



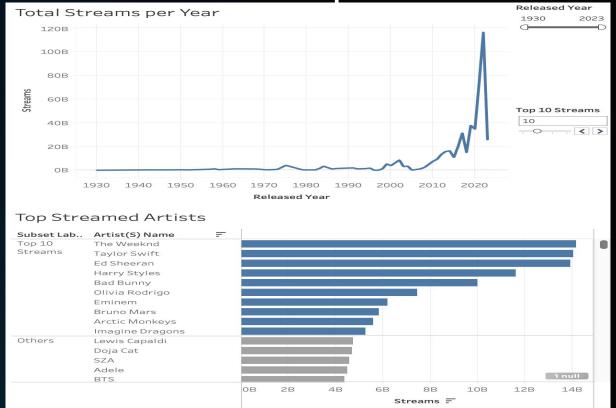
Overview

- The music market is extremely competitive with artists always trying to make the next viral song and get the most streams. Our group aims to find a way to see if we can develop an algorithm that can give artists a competitive edge.
- Based on the date it was released, bpm, energy, danceability, key, mode, dancebility%, valence%, energy%, acousticness%, instrumentalness%, liveness_speechiness% we want to predict the following:
 - How many Spotify streams?
 - Is it in spotify's charts?

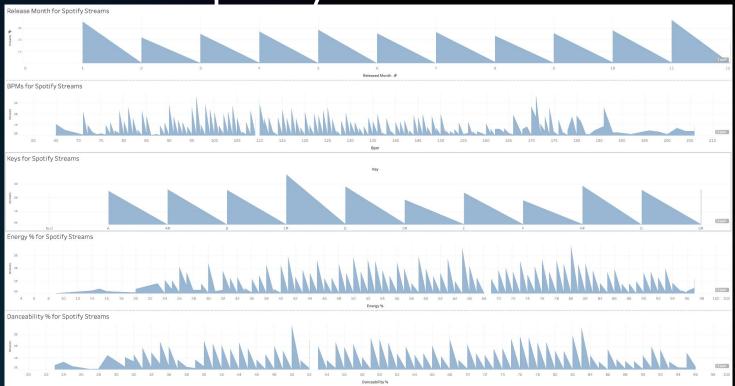






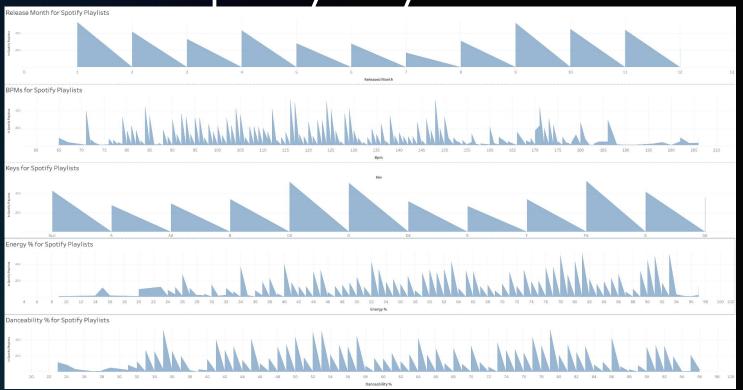


Stats for Spotify Streams



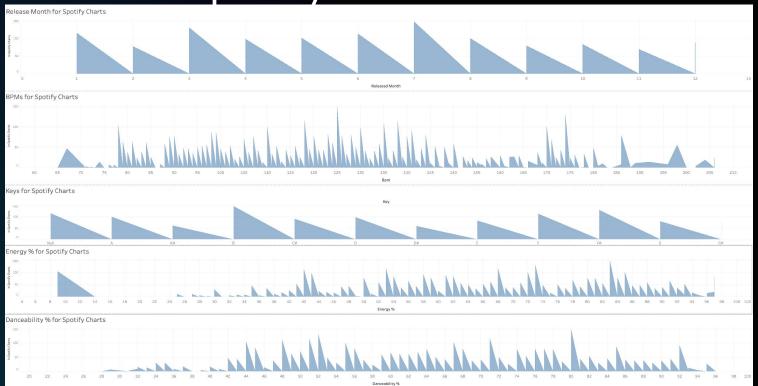


Stats for Spotify Playlists





Stats for Spotify Charts





Stats: Overview

- Release Month
 - Most Streamed Release Month: November
 - Most Playlisted Release Month: January
 - Most Charted Release Month: July
- BPM
