Food delivery apps in Mexico: Where can it works?

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Table of contents:

I. Introduction 2
 A. Assumptions 2
 B. Business problem 2
II. Data acquisition and cleaning 2
 A. Data sources 2
 B. Data cleaning 3
 C. Exploratory data analysis 4
  1. The most populated postal codes in Mexico 4
  2. The venues in Mexico 5
III. Methodology 5
 A. Clusters 6
 B. Revenues projections 6
IV. Results 7
 A. Clusters of cities 7
 B. Profit prediction 8
V. Conclusions 11
VI. Future directions 12
VII. Appendix I: Food venues categories 13
VIII. Appendix II: Recommended neighborhoods 15

I. Introduction

A. Assumptions

To understand this project, it is necessary to suppose the followings statements. First, there are no delivery food services, like UberEATS, Postmates or Rappi in Mexico, yet. Second, you work for a food delivery service company, specifically, at the strategical area. Finally, this company has decided to enter the Mexican market.

B. Business problem

The food delivery service company chosen Mexico due to its size and consumption habits. In numbers, Mexico is the 10^{th} most populated country in the world, the 11^{th} largest economy by Purchase Power Parity GDP and the 13^{th} largest country with an area of 1.9 million of km^2. Its capital, Mexico City, is the 5^{th} largest city in the world with an urban area population of 20 million. So, the company infer that Mexico City can be a great market, but they want to know if there are more cities that can be profitable and confirm his hypothesis about Mexico City.

However, within the largest cities there is a huge difference between neighborhoods in incomes, population, and consumption habits. This heterogeneity between neighborhoods cannot be geographically separable. That is two neighborhoods with such different characteristics can be next to each other. Therefore, this project aims to answer the next questions:

1) In which neighborhoods can the service work?
2) Which cities are the most profitable for the service?

In order to answer the previous questions, the project takes postal code data to determinate the which postal codes has a huge population and restaurant to implement the food delivery service. Then the postal codes are grouped in cities and made clusters of cities depending the density of population and restaurants. Finally, calculate the forecast revenues by cluster in tree scenarios.

II. Data acquisition and cleaning

A. Data sources

The required data needed for knowing the most profitable neighborhoods will come from the following sources:

<u>Population density by postal code</u>

> CYBO is a web site that uses tools and data from other sites like Google maps, Wikipedia, national census, etc. In this page the postal codes are listed with their city, administrative region, population, and area.
>
> With this information the population density can be obtained using the formula:

Density = Population/ Area

Geographical location for the postal codes

ArcGIS Online Geocoding service turn addresses into coordinates, coordinates into addresses, or to locate a point-of-interest. With this tool it can obtain the latitude and longitude of the postal codes.

Number and type of restaurants by postal codes

Foursquare is a technology company that built a massive dataset of location data. Using the Foursquare API, we can search for specific type of venues or stores at a given location.

In this data base it can query the venues by a specific postal code. Then, the venues are filtered to keep only the restaurants.

Parameters about the consumer behavior observed by the company in other counties

For example, the ¿ percentage of people and restaurants that used the delivery service (the penetration market index). This data is unavailable because this is a fictious company and other similar companies do not publish this kind of information.

Consequently, 3 possible scenarios —best- case, base-case and worst-case— can be established.

B. Data cleaning

The most relevant data cleaning tasks was the followings:

- The area information in CYBO comes in different measure, then it was necessary to convert to the same. So, the area information that comes in m^2 has been converted to km^2 divided entity 1e+6.
- For some postal codes, the information about the city is not disponible in CYBO. To correct this, it be replaced with the most similar information that was “Administrative regions.”
- For making the forecast revenue per cluster the numerical variables like number of restaurants and variety of restaurants was been normalization with a min-max normalization:

$$X_{new} = \frac{X_{old} - X_{min}}{X_{max} - X_{min}}$$

C. Exploratory data analysis

1. The most populated postal codes in Mexico

In Mexico there are 37,635 postal codes. This analysis considers the 3000 most populated postal codes. In sum these 3000 postal codes concentrated 61 million of habits— the 47% of the country population. Hence, it is a representative sample. In the following map it can be observed the concentration of the most populated postal codes.

The postal codes had the next attributes:

	Population	Area_km	Population_Density
count	3000.000000	3000.000000	3000.000000
mean	20333.511667	21.720269	7747.386383
std	15786.279129	91.695397	12872.839112
min	9554.000000	0.045987	4.778035
25%	11681.500000	1.652000	2130.328510
50%	15325.500000	3.333000	5478.115801
75%	22695.500000	9.200000	10256.145458
max	318988.000000	2072.400000	266511.165824

2. The venues in Mexico

The data base of Foursquare offer 7,807 venues in the selected postal codes. If it considers only the restaurants and food venues[1], there are 3,562 venues in 618 postal codes. The following map show the venues that are disponible in Foursquare. The purple points are food venues and the red point are the rest.

