# Capstone Project 1: Super Zips Milestone Report

## Problem Statement

This project intends to model which areas of the U.S. have improving (or worsening) overall standards of living over time.

My intended client would be government policymakers at all three levels (local, state, and federal) that would use my analysis and results in developing public policy. My project would serve as a reference and basis for implementing income/tax credits, subsidies, financial aid, public education programs, and other incentives supporting increases in education levels and eliminating poverty.

The source data I plan to clean and analyze are income statistics publicly provided by the Internal Revenue Service and educational attainment data publicly provided by the U.S. Census Bureau. Calculating these two together as a ratio would measure the overall standard of living.

Then, I would predict areas of growing/contracting economic inequality by plotting the education and income based descriptive statistics over time for each zip code. Additionally, using regression would predict how these statistics may change for a given number of years into the future. To visualize this, I plan to use Python to plot a map of all the US zip codes with color gradients respective to education and income statistics. A slider bar or animation would be integrated into the visualization to show color changes/trends over time.

## Data Wrangling

The following steps were taken to obtain, wrangle, then clean data into a form that is suited for analysis.

1) Obtain main source data files needed from irs.gov and data.census.gov
2) Select relevant columns using documentation files provided with main source data files
3) Create subset data files from main source date files due to big source file sizes
4) Determine how to address missing data:
    a) For the IRS AGI (Adjusted Gross Income) data, the missing data was filled in thanks to cross-referencing smaller data subset files divided from the main aggregate source file and grouped by state.
    b) For the Census data, all rows containing missing data were removed from the dataset since certain estimates could not be calculated due to either no or too few observations as explained in the Symbols Dictionary
5) Re-define appropriate data types for all columns in data
6) Regroup/Tidy Data into a format appropriate for analysis using the .melt() and .pivot() dataframe methods

7) Calculate scores from raw data as described below. **EDA was not performed on the raw data due to file size and computational cost**
8) Perform EDA by the following steps and repeat for every year of data obtained (i.e. 2011-2018 for Census data and 2006-2017 for IRS AGI data)
    a) Using .info() dataframe method to confirm numeric data uniformity and no missing data as well as data types
    b) Use .describe() dataframe method to generate descriptive statistics and confirm data integrity
    c) Plot a histogram to visualize distribution of all zip code scores from all 51 states
    d) Use FacetGrid function from Seaborn to plot multiple swarmplots visualizing the score distributions by state
9) Create data analysis files suited for visualizations

***<u>Calculating Education and Income Scores per Zip Code:</u>***

This score is calculated using the weighted average formula below

$$Score = \sum_{n=1}^{i} x_n \frac{y_n}{p}$$

Where

- $x_n$ = Education Attainment or IRS AGI score using the scale below (unitless)
- $y_n$ = population satisfying the nth category (# of people)
- $i$ = last category in either scale (i.e. 6 or 7)
- $p$ = population for the zip code specified (# of people)

| **<u>Education Scoring Scale</u>** | **<u>IRS AGI Scoring Scale</u>** |
|---|---|
| Categories obtained from column names in source data.<br>• 1 = Less than 9th grade<br>• 2 = 9th to 12th grade, no diploma<br>• 3 = High school graduate (includes equivalency)<br>• 4 = Some college, no degree<br>• 5 = Associate's degree<br>• 6 = Bachelor's degree<br>• 7 = Graduate or professional degree | Determined by Adjusted Gross Income submitted by IRS Forms 1040, 1040A, 1040EZ (column named as “AGI_STUB” or “AGI_CLASS” depending on which annual dataset)<br>• 1 = $1 under $25,000<br>• 2 = $25,000 under $50,000<br>• 3 = $50,000 under $75,000<br>• 4 = $75,000 under $100,000<br>• 5 = $100,000 under $200,000<br>• 6 = $200,000 or more |

## Data Storytelling

For this section, IRS AGI and Census Educational Attainment data are analyzed to answer the following questions below. Numerous plots were generated and can be viewed in this GitHub repo link to the Jupyter Notebook containing the analysis.

1) How are states and zip codes performing over time in terms of Educational Attainment and Income?

Analysis and Outcome: After calculating the Education and Income scores for each zip code (column name is "ZipScore" in both IRS AGI and Census datasets), the scores were aggregated by arithmetic averaging on each State. Examining high-level trends of 51 states is much easier than examining thousands of zip codes at once. If upon visual inspection, I examine a state trending a certain way, I can then narrow in and look at the zip code trends within that state. As a result, this is done to answer the next question.

2) Which states and zip codes perform the best/worst over time in terms of Educational Attainment and Income?

