

DAT-5317 FMAN2  
A3: Business Insight Report  
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## Business Insight Report

In this report, I will be using chat transcripts exported from my two MBAN cohort groups on WhatsApp. Those are in the format of .txt files. One chat group is named “MBAN lost in code” while the other chat group is “Business Analytics SFR21”. Both groups were created around the same time at the beginning of this school year for the same purposes.

As a virtual student, I tried my best to stay up to date with the chat contents in the beginning especially since my method of communication with my peers are limited to online. However, as time went on, through quick previews of the messages from the notifications, a lot of the conversations outside of pure code sharing seemed either irrelevant to the course or mostly catered toward in-person students. Sometimes, a lot of information were duplicated and repeated since both groups consisted of people from the same cohort. In the end, there were at least two months’ worth of conversations from both groups that I have not carefully paid attention to.

Instead of revisiting the WhatsApp groups and read the chat line by line, I would like to use this opportunity to set up my business objective which is to first understand the gist of the chats, then decide if the contents suggest that I should invest more time and pay closer attention to them in the future.

### **Challenges**

WhatsApp is not particularly user-friendly for text analytics purposes. Much noise was generated from WhatsApp’s frequent systemic message such as “[10/5/21, 12:15:11 PM] +1 (XXX) 451-XXXX joined using this group's invite link” in the txt file. Moreover, WhatsApp automatically converts any images that were attached in the original chat to “image omitted” in

words. And any other media attached such as stickers and gifs also generated further noise for the data.

Example: “<attached: 00000809-STICKER-2021-11-10-17-34-57.webp>”.

Although slang words were expected in a chat setting, this resulted in an immense amount of unique word tokens, such as “hahahaah”, “haha”, “yeahhhhh”, “lmk” and more.

### **Addressing the Challenges**

After separating the text into individual word tokens, I removed all numbers using the `gsub()` function. This is to reduce noise generated from WhatsApp’s frequent systemic messages.

Next, after removing the default stop words, in the same filter function I also added a list of “junk words” that appeared frequently that delivered no business insights. Some of these words are “joined”, “using”, “this”, “group’s”, “image”, “omitted” and more.

Some technical terms such as codes and jargon are also removed as they are usually R scripts shared by peers.

Although not exhaustive, the list of “junk words” to be filtered grew quickly as the analyses continued.

### **Frameworks**

*Bigram.* By combining individual tokens into bigrams, I can understand the order of words that they come in. The most common two-word phrase is “hey guys” with 28 appearances followed by other common phrases such as “san francisco” and “winter ball”. Although many stop words

and junk words have already been filtered, there are still more than 1600 rows of bigrams in total.

```
> bigram_counts
```

	word1	word2	n
1	hey	guys	28
2	photo	jpg	10
3	normal	var	8
4	san	francisco	8
5	winter	ball	7
6	github	workshop	6
7	text	mining	6
8	word	text	6
9	zoom	meeting	6
10	business_	decision	5
11	dean	foster	5
12	foster	statistics	5

*Quadrogram.* Next, to gain more contextual information, the number of tokens together increased to four. With some scrutinization, there are some notable quadrograms that raise interest such as “daly academic program specialist”, “digital transformations marketing sales”, “dress fancy dress bougie”, “dynamic thinking embraces change”, etc. Having been somewhat familiar with the past conversations, these phrases suggest something about internship opportunities, winter ball event, and occasional peers’ sharing of opinions. However, there still existed some R-related jargon that added noise.

