ITC6001A1 - INTRODUCTION TO BIG DATA - FALL TERM 2023

Final Project - Last.FM dataset

Alkiviadis Kariotis 241735
Konstantinos Margaritis 122451

Prof.: Dr. Dimitrios Vogiatzis

Presentation Overview

Data Processing

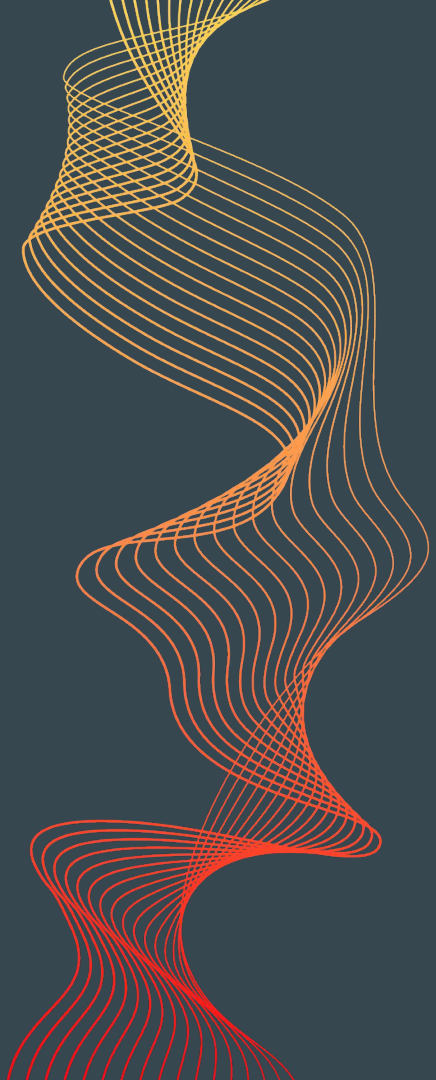
Similarity Assessment

Correlation Analysis

Dynamics of Listening and Tagging

Libraries Used for the entire project

- pandas: Data manipulation
- numpy: Numerical computing
- matplotlib.pyplot: Data visualization
- seaborn: better plotting
- scipy.stats.zscore: Standardization
- sklearn.metrics.pairwise.cosine_similarity: Similarity measurement
- scipy.sparse.csr_matrix: Sparse matrix representation
- json: Data serialization
- plotly.express: Interactive plotting
- plotly.graph_objs: Plotly graph objects
- ipywidgets: Interactive widgets



Data Processing Overview

Number of unique artists	17632
Number of unique tags	11946
Number of unique users	1892

- Data Loading: Process of loading data using pandas.
  - Inspecting the files to see what the separator is
  - Load the 6 .data files through the use of pandas with tab (\t) delimiter
  - For encoding we used 'ISO-8859-1' (Latin-1 WE)
- Data Overview: Description of the Last.fm dataset.
  - For all of the 6 files checked key statistics and information, through the functions
    - .info()
    - .describe()

Datasets: artists, tags, user_artists, user_friends, user_taggedartists & user_taggedartists-timestamps

