# Hip Hop Lyric Comparison

**IST 736 Final Project** 

Team Members:
Charles Vanleuvan
Eric Gillis
Jeffrey Chao



#### Introduction to Hip Hop

- Hip Hop has grown from an underground sound in the 1970s into the most streamed music genre in the US in 2018<sup>1</sup>
- Cultural influences, past musical influences, and regional influences are prevalent in the beats and lyrics (sample culture)
- Started in the late 1970s in the Bronx, quickly gained footholds in neighborhoods across the US
  - The sound has evolved into distinct sub genres over 5 decades and across regions/cities
- The sound has evolved so much that different regions and decades have produced very different sounds
- What we really want to know: How different is the lyrical composition of Hip Hop songs across decades and regions?



#### Hip Hop Subgenres

#### **West Coast**

G Funk Gangsta rap

#### **East Coast**

Free-flow Aggressive Lyrical Consciousness



#### **South**

Dirty South Trap Midwest Chopper

# Why This Topic Matters

- The big question: Can a subgenre of hip hop be predicted from the lyrics?
- Sample culture in hip hop has produced radically different beats across regions (G funk on West Coast, East Coast rhyming patterns) and is well known
  - The differences in diction, word frequency, and lyrical relations across regions/decades can offer great insight in identifying differences between regions/decades
- Prominent influences can be identified in songs produced by collaborations
- Big Tech: This type of text modeling is likely very active at Spotify, Apple Music, Amazon Prime
  - Can provide recommended songs to listeners even if they are listening to a new artist that isn't in an established class yet
  - Provides a pathway to recommending songs to users building a playlist

#### Obtain Data

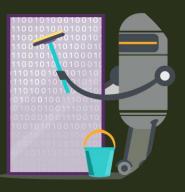
• The Genius lyrics API enables you to get album, artist, and songs information for the most popular songs in a genre

```
import lyricsgenius
genius = lyricsgenius.Genius(token)
```

Sample JSON response:

```
'name': 'Eminem',
    'slug': 'Eminem',
    'url': 'https://genius.com/artists/Eminem',
    'iq': 231909}},
    '_client': <lyricsgenius.genius.Genius at 0x2ae13e09278>,
    'artist': 'Eminem',
    'lyrics': 'Obie Trice! Real name, no gimmicks (*record scratch*)\n\nT\text{the outside, \'round the outside\n\nGuess who\'s back, back again\nShady'
who\'s back\nI\'ve created a monster, \'cause nobody wants to\nSee Marsha
```

Used Billboard to get list of hip hop artists and #1 songs



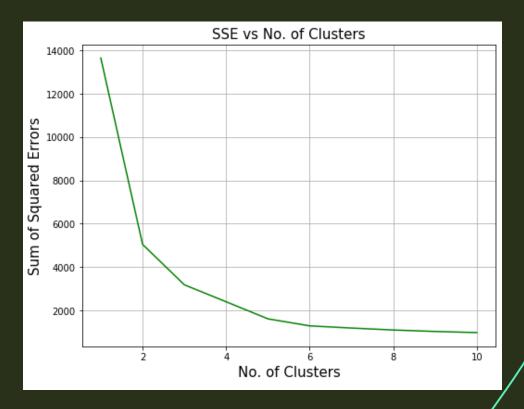
Title(from Genius)	Searched Song	Artist(from Genius) 🔻	Searched Artist 🔻	Lyrics 🔻 I	Date 🔻	State 🔻
Hotline Bling	Hotline Bling	Drake	Drake	you used to call me on my you used to you used to yeah you used to	10/10/2015	CAN
Summer Sixteen	Summer Sixteen	Drake	Drake	looking looking looking looking looking looking looking look	2/20/2016	CAN
God's Plan	God's Plan	Drake	Drake	and they wishin and wishin and wishin and wishin they wishin on m	2/3/2018	CAN



LABEL 🔻	act 🔻	actin 🔽	acting 🔽	action 💌	actions 💌	activate 💌	activated 💌
GA, CAN	0	0	0.021845	0	0	0	0
CA	0	0	0	0	0	0	0
CA	0	0	0	0	0	0	0
CA	0	0	0	0	0	0	0
CA	0	0	0	0	0	0	0
CA	0	0	0	0	0	0	0
CA	0	0	0	0	0	0	0
CA, NC	0	0.027432	0	0	0	0.0402331	0
CA, NC	0	0.027432	0	0	0	0.0402331	0
NY	0	0	0	0	0	0	0
NY	0.026804	0	0	0	0	0	0
NY	0	0	0	0	0	0	0
NY	0	0	0	0	0	0	0
NY, CA	0	0	0	0	0	0	0
NY	0	0	0	0	0	0	0

