Mysteries of the (Yelp) Orient

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Background and Summary

For the Springboard Capstone project, I analyzed Yelp's public dataset to explore hacks that could enhance the customer experience and ultimately user retention.

The Yelp app does a reasonably good job of recommending restaurants using a top-down approach comprising proximity, star ratings and review counts.

During a trip to San Francisco, however, I had a hard time locating a Chinese restaurant that served a dish called 'Ee-Fu Noodles'. The search results seem to favour highly-rated Chinese restaurants whose reviews merely contain 'noodles' but do not precisely match the actual dish name.

First-time visitors to a city might be in the same situation as me but now the problem is picking the right restaurant out of a ton of listings with similar ratings. Even after all of that, they might be disappointed to arrive at the restaurant and find out the dish isn't on the menu!

In his excellent Springboard capstone 'Eat, Rate, Love', Robert Chen proposed upweighting frequent reviewers and generating authenticity ratings based on the reviewers' names. His approach cracks the 'restaurant authencity' problem from the top-down; my solution is bottom-up as it helps users narrow their search quickly according to their favorite dishes.

With that I came up with a Shiny App to query Chinese restaurants by popular dishes ranked according to how often they were mentioned. I focused on reviews from Arizona and Nevada as they contributed 83% of the total reviews in the dataset.

The following report details my approach to extracting and contextualising the insights from the Yelp dataset. Hope you enjoy reading it as much as I had fun working on it!

Data Exploration and Cleaning

Importing Datasets

Normally I would run `sapply` on the vector of package names but this doesn't work in RMarkdown due to error messages.

```
library(jsonlite)
library(dplyr)
library(tidyr)
```

```
library(stringr)
library(qdap)
library(ggplot2)
library(scales)
library(tm)
```

Next I import the Business and Reviews datasets using `stream_in` function from the 'jsonlite' package, after which I save in .Rds format for faster importing.

```
## Load JSON files and save in .Rds format
#biz_json <- stream_in(file("yelp_academic_dataset_business.json"))
#review_json <- stream_in(file("yelp_academic_dataset_review.json"))
#saveRDS(biz_json, "biz.Rds")
#saveRDS(review_rds, "review.Rds")

## Import .Rds files
biz <- readRDS("biz.Rds")
biz_df <- as.data.frame(biz)
review <- readRDS("review.Rds")
review_df <- as.data.frame(review)
```

Inspecting the data with `str` and `summary` show the Reviews dataset contains votes, user ids, star ratings and the review texts. The Business dataset - with `summary` hidden due to length - shows the business details such as shop names & addresses, opening hours, attributes such as 'Good for Kids', 'Wi-Fi' or 'Takes Reservations'.

The common variable between the tables is **Business ID**, which I will use as the matching criteria to join both datasets later on.

```
str(review_df, max.level = 1)
```

```
## 'data.frame':    2225213 obs. of  8 variables:
##  $ votes      :'data.frame': 2225213 obs. of  3 variables:
##  $ user_id    : chr  "PUFPaY9KxDAcGqfsorJp3Q" "Iu6AxdBYGR4A0wspR9BYHA" "au
ESFwWvW42h6alXgFxAXQ" "uK8tzraOp4M5u3uYrqIBXg" ...
##  $ review_id  : chr  "Ya85v4eqdd6k9Od8HbQjyA" "KPvLNJ21_4wbYNctrOwWdQ" "fF
SoGV46Yxuwbr3fHNuZig" "Di3exaUCFNw1V4kSNW5pgA" ...
##  $ stars      : int  4 5 5 5 3 1 4 5 5 3 ...
##  $ date       : chr  "2012-08-01" "2014-02-13" "2015-10-31" "2013-11-08" .
..
##  $ text       : chr  "Mr Hoagie is an institution. Walking in, it does see
m like a throwback to 30 years ago, old fashioned menu board, booths out of"|
__truncated__ "Excellent food. Superb customer service. I miss the mario mach
ines they used to have, but it's still a great place steeped in t"| __truncat
ed__ "Yes this place is a little out dated and not opened on the weekend. But
other than that the staff is always pleasant and fast t"| __truncated__ "All
the food is great here. But the best thing they have is their wings. Their wi
ngs are simply fantastic!!  The \"Wet Cajun\" "| __truncated__ ...
##  $ type       : chr  "review" "review" "review" "review" ...
##  $ business_id: chr  "5UmKMjUEUNdYWqANhGckJw" "5UmKMjUEUNdYWqANhGckJw" "5U
mKMjUEUNdYWqANhGckJw" "UsFtqoBl7naz8AVUBZMjQQ" ...
```

```r
summary(review_df)
```

```
##      votes.funny         votes.useful         votes.cool
##  Min.   :  0.00000   Min.   :  0.00000   Min.   :  0.00000
##  1st Qu.:  0.00000   1st Qu.:  0.00000   1st Qu.:  0.00000
##  Median :  0.00000   Median :  0.00000   Median :  0.00000
##  Mean   :  0.44123   Mean   :  1.02101   Mean   :  0.54964
##  3rd Qu.:  0.00000   3rd Qu.:  1.00000   3rd Qu.:  1.00000
##  Max.   :142.00000   Max.   :167.00000   Max.   :138.00000
##    user_id           review_id             stars           date
##  Length:2225213     Length:2225213     Min.   :1.000   Length:2225213
##  Class :character   Class :character   1st Qu.:3.000   Class :character
##  Mode  :character   Mode  :character   Median :4.000   Mode  :character
##                                        Mean   :3.756
##                                        3rd Qu.:5.000
##                                        Max.   :5.000
##      text               type           business_id
##  Length:2225213     Length:2225213     Length:2225213
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
##
##
##
```

```r
str(biz_df, max.level = 1)
```

