FinalProject530YoungDeborah

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1 Final Project DSC 530

"This data set has overdose deaths and overdose death rates for the different States in the United States for the years 2013 to 2019 and also has different population and income data for the States. In this notebook, we'll be looking at death rates across the different States over time, and seeing what trends we see in the data, and we'll also be looking at what characteristics of the States affect the death rates." (https://www.kaggle.com/code/craigchilvers/us-drug-overdose-eda-and-visualisation/notebook)

-Exploratory Data Analysis-

1.0.1 A minimum of 5 variables in your dataset used during your analysis (for help with selecting, the author made his selection on page 6 of your book). Consider what you think could have an impact on your question – remember this is never perfect, so don't be worried if you miss one (Chapter 1).

First, I'm importing libraries and datasets.

[400]:
```
import numpy as np
import pandas as pd
pd.plotting.register_matplotlib_converters()
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# save filepath
drug_overdose_filepath = '/Users/debane/Documents/MS Data Science/530 Data␣
↪Exploration & Analysis/Final Project/CDC Injury Center Drug Overdose Deaths.
↪csv'

# read the data and store data in DataFrame
# adding encoding to prevent a 'UnicodeDecodeError'
drug_overdose_data = pd.read_csv(drug_overdose_filepath, encoding =␣
↪"ISO-8859-1")
```

[401]:
```python
from os.path import basename, exists


def download(url):
    filename = basename(url)
    if not exists(filename):
        from urllib.request import urlretrieve

        local, _ = urlretrieve(url, filename)
        print("Downloaded " + local)


download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/
↪thinkstats2.py")
download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/thinkplot.
↪py")
```

[402]:
```python
import thinkstats2
import thinkplot
```

1.0.2 Describe what the 5 variables mean in the dataset (Chapter 1).

The dataset I've selected has 24 variables including state & state abbreviation, deaths & adjusted deats by year, poverty rate & Gini coeffcient of income inequlaity, GPP per capita and nominal GDP (determined by multiplying the current year quantity output by the current market price), urban population out of total population, population & population density per km². Throughout this exploration, I am following the author of "Opioids prescription in the US" on Kaggle.

The dataset is small enough to print the whole set in my notebook, so I included it here for reference, but I am commenting out this function so that it doesn't print in the output for the sake of the reader. I'll include the head of the data instead.

[403]:
```python
## print the data
#drug_overdose_data
drug_overdose_data.head()
```

[403]:
```
        State State Abbreviation  \
0     Alabama                 AL
1      Alaska                 AK
2     Arizona                 AZ
3    Arkansas                 AR
4  California                 CA

   2019 Age-adjusted Rate (per 100,000 population)  2019 Number of Deaths  \
0                                             16.3                    768
1                                             17.8                    132
2                                             26.8                   1907
3                                             13.5                    388
```

```
4                                          15.0                    6198

   2018 Age-adjusted Rate (per 100,000 population)  2018 Number of Deaths  \
0                                             16.6                    775
1                                             14.6                    110
2                                             23.8                   1670
3                                             15.7                    444
4                                             12.8                   5348

   2017 Age-adjusted Rate (per 100,000 population)  2017 Number of Deaths  \
0                                             18.0                  835.0
1                                             20.2                  147.0
2                                             22.2                 1532.0
3                                             15.5                  446.0
4                                             11.7                 4868.0

   2016 Age-adjusted Rate (per 100,000 population)  2016 Number of Deaths  \
0                                             16.2                  756.0
1                                             16.8                  128.0
2                                             20.3                 1382.0
3                                             14.0                  401.0
4                                             11.2                 4654.0

   …  2013 Age-adjusted Rate (per 100,000 population)  \
0  …                                             12.7
1  …                                             14.4
2  …                                             18.7
3  …                                             11.1
4  …                                             11.1

   2013 Number of Deaths  2019 Poverty rate (percent of persons in poverty)  \
0                    598                                               15.5
1                    105                                               10.1
2                   1222                                               13.5
3                    319                                               16.2
4                   4452                                               11.8

   Gini coefficient of income inequality  GDP per capita 2021  \
0                                 0.4847                48475
1                                 0.4081                69336
2                                 0.4713                55954
3                                 0.4719                47629
4                                 0.4899                83213

   GDP (nominal in millions of USD) 2021  \
0                                 243555
1                                  54020
```

```
2                                400156
3                                143438
4                               3290170

   Urban population as a percentage of the total population in 2010  \
0                                               59.0
1                                               66.0
2                                               89.8
3                                               56.2
4                                               95.0

   Population density per km²  Population  Land Area (km²)
0                   37.043399     4858979         131169.9
1                    0.499631      738432        1477953.4
2                   23.208362     6828065         294207.1
3                   22.098420     2978204         134770.0
4                   96.909425    39144818         403932.0

[5 rows x 24 columns]
```

1.0.3 Include the other descriptive characteristics about the variables: Mean, Mode, Spread, and Tails (Chapter 2).

I will use Pandas describe() function to review mean, standard deviation (spread), and percentiles. We will review the tails of distributions later.

[404]:
```
drug_overdose_data.describe()
```

[404]:
```
       2019 Age-adjusted Rate (per 100,000 population)  2019 Number of Deaths  \
count                                        51.000000              51.000000
mean                                         23.139216            1384.901961
std                                          10.184009            1407.558557
min                                           8.700000              79.000000
25%                                          14.650000             379.500000
50%                                          21.100000             870.000000
75%                                          30.050000            1998.000000
max                                          52.800000            6198.000000

       2018 Age-adjusted Rate (per 100,000 population)  2018 Number of Deaths  \
count                                        51.000000              51.000000
mean                                         22.039216            1320.921569
std                                          10.025389            1320.472171
min                                           6.900000              57.000000
25%                                          13.750000             331.000000
50%                                          21.200000             856.000000
75%                                          27.700000            1746.500000
max                                          51.500000            5348.000000
```

```
       2017 Age-adjusted Rate (per 100,000 population)  2017 Number of Deaths  \
count                                        50.000000              50.000000
mean                                         22.644000            1398.540000
std                                          10.731551            1425.809161
min                                           8.100000              68.000000
25%                                          13.950000             344.250000
50%                                          21.400000             991.000000
75%                                          29.000000            1833.000000
max                                          57.800000            5388.000000

       2016 Age-adjusted Rate (per 100,000 population)  2016 Number of Deaths  \
count                                        50.000000              50.000000
mean                                         20.964000            1267.260000
std                                           9.372077            1272.251047
min                                           6.400000              69.000000
25%                                          13.475000             332.500000
50%                                          19.500000             881.500000
75%                                          24.475000            1604.000000
max                                          52.000000            4728.000000

       2015 Age-adjusted Rate (per 100,000 population)  2015 Number of Deaths  \
count                                        50.000000              50.000000
mean                                         17.800000            1045.580000
std                                           6.977515            1006.145972
min                                           6.900000              61.000000
25%                                          12.925000             314.750000
50%                                          16.100000             748.500000
75%                                          21.125000            1297.750000
max                                          41.500000            4659.000000

       …  2013 Age-adjusted Rate (per 100,000 population)  \
count  …                                        51.000000
mean   …                                        14.870588
std    …                                         5.051625
min    …                                         2.800000
25%    …                                        11.300000
50%    …                                        14.500000
75%    …                                        17.650000
max    …                                        32.200000

       2013 Number of Deaths  \
count              51.000000
mean              862.392157
std               849.536958
min                20.000000
25%               224.000000
```

```
50%              614.000000
75%             1089.500000
max             4452.000000

       2019 Poverty rate (percent of persons in poverty)  \
count                                          51.000000
mean                                           12.190196
std                                             2.736513
min                                             7.300000
25%                                            10.100000
50%                                            11.800000
75%                                            13.500000
max                                            20.600000

       Gini coefficient of income inequality  GDP per capita 2021  \
count                              51.000000             51.00000
mean                                0.466165          67222.45098
std                                 0.023455          24620.89611
min                                 0.406300          41796.00000
25%                                 0.452050          55591.00000
50%                                 0.468000          62331.00000
75%                                 0.479500          71626.50000
max                                 0.542000         219550.00000

       GDP (nominal in millions of USD) 2021  \
count                           5.100000e+01
mean                            4.431309e+05
std                             5.750120e+05
min                             3.608900e+04
25%                             1.010660e+05
50%                             2.533150e+05
75%                             5.728645e+05
max                             3.290170e+06

       Urban population as a percentage of the total population in 2010  \
count                                          51.000000
mean                                           74.103922
std                                            14.887471
min                                            38.700000
25%                                            65.400000
50%                                            74.200000
75%                                            87.550000
max                                           100.000000

       Population density per km²    Population  Land Area (km²)
count                   51.000000  5.100000e+01     5.100000e+01
mean                   159.322134  6.302348e+06     1.793738e+05
```

```
std                      593.702919  7.201114e+06     2.215210e+05
min                        0.499631  5.861070e+05     1.580000e+02
25%                       18.484280  1.749529e+06     8.633595e+04
50%                       41.144896  4.425092e+06     1.388881e+05
75%                       87.745439  6.999208e+06     2.089939e+05
max                     4254.607595  3.914482e+07     1.477953e+06

[8 rows x 22 columns]
```

To clean up the data, I want to deal with any missing values first.

[405]:
```
# dataset columns, values, types
drug_overdose_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 24 columns):
 #   Column                                                       Non-Null
Count  Dtype
---  ------
--------------  -----
 0   State                                                        51 non-
null     object
 1   State Abbreviation                                           51 non-
null     object
 2   2019 Age-adjusted Rate (per 100,000 population)              51 non-
null     float64
 3   2019 Number of Deaths                                        51 non-
null     int64
 4   2018 Age-adjusted Rate (per 100,000 population)              51 non-
null     float64
 5   2018 Number of Deaths                                        51 non-
null     int64
 6   2017 Age-adjusted Rate (per 100,000 population)              50 non-
null     float64
 7   2017 Number of Deaths                                        50 non-
null     float64
 8   2016 Age-adjusted Rate (per 100,000 population)              50 non-
null     float64
 9   2016 Number of Deaths                                        50 non-
null     float64
 10  2015 Age-adjusted Rate (per 100,000 population)              50 non-
null     float64
 11  2015 Number of Deaths                                        50 non-
null     float64
 12  2014 Age-adjusted Rate (per 100,000 population)              51 non-
null     float64
 13  2014 Number of Deaths                                        51 non-
```

```
null      int64
 14  2013 Age-adjusted Rate (per 100,000 population)                   51 non-
null      float64
 15  2013 Number of Deaths                                             51 non-
null      int64
 16  2019 Poverty rate (percent of persons in poverty)                 51 non-
null      float64
 17  Gini coefficient of income inequality                             51 non-
null      float64
 18  GDP per capita 2021                                               51 non-
null      int64
 19  GDP (nominal in millions of USD) 2021                             51 non-
null      int64
 20  Urban population as a percentage of the total population in 2010  51 non-
null      float64
 21  Population density per km²                                        51 non-
null      float64
 22  Population                                                        51 non-
null      int64
 23  Land Area (km²)                                                   51 non-
null      float64
dtypes: float64(15), int64(7), object(2)
memory usage: 9.7+ KB
```

From the above information, we can see that there are some null values throughout the data, so I will use the Pandas insull() function to find these.

[406]:
```
# look for missing data
drug_overdose_data.isnull().values.any()
```

[406]:
```
True
```

[407]:
```
# use insull() function to sum null values
drug_overdose_data.isnull().sum()
```

[407]:
```
State                                                                0
State Abbreviation                                                   0
2019 Age-adjusted Rate (per 100,000 population)                      0
2019 Number of Deaths                                                0
2018 Age-adjusted Rate (per 100,000 population)                      0
2018 Number of Deaths                                                0
2017 Age-adjusted Rate (per 100,000 population)                      1
2017 Number of Deaths                                                1
2016 Age-adjusted Rate (per 100,000 population)                      1
2016 Number of Deaths                                                1
2015 Age-adjusted Rate (per 100,000 population)                      1
2015 Number of Deaths                                                1
2014 Age-adjusted Rate (per 100,000 population)                      0
```

```
2014 Number of Deaths                                                    0
2013 Age-adjusted Rate (per 100,000 population)                          0
2013 Number of Deaths                                                    0
2019 Poverty rate (percent of persons in poverty)                        0
Gini coefficient of income inequality                                    0
GDP per capita 2021                                                      0
GDP (nominal in millions of USD) 2021                                    0
Urban population as a percentage of the total population in 2010         0
Population density per km²                                               0
Population                                                               0
Land Area (km²)                                                          0
dtype: int64
```

This dataset includes data for all 50 States and Washington D.C. (District of Columbia). In the fully printed dataset, we can see that the missing data is in the Overdose deaths from the District of Columbia from 2015-2017, so we'll drop the District of Columbia when we need to use 2015-2017 data. In order to remove these values, I need to do some other clean up first.

