Kyiv's Best Locations Analysis for a New Venue Opening

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1. Description and Discussion of the Background

Kyiv, a capital of Ukraine is middle-sized European city with population of about 3 mln. people and average population density of 3 299 people per square kilometer. There are 10 Administrative Divisions in Kyiv that we'll consider.

For last several years, Kyiv HoReCa segment has been growing very fast. Currently Kyiv central areas are fulfilled with restaurants and coffeeshops, new venues are to be opened every day, so the market in general is still in positive dynamics.

At the same time, residential areas far from city center are yet feel the lack of the venues to socialize and have a rest. An entrance level to open a new restaurant there is still rather low instead of city center with its uprising rent rates and high concentration of venues.

Therefore, to find a proper location with low rent and a stable flow of consumers in the non-center Boroughs with the highest development potential is a question to define in a further research. To make a decision on the location of a new venue to be opened the vendor has to consider all the aspects of surrounding environment – rent rates, neighborhood population density, demographics, nearby venues and sightseeing.

So, our analysis is addressed to the vendors looking for the best locations to open a new venue – restaurant or coffee shop.

2. Data Description

To solve the problem we have to explore the Boroughs using open data sources:

- Administrative Divisions of Kyiv city downloaded from Github. The .json file has coordinates of all Kyiv districts (Boroughs). In further we'll use it to create a choropleth map of Kyiv property values.
- Forsquare API to get the venues (restaurants and coffee shops in particular) of given Kyiv Boroughs.
- Actual Kyiv primary commercial property market prices from realt.ua - average for each Borough – for the lack of affordable online information on commercial property rent rates, we'll use it to create a choropleth map of Kyiv commercial property values.
- Previously prepared and downloaded xslx. file to get the center coordinates of the each Borough.

- Kyiv Wikipedia page to get data on Boroughs population density.

3. Methodology

My master Data Frame consist of all necessary data grabbed from different sources and joint together in the columns:

- Borough
- Population Density
- Commercial Property Price

```
141]: Kyiv_com_prop
```

141]:

	Distr	District	Price UAH per sq m	Density(people on 1 km^2)
0	Holosiivskyi district	Holosiivskyi	26876	1301
1	Darnytskyi district	Darnytskyi	17913	2107
2	Desnianskyi district	Desnianskyi	30000	2272
3	Obolonskyi district	Obolonskyi	15360	2783
4	Pecherskyi district	Pecherskyi	52940	6556
5	Podilskyi district	Podilskyi	28764	5307
6	Dniprovskyi district	Dniprovskyi	82180	4950
7	Shevchenkivskyi district	Shevchenkivskyi	21600	8786
8	Solomianskyi district	Solomianskyi	15343	7195
9	Sviatoshynskyi district	Sviatoshynskyi	32200	3062

Then I used **python folium** to visualize boroughs of Kyiv to superimpose the rest of data in further steps.

I utilized the Foursquare API to explore the boroughs and segment them. I set by default limit as **100 venues** and the radius **1000 meter** for each borough from their given latitude and longitude informations. Here is a head of the list Venues name, category, latitude and longitude informations from Forsquare API.

```
[107]: #Let's check the size of the resulting dataframe
print(kyiv_venues.shape)
kyiv_venues.head()

(869, 7)
```

[107]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Holosiivskyi	50.402778	30.515278	Biblecoffee	50.403717	30.514421	Coffee Shop
1	Holosiivskyi	50.402778	30.515278	Закарпатський & Ko	50.402728	30.515700	West-Ukrainian Restaurant
2	Holosiivskyi	50.402778	30.515278	I Love Sport	50.402141	30.517561	Gym / Fitness Center
3	Holosiivskyi	50.402778	30.515278	OKwine	50.400648	30.520036	Wine Shop
4	Holosiivskyi	50.402778	30.515278	Home Cafe	50.400455	30.520258	Café

Summary there were **869** venues returned by Foursquare. Here is a head of data frame of boroughs and venues.

Than I noticed that just 4 of the Boroughs have reached the **100** limit of venues – Darnytskyi, Dniprovskyi, Obolonskyi, Podilskyi in particular. Svyatoshynskyi has less than 50 venues.

The result doesn't mean that inquiry run all the possible results in boroughs. Actually, it depends on given Latitude and Longitude informations and here we just run single Latitude and Longitude pair for each borough.

In summary of this graph **201** unique categories were returned by Foursquare, then I created a table which shows list of top 10 venue category for each borough in below table.