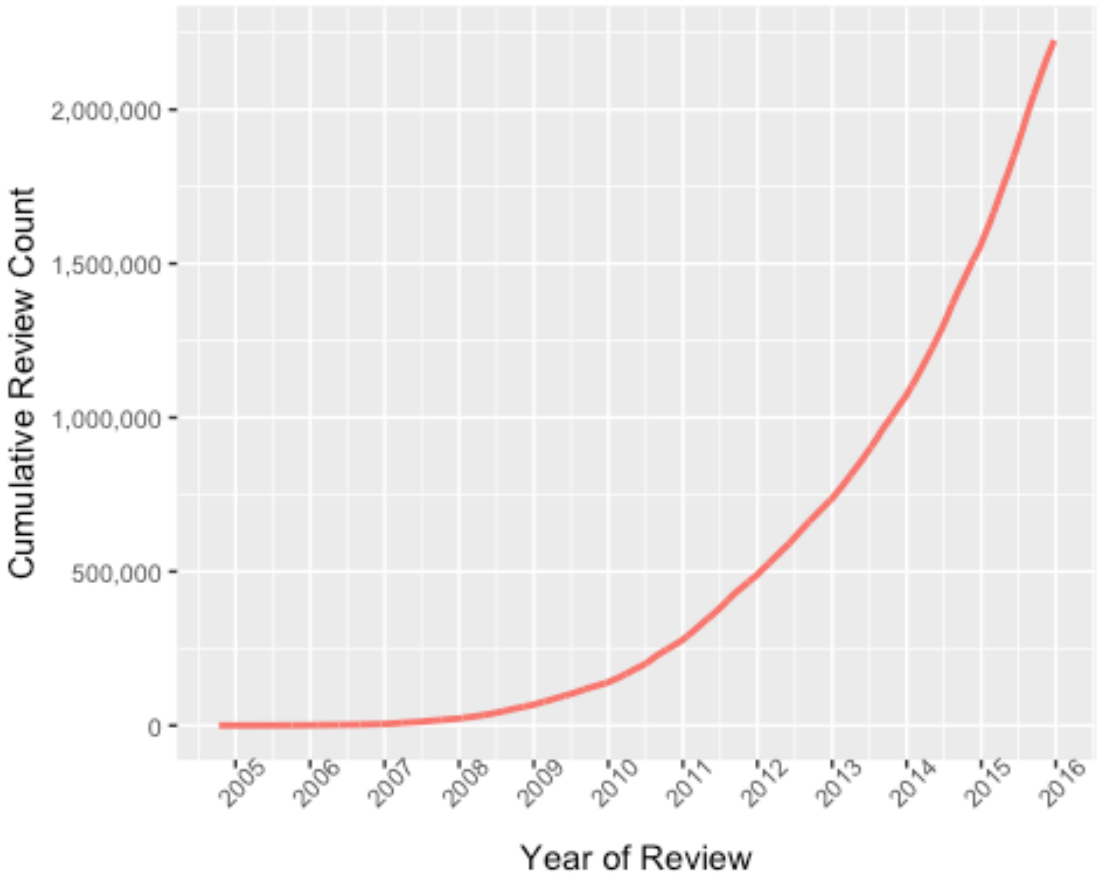
```
## 'data.frame':    77445 obs. of  15 variables:
##  $ business_id  : chr  "5UmKMjUEUNdYWqANhGckJw" "UsFtqoBl7naz8AVUBZMjQQ" "
3eu6MEFlq2Dg7bQh8QbdOg" "cE27W9VPgO88Qxe4ol6y_g" ...
##  $ full_address : chr  "4734 Lebanon Church Rd\nDravosburg, PA 15034" "202
McClure St\nDravosburg, PA 15034" "1 Ravine St\nDravosburg, PA 15034" "1530 H
amilton Rd\nBethel Park, PA 15234" ...
##  $ hours        :'data.frame':   77445 obs. of  7 variables:
##  $ open         : logi  TRUE TRUE TRUE FALSE TRUE TRUE ...
##  $ categories   :List of 77445
##   .. [list output truncated]
##  $ city         : chr  "Dravosburg" "Dravosburg" "Dravosburg" "Bethel Park
" ...
##  $ review_count : int  4 4 3 5 5 20 3 21 7 4 ...
##  $ name         : chr  "Mr Hoagie" "Clancy's Pub" "Joe Cislo's Auto" "Cool
Springs Golf Center" ...
##  $ neighborhoods:List of 77445
##   .. [list output truncated]
##  $ longitude    : num  -79.9 -79.9 -79.9 -80 -80.1 ...
##  $ state        : chr  "PA" "PA" "PA" "PA" ...
##  $ stars        : num  4.5 3.5 5 2.5 2.5 5 2.5 4 2.5 4 ...
##  $ latitude     : num  40.4 40.4 40.4 40.4 40.4 ...
##  $ attributes   :'data.frame':   77445 obs. of  36 variables:
##  $ type         : chr  "business" "business" "business" "business" ...
```

Exploratory Data Analysis

Do we have enough reviews to analyse?

I'd like to first get a handle on the volume of reviews since the start date of the dataset. It seems we do have a large sample size (N = 2,225,213) amassed over 10 years, with the latter half coming in exponentially after 2013:

```
## Arranging into two columns comprising date and cumulative review count
ts_reviews <- review_df %>%
  select(date, review_id) %>%
  group_by(date) %>%
  summarise_all(funs("reviews" = n())) %>%
  mutate(dates = as.Date(date), cumulative = cumsum(reviews)) %>%
  arrange(dates)

# Plot time series chart of review count
ggplot(ts_reviews, aes(x = dates, y = cumulative, col = "red")) +
  geom_line(size = 1) +
  scale_y_continuous(labels = comma) +
  labs(x = "Year of Review", y = "Cumulative Review Count") +
  scale_x_date(date_breaks = "1 year", date_labels = "%Y") +
  theme(legend.position = "none", axis.text.x = element_text(size = 8, angle
= 45), axis.text.y = element_text(size = 8))
```



Scrubbing Inactive Users

Quick statistics on the reviews - there are users who posted only ONCE over the past 10 years!

```
ratings_stats <- review_df %>%
  select(user_id, stars) %>%
  group_by(user_id) %>%
  summarise_all(funs("count" = n(), "mean" = mean, "median" = median)) %>%
  arrange(count) %>%
  ungroup()

head(ratings_stats)
```

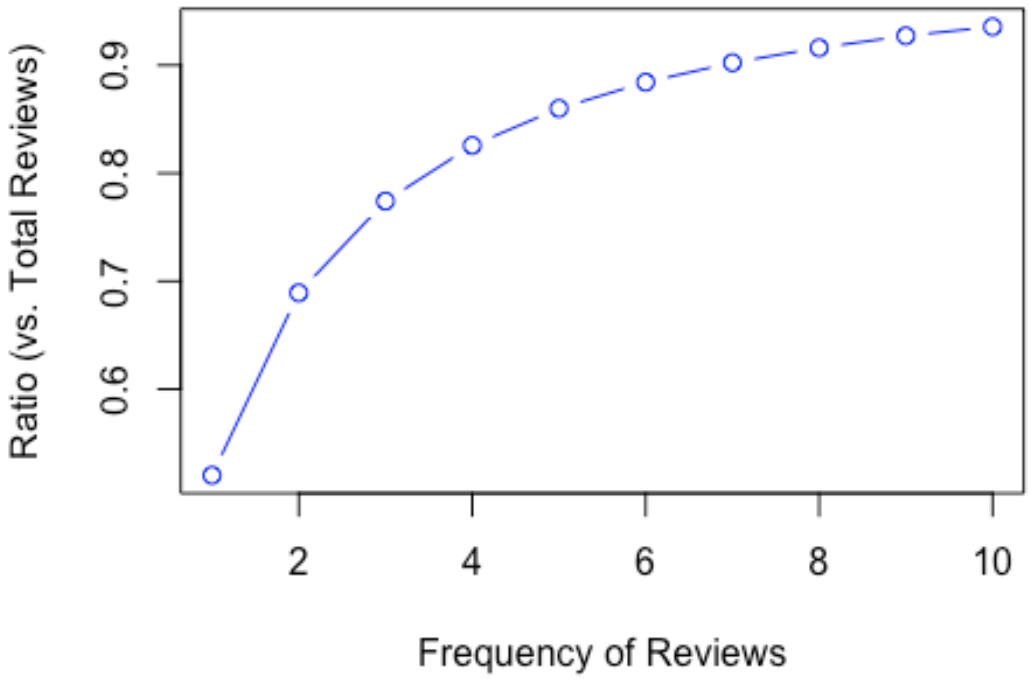
```
## # A tibble: 6 <U+00D7> 4
##                  user_id count  mean median
##                    <chr> <int> <dbl>  <dbl>
## 1 --0mI_q_0D1CdU4P_hoImQ     1     5      5
## 2 --20-ljZD5NnAnkwBBC_uQ     1     5      5
## 3 --37T3V10ZeoJ1Il7D2Wzw     1     3      3
## 4 --52YqcuRttZN62TCKQdbw     1     5      5
## 5 --82_AVgRBsLw6Dhy8sEnA     1     4      4
## 6 --BGW_TY55SH-9OiHmtitg     1     1      1
```

This isn't surprising given that social platforms generally maintain many inactive accounts. Yelp is the largest user-generated review platform in the US and inevitably collects large swathes of inactive users (lose interest after leaving 1 to 2 reviews) or fake accounts maintained by unscrupulous businesses.

Yelp's recommendation engine ensures that only ratings from friends, foodies and credible users (e.g. an Italian rating Italian cuisine) are counted toward the aggregate Recommended Ratings. Assuming the ratings in the dataset are already clean, I'll need to scrub inactive users once more to improve reliability of the reviews.

