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A3: Business Insight Report

The luxury sector's transition during the Covid-19 era

Case introduction

The following report aims to analyze the luxury sector's behavior before, during, and after the pandemic of COVID-19, as well as suggest some strategies to create competitive advantage based on the main characteristics of these periods. In order to understand the general sentiment of luxury and what differentiates the three periods, a total of six different articles were used to perform sentiment analysis and TF_DIF calculations. The documents are industry reports and articles retrieved online and published in 2018-2019 (before the pandemic), 2020 (during the pandemic), and 2021 (end of the pandemic). For each period, two articles were chosen in order to reduce bias of the author/consulting firm. In fact, the goal is to understand the general thoughts about luxury during a certain period, regardless of who wrote the document.

Insights

Sentiment analysis

After structuring the articles' text into tidy data frames, removing stop words, and tokenizing them, a sentiment analysis was conducted. The aim of this analysis is to understand the general opinion or feeling regarding luxury that emerged from each period.

negative	positive	sentiment
57	86	29

Before the pandemic (2018)

anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust	sentiment
30	56	11	38	32	72	142	32	18	78	70

negative	positive	sentiment
64	93	29

During the pandemic (April 2020)

anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust	sentiment
31	61	14	43	37	66	165	22	29	88	99

negative	positive	sentiment
37	118	81

End of the pandemic (January 20201)

anger	anticipation	disgust	fear	joy	negative	positive	sadness	surprise	trust	sentiment
19	81	8	30	60	53	195	18	25	89	142

As we can observe from the sentiment analysis performed with "bing" and "nrc" packages, the overall sentiment remained almost the same before and during the pandemic, while it is becoming more positive as the pandemic is coming to an end. This might be because the luxury sector was already going slightly down in 2018, generating no big difference with the overall sentiment of the pandemic. However, now that the pandemic is coming to an end, people try to use more positive words that express sentiments of hope, joy and trust in what the future has to offer.

Contribution to negative sentiment:

2018

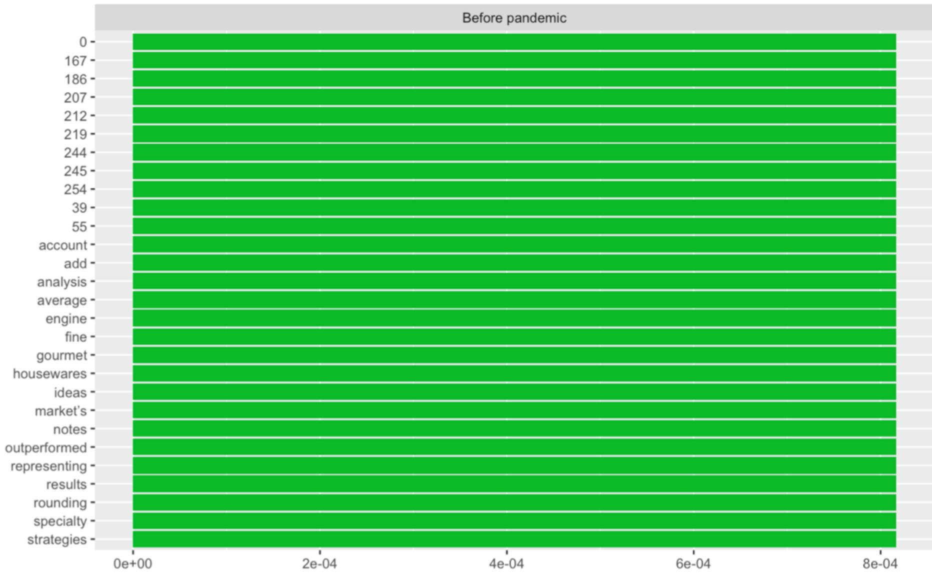
2020

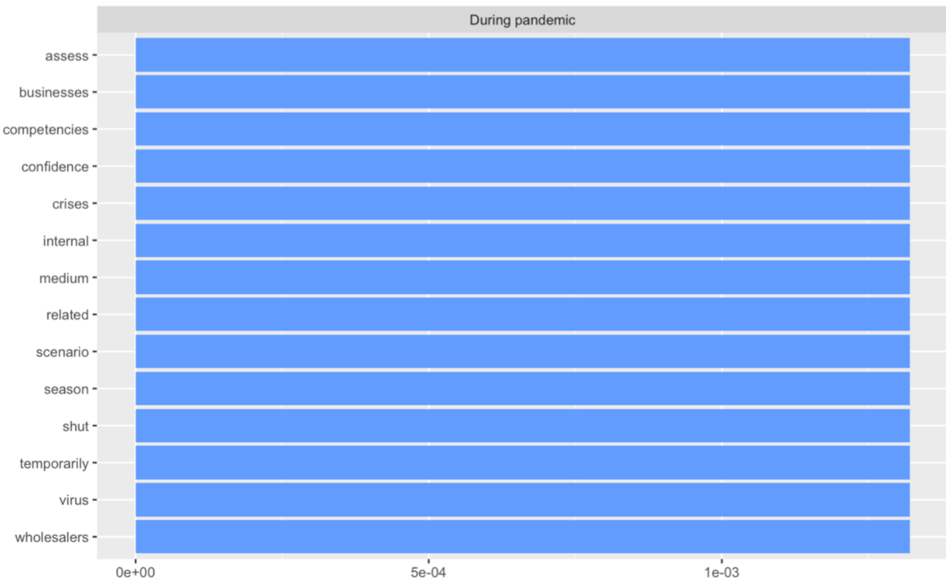
2021

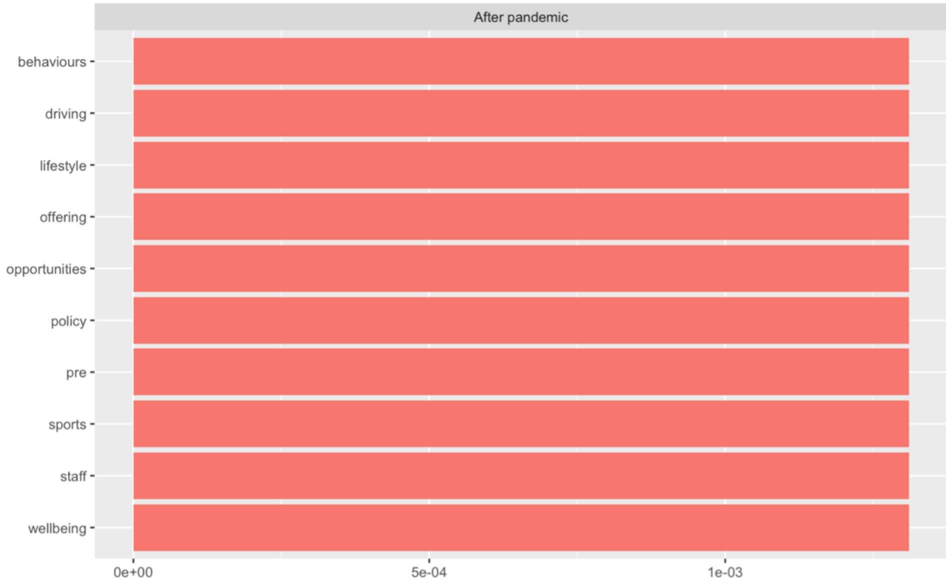
The negative sentiment deserves a particular highlight, as it is interesting to note what it was determined by. In 2018, as we already mentioned, the negative sentiment was mainly due to the general economic instability and the downsizing of the luxury sector. In fact, we see words such as "worries", "turbulent", and "threat", that define the situation on overall uncertainty. In 2020, then, words like “virus”, “urgent”, and “uncertain” start shaping a new negative feeling, the one caused by the pandemic of Covid-19, that floated the already suffering global economy. Today we are assisting a new era, “volatile” and “unclear”, where most issues caused by the pandemic are still “unresolved”; all these words express mainly fear, disgust and sadness, as well as (negative) surprise, and can be found in the deeper sentiment analysis performed with “nrc”.

TF-IDF analysis

The Tf-idf (Term Frequency – Inverse Document Frequency) analysis’ main purpose is to identify the most original and unique words, present in one specific document and not in the others, making it substantially differentiable. According to the Zipf’s Law, there is an inverse proportion between the frequency that a word appears and its rank. In fact, the brightest insights are often offered by less common words, the ones that do not appear too often, but that characterize the documents that contains them and make it unique.







The articles that describe the luxury sector before the pandemic contain mainly numbers that describe the economic and financial performance of the industry. Other unique words found in these documents represent, in fact, indexes of performance, such as “account”, “add”, “analysis”, “average”, “outperformed”, “market” and “results”. The other words indicate common trends, such as housewares and gourmet products.

During the pandemic the situation changes drastically and articles about luxury mainly talk about “crises” and “temporarily shut”, probably referring to many companies’ activity. They also try to imagine possible “scenarios” and talk about the “virus”.

At the moment, in January 2021, the pandemic is hopefully almost over, as hospitals started to vaccinate people; restaurants and shops became to reopen. During this period, companies are trying to understand consumers and markets’ “behaviours”, in order to plan the strategy that will help them survive in a post-pandemic era. “Lifestyle”, “wellbeing” and “sports” are powerful keywords, as during the pandemic at-home fitness, personal health and home décor became extremely popular topics and incredible “opportunities”.

Conclusion

As we are finally coming to the end of the Covid-19 pandemic, that destroyed many businesses and made other ones rise, luxury should focus mainly on the better understanding of consumer behaviors. In fact, these changed drastically during the past months, as people's priorities shifted toward more responsible and well-being-oriented ones. Being healthy and happy at home became the main new trend, and every company that can satisfy these needs has certainly a higher probability of survival.