user_artists data fame

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 92834 entries, 0 to 92833
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   userID    92834 non-null  int64
 1   artistID  92834 non-null  int64
 2   weight    92834 non-null  int64
dtypes: int64(3)
memory usage: 2.1 MB
None
```

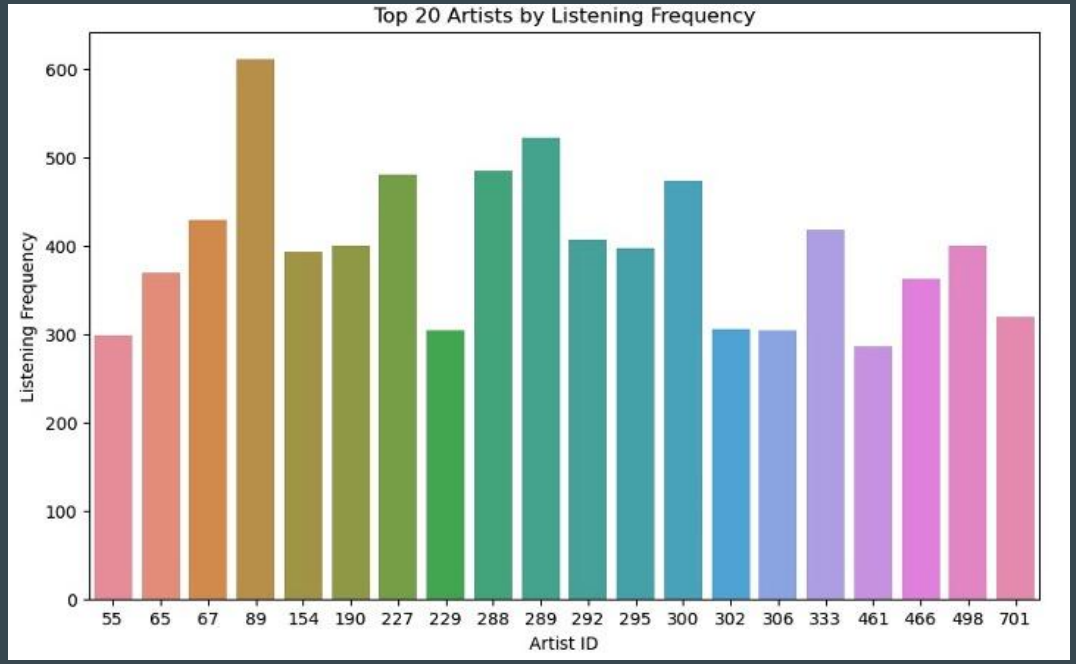
	userID	artistID	weight
count	92834.000000	92834.000000	92834.00000
mean	1037.010481	3331.123145	745.24393
std	610.870436	4383.590502	3751.32208
min	2.000000	1.000000	1.00000
25%	502.000000	436.000000	107.00000
50%	1029.000000	1246.000000	260.00000
75%	1568.000000	4350.000000	614.00000
max	2100.000000	18745.000000	352698.00000

