The Opioid Crisis

Group 5: Ben Glicksman, Jonah Lourie, Sharon Luo, Natalie Edman

Research Question

1. How has the opioid crisis affected Connecticut?
   a. Opioid Prescriptions
   b. Opioid Rehab Admissions
   c. Opioid deaths
2. How does this data fit into the larger federal opioid crisis?
   a. Federal drug overdose
   b. Federal prescribing rates

CT Prescriptions Dataframe

In [3]:
```
CT_Prescript_per_Year_df
```

Out[3]:

	Year	Controlled Substance Prescriptions	Opioid Prescriptions	Benzodiazepine Prescriptions
0	2014	6064563	2602050	1729192
1	2015	6249637	2625042	1667184
2	2016	6545550	2510702	1687910
3	2017	6724447	2161959	1617171
4	2018	6908152	1960988	1532053
5	2019	7330910	1946427	1458611
6	2020	8516519	1785575	1454611

Create an opioid filter

In [6]:
```
#Step 2: Create an opioid filter
opioid_filter = CT_Prescript_per_Year_df[['opioid_prescriptions', 'Year']]
opioid_filter
```

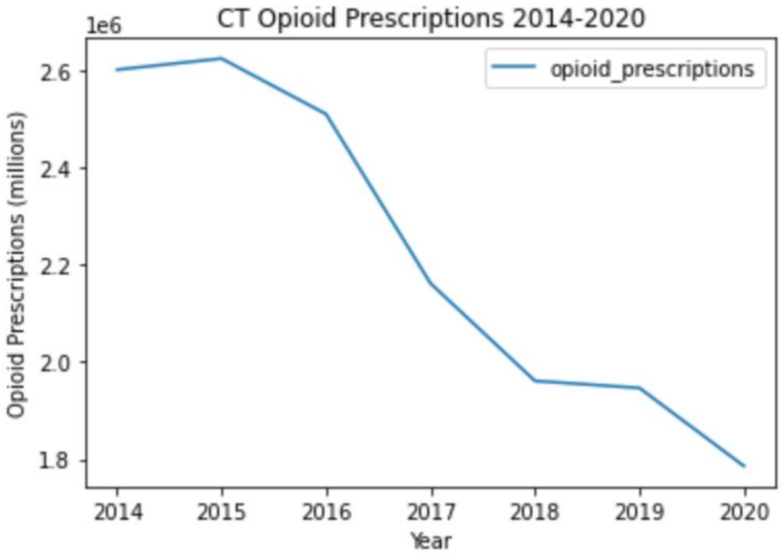
Out[6]:

	opioid_prescriptions	Year
0	2602050	2014
1	2625042	2015
2	2510702	2016
3	2161959	2017
4	1960988	2018
5	1946427	2019
6	1785575	2020

Plot Opioid Prescriptions per Year

In [7]:
```
#Step 3: Create a plot
opioid_filter.set_index('Year').plot()
plt.ylabel('Opioid Prescriptions (millions)')
plt.title('CT Opioid Prescriptions 2014-2020')
```

Out[7]:
```
Text(0.5, 1.0, 'CT Opioid Prescriptions 2014-2020')
```



Calculate percent change from 2012 to 2020

```
In [8]: #Step 4: Calculate the percent change from 2014 to 2020 using the pct_change function
        opioid_filter.set_index('Year').loc[[2014, 2020]].pct_change()
```

Out[8]:

	opioid_prescriptions
Year	
2014	NaN
2020	-0.313781

A 31.4% **decrease** in perscriptions

CT Rehab Admissions

1. Load in opioid rehab admissions by year/town DF

	FiscalYear	Town	Admissions	Unduplicated Clients	TownGeo
0	2016	Suffield	35.0	24.0	Suffield, CT\n(41.983549, -72.663124)
1	2014	Thomaston	51.0	34.0	Thomaston, CT\n(41.674124, -73.073189)
2	2013	Sprague	35.0	16.0	Sprague, CT\n(41.640692, -72.066224)
3	2015	Monroe	83.0	46.0	Monroe, CT\n(41.331612, -73.206797)
4	2016	Cheshire	85.0	50.0	Cheshire, CT\n(41.498834, -72.901448)
...	...	...	...	...	...
845	2012	Salisbury	6.0	NaN	Salisbury, CT\n(41.983411, -73.422268)
846	2013	Bridgewater	7.0	NaN	Bridgewater, CT\n(41.535109, -73.366386)
847	2012	Lisbon	NaN	NaN	Lisbon, CT\n(41.614599, -71.960584)
848	2016	Goshen	15.0	NaN	Goshen, CT\n(41.831925, -73.225323)
849	2016	Scotland	8.0	NaN	Scotland, CT\n(41.6975, -72.119465)

850 rows × 5 columns

CT Rehab Admissions

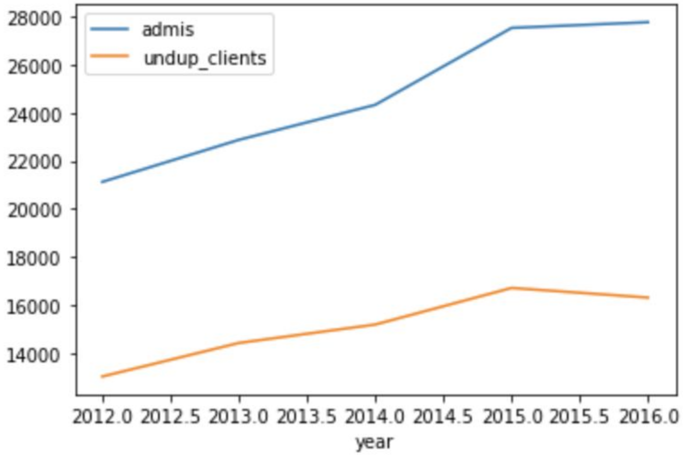
1. Load in opioid rehab admissions by year/town DF
2. Clean up data

	year	town	admis	undup_clients	lat	lng
0	2012	Andover	NaN	NaN	41.728789	-72.370309
1	2012	Ansonia	134.0	85.0	41.341980	-73.078296
2	2012	Ashford	20.0	13.0	41.871915	-72.124128
3	2012	Avon	8.0	6.0	41.809641	-72.830547
4	2012	Barkhamsted	18.0	10.0	41.927066	-72.911918
...	...	...	...	...	...	...
845	2016	Windsor Locks	70.0	46.0	41.924953	-72.627177
846	2016	Wolcott	141.0	87.0	41.601588	-72.986414
847	2016	Woodbridge	15.0	10.0	41.352933	-73.014356
848	2016	Woodbury	32.0	21.0	41.545058	-73.208654
849	2016	Woodstock	35.0	17.0	41.950652	-71.977285

850 rows × 6 columns

CT Rehab Admissions

1. Load in opioid rehab admissions by year/town DF
2. Clean up data
3. Group data by yr & graph



Conclusions:

- Admissions are going up

CT Rehab Admissions

1. Load in opioid rehab admissions by year/town DF
2. Clean up data
3. Group data by yr & graph
4. Transform data into GeoPandas DF & merge w/ CT town geodata

Conclusions:

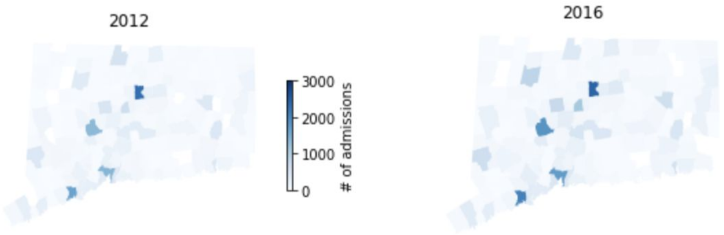
- Admissions are going up

year	shape_area	shape_len	town_left	town_no	geometry	index_right	town_right	admis	undup_clients	town_geo	lat	
2016	438072078.45	86301.9757031	Andover	1	MULTIPOLYGON (((-72.32832 41.73850, -72.32908 ...	16	Andover	22.0	9.0	Andover, CT\n(41.728789, -72.370309)	41.728789	-72.370
2012	438072078.45	86301.9757031	Andover	1	MULTIPOLYGON (((-72.32832 41.73850, -72.32908 ...	823	Andover	NaN	NaN	Andover, CT\n(41.728789, -72.370309)	41.728789	-72.370
2014	438072078.45	86301.9757031	Andover	1	MULTIPOLYGON (((-72.32832 41.73850, -72.32908 ...	124	Andover	9.0	7.0	Andover, CT\n(41.728789, -72.370309)	41.728789	-72.370
2015	438072078.45	86301.9757031	Andover	1	MULTIPOLYGON (((-72.32832 41.73850, -72.32908 ...	71	Andover	17.0	10.0	Andover, CT\n(41.728789, -72.370309)	41.728789	-72.370
2013	438072078.45	86301.9757031	Andover	1	MULTIPOLYGON (((-72.32832 41.73850, -72.32908 ...	837	Andover	NaN	NaN	Andover, CT\n(41.728789, -72.370309)	41.728789	-72.370
...	...	...	...	...	...	...	...	...	...	...	...	
2015	1719966271.12	166595.548744	Woodstock	169	MULTIPOLYGON (((-71.96318 42.02619, -71.95353 ...	384	Woodstock	19.0	11.0	Woodstock, CT\n(41.950652, -71.977285)	41.950652	-71.977
2013	1719966271.12	166595.548744	Woodstock	169	MULTIPOLYGON (((-71.96318 42.02619, -71.95353 ...	512	Woodstock	16.0	14.0	Woodstock, CT\n(41.950652, -71.977285)	41.950652	-71.977
2014	1719966271.12	166595.548744	Woodstock	169	MULTIPOLYGON (((-71.96318 42.02619, -71.95353 ...	748	Woodstock	18.0	12.0	Woodstock, CT\n(41.950652, -71.977285)	41.950652	-71.977
2016	1719966271.12	166595.548744	Woodstock	169	MULTIPOLYGON (((-71.96318 42.02619, -71.95353 ...	160	Woodstock	35.0	17.0	Woodstock, CT\n(41.950652, -71.977285)	41.950652	-71.977
2012	1719966271.12	166595.548744	Woodstock	169	MULTIPOLYGON (((-71.96318 42.02619, -71.95353 ...	441	Woodstock	19.0	13.0	Woodstock, CT\n(41.950652, -71.977285)	41.950652	-71.977

850 rows × 12 columns

CT Rehab Admissions

1. Load in opioid rehab admissions by year/town DF
2. Clean up data
3. Group data by yr & graph
4. Transform data into GeoPandas DF & merge w/ CT town geodata
5. Map geodata to CT towns & compare across years



Conclusions:

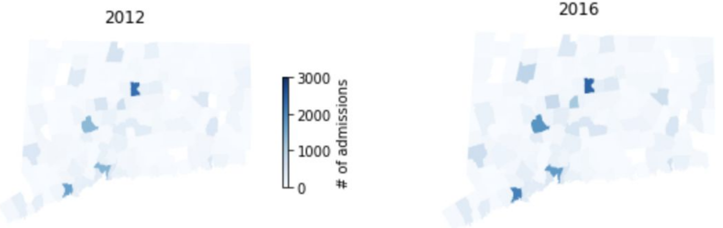
- Admissions are going up
- Not much change by town from 2012 to 2016

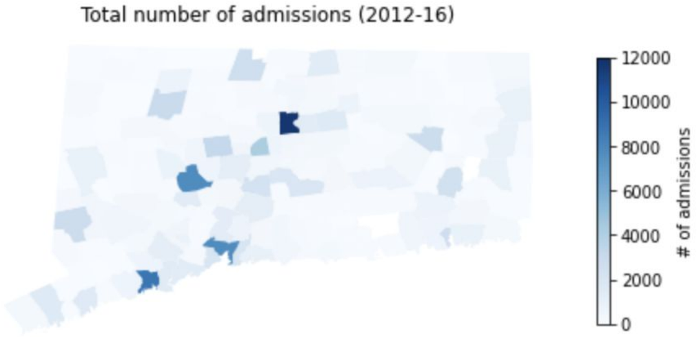
CT Rehab Admissions

1. Load in opioid rehab admissions by year/town DF
2. Clean up data
3. Group data by yr & graph
4. Transform data into GeoPandas DF & merge w/ CT town geodata
5. Map geodata to CT towns & compare across years
6. Sum admissions data for further analyses of CT towns

