	0.7058109647851379
1587557	34	0.7092062918941878
75562	51	0.7102731458187951
2156491	68	0.7126346736912084
3665179	85	0.7129129849888168
19624	102	0.7134667194446199
2208866	119	0.7139743002200348
3236947	136	0.7141606192279557
3031763	153	0.7148052168459772
2229286	170	0.7152644128448189

Cluster’s Viewing Analysis

In [0]:

```
from pyspark.sql.functions import col, count, lit

# סופרים רק צפיות עם מספר תחנה תקין
all_count = viewing_static_df.where(col("station_num").\
  isNotNull()).count()

# שומרים על שם העמודה המקורי כדי לא לשבור קוד בהמשך
general_population = (
    viewing_static_df
      .where(col("station_num").isNotNull())
      .groupBy("station_num")
      .agg(count("*").alias("count"))
      .withColumn("genreal_precentage", (col("count") / \
        lit(all_count)) * 100)  # אחוזים
)
```

```
display(general_population.limit(20))
print(all_count)
```

station_num	count	genreal_precentage
11458	7864	0.108872122741966
11858	1777	0.02460144482610295
32414	644	0.00891577403939803
31035	2826	0.03912418856419074
11317	8777	0.12151203221086415
10817	196	0.002713496446773314
31236	863	0.011947690987578417
43714	497	0.0068806517043180455
59355	33	4.5686419767101706E-4
22223	6	8.306621775836674E-5

```
7223153
```

In [0]:

```
from pyspark.sql.functions import col, count

tmp = (
    viewing_static_df
      .where(col("station_num").isNotNull())
      .groupBy("household_id")
      .agg(count("*").alias("count"))
      .select("household_id", "count")
      .orderBy("count", ascending=False)
)

tmp.show()
```

```
+------------+-----+
|household_id|count|
+------------+-----+
|     2724124| 3388|
|     3611285| 2570|
|     2509469| 2037|
|     2901019| 1845|
|     3617223| 1797|
|     2460935| 1745|
|      408868| 1709|
|     2663349| 1636|
|     2057408| 1624|
|     3616005| 1587|
|     2903914| 1578|
|     2904998| 1478|
|     2715652| 1471|
|     2257104| 1429|
|     1471911| 1421|
|      649170| 1407|
|       45491| 1405|
|     2691943| 1388|
|     3798503| 1381|
|      404684| 1286|
+------------+-----+
only showing top 20 rows
```

In [0]:

```
from pyspark.sql.functions import col, broadcast

viewing_full = {}
viewing_thirds = {}
viewing_seventeenths = {}
viewing_counts = {"full": [], "thirds": [], "seventeenths": []}

viewing_static_df.cache()

for i in range(6):
    print(f"\nCluster {i}:")
    full_ids = (
        broadcast(
            full_subsets[i]
              .filter(col("household_id").isNotNull())
              .select("household_id")
              .distinct()
              .alias("subset")
        )
    )

    thirds_ids = (
        broadcast(
            thirds_subsets[i]
              .filter(col("household_id").isNotNull())
              .select("household_id")
              .distinct()
              .alias("subset")
        )
```

```
    )

    seventeenths_ids = (
        broadcast(
            seventeenths_subsets[i]
              .filter(col("household_id").isNotNull())
              .select("household_id")
              .distinct()
              .alias("subset")
        )
    )

    # סינון חשוב: station_num ה לפני תקין-join
    viewing_full[i] = (
        viewing_static_df
          .where(col("station_num").isNotNull())
          .alias("viewing")
          .join(full_ids, col("viewing.household_id") ==\
              col("subset.household_id"))
    )
    view_full_count = viewing_full[i].count()
    print(f"  Full subset → {full_subsets[i].count()} households")
    print(f"  Viewing rows (Full) → {view_full_count}")
    display(viewing_full[i].select("viewing.household_id", \
        "viewing.station_num").limit(5))
    viewing_counts["full"].append(view_full_count)

    viewing_thirds[i] = (
        viewing_static_df
          .where(col("station_num").isNotNull())
          .alias("viewing")
          .join(thirds_ids, col("viewing.household_id") == \
              col("subset.household_id"))
    )
    view_thirds_count = viewing_thirds[i].count()
    print(f"  Thirds subset → {thirds_subsets[i].count()} households")
    print(f"  Viewing rows (Thirds) → {view_thirds_count}")
    display(viewing_thirds[i].select("viewing.household_id",\
         "viewing.station_num").limit(5))
    viewing_counts["thirds"].append(view_thirds_count)

    viewing_seventeenths[i] = (
        viewing_static_df
          .where(col("station_num").isNotNull())
          .alias("viewing")
          .join(seventeenths_ids, col("viewing.household_id") == col("subset
    )
    view_sevenths_count = viewing_seventeenths[i].count()
    print(f"  17ths subset → {seventeenths_subsets[i].count()} households")
    print(f"  Viewing rows (17ths) → {view_sevenths_count}")
    display(viewing_seventeenths[i].select("viewing.household_id",\
         "viewing.station_num").limit(5))
    viewing_counts["seventeenths"].append(view_sevenths_count)
```

```
Cluster 0:
  Full subset → 78987 households
  Viewing rows (Full) → 1565983
```