My initial hypothesis is users with 2 or fewer reviews belong to the Inactive bucket and should be removed. Let's create a frequency chart to verify this:

```
inactive_ratio <- function(criteria){
  ratio <- rep(0, as.numeric(criteria))
  for (i in 1:as.numeric(criteria)){
    ratio[i] <- nrow(filter(ratings_stats, count <= i)) / nrow(ratings_stats)
  }
  plot(ratio, type = "b", xlim = c(1,i), xlab = "Frequency of Reviews", ylab
= "Ratio (vs. Total Reviews)", col = "blue")
}

inactive_ratio(10)
```



Filtering out users who posted 1 to 2 reviews would remove ***70%*** of our observations! Unfortunately this confirms my suspicion that a large number of users are casual (albeit thoughtful) reviewers; that leaves me with no choice but to remove the single-review users!

```
## Remove these users from the Review dataset
inactive_raters <- ratings_stats %>%
      filter(count == 1)

review_clean_df <- review_df[!(review_df$user_id %in% inactive_raters$user_id
),]
```

The cleaning removed 13% of our observations.

```
round(nrow(review_clean_df) / nrow(review_df), 2)

## [1] 0.87
```

Another point to consider is **Review Recency** such that restaurants reviewed more than 5 years ago may not exist today. In our case, the bulk of reviews came during the last 4 years plus Chinese restaurants tend to operate a very long time. For the purpose of the analysis, we'll assume that all reviewed restaurants are still operating.

Selecting States

Summary

I decide to focus on the reviews in Nevada and Arizona for my project and this section walks you through how I arrived at that conclusion.

The first step was merging the Business and Review data to produce a table of all reviews with matching business information. Parsing by business category gave me a showed Chinese contributing 15% of the Top 5 Restaurant categories. I'd definitely consider this a sizeable quantity to justify our focus on Chinese food reviews.

A view by state showed Nevada and Arizona contributing a overwhelming 83% of reviews. The count of total reviews and Chinese food reviews were much lower in subsequent states so they were dropped from analysis.

Step 1: Merging the Business and Review data

First things first, I consolidated business details, ratings and reviews into the same table while removing extraneous variables to trim the file:

```
review_biz <- merge(review_clean_df, biz_df, by = "business_id")
rev_biz_tidy <- review_biz %>%
                  select(-starts_with("hour"), -starts_with("attribute"), -co
ntains("votes"), -contains("type"))
```

Step 2: Confirming Restaurant Category has Sufficient Chinese Reviews

We see approximately 190K reviews covering the Top 5 restaurant categories - Mexican, Italian, Pizza, American and Chinese. 15% of these were for Chinese and this justifies our focus.

```
cat_count <- rev_biz_tidy %>%
              group_by(as.character(categories)) %>%
              summarise(Count = n()) %>%
              arrange(desc(Count))

head(cat_count[, 1:2])
```

```
## # A tibble: 6 <U+00D7> 2
##                   `as.character(categories)` Count
##                                        <chr> <int>
## 1               c("Mexican", "Restaurants") 71496
## 2                 c("Pizza", "Restaurants") 33265
## 3               c("Restaurants", "Italian") 28811
## 4         c("American (New)", "Restaurants") 28779
## 5               c("Chinese", "Restaurants") 28187
## 6 c("Sushi Bars", "Japanese", "Restaurants") 27196
```

Step 3: Zooming in on Arizona and Nevada Chinese Restaurants

You'll notice the **Categories** column is made up of lists of descriptions tagged by users. The problem with this is an American restaurant could be categorised wrongly as a bar or a lounge. To be doubly sure we're not barking up the wrong tree, I separated the values in the lists:

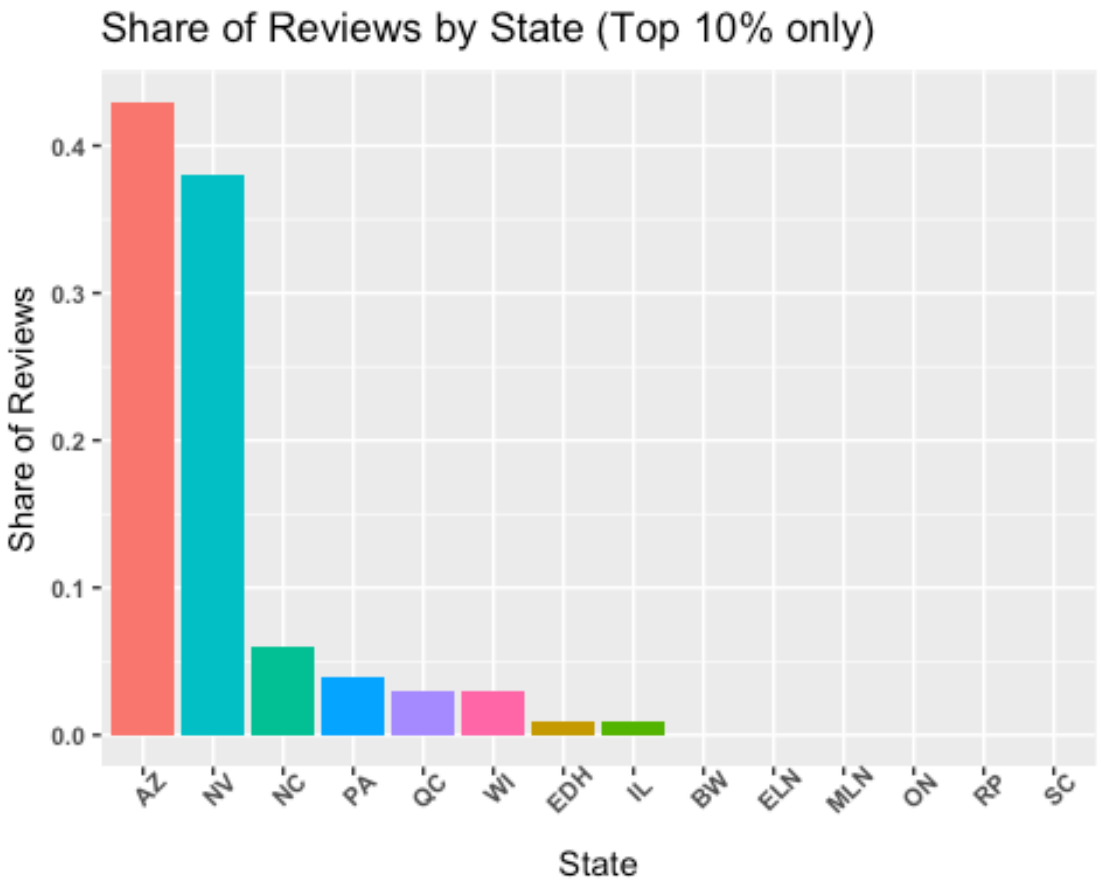
```
genre_count <- rev_biz_tidy %>%
                select(state, categories) %>%
                filter(str_detect(categories, "Restaurant")) %>%
                unnest(categories) %>%
                group_by(state) %>%
                count(categories) %>%
                arrange(desc(n))

genre_count[1:10,]
```

```
## Source: local data frame [10 x 3]
## Groups: state [3]
##
##    state             categories      n
##    <chr>                  <chr>  <int>
## 1     NV            Restaurants 480798
## 2     AZ            Restaurants 477563
## 3     AZ              Nightlife  80805
## 4     NC            Restaurants  80673
## 5     AZ                   Bars  77834
## 6     AZ         American (New)  69778
## 7     AZ                Mexican  67071
## 8     NV American (Traditional)  64480
## 9     NV              Nightlife  61227
## 10    AZ American (Traditional)  59497
```

