geopandas_intro

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1 Introduction to GeoPandas

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The second library in the Python geospatial stack that we examine is GeoPandas. GeoPandas builds on the capabilities of Shapely and combines these with the popular pandas library that provides high-performance and easy-to-use data structures for data analysis in Python.

1.1 Objectives

- Understand GeoDataSeries and GeoDatatFrames
- Learn reading and writing common vector spatial data formats
- Carry out geoprocessing with GeoPandas

1.2 Setup and Imports

We utilize our common imports

```
In [1]: %matplotlib inline
        import matplotlib
        import numpy as np
        import matplotlib.pyplot as plt
```

and import geopandas as an alias `gpd`

```
In [2]: import geopandas as gpd
```

2 GeoPandas Structure

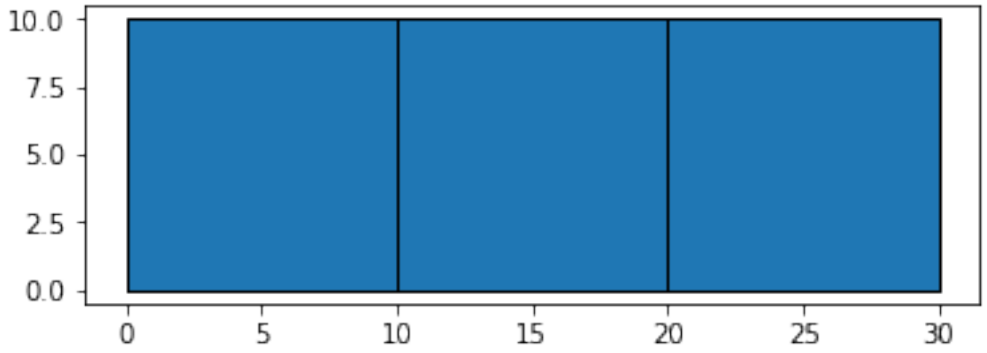
As mentioned above, geopandas builds on-top of shapely which means we have access to all the functionality we saw in the previous notebook. To get a better sense of this connection, let's create a few shapely Polygons and then see how they are used in geopandas:

```
In [3]: from shapely.geometry import Polygon
        poly_1 = Polygon([ (0,0), (0,10), (10, 10), (10, 0) ] )
        poly_2 = Polygon([ (10,0), (10,10), (20, 10), (20, 0) ] )
        poly_3 = Polygon([ (20,0), (20,10), (30, 10), (30, 0) ] )
```

2.1 GeoSeries: Putting the Geo in GeoPandas

We are going to combine these three polygons in a geopandas `GeoSeries`:

```
In [4]: polys = gpd.GeoSeries([poly_1, poly_2, poly_3])
        polys.plot(edgecolor='k')

Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x7f107b0a95c0>
```



The `GeoSeries` can be thought of as a vector, with each element of the vector corresponding to one or more Shapely geometry objects:

```
In [5]: polys

Out[5]: 0       POLYGON ((0 0, 0 10, 10 10, 10 0, 0 0))
        1    POLYGON ((10 0, 10 10, 20 10, 20 0, 10 0))
        2    POLYGON ((20 0, 20 10, 30 10, 30 0, 20 0))
        dtype: object
```

so here we see three elements, each of type `POLYGON` along with their coordinates.

```
In [6]: type(polys)

Out[6]: geopandas.geoseries.GeoSeries
```

Depending on what we need, we can either work on an *element-wise* basis or with the geoseries as a unified object. For example, an example of the former is:

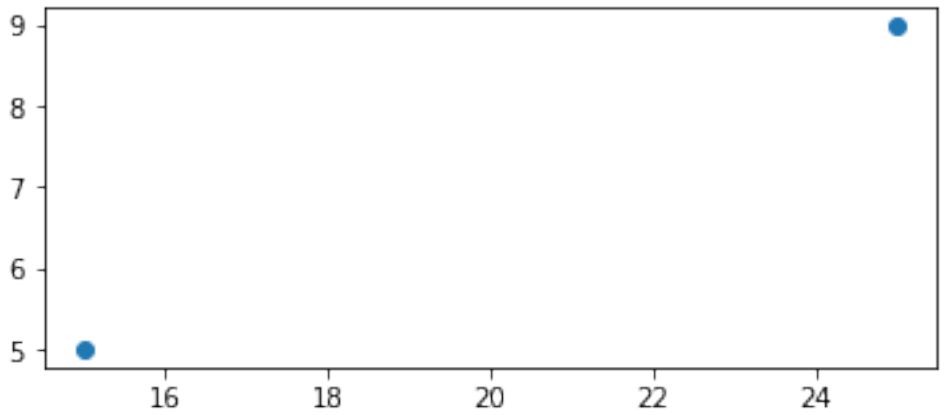
```
In [7]: polys.bounds

Out[7]:    minx  miny  maxx  maxy
        0   0.0   0.0  10.0  10.0
        1  10.0   0.0  20.0  10.0
        2  20.0   0.0  30.0  10.0
```

which returns the bounds of each of the polygons. Alternatively, if we want the bounds for the collection:

```
In [8]: polys.total_bounds

Out[8]: array([ 0.,  0., 30., 10.])
```