Conclusions:

- Admissions are going up
- Not much change by town from 2012 to 2016
- Certain towns have more admissions across time





Group the opioid deaths by year

In [10]:
```
# distribution by year
accidental_opioid_deaths_df.groupby('year').size()
```

Out[10]:
```
year
2012     257
2013     356
2014     449
2015     593
2016     803
2017     898
2018     901
2019    1091
2020    1224
dtype: int64
```

CT Opioid Deaths

```
In [7]: accidental_drug_deaths_df.columns

Out[7]: Index(['ID', 'Date', 'Date Type', 'Age', 'Sex', 'Race', 'Residence City',
               'Residence County', 'Residence State', 'Death City', 'Death County',
               'Location', 'Location if Other', 'Description of Injury',
               'Injury Place', 'Injury City', 'Injury County', 'Injury State',
               'Cause of Death', 'Other Significant Conditions ', 'Heroin', 'Cocaine',
               'Fentanyl', 'Fentanyl Analogue', 'Oxycodone', 'Oxymorphone', 'Ethanol',
               'Hydrocodone', 'Benzodiazepine', 'Methadone', 'Amphet', 'Tramad',
               'Morphine (Not Heroin)', 'Hydromorphone', 'Xylazine', 'Other',
               'Opiate NOS', 'Any Opioid', 'Manner of Death', 'DeathCityGeo',
               'ResidenceCityGeo', 'InjuryCityGeo'],
              dtype='object')
```

Create a filter that looks at all opioid deaths

```
# Step 2: Create an opioid filter
# Note: Using the 'Any_Opioid' filter did not work since the data was not updated in this column and there was a lot of
# Therefore, I will create my own 'all_opioid' column to include all of the drugs that are considered opioids.
# Now I will create filters for all of the different opioids in this data set
heroin_filter = accidental_drug_deaths_df['Heroin'] == 'Y'
fetanyl_filter = accidental_drug_deaths_df['Fentanyl'] == 'Y'
fentanyl_analogue_filter = accidental_drug_deaths_df['Fentanyl_Analogue'] == 'Y'
oxycodone_filter = accidental_drug_deaths_df['Oxycodone'] == 'Y'
oxymorphone_filter = accidental_drug_deaths_df['Oxymorphone'] == 'Y'
hydrocodone_filter = accidental_drug_deaths_df['Hydrocodone'] == 'Y'
morphine_filter = accidental_drug_deaths_df['Morphine_Not_Heroin'] == 'Y'
hydromorphone_filter = accidental_drug_deaths_df['Hydromorphone'] == 'Y'
opiate_filter = accidental_drug_deaths_df['Opiate_NOS'] == 'Y'
```

```
# Now I will add a column that incorporates all of these filters

all_opioids_filter = heroin_filter | fetanyl_filter | fentanyl_analogue_filter | oxycodone_filter | oxymorphone_filter

# now create a new column 'all_opioids' with True/False
accidental_drug_deaths_df['all_opioids'] = all_opioids_filter
```

Look at all drug deaths vs. opioid deaths

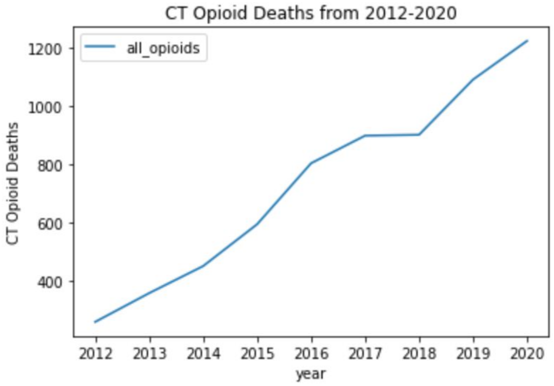
```
# check the shape of the two data frames
print('All drug deaths', accidental_drug_deaths_df.shape)

print('Opioid drug deaths', accidental_opioid_deaths_df.shape)
```

```
All drug deaths (7679, 41)
Opioid drug deaths (6572, 41)
```

