Foursquare Point-of-Interest Matching

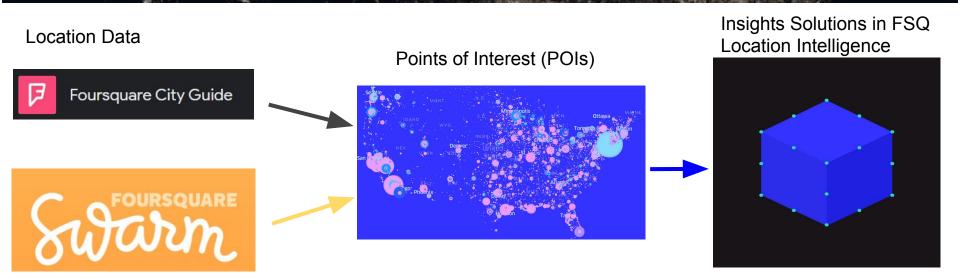
New Horizons: Yu Cao, Tim Gorman, Ling Zhou

Developing Machine Learning to Correctly Identify Points-of-Interest from Foursquare Location Data

[https://github.com/gormantt/foursquare-location-matching]

Foursquare - Location Matching

Match point of interest data across datasets



Who uses this data?



jetBlue



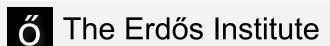


Uber





kaggle



May 2022 Data Science Boot Camp

Match point of interest data across datasets



Goal: correctly identify duplicate points-of-interest

Datasets from Kaggle competition: train.csv pairs.csv

https://www.kaggle.com/competitions/foursquare-location-matching

Foursquare - Location Matching

Match point of interest data across datasets

kaggle

11 attribute fields

train.csv

id	name	latitude	longitude	address	city	state	zip	country	url	phone	categories	point_of_interest
E_263a142bd817bc	Susans	-33.934817	151.069265	NaN	NaN	NaN	NaN	AU	NaN	NaN	Women's Stores	P_d6898efecc074f
E_df41d13127f11d	清玉手調原味 茶 King Tea	25.044300	121.515972	中正區南陽 街26號	台北市	NaN	100	TW	http://qingyutea.blogspot.com	223709633	Tea Rooms, Bubble Tea Shops	P_691d41e345da73
E_473cd396422be0	Everybody Offer Center (7th mile)	1.469906	110.329860	NaN	NaN	NaN	NaN	MY	NaN	NaN	Clothing Stores	P_9c68d66db57814
E_73d94497af3313	Cancún Center	21.134743	-86.747002	Blvd. Kukulcan Km. 9.5	Cancún	QR	77500	МХ	NaN	NaN	Convention Centers, Meeting Rooms, Event Spaces	P_e57277af20886d
E_f816e07f244bc9	Outback Steakhouse	39.991958	-74.176346	Hwy. 35 & Woodland Dr.	Middletown	NJ	07748	US	NaN	NaN	Steakhouses	P_bc5a827b040abf

1 million+ places entries Places entries were heavily altered to include noise, duplications, extraneous, or incorrect information.



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Match point of interest data across datasets

