CA1: Dataframe Manipulation with Spotify Data

Introduction

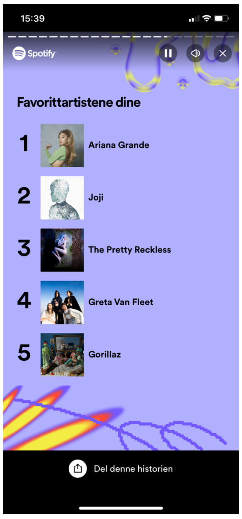
Pandas is an extremely powerful tool to handle large amounts of tabular data. In this compulsory assignment, you will use Pandas to explore one of the TA's personal spotify data in depth.

Additional information:

- Feel free to create additional code cells if you feel that one cell per subtask is not sufficient.
- Remember, Pandas uses very efficient code to handle large amounts of data. For-loops are not efficient. If you ever have to use a for-loop to loop over the rows in the DataFrame, you have *probably* done something wrong.
- Label all graphs and charts if applicable.

Task

I typically enjoy indie and rock music. I am a big fan of everything from old-fashioned rock and roll like Led Zeppelin and Jimi Hendrix, to newer indie artists like Joji and Lana Del Rey. This is why my spotify wrapped for 2023 came as quite a surprise:



Now, I'm no hater of pop music, but this was unexpected. For this assignment, you will investigate my listening habits, including a deep dive into my Ariana Grande listening habits, and try to find an answer to why she was my top artist; was there a fault in the spotify algorithm? Am I actually secretly an *Arianator*? (yes, I did have to look that up). Or am I just lying to myself about how often I listen to guilty pleasure music?

Part 1: Initial loading and exploration

1.0 Import necessary libraries:

pandas, numpy, matplotlib.pyplot (other libraries such as seaborn or plotly are also allowed if you want prettier plots). It might also be a good idea to use **os** for task 2.0

In [72]:
```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import os
```

1.1 Loading the data

Load the dataset in the file `streaming_history_0.csv` into a Pandas DataFrame called `df_spotify_0`.

In [73]:
```
df_spotify_0 = pd.read_csv("spotify_data/streaminghistory0.csv")
```

1.2 Help function

Use the Python command `help` to help you understand how to use the `pd.DataFrame.head` and `pd.DataFrame.tail` methods.

In [74]:
```
print(help(pd.DataFrame.head))
print(help(pd.DataFrame.tail))
```

```
Help on function head in module pandas.core.generic:

head(self, n: 'int' = 5) -> 'Self'
    Return the first `n` rows.

    This function returns the first `n` rows for the object based
    on position. It is useful for quickly testing if your object
    has the right type of data in it.

    For negative values of `n`, this function returns all rows except
    the last `|n|` rows, equivalent to ``df[:n]``.

    If n is larger than the number of rows, this function returns all ro
ws.

    Parameters
```

```
    ----------
    n : int, default 5
        Number of rows to select.

    Returns
    -------
    same type as caller
        The first `n` rows of the caller object.

    See Also
    --------
    DataFrame.tail: Returns the last `n` rows.

    Examples
    --------
    >>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lio
n',
    ...                    'monkey', 'parrot', 'shark', 'whale', 'zebr
a']})
    >>> df
          animal
    0  alligator
    1        bee
    2     falcon
    3       lion
    4     monkey
    5     parrot
    6      shark
    7      whale
    8      zebra

    Viewing the first 5 lines

    >>> df.head()
          animal
    0  alligator
    1        bee
    2     falcon
    3       lion
    4     monkey

    Viewing the first `n` lines (three in this case)

    >>> df.head(3)
          animal
    0  alligator
    1        bee
    2     falcon

    For negative values of `n`

    >>> df.head(-3)
          animal
    0  alligator
    1        bee
    2     falcon
    3       lion
```

```
    4     monkey
    5     parrot

None
Help on function tail in module pandas.core.generic:

tail(self, n: 'int' = 5) -> 'Self'
    Return the last `n` rows.

    This function returns last `n` rows from the object based on
    position. It is useful for quickly verifying data, for example,
    after sorting or appending rows.

    For negative values of `n`, this function returns all rows except
    the first `|n|` rows, equivalent to ``df[|n|:]``.

    If n is larger than the number of rows, this function returns all ro
ws.

    Parameters
    ----------
    n : int, default 5
        Number of rows to select.

    Returns
    -------
    type of caller
        The last `n` rows of the caller object.

    See Also
    --------
    DataFrame.head : The first `n` rows of the caller object.

    Examples
    --------
    >>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lio
n',
    ...                    'monkey', 'parrot', 'shark', 'whale', 'zebr
a']})
    >>> df
          animal
    0  alligator
    1        bee
    2     falcon
    3       lion
    4     monkey
    5     parrot
    6      shark
    7      whale
    8      zebra

    Viewing the last 5 lines

    >>> df.tail()
       animal
    4  monkey
    5  parrot
```

```
    6   shark
    7   whale
    8   zebra

    Viewing the last `n` lines (three in this case)

    >>> df.tail(3)
      animal
    6  shark
    7  whale
    8  zebra

    For negative values of `n`

    >>> df.tail(-3)
       animal
    3    lion
    4  monkey
    5  parrot
    6   shark
    7   whale
    8   zebra

None
```

1.3 Getting an overview

Print the first `five` and last `ten` rows of the dataframe. Have a quick look at which columns are in the dataset.