Change the dates into a date format using Pandas .rename function

[408]:
```
drug_overdose_data.rename(columns={'2019 Age-adjusted Rate (per 100,000␣
↪population)': '2019', '2018 Age-adjusted Rate (per 100,000 population)':␣
↪'2018', '2017 Age-adjusted Rate (per 100,000 population)': '2017', '2016␣
↪Age-adjusted Rate (per 100,000 population)': '2016', '2015 Age-adjusted Rate␣
↪(per 100,000 population)': '2015', '2014 Age-adjusted Rate (per 100,000␣
↪population)': '2014', '2013 Age-adjusted Rate (per 100,000 population)':␣
↪'2013'}, inplace=True)
```

[409]:
```
# check it - (commenting out for sake of brevity)
# drug_overdose_data.head()
```

Now I want to review the deaths in each state by year.

[410]:
```
# select years
drug_overdose_features = ['State', '2019', '2018', '2017', '2016', '2015',␣
↪'2014', '2013']
selected_drug_overdose_data = drug_overdose_data[drug_overdose_features]

# print the table (commented this out so that the whole table doesn't have to␣
↪print - the NaN values are in row 9)

#pd.set_option('display.max_rows', None)
#selected_drug_overdose_data.head(100)
selected_drug_overdose_data.head(9)
```

[410]:

	State	2019	2018	2017	2016	2015	2014	2013
0	Alabama	16.3	16.6	18.0	16.2	15.7	15.2	12.7
1	Alaska	17.8	14.6	20.2	16.8	16.0	16.8	14.4

```
2                Arizona  26.8  23.8  22.2  20.3  19.0  18.2  18.7
3               Arkansas  13.5  15.7  15.5  14.0  13.8  12.6  11.1
4             California  15.0  12.8  11.7  11.2  11.3  11.1  11.1
5               Colorado  18.0  16.8  17.6  16.6  15.4  16.3  15.5
6            Connecticut  34.7  30.7  30.9  27.4  22.1  17.6  16.0
7               Delaware  48.0  43.8  37.0  30.8  22.0  20.9  18.7
8   District of Columbia  43.2  35.4   NaN   NaN   NaN  14.2  15.0
```

Now I can remove the NA values using pandas .dropna()

[411]:
```
# Remove District of Columbia missing values
new_selected_drug_overdose_data = selected_drug_overdose_data.dropna()

# print the table (commented this out so that the whole table doesn't have to␣
↪print - the DC row is removed)
#pd.set_option('display.max_rows', None)
#new_selected_drug_overdose_data.head(100)
```

-Visualizations-

I'd like to see the trends over the years to inform further analysis. I can use Seaborn to make a beautiful line graph, but since the data has the states as the row names and the years as the column names, I'll have to reverse this to have the overdose rates over time for each state, so I'll transpose the data table.

[412]:
```
# first, set the index to the State
new_selected_drug_overdose_data.set_index("State", inplace=True)
new_selected_drug_overdose_data.rename_axis(None, axis = 0, inplace = True)
new_selected_drug_overdose_data.head()
```

[412]:
```
            2019  2018  2017  2016  2015  2014  2013
Alabama     16.3  16.6  18.0  16.2  15.7  15.2  12.7
Alaska      17.8  14.6  20.2  16.8  16.0  16.8  14.4
Arizona     26.8  23.8  22.2  20.3  19.0  18.2  18.7
Arkansas    13.5  15.7  15.5  14.0  13.8  12.6  11.1
California  15.0  12.8  11.7  11.2  11.3  11.1  11.1
```

[413]:
```
#The transpose function will do the rest!
transposed_drug_overdose_data = new_selected_drug_overdose_data.transpose()
transposed_drug_overdose_data.head()
```

[413]:
```
      Alabama  Alaska  Arizona  Arkansas  California  Colorado  Connecticut  \
2019     16.3    17.8     26.8      13.5        15.0      18.0         34.7
2018     16.6    14.6     23.8      15.7        12.8      16.8         30.7
2017     18.0    20.2     22.2      15.5        11.7      17.6         30.9
2016     16.2    16.8     20.3      14.0        11.2      16.6         27.4
2015     15.7    16.0     19.0      13.8        11.3      15.4         22.1
```

```
      Delaware  Florida  Georgia  ...  South Dakota  Tennessee  Texas  Utah  \
2019      48.0     25.5     13.1  ...          10.5       31.2   10.8  18.9
2018      43.8     22.8     13.2  ...           6.9       27.5   10.4  21.2
2017      37.0     25.1     14.7  ...           8.5       26.6   10.5  22.3
2016      30.8     23.7     13.3  ...           8.4       24.5   10.1  22.4
2015      22.0     16.2     12.7  ...           8.4       22.2    9.4  23.4

      Vermont  Virginia  Washington  West Virginia  Wisconsin  Wyoming
2019     23.8      18.3        15.8           52.8       21.1     14.1
2018     26.6      17.1        14.8           51.5       19.2     11.1
2017     23.2      17.9        15.2           57.8       21.2     12.2
2016     22.2      16.7        14.5           52.0       19.3     17.6
2015     16.7      12.4        14.7           41.5       15.5     16.4

[5 rows x 50 columns]
```

The table has the years in descending order, so I'll sort it so they are in chronological order.

[414]:
```
transposed_drug_overdose_data.sort_index()
```

[414]:
```
      Alabama  Alaska  Arizona  Arkansas  California  Colorado  Connecticut  \
2013     12.7    14.4     18.7      11.1        11.1      15.5         16.0
2014     15.2    16.8     18.2      12.6        11.1      16.3         17.6
2015     15.7    16.0     19.0      13.8        11.3      15.4         22.1
2016     16.2    16.8     20.3      14.0        11.2      16.6         27.4
2017     18.0    20.2     22.2      15.5        11.7      17.6         30.9
2018     16.6    14.6     23.8      15.7        12.8      16.8         30.7
2019     16.3    17.8     26.8      13.5        15.0      18.0         34.7

      Delaware  Florida  Georgia  ...  South Dakota  Tennessee  Texas  Utah  \
2013      18.7     12.6     10.8  ...           6.9       18.1    9.3  22.1
2014      20.9     13.2     11.9  ...           7.8       19.5    9.7  22.4
2015      22.0     16.2     12.7  ...           8.4       22.2    9.4  23.4
2016      30.8     23.7     13.3  ...           8.4       24.5   10.1  22.4
2017      37.0     25.1     14.7  ...           8.5       26.6   10.5  22.3
2018      43.8     22.8     13.2  ...           6.9       27.5   10.4  21.2
2019      48.0     25.5     13.1  ...          10.5       31.2   10.8  18.9

      Vermont  Virginia  Washington  West Virginia  Wisconsin  Wyoming
2013     15.1      10.2        13.4           32.2       15.0     17.2
2014     13.9      11.7        13.3           35.5       15.1     19.4
2015     16.7      12.4        14.7           41.5       15.5     16.4
2016     22.2      16.7        14.5           52.0       19.3     17.6
2017     23.2      17.9        15.2           57.8       21.2     12.2
2018     26.6      17.1        14.8           51.5       19.2     11.1
2019     23.8      18.3        15.8           52.8       21.1     14.1
```

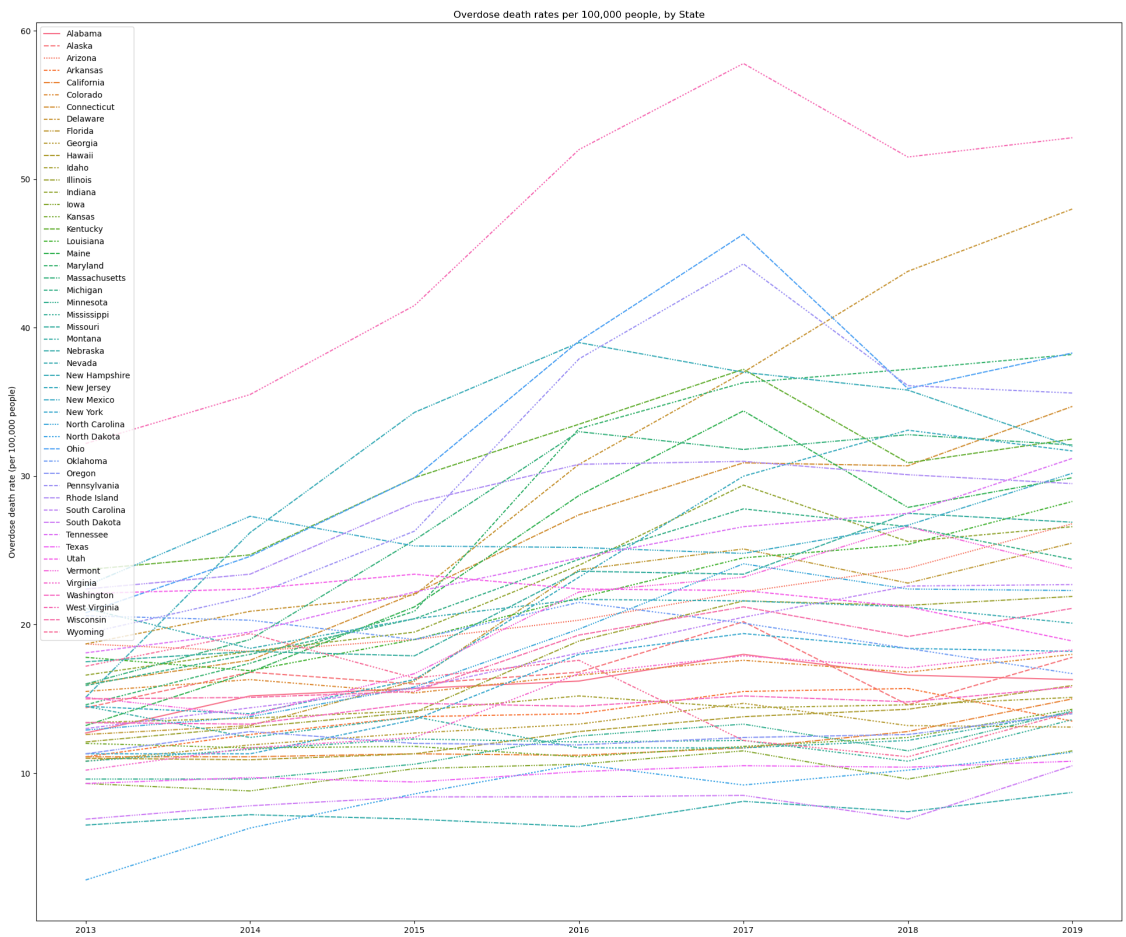
```
[7 rows x 50 columns]
```

I'm going to save this as a new dataframe now that everything has been transformed.

[415]:
```
sorted_drug_overdose_data = transposed_drug_overdose_data.sort_index()
```

[416]:
```
# set the width and height of the figure
plt.figure(figsize=(24,20))

# add title
plt.title("Overdose death rates per 100,000 people, by State")

# add label for vertical axis
plt.ylabel("Overdose death rate (per 100,000 people)")

# plot graph
sns.lineplot(data = sorted_drug_overdose_data)
```

[416]:
```
<AxesSubplot:title={'center':'Overdose death rates per 100,000 people, by
State'}, ylabel='Overdose death rate (per 100,000 people)'>
```



Now I can see that the overdose rate was dramatically increasing over time 2013-2017, but the rates have begun dropping since then. Although we know that the epidemic became worse in 2020, we don't have the data for 2020-2022 here, so we will continue the exploration with a hopeful mindset.

