BIKE STATIONS AND BUSINESSES STATISTICAL MODELLING PROJECT

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PROJECT OVERVIEW

1. Get data from CityBikes API
2. Get data from Foursquare and Yelp APIs
3. Join data and create database
4. Create regression model

PROJECT SCOPE

1. Looked at Mobi bikes in Vancouver, BC
2. Investigated following business types within 100 m of every bike station:
   - Bars
   - Restaurants

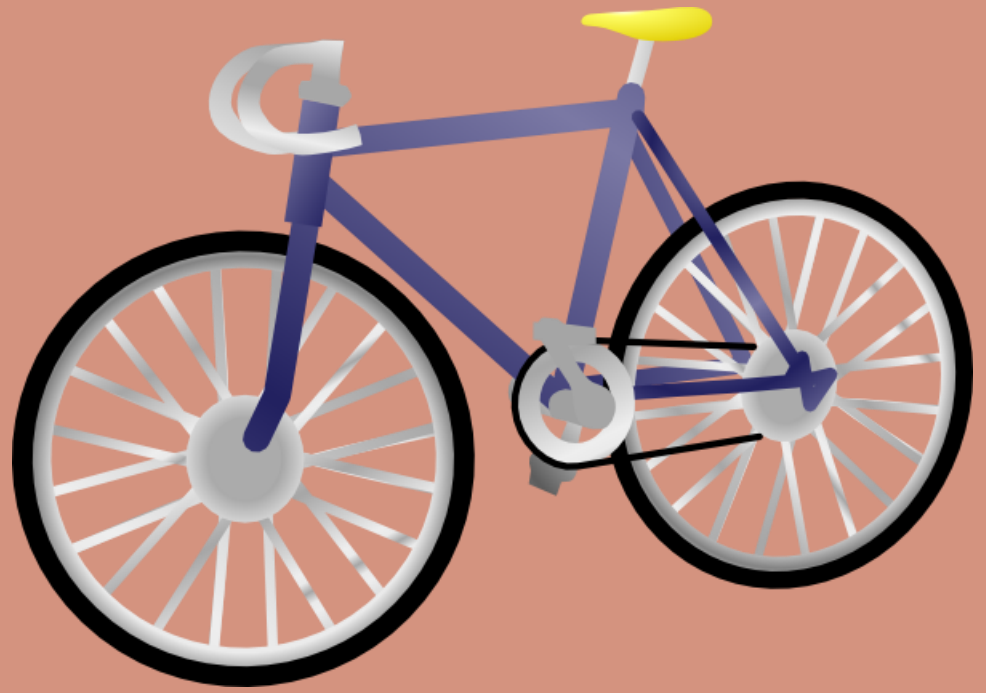
KEY QUESTIONS

1. Are business attributes correlated with the proportion of available bikes?

2. Is the number of nearby bars and restaurants correlated with the proportion of available bikes?

STEP 1: CITY BIKE API

1. Parsed JSON file
2. Removed stations with status “offline”