Visualize the data: opioid deaths by year

In [44]:
```
# plot the amount of opioid deaths per year
opi_years.plot()
plt.ylabel('CT Opioid Deaths')
plt.title('CT Opioid Deaths from 2012-2020')
```

Out[44]:
```
Text(0.5, 1.0, 'CT Opioid Deaths from 2012-2020')
```



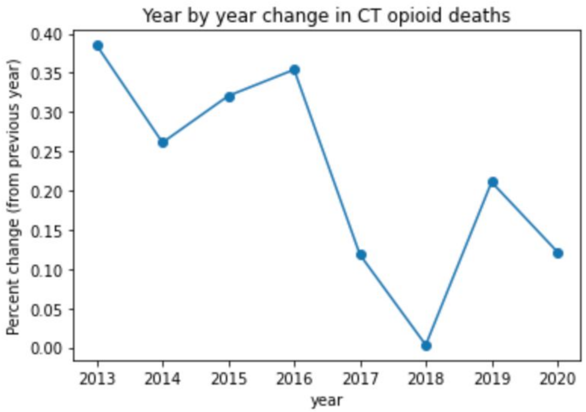
Look at percent change by year

In [12]:
```
# clearly increasing

# you can quantify the rate year by year with the pct_change function
# so 2016 is a 29.4% increase over 2015

accidental_opioid_deaths_df.groupby('year').size().pct_change()
```

Out[12]:
```
year
2012         NaN
2013    0.385214
2014    0.261236
2015    0.320713
2016    0.354132
2017    0.118306
2018    0.003341
2019    0.210877
2020    0.121907
dtype: float64
```

Visualize percent change by year

```
In [13]: deaths_year_pct_change=accidental_opioid_deaths_df.groupby('year').size().pct_change()

         deaths_year_pct_change.plot(style='-o')
         plt.title('Year by year change in CT opioid deaths')
         plt.ylabel('Percent change (from previous year)')
         plt.show()
```



Federal Drug Overdose Death Data

Questions:

- Have total number of deaths increased or decreased?
- Have total opioid deaths increased or decreased?
- Which states have the highest and lowest number of opioid deaths?

Steps

- Load the Data
- Create two filters: one for number of deaths and opioid deaths
- Group the filtered data sets by year, sum the data, and sort
- Plot the grouped and filtered sums to see the trend of the data over time
- Group the data by state and sum to see the total number of opioid deaths

Load Data

The data comes from https://catalog.data.gov/dataset/vsrr-provisional-drug-overdose-death-counts and shows the different number of overdose deaths for each drug, total drug overdose deaths, and percentages of deaths with specific drugs.

Named the DataFrame od_df

Clean Data has 41624 rows and 8 cols

	State	Year	Month	Indicator	Data_Value	Percent_Complete	Percent_Pending_Investigation	Predicted_Value
0	AK	2015	April	Natural, semi-synthetic, & synthetic opioids, ...	NaN	100	0.000000	NaN
1	AK	2015	April	Natural & semi-synthetic opioids (T40.2)	NaN	100	0.000000	NaN
2	AK	2015	April	Natural & semi-synthetic opioids, incl. methad...	NaN	100	0.000000	NaN
3	AK	2015	April	Number of Deaths	4133.000000	100	0.000000	NaN
4	AK	2015	April	Opioids (T40.0-T40.4,T40.6)	NaN	100	0.000000	NaN
...	...	...	...	...	...	...	...	...
41620	YC	2021	March	Cocaine (T40.5)	908.000000	100	0.258858	937.0
41621	YC	2021	March	Percent with drugs specified	99.063754	100	0.258858	NaN
41622	YC	2021	March	Natural, semi-synthetic, & synthetic opioids, ...	1853.000000	100	0.258858	1914.0
41623	YC	2021	March	Natural & semi-synthetic opioids, incl. methad...	672.000000	100	0.258858	693.0
41624	YC	2021	March	Synthetic opioids, excl. methadone (T40.4)	1718.000000	100	0.258858	1778.0

