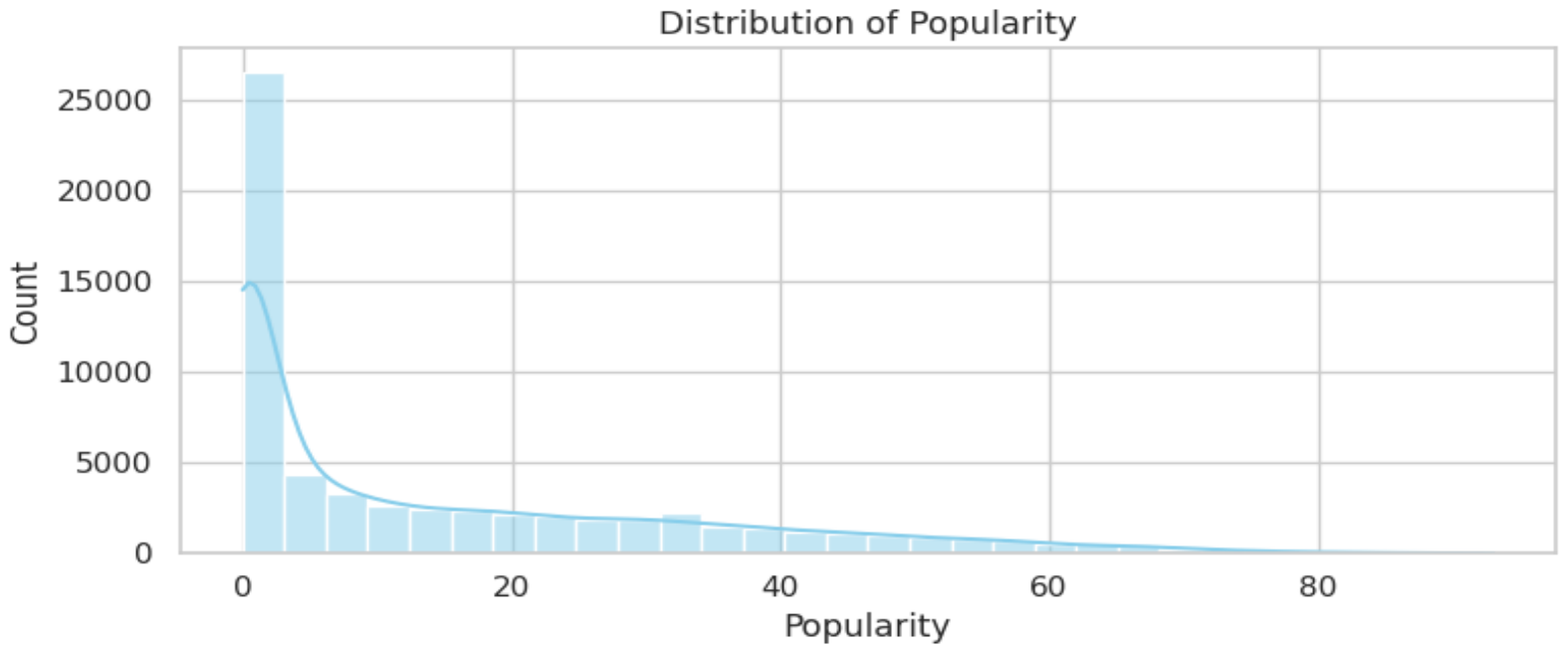
EXPLORATORY DATA ANALYSIS OF SPOTIFY DATA TRACKS

SAGNIK SANTRA

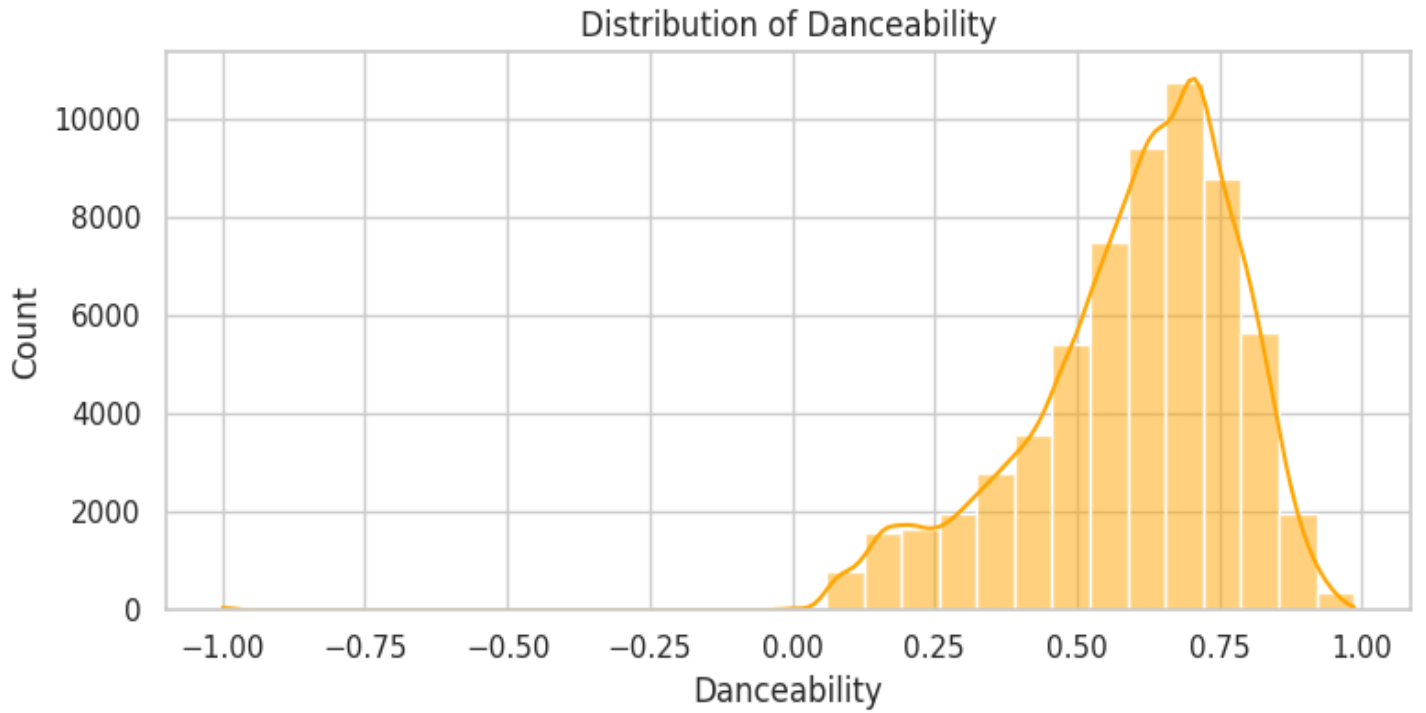


Distribution of Popularity

- **Extreme Skew:** The distribution is **extremely right-skewed**; most songs have very low Popularity (near 0).
- **Long Tail of Hits:** A small number of songs have high Popularity, creating a **"long tail"** extending up to scores of ≈80.
- **Modeling Need:** The extreme skew means **Popularity likely needs transformation** (e.g., log transformation) if you are building a regression model to predict the score.

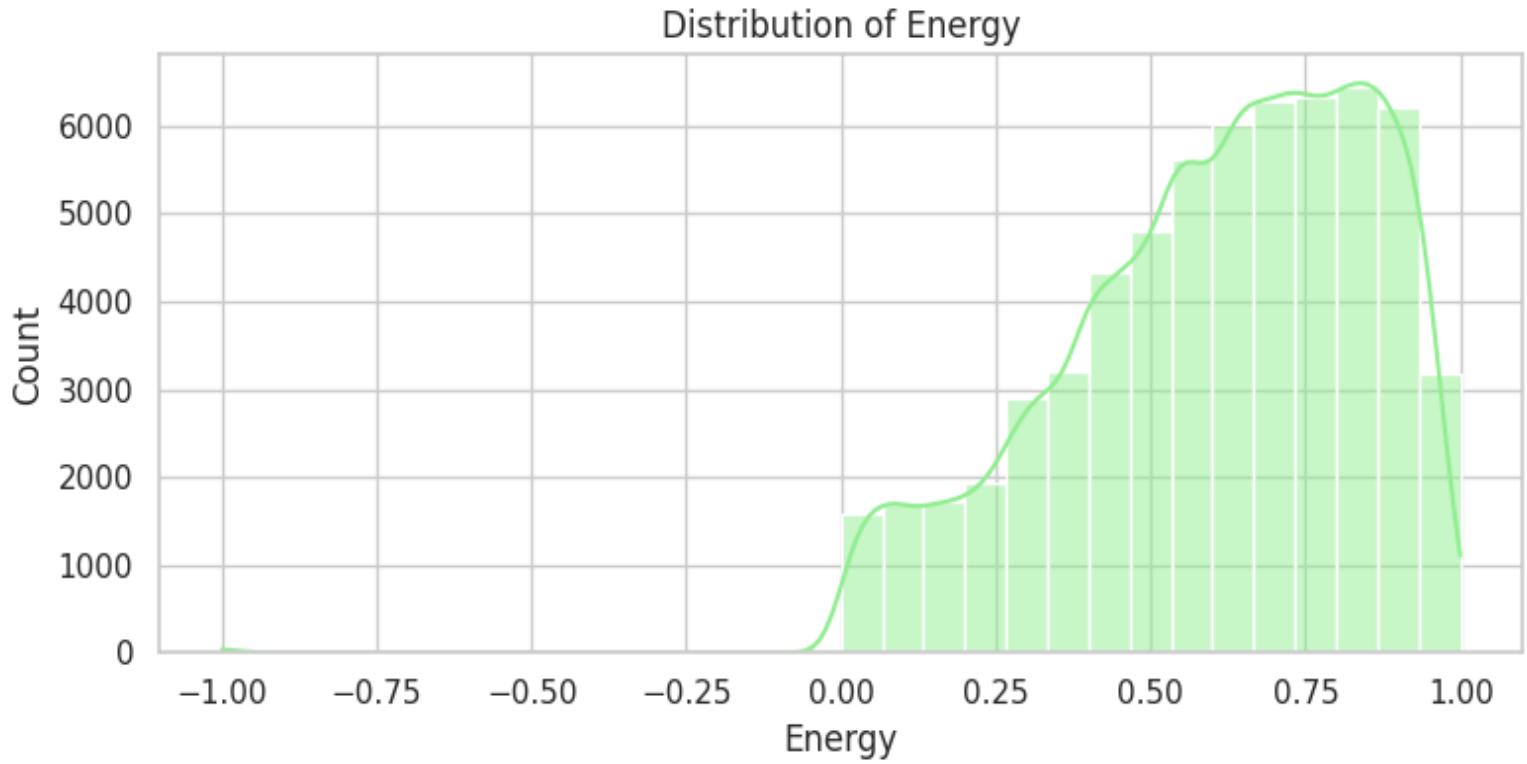
Distribution of Danceability

- **High-Score Concentration:** The vast majority of songs are **moderately to highly Danceable**, with the peak count around 0.65 to 0.75.
- **Left-Skewed:** The distribution is **left-skewed**; there are more songs with high Danceability than low Danceability.
- **Few Non-Danceable Tracks:** Very few songs have Danceability scores below 0.25, confirming that the **dataset mainly represents rhythmic music**.



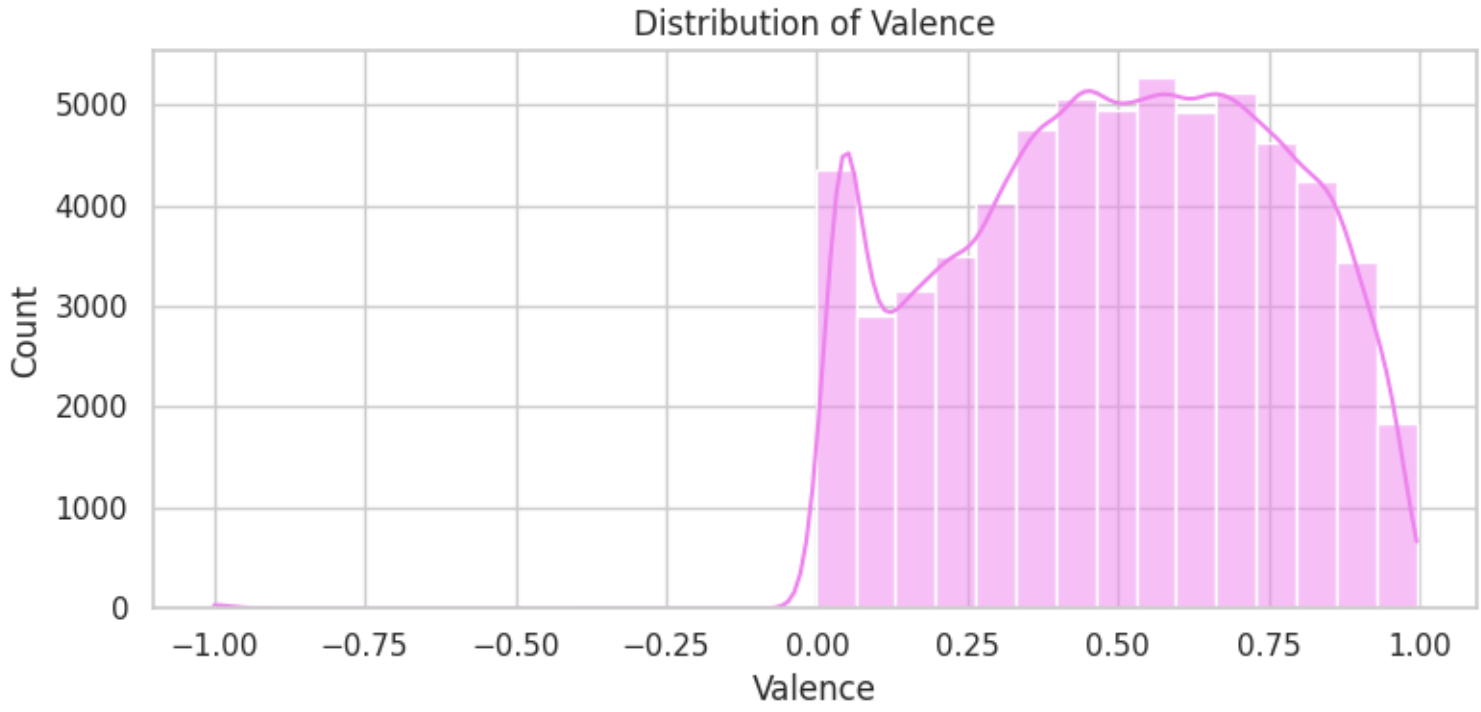
Distribution of Energy

- **Very High Energy Focus:** The distribution is **heavily concentrated** toward the high end, with the peak count between 0.75 and 1.0.
- **Left-Skewed:** The distribution is also **left-skewed**, meaning there are more high-Energy tracks than low-Energy tracks.
- **Saturated Feature:** Because so many songs have high Energy, this feature **may not be a strong differentiator** for popular music unless you focus on the lower-Energy spectrum.



