B-Tech Project Presentation

Songs Hit Prediction

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OUTLINE

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Motivation

- Why songs hit prediction is important?
  - To benefit Record Companies before releasing their songs.

- What exactly was the reason that fuelled the Beatles' or any other band rise to fame?

- Is there any Intrinsic quality in music that predisposes it to greatness?

Previous Works

- Dhanaraj and logan [1] explored the **use of support vector machine (SVM) and boosting classifiers** to distinguish **top 10 hits** from other songs in various styles based on **acoustic and Lyric- based features**.
- .Pachet and Roy [2] tried to develop an accurate classification model for **low, medium or high popularity** based on **acoustic and human features but were unsuccessful.**
- The experiment by Ni.et.al. [3] has more optimistic results when predicting if a song would reach a **top 5 position** on the UK top 40 singles chart compared to top 30-40 position.
- Herremans.et.al [8] focuses on predicting whether a song is a "**top 10**" dance hit versus a lower listed position using **SVM classifier**.

Objective

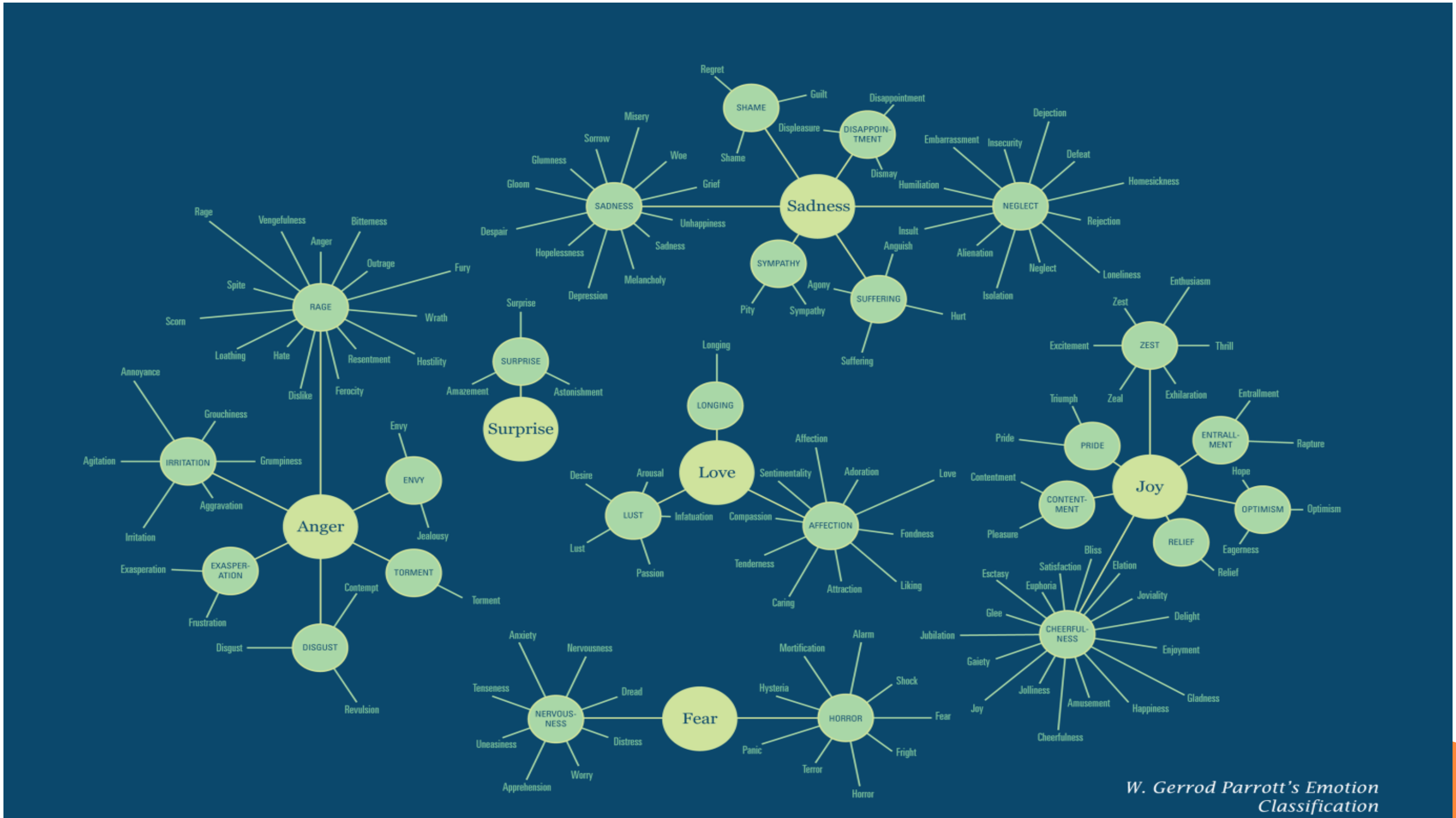
- To find all the features that distinguish a Hit song from a non-hit one.
- Using the set of features, we aim to classify any given new song as a potential hit or not by using the following classifiers
  - Linear Regression
  - Logistic Regression
  - Support Vector Machines
- To find the best classifier with high rate of accuracy to make a prediction.

Our Approach

- For Audio features, we used an product API called EchoNest

- For Lyrical features, we used a novel approach of emotion classification using Parrott's hierarchy.

