# How well do we know our...



...And can machine learning improve it?

# How big is the Music Industry?

Huge - \$16.1bn in 2016, and up 7% YoY

• Digital music: 33%

Streaming revenue - \$5.4bn in 2016, up 57% YoY

• Spotify - 43% of 106.3m worldwide subscribers.

• Will increase by 40.3m by the end of 2017.

# Digitial music management

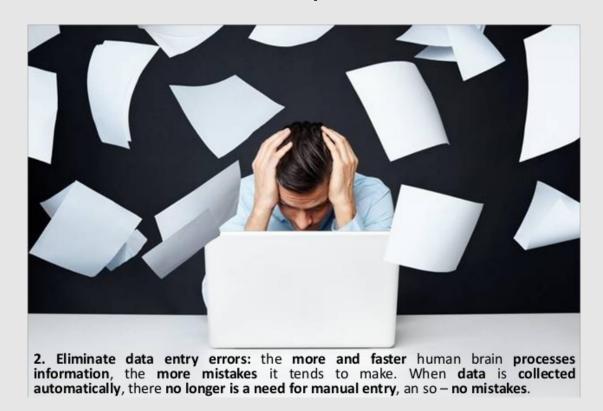
• Spotify and Apple Music – 30-40 million song catalogue!

Classification of music increasingly important

- A) Discovery
- B) Subscriber attrition

# How do we classify music?

• Imagine if this all had to be done by hand....



## Goals: Genre Classification

• strong to suggest that automatic genre classification is mistake free...

• ...but can be more efficient than manual input

 Use machine learning to classify music based on the features of the track

 beneficial to any organization that needs to classify and group data within a large pool of observations



# Method of analysis

- Obtain Data from multiple sources and aggregate
- Clean the dataset (null values, unnecessary fields)
- Perform EDA
- Modelling
- Review

#### Potential datasets

• few datasets available - copyright restrictions

million song dataset - 300gb, and no genres

Sample sets with genres, but no features

- Solution! to create a new dataset using the spotify api
  - link the features to genres by combining datasets

# Million Song Dataset

- Freely-available collection of audio features and metadata for a million contemporary popular music tracks
- https://labrosa.ee.columbia.edu/millionsong/

```
# PATH TO Track Metadata from Million Song dataset
dbfile = '../../resource-datasets/msdextra/AdditionalFiles/track_metadata.db'

# connect to the SQLite database
conn = sqlite3.connect(dbfile)

# from that connection, get a cursor to do queries
c = conn.cursor()
q = "SELECT * FROM songs"
res = c.execute(q)
ids = res.fetchall()
```

#### Acoustic Brainz

- Dataset of corresponding track ids from the million song dataset to other services such as Spotify (json format)
- <a href="http://labs.acousticbrainz.org/million-song-dataset-echonest-archive">http://labs.acousticbrainz.org/million-song-dataset-echonest-archive</a>



# Spotify

- Provides the API to extract music features
- https://developer.spotify.com/web-api/
- Output: List of list of dictionaries

```
import spotipy
from spotipy.oauth2 import SpotifyClientCredentials

client_credentials_manager = SpotifyClientCredentials(client_id='77d05ef2544d4bd9b0f6e5a6119f4d3
sp = spotipy.Spotify(client_credentials_manager=client_credentials_manager)

for x in sptable.spotify_uri:
    time.sleep(0.1)
    spdata.append(sp.audio_features(str(x)))
```



# Data Dictionary

Liveness Acousticness Energy Danceability Instrumentalness Tempo Speechiness Loudness Mode Key Valence