A view by state show Nevada and Arizona dominating with a combined 83% of counts:

```
## Remove non-essential categories AND filtering the 90th percentile
state_rest_count <- genre_count %>%
  group_by(state) %>%
  filter(categories != "Restaurants" || categories != "Nightlife" || categori
es != "Bars") %>%
  filter(n > quantile(n, 0.9))

## Visualise Share of Reviews by State (90% percentile)
state_table <- state_rest_count %>%
                select(state, n) %>%
                group_by(state) %>%
                summarise_all(funs("count" = sum(n))) %>%
                arrange(desc(count)) %>%
                mutate(proportion = round(count / sum(count), 2))

plot_state_table <- state_table %>%
    ggplot(aes(x = reorder(state, -proportion), y = proportion, fill = state)
```

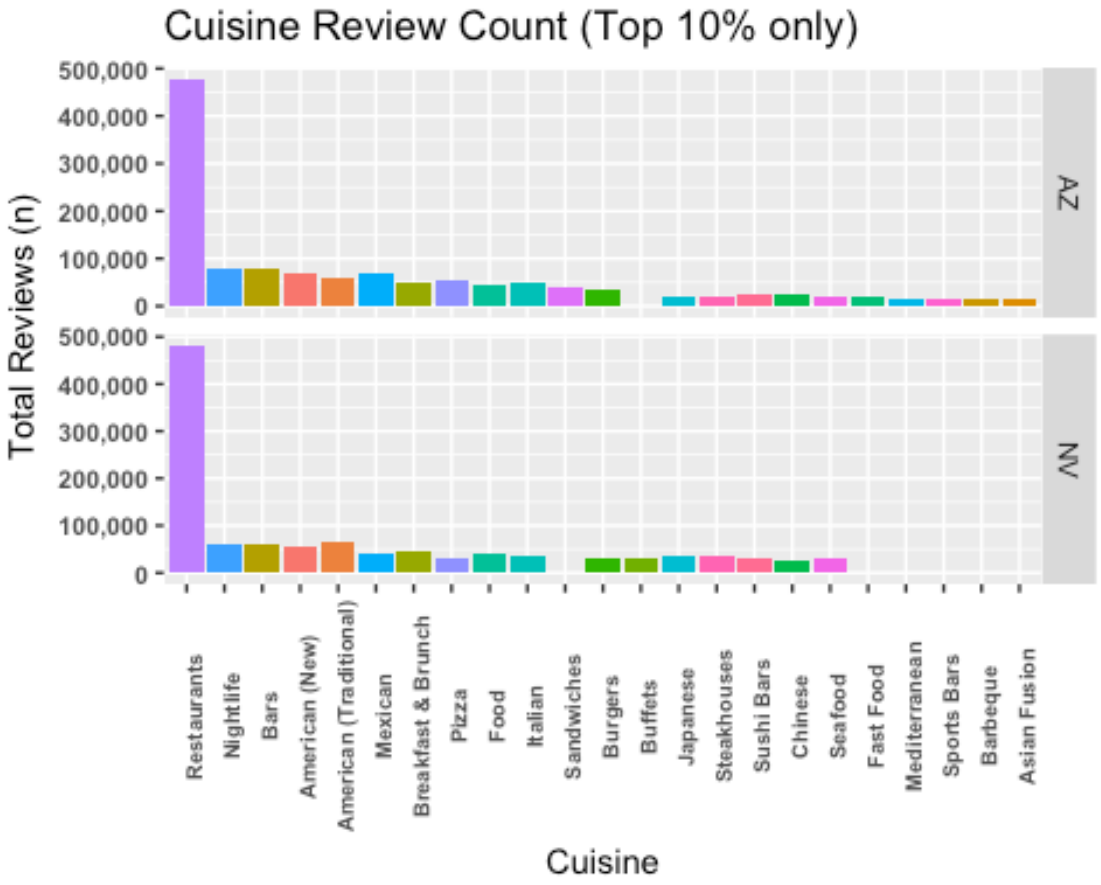
```
) +
    geom_bar(stat = "identity") +
    scale_y_continuous(labels = comma) + # Requires 'scales' package
    ggtitle("Share of Reviews by State (Top 10% only)") +
    labs(x = "State", y = "Share of Reviews") +
    theme(legend.position = "none", axis.text.x = element_text(face = "bold",
size = 8, angle = 45), axis.text.y = element_text(face = "bold", size = 8))

plot_state_table
```



A final inspection reveals 20K to 30K reviews per state in Nevada and Arizona for Chinese. The same charts for the other states (not shown here) reveal much lower counts for Chinese and supports our decision to drop them from the analysis. Furthermore, the sample sizes for those states are too small to yield meaningful dish insights, let alone mentions of the dish names!

```
## Visualise cuisine review counts in Arizona and Nevada
library(scales) #add comma separators to Y-axis labels
plot_aznv_cuisine <- state_rest_count %>%
        filter(state == "AZ" | state == "NV") %>%
        ggplot(aes(x = reorder(categories, -n), y = n, fill = categories)) +
        geom_bar(stat = "identity") +
        facet_grid(state ~., scales = "free") +
        scale_y_continuous(labels = comma) +
        ggtitle("Cuisine Review Count (Top 10% only)") +
        labs(x = "Cuisine", y = "Total Reviews (n)") +
```

```
        theme(legend.position = "none", axis.text.x = element_text(face = "bo
ld", size = 7, angle = 90),
        axis.text.y = element_text(face = "bold", size = 8))

plot_aznv_cuisine
```



Creating The Corpus

I will focus on **positive** reviews since our goal is recommending the best Chinese restaurants that serve a specific dish. To reduce computational time on my ancient Macbook, I sampled 30% of positive reviews:

```
## Filtering Chinese reviews from Nevada and Arizona
aznv_ch <- rev_biz_tidy %>%
    filter(state == "AZ" | state == "NV") %>%
    filter(str_detect(categories, "Chinese"))

# Filtering only positive reviews and converting to matrix
aznv_ch_text <- aznv_ch[aznv_ch$stars.x >= 4,]$text
aznv_ch_matrix <- as.matrix(aznv_ch_text)
# Randomised sampling
random.rows <- sample(1:nrow(aznv_ch_matrix), 0.3 * nrow(aznv_ch_matrix), rep
lace = FALSE)
aznv_ch_sample <- aznv_ch_matrix[random.rows,]
```

Next we'll create a corpus from the matrix of reviews, essentially a structured set of texts that will be the input for the topic mining and sentiment analysis. As shown, the corpus of sampled reviews contains 9,400 documents. Each document here corresponds to a single review.

```
## Creating the corpus
aznv_ch_corpus <- VCorpus(VectorSource(aznv_ch_sample))
aznv_ch_corpus

## <<VCorpus>>
## Metadata:  corpus specific: 0, document level (indexed): 0
## Content:  documents: 9400
```

Extracting Names of Popular Dishes

Preprocessing the Review Texts

Human-written sentences contain punctuation, abbreviations, numbers and English stopwords such as "my", "your", "to" and "from". Also, people tend to use abbreviations liberally and get sloppy with capitalisation; we need the word counting algorithm to know that "shouldn't" and "Chicken" are identical to "should not" and "chicken" - essentially reducing duplicated words.