		quadrogram	n	tf	idf	tf_idf
1		distribution cheat sheet.pdf pages	4	1	5.926926	5.926926
2		exponential distribution cheat sheet.pdf	4	1	5.926926	5.926926
3		person student attending online	3	1	5.926926	5.926926
4		robert stine_ dean foster	3	1	5.926926	5.926926
5		stine_ dean foster statistics	3	1	5.926926	5.926926
6		amount savings installp coapp	2	1	5.926926	5.926926
7		analysis pearson education limited	2	1	5.926926	5.926926
8		applying artificial intelligence techniques	2	1	5.926926	5.926926
9		ardith daly academic program	2	1	5.926926	5.926926
10		ardith daly darien mitchell	2	1	5.926926	5.926926
11		b.notion.site github workshop guide	2	1	5.926926	5.926926
12		ball tickets aff emvba0	2	1	5.926926	5.926926
13		boulder raccoon b.notion.site github	2	1	5.926926	5.926926
14		canada join zoom meeting	2	1	5.926926	5.926926
15		count word sort true	2	1	5.926926	5.926926
16		country word sort true	2	1	5.926926	5.926926
17		daly academic program specialist	2	1	5.926926	5.926926
18		daly darien mitchell tontar	2	1	5.926926	5.926926
19		dataiku ardith daly darien	2	1	5.926926	5.926926
20		dataiku dss workshop dataiku	2	1	5.926926	5.926926
21		digital transformations marketing sales	2	1	5.926926	5.926926
22		divisadero st san francisco	2	1	5.926926	5.926926

In addition, I used the `igraph` and `ggraph` function to create two visualizations on the relationship between words. `Ggraph1` in appendix limits to `n` greater than 1 whereas `Ggraph2` is set to equal to 1 for the more unique quadrograms. `Ggraph1` is more readable but has relatively fewer information compared to `Ggraph2`.

*LDA.* Finally, an LDA graph is created to see the probability of a certain word that belongs to either topic 1 or 2. LDA graph from Appendix suggests that words such as “exam”, “tomorrow”, “feel”, “email” and more belong to one topic, while words such as “gif”, “zoom”, “join”, “lol”

belong to the other. This makes some sense as the first group seems to have a more serious tone whereas the second group is more casual.

## **Result and Conclusion**

With some of the technical words removed, more conversational rather than code-related technical information was revealed. However, the important tradeoff is that the more information removed, the less data granularity we have for the analysis.

Second, although less term frequency usually derives more business value, in this dataset, however, it was impossible to read through thousands of unique tokens as a result of prominent use of slang and typos in casual chats. Instead, this analysis would be more suitable in a group that has a more professional atmosphere with proper use of word choices. These analyses suggest that even though not reading through every text may result in missed opportunities such as internship opportunities and important messages shared by peers, the frequencies of such incidence are comparably low.

Getting up-to-date information from the current WhatsApp group chats would be less crucial than if it were from live Zoom chat, Announcements in MyCourses, or school emails. As a graduate student, we not only have limited time with different obligations in a day but must manage online communications across multiple platforms. Therefore, I believe I am not the only one who rarely reads through every single message from the group chats. Therefore, if I wish to gather my peers' attention and hope for quicker responses such as a time-limited survey for example, I should not rely on the group chat as my only channel for communication.

## Appendix

```

library(textreadr)
library(tm)
library(dplyr)
library(magrittr)
library(stringi)
library(tidyverse)
library(tidytext)

setwd("/Users/tsztinviviansoo/Desktop/Text analytics/whatsapp")
nm <- list.files(path="/Users/tsztinviviansoo/Desktop/Text analytics/
whatsapp")
my_data <- read_document(file=nm[1])
my_data_together <- paste(my_data, collapse = " ")

View(my_data_together)
my_txt_text <- do.call(rbind, lapply(nm, function(x)
paste(read_document(file=x), collapse = " ")))
my_txt_df <- as.data.frame(my_txt_text)
colnames(my_txt_df)[1] <- "text"

#####
### txt_token ###
#####
txt_token <- my_txt_df %>%
  mutate(my_txt_df, text = gsub(x = text, pattern = "[0-9]", replacement
= "")) %>%
  unnest_tokens(word, text) %>%
  filter(!word %in% c(stop_words$word, "pm", "time", "free", "attached",
"message", "document", "class", "hult", "image",
"omitted", "deleted", "sticker", "age_standard",
"invite", "joined", "it's", "i'm", "link", "group's", "https",
"library", "tidytuesday", "netflix", "checking", "data",
"binary", "checking_norm", "duration_norm", "age_norm",
"germ_train", "good_bad", "my_logit", "my_logit_norm",
"unnest_tokens", "geom_jitter", "duration",
"german_credit_card", "anti_join", "ggplot")) %>%
  #removing more noise in addition to stop words
  count(word, sort=TRUE)
#filter is the alternative to anti_join according to class
View(txt_token)

txt_token%>%
  filter(word=="happy")
# the frequency of word "happy" is 8
txt_token%>%
  filter(word=="love")

#####
### BIGRAM ###
#####

txt_bigrams <- my_txt_df %>%
  mutate(my_txt_df, text = gsub(x = text, pattern = "[0-9]", replacement
= "")) %>%
  #omitted numbers because random phone numbers popped up too frequently
  unnest_tokens(bigram, text, token = "ngrams", n=2) %>%
  count(bigram, sort = TRUE)
View(txt_bigrams)