Create Row Filters

- Created two row filters:
  - One for total number of drug overdose deaths called “num_deaths_filter”
  - One for opioid overdose deaths called “opioid_filter”

```
#create row filters
num_deaths_filter = od_df['Indicator']=='Number of Deaths'
opioid_filter = od_df['Indicator']=='Opioids (T40.0-T40.4,T40.6

num_deaths_df = od_df[num_deaths_filter]
opioid_df = od_df[opioid_filter]
```

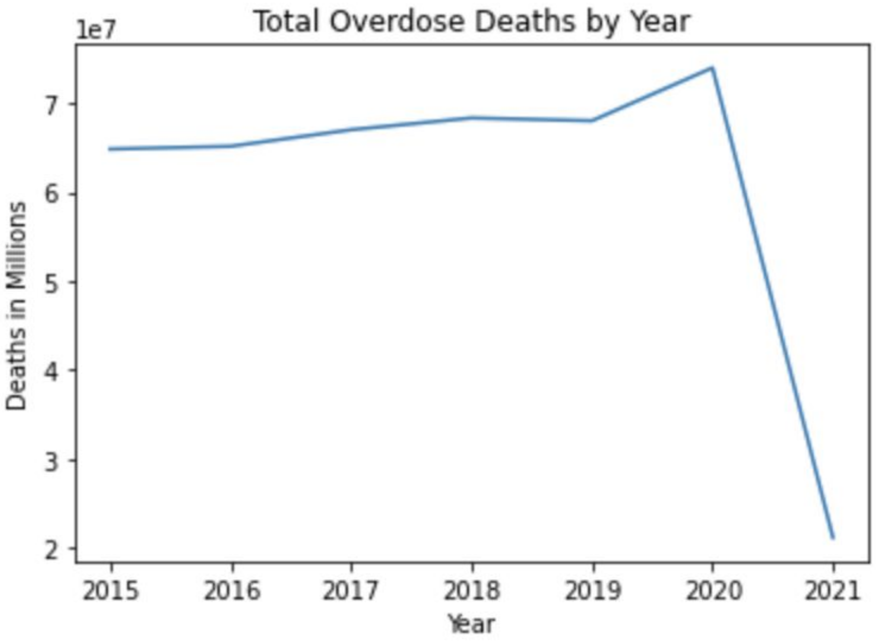
Group by Year and Sum Deaths

```python
#grouping by year and summing the deaths
num_deaths_df.groupby('Year')['Data_Value'].sum().sort_values(ascending=False)
```

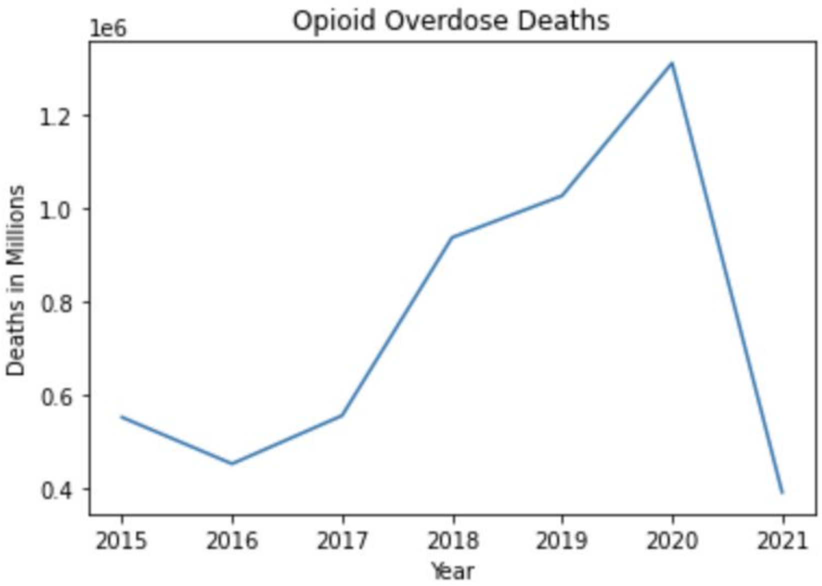
```python
opioid_df.groupby('Year')['Data_Value'].sum().sort_values(ascending=False)
```

