Introduction - Business Problem:

Quite recently I have been conducting some Real Estate research in order to buy myself an apartment as official Government-controlled interest rate in Brazil (SELIC) is reaching its historical lowest point (2,0% on a monthly basis) and financial investments are losing their attractiveness after decades of good returns. A frequent answer to this “bear-like” scenario lies on the Real Estate market. Some people buy just for diversification purposes and some buy for future renting purposes.

For some months I have been visiting showrooms and talking a lot to Residential Real Estate Professionals in order to understand their mindset when trying to sell and see how they could help me finding a decent offer.

Because of the new generation of young professionals´ aspirations, these salespeople had to relearn their trade and had to become more sophisticated even for words selection. But it is quite clear they lack methods and systems to leverage their daily work.

After spending all this time observing and taking mental notes, I could visualize some patterns emerging from these conversations. On the side of demand, there were prospective customers that wanted to extract very precise information not only about apartments but also about the neighborhood where the future building would be erected.

Young professionals, usually newly graduated, singles, averse to car driving and addicted to technology and exotic cuisines asked about subway stations, fitness gym and laundry services.

On the other hand, car-loving married people with children and years of professional life under their belts asked about supermarkets, drugstores, schools and the like.

It seems that different people in different moments of their lives want different places to live with very specific surroundings, albeit sometimes they asked for common services but valuated them differently like Coworking spaces.

For all these questions, Real Estate salespeople had average answers for most of the time, because, in order to make their living, they are frequently allocated to several sites and regardless of their efforts, they fail to catch up what is around when they set foot for the first time on a new showroom.

São Paulo is a very big city, Its 15 million inhabitants give it “the most populated brazilian city” title. Some city boroughs have excellent reputation when it comes to Real Estate and, apart from possessing the financial power to live in any of these boroughs, most people visit showrooms there. Satellite cities of the metropolitan area display a total population of 6 million and most of them waste 3 hours on a daily basis commuting from home to work and back home. Their dream? Easy…they want to move to São Paulo.

In a nutshell, it is a big market and opportunities could be better seized if a model could translate to real estate salesforce what prospective buyers care at most (and vice-versa), so that they could calibrate their recommendations using what they have to offer and where accordingly.

Buyers´ choices depend on several factors:

- Professional moment combined with age (newly graduated, seasoned or retired);
- Family structure (single, newly married, married with or without children or divorced);
- Purchasing Power (low income, high income, combined income);
- Resale value, which also depends on items 'a' and 'b' because people´s lives changes;
- Driver for this analysis: What does the surroundings offer to make their life more pleasant (supermarkets, gym, subway or bus transportation, schools, shopping malls, etc)?

In other words, a diverse set of needs and values is just around the corner and it is subject to change as time passes by. What is important for someone might be utterly irrelevant to others and to him(her)self in the future. But the idea of giving **Value** to every feature of a place to live is always there and it can be of *subjectivity nature*, albeit any market research will trace common trends like borough reputation, closeness to good schools and to functional public transportation .

Another interesting aspect of this study lies on its **double utility** => what might play an essential role for a prospective buyer to acquire his-her "home, sweet home" might also be a powerful resource for a good Real Estate salesperson if he-she reads the customer aspirations accurately and have both data and portfolio to make ends meet. Demand and Supply.

Therefore, the Model will use geographical data of boroughs from the City of São Paulo to provide lists of venues, services, facilities and utilities to which prospective customers give values as percentage or absolute numbers.

For instance: as noted above, an young professional might value a subway station as the most important venue around (7 in a scale from 1 to 10) whereas a more seasoned professional would give it a 3 as a car is more than a vehicle but also a symbol of social status.

The Model will work with venues, services, facilities and utilities and the values given to them by different types of prospective buyers to build a mathematical “Attractiveness Index” to each borough and recommend the best borough for every type of buyer.

Data:

Two datasets will be enough to build the model foundations:

- Data from FourSquare for all boroughs selected for the study. I will need type of venue (restaurant or gym or medical center or whatever comes from it) and its correspondent geographical coordinates.
- Data from customers´ valuation for all these venue types according to their needs or to their social aspirations or simply to their present moment of life.

The second batch of data was obtained from informal interviews with both buyers (myself included) and sellers. The underlying idea was to cast a batch of grades to all venue types with the total sum being 1 (or 100%).

The multiplication of the venue occurrence frequency for each borough by the value cast by different type of buyers will build the “Attractiveness Index” of that borough to that type of buyer. After all computations are performed both sides (demand and supply) can use the model to leverage their positions.

A very simple example to help illustrate the model:

Burough A:

- supermarkets = 4
- young buyer value to supermarkets = 0,2
- seasoned professional value to supermarkets = 0,8
- “Attractiveness Index” are 0,8 and 3,2 respectively and a seller should not recommend this borough for young buyers.

Burough B:

- fitness centers = 6
- young buyer value to fitness centers = 0,7
- seasoned professional value to fitness centers = 0,3
- “Attractiveness Index” are 4,2 and 1,8 respectively and a seller should not recommend this borough for seasoned professionals.

Methodology:

In a city as big and diverse as São Paulo, it comes not as a surprise that people display a broad palette of preferences. The same thing can be said about real estate offerings. However, in order to keep this task´s dimensions compatible to the purpose of concepts learning and experimentation, I will restrain it to 2 main types of real estate.

By the way, this is not "a jump in the dark" at all. Quite recently I was interested in acquiring a Studio for personal investiment and spent a couple of months talking to more than 50 salesperson in their showrooms and launching site. From these conversations, I got valuable insights of what the market offers nowadays and what prospective buyers want.

I was also told that nowadays the market displays two major offerings:

- **Studio**: It looks like a hotel room with some. Area ranges from 25 to 33 square meters;
- **Regular**: It is the "regular" apartment everybody is used to => 2, 3 or 4 bedrooms (sometimes with exclusive bathrooms), living room, kitchen, dining room, etc. Area ranges from 50 to 180 square meters.

In a city that never ceases to grow, growth means going upwards, it means buildings at most. Supply and Demand for houses are proportionally low because of family security issues. Urban violence scares every São Paulo inhabitant who is led to make the option for apartments rather than houses. In the last decades, market for houses in private and exclusive condos has been booming and it deserves an study by itself; but for the present, we will restrain ourselves to apartments.

Potential Real Estate buyers can be summarized as follows:

- **Studio Buyer**: usually a single young person starting a career and who has different values from their parents. A car is no longer desirable and Uber or Public Transportation are preferred. Technology-addicted with a taste for cosmopolitan cuisines;
- **Regular Buyer**: for them being married is the most common marital status and they want a place to live for several years and build a family. They are people that **could** once have been Studio buyers but also people from neighbor towns that want to save precious time by quitting commuting. Car (or cars) is a statement of social position and so are expensive Health plans;
- **Investor Buyer**: this buyer is the most senior of all types. It is common in Brazil people who retire but still need to have income. Some of these people acquire apartments (and houses) to rent. They might acquire any type of housing, Studios os Regulars, in any combination they think may maximize their income.

