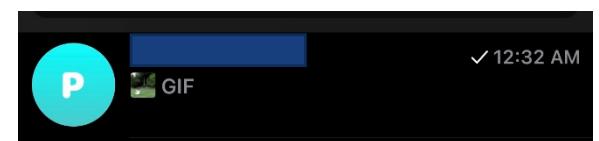
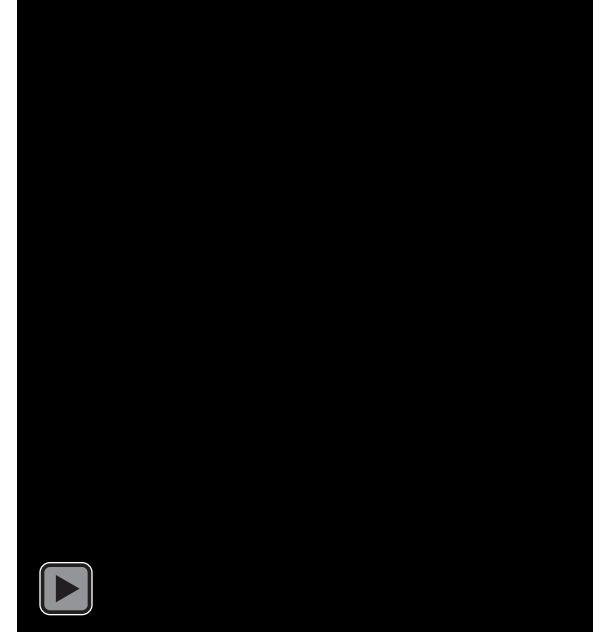
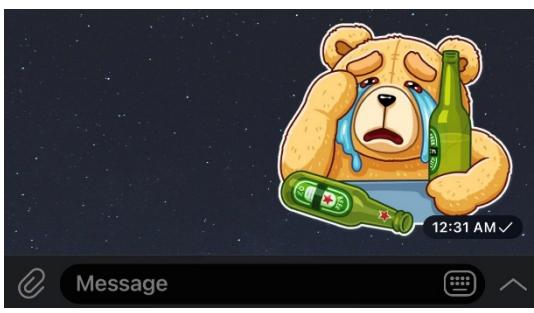
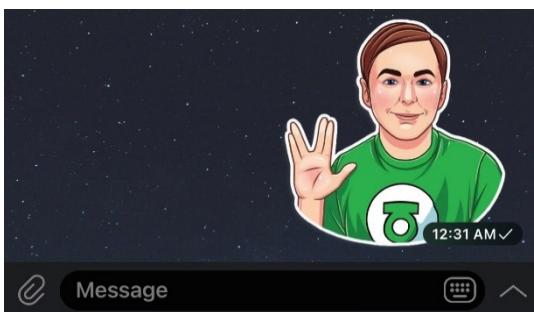
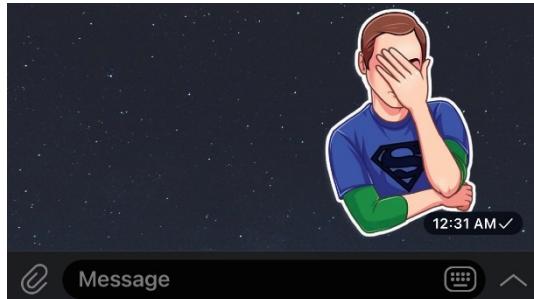


# Other Key Considerations/Challenges

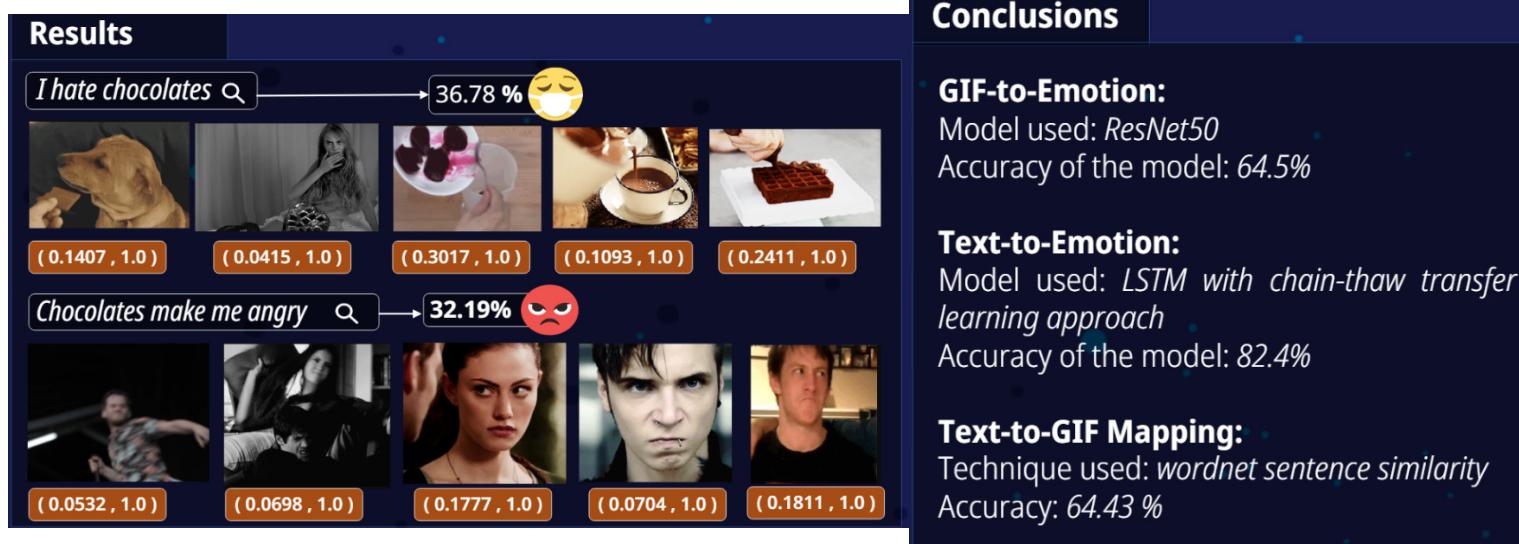
- Rapid shift in how we communicate
  - Examples: Gifs & active Emoji's in text for communication



