Data Visualization and Analysis of Taylor Swift's Song Lyrics

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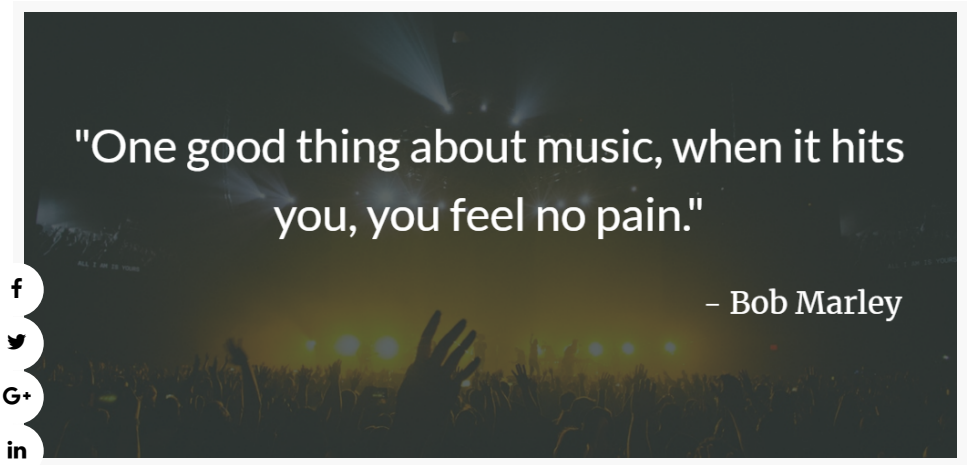

Did you know that Taylor Swift is the youngest person to single-handedly write and perform a number-one song on the Hot Country Songs chart published by Billboard magazine in the United States? Apart from that she is also the recipient of 10 Grammys, one Emmy Award, 23 Billboard Music Awards, and 12 Country Music Association Awards (enough said)! She is particularly known for infusing her personal life into her music which has received a lot of media coverage. Hence, it would be interesting to analyze her songs' content via exploratory analysis and sentiment analysis to find out various underlying themes.

Data set

Thanks to the amazing API exposed by Genius.com, we were able to extract the various data points associated with Taylor Swift's songs. We've selected only the six albums released by her and removed the duplicate tracks (acoustic, US version, pop mix, demo recording etc.). This resulted in 94 unique tracks with the following data fields:

- album name
- track title
- track number
- lyric text
- line number
- year of release of the album

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Goals

Our goal is to first perform exploratory analysis and then move to text mining including sentiment analysis which involves Natural Language Processing.

– Exploratory analysis

- word counts based on tracks and albums
- time series analysis of word counts
- distribution of word counts

– Text mining

- word cloud
- bigram network
- sentiment analysis (includes chord diagram)

We'll be using `R` and `ggplot2` to analyse and visualize the data. Code is also included in this post, so if you download the data, you can follow along.

Exploratory analysis

Let's first find out the top 10 songs with the most number of words. The code snippet given below includes the packages required in this analysis and finds out the top songs in terms of length.

```
library(magrittr)
library(stringr)
library(dplyr)
library(ggplot2)
library(tm)
library(wordcloud)
library(syuzhet)
library(tidytext)
library(tidyr)
library(igraph)
library(ggraph)
library(readr)
library(circlize)
library(reshape2)

lyrics <- read.csv(file.choose())

lyrics$length <- str_count(lyrics$lyric,"\\S+")

length_df <- lyrics %>%
             group_by(track_title) %>%
             summarise(length = sum(length))

length_df %>%
  arrange(desc(length)) %>%
  slice(1:10) %>%
  ggplot(., aes(x= reorder(track_title, -length), y=length)
  geom_bar(stat='identity', fill="#1CCCC6") +
  ylab("Word count") + xlab ("Track title") +
```