Visualization of Top20 artists by Listening Frequency

In the user_artists data frame we proceeded with:

- Slicing and keeping only the artistID column
- Counting the values (corresponds to frequency)
- Sorting the values
- Keeping the biggest 20 frequency values

```
artist_listening_frequency =
user_artists_df['artistID'].value_counts().
sort_values(ascending=False).head(20)
```

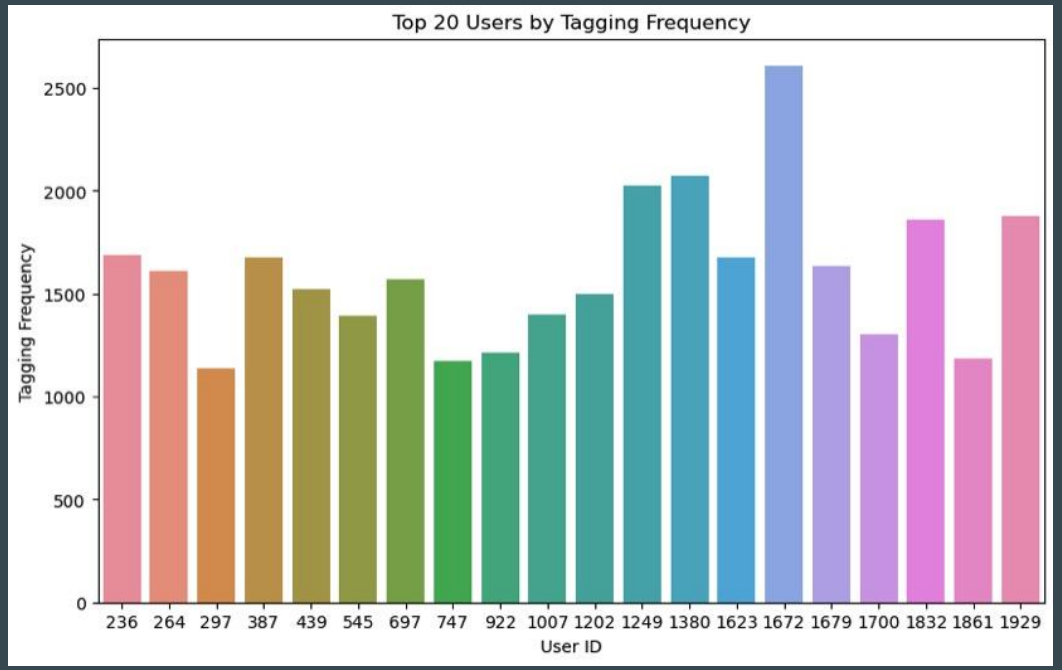


Visualization of Top20 users by Tagging Frequency

In the user_taggedartists data frame we proceeded with:

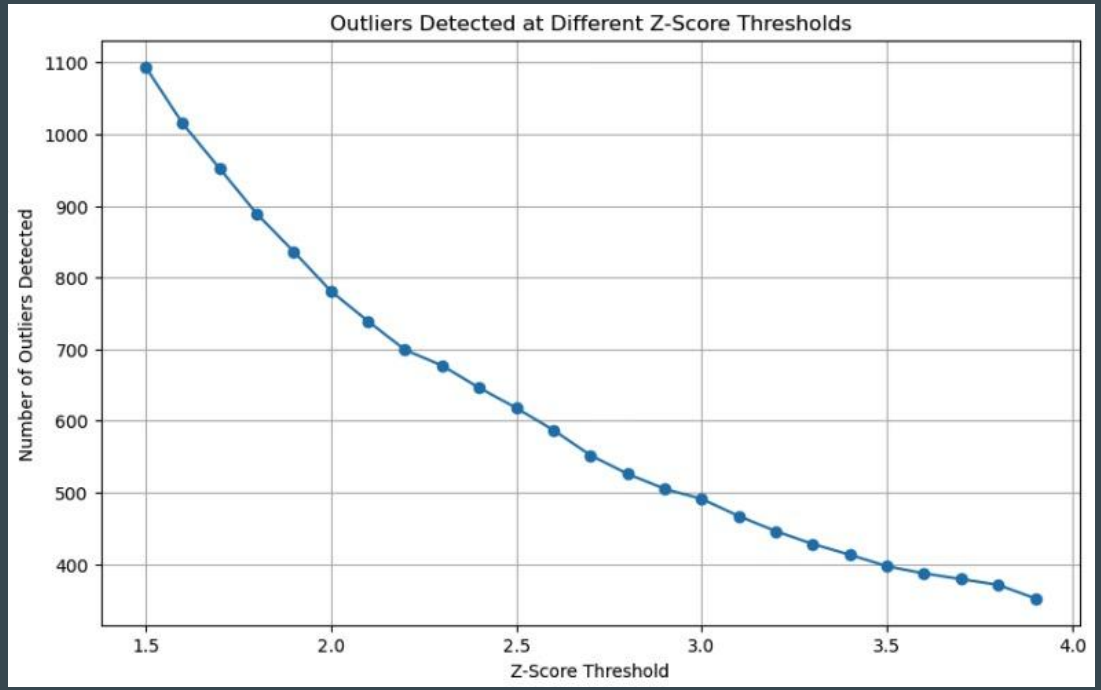
- Slicing and keeping only the userID column
- Counting the values (corresponds to frequency)
- Sorting the values
- Keeping the biggest 20 frequency values