# Other Key Considerations/Challenges

Many researchers are working on Gifs and some recent papers show some techniques that can be used.

- [https://github.com/Subikshaa/GIF-Based-Communication-Using-Sentiment-Analysis/blob/master/Project\\_report.pdf](https://github.com/Subikshaa/GIF-Based-Communication-Using-Sentiment-Analysis/blob/master/Project_report.pdf)
- [https://github.com/Subikshaa/GIF-Based-Communication-Using-Sentiment-Analysis/blob/master/Project\\_poster.pdf](https://github.com/Subikshaa/GIF-Based-Communication-Using-Sentiment-Analysis/blob/master/Project_poster.pdf)



Some more links

# **CASE 1:**

## **COCA COLA VS PEPSI SENTIMENT**

## **CUSTOMER PREFERENCES**

### **OPINION MINING ON SOCIAL MEDIA DATA:**

### **SENTIMENT ANALYSIS OF USER**

### **PREFERENCES**

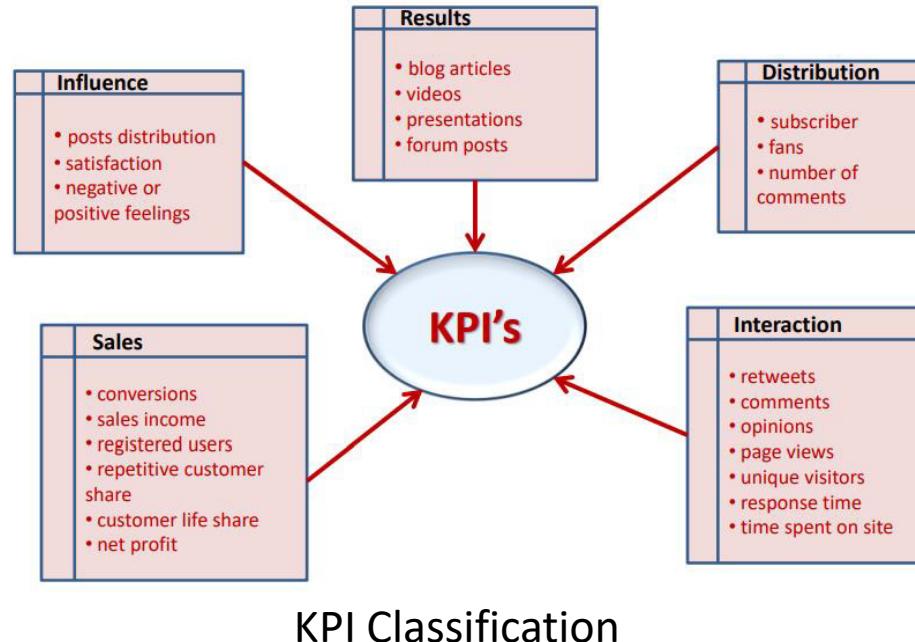
# Customer Preferences

- Brand –All brands seek to have significant impact on emotional reactions of its users
- Engagement -Understanding preferred types of posts (photo or video) based reactions, is important in designing engagement/communication strategy
- Analysis –Evidence and reaction on the differences and similarities between customer behaviors of highly competitive brands
- Evidence Based -Reaction to two types of posts (photos or videos) on three social networks: Facebook, Twitter and Instagram.

