Measuring Segregation: The Index of Dissimilarity

ANALYZING US CENSUS DATA IN PYTHON

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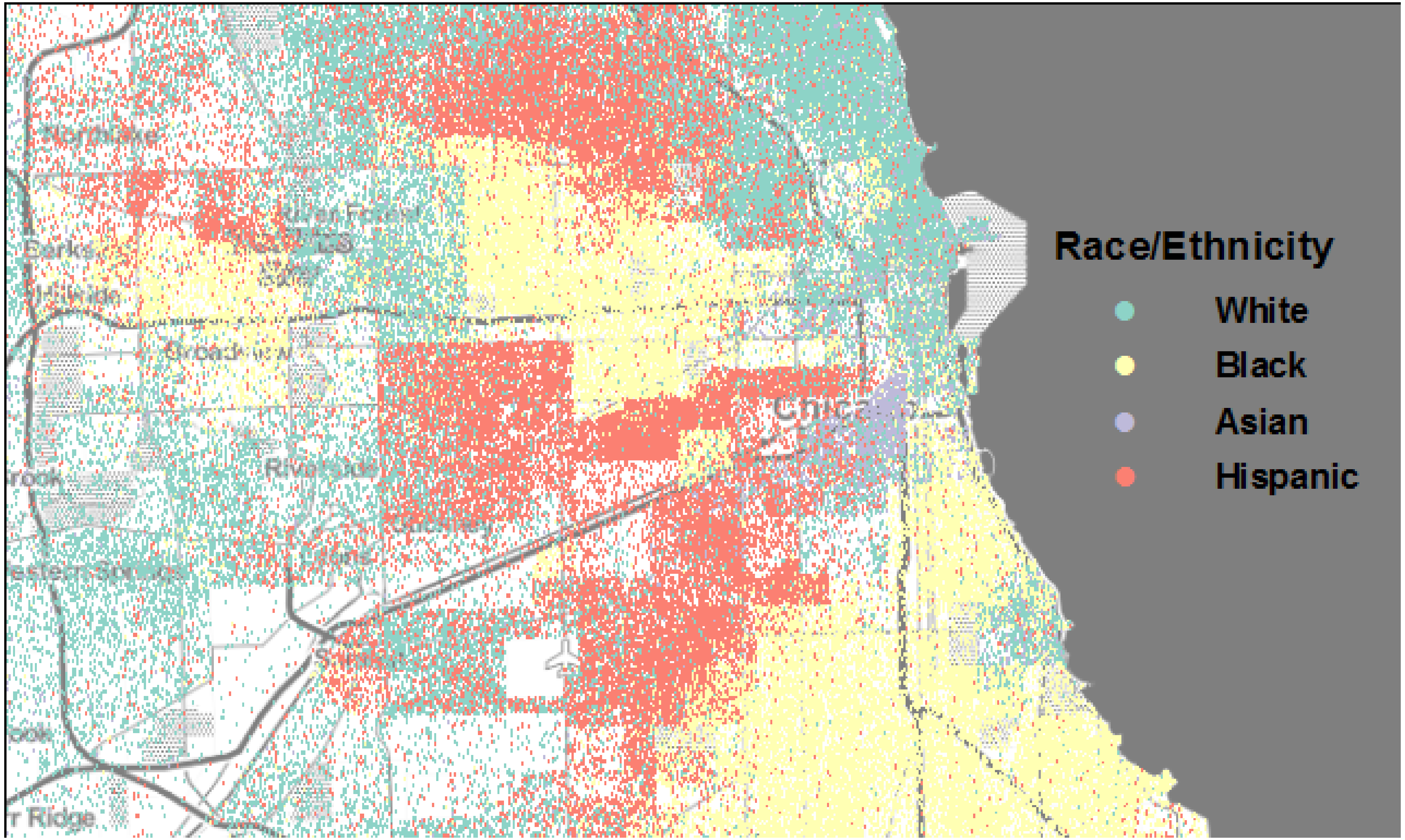
What is Segregation?



