city_health_dash_500_cities_opioid_corr

September 21, 2019

1 Comments and goals:

- 500 Cities data will not be part of final project (data from all over US, cities only - limited), but may be useful to predict which variables correlate with opioid overdose/may be predictive of opioid overdose
- Will do some limited EDA and analysis, will keep to only one notebook

1.0.1 Notebook outputs:

- 500_cities_opioid_corr.png
- /data/tidy_data/500_cities_totpop_metric_pivot_table.csv

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

1.1 Pull in raw 500 cities dashboard data

[2]:
```
city_raw = pd.read_csv("../../../data/raw_data/500_cities_data/
↪CHDB_data_city_all v7_0.csv")
```

```
C:\Users\Dasha\Anaconda3\lib\site-
packages\IPython\core\interactiveshell.py:3058: DtypeWarning: Columns (21) have
mixed types. Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

[3]:
```
city_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60500 entries, 0 to 60499
Data columns (total 22 columns):
state_abbr                          60500 non-null object
state_fips                          60500 non-null int64
```

```
place_fips                        60500 non-null int64
stpl_fips                         60500 non-null int64
city_name                         60500 non-null object
metric_name                       60500 non-null object
group_name                        60500 non-null object
metric_number                     60500 non-null int64
group_number                      60500 non-null int64
num                               59421 non-null float64
denom                             59421 non-null float64
est                               54485 non-null float64
lci                               54060 non-null float64
uci                               54060 non-null float64
county_indicator                  55185 non-null float64
educ_indicator                    59886 non-null float64
multiplier_indicator              55217 non-null float64
data_yr_type                      60302 non-null object
geo_level                         60500 non-null object
Date of export to MySQL database  60500 non-null object
version                           60500 non-null int64
NOTE - NCHS Disclaimer            1 non-null object
dtypes: float64(8), int64(6), object(8)
memory usage: 10.2+ MB
```

[4]:
```python
city = city_raw.copy()
```

[5]:
```python
city.drop(['Date of export to MySQL database', 'version', 'NOTE - NCHS␣
↪Disclaimer'], axis=1, inplace=True)
```

[6]:
```python
city.head()
```

[6]:
```
  state_abbr  state_fips  place_fips  stpl_fips   city_name  metric_name  \
0         HI          15           3      15003    Honolulu  Absenteeism
1         AL           1        7000     107000  Birmingham  Absenteeism
2         AL           1       35896     135896      Hoover  Absenteeism
3         AL           1       37000     137000  Huntsville  Absenteeism
4         AL           1       50000     150000      Mobile  Absenteeism

         group_name  metric_number  group_number     num    denom   est  \
0  total population              1             1  9625.0  59827.0  16.1
1  total population              1             1  2250.0  10415.0  21.6
2  total population              1             1  1517.0  14571.0  10.4
3  total population              1             1  2376.0   9369.0  25.4
4  total population              1             1  2826.0  15034.0  18.8

     lci    uci  county_indicator  educ_indicator  multiplier_indicator  \
0 -999.0 -999.0            -999.0          -999.0                -999.0
1 -999.0 -999.0            -999.0          -999.0                -999.0
2 -999.0 -999.0            -999.0          -999.0                -999.0
3 -999.0 -999.0            -999.0          -999.0                -999.0
```

```
4 -999.0 -999.0            -999.0          -999.0                -999.0

  data_yr_type geo_level
0    2015-2016      city
1    2015-2016      city
2    2015-2016      city
3    2015-2016      city
4    2015-2016      city
```

[7]:
```
city.drop(['geo_level', 'state_fips', 'place_fips', 'stpl_fips'], axis=1,␣
 ↪inplace=True)
```

[8]:
```
city.head()
```

[8]:
```
  state_abbr   city_name  metric_name        group_name  metric_number  \
0         HI    Honolulu  Absenteeism  total population              1
1         AL  Birmingham  Absenteeism  total population              1
2         AL      Hoover  Absenteeism  total population              1
3         AL  Huntsville  Absenteeism  total population              1
4         AL      Mobile  Absenteeism  total population              1

   group_number     num    denom   est    lci    uci  county_indicator  \
0             1  9625.0  59827.0  16.1 -999.0 -999.0            -999.0
1             1  2250.0  10415.0  21.6 -999.0 -999.0            -999.0
2             1  1517.0  14571.0  10.4 -999.0 -999.0            -999.0
3             1  2376.0   9369.0  25.4 -999.0 -999.0            -999.0
4             1  2826.0  15034.0  18.8 -999.0 -999.0            -999.0

   educ_indicator  multiplier_indicator data_yr_type
0          -999.0                -999.0    2015-2016
1          -999.0                -999.0    2015-2016
2          -999.0                -999.0    2015-2016
3          -999.0                -999.0    2015-2016
4          -999.0                -999.0    2015-2016
```

[9]:
```
# demographic groups:
set(city['group_name'])
```

[9]:
```
{'age 0-18',
 'age 19-25',
 'age 26-34',
 'age 35-44',
 'age 45-64',
 'asian',
 'black',
 'female',
 'hispanic',
 'limited english proficiency',
 'male',
```

```
 'other',
 'total population',
 'white'}
```

[10]:
```
# metrics measured
set(city['metric_name'])
```

[10]:
```
{'Absenteeism',
 'Air pollution - particulate matter',
 'Binge drinking',
 'Breast cancer deaths',
 'Cardiovascular disease deaths',
 'Children in Poverty',
 'Colorectal cancer deaths',
 'Dental care',
 'Diabetes',
 'Frequent mental distress',
 'Frequent physical distress',
 'High blood pressure',
 'High school graduation',
 'Housing cost, excessive',
 'Housing with potential lead risk',
 'Income Inequality',
 'Lead exposure risk index',
 'Life expectancy',
 'Limited access to healthy foods',
 'Low birthweight',
 'Neighborhood racial/ethnic segregation',
 'Obesity',
 'Opioid overdose deaths',
 'Park access',
 'Physical inactivity',
 'Premature deaths (all causes)',
 'Prenatal care',
 'Preventive services',
 'Racial/ethnic diversity',
 'Smoking',
 'Teen births',
 'Third-grade reading proficiency',
 'Unemployment',
 'Uninsured',
 'Violent crime',
 'Walkability'}
```

[11]:
```
# which deomographic groups is opioid overdose info available for?
city[city['metric_name'] == 'Opioid overdose deaths'].groupby('group_name').
 ↪count()
```

[11]:
```
                      state_abbr  city_name  metric_name  metric_number  \
group_name
total population             500        500          500            500

                      group_number  num  denom  est  lci  uci  county_indicator  \
group_name
total population               500  500    500  428  428  428               428

                      educ_indicator  multiplier_indicator  data_yr_type
group_name
total population                 500                   428           500
```

[12]:
```python
opioid_overdose = city[city['metric_name'] == 'Opioid overdose deaths'].copy()
opioid_overdose.head()
```

[12]:
```
      state_abbr   city_name              metric_name        group_name  \
49000         HI    Honolulu  Opioid overdose deaths  total population
49001         AL  Birmingham  Opioid overdose deaths  total population
49002         AL      Hoover  Opioid overdose deaths  total population
49003         AL  Huntsville  Opioid overdose deaths  total population
49004         AL      Mobile  Opioid overdose deaths  total population

       metric_number  group_number    num  denom   est   lci   uci  \
49000             32             1 -999.0 -999.0   4.3   3.6   4.9
49001             32             1 -999.0 -999.0  28.0  24.6  31.5
49002             32             1 -999.0 -999.0  12.0   8.2  15.9
49003             32             1 -999.0 -999.0   3.5   2.2   4.8
49004             32             1 -999.0 -999.0   5.1   3.5   6.7

       county_indicator  educ_indicator  multiplier_indicator data_yr_type
49000               2.0          -999.0                   3.0    2015-2017
49001               0.0          -999.0                   3.0    2015-2017
49002               0.0          -999.0                   3.0    2015-2017
49003               0.0          -999.0                   3.0    2015-2017
49004               0.0          -999.0                   3.0    2015-2017
```

[13]:
```python
print(set(opioid_overdose['group_name']))
print(set(opioid_overdose['group_number']))
```

```
{'total population'}
{1}
```

[14]:
```python
city_totpop = city[city['group_name'] == 'total population'].copy()
city_totpop.head()
```

[14]:
```
  state_abbr   city_name  metric_name        group_name  metric_number  \
0         HI    Honolulu  Absenteeism  total population              1
1         AL  Birmingham  Absenteeism  total population              1
2         AL      Hoover  Absenteeism  total population              1
```

```
3          AL  Huntsville  Absenteeism  total population              1
4          AL      Mobile  Absenteeism  total population              1

   group_number     num    denom   est    lci    uci  county_indicator  \
0             1  9625.0  59827.0  16.1 -999.0 -999.0            -999.0
1             1  2250.0  10415.0  21.6 -999.0 -999.0            -999.0
2             1  1517.0  14571.0  10.4 -999.0 -999.0            -999.0
3             1  2376.0   9369.0  25.4 -999.0 -999.0            -999.0
4             1  2826.0  15034.0  18.8 -999.0 -999.0            -999.0

   educ_indicator  multiplier_indicator data_yr_type
0          -999.0                -999.0    2015-2016
1          -999.0                -999.0    2015-2016
2          -999.0                -999.0    2015-2016
3          -999.0                -999.0    2015-2016
4          -999.0                -999.0    2015-2016
```

[15]:
```python
# what's in some of the columns?
print(set(city_totpop['group_name']))
print(set(city_totpop['group_number']))
print(set(city_totpop['data_yr_type']))
```

