## MUSIC MOOD CLASSIFICATION

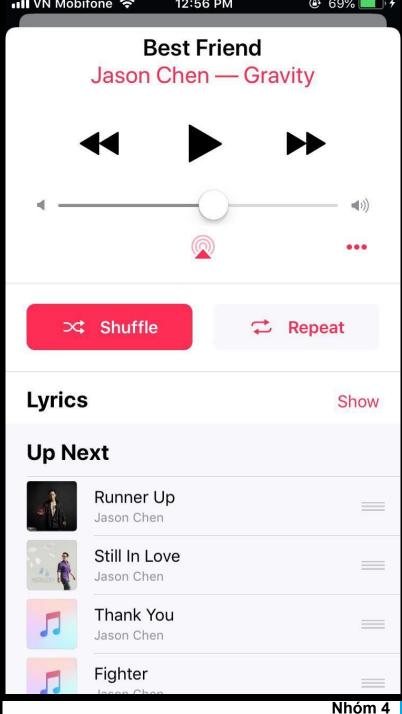
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### Motivation

- Since the shuffle function doesn't suggest her the similar song for our mood.
- A good chance for all of us to study about machine learning.
- Similar projects is available.

### Objective

- Making an AI function that can suggest a similar song base on the mood of the first song user selected.
- Apply this to shuffle function, which can be used offline.
- Break the objective into small objectives



### Break the objective into small objectives

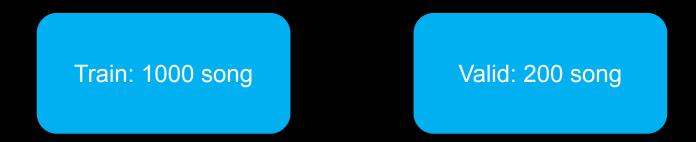


### Heuristic

- Step 1: Find the similar project that have a dataset.
- Step 2: Reimplement the project to get the result as the first result
- Step 3: Classify music by our own method and get the second result
- Step 4: Compare the first result to the second result

## Dataset

- Feature analysis and metadata from Million Song Dataset (The Echo Nest)
- 1200 songs, 2 Mood, removed all non-English songs labeled as happy and sad (by Sebastian Raschka University of Wisconsin-Madison)



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## Methodology

## Author's method

• Built upon on a Naive Bayes classifier.

## **Our method**

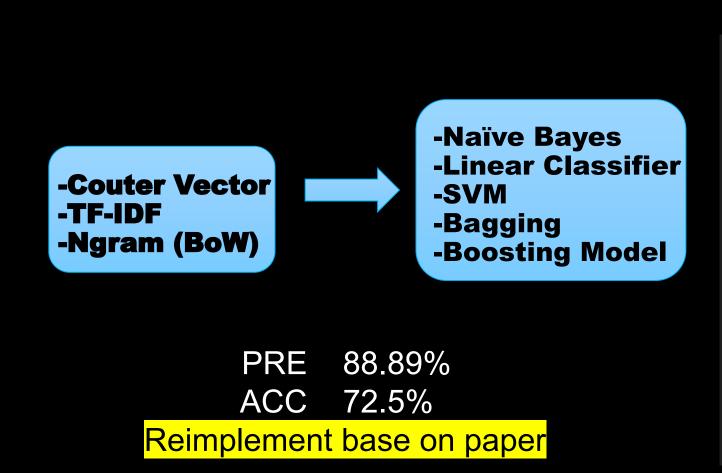
- Use both audio features and lyrics to measure.
- Try manual
- Use Deep learning