An important information is the venue category because it is better for the food delivery service offer a variety of food categories in a determinate neighborhood. For example, imagine two neighborhoods with 10 restaurants, in one there are only pizza places and in the other there are pizza places, Mexican, sushi and seafood restaurants. The second neighborhood has mayor possibilities to have more delivery orders so the number of venue category per neighborhood is a fundamental variable.

	no_restaurant	no_categories
count	618.000000	618.000000
mean	5.763754	4.012945
std	8.451742	4.263200
min	1.000000	1.000000
25%	1.000000	1.000000
50%	3.000000	2.000000
75%	6.000000	5.000000
max	64.000000	30.000000

III. Methodology

With the information obtained, to make the projections of revenues it is necessary to summarize the postal codes data in cities. The reason behind this is that the company need to decide in which cities it can enter regardless of whether in cities the delivery service only

[1] See Appendix I for more information about which venues was considered food venues.

works in some postal codes. So, with the data grouped by city it could be make clusters and then projections of the revenues.

A. Clusters

For the revenue projections, it is easier to have only four groups of cities instead of a list of 100 cities. To do that it is used a clustering method because it is unlabeled data and unsupervised algorithm. We can determinate which clusters are profitable to the food delivery service.

K-means is a method of grouping data where n observations partition into k non-overlapping clusters in which each observation belong to the cluster with the nearest mean. In this case, it is used the minimization of Euclidean distance. The variables considered in the algorithm are the population density, the number of restaurants and the number of categories. Then, the minimization of the distance adheres to the next equation:

$$Dis(p,r,c) = \sqrt{\sum_{i=1}^{n}(p_i - p_{i+1})^2 + (r_i - r_{i+1})^2 + (c_i - c_{i+1})^2}$$

Where, for a $city_i$, p is the population density, r is the number of restaurants and c is the number of venues categories.

B. Revenues projections

To calculate the future revenues in a $city_i$ the company had the next profit function:

$$\pi_i = P \cdot Q(X_i) - C(X_i)$$

Where the benefits per city (π_i) function is equal to the price times the demand ($P \cdot Q(X_i)$) minus the cost function ($C(X_i)$)

The demand function is defined at the probability that an individual had to use the delivery service times the number of individuals that life in the $city_i$

$$Q(X_i) = p(x) \cdot population_i$$

The probability is pondered tree variables. With a pound of 0.8, α is the expected market penetration. β with a ponderation of 0.15 is the normalization of the number of restaurants in the $city_i$. Finally, γ with a smallest ponderation is the normalization of number of categories in the $city_i$.

$$p(x) = 0.8 \cdot \alpha_s + 0.15 \cdot \beta_i + 0.05 \cdot \gamma_i$$

The cost function is defined by the variable cost and a fixed cost per city of above $20,000. The fixed cost is basically the publicity and the administrative cost:

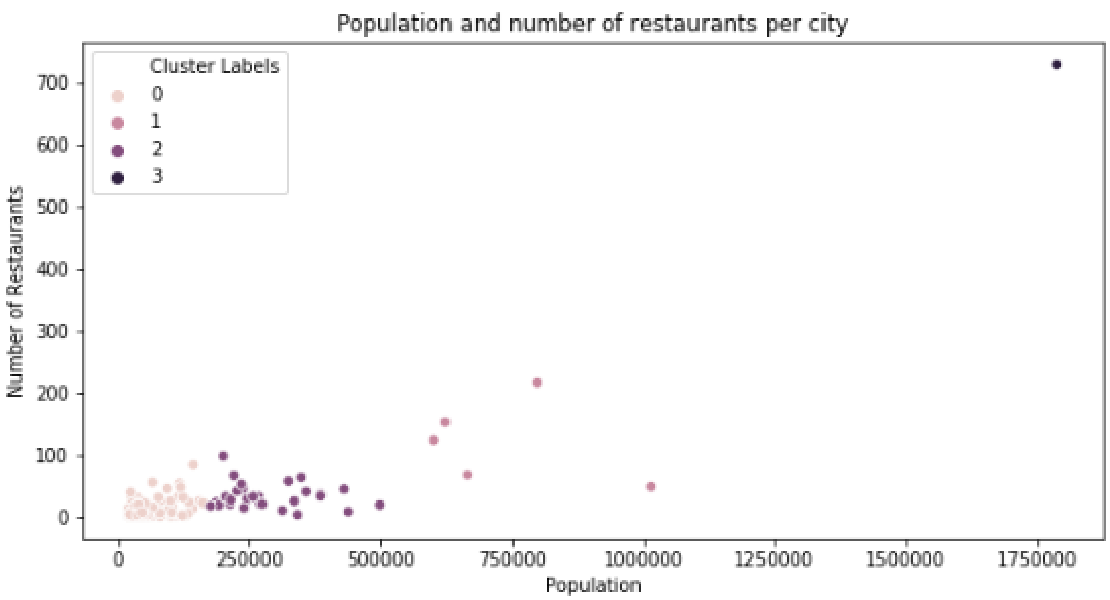
$$C(X_i) = c \cdot Q(X_i) - C$$

The expected market penetration assume three possible values: the best-case in which the food delivery service has a very good acceptation in Mexico, the base-case with a normal acceptation and the worst-case where the Mexicans use a little the service. In all scenarios the price and the costs per delivery service and cities are the same.

Assumptions:	**Variable**	**Value**
Price	P	\$1.00
Cost (variable)	c	\$0.05
Cost (fixed)	C	\$20,000
Alpha (best-case)	α^{+}	18%
Alpha (base-case)	α^{0}	10%
Alpha (worst-case)	α^{-}	3%

IV. Results

A. Clusters of cities



The Mexico City is an outlier observation with 774 restaurants and a population of 1,821,959 so it has a properly cluster (cluster label 3).

The others three clusters have the followings characteristics:

	no_restaurant								Population							
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max
Cluster Labels																
0	183.0	6.901639	10.600702	1.0	2.00	3.0	6.50	83.0	183.0	5.018984e+04	36371.628306	19999.0	24847.50	33258.0	55151.0	161258.0
1	6.0	101.333333	72.389686	19.0	48.75	90.5	147.25	207.0	6.0	6.736747e+05	161249.758499	498953.0	574962.25	623692.0	760046.5	931494.0
2	25.0	32.240000	17.161682	3.0	21.00	27.0	41.00	67.0	25.0	2.798054e+05	78049.524650	178390.0	220404.00	247883.0	341491.0	437808.0
3	1.0	774.000000	NaN	774.0	774.00	774.0	774.00	774.0	1.0	1.821959e+06	NaN	1821959.0	1821959.00	1821959.0	1821959.0	1821959.0

It is important to recall that cluster 0 has 183 cities, cluster 1 includes 6 cities and cluster number 2 are conformed for 25 cities.

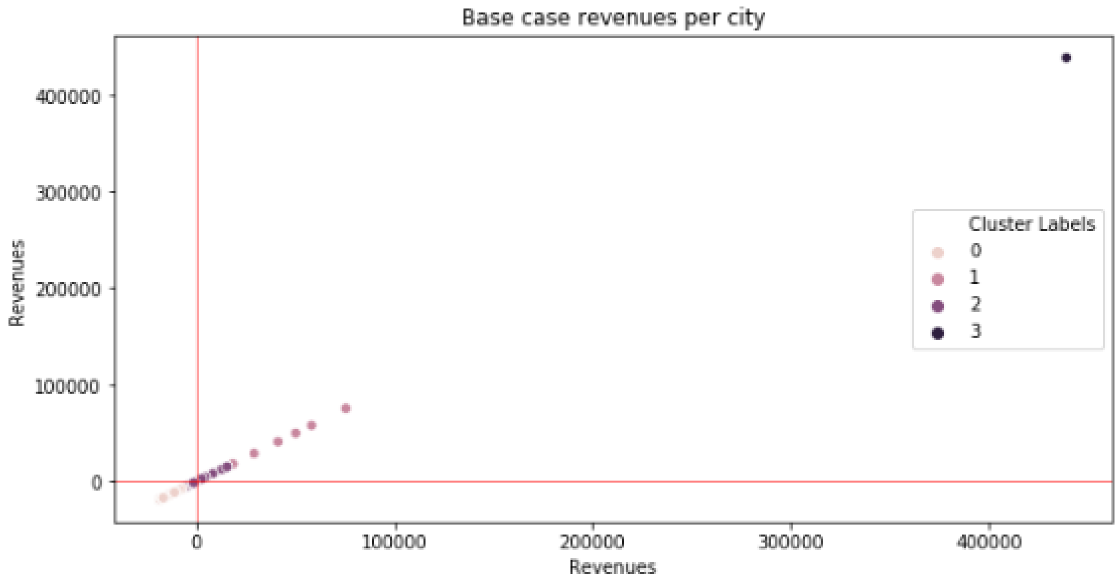
The clusters 3 and 1 have more possibilities to be profitable in all scenarios because it can be observed that have more population and restaurants. In the next section it is analyzed.