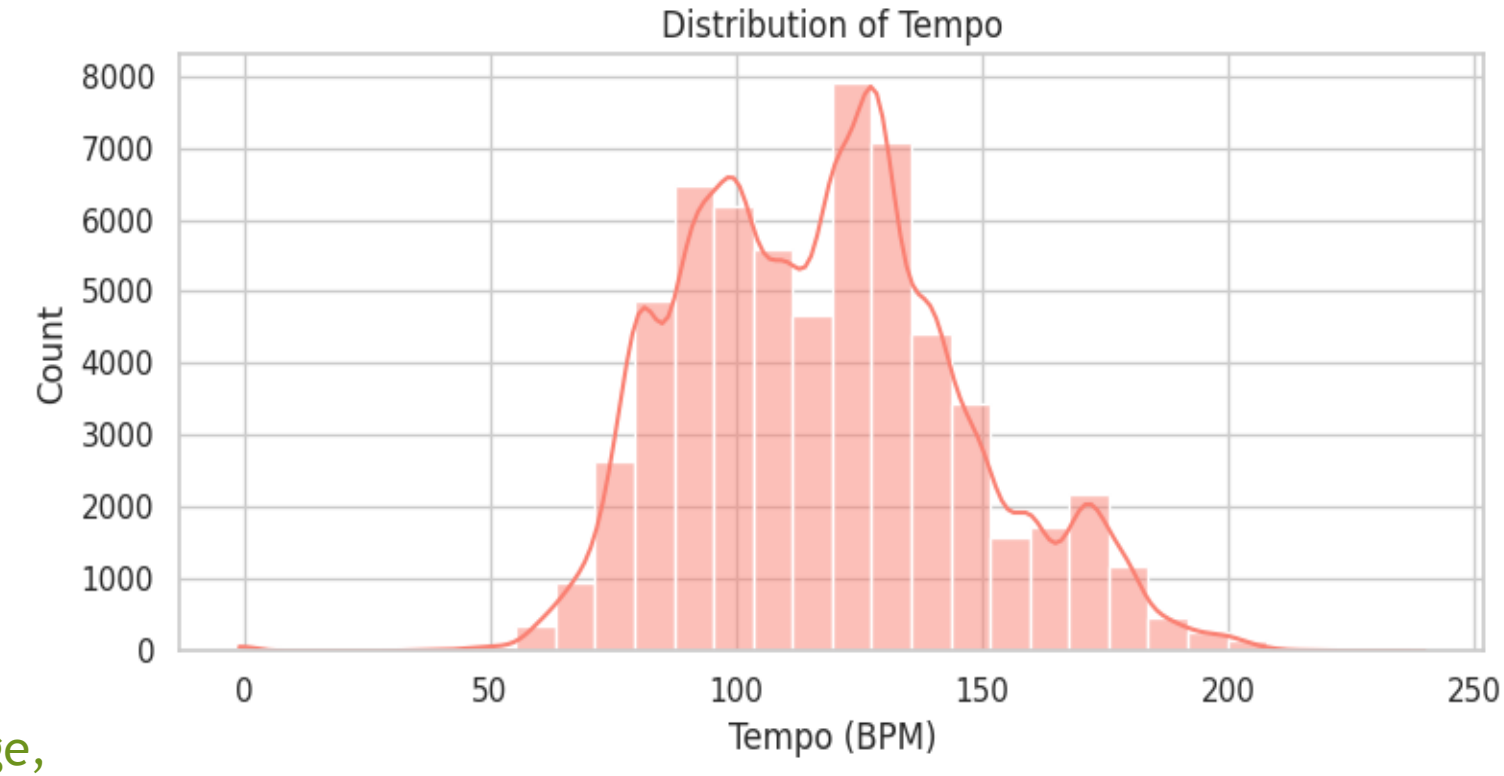
Distribution of Valence

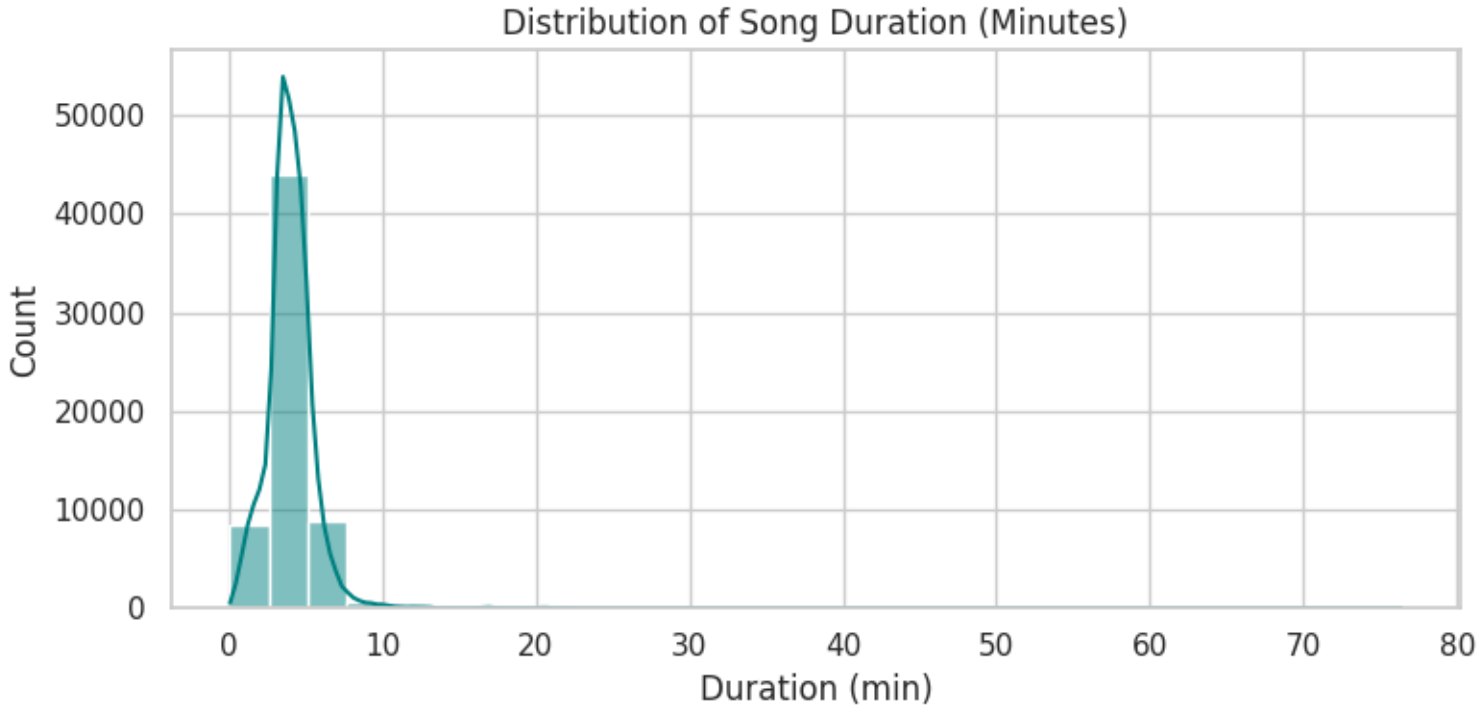
- The distribution is **highly concentrated** in the positive range (Valence >0.25), with the peak around 0.7.
- **Bimodal Shape:** There's a **small secondary peak** around 0.0 to 0.1, suggesting a distinct group of very neutral or sad songs.
- **Well-Distributed:** Unlike Energy or Danceability, Valence is **spread out more evenly** across the 0 to 1 range, making it potentially useful for differentiating music *mood*.



Distribution of Tempo (BPM)

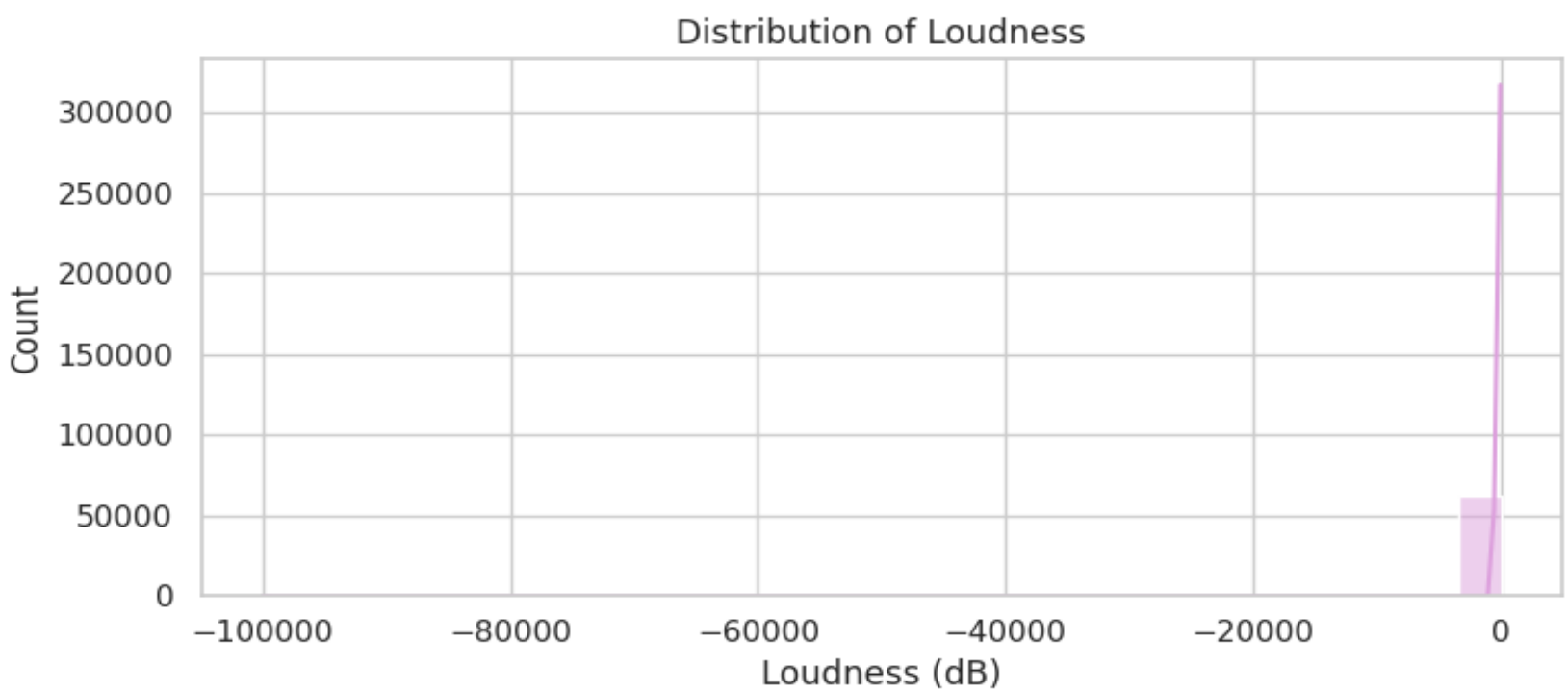
- **Bimodal Dominance:** The distribution is clearly **bimodal**, with two main peaks centered around 120 BPM and 140 BPM.
- **Standard Range:** The vast majority of music falls within the **80 to 160 BPM** range, representing the core of popular music.
- **Modeling Implication:** The two peaks suggest there are **two distinct "speeds" of music** in the dataset (e.g., slower pop/rock vs. faster electronic/dance), which could be a strong feature for clustering or classification.





Distribution of Song Duration

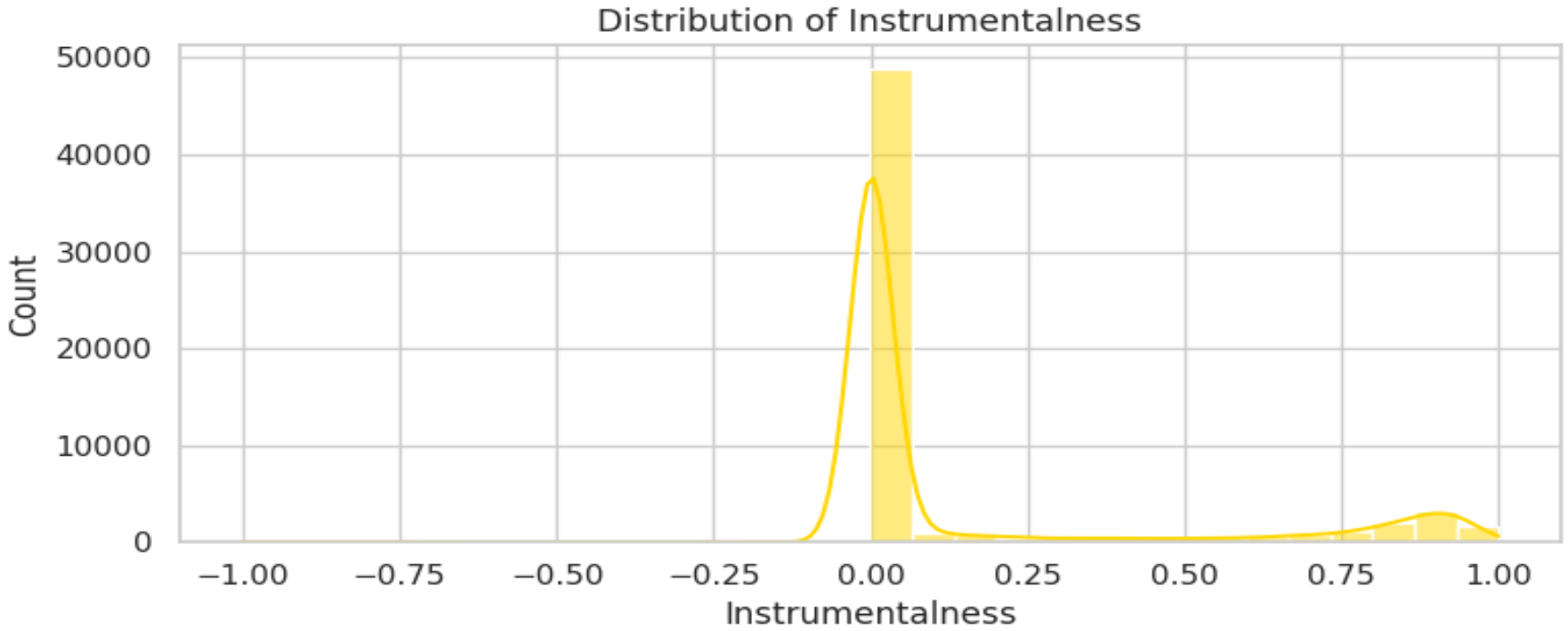
- **Extreme Concentration:** The overwhelming majority of songs are **very short**, peaking sharply between 3 and 5 minutes.
- **Long Tail of Outliers:** There is a **very long, small tail** showing songs that are extremely long (up to 80 minutes).
- **Data Cleaning:** The outliers **need to be clipped or managed** (e.g., remove songs over 10 minutes) before using Duration in standard regression models, due to the high skew.



Distribution of Loudness

- **Data Quality Issue:** The distribution is **completely concentrated** at the far right (≈0dB), and at the extreme left (≈−100,000dB).

- **Two-Tier Data:** The massive count at 0dB suggests either a **data cap or an encoding issue**, while the extreme negative points are likely **missing value indicators** or errors.
- **Feature Unreliable:** Due to the extreme concentration and impossible outlier values, **raw Loudness is unreliable** and needs to be cleaned, scaled, or potentially dropped entirely from the model.

