lab_01

September 15, 2016

1 Geographic Data Science - Lab 01, Part I

Dani Arribas-Bel

2 Data "munging"

Real world datasets are messy. There is no way around it: datasets have "holes" (missing data), the amount of formats in which data can be stored is endless, and the best structure to share data is not always the optimum to analyze them, hence the need to munge them. As has been correctly pointed out in many outlets (e.g.), much of the time spent in what is called (Geo-)Data Science is related not only to sophisticated modeling and insight, but has to do with much more basic and less exotic tasks such as obtaining data, processing, turning them into a shape that makes analysis possible, and exploring it to get to know their basic properties.

For how labor intensive and relevant this aspect is, there is surprisingly very little published on patterns, techniques, and best practices for quick and efficient data cleaning, manipulation, and transformation. In this session, you will use a few real world datasets and learn how to process them into Python so they can be transformed and manipulated, if necessary, and analyzed. For this, we will introduce some of the bread and butter of data analysis and scientific computing in Python. These are fundamental tools that are constantly used in almost any task relating to data analysis.

This notebook covers the basic and the content that is expected to be learnt by every student. We use a prepared dataset that saves us much of the more intricate processing that goes beyond the introductory level the session is aimed at. As a companion to this introduction, there is an additional notebook (see link on the website page for Lab 01) that covers how the dataset used here was prepared from raw data downloaded from the internet, and includes some additional exercises you can do if you want dig deeper into the content of this lab.

In this notebook, we discuss several patterns to clean and structure data properly, including tidying, subsetting, and aggregating; and we finish with some basic visualization. An additional extension presents more advanced tricks to manipulate tabular data.

Before we get our hands data-dirty, let us import all the additional libraries we will need, so we can get that out of the way and focus on the task at hand:

In [1]:
```
# This ensures visualizations are plotted inside the notebook
%matplotlib inline

import os              # This provides several system utilities
import pandas as pd    # This is the workhorse of data munging in Python
import seaborn as sns  # This allows us to easily and beautifully plot
```

```
/Users/dani/anaconda/envs/gds/lib/python2.7/site-packages/matplotlib/font_manager.py:273: UserWarning: M
  warnings.warn('Matplotlib is building the font cache using fc-list. This may take a moment.')
```

2.1 Dataset

We will be exploring some of the characteristics of the population in Liverpool. To do that, we will use a dataset that contains population counts, split by ethnic origin. These counts are aggregated at the Lower Layer Super Output Area (LSOA from now on). LSOAs are an official Census geography defined by the Office of National Statistics that is small enough to create variation within cities, but large enough also to preserve privacy. For that reason, many data products (Census, deprivation indices, etc.) use LSOAs as one of their main geographies.

To read a "comma separated values" (`.csv`) file, we can run:

```
In [2]: # Important! You need to specify the path to the data in *your* machine
        # If you have placed the data folder in the same directory as this notebook,
        # you would do:
        # f = 'liv_pop.csv'
        f = 'data/liv_pop.csv'                              # Path to file containing the table
        db = pd.read_csv(f, index_col='GeographyCode')     # Read the table in
```

Let us stop for a minute to learn how we have read the file. Here are the main aspects to keep in mind:

- We are using the method `read_csv` from the `pandas` library, which we have imported with the alias `pd`.
- In this simple form, all that is required is to pass the path to the file we want to read, which in this case we have created by concatenating two strings. We can see the full path we have used:

```
In [3]: f

Out[3]: 'data/liv_pop.csv'
```

- The argument `index_col` is not strictly necessary but allows us to choose one of the columns as the index of the table. More on indices below.
- We are using `read_csv` because the file we want to read is in the `csv` format. However, `pandas` allows for many more formats to be read (and written, just replace `read` by `to`! For example, `read_csv` reads in, `to_csv` writes out). A full list of formats supported may be found here.

2.2 Data, sliced and diced

Now we are ready to start playing and interrogating the dataset! What we have at our fingertips is a table that summarizes, for each of the LSOAs in Liverpool, how many people live in each, by the region of the world where they were born. Now, let us learn a few cool tricks built into `pandas` that work out-of-the box with a table like ours.

- Inspecting what it looks like. We can check the top (bottom) X lines of the table by passing X to the method `head` (`tail`). For example, for the top/bottom five lines:

```
In [4]: db.head()

Out[4]:                Europe  Africa  Middle East and Asia  \
        GeographyCode
        E01006512         910     106                   840
        E01006513        2225      61                   595
        E01006514        1786      63                   193
        E01006515         974      29                   185
        E01006518        1531      69                    73

                       The Americas and the Caribbean  Antarctica and Oceania
        GeographyCode
        E01006512                                  24                       0
```

```
E01006513                          53          7
E01006514                          61          5
E01006515                          18          2
E01006518                          19          4
```

```
In [5]: db.tail()
```

```
Out[5]:               Europe  Africa  Middle East and Asia  \
        GeographyCode
        E01033764       2106      32                    49
        E01033765       1277      21                    33
        E01033766       1028      12                    20
        E01033767       1003      29                    29
        E01033768       1016      69                   111

                      The Americas and the Caribbean  Antarctica and Oceania
        GeographyCode
        E01033764                                 15                       0
        E01033765                                 17                       3
        E01033766                                  8                       7
        E01033767                                  5                       1
        E01033768                                 21                       6
```