Index of Dissimilarity Formula

Given two groups A and B:

$a_1 = 10$ $b_1 = 200$	$a_2 = 20$ $b_2 = 100$
$a_3 = 30$ $b_3 = 50$	$a_4 = 40$ $b_4 = 50$

$$A = 100$$
$$B = 400$$

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- a_i = Small area Group A count
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Index of Dissimilarity Formula

Given two groups A and B:

$$D = \frac{1}{2} \sum_i \left| \frac{a_i}{A} - \frac{b_i}{B} \right|$$

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Suitable Data

```
tracts.head()
```

```
  state county   tract  white  black
0    01    001  020100   1601    217
1    01    001  020200    844   1214
2    01    001  020300   2538    647
3    01    001  020400   4030    191
4    01    001  020500   8438   1418
```

Source: Table P5 - 2010 Decennial Census

- `white` = Nonhispanic White population
- `black` = Nonhispanic Black population

Calculating the Index of Dissimilarity (D)

```
# Extract California tracts using state FIPS "06"
ca_tracts = tracts[tracts["state"] == "06"]

# Define convenience variables to hold column names
w = "white"
b = "black"
```

Calculating the Index of Dissimilarity (D)

```
# Print the sum of Black population for all tracts in California
print(ca_tracts[b].sum())
```

```
2163804
```

```
# Print the sum of White population for all tracts in California
print(ca_tracts[w].sum())
```

```
14956253
```

Calculating the Index of Dissimilarity (D)

$$D = \frac{1}{2} \sum_i \left| \frac{a_i}{A} - \frac{b_i}{B} \right|$$

```
# Calculate Index of Dissimilarity
print(0.5 * sum(abs(
  ca_tracts[w] / ca_tracts[w].sum() - ca_tracts[b] / ca_tracts[b].sum()
  )))
```

```
0.6033425039167011
```

Let's Practice!

ANALYZING US CENSUS DATA IN PYTHON

Metropolitan Segregation

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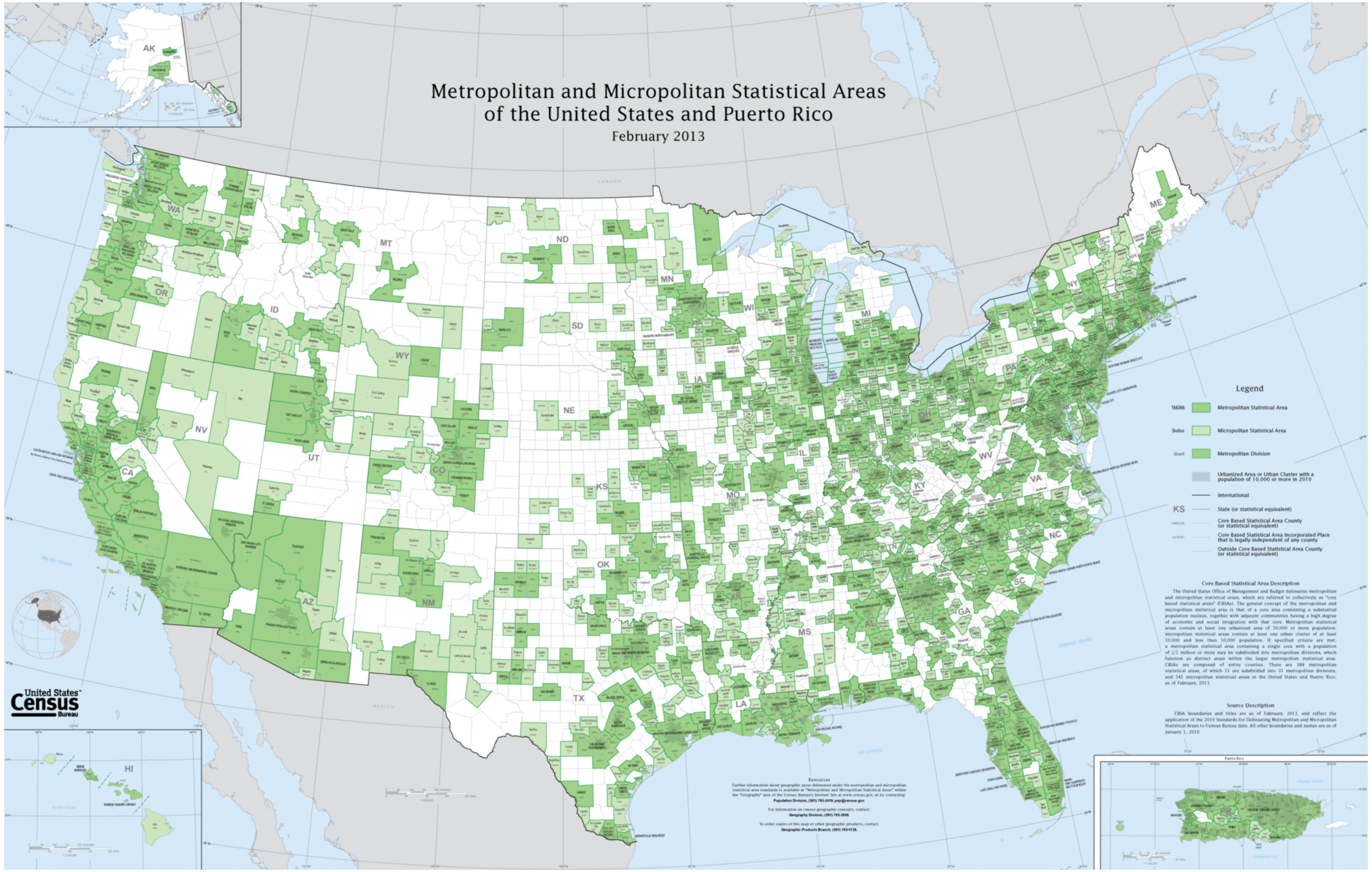

