Do Musicians learn? Evidence from Song Popularity

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Abstract

Using a dataset of 5,86,672 songs from Spotify, we evaluate whether artists are gifted beings who stick to their core creativity or learn and adapt basis their the response their songs get. We find that popularity of songs does not improve with iterations which could mean unpredictability of taste or inability of artists to adapt.

1 Introduction

In a series of papers (Singh [2021b]) , I try to examine the following questions.

- What does the average album look like: how many sad, what balance
- Do albums with similar songs do better
- Do albums have multiple hit songs or only 1/2 songs make it ?
- Do artists experiment after a hit or do more of the same? Are they scare or overconfident?
- Do negative songs do better?
- Do winter songs do better?
- When does a artist shine to fame: first or next or last?
- Is the same song a hit in multiple places? What are unique geographic hits?

Some of my other work pertains to perceptions of founders in startups ([Singh, 2021i,d,e,f,j,g]), Olympic medals ([Singh, 2021c,h]), Covid data [Singh, 2020a,b], trading strategy [Singh, 2015], CSR [Singh and Poonawala, 2016], Crowdfunding [Singh and Poonawala, 2021, Singh, 2021a] and some Finance and Director diligence stuff [Singh and Singla, 2016b,a, Singh, 2017] .

In this paper, I look at the most popular hits of artists. I examine whether artists get their biggest hits in the first go and spend the rest of their lives trying to match that success or whether artists enter the market, release music, take feedback and improve in order to produce more popular songs. In case artists are learning from feedback, the popularity of their songs would have an upward trend.

In case artists do not take feedback, their most popular songs would be spread randomly across their careers. For artists who had their most popular song in their first year, the subsequent years would entail a lot of experiments, most of which would fail and eventually they would retire. This means we should see artists with their best hits coming in the first year, dropping off in a couple of years post that. The year/date of the last song by a particular band can be used to check this hypothesis.

To examine learning we regress popularity of the songs on their sequence. We find that sequence has a negative coefficient that is statistically significant while controlling for other song traits. We remove remastered songs from our dataset for the purpose of analyses.

Our data spans a total of 586672 songs by 115062 across 102 years. This includes 25864 explicit songs.

2 Data

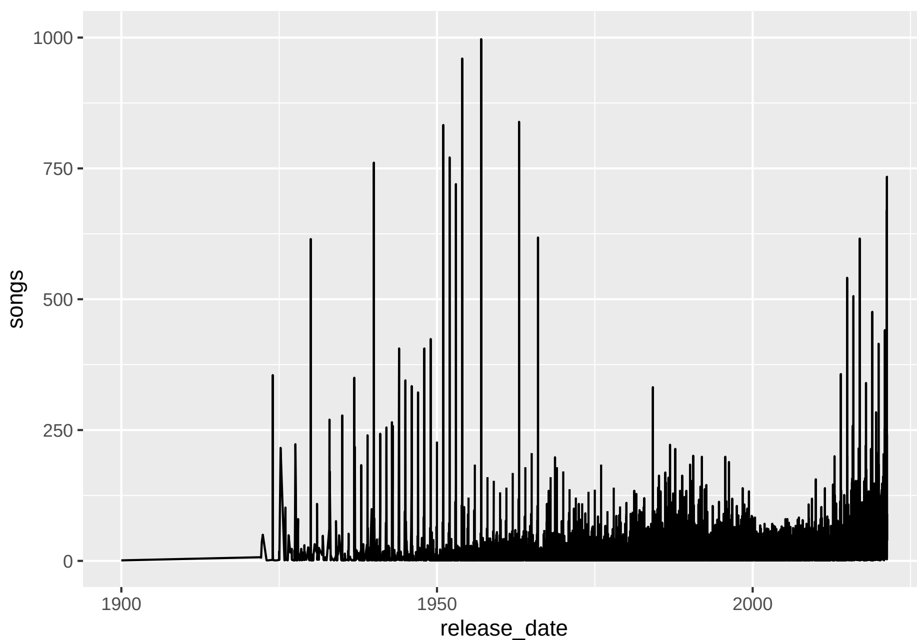
2.1 Summary

- Total songs
- Total Artists
- Total Albums
- Average Popularity
- Year wise distribution

Figure **??** shows the date wise distribution of songs in our dataset. Figure 1 shows the year wise distribution of songs in our dataset. ##IF this is correct, use the same label command in the previous one.