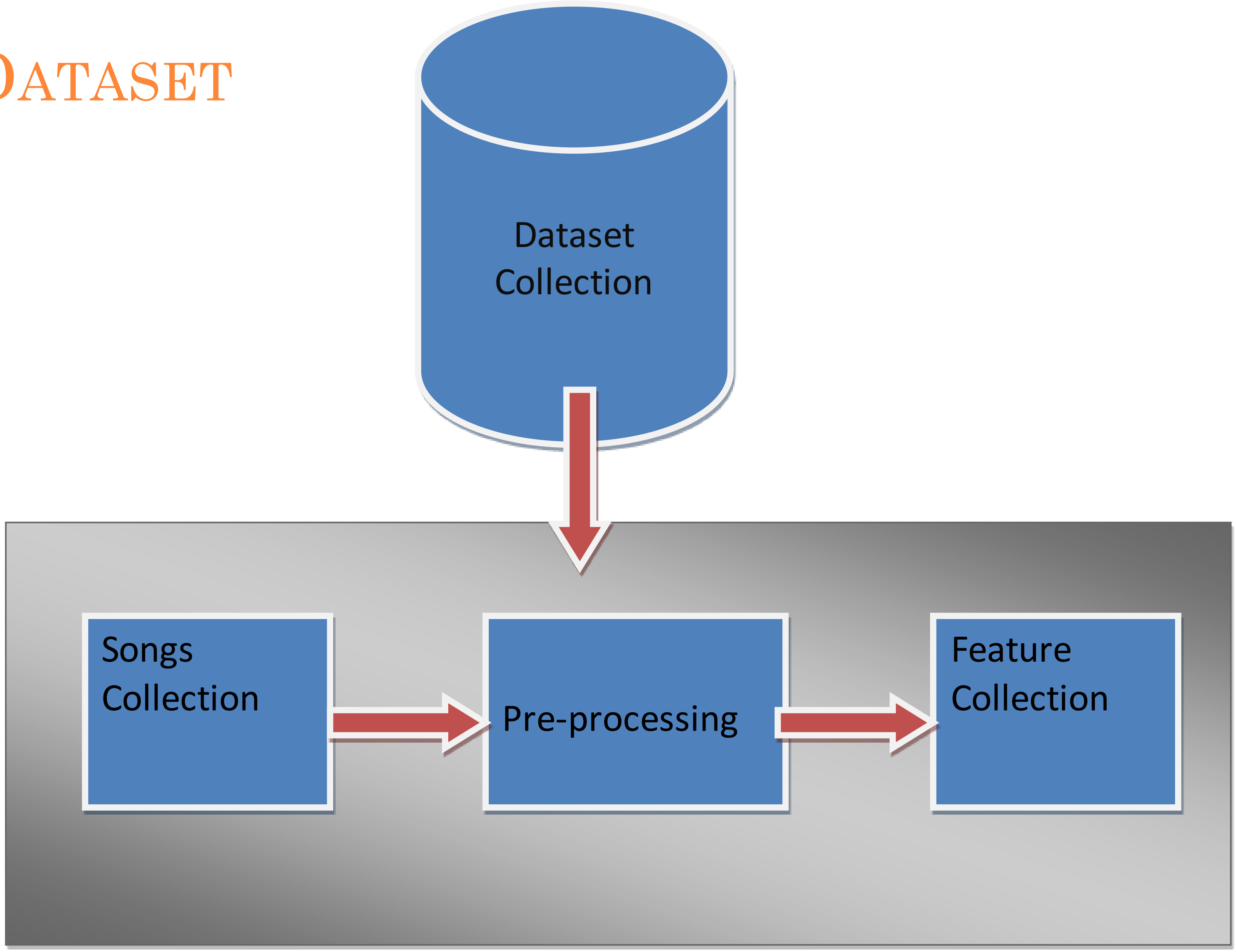
Parrott's Emotion Classification



W. Gerrod Parrott's Emotion Classification

Source: Parrott, W. (2001), Emotions in Social Psychology, Psychology Press, Philadelphia.

Dataset

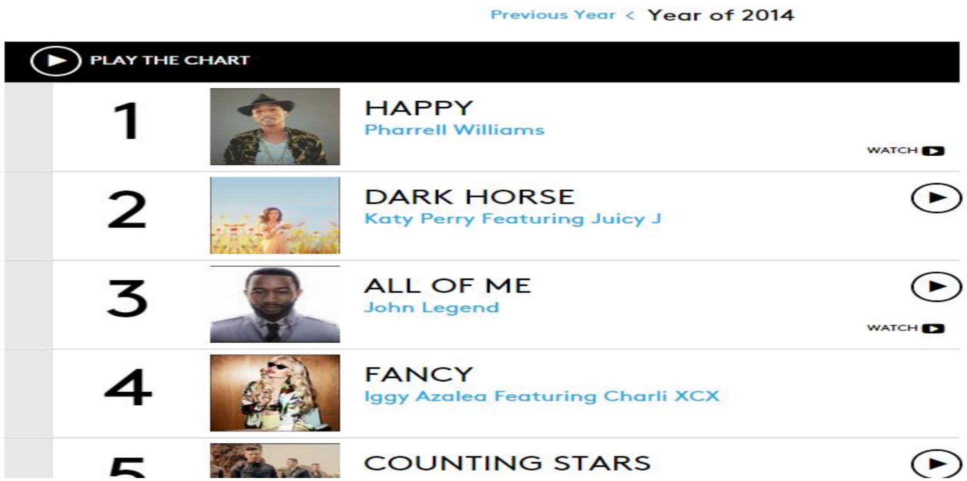

Dataset
Collection
Songs
Collection
Pre-processing
Feature
Collection

Dataset(Cont.)

Song Collection

1. We have taken the dataset from billboards.com

- ***Billboard* Year-End** charts are a cumulative measure of a single or album’s performance in the United States. Year-end charts were calculated by an **inverse-point system** based solely on a title's performance. Other factors including the total weeks a song spent on the chart and at its peak position were calculated into its year-end total.



Dataset(Cont.)

2. Extracting audio features using Echonest API
3. Following features are found for each song using the EchoNest API :
   - Acousticness, danceability, etc.

rank	song_name	artist	latitude	longitude	acousticness	danceability	duration	energy	key	liveness	loudness	mode	speechiness	tempo	time_	valence
1	Hey Jude	Beatles	53.4098	-2.97848	0.275356	0.464355	300.06907	0.462577	5	0.106562	-10.116	1	0.024347	148.13	4	0.527583
2	Love Is Blue	Paul Mauriat	43.3	5.4	0.120112	0.380633	294.33288	0.526747	2	0.789219	-15.552	1	0.048691	111.93	4	0.382058
3	Honey	Bobby Goldsboro	30.7754	-85.2268	0.103549	0.473622	229.53333	0.176127	7	0.096748	-18.802	1	0.028081	96.161	4	0.447784
4	(Sittin' On) The D	Otis Redding	32.804382	-83.617554	0.684492	0.768707	163.75578	0.367428	2	0.080979	-11.226	1	0.031158	103.62	4	0.541401
5	People Got To Be	Rascals	40.7146	-74.0071	0.412402	0.666801	179.70621	0.559847	10	0.144432	-11.73	1	0.03501	126.34	4	0.962275

DATASET(CONT.)

