# Capstone Project - The Battle of the Neighborhoods (Week 2)

Choosing a Minneapolis neighborhood for a family of three.

# Introduction

## Business Problem

In this project we will try to find an optimal location that a family of three can move into, based on their preferences and requirements. Specifically, this report will be targeted to stakeholders interested in moving to Minneapolis, Minnesota.

Minneapolis is known as one of the most comfortable cities in the US. It is praised for its parks and theaters; it also reportedly has rather low crime rates. Most importantly, the Minneapolis-St.Paul metropolitan area is home to some 24 Fortune 1000 companies, and it is one of the country's top economies. Some people even like to compare this city to New York.

# Introduction

Business Problem

In our case, a family of three is considering moving to Minneapolis since one of the parents was offered an interesting job opportunity there. They have never been to the state of Minnesota (and Minneapolis in particular), so they decided to consult a specialist on which neighborhood they should pick.

# Introduction

## Objective

The objective is to identify a neighborhood in Minneapolis that is most suitable for the given family. This analysis would be relevant and useful for other individuals planning to move to this city.

# Introduction

Problem Statement

The family needs to find a neighborhood that will meet **the following criteria**:

1) be reasonably close to the earning parent’s workplace in Downtown East

2) have a some grocery shops/farmers markets etc

3) have a selection of places to eat out

4) have a green zone in the vicinity

5) have low crime rates

6) offer some form of entertainment and sports facilities (movies, gyms, etc.)

Data analysis will help to find the most suitable neighborhoods that the family will consider for relocation.

# Data

We will begin our analysis by identifying the neighborhoods in Minneapolis using information from OpenData (http://opendata.minneapolismn.gov/datasets/minneapolis-neighborhoods/data). We will use geodata to visualize neighborhoods on the map to see which neighborhoods are closer to Downtown East.

## Below is the dataframe with the geometry data that will be used to map out neighborhood borders.

As we can see, neighborhoods are not in all caps (as they are in our crime data), so we need to adjust them for consistency

In [15]:
```
df_neighb['BDNAME'] = df_neighb['BDNAME'].str.upper()
df_neighb.drop(columns=['BDNUM','TEXT_NBR','NCR_LINK','IMAGE'],axis=1,inplace=True)
```

In [16]:
```
df_neighb.head()
```

Out[16]:

| | FID | BDNAME | Shape_STAr | Shape_STLe | SHAPE_Length | SHAPE_Area | geometry |
|---|---|---|---|---|---|---|---|
| 0 | 1 | PHILLIPS WEST | 1.066925e+07 | 14403.885934 | 0.045801 | 0.000113 | MULTIPOLYGON (((-93.26258 44.96091, -93.26258 ... |
| 1 | 2 | DOWNTOWN WEST | 2.075613e+07 | 19220.602541 | 0.063671 | 0.000220 | MULTIPOLYGON (((-93.26011 44.98300, -93.26010 ... |
| 2 | 3 | DOWNTOWN EAST | 1.025499e+07 | 13436.601366 | 0.045179 | 0.000109 | MULTIPOLYGON (((-93.24499 44.97893, -93.24499 ... |
| 3 | 4 | VENTURA VILLAGE | 1.263526e+07 | 16988.532717 | 0.059590 | 0.000134 | MULTIPOLYGON (((-93.24958 44.96630, -93.24961 ... |
| 4 | 5 | SUMNER - GLENWOOD | 5.741860e+06 | 11065.343364 | 0.035535 | 0.000061 | MULTIPOLYGON (((-93.28830 44.98904, -93.28830 ... |

# The map created:

```
map_minneapolis = folium.Map(location=[latitude, longitude], zoom_start=10)

#show neighborhoods on the map

folium.GeoJson(data = df_neighb, name='Neighborhoods', tooltip=folium.features.GeoJsonTooltip(fields=['BDNAME'], localize=True)).add_to(map_minneapolis)
map_minneapolis
```

Out[19]:

## We also needed to extract latitude and longitude values for each neighborhood (to further work with Foursquare API)

The geojson file contained only the geometry, so we needed to first extract centroids, and then get latitude and longitude from the centroid points.

