











DATS-6501 CAPSTONE PROJECT











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The Yelp dataset containing its businesses, reviews and user data in Json file format. This dataset involves 5,996,996 reviews,



188,593 businesses, 1,185,348 tips by 1,518,169 users, and business attributes like hours, parking, availability, and ambience



in 10 metropolitan areas of US.

Business file		Review file	
Attribute	ttribute Meaning		Meaning
business_id	Business ID (index for datasets merging)	busindess_id	Business ID(index for datasets merging)
neighborhood	The neighborhood of the restaurant	date	Date of this review
is_open	Weather the restaurant is open	stars	Yelper rating levels
categories	Classify by cuisine, abstention, etc.	text	Review text
review_count	Number of reviews	cool	"cool" counts this review received
name	Name of the restaurant	funny	"funny" counts this review received
stars	Business/Restaurant rating levels	useful	"useful" counts this review received
postal_code	Restaurant's location		





- · Identify top-rated geographic area for different business type.
- Examine the most important attributes affect people's choice among identical restaurants.
- · Predict STAR ratings that consumer would score based on business attributes and their reviews.
- · Identify the common words that consumer tend to write in their reviews for certain businesses.









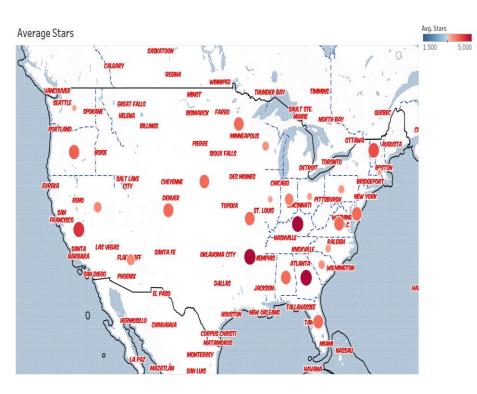


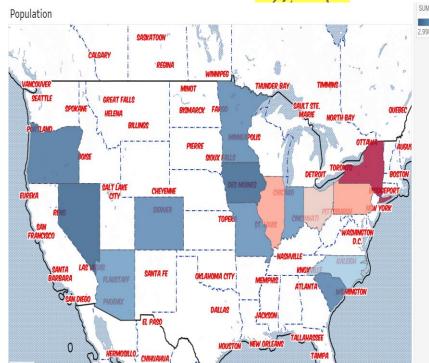


Top-Rated Geographic Areas









19,849,3



Top-Rated Geographic Areas' Business





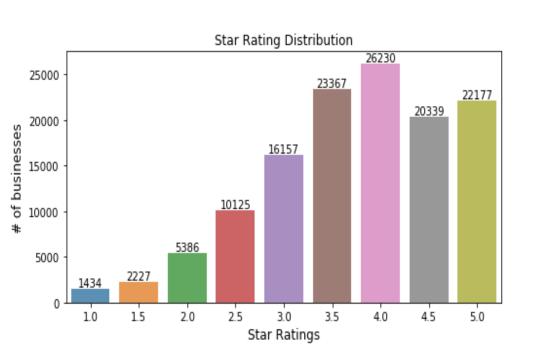
categories	n ⊲int> sta	tate	categories	n
Restaurants, Pizza	1092		(dip*	n dn>
Pizza, Restaurants	1060 AZ		Restaurants, Mexican	394
Coffee & Tea, Food	1036 ON	N	Restaurants, Chinese	305
Nail Salons, Beauty & Spas	1015 NV	V	Mexican, Restaurants	181
Beauty & Spas, Nail Salons	981 OH	Н	Pizza, Restaurants	156
	PA PA	4	Restaurants, Pizza	151
Food, Coffee & Tea	966 QC	С	Restaurants, Pizza	102
Restaurants, Mexican	932 AB	8	Restaurants, Pizza	86
Mexican, Restaurants	908 NC	С	Restaurants, Chinese	82
Beauty & Spas, Hair Salons	893 W		Restaurants, Mexican	37
Destructe Chloses	000			•

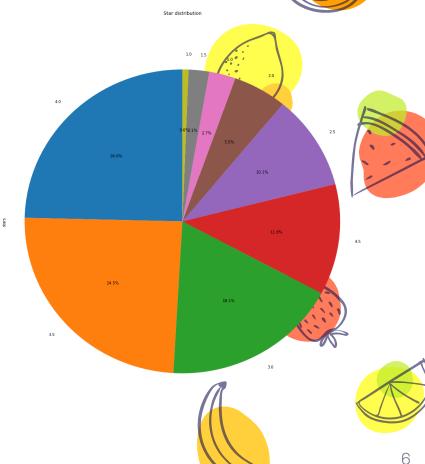
Restaurants, Mexican





Stars Distribution







- Selected the business who have "restaurant" type.
- o Flatten all the attributes.
- O Delete the attributes which have a lot of Null values
- o One hot encoding.







