Capstone

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```
library(dplyr)
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
##
       intersect, setdiff, setequal, union
library(ggplot2)
library(qdap)
## Loading required package: qdapDictionaries
## Loading required package: qdapRegex
##
## Attaching package: 'qdapRegex'
## The following object is masked from 'package:ggplot2':
##
##
       %+%
## The following object is masked from 'package:dplyr':
##
##
       explain
## Loading required package: qdapTools
##
## Attaching package: 'qdapTools'
## The following object is masked from 'package:dplyr':
##
##
       id
## Loading required package: RColorBrewer
##
## Attaching package: 'qdap'
## The following object is masked from 'package:dplyr':
##
##
       %>%
## The following object is masked from 'package:base':
##
##
       Filter
library(tidyr)
```

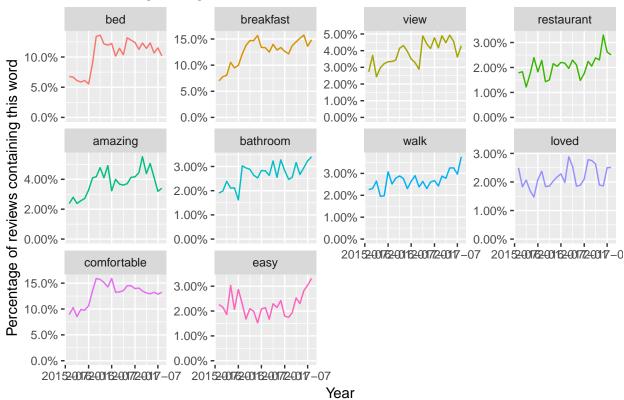
```
##
## Attaching package: 'tidyr'
## The following object is masked from 'package:qdap':
##
##
       %>%
library(tidytext)
library(tm)
## Loading required package: NLP
##
## Attaching package: 'NLP'
## The following object is masked from 'package:qdap':
##
##
       ngrams
## The following object is masked from 'package:ggplot2':
##
       annotate
##
## Attaching package: 'tm'
## The following objects are masked from 'package:qdap':
       as.DocumentTermMatrix, as.TermDocumentMatrix
##
library(SnowballC)
library(stringr)
##
## Attaching package: 'stringr'
## The following object is masked from 'package:qdap':
##
       %>%
##
library(lubridate)
##
## Attaching package: 'lubridate'
## The following object is masked from 'package:base':
##
##
       date
library(broom)
library(scales)
library(LSAfun)
## Loading required package: lsa
## Loading required package: rgl
## Attaching package: 'rgl'
## The following object is masked from 'package:qdap':
##
```