The end goal here is to count only the words that matter - dish names and sentiment words. The cleaning function below removes the noise from the corpus by deduplicating words and removing stopwords:

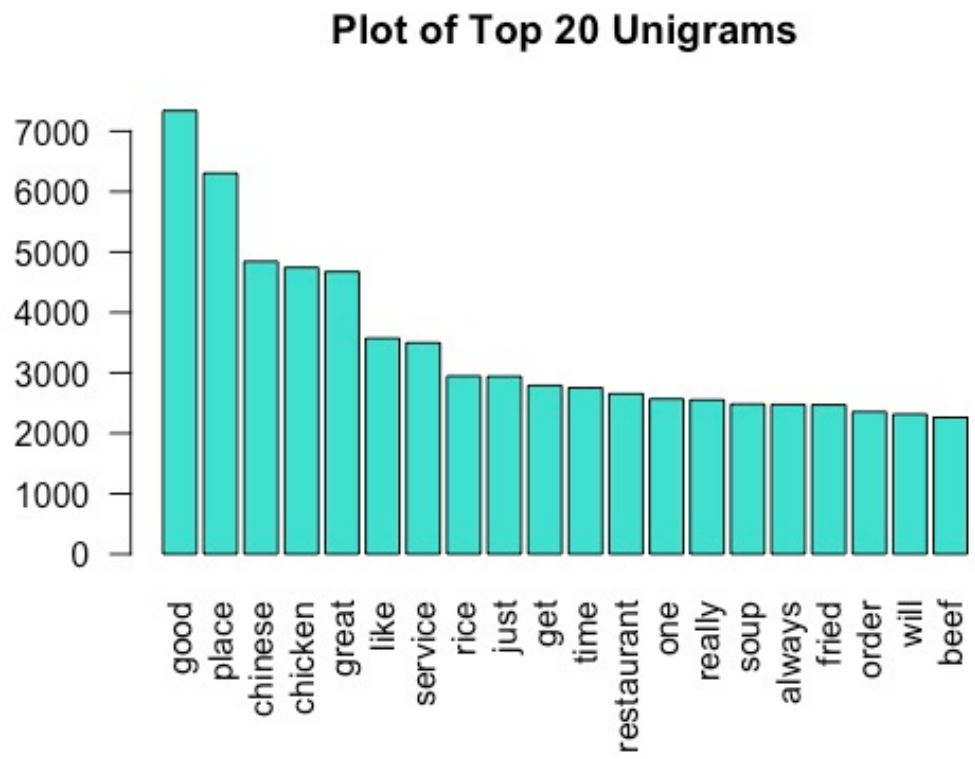
```
clean_corpus <- function(corpus){
  corpus <- tm_map(corpus, content_transformer(function(x) iconv(x,to='UTF-8-
MAC', sub='byte')),  mc.cores=1)
  corpus <- tm_map(corpus, removePunctuation)
  corpus <- tm_map(corpus, content_transformer(tolower))
  corpus <- tm_map(corpus, content_transformer(replace_abbreviation))
  corpus <- tm_map(corpus, removeNumbers)
  corpus <- tm_map(corpus, removeWords, c(stopwords("en"), "food"))
  corpus <- tm_map(corpus, stripWhitespace)
  return(corpus)
}
```

Counting N-Grams

After cleaning the corpus, we'll list the 20 most frequently occurring single words or 'unigrams' in the reviews as a first attempt at extracting popular dish names. A term document matrix is a table with unigrams as rows and review number as columns.

The unigram counts per document (or review) will thus be the values in the table. Summing the rows gives us the total count of every unigram in the corpus:

```
unigram_count <- function(cleaned_corpus) {
                tdm <- TermDocumentMatrix(cleaned_corpus)
                tdm_matrix <- as.matrix(tdm)
                term_freq <- rowSums(tdm_matrix)
                term_freq <- sort(term_freq, decreasing = TRUE)
                barplot(term_freq[1:20], col = "red", las = 2, main = "Plot o
f Top 20 Unigrams")
}

clean_aznv_ch <- clean_corpus(aznv_ch_corpus)
unigram_count(clean_aznv_ch)
```



Two things are clear on closer inspection - we need to get better at removing stopwords AND we'll need longer phrases to get any meaningful dish insights. From personal experience, Chinese dish names tend to be three words or longer i.e. 'wanton noodle soup', 'black pepper beef' so we should be on the right track.

Expanding the stopword list in the corpus cleaner to capture superlatives and unnecessary nouns:

```
clean_corpus2 <- function(corpus){
  corpus <- tm_map(corpus, content_transformer(function(x) iconv(x, to = "UTF
-8-MAC", sub = "byte")), mc.cores=1)
  corpus <- tm_map(corpus, removePunctuation)
  corpus <- tm_map(corpus, content_transformer(tolower))
  corpus <- tm_map(corpus, content_transformer(replace_abbreviation))
  corpus <- tm_map(corpus, removeNumbers)
  corpus <- tm_map(corpus, removeWords, c(stopwords("en"), "food", "good", "p
lace", "great", "service", "time", "really", "restaurant", "always", "just",
```

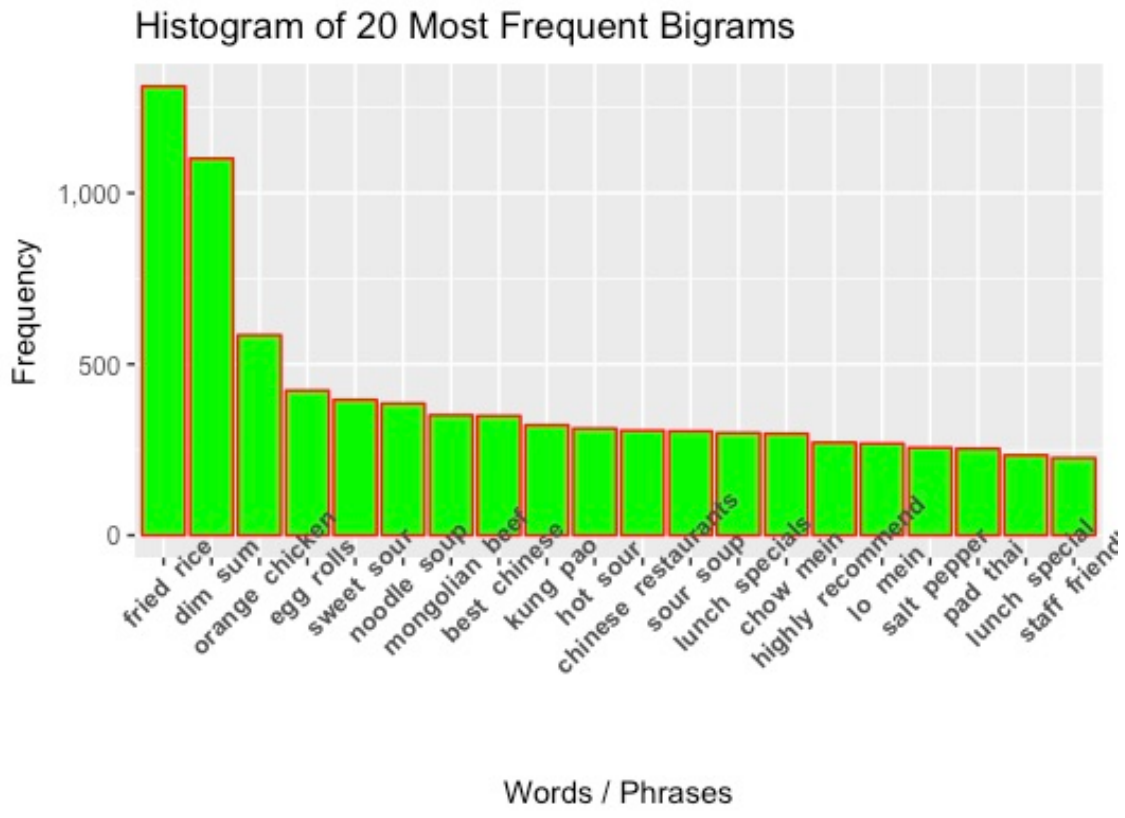
```
"get", "one", "will", "also", "ordered", "can", "try", "ive", "well", "eat",
"little", "definitely", "vegas", "back", "amazing", "got", "dont"))
  corpus <- tm_map(corpus, stripWhitespace)
  return(corpus)
}
## Cleaning the corpus with the new and improved function
clean_aznv_ch2 <- clean_corpus2(aznv_ch_corpus)
```

The next step of preprocessing is to tokenize the cleaned corpus. What we are doing here is breaking up the text review strings into groups of keywords, or phrases, called 'tokens'. As mentioned earlier, the unigrams do not contain meaningful information about the Chinese dishes and we are now listing the most frequently occurring phrases containing 2 words ('Bigrams') or 3 words ('Trigrams').

