# Predicting The Popularity of Songs on Spotify

Sean Rubin, David Schaffer, Malek Kheirddin Gerardo Lopez Rodriguez

#### What's Our Goal

The purpose of this project is to utilize the Spotify tracks dataset to develop a model that can predict the popularity of a song. This model will assist future artists and musicians by providing insights into what factors contribute to a song's popularity.

#### **Data Table**

We first went to look for data that would have the most popular streamed songs on Spotify

We gathered this dataset from Kaggle

https://www.kaggle.com/datasets/maharshipandya/-spotify-tracks-dataset/data

_0	ne_signature t				ousticness inst					0, 1		50	_		track_name	_		track_id
dance	4			4.51e-06	0.013	0.0864	1	-7.375				False	156943			Unholy (feat. Kim		
hip-hop	4	0.55 128.033	0.23	0.033	0.0125	0.044	1	-5.548	2	0.782	0.621	False	198937	99	Quevedo: Bzrp Mus	Quevedo: Bzrp Mus	Bizarrap;Quevedo	2tTmW7RDtMQtBk7m2
dance	4	0.304   128.04	0.371	7.07e-06	0.00383	0.0343	0	-3.673	7	0.965	0.561	True	175238	98	I'm Good (Blue)	I'm Good (Blue)	David Guetta; Bebe	uUG5RXrOk84mYEfF
latin	4	0.85   124.98	0.218	1.98e-06	0.583	0.0364	0	-5.329	7	0.679	0.835	False	162637	98	La Bachata	La Bachata	Manuel Turizo	5ww2BF9slyYgNOk37
latin	4	0.425 92.005	0.0933	2.68e-05	0.0901	0.0817	0	-5.105	1	0.712	0.911	True	178567	97	Me Porto Bonito	Un Verano Sin Ti	Bad Bunny; Chencho	6Sq7ltF9Qa7SNFBsV
latin	4	0.187   106.672	0.126	0.000291	0.0993	0.253	0	-5.198	5	0.715	0.65	False	243716	97	Tití Me Preguntó	Un Verano Sin Ti	Bad Bunny	LIHW15LamUGEuP4oz
latin	4	0.234 98.047	0.0639	1.73e-05	0.141	0.0516	0	-8.797	7	0.475	0.801	False	213061	96	Efecto	Un Verano Sin Ti	Bad Bunny	5Eax0qFko2dh7R121
dance	4	0.31   116.992	0.105	1.18e-06	0.0635	0.0427	0	-5.529	9	0.69	0.733	True	184613	96	Under The Influence	Indigo (Extended)	Chris Brown	5IgjP7X4th6nMNDh4
piano	4	0.825   139.994	0.0546	0.000745	0.0826	0.0475	1	-5.927	0	0.797	0.704	False	148485	96	I Ain't Worried	"I Ain't Worried	OneRepublic	4h9wh7i0Z0GGn8QVp
pop	4	0.662   173.93	0.311	0.00101	0.342	0.0557	0	-5.338	6	0.731	0.52	False	167303	95	As It Was	As It Was	Harry Styles	4LRPiXqCikLlN15c3
latin	4	0.268 79.928	0.528	1.34e-06	0.08	0.0413	0	-5.745	3	0.686	0.647	False	258298	95	Ojitos Lindos	Un Verano Sin Ti	Bad Bunny;Bomba E	3k3NWokhRRkEPhCzP
latin	4	0.292 99.968	0.115	1.18e-06	0.294	0.0333	0	-5.453	5	0.674	0.804	True	245939	94	Moscow Mule	Un Verano Sin Ti	Bad Bunny	6Xom5800Xk2SoU711
pop	3	0.268   169.914	0.141	4.78e-06	0.891	0.0531	1	-9.258	8	0.317	0.44	False	233456	94	Glimpse of Us	Glimpse of Us	Joji	6xGruZOHLs39ZbVcc
dance	4	0.642 115.042	0.0698	9.69e-06	0.0368	0.141	1	-5.668	7	0.689	0.78	True	225388	93	CUFF IT	RENAISSANCE	Beyoncé	1xzi1Jcr7mEi9K2Rf
alt-rock	4	0.398   124.053	0.101	0.0177	0.0495	0.0336	1	-2.81	10	0.807	0.612	False	240400	93	Sweater Weather	I Love You.	The Neighbourhood	2QjOHCTQ1Jl3zawyY
chill	4	0.131   122.769	0.0944	1.65e-05	0.695	0.04	0	-8.532	4	0.537	0.445	True	244360	93	Another Love	Long Way Down (De	Tom Odell	3JvKfv6T31z00ini8
latin	4	0.428   122.016	0.143	0.0	0.0706	0.0478	1	-7.511	10	0.498	0.876	False	173119	93	Neverita	Un Verano Sin Ti	Bad Bunny	31i56LZnwE6uSu3ex
reggae	4	0.53   111.005	0.11	0.00823	0.656	0.0541	1	-8.006	1	0.516	0.87	False	210200	93	PROVENZA	PROVENZA	KAROL G	7dSZ6zGTQx66c2GF9
pop	4	0.662 173.93	0.311	0.00101	0.342	0.0557	0	-5.338	6	0.731	0.52	False	167303	92	As It Was	Harry's House	Harry Styles	4Dvkj6JhhA12EX05f
dance	4	0.719   101.058	0.0901	1.32e-05	0.619	0.0324	1	-4.898	2	0.592	0.881	False	154486	92	Left and Right (F	Left and Right (F	Charlie Puth; Jung	OmBP9X2gPCuapvpZ7

