YELP DATA CHALLENGE

ANALYZING AND PREDICTING BUSINESS SUCCESS USING BUSINESS ATTRIBUTES AND CUSTOMER REVIEWS

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Abstract: Restaurant review platforms have become our default way of searching for restaurants for every occasion. However, when looking for specific attributes of a restaurant or less generic contexts, this search isn't as straightforward. This gives rise to a need to analyze the specific features as well as customer's perception of a restaurants to understand what customers look for in a food business and what distinguishes a successful one from the others. Through this project, we hope to achieve two purposes. First, we want to analyze the reviews and tips given for the businesses to give personalized recommendations for future users about the businesses' ambience. Second, we want to employ machine learning models and natural language processing to gain insights into the success factors of a business, and predict whether a business is going to succeed based on those factors.

1. DATASET DESCRIPTION

The dataset used for this project is the Yelp Dataset (https://www.yelp.com/dataset). This includes:

- Business.json: includes information directly related to the business such as latitude, longitude, attributes and categories
- Review.json: includes the reviews received by the businesses above
- User.json: includes the information about the users who wrote the review
- Checkin.json: includes information about check-ins for the businesses
- Tip.json: includes short pieces of suggestion and advice written by the users

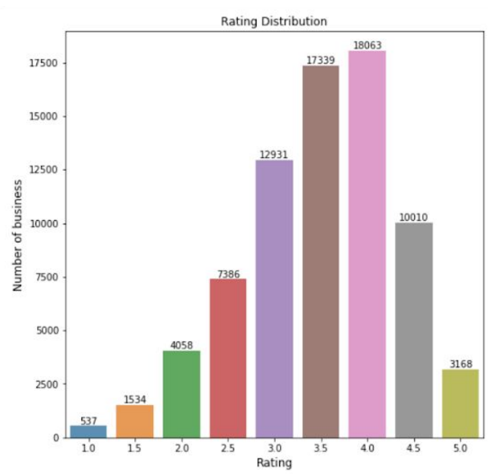
2. DATA PREPROCESSING

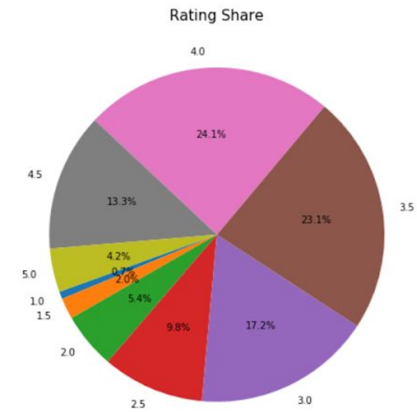
We perform these preprocessing steps:

1. Convert json to csv: For some analyses, we use json_to_csv.py converter provided by Yelp to convert the above files into CSV. For some other analyses, we converted it directly for memory efficiency purpose.
2. Slice the data location-wise and category-wise: Location-wise, for the scope of this project, we will only be looking at business and reviews coming from North American business and users (USA and Canada). In addition, we will only look at the food, drink and restaurant sector.
3. Merge the business, review and user data sets (using left join) to perform exploratory data analysis and building models
4. For machine learning purpose:
    a. Label the attributes with either one-hot encoding (creating dummy variables) or label encoding.
    b. Transform the date features in the reviews dataset to perform datetime operations.

