Business Insight Report

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Introduction

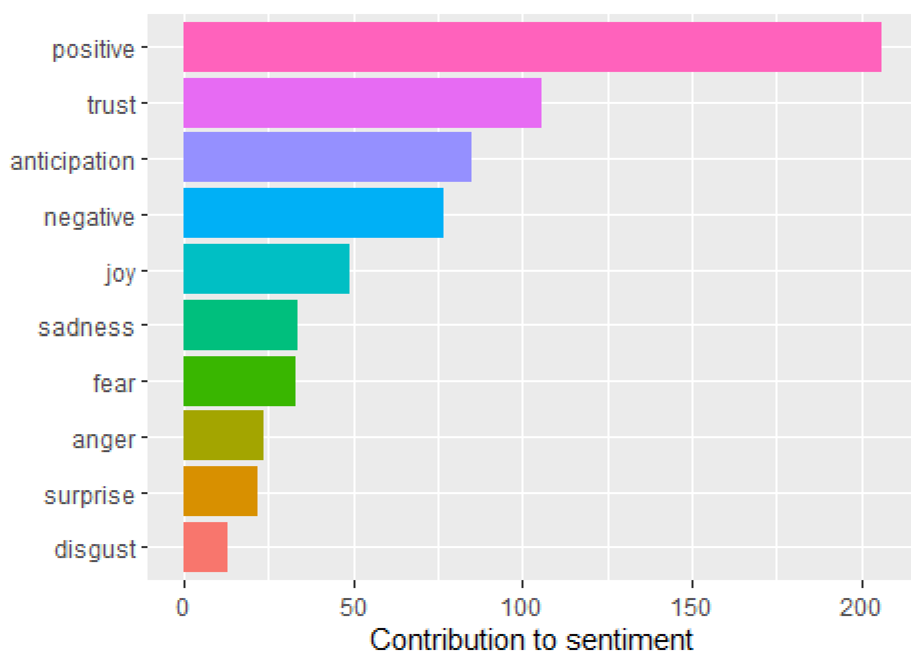
Tesla was founded by group of engineers in 2003 who wanted to prove that electric cars can be quicker, better and much fun to drive compared to gasoline cars. Since then, Tesla have been building all-electric cars, trucks, scalable clean energy generation and storage products. Tesla believes its better for the world as soon as they stop relying on fossil fuels and move towards clean emission technology.

The following analysis is based on the quarterly financial report of 2018 and 2019. The process includes text mining, collapsing the documents into blob, tokenizing and analyzing the sentiment to draw business insights.

Analysis using Frameworks

NRC Sentiment analysis:

This framework analyzes the frequency of words quarterly reports associated with each sentiment. The chart below shows the range of sentiments differentiated by different colors.



Here, we can observe that most of the words are positive followed by trust. This indicates that the company is experiencing growth and proud of their achievement in the short span. They think the company has been able to build trust in the consumer's mind as reliable and innovative brand. The anticipation might be suggesting that they are anticipating the success of upcoming new car models. The negative sentiment is one third of the positive sentiment. The further dive into negative words reveals that the concern for the company is mainly gross revenue, cash and production delays. Looking at the Tesla's cashflow statement and balance sheet verifies this sentiment. However, the overall positive sentiment indicates that company thinks they are in a good position at the moment even with the few major issues and rely on future sales and success of new models to emerge not only as the innovative company but also the profitable company.

AFINN Sentiment analysis:

