

# Data Driven Business Decisions for New Restaurants Using Heterogeneous Datasets

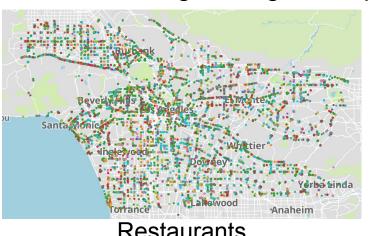


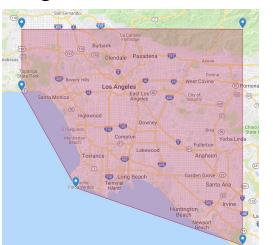


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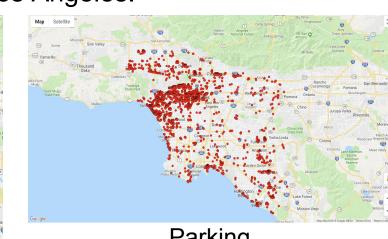
# Abstract

New restaurant business owners have numerous factors to consider before making important decisions. With the rise in the number of social media platforms, large amounts of user-driven data are being generated on a daily business. We aim to help new entrepreneurs capitalize on this data before undertaking a venture. Utilizing data from various different sources our objective is to predict a list of cuisines that are likely to receive a high rating on Yelp at a given location in Los Angeles.