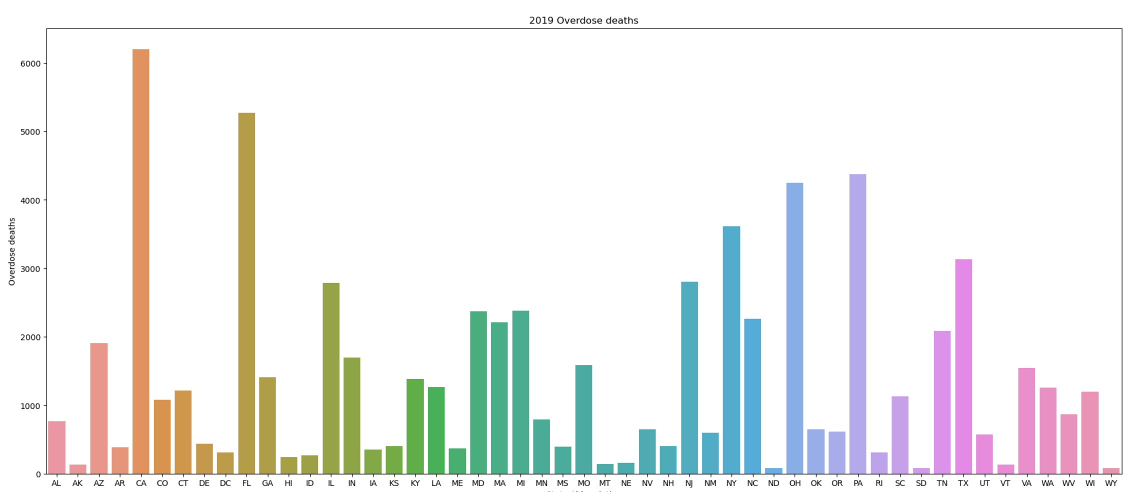
Histograms

1.0.4 Include a histogram of each of the 5 variables – in your summary and analysis, identify any outliers and explain the reasoning for them being outliers and how you believe they should be handled (Chapter 2).

I'm starting with a histogram for overdoses by state using Matplotlib with Seaborn. This plot uses the most recent data (2019) to get a general idea of distribution of overdoses throughout the country.

[417]:
```
# set the width and height of the figure
plt.figure(figsize=(24,10))

# add title
plt.title("2019 Overdose deaths")

# bar chart showing 2019 Overdose deaths, by State
sns.barplot(x=drug_overdose_data['State Abbreviation'],␣
 ↪y=drug_overdose_data['2019 Number of Deaths'])

# add label for vertical axis
plt.ylabel("Overdose deaths")
```

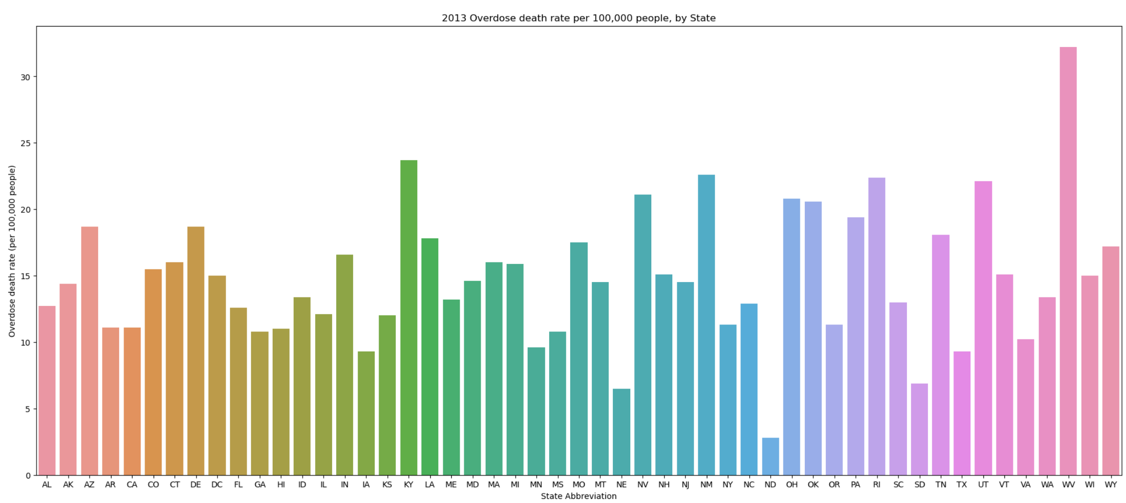
[417]:
```
Text(0, 0.5, 'Overdose deaths')
```



We can see that the states with the large populations have the highest rates of overdoses , which makes sense, and lets us know that reducing the overdoses in states with the highest rates ((California, Florida, New York, Ohio, Pennsylvania,and Texas) would be influential in reducing overdose rates, but this dosen't necessarily tell us where occurences are most prevalent. To see a more clear representation, I'll use the same method to review overdose rates per population, starting furthest in the past - 2013.

[418]:
```
# Set the width and height of the figure
plt.figure(figsize=(24,10))

# Add title
plt.title("2013 Overdose death rate per 100,000 people, by State")

# Bar chart showing 2013 Overdose death rate per 100,000 people, by State
sns.barplot(x=drug_overdose_data['State Abbreviation'],␣
 ↪y=drug_overdose_data['2013'])

# Add label for vertical axis
plt.ylabel("Overdose death rate (per 100,000 people)")
```

[418]:
```
Text(0, 0.5, 'Overdose death rate (per 100,000 people)')
```



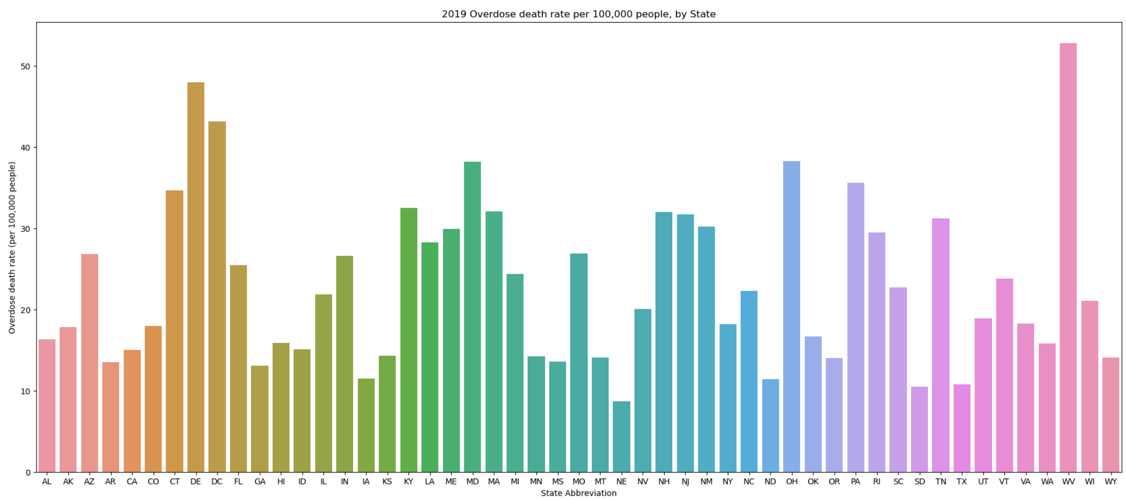
Back in 2013 the hardest hit region was the Appalachias (West Virginia, Kentucky, Ohio, Pennsylvania), areas of the South West near Las Vegas (New Mexico, Nevada, Arizona, Utah) and parts of New England (Rhode Island, New Hampshire).

We also see some sparsely populated rural States doing relatively well (North Dakota, South Dakota and Nebraska).

Now I'll look at the most recent data (2019)

[419]:
```
# Set the width and height of the figure
plt.figure(figsize=(24,10))

# Add title
plt.title("2019 Overdose death rate per 100,000 people, by State")

# Bar chart showing 2019 Overdose death rate per 100,000 people, by State
sns.barplot(x=drug_overdose_data['State Abbreviation'],␣
↪y=drug_overdose_data['2019'])

# Add label for vertical axis
plt.ylabel("Overdose death rate (per 100,000 people)")
```

[419]:
```
Text(0, 0.5, 'Overdose death rate (per 100,000 people)')
```

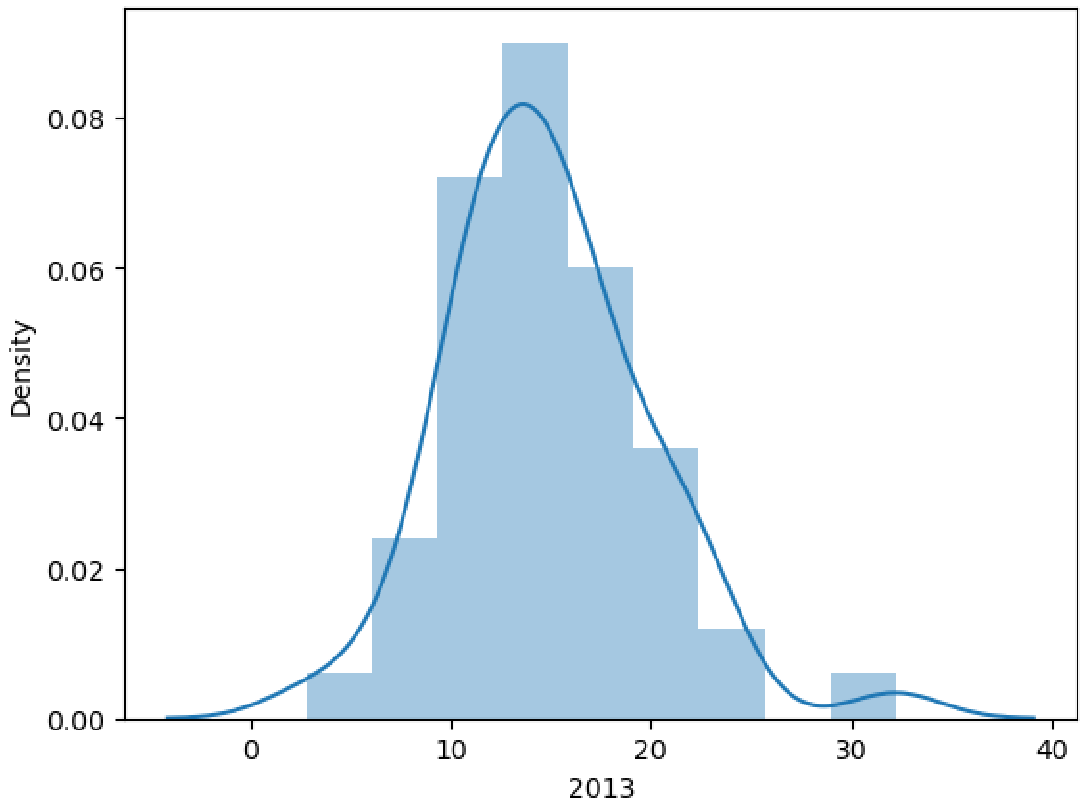


By 2019 the situation had gotten much worse across the board. The situation in the Appalachias had deteriorated significantly from it's already high starting rate. Also striking is the deterioration already the US Capitol, which significant increases for the Delaware, the District of Columbia and Maryland.

Histograms using kernel density

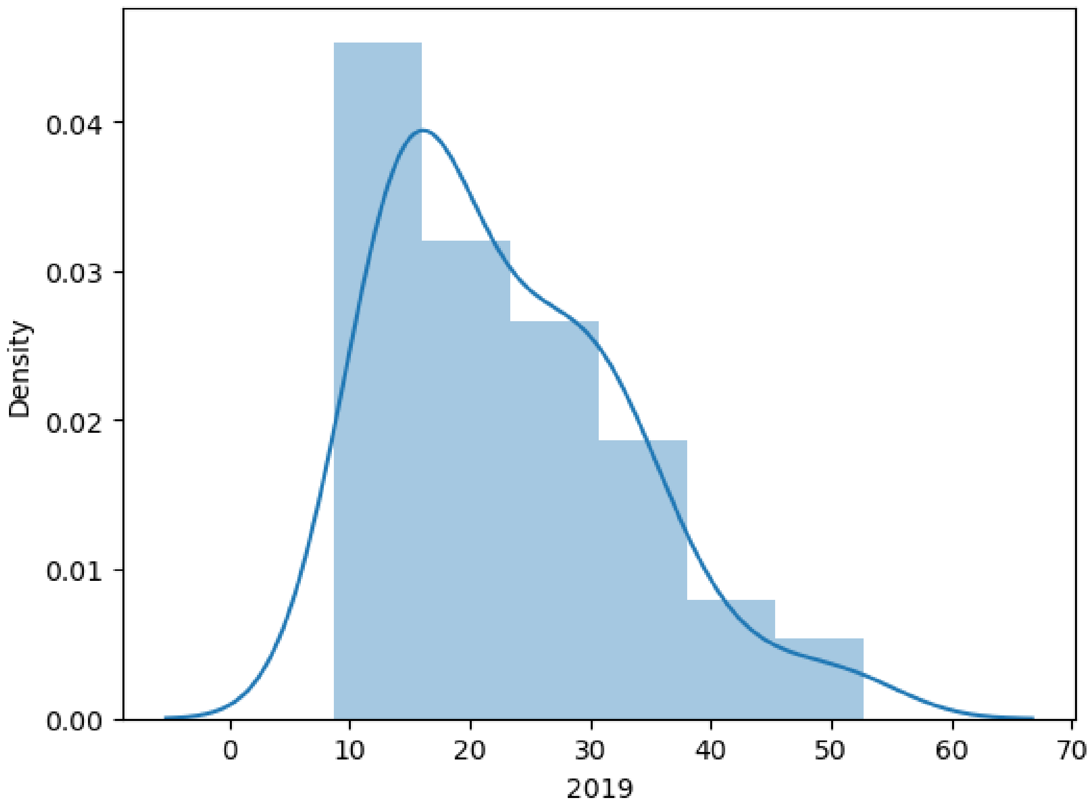
[420]:
```
sns.distplot(a=drug_overdose_data['2013'], kde=True)
```