# Scope and KPIs

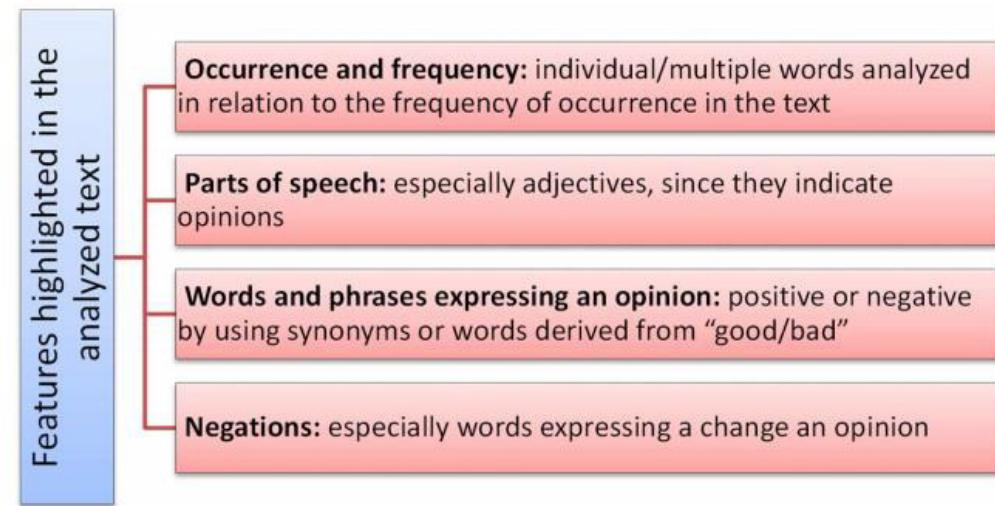
Assessment Scope:

- Social Network pages of Coca-Cola and Pepsi
- Covered Top 50 Posts
- At least 5 months
- KPIs –Sales, Influence, Results Distribution and Interaction



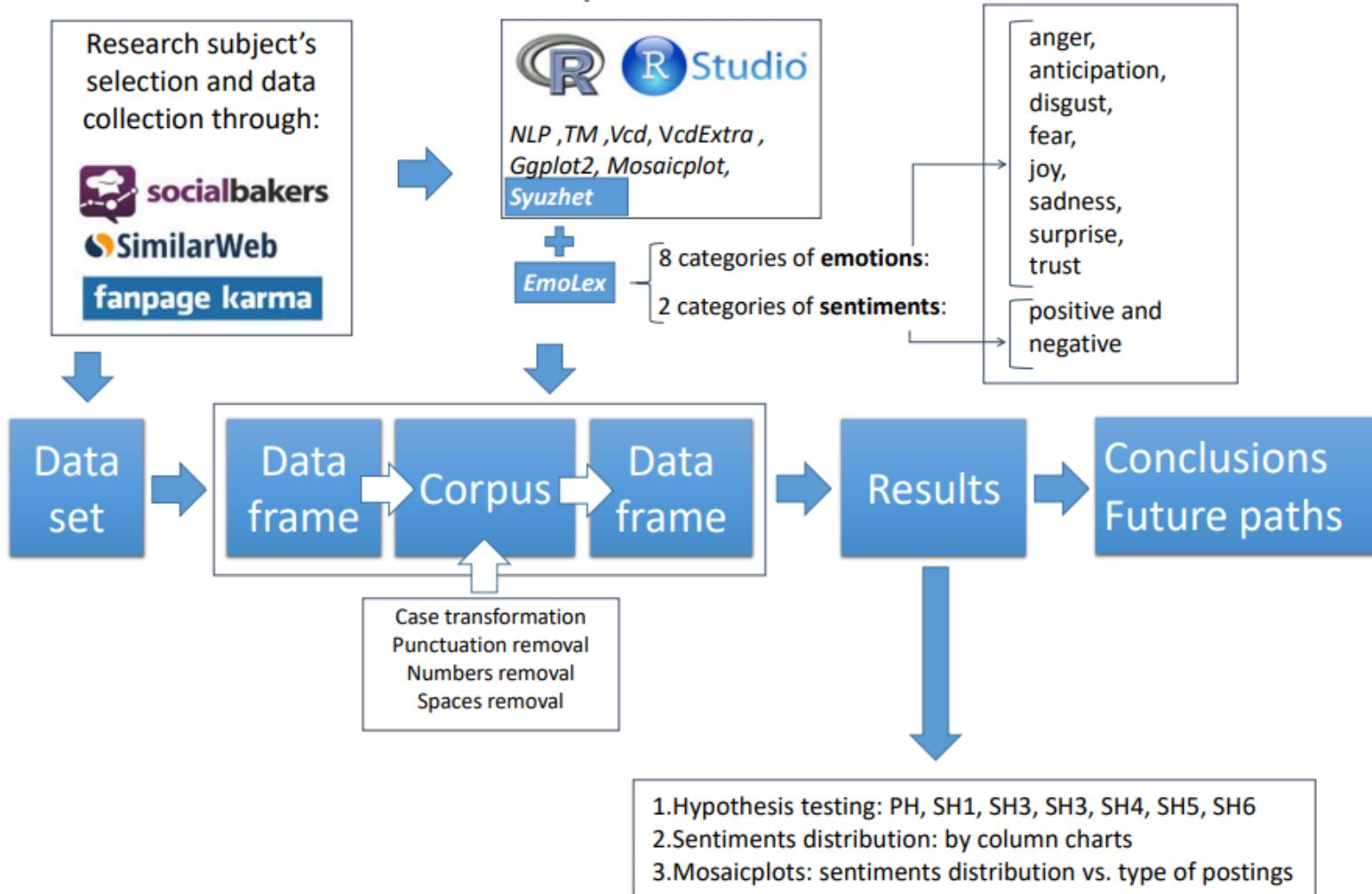
# Approach

1. Establish positive, negative or neutral significance
2. Highlighted with features listed
3. Associated with:
  - Eight categories of emotions
    - Anger
    - Fear
    - Anticipation
    - Trust
    - Surprise
    - Sadness
    - Joy
    - Disgust
  - Two categories of sentiments
    - Positive
    - Negative