household_id	station_num
3642303	18510
2971023	10035
3760805	21250
49895	19326
2276833	32786

```
  Thirds subset → 26329 households
  Viewing rows (Thirds) → 526001
```

household_id	station_num
3642303	18510
3760805	21250
52858	19313
3224853	31042
2744790	64244

```
  17ths subset → 4646 households
  Viewing rows (17ths) → 96688
```

household_id	station_num
1518381	32645
2715978	80619
20635	14771
2424532	21883
2673747	32677

```
Cluster 1:
  Full subset → 87383 households
  Viewing rows (Full) → 1701257
```

household_id	station_num
3787015	11218
3645541	58812
3825751	35513
2838674	14771
2679446	16752

```
  Thirds subset → 29127 households
  Viewing rows (Thirds) → 559437
```

household_id	station_num
3787015	11218
3645541	58812
1605319	49788
2054439	60468
1489172	12574

```
  17ths subset → 5140 households
  Viewing rows (17ths) → 97810
```

household_id	station_num
2054439	60468
3821486	45507
2054439	59337
2670137	42642
2116032	10325

```
Cluster 2:
  Full subset → 16545 households
  Viewing rows (Full) → 283916
```

household_id	station_num
43921	11713
2101605	18480
2029846	10568
2428475	18480
43921	11713

```
  Thirds subset → 5515 households
  Viewing rows (Thirds) → 90185
```

household_id	station_num
43921	11713
43921	11713
3601868	16046
3124313	70387
3601868	44714

```
  17ths subset → 973 households
  Viewing rows (17ths) → 19048
```

household_id	station_num
1980937	10057
2852949	65732
2289579	70225
2974452	31658
1947982	60179

```
Cluster 3:
  Full subset → 22534 households
  Viewing rows (Full) → 507936
```

household_id	station_num
3850378	47540
2327767	10537
1980391	10458
3216462	23315
2348192	14815

```
  Thirds subset → 7511 households
  Viewing rows (Thirds) → 175179
```

household_id	station_num
3216462	23315
2348192	14815
3491582	12574
2148557	12729
2788047	10162

```
  17ths subset → 1325 households
  Viewing rows (17ths) → 31641
```

household_id	station_num
3016583	44940
3016583	10918
2136400	10145
2483168	11158
3016583	44940

```
Cluster 4:
  Full subset → 12389 households
  Viewing rows (Full) → 245972
```

household_id	station_num
3672067	65626
2966025	64065
3704832	11150
3460567	99995
2084973	64490

```
  Thirds subset → 4129 households
  Viewing rows (Thirds) → 81700
```

household_id	station_num
2084973	64490
2451093	10556
2187632	10142
1965232	35312
2182981	58515

```
  17ths subset → 728 households
  Viewing rows (17ths) → 13737
```

household_id	station_num
2182981	58515
3761306	10377
3158329	18480
3516159	18480
2715058	61522

```
Cluster 5:
  Full subset → 139883 households
  Viewing rows (Full) → 2918089
```

household_id	station_num
3783713	75523
2358722	59337
2965021	48999
91472	12574
1601677	11919

```
  Thirds subset → 46627 households
  Viewing rows (Thirds) → 979441
```

household_id	station_num
2041418	24824
2802843	12510
1593610	60179
2804129	34240
3069472	35885

```
17ths subset → 8228 households
Viewing rows (17ths) → 176402
```

household_id	station_num
3783713	75523
3625465	47540
118915	16485
2983237	14321
2724596	58780

