### Yelp Data Analysis

Machine Learning with R

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## Agenda

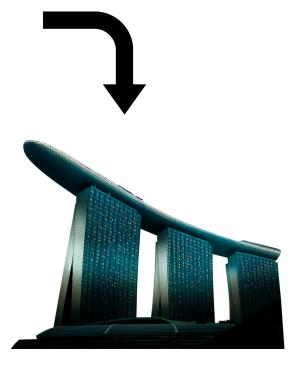
- Introduction
- Questions we answered
- Conclusion
- Question and answers

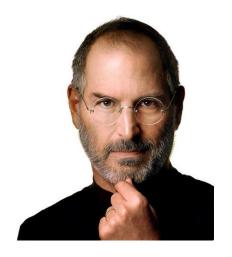
#### Introduction









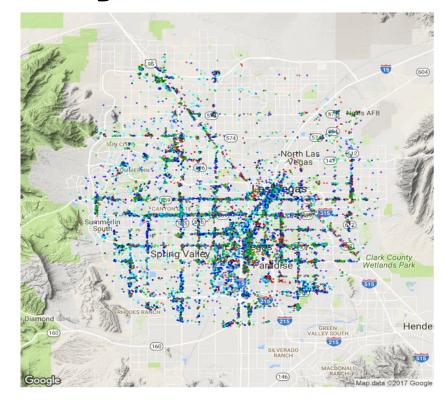


## The most common restaurant types in a state

Show 25 ve	itries		Search:	
	state	categories	φ.	n ÷
17	NV	American (Traditional)		8.53
20	NV	Mexican		821
22	NV	Nightlife		8 13
27	NV	Bars		767
31	NV	Sandwiches		724
32	NV	Pizza		699
34	NV	American (New)		6.48
43	NV	Burgers		571
53	NV	Chinese		471
56	NV	Italian		4.42
63	NV	Breakfast & Brunch		4.25
84	NV	Japanese		3.58
93	NV	Seafood		3 20

#### Popular Location and Star Ratings

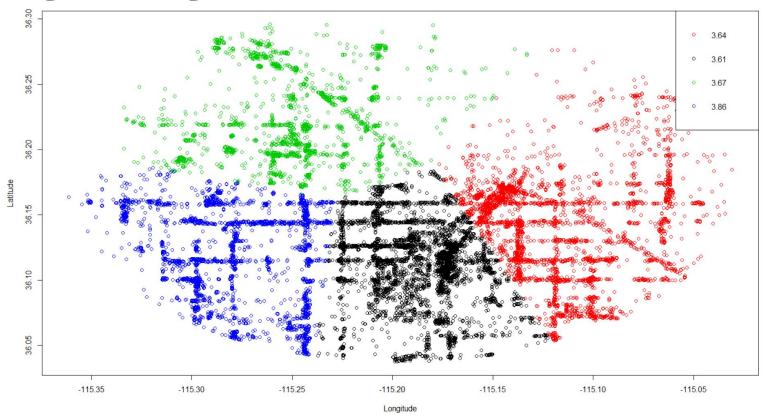
- The star rating of a business does not really depend on the location of business.
- The distance is a bit more correlated to the number of reviews though as compared to the star rating, but that figure too is very small and not really effective.



## Average Ratings

- In the previous map, we noticed the difference in density of businesses across the city.
- This affects the intensity of competition in various parts of the city.
- We tried finding out the average ratings across different regions of the city.
- Thus we divided the city into 4 primary clusters.
- For the comparison, we calculate the average rating per cluster.
- Following is the outcome which we see:

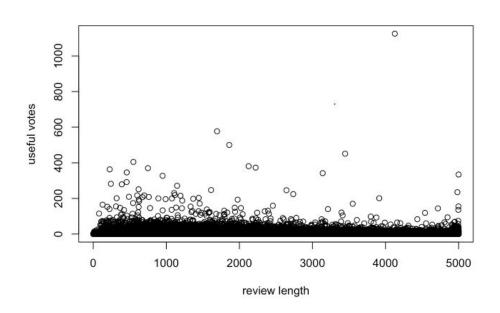
# Average Ratings



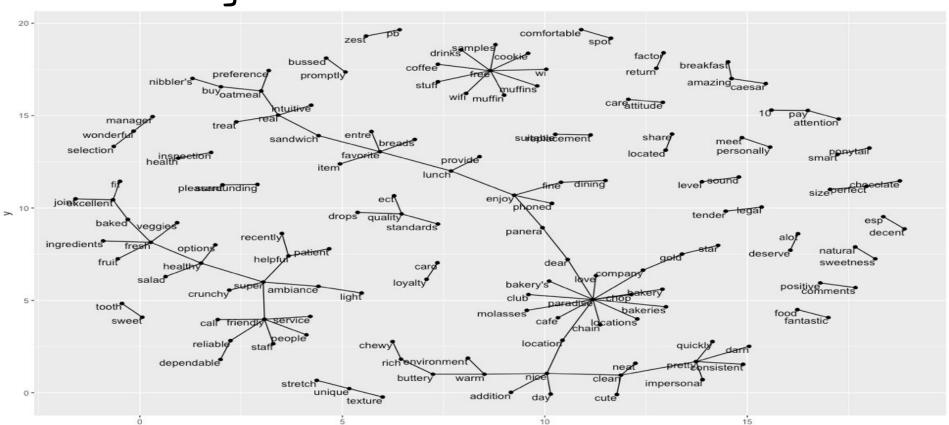
# Regression (Review Sentiment and Rest Rating)

```
Call:
lm(formula = business_score_rating$SentimentScore ~ business_score_rating$stars)
Residuals:
            10 Median
   Min
                         30
                                  Max
-109.29 -21.40 -10.18 8.82 605.77
Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)
                                      1.4733 7.89 3.32e-15 ***
                           11.6247
                                      0.3938 14.95 < 2e-16 ***
business_score_rating$stars 5.8879
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 40.28 on 10275 degrees of freedom
 (4399 observations deleted due to missingness)
Multiple R-squared: 0.02129, Adjusted R-squared: 0.02119
F-statistic: 223.5 on 1 and 10275 DF, p-value: < 2.2e-16
```

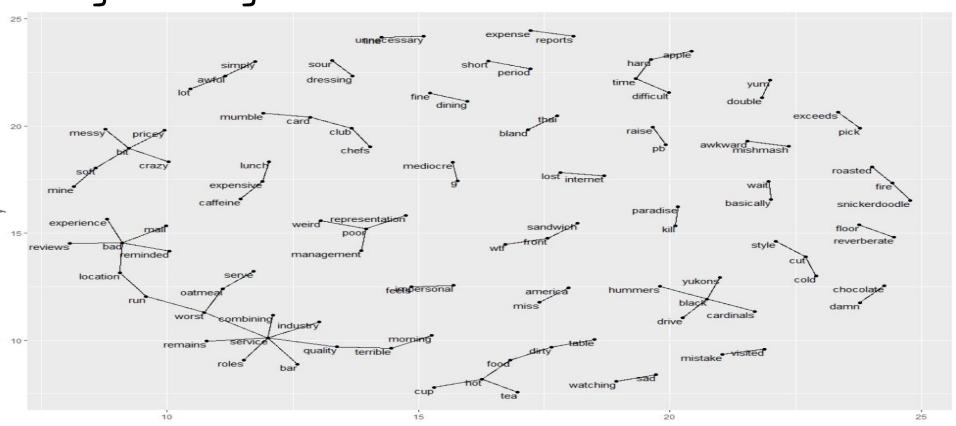
### Relation between review length and usefulness



### Positive Bigrams



# Negative Bigrams

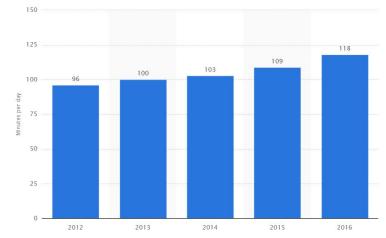


#### Identify influential customers

- In a world powered by the Internet, we spend more time on social networks – 1.7 hours per day, on average.[1]
- There are many customers who review a business, finding the most influential from them and increasing engagement with them can increase

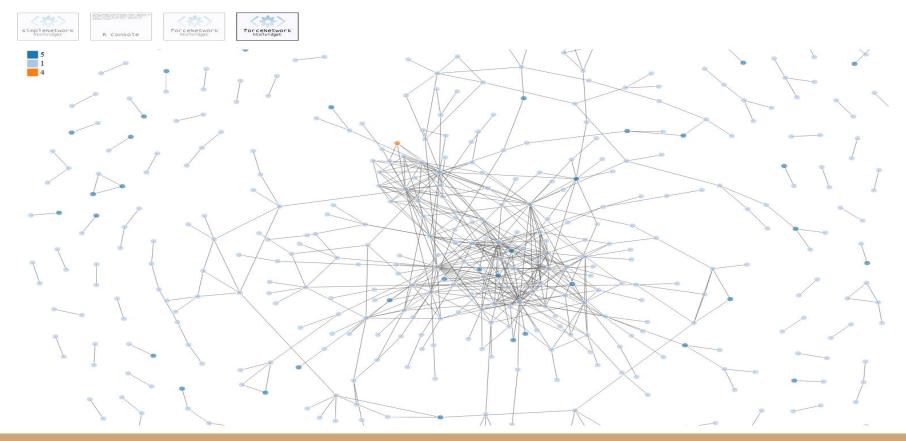
their revenue and social media footprint.