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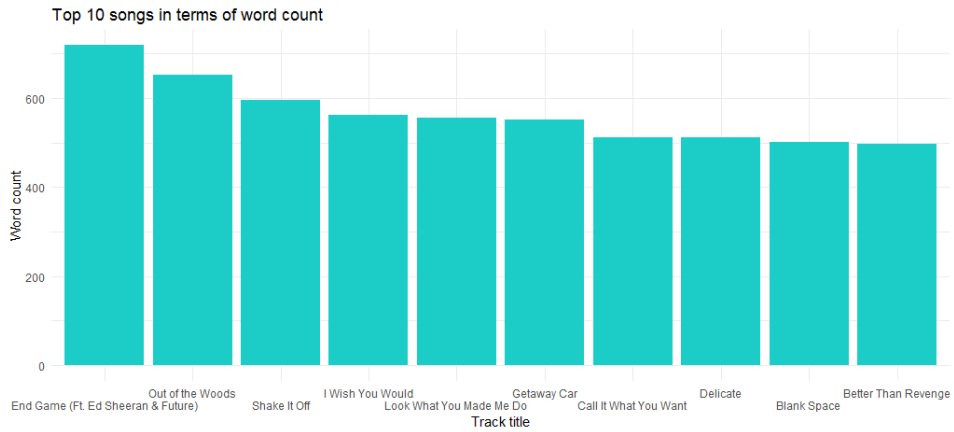
```
    ggtitle("Top 10 songs in terms of word count") +
    theme_minimal() +
    scale_x_discrete(labels = function(labels) {
      sapply(seq_along(labels), function(i) paste0(ifelse(i %%
    })
```

This gives us the following chart:

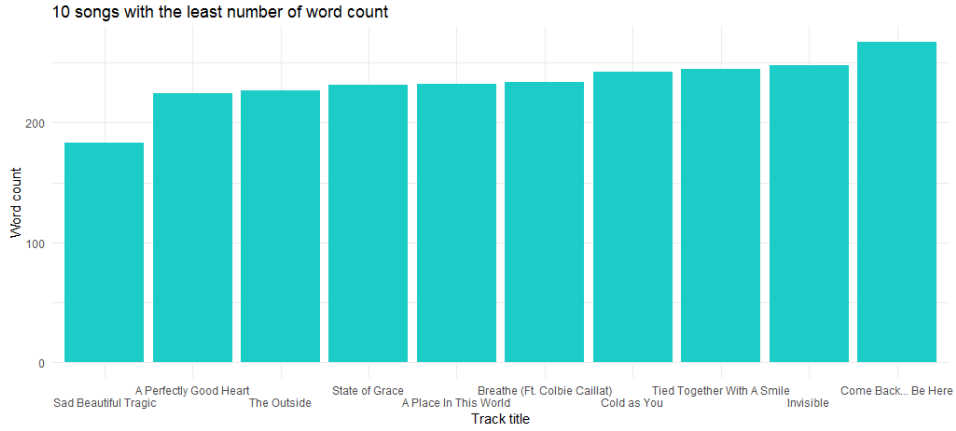


We can see that "End Game" (released in her latest album) is the song with maximum number of words and next in line is "Out of the Woods".

Now, how about the songs with the lowest number of words? Let's find out using the following code:

```
length_df %>%
  arrange(length) %>%
  slice(1:10) %>%
  ggplot(., aes(x= reorder(track_title, length), y=length))
  geom_bar(stat='identity', fill="#1CCCC6") +
  ylab("Word count") + xlab ("Track title") +
  ggtitle("10 songs with least number of word count") +
  theme_minimal() +
  scale_x_discrete(labels = function(labels) {
    sapply(seq_along(labels), function(i) paste0(ifelse(i %%
  })
```

This results in the following chart:



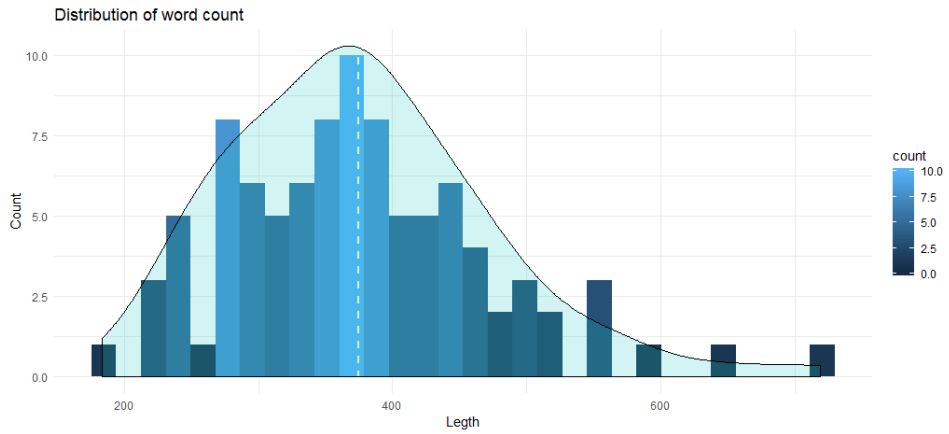
"Sad Beautiful Tragic" song which was released in 2012 as part of the album "Red" is the song with least number of words.