In [73]:
```
neighb_latlng.head() #check the results
```

Out[73]:

| | FID | BDNAME | Shape_STAr | Shape_STLe | SHAPE_Length | SHAPE_Area | geometry | Centroid | Latitude | Longitude |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | PHILLIPS WEST | 1.066925e+07 | 14403.885934 | 0.045801 | 0.000113 | MULTIPOLYGON (((-93.26258 44.96091, -93.26258 ... | POINT (-93.26734 44.95386) | 44.9539 | -93.2673 |
| 1 | 2 | DOWNTOWN WEST | 2.075613e+07 | 19220.602541 | 0.063671 | 0.000220 | MULTIPOLYGON (((-93.26011 44.98300, -93.26010 ... | POINT (-93.27012 44.97784) | 44.9778 | -93.2701 |
| 2 | 3 | DOWNTOWN EAST | 1.025499e+07 | 13436.601356 | 0.045179 | 0.000109 | MULTIPOLYGON (((-93.24499 44.97893, -93.24499 ... | POINT (-93.25411 44.97606) | 44.9761 | -93.2541 |
| 3 | 4 | VENTURA VILLAGE | 1.263526e+07 | 16988.532717 | 0.059690 | 0.000134 | MULTIPOLYGON (((-93.24958 44.96630, -93.24951 ... | POINT (-93.25790 44.96278) | 44.9628 | -93.2579 |
| 4 | 5 | SUMNER - GLENWOOD | 5.741860e+06 | 11065.343364 | 0.035535 | 0.000061 | MULTIPOLYGON (((-93.28830 44.98904, -93.28830 ... | POINT (-93.29160 44.98403) | 44.984 | -93.2916 |

**Let's create a new dataframe with only the neighborhood names and corresponding lat/lng values, which will be used for working with Foursquare**

In [74]:
```
neighborhood_ll = neighb_latlng[['BDNAME','Latitude','Longitude']]
neighborhood_ll.rename(columns={'BDNAME':'Neighborhood'}, inplace=True)
neighborhood_ll.head()
```

Out[74]:

| | Neighborhood | Latitude | Longitude |
|---|---|---|---|
| 0 | PHILLIPS WEST | 44.9539 | -93.2673 |
| 1 | DOWNTOWN WEST | 44.9778 | -93.2701 |
| 2 | DOWNTOWN EAST | 44.9761 | -93.2541 |

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# We then examined the data on crime levels

**Let's make a new dataframe with only the relevant data (neighborhood name, type of crime, and lat/lng values)**

In [7]:
```
neighborhoods_crime = crime_2018[['Neighborhood','Description','Lat', 'Long']]
neighborhoods_crime = neighborhoods_crime.rename(columns={'Description':'Type of Crime', 'Lat':'Latitude', 'Long': 'Longitude'})
neighborhoods_crime.head()
```

Out[7]:

| | Neighborhood | Type of Crime | Latitude | Longitude |
|---|---|---|---|---|
| 0 | REGINA | Burglary Of Business | 44.919705 | -93.269608 |
| 1 | MARCY HOLMES | Motor Vehicle Theft | 44.986351 | -93.237514 |
| 2 | MARCY HOLMES | Theft From Motr Vehc | 44.985314 | -93.233748 |
| 3 | NORTH LOOP | Shoplifting | 44.982576 | -93.268417 |
| 4 | NORTHEAST PARK | Other Theft | 45.003639 | -93.228834 |