Analysis and Outcome: Upon visual inspection, I noticed the following:

- Education:
    - District of Columbia (DC) has the highest Education scores and the steepest positive trend, thus performing the best. Narrowing in, we see that most zip codes are generally trending above a Education Score of 5 which is outside the range of the states (around 4-5).
    - Louisiana (LA) has the lowest Education scores and a gradual positive trend, but overall perform the worst. Narrowing in, we see that most zip codes are generally trending below a Education Score of 4 which is outside the range of the states (around 4-5).
- Income:
    - District of Columbia (DC) has the highest Income scores and the steepest positive trend, thus performing the best. Narrowing in, we see that most zip codes are generally trending above a Income Score of 3 which is outside the range of the states (around 2-3).
    - Mississippi (MS) has the lowest Education scores and a gradual positive trend, but overall performs the worst. Narrowing in, we see that most zip codes are generally trending a little over a Income Score of 2 which is in the lower half of the range of the states (around 2-3).

3) Is there a relationship/correlation between Educational Attainment and Income?

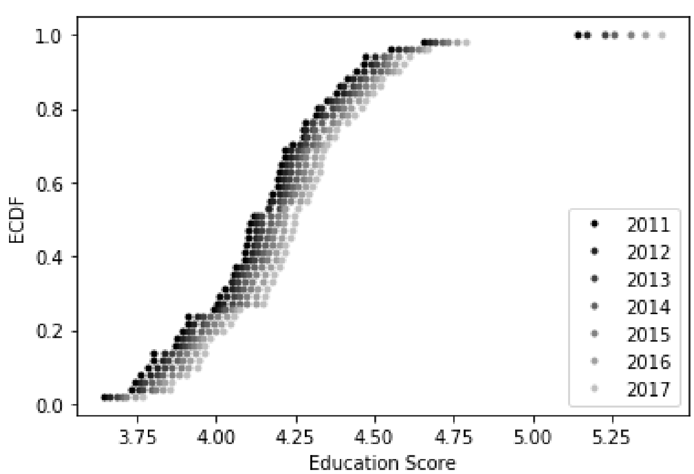
Analysis and Outcome: For this case, again, data was aggregated by State and not by Zip Code due to too many Zip Code data points resulting in a "blobplot" and not a scatter plot. By combining the Census and IRS AGI data frames then using a scatter plot for the Education and Income Scores by State, we can see that there is certainly a positive relationship between the two. In other words, the higher your education, the higher your income.

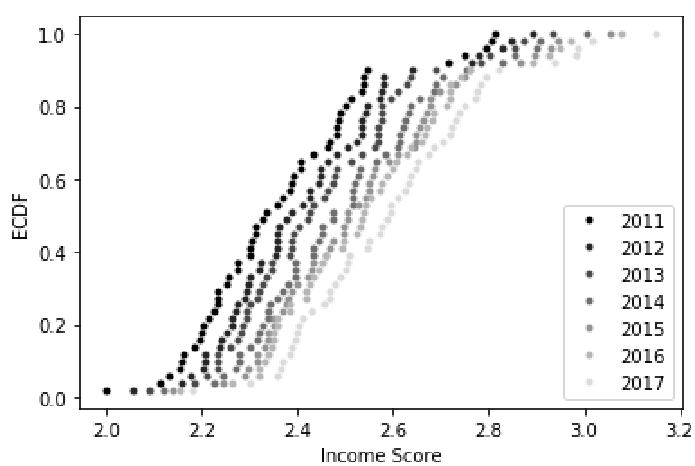
## Statistical Data Analysis

This section summarizes the steps and corresponding results of performing Statistical Data Analysis on Education (obtained from the US Census) and Income (obtained from the IRS) data. For this analysis, these two variables are defined to be the primary factors of an area's overall standard of living. Also, they're shown to be linearly related and vary together. **Only 2011 and 2017 data are used due to intersection of annual releases of datasets**

***Steps and Findings***

1. Conduct EDA: Plot ECDFs for all years available for Education and Income Scores with color variation to show change over time.
   **Results and Findings:** The ECDF plots for Education and Income Scores show gradual shifts to the right over time as indicated by the color variation from black to light gray. This is a good sign that overall people are gradually becoming more educated and earning more money to live better.



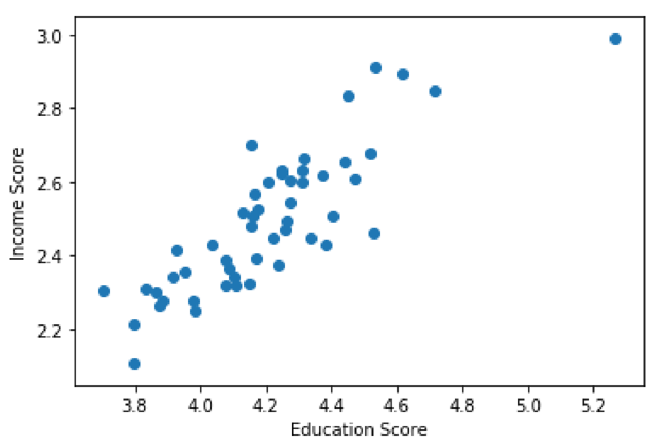

2. Parameter Estimation: Estimate the *difference* of the mean Education and Income Scores of all zip codes from 2011-2017.
   **Results and Findings:** Difference of Education Score means = 0.126 and Difference of Income Score means = 0.231, which shows, on average, how much the Education and Income scores have changed in 7 years (including the year of 2017).

