

The Battle of Neighborhood

...

Opening Restaurant

Introduction

Nowadays, it is difficult to imagine a city without a restaurant or a venue for food where people can have a meal or drink.

The city of my choice is Taganrog that has following industry and businesses:

- Aerospace
- Steel
- Food
- Farming
- Sea port
- etc.

That means there are a lot of business opportunities for restaurant business what leads to high competition.

Problem

There are a lot of business opportunities for restaurant business what leads to high competition.

To survive in such competitive market it is very important to find right place and take into account many other important factors such as:

- City population
- Sport and Entertainment zones
- Food markets with products of local farmers
- Local competitors and their ratings
- etc.

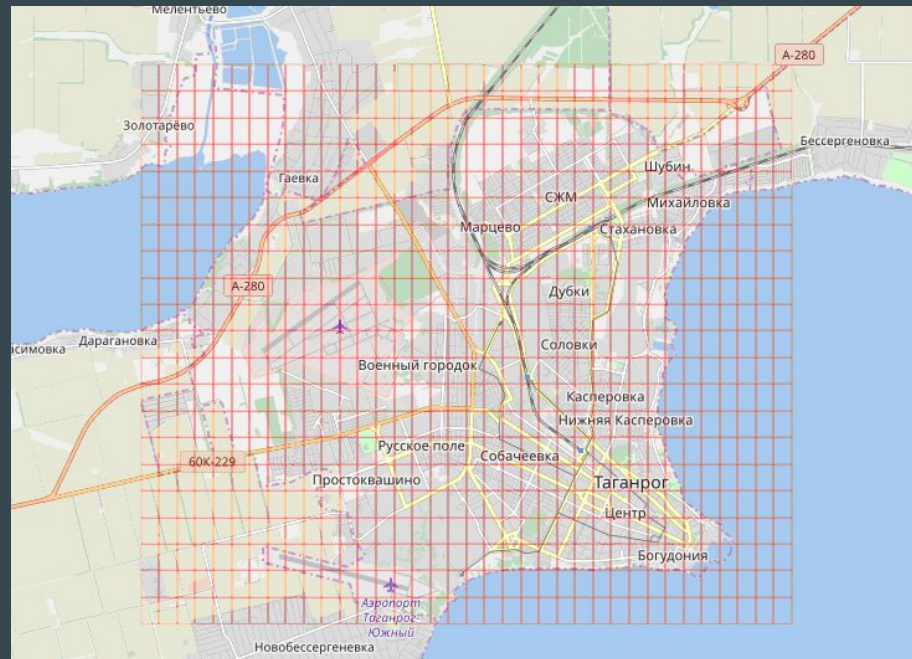
Data Description

For further analysis will be used the following data sources:

- Wikipedia page for city population (<https://en.wikipedia.org/wiki/Taganrog>)
- Nominatim search engine for OpenStreetMap data to get the bounding box of the city (https://nominatim.openstreetmap.org/search?format=json&q=Taganrog&polygon_geojson=1)
- Data from Foursquare API
 - search endpoint
 - categories (list of all categories)
 - details (full details about a venue)

Data Example

- Taganrog city has no neighborhood division, that why a coordinate grid covering the entire city by cells will build
- The first five venues within such cell (about 700 meters) from foursquare data