The next analysis is centered around the distribution of the number of words. Given below is the code:

```
ggplot(length_df, aes(x=length)) +
  geom_histogram(bins=30,aes(fill = ..count..)) +
  geom_vline(aes(xintercept=mean(length)),
             color="#FFFFFF", linetype="dashed", size=1) +
```

```
    geom_density(aes(y=25 * ..count..),alpha=.2, fill="#1CCCC6'
    ylab("Count") + xlab ("Legth") +
    ggtitle("Distribution of word count") +
    theme_minimal()
```

This code give us the following histogram along with density curve:



The average word count for the tracks stands close to 375, and chart shows that maximum number of songs fall in between 345 to 400 words.

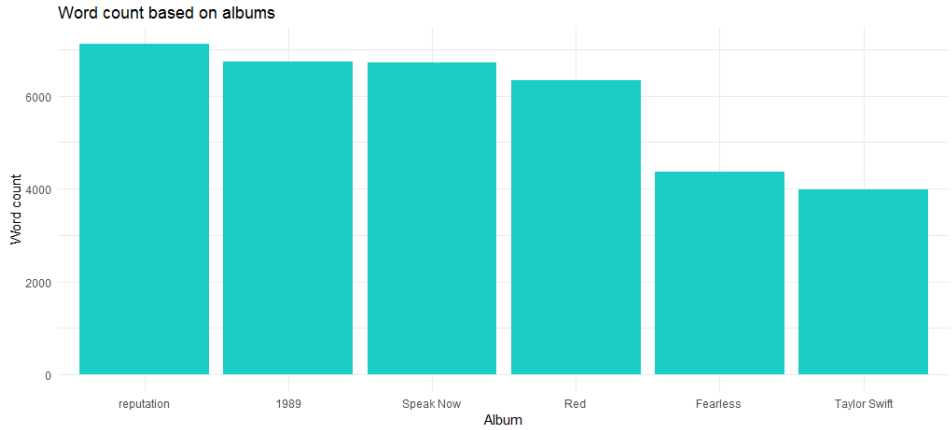
Now, we'll move to the analysis based on albums. Let's first create a data frame with word counts based on album and year of release.

```
lyrics %>%
group_by(album,year) %>%
summarise(length = sum(length)) -> length_df_album
```

The next step for us is to create a chart that will depict the length of the albums based on the cumulative word count of the songs.

```
ggplot(length_df_album, aes(x= reorder(album, -length), y=ler
geom_bar(stat='identity', fill="#1CCCC6") +
ylab("Word count") + xlab ("Album") +
ggtitle("Word count based on albums") +
theme_minimal()
```

The resulting chart shows that "Reputation" album which also the latest album has maximum number of words.

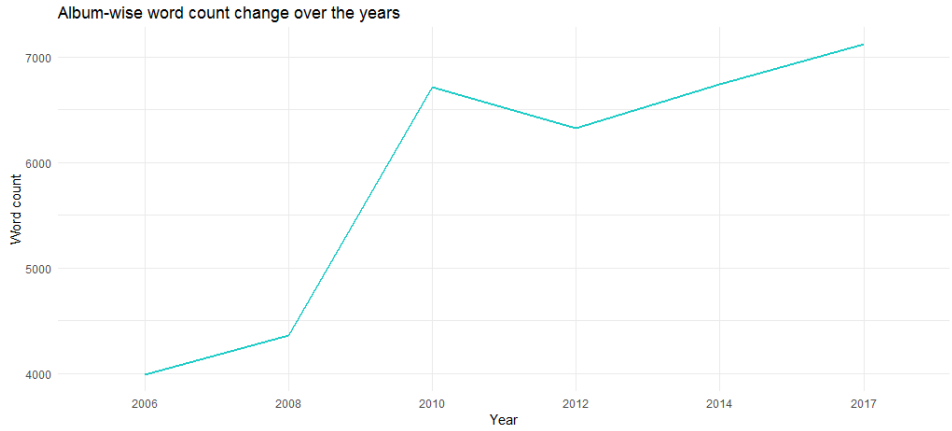


Now, how has the length of songs changed since the debut from 2006? The following code answers this:

```
length_df_album %>%
arrange(desc(year)) %>%
ggplot(., aes(x= factor(year), y=length, group = 1)) +
geom_line(colour="#1CCCC6", size=1) +
ylab("Word count") + xlab ("Year") +
ggtitle("Word count change over the years") +
```

```
7 | theme_minimal()
```

The resulting chart shows that the length of the albums have increased over the years — from close to 4000 words in 2006 to more than 6700 in 2017.