2020	74011854.0
2018	68362228.0
2019	68048908.0
2017	67034290.0
2016	65172392.0
2015	64861344.0
2021	21141198.0

2020	1311148.0
2019	1026757.0
2018	937172.0
2017	555589.0
2015	552054.0
2016	452369.0
2021	391396.0



Total Overdose Deaths by Year
1e7
7
6
5
4
3
2
Deaths in Millions
2015
2016
2017
2018
2019
2020
2021
Year



Opioid Overdose Deaths
1e6
1.2
1.0
0.8
0.6
0.4
Deaths in Millions
2015
2016
2017
2018
2019
2020
2021
Year

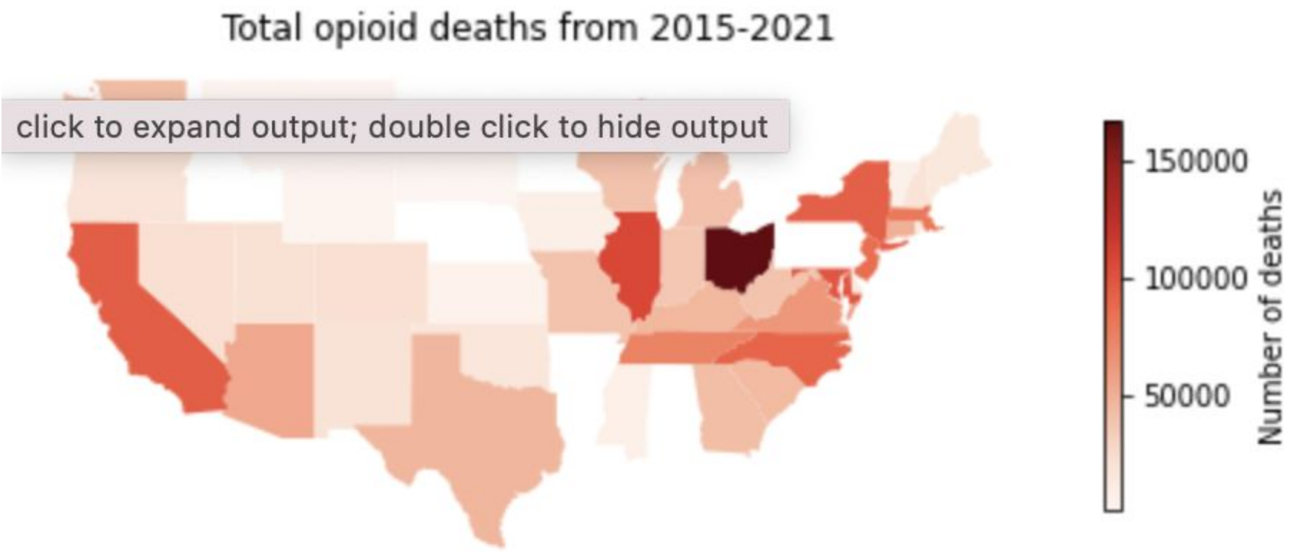
Group by State and Sum Opioid Deaths

```
#grouping by state and summing total opioid deaths
opioid_df.groupby('State')['Data_Value'].sum().sort_values(ascending=False)
```

```
State
US    3465069.0
OH     166984.0
IL     107298.0
MD      98016.0
CA      93749.0
NY      92622.0
NC      90928.0
NJ      85345.0
MA      79635.0
TN      73661.0
VA      62762.0
YC      60343.0
AZ      52996.0
CT      49339.0
TX      46112.0
KY      45278.0
SC      44013.0
```

Connecticut has the 12th most opioid deaths for states in this data set

Geopandas Map by State



Conclusions

- The total number of deaths has increased over time.
  - This can be seen by the increased in the plot of the deaths graph up until 2021, which is so because the data was taken during this year and does not represent the full years worth of data. Looking at similar data taken from the entire year of 2021 will likely show continued increase.
- The total number of opioid deaths has also increased over time.
  - The same issue with 2021 as with total deaths can be seen here.
- The states with the highest number of opioid deaths were Ohio, Illinois, Maryland, California, and New York. The states with the lowest number were Montana, South Dakota, Wyoming, Hawaii and Alaska.
  - These states make sense because large more populous states have more deaths and smaller less populous states have less deaths, with some exceptions.