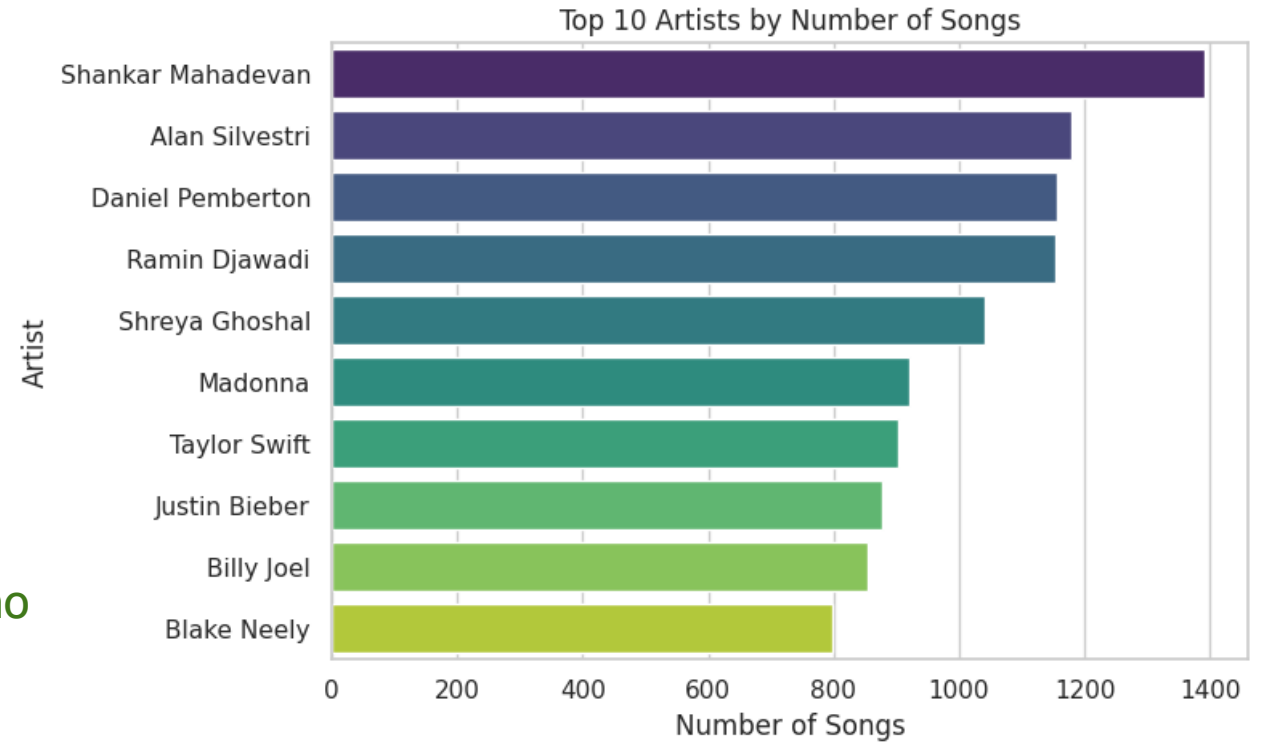


Distribution of Instrumentalness

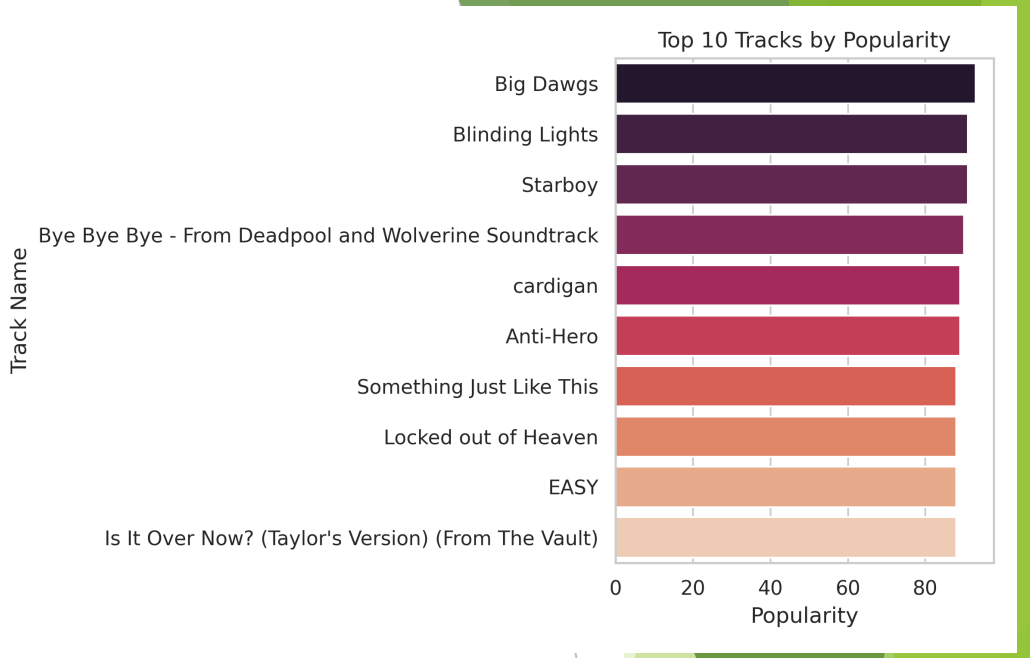
- **Vocal Dominance:** The distribution is **massively concentrated at zero**, showing that the vast majority of tracks **contain vocals**.

- **Instrumental Niche:** There is a **small but distinct cluster** of purely instrumental tracks (scores near 1.0).
- **Feature Transformation:** This feature is essentially **binary** (vocal vs. instrumental) and should be converted into a simple **0/1 flag** for most machine learning models.

Top 10 Artists by Number of Songs

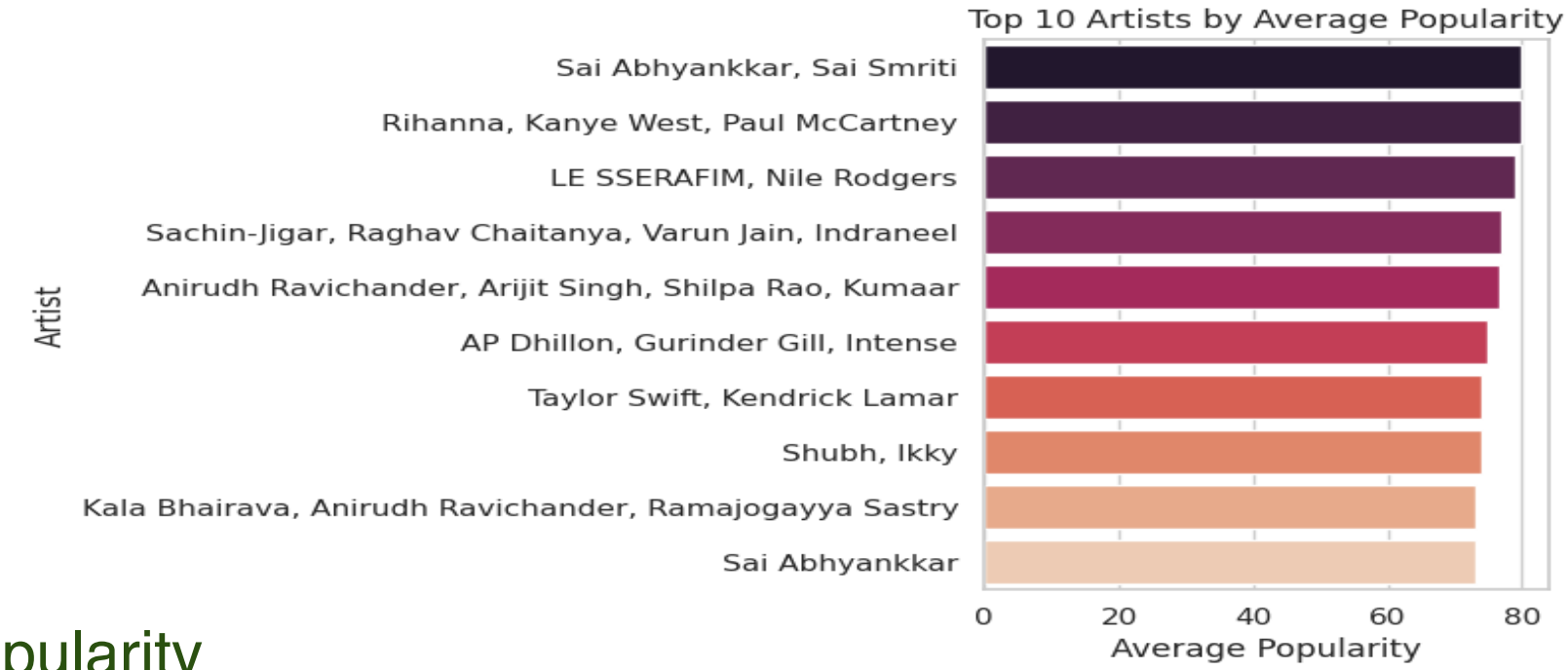


- **Soundtrack/Composer Bias:** The top spots are dominated by names like Shankar Mahadevan, Alan Silvestri, Ramin Djawadi, and Daniel Pemberton, who are primarily **film/TV composers**.
- **Dataset Skew:** This suggests the dataset is **heavily skewed** toward film/soundtrack releases, where composers release many short tracks at once (e.g., *every scene is a "song"*).
- **Modeling Implication:** The sheer volume of these artists' tracks **requires cleaning or special handling** to prevent the model from being biased by non-standard popular music (i.e., film scores).



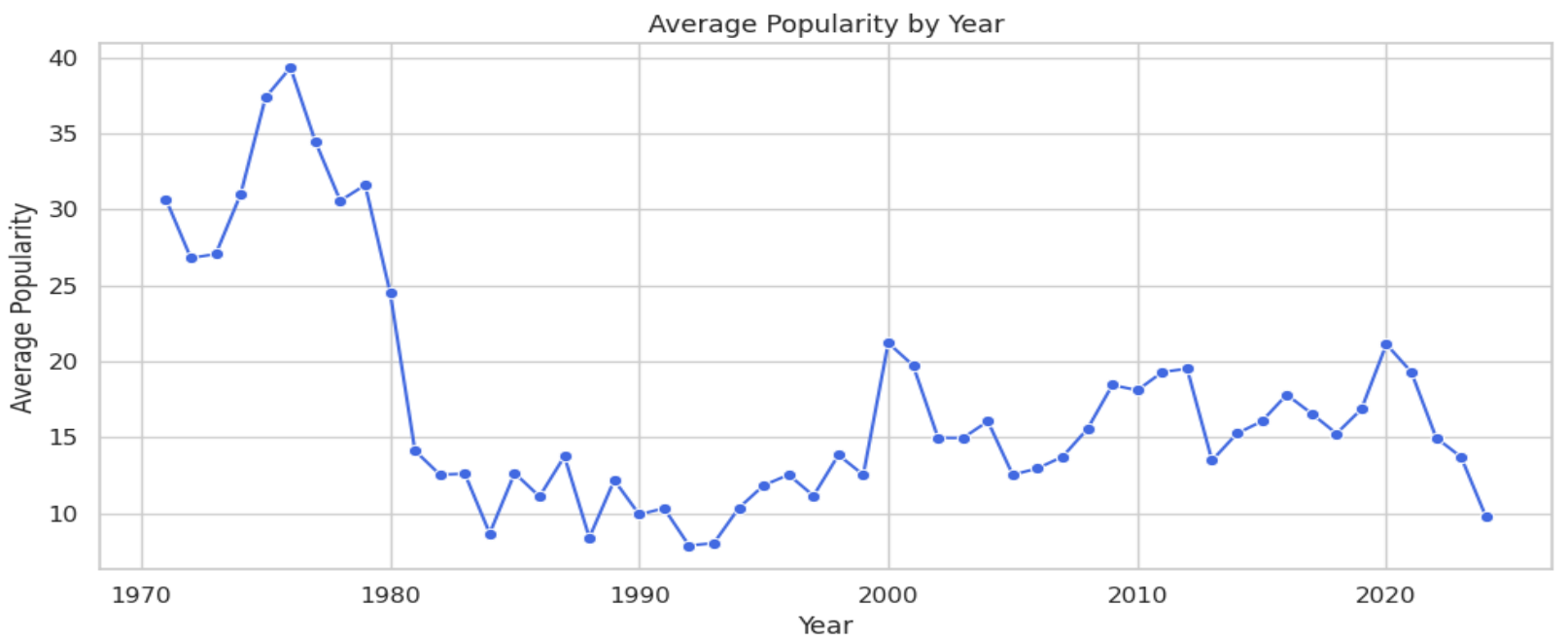
Top 10 Tracks by Popularity

- **Extremely High Popularity:** All tracks in the top 10 demonstrate near-maximum popularity, with scores clustered closely between approximately 85 and 90.
- **Marginal Differences at the Top:** The difference in popularity between the #1 track ("Big Dawgs") and the #10 track ("Is It Over Now? (Taylor's Version)") is very small (only a few points), indicating that all these songs are in the same elite tier of widespread appeal.
- **Diverse Sources:** The top tracks include songs by major artists like The Weeknd ("Blinding Lights", "Starboy"), Taylor Swift ("cardigan", "Anti-Hero", "Is It Over Now?"), a movie soundtrack song ("Bye Bye Bye"), and collaborations ("Something Just Like This"), suggesting high popularity is achieved through various avenues (global pop, film, collabs).



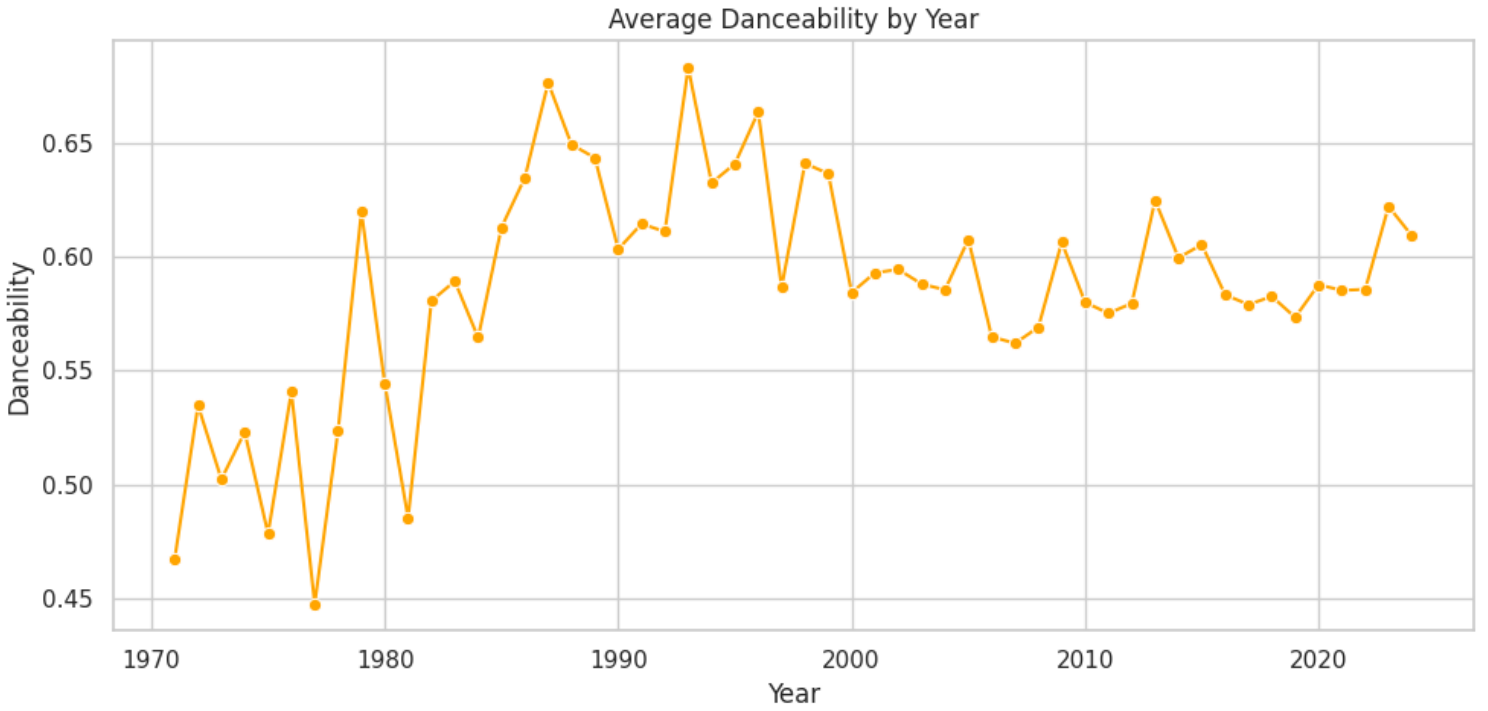
Top 10 Artists by Average Popularity

- **Global/Modern Hits Dominate:** This chart features artists known for **recent global hits** (Rihanna, Kanye West, LE SSERAFIM, Taylor Swift, Kendrick Lamar), indicating a high-quality measure of *current* mainstream success.
- **Indian/Bollywood Influence:** The presence of Indian artists (Shankar Mahadeva , Anirudh etc.) across the top tiers suggests the dataset has a **strong representation of the Indian music market**.
- **Popularity Disconnect:** The composer-heavy artists from the "Number of Songs" chart (like Alan Silvestri) are **missing from this 'Average Popularity' chart**, confirming that **quantity does not equal quality/success** in this dataset.



