SENTIMENT AND TOPIC ANALYSIS – FASHION INDUSTRY AND THE METAVERSE

Web Data & Digital Analytics - *Spring Semester 2022*

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Our Team

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Agenda

1. RESEARCH OUTLINE AND ASSUMPTIONS
2. BACKGROUND RESEARCH
3. SENTIMENT ANALYSIS
4. TOPIC MODELLING
5. RESULTS
6. LIMITATIONS & BUSINESS IMPLICATIONS
7. FURTHER INSIGHTS

What about you?

What are the first **2-3 words** you associate with the metaverse/Metaverse Fashion Week?

https://admin.sli.do/event/hT9LsV4ETM7zxzJv4F3U7h/polls

Research Outline

Background Research	• Goal: understand the Metaverse and the Metaverse Fashion Week (MVFW)
Sentiment Analysis	• Assumptions: the detected "hype" is replicated in the sentiment trend • Goal: discover the sentiment surrounding the event and assess its evolution during the 3 selected periods (before – during – after)
Topic Modelling	• Hypothesis: - Before → innovation, excitement & (presentation of) brands/participants - During → specifics of the event - After → failure and disappointment • Goal: finding out the most relevant topics of the tweets containing "#metaversefashionweek", based on the three defined temporal periods

Background research

What is the Metaverse

*"The metaverse is a **seamless convergence** of our physical and digital lives, creating a unified, **virtual community** where we can work, play, relax, transact and socialize"*

(JP Morgan, 2022).

1

Massive Multiplayer Online Video Games (MMO)

SECOND LIFE

MINECRAFT

FORTNITE

ROBLOX

2

Decentralized Virtual Worlds

CRYPTOVOXELS

Decentraland

What about the World?

December 2021- May 2022

Background research

What is the Metaverse Fashion Week?

	MVFW	MFW
When	24th – 27th March 2022	22nd – 28th February 2022
Where	Decentraland platform	Unicredit Pavilion
# unique attendees	108,000	6,000
# brands	> 55	70

ETRO	TOMMY HILFIGER	PERRY ELLIS	ESTĒE LAUDER	NICHOLAS KIRKWOOD
27.8 K	1.5 M	19.9 K	411.4 K	7.79 K
ELIE SAAB	HOGAN	DUNDAS	DOLCE & GABBANA	imitation +++
398 K	14.9 K	/	5.3 M	72

Background research

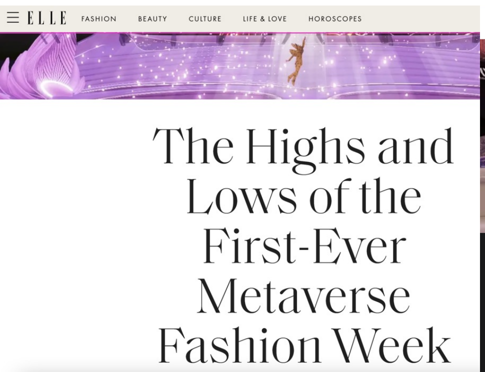
Comments from the press on the MVFW

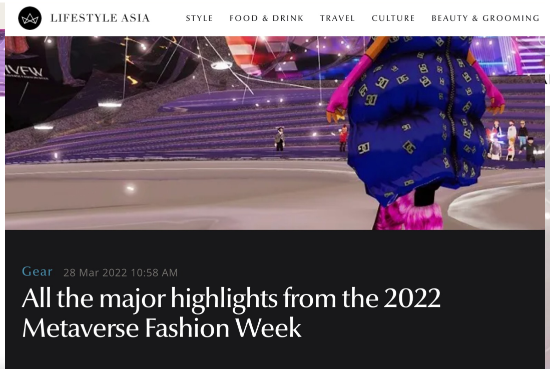
HIGHS:

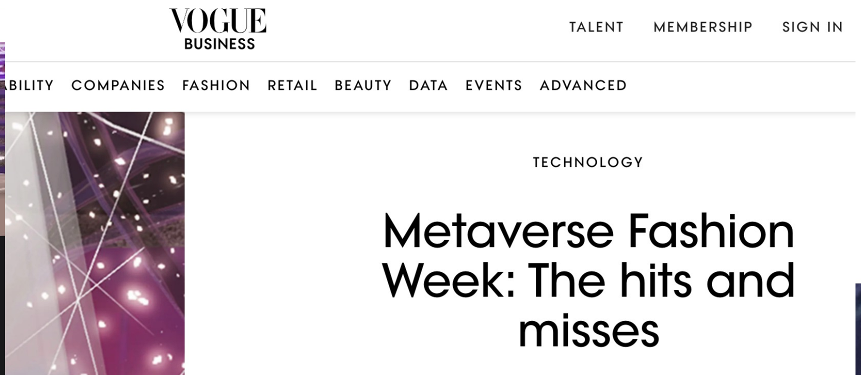
Democratization of luxury
Promising prototype
Sustainability
Creativity boost
Good mood

LOWS:

- ✗ Sociability
- ✗ Rudimentary UX
- ✗ Downside of sustainability
- ✗ Simplified aesthetics
- ✗ Chaotic and unregulated Interactions



