

# Get Yelp

A Comprehensive Analysis of Review Trends

Michael Gigiolio, Dante Pasionek and Dominic Deckys

# Question

What lies in our data?

What relationships lie within the different components of Yelp reviews? What patterns exist within presumably unrelated data such as stars, location and hours of business? How does a user's profile and activity affect the ratings they give?

---

# The Dataset

## Reviews

- Review ID
- User ID
- Business ID
- Stars
- Date

## Companies

- Business ID
- Name
- Address
- Latitude
- Longitude
- Stars
- Review Count
- Categories

## Users

- User ID
- Name
- Review Count
- Average Stars

# Process

## Exploration

### Understanding Data

Determining the content of the datasets and considering how they could be applied.  
Identifying areas where there may be trends to uncover.

## Cleaning

### Preprocessing

Making the dataset easy to work with.

- Removing useless columns
- Handling missing values
- Chunking data

## Mining

### Trend Location

Processing the data and comparing one field to another. Plotting the data types to provide visualization. Narrowing down where trends are located for further investigation.

# Tools

## Python

- Base code for project
- Easily accessible notebooks
- Easy to import modules

## SciPy

- Useful for complicated math and statistics
- K-means clustering

## Seaborn

- Logistic Regression
- Graph display

# Tools

## Folium

- Facilitated mapping
- Easy to plot points and clusters
- Provided intuitive visualization

## Matplotlib

- Easy graphing
- Customizable labels
- Allowed different displays of data
- Allowed for advanced visualization

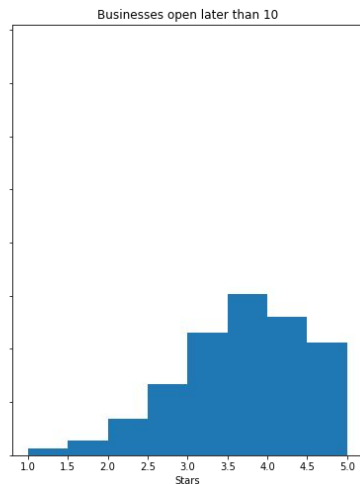
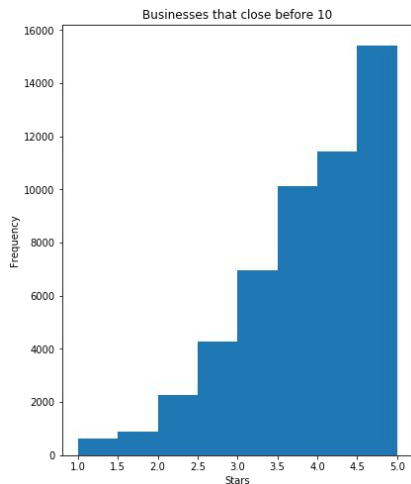
## Pandas

- Allowed easy import of data
- Facilitated data cleaning
- Provided some easy calculation techniques

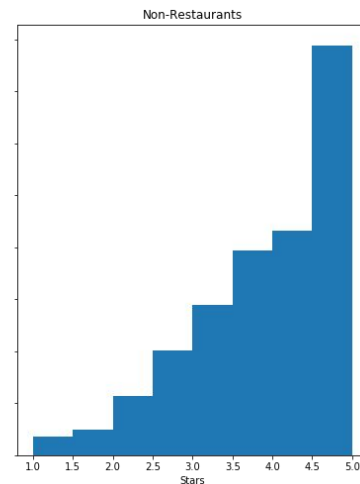
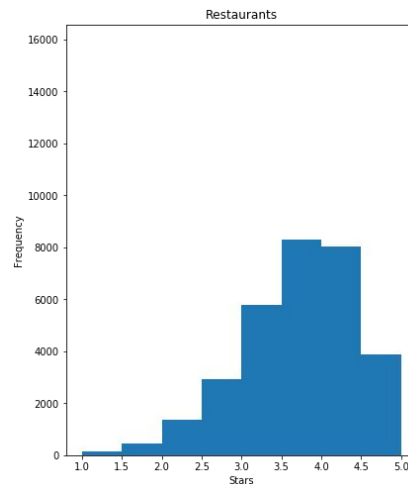
# Findings

# Rating Frequency

- Businesses that close early fair better
- Most businesses close early
- Businesses open later have a mean closer to the sample average

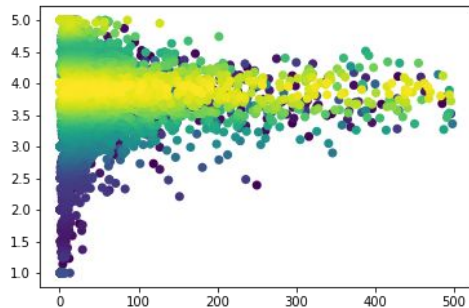
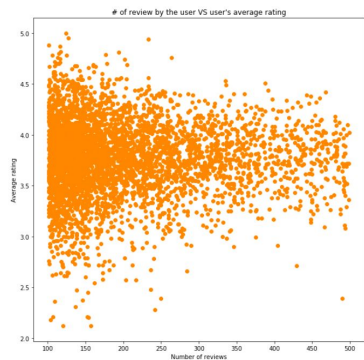


