Data Analytics Lab: Assignment-1
A Mathematical Essay on Linear Regression

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***Abstract*—In this study, we examine the effect of low income on cancer diagnosis and treatment among populations in the United States. We demonstrate the correlation between cancer incidence, mortality, and socioeconomic status and provide quantitative and visual evidence.**

***Index Terms*—Introduction, Linear Regression, Problem, Conclusion**

I. Introduction

Cancer survival disparities linked to socioeconomic groups are well-established. A 1997 report from the International Agency for Research on Cancer (IARC) highlighted that lower socioeconomic status (SES) is associated with higher cancer incidence and worse survival rates in developed and less-developed countries. Our study employs data from the CDC's National Program of Cancer Registries Cancer Surveillance System (NPCR-CSS) and SEER Program's Incidence data to investigate these relationships using linear regression models.

Linear regression, a technique to model the relationship between variables, fits a linear equation to observed data. It designates certain variables as explanatory and one as the dependent variable. The prevalent least-squares method computes the best-fitting line by minimizing the sum of squared deviations between data points and the line.

Here, we utilize linear regression to investigate links between cancer incidence, mortality rates, socioeconomic factors, and race. We initially gather, refine, and prepare data, followed by exploratory analysis. Subsequently, we construct statistical models and visualizations to offer quantitative and visual confirmation of our findings. The subsequent section outlines fundamental Linear Regression principles, while section 3 presents insights from data and models. Finally, section 4 summarizes the study's key aspects and suggests potential future research directions.

II. Linear Regression

Linear regression is a statistical method of estimating the relationship between a scalar response and independent and dependent variables (also called dependent variables and independent variables). The case of one explanatory variable is called *simple linear regression*; for more than one, the process is called *multiple linear regression*.

This form of analysis estimates the coefficients of the linear equation involving one or more independent variables that best predict the value of the dependent variable. Linear Regression fits a straight line or surface that minimizes the discrepancies between predicted and actual output values.

Linear Regression models are relatively simple and provide an easy-to-interpret mathematical formula that can generate predictions. Because linear regression is a long-established statistical procedure, the properties of linear regression models are well understood and can be trained very quickly.

Linear regression has many practical uses. Most applications fall into one of the following two broad categories:

- Linear regression is used for prediction by fitting a model to observed data, enabling future response predictions even when explanatory variables change.
- Linear regression explains how the response variable's variation relates to explanatory variables, identifying strengths and redundancies in their relationships.

A. Formulation

Given a dataset $\{y_i, x_{i1}, \ldots, x_{ip}\}_{i=1}^{n}$ of n **x** p size, a linear regression model assumes a linear relationship between the dependent variable y and the vector of regressors $\mathbf{x}$. This relationship is modeled through a disturbance term or error variable ε — an unobserved random variable that adds "noise" to the dependent and regressors' linear relationship. Thus, the model takes the form:

$$y_i = \theta_0 + \theta_1 x_{i1} + \cdots + \theta_p x_{ip} + \varepsilon_i = \mathbf{x}_i^{\mathsf{T}}\boldsymbol{\theta} + \varepsilon_i, \quad i = 1, \ldots, n,$$

where T denotes the transpose so that $\mathbf{x}_i^{\mathsf{T}}\boldsymbol{\theta}$ is the inner product between vectors $\mathbf{x}_i$ and $\boldsymbol{\theta}$. Often, these n equations are stacked together and written in matrix notation as:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\theta} + \boldsymbol{\varepsilon},$$

where $\mathbf{y}$ is a column vector, $\mathbf{X}$ is a matrix, $\boldsymbol{\theta}$ is a column vector of coefficients, and $\boldsymbol{\varepsilon}$ is a column vector of errors.

The following are the major assumptions made by standard linear regression models with standard estimation techniques:

- **Weak exogeneity**. This basically means that predictor variables $\mathbf{X}$ can be treated as fixed values rather than random variables.
- **Linearity**. This means that the mean of the response variable is a linear combination of the parameters (regression coefficients) and the predictor variables.

- **Constant variance/homoscedasticity**. This implies that the variability or variance of the errors is independent of predictor variable values. Consequently, the response variability remains consistent across differing response magnitudes for fixed predictor values.
- **Independence of errors**. This assumes that the errors of the response variables are uncorrelated with each other.

B. Cost Function

A cost function measures how wrong the model is in terms of its ability to estimate the relation between inputs and outputs. Different types of cost functions exist, and the most popular among them is the Squared Error between the predicted and observed outputs. The formula for the mean squared error for a dataset with N samples is given by:

$$J(\theta) = \sum_{i=1}^{N} (\hat{y}_i - y_i)^2$$

where $\hat{y}_i$ is the predicted output, and y_i is the observed or given output. The objective is to find θ that minimizes the cost function J.

C. Parameter estimation using Least Square

Many procedures have been developed for parameter estimation and inference in linear regression. These methods differ in computational simplicity of algorithms, presence of a closed-form solution, etc. One of the most common methods is the Least Square Estimation.

Assuming that the independent variable is $\vec{\mathbf{x}}_i = [x_{i1}, x_{i2}, \ldots, x_{im}]$, and the model's parameters are $\boldsymbol{\theta} = [\theta_0, \theta_1, \ldots, \theta_m]$, then the model's prediction would be:

$$y_i \approx \theta_0 + \sum_{j=1}^{m} \theta_j \times x_{ij}$$

If $\mathbf{x}_i$ is extended to $\vec{\mathbf{x}}_i = [1, x_{i1}, x_{i2}, \ldots, x_{im}]$, then y_i would become a dot product of the parameter and the independent variable, i.e.

$$y_i \approx \sum_{j=1}^{m} \theta_j \times x_{ij} \approx \boldsymbol{\theta} \cdot \vec{\mathbf{x}}_i$$

In the least-squares setting, the optimum parameter is defined as the one that minimizes the sum of mean squared loss:

$$\boldsymbol{\theta} = \arg\min_{\boldsymbol{\theta}} L(D, \boldsymbol{\theta}) = \arg\min_{\boldsymbol{\theta}} \sum_{i=1}^{n} (\boldsymbol{\theta} \cdot \vec{\mathbf{x}}_i - y_i)^2$$

Now putting the independent and dependent variables in matrices $\mathbf{X}$ and $\mathbf{Y}$, respectively, the loss function can be rewritten as:

$$L(D, \boldsymbol{\theta}) = \|\mathbf{X}\boldsymbol{\theta} - \mathbf{Y}\|^2$$

$$= (\mathbf{X}\boldsymbol{\theta} - \mathbf{Y})^T (\mathbf{X}\boldsymbol{\theta} - \mathbf{Y})$$

$$= \mathbf{Y}^T\mathbf{Y} - \mathbf{Y}^T\mathbf{X}\boldsymbol{\theta} - \boldsymbol{\theta}^T\mathbf{X}^T\mathbf{Y} + \boldsymbol{\theta}^T\mathbf{X}^T\mathbf{X}\boldsymbol{\theta}$$

As the loss is convex, the optimum solution lies at gradient zero. The gradient of the loss function is (using the denominator layout convention):

$$\frac{\partial L(D, \boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = -2\mathbf{X}^T\mathbf{Y} + 2\mathbf{X}^T\mathbf{X}\boldsymbol{\theta}$$

Setting the gradient to zero produces the optimum parameter:

$$-2\mathbf{X}^T\mathbf{Y} + 2\mathbf{X}^T\mathbf{X}\boldsymbol{\theta} = 0$$

$$\mathbf{X}^T\mathbf{Y} = \mathbf{X}^T\mathbf{X}\boldsymbol{\theta}$$

$$\boldsymbol{\theta} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}$$

D. Metrics for model evaluation

1) **R-squared value**: This value ranges from 0 to 1. Value '1' indicates that the predictor perfectly accounts for all the variation in Y. Value '0' indicates that predictor 'x' accounts for no variation in 'y'.
   - **Regression sum of squares (SSR)**. This gives information about how far the estimated regression line is from the average of the actual output.
   $$Error = \sum_{i=1}^{n} (\hat{y} - \bar{y})^2$$
   - **Sum of Squared error (SSE)**. How much the data varies around the regression line (predicted values).
   $$Error = \sum_{i=1}^{n} (y - \hat{y})^2$$
   - **Total sum of squares (TSS)**. This tells how much the data point moves around the mean.
   $$Error = \sum_{i=1}^{n} (y - \bar{y})^2$$
   $$R^2 = 1 - \frac{SSE}{SSTO}$$
2) **Null-Hypothesis and P-value**: The p-value attributed to each term assesses the null hypothesis, implying the coefficient's equality to zero, thus indicating no impact. A p-value below 0.05 indicates grounds for rejecting the null hypothesis. In simpler terms, a predictor with a low p-value is likely to significantly enhance your model, as alterations in the predictor correspond to shifts in the response variable. On the contrary, a higher (insignificant) p-value implies a lack of connection between predictor alterations and response variations.

III. Problem

We are faced with a task involving testing the hypothesis that cancer incidence and mortality are linked to socioeconomic status. The metrics for socioeconomic status are provided through Poverty, Income, and Insurance data. The dependent variables for testing the hypothesis encompass Incidence rate, Average incidence rate, mortality rate, and average death rate. For this, we will demonstrate how well cancer incidence and mortality correlate with socioeconomic status by providing quantitative and visual evidence.

A. Data pre-processing

Existing features in the data set: The merged dataset used in this study consists of 25 columns and 3134 samples, which are areas in various states. Interpretation of the features is as follows:

- State: State of the respective area, total 51.
- Area: Name of area in which sampling is done.
- All Poverty: Number of people of both genders below the poverty line. Similarly, M poverty is for males, and F Poverty is for females.
- FIPS: Zipcode of the area.
- Med Income: Median Income of all ethnic groups in the area.
- All With: Number of individuals having insurance in the area; Along these lines, All Without, Without Male, With Male, Without Female, With Female are defined.
- Incidence Rate: Number of cancer cases detected per 100,000 people in the area.
- Mortality Rate: Number of mortalities per 100,000 people

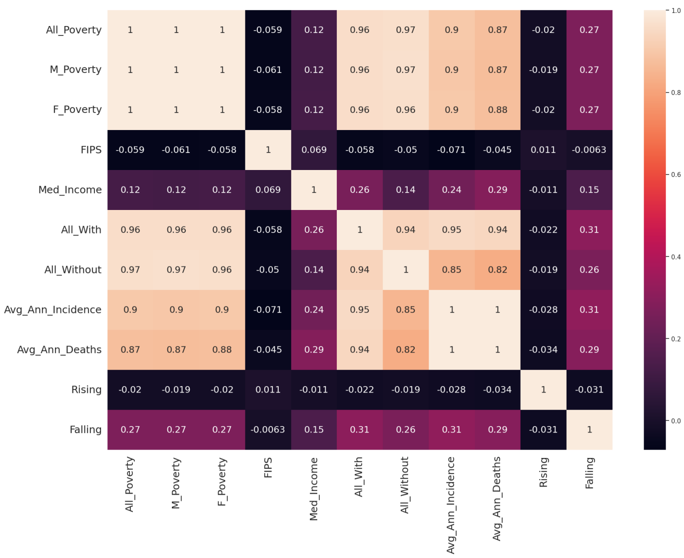

Fig. 1. Pearson Correlation Coefficient among all numeric features.

In Figure 1, we see the correlation matrix forming clusters of features, indicating that groups of features are highly linearly related to others in that group. From this, we can already see that median income and mortality rate have a negative moderate correlation coefficient, indicating that the median income increases, and mortality rates decrease.

We begin by examining the impact of social status on median income, focusing on the only available social data. We create a distribution plot (Figure 2) illustrating the median incomes of various communities in different states. Preliminary observations reveal a trend where Asians tend to have higher incomes, while incomes for Black individuals are generally lower. These distinct income distributions across social groups and states suggest that median income could be a valid

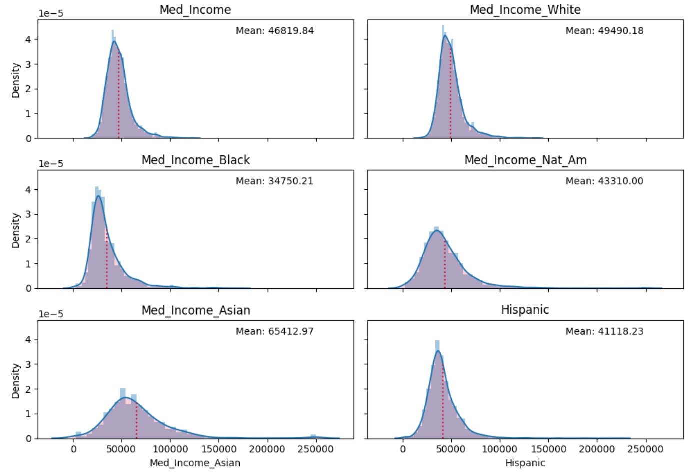

Fig. 2. Median income by state.

factor in determining Average Annual Incidence and Deaths. Consequently, we can infer that social status is also likely to be a relevant factor.

Next, we assess the presence of null values in each column, revealing that columns containing Median Income data for social groups such as Native Americans, Asians, Blacks, and Hispanics have a substantial number of missing values, ranging from 20% to 55%. To address this issue, we opt to remove these columns. Additionally, we identify columns with non-numeric values, including Incidence Rate, Average Annual Incidence, Recent Trend, Mortality Rate, and Average Annual Deaths.

An important observation is that the independent columns are not population-normalized and lack population data. Consequently, it is prudent to train our model using Average Annual Incidence and Average Annual Deaths rather than Incidence Rate and Mortality Rate, as the latter are merely normalized versions of the average values. Consequently, we drop these two dependent columns.

Upon evaluating the Average Annual Deaths column data, we notice that 325 data points are marked with an asterisk. These asterisks denote data suppressed due to confidentiality when fewer than 16 cases were reported. We must address this missing data, but we will evaluate the other columns before proceeding.

In the Average Annual Incidence column, we encounter three types of non-numeric data: '3 or fewer,' ' ', and ' '. These instances are relatively small compared to the total dataset. We replace '3 or fewer' with 3 and the other instances with null values to address this.

Furthermore, we employ feature extraction to create two new columns, indicating whether the recent trend is rising or falling, and subsequently, we drop the original recent trend column. With some data points now containing null values, we must handle these gaps before training our model. Several methods exist, including removing rows with missing data, imputing missing values with the median within each state, or utilizing a model capable of handling missing data. In this paper, we choose the latter approach.

B. Visualization

Our analysis begins with creating scatter plots illustrating the relationship between Average Annual Incidence and Average Annual Deaths (Figure 3). These plots reveal a strong correlation between the two variables, suggesting that testing on one of these variables would yield similar results for the other. This assumption can be reasonably made. Subsequently, we generate a pair plot including all poverty-related and median income columns. This analysis confirms the presence of a significant correlation, as supported by a correlation heat map (Figure 4), among the poverty-related columns—namely, All Poverty, M Poverty, and F Poverty. This high multicollinearity issue prompts us to address it by removing the M Poverty and F Poverty columns.

Following the same procedure, we repeat this analysis for the insurance-related columns and drop the M With, M Without, F With, and F Without columns. Moving forward, we create pair plots (Figure 5) for the remaining columns—All Poverty, Median Income, All With, and All Without. These visualizations indicate a substantial correlation between All Poverty and the Insurance columns (Figures 6, 7, 8, 9). However, we will address this issue in subsequent steps. Additionally, we examine scatter plots illustrating the relationships between the independent and dependent columns.