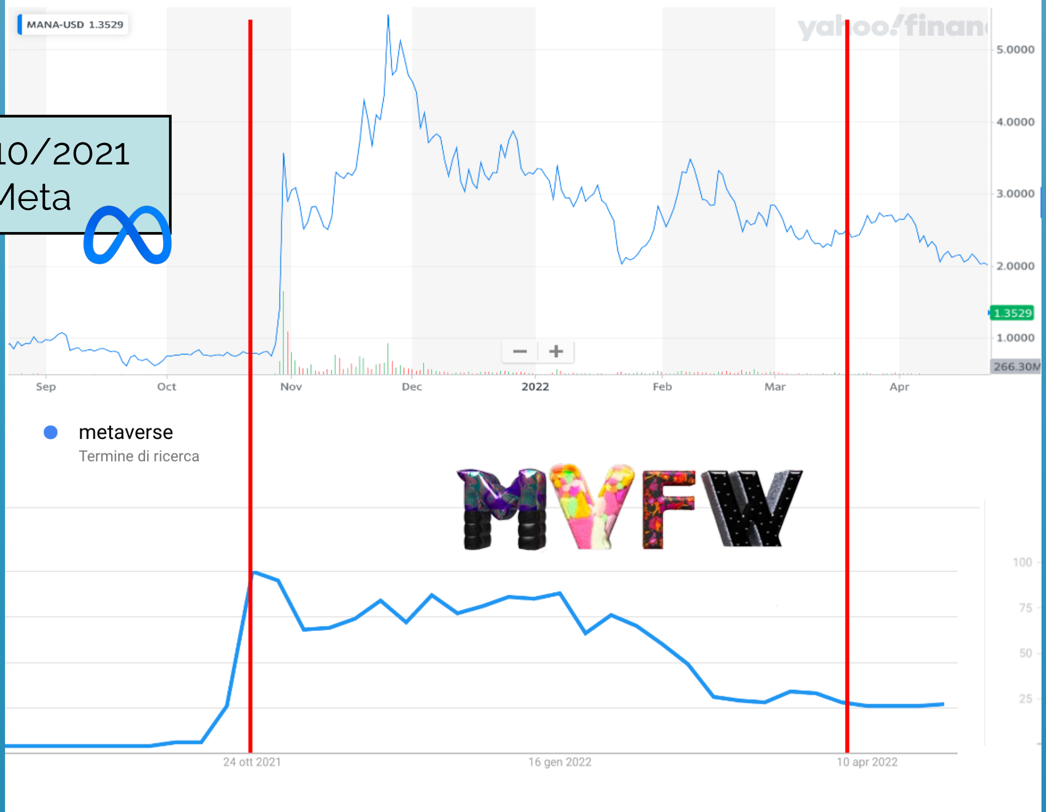




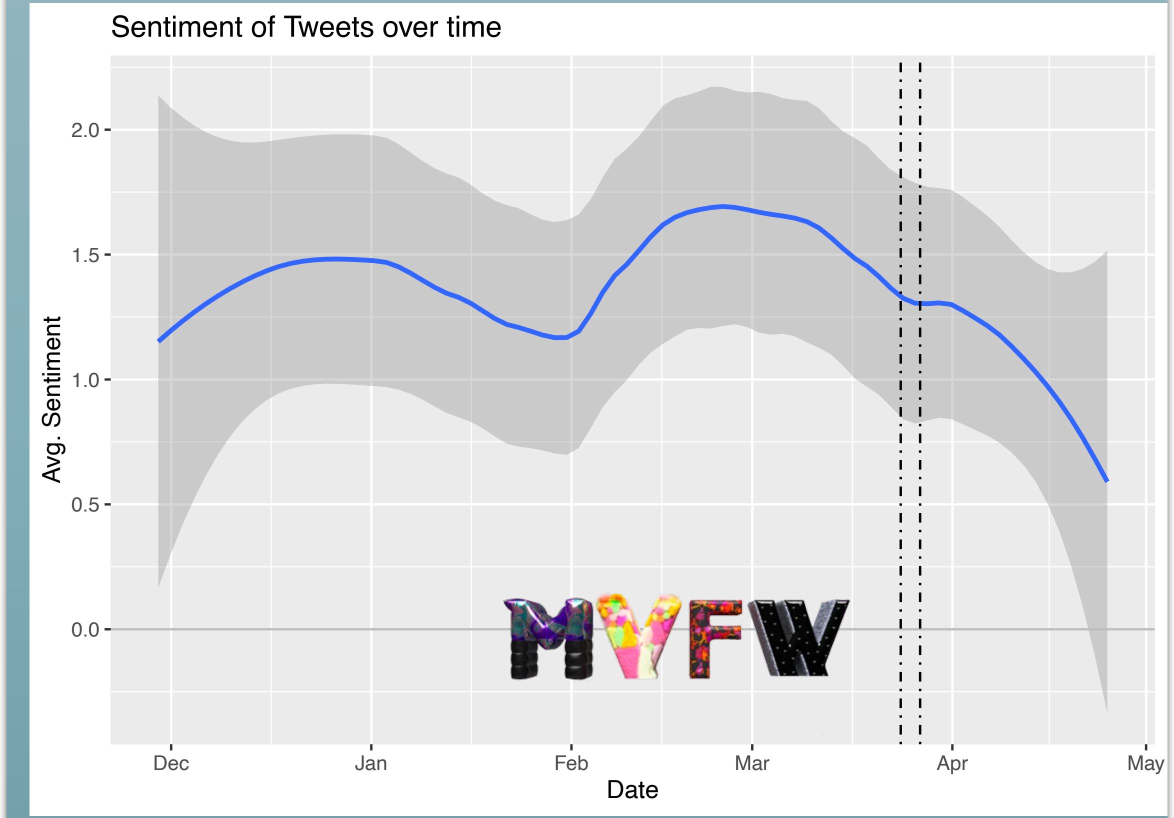
Trend Comparison

Sentiment Analysis vs Stock Market Activity & Google Trends

28/10/2021
Meta



24 – 27/03/2022
MVFW



24 – 27/03/2022
MVFW

Research Outline

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Sentiment Analysis

Methodology

Methods:

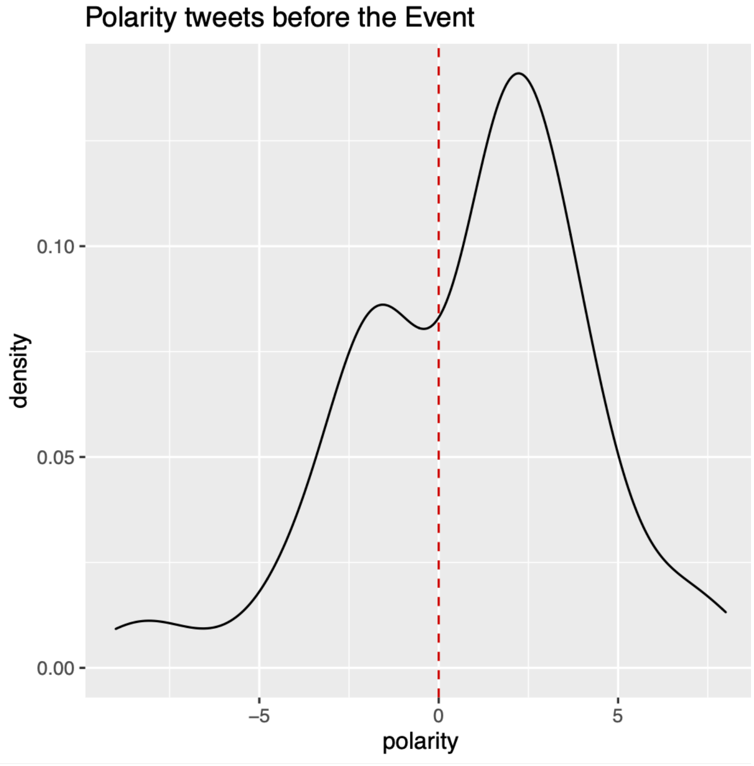
Scraping > Cleaning data > Dividing by periods > Sentiment Analysis

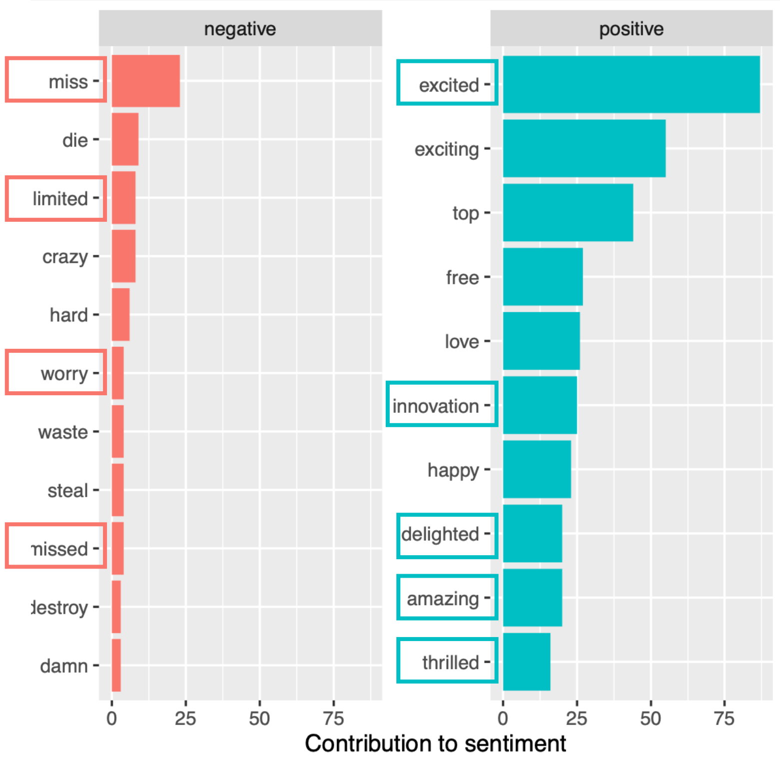
Sentiment Analysis:

- Word cloud
- Lexicons: “afinn”, “bing” and “nrc”
- Sentiment before, during, and after
- Graph > ggplot

