Spotify Data Analysis

- Bigdata project

EGCO 466 Big Data Processing

Spotify-Data

Sample of data

	A	B	C	D	E	F	G	H	I	J
1	id	name	artists	duration_ms	release_date	year	acousticness	danceability	energy	instrumentalness
2	6KbQ3uYMLKb5	Singende Bataill	['Carl Woitschacl	158648	1928	1928	0.995	0.708	0.195	0.563
3	6KuQTIu1KoTTk	Fantasiestücke,	['Robert Schuma	282133	1928	1928	0.994	0.379	0.0135	0.901
4	6L63VW0PibdM	Chapter 1.18 - Z	['Seweryn Goszc	104300	1928	1928	0.604	0.749	0.22	0
5	6M94FkXd15sO.	Bebamos Juntos	['Francisco Cana	180760	9/25/28	1928	0.995	0.781	0.13	0.887
6	6N6tiFZ9vLTSOI	Polonaise-Fanta	['Frédéric Chopir	687733	1928	1928	0.99	0.21	0.204	0.908
7	6NxAf7M8DNHC	Scherzo a capric	['Felix Mendelss	352600	1928	1928	0.995	0.424	0.12	0.911
8	6O0puPuyrxPjD	Valse oubliée Nc	['Franz Liszt', 'Vl	136627	1928	1928	0.956	0.444	0.197	0.435
9	6OJjveoYwJdlt7	Per aspera ad as	['Carl Woitschacl	153967	1928	1928	0.988	0.555	0.421	0.836
10	6OaJ8Bh7lsBeY	Moneda Corrient	['Francisco Cana	162493	10/3/28	1928	0.995	0.683	0.207	0.206
11	6PrZexNb16cab.	Chapter 1.3 - Za	['Seweryn Goszc	111600	1928	1928	0.846	0.674	0.205	0
12	6QBInZBkQNIQ	Piano Sonata Nc	['Sergei Rachma	590293	1928	1928	0.994	0.376	0.0719	0.883
13	6QIONtzbQCbnr	Piano Sonata Nc	['Frédéric Chopir	85133	1928	1928	0.989	0.17	0.0823	0.911
14	6QgdUySTRGVI	Piano Sonata in	['Samuel Barber'	338333	1928	1928	0.99	0.359	0.0435	0.899

Data Cleansing

```
df.count()
```

```
169909
```

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

null_counts = df.select([sum(col(c).isNull().cast("int")).alias(c) for c in df.columns])
null_counts.show()
```

```
df = df.dropna()
```

```
#No. of column after drop null
df.count()
```

```
168462
```

Extract artist name

```
from pyspark.sql.functions import split, regexp_replace, explode


df_exploded = df.withColumn("artist_array", split(regexp_replace("artists", r"[\[\]']", ""), ", "))
df_exploded = df_exploded.withColumn("artist", explode("artist_array"))
```

```
df_exploded.select("artist_array", "artist").show()
```

```
+--------------------+-------------------+
|        artist_array|             artist|
+--------------------+-------------------+
|    [Carl Woitschach]|     Carl Woitschach|
|[Robert Schumann,...|     Robert Schumann|
|[Robert Schumann,...|   Vladimir Horowitz|
|[Seweryn Goszczyń...|Seweryn Goszczyński|
|   [Francisco Canaro]|    Francisco Canaro|
|[Frédéric Chopin,...|     Frédéric Chopin|
|[Frédéric Chopin,...|   Vladimir Horowitz|
|[Felix Mendelssoh...|  Felix Mendelssohn|
|[Felix Mendelssoh...|   Vladimir Horowitz|
|[Franz Liszt, Vla...|         Franz Liszt|
|[Franz Liszt, Vla...|   Vladimir Horowitz|
|    [Carl Woitschach]|     Carl Woitschach|
|[Francisco Canaro...|    Francisco Canaro|
|[Francisco Canaro...|              Charlo|
|[Seweryn Goszczyń...|Seweryn Goszczyński|
|[Sergei Rachmanin...|Sergei Rachmaninoff|
|[Sergei Rachmanin...|   Vladimir Horowitz|
|[Frédéric Chopin,...|     Frédéric Chopin|
|[Frédéric Chopin,...|   Vladimir Horowitz|
|[Samuel Barber, V...|       Samuel Barber|
+--------------------+-------------------+
only showing top 20 rows
```

Explore Data