3. DATA EXPLORATORY ANALYSIS

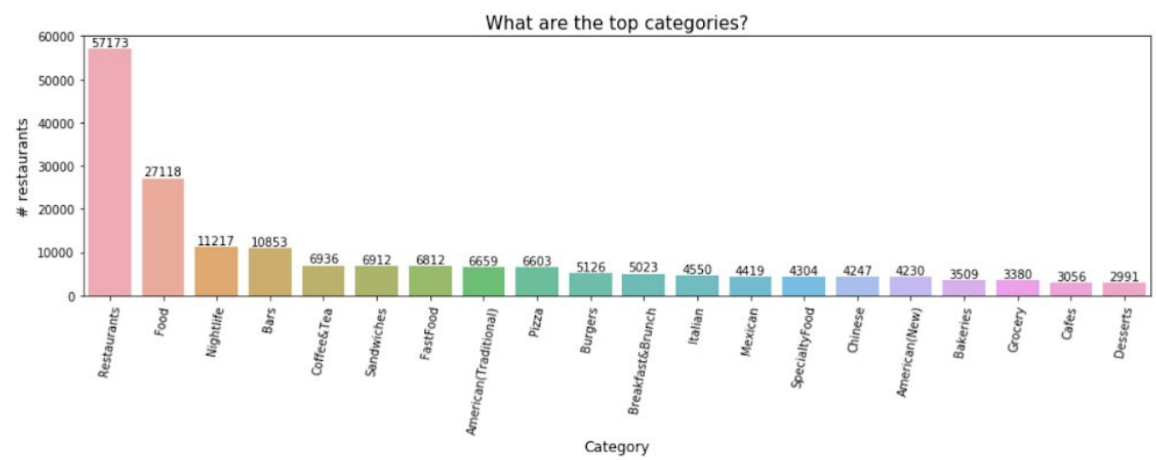
a. Rating share and distribution

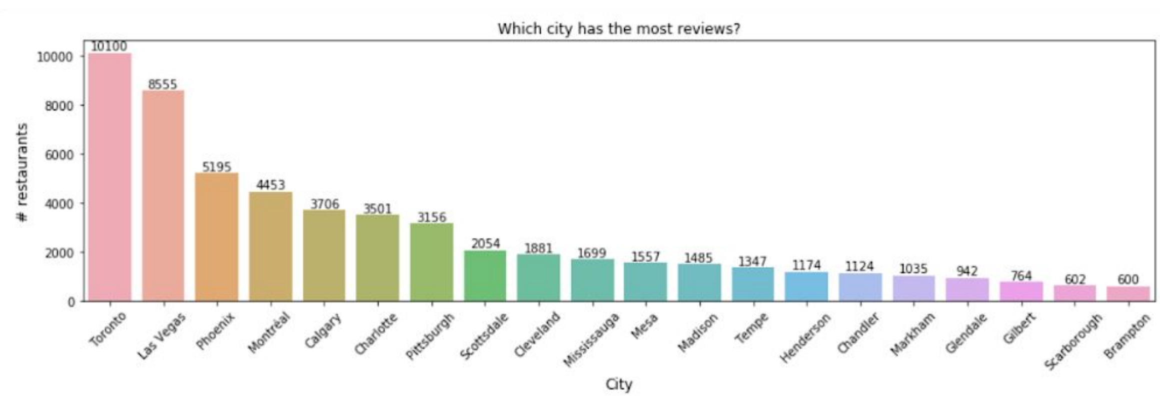




We observe that the ratings are mostly in the range of 3.5 (23.1% of total ratings) to 4 stars (24.1% of total ratings).

b. **Distribution of businesses across categories and cities**





4. ANALYSIS AND METHODS

a. Topic modelling

b. Word Embeddings using Word2Vec

It is essential to develop a sophisticated word representation model to analyze similarities and establish connections among customer reviews and tips. We compute continuous vector representations of words from Yelp's customer reviews using Word2Vec. The Word2Vec model produces a vocabulary, with each word being represented by an n-dimensional numpy array.

These vectors prove to perform much more better on our test set with regards to measuring syntactic and semantic word similarities. Being able to measure similarity means being able to quickly analyze and measure sentiments and topics in customer reviews. The result of this embedding is a spatial space displaying scatter points. The points with the same colors representing words that are highly correlated.

After converting the review TSNE is pretty useful when it comes to visualizing similarity between objects. It works by taking a group of high-dimensional (100 dimensions via Word2Vec) vocabulary word feature vectors, then compresses them down to 2-dimensional x,y coordinate pairs. The idea is to keep similar words close together on the plane, while maximizing the distance between dissimilar words.

c. Attributes Analysis and Predictions

The machine learning models we use for this project includes linear regression, logistic regression, decision tree, random forest and bootstrapping. We decided to choose many models and compare the results among them to figure out which model perform the best on the set of features that we have as well as the importance of features with respect to each models. For regression tasks, we use the star ratings (on the continuous scale of 0.0 to 5.0) as the label. For classification tasks, we also 1 and 0 to indicate success (a restaurant achieving 3.5 stars and above on average will receive a 1 and a 0 otherwise).