3. Confidence Interval Calculation: Use Bootstrap replicates method for 2011 and 2017 datasets only for both Education and Income scores to report a 95% bootstrap confidence interval.
   **Results and Findings:**
   - 95% bootstrap Conf. Int. bounds of Education Scores = [0.112  0.140]
   - 95% bootstrap Conf. Int. bounds of Income Scores = [0.221   0.241]

   These bounds show the Confidence Interval containing the differences of means of Education and Income estimated in Step 2.

4. Hypothesis Testing: Answer the question, "Have Education and Income Scores improved?" (i.e. Null Hypothesis: $\mu_{2017} - \mu_{2011} = 0$, Alternate Hypothesis: $\mu_{2017} - \mu_{2011} > 0$) by performing a bootstrap permutation test by shifting the two data sets so that they have the same mean and then use bootstrap sampling to compute the difference of means.
   **Results and Findings:** The p-values for both bootstrap hypothesis tests are so small that Python essentially returns zero resulting in statistical signifying that the null hypotheses for both Education and Income can be rejected. Thus, the two means are different which indicate change between 2011 and 2017.

5. Correlation and Covariance Analysis: Calculate Pearson correlation coefficient and covariance between Education Scores and Income Scores from 2011-2017 (confirm relationship between Education and Income).
   **Results and Findings:** The scatterplot suggests, at first glance, that there is a positive relationship between Education and Income plus the two variables vary together. This is confirmed by calculating the Pearson Correlation Coefficient (r = 0.845, confirm the strong relationship) and Covariance (cov = 0.044) between the two sets of scores.



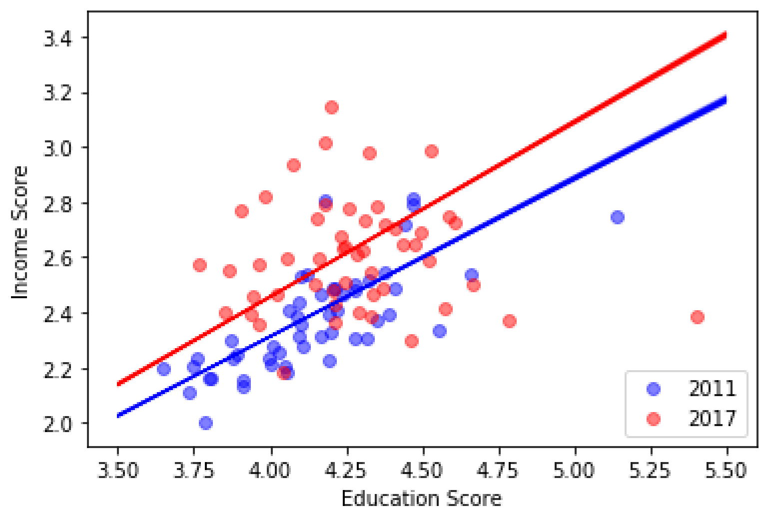

6. Linear Regression: Perform a linear regression for both the 2011 and 2017 data. Then, perform pairs bootstrap estimates for the regression parameters. Report 95% confidence

intervals on the slope and intercept of the regression line (show how Education and Income change together over time).

**Results and Findings:**

- 2011: slope = 0.573, conf int = [0.565  0.580]
- 2011: intercept = 0.020,  conf int = [-0.007  0.052]
- 2017: slope = 0.634, conf int = [0.626  0.642]
- 2017: intercept = -0.079,  conf int = [-0.112  -0.047]

Calculating these bootstrap results quantify how Education and Income change together over time. These are shown visually from the combined line and scatter plot below as the regressing line changes from 2011 to 2017.




7. Calculate 95% bootstrap confidence interval for overall standard of living: Compare the *mean ratio* of Education Scores to Income Scores.

   **Results and Findings:**

   - 2011: mean ratio = 1.750, conf int = [1.747 1.753]
   - 2017: mean ratio = 1.644, conf int = [1.641 1.647]

   These results suggest changes in overall standard of living over 7 years (including the year of 2017) and even the confidence intervals overlap. To confirm, bootstrap hypothesis testing is done in the next and final step.

8. Bootstrap hypothesis testing on ratios: Perform a bootstrap permutation test (like in Step 4) by shifting the two data sets so that they have the same mean. Then use bootstrap sampling to compute the difference of means.

   **Results and Findings:** The p-value for the bootstrap hypothesis tests are so small that Python essentially returns zero resulting in statistical signifying that the two means are different. This indicates a change in overall standard of living between 2011 and 2017.