Lab 4

May 10, 2020

0.1 Introduction

This lab will practice the exercises in the demo document of the `pandas` package. We will also look at some geospatial techniques applied in Python and discuss the differences between spatial analysis in Python and R.

0.2 Data import and cleaning (included in the demo):

[11]:
```
import pandas
import numpy as np
```

[12]:
```
data = pandas.read_csv('data/CAINC1__ALL_STATES_1969_2017.csv',␣
 ↪encoding='latin-1',
                      skipfooter=3, engine='python')
data.isna().sum() # so no na values in the numpy / pandas sense
data1 = data.replace("(NA)", 0)
data1['1969'] = data1['1969'].astype(int)
small = data[data.LineCode.isin( [2, 3] )]
for year in range(1969, 2018):
    small = small[small[str(year)] != "(NA)"] #drop all records with NA

convert_dict = dict([(str(year), int) for year in range (1969, 2018)])
small = small.astype(convert_dict)
geofips = pandas.unique(small.GeoFIPS)
small['GeoFIPS'] = [fips.replace("\"", "").strip() for fips in small.GeoFIPS]
geofips = pandas.unique(small.GeoFIPS)
pc_inc = small[small.LineCode==3]
```

1 Pandas

Exercise:
Identify the area with the lowest per-capita income each year.

[13]:
```
min_ids = pc_inc.iloc[:, 8:].idxmin()
for y, min_id in enumerate(min_ids):
    year = y + 1969
    name = pc_inc.loc[min_id].GeoName
    pci = pc_inc.loc[min_id, str(year)]
```

```python
    print(year, pci, name)
```

```
1969 1166 Loving, TX
1970 1381 Starr, TX
1971 1497 Dimmit, TX
1972 1702 Zavala, TX
1973 1971 Dimmit, TX
1974 2067 Starr, TX
1975 2215 Starr, TX
1976 2326 Starr, TX
1977 2355 Starr, TX
1978 2654 Starr, TX
1979 2928 Haskell, KS
1980 2510 Slope, ND
1981 3898 Starr, TX
1982 4301 Starr, TX
1983 4347 Starr, TX
1984 4396 Starr, TX
1985 4022 Petroleum, MT
1986 4444 Starr, TX
1987 4362 Starr, TX
1988 4768 Starr, TX
1989 5016 Starr, TX
1990 5723 Starr, TX
1991 6329 Starr, TX
1992 7096 Starr, TX
1993 7454 Starr, TX
1994 7730 Starr, TX
1995 7561 Loup, NE
1996 4979 Arthur, NE
1997 7108 Loup, NE
1998 8331 Loup, NE
1999 9350 Loup, NE
2000 10257 Starr, TX
2001 12442 Starr, TX
2002 12810 Buffalo, SD
2003 14280 Starr, TX
2004 14478 Starr, TX
2005 15418 Madison, ID
2006 11610 Ziebach, SD
2007 14405 Ziebach, SD
2008 14756 Wheeler, GA
2009 14615 Wheeler, GA
2010 15032 Wheeler, GA
2011 16045 Wheeler, GA
2012 17270 Wheeler, GA
2013 17564 Telfair, GA
```

```
2014 14165 Issaquena, MS
2015 13239 Issaquena, MS
2016 17812 Issaquena, MS
2017 11937 Issaquena, MS
```

Exercise: As a percentage of the minimum per-captia income, calculate the relative income gap between the extremes of the income distribution each year. Identify the year with the maximum relative income gap.

[14]:
```
max_ids = pc_inc.iloc[:, 8:].idxmax()
idxs = zip(min_ids, max_ids)
ratio = 0.0
ratios = []
for y, ids in enumerate(idxs):
    min_id, max_id = ids
    year = y + 1969
    name = pc_inc.loc[min_id].GeoName
    pci_min = pc_inc.loc[min_id, str(year)]
    pci_max = pc_inc.loc[max_id, str(year)]
    r = pci_max / pci_min
    ratios.append(r)
    if r > ratio:
        ratio = r
        max_year = year
print("Maximum relative gap: {} occurred in {}".format(ratio, max_year))
res_df = pandas.DataFrame({'year': range(1969, 2018), 'ratio': ratios})
res_df
```

```
Maximum relative gap: 19.591187065426823 occurred in 2017
```