# Prepared this data for the map

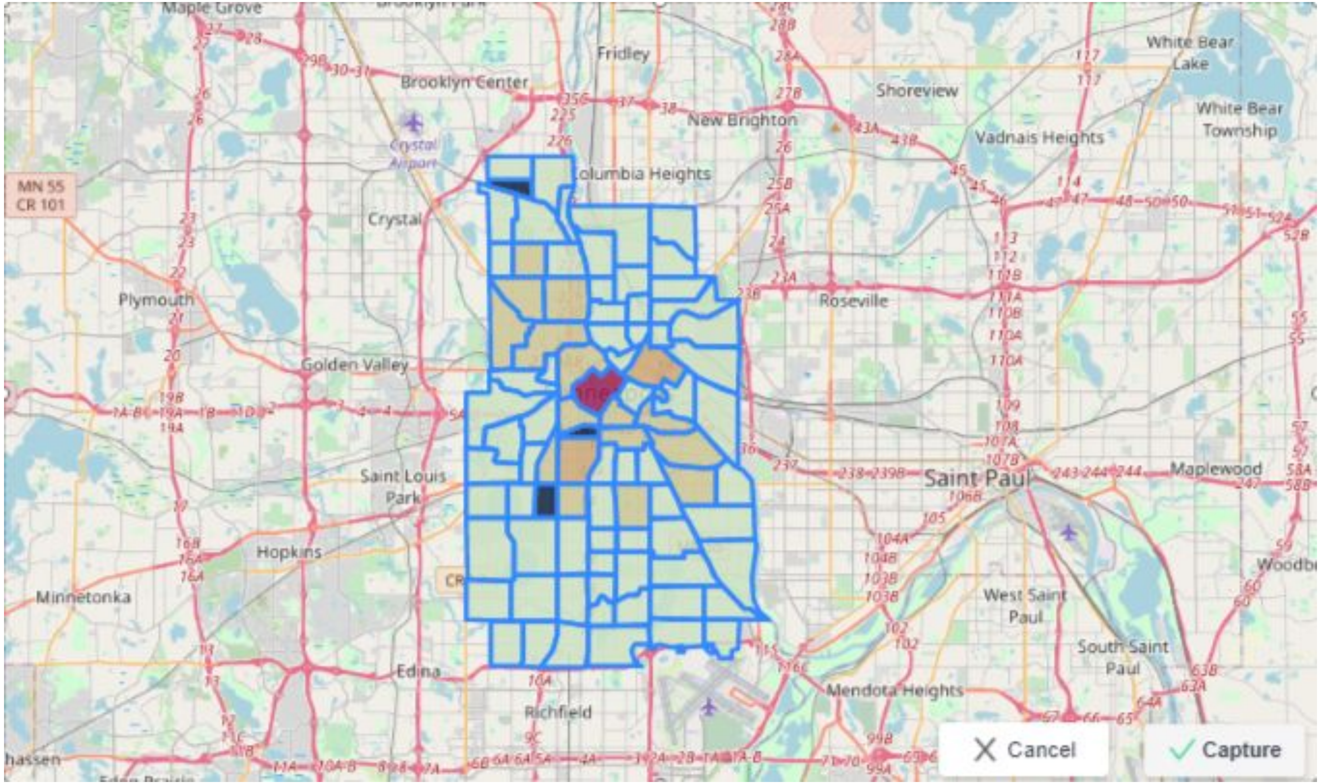
**First we need t o create a new dataframe with generalized crime data per neighborhood**

In [20]:
```
neigh_crime_counts = neighborhoods_crime['Neighborhood'].value_counts().to_frame()
crime_per_neighborhood = neigh_crime_counts.reset_index().rename(columns={'index': 'Neighborhood', 'Neighborhood':'Count'})
crime_per_neighborhood.head()
```

Out[20]:

| | Neighborhood | Count |
|---|---|---|
| 0 | DOWNTOWN WEST | 568 |
| 1 | WHITTIER | 202 |
| 2 | MARCY HOLMES | 201 |
| 3 | JORDAN | 173 |
| 4 | LOWRY HILL EAST | 168 |

# And visualized it on the choropleth map



# As we would later use Matplotlib to visualize crime levels, we also prepared a dataframe for that

Out[129]:

| | Neighborhood | Arson | Aslt-great Bodily Hm | Aslt-sgnfcnt Bdly Hm | Asslt W/dngrs Weapon | Burglary Of Dwelling | Crim Sex Cond-rape | Motor Vehicle Theft | Murder (general) | Other Theft | Robbery Of Person | Theft From Motr Vehc | Theft From Person |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | MARCY HOLMES | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 2 | MARCY HOLMES | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 4 | NORTHEAST PARK | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 5 | ST. ANTHONY EAST | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 6 | ELLIOT PARK | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |

Group rows by neighborhood and by taking the mean of category occurence frequency

In [130]:

```
crime_grouped =crime_onehot.groupby('Neighborhood').mean().reset_index()
crime_grouped.head()
```

Out[130]:

| | Neighborhood | Arson | Aslt-great Bodily Hm | Aslt-sgnfcnt Bdly Hm | Asslt W/dngrs Weapon | Burglary Of Dwelling | Crim Sex Cond-rape | Motor Vehicle Theft | Murder (general) | Other Theft | Robbery Of Person | Theft From Motr Vehc | Theft From Person |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | ARMATAGE | 0.0 | 0.000000 | 0.0 | 0.000000 | 0.190476 | 0.000000 | 0.000000 | 0.0 | 0.190476 | 0.000000 | 0.619048 | 0.000000 |
| 1 | AUDUBON PARK | 0.0 | 0.000000 | 0.0 | 0.000000 | 0.485714 | 0.028571 | 0.100000 | 0.0 | 0.242857 | 0.000000 | 0.128571 | 0.014286 |
| 2 | BANCROFT | 0.0 | 0.000000 | 0.0 | 0.000000 | 0.333333 | 0.000000 | 0.190476 | 0.0 | 0.238095 | 0.000000 | 0.238095 | 0.000000 |
| 3 | BELTRAMI | 0.0 | 0.000000 | 0.0 | 0.076923 | 0.076923 | 0.000000 | 0.000000 | 0.0 | 0.230769 | 0.000000 | 0.615385 | 0.000000 |
| 4 | BOTTINEAU | 0.0 | 0.043478 | 0.0 | 0.043478 | 0.173913 | 0.000000 | 0.217391 | 0.0 | 0.173913 | 0.043478 | 0.260870 | 0.043478 |

Set neighborhood as index

In [131]:

```
crime_grouped.set_index('Neighborhood', inplace=True)
```

Cancel Capture

# Methodology

In this project we will direct our efforts on detecting neighborhoods of Minneapolis that have low crime rates, particularly those with low number of crimes that involve individuals (as opposed to businesses/establishments), as well as neighborhoods that offer infrastructure that is appealing to the stakeholder (i.e. the family).

The most suitable neighborhoods will have some green zones (parks, trails, playgrounds), grocery shops or farmers' markets, as well as a sufficient number of cafes/restaurants.

## Using foursquare API we will get location and type (category) of venues in each neighborhood of Minneapolis.

In [84]:
```
minneapolis_venues.head()
```

Out[84]:

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|
| 0 | PHILLIPS WEST | 44.953863 | -93.267343 | American Swedish Institute | 44.954641 | -93.265787 | Museum |
| 1 | PHILLIPS WEST | 44.953863 | -93.267343 | FIKA | 44.954555 | -93.265717 | Scandinavian Restaurant |
| 2 | PHILLIPS WEST | 44.953863 | -93.267343 | Minneapolis Institute of Art | 44.958554 | -93.273284 | Art Museum |
| 3 | PHILLIPS WEST | 44.953863 | -93.267343 | Taqueria La Hacienda | 44.948605 | -93.271181 | Mexican Restaurant |
| 4 | PHILLIPS WEST | 44.953863 | -93.267343 | Children's Theatre Company | 44.957949 | -93.273466 | Theater |

### Check how many unique venue categories we have

In [86]:
```
print('There are {} uniques categories.'.format(len(minneapolis_venues['Venue Category'].unique())))
```

```
There are 253 uniques categories.
```

# Most common venues for every neighborhood:

```
neighborhoods_venues_sorted = pd.DataFrame(columns = columns)
neighborhoods_venues_sorted['Neighborhood'] = minneapolis_grouped['Neighborhood']

for ind in np.arange(minneapolis_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common_venues(minneapolis_grouped.iloc[ind, : ], num_top_venues)

neighborhoods_venues_sorted.head()
```