- Getting an overview of the table:

```
In [6]: db.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 298 entries, E01006512 to E01033768
Data columns (total 5 columns):
Europe                            298 non-null int64
Africa                            298 non-null int64
Middle East and Asia              298 non-null int64
The Americas and the Caribbean    298 non-null int64
Antarctica and Oceania            298 non-null int64
dtypes: int64(5)
memory usage: 14.0+ KB
```

- Getting an overview of the values of the table:

```
In [7]: db.describe()
```

```
Out[7]:            Europe      Africa  Middle East and Asia  \
        count   298.00000  298.000000            298.000000
        mean   1462.38255   29.818792             62.909396
        std     248.67329   51.606065            102.519614
        min     731.00000    0.000000              1.000000
        25%    1331.25000    7.000000             16.000000
        50%    1446.00000   14.000000             33.500000
        75%    1579.75000   30.000000             62.750000
        max    2551.00000  484.000000            840.000000

               The Americas and the Caribbean  Antarctica and Oceania
        count                      298.000000              298.000000
        mean                         8.087248                1.949664
        std                          9.397638                2.168216
```

```
min                                0.000000               0.000000
25%                                2.000000               0.000000
50%                                5.000000               1.000000
75%                               10.000000               3.000000
max                               61.000000              11.000000
```

Note how the output is also a `DataFrame` object, so you can do with it the same things you would with the original table (e.g. writing it to a file).

In this case, the summary might be better presented if the table is "transposed":

In [8]:
```
db.describe().T
```

Out[8]:
```
                                count         mean         std    min  \
Europe                          298.0  1462.382550  248.673290  731.0
Africa                          298.0    29.818792   51.606065    0.0
Middle East and Asia            298.0    62.909396  102.519614    1.0
The Americas and the Caribbean  298.0     8.087248    9.397638    0.0
Antarctica and Oceania          298.0     1.949664    2.168216    0.0

                                    25%     50%      75%     max
Europe                          1331.25  1446.0  1579.75  2551.0
Africa                             7.00    14.0    30.00   484.0
Middle East and Asia              16.00    33.5    62.75   840.0
The Americas and the Caribbean     2.00     5.0    10.00    61.0
Antarctica and Oceania             0.00     1.0     3.00    11.0
```

- Equally, common descriptive statistics are also available:

In [9]:
```
# Obtain minimum values for each table
db.min()
```

Out[9]:
```
Europe                            731
Africa                              0
Middle East and Asia                1
The Americas and the Caribbean      0
Antarctica and Oceania              0
dtype: int64
```

In [10]:
```
# Obtain minimum value for the column ‘Europe‘
db['Europe'].min()
```

Out[10]:
```
731
```

Note here how we have restricted the calculation of the maximum value to one column only.

Similarly, we can restrict the calculations to a single row:

In [11]:
```
# Obtain standard deviation for the row ‘E01006512‘,
# which represents a particular LSOA
db.loc['E01006512', :].std()
```

Out[11]:
```
457.88426485303029
```

- Simple creation of new variables: we can generate new variables by applying operations on existing ones. For example, we can calculate the total population by area. Here is a couple of ways to do it:

In [12]:
```
# Longer, hardcoded
total = db['Europe'] + db['Africa'] + db['Middle East and Asia'] + \
        db['The Americas and the Caribbean'] + db['Antarctica and Oceania']
# Print the top of the variable
total.head()
```

```
Out[12]: GeographyCode
         E01006512    1880
         E01006513    2941
         E01006514    2108
         E01006515    1208
         E01006518    1696
         dtype: int64
```

```
In [13]: # One shot
         total = db.sum(axis=1)
         # Print the top of the variable
         total.head()
```

```
Out[13]: GeographyCode
         E01006512    1880
         E01006513    2941
         E01006514    2108
         E01006515    1208
         E01006518    1696
         dtype: int64
```

Note how we are using the command **sum**, just like we did with **max** or **min** before but, in this case, we are not applying it over columns (e.g. the max of each column), but over rows, so we get the total sum of populations by areas.

Once we have created the variable, we can make it part of the table:

```
In [14]: db['Total'] = total
         db.head()
```

```
Out[14]:                Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01006512         910     106                   840
         E01006513        2225      61                   595
         E01006514        1786      63                   193
         E01006515         974      29                   185
         E01006518        1531      69                    73

                        The Americas and the Caribbean  Antarctica and Oceania  Total
         GeographyCode
         E01006512                                  24                       0   1880
         E01006513                                  53                       7   2941
         E01006514                                  61                       5   2108
         E01006515                                  18                       2   1208
         E01006518                                  19                       4   1696
```

- Assigning new values: we can easily generate new variables with scalars, and modify those.

```
In [15]: # New variable with all ones
         db['ones'] = 1
         db.head()
```

```
Out[15]:                Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01006512         910     106                   840
         E01006513        2225      61                   595
         E01006514        1786      63                   193
```

```
E01006515        974      29                   185
E01006518       1531      69                    73

               The Americas and the Caribbean  Antarctica and Oceania  Total  \
GeographyCode
E01006512                                  24                       0   1880
E01006513                                  53                       7   2941
E01006514                                  61                       5   2108
E01006515                                  18                       2   1208
E01006518                                  19                       4   1696

               ones
GeographyCode
E01006512         1
E01006513         1
E01006514         1
E01006515         1
E01006518         1
```