```
{'total population'}
{1}
{nan, '2018', '2017-2018', '2016, 1 Year Modeled Estimate', '2015, 1 Year
Modeled Estimate', '2016-2017', '2010-2015, 6 Year Modeled Estimate', '2017',
'2015-2016', '2015-2017', '2015', '2017, 5 Year Estimate', '2014-2015'}
```

[16]:
```python
# drop uninformative columns
city_totpop.drop(['group_name', 'group_number'], axis=1, inplace=True)
city_totpop.head()
```

[16]:
```
  state_abbr   city_name  metric_name  metric_number     num    denom   est  \
0         HI    Honolulu  Absenteeism              1  9625.0  59827.0  16.1
1         AL  Birmingham  Absenteeism              1  2250.0  10415.0  21.6
2         AL      Hoover  Absenteeism              1  1517.0  14571.0  10.4
3         AL  Huntsville  Absenteeism              1  2376.0   9369.0  25.4
4         AL      Mobile  Absenteeism              1  2826.0  15034.0  18.8

     lci    uci  county_indicator  educ_indicator  multiplier_indicator  \
0 -999.0 -999.0            -999.0          -999.0                -999.0
1 -999.0 -999.0            -999.0          -999.0                -999.0
2 -999.0 -999.0            -999.0          -999.0                -999.0
3 -999.0 -999.0            -999.0          -999.0                -999.0
4 -999.0 -999.0            -999.0          -999.0                -999.0

  data_yr_type
0    2015-2016
```

```
1    2015-2016
2    2015-2016
3    2015-2016
4    2015-2016
```

[17]:
```
city_totpop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18000 entries, 0 to 60499
Data columns (total 13 columns):
state_abbr              18000 non-null object
city_name               18000 non-null object
metric_name             18000 non-null object
metric_number           18000 non-null int64
num                     17893 non-null float64
denom                   17893 non-null float64
est                     17128 non-null float64
lci                     17078 non-null float64
uci                     17078 non-null float64
county_indicator        17161 non-null float64
educ_indicator          17977 non-null float64
multiplier_indicator    17193 non-null float64
data_yr_type            17978 non-null object
dtypes: float64(8), int64(1), object(4)
memory usage: 1.9+ MB
```

[18]:
```
city_totpop.describe()
```

[18]:
```
       metric_number           num         denom           est           lci  \
count   18000.000000  1.789300e+04  1.789300e+04  17128.000000  17078.000000
mean       18.972222  5.669836e+03  2.378344e+04    264.294021     16.246498
std        10.823337  4.184871e+04  1.535921e+05   1345.134173   1417.441817
min         1.000000 -9.990000e+02 -9.990000e+02    -45.900000   -999.000000
25%         9.750000 -9.990000e+02 -9.990000e+02     11.900000      3.900000
50%        18.500000 -9.990000e+02 -9.990000e+02     24.300000     16.050000
75%        28.250000 -9.990000e+02 -9.990000e+02     57.500000     39.600000
max        37.000000  2.157108e+06  8.461961e+06  18100.000000  17700.000000

                uci  county_indicator  educ_indicator  multiplier_indicator
count  17078.000000      17161.000000    17977.000000          17193.000000
mean      33.989173       -145.528815     -944.650387           -812.913453
std     1493.391737        352.443690      226.717857            389.665688
min     -999.000000       -999.000000     -999.000000           -999.000000
25%        5.900000          0.000000     -999.000000           -999.000000
50%       18.700000          0.000000     -999.000000           -999.000000
75%       42.700000          0.000000     -999.000000           -999.000000
max    18400.000000          2.000000        2.000000              3.000000
```

[19]:
```
city_totpop_metric = city_totpop[['state_abbr', 'city_name', 'metric_name',␣
↪'est']].copy()
city_totpop_metric.head()
```

[19]:
```
  state_abbr   city_name  metric_name   est
0         HI    Honolulu  Absenteeism  16.1
1         AL  Birmingham  Absenteeism  21.6
2         AL      Hoover  Absenteeism  10.4
3         AL  Huntsville  Absenteeism  25.4
4         AL      Mobile  Absenteeism  18.8
```

[20]:
```
city_totpop_metric['uniq_name'] = city_totpop_metric['state_abbr'] + '_' +␣
↪city_totpop_metric['city_name']
city_totpop_metric.drop(['state_abbr', 'city_name'], axis=1, inplace=True)
city_totpop_metric.set_index('uniq_name', inplace=True)
city_totpop_metric.head()
```

[20]:
```
               metric_name   est
uniq_name
HI_Honolulu    Absenteeism  16.1
AL_Birmingham  Absenteeism  21.6
AL_Hoover      Absenteeism  10.4
AL_Huntsville  Absenteeism  25.4
AL_Mobile      Absenteeism  18.8
```

[21]:
```
city_totpop_metric['metric_name'] = city_totpop_metric['metric_name'].str.
↪lower().str.replace(' ', "_")
```

[22]:
```
city_metric_pivot = city_totpop_metric.pivot(columns='metric_name',␣
↪values='est')
```

[23]:
```
city_metric_pivot.head()
```

[23]:
```
metric_name    absenteeism  air_pollution_-_particulate_matter  \
uniq_name
AK_Anchorage          25.8                                 NaN
AL_Birmingham         21.6                                11.5
AL_Hoover             10.4                                11.4
AL_Huntsville         25.4                                10.4
AL_Mobile             18.8                                10.3

metric_name    binge_drinking  breast_cancer_deaths  \
uniq_name
AK_Anchorage             19.4                  17.8
AL_Birmingham            13.2                  42.5
AL_Hoover                17.8                  11.9
AL_Huntsville            14.1                  21.2
AL_Mobile                14.7                  29.4

metric_name    cardiovascular_disease_deaths  children_in_poverty  \
```

```
uniq_name
AK_Anchorage                     135.2                 11.5
AL_Birmingham                    293.8                 45.4
AL_Hoover                         81.9                  8.0
AL_Huntsville                    171.2                 28.7
AL_Mobile                        267.1                 34.8

metric_name    colorectal_cancer_deaths  dental_care  diabetes  \
uniq_name
AK_Anchorage                       13.5         65.2       7.6
AL_Birmingham                      25.1         52.6      16.7
AL_Hoover                           4.1         74.5       8.3
AL_Huntsville                      13.9         61.2      12.2
AL_Mobile                          19.8         58.7      15.2

metric_name    frequent_mental_distress  ...  prenatal_care  \
uniq_name                                ...
AK_Anchorage                       11.4  ...           77.0
AL_Birmingham                      15.2  ...           66.3
AL_Hoover                          10.4  ...            NaN
AL_Huntsville                      13.3  ...           63.3
AL_Mobile                          14.7  ...           82.1

metric_name    preventive_services  racial/ethnic_diversity  smoking  \
uniq_name
AK_Anchorage                  36.5                     75.5     18.0
AL_Birmingham                 29.5                     59.8     22.3
AL_Hoover                     42.5                     56.3     14.1
AL_Huntsville                 43.0                     61.6     18.5
AL_Mobile                     31.3                     59.6     20.2

metric_name    teen_births  third-grade_reading_proficiency  unemployment  \
uniq_name
AK_Anchorage          20.8                             36.9           5.8
AL_Birmingham         49.4                             14.6          10.7
AL_Hoover              NaN                             53.3           4.2
AL_Huntsville         22.8                             36.2           7.3
AL_Mobile             36.6                             26.0           7.9

metric_name    uninsured  violent_crime  walkability
uniq_name
AK_Anchorage        14.4         1190.7         32.0
AL_Birmingham       15.9            NaN         39.4
AL_Hoover            7.4           97.5         22.6
AL_Huntsville       13.0          934.5         23.4
AL_Mobile           14.7          949.3         32.6
```

```
[5 rows x 36 columns]
```

2 Write to tidy_data for potential future use

[25]:
```
#city_metric_pivot.to_csv("../../../data/tidy_data/
→500_cities_totpop_metric_pivot_table.csv")
### optional import:
#city_metric_pivot = pd.read_csv("../../../data/tidy_data/
→500_cities_totpop_metric_pivot_table.csv")
```

[26]:
```
# missing values?
city_metric_pivot.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 37 columns):
uniq_name                                 500 non-null object
absenteeism                               500 non-null float64
air_pollution_-_particulate_matter        498 non-null float64
binge_drinking                            500 non-null float64
breast_cancer_deaths                      492 non-null float64
cardiovascular_disease_deaths             494 non-null float64
children_in_poverty                       500 non-null float64
colorectal_cancer_deaths                  492 non-null float64
dental_care                               500 non-null float64
diabetes                                  500 non-null float64
frequent_mental_distress                  500 non-null float64
frequent_physical_distress                500 non-null float64
high_blood_pressure                       500 non-null float64
high_school_graduation                    478 non-null float64
housing_cost,_excessive                   500 non-null float64
housing_with_potential_lead_risk          500 non-null float64
income_inequality                         500 non-null float64
lead_exposure_risk_index                  500 non-null float64
life_expectancy                           492 non-null float64
limited_access_to_healthy_foods           500 non-null float64
low_birthweight                           273 non-null float64
neighborhood_racial/ethnic_segregation    500 non-null float64
obesity                                   500 non-null float64
opioid_overdose_deaths                    428 non-null float64
park_access                               500 non-null float64
physical_inactivity                       500 non-null float64
premature_deaths_(all_causes)             495 non-null float64
prenatal_care                             246 non-null float64
preventive_services                       500 non-null float64
racial/ethnic_diversity                   500 non-null float64
```

```
smoking                                   500 non-null float64
teen_births                               273 non-null float64
third-grade_reading_proficiency           499 non-null float64
unemployment                              500 non-null float64
uninsured                                 500 non-null float64
violent_crime                             468 non-null float64
walkability                               500 non-null float64
dtypes: float64(36), object(1)
memory usage: 144.7+ KB
```

[27]:
```
# low_birthweight, prenatal_care, and teen_births are missing < 200 values -
↪remove columns
city_metric_pivot.drop(['low_birthweight', 'prenatal_care', 'teen_births'],
↪axis=1, inplace=True)
```

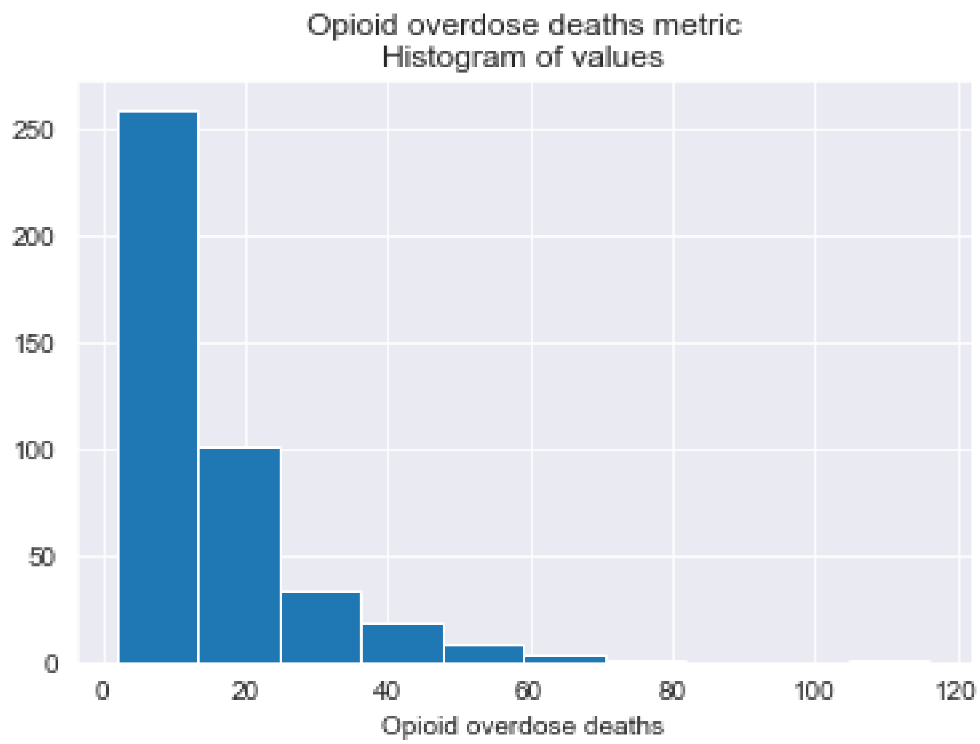
[28]:
```
# distributions:
city_metric_pivot.describe()
```

[28]:
```
       absenteeism  air_pollution_-_particulate_matter  binge_drinking  \
count   500.000000                          498.000000      500.000000
mean     18.073200                            9.191165       17.656200
std       9.341169                            1.692985        2.684346
min       0.000000                            4.900000        9.100000
25%      11.800000                            7.900000       16.000000
50%      16.250000                            9.150000       17.550000
75%      22.500000                           10.300000       19.200000
max      65.800000                           15.700000       27.400000

       breast_cancer_deaths  cardiovascular_disease_deaths  \
count            492.000000                     494.000000
mean              24.428049                     210.440486
std                6.056955                      58.725131
min               11.300000                      46.700000
25%               20.300000                     171.350000
50%               23.700000                     202.750000
75%               27.900000                     236.825000
max               50.600000                     515.200000

       children_in_poverty  colorectal_cancer_deaths  dental_care    diabetes  \
count           500.000000                492.000000   500.000000  500.000000
mean             22.625400                 16.099187    63.196000    9.997800
std              10.899536                  4.207326     7.546653    2.397196
min               2.400000                  4.100000    42.300000    4.200000
25%              14.375000                 13.500000    57.600000    8.275000
50%              22.150000                 15.700000    63.300000    9.800000
75%              29.725000                 18.325000    68.700000   11.500000
max              60.000000                 34.300000    81.800000   21.600000
```

```
       frequent_mental_distress  ...  physical_inactivity  \
count                500.000000  ...           500.000000
mean                  12.833200  ...            23.992000
std                    2.061543  ...             6.468535
min                    7.900000  ...            10.100000
25%                   11.400000  ...            18.800000
50%                   12.900000  ...            23.850000
75%                   14.300000  ...            28.200000
max                   18.400000  ...            46.800000

       premature_deaths_(all_causes)  preventive_services  \
count                     495.000000           500.000000
mean                     7510.505051            32.585800
std                      2856.353588             4.954973
min                       100.000000            18.400000
25%                      5400.000000            29.500000
50%                      7000.000000            32.450000
75%                      9300.000000            35.925000
max                     18100.000000            47.700000

       racial/ethnic_diversity     smoking  third-grade_reading_proficiency  \
count               500.000000  500.000000                       499.000000
mean                 64.086800   17.394000                        46.192585
std                  14.622094    4.098042                        17.990903
min                  13.700000    8.600000                        11.200000
25%                  55.600000   14.300000                        31.600000
50%                  66.000000   17.100000                        44.200000
75%                  74.925000   20.100000                        58.650000
max                  94.300000   29.700000                        91.100000

       unemployment  uninsured  violent_crime  walkability
count    500.000000  500.00000     468.000000   500.000000
mean       7.169400   12.86000     513.545940    44.509000
std        2.694908    5.69098     366.814577    15.788077
min        3.000000    2.00000      19.600000     6.500000
25%        5.300000    9.00000     242.875000    33.700000
50%        6.650000   11.95000     416.900000    41.500000
75%        8.425000   15.90000     697.650000    54.350000
max       22.200000   35.20000    2044.400000    94.200000

[8 rows x 33 columns]
```

[32]:

```
city_metric_pivot['opioid_overdose_deaths'].hist()
plt.xlabel('Opioid overdose deaths')
plt.title('Opioid overdose deaths metric\nHistogram of values')
plt.show()
```



Opioid data has a non-normal distribution - use spearman correlation

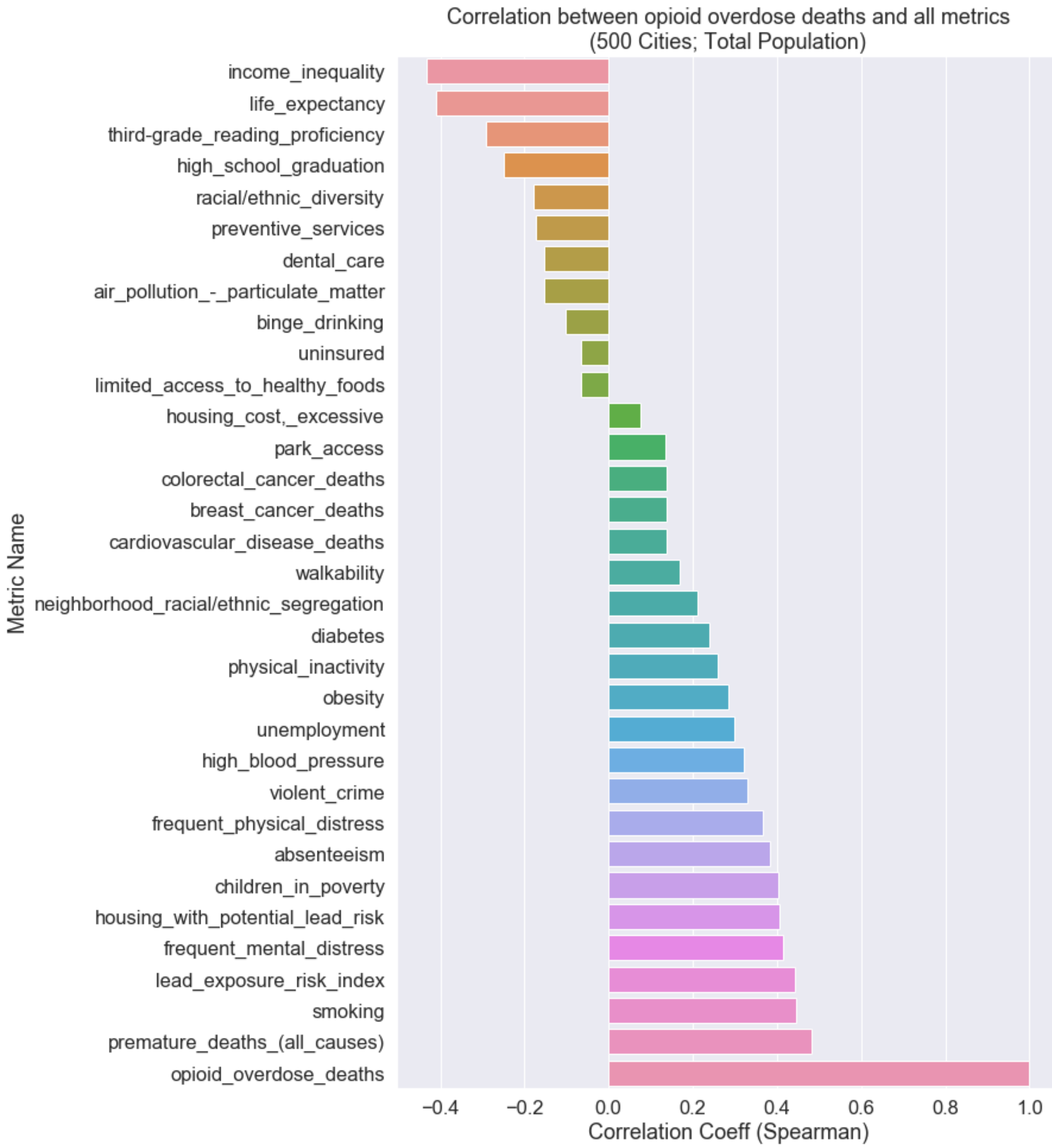
[37]:
```
opioid_corr_spear = pd.DataFrame(city_metric_pivot.
  ↪corr(method='spearman'))['opioid_overdose_deaths'].reset_index()
opioid_corr_spear.columns = ['metric_name', 'opioid_corr_spear']
opioid_corr_spear.head()
```

[37]:

	metric_name	opioid_corr_spear
0	absenteeism	0.382007
1	air_pollution_-_particulate_matter	-0.152266
2	binge_drinking	-0.101245
3	breast_cancer_deaths	0.137509
4	cardiovascular_disease_deaths	0.137706

[38]:
```
opioid_corr_spear.sort_values('opioid_corr_spear', inplace=True)
```

[39]:
```
sns.set(font_scale=1.5)
plt.figure(figsize=(10,16))
sns.barplot(y='metric_name', x='opioid_corr_spear', data=opioid_corr_spear,␣
  ↪orient="h")
plt.xlabel('Correlation Coeff (Spearman)')
plt.ylabel('Metric Name')
plt.title('Correlation between opioid overdose deaths and all metrics\n(500␣
  ↪Cities; Total Population)')
plt.show()
```



[41]:
```
# select some of the correlated metrics:
city_piv_sub = city_metric_pivot[['opioid_overdose_deaths', 'smoking',␣
↪'frequent_mental_distress', 'life_expectancy', 'income_inequality']].copy()
city_piv_sub.dropna().describe()
```

[41]:
```
       opioid_overdose_deaths     smoking  frequent_mental_distress  \
count              420.000000  420.000000                420.000000
mean                14.837143   17.608810                 12.899524
std                 13.353835    4.096601                  2.037313
min                  2.000000    8.600000                  7.900000
25%                  6.500000   14.700000                 11.500000
```

```
50%                 10.100000   17.300000                 13.000000
75%                 17.250000   20.225000                 14.300000
max                116.200000   29.700000                 18.400000

       life_expectancy  income_inequality
count       420.000000         420.000000
mean         78.744762          -6.023571
std           2.285149          17.145394
min          72.000000         -45.900000
25%          77.300000         -18.125000
50%          78.700000          -8.650000
75%          80.400000           5.025000
max          85.100000          44.000000
```

[49]:

```
# one city with a lot of opioid overdose deaths
city_metric_pivot[['uniq_name',␣
↪'opioid_overdose_deaths']][city_metric_pivot['opioid_overdose_deaths'] > 50].
↪sort_values('opioid_overdose_deaths', ascending=False)
```

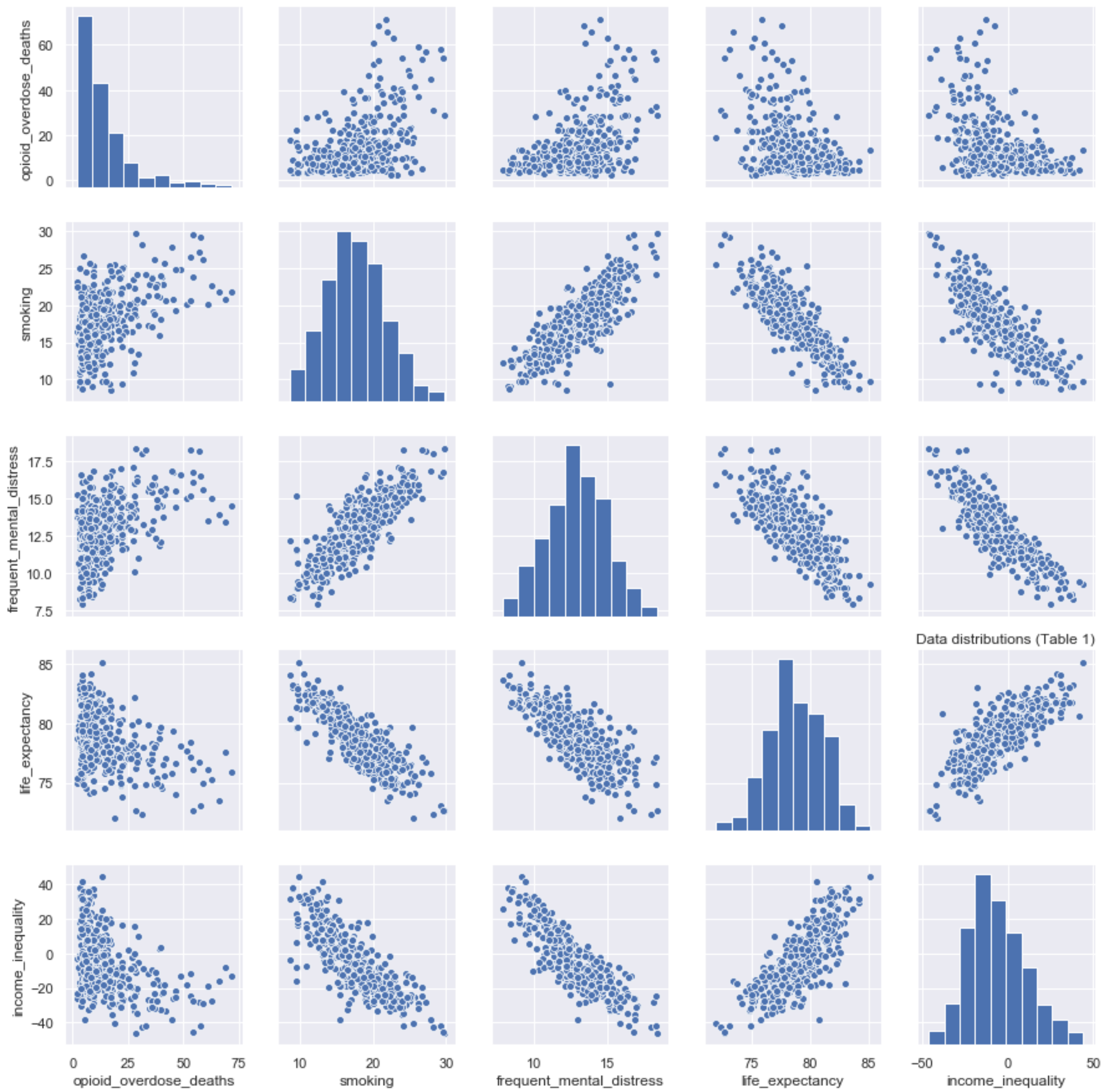
[49]:

```
          uniq_name  opioid_overdose_deaths
367       OH_Dayton                   116.2
498   WV_Charleston                    71.4
333   NH_Manchester                    68.8
279    MD_Baltimore                    66.0
364   OH_Cincinnati                    62.8
389   PA_Pittsburgh                    61.1
362        OH_Akron                    58.9
365    OH_Cleveland                    57.9
269   MA_Fall River                    57.1
405    TN_Knoxville                    54.4
370   OH_Youngstown                    54.2
273  MA_New Bedford                    53.4
272         MA_Lynn                    53.0
271       MA_Lowell                    51.2
```

4 MA towns with a lot of high opioid overdose deaths - interesting

[50]:

```
# remove Dayton OH - too high, skews plots
sns.set(font_scale=1)
sns.pairplot(city_piv_sub[city_piv_sub['opioid_overdose_deaths'] < 100].
↪dropna())
plt.title('Data distributions (Table 1)')
plt.show()
```



- The other selected metrics are highly correlated with each other - something to watch out for in general
- opioid overdose deaths highly skewed, has some relationship with these variables
- variables might be a proxy for something else - poverty maybe?