3. Extracting Lyrics using python package 'songtext-0.1.3' and its LyricsWiki API

```
$ songtext --api lyricsnmusic london grammar nightcall

33 track(s) matched your search query.

London Grammar: Nightcall

--------------------------

I'm giving you a nightcall

To tell you how I feel

I'm gonna drive you through the night

Down the hills

I'm gonna tell you something

You don't want to hear

I'm gonna show you where it's dumped

But have no fear
```

DATASET(CONT.)

4. Next we calculated and ranked all the words of all the songs by its TF-IDF (There are 100 songs in a year).
5. We used **Latent Semantic Analysis and inputs form WordNet** to give a measure of similarity between two words.
6. Find the similarity index of top 20 words (according to TF-IDF) with the 6 primary emotions of Parrot's Emotion Classification.
7. Add the above similarity index multiplied by the TF-IDF to the corresponding emotion in emotion vector.

DATASET(CONT.)

Ex – Suppose a song has the word 'lover' in it and the emotion vector of the song be assumed to be [0,0,0,0,0,0] (0-for each of the emotions love, joy, sadness, anger, surprise, fear)

'lover' gives the following degrees of similarities with the primary emotions:

Lover-Love	0.7506343
Lover-Joy	0.17573524
Lover-Sadness	0.040953867
Lover-Anger	0.013633692
Lover-Surprise	0.06152932
Lover-Fear	0.09170411

Maximum Similarity

So, here we see that 'lover' gives maximum similarity with the emotion Love, so we multiply 0.7506343 with 'lover' 's TF-IDF (say 0.1) and add it to the emotion vector.

So, the emotion vector becomes [0.07506343,0,0,0,0,0]

This way, we calculate the emotion vector for each of the songs

DATASET(CONT.)

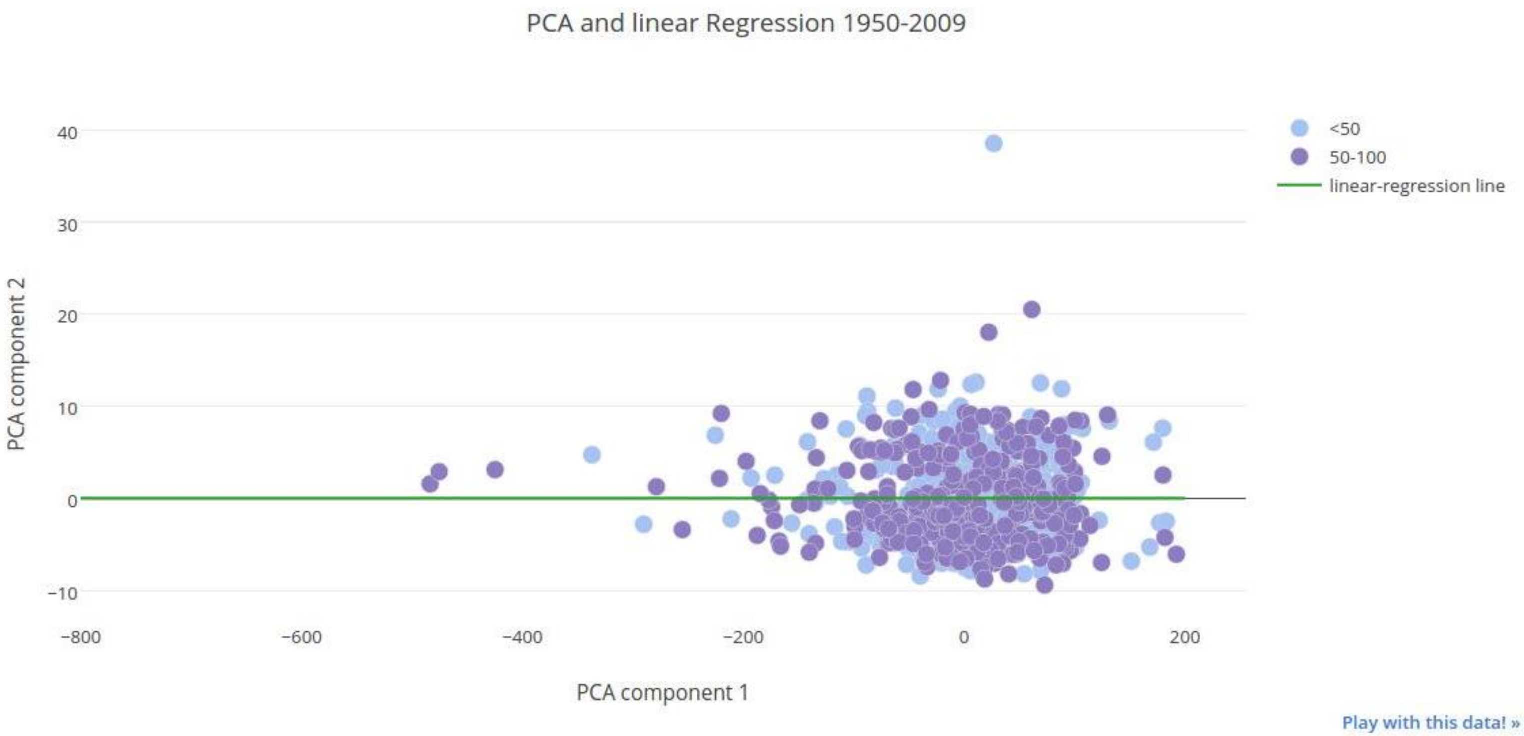
- Now, we are ready with our final dataset i.e. songs with 17 features containing both acoustic and lyrical as well.
- 'song_rank','acousticness','danceability','duration','energy','key','liveness','loudness','mode','speechiness','time_signature','valence','love','joy','surprise','anger','sadness','fear'.