#### How are these features derived?

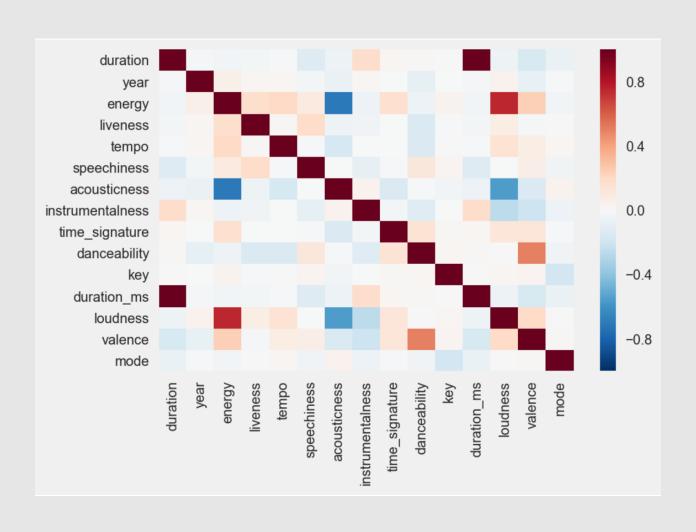
- Analyse the audio of a track electronically, directly
  - Instruments
  - Vocals
  - Decibels
- User derived metadata
  - How does a song make you feel?
  - Mood -> Valence

## Final Dataset

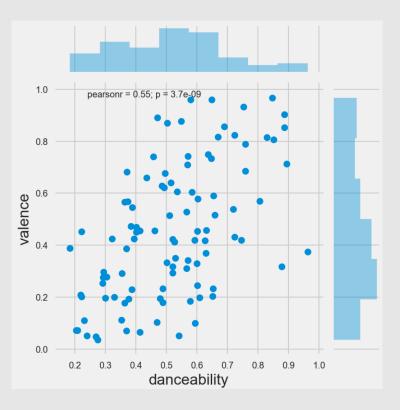
Pop_Rock	61846
Electronic	9126
Rap	5375
Jazz	4099
Latin	3925
International	3606
RnB	3155
Country	2793
Blues	2167
Folk	1488
Vocal	1185
New Age	1168
Reggae	1039

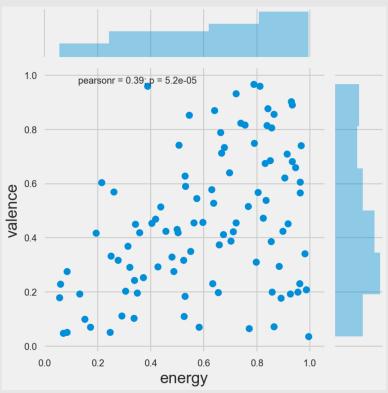
- 100,972 Observations
- 13 Top-level Genres
- Baseline Accuracy: 0.6125
- A lot of Pop-Rock Songs!