Binary operations between two geoseries will be carried out element wise, and this can lead to some counter intuitive results. For example, a second `GeoSeries` created as:

```
In [9]: from shapely.geometry import Point
        p_1 = Point(15, 5)
        p_2 = Point(25, 9)
        points = gpd.GeoSeries([p_1, p_2])
        points.plot()

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1078babeb8>
```



consists of two points. Each of the points is contained by the `polys` `GeoSeries`:

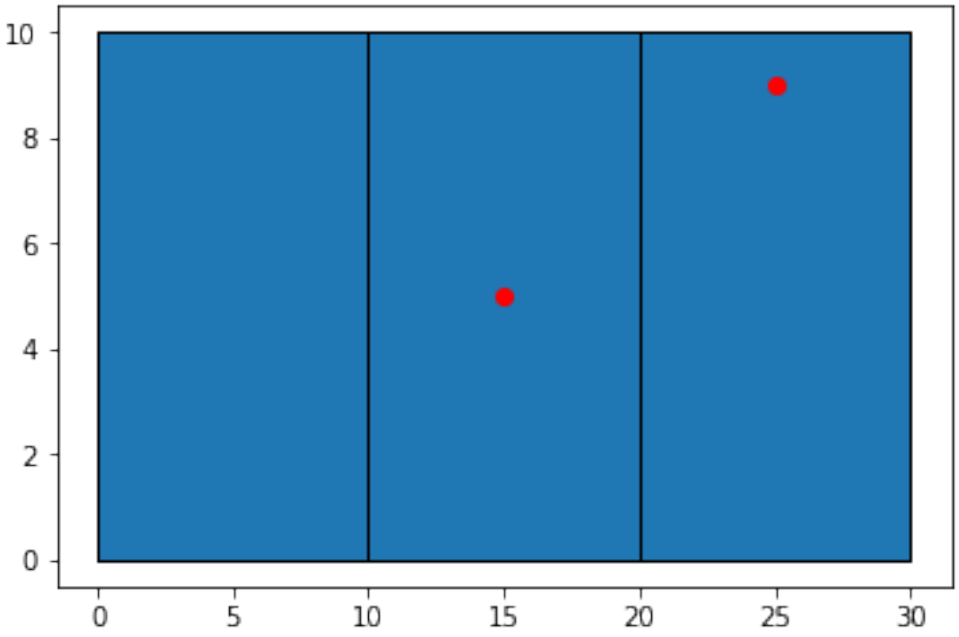
```
In [10]: polys.contains(p_1)

Out[10]: 0    False
         1     True
         2    False
         dtype: bool
```

and

```
In [11]: polys.contains(p_2)

Out[11]: 0    False
         1    False
         2     True
         dtype: bool
```

Plotting the two `GeoSeries` confirms this:

```
In [12]: ax = plt.gca()
         polys.plot(ax=ax, edgecolor='k')
         points.plot(ax=ax, edgecolor='r', facecolor='r')
         plt.show()
```



Yet, when we check if the points as a `GeoSeries` are contained by the `polys` `GeoSeries` we get:

```
In [13]: polys.contains(points)

Out[13]: 0    False
         1    False
         2    False
         dtype: bool
```

This is because the first point is not contained in the first polygon, and the second point is not contained in the second polygon, while there is no third point.

A second point geoseries can clarify this:

```
In [14]: points = gpd.GeoSeries([Point(5,5), Point(15, 6), Point([25,9])])
         polys.contains(points)

Out[14]: 0    True
         1    True
         2    True
         dtype: bool
```

whereas if we change the ordering of the second and third points we get:

```
In [15]: points = gpd.GeoSeries([Point(5,5), Point(25, 9), Point([15,6])])
         polys.contains(points)

Out[15]: 0     True
         1    False
         2    False
         dtype: bool
```

2.2 GeoDataFrame: Putting the Panda in GeoPandas

- geometry column is populated with a geoseries
-

```
In [16]: polys_df = gpd.GeoDataFrame({'names': ['west', 'central', 'east'], 'geometry': polys})
         polys_df

Out[16]:                                      geometry    names
         0     POLYGON ((0 0, 0 10, 10 10, 10 0, 0 0))     west
         1  POLYGON ((10 0, 10 10, 20 10, 20 0, 10 0))  central
         2  POLYGON ((20 0, 20 10, 30 10, 30 0, 20 0))     east
```

The dataframe provides the ability to add add additional columns:

```
In [17]: polys_df['Unemployment'] = [ 7.8, 5.3, 8.2]
         polys_df

Out[17]:                                      geometry    names  Unemployment
         0     POLYGON ((0 0, 0 10, 10 10, 10 0, 0 0))     west           7.8
         1  POLYGON ((10 0, 10 10, 20 10, 20 0, 10 0))  central           5.3
         2  POLYGON ((20 0, 20 10, 30 10, 30 0, 20 0))     east           8.2
```

and it supports different types of subsetting and traditional (i.e., nonspatial) queries. For example, find the regions with unemployment rates above 6 percent:

```
In [18]: polys_df[polys_df['Unemployment']>6.0]

Out[18]:                                      geometry names  Unemployment
         0     POLYGON ((0 0, 0 10, 10 10, 10 0, 0 0))  west           7.8
         2  POLYGON ((20 0, 20 10, 30 10, 30 0, 20 0))  east           8.2
```

There is nothing sacred about the column labeled 'geometry' in the GeoDataFrame. Moreover, we can add additional GeoSeries to the same dataframe, as they will be treated as regular columns. However, only one GeoSeries can serve as the column against which any spatial methods are applied when called upon. This column can be accessed through the `geometry` attribute of the `GeoDataFrame`:

```
In [19]: polys_df.geometry
```

```
Out[19]: 0       POLYGON ((0 0, 0 10, 10 10, 10 0, 0 0))
         1    POLYGON ((10 0, 10 10, 20 10, 20 0, 10 0))
         2    POLYGON ((20 0, 20 10, 30 10, 30 0, 20 0))
         Name: geometry, dtype: object
```

Let's create a new Points GeoSeries and add it to this GeoDataFrame as a regular column:

```
In [20]: points = gpd.GeoSeries([Point(5,5), Point(15, 6), Point([25,9])])
         polys_df['points'] = points
         polys_df.geometry
```

```
Out[20]: 0       POLYGON ((0 0, 0 10, 10 10, 10 0, 0 0))
         1    POLYGON ((10 0, 10 10, 20 10, 20 0, 10 0))
         2    POLYGON ((20 0, 20 10, 30 10, 30 0, 20 0))
         Name: geometry, dtype: object
```

So the `polys` column is currently serving as the `geometry` property for the `GeoDataFrame` and `points` is just another column:

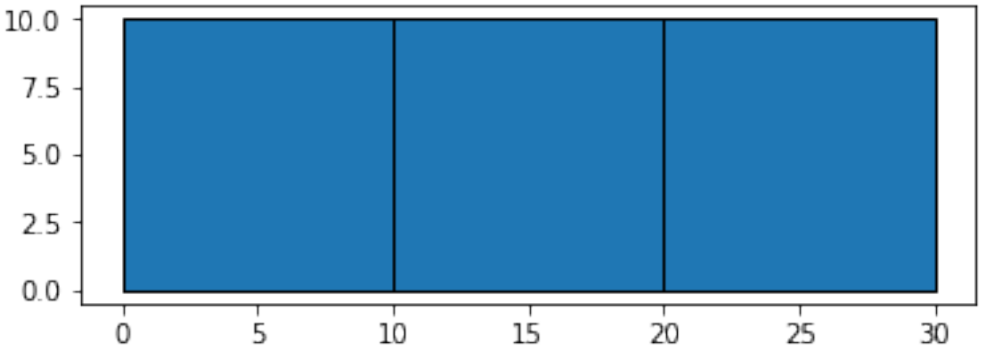
```
In [21]: polys_df
```

```
Out[21]:                                      geometry    names  Unemployment  \
         0     POLYGON ((0 0, 0 10, 10 10, 10 0, 0 0))     west           7.8
         1  POLYGON ((10 0, 10 10, 20 10, 20 0, 10 0))  central           5.3
         2  POLYGON ((20 0, 20 10, 30 10, 30 0, 20 0))     east           8.2

                points
         0   POINT (5 5)
         1  POINT (15 6)
         2  POINT (25 9)
```

so when we call the `plot` method we get the polygon representation:

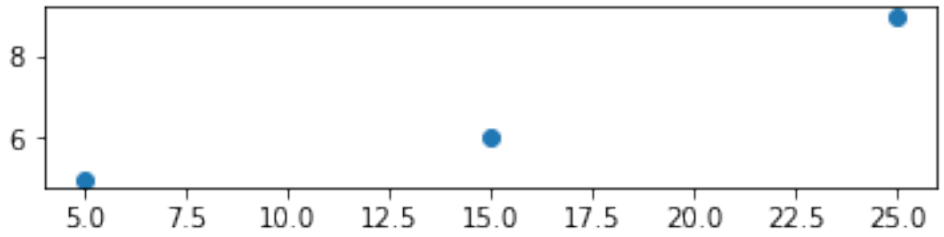
```
In [22]: polys_df.plot(edgecolor='k')
```

```
Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1078b0b898>
```



However, if we explicity set the geometry property (and assign this to a new object with the same name), and plot, things change:

```
In [23]: polys_df = polys_df.set_geometry('points')
         polys_df.plot()

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1078a73e80>
```



and this is because

```
In [24]: polys_df.geometry

Out[24]: 0     POINT (5 5)
         1    POINT (15 6)
         2    POINT (25 9)
         Name: points, dtype: object
```

3 Read a Polygon Shapefile

```
In [25]: tracts_df = gpd.read_file('data/california_tracts.shp')

In [26]: tracts_df.head()

Out[26]:        GEOID10          NAMELSAD10     ALAND10  AWATER10   INTPTLAT10  \
         0  06083002103  Census Tract 21.03   2838200.0    7603.0  +34.9306689
         1  06083002402  Census Tract 24.02  16288573.0   44468.0  +34.9287963
         2  06083002102  Census Tract 21.02   1352551.0       0.0  +34.9421111
         3  06083002010  Census Tract 20.10   2417990.0       0.0  +34.8714281
         4  06083002009  Census Tract 20.09   2603281.0       0.0  +34.8722878

              INTPTLON10  DP0010001  DP0010002  DP0010003  DP0010004  \
         0  -120.4270588       3930        354        290        253
         1  -120.4780833      11406       1250       1099        969
         2  -120.4267767       2084        156        141        139
         3  -120.4100285       4375        215        264        341
         4  -120.4277159       3826        170        232        318
```

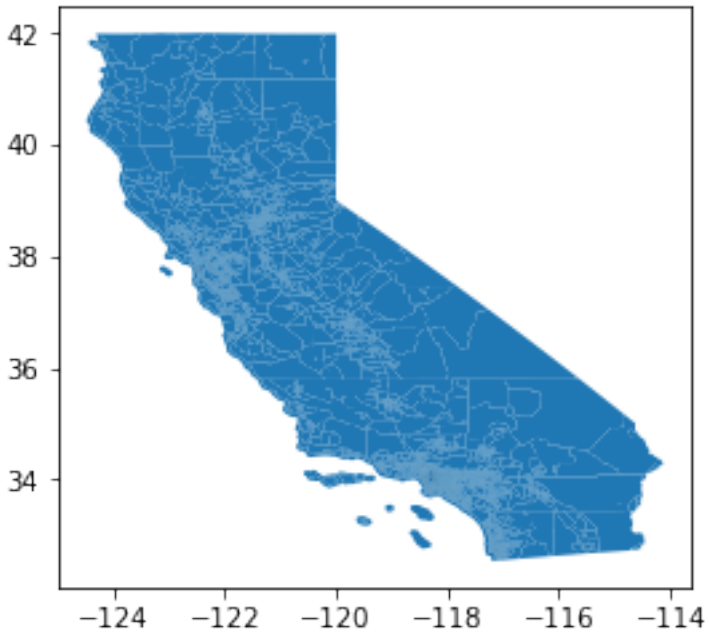
```
                          ...                          DP0210001  DP0210002  \
0                         ...                               1469        476
1                         ...                               2920       1444
2                         ...                                739        433
3                         ...                               1522       1303
4                         ...                               1326        969

   DP0210003  DP0220001  DP0220002  DP0230001  DP0230002  Shape_Leng  \
0        993       1360       2492       2.86       2.51    0.069451
1       1476       5161       6240       3.57       4.23    0.190631
2        306       1179        905       2.72       2.96    0.051289
3        219       3609        761       2.77       3.47    0.066269
4        357       2730       1045       2.82       2.93    0.065523

   Shape_Area                                           geometry
0    0.000281  POLYGON ((-120.417938 34.93834100000004, -120...
1    0.001611  POLYGON ((-120.4738929999999 34.92081400000006...
2    0.000133  POLYGON ((-120.417658 34.93834500000003, -120...
3    0.000238  POLYGON ((-120.411468 34.87961900000005, -120...
4    0.000257  POLYGON ((-120.423524 34.87928299999999, -120...

[5 rows x 195 columns]
```

In [27]:
```
tracts_df.shape
```

Out[27]:
```
(8057, 195)
```

In [28]:
```
tracts_df.plot()
```

Out[28]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f10789b7898>
```




```
In [29]: tracts_df.crs
```

```
Out[29]: {'init': 'epsg:4269'}
```

```
In [30]: tracts_df.columns
```

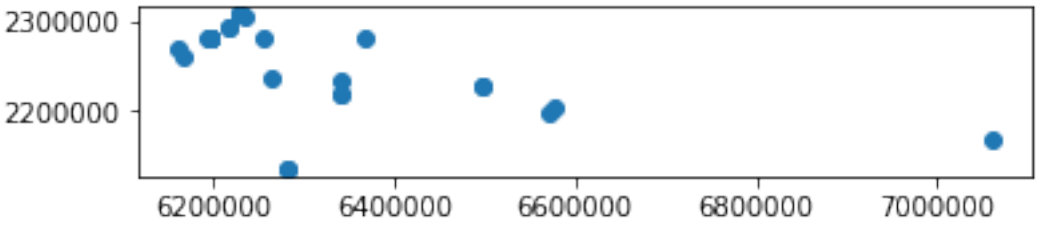
```
Out[30]: Index(['GEOID10', 'NAMELSAD10', 'ALAND10', 'AWATER10', 'INTPTLAT10',
                'INTPTLON10', 'DP0010001', 'DP0010002', 'DP0010003', 'DP0010004',
                ...
                'DP0210001', 'DP0210002', 'DP0210003', 'DP0220001', 'DP0220002',
                'DP0230001', 'DP0230002', 'Shape_Leng', 'Shape_Area', 'geometry'],
               dtype='object', length=195)
```

4 Read a Point Shapefile

```
In [31]: clinics_df = gpd.read_file('data/behavioralHealth.shp')
```

```
In [32]: clinics_df.plot()
```

```
Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1078128358>
```



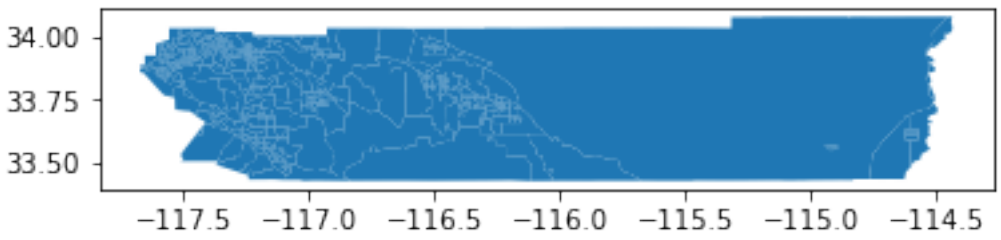
```
In [33]: clinics_df.columns

Out[33]: Index(['OBJECTID', 'SITE_TYPE', 'SITE_NAME', 'ADDRESS', 'CITY', 'ZIPCODE',
                'PHONE', 'geometry'],
               dtype='object')

In [34]: clinics_df.shape

Out[34]: (28, 8)

In [35]: clinics_df['geometry'].head()

Out[35]: 0    POINT (6216487.156141102 2291913.663858846)
         1    POINT (6195566.225542113 2280519.189600602)
         2    POINT (6168252.101364687 2261023.951032102)
         3    POINT (7059944.605377689 2169652.045521691)
         4    POINT (6195949.671953693 2280510.302151188)
         Name: geometry, dtype: object
```

What we want to do now is focus on the relationships between the locations of these clinics in Riverside county and the census tracts in that county. We have two issues to deal with in order to do so.

First, our dataframe for the tracts includes all 58 counties, whereas we only need Riverside county. Second, if you look closely at the plot of the clinics you will see that the units on the axes are different from those in the plot of the census tracts. This is because the two dataframes have different coordinate reference systems (CRS).

5 Extracting Riverside County Tracts

```
In [36]: riverside_tracts = tracts_df[tracts_df['GEOID10'].str.match("^06065")]

In [37]: riverside_tracts.plot()

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1078af02e8>
```



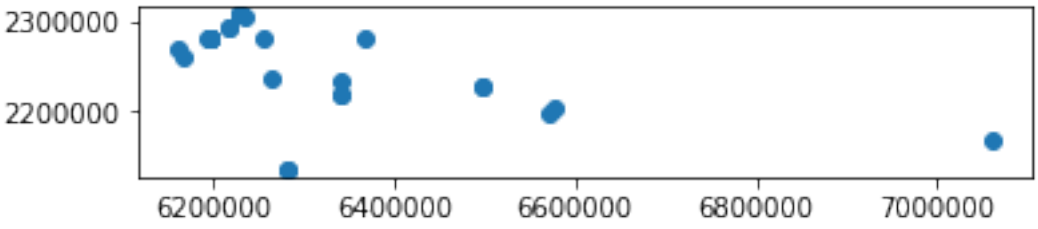
6 Coordinate Reference Systems

7 Spatial Joins

Let's find out which tracts have clinics.

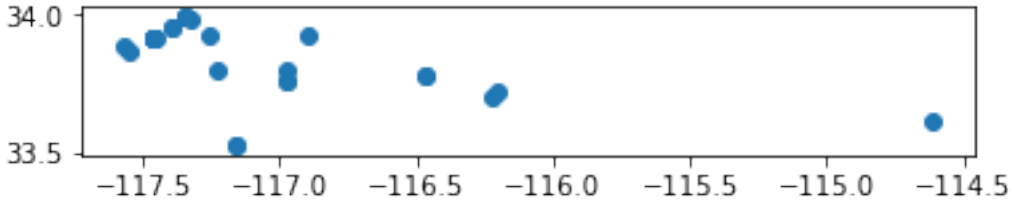
```
In [38]: clinics_df.plot()
```

```
Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1076f7f5f8>
```




```
In [39]: clinics_df.to_crs(riverside_tracts.crs).plot()
```

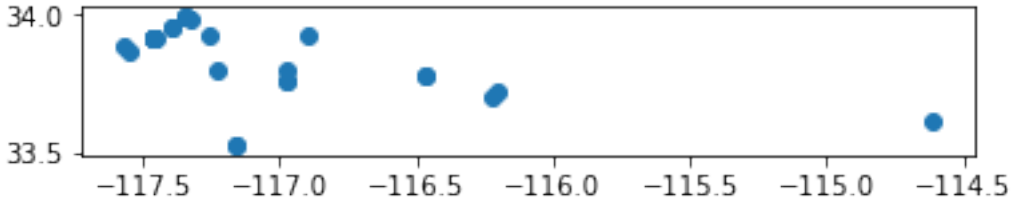
```
Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7f107659d358>
```




```
In [40]: # convert crs of clinics to match that of tracts
         clinics_df = clinics_df.to_crs(riverside_tracts.crs)
```

```
In [41]: clinics_df.plot()
```

```
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1077800400>
```



```
In [42]: clinics_tracts = gpd.sjoin(clinics_df, riverside_tracts, op='within')

In [43]: clinics_tracts.head()
```

Out[43]:

	OBJECTID	SITE_TYPE	SITE_NAME	ADDRESS	CITY	ZIPCODE	PHONE	geometry	index_right	GEOID10	...	DP0200001	DP0210001	DP0210002	DP0210003	DP0220001	DP0220002	DP0230001	DP0230002	Shape_Leng	Shape_Area
0	149.0	Behavioral Health	Older Adult Services	6355 Riverside Ave	Riverside	92506	951-369-0219	POINT (-117.3882025693238 33.95198116571336)	4314	06065031100	...	10.3	1613	905	708	2350	2069	2.60	2.92	0.075878	0.000283
25	146.0	Behavioral Health	Adult Mental Health Services - Central Clinic	6355 Riverside Ave	Riverside	92506	951-369-5714	POINT (-117.388194153081 33.95197775226008)	4314	06065031100	...	10.3	1613	905	708	2350	2069	2.60	2.92	0.075878	0.000283
1	150.0	Behavioral Health	Children'S Treatment Services	9990 County Farm Rd	Riverside	92503	951-358-4840	POINT (-117.4567468879782 33.92002609584612)	4291	06065041201	...	4.0	1064	628	436	2592	1423	4.13	3.26	0.071462	0.000252
4	152.0	Behavioral Health	Interagency Services For Families	9890 County Farm Rd	Riverside	92503	951-358-4850	POINT (-117.4554827389969 33.92001386400798)	4291	06065041201	...	4.0	1064	628	436	2592	1423	4.13	3.26	0.071462	0.000252
5	448.0	Behavioral Health	Children'S Evaluation Services Unite	9990 County Farm Rd	Riverside	92503	951-358-7380	POINT (-117.4567468879782 33.92002609584612)	4291	06065041201	...	4.0	1064	628	436	2592	1423	4.13	3.26	0.071462	0.000252

```
[5 rows x 203 columns]
```

```
In [44]: clinics_tracts.shape
```

```
Out[44]: (28, 203)
```

```
In [45]: clinics_df.columns
```

```
Out[45]: Index(['OBJECTID', 'SITE_TYPE', 'SITE_NAME', 'ADDRESS', 'CITY', 'ZIPCODE',
                'PHONE', 'geometry'],
               dtype='object')
```

```
In [46]: clinics_tracts.columns
```

```
Out[46]: Index(['OBJECTID', 'SITE_TYPE', 'SITE_NAME', 'ADDRESS', 'CITY', 'ZIPCODE',
                'PHONE', 'geometry', 'index_right', 'GEOID10',
                ...
                'DP0200001', 'DP0210001', 'DP0210002', 'DP0210003', 'DP0220001',
                'DP0220002', 'DP0230001', 'DP0230002', 'Shape_Leng', 'Shape_Area'],
               dtype='object', length=203)
```

```
In [47]: # GEOID10 is now attached to each clinic (i.e., tract identifier)
```

```
In [48]: clinics_tracts[['GEOID10', 'index_right']].groupby('GEOID10').agg('count')
```

```
Out[48]:             index_right
         GEOID10
         06065031100            2
         06065040809            1
         06065041201            7
         06065041813            1
         06065042209            3
         06065042210            1
         06065042512            1
         06065042620            1
         06065043507            2
         06065044101            1
         06065045000            2
         06065045303            1
         06065045501            1
         06065046102            1
         06065049600            2
         06065051300            1
```

```
In [49]: clinics_tracts.groupby(['GEOID10']).size()
```

```
Out[49]: GEOID10
         06065031100    2
         06065040809    1
```

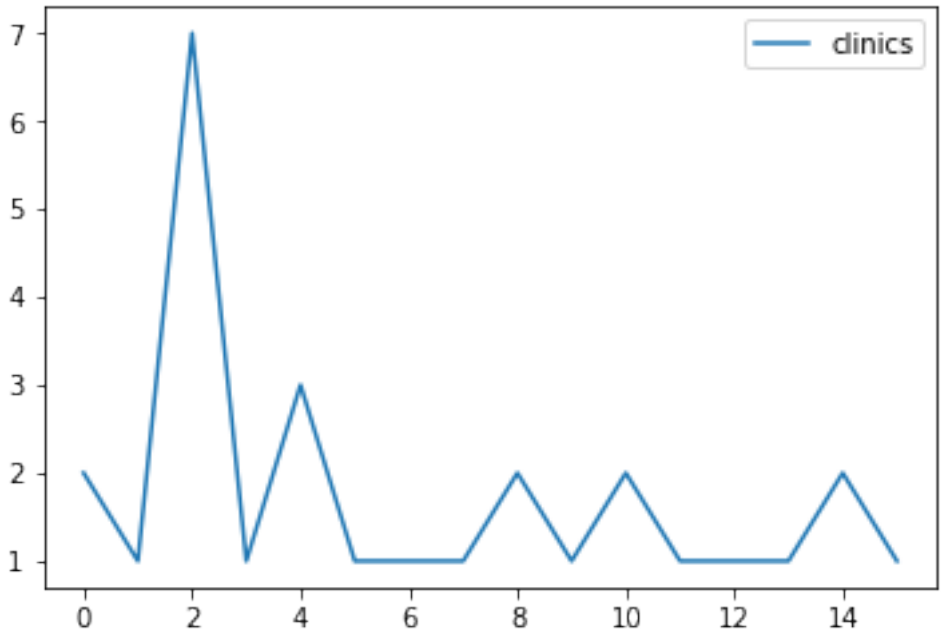
```
06065041201    7
06065041813    1
06065042209    3
06065042210    1
06065042512    1
06065042620    1
06065043507    2
06065044101    1
06065045000    2
06065045303    1
06065045501    1
06065046102    1
06065049600    2
06065051300    1
dtype: int64
```

```
In [50]: clinics_tracts.groupby(['GEOID10']).size().reset_index(name='clinics')
```

Out[50]:

	GEOID10	clinics
0	06065031100	2
1	06065040809	1
2	06065041201	7
3	06065041813	1
4	06065042209	3
5	06065042210	1
6	06065042512	1
7	06065042620	1
8	06065043507	2
9	06065044101	1
10	06065045000	2
11	06065045303	1
12	06065045501	1
13	06065046102	1
14	06065049600	2
15	06065051300	1

```
In [51]: twc = clinics_tracts.groupby(['GEOID10']).size().reset_index(name='clinics')