FINAL USABLE DATASET

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1	rank	song_nam	artist	latitude	longitude	acousticn	danceabil	duration	energy	key	liveness	loudness	mode	speechine	tempo	time_sign	valence	love	joy	surprise	anger	sadness	fear
2	1	Tonight's '	Rod Stewa	51.5073	-0.12783	0.05916	0.56357	215.967	0.2867	11	0.12853	-23.099	1	0.05305	135.384	3	0.6141	0.02807	0	0.0155	0.00511	0.00266	0.0378
3	2	I Just War	Andy Gibb	-27.2333	153.117	0.06469	0.60427	225.093	0.75812	9	0.15393	-4.89	1	0.03609	96.804	4	0.88711	0.08406	0.02927	0.02991	0.00434	0.00398	0.0279
4	3	Best Of M	Emotions	41.85	-87.6501	0.09974	0.83858	102.243	0.67053	7	0.0479	-8.739	1	0.03472	114.452	4	0.98167	0	0	0	0	0	
5	4	Love Them	Barbra Str	0	0	0	0	0	0														
6	5	Angel In Y	Hot	0.09294	0.00706	0.07484	0.01914	0	0.05668														
7	6	I Like Drea	Kenny Nol	37.1679	-95.845	0.42956	0.39678	212.067	0.50529	6	0.0666	-11.49	1	0.03435	136.864	4	0.48911	0.04171	0.02814	0.00091	0.00655	0.00637	0.0073
8	7	Don't Leav	Thelma Hc	33.4041	-90.8988	0.23335	0.66369	247.84	0.49041	0	0.31229	-11.24	0	0.03619	120.044	4	0.33922	0.17671	0.03642	0.02396	0.00394	0	0.0515
9	8	(Your Love	Rita Cooli	36.5277	-86.0256	0.04385	0.4091	209.84	0.77149	1	0.81942	-8.426	1	0.06136	137.895	4	0.74303	0.18367	0.00354	0.04354	0.0341	0.06612	
10	9	Undercove	Alan O'Da	34.0535	-118.245	0.31746	0.671	217.44	0.52915	5	0.0757	-9.976	1	0.03682	103.143	4	0.79821	0.17909	0.00876	0.02047	0	0	0.0544
11	10	Torn Betw	Mary Mac	43.8438	-82.6514	0.83865	0.55723	230.623	0.26182	10	0.09483	-17.264	1	0.0405	133.657	4	0.35698	0.19611	0	0.00243	0	0.03646	0.0076
12	11	I'm Your B	K.C. and Tl	0.14996	0.016	0.02784	0.00547	0.00584	0.06402														
13	12	Dancing C	ABBA	0.13582	0.06837	0.03293	0.04016	0	0														
14	13	You Make	Leo Sayer	50.8322	-0.27467	0.02216	0.53652	256.133	0.90062	8	0.81308	-5.356	0	0.153	102.555	4	0.63515	0.02219	0.1017	0.0032	0.00744	0	0.0555
15	14	Margarita	Jimmy Buf	30.3653	-88.5564	0.5456	0.57227	274.32	0.93194	2	0.79084	-4.479	1	0.04537	125.715	4	0.86817	0.04989	0	0.01169	0.00238	0	0.0738
16	15	Telephone	Electric Li	52.4814	-1.89807	0.73651	0.37316	279.146	0.43775	9	0.1264	-6.775	1	0.02955	72.17	4	0.15637	0.03206	0.00727	0.02149	0.00346	0.03431	0.0072
17	16	Whatcha	Pablo Cru	37.7796	-122.42	0.02768	0.72805	200.829	0.38419	0	0.12297	-18.022	1	0.03648	110.073	4	0.96038	0.08498	0.00545	0.01106	0.00265	0.00368	0.0430
18	17	Do You W	Peter McC	0	0	0	0	0	0														
19	18	Sir Duke	Stevie Wo	42.347	-83.0602	0.15575	0.61484	232.533	0.54064	6	0.12941	-8.893	1	0.10676	106.863	4	0.96051	0.02173	0.0159	0.00489	0	0.00137	0.1860
20	19	Hotel Cali	Eagles	34.0535	-118.245	0.00665	0.55539	372.307	0.50469	2	0.14244	-10.541	1	0.02664	147.594	4	0.59321	0	0	0	0	0	
21	20	Got To Giv	Marvin Ga	0	0	0	0	0	0														
22	21	Theme Fro	Bill Conti	0	0	0	0	0	0														
23	22	Southern I	Glen Cam	34.0314	-93.5028	0.00885	0.64036	177.987	0.82579	11	0.08031	-8.19	0	0.03109	95.243	4	0.80676	0.07941	0.09586	0.01827	0	0.02461	0.0784
24	23	Rich Girl	Daryl Hall	0.15317	0	0.01172	0.00343	0	0.09175														
25	24	When I Ne	Leo Sayer	50.8322	-0.27467	0.7273	0.432	260.84	0.52053	11	0.91906	-7.019	1	0.04181	113.334	3	0.34322	0.07193	0.00348	0.00347	0.00263	0.02018	0.0119
26	25	Hot Line	Sylvers	33.9395	-118.243	0.77908	0.84146	181.733	0.63572	4	0.19643	-17.434	0	0.04097	132.948	4	0.97445	0	0	0	0	0	
27	26	Car Wash	Rose Royc	34.0535	-118.245	0.22022	0.78154	310.08	0.62237	9	0.04731	-6.702	0	0.06218	114.372	4	0.90599	0.03465	0.01921	0.02483	0.00387	0.00111	0.0497
28	27	You Don't	Marilyn M	0	0	0	0	0	0														

Applying Classifiers:

- To have a visual intuition, we attempt to reduce the number of features from 17 to 2 using PCA (Principle Component Analysis)



PCA (CONTD.)

- As we were not able to visually locate a clear dividing line among the classes in the dataset, we discard this approach.

- Hence, we take the entire 17 features vectors into account instead of reduced features.

Initial run on The entire dataset

- On running the classifiers on the entire dataset from 1950-2010, we obtained the following results.
- We can see all the classifiers have performed poorly. This is because we have not considered any temporal dependecy to the ranks

	Audio Only	Lyrics Only	Audio+Lyrics
Linear	0.513788098694	0.503628447025	0.510885341074
Logistic	0.515239477504	0.502177068215	0.502177068215
SVM	0.505079825835	0.518142235123	0.500725689405

Applying Classifiers: Linear regression

- Using linear regression we get the prediction for the test data and we take a threshold value of 0.5, i.e. if the prediction of the value is <0.5, then we classify it as Class 0 otherwise Class 1.

- Accuracy Percentage = $\frac{No.\ of\ Songs\ Correctly\ Classified}{Total\ No.\ of\ songs}$

- The maximum accuracy obtained on any decade was in 2000-2010, when it was 58% while considering lyrics only.

Applying Classifiers: Logistic regression

- The logistic classifier returns the probability that the test sample belongs to class 1. If it is > 0.5, then we say it is class 1 else in class 0.