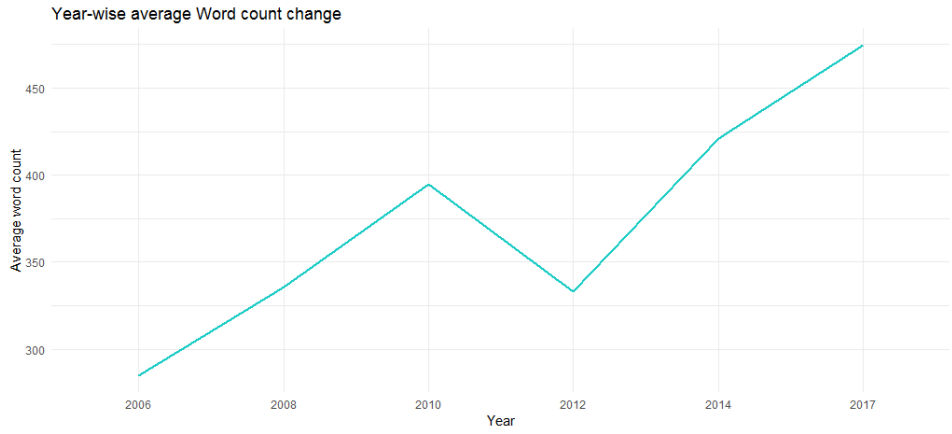


But, is that because of the number of words in individual tracks? Let's find out using the following code:

```
#adding year column by matching track_title
length_df$year <- lyrics$year[match(length_df$track_title, 

length_df %>%
 group_by(year) %>%
 summarise(length = mean(length)) %>%
   ggplot(., aes(x= factor(year), y=length, group = 1)) +
   geom_line(colour="#1CCCC6", size=1) +
   ylab("Average word count") + xlab ("Year") +
   ggtitle("Year-wise average Word count change") +
   theme_minimal()
```

e resulting chart confirms that the average word count has increased over the years om 285 in 2006 to 475 in 2017), i.e., her songs have gradually become lengthier in terms content.



We'll conclude exploratory analysis here and move to text mining.

Text mining

Our first activity would be to create a word cloud so that we can visualize the frequently of used words in her lyrics. Execute the following code to get started:

```
library("tm")
library("wordcloud")

lyrics_text <- lyrics$lyric
#Removing punctations and alphanumeric content
lyrics_text<- gsub('[[:punct:]]+', '', lyrics_text)
lyrics_text<- gsub("([[:alpha:]])\1+", "", lyrics_text)
```

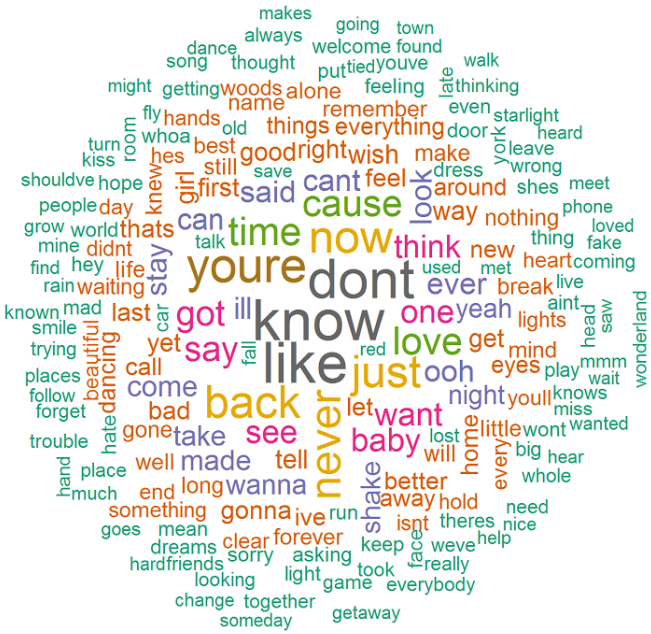
```
#creating a text corpus
docs <- Corpus(VectorSource(lyrics_text))
# Converting the text to lower case
docs <- tm_map(docs, content_transformer(tolower))
# Removing english common stopwords
docs <- tm_map(docs, removeWords, stopwords("english"))
# creating term document matrix
tdm <- TermDocumentMatrix(docs)
# defining tdm as matrix
m <- as.matrix(tdm)
# getting word counts in decreasing order
word_freqs = sort(rowSums(m), decreasing=TRUE)
# creating a data frame with words and their frequencies
lyrics_wc_df <- data.frame(word=names(word_freqs), freq=wor

lyrics_wc_df <- lyrics_wc_df[1:300,]

# plotting wordcloud

set.seed(1234)
wordcloud(words = lyrics_wc_df$word, freq = lyrics_wc_df$fr
min.freq = 1,scale=c(1.8,.5),
max.words=200, random.order=FALSE, rot.per=0.15,
colors=brewer.pal(8, "Dark2"))
```

The resulting word cloud shows that the most frequently used words are `know`, `like`, `don't`, `you're`, `now`, `back`. This confirms that her songs are predominantly about someone as `you're` has significant number of occurrences.