[14]:

	year	ratio
0	1969	6.724700
1	1970	6.891383
2	1971	6.822979
3	1972	6.873678
4	1973	6.931507
5	1974	6.795356
6	1975	9.129120
7	1976	8.221840
8	1977	7.513376
9	1978	7.672946
10	1979	7.225410
11	1980	9.087251
12	1981	5.801437
13	1982	5.507789
14	1983	5.558776
15	1984	7.159463
16	1985	7.026106

```
17  1986   6.904815
18  1987   7.965383
19  1988   8.625419
20  1989   8.819179
21  1990   8.752577
22  1991   7.324538
23  1992   7.220406
24  1993   7.125973
25  1994   7.054981
26  1995   7.814839
27  1996  12.937739
28  1997   9.740574
29  1998   9.037811
30  1999   8.672299
31  2000   8.644048
32  2001   7.509645
33  2002   7.101952
34  2003   6.202381
35  2004   6.962426
36  2005   7.640291
37  2006  12.725581
38  2007  10.881291
39  2008  10.338710
40  2009   8.596168
41  2010   9.647219
42  2011   9.457027
43  2012  11.249392
44  2013  10.143703
45  2014  14.119802
46  2015  15.477982
47  2016  12.596340
48  2017  19.591187
```

2 Visualization

This section will explore spatial data visualization functions within Python.

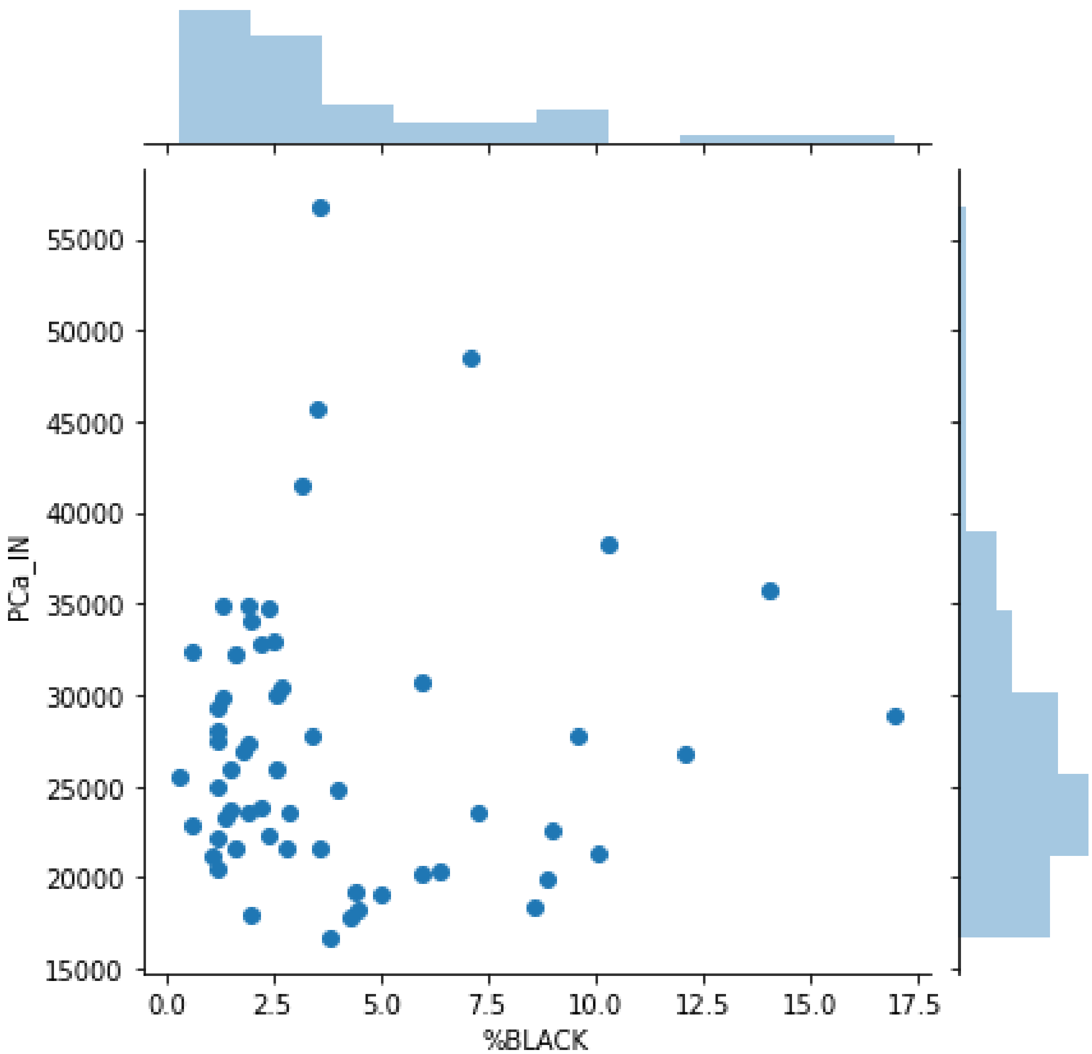
[15]:
```
%matplotlib inline

import geopandas
import seaborn
import contextily
import matplotlib.pyplot as plt
import pandas
```

```
db = geopandas.read_file('/Users/ryan/Desktop/UChicago/SOCI 30253/
↪Final_Project_CA_Aviation/geo_export_7550259c-c552-465b-add9-d4ec4ffcee81.
↪shp')
```