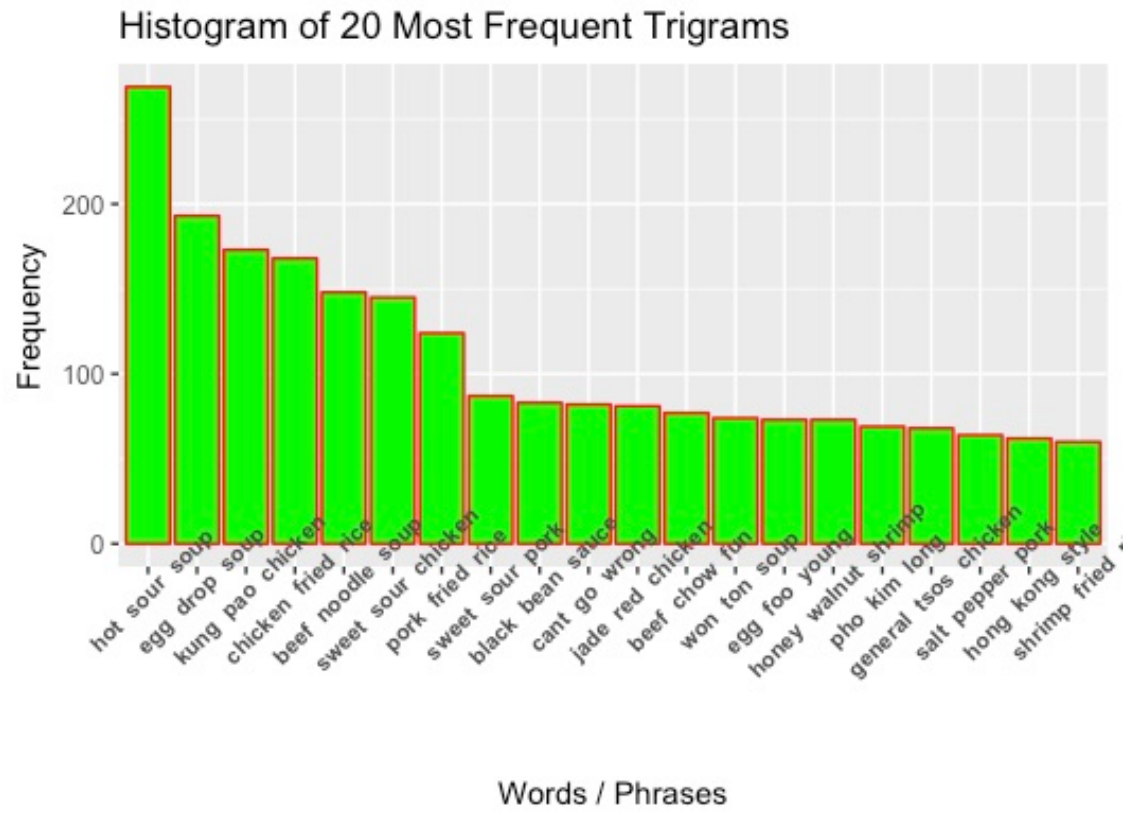
```
## Create term document matrix for two-word (bigram) and three-word (trigram)
phrases
install.packages("SnowballC")
library(SnowballC) #required by latest version of 'tm' package
library(tm)
update.packages("tm",  checkBuilt = TRUE) #updating 'tm' package

# Create bigram and trigram tokenizer functions
BigramTokenizer <- function(x) unlist(lapply(ngrams(words(x), 2), paste, "",
collapse = " "), use.names = FALSE)
TrigramTokenizer <- function(x) unlist(lapply(ngrams(words(x), 3), paste, "",
collapse = " "), use.names = FALSE)

## Create term document matrix (tdm) of bigrams and trigrams
bigram_ch_tdm <- TermDocumentMatrix(clean_aznv_ch2, control = list(tokenize =
BigramTokenizer))
trigram_ch_tdm <- TermDocumentMatrix(clean_aznv_ch2, control = list(tokenize
= TrigramTokenizer))

## Convert tdm into data frames of bigram and trigram counts
ngram_freq <- function(tdm){
                freq <- sort(rowSums(as.matrix(tdm)), decreasing=TRUE)
                freq_df <- data.frame(word=names(freq), freq=freq)
                return(freq_df)
}

bigram_ch_freq <- ngram_freq(bigram_ch_tdm)
trigram_ch_freq <- ngram_freq(trigram_ch_tdm)
```

Plotting frequencies of the Bigrams and Trigams reveals the information gained as the phrase length increases:

```
plot_bigram_ch <- bigram_ch_freq[1:20,] %>%
                  ggplot(aes(x = reorder(word, -freq), y = freq)) +
                  geom_bar(stat = "identity", fill = "green", col = "red") +
                  scale_y_continuous(labels = comma) +
                  ggtitle("Histogram of 20 Most Frequent Bigrams") +
                  labs(x = "Words / Phrases", y = "Frequency") +
                  theme(legend.position = "none", axis.text.x = element_text(fa
ce = "bold", size = 9, angle = 45), axis.text.y = element_text(size = 9))

plot_bigram_ch
```




```
plot_trigram_ch <- trigram_ch_freq[1:20,] %>%
                   ggplot(aes(x = reorder(word, -freq), y = freq)) +
                   geom_bar(stat = "identity", fill = "green", col = "red")
+
                   scale_y_continuous(labels = comma) +
                   ggtitle("Histogram of 20 Most Frequent Trigrams") +
                   labs(x = "Words / Phrases", y = "Frequency") +
                   theme(legend.position = "none", axis.text.x = element_tex
t(face = "bold", size = 8, angle = 45), axis.text.y = element_text(size = 9))

plot_trigram_ch
```



Takeaways

The most positively reviewed dish in Nevada and Arizona was hot & sour soup by a wide margin, followed by egg drop soup, kung pao chicken, chicken fried rice and beef noodle soup. The same dishes were also staples on most menus I saw in San Francisco, pointing to their popularity among Americans. However, the majority of these dishes are not as popular in China, Hong Kong, Taiwan and Singapore and casts suspicion on the authenticity of the American interpretations.

My dish, ee-fu noodles, is not on the list due to low popularity or it is simply not served in most restaurants. If I could influence engineering decisions at Yelp, I'd recommend menu items to be included in search results. That way less popular dishes get surfaced and diversifies the restaurants' revenue sources.

