lab 04

October 22, 2015

1 Data mapping

```
In [1]: %matplotlib inline
    import seaborn as sns
    import pandas as pd
    import pysal as ps
    import geopandas as gpd
    import numpy as np
    import matplotlib.pyplot as plt
```

1.1 Dataset

For this tutorial, we will use the recently released Index of Multiple Deprivation from 2015.

- How to download it (link).
- Download background from the course website (link).

```
In [2]: # This will be different on your computer and will depend on where
        # you have downloaded the files
        imd_shp = '../../../data/E08000012_IMD/shapefiles/E08000012.shp'
        bkg_path = 'figs/lab04_liverpool_color.tif'
        data_path = '../../../data/Liverpool/'
  Load the IMD data:
In [3]: imd = gpd.read_file(imd_shp).set_index('LSOA11CD')
        imd.info()
<class 'geopandas.geodataframe.GeoDataFrame'>
Index: 298 entries, E01006512 to E01033768
Data columns (total 12 columns):
crime
              298 non-null float64
education
              298 non-null float64
              298 non-null float64
employment
geometry
              298 non-null object
              298 non-null float64
health
              298 non-null float64
housing
idaci
              298 non-null float64
              298 non-null float64
idaopi
imd\_rank
             298 non-null int64
imd_score
             298 non-null float64
income
              298 non-null float64
             298 non-null float64
living_env
dtypes: float64(10), int64(1), object(1)
memory usage: 30.3+ KB
```

Additional data:

NOTE: this part loads up data that will be used for the rest of the tutorial but loading it involves some data transformations that are a bit more advanced that what is covered in this course. Simply run them to load the data, but you are not expected to know some of the coding tricks required in this cell.

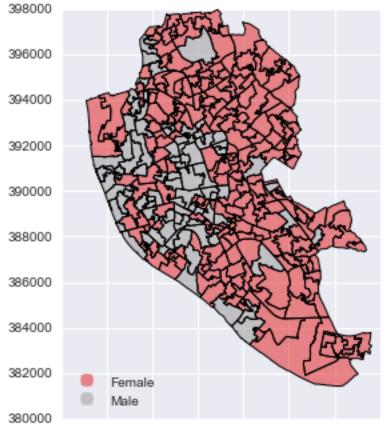
```
In [4]: # Gender breakup
        gender = pd.read_csv(data_path+'tables/QS104EW_lsoa11.csv', index_col='GeographyCode')
        gender = gender.rename(columns={'QS104EW0002': 'Male', 'QS104EW0003': 'Female'})[['Male', 'Female']
        maj_male = gender['Male'] > gender['Female']
        gender['Gender_Majority'] = maj_male
        gender.loc[gender['Gender_Majority']==True, 'Gender_Majority'] = 'Male'
        gender.loc[gender['Gender_Majority'] == False, 'Gender_Majority'] = 'Female'
        # Status breakup
        sinmar = pd.read_csv(data_path+'tables/KS103EW_lsoa11.csv', index_col='GeographyCode')
        sinmar = sinmar.rename(columns={'KS103EW0002': 'Single', 'KS103EW0003': 'Married'})[['Single',
        maj_sin = sinmar['Single'] > sinmar['Married']
        sinmar['Status_Majority'] = maj_sin
        sinmar.loc[sinmar['Status_Majority'] == True, 'Status_Majority'] = 'Single'
        sinmar.loc[sinmar['Status_Majority'] == False, 'Status_Majority'] = 'Married'
        # Join
        both = imd.join(sinmar).join(gender)
        both.crs = imd.crs
        both.head()
Out[4]:
                   crime
                          education employment
        LSOA11CD
        E01006512 -0.20
                              10.06
                                           0.08
        E01006513
                   1.50
                              20.13
                                           0.03
        E01006514
                    0.74
                              15.50
                                           0.15
        E01006515
                    1.16
                              33.51
                                           0.30
        E01006518
                    0.67
                              49.90
                                           0.34
                                                             geometry health housing \
       LSOA11CD
        E01006512 POLYGON ((336103.358 389628.58, 336103.416 389...
                                                                                 24.49
        E01006513 POLYGON ((335173.781 389691.538, 335169.798 38...
                                                                         0.58
                                                                                 25.15
        E01006514 POLYGON ((335495.676 389697.267, 335495.444 38...
                                                                                 21.85
                                                                         1.86
        E01006515 POLYGON ((334953.001 389029, 334951 389035, 33...
                                                                         1.90
                                                                                 17.40
        E01006518 POLYGON ((335354.015 388601.947, 335354 388602...
                                                                                 15.52
                   idaci idaopi imd_rank imd_score income living_env Single \
        LSOA11CD
        E01006512
                    0.16
                            0.31
                                     10518
                                                 25.61
                                                          0.10
                                                                     68.91
                                                                              1288
                            0.20
        E01006513
                    0.21
                                     10339
                                                 25.91
                                                          0.04
                                                                     85.48
                                                                              2613
        E01006514
                    0.23
                            0.48
                                      5247
                                                 37.64
                                                          0.19
                                                                     58.90
                                                                              1583
        E01006515
                    0.46
                            0.76
                                      1019
                                                 58.99
                                                          0.43
                                                                     29.78
                                                                               587
        E01006518
                    0.50
                            0.52
                                       662
                                                 63.37
                                                          0.43
                                                                     31.03
                                                                               716
                   Married Status_Majority Male Female Gender_Majority
        LSOA11CD
        E01006512
                       287
                                    Single 1070
                                                      810
                                                                     Male
        E01006513
                       170
                                    Single
                                            1461
                                                     1480
                                                                   Female
        E01006514
                       204
                                    Single
                                            1177
                                                      931
                                                                     Male
```

