Parks and Income

February 7, 2021

1 Who has access to LA's parks?

Since the pandemic began, a person's ability to maintain good physical and mental health has become even more dependent on their access to outdoor spaces.

Therefore, we want to know: **How accessible are parks and other public recreation facilities in the lowest income neighborhoods and highest income neighborhoods in Los Angeles, CA?**

We will explore this question by creating charts, static maps, and interactive maps to better understand the socioeconomic landscape of Los Angeles. Let's jump in!

1.1 Data sources

We based our research on the following data sources:

LA city income data from the U.S. Census Bureau

Park data from the County of Los Angeles Department of Parks and Recreation

1.2 Importing the libraries

The first thing we need to do is import all of the libraries that will allow us to explore our data and create our beautiful charts and maps.

[1]:
```
import pandas as pd
import geopandas as gpd
import folium
import matplotlib.pyplot as plt
import networkx as nx
import osmnx as ox
from shapely.geometry import Point, LineString, Polygon
import contextily as ctx
```

1.3 Analyzing LA incomes by census tract

We will create 3 charts that will help us compare the median household per income of all LA census tracts. We will do this to identify which census tracts are of interest to us for our research. The charts we will create include:

- City of Los Angeles Census Tract Income Frequency

- Top 10 Census Tracts with Lowest Incomes in the City of Los Angeles
- Top 10 Census Tracts with Highest Incomes in the City of Los Angeles

1.3.1 Cleaning the data

Before we create our charts, we need to import our income data and then rename the columns so that they make more sense.

[2]:
```
income1=pd.read_csv('Data1/Income_KB2.csv')
columns_to_keep = ['geoid','name','B19013001']
income1 = income1[columns_to_keep]
income1.head()
```

[2]:
```
                 geoid                                 name  B19013001
0  14000US06037101110  Census Tract 1011.10, Los Angeles, CA    63534.0
1  14000US06037101122  Census Tract 1011.22, Los Angeles, CA    90389.0
2  14000US06037101210  Census Tract 1012.10, Los Angeles, CA    44083.0
3  14000US06037101220  Census Tract 1012.20, Los Angeles, CA    43713.0
4  14000US06037101300     Census Tract 1013, Los Angeles, CA    81776.0
```

[3]:
```
income1.columns = ['geoid',
 'Census_Tract',
 'Median_Household_Income']
income1.head()
```

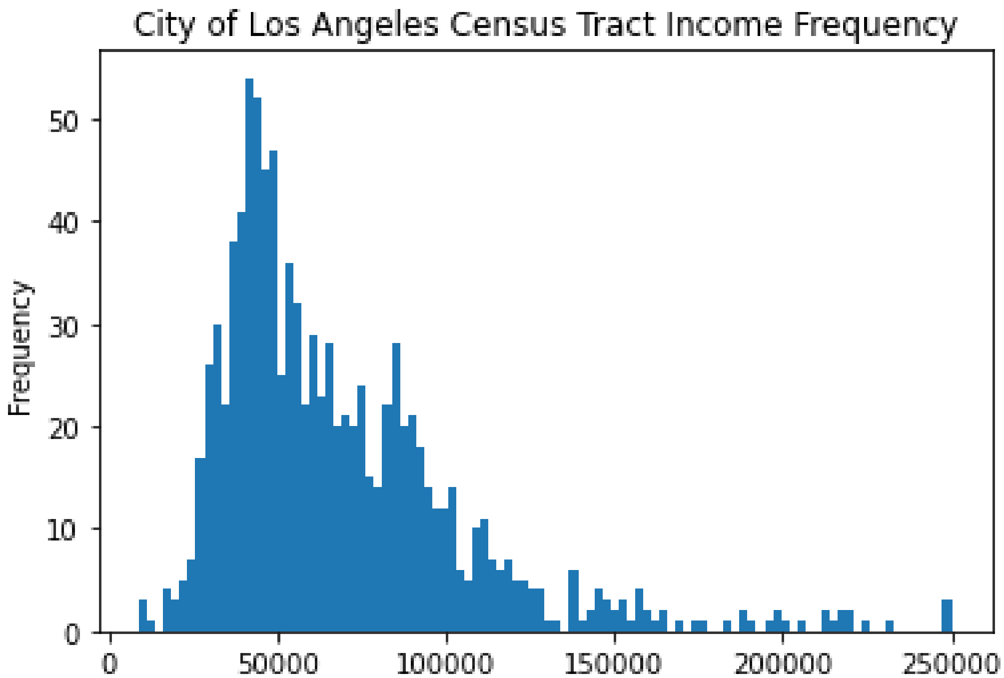
[3]:
```
                 geoid                           Census_Tract  \
0  14000US06037101110  Census Tract 1011.10, Los Angeles, CA
1  14000US06037101122  Census Tract 1011.22, Los Angeles, CA
2  14000US06037101210  Census Tract 1012.10, Los Angeles, CA
3  14000US06037101220  Census Tract 1012.20, Los Angeles, CA
4  14000US06037101300     Census Tract 1013, Los Angeles, CA

   Median_Household_Income
0                  63534.0
1                  90389.0
2                  44083.0
3                  43713.0
4                  81776.0
```