```



```

library(tidyr)

bigrams_separated <- txt_bigrams %>%
  separate(bigram, c("word1", "word2"), sep = " ")

bigrams_filtered <- bigrams_separated %>%
  filter(!word1 %in% c(stop_words$word, "pm", "time", "free", "attached",
    "message", "document", "class", "hult", "image",
    "omitted", "deleted", "sticker", "age_standard",
    "invite", "joined", "it's", "i'm", "link", "group's", "https",
    "library", "tidytuesday", "netflix", "checking", "data",
    "binary", "checking_norm", "duration_norm", "age_norm",
    "germ_train", "good_bad", "my_logit", "my_logit_norm",
    "unnest_tokens", "geom_jitter", "duration",
    "german_credit_card", "anti_join", "ggplot")) %>%
  filter(!word2 %in% c(stop_words$word, "pm", "time", "free", "attached",
    "message", "document", "class", "hult", "image",
    "omitted", "deleted", "sticker", "age_standard",
    "invite", "joined", "it's", "i'm", "link", "group's", "https",
    "library", "tidytuesday", "netflix", "checking", "data",
    "binary", "checking_norm", "duration_norm", "age_norm",
    "germ_train", "good_bad", "my_logit", "my_logit_norm",
    "unnest_tokens", "geom_jitter", "duration",
    "german_credit_card", "anti_join", "ggplot"))

bigram_counts <- bigrams_filtered %>%
  count(word1, word2, sort = TRUE)

View(bigram_counts)

#####
### QUADROGRAM ###
#####
quadrogram <- my_txt_df %>%
  mutate(my_txt_df, text = gsub(x = text, pattern = "[0-9]", replacement
= "")) %>%
  unnest_tokens(quadrogram, text, token = "ngrams", n=4) %>%
  separate(quadrogram, c("word1", "word2", "word3", "word4"), sep=" ")
%>%
  filter(!word1 %in% c(stop_words$word, "pm", "time", "free", "attached",
    "message", "document", "class", "hult", "image",
    "omitted", "deleted", "sticker", "age_standard",
    "invite", "joined", "it's", "i'm", "link", "group's", "https",
    "library", "tidytuesday", "netflix", "checking", "data",
    "binary", "checking_norm", "duration_norm", "age_norm",
    "germ_train", "good_bad", "my_logit", "my_logit_norm",
    "unnest_tokens", "geom_jitter", "duration",
    "german_credit_card", "anti_join", "ggplot")) %>%
  filter(!word2 %in% c(stop_words$word, "pm", "time", "free", "attached",
    "message", "document", "class", "hult", "image",
    "omitted", "deleted", "sticker", "age_standard",
    "invite", "joined", "it's", "i'm", "link", "group's", "https",
    "library", "tidytuesday", "netflix", "checking", "data",