```
#Top 20 artist by number of song
from pyspark.sql.functions import desc
df_exploded.groupBy('artist').count().orderBy(desc('count')).show()
```

```
+--------------------+-----+
|              artist|count|
+--------------------+-----+
|    Francisco Canaro| 2234|
|    Эрнест Хемингуэй| 1215|
|     Frédéric Chopin| 1033|
|Ludwig van Beethoven|  935|
|Wolfgang Amadeus ...|  904|
|Johann Sebastian ...|  838|
|   Эрих Мария Ремарк|  781|
|       Frank Sinatra|  732|
|      Billie Holiday|  680|
|    Arturo Toscanini|  628|
|     Igor Stravinsky|  623|
|     Ignacio Corsini|  620|
|   Vladimir Horowitz|  612|
|         Johnny Cash|  589|
|New York Philharm...|  556|
|           Bob Dylan|  553|
|  The Rolling Stones|  522|
|      The Beach Boys|  503|
|     Lata Mangeshkar|  502|
|       Elvis Presley|  501|
+--------------------+-----+
only showing top 20 rows
```

```
#Top 20 year with highest song
df.groupBy('year').count().orderBy(desc('count')).show()
```

```
+----+-----+
|year|count|
+----+-----+
|1973| 2000|
|1978| 1999|
|1976| 1999|
|2017| 1999|
|1977| 1998|
|2018| 1998|
|1988| 1998|
|1979| 1998|
|2019| 1998|
|1982| 1998|
|1970| 1998|
|1987| 1998|
|2005| 1998|
|1984| 1998|
|2010| 1998|
|1975| 1997|
|2006| 1997|
|1992| 1997|
|1969| 1997|
|1965| 1997|
+----+-----+
only showing top 20 rows
```

```
# Top 20 years with least song
df.groupBy('year').count().orderBy('count').show()
```

```
+----+-----+
|year|count|
+----+-----+
|1922|   72|
|1921|  128|
|1923|  168|
|1924|  237|
|1925|  262|
|1932|  478|
|1934|  550|
|1938|  576|
|1927|  594|
|1931|  595|
|1937|  596|
|1933|  622|
|1943|  628|
|1944|  769|
|1926|  874|
|1929|  924|
|1941|  956|
|1939|  999|
|1936| 1046|
|1928| 1182|
+----+-----+
only showing top 20 rows
```

Explore Data

```
# Number of artist
df_exploded.select("artist").distinct().count()
```

```
27389
```

```
# Average songs of each artist
from pyspark.sql.functions import count, avg
artist_song_counts = df_exploded.groupBy("artist").agg(count("id").alias("num_songs"))
artist_song_counts.agg(avg("num_songs")).show()
```

```
+-----------------+
|   avg(num_songs)|
+-----------------+
|8.036730074117346|
+-----------------+
```

```
# Average songs over the year
year_song_counts = df.groupBy("year").agg(count("name").alias("num_songs"))
year_song_counts.agg(avg("num_songs")).show()
```

```
+--------------+
|avg(num_songs)|
+--------------+
|       1684.62|
+--------------+
```

```
# Total song
df.count()
```

```
168462
```

```
# Song release in recent years
df.groupBy('year').count().orderBy(desc('year')).show()
```

```
+----+-----+
|year|count|
+----+-----+
|2020| 1752|
|2019| 1998|
|2018| 1998|
|2017| 1999|
|2016| 1963|
|2015| 1929|
|2014| 1996|
|2013| 1995|
|2012| 1997|
|2011| 1993|
|2010| 1998|
|2009| 1991|
|2008| 1993|
|2007| 1981|
|2006| 1997|
|2005| 1998|
|2004| 1989|
|2003| 1994|
|2002| 1990|
|2001| 1992|
+----+-----+
only showing top 20 rows
```

Regression

Attribute Selection