And we can modify specific values too:

```
In [16]: db.loc['E01006512', 'ones'] = 3
         db.head()
```

```
Out[16]:                Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01006512         910     106                   840
         E01006513        2225      61                   595
         E01006514        1786      63                   193
         E01006515         974      29                   185
         E01006518        1531      69                    73

                        The Americas and the Caribbean  Antarctica and Oceania  Total  \
         GeographyCode
         E01006512                                  24                       0   1880
         E01006513                                  53                       7   2941
         E01006514                                  61                       5   2108
         E01006515                                  18                       2   1208
         E01006518                                  19                       4   1696

                        ones
         GeographyCode
         E01006512         3
         E01006513         1
         E01006514         1
         E01006515         1
         E01006518         1
```

- Deleting variables is also trivial:

```
In [17]: del db['ones']
         db.head()
```

```
Out[17]:                Europe  Africa  Middle East and Asia  \
         GeographyCode
```

```
E01006512        910     106                       840
E01006513       2225      61                       595
E01006514       1786      63                       193
E01006515        974      29                       185
E01006518       1531      69                        73

               The Americas and the Caribbean  Antarctica and Oceania  Total
GeographyCode
E01006512                                  24                       0   1880
E01006513                                  53                       7   2941
E01006514                                  61                       5   2108
E01006515                                  18                       2   1208
E01006518                                  19                       4   1696
```

- Simple querying.

We have already seen how to subset parts of a `DataFrame` if we know exactly which bits we want. For example, if we want to extract the total and European population of the first four areas in the table, we use `loc` with lists:

```
In [18]: eu_tot_first4 = db.loc[['E01006512', 'E01006513', 'E01006514', 'E01006515'], \
                                ['Total', 'Europe']]
         eu_tot_first4
```

```
Out[18]:                Total  Europe
         GeographyCode
         E01006512       1880     910
         E01006513       2941    2225
         E01006514       2108    1786
         E01006515       1208     974
```

- Querying based on conditions.

However, sometimes, we do not know exactly which observations we want, but we do know what conditions they need to satisfy (e.g. areas with more than 2,000 inhabitants). For these cases, `DataFrames` support selection based on conditions. Let us see a few examples. Suppose we want to select…

… areas with more than 2,500 people in Total:

```
In [19]: m5k = db.loc[db['Total'] > 2500, :]
         m5k
```

```
Out[19]:                Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01006513        2225      61                   595
         E01006747        2551     163                   812
         E01006751        1843     139                   568

                        The Americas and the Caribbean  Antarctica and Oceania  Total
         GeographyCode
         E01006513                                  53                       7   2941
         E01006747                                  24                       2   3552
         E01006751                                  21                       1   2572
```

… areas where there are no more than 750 Europeans:

```
In [20]: nm5ke = db.loc[db['Europe'] < 750, :]
         nm5ke
```

```
Out[20]:                Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01033757         731      39                   223

                        The Americas and the Caribbean  Antarctica and Oceania  Total
         GeographyCode
         E01033757                                  29                       3   1025
```

... areas with exactly ten person from Antarctica and Oceania:

```
In [21]: oneOA = db.loc[db['Antarctica and Oceania'] == 10, :]
         oneOA
```

```
Out[21]:                Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01006679        1353     484                   354

                        The Americas and the Caribbean  Antarctica and Oceania  Total
         GeographyCode
         E01006679                                  31                      10   2232
```

Pro-tip: these queries can grow in sophistication with almost no limits. For example, here is a case where we want to find out the areas where European population is less than half the population:

```
In [22]: eu_lth = db.loc[(db['Europe'] * 100. / db['Total']) < 50, :]
         eu_lth
```

```
Out[22]:                Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01006512         910     106                   840

                        The Americas and the Caribbean  Antarctica and Oceania  Total
         GeographyCode
         E01006512                                  24                       0   1880
```

- Combining queries.

Now all of these queries can be combined with each other, for further flexibility. For example, imagine we want areas with more than 25 people from the Americas and Caribbean, but less than 1,500 in total:

```
In [23]: ac25_l500 = db.loc[(db['The Americas and the Caribbean'] > 25) & \
                            (db['Total'] < 1500), :]
         ac25_l500
```

```
Out[23]:                Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01033750        1235      53                   129
         E01033752        1024      19                   114
         E01033754        1262      37                   112
         E01033756         886      31                   221
         E01033757         731      39                   223
         E01033761        1138      52                   138

                        The Americas and the Caribbean  Antarctica and Oceania  Total
         GeographyCode
         E01033750                                  26                       5   1448
```

```
E01033752                                 33                          6   1196
E01033754                                 32                          9   1452
E01033756                                 42                          5   1185
E01033757                                 29                          3   1025
E01033761                                 33                         11   1372
```

- Sorting.

