American Community Survey: Annual Change

ANALYZING US CENSUS DATA IN PYTHON

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Census History: Counts and Samples

Full count of core demographic characteristics:

- Decennial Census 1790 - 2010+

Sample of extensive social and economic characteristics:

- Decennial Census "Long Form" (SF3) 1970 - 2000, ~15% of households
- Annual American Community Survey 2005+, ~1% of households

B25045 - Tenure by Vehicles Available by Age

```
Variable    |  Label
-----------|--------------------------------------
B25045001  |  Total
B25045002  |    Owner Occupied
B25045003  |      No Vehicle Available
B25045004  |        Householder 15 to 34 Years
B25045005  |        Householder 35 to 64 Years
B25045006  |        Householder 65 Years and Over
B25045007  |      1 or More Vehicles Available
B25045008  |        Householder 15 to 34 Years
B25045009  |        Householder 35 to 64 Years
B25045010  |        Householder 65 Years and Over
B25045011  |    Renter Occupied
B25045012  |      No Vehicle Available
B25045013  |        Householder 15 to 34 Years
B25045014  |        Householder 35 to 64 Years
B25045015  |        Householder 65 Years and Over
B25045016  |      1 or More Vehicles Available
B25045017  |        Householder 15 to 34 Years
B25045018  |        Householder 35 to 64 Years
B25045019  |        Householder 65 Years and Over
```

ACS Detailed Table Request - Setup

```python
import requests
import pandas as pd

HOST, dataset = "https://api.census.gov/data", "acs/acs1"
get_vars = ["B25045_" + str(i + 1).zfill(3) + "E" for i in range(19)]
get_vars = ["NAME"] + get_vars
print(get_vars)
```

```
['NAME', 'B25045_001E', 'B25045_002E', 'B25045_003E', 'B25045_004E',
'B25045_005E', 'B25045_006E', 'B25045_007E', 'B25045_008E', 'B25045_009E',
'B25045_010E', 'B25045_011E', 'B25045_012E', 'B25045_013E', 'B25045_014E',
'B25045_015E', 'B25045_016E', 'B25045_017E', 'B25045_018E', 'B25045_019E']
```

ACS Detailed Table Request - Setup

```
import requests
import pandas as pd

HOST, dataset = "https://api.census.gov/data", "acs/acs1"
get_vars = ["B25045_" + str(i + 1).zfill(3) + "E" for i in range(19)]
get_vars = ["NAME"] + get_vars
# print(get_vars)
predicates = {}
predicates["get"] = ",".join(get_vars)
predicates["for"] = "us:*"
```

Requesting Same Variables from Multiple Years

```
# Initialize data frame collector
dfs = []
for year in range(2011, 2018):
    base_url = "/".join([HOST, str(year), dataset])
    r = requests.get(base_url, params=predicates)
    df = pd.DataFrame(columns=r.json()[0], data=r.json()[1:])
    # Add column to hold year value
    df["year"] = year
    dfs.append(df)

# Concatenate all data frames in collector
us = pd.concat(dfs)
```

Requesting Same Variables from Multiple Years

```
print(us.head())
```

```
            NAME B25045_001E B25045_002E  ... B25045_019E us  year
0  United States   114991725    74264435  ...     3232812  1  2011
0  United States   115969540    74119256  ...     3447172  1  2012
0  United States   116291033    73843861  ...     3662322  1  2013
0  United States   117259427    73991995  ...     3847400  1  2014
0  United States   118208250    74506512  ...     4044430  1  2015

[5 rows x 22 columns]
```

Let's Get Some Data!

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Margins of Error

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Margins of Error

- Table B25045 - Tenure by Vehicles Available by Age of Householder
  - B25045_001E - **Estimate** of total occupied housing units
  - B25045_001M - **Margin of Error** of the estimate

name	B25045_001E	B25045_001M
Alabama	1,844,546	±11,416
Alaska	257,330	±3,380
Arizona	2,356,055	±12,130
Arkansas	1,127,621	±7,837

Margins of Error

```
B25045.head()
```

```
         NAME  B25045_001E  B25045_001M state
0     Alabama      1844546        11416    01
1      Alaska       257330         3380    02
2     Arizona      2356055        12130    04
3    Arkansas      1127621         7837    05
4  California     12468743        22250    06
```

Margins of Error

```
B25045.columns = ["name", "total", "total_moe", "state"]
B25045.head()
```

```
         name     total  total_moe state
0     Alabama   1844546      11416    01
1      Alaska    257330       3380    02
2     Arizona   2356055      12130    04
3    Arkansas   1127621       7837    05
4  California  12468743      22250    06
```