Notes:

- Missing overdose death data for some states from some years

Federal Opioid Prescribing Rates

- Used data from Department of Veterans Affairs medical centers on 2012 and 2018 opioid prescribing rates
  - Prescribing rate is the percentage of total prescriptions administered by the medical centers
- Grouping data by state, CT was the 4th lowest in 2012 with an 8.9% rate and was the 8th lowest in 2018 with a 6.5% rate. So which states have the highest rates?

States with highest prescribing rates in 2012

Oklahoma	0.243
Nevada	0.238
Oregon	0.238
Arkansas	0.236
New Mexico	0.234

OK's rate is 2.73x of CT's rate in 2012!

States with highest prescribing rates in 2018

Idaho	0.150
Oklahoma	0.133
New Mexico	0.131
Oregon	0.130
Montana	0.127

ID's rate is 2.31x of CT's rate in 2018!

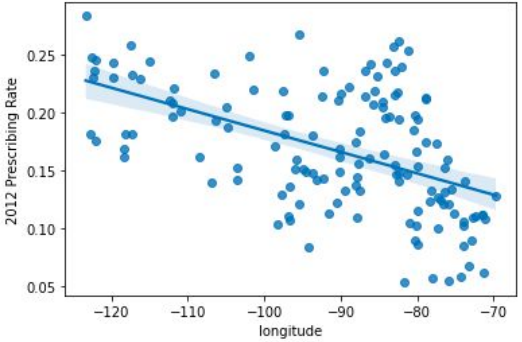
Federal Opioid Prescribing Rates (cont'd)

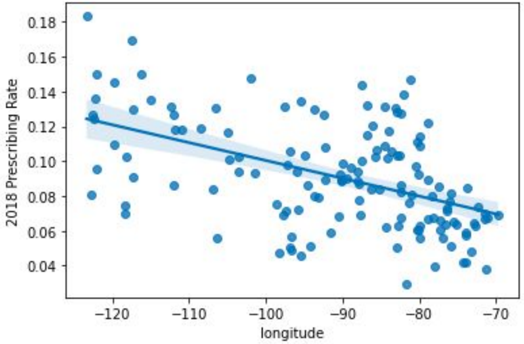
- Based on the observations, states in the Midwest/West had the highest prescribing rates → is this a national trend?
    - Question: Does **longitude** have an effect on the opioid prescribing rates?

(Note: Filtered out Alaska, Hawaii, Philippines, and PR)

	longitude	2012 Prescribing Rate
longitude	1.000	-0.508
2012 Prescribing Rate	-0.508	1.000

	longitude	2018 Prescribing Rate
longitude	1.000	-0.496
2018 Prescribing Rate	-0.496	1.000





Yes! There is a **moderate negative correlation** between longitude and opioid prescribing rates in both 2012 and 2018. As you move further East the rate decreases, or as you move further West the rate increases!

Geographic Pattern in Opioid Prescribing Rates

- Used geopandas and US state map to plot data points, focusing on most recent data (2018 opioid prescribing rate) → visually see that prescribing rates increase further West

2018 opioid prescribing rates by location of VA medical centers

Lighter color means higher rate

2018 mean opioid prescribing rate by state

CT has darker color, 8th lowest rate nationwide

ID is highest at 15%, lightest color

Review of main findings

- CT Prescriptions have decreased from 2012 to 2020.
- CT rehab admissions are increasing.
- Accidental opioid deaths have increased from 2012 to 2020.
- Federal overdose deaths increased from 2015-2020, and opioid deaths also increased in the same time frame at a faster rate
- Connecticut has a large amount of opioid overdose deaths compared to other states
- Federal opioid prescribing rates for CT are low
    - Nationwide trend that prescribing rates increase as you move further West