

Coursera_Capstone (/github/AndrAndreyev/Coursera_Capstone/tree/master)
/ ADSC-FPr.ipynb (/github/AndrAndreyev/Coursera_Capstone/tree/master/ADSC-FPr.ipynb)

Capstone Project. The Battle of the Neighborhoods (Week 2)

This notebooks is used for the project within the Courser course 'Applied Data Science Capstone'
It is recommended to run the code in Chrome environment to see the interactive maps.

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Introduction. The Problem Description

In this project we are going to help families with kids to plan their day-off.

In big cities, such as Moscow, there are thousands of venues that could be **interesting for families with kids**. But unfortunately parents do not know about them. In fact, there is a very limited list of popular venues mostly placed in the downtown, that are known well to everybody. They are nice but always overcrowded and it could take more than an hour to get there through traffic jams. And parents encounter more problems when they are going to plan several activities for the same day. For example, where they could eat with kids, or what they will do if their plans, weather or mud suddenly change.

We will use the data science and data visualization tools to display on the interactive map **the clustered venues affordable for families with kids**. That clusters will include **venues for education and entertainment** and will be placed in the specified neighbourhood.

Data

Taking into account the problem definition, we will have to mine two types of data:

1. We have to determine how to split the Moscow area into neighbourhoods with determined geo coordinates;
2. We have to mine information of venues placed in some specified neighbourhood.

How to Split the Moscow Area Into Neighbourhoods

There are several ways to determine neighbourhoods in Moscow. The

For example, it could be done **by the municipalities**. There are 12 administrative districts in Moscow that include 146 municipalities. The list of them that includes their boundaries can be downloaded at <http://gis-lab.info/qa/moscow-atd.html> (<http://gis-lab.info/qa/moscow-atd.html>) in ESRI Shape, GeoJSON, CSV+VRT or KML formats.

The second way is **by the post offices locations**. There are 13 post regions in Moscow that include 524 post offices. The geo locations of the post offices can be downloaded at <http://hubofdata.ru/dataset/ruspost-msk> (<http://hubofdata.ru/dataset/ruspost-msk>) in JSON format.

Using the post offices locations as neighbourhoods centers is easier since we can get their geo coordinates and the most of the venues have postcodes (except such as parks, playgrounds etc). For those that have not, it can be determined by the closest venues. But the size of such neighbourhoods seems to be too small to get a proper point of view.

So, we will **determine the neighbourhoods as the Moscow municipalities**.

Let's download the libraries we'll need

In [1]:

```
!conda install -c conda-forge folium=0.5.0 --yes # uncomment this line if you run the
import folium # map rendering library

!conda install -c conda-forge geopy --yes # uncomment this line if you run the cell fo
from geopy.geocoders import Nominatim # convert an address into Latitude and Longitude

import requests # library to handle requests
from pandas.io.json import json_normalize # tranform JSON file into a pandas dataframe

import pandas as pd
import numpy as np
```

Solving environment: done

All requested packages already installed.

Solving environment: done

All requested packages already installed.

Let's download data for Moscow municipalities. The link is <http://gis-lab.info/data/mos-adm/mo-csv.zip>
(<http://gis-lab.info/data/mos-adm/mo-csv.zip>)

Since data are stored in zip file we will need to unzip it first.

In [2]:

```
# importing required modules
from zipfile import ZipFile

# downloading zip file
!wget -q -O 'mun_coordinates.zip' http://gis-lab.info/data/mos-adm/mo-csv.zip

# specifying the zip file name
file_name = "mun_coordinates.zip"

# opening the zip file in READ mode
with ZipFile(file_name, 'r') as zip1:
    # printing all the contents of the zip file
    zip1.printdir()

    # extracting all the files
    print('Extracting all the files now...')
    zip1.extractall()
    print('Done!')

print('Data downloaded!')
mun_coord = pd.read_csv('mo.csv')
```

File Name	Modified
mo.csv	2014-06-14 15:29:14
mo.csvt	2014-06-14 15:29:14
mo.prj	2014-06-13 20:27:22
mo.qml	2014-03-23 21:21:22
mo.vrt	2014-03-29 23:06:40
Extracting all the files now...	
Done!	
Data downloaded!	

Let's have a look at data we got.

In [3]:

```
mun_coord.head()
```

Out[3]:

	WKT	NAME	OKATO	OKTMO	NAME_AO	OKATO_A
0	MULTIPOLYGON (((36.8031012 55.4408329,36.80319...	Киевский	45298555	45945000	Троицкий	4529800
1	POLYGON ((37.4276499 55.7482092,37.4284863 55....	Филёвский Парк	45268595	45328000	Западный	4526800
2	POLYGON (((36.8035692 55.4516224,36.8045117 55....	Новофёдоровское	45298567	45954000	Троицкий	4529800
3	POLYGON (((36.9372397 55.2413907,36.9372604 55....	Роговское	45298575	45956000	Троицкий	4529800
4	POLYGON ((37.4395575 55.6273129,37.4401803 55....	"Мосрентген"	45297568	45953000	Новомосковский	4529700

It turned out that some columns have information in Cyrillic. To make data more convinient for review within this project we have to **transliterate the Cyrillic symbols into English ones** with similar or alike articulation.

The cell below makes transliteration by replacing the Cyrillic symbols for the whole 'mo.csv' file.

In [4]:

```
import os
import fileinput

def latinizator(letter, dic):
    for i, j in dic.items():
        letter = letter.replace(i, j)
    return letter
```

```
legend = {
    'а': 'a',
    'б': 'b',
    'в': 'v',
    'г': 'g',
    'д': 'd',
    'е': 'e',
    'ё': 'yo',
    'ж': 'zh',
    'з': 'z',
    'и': 'i',
    'й': 'y',
    'к': 'k',
    'л': 'l',
    'м': 'm',
    'н': 'n',
    'о': 'o',
    'п': 'p',
    'р': 'r',
    'с': 's',
    'т': 't',
    'у': 'u',
    'ф': 'f',
    'х': 'h',
    'ц': 'ts',
    'ч': 'ch',
    'ш': 'sh',
    'щ': 'shch',
    'ъ': 'y',
    'ы': 'y',
    'ь': "'",
    'э': 'e',
    'ю': 'yu',
    'я': 'ya',
```

```
'А': 'A',
'Б': 'B',
'В': 'V',
'Г': 'G',
'Д': 'D',
'Е': 'E',
'Ё': 'Yo',
'Ж': 'Zh',
'З': 'Z',
'И': 'I',
'Й': 'Y',
'К': 'K',
'Л': 'L',
'М': 'M',
'Н': 'N',
'О': 'O',
```

```

'П': 'P',
'Р': 'R',
'С': 'S',
'Т': 'T',
'У': 'U',
'Ф': 'F',
'Х': 'H',
'Ц': 'Ts',
'Ч': 'Ch',
'Ш': 'Sh',
'Щ': 'Shch',
'Ъ': 'Y',
'Ы': 'Y',
'Ь': '"',
'Э': 'E',
'Ю': 'Yu',
'Я': 'Ya',
}

with fileinput.FileInput('mo.csv', inplace=True, backup='.bak') as f:
    for line in f:
        print(latinizator(line, legend), end='')