8]:

	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	Darnytskyi	Coffee Shop	Gym / Fitness Center	Gym	Boutique	Italian Restaurant	Pharmacy	Hookah Bar	Middle Eastern Restaurant	Caucasian Restaurant	Pizza Place
1	Desnianskyi	Coffee Shop	Clothing Store	Park	Cosmetics Shop	Pizza Place	Supermarket	Sushi Restaurant	Movie Theater	Shopping Mall	Sculpture Garden
2	Dniprovskyi	Coffee Shop	Dance Studio	Restaurant	Café	Salon / Barbershop	Gym / Fitness Center	Caucasian Restaurant	Vegetarian / Vegan Restaurant	Dessert Shop	Arcade
3	Holosiivskyi	Coffee Shop	Café	Salon / Barbershop	Dance Studio	Gym	Pharmacy	Bus Stop	Beer Store	Gym / Fitness Center	Playground
4	Obolonskyi	Coffee Shop	Health & Beauty Service	Gym	Gym / Fitness Center	Bakery	Clothing Store	Pizza Place	Café	Supermarket	Dance Studio
5	Pecherskyi	Coffee Shop	Park	Café	Bakery	Spa	Gym	Caucasian Restaurant	Health & Beauty Service	Garden	Dance Studio
6	Podilskyi	Coffee Shop	Escape Room	Nightclub	Gym / Fitness Center	Art Gallery	Café	Hotel	Music Venue	Electronics Store	Seafood Restaurant
7	Shevchenkivskyi	Coffee Shop	Beach	Ukrainian Restaurant	Cosmetics Shop	Park	Soccer Field	Health & Beauty Service	Tea Room	Pet Store	Gym / Fitness Center
8	Solomianskyi	Coffee Shop	Park	Eastern European Restaurant	Restaurant	Café	Pet Store	Pizza Place	Italian Restaurant	Furniture / Home Store	Gym
9	Sviatoshynskyi	Coffee Shop	Park	Gym	Pizza Place	Convenience Store	Cosmetics Shop	Bus Stop	Café	Restaurant	Plaza

We have some common venue categories in boroughs. In this reason I used unsupervised learning **K-means algorithm** to cluster the boroughs. K-Means algorithm is one of the most common cluster method of unsupervised learning.

I run K-Means to cluster the boroughs into 3 and 4 numbers, therefore the best results were received with 4 clusters.

Here is my resulting data frame with cluster labels for each borough.

	Distr	lat	lon	Cluster Labels	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	9 C
0	Holosiivskyi	50.402778	30.515278	0	Coffee Shop	Café	Salon / Barbershop	Dance Studio	Gym	Pharmacy	Bus Stop	Beer Store	
1	Darnytskyi	50.406111	30.626667	0	Coffee Shop	Gym / Fitness Center	Gym	Boutique	Italian Restaurant	Pharmacy	Hookah Bar	Middle Eastern Restaurant	C Re
2	Desnianskyi	50.510000	30.604167	1	Coffee Shop	Clothing Store	Park	Cosmetics Shop	Pizza Place	Supermarket	Sushi Restaurant	Movie Theater	S
3	Obolonskyi	50.505528	30.499278	0	Coffee Shop	Health & Beauty Service	Gym	Gym / Fitness Center	Bakery	Clothing Store	Pizza Place	Café	Supe
4	Pecherskyi	50.420556	30.549444	0	Coffee Shop	Park	Café	Bakery	Spa	Gym	Caucasian Restaurant	Health & Beauty Service	
5	Podilskyi	50.473889	30.501944	2	Coffee Shop	Escape Room	Nightclub	Gym / Fitness Center	Art Gallery	Café	Hotel	Music Venue	Ele
6	Dniprovskyi	50.450000	30.487333	0	Coffee Shop	Dance Studio	Restaurant	Café	Salon / Barbershop	Gym / Fitness Center	Caucasian Restaurant	Vegetarian / Vegan Restaurant	

After having analyzed the data frame, we can label each cluster based on first 10 most common venues as follow:

- Cluster 0 : “Socializing and leisure” with coffee shops and restaurants as a dominating venues
- Cluster 1 : “Residential area” within shops and supermarkets as a dominating venues
- Cluster 2 : “Culture and entertainment area” within high concentration of clubs and music venues

We can also examine the level of average commercial property sales prices in different boroughs.