```

```

      "binary", "checking_norm", "duration_norm", "age_norm",
      "germ_train", "good_bad", "my_logit", "my_logit_norm",
      "unnest_tokens", "geom_jitter", "duration",
      "german_credit_card", "anti_join", "ggplot")) %>%
filter(!word3 %in% c(stop_words$word, "pm", "time", "free", "attached",
      "message", "document", "class", "hult", "image",
      "omitted", "deleted", "sticker", "age_standard",
      "invite", "joined", "it's", "i'm", "link", "group's", "https",
      "library", "tidytuesday", "netflix", "checking", "data",
      "binary", "checking_norm", "duration_norm", "age_norm",
      "germ_train", "good_bad", "my_logit", "my_logit_norm",
      "unnest_tokens", "geom_jitter", "duration",
      "german_credit_card", "anti_join", "ggplot")) %>%
filter(!word4 %in% c(stop_words$word, "pm", "time", "free", "attached",
      "message", "document", "class", "hult", "image",
      "omitted", "deleted", "sticker", "age_standard",
      "invite", "joined", "it's", "i'm", "link", "group's", "https",
      "library", "tidytuesday", "netflix", "checking", "data",
      "binary", "checking_norm", "duration_norm", "age_norm",
      "germ_train", "good_bad", "my_logit", "my_logit_norm",
      "unnest_tokens", "geom_jitter", "duration",
      "german_credit_card", "anti_join", "ggplot"))

quadrogram

quadrogram_united <- quadrogram %>%
  unite(quadrogram, word1, word2, word3, word4, sep=" ")
View(quadrogram_united)
quadrogram_tf_idf <- quadrogram_united %>%
  count(quadrogram) %>%
  bind_tf_idf(quadrogram, quadrogram, n) %>%
  arrange(desc(n)) #here i changed desc(tf_idf) to desc(n) since for some
reason,
#all the idf and tf_idf were the same....

quad_counts <- quadrogram %>%
  count(word1, word2, word3, word4, sort = TRUE)

View(quad_counts)
#####

word_cors %>%
  filter(item1 == "love")
#####
#####
### BIGRAM AND QUADGRAM GRAPHS ###
#####
library(igraph)
bigram_graph <- bigram_counts %>%
  filter(n>3) %>%
  graph_from_data_frame()

bigram_graph

library(gggraph)
gggraph(bigram_graph, layout = "fr") +
  geom_edge_link()+

```

```

    geom_node_point()+
    geom_node_text(aes(label=name), vjust =1, hjust=1)

quad_graph <- quad_counts %>%
  filter(n>1) %>%
  graph_from_data_frame()

ggraph(quad_graph, layout = "fr") +
  geom_edge_link()+
  geom_node_point()+
  geom_node_text(aes(label=name), vjust =1, hjust=1)

quad_graph2 <- quad_counts %>%
  filter(n==1) %>%
  graph_from_data_frame()

ggraph(quad_graph2, layout = "fr") +
  geom_edge_link()+
  geom_node_point()+
  geom_node_text(aes(label=name), vjust =1, hjust=1)
#####
### CORRELATION ###
#####
word_cors <- txt_token %>%
  group_by(word) %>%
  filter(n>=30) %>%
  pairwise_cor(word,txt_token, sort=TRUE)
word_cors
View(word_cors)

###
my_txt_dtm <- my_txt_df %>%
  mutate(my_txt_df, text = gsub(x = text, pattern = "[0-9]", replacement
= "")) %>%
  unnest_tokens(word, text) %>%
  filter(!word %in% c(stop_words$word, "pm","time","free","attached",
    "message","document","class","hult", "image",
    "omitted", "deleted", "sticker", "age_standard",
    "invite","joined","it's","i'm","link","group's","https",
    "library","tidytuesday","netflix","checking","data",
    "binary","checking_norm","duration_norm","age_norm",
    "germ_train","good_bad","my_logit","my_logit_norm",
    "unnest_tokens","geom_jitter","duration",
    "german_credit_card","anti_join","ggplot")) %>%
  count(word, word) %>%
  cast_dtm(word, word, n)

my_txt_dtm

#####
### LDA ###
#####
#now that we have a dtm, we can use LDA to find topics
library(topicmodels)
txt_lda <- LDA(my_txt_dtm, k=2, control=list(seed=123))