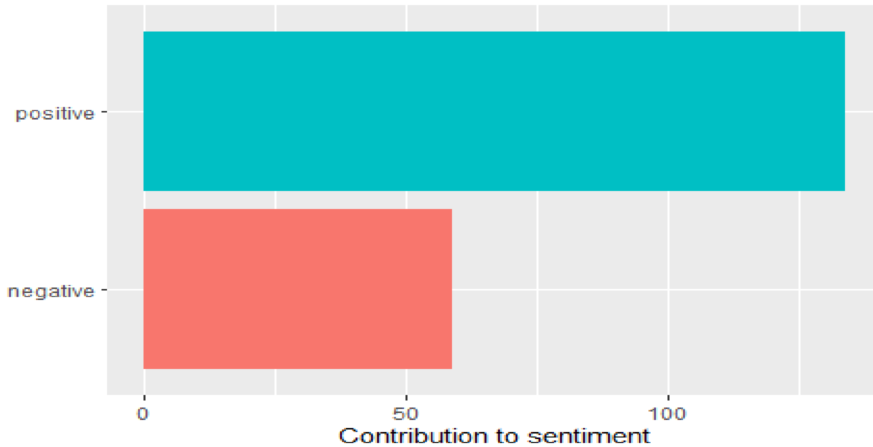
This framework assigns numbers to the sentiment, words with positive sentiment gets positive value and words with negative sentiment gets negative value. By taking the average of these would let us know whether the overall sentiment of the quarterly reports from 2018 and 2019 was positive or negative.

```
> mean(my_afinn$value)
[1] 0.8920863
```

This positive value indicates that overall sentiment is positive for quarterly reports from 2018 and 2019.

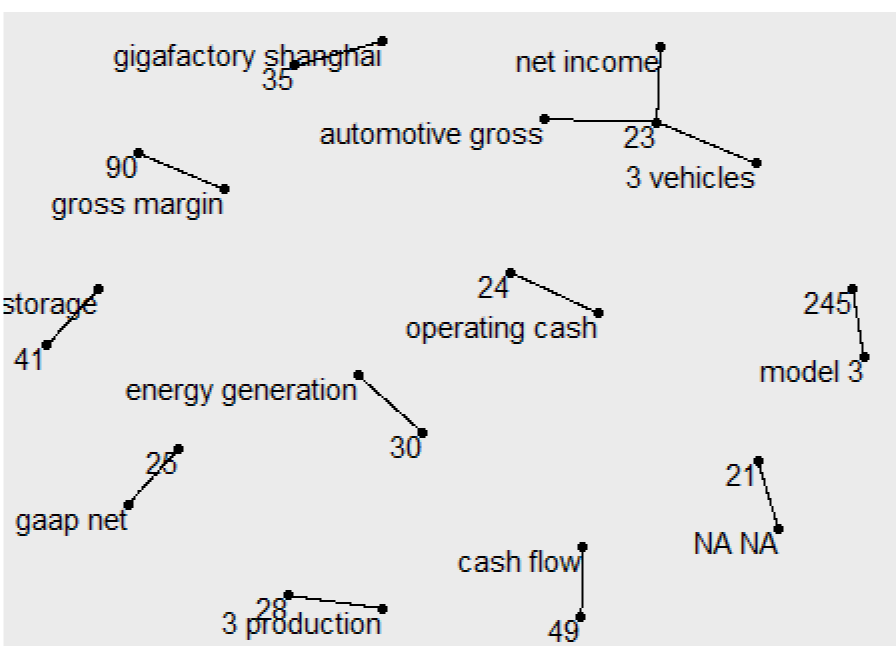
Bing Sentiment analysis:

This framework bifurcates the data frame into positive and negative based on their associated sentiment. This would help us see the holistic sentiment quantitatively. The below charts indicate that positive sentiment is twice as much of the negative sentiment. We can speculate based on this analysis that Tesla thinks their performance in the market is growing and their success triumphs any difficulty they are facing currently.



Bigrams Framework:

This framework tokenizes the words as a pair rather than individual words, which we could plot and create a network diagram to draw insights. This helps us get the context of their message rather than sentiment. We could make connections based on key words to tell a business story which could impact our business decision.



This plot projects the keywords from the quarterly reports which are significant. We could take these words and dive down to get the business insights. For example, “energy generation” indicates the Tesla’s involvement in the production of solar roofs, batteries (Tesla Powerwall) etc.