In [75]:
```
df_spotify_0.head()
```

Out[75]:

	endTime	artistName	trackName	msPlayed
0	2022-12-03 02:02	Cigarettes After Sex	Truly	30000.0
1	2022-12-03 02:02	Leonard Cohen	Take This Waltz - Paris Version	8210.0
2	2022-12-06 21:05	Vlad Holiday	So Damn Into You	37895.0
3	2022-12-06 21:05	Lorde	Team	8984.0
4	2022-12-06 21:05	Ariana Grande	Into You	1221.0

In [76]:
```
df_spotify_0.tail(10)
```

Out[76]:

	endTime	artistName	trackName	msPlayed
11949	2023-01-02 20:58	Ariana Grande	six thirty	1699.0
11950	2023-01-02 20:58	Leonard Cohen	Thanks for the Dance	19483.0
11951	2023-01-02 20:59	Des Rocs	Used to the Darkness	185.0
11952	2023-01-02 20:59	Caroline Polachek	Hit Me Where It Hurts	603.0
11953	2023-01-02 20:59	Caroline Polachek	Hit Me Where It Hurts	208.0
11954	2023-01-02 20:59	Kaizers Orchestra	Resistansen	208.0
11955	2023-01-02 20:59	Mr.Kitty	After Dark	101447.0
11956	2023-01-02 20:59	daddy's girl	after dark x sweater weather	301.0
11957	2023-01-02 20:59	daddy's girl	after dark x sweater weather	208.0
11958	2023-01-02 20:59	daddy's girl	after dark x sweater weather	789.0

1.4 Formatting correctly

When working with Pandas, it's very useful to have columns which contains dates in a specific format called *datetime*. This allows for efficient manipulation and analysis of time-series data, such as sorting, filtering by date or time, and resampling for different time periods. Figure out which column(s) would be appropriate to convert to datetime, if any, and if so, perform the conversion to the correct format.

In [77]:
```
# Useful to convert the column "endTime" from object type to datetime typ
print(df_spotify_0.dtypes)
df_spotify_0["endTime"] = pd.to_datetime(df_spotify_0["endTime"])
print(df_spotify_0.dtypes)
```

```
endTime        object
artistName     object
trackName      object
msPlayed      float64
dtype: object
endTime       datetime64[ns]
artistName            object
trackName             object
msPlayed             float64
dtype: object
```

1.5 Unique artists

Find how many unique artists are in the dataset.

In [78]:
```
print(len(df_spotify_0["artistName"].unique()))
```

```
495
```

1.6 Unique songs

Find how many unique songs are in the dataset.

In [79]:
```
print(len(df_spotify_0["trackName"].unique()))
```

```
1308
```

Part 1: Questions

Q1: Which columns are in the dataset?

The columns in the dataset are "endTime", "artistName", "trackName" and "msplayed".

Q2: What timeframe does the dataset span?

The dataset spans from 2022-12-03 until 2023-01-02 according to the endTime column shown in the head and tail of the dataset.

Q3: How many unique artists are in the dataset?

The amount of unique artists played are 495.

Q4: How many unique songs are in the dataset?

The amount of unique songs played are 1308 songs.

Part 2: Working with all the data

2.0 Importing all the dataframes

In Task 1, you only worked with about a month worth of data. Now, you will work with over a year worth.

In the *spotify_data* folder, there is more than just one listening record. Load each of the 14 listening records into a dataframe (1 dataframe per listening record), and concatenate them together into one large dataframe named `df`.

In [80]:
```
import glob

csv_files = sorted(glob.glob("spotify_data/streaminghistory*.csv"))

dfs = {f"df_spotify_{i}": pd.read_csv(file) for i, file in enumerate(csv_

df = pd.concat(dfs.values(), ignore_index=True)
```

2.1 Sorting by time

Datasets often aren't perfect. One example of an issue that could occur is that the time-based data might not be in chronological order. If this were to happen, the rows in your dataframe could be in the wrong order. To ensure this isn't an issue in your dataframe, you should sort the dataframe in chronological order, from oldest to newest.

In [81]:
```
df['endTime'] = pd.to_datetime(df['endTime'])
df = df.sort_values(by="endTime")

df
```

Out[81]:

	endTime	artistName	trackName	msPlayed
0	2022-12-03 02:02:00	Cigarettes After Sex	Truly	30000.0
1	2022-12-03 02:02:00	Leonard Cohen	Take This Waltz - Paris Version	8210.0
2	2022-12-06 21:05:00	Vlad Holiday	So Damn Into You	37895.0
3	2022-12-06 21:05:00	Lorde	Team	8984.0
4	2022-12-06 21:05:00	Ariana Grande	Into You	1221.0
...	...	...	...	...
71759	2023-12-07 21:13:00	Lana Del Rey	Ride	1126.0
71764	2023-12-07 21:14:00	Ariana Grande	my hair	23757.0
71765	2023-12-07 21:14:00	Leonard Cohen	Thanks for the Dance	9317.0
71766	2023-12-07 21:17:00	The Vaccines	Your Love Is My Favourite Band	14661.0
68857	NaT	The Lumineers	Ophelia	371.0

167439 rows × 4 columns

2.2 Setting a timeframe

For this investigation, we are only interested in investigating listening patterns from **2023**. Remove any data not from **2023** from the DataFrame.

