Applied Data Science Capstone by IBM/Coursera

The Battle of the Neighborhoods Week 2

Where to buy a flat for Airbnb in Budapest?

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Introduction: Business Problem

Background

Airbnb, the worldwide online marketplace for hospitality services, is getting more and more popular. In the Hungarian capital Budapest - where I currently live - the number of overnight stays reached almost 1.5 million in 2017, 35% more than 2016, according to a 2018 report by Colliers. (Colliers, 2018) In 2017 there were 42.5 thousand Airbnb accommodations in the city, almost as many as in hotels. (Jancsik, Michalkó, Csernyik, 2018) A lot of investors buy flats specifically to rent them as Airbnb accommodations. The rent for one flat is between 700 and 1000 USD per month. (Jancsik, Michalkó, Csernyik, 2018) However, it is very important that the flat has an excellent location that is attractive for tourists. In Budapest, the Airbnb letting market is mostly concentrated within the downtown area – District V, VI and VII – followed by districts VIII, IX, XIII and I. The top 3 neighborhoods account for 69% of the total Airbnb supply in Budapest. (Colliers, 2018)

Problem

Let's imagine that an investor wants to buy a flat to rent it as Airbnb. What is the right location for such a flat? It should be in one of those neighborhoods where there are lots of tourist attractions, bars, restaurants and other venues that are attractive for tourists, because if it is too far away from these places of interest, they will not rent it. However, housing prices should also be considered. In the inner city, average housing prices are much higher, and the investment might not pay off. The goal of this project is to find the best neighborhoods in Budapest to buy a flat for Airbnb based on the nearby venues of interest and housing prices.

Interest

The results can be useful for any investor who wants to buy a flat in Budapest to rent as an Airbnb accommodation. The Budapest Airbnb market is driven by professional operators who own multiple accommodations. Around 65% of listings are offered by hosts that have at least two listings, which is much higher than the 40-50% average multi- listers ratio across most other European cities. Around 31% of listings are offered by a host that offers 3-10 accommodations while in the 10+ category it is 19.5%. (Colliers, 2018) However, there are also small investors who rent only one apartment.

Data

To determine which neighborhoods are the most suitable for Airbnb flats, I will take two main factors into consideration: places of interest in the neighborhood and average housing prices.

Neighborhood candidates

First, we need the data of the potential neighborhoods. Budapest has 23 districts numbered from I to XXIII. According to the Colliers report, the Airbnb room demand is concentrated within the downtown area and is insignificant in the rest of the districts, so I work only with districts I, V, VI, VII, VIII, IX and XIII. In these 7 districts there are 17 neighborhoods. I got their data from Wikipedia (https://hu.wikipedia.org/wiki/Budapest_v%C3%A1rosr%C3%A9szeinek_list%C3%A1ja), including their coordinates, because the Python Geocoder package was very unreliable. The latitudes and longitudes are all on the separate Wikipedia pages of the neighborhoods, so it could not be scraped, however, I already had the necessary data in csv format, so I uploaded the it to my Capstone Project in IBM Watson Studio, and inserted it into a Pandas dataframe.

	District	Neighborhood	Latitude	Longitude
0	I.	Tabán	47.491667	19.040833
1	I.	Vár	47.501667	19.033333
2	I.	Gellérthegy	47.486667	19.045556
3	I.	Krisztinaváros	47.496806	19.031933
4	V.	Belváros	47.492397	19.053314
5	V.	Lipótváros	47.502500	19.050833
6	VI.	Terézváros	47.509667	19.069833
7	VII.	Erzsébetváros	47.500556	19.068725
8	VIII.	Corvin-negyed	47.486991	19.073339
9	VIII.	Magdolnanegyed	47.491500	19.084200
10	VIII.	Orczynegyed	47.483424	19.090569
11	VIII.	Palotanegyed	47.491667	19.066667
12	VIII.	Tisztviselőtelep	47.481667	19.096864
13	IX.	Ferencváros	47.466667	19.083333
14	XIII.	Angyalföld	47.516667	19.060000
15	XIII.	Újlipótváros	47.518611	19.054167
16	XIII.	Vizafogó	47.535556	19.061944

Table 1: Neighborhood candidates with latitudes and longitudes

On the following map we can see our neighborhood candidates.