```
[ ] df_select = df.select('year','acousticness','danceability','energy','instrumentalness','liveness','loudness','speechiness','tempo','valence','mode','key','explicit','duration_ms','popularity')
```

```
[ ] #Check correlation
    features = df_select.columns[:-1]

    for col in features:
        corr = df.stat.corr(col, "popularity")
        print(f"Correlation between {col} and popularity: {corr:.4f}")
```

```
Correlation between year and popularity: 0.8801
Correlation between acousticness and popularity: -0.5897
Correlation between danceability and popularity: 0.2142
Correlation between energy and popularity: 0.4937
Correlation between instrumentalness and popularity: -0.3030
Correlation between liveness and popularity: -0.0739
Correlation between loudness and popularity: 0.4637
Correlation between speechiness and popularity: -0.1375
Correlation between tempo and popularity: 0.1318
Correlation between valence and popularity: -0.0011
Correlation between mode and popularity: -0.0325
Correlation between key and popularity: 0.0099
Correlation between explicit and popularity: 0.2127
Correlation between duration_ms and popularity: 0.0650
```

Regression

```
[ ] df_select = df.select('year','acousticness','danceability','energy','instrumentalness','loudness','tempo','explicit','popularity')
```

```
[ ] featureColumns = df_select.columns[:-1]
```

```
featureColumns
```

```
['year',
 'acousticness',
 'danceability',
 'energy',
 'instrumentalness',
 'loudness',
 'tempo',
 'explicit']
```

```
[ ] (trainData, testData) = df_select.randomSplit([0.8,0.2], seed = 13234 )
```

```
[ ] assembler = VectorAssembler(inputCols=featureColumns, outputCol="features")
    scaler = StandardScaler(inputCol = 'features',outputCol='scaledFeatures',withStd=True,withMean=False)
```

```
[ ] lr = LinearRegression(featuresCol="scaledFeatures", labelCol="popularity")
```

Regression

```
[ ] from pyspark.ml import Pipeline
    pipeline = Pipeline(stages=[assembler,scaler,lr])
```

```
[ ] from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
    paramGrid = ParamGridBuilder() \
        .addGrid(lr.fitIntercept, [False, True]) \
        .addGrid(lr.maxIter, [5, 10, 20]) \
        .build()
```

```
[ ] from pyspark.ml.evaluation import RegressionEvaluator
    crossval = CrossValidator(estimator=pipeline,
                              estimatorParamMaps=paramGrid,
                              evaluator=RegressionEvaluator(labelCol="popularity", metricName="rmse"),
                              numFolds=5)
    cvModel = crossval.fit(trainData)
```

```
[ ] predictions =  cvModel.transform(testData)
```

```
[ ] rmse_evaluator = RegressionEvaluator(labelCol="popularity", metricName="rmse")
    r2_evaluator = RegressionEvaluator(labelCol="popularity", metricName="r2")
    rmse = rmse_evaluator.evaluate(predictions)
    r2 = r2_evaluator.evaluate(predictions)

    # Print the results
    print(f"Root Mean Squared Error (RMSE): {rmse}")
    print(f"R-squared (R2): {r2}")
```

```
Root Mean Squared Error (RMSE): 10.040384945080456
R-squared (R2): 0.7813629999625085
```

Classification

Attribute Selection

```
df_select = df.select('year','acousticness','danceability','energy','instrumentalness','liveness','loudness','speechiness','tempo','valence','key','duration_ms','popularity','mode','explicit')
features = df_select.columns[:-1]

for col in features:
    corr = df.stat.corr(col, "explicit")
    print(f"Correlation between {col} and explicit: {corr:.4f}")
```