```
##
       %>%
library(lsa)
library(topicmodels)
library(sentimentr)
library(purrr)
##
## Attaching package: 'purrr'
## The following object is masked from 'package:LSAfun':
##
##
## The following object is masked from 'package:scales':
##
##
       discard
## The following object is masked from 'package:qdap':
##
##
       %>%
library(devtools)
library(pluralize)
library(NLP)
#Loading data
df <- read.csv("C:/Users/sarah ahn/Documents/Chang School/CAPSTONE/Text Analysis/Dataset/515k-hotel-rev
#limit dataset and remove irrelevant columnes
df[, c("Hotel_Address", "Additional_Number_of_Scoring", "Average_Score", "Reviewer_Nationality", "days_s
hotel_name <- df %>%
  group_by(Hotel_Name) %>%
  summarise(count=n())
hotel_name <- data.frame(hotel_name)</pre>
hotel_name <- hotel_name[order(hotel_name$count, decreasing=T), ]</pre>
hotel_name <- hotel_name[1:20,]</pre>
df_reduced <- df %>%
  filter(Hotel_Name %in% hotel_name$Hotel_Name)
sum(is.na(df_reduced))
## [1] 0
#Date cleaning
df_reduced$Review_Date <- as.Date(df_reduced$Review_Date, "%m/%d/%Y")
df_reduced[ ,c("Negative_Review", "Positive_Review", "Tags")] <- lapply(df_reduced[ ,c("Negative_Review")]</pre>
df_reduced <- df_reduced %>%
  mutate(id = seq_along(Positive_Review)) %>%
  mutate(month = round_date(Review_Date, "month"))
#Date pre-processing
data("stop_words")
```

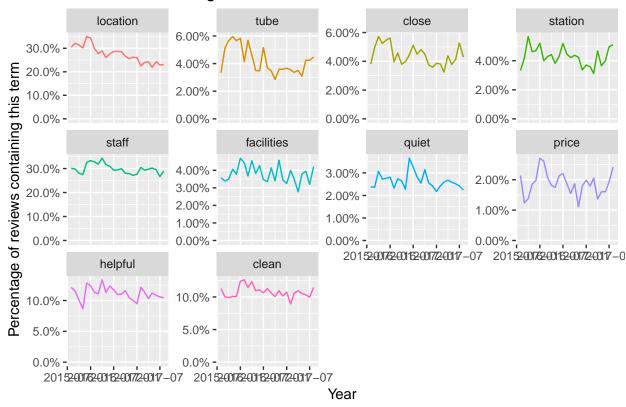
```
my_stopwords <- data_frame(word = c("hotel","didn", "wasn", "bit", "2", "wih"))</pre>
pos_review <- df_reduced %>%
 filter(Positive Review != "No Positive") %>%
  mutate(Positive_Review = gsub('comfy', 'comfortable', Positive_Review)) %>%
  unnest_tokens(word, Positive_Review) %>%
  anti_join(stop_words) %>%
  anti join(my stopwords) %>%
  count(word, sort=T) %>%
  ungroup()
## Joining, by = "word"
## Joining, by = "word"
neg_review <- df_reduced %>%
  filter(Negative_Review != "No Negative") %>%
  unnest_tokens(word, Negative_Review) %>%
  anti_join(my_stopwords) %>%
  anti_join(stop_words) %>%
  count(word, sort=T) %>%
  ungroup()
## Joining, by = "word"
## Joining, by = "word"
#Bi-qrams
pos_bigrams_filtered <- df_reduced %>%
 filter(Positive_Review != "No Positive") %>%
  mutate(Positive_Review = gsub('beds', 'bed', Positive_Review)) %>%
  unnest_tokens(bigram, Positive_Review, token = "ngrams", n = 2) %>%
  separate(bigram, c("word1", "word2"), sep = " ") %>%
  filter(!word1 %in% stop_words$word) %>%
  filter(!word2 %in% stop_words$word) %>%
  mutate(word1 = str_replace_all(word1, 'comfy', 'comfortable')) %>%
  mutate(word2 = str_replace_all(word2, 'comfy', 'comfortable')) %>%
  drop_na() %>%
  count(word1, word2, sort = TRUE)
pos bigrams <- pos bigrams filtered %>%
  unite(bigram, word1, word2, sep=" ")
df_reduced$Negative_Review <- gsub("\\<air con\\>", "air conditioning", df_reduced$Negative_Review)
df_reduced$Negative_Review <- gsub("(wi).(\\w+)", "\1\\2", df_reduced$Negative_Review, ignore.case = T.
stop_words5 <- data.frame(word = c("20", "minutes", "4", "star"))</pre>
stop_words5$word <- as.character(stop_words5$word)</pre>
neg_bigrams_filtered <- df_reduced %>%
  filter(Negative_Review != "No Negative") %>%
  unnest_tokens(bigram, Negative_Review, token = "ngrams", n = 2) %>%
  separate(bigram, c("word1", "word2"), sep = " ") %>%
  filter(!word1 %in% stop_words$word) %>%
  filter(!word2 %in% stop_words$word) %>%
```

