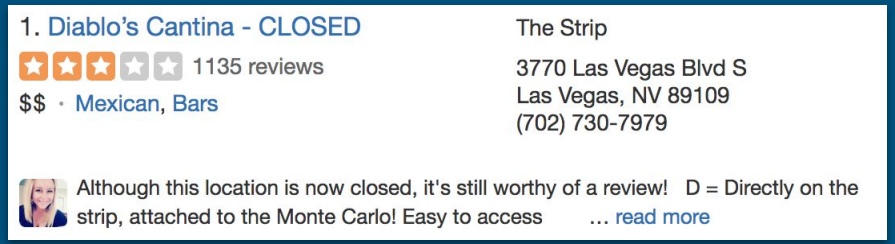
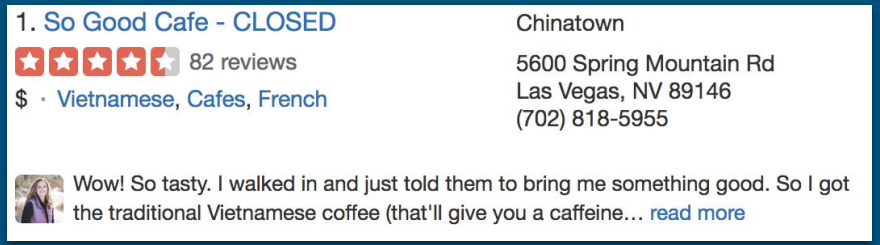
Predict Business Closure With Yelp Data

An Exercise In Supervised Learning By: Emy Parparita

Objective

Predict business closure using Yelp data.





Data Source

- The Yelp Dataset, as a SQL dump (MySQL): “... is a subset of our businesses, reviews, and user data for use in personal, educational, and academic purposes”
- Relevant Tables:
  - attribute
  - business
  - category
  - review

Schema

attribute

Field	Type
id	int(11)
business_id	varchar(22)
name	varchar(255)
value	mediumtext

category

Field	Type
id	int(11)
business_id	varchar(22)
category	varchar(255)

business

Field	Type
id	varchar(22)
name	varchar(255)
neighborhood	varchar(255)
address	varchar(255)
city	varchar(255)
state	varchar(255)
postal_code	varchar(255)
latitude	float
longitude	float
stars	float
review_count	int(11)
is_open	tinyint(1)

review

Field	Type
id	varchar(22)
business_id	varchar(22)
user_id	varchar(22)
stars	int(11)
date	datetime
text	mediumtext
useful	int(11)
funny	int(11)
cool	int(11)

Data Selection

Cities with most businesses

city	business_cnt
Las Vegas	26809
Phoenix	17213
Toronto	17211
Charlotte	8554
Scottsdale	8228
Pittsburgh	6355
Montréal	5973

Cities with most reviews

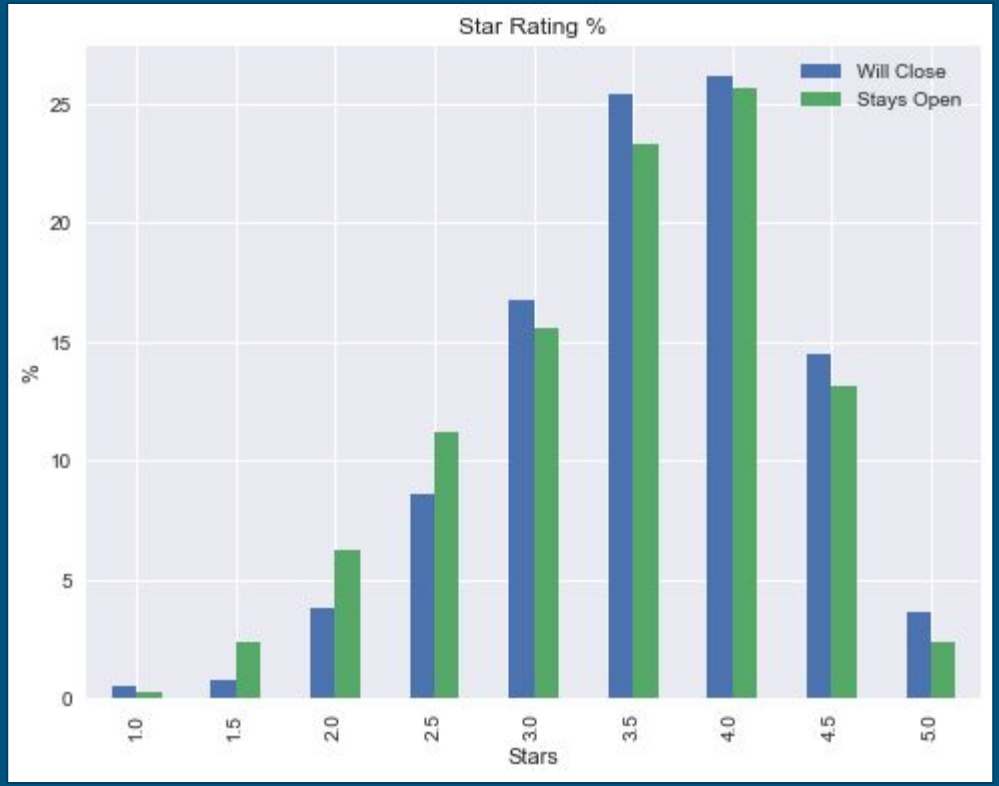
city	review_cnt
Las Vegas	1605343
Phoenix	576709
Toronto	430985
Scottsdale	308529
Charlotte	237118
Pittsburgh	179471
Henderson	166884