```
Correlation between year and explicit: 0.2440
Correlation between acousticness and explicit: -0.2524
Correlation between danceability and explicit: 0.2410
Correlation between energy and explicit: 0.1410
Correlation between instrumentalness and explicit: -0.1387
Correlation between liveness and explicit: 0.0401
Correlation between loudness and explicit: 0.1513
Correlation between speechiness and explicit: 0.4141
Correlation between tempo and explicit: 0.0105
Correlation between valence and explicit: -0.0251
Correlation between key and explicit: 0.0086
Correlation between duration_ms and explicit: -0.0443
Correlation between popularity and explicit: 0.2127
Correlation between mode and explicit: -0.0832
```

Classification

```
[ ] df_select = df.select('year','acousticness','danceability','energy','instrumentalness','loudness','speechiness','popularity','explicit')

[ ] featureColumns = df_select.columns[:-1]

[ ] featureColumns

    ['year',
     'acousticness',
     'danceability',
     'energy',
     'instrumentalness',
     'loudness',
     'speechiness',
     'popularity']

[ ] (trainData, testData) = df_select.randomSplit([0.8,0.2], seed = 13234 )

[ ] assembler = VectorAssembler(inputCols=featureColumns, outputCol="features")
    scaler = StandardScaler(inputCol = 'features',outputCol='scaledFeatures',withStd=True,withMean=False)

[ ] lr = LogisticRegression(featuresCol="scaledFeatures", labelCol="explicit")
```

Classification

```
[ ]  from pyspark.ml import Pipeline
     pipeline = Pipeline(stages=[assembler,scaler,lr])
```

```
[ ]  paramGrid = ParamGridBuilder() \
         .addGrid(lr.fitIntercept, [False, True]) \
         .addGrid(lr.maxIter, [5, 10,20]) \
         .build()
```

```
[ ]  from pyspark.ml.evaluation import MulticlassClassificationEvaluator
     crossval = CrossValidator(estimator=pipeline,
                               estimatorParamMaps=paramGrid,
                               evaluator = MulticlassClassificationEvaluator(labelCol="explicit", predictionCol="prediction", metricName="accuracy"),
                               numFolds=5)
     cvModel = crossval.fit(trainData)
```

