BEST LOCATION FOR A CHINESE FOOD RESTAURANT

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1 Introduction

This project aims to find an optimal place to locate a Chinese food restaurant in Bogota, preferably close to Simon Bolivar Park. However, a site is being sought where the competition is as low as possible and for this it is required to analyze which places do not have nearby Chinese restaurants and if possible close to Simon Bolivar Park.

To find this location, data science tools will be used to find nearby neighborhoods based on the criteria of having little commercial competition and in the end determine a list of possible places with the best possible location.

2 Data

Based on the definition of the problem, the decision factors will be:

- Number of restaurants in the neighborhood
- Quantity and distance from Chinese food restaurants, if any.
- Distance to Simon Bolivar Park

The data will be taken from:

- centers of candidate areas will be generated algorithmically and approximate addresses of centers of those areas will be obtained using Google Maps API reverse geocoding
- number of restaurants and their type and location in every neighborhood will be obtained using Foursquare API
- coordinate of Simon Bolivar will be obtained using Google Maps API geocoding or Foursquare API
- coordinate of the polygons of the localities will be obtained using data of https://bogota-laburbano.opendatasoft.com/

3 Development

Let's create latitude & longitude coordinates for centroids of our candidate neighborhoods. We will create a grid of cells covering our area of interest which is aprox. 4x4 killometers centered around Parque Simon Bolivar Bogota.

Let's first find the latitude & longitude of Simon Bolivar Park

In [3]:
```
address = 'parque simon bolivar Bogota'

geolocator = Nominatim(user_agent="foursquare_agent")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print(latitude, longitude)
```

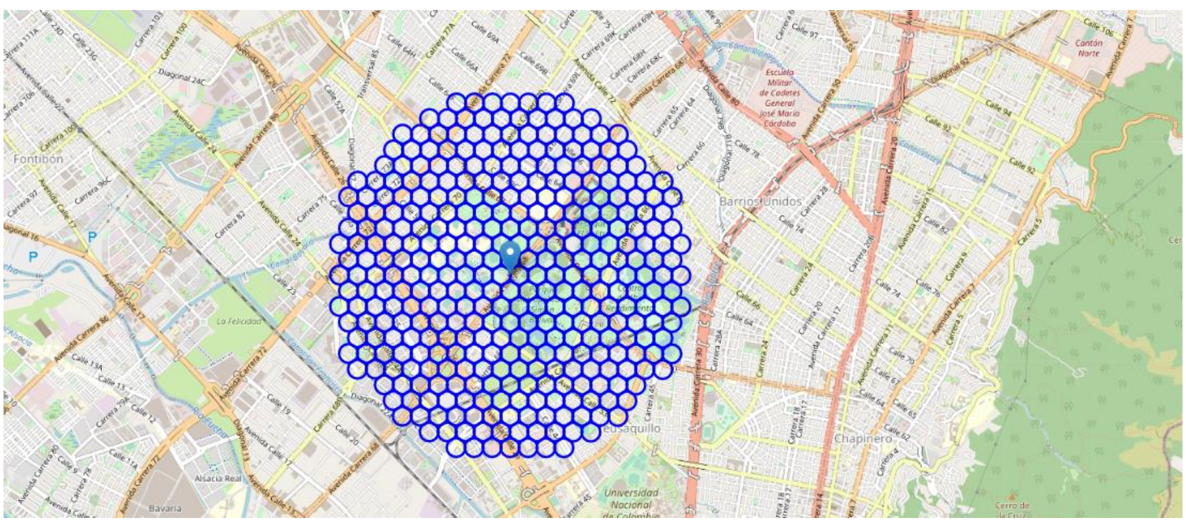
```
4.6616218 -74.0973687
```

In [4]:
```
point_center=[location.latitude,location.longitude]
point_center
```

Out[4]:
```
[4.6616218, -74.0973687]
```

Now let's create a grid of area candidates, equaly spaced, centered around city center and within ~2km from Simon Bolivar Park. Our neighborhoods will be defined as circular areas with a radius of 100 meters, so our neighborhood centers will be 200 meters apart.