Relative Margin of Error

Margin of Error as a Percent of the Estimate:

$$RMOE = 100 \times MOE/Estimate$$

```
         NAME  B25045_001E  B25045_001M state      rmoe
0  California     13005097        17539    06  0.134863
1     Wyoming       225796         3968    56  1.757338
```

```
                 NAME  B25045_001E  B25045_001M state county      rmoe
0  Los Angeles County      3311231         8549    06    037  0.258182
1  Sutter County, Cal        31945          907    06    101  2.839255
```

Margins of Error of Breakdown Columns

B25045_004E — Owner Occupied?No Vehicle Available?Householder 15 to 34 Years

```
         NAME  B25045_004E  B25045_004M state        rmoe
0  California        10964         1519    06   13.854433
1     Wyoming           25           48    56  192.000000
```

```
              NAME  B25045_004E  B25045_004M state county       rmoe
0  Los Angeles Cou         1942          634    06    037  32.646756
1  Sutter County,             0          210    06    101        inf
```

Standard Errors

$$Z_{90} = 1.645$$

$$SE_x = \frac{MOE_x}{Z_{90}}$$

Statistically Significant Difference

$$Z = \frac{x_1 - x_2}{\sqrt{SE_{x_1}^2 + SE_{x_2}^2}}$$

```
       total  total_moe  year
4   12944178      15703  2016
4   13005097      17539  2017
```

```
Z_CRIT = 1.645
x1 = int(ca["total"][ca["year"] == 2017])
x2 = int(ca["total"][ca["year"] == 2016])

se_x1 = float(ca["total_moe"][ca["year"] == 2017] / Z_CRIT)
se_x2 = float(ca["total_moe"][ca["year"] == 2016] / Z_CRIT)
```

Statistically Significant Difference

$$Z = \frac{x_1 - x_2}{\sqrt{SE_{x_1}^2 + SE_{x_2}^2}}$$

```
      total  total_moe  year
4  12944178      15703  2016
4  13005097      17539  2017
```

```
Z = (x1 - x2) / __________(___________________)
```

Statistically Significant Difference

$$Z = \frac{x_1 - x_2}{\sqrt{SE_{x_1}^2 + SE_{x_2}^2}}$$

```
      total  total_moe  year
4  12944178      15703  2016
4  13005097      17539  2017
```

```
Z = (x1 - x2) / numpy.sqrt(___________________)
```

Statistically Significant Difference

$$Z = \frac{x_1 - x_2}{\sqrt{SE_{x_1}^2 + SE_{x_2}^2}}$$

```
      total  total_moe  year
4  12944178      15703  2016
4  13005097      17539  2017
```

```
Z = (x1 - x2) / numpy.sqrt(se_x1**2 + se_x2**2)
print(abs(Z) > Z_CRIT)
```

```
True
```

Approximating SE for Derived Estimates

$$SE_{a+b+\ldots} = \sqrt{SE_a^2 + SE_b^2 + \ldots}$$

$$MOE_{a+b+\ldots} = Z_{90} SE_{a+b+\ldots}$$

```
states["novehicle_65over"] = \
  states["owned_novehicle_65over"] + states["rented_novehicle_65over"]

states["novehicle_65over_moe"] = Z_CRIT * numpy.sqrt(\
  states["owned_novehicle_65over_moe"]**2 + \
  states["rented_novehicle_65over_moe"]**2\
  )
```

Approximating SE for Derived Estimates

```
print(states[["name", "novehicle_65over", "novehicle_65over_moe"]].head())
```

```
         name  novehicle_65over  novehicle_65over_moe
0     Alabama             42267           4867.038791
1      Alaska              5575           1473.170747
2     Arizona             52331           6598.753623
3    Arkansas             22533           3155.583824
4  California            372772          15183.882878
```

Let's Practice!