A little bit into the Model.

- ✓ ***Professionals targeted***:

  Taking into account everything that was briefly explained above, the underlying idea for this Notebook lies on providing **Potential Buyers and Residential Real Estate Professionals** an index-based tool to help them identifying their targets and making together the best of business opportunities.

- ✓ ***Methodology:***
  - Selection of 25 São Paulo boroughs, known for decades as the best locations in the city for real estate investment;
  - Extraction by FourSquare API of all interesting venues around each of these boroughs;
  - Further Classification of borough venues. It means concatenation of similar ones into a wider one (Bar and Pub tags into one single tag "Bar");
  - Development of "Buyer-Drivers-and-Preferences" dataframe which will lock to the Classification labels built on previous item;
  - **"Attractiveness Index"** calculation which will be the multiplication of the number(frequency) of venue occurrence by the "power of attraction" it displays for each type of buyer. It is a Weighted Average calculation;
  - Index-based Decisions, Insights and Statistical Inferences

A note about "Attractiveness Index" calculation:

It is quite simple indeed: A Studio buyer prioritizes Public Transportation, therefore any proximity to subway stations will be way more important to him-her than any Auto-Retail or Auto-Services facilities around their future "home, sweet home". For Regular buyers it is exactly the opposite and Investor buyers will be some sort of average between the two former types.

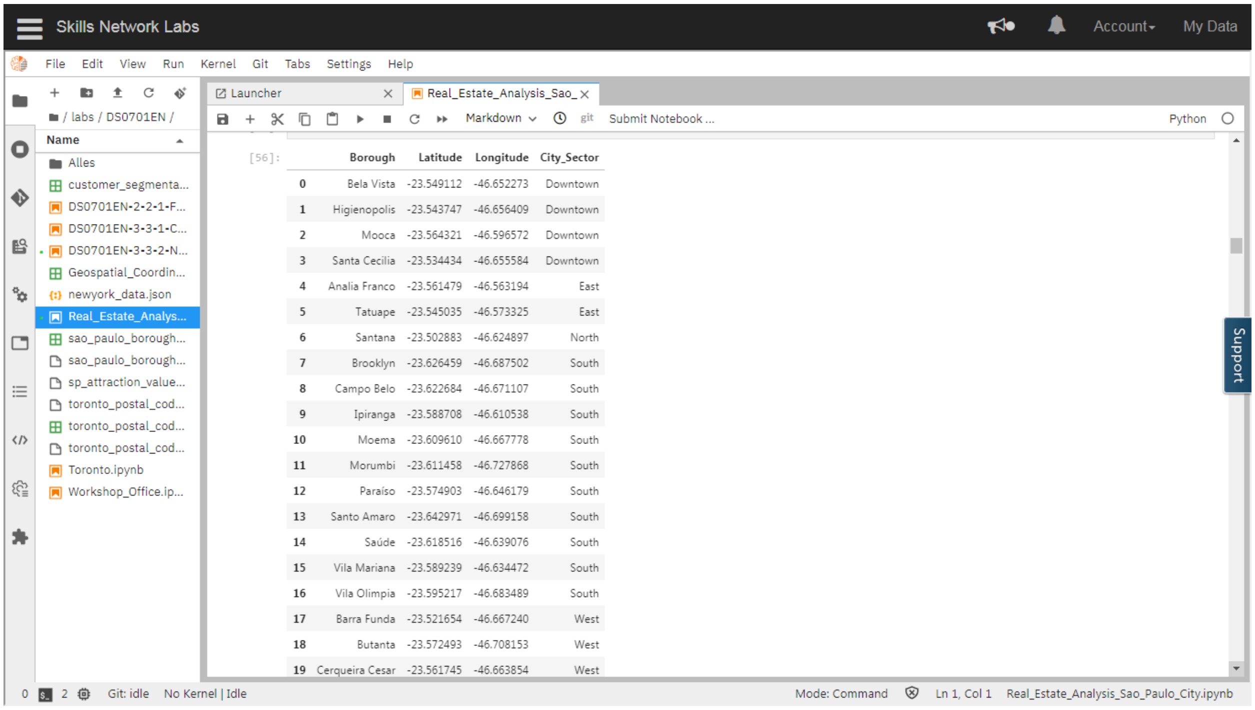
For statistical inferences Box Plot and Histograms will be tools of choice because they offer an invaluable chance to make head-to-head comparisons which will undoubtedly a good source for insights.

Diversity is a word that I came across many times when working on this assignment. In any town of the world, its boroughs may display a concentration of something (services or people) that end up labelling them like "Chinatown" or "Financial District". It is no different here in São Paulo from this work standpoint.

Some boroughs might be known and hopefully correctly classified (not clustered) by this Model as "Studio Buyer Profile" type which does not mean that good opportunities for other buyer types do not exist. They do, but perhaps, is less proportions and not attractive prices. That said, after calculating all Attractiveness Indexes for all boroughs and considering all type of prospective buyers, a map will be generated to display how city´s areas are naturally going into a business-driven Clusterization.

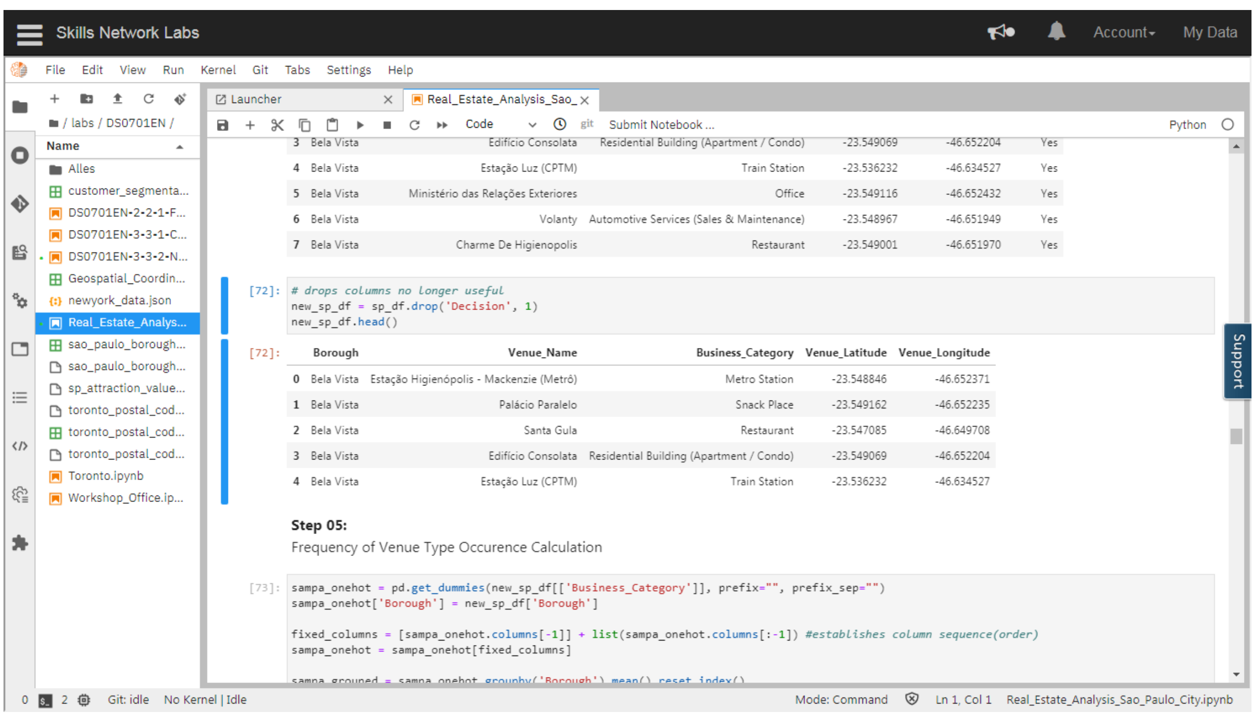
Results and Discussions:

Information and details about São Paulo Boroughs:



	Borough	Latitude	Longitude	City_Sector
0	Bela Vista	-23.549112	-46.652273	Downtown
1	Higienopolis	-23.543747	-46.656409	Downtown
2	Mooca	-23.564321	-46.596572	Downtown
3	Santa Cecilia	-23.534434	-46.655584	Downtown
4	Analia Franco	-23.561479	-46.563194	East
5	Tatuape	-23.545035	-46.573325	East
6	Santana	-23.502883	-46.624897	North
7	Brooklyn	-23.626459	-46.687502	South
8	Campo Belo	-23.622684	-46.671107	South
9	Ipiranga	-23.588708	-46.610538	South
10	Moema	-23.609610	-46.667778	South
11	Morumbi	-23.611458	-46.727868	South
12	Paraiso	-23.574903	-46.646179	South
13	Santo Amaro	-23.642971	-46.699158	South
14	Saúde	-23.618516	-46.639076	South
15	Vila Mariana	-23.589239	-46.634472	South
16	Vila Olimpia	-23.595217	-46.683489	South
17	Barra Funda	-23.521654	-46.667240	West
18	Butanta	-23.572493	-46.708153	West
19	Cerqueira Cesar	-23.561745	-46.663854	West

After Foursquare data extraction and data cleasing:



3	Bela Vista	Edifício Consolata	Residential Building (Apartment / Condo)	-23.549069	-46.652204	Yes
4	Bela Vista	Estação Luz (CPTM)	Train Station	-23.536232	-46.634527	Yes
5	Bela Vista	Ministério das Relações Exteriores	Office	-23.549116	-46.652432	Yes
6	Bela Vista	Volanty	Automotive Services (Sales & Maintenance)	-23.548967	-46.651949	Yes
7	Bela Vista	Charme De Higienopolis	Restaurant	-23.549001	-46.651970	Yes

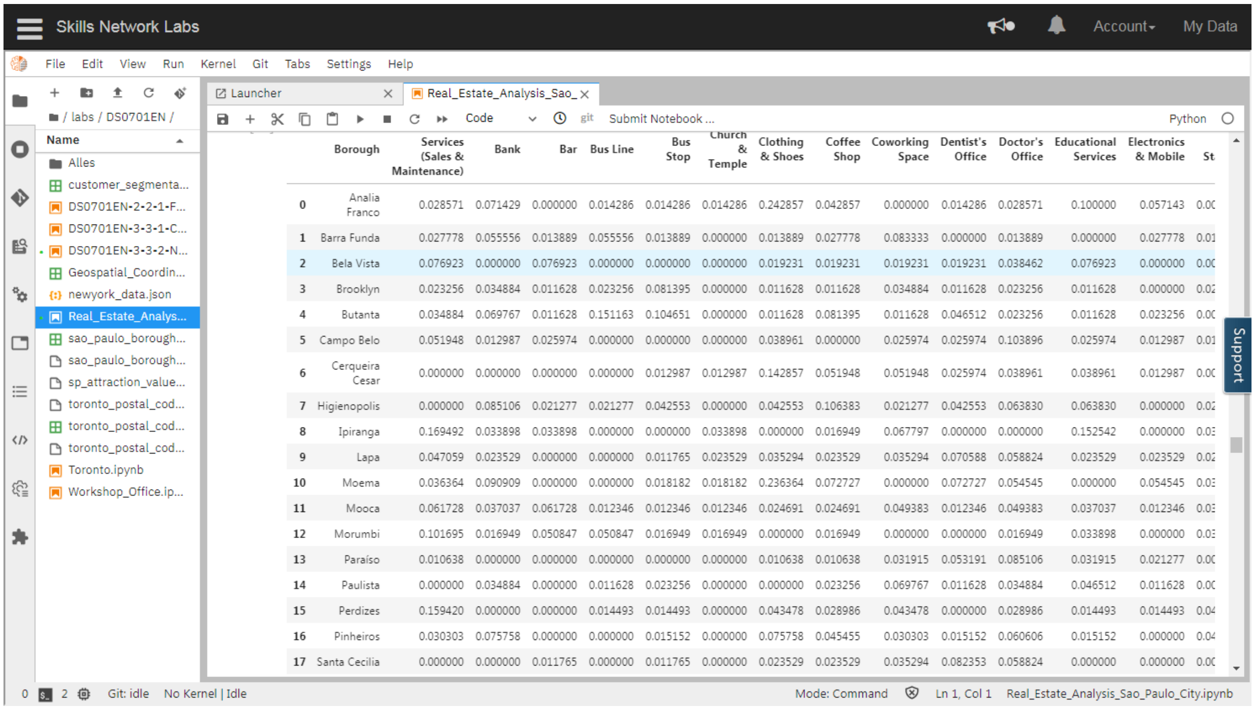
```
# drops columns no longer useful
new_sp_df = sp_df.drop('Decision', 1)
new_sp_df.head()
```

	Borough	Venue_Name	Business_Category	Venue_Latitude	Venue_Longitude
0	Bela Vista	Estação Higienópolis - Mackenzie (Metrô)	Metro Station	-23.548846	-46.652371
1	Bela Vista	Palácio Paralelo	Snack Place	-23.549162	-46.652235
2	Bela Vista	Santa Gula	Restaurant	-23.547085	-46.649708
3	Bela Vista	Edifício Consolata	Residential Building (Apartment / Condo)	-23.549069	-46.652204
4	Bela Vista	Estação Luz (CPTM)	Train Station	-23.536232	-46.634527