```

Let's add two new columns for geo coordinates and let's check the result.

In [5]:

```
mun_coord = pd.read_csv('mo.csv')

# Let's add two columns for centroid information
mun_coord.insert(2, 'LAT', 0.0)
mun_coord.insert(3, 'LNG', 0.0)
mun_coord['LAT'].astype('float')
mun_coord['LNG'].astype('float')

mun_coord.head()
```

Out[5]:

	WKT	NAME	LAT	LNG	OKATO	OKTMO	NAME_AO
0	MULTIPOLYGON (((36.8031012 55.4408329,36.80319...	Kievskiy	0.0	0.0	45298555	45945000	Troitskiy
1	POLYGON ((37.4276499 55.7482092,37.4284863 55....	Filyovskiy Park	0.0	0.0	45268595	45328000	Zapadnyy
2	POLYGON (((36.8035692 55.4516224,36.8045117 55....	Novofyodorovskoe	0.0	0.0	45298567	45954000	Troitskiy
3	POLYGON (((36.9372397 55.2413907,36.9372604 55....	Rogovskoe	0.0	0.0	45298575	45956000	Troitskiy
4	POLYGON (((37.4395575 55.6273129,37.4401803 55....	"Mosrentgen"	0.0	0.0	45297568	45953000	Novomoskovskiy

So, we have managed to:

- get the list of the Moscow municipalities as our neighbourhoods;
- get the data about the neighbourhoods boundaries as polygons descriptions;

A polygon description is a list of points that are connected one by one with direct lines. In our case each polygon consists of about 500 and more point. Each point is represented by a couple that is latitude and longitude coordinates separated by space symbol. Since we downloaded .csv file polygon description is in string format;

- replace the Cyrillic symbols in the neighbourhoods data with English ones similar or alike in articulation.

How to Mine Information of venues placed in some specified neighbourhood

We can do it with **the Foursquare API** and the method called **'explore'**.

With that method we can download the data of venues we are interested in placed no farther than some specified distance from some specified geo coordinates.

Let's find the geographical coordinates of Moscow

In [6]:

```
address = 'Moscow'

geolocator = Nominatim(user_agent="ny_explorer")
mos_location = geolocator.geocode(address)

mos_latitude = mos_location.latitude
mos_longitude = mos_location.longitude

print('The geographical coordinate of Moscow are {}, {}'.format(mos_latitude, mos_longitude))
```

The geographical coordinate of Moscow are 55.7504461, 37.6174943.

Let's make request for FourSquare API. To do it we start with the credentials determination.

In [7]:

```
CLIENT_ID = 'VC5VAI2CNSBEQ1BIWEREK0RDJX2VK4WVRYEXQTSLB4Q4XXFB' # Foursquare ID
CLIENT_SECRET = 'HRGWOCZXY55UGMEUD4APX5LYXYTREVQNOLEQZJT1YFRW3U3' # Foursquare Secret
VERSION = '20180605' # Foursquare API version. In fact, I didn't find the information

print('The credentials:')
print('CLIENT_ID: ' + CLIENT_ID)
print('CLIENT_SECRET: ' + CLIENT_SECRET)
```

The credentials:

```
CLIENT_ID: VC5VAI2CNSBEQ1BIWEREK0RDJX2VK4WVRYEXQTSLB4Q4XXFB
CLIENT_SECRET: HRGWOCZXY55UGMEUD4APX5LYXYTREVQNOLEQZJT1YFRW3U3
```

Now we will form the url request for the Foursquare API to download the data of no more than 20 venues in distance no more than 1000 meters from the point determined as Moscow center.

In [8]:

```
LIMIT = 20 # limit of number of venues returned by Foursquare API
radius = 1000 # define radius
# create URL
url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    mos_latitude,
    mos_longitude,
    radius,
    LIMIT)
url # display URL
```

Out[8]:

```
'https://api.foursquare.com/v2/venues/explore?&client_id=VC5VAI2CNSBEQ1BIW
```

We are sending the request and receives the data of venues in json format.

In [9]:

```
results = requests.get(url).json()
```

Let's have a look at the data we mined.