In [82]:
```
drop = df[df['endTime'].dt.year != 2023].index
df = df.drop(drop)

df.head()
```

Out [82]:

	endTime	artistName	trackName	msPlayed
10881	2023-01-01 01:17:00	Ariana Grande	7 rings	139.0
10882	2023-01-01 01:17:00	Ariana Grande	7 rings	487.0
10883	2023-01-01 01:17:00	Ariana Grande	positions	417.0
10884	2023-01-01 01:17:00	Peach Pit	Being so Normal	2205.0
10885	2023-01-01 01:17:00	Kelly Clarkson	Santa, Can't You Hear Me	278.0

2.3 Deleting rows

Often in Data Science, you will encounter when a row entry has the value *NaN*, indicating missing data. These entries can skew your analysis, leading to inaccurate conclusions. For this task, identify and remove any rows in your DataFrame that contain NaN values.
Later in the course, you might encounter other techniques of dealing with missing data, typically reffered to as *data imputation*. Here, though, you are just supposed to delete the entire rows with missing data.

In [83]:

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

Out [83]:

	endTime	artistName	trackName	msPlayed
10881	2023-01-01 01:17:00	Ariana Grande	7 rings	139.0
10882	2023-01-01 01:17:00	Ariana Grande	7 rings	487.0
10883	2023-01-01 01:17:00	Ariana Grande	positions	417.0
10884	2023-01-01 01:17:00	Peach Pit	Being so Normal	2205.0
10885	2023-01-01 01:17:00	Kelly Clarkson	Santa, Can't You Hear Me	278.0
...	...	...	...	...
71754	2023-12-07 21:13:00	Lana Del Rey	Young And Beautiful	3146.0
71759	2023-12-07 21:13:00	Lana Del Rey	Ride	1126.0
71764	2023-12-07 21:14:00	Ariana Grande	my hair	23757.0
71765	2023-12-07 21:14:00	Leonard Cohen	Thanks for the Dance	9317.0
71766	2023-12-07 21:17:00	The Vaccines	Your Love Is My Favourite Band	14661.0

156539 rows × 4 columns

2.4 Convert from milliseconds to seconds

From `msPlayed`, create a new column `secPlayed` with the data converted from milliseconds to seconds. Then delete the column `msPlayed`.

In [84]:
```
clean_df = clean_df.copy()  # Ensure it's a new DataFrame
clean_df.loc[:, "secPlayed"] = clean_df["msPlayed"] / 1000
clean_df = clean_df.drop(columns="msPlayed")
clean_df
```

Out[84]:

	endTime	artistName	trackName	secPlayed
10881	2023-01-01 01:17:00	Ariana Grande	7 rings	0.139
10882	2023-01-01 01:17:00	Ariana Grande	7 rings	0.487
10883	2023-01-01 01:17:00	Ariana Grande	positions	0.417
10884	2023-01-01 01:17:00	Peach Pit	Being so Normal	2.205
10885	2023-01-01 01:17:00	Kelly Clarkson	Santa, Can't You Hear Me	0.278
...	...	...	...	...
71754	2023-12-07 21:13:00	Lana Del Rey	Young And Beautiful	3.146
71759	2023-12-07 21:13:00	Lana Del Rey	Ride	1.126
71764	2023-12-07 21:14:00	Ariana Grande	my hair	23.757
71765	2023-12-07 21:14:00	Leonard Cohen	Thanks for the Dance	9.317
71766	2023-12-07 21:17:00	The Vaccines	Your Love Is My Favourite Band	14.661