Out[91]:

| | 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 | ARMATAGE | Pizza Place | Trail | Restaurant | Arts & Crafts Store | Flower Shop | Mexican Restaurant | Pet Store | French Restaurant | Supermarket | Chinese Restaurant |
| 1 | AUDUBON PARK | Park | Bakery | Pharmacy | Brewery | Pizza Place | Coffee Shop | Thai Restaurant | Hotel Bar | Organic Grocery | Liquor Store |
| 2 | BANCROFT | Park | Food & Drink Shop | Coffee Shop | Pharmacy | BBQ Joint | Mexican Restaurant | Food Truck | South American Restaurant | Chinese Restaurant | Furniture / Home Store |
| 3 | BELTRAMI | Brewery | BBQ Joint | Dive Bar | Coffee Shop | Yoga Studio | Park | Cosmetics Shop | Donut Shop | Event Space | Café |
| 4 | BOTTINEAU | Dive Bar | Coffee Shop | Theme Restaurant | Ice Cream Shop | American Restaurant | Café | Pet Store | Bookstore | Speakeasy | New American Restaurant |

## We also prepared the data for visualization with Matplotlib

Since we cannot display all 253 venue categories on a plot (and keep it visually appealing and easy t
neighborhoods

In [269]:
```
cols_to_remove = set()

for i in mn_venues:
    if mn_venues[i].mean() < 0.01: #Let's leave only those venue categories that have at l
        cols_to_remove.add(i)

for i in cols_to_remove:
    mn_venues.drop(i, axis=1, inplace=True)
```

In [270]:
```
mn_venues.head() #a preview
```

Out[270]:

| Neighborhood | American Restaurant | Art Gallery | Asian Restaurant | Bakery | Bar | Brewery | Café | Chinese Restaurant | |
|---|---|---|---|---|---|---|---|---|---|
| ARMATAGE | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.043478 | 0. |
| AUDUBON PARK | 0.033333 | 0.000000 | 0.000000 | 0.100000 | 0.000000 | 0.066667 | 0.000000 | 0.000000 | 0. |
| BANCROFT | 0.033333 | 0.033333 | 0.000000 | 0.033333 | 0.033333 | 0.000000 | 0.000000 | 0.033333 | 0. |
| BELTRAMI | 0.033333 | 0.033333 | 0.033333 | 0.000000 | 0.000000 | 0.133333 | 0.033333 | 0.000000 | 0. |
| BOTTINEAU | 0.066667 | 0.033333 | 0.000000 | 0.000000 | 0.033333 | 0.033333 | 0.066667 | 0.000000 | 0. |

5 rows × 23 columns

**The second step in our analysis was finding the most popular venues in each neighborhood and clustering the neighborhoods based on this information (using KMeans clustering).**

**First we grouped rows by neighborhoods and calculated the mean of each category's occurrence frequency**

### Group rows by neighborhood and by taking the mean of category occurence frequency

In [88]:
```
minneapolis_grouped = minneapolis_onehot.groupby('Neighborhood').mean().reset_index()
minneapolis_grouped.head()
```

Out[88]:

| | Neighborhood | ATM | Accessories Store | Acupuncturist | Adult Boutique | Advertising Agency | African Restaurant | American Restaurant | Antique Shop | Arcade | ... | Vegetarian / Vegan Restaurant | Video Store | Vietnamese Restaurant | Warehouse Store |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | ARMATAGE | 0.0 | 0.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.000000 | 0.0 | 0.0 | ... | 0.0 | 0.043478 | 0.000000 | 0.0 |
| 1 | AUDUBON PARK | 0.0 | 0.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.033333 | 0.0 | 0.0 | ... | 0.0 | 0.033333 | 0.033333 | 0.0 |
| 2 | BANCROFT | 0.0 | 0.033333 | 0.0 | 0.0 | 0.0 | 0.0 | 0.033333 | 0.0 | 0.0 | ... | 0.0 | 0.033333 | 0.000000 | 0.0 |
| 3 | BELTRAMI | 0.0 | 0.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.033333 | 0.0 | 0.0 | ... | 0.0 | 0.000000 | 0.033333 | 0.0 |
| 4 | BOTTINEAU | 0.0 | 0.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.066667 | 0.0 | 0.0 | ... | 0.0 | 0.000000 | 0.033333 | 0.0 |