We can observe a small network of “net income”, “automotive gross” and “vehicles” which could be telling us Tesla needs to increase the sales of vehicles to increase their gross and net income. Similarly diving deep into these key words and further research tell us that Tesla has invested a lot of money in the building of Gigafactory in Shanghai and their operating cash is getting depleted because of low number of sales and their vision to keep the prices low is impacting their net income. The delay in production of model 3 is also impacting their sales since customers are losing faith in Tesla’s promise to deliver the product on time. Customers are feeling Tesla is overpromising and underdelivering when it comes to their ability to meet the demand worldwide.

Business Insights

Tesla is relatively new company who innovated the electric car industry. Their performance on the market sets the benchmark when it comes to electric vehicles. Their vision of selling all electric zero emission cars to people for affordable prices is hindering their gross margin now. If Tesla needs to turn profit and maintain their vision, then they need to bring down the manufacturing cost a lot. Their current cashflow is negative because of their investment to build Gigafactory in Shanghai and moderate sales numbers. There is a demand for model 3 however waiting period for customer to get delivery still takes months. The anticipated release of model Y, cyber truck might give Tesla the bump it needs to increase overall sales. The competitors like Volkswagen, Ford, GM are catching up to Tesla, they need to get these problems sorted out quickly and continue innovating to stay ahead of the curve. Overall, Tesla seems to project positive message in their quarterly reports of 2018 and 2019.

Decision: Investors should investigate more details before deciding. The investment amount depends on how much risk they are willing to take. Tesla is an interesting company with a lot of potential to grow into something much bigger. My personal recommendation for investors based on my findings, research and analysis of quarterly reports of 2018 and 2019 is to trust in their vision and invest in the company.

Appendix

R code Input:

```
library(dplyr)

library(stringr)

library(tidytext)

library(tidyr)

library(scales)

library(textreadr)

library(ggraph)

library(igraph)

library(textdata)

data(stop_words)


setwd("C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla")

nm <- list.files(path="C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla")

Q1_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla/Q1.txt')

Q2_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla/Q2.txt')

Q3_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla/Q3.txt')

Q4_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla/Q4.txt')

Q5_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla/Q5.txt')

Q6_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla/Q6.txt')
```

```
Q7_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla/Q7.txt')

Q8_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla/Q8.txt')


Q1_data <- data.frame(line=1:length(Q1_data), text=Q1_data, stringAsFactors = FALSE)

Q2_data <- data.frame(line=1:length(Q2_data), text=Q2_data, stringAsFactors = FALSE)

Q3_data <- data.frame(line=1:length(Q3_data), text=Q3_data, stringAsFactors = FALSE)

Q4_data <- data.frame(line=1:length(Q4_data), text=Q4_data, stringAsFactors = FALSE)

Q5_data <- data.frame(line=1:length(Q5_data), text=Q5_data, stringAsFactors = FALSE)

Q6_data <- data.frame(line=1:length(Q6_data), text=Q6_data, stringAsFactors = FALSE)

Q7_data <- data.frame(line=1:length(Q7_data), text=Q7_data, stringAsFactors = FALSE)

Q8_data <- data.frame(line=1:length(Q8_data), text=Q8_data, stringAsFactors = FALSE)


my_text <- bind_rows(mutate(Q1_data, author="Q1"),

                     mutate(Q2_data, author="Q2"),

                     mutate(Q3_data, author="Q3"),

                     mutate(Q4_data, author="Q4"),

                     mutate(Q5_data, author="Q5"),

                     mutate(Q6_data, author="Q6"),

                     mutate(Q7_data, author="Q7"),

                     mutate(Q8_data, author="Q8"))


##Tokenization

my_tokens <- my_text %>%

  unnest_tokens(word, text) %>%

  anti_join(stop_words) %>% #here's where we remove tokens

  count(word, sort=TRUE)
```

```
##nrc sentiment analysis
my_nrc <- my_tokens %>%
  inner_join(get_sentiments("nrc")) %>%
  count(sentiment)

##Afinn sentiment analysis
my_afinn <- my_tokens %>%
  inner_join(get_sentiments("afinn"))

sum(my_afinn$value)
mean(my_afinn$value)

##bing sentiment analysis
my_bing <- my_tokens %>%
  inner_join(get_sentiments("bing")) %>%
  count(sentiment)

##nrc sentiment plot
my_nrc %>%
  group_by(sentiment) %>%
  top_n(10) %>%
  ungroup() %>%
  mutate(sentiment=reorder(sentiment, n)) %>%
  ggplot(aes(sentiment, n, fill=sentiment)) +
  geom_col(show.legend = FALSE) +
  labs(y="Contribution to sentiment", x=NULL)+
```

```
  coord_flip()

##bing sentiment plot
my_bing %>%
  group_by(sentiment) %>%
  top_n(10) %>%
  ungroup() %>%
  mutate(sentiment=reorder(sentiment, n)) %>%
  ggplot(aes(sentiment, n, fill=sentiment)) +
  geom_col(show.legend = FALSE) +
  labs(y="Contribution to sentiment", x=NULL)+
  coord_flip()

##Bigrams
my_bigrams <- my_text %>%
  unnest_tokens(bigram, text, token = "ngrams", n=2)

my_bigrams #We want to see the bigrams (words that appear together, "pairs")

my_bigrams_count <- my_bigrams %>%
  count(bigram, sort = TRUE) #this has many stop words, need to remove them

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

bigrams_filtered <- bigrams_separated %>%
  filter(!word1 %in% stop_words$word) %>%
```

```
  filter(!word2 %in% stop_words$word)


#creating the new bigram, "no-stop-words":
bigram_counts <- bigrams_filtered %>%
  unite(bigram, word1, word2, sep=' ')
#want to see the new bigrams
bigram_counts


bigram_graph <- bigram_counts %>%
  filter(n>20) %>% #change to 3 or 4
  graph_from_data_frame()


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

Output:

```
> library(dplyr)
> library(stringr)
> library(tidytext)
> library(tidyr)
> library(scales)
> library(textreadr)
> library(ggraph)
> library(igraph)
> library(textdata)
> data(stop_words)
> setwd("C:/Users/SHEETHAL/Desktop/Text analytics/Individual Assignment/Tesla
")
> nm <- list.files(path="C:/Users/SHEETHAL/Desktop/Text analytics/Individual
Assignment/Tesla")
> Q1_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Ind
ividual Assignment/Tesla/Q1.txt')
> Q2_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Ind
ividual Assignment/Tesla/Q2.txt')
```

```
> Q3_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Ind
ividual Assignment/Tesla/Q3.txt')
> Q4_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Ind
ividual Assignment/Tesla/Q4.txt')
> Q5_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Ind
ividual Assignment/Tesla/Q5.txt')
> Q6_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Ind
ividual Assignment/Tesla/Q6.txt')
> Q7_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Ind
ividual Assignment/Tesla/Q7.txt')
> Q8_data <- read_document(file='C:/Users/SHEETHAL/Desktop/Text analytics/Ind
ividual Assignment/Tesla/Q8.txt')
>
>
> Q1_data <- data.frame(line=1:length(Q1_data), text=Q1_data, stringAsFactors
= FALSE)
> Q2_data <- data.frame(line=1:length(Q2_data), text=Q2_data, stringAsFactors
= FALSE)
> Q3_data <- data.frame(line=1:length(Q3_data), text=Q3_data, stringAsFactors
= FALSE)
> Q4_data <- data.frame(line=1:length(Q4_data), text=Q4_data, stringAsFactors
= FALSE)
> Q5_data <- data.frame(line=1:length(Q5_data), text=Q5_data, stringAsFactors
= FALSE)
> Q6_data <- data.frame(line=1:length(Q6_data), text=Q6_data, stringAsFactors
= FALSE)
> Q7_data <- data.frame(line=1:length(Q7_data), text=Q7_data, stringAsFactors
= FALSE)
> Q8_data <- data.frame(line=1:length(Q8_data), text=Q8_data, stringAsFactors
= FALSE)
>
>
> my_text <- bind_rows(mutate(Q1_data, author="Q1"),
+                      mutate(Q2_data, author="Q2"),
+                      mutate(Q3_data, author="Q3"),
+                      mutate(Q4_data, author="Q4"),
+                      mutate(Q5_data, author="Q5"),
+                      mutate(Q6_data, author="Q6"),
+                      mutate(Q7_data, author="Q7"),
+                      mutate(Q8_data, author="Q8"))
Warning messages:
1: In bind_rows_(x, .id) : Unequal factor levels: coercing to character
2: In bind_rows_(x, .id) :
  binding character and factor vector, coercing into character vector
3: In bind_rows_(x, .id) :
  binding character and factor vector, coercing into character vector
4: In bind_rows_(x, .id) :
  binding character and factor vector, coercing into character vector
5: In bind_rows_(x, .id) :
  binding character and factor vector, coercing into character vector
6: In bind_rows_(x, .id) :
  binding character and factor vector, coercing into character vector
7: In bind_rows_(x, .id) :
  binding character and factor vector, coercing into character vector
8: In bind_rows_(x, .id) :
  binding character and factor vector, coercing into character vector
9: In bind_rows_(x, .id) :
  binding character and factor vector, coercing into character vector
> my_tokens <- my_text %>%
+   unnest_tokens(word, text) %>%
+   anti_join(stop_words) %>% #here's where we remove tokens
+   count(word, sort=TRUE)
Joining, by = "word"
> my_nrc <- my_tokens %>%
```