[420]:
```
<AxesSubplot:xlabel='2013', ylabel='Density'>
```




```
[421]: sns.distplot(a=drug_overdose_data['2019'], kde=True)
```

```
[421]: <AxesSubplot:xlabel='2019', ylabel='Density'>
```

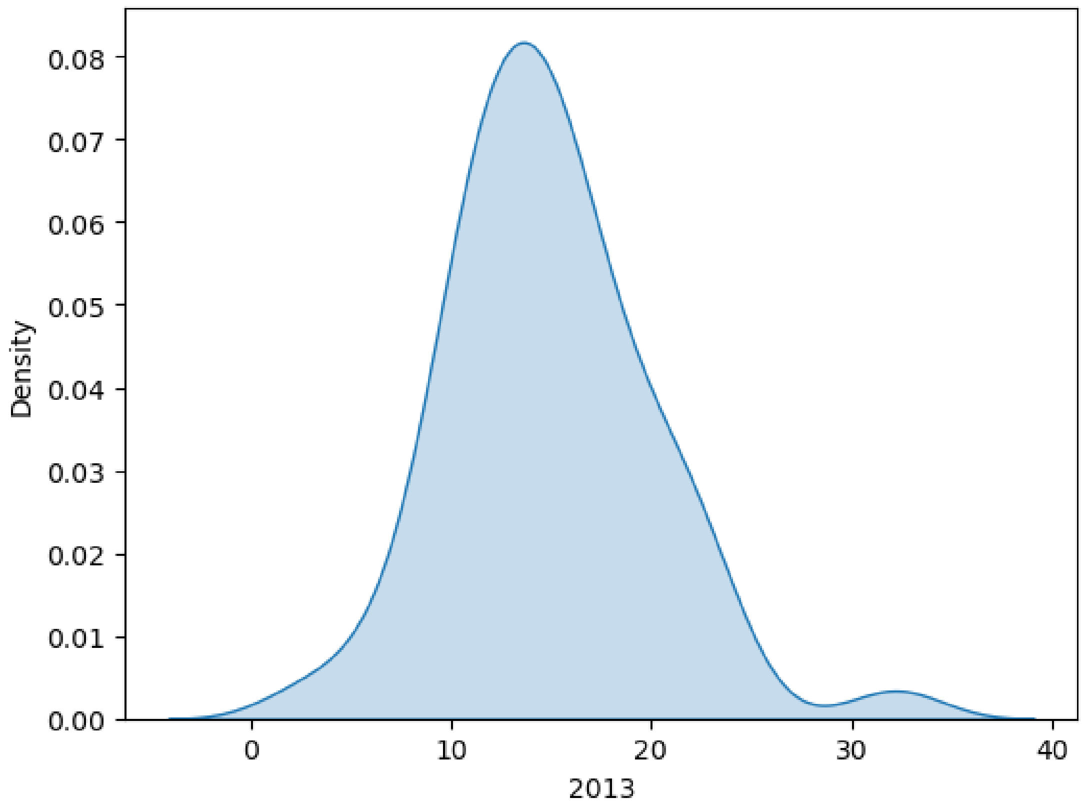


The number of States with lower rates (<10) has decreased and the number with higher rates (>20) has increased and there is a fat tail on the right hand side of the distribution (more States with very high rates).

Kernel density estimates (KDEs) (smoothed histograms)

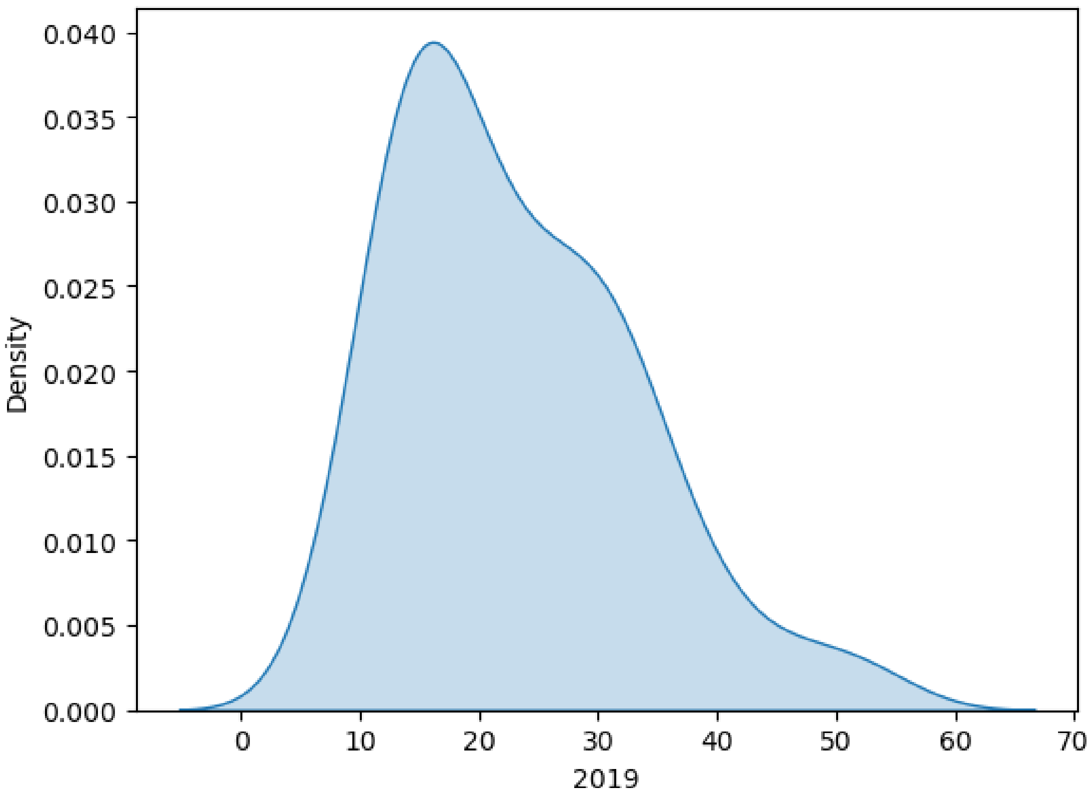
[422]:
```
#KDE plot
# 2013
sns.kdeplot(data=drug_overdose_data['2013'], shade=True)
```

[422]:
```
<AxesSubplot:xlabel='2013', ylabel='Density'>
```



[423]:
```
# 2019
sns.kdeplot(data=drug_overdose_data['2019'], shade=True)
```

[423]:
```
<AxesSubplot:xlabel='2019', ylabel='Density'>
```



1.0.5 Using pg. 29 of your text as an example, compare two scenarios in your data using a PMF. Reminder, this isn't comparing two variables against each other – it is the same variable, but a different scenario. Almost like a filter. The example in the book is first babies compared to all other babies, it is still the same variable, but breaking the data out based on criteria we are exploring (Chapter 3).

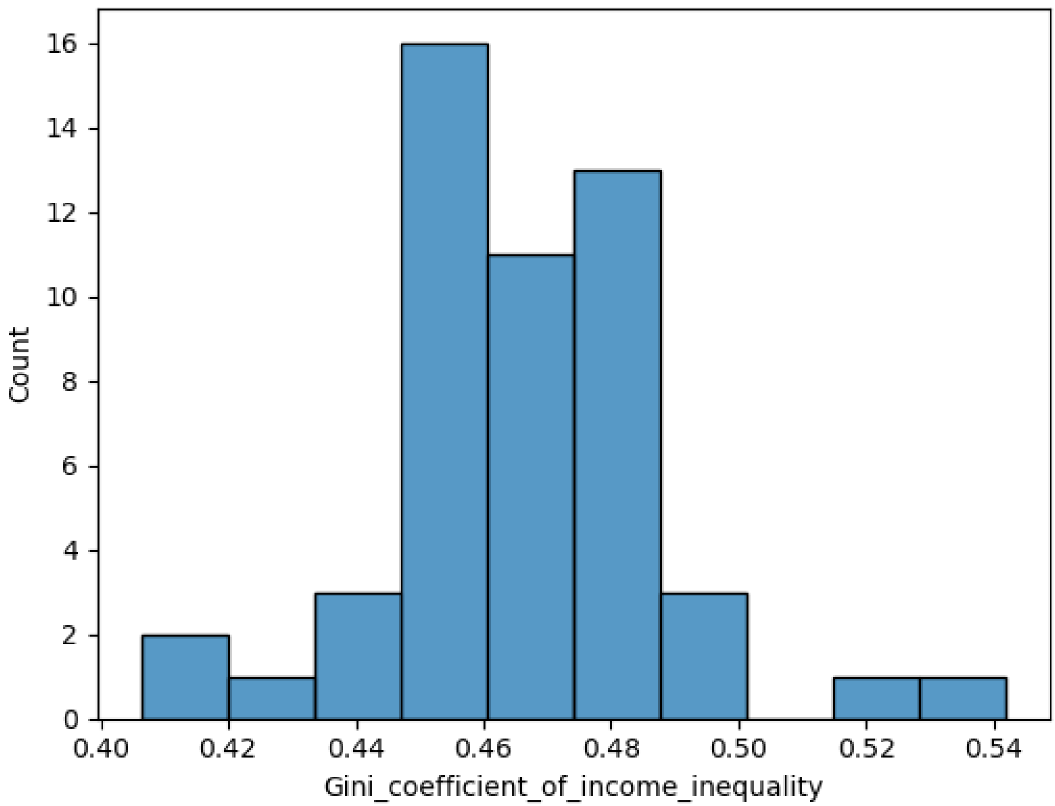
I want to determine the probabilty of an overdose occuring (using the age-adjusted Rate (per 100,000 population)) so that we can see where is the highest probability of an overdose occuring. First I will rank the rates as percentile.

[424]:
```
#clean up dataframe and column names for easier reference
df = drug_overdose_data
df.columns = df.columns.str.replace(' ', '_')
df.columns = df.columns.str.replace('2', 'x2')
df.columns
```

[424]:
```
Index(['State', 'State_Abbreviation', 'x2019', 'x2019_Number_of_Deaths',
       'x2018', 'x2018_Number_of_Deaths', 'x2017', 'x2017_Number_of_Deaths',
       'x2016', 'x2016_Number_of_Deaths', 'x2015', 'x2015_Number_of_Deaths',
       'x2014', 'x2014_Number_of_Deaths', 'x2013', 'x2013_Number_of_Deaths',
```

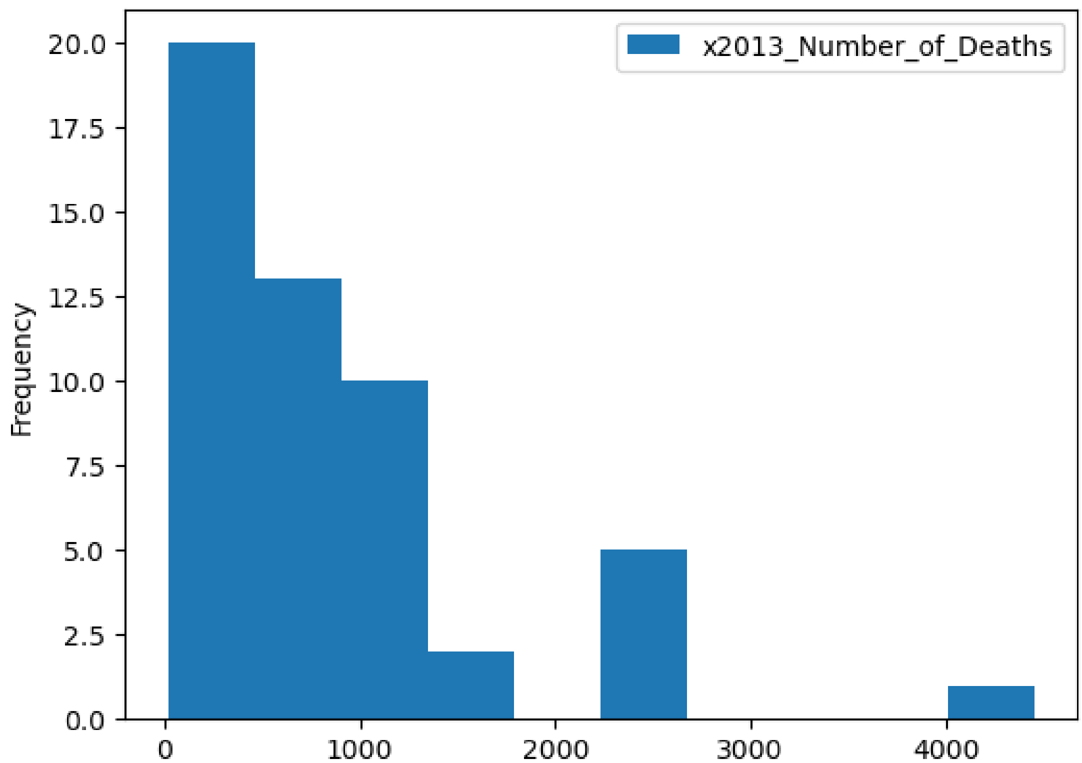
```
'x2019_Poverty_rate_(percent_of_persons_in_poverty)',
'Gini_coefficient_of_income_inequality', 'GDP_per_capita_x20x21',
'GDP_(nominal_in_millions_of_USD)_x20x21',
'Urban_population_as_a_percentage_of_the_total_population_in_x2010',
'Population_density_per_km²', 'Population', 'Land_Area_(km²)'],
dtype='object')
```