 - Most Streamed BPM: 171
 - Most Plaulisted BPM: 116
 - Most Charted BPM: 125
- Keys
 - Most Streamed Keys: C# (C Sharp)
 - Most Plaulisted Keys F# (F Sharp):
 - Most Charted Keys: B (B Major)
- Energy %
 - Most Streamed Energy %: 80%
 - Most Playlisted Energy%: 81%
 - Most Charted Energy %: 83%
- Danceability %
 - Most Streamed Danceability %: 50%
 - Most Playlisted Danceability %: 79%
 - Most Charted Danceability %: 80%

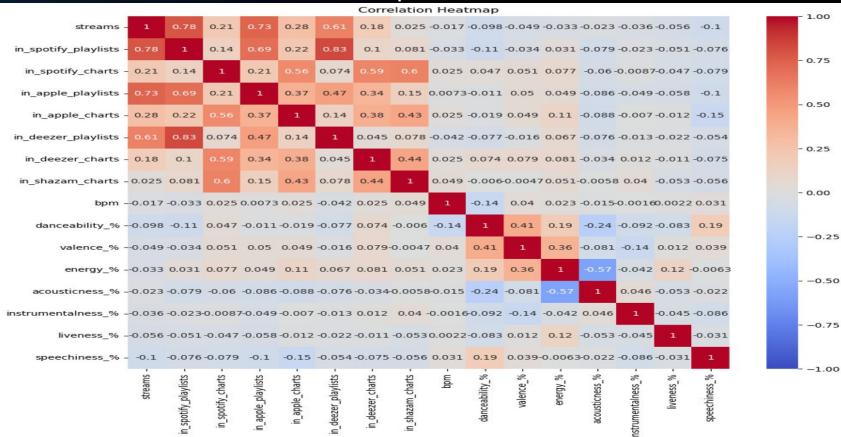
- Most Spotify Streamed Song:
 - Blinding Lights The Weeknd
- Most Spotify Playlisted:
 - Get Lucky Pharrell
- Most Spotify Charted:
 - Seven Latto, Jung Kook
- Top 5 Streamed Artists
 - The Weeknd
 - Taylor Swift
 - Ed Sheeran
 - Harry Styles
 - Bad Bunny



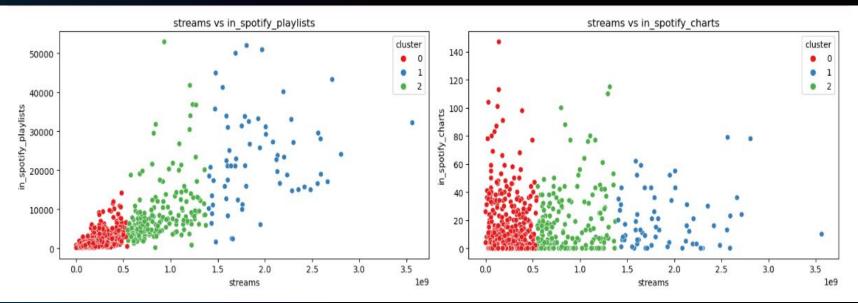




Seaborn: Correlation Heatmap

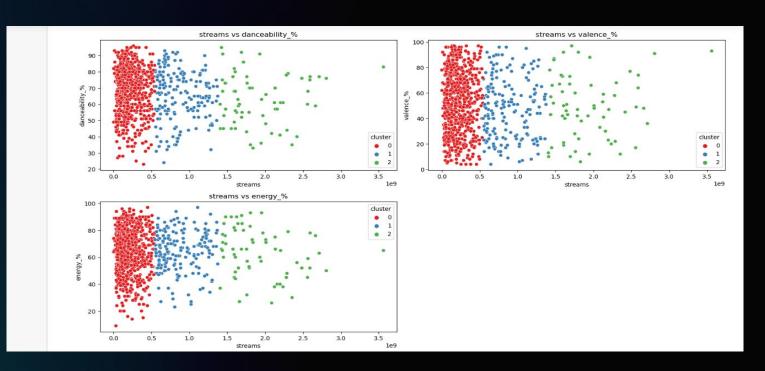


Seaborn: Cluster Pairplot





Seaborn: Cluster Pairplot







What methods are we using to Predict?

