Billboard Hot 100 Analysis &

Machine Learning Project

Name:

- Cesario Angel Ibarra

Details

Investigate and exploit the insights of the Billboard Hot 100 (1958 to 2020)

- Exploit how similar the majority of tracks are on the list; no matter the genre
- Understand why Hot 100 tracks all sound the same and are very similar in compositional structure
- Although musical genre is established by supposedly a myriad of determining factors e.g. culture, time and place etc. not to forget all of the rules that music theory has to offer.
- Nevertheless here in this Analysis we will only worry about the empirical data; the audio features of a given track. the only musical theory involved here is Key Signature(Key and Mode), Time Signature and Tempo. These features are simply semantic representions of Frequency, Beats per Measure, and Beats per minute. Nothing theoretical here will be considered.
- Fundamentally, music is time, energy, and motion.
- Music is math and we will explore these virtues of the music on the Billboard Hot 100 ## Explorative Analysis ### Part 2

I will use both barcharts and density plots to check the distribution of variables in the dataset.

In [1]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib as mpl
from matplotlib import cm
import numpy as np
import pandas as pd
import os
%matplotlib inline
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)

# Where to save the figures
PROJECT_ROOT_DIR = "."
FOLDER = "figures"
IMAGES_PATH = os.path.join(PROJECT_ROOT_DIR, FOLDER)
os.makedirs(IMAGES_PATH, exist_ok=True)

def save_fig(fig_id, tight_layout=True, fig_extension="png", resolution=300):
    path = os.path.join(IMAGES_PATH, fig_id + "." + fig_extension)
    print("Saving figure", fig_id)
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)
```

```
# Set columns view to max
pd.set_option('display.max_columns', None)
```

In [2]:
```
# read the df from the pickle file
viz_df = pd.read_pickle('hot100df_distinct.pkl')
viz_df
```

Out[2]:

	performer	song_performer	song	track_duration_s	danceability	energy	key	loudness	mode	speech
0	Andy Williams	.....And Roses And Roses | Andy Williams	.....And Roses And Roses	166.106	0.154	0.185	F	-14.063	major	0
1	Britney Spears	...Baby One More Time | Britney Spears	...Baby One More Time	211.066	0.759	0.699	C	-5.745	minor	0
2	Paul Davis	'65 Love Affair | Paul Davis	'65 Love Affair	219.813	0.647	0.686	D	-4.247	minor	0
3	Tammy Wynette	'til I Can Make It On My Own | Tammy Wynette	'til I Can Make It On My Own	182.080	0.450	0.294	G	-12.022	major	0
4	Luther Vandross	'Til My Baby Comes Home | Luther Vandross	'Til My Baby Comes Home	332.226	0.804	0.714	B	-6.714	minor	0
...	...	...	...	...	...	...	...	...	...	
13053	The Trammps	Zing Went The Strings Of My Heart | The Trammps	Zing Went The Strings Of My Heart	202.693	0.667	0.851	E	-5.257	major	0
13054	The Five Americans	Zip Code | The Five Americans	Zip Code	175.040	0.393	0.594	A	-5.986	major	0
13055	Bad Wolves	Zombie | Bad Wolves	Zombie	254.805	0.448	0.826	D	-3.244	minor	0
13056	Herb Alpert & The Tijuana Brass	Zorba The Greek | Herb Alpert & The Tijuana Brass	Zorba The Greek	264.853	0.531	0.642	F	-12.702	major	0
13057	K7	Zunga Zeng | K7	Zunga Zeng	273.000	0.846	0.657	C#	-9.642	major	0

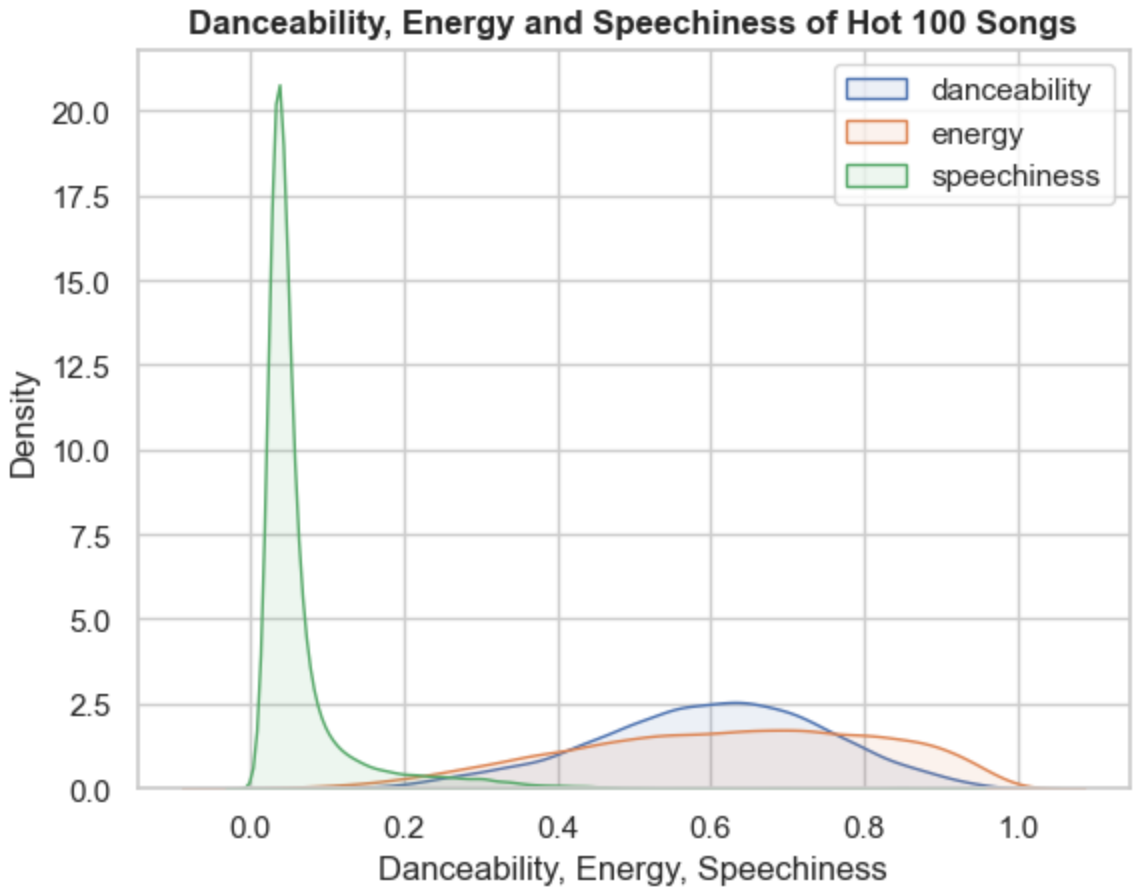
13058 rows × 23 columns

Density Plot, visualizing:

- Danceability: Based on a combo of tempo, rhytmic stability, beat; measuring how suitable a song is for dancing.

- Energy: Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity.
- Speechiness: speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value.

In [3]:
```
# Viz w Density plot
sns.set_palette('Accent')
sns.set(style='whitegrid')
sns.kdeplot(data=viz_df, x='danceability', fill=True, alpha=0.1, label='danceability')
sns.kdeplot(data=viz_df, x='energy', fill=True, alpha=0.1, label='energy')
sns.kdeplot(data=viz_df, x='speechiness', fill=True, alpha=0.1, label='speechiness')
plt.xlabel('Danceability, Energy, Speechiness')
plt.ylabel('Density')
plt.title('Danceability, Energy and Speechiness of Hot 100 Songs', fontsize=12, fontweig
plt.legend(title='')
plt.show()
```

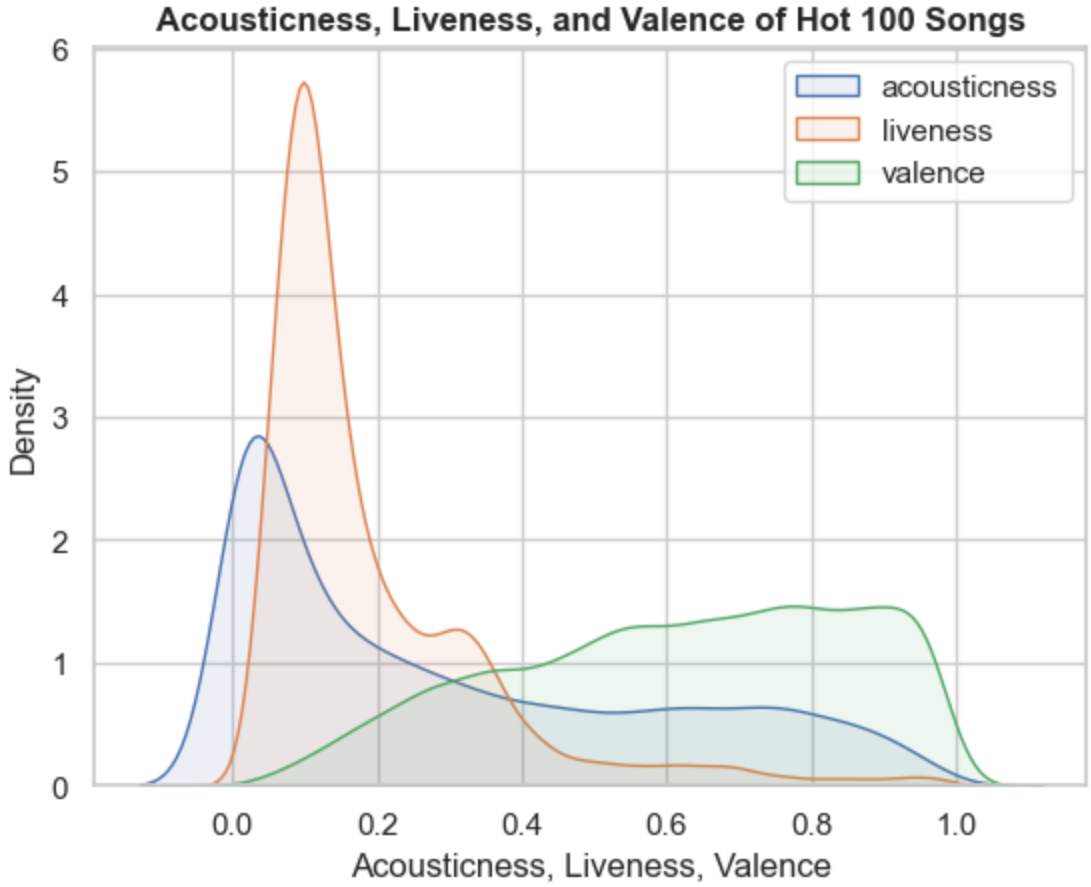


Visualizing:

- Acousticness: Confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
- Valence: Measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g., happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g., sad, depressed, angry).
- Liveness: Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live.

In [4]:
```
# Viz w Density plot
sns.set_palette('Accent')
sns.set(style='whitegrid')
```