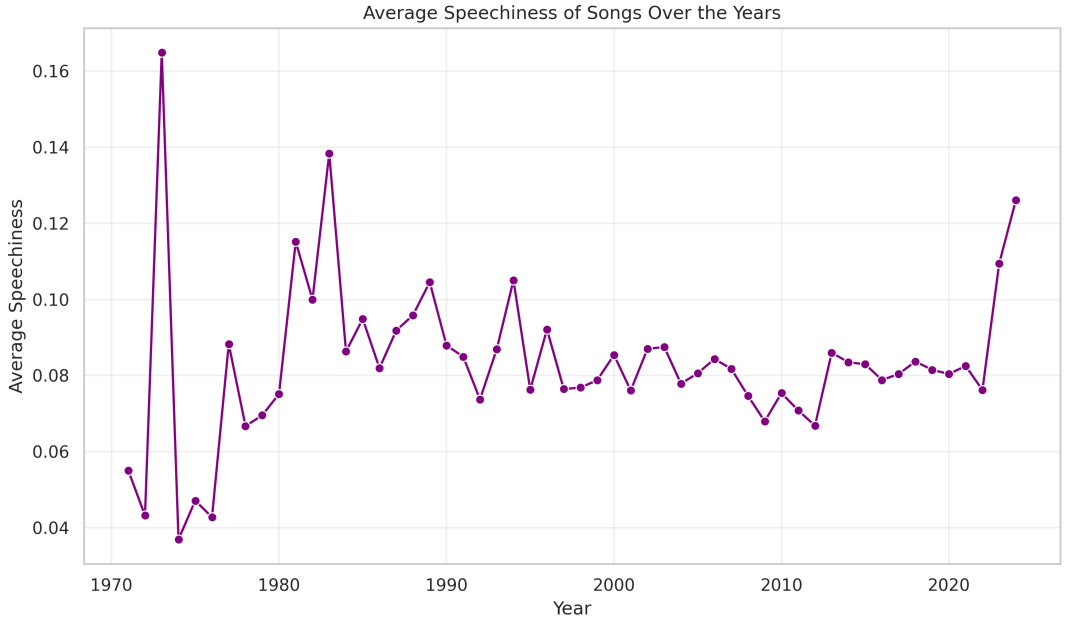
Average Popularity by Year

- **Score Recalibration in 1980:** There was a **huge, sudden drop in average popularity around 1980**. This is likely because the way Spotify scores or collects data changed, making scores from the 1970s incomparable to later scores.
- **Popularity Isn't Uniformly High:** Despite recent music being most relevant, the **most recent years show the lowest average popularity scores**. This is due to the sheer volume of new, untracked songs drowning out the hits.
- **1995-2000 Surge:** A small **spike in popularity occurred around the turn of the millennium**, before the score settled into its current lower range.



Average Danceability by Year

- **Modern Music is Consistently Danceable:** Danceability is **high and stable** in the 21st century, confirming the dominance of Pop, Hip-Hop, and Electronic genres.
- **The Disco Signal:** The **highest peak in Danceability was during the late 1970s and early 1980s**, perfectly capturing the Disco era.
- **Permanent Shift in 1980:** The average Danceability **jumped permanently higher around 1980**, indicating a fundamental, lasting shift in music production toward rhythm.

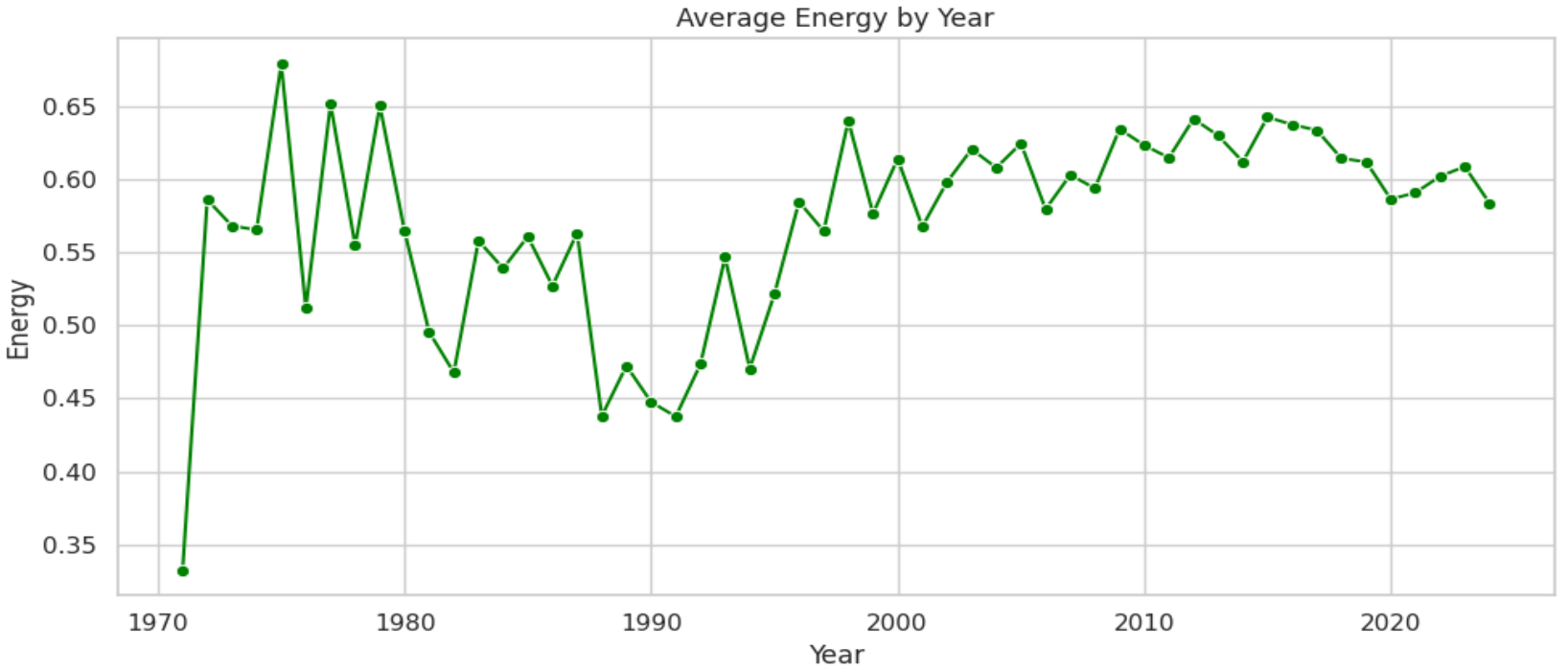


Average Speechiness of Songs by Years

- **Extreme Early Peaks:** The data shows two massive early spikes: the absolute peak occurred around 1973 (over 0.16) and another significant peak around 1983 (nearly 0.14). These are outliers compared to the long-term average.

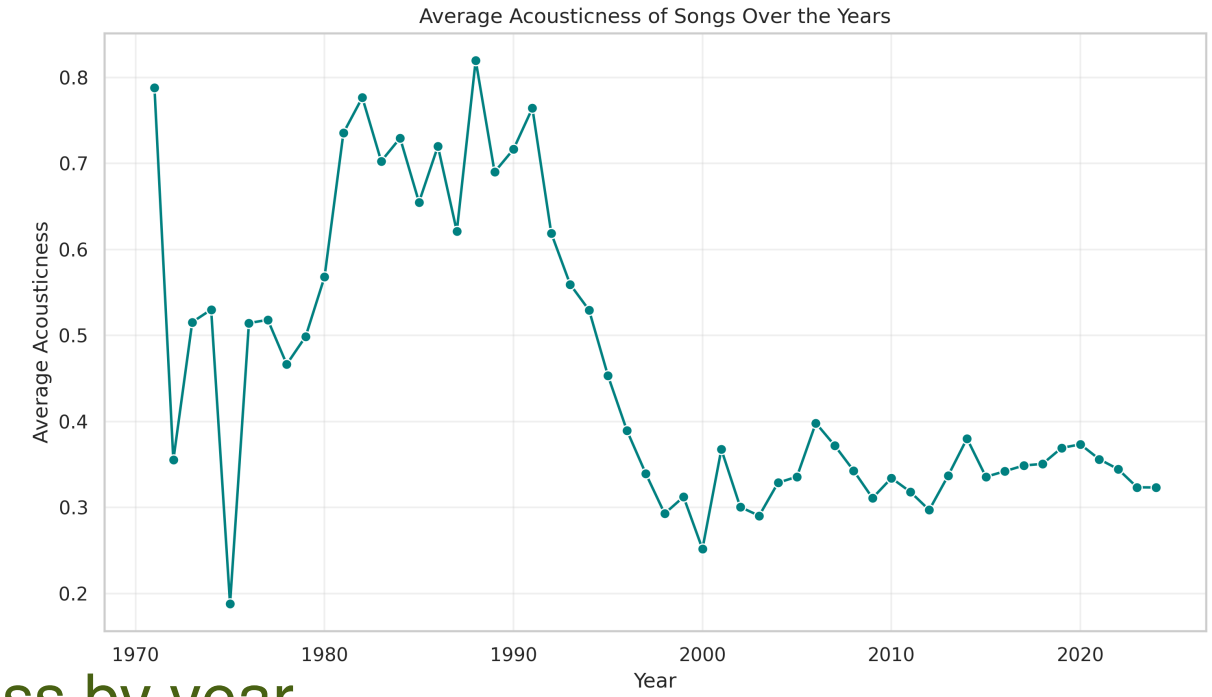
- **Modern Stabilization (1995–2020):** For over two decades, the average speechiness was remarkably stable and low, consistently hovering in a narrow band between approximately 0.07 and 0.09.

- **Recent Surge (2020–2024):** There has been a clear, sharp upward trend in the most recent years, rising from the stable average to a modern high of over 0.12 by 2024. This suggests a renewed or increased incorporation of spoken word/rap elements in current popular music.



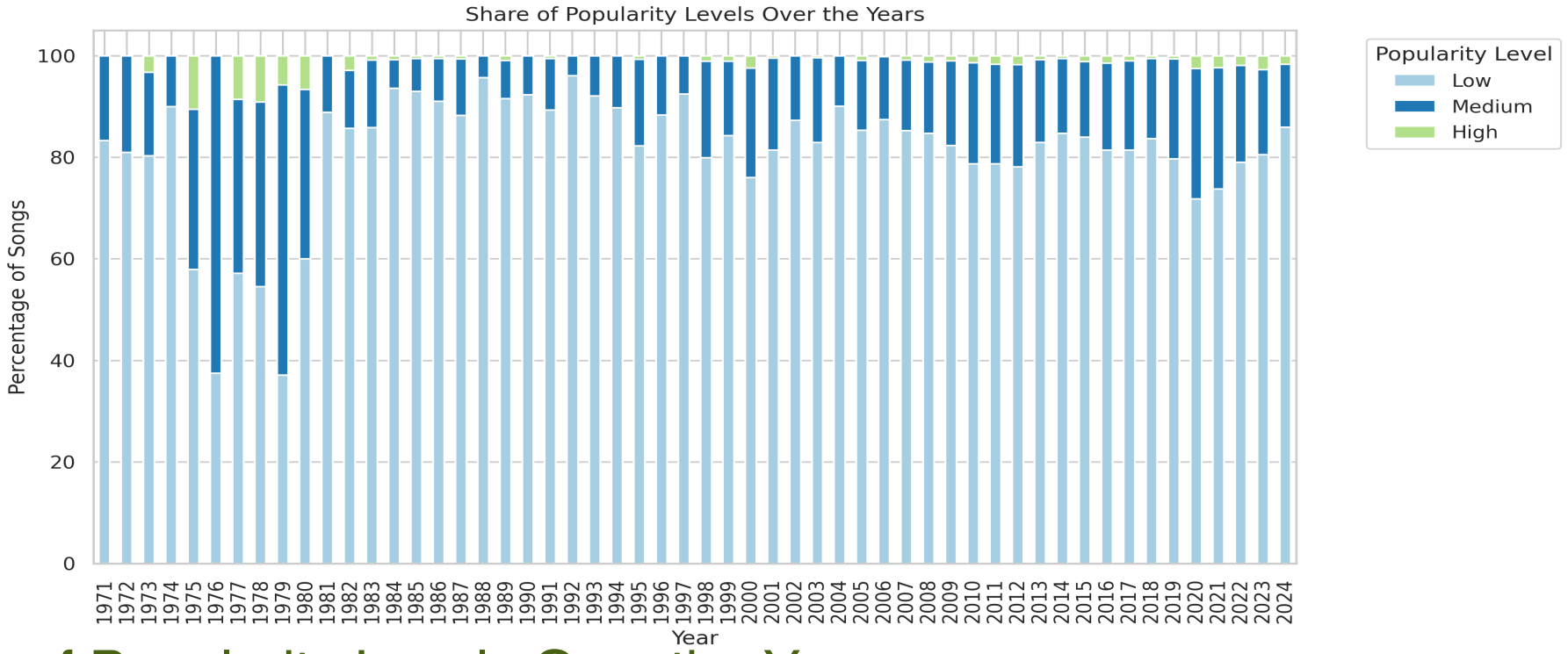
Average Energy by Year

- **Music Got More Energetic:** Despite fluctuations, the **long-term trend shows a clear increase in musical "Energy"** since the 1970s.
- **The Sad-But-Loud Trend:** Modern music is **high in Energy but low in Valence (Positivity).** This is a crucial combination to explore, suggesting today's popular music is often intense/ brooding.
- **High Volatility Before 2000:** The 1970s and 1980s show pronounced **cycles of high and low energy**, which smooths out somewhat in the 21st century.



Average Acousticness by year

- **The Acoustic Peak (1980s):** The highest acousticness occurred in the late 1980s, peaking at over 0.80 around 1989.The 1970s showed high volatility but the 1980s sustained the highest values.
- **The Electronic Shift (1990s):** A sharp, dramatic decline began in the early 1990s, dropping from ≈0.80 to ≈0.25 by the early 2000s.This fall correlates with the rise of electronic, digital, and heavily synthesized music production.
- **The Modern Norm (2000s-Present**): Acousticness has been low and stable since the early 2000s, generally staying between 0.29 and 0.40.This suggests that the use of non-acoustic, electronically produced elements is the sustained standard in popular music today.