To accurately calculate distances we need to create our grid of locations in Cartesian 2D coordinate system which allows us to calculate distances in meters (not in latitude/longitude degrees). Then we'll project those coordinates back to latitude/longitude degrees to be shown on Folium map. So let's create functions to convert between WGS84 spherical coordinate system (latitude/longitude degrees) and UTM Cartesian coordinate system (X/Y coordinates in meters).



OK, we now have the coordinates of centers of neighborhoods/areas to be evaluated, equally spaced (distance from every point to it's neighbors is exactly the same) and within ~2km from Simon Bolivar Park.

Let's now use Google Maps API to get approximate addresses of those locations.

In [12]:

```
import pandas as pd

df_locations = pd.DataFrame({'Address': addresses,
                             'Latitude': latitudes,
                             'Longitude': longitudes,
                             'X': xs,
                             'Y': ys,
                             'Distance from center': distances_from_center})

df_locations.head(10)
```

Out[12]:

	Address	Latitude	Longitude	X	Y	Distance from center
0	Cl. 23a #59-72, Bogotá	4.644395	-74.102800	599514.340245	513419.512088	1997.498436
1	Cl. 24a #59-59, Bogotá	4.644392	-74.100997	599714.340245	513419.512088	1946.792233
2	Cl. 24a ##57, Bogotá	4.644390	-74.099194	599914.340245	513419.512088	1915.724406
3	Ac. 26 #54-94, Bogotá	4.644388	-74.097391	600114.340245	513419.512088	1905.255888
4	Cra. 54 #26-25, Bogotá	4.644385	-74.095588	600314.340245	513419.512088	1915.724406
5	Cra 45 #24b13, Bogotá	4.644383	-74.093785	600514.340245	513419.512088	1946.792233
6	Cl. 44 #53-54, Bogotá	4.644381	-74.091982	600714.340245	513419.512088	1997.498436
7	Carrera 7 #173-64, Cl. 22b #No. 66 – 46, Bogotá	4.645965	-74.105502	599214.340245	513592.717169	1951.922130
8	AV. Esperanza - AK 60, Bogotá	4.645962	-74.103699	599414.340245	513592.717169	1868.154169
9	Cl. 24a #60-49, Bogotá	4.645960	-74.101896	599614.340245	513592.717169	1802.775638

Now that we have our location candidates, let's use Foursquare API to get info on restaurants in each neighborhood.

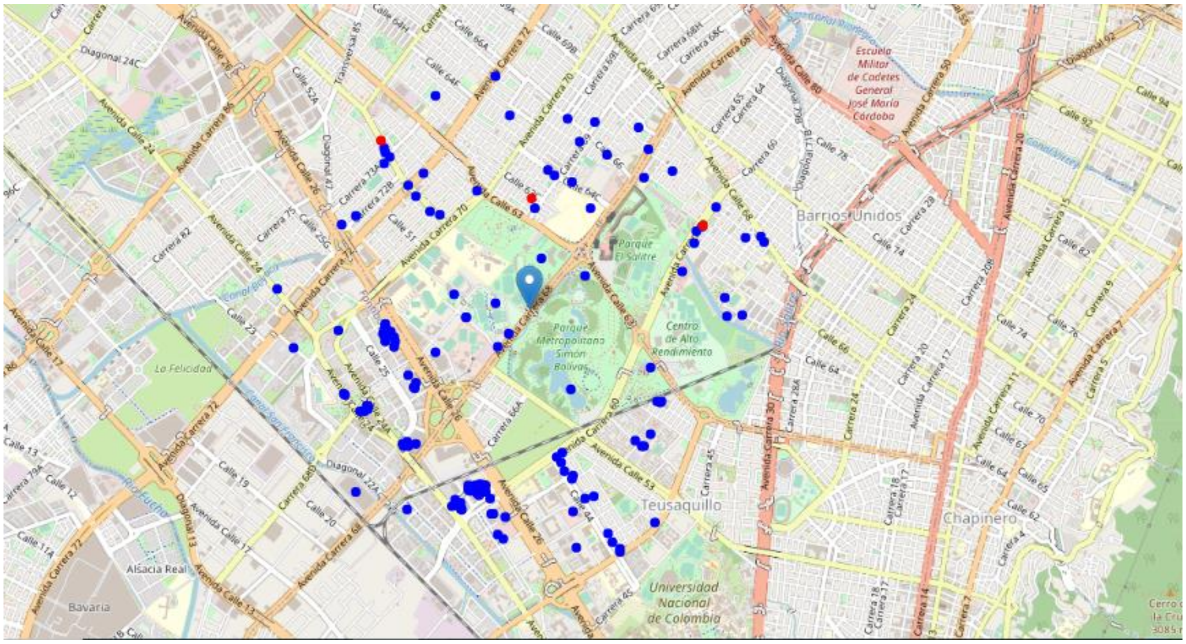
We're interested in venues in 'food' category, but only those that are proper restaurants - coffe shops, pizza places, bakeries etc. are not direct competitors so we don't care about those. So we will include in out list only venues that have 'restaurant' in category name, and we'll make sure to detect and include all the subcategories of specific 'Chinese restaurant' category, as we need info on Chinese restaurants in the neighborhood.