```

```

library(tidytext)
txt_topics <- tidy(txt_lda, matrix="beta")
txt_topics

top_terms <- txt_topics %>%
  group_by(topic) %>%
  top_n(10, beta) %>%
  ungroup() %>%
  arrange(topic, -beta)
View(top_terms)

top_terms %>%
  mutate(term=reorder(term, beta)) %>%
  ggplot(aes(term, beta, fill = factor(topic))) +
  geom_col(show.legend=FALSE) +
  facet_wrap(~topic, scales = "free") +
  coord_flip()
#topic on the left seems more casual whereas topic on the right more
serious

beta_spread <- txt_topics %>%
  mutate(topic=paste0("topic", topic)) %>%
  spread(topic, beta) %>%
  filter(topic1>0.001 | topic2 >0.001) %>%
  mutate(log_rate = log2(topic2/topic1))

View(beta_spread)
#####GAMMA
chapters_gamma <- tidy(txt_lda, matrix="gamma") #we created ap_lda in our
LDA scripts
View(chapters_gamma)
str(chapters_gamma)
gamma_df<- as.data.frame(chapters_gamma) %>%
  arrange(desc(gamma))

write.csv(gamma_df, file = '/Users/tsztinviviansoo/Desktop/Text
analytics/gammapdf.csv', row.names = FALSE)
#I exported this table to a csv file
#####

mutate(my_txt_df, text = gsub(x = text, pattern = "[0-9]", replacement =
"")) %>%
  unnest_tokens(word, text) %>%
  filter(!word %in% c(stop_words$word, "pm", "time", "free", "attached",
    "message", "document", "class", "hult", "image",
    "omitted", "deleted", "sticker", "age_standard",
    "invite", "joined", "it's", "i'm", "link", "group's", "https",
    "library", "tidytuesday", "netflix", "checking", "data",
    "binary", "checking_norm", "duration_norm", "age_norm",
    "germ_train", "good_bad", "my_logit", "my_logit_norm",
    "unnest_tokens", "geom_jitter", "duration",
    "german_credit_card", "anti_join", "ggplot")) %>%
#removing pm in addition to stop words
  count(word, sort=TRUE)

#####

```

```

my_txt_df %>%
  mutate(my_txt_df, text = gsub(x = text, pattern = "[0-9]", replacement
= "")) %>%
  unnest_tokens(word, text) %>%
#####
### Frequency ###
#####
library(ggplot2)
freq_hist <- my_txt_df %>%
  mutate(my_txt_df, text = gsub(x = text, pattern = "[0-9]", replacement
= "")) %>%
  unnest_tokens(word, text) %>%
  filter(!word %in% c(stop_words$word, "pm", "time", "free", "attached",
    "message", "document", "class", "hult", "image",
    "omitted", "deleted", "sticker", "age_standard",
    "invite", "joined", "it's", "i'm", "link", "group's", "https",
    "library", "tidytuesday", "netflix", "checking", "data",
    "binary", "checking_norm", "duration_norm", "age_norm",
    "germ_train", "good_bad", "my_logit", "my_logit_norm",
    "unnest_tokens", "geom_jitter", "duration",
    "german_credit_card", "anti_join", "ggplot")) %>%
  count(word, sort=TRUE) %>%
  filter(n>15) %>%
  mutate(word=reorder(word, n)) %>%
  ggplot(aes(word, n))+
  geom_col()+
  xlab(NULL)+
  coord_flip()
print(freq_hist)

#total words
total_words <- txt_token %>%
  summarize(total=sum(n))

txt_words <- c(txt_token, total_words)
txt_words <- as.data.frame(txt_words)

freq_by_rank <- txt_words %>%
  mutate(rank = row_number(),
    `term frequency`=n/total) %>%

View(freq_by_rank)

freq_by_rank %>%
  ggplot(aes(rank, `term frequency`))+
  #let's add a tangent line , the first derivative, and see what the slop
is
  geom_abline(intercept=-0.62, slope= -1.1, color='gray50', linetype=2)+
  geom_line(size= 1.1, alpha = 0.8, show.legend = FALSE)+
  scale_x_log10()+
  scale_y_log10()

txt_tfidf_words <- txt_words %>%
  bind_tf_idf(word, word, n) %>%
  arrange(desc(tf_idf))