Among the many operations `DataFrame` objects support, one of the most useful ones is to sort a table based on a given column. For example, imagine we want to sort the table by total population:

```
In [24]: db_pop_sorted = db.sort_values('Total', ascending=False)
         db_pop_sorted.head()
```

```
Out[24]:                 Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01006747         2551     163                   812
         E01006513         2225      61                   595
         E01006751         1843     139                   568
         E01006524         2235      36                   125
         E01006787         2187      53                    75

                         The Americas and the Caribbean  Antarctica and Oceania  Total
         GeographyCode
         E01006747                                   24                       2   3552
         E01006513                                   53                       7   2941
         E01006751                                   21                       1   2572
         E01006524                                   24                      11   2431
         E01006787                                   13                       2   2330
```

If you inspect the help of `db.sort`, you will find that you can pass more than one column to sort the table by. This allows you to do so-called hiearchical sorting: sort first based on one column, if equal then based on another column, etc.

2.3 Visual exploration

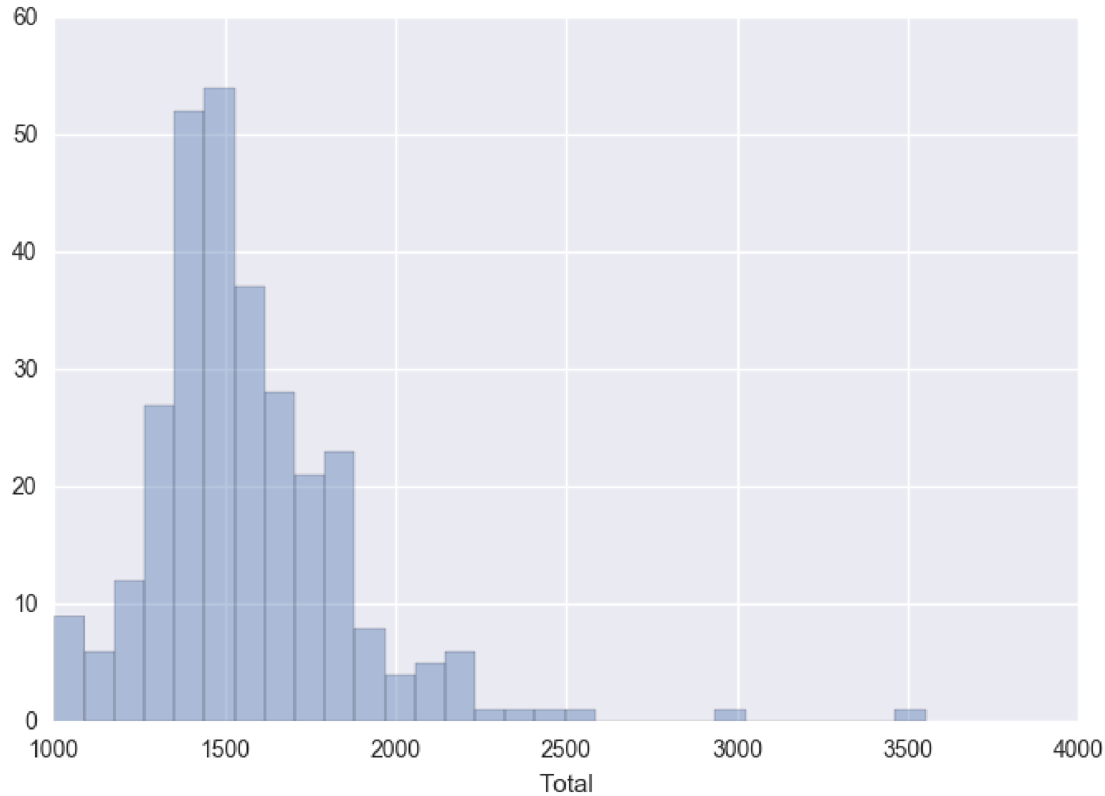
The next step to continue exploring a dataset is to get a feel for what it looks like, visually. We have already learnt how to unconver and inspect specific parts of the data, to check for particular cases we might be intersted in. Now we will see how to plot the data to get a sense of the overall distribution of values. For that, we will be using the Python library `seaborn`.

- Histograms.

One of the simplest graphical devices to display the distribution of values in a variable is a histogram. Values are assigned into groups of equal intervals, and the groups are plotted as bars rising as high as the number of values into the group.

A histogram is easily created with the following command. In this case, let us have a look at the shape of the overall population:

```
In [25]: _ = sns.distplot(db['Total'], kde=False)
```