[425]:
```
hist = sns.histplot(drug_overdose_data, x=
↪'Gini_coefficient_of_income_inequality')
```



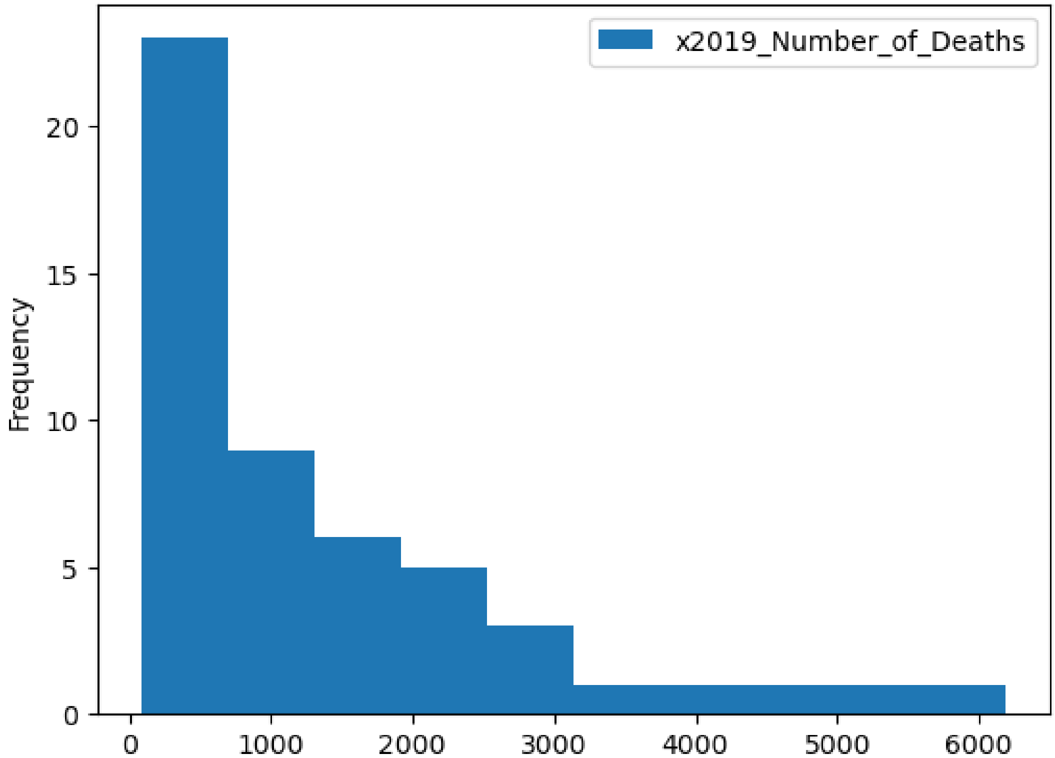
[426]:
```
df.plot( x='Population_density_per_km²', y='x2013_Number_of_Deaths',
↪kind='hist')
```

[426]: <AxesSubplot:ylabel='Frequency'>



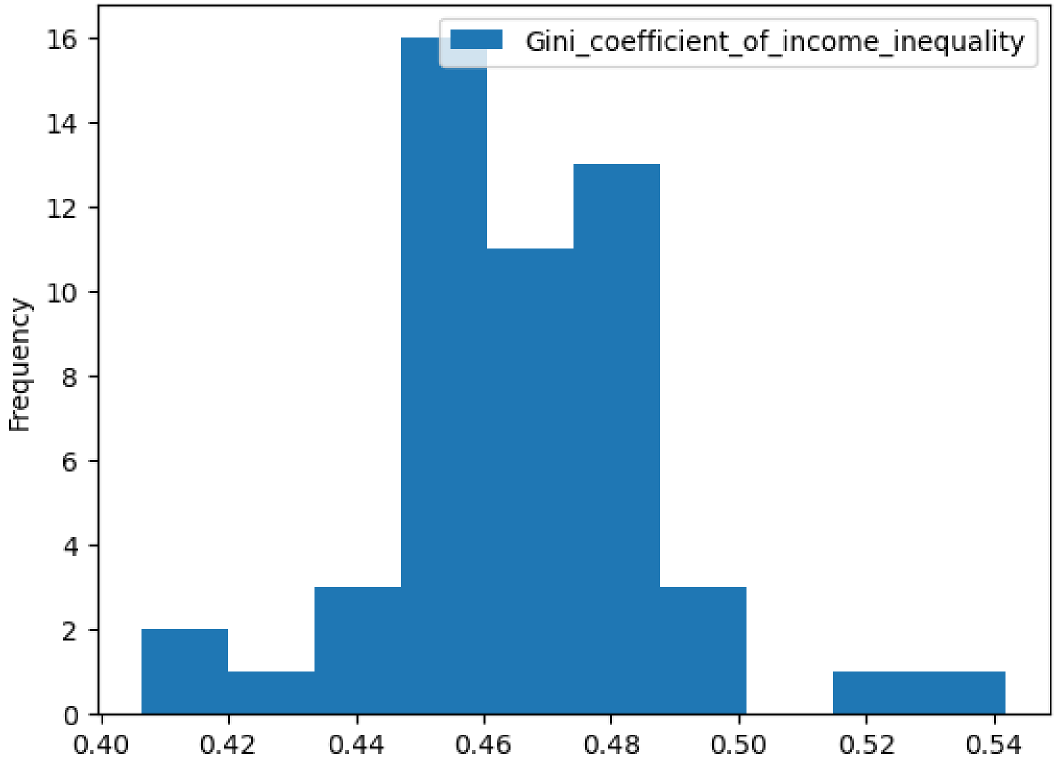
[427]:
```
df.plot( x='Population_density_per_km²', y='x2019_Number_of_Deaths',␣
↪kind='hist')
```

[427]: <AxesSubplot:ylabel='Frequency'>



[428]:
```
df.plot( x='Population_density_per_km²',␣
↪y='Gini_coefficient_of_income_inequality', kind='hist')
```

[428]: <AxesSubplot:ylabel='Frequency'>



[429]:
```
pmf_2019 = thinkstats2.Pmf(df.x2019_Number_of_Deaths)
```

[430]:
```
pmf_gini = thinkstats2.Pmf(df.Gini_coefficient_of_income_inequality)
```

[431]:
```
pmf_2013 = thinkstats2.Pmf(df.x2013_Number_of_Deaths)
```

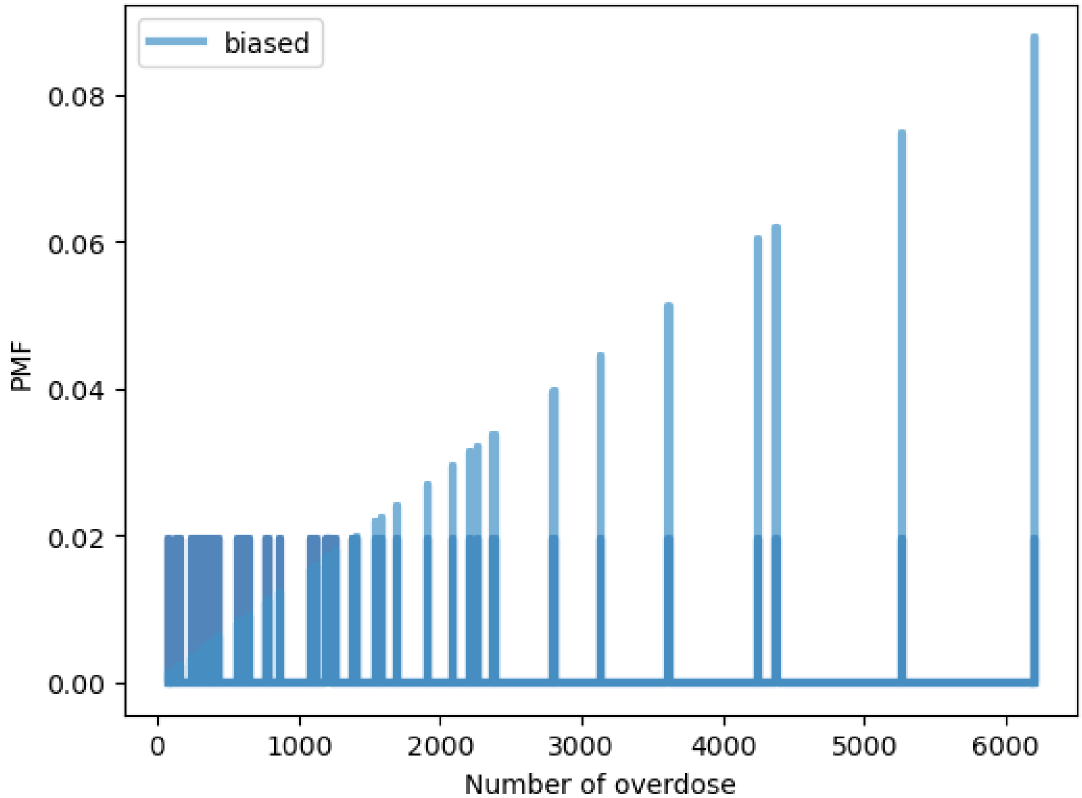
[432]:
```
def BiasPmf(pmf, label):
    new_pmf = pmf.Copy(label=label)

    for x, p in pmf.Items():
        new_pmf.Mult(x, x)

    new_pmf.Normalize()
    return new_pmf
```

[433]:
```
biased_2019 = BiasPmf(pmf_2019, label="biased")
```

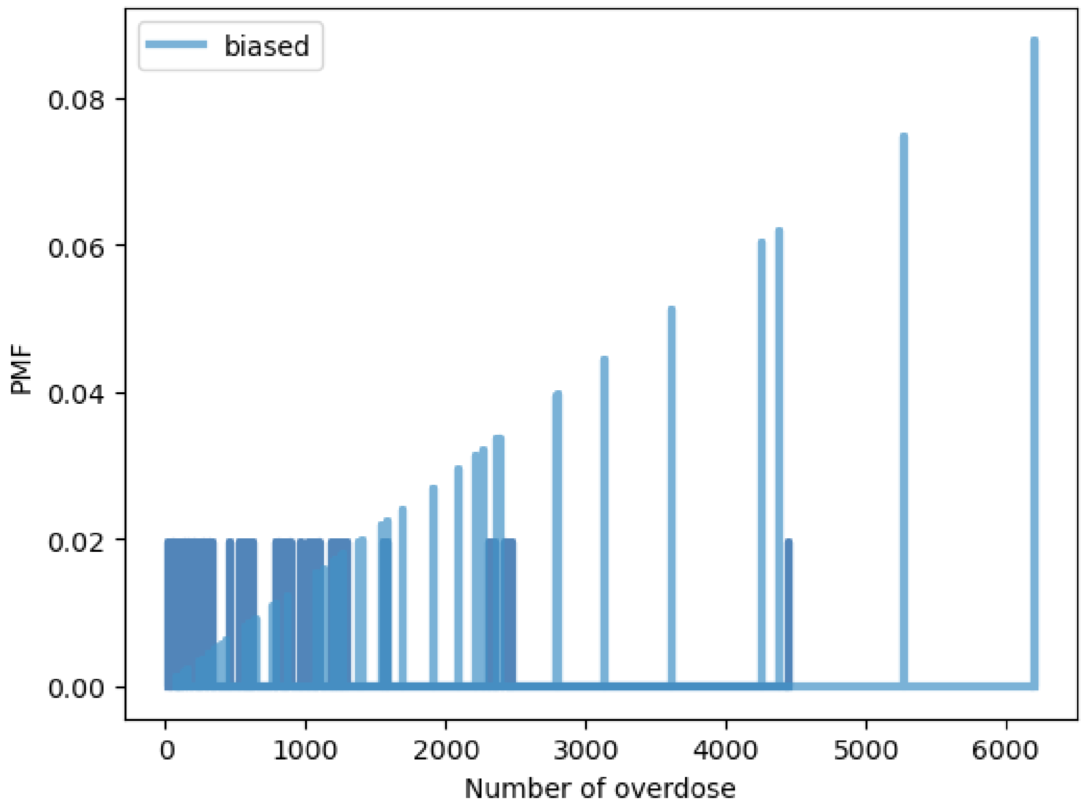
[434]:
```
biased_gini = BiasPmf(pmf_gini, label="biased")
```