- As mentioned before, we are trying to predict Streams and if the song made it to spotify's charts and where it charted.

 Range Index: 953 entries, 0 to 952
- First we decided to remove all of the variables that was not a Float or integer.
- Converted the streams from object to int64
- Then we tried to predict the two fields mentioned above With Linear Regression and Random Forest

| Rang | eIndex: 953 entries, 0 | to 952 | |
|------|------------------------|----------------|--------|
| Data | columns (total 24 col | umns): | |
| # | Column | Non-Null Count | Dtype |
| | | | |
| 0 | track_name | 953 non-null | object |
| 1 | artist(s)_name | 953 non-null | object |
| 2 | artist_count | 953 non-null | int64 |
| | released_year | 953 non-null | int64 |
| 4 | released_month | 953 non-null | int64 |
| | released_day | 953 non-null | int64 |
| | in_spotify_playlists | 953 non-null | int64 |
| | in_spotify_charts | 953 non-null | int64 |
| 8 | streams | 953 non-null | object |
| | in_apple_playlists | 953 non-null | int64 |
| 10 | in_apple_charts | 953 non-null | int64 |
| 11 | in_deezer_playlists | 953 non-null | object |
| 12 | in_deezer_charts | 953 non-null | int64 |
| 13 | in_shazam_charts | 903 non-null | object |
| 14 | bpm | 953 non-null | int64 |
| 15 | key | 858 non-null | object |
| 16 | mode | 953 non-null | object |
| 17 | danceability_% | 953 non-null | int64 |
| 18 | valence_% | 953 non-null | int64 |
| 19 | energy_% | 953 non-null | int64 |
| | | | |
| 22 | liveness_% | 953 non-null | int64 |
| 23 | speechiness_% | 953 non-null | int64 |





Linear Regression

Used this model to find if there is relation between streams/charts (dependant variable) to all the other variables (independent variables)

| 373 14.773431 (791 10.716496 (791 | | Predictions | (charts) | Actual (charts) |
|--|-----|-------------|-----------|-----------------|
| 791 10.716496 | 256 | | 11.181750 | 13 |
| | 373 | | 14.773431 | 0 |
| 39 10.601805 28 | 791 | | 10.716496 | 0 |
| | 39 | | 10.601805 | 28 |
| 619 10.774929 | 619 | | 10.774929 | 0 |

| | Predictions (Streams) | Actual (streams) |
|-----|-----------------------|------------------|
| 604 | 3.444988e+12 | 956865266 |
| 559 | 1.958588e+12 | 421040617 |
| 750 | 3.531927e+12 | 1023187129 |
| 353 | 1.874600e+12 | 372476382 |
| 311 | 1.593008e+12 | 449701773 |
| | | |







Random Forest

 Wanted to use a model that is the "opposite" to linear regression and is robust against non-linear data to see if there is improvement here

| | Predictions | (charts) | Actual (charts) |
|-----|-------------|----------|-----------------|
| 256 | | 6.590 | 13 |
| 373 | | 10.842 | 0 |
| 791 | | 7.588 | 0 |
| 39 | | 14.988 | 28 |
| 619 | | 9.056 | 0 |
| | | | |

| | Predictions (Streams) | Actual (Streams) |
|-----|-----------------------|------------------|
| 604 | 2.277614e+09 | 956865266 |
| 559 | 2.195415e+09 | 421040617 |
| 750 | 2.277614e+09 | 1023187129 |
| 353 | 2.320015e+09 | 372476382 |
| 311 | 2.288452e+09 | 449701773 |
| | 2.2001020100 | |