In [0]:

```
from pyspark.sql.functions import col, count, lit

full_final = {}
thirds_final = {}
seventeenths_final = {}

for i in range(6):
    print(f"\n📊 Cluster {i} — Full subset station distribution:")
    full_final[i] = (
        viewing_full[i]
          .groupBy("station_num")
          .agg(count("*").alias("count"))
          .withColumn("sub_rat", (col("count") / \
            lit(viewing_counts["full"][i])) * 100)  # אחוזים
          .orderBy(col("sub_rat").desc())
    )
    display(full_final[i].limit(5))

    print(f"📊 Cluster {i} — Thirds subset station distribution:")
    thirds_final[i] = (
        viewing_thirds[i]
          .groupBy("station_num")
          .agg(count("*").alias("count"))
          .withColumn("sub_rat", (col("count") /\
             lit(viewing_counts["thirds"][i])) * 100)  # אחוזים
          .orderBy(col("sub_rat").desc())
    )
    display(thirds_final[i].limit(5))

    print(f"📊 Cluster {i} — 17ths subset station distribution:")
    seventeenths_final[i] = (
```

```
        viewing_seventeenths[i]
          .groupBy("station_num")
          .agg(count("*").alias("count"))
          .withColumn("sub_rat", (col("count") / \
            lit(viewing_counts["seventeenths"][i])) * 100)  # אחוזים
          .orderBy(col("sub_rat").desc())
    )
    display(seventeenths_final[i].limit(5))
```

📊 Cluster 0 – Full subset station distribution:

station_num	count	sub_rat
60179	28367	1.811450060441269
16374	27062	1.7281158224578426
32645	19927	1.2724914638281513
14771	18878	1.2055047851732745
49788	18391	1.174406107856854

📊 Cluster 0 – Thirds subset station distribution:

station_num	count	sub_rat
16374	9000	1.7110233630734544
60179	8922	1.6961944939268176
32645	7466	1.4193889365229344
14771	6236	1.1855490769028956
49788	5841	1.1104541626346718

📊 Cluster 0 – 17ths subset station distribution:

station_num	count	sub_rat
16374	2248	2.3250041370180377
10142	1191	1.231797120635446
14902	1189	1.2297286116167467
32645	1142	1.1811186496773125
60179	1080	1.1169948700976338

📊 Cluster 1 – Full subset station distribution:

station_num	count	sub_rat
16374	24039	1.413014024336123
60179	20754	1.2199215050988768
14771	20403	1.1992897016735273
32645	20301	1.1932941348661608
11207	19799	1.1637865413632391

📊 Cluster 1 — Thirds subset station distribution:

station_num	count	sub_rat
16374	7496	1.3399185252316168
32645	6866	1.2273053087300267
60179	6638	1.1865500494246894
14771	6428	1.149012310590826
11207	6207	1.1095083092466176

📊 Cluster 1 — 17ths subset station distribution:

station_num	count	sub_rat
16374	1487	1.5202944484204068
12131	1383	1.4139658521623557
32645	1338	1.3679582864737756
14902	1287	1.3158163786933852
60179	1274	1.3025253041611289

📊 Cluster 2 — Full subset station distribution:

station_num	count	sub_rat
12131	6203	2.1848011383648687
10171	4639	1.6339339804730977
11207	3105	1.0936333281674862
59684	3080	1.0848279068456868
14771	3035	1.0689781484664478

📊 Cluster 2 — Thirds subset station distribution:

station_num	count	sub_rat
12131	2409	2.6711759161723125
10171	1557	1.726451183677995
32645	929	1.030104784609414
11207	924	1.024560625381161
10021	916	1.0156899706159561