```
+   inner_join(get_sentiments("nrc")) %>%
+   count(sentiment)
Joining, by = "word"
> my_afinn <- my_tokens %>%
+   inner_join(get_sentiments("afinn"))
Joining, by = "word"
> sum(my_afinn$value)
[1] 124
> mean(my_afinn$value)
[1] 0.8920863
> my_bing <- my_tokens %>%
+   inner_join(get_sentiments("bing")) %>%
+   count(sentiment)
Joining, by = "word"
> my_nrc %>%
+   group_by(sentiment) %>%
+   top_n(10) %>%
+   ungroup() %>%
+   mutate(sentiment=reorder(sentiment, n)) %>%
+   ggplot(aes(sentiment, n, fill=sentiment)) +
+   geom_col(show.legend = FALSE) +
+   labs(y="Contribution to sentiment", x=NULL)+
+   coord_flip()
Selecting by n
> my_bing %>%
+   group_by(sentiment) %>%
+   top_n(10) %>%
+   ungroup() %>%
+   mutate(sentiment=reorder(sentiment, n)) %>%
+   ggplot(aes(sentiment, n, fill=sentiment)) +
+   geom_col(show.legend = FALSE) +
+   labs(y="Contribution to sentiment", x=NULL)+
+   coord_flip()
Selecting by n
> my_bigrams <- my_text %>%
+   unnest_tokens(bigram, text, token = "ngrams", n=2)
>
> my_bigrams #We want to see the bigrams (words that appear together, "pairs"
)
    line stringAsFactors author              bigram
1      1           FALSE     Q1         tesla first
2      1           FALSE     Q1       first quarter
3      1           FALSE     Q1        quarter 2019
4      1           FALSE     Q1         2019 update
5      1           FALSE     Q1            update â
6      1           FALSE     Q1              â gaap
7      1           FALSE     Q1      gaap operating
8      1           FALSE     Q1      operating loss
9      1           FALSE     Q1             loss of
10     1           FALSE     Q1             of 522m
11     1           FALSE     Q1           522m gaap
12     1           FALSE     Q1            gaap net
13     1           FALSE     Q1            net loss
14     1           FALSE     Q1             loss of
15     1           FALSE     Q1             of 702m
16     1           FALSE     Q1      702m including
17     1           FALSE     Q1      including 188m
18     1           FALSE     Q1             188m of
19     1           FALSE     Q1              of non
20     1           FALSE     Q1       non recurring
21     1           FALSE     Q1   recurring charges
22     1           FALSE     Q1           charges â
23     1           FALSE     Q1              â cash
24     1           FALSE     Q1            cash and
```

25	1	FALSE	Q1	and cash
26	1	FALSE	Q1	cash equivalents
