The Starbucks Exploration

STARBUCKS®

Contents

1. Introduction

1.1. Context

Thanks to Coursera and IBM, we are certified in Python and machine learning, and it did not take long for coffee company Starbucks to hire us as data scientists! We will work for the European Division!

Starbucks has only been growing bigger[1] since its creation, and continuously open more stores across the world.

Year	Revenue in mil. US$	Net income in mil. US$	Total Assets in mil. US$	Average Price per Share in US$	Employees
2013	14867	8	11517	33.71	182000
2014	16448	2068	10753	37.78	191000
2015	19163	2757	12416	53.25	238000
2016	21316	2818	14313	56.59	254000
2017	22387	2885	14366	57.27	277000
2018	24720	4518	24156	57.50	291000
2019	26509	3599	19220	81.44	346000

According to this same Wikipedia page, as of May 2020, Starbucks is present in over 30,000 locations, on 6 continents and 79 countries.

1.2. Business Problem

Our mission is to keep this global expansion going by opening a new store in Europe, but the location must be carefully chosen to guarantee success.

Our problem will be solved by studying the current stores locations. We will then choose a highly populous big city where Starbucks is not yet too present.

We will then try to find a more precise location within this city. In order to do so, we will select several successful Starbucks coffees and use Foursquare API to characterize their

[1] https://en.wikipedia.org/wiki/Starbucks#Locations

neighbourhood and try to find a similar location in our target city where there is no store yet!

2. Data

2.1. City Populations

We will need some population data to be able to find out where Starbucks is not yet heavily present.
The table from Wikipedia[2] also contains GPS coordinates, which will be useful later, therefore I put this under usable form.

City	Country	Population	Latitude	Longitude
Istanbul	Turkey	15519267	41.013611	28.955000
Moscow	Russia	12615279	55.750000	37.616669
London	United Kingdom	9126366	51.507221	0.127500
Saint Petersburg	Russia	5383890	59.950001	-30.299999
Berlin	Germany	3748148	52.516666	13.383333
Madrid	Spain	3223334	40.383331	-3.716667
Kiev	Ukraine	2950800	50.450001	30.523333
Rome	Italy	2844750	41.900002	12.500000
Paris	France	2140526	48.856701	2.350800
Bucharest	Romania	2106144	44.432499	26.103889

2.2. Starbucks and Neighbourhood Venues from Foursquare API

Foursquare API will be used to find the number of Starbucks store for each city and which stores have the most reviews, and hence are likely to be top spots in their respective cities!

We will also use the Foursquare API again to characterize the surroundings and try to find a similar neighbourhood in our target city.

[2] https://en.wikipedia.org/wiki/List_of_European_cities_by_population_within_city_limits

3. Methodology

3.1. Finding the City with the Fewest Stores

A big limitation of Foursquare API is that the maximum number of results for a venue search is 50.

It is OK for our application because we are interested in cities with a low number of stores!

The first step of our study is to group Starbucks stores by city and count the number of occurrences.

Let us query Foursquare API to find Starbucks Stores for each city above.

City	Country	Population	Starbucks Stores Count
Istanbul	Turkey	15519267	50
Moscow	Russia	12615279	50
London	United Kingdom	9126366	50
Saint Petersburg	Russia	5383890	0
Berlin	Germany	3748148	22
Madrid	Spain	3223334	50
Kiev	Ukraine	2950800	1
Rome	Italy	2844750	2
Paris	France	2140526	50
Bucharest	Romania	2106144	32
Minsk	Belarus	1982444	1
Hamburg	Germany	1930996	14
Vienna	Austria	1899055	22
Warsaw	Poland	1802237	30
Budapest	Hungary	1768073	32

Let us now add a column SB_Density as Starbucks Density.
This will calculate the number of people per Starbucks. The higher, the better for our study!

City	Country	Officialpopulation	StarbucksStoresCount	SB_Density
Nizhny Novgorod	Russia	1259013	0	inf
Saint Petersburg	Russia	5383890	0	inf
Perm	Russia	1051583	0	inf
Ufa	Russia	1121429	0	inf
Kiev	Ukraine	2950800	1	2.950800e+06
Minsk	Belarus	1982444	1	1.982444e+06
Kharkiv	Ukraine	1451132	1	1.451132e+06
Rome	Italy	2844750	2	1.422375e+06
Tekirdağ	Turkey	1055412	1	1.055412e+06
Volgograd	Russia	1013533	1	1.013533e+06
Voronezh	Russia	1054537	2	5.272685e+05
Odessa	Ukraine	1011494	2	5.057470e+05
Belgrade	Serbia	1397939	3	4.659797e+05
Samara	Russia	1170910	3	3.903033e+05
Istanbul	Turkey	15519267	50	3.103853e+05
Moscow	Russia	12615279	50	2.523056e+05
Kazan	Russia	1243500	5	2.487000e+05
London	United Kingdom	9126366	50	1.825273e+05
Milan	Italy	1390434	8	1.738042e+05
Berlin	Germany	3748148	22	1.703704e+05
Rostov-on-Don	Russia	1119875	7	1.599821e+05
Sofia	Bulgaria	1238438	8	1.548048e+05
Hamburg	Germany	1930996	14	1.379283e+05
Cologne	Germany	1085664	8	1.357080e+05
Munich	Germany	1471508	17	8.655929e+04