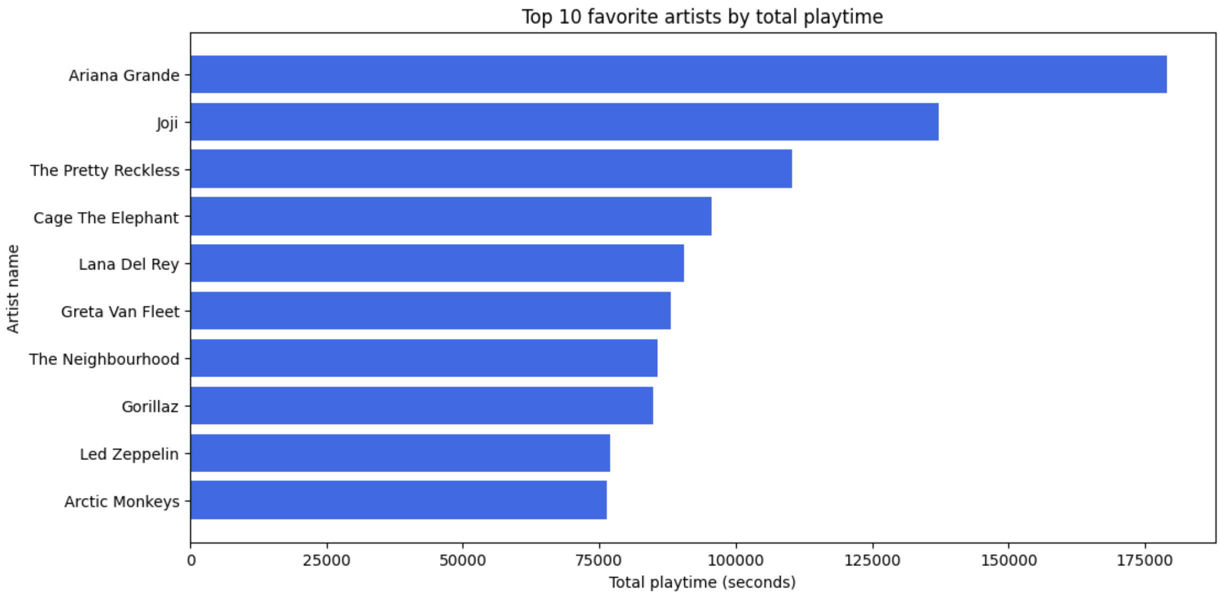
156539 rows × 4 columns

2.5 Finding top 10 favorite artists

Find the top `ten` artists with the highest total play time (in seconds). Plot your findings in a bar graph.
(hint: start by creating a new DataFrame with only `artistName` and your time column. To proceed, you will also likely need the `groupby` command from Pandas.)

In [85]:
```
artists_df = clean_df[["artistName", "secPlayed"]].copy()
artists_df = artists_df.groupby(["artistName"]).sum()
artists_df = artists_df.sort_values("secPlayed", ascending=False)
top_10_artists = artists_df.head(10).reset_index()

plt.figure(figsize=(12, 6))
plt.barh(top_10_artists["artistName"], top_10_artists["secPlayed"], color
plt.xlabel("Total playtime (seconds)")
plt.ylabel("Artist name")
plt.title("Top 10 favorite artists by total playtime")
plt.gca().invert_yaxis()
plt.show()
```

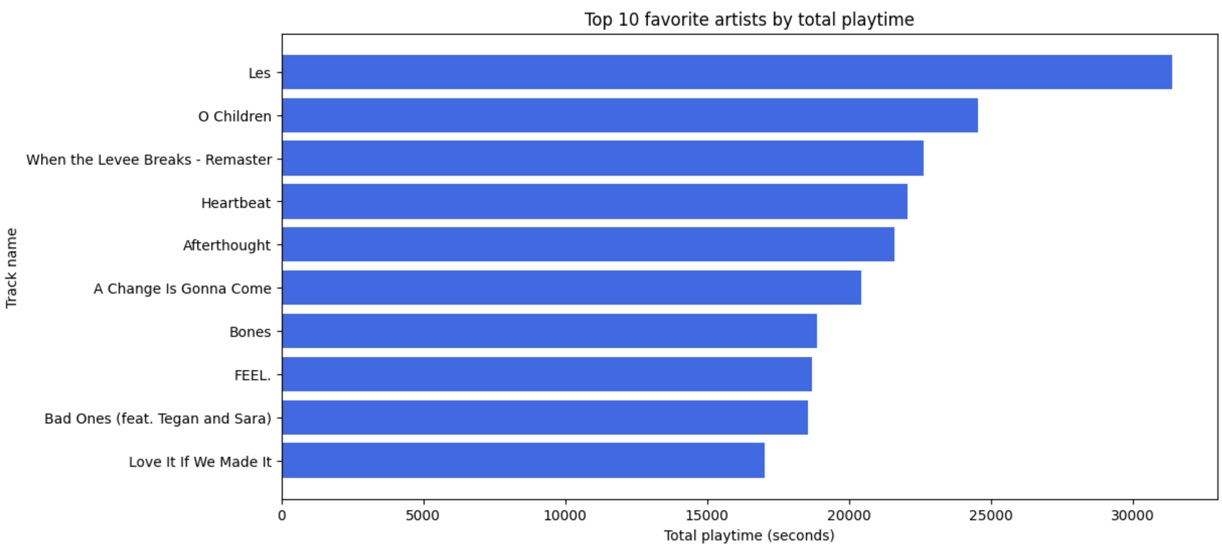


2.6 Finding top 10 favorite songs

Find the top `ten` songs with the highest play time. Create a graph visualizing the results.

In [86]:
```
songs_df = clean_df[["trackName", "secPlayed"]].copy()
songs_df = songs_df.groupby(["trackName"]).sum()
songs_df = songs_df.sort_values("secPlayed", ascending=False)
top_10_songs = songs_df.head(10).reset_index()


plt.figure(figsize=(12, 6))
plt.barh(top_10_songs["trackName"], top_10_songs["secPlayed"], color="roy
plt.xlabel("Total playtime (seconds)")
plt.ylabel("Track name")
plt.title("Top 10 favorite artists by total playtime")
plt.gca().invert_yaxis()
plt.show()
```