```
filter(!word1 %in% stop_words5$word) %>%
  filter(!word2 %in% stop_words5$word) %>%
  drop_na() %>%
  count(word1, word2, sort = TRUE)
neg_bigrams <- neg_bigrams_filtered %>%
  unite(bigram, word1, word2, sep=" ")
#Trends in positive reviews
pos_review_month <- df_reduced %>%
  filter(Positive_Review != "No Positive") %>%
  mutate(Positive Review = str replace all(Positive Review, 'comfy', 'comfortable')) %>%
  mutate(Positive_Review = gsub('beds', 'bed', Positive_Review)) %>%
  distinct(Positive_Review, .keep_all = TRUE) %>%
  unnest_tokens(word, Positive_Review, drop = FALSE) %>%
  distinct(id, word, .keep_all = TRUE) %>%
  anti_join(stop_words, by = "word") %>%
  group by (word) %>%
  mutate(word_total = n()) %>%
  ungroup()
pos_per_month <- df_reduced %>%
  group_by(month) %>%
  summarize(month total = n())
pos_month_count <- pos_review_month %>%
  filter(word_total >= 1000) %>%
  count(word, month) %>%
  complete(word, month, fill = list(n = 0)) %>%
  inner_join(pos_per_month, by = "month") %>%
  mutate(percent = n / month_total) %>%
  mutate(year = year(month) + yday(month) / 365)
pos_mod <- ~ glm(cbind(n, month_total - n) ~ year, ., family = "binomial")</pre>
pos_slopes <- pos_month_count %>%
  nest(-word) %>%
  mutate(model = map(data, pos_mod)) %>%
  unnest(purrr::map(model, tidy)) %>%
  filter(term == "year") %>%
  arrange(desc(estimate))
pos_slopes %>%
  head(10) %>%
  inner_join(pos_month_count, by = "word") %>%
  mutate(word = reorder(word, -estimate)) %>%
  ggplot(aes(month, n / month_total, color = word)) +
  geom_line(show.legend = FALSE) +
  scale_y_continuous(labels = scales::percent_format()) +
  facet_wrap(~ word, scales = "free_y") +
  expand_limits(y = 0) +
  labs(x = "Year",
       y = "Percentage of reviews containing this word",
       title = "10 fastest growing words in all Positive Reviews")
```

10 fastest growing words in all Positive Reviews



10 fastest shrinking words in all Positive Reviews



```
#Trends in Negative Reviews

neg_review_month <- df_reduced %>%
    distinct(Negative_Review, .keep_all = TRUE) %>%
    filter(Negative_Review != "No Negative") %>%
    unnest_tokens(word, Negative_Review, drop = FALSE) %>%
    distinct(id, word, .keep_all = TRUE) %>%
    anti_join(my_stopwords) %>%
    anti_join(stop_words, by = "word") %>%
    group_by(word) %>%
    mutate(word_total = n()) %>%
    ungroup()
```

```
## Joining, by = "word"
```

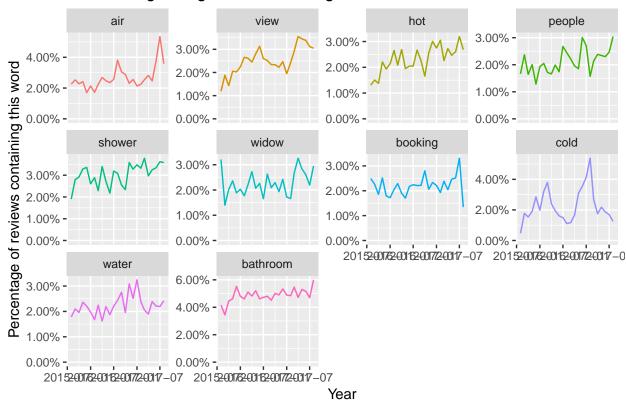
```
neg_per_month <- df_reduced %>%
  group_by(month) %>%
  summarize(month_total = n())