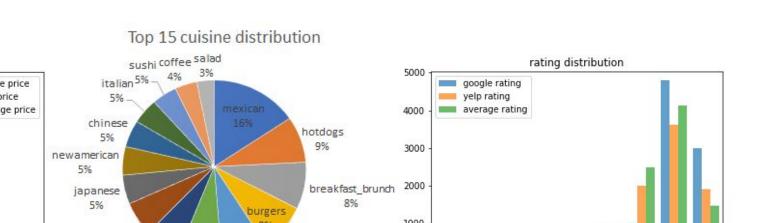


Data Collection and Feature Extraction

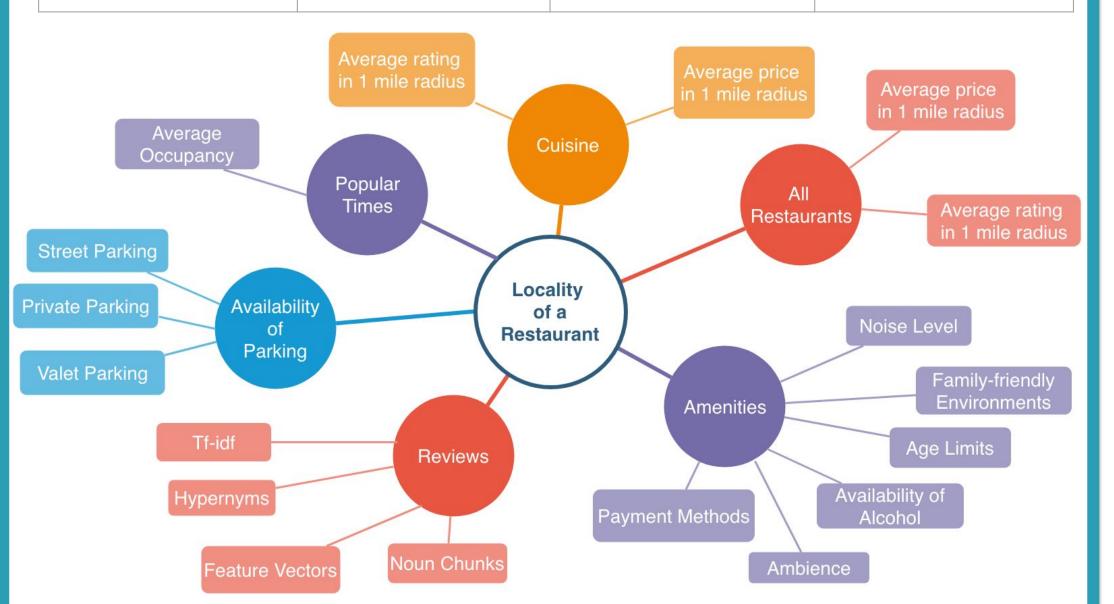


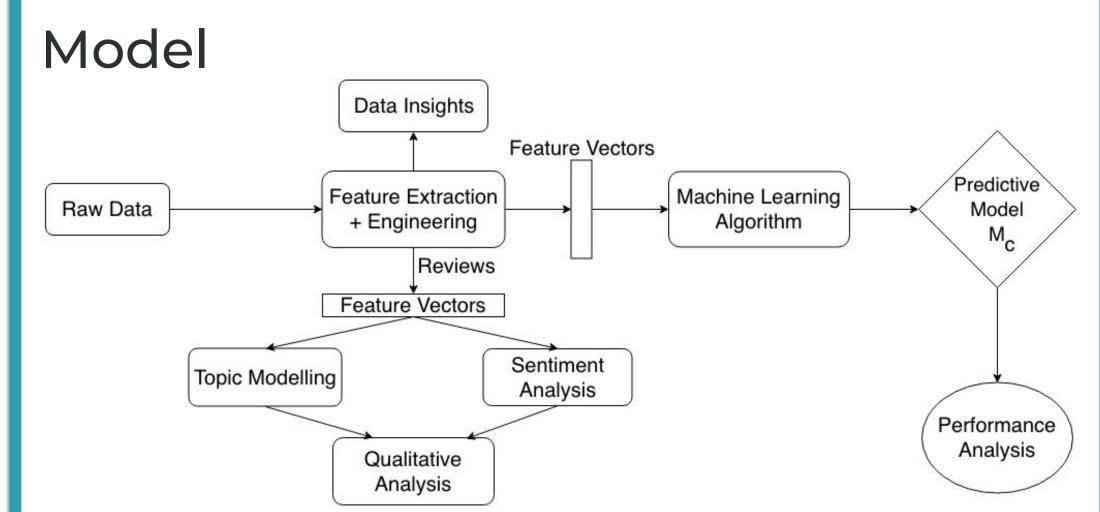
# Interesting Facts

- Most Common Cuisine: Mexican
- Most Correlated Amenity: Street Parking
- Most Correlated Cuisine: Hot dogs Most Correlated Feature: Average rating
- of nearby restaurants • Highest Average Rated Cuisine: Vegan, Tacos, Mediterranean
- Lowest Average Rated Cuisine: Hot Dogs, Chicken Wings, Burgers
- Cuisine with the Highest Average Price Level: Steak, Bars, Sushi
- Cuisine with the Lowest Average Price Level: Hot dogs, Tacos, Mexican



### os Angele Raw Data Google **Raw Data** Parking Maps Google Maps Yelp **UI Crawler for Google UI Crawler for Yelp** URL Rating Yelp ID Rating **Popular Times** Price **Review Text** Price Level Place ID **Amenities** Place ID Location Reviews Posted Date Address Name Phone Number **Phone Number Amenities Review Count** Name