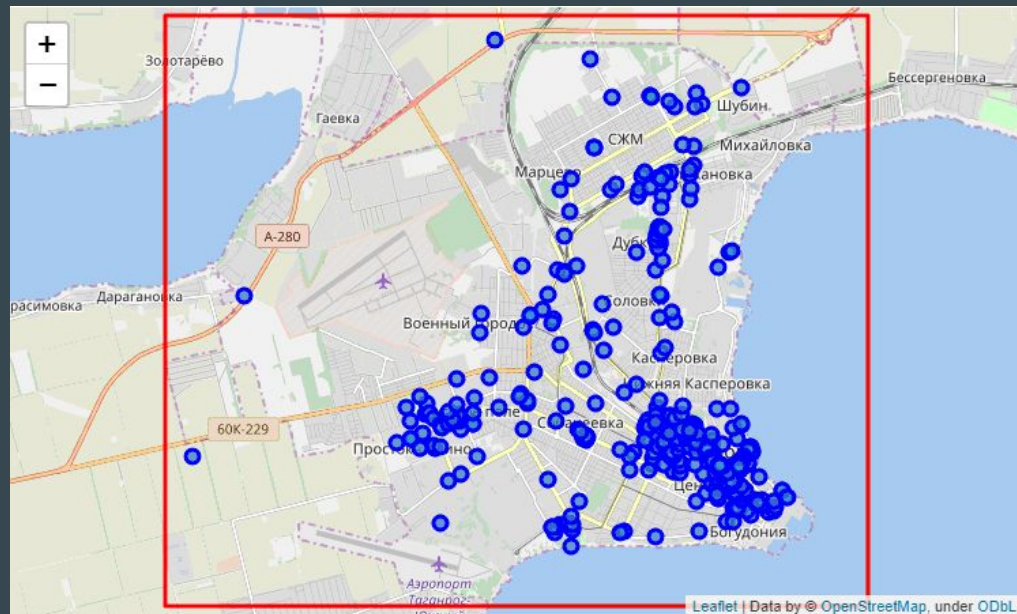


| | Venue | Latitude | Longitude | Category | Id |
|---|-------------------------------------|-----------|-----------|----------------|---------------------------|
| 0 | Площадь перед администрацией города | 47.215733 | 38.928230 | Plaza | 5368f4ad498ea0cb80cef632 |
| 1 | Культ вина | 47.215510 | 38.929310 | Wine Bar | 5c74142e60255e002c1aefbc |
| 2 | Театр имени А. П. Чехова | 47.216325 | 38.928217 | Theater | 4dcbe98a1f6ea1401d49d12a |
| 3 | Администрация Таганрога | 47.215517 | 38.928420 | City Hall | 4da693d90cb66f658708dafc |
| 4 | Л'Этуаль | 47.215416 | 38.929266 | Cosmetics Shop | 4f83002ee4b0b2237e8a6cbb1 |

Data Collection

This section covers data acquisition steps:

- Display venues on map with the bounding box
- Get detailed information about each venue and put it in a new dataset



Methodology

Understanding and preparation

Data needs to be cleaned and prepared

Fields renamed and NaN's fixed

Exploratory analysis

- Check distributions,
- Detect any outliers,
- Exploring correlation between fields
- Discarding erroneous or not needed data

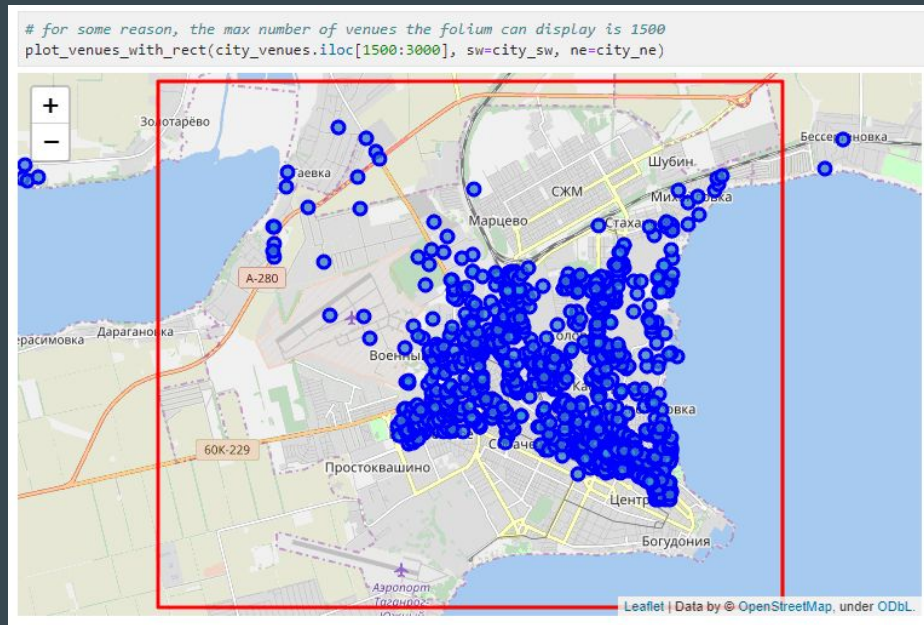
Clustering

- Determine the optimum number of clusters
- Finding suitable cluster

Understanding and Preparation

There are a number of venues out of city bounding box.

Remove them.