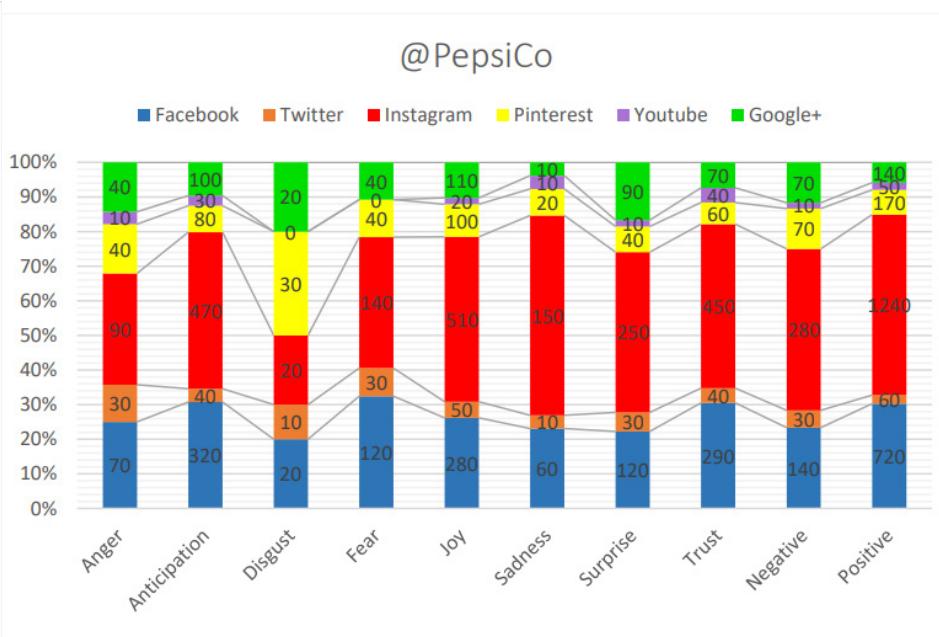
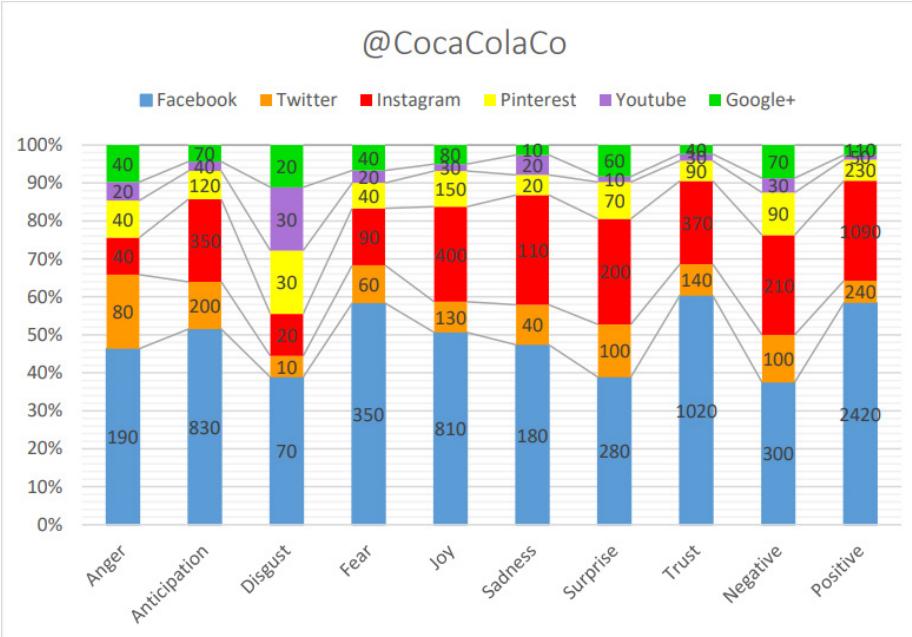
# Methodology

- Combination of Qualitative and Quantitative methods



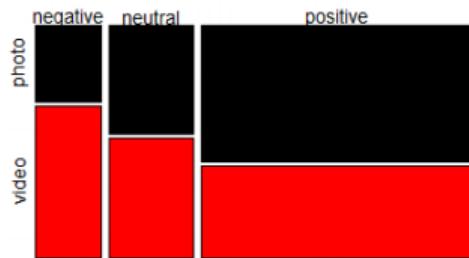
# Distribution of Emotions

- Cumulative histogram charts displaying the sentiment distribution on each of the six social network pages for Coca-Cola and PepsiCo official channels

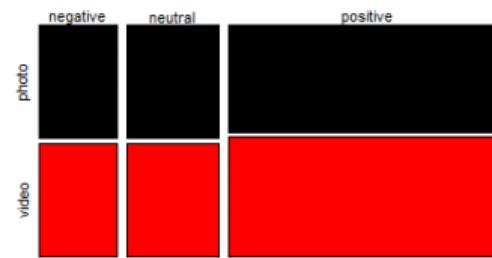


# Different Sentiments for Different Media

- Users tend to express their sentiments differently depending on the type of post and Media