Therefore, in order to create and sustain competitive advantage, a company that operates in the luxury sector must focus on these emerging trends:

1. Lifestyle – everything that goes beyond the simple, ephemerae products and generates value by providing long-lasting quality. Products and services must reflet people's new values and priorities
2. Personal health and well-being – focus on improving people's quality of life, under every aspect
3. Sport – with more free time, most of the people decided to dedicate more time to sports and physical activity.

A shift toward this direction can be the best choice that a company could make during these unprecedented times.

Appendix:

Code

```
# importing libraries
library(dplyr)
library(stringr)
library(tidytext)
library(tidyr)
library(tm)
library(pdftools)
library(ggplot2)

# importing files as PDFs
setwd("/Users/camillabrossa/Desktop/HULT Business School/MBAN/TEXT ANALYTICS & NLP/BUSINESS REPORT/2019")
nm1 <- list.files(path="/Users/camillabrossa/Desktop/HULT Business School/MBAN/TEXT ANALYTICS & NLP/BUSINESS REPORT/2019")
articles_2019 <- do.call(rbind, lapply(nm1, function(x) paste(pdf_text(x), collapse = " ")))

setwd("/Users/camillabrossa/Desktop/HULT Business School/MBAN/TEXT ANALYTICS & NLP/BUSINESS REPORT/2020")
```

```
nm2 <- list.files(path="/Users/camillabrossa/Desktop/HULT Business School/MBAN/TEXT ANALYTICS & NLP/BUSINESS REPORT/2020")

articles_2020 <- do.call(rbind, lapply(nm2, function(x) paste(pdf_text(x), collapse = " ")))


setwd("/Users/camillabrossa/Desktop/HULT Business School/MBAN/TEXT ANALYTICS & NLP/BUSINESS REPORT/2021")

nm3 <- list.files(path="/Users/camillabrossa/Desktop/HULT Business School/MBAN/TEXT ANALYTICS & NLP/BUSINESS REPORT/2021")

articles_2021 <- do.call(rbind, lapply(nm3, function(x) paste(pdf_text(x), collapse = " ")))



## FROM UNSTRUCTURED TO STRUCTURED DATA

# Tokenization


# 2019


colnames(articles_2019) <- c("text")


mydf19 <- data.frame(line=1:2, text = articles_2019[,1])


token_list19 <-  mydf19 %>%
  unnest_tokens(word, text) %>%
  anti_join(stop_words) %>%
  count(word, sort=TRUE)


# 2020


colnames(articles_2020) <- c("text")


mydf20 <- data.frame(line=1:2, text = articles_2020[,1])


token_list20 <-  mydf20 %>%
  unnest_tokens(word, text) %>%
  anti_join(stop_words) %>%
  count(word, sort=TRUE)


# 2021


colnames(articles_2021) <- c("text")


mydf21 <- data.frame(line=1:2, text = articles_2021[,1])


token_list21 <-  mydf21 %>%
  unnest_tokens(word, text) %>%
  anti_join(stop_words) %>%
  count(word, sort=TRUE)
```

```
## SENTIMENT ANALYSIS
# get the sentiment with BING (binary: positive/negative)
bing_2019 <- token_list19 %>%
  inner_join(get_sentiments("bing")) %>%
  count(sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)
bing_2019
```

```
> bing_2019
  negative positive sentiment
1       57       86        29
>
```

```
bing_2020 <- token_list20 %>%
  inner_join(get_sentiments("bing")) %>%
  count(sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)

bing_2020
```

```
> bing_2020
  negative positive sentiment
1       64       93        29
>
```

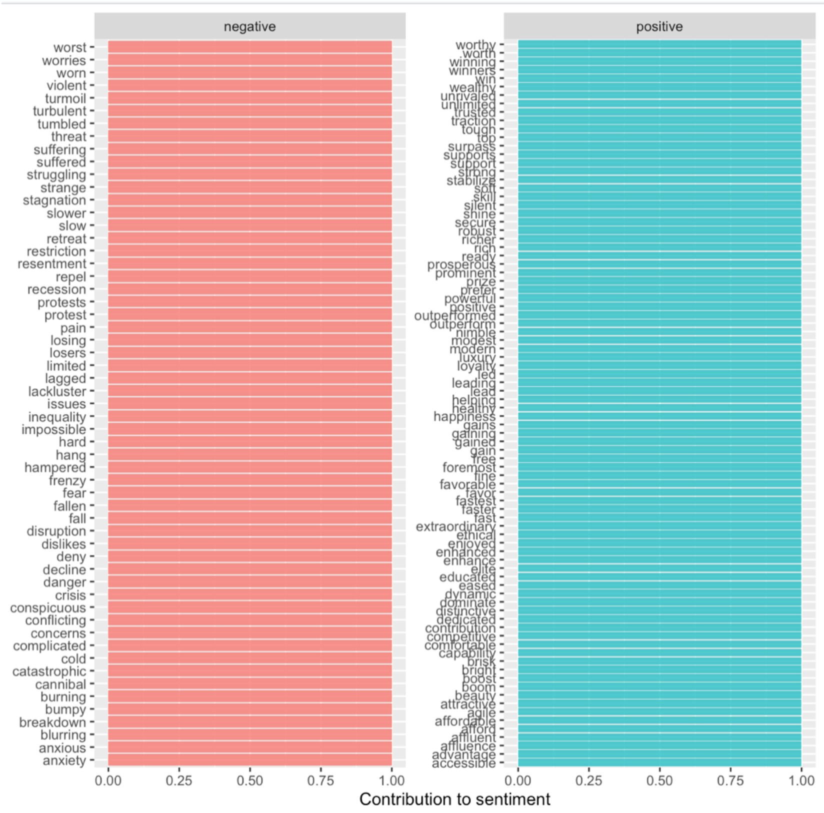
```
bing_2021 <- token_list21 %>%
  inner_join(get_sentiments("bing")) %>%
  count(sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)

bing_2021
```

```
> bing_2021
  negative positive sentiment
1       37      118        81
>
```