📊 Cluster 2 — 17ths subset station distribution:

station_num	count	sub_rat
10171	344	1.8059638807223857
12131	325	1.7062158756824863
59684	278	1.4594708105837884
11867	232	1.2179756404871904
58515	220	1.1549769004619908

📊 Cluster 3 — Full subset station distribution:

station_num	count	sub_rat
12131	9448	1.8600768600768602
10171	8755	1.7236423486423487
10179	8682	1.7092704592704595
11207	8456	1.6647766647766646
10918	8140	1.6025641025641024

📊 Cluster 3 — Thirds subset station distribution:

station_num	count	sub_rat
10179	3170	1.809577632022103
11207	2996	1.7102506578984922
12131	2945	1.6811375792760548
35513	2847	1.625194800746648
10171	2668	1.5230136032286976

📊 Cluster 3 — 17ths subset station distribution:

station_num	count	sub_rat
10171	908	2.8696943838690308
10179	810	2.559969659618849
12131	625	1.9752852311873834
32645	523	1.6529186814576027
16615	454	1.4348471919345154

📊 Cluster 4 — Full subset station distribution:

station_num	count	sub_rat
12131	4691	1.9071276405444524
10171	3771	1.533101328606508
32645	3133	1.273722212284325
11207	2992	1.2163986144764445
10918	2952	1.2001366009139252

📊 Cluster 4 — Thirds subset station distribution:

station_num	count	sub_rat
12131	1478	1.8090575275397796
10171	1362	1.6670746634026927
11207	1242	1.5201958384332925
32645	1235	1.5116279069767442
10918	1010	1.2362301101591189

📊 Cluster 4 — 17ths subset station distribution:

station_num	count	sub_rat
10171	401	2.9191235349785254
12131	322	2.344034359758317
11207	211	1.53599767052486
11221	195	1.4195239135182356
10918	192	1.3976850840794932

📊 Cluster 5 — Full subset station distribution:

station_num	count	sub_rat
16374	48065	1.6471396177429816
60179	46390	1.5897390381170688
14771	37482	1.2844707615154987
32645	32706	1.1208020043254334
14902	32418	1.1109325315300527

📊 Cluster 5 – Thirds subset station distribution:

station_num	count	sub_rat
60179	15606	1.5933578439130076
16374	15356	1.5678330802978435
14771	12544	1.2807305391544768
11207	11073	1.130542830042851
14902	10911	1.1140027832202246

📊 Cluster 5 – 17ths subset station distribution:

station_num	count	sub_rat
16374	2726	1.545333953129783
60179	2338	1.3253817983923084
14771	2146	1.2165394950170634
11207	1941	1.1003276606841192
32645	1776	1.0067913062210179

In [0]:

```
from pyspark.sql.functions import col, coalesce

full_result = {}
thirds_result = {}
seventeenths_result = {}

for i in range(6):
    print(f"\n📊 Cluster {i} – Full subset:")
    full_result[i] = (
        full_final[i].alias("subset")
        .join(
            general_population.alias("general"),
            col("subset.station_num") == col("general.station_num"),
            how="full_outer"  # חשוב
        )
        .select(
            coalesce(col("subset.station_num"),\
                 col("general.station_num")).alias("station_num"),
            col("subset.sub_rat").alias("sub_rat"),
            col("general.genreal_precentage").alias("genreal_precentage")
```

```
        )
        .fillna({"sub_rat": 0.0, "genreal_precentage": 0.0})
        .withColumn("diff_rank", col("sub_rat") - col("genreal_precentage"))
        .select("station_num", "diff_rank")
        .orderBy(col("diff_rank").desc())
    )
    display(full_result[i].limit(7))  # 7 לפי הדרישה - הטופ

    print(f"📊 Cluster {i} – Thirds subset:")
    thirds_result[i] = (
        thirds_final[i].alias("subset")
        .join(
            general_population.alias("general"),
            col("subset.station_num") == col("general.station_num"),
            how="full_outer"
        )
        .select(
            coalesce(col("subset.station_num"), \
                col("general.station_num")).alias("station_num"),
            col("subset.sub_rat").alias("sub_rat"),
            col("general.genreal_precentage").alias("genreal_precentage")
        )
        .fillna({"sub_rat": 0.0, "genreal_precentage": 0.0})
        .withColumn("diff_rank", col("sub_rat") - col("genreal_precentage"))
        .select("station_num", "diff_rank")
        .orderBy(col("diff_rank").desc())
    )
    display(thirds_result[i].limit(7))

    print(f"📊 Cluster {i} – 17ths subset:")
    seventeenths_result[i] = (
        seventeenths_final[i].alias("subset")
        .join(
            general_population.alias("general"),
            col("subset.station_num") == col("general.station_num"),
            how="full_outer"
        )
        .select(
            coalesce(col("subset.station_num"), \
                col("general.station_num")).alias("station_num"),
            col("subset.sub_rat").alias("sub_rat"),
            col("general.genreal_precentage").alias("genreal_precentage")
        )
        .fillna({"sub_rat": 0.0, "genreal_precentage": 0.0})
        .withColumn("diff_rank", col("sub_rat") - col("genreal_precentage"))
        .select("station_num", "diff_rank")
        .orderBy(col("diff_rank").desc())
    )
    display(seventeenths_result[i].limit(7))
```