- The maximum accuracy obtained using this classifier was 0.57857 obtained for 1980-90 decade using audio and lyrics features.

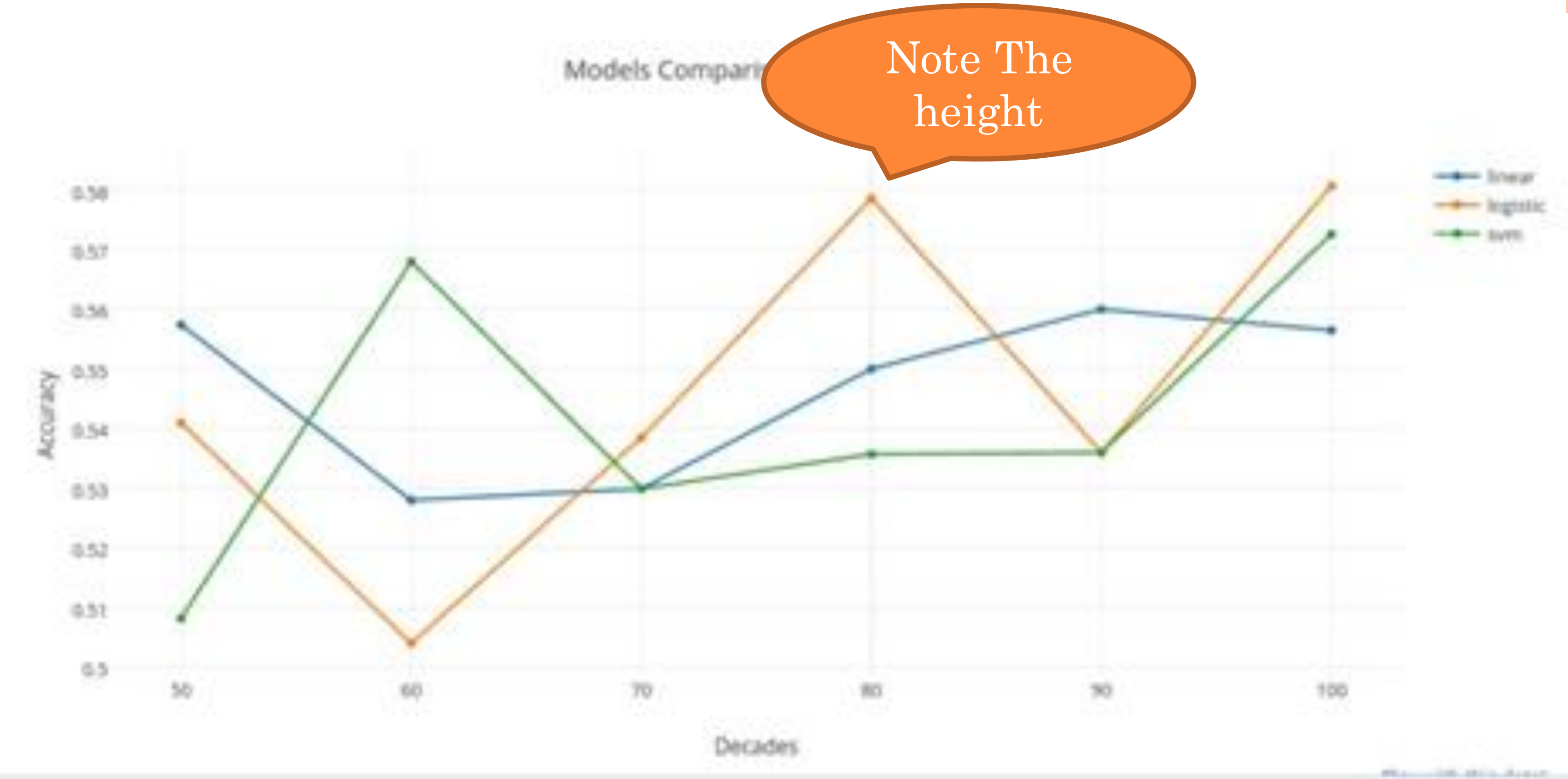
Applying Classifiers: Support Vector Machines

- The SVM classifies data points by dividing the training data into a set of hyperplanes while maximizing the distance to the nearest training data point of any class.

- The maximum accuracy obtained was 0.6 obtained for the 1960-70 decade using audio as well as lyric features.