```
[ ]  predictions = cvModel.transform(testData)
```

Classification

```
[ ] def evaluate(result):
        predictionAndLabels = result.select("prediction", "explicit")
        metrics = ["f1", "precisionByLabel", "recallByLabel", "weightedPrecision", "weightedRecall", "accuracy"]
        for m in metrics:
            evaluator = MulticlassClassificationEvaluator(labelCol="explicit", predictionCol="prediction", metricName=m)
            print(f"{m}: {evaluator.evaluate(predictionAndLabels):.4f}")
```

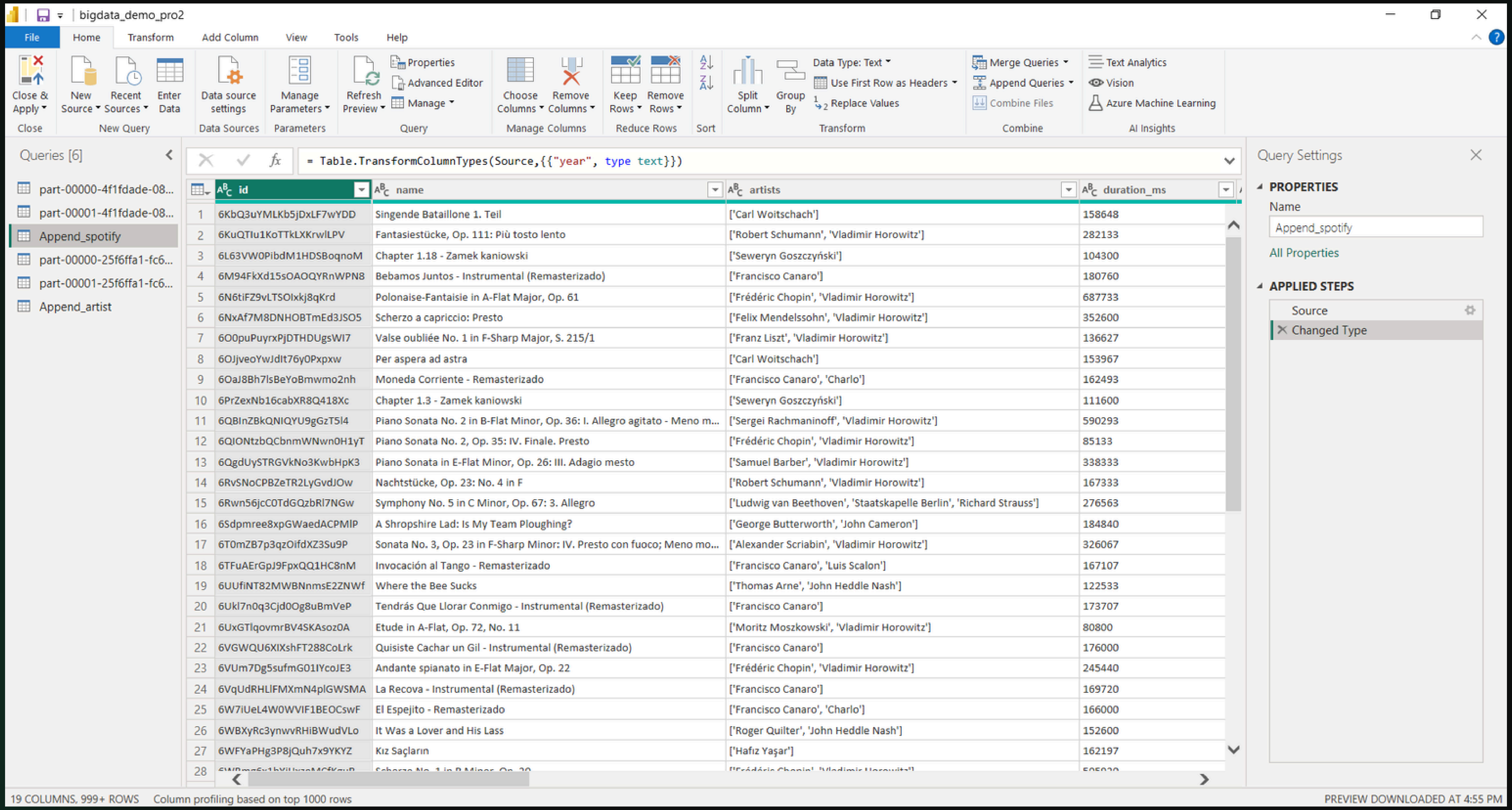
```
[ ] evaluate(predictions)
```