```
tag_frequency = user_taggedartists_df['userID'].value_counts().sort_values(ascending=False).head(20)
```



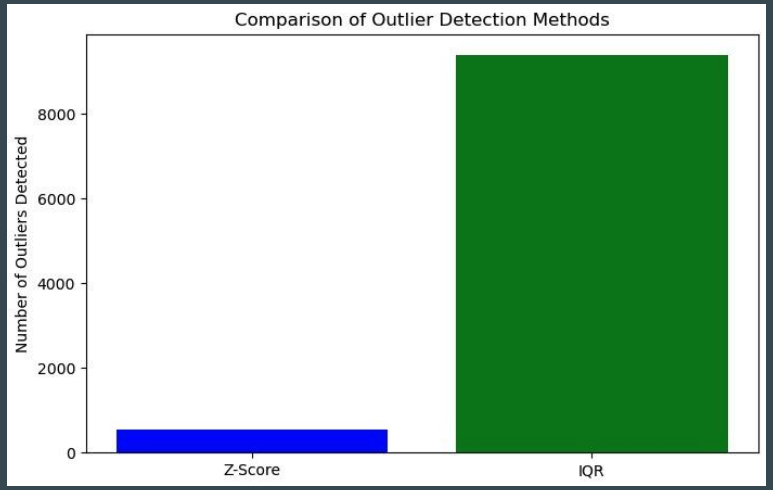
Outlier Detection | Z-score

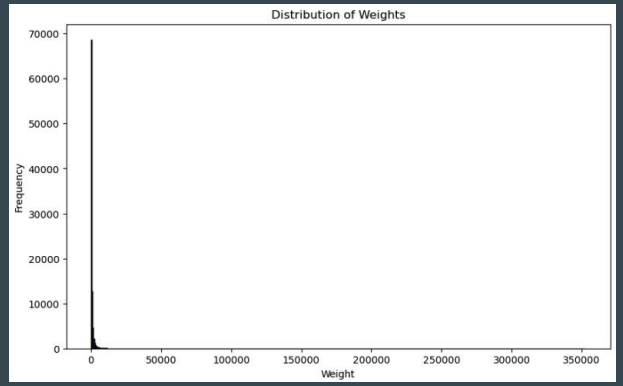
- Firstly, we looked at the listening frequencies (weight column of user_artists).
- We started by trying to estimate the optimal threshold for the z-score function.
- Picked values from 1.5-4 with step 0.1 and looped everything to get the plot based on the number of outliers detected.
- The area where the rate of decrease, of the number of outliers started to significantly slow down, should show the optimal threshold point.
- This is between 2.5 and 3, based on the plot.

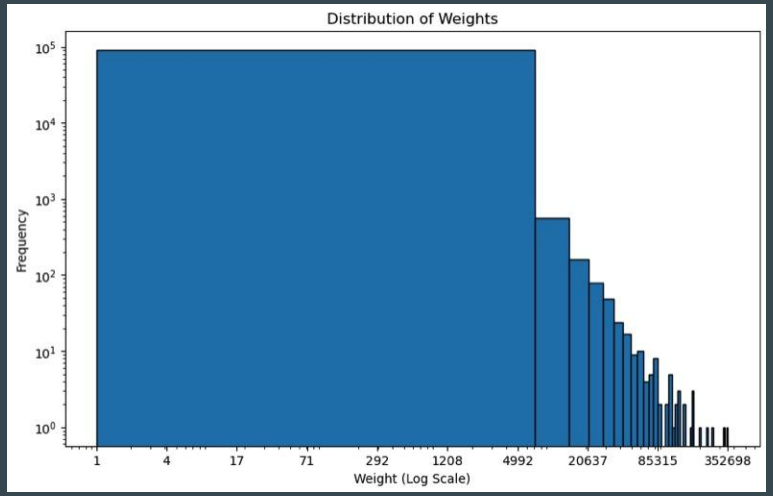


Outlier Detection | IQR

- The IQR (Interquartile Range) method for outliers involves calculating the range between the first quartile (25th percentile) and the third quartile (75th percentile) of a dataset and identifying any data points that fall below the first quartile minus 1.5 times the IQR or above the third quartile plus 1.5 times the IQR as potential outliers.
- On the listening frequency we applied this method, and the difference of outliers in terms of number was significant.