Table 1: This table shows the summary of the dataset.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
popularity	561,727	27.733	18.364	0	13	41	100
duration_ms	561,727	229,729.200	126,944.300	3,344	175,347	263,427	5,621,218
explicit	561,727	0.046	0.209	0	0	0	1
danceability	561,727	0.566	0.166	0.000	0.456	0.688	0.991
energy	561,727	0.542	0.251	0.000	0.344	0.747	1.000
key	561,727	5.224	3.521	0	2	8	11
loudness	561,727	−10.204	5.098	−60.000	−12.908	−6.464	5.376
mode	561,727	0.657	0.475	0	0	1	1
speechiness	561,727	0.107	0.183	0.000	0.034	0.077	0.971
acousticness	561,727	0.450	0.348	0.000	0.099	0.783	0.996
instrumentalness	561,727	0.111	0.265	0.000	0.000	0.008	1.000
liveness	561,727	0.214	0.184	0.000	0.098	0.278	1.000
valence	561,727	0.552	0.258	0.000	0.346	0.769	1.000
tempo	561,727	118.377	29.794	0.000	95.407	136.286	246.381
time_signature	561,727	3.873	0.475	0	4	4	5



% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu % Date and time: Fri, Nov 19, 2021 - 22:28:09

We look at the year of the first song by the artist and the year of the most

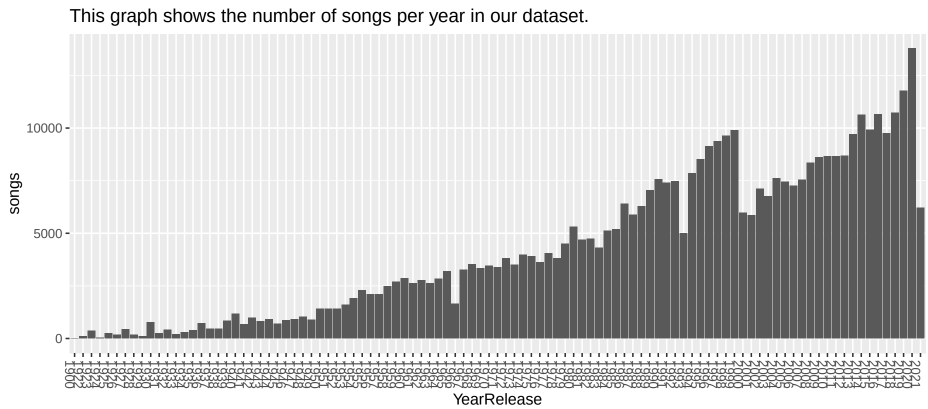


Figure 1: This graph shows the number of songs per year in our dataset

Table 2: This table shows the summary of the dates of first song, biggest hit and last song per artist.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
X1	86,965	61,652.360	31,079.330	26	34,810	88,158	115,062
Year1	86,965	2,005.602	12.962	1,970	1,997	2,016	2,021
LastYear	86,965	2,007.843	11.948	1,970	2,001	2,017	2,021
GYear	86,965	2,018.000	0.000	2,018	2,018	2,018	2,018
HitYearDiff	86,965	12.398	12.962	−3	2	21	48
LastHitYearDiff	86,965	−10.157	11.948	−48	−17	−1	3