Part 3: Further analysis

3.0 Average listening time by hour

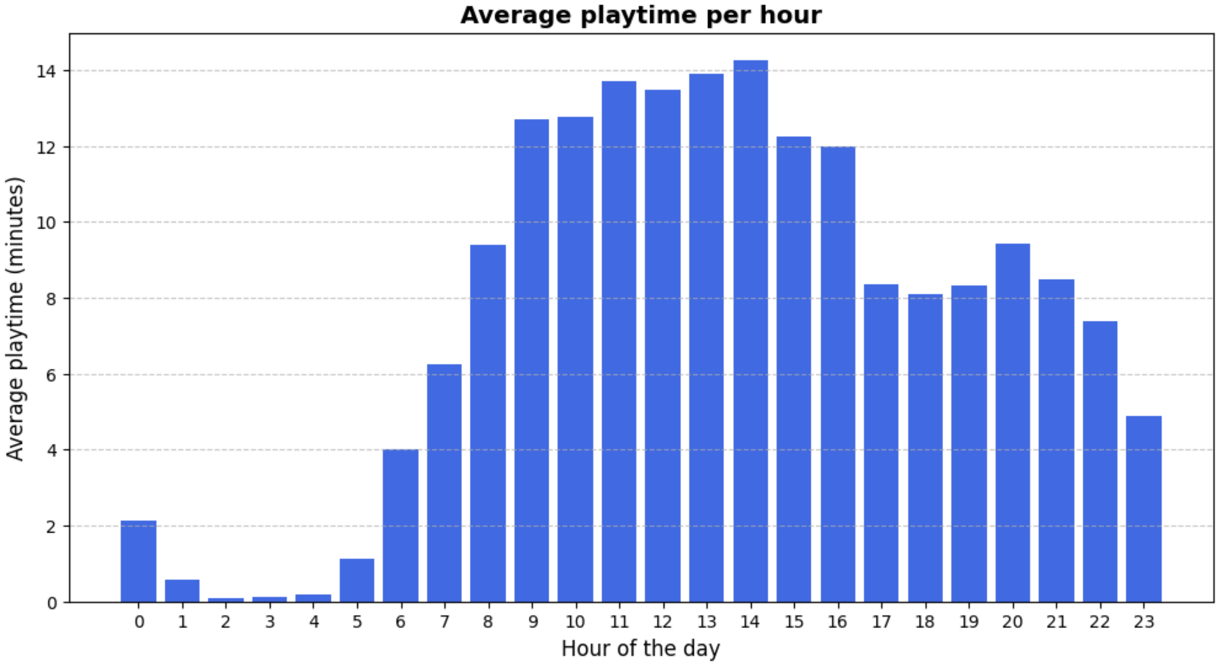
Generate a plot that displays the average amount of time that music is played for each hour of the day.

In [87]:
```
avg_time = clean_df[["endTime", "secPlayed"]].copy()
avg_time["hour"] = avg_time["endTime"].dt.hour  # Extract hour (0–23)

# Finne antall dager som musikk ble hørt på
avg_time = avg_time.groupby("hour")["secPlayed"].sum().reset_index()
days = clean_df["endTime"].dt.dayofyear.iloc[-1]

# Beregner gjennomsnittlig antall minutt per time
avg_time["avgMinPlayed"] = avg_time["secPlayed"] / days / 60

plt.figure(figsize=(12, 6))
plt.bar(avg_time["hour"], avg_time["avgMinPlayed"], color="royalblue")
plt.xlabel("Hour of the day", fontsize=12)
plt.ylabel("Average playtime (minutes)", fontsize=12)
plt.title("Average playtime per hour", fontsize=14, fontweight="bold")
plt.xticks(range(24))
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```



3.1 Morning music and evening music

I think many people find that some types of music are more suitable for morning listening and some music is more suitable for evening listening. Create a plot that compares the play time of the artists *Leonard Cohen* and *Rage Against the Machine* on an hour-by-hour basis. See if there are any differences.

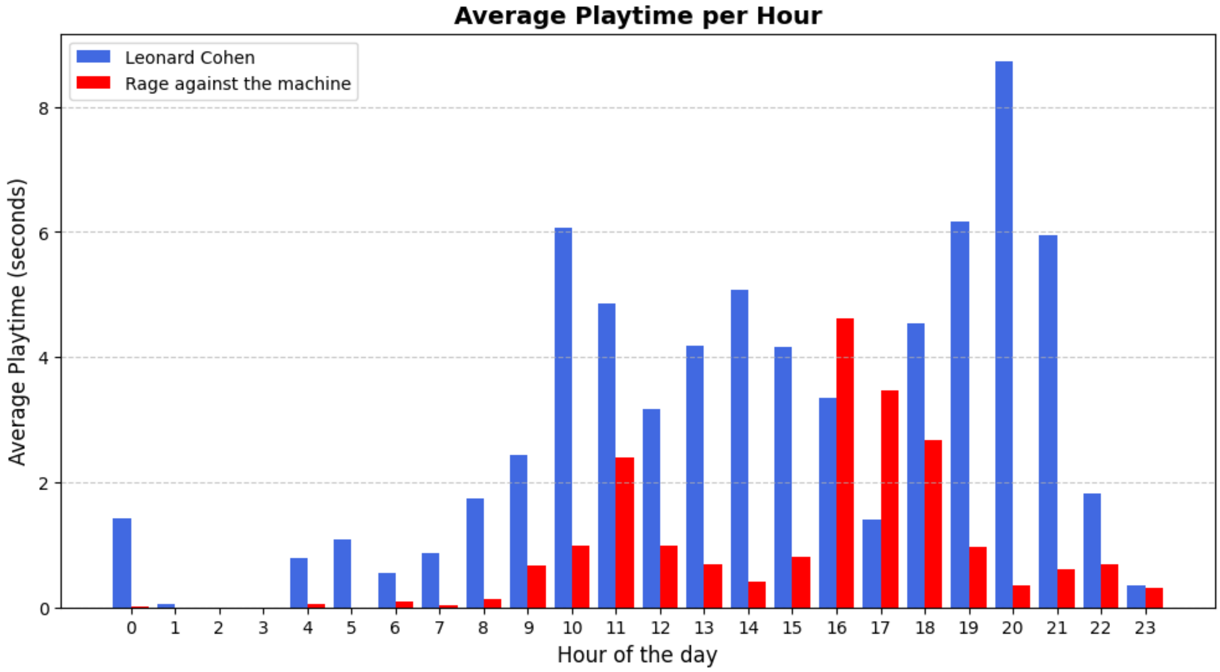
In [88]:
```python
music_type_df = clean_df[["endTime", "artistName", "secPlayed"]].copy()
music_type_df = music_type_df[music_type_df["artistName"].isin(["Leonard
music_type_df["hour"] = music_type_df["endTime"].dt.hour
music_type_df = music_type_df.groupby(["artistName", "hour"])["secPlayed"