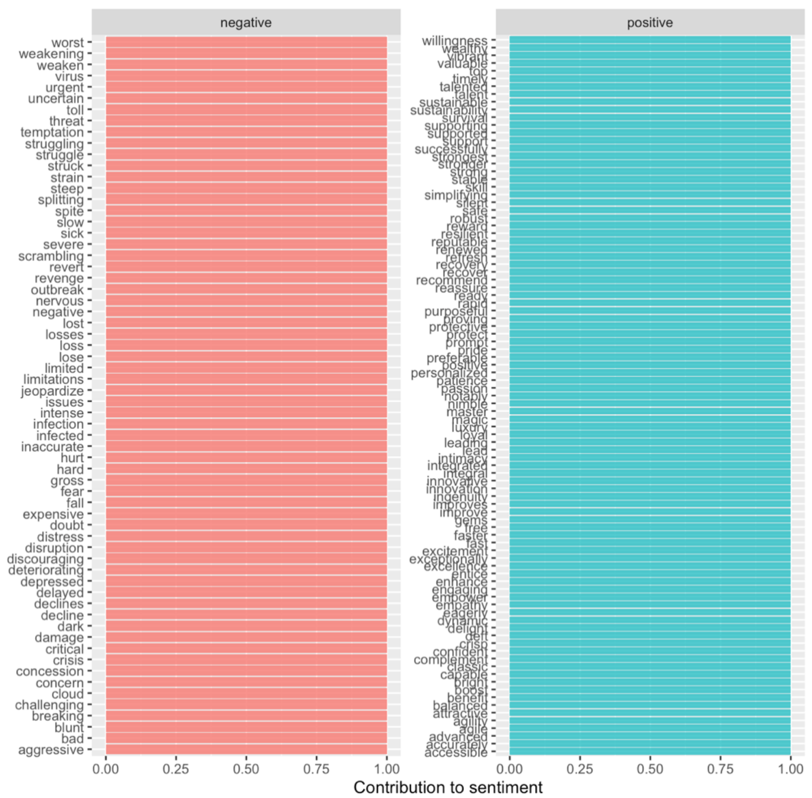
```
# get a deeper view of sentiment with NRC
nrc_2019 <- token_list19 %>%
```

```
  inner_join(get_sentiments("nrc")) %>%
  count(sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)
nrc_2019

> nrc_2019
  anger anticipation disgust fear joy negative positive sadness surprise trust sentiment
1    30           56      11   38  32       72      142      32       18    78        70
>

nrc_2020 <- token_list20 %>%
  inner_join(get_sentiments("nrc")) %>%
  count(sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)
nrc_2020
> nrc_2020
  anger anticipation disgust fear joy negative positive sadness surprise trust sentiment
1    31           61      14   43  37       66      165      22       29    88        99
>

nrc_2021 <- token_list21 %>%
  inner_join(get_sentiments("nrc")) %>%
  count(sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(sentiment = positive - negative)
nrc_2021

> nrc_2021
  anger anticipation disgust fear joy negative positive sadness surprise trust sentiment
1    19           81       8   30  60       53      195      18       25    89       142
>

# QUANTIFYING SENTIMENT
# counting bing words 2019
bing_words_19 <- token_list19 %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()


# counting bing words 2020
bing_words_20 <- token_list20 %>%
  inner_join(get_sentiments("bing")) %>%
```

