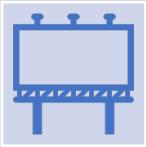


Predicting Top 10 Songs on Billboard Hot 100 Chart

Cassie Buhler

Billboard Charts



Billboard publishes musical charts of the most popular (highest sales, streams, etc.) songs & artists



Charts are released on a weekly and/or yearly basis



Great way to look at how trends and pop culture changes and evolves

Top 10 songs in 2010's Hot 100 Chart

The Hot 100

- *The Hot 100* is a popular Billboard chart
- Publishes 100 songs at end of year
- Songs are listed in ascending order— most popular at #1

1	TiK ToK	Ke\$ha	▼
2	Need You Now	Lady Antebellum	▼
3	Hey, Soul Sister	Train	▼
4	California Gurls	Katy Perry Featuring Snoop Dogg	▼
5	OMG	Usher Featuring will.i.am	▼
6	Airplanes	B.o.B Featuring Hayley Williams	▼
7	Love The Way You Lie	Eminem Featuring Rihanna	▼
8	Bad Romance	Lady Gaga	▼
9	Dynamite	Taio Cruz	▼
10	Break Your Heart	Taio Cruz Featuring Ludacris	▼

The Dataset

Hot 100 songs from 2010-2020 yearly charts

- **1100 songs** in total

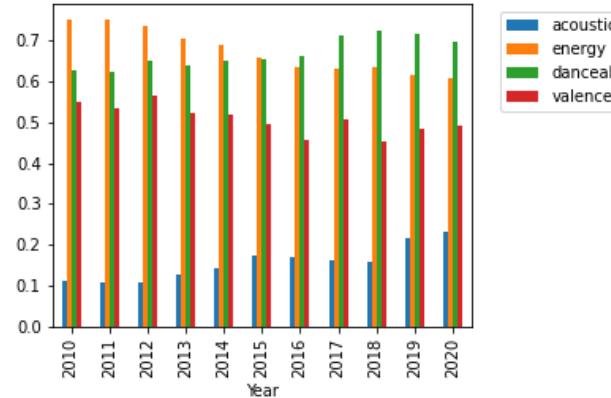
Split data into 3 sets

- Train: 2010-2015
- Validate: 2016-2017
- Test: 2018-2020

Spotify API Features:

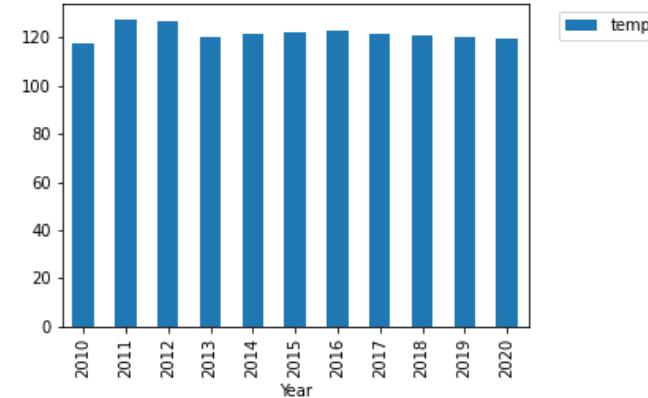
- Accousticness
- Danceability
- Duration
- Energy
- Instrumentalness
- Key
- Liveness
- Loudness
- Speechiness
- Tempo
- Time signature
- Valence
- Artist popularity
- Artist genre

Average Audio Features of Top 100 Songs: 2010-2020



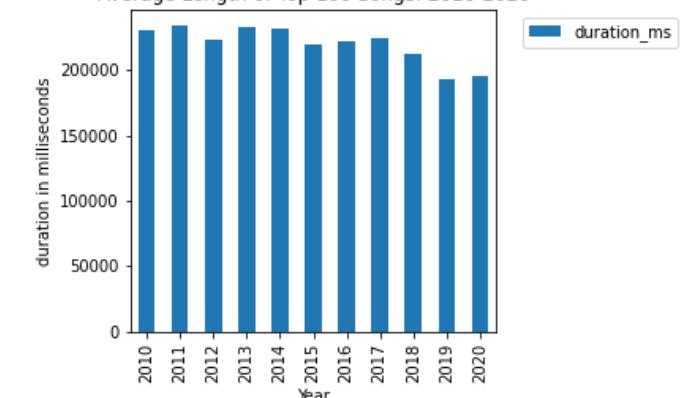
- Increase in acousticness & danceability
- Decrease in energy