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Basic Mapping with Geopandas

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Geospatial Data - Further Learning

- Working with Geospatial Data in Python
- Visualizing Geospatial Data in Python

Loading Geospatial Data

```
import geopandas as gpd

# Load a geospatial file
geo_state = gpd.read_file("state_computer_use.gpkg")

type(geo_state)
```

```
geopandas.geodataframe.GeoDataFrame
```

Geopandas Data Frames

```
print(geo_state.columns)
```

```
Index(['state', 'postal', 'name', 'geometry', 'total', 'has_computer',
       'desktop_laptop', 'desktop_laptop_only', 'portable_device',
       'portable_device_only', 'no_computer'],
      dtype='object')
```

Geopandas Data Frames

```
print(geo_state.head())
```

```
  state postal  ... portable_device_only no_computer
0    06      CA  ...              1052406     1263635
1    08      CO  ...               148749      168639
2    11      DC  ...                23554       32916
3    16      ID  ...                46565       67454
4    17      IL  ...               415840      640062

[5 rows x 11 columns]
```

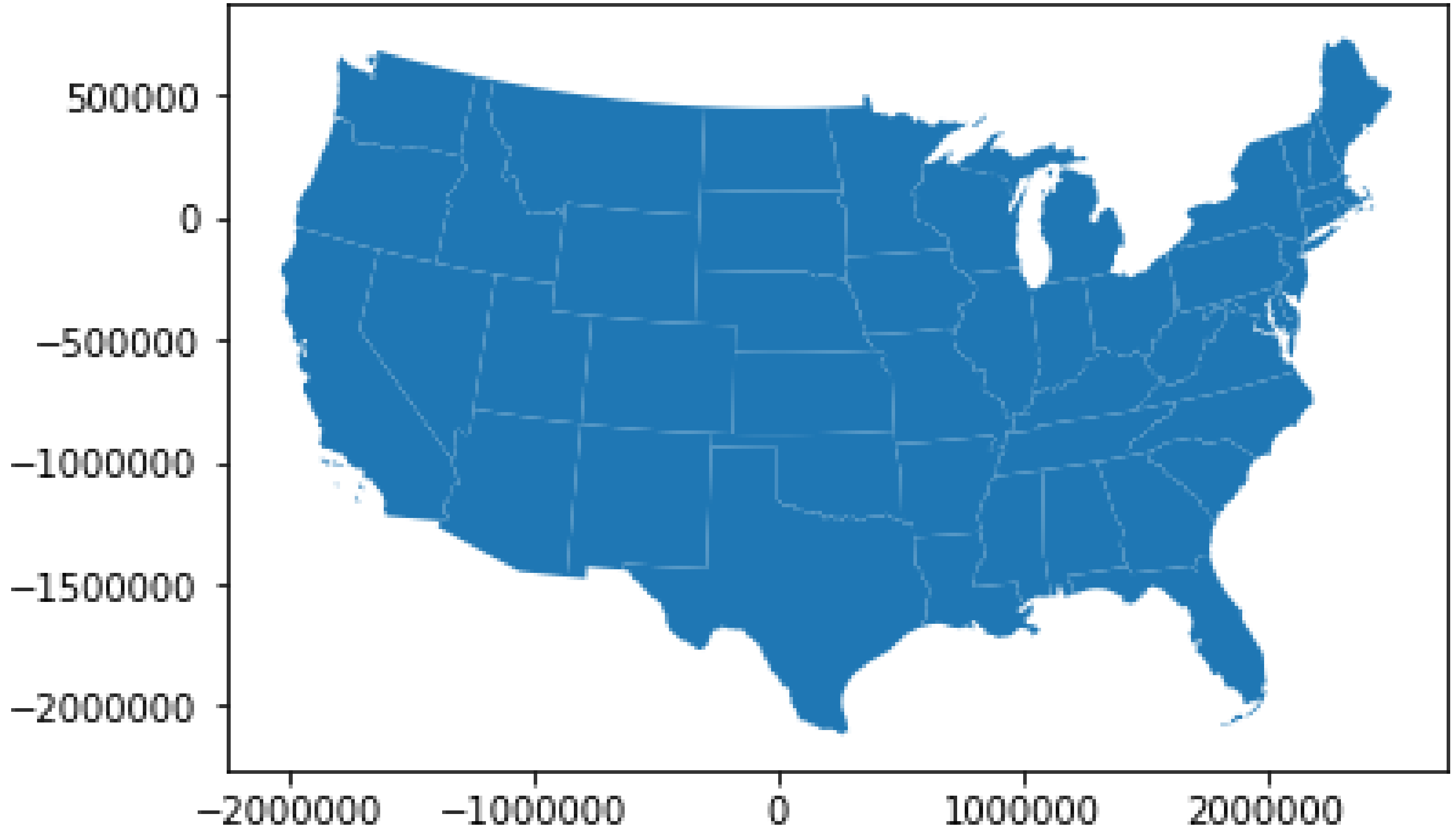
Geopandas geometry Column

```
print(geo_state["geometry"].head())
```

```
0    (POLYGON ((-1716661.572795197 -1091585.2669098...
1    (POLYGON ((-787764.8711845676 -679501.90042785...
2    (POLYGON ((1950824.825659711 -402441.066172522...
3    (POLYGON ((-1357254.591159301 77405.1771214068...
4    (POLYGON ((720437.1241238854 -496471.759394428...
Name: geometry, dtype: object
```