```
sns.kdeplot(data=viz_df, x='acousticness', fill=True, alpha=0.1, label='acousticness')
sns.kdeplot(data=viz_df, x='liveness', fill=True, alpha=0.1, label='liveness')
sns.kdeplot(data=viz_df, x='valence', fill=True, alpha=0.1, label='valence')
plt.xlabel('Acousticness, Liveness, Valence')
plt.ylabel('Density')
plt.title('Acousticness, Liveness, and Valence of Hot 100 Songs', fontsize=12, fontweigh
plt.legend(title='')
plt.show()
```



Based on these plots a few things about Billboard Hot 100 songs can be noted:

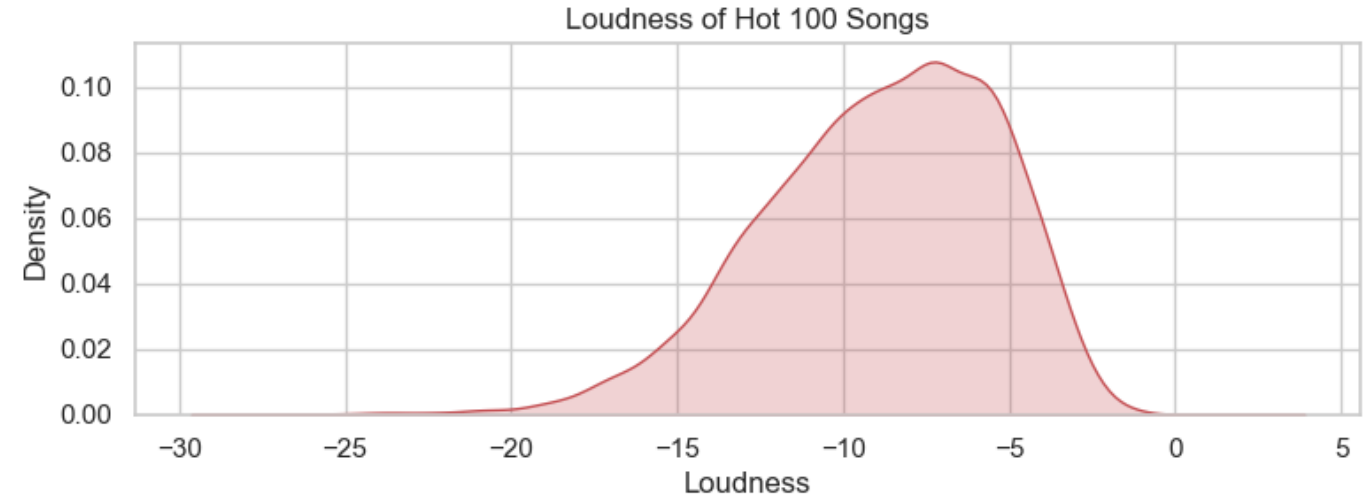
- most songs have quite a high danceability, between 0.5 and 0.75;
- the distribution of energy across songs is almost normal, meaning that songs range from up-beat to slow and calm options;
- a prevailing majority of tracks have speechiness between 0 and 0.1, meaning that a lot of tracks have very few lyrics;
- acousticness of songs is also quite left-skewed. Highly acoustic songs mainly contain orchestral instruments, an unaltered voice, acoustic guitars and natural drum kits, whereas less acoustic songs contain, for example, synthesizers, electric guitars and amplified instruments;
- liveness is very left-skewed, which makes sense as most of the tracks on Billboard are studio recordings, with a low probability of audience being present;
- valence of most of the songs is higher than 0.5, meaning that most Billboard tracks are indeed positive.

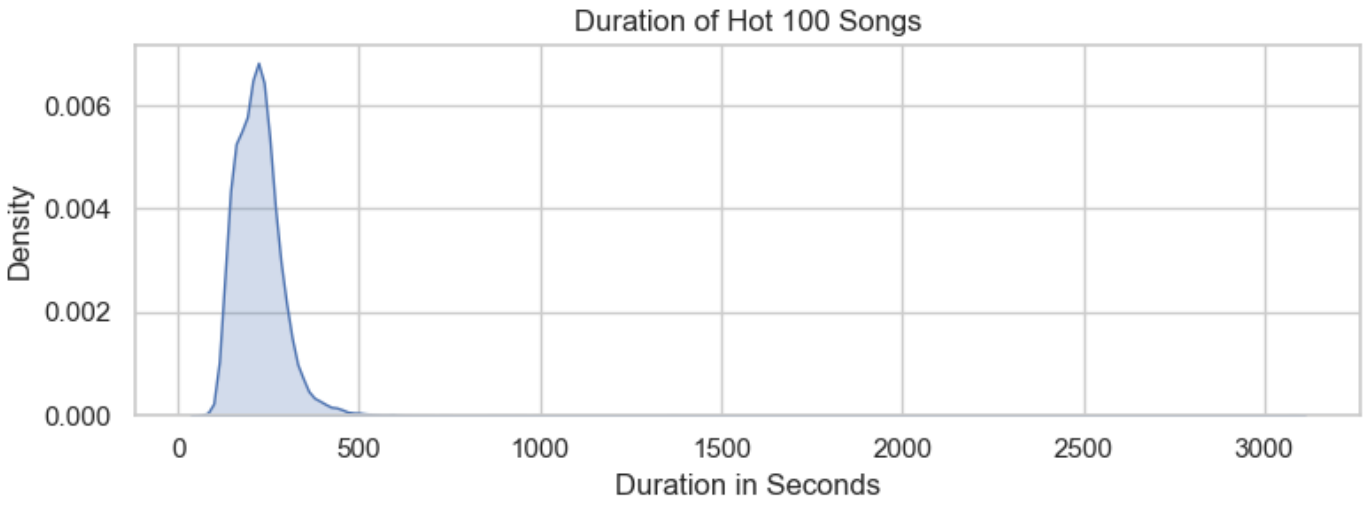
Now we can have a look at the distribution of

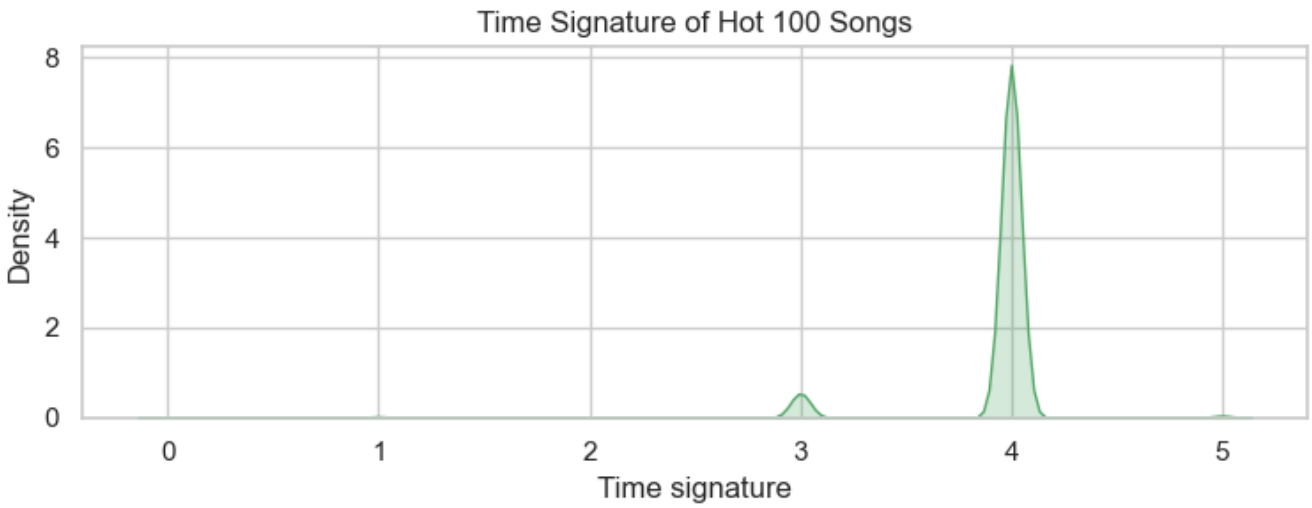
- loudness
- duration in seconds
- time signature

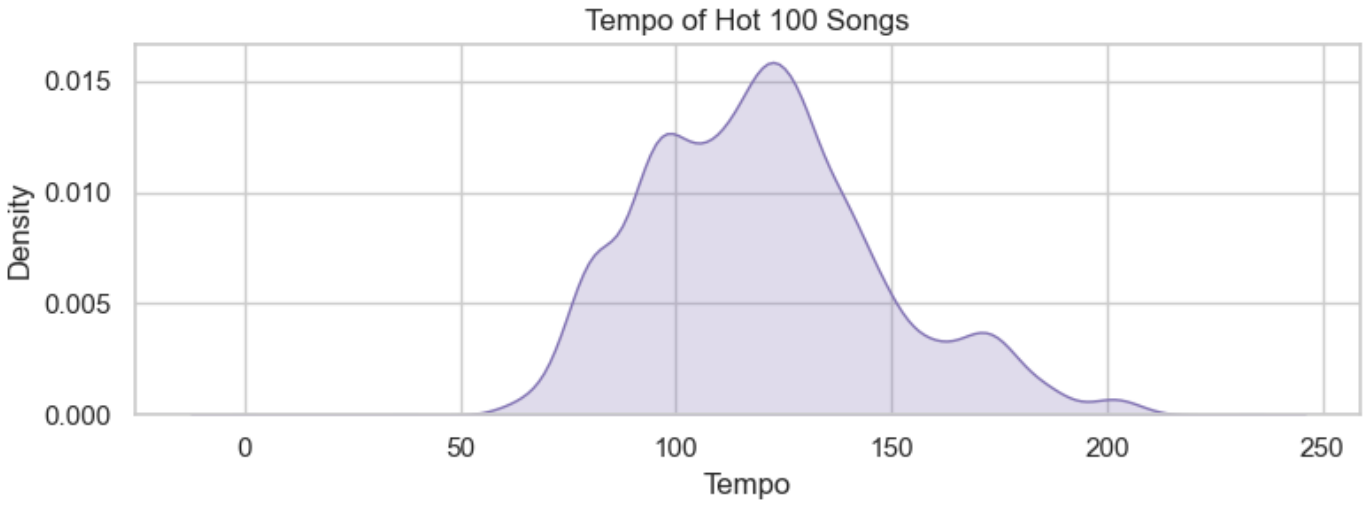
- tempo
- liveness
- acousticness
- energy
- valence
- danceability

In [5]:
```
sns.set_palette('Accent')
sns.set(style='whitegrid')