We use a dataset of California Counties containing information regarding demographic and socioeconomic data. For this joint plot, we visualize the Percentage of African American Population within each couty compared to Per Capita Income within the counties.

[25]:
```
seaborn.jointplot('%BLACK',
                  'PCa_IN',
                  data=db,
                  kind='scatter')
```

[25]: <seaborn.axisgrid.JointGrid at 0x116490950>



3 Discussions

This section discusses differences in data analytics in R and Python.

3.1 Data Storage

Both Python and R can store data in a **dataframe**. The way that Python and R handles such dataframes is a little different. Python relies on the `pandas` package to clean and do other operations with the dataframe. There are other types of data in both R and Python, ranging from arrary(atomic vectors, matrices, and arrays in R, numpy in Python), list to factors and tuples. Python requires more non-built-in pacakge installations to store and deal with data.

3.2 Spatial Data Storage

sf in R stores spatial data as sf objects, which is a `data.frame` like object with a simple feature list column. This `sf` object is a geospatial geometry with attributes, which could be assembled from `sfg`(geometry) object or `sfc`(geospatial geometry, basically a list of `sfg` objects) objects.
geopandas in Python stores spatial data as `GeoDataSeries` and `GeoDataFrames`, which is similar to the `sfc` and `sfg` obejects to a `sf` object concept in R. In Python language, `GeoDataSeries` is basically the "geo" in `geopands` and `GeoDataFrames` is the "pandas" in `geopandas`.

3.3 Other Differences

This section will discuss some other differences between data operations in Python and R:
1. **group by**. This functionality in Python is slightly different in syntax compared to in R. In R, all the functionalities are achieved inside the bracket (such as which variables to include and what logic to use (e.g. summation.)) In Python, the syntax will extend outside of the `groupby` bracket and uses "."(dots) to continue the code. This is also a general syntax difference between Python and R (the use of dots in coding.)
2. **`df.merge` vs. `merge`** In Python, `df.merge` merges the target dataframe onto the current dataframe. In R, `merge` merges the two dataframes together. The way to join in R is sometimes not achieved through a "join" specification, but an "all" specification.
3. **General Syntax** As mentioned before, a lot of functionalities in Python is achieved through "." whereas in R, it is achieved through many other forms of syntax. In selection variable for plotting, for example, the variable is specified through "." (e.g. `db.HR90`) and some plotting commands are also achieved through dots. (e.g. `db.HR90.plot.hist`). I find this to be more confusing than in R as different categories of fucntionalities are achieved using the same syntax (for example, I find the dollar sign to select variables to be quite a bit clearer than in Python.) The way R selects variables and plots visualizations, however, also might result in longer code.

–This is the end of Lab 4.–