5 rows × 254 columns

# We then clustered the neighborhoods based on most common venues

```
minneapolis_merged.head()
```

Out[101]:

| | Neighborhood | Latitude | Longitude | 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 | 9th Most Common Venue | 10th Most Common Venue |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | PHILLIPS WEST | 44.9539 | -93.2673 | 3 | Mexican Restaurant | Vietnamese Restaurant | American Restaurant | Performing Arts Venue | Theater | Sandwich Place | Scandinavian Restaurant | Bar | Taco Place | College Arts Building |
| 1 | DOWNTOWN WEST | 44.9778 | -93.2701 | 4 | Theater | Italian Restaurant | New American Restaurant | Music Venue | Baseball Stadium | Restaurant | Bar | Sushi Restaurant | Pedestrian Plaza | Donut Shop |
| 2 | DOWNTOWN EAST | 44.9761 | -93.2541 | 4 | Bar | Hotel | Park | Japanese Restaurant | Yoga Studio | Scenic Lookout | Public Art | Non-Profit | Music Venue | Music School |
| 3 | VENTURA VILLAGE | 44.9628 | -93.2579 | 2 | Coffee Shop | Park | Grocery Store | Pharmacy | Theater | Café | Flower Shop | Bridge | Shopping Mall | Breakfast Spot |
| 4 | SUMNER - GLENWOOD | 44.984 | -93.2916 | 4 | Brewery | Thrift / Vintage Store | Farmers Market | Food Truck | Deli / Bodega | Business Service | Café | Fish Market | Bar | Clothing Store |

# The first cluster:

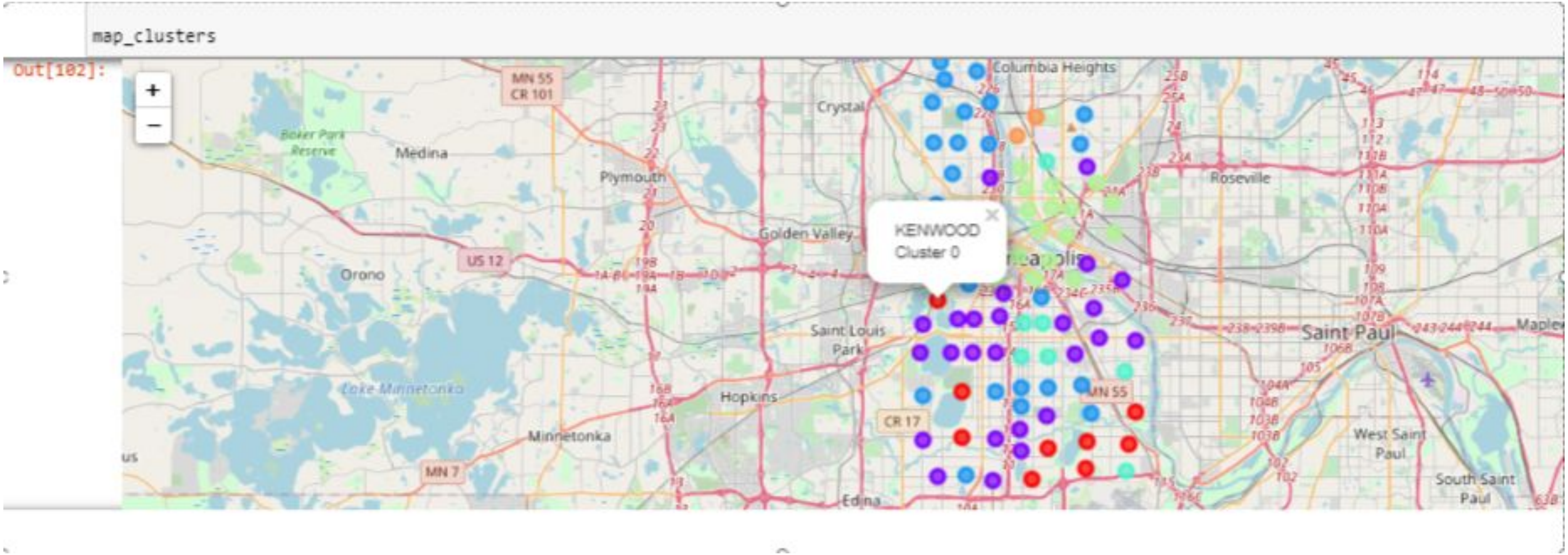
### Cluster 0

```
n [110]: minneapolis_merged.loc[minneapolis_merged['Cluster Labels'] == 0, minneapolis_merged.columns[[0] + list(range(3, minneapolis_merged.shape[1]))]]
```