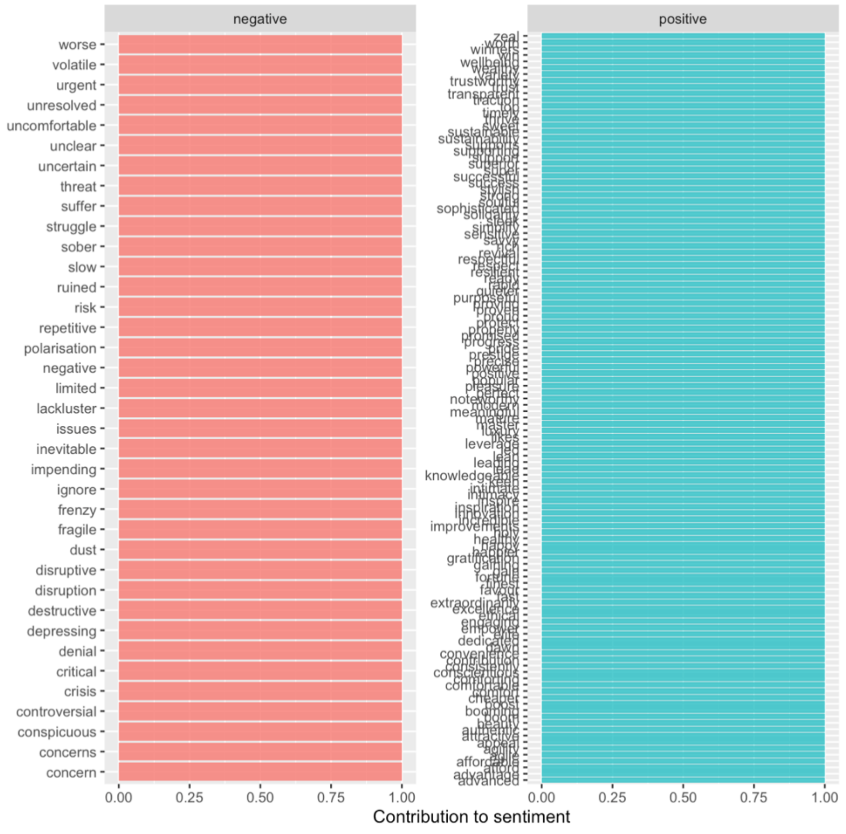
```
  count(word, sentiment, sort = TRUE) %>%
  ungroup()


# counting bing words 2021
bing_words_21 <- token_list21 %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()


########################

# counting nrc words 2019
nrc_words_19 <- token_list19 %>%
  inner_join(get_sentiments("nrc")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()


# counting nrc words 2020
nrc_words_20 <- token_list20 %>%
  inner_join(get_sentiments("nrc")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()


# counting nrc words 2021
nrc_words_21 <- token_list21 %>%
  inner_join(get_sentiments("nrc")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()


# VISUALIZATION: CONTRIBUTION TO SENTIMENT
# 2019 - Bing
bing_words_19 %>%
  group_by(sentiment) %>%
  top_n(3) %>%
  ggplot(aes(reorder(word, n), n, fill = sentiment)) +
  geom_bar(alpha = 0.8, stat = "identity", show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment", x = NULL) +
  coord_flip()
```




```
# 2020 - Bing
bing_words_20 %>%
  group_by(sentiment) %>%
  top_n(3) %>%
  ggplot(aes(reorder(word, n), n, fill = sentiment)) +
  geom_bar(alpha = 0.8, stat = "identity", show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment", x = NULL) +
  coord_flip()
```



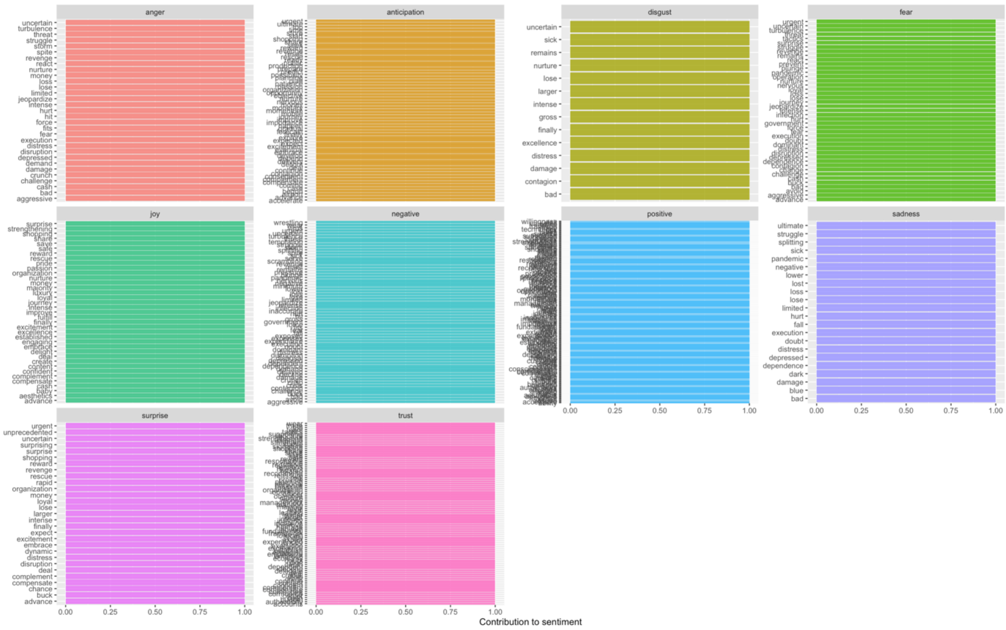
```
# 2021 - Bing
bing_words_21 %>%
  group_by(sentiment) %>%
  top_n(2) %>%
  ggplot(aes(reorder(word, n), n, fill = sentiment)) +
  geom_bar(alpha = 0.8, stat = "identity", show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment", x = NULL) +
  coord_flip()
```