# Creating two separate dataframes for the artists
leonard_cohen_data = music_type_df[music_type_df["artistName"] == "Leonar
R_a_t_M_data = music_type_df[music_type_df["artistName"] == "Rage Against

# Adding the average seconds played per day
leonard_cohen_data["avgSecPlayed"] = leonard_cohen_data["secPlayed"] / da
R_a_t_M_data["avgSecPlayed"] = R_a_t_M_data["secPlayed"] / days

#Plotting the bar plots next to eachother
plt.figure(figsize=(12, 6))
plt.bar(leonard_cohen_data["hour"] - 0.2, leonard_cohen_data["avgSecPlaye
plt.bar(R_a_t_M_data["hour"]+ 0.2, R_a_t_M_data["avgSecPlayed"], 0.4, col

plt.xlabel("Hour of the day", fontsize=12)
plt.ylabel("Average Playtime (seconds)", fontsize=12)
plt.title("Average Playtime per Hour", fontsize=14, fontweight="bold")
plt.xticks(range(24))
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.legend()
plt.show()
```



3.2 Analysing skipped songs

Determining whether a song was skipped or listened to can be challenging. For this analysis, we'll simplify by defining a skipped song as any track played for less than 30 seconds. Conversely, a song played for 30 seconds or more is considered listened to.
Add a column to your DataFrame to reflect this criteria: set the value to 1 if the song was played for less than 30 seconds (indicating a skipped song), and 0 if it was played for 30 seconds or longer.

In [89]:
```
clean_df["skipped"] = (clean_df["secPlayed"] <= 30).astype(int)
clean_df
```

Out[89]:

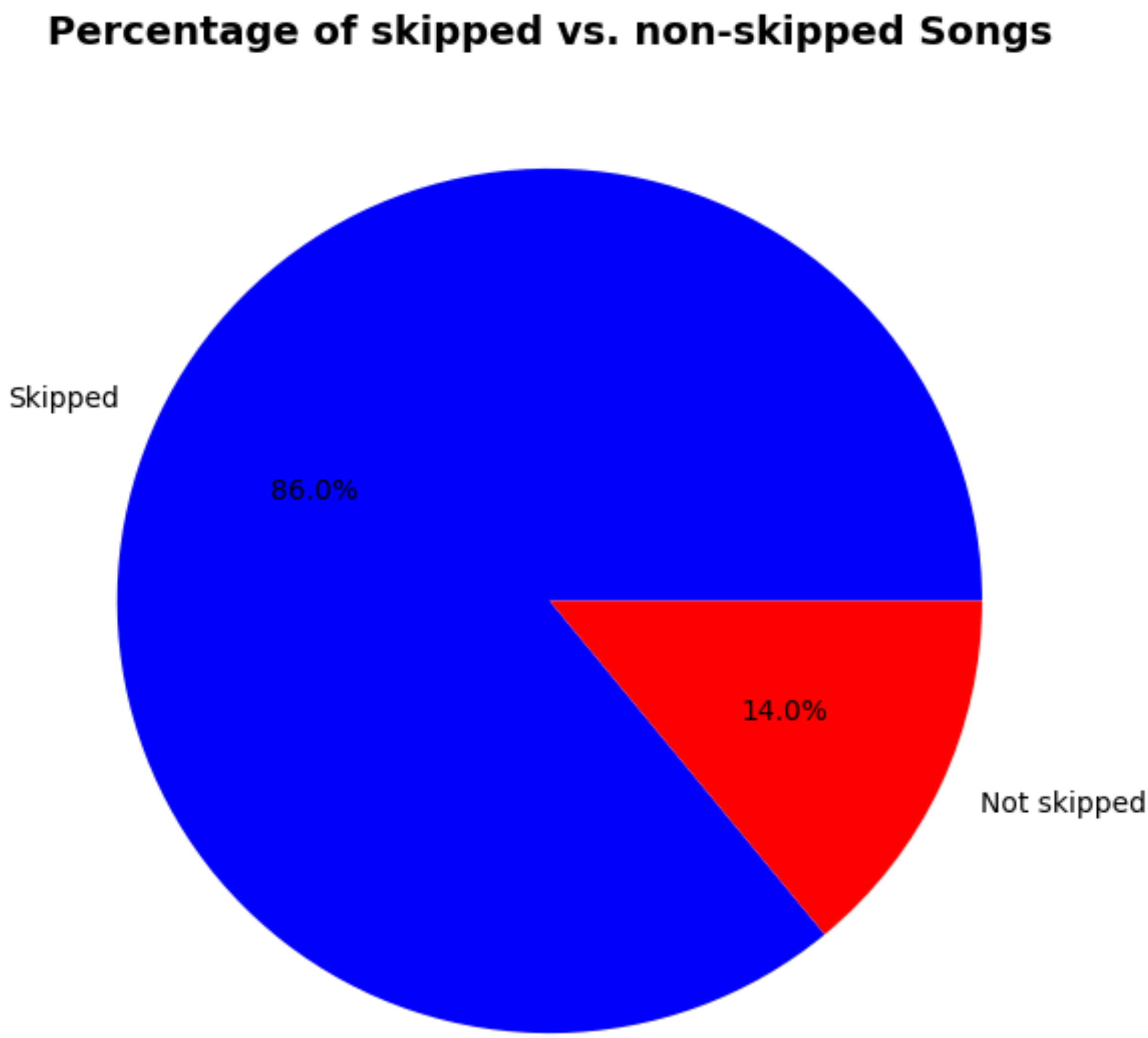
	endTime	artistName	trackName	secPlayed	skipped
10881	2023-01-01 01:17:00	Ariana Grande	7 rings	0.139	1
10882	2023-01-01 01:17:00	Ariana Grande	7 rings	0.487	1
10883	2023-01-01 01:17:00	Ariana Grande	positions	0.417	1
10884	2023-01-01 01:17:00	Peach Pit	Being so Normal	2.205	1
10885	2023-01-01 01:17:00	Kelly Clarkson	Santa, Can't You Hear Me	0.278	1
...	...	...	...	...	...
71754	2023-12-07 21:13:00	Lana Del Rey	Young And Beautiful	3.146	1
71759	2023-12-07 21:13:00	Lana Del Rey	Ride	1.126	1
71764	2023-12-07 21:14:00	Ariana Grande	my hair	23.757	1
71765	2023-12-07 21:14:00	Leonard Cohen	Thanks for the Dance	9.317	1
71766	2023-12-07 21:17:00	The Vaccines	Your Love Is My Favourite Band	14.661	1

156539 rows × 5 columns

3.3 Plotting skipped songs

Create a pie-chart that compares amount of skipped songs to amount of non-skipped songs.