In both regression and classifications tasks, we ran OLS regression beforehand to narrow down the features that explain the variances in our labels. In addition, for classification task, we also ran recursive feature elimination to pick the most important features. These features, as well as the features appearing in feature importance as a result of the random forest algorithm, are important to restaurant owners because they can infer future business performance.

5. RESULTS

a. Topic modelling

b. Word Embeddings

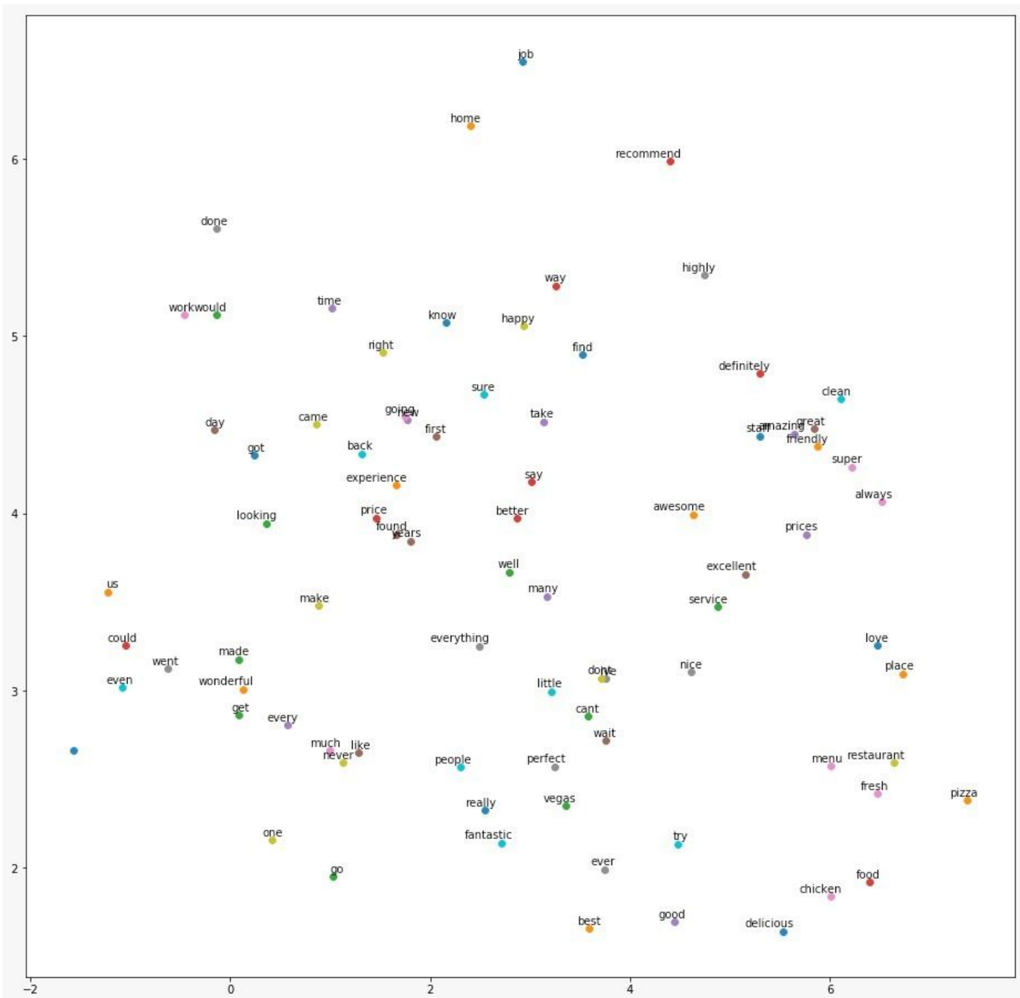
The result for word similarity using Word2Vec is displayed below. Using this tool will help us quickly analyze and understand a customer review and gain insights into the sentiments shared among words.