[435]:
```
biased_2013 = BiasPmf(pmf_2013, label="biased")
```

[436]:
```
thinkplot.PrePlot(2)
thinkplot.Pmfs([pmf_2019, biased])
thinkplot.Config(xlabel="Number of overdose", ylabel="PMF")
```



[437]:
```
thinkplot.PrePlot(2)
thinkplot.Pmfs([pmf_2013, biased])
thinkplot.Config(xlabel="Number of overdose", ylabel="PMF")
```



[438]:
```
def PmfMean(pmf):
    return sum(p * x for x, p in pmf.Items())
```

[439]:
```
def PmfVar(pmf, mu=None):
    if mu is None:
        mu = PmfMean(pmf)

    return sum(p * (x - mu) ** 2 for x, p in pmf.Items())
```

[440]:
```
PmfMean(pmf_2019)
```

[440]: 1384.9019607843134

[441]:
```
PmfMean(pmf_2013)
```

[441]: 862.3921568627452

[442]:
```
biased_2019.Mean()
```

[442]: 2787.43706640238

[443]:
```
PmfMean(pmf_2013)
```

[443]: 862.3921568627452

[444]:
```
biased_2013.Mean()
```

[444]: 1682.8562593788363

1.0.6 Create 1 CDF with one of your variables, using page 41-44 as your guide, what does this tell you about your variable and how does it address the question you are trying to answer (Chapter 4).

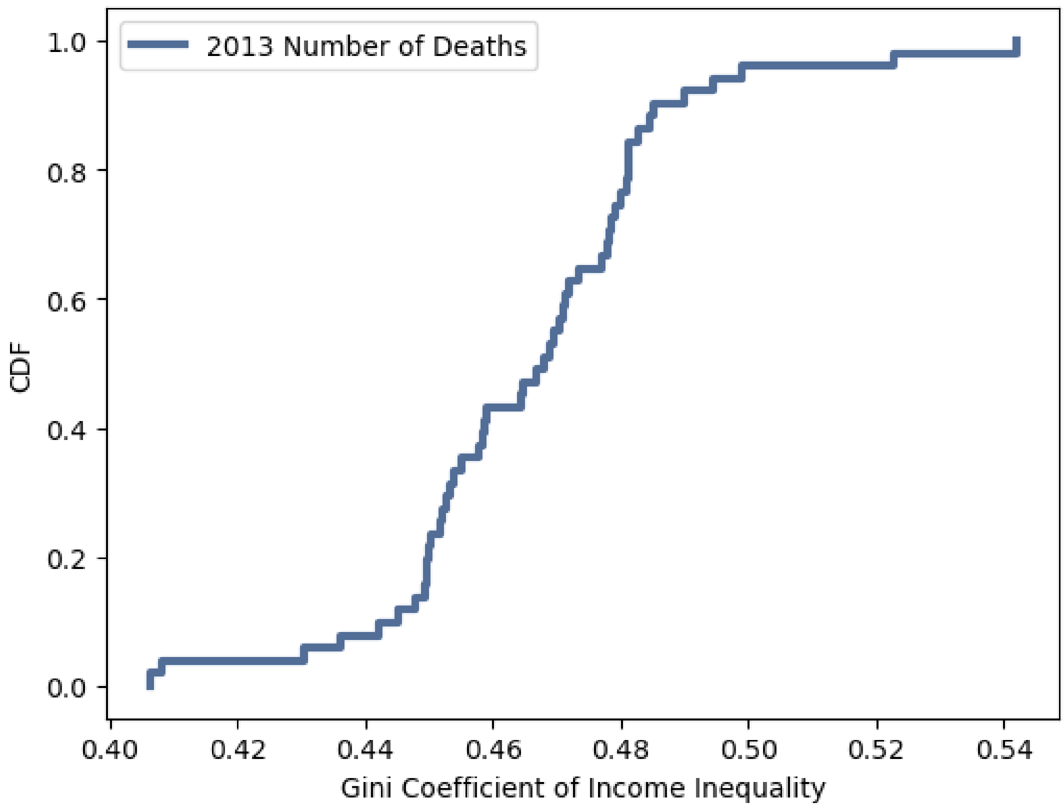
[445]:
```
def EvalCdf(t, x):
    count = 0.0
    for value in t:
        if value <= x:
            count += 1

    prob = count / len(t)
    return prob
```

[446]:
```
cdf_2019 = thinkstats2.Cdf(df.x2019_Number_of_Deaths, label='2019 Number of␣
↪Deaths')
```

[447]:
```
cdf_2013 = thinkstats2.Cdf(df.x2019_Number_of_Deaths, label='2013 Number of␣
↪Deaths')
```

[448]:
```
cdf_gini = thinkstats2.Cdf(df.Gini_coefficient_of_income_inequality,␣
↪label='2013 Number of Deaths')
```

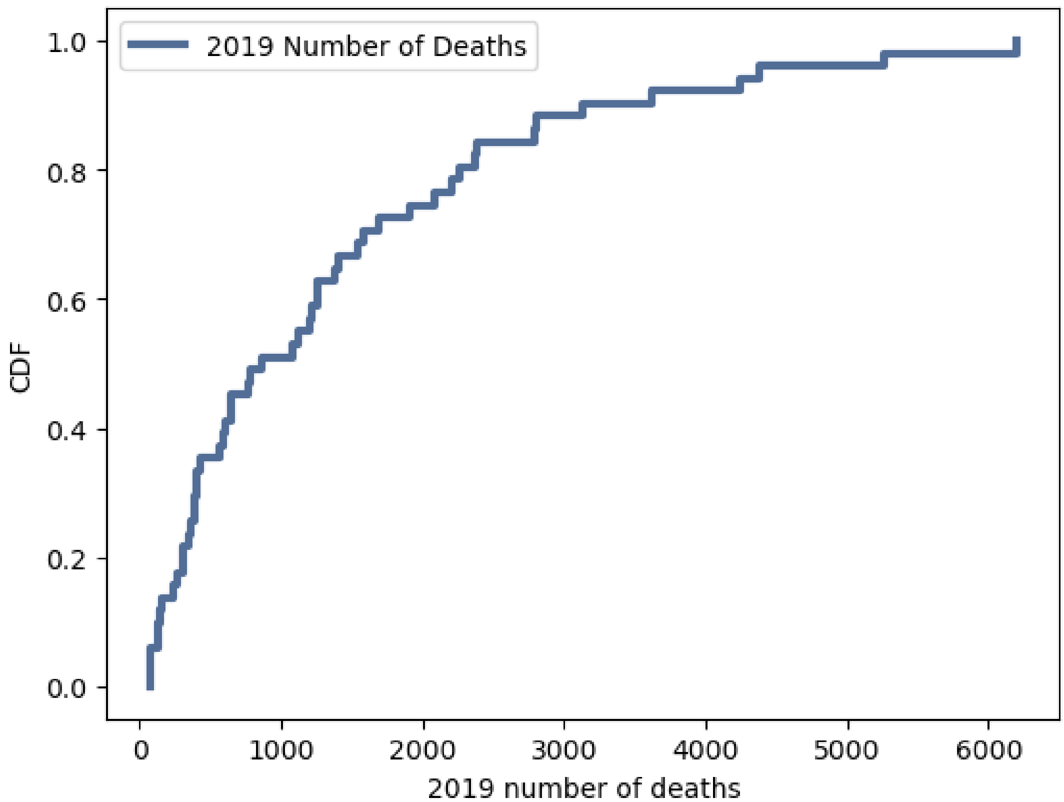
[449]:
```
thinkplot.Cdf(cdf_gini)
thinkplot.Show(xlabel='Gini Coefficient of Income Inequality', ylabel='CDF')
```




```
<Figure size 800x600 with 0 Axes>
```

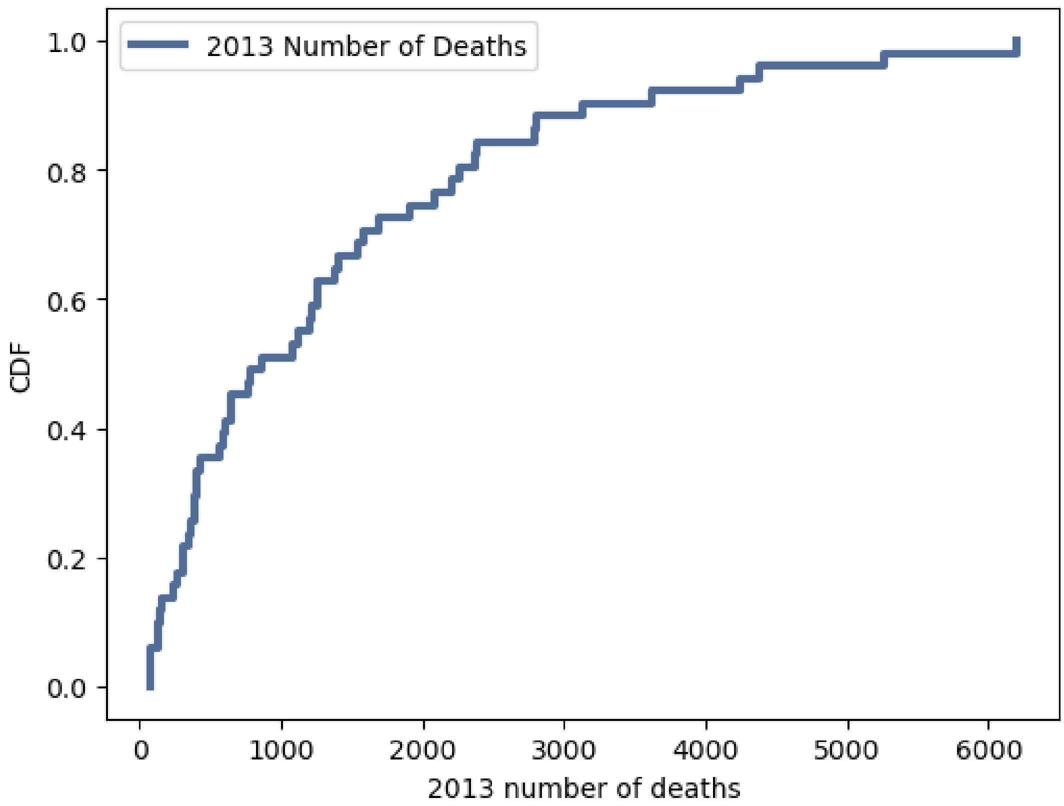
[450]:

```
thinkplot.Cdf(cdf_2019)
thinkplot.Show(xlabel='2019 number of deaths', ylabel='CDF')
```



<Figure size 800x600 with 0 Axes>

[451]:
```
thinkplot.Cdf(cdf_2013)
thinkplot.Show(xlabel='2013 number of deaths', ylabel='CDF')
```




```
<Figure size 800x600 with 0 Axes>
```

[452]:
```
cdf_2019.Prob(3000)
```

[452]: 0.8823529411764706

[453]:
```
cdf_2013.Prob(3000)
```

[453]: 0.8823529411764706

1.0.7 Plot 1 analytical distribution and provide your analysis on how it applies to the dataset you have chosen (Chapter 5).