Analysis

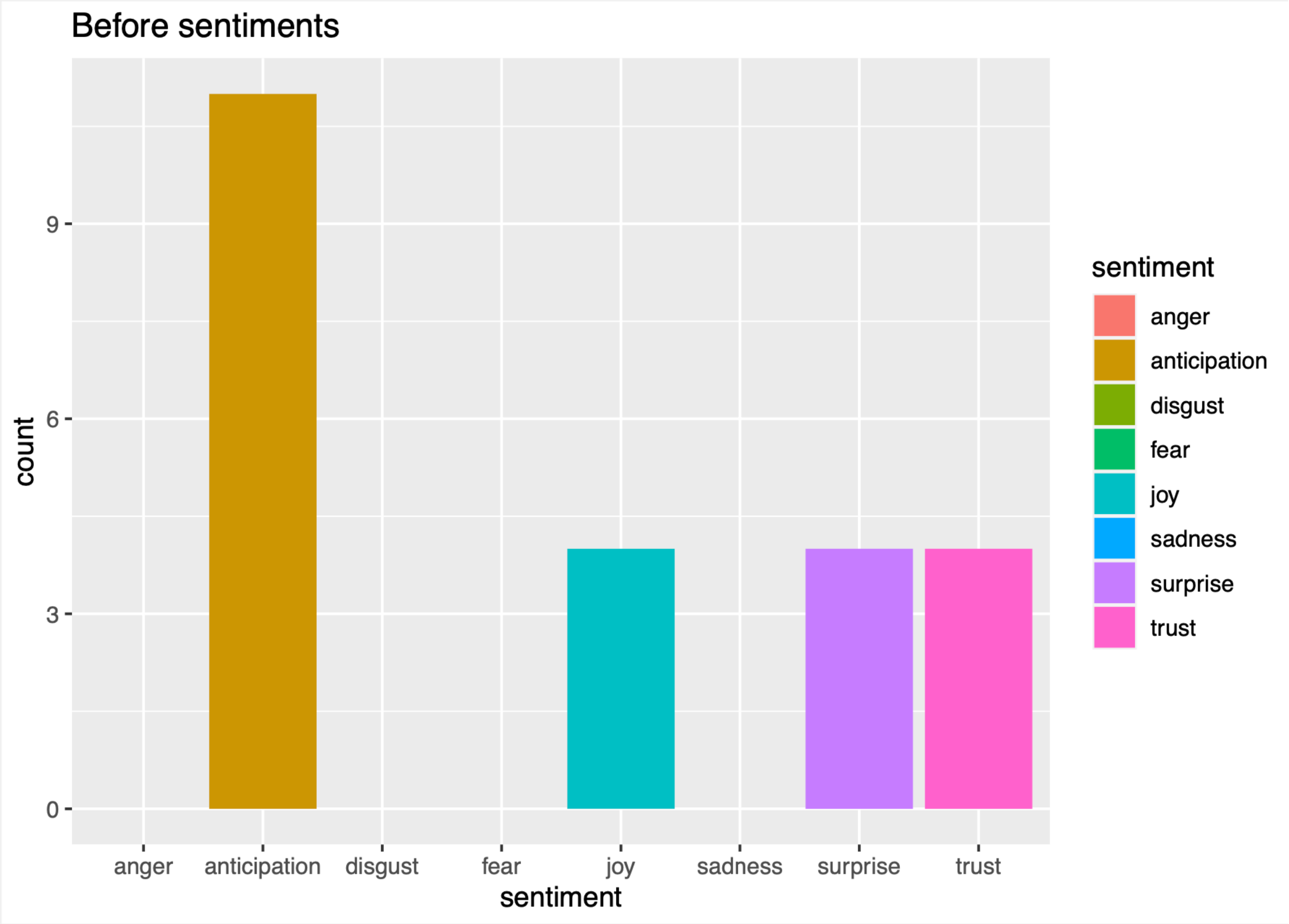
Sentiment Analysis – Before the MVFW





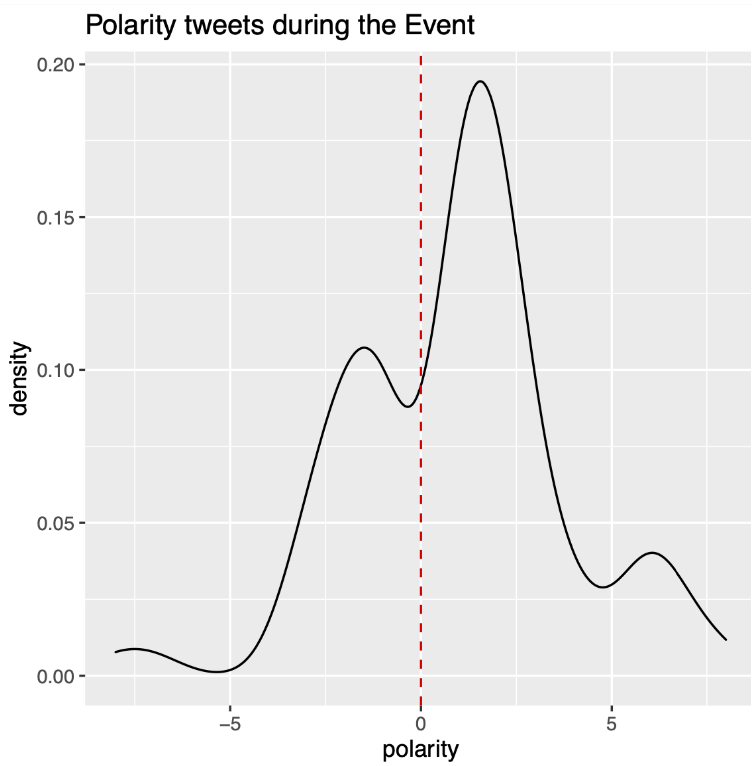
Analysis

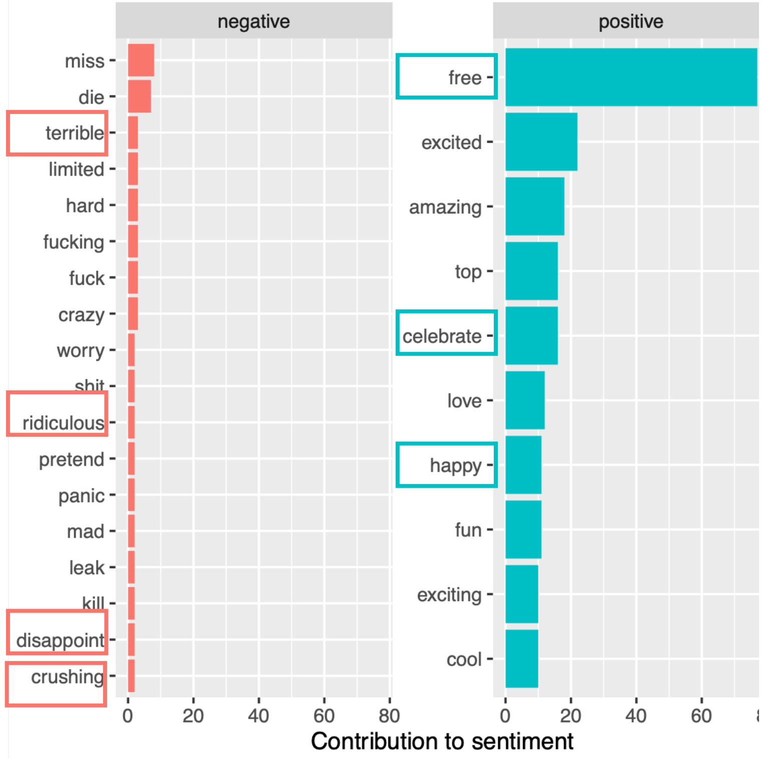
Sentiment Analysis – Before the MVFW (“nrc” lexicon)