Here we use Python library Genism's implementation of word2vec model to train our word vectors.

In order to better capture the global corpus statistics, such as word-word co-occurrence matrix, we train global word vectors. Similar to Word2Vec, GloVe represents words by input and output vectors, and models the probability of two words being contexts. Different than Word2Vec, GloVe uses the co-occurrence matrix as responses and a weighted least square model to train the parameters. The cost function of GloVe model is

V

J = ⊚ f(Xij)(wiTwj̃ +bi +b̃j −logXij)2.
i,j =1
Here Xij is the (i,j) entry of the co-occurrence matrix denoting the number of co-occurrence of wordi and wordj; w, w̃, b and b̃ are input and output word vector and intercept terms as in Word2Vec. The weight function f(Xij) is defined as,
f(x) = ⊚ (x/xmax)α if x < xmax1 otherwise.
We use the implementation package from http://nlp.stanford.edu/projects/glove/ to train our word vectors on the movie review dataset.



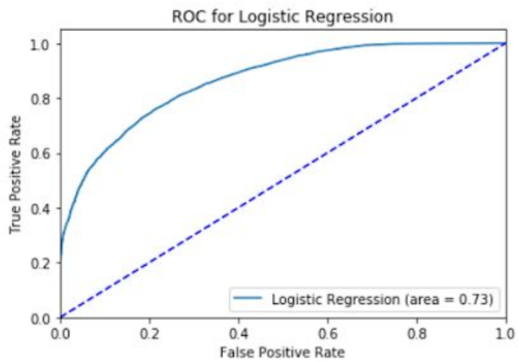
c. Attributes Analysis and Predictions

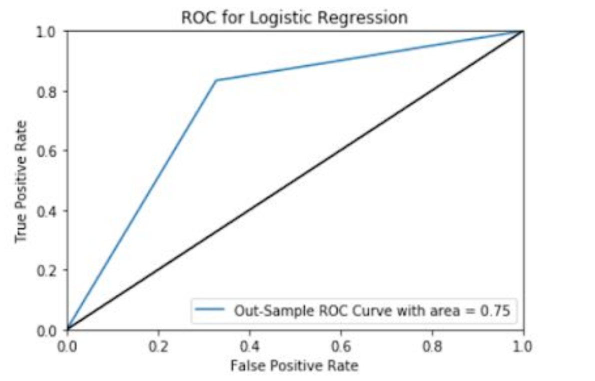
We achieve relatively positive result for all of our models. The results are as follows:

	Mean-squared Error	**Variance Score**
Linear Regression	0.29	57.00%
	Accuracy	**Area under the ROC**
Logistic Regression	79.00%	73.00%
Decision Tree	76.36%	72.00%
Random Forest	77.40%	75.15%

Bootstrapping	76.90%	75.30%

We suggest to use either logistic regression or random forest ensembles because they are relatively simple and yield good results while not computational expensive. Bootstrapping doesn't perform as well as expected because our dataset is relatively sparse after preprocessing.