Will use **Las Vegas**, **Restaurants** category (most likely to be reviewed), reviews after **2015/01/01**.
Number of selected businesses: **4085**, out of which **795** are closed
Train/Test Split: **80/20**, indexed by **business_id**

Stars Relevance

Is the average star rating a good predictor?

It doesn't look that way.



Feature Selection

Feature	Desc	Indicator	Engineered	Keep
bpnr_cnt	Number of similar businesses/neighborhood	⊘	✓	✓
cat_...	Category	✓	⊘	⊘
nbr_...	Neighborhood	✓	⊘	⊘
rating	Global -1/0/1 based on stars binning	⊘	✓	✓
review_count	Total number of reviews	⊘	⊘	✓
review_sentiment	Most recent N/% reviews, converted to -1/0/1 sentiment and summed up	⊘	✓	✓
same_name_cnt	Number of businesses with the same name (chain?)	⊘	✓	✓
stars	Global number of stars	⊘	⊘	⊘
zip_	Postal code	✓	⊘	⊘

Target and Score Selection

Target: will_close, 0/1 derived as (1 - is_open)

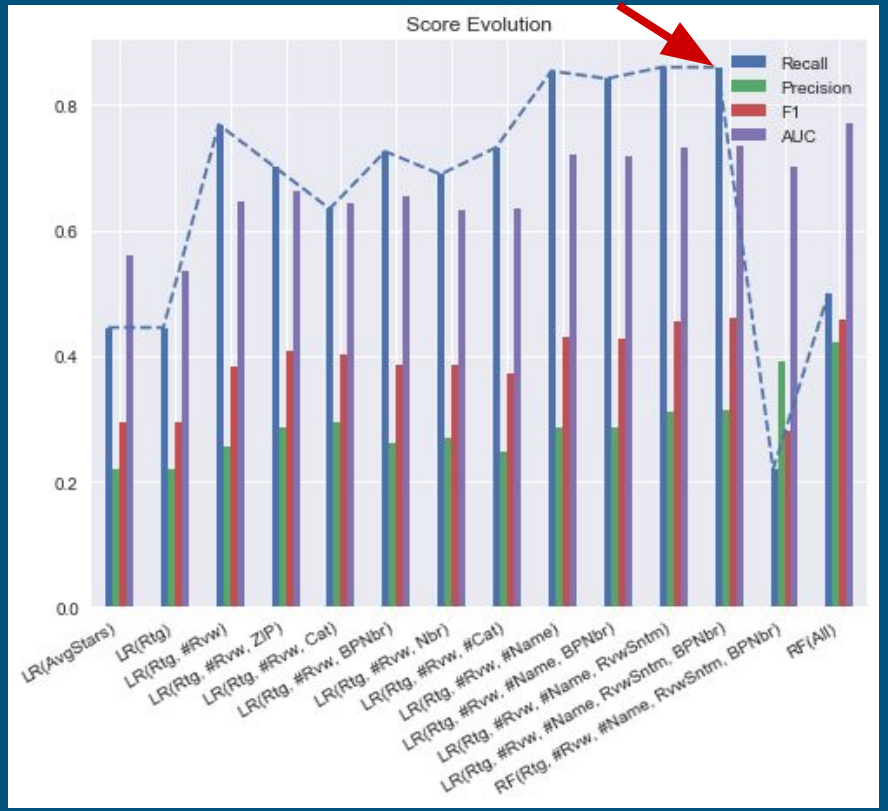
Scores:

- **Recall** (the most important score, false positives are less risky than false negatives)
- Precision
- F1
- AUC

Feature Trials

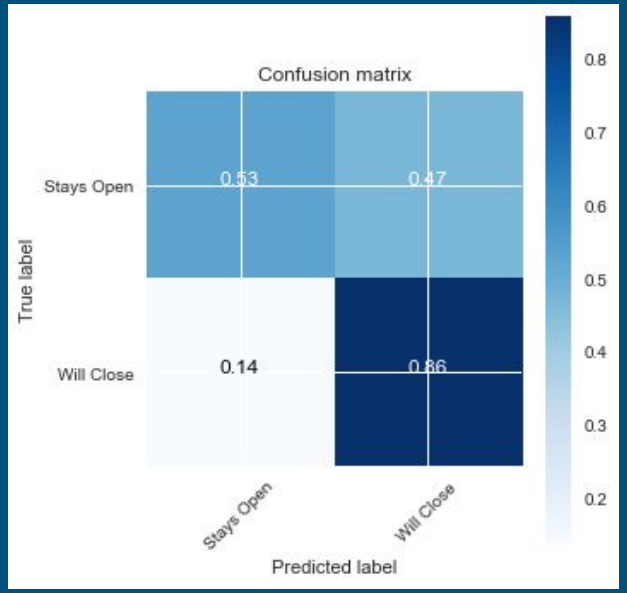
Different sets of features and models were tried:

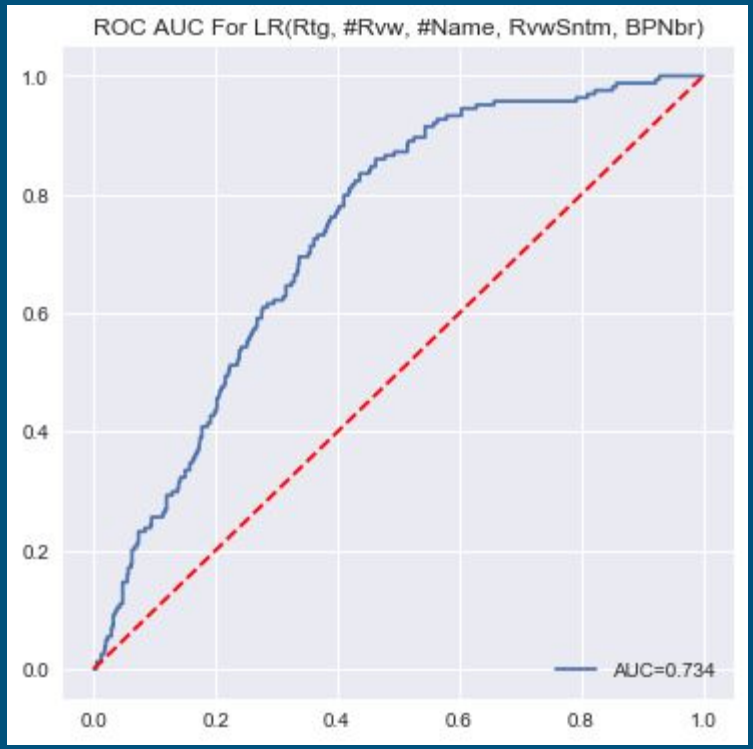
- Location (ZIP, neighborhood) and categories do not help
- Logistic Regression has better recall than RandomForest
- Precision is low



Final Test Score

Recall	0.860
Precision	0.314
F1	0.460
AUC	0.734





Conclusions

- The model could be deployed as a Web App to be used by owners to check if their business is at risk of closing
- Unfortunately the current implementation has very low precision, “cry wolf” syndrome would lead to dismissal
- Possible refinements:
  - NLP for review and tips parsing
  - Better feature engineering
  - Include economic data, e.g. changes in lease or energy costs
  - Include demographics data

Fun Fact

Feature importance as reported by RandomForest running with all features:

zip_93013	0.152091
bpnr_cnt	0.118295
zip_89199	0.102510
zip_89183	0.038803
cat_brazilian	0.031475
cat_seafood	0.029128
zip_89179	0.025255
cat_hot_dogs	0.011923
cat_hookah_bars	0.011857
zip_89121	0.010710
rating	0.010450