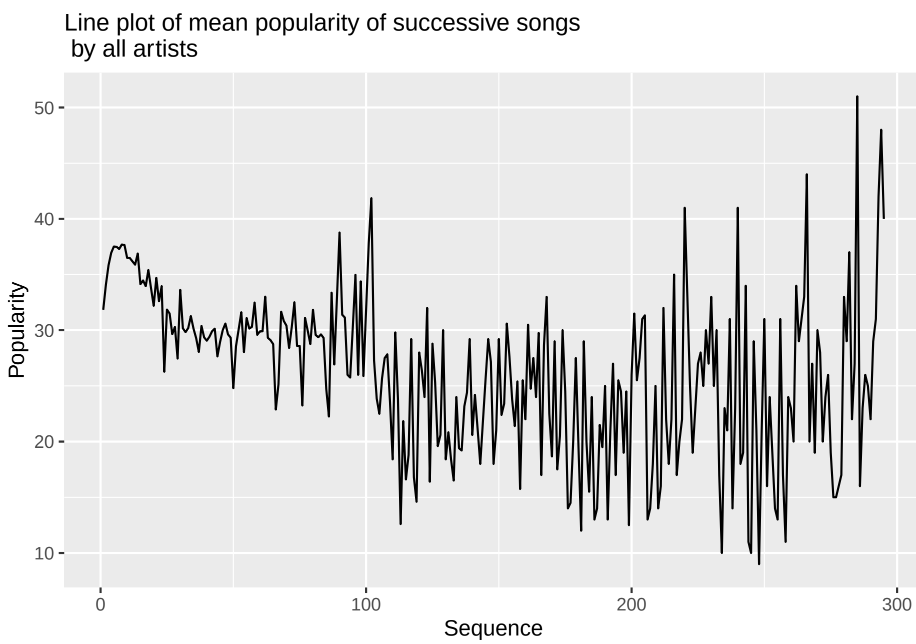
popular song by the artist. For example, if the artist released the first song in 1997, and their most popular song was released in 2001, then we note 2001-1997 = 4 as the time till the first hit. In case the most popular song was released in the same year, this number would be 0.

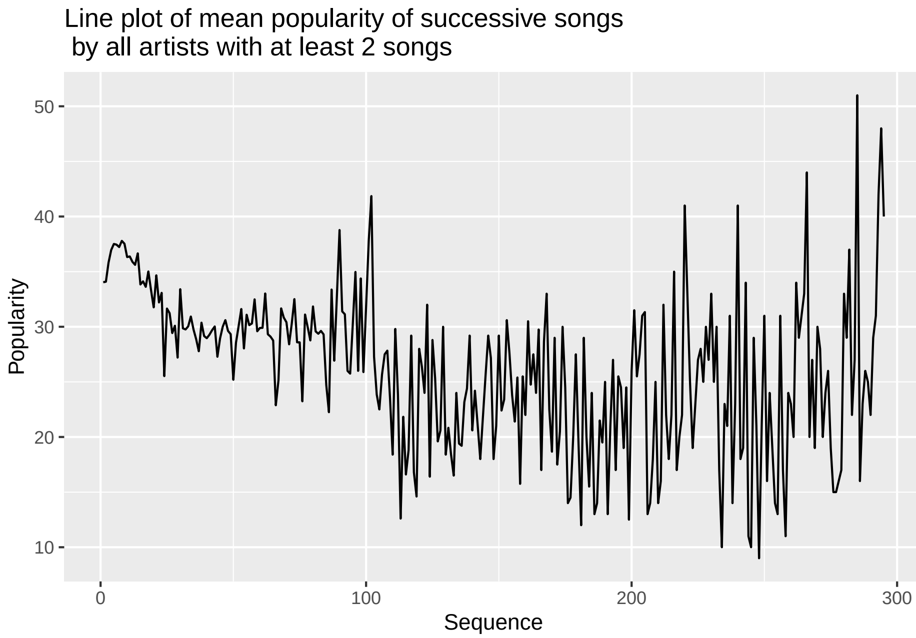
This analysis allows us to answer the following questions

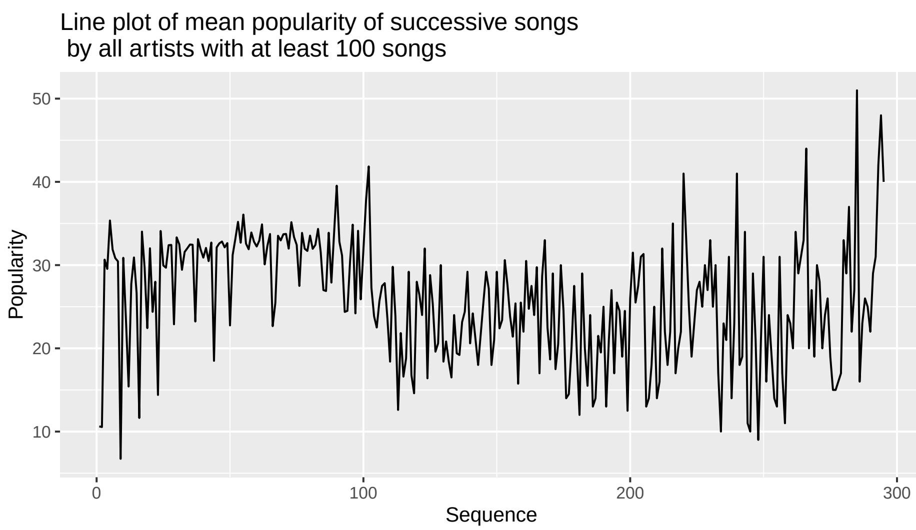
- Who got it soonest
- How many got it soonest
- How many in 1 year
- Who got it late
- How many after 5 years

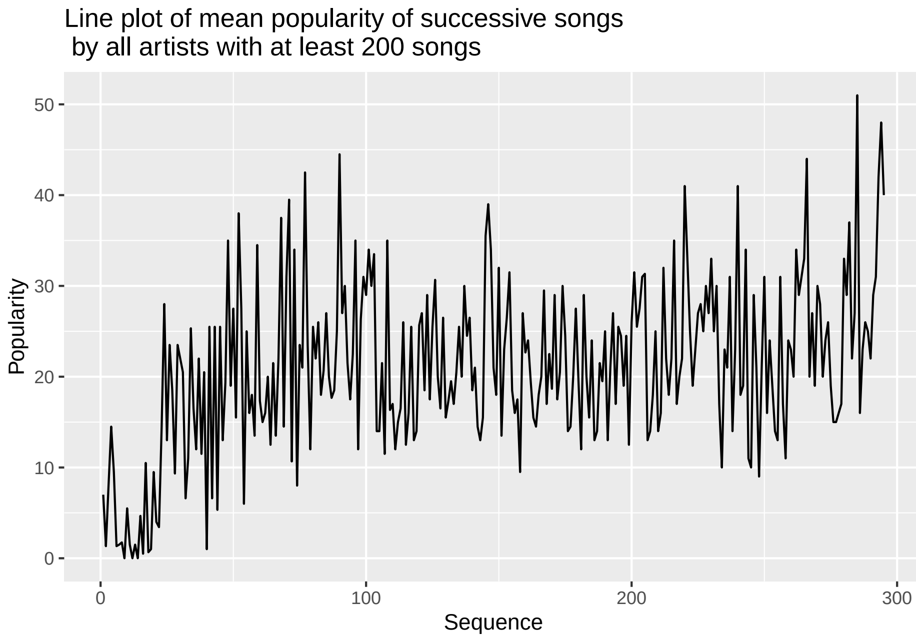
2.2 Visually

We look at the average popularity of songs based on their sequence number.




Line plot of mean popularity of successive songs
by all artists with at least 2 songs
Popularity
Sequence
50
40
30
20
10
0
100
200
300


Line plot of mean popularity of successive songs
by all artists with at least 100 songs
Popularity
Sequence
50
40
30
20
10
0
100
200
300



2.3 Regression

Sequence of songs Only the most popular song on any date, incase there were multiple songs on the same date Only artists with more than 1 song Get details of the music Regression on Popularity on All the factors Find that sequence is a major contributor along with Explicit

2.4 Drilling Down

In order to examine whether any learning takes place at the start of the career or during the later part, we run part regressions.

3 Limitations

Limited dataset: It is possible that there are some songs by certain artists that are not part of the half a million songs I use. In some cases, the biggest hit of a few artists might have existed in a particular year and is not accounted for in this study. However, our data is not biased on vintage. Therefore, I do not expect this to be systematically lopsided. This data is from Spotify. The popularity of the app has gone up in each of the previous few years. It is possible that songs that were not hits in the first go, in the first geography subsequently

Table 3: This table shows the results of regression of popularity on sequence and other control variables.