[454]:
```
deaths = df.x2019_Number_of_Deaths
```

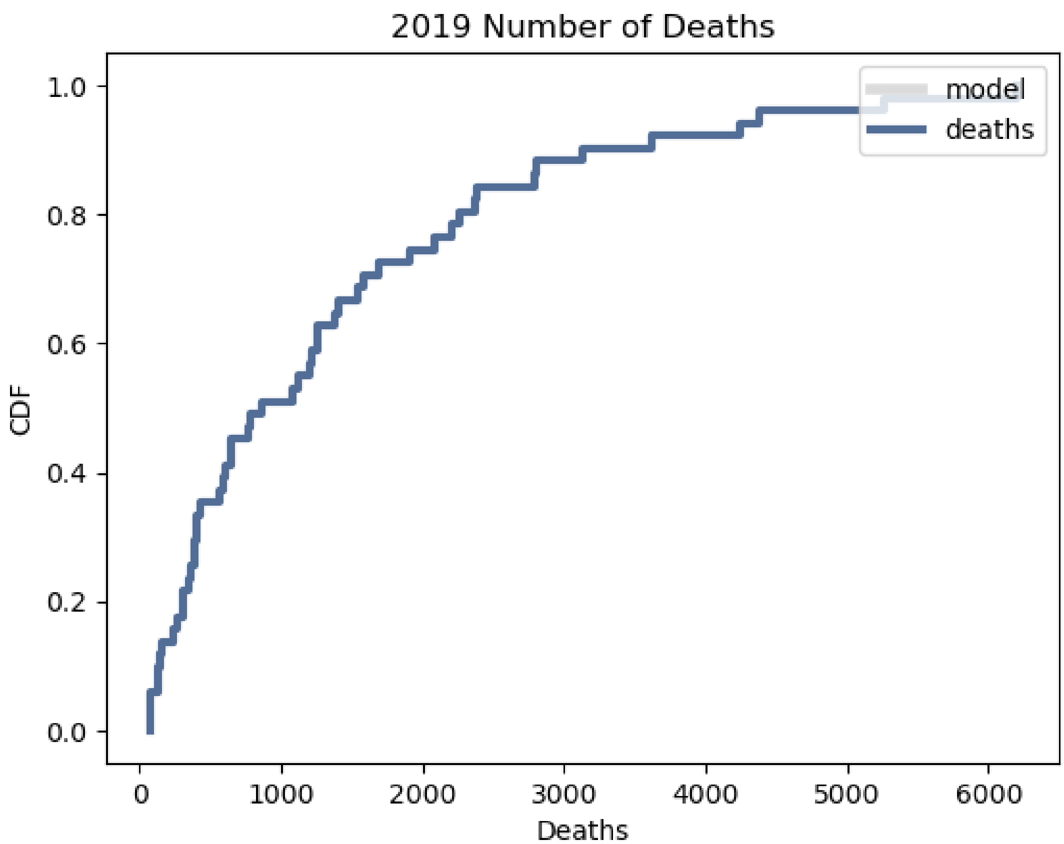
[455]:
```
def MakeNormalModel(deaths):
    cdf = thinkstats2.Cdf(deaths, label="deaths")

    mean, var = thinkstats2.TrimmedMeanVar(deaths)
    std = np.sqrt(var)
    print("n, mean, std", len(deaths), mean, std)
```

```
    xmin = mean - 4 * std
    xmax = mean + 4 * std

    xs, ps = thinkstats2.RenderNormalCdf(mean, std, xmin, xmax)
    thinkplot.Plot(xs, ps, label="model", linewidth=4, color="0.8")
    thinkplot.Cdf(cdf)
```

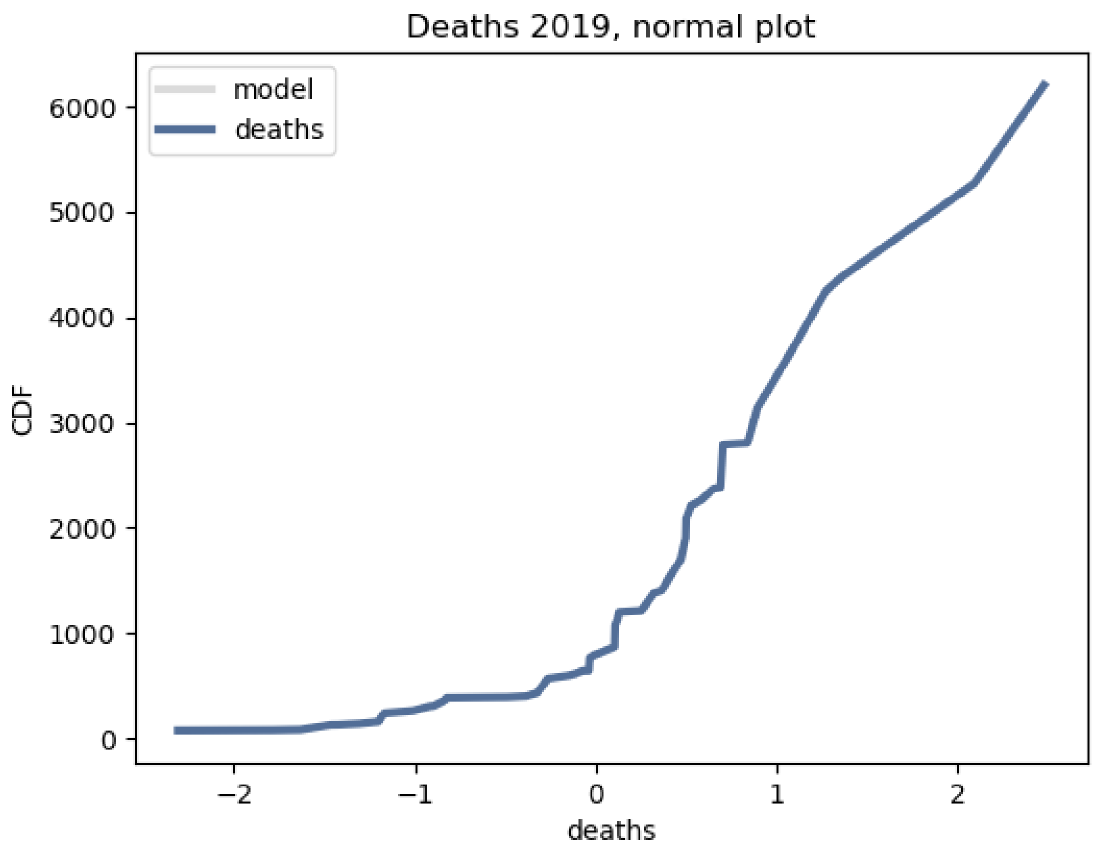
[456]:
```
def MakeNormalPlot(deaths):
    mean, var = thinkstats2.TrimmedMeanVar(deaths, p=0.01)
    std = np.sqrt(var)

    xs = [-5, 5]
    xs, ys = thinkstats2.FitLine(xs, mean, std)
    thinkplot.Plot(xs, ys, color="0.8", label="model")

    xs, ys = thinkstats2.NormalProbability(deaths)
    thinkplot.Plot(xs, ys, label="deaths")
```

[457]:
```
MakeNormalModel(deaths)
thinkplot.Config(
    title="2019 Number of Deaths",
    xlabel="Deaths",
    ylabel="CDF",
    loc="upper right",
)
```

```
n, mean, std 51 nan nan
```

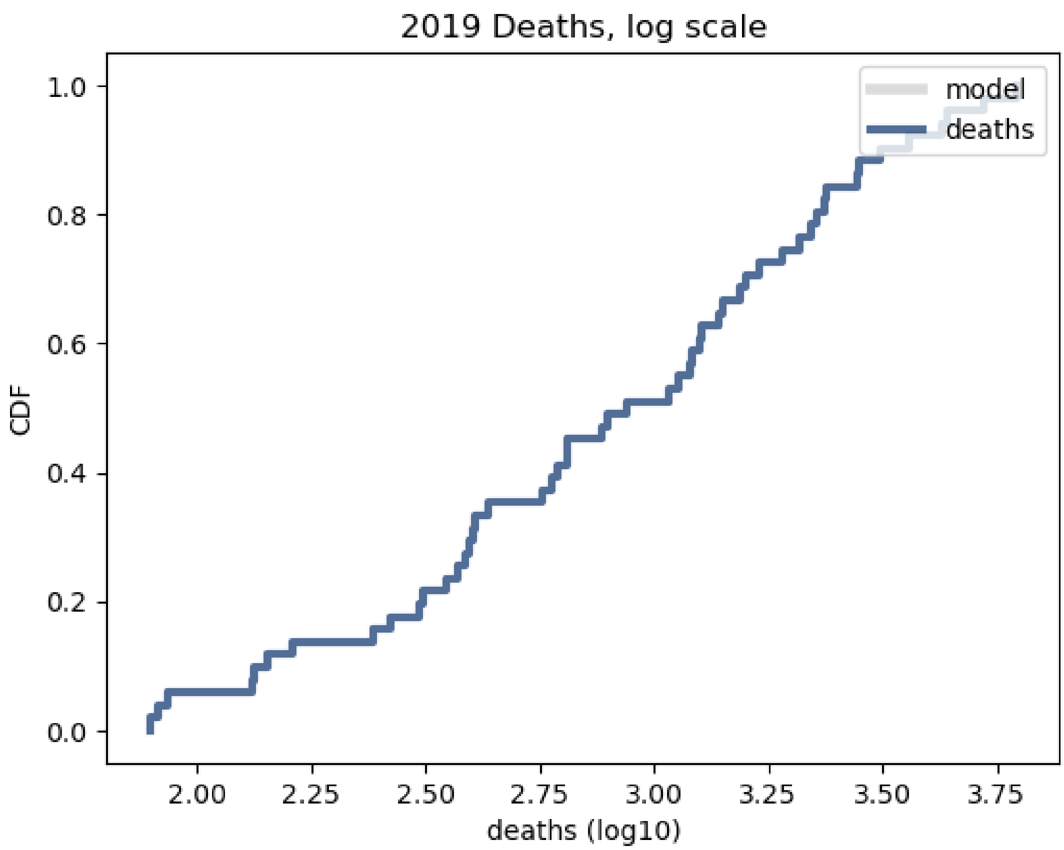


[458]:
```
MakeNormalPlot(deaths)
thinkplot.Config(
    title="Deaths 2019, normal plot",
    xlabel="deaths",
    ylabel="CDF",
    loc="upper left",
)
```

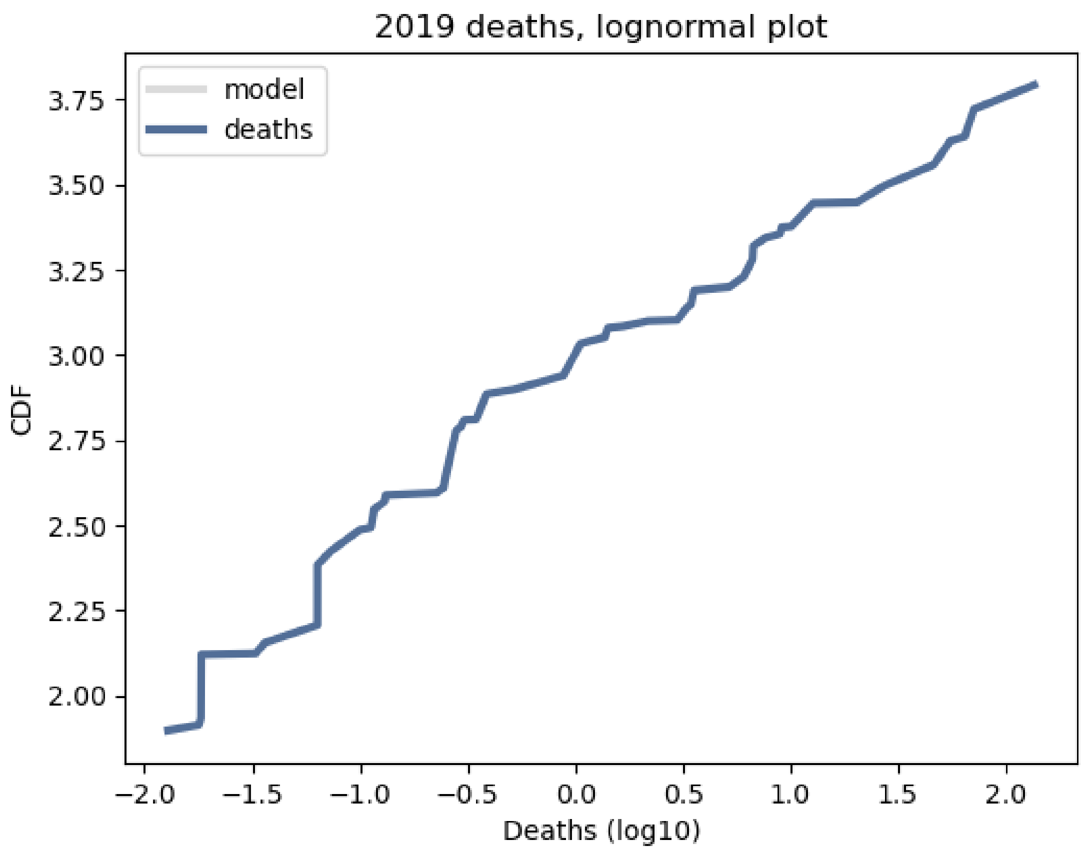


[459]:
```
log_deaths = np.log10(deaths)
MakeNormalModel(log_deaths)
thinkplot.Config(
    title="2019 Deaths, log scale",
    xlabel="deaths (log10)",
    ylabel="CDF",
    loc="upper right",
)
```

```
n, mean, std 51 nan nan
```