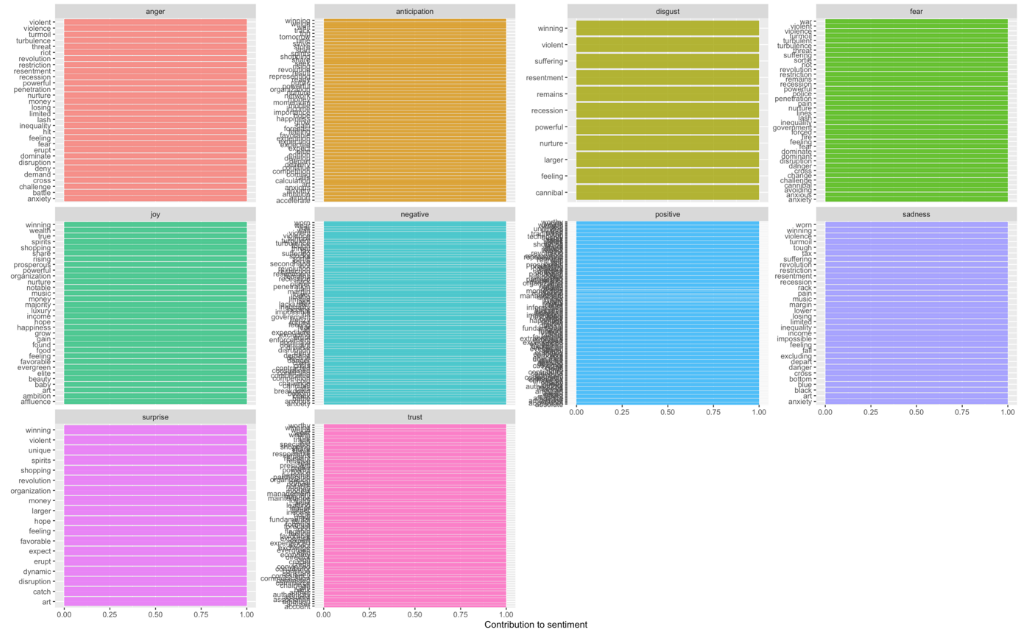



```
###############
# 2019 - Nrc
nrc_words_19 %>%
  group_by(sentiment) %>%
  top_n(3) %>%
  ggplot(aes(reorder(word, n), n, fill = sentiment)) +
  geom_bar(alpha = 0.8, stat = "identity", show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment", x = NULL) +
  coord_flip()
```

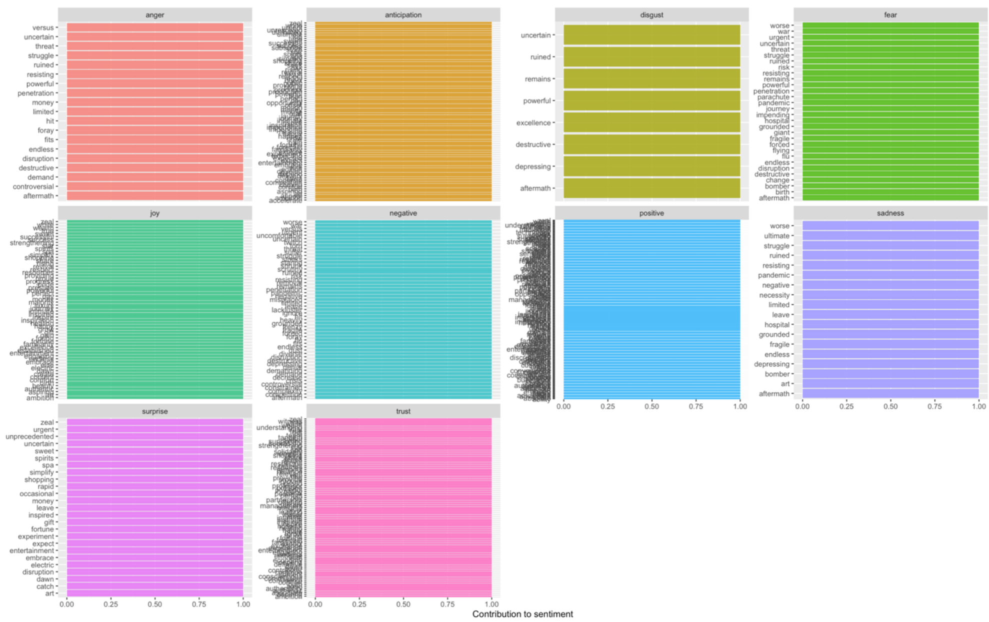
```
# 2020 - Nrc
nrc_words_20 %>%
  group_by(sentiment) %>%
  top_n(3) %>%
  ggplot(aes(reorder(word, n), n, fill = sentiment)) +
  geom_bar(alpha = 0.8, stat = "identity", show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment", x = NULL) +
  coord_flip()
```

```
# 2021 - Nrc
nrc_words_21 %>%
  group_by(sentiment) %>%
  top_n(3) %>%
  ggplot(aes(reorder(word, n), n, fill = sentiment)) +
  geom_bar(alpha = 0.8, stat = "identity", show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment", x = NULL) +
  coord_flip()
```






```
####################
```




```
##
```

```
##TF_IDF
# creating a single dataframe where we store all the document tokens
global_idf <- bind_rows(mutate(token_list19, period="Before pandemic"),
                        mutate(token_list20, period="During pandemic"),
                        mutate(token_list21, period= "After pandemic"))

# calculating the td_idf for each token
token_tf_idf <- global_idf %>%
  bind_tf_idf(word, period, n)
token_tf_idf
```