Analysis

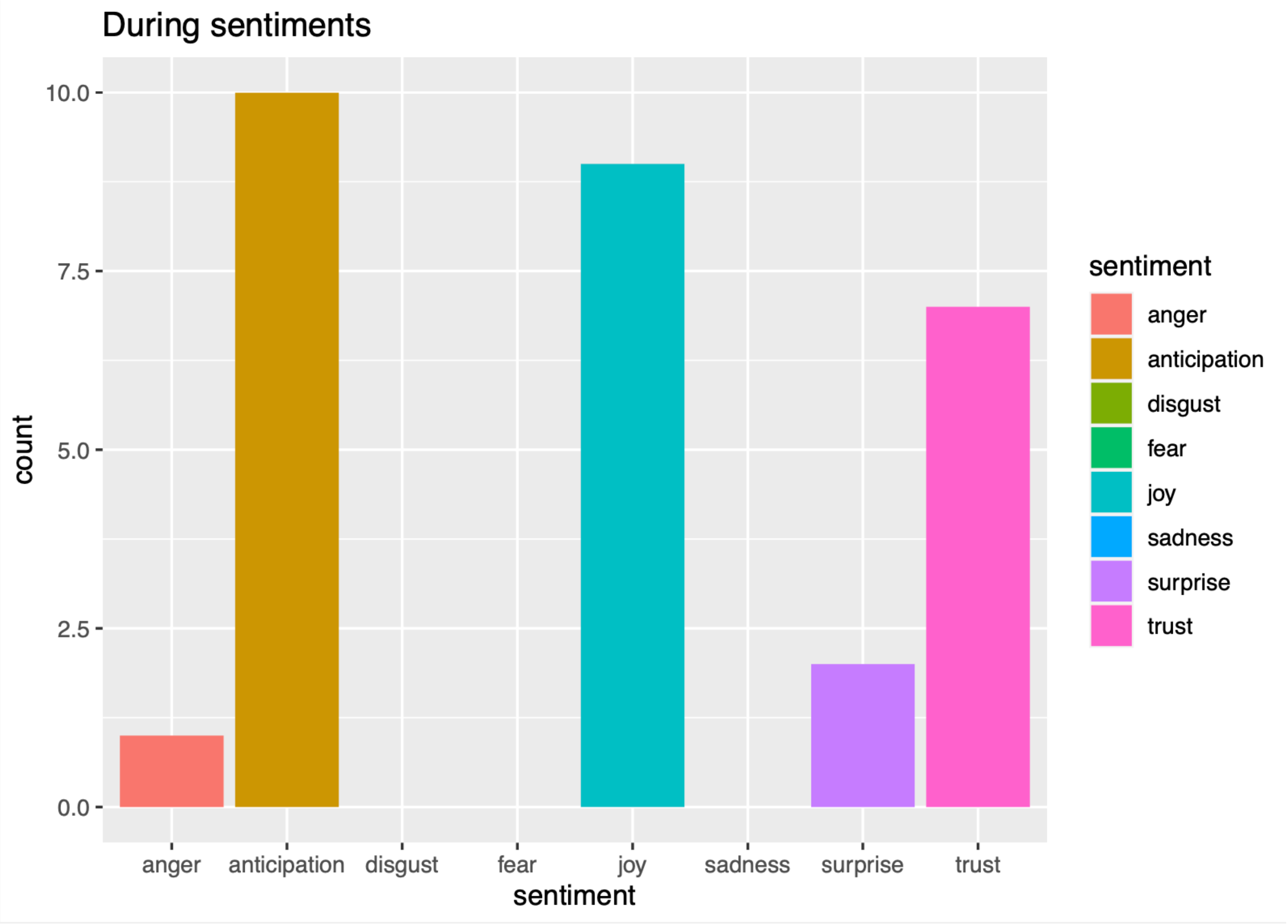
Sentiment Analysis – During the MVFW





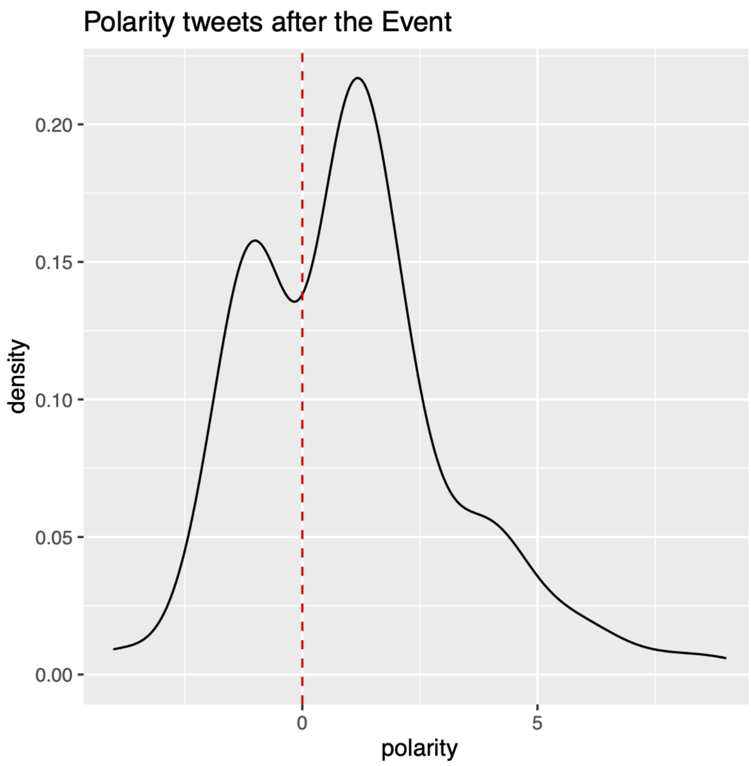
Analysis

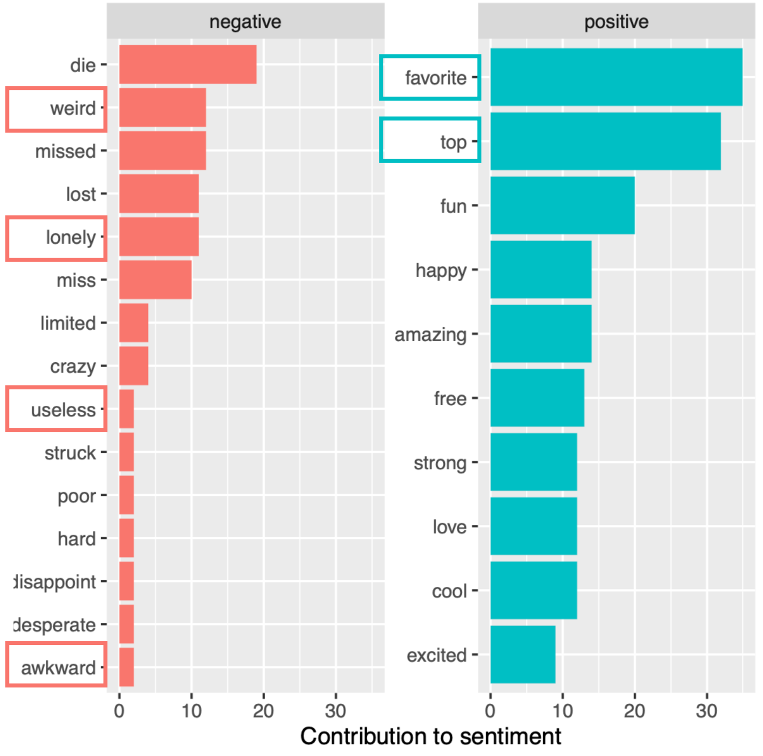
Sentiment Analysis – During the MVFW (“nrc” lexicon)