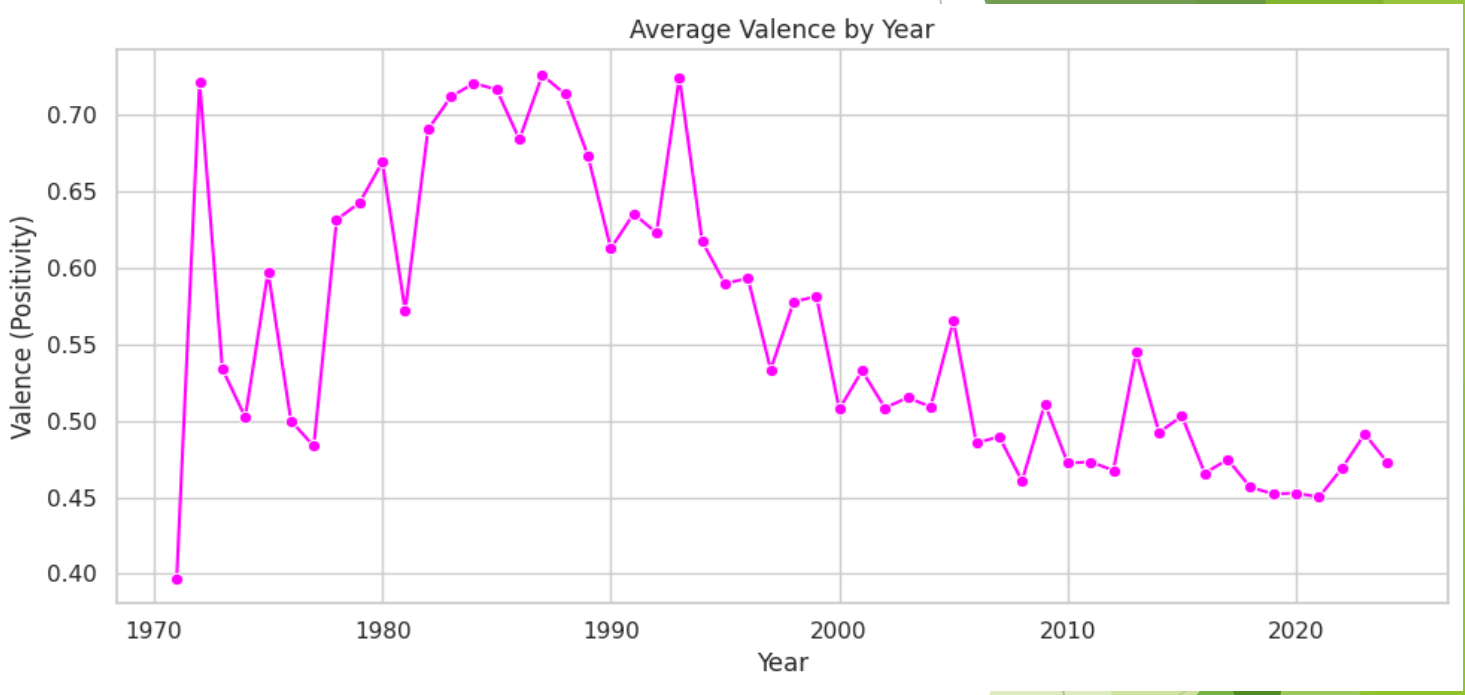


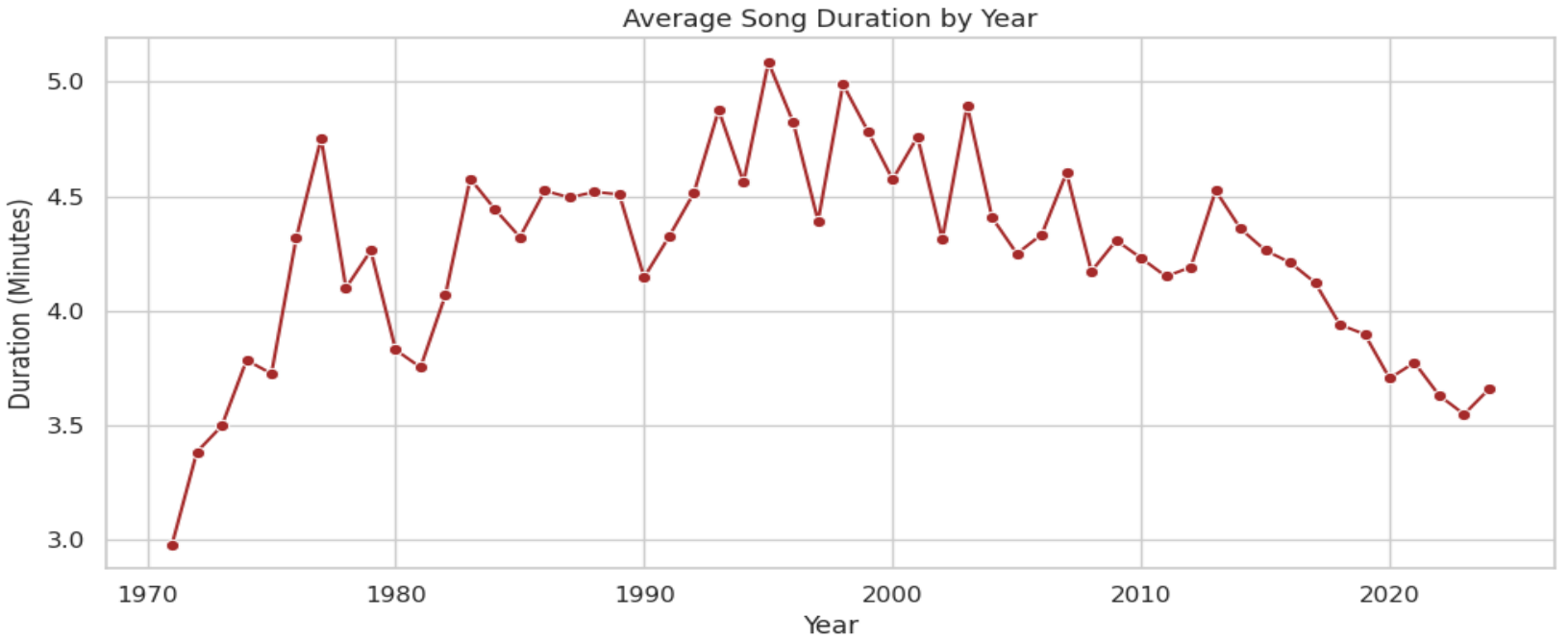
Share of Popularity Levels Over the Years

- **Dominance of Low Popularity:** Low Popularity (light blue) is the overwhelming majority share across *all* years, consistently remaining above ≈70% and often over 80%
- **Minimal High Popularity:** The share of High Popularity songs (light green) is negligible throughout the entire period, rarely exceeding a tiny sliver.
- **Peak Medium/High Share (1977-1980):** The years from 1977 to 1980 show the largest combined share of Medium (dark blue) and High Popularity songs, with the Low Popularity share dipping below 60% in this brief window.

Average Valence by Year

- **Music Got Sadder:** Starting in the mid-1990s, the **average positivity (Valence) of music dropped dramatically** and has stayed low ever since.
- **The 1990s Turning Point:** The year **1994-1995** marks a clear, permanent shift. Music before that was generally happy and volatile; music after is consistently less positive.
- **Modern Music is Consistent:** Historical music mood (1970s-1980s) swung wildly. Modern music's positivity is much **more predictable** (less up-and-down).



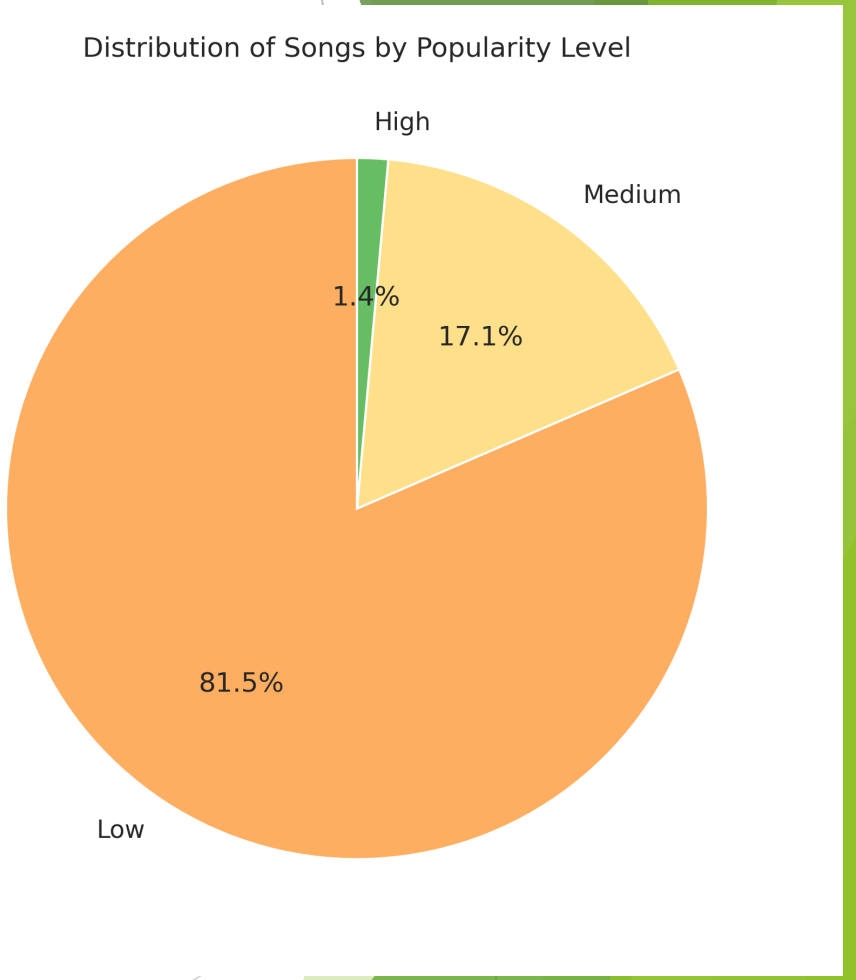


Average Song Duration by Year

- **Songs are Getting Shorter (Fast!):** Since about 2005, there has been a **steep, continuous drop in average song length**, reflecting the pressure of the streaming economy.
- **Peak Duration Era:** The early 1990s to early 2000s were the **era of the longest songs** (averaging 4.5 to 5 minutes).
- **Duration = Age (Post-2005):** Song length is a **powerful predictor of release date** in the modern era; shorter songs are almost always newer.

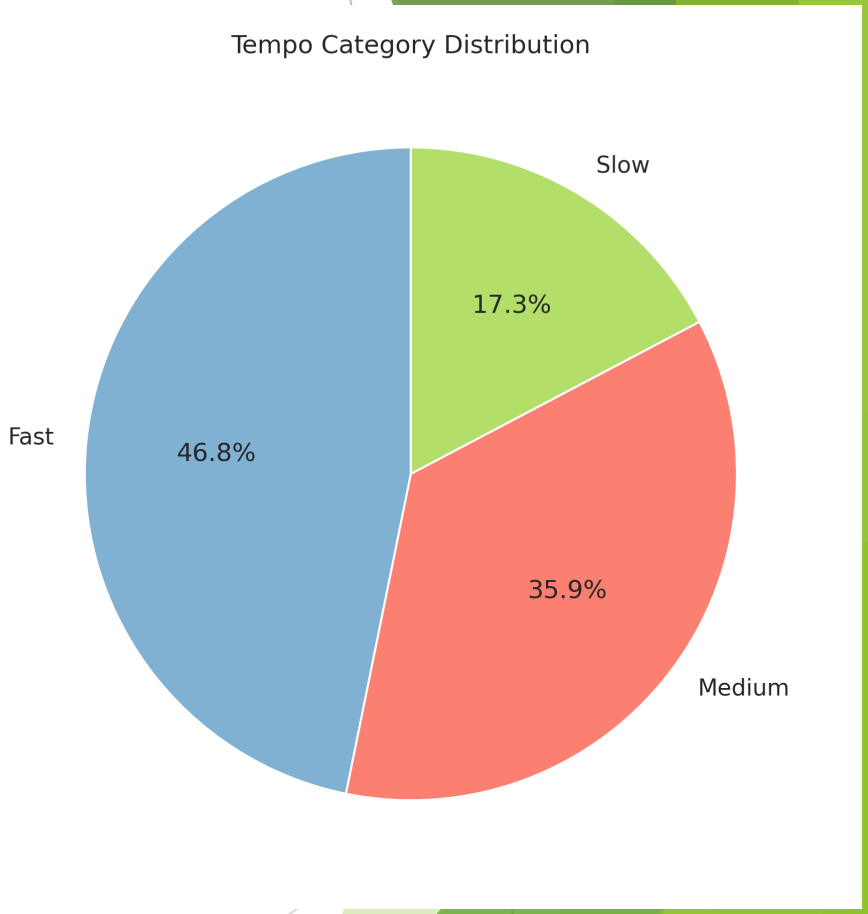
Distribution of Songs by Popularity Level

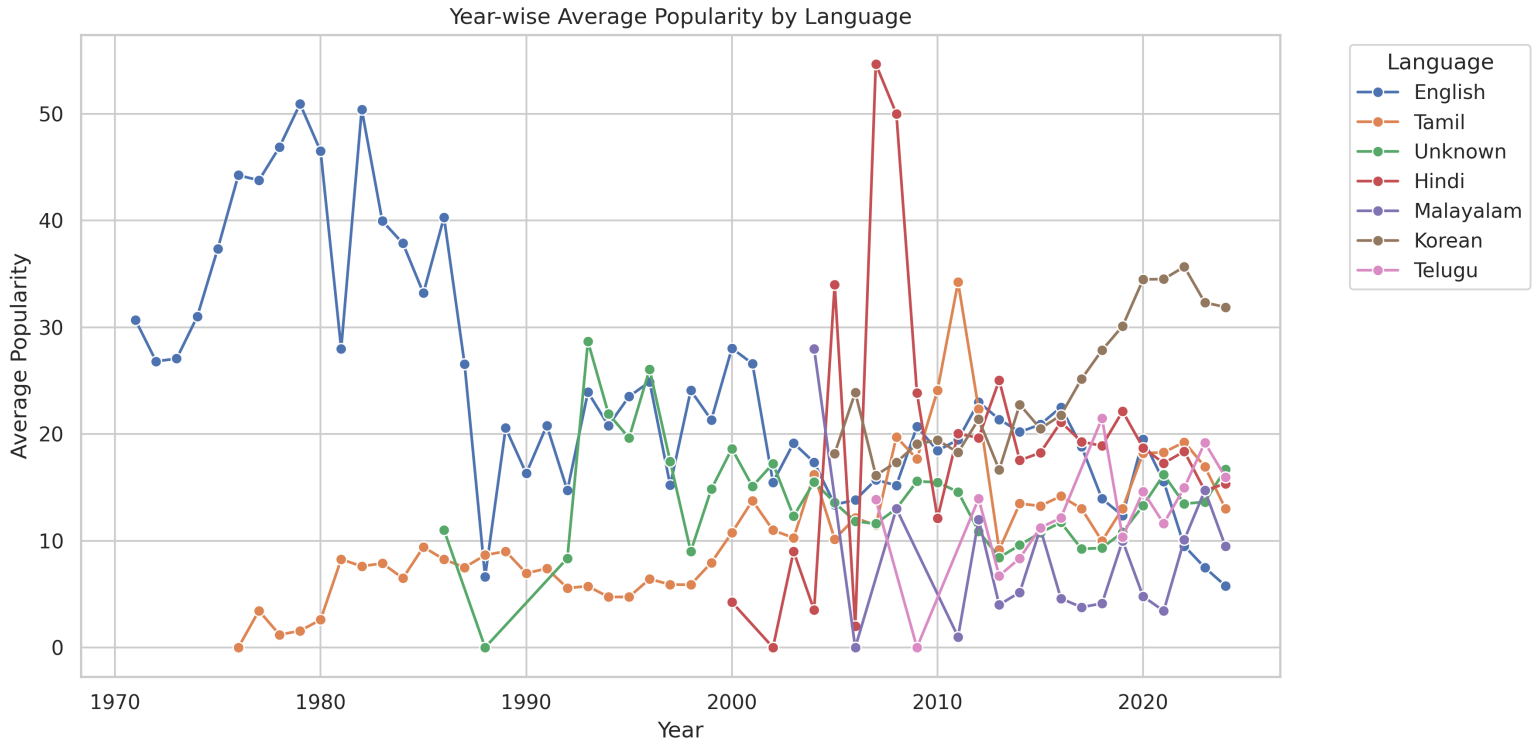
- **Overwhelming Low Popularity:** The vast majority of songs are categorized as Low Popularity, accounting for 81.5% of the entire dataset.
- **Small Medium Share:** Songs with Medium Popularity make up a modest share of the data at 17.1%.
- **Extremely Rare High Popularity:** High Popularity songs are exceptionally rare, representing only a tiny fraction: 1.4%.