```
In [90]: plt.figure(figsize=(7, 7))
plt.pie(clean_df["skipped"].value_counts(), labels=["Skipped", "Not skipp
plt.title("Percentage of skipped vs. non-skipped Songs", fontsize=14, fon
plt.show()
```



3.4 Artists by percentage of songs skipped

For each artist in the dataset, calculate which percentage of their songs was skipped. Store this information in a new DataFrame called `df_skipped`. Store the percentage of skipped songs in a new column named `SkipRate`

Example: If an artist has **100** songs in your dataset and **25** of these were skipped, the percentage of skipped songs for this artist would be $\frac{25}{100} = 25\%$

In [91]:
```python
df_skipped = ((clean_df[clean_df["skipped"] == 1].groupby("artistName")["
              clean_df.groupby("artistName")["skipped"].count()) * 100).r

df_skipped = df_skipped.reset_index().rename(columns={"skipped": "SkipRat

df_skipped
```

Out[91]:

	artistName	SkipRate
0	10cc	67.86
1	2Pac	86.16
2	3 Doors Down	50.00
3	4 Non Blondes	72.13
4	50 Cent	67.86
...	...	...
951	squeeda	66.67
952	tenkousei.	100.00
953	trxxshed	50.00
954	xander.	37.50
955	Édith Piaf	94.19

956 rows × 2 columns

3.5 Comparing artists by skip-rate

Find the `three` top artists with the lowest skip-rate and the `three` with the highest. Print their names, along with their skip-rate.

In [92]:
```python
top_3 = df_skipped.nlargest(3, "SkipRate")
bottom_3 = df_skipped.nsmallest(3, "SkipRate")