B. Profit prediction

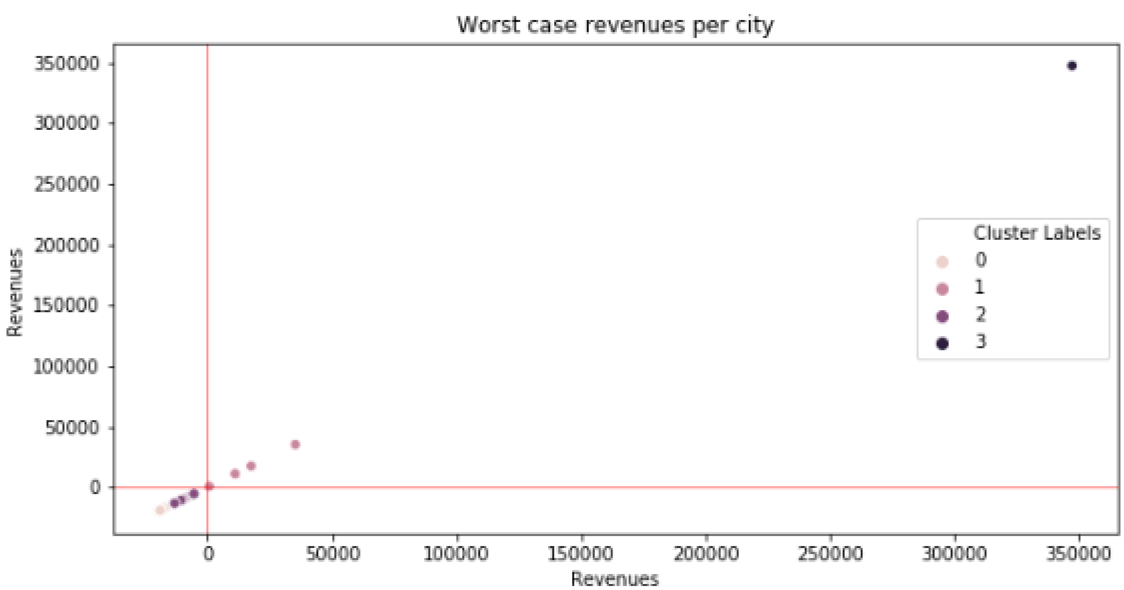
The revenues in the best case are the followings:

It can be observed that the clusters 3, 2 and 1 have a positive revenue.

In the base case only the clusters 3 and 1 have a completely positive revenue. The cluster 2 have some cities with a negative revenue and all the cluster 0 has negatives revenues.



Finally, in the worst case the clusters 3 and 1 have positives revenues and the cities in clusters 0 and 2 have negatives revenues.



If it is analyzed the revenues by clusters, it can observe the next results.

First the cluster 3, that is Mexico City, has positives revenues in all scenarios, in the best case the revenue is going to be $544,078 and in the worst case $347,306.9 so it is profitable to offer the delivery city in Mexico City.

	r_best	r_base	r_worst	Cluster Labels
count	1.0000	1.000	1.0000	1.0
mean	544078.5064	439133.668	347306.9344	3.0
std	NaN	NaN	NaN	NaN
min	544078.5064	439133.668	347306.9344	3.0
25%	544078.5064	439133.668	347306.9344	3.0
50%	544078.5064	439133.668	347306.9344	3.0
75%	544078.5064	439133.668	347306.9344	3.0
max	544078.5064	439133.668	347306.9344	3.0

The cluster 2, with 25 cities, has positives revenues in the best and base cases. In the worst case the company is going to lose $11,754.8. So, it is an investment with a moderate risk, however it is nor recommended.

	r_best	r_base	r_worst	Cluster Labels
count	25.000000	25.000000	25.000000	25.0
mean	18464.093312	2347.304576	-11754.885568	2.0
std	10897.035035	6456.136682	2722.036662	0.0
min	5172.901188	-5533.563357	-15155.074557	2.0
25%	11327.206524	-1722.707076	-13524.762552	2.0
50%	13406.182145	-570.389233	-12437.263469	2.0
75%	24443.764531	4773.882931	-10625.215496	2.0
max	40131.326141	15422.697570	-5404.749630	2.0