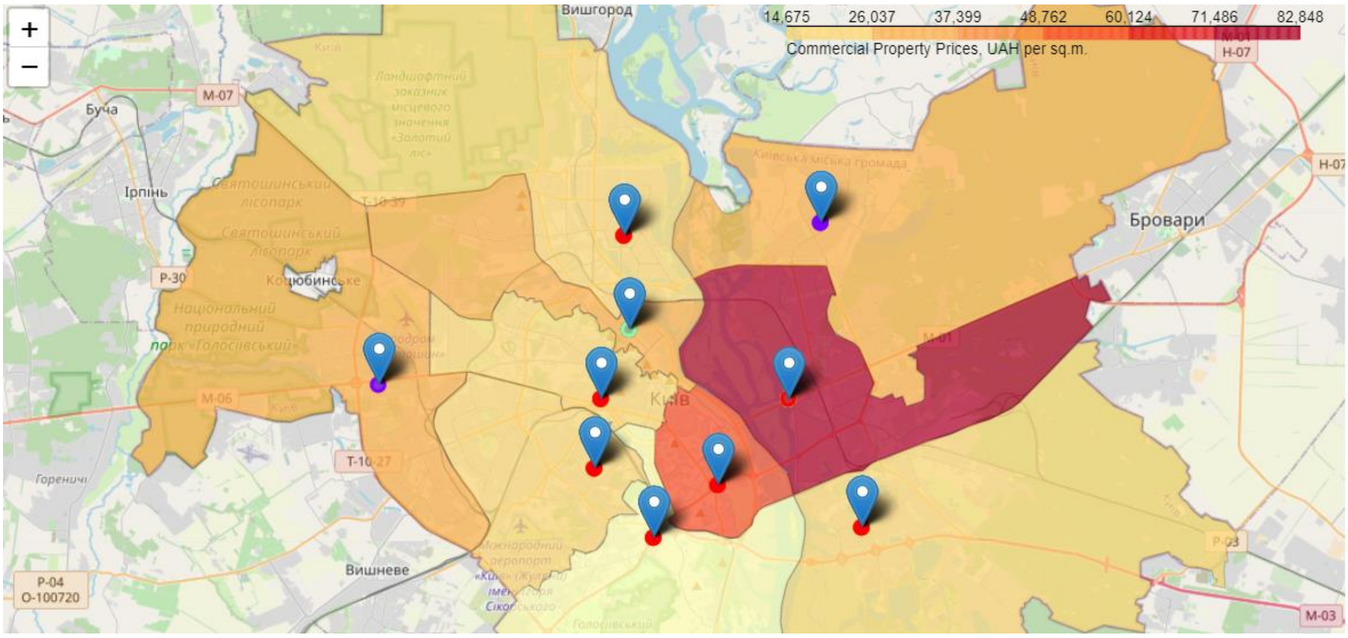
As it looks at choropleth map, we can define the ranges as below:

- Less than 37399 UAH per sq. m. – Low Level
- 37399 – 48762 UAH per sq. m. – Lower Medium Level
- 48762 – 60124 UAH per sq. m. – Medium Level
- 60124 – 71486 UAH per sq. m. Upper Medium Level
- more than 71486 UAH per sq. m. – High Level

4. Results

As a result of above research we received a clustered map of Kyiv boroughs with choropleth layer added visualizing the average commercial property sale prices. The map consists of follow information for each borough:

- Borough name
- Cluster name,
- Housing Sales Price (HSP) Levels



5. Discussion

As it was mentioned before, Kyiv is a medium sized European city with an average high population density that may vary for each Borough and therefore very different approaches can be tried in clustering and classification studies.

Due to a limited number of venues returned by Foursquare API the resulting data frame of venues didn`t depict all the possible variability of the Borough as I supposed. For more detailed and accurate guidance, the data frame would be expanded and the extra details of the borough’s social and culture environment can be drilled as well.

I also performed data analysis through this information by adding the coordinates of districts and home sales price averages as static data on GitHub. In future studies, these data can also be accessed dynamically from specific platforms or packages.

I concluded my research by visualizing the data and clustering information on the Kyiv map. In future studies, other types of user interfaces would be carried out to the vendors.

6. Conclusion

While working on the project I felt an unexpected lack of classified information in the open data sources on Kyiv city environment, as well as very poor level of customized online tools to analyze it.

The results of my project could be just a small part of further research to be done and settled as an open source platform performing analysis and providing structured information for interested vendors.

For this reason, vendors would be rather interested in having access to the platforms where such information is provided, and achieve better outcomes through it.

As well urban research organizations are another interested body to perform and utilize such a platform in their activities.