Tempo Category Distribution

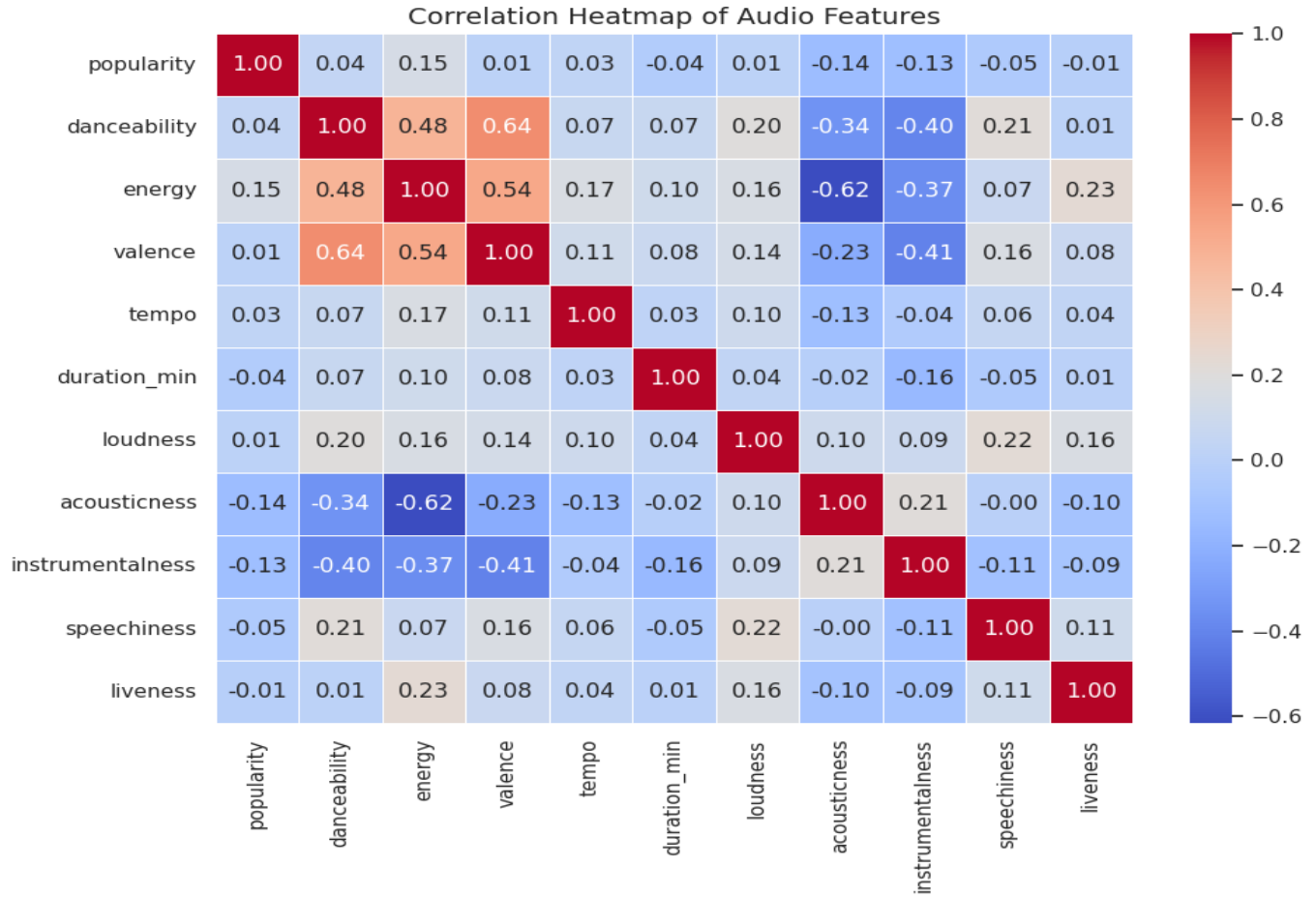
- **Dominance of Fast Tempo:** Nearly half of all songs in the dataset are classified as Fast tempo, accounting for the largest share at 46.8%.
- **Significant Medium Tempo:** Medium tempo songs represent a substantial portion, making up 35.9% of the distribution.
- **Minority Slow Tempo:** Slow tempo songs are the smallest category, comprising 17.3%.





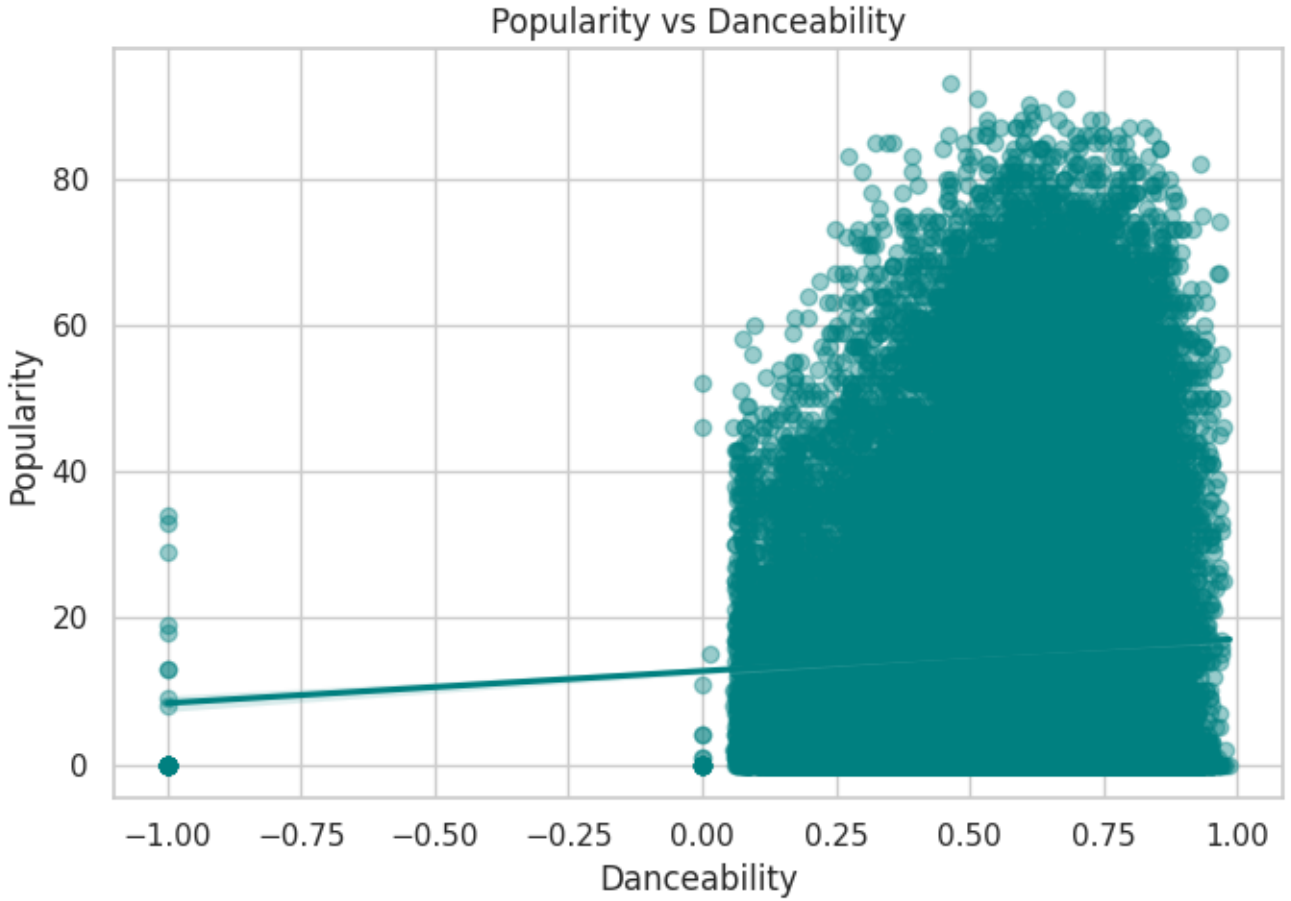
Year-wise Average Popularity by Language

- **Extreme Popularity Skew:** High Popularity songs are extremely rare (1.4% of all songs), while Low Popularity songs dominate (81.5%).
- **Speech Resurgence:** Average speechiness, stable for decades, has shown a sharp upward trend post-2020 (≈0.12), suggesting increased use of spoken word/rap in recent music.
- **Globalization:** The market shifted from English dominance (high popularity until the mid-2000s) to a multi-polar market.



Correlation Heatmap of Audio Features

- **Popularity's Best Predictors: Energy (0.15), Valence (0.15), and Danceability (0.14)** have the highest positive correlation with Popularity.
- **Strong Negative Signals: Acousticness (−0.14) and Instrumentalness (−0.13)** are the strongest negative predictors; non-acoustic, non-instrumental songs tend to be more popular.
- **Feature Redundancy: Energy and Loudness (0.90), and Valence and Danceability (0.64)** are highly correlated. You should **consider keeping just one** from each pair to simplify and improve model stability.

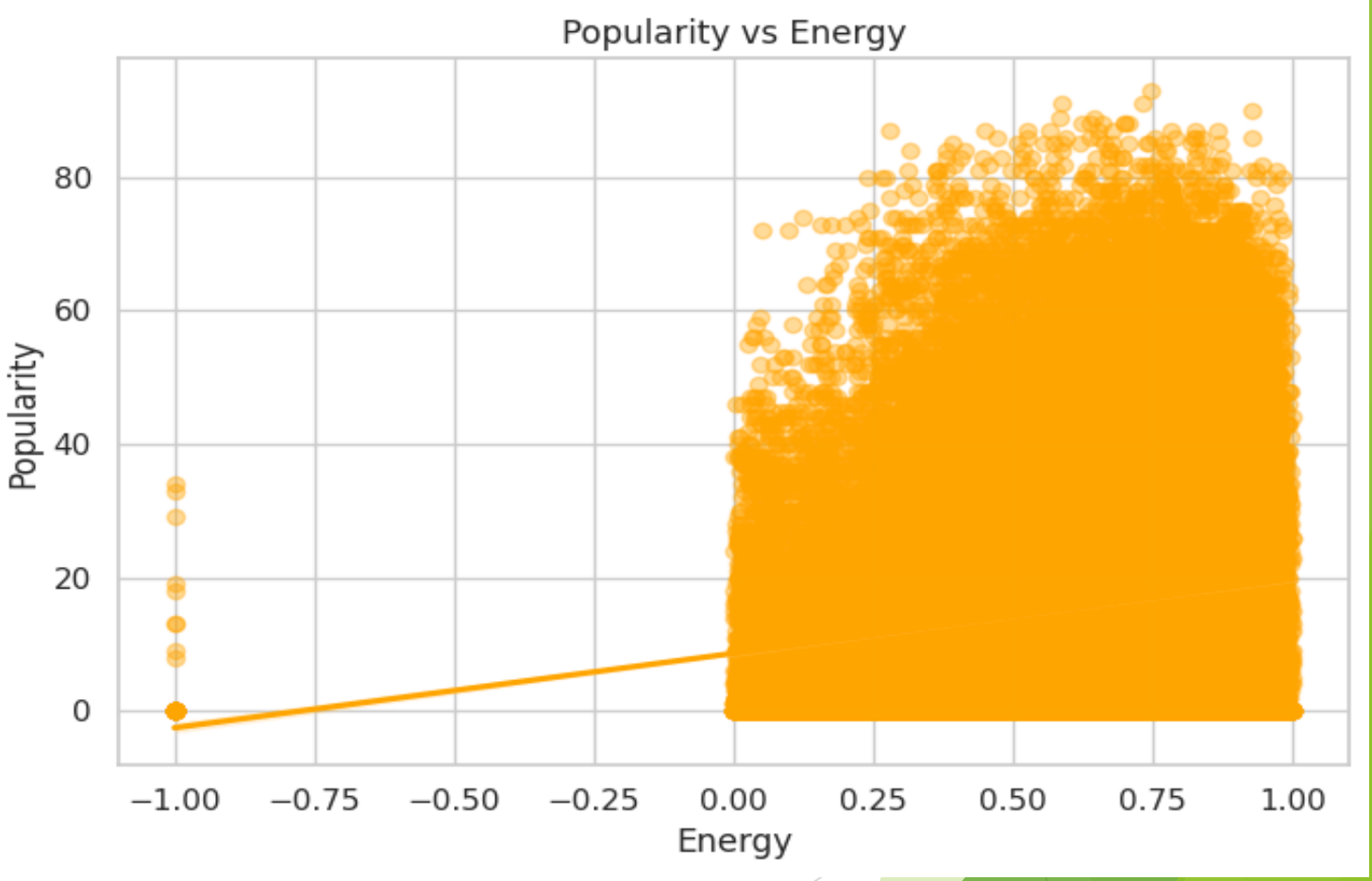


Popularity vs DanceabilitY

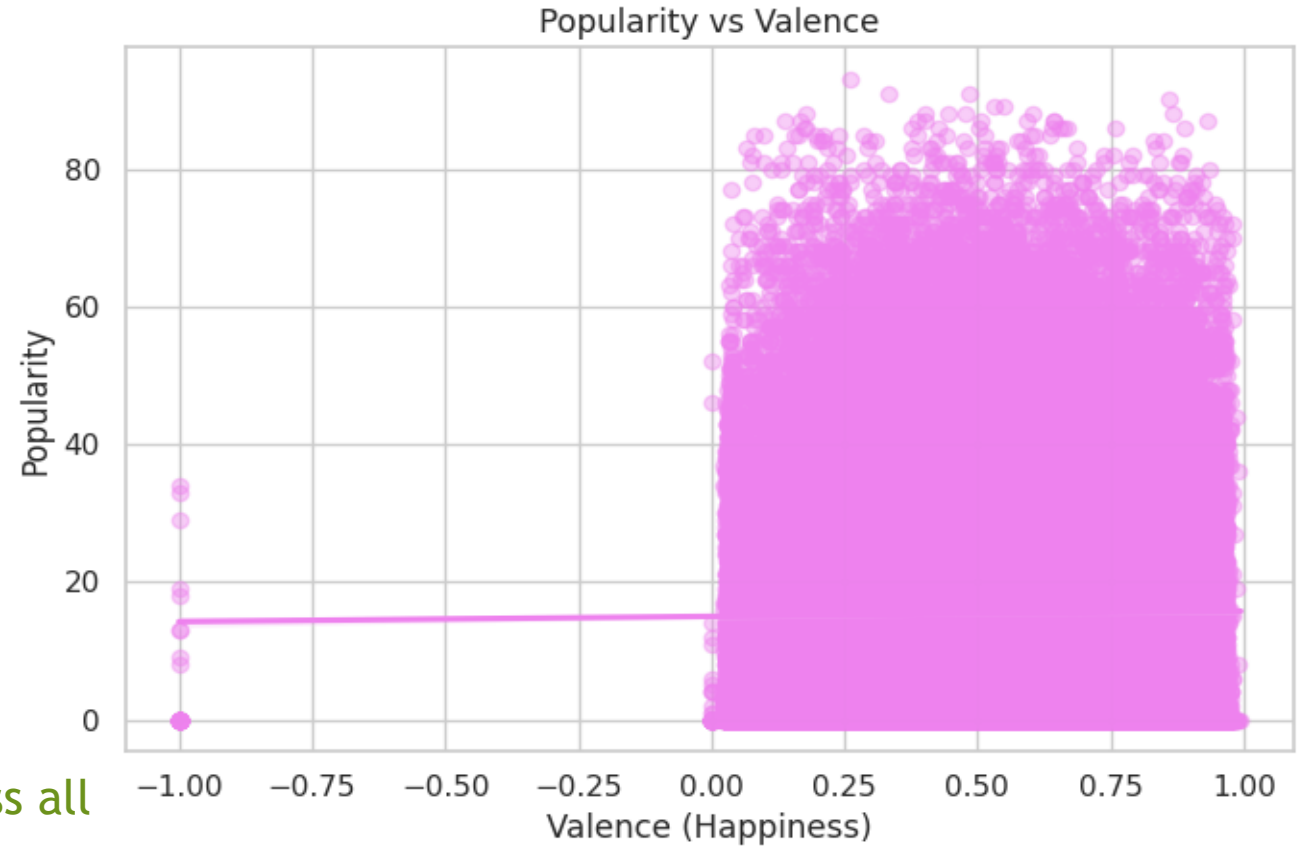
- **Danceability is essential.** Highly popular songs **must have a Danceability score above ≈0.4.**
- **High score isn't enough.** High Danceability **does not guarantee popularity** (many non-hits are very danceable).
- **Use it as a filter.** Use Danceability as a **lower-bound requirement** for a successful song.