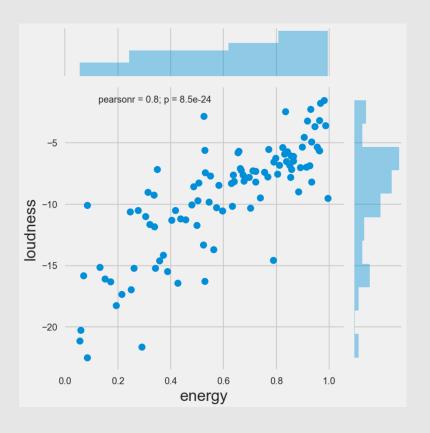
# Correlation plots



## Correlations – A closer look

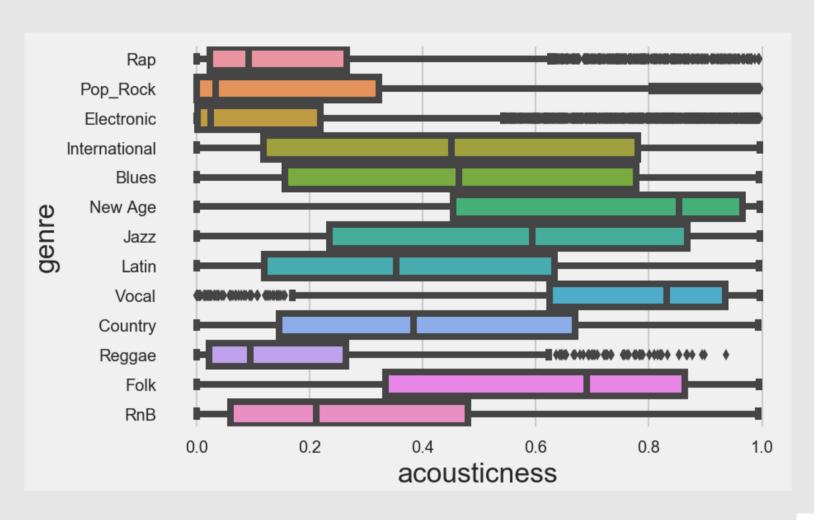




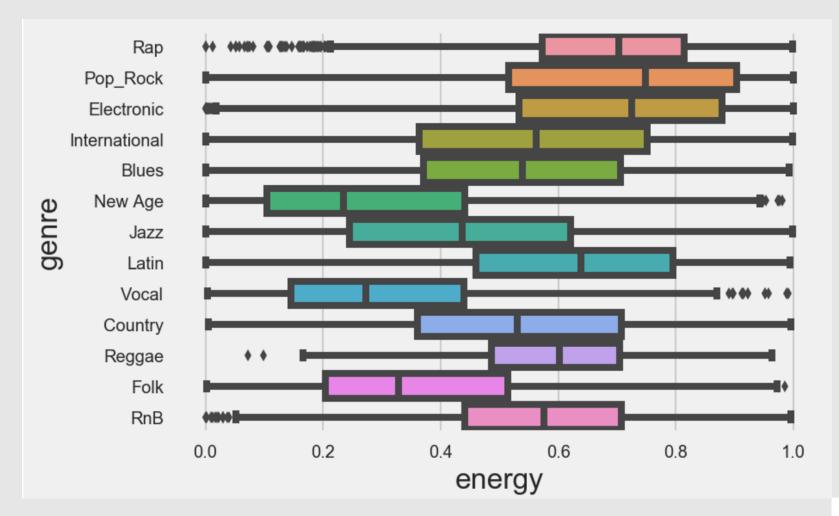




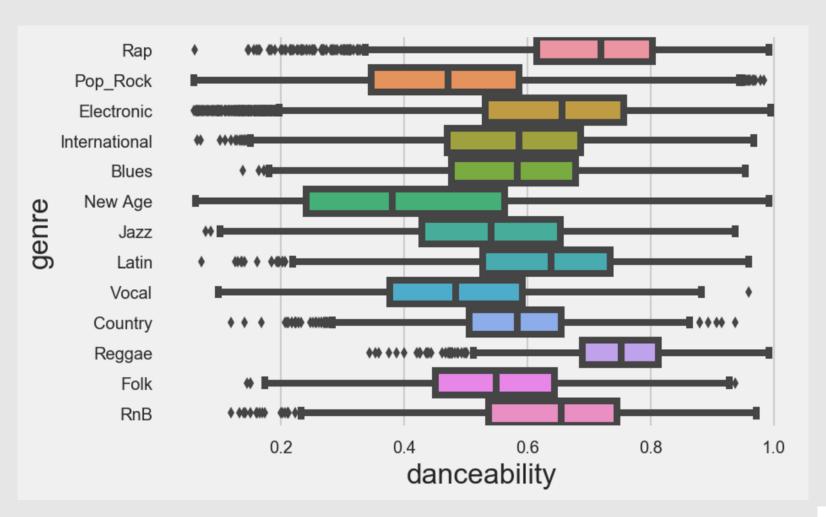
## Acousticness



# Energy



# Danceability



# Types of Models

- Multinomial Logistic Regression
  - Similar to linear regression
  - Predicts to a particular class based on numerical variables
- Random Forest
  - Ensemble Method
  - Fit multiple decision trees
  - Returns the mean of the trees fitted for each class
  - Corrects for overfitting when using decision trees

## Model Performance

	<b>Logistic Regression</b>	Random Forest
<b>Accuracy Score pre optimization</b>	0.647857521	0.65716737
<b>Accuracy Score post optimization</b>	0.647907201	0.682174381
Accuracy Score on unseen test data	0.647586036	0.682891805