# Create a figure with four subplots
fig, axs = plt.subplots(4, 1, figsize=(8, 12))

# Plot the loudness density
sns.kdeplot(viz_df['loudness'], fill=True, color="r", ax=axs[0])
axs[0].set_title("Loudness of Hot 100 Songs")
axs[0].set_xlabel("Loudness")
axs[0].set_ylabel("Density")

# Plot the duration density
sns.kdeplot(viz_df['track_duration_s'], fill=True, color="b", ax=axs[1])
axs[1].set_title("Duration of Hot 100 Songs")
axs[1].set_xlabel("Duration in Seconds")
axs[1].set_ylabel("Density")

# Plot the time signature density
sns.kdeplot(viz_df['time_signature'], fill=True, color="g", ax=axs[2])
axs[2].set_title("Time Signature of Hot 100 Songs")
axs[2].set_xlabel("Time signature")
axs[2].set_ylabel("Density")

# Plot the tempo density
sns.kdeplot(viz_df['tempo'], fill=True, color="m", ax=axs[3])
axs[3].set_title("Tempo of Hot 100 Songs")
axs[3].set_xlabel("Tempo")
axs[3].set_ylabel("Density")

# Show the plot
plt.tight_layout()
plt.show()
```


Loudness of Hot 100 Songs
Density
0.10
0.08
0.06
0.04
0.02
0.00
−30
−25
−20
−15
−10
−5
0
5
Loudness


Duration of Hot 100 Songs
Density
0.006
0.004
0.002
0.000
0
500
1000
1500
2000
2500
3000
Duration in Seconds


Time Signature of Hot 100 Songs
Density
8
6
4
2
0
0
1
2
3
4
5
Time signature

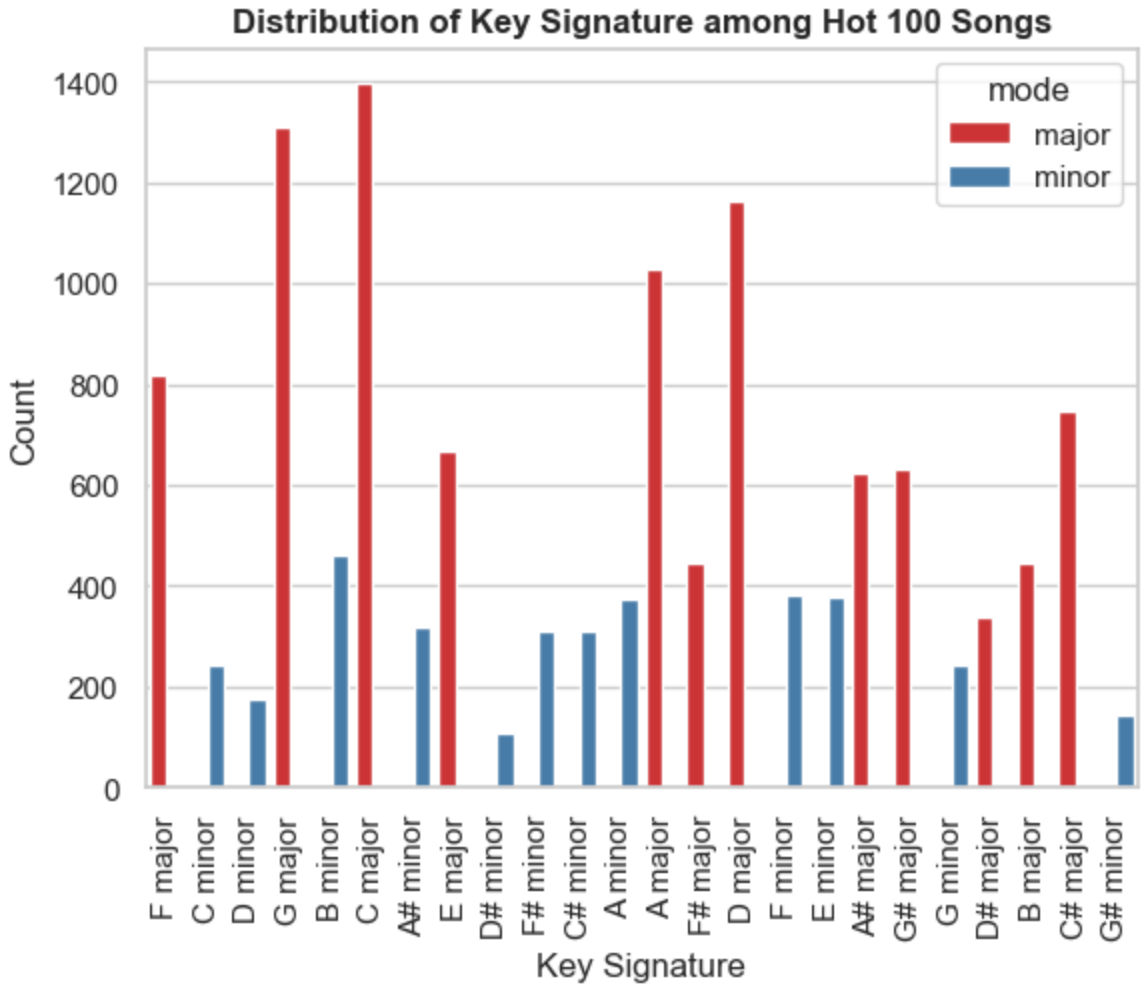

Tempo of Hot 100 Songs
Density
0.015
0.010
0.005
0.000
0
50
100
150
200
250
Tempo

Based on these graphs the following insights can be derived:

- Most of the Billboard tracks indeed are moderately loud;
- Duration is on average 225 seconds (3 minutes and 45 seconds);
- Majority of tracks has a time signature of 4/4 or four quarter note beats, which is extremely common in the music industry;
- most of the tracks have the tempo of around 125 beats per minute (BPM), again extremely commmon

Now lets plot key signatures across all tracks

In [6]:
```
# Plot the distribution of key signatures
sns.countplot(x='key_signature', hue='mode', data=viz_df, palette='Set1')

# Set the title and axis labels
plt.title("Distribution of Key Signature among Hot 100 Songs", fontweight='bold')
plt.xlabel("Key Signature")
plt.ylabel("Count")