- Useful for identifying outliers in skewed distributions and less influenced by extreme values → robust application when dealing with non-normal distributions datasets → identifies more outlies than the z-score method.



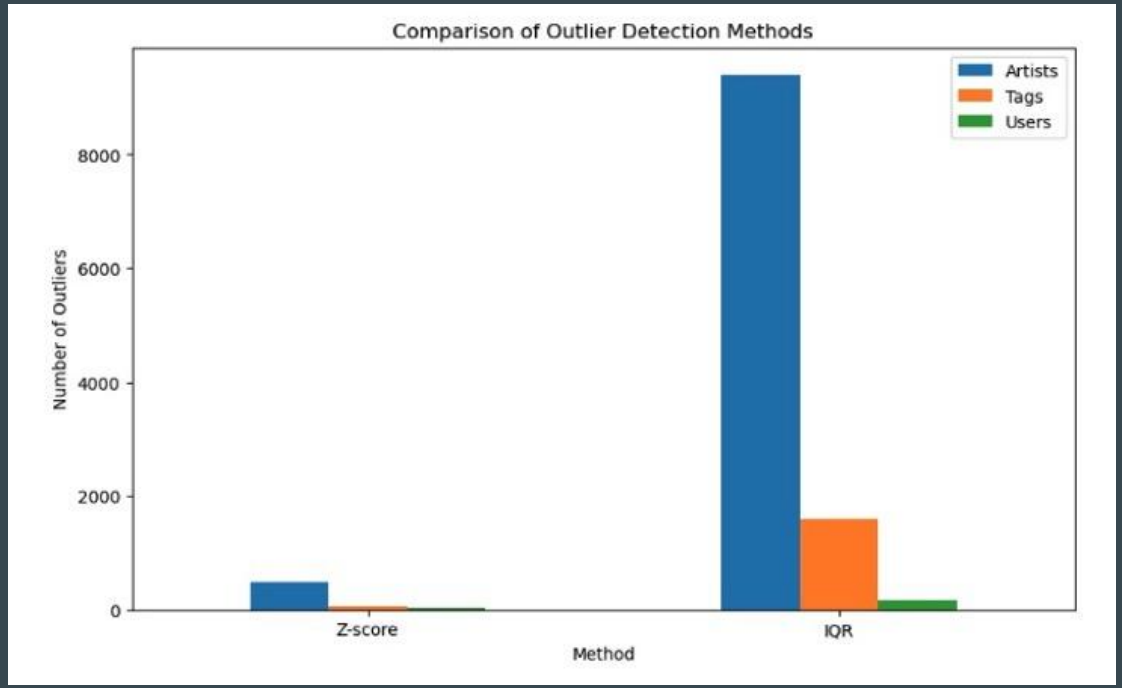




Outlier Detection | Both methods for artists, tags and users

- Then we calculated based on z-score and IQR for all three cases, by firstly finding the respective frequencies, and then applying the following formula: (Frequency - mean) / std

- Artists → Listening Frequency
- Tags → Tag usage Frequency
- Users → Listening time (weight_sum)

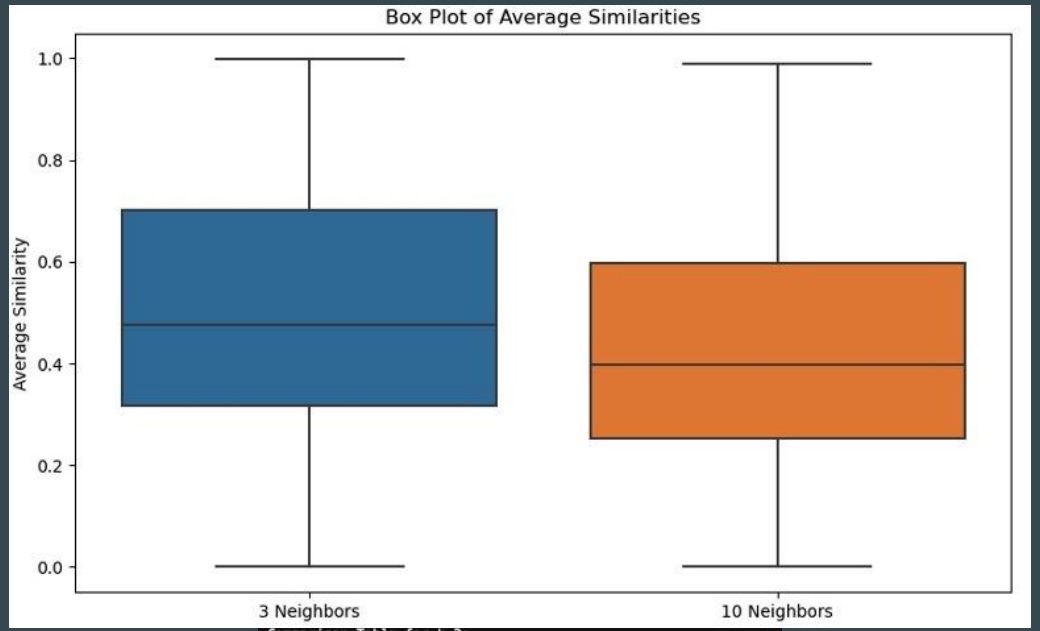


	userID	artistID	weight	z_score
0	2	51	13883	3.502167
50	3	101	13176	3.313700
254	7	288	43864	11.494283
506	12	333	23961	6.188686
508	12	377	59695	15.714395
...	...	...	...	...
91717	2072	3489	12842	3.224665
91986	2080	72	80721	21.319352
92138	2084	207	12498	3.132964
92551	2094	1459	26090	6.756220
92649	2096	436	14690	3.717291

[491 rows x 4 columns],

Similarity Assessment

- To identify the listening habits of the users, we performed a cosine similarity analysis.
- We created a pivot table, using as index the userID, as column the artistID and as values the weight.
- Then used the function of cosine similarity to find the angle between the non-zero vectors from the pivot table.
- Finally stored that to a csv file in order to be used with the KNN method.