How about bigrams (word pairs that appear in conjunction)? The following code will give us the top 10 bigrams:

```
count_bigrams <- function(dataset) {
dataset %>%
unnest_tokens(bigram, lyric, token = "ngrams", n = 2) %>%
separate(bigram, c("word1", "word2"), sep = " ") %>%
filter(!word1 %in% stop_words$word,
!word2 %in% stop_words$word) %>%
count(word1, word2, sort = TRUE)
}

lyrics_bigrams <- lyrics %>%
count_bigrams()

head(lyrics_bigrams, 10)
```

Given below is the list of bigrams:

Word 1	Word 2
ey	ey
ooh	ooh
la	la
shake	shake
stay	stay
getaway	car
ha	ha
ooh	whoa
uh	uh
ha	ah

Although we found out the word list, it doesn't divulge any insight on several relationships that exist among words. To get a visualization of the multiple relationships that can exist we will leverage network graph. Let's get started with the following:

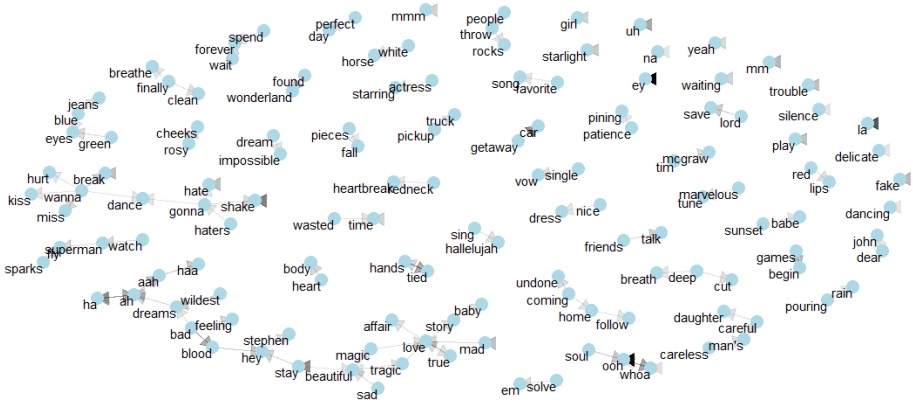
```
visualize_bigrams <- function(bigrams) {
set.seed(2016)
a <- grid::arrow(type = "closed", length = unit(.15, "inches

bigrams %>%
graph_from_data_frame() %>%
ggraph(layout = "fr") +
geom_edge_link(aes(edge_alpha = n), show.legend = FALSE, arr
geom_node_point(color = "lightblue", size = 5) +
geom_node_text(aes(label = name), vjust = 1, hjust = 1) +
ggtitle("Network graph of bigrams") +
theme_void()
}

lyrics_bigrams %>%
 filter(n > 3,
        !str_detect(word1, "\\d"),
        !str_detect(word2, "\\d")) %>%
visualize_bigrams()
```

Check out the graph given below to see how `love` is connected with `story`, `mad`, `true`, `tragic`, `magic` and `affair`. Also, both `tragic` and `magic` are connected with `beautiful`.

Network graph of bigrams



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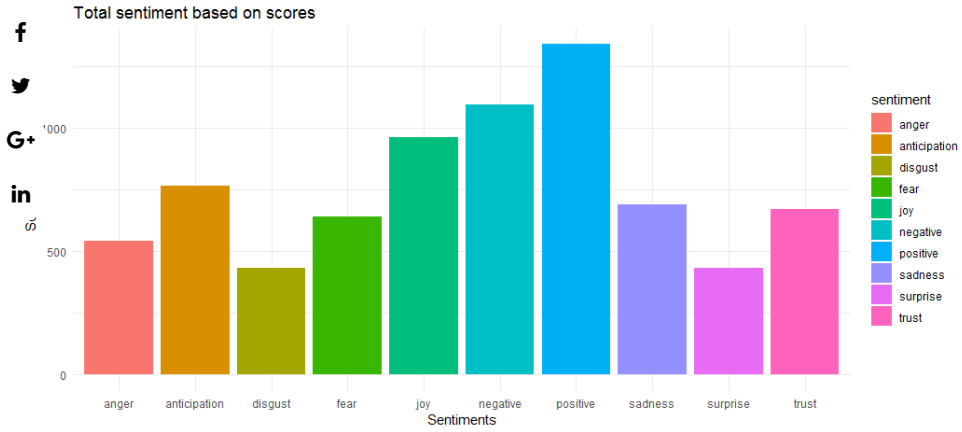
Let's now move to sentiment analysis which is a text mining technique.