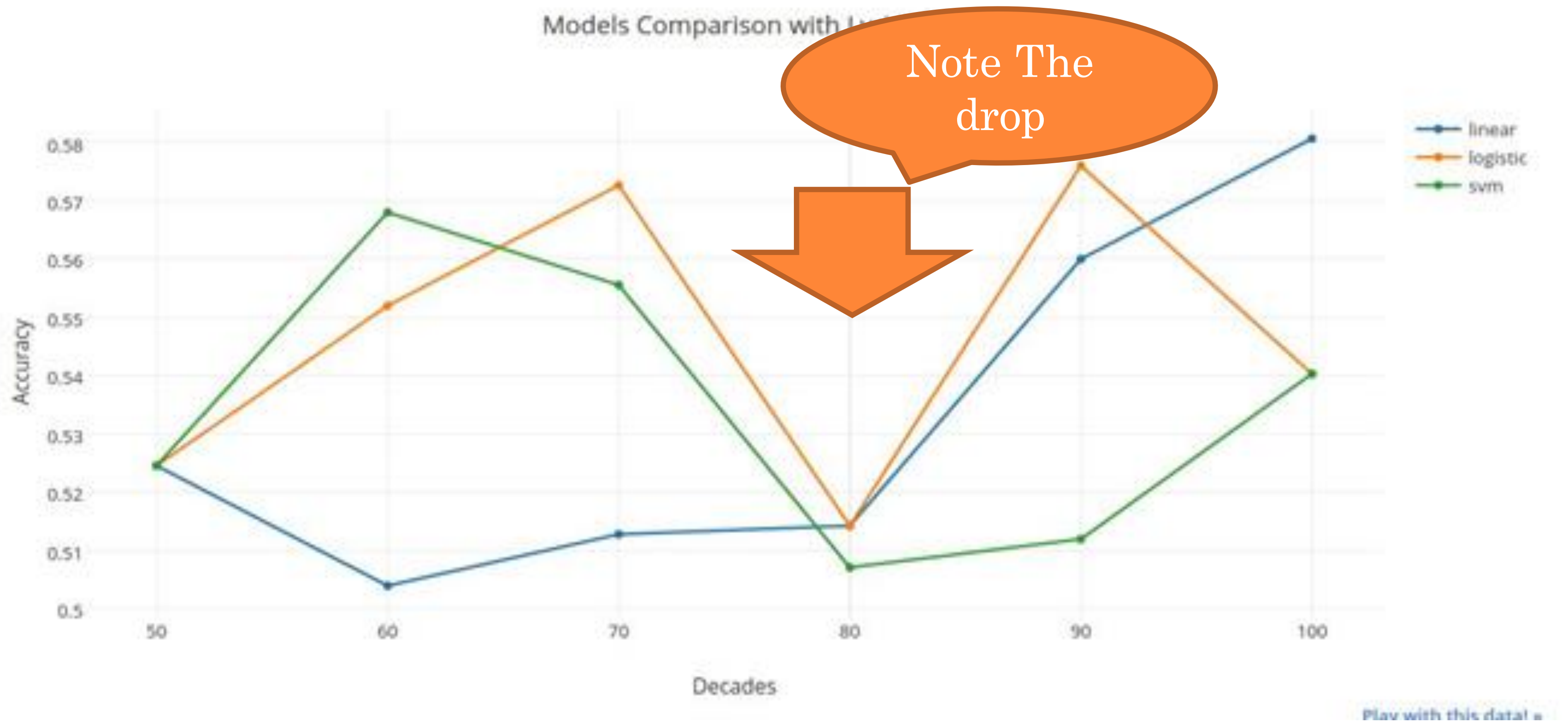
Some Comparisons

1. <u>Using Audio Features Only</u>:
   - Notice the drop in accuracy in the 1980-90 decade.



Some Comparisons

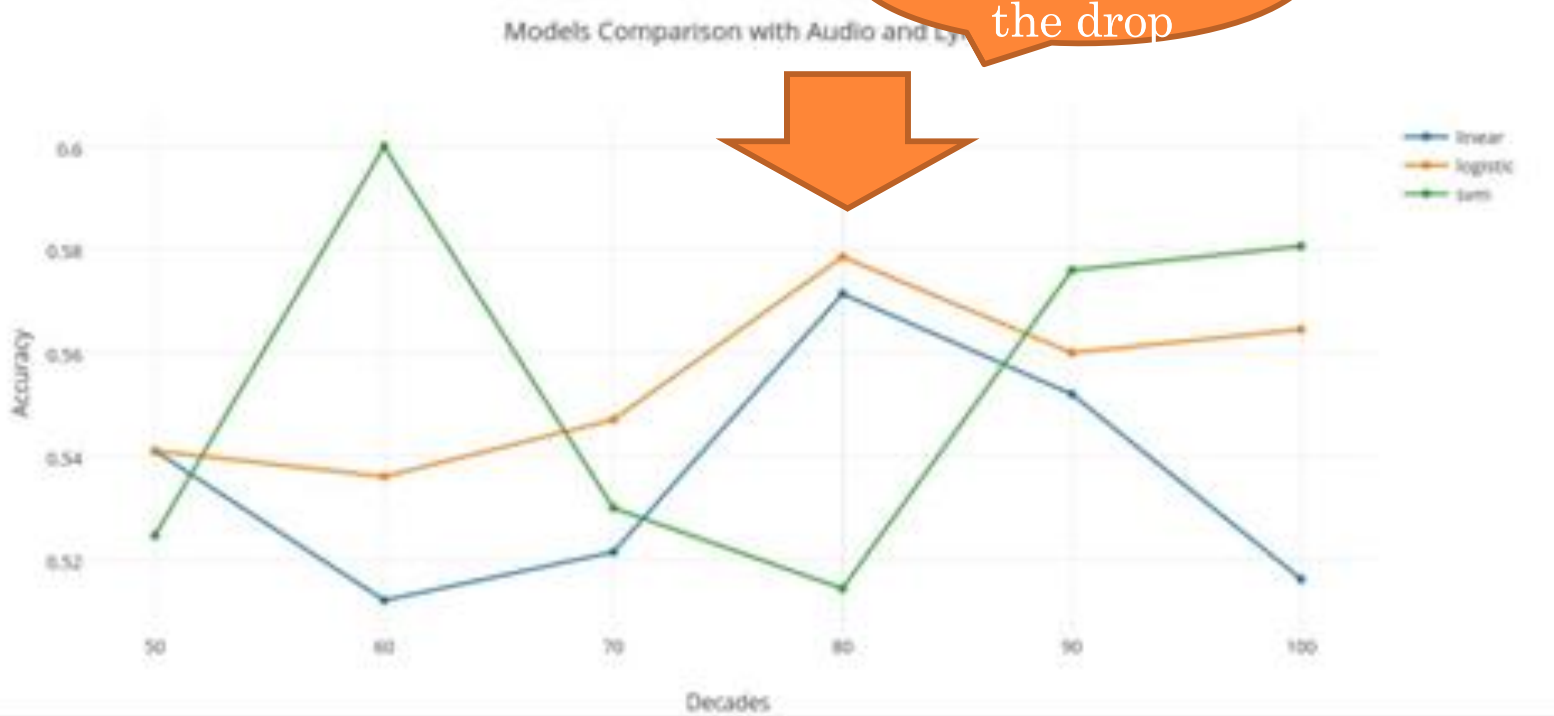
1. <u>Using Lyric Features Only</u>:



Some Comparisons

1. <u>Using Lyric + Audio Features</u>:

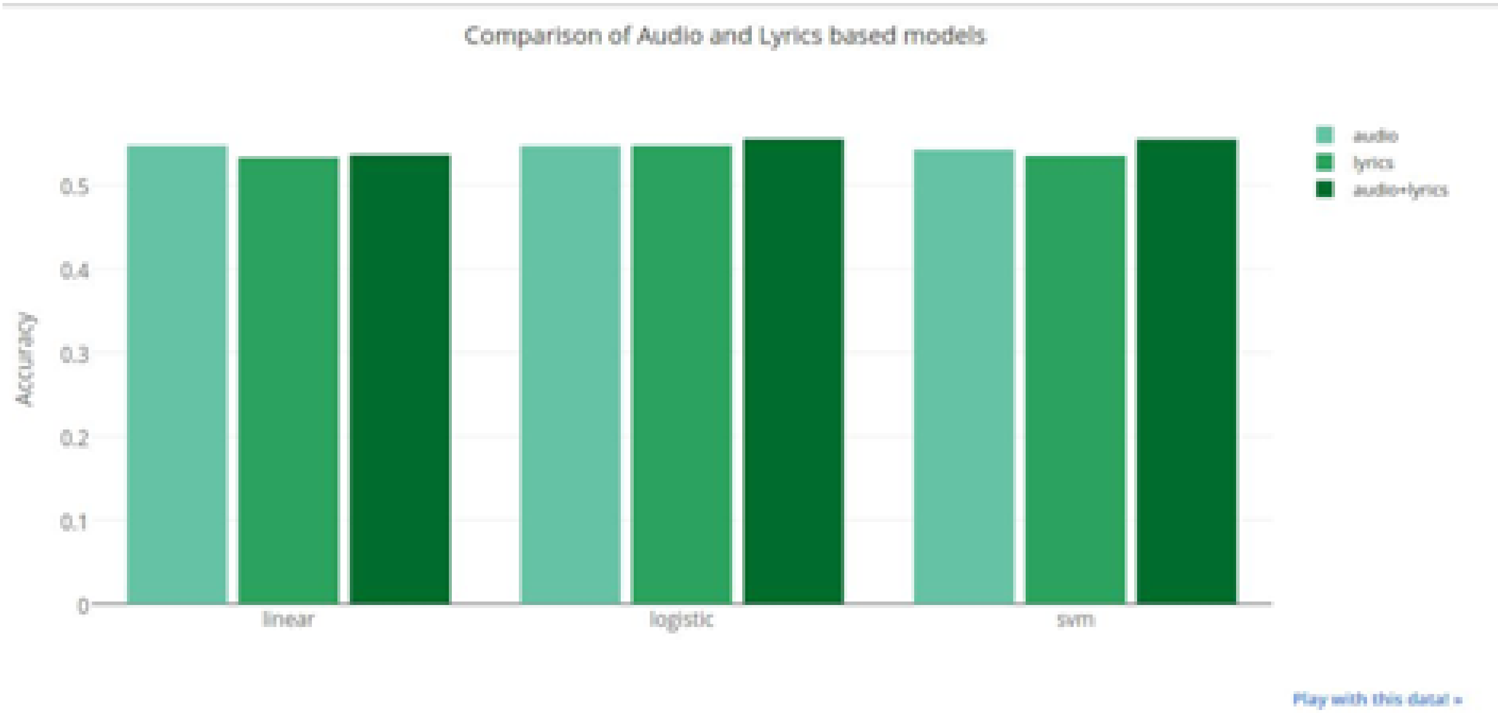
Height cancel led the drop



INFERENCES

- We can clearly see in the case of SVM classifier, the height cancelled the drop for the 1980-90 decade.
- So we can say the **logistic regression** classifier got more **robust** if we consider both the audio as well as lyric features.
- The same cannot be said in case of other classifiers, which have many fluctuations from decade to decade.

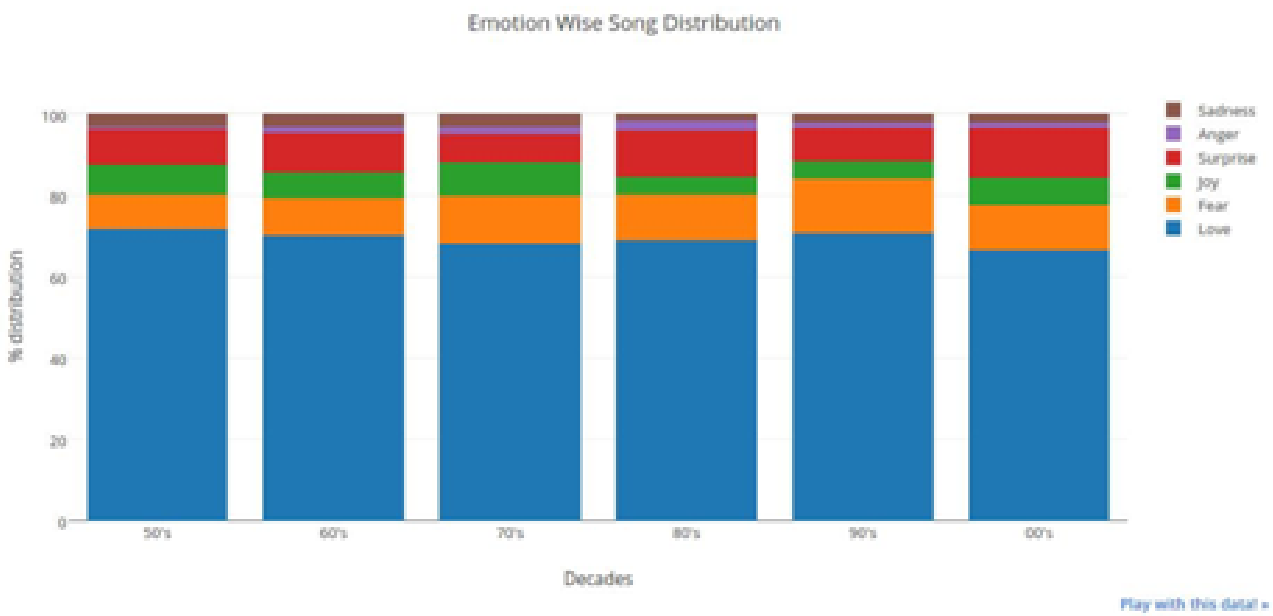
Analysis of accuracy of classifiers using audio and lyric features



- In this plot, we consider the average accuracies of each of the decades.
- The linear model doesn't show any improvement, but the logistic and SVM models show improvement when we include both the audio and lyrical features.