Step 05:
Frequency of Venue Type Occurence Calculation

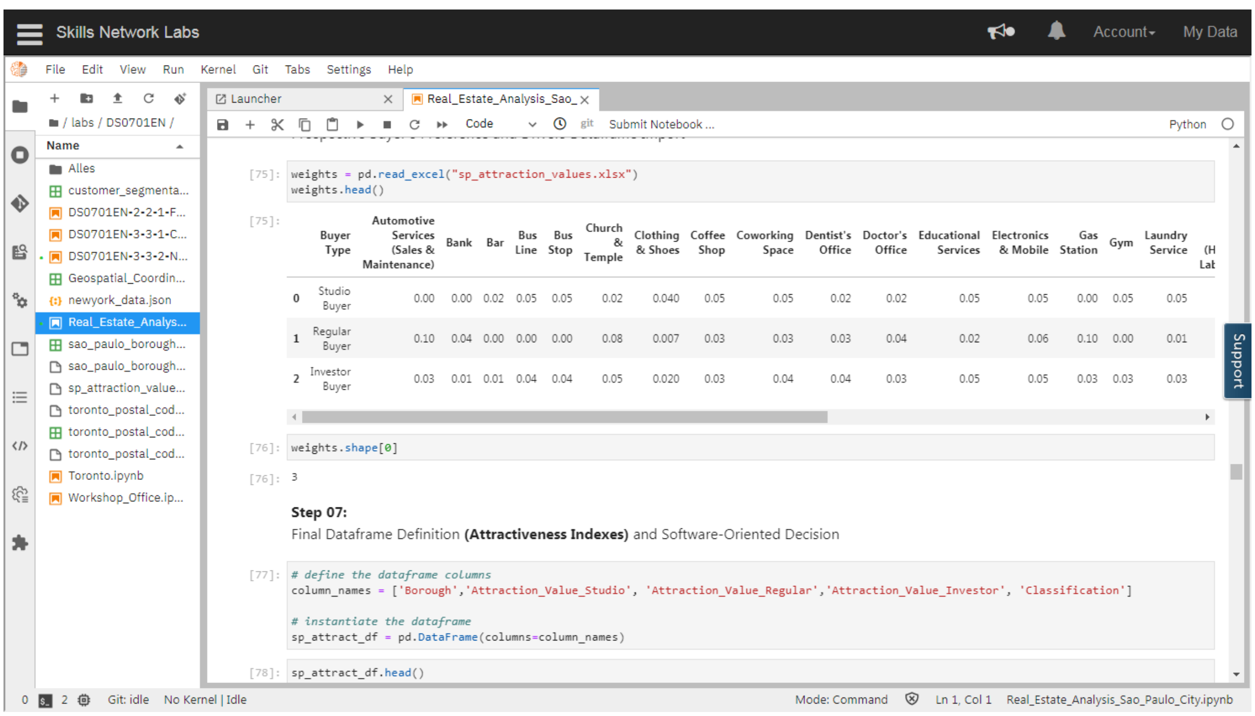
```
sampa_onehot = pd.get_dummies(new_sp_df[['Business_Category']], prefix="", prefix_sep="")
sampa_onehot['Borough'] = new_sp_df['Borough']

fixed_columns = [sampa_onehot.columns[-1]] + list(sampa_onehot.columns[:-1]) #establishes column sequence(order)
sampa_onehot = sampa_onehot[fixed_columns]
```

Occurrence Frequency calculation:



	Borough	Services (Sales & Maintenance)	Bank	Bar	Bus Line	Bus Stop	Church & Temple	Clothing & Shoes	Coffee Shop	Coworking Space	Dentist's Office	Doctor's Office	Educational Services	Electronics & Mobile
0	Analia Franco	0.028571	0.071429	0.000000	0.014286	0.014286	0.014286	0.242857	0.042857	0.000000	0.014286	0.028571	0.100000	0.057143
1	Barra Funda	0.027778	0.055556	0.013889	0.055556	0.013889	0.000000	0.013889	0.027778	0.083333	0.000000	0.013889	0.000000	0.027778
2	Bela Vista	0.076923	0.000000	0.076923	0.000000	0.000000	0.000000	0.019231	0.019231	0.019231	0.019231	0.038462	0.076923	0.000000
3	Brooklyn	0.023256	0.034884	0.011628	0.023256	0.081395	0.000000	0.011628	0.011628	0.034884	0.011628	0.023256	0.011628	0.000000
4	Butanta	0.034884	0.069767	0.011628	0.151163	0.104651	0.000000	0.011628	0.081395	0.011628	0.046512	0.023256	0.011628	0.023256
5	Campo Belo	0.051948	0.012987	0.025974	0.000000	0.000000	0.000000	0.038961	0.000000	0.025974	0.025974	0.103896	0.025974	0.012987
6	Cerqueira Cesar	0.000000	0.000000	0.000000	0.000000	0.012987	0.012987	0.142857	0.051948	0.051948	0.025974	0.038961	0.038961	0.012987
7	Higienopolis	0.000000	0.085106	0.021277	0.021277	0.042553	0.000000	0.042553	0.106383	0.021277	0.042553	0.063830	0.063830	0.000000
8	Ipiranga	0.169492	0.033898	0.033898	0.000000	0.000000	0.033898	0.000000	0.016949	0.067797	0.000000	0.000000	0.152542	0.000000
9	Lapa	0.047059	0.023529	0.000000	0.000000	0.011765	0.023529	0.035294	0.023529	0.035294	0.070588	0.058824	0.023529	0.023529
10	Moema	0.036364	0.090909	0.000000	0.000000	0.018182	0.018182	0.236364	0.072727	0.000000	0.072727	0.054545	0.000000	0.054545
11	Mooca	0.061728	0.037037	0.061728	0.012346	0.012346	0.012346	0.024691	0.024691	0.049383	0.012346	0.049383	0.037037	0.012346
12	Morumbi	0.101695	0.016949	0.050847	0.050847	0.016949	0.016949	0.000000	0.016949	0.000000	0.000000	0.016949	0.033898	0.000000
13	Paraíso	0.010638	0.000000	0.000000	0.000000	0.000000	0.000000	0.010638	0.010638	0.031915	0.053191	0.085106	0.031915	0.021277
14	Paulista	0.000000	0.034884	0.000000	0.011628	0.023256	0.000000	0.000000	0.023256	0.069767	0.011628	0.034884	0.046512	0.011628
15	Perdizes	0.159420	0.000000	0.000000	0.014493	0.014493	0.000000	0.043478	0.028986	0.043478	0.000000	0.028986	0.014493	0.014493
16	Pinheiros	0.030303	0.075758	0.000000	0.000000	0.015152	0.000000	0.075758	0.045455	0.030303	0.015152	0.060606	0.015152	0.000000
17	Santa Cecilia	0.000000	0.000000	0.011765	0.000000	0.011765	0.000000	0.023529	0.023529	0.035294	0.082353	0.058824	0.000000	0.000000

Prospective Buyers´ Preferences and Venue Valuations:



```
[75]: weights = pd.read_excel("sp_attraction_values.xlsx")
      weights.head()
```