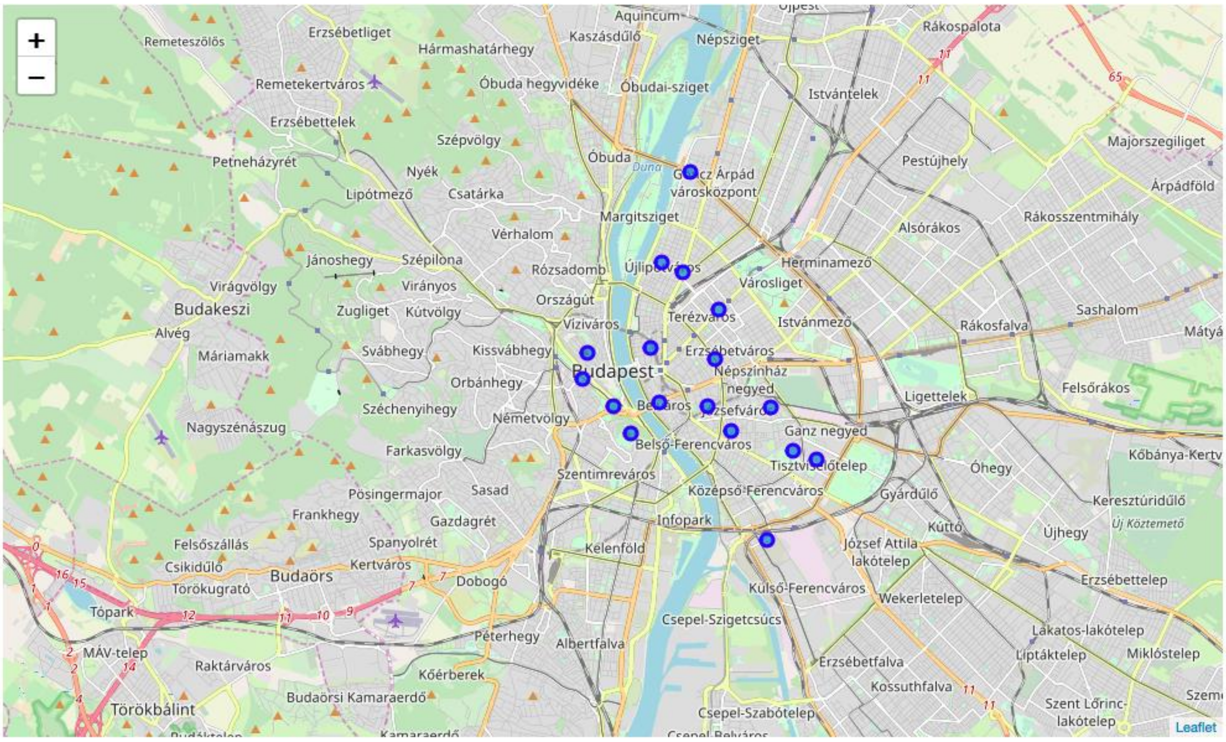

Figure 1: Neighborhood candidates

Housing prices

The second group of data we need is the average housing price in each potential borough. I found the average price in Hungarian Forint / m2 in each neighborhood on the website https://www.ingatlannet.hu/statisztika/Budapest. Again, the necessary values were on separate pages, so I had to write them manually into a csv file, which I uploaded to my project on IBM Watson Studio and inserted into the code as a Pandas dataframe.

	District	Neighborhood	Average price HUF/m2
0	I.	Tabán	970833
1	I.	Vár	916666
2	I.	Gellérthegy	1406771
3	I.	Krisztinaváros	1029796
4	V.	Belváros	2331877
5	V.	Lipótváros	1196756
6	VI.	Terézváros	988124
7	VII.	Erzsébetváros	846815
8	VIII.	Corvin-negyed	695030
9	VIII.	Magdolnanegyed	580193
10	VIII.	Orczy-negyed	615275
11	VIII.	Palotanegyed	776259
12	VIII.	Tisztviselőtelep	857984
13	IX.	Ferencváros	891986
14	XIII.	Angyalföld	797515
15	XIII.	Újlipótváros	908285
16	XIII.	Vizafogó	707204

Table 2: Housing prices in our candidate neighborhoods

Nearby venues

Finally, our last data source is the Foursquare API, which can give us the venues of interest in each candidate neighborhood. I requested the top 100 venues in each neighborhood within a radius of 500 meters and created a dataframe.

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Tabán	47.491667	19.040833	Oxygen Wellness Naphegy	47.491025	19.037900	Gym / Fitness Center
1	Tabán	47.491667	19.040833	Asztalka	47.492193	19.044231	Dessert Shop
2	Tabán	47.491667	19.040833	Filozófusok kertje	47.489381	19.039051	Sculpture Garden
3	Tabán	47.491667	19.040833	Várkert	47.493569	19.041017	Park
4	Tabán	47.491667	19.040833	Picnic	47.491330	19.044697	Café

Table 3: The head of the venues dataframe

As I am planning to use k-means clustering later, I wanted to know the most frequent venue categories in each neighborhood. I used one hot encoding for the venue categories, then grouped rows by neighborhood and took the mean of the frequency of occurrence of each category. After that, I created a function to sort the venues in descending order and made a new dataframe that displays the ten most frequent venue categories for ach neighborhood. We can use this information for clustering in the next section.