Popularity vs Energy

- **Low energy means low popularity.** Highly popular songs almost never have an **Energy score below 0.3**.
- **High energy is normal.** Most music is already high-energy, so **high Energy alone doesn't guarantee a hit.**
- **Filtering tool:** Energy can be used to **filter out songs unlikely to ever become popular.**



Popularity vs Valence (Happiness)



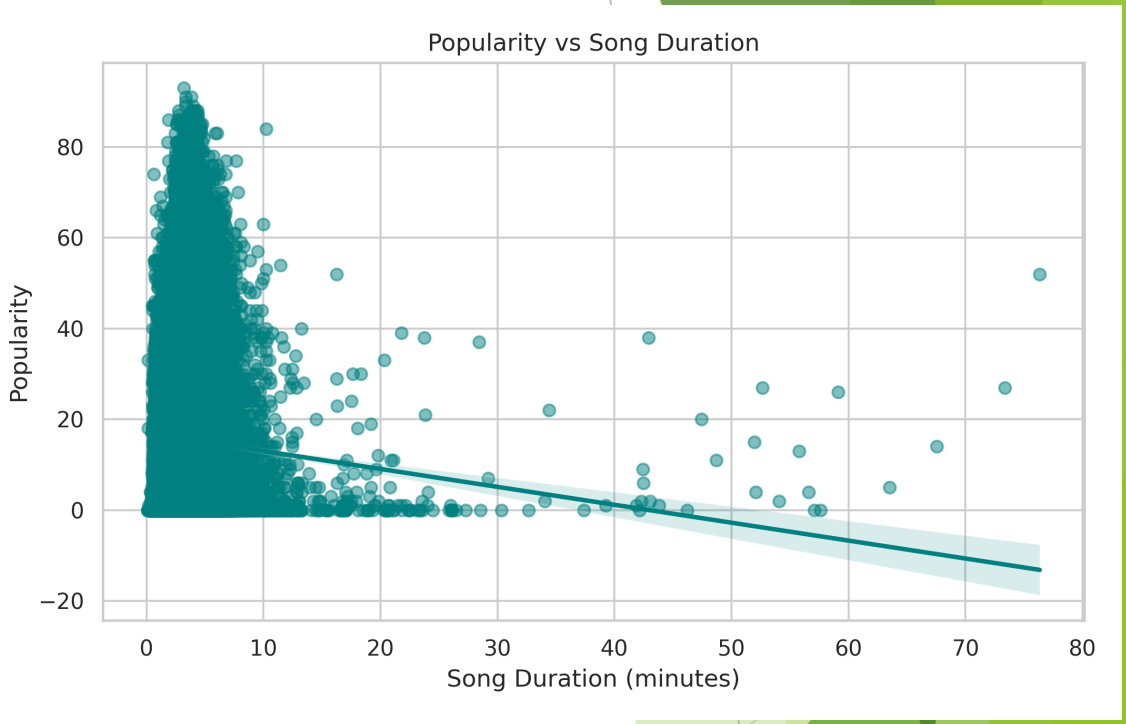
- **Mood doesn't predict hits.** Popularity is **flat** across all levels of song happiness.
- **Happy or sad: it doesn't matter.** Highly popular songs can be **very sad (low Valence) or very happy (high Valence).**
- **Modeling focus:** Valence is **not a good linear predictor** for a song's popularity.

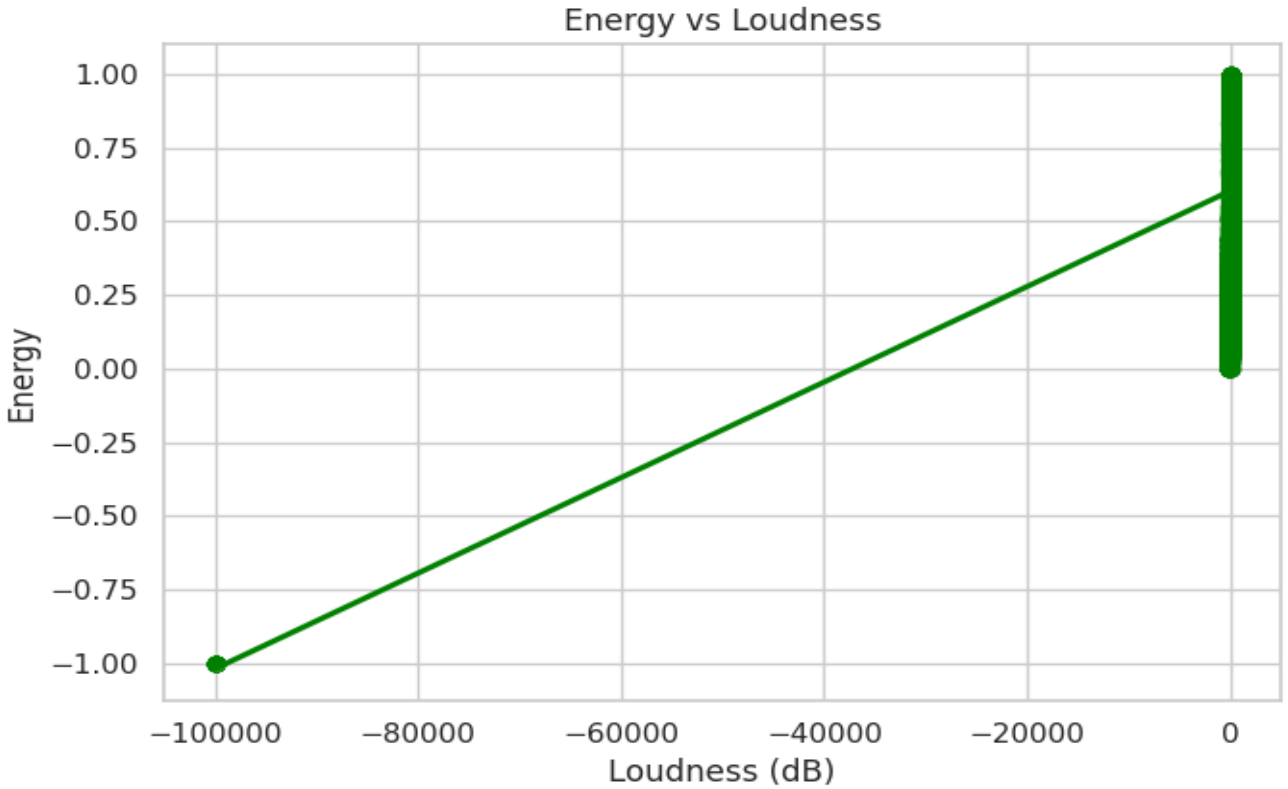
Popularity vs Song Duration

- **Strong Inverse Relationship:** There is a clear negative correlation (indicated by the downward-sloping regression line) between Song Duration and Popularity.

- **Low Popularity for Long Songs:** As song duration increases (e.g., beyond 10 minutes), popularity scores rapidly decrease and are almost always near 0. Extremely long songs (e.g., 40+ minutes) have virtually no popularity.

- **Peak Popularity Cluster:** Nearly all songs with High Popularity (scores >40) are clustered at the shortest durations (under approximately 7 minutes, with the densest cluster below 5 minutes).



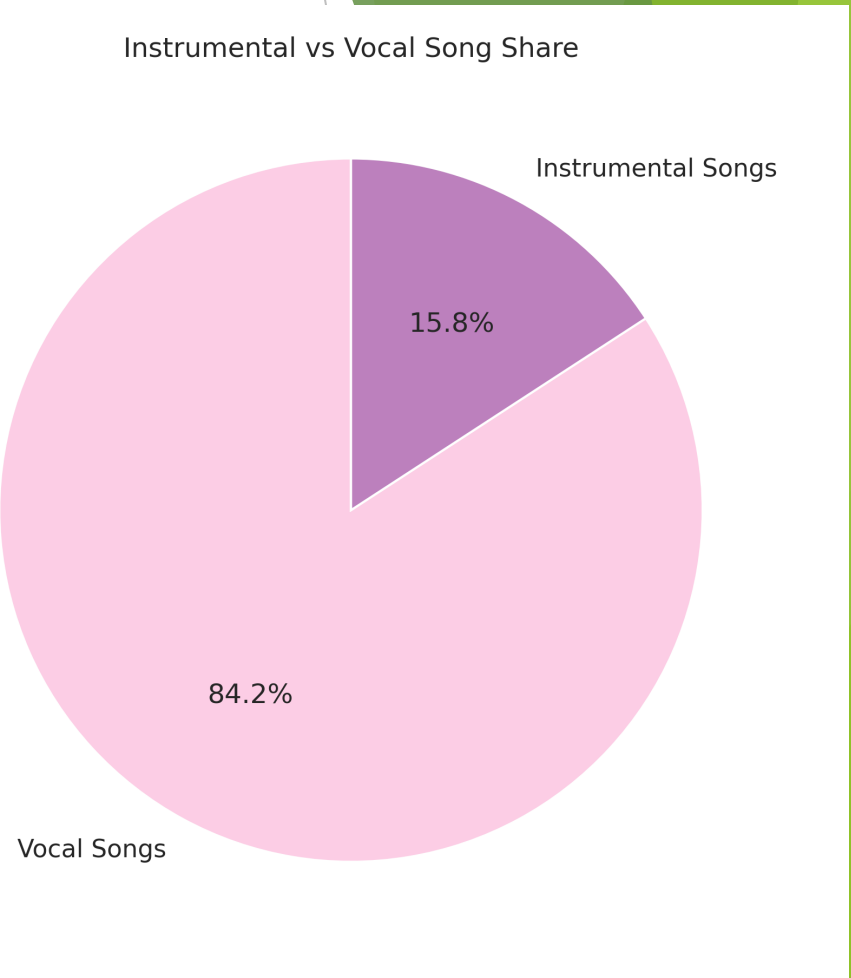


Energy vs Loudness

- **They are the same thing. Energy and Loudness** are almost perfectly correlated.
- **Avoid redundancy.** Using both features in a simple model is **redundant** and should be avoided.
- **Loudness is the driver.** As a song gets **louder, its Energy score increases** predictably.

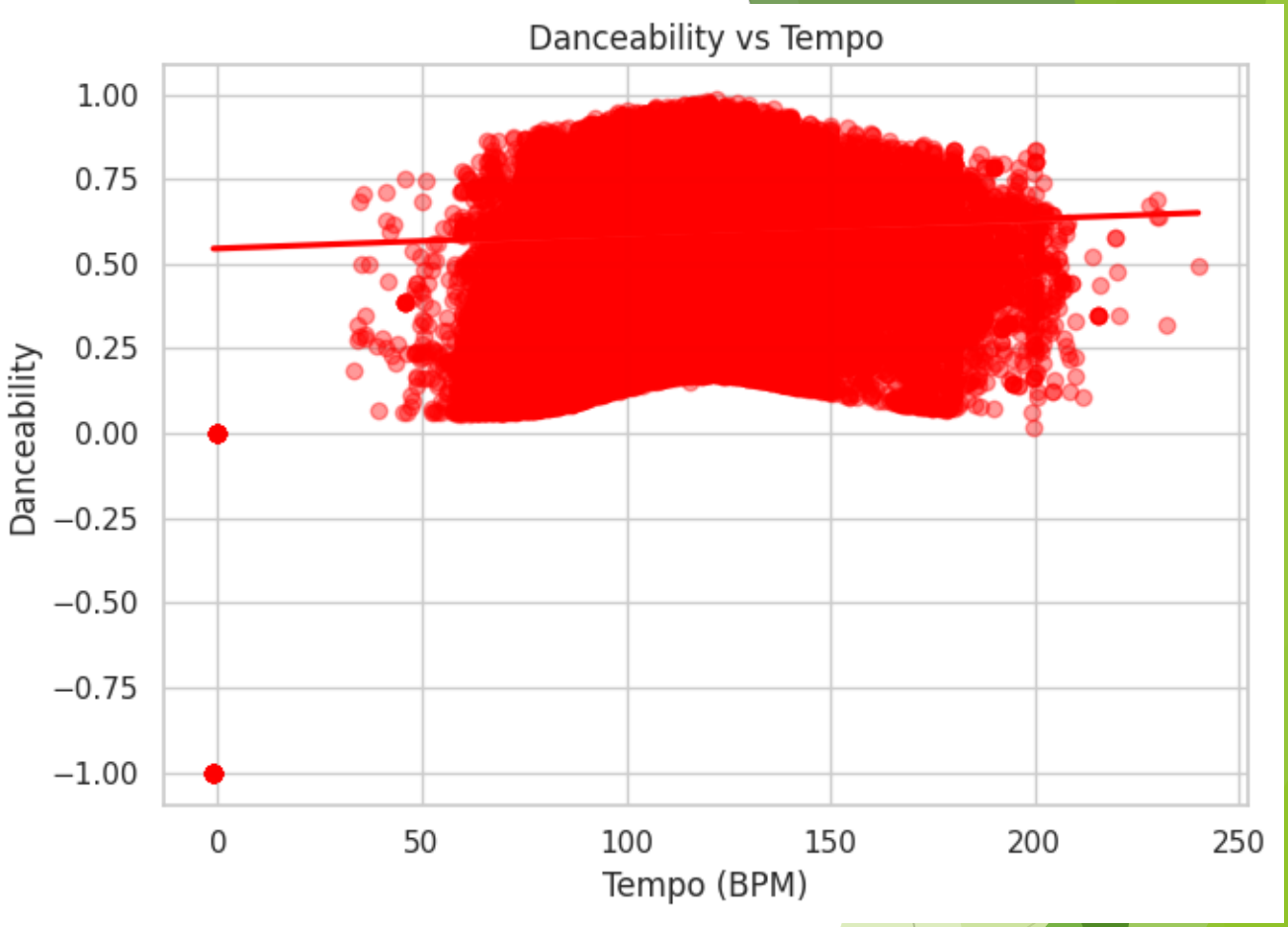
Instrumental vs vocal song share

- **Dominance of Vocal Songs:** The vast majority of songs in the dataset are Vocal Songs, accounting for 84.2% of the total share.
- **Minority Share of Instrumentals:** Instrumental Songs make up a small minority share, representing only 15.8%.