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# Lyrics

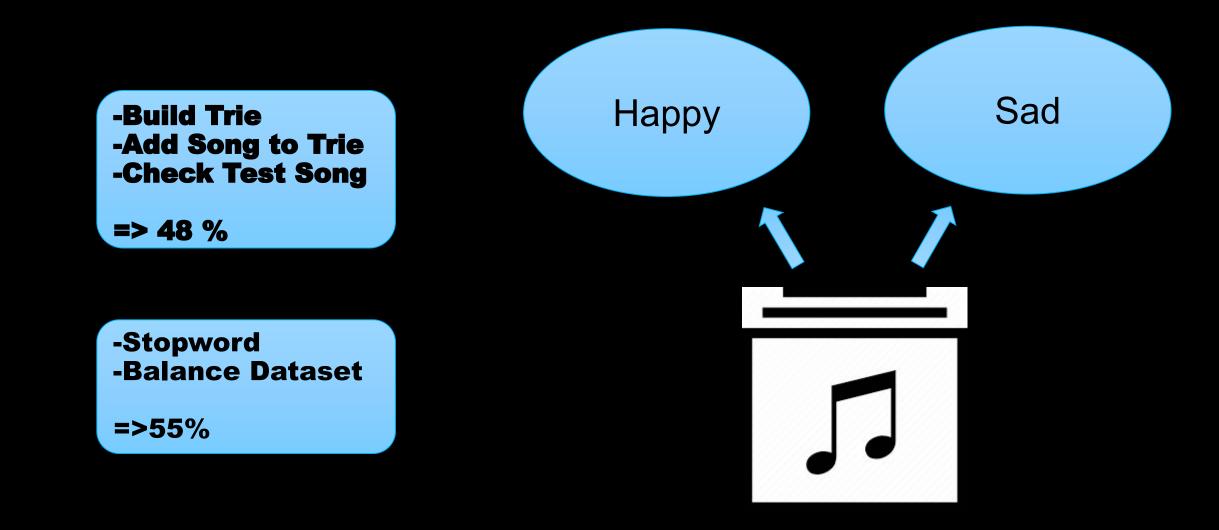
Downloaded from http://lyrics.wikia.com Base on metadata

### **Author Method**



NB, Count Vectors: 0.725 NB, WordLevel TF-IDF: 0.54 NB, N-Gram Vectors: 0.54 NB, CharLevel Vectors: 0.54 -> LR, Count Vectors: 0.645 LR, WordLevel TF-IDF: 0.655 LR, N-Gram Vectors: 0.615 LR, CharLevel Vectors: 0.67 -> SVM, N-Gram Vectors: 0.475 SVM, CharLevel Vectors: 0.475 -> RF, Count Vectors: 0.545 RF, WordLevel TF-IDF: 0.535 -> Xgb, Count Vectors: 0.645 Xgb, WordLevel TF-IDF: 0.61 Xgb, CharLevel Vectors: 0.695

## Manual method: lexicon-based



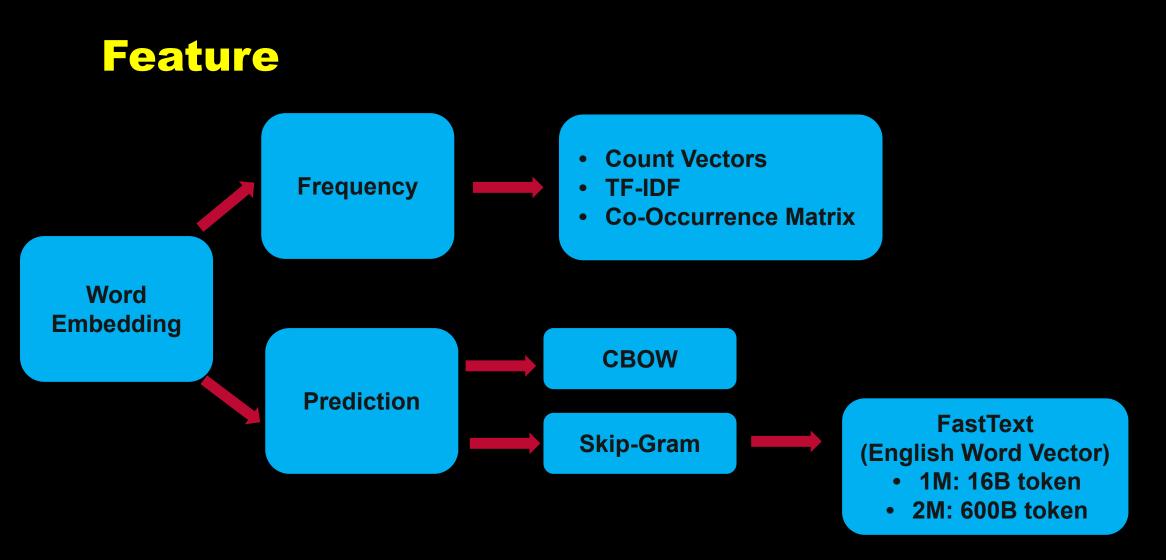
### Deep Learning: Preprocessing:

Remove Stopword punctuations

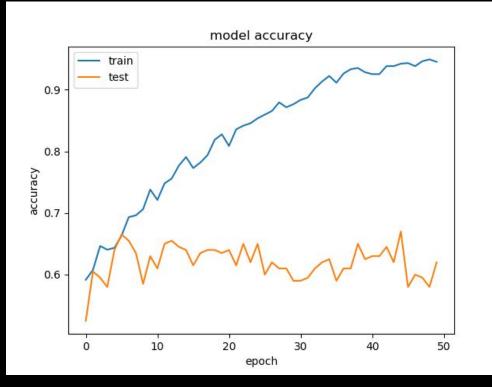
#### Lemmatization

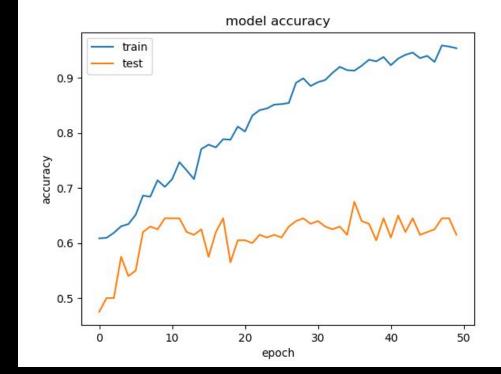
Stemming !!!

## Exaggerated word shortening



### Model: RNN





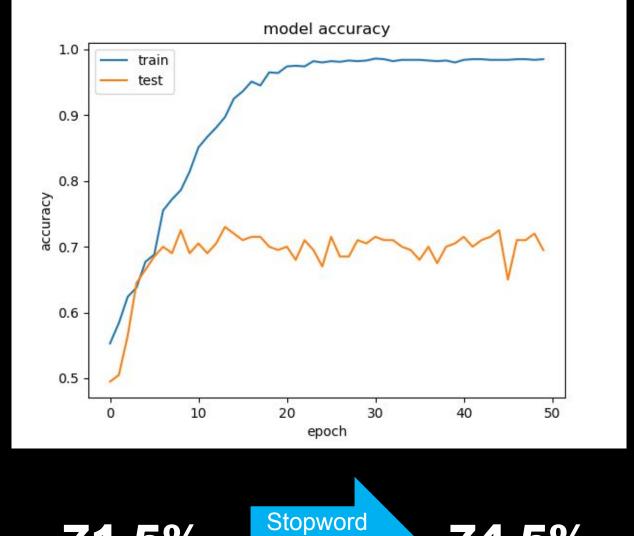
LSTM

68%

GRU



### Model: CNN



Lema

71.5%

**74.5%** (best case)

## Audio

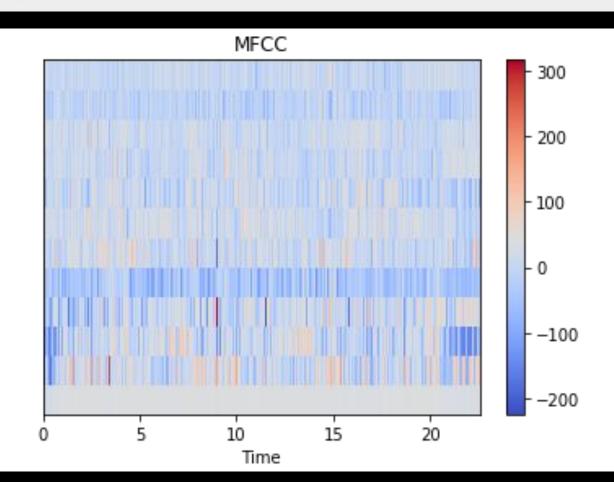
## **MFCC** features

- The shape of the vocal tract including tongue, teeth etc determines what sound comes out
- The shape of the vocal tract manifests itself in the envelope of the short time power spectrum, and the job of MFCCs is to accurately represent this envelope

### **MFCC** features retrive from dataset

segments\_timbre: shape = (935, 12)

MFCC-like features for each segment



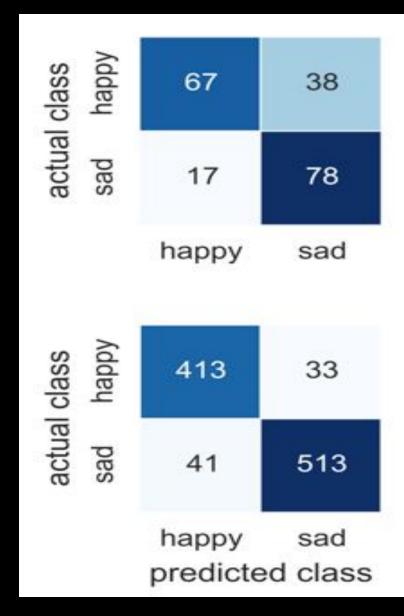
### **Training model**

Input_1	Input	(None, 814, 12)
	Output	(None, 814, 12)
Time_distributed_ 1: Dense_1	Input	(None, 814, 12)
	Output	(None, 814, 64)
Time_distributed_ 2: Dense_2	Input	(None, 814, 64)
	Output	(None, 814, 64)
LSTM	Input	(None, 814, 64)
	Output	(None, 256)
Dense_3	Input	(None, 256)
	Output	(None, 1)