Sentiment analysis

We'll first find out the overall sentiment via `nrc` method of `syuzhet` package. The following code will generate the chart of positive and negative polarity along with associated emotions.

```
# Getting the sentiment value for the lyrics
ty_sentiment <- get_nrc_sentiment((lyrics_text))

# Dataframe with cumulative value of the sentiments
sentimentscores<-data.frame(colSums(ty_sentiment[,]))

# Dataframe with sentiment and score as columns
names(sentimentscores) <- "Score"
sentimentscores <- cbind("sentiment"=rownames(sentimentscore
rownames(sentimentscores) <- NULL

# Plot for the cumulative sentiments
ggplot(data=sentimentscores,aes(x=sentiment,y=Score))+
geom_bar(aes(fill=sentiment),stat = "identity")+
theme(legend.position="none")+
xlab("Sentiments")+ylab("Scores")+
ggtitle("Total sentiment based on scores")+
theme_minimal()
```

The resulting chart shows that the positive and negative sentiment scores are relatively close with 1340 and 1092 value respectively. Coming to the emotions, `joy`, `anticipation` and `trust` emerge as the top 3.

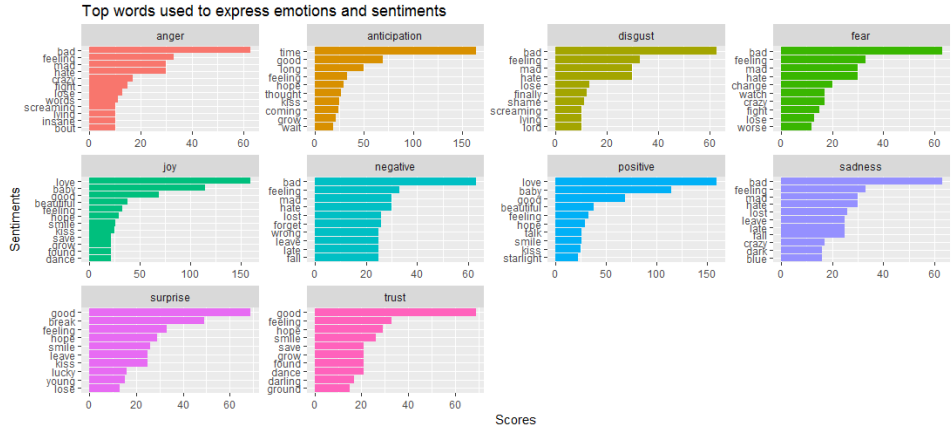


Now that we have figured out the overall sentiment scores, we should find out the top words that contribute to various emotions and positive/negative sentiment.

```
lyrics$lyric <- as.character(lyrics$lyric)

tidy_lyrics <- lyrics %>%
unnest_tokens(word,lyric)

song_wrd_count <- tidy_lyrics %>% count(track_title)

lyric_counts <- tidy_lyrics %>%
left_join(song_wrd_count, by = "track_title") %>%
rename(total_words=n)

lyric_sentiment <- tidy_lyrics %>%
inner_join(get_sentiments("nrc"),by="word")

lyric_sentiment %>%
count(word,sentiment,sort=TRUE) %>%
group_by(sentiment)%>%top_n(n=10) %>%
ungroup() %>%
ggplot(aes(x=reorder(word,n),y=n,fill=sentiment)) +
geom_col(show.legend = FALSE) +
```

```
facet_wrap(~sentiment,scales="free") +
xlab("Sentiments") + ylab("Scores")+
ggtitle("Top words used to express emotions and sentiments")+
coord_flip()
```