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Angyalföld	Clothing Store	Cosmetics Shop	Electronics Store	Pharmacy	Bar	Women's Store	Chinese Restaurant	Café	Bus Stop	Diner
1	Belváros	Coffee Shop	Café	Hotel	Hungarian Restaurant	Italian Restaurant	Plaza	Eastern European Restaurant	Dessert Shop	Theater	Restaurant
2	Corvin-negyed	Hotel	Dessert Shop	Bakery	Clothing Store	Beer Bar	Coffee Shop	Plaza	Italian Restaurant	Wine Bar	Electronics Store
3	Erzsébetváros	Hotel	Coffee Shop	Hungarian Restaurant	Restaurant	Bar	Burger Joint	Beer Bar	Dessert Shop	Indian Restaurant	Bistro
4	Ferencváros	Music Venue	Fast Food Restaurant	Playground	Gym / Fitness Center	Diner	Cosmetics Shop	Office	Mobile Phone Shop	Café	Fried Chicken Joint

Table 4: The head of the most common venue categories dataframe

Now we have all the data we need to find out which Budapest neighborhood wins the battle of the neighborhoods for being the best Airbnb location.

Methodology

Clustering

How can we use our data to determine which neighborhood is the best location for an Airbnb flat? It would help us to divide the neighborhoods into clusters based on the types of venues. I ran k-means clustering to cluster the neighborhoods into four categories based on the most common venue categories in each neighborhood.

On the map below, we can see that most neighborhoods belong to the second cluster, which covers the inner city of Budapest. The most common venues here are cafés, hotels, restaurant - those places tourists are usually interested in. This cluster seems like a good place to rent an Airbnb. However, there are a lot of neighborhoods in this cluster. How do we choose the best ones?

To get a clearer result, we can look at some other characteristics of the neighborhoods: the number of "tourist venues" in the neighborhood and the average housing prices in the neighborhood.

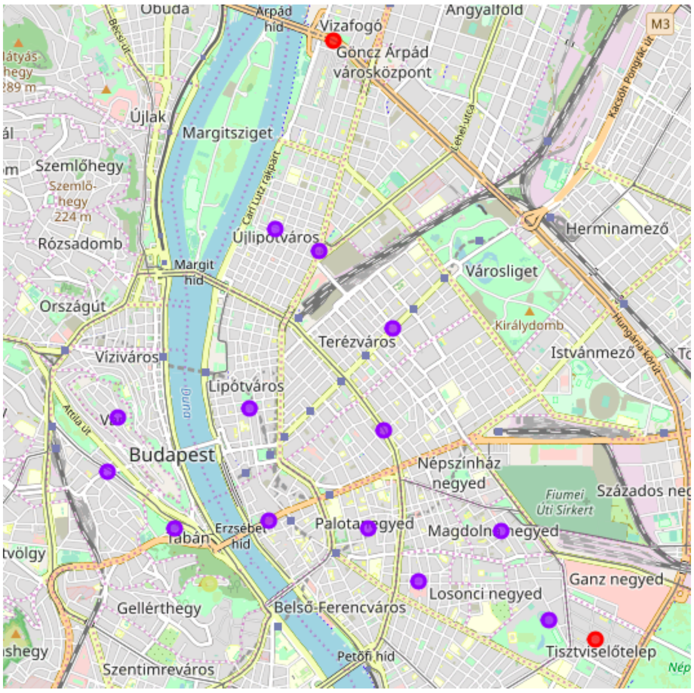

Figure 2: Neighborhood clusters

Categories of interest and housing prices

People who rent an Airbnb flat typically want to visit specific types of venues, and they are likely to choose an accommodation that is close to these places, in a vibrant neighborhood. Tourists are most likely to visit restaurants, bars, different tourist attractions and other entertainment facilities, and are not likely to visit stores or playgrounds. It seems like a good idea to filter which venue categories are attractive for tourists and see how many of these interesting venues each neighborhood has.