📊 Cluster 0 – Full subset:

station_num	diff_rank
60179	0.3920006870166719
16374	0.22730308873892513
49788	0.2045526380494167
32645	0.1001779326043215
10335	0.08745533979025041
50747	0.08060981371936737
61854	0.07566834124361119

📊 Cluster 0 – Thirds subset:

station_num	diff_rank
16374	0.256218146450512
60179	0.22104180434882914
32645	0.1735014006869462
45507	0.1097926770565591
49788	0.10752090780781431
11865	0.09379017355144018
11069	0.0891289484237503

📊 Cluster 0 – 17ths subset:

station_num	diff_rank
16374	0.33292051135803113
35070	0.19492094633199625
11069	0.1932363748678282
49788	0.18334030811743451
61522	0.1804327586777299
59684	0.17904090797268046
30754	0.1670806972293202

📊 Cluster 1 – Full subset:

station_num	diff_rank
74796	0.09908511426226463
16615	0.07821507285923013
58515	0.0729052049584783
15433	0.06216254750469358
11867	0.05490510429148865
10145	0.05024015654787872
18151	0.045981363105474835

📊 Cluster 1 — Thirds subset:

station_num	diff_rank
74796	0.1392865993066058
16615	0.11075668989285414
11867	0.1096502217405041
35859	0.10889860721950724
15433	0.10125561152544815
10145	0.09221123263989317
58515	0.08846224323634289

📊 Cluster 1 — 17ths subset:

station_num	diff_rank
12574	0.42009922429903135
16374	0.36913921393469673
14902	0.32957228735556776
11158	0.2609606369274394
16615	0.2540155817987787
16123	0.2534212311635268
10057	0.25319885004926873

📊 Cluster 2 — Full subset:

station_num	diff_rank
12131	1.0873718024502066
11118	0.7932517659986893
10222	0.732710780236983
10171	0.6282651264421779
59684	0.49541771437156923
44714	0.3917355689600071
21883	0.3498073553587867

📊 Cluster 2 — Thirds subset:

station_num	diff_rank
12131	1.5737465802576505
10222	0.7723033249399333
11118	0.7675798303462545
10171	0.7207823296470752
21883	0.5843193660815698
17927	0.4054949480904666
10153	0.3403690111704121

📊 Cluster 2 — 17ths subset:

station_num	diff_rank
10222	0.8519435073760694
59684	0.7493130330613718
11118	0.6866909314085933
44714	0.5983916698508663
10171	0.5745495416011677
10239	0.545472181112538
14968	0.5122555590674094

📊 Cluster 3 — Full subset:

station_num	diff_rank
35513	1.240484333024132
70387	0.9286958286186878
11706	0.8767181790254264
10918	0.8436296040147847
10179	0.7654444043606439
12131	0.7626475241621982
10171	0.7179734946114289

📊 Cluster 3 — Thirds subset:

station_num	diff_rank
35513	1.3144994575911204
11706	0.9622786500344955
10179	0.8657515771122875
70387	0.7954536704334713
10918	0.7349660260569423
16615	0.6604763228512717
11164	0.6154874482562301