### **Predictive Model** Input: Coordinates - latitude, longitude

Output: Top 3 cuisines with the highest

rating

### Algorithm:

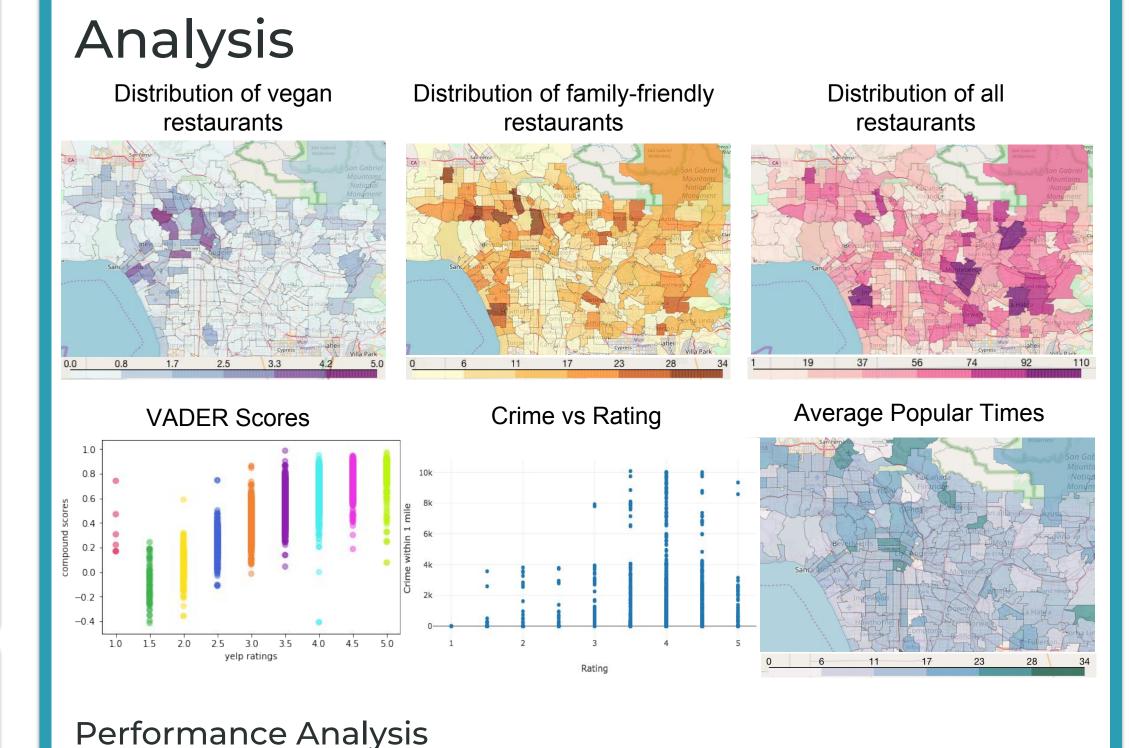
- Generate geolocalized features
- For each **cuisine**:
- a. For each **price level**: i. Predict rating using M
- Return top 3 cuisines and price level for a location based on ratings

## Qualitative Analysis

To understand the quality of food, service, and ambiance of each restaurant, the following methods were used to extract the above topics from reviews:

- Method 1: Topic modeling on each review to extract topics using LDA algorithm.
- Method 2: Topic modeling on each sentence of each review to extract topics using LDA Multicore algorithm.
- Method 3: Generate hypernyms of each word to get the topic of each sentence using NLTK.
- Method 4: Generate feature vectors for noun chunks and the context of the chunks to train a LSTM network where the labels are topics which were generated using NLTK.

Once the sentence/review had been classified, VADER scores were calculated to get the compound sentiment for each class.



## • can increase their rating by at least 0.5 by introducing valet parking: 28

**Qualitative Analysis** 

				core	0.3		
Topic	Method 1	Method 2	Method 3 & 4	S punod	0.2	r.	
Food	Order, Food	Food, Order	Food	Com	0.1		
Service	-	Time, Service	Service	Average			4
Ambience	Place, Food	Place	Ambience		1		2

The size of the test dataset is 910. The number of restaurants that:

can increase their rating by at least 0.5 by changing the cuisine: 77

• can increase their rating by at least 0.5 by reducing the price: 31

**Topic Modeling on Reviews** 

• are currently performing at their best: 10

VADER score of each topic vs rating

Topic 2 Service

Score

0.9705

0.9647

0.9683

0.9686

0.9683

# Results

Method	MAE	R <sup>2</sup> Score	MAE for restaurants with rating less than 3	Method					
Ridge Regression	0.2771	0.4086	0.6177	Support Vector Machines					
Support Vector Regression	0.2690	0.4345	0.5231	Decision Tree					
Gradient Boosting	0.2895	0.3685	0.8005	AdaBoost					
Adaptive Boosting	0.2836	0.3749	0.6717	Random Forests					
Random Forests	0.2681	0.4393	0.53	Artificial Neural					
Artificial Neural Networks	0.30	0.3059	0.3943	Networks  Classifica					
	Reg	ression							

Classification