In [10]:

```
results
```

Out[10]:

```
{'meta': {'code': 200, 'requestId': '5d8e71e5f96b2c00380e3d48'},
 'response': {'suggestedFilters': {'header': 'Tap to show:',
   'filters': [{'name': 'Open now', 'key': 'openNow'}]},
  'headerLocation': 'Khamovniki',
  'headerFullLocation': 'Khamovniki, Moscow',
  'headerLocationGranularity': 'neighborhood',
  'totalResults': 209,
  'suggestedBounds': {'ne': {'lat': 55.75944610900001,
    'lng': 37.63345597204126},
    'sw': {'lat': 55.741446090999986, 'lng': 37.60153262795873}},
  'groups': [{'type': 'Recommended Places',
    'name': 'recommended',
    'items': [{'reasons': {'count': 0,
      'items': [{'summary': 'This spot is popular',
        'type': 'general',
        'reasonName': 'globalInteractionReason'}]}],
    'venue': {'id': '4bfbb199565f76b04ccf05db',
      'name': 'The Kremlin (Кремль)',
      'location': {'address': 'Красная пл.',
        'lat': 55.751999,
        'lng': 37.617734,
        'labeledLatLngs': [{'label': 'display',
          'lat': 55.751999,
          'lng': 37.617734}]},
        'distance': 173,
        'postalCode': '101000',
        'cc': 'RU',
        'city': 'Москва',
        'state': 'Москва',
        'country': 'Россия',
        'formattedAddress': ['Красная пл.', '101000, Москва', 'Россия']},
        'categories': [{'id': '4bf58dd8d48988d126941735',
          'name': 'Government Building',
          'pluralName': 'Government Buildings',
          'shortName': 'Government',
          'icon': {'prefix': 'https://ss3.4sqi.net/img/categories_v2/buildi',
            'suffix': '.png'},
          'primary': True}],
        'photos': {'count': 0, 'groups': []}},
      'referralId': 'e-0-4bfbb199565f76b04ccf05db-0'},
    {'reasons': {'count': 0,
      'items': [{'summary': 'This spot is popular',
        'type': 'general',
        'reasonName': 'globalInteractionReason'}]}],
    'venue': {'id': '4da9654f43a1128196dbea8b',
      'name': 'Cathedral Square (Соборная площадь)',
      'location': {'address': 'Соборная пл.',
        'lat': 55.75067703638466,
        'lng': 37.61744217329331,
        'labeledLatLngs': [{'label': 'display',
          'lat': 55.75067703638466,
          'lng': 37.61744217329331}]},
        'distance': 25,
        'postalCode': '101000',
        'cc': 'RU',
```

```
'neighborhood': 'Krasnaya Ploshchad', Moscow',
'city': 'Москва',
'state': 'Москва',
'country': 'Россия',
'formattedAddress': ['Соборная пл.', '101000, Москва', 'Россия']],
'categories': [{'id': '4bf58dd8d48988d164941735',
'name': 'Plaza',
'pluralName': 'Plazas',
'shortName': 'Plaza',
'icon': {'prefix': 'https://ss3.4sqi.net/img/categories_v2/parks_
'suffix': '.png'},
'primary': True}],
'photos': {'count': 0, 'groups': []}},
'referralId': 'e-0-4da9654f43a1128196dbea8b-1'},
{'reasons': {'count': 0,
'items': [{'summary': 'This spot is popular',
'type': 'general',
'reasonName': 'globalInteractionReason'}]},
'venue': {'id': '4bf7fa734a67c928e27624cf',
'name': 'Aleksandrovskiy Garden (Александровский сад)',
'location': {'address': 'Манежная ул.',
'lat': 55.75270677200052,
'lng': 37.61373281478882,
'labeledLatLngs': [{'label': 'display',
'lat': 55.75270677200052,
'lng': 37.61373281478882}],
'distance': 344,
'postalCode': '119019',
'cc': 'RU',
'city': 'Москва',
'state': 'Москва',
'country': 'Россия',
'formattedAddress': ['Манежная ул.', '119019, Москва', 'Россия']],
'categories': [{'id': '4bf58dd8d48988d163941735',
'name': 'Park',
'pluralName': 'Parks',
'shortName': 'Park',
'icon': {'prefix': 'https://ss3.4sqi.net/img/categories_v2/parks_
'suffix': '.png'},
'primary': True}],
'photos': {'count': 0, 'groups': []}},
'referralId': 'e-0-4bf7fa734a67c928e27624cf-2'},
{'reasons': {'count': 0,
'items': [{'summary': 'This spot is popular',
'type': 'general',
'reasonName': 'globalInteractionReason'}]},
'venue': {'id': '53735cbc498e64c3501c3803',
'name': 'Музеи Московского Кремля',
'location': {'address': 'Кремль',
'lat': 55.751789009887695,
'lng': 37.616476723476346,
'labeledLatLngs': [{'label': 'display',
'lat': 55.751789009887695,
'lng': 37.616476723476346}],
'distance': 162,
'postalCode': '103073',
'cc': 'RU',
'city': 'Москва',
'state': 'Москва',
'country': 'Россия',
'formattedAddress': ['Кремль', '103073, Москва', 'Россия']],
```

```
'categories': [{ 'id': '4bf58dd8d48988d190941735',
  'name': 'History Museum',
  'pluralName': 'History Museums',
  'shortName': 'History Museum',
  'icon': { 'prefix': 'https://ss3.4sqi.net/img/categories_v2/arts_e
    'suffix': '.png' },
  'primary': True }],
'photos': { 'count': 0, 'groups': [] },
'referralId': 'e-0-53735cbc498e64c3501c3803-3',
{'reasons': { 'count': 0,
  'items': [{ 'summary': 'This spot is popular',
    'type': 'general',
    'reasonName': 'globalInteractionReason' } ] },
'venue': { 'id': '4bbf5311b083a593a032a3e9',
  'name': 'State Kremlin Palace (Государственный Кремлёвский дворец)',
  'location': { 'address': 'Кремль',
    'lat': 55.751499,
    'lng': 37.615622,
    'labeledLatLngs': [ { 'label': 'display',
      'lat': 55.751499,
      'lng': 37.615622 } ],
    'distance': 165,
    'postalCode': '119019',
    'cc': 'RU',
    'city': 'Москва',
    'state': 'Москва',
    'country': 'Россия',
    'formattedAddress': [ 'Кремль', '119019, Москва', 'Россия' ] },
  'categories': [ { 'id': '5032792091d4c4b30a586d5c',
    'name': 'Concert Hall',
    'pluralName': 'Concert Halls',
    'shortName': 'Concert Hall',
    'icon': { 'prefix': 'https://ss3.4sqi.net/img/categories_v2/arts_e
      'suffix': '.png' },
    'primary': True } ],
  'photos': { 'count': 0, 'groups': [] },
  'referralId': 'e-0-4bbf5311b083a593a032a3e9-4' },
{'reasons': { 'count': 0,
  'items': [{ 'summary': 'This spot is popular',
    'type': 'general',
    'reasonName': 'globalInteractionReason' } ] },
'venue': { 'id': '4bb3345942959c74d79d212c',
  'name': 'Red Square (Красная площадь)',
  'location': { 'address': 'Красная пл.',
    'lat': 55.753595,
    'lng': 37.621031,
    'labeledLatLngs': [ { 'label': 'display',
      'lat': 55.753595,
      'lng': 37.621031 } ],
    'distance': 414,
    'postalCode': '109012',
    'cc': 'RU',
    'city': 'Москва',
    'state': 'Москва',
    'country': 'Россия',
    'formattedAddress': [ 'Красная пл.', '109012, Москва', 'Россия' ] },
  'categories': [ { 'id': '4bf58dd8d48988d164941735',
    'name': 'Plaza',
    'pluralName': 'Plazas',
    'shortName': 'Plaza',
    'icon': { 'prefix': 'https://ss3.4sqi.net/img/categories_v2/parks_
```

```

    'suffix': '.png'},
    'primary': True]],
    'photos': {'count': 0, 'groups': []}},
    'referralId': 'e-0-4bb3345942959c74d79d212c-5'},
    {'reasons': {'count': 0,
    'items': [{ 'summary': 'This spot is popular',
    'type': 'general',
    'reasonName': 'globalInteractionReason' } ]},
    'venue': { 'id': '4bee5d152c082d7f2b5d3042',
    'name': 'St. Basil's Cathedral (Храм Василия Блаженного)',
    'location': { 'address': 'Красная пл.',
    'crossStreet': 'пл. Васильевский Спуск',
    'lat': 55.75252441045641,
    'lng': 37.62310981750488,
    'labeledLatLngs': [{ 'label': 'display',
    'lat': 55.75252441045641,
    'lng': 37.62310981750488 } ]},
    'distance': 421,
    'postalCode': '109012',
    'cc': 'RU',
    'city': 'Москва',
    'state': 'Москва',
    'country': 'Россия',
    'formattedAddress': [ 'Красная пл. (пл. Васильевский Спуск)',
    '109012, Москва',
    'Россия' ]},
    'categories': [{ 'id': '4bf58dd8d48988d132941735',
    'name': 'Church',
    'pluralName': 'Churches',
    'shortName': 'Church',
    'icon': { 'prefix': 'https://ss3.4sqi.net/img/categories_v2/buildi
    'suffix': '.png'},
    'primary': True } ]},
    'photos': {'count': 0, 'groups': []}},
    'referralId': 'e-0-4bee5d152c082d7f2b5d3042-6'},
    {'reasons': {'count': 0,
    'items': [{ 'summary': 'This spot is popular',
    'type': 'general',
    'reasonName': 'globalInteractionReason' } ]},
    'venue': { 'id': '4bdbffff73904a593ed9a4c9e',
    'name': 'Kremlin Armory (Оружейная палата)',
    'location': { 'address': 'Московский Кремль',
    'lat': 55.74938922748553,
    'lng': 37.613328784627306,
    'labeledLatLngs': [{ 'label': 'display',
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    'city': 'Москва',
    'state': 'Москва',
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    'categories': [{ 'id': '4bf58dd8d48988d190941735',
    'name': 'History Museum',
    'pluralName': 'History Museums',
    'shortName': 'History Museum',
    'icon': { 'prefix': 'https://ss3.4sqi.net/img/categories_v2/arts_e
    'suffix': '.png'},
    'primary': True } ]},