In [18]:

```
print('Total number of restaurants:', len(restaurants))
print('Total number of chinese restaurants:', len(chinese_restaurants))
print('Percentage of chinese restaurants: {:.2f}%'.format(len(chinese_restaurants) / len(restaurants) * 100))
print('Average number of restaurants in neighborhood:', np.array([len(r) for r in location_restaurants]).mean())
```

```
Total number of restaurants: 152
Total number of chinese restaurants: 5
Percentage of chinese restaurants: 3.29%
Average number of restaurants in neighborhood: 2.2225274725274726
```

Let's now see all the collected restaurants in our area of interest on map, and let's also show Chinese restaurants in different color.



Restaurants in área:

```
In [24]: location_restaurants_count = [len(res) for res in location_restaurants]

         df_locations['Restaurants in area'] = location_restaurants_count

         print('Average number of restaurants in every area with radius=100m:', np.array(location_restaurants_count).mean())

         df_locations.head(10)
```

```
Average number of restaurants in every area with radius=100m: 2.2225274725274726
```

Out[24]:

	Address	Latitude	Longitude	X	Y	Distance from center	Restaurants in area
0	Cl. 23a #59-72, Bogotá	4.644395	-74.102800	599514.340245	513419.512088	1997.498436	10
1	Cl. 24a #59-59, Bogotá	4.644392	-74.100997	599714.340245	513419.512088	1946.792233	8
2	Cl. 24a ##57, Bogotá	4.644390	-74.099194	599914.340245	513419.512088	1915.724406	4
3	Ac. 26 #54-94, Bogotá	4.644388	-74.097391	600114.340245	513419.512088	1905.255888	2
4	Cra. 54 #26-25, Bogotá	4.644385	-74.095588	600314.340245	513419.512088	1915.724406	1
5	Cra 45 #24b13, Bogotá	4.644383	-74.093785	600514.340245	513419.512088	1946.792233	3
6	Cl. 44 #53-54, Bogotá	4.644381	-74.091982	600714.340245	513419.512088	1997.498436	8
7	Carrera 7 #173-64, Cl. 22b #No. 66 – 46, Bogotá	4.645965	-74.105502	599214.340245	513592.717169	1951.922130	5
8	AV. Esperanza - AK 60, Bogotá	4.645962	-74.103699	599414.340245	513592.717169	1868.154169	15
9	Cl. 24a #60-49, Bogotá	4.645960	-74.101896	599614.340245	513592.717169	1802.775638	33

Restaurants Chinese in área:

In [26]:
```
df_locations.head(10)
```
Out[26]:

	Address	Latitude	Longitude	X	Y	Distance from center	Restaurants in area	Distance to Chinese restaurant
0	Cl. 23a #59-72, Bogotá	4.644395	-74.102800	599514.340245	513419.512088	1997.498436	10	224.998928
1	Cl. 24a #59-59, Bogotá	4.644392	-74.100997	599714.340245	513419.512088	1946.792233	8	312.836976
2	Cl. 24a ##57, Bogotá	4.644390	-74.099194	599914.340245	513419.512088	1915.724406	4	393.765426
3	Ac. 26 #54-94, Bogotá	4.644388	-74.097391	600114.340245	513419.512088	1905.255888	2	536.285325
4	Cra. 54 #26-25, Bogotá	4.644385	-74.095588	600314.340245	513419.512088	1915.724406	1	707.214740
5	Cra 45 #24b13, Bogotá	4.644383	-74.093785	600514.340245	513419.512088	1946.792233	3	890.338940
6	Cl. 44 #53-54, Bogotá	4.644381	-74.091982	600714.340245	513419.512088	1997.498436	8	1079.469391
7	Carrera 7 #173-64, Cl. 22b #No. 66 – 46, Bogotá	4.645965	-74.105502	599214.340245	513592.717169	1951.922130	5	286.481578
8	AV. Esperanza - AK 60, Bogotá	4.645962	-74.103699	599414.340245	513592.717169	1868.154169	15	96.509849
9	Cl. 24a #60-49, Bogotá	4.645960	-74.101896	599614.340245	513592.717169	1802.775638	33	128.672480

In [27]:
```
print('Average distance to closest Chinese restaurant from each area center:', df_locations['Distance to Chinese restaurant'].mean())
```
```
Average distance to closest Chinese restaurant from each area center: 869.3961656364597
```

OK, so **on average Chinese restaurant can be found within ~850m** from every area center candidate. That's fairly close, so we need to filter our areas carefully!

Let's crete a map showing **heatmap / density of restaurants** and try to extract some meaningfull info from that. Also, let's show **borders of Bogota** on our map and a few circles indicating distance of 0.5km, 0.8km and 1.2km from Simon bolivar Park.

Looks no like a few pockets of low restaurant density closest to city center cant be found

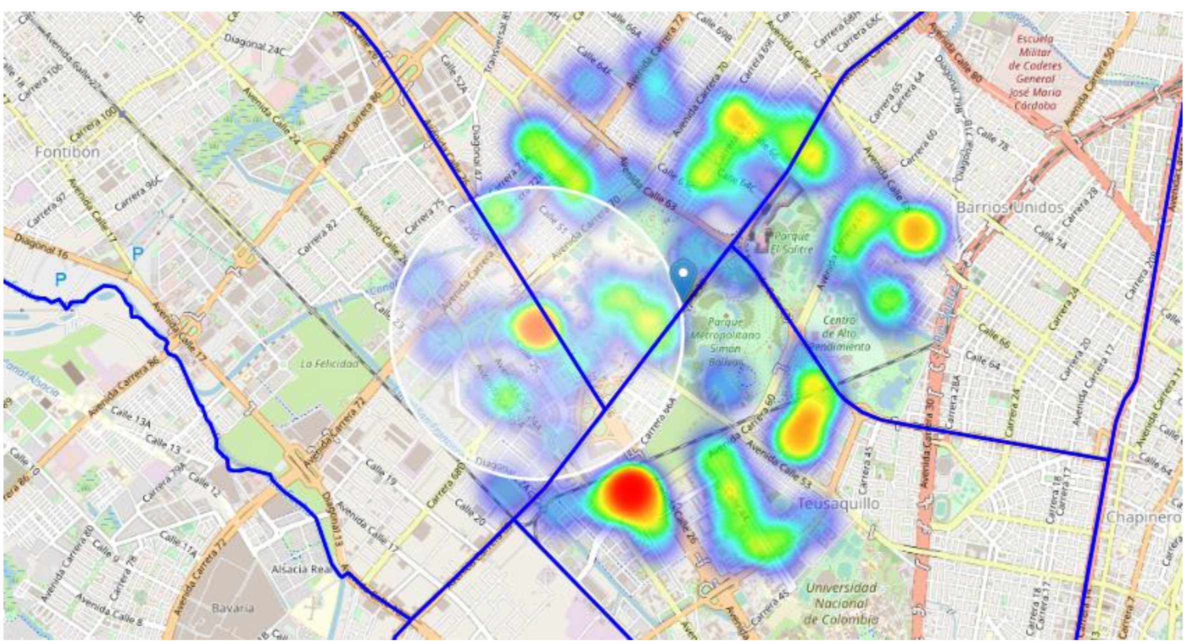
Let's create another heatmap map showing **heatmap/density of Chinese restaurants** only.