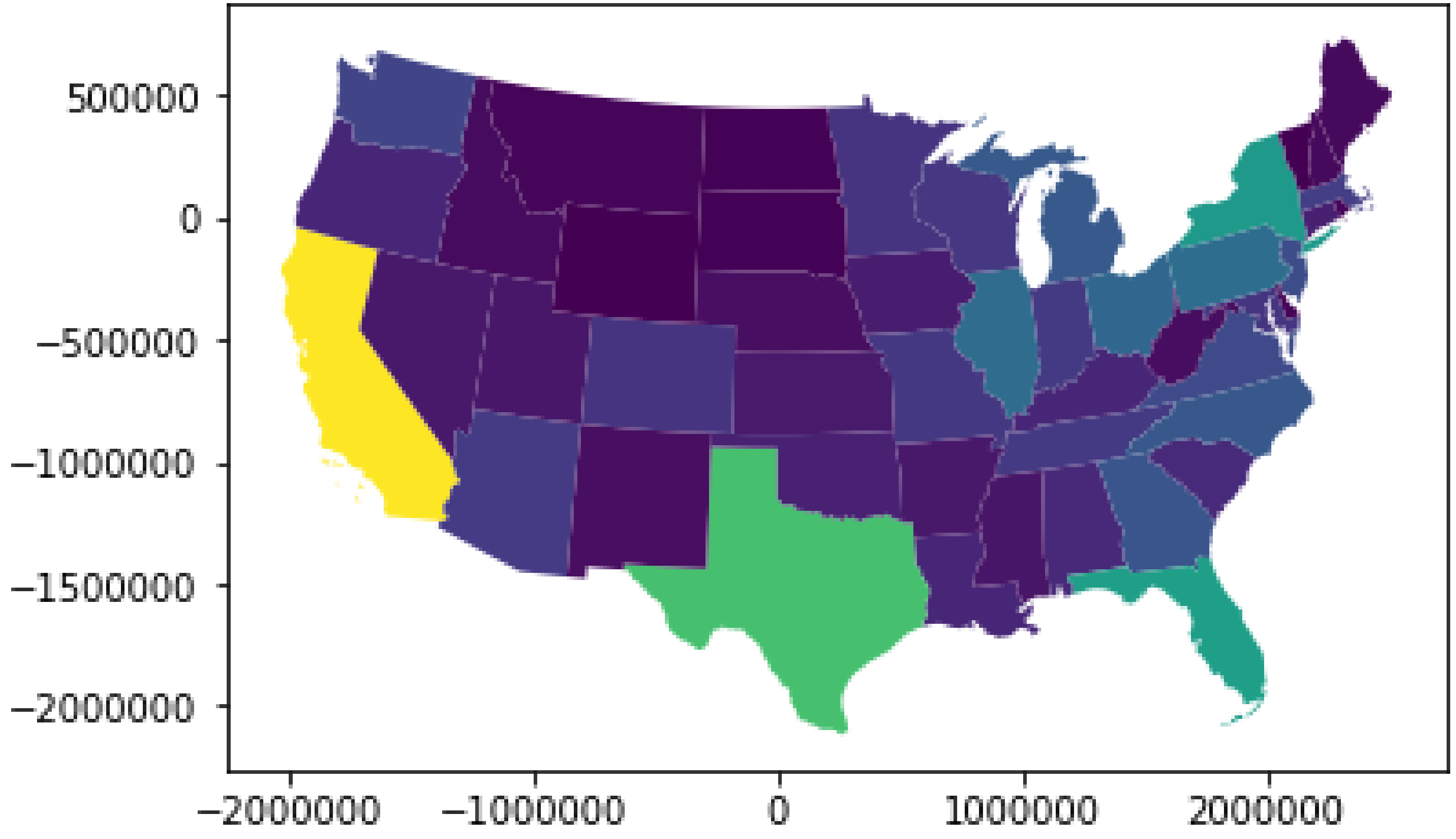
Geopandas Plotting

```
geo_state.plot()
```