E01006515	218	Single	595	613	Female
E01006518	363	Single	843	853	Female

1.2 Unique values

In [5]: both.plot(column='Gender_Majority', categorical=True, legend=True)

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x10edb70d0>



332000 334000 336000 338000 340000 342000 344000 346000

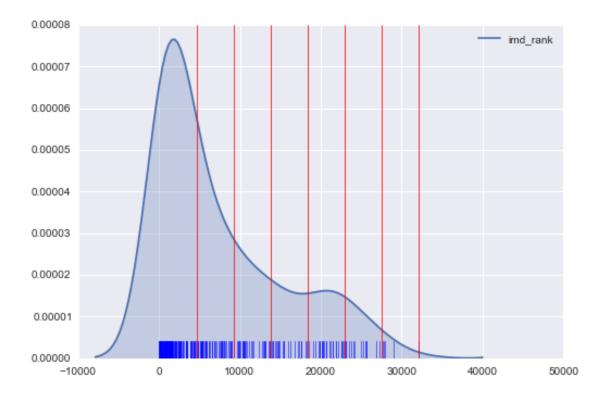
1.3 Equal interval

Out[6]:
Equal Interval

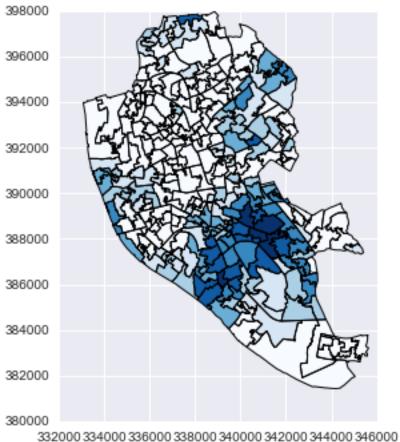
Lower		Upper	Count
========	=======	========	
	x[i] <=	4604.857	156
4604.857	< x[i] <=	9185.714	48
9185.714	< x[i] <=	13766.571	30
13766.571	< x[i] <=	18347.429	21

In [7]: classi.bins

In [8]: f, ax = plt.subplots(1)
 sns.kdeplot(imd['imd_rank'], shade=True)
 sns.rugplot(imd['imd_rank'], alpha=0.5)
 for cut in classi.bins:
 plt.axvline(cut, color='red', linewidth=0.75)
 plt.show()