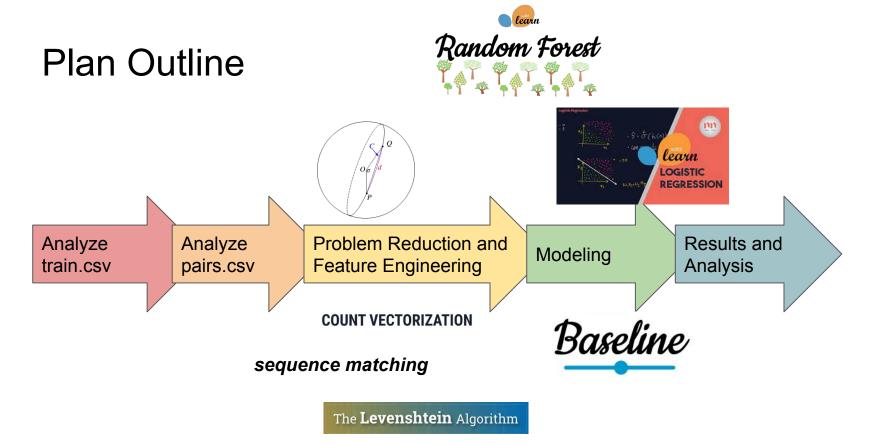


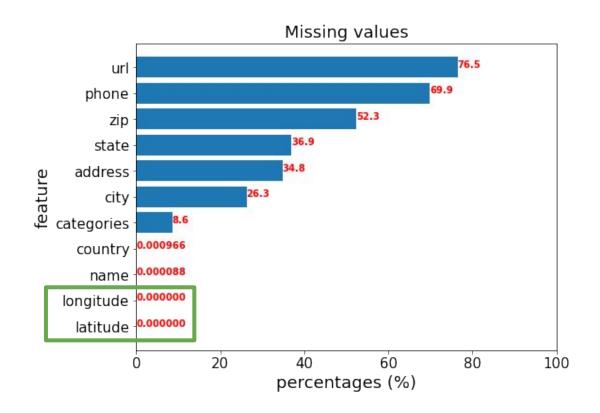
pairs.csv

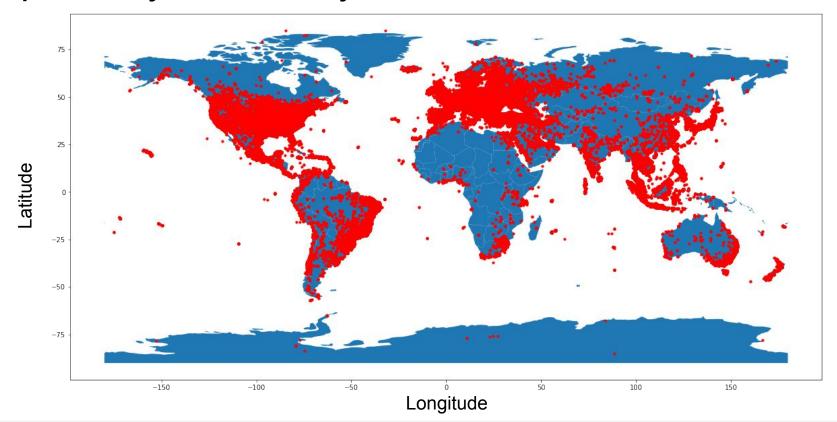
A pregenerated subset of pairs of entries from train.csv:

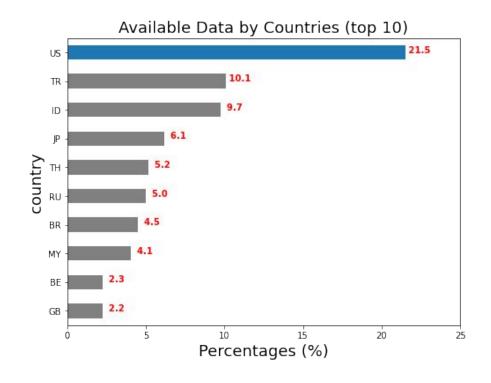
```
'id_1' 'name_1' 'latitude_1' 'longitude_1' 'address_1' 'city_1' 'state_1' 'zip_1' 'country_1' 'url_1' 'phone_1' 'categories_1' 'id_2' 'name_2' 'latitude_2' 'longitude_2' 'address_2' 'city_2' 'state_2' 'zip_2' 'country_2' 'url_2' 'phone_2' 'categories_2' 'match'
```

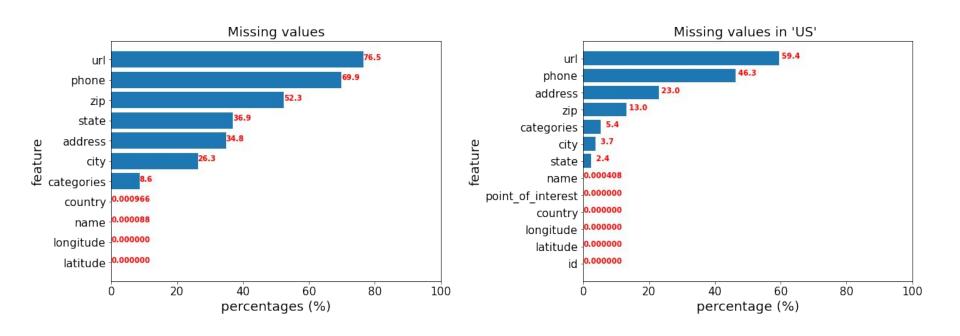
'match'=True if two entries have the same POI value in train.csv