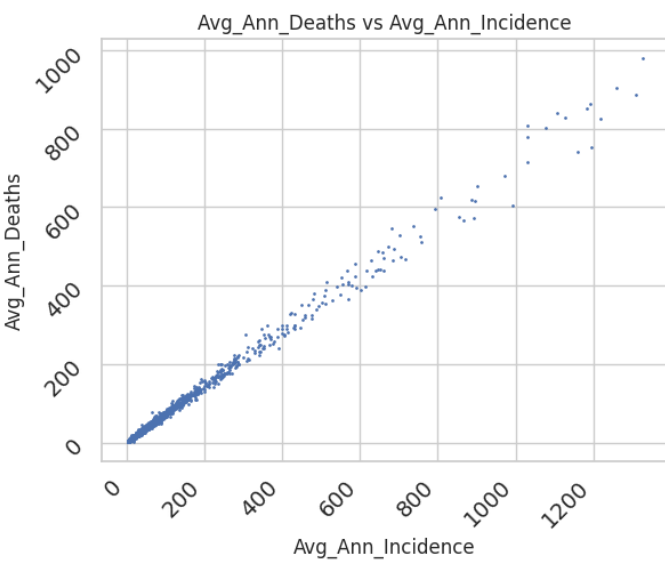

Fig. 3. Average Annual Death vs Average Annual Incidence.

C. Statistical Linear Regression Modelling

We employed the Statsmodels library in Python to construct linear regression models, offering the advantage of obtaining significance values for the regression coefficients. Initially, we created two separate models for the dependent variables, Average Annual Deaths and Average Annual Incidence, with the independent variables being All Poverty, Median Income, All

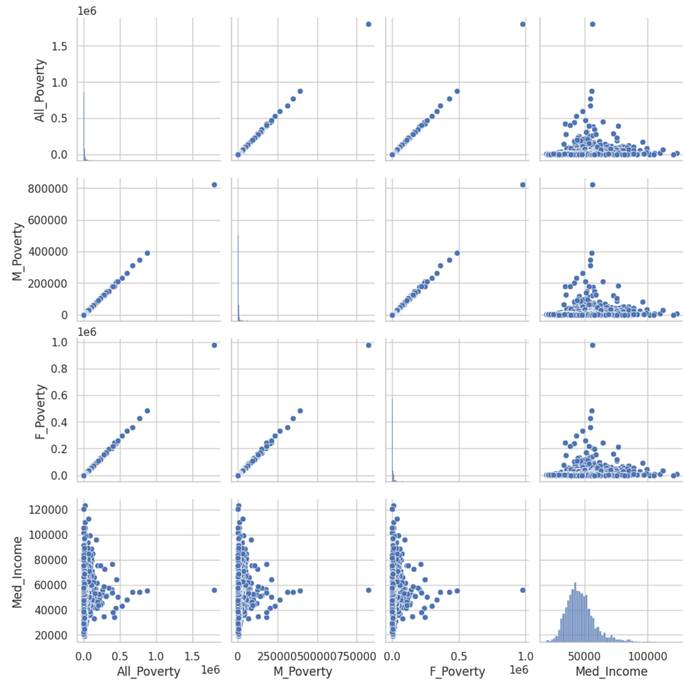

Fig. 4. Pairplots of Poverty vs Median Income.

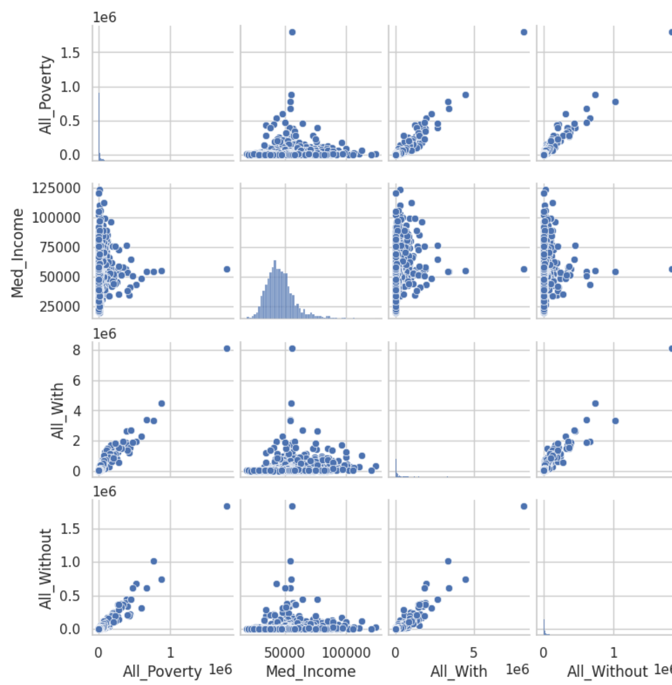

Fig. 5. Pairplots of Poverty vs Median Income.

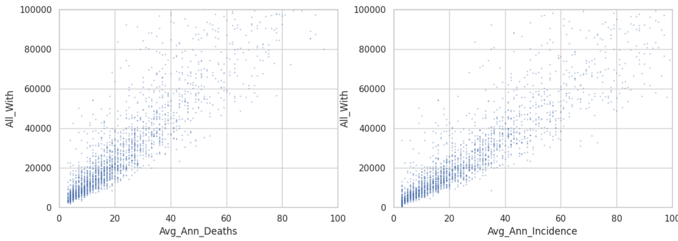

Fig. 6. All with insurance vs Average annual Death and Average annual Incidence.

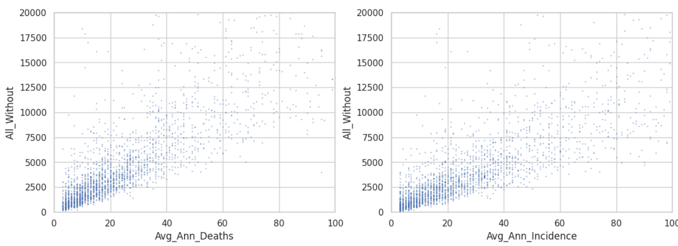

Fig. 7. All without insurance vs Average annual Death and Average annual Incidence.

With, All Without, Rising, and Falling. Both models yielded an Adjusted R-squared value of 0.922, and all coefficients were statistically significant except for Rising, which had a P-value exceeding 0.05 (for a 95% confidence level). It's worth noting that the Statsmodels library automatically handled null values in the dataset.

Next, we assessed whether our model met the assumptions for linear regression. We began by calculating the Variance Inflation Factor (VIF) for all independent variables to check

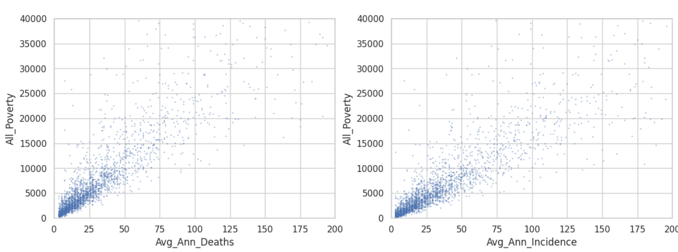

Fig. 8. All Poverty vs Average annual Death and Average annual Incidence.

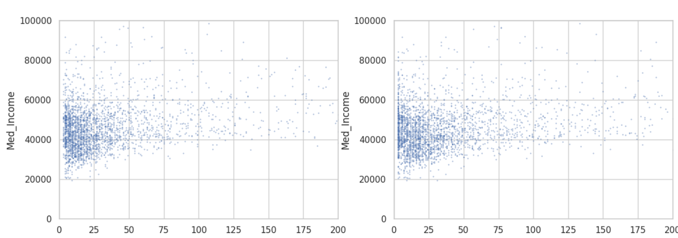

Fig. 9. Median Income vs Average annual Death and Average annual Incidence.

for multicollinearity. The first model revealed that All Poverty had the highest VIF, approximately 25.7, which could lead to statistically insignificant coefficients. Consequently, we iteratively removed variables until all VIF values were below the threshold of 5.

Subsequently, we examined the normality of the residuals. By plotting histograms of our data alongside normal and t distributions (Figure 10) and creating QQ plots (Figure 11) for both distributions, we observed that the QQ plot for the normal distribution did not closely align with the straight line at the ends, deviating upwards on the right and downwards on the left. This indicated that the residuals had heavier tails than a normal distribution. To address this, we explored the QQ plot for the t distribution, which exhibited a much better fit, confirming that the residuals followed a t distribution. The presence of fatter tails in the distribution suggested the presence of more outliers.

Next, we turn our attention to assessing heteroscedasticity. Initially, we visualize this by creating a regression plot (Figure 12) and consistently find a strong Pearson R coefficient, indicating a high correlation.

Subsequently, we delve into analyzing the data further. We construct a Lowess curve (Figure 12) and a scatter plot for our residuals (Figure 14) to scrutinize any discernible trends. We notice that the Lowess curve consistently falls below the y=0 line for lower values, suggesting our model tends to overpredict these values. Conversely, for most of the residuals, they cluster above the y=0 line, indicating that our model tends to underpredict these values.

Finally, we proceed to visualize the residuals, looking for any patterns in the changing variance across different model values. What we observe is a distinctive cone-shaped pattern in the residual plot, a common indication of heteroscedasticity. This phenomenon suggests that as the fitted values increase, the variance in the residuals also increases, signifying a notable presence of heteroscedasticity in our model.

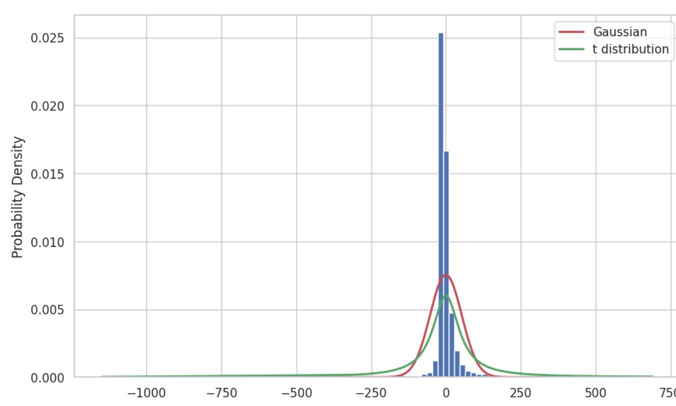

Fig. 10. Probability Density with common distributions.

IV. Conclusion

After constructing a statistical model that incorporates various features as proxies for socioeconomic status and treats

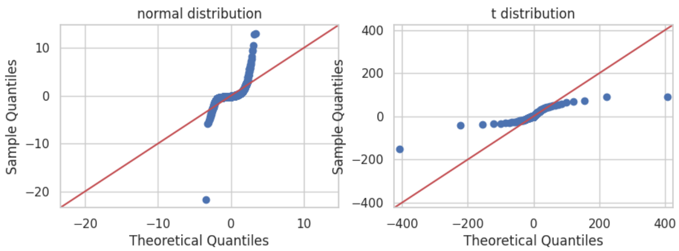

Fig. 11. QQ Plots.

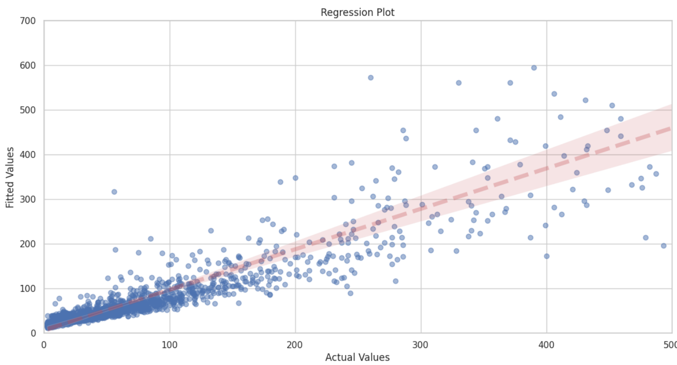

Fig. 12. Regression Plot.

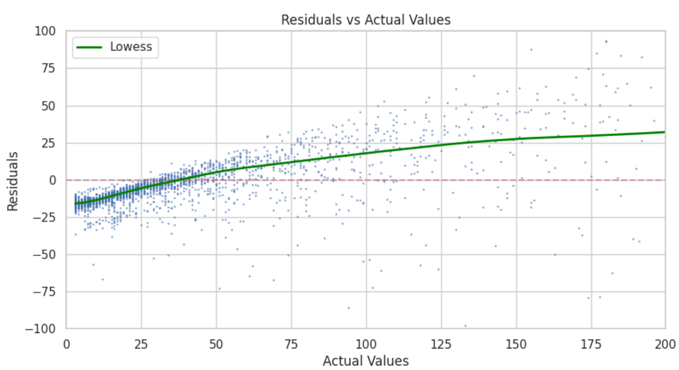

Fig. 13. Residual vs Actual Values.

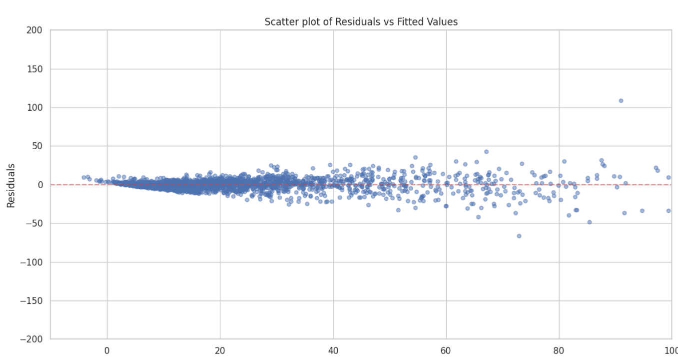

Fig. 14. Heteroscadasticity.

Average Incidence and Deaths as the dependent variables, we observed significant correlations among these features. Notably, factors such as Poverty, Median Income, and Insurance, which serve as economic indicators, displayed substantial relationships. Additionally, our analysis of Median Income data across different communities and states revealed varying mean values, suggesting that Median Income plays a crucial role in determining mortality rates. Furthermore, the disparities in Median Income among different social groups support the notion that socioeconomic factors are indeed significant. Consequently, we accept our hypothesis that there exists a correlation between socioeconomic status and cancer incidence as well as mortality.

While assessing the assumptions of Linear Regression, we identified and addressed issues such as multicollinearity (which has been resolved), non-normality (with residuals aligning better with a t-distribution), and heteroscedasticity (indicated by a cone-shaped residual plot). To further enhance our model, potential future improvements could involve the identification and treatment of outliers. Additionally, investigating the root causes of variable variance could be beneficial. Some potential solutions may include employing weighted regression models or applying transformations to the dependent variable. One such transformation could involve normalizing all independent variables with population data and then utilizing Mortality Rate and Death Rate for modeling purposes, thereby eliminating the population's effect on the data.