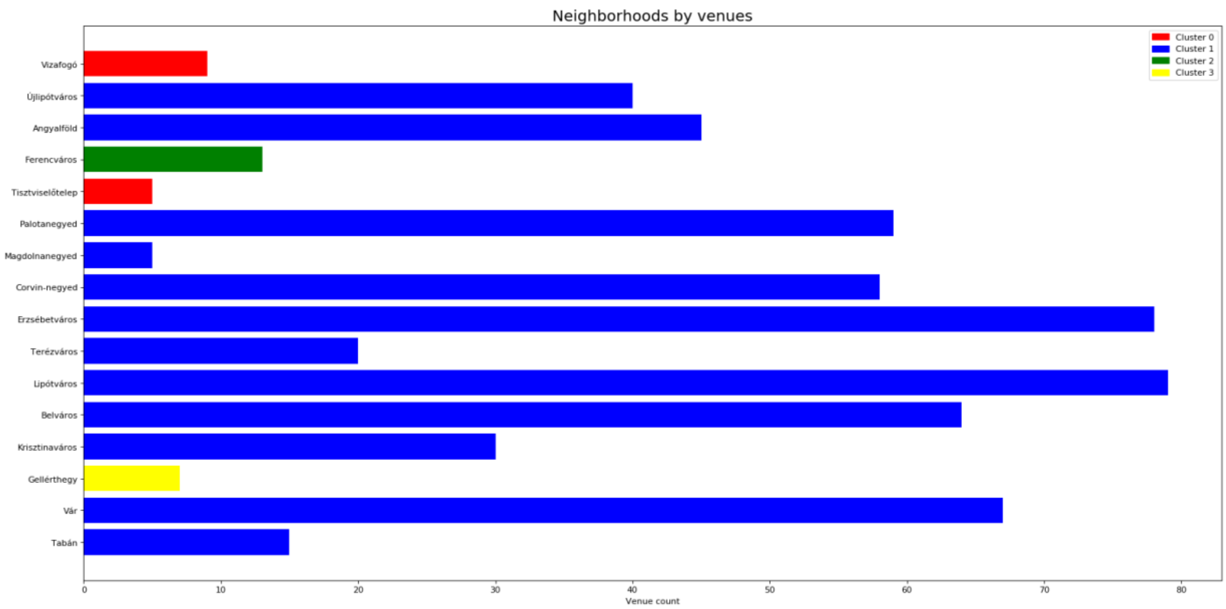

Figure 3: Number of interesting venues in each neighborhood

We can see that the neighborhoods Lipótváros and Erzsébetváros have the most venues that tourists typically seek.

Now let’s see the average housing prices!

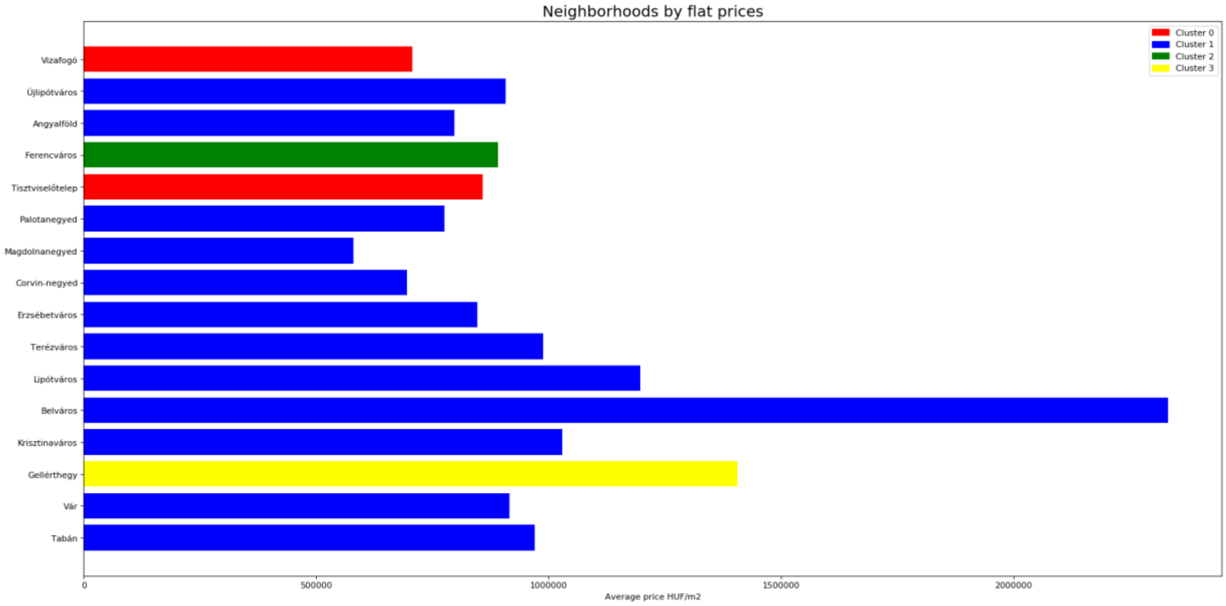

Figure 4: Average housing prices in each neighborhood

We can see that there are huge differences between the housing prices. The neighborhood Belváros is by far the most expensive, this is the city center where there are very few flats and most of them are luxury penthouses. The cheapest one is Magdolnanegyed, but we have seen that this is more of a residential neighborhood with very few interesting venues.