In [9]: imd.plot(column='imd_rank', scheme='equal_interval', alpha=1, k=7, colormap=plt.cm.Blues)
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1136f9150>



1.4 Quantiles

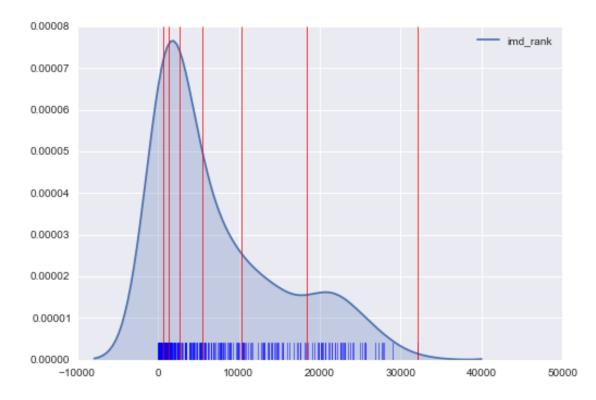
In [10]: classi = ps.Quantiles(imd['imd_rank'], k=7) classi

Out[10]: Quantiles

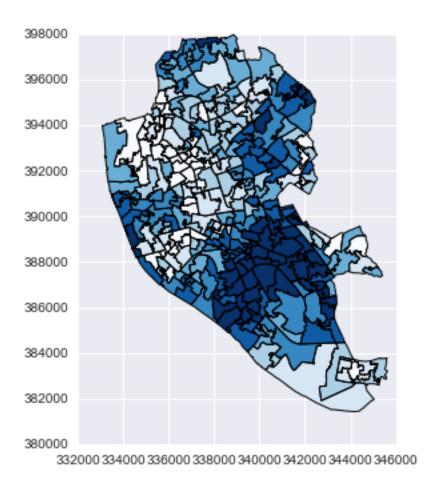
Lower			Upper	Count
	x[i]	<=	633.714	43
633.714	< x[i]	<=	1335.714	42
1335.714	< x[i]	<=	2641.000	43
2641.000	< x[i]	<=	5540.143	42
5540.143	< x[i]	<=	10355.857	43
10355.857	< x[i]	<=	18401.143	42
18401.143	< x[i]	<=	32090.000	43

In [11]: classi.bins

```
In [12]: f, ax = plt.subplots(1)
    sns.kdeplot(imd['imd_rank'], shade=True)
    sns.rugplot(imd['imd_rank'], alpha=0.5)
    for cut in classi.bins:
        plt.axvline(cut, color='red', linewidth=0.75)
    plt.show()
```



In [13]: imd.plot(column='imd_rank', scheme='QUANTILES', alpha=1, k=7, colormap=plt.cm.Blues)
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x11473fbd0>



1.5 Fisher-Jenks

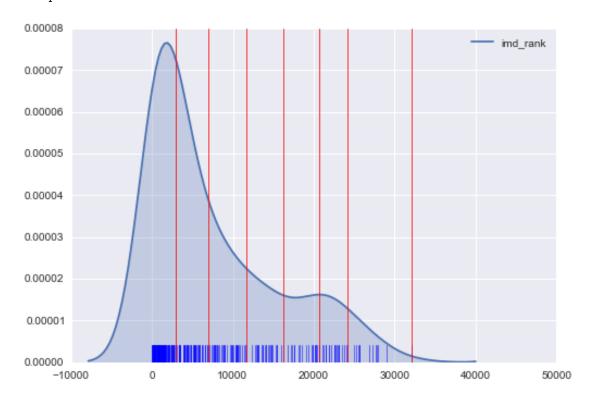
Out[14]: Fisher_Jenks

Lower			Upper	Count
=======	x[i]	===: <=	2930.000	133
2930.000	< x[i]	<=	6946.000	52
6946.000	< x[i]	<=	11656.000	39
11656.000	< x[i]	<=	16185.000	24
16185.000	< x[i]	<=	20719.000	20
20719.000	< x[i]	<=	24098.000	18
24098.000	< x[i]	<=	32090.000	12