	Buyer Type	Automotive Services (Sales & Maintenance)	Bank	Bar	Bus Line	Bus Stop	Church & Temple	Clothing & Shoes	Coffee Shop	Coworking Space	Dentist's Office	Doctor's Office	Educational Services	Electronics & Mobile	Gas Station	Gym	Laundry Service
0	Studio Buyer	0.00	0.00	0.02	0.05	0.05	0.02	0.040	0.05	0.05	0.02	0.02	0.05	0.05	0.00	0.05	0.05
1	Regular Buyer	0.10	0.04	0.00	0.00	0.00	0.08	0.007	0.03	0.03	0.03	0.04	0.02	0.06	0.10	0.00	0.01
2	Investor Buyer	0.03	0.01	0.01	0.04	0.04	0.05	0.020	0.03	0.04	0.04	0.03	0.05	0.05	0.03	0.03	0.03

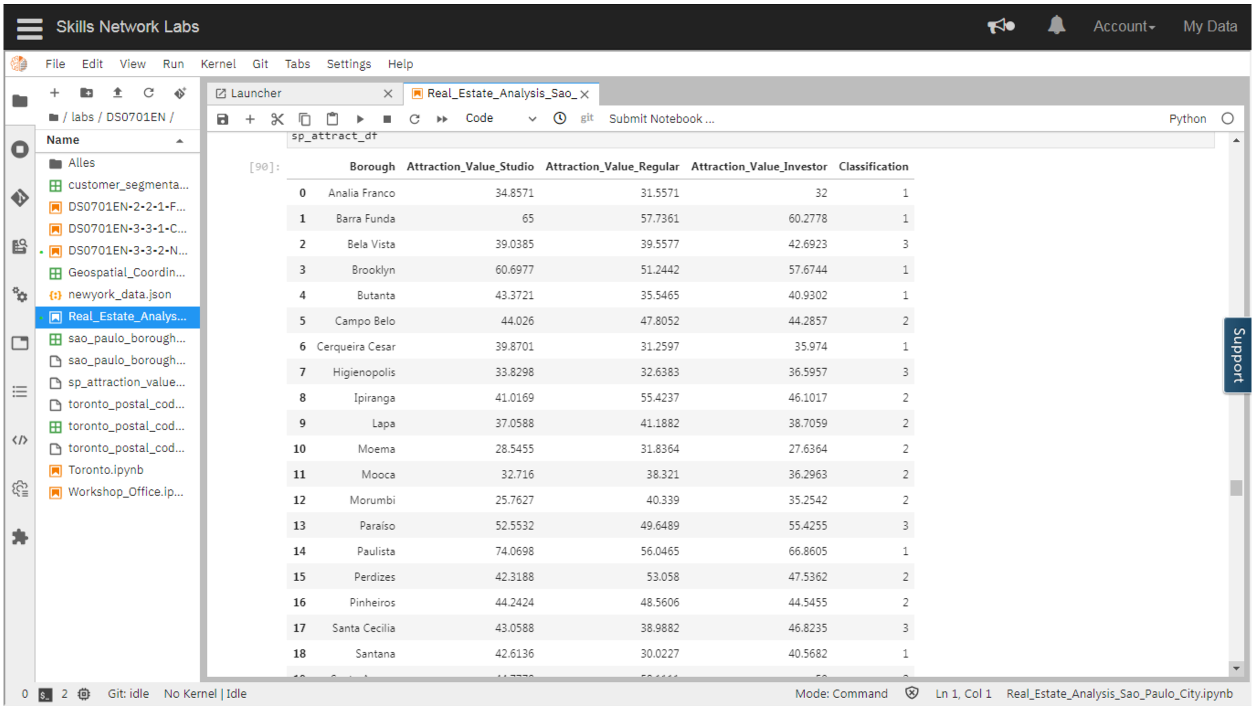
```
[76]: weights.shape[0]
[76]: 3
```

Step 07:
Final Dataframe Definition **(Attractiveness Indexes)** and Software-Oriented Decision

```
[77]: # define the dataframe columns
      column_names = ['Borough','Attraction_Value_Studio', 'Attraction_Value_Regular','Attraction_Value_Investor', 'Classification']

      # instantiate the dataframe
      sp_attract_df = pd.DataFrame(columns=column_names)

[78]: sp_attract_df.head()
```

Final Dataframe for Statistical Analysis and Modelling Testing:

Column “Classification”: 1 for Studio Profile, 2 for Regular Profile and 3 for Investor Profile.

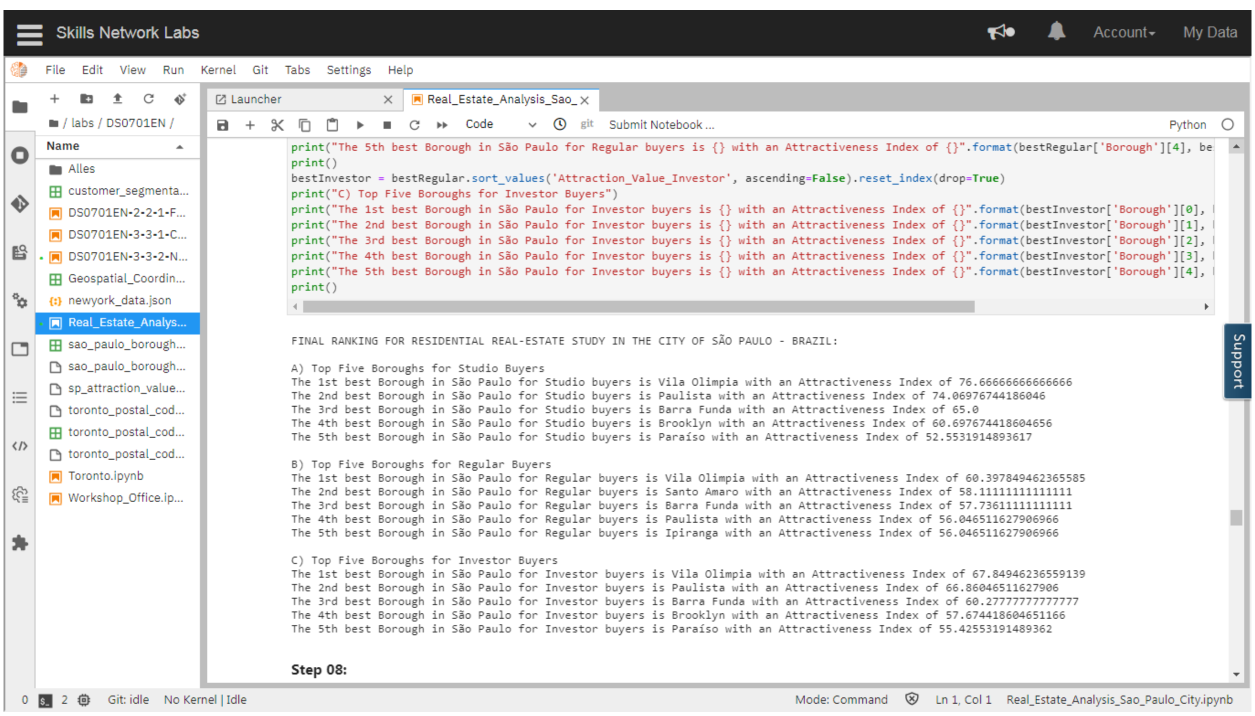


```
sp_attract_df
```

[90]:

	Borough	Attraction_Value_Studio	Attraction_Value_Regular	Attraction_Value_Investor	Classification
0	Analia Franco	34.8571	31.5571	32	1
1	Barra Funda	65	57.7361	60.2778	1
2	Bela Vista	39.0385	39.5577	42.6923	3
3	Brooklyn	60.6977	51.2442	57.6744	1
4	Butanta	43.3721	35.5465	40.9302	1
5	Campo Belo	44.026	47.8052	44.2857	2
6	Cerqueira Cesar	39.8701	31.2597	35.974	1
7	Higienopolis	33.8298	32.6383	36.5957	3
8	Ipiranga	41.0169	55.4237	46.1017	2
9	Lapa	37.0588	41.1882	38.7059	2
10	Moema	28.5455	31.8364	27.6364	2
11	Mooca	32.716	38.321	36.2963	2
12	Morumbi	25.7627	40.339	35.2542	2
13	Paraíso	52.5532	49.6489	55.4255	3
14	Paulista	74.0698	56.0465	66.8605	1
15	Perdizes	42.3188	53.058	47.5362	2
16	Pinheiros	44.2424	48.5606	44.5455	2
17	Santa Cecilia	43.0588	38.9882	46.8235	3
18	Santana	42.6136	30.0227	40.5682	1

Model Recommendations:



```
print("The 5th best Borough in São Paulo for Regular buyers is {} with an Attractiveness Index of {}".format(bestRegular['Borough'][4], be
print()
bestInvestor = bestRegular.sort_values('Attraction_Value_Investor', ascending=False).reset_index(drop=True)
print("C) Top Five Boroughs for Investor Buyers")
print("The 1st best Borough in São Paulo for Investor buyers is {} with an Attractiveness Index of {}".format(bestInvestor['Borough'][0],
print("The 2nd best Borough in São Paulo for Investor buyers is {} with an Attractiveness Index of {}".format(bestInvestor['Borough'][1],
print("The 3rd best Borough in São Paulo for Investor buyers is {} with an Attractiveness Index of {}".format(bestInvestor['Borough'][2],
print("The 4th best Borough in São Paulo for Investor buyers is {} with an Attractiveness Index of {}".format(bestInvestor['Borough'][3],
print("The 5th best Borough in São Paulo for Investor buyers is {} with an Attractiveness Index of {}".format(bestInvestor['Borough'][4],
print()
```

```
FINAL RANKING FOR RESIDENTIAL REAL-ESTATE STUDY IN THE CITY OF SÃO PAULO - BRAZIL:

A) Top Five Boroughs for Studio Buyers
The 1st best Borough in São Paulo for Studio buyers is Vila Olimpia with an Attractiveness Index of 76.66666666666666
The 2nd best Borough in São Paulo for Studio buyers is Paulista with an Attractiveness Index of 74.06976744186046
The 3rd best Borough in São Paulo for Studio buyers is Barra Funda with an Attractiveness Index of 65.0
The 4th best Borough in São Paulo for Studio buyers is Brooklyn with an Attractiveness Index of 60.697674418604656
The 5th best Borough in São Paulo for Studio buyers is Paraíso with an Attractiveness Index of 52.5531914893617

B) Top Five Boroughs for Regular Buyers
The 1st best Borough in São Paulo for Regular buyers is Vila Olimpia with an Attractiveness Index of 60.397849462365585
The 2nd best Borough in São Paulo for Regular buyers is Santo Amaro with an Attractiveness Index of 58.11111111111111
The 3rd best Borough in São Paulo for Regular buyers is Barra Funda with an Attractiveness Index of 57.73611111111111
The 4th best Borough in São Paulo for Regular buyers is Paulista with an Attractiveness Index of 56.046511627906966
The 5th best Borough in São Paulo for Regular buyers is Ipiranga with an Attractiveness Index of 56.046511627906966

C) Top Five Boroughs for Investor Buyers
The 1st best Borough in São Paulo for Investor buyers is Vila Olimpia with an Attractiveness Index of 67.84946236559139
The 2nd best Borough in São Paulo for Investor buyers is Paulista with an Attractiveness Index of 66.86046511627906
The 3rd best Borough in São Paulo for Investor buyers is Barra Funda with an Attractiveness Index of 60.27777777777777
The 4th best Borough in São Paulo for Investor buyers is Brooklyn with an Attractiveness Index of 57.674418604651166
The 5th best Borough in São Paulo for Investor buyers is Paraíso with an Attractiveness Index of 55.42553191489362
```

Step 08:

Statistical Analysis:

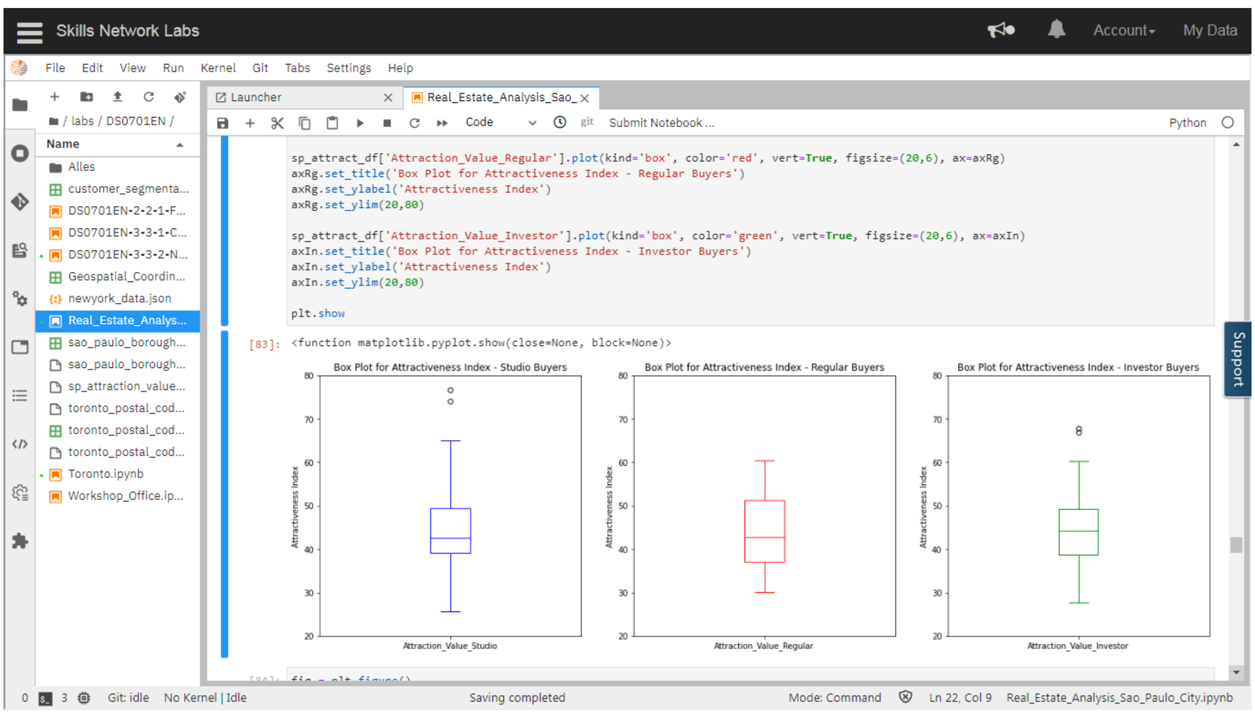
Insights:

Before proceeding to insights, it is interesting to delve a little bit into the mechanics of Attractiveness Index **(Attr_Idx)** calculation.

It is a Weighted Average calculation whose weights are the grades buyers give to all Business Categories according to their needs or preferences.\

Therefore, a high **Attr_Idx** means that not only a specific business category is available in good quantity (number of shops, schools, public transportation) but it is also highly regarded as very important by their future users. On the other hand, a low **Attr_Idx** means a specific business category is neither available in quantity (number of shops, schools, public transportation) nor it is highly regarded as very important by their future users. Of course, between these two ends, there are several possible combinations of venue availability and venue perceived importance.

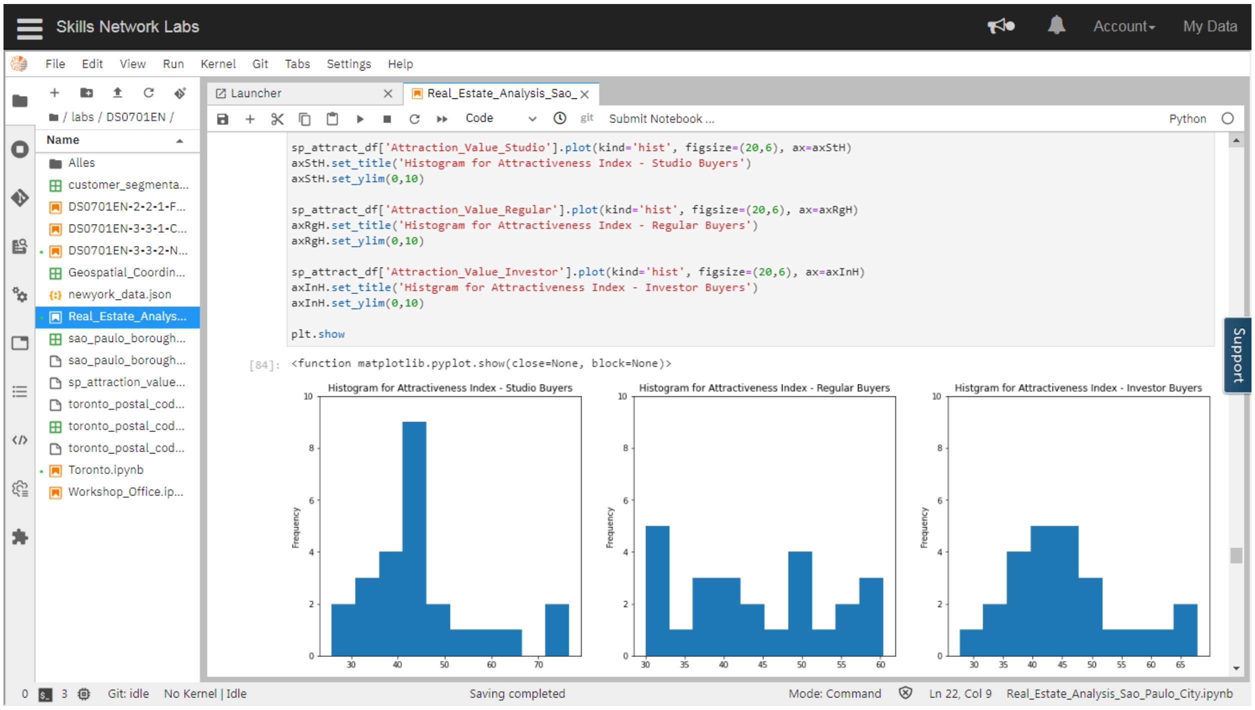
Box Plot:



Dispersion for Studio **Attr_Idx** is the highest of all three and it probably indicates that Real Estate Enterprises are doing their homework as they have been placing their "Studio Launch Sites" in areas already perceived by prospective buyers as very promising to their life style.

Now, putting Interquartile Range (IQR) under the microscope for all three Buyers' profile shows Regular **Attr_Idx** displays the broadest dispersion which is clearly visible by histogram visual inspection. Regular Buyer is the most frequent buyer in Showrooms and this availability in numbers translates into a more diverse palette of needs and preferences. It explains this ‘fatter' histogram without any clear unique peak.

Histogram:



Still about IQR and histograms, **Attr_Idx** for Studio and Investor profiles show a slight tendency to symmentry, albeit being asymmentrical. The former displays a peak that indicates more focus from buyers and sellers and the latter displays a hedge-like behaviour as the result of a balanced-game between Studio and Regular profiles.

Finally, the Median (Q2) for the three **Attr_Idx** are very similar (as the mean average) which could indicate that the whole Residential Real Estate Market for Studios is still in its infancy in São Paulo and perhaps there are still room for information delivery and training for Sellers in order to improve their delivery and minimize gray areas for buyers´ clear understanding.