📊 Cluster 3 — 17ths subset:

station_num	diff_rank
10179	1.5940204101197344
10171	1.1307996520213544
11706	0.8654456506864336
35513	0.7701807353501917
10559	0.6934717557767988
12131	0.6850680567088328
11809	0.640488085647964

📊 Cluster 4 — Full subset:

station_num	diff_rank
12131	0.8096983046297903
10171	0.5274324745755883
70387	0.480288515812175
10918	0.44120210236460744
11706	0.3840230810500525
35513	0.38084678359058927
10642	0.36311743823346204

📊 Cluster 4 – Thirds subset:

station_num	diff_rank
12131	0.7116281916251175
10171	0.661405809371773
11809	0.5424399749916053
10642	0.523644730340886
11706	0.518470402784994
70387	0.49605184089514076
10918	0.47729561160980116

📊 Cluster 4 – 17ths subset:

station_num	diff_rank
10171	1.2073325290949448
12131	1.1665293159016008
35513	0.9850752035431527
10642	0.9316990260724951
10918	0.8061816112271983
14767	0.6493799613609541
70387	0.6182714108564235

📊 Cluster 5 – Full subset:

station_num	diff_rank
60179	0.17028966469247164
16374	0.14632688402406413
19606	0.10247038444002322
11713	0.09290124219643248
14771	0.08079973308788535
11661	0.0792271519320012
57708	0.06647335945716687

📊 Cluster 5 — Thirds subset:

station_num	diff_rank
60179	0.1739084704884104
19606	0.09859784122661984
11661	0.09046155511766307
11954	0.08788048485578892
30754	0.08519435587452426
14771	0.07705951072686346
11765	0.07349965224943972

📊 Cluster 5 — 17ths subset:

station_num	diff_rank
16374	0.28884951500842115
60179	0.2477652840055906
18544	0.14507241822226394
31258	0.13235024132470305
19630	0.13088946082804936
20290	0.11982721060094331
10139	0.11142573987957238

Dynamic Data Analysis - Streaming (35 points)

In [0]:
```
SCHEMA = "device_id STRING, event_date INT, event_time INT, \
    station_num STRING, prog_code STRING, household_id STRING"
kafka_server = "kafka.eastus.cloudapp.azure.com:29092"
topic = "view_data"
OFFSETS_PER_TRIGGER = 50000
```

```python
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(from_csv(decode("value", "US-ASCII")\
                      , schema=SCHEMA).alias("value")).select("value.*")
```

In [0]:

```python
batch_counter = 0
query_handle = None
all_batches_df = spark.createDataFrame([], schema=streaming_df.schema)
```

In [0]:

```python
def process_batch(batch_df, batch_id):
    print("Batch Triggered!")
    global batch_counter, query_handle, all_batches_df
    batch_counter += 1
    print(f"\n=== Processing Batch {batch_counter}\
     (Kafka batch_id: {batch_id}) ===")

    # איחוד באצ'ים בצורה בטוחה לסכמה
    all_batches_df = all_batches_df.unionByName\
        (batch_df, allowMissingColumns=True)

    # כלל האוכלוסייה המצטברת: סינון + אחוזים
    filtered_df = all_batches_df.where(col("station_num").isNotNull())
    full_count  = filtered_df.count()
    filtered_df = (filtered_df
                   .groupBy("station_num").agg(count("*").alias("count"))
                   .withColumn("general_rating", (col("count") \
                       / full_count) * 100))

    dynamic_viewing = {}
    viewing_counts = []

    for i in range(6):
        thirds_ids = broadcast(
            thirds_subsets[i]
              .filter(col("household_id").isNotNull())
              .select("household_id")
        )

        dynamic_viewing[i] = (
            all_batches_df.where(col("station_num").isNotNull())\
                .alias("viewing")
            .join(thirds_ids.alias("subset"),
                  col("viewing.household_id") == col("subset.household_id"))
        )

        view_thirds_count = dynamic_viewing[i].count()
        viewing_counts.append(view_thirds_count)

        if view_thirds_count == 0:
```

```
            print(f"Cluster {i}, Batch {batch_counter}\
                 → No matching 3rds rows.")
            continue

        dynamic_viewing[i] = (dynamic_viewing[i]
            .groupBy("station_num").agg(count("*").alias("count"))
            .withColumn("sub_rat", (col("count") / \
                view_thirds_count) * 100))

        joined = (dynamic_viewing[i]
            .join(filtered_df.select("station_num", \
                "general_rating"), on="station_num")
            .withColumn("diff_rank", col("sub_rat") - \
                col("general_rating"))
            .select("station_num", "diff_rank")
            .orderBy(col("diff_rank").desc()))

        print(f"Top 7 stations for Cluster {i}, Batch {batch_counter}")
        joined.select("station_num","diff_rank").show(7, truncate=False)
        joined.limit(7).createOrReplaceTempView\
            (f"top7_cluster_{i}_batch_{batch_counter}")

    if batch_counter >= 3:
        print("Stopping stream after 3 batches.")
        query_handle.stop()

query_handle = (streaming_df.writeStream
    .foreachBatch(process_batch)
    .outputMode("append")
    .start())
```