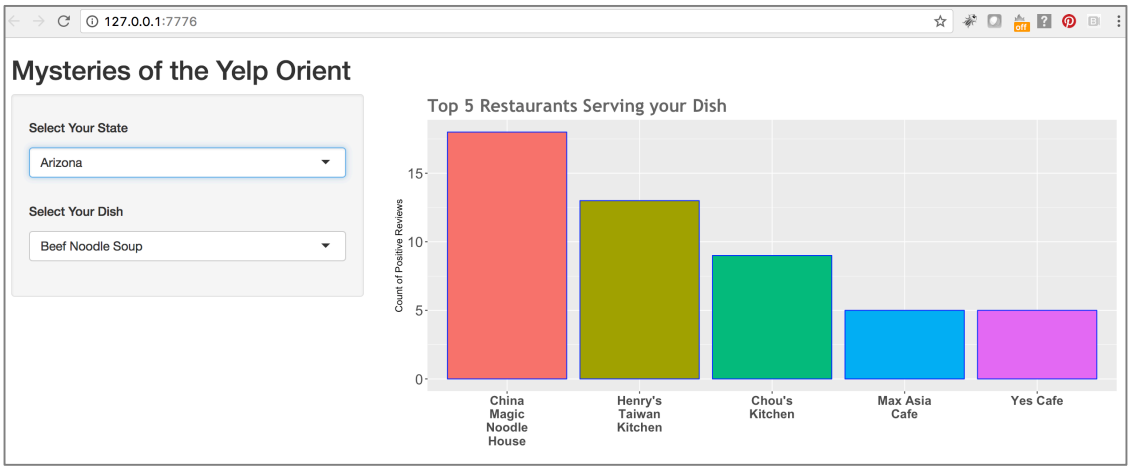
Deploying the Mini Search Engine

The Shiny App allows users to select state and dish from the dropdown menus. The app searches for exact matches with positive reviews and finally returns the names of the top 5 corresponding restaurants with the most reviews.

In summary, the user is now able to query a restaurant serving his or her favourite dish!

Results indicate that **P. F. Chang** is a popular chain for many well-known Chinese dishes in Nevada and Arizona.

Click on this LINK to try out the Shiny App



Limitations

Due to computating resource limitations, I only analysed a sample of the reviews and focused on Nevada and Arizona. With more processing juice, I would extend this methodology to the other cuisines across all US states - it would be interesting to examine the impact of ethnic and location-specific nuances on cuisine reviews.

In a perfect world where I knew every data mining trick, I would have calculated the specific dish sentiments by examining the sentiment of 5 words immediately before and after the dish name. This would have contained more useful information than the overall rating. Simply put, the customer might have enjoyed the meal at P.F. Chang's but hated the Sweet & Sour Soup and my framework does not capture that nuance.

Lastly, I would have liked to have data around user reliability and engagement history which would have made my restaurant recommendations more relevant.

Target Audience at Yelp

The Search team inject an expanded version of my project into their search algorithm, allowing users unaccustomed to American-style Chinese food to enjoy the benefits of using Yelp.

The Ads Product team invite businesses to beta test 'bidding for dish names appearing in search queries'; doing so will improve the precision of their ad targeting and drive more high-intent traffic to their advertisers' pages.

One More Thing ...

The Yelp dataset challange has led to excellent white papers on predicting votes and ratings based on review sentiments and business attributes. Machine Learning is a topic for another project another day but I'll leave you with these as food for thought, pun unintended.

Sentiment Analysis

First I look into the Sentiment distribution for Chinese restaurants in Arizona and Nevada, just to check for interesting patterns.

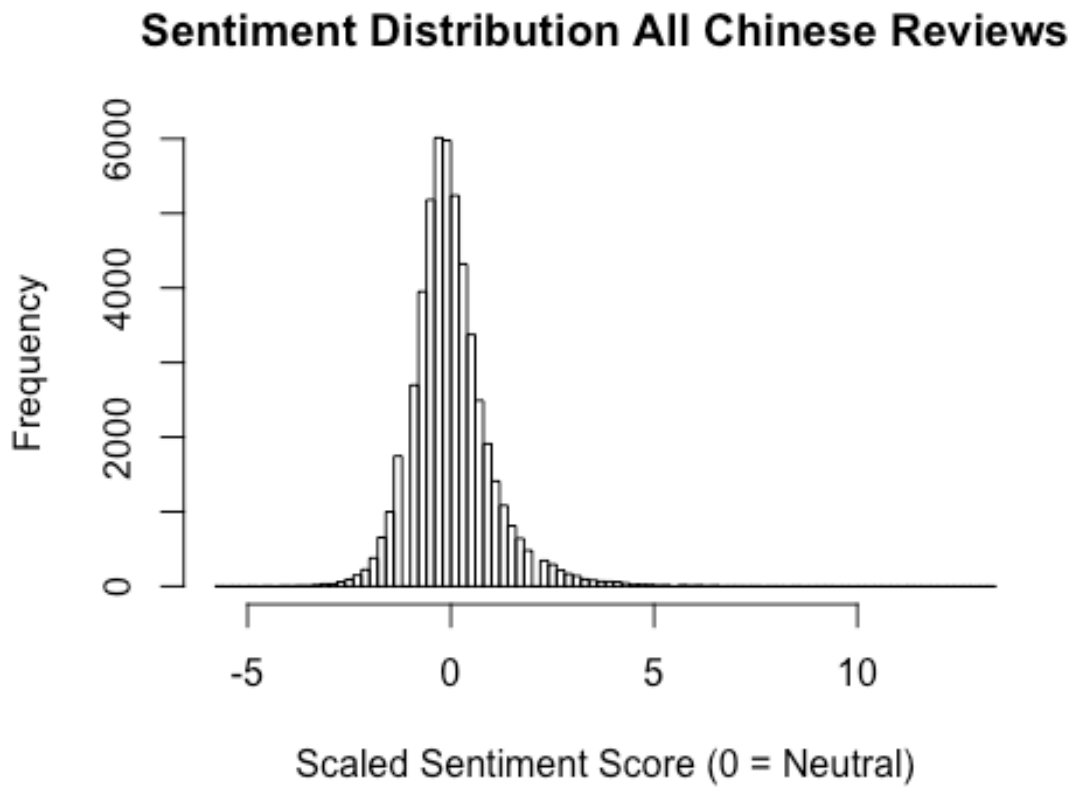
```
chreviews <- aznv_ch$text

## Sentiment lexicon from Bing Liu (cs.uic.edu/~liub/FBS/sentiment-analysis.h
tml)
pos_words <- scan("positive-words.txt", what='character', comment.char=';')
neg_words <- scan("negative-words.txt", what='character', comment.char=';')

## Sentiment analysis function
score.sentiment <- function(text_vector, pos.words, neg.words, .progress='non
e')
{
  require(plyr)
  require(stringr)

  scores <- ldply(text_vector, function(text_vector, pos.words, neg.words) {

    # clean up text with regex
    text_vector <- gsub('[[:punct:]]', '', text_vector)
    text_vector <- gsub('[[:cntrl:]]', '', text_vector)
    text_vector <- gsub('\\d+', '', text_vector)
    text_vector <- tolower(text_vector)

    # split into words using 'stringr' package
    word.list <- str_split(text_vector, '\\s+')
    words <- unlist(word.list)

    # compare our words to the dictionaries of positive & negative terms
    pos.matches <- match(words, pos.words)
    neg.matches <- match(words, neg.words)

    # match() returns the position of the matched term or NA
    # we just want a TRUE/FALSE:
    pos_matches <- !is.na(pos.matches)
    neg_matches <- !is.na(neg.matches)
    score <- sum(pos_matches) - sum(neg_matches)

  }, pos.words, neg.words, .progress=.progress)

  scores_final <- data.frame(sentiment_score = scores, text = text_vector)
  return(scores_final)
```

```
}

# Score sentiment of review texts
ch_sentiment <- score.sentiment(chreviews, pos_words, neg_words)
```