#### Scrub Data

- Manually annotated corpus for supervised learning
  - Decade labels (80s, 90s, 00s, 10s)
  - Region labels (East, West, South, MW, Can)
- String formatting for "feat." Vs "ft."
- Vectorize to create term document matrices
  - Add label for State/region in vectorization steps
- Remove non ASCII characters, line breaks, dashes,
- Keep numbers (e.g., 6 -> Drake)

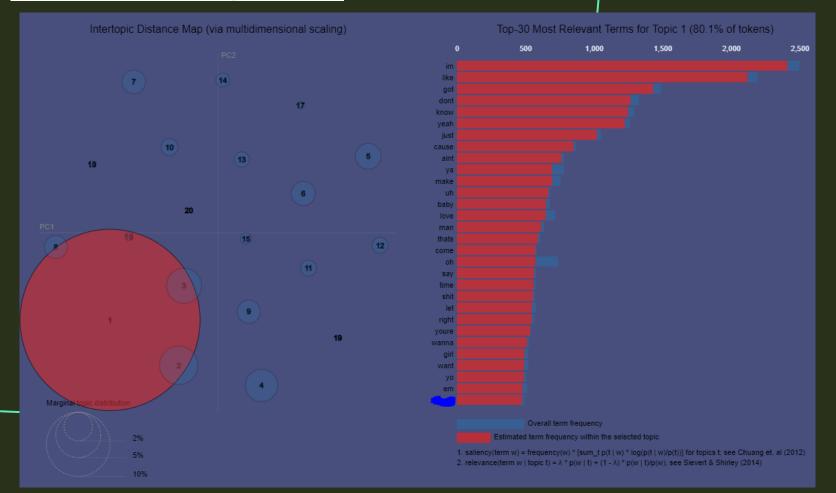


# Topic Modeling and Clustering

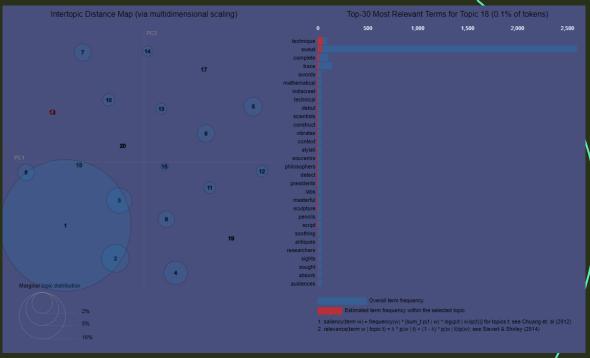
- Clustering via KMeans to inspect natural patterns across the lyrics
  - Used entire lyrics dictionary to build 10 clusters to look for elbow point
  - Depending on interpretation, 3 or 5 clusters is ideal.
    - Using regional labels, 4 is the ideal number of clusters we expected to represent potentially 4 distinct vocabularies across the US.

# The LDA Model For each document, Choose θ~Dirichlet(a) For each of the N words wn: Choose a topic z<sub>n</sub>» Multinomial(θ) Choose a word w<sub>n</sub> from p(w<sub>n</sub>|z<sub>n</sub>,β), a multinomial probability conditioned on the topic z<sub>n</sub>.

# Topic Modeling and Clustering



- LDA Topic Modeling
  - Largest topic includes the common "song" words like "love", "baby"

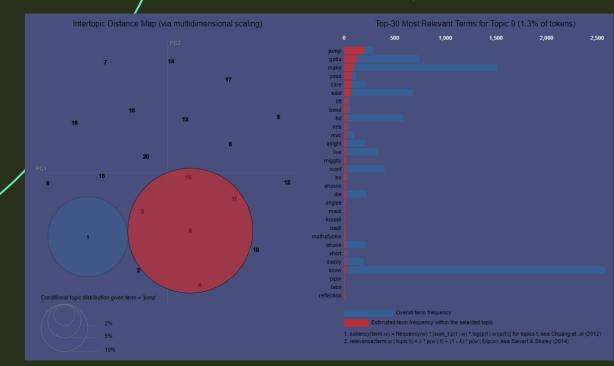


# Topic Modeling and Clustering

- LDA Topic Modeling
  - Other topics are extremely specific to artist or song



- Rakim with larger, more complex words
- **↓**`
- Kriss Kross "Jump" becomes a separate topic