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MM20B007 : Data Analytics Lab Assignment 1

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
```

Getting necessary packages

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.formula.api as smf
import statsmodels.api as sm
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
```

Reading the data

```
mdf = pd.read_csv('/content/drive/MyDrive/sem 7/EE5708/Assignment
1/Data/merged_data.csv', index_col = 0)
```

Visualizing the data

```
mdf.head()
```

```
  State                            AreaName  All_Poverty  M_Poverty  \
0    AK      Aleutians East Borough, Alaska          553        334   
1    AK  Aleutians West Census Area, Alaska          499        273   
2    AK      Anchorage Municipality, Alaska        23914      10698   
3    AK          Bethel Census Area, Alaska         4364       2199   
4    AK         Bristol Bay Borough, Alaska           69         33   

   F_Poverty  FIPS  Med_Income  Med_Income_White  Med_Income_Black  \
0        219  2013     61518.0           72639.0           31250.0   
1        226  2016     84306.0           97321.0           93750.0   
2      13216  2020     78326.0           87235.0           50535.0   
3       2165  2050     51012.0           92647.0           73661.0   
4         36  2060     79750.0           88000.0               NaN   

   Med_Income_Nat_Am  ...  F_Without  All_With  All_Without  fips_x  \
0            54750.0  ...        540      1442         1857    2013   
1            48750.0  ...        564      4177         1333    2016   
```

```
2           53935.0  ...      21393    243173         44638    2020
3           41594.0  ...       1774     13023          4482    2050
4           63333.0  ...         67       768           191    2060

   Incidence_Rate  Avg_Ann_Incidence  recent_trend  fips_y  
Mortality_Rate  \
0               *          3 or fewer             *    2013  
*   
1               *          3 or fewer             *    2016  
*   
2            61.5                131        stable    2020  
47.3   
3            62.7                  6        stable    2050  
58.3   
4               *          3 or fewer             *    2060  
*   

  Avg_Ann_Deaths  
0              *  
1              *  
2             96  
3              5  
4              *  

[5 rows x 25 columns]
```

Preprocessing and Data Cleaning

```
mdf.columns
```

```
Index(['State', 'AreaName', 'All_Poverty', 'M_Poverty', 'F_Poverty', 
'FIPS',
       'Med_Income', 'Med_Income_White', 'Med_Income_Black',
       'Med_Income_Nat_Am', 'Med_Income_Asian', 'Hispanic', 'M_With',
       'M_Without', 'F_With', 'F_Without', 'All_With', 'All_Without', 
'fips_x',
       'Incidence_Rate', 'Avg_Ann_Incidence', 'recent_trend', 
'fips_y',
       'Mortality_Rate', 'Avg_Ann_Deaths'],
      dtype='object')
```

Dropping unwanted columns

```
mdf.drop(['fips_x', 'fips_y'], axis = 1, inplace = True)
mdf.columns
```

```
Index(['State', 'AreaName', 'All_Poverty', 'M_Poverty', 'F_Poverty', 
'FIPS',
       'Med_Income', 'Med_Income_White', 'Med_Income_Black',
```

```
       'Med_Income_Nat_Am', 'Med_Income_Asian', 'Hispanic', 'M_With',
       'M_Without', 'F_With', 'F_Without', 'All_With', 'All_Without',
       'Incidence_Rate', 'Avg_Ann_Incidence', 'recent_trend',
'Mortality_Rate',
       'Avg_Ann_Deaths'],
      dtype='object')
```

```
mdf.shape
```

```
(3134, 23)
```

```
df = mdf.copy()
```

```
df[['Med_Income', 'Med_Income_White', 'Med_Income_Black',
       'Med_Income_Nat_Am', 'Med_Income_Asian', 'Hispanic']].mean()
```

```
Med_Income           46819.837855
Med_Income_White     49490.181992
Med_Income_Black     34750.214137
Med_Income_Nat_Am    43309.998643
Med_Income_Asian     65412.969499
Hispanic             41118.231553
dtype: float64
```

Function to plot distributions as subplots

```
def dist_plot(features, rows, cols, data, figsize=(10, 7)):
    """
    Plot distributions of features in subplots and display the mean
value in each subplot.

    Parameters:
        features (list): List of feature names to plot.
        rows (int): Number of subplot rows.
        cols (int): Number of subplot columns.
        data (DataFrame): The data containing the features.
        figsize (tuple): Figure size (width, height).

    Returns:
        None
    """
    fig, axes = plt.subplots(rows, cols, figsize=figsize, sharex=True,
sharey=True)

    # Flatten the 2D array of subplots for easier iteration
    for i, ax in enumerate(axes.flatten()):
        feature_name = features[i]
        feature_data = data[feature_name]

        # Plot the distribution using Seaborn
```

```
        sns.distplot(feature_data, ax=ax)

        # Set title for the subplot
        ax.set_title(feature_name)

        # Get the KDE line and calculate mean height
        kde_line = ax.lines[0]
        mean = feature_data.mean()
        xs = kde_line.get_xdata()
        ys = kde_line.get_ydata()
        height = np.interp(mean, xs, ys)

        # Add a vertical line at the mean and fill area under the KDE
curve
        ax.vlines(mean, 0, height, color='crimson', linestyle=':')
        ax.fill_between(xs, 0, ys, facecolor='crimson', alpha=0.2)

        # Add text to display the mean value
        ax.text(0.75, 0.9, "Mean: {:.2f}".format(mean),
                horizontalalignment='center',
verticalalignment='center',
                transform=ax.transAxes)

    plt.tight_layout()
    plt.show()

income = ['Med_Income', 'Med_Income_White', 'Med_Income_Black',
       'Med_Income_Nat_Am', 'Med_Income_Asian', 'Hispanic']
dist_plot(income, 3, 2, df)
```

```
<ipython-input-137-ddcc233c517a>:23: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(feature_data, ax=ax)
<ipython-input-137-ddcc233c517a>:23: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
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```

```
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<ipython-input-137-ddcc233c517a>:23: UserWarning:
```

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v0.14.0.

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function with
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histograms).

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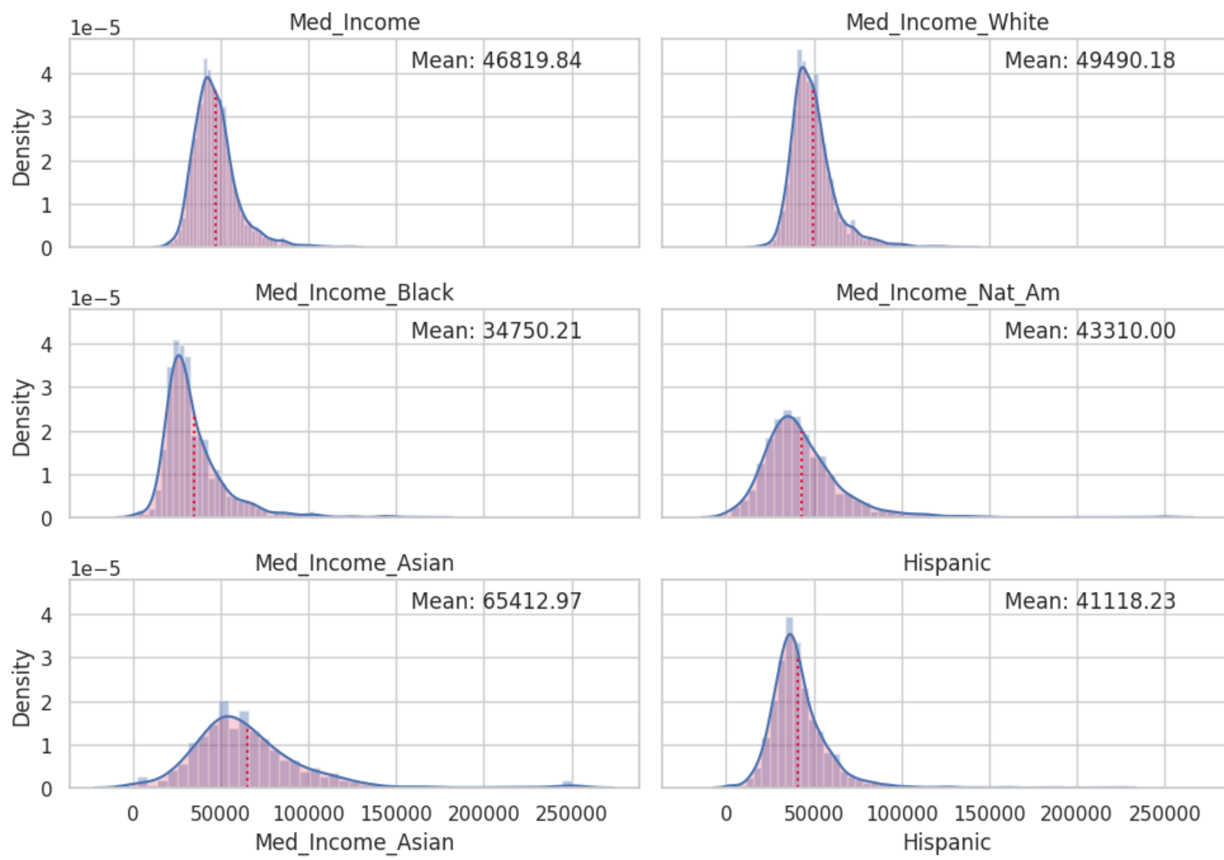
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(feature_data, ax=ax)
```



These graphs show that different social groups have different mean incomes for other states; hence, if we can prove that the median income is a valid factor in determining the average annual incidence or death, we can also assume that socioeconomic status would be a valid factor!

Checking the number of null values in each of the features

```
mdf.isnull().sum()

State                        0
AreaName                     0
```

```
All_Poverty              0
M_Poverty                0
F_Poverty                0
FIPS                     0
Med_Income               1
Med_Income_White         2
Med_Income_Black      1210
Med_Income_Nat_Am     1660
Med_Income_Asian      1757
Hispanic               681
M_With                   0
M_Without                0
F_With                   0
F_Without                0
All_With                 0
All_Without              0
Incidence_Rate           0
Avg_Ann_Incidence        0
recent_trend             0
Mortality_Rate           0
Avg_Ann_Deaths           0
dtype: int64
```

The columns 'Med_Income_White', 'Med_Income_Black', 'Med_Income_Nat_Am', 'Med_Income_Asian', and 'Hispanic' have too many null values hence we will be dropping them.

```
df.drop(['Med_Income_White', 'Med_Income_Black', 'Med_Income_Nat_Am',
'Med_Income_Asian', 'Hispanic'], axis = 1, inplace = True)
```

Checking, what all columns have numeric data type

```
df.apply(lambda s: pd.to_numeric(s, errors='coerce').notnull().all())
```

```
State                 False
AreaName              False
All_Poverty            True
M_Poverty              True
F_Poverty              True
FIPS                   True
Med_Income            False
M_With                 True
M_Without              True
F_With                 True
F_Without              True
All_With               True
All_Without            True
Incidence_Rate        False
Avg_Ann_Incidence     False
recent_trend          False
```

```
Mortality_Rate        False
Avg_Ann_Deaths        False
dtype: bool
```

```
df.describe()
```

```
         All_Poverty     M_Poverty     F_Poverty          FIPS  \
count   3.134000e+03   3134.000000   3134.000000   3134.000000
mean    1.522966e+04   6828.800893   8400.855775  30426.019145
std     5.457122e+04  24719.078097  29865.855831  15124.491165
min     1.000000e+01      5.000000      5.000000   1001.000000
25%     1.731250e+03    758.750000    957.000000  19001.500000
50%     4.294000e+03   1925.000000   2372.000000  29180.000000
75%     1.034550e+04   4697.500000   5812.500000  45080.500000
max     1.800265e+06 823612.000000 976653.000000  56045.000000

           Med_Income        M_With     M_Without        F_With  \
count     3133.000000  3.134000e+03   3134.000000  3.134000e+03
mean     46819.837855  4.158963e+04   6930.955329  4.487357e+04
std      12246.380184  1.293894e+05  28686.089548  1.406455e+05
min      19328.000000  3.200000e+01      4.000000  3.300000e+01
25%      38826.000000  4.506750e+03    750.000000  4.657500e+03
50%      45075.000000  1.040450e+04   1763.000000  1.110800e+04
75%      52224.000000  2.788775e+04   4407.250000  2.976475e+04
max     123453.000000  3.904322e+06 997326.000000  4.230137e+06

            F_Without      All_With   All_Without
count     3134.000000  3.134000e+03  3.134000e+03
mean      5968.701021  8.646320e+04  1.289966e+04
std      24657.276997  2.699985e+05  5.331494e+04
min          4.000000  6.700000e+01  8.000000e+00
25%        633.000000  9.173500e+03  1.388250e+03
50%       1529.000000  2.144800e+04  3.323500e+03
75%       3834.000000  5.756150e+04  8.240000e+03
max     837175.000000  8.134459e+06  1.834501e+06
```

Thus we can see we have to treat the columns [Incidence_Rate, Avg_Ann_Incidence, recent_trend, Mortality_Rate, Avg_Ann_Deaths] for values that are not numeric.