Source: United States Census Bureau

Census API Request: Metro/Micropolitan Data

```python
import requests

# Build base URL
HOST = "https://api.census.gov/data"
year = "2012"
dataset = "acs/acs5"
base_url = "/".join([HOST, year, dataset])

# Specify requested variables
# B01001_001E = Total population (estimate)
# B03002_003E = Nonhispanic White population (estimate)
# B03002_004E = Nonhispanic Black population (estimate)
get_vars = ["NAME", "B01001_001E", "B03002_003E", "B03002_004E"]
```

Census API Request: Metro/Micropolitan Data

```
# Specify requested variables
get_vars = ["NAME", "B01001_001E", "B03002_003E", "B03002_004E"]

# Create dictionary of predicates
predicates = {}
predicates["get"] = ",".join(get_vars)

# Requested geography
predicates["for"] = \
    "metropolitan statistical area/micropolitan statistical area:*"
```

Census API Request: Metro/Micropolitan Data

```
r = requests.get(base_url, params=predicates)

print(r.json()[:5])
```

```
[['NAME', 'B01001_001E', 'B03002_003E', 'B03002_004E', 'metropolitan statistical area/mi
 ['Adjuntas, PR Micro Area', '19458', '140', '0', '10260'],
 ['Aguadilla-Isabela-San Sebastián, PR Metro Area', '305538', '5602', '231', '10380'],
 ['Coamo, PR Micro Area', '71596', '228', '53', '17620'],
 ['Fajardo, PR Metro Area', '70633', '543', '195', '21940']]
```

Census API Request: Metro/Micropolitan Data

```
# Create user-friendly column names
col_names = ["name", "pop", "white", "black", "msa"]

# Load JSON response into data frame
msa = pd.DataFrame(columns=col_names, data=r.json()[1:])

# Cast count columns to int data type
msa[["pop", "white", "black"]] = msa["pop", "white", "black"]].astype(int)
```

Metropolitan Area Definition

```
  state county   tract  white  black
0    01    001  020100   1601    217
1    01    001  020200    844   1214
2    01    001  020300   2538    647
3    01    001  020400   4030    191
4    01    001  020500   8438   1418
```

```
     msa       msa_name           county_name    state_name state county
0  10100  Aberdeen, SD         Brown County  South Dakota    46    013
1  10100  Aberdeen, SD       Edmunds County  South Dakota    46    045
2  10140  Aberdeen, WA  Grays Harbor County    Washington    53    027
3  10180   Abilene, TX      Callahan County         Texas    48    059
4  10180   Abilene, TX         Jones County         Texas    48    253
```

Pandas Merge Method

```
import pandas as pd
```

```
# Join data frames on matching columns
tracts_with_msa_id = pd.merge(...)
```

Pandas Merge Method

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import pandas as pd
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# Join data frames on matching columns
tracts_with_msa_id = pd.merge(tracts, msa_def, ...)
```

Pandas Merge Method

```
import pandas as pd
```

```
# Join data frames on matching columns
tracts_with_msa_id = pd.merge(tracts, msa_def,
    left_on = ["state", "county"], right_on = ["state", "county"])
```

```
# Alternative when column names are the same
tracts_with_msa_id = pd.merge(tracts, msa_def, on = ["state", "county"])
```

Pandas Merge Method

