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Final Project - Milestone 3: EDA & Revised Project Statement

Data Science I - Fall 2017

28 November 2017

Data Description:

After sourcing the 8466 Spotify users who "own" a large number of playlists, the spotipy library was employed to collect user playlists, tracks, user followers, and genre data from Spotify's API, each saved as JSON files. Genre information for each playlist was harder to source and incorporate than one would think. It does not come directly from each playlist, but rather from the artists of each track as a separate query. In its basic form the playlists file contains 8,231 observations across seven features:

user	num_tracks	name	id	followers	desc	collab	
ellenholstad	6	Allgott o villgott	3ftsSOkyCsILZeAZYQr2jH	2.0	None	False	0
ellenholstad	9	Emelie och Nelli	27NLrsj0rlUi9S9Buj7NEl	0.0	None	False	1
maka_97	54	Dame mas chocolinas	2DVuNt17JxlUUwP8VbjYMZ	9.0	None	False	10
thefamousnobody	46	Miami Morty 💎 <	07nCTAAPUQI3O9835StlnA	22.0	None	False	100
vimmel76	13	Michael Bublé - Call Me Irresponsible	2nLFBeJkALxMcmYHqOnBAE	0.0	None	False	1000

The tracks file contains 367,949 observations across eight features:

	added_at	artist	duration	explicit	id	name	playlist_id	popularity
0	2013-09-30 16:12:24	Allgott & Villgott	119907.0	0.0	3alptaHMnblXRxPWKlqwc6	Klappa lamm	3ftsSOkyCsILZeAZYQr2jH	2.0
1	2013-10-05 15:22:13	Allgott & Villgott	67918.0	0.0	0rPBIDWP6wcfax63Vs8nAF	Hej på dej	3ftsSOkyCsILZeAZYQr2jH	4.0
10	2014-07-16 13:50:24	J Boog	217270.0	0.0	4RjHalDdUreXDJSJLo44lK	Sunshine Girl	35XFuuqgCvTYQARix7CFpm	53.0
100	2014-07-06 09:12:01	Brennan Heart	222919.0	0.0	6A04TZRVZw8db1VsHeYOEx	Never Break Me - Toneshifterz Remix	0gGfciue2ZDCOG5uMv46gU	0.0
1000	2012-06-29 11:53:52	Johnny Ray	153375.0	0.0	1k4p7c69Dkh2b7s813ooR8	Yes Tonight, Josephine	6Tuex6CIDfZRyRtsmb5rwE	0.0

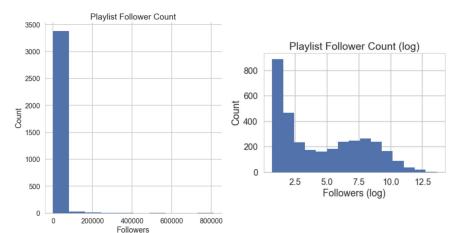
And the followers and genre files contain 8,457 and 39,998 observations as follows:

	user user_followers			artist	artist_followers	artist_genre	artist_id	artist_pop
0	11132487979	59.0	0	Allgott & Villgott	76.0	None	5psFWO0ApFkCgzjuToEHx3	8.0
1	1214248943	29.0	1	J Boog	103793.0	[polynesian pop]	7oEWmZ9dKIAVxTgmjUbYr4	63.0
10	1231537904	23.0	10	Trouble Maker	57509.0	[dance pop, k-pop]	0ztjVBmFk6OuHq6XBBwMI9	48.0
100	asrais	306.0	100	Whigfield	14986.0	[bubblegum dance, dance pop, eurodance, europo	0lHoDF96DNKSlclpcOfMnq	56.0
1000	colib21	9.0	100000	Los Violadores	15328.0	[argentine rock, latin alternative, latin meta	4EkrhlCS2DbFxvC3Uhq6p2	45.0

The files were combined and manipulated into a single DataFrame via the playlist ID, username, and artist name attributes. While cleaning, we decided to eliminate any playlist with only one follower (the owner).

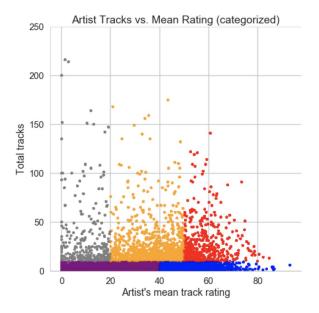
EDA:

Engineering more features around artist and playlist data yielded interesting relationships. A cursory measure of playlist success, our generalized project goal, is the number of followers per playlist. Looking at the histograms to the right shows a significant right-skew, with most playlists having few followers, and a few approach the 1M mark. The log-transform of followers illustrates a potentially more useful response variable.