# Exploratory Data Analysis



## Exploratory Data Analysis

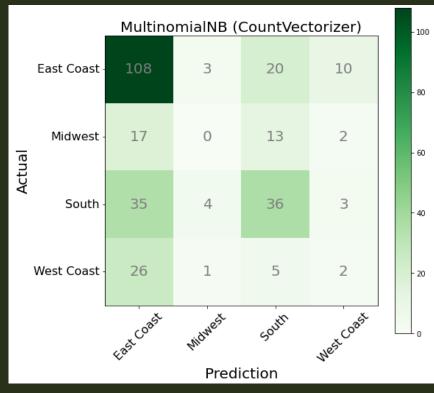


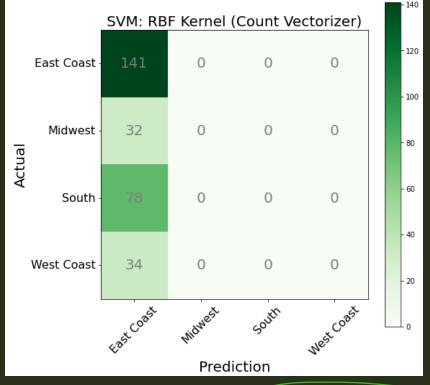
- Across both region and decade, no major visual difference is seen in word frequency
- The lyrics explain the core motivations of the artists:
  - Who/what they are → "I'm"
  - What they have → "Got"
  - What they know and want the listener to know → "Know"

# Model Data (Regions)

- Started modeling with the vectorized dataset.
- Results heavily skewed due to imbalanced data.

Region	Song Count
East Coast	141
South	78
West Coast	34
Midwest	32





**Accuracy: 51.23%** 

**Accuracy: 49.47%** 

## Model Data (Regions)

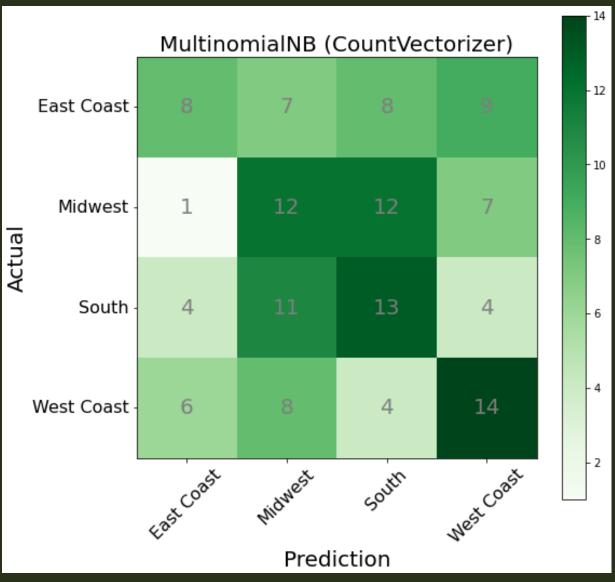
- Solution: Resample the dataset to equally represent each region.
- Under-sample each region to match the lowest count.

