MA_overdose_deaths_by_town_cleanup_and_explore

September 21, 2019

1 Notebook to EDA and prep of the target MA opioid overdose deaths yearly table data

- City/Town name cleanup and matching, if needed
- EDA on the raw counts - data distribution, etc
- Note: the reporting style for MA city/town-level opioid overdose deaths has changed over the years, could only find data going back to 2012. Formatting was changed to tabulate opioid overdose deaths based on place of residence of descendent of deceased (Table 1) and by location of death (Table 2).

1.0.1 Outputs:

- Opioid overdose deaths by MA town/city Table 1: /data/tidy_data/ma_town_opioid_overdose_death_by_
- Opioid overdose deaths by MA town/city Table 2: /data/tidy_data/ma_town_opioid_overdose_death_by_
- Opioid overdose deaths Table 2 (2014-2018) + Older data (unintended opioid death), 2012-2013: /data/tidy_data/ma_town_opioid_overdose_death_by_place_of_death_2012_to_2018_merge.csv

[1]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
sns.set_style('darkgrid')
```

[2]:
```
# MA gov opioid overdose deaths table 1 (by town of residence of descendent)
table1_raw = pd.read_csv("../../data/raw_data/
 ↪ma_overdose_death_by_town_2014_2018_table1.csv")
# MA gov opioid overdose deaths table 2 (by town of death)
table2_raw = pd.read_csv("../../data/raw_data/
 ↪ma_town_opioid_overdose_death_by_place_of_death_2014_to_2018.csv")
# add on 2012-2014 "unintentional opioid overdose deaths" - based on info,␣
 ↪tabulation seems to be based on
# location of death (similar to table 2 data)
table_12_to_14 = pd.read_csv("../../data/raw_data/
 ↪ma_overdose_death_by_town_2012_to_2014_uninten_deaths.csv")
```

[3]:
```
print(table1_raw.shape)
print(table2_raw.shape)
```

```
print(table_12_to_14.shape)
display(table1_raw.head())
display(table2_raw.head())
display(table_12_to_14.head())
```

```
(353, 6)
(354, 6)
(353, 4)
```

	City/Town of Residence	2014	2015	2016	2017	2018
0	Abington	2	6	2	4	11
1	Acton	3	4	7	1	4
2	Acushnet	1	4	4	7	2
3	Adams	2	3	1	0	7
4	Agawam	3	5	4	7	12

	City/Town of Death	2014	2015	2016	2017	2018
0	Abington	0	6	1	3	5
1	Acton	1	2	3	0	1
2	Acushnet	0	4	2	4	0
3	Adams	2	3	1	0	4
4	Agawam	1	2	0	4	8

	City/Town	2012	2013	2014
0	Abington	1	2	2
1	Acton	2	0	3
2	Acushnet	2	0	0
3	Adams	1	1	2
4	Agawam	1	3	3

[4]:
```
table1 = table1_raw.copy()
table2 = table2_raw.copy()
table_older = table_12_to_14.copy()
table1.columns = ['city_resid'] + list(table1_raw.columns[1:])
table2.columns = ['city_death'] + list(table2_raw.columns[1:])
table_older.columns = ['city_death'] + list(table_12_to_14.columns[1:])
```

[5]:
```
# why more 1 more row in table 2?
print(set(table2['city_death']) - set(table1['city_resid']))
# this is mass residents that died outside of massachusetts
print(set(table2['city_death']) - set(table_older['city_death']))
```

```
{'Out Of Massachusetts'}
{'Out Of Massachusetts', 'Total'}
```

[6]:
```
# convert city names to lowercase, use as index
table1['city_resid'] = table1['city_resid'].str.lower()
table2['city_death'] = table2['city_death'].str.lower()
table_older['city_death'] = table_older['city_death'].str.lower()
table1.set_index('city_resid', inplace=True)
table2.set_index('city_death', inplace=True)
table_older.set_index('city_death', inplace=True)
```

[7]:
```
display(table1.head())
display(table2.head())
display(table_older.head())
```

city_resid	2014	2015	2016	2017	2018
abington	2	6	2	4	11
acton	3	4	7	1	4
acushnet	1	4	4	7	2
adams	2	3	1	0	7
agawam	3	5	4	7	12

city_death	2014	2015	2016	2017	2018
abington	0	6	1	3	5
acton	1	2	3	0	1
acushnet	0	4	2	4	0
adams	2	3	1	0	4
agawam	1	2	0	4	8

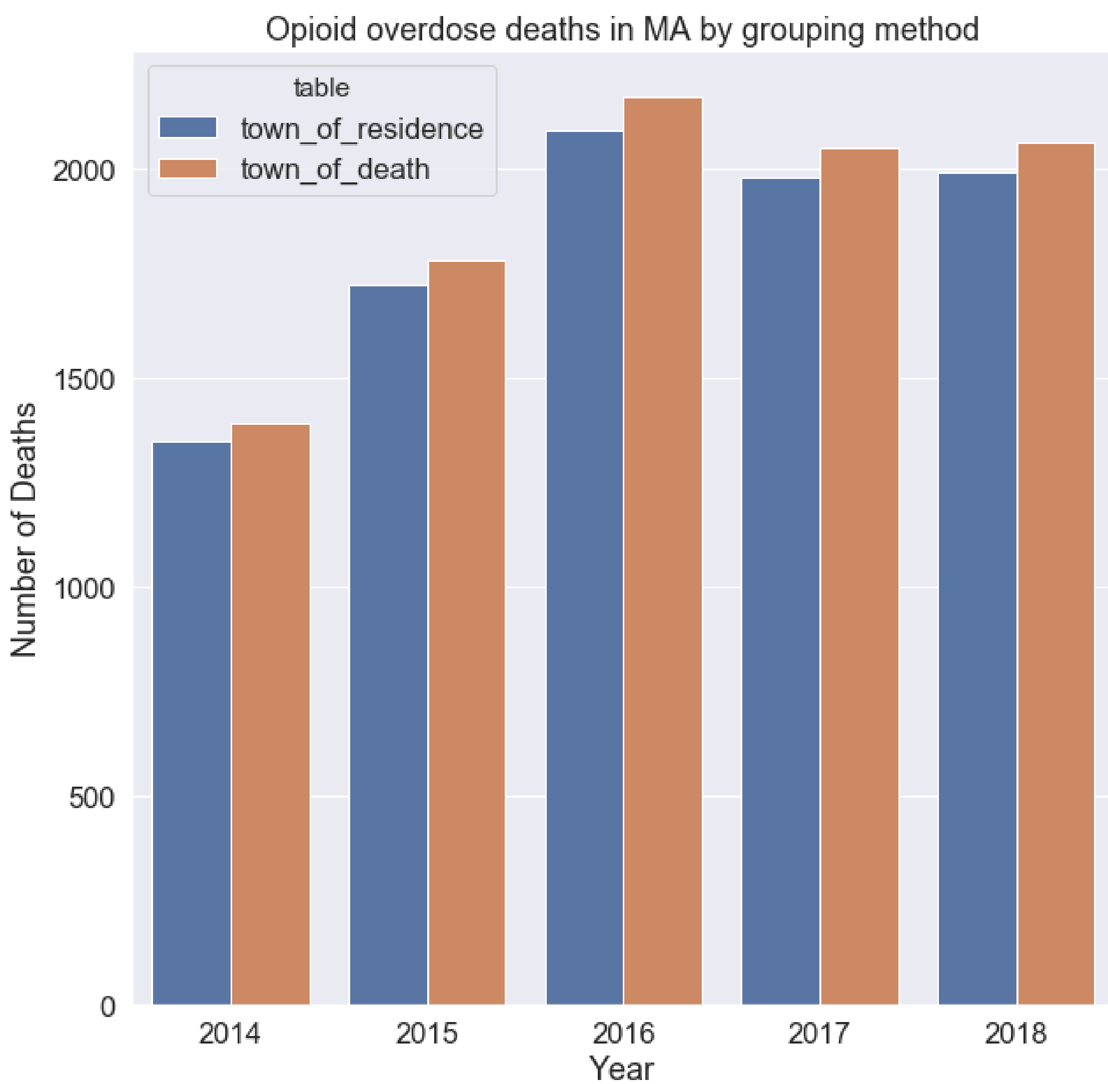
city_death	2012	2013	2014
abington	1	2	2
acton	2	0	3
acushnet	2	0	0
adams	1	1	2
agawam	1	3	3

[8]:
```
table2.loc['out of massachusetts']
```

[8]:
```
2014    29
2015    52
2016    90
2017    80
2018    62
Name: out of massachusetts, dtype: int64
```

[9]:
```
totals = pd.concat([table1.loc[['total']], table2.loc[['total']]], axis=0).
 ↪reset_index()
totals['table'] = ['town_of_residence', 'town_of_death']
totals.drop('index', inplace=True, axis=1)
```

[10]:
```
# how do the total death counts compare between the two tables?
sns.set(font_scale=1.5)
plt.figure(figsize=(10,10))
sns.barplot(x='variable', y='value', hue='table', data=totals.
 ↪melt(id_vars=['table']))
plt.xlabel('Year')
plt.ylabel('Number of Deaths')
plt.title('Opioid overdose deaths in MA by grouping method')
plt.show()
```



[11]:
```
# totals check to make sure sum of all rows matches Total row
table1_tot = table1.loc['total']
table2_tot = table2.loc['total']
table1.drop('total', inplace=True)
table2.drop('total', inplace=True)
print(table1.sum() - table1_tot)
print(table2.sum() - table2_tot)
# everything matches up
```

```
2014    0
2015    0
2016    0
2017    0
2018    0
dtype: int64
2014    0
2015    0
2016    0
2017    0
2018    0
dtype: int64
```

[16]:
```
# drop a couple of extra rows that will not be used in prediction model
table1.drop('unknown', inplace=True)
table2.drop(['unknown', 'out of massachusetts'], inplace=True)
print(table1.shape)
print(table2.shape)
```

```
(351, 5)
(351, 5)
```

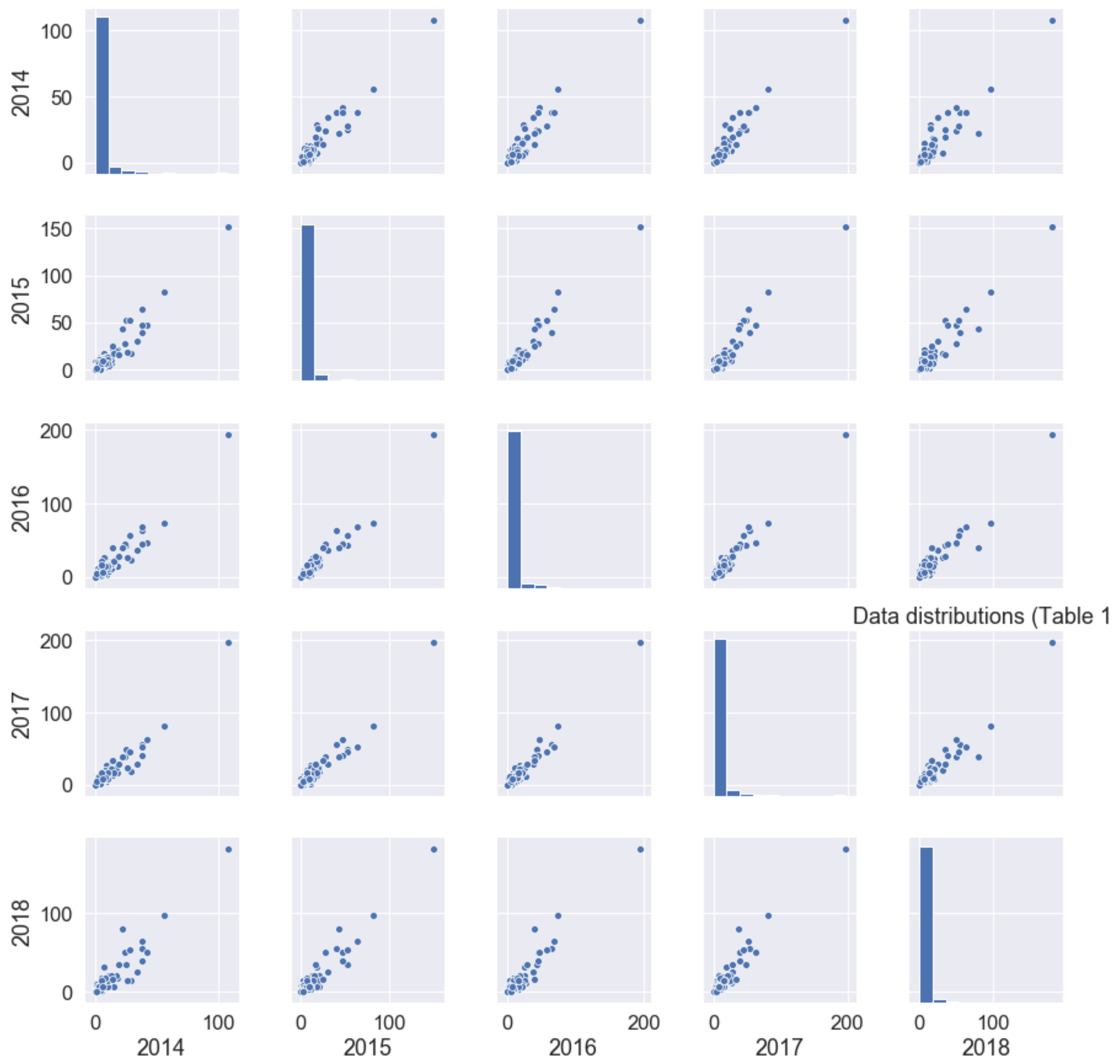
[17]:
```
display(table1.describe())
display(table2.describe())
```

	2014	2015	2016	2017	2018
count	351.000000	351.000000	351.000000	351.000000	351.000000
mean	3.846154	4.905983	5.965812	5.638177	5.669516
std	8.769051	12.030188	14.216850	14.080488	14.013021
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	2.000000	2.000000	2.000000	2.000000
75%	4.000000	5.000000	6.000000	6.000000	6.000000
max	108.000000	151.000000	194.000000	198.000000	181.000000

	2014	2015	2016	2017	2018
count	351.000000	351.000000	351.000000	351.000000	351.000000

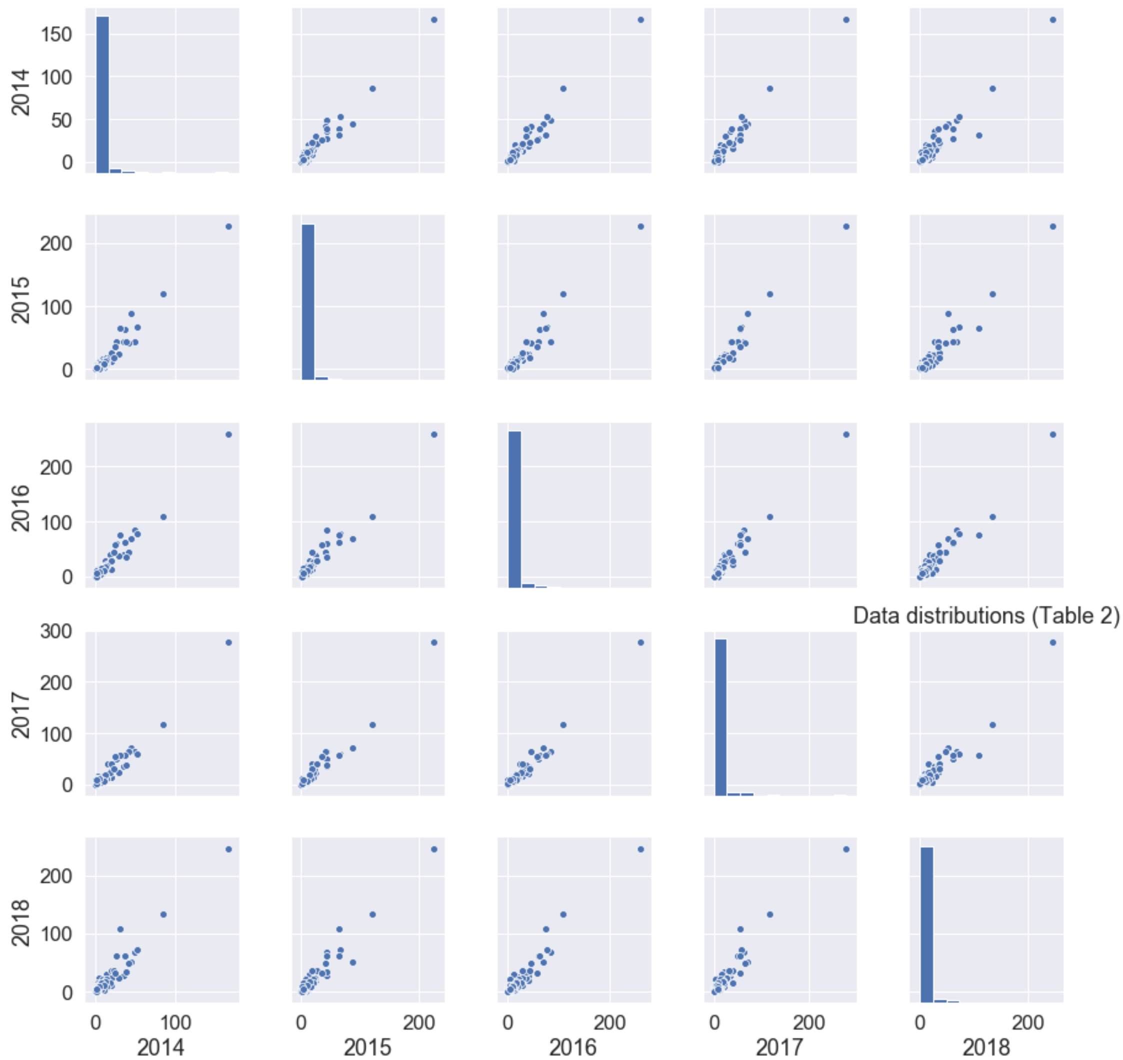
```
mean      3.888889    4.931624    5.940171    5.615385    5.700855
std      12.331222   16.672335   18.792684   18.965463   18.375729
min       0.000000    0.000000    0.000000    0.000000    0.000000
25%       0.000000    0.000000    0.000000    0.000000    0.000000
50%       1.000000    1.000000    1.000000    1.000000    1.000000
75%       2.000000    3.000000    3.500000    4.000000    4.000000
max     167.000000  226.000000  259.000000  279.000000  245.000000
```

[18]:
```
sns.pairplot(table1)
plt.title('Data distributions (Table 1)')
plt.show()
```



[19]:
```
sns.pairplot(table2)
plt.title('Data distributions (Table 2)')
```

```
plt.show()
```



[20]:
```
display(table1[table1['2014'] > 50])
display(table2[table2['2017'] > 100])
```

city_resid	2014	2015	2016	2017	2018
boston	108	151	194	198	181
worcester	56	82	74	82	97

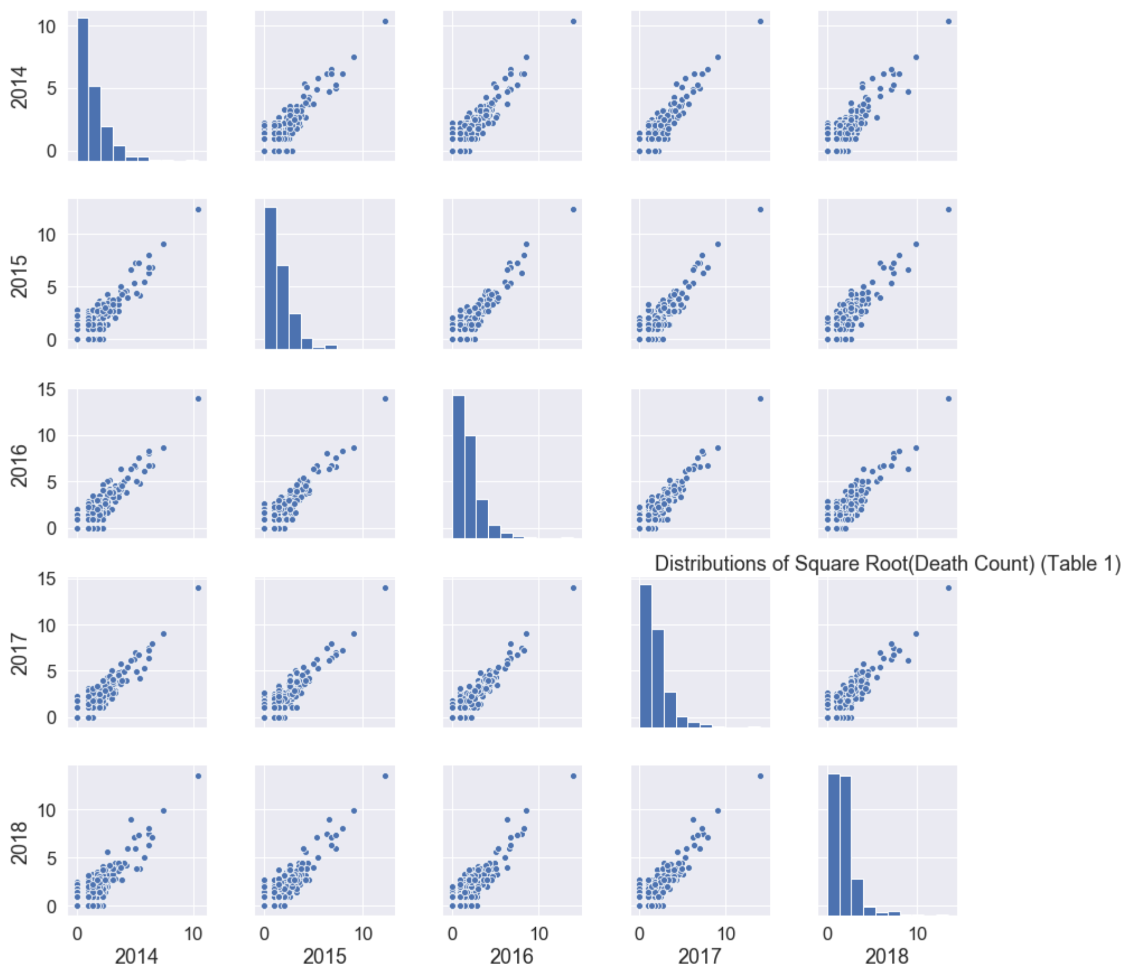
city_death	2014	2015	2016	2017	2018
boston	167	226	259	279	245
worcester	86	120	109	118	134

[21]:
```
table2.head()
```

[21]:

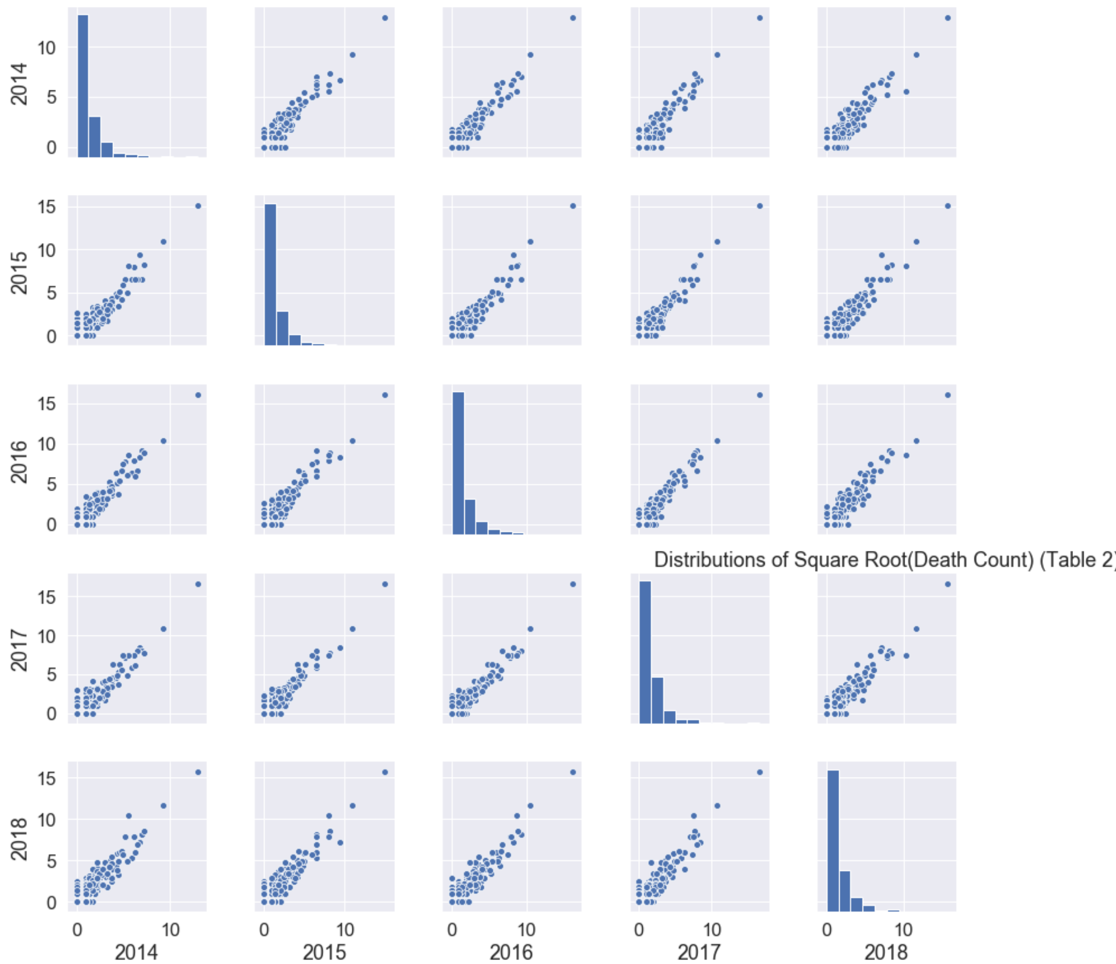
city_death	2014	2015	2016	2017	2018
abington	0	6	1	3	5
acton	1	2	3	0	1
acushnet	0	4	2	4	0
adams	2	3	1	0	4
agawam	1	2	0	4	8

[22]:
```
# square root all values to get a better look at data (vs log - infinity for␣
↪all zeroes)
sns.pairplot(table1.apply(np.sqrt))
plt.title('Distributions of Square Root(Death Count) (Table 1)')
plt.show()
```



[23]:
```
# square root all values to get a better look at data (vs log - infinity for␣
↪all zeroes)
```

```
sns.pairplot(table2.apply(np.sqrt))
plt.title('Distributions of Square Root(Death Count) (Table 2)')
plt.show()
```



Notes: * Overall, most death counts are close to 0 for MA towns - zero heavy distributions * Boston and Worcester have highest death counts, but these are the cities with highest population counts in MA * Strong positive relationship between death counts year over year for each town (not surprising) * Normalize death count to population count for each town - need population estimate for each town

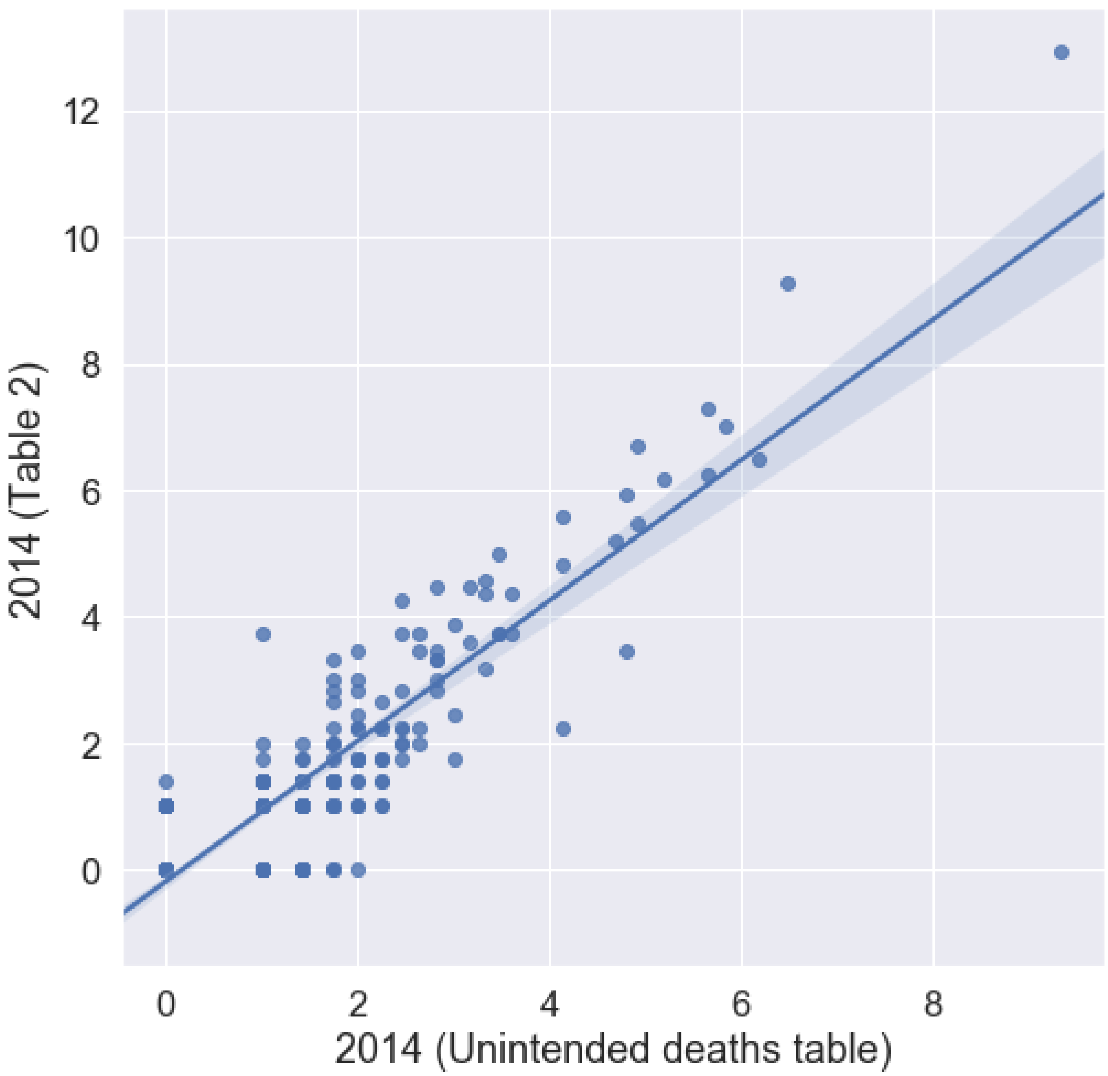
[24]:
```
#table1.to_csv("../../data/tidy_data/
↪ma_town_opioid_overdose_death_by_place_of_resid_2014_to_2018.csv")
#table2.to_csv("../../data/tidy_data/
↪ma_town_opioid_overdose_death_by_place_of_death_2014_to_2018.csv")
```

[33]:
```
# merge to determine if compantible
table_data_test = table_older.merge(table2, on="city_death", suffixes =␣
↪["_old", "_updt"], how="inner")
table_data_test.head()
```

[33]:

city_death	2012	2013	2014_old	2014_updt	2015	2016	2017	2018
abington	1	2	2	0	6	1	3	5
acton	2	0	3	1	2	3	0	1
acushnet	2	0	0	0	4	2	4	0
adams	1	1	2	2	3	1	0	4
agawam	1	3	3	1	2	0	4	8

[34]:
```
plt.figure(figsize=(8,8))
sns.regplot(x='2014_old', y='2014_updt', data=table_data_test.apply(np.sqrt))
plt.xlabel('2014 (Unintended deaths table)')
plt.ylabel('2014 (Table 2)')
plt.show()
```



[35]:
```
table_data_test.shape
```

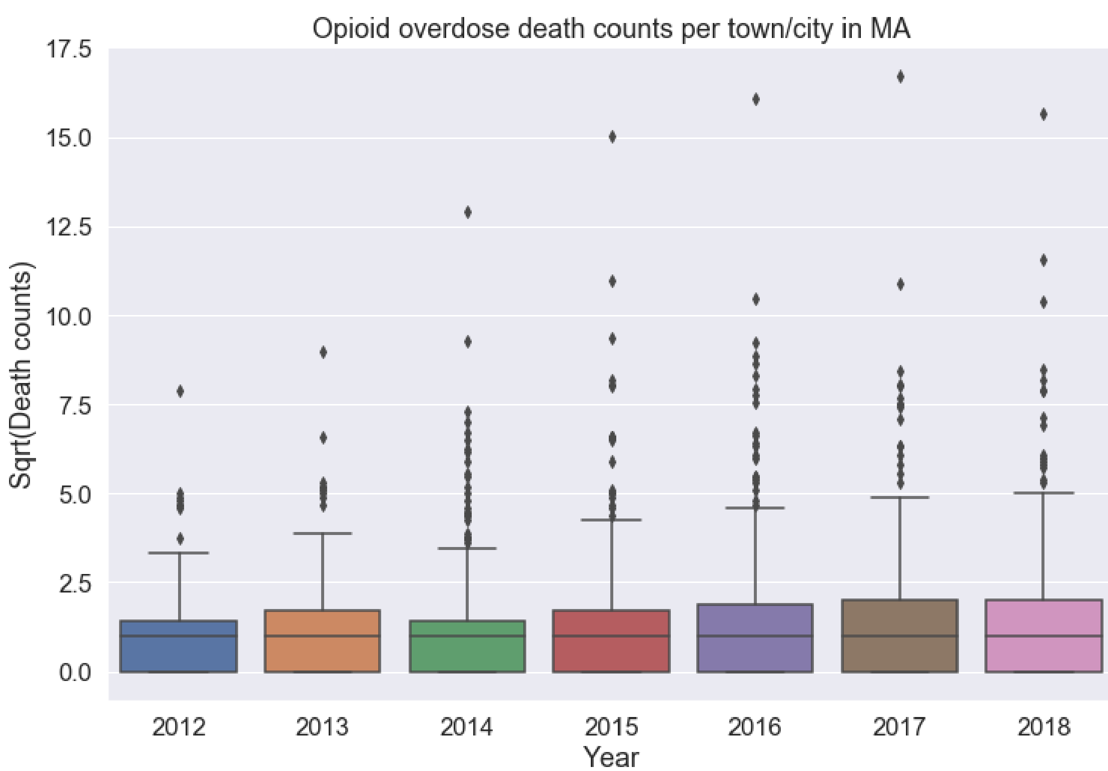
[35]: (351, 8)

[38]:
```
opioid_death_merge = table_older.drop('2014', axis=1).merge(table2,␣
↪on="city_death", suffixes = ["_old", "_updt"], how="inner")
opioid_death_merge.head()
```

[38]:

city_death	2012	2013	2014	2015	2016	2017	2018
abington	1	2	0	6	1	3	5
acton	2	0	1	2	3	0	1
acushnet	2	0	0	4	2	4	0
adams	1	1	2	3	1	0	4
agawam	1	3	1	2	0	4	8

[42]:
```
plt.figure(figsize=(12,8))
sns.boxplot(data=opioid_death_merge.apply(np.sqrt))
plt.xlabel('Year')
plt.ylabel('Sqrt(Death counts)')
plt.title('Opioid overdose death counts per town/city in MA')
plt.show()
```



[44]:
```
#opioid_death_merge.to_csv("../../data/tidy_data/
↪ma_town_opioid_overdose_death_by_place_of_death_2012_to_2018_merge.csv")
```