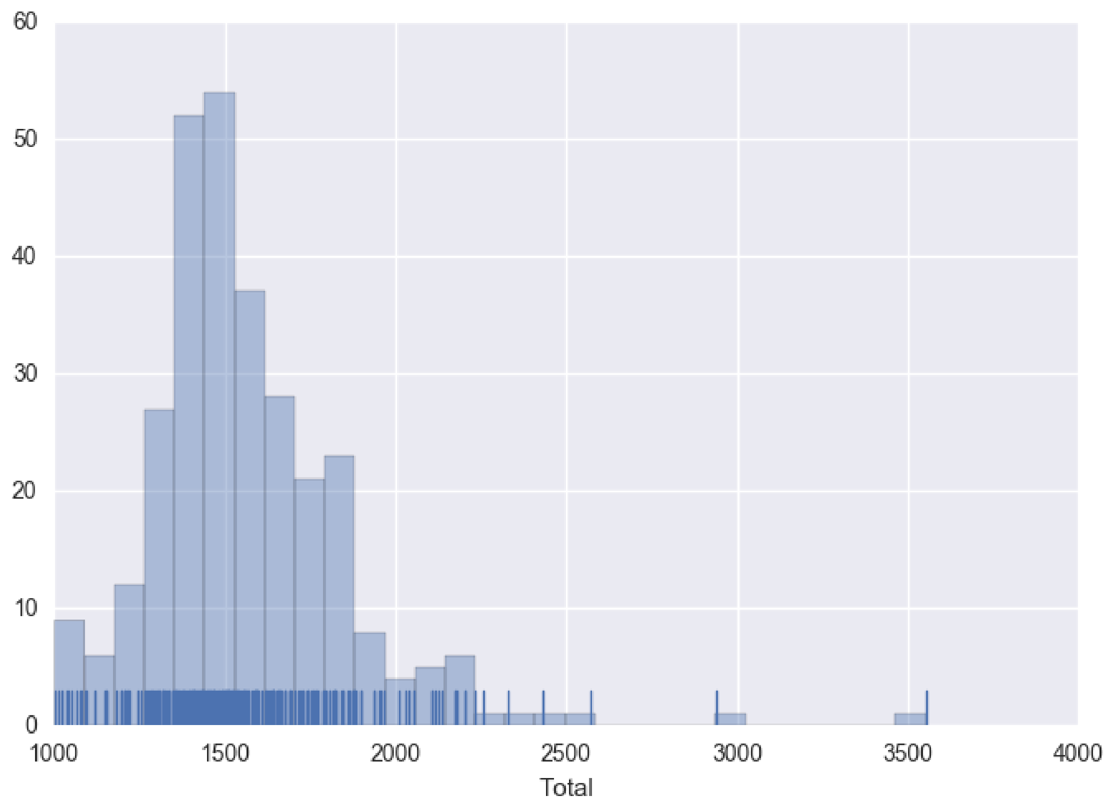


Note we are using `sns` instead of `pd`, as the function belongs to `seaborn` instead of `pandas`.

We can quickly see most of the areas contain somewhere between 1,200 and 1,700 people, approx. However, there are a few areas that have many more, even up to 3,500 people.

An additinal feature to visualize the density of values is called `rug`, and adds a little tick for each value on the horizontal axis:

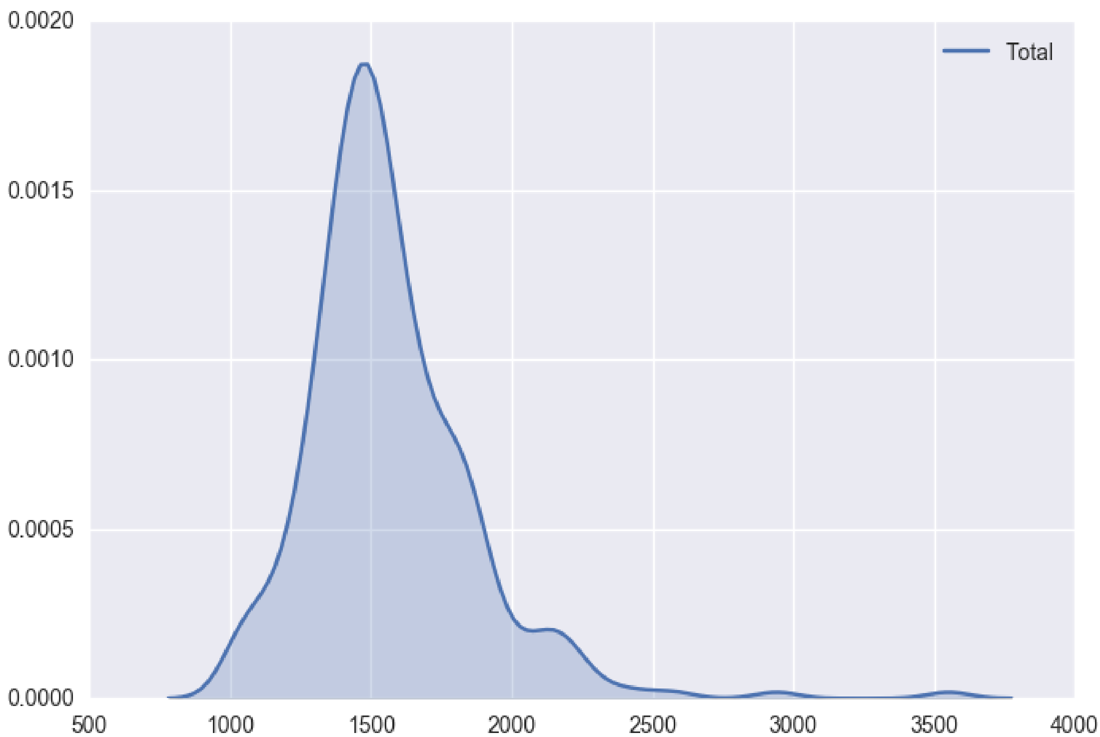
```
In [26]: _ = sns.distplot(db['Total'], kde=False, rug=True)
```



- Kernel Density Plots

Histograms are useful, but they are artificial in the sense that a continuous variable is made discrete by turning the values into discrete groups. An alternative is kernel density estimation (KDE), which produces an empirical density function:

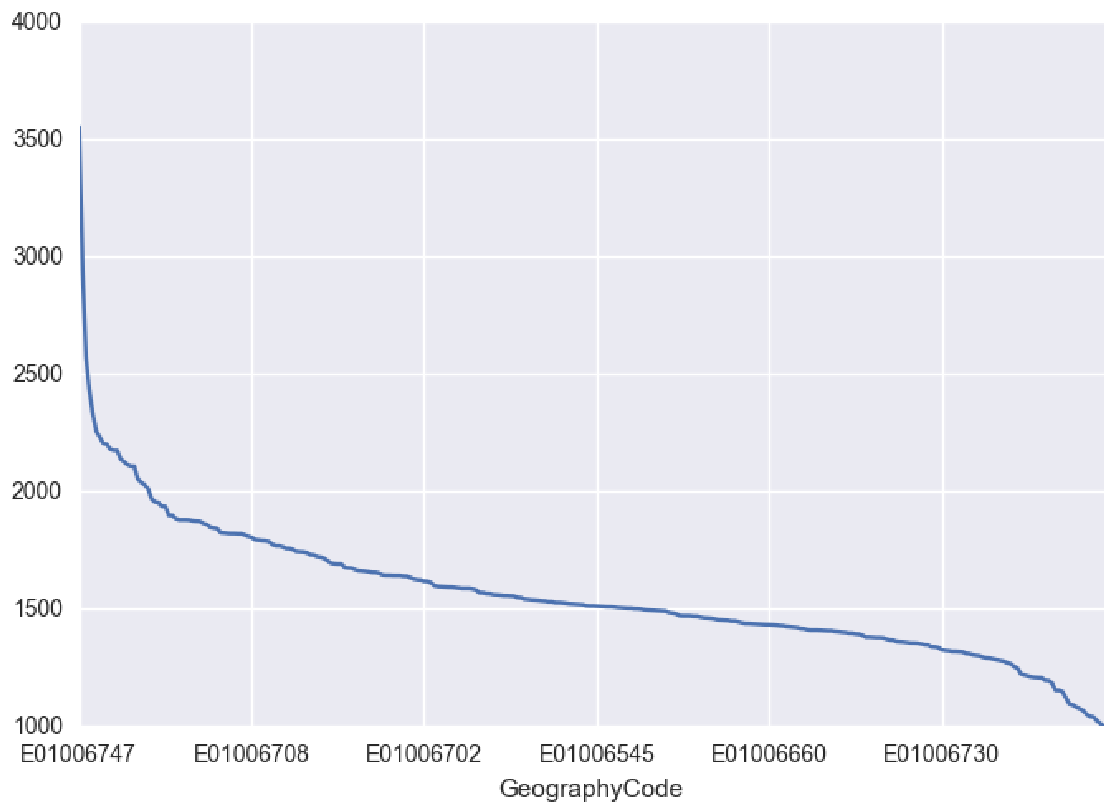
```
In [27]: _ = sns.kdeplot(db['Total'], shade=True)
```



- Line and bar plots

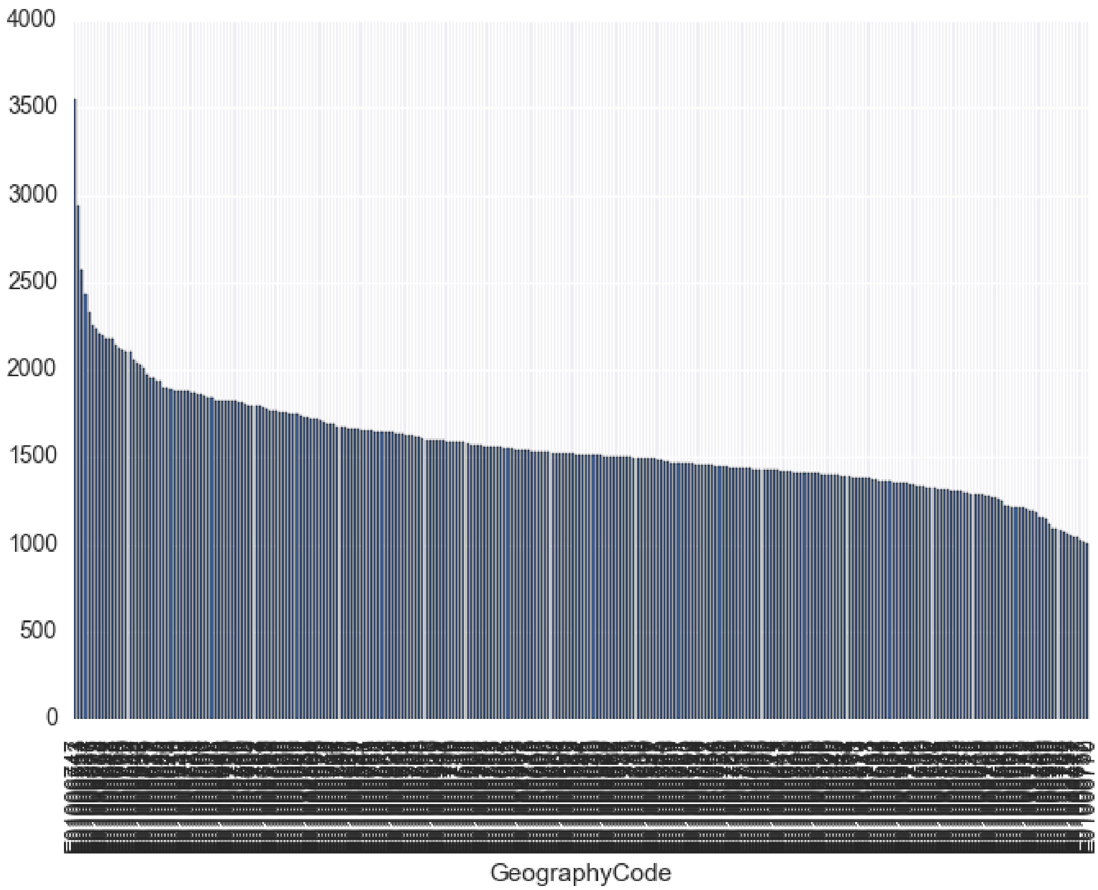
Another very common way of visually displaying a variable is with a line or a bar chart. For example, if we want to generate a line plot of the (sorted) total population by area:

```
In [28]: _ = db['Total'].sort_values(ascending=False).plot()
```