27	1	FALSE	Q1	equivalents of
28	1	FALSE	Q1	of 2.2b
29	1	FALSE	Q1	2.2b at
30	1	FALSE	Q1	at q1
31	1	FALSE	Q1	q1 end
32	1	FALSE	Q1	end â
33	1	FALSE	Q1	â model
34	1	FALSE	Q1	model 3
35	1	FALSE	Q1	3 gross
36	1	FALSE	Q1	gross margin
37	1	FALSE	Q1	margin 20
38	1	FALSE	Q1	20 in
39	1	FALSE	Q1	in q1
40	1	FALSE	Q1	q1 â
41	1	FALSE	Q1	â revealed
42	1	FALSE	Q1	revealed tesla
43	1	FALSE	Q1	tesla model
44	1	FALSE	Q1	model y
45	1	FALSE	Q1	y â
46	1	FALSE	Q1	â started
47	1	FALSE	Q1	started production
48	1	FALSE	Q1	production of
49	1	FALSE	Q1	of full
50	1	FALSE	Q1	full self
51	1	FALSE	Q1	self driving
52	1	FALSE	Q1	driving computer
53	1	FALSE	Q1	computer we
54	1	FALSE	Q1	we ended
55	1	FALSE	Q1	ended the
56	1	FALSE	Q1	the quarter
57	1	FALSE	Q1	quarter with
58	1	FALSE	Q1	with 2.2
59	1	FALSE	Q1	2.2 billion
60	1	FALSE	Q1	billion of
61	1	FALSE	Q1	of cash
62	1	FALSE	Q1	cash and
63	1	FALSE	Q1	and cash
64	1	FALSE	Q1	cash equivalents
65	1	FALSE	Q1	equivalents a
66	1	FALSE	Q1	a 1.5
67	1	FALSE	Q1	1.5 billion
68	1	FALSE	Q1	billion reduction
69	1	FALSE	Q1	reduction from
70	1	FALSE	Q1	from the
71	1	FALSE	Q1	the end
72	1	FALSE	Q1	end of
73	1	FALSE	Q1	of 2018
74	1	FALSE	Q1	2018 this
75	1	FALSE	Q1	this reduction
76	1	FALSE	Q1	reduction was
77	1	FALSE	Q1	was driven
78	1	FALSE	Q1	driven by
79	1	FALSE	Q1	by a
80	1	FALSE	Q1	a 920
81	1	FALSE	Q1	920 million
82	1	FALSE	Q1	million convertible
83	1	FALSE	Q1	convertible bond
84	1	FALSE	Q1	bond repayment
85	1	FALSE	Q1	repayment and
86	1	FALSE	Q1	and an
87	1	FALSE	Q1	an increase
88	1	FALSE	Q1	increase in

89	1	FALSE	Q1	in the
90	1	FALSE	Q1	the number
91	1	FALSE	Q1	number of
92	1	FALSE	Q1	of vehicles
93	1	FALSE	Q1	vehicles in
94	1	FALSE	Q1	in transit
95	1	FALSE	Q1	transit to
96	1	FALSE	Q1	to customers
97	1	FALSE	Q1	customers at
98	1	FALSE	Q1	at the
99	1	FALSE	Q1	the end
100	1	FALSE	Q1	end of
101	1	FALSE	Q1	of q1
102	1	FALSE	Q1	q1 in
103	1	FALSE	Q1	in addition
104	1	FALSE	Q1	addition we
105	1	FALSE	Q1	we began
106	1	FALSE	Q1	began production
107	1	FALSE	Q1	production and
108	1	FALSE	Q1	and deliveries
109	1	FALSE	Q1	deliveries of
110	1	FALSE	Q1	of model
111	1	FALSE	Q1	model 3
112	1	FALSE	Q1	3 vehicles
113	1	FALSE	Q1	vehicles for
114	1	FALSE	Q1	for overseas
115	1	FALSE	Q1	overseas markets
116	1	FALSE	Q1	markets as
117	1	FALSE	Q1	as noted
118	1	FALSE	Q1	noted in
119	1	FALSE	Q1	in our
120	1	FALSE	Q1	our q1
121	1	FALSE	Q1	q1 2019
122	1	FALSE	Q1	2019 vehicle
123	1	FALSE	Q1	vehicle production