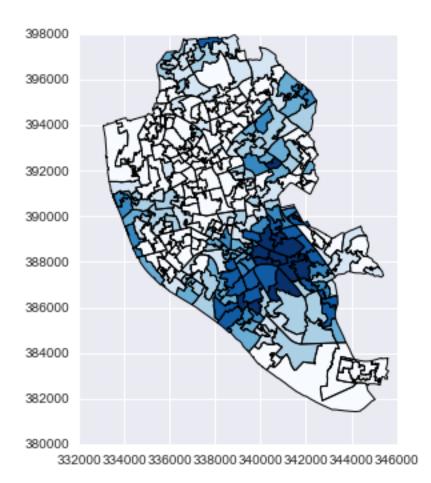
```
In [15]: classi.bins
```

```
Out[15]: array([ 2930., 6946., 11656., 16185., 20719., 24098., 32090.])
```

```
sns.rugplot(imd['imd_rank'], alpha=0.5)
for cut in classi.bins:
   plt.axvline(cut, color='red', linewidth=0.75)
plt.show()
```



In [17]: imd.plot(column='imd_rank', scheme='fisher_jenks', alpha=1, k=7, colormap=plt.cm.Blues)
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x111430310>



1.6 [Extension 1] Conditional maps

```
In [131]: def map_subset(vals, db, color=None, norm=True):
              Internal function to pass to 'FaceGrid' to build a single map
              Arguments
              vals
                     : Series
                         Values of the subplot to be mapped
                      : GeoDataFrame
              db
                        Table with geometries
                      : None
              color
              ,,,
              ax = plt.gca()
              for poly in db['geometry']:
                  gpd.plotting.plot_multipolygon(ax, poly, facecolor='grey', linewidth=0.)
              vari = vals.name
              if norm:
                  db.reindex(vals.index).plot(column=vari, axes=ax, colormap='Blues', linewidth=0., \
                                         vmin=db[vari].min(), vmax=db[vari].max())
```

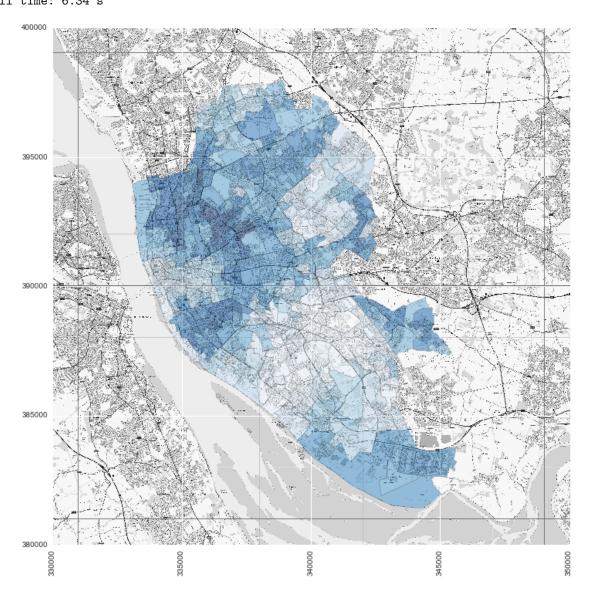
```
else:
                   db.reindex(vals.index).plot(column=vari, axes=ax, colormap='Blues', linewidth=0.)
              ax.set_axis_off()
              plt.axis('equal')
In [146]: %%time
          g = sns.FacetGrid(both, row="Gender_Majority", col="Status_Majority", \
                             margin_titles=True, size=5)
          g.map(map_subset, "imd_score", db=both)
          plt.savefig('../lectures/figs/104_conditional_plot.png')
          plt.tight_layout()
          plt.show()
                      Status_Majority = Single
                                                             Status_Majority = Married
```