neg_month_count <- neg_review_month %>%
  filter(word_total >= 1000) %>%
  count(word, month) %>%
  count(word, month) %>%
  complete(word, month, fill = list(n = 0)) %>%
  inner_join(pos_per_month, by = "month") %>%
  mutate(percent = n / month_total) %>%
  mutate(year = year(month) + yday(month) / 365)
```

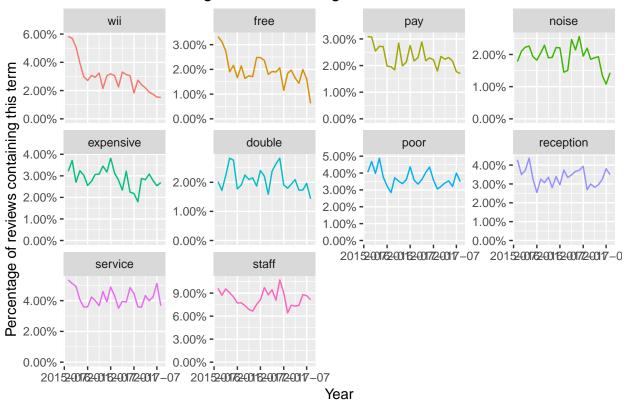
```
neg_mod <- ~ glm(cbind(n, month_total - n) ~ year, ., family = "binomial")</pre>
neg_slopes <- neg_month_count %>%
  nest(-word) %>%
  mutate(model = purrr::map(data, pos_mod)) %>%
  unnest(purrr::map(model, tidy)) %>%
  filter(term == "year") %>%
  arrange(desc(estimate))
stop_words6 <- data.frame(word = c("day", "time", "couldn", "paid"))</pre>
stop_words6$word <- as.character(stop_words6$word)</pre>
neg_slopes %>%
  anti_join(stop_words6) %>%
  head(10) %>%
  inner_join(neg_month_count, by = "word") %>%
  mutate(word = reorder(word, -estimate)) %>%
  ggplot(aes(month, n / month_total, color = word)) +
  geom_line(show.legend = FALSE) +
  scale_y_continuous(labels = scales::percent_format()) +
  facet_wrap(~ word, scales = "free_y") +
  expand_limits(y = 0) +
  labs(x = "Year",
       y = "Percentage of reviews containing this word",
       title = "10 fastest growing words in all Negative Reviews")
```

Joining, by = "word"

10 fastest growing words in all Negative Reviews

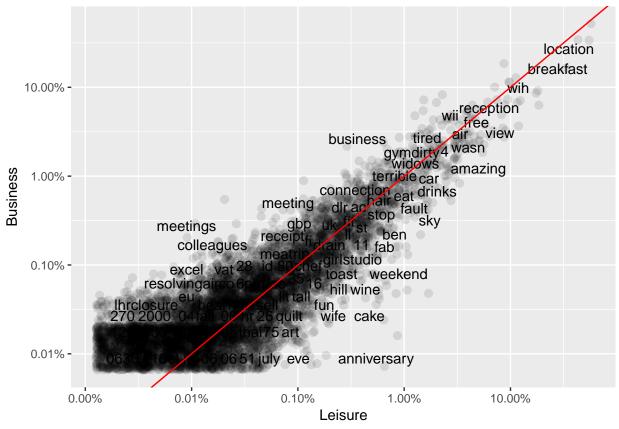


10 fastest shrinking words in all Negative Reviews



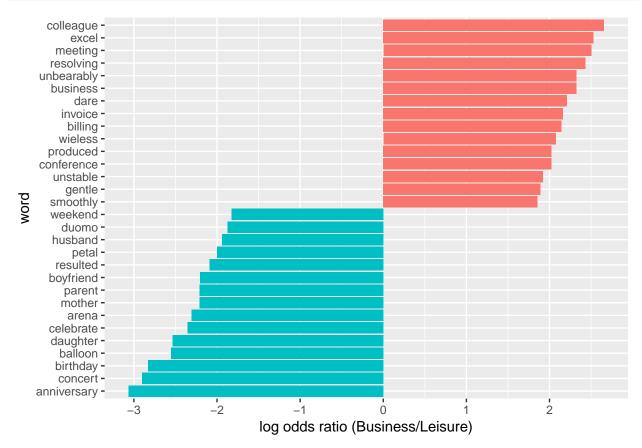
```
#Leisure Reviews
df leisure <- df reduced[with(df reduced, str detect(Tags, 'Leisure')),]</pre>
df_leisure <- df_leisure[ , c("Positive_Review", "Negative_Review", "month", "Reviewer_Score")]</pre>
leisure <- unite(df_leisure, "Reviews", Positive_Review, Negative_Review, sep = " ")</pre>
stop_words2 <- c("No Positive", "No Negative")</pre>
leisure$Reviews <- removeWords(leisure$Reviews, stop_words2)</pre>
#Business Reviews
df_business <- df_reduced[with(df_reduced, str_detect(Tags, 'Business')),]</pre>
df_business <- df_business[ , c("Positive_Review", "Negative_Review", "month", "Reviewer_Score")]</pre>
business <- unite(df_business, "Reviews", Positive_Review, Negative_Review, sep = " ")</pre>
business Reviews <- removeWords (business Reviews, stop words2)
travellers <- bind rows(leisure %>%
                            mutate(type = "Leisure"),
                         business %>%
                            mutate(type = "Business"))
#Travellers word frequency
stop_words4 <- data.frame(word = c("o2", "sse"))</pre>
stop_words4$word <- as.character(stop_words4$word)</pre>
travellers_freq <- travellers %>%
  mutate(Reviews = singularize(Reviews)) %>%
```