```

```

    'photos': {'count': 0, 'groups': []}},
    'referralId': 'e-0-4bdbfff73904a593ed9a4c9e-7'},
  {'reasons': {'count': 0,
    'items': [{ 'summary': 'This spot is popular',
      'type': 'general',
      'reasonName': 'globalInteractionReason' } ]},
    'venue': {'id': '4c2dc26ae307d13a0a4b0eda',
      'name': 'Васильевский Спуск',
      'location': {'address': 'пл. Васильевский Спуск',
        'lat': 55.751502143545096,
        'lng': 37.6233315632182,
        'labeledLatLngs': [{ 'label': 'display',
          'lat': 55.751502143545096,
          'lng': 37.6233315632182 } ]},
        'distance': 384,
        'cc': 'RU',
        'city': 'Москва',
        'state': 'Москва',
        'country': 'Россия',
        'formattedAddress': [ 'пл. Васильевский Спуск', 'Москва', 'Россия' ]
      },
      'categories': [{ 'id': '4bf58dd8d48988d164941735',
        'name': 'Plaza',
        'pluralName': 'Plazas',
        'shortName': 'Plaza',
        'icon': { 'prefix': 'https://ss3.4sqi.net/img/categories_v2/parks_
          'suffix': '.png' },
        'primary': True } ]},
      'photos': {'count': 0, 'groups': []}},
      'referralId': 'e-0-4c2dc26ae307d13a0a4b0eda-8'},
    {'reasons': {'count': 0,
      'items': [{ 'summary': 'This spot is popular',
        'type': 'general',
        'reasonName': 'globalInteractionReason' } ]},
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```

```

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```

```
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'shortName': 'Boutique',
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```



```
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```

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```

```

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    'shortName': 'Boutique',
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    'suffix': '.png'},
    'primary': True}],
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    'shortName': 'Boutique',
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    'suffix': '.png'},
    'primary': True}],
    'photos': {'count': 0, 'groups': []}},
    'referralId': 'e-0-4ec7965bf79041351cd263a9-19'}]]]]}

```

We can see that we got significant amount of data including for those venues we are not interested in, such as boutiques, for example. Of course, we can use this raw data for the following sorting and picking up the venues affordable for families with kids, but in this case we will have to deal with huge data massive and encounter significant computational resources needs. Besides, 'explore' method deals with a point coordinates as a center of investigating area, whereas our neighbourhoods are determined by polygon boundaries.

In fact that means that we have to solve two problems:

1. How to find the center for each of our neighbourhoods if we have just their boundaries as polygons?
2. How to download from the Foursquare API the data just for venues we are interested in?

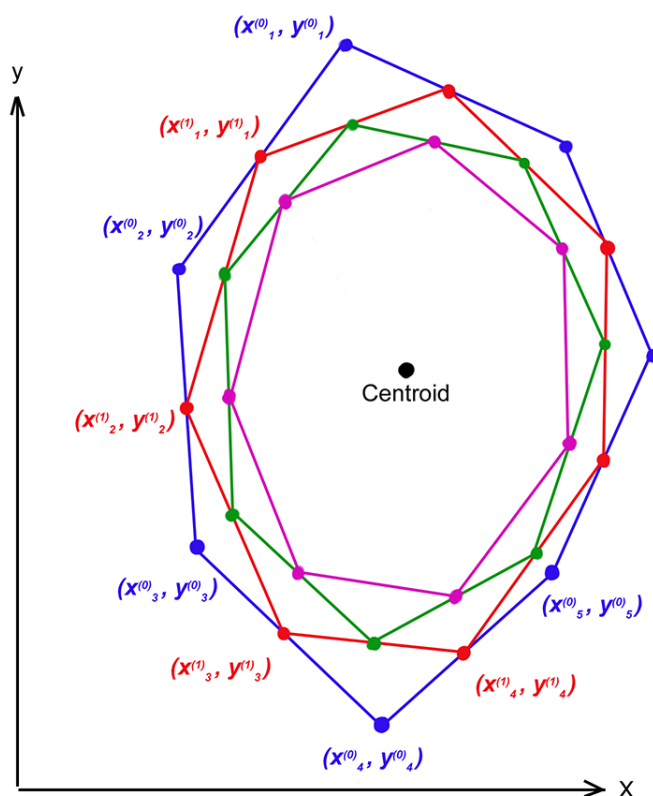
Methodology

How To Find The Center For Each Of Our Neighbourhoods.