Analysis

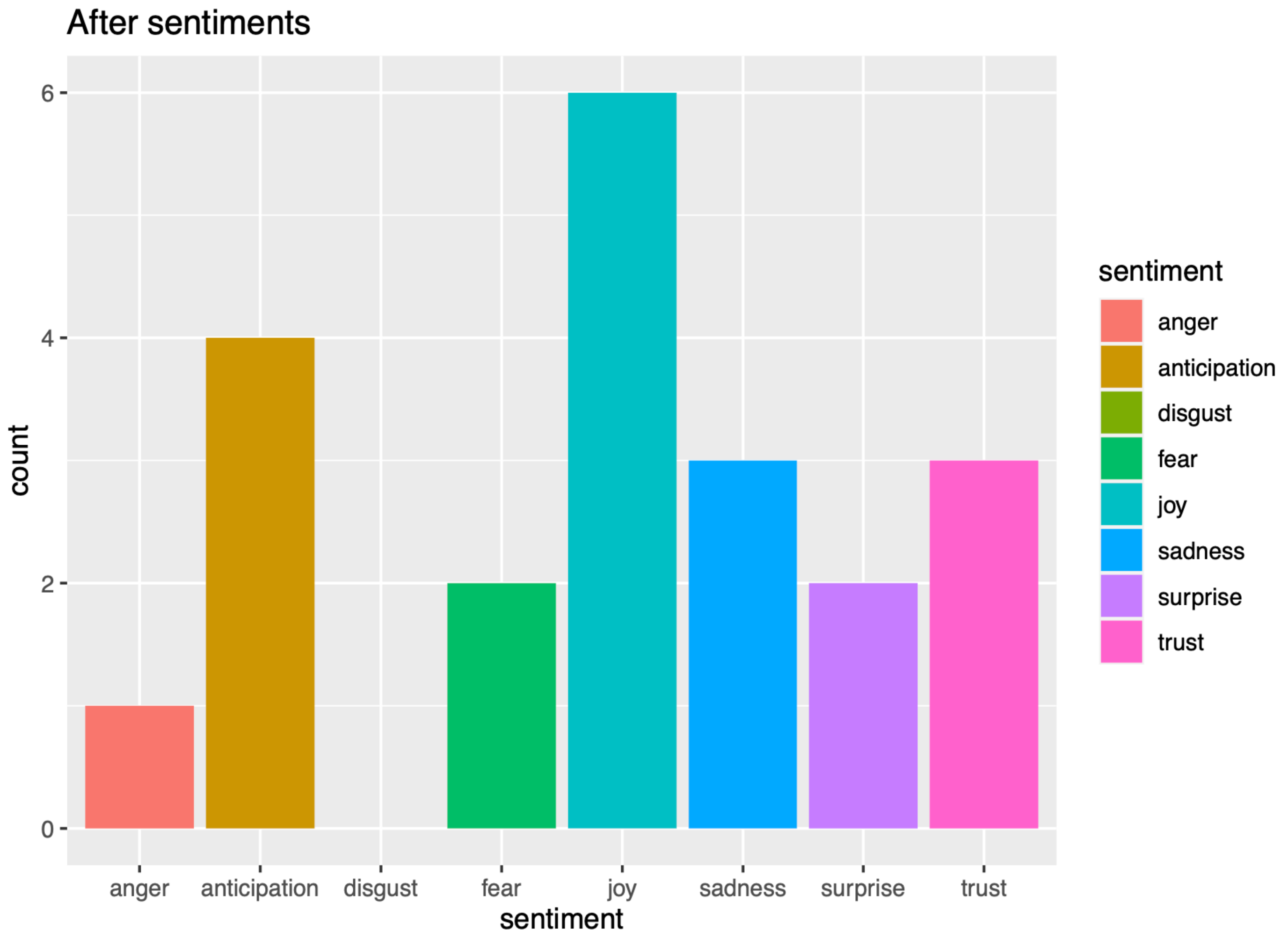
Sentiment Analysis – After the MVFW





Analysis

Sentiment Analysis – After the MVFW ("nrc" lexicon)



Results

Sentiment Analysis overview

	Before MVFW	During MVFW	After MVFW
Positive Sentiment	• Excitement • Innovation	• Democratization of luxury • Celebration	• Ratings • Greetings
Negative Sentiment	• Fear of missing out (FOMO) • Urgency	• Disappointment • Glitches	• Loneliness • Awkwardness

Sentiment Analysis **confirms** the results obtained from the Background Research

- **Before MVFW** – participating brands contributed to fuelling the hype leveraging on excitement and FOMO
- **During MVFW** – the positive sentiment is driven by the greater accessibility of the event ("free") compared to its physical correspondents, but some complaints about the state of technology start to appear
- **After MVFW** – users talk about feeling lonely and uncomfortable

Research Outline

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Topic Modelling

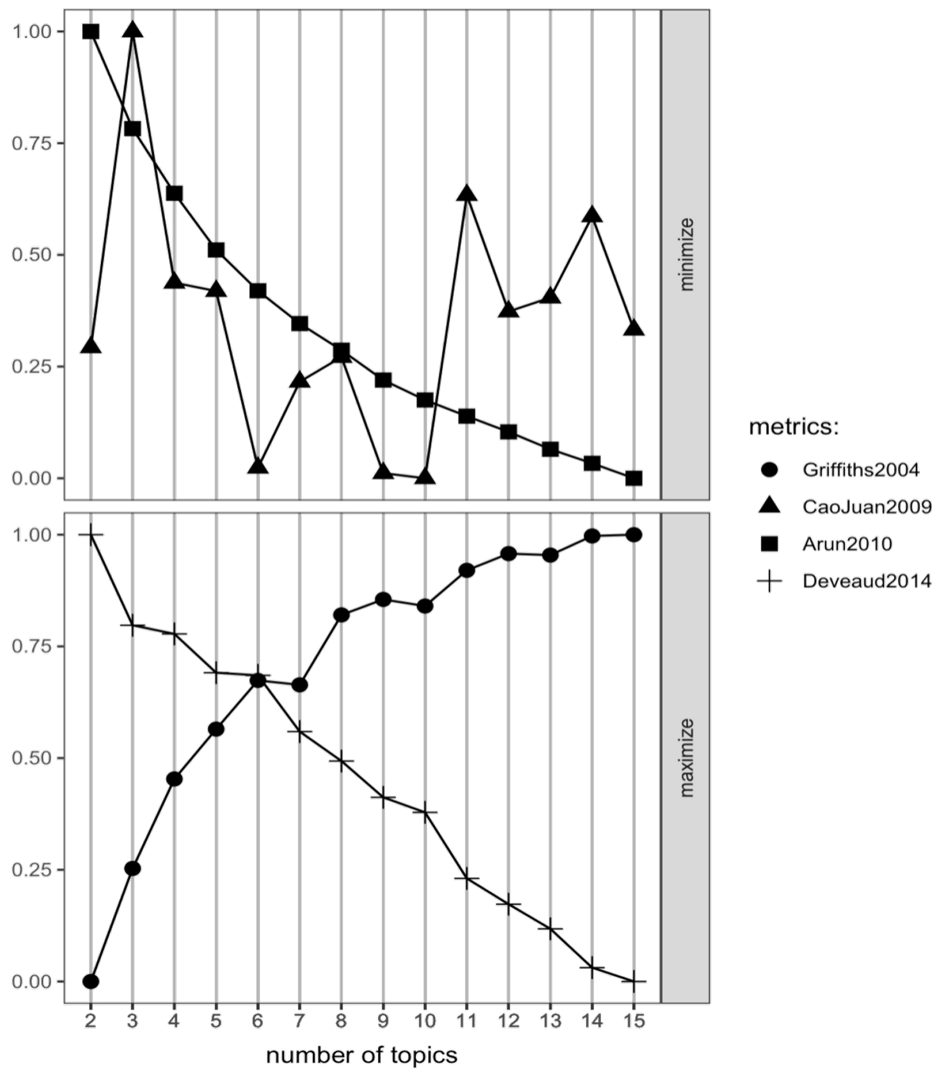
Methodology

Methods:

- Scraping > Cleaning data > Dividing by periods > Topic Analysis

Topic Analysis:

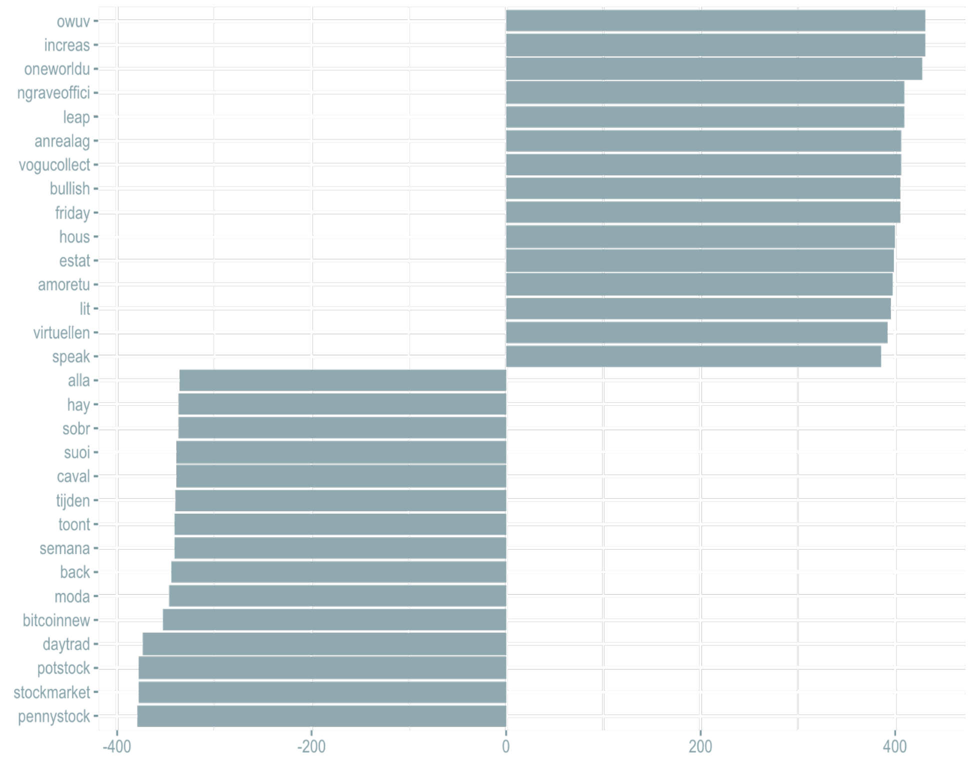
- Finding the optimal number of topics per period
- Interpreting the topics (with the Beta spread)
- Tracing back some tweets (Gamma probability)