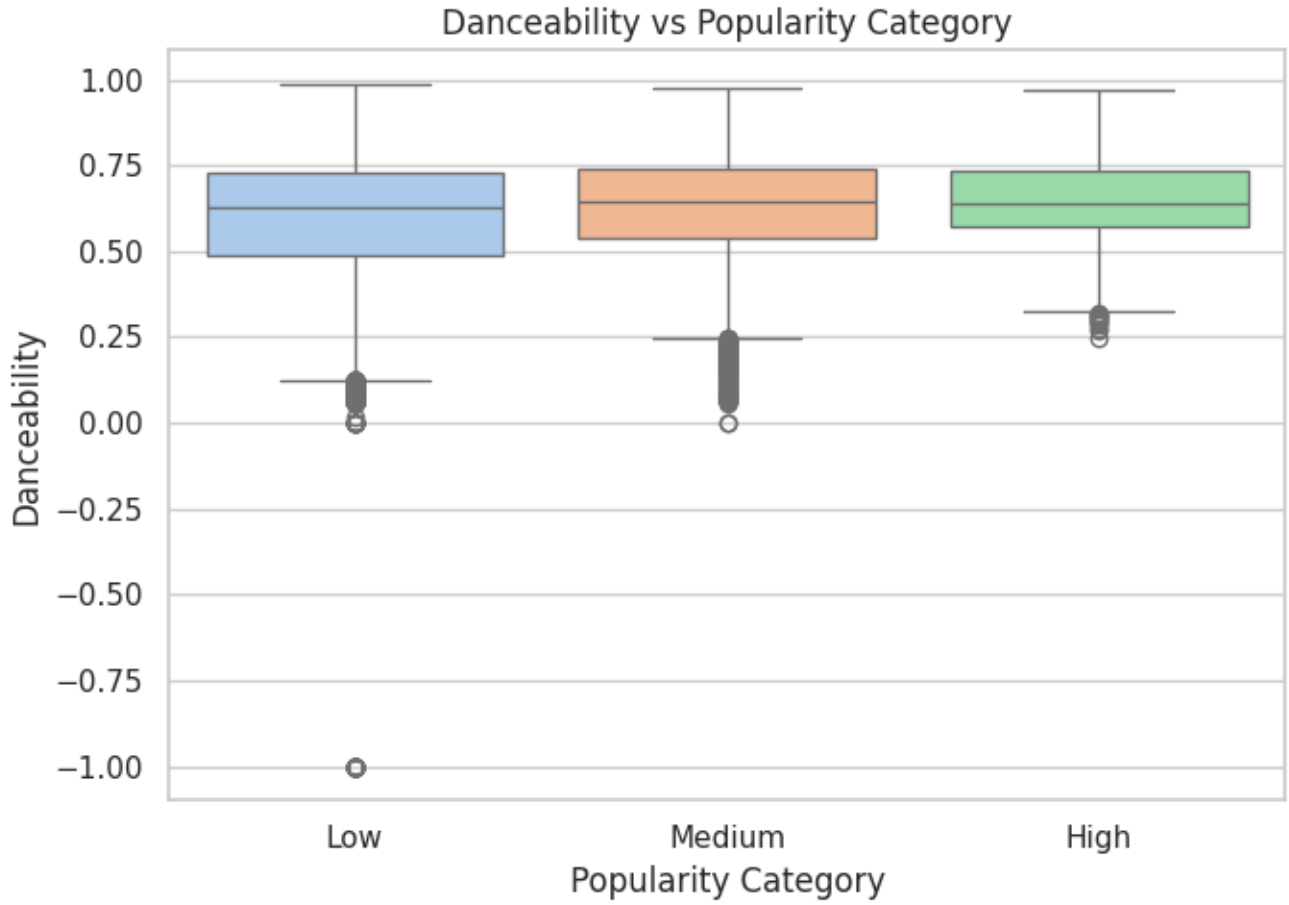
Danceability vs Tempo

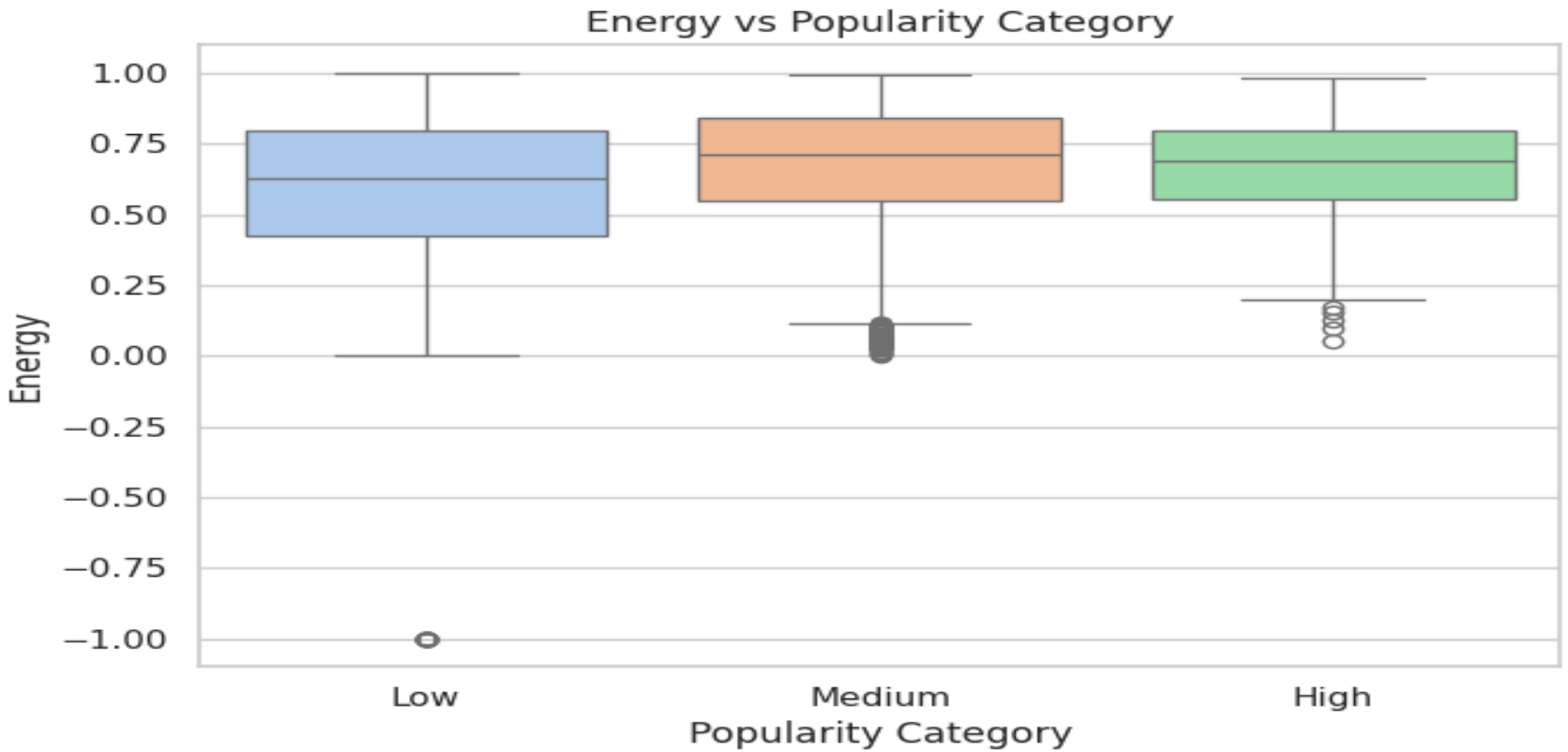
- **Speed doesn't matter.** A song's **speed (Tempo) has little correlation** with its Danceability score.
- **Danceable music is everywhere.** Highly danceable songs exist **across all common Tempos** (e.g., fast or slow).
- **Not a predictor:** Tempo will **not be a good predictor** for a song's Danceability.



Energy vs Popularity Category

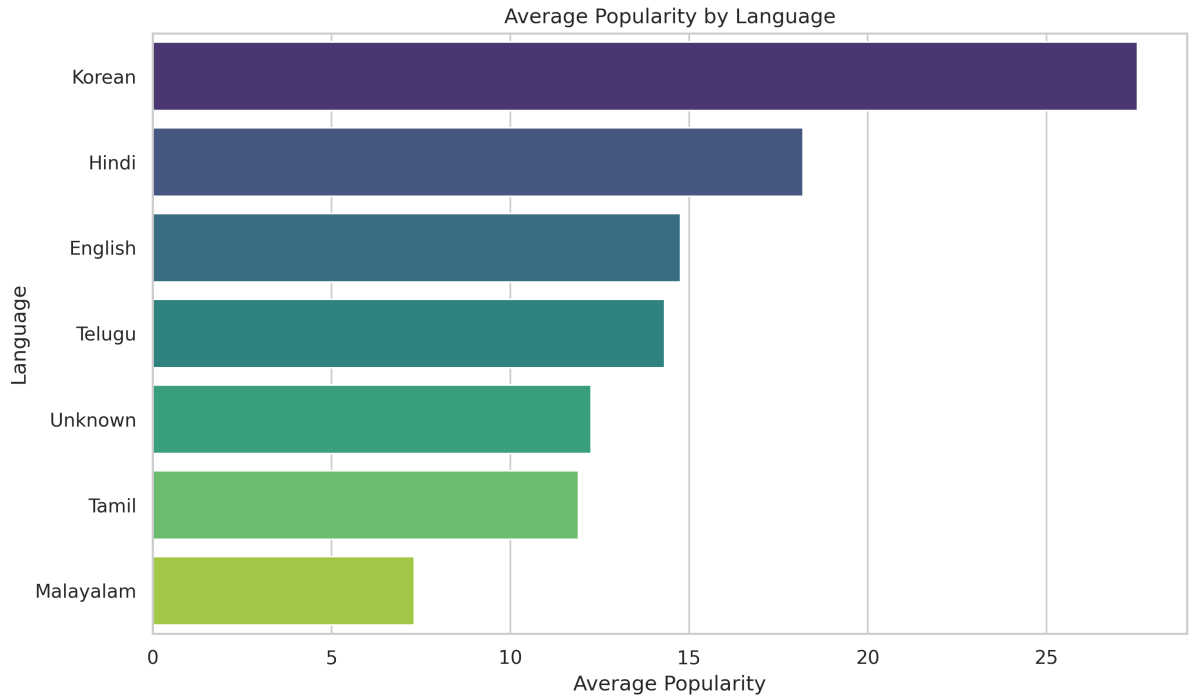
- **More Popular, More Energy:** High and Medium popular songs have a **higher median Energy** (≈0.7) than Low popular songs (≈0.6).
- **Low Energy is a Miss:** Songs with **low Energy are concentrated in the 'Low' Popularity** category; high-Energy songs dominate the hits.
- **Energy Range is Narrow:** The **range of Energy is tight** for Medium and High hits (≈0.5 to 0.8), suggesting a **sweet spot for Energy** that drives success.





Danceability vs Popularity Category

- **Danceability is Crucial:** High and Medium popular songs have a **higher median Danceability** (≈0.65) than Low popular songs (≈0.60).
- **Hits are More Consistent:** The **interquartile range (the box)** for High Popularity is slightly **narrower and higher**, meaning successful songs are consistently more danceable.
- **Low-Score Filtering:** Songs with very low Danceability are mostly in the 'Low' category, reinforcing it as a **good initial filter for potential hits**.

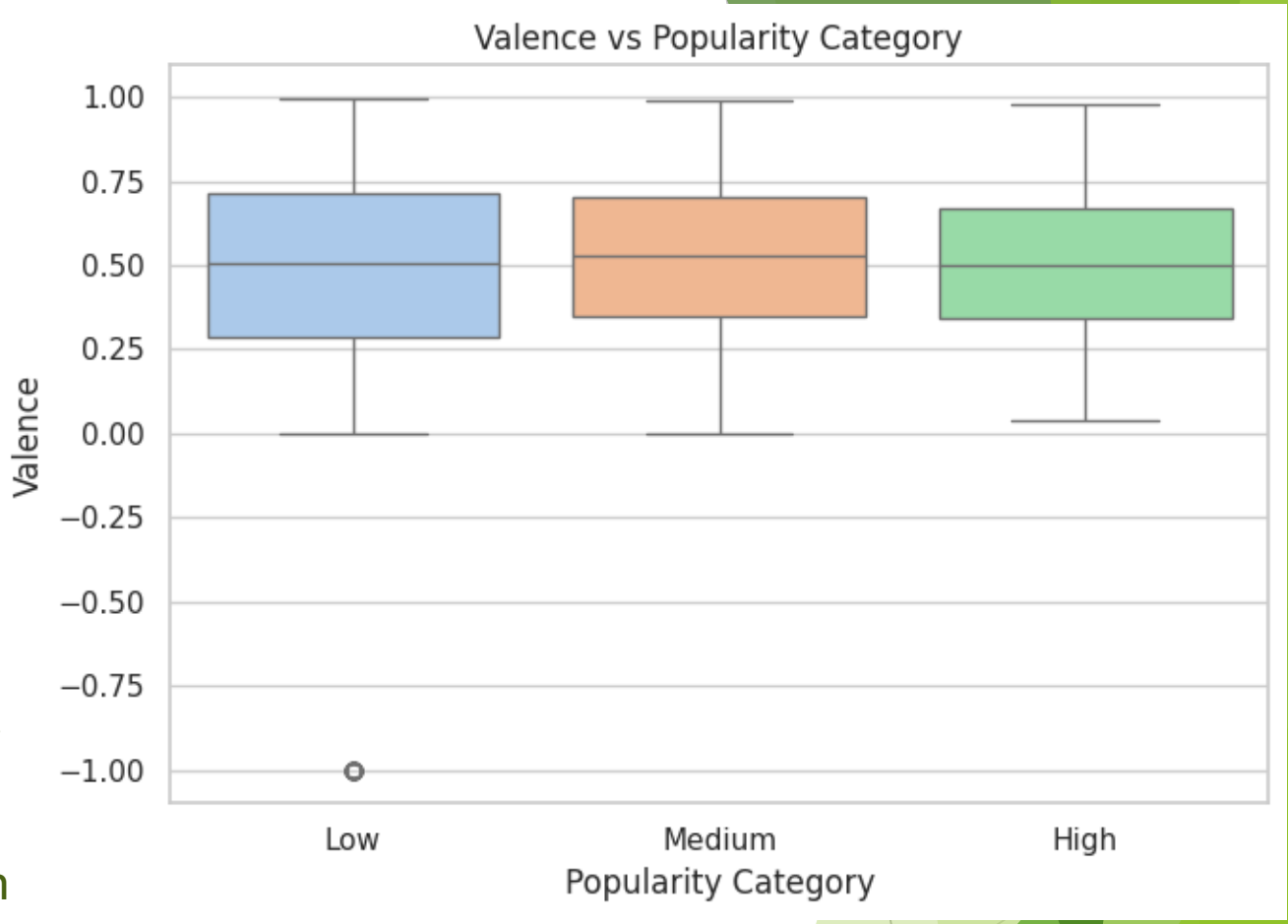


Average Popularity vs Language

- **Korean Dominance:** Songs in **Korean** have the highest average popularity, significantly outperforming all other languages (≈27.5).
- **Lowest Popularity: Malayalam** has the lowest average popularity among the listed languages (≈7.0).
- **High Popularity Tier: Hindi** follows as the second most popular language (≈18.5), establishing a high-popularity tier with Korean.

Valence vs Popularity Category

- **Mood Doesn't Predict Category:** The **median Valence is almost identical** (≈0.5) across all three Popularity categories (Low, Medium, High).
- **Full Emotional Range:** All categories have a **similarly wide range of emotions** (Valence) from very sad to very happy.
- **Modeling Confirmation:** The box plots confirm the scatter plot finding: **Valence has minimal independent power** to predict if a song will be a hit.



conclusion

- Shift Goal to Classification**:** Stop predicting scores; start classifying songs as **"Hit"** or **"Miss.“**
- Purge Composer Tracks**: Remove all film score entries** to focus your model only on standard popular music.
- Mandatory Threshold Filters**: Discard any song** that is too **low in Energy or Danceability** before modeling.
- Combine Emotional Features**:** Use the **interaction of Energy and Valence** (mood) together, as mood alone is weak.
- Simplify Redundant Features**: Drop one feature** from highly correlated pairs (like **Loudness or Valence**) to streamline the final model.

THANK YOU