The cluster number 1 that includes 6 cities have a positive mean revenue in all scenarios. It can be observed that one city in the worst scenario has a negative revenue of $6,769. But it is only one city, and, in the average, it is a profitable cluster with a base revenue of $45,432. In summarize, these 6 cities are an option to implement the food delivery service.

	r_best	r_base	r_worst	Cluster Labels
count	6.000000	6.000000	6.000000	6.0
mean	84235.729138	45432.068338	11478.865138	1.0
std	28641.695645	20488.653035	14519.799802	0.0
min	47117.174352	18377.481552	-6769.749648	1.0
25%	65352.626284	32234.800684	3256.703284	1.0
50%	81624.223745	45699.564545	11050.116120	1.0
75%	105637.722424	56091.325624	15953.600050	1.0
max	121477.770535	75514.007335	35295.714535	1.0

V. Conclusions

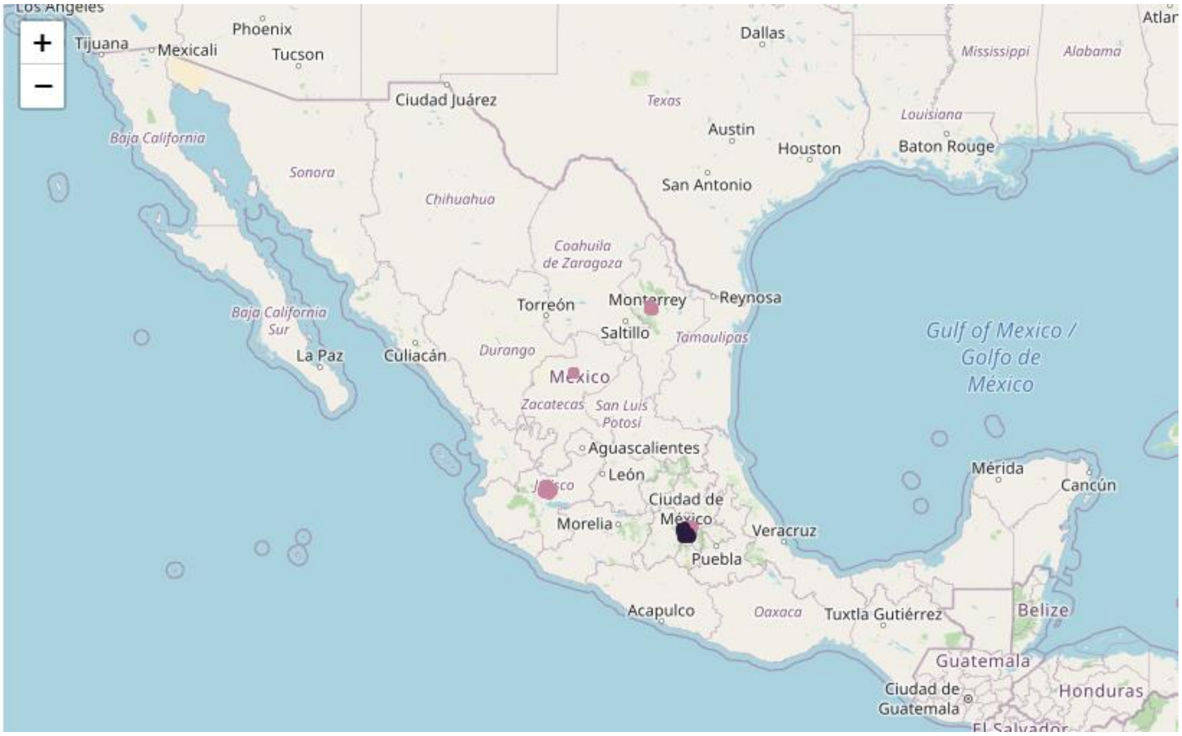
This project had the aim to answer the questions: which cities are the most profitable for the service? and in which neighborhoods can the service work? To answer these questions, the project consisted of analyzed data about the population and restaurants information by zip code.

The result was that the most profitable cities for the service are:

1) Mexico City
2) Guadalajara
3) Ecatepec de Morelos
4) Nezahualcoyotl City
5) State of Mexico
6) Zapopan
7) Apodaca

These cities are included in the clusters 3 and 1. In all scenarios the forecast is that the revenues are going to be positives. The rest of the cities are riskier because in some cases the revenues are going to be negatives.

Finally, the neighborhoods can work the service are the zip codes included in the 7 cities mentioned before. The appendix II listed these postal codes.



VI. Future directions

For future research, he recommended exploring with more data because the Foursquare API does not have all the places in Mexico. The Google API which has been more popular in recent years may be useful.