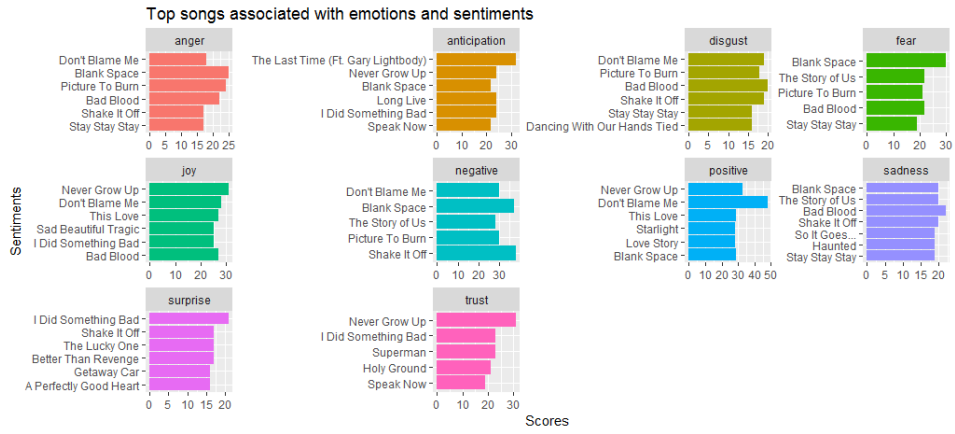
The visualization given shows that while the word `bad` is predominant in emotions such as `anger`, `disgust`, `sadness` and `fear,` `Surprise` and `trust` are driven by the word `good`.



This brings to the following question – which songs are closely associated with different emotions? Let's find out via the code given below:

```
lyric_sentiment %>%
count(track_title,sentiment,sort=TRUE) %>%
group_by(sentiment) %>%
top_n(n=5) %>%
ggplot(aes(x=reorder(track_title,n),y=n,fill=sentiment)) +
geom_bar(stat="identity",show.legend = FALSE) +
facet_wrap(~sentiment,scales="free") +
xlab("Sentiments") + ylab("Scores")+
ggtitle("Top songs associated with emotions and sentiments")+
coord_flip()
```

We see that the song `Black Space` has a lot of anger and fear in comparison to other songs. Don't blame me has considerable score for both `positive` and `negative` sentiment. We also see that `Shake it off` scores high for `negative` sentiment; mostly because of high frequency words such as `hate` and `fake`.



Let's now move to another sentiment analysis method, `bing` to create a comparative word cloud of positive and negative sentiment.

```
bng <- get_sentiments("bing")

set.seed(1234)

tidy_lyrics %>%
```

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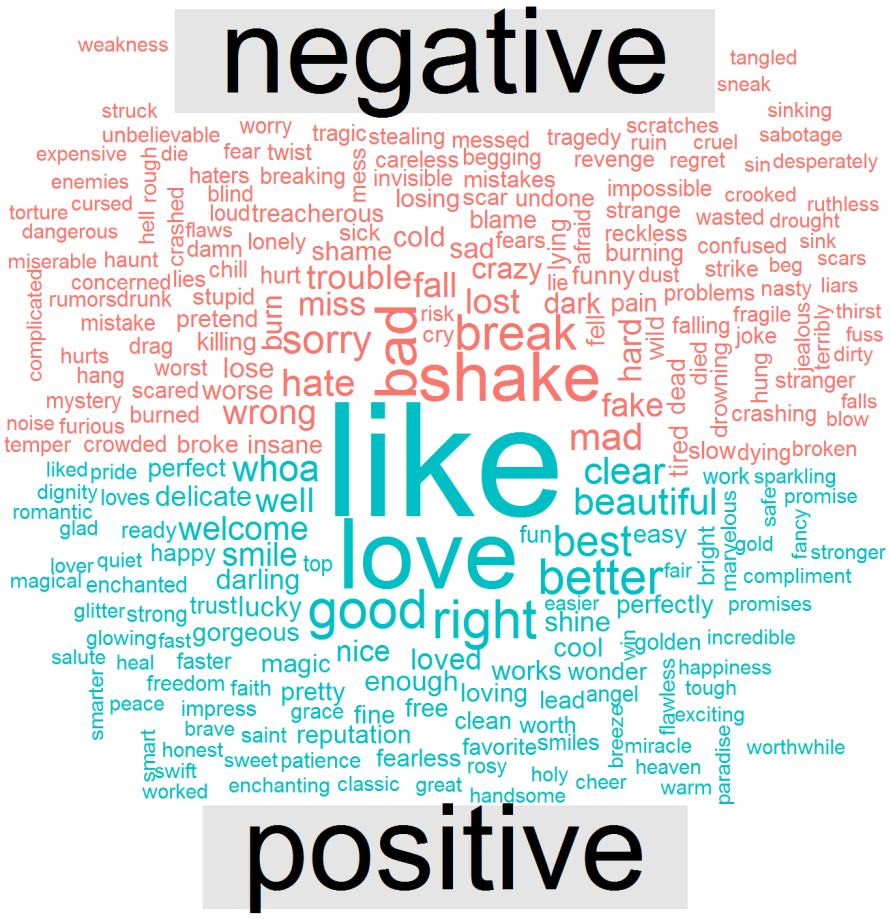
```
inner_join(get_sentiments("bing")) %>%
count(word, sentiment, sort = TRUE) %>%
acast(word ~ sentiment, value.var = "n", fill = 0) %>%
comparison.cloud(colors = c("#F8766D", "#00BFC4"),
max.words = 250)
```