# Rotate the x-axis labels
plt.xticks(rotation=90)

# Show the plot
plt.show()
```



The most popular keys among billboard tracks are C major, G major and D major:

It's logical that major keys dominate the distribution as they are perceived to be happy, while minor keys are perceived to be sad.

Personal Note

AS for us musicians and composers, we have all known this for a very long time. Although not displayed here, the four most chords in C major are C, G, Am, F, also Dm, E. As for this chord progression (I-IV-V-vi) can be heard and seen in all throughout the Hot 100

- Best example of this fact being exploited, is by the band Axis of Awesome https://www.youtube.com/watch?v=5pidokakU4I&t=4s
- This is also why musicians in Pop cover bands can easily remember hundreds of songs;

SPOILER ALERT because they're all the same

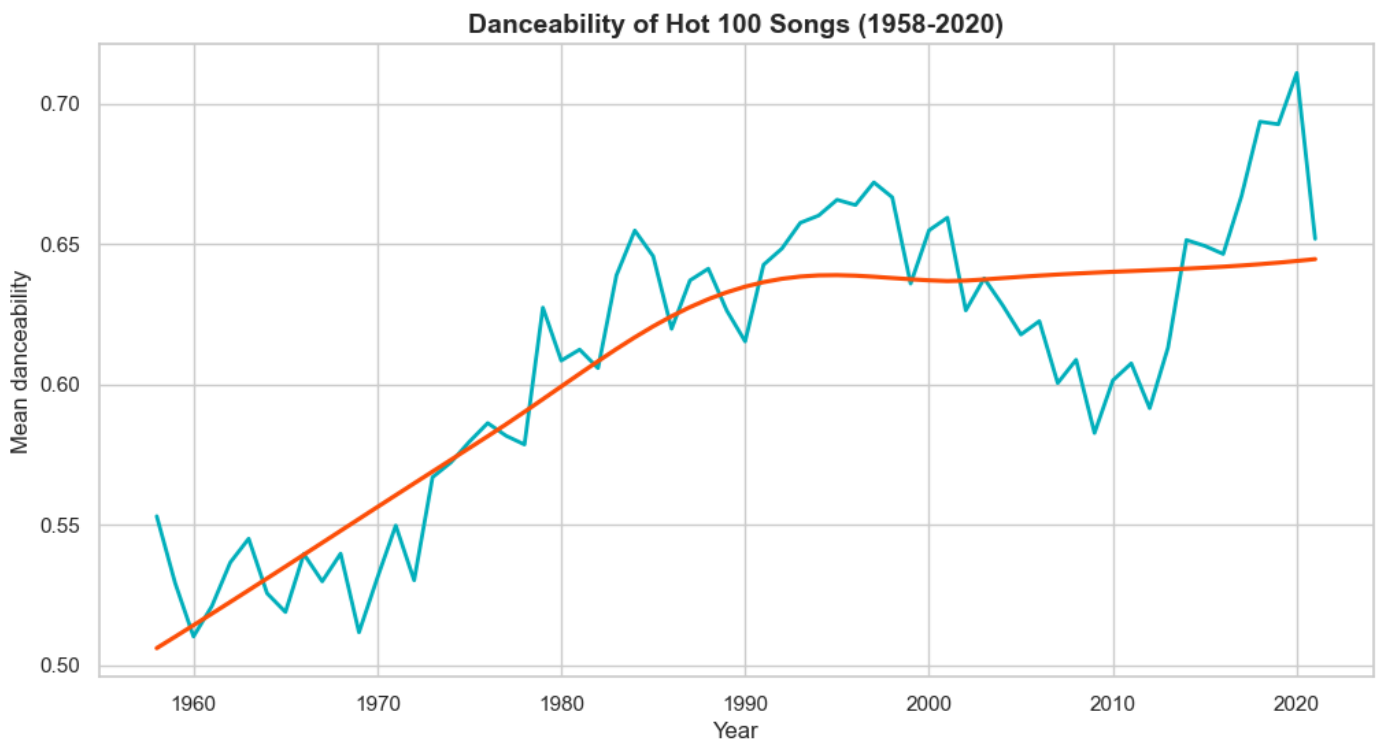
Variation of Grooves and Emotional State

Displaying the variation of each feature over time; from 1958 to 2020

- Danceability
- Energy
- Valence
- Loudness
- Acousticness
- Duration

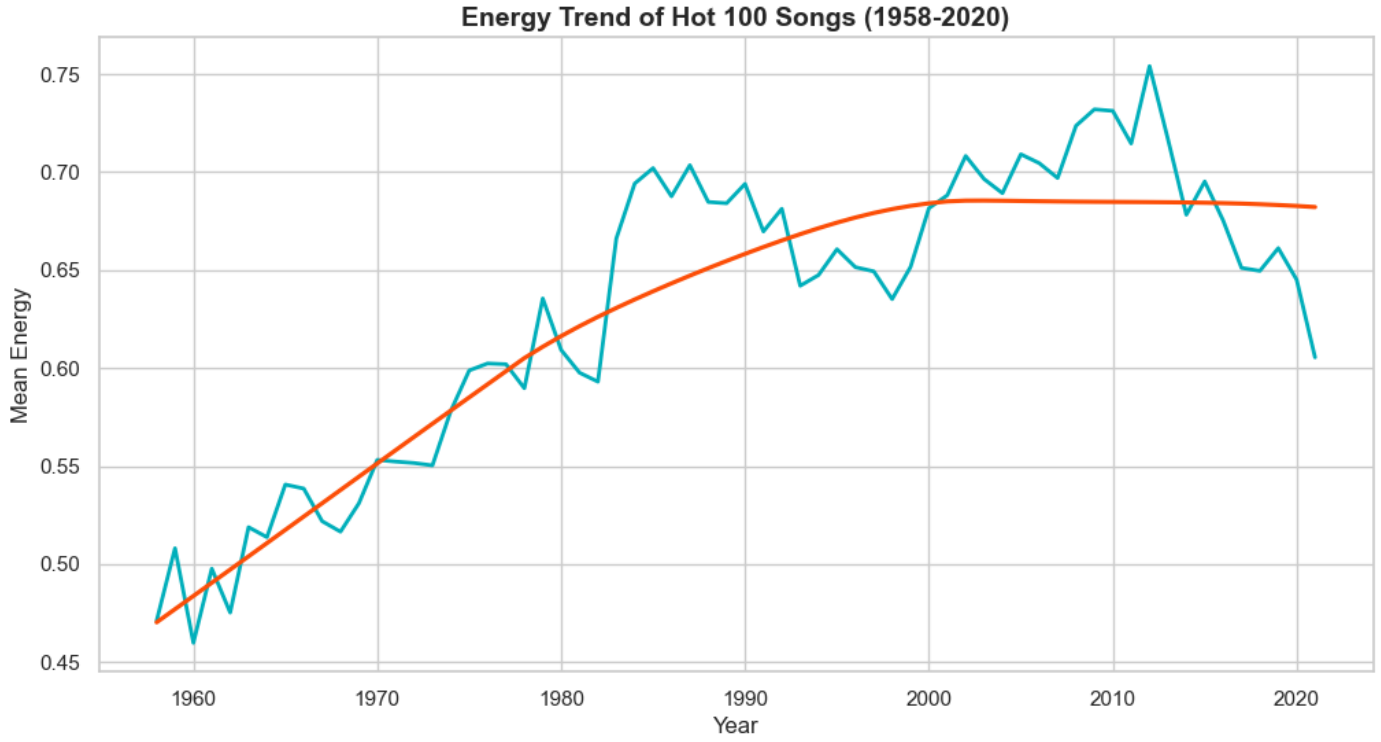
Let's check out Danceability

In [7]:
```
danceability_trend = viz_df[['danceability', 'year']].groupby('year').mean().reset_index
danceability_trend.columns = ['year', 'danceability_mean']

sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))
sns.lineplot(x='year', y='danceability_mean', data=danceability_trend, color="#00AFBB",
sns.regplot(x='year', y='danceability_mean', data=danceability_trend, scatter=False, col
plt.title("Danceability of Hot 100 Songs (1958-2020)", fontsize=14, fontweight='bold')
plt.xlabel("Year")
plt.ylabel("Mean danceability")
plt.show()
```



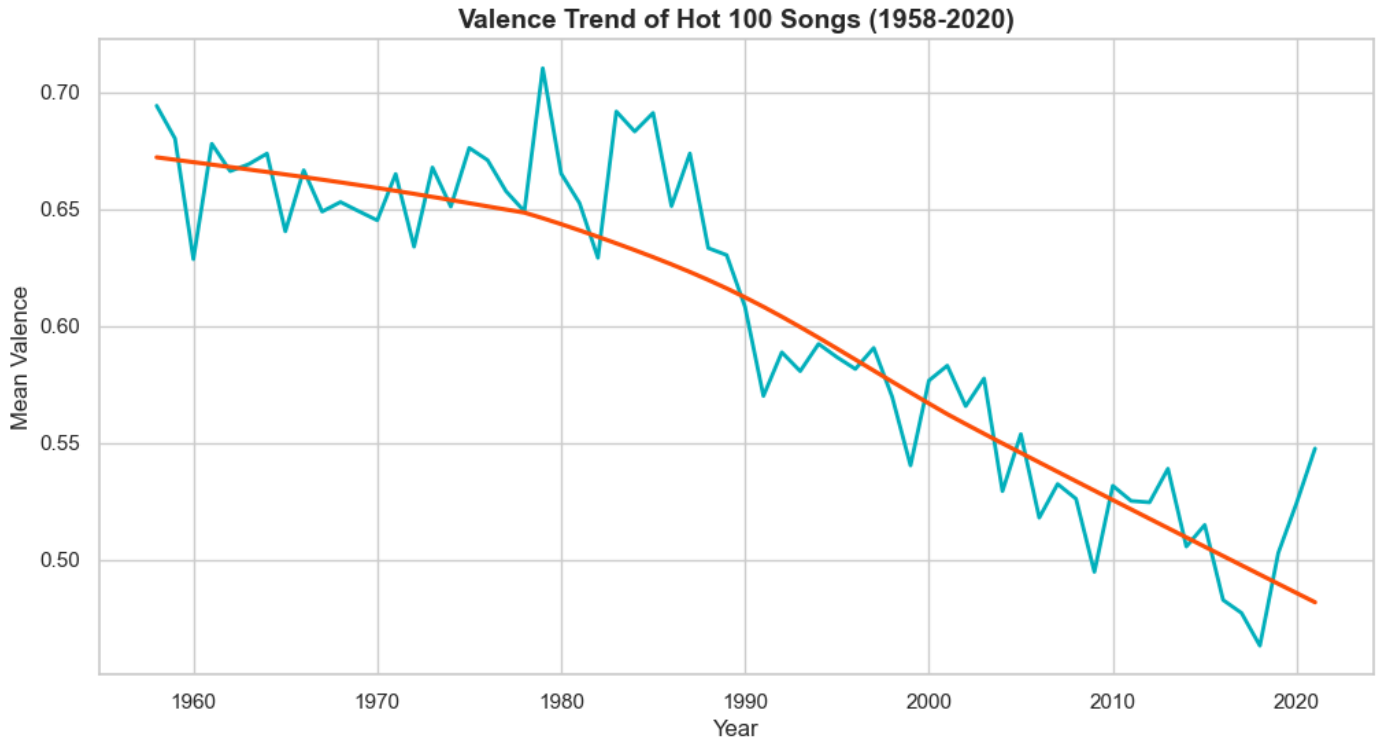
Energy over time

In [8]:
```
energy_trend = viz_df[['energy', 'year']].groupby('year').mean().reset_index()
energy_trend.columns = ['year', 'energy_mean']

sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))
sns.lineplot(x='year', y='energy_mean', data=energy_trend, color="#00AFBB", linewidth=2)
sns.regplot(x='year', y='energy_mean', data=energy_trend, scatter=False, color="#FC4E07"
plt.title("Energy Trend of Hot 100 Songs (1958-2020)", fontsize=14, fontweight='bold')
plt.xlabel("Year")
plt.ylabel("Mean Energy")
plt.show()
```



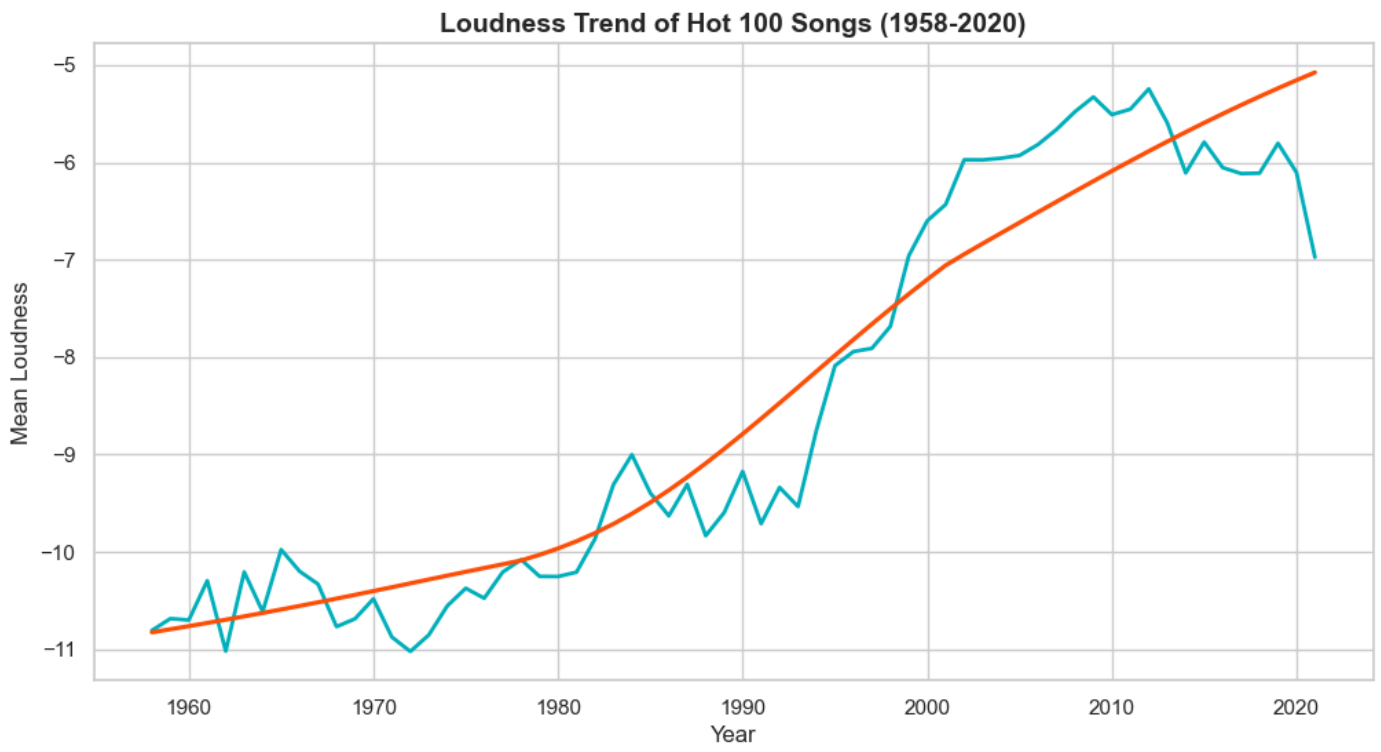
Valence or Emotioal State Trend Over Time

In [9]:
```
valence_trend = viz_df[['valence', 'year']].groupby('year').mean().reset_index()
valence_trend.columns = ['year', 'valence_mean']

sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))
sns.lineplot(x='year', y='valence_mean', data=valence_trend, color="#00AFBB", linewidth=
sns.regplot(x='year', y='valence_mean', data=valence_trend, scatter=False, color="#FC4E0
plt.title("Valence Trend of Hot 100 Songs (1958-2020)", fontsize=14, fontweight='bold')
plt.xlabel("Year")
plt.ylabel("Mean Valence")
plt.show()
```



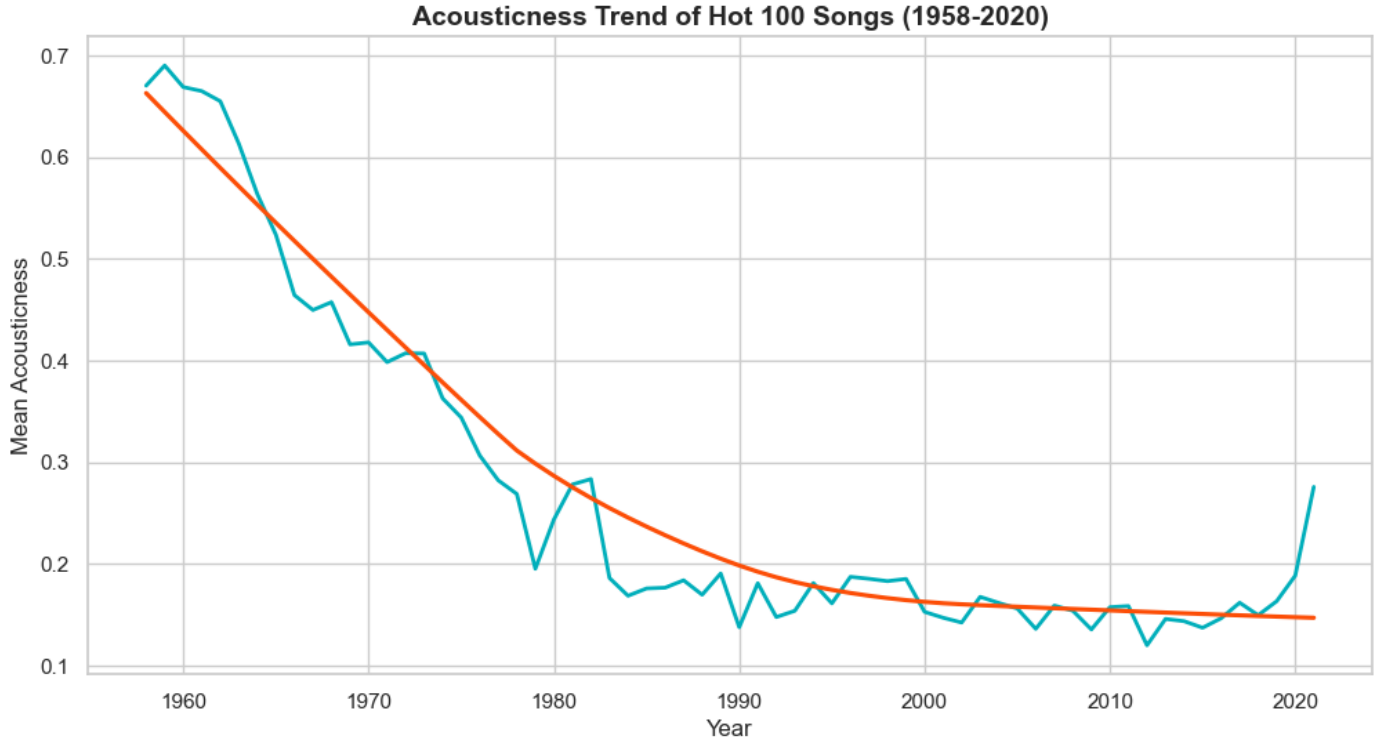
Loudness

In [10]:
```
loudness_trend = viz_df[['loudness', 'year']].groupby('year').mean().reset_index()
loudness_trend.columns = ['year', 'loudness_mean']

sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))
sns.lineplot(x='year', y='loudness_mean', data=loudness_trend, color="#00AFBB", linewidt
sns.regplot(x='year', y='loudness_mean', data=loudness_trend, scatter=False, color="#FC4
plt.title("Loudness Trend of Hot 100 Songs (1958-2020)", fontsize=14, fontweight='bold')
plt.xlabel("Year")
plt.ylabel("Mean Loudness")
plt.show()
```



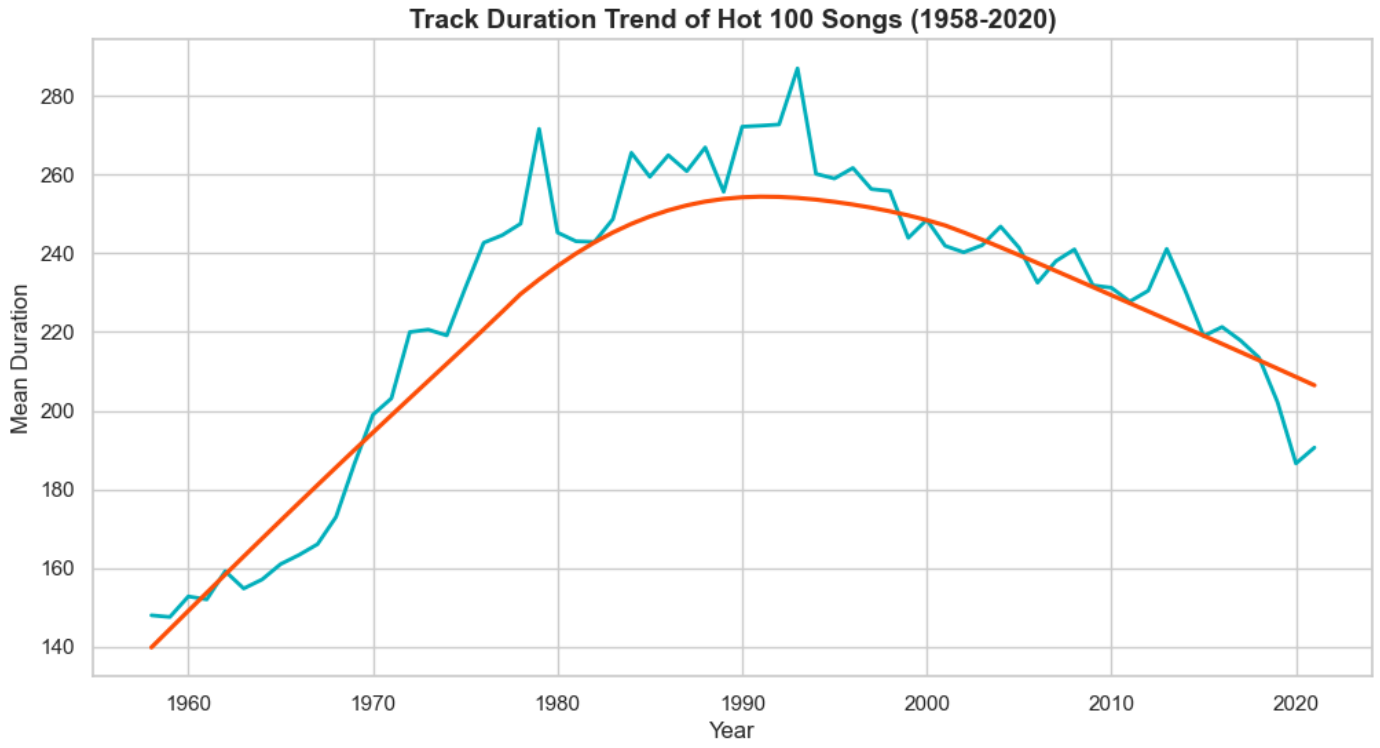
Acousticness Trend

In [11]:
```
acousticness_trend = viz_df[['acousticness', 'year']].groupby('year').mean().reset_index
acousticness_trend.columns = ['year', 'acousticness_mean']

sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))
sns.lineplot(x='year', y='acousticness_mean', data=acousticness_trend, color="#00AFBB",
sns.regplot(x='year', y='acousticness_mean', data=acousticness_trend, scatter=False, col
plt.title("Acousticness Trend of Hot 100 Songs (1958-2020)", fontsize=14, fontweight='bo
plt.xlabel("Year")
plt.ylabel("Mean Acousticness")
plt.show()
```



Duration of Tracks Over Time

In [12]:
```
track_duration_trend = viz_df[['track_duration_s', 'year']].groupby('year').mean().reset
track_duration_trend.columns = ['year', 'track_duration_s_mean']

sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))
sns.lineplot(x='year', y='track_duration_s_mean', data=track_duration_trend, color="#00A
sns.regplot(x='year', y='track_duration_s_mean', data=track_duration_trend, scatter=Fals
plt.title("Track Duration Trend of Hot 100 Songs (1958-2020)", fontsize=14, fontweight='
plt.xlabel("Year")
plt.ylabel("Mean Duration")
plt.show()
```



Valence-arousal model

- Valence arousal is the combination of the emotional state of a track and the amount of emotion articulated. (Valence and Energy = Arousal)
- High valence = happy
- Low valence = sad
- Q1 — “happy”: valence > 0.5, arousal (energy) > 0.5;
- Q2 — “excited”: valence <= 0.5, arousal (energy) > 0.5;
- Q3 — “sad”: valence <= 0.5, arousal (energy) <= 0.5;
- Q4 — “peaceful”: valence > 0.5, arousal (energy) <= 0.5

In [13]:
```
viz_df
```

Out[13]:

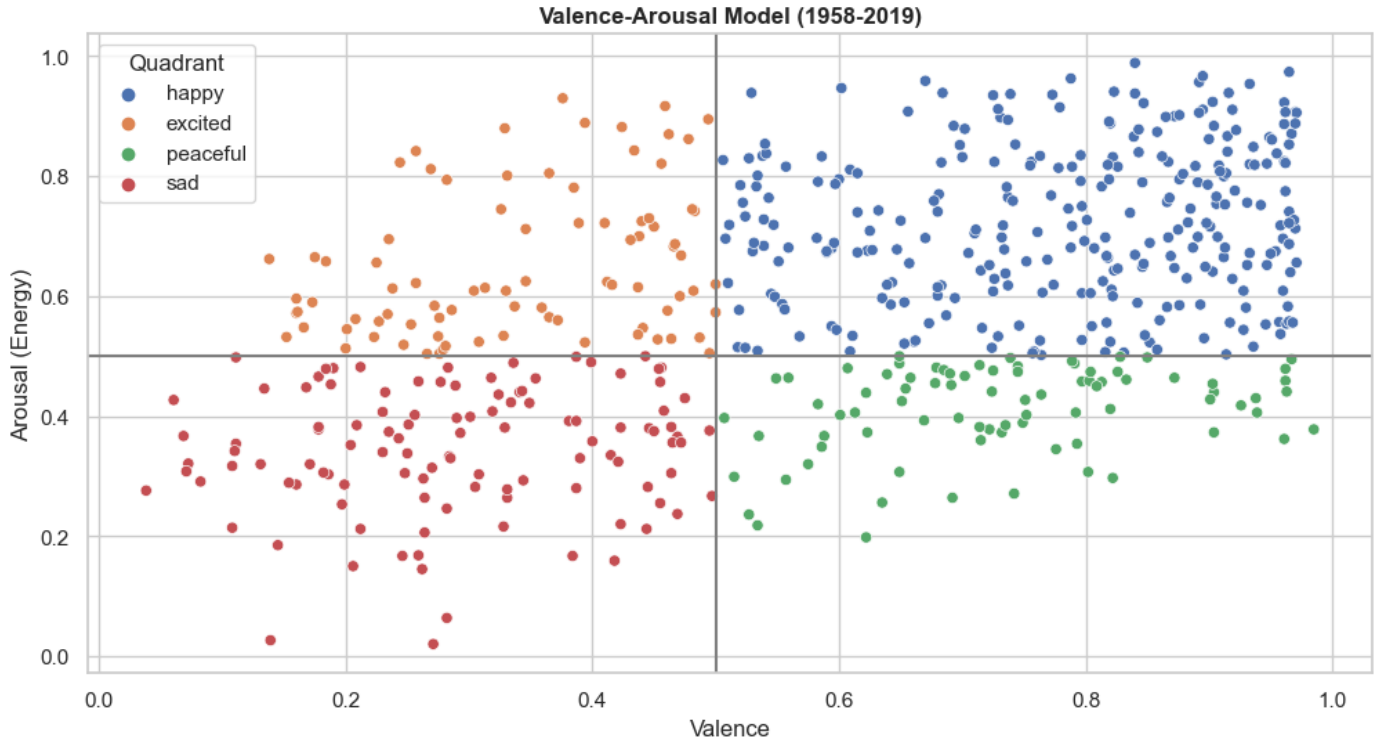
	performer	song_performer	song	track_duration_s	danceability	energy	key	loudness	mode	speech
0	Andy Williams	.....And Roses And Roses | Andy Williams	.....And Roses And Roses	166.106	0.154	0.185	F	-14.063	major	0
1	Britney Spears	...Baby One More Time | Britney	...Baby One	211.066	0.759	0.699	C	-5.745	minor	0

		Spears	More Time							
2	Paul Davis	'65 Love Affair | Paul Davis	'65 Love Affair	219.813	0.647	0.686	D	-4.247	minor	0
3	Tammy Wynette	'til I Can Make It On My Own | Tammy Wynette	'til I Can Make It On My Own	182.080	0.450	0.294	G	-12.022	major	0
4	Luther Vandross	'Til My Baby Comes Home | Luther Vandross	'Til My Baby Comes Home	332.226	0.804	0.714	B	-6.714	minor	0
...	...	...	...	...	...	...	...	...	...	
13053	The Trammps	Zing Went The Strings Of My Heart | The Trammps	Zing Went The Strings Of My Heart	202.693	0.667	0.851	E	-5.257	major	0
13054	The Five Americans	Zip Code | The Five Americans	Zip Code	175.040	0.393	0.594	A	-5.986	major	0
13055	Bad Wolves	Zombie | Bad Wolves	Zombie	254.805	0.448	0.826	D	-3.244	minor	0
13056	Herb Alpert & The Tijuana Brass	Zorba The Greek | Herb Alpert & The Tijuana Brass	Zorba The Greek	264.853	0.531	0.642	F	-12.702	major	0
13057	K7	Zunga Zeng | K7	Zunga Zeng	273.000	0.846	0.657	C#	-9.642	major	0

13058 rows × 23 columns

In [14]:
```
# New object for all peak rank of 1
billboard_filtered = viz_df[viz_df['peak_rank'] == 1].copy()

# New object for Quads
billboard_filtered['quadrant'] = np.where(billboard_filtered['energy'] > 0.5,
np.where(billboard_filtered['valence'] > 0.5, 'happy', 'excited'),
np.where(billboard_filtered['valence'] > 0.5, 'peaceful', 'sad'))