The recommendations made with this model can be complemented with more information of different kinds. For example, with an experiment with a focus group by zip code, where the company asks people the probability of ordering food with the delivery service.

VII. Appendix I: Food venues categories

"Restaurant",
"Bakery",
"Brazilian Restaurant",
"Brewery",
"Ice Cream Shop",
"Fish & Chips Shop",
"Breakfast Spot",
"Restaurant",
"Wings Joint",
"Food Stand",
"Spanish Restaurant",
"Burger Joint",
"BBQ Joint",
"Coffee Shop",
"Seafood Restaurant",
"Southern / Soul Food Restaurant",
"Sports Club",
"Food",
"Beer Garden",
"Sandwich Place",
"Soup Place",
"Asian Restaurant",
"Fast Food Restaurant",
"French Restaurant",
"Fried Chicken Joint",
"Food Court",
"Empanada Restaurant",
"Snack Place",
"Wine Bar",
"Dessert Shop",
"Pastry Shop",
"Pie Shop",
"Bar",
"Juice Bar",
"Diner",
"CafÃ©",
"Tea Room",
"Italian Restaurant",
"Food Truck",
"Cheese Shop",
"Creperie",
"Sushi Restaurant",
"Wine Shop",
"Steakhouse",
"American Restaurant",
"Comfort Food Restaurant",
"Skating Rink",
"Chinese Restaurant",
"Frozen Yogurt Shop",
"Donut Shop",
"Gluten-free Restaurant",
"Japanese Restaurant",
"Buffet",
"Bistro",
"Falafel Restaurant",
"Rock Club",
"Vegetarian / Vegan Restaurant",
"Sports Bar",
"Latin American Restaurant",
"Tapas Restaurant",

"Caribbean Restaurant",
"Middle Eastern Restaurant",
"Food & Drink Shop",
"Cupcake Shop",
"Fondue Restaurant",
"New American Restaurant",
"Hot Dog Joint",
"Argentinian Restaurant",
"Cajun / Creole Restaurant",
"Russian Restaurant",
"Salad Place",
"Bed & Breakfast",
"Korean Restaurant",
"Peruvian Restaurant",
"Ukrainian Restaurant",
"Cantonese Restaurant",
"Cafeteria",
"Fruit & Vegetable Store",
"Molecular Gastronomy Restaurant",
"Yucatecan Restaurant",
"Cocktail Bar",
"Beer Bar",
"Tex-Mex Restaurant",
"Health Food Store",
"Bagel Shop",
"Chocolate Shop",
"Thai Restaurant",
"Greek Restaurant",
"Paella Restaurant",
"Lebanese Restaurant",
"Cuban Restaurant",
"Food Service",
"Kebab Restaurant",
"Vietnamese Restaurant",
"Pet CafÃ©",
"Modern European Restaurant",
"Noodle House",
"South American Restaurant",
"Eastern European Restaurant",
"Venezuelan Restaurant",
"Theme Restaurant",
"Mediterranean Restaurant"

VIII. Appendix II: Recommended neighborhoods

Zip Code (Neighborhood)	City	Administrative Region
57000	Ciudad Nezahualcoyotl	State of Mexico
57200	Ciudad Nezahualcoyotl	State of Mexico
57100	Ciudad Nezahualcoyotl	State of Mexico
57500	Ciudad Nezahualcoyotl	State of Mexico
57800	Ciudad Nezahualcoyotl	State of Mexico
57170	Ciudad Nezahualcoyotl	State of Mexico
57410	Ciudad Nezahualcoyotl	State of Mexico
57700	Ciudad Nezahualcoyotl	State of Mexico
57130	Ciudad Nezahualcoyotl	State of Mexico
57120	Ciudad Nezahualcoyotl	State of Mexico
57710	Ciudad Nezahualcoyotl	State of Mexico
57740	Ciudad Nezahualcoyotl	State of Mexico
57750	Ciudad Nezahualcoyotl	State of Mexico
57300	Ciudad Nezahualcoyotl	State of Mexico
57310	Ciudad Nezahualcoyotl	State of Mexico
57849	Ciudad Nezahualcoyotl	State of Mexico
57830	Ciudad Nezahualcoyotl	State of Mexico
57940	Ciudad Nezahualcoyotl	State of Mexico
57620	Ciudad Nezahualcoyotl	State of Mexico
57900	Ciudad Nezahualcoyotl	State of Mexico
57718	Ciudad Nezahualcoyotl	State of Mexico
57820	Ciudad Nezahualcoyotl	State of Mexico
57760	Ciudad Nezahualcoyotl	State of Mexico
57139	Ciudad Nezahualcoyotl	State of Mexico
57460	Ciudad Nezahualcoyotl	State of Mexico
57180	Ciudad Nezahualcoyotl	State of Mexico
57719	Ciudad Nezahualcoyotl	State of Mexico
57185	Ciudad Nezahualcoyotl	State of Mexico
57840	Ciudad Nezahualcoyotl	State of Mexico
57950	Ciudad Nezahualcoyotl	State of Mexico
55264	Ciudad Nezahualcoyotl	State of Mexico
57150	Ciudad Nezahualcoyotl	State of Mexico
57809	Ciudad Nezahualcoyotl	State of Mexico
57730	Ciudad Nezahualcoyotl	State of Mexico
57709	Ciudad Nezahualcoyotl	State of Mexico
57465	Ciudad Nezahualcoyotl	State of Mexico
66612	Apodaca	Nuevo Leon
66636	Apodaca	Nuevo Leon
66646	Apodaca	Nuevo Leon
66635	Apodaca	Nuevo Leon