It is useful to see both the venue counts and the housing prices together to be able to choose the neighborhoods that are ideal in both aspects. On the bubble chart below the x axis shows the number of venues, the y axis is the average housing price, and the color of the bubbles represent the cluster the neighborhood belongs to.

Now we can see which neighborhoods are strong in both dimensions. We need those neighborhoods where there are a lot of interesting venues, but the housing prices are quite low – these are located in the lower right corner of the chart.

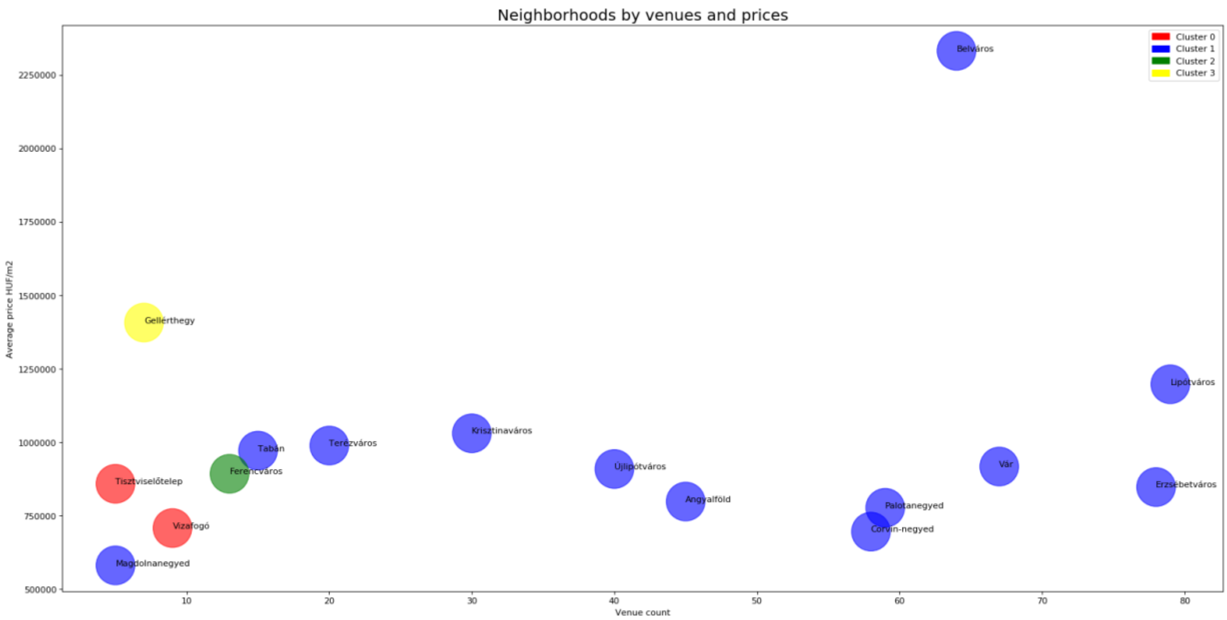

Figure 5: Number of interesting venues, average housing prices and clusters of each neighborhood

Results

We can finally determine which neighborhoods are the best locations for Airbnb flats and announce **the winners of the battle of neighborhoods: Erzsébetváros and Lipótváros**.

Figure 6: A bar in the neighborhood Erzsébetváros

Figure 7: A street in Lipótváros

Discussion

The neighborhoods Erzsébetváros and Lipótváros are the locations I would most recommend investors to buy a flat.
This result seems correct, as this is the area that is referred to as the "Party District" by locals. With its countless bars, cafés and restaurants, it is the most popular spot for young people.

For further research, it would be interesting to analyze not only the categories, but also the ratings and typical guests of the venues, so that we could determine which customer segments (demographic groups etc.) favor these places.

Conclusion

In this project I used data from the Foursquare API and average housing prices to find the best neighborhoods in Budapest to buy a flat for Airbnb. I used k-means clustering to divide the neighborhoods into four clusters, then compared them based on the nearby venues of interest and housing prices. I concluded that the best neighborhoods for an investor to buy a flat are Erzsébetváros and Lipótváros.

References

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