@CocaColaCo – Facebook platform



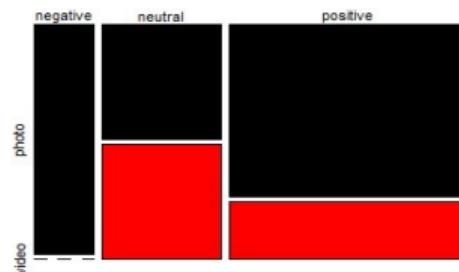
@PepsiCo – Facebook platform



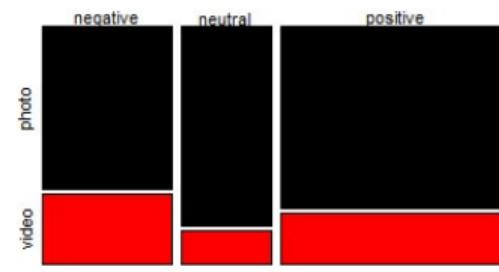
@CocaColaCo – Instagram platform



@PepsiCo – Instagram platform



@CocaColaCo – Twitter platform



@PepsiCo – Twitter platform

# Key Takeaways

- There are significant differences in user emotions and sentiments expressed on different Social Media networks and dependent on types of media used (photos or videos)
- The activity of the two brands in the online environment has an emotional impact on current or potential customers
- Emotional reactions on SM of users have direct correlation to purchasing decisions
- With growing medium of mobile, interactions in exchanging opinions in communities is increasing exponential, nor will slow down

# CASE 2: **BEYOND THE BTS ( BANGTAN BOYS)** **SENTIMENT**

## IDENTIFYING PRODUCT CHARACTERISTICS



<https://www.youtube.com/watch?v=9rTGDBwI41Y>

# Phenomenal sentiment towards BTS, but WHY?



What makes this group so deserving of all this attention?

What makes them so unique compared to their competitors?

How to answer the question with scientific investigation and real validation?

# Identifying Product Characteristics

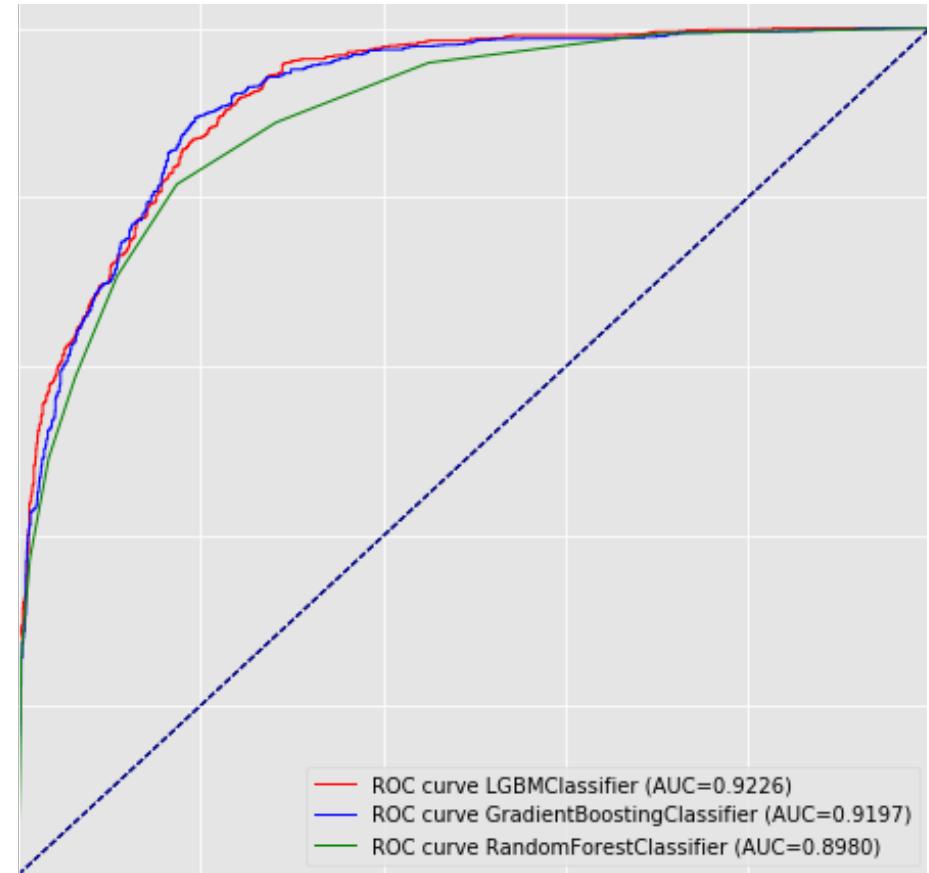
- Product –Others have tried to explain via:
  - The members “completely understand the values of a team” —TIME
  - “High Quality of Music” —Kpopmap
  - Confucian values of hard work —Psychologist Watches
  - “Emotional resonance, sincerity, and an ARMY of fans.” —Vox
- The problem –These explanations aren’t really compelling i.e. can easily be applied to say BigBang, another famous Korean boy band, which also been recognized for “musical variety/non-conformity” while “still maintaining unique identity”
- Analysis –Using the latest data science techniques in machine learning and A.I. to scientifically answer the question of the group’s true identity