124	1	FALSE	Q1	production deliveries
125	1	FALSE	Q1	deliveries letter
126	1	FALSE	Q1	letter due
127	1	FALSE	Q1	due to
128	1	FALSE	Q1	to unforeseen
129	1	FALSE	Q1	unforeseen challenges
130	1	FALSE	Q1	challenges we
131	1	FALSE	Q1	we had
132	1	FALSE	Q1	had only
133	1	FALSE	Q1	only delivered
134	1	FALSE	Q1	delivered half
135	1	FALSE	Q1	half of
136	1	FALSE	Q1	of the
137	1	FALSE	Q1	the quarterâ
138	1	FALSE	Q1	quarterâ s
139	1	FALSE	Q1	s numbers
140	1	FALSE	Q1	numbers ten
141	1	FALSE	Q1	ten days
142	1	FALSE	Q1	days before
143	1	FALSE	Q1	before the
144	1	FALSE	Q1	the end
145	1	FALSE	Q1	end of
146	1	FALSE	Q1	of the
147	1	FALSE	Q1	the quarter
148	1	FALSE	Q1	quarter this
149	1	FALSE	Q1	this caused
150	1	FALSE	Q1	caused a
151	1	FALSE	Q1	a large
152	1	FALSE	Q1	large number

153	1	FALSE	Q1	number of
154	1	FALSE	Q1	of vehicle
155	1	FALSE	Q1	vehicle deliveries
156	1	FALSE	Q1	deliveries to
157	1	FALSE	Q1	to shift
158	1	FALSE	Q1	shift into
159	1	FALSE	Q1	into q2
160	1	FALSE	Q1	q2 in
161	1	FALSE	Q1	in q1
162	1	FALSE	Q1	q1 we
163	1	FALSE	Q1	we experienced
164	1	FALSE	Q1	experienced non
165	1	FALSE	Q1	non recurring
166	1	FALSE	Q1	recurring items
167	1	FALSE	Q1	items that
168	1	FALSE	Q1	that negatively
169	1	FALSE	Q1	negatively impacted
170	1	FALSE	Q1	impacted our
171	1	FALSE	Q1	our net
172	1	FALSE	Q1	net loss
173	1	FALSE	Q1	loss by
174	1	FALSE	Q1	by 188
175	1	FALSE	Q1	188 million
176	1	FALSE	Q1	million as
177	1	FALSE	Q1	as a
178	1	FALSE	Q1	a result
179	1	FALSE	Q1	result of
180	1	FALSE	Q1	of q1
181	1	FALSE	Q1	q1 pricing
182	1	FALSE	Q1	pricing actions
183	1	FALSE	Q1	actions taken
184	1	FALSE	Q1	taken on
185	1	FALSE	Q1	on model
186	1	FALSE	Q1	model s
187	1	FALSE	Q1	s and
188	1	FALSE	Q1	and model
189	1	FALSE	Q1	model x
190	1	FALSE	Q1	x we
191	1	FALSE	Q1	we incurred
192	1	FALSE	Q1	incurred net
193	1	FALSE	Q1	net 121
194	1	FALSE	Q1	121 million
195	1	FALSE	Q1	million loss
196	1	FALSE	Q1	loss for
197	1	FALSE	Q1	for increases
198	1	FALSE	Q1	increases in
199	1	FALSE	Q1	in the
200	1	FALSE	Q1	the assumed
201	1	FALSE	Q1	assumed forecasted
202	1	FALSE	Q1	forecasted return
203	1	FALSE	Q1	return rates
204	1	FALSE	Q1	rates for
205	1	FALSE	Q1	for cars
206	1	FALSE	Q1	cars sold
207	1	FALSE	Q1	sold under
208	1	FALSE	Q1	under our
209	1	FALSE	Q1	our residual
210	1	FALSE	Q1	residual value
211	1	FALSE	Q1	value guarantee
212	1	FALSE	Q1	guarantee and
213	1	FALSE	Q1	and buy
214	1	FALSE	Q1	buy back
215	1	FALSE	Q1	back guarantee
216	1	FALSE	Q1	guarantee programs