#### **Cross-Validation Accuracy Scores for Different Classifiers**

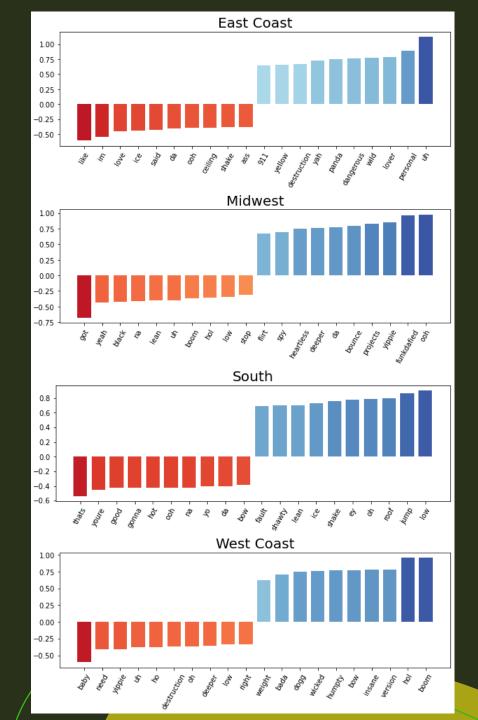
Model	5-Fold CV Accuracy	
Bernoulli Naïve Bayes	26.56%	
Multinomial NB (Count Vectorizer)	36.72%	
Multinomial NB (TF-IDF Vectorizer)	22.66%	
SVM: Linear Kernel (Count Vectorizer)	34.38%	
SVM: Linear Kernel (TF-IDF Vectorizer)	35.16%	
SVM: RBF Kernel (Count Vectorizer)	17.19%	
SVM: RBF Kernel (TF-IDF Vectorizer)	14.84%	
SVM: Polynomial Kernel (Count Vectorizer)	13.28%	
SVM: Polynomial Kernel (TF-IDF Vectorizer)	14.06%	

Region	Song Count
East Coast	32
South	32
West Coast	32
Midwest	32

# Model Data (Regions)



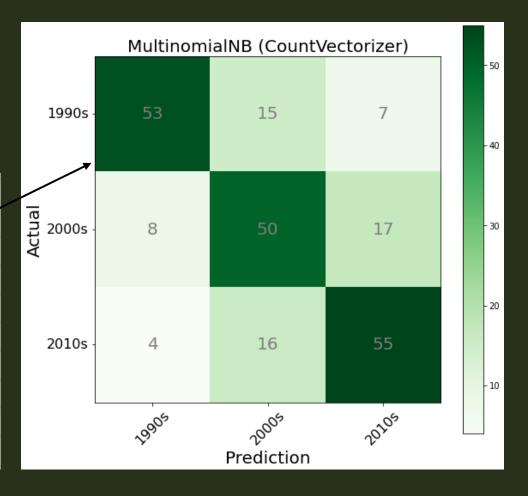
**Accuracy: 36.72%** 

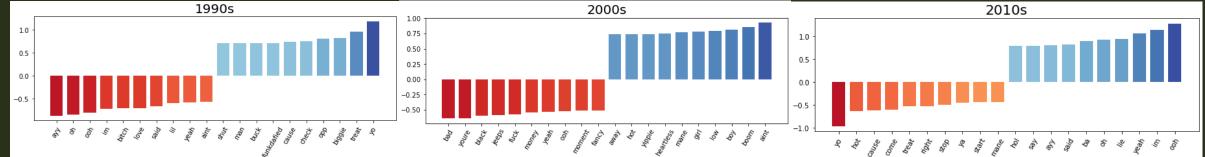


## Model Data (Decades)

Repeated process with decade labels

Model	5-Fold CV Accuracy
Bernoulli Naïve Bayes	56.89%
Multinomial NB (Count Vectorizer)	70.22%
Multinomial NB (TF-IDF Vectorizer)	49.33%
SVM: Linear Kernel (Count Vectorizer)	58.22%
SVM: Linear Kernel (TF-IDF Vectorizer)	66.22%
SVM: RBF Kernel (Count Vectorizer)	42.22%
SVM: RBF Kernel (TF-IDF Vectorizer)	37.78%
SVM: Polynomial Kernel (Count Vectorizer)	21.78%
SVM: Polynomial Kernel (TF-IDF Vectorizer)	27.11%





#### Interpret Results

- The lyrical vocabulary of hip-hop songs between regions
  does not differ enough to create an accurate prediction model.
- The vocabulary choice between different decades has enough differences to distinguish between the time periods.



*1989* **2019** 



#### Interpret Results

- Possible reasons that lyric data could not accurately model the region:
  - 1) There is not much difference in word choice across the country.

#### 2) Selection Bias:

- Songs that hit *Billboard* number-one are typically nationally known artists.
- These artists may choose to use vocabulary that will not isolate them from particular regions.

#### 3) Insufficient Cleaning:

- Dimensionality was mostly reduced by removing stop words from sci-kit learn.
- Subject-matter-expert could help change the stop word vocabulary to improve model accuracy.