# Methodology

- Using data to mathematically measure BTS's
  - Acoustic-ness, danceability, instrumental-ness, etc.
  - 11 acoustic qualities
  - Spotify API
- Comparison to other Korean artists
- Comparison BTS's music characteristics to Western popular artists
  - Machine learning models learning these 11 musical features
  - Predict whether from BTS or not
  - Identify correlation

# Analysis Computing the Data

- Using ensemble models of LightGBM, Gradient Boosting and Random Forest, with a one-v-all approach where the target label was 1 when if the features corresponded to a BTS song and 0 if else.
- Without any model optimization or feature engineering, all three models near **0.9** in AUC. Oversampling was used to combat class imbalance.



# Analysis Categorisation

Comparing to other K-Pop Groups

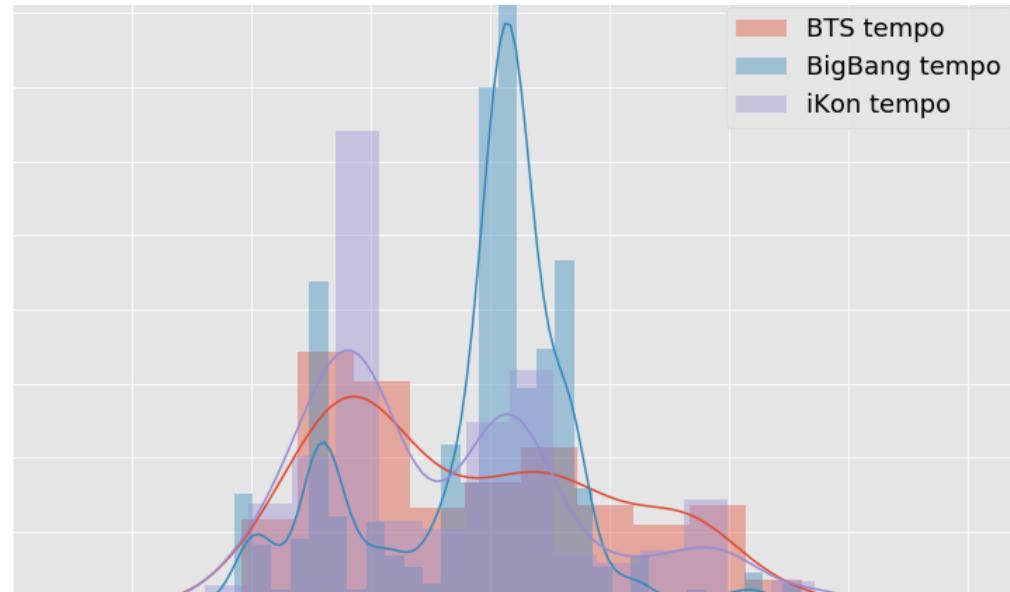
- Highest level of speechiness\*
  - detection of spoken words in a track
- Relatively low level of instrumentalness
  - a measurement of whether a track contains vocals

artist_name	speechiness	instrumentalness	danceability	energy	acousticness
bts	0.158097	0.012689	0.601540	0.812572	0.100711
bigbang	0.108219	0.006586	0.582627	0.832900	0.109640
red velvet	0.094951	0.017682	0.668874	0.748158	0.224725
wanna one	0.094881	0.000000	0.616815	0.787222	0.199652
ikon	0.094139	0.026383	0.629316	0.797978	0.192225
shinee	0.083504	0.014346	0.637085	0.807092	0.143948
aoa	0.073649	0.098046	0.665081	0.847846	0.159874
girls generation	0.073255	0.049220	0.671842	0.798758	0.224972
gfriend	0.054407	0.289859	0.617545	0.719066	0.253075