Emotion Analysis

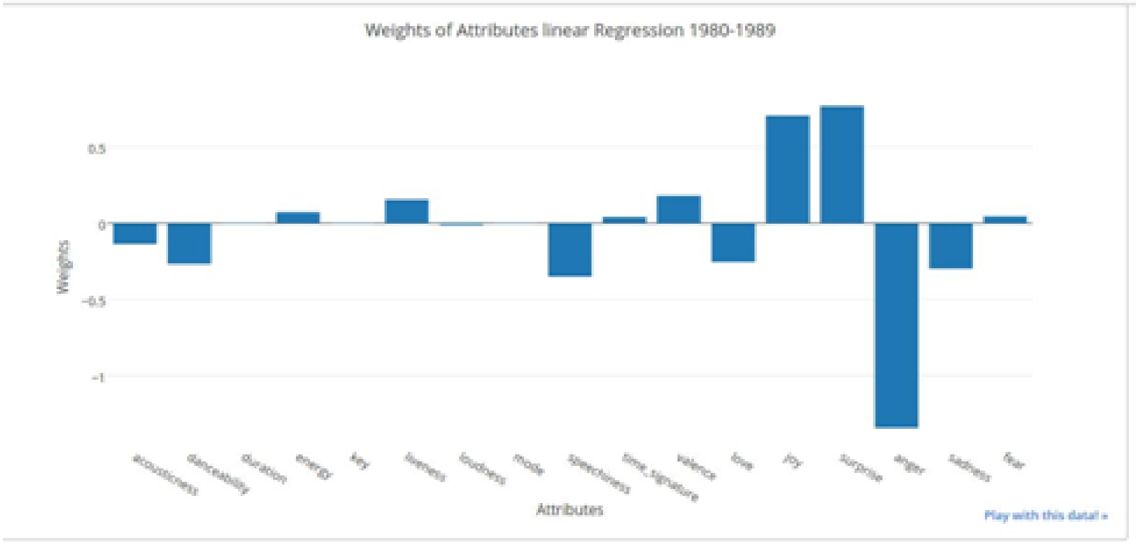
- We plot the degrees of emotional quotient of each of the primary emotions i.e. Love/Joy/Surprise/anger/sadness/fear, in each of the decade.



- As we expected, the **most** sung-about emotion is '**Love**' followed by either 'Surprise' or 'Fear'

Features Analysis

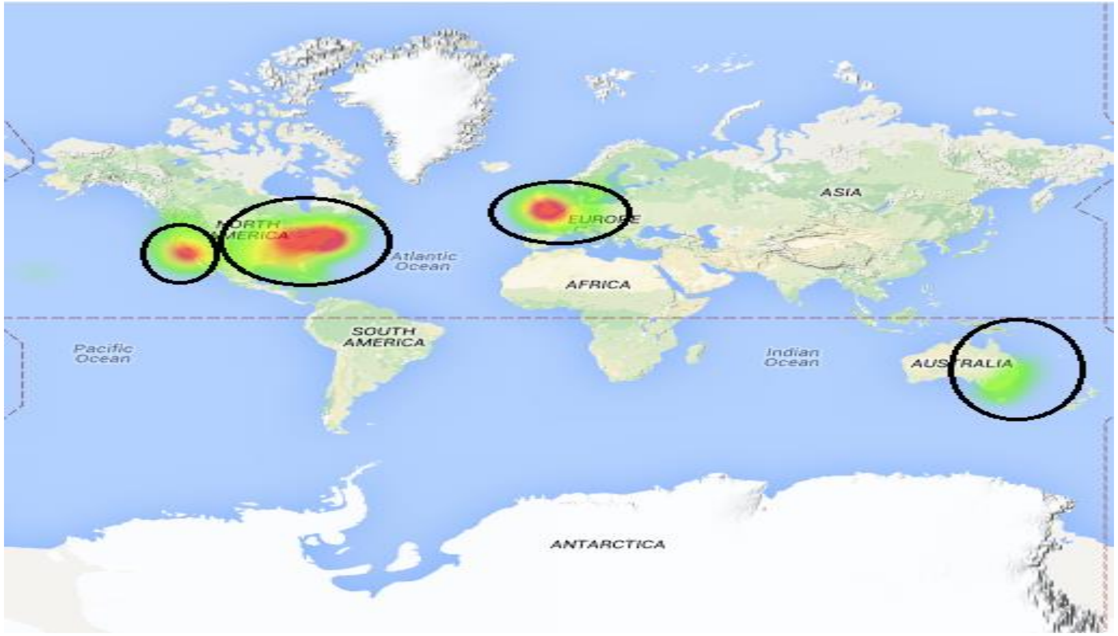
- The weights of the features of the trained Linear Regression model give us some clues.



- we see that anger is the one emotion and feature that contributes the most towards prediction but also make the song unpopular.
- Surprise has maximum positive weight thus mainly responsible for popularity.

Some other analysis

- Plot the artist location on a heatmap to identify the location from where most of the hit songs originate.



Circles in image given in previous slide shows that majority of artists belongs to areas like east and west coast of USA, United Kingdom and Eastern coast of Australia.

Some other analysis(Cont.)

- Analysis done using K-means Clustering

  - We classify the songs into clusters on the basis of its acoustic features and analyze its results. Experimentation, we used 7 clusters centroids

  - These clusters correspond to various genres of music as the it can be assumed with little margin of error that music of a genre must have similar acoustic features.

Some other analysis(Cont.)

```
print data_param[(data_param['artist']=='Carpenters') & ()][['song_name','artist','cluster']]
```

```
                         song_name      artist  cluster
1    (They Long To Be) Close To You  Carpenters        6
49            We've Only Just Begun  Carpenters        4
100                       Superstar  Carpenters        6
104                 For All We Know  Carpenters        6
107         Rainy Days And Mondays  Carpenters        6
212             Hurting Each Other  Carpenters        1
284                            Sing  Carpenters        4
294             Yesterday Once More  Carpenters        1
356                Top Of The World  Carpenters        1
433              Please Mr. Postman  Carpenters        1
485                  Only Yesterday  Carpenters        4
```

- In the above figure, it is seen that all of the songs by ‘Carpenters’ can be classified only in three categories.
- This confirms the notion that a particular artist usually makes music specific to certain genres mostly.

Conclusion

- We found that the combination of both audio & lyrical features provides us with a more robust metric for prediction than their individual contributions.
- Though the SVM model gave the highest accuracy in a particular decade, the Logistic Regression gave the most consistent prediction.

Improvements & Future Work

- We can use the entire hierarchy of Parrott's emotion classification for emotional analysis.
- We can use a better scientific temporal division for predictions than the decade-wise analysis.
- The locations of the artists could also be considered as parameters to the model.
- One could also mine cultural and social emotions from news, social media to see if it impacts the short term ranking of a song.

References

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Thank You