Also, we can see, all the independent columns are not normalized by population and we also do not have population data, it is better to delete the Mortality rate and Incidence rate columns as these are just the average values normalized by population and hence can be dropped !!

```python
df.drop(['Mortality_Rate', 'Incidence_Rate'], axis = 1, inplace =
True)

# we create a filter to convert the non-numeric data to either numeric
or to replace by NULL
def filter_(x):
    try:
```

```
        return float(str(x).split(' ')[0])
    except ValueError:
        return float('NaN')

# Using the filter on different columns
df['Avg_Ann_Incidence'] = df['Avg_Ann_Incidence'].map(filter_)

df['Avg_Ann_Deaths'] = df['Avg_Ann_Deaths'].map(filter_)
df['Med_Income'] = df['Med_Income'].map(filter_)

print([i for i in df['Avg_Ann_Incidence'].unique() if type(i)==str])
print([i for i in df['Avg_Ann_Deaths'].unique() if type(i)==str])
```

```
[]
[]
```

```
# creating columns with Rising and falling !!

def boo(col, chck):
    if col == chck:
        return 1
    return 0

df['Rising'] = df['recent_trend'].apply(lambda x: boo(x, 'rising'))
df['Falling'] = df['recent_trend'].apply(lambda x: boo(x, 'falling'))

df.select_dtypes(include=np.number)
```

```
      All_Poverty  M_Poverty  F_Poverty   FIPS  Med_Income  M_With
M_Without  \
0             553        334        219   2013     61518.0     876
1317
1             499        273        226   2016     84306.0    2470
769
2           23914      10698      13216   2020     78326.0  120747
23245
3            4364       2199       2165   2050     51012.0    6396
2708
4              69         33         36   2060     79750.0     419
124
...           ...        ...        ...    ...         ...     ...
...
3129         5058       2177       2881  56037     69022.0   19891
3318
3130         1638       1026        612  56039     75325.0    8948
2558
3131         2845       1453       1392  56041     56569.0    9132
1413
3132         1137        489        648  56043     47652.0    3349
691
3133          958        354        604  56045     57738.0    2927
```

```
454

      F_With  F_Without  All_With  All_Without  Avg_Ann_Incidence  \
0        566        540      1442         1857                3.0   
1       1707        564      4177         1333                3.0   
2     122426      21393    243173        44638              131.0   
3       6627       1774     13023         4482                6.0   
4        349         67       768          191                3.0   
...      ...        ...       ...          ...                ...   
3129   18600       2683     38491         6001               14.0   
3130    9555       1192     18503         3750                5.0   
3131    8711       1503     17843         2916                6.0   
3132    3490        703      6839         1394                6.0   
3133    3087        314      6014          768                4.0   

      Avg_Ann_Deaths  Rising  Falling  
0                NaN       0        0  
1                NaN       0        0  
2               96.0       0        0  
3                5.0       0        0  
4                NaN       0        0  
...              ...     ...      ...  
3129             9.0       0        0  
3130             5.0       0        0  
3131             4.0       0        0  
3132             5.0       0        0  
3133             4.0       0        0  

[3134 rows x 15 columns]
```

```
#checking for null values post the pre-processing
df.isnull().sum()
```

```
State                  0
AreaName               0
All_Poverty            0
M_Poverty              0
F_Poverty              0
FIPS                   0
Med_Income             1
M_With                 0
M_Without              0
F_With                 0
F_Without              0
All_With               0
All_Without            0
Avg_Ann_Incidence    209
recent_trend           0
Avg_Ann_Deaths       331
Rising                 0
```

```
Falling                0
dtype: int64
```

```python
#Checking for mean values for different features, grouped by state
df.groupby(['State']).mean()
```

```
<ipython-input-150-94714262a348>:2: FutureWarning: The default value
of numeric_only in DataFrameGroupBy.mean is deprecated. In a future
version, numeric_only will default to False. Either specify
numeric_only or select only columns which should be valid for the
function.
  df.groupby(['State']).mean()
```

```
         All_Poverty     M_Poverty     F_Poverty          FIPS
Med_Income  \
State

AK        2978.782609   1425.260870   1553.521739   2138.217391
66812.565217
AL       13242.686567   5740.791045   7501.895522   1067.000000
37973.134328
AR        7381.920000   3303.280000   4078.640000   5075.000000
36626.480000
AZ       78712.666667  36501.133333  42211.533333   4013.866667
43252.200000
CA      105778.310345  48712.758621  57065.551724   6058.000000
56013.155172
CO       10218.265625   4729.312500   5488.953125   8062.234375
51263.187500
CT       45793.875000  20125.000000  25668.875000   9008.000000
71184.125000
DC      110365.000000  48069.000000  62296.000000  11001.000000
70848.000000
DE       36105.000000  15373.000000  20732.000000  10003.000000
58067.666667
FL       47464.313433  21485.835821  25978.477612  12067.910448
44046.477612
GA       11251.238994   4968.270440   6282.968553  13161.490566
40704.911950
HI       30788.800000  14142.200000  16646.600000  15005.000000
64879.000000
IA        3776.595960   1693.616162   2082.979798  19099.000000
50483.121212
ID        5572.204545   2591.636364   2980.568182  16044.000000
43607.750000
IL       17658.019608   7873.049020   9784.970588  17102.000000
50163.441176
IN       10630.902174   4719.782609   5911.119565  18092.000000
48745.402174
KS        3631.933333   1651.476190   1980.457143  20105.000000
```

```
47322.209524
KY       6715.341667   3007.733333   3707.608333  21120.000000
39137.300000
LA      13879.375000   5932.671875   7946.703125  22064.000000
41411.781250
MA      53493.214286  23007.857143  30485.357143  25014.000000
65974.428571
MD      24033.541667  10270.708333  13762.833333  24044.958333
69200.375000
ME      11267.375000   5047.500000   6219.875000  23016.000000
46141.750000
MI      19480.361446   8863.554217  10616.807229  26083.000000
44464.987952
MN       6858.183908   3145.494253   3712.689655  27087.000000
53926.988506
MO       7964.973913   3553.165217   4411.808696  29117.713043
41755.400000
MS       7945.670732   3430.256098   4515.414634  28082.000000
34938.926829
MT       2689.035714   1246.785714   1442.250000  30056.000000
44497.017857
NC      16674.650000   7399.320000   9275.330000  37100.000000
41784.200000
ND       1504.867925    669.962264    834.905660  38053.000000
55574.867925
NE       2485.107527   1088.548387   1396.559140  31093.000000
48646.129032
NH      11384.000000   5107.000000   6277.000000  33010.000000
60648.900000
NJ      44992.714286  19710.857143  25281.857143  34021.000000
73014.095238
NM      13010.939394   6034.939394   6976.000000  35030.151515
40183.666667
NV      25078.647059  11705.352941  13373.294118  32045.529412
53689.705882
NY      48482.951613  21388.532258  27094.419355  36062.000000
55275.693548
OH      20179.954545   8994.931818  11185.022727  39088.000000
48446.409091
OK       8104.454545   3612.857143   4491.597403  40077.000000
44097.376623
OR      17692.972222   8237.222222   9455.750000  41036.000000
45171.222222
PA      24874.164179  11000.119403  13874.044776  42067.000000
50316.253731
RI      28844.600000  12603.400000  16241.200000  44005.000000
65783.400000
SC      18063.065217   7840.521739  10222.543478  45046.000000
39756.695652
```

```
SD       1652.692308    756.615385    896.076923  46067.430769
47679.738462
TN      11764.147368   5240.600000   6523.547368  47095.000000
40168.031579
TX      17608.074803   7883.543307   9724.531496  48254.000000
46745.778656
UT      12124.172414   5646.620690   6477.551724  49029.000000
54687.034483
VA       6927.651515   3028.363636   3899.287879  51265.848485
53059.212121
VT       4945.214286   2213.642857   2731.571429  50014.000000
52653.500000
WA      23295.179487  10715.025641  12580.153846  53039.000000
50217.076923
WI      10060.388889   4519.638889   5540.750000  55071.097222
50649.000000
WV       5879.709091   2635.436364   3244.272727  54055.000000
39411.818182
WY       2825.869565   1255.739130   1570.130435  56023.000000
57042.304348

              M_With     M_Without          F_With     F_Without  \
State
AK      12366.565217   2917.739130   12147.608696   2411.217391
AL      29389.671642   4678.328358   32530.134328   4294.194030
AR      16012.226667   2881.893333   17237.906667   2603.880000
AZ     178389.533333  35436.066667  191685.466667  30056.200000
CA     269831.241379  52388.275862  287728.534483  43712.500000
CO      34745.546875   5534.781250   36322.625000   4447.265625
CT     194827.125000  19867.500000  212544.125000  15086.125000
DC     276285.000000  22198.000000  323314.000000  14813.000000
DE     132112.666667  13828.000000  146781.000000  11207.666667
FL     112310.552239  27464.761194  124417.328358  24393.179104
GA      24288.446541   5449.440252   26859.364780   5116.691824
HI     123945.400000   8997.200000  130480.400000   7047.000000
IA      14020.090909   1243.060606   14529.464646   1006.444444
ID      15305.886364   2773.363636   15626.613636   2562.863636
IL      53124.647059   7664.294118   57616.421569   6047.813725
IN      29740.010870   4733.456522   31571.097826   4270.260870
KS      11722.238095   1594.009524   12237.314286   1435.695238
KY      15362.841667   2174.991667   16486.958333   1910.525000
LA      28475.515625   5594.515625   31249.015625   5339.109375
MA     218643.642857  10231.071429  237913.857143   6623.428571
MD     104805.500000  12109.708333  116597.083333   9684.958333
ME      35496.687500   4614.687500   38427.937500   3637.187500
MI      51325.879518   6328.108434   55251.277108   5036.240964
MN      28082.068966   2476.908046   29202.885057   1857.229885
MO      21828.939130   3295.878261   23439.895652   3021.800000
MS      14163.085366   2915.890244   15824.743902   2720.536585
```

MT	7459.232143	1468.642857	7611.232143	1303.982143
NC	39094.400000	7360.030000	43500.040000	6541.590000
ND	6080.886792	679.924528	6035.056604	530.679245
NE	8726.322581	1086.344086	9035.322581	947.000000
NH	57839.500000	6636.700000	60861.000000	5568.500000
NJ	176838.857143	26562.190476	193311.333333	22173.523810
NM	25007.909091	5452.000000	26911.939394	4740.333333
NV	65350.588235	15792.000000	67480.411765	13947.588235
NY	134038.258065	17297.806452	149030.435484	12977.209677
OH	56197.590909	6936.954545	60783.000000	5660.829545
OK	19749.077922	4244.116883	21039.896104	3907.480519
OR	46073.055556	7253.416667	48939.194444	6089.083333
PA	82057.477612	9146.940299	89112.880597	7370.582090
RI	89317.200000	10941.000000	99037.000000	8290.800000
SC	41092.608696	7752.934783	45848.934783	7033.695652
SD	5532.461538	709.692308	5630.861538	609.646154
TN	27868.221053	4724.884211	30850.915789	3897.357895
TX	39586.787402	10816.748031	41903.157480	10301.303150
UT	42691.068966	6939.689655	43393.172414	6177.206897
VA	25542.757576	3658.446970	27926.901515	3227.848485
VT	20227.000000	1575.571429	21508.642857	1007.142857
WA	76236.564103	11122.410256	79952.794872	9069.102564
WI	35358.930556	3563.430556	37140.777778	2664.125000
WV	14296.309091	1975.145455	15042.254545	1820.836364
WY	10802.956522	1764.608696	10670.782609	1552.869565

	All_With	All_Without	Avg_Ann_Incidence	Avg_Ann_Deaths \
State				
AK	24514.173913	5328.956522	15.130435	19.833333
AL	61919.805970	8972.522388	59.597015	47.552239
AR	33250.133333	5485.773333	35.733333	28.546667
AZ	370075.000000	65492.266667	252.600000	91.214286
CA	557559.775862	96100.775862	294.396552	165.603774
CO	71068.171875	9982.046875	35.281250	39.075000
CT	407371.250000	34953.625000	332.875000	216.875000
DC	599599.000000	37011.000000	351.000000	240.000000
DE	278893.666667	25035.666667	257.666667	188.333333
FL	236727.880597	51857.940299	245.462687	178.029851

GA	51147.811321	10566.132075	39.823899	29.841060
HI	254425.800000	16044.200000	155.800000	134.250000
IA	28549.555556	2249.505051	24.131313	18.051546
ID	30932.500000	5336.227273	19.500000	20.586207
IL	110741.068627	13712.107843	91.254902	42.178218
IN	61311.108696	9003.717391	57.771739	43.586957
KS	23959.552381	3029.704762	NaN	20.826087
KY	31849.800000	4085.516667	40.083333	29.008403
LA	59724.531250	10933.625000	54.453125	42.500000
MA	456557.500000	16854.500000	358.785714	247.500000
MD	221402.583333	21794.666667	152.458333	114.083333
ME	73924.625000	8251.875000	82.750000	59.750000
MI	106577.156627	11364.349398	95.012048	58.592593
MN	57284.954023	4334.137931	NaN	28.719512
MO	45268.834783	6317.678261	46.243478	34.333333
MS	29987.829268	5636.426829	30.487805	23.975309
MT	15070.464286	2772.625000	13.321429	13.485714
NC	82594.440000	13901.620000	75.580000	54.840000
ND	12115.943396	1210.603774	9.094340	12.000000
NE	17761.645161	2033.344086	13.473118	15.035714
NH	118700.500000	12205.200000	105.600000	73.600000
NJ	370150.190476	48735.714286	280.904762	195.095238
NM	51919.848485	10192.333333	29.424242	27.653846
NV	132831.000000	29739.588235	NaN	108.500000
NY	283068.693548	30275.016129	219.532258	146.677419
OH	116980.590909	12597.784091	109.670455	84.204545

OK	40788.974026	8151.597403	39.272727	33.791667
OR	95012.250000	13342.500000	74.694444	62.363636
PA	171170.358209	16517.522388	159.074627	116.621212
RI	188354.200000	19231.800000	172.800000	124.600000
SC	86941.543478	14786.630435	81.413043	60.826087
SD	11163.323077	1319.338462	8.969231	10.882353
TN	58719.136842	8622.242105	59.515789	45.873684
TX	81489.944882	21118.051181	51.480315	41.954315
UT	86084.241379	13116.896552	22.241379	24.764706
VA	53469.659091	6886.295455	39.659091	30.387597
VT	41735.642857	2582.714286	37.357143	26.500000
WA	156189.358974	20191.512821	110.282051	84.837838
WI	72499.708333	6227.555556	55.888889	41.732394
WV	29338.563636	3795.981818	36.436364	27.436364
WY	21473.739130	3317.478261	12.739130	10.857143

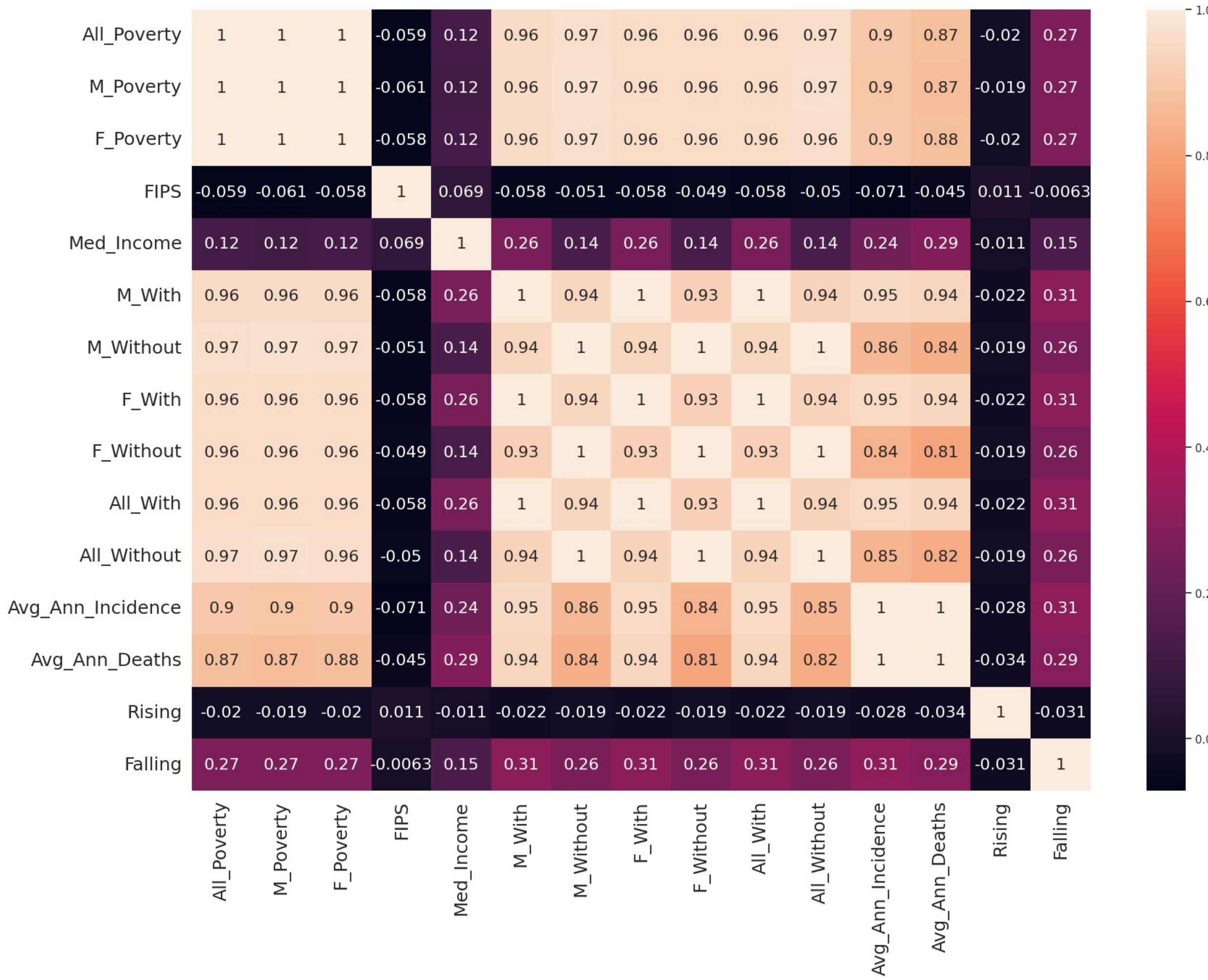
	Rising	Falling
State		
AK	0.000000	0.000000
AL	0.000000	0.074627
AR	0.000000	0.040000
AZ	0.066667	0.133333
CA	0.000000	0.258621
CO	0.015625	0.062500
CT	0.000000	0.375000
DC	0.000000	0.000000
DE	0.000000	0.000000
FL	0.000000	0.134328
GA	0.000000	0.050314
HI	0.000000	0.000000
IA	0.060606	0.030303
ID	0.000000	0.000000
IL	0.009804	0.127451
IN	0.032609	0.032609
KS	0.000000	0.000000
KY	0.016667	0.041667

```
LA      0.000000  0.031250
MA      0.000000  0.142857
MD      0.041667  0.125000
ME      0.000000  0.000000
MI      0.000000  0.072289
MN      0.000000  0.000000
MO      0.052174  0.034783
MS      0.012195  0.048780
MT      0.035714  0.017857
NC      0.010000  0.040000
ND      0.056604  0.037736
NE      0.010753  0.000000
NH      0.000000  0.100000
NJ      0.000000  0.666667
NM      0.000000  0.121212
NV      0.000000  0.000000
NY      0.032258  0.096774
OH      0.000000  0.113636
OK      0.000000  0.038961
OR      0.000000  0.055556
PA      0.029851  0.029851
RI      0.000000  0.000000
SC      0.043478  0.086957
SD      0.000000  0.030769
TN      0.010526  0.063158
TX      0.007874  0.031496
UT      0.000000  0.068966
VA      0.015152  0.106061
VT      0.000000  0.142857
WA      0.000000  0.282051
WI      0.027778  0.055556
WV      0.018182  0.018182
WY      0.000000  0.043478
```

```python
plt.figure(figsize=(20, 14))
corr_matrix = df.corr()
annot_kws = {"size": 16}

# Create the heatmap of Correlation matrix
heatmap = sns.heatmap(corr_matrix, annot=True, annot_kws=annot_kws,
xticklabels=True, yticklabels=True)

plt.xticks(fontsize=18)
plt.yticks(fontsize=18)

plt.show()
```

```
<ipython-input-151-4e706e5e56c5>:2: FutureWarning: The default value
of numeric_only in DataFrame.corr is deprecated. In a future version,
it will default to False. Select only valid columns or specify the
```

```
value of numeric_only to silence this warning.
  corr_matrix = df.corr()
```




```python
#Converting the Median Income column to numeric type
df['Med_Income'] = pd.to_numeric(df.Med_Income)

# Checks what all columns in the dataframe contain only numeric values
df.apply(lambda s: pd.to_numeric(s, errors='coerce').notnull().all())
```