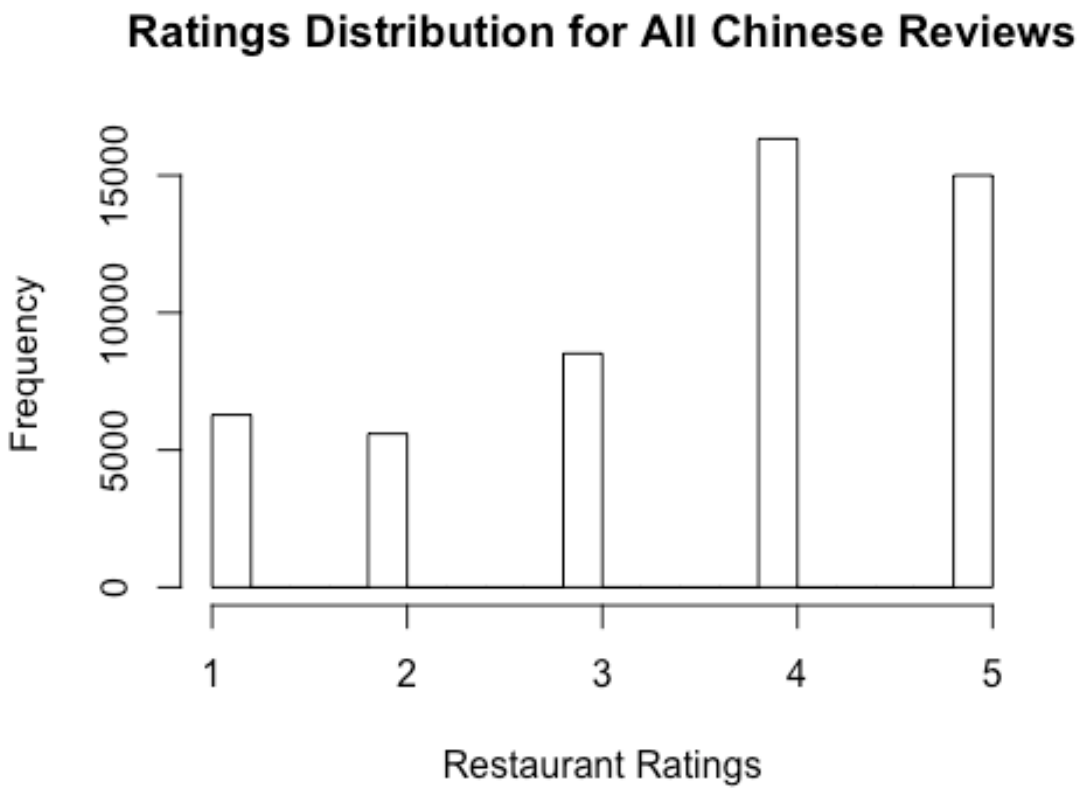
The charts clearly demonstrate the inherent difference in Star Ratings and Review Sentiment - the former are biased toward 4- and 5-stars while Sentiment is normally distributed, in other words, mostly neutral.

If I was to predict Ratings from Sentiments, I would have at least expected to see a left-skewed sentiment distribution that reflects the Star Ratings.

```
hist(scale(as.numeric(as.matrix(ch_sentiment))), breaks = 100, main = "Sentim
ent Distribution All Chinese Reviews", xlab = "Scaled Sentiment Score (0 = Ne
utral)")
```




```
hist(aznv_ch$stars.x, main = "Ratings Distribution for All Chinese Reviews",
xlab = "Restaurant Ratings")
```



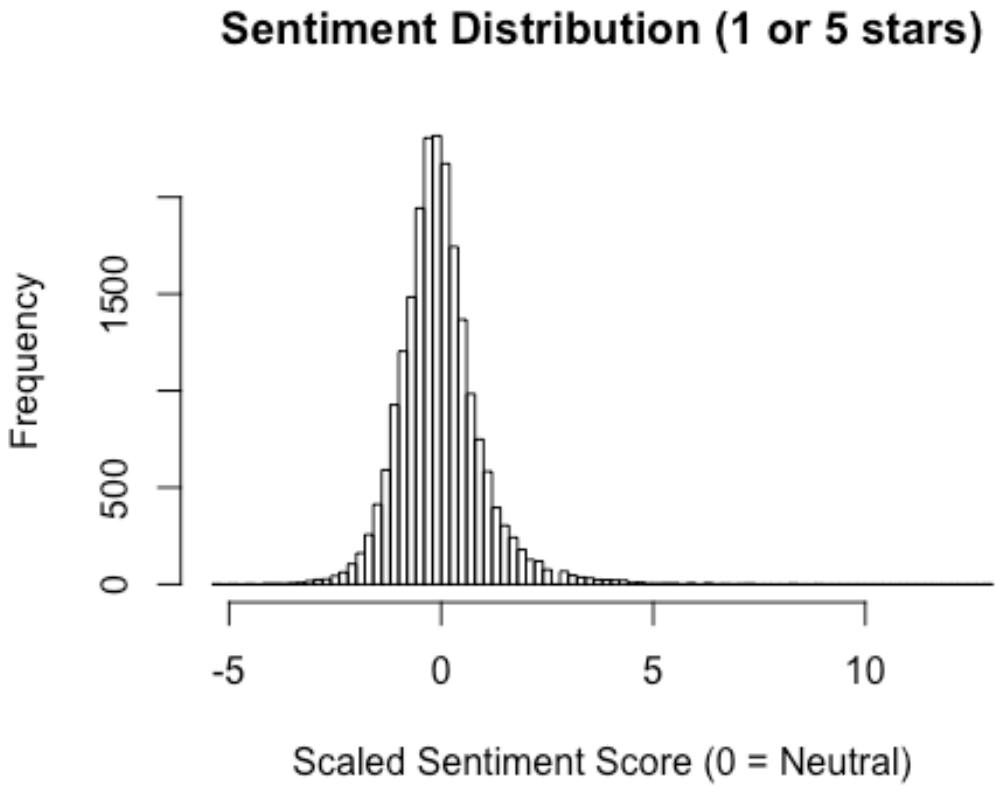
My hunch is that Review Sentiment is probably not the best predictor of Ratings. Running a Pearson product-moment test reveals only a **moderate** correlation of +41%.

```
cor.test(aznv_ch$stars.x, ch_sentiment[,1])

##
##  Pearson's product-moment correlation
##
## data:  aznv_ch$stars.x and ch_sentiment[, 1]
## t = 101.89, df = 51719, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.4016634 0.4160185
## sample estimates:
##       cor
## 0.4088663
```

The normality of Review Sentiment persists even for the extreme ratings of 1- and 5-stars ratings.

```
# Arranging Sentiment Scores alongside Star Ratings
ch_starsentiment <- cbind(ch_sentiment, aznv_ch$stars.x)
ch_starsentiment$text <- as.character(ch_starsentiment$text)
colnames(ch_starsentiment) <- c("sentiment_score", "text_review", "star_ratin
g")

# Normality persists for 1 and 5 star ratings
```

```
extreme_stars <- filter(ch_starsentiment, star_rating == 1 | star_rating == 5
)
hist(scale(extreme_stars$sentiment_score), breaks = 100, main = "Sentiment Di
stribution (1 or 5 stars)", xlab = "Scaled Sentiment Score (0 = Neutral)")
```



The correlation between Low/High Ratings and Sentiment Scores improves *slightly* but remains moderate. My best guess is that users are cagey about writing negative reviews because their names are attached OR that overall sentiment is different than the topic that people anchor for their overall rating.

As I mentioned in the limitations, perhaps the DISH sentiment influences overall ratings more than overall sentiment and might be a plausible explanatory variable.

```
attach(extreme_stars)
cor.test(star_rating, sentiment_score)

##
##  Pearson's product-moment correlation
##
## data:  star_rating and sentiment_score
## t = 96.929, df = 21281, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.5440264 0.5626679
## sample estimates:
##       cor
## 0.5534165
```

Full code and reports available on Github