A few observations on these results:

- Russia, Ukraine and Belarus all look like promising markets. Starbucks are already successful in Moscow and many other populous cities could be good locations for a new store. However, the alphabet being different, it would be difficult to do the next part of this project (with some neighbourhoods spelt in Cyrillic!).

- Italy is a peculiar case, with 2 cities (Roma, Milan) in our top 25. It may sound astonishing that Starbucks has not already taken over this market, but in fact the coffee culture is very traditional and deeply rooted in Italy. This Forbes Article[3] is a good read. Still, Starbucks is not only about coffee, the lifestyle experience is equally important, as proves the recent store addition in Milan!

- Germany is another country with a reasonably small density of Starbucks stores!

- SB_Density for cities with more than 50 stores are naturally wrong, because of the API results limit.

Rome therefore looks like a good place to build a new store!

3.2. Finding the City with the Most Stores

The number of results limit from the API is quite annoying for this point, but a quick Google Search[4] shows that London has the most Starbucks stores.

The best method would have been to simply count the number of stores in the results of the API query.

3.3. Finding the Most Popular Starbucks & Reference Neighbourhood

Let us explore the centre of London and try to find the most popular Starbucks!

Name	Address	Postcode	City
Starbucks	1-3 Villiers street	WC2N 6NN	London
Starbucks	10 Kingsway, Unit B2; St Catherines House	WC2B 6LH	London
Starbucks	Charing Cross Road, Unit 1 129-133	WC2H 0EA	London
Starbucks	10 Russell Street	WC2B 5HZ	London
Starbucks	112 - 116 New Oxford Street	WC1A 1HH	Bloomsbury

3.4. Finding the Best Rated Store in London and Study its Neighbourhood

[3] https://www.forbes.com/sites/jennawang/2018/09/13/why-it-took-starbucks-47-years-to-open-a-store-in-italy/
[4] https://www.newstatesman.com/jonn-elledge/2014/05/london-has-more-branches-starbucks-any-eu-country

We can get the rating of each store in Central London by using Foursquare API and sort the results by descending order.

Name	Address	Rating	Likes
Starbucks	52 Berkeley St.	7.3	186
Starbucks	10 Kingsway, Unit B2; St Catherines House	7.3	70
Starbucks	27 Berkeley St	7.1	96
Starbucks	34 Great Marlborough St, (Carnaby Street)	7.0	108
Starbucks	6A Vigo Street, London	7.0	380

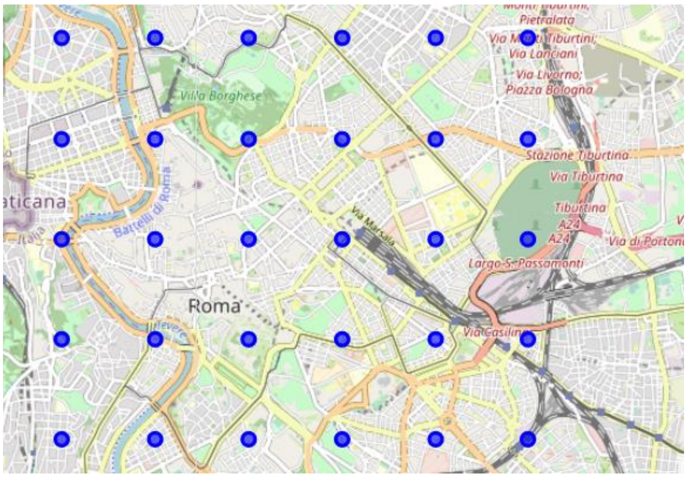
We have 2 winners! However, the first one has more likes, so it sounds like a good place to start from.

52 Berkeley St. is the reference location for the remainder of this battle.

3.5. Studying Neighbourhoods in Rome

I could not find a list of Rome neighbourhoods along with GPS coordinates, so I created my own using Folium.

I fine-tuned my grid until I was visually happy with the point positions. I wanted them to cover most of the city centre.



Each of these neighbourhoods is given a name from R0 to R29.