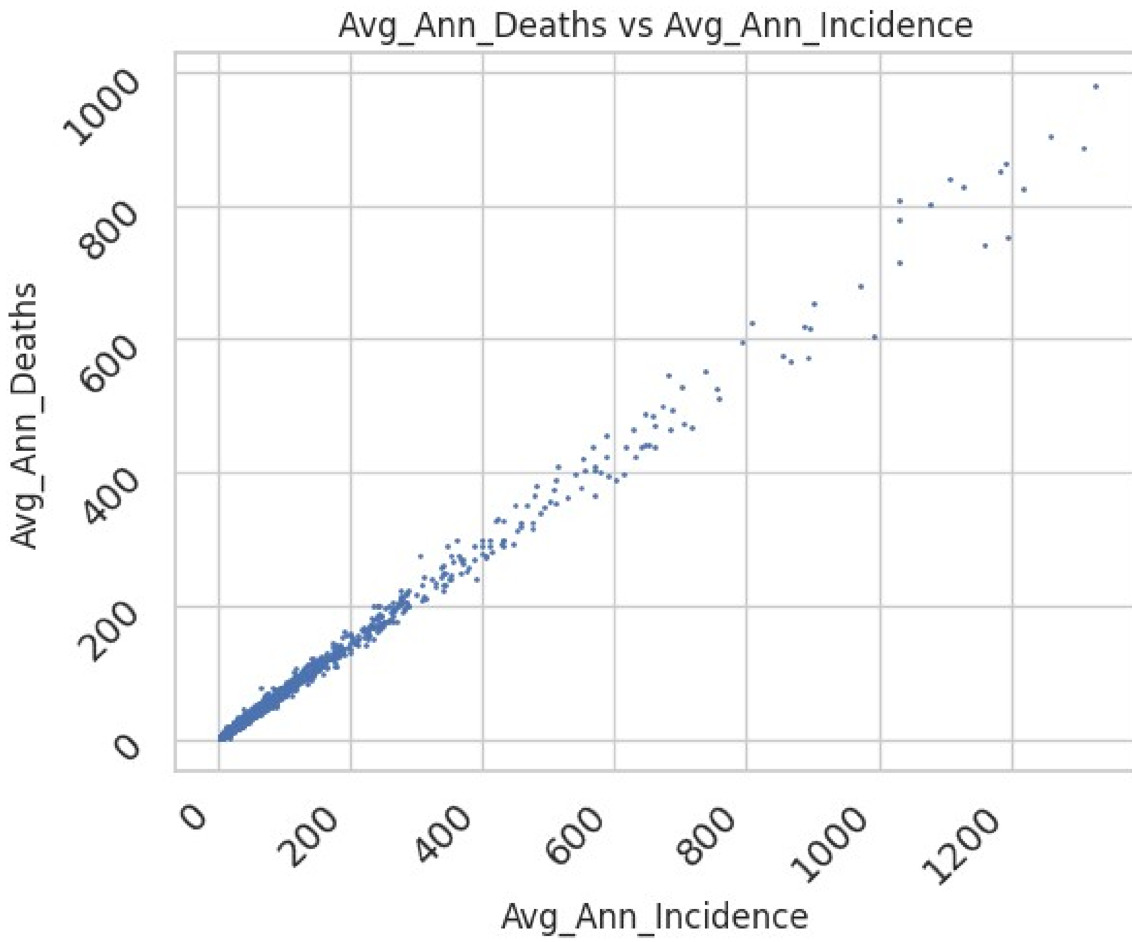
```
State                False
AreaName             False
All_Poverty           True
M_Poverty             True
F_Poverty             True
FIPS                  True
Med_Income           False
M_With                True
M_Without             True
F_With                True
```

```
F_Without              True
All_With               True
All_Without            True
Avg_Ann_Incidence     False
recent_trend          False
Avg_Ann_Deaths        False
Rising                 True
Falling                True
dtype: bool
```

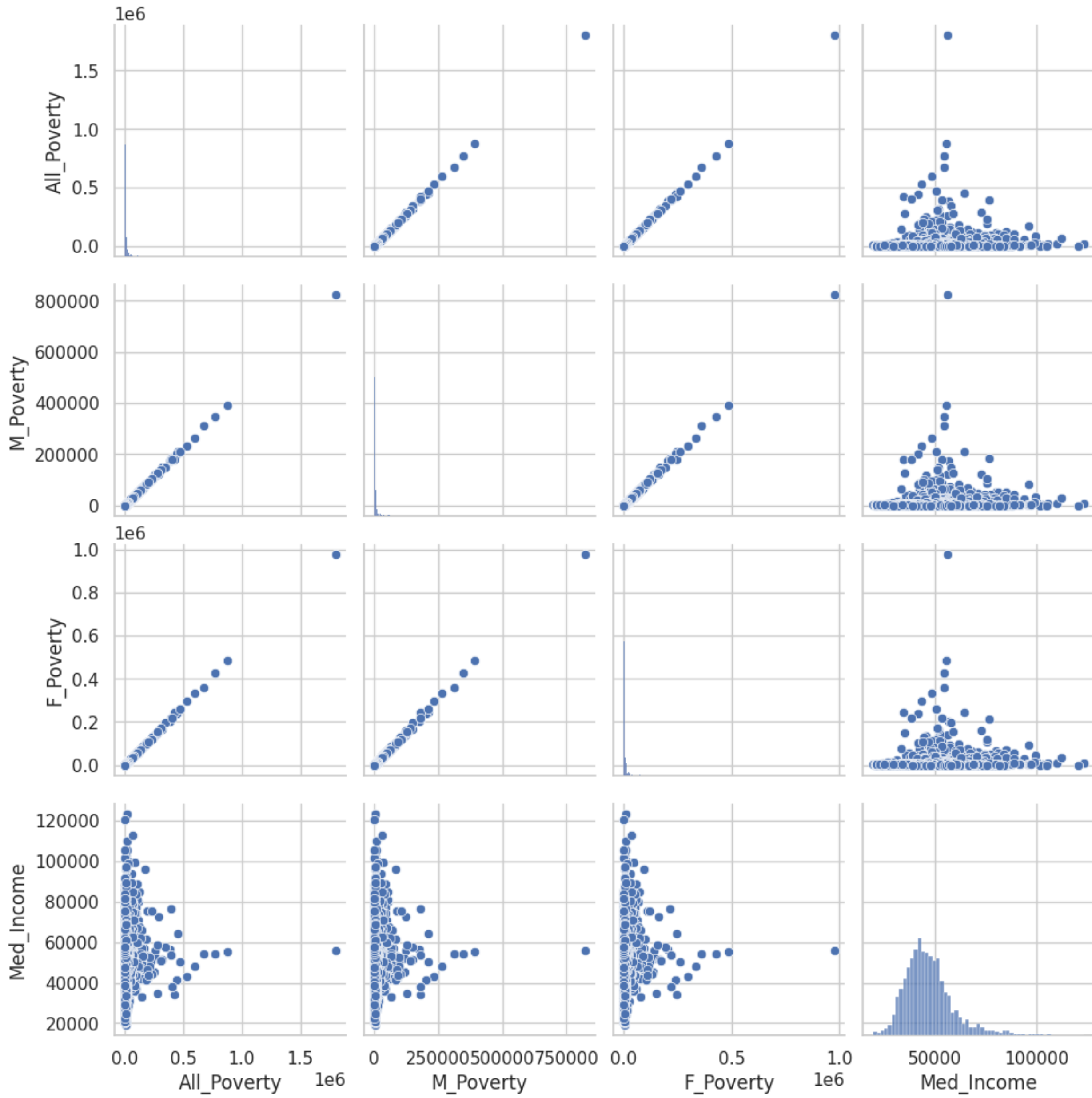
Visualization

```
# Scatter plot Avg_Ann_Incidence vs Avg_Ann_Deaths
df.plot(x = 'Avg_Ann_Incidence', y = 'Avg_Ann_Deaths', kind=
'scatter', s=0.9)
plt.grid(True)
plt.title('Avg_Ann_Deaths vs Avg_Ann_Incidence')
plt.xticks(rotation=45, ha="right", fontsize=14)
plt.yticks(rotation=45, ha="right", fontsize=14)
```

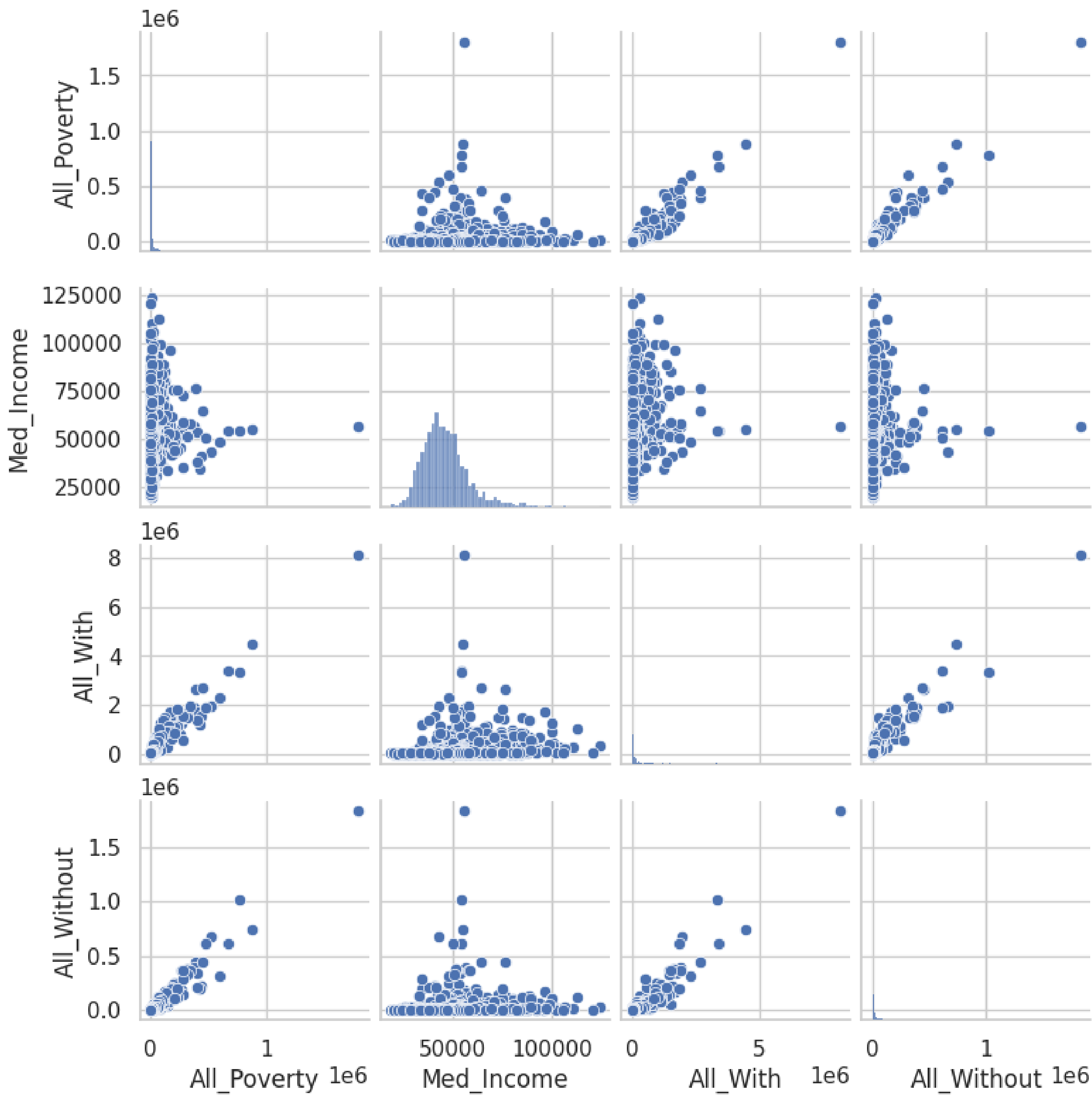
```
(array([-200.,    0.,  200.,  400.,  600.,  800., 1000., 1200.]),
 [Text(0, -200.0, '−200'),
  Text(0, 0.0, '0'),
  Text(0, 200.0, '200'),
  Text(0, 400.0, '400'),
  Text(0, 600.0, '600'),
  Text(0, 800.0, '800'),
  Text(0, 1000.0, '1000'),
  Text(0, 1200.0, '1200')])
```