				Confus	ion ma	trix - Ra	andom l	Forest -	Optimi	ized hyp	perpara	meters				
	Blues	28	1	5	0	3	19	7	0	362	3	0	3	2		
	Country	3	23	0	0	2	6	13	0	501	11	0	0	0		10000
	Electronic	0	1	764	0	1	24	6	14	954	58	1	1	1		
	Folk	1	1	5	16	3	10	3	0	251	6	0	1	1		8000
ı	nternational	1	2	30	0	53	28	20	7	534	36	0	6	4		
enre	Jazz	2	0	37	0	3	205	4	23	528	7	0	4	7		
True Music Genre	Latin	2	5	7	1	1	9	135	0	585	35	1	3	1		6000
True	New Age	0	0	12	0	2	26	0	30	159	1	0	0	4		
	Pop_Rock	10	13	292	2	6	87	55	15	11711	150	5	12	11		4000
	Rap	0	1	53	1	1	5	5	0	282	720	3	4	0		4000
	Reggae	0	0	19	0	0	0	8	0	110	47	18	6	0		
	RnB	2	1	12	0	0	7	14	1	470	56	3	64	1		2000
	Vocal	2	0	1	0	1	6	1	0	197	5	0	0	24		
		Alues	Country	Electronic	€0l¥	International	1822	Latin	Henage	bob book	RaR	<b>Peddy</b> e	RINE	Jocal		
				Ø.	,	Intern.	Predicte	ed Music								0

#### y\_test.value\_counts()

Pop_Rock	12369					
Electronic	1825					
Rap	1075					
Jazz	820					
Latin	785					
International	721					
RnB	631					
Country	559					
Blues	433					
Folk	298					
Vocal	237					
New Age	234					
Reggae	208					
Name: genre, d	type: int64					

Pop: 94%Rap: 67%

• Electronic: 41%

• Jazz: 25%

# But does it work in practice?

- Lets see how it looks in production:
  - Google a track
  - Check the Spotify API for the features
  - Enter into webpage
  - Analyze predictions
- http://localhost:4000/musicpage

# Misclassification – why?





## Test data – Class Imbalance

y_test.value_counts()						
Pop_Rock	12369					
Electronic	1825					
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Name: genre,	dtype: int64					

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## Save time

Classify up and coming Artists automatically



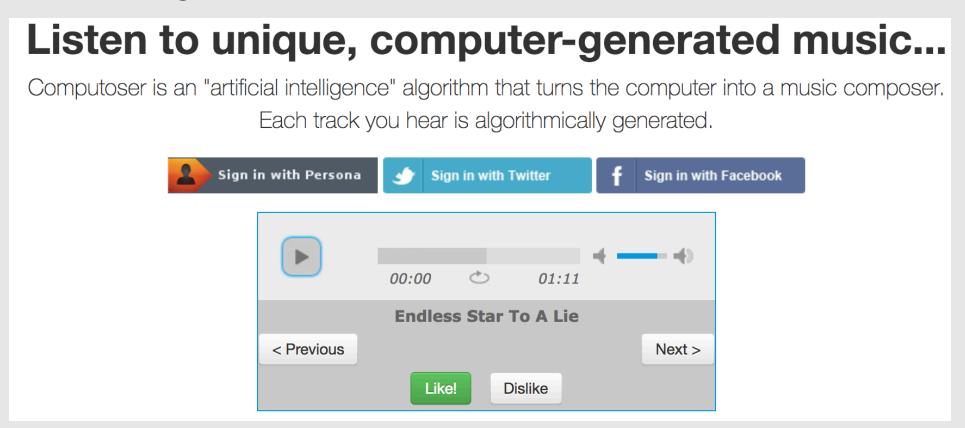
# Save money

Especially Man hours!



# Make money

New Music generation





#### Recommendations

- Correct class imbalance for training the model
  - Under/oversampling
  - More Samples
- log the accuracy scores when predicting on new data
  - Monitor for degradation
  - Opportunity for retraining
- Combine with user metadata
  - Genres could be considered subjective at a song level
- Construct features from scratch using fingerprinting (Shazam)



# Check out my blog....



http://www.chi-squared.com



# Thank you!