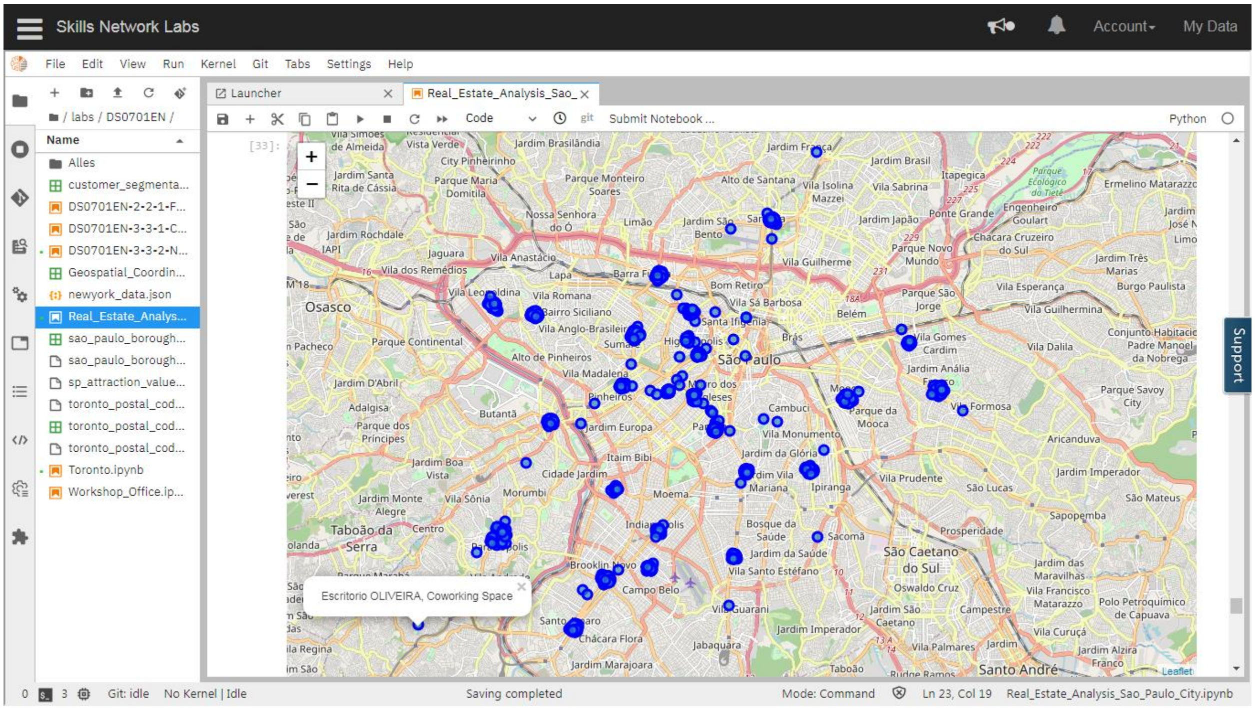
Map Visualizations:

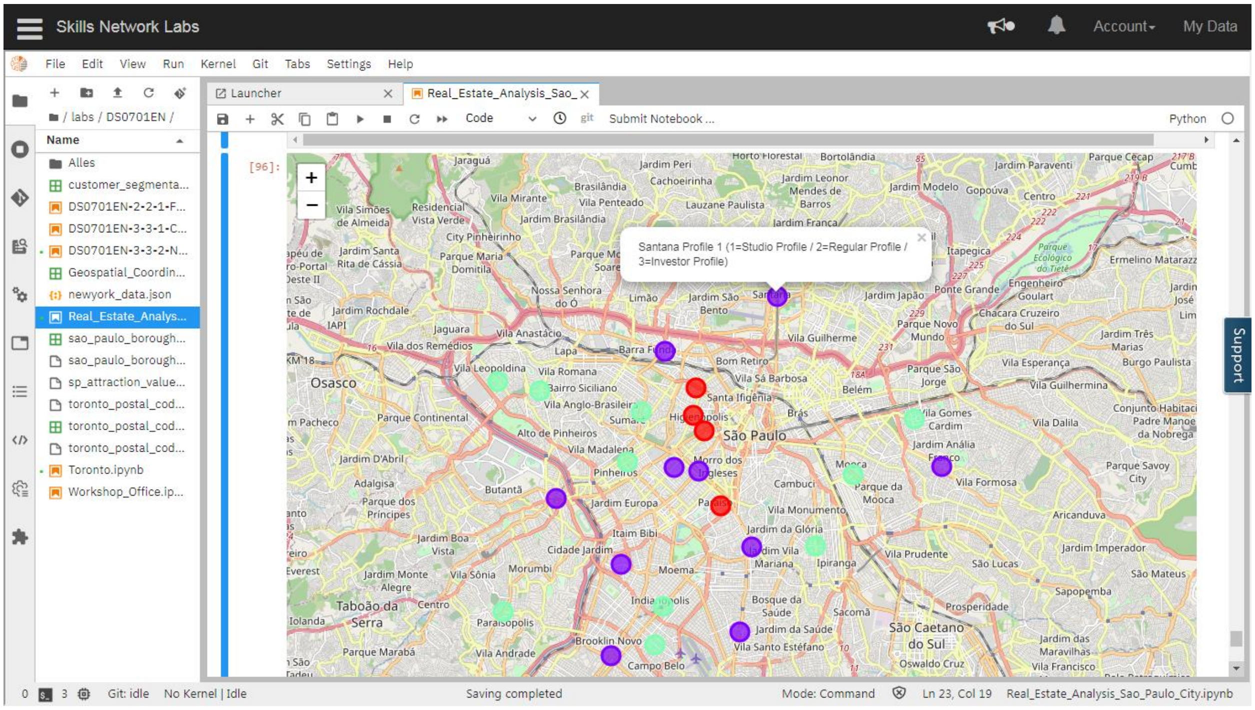
I expect very few people to be familiar with the city of São Paulo. In order to help people understand what this work is about, two maps will be generated:

The first map displays all Business Ventures extracted from Foursquare with a pop-up label showing its name and business category.\

The second map displays only boroughs' names and their "predominant vocation", that is, how boroughs are perceived by both sides of the Residential Real Estate market.

About second map, it must be stated that burough's "vocational nature" should not be taken to the letter; a borough noted as "Studio Profile" can also be a target for "Regular Profile" as the two options coexist and maybe even price for the latter type of apartment is more attractive than it is for the former. **It can also work as an Indicator to future Real Estate enterprises. It is not a formal Clusterization process but it may give some good tips.**





Conclusions:

- Regardless of Buyer Profile, Vila Olimpia Borough topped the bill three times which comes at no surprise at all as lots of Tech Companies and Start-Ups are establishing themselves in the area, nicknamed by the midia as the SP Sillicon Valley;

- Paulista borough also appears on the 3 rankings but it is less regarded by Regular buyers than by others. It is a borough characterized by lots of financial companies, services and goverment buildings making it not a good decision to raise kids, but a good one for young people and investors;

- Talking about Buyer Profile, choices for Studio and Investor Buyers were the same for the Top Five positions. Although it might look confusing, there is an underlying logic as Investors want the highest possible ROI, the faster the better. It takes less time to build Studio aparments and tennant turnoround is expected to be higher thus generating quick profit;

- Not a single 'Downtown' borough made the Top Five. Unfortunately, this was expected as these boroughs are still linked to a bad reputation São Paulo downtown got in the 70's and 80's;

- Another borough absent from Top Five is Morumbi, a former powerful attractor area in past decades but still lacking improvements like subway lines that are yet to reach the borough and houses are still the most commom housing. Being at the 'wrong side of the tracks', that is, at the west bank of Pinheiros river does not help either as it is widely accepted that such locations devaluate any Real Estate investment;

- In general terms, the Model works fine as it translates what is known as "common sense" into data-based recommendations for both sides of the equation (buyers and sellers). **Further enhancements could be added to it in next versions like financial data to reckon ROI versus land value (BRL/sqmt) or it could provide interaction with users via website to make the decision process faster**.