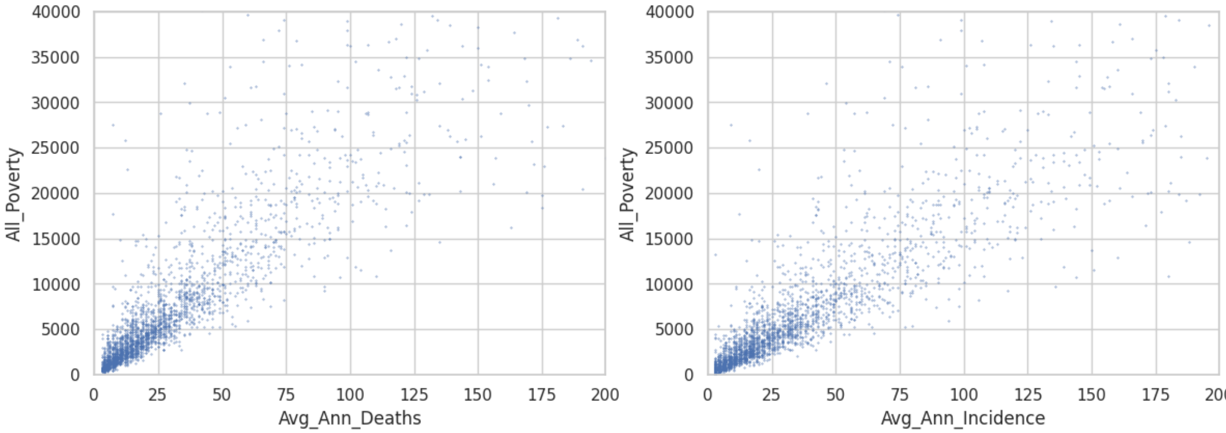

```
# Pair Plots
sns.set(style='whitegrid', context='notebook')

columns = ['All_Poverty', 'M_Poverty', 'F_Poverty', 'Med_Income']

pairplot = sns.pairplot(df[columns])

# pairplot.fig.suptitle('Pairplot of Poverty and Median Income',
y=1.08, fontsize=16)
plt.show()
```



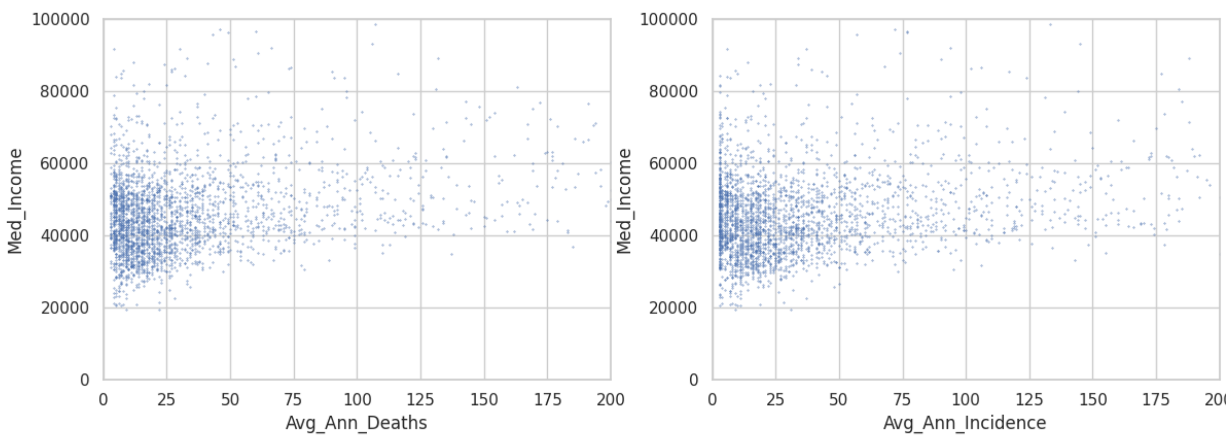

```
df.drop(['M_With', 'M_Without', 'F_With', 'F_Without'], axis=1,
inplace=True)

sns.set(style='whitegrid', context='notebook')
sns.pairplot(df[['All_Poverty', 'Med_Income', 'All_With',
       'All_Without']], height=2)

<seaborn.axisgrid.PairGrid at 0x7a8e0a4366e0>
```



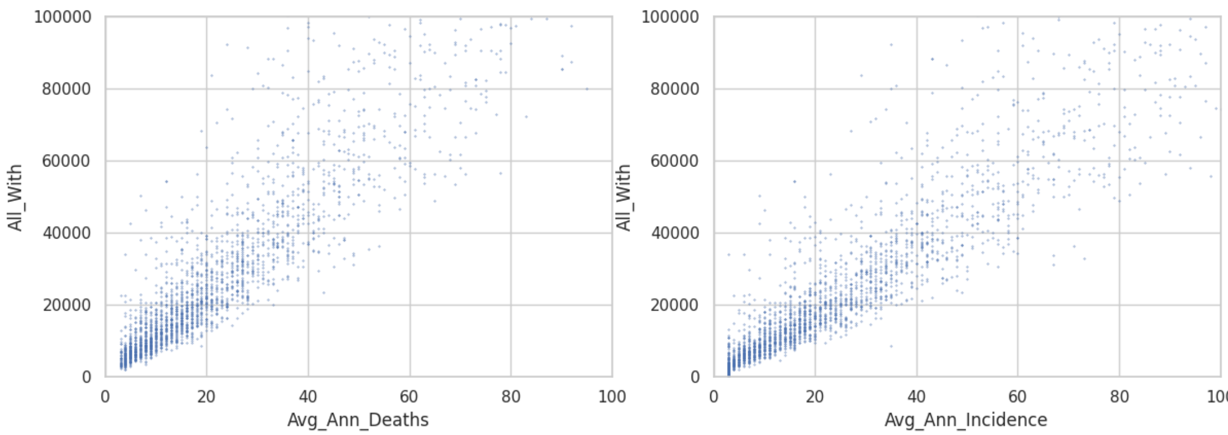

```
# Scatter Plot
def visualize_scatter_pov(col):
    fig1 = plt.figure(figsize = (14,10))

    ax3 = fig1.add_subplot(223)
    df.plot(x = 'Avg_Ann_Deaths', y = col, kind= 'scatter', s=0.1,
xlim = [0, 200], ylim = [0, 40000], ax = ax3)
    ax4 = fig1.add_subplot(224)
    df.plot(x = 'Avg_Ann_Incidence', y = col, kind= 'scatter',
s=0.1,xlim = [0, 200], ylim = [0, 40000], ax = ax4)

visualize_scatter_pov('All_Poverty')
```



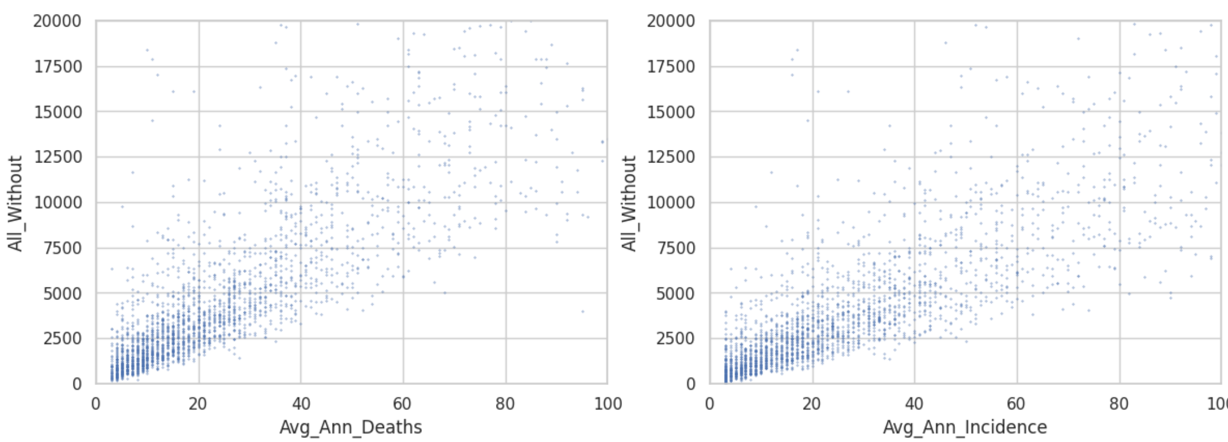

```
def visualize_scatter_inc(col):
    fig1 = plt.figure(figsize = (14,10))
    ax3 = fig1.add_subplot(223)
    df.plot(x = 'Avg_Ann_Deaths', y = col, kind= 'scatter',xlim = [0,
200], ylim = [0, 100000], s=0.1, ax = ax3)
    ax4 = fig1.add_subplot(224)
    df.plot(x = 'Avg_Ann_Incidence', y = col, kind= 'scatter',
s=0.1,xlim = [0, 200], ylim = [0, 100000], ax = ax4)

visualize_scatter_inc('Med_Income')
```




```
def visualize_scatter_with(col):
    fig1 = plt.figure(figsize = (14,10))
    ax3 = fig1.add_subplot(223)
    df.plot(x = 'Avg_Ann_Deaths', y = col, kind= 'scatter',xlim = [0,
100], ylim = [0, 100000], s=0.1, ax = ax3)
    ax4 = fig1.add_subplot(224)
    df.plot(x = 'Avg_Ann_Incidence', y = col, kind= 'scatter',
s=0.1,xlim = [0, 100], ylim = [0, 100000], ax = ax4)

visualize_scatter_with('All_With')
```




```
def visualize_scatter_without(col):
    fig1 = plt.figure(figsize = (14,10))
    ax3 = fig1.add_subplot(223)
    df.plot(x = 'Avg_Ann_Deaths', y = col, kind= 'scatter',xlim = [0, 
100], ylim = [0, 20000], s=0.1, ax = ax3)
    ax4 = fig1.add_subplot(224)
    df.plot(x = 'Avg_Ann_Incidence', y = col, kind= 'scatter', 
s=0.1,xlim = [0, 100], ylim = [0, 20000], ax = ax4)

visualize_scatter_without('All_Without')
```



Statistical Linear Regression Modelling using Statsmodel Library

Unlike SKLearn, statsmodels does not automatically include a constant term when fitting models. Therefore, to incorporate a constant term, you should utilize the method sm.add_constant(X) within statsmodels. This addition of a constant term, although not obligatory, significantly enhances the quality of the fitted line. For instance, if your original line has an intercept of -2000 and you attempt to fit the same line through the origin, the resulting line will be of lower quality. However, upon introducing a constant term (intercept), you will observe that the coefficients align between SKLearn and statsmodels.

```python
res = ''
for i in df.columns:
    res += str(i) + ' + '
print(res)
```

```
State + AreaName + All_Poverty + M_Poverty + F_Poverty + FIPS +
Med_Income + All_With + All_Without + Avg_Ann_Incidence + recent_trend
+ Avg_Ann_Deaths + Rising + Falling +
```

```python
# Using statmodels library for Linear Regression Modelling
model1 = smf.ols(formula='Avg_Ann_Incidence ~ All_Poverty + Med_Income
+ All_With + All_Without + Rising + Falling', data=df).fit()
print(model1.summary())
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:      Avg_Ann_Incidence   R-squared:
0.922
Model:                            OLS   Adj. R-squared:
0.921
Method:                 Least Squares   F-statistic:
5707.
Date:                Fri, 01 Sep 2023   Prob (F-statistic):
0.00
Time:                        09:53:57   Log-Likelihood:
-15493.
No. Observations:                2924   AIC:
3.100e+04
Df Residuals:                    2917   BIC:
3.104e+04
Df Model:                           6

Covariance Type:            nonrobust

======================================================================
=========
                  coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
---------
Intercept      36.8125      3.931      9.365      0.000      29.105
44.520
All_Poverty     0.0005   8.38e-05      6.497      0.000       0.000
0.001
Med_Income     -0.0005   8.48e-05     -5.914      0.000      -0.001
-0.000
All_With        0.0008   1.36e-05     55.181      0.000       0.001
0.001
```

```
All_Without    -0.0014   6.39e-05    -22.047      0.000      -0.002
-0.001
Rising         -6.5225      7.452     -0.875      0.381     -21.134
8.089
Falling        11.5051      3.775      3.047      0.002       4.102
18.908
======================================================================
========
Omnibus:                     1643.837   Durbin-Watson:
1.614
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
599626.270
Skew:                           1.406   Prob(JB):
0.00
Kurtosis:                      73.098   Cond. No.
2.50e+06
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 2.5e+06. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

```
# Fitting to Average Deaths
model2 = smf.ols(formula='Avg_Ann_Deaths ~ All_Poverty + Med_Income  +
All_With + All_Without + Rising + Falling', data=df).fit()
print(model2.summary())
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:         Avg_Ann_Deaths   R-squared:
0.893
Model:                            OLS   Adj. R-squared:
0.893
Method:                 Least Squares   F-statistic:
3900.
Date:                Fri, 01 Sep 2023   Prob (F-statistic):
0.00
Time:                        09:53:58   Log-Likelihood:
-13688.
No. Observations:                2803   AIC:
2.739e+04
Df Residuals:                    2796   BIC:
2.743e+04
Df Model:                           6
```

```
Covariance Type:            nonrobust

==============================================================================
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
Intercept     33.0356      2.701     12.233      0.000      27.740
38.331
All_Poverty    0.0003   5.89e-05      4.351      0.000       0.000
0.000
Med_Income    -0.0005   5.83e-05     -8.285      0.000      -0.001
-0.000
All_With       0.0005   9.38e-06     52.767      0.000       0.000
0.001
All_Without   -0.0004   5.02e-05     -8.832      0.000      -0.001
-0.000
Rising        -5.6806      5.163     -1.100      0.271     -15.805
4.443
Falling        2.4960      2.521      0.990      0.322      -2.446
7.438
==============================================================================
Omnibus:                     1466.445   Durbin-Watson:
1.582
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
187089.919
Skew:                           1.474   Prob(JB):
0.00
Kurtosis:                      42.915   Cond. No.
1.93e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.93e+06. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

Multicollinearity

```
# Importing VIF to check for multicollinearity
from statsmodels.stats.outliers_influence import
variance_inflation_factor
```

```
X = df[[ 'All_Poverty',  'Med_Income', 'All_With', 'All_Without',
'Rising', 'Falling', 'Avg_Ann_Incidence']]

X.dropna(inplace=True)

<ipython-input-167-32f8c2353909>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  X.dropna(inplace=True)

X1 = X[['All_Poverty', 'Med_Income', 'All_With', 'All_Without',
'Rising',
       'Falling']]

# Getting the VIFs corresponding to each of the features and then
treating the one with the highest value
pd.DataFrame([[var, variance_inflation_factor(X1.values,
X1.columns.get_loc(var))] for var in X1.columns],
                   index=range(X1.shape[1]), columns=['Variable',
'VIF'])

      Variable        VIF
0  All_Poverty  25.654166
1   Med_Income   1.271954
2     All_With  15.627624
3  All_Without  16.031002
4       Rising   1.015347
5      Falling   1.201154
```

The model's performance is impacted by considerable multicollinearity, evident from the elevated value of the variable's VIF (Variance Inflation Factor). This situation could potentially result in coefficients that lack statistical significance.

```
X.drop('All_Poverty', axis = 1, inplace=True)
X1.drop('All_Poverty', axis = 1, inplace=True)

<ipython-input-170-5a3ca0a533f8>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  X.drop('All_Poverty', axis = 1, inplace=True)
<ipython-input-170-5a3ca0a533f8>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
```