print(top_3)
print(bottom_3)
```

```
              artistName  SkipRate
7    A Problem Squared     100.0
16          Acid Ghost     100.0
25   Albert Hammond Jr     100.0
    artistName  SkipRate
645   Roc Boyz     11.11
437      LACES     14.29
878      Wham!     16.67
```

Part 4: God Is a Data Scientist - The Ariana Deep-Dive

4.0 Ariana-DataFrame:

Create a new DataFrame called *df_ariana*, containing only rows with music by Ariana Grande.

In [93]:
```
df_ariana = clean_df[clean_df["artistName"] == "Ariana Grande"]
df_ariana
```

Out[93]:

	endTime	artistName	trackName	secPlayed	skipped
10881	2023-01-01 01:17:00	Ariana Grande	7 rings	0.139	1
10882	2023-01-01 01:17:00	Ariana Grande	7 rings	0.487	1
10883	2023-01-01 01:17:00	Ariana Grande	positions	0.417	1
10887	2023-01-01 01:17:00	Ariana Grande	Santa Baby	12.293	1
10888	2023-01-01 01:17:00	Ariana Grande	Right There (feat. Big Sean)	22.929	1
...	...	...	...	...	...
71743	2023-12-07 17:46:00	Ariana Grande	Almost Is Never Enough	28.483	1
71750	2023-12-07 20:51:00	Ariana Grande	needy	26.220	1
71756	2023-12-07 21:13:00	Ariana Grande	pete davidson	0.603	1
71763	2023-12-07 21:13:00	Ariana Grande	off the table (with The Weeknd)	13.448	1
71764	2023-12-07 21:14:00	Ariana Grande	my hair	23.757	1

19337 rows × 5 columns

4.1 Average skip rate

Create a histogram of the distribution of the skip-rate values of the different artists in your DataFrame `df_skipped`, with skip rates on one axis and number of artists on the other.

Then, retrieve the skip rate for Ariana Grande from your DataFrame `df_skipped`. Run the code in the cell below. Where on this distribution does Ariana Grande fall? Do I skip her songs more than average, or less?

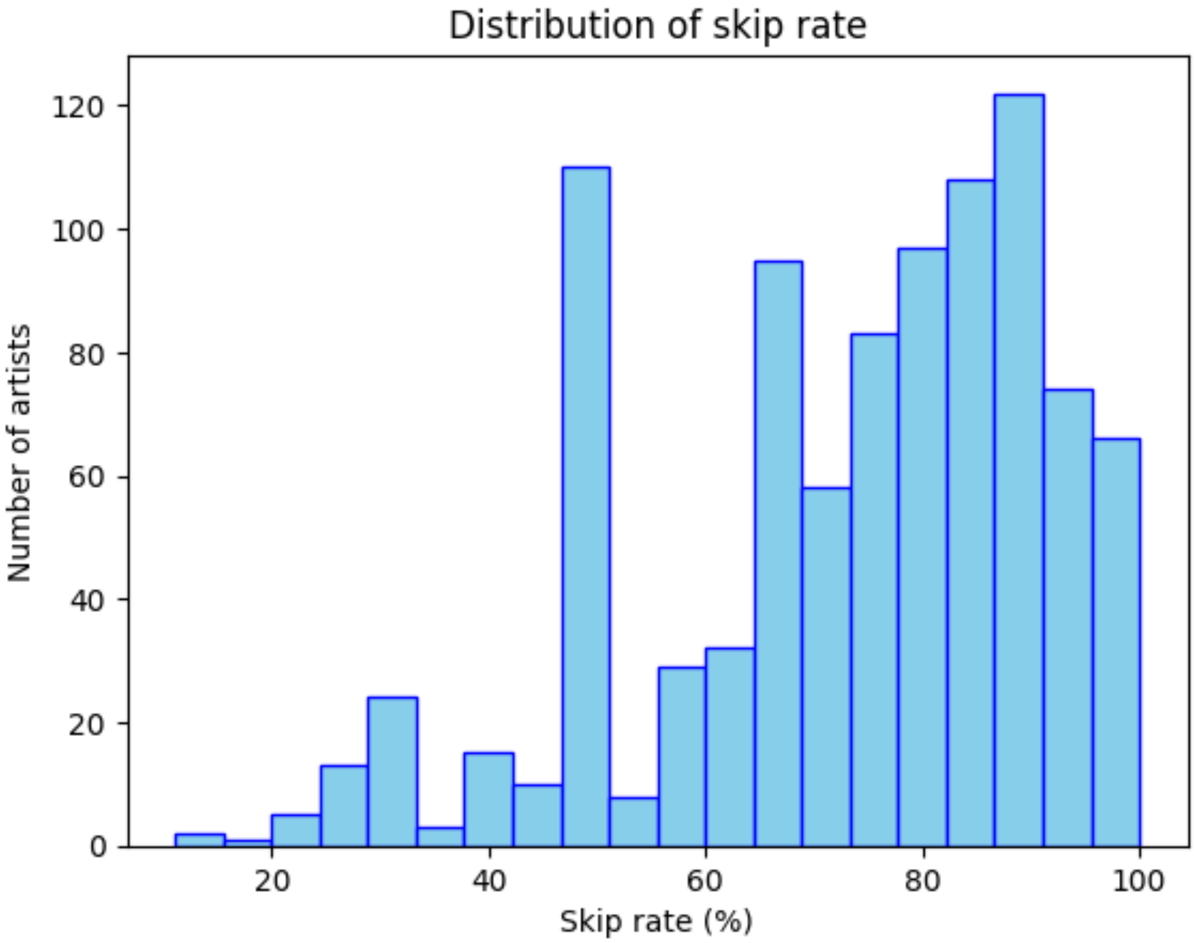
In [94]:
```
plt.hist(df_skipped["SkipRate"], bins=20, color="skyblue", edgecolor="blu

plt.xlabel("Skip rate (%)")
plt.ylabel("Number of artists")
plt.title("Distribution of skip rate")

plt.show()

skiprate_ariana = (df_skipped[df_skipped["artistName"] == "Ariana Grande"
average_skiprate = df_skipped["SkipRate"].mean().__round__(2)

print(f"Skiprate Ariana: {skiprate_ariana}%, average skiprate: {average_s
```




```
Skiprate Ariana: 99.53%, average skiprate: 73.13%
```

Part 4: Questions

Q1: Did I skip a lot of Ariana Grande's songs, or did I not, compared to the rest of the dataset?

Compared to an average skiprate of 73.13%, your skiprate for Ariana Grande's songs is higher at 99.53%. This indicates that you skipped most of her songs more frequently than other tracks.

Q2: What might be some possible reasons for Ariana Grande to be my nr.1 artist?

Possible reasons for Ariana Grande to be your nr. 1 artist might be that you listened to a large number of her songs. This might be because her songs were included in playlists you frequently listened to.