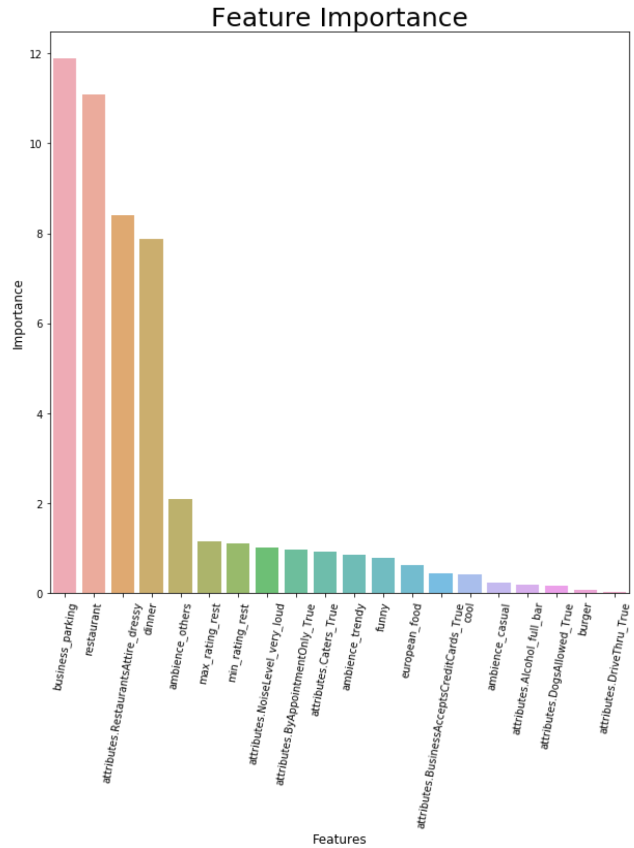




The features that are used as input of the above classification algorithms are:

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
attributes.RestaurantsAttire_dressy	0.6200	0.0785	7.8988	0.0000	0.4662	0.7739
attributes.Alcohol_full_bar	-0.2024	0.0227	-8.9350	0.0000	-0.2468	-0.1580
attributes.NoiseLevel_very_loud	-0.7574	0.0610	-12.4157	0.0000	-0.8769	-0.6378
attributes.ByAppointmentOnly_True	0.5168	0.2591	1.9948	0.0461	0.0090	1.0246
attributes.DogsAllowed_True	0.8484	0.0780	10.8770	0.0000	0.6955	1.0013
attributes.BusinessAcceptsCreditCards_True	-0.6602	0.0259	-25.4593	0.0000	-0.7110	-0.6093
attributes.DriveThru_True	-1.1932	0.0567	-21.0286	0.0000	-1.3044	-1.0820
attributes.Caters_True	0.4246	0.0217	19.5279	0.0000	0.3819	0.4672
ambience_casual	0.6220	0.0242	25.6751	0.0000	0.5746	0.6695
ambience_trendy	0.9429	0.0627	15.0489	0.0000	0.8201	1.0657
ambience_others	1.1081	0.0471	23.5257	0.0000	1.0158	1.2004
max_rating_rest	-0.0493	0.0078	-6.3458	0.0000	-0.0646	-0.0341
min_rating_rest	1.1494	0.0176	65.4110	0.0000	1.1150	1.1839
funny	-1.3718	0.0289	-47.4233	0.0000	-1.4285	-1.3151
cool	1.1749	0.0265	44.2799	0.0000	1.1229	1.2269
european_food	0.2552	0.0299	8.5408	0.0000	0.1967	0.3138
burger	-0.3653	0.0367	-9.9397	0.0000	-0.4373	-0.2932
restaurant	-0.8273	0.0242	-34.2289	0.0000	-0.8747	-0.7800
business_parking	0.4737	0.0217	21.8459	0.0000	0.4312	0.5162
dinner	0.4466	0.0259	17.2682	0.0000	0.3959	0.4973

The important feature suggested by our Random Forest Ensembles are as follows:



From the above feature, we have the following suggestions for the restaurant owners:

1. Maintaining good facility is essential for a successful restaurants. Customers seem to favor those with good business parking and avoid those with loud noises.
2. Ambience seems to play a decent role in the success of a business. In general, a trendy ambience will help a business to gain interest from customers. It it important to maintain a certain ambience because on average these businesses tend to do better ('Others' are agregation of ambiences that are not trendy or classy).
3. Other features are harder to interpret and built into a strategy. However, they should be kept in consideration for further analysis.

6. CONCLUSIONS

In this project, we employs many techniques to analyze users' reviews as well as machine learning algorithms to classify business to predict their successes. Logistic regression and random forest ensembles are shown to perform well enough compared to other models, and can be used to gain insights into how their business will perform based on a number of input features.

In future works, we plan to extend the Word2Vec model to infer hidden messages in the user reviews and use more sophisticated machine learning algorithms such as neural networks and XGBoost to improve our success predictions even more.

REFERENCES:

1. Yelp Dataset and Data Challenge Website: https://www.yelp.com/dataset/challenge
2. Mikolov et al., "Efficient Estimation of Word Representations in Vector Space" (2013)
3. Hood et al., "Inferring Future Business Attention" (2014)