```
unnest_tokens(word, Reviews) %>%
  anti_join(stop_words) %>%
  anti_join(stop_words4) %>%
  group_by(type) %>%
  count(word, sort=T) %>%
 left_join(travellers %>%
              group_by(type) %>%
              summarise(total = n())) %>%
 mutate(freq = n/total)
## Joining, by = "word"
## Joining, by = "word"
## Joining, by = "type"
travellers_freq <- travellers_freq %>%
  select(type, word, freq) %>%
  spread(type, freq) %>%
  arrange(Leisure, Business)
ggplot(travellers_freq, aes(Leisure, Business)) +
  geom_jitter(alpha = 0.1, size = 2.5, width = 0.25, height = 0.25) +
 geom_text(aes(label = word), check_overlap = TRUE, vjust = 1.5) +
  scale_x_log10(labels = percent_format()) +
 scale_y_log10(labels = percent_format()) +
 geom_abline(color = "red")
## Warning: Removed 14997 rows containing missing values (geom_point).
## Warning: Removed 14997 rows containing missing values (geom_text).
```



```
#travellers word usage
travellers_usage <- travellers %>%
  unnest_tokens(word, Reviews) %>%
  anti_join(stop_words) %>%
  anti_join(stop_words4) %>%
  mutate(word = singularize(word)) %>%
  count(word, type) %>%
  group_by(word) %>%
  filter(sum(n) >= 10) %>%
  ungroup() %>%
  spread(type, n, fill = 0) %>%
  mutate_if(is.numeric, funs((. + 1) / (sum(.) + 1))) %>%
  mutate(logratio = log(Business / Leisure)) %>%
  arrange(desc(logratio))
## Joining, by = "word"
## Joining, by = "word"
#equally likely?
travellers_usage %>%
  arrange(abs(logratio))
## # A tibble: 3,985 x 4
##
     word
                Business
                           Leisure
                                     logratio
```