To do so:

- We will transform polygon that is a string into a list of float pairs that represent longitude and latitude.
- The idea of centroid finding is the following:

Polygon is a set of lines connecting points one by one. We will find the middle of each such line and redraw the polygon by connecting them. That's an iteration procedure. At every iteration polygon will be convoluting around some point that is centroid we are looking for. The indicator of the process called 'gradient' is an averages of longitude and latitude for all points. If after some iteration gradient stayed the same, we can tell that centroid was found. The Picture 1 below illustrates the algorithm.



Iteration	Polygon
0	$[(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)]$
1	$[(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)]$
2	$[(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)]$
3	$[(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)]$
...	...
n	$[(x^{(n)}_1, y^{(n)}_1), (x^{(n)}_2, y^{(n)}_2), \dots, (x^{(n)}_m, y^{(n)}_m)]$

$$(x^{(i)}_i, y^{(i)}_i) = \frac{(x^{(i-1)}_i, y^{(i-1)}_i) + (x^{(i-1)}_{i+1}, y^{(i-1)}_{i+1})}{2}, i \neq m$$

$$(x^{(i)}_m, y^{(i)}_m) = \frac{(x^{(i-1)}_m, y^{(i-1)}_m) + (x^{(i-1)}_1, y^{(i-1)}_1)}{2}$$

$$\text{gradient}^{(i)} = \frac{1}{m} \left(\sum_{i=1}^m x^{(i)}_i, \sum_{i=1}^m y^{(i)}_i \right)$$

$$\Delta_{\text{grad}}^{(i)} = \text{gradient}^{(i)} - \text{gradient}^{(i-1)}$$

$$(x_{\text{centroid}}, y_{\text{centroid}}) = \text{gradient}^{(i)} \quad \Delta_{\text{grad}}^{(i)} = 0$$

Picture 1

The code for the algorithm described above is in the cell below.

Note: This task is rather resource intensive concerning that we have to find centroids for 146

neighbourhoods with 500+ points polygon each.

In [11]:

```
m = mun_coord.shape[0]

# Python code to convert string to list with ',' as separator
def Convert(string):
    li = list(string.split(","))
    return li

for i in range(0,m):

    # Convert string into list
    poly = Convert(mun_coord.iat[i,0])
    p = len(poly)

    lat_lng = []
    jj = 0
    # Convert list of strings into array of floats
    for j in range(0,p):
        ll = poly[j]
        if len(ll) == 21 and ll[:1] != '(' and ll[-1:] != ')':
            pol_lng = float(ll[:10])
            pol_lat = float(ll[-10:])
            lat_lng.append([pol_lat, pol_lng])

    # Iteration procedure to find centroid coordinates
    dll = len(lat_lng)
    grad_old = [round(sum(row[0] for row in lat_lng)/dll, 7), round(sum(row[1] for row
    grad_new = [0, 0]
    while grad_new != grad_old:
        grad_old = grad_new
        latlng0 = lat_lng[0]
        for ii in range(0,dll):
            if ii != dll-1:
                lat_lng[ii][0] = (lat_lng[ii][0] + lat_lng[ii+1][0]) / 2
                lat_lng[ii][1] = (lat_lng[ii][1] + lat_lng[ii+1][1]) / 2
            else:
                lat_lng[ii][0] = (lat_lng[ii][0] + latlng0[0]) / 2
                lat_lng[ii][1] = (lat_lng[ii][1] + latlng0[1]) / 2
        grad_new = [round(sum(row[0] for row in lat_lng)/dll, 7), round(sum(row[1] for

    # Now we are transferring found centroid coordinates to dataframe
    mun_coord.iat[i,2] = grad_new[0]
    mun_coord.iat[i,3] = grad_new[1]
```

Let's look at the results.

In [12]:

```
mun_coord.head()
```

Out[12]:

	WKT	NAME	LAT	LNG	OKATO	OKTMO
0	MULTIPOLYGON (((36.8031012 55.4408329,36.80319...	Kievskiy	55.383952	36.909133	45298555	45945000
1	POLYGON ((37.4276499 55.7482092,37.4284863 55....	Filyovskiy Park	55.748470	37.476145	45268595	45328000
2	POLYGON ((36.8035692 55.4516224,36.8045117 55....	Novofyodorovskoe	55.420282	36.974195	45298567	45954000
3	POLYGON ((36.9372397 55.2413907,36.9372604 55....	Rogovskoe	55.228378	37.037273	45298575	45956000
4	POLYGON ((37.4395575 55.6273129,37.4401803 55....	"Mosrentgen"	55.621927	37.465978	45297568	45953000 Novc

Now we have a list of the neighbourhoods with determined coordinates of center for each of them in the columns 'LAT' and 'LNG'. The first of the two two problems is solved.

How to download from the Foursquare API the data just for venues we are interested in?

Now let us clarify what venue categories we are interested in. To do so we can look through the content by the link <https://developer.foursquare.com/docs/resources/categories> (<https://developer.foursquare.com/docs/resources/categories>) that includes categories id. After looking it through we can determine that we are looking for venues from the categories that could be affordable for families with kids:

Venue type	Catergory Id
Parks	4bf58dd8d48988d163941735
Entertainment centers	4bf58dd8d48988d1e1931735
Amusement parks	4bf58dd8d48988d182941735
Playgrounds	4bf58dd8d48988d1e7941735
Museums	4bf58dd8d48988d181941735
Cinema	4bf58dd8d48988d17f941735
Kids cafe	4bf58dd8d48988d1d0941735

To optimize computational resources we'll pick up venues we are interested in for a neighbourhood called 'Akademichesky'. In fact, it can be any other municipality or current user's location.

