Lecture 5:
Spatial Analysis of Census Data

Today

1) Summary Network Science and Models

2) Cenpy Library

3) Basic Calculations with Census Data

4) Guest Speaker (Analyzing Philippine Election Data

Summary Network Science and Models

Which properties have we studied?

1)Degree

2) Clustering Coefficient

3) Average Shortest Path

Random networks: summary

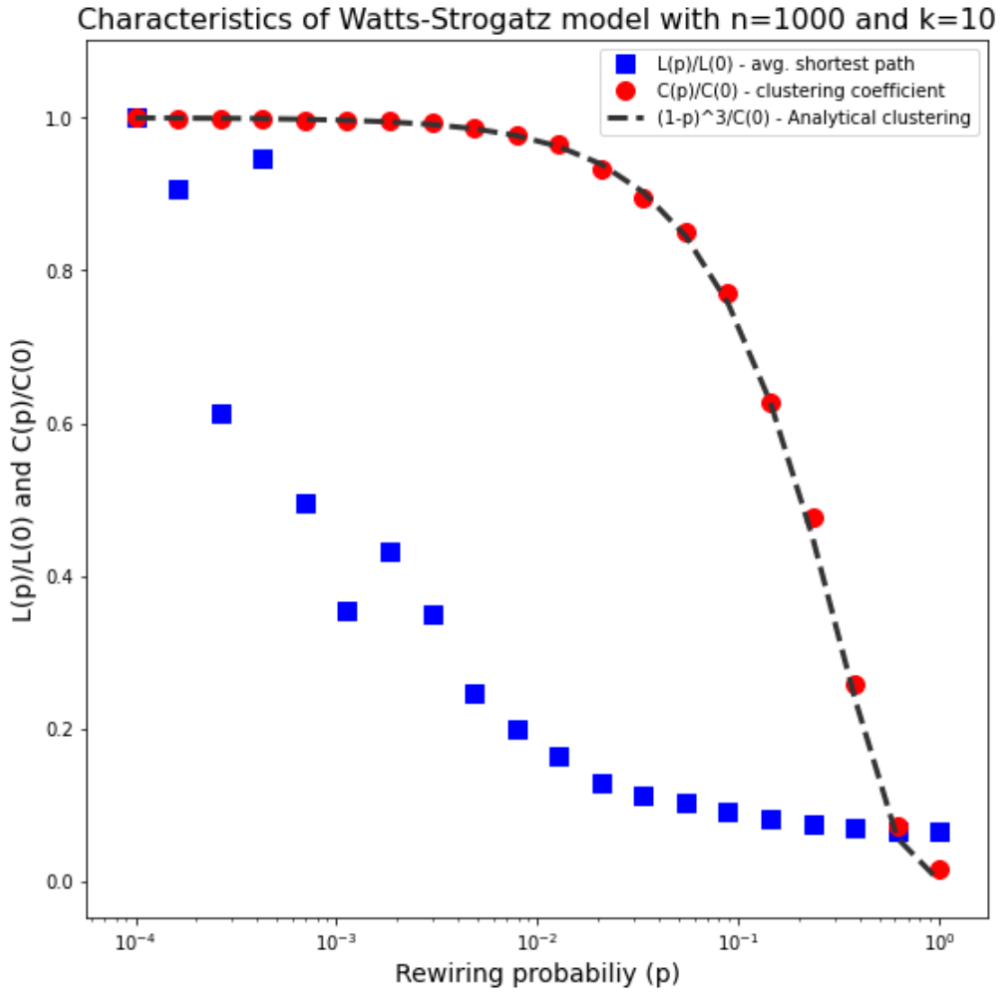
A Random Graph defined by (p,N), is built connecting each pair of nodes with probability p. its analytical properties were shown in Lecture 3. Summarized here:

- Degree distribution Bell shaped curve around average, $P(k) = e^{-<k>} \frac{<k>^k}{k!}$
- $<k_{random}>=p(N-1)=2L/N$, where L is the number of links and N and p are input parameters of the model
- Average shortest path length $<l_{random}>\sim \log(N)/\log(k)$
- Clustering Coefficient $<C_{random}> = p$

Note: You can generate desired <k> by selecting p and N… In the assignment you will use <k> from empirical networks to select p (see next slide)

Small World Model: summary

- Degree distribution Delta shaped curve around average
- <k> is an input parameter
- Average shortest path length <l>~log(N)/log(k) for p in the range (0.01,0.1), e.g. when we rewire a small fraction of the links
- Clustering Coefficient $C(p,k,n) = C(0,k,n)(1-p)^3$



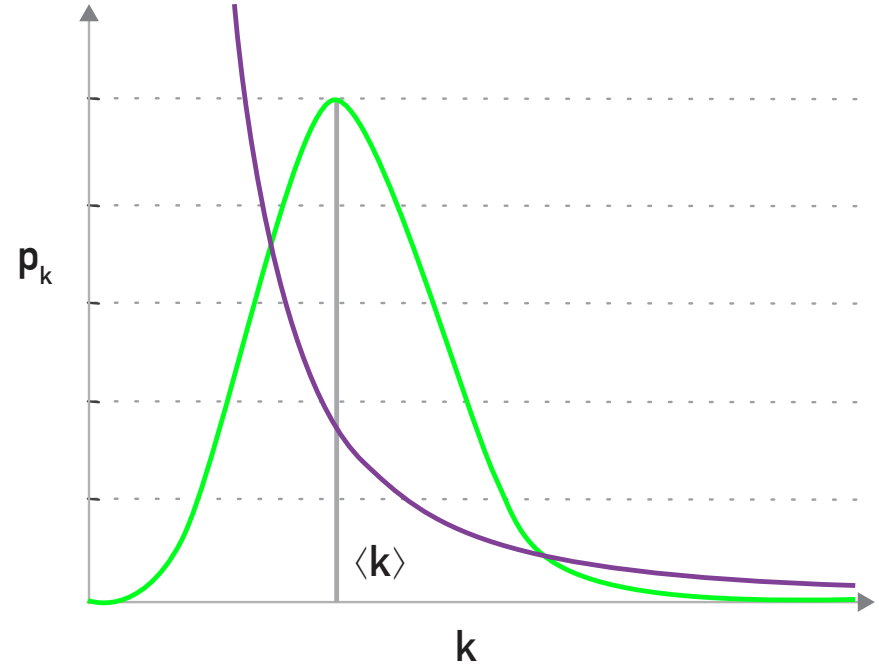

```
for p in p_range:

    # Create a Watts-Strogatz graph
    graph = nx.watts_strogatz_graph( n, k, p )

    # Compute the average shortest-path length L(p)
    sp_length.append( nx.average_shortest_path_length( graph ) )

    # Compute the clustering coefficient C(p)
    clustering.append( nx.average_clustering( graph ) )
```

```
plt.semilogx(p_range[1:] , [L / sp_length[0]  for L in sp_length[1:]]  ,
plt.semilogx(p_range[1:] , [C / clustering[0] for C in clustering[1:]] ,
plt.semilogx(p_range[1:] , [ (1-p)**3.0 for p in p_range[1:]] , '--', co
```

Note that clustering[0] is the ring with the same n and k

Barabasi Model: summary

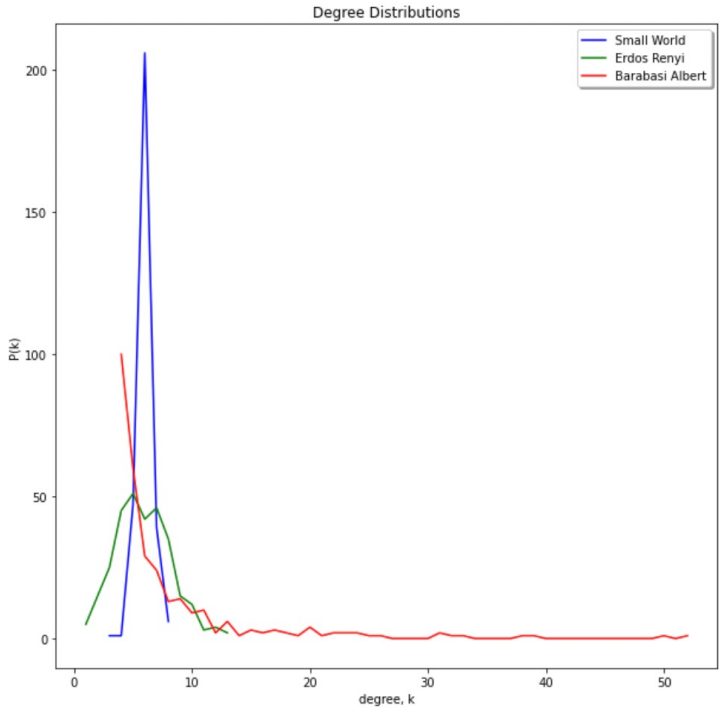
- Input parameters are (N,k_{min})
- <k> =2k_{min} (from slide 27 Lecture 4)
- Degree distribution power law P(k)=$2k_{min}k^{-3}$
- Average shortest path length <l>~log(N)/log<k>
- Clustering Coefficient C~<k>/N



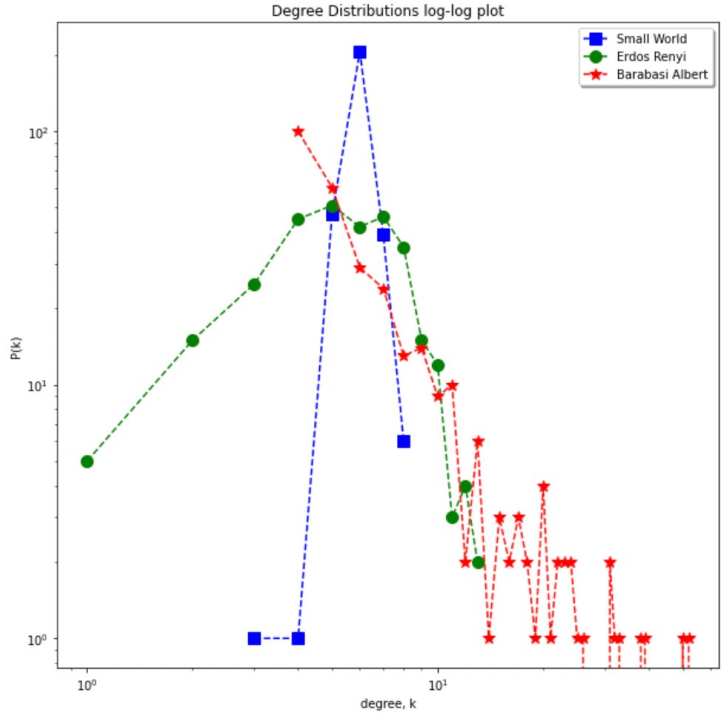
Use line plot instead of barplots to better compare the histograms

```
#G1:
degs1 = list(dict(nx.degree(gs)).values())
n1, bins1 = np.histogram(degs1, bins = list(range(min(degs1), max(degs1)+1, 1)))
```

plt.plot(bins1[:-1],n1)



same plot as the left in log-log scale (plt.loglog(bins1[:-1],n1))



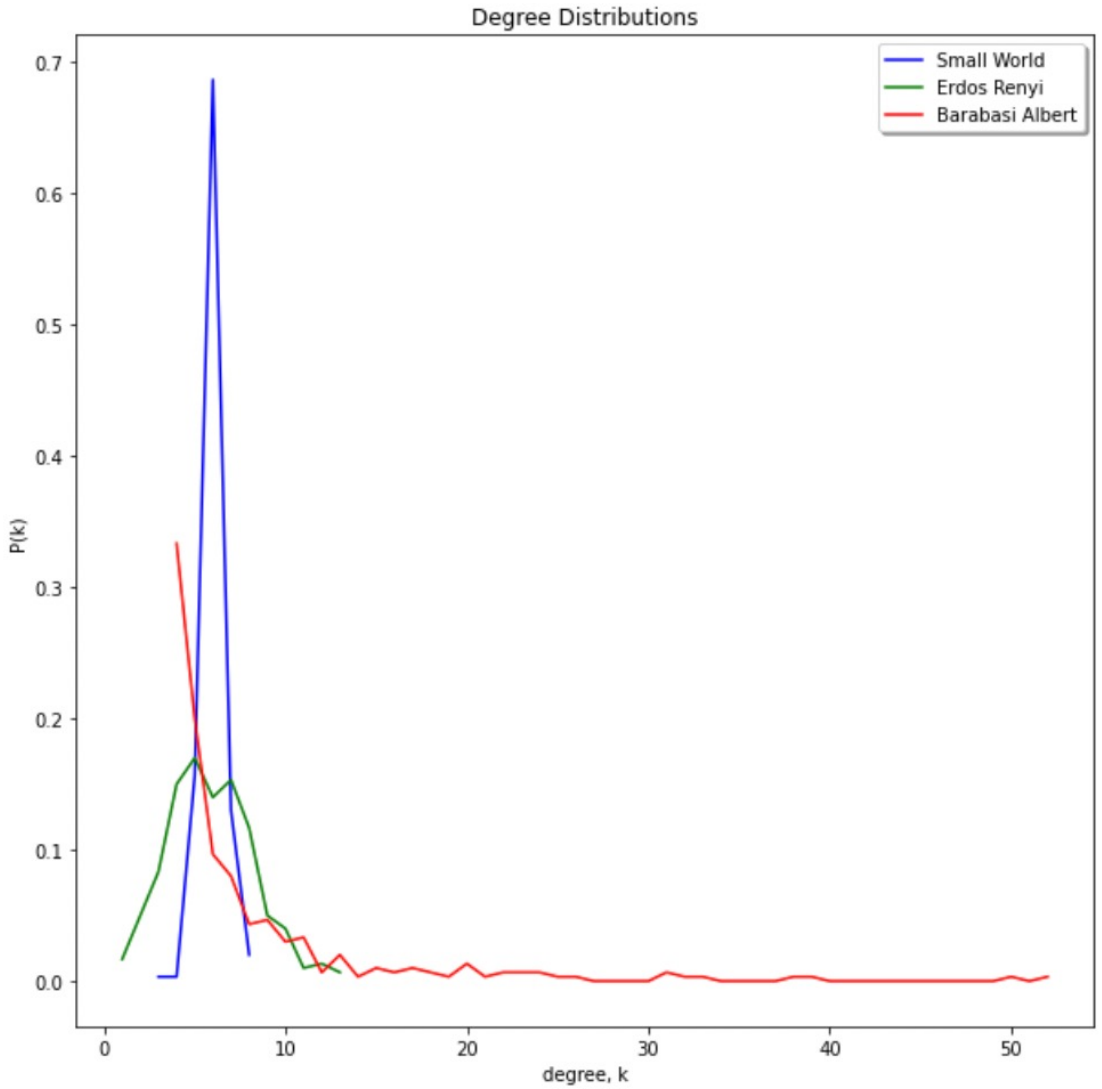
gs = nx.watts_strogatz_graph(n, k, p) → select n, k and p to model n, <k> and C from empirical networks

Ger =nx.erdos_renyi_graph(n, p) → select n and p to model n, <k> from empirical networks

Gba=nx.barabasi_albert_graph(n,kmin) → select n and kmin to model n and <k> from empirical networks

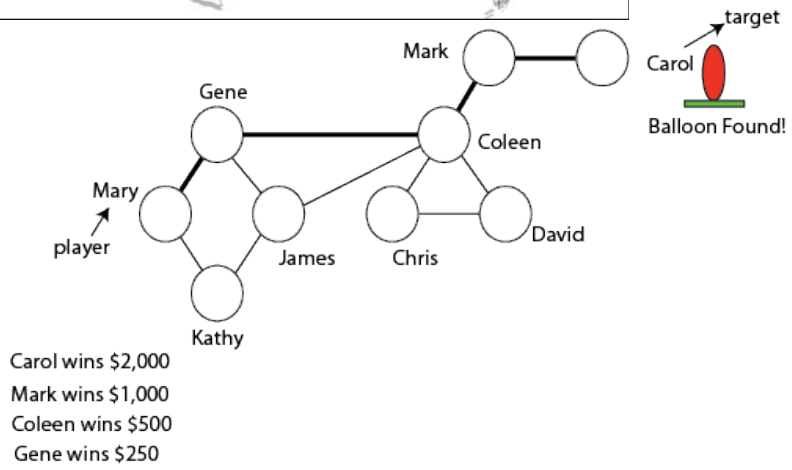
The normalized histograms are the probability density function or distribution of probability

```
:
#G1:
degs1 = list(dict(nx.degree(gs)).values())
n1, bins1 = np.histogram(degs1, bins = list(range(min(degs1), max(degs1)+1, 1)),density='True')

#G2:
degs2 = list(dict(nx.degree(Ger)).values())
n2, bins2 = np.histogram(degs2, bins = list(range(min(degs2), max(degs2)+1, 1)),density='True')

#G3:
degs3 = list(dict(nx.degree(Gba)).values())
n3, bins3 = np.histogram(degs3, bins = list(range(min(degs3), max(degs3)+1, 1)),density='True')

#to plot:
plt.figure(figsize=(10,10)) #use once and set figure size

plt.plot(bins1[:-1],n1,'b-', markersize=10, label="Small World")
plt.plot(bins2[:-1],n2,'g-', markersize=10, label="Erdos Renyi")
plt.plot(bins3[:-1],n3,'r-', markersize=10, label="Barabasi Albert")
plt.legend(loc='upper right', shadow=True)
plt.title('Degree Distributions')
plt.xlabel('degree, k')
plt.ylabel('P(k)')
```



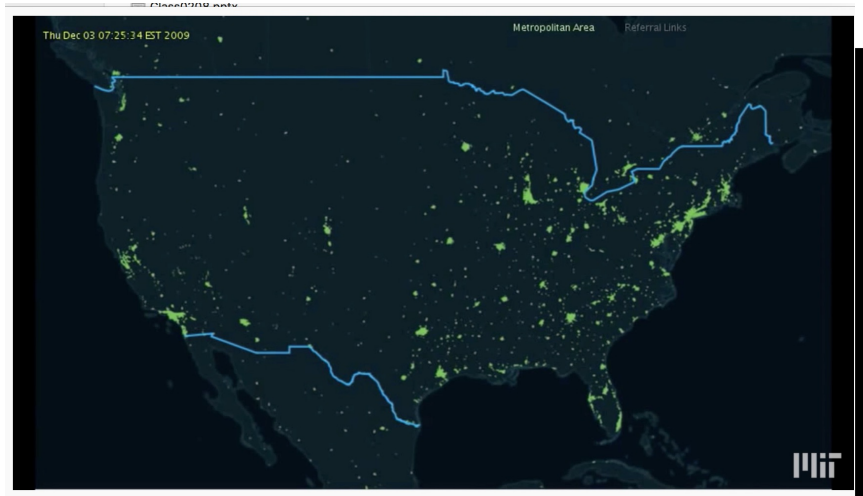
The Power of Six Degrees

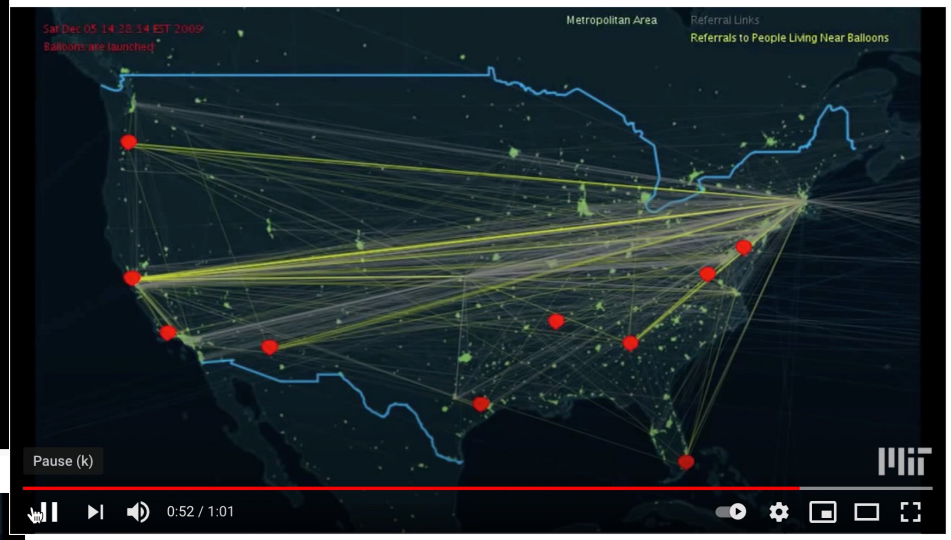
Power of Social Network: Crowdsourcing

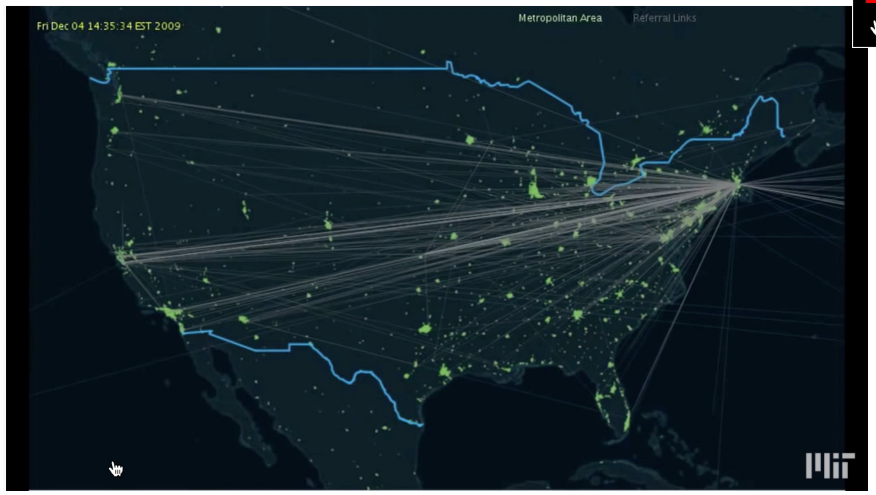


Red Balloon Experiment: 8 balloons randomly placed in the U.S. were found within 8 hours via social media

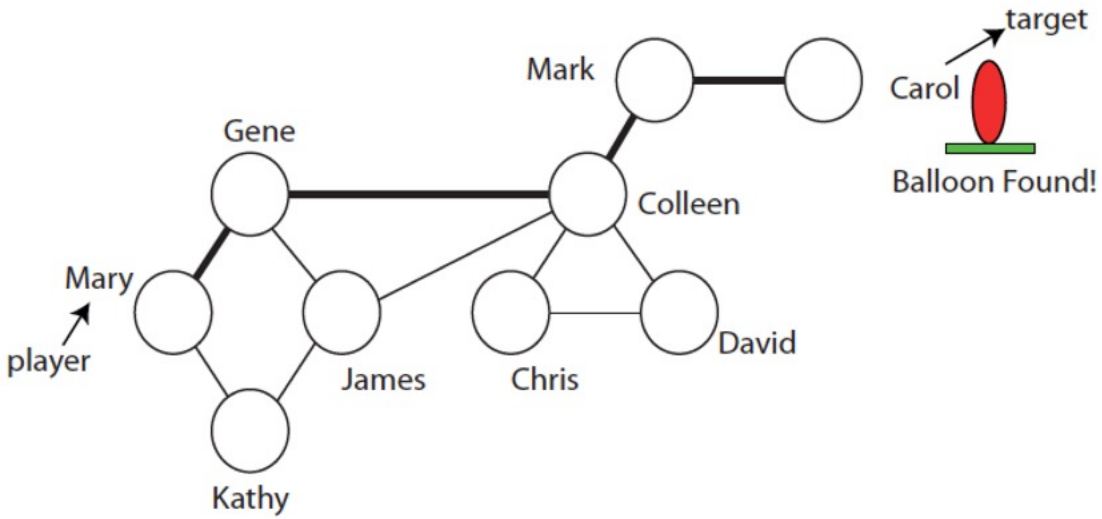
https://www.cc.com/video/r8x6ag/the-colbert-report-riley-crane







https://www.youtube.com/watch?v=6Ga_EJWLzHA



Consider the sample figure above. If the person who finds the target (Carol) wins $2, 000; and each person in the shortest path to the player wins 1/2 of the money.

What is the total cost of the chain?

Expected Cost for paths of length 6, and 7 people: 2000+1000+500+250+125+62.5+31.25= 3968.75
10 balloons would cost ~ 40,000 the prize amount was distributed and they won the game!

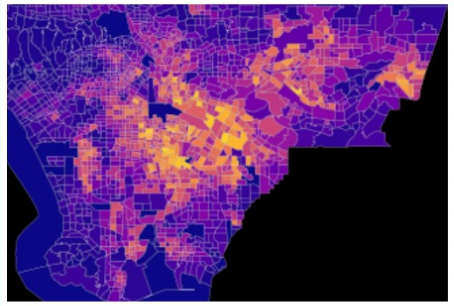
Lecture 5

Exploring variables in Census Data

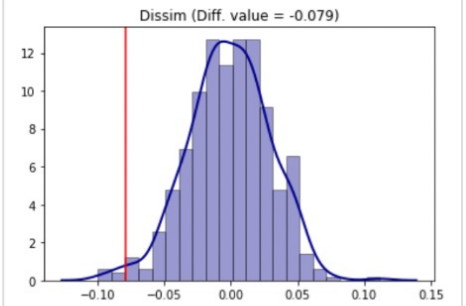
- cenpy_api.ipynb
- sandiego_tracts_calculations.ipynb

Cenpy

Cenpy (pronounced sen-pie) is a package that automatically discovers US Census Bureau API endpoints and exposes them to Python in a consistent fashion. It also provides easy-to-use access to certain well-used data products, like the American Community Survey (ACS) and 2010 Decennial Census. To get started, check out one of the case studies shown below.



Getting Data using cenpy



Segregation in Time and Space with cenpy and pysal

A Road to Frictionless Urban Data Science: osmnx and cenpy

Cenpy is easiest to install using `conda`, a commonly-used package manager for scientific python. First, install Anaconda.

Then, `cenpy` is available on the `conda-forge` channel. You can install this using the *Anaconda Prompt*, or from within the Anaconda Navigator program. If you want to install the package from within the Anaconda Prompt, you can use:

```
conda install -c conda-forge cenpy
```

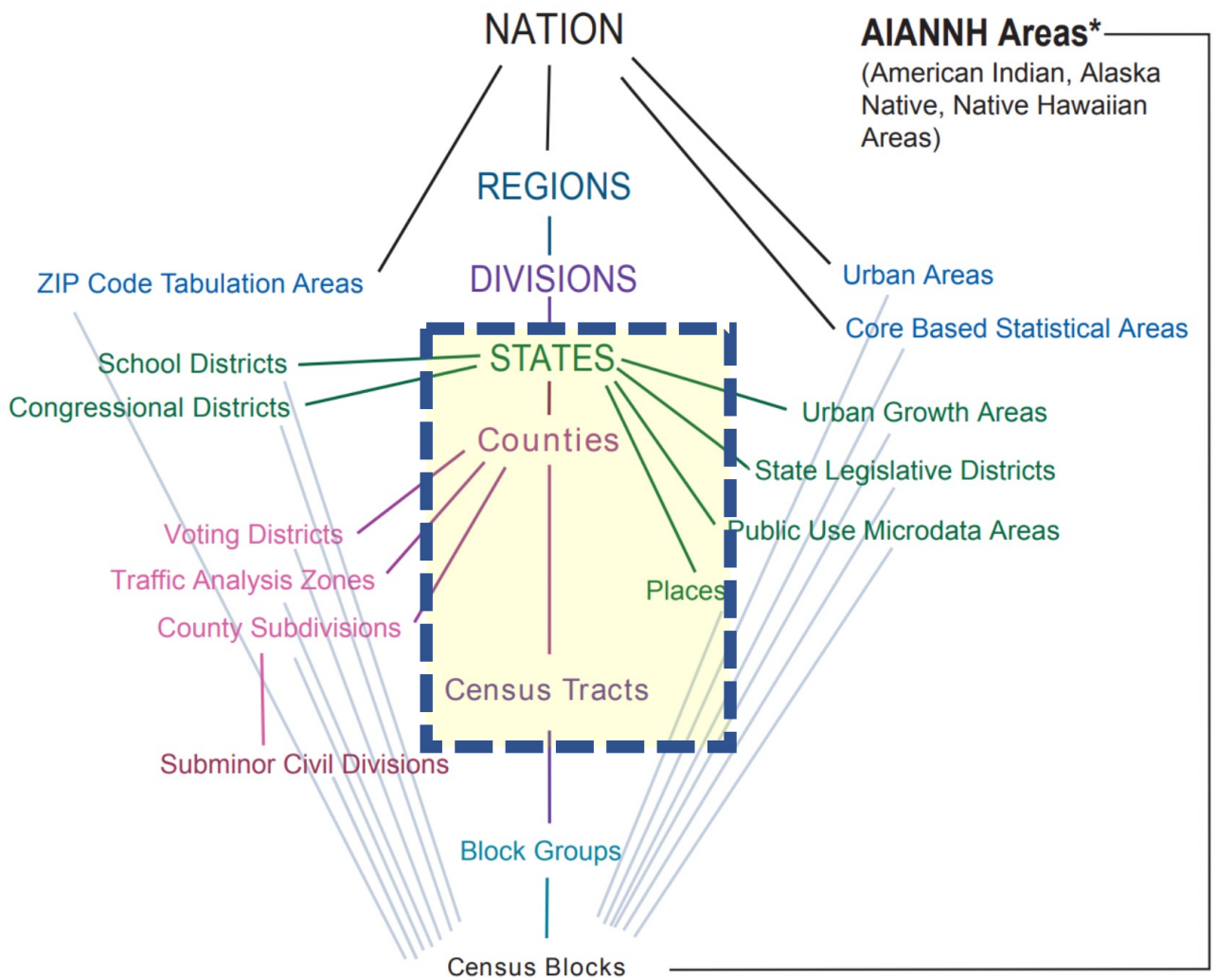
Alternatively, you can install cenpy *via* `pip`, the python package manager, if you have installed `geopandas` and `rtree`:

```
pip install cenpy
```

https://cenpy-devs.github.io/cenpy/index.html

Geographic Hierarchy of the United States

All of the packages I've seen (including `cenpy` itself) involved a very stilted/specific API query due to the way the census API worked. Basically, it's difficult to construct an efficiently query against the census API without knowing the so-called "geographic hierarchy" in which your query fell:



50 States
3,243 Counties
12,098 Census Designated Places
84,414 Census Tracts

The main census API does not allow a user to leave middle levels of the hierarchy vague: For you to get a collection of census tracts in a state, you need to query for all the *counties* in that state, then express your query about tracts in terms of a query about all the tracts in those counties. Even `tidycensus` in `R` requires this

Cenpy Products

http://cenpy-devs.github.io/cenpy/api.html

A product that integrates the data & geographic APIs for the 5-year 2013-2017 ACSs.

`cenpy.products.ACS`	The American Community Survey (5-year vintages) from the Census Bureau

A product that integrates the data & geographic APIs for the 2010 Census.

`cenpy.products.Decennial2010`	The 2010 Decennial Census from the Census Bureau

ACS: American Community Survey
ACS5 every 5 years
ACS1 every year

https://www.census.gov/programs-surveys/acs/guidance/subjects.html

Social

- Ancestry
- Citizen Voting-Age Population
- Citizenship Status
- Disability Status
- Educational Attainment
- Fertility
- Grandparents as Caregivers
- Language Spoken at Home
- Marital History
- Marital Status
- Migration/Residence 1 Year Ago
- Place of Birth
- School Enrollment
- Undergraduate Field of Degree
- Veteran Status; Period of Military Service
- Year of Entry

Housing

- Bedrooms
- Computer and Internet Use
- House Heating Fuel
- Kitchen Facilities
- Occupancy/Vacancy Status
- Occupants per Room
- Plumbing Facilities
- Rent
- Rooms
- Selected Monthly Owner Costs
- Telephone Service Available
- Tenure (Owner/Renter)
- Units in Structure
- Value of Home
- Vehicles Available
- Year Householder Moved Into Unit
- Year Structure Built

Economic

- Class of Worker
- Commuting (Journey to Work) and Place of Work
- Employment Status
- Food Stamps/Supplemental Nutrition Assistance Program (SNAP)
- Health Insurance Coverage
- Income and Earnings
- Industry
- Occupation
- Poverty Status
- Work Status Last Year

Demographic

- Age; Sex
- Group Quarters Population
- Hispanic or Latino Origin
- Race
- Relationship to Householder
- Total Population

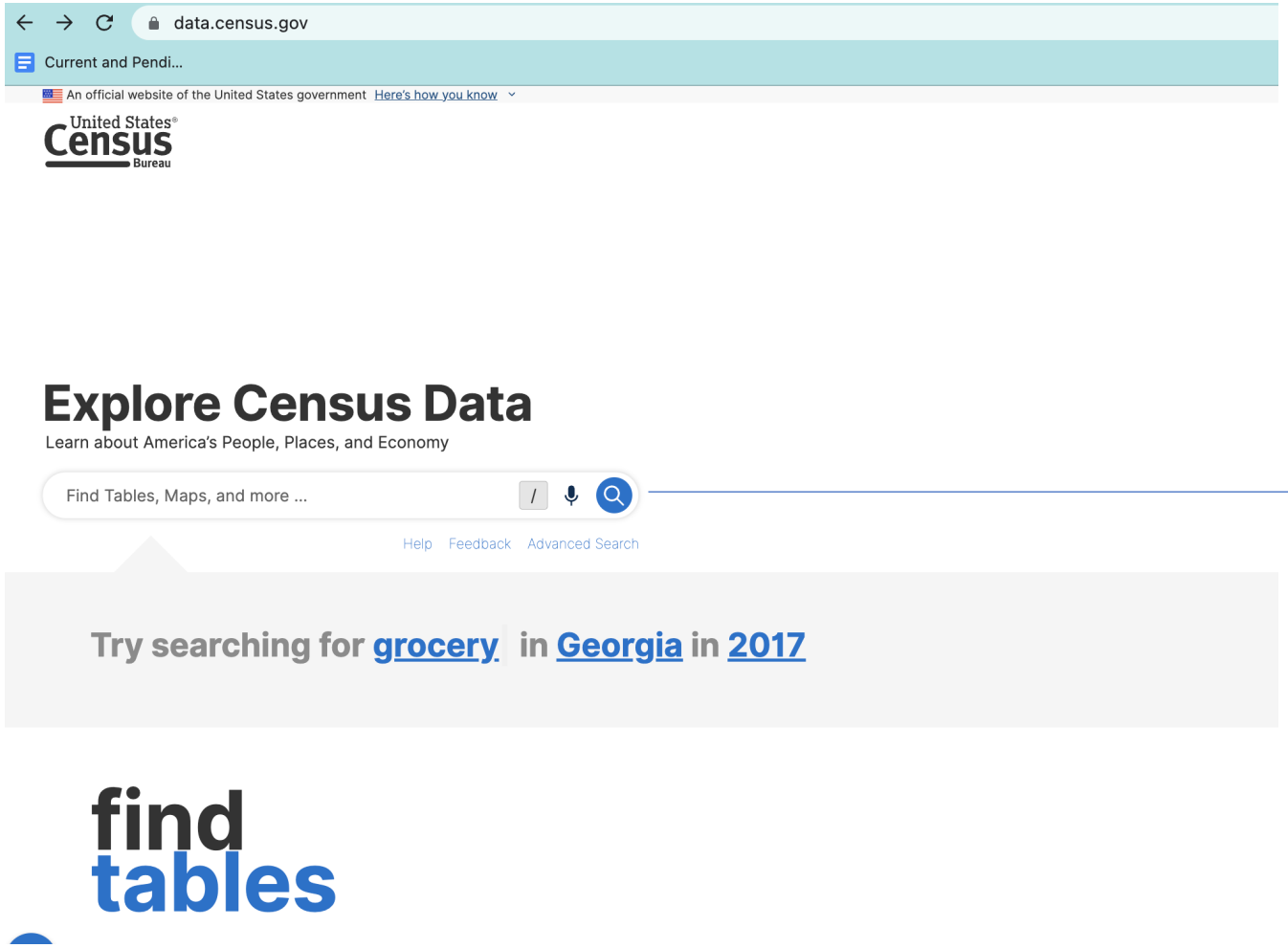
- **Subject Tables** provide an overview of the estimates available in a particular topic. The data are presented as population counts and percentages. There are over 18,000 variables in this dataset.
- **Data Profiles** contain broad social, economic, housing, and demographic information. The data are presented as population counts and percentages. There are over 1,000 variables in this dataset.

You will select your variables of study following the 3 steps in the next slides

We are limited to the variables available in the ACS or the Decennial2010 products

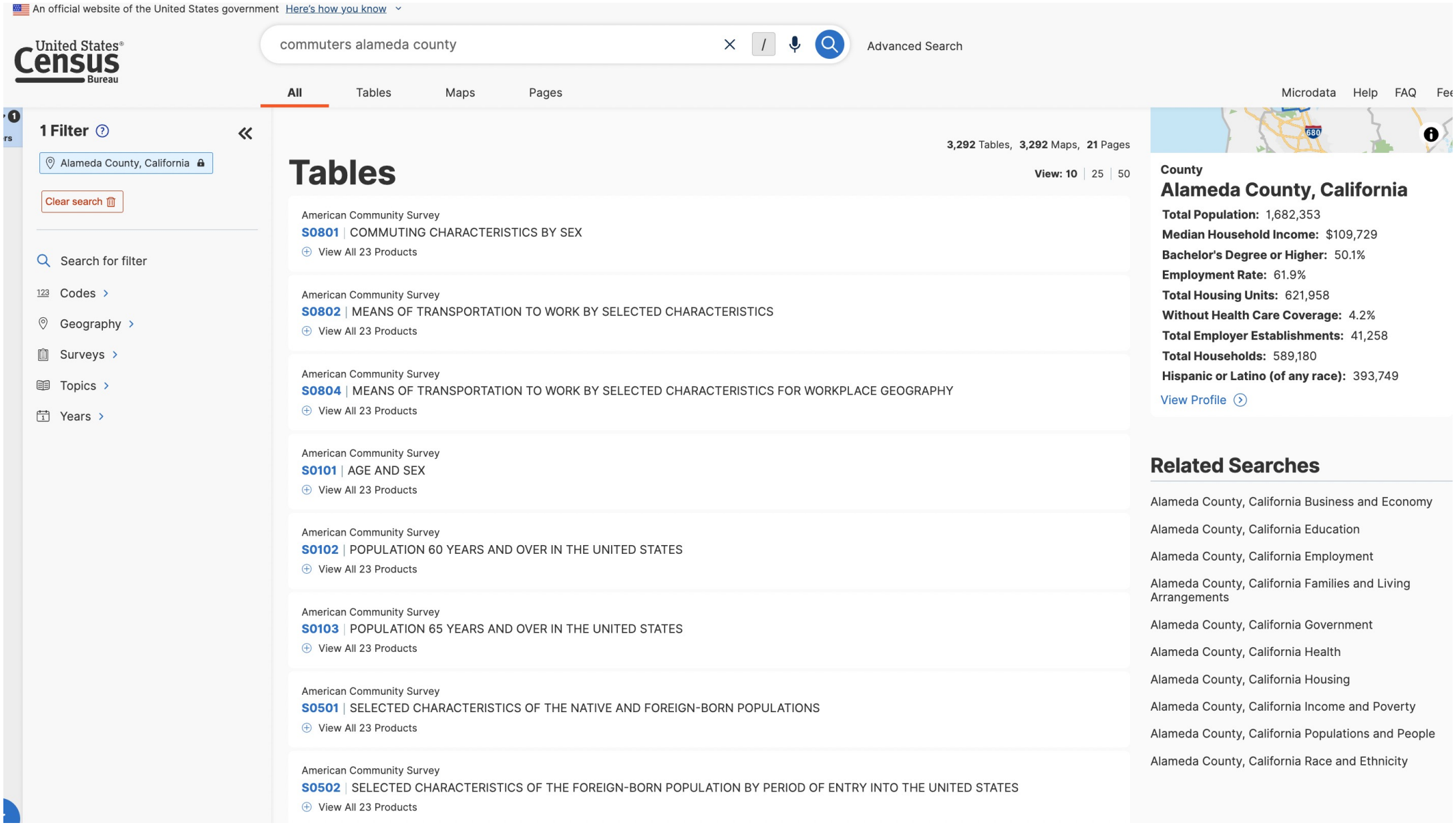
Step 1: Explore here variable names: https://data.census.gov/

In this example we search the associated variables for commuting

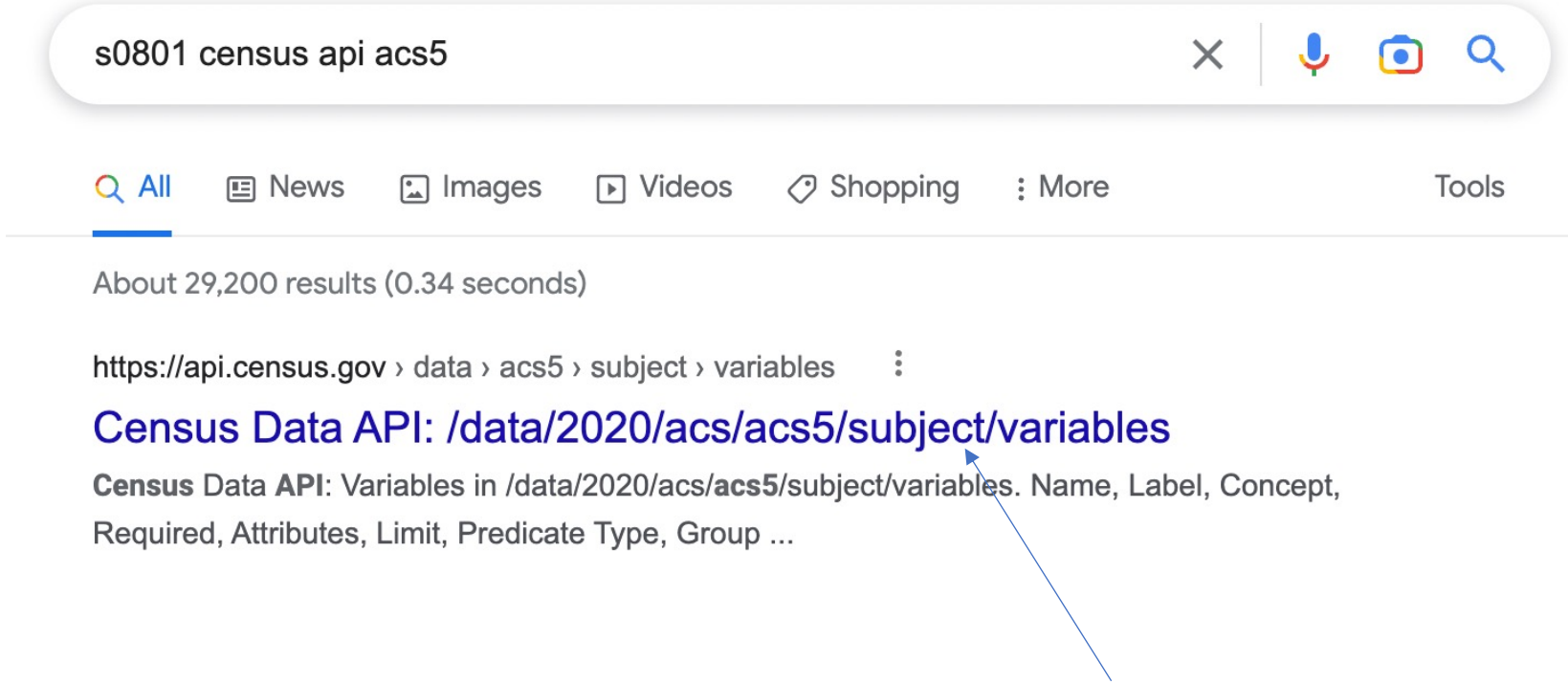


Type a desired search

Commuters alameda county

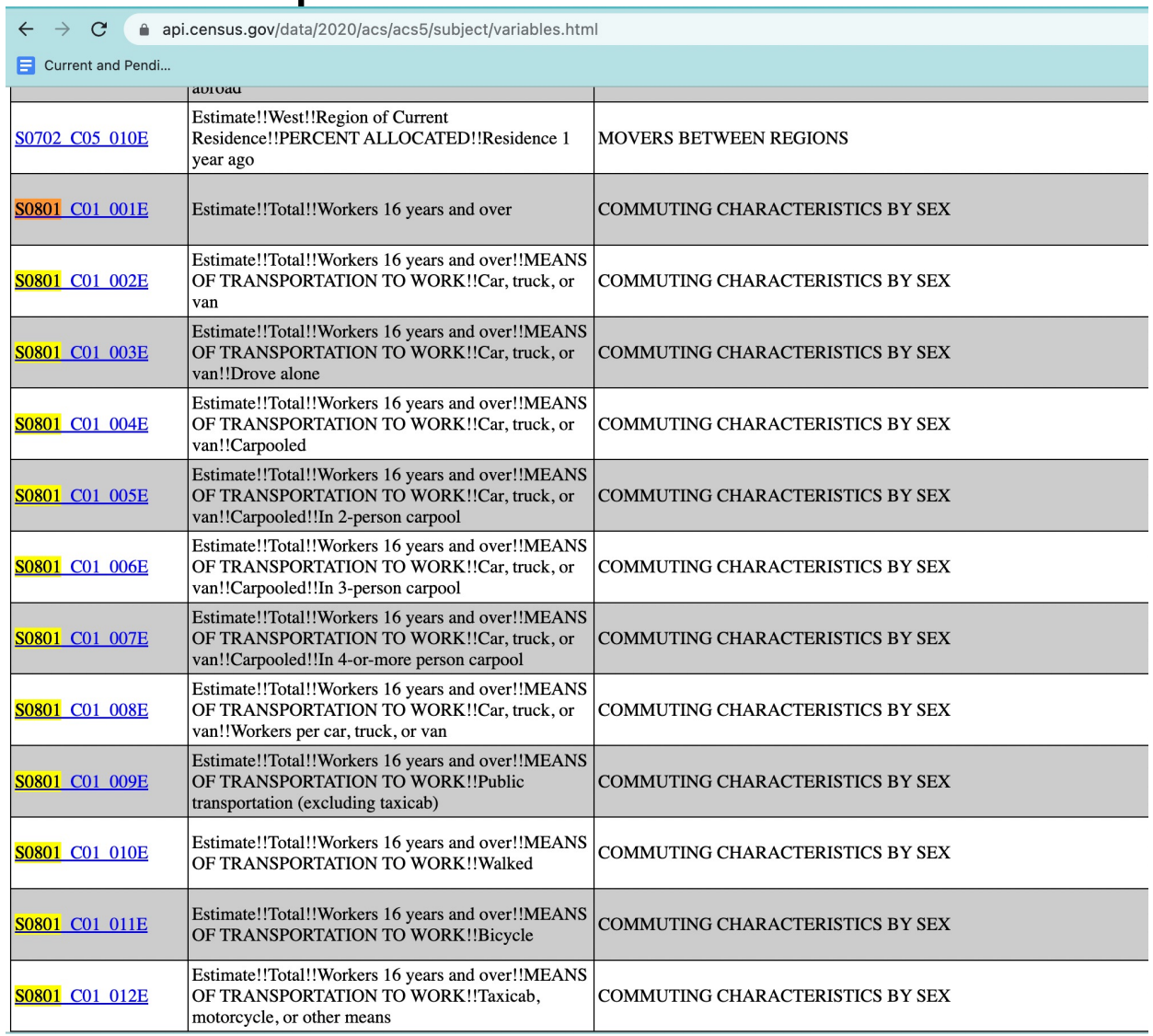


Step 2: google search the variable group name in the census api



s0801 is the name of the variable group

Step 3: See the specific variable name to use in cenpy



	abroad	
S0702_C05_010E	Estimate!!West!!Region of Current Residence!!PERCENT ALLOCATED!!Residence 1 year ago	MOVERS BETWEEN REGIONS
S0801_C01_001E	Estimate!!Total!!Workers 16 years and over	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_002E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Car, truck, or van	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_003E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Car, truck, or van!!Drove alone	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_004E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Car, truck, or van!!Carpooled	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_005E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Car, truck, or van!!Carpooled!!In 2-person carpool	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_006E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Car, truck, or van!!Carpooled!!In 3-person carpool	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_007E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Car, truck, or van!!Carpooled!!In 4-or-more person carpool	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_008E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Car, truck, or van!!Workers per car, truck, or van	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_009E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Public transportation (excluding taxicab)	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_010E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Walked	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_011E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Bicycle	COMMUTING CHARACTERISTICS BY SEX
S0801_C01_012E	Estimate!!Total!!Workers 16 years and over!!MEANS OF TRANSPORTATION TO WORK!!Taxicab, motorcycle, or other means	COMMUTING CHARACTERISTICS BY SEX

https://api.census.gov/data/2019/acs/acs5/variables.html

cenpy-api.ipynb

- Tutorial to use the Cenpy library

- Cenpy is a Python library that provides a simple interface to access data from the United States Census Bureau's APIs. It enables users to easily download and manipulate US Census data within a Pandas DataFrame.

Median household income: B19013_001E

Median Contract Rent: B25058_001E

Households with food stamp: B19058_002E ¶

Households food stamp Estimate Total: B19058_001E

```
from cenpy import products
import matplotlib.pyplot as plt
import matplotlib as mpl
%matplotlib inline
```

In California we have five combined statistical areas, 26 metropolitan statistical areas

```
#from_csa means it will extract the map of a Combined Statistical Area.
#List of 172 US CSA: https://en.wikipedia.org/wiki/Combined_statistical_area
#'B19013_001E' Estimate!!Median household income in the past 12 months (in 2019 inflation-adjusted dollars)

sj_csa= products.ACS(2019).from_csa('San Jose-San Francisco-Oakland',level='tract',
                                    variables=['B19013_001E'])
```

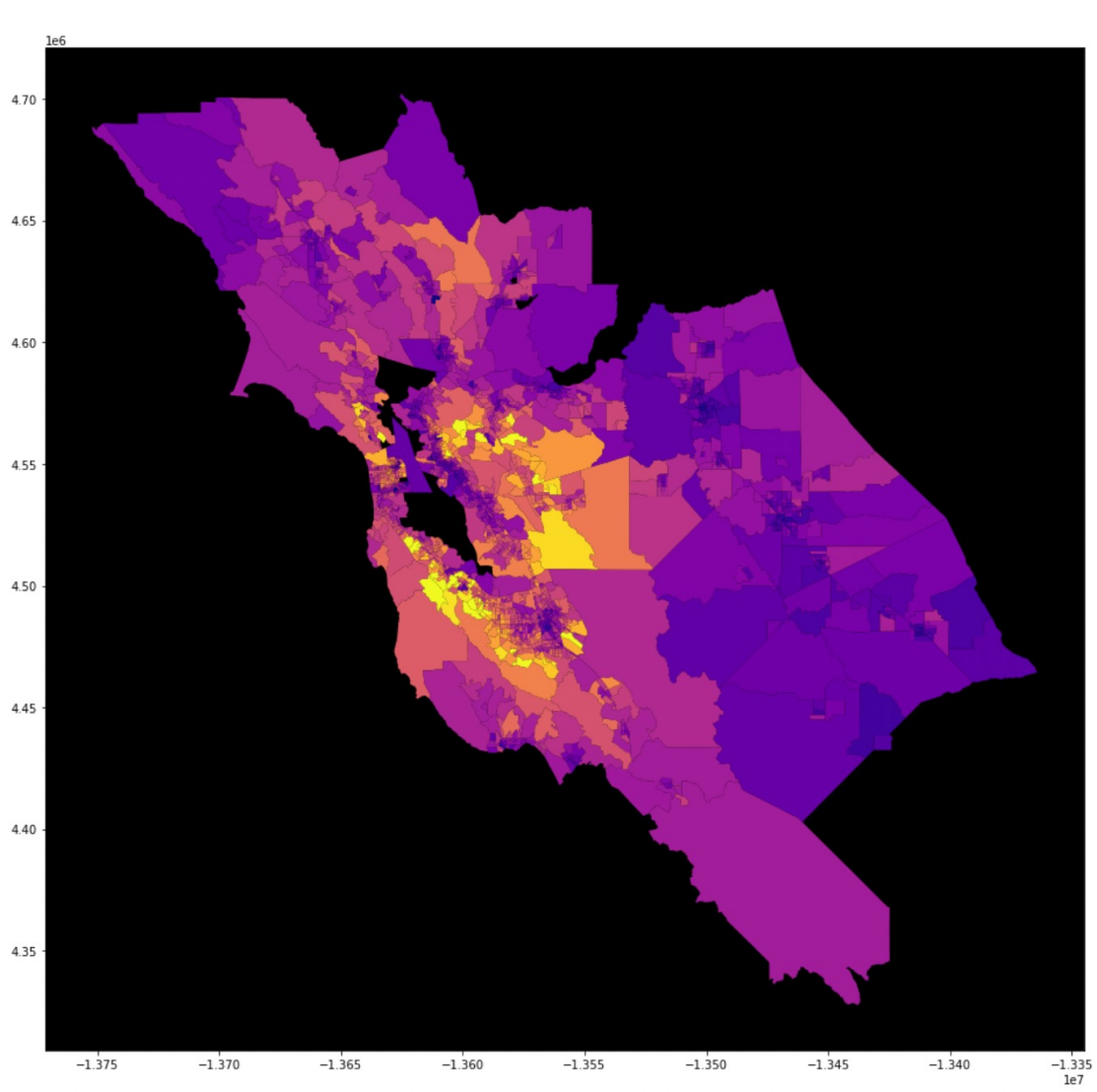
```
sj_csa
```

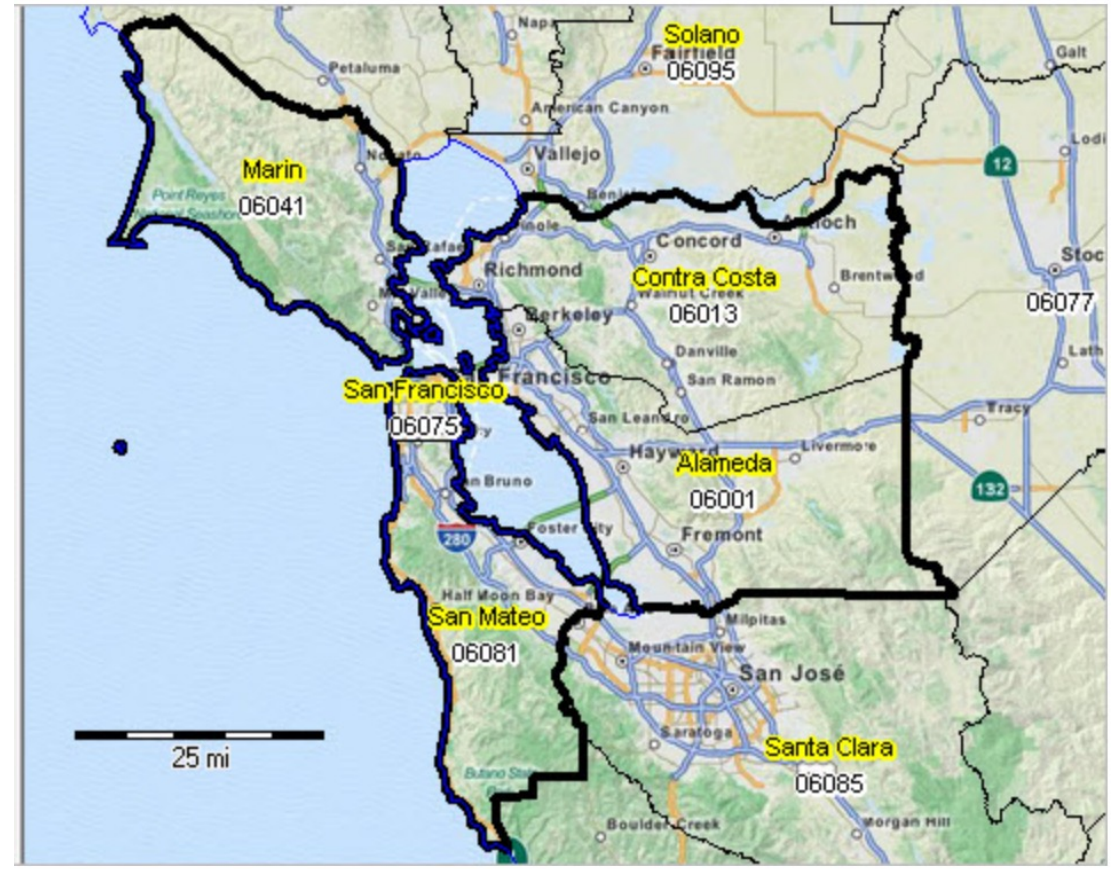
	GEOID	geometry	B19013_001E	NAME	state	county	tract
0	06097990100	POLYGON ((-13762706.610 4687083.180, -13761997...	NaN	Census Tract 9901, Sonoma County, California	06	097	990100
1	06075980401	POLYGON ((-13711647.480 4547791.830, -13711635...	NaN	Census Tract 9804.01, San Francisco County, Ca...	06	075	980401
2	06081612700	POLYGON ((-13603249.680 4500745.130, -13603146...	250001.0	Census Tract 6127, San Mateo County, California	06	081	612700
3	06081612000	POLYGON ((-13598390.690 4504780.430, -13598369...	71234.0	Census Tract 6120, San Mateo County, California	06	081	612000
4	06081612100	POLYGON ((-13598117.850 4502972.090, -13598103...	57627.0	Census Tract 6121, San Mateo County, California	06	081	612100
...	...	...	...	...	...	...	...
1929	06099002701	POLYGON ((-13465889.440 4526163.430, -13465889...	74063.0	Census Tract 27.01, Stanislaus County, California	06	099	002701
1930	06099002605	POLYGON ((-13463858.860 4524354.770, -13463858...	48892.0	Census Tract 26.05, Stanislaus County, California	06	099	002605
1931	06077004902	POLYGON ((-13486050.400 4566015.310, -13485973...	63565.0	Census Tract 49.02, San Joaquin County, Califo...	06	077	004902
1932	06099003909	POLYGON ((-13456035.220 4512110.920, -13456017...	52671.0	Census Tract 39.09, Stanislaus County, California	06	099	003909
1933	06099003905	POLYGON ((-13451642.770 4509065.350, -13451614...	92500.0	Census Tract 39.05, Stanislaus County, California	06	099	003905

1934 rows × 7 columns

- Cenpy generates a geopandas with rows having geoid of the unit of analysis (county or tract) a polygon, name, and the variable of census extracted
- We can extract several variables comma separated in the variables list

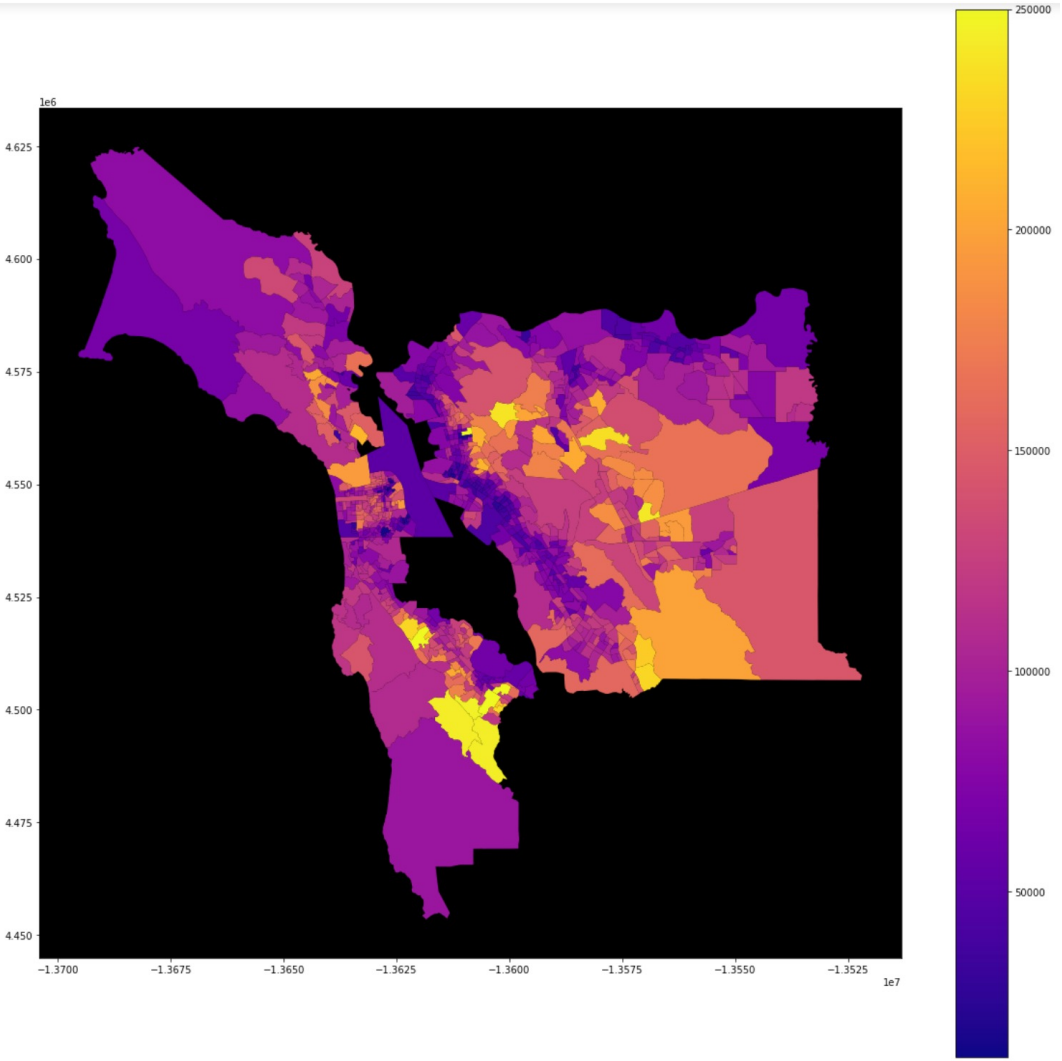
```
### Note drop removes any rows with missing values in the column named 'B19013_001E'.
## sj_csa is a geopandas a table with geoid and geometry that can be displayed as a map
f, ax = plt.subplots(1,1,figsize=(20,20))
sj_csa.dropna(subset=['B19013_001E'], axis=0).plot('B19013_001E', ax=ax, cmap='plasma',legend=True)
ax.set_facecolor('k')
```

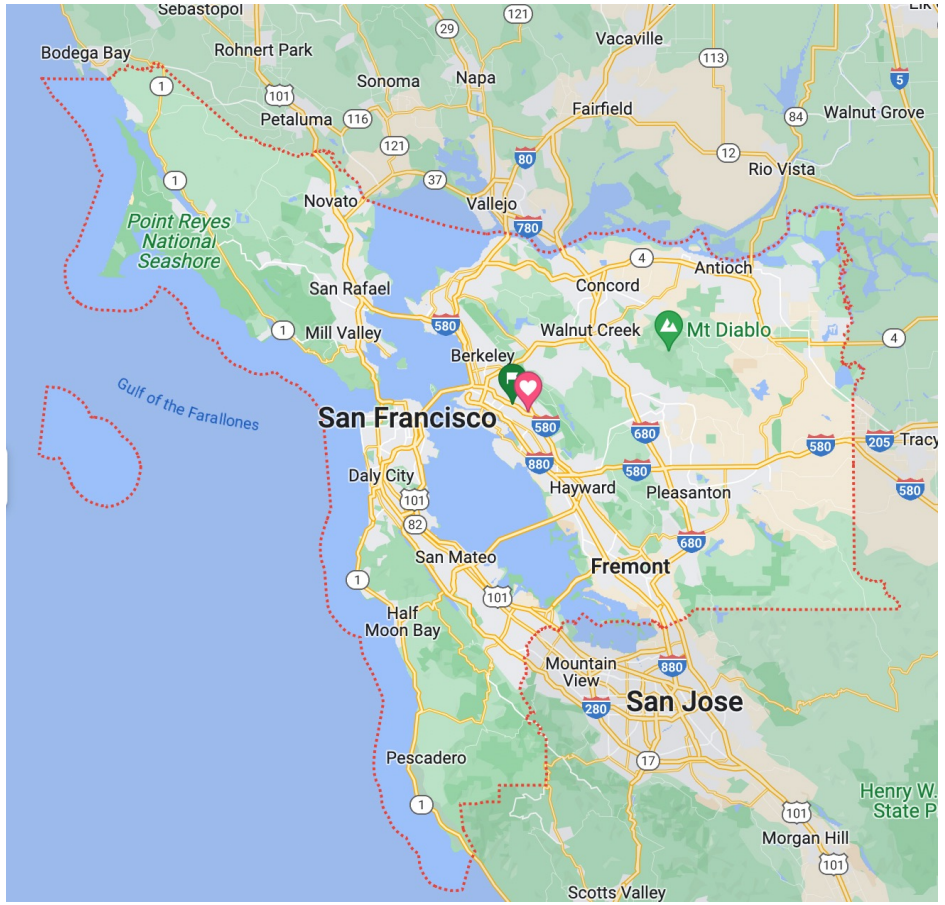




```
###from_msa means it will extract the map of a  Metropolitan Statistical Area.
## There are 384 metropolitan statistical areas: https://en.wikipedia.org/wiki/Metropolitan_statistical_area
sf_msa = products.ACS(2019).from_msa('San Francisco-Oakland-Berkeley',level='tract',
                                     variables=['B19013_001E'])
```

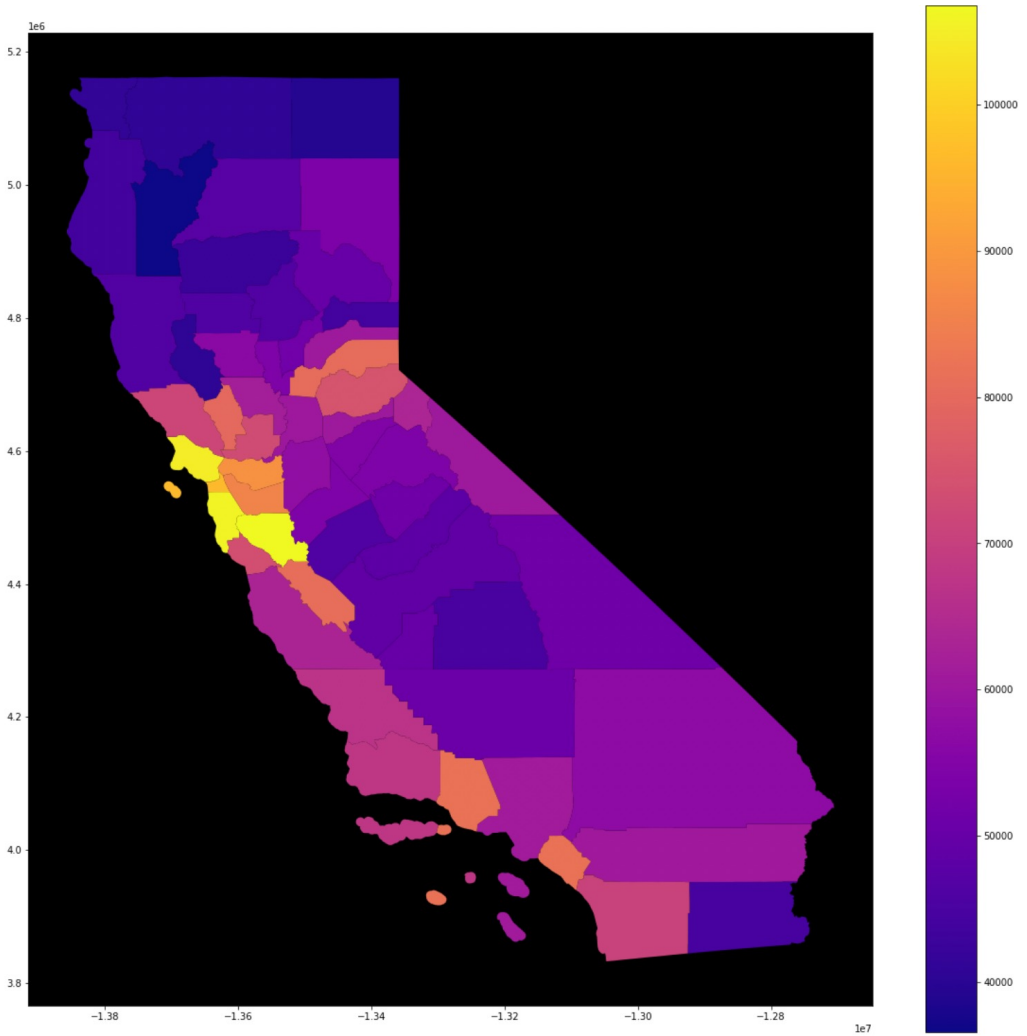
```
f, ax = plt.subplots(1,1,figsize=(20,20))
sf_msa.dropna(subset=['B19013_001E'], axis=0).plot('B19013_001E', ax=ax, cmap='plasma',legend=True)
ax.set_facecolor('k')
```





```
ca = products.ACS(2019).from_state('California',level='county',
                                   variables=['B19013_001E'])
```

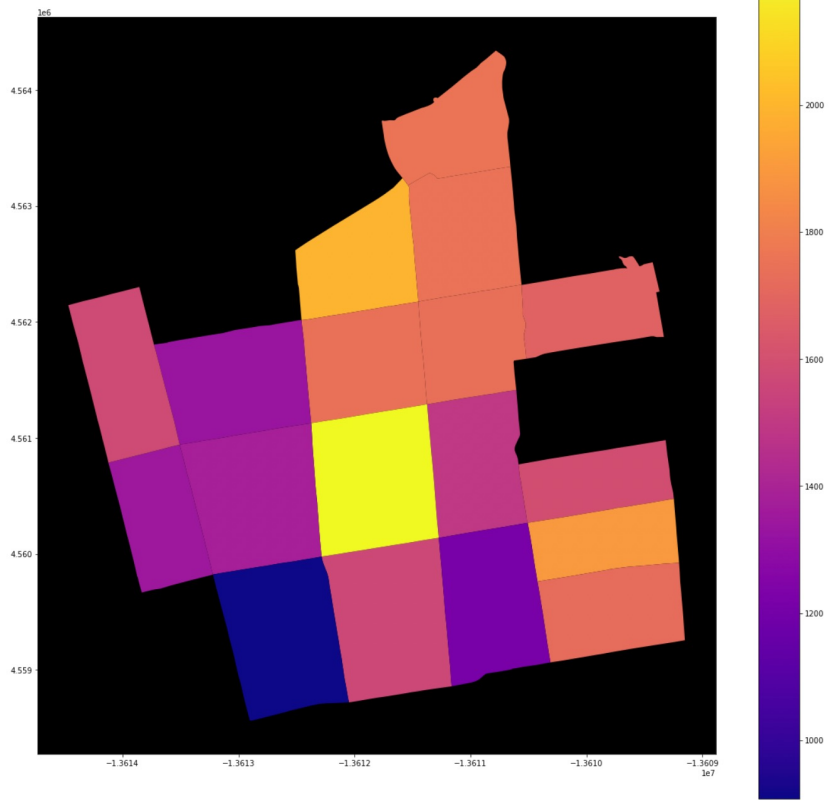
```
f, ax = plt.subplots(1,1,figsize=(20,20))
ca.dropna(subset=['B19013_001E'], axis=0).plot('B19013_001E', ax=ax, cmap='plasma',legend=True)
ax.set_facecolor('k')
```

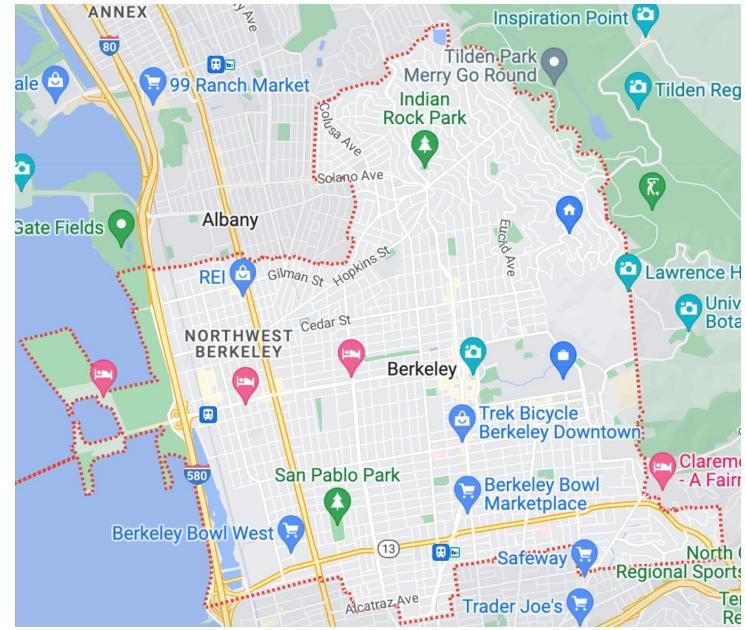


58 counties

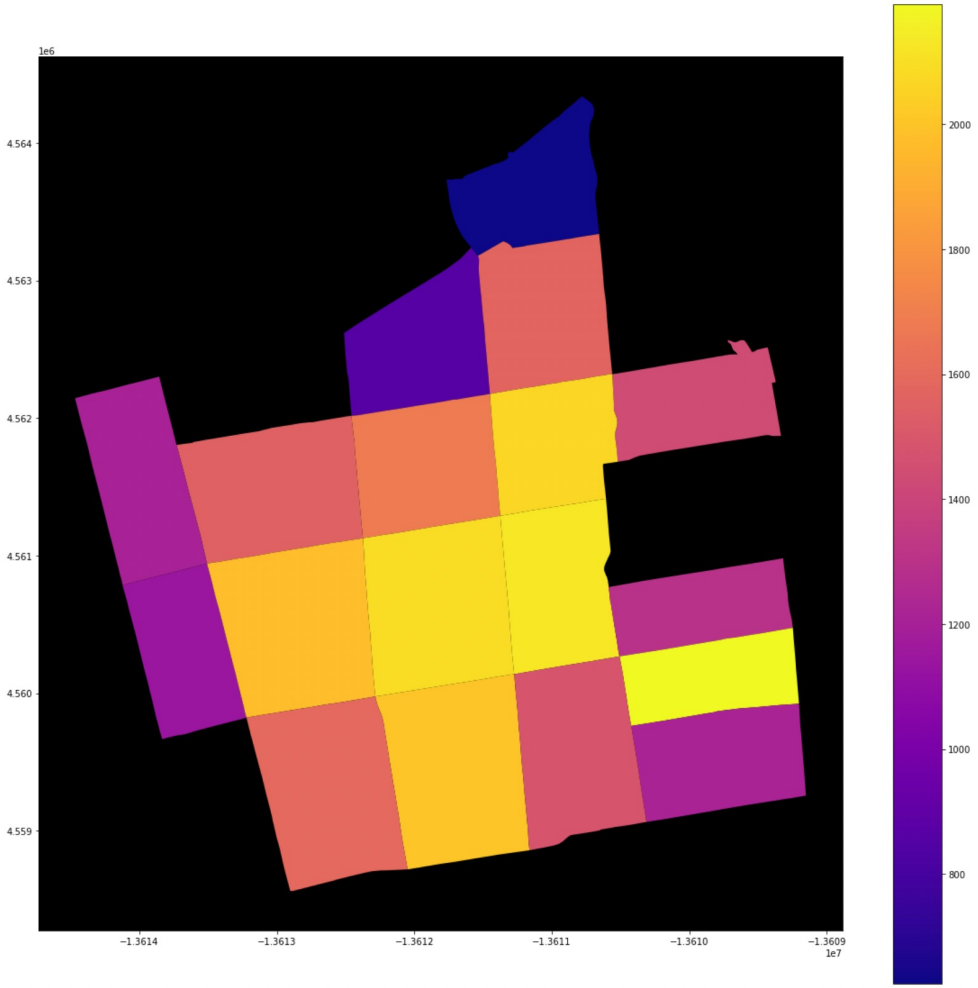
Median Household Income

Median contract rent

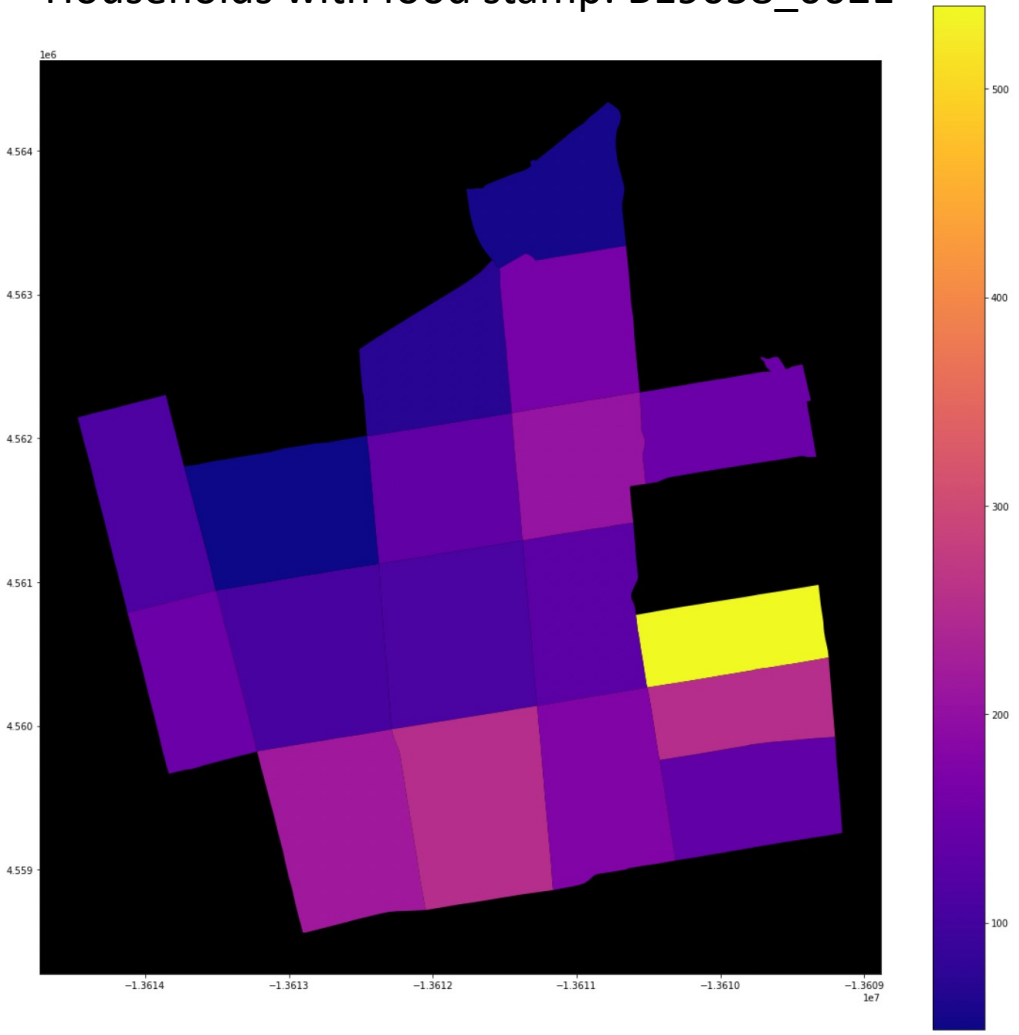


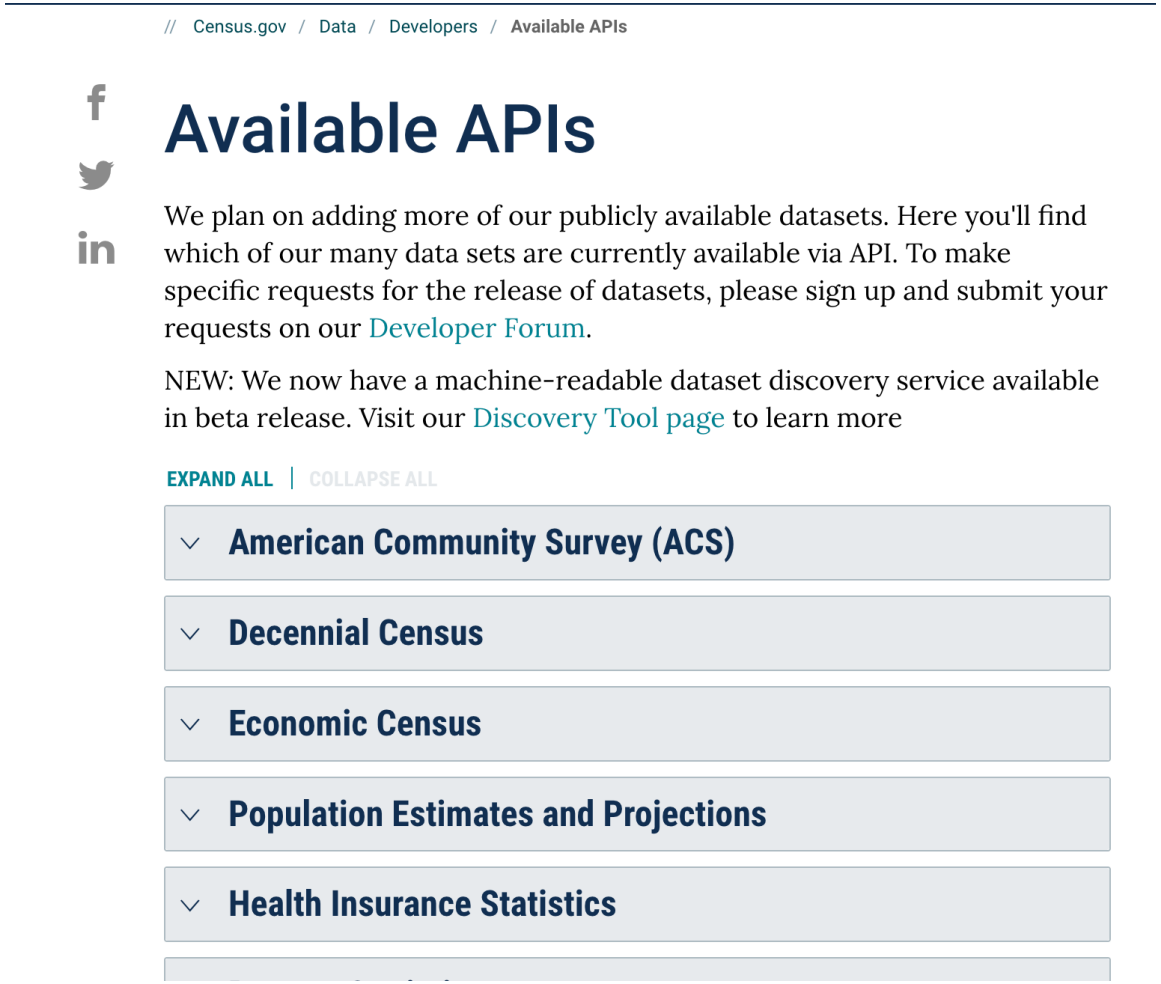


Households food stamp Estimate Total



Households with food stamp: B19058_002E





https://www.census.gov/data/developers/data-sets.html

CENPY uses the Census API, we can work with their prepared products (ACS and Decennial2010)

Via the US Census API one can get more products

I have code that imports data from the API without Cenpy(ask me if you would like to explore it)

sandiego_tracts_calculations.ipynb

We select a set of Census variables that are meaningful for a Data Science Story, gives short friendly names

```python
import contextily
import geopandas
import cenpy

acs = cenpy.products.ACS(2017)
```

Download Data

- Set variables to download

```python
vars_to_download = {
    "B25077_001E": "median_house_value",  # Median house value
    "B02001_002E": "total_pop_white",     # Total white population
    "B01003_001E": "total_pop",           # Total population
    "B25003_003E": "total_rented",        # Total rented occupied
    "B25001_001E": "total_housing_units", # Total housing units
    "B09019_006E": "hh_female",           # Female households
    "B09019_001E": "hh_total",            # Total households
    "B15003_002E": "total_bachelor",      # Total w/ Bachelor degree
    "B25018_001E": "median_no_rooms",     # Median number of rooms
    "B19083_001E": "income_gini",         # Gini index of income inequality
    "B01002_001E": "median_age",          # Median age
    "B08303_001E": "tt_work",              # Aggregate travel time to work
    "B19013_001E": "median_hh_income"     # Median household income
}
vars_to_download_l = list(vars_to_download.keys())
```

Source: https://geographicdata.science/book/data/sandiego/sandiego_tracts_cleaning.html
Book: ***Geographic Data Science with Python***

- Download geometries and attributes

:

```
%%time
db = acs.from_msa("San Diego, CA",
                  level="tract",
                  variables=vars_to_download_l
                 )
```

```
CPU times: user 1.13 s, sys: 80.1 ms, total: 1.21 s
Wall time: 20.3 s
```

Metadata

We create a DataFrame that contains information about the variables to be downloaded, including the variable name (stored as "var_id"), a short name (stored as "short_name"), the label of the variable, and its associated concept. This information allows us to keep track of what each variable represents.

```
var_names = acs.variables\
                .reindex(vars_to_download)\
                [["label", "concept"]]\
                .reset_index()\
                .rename(columns={"index": "var_id"})
var_names["short_name"] = var_names["var_id"].map(vars_to_download)
```

```
var_names
```

	var_id	label	concept	short_name
0	B25077_001E	Estimate!!Median value (dollars)	MEDIAN VALUE (DOLLARS)	median_house_value
1	B02001_002E	Estimate!!Total!!White alone	RACE	total_pop_white
2	B01003_001E	Estimate!!Total	TOTAL POPULATION	total_pop
3	B25003_003E	Estimate!!Total!!Renter occupied	TENURE	total_rented
4	B25001_001E	Estimate!!Total	HOUSING UNITS	total_housing_units
5	B09019_006E	Estimate!!Total!!In households!!In family hous...	HOUSEHOLD TYPE (INCLUDING LIVING ALONE) BY REL...	hh_female
6	B09019_001E	Estimate!!Total	HOUSEHOLD TYPE (INCLUDING LIVING ALONE) BY REL...	hh_total
7	B15003_002E	Estimate!!Total!!No schooling completed	EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 Y...	total_bachelor
8	B25018_001E	Estimate!!Median number of rooms	MEDIAN NUMBER OF ROOMS	median_no_rooms
9	B19083_001E	Estimate!!Gini Index	GINI INDEX OF INCOME INEQUALITY	income_gini
10	B01002_001E	Estimate!!Median age --!!Total	MEDIAN AGE BY SEX	median_age
11	B08303_001E	Estimate!!Total	TRAVEL TIME TO WORK	tt_work
12	B19013_001E	Estimate!!Median household income in the past ...	MEDIAN HOUSEHOLD INCOME IN THE PAST 12 MONTHS ...	median_hh_income

Process data

While the ACS comes with a large number of attributes, we are not limited to the original variables at hand; we can construct additional variables. This is particularly useful when we want to compare areas that are not very similar in some structural characteristic, such as area or population. For example, a quick look into the variable names shows most variables are counts. For tracts of different sizes, these variables will mainly reflect their overall population, rather than provide direct information about the variables itself. To get around this, we will cast many of these count variables to rates, and use them in addition to a subset of the original variables.

- Replace missing values with columns mean

In [33]:
```
filler = lambda col: col.fillna(col.mean())
db.loc[:, vars_to_download] = db.loc[:, vars_to_download]\
                                .apply(filler)
```

- Replace variable codes with short names

In [34]:
```
db = db.rename(columns=vars_to_download)
```

- Calculate area in Sq.Km (we use the Conus Albers CRS)

In [35]:
```
db["area_sqm"] = db.to_crs(epsg=5070).area / 1e6
```

EPSG stands for European Petroleum Survey Group, which is a defunct organization that maintained a database of coordinate reference systems (CRSs)

- Percentage of renter occupied units

In [36]:
```
db["pct_rented"] = db["total_rented"] / \
                   (db["total_housing_units"] + \
                    (db["total_housing_units"]==0) * 1
                   )
```

- Percentage of female households

In [37]:
```
db["pct_hh_female"] = db["hh_female"] / \
                      (db["hh_total"] + \
                       (db["hh_total"]==0) * 1
                      )
```

Note: if the denominator is 0, it divides by 1

- Percentage without completing Schooling

```
:
1 db["pct_bachelor"] = db["total_bachelor"] / \
2                      (db["total_pop"] + \
3                       (db["total_pop"]==0) * 1
4                      )
```

- Percentage of white population

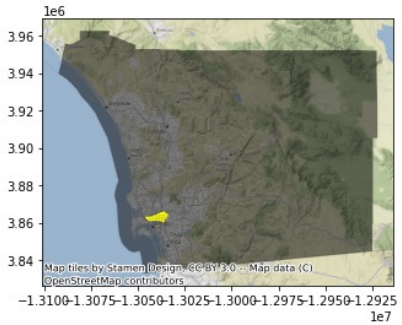
```
:
1 db["pct_white"] = db["total_pop_white"] / \
2                   (db["total_pop"] + \
3                    (db["total_pop"]==0) * 1
4                   )
```

This shows how to sample a selected number of 30 tracts and color them in yellow on top of all the other tracts (628) colored in black with transparency (alpha=0.5)

- Generate indicator for subset of contiguous 30 tracts

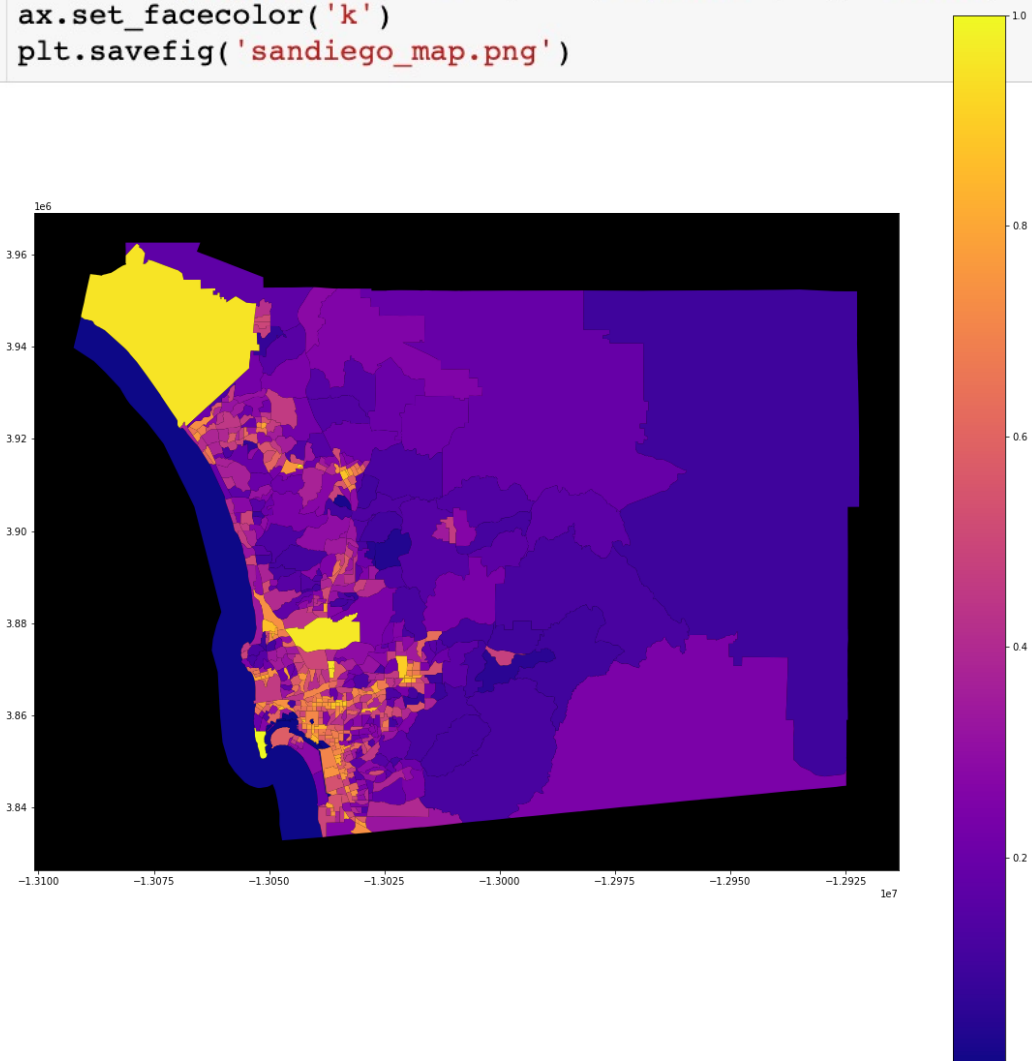
```
]:
1  tract_geoids = [
2       '06073000100',
3       '06073000201',
4       '06073000202',
5       '06073000300',
6       '06073000400',
7       '06073000500',
8       '06073000600',
9       '06073000700',
10      '06073000800',
11      '06073000900',
12      '06073001000',
13      '06073001100',
14      '06073001200',
15      '06073001300',
16      '06073001400',
17      '06073001500',
18      '06073001600',
19      '06073001700',
20      '06073001800',
21      '06073001900',
22      '06073002001',
23      '06073002002',
24      '06073002100',
25      '06073002201',
26      '06073002202',
27      '06073002301',
28      '06073002302',
29      '06073002401',
30      '06073002402',
31      '06073002501'
32  ]
33  db["sub_30"] = False
34  db.loc[db["GEOID"].isin(tract_geoids), "sub_30"] = True
```

```
]:
1  ax = db.plot(alpha=0.5, color="k")
2  db[db["sub_30"]].plot(ax=ax, color="yellow")
3  contextily.add_basemap(ax, crs=db.crs);
```



Mapping one selected variable:

```
#ax = db.plot(figsize=(20, 20),cmap='plasma',legend=True)
#db[db["sub_30"]].plot(ax=ax, color="yellow")
#contextily.add_basemap(ax, crs=db.crs);

f, ax = plt.subplots(1,1,figsize=(20,20))
db.plot('pct_rented', ax=ax, cmap='plasma',legend=True)
ax.set_facecolor('k')
plt.savefig('sandiego_map.png')
```



Explore your results quantitatively

```
min(db['pct_rented'])
```

```
0.0
```

```
db['pct_rented'].max()
```

```
1.0
```

```
n1, bins1 = np.histogram(db['pct_rented'],density='True')
```

```
n1
```

```
array([0.30254777, 1.56050955, 1.62420382, 1.44904459, 1.36942675,
       1.11464968, 1.05095541, 0.97133758, 0.44585987, 0.11146497])
```

```
bins1[:-1]
```

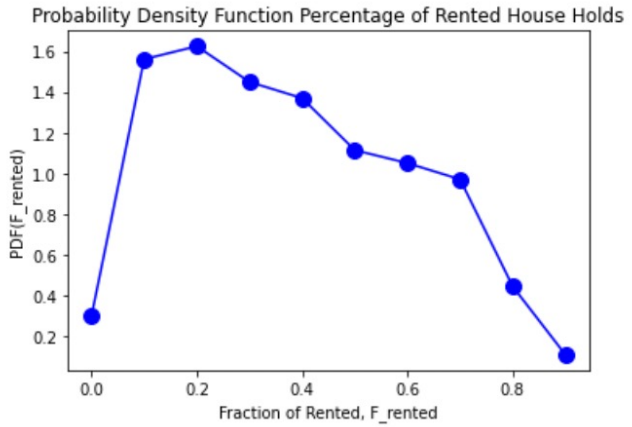
```
array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9])
```

```
sum(n1*0.1)
```

```
1.0
```

```
plt.plot(bins1[:-1],n1,'bo-', markersize=10)
plt.title('Probability Density Function Percentage of Rented House Holds')
plt.xlabel('Fraction of Rented, F_rented')
plt.ylabel('PDF(F_rented)')
```

```
Text(0, 0.5, 'PDF(F_rented)')
```



In probability theory, a **probability density function** (**PDF**), or **density** of a continuous random variable, is a function whose value at any given sample can be interpreted as providing a *relative likelihood* that the value of the random variable would equal that sample

$$\Pr[a \leq X \leq b] = \int_a^b f_X(x)\,dx.$$

Probability Density curves have the following properties:

- The area under the curve always adds up to 1.
- The curve is nonnegative

```
1 min(db['pct_rented'])
```

```
0.0
```

```
1 db['pct_rented'].max()
```

```
1.0
```

```
1 n1, bins1 = np.histogram(db['pct_rented'],density='True')
```

```
1 n1
```

```
array([0.30254777, 1.56050955, 1.62420382, 1.44904459, 1.36942675,
       1.11464968, 1.05095541, 0.97133758, 0.44585987, 0.11146497])
```

```
1 bins1[:-1]
```

```
array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9])
```

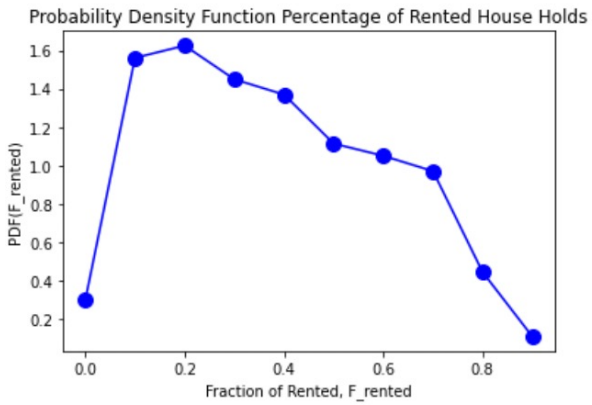
dx=0.1

```
1 sum(n1*0.1)
```

```
1.0
```

```
1 plt.plot(bins1[:-1],n1,'bo-', markersize=10)
2 plt.title('Probability Density Function Percentage of Rented House Holds')
3 plt.xlabel('Fraction of Rented, F_rented')
4 plt.ylabel('PDF(F_rented)')
```

```
Text(0, 0.5, 'PDF(F_rented)')
```



The data is saved as gpkg and json files

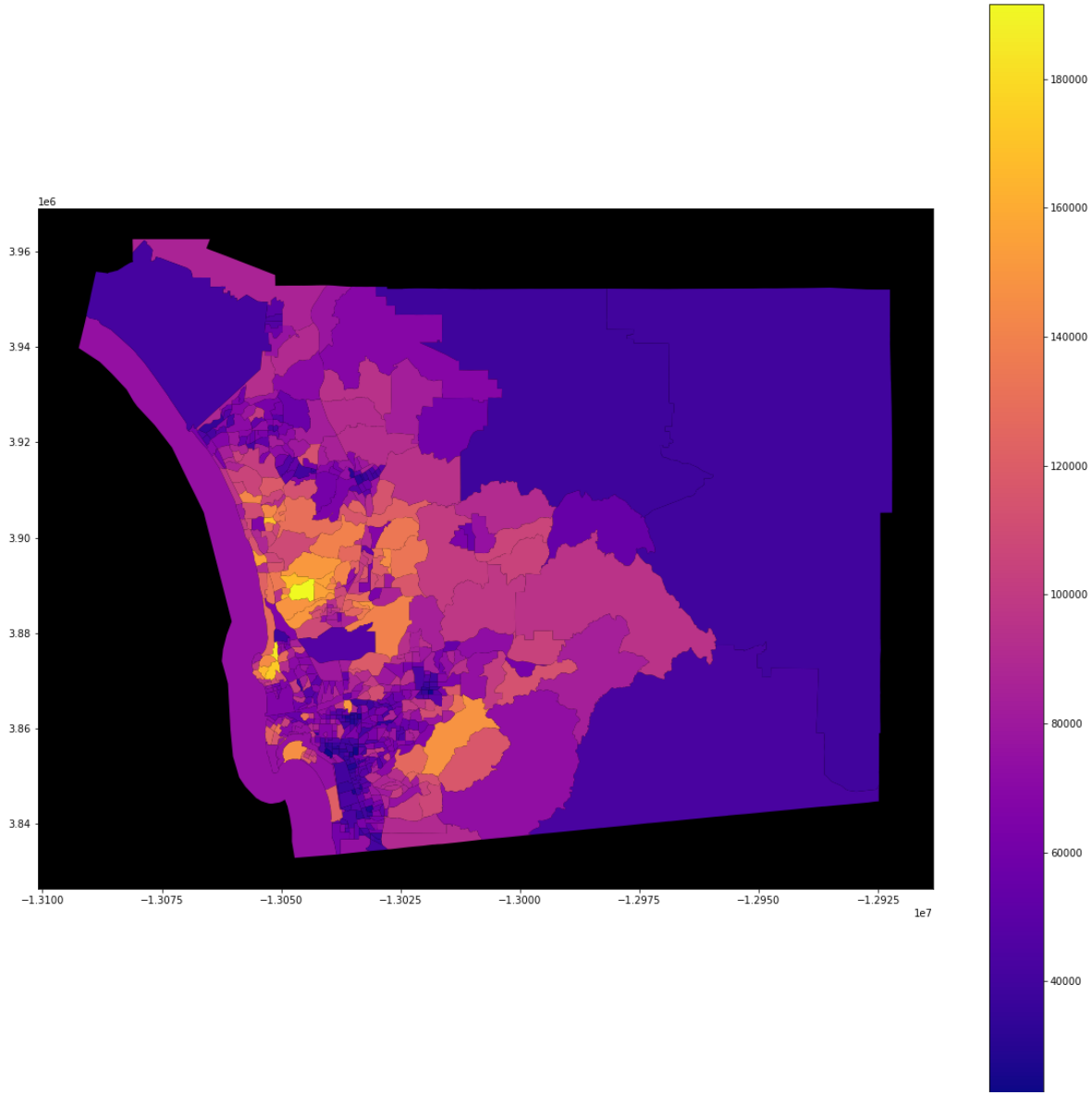
- Dataset

[47]:
```
! rm -f sandiego_tracts.gpkg
db.to_file("sandiego_tracts.gpkg", driver="GPKG")
```

- Metadata

[44]:
```
! rm -f sandiego_tracts_varnames.json
var_names.to_json("sandiego_tracts_varnames.json")
```

See: https://www.gis-blog.com/geopackage-vs-shapefile/




```
1 n2, bins2 = np.histogram(db['median_hh_income'],density='True')
```

```
1 n2
```

```
array([5.65240086e-06, 1.20584552e-05, 1.39425888e-05, 1.14932151e-05,
       7.25391444e-06, 4.14509396e-06, 2.26096034e-06, 1.69572026e-06,
       4.71033405e-07, 1.88413362e-07])
```

```
1 bins2
```

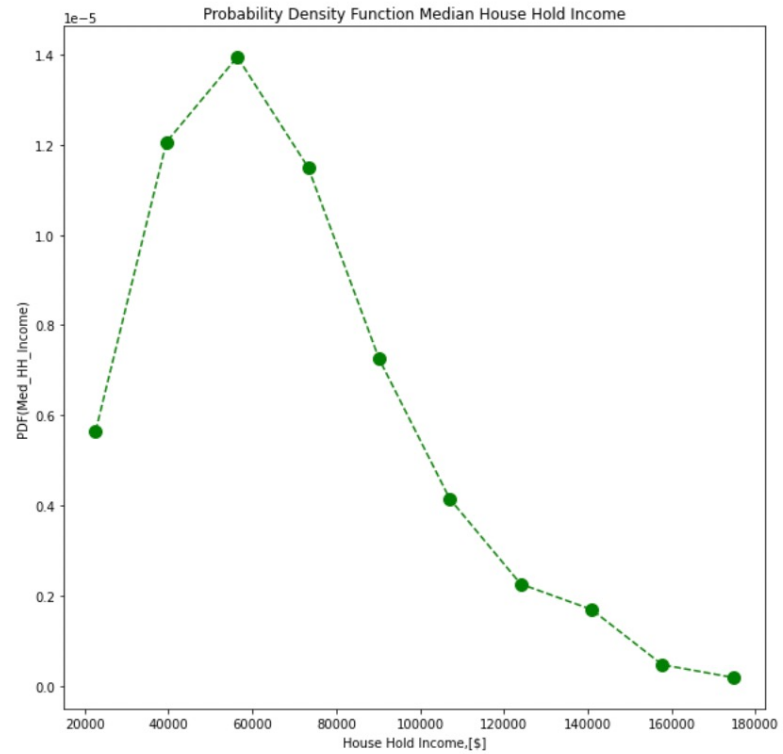
```
array([ 22614. ,  39516.8,  56419.6,  73322.4,  90225.2, 107128. ,
       124030.8, 140933.6, 157836.4, 174739.2, 191642. ])
```

```
1 sum(n2*(bins2[1]-bins2[0]))
```

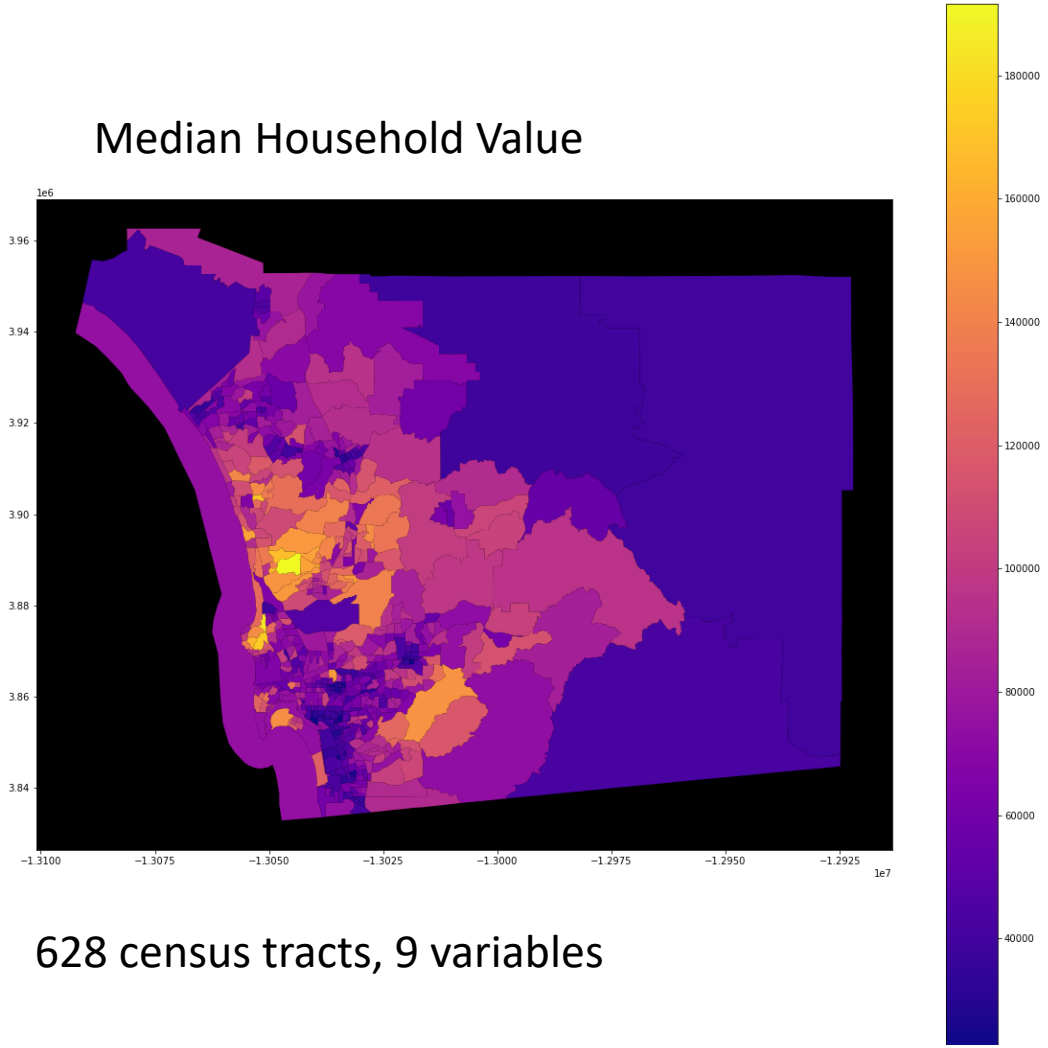
```
1.0000000000000002
```

```
1 plt.figure(figsize=(10,10))
2 plt.plot(bins2[:-1],n2,'go--', markersize=10)
3 plt.title('Probability Density Function Median House Hold Income')
4 plt.xlabel('House Hold Income,[$]')
5 plt.ylabel('PDF(Med_HH_Income)')
```

```
Text(0, 0.5, 'PDF(Med_HH_Income)')
```



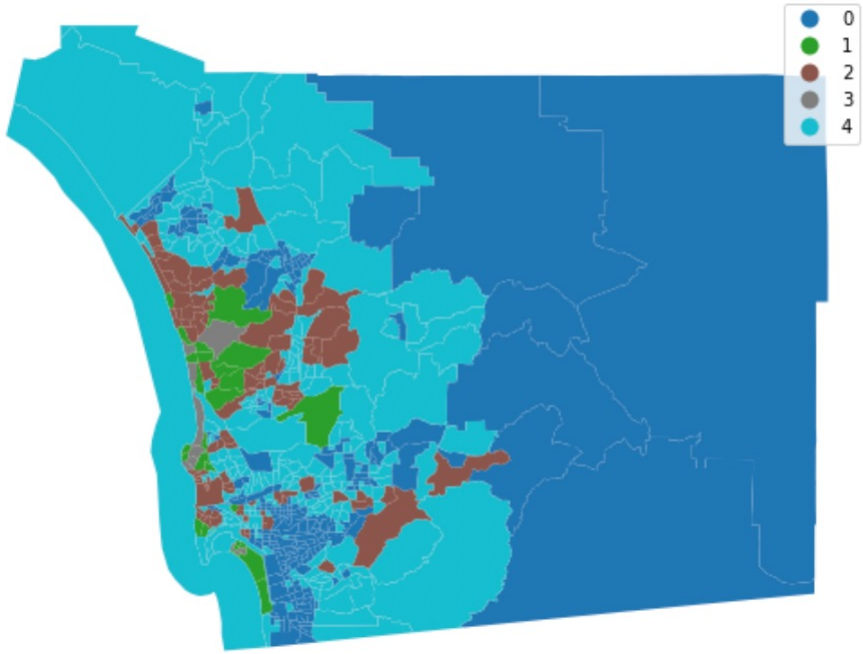
Median Household Value



628 census tracts, 9 variables

Exercise: Name the clusters in decreasing order of Median Household Value

5 Clusters



k5cls	0	1	2	3	4
median_house_value	326728.97	1168004.00	736881.37	1876867.22	500787.57
pct_white	0.66	0.84	0.81	0.91	0.72
pct_rented	0.51	0.29	0.33	0.25	0.41
pct_hh_female	0.11	0.11	0.10	0.12	0.10
pct_bachelor	0.02	0.00	0.00	0.00	0.01
median_no_rooms	4.63	6.02	5.73	6.42	5.29
income_gini	0.40	0.47	0.43	0.52	0.40
median_age	34.25	44.44	41.60	50.54	37.21
tt_work	2187.75	2182.00	2336.28	1237.78	2539.43

Motivation for next class

For next class

- Finish assignment 2

- Participate in Lecture 6: https://docs.google.com/presentation/d/1IxmXNjFCS1TXb7FQMB2TByHb8zHVyMBHzSzfWsuTwGU/edit?usp=sharing

- Optional Review Content of next class:

https://geographicdata.science/book/notebooks/10_clustering_and_regionalization.html

- Clustering is a method of data analysis that draws insights from large, complex multivariate data.

- It works by finding similarities among the many dimensions in multivariate data, condensing them down into a simpler representation. Thus, through clustering, we seek to reduce the complexity of the system

- Clustering involves sorting observations into groups. For these groups to be meaningful, members of a group should be more similar to one another than they are to members of a different group.

- Each group is referred to as a *cluster* while the process of assigning objects to groups is known as *clustering*. Since a good cluster is more similar internally than it is to any other cluster, these cluster-level profiles provide a convenient shorthand to describe the original complex multivariate data.

K-means Clustering

Given a set of observations ($\mathbf{x}_1$, $\mathbf{x}_2$, ..., $\mathbf{x}_n$), where each observation is a *d*-dimensional real vector, *k*-means clustering aims to partition the *n* observations into *k* (≤ *n*) sets $\mathbf{S} = \{S_1, S_2, ..., S_k\}$ so as to minimize the within-cluster sum of squares (WCSS) (i.e. variance). Formally, the objective is to find:

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2$$

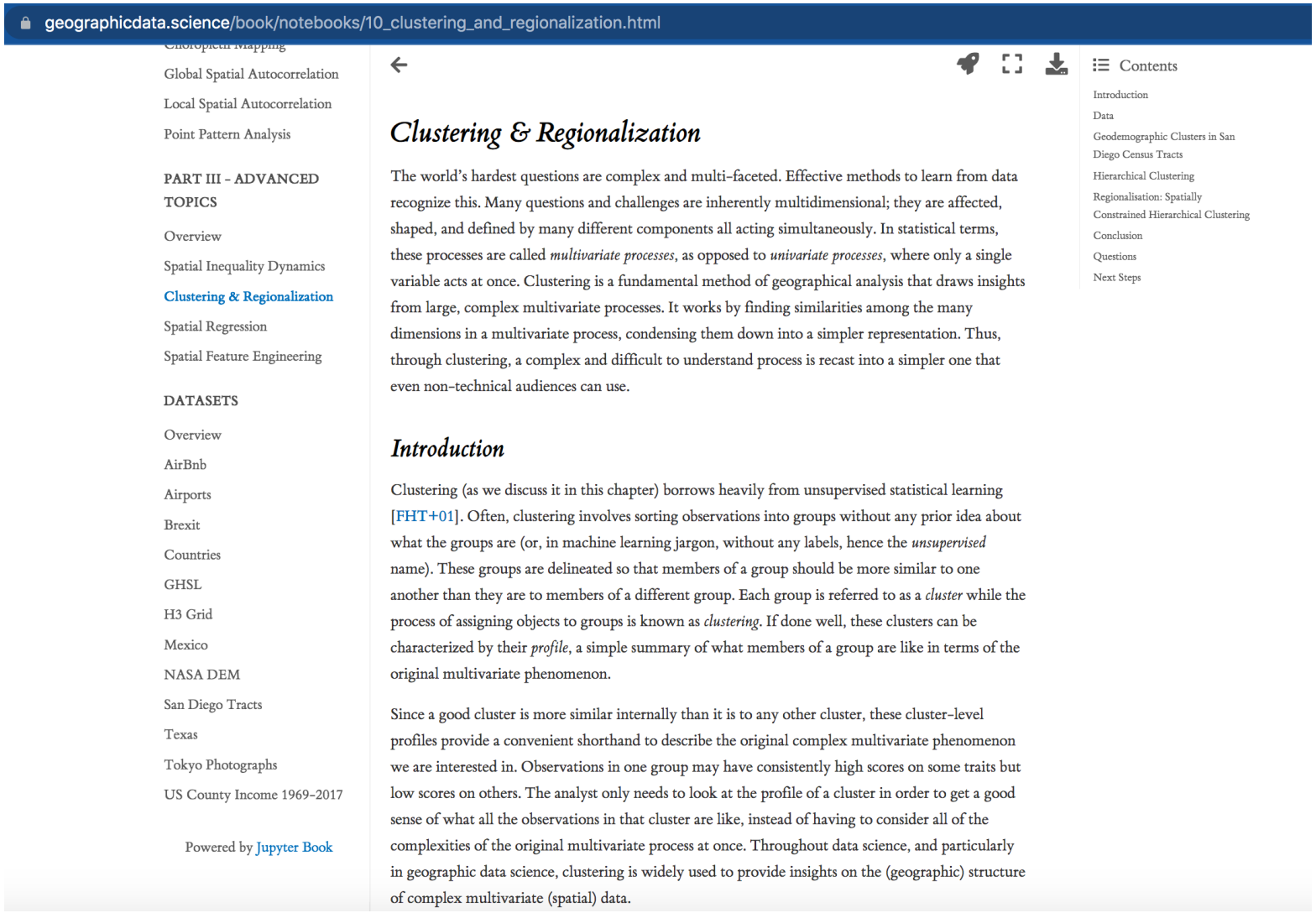
Vector X contains the variables of element i
Each Set S_i has a list of elements close to their mean $\boldsymbol{\mu}_i$

where $\boldsymbol{\mu}_i$ is the mean of points in S_i.

This is equivalent to minimizing the pairwise squared deviations of points in the same cluster

This is equivalent to maximizing the sum of squared deviations between points in *different* clusters (between-cluster sum of squares, BCSS)

Book chapter for Lectures 5 and 6:



https://geographicdata.science/book/notebooks/10_clustering_and_regionalization.html