```
f1: 0.9334
precisionByLabel: 0.9522
recallByLabel: 0.9834
weightedPrecision: 0.9325
weightedRecall: 0.9395
accuracy: 0.9395
```

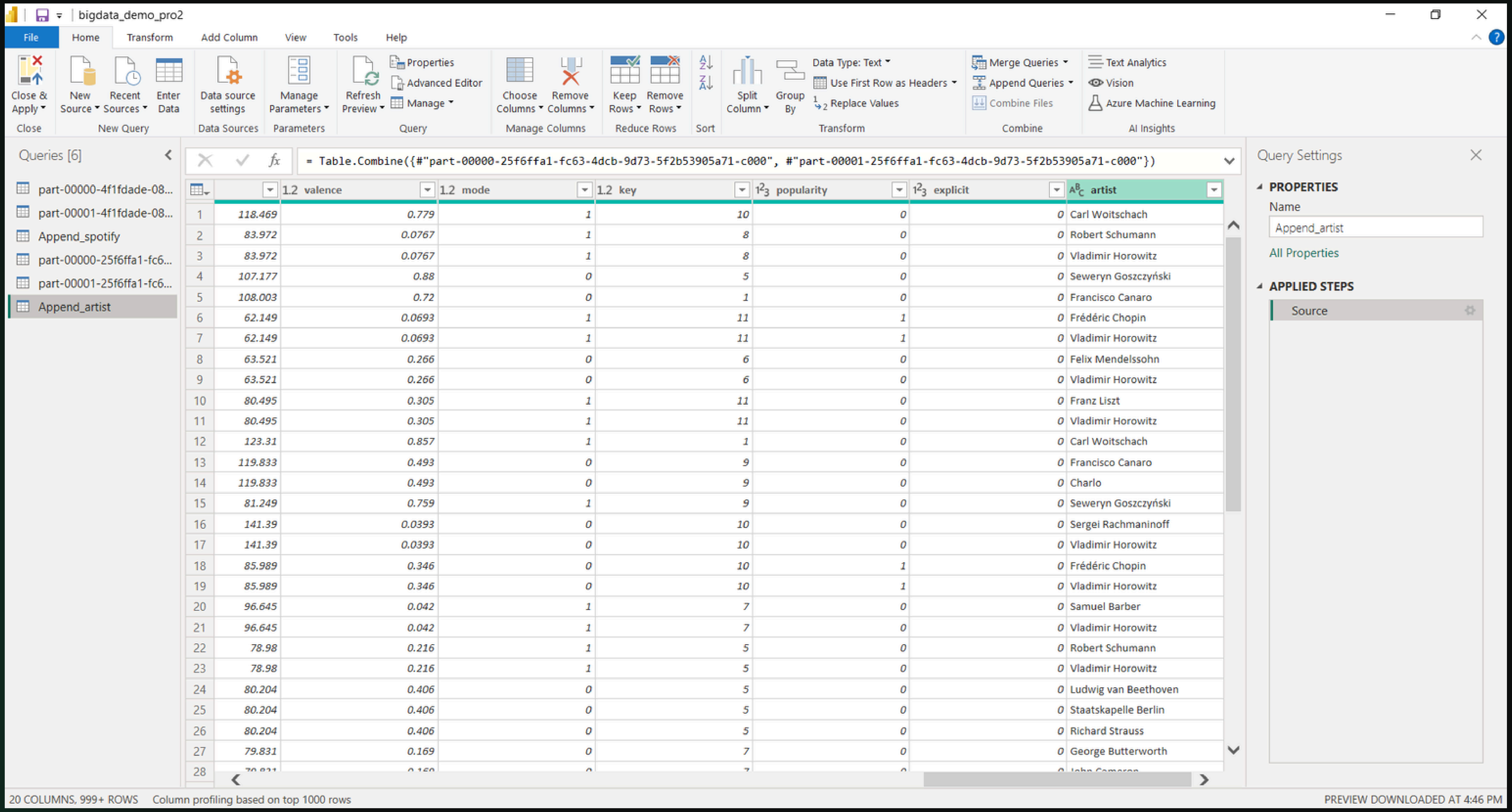
Model Summary

พบว่าผลลัพธ์ที่ได้จาก Regression Model ในการทำนายค่า Popularity ของเพลงด้วยการใช้ค่าจาก year, acousticness, danceability, energy, instrumentalness, loudness, tempo, explicit, popularity โมเดลให้ค่าผลลัพธ์ค่า RMSE 10.04 และ R-squared 