At this latitude and for 1/110 deg of latitude and 1/80 deg of longitude, 1 grid step is approximately 1000m.[5]

[5] http://www.csgnetwork.com/degreelenllavcalc.html

A function was defined to extract all venues within 700m radius of each of these neighbourhood centres, including the reference London neighbourhood.

The first elements are shown below:

Neigh.	Venue	Venue Latitude	Venue Longitude	Venue Category
London	The Ritz London	51.507078	-0.141627	Hotel
London	Novikov	51.507767	-0.142850	Asian Restaurant
London	Brown's Hotel	51.509127	-0.142077	Hotel
London	Burger & Lobster	51.507118	-0.145477	Seafood Restaurant
London	Prada	51.508998	-0.140959	Boutique

To characterize each neighbourhood, we used one-hot encoding and calculated the frequency of each venue category.

Ideally, I would need to spend a lot of time post-treating this data in order to have better groups of venues. I have only so much time, so I simply grouped together restaurants, bars, etc. There are still 114 categories at the end, so quite a lot...

The top 5 venues for the first 5 neighbourhoods of our list:

```
----London----
venue  freq
0     Store  0.17
1       Art  0.09
2  Boutique  0.05
3     Hotel  0.05
4    Lounge  0.04


----R0----
venue  freq
0        Hotel  0.09
1        Plaza  0.06
2       Winery  0.06
3  Pizza Place  0.06
4         Café  0.06


----R1----
venue  freq
0              Plaza  0.09
1     Ice Cream Shop  0.07
2              Hotel  0.07
3               Café  0.07
4  Trattoria/Osteria  0.05


----R10----
venue  freq
0              Hotel  0.10
1     Ice Cream Shop  0.07
2        Pizza Place  0.07
3    Bed & Breakfast  0.05
4  Trattoria/Osteria  0.05
```

```
----R11----
venue  freq
0     Pizza Place  0.19
1            Café  0.07
2          Bistro  0.05
3           Plaza  0.05
4  Ice Cream Shop  0.05
```

A proper classification of the venues would be necessary to improve the accuracy of the correlation between neighbourhoods.

I have done a first step but for example perhaps not all Restaurants are equal! For now, I am happy with this.

3.6. Similarity between Neighbourhoods

Let us assume that we did all the necessary work to properly classify venues of the same type.

We can now calculate the correlation between our London reference neighbourhood and each Rome neighbourhood. I will use Pearson correlation for this task.

The results are sorted by descending correlation score:

Neighbourhood	Correlation	Latitude	Longitude
London	1.000000	51.507442	-0.142527
R20	0.448627	41.909093	12.487500
R19	0.435693	41.909093	12.475000
R15	0.408138	41.900002	12.500000
R28	0.326147	41.918184	12.512500

Naturally, correlation of London with itself is 1. We also found that R20, R19 and R15 are all plausible location for a new Starbucks store!

Let us map these places in Rome.

4. Results

Let us plot the location of the 3 suggested locations for a new Starbucks Store in Rome.

Looking back at the typical venues of each neighbourhood, the main common point between our London "reference" neighbourhood is the high presence of hotels, restaurant and cafes.

Interestingly, Termini Station comes as a potential location (R15), which is a major transportation hub of the city. In fact, the only "Starbucks" location that the Foursquare API search query returned for Rome is located inside Termini station. It is not a licensed Starbucks store but very much looks like it. This is a good sign that this algorithm has not completely lost it!

The other 2 are essentially next to Villa Borghese park. R19 is next to the river. I would certainly enjoy a coffee in either place!

5. Discussion

There are several ways this analysis could be improved.

Because of time and resources limitations, I have taken certain shortcuts, but I believe the method would still apply.

Major improvements would consist in:

- An up to date list of current Starbucks locations, including coordinates and sales volume. This would certainly be available as an employee of the company.

- Not limiting the study to European countries. In a situation where Starbucks wanted to expand to areas where alphabet/culture can be challenging to non-locals, the best would be to have local offices able to carry out this job.

- Improving the queries to the API and sorting the request results better. This is as time consuming as necessary to get good quality data. Still the results are far from illogical.

6. Conclusion

As a new data scientist for Starbucks, the mission was to find the best location to open a new store. To do so, I have:

- Determined which cities in Europe have the fewest stores per inhabitant. I decided to focus on Rome.
- Chosen a neighbourhood where Starbucks is highly present, with a high user rating. The store is in London.
- Searched venues in Rome and near the reference store in London and worked out the similarity between all those neighbourhoods.

I have determined that 3 specific locations in Rome were similar to the neighbourhood in London where one of the most popular Starbucks stores in Europe is located. This result is a good point to start from.

Next step would be to verify if customers would be likely to visit these new locations.