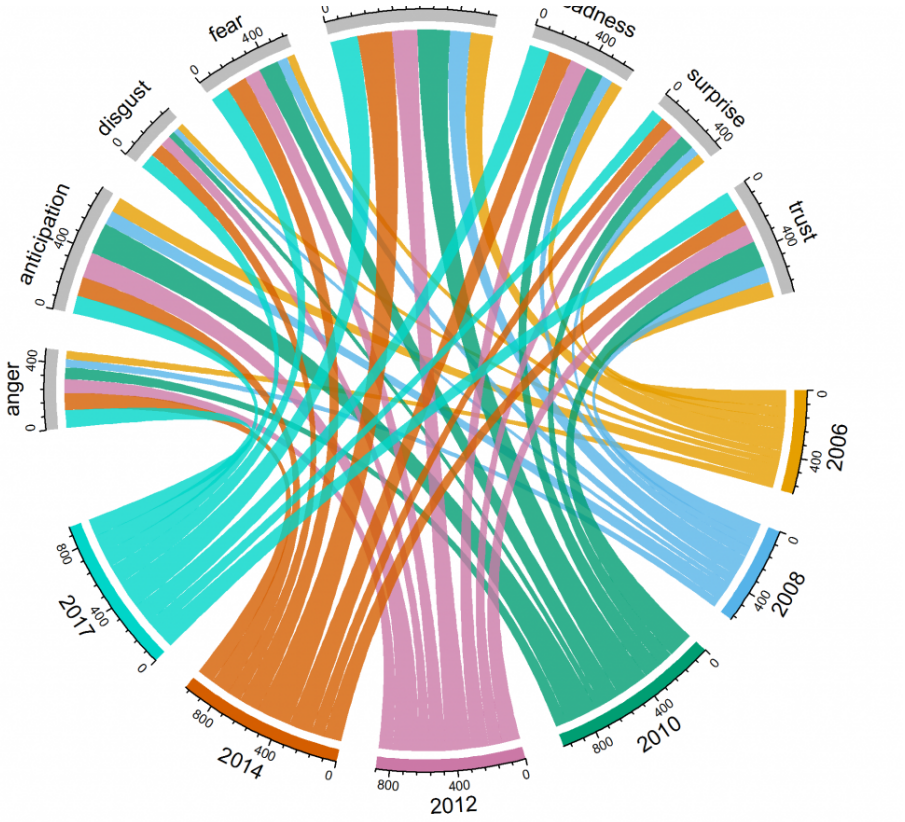
Following visualization shows that her songs have positive words such as `like`, `love`, `good`, `right` and negative words such as `bad`, `break`, `shake`, `mad`, `wrong`.



This brings to the final question – how has her sentiment and emotions changed over the years? For this particular answer we will create a visualization called `chord diagram`. Here is the code:

```
grid.col = c("2006" = "#E69F00", "2008" = "#56B4E9", "2010"

year_emotion <- lyric_sentiment %>%
filter(!sentiment %in% c("positive", "negative")) %>%
count(sentiment, year) %>%
group_by(year, sentiment) %>%
summarise(sentiment_sum = sum(n)) %>%
ungroup()

circos.clear()

#Setting the gap size
circos.par(gap.after = c(rep(6, length(unique(year_emotion[|
rep(6, length(unique(year_emotion[[2]])) - 1), 15))

chordDiagram(year_emotion, grid.col = grid.col, transparency
title("Relationship between emotion and song's year of relea
```

It gives us the following visualization:



e can see that `joy` has maximum share for the years 2010 and 2014. Overall, `urprise`, `disgust` and `anger` are the emotions with least score; however, in mparison to other years 2017 has maximum contribution for `disgust`. Coming to `ıticipation`, 2010 and 2012 have higher contribution in comparison to other years.

ver to you

In this study we performed exploratory analysis and text mining, which includes NLP for sentiment analysis. If you'd like to perform additional analyses (e.g., lexical density of lyrics and topic modeling) or simply replicate the results for learning, download the data set for free from DataStock. Simply follow the link given below and select "free" category on DataStock.

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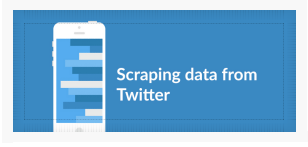

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