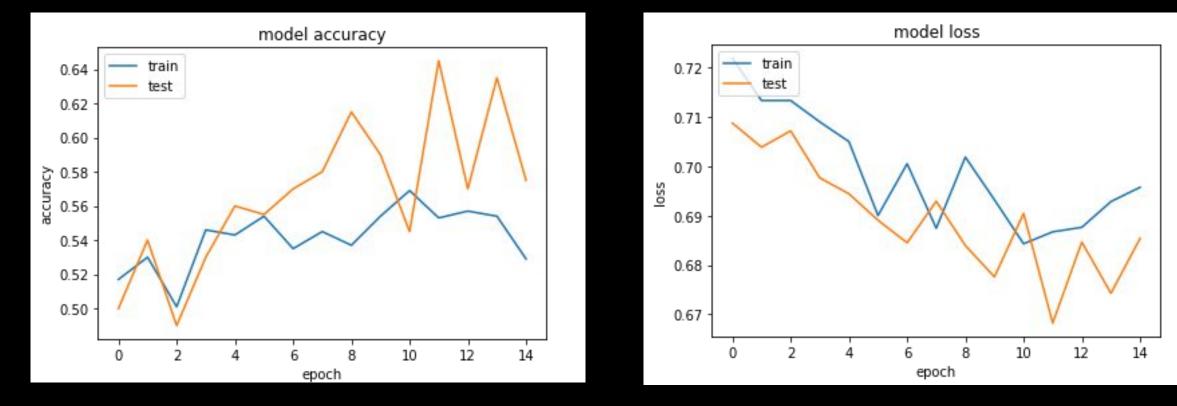
### **Compare the results**

### The existed method

- Hand label: 67+38 happy songs
- Model label: 67 songs, 38 songs were labeled wrongly

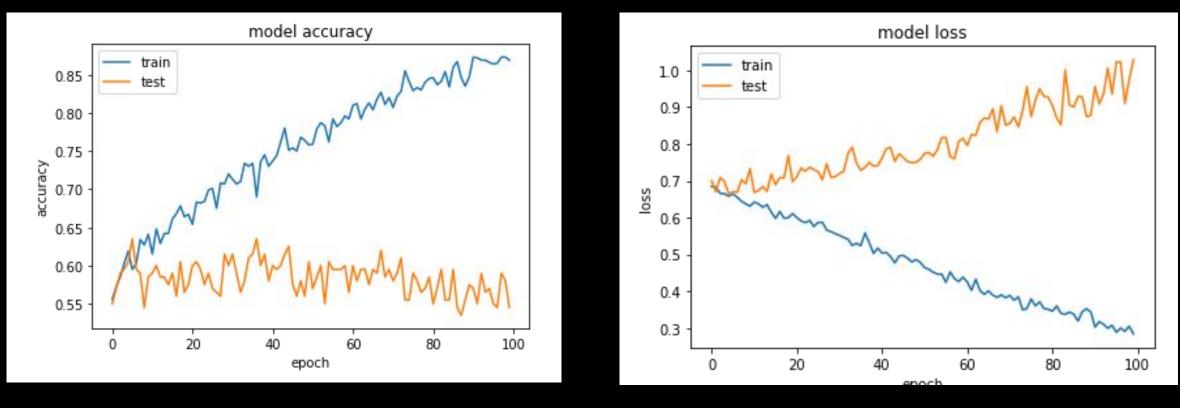


### **Our method** Initial result



### **LSTM networks**

### **Our method** Initial result



#### **LSTM** networks

### Let's try it in real life

2 song to let the model predictOasis – Morning Glory <</td>49% sadXi Guan Liang Ge Ren <</td>80% sad

## **Future work**

- Combine both audio features and lyrics
- Trying Lexicon based model in NLP
- Apply Treebank to RNTN (Recursive Neural Tensor Network) in Deep learning)
- Apply adjective annotation dataset
- Try Glove, Word2vec, self-train in embedding step
- Use different song's mood grid (spotify and gracenote)
- Testing on large and more precise, mood dataset

## References

- Dataset: <a href="https://github.com/rasbt/musicmood">https://github.com/rasbt/musicmood</a>
- Paper: <u>https://arxiv.org/abs/1611.00138</u>
- Method deeplearning: <u>https://www.analyticsvidhya.com</u>



## Thank You

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