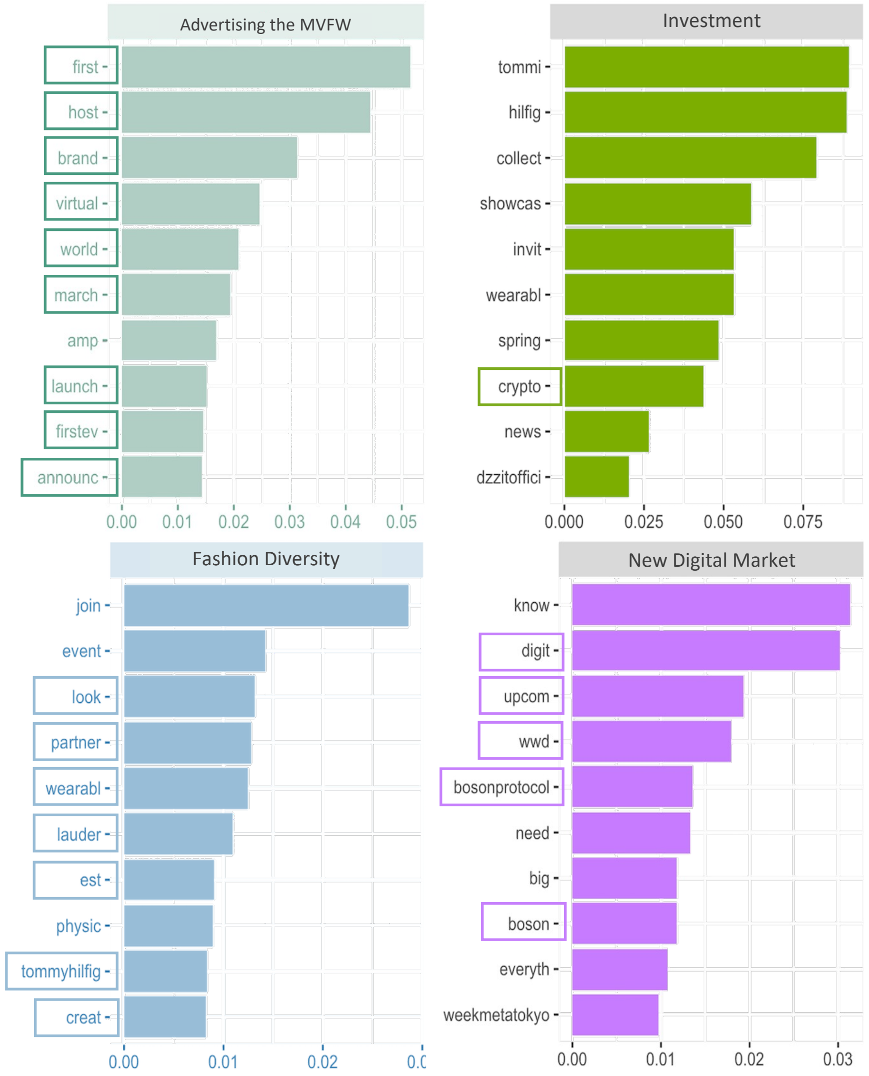


Analysis

Topic Modelling – Before the MVFW

	TOPIC 1	TOPIC 2	TOPIC 3	TOPIC 4
TOPIC 2	pennystock potstock stockmarket ser		pennystock stockmarket daytrad potstock bitcoinnew	pennystock stockmarket potstock daytrad bitcoinnew





Analysis

Topic Modelling – Before the MVFW – Tweets example

- *"The world's first ever Metaverse Fashion Week is on the horizon"*
- *Metaverse Fashion Week starts tomorrow on @decentraland! Check it out*

TOPIC 1
Advertising the MVFW

TOPIC 4
Digital Market

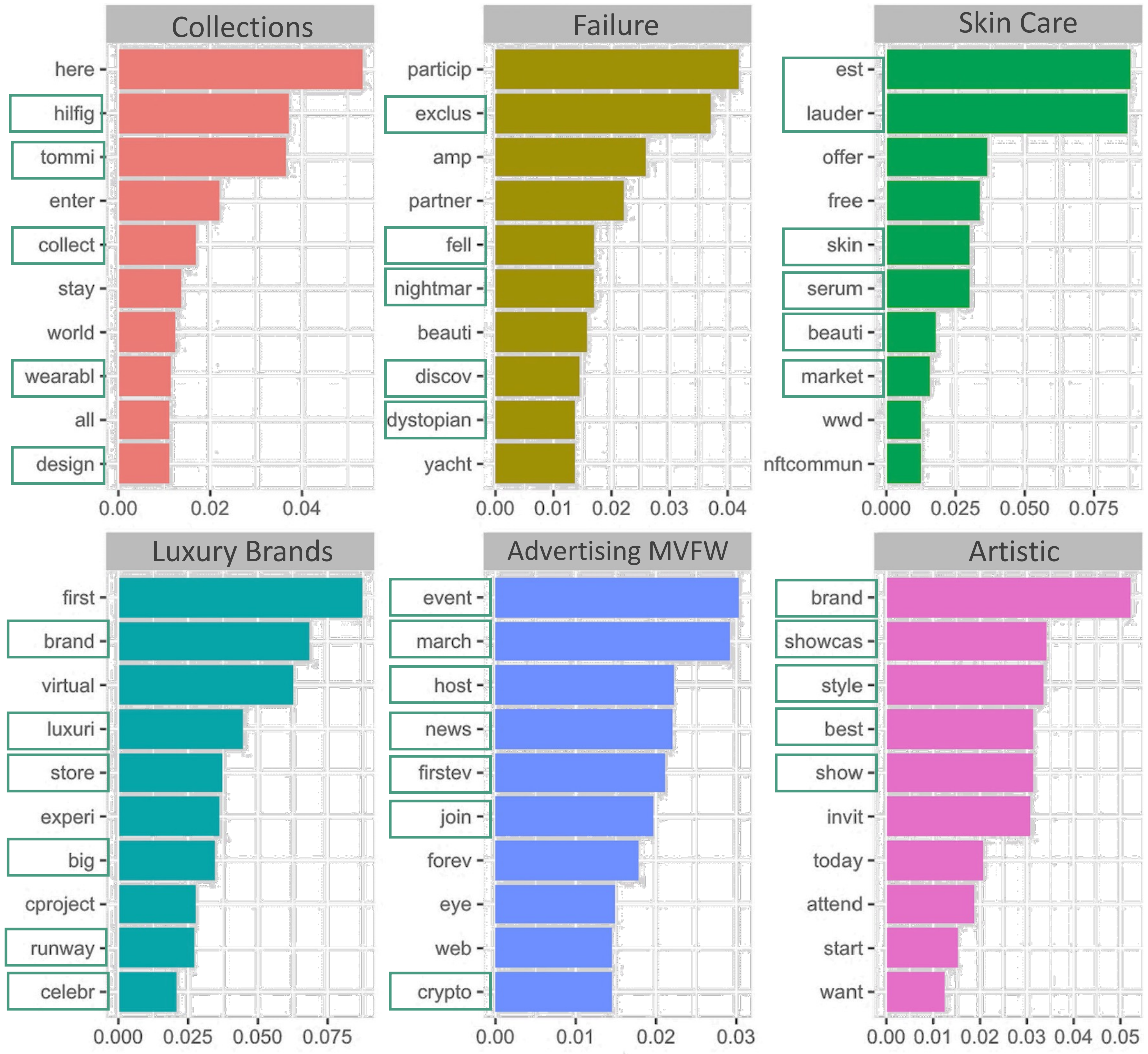
- *"@OneWorldU Do you think all the attention on the Metaverse Fashion Week will increase the value of your #metaverse real estate investments?*
- *This week's #digitalidentity events; The Future of Programmable Money: March 30 @getsomm_ @TechCrunch.*

Analysis

Topic Modelling – During the MVFW

Example of terms from the beta spread for topic 6

	TOPIC 1	TOPIC 2	TOPIC 3	TOPIC 4	TOPIC 5
TOPIC 6	code	nounsdao	artsi	artsi	creativ
	artsi	favourit$	pre	pre	pre
	danc	tezo	danc	hey	explain
	own	renovi	build	inaugur	produc
	youll	bitcoin	release	send	nounsdao



Analysis

Topic Modelling – During the MVFW – Tweets example

- *"I went to metaverse fashion week and it was like a dystopian nightmare , I fell off a yacht and had to leave"*