0.78 ซึ่งเป็นผลลัพธ์ที่ดีที่บ่งบอกว่าโมเดลมีประสิทธิภาพในการทำนายค่า Popularity ได้และจากผลลัพธ์ที่ได้จาก Classification Model ในการทำนายค่า Explicit ของเพลงด้วยการใช้ค่าจาก year, acousticness, danceability, energy, instrumentalness, loudness, speechiness, popularity, explicit พบว่าโมเดลให้ค่าผลลัพธ์ค่า Accuracy 0.9395, F1-score 0.9334, Precision (by label) 0.9522, Recall (by label) 0.9834, Weighted Precision 0.9325, และ Weighted Recall 0.9395 ซึ่งบ่งบอกว่าโมเดลมีประสิทธิภาพที่ดีในการ predict ข้อมูลทั้ง 2 class

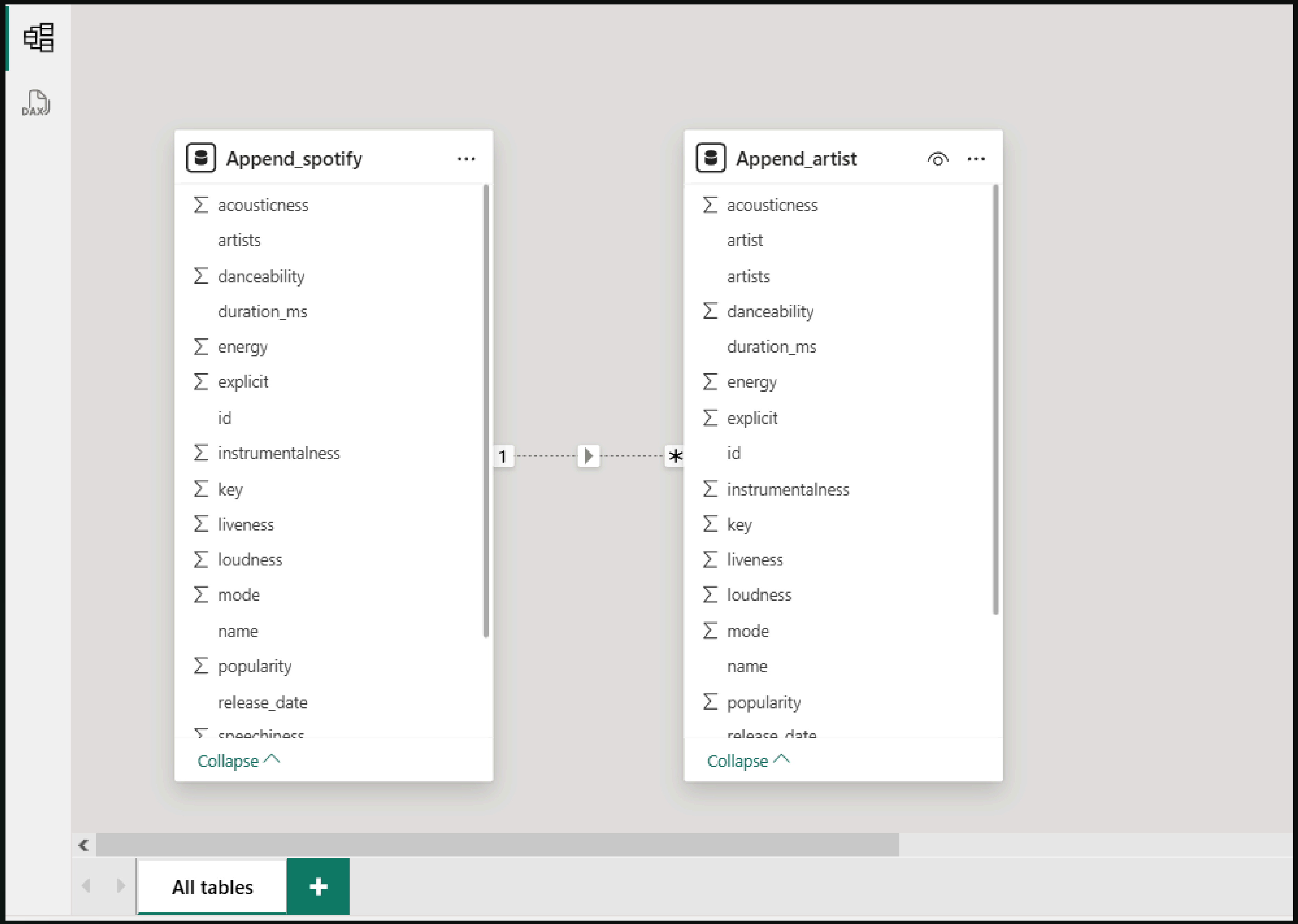
Append Spotify Data



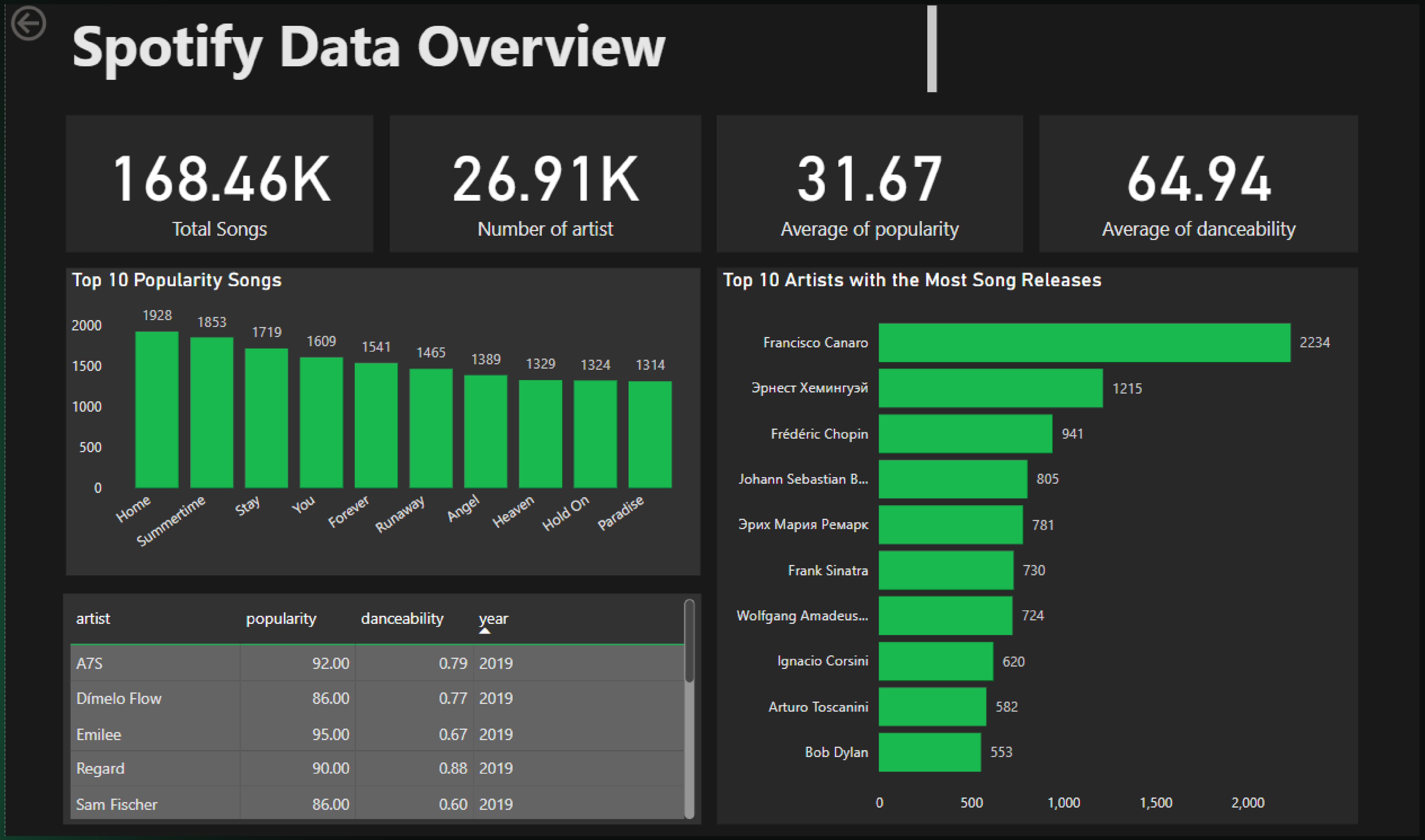
Append Artists Data



Visualization



Visualization by Power BI



Team members

6513114 Nipatsa Chainiwattana

6513134 Puthipong Yomabut

6513170 Patiharn Kamenkit

6513172 Phattaradanai Sornsawang

Thank You