STEP 2: GET DATA FROM FOURSQUARE AND YELP APIS

1. Used requests.get() function
2. For each of the Yelp and Foursquare APIs, created the following:

STEP 2: GET DATA FROM FOURSQUARE AND YELP APIS

1. Used data from previous step to create 3 tables (for each Foursquare and Yelp):

Bike Station Table:
information about **unique** bike stations

key = station_id

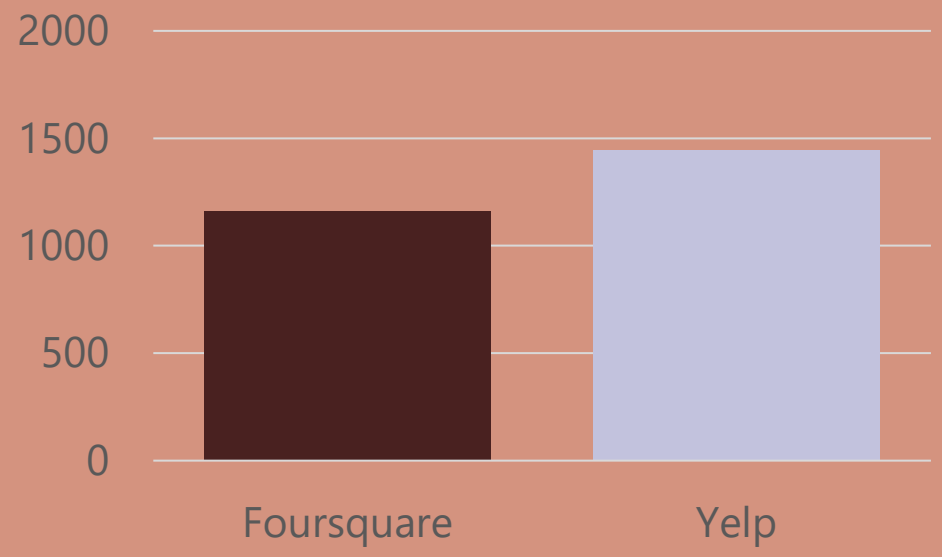
Intermediary Table:
two columns only:
business id & bike station id

key = two above columns combined

Business Table:
information about **unique** businesses

key = business id (fsq_id for Foursqare and id for Yelp)

STEP 2: COMPARE RESULTS FROM FOURSQUARE AND YELP



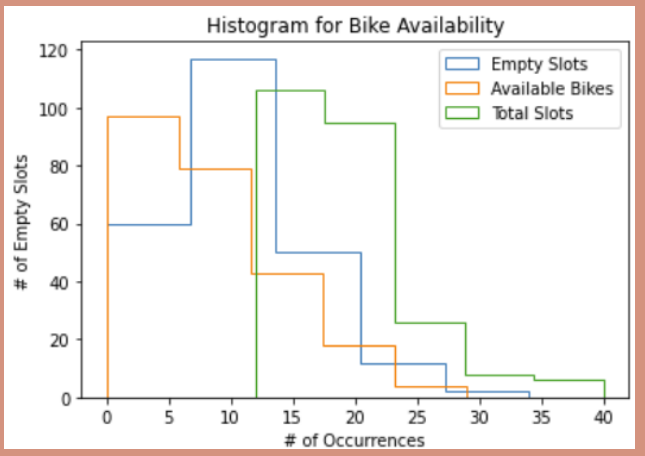
Yelp had more businesses, so used yelp data for further analysis