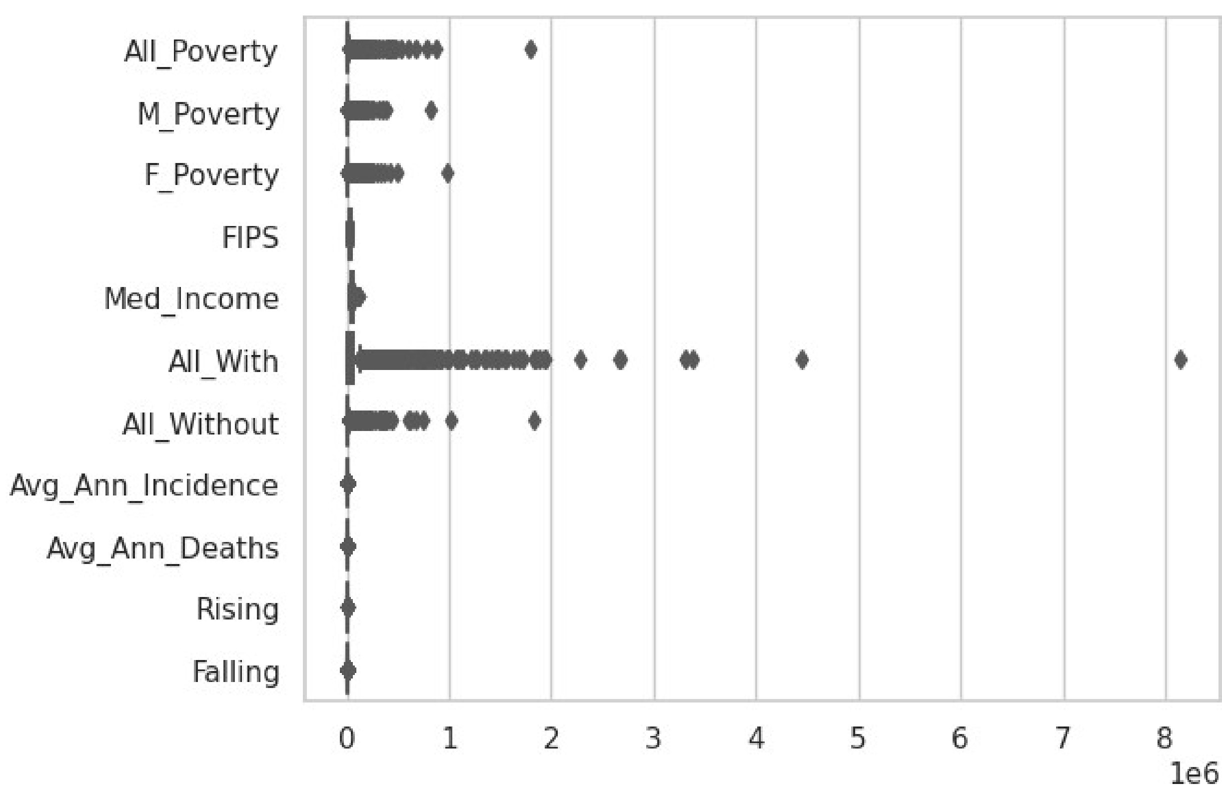
```
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X1.drop('All_Poverty', axis = 1, inplace=True)

pd.DataFrame([[var, variance_inflation_factor(X1.values, X1.columns.get_loc(var))] for var in X1.columns],
                   index=range(X1.shape[1]), columns=['Variable', 'VIF'])

      Variable       VIF
0   Med_Income  1.265045
1     All_With  9.776656
2  All_Without  8.926300
3       Rising  1.015175
4      Falling  1.199055

X.drop('All_Without', axis = 1, inplace=True)
X1.drop('All_Without', axis = 1, inplace=True)

<ipython-input-172-97aa2e8cd206>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X.drop('All_Without', axis = 1, inplace=True)
<ipython-input-172-97aa2e8cd206>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X1.drop('All_Without', axis = 1, inplace=True)

pd.DataFrame([[var, variance_inflation_factor(X1.values, X1.columns.get_loc(var))] for var in X1.columns],
                   index=range(X1.shape[1]), columns=['Variable', 'VIF'])

     Variable       VIF
0  Med_Income  1.207631
1    All_With  1.257105
2      Rising  1.015051
3     Falling  1.193283

# Final model after treating for multicollinearity
model1 = smf.ols(formula='Avg_Ann_Incidence ~Med_Income  + All_With + Rising + Falling', data=df).fit()
print(model1.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:      Avg_Ann_Incidence   R-squared:                       0.906
Model:                            OLS   Adj. R-squared:                  0.906
Method:                 Least Squares   F-statistic:                     7020.
Date:                Fri, 01 Sep 2023   Prob (F-statistic):               0.00
Time:                        09:53:58   Log-Likelihood:                -15759.
No. Observations:                2924   AIC:                         3.153e+04
Df Residuals:                    2919   BIC:                         3.156e+04
Df Model:                           4                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     24.4731      3.875      6.315      0.000      16.874      32.072
Med_Income    -0.0002   8.23e-05     -1.898      0.058      -0.000    5.17e-06
All_With       0.0006   3.84e-06    154.332      0.000       0.001       0.001
Rising        -6.8821      8.159     -0.844      0.399     -22.879       9.115
Falling       16.1143      4.122      3.909      0.000       8.032      24.196
==============================================================================
Omnibus:                     1260.365   Durbin-Watson:                   1.646
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1570186.457
Skew:                           0.370   Prob(JB):                         0.00
Kurtosis:                     116.523   Cond. No.                     2.42e+06
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 2.42e+06. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

Detecting Outliers

```
data_mod1 = df.copy()
#using IQR method
dat = data_mod1['Med_Income']
Q1 = dat.quantile(0.25)
Q3 = dat.quantile(0.75)
IQR = Q3 - Q1    #IQR is interquartile range.

filter = (dat >= Q1 - 3 * IQR) & (dat <= Q3 + 3 *IQR)
data_mod1 = data_mod1.loc[filter]
print(data_mod1.shape)

(3112, 14)

# Boxplot for the initial data
ax = sns.boxplot(data=df, orient="h", palette="Set2")
```



```python
# Fitting to Average Deaths
model2 = smf.ols(formula='Avg_Ann_Deaths ~ All_Poverty + Med_Income  +
All_With + All_Without + Rising + Falling', data=data_mod1).fit()
print(model2.summary())
```

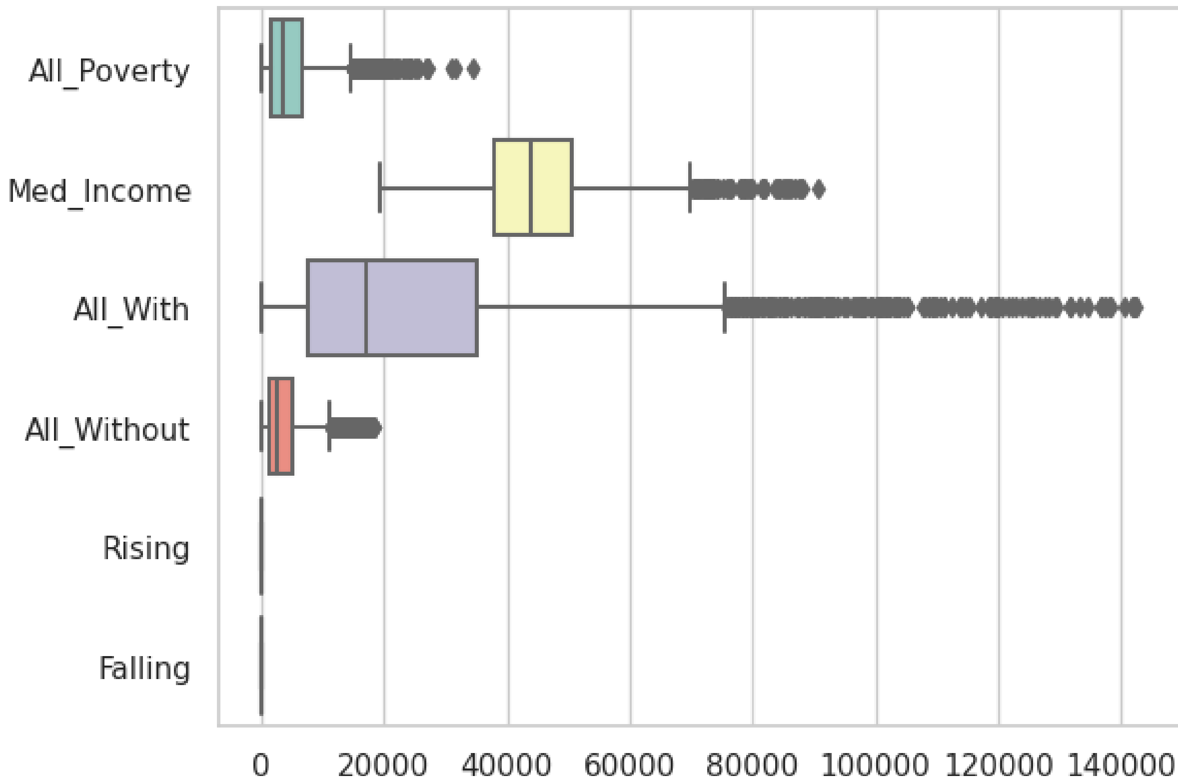
```
                            OLS Regression Results                            

==============================================================================
========
Dep. Variable:         Avg_Ann_Deaths   R-squared:                       
0.898
Model:                            OLS   Adj. R-squared:                  
0.898
Method:                 Least Squares   F-statistic:                     
4089.
Date:                Fri, 01 Sep 2023   Prob (F-statistic):              
0.00
Time:                        09:53:58   Log-Likelihood:                
-13494.
No. Observations:                2782   AIC:                         
2.700e+04
Df Residuals:                    2775   BIC:                         
2.704e+04
Df Model:                           6                                         

Covariance Type:            nonrobust                                         

==============================================================================
=========
                  coef    std err          t      P>|t|      [0.025      
0.975]
------------------------------------------------------------------------------
---------
Intercept      32.2407      2.773     11.628      0.000      26.804      
37.677
All_Poverty  7.577e-05   5.94e-05      1.276      0.202   -4.07e-05      
0.000
Med_Income     -0.0005   6.04e-05     -7.836      0.000      -0.001      
-0.000
All_With        0.0005    9.7e-06     54.729      0.000       0.001      
0.001
All_Without    -0.0004   4.88e-05     -8.435      0.000      -0.001      
-0.000
Rising         -5.6779      4.996     -1.136      0.256     -15.474      
4.119
Falling         1.0933      2.481      0.441      0.660      -3.772      
5.958
==============================================================================
========
Omnibus:                     1576.591   Durbin-Watson:                   
```

```
1.582
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
187369.073
Skew:                           1.716   Prob(JB):
0.00
Kurtosis:                      43.058   Cond. No.
1.87e+06
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.87e+06. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

```
data_mod1 = df.copy()
for i in ['All_Poverty', 'Med_Income', 'All_With', 'All_Without',
'Rising', 'Falling']:
    #using IQR method
    dat = data_mod1[i]
    Q1 = dat.quantile(0.25)
    Q3 = dat.quantile(0.75)
    IQR = Q3 - Q1    #IQR is interquartile range.

    filter = (dat >= Q1 - 3 * IQR) & (dat <= Q3 + 3 *IQR)
    data_mod1 = data_mod1.loc[filter]
    print(data_mod1.shape)
```

```
(2875, 14)
(2855, 14)
(2730, 14)
(2671, 14)
(2631, 14)
(2527, 14)
```

```
# Boxplot for the filtered data
ax = sns.boxplot(data=data_mod1[['All_Poverty', 'Med_Income',
'All_With', 'All_Without', 'Rising', 'Falling']], orient="h", palette=
'Set3')
```




```
fin_df = data_mod1
# Fitting to Average Deaths
model1 = smf.ols(formula='Avg_Ann_Incidence ~Med_Income  + All_With +
Rising + Falling', data=df).fit()
print(model1.summary())
```

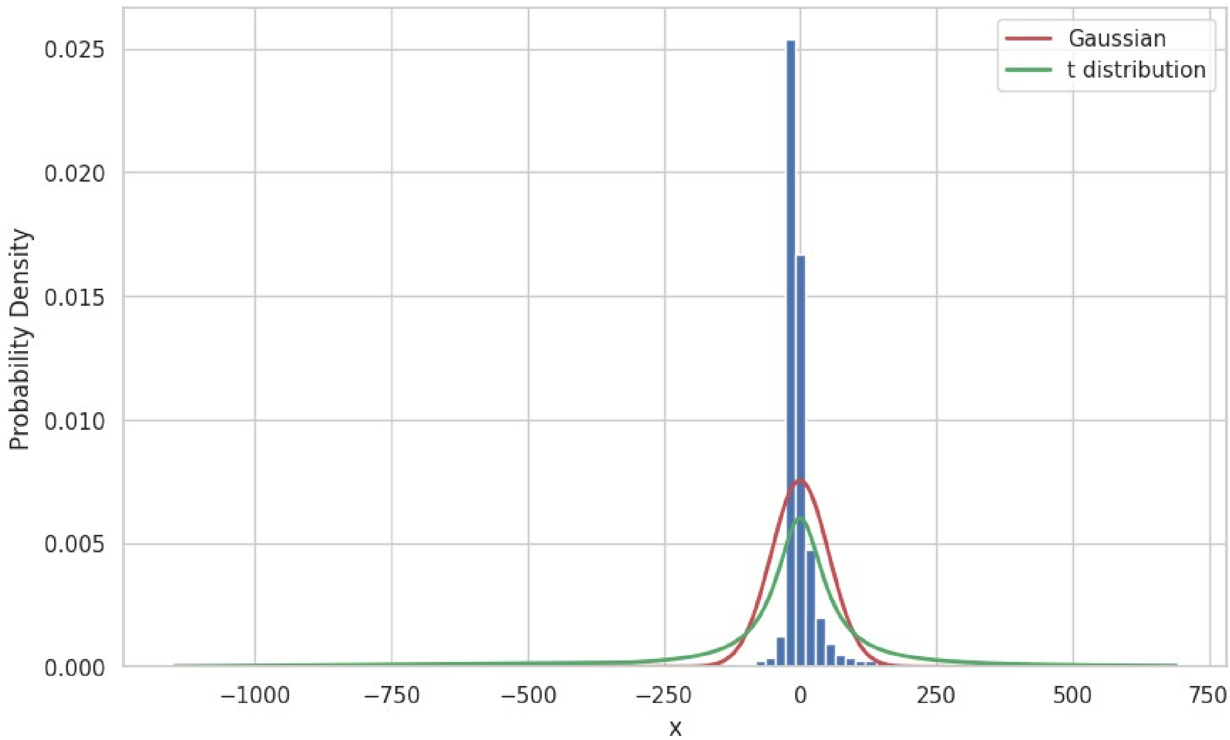
```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:      Avg_Ann_Incidence   R-squared:
0.906
Model:                            OLS   Adj. R-squared:
0.906
Method:                 Least Squares   F-statistic:
7020.
Date:                Fri, 01 Sep 2023   Prob (F-statistic):
0.00
Time:                        10:12:47   Log-Likelihood:
-15759.
No. Observations:                2924   AIC:
3.153e+04
Df Residuals:                    2919   BIC:
3.156e+04
Df Model:                           4
```

```
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     24.4731      3.875      6.315      0.000      16.874      32.072
Med_Income    -0.0002   8.23e-05     -1.898      0.058      -0.000    5.17e-06
All_With       0.0006   3.84e-06    154.332      0.000       0.001       0.001
Rising        -6.8821      8.159     -0.844      0.399     -22.879       9.115
Falling       16.1143      4.122      3.909      0.000       8.032      24.196
==============================================================================
Omnibus:                     1260.365   Durbin-Watson:                   1.646
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1570186.457
Skew:                           0.370   Prob(JB):                         0.00
Kurtosis:                     116.523   Cond. No.                     2.42e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.42e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

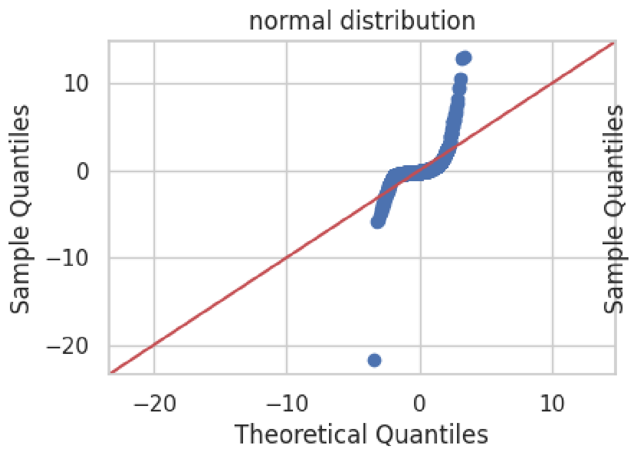
Normality of Errors

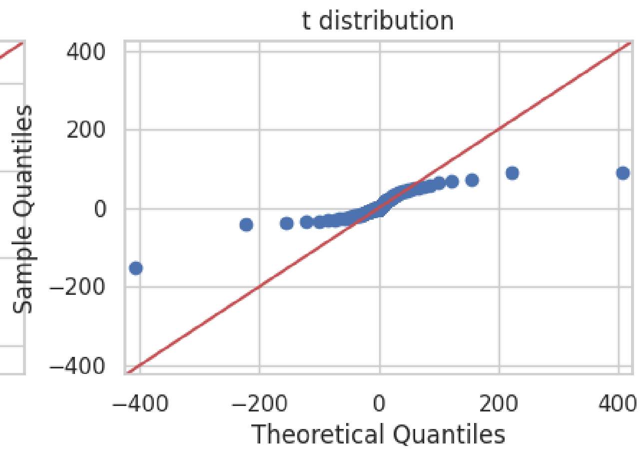
```
# histogram superimposed by normal curve
plt.figure(figsize=(10,6))
import scipy.stats as stats
mu = np.mean(model1.resid)
sigma = np.std(model1.resid)
pdf = stats.norm.pdf(sorted(model1.resid), mu, sigma)
pdf2 = stats.t.pdf(sorted(model1.resid), df = 1, loc = mu, scale=sigma,)
```