```



```

nrcsurprise <- get_sentiments("nrc") %>%
  filter(sentiment == "surprise")
nrcanger <- get_sentiments("nrc") %>%
  filter(sentiment == "anger")
nrcdisgust <- get_sentiments("nrc") %>%
  filter(sentiment == "disgust")
nrcfear <- get_sentiments("nrc") %>%
  filter(sentiment == "fear")
nrctrust <- get_sentiments("nrc") %>%
  filter(sentiment == "trust")

txt_token %>%
  inner_join(nrctrust) %>%
  count(word, sort=T)

txt_token %>%
  inner_join(nrcsurprise) %>%
  count(word, sort=T)

txt_token %>%
  inner_join(nrcanger) %>%
  count(word, sort=T)

txt_token %>%
  inner_join(nrcdisgust) %>%
  count(word, sort=T)

txt_token %>%
  inner_join(nrcfear) %>%
  count(word, sort=T)

afinn <- txt_token %>%
  inner_join(get_sentiments("afinn")) %>%
  summarise(sentiment=sum(value)) %>%
  mutate(method="AFINN")

bing_and_nrc <- bind_rows(
  txt_token %>%
    inner_join(get_sentiments("bing")) %>%
    mutate(method = "Bing et al."),
  txt_token %>%
    inner_join(get_sentiments("nrc") %>%
      filter(sentiment %in% c("positive", "negative"))) %>%
    mutate(method = "NRC")) %>%
  count(method, sentiment) %>%
  spread(sentiment, n, fill=0) %>%
  mutate(sentiment = positive-negative)

bing_and_nrc

bind_rows(afinn, bing_and_nrc) %>%
  ggplot(aes(method, sentiment, fill=method))+
  geom_col(show.legend=FALSE)+

```

```
facet_wrap(~method, ncol =1, scales= "free_y")

bing_counts <- txt_token %>%
  inner_join(get_sentiments("bing")) %>%
  top_n(10) %>%
  count(word, sentiment, sort=T) %>%
  ungroup()

bing_counts
summary(bing_counts)
```

```
bing_counts %>%
  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()
```



```
> bigram_graph
```

```
IGRAPH ddafb03 DN-- 74 42 --
```

```
+ attr: name (v/c), n (e/n)
```

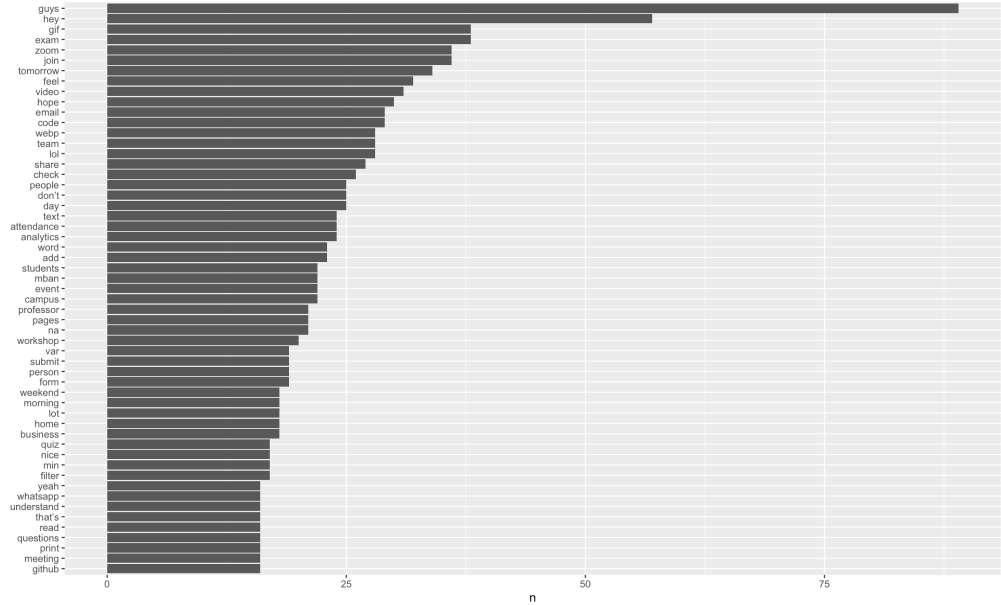
```
+ edges from ddafb03 (vertex names):
```