CPU times: user 12.4 s, sys: 46.7 ms, total: 12.4 s $\,$

Wall time: 12.4 s

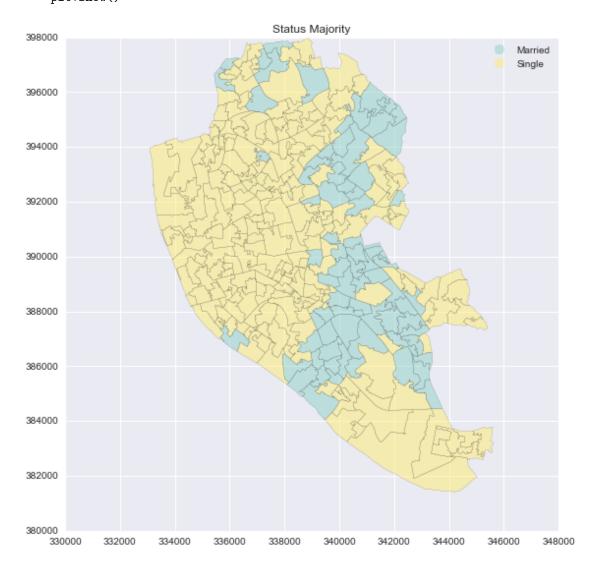
1.7 [Extension 2] Base maps

CPU times: user 5 s, sys: 1.34 s, total: 6.34 s Wall time: 6.34 s



1.8 [Extension 3] Maps from lecture slides

• Unique values

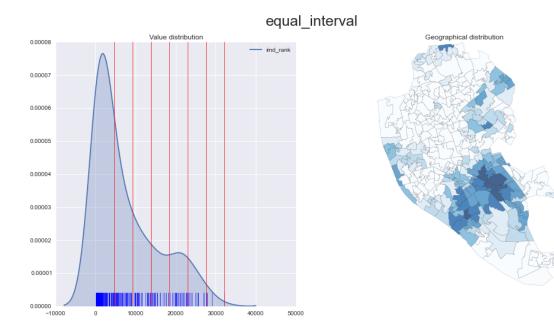


• Choropleth classifiers

```
Plot the distribution over value and geographical space of variable 'var' using scheme 'sc
Arguments
_____
       : str
scheme
          Name of the classification scheme to use
var
        : str
           Variable name
        : GeoDataFrame
db
           Table with input data
fiqsize : Tuple
           [Optional. Default = (16, 8)] Size of the figure to be created.
        : None/str
           [Optional. Default = None] Path for file to save the plot.
from pysal.esda.mapclassify import Quantiles, Equal_Interval, Fisher_Jenks
schemes = {'equal_interval': Equal_Interval, \
           'quantiles': Quantiles, \
           'fisher_jenks': Fisher_Jenks}
classi = schemes[scheme](db[var], k=7)
f, (ax1, ax2) = plt.subplots(1, 2, figsize=figsize)
# KDE
sns.kdeplot(db[var], shade=True, ax=ax1)
sns.rugplot(db[var], alpha=0.5, ax=ax1)
for cut in classi.bins:
    ax1.axvline(cut, color='red', linewidth=0.75)
ax1.set_title('Value distribution')
p = db.plot(column=var, scheme=scheme, alpha=0.75, k=7, \
         colormap=plt.cm.Blues, axes=ax2, linewidth=0.1)
ax2.axis('equal')
ax2.set_axis_off()
ax2.set_title('Geographical distribution')
f.suptitle(scheme, size=25)
if saveto:
    plt.savefig(saveto)
plt.show()
```

In [22]: plot_scheme('equal_interval', 'imd_rank', imd, saveto='../lectures/figs/104_equal_interval.png

In [21]: def plot_scheme(scheme, var, db, figsize=(16, 8), saveto=None):



• Conditional map

In [23]: plot_scheme('quantiles', 'imd_rank', imd, saveto='../lectures/figs/104_quantiles.png')