sns.set(style="whitegrid")
plt.figure(figsize=(12, 6))
sns.scatterplot(x='valence', y='energy', hue='quadrant', data=billboard_filtered)
plt.axvline(x=0.5, color='gray')
plt.axhline(y=0.5, color='gray')
plt.title("Valence-Arousal Model (1958-2019)", fontsize=12, fontweight='bold')
plt.suptitle("Based on Top Hits from Hot 100", fontsize=10, fontstyle='italic')
plt.xlabel("Valence")
plt.ylabel("Arousal (Energy)")
plt.legend(title="Quadrant")
plt.show()
```

Based on Top Hits from Hot 100

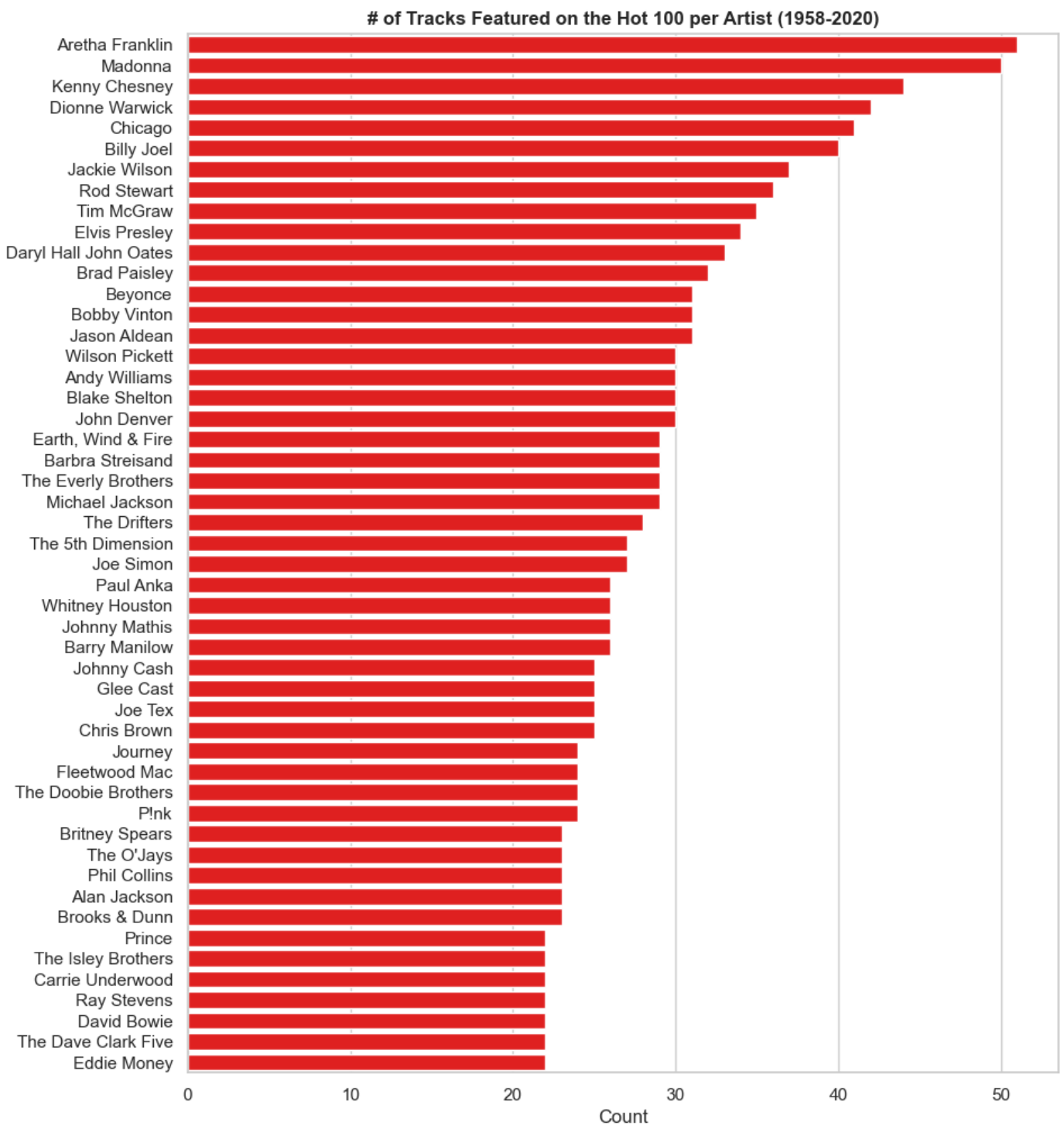


Notice most of tracks on the Billboard Hot 100 hits are “happy”, with a significant share of “sad” tracks.

Last obvservations into Top Artist and Track Frequency:

- Groupby Performer
- Agg number of song_performer entries
- Plot Most Tracks by one artist

In [15]:
```
# New object for performers_entries
performers_entries = (viz_df[['performer', 'song', 'song_performer']]
                      .groupby('performer')
                      .agg(n_entries=('song_performer', 'nunique'))
                      .reset_index()
                      .sort_values('n_entries', ascending=False)
                      .head(50))
# Plot Most Tracks by 1 Artist
sns.set_style("whitegrid")
plt.figure(figsize=(10, 12))
ax = sns.barplot(x='n_entries', y='performer', data=performers_entries, color="red")
ax.set_title("# of Tracks Featured on the Hot 100 per Artist (1958-2020)", fontsize=12,
ax.set(xlabel='Count', ylabel='')
plt.show()
```



First, there is a discrepancy;

this is due to dropping all the null values and a few top artists are obviously missing

- Import uncleaned dataset from hot100.csv
- visualize the difference

In [16]:
```
file1 = 'Hot100.csv'
unclean_hot_df = pd.read_csv(file1)
unclean_hot_df
```

Out[16]:

	Song_Performer	Song	Performer	Genre	Track_Duration_s	Track_Album	Danceability	Key	Mo
0	'03 Bonnie & Clyde | Jay-Z	'03 Bonnie & Clyde	Jay-Z Featuring	['east coast hip hop',	205.560	The Blueprint 2 The Gift & The Curse	NaN	NaN	Na

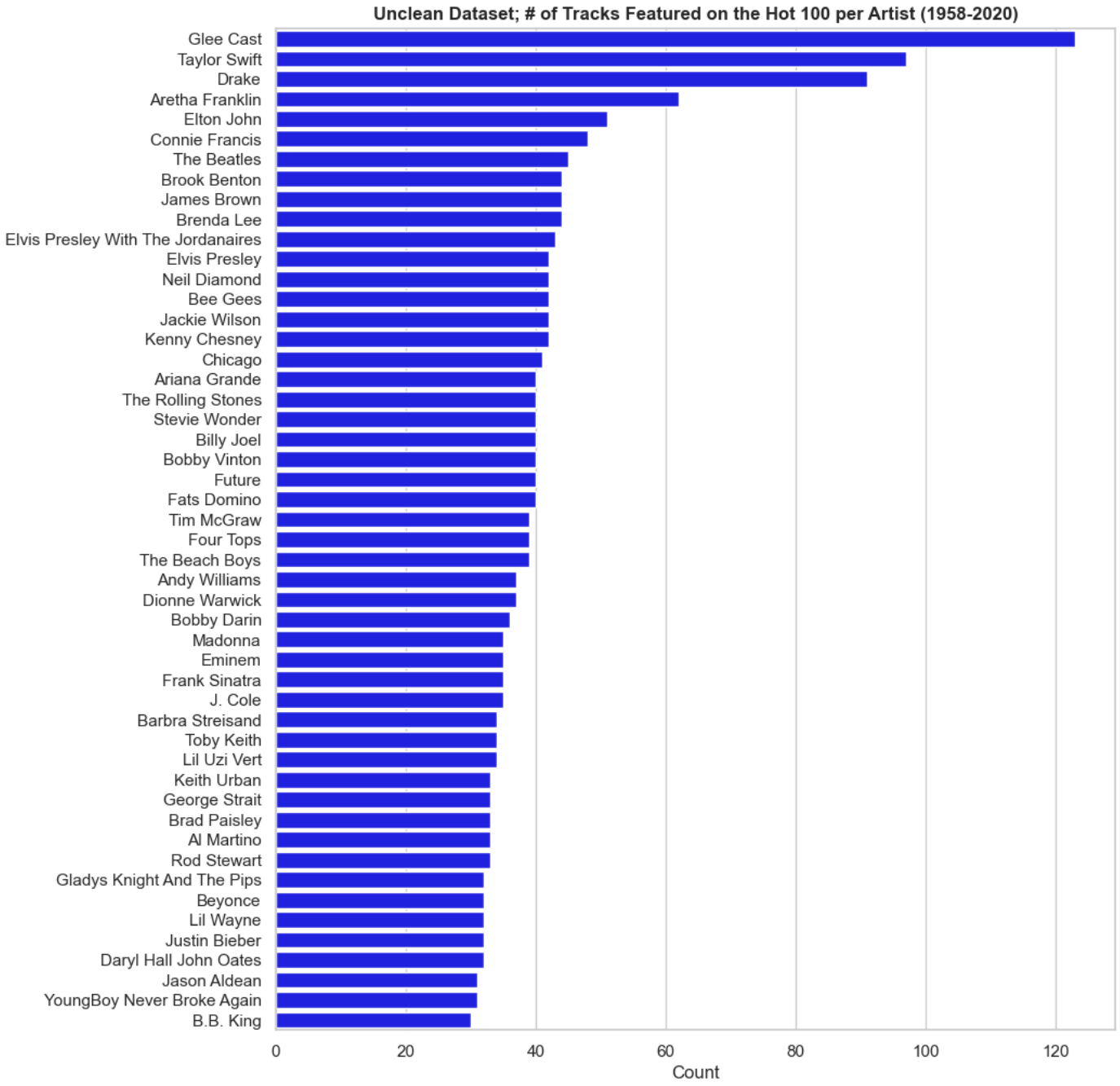
	Featuring Beyonce K...		Beyonce Knowles	'hip hop', 'pop rap', '...					
1	'65 Love Affair | Paul Davis	'65 Love Affair	Paul Davis	['album rock', 'bubblegum pop', 'country rock'...	219.813	Radio Hits Of the '80s	0.647	D	min
2	'98 Thug Paradise | Tragedy, Capone, Infinite	'98 Thug Paradise	Tragedy, Capone, Infinite	['english indie rock']	NaN	NaN	NaN	NaN	Na
3	'Round We Go | Big Sister	'Round We Go	Big Sister	[]	NaN	NaN	NaN	NaN	Na
4	'til I Can Make It On My Own | Tammy Wynette	'til I Can Make It On My Own	Tammy Wynette	['country', 'country dawn', 'nashville sound']	182.080	The Essential Tammy Wynette	0.450	G	maj
...	...	...	...	...	...	...	...	...	
24245	Zombie | Bad Wolves	Zombie	Bad Wolves	['alternative metal', 'metal', 'post-grunge']	254.805	Zombie	0.448	D	min
24246	Zoo York | Lil Tjay Featuring Fivio Foreign & ...	Zoo York	Lil Tjay Featuring Fivio Foreign & Pop Smoke	NaN	NaN	NaN	NaN	NaN	Na
24247	Zoom | Future	Zoom	Future	['atl hip hop', 'hip hop', 'pop rap', 'rap', '...	278.429	FUTURE	0.852	A	maj
24248	Zorba The Greek | Herb Alpert & The Tijuana Brass	Zorba The Greek	Herb Alpert & The Tijuana Brass	['adult standards', 'easy listening', 'lounge']	264.853	!!!Going Places!!!	0.531	F	maj
24249	Zunga Zeng | K7	Zunga Zeng	K7	['freestyle']	273.000	Swing Batta Swing!	0.846	C#	maj

24250 rows × 19 columns

Now let's plot the difference

In [17]:
```
# New object for performers_entries
unclean_perform_entries = (unclean_hot_df[['Performer', 'Song', 'Song_Performer']]
                      .groupby('Performer')
                      .agg(n_entries=('Song_Performer', 'nunique'))
                      .reset_index()
                      .sort_values('n_entries', ascending=False)
                      .head(50))
# Plot Most Tracks by 1 Artist
```

```
sns.set_style("whitegrid")
plt.figure(figsize=(10, 12))
ax = sns.barplot(x='n_entries', y='Performer', data=unclean_perform_entries, color="blue
ax.set_title("Unclean Dataset; # of Tracks Featured on the Hot 100 per Artist (1958-2020
ax.set(xlabel='Count', ylabel='')
plt.show()
```



Here we can see the missing Artist

- removing null values can sometimes hide the truth
- be cautious
- Important Artist like The Beatles, Ariana Grande, Drake, Taylor Swift and surprisingly, the Cast of Glee; all missing and also occupying spots in the top thirty.

Let's use another unclean dataset to explore a few more insights

- Number of times a single track appears per artist

In [18]:
```
unclean_total_hotdf = pd.read_pickle('hot100_total_unclean.pkl')
```