In [0]:

```
from IPython.display import display, Markdown
from pyspark.sql.functions import col

total_batches = 3
total_clusters = 6

for batch_no in range(1, total_batches + 1):  # 1..3
    for cluster_id in range(total_clusters):
        view_name = f"top7_cluster_{cluster_id}_batch_{batch_no}"
        try:
            df = spark.sql(f"SELECT * FROM {view_name}")
            display(Markdown(f"### 📊 Cluster {cluster_id} \
                — Batch {batch_no}"))
            df.show(7, truncate=False)
        except Exception as e:
            print(f"❌ Could not load {view_name}: {e}")
```

📊 Cluster 0 — Batch 1

station_num	diff_rank
11150	0.7932529550827423
32645	0.7336926713947989
11164	0.4609314420803782
10021	0.4296264775413712
11913	0.31636406619385343
31709	0.31011820330969264
11187	0.30615130023640647

📊 Cluster 1 — Batch 1

station_num	diff_rank
14771	0.5273573291601461
10145	0.5229452269170578
15433	0.44296713615023475
18001	0.3759780907668232
34215	0.32581324986958793
12131	0.28412102243088144
11069	0.27573082942097027

📊 Cluster 2 — Batch 1

station_num	diff_rank
32645	2.4915675675675675
10918	1.7647027027027027
18480	1.493945945945946
59684	1.419027027027027
10179	1.3056216216216219
12510	1.1233513513513513
10830	1.0644324324324324

📊 Cluster 3 — Batch 1

station_num	diff_rank
10918	1.9762381348875937
10171	1.6509741881765196
10021	1.5655986677768525
70387	1.563070774354704
10057	1.4695986677768524
10179	1.4315020815986677
14909	1.2187510407993338

📊 Cluster 4 — Batch 1

station_num	diff_rank
11221	1.6858620689655173
49788	1.6686206896551725
10918	1.6482068965517243
56905	1.2669655172413794
16300	1.1357241379310345
11809	1.026896551724138
10162	0.9404827586206898

📊 Cluster 5 — Batch 1

station_num	diff_rank
11713	0.6569836801916453
11661	0.39094744722263813
31709	0.3337535559215451
16331	0.32986435095074107
16616	0.28169815840694706
57708	0.24850426710585416
11069	0.23705824225183414

📊 Cluster 0 — Batch 2

station_num	diff_rank
11150	0.7131325673884226
32645	0.5270231256444249
14321	0.3364579466784504
49788	0.2940521431727796
10549	0.28851303579319487
11865	0.28729636176167334
66268	0.2849717189571366

📊 Cluster 1 — Batch 2

```
+-----------+-------------------+
|station_num|diff_rank          |
+-----------+-------------------+
|10145      |0.37380066958537217|
|18480      |0.28711820757146544|
|10563      |0.25279268606747357|
|14771      |0.23491089363893902|
|11069      |0.23394231264486226|
|11765      |0.22457223796033998|
|87317      |0.22229925315477725|
+-----------+-------------------+
```