**Note :** \* Speechiness is a number between zero and one that indicates how likely a particular audio file is speech

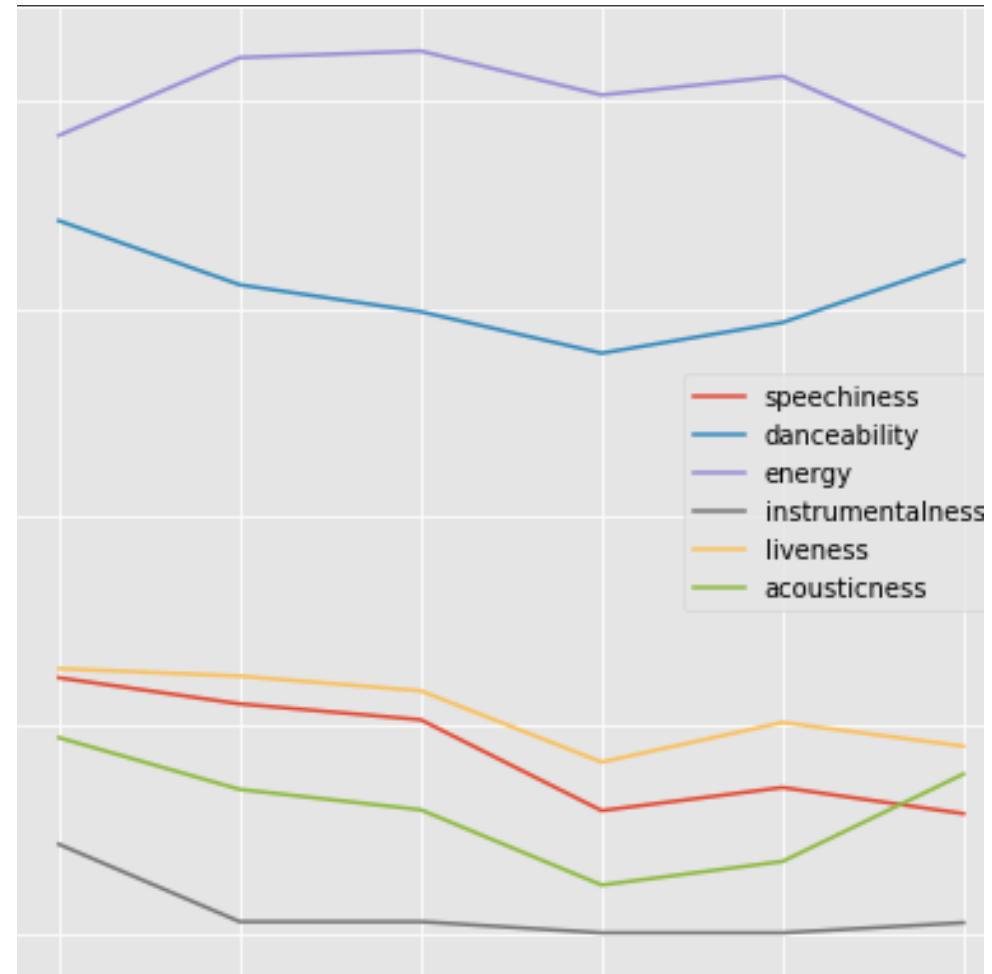
# Analysis Categorisation

- BTS's music
  - More distributed in the beats
  - Diverse in rhythm and speed -
   
Comprising of songs that are both extremely fast and slow in pace
- BigBang and iKon's music
  - center around a specific tempo 100 BPM, 130BPM



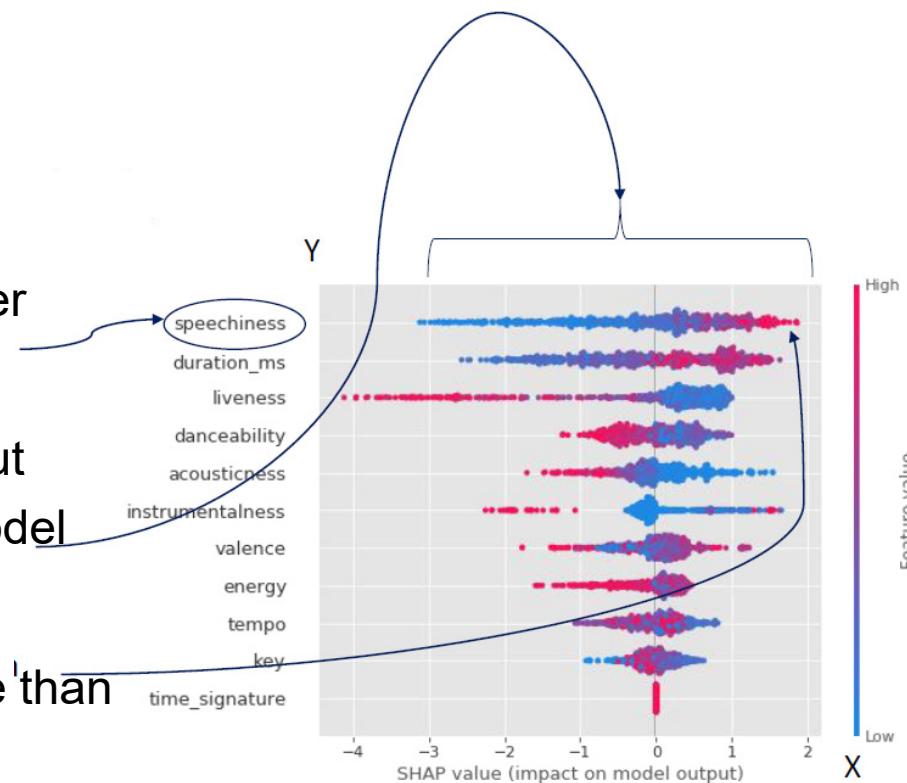
# Analysis BTS music trend across years

- Measurements in liveness, danceability, speechiness, even acoustic-ness all fell gradually until the year 2016
- Danceability and Acousticness rose significantly in 2018 although we saw Energy being decreased from 2017