```
##
      <chr>
                   <dbl>
                             <dbl>
                                        <dbl>
##
   1 missed
               0.000155 0.000155
                                    0.0000785
##
   2 bath
               0.00165
                         0.00165
                                   -0.000371
               0.00110
                         0.00110
                                   -0.000885
##
   3 staying
##
   4 mattress 0.000667
                         0.000666
                                    0.00119
   5 advise
               0.0000966 0.0000968 -0.00212
##
   6 local
               0.000386 0.000387 -0.00212
##
   7 hotel
               0.0283
                         0.0284
                                   -0.00339
##
##
   8 slept
               0.000377
                         0.000375
                                    0.00375
   9 advice
               0.0000870 0.0000866 0.00375
##
## 10 beaten
               0.0000290 0.0000289
                                    0.00375
## # ... with 3,975 more rows
#less or more likely?
travellers_usage %>%
  group_by(logratio < 0) %>%
  top_n(15, abs(logratio)) %>%
  ungroup() %>%
  mutate(word = reorder(word, logratio)) %>%
  ggplot(aes(word, logratio, fill = logratio < 0)) +</pre>
  geom_col(show.legend = FALSE) +
  coord_flip() +
  ylab("log odds ratio (Business/Leisure)") +
  scale_fill_discrete(name = "", labels = c("Business", "Leisure"))
```



#Data Visualization

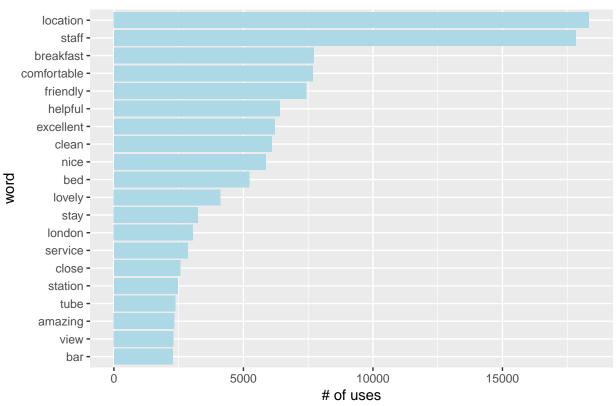
```
hotel_name %>%
  mutate(Hotel_Name = reorder(Hotel_Name, count)) %>%
  ggplot(aes(Hotel_Name, count)) +
  geom_col(fill = "lightblue") +
  scale_y_continuous() +
  coord_flip() +
  labs(x = 'Hotel Name',title = "Number of Reviews per Hotel", y = 'Count')
```

Number of Reviews per Hotel

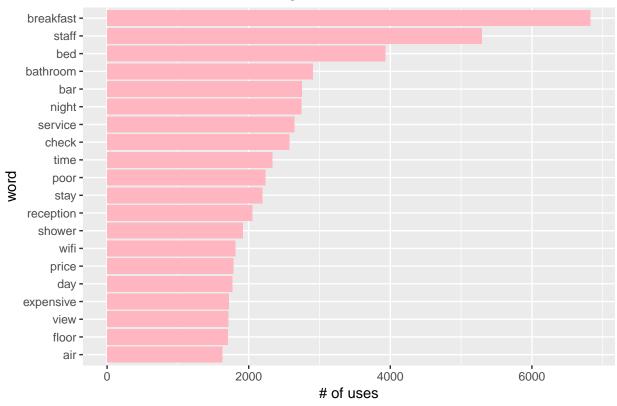