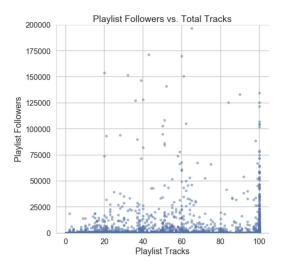
We separated artists into five distinct categories using combinations of their mean popularity and total number of tracks as follows: superstar, star, one_hit_wonder, garage_band, and crap_factory.

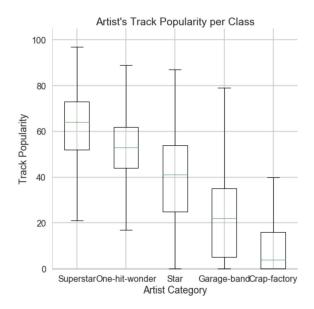
These categories should be self-descriptive, but the two plots below do a fantastic job of illustrating each in terms of their thresholds and relationships.

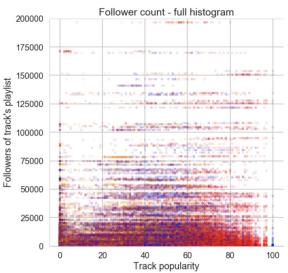


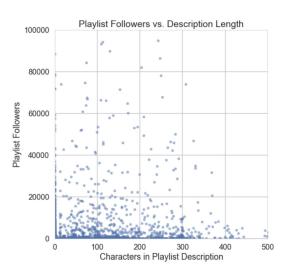
Comparing these five artist categories with specific track popularities (as determined by Spotify) and those tracks' playlists' followers shows us that not only do most playlists incorporate popular artists (red/orange), but a lot of them have the "superstar" artists' best songs (the mostly red right side), as well as a smattering of "one-hit-wonders" (blue in the middle) and a dense area of moderately popular songs throughout (between 30 and 70 popularity). This relationship and playlist architecture should also be intuitive, and the scatterplot to the left illustrates it well.

It appears that there may be a relationship between the number of tracks a playlist has and its number of followers (below), as well as length of its description (below-right).

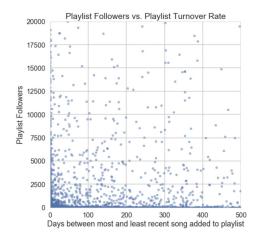


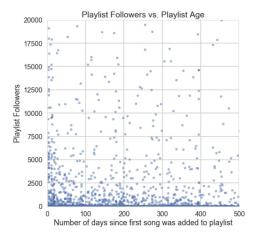




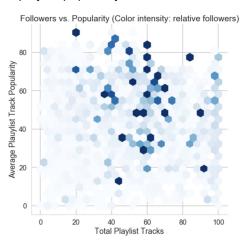


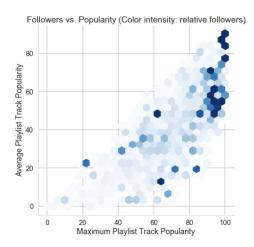
We also investigated the impact of playlist turnover rate, or relative age (days between the oldest and newest track being added), as well as the the absolute age (days since first song was added) on playlist follower count (below plots).





Two more illustrative hexagon bin plots are below. They show interesting relationships between relative number of playlist followers with playlist popularity and track metrics.





The overarching goal of the preceding EDA was to find trends in the playlist data indicating "success" of a playlist. How do we measure that success? The simple metric of total followers may not the best measure. In that regard, we propose use of a response variable analogous to "Playlist Velocity" (PV), or playlist followers over time. The time component may change (time since inception, time since last song added, mean age of song in playlist, etc.) during model analysis, but PV will remain as our response variable "theme."

We also plan to incorporate track audio data from the Million Song Dataset (MSD), and hope to combine some of those features into a significant composite predictor for PV. One downside to including this audio data is that is may shrink our overall dataset since some of the songs included in playlists may or may not be included in the MSD. There will be more to follow on that front in the final submission report.

Revised Project Question:

Our team's original two project questions were intentionally general. The preceding EDA has cemented their applicability to this project: Can we predict the general success of a Spotify playlist using regression? Can we classify a playlist into different popularity classes using the predictors we use for the regression model?

Based on our data collection and exploration, we have revised our questions by maintaining the original two and adding a third: Can we generate a successful Spotify playlist with user specified genre and length using our regression model?