# COURSERA CAPSTONE PROJECT GEOLOCATION DATA ANALYSIS

# Analyzing Neighborhood in the City of Buenos Aires to Help Strategic Business Expansion for a Coffee Shop Franchise Chain

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## 1. Introduction

## 1.1 Background

Argentina has a well-known culture of meeting with a friend or relative to have a small *cortado* coffee over a nice, warm talk. As such, in the City of Buenos Aires, its capital city, there are many small coffee shops and coffee chains. Some neighborhoods seem to be overpopulated with venues, and many are struggling to make their business work. On the contrary, other neighborhoods have grown in population over the last years, and there are business opportunities for new coffee shops to open.



#### 1.2 Problem

Data that might help determine which of the almost 50 *Barrios Porteños* (Buenos Aires neighborhoods) have too many coffee venues, and which of the lack of good places where to have a *cortado*, would help brands thrive and take data-driven decision on their expansion strategies.

### 1.3 Interest

One of Argentina's biggest Coffee Franchise Chains, is analyzing where to expand and open new brunches within the City of Buenos Aires. They need to relate population density with coffee shop density of each of the city's neighborhoods. This would definitely help them avoid wrong locations and increase chance of success for the new franchises.

# 2. Data Gathering and Processing

#### 2.1 Data Sources

A list and census of all the neighborhoods of the city is available as annex for Buenos Aires's article.

https://es.wikipedia.org/wiki/Anexo:Barrios\_de\_la\_ciudad\_de\_Buenos\_Aires The features included are: Name, area, population, district.

From Geopy Library for Python, we locate the coordinates for each neighborhood. Finally, Foursquare Database, gives us access to the already existing coffee venues in the City and allows us to establish a measure of density for this kind of stores.



## 2.2 Data Wrangling

First, we create a dataframe with all the neighborhoods and the needed features to establish the population density. We read the Wikipedia article CSV file and drop the unwanted features. Then, we use that list to iterate a process in Geopy's Nominatin and get Longitude and Latitude for each neighborhood. We add this values to the above dataframe.

Connecting to Foursquare's API with our credentials, we get all the top venues ina a specific radius for each neighborhood.

	name	categories	lat	Ing
0	Megatlon	Gym	-34.579216	-58.426123
1	Nicolo Helados	Ice Cream Shop	-34.581652	-58.426735
2	La Carnicería	Argentinian Restaurant	-34.582814	-58.423778
3	Distrito Arcos	Shopping Mall	-34.580494	-58.427621
4	Vain Boutique Hotel Buenos Aires	Hotel	-34.583672	-58.424980

## 3. Exploratory Data Analysis

## 3.1 Statistical Data

Once we count with all the listed venues, we identify and keep only the categories of coffee places that could be a business competitor to our new potential stores.

We take the average occurrence for these kinds of venues (coffee shops, tea house, pie store, etc) and add them to establish a unique value.

Doing simple arithmetic, we use are and population in our former dataframe, to calculate the density of population for each neighborhood.

Finally, we combine the two density indexes (for citizens and coffee stores), and generate a new unique variable that could determine if there enough venues for the density of people or if there is a business opportunity in each neighborhood.

	Neighbourhoods	Area	Population	District	Longitude	Latitude	COFFEES	PopDensity	CoffeeDensity
19	Nueva Pompeya, Ciudad de Buenos Aires, Argentina	6.2	63276	4	-58.414710	-34.652630	0.000000	0.010206	0.00
3	Barracas, Ciudad de Buenos Aires, Argentina	7.6	77474	4	-58.387562	-34.645285	0.000000	0.010194	0.00
43	Villa Real, Ciudad de Buenos Aires, Argentina	1.3	14278	10	-58.525877	-34.618943	0.000000	0.010983	0.00
39	Villa Lugano, Ciudad de Buenos Aires, Argentina	9.0	114253	8	-58.477689	-34.674153	0.000000	0.012695	0.00
1	Almagro, Ciudad de Buenos Aires, Argentina	4.1	139262	5	-58.422233	-34.609988	0.100000	0.033966	2.94
36	Villa del Parque, Ciudad de Buenos Aires, Arge	3.4	58573	11	-58.493821	-34.604797	0.076923	0.017227	4.47
12	Floresta, Ciudad de Buenos Aires, Argentina	2.3	39473	10	-58.483791	-34.628105	0.076923	0.017162	4.48
32	San Telmo, Ciudad de Buenos Aires, Argentina	1.2	25969	1	-58.373750	-34.621401	0.100000	0.021641	4.62
2	Balvanera, Ciudad de Buenos Aires, Argentina	4.4	152198	3	-58.403140	-34.609215	0.160000	0.034590	4.63
30	San Cristóbal, Ciudad de Buenos Aires, Argentina	2.1	49986	3	-58.402390	-34.624060	0.113636	0.023803	4.77
27	Recoleta, Ciudad de Buenos Aires, Argentina	5.9	188780	2	-58.391570	-34.587358	0.160000	0.031997	5.00
22	Parque Avellaneda, Ciudad de Buenos Aires, Arg	5.1	54191	9	-58.476905	-34.649480	0.058824	0.010626	5.54
41	Villa Ortúzar, Ciudad de Buenos Aires, Argentina	1.8	22591	15	-58.468245	-34.581302	0.076923	0.012551	6.13

# 4. Conclusions and Further Analysis

#### **4.1 Conclusions**

With this study, we could identify those neighborhoods with better opportunities for expansion of coffee shops. Those in the highest part of the table, have a low density of venues to satisfy the population living in that specific area. Some of those neighborhoods have really few places and they have grown a lot in its density. As people moved from more classic downtown neighborhoods to new areas in the outskirts, new opportunities arise. Neighborhoods as Nueva Pompeya, Barracas, Villa del Parque, Floresta, to name a few, are examples of this. On the contrary, there are many neighborhoods, like Puerto Madero or Villa Riachuelo, which seem to be saturated with places and not a good opportunity for an expansion.

	DISTRICT	NEIGHBORHOOD	COFFEE DENSITY
0	19	Nueva Pompeya	0.00
1	3	Barracas	0.00
2	43	Villa Real	0.00

3	39	Villa Lugano	0.00	
4	1	Almagro	2.94	
5	36	Villa del Parque	4.47	
6	12	Floresta	4.48	
7	32	San Telmo	4.62	
8	2	Balvanera	4.63	
9	30	San Cristóbal	4.77	
10	27	Recoleta	5.00	
11	22	Parque Avellaneda	5.54	
12	41	Villa Ortúzar	6.13	
13	15	Liniers	6.70	
14	20	Núñez	6.79	
15	9	Colegiales	6.86	
16	21	Palermo	6.93	
17	13	La Boca	6.95	
18	0	Agronomía	7.01	
19	37	Villa Devoto	8.19	
20	33	Vélez Sarsfield	8.34	
21	24	Parque Chas	8.40	
22	5	Boedo	8.41	
23	17	Montserrat	8.42	
24	35	Villa Crespo	9.35	
25	45	Villa Santa Rita	9.45	
26	10	Constitución	9.62	
27	8	Coghlan	10.00	
28	6	Caballito	10.01	
29	4	Belgrano	10.77	
30	40	Villa Luro	10.92	
31	11	Flores	11.59	
32	29	Saavedra	12.22	
33	28	Retiro	13.07	
34	18	Monte Castro	13.53	

35	25	Parque Patricios	14.08
36	14	La Paternal	14.63
37	42	Villa Pueyrredón	15.87
38	31	San Nicolás	15.88
39	7	Chacarita	15.93
40	34	Versalles	16.93
41	16	Mataderos	17.99
42	23	Parque Chacabuco	18.05
43	46	Villa Soldati	19.40
44	26	Puerto Madero	33.00
45	44	Villa Riachuelo	49.33

# 4.2 Further Analysis

This final table is a good starting point for a better reallocation of resources. Other variables as average income or average renting price for commercial properties, is also an information worth considering.