```
#Word frequency of postive and negative reviews
pos_review %>%
  head(20) %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(word, n)) +
    geom_col(fill = "lightblue") +
    scale_y_continuous() +
    coord_flip() +
  labs(title = "Most common words in Positive Reviews of all Hotels",
        y = "# of uses")
```

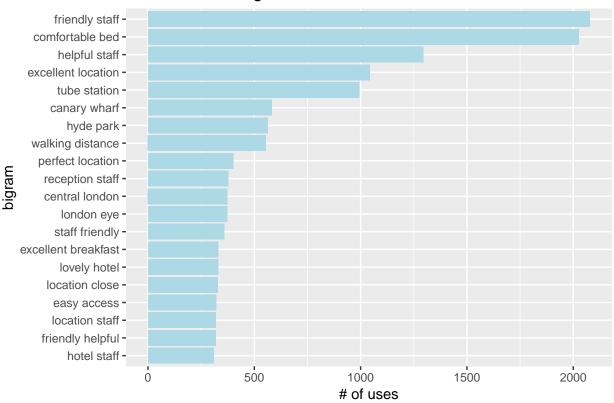
Most common words in Positive Reviews of all Hotels



Most common words in Negative Reviews of all Hotels

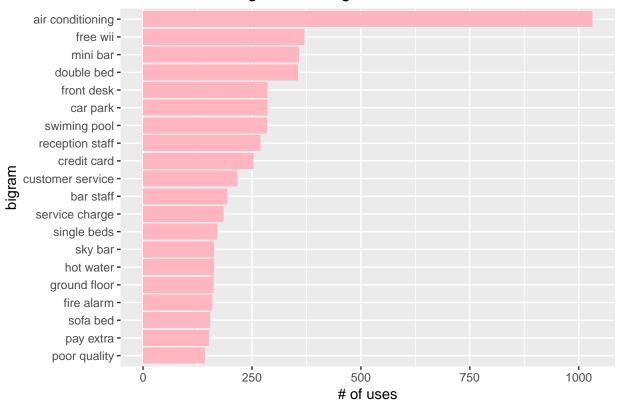


Most common bigrams in Positive Reviews of all Hotels

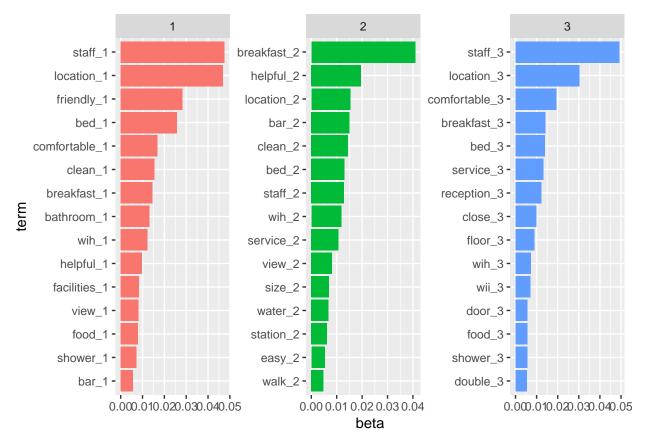


```
neg_bigrams %>%
  head(20) %>%
  mutate(bigram = reorder(bigram, n)) %>%
  ggplot(aes(bigram, n)) +
  geom_col(fill = "lightpink") +
  scale_y_continuous() +
  coord_flip() +
  labs(title = "Most common bigrams in Negative Reviews of all Hotels",
      y = "# of uses")
```

Most common bigrams in Negative Reviews of all Hotels

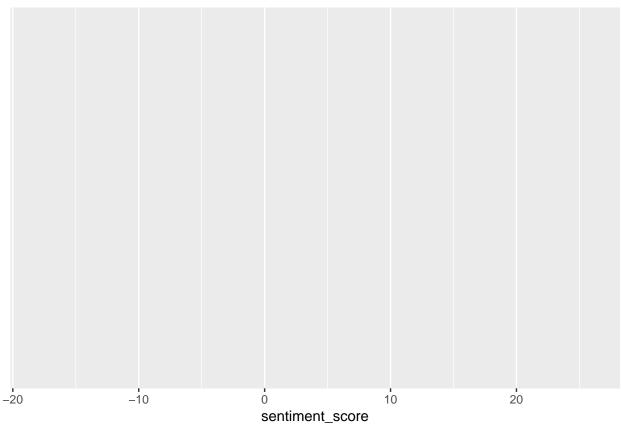


```
#Topic Modelling
stop words3 <- data frame(word = c("london", "hotel", "bit", "didn", "wasn", "told", "positive", "negat
                                    "air", "stayed", "amazing", "perfect", "not", "3", "night", "day", "
                                    ,"fantastic", "nice", "excellent", "loved", "check", "minutes", "fre
                                    "booked", "price", "money", "paid", "4", "expensive"))
travellers_topic <- travellers %>%
  mutate(id = seq_along(Reviews)) %>%
  mutate(Reviews = gsub('comfy', 'comfortable', Reviews)) %>%
  mutate(Reviews = gsub('beds', 'bed', Reviews))
trav dtm <- travellers topic %>%
   unnest_tokens(word, Reviews) %>%
   anti_join(stop_words3) %>%
   anti_join(stop_words) %>%
   count(id, word, sort=TRUE) %>%
   ungroup() %>%
   cast_dtm(id, word, n)
## Joining, by = "word"
## Joining, by = "word"
trav_lda <- LDA(trav_dtm, k = 3, control = set.seed(1234))</pre>
trav_topics <- tidytext::tidy(trav_lda, matrix = "beta")</pre>
trav_top <- trav_topics %>%
```