📊 Cluster 2 — Batch 2

```
+-----------+------------------+
|station_num|diff_rank         |
+-----------+------------------+
|32645      |2.0425157232704403|
|10918      |1.536490566037736 |
|59684      |1.4450251572327042|
|66379      |1.1283270440251574|
|12131      |1.0800251572327042|
|59337      |0.9820943396226417|
|18480      |0.9323270440251573|
+-----------+------------------+
```

📊 Cluster 3 — Batch 2

```
+-----------+------------------+
|station_num|diff_rank         |
+-----------+------------------+
|10918      |1.6111870761866771|
|10021      |1.5037455125648185|
|10171      |1.4878520143597926|
|70387      |1.3311974471479857|
|10057      |1.2399740725967292|
|10179      |1.174516952532908 |
|14909      |1.08320263262864  |
+-----------+------------------+
```

📊 Cluster 4 — Batch 2

```
+-----------+------------------+
|station_num|diff_rank         |
+-----------+------------------+
|49788      |1.641506276150628 |
|56905      |1.2860502092050208|
|10918      |1.2700502092050208|
|45980      |1.0695481171548116|
|51529      |0.916276150627615 |
|10162      |0.90418410041841  |
|11221      |0.8861422594142256|
+-----------+------------------+
```

📊 Cluster 5 — Batch 2

```
+-----------+-------------------+
|station_num|diff_rank          |
+-----------+-------------------+
|11713      |0.43602653726590357|
|31709      |0.297730229736902  |
|16616      |0.2606406095989083 |
|11661      |0.24735757070285846|
|57708      |0.22187929335051937|
|11867      |0.21172931988778532|
|16331      |0.20050663431647586|
+-----------+-------------------+
```

📊 Cluster 0 — Batch 3

```
+-----------+-------------------+
|station_num|diff_rank          |
+-----------+-------------------+
|11150      |0.6079760997688124 |
|32645      |0.5312878121845594 |
|31709      |0.3435068216599916 |
|14321      |0.3341262739734947 |
|66268      |0.28229351046856177|
|49788      |0.24593116472925014|
|58812      |0.24321956302302095|
+-----------+-------------------+
```

📊 Cluster 1 — Batch 3

```
+-----------+-------------------+
|station_num|diff_rank          |
+-----------+-------------------+
|10145      |0.29007353981049366|
|11187      |0.25601301088954886|
|11344      |0.24665337293169276|
|15433      |0.23440220619431473|
|34215      |0.23342016687880074|
|11069      |0.22615669636543628|
|18480      |0.22483467684910197|
+-----------+-------------------+
```

📊 Cluster 2 — Batch 3

```
+-----------+------------------+
|station_num|diff_rank         |
+-----------+------------------+
|10918      |1.3849535309184047|
|59684      |1.2980812294182216|
|32645      |1.2064178558360776|
|10222      |1.0685795828759603|
|12131      |1.0538507135016464|
|66379      |0.9747852177094769|
|59337      |0.9494518843761435|
+-----------+------------------+
```

📊 Cluster 3 — Batch 3

```
+-----------+------------------+
|station_num|diff_rank         |
+-----------+------------------+
|10918      |1.4057335493743812|
|10171      |1.3224310018903596|
|10021      |1.2837130254748401|
|70387      |1.232318120442884 |
|11164      |1.1653950850661623|
|10057      |1.089641191826447 |
|10559      |1.056615536952021 |
+-----------+------------------+
```

📊 Cluster 4 — Batch 3

```
+-----------+------------------+
|station_num|diff_rank         |
+-----------+------------------+
|49788      |1.492320030846347 |
|56905      |1.1892843647580489|
|10918      |0.9766034316560633|
|45980      |0.8792272990167727|
|11221      |0.809312897628687 |
|51529      |0.8055820320030845|
|32645      |0.8051783304414886|
+-----------+------------------+
```

📊 Cluster 5 — Batch 3

```
+-----------+-------------------+
|station_num|diff_rank          |
+-----------+-------------------+
|11713      |0.34143917477277697|
|31709      |0.30198299816877516|
|16616      |0.2160614216353342 |
|57708      |0.21120891084118742|
|11867      |0.20156188364161753|
|19630      |0.16925833711338478|
|14902      |0.16892250054600744|
+-----------+-------------------+
```