- Here we identified the nearest neighbors for each of the two cases (3&10) based on the similarity scores of each user, stored in the csv file from above.



Comparison Table for k=3:

	User	Nearest Neighbors (k=3)
0	2	428, 1210, 1866
1	3	1740, 255, 1891
2	4	1642, 62, 1163
3	5	567, 277, 1785
4	6	1533, 924, 1248
...	...	...
1887	2095	1976, 601, 33
1888	2096	856, 1414, 1402
1889	2097	1642, 2080, 31
1890	2099	842, 1060, 1874
1891	2100	586, 108, 33

[1892 rows x 2 columns]

Comparison Table for k=10:

	User	Nearest Neighbors (k=10)
0	2	428, 1210, 1866, 374, 1643, 1209, 1585, 1202, ...
1	3	1740, 255, 1891, 78, 60, 1054, 1638, 426, 951,...
2	4	1642, 62, 1163, 767, 2080, 124, 446, 103, 566, 31
3	5	567, 277, 1785, 913, 1797, 919, 1411, 171, 42,...
4	6	1533, 924, 1248, 498, 1697, 1663, 1791, 1435, ...

Dynamics of Listening and Tagging

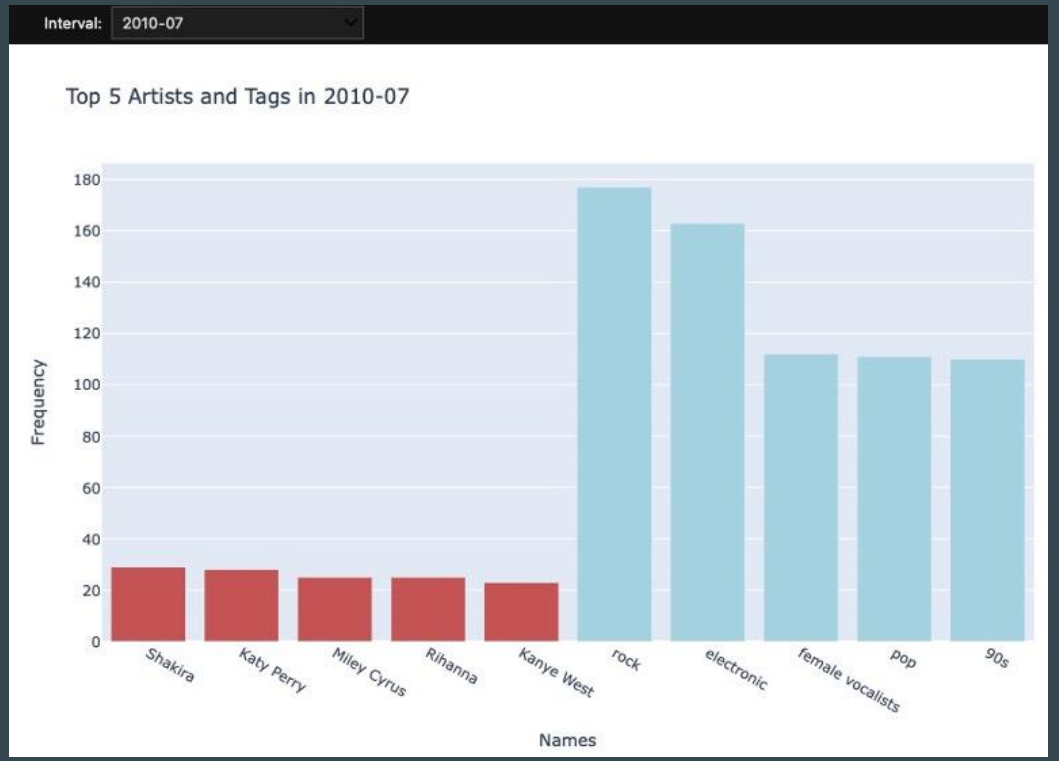
- We started by making the necessary transformation to the timestamp column, assigning also a safety function to turn milliseconds to seconds.
- We created a dynamically changing code for the choice of the time interval changing from monthly to trimester with just changing M to Q
- Then we grouped the data by interval and started to assigning to a dictionary the following values for each one of them:

```
#store results in a dictionary
results[interval] = {
    'unique_users': unique_users,
    'unique_tags': unique_tags,
    'unique_artists': unique_artists,
    'top_artists': top_artists,
    'top_tags': top_tags
```

```
Interval: 2005-07
  Number of unique users: 11
  Number of unique tags: 78
  Number of unique artists: 465
  Top 5 artists (by ID): [599, 59, 2861, 1083, 1013]
  Top 5 tags (by ID): [2191, 17, 370, 3496, 642]

Interval: 2005-08
  Number of unique users: 13
  Number of unique tags: 58
  Number of unique artists: 111
  Top 5 artists (by ID): [11892, 227, 234, 550, 14468]
  Top 5 tags (by ID): [73, 828, 371, 735, 1]

Interval: 2005-09
  Number of unique users: 8
  Number of unique tags: 81
  Number of unique artists: 178
  Top 5 artists (by ID): [11892, 1377, 5555, 6852, 51]
  Top 5 tags (by ID): [2726, 824, 839, 424, 76]

Interval: 2005-10
  Number of unique users: 5
  Number of unique tags: 73
  Number of unique artists: 142
  Top 5 artists (by ID): [227, 51, 59, 225, 235]
  Top 5 tags (by ID): [73, 79, 84, 134, 296]
```

Dynamics of Listening and Tagging | Interactive Plots

- Then we proceeded with two interactive plots for visualization by using plotly and ipywidgets.



Correlation Analysis

Gathering Artist and Listening Data for Each User:

- Music Habits: for each user, count how many different artists they've listened to and calculate the total time they've spent listening.

Finding Out How Social Each User Is:

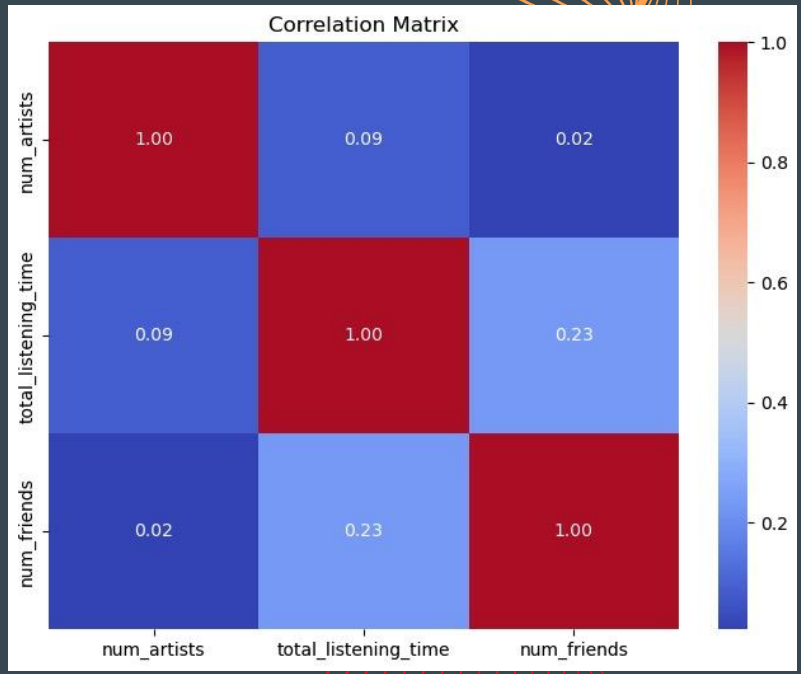
- How many friends each user has. This is done by counting the number of connections each user has in our friends' data.

Bringing It All Together:

- Combine the music and social data. We merged the artist and listening information with the friends' data → make sure to account for users who might not have any friends listed in our data by assigning them a friend count of zero→ ensures that no user is left out.

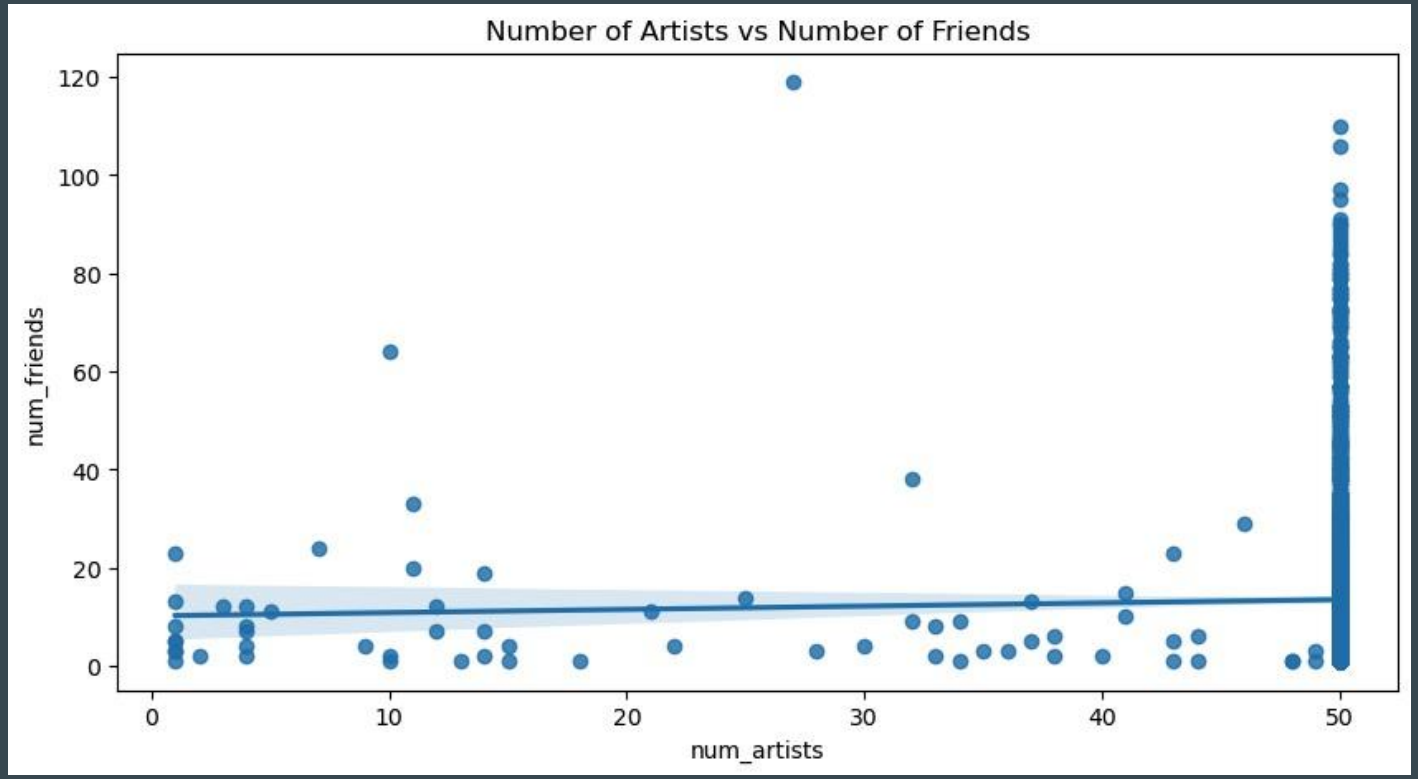
Uncovering Relationships in the Data:

- All the data compiled together → explore the relationships between how many artists a user listens to, their total listening time, and the number of friends they have →correlation matrix to see if and how these different aspects are related to each other.



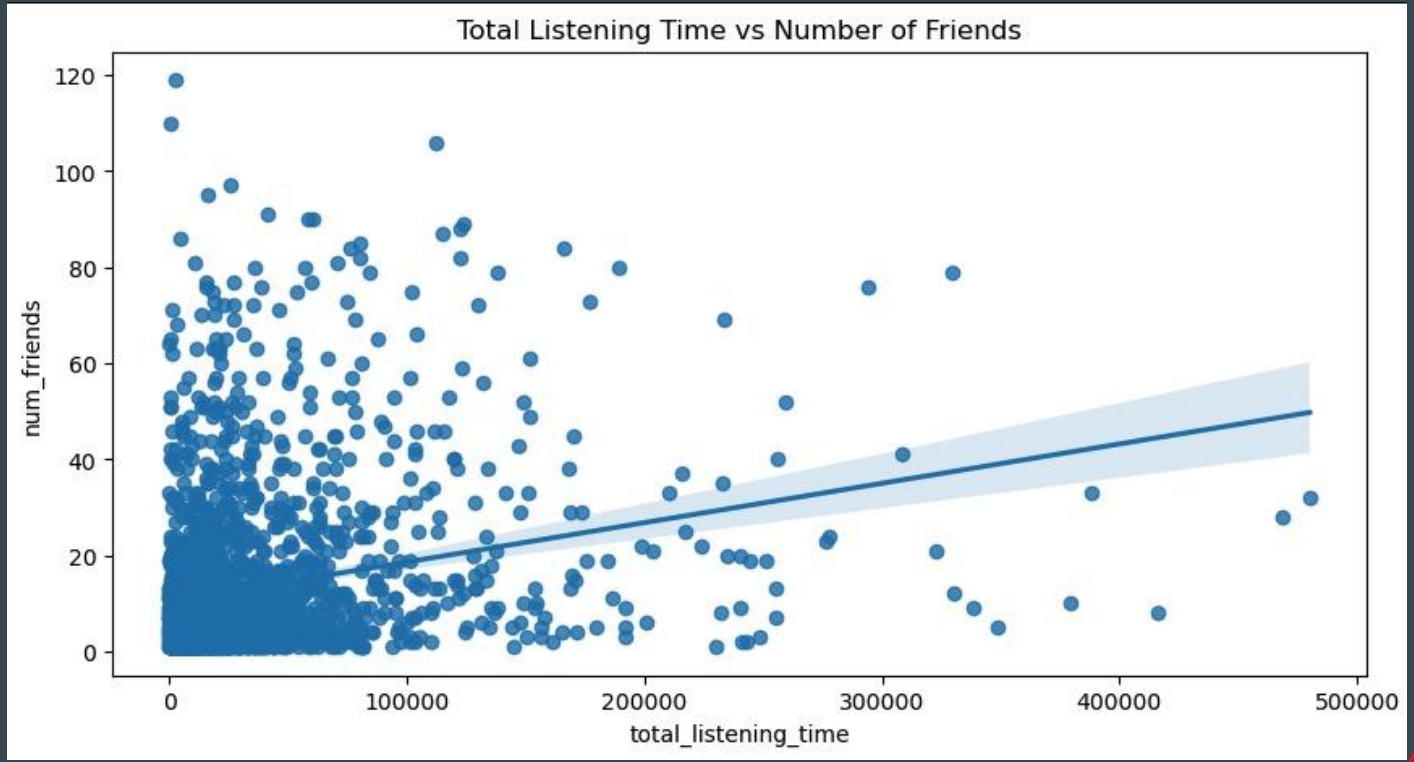
Number of Artists vs Number of Friends

- Scatter plot with Regression Line



Total Listening Time vs Number of Friends

- Scatter plot with Regression Line



Thank you for your time 😊

Github link:

https://github.com/alkisKariotis/Data_Science_Master/blob/main/ITC6001_Final_Project_Code_241735%26122451.ipynb