```
# Data frame with state names
st.head()
```

```
      state_name
state
01       Alabama
02        Alaska
04       Arizona
05      Arkansas
06    California
```

Pandas Merge Method

```
# Join tracts and st data frames
tracts_st = pd.merge(tracts, st, left_on = "state", right_index = True)

tracts_st.head()
```

```
  state county  tract  white  black state_name
0    01    001  020100   1601    217    Alabama
1    01    001  020200    844   1214    Alabama
2    01    001  020300   2538    647    Alabama
3    01    001  020400   4030    191    Alabama
```

Let's Practice

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Segregation Impacts: Unemployment

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Deciphering ACS Subject Table IDs

[B|C]ssnnn[A-I]

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`B` or `C` = "Base Table" or "Collapsed Table"

B15002	**C15002[A-I]**
No schooling	Less than high school diploma
Nursery to 4th grade	High school grad, GED, or alt.
5th and 6th grade	Some college or associate's
7th and 8th grade	Bachelor's degree or higher
9th grade	
etc...	

[B|C]ssnnn[A-I]

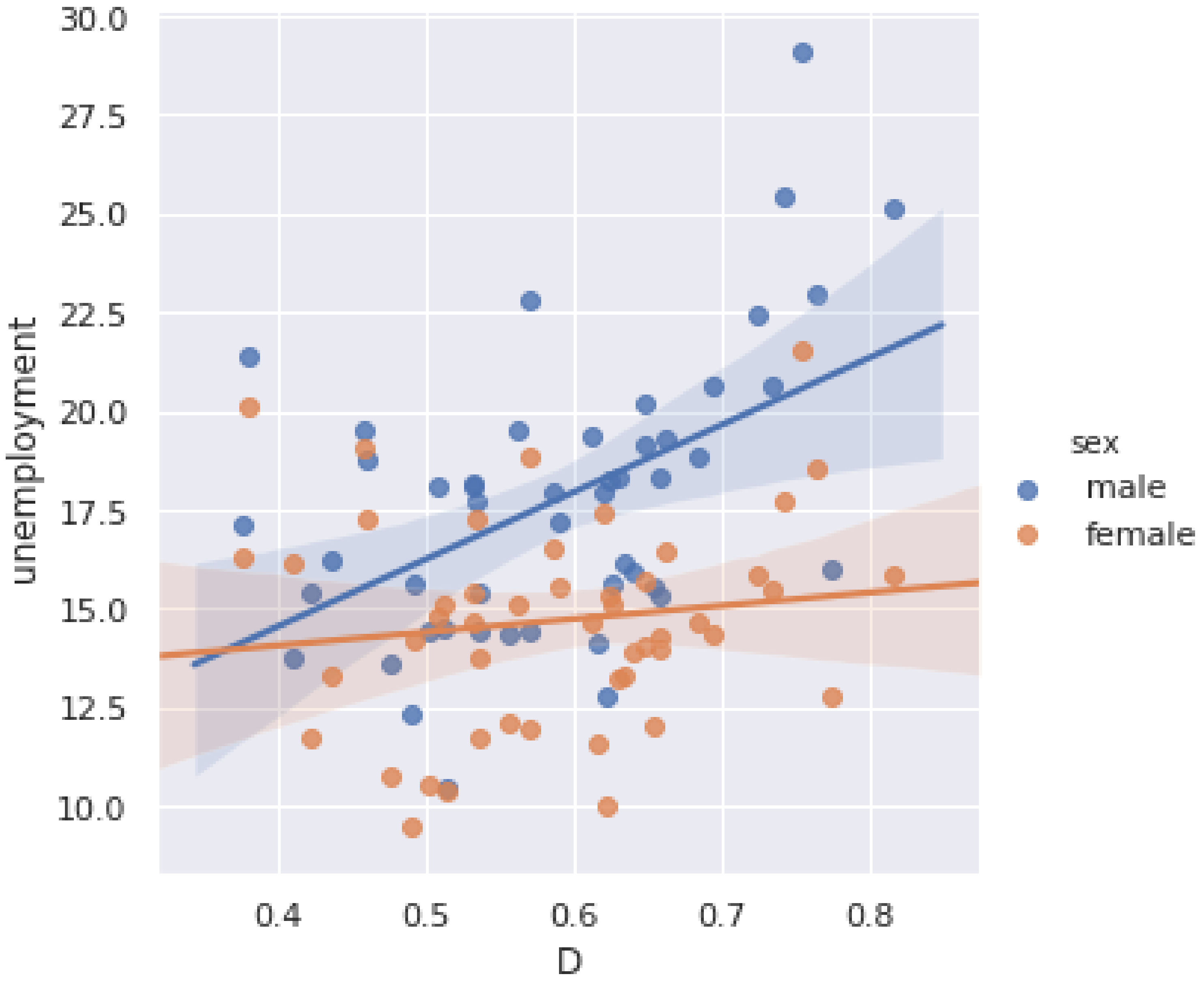
- `A` = White alone
- `B` = Black or African American Alone
- `C` = American Indian and Alaska Native Alone
- `D` = Asian Alone
- `E` = Native Hawaiian and Other Pacific Islander Alone
- `F` = Some Other Race Alone
- `G` = Two or More Races
- `H` = White Alone, Not Hispanic or Latino
- `I` = Hispanic or Latino

[B|C]ssnnn[A-I]

- 01 = Age and Sex
- 02 = Race
- 03 = Hispanic or Latino Origin
- 05 = Foreign Born; Citizenship; Year of Entry; Nativity
- 15 = Educational Attainment
- 19 = Income (Households and Families)
- 23 = Employment Status; Work Experience; Labor Force

Source: **https://www.census.gov/programs-surveys/acs/guidance/which-data-tool/table-ids-explained.html**

Comparing Segregation Impacts



Tidy Data

Wide data frame: `msa_labor_force`