TOPIC 2
Failure

TOPIC 3
Skin care

- *"Estée Lauder to Offer Free Skin Serum NFT at Metaverse Fashion Week"*

- *"Are you ready for the the first ever Metaverse Fashion Week? Join Paco Rabanne"*

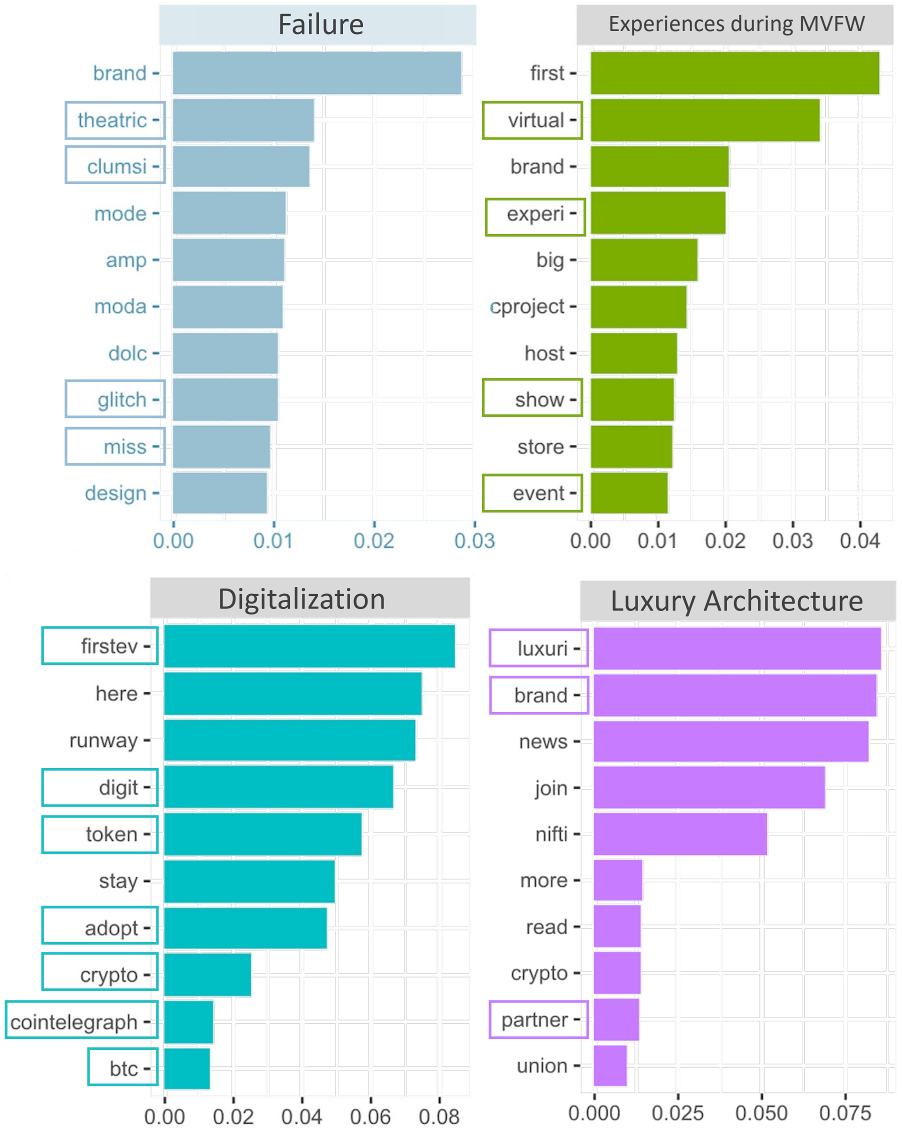
TOPIC 4 & 5
Advertising & Brands

Analysis

Topic Modelling – After the MVFW

Example of terms from the beta spread for topic 2

	TOPIC 1	TOPIC 2	TOPIC 3	TOPIC4
TOPIC 2	piuma metayacht superyacht miaminftweek		metayacht piuma superyacht booth miaminftweek	voxel metayacht superyacht piuma miaminftweek
TOPIC 4	few grand rais island heywave	digitalarchitectur interior sdk decentrabuild exterior	digitalarchitectur interior sdk decentrabuild exterior	



Analysis

Topic Modelling – After the MVFW – Tweets example

"The long-awaited buffoonery is live on Youtube now. [...] #Decentraland #MVFW #Metaverse #Broccoli

Tweet 1

Failure

Tweet 2

Failure

"The Clumsy Theatrics of Metaverse Fashion Week #metaverse" [...]

"Metaverse Fashion Week was a weird dystopian fever dream (@t_jsidhu - @TheFaceMagazine) [...]

Tweet 3

Failure

Results

Topic Comparison

	Before MVFW	During MVFW	After MVFW
Topic 1	Advertising the MVFW	Collections	Failure
Topic 2	Investment	Failure	Experience during MVFW
Topic 3	Fashion Diversity	Skin Care	Digitalization
Topic 4	New Digital Market	Luxury Brands	Luxury Architercure
Topic 5		Advertising the MVFW	
Topic 6		Artistic	

Topic Modelling **confirms** the results obtained from the Sentiment Analysis

- **Before MVFW:** advertising of brands (Topic Modelling)
- **During MVFW:** specific event (e.g. Skin Care Product), first divergent reactions (failure)
- **After MVFW:** failure is the most relevant topic

Limitations

Key points to consider

DIFFERENT LANGUAGES

MANY PROPER NOUNS

SUBJECTIVE INTERPRETATION

ONLY ONE SOURCE OF ANALYSIS

LACK OF SPECIFIC LEXICON

LACK OF AWARENESS

Further Insights

Improvements & recommendations

Technology is not there yet; what does this mean for brands and the way they are perceived?

Negative Effects

Reputational consequences in case of failure

Learning by doing vs. wait and see

Positive Effects

Bridging the gap with younger generations

Brand Innovativeness (?)

Brand Identification (?)

Further Insights

Improvements & recommendati

FURTHER RESEARCH

- Focusing on the evolution of the sentiment of specific brand (e.g. Gucci, Balenciaga)
- Measure the correlation between sentiment and the interest on fashion/metaverse

Thank you for your attention!

Bonus:

https://www.youtube.com/watch?v=X2-WlCAW6bI

Appendix

Sentiment analysis

```
metaverseUnnested %>%
  count(word) %>%
  with(wordcloud(word, n, max.words = 200, colors="turquoise4"))
metaverseUnnested <-  inner_join(metaverseUnnested, get_sentiments("afinn"), by = "word")
tweetPolarity <- aggregate(value ~ ...1, metaverseUnnested, mean)

metaverseUnnested$date <- as.Date(as.character(metaverseUnnested$date), "%d/%m/%Y")
date_sentiment <- aggregate(value ~ date, metaverseUnnested, mean)
tweets <-  inner_join(metaverseUnnested, tweetPolarity, by = "...1")

ggplot(date_sentiment, aes(x = date, y = value)) +
  geom_smooth(method="loess", size=1, se=T, span = .5) +
  geom_hline(yintercept=0, color = "grey") + #plot a grey line at 0, i.e. neutral sentiment
  ylab("Avg. Sentiment") +  #set a name to the y-axis
  xlab("Date") + #set name to x-axis
  ggtitle("Sentiment of Tweets over time") +
  geom_vline(xintercept = as.numeric(as.Date("2022-03-24")), linetype=4) +
  geom_vline(xintercept = as.numeric(as.Date("2022-03-27")), linetype=4)
```

```
#sentiment for before event
sentiment_beforeEvent <- beforeEvent %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()

library(ggplot2)
sentiment_beforeEvent %>%
  group_by(sentiment) %>%
  top_n(10) %>%
  ungroup() %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(word, n, fill = sentiment)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment",
       x = NULL) +
  coord_flip()
```

```
install.packages("reshape2")
library(reshape2)

dev.new(width = 1000, height = 1000, unit = "px")
sentiment_beforeEvent %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  acast(word ~ sentiment, value.var = "n", fill = 0) %>%
  comparison.cloud(colors = c("red", "green"),
                   max.words = 10000)

sentiment_beforeEvent %>%
  group_by(sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(polarity = positive - negative) %>%
  filter(abs(polarity)<10) %>%
  ggplot(aes(polarity)) +
  geom_density(alpha = 0.3) +
  geom_vline(xintercept=0, linetype="dashed", color = "red")+
  ggtitle("Polarity tweets before the Event")

#sentiment for during event
sentiment_duringEvent <- duringEvent %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()

library(ggplot2)
sentiment_duringEvent %>%
  group_by(sentiment) %>%
  top_n(10) %>%
  ungroup() %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(word, n, fill = sentiment)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment",
       x = NULL) +
  coord_flip()

install.packages("reshape2")
library(reshape2)
```