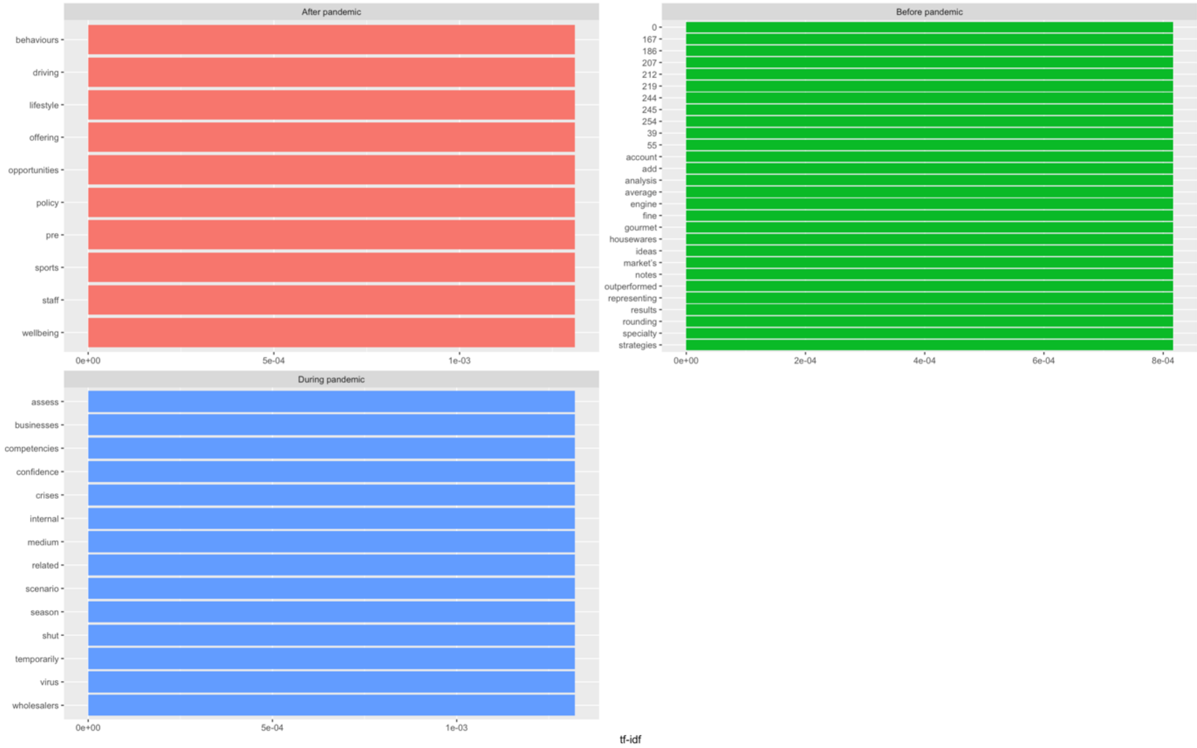
```
# sorting it in descending order, filtering for frequency < 10
token_tf_idf %>%
  arrange(desc(tf_idf)) %>%
  filter(n<10)
```