```
     msa   male_lf   female_lf
0  12060    400843      481425
1  25540     30656       35046
2  26420    231346      268923
3  26900     55943       71036
...
```

```
msa_labor_force.columns =
    ["msa", "male", "female"]
```

Tidy data frame: `tidy_msa_labor_force`

```
       msa     sex   labor_force
0    12060    male        400843
1    25540    male         30656
2    26420    male        231346
3    26900    male         55943
...
49   12060  female        481425
50   25540  female         35046
51   26420  female        268923
52   26900  female         71036
...
```

pandas.melt

```
tidy_msa_labor_force = msa_labor_force.melt(
    id_vars = ["msa"],
    value_vars = ["male", "female"],
    var_name = "sex",
    value_name = "labor_force"
    )
```

pandas.melt

```
tidy_msa_labor_force
```

```
      msa     sex  labor_force
0   12060    male       400843
1   25540    male        30656
2   26420    male       231346
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...
```

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Neighborhood Segregation Over Time

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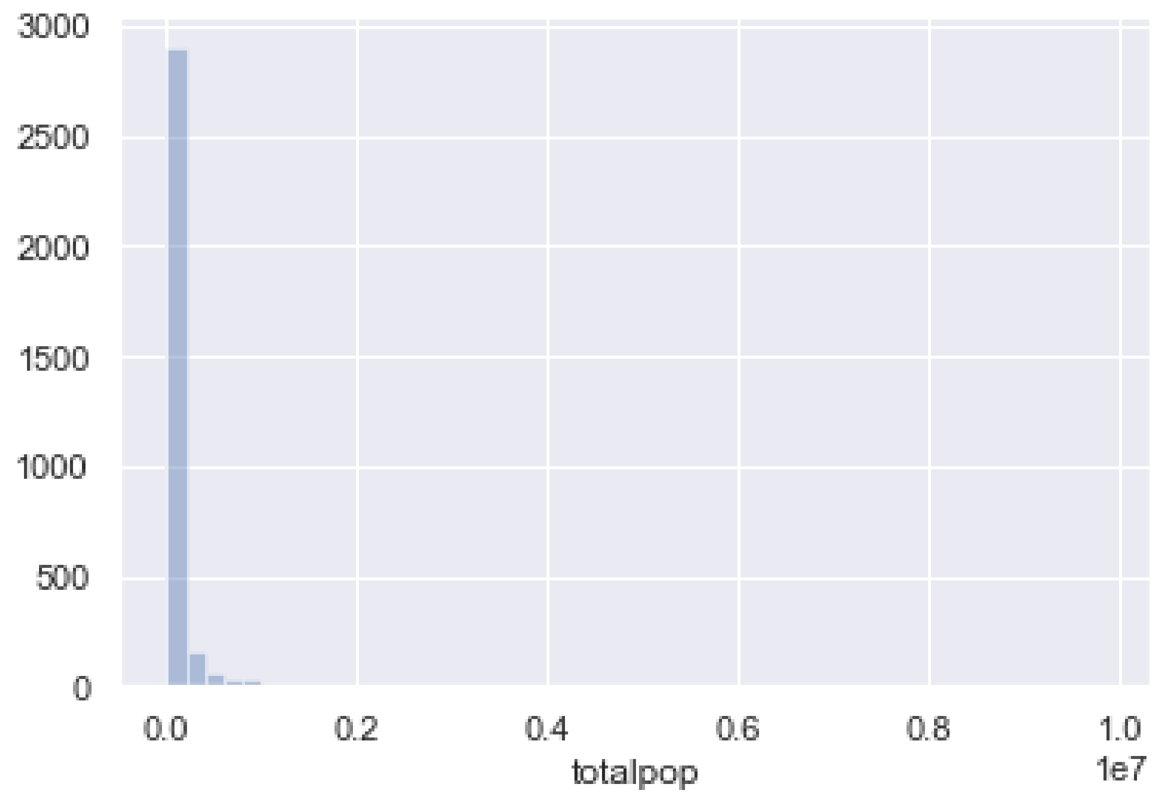
Histograms