Out[110]:

| | Neighborhood | 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 Cc |
|---|---|---|---|---|---|---|---|---|---|
| 12 | HIAWATHA | 0 | Park | Trail | Scenic Lookout | Pizza Place | History Museum | Brewery | Bus |
| 28 | MINNEHAHA | 0 | Park | Trail | Historic Site | Liquor Store | Breakfast Spot | Shoe Store | Seafood Res |
| 29 | DIAMOND LAKE | 0 | Food Truck | Pet Store | Gas Station | Dog Run | Park | Grocery Store | Asian Res |
| 33 | HALE | 0 | Lake | Farmers Market | Restaurant | Sculpture Garden | Asian Restaurant | Furniture / Home Store | Thrift / Vintag |
| 34 | KEEWAYDIN | 0 | Park | Beach | Yoga Studio | Grocery Store | Restaurant | Playground | Mexican Res |
| 36 | LYNNHURST | 0 | Italian Restaurant | Park | Sporting Goods Shop | Taco Place | Bike Rental / Bike Share | French Restaurant | Bo |
| 46 | WENONAH | 0 | Mexican Restaurant | Yoga Studio | Dog Run | Baseball Field | Sandwich Place | Asian Restaurant | Fast Food Res |
| 55 | EAST HARRIET | 0 | Playground | Park | Garden | Snack Place | Carpet Store | Beach | Ca |
| 73 | KENWOOD | 0 | Lake | Beach | Park | Trail | Café | Bookstore | American Res |

# We visualized all clusters on the map



# Methodology

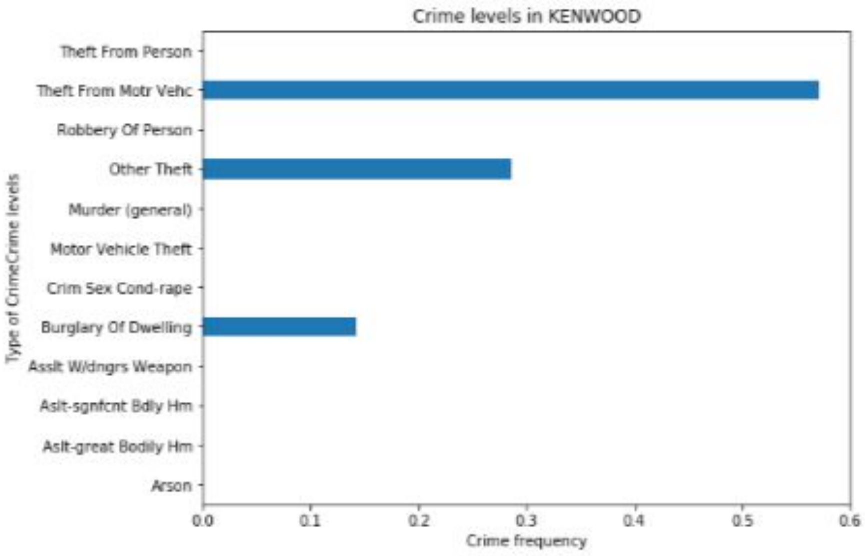
Final analysis

**In third and final step** we will focus on most promising neighborhoods in each cluster and choose the most suitable neighborhoods by visualizing crime and venue data for the most promising neighborhoods (visualization will help to decide on the final neighborhood recommendations).