	Dependent variable:	
	popularity.x	
	(1)	(2)
seq	-0.020^{***}	-0.005
	(0.003)	(0.003)
duration_ms.x	-0.00000^{***}	-0.00000^{***}
	(0.00000)	(0.00000)
danceability	1.644^{***}	19.192^{***}
	(0.359)	(0.378)
energy	-7.196^{***}	-3.021^{***}
	(0.368)	(0.405)
key	-0.012	0.010
	(0.012)	(0.014)
loudness	0.230^{***}	0.741^{***}
	(0.016)	(0.018)
mode	1.033^{***}	0.405^{***}
	(0.091)	(0.100)
speechiness	-2.931^{***}	-9.196^{***}
	(0.281)	(0.303)
acousticness	-3.821^{***}	-11.273^{***}
	(0.196)	(0.211)
instrumentalness	-12.321^{***}	-16.184^{***}
	(0.200)	(0.220)
valence	0.087	-14.306^{***}
	(0.232)	(0.238)
tempo	-0.003^{*}	0.019^{***}
	(0.002)	(0.002)
time_signature	0.267^{***}	0.670^{***}
	(0.102)	(0.112)
explicit.x	7.486^{***}	
	(0.198)	
Constant	-840.374^{***}	43.028^{***}
	(5.557)	(0.660)
Year	Yes	No
Observations	129,541	129,541
R^2	0.351	0.208
Adjusted R^2	0.351	0.208
Residual Std. Error	15.533 (df = 129525)	17.157 (df = 129527)
F Statistic	$4{,}665.166^{***}$ (df = 15; 129525)	$2{,}615.759^{***}$ (df = 13; 129527)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4: This table shows the results of regression of popularity on sequence and other control variables

	Dependent variable:			
	First50			
	(1)	(2)	(3)	(4)
seq	0.002	0.005	-0.013^{***}	-0.042^{***}
	(0.007)	(0.015)	(0.004)	(0.003)
duration_ms.x	-0.00000^{***}	0.00000^{***}	0.00001^{***}	-0.00000^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
danceability	1.663^{***}	10.901^{***}	8.982^{***}	2.725^{***}
	(0.365)	(2.035)	(1.791)	(0.388)
energy	-7.225^{***}	-3.139^{*}	-2.357	-10.382^{***}
	(0.376)	(1.705)	(1.521)	(0.407)
key	-0.012	-0.006	-0.003	-0.013
	(0.013)	(0.053)	(0.048)	(0.013)
loudness	0.225^{***}	-0.118	-0.138^{*}	0.463^{***}
	(0.016)	(0.088)	(0.076)	(0.020)
mode	1.034^{***}	0.363	0.700^{**}	0.955^{***}
	(0.093)	(0.393)	(0.354)	(0.099)
speechiness	-3.754^{***}	5.569^{***}	7.396^{***}	-0.369
	(0.309)	(0.727)	(0.710)	(0.328)
acousticness	-3.921^{***}	-1.881^{**}	-2.431^{***}	-2.924^{***}
	(0.201)	(0.899)	(0.836)	(0.213)
instrumentalness	-12.375^{***}	-8.508^{***}	-7.245^{***}	-13.074^{***}
	(0.203)	(1.484)	(1.307)	(0.254)
valence	0.180	-8.155^{***}	-7.074^{***}	-0.175
	(0.236)	(1.115)	(1.014)	(0.250)
tempo	-0.002	-0.002	-0.003	-0.002
	(0.002)	(0.007)	(0.006)	(0.002)
time_signature	0.211^{**}	0.629^{***}	0.570^{***}	0.073
	(0.107)	(0.225)	(0.213)	(0.122)
explicit.x	7.585^{***}			7.771^{***}
	(0.201)			(0.204)
Constant	-840.631^{***}	-292.962^{***}	-392.815^{***}	-661.565^{***}
	(5.653)	(39.151)	(35.526)	(8.516)
Year	Yes	Yes	Yes	Yes
Observations	126,356	2,611	3,123	113,329
R^2	0.351	0.220	0.272	0.166
Adjusted R^2	0.351	0.216	0.269	0.166
Residual Std. Error	15.642 (df = 126340)	9.423 (df = 2596)	9.300 (df = 3108)	15.851 (df = 113313)
Note:				*p<0.1; **p<0.05; ***p<0.01

became hits. This would not be accounted for in the study. While the songs from our study are from almost a century ago, Spotify as an app has only started recording popularity in the past decade or so. This study assumes that the preference of people has been similar if not same. The study also assumes that the information regarding the popularity of songs was available to the artists. This would not be far-fetched as radio and record sales were always availing on a periodic basis.

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