```
counties.head()
```

```
   totalpop state county
0     54571    01    001
1     22915    01    007
2     34215    01    017
3     25989    01    019
4     25833    01    025
```

```
sns.distplot(counties["totalpop"],
             kde = False)
```

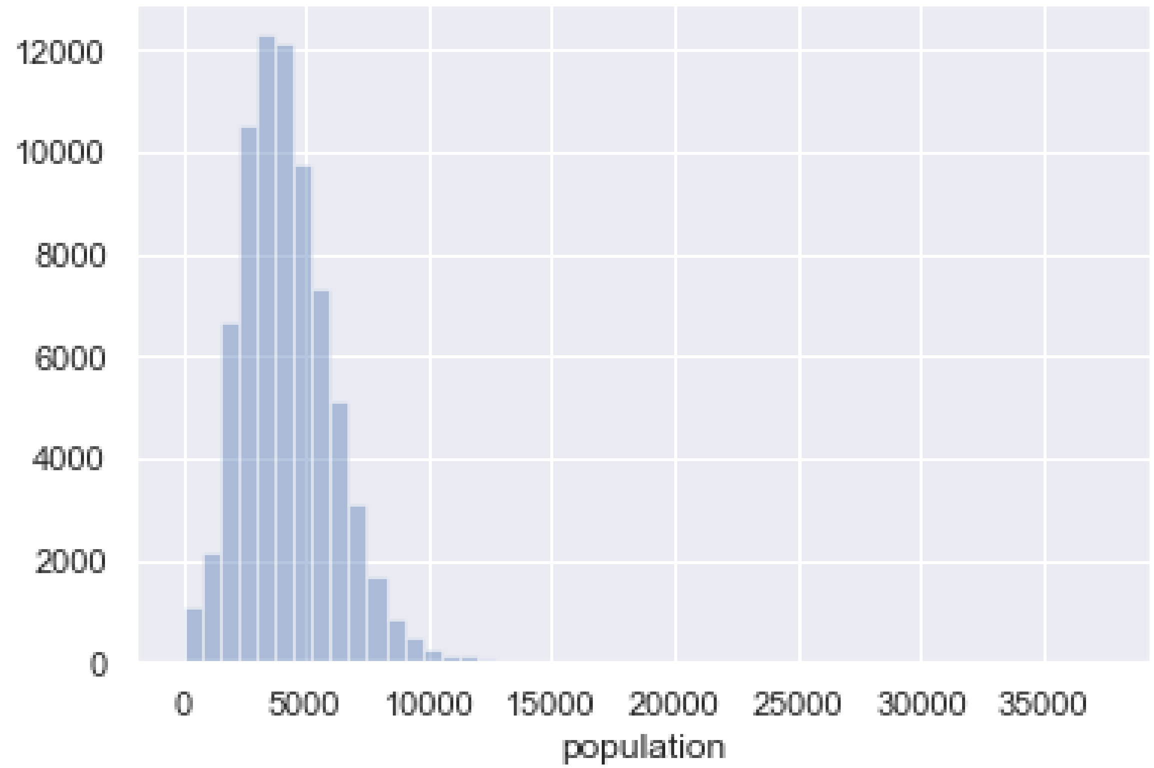


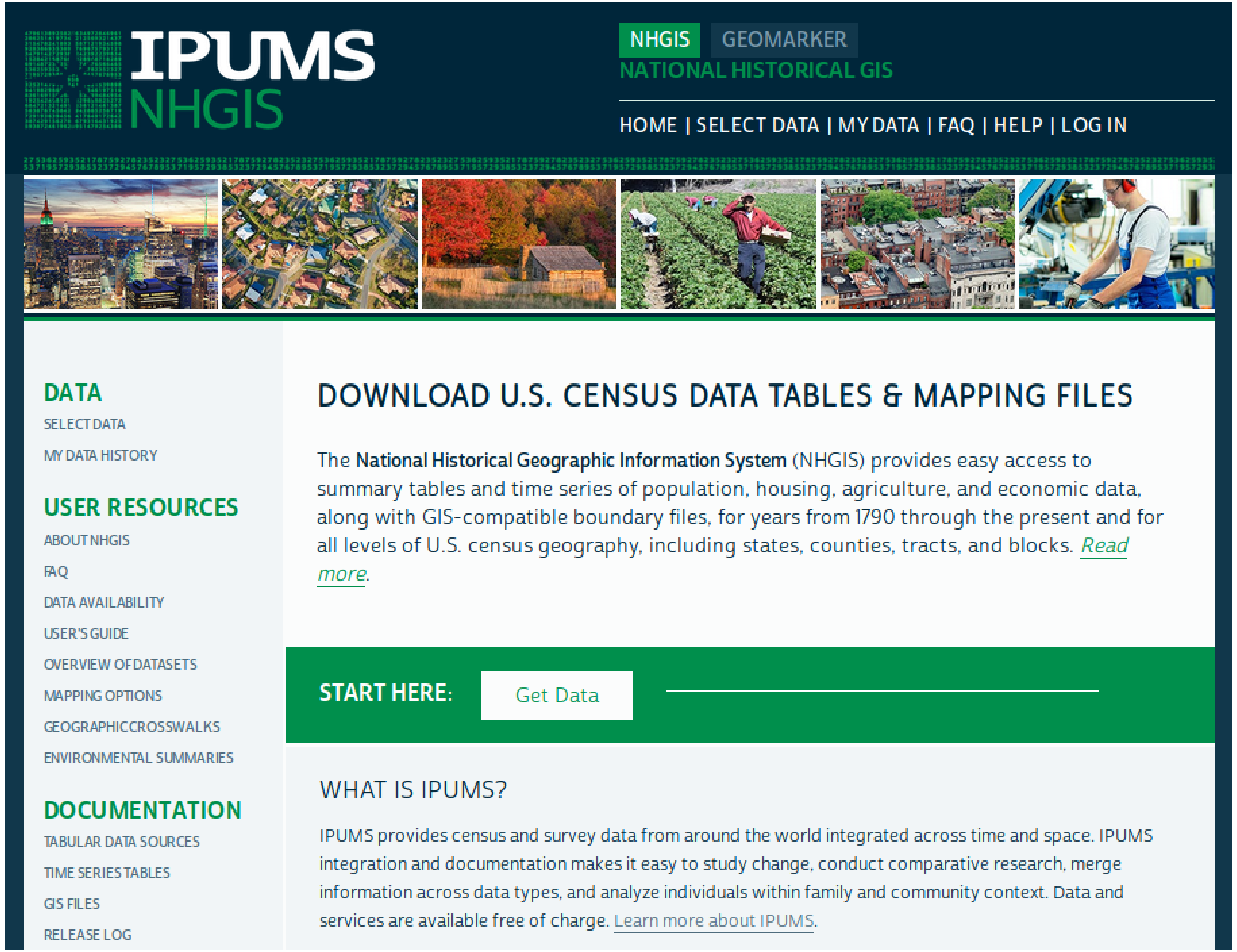
Histograms

```
tracts.head()
```

	totalpop	state	county	tract
0	1912	01	001	020100
1	2170	01	001	020200
2	3373	01	001	020300
3	4386	01	001	020400
4	10766	01	001	020500

```
sns.distplot(tracts["totalpop"],
             kde = False)
```





IPUMS NHGIS, University of Minnesota, www.nhgis.org

NHGIS vs. Census Bureau FTP

1. Historical data going back to 1790 (first United States Census)
2. GIS files for mapping Census data
3. Time series data for consistent geographic areas

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