## Analyzing crime levels in a neighborhood chosen from a cluster:

Crime

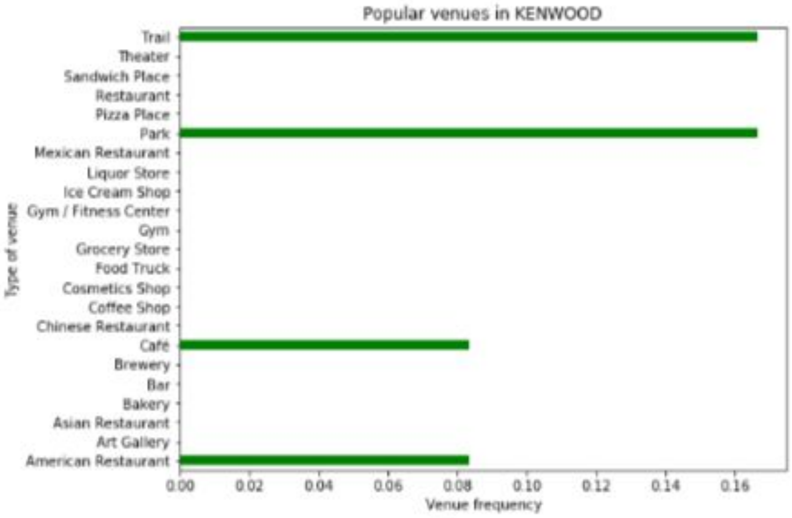
```
[250]: kenwood = crime_grouped.loc['KENWOOD']
kenwood.plot(kind='barh', figsize = (8, 6))
plt.title('Crime levels in KENWOOD')
plt.ylabel('Type of Crime''Crime levels')
plt.xlabel('Crime frequency')
plt.show()
```



# Analyzing popular venues in the same neighborhood:

## Venues

[271]:
```
kenwood_venues = mn_venues.loc['KENWOOD']
kenwood_venues.plot(kind='barh', figsize = (8, 6), color='green')
plt.title('Popular venues in KENWOOD')
plt.ylabel('Type of venue')
plt.xlabel('Venue frequency')
plt.show()
```



# Results and Discussion

Cluster analysis showed that two (2) out of six (6) formed clusters did not meet the requirements of the stakeholders, so neighborhoods from those clusters were not considered.

Out of other four (4) clusters, a total of five (5) neighborhoods were chosen as suitable options for the stakeholders.

# Results and Discussion

The **first cluster (cluster 0)** includes relatively quiet neighborhoods with access to green zones. Two neighborhoods (**Kenwood and Keewaydin**) were identified as suitable options. These neighborhoods are generally more family-friendly and have low crime rates. However, they are both farther from Downtown East, which is the neighborhood where one of the parents in the family plans to work. So, the stakeholders will need to consider whether the commute time is acceptable.

# Results and Discussion

The **third cluster (cluster 2)** also has neighborhoods that are close to parks and have a good selection of restaurants/shops. However, most neighborhoods in this cluster also have relatively high crime rates (because they are closer to downtown), so only one neighborhood was recommended - **Harrison**.

# Results and Discussion

In the **fifth cluster (cluster 4)**, two neighborhoods were identified as suitable (both have access to a park, in addition to various options to eat out); both have sufficiently low crime rates, so both were recommended - **St.Anthony West and Beltrami**.

# Conclusion

Purpose of this project was to identify neighborhoods in Minneapolis that the stakeholder family could relocate to. Using data from Foursquare API we identified the most common venue categories in each neighborhood and were able to cluster Minneapolis neighborhoods using that information. Each cluster was analyzed to identify neighborhoods that suited the family's preferences (if such neighborhoods were present in the cluster). The chosen neighborhoods were compared using data on crime levels and the most popular venues.

The final decision on optimal neighborhood will be made by the stakeholders (i.e. the family) based on specific characteristics of the recommended neighborhoods.