- Restaurants fair worse than non-restaurants
- Very unlikely for restaurants to get 5 stars
- It is likely for non-restaurants to get 5 stars





# Correlations



Monomodal, negatively skewed data

Global mean of 3.7277

Notable outliers

High density as count grows large around the mean

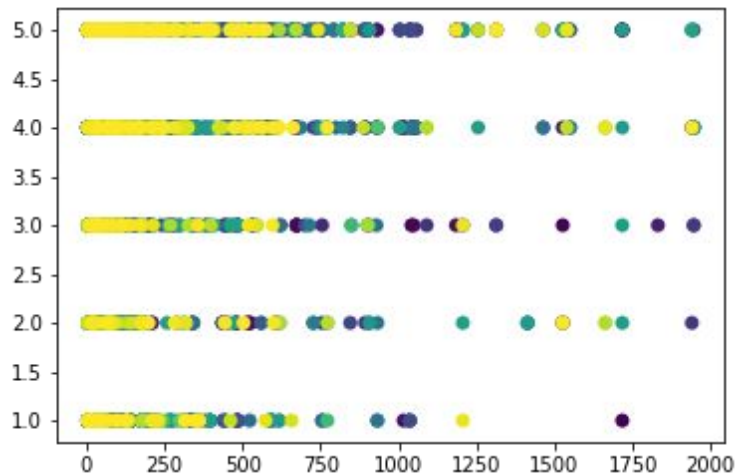
High density of 5s

Restaurants given rounded scores

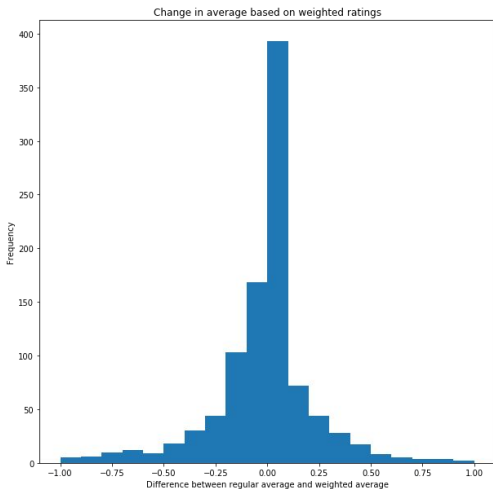
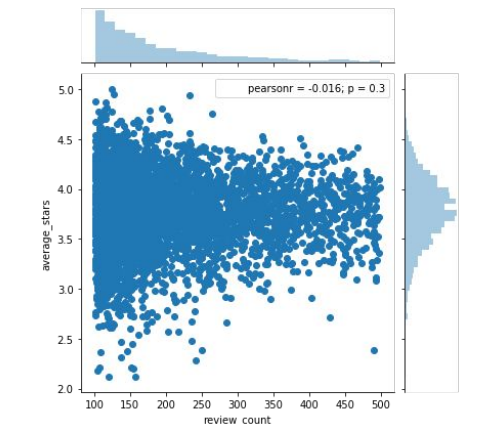
Similar trends to user graphs

Interesting high density outliers

—



# Normalization



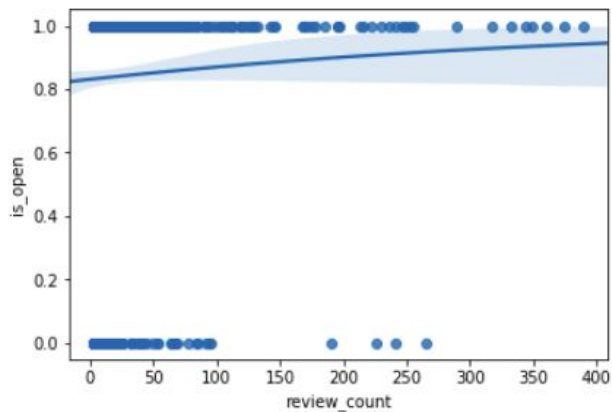
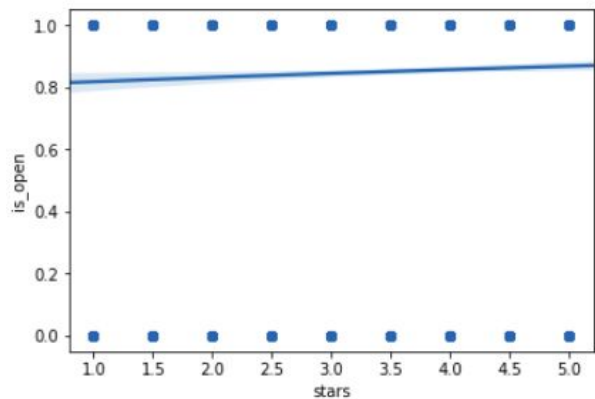
Problems with reviews:

- User bias
- User reliability

Normalization based on:

- User review average
- Number of user reviews

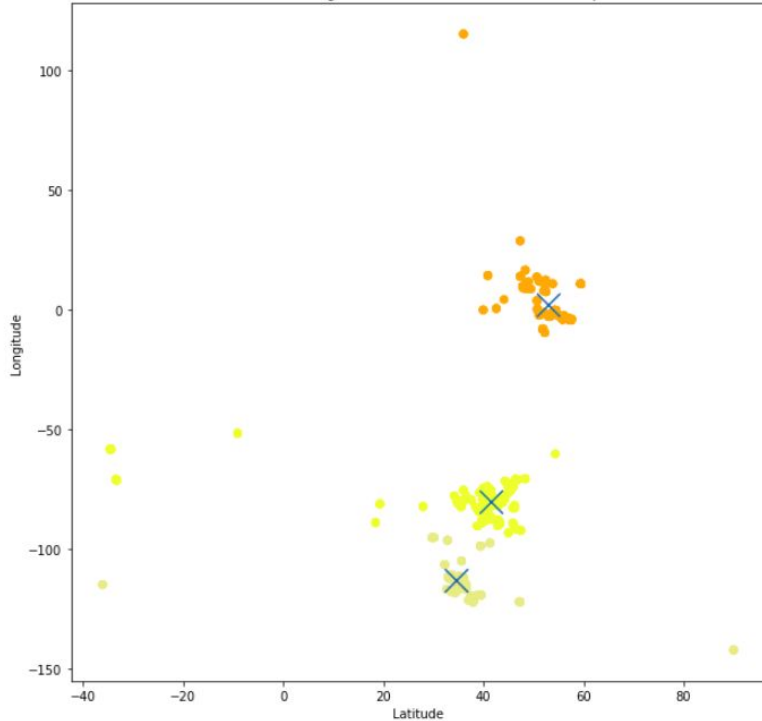
# Regression



- Logistic regression to determine if Star rating had effect on if a business is currently open
- No effect!

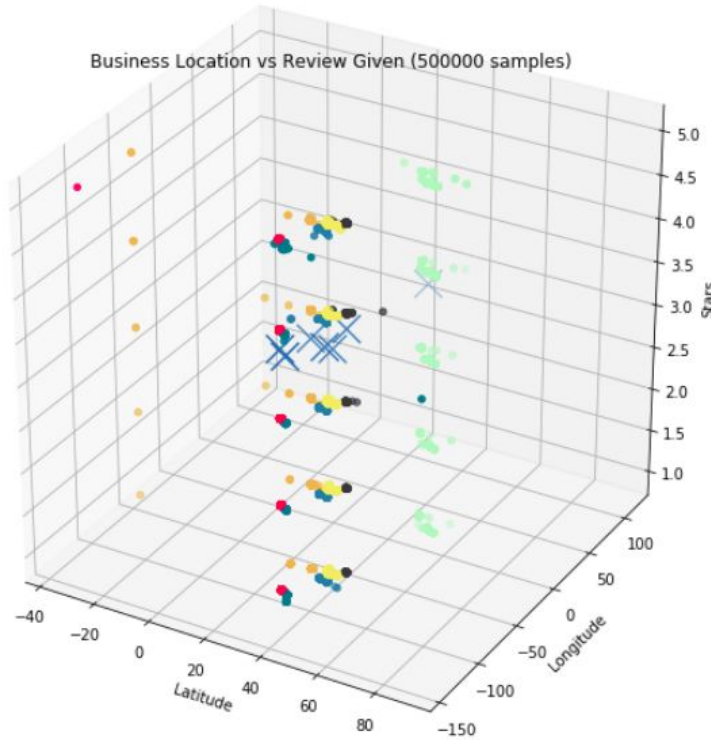
# KMeans

Latitude vs. Longitude for Businesses (999995 samples)



- 2D/3D clustering for business location and star reviews
- 3 large clusters across two continents
- Relatively even distribution across location

# KMeans cont.



- 2D/3D clustering for business location and star reviews
- 3 large clusters across two continents
- Relatively even distribution across location

# Knowledge & Applications

- Restaurants perform worse than other businesses
  - Businesses open later do not rate as well
  - All businesses receive bad reviews
  - Location isn't extremely important
- 
- Creating a more comprehensive review system
  - Remove location factor from real estate analyses