66647	Apodaca	Nuevo Leon
66610	Apodaca	Nuevo Leon
66633	Apodaca	Nuevo Leon
66640	Apodaca	Nuevo Leon
66648	Apodaca	Nuevo Leon
66613	Apodaca	Nuevo Leon
66614	Apodaca	Nuevo Leon
66634	Apodaca	Nuevo Leon
66632	Apodaca	Nuevo Leon
66649	Apodaca	Nuevo Leon
66630	Apodaca	Nuevo Leon
66644	Apodaca	Nuevo Leon
45138	Zapopan	Jalisco
45180	Zapopan	Jalisco
45130	Zapopan	Jalisco
45189	Zapopan	Jalisco
45190	Zapopan	Jalisco
45405	Zapopan	Jalisco
45066	Zapopan	Jalisco
45070	Zapopan	Jalisco
45140	Zapopan	Jalisco
45185	Zapopan	Jalisco
45060	Zapopan	Jalisco
45019	Zapopan	Jalisco
45080	Zapopan	Jalisco
45136	Zapopan	Jalisco
45230	Zapopan	Jalisco
45134	Zapopan	Jalisco
45010	Zapopan	Jalisco
45236	Zapopan	Jalisco
45079	Zapopan	Jalisco
45234	Zapopan	Jalisco
45188	Zapopan	Jalisco
45133	Zapopan	Jalisco
45065	Zapopan	Jalisco
45069	Zapopan	Jalisco
45110	Zapopan	Jalisco
45050	Zapopan	Jalisco
45100	Zapopan	Jalisco
45187	Zapopan	Jalisco
45068	Zapopan	Jalisco
45040	Zapopan	Jalisco
45150	Zapopan	Jalisco

45036	Zapopan	Jalisco
45067	Zapopan	Jalisco
45085	Zapopan	Jalisco
45199	Zapopan	Jalisco
45235	Zapopan	Jalisco
45058	Zapopan	Jalisco
55070	Ecatepec de Morelos	State of Mexico
55067	Ecatepec de Morelos	State of Mexico
55270	Ecatepec de Morelos	State of Mexico
55120	Ecatepec de Morelos	State of Mexico
55029	Ecatepec de Morelos	State of Mexico
55130	Ecatepec de Morelos	State of Mexico
6200	Ecatepec de Morelos	State of Mexico
55280	Ecatepec de Morelos	State of Mexico
55100	Ecatepec de Morelos	State of Mexico
55210	Ecatepec de Morelos	State of Mexico
55010	Ecatepec de Morelos	State of Mexico
55050	Ecatepec de Morelos	State of Mexico
15270	Ecatepec de Morelos	State of Mexico
55076	Ecatepec de Morelos	State of Mexico
55066	Ecatepec de Morelos	State of Mexico
55510	Ecatepec de Morelos	State of Mexico
55520	Ecatepec de Morelos	State of Mexico
55220	Ecatepec de Morelos	State of Mexico
55024	Ecatepec de Morelos	State of Mexico
55450	Ecatepec de Morelos	State of Mexico
55023	Ecatepec de Morelos	State of Mexico
55060	Ecatepec de Morelos	State of Mexico
55310	Ecatepec de Morelos	State of Mexico
55055	Ecatepec de Morelos	State of Mexico
55020	Ecatepec de Morelos	State of Mexico
55490	Ecatepec de Morelos	State of Mexico
55400	Ecatepec de Morelos	State of Mexico
55200	Ecatepec de Morelos	State of Mexico
55248	Ecatepec de Morelos	State of Mexico
55080	Ecatepec de Morelos	State of Mexico
55290	Ecatepec de Morelos	State of Mexico
55339	Ecatepec de Morelos	State of Mexico
55064	Ecatepec de Morelos	State of Mexico
54193	Ecatepec de Morelos	State of Mexico
55519	Ecatepec de Morelos	State of Mexico
55330	Ecatepec de Morelos	State of Mexico
55030	Ecatepec de Morelos	State of Mexico