Appendix

Sentiment analysis

```r
dev.new(width = 1000, height = 1000, unit = "px")
sentiment_duringEvent %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  acast(word ~ sentiment, value.var = "n", fill = 0) %>%
  comparison.cloud(colors = c("red", "green"),
                   max.words = 10000)

library(tidyr)
sentiment_duringEvent %>%
  group_by(sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(polarity = positive - negative) %>%
  filter(abs(polarity)<10) %>%
  ggplot(aes(polarity)) +
  geom_density(alpha = 0.3) +
  geom_vline(xintercept=0, linetype="dashed", color = "red")+
  ggtitle("Polarity tweets during the Event")

#sentiment for after event
sentiment_afterEvent <- afterEvent %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()

library(ggplot2)
sentiment_afterEvent %>%
  group_by(sentiment) %>%
  top_n(10) %>%
  ungroup() %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(word, n, fill = sentiment)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~sentiment, scales = "free_y") +
  labs(y = "Contribution to sentiment",
       x = NULL) +
  coord_flip()

install.packages("reshape2")
library(reshape2)
```

```r
dev.new(width = 1000, height = 1000, unit = "px")
sentiment_afterEvent %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, sentiment, sort = TRUE) %>%
  acast(word ~ sentiment, value.var = "n", fill = 0) %>%
  comparison.cloud(colors = c("red", "green"),
                   max.words = 10000)

library(tidyr)
sentiment_afterEvent %>%
  group_by(sentiment) %>%
  spread(sentiment, n, fill = 0) %>%
  mutate(polarity = positive - negative) %>%
  filter(abs(polarity)<10) %>%
  ggplot(aes(polarity)) +
  geom_density(alpha = 0.3) +
  geom_vline(xintercept=0, linetype="dashed", color = "red")+
  ggtitle("Polarity tweets after the Event")
```

Appendix

Sentiment analysis – “nrc” lexicon

```
#before
beforeEvent$word <- as.character(beforeEvent$word)
beforeEvent_sample <- sample_n(beforeEvent, 000)
before_nrc <-get_nrc_sentiment(beforeEvent_sample$word)

td<-data.frame(t(before_nrc))
#The function rowSums computes column sums across rows for each level of a grouping variable.
td_new <- data.frame(rowSums(td[2:253]))
#Transformation and cleaning
names(td_new)[1] <- "count"
td_new <- cbind("sentiment" = rownames(td_new), td_new)
rownames(td_new) <- NULL
td_new2<-td_new[1:8,]
#Plot One - count of words associated with each sentiment
quickplot(sentiment, data=td_new2, weight=count, geom="bar", fill=sentiment, ylab="count")+ggtitle("Before sentiments")

#during
duringEvent$word <- as.character(duringEvent$word)
duringEvent_sample <- sample_n(duringEvent, 3000)
during_nrc <-get_nrc_sentiment(duringEvent_sample$word)

td<-data.frame(t(during_nrc))
#The function rowSums computes column sums across rows for each level of a grouping variable.
td_new <- data.frame(rowSums(td[2:253]))
#Transformation and cleaning
names(td_new)[1] <- "count"
td_new <- cbind("sentiment" = rownames(td_new), td_new)
rownames(td_new) <- NULL
td_new2<-td_new[1:8,]
#Plot One - count of words associated with each sentiment
quickplot(sentiment, data=td_new2, weight=count, geom="bar", fill=sentiment, ylab="count")+ggtitle("During sentiments")
#after
afterEvent$word <- as.character(afterEvent$word)
afterEvent_sample <- sample_n(afterEvent, 3000)
after_nrc <-get_nrc_sentiment(afterEvent_sample$word)

td<-data.frame(t(after_nrc))
#The function rowSums computes column sums across rows for each level of a grouping variable.
td_new <- data.frame(rowSums(td[2:253]))
#Transformation and cleaning
names(td_new)[1] <- "count"
td_new <- cbind("sentiment" = rownames(td_new), td_new)
rownames(td_new) <- NULL
td_new2<-td_new[1:8,]
#Plot One - count of words associated with each sentiment
quickplot(sentiment, data=td_new2, weight=count, geom="bar", fill=sentiment, ylab="count")+ggtitle("After sentiments")
```

Appendix

Extract - Topic Modelling

```
# TOPIC ANALYSIS
raw_duringDTM <- DocumentTermMatrix(raw_duringCorpus)
raw_duringDTM
#pick only non-zero entry documents
raw_duringDTM <- raw_duringDTM[unique(raw_duringDTM$i), ] #pick only non ze
raw_duringDTM

#install.packages("ldatuning")
library(ldatuning)
during_topicNumberMetrics <- FindTopicsNumber(
  raw_duringDTM, #DTM object
  topics = seq(from = 2, to = 15, by = 1), #Number of topics to test, i.e. |
  metrics = c("Griffiths2004", "CaoJuan2009", "Arun2010", "Deveaud2014"), #|
  control = list(seed = 100), #Random seed
  verbose = TRUE

)

#see the plot
FindTopicsNumber_plot(during_topicNumberMetrics)
#create LDA
raw_duringLDA <- LDA(raw_duringDTM, k = 6, control = list(seed = 100))
#see the graph
library(tidytext)
library(dplyr)
library(ggplot2)
during_tidyLda <- tidy(raw_duringLDA)

during_topTerms <- during_tidyLda %>%
  group_by(topic) %>%
  top_n(10, beta) %>%
  ungroup() %>%
  arrange(topic, -beta)

during_topTerms %>%
  mutate(term = reorder(term, beta)) %>%
  group_by(topic, term) %>%
  arrange(desc(beta)) %>%
  ungroup() %>%
  mutate(term = factor(paste(term, topic, sep = "__"),
                       levels = rev(paste(term, topic, sep = "__")))) %>% #|
```

```
  ggplot(aes(term, beta, fill = as.factor(topic))) + # x axis to t
  geom_col(show.legend = FALSE) + #column graph without legend
  coord_flip() + #flip graphs
  scale_x_discrete(labels = function(x) gsub("__.+$", "", x)) +
  labs(title = "Top 10 terms in each LDA topic",
       x = NULL, y = expression(beta)) +  #set title annd y label.
  facet_wrap(~ topic, ncol = 3, scales = "free") #divide by topic

# further see probability gamma
during_tidyLdaGamma <- tidy(raw_duringLDA, matrix = "gamma")
head(during_tidyLdaGamma, 10)
#see range of tweet with gamma
during_topTopics <- during_tidyLdaGamma %>%
  group_by(document) %>%
  top_n(3, gamma) %>%
  ungroup()

ggplot(during_topTopics[during_topTopics$document %in% unique(during_topTopics$document)[16:27],], aes(topic, gamma,
  geom_col(show.legend = TRUE) + #column graph with legend
  coord_flip() + #flip graphs
  scale_x_continuous(breaks=1:10, labels=c("1", "2", "3", "4", "5"
  labs(title = "Top 3 LDA topics for each of the first 12 document
       y = expression(gamma)) +  #set title annd y label.
  facet_wrap(~ document, ncol = 3, scales = "free")  #divide by do

#### Differences between topics - beta spread
#installed.packages("tidylda")

during_beta_spread <- during_tidyLda %>%
  mutate(topic = paste0("topic", topic)) %>%
  spread(topic, beta) %>%
  filter(topic1 > .001 | topic2 > .001) %>%
  mutate(log_ratio = log2(topic2 / topic1))

during_beta_spread %>%
  group_by(direction = log_ratio > 0) %>%
  top_n(15, abs(log_ratio)) %>%
  ungroup() %>%
  mutate(term = reorder(term, log_ratio)) %>%
  ggplot(aes(term, log_ratio)) +
  geom_col() +
  labs(y = "Log2 ratio of beta in topic 2 / topic 1") +
  coord_flip()
```

[...]

References

Literature

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