To do it we have to add to the request url additional parameter describing id of the categories we are looking for.

In [13]:

```
# Let' pick up the centroid coordinates for 'Akademichesky' neighbourhood
neighbourhood_latitude = mun_coord.iat[76,2]
neighbourhood_longitude = mun_coord.iat[76,3]

# id for categories we are interested in
cat_id = '4bf58dd8d48988d163941735,4bf58dd8d48988d1e1931735,4bf58dd8d48988d182941735,4
```

Let's arrange that we are going to display no more than 100 venues (parameter 'LIMIT') in the radius 3000 meters from the center of the neighbourhood (parameter 'radius') that is comfortable for half an hour walk.

In [14]:

```
LIMIT = 100 # Limit of number of venues returned by Foursquare API
radius = 3000 # define radius
# create URL
url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    neighbourhood_latitude,
    neighbourhood_longitude,
    cat_id,
    radius,
    LIMIT)
url # display URL
```

Out[14]:

```
'https://api.foursquare.com/v2/venues/explore?&client_id=VC5VAI2CNSBEÇ
```

We are sending the request and receives data of venues in json format.

In [15]:

```
results = requests.get(url).json()
```

Now we are going to transfer the data from json format to dataframe.

In [16]:

```
# function that extracts the category of the venue
def get_category_type(row):
    try:
        categories_list = row['categories']
    except:
        categories_list = row['venue.categories']

    if len(categories_list) == 0:
        return None
    else:
        return categories_list[0]['name']
```

In [17]:

```
venues = results['response']['groups'][0]['items']

nearby_venues = json_normalize(venues) # flatten JSON

# filter columns
filtered_columns = ['venue.id', 'venue.name', 'venue.categories', 'venue.location.lat',
nearby_venues = nearby_venues.loc[:, filtered_columns]

# filter the category for each row
nearby_venues['venue.categories'] = nearby_venues.apply(get_category_type, axis=1)

# clean columns
nearby_venues.columns = [col.split(".")[0] for col in nearby_venues.columns]
```

Let's have a look at the data of venues we mined.

In [18]:

```
nearby_venues.head(10)
```

Out[18]:

	id	name	categories	lat	lng
0	59a2a8c3c0cacb5d0ff796eb	Академический парк	Park	55.691777	37.568886
1	4e7b0341b0fbf3d6be9917d3	Парк «Новые Черёмушки»	Park	55.693547	37.589786
2	4fb90be5e4b0c86152260256	Двор с фонтаном	Playground	55.692286	37.577203
3	4fbbaa56e4b0c852de6b3a36	Сквер «200 лет А. С. Пушкину»	Park	55.687814	37.575538
4	54ae6d16498e18b8bce5838	Эндорфин квест	Arcade	55.680578	37.570033
5	4f8c484ee4b0e67b87bb83e1	Аллея	Park	55.678210	37.558306
6	4e527a86d4c075ade75b3f06	Парк Дворца Пионеров	Park	55.702327	37.556238
7	4ed851fcbe7be28335359dac	Молодёжная улица	Park	55.693817	37.546515
8	56d097b7cd10ac3eb8a5d793	Батутный парк «Небо»	Athletics & Sports	55.687681	37.603730
9	57c85b83498eec7de643b658	Kuzina	Dessert Shop	55.688509	37.547529

Let's look at the number of venues we found.

In [19]:

```
nearby_venues.shape
```

Out[19]:

(84, 5)

The number of the venues found is rather high. So, it will be more convinient to analyze them after procedure of clustering.

Clustering and Map Compilation Section

Let's look how the found venues of the neighbourhood are distributed on the map.

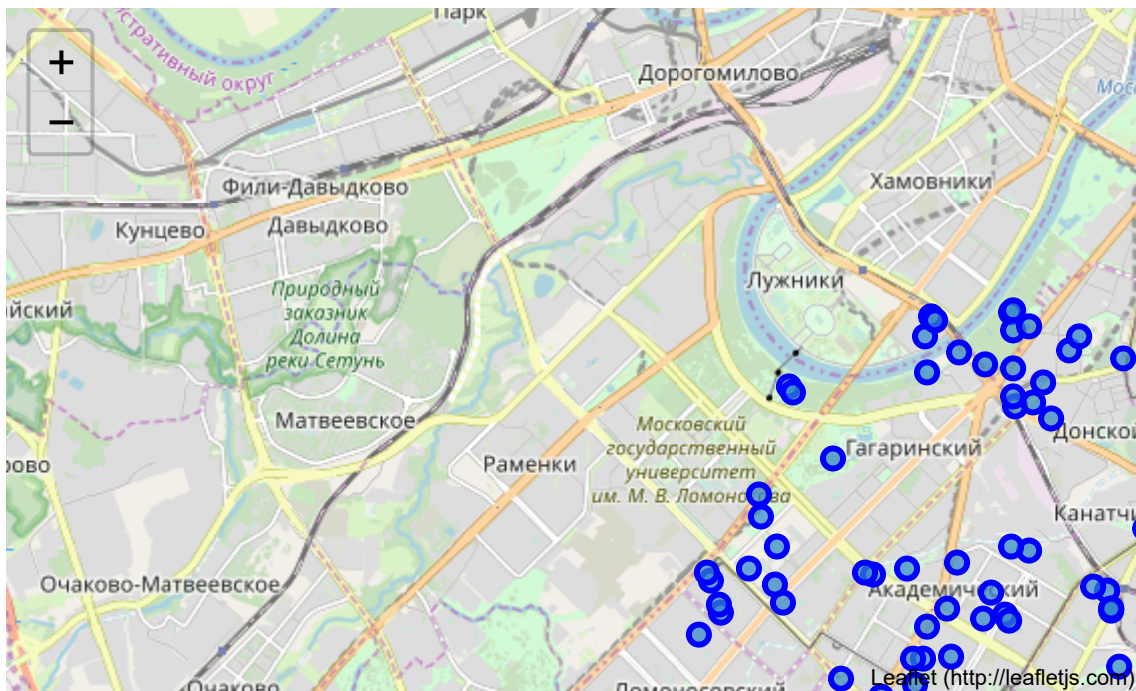
In [20]:

```
# create map of Moscow using Latitude and Longitude values
map_moscow = folium.Map(location=[neighbourhood_latitude, neighbourhood_longitude], zoom_start=14)

# add markers to map
for lat, lng, ven_name, cat in zip(nearby_venues['lat'], nearby_venues['lng'], nearby_venues['name'], nearby_venues['category']):
    label = '{}, {}'.format(ven_name, cat)
    popup = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=popup,
        color='blue',
        fill=True,
        fill_color='blue',
        fill_opacity=0.7,
        parse_html=False).add_to(map_moscow)

map_moscow
```

Out[20]:



We see that our venues are distributed into five clusters. To split the venues into clusters we'll use K-Means method to group together the venue situated close to each other.