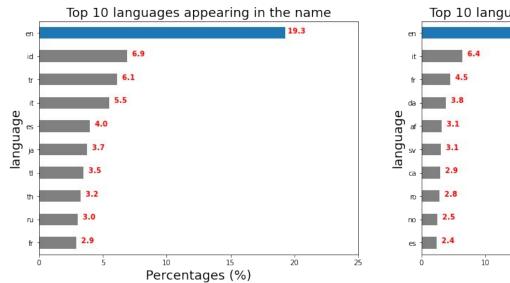


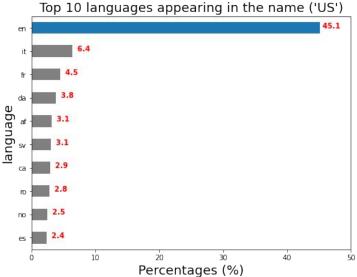




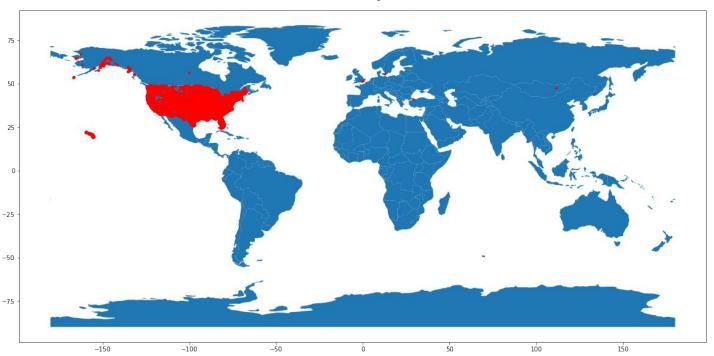








Data with country = "US"



Noise in the Data: Same POI, Same Brand, but Different Places

name	latitude	longitude	address	city	state	zip	country	url	phone	categories	point_of_interest
Gregg Steiner - Nationwide Insurance & Financi	33.607341	-117.877248	3 Corporate Plaza Dr Ste 250	Newport Beach	CA	92660	US	http://t.co/4eDIQ4ptQn	+19492200701	Financial or Legal Services	P_399ab9d64f2a2e
James S Wills Agency - Nationwide Insurance	34.002130	-81.772107	100 North Main St	Saluda	sc	29138	US	http://agency.nationwide.com/agent/james- wills	8644450011	NaN	P_399ab9d64f2a2e
Nationwide Insurance	39.962014	-82.885847	583 S Yearling Rd	Columbus	ОН	43213	us	http://t.co/4eDIQ4ptQn	+16145752643	Financial or Legal Services	P_399ab9d64f2a2e
Nationwide Insurance	39.280624	-76.611005	209 Key Hwy	Baltimore	MD	21230	us	http://agency.nationwide.com/agent/lawrence-I	+14108376400	Financial or Legal Services	P_399ab9d64f2a2e
Nationwide Insurance	41.224360	-73.071814	333 Boston Post Rd	Milford	СТ	06460	US	http://t.co/4eDIQ4ptQn	+12038789003	Financial or Legal Services	P_399ab9d64f2a2e

Noise in the Data: Same POIs, Different Names

name	latitude	longitude	address	city	state	zip	country	url	phone	categories	point_of_interest
Amanda C. Castro, MD	39.779379	-75.555298	1600 Rockland Rd	Wilmington	DE	19803	US	https://findaprovider.nemours.org/details/1666	+18004164441	Mental Health Offices, Doctor's Offices	P_ce9291000a8f0b
Arieda Gjikopulli, MD	39.779379	-75.555298	1600 Rockland Rd	Wilmington	DE	19803	US	https://findaprovider.nemours.org/details/1572	+18004164441	Doctor's Offices	P_ce9291000a8f0b
Cara J. Lasley, MD	39.779379	-75.555298	1600 Rockland Rd	Wilmington	DE	19803	US	https://findaprovider.nemours.org/details/1877	+18004164441	Doctor's Offices	P_ce9291000a8f0b
Charles D. Vinocur, MD	39.779379	-75.555298	1600 Rockland Rd	Wilmington	DE	19803	US	https://findaprovider.nemours.org/details/1148	+18004164441	Doctor's Offices	P_ce9291000a8f0b
Christian Pizarro, MD	39.779379	-75.555298	1600 Rockland Rd	Wilmington	DE	19803	US	https://findaprovider.nemours.org/details/1312	+18004164441	Doctor's Offices	P_ce9291000a8f0b