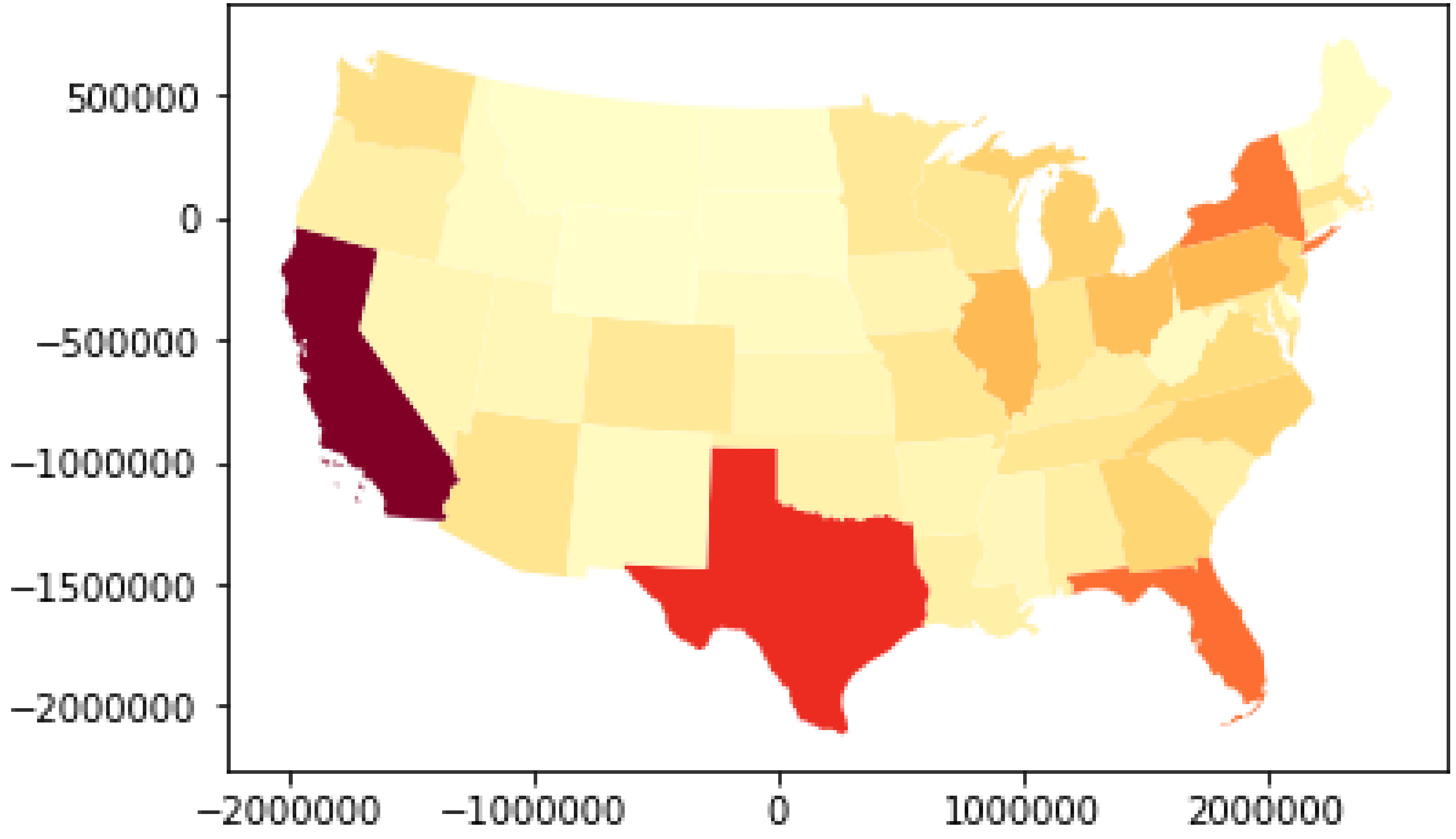
Choropleth Maps

```
geo_state.plot(column = "has_computer")
```



Choropleth Maps

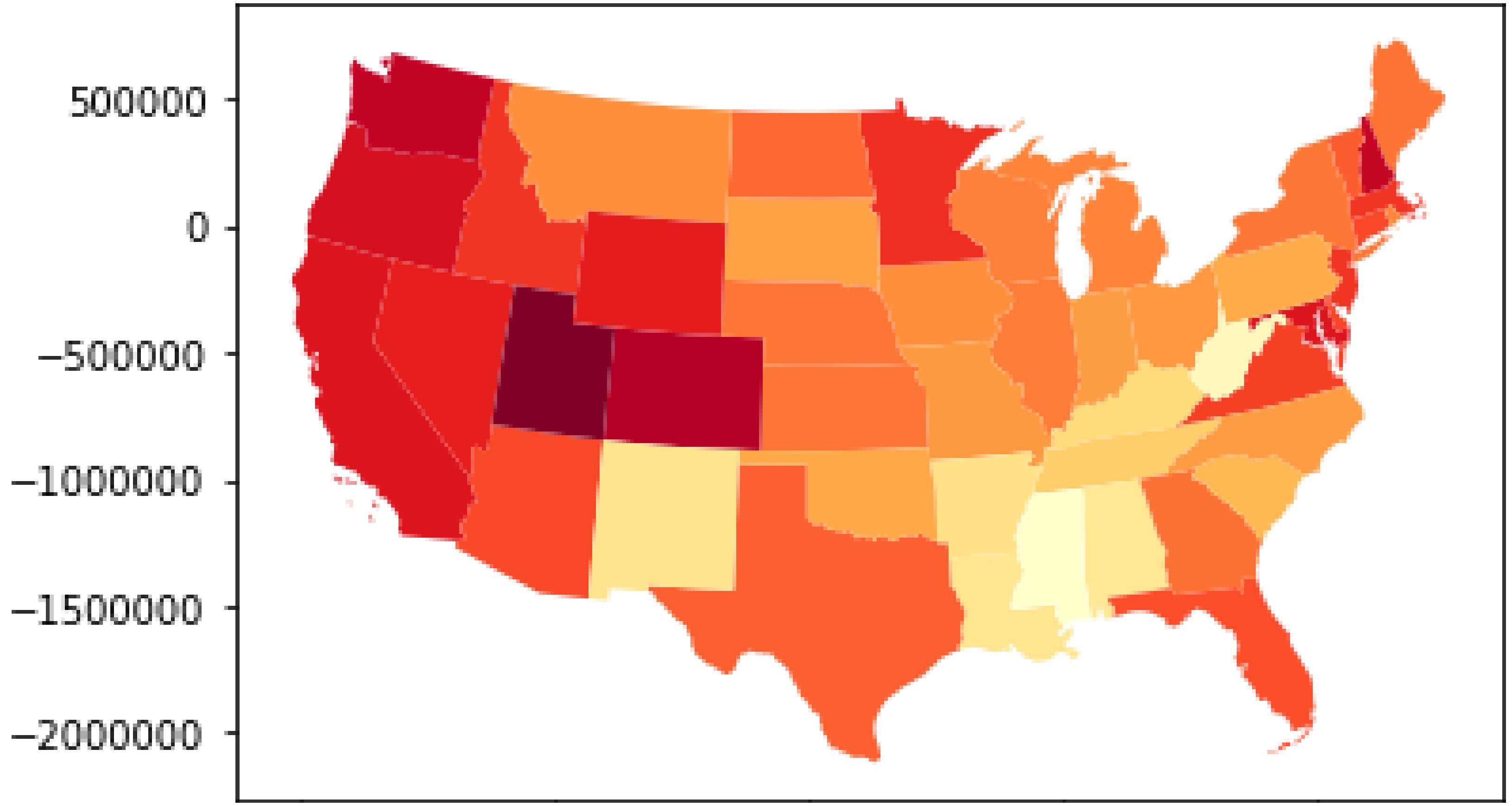
```
geo_state.plot(column = "has_computer", cmap = "YlOrRd")
```

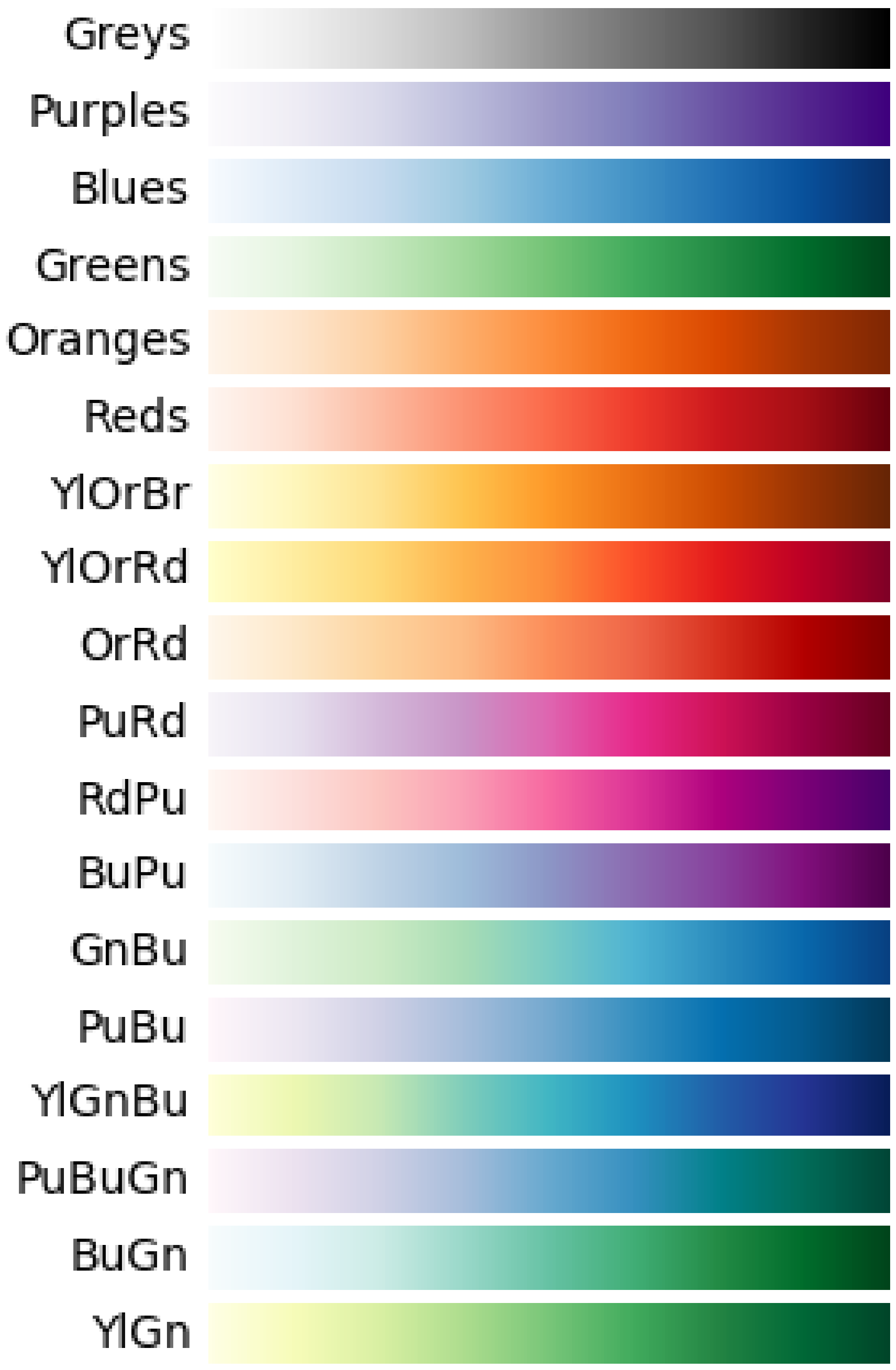


Choropleth Maps

```
geo_state["pct_has_computer"] = 100 * geo_state["has_computer"]/geo_state["total"]

geo_state.plot(column = "pct_has_computer", cmap = "YlOrRd")
```





Matplotlib Sequential Colormaps

https://matplotlib.org/users/colormaps.html

Let's practice!

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Neighborhood Change

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What Is Gentrification?

- Disinvestment in urban core
- Declining middle-class population and deteriorating housing stock
- Return of middle and upper-middle class households who renovate older housing stock
- Potential displacement of working class, Black, and immigrant households

Operationalizing Gentrification

- **Gentrifiable**
  - **Low median income**: Median household income (MHI) below metro area median
  - **Slow housing construction**: New build in previous two decades less than metro area
- **Gentrifying**
  - **Increasing educational attainment**: % with BA or higher is growing faster than metropolitan area
  - **Increasing house value**: Median house value greater than previous time period (adjusted for inflation)

[1] Freeman, Lance. 2005. "Displacement or Succession?: Residential Mobility in Gentrifying Neighborhoods." Urban Affairs Review 40 (4): 463–91.

Data Sources

- **2000 Census of Population and Housing - Summary File 3**
    - **P53**: Median Household Income in 1999 (Dollars)
    - **H34**: Year Structure Built
    - **P37**: Sex by Educational Attainment for the Population 25 Years and Over
    - **H85**: Median Value (Dollars) for All Owner-Occupied Housing Units
- **American Community Survey 5-Year Data (2008-20012)**
    - **B15003**: Educational Attainment for the Population 25 Years and Over
    - **B25077**: Median Value (Dollars) - Owner-occupied housing units

bk_2000: Brooklyn Census Tracts 2000

```
state                | State FIPS
county               | County FIPS
tract                | Tract FIPS
geometry             | Geometry column
mhi                  | Median Household Income (tract)
mhi_msa              | Median Household Income (NY Metro Area)
median_value         | Median House Value (tract)
median_value_msa     | Median House Value(NY Metro Area)
pct_recent_build     | Percent of housing built between 1980 and 1999 (tract)
pct_recent_build_msa | Percent of housing built between 1980 and 1999 (NY Metro Area)
pct_ba               | Percentage of 25 year olds with BA or higher (tract)
pct_ba_msa           | Percentage of 25 year olds with BA or higher(NY Metro Area)
```

Boolean Criteria

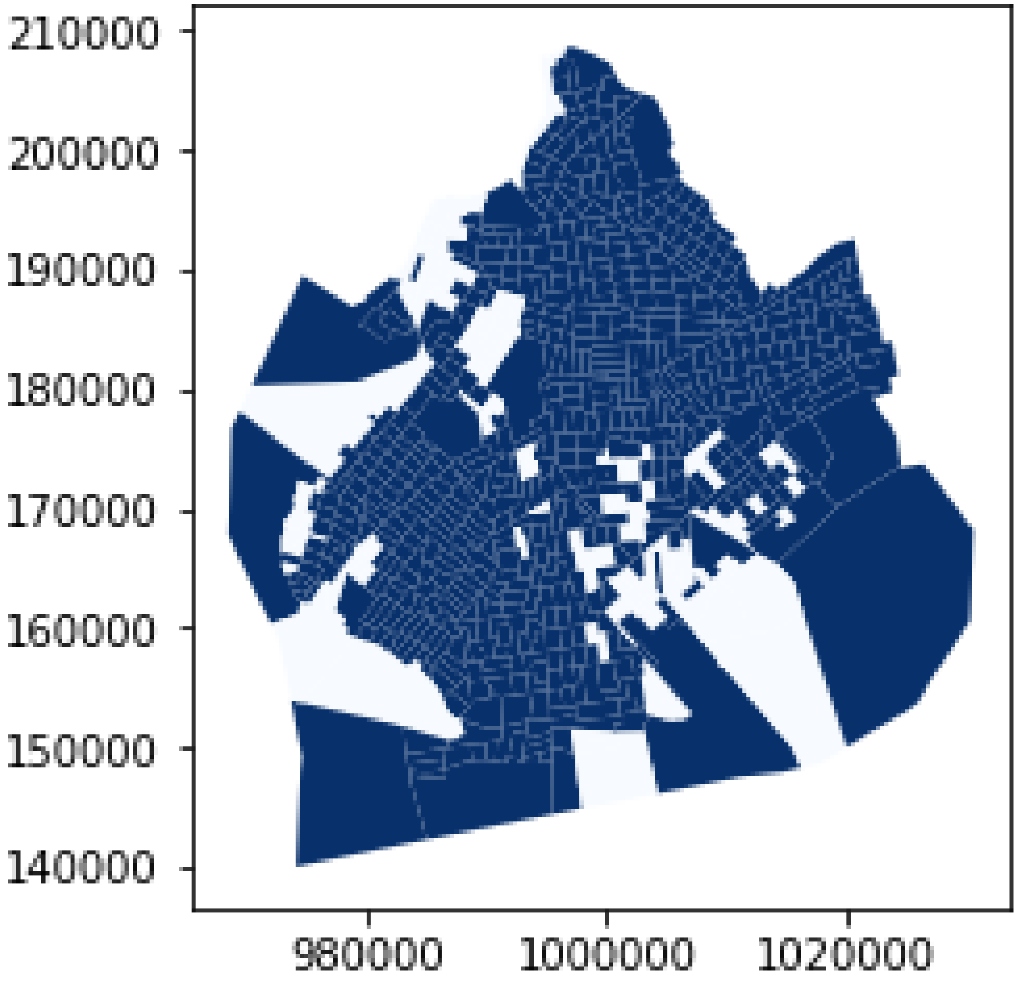
```
bk_2000[["tract", "mhi", "mhi_msa"]].head()
```

```
    tract    mhi  mhi_msa
0  051200  31393    50795
1  051300  30000    50795
2  051400  32103    50795
3  051500  36107    50795
4  051600  25148    50795
```

```
bk_2000["low_mhi"] = bk_2000["mhi"] < bk_2000["mhi_msa"]
```

Mapping Low Income Tracts

```
bk_2000.plot(column = "low_mhi", cmap = "Blues")
```



Let's practice!

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