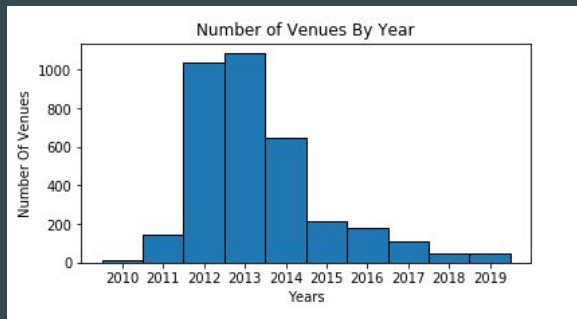
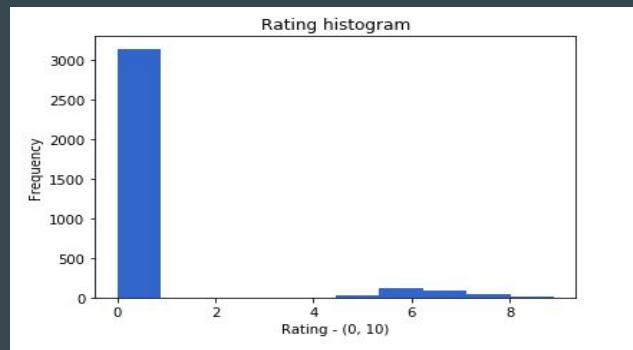
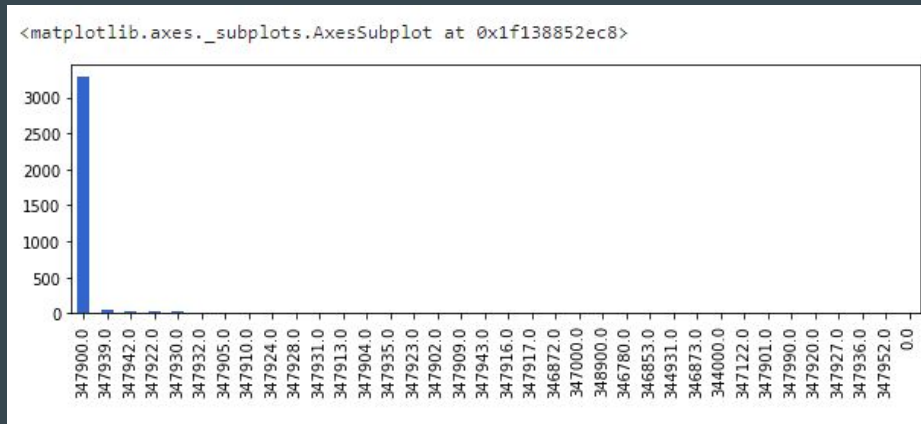


Exploratory Analysis

Explore the PostalCode field and plot its values.

Next explore the Rating field and plot its histogram.

Convert timestamp in seconds to years
and find a range of years



Correlation between fields

| | Latitude | Longitude | Rating | Likes | Tips | Price_tier | Food_venue | Created_year | Venue_age |
|--------------|-----------|-----------|-----------|-----------|-----------|------------|------------|--------------|-----------|
| Latitude | 1.000000 | -0.115304 | -0.045754 | -0.061645 | -0.062015 | -0.054484 | -0.076316 | -0.026311 | 0.026311 |
| Longitude | -0.115304 | 1.000000 | 0.055542 | 0.068591 | 0.080413 | 0.087981 | 0.088966 | 0.025289 | -0.025289 |
| Rating | -0.045754 | 0.055542 | 1.000000 | 0.495428 | 0.435916 | 0.153763 | 0.142334 | -0.151191 | 0.151191 |
| Likes | -0.061645 | 0.068591 | 0.495428 | 1.000000 | 0.871930 | 0.144708 | 0.128512 | -0.128767 | 0.128767 |
| Tips | -0.062015 | 0.080413 | 0.435916 | 0.871930 | 1.000000 | 0.203122 | 0.182537 | -0.117383 | 0.117383 |
| Price_tier | -0.054484 | 0.087981 | 0.153763 | 0.144708 | 0.203122 | 1.000000 | 0.673304 | 0.046388 | -0.046388 |
| Food_venue | -0.076316 | 0.088966 | 0.142334 | 0.128512 | 0.182537 | 0.673304 | 1.000000 | 0.095791 | -0.095791 |
| Created_year | -0.026311 | 0.025289 | -0.151191 | -0.128767 | -0.117383 | 0.046388 | 0.095791 | 1.000000 | -1.000000 |
| Venue_age | 0.026311 | -0.025289 | 0.151191 | 0.128767 | 0.117383 | -0.046388 | -0.095791 | -1.000000 | 1.000000 |