```
trav_doc <- tidytext::tidy(trav_lda, matrix = "gamma")
trav_doc2 <- spread(trav_doc, topic, gamma)
trav_doc2 <- data.frame(trav_doc2)
trav_doc2$document <- as.numeric(trav_doc2$document)
trav_doc2 <- trav_doc2[order(trav_doc2$document), ]
names(trav_doc2) <- c("id", "Topic_1_hotel_rooms", "Topic_2_staff", "Topic_3_location")
max_topic <- cbind(trav_doc2, Topic = names(trav_doc2[2:4])[apply(trav_doc2[2:4],1,which.max)] )</pre>
```

```
head(trav_doc2)
##
         id Topic_1_hotel_rooms Topic_2_staff Topic_3_location
## 1
                      0.3256901
                                    0.3529234
                                                     0.3213865
## 10912 2
                      0.3238252
                                    0.3347758
                                                     0.3413990
## 21888 3
                     0.3409699
                                    0.3475427
                                                     0.3114874
## 32777 4
                      0.3412398
                                    0.3265211
                                                     0.3322391
## 43675 5
                      0.3337379
                                    0.3385706
                                                     0.3276914
## 47822 6
                      0.3400372
                                    0.3216614
                                                     0.3383014
#Sentiment Analysis
trav_sentiment <- travellers_topic</pre>
trav_sentiment$Reviews <- removeWords(trav_sentiment$Reviews, stop_words2)
trav_sentiment <- trav_sentiment %>%
  unnest_tokens(word, Reviews) %>%
  anti_join(stop_words) %>%
  inner_join(get_sentiments("bing")) %>%
  group_by(id, sentiment) %>%
  summarise(count = n()) %>%
  spread(sentiment, count, fill=0) %>%
  mutate(sentiment_score = positive - negative) %>%
  mutate(review_sentiment = ifelse(sentiment_score == 0, "Neutral", ifelse(sentiment_score > 0, "Positi
## Joining, by = "word"
## Joining, by = "word"
trav_sentiment %>%
  ggplot(aes(sentiment_score, ))
```



```
#Building dataframe for analysis
df_analysis <- travellers_topic %>%
 full_join(max_topic)
## Joining, by = "id"
df_analysis <- df_analysis %>%
 full_join(trav_sentiment)
## Joining, by = "id"
df_analysis <- df_analysis[, c("type", "id", "Topic", "review_sentiment", "Reviewer_Score")]</pre>
df_analysis [ , c("type", "review_sentiment")] <- lapply(df_analysis[, c("type", "review_sentiment")],</pre>
df_analysis$id <- NULL</pre>
#Reression Analysis
model1 <- lm(data = df_analysis, Reviewer_Score ~ .,)</pre>
summary(model1)
##
## Call:
## lm(formula = Reviewer_Score ~ ., data = df_analysis)
```

Max

Residuals:

Min

1Q Median

ЗQ

##

```
## -6.4185 -0.9066 0.2815 1.0815 3.8771
##
## Coefficients:
##
                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                       ## typeLeisure
                       ## TopicTopic_2_staff -0.23796 0.01727 -13.78 <2e-16 ***
## TopicTopic_3_location -0.20354 0.01758 -11.58 <2e-16 ***
## review_sentimentNeutral 0.96767 0.02702 35.81 <2e-16 ***
## review_sentimentPositive 2.04572 0.01812 112.88 <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 1.522 on 45243 degrees of freedom
    (7898 observations deleted due to missingness)
## Multiple R-squared: 0.2592, Adjusted R-squared: 0.2591
## F-statistic: 3166 on 5 and 45243 DF, p-value: < 2.2e-16
```