```
plt.xlabel('x')
plt.ylabel('Probability Density')
plt.hist(model1.resid, bins=100, density= True)
plt.plot(sorted(model1.resid), pdf, color='r', linewidth=2, label =
'Gaussian')
plt.plot(sorted(model1.resid), pdf2, color='g', linewidth=2, label =
't distribution')
plt.legend()
plt.show()
```




```
# QQplot
fig, [ax1, ax2] = plt.subplots(1,2, figsize=(10,3))
sm.qqplot(model1.resid, stats.norm, fit=True, line='45', ax=ax1)
ax1.set_title("normal distribution")
sm.qqplot(model1.resid, stats.t, fit=True, line='45', ax = ax2)
ax2.set_title("t distribution")

plt.show()
```

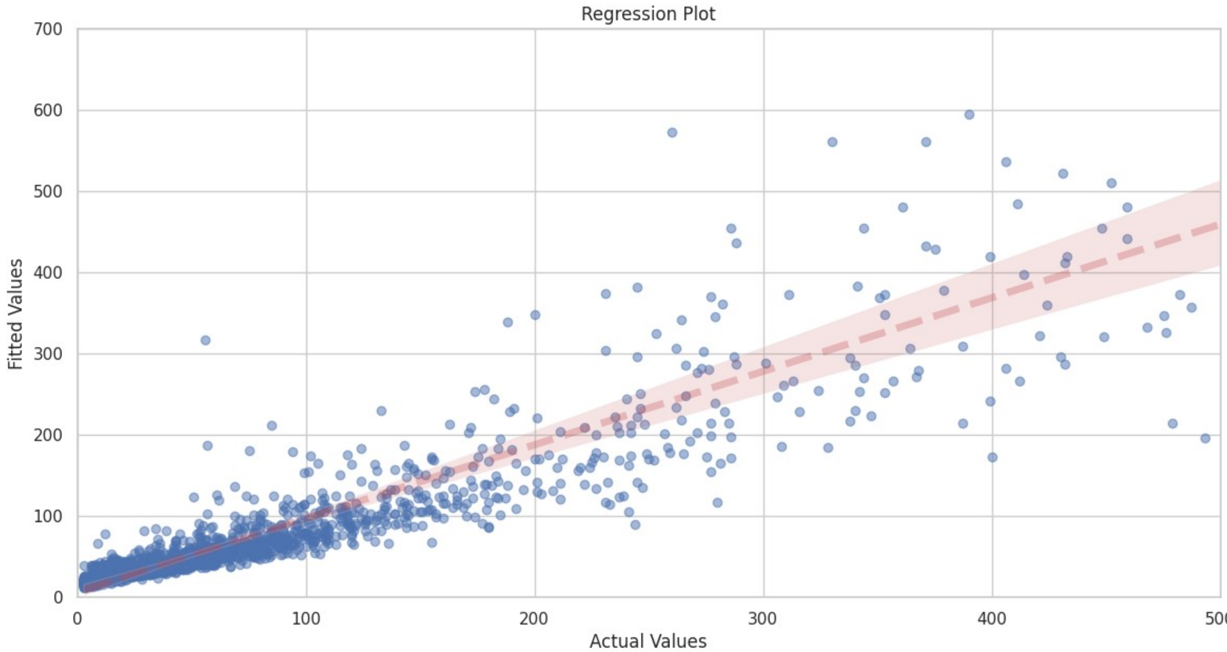




As we can see that the QQ plot for the normal distribution is not close to the straight line at the ends and it deviates to the top at the right and to the bottom at the left, we can say that the tails for the residuals are heavier than a normal distribution, hence on following that I tried using a t distribution, which gives a much better QQ plot and hence we can confirm that the residuals come from the t distribution !! Fatter tails suggest we have more number of outliers !

Heteroscedasticity

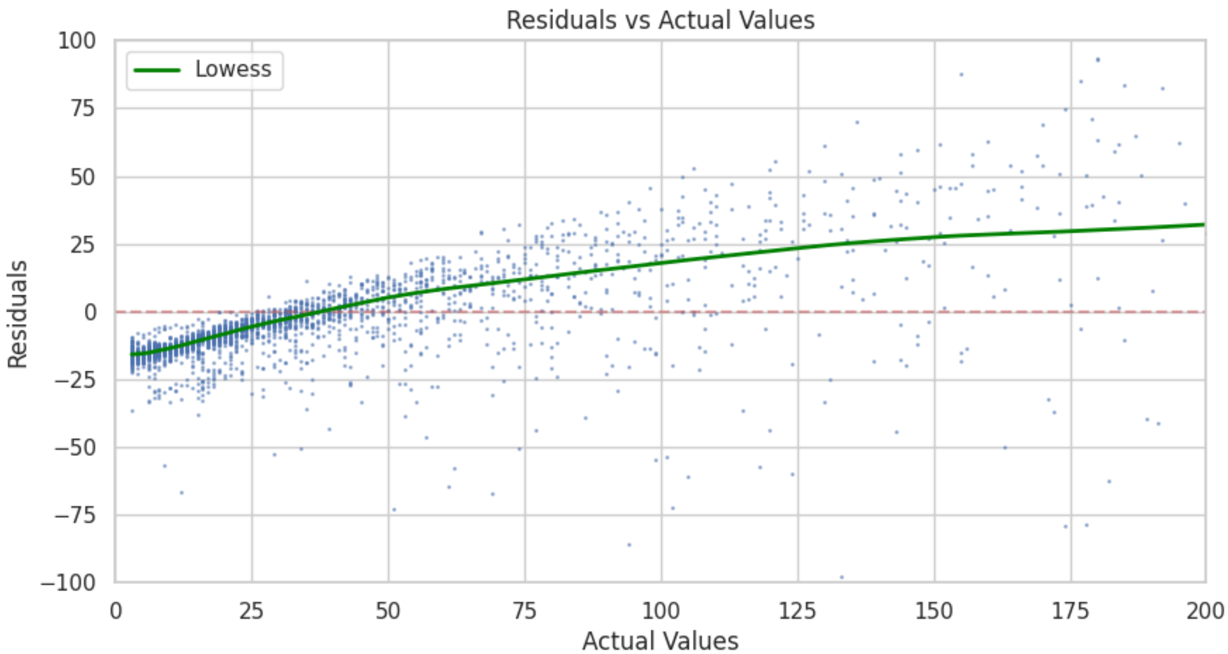
```
plt.figure(figsize=(14,7))
sns.regplot(x = X['Avg_Ann_Incidence'], y = model1.fittedvalues,
line_kws={'color':'r', 'alpha':0.3,
                                                              'linestyle':'--',
'linewidth':5},
                scatter_kws={'alpha':0.5})
plt.xlim(0,500)
plt.ylim(0,700)
plt.title('Regression Plot')
plt.xlabel('Actual Values')
plt.ylabel('Fitted Values')
plt.show()
print("Pearson R: ", stats.pearsonr(model1.fittedvalues,
X['Avg_Ann_Incidence']))
```




```
Pearson R:  PearsonRResult(statistic=0.9517556839499244, pvalue=0.0)
```

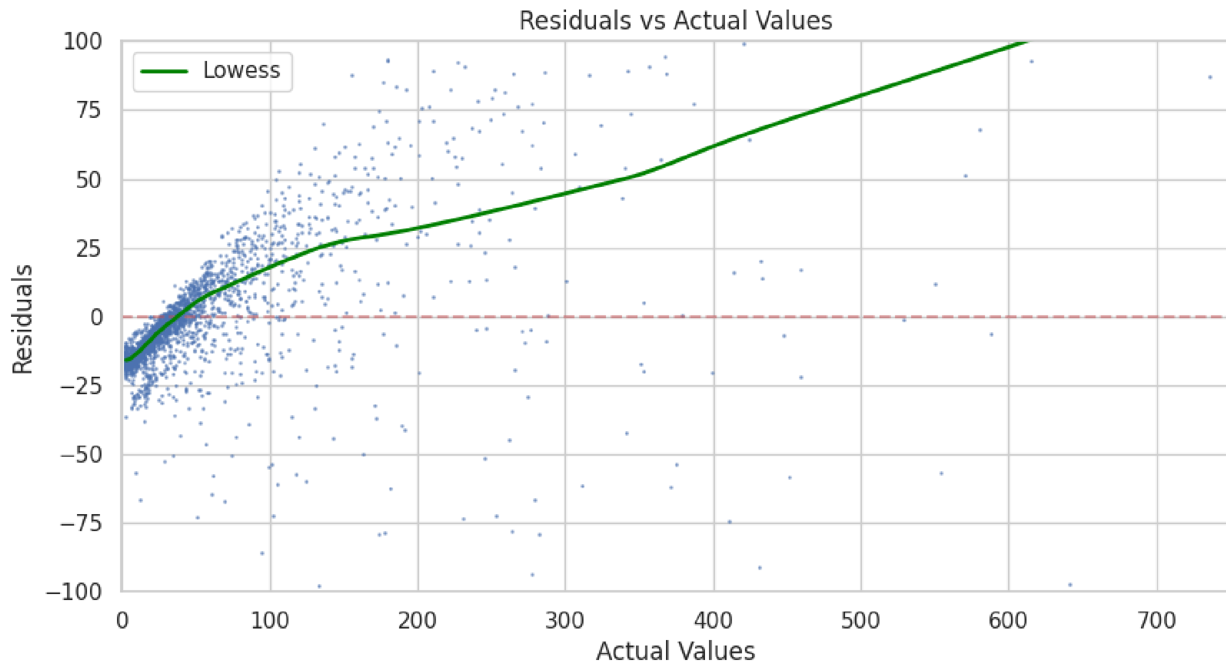
We can see that the point do lie close to our line and follow the trend which is also confirmed by the high Pearson Coefficient for Correlation !

```
y = X['Avg_Ann_Incidence']

# plot actual values versus residuals
from statsmodels.nonparametric.smoothers_lowess import lowess
ys = lowess(model1.resid.values, y, frac=0.2)
ys = pd.DataFrame(ys, index=range(len(ys)), columns=['a', 'b'])
ys = ys.sort_values(by='a')

fig, ax = plt.subplots(figsize=(10,5))
ax.set_xlim([0,200])
ax.set_ylim([-100,100])
plt.title('Residuals vs Actual Values')
plt.scatter(y, model1.resid, alpha=0.5, s=1)
plt.axhline(y=0, color='r', linestyle="--", alpha=0.5)
plt.xlabel("Actual Values")
plt.ylabel("Residuals")

plt.plot(ys.a, ys.b, c='green', linewidth=2, label="Lowess")
plt.legend()
plt.show()
print("Pearson R:", stats.pearsonr(y, model1.resid))
```




```
Pearson R: PearsonRResult(statistic=0.3068568364381449,
pvalue=8.553812422161798e-65)
```

```python
#Same plot from a higher view
from statsmodels.nonparametric.smoothers_lowess import lowess
ys = lowess(model1.resid.values, y, frac=0.2)
ys = pd.DataFrame(ys, index=range(len(ys)), columns=['a', 'b'])
ys = ys.sort_values(by='a')

fig, ax = plt.subplots(figsize=(10,5))
ax.set_xlim([0,750])
ax.set_ylim([-100,100])
plt.title('Residuals vs Actual Values')
plt.scatter(y, model1.resid, alpha=0.5, s=1)
plt.axhline(y=0, color='r', linestyle="--", alpha=0.5)
plt.xlabel("Actual Values")
plt.ylabel("Residuals")

plt.plot(ys.a, ys.b, c='green', linewidth=2, label="Lowess")
plt.legend()
plt.show()
print("Pearson R:", stats.pearsonr(y, model1.resid))
```




```
Pearson R: PearsonRResult(statistic=0.3068568364381449,
pvalue=8.553812422161798e-65)
```

From the above curve we can see that the Lowess curve is below the y=0 line for lower values which mean our model is overpredicting these values and then goes to the upper side for most of the residuals are about the y=0 line which means our model is underpredicting these values !

```
result = model1

# plot actual values versus residuals
plt.figure(figsize=(14,7))
plt.title('Scatter plot of Residuals vs Fitted Values')
plt.scatter(y=result.resid, x=result.fittedvalues, alpha=0.5, s=22)
plt.axhline(y=0, color='r', linestyle="--", alpha=0.5)
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.xlim(-10, 100)
plt.ylim(-200, 200)
plt.show()
```

We observe a distinctive cone-shaped pattern in the residual plot, which is a characteristic indication of heteroscedasticity. This phenomenon implies that as the fitted values increase, the variance of the residuals also increases. Consequently, our model is significantly affected by pronounced heteroscedasticity.

Heteroscedasticity refers to a systematic alteration in the dispersion of residuals across the spectrum of observed values. The challenge arises because ordinary least squares (OLS) regression assumes a consistent variance of residuals (homoscedasticity) across the data. Heteroscedasticity, alternatively spelled heteroskedasticity, is more common in datasets that exhibit considerable variation between the smallest and largest observed values. While several factors can contribute to the existence of heteroscedasticity, a prevalent explanation is that the variability of errors changes in proportion to a certain factor. This factor might even be a variable present in the model.

Although heteroscedasticity itself does not introduce bias in the coefficient estimations, it does reduce their precision. Decreased precision elevates the likelihood of coefficient estimates deviating further from the true population values. Notably, heteroscedasticity tends to yield p-values that appear smaller than they actually should be. This discrepancy emerges because heteroscedasticity inflates the variance of coefficient estimates, yet the OLS procedure remains oblivious to this inflation. Consequently, OLS calculates t-values and F-values using an underestimated level of variance. This issue can lead to the erroneous conclusion that a particular model term holds statistical significance when, in reality, it might not be statistically significant.