



# The Rise of K-Pop

Can Spotify's audio features show  
what makes certain music popular?

Presented by:  
Jessica Veilleaux, Kailey Davis, Kenneth Beadle, Miranda Wylie



# Why K-Pop?

## Why K-Pop?

K-Pop is short for Korean popular music, and its rise in popularity - as well as the dedication of its fans - has taken social media by storm. The cultural impact of K-Pop fans was even highlighted by CNN in 2020, documenting the political activism of fans of Korean pop idol groups, and is driving international sales by groups like BTS partnering with brands like McDonalds.

With as much social and purchasing power as these fans wield, we wanted to know: will their songs have staying power - and therefore the communities surrounding them?



# What do we hope to find?



## **Is K-Pop that popular in the U.S.?**

With headlines and news stories coming out covering it, K-Pop seems like the ultimate new music trend - but will the data show its popularity?

## **What makes certain songs popular?**

Using Spotify's audio features, we hope to determine if certain features are more likely to cause a song or genre to be popular.

## **Can we predict how long a song will be popular?**

Using our machine learning model, we hope to be able to accurately predict how many weeks a song will stay on the Hot 100 Billboard.

[illegible]

What data can we find on K-Pop specifically, and popular music generally?

Rather than determine a band's popularity by scraping a million different sources manually, we decided to rely on the methods of the Billboard Hot 100.

Also, artist and song information tends to be separate, so we would need to go to the source: Spotify.



# Data Sources

- **CSV's from Kaggle**

- Billboard Hot 100 charts from 1958 - summer 2021
- Misc. Spotify artist and track information
- Used to explore data features and what questions we could ask

- **Spotify API**

- Used to pull audio features on the specific Hot 100 songs
- Used to create final, clean database in Postgres

```
7 SELECT * FROM popular_songs;
```

Messages	Data Output							Explain	Notifications
Successfully run. Total query runtime: 2 secs 969 msec. 52524 rows affected.		song text	artist text	release_date text	popularity double precision	acousticness double precision	danceability double precision		
	1	Take W...	Post Malone	2019-09-06		76	0.0906	0.49	
	2	RITMO ...	Black Eyed Peas	2019-10-12		78	0.0334	0.72	
	3	BEST O...	Russ	2020-01-31		71	0.188	0.84	
	4	Tusa	Various Artists	2019-12-20		45	0.295	0.80	
	5	I Wish ...	Riley Green	2019-09-20		71	0.036	0.44	
	6	Slide	H.E.R.	2019-09-27		70	0.0807	0.83	
	7	We Back	Jason Aldean	2019-11-22		61	0.0135	0.43	
	8	What S...	Luke Bryan	2019-10-24		59	0.0649	0.48	
	9	Make ...	Jimmie Allen	2018-10-12		63	0.0793	0.51	

# Machine Learning Model

Random  
Oversampling  
+  
SMOTE

Linear  
Regression

Decision Tree

Neural  
Network

K-Nearest  
Neighbors

Use oversampling techniques to tackle imbalance of data. Imbalance is caused by Spotify dataset of 600,000 tracks. We do not know which tracks were /are on the top 100 billboard yet so, we will choose over\_sampling methods in anticipation of there being an abundance of non-top 100 songs.

1. Quick to compute and can be updated easily with new data.
2. Relatively easy to understand

1. A single decision tree is fast to train
2. Robust to noise and missing values
3. RF performs well "out-of-the-box"

1. Can learn very complex relationships
2. Extremely powerful for many domains
3. Hidden layers reduce need for feature engineering

1. Simple
2. Powerful
3. No training involved

According to <https://srngn.medium.com/machine-learning-trying-to-predict-a-numerical-value-8aafb9ad4d36> these are the most common ML models for predicting a numerical outcome. So for the purpose of education it will be good to employ all four to see what could be the best outcome. We believe Decision Tree and Neural Network are going to work best.

# Machine Learning Model

## Model Selection & Preliminary Data Preprocessing

- After further evaluation of the models, the most promising machine learning model was the Neural Network. The dataset we have is from Spotify data that contains a large amount of musical characteristic values. We initially believed these values to be a bit more complex especially when trying to find the best way to interpret a songs popularity. Due to these factors, we chose the Neural Network model. According to an article on Medium.com Neural Networks “*can learn complex patterns... ..and relationships between features that other algorithms cannot easily discover*”. Furthermore, the hidden layers reduce the need for feature engineering.
- To prepare the data, it was imported as csv files into jupyter notebook to drop null values and transform values. Then stored in an AWS RDS where it is synced to an SQL database in PgAdmin. Then, we import the data into jupyter notebook again and run it through the model

## Feature engineering, selection, and decision-making process

- Because we chose the Neural Network, we did not find it necessary to engineer the features. To create our features we set `X=df.drop(columns = "weeks_on_board")` and `y=df["weeks_on_board"]` since we're predicting if a song will be on top 100

## Training & Testing Sets

- We used the `train_test_split()` model from `sklearn.model_selection`. While instantiating the model we declared a test size of 25%. Since we have a large dataset with tens of thousands of rows we decided that splitting it 75/25 would be good.

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Currently the dashboard is connected to our database and runs locally. Running the dashboard through Heroku dashboard is in progress.

- Line graph noting the rise of K-pop by year
- Comparison of a song's audio features and how long a song stays on the Billboard's Top 100. Are songs with the highest danceability more likely to stay on the Billboard Top 100 longer?