# Cleaning The Data

- Dropped rows with missing values
- Removed duplicate entries
- Lessened the dataset to the 10,000 entries

### Narrowing Down Our Search

To get an even more accurate model we decided to look at just the 75th percentile

```
test = final['popularity'].quantile(0.75)
print(test)
```

71.0

# **Most Popular Songs**

We searched for what the most popular songs were

oularity	Track_Name Pop
100	Unholy (feat. Kim
99	Quevedo: Bzrp Mus
98	I'm Good (Blue)
98	La Bachata
97	Me Porto Bonito
97	Tití Me Preguntó
96	Efecto
96	Under The Influence
96	I Ain't Worried
95	As It Was
95	Ojitos Lindos
94	Moscow Mule
94	Glimpse of Us
93	CUFF IT
93	Sweater Weather
93	Another Love
93	Neverita
93	PROVENZA
92	As It Was
92	Left and Right (F

only showing top 20 rows

#### **Most Seen Genres**

We went to see what genres the most streamed songs

e Genre_Count	Genre
e  239	dance
7,000	k-pop
1 12	alt-rock
	latino
0 119	electro
p  112	indie-pop
p 109	hip-hop
m  103	edm
p 93	pop
k  92	hard-rock
y  68	country
k  68	rock
62	emo
k  57	folk
s   56	blues
h  55	british
o  51	disco
e  50	alternative
r  48	singer-songwriter
n 45	latin

only showing top 20 rows

#### Create And Train The Model

```
# Define the deep learning model
nn model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(units=80, activation="relu", input shape=(X train scaled.shape[1],)),
    tf.keras.layers.Dense(units=30, activation="relu"),
    tf.keras.layers.Dense(units=1, activation="sigmoid")
# Compile the Sequential model
nn_model.compile(loss="binary_crossentropy", optimizer="adam", metrics=["accuracy"])
# Train the model
history = nn model.fit(X train scaled, y train, epochs=3, validation_split=0.2, verbose=1)
model loss, model accuracy = nn model.evaluate(X test scaled, y test, verbose=2)
print(f"Loss: {model_loss:.4f}, Accuracy: {model_accuracy*100:.2f}%")
```

# Find The Average Popularity

+					+		+-	+-	+				+			+
Avg_Popular	rity track_g	genre  artists a	ilbum_name dur	ation_ms ex	olicit danc	eability energy K	ey 1	Louaness   m	oae sp	eecniness ac	ousticness in	strumentainess i	iveness	valence  tempo tim	ne_signature tr	ack_genre
1	86.0	pop Taylor Swift	folklore	261922	False	0.532   0.623	5	-9.208	1	0.0331	0.538	7.28e-05	0.0925	0.403 89.937	4	pop

## Plug The Data Into The Model

```
my song = pd.DataFrame({
   "duration_ms": [261922],
   "danceability": [0.532],
   "energy": [0.623],
   "key": [5],
    "loudness": [-9.208],
    "mode": [1],
    "speechiness": [0.0864],
   "acousticness": [0.538],
   "instrumentalness": [7.28e-05],
   "liveness": [0.0925],
   "valence": [0.403],
   "tempo": [89.937],
   "time_signature": [4]
# Apply the same scaling used during training
my_song_scaled = scaler.transform(my_song)
# Make predictions
predicted_popularity = nn_model.predict(my_song_scaled)
# Print the predicted popularity
print(f"Predicted popularity: {predicted_popularity.item()*100:.1f}%")
                    --- Øs 12ms/step
Predicted popularity: 16.2%
# Make y_pred
y_pred = (nn_model.predict(X_test) > 0.5).astype(int).flatten()
# Print classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
63/63 ----
            ---- 0s 419us/step
Classification Report:
             precision recall f1-score support
                 0.76 1.00
                                             1512
                                               488
                                              2000
                 0.38 0.50 0.43
                                              2000
   macro avg
weighted avg
```

# **Predict Song Popularity**

With this model, we can enter theoretical statistics of a song and see a predicted popularity and how successful the song will be on Spotify



# Some Things We've Learned

- The longer a song is the less popular it will be on average
- The higher energy a song is the more popular it will be
- Dance is the most abundant genre of music between the most popular songs
- This model is a good tool to steer a song in the right direction but it does not account for unmeasurable "It Factors" and cannot pump out hits scientifically otherwise someone would have discovered it before