 Building a network of reviewers and their friends will enable a business owner to easily identify the influential reviewers.



Time spent on social networking - from Statista

# Identify influential customers



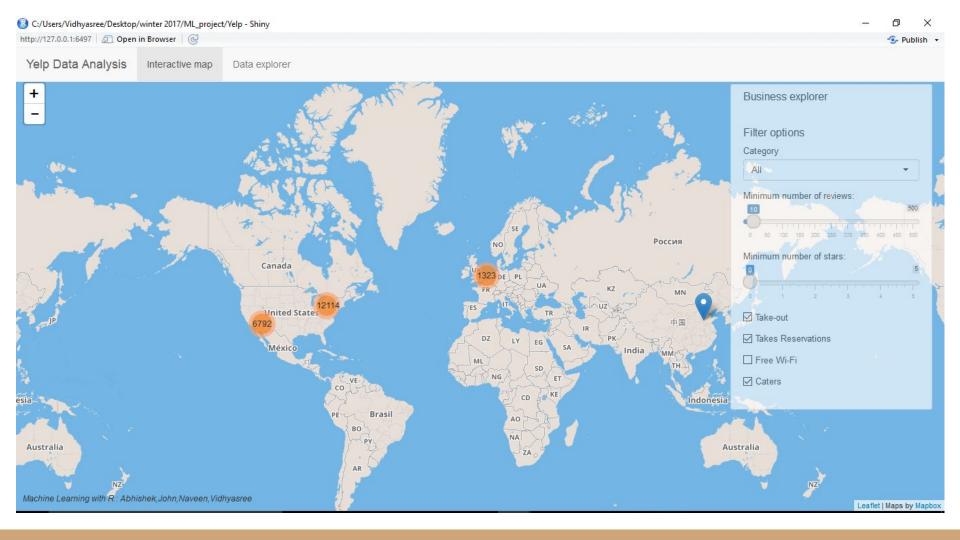
#### Recommendation for Customers

- Reviewers share their opinion and ratings for a business. We used that and built a matrix with customers and business.
- We built a recommendation system, which will recommend customers with a set of business.
- This recommendation system results are based on past reviewer ratings.
- We used ALS and built a recommendation system.

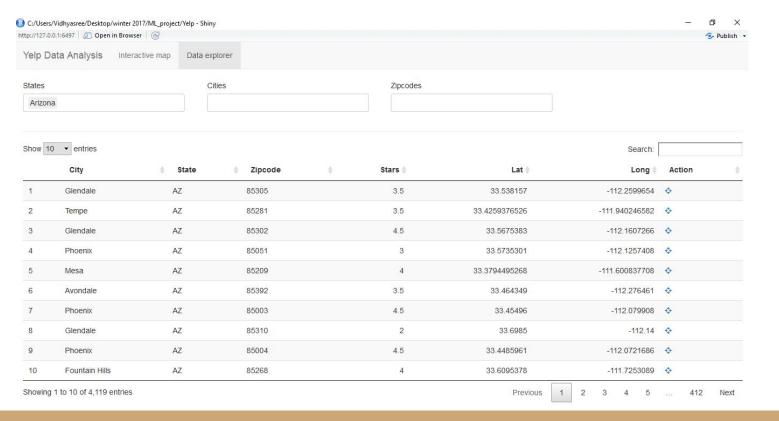
"List of Business recommended based on users past rating" 61 107 50 99 137 69

```
Iteration (opt. S): 1, RSS: 16238228, RD: 0.1111018
Iteration (opt. C): 2, RSS: 49159.49, RD: 0.9969726
Iteration (opt. S): 3, RSS: 8187.716, RD: 0.8334459
Iteration (opt. C): 4, RSS: 8187.629, RD: 1.068255e-05
Initial RSS / Final RSS = 18267814 / 8187.629 = 2231.148
```

# Shiny Time!



## Data Explorer



#### Learnings and Challenges

- Advantage of having demographic information
- Plotting and calculating distances using ggmap package
- Identify and filter relevant information
- Simple Recommendation system using ALS
- The JSON formatted entries had to be joined into a complete JSON object in order to be read into R and converted to a dataframe.

- Bigram Sentiment Analysis
- Regression may not be as expected
- RSentiment tough package
- Restricting production data on laptops
- Coordination of each view to create an integrate and reactive design in Shiny
- None of the predictor variables of interest (category, attributes) was in the proper format for analysis. It was in the **nested list**

# Thank you!