This map is not so 'hot' (Chinese restaurants represent a subset of ~3.5% of all restaurants near of Simon Bolivar Park) but it also indicates Lower density of existing Chinese restaurants from Simon Bolivar Park

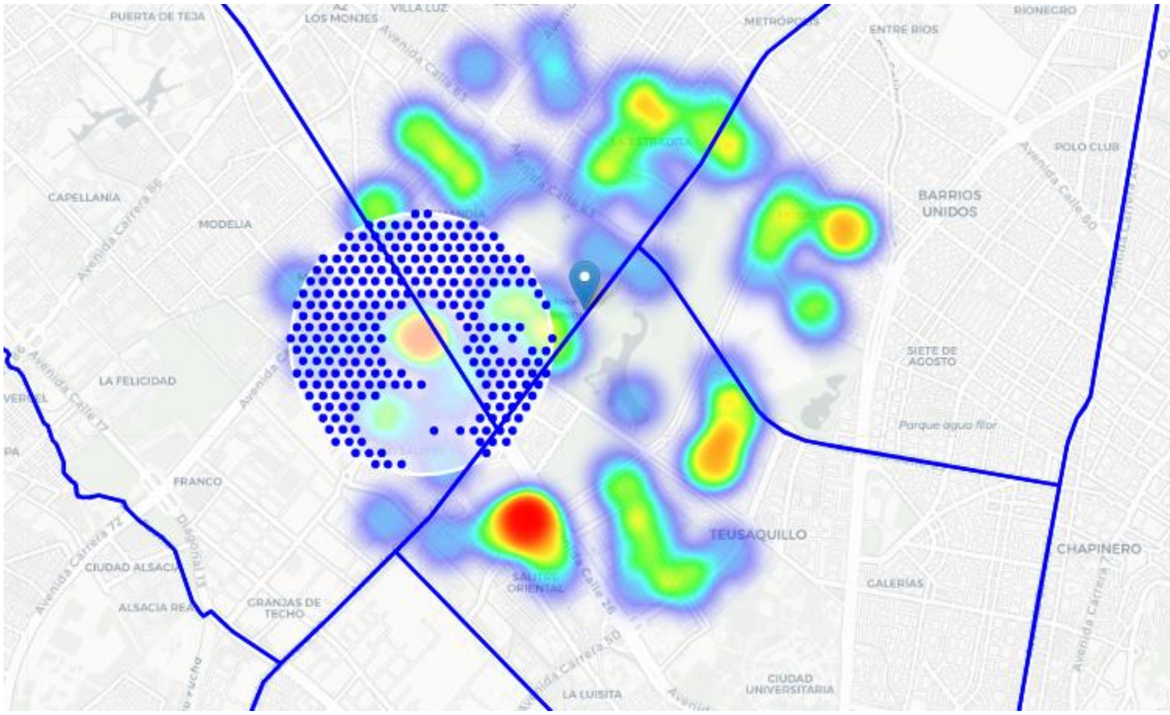
Based on this, we will now focus our analysis on the Barrio Ciudad Salitre neighborhood.