Average Tempo of Top 100 Songs: 2010-2020



- Tempo is consistent

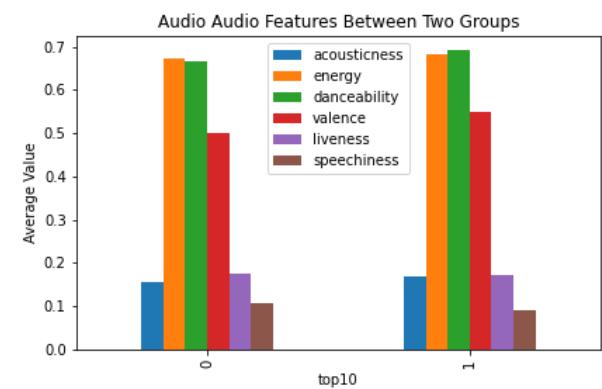
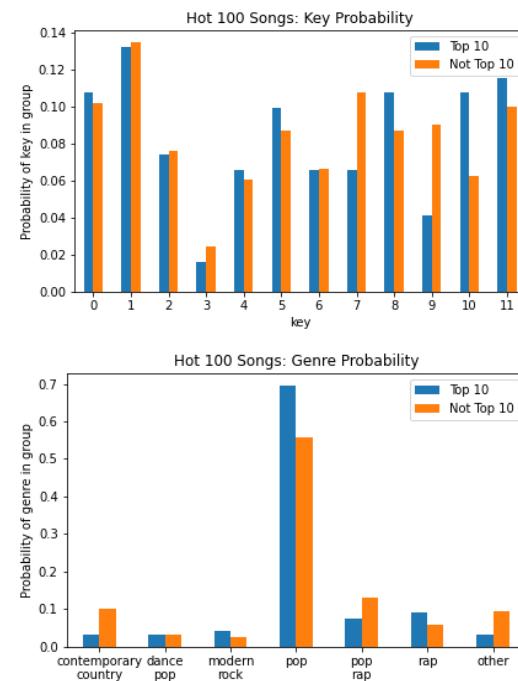
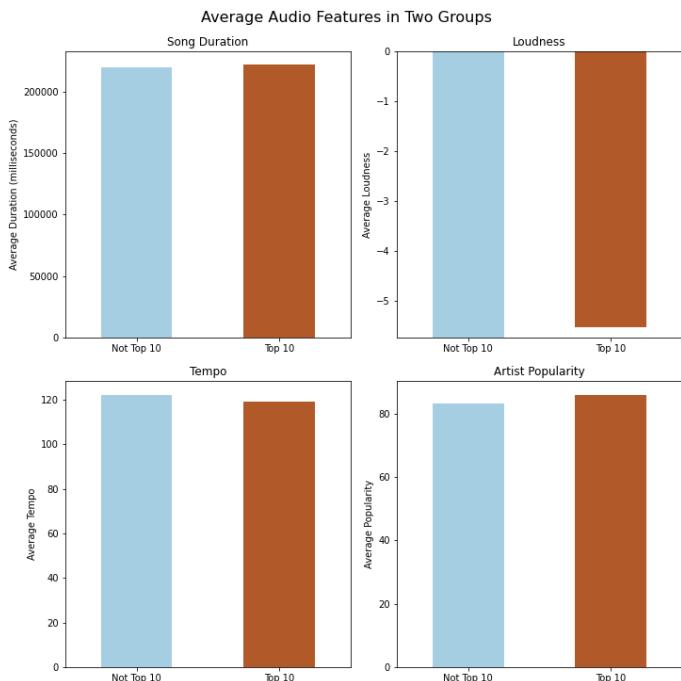
Average Length of Top 100 Songs: 2010-2020



- Decrease in song length

How has the Hot 100 changed over the past decade?

How do Top 10 songs compare to the rest of the Hot 100?



- Higher valence and danceability
- Less loud, slower tempo
- More popular artists
- Pop and rap are most common



The Project

Which **features** best predict the **top 10** songs on Billboard Hot 100 charts?

Project Use & Intentions:

- Artists wanting to reach larger audiences can know what to focus on
- Music companies seek out songs that meet these features
- Predicting trends

Project Overview

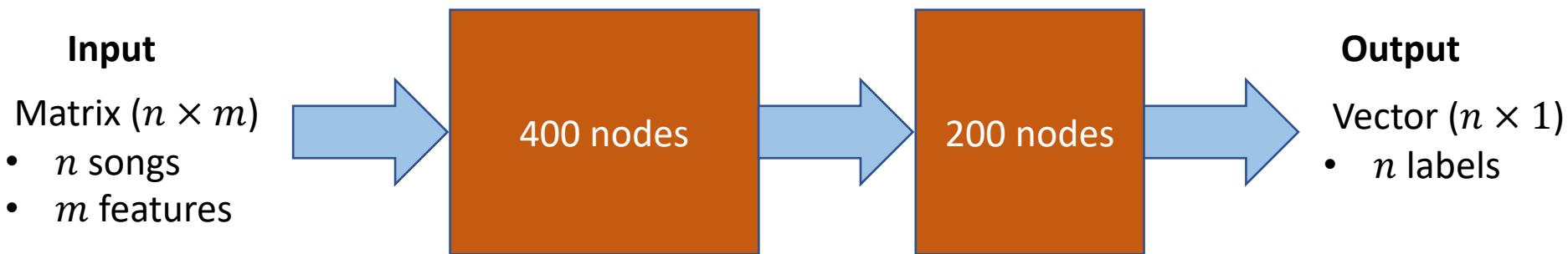
Use neural networks to solve binary classification problem