[1]	hey	->guys	photo	->jpg	normal	->var	san	->francisco
[5]	winter	->ball	github	->workshop	text	->mining	word	->text
[9]	zoom	->meeting	business_	->decision	dean	->foster	foster	->statistics
[13]	pdf	->page	sort	->>true	amount	->color	ardith	->daly
[17]	assignment	->section	bcg	->gamma	binomial	->summary	bit.ly	->liqrbc
[21]	business	->analytics	cheat	->sheet.pdf	consulting	->club	darien	->mittchell
[25]	dataiku	->dss	detail	->eid	distribution	->cheat	emilio	->lapiello
[29]	exponential	->distribution	family	->binomial	fireside	->chat	mittchell	->tontar

```
+ ... omitted several edges
```

```
> quadrogram_united
```

1	quadrogram
2	robert stine_ dean foster
3	stine_ dean foster statistics
4	stine dean foster statistics
5	analysis pearson education limited
6	pearson education limited pdf
7	education limited pdf pages
8	robert stine_ dean foster
9	stine_ dean foster statistics
10	frsibee ball throwing spikeball
11	zujdyjzbt_znlqlwrxyveqruciuzrepbo edit usp sharing
12	trial search utm_source google
13	search utm_source google utm_medium
14	utm_source google utm_medium cpc
15	google utm_medium cpc utm_content
16	utm_medium cpc utm_content branded
17	cpc utm_content branded utm_campaign
	utm content branded utm campaign branded



```

> bigram_counts

```

	word1	word2	n
1	hey	guys	28
2	photo	jpg	10
3	normal	var	8
4	san	francisco	8
5	winter	ball	7
6	github	workshop	6
7	text	mining	6
8	word	text	6
9	zoom	meeting	6
10	business_	decision	5
11	dean	foster	5
12	foster	statistics	5
13	pdf	page	5
14	sort	true	5
15	amount	color	4
16	ardith	daly	4
17	assignment	section	4
18	bcg	gamma	4
19	binomial	summary	4
20	bit.ly	liqrbc	4
21	business	analytics	4
22	cheat	sheet.pdf	4
23	consulting	club	4
24	darien	mittchell	4
25	dataiku	dss	4
26	detail	eid	4
27	distribution	cheat	4
28	emilio	lapiello	4
29	exponential	distribution	4
30	family	binomial	4
31	fireside	chat	4
32	mittchell	tontar	4
33	multiple	columns	4
34	multiple	regression	4
35	pdt	est	4
36	cheat	liqrbc	4

```
> bing_and_nrc
```

	method	negative	positive	sentiment
1	Bing et al.	141	139	-2
2	NRC	142	263	121

```
> |
```