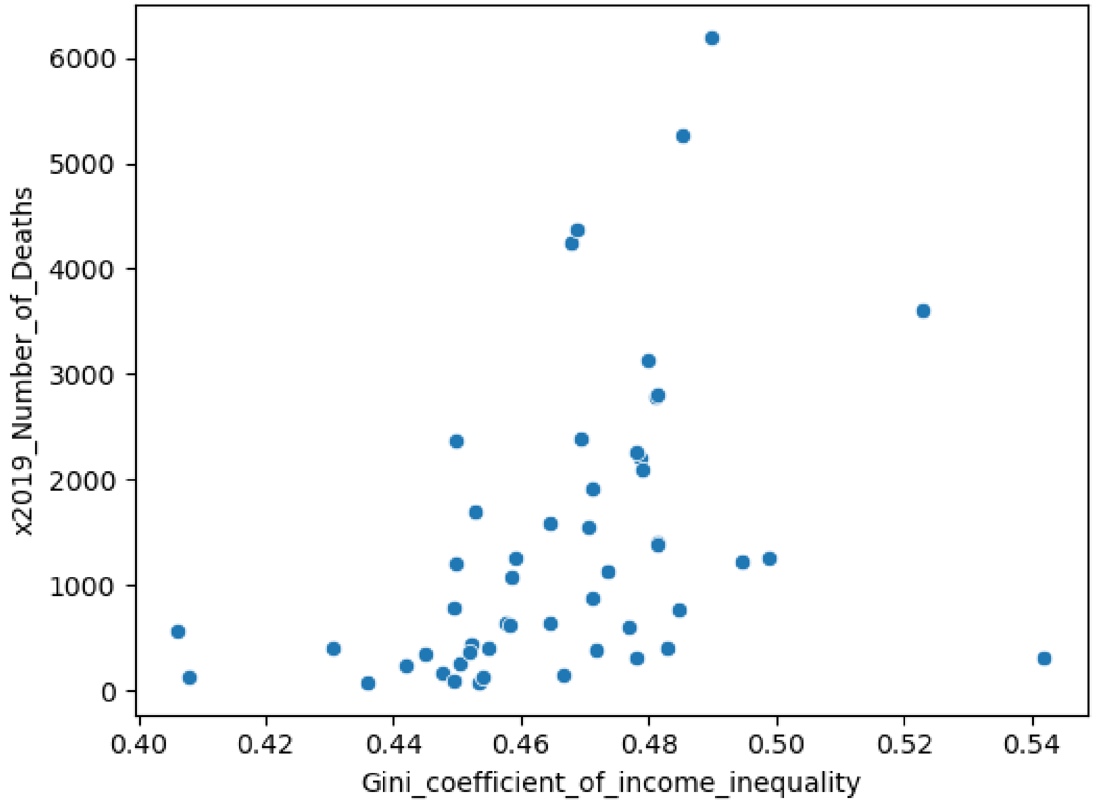
[460]:
```
MakeNormalPlot(log_deaths)
thinkplot.Config(
    title="2019 deaths, lognormal plot",
    xlabel="Deaths (log10)",
    ylabel="CDF",
    loc="upper left",
)
```



1.0.8 Create two scatter plots comparing two variables and provide your analysis on correlation and causation. Remember, covariance, Pearson's correlation, and Non-Linear Relationships should also be considered during your analysis (Chapter 7).

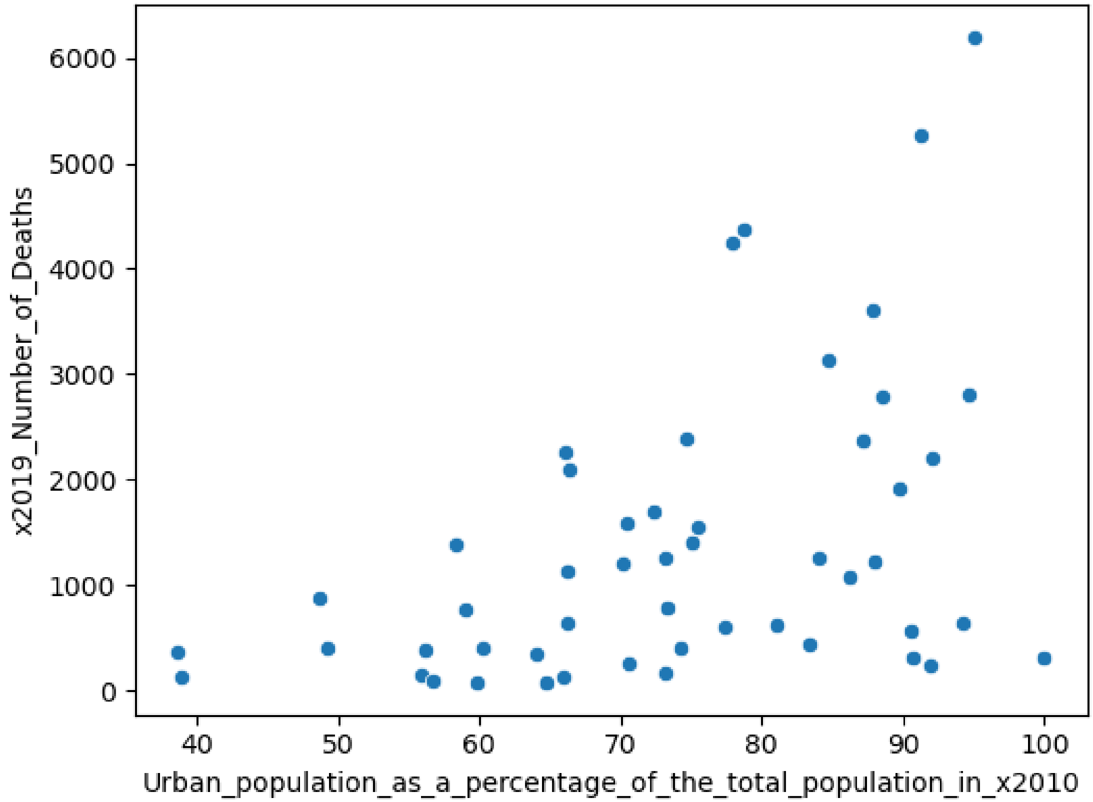
[461]:
```
sns.scatterplot(data=df, x= "Gini_coefficient_of_income_inequality",␣
↪y="x2019_Number_of_Deaths")
```

[461]:
```
<AxesSubplot:xlabel='Gini_coefficient_of_income_inequality',
ylabel='x2019_Number_of_Deaths'>
```



[462]:
```
sns.scatterplot(data=df, x=
↪"Urban_population_as_a_percentage_of_the_total_population_in_x2010",
↪y="x2019_Number_of_Deaths")
```

[462]: <AxesSubplot:xlabel='Urban_population_as_a_percentage_of_the_total_population_in
_x2010', ylabel='x2019_Number_of_Deaths'>



1.0.9 Conduct a test on your hypothesis using one of the methods covered in Chapter 9.

[463]:
```
class CorrelationPermute(thinkstats2.HypothesisTest):

    def TestStatistic(self, data):
        xs, ys = data
        test_stat = abs(thinkstats2.Corr(xs, ys))
        return test_stat

    def RunModel(self):
        xs, ys = self.data
        xs = np.random.permutation(xs)
        return xs, ys
```

[464]:
```
cleaned = df.dropna(subset=['x2019_Number_of_Deaths',␣
 ↪'Gini_coefficient_of_income_inequality'])
data = cleaned.x2019_Number_of_Deaths.values, cleaned.
 ↪Gini_coefficient_of_income_inequality.values
ht = CorrelationPermute(data)
pvalue = ht.PValue()
```

```
pvalue
```

[464]: 0.007

This statistically significant, indicating that there is liklely a correlation between these variables.

[465]:
```
df.columns
```

[465]:
```
Index(['State', 'State_Abbreviation', 'x2019', 'x2019_Number_of_Deaths',
       'x2018', 'x2018_Number_of_Deaths', 'x2017', 'x2017_Number_of_Deaths',
       'x2016', 'x2016_Number_of_Deaths', 'x2015', 'x2015_Number_of_Deaths',
       'x2014', 'x2014_Number_of_Deaths', 'x2013', 'x2013_Number_of_Deaths',
       'x2019_Poverty_rate_(percent_of_persons_in_poverty)',
       'Gini_coefficient_of_income_inequality', 'GDP_per_capita_x20x21',
       'GDP_(nominal_in_millions_of_USD)_x20x21',
       'Urban_population_as_a_percentage_of_the_total_population_in_x2010',
       'Population_density_per_km²', 'Population', 'Land_Area_(km²)'],
      dtype='object')
```

1.0.10 For this project, conduct a regression analysis on either one dependent and one explanatory variable, or multiple explanatory variables (Chapter 10 & 11

[466]:
```
from sklearn import linear_model
import statsmodels.api as sm
```

[467]:
```
x = df[['Gini_coefficient_of_income_inequality', 'Population_density_per_km²']]
y = df['x2019_Number_of_Deaths']
```

[468]:
```
regr = linear_model.LinearRegression()
regr.fit(x, y)
```

[468]: LinearRegression()

[469]:
```
print('Intercept: \n', regr.intercept_)
print('Coefficients: \n', regr.coef_)
```

```
Intercept:
 -14726.530438181831
Coefficients:
 [ 3.48409495e+04 -8.17140415e-01]
```

[470]:
```
x = sm.add_constant(x) # adding a constant
```

[471]:
```
model = sm.OLS(y, x).fit()
predictions = model.predict(x)
```

[472]:
```python
print_model = model.summary()
print(print_model)
```

```
                                    OLS Regression Results
================================================================================
==
Dep. Variable:     x2019_Number_of_Deaths   R-squared:
0.252
Model:                                OLS   Adj. R-squared:
0.221
Method:                     Least Squares   F-statistic:
8.081
Date:                    Sat, 04 Mar 2023   Prob (F-statistic):
0.000944
Time:                            17:05:27   Log-Likelihood:
-434.19
No. Observations:                      51   AIC:
874.4
Df Residuals:                          48   BIC:
880.2
Df Model:                               2
Covariance Type:                nonrobust
================================================================================
=========================
                                          coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
-------------------------
const                               -1.473e+04   4035.322     -3.649
0.001   -2.28e+04   -6612.972
Gini_coefficient_of_income_inequality  3.484e+04   8707.708      4.001
0.000    1.73e+04    5.23e+04
Population_density_per_km²             -0.8171      0.344     -2.375
0.022      -1.509      -0.125
==============================================================================
Omnibus:                       18.481   Durbin-Watson:                   2.397
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               23.028
Skew:                           1.377   Prob(JB):                     9.99e-06
Kurtosis:                       4.803   Cond. No.                     3.36e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.36e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

-Conclusion-

1.0.11 Outcome of your EDA

1.0.12 What do you feel was missed during the analysis? Were there any variables you felt could have helped in the analysis? Were there any assumptions made you felt were incorrect? What challenges did you face, what did you not fully understand?

This EDA super fun and interesting. I enjoyed reviewing the data as a whole, cleaning it, making and seeing the visualizations, and attempting to find relationships between variables. I utilized Because there were so many variables, I likely could have explored a lot further, but narrowing my hypothesis down was still a good exploration.

I could have created a density map for the country to visualize where opioid rates were highest. In the future, I would like to have more information about geography, like zip code, to be able to explore regions that have a higher rate of opioid abuse. Instead of focusing on regions, I was able to focus on factors influencing the rates overall. I do think I could have used the PMF and CDF functions in a more effective way. I appreciate having access to the ThinkStats and ThinkPlot libraries for executing functions. I also enjoyed using Pandas, Seaborn, and MatPlotLib to advance my capabilities in Python.

My hypothesis was that there is a significant correlation between the Gini Coefficient of Income Equality and the rate of overdose deaths. In the regression portion, I also included population density because the spread of opioid usage can occur rapidly in more densely populated areas with wider access to both prescription and street drugs. My hypothesis was proven correct based on the hypothesis test and regression results showing that there is very, very small chance (p-value) that the null hypothesis is true. These outcomes indicate that there is statistical significance between the income inequality and rate of overdose deaths. In a real-world scenario, I would hope to use this information (and further analysis) to determine hotspots for opioid crises, and hope to expand access to opioid-care facilities in these regions.

[ ]:

```

```