- O Label the good restaurants data and bad restaurants data.
 - O Good(star 5.0/ star 5.0 and 4.5)
 - O Bad(star 1.0,1.5 and 2.0 /star 1.0,1.5,2.0 and 2.5)
- O Models
- O Split training and testing dataset
- O 10 cross validation











Model	Training Accuracy	Testing Accuracy	Recall- Good	Recall- Bad	Model Parameter
GaussianNB	0.530	0.519	0.06	0.99	
Logistic Regression	0.734	0.705	0.69	0.72	LogisticRegression(C=10.01, class_weight=None,dual=False, fit_intercept=True,
linear SVC	0.725	0.692	0.66	0.72	LinearSVC(C=0.01, class_weight=None, dual=True, fit_intercept=True,iintercept_scaling=1, loss='squared_hinge', max_iter=1000, multi_class='ovr', penalty='l2', random_state=None,tol=0.0001,verbose=0)
Random Forest	0.823	0.721	0.75	0.70	RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini', max_depth=8,max_features='auto', max_leaf_nodes=None,min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=1, min_samples_split=2,min_weight_fraction_leaf=0.0, n_estimators=500,n_jobs=1, oob_score=False, random_state=42, verbose=0,warm_start=False)
KNN	0.780	0.677	0.59	0.77	KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski', metric_params=None, n_jobs=1, n_neighbors=5, p=2,weights='uniform')















Less attributes sometimes will improve the model's performance, because there are a lot of Null values in these attributes.

x If we define the bad and good more extremely, we can get higher accuracy.

The average accuracy of these models is less than 0.8

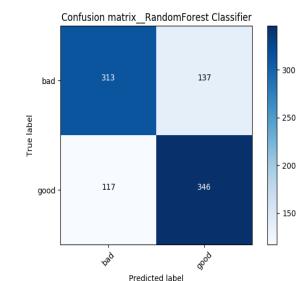
In all of the models, we got our best model:

Random Forest Model, Training Accuracy: 0.8228383458646616

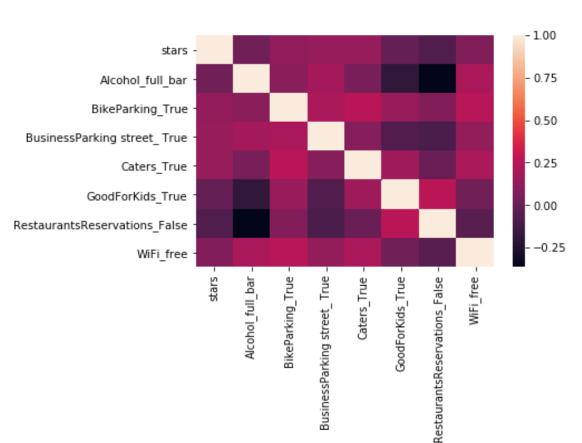
Training Accuracy: 0.8228383458646616 Classification Report: recall f1-score precision support 0.73 0.70 0.71 450 0.72 0.75 0.73 463 0.72 0.72 0.72 913 total

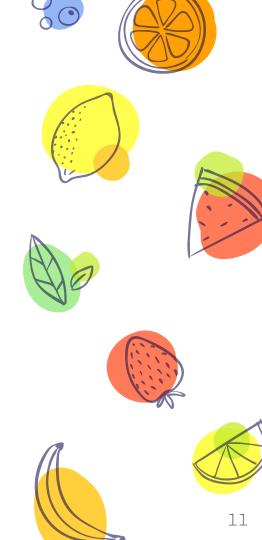
Testing Accuracy : 0.7217962760131434













Feature	Coefficients		
BusinessParking street_ True	-4.931739e+12		
BusinessParking valet_ True	4.047394e+12		
Ambience classy_ True	3.362815e+12		
GoodForMeal breakfast_True	-3.256624e+12		
Ambienceromantic_ True	-2.815944e+12		
Training MSE: 0.7412492567199715 Test MSE: 0.7572142703112591			



K-Fold Cross Validation:

10-fold RMSEs:

[0.7376264896385099, 0.7534747627960025, 0.7410598543565764, 0.736387835472943, 0.7600223523964008, 0.7342258835840773, 0.7399

CV RMSE:

0.745991924440831

Std of CV RMSE:

0.012895228941877555

3.4353085182042027



Without Polynomial Features:	MSE:0.7458908459319094			
With Polynomial Features:	MSE:0.7289958883334875			









Support Vector Regression

Training MSE	0.7360020615112289
Test MSE	0.7572142703112591



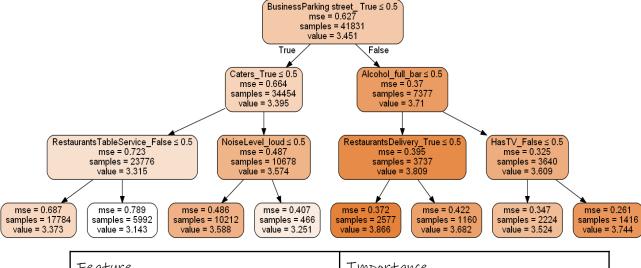








Decision Tree Regression



Feature	Importance		
BusinessParking street_ True	0.395462		
Cater_True	0.322624		
RestaurantsTableService_False	0.155524		
Alchohol_full_bar	0.048029		
NoiseLevel_loud	0.033251		















Regression Model Selection





Coefficients
-4.931739e+12
4.047394e+12
3.362815e+12
-3.256624e+12
-2.815944e+12

Training MSE

Test MSE

Ridge Regression

Without Polynomial Features

With Polynomial Features





Reviews Exploration - Word Cloud













negative Displaying 1 of 16376 matches: e twice locat desert ridg first time good last time veri disappoint order pepp positive Displaying 1 of 23305 matches: look good authent chines food care craft tri p

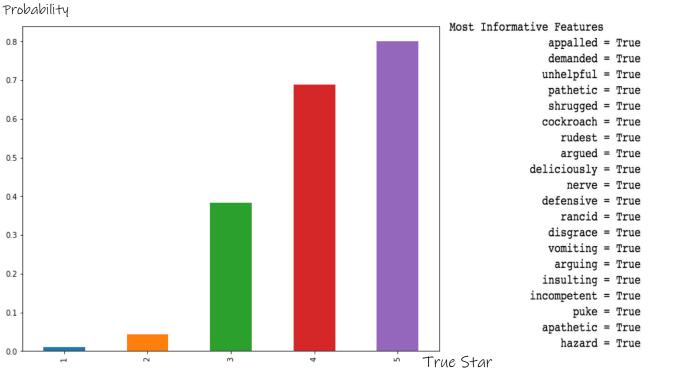




Reviews Exploration - Naïve Bayes







neg	:	pos	=	40.5	:	1.0
neg	:	pos	=	26.5	:	1.0
neg	:	pos	=	24.5	:	1.0
neg	:	pos	=	24.2	:	1.0
neg	:	pos	=	21.9	:	1.0
neg	:	pos	=	21.5	:	1.0
neg	:	pos	=	21.3	:	1.0
neg	:	pos	=	21.2	:	1.0
pos	:	neg	=	21.1	:	1.0
neg	:	pos	=	20.7	:	1.0
neg	:	pos	=	20.5	:	1.0
neg	:	pos	=	20.5	:	1.0
neg	:	pos	=	19.5	:	1.0
neg	:	pos	=	19.5	:	1.0
neg	:	pos	=	19.5	:	1.0
neg	:	pos	=	18.9	:	1.0
neg	:	pos	=	18.6	:	1.0
neg	:	pos	=	18.5	:	1.0
neg	:	pos	=	17.5	:	1.0
neg	:	pos	=	17.5	:	1.0
	//					

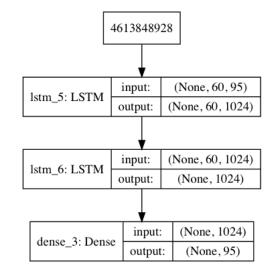




word_algebra(add=[u'breakfast', u'lunch'])

brunch

LSTM







get related terms(u'service')

staff	0.666
food	0.594
customer	0.591
attentive	0.526
atmosphere	0.526
ambience	0.52
prices	0.517
friendly	0.513
prompt	0.501
polite	0.495











What makes a great restaurants?

- o Location
- · Parking Even bike parking
- Service seems more important than the food.
- · Generate 5 star reviews by yourself!













- 1. More models or more encoding methods can be tried to improve the accuracy of business.
- 2. We didn't go too in depth with each model when we trained, maybe there will be more parameters could be tuned in the future.
- 3. We could establish times series model to examine how previous reviews impact the future review.
- 4. For the review generator part, word sequence models can be tried.