```
217    1            FALSE     Q1          programs as
218    1            FALSE     Q1              as well
219    1            FALSE     Q1              well as
220    1            FALSE     Q1         as inventory
221    1            FALSE     Q1      inventory write
222    1            FALSE     Q1          write downs
223    1            FALSE     Q1            downs for
224    1            FALSE     Q1             for used
225    1            FALSE     Q1             used and
226    1            FALSE     Q1          and service
227    1            FALSE     Q1       service loaner
228    1            FALSE     Q1     loaner inventory
229    1            FALSE     Q1         inventory we
230    1            FALSE     Q1              we also
231    1            FALSE     Q1        also incurred
232    1            FALSE     Q1          incurred 67
233    1            FALSE     Q1           67 million
234    1            FALSE     Q1          million due
235    1            FALSE     Q1               due to
236    1            FALSE     Q1                 to a
237    1            FALSE     Q1        a combination
238    1            FALSE     Q1       combination of
239    1            FALSE     Q1     of restructuring
240    1            FALSE     Q1    restructuring and
241    1            FALSE     Q1            and other
242    1            FALSE     Q1            other non
243    1            FALSE     Q1        non recurring
244    1            FALSE     Q1    recurring charges
245    1            FALSE     Q1      charges vehicle
246    1            FALSE     Q1   vehicle production
247    1            FALSE     Q1       production and
248    1            FALSE     Q1       and deliveries
249    1            FALSE     Q1        deliveries we
250    1            FALSE     Q1          we produced
 [ reached 'max' / getOption("max.print") -- omitted 22925 rows ]
>
> my_bigrams_count <- my_bigrams %>%
+   count(bigram, sort = TRUE) #this has many stop words, need to remove them
>
> bigrams_separated <- my_bigrams_count %>%
+   separate(bigram, c("word1", "word2"), sep = " ")
>
> bigrams_filtered <- bigrams_separated %>%
+   filter(!word1 %in% stop_words$word) %>%
+   filter(!word2 %in% stop_words$word)
>
> #creating the new bigram, "no-stop-words":
> bigram_counts <- bigrams_filtered %>%
+   unite(bigram, word1, word2, sep=' ')
> #want to see the new bigrams
> bigram_counts
# A tibble: 3,743 x 2
   bigram                   n
   <chr>                <int>
 1 model 3                245
 2 gross margin            90
 3 cash flow               49
 4 energy storage          41
 5 gigafactory shanghai    35
 6 energy generation       30
 7 3 production            28
 8 gaap net                25
 9 operating cash          24
10 3 vehicles              23
```

```
# ... with 3,733 more rows
>
> bigram_graph <- bigram_counts %>%
+   filter(n>20) %>% #change to 3 or 4
+   graph_from_data_frame()
>
> bigram_graph
IGRAPH 4964561 DN-- 24 13 --
+ attr: name (v/c)
+ edges from 4964561 (vertex names):
 [1] model 3            ->245 gross margin        ->90  cash flow
->49
 [4] energy storage      ->41  gigafactory shanghai->35  energy generation
->30
 [7] 3 production        ->28  gaap net            ->25  operating cash
->24
[10] 3 vehicles          ->23  automotive gross    ->23  net income
->23
[13] NA NA               ->21
> ggraph(bigram_graph, layout = "fr") +
+   geom_edge_link()+
+   geom_node_point()+
+   geom_node_text(aes(label=name), vjust =1, hjust=1)
```

Sources

About Tesla: Tesla. (n.d.). Retrieved February 14, 2020, from https://www.tesla.com/about

Financials & Accounting. (n.d.). Retrieved February 14, 2020, from https://ir.tesla.com/financial-information/quarterly-results