Ciudad Salitre neighborhood Analisys

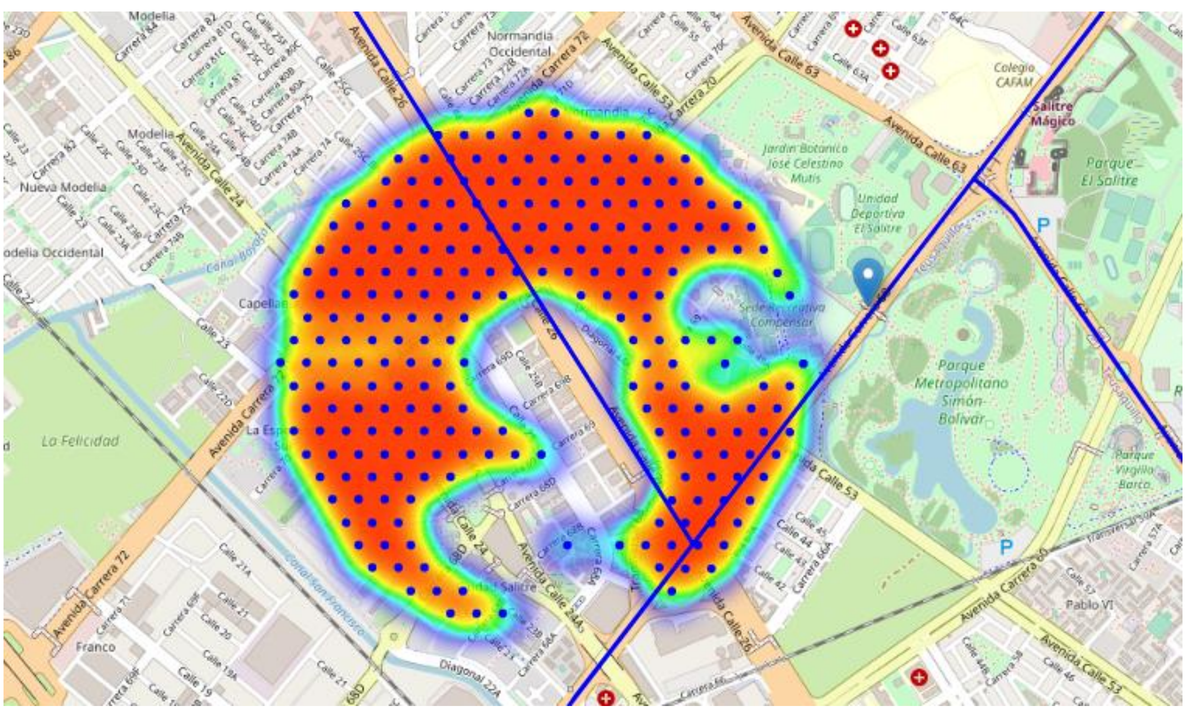
Let's define new, more narrow region of interest, which will include low-restaurant-count parts of Kreuzberg and Friedrichshain closest to Alexanderplatz.



Now let's calculate two most important things for each location candidate: **number of restaurants in Ciudad Salitre** (we'll use radius of **250 meters**) and **distance to closest Chinese restaurant



Let's now show those good locations in a form of heatmap:



Looking good. What we have now is a clear indication of zones with low number of restaurants in Ciudad Salitre, and *no* Chinese restaurants at all nearby.