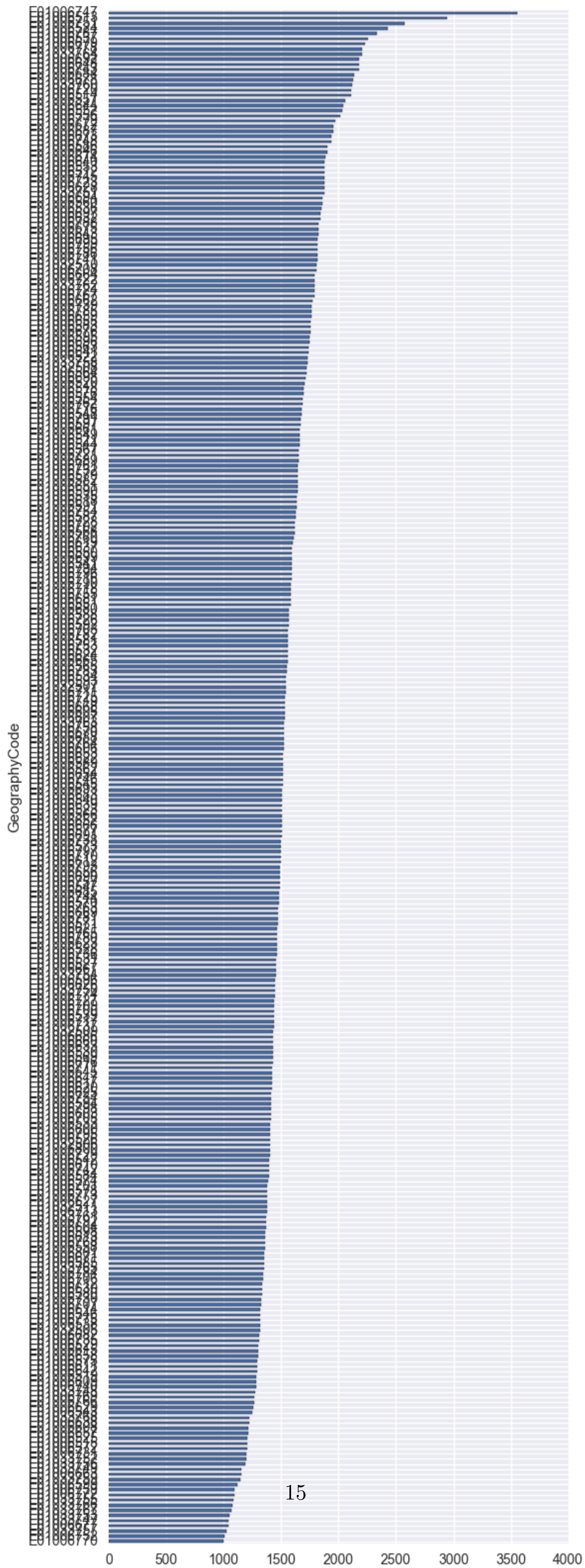
For a bar plot all we need to do is to change an argument of the call:

```
In [29]: _ = db['Total'].sort_values(ascending=False).plot(kind='bar')
```



Note that the large number of areas makes the horizontal axis unreadable. We can try to turn the plot around by displaying the bars horizontally (see how it's just changing `bar` for `barh`). To make it readable, let us expand the plot's height:

```
In [30]: _ = db['Total'].sort_values().plot(kind='barh', figsize=(6, 20))
```


GeographyCode
E01006747
E01006770
0
500
1000
1500
2000
2500
3000
3500
4000

2.3.1 Un/tidy data

> Happy families are all alike; every unhappy family is unhappy in its own way.
>
> Leo Tolstoy.

Once you can read your data in, explore specific cases, and have a first visual approach to the entire set, the next step can be preparing it for more sophisticated analysis. Maybe you are thinking of modeling it through regression, or on creating subgroups in the dataset with particular characteristics, or maybe you simply need to present summary measures that relate to a slightly different arrangement of the data than you have been presented with.