In [52]: twc.plot()

Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x7f10756a69b0>
```




```
In [53]: riverside_tracts_clinics = riverside_tracts.merge(twc, how='left', on='GEOID10')

In [54]: riverside_tracts_clinics.head()
```

Out[54]:

	GEOID10	NAMELSAD10	ALAND10	AWATER10	INTPTLAT10	\
0	06065042012	Census Tract 420.12	2687173.0	0.0	+33.9108776	
1	06065041911	Census Tract 419.11	70257842.0	0.0	+33.7428832	
2	06065041910	Census Tract 419.10	11167489.0	64225.0	+33.7892199	
3	06065040816	Census Tract 408.16	1788821.0	0.0	+33.9024569	
4	06065040815	Census Tract 408.15	1266779.0	0.0	+33.8930776	

	INTPTLON10	DP0010001	DP0010002	DP0010003	DP0010004	...	\
0	-117.3205065	6242	420	545	620	...	
1	-117.4957943	10258	840	844	806	...	
2	-117.4949771	6342	404	453	447	...	
3	-117.5246107	2594	162	161	227	...	
4	-117.5114997	3586	231	235	257	...	

	DP0210002	DP0210003	DP0220001	DP0220002	DP0230001	DP0230002	\
0	1142	826	3927	2299	3.44	2.78	
1	2881	430	8710	1543	3.02	3.59	
2	1823	350	5177	1165	2.84	3.33	
3	688	171	2133	451	3.10	2.64	
4	756	399	2462	1124	3.26	2.82	

	Shape_Leng	Shape_Area	geometry	\

```
0    0.095958    0.000262  POLYGON ((-117.300465 33.91310800000002, -117...
1    0.466106    0.006836  POLYGON ((-117.5101979999999 33.800273, -117.5...
2    0.200974    0.001093  POLYGON ((-117.5029849999999 33.82494899999995...
3    0.082444    0.000174  POLYGON ((-117.515118 33.90096800000009, -117...
4    0.050637    0.000123  POLYGON ((-117.503863 33.89735700000011, -117...

   clinics
0      NaN
1      NaN
2      NaN
3      NaN
4      NaN

[5 rows x 196 columns]
```

```
In [55]: riverside_tracts_clinics.fillna(value=0, inplace=True)
```

```
In [56]: riverside_tracts_clinics.head()
```

Out[56]:

	GEOID10	NAMELSAD10	ALAND10	AWATER10	INTPTLAT10	\
0	06065042012	Census Tract 420.12	2687173.0	0.0	+33.9108776	
1	06065041911	Census Tract 419.11	70257842.0	0.0	+33.7428832	
2	06065041910	Census Tract 419.10	11167489.0	64225.0	+33.7892199	
3	06065040816	Census Tract 408.16	1788821.0	0.0	+33.9024569	
4	06065040815	Census Tract 408.15	1266779.0	0.0	+33.8930776	

	INTPTLON10	DP0010001	DP0010002	DP0010003	DP0010004	...	\
0	-117.3205065	6242	420	545	620	...	
1	-117.4957943	10258	840	844	806	...	
2	-117.4949771	6342	404	453	447	...	
3	-117.5246107	2594	162	161	227	...	
4	-117.5114997	3586	231	235	257	...	

	DP0210002	DP0210003	DP0220001	DP0220002	DP0230001	DP0230002	\
0	1142	826	3927	2299	3.44	2.78	
1	2881	430	8710	1543	3.02	3.59	
2	1823	350	5177	1165	2.84	3.33	
3	688	171	2133	451	3.10	2.64	
4	756	399	2462	1124	3.26	2.82	

	Shape_Leng	Shape_Area	geometry	\
0	0.095958	0.000262	POLYGON ((-117.300465 33.91310800000002, -117...	
1	0.466106	0.006836	POLYGON ((-117.5101979999999 33.800273, -117.5...	
2	0.200974	0.001093	POLYGON ((-117.5029849999999 33.82494899999995...	
3	0.082444	0.000174	POLYGON ((-117.515118 33.90096800000009, -117...	
4	0.050637	0.000123	POLYGON ((-117.503863 33.89735700000011, -117...	

	clinics

```
0      0.0
1      0.0
2      0.0
3      0.0
4      0.0

[5 rows x 196 columns]
```

```
In [57]: riverside_tracts_clinics['clinics'].sum()
```

```
Out[57]: 28.0
```

8 Writing Shapefiles

```
In [58]: # save to a new shapefile
         riverside_tracts_clinics.to_file('data/clinics.shp')
```