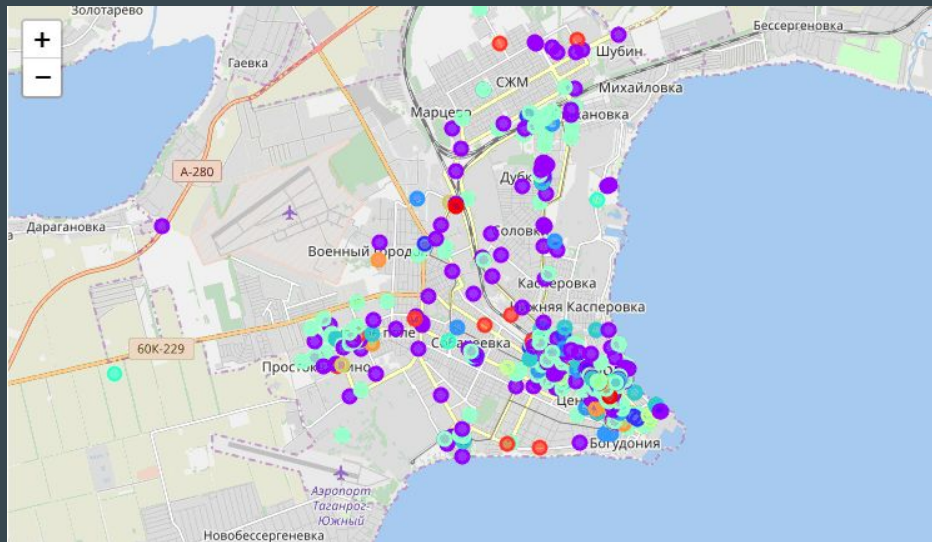
Summary.

Almost all variables demonstrate very weak positive and negative correlations except those that obviously related to each other. For example **Tips**, **Likes** and **Rating** correlate between each other as well as **Food_venue** and **Food_tier**.

Clustering

The core of the analytic method is clustering of all venues in Taganrog city by its fields, determining the optimum number of clusters and find suitable cluster for a new restaurant.

- Transform categorical field **Category** to dummies
- Normalize the dataset
- Run k-means to cluster all venues into 11 clusters
- Assign labels to venues
- Display our clustered venues on map



Results

To help with interpreting the data, let's sort the clusters by a meaningful attribute. A good candidate for such attribute is total number of venues in each cluster.

1. Clusters 1 and 6 show that the number of restaurants is high and it is risky to open a restaurant here
2. Cluster 4 contains of cuisines of different countries: Eastern European, Italian, Japanese
3. Assign labels to venues
4. The rest clusters have a small number of venues and introduced by a single category

| Label | | 1st | 2nd | 3rd | 4th | 5th | Total |
|-------|----|-----------------------------|--------------------|-------------|----------------------|-------------|-------|
| 1 | 1 | Restaurant | Sushi Restaurant | Pizza Place | Snack Place | BBQ Joint | 162 |
| 6 | 6 | Café | Cafeteria | Bistro | Caucasian Restaurant | Pastry Shop | 146 |
| 4 | 4 | Eastern European Restaurant | Italian Restaurant | Restaurant | Japanese Restaurant | Café | 27 |
| 7 | 7 | Coffee Shop | None | None | None | None | 23 |
| 2 | 2 | Fast Food Restaurant | None | None | None | None | 18 |
| 10 | 10 | Bakery | None | None | None | None | 15 |
| 3 | 3 | Diner | None | None | None | None | 12 |
| 9 | 9 | Burger Joint | None | None | None | None | 10 |
| 8 | 8 | Sandwich Place | None | None | None | None | 9 |
| 0 | 0 | Dessert Shop | None | None | None | None | 7 |
| 5 | 5 | Modern European Restaurant | None | None | None | None | 5 |

A hand is pouring a large portion of golden-brown, fried food (possibly fritters or dumplings) from a metal strainer into a large, shallow metal bowl. The bowl already contains some liquid and other ingredients. The background is slightly blurred, showing more of the cooking process.

Discussion:

One interesting observation is that small restaurants (such as Cafe, Cafeteria, Sushi, Pizza, etc.) prevail over big restaurants.

There is a small number of restaurants of different cuisines and a recommendation might be to open a restaurant of national cuisine (for instance Indian Restaurant).

Conclusion

- The project analyzes venue similarity based on data obtained from Foursquare.
- The data needed cleaning as it contained nonexistent venues and missing data. We can observe a lack of restaurants of national cuisines and suitable cluster for opening a restaurant.
- However, we wish Foursquare had returned more venues as the data was very sparse and difficult to use for clustering. In future work, it may also be useful to include data pertaining to schools, universities, and such.