- Class 0: Not top 10 song (90% of dataset)
- Class 1: Top 10 song (10% of dataset)

Reduce dataset by using **feature selection** techniques

- Irrelevant features can impact the accuracy of our model
- Which features yield the best predictive model?

Classification with Neural Networks

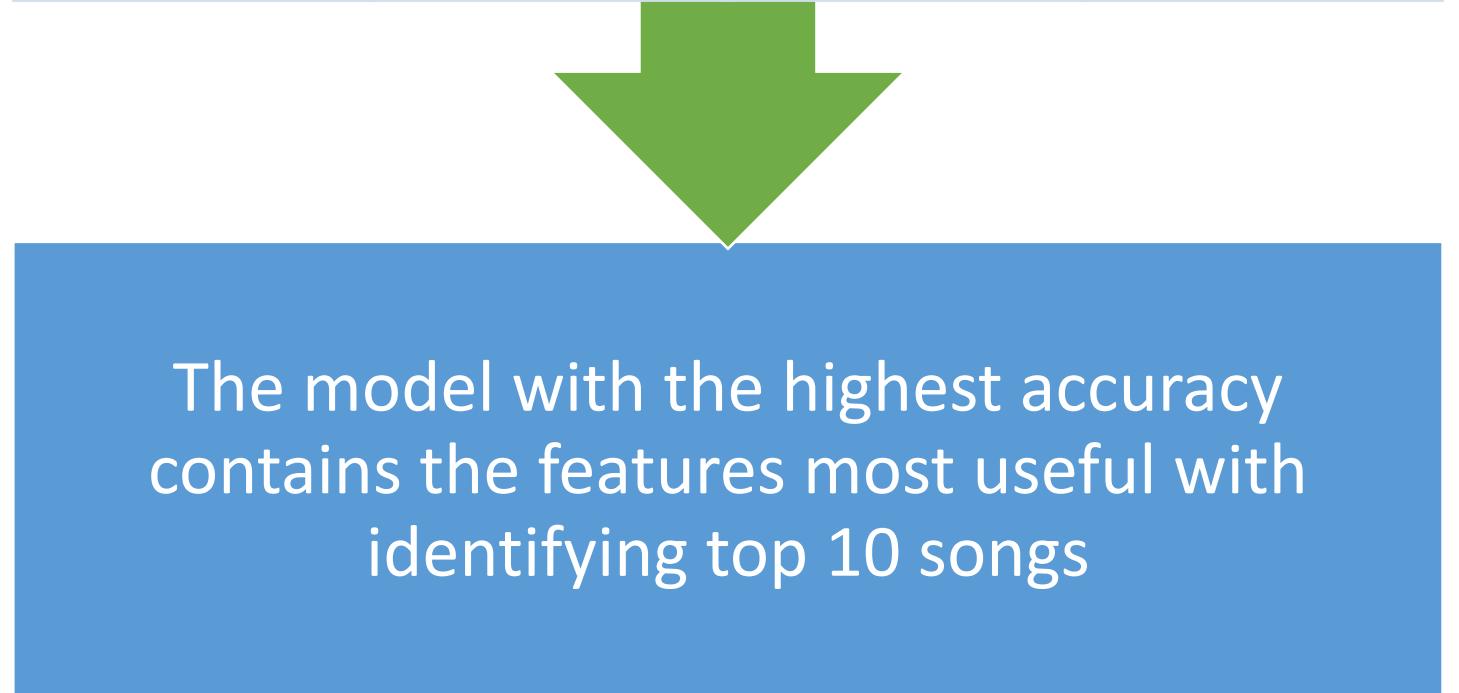


1. Train network with training data
2. Use validation data to improve parameters
3. Feed network testing data
4. Use the network's output and compare with true classes of testing data

Applying Feature Selection to Neural Networks

Train and test the neural network using data that contains:

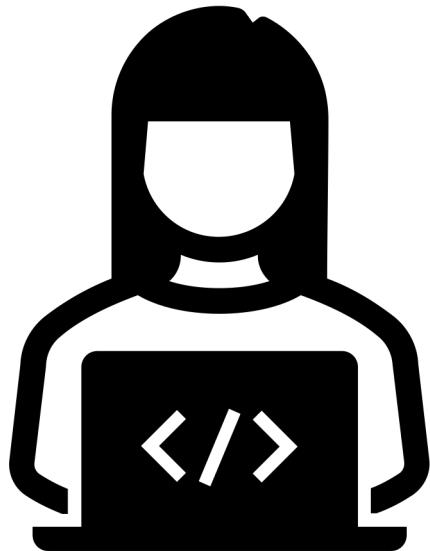
All features	Features selected by ExtraTreesClassifier	Features selected by Lasso	Features selected by SVM
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Results

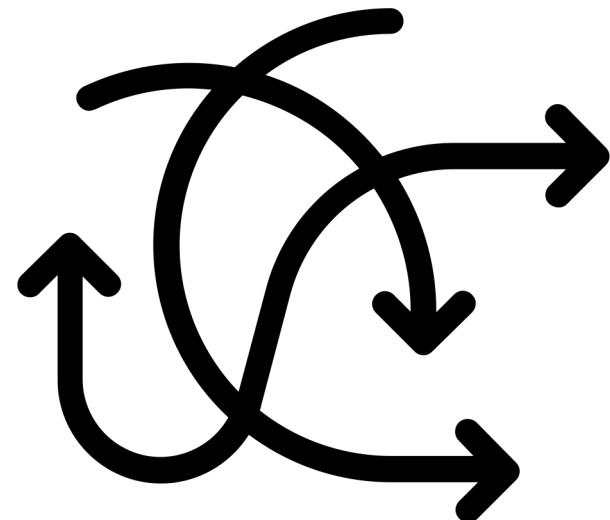
Method	ExtraTreesClassifier	SVM	Lasso	No Feature Selection																																				
	<p>Feature Importance using ExtraTreesClassifier Model</p>	<p>Selecting Features using SVM Model</p>	<p>Selecting Features using Lasso Model</p>																																					
# Features	10	10	5	14																																				
	<p>Confusion Matrix</p> <table border="1"> <thead> <tr> <th>Predicted label</th> <th>0</th> <th>1</th> </tr> </thead> <tbody> <tr> <th>True label</th> <td>218</td> <td>48</td> </tr> <tr> <td>0</td> <td>31</td> <td>2</td> </tr> </tbody> </table>	Predicted label	0	1	True label	218	48	0	31	2	<p>Confusion Matrix</p> <table border="1"> <thead> <tr> <th>Predicted label</th> <th>0</th> <th>1</th> </tr> </thead> <tbody> <tr> <th>True label</th> <td>212</td> <td>54</td> </tr> <tr> <td>0</td> <td>22</td> <td>11</td> </tr> </tbody> </table>	Predicted label	0	1	True label	212	54	0	22	11	<p>Confusion Matrix</p> <table border="1"> <thead> <tr> <th>Predicted label</th> <th>0</th> <th>1</th> </tr> </thead> <tbody> <tr> <th>True label</th> <td>144</td> <td>122</td> </tr> <tr> <td>0</td> <td>12</td> <td>21</td> </tr> </tbody> </table>	Predicted label	0	1	True label	144	122	0	12	21	<p>Confusion Matrix</p> <table border="1"> <thead> <tr> <th>Predicted label</th> <th>0</th> <th>1</th> </tr> </thead> <tbody> <tr> <th>True label</th> <td>202</td> <td>64</td> </tr> <tr> <td>0</td> <td>26</td> <td>7</td> </tr> </tbody> </table>	Predicted label	0	1	True label	202	64	0	26	7
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The Team



- I worked alone on this project
- Skills: programming, machine learning, listens to music
- I collected the data and ran the analysis

Project Challenges & Limitations



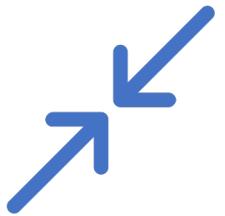
- Spotify API was irritating
 - Features are only for songs in a playlist or on the same album
 - Had to manually create Spotify playlists for 1100 Billboard songs
- Limited Data
 - Unable to obtain artists net worth demographics
 - No database for this information

Conclusion



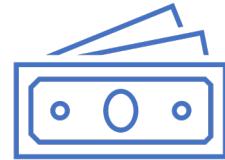
SVM performed the best with the following features:

- Artist popularity
- Danceability
- Valence
- Genre
- Acousticness
- Energy
- Tempo
- Instrumentalness
- Key
- Speechiness



Lasso performed the worst

- Had smallest # of features
- Likely too much data reduction



It'd be interesting to consider additional features

- artist net worth
- artist demographics