55090	Ecatepec de Morelos	State of Mexico
55418	Ecatepec de Morelos	State of Mexico
55390	Ecatepec de Morelos	State of Mexico
55074	Ecatepec de Morelos	State of Mexico
55540	Ecatepec de Morelos	State of Mexico
55016	Ecatepec de Morelos	State of Mexico
55415	Ecatepec de Morelos	State of Mexico
55028	Ecatepec de Morelos	State of Mexico
55340	Ecatepec de Morelos	State of Mexico
56003	Ecatepec de Morelos	State of Mexico
55118	Ecatepec de Morelos	State of Mexico
55238	Ecatepec de Morelos	State of Mexico
55430	Ecatepec de Morelos	State of Mexico
55127	Ecatepec de Morelos	State of Mexico
55129	Ecatepec de Morelos	State of Mexico
55404	Ecatepec de Morelos	State of Mexico
55515	Ecatepec de Morelos	State of Mexico
55140	Ecatepec de Morelos	State of Mexico
55416	Ecatepec de Morelos	State of Mexico
55300	Ecatepec de Morelos	State of Mexico
44720	Guadalajara	Jalisco
45400	Guadalajara	Jalisco
44700	Guadalajara	Jalisco
44820	Guadalajara	Jalisco
44970	Guadalajara	Jalisco
44730	Guadalajara	Jalisco
44300	Guadalajara	Jalisco
44250	Guadalajara	Jalisco
44950	Guadalajara	Jalisco
44810	Guadalajara	Jalisco
44330	Guadalajara	Jalisco
44960	Guadalajara	Jalisco
44760	Guadalajara	Jalisco
44240	Guadalajara	Jalisco
44200	Guadalajara	Jalisco
44790	Guadalajara	Jalisco
44260	Guadalajara	Jalisco
44770	Guadalajara	Jalisco
44980	Guadalajara	Jalisco
44860	Guadalajara	Jalisco
44360	Guadalajara	Jalisco
45590	Guadalajara	Jalisco
44270	Guadalajara	Jalisco

44987	Guadalajara	Jalisco
44750	Guadalajara	Jalisco
45030	Guadalajara	Jalisco
44230	Guadalajara	Jalisco
45693	Guadalajara	Jalisco
44390	Guadalajara	Jalisco
44220	Guadalajara	Jalisco
44320	Guadalajara	Jalisco
44900	Guadalajara	Jalisco
44990	Guadalajara	Jalisco
44840	Guadalajara	Jalisco
44400	Guadalajara	Jalisco
45598	Guadalajara	Jalisco
44350	Guadalajara	Jalisco
44440	Guadalajara	Jalisco
44870	Guadalajara	Jalisco
44290	Guadalajara	Jalisco
44710	Guadalajara	Jalisco
44755	Guadalajara	Jalisco
44719	Guadalajara	Jalisco
44600	Guadalajara	Jalisco
44410	Guadalajara	Jalisco
44800	Guadalajara	Jalisco
44890	Guadalajara	Jalisco
44340	Guadalajara	Jalisco
9000	Mexico City	Mexico City
57210	Mexico City	Mexico City
6800	Mexico City	Mexico City
3023	Mexico City	Mexico City
3104	Mexico City	Mexico City
6700	Mexico City	Mexico City
3100	Mexico City	Mexico City
9570	Mexico City	Mexico City
3020	Mexico City	Mexico City
54945	Mexico City	Mexico City
3303	Mexico City	Mexico City
3103	Mexico City	Mexico City
8000	Mexico City	Mexico City
3400	Mexico City	Mexico City
6470	Mexico City	Mexico City
6760	Mexico City	Mexico City
9500	Mexico City	Mexico City
52966	Mexico City	Mexico City

3810	Mexico City	Mexico City
6100	Mexico City	Mexico City
1900	Mexico City	Mexico City
6450	Mexico City	Mexico City
1150	Mexico City	Mexico City
3630	Mexico City	Mexico City
4380	Mexico City	Mexico City
3660	Mexico City	Mexico City
13400	Mexico City	Mexico City
11850	Mexico City	Mexico City
53428	Mexico City	Mexico City
8730	Mexico City	Mexico City