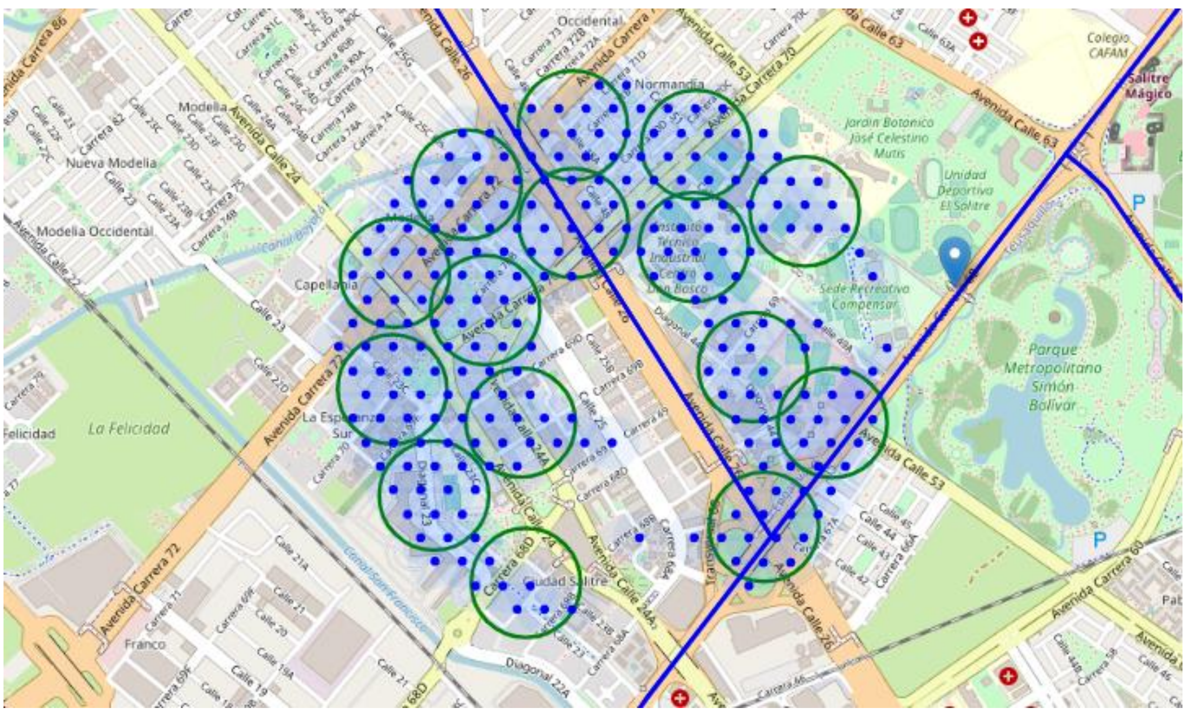
Let us now **cluster** those locations to create **centers of zones containing good locations**. Those zones, their centers and addresses will be the final result of our analysis.

Not bad - our clusters represent groupings of most of the candidate locations and cluster centers are placed nicely in the middle of the zones 'rich' with location candidates.

Addresses of those cluster centers will be a good starting point for exploring the neighborhoods to find the best possible location based on neighborhood specifics.

Let's see those zones on a city map without heatmap, using shaded areas to indicate our clusters:

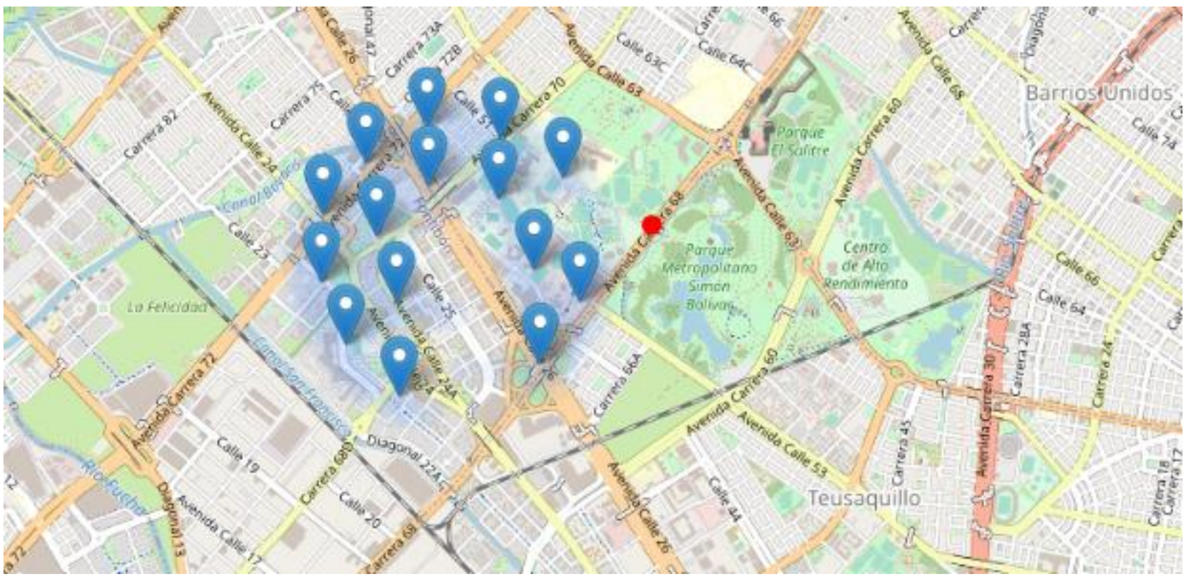
Let's zoom in on candidate areas in **Terminal Ciudad Salitre**:



Finaly, let's **reverse geocode those candidate area centers to get the addresses** which can be presented to stakeholders.

```
============================================================
Addresses of centers of areas recommended for further analysis
============================================================

Cra. 69 #5263, Bogotá, Colombia                      => 0.6km from Simon Bolibar Park
Cra. 70 #22d97, Bogotá, Colombia                     => 2.1km from Simon Bolibar Park
Ac. 26 #1001, Bogotá, Cundinamarca, Colombia         => 1.4km from Simon Bolibar Park
Ak 68 #26-22, Bogotá, Colombia                       => 1.1km from Simon Bolibar Park
Cra. 68c #23-31, Bogotá, Colombia                    => 1.9km from Simon Bolibar Park
Cra. 69b #24-51, Bogotá, Colombia                    => 1.7km from Simon Bolibar Park
Dg. 44 ##68b-80, Bogotá, Cundinamarca, Colombia      => 0.8km from Simon Bolibar Park
Ak. 70 #51-14, Bogotá, Cundinamarca, Colombia        => 1.1km from Simon Bolibar Park
007C06, Bogotá, Colombia                             => 2.0km from Simon Bolibar Park
Cra. 71d #4822, Bogotá, Colombia                     => 1.5km from Simon Bolibar Park
Terminal de Transportes de Bogota, Bogotá, Colombia => 2.0km from Simon Bolibar Park
Entrada Occidental a Centro Don Bosco #16, Bogotá, Colombia => 1.0km from Simon Bolibar Park
AK 68 - Cl 46, Bogotá, Colombia                      => 0.7km from Simon Bolibar Park
Ac. 24 #7025, Bogotá, Colombia                       => 1.7km from Simon Bolibar Park
Cl. 25B #72-20, Bogotá, Colombia                     => 1.8km from Simon Bolibar Park
```



This concludes our analysis. We have created 15 addresses representing centers of zones containing locations with low number of restaurants and no Chinese restaurants nearby, all zones being fairly close to Simon Bolivar Park (all less than 2km).

4 Conclusion

The objective of this project was to identify areas of Bogota near Simon Bolivar Park with a low number of restaurants (particularly Chinese restaurants) to help stakeholders narrow the search for an optimal location for a new Chinese restaurant. When calculating the density distribution of restaurants from Foursquare data, we first identified general districts that warrant further analysis (Barrio Ciudad Salitre), and then generated a broad collection of locations that satisfy some basic requirements regarding nearby restaurants existing. These locations were then grouped together to create the main areas of interest (containing the largest number of potential locations) and the addresses of those area centers were created to be used as starting points for final exploration by the interested.

Stakeholders will make the final decision on the optimal location of the restaurant based on the specific characteristics of the neighborhoods and locations in each recommended area, taking into account additional factors such as the attractiveness of each location (proximity to the park or water), levels noise / proximity to main roads, availability of real estate, prices, social and economic dynamics of each neighborhood, etc.

5 Reference:

For the development of this project, the example of the course has been taken, in the following route as a reference:

https://cocl.us/coursera_capstone_notebook