# Analysis Impact on Model Output

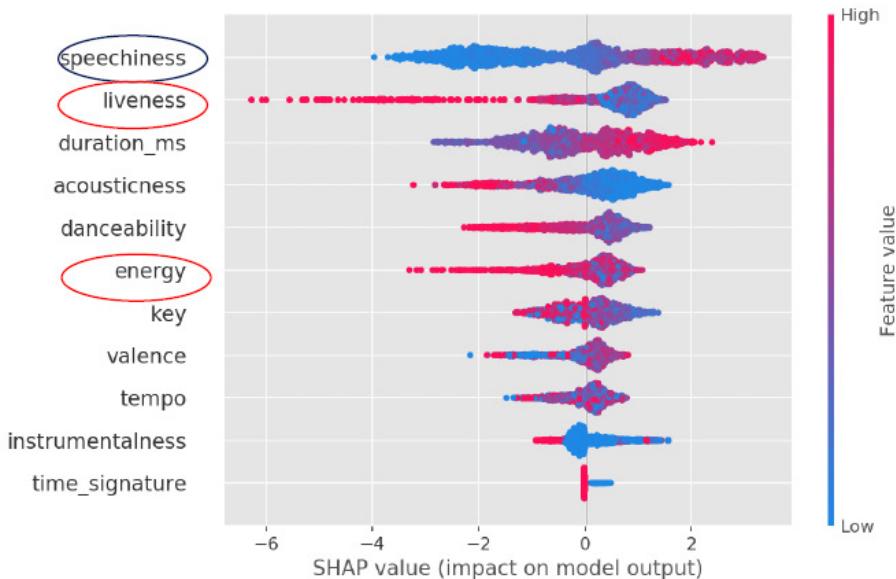
- High speechiness are more likely to be by BTS
- Higher ranking on the left y-axis = heavier impact on model prediction
- The magnitude of impact on model output  
More spread out = heavier impact on model prediction
- Red dots has higher value on the feature than blue dots



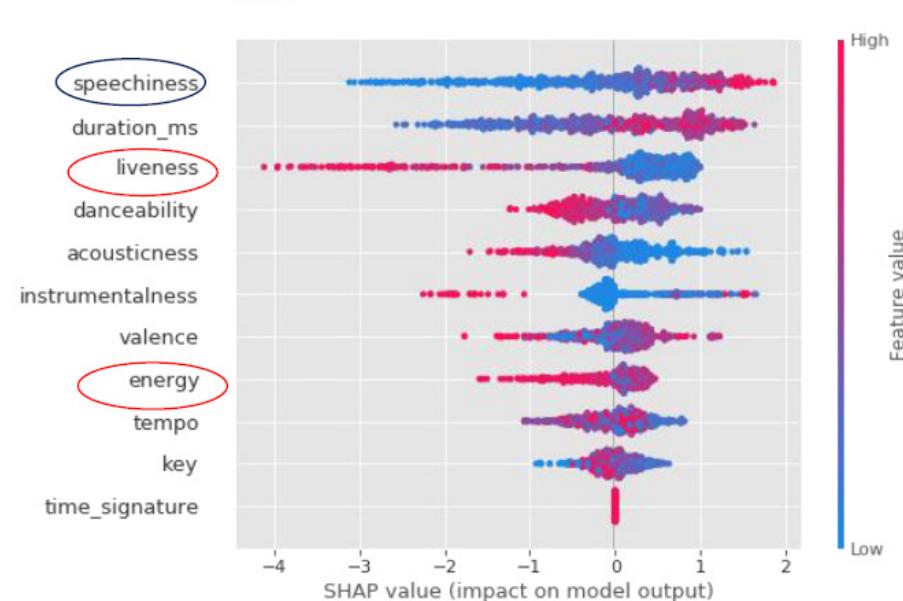
# Analysis Correlations

- Correlation between popular western artists and BTS
  - Kelly Clarkson, One Direction, Bruno Mars, etc.

**Euro-American**



**BTS**



# Analysis Comparison Western Artists

- BTS compared to other western artists
  - Highest speechiness, again
  - Highest energetic level

artist_name	speechiness	instrumentalness	danceability	energy	acousticness
bts	0.158097	0.012689	0.601540	0.812572	0.100711
Christina Aguilera	0.108485	0.063259	0.612107	0.668288	0.238418
Lady Gaga	0.084522	0.015907	0.632386	0.705692	0.167523
Kelly Clarkson	0.082163	0.007363	0.551369	0.702889	0.166611
Rihanna	0.080839	0.011942	0.617027	0.675086	0.156436
Bruno Mars	0.073292	0.026226	0.647408	0.644171	0.238233
Katy Perry	0.061527	0.001338	0.632005	0.751266	0.088522
*NSYNC	0.058087	0.020642	0.606690	0.676935	0.224102
Backstreet Boys	0.054636	0.011073	0.609911	0.721334	0.138418
Taylor Swift	0.052205	0.142733	0.585547	0.641625	0.157794
One Direction	0.049238	0.002887	0.588810	0.746526	0.122309

# Unique Characteristics

Key qualities that has driven sentiments, unique to BTS

- Diverse and distributed tempo
- High rates of speechiness
- Low rates of instrumentalness
- Significantly more energy than popular western pop artists



# Keys Takeaways

- Music Products have shown to have direct correlation to 11 acoustic qualities driving popular sentiment
- Qualities such as speechiness and energy have shown to be key characteristics creating popular sentiment
- This model can be used for other products and services to help drive popularity
- Analysis has shown to help song writers, artist, investors, agencies & MCNs (Multi Channel Network)