```
unclean_total_hotdf
```

Out[18]:

	Performer	Song	spotify_track_duration_ms	danceability	energy	key	loudness	mode	speechiness	a
6	Andy Williams	.....And Roses And Roses	166106.0	0.154	0.185	5.0	-14.063	1.0	0.0315	
7	Andy Williams	.....And Roses And Roses	166106.0	0.154	0.185	5.0	-14.063	1.0	0.0315	
8	Andy Williams	.....And Roses And Roses	166106.0	0.154	0.185	5.0	-14.063	1.0	0.0315	
9	Andy Williams	.....And Roses And Roses	166106.0	0.154	0.185	5.0	-14.063	1.0	0.0315	
10	Andy Williams	.....And Roses And Roses	166106.0	0.154	0.185	5.0	-14.063	1.0	0.0315	
...	...	...	...	...	...	...	...	...	...	...
328980	K7	Zunga Zeng	273000.0	0.846	0.657	1.0	-9.642	1.0	0.1400	
328981	K7	Zunga Zeng	273000.0	0.846	0.657	1.0	-9.642	1.0	0.1400	
328982	K7	Zunga Zeng	273000.0	0.846	0.657	1.0	-9.642	1.0	0.1400	
328983	K7	Zunga Zeng	273000.0	0.846	0.657	1.0	-9.642	1.0	0.1400	
328984	K7	Zunga Zeng	273000.0	0.846	0.657	1.0	-9.642	1.0	0.1400	

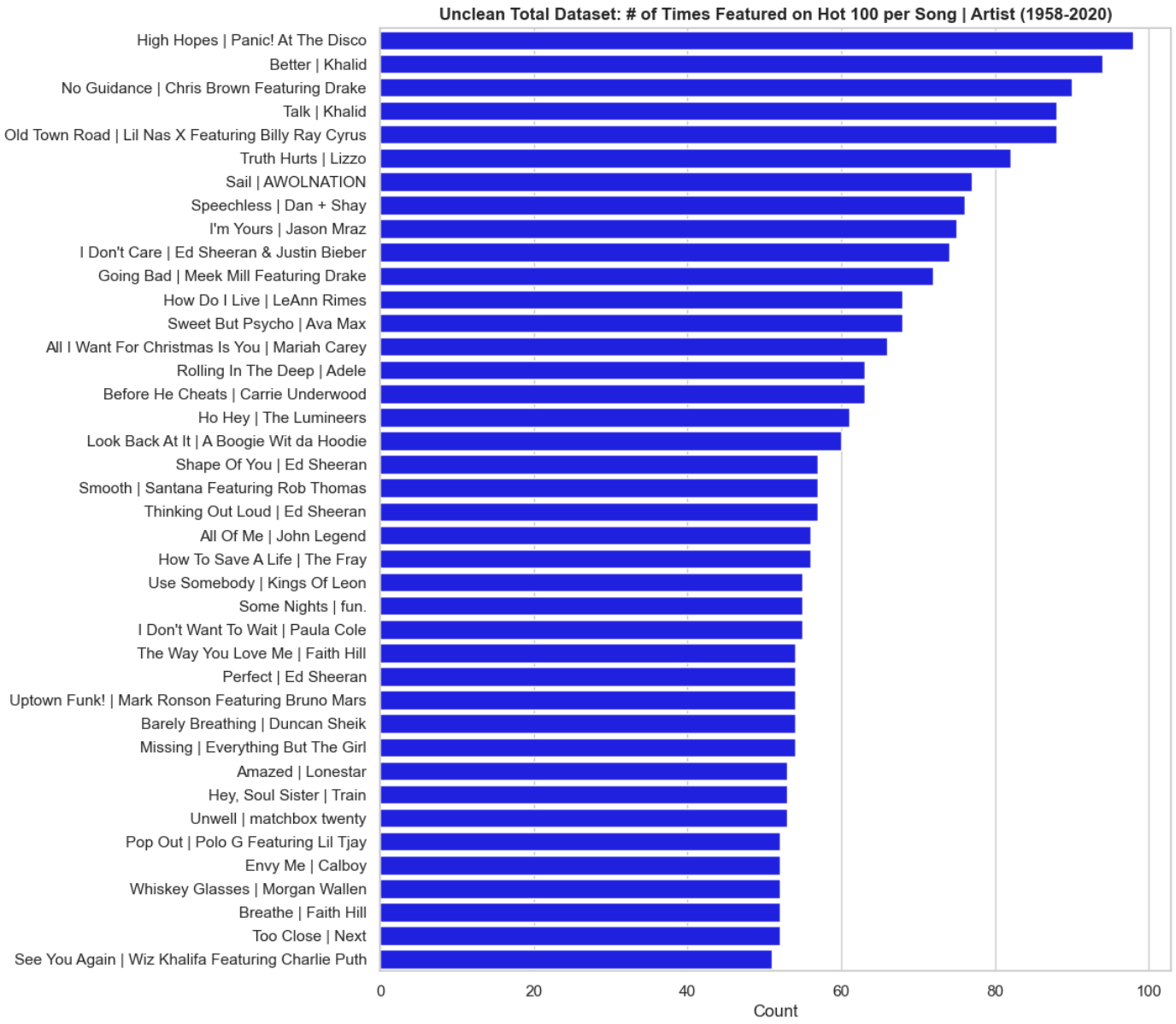
152077 rows × 20 columns

Create new column for number of times a single track (song) appears on the Hot 100

In [19]:
```
unclean_total_hotdf['song_performer'] = unclean_total_hotdf['Song'].str.cat(unclean_tota
cols = list(unclean_total_hotdf.columns)
cols.insert(cols.index('Song'), cols.pop(cols.index('song_performer')))
unclean_total_hotdf = unclean_total_hotdf[cols]
```

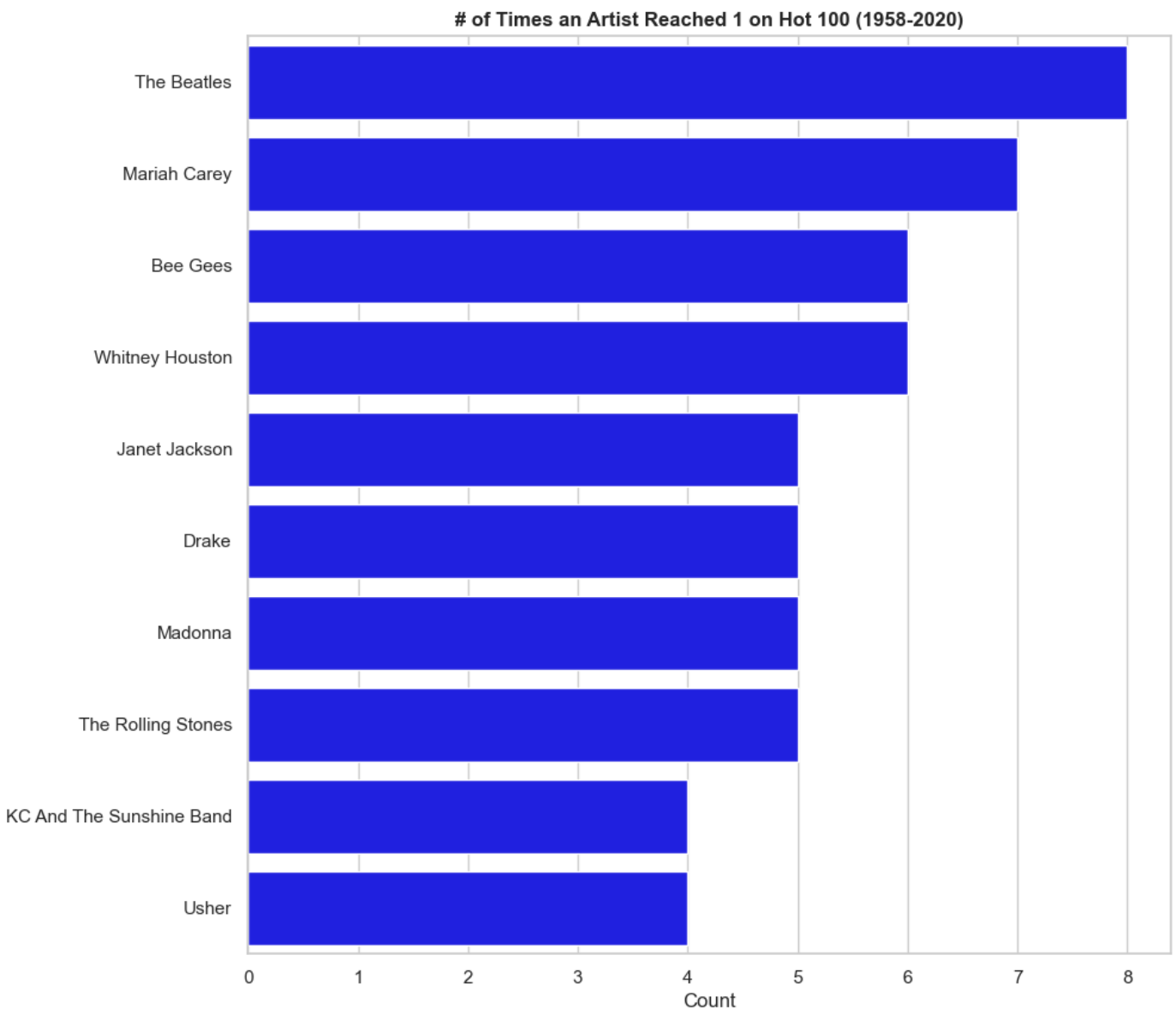
In [20]:
```
# New object for song_entries
unclean_songs_entries = (unclean_total_hotdf[['song_performer']]
                .groupby('song_performer')
                .size()
                .reset_index(name='n_entries')
                .sort_values('n_entries', ascending=False)
                .head(40))
```

```
sns.set_style("whitegrid")
plt.figure(figsize=(10, 12))
ax = sns.barplot(x='n_entries', y='song_performer', data=unclean_songs_entries, color="b
ax.set_title("Unclean Total Dataset: # of Times Featured on Hot 100 per Song | Artist (1
ax.set(xlabel='Count', ylabel='')
plt.show()
```



Number of times an Artist reached the No. 1 Spot

In [21]:
```
# Create new object
top_performers = (unclean_hot_df[unclean_hot_df['Peak_Rank'] == 1][['Performer', 'Song',
                  .groupby('Performer')
                  .agg(n_entries=('Song_Performer', 'nunique'))
                  .reset_index()
                  .sort_values('n_entries', ascending=False)
                  .head(10))

# Plot
sns.set_style("whitegrid")
plt.figure(figsize=(10, 10))
ax = sns.barplot(x='n_entries', y='Performer', data=top_performers, color="blue")
ax.set_title("# of Times an Artist Reached 1 on Hot 100 (1958-2020)", fontsize=12, fontw
ax.set(xlabel='Count', ylabel='')
plt.show()
```



In the end we can see The Beatles remain on top:

- After all this time and with two Beatles still rocking (Paul and Ringo) at the age of 81 and 82, The Beatles still reign supreme at capturing the Number 1 Spot.
- Cool

Pickle df's for future use

In [24]:
```
viz_df.to_pickle('vizual_df.pkl')
unclean_hot_df.to_pickle('semiclean_hot_df.pkl')
unclean_total_hotdf.to_pickle('unclean_total_hot_df.pkl')
```