	word	n	period	tf	idf	tf_idf
1	first	9	During pandemic	0.0027051398	1.0986123	0.0029718998
2	resilience	9	During pandemic	0.0027051398	1.0986123	0.0029718998
3	3753954532e8	9	After pandemic	0.0026841634	1.0986123	0.0029488549
4	stephanegirod	9	After pandemic	0.0026841634	1.0986123	0.0029488549
5	scenarios	8	During pandemic	0.0024045687	1.0986123	0.0026416887
6	rst	8	After pandemic	0.0023859231	1.0986123	0.0026212044
7	tier	7	During pandemic	0.0021039976	1.0986123	0.0023114776
8	maximize	6	During pandemic	0.0018034265	1.0986123	0.0019812665
9	perspective	6	During pandemic	0.0018034265	1.0986123	0.0019812665
10	plans	6	During pandemic	0.0018034265	1.0986123	0.0019812665
11	quarter	6	During pandemic	0.0018034265	1.0986123	0.0019812665
12	teams	6	During pandemic	0.0018034265	1.0986123	0.0019812665
13	alibaba	6	After pandemic	0.0017894423	1.0986123	0.0019659033
14	st	6	After pandemic	0.0017894423	1.0986123	0.0019659033

```
# visualizing it
token_tf_idf %>%
  arrange(desc(tf_idf)) %>%
  mutate(word=factor(word, levels=rev(unique(word)))) %>%
  group_by(period) %>%
  filter(n<5) %>%
  top_n(7) %>%
  ungroup() %>%
  ggplot(aes(word, tf_idf, fill=period))+
  geom_col(show.legend=FALSE)+
  labs(x=NULL, y="tf-idf")+
  facet_wrap(~period, ncol=2, scales="free")+
```

	word	n	period	tf	idf	tf_idf
1	luxury	270	Before pandemic	0.050157905	0.0000000	0.0000000000
2	market	130	Before pandemic	0.024150102	0.0000000	0.0000000000
3	sales	73	Before pandemic	0.013561211	0.0000000	0.0000000000
4	growth	70	Before pandemic	0.013003901	0.0000000	0.0000000000
5	2018	69	Before pandemic	0.012818131	0.4054651	0.0051973049
6	4	47	Before pandemic	0.008731191	0.0000000	0.0000000000
7	brands	46	Before pandemic	0.008545421	0.0000000	0.0000000000
8	personal	45	Before pandemic	0.008359651	0.0000000	0.0000000000
9	consumers	41	Before pandemic	0.007616571	0.0000000	0.0000000000
10	global	40	Before pandemic	0.007430801	0.0000000	0.0000000000
11	2019	39	Before pandemic	0.007245031	0.0000000	0.0000000000
12	2017	38	Before pandemic	0.007059261	1.0986123	0.0077553905
13	online	38	Before pandemic	0.007059261	0.0000000	0.0000000000
14	bain	37	Before pandemic	0.006873491	0.4054651	0.0027869606

```
coord_flip()
```



After pandemic
behaviours
driving
lifestyle
offering
opportunities
policy
pre
sports
staff
wellbeing
0e+00
5e-04
1e-03
Before pandemic
0
167
186
207
212
219
244
245
254
39
55
account
add
analysis
average
engine
fine
gourmet
housewares
ideas
market's
notes
outperformed
representing
results
rounding
specialty
strategies
0e+00
2e-04
4e-04
6e-04
8e-04
During pandemic
assess
businesses
competencies
confidence
crises
internal
medium
related
scenario
season
shut
temporarily
virus
wholesalers
0e+00
5e-04
1e-03
tf-idf

Bibliography:

Achille, A., & Zipser, D. (2020, December 14). A perspective for the luxury-goods industry during--and after--coronavirus. Retrieved February 11, 2021, from https://www.mckinsey.com/industries/retail/our-insights/a-perspective-for-the-luxury-goods-industry-during-and-after-coronavirus

Beauloye, F. E. (2021). The future of LUXURY: 6 Luxury trends to stay ahead in 2021. Retrieved February 11, 2021, from https://luxe.digital/business/digital-luxury-trends/luxury-future-trends/

D'Arpizio, C., Levato, F., & Montgolfier, J. (2019, October 24). The future of LUXURY: A look into tomorrow to understand today. Retrieved February 11, 2021, from https://www.bain.com/insights/luxury-goods-worldwide-market-study-fall-winter-2018/

D'Arpizio, C., Levato, F., Fenili, S., Colacchio, F., & Prete, F. (2020, December 04). Luxury after Covid-19: Changed FOR (THE) GOOD? Retrieved February 11, 2021, from https://www.bain.com/insights/luxury-after-coronavirus/

Danziger, P. (2018, December 21). 4 mega-trends ahead for the luxury market in 2019: Expect turmoil and slowing sales. Retrieved February 11, 2021, from https://www.forbes.com/sites/pamdanziger/2018/12/18/whats-ahead-for-the-luxury-market-in-2019-expect-turmoil-and-slowing-sales/

Girod, S. (2021, January 26). How luxury brands plan to reconnect with local consumers in post-covid 2021. Retrieved February 11, 2021, from https://www.forbes.com/sites/stephanegirod/2021/01/13/how-luxury-brands-plan-to-reconnect-with-local-consumers-in-post-covid-2021/?sh=3753954532e8