> bigram\_graph

IGRAPH ddafb03 DN-- 74 42 --

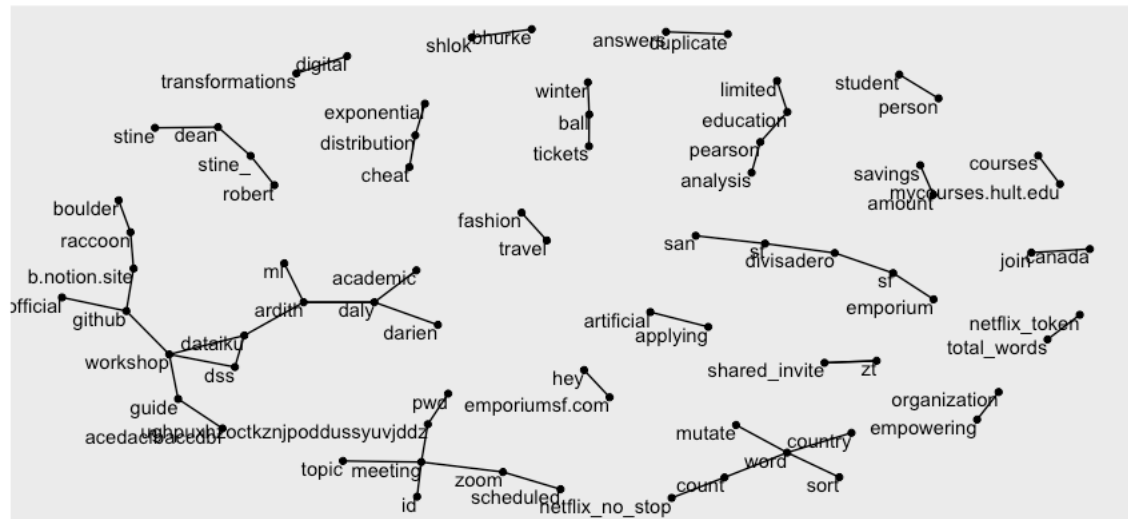
+ attr: name (v/c), n (e/n)

+ edges from ddafb03 (vertex names):

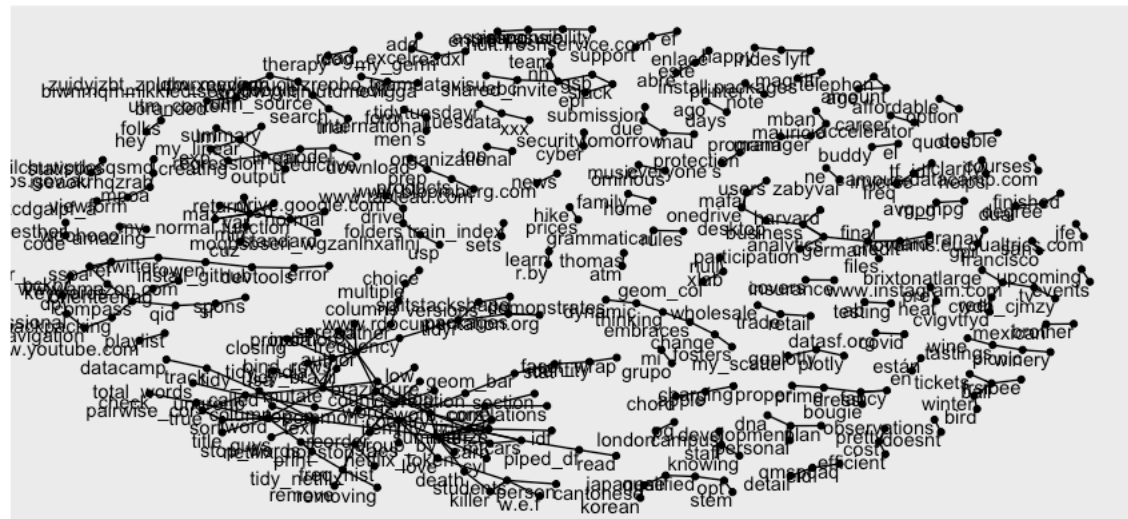
[1]	hey	->guys	photo	->jpg	normal	->var	san	->francisco
[5]	winter	->ball	github	->workshop	text	->mining	word	->text
[9]	zoom	->meeting	business_	->decision	dean	->foster	foster	->statistics
[13]	pdf	->page	sort	->>true	amount	->color	ardith	->daly
[17]	assignment	->section	bcg	->gamma	binomial	->summary	bit.ly	->liqrbc
[21]	business	->analytics	cheat	->sheet.pdf	consulting	->club	darien	->mitchell
[25]	dataiku	->dss	detail	->eid	distribution	->cheat	emilio	->lapiello
[29]	exponential	->distribution	family	->binomial	fireside	->chat	mitchell	->tontar

+ ... omitted several edges

### Ggraph 1



## Ggraph2



LDA Graph