Noise in the Data: Same POI, but Inaccurate Information (e.g. zip)

name	latitude	longitude	address	city	state	zip	country	url	phone	categories	point_of_interest
12 hour work day = lost voice	28.473537	-81.464653	NaN	Orlando	FL	32819	US	NaN	NaN	Coworking Spaces	P_a3fddc2f0a77e7
@ Work	28.473057	-81.272141	NaN	Orlando	FL	32829	US	NaN	NaN	Fairs	P_a3fddc2f0a77e7
@ work	28.588776	-81.416936	Parkway Commerce Blvd.	Orlando	FL	32808	US	NaN	NaN	NaN	P_a3fddc2f0a77e7
Heading to work!	28.484512	-81.408905	NaN	Orlando	FL	32839	US	NaN	NaN	Bowling Alleys	P_a3fddc2f0a77e7
Hell Aka Work	28.798779	-81.296295	132 commerce way	Sanford	FL	NaN	US	NaN	NaN	Tech Startups	P_a3fddc2f0a77e7

EDA Summary of train.csv

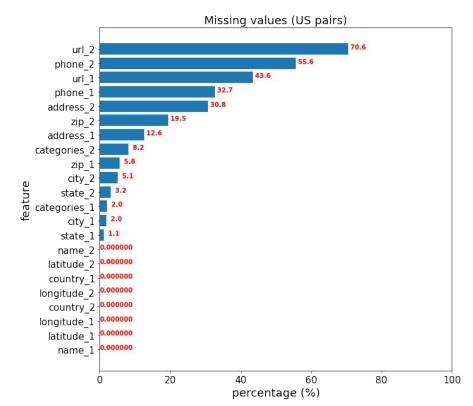
- `train.csv` is full of complexity, missing values, and errors.
- Reducing to US data simplifies classification problem:
 - Reduces Missing Values
 - Reduces language variation
- Many-to-many classification will be a difficult first step
 - Solution: Build first models on pairs.csv
 - Reduces many-to-many classification to binary classification problem

EDA and Data Preparation of pairs.csv

EDA and Data Preparation of pairs.csv (US)

- 117708 US pairs (578907 in total)
- Missing values vary by feature
- US True/False Imbalance:

True / False: 72% / 28%



EDA and Data Preparation of pairs.csv (US)

Steps to clean the (US) data:

- Fill the missing (string) values with the empty string
- Change the format in the "state" pairs

EDA and Data Preparation of pairs.csv: State Data

After Cleaning:

```
unique values in state_1:
['CA' 'GA' 'NM' 'FL' 'VA' 'TN' 'NJ' 'UT' 'IN' 'NC' 'WI' '' 'NV' 'KS' 'MA'
 'MS' 'AZ' 'MI' 'NY' 'TX' 'IL' 'AL' 'PA' 'OK' 'AR' 'KY' 'MO' 'WV' 'CO'
 'NE' 'OH' 'OR' 'MT' 'CT' 'NH' 'MD' 'HI' 'WA' 'WY' 'RI' 'VT' 'IA' 'MN'
 'LA' 'SC' 'ND' 'DE' 'DC' 'SD' 'AK' 'ID' 'ME' 'CE']
unique values in state_2:
['CA' 'GA' 'NM' 'FL' 'VA' 'TN' '' 'NJ' 'UT' 'IN' 'NC' 'WI' 'NV' 'KS' 'MA'
 'MS' 'AZ' 'MI' 'NY' 'TX' 'IL' 'AL' 'PA' 'OK' 'AR' 'KY' 'WV' 'CO' 'NE'
 'OH' 'OR' 'MT' 'SC' 'CT' 'NH' 'MO' 'MD' 'HI' 'WA' 'WY' 'VT' 'IA' 'MN'
 'LA' 'ND' 'DE' 'DC' 'SD' 'AK' 'ID' 'ME' 'RI' 'UK' 'CE' 'NU' '国外'
```

Feature Engineering

- Quantify relationship between (US) pairs in pairs.csv for modeling
 - String Feature Differences (everything but latitude and longitude):
 - Sequence Matching
 - Levenshtein Distance
 - Count Vectorization and Cosine Similarity
 - Location Feature Difference:
 - Angular difference between lat/long. pairs

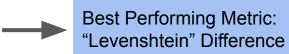
These features will be used as model input.