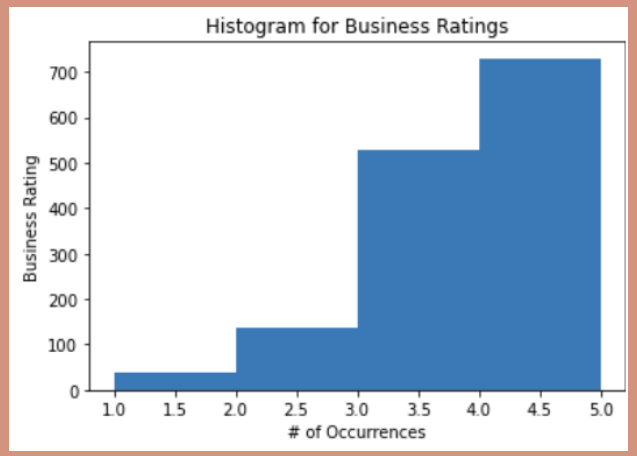
STEP 3: JOINING AND EXPLORING DATA

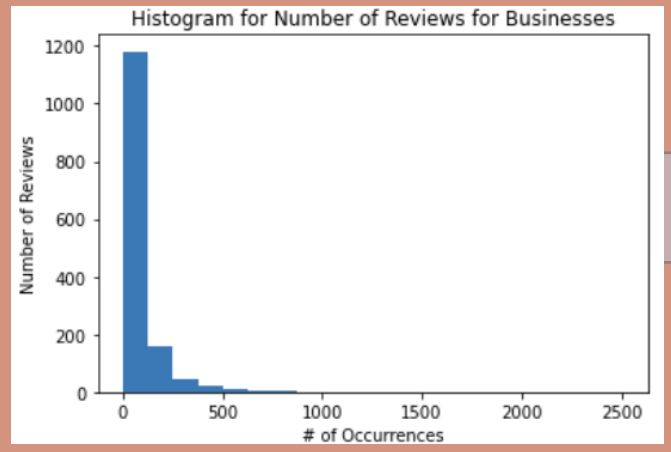
1. Combined Yelp and Citybike data using pd.merge
2. Since there was a ‘many-to-many’ relationship between bike stations and restaurants, used an intermediary table to join them.

STEP 3: EXPLORATORY DATA ANALYSIS

1. Explored data using:
   - histograms



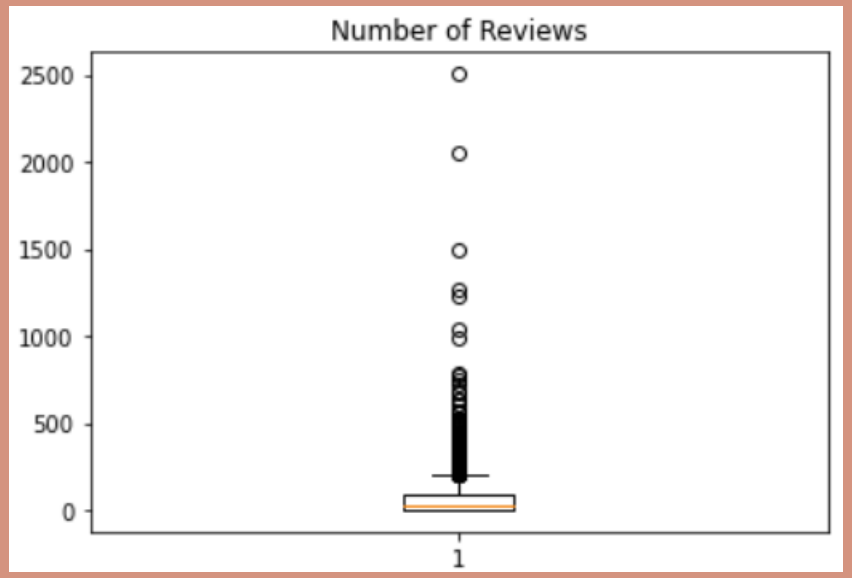




Data not normally distributed

STEP 3: JOINING AND EXPLORING DATA

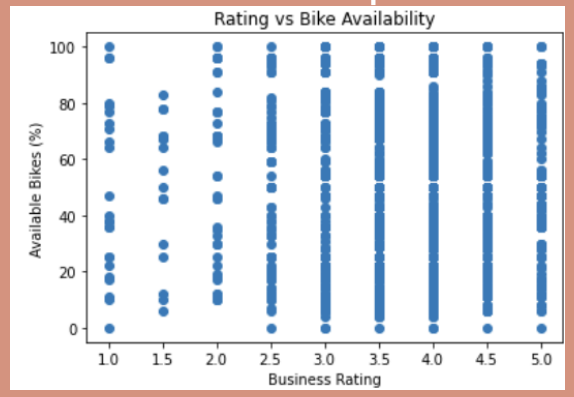
1. Explored data using:
    - boxlots

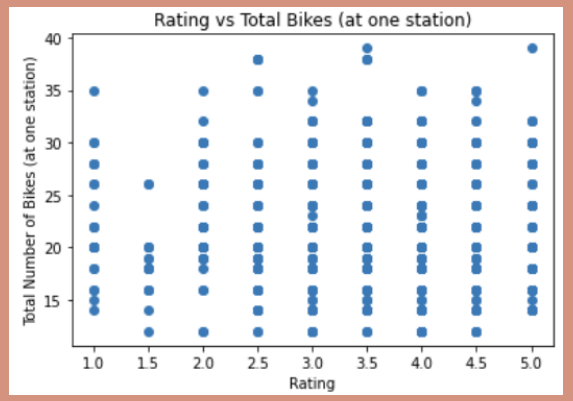


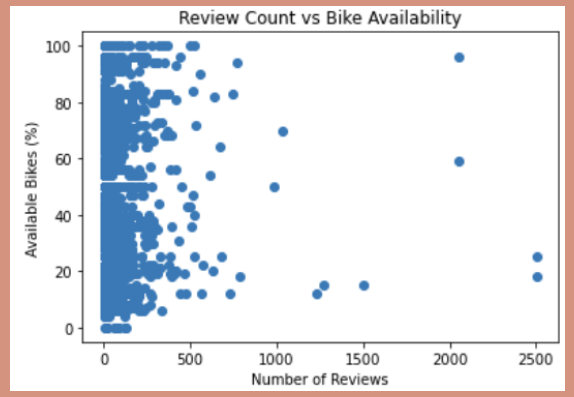
Many outliers!

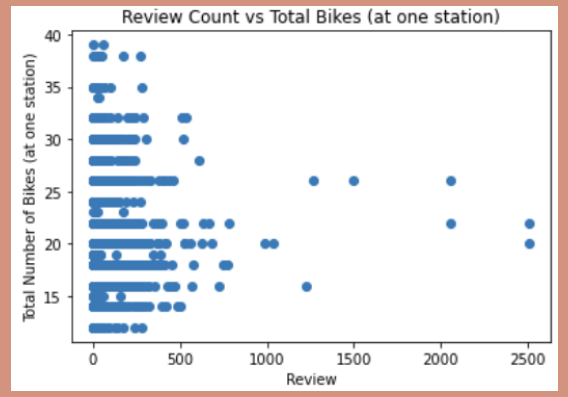
STEP 3: JOINING AND EXPLORING DATA

1. Explored data using:
   - scatter plots









No clear linear relationships

STEP 3: JOINING AND EXPLORING DATA

1. Explored data using:
   - correlation coefficients

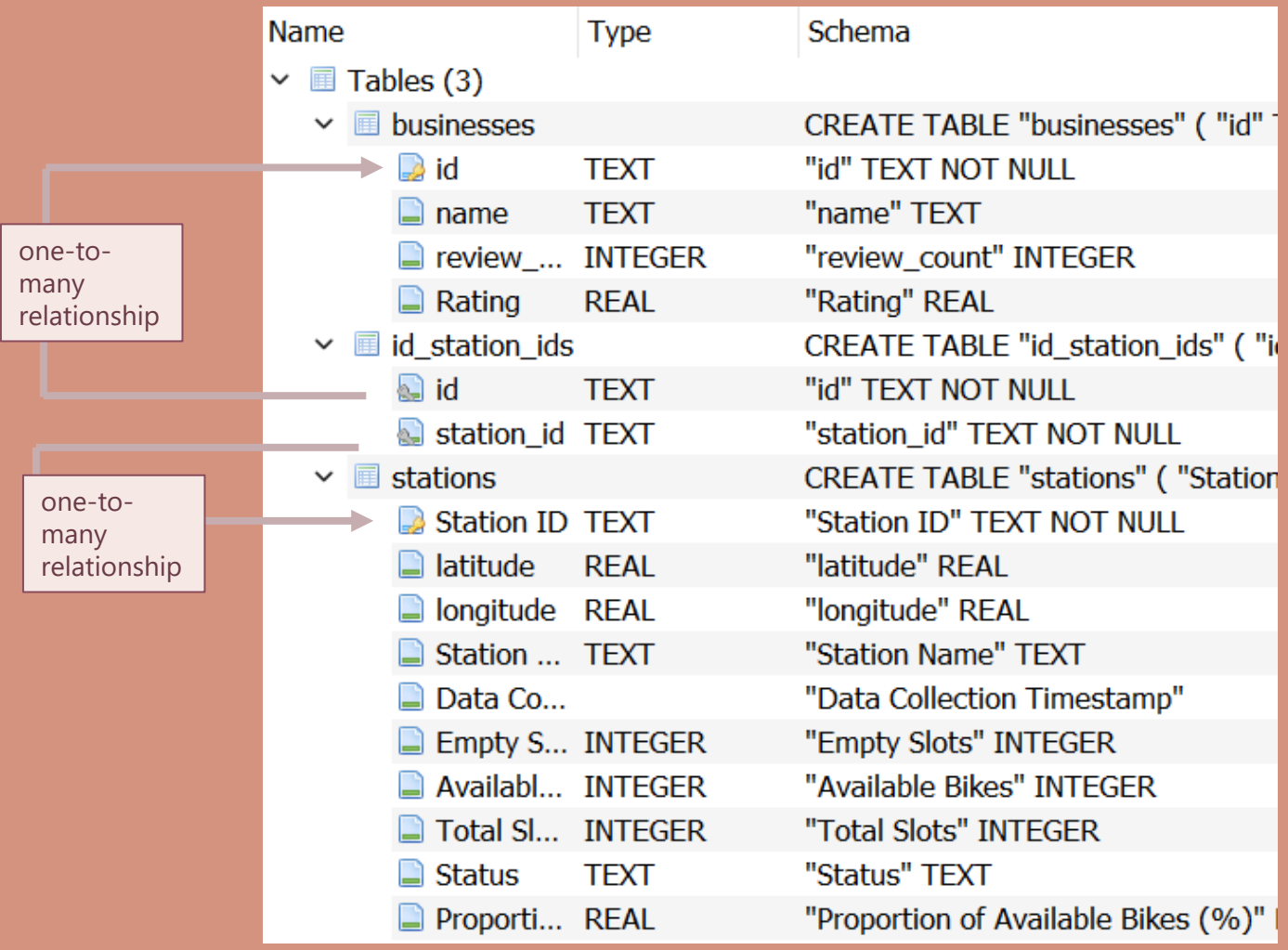
	review_count	rating	latitude	longitude	Empty Slots	Available Bikes	Total Slots	Proportion of Bikes Available (%)
review_count	1.000000	0.072655	0.028079	0.004272	-0.000060	-0.009892	-0.012523	-0.011278
rating	0.072655	1.000000	-0.084393	-0.010481	-0.044029	-0.020562	-0.080132	0.016514
latitude	0.028079	-0.084393	1.000000	-0.159771	-0.063980	0.283725	0.297182	0.224617
longitude	0.004272	-0.010481	-0.159771	1.000000	-0.068715	-0.054827	-0.150378	-0.021609
Empty Slots	-0.000060	-0.044029	-0.063980	-0.068715	1.000000	-0.670870	0.305931	-0.875898
Available Bikes	-0.009892	-0.020562	0.283725	-0.054827	-0.670870	1.000000	0.498399	0.900851
Total Slots	-0.012523	-0.080132	0.297182	-0.150378	0.305931	0.498399	1.000000	0.132649
Proportion of Bikes Available (%)	-0.011278	0.016514	0.224617	-0.021609	-0.875898	0.900851	0.132649	1.000000

Low correlation coefficients!

INITIAL FINDINGS FROM EDA:

1. No correlation between business attributes an proportion of available bikes
2. No correlation between quantity of open businesses and proportion of available bikes

STEP 3: CREATE SQLITE DATABASE



Businesses Table:

- used ‘id’ (automatically assigned by Yelp) as primary key

Bike Stations Table:

- Used “Station ID” as primary key

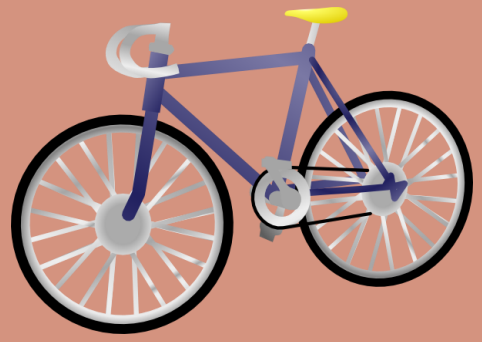
Intermediary Table (called ‘id_station_ids’:

- id and station_id combined as key
- id was foreign key linked to businesses table
- station_id was foreign key linked to stations table

STEP 4: CREATE MODEL

Model 1: number of available bikes as a function of attributes of nearby restaurants and bars?

- Dependent variable is **Available Proportion of Bikes (%)**
- Independent variables (x_1, x_2)
  - review_count
  - ratings



R-squared: 0.000
Model does not predict bike availability whatsoever

OLS Regression Results

Dep. Variable:	Available Bikes	R-squared:	0.000
Model:	OLS	Adj. R-squared:	-0.001
Method:	Least Squares	F-statistic:	0.3944
Date:	Mon, 14 Nov 2022	Prob (F-statistic):	0.674
Time:	20:22:01	Log-Likelihood:	-5363.5
No. Observations:	1600	AIC:	1.073e+04
Df Residuals:	1597	BIC:	1.075e+04
Df Model:	2		
Covariance Type:	nonrobust		

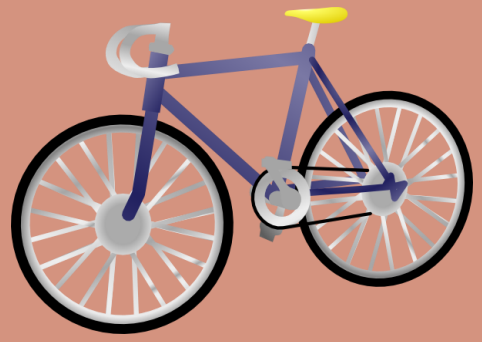
	coef	std err	t	P>|t|	[0.025	0.975]
const	10.7000	0.793	13.487	0.000	9.144	12.256
review_count	-0.0004	0.001	-0.337	0.736	-0.002	0.002
rating	-0.1678	0.211	-0.795	0.427	-0.582	0.246

Omnibus:	170.346	Durbin-Watson:	0.177
Prob(Omnibus):	0.000	Jarque-Bera (JB):	135.492
Skew:	0.621	Prob(JB):	3.79e-30
Kurtosis:	2.301	Cond. No.	857.

STEP 4: CREATE MODEL

Model 2: number of available bikes as a function of count of nearby restaurants and bars?

- Dependent variable is **Available Proportion of Bikes (%)**
- Independent variables (x_1)
  - number of nearby businesses



R-squared: 0.000
Model does not predict bike availability whatsoever

OLS Regression Results

Dep. Variable:	Proportion of Bikes Available (%)	R-squared:	0.000
Model:	OLS	Adj. R-squared:	-0.004
Method:	Least Squares	F-statistic:	0.09119
Date:	Mon, 14 Nov 2022	Prob (F-statistic):	0.763
Time:	20:22:05	Log-Likelihood:	-1122.1
No. Observations:	241	AIC:	2248.
Df Residuals:	239	BIC:	2255.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	44.4835	2.031	21.902	0.000	40.482	48.484
count of businesses	-0.0541	0.179	-0.302	0.763	-0.407	0.299

Omnibus:	17.509	Durbin-Watson:	1.966
Prob(Omnibus):	0.000	Jarque-Bera (JB):	11.843
Skew:	0.416	Prob(JB):	0.00268
Kurtosis:	2.302	Cond. No.	14.0

IF I HAD MORE TIME

- See how open-ness affects availability of bikes by looking at bike availability at different times
- Would look at density of total bikes, not just bikes per station