1.3.2 Creating the charts

Now that our income data is clean, we can start to create the 3 charts! We will start by creating a chart that will allow us to see the distribution of incomes across Los Angeles.

[4]:
```
income1['Median_Household_Income'].plot.hist(bins=100)
plt.title('City of Los Angeles Census Tract Income Frequency')
```

[4]:
```
Text(0.5, 1.0, 'City of Los Angeles Census Tract Income Frequency')
```



It looks like most people make below $50,000.

Now we want to get started on creating charts of the top 10 census tracts with the highest and lowest median household incomes. The first thing we need to do is to sort our data set by income and create variables that will store the sorted data.

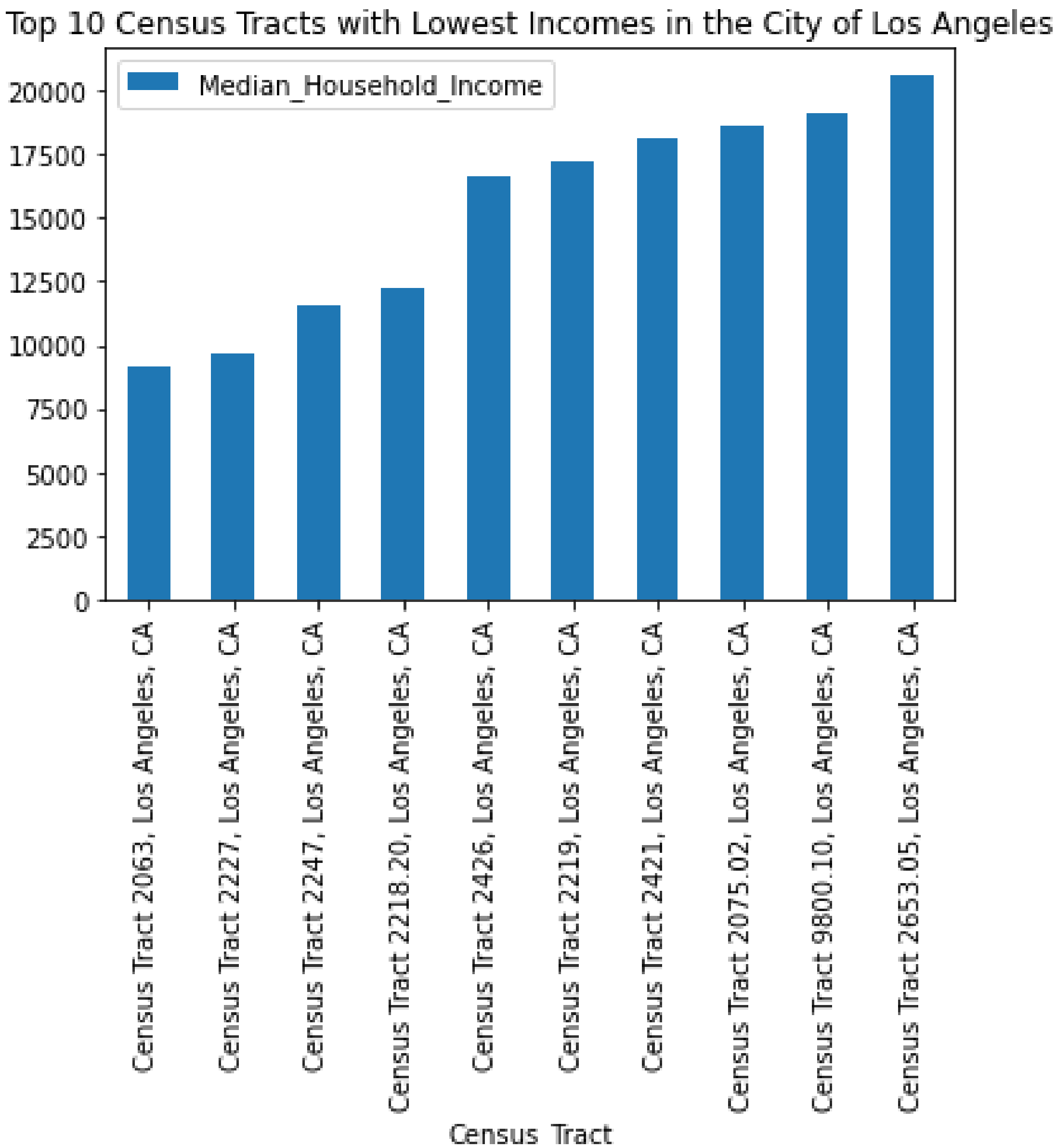
[5]:
```
lowest_incomes = income1.sort_values(by='Median_Household_Income',ascending =
 ↪True)
highest_incomes = income1.sort_values(by='Median_Household_Income',ascending =
 ↪False)
highest_incomes.head()
```

[5]:
```
                  geoid                            Census_Tract  \
831  14000US06037262303  Census Tract 2623.03, Los Angeles, CA
832  14000US06037262400     Census Tract 2624, Los Angeles, CA
340  14000US06037141700     Census Tract 1417, Los Angeles, CA
994  14000US06037980019  Census Tract 9800.19, Los Angeles, CA
833  14000US06037262501  Census Tract 2625.01, Los Angeles, CA

     Median_Household_Income
831                 250001.0
832                 250001.0
340                 250001.0
994                 231250.0
833                 224962.0
```

Next we can create an income bar chart of the lowest incomes.

```
[6]: lowest_incomes.head(10).plot.bar(x='Census_Tract',
                                   y='Median_Household_Income',
                                   title='Top 10 Census Tracts with Lowest Incomes in␣
 ↪the City of Los Angeles')
```

```
[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f41aae0b5e0>
```



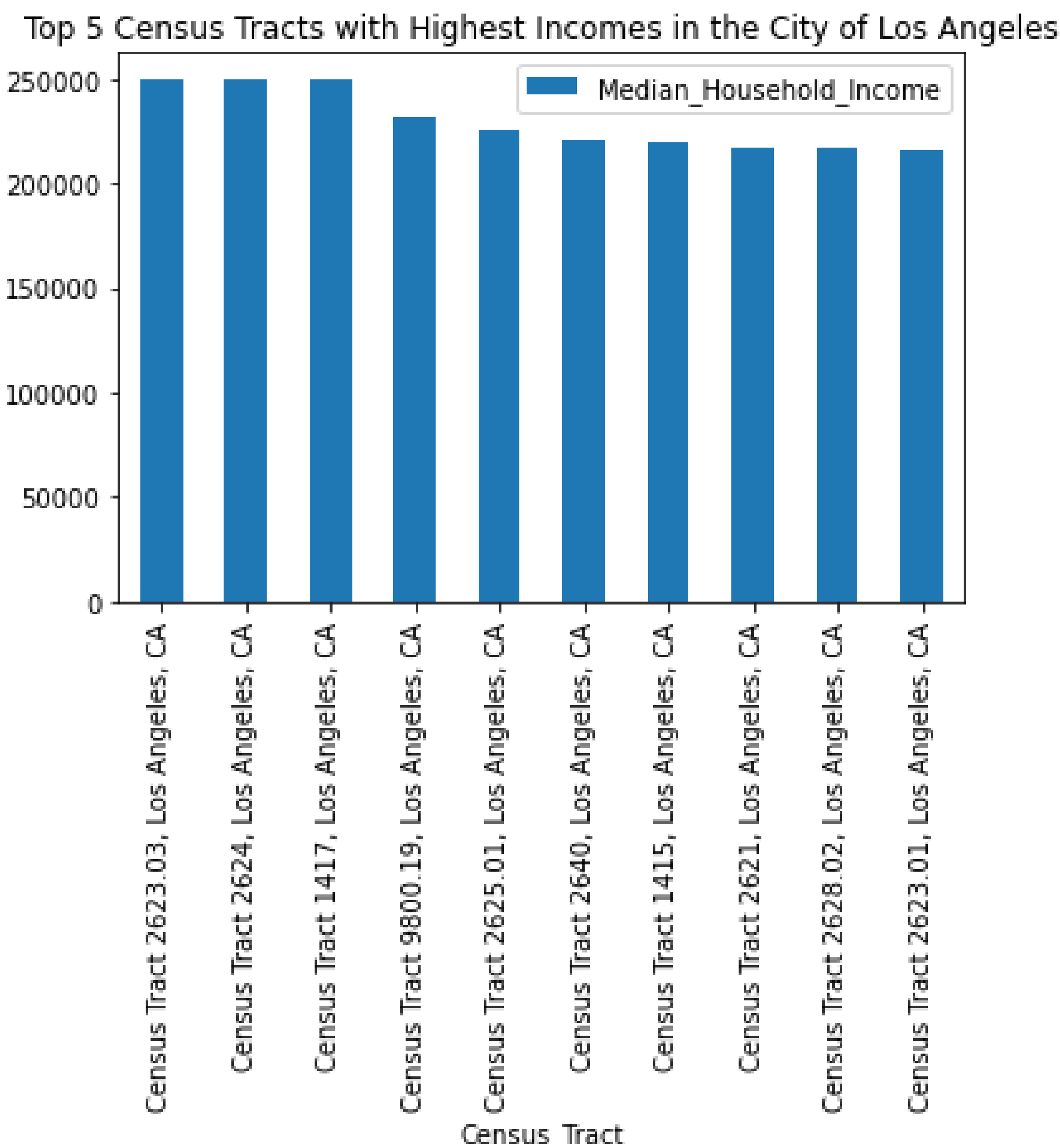
The output of our code is a chart titled "Top 5 Census Tracts with Lowest Incomes in the City of Los Angeles", which has census tracts in the x axis and median household income in the y axis.

From this chart, we learn that the census tracts with the lowest median household incomes have incomes ranging from below 10,000 to slightly above 20,000.

Now we can make a chart for the highest incomes.

[7]:
```
highest_incomes.head(10).plot.bar(x='Census_Tract',
                                  y='Median_Household_Income',
                                  title='Top 5 Census Tracts with Highest Incomes in␣
 ↪the City of Los Angeles')
```

[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7f41aad9fc10>



The output of our code is a chart titled "Top 5 Census Tracts with Highest Incomes in the City of Los Angeles", which has census tracts in the x axis and median household income in the y axis. From this chart we learn that the census tracts with the hgihest median household incomes have incomes around 250,000.

1.4 Mapping parks and income

Perfect! Now that we have created our charts, the next thing we want to do is create interactive maps featuring park and income layers.

1.4.1 Cleaning the Data

We need to do some data cleaning before we create the maps.

Looking at the bottomn of this chart we can see that there are some null values we want to get rid of.

[8]:
```
income2=gpd.read_file('Data2/Income_KB.geojson')
columns_to_keep2 = ['geoid','name','B19013001','geometry']
income2 = income2[columns_to_keep2]
income2
```

[8]:
```
                    geoid                                  name  B19013001  \
0     14000US06037101110  Census Tract 1011.10, Los Angeles, CA    63534.0
1     14000US06037101122  Census Tract 1011.22, Los Angeles, CA    90389.0
2     14000US06037101210  Census Tract 1012.10, Los Angeles, CA    44083.0
3     14000US06037101220  Census Tract 1012.20, Los Angeles, CA    43713.0
4     14000US06037101300     Census Tract 1013, Los Angeles, CA    81776.0
…                    …                                      …         …
999   14000US06037980024  Census Tract 9800.24, Los Angeles, CA   150250.0
1000  14000US06037980026  Census Tract 9800.26, Los Angeles, CA        NaN
1001  14000US06037980028  Census Tract 9800.28, Los Angeles, CA        NaN
1002  14000US06037980031  Census Tract 9800.31, Los Angeles, CA        NaN
1003  14000US06037990200     Census Tract 9902, Los Angeles, CA        NaN

                                               geometry
0     MULTIPOLYGON (((-118.30229 34.25870, -118.3009…
1     MULTIPOLYGON (((-118.30334 34.27371, -118.3033…
2     MULTIPOLYGON (((-118.29945 34.25598, -118.2979…
3     MULTIPOLYGON (((-118.28593 34.25227, -118.2859…
4     MULTIPOLYGON (((-118.27822 34.25068, -118.2782…
…                                                   …
999   MULTIPOLYGON (((-118.51849 34.18389, -118.5184…
1000  MULTIPOLYGON (((-118.35173 34.28034, -118.3517…
1001  MULTIPOLYGON (((-118.45246 33.94315, -118.4464…
1002  MULTIPOLYGON (((-118.29105 33.75378, -118.2905…
1003  MULTIPOLYGON (((-118.63598 34.03255, -118.6325…

[1004 rows x 4 columns]
```

Let's see how many null values there are.

```
[9]: lowest_incomes2 = income2.sort_values(by='B19013001',ascending = True)
     lowest_incomes2.tail(15)
```

```
[9]:                   geoid                                name  B19013001  \
     340   14000US06037141700     Census Tract 1417, Los Angeles, CA   250001.0
     831   14000US06037262303  Census Tract 2623.03, Los Angeles, CA   250001.0
     832   14000US06037262400     Census Tract 2624, Los Angeles, CA   250001.0
     847   14000US06037265301  Census Tract 2653.01, Los Angeles, CA        NaN
     989   14000US06037980008  Census Tract 9800.08, Los Angeles, CA        NaN
     990   14000US06037980009  Census Tract 9800.09, Los Angeles, CA        NaN
     992   14000US06037980014  Census Tract 9800.14, Los Angeles, CA        NaN
     995   14000US06037980020  Census Tract 9800.20, Los Angeles, CA        NaN
     996   14000US06037980021  Census Tract 9800.21, Los Angeles, CA        NaN
     997   14000US06037980022  Census Tract 9800.22, Los Angeles, CA        NaN
     998   14000US06037980023  Census Tract 9800.23, Los Angeles, CA        NaN
     1000  14000US06037980026  Census Tract 9800.26, Los Angeles, CA        NaN
     1001  14000US06037980028  Census Tract 9800.28, Los Angeles, CA        NaN
     1002  14000US06037980031  Census Tract 9800.31, Los Angeles, CA        NaN
     1003  14000US06037990200     Census Tract 9902, Los Angeles, CA        NaN

                                                   geometry
     340   MULTIPOLYGON (((-118.45322 34.13557, -118.4531…
     831   MULTIPOLYGON (((-118.49599 34.07105, -118.4959…
     832   MULTIPOLYGON (((-118.52146 34.11764, -118.5214…
     847   MULTIPOLYGON (((-118.45549 34.07585, -118.4546…
     989   MULTIPOLYGON (((-118.50267 34.22121, -118.5015…
     990   MULTIPOLYGON (((-118.33707 34.14160, -118.3361…
     992   MULTIPOLYGON (((-118.26088 33.76850, -118.2602…
     995   MULTIPOLYGON (((-118.34412 34.21700, -118.3438…
     996   MULTIPOLYGON (((-118.40183 34.26509, -118.4017…
     997   MULTIPOLYGON (((-118.50266 34.30809, -118.5026…
     998   MULTIPOLYGON (((-118.64870 34.23120, -118.6480…
     1000  MULTIPOLYGON (((-118.35173 34.28034, -118.3517…
     1001  MULTIPOLYGON (((-118.45246 33.94315, -118.4464…
     1002  MULTIPOLYGON (((-118.29105 33.75378, -118.2905…
     1003  MULTIPOLYGON (((-118.63598 34.03255, -118.6325…
```

Now we will get rid of the null values.

```
[10]: income2 = income2.drop([847, 989, 990, 992, 995, 996, 997, 998, 1000, 1001,␣
       ↪1002, 1003])
```

Now we can rename our columns so that they make more sense.

```
[11]: income2.columns = ['geoid',
       'Census_Tract',
```

```
 'Median_Household_Income',
 'geometry']
income2.head()
```

[11]:
```
                 geoid                           Census_Tract  \
0  14000US06037101110  Census Tract 1011.10, Los Angeles, CA
1  14000US06037101122  Census Tract 1011.22, Los Angeles, CA
2  14000US06037101210  Census Tract 1012.10, Los Angeles, CA
3  14000US06037101220  Census Tract 1012.20, Los Angeles, CA
4  14000US06037101300     Census Tract 1013, Los Angeles, CA

   Median_Household_Income                                           geometry
0                  63534.0  MULTIPOLYGON (((-118.30229 34.25870, -118.3009…
1                  90389.0  MULTIPOLYGON (((-118.30334 34.27371, -118.3033…
2                  44083.0  MULTIPOLYGON (((-118.29945 34.25598, -118.2979…
3                  43713.0  MULTIPOLYGON (((-118.28593 34.25227, -118.2859…
4                  81776.0  MULTIPOLYGON (((-118.27822 34.25068, -118.2782…
```

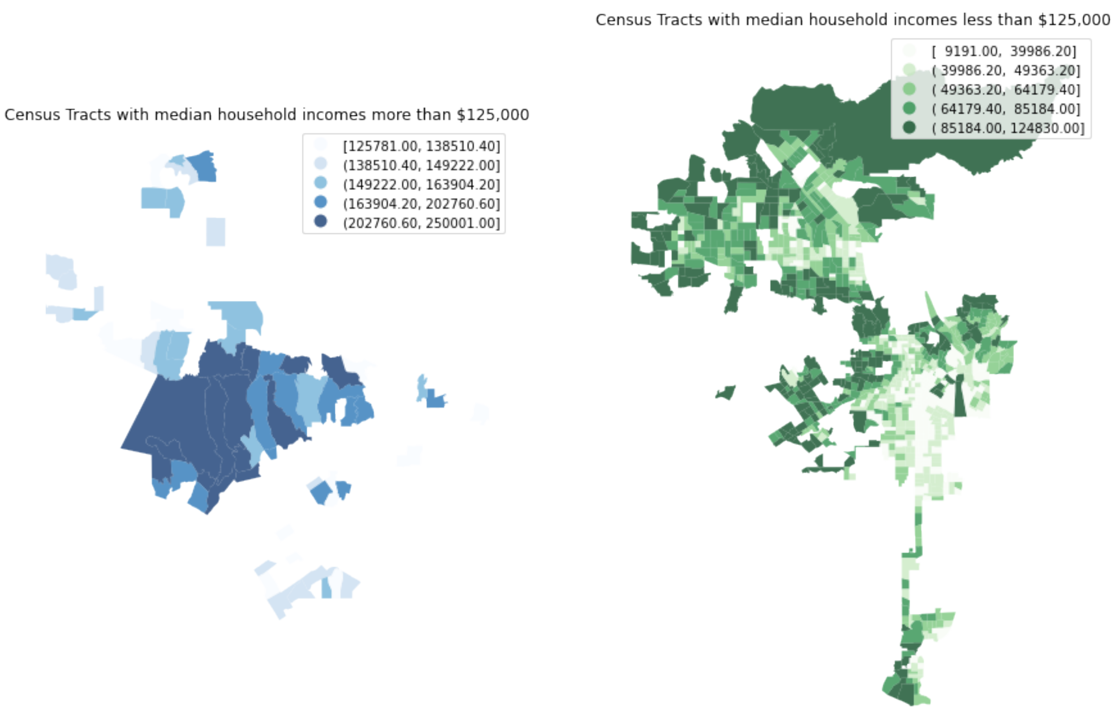
1.4.2 Creating the static maps

Before we begin to create our interactive map, we should first create a nice static map of median household incomes. This will allow us to really visualize where the higher income and lower income communities are in Los Angeles. Having these communities in mind will help us be more intentional when we bring in our park data!

[12]:
```
fig, axs = plt.subplots(1, 2, figsize=(15, 12))

ax1, ax2 = axs

income2[income2.Median_Household_Income > 125000].
 ↪plot(column='Median_Household_Income',
            cmap='Blues',
            scheme='quantiles',
            k=5,
            edgecolor='white',
            linewidth=0.,
            alpha=0.75,
            ax=ax1, # this assigns the map to the subplot,
            legend=True
           )

ax1.axis("off")
ax1.set_title("Census Tracts with median household incomes more than $125,000")

income2[income2.Median_Household_Income < 125000].
 ↪plot(column='Median_Household_Income',
            cmap='Greens',
```

```
            scheme='quantiles',
            k=5,
            edgecolor='white',
            linewidth=0.,
            alpha=0.75,
            ax=ax2, # this assigns the map to the subplot
            legend=True
           )

ax2.axis("off")
ax2.set_title("Census Tracts with median household incomes less than $125,000")
```

[12]: Text(0.5, 1.0, 'Census Tracts with median household incomes less than $125,000')



TWO MAPS?!?! WOW! One map features the bottom half of median household incomes and one features the upper half of median household incomes in Los Angeles. These maps show that the higher income communities are concentrated in hills and valleys north west of Los Angeles. Conversely, the lower income communities are spread around Los Angeles, with the lowest incomes being in the South LA area.

1.4.3 Creating the interactive map

Now we can get started on creating our interactive data maps! We will first make an interactive choropleth map that shades the census tracts according to how high or low their median household income is. We are able to hover over each census tract to see the census tract number.

[13]:
```
m = folium.Map(location=[34.2,-118.2],
               zoom_start = 10,
               tiles='OpenStreetMap',
               attribution='CartoDB')

choropleth = folium.Choropleth(
                  geo_data=income2,
                  data=income2,
                  key_on='feature.properties.Census_Tract',
                  columns=['Census_Tract', 'Median_Household_Income'],
                  fill_color='YlOrRd',
                  line_weight=1,
                  fill_opacity=0.8,
                  line_opacity=0.5,
                  legend_name='Median Household Income per Census Tract (ACS␣
 ↪2019 5-Year Estimates)').add_to(m)

choropleth.geojson.add_child(
    folium.features.GeoJsonTooltip(['Census_Tract'],labels=False)
)
m
```

[13]: <folium.folium.Map at 0x7f41a322e520>

How beautiful!! The census tracts with higher incomes have a darker red color. This color scheme is presented in the key in the top right.

Now it's time to import our park data so we can add it as a layer to the map!

[14]:
```
parks2 = pd.read_csv('Data3/PR2.csv')
parks2.head()
```

[14]:

	LocationType	Location_Name	StNumber	StNumberFraction
0	Parks	La Mirada Park Acquisition Site	5401.0	NaN
1	Parks	Avalon-San Pedro Park	4025.0	NaN
2	Parks	11th Avenue Park	6116.0	NaN
3	Parks	Imperial Courts Park	2250.0	NaN
4	Parks	Eagle Rock Hillside Park	NaN	NaN

	StDirection	StName	StSuffix	StSuffixDirection	AddressType
0	W	La Mirada	Ave	NaN	NaN
1	NaN	Avalon	Blvd	NaN	NaN
2	NaN	11th	Ave	NaN	NaN
3	E	114th	St	NaN	NaN
4	NaN	N. of Ventura Freeway	NaN	NaN	NaN

```
   AddressTypeValue  …  CrossStSuffix CrossStSuffixDirection  \
0               NaN  …            NaN                    NaN
1               NaN  …            NaN                    NaN
2               NaN  …            NaN                    NaN
3               NaN  …            NaN                    NaN
4               NaN  …            NaN                    NaN

                                                City  State    Zip  \
0  Los Angeles, CA 90029\n(34.0942, -118.307)     CA  90029
1  Los Angeles, CA 90011\n(34.0104, -118.266)     CA  90011
2  Los Angeles, CA 90043\n(33.9845, -118.329)     CA  90043
3  Los Angeles, CA 90059\n(33.9313, -118.232)     CA  90059
4   Los Angeles, CA 90041\n(34.149, -118.202)     CA  90041

                                             Website           Phone  \
0                                                NaN  (310) 548-7675
1                                                NaN  (310) 548-7675
2                                                NaN  (310) 548-7675
3  http://www.laparks.org/dos/reccenter/facility/…  (323) 564-1834
4  http://www.laparks.org/dos/parks/facility/eagl…  (213) 485-5054

  CouncilDistrict          X           Y
0              13  34.094208 -118.306999
1               9  34.010389 -118.265542
2               8  33.984488 -118.329232
3              15  33.931257 -118.232420
4              14  34.149007 -118.202226

[5 rows x 22 columns]
```

Now that we got our income data AND our park data, we can display both on our interactive map! How exciting! Since we have extensive data sets including parks and other public facilities, we will create two maps. One with only parks and the other with both parks and public facilities!

The markers on this map only show parks. You can hover over the markers to see the park names. You can also still hover over the census tracts to see what tract they are.

[15]:
```
for index, row in parks2.iterrows():
    tooltip_text = row.Location_Name
    folium.Marker(
        [row.X,row.Y],
        popup=row.Location_Name,
        tooltip=tooltip_text,
        icon=folium.Icon(color='green')
).add_to(m)


m
```

[15]: <folium.folium.Map at 0x7f41a322e520>

Now let's bring in the rest of our public recreational facilities.

[16]:
```
parks = pd.read_csv('Data3/PR1.csv')
parks.head()
```

[16]:
```
  LocationType                    Location_Name  StNumber StNumberFraction  \
0        Parks  La Mirada Park Acquisition Site    5401.0              NaN
1      Gardens                          Drew St    3304.0              NaN
2        Parks             Avalon-San Pedro Park    4025.0              NaN
3        Parks                  11th Avenue Park    6116.0              NaN
4      Gardens       El Sereno Community Garden    5450.0              NaN

  StDirection      StName StSuffix  StSuffixDirection  AddressType  \
0           W   La Mirada      Ave                NaN          NaN
1           N        Drew       St                NaN          NaN
2         NaN      Avalon     Blvd                NaN          NaN
3         NaN        11th      Ave                NaN          NaN
4           E  Huntington       Dr                NaN          NaN

   AddressTypeValue  …  CrossStSuffix CrossStSuffixDirection  \
0               NaN  …            NaN                    NaN
1               NaN  …            NaN                    NaN
2               NaN  …            NaN                    NaN
3               NaN  …            NaN                    NaN
4               NaN  …            NaN                    NaN

                                            City  State    Zip Website  \
0  Los Angeles, CA 90029\n(34.0942, -118.307)     CA  90029     NaN
1    Los Angeles, CA 90065\n(34.12, -118.243)     CA  90065     NaN
2  Los Angeles, CA 90011\n(34.0104, -118.266)     CA  90011     NaN
3  Los Angeles, CA 90043\n(33.9845, -118.329)     CA  90043     NaN
4  Los Angeles, CA 90032\n(34.0923, -118.162)     CA  90032     NaN

            Phone CouncilDistrict          X           Y
0  (310) 548-7675              13  34.094208 -118.306999
1  (213) 485-5572              13  34.119958 -118.242682
2  (310) 548-7675               9  34.010389 -118.265542
3  (310) 548-7675               8  33.984488 -118.329232
4  (213) 485-5572              14  34.092346 -118.161574

[5 rows x 22 columns]
```

Let's make a map with all the public recreational facilities.

[17]:
```
for index, row in parks.iterrows():
    tooltip_text = row.Location_Name
```

```
    folium.Marker(
        [row.X,row.Y],
        popup=row.Location_Name,
        tooltip=tooltip_text,
        icon=folium.Icon(color='green')
).add_to(m)

m
```

[17]: <folium.folium.Map at 0x7f41a322e520>

1.5 Conclusion

WOW!! From this map we can see that the highest income areas actually have fewer parks than the lower income areas. This is surprising to us because we had hypothesized that the opposite would be true. The highest income areas might have fewer parks because the people there tend to own single family homes with large yards that can substitute a park. Also, those neighborhoods are close to hiking trails. Finally, the residents there are more likely to own a car that they can drive to a park.

We look forward to deeping our analysis by applying new tools we learn in the upcoming labs.

1.5.1 Group division of labor

Brian Ramirez helped kickstart the project by acquiring the income census data and creating several insightful charts from the data. Kimberly Venegas found the park data and focused on creating the maps. Both of them worked together to improve what they each created and they helped each other solve issues that came up.