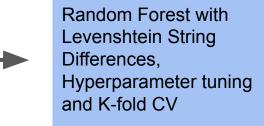
Modeling

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Modeling Process

Compare String Diff.
Metrics through
Logistic Regression
with Hyperparameter
tuning and K-fold CV



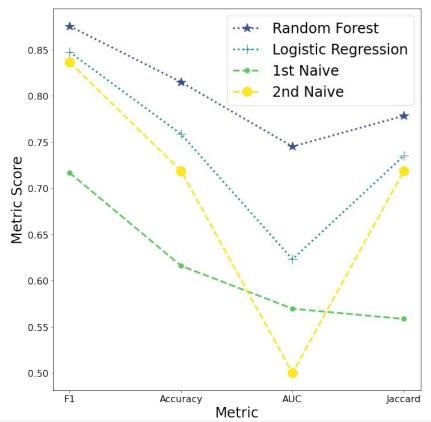




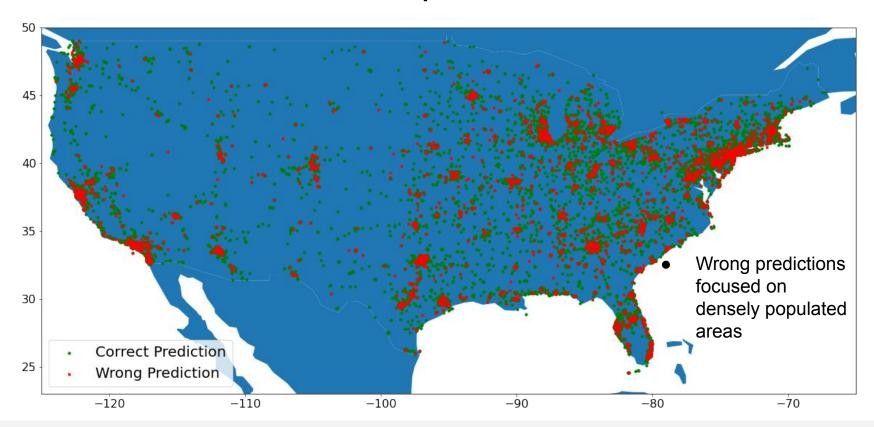
- Else: Random Assignment
- Differenced Features:
 - Address
 - Name
 - Category
- 2nd Naive Model: Guess all match = True

Compare Log Reg and Random Forest to Naive Models on train-test-split

Analysis of Results: Random Forest Wins!



Random Forest Results Spatial Distribution

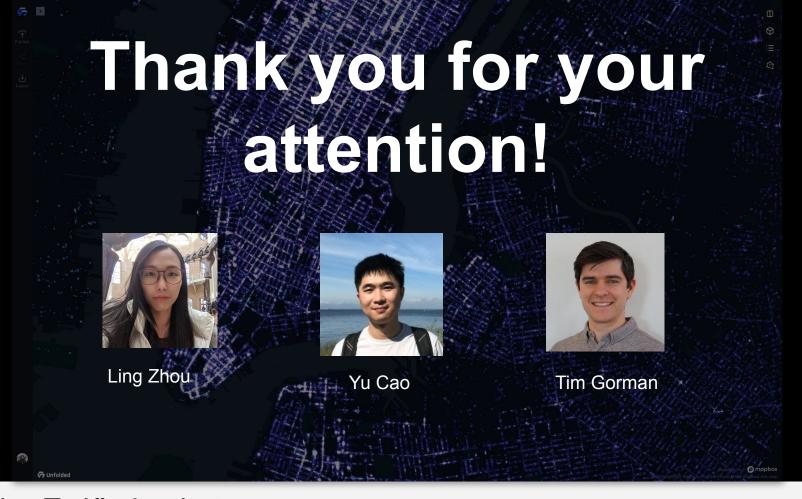


Conclusions and Future Work

A random forest does the best job correctly predicting POI matches

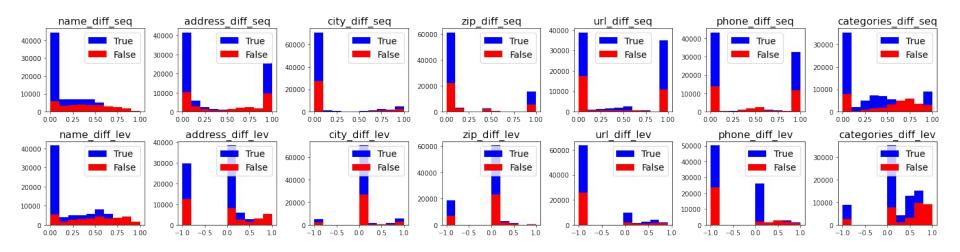
- Expand the random forest model to other countries in pairs.csv
 - May require adapting for different languages

Apply updated model to training set (train.csv)



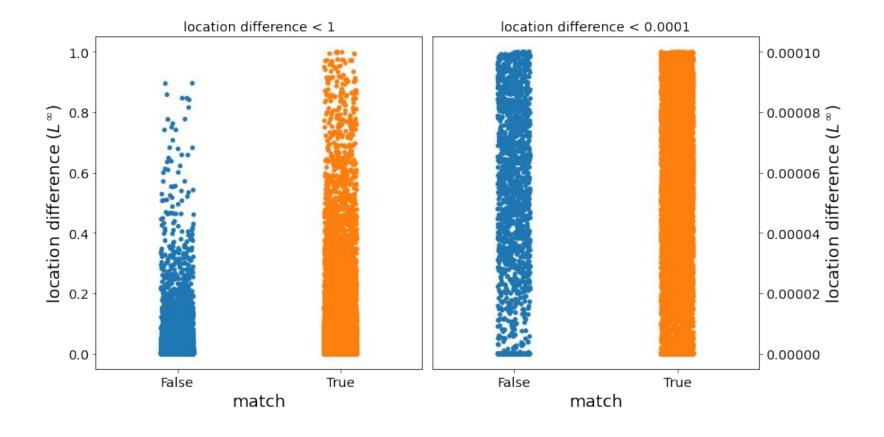
Extra Slides

SequenceMatcher vs. Levenshtein



Logistic Regression: Verifying Best String Metric

String Metric	Best Accuracy Score	Best Hyper Parameters
Sequence Matching	0.752	'C': 0.1, 'penalty': 'l2', 'solver': 'liblinear'
Levenshtein Distance	0.761	C': 0.01, 'penalty': 'l2', 'solver': 'liblinear'
Cosine Similarity	0.739	'C': 0.05, 'penalty': 'l2', 'solver': 'newton-cg'



Foursquare - Location Matching

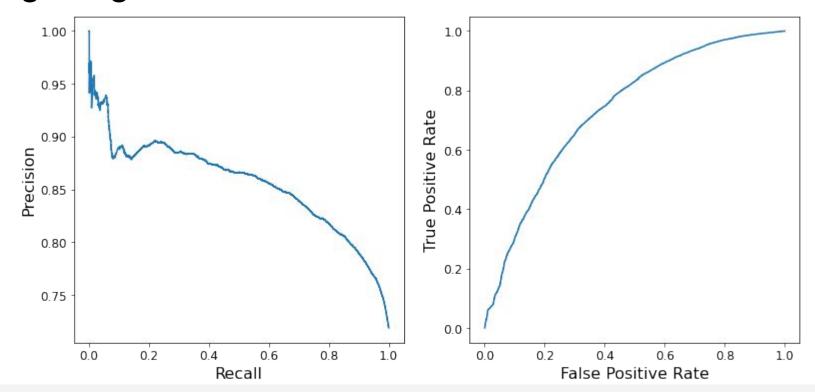
Match point of interest data across datasets



Example Data from "train.csv"

<u>▲</u> id =	▲ name =	A latitude =	▲ longitude =	▲ address =	▲ city =	▲ state =	▲ zip	▲ country =	⇔ url =
E_00002a131a2bf	ministry of youth	29.364352359083 48	47.971362300159 56					KW	
E_0000764d65557 e	McDonald's	-7.265894412994 385	112.74938201904 295	Plaza Surabaya, Pemuda Building				ID	
E_00007dcd2bb53 f	TOGO'S Sandwiches	38.257796964306 81	-122.0645993790 0875	1380 Holiday Ln., Ste. B	Fairfield	CA	94534	US	https://locatio ns.togos.com/ll /US/CA/Fairfiel d/1380-Holiday- Ln_*-SteB
E_0000890af22ff 5	Flohmarkt Am Rathaus Steglitz	52.457044985466 5	13.322475492148 42					DE	
E_00009ab517afa c	Starbucks	26.305219795470 677	50.129443774938 89	Ibis Avenue	Dhahran	Ash Sharqiyah	34465	SA	
E_0000c362229d9	Coffee Cat	7.0822175701207 76	125.61024431048 877	F. Torres St.	Davao City	Davao Region	8000	РН	

Log. Reg. Results for Lev. Diff.



Log. Reg. Results for Lev. Diff.