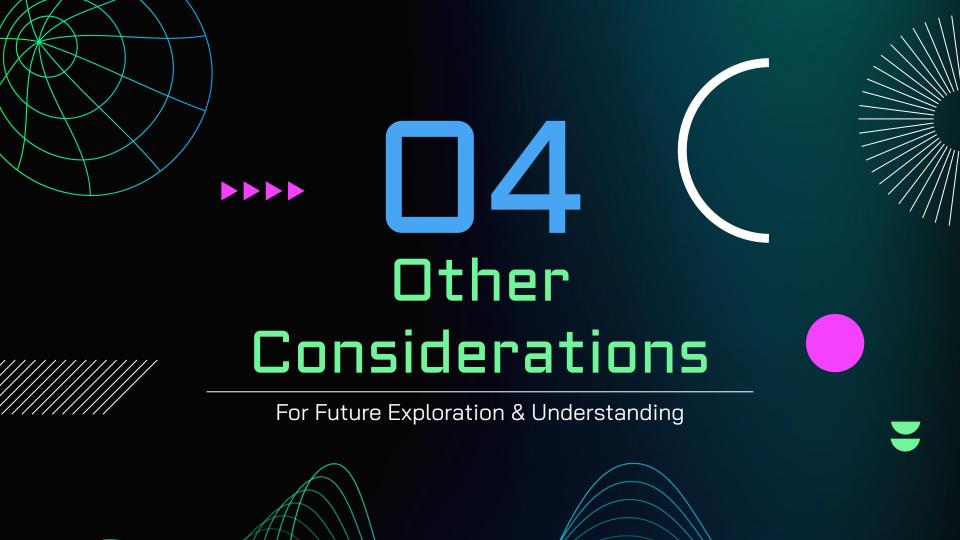
Which is Better?

- Overall Both of them are not great but random forest is slightly better, this is backed up by how accurate the mode "thinks" it is using the score method on the test data.
 - Streams: 97% Random Forest, 65% Linear Regression
 - Charts: 90% Random Forest, 6% Linear Regression
- While Random Forest is closer to the actual value in magnitude, it tends to cluster its
 predicted number and does not deviate much









Future Considerations

- Include Artist Name for modeling & predictions to be likely more accurate
- Further understanding on Spotify % of
 - Danceability %
 - Valence %
 - Energy %
 - Acousticness %
 - Instrumentalness %
 - Liveness %
 - Speechiness %
- Track YoY changes in statistics for developing further modeling & identifying YoY trends
- Knowing the length of the song will add the to model's robustness.









Links

- Dataset Link:
 - https://www.kaggle.com/datasets/zeesolver/spotfu
- Tableau (Public) Link:
 - https://public.tableau.com/views/SpotifyDataVisualizations/Story1?:language= en-US&:sid=&:display_count=n&:origin=viz_share_link
- GitHub Link:
 - https://github.com/jithu-ann/Project-4







GitHub Detail

- GitHub uploads and final repository have been completed
 - free of unnecessary files and folders
 - o appropriate .gitignore in use
 - contains a README file







Data Set Glossary

- track name: The name of the track.
- artist(s)_name: The name(s) of the artist(s) who created the track.
- artist count: The number of artists associated with the track.
- released_year: The year when the track was released.
- released_month: The month when the track was released.
- released_day: The day when the track was released.
- in_spotify_playlists: Indicates whether the track is included in Spotify playlists.
- in_spotify_charts: Indicates whether the track is present in Spotify charts.
- streams: The total number of streams the track has accumulated.
- in_apple_playlists: Indicates whether the track is included in Apple Music playlists.
- in_apple_charts: Indicates whether the track is present in Apple Music charts.
- in_deezer_playlists: Indicates whether the track is included in Deezer playlists.
- in_deezer_charts: Indicates whether the track is present in Deezer charts.
- in_shazam_charts: Indicates whether the track is present in Shazam charts.
- bpm: Beats per minute a measure of tempo in music.
- key: The musical key in which the track is composed.
- mode: Indicates whether the track is in a major or minor key.
- danceability_: A measure of how suitable a track is for dancing.
- valence_: The musical positiveness conveyed by a track.
- energy_: The perceived energy of a track.
- acousticness_: A measure of how acoustic a track is.
- instrumentalness_: A measure of whether a track contains vocals.
- liveness_speechiness_: A measure of presence of live elements or spoken words in a track.