This approach will help customer to pick up the most appropriate cluster concerning distance and a set of the venues in it.

The code below is splitting the venue of our dataset into five clusters.

In [21]:

```
# import k-means from clustering stage
from sklearn.cluster import KMeans

# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors

# set number of clusters
kclusters = 5

# prepare data for clustering
n_venues = nearby_venues.drop('id', 1)
n_venues = n_venues.drop('name', 1)
n_venues = n_venues.drop('categories', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(n_venues)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:82]
```

Out[21]:

```
array([3, 3, 3, 3, 3, 1, 4, 4, 0, 4, 3, 0, 3, 2, 3, 3, 3, 3, 2, 3, 3, 4,
       3, 4, 2, 1, 4, 2, 3, 4, 3, 2, 2, 1, 2, 2, 3, 1, 1, 2, 0, 4, 0, 0,
       0, 2, 0, 4, 0, 1, 0, 0, 0, 2, 2, 1, 1, 1, 3, 4, 0, 0, 0, 1, 0, 0,
       4, 2, 2, 0, 4, 1, 2, 0, 3, 4, 2, 2, 1, 1, 0, 1], dtype=int32)
```

In [22]:

```
# add clustering labels
nearby_venues.insert(0, 'Cluster Labels', kmeans.labels_)
```

Results

To see the results let's show the first ten rows of the dataset.

In [23]:

```
nearby_venues.head(10)
```

Out[23]:

	Cluster Labels	id	name	categories	lat	lng
0	3	59a2a8c3c0cacb5d0ff796eb	Академический парк	Park	55.691777	37.568886
1	3	4e7b0341b0fbf3d6be9917d3	Парк «Новые Черёмушки»	Park	55.693547	37.589786
2	3	4fb90be5e4b0c86152260256	Двор с фонтаном	Playground	55.692286	37.577203
3	3	4fbbaa56e4b0c852de6b3a36	Сквер «200 лет А. С. Пушкину»	Park	55.687814	37.575538
4	3	54ae6d16498e18b8bcce5838	Эндорфин квест	Arcade	55.680578	37.570033
5	1	4f8c484ee4b0e67b87bb83e1	Аллея	Park	55.678210	37.558306
6	4	4e527a86d4c075ade75b3f06	Парк Дворца Пионеров	Park	55.702327	37.556238
7	4	4ed851fcbe7be28335359dac	Молодёжная улица	Park	55.693817	37.546515
8	0	56d097b7cd10ac3eb8a5d793	Батутный парк «Небо»	Athletics & Sports	55.687681	37.603730
9	4	57c85b83498eec7de643b658	Kuzina	Dessert Shop	55.688509	37.547529

We can see in the list the parks, a trampoline venue, a playground, a quest room and a dessert shop.

There is no sense to transliterate the venue names since they remained senseless for English speaking person. For example, 'Батутный парк "Небо" is the trampoline park called 'Sky'. Its transliteration will be 'Batutny park "Nebo" and is useless. Some venues in Foursquare (mostly placed in the center of Moscow) has both Russian and English names slashed.

Let's look at the list of the venue categories to ensure that all the venue are suitable for families with kids.

In [24]:

```
cat_venues = nearby_venues
cat_ven = cat_venues.groupby('categories').mean()
cat_ven.index
```

Out[24]:

```
Index(['Arcade', 'Art Museum', 'Athletics & Sports', 'Cupcake Shop',
      'Dessert Shop', 'Frozen Yogurt Shop', 'Ice Cream Shop', 'Movie Thea
      'Multiplex', 'Museum', 'Park', 'Pie Shop', 'Playground',
      'Science Museum', 'Shopping Mall', 'Theme Park Ride / Attraction'],
      dtype='object', name='categories')
```

It looks like all the venues are affordable for families with kids. The 'Shopping Mall' got in the list since there are cinema multiplexes there together with kids' cafe and some attractions.

Let's visualize the results of clustering on the map. We'll also add labels for the venue marks to make the map more convenient.

In [25]:

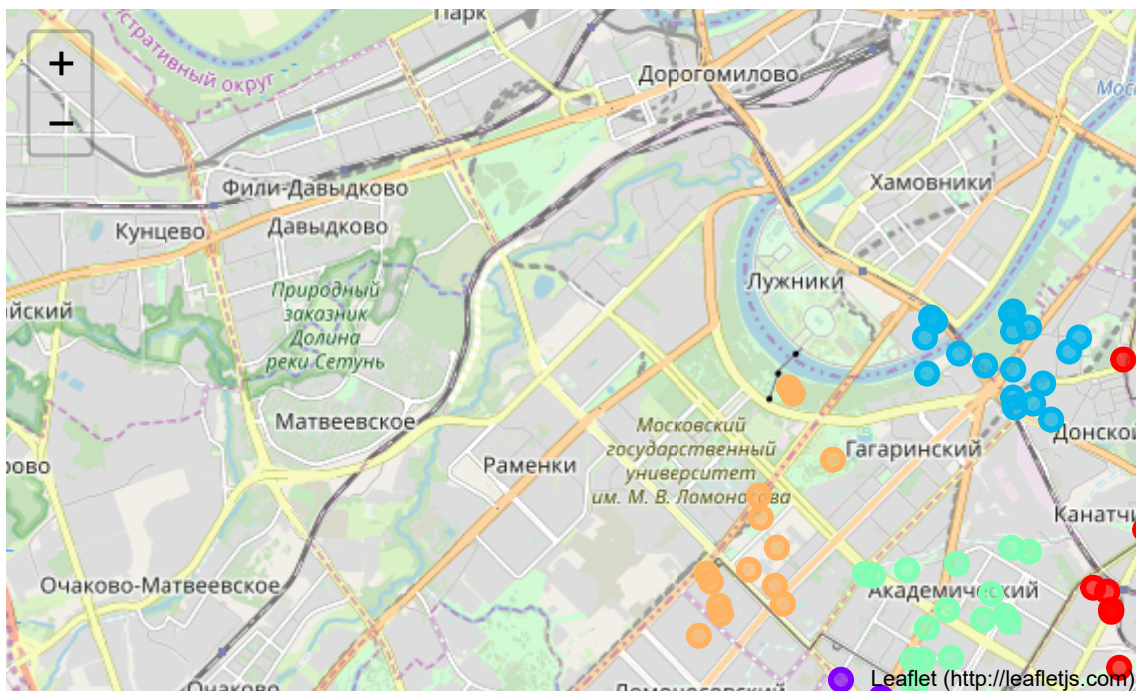
```
# create map
map_clusters = folium.Map(location=[neighbourhood_latitude, neighbourhood_longitude],

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i + x + (i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, name, cat, cluster in zip(nearby_venues['lat'], nearby_venues['lng'], ne
    label = folium.Popup(name + ', ' + cat + ', Cluster ' + str(cluster+1), parse_html
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

Out[25]:



Discussion

Looking at the map we can see that the most interesting are the clusters 2 and 3 since they are compact. That means that it will be a little more convenient to move from one venue to other by walk. Let's make a list of the venues for the clusters 2 and 3 separately.

Cluster #2

In [26]:

```
cluster2 = nearby_venues.loc[nearby_venues['Cluster Labels'] == 2, ['name', 'categories', 'lat', 'lng']]
```

Out[26]:

	name	categories	lat	lng
13	Детская площадка	Playground	55.711351	37.582281
18	Клаустрофобия	Arcade	55.712843	37.596536
24	Prostokvest	Arcade	55.714083	37.571709
27	Детская Площадка	Playground	55.716544	37.586733
31	Донской сквер	Park	55.714075	37.598430
32	CityQuest	Arcade	55.716126	37.572923
34	Neskuchny Garden (Нескучный сад)	Park	55.716678	37.586922
35	Сквер у метро Ленинский проспект	Park	55.707312	37.587318
39	Шоколадница	Dessert Shop	55.707768	37.590500
45	Итальянская кондитерская	Dessert Shop	55.711032	37.586948
53	Детская площадка у Андреевских прудов	Playground	55.710598	37.572182
54	Народный парк "Бульвар Архитекторов"	Park	55.709798	37.591990
67	Детская Площадка 2	Playground	55.714793	37.586821
68	Детская площадка "Стройка"	Playground	55.715172	37.589886
72	Baskin Robbins (Баскин Роббинс)	Ice Cream Shop	55.706239	37.593475
76	Музей Ар Деко	Art Museum	55.715618	37.573741
77	Экоцентр «Воробьёвы горы»	Science Museum	55.712644	37.577606
82	Линдфорс	Pie Shop	55.708414	37.587119

In [27]:

```
# the list of categories
cluster2.groupby('categories').sum().index
```

Out[27]:

```
Index(['Arcade', 'Art Museum', 'Dessert Shop', 'Ice Cream Shop', 'Park',  
      'Pie Shop', 'Playground', 'Science Museum'],  
      dtype='object', name='categories')
```

In [28]:

```
print('Quantity of venues categories in Cluster 2 = ', len(cluster2.groupby('categories')))
```

Quantity of venues categories in Cluster 2 = 8

Cluster #3

In [29]:

```
cluster3 = nearby_venues.loc[nearby_venues['Cluster Labels'] == 3, ['name', 'categories', 'lat', 'lng']]
```

Out[29]:

	name	categories	lat	lng
0	Академический парк	Park	55.691777	37.568886
1	Парк «Новые Черёмушки»	Park	55.693547	37.589786
2	Двор с фонтаном	Playground	55.692286	37.577203
3	Сквер «200 лет А. С. Пушкину»	Park	55.687814	37.575538
4	Эндорфин квест	Arcade	55.680578	37.570033
10	Сквер на винокурова	Park	55.689456	37.583141
12	детская площадка	Playground	55.686949	37.581865
14	Салют	Movie Theater	55.682933	37.571550
15	Квест Клуб	Arcade	55.687250	37.585670
16	Квест Белый Лебедь	Arcade	55.686636	37.586239
17	Тютчевский сквер	Park	55.686196	37.572171
19	Детская Площадка Ул. Шверника	Playground	55.693883	37.586755
20	Парк «Сосенки»	Park	55.670098	37.592706
22	Детская площадка	Playground	55.683160	37.576410
28	Лермонтовский сквер	Park	55.683000	37.569900
30	Палеопарк	Park	55.691128	37.562875
36	Новочеремушкинская Аллея	Park	55.676064	37.573920
58	Сквер	Park	55.666480	37.585908
74	Государственный Дарвиновский музей / State Dar...	Science Museum	55.691300	37.561420

In [30]:

```
# the list of categories
cluster3.groupby('categories').sum().index
```

Out[30]:

```
Index(['Arcade', 'Movie Theater', 'Park', 'Playground', 'Science Museum'], dtype=object)
```


In [31]:

```
print('Quantity of venues categories in Cluster 3 = ', len(cluster3.groupby('categorie
```

Quantity of venues categories in Cluster 3 = 5

So Cluster 2 is more affordable than Cluster 3 since it consists of the venues from more categories (8 vs 5) what means more flexibility and choice for families.

Conclusion

We have managed within the project to solve the following problems:

1. We found the way to determine neighbourhoods for Moscow area and download corresponding geo data;
2. We transliterated the names of municipalities by replacing Cyrillic symbols with English ones;
3. We developed the algorithm and code for finding geo coordinates of polygon centroids on the base of boundaries polygon by iteration procedure of polygon convolution;
4. We determined the target categories of venues that are affordable for families with kids;
5. We got data of the venues we are interested in through Foursquare API;
6. We clustered the venues according their locations;
7. We displayed the map with marks indicating venues and clusters with pop-up labels;
8. We analyze the results and found the most promising and convinient cluster of venues for families with kids.

In []: