Exploring São Paulo Neighbourhoods Venues

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1 Introduction

The work is a capstone project for the Coursera course IBM Data Science Professional Certificate Specialization. The objective of this first part is to present a description of the problem and also point out with data will be used on the development of de project.

1.1 Problem Statement

- It's possible replicate parts of the analysis performed during the course with São Paulo Data?
- How can performed a grouping the neighborhoods and find out top 10 venues corresponding to that neighborhood in São Paulo, SP - Brazil?

1.2 Problem Description

Grouped by neighborhood exploring the venues around creating a top 10 venues by neighborhood in São Paulo. This kind of analysis can lead to possibility of identification of new opportunities for businesses, identification of the saturation of business segments in the neighborhood and also possibility to better understand the city with its characteristics based on distribution of the venues.

1.3 Target Audience

- Payment industry, this segment could take advantage of an analysis like to that to better position their self on the market, knowing where their product could have a better acceptance.
- Investors thinking on open a new business in town, this kind of person could benefit from this analysis to rule out segment of business in tow due saturation of the kind of business on the neighborhood.
- Social Science researchers curious with the behavior and distribution of venues in the city.

1.4 Success Criteria

The success criteria of the project will be a good presentation of which are the top 10 kind of venue by neighborhood and some recommendation regarding which are the worst business segments to be opened on some neighborhoods.

2 Data

On this project was used data originated from three different sources, the first data set gathered was the Brazilian postal code data set, the next one was data retrieved from the geocoder ArcGIS

APIs/Python Library and the third and last source Foursquare API data. It's important to say that the data gathered from the APIs was used to enrich the original postal code data set.

- Postal code: In Brazil is known as CEP, but differently from the data provided on the course a single neighborhood can have several CEPs assigned to it. Link to data: http://cep.la/CEP-dados-2018-UTF8.zip
- Geocoder ArcGIS: This API was used to retrieve Latitude and Longitude based on Postal code (CEP). ArcGIS API for Python is a Python library for working with maps and geospatial data, powered by web GIS. It provides simple and efficient tools for sophisticated vector and raster analysis, geocoding, map making, routing and directions, as well as for organizing and managing a GIS with users, groups and information items. Link to documentation: https://developers.arcgis.com/python/guide/
- Foursquare: This API was used to retrieve venue information based on Latitude and Longitude. Back in 2009, Foursquare invented the check-in. Today, those 13+ billion check-ins are the foundation of our powerful, proprietary Pilgrim technology that helps make sense of where phones go for the more than 150,000 partners. Link to API documentation: https://developer.foursquare.com/docs/api

2.1 Data Cleansing

The original postal code data gathered on http://cep.la/CEP-dados-2018-UTF8.zip was loaded into the environment and below is presented its representation. And as can be observed the data has several problems as for example:

- Name of the city separated on more than one column
- State abbreviation combined with second column of the city name
- Neighborhood name and Street name concatenated
- Three empty columns

	0	1	2	3	4	5	6
0	1001000	São	Paulo/SP	Sé\tPraça da Sé - lado ímpar	NaN	NaN	NaN
1	1001001	São	Paulo/SP	Sé\tPraça da Sé - lado par	NaN	NaN	NaN
2	1001010	São	Paulo/SP	Sé\tRua Filipe de Oliveira	NaN	NaN	NaN
3	1001900	São	Paulo/SP	Sé\tPraça da Sé, 108 \t UNESP - Universidade E...	NaN	NaN	NaN
4	1001901	São	Paulo/SP	Sé\tPraça da Sé, 371 \t Edifício Santa Lídia	NaN	NaN	NaN

To mitigate this issue and enable analyses continuation a data cleansing must be applied, techniques of string handling, and data frame entanglements were utilized on this cleansing. In order to demonstrate the result of cleansing process below is presented the cleaned data set.

	City	State	CEP	Neighborhood	Street
0	São Paulo	SP	1001000	Sé	Praça da Sé - lado ímpar
9	São Paulo	SP	1002020	Centro	Viaduto do Chá
173	São Paulo	SP	1017000	Brás	Avenida Rangel Pestana - até 499/500
337	São Paulo	SP	1035100	República	Avenida São João - de 651 a 1339 - lado ímpar
540	São Paulo	SP	1101000	Luz	Avenida Santos Dumont - até 999/1000
546	São Paulo	SP	1101080	Ponte Pequena	Ponte Santos Dumont
591	São Paulo	SP	1107000	Bom Retiro	Avenida do Estado - até 2599 - lado ímpar
602	São Paulo	SP	1109000	Canindé	Avenida Cruzeiro do Sul - até 1299 - lado ímpar
723	São Paulo	SP	1134901	Barra Funda	Avenida Rudge, 700
734	São Paulo	SP	1136005	Várzea da Barra Funda	Rua Américo Del Veneri

3 Methodology

Acquire Postal Code data from Brazilian cities, clean the data, perform data exploration, plot basic statistics to describe the data and present metrics, plot maps to present the data gathered, perform feature engineering, clusterization using K-Means, demonstrate results.

3.1 Data Exploration

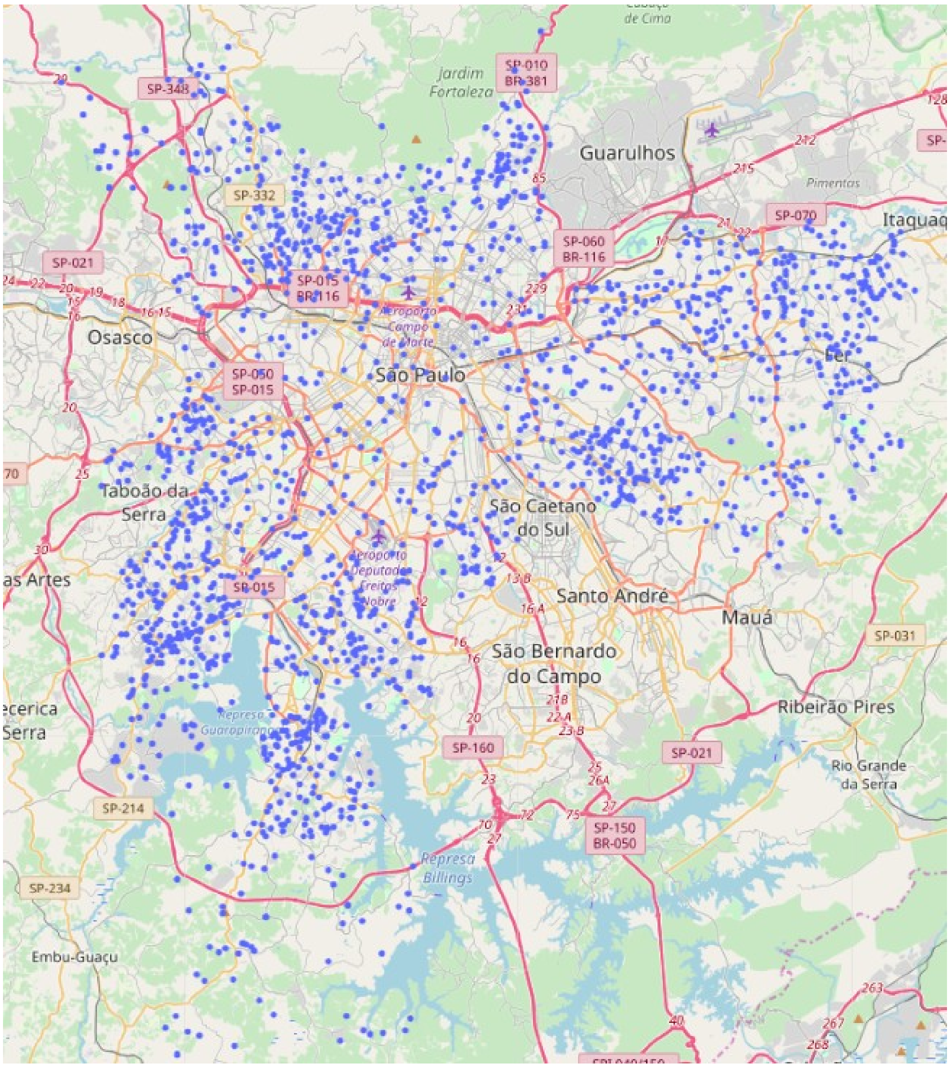
The first step of the data exploration was performed the enrichment of the postal code data with geolocation information, on another words latitude and longitude was added to the original cleaned data in order o enrich it. Below is presented the process of data enrichment by the creation of a function, the execution of the function and result data set.

```
# Creating a function to get the Lat Long data from the Postal Code
def get_geocoder(postal_code_from_df):
    lat_lng_coords = None
    while(lat_lng_coords is None):
        g = geocoder.arcgis('{}, São Paulo, São Paulo'.format(str(postal_code_from_df).strip()))
        lat_lng_coords = g.latlng
        latitude = lat_lng_coords[0]
        longitude = lat_lng_coords[1]
    return latitude,longitude
```

```
# Adding Latitude and Longitude columns to dataframe
dt1['Latitude'], dt1['Longitude'] = zip(*dt1['CEP'].apply(get_geocoder))
dt1.head()
```

	City	State	CEP	Neighborhood	Street	Latitude	Longitude
0	São Paulo	SP	1001000	Sé	Praça da Sé - lado ímpar	-23.562870	-46.654680
9	São Paulo	SP	1002020	Centro	Viaduto do Chá	-23.546685	-46.637805
173	São Paulo	SP	1017000	Brás	Avenida Rangel Pestana - até 499/500	-23.549709	-46.630488
337	São Paulo	SP	1035100	República	Avenida São João - de 651 a 1339 - lado ímpar	-23.540970	-46.642602
540	São Paulo	SP	1101000	Luz	Avenida Santos Dumont - até 999/1000	-23.562870	-46.654680

Still on the first step, it was plotted a map pinning all neighborhoods on the city, below the result map can be observed below.



The second step of the data exploration is very similar to the first one, it also aimed into enrich the original data. But this turn the data source utilized was the Foursquare API, to do that, it was created a function responsible for based on a input of the neighborhood name, latitude and longitude performed a API call to retrieve the foursquare data. The result of put all this API response data into a data frame can be observed below.

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Sé	-23.56287	-46.65468	Museu de Arte de São Paulo (MASP)	-23.561585	-46.655832	Art Museum
1	Sé	-23.56287	-46.65468	Seen	-23.563984	-46.656098	Restaurant
2	Sé	-23.56287	-46.65468	Teatro Popular do Sesi	-23.563635	-46.654605	Theater
3	Sé	-23.56287	-46.65468	Tivoli Mofarrej - São Paulo	-23.563923	-46.656146	Hotel
4	Sé	-23.56287	-46.65468	Starbucks	-23.562082	-46.655736	Coffee Shop
5	Sé	-23.56287	-46.65468	Centro Cultural FIESP - Ruth Cardoso	-23.563376	-46.654245	Cultural Center
6	Sé	-23.56287	-46.65468	Pello Menos	-23.562758	-46.656545	Health & Beauty Service
7	Sé	-23.56287	-46.65468	Starbucks	-23.563384	-46.653057	Coffee Shop
8	Sé	-23.56287	-46.65468	Granado	-23.563961	-46.652955	Cosmetics Shop
9	Sé	-23.56287	-46.65468	Lindt	-23.564155	-46.653155	Chocolate Shop

3.2 Data Presentation

In order to better understand the problem several indicators and metrics will be presented to provide a background into the city and project.

- Top 10 Venues Categories

Venue Category	counts
Brazilian Restaurant	1858
Bakery	1808
Pizza Place	1461
Hotel	1060
Pharmacy	1007
Burger Joint	1003
Gym / Fitness Center	1002
Coffee Shop	908
Restaurant	906
Middle Eastern Restaurant	856

- Top 10 Venues Categories in the neighborhoods

Neighborhood	Venue Category	counts
Vila São Francisco	Brazilian Restaurant	16
Sumarezinho	Bar	15
Vila Guarani (Z Sul)	Brazilian Restaurant	12
Cerqueira César	Bar	12
Itaim Bibi	Restaurant	11
Sumarezinho	Art Gallery	11
Vila São Francisco (Zona Sul)	Brazilian Restaurant	11
Centro	Brazilian Restaurant	10
Paraíso	Coffee Shop	10
Itaim Bibi	Italian Restaurant	10

- Top 3 Venues Categories by neighborhoods (sample)

Neighborhood	Venue Category	counts
Área Rural de São Paulo	Hotel	7
Área Rural de São Paulo	Brazilian Restaurant	6
Área Rural de São Paulo	Coffee Shop	5
Água Rasa	Brazilian Restaurant	3
Água Rasa	Bakery	2
Água Rasa	Farmers Market	2
Água Funda	Bakery	1
Água Funda	Brazilian Restaurant	1
Água Funda	Furniture / Home Store	1
Água Fria	Japanese Restaurant	4
Água Fria	Pharmacy	4
Água Fria	Pizza Place	4
Água Branca	Hotel	7
Água Branca	Brazilian Restaurant	6
Água Branca	Coffee Shop	5
Várzea de Baixo	Farmers Market	2
Várzea de Baixo	Italian Restaurant	2
Várzea de Baixo	Mineiro Restaurant	2

- Top 10 neighborhoods with more venues

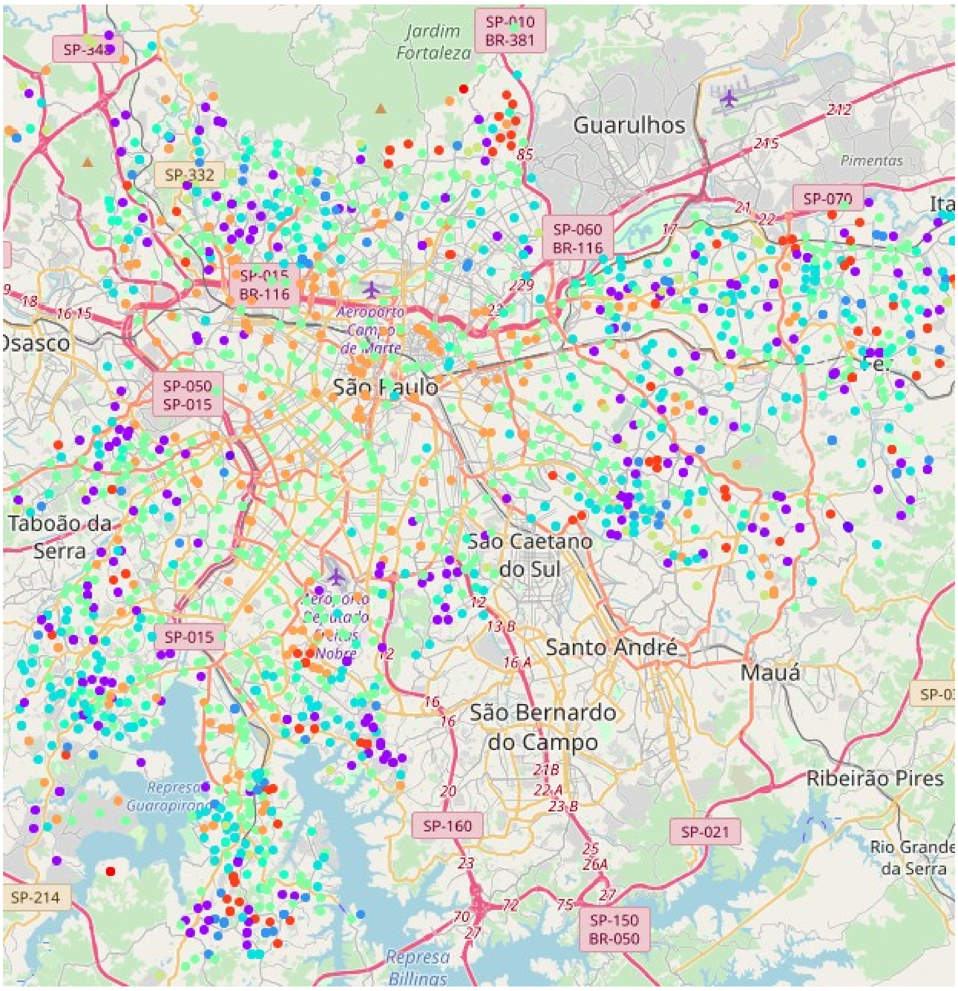
	Neighborhood	counts
1871	Área Rural de São Paulo	100
1071	Moema	100
1278	Santa Amélia	100
1266	Roda a Roda Jequiti	100
1258	República	100
1245	Protendit	100
1232	Pinheiros	100
1180	Parque Rodrigues Alves	100
244	Jardim Aladim	100
321	Jardim Bronzato	100

*Obs.: Due Foursquare API restriction, the maximum number of venues by neighborhood is 100

4 Results

The result of this project can be understood as the clustering of the neighborhoods based on the similarity of the top 10 venues. To define the ideal amount of clusters several tests were performed with several different number of clusters as for example 3, 4, 5, 6, 7, 8, 9 and 10 clusters.

Below is the plot that represents the distribution of the ten clusters:



Regarding the Cluster size, below is presented the amount of clusters created in this analysis and also the amount of neighborhoods on each of this clusters.

Cluster #	Amount of Neighborhoods
Cluster 0	238
Cluster 1	5
Cluster 2	83
Cluster 3	327
Cluster 4	95
Cluster 5	681
Cluster 6	65
Cluster 7	278
Cluster 8	96
Cluster 9	4

5 Discussion

As presented on the previous section, the map plot and the frequency of neighborhoods by cluster. Adding to that, when looking at this data and the data of the data exploration it’s possible to extrapolate some recommendations having on mind the target audience mentioned at the beginning of the work.

- Payment industry: could use this data to improve market research and target specific segments to get a better penetration and capillarity in terms os sales. Also, another point it would be knowing the neighborhood distribution on the clusters would be easier to target campaigns to stimulate sales.
- Investors: São Paulo is one of best gastronomical city in the world, several excellent restaurants. I would recommend open a niche restaurant on neighborhoods of cluster 4 because its already a place where the best restaurants are located.
- Social Science researchers: the cluster distribution in the map denote a clear income difference, as rings the clusters are opening letting clear the differences on social class.

6 Conclusion

To conclude is important to point out that all problem statements and description were achieved and provided insightful response and recommendations about which would be the best actions depending on certain scenarios. So in a whole this analysis was successful and achieved its objectives.