For all these cases, you first need what statistitian, and general R wizard, Hadley Wickham calls "tidy data". The general idea to "tidy" your data is to convert them from whatever structure they were handed in to you into one that allows easy and standardized manipulation, and that supports directly inputting the data into what he calls "tidy" analysis tools. But, at a more practical level, what is exactly "tidy data"? In Wickham's own words:

> Tidy data is a standard way of mapping the meaning of a dataset to its structure. A dataset is messy or tidy depending on how rows, columns and tables are matched up with observations, variables and types.

He then goes on to list the three fundamental characteristics of "tidy data":

1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

If you are further interested in the concept of "tidy data", I recommend you check out the original paper (open access) and the public repository associated with it.

Let us bring in the concept of "tidy data" to our own Liverpool dataset. First, remember its structure:

```
In [31]: db.head()
```

```
Out[31]:                Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01006512         910     106                   840
         E01006513        2225      61                   595
         E01006514        1786      63                   193
         E01006515         974      29                   185
         E01006518        1531      69                    73

                        The Americas and the Caribbean  Antarctica and Oceania  Total
         GeographyCode
         E01006512                                  24                       0   1880
         E01006513                                  53                       7   2941
         E01006514                                  61                       5   2108
         E01006515                                  18                       2   1208
         E01006518                                  19                       4   1696
```

Thinking through tidy lenses, this is not a tidy dataset. It is not so for each of the three conditions:

- Starting by the last one (each type of observational unit forms a table), this dataset actually contains not one but two observational units: the different areas of Liverpool, captured by `GeographyCode`; and subgroups of an area. To tidy up this aspect, we can create two different tables:

```
In [32]: # Assign column `Total` into its own as a single-column table
         db_totals = db[['Total']]
         db_totals.head()
```

```
Out[32]:                 Total
         GeographyCode
         E01006512       1880
         E01006513       2941
         E01006514       2108
         E01006515       1208
         E01006518       1696
```

```
In [33]: # Create a table `db_subgroups` that contains every column in `db` without `Total`
         db_subgroups = db.drop('Total', axis=1)
         db_subgroups.head()
```

```
Out[33]:                 Europe  Africa  Middle East and Asia  \
         GeographyCode
         E01006512          910     106                   840
         E01006513         2225      61                   595
         E01006514         1786      63                   193
         E01006515          974      29                   185
         E01006518         1531      69                    73

                         The Americas and the Caribbean  Antarctica and Oceania
         GeographyCode
         E01006512                                   24                       0
         E01006513                                   53                       7
         E01006514                                   61                       5
         E01006515                                   18                       2
         E01006518                                   19                       4
```

Note we use `drop` to exclude "Total", but we could also use a list with the names of all the columns to keep.

At this point, the table `db_totals` is tidy: every row is an observation, every table is a variable, and there is only one observational unit in the table.

The other table (`db_subgroups`), however, is not entirely tidied up yet: there is only one observational unit in the table, true; but every row is not an observation, and there are variable values as the names of columns (in other words, every column is not a variable). To obtain a fully tidy version of the table, we need to re-arrange it in a way that every row is a population subgroup in an area, and there are three variables: `GeographyCode`, population subgroup, and population count (or frequency).

Because this is actually a fairly common pattern, there is a direct way to solve it in `pandas`:

```
In [34]: tidy_subgroups = db_subgroups.stack()
         tidy_subgroups.head()
```

```
Out[34]: GeographyCode
         E01006512      Europe                            910
                        Africa                            106
                        Middle East and Asia              840
                        The Americas and the Caribbean     24
                        Antarctica and Oceania              0
         dtype: int64
```

The method `stack`, well, "stacks" the different columns into rows. This fixes our "tidiness" problems but the type of object that is returning is not a `DataFrame`:

```
In [35]: type(tidy_subgroups)
```

```
Out[35]: pandas.core.series.Series
```

It is a `Series`, which really is like a `DataFrame`, but with only one column. The additional information (`GeographyCode` and population group) are stored in what is called an multi-index. We will skip these for now, so we would really just want to get a `DataFrame` as we know it out of the `Series`. This is also one line of code away:

```
In [36]: # Unfold the multi-index into different, new columns
         tidy_subgroupsDF = tidy_subgroups.reset_index()
         tidy_subgroupsDF.head()
```

```
Out[36]:   GeographyCode                       level_1    0
         0     E01006512                        Europe  910
         1     E01006512                        Africa  106
         2     E01006512           Middle East and Asia  840
         3     E01006512  The Americas and the Caribbean   24
         4     E01006512          Antarctica and Oceania    0
```

To which we can apply to renaming to make it look better:

```
In [37]: tidy_subgroupsDF = tidy_subgroupsDF.rename(columns={'level_1': 'Subgroup', 0: 'Freq'})
         tidy_subgroupsDF.head()
```

```
Out[37]:   GeographyCode                      Subgroup  Freq
         0     E01006512                        Europe   910
         1     E01006512                        Africa   106
         2     E01006512           Middle East and Asia   840
         3     E01006512  The Americas and the Caribbean    24
         4     E01006512          Antarctica and Oceania     0
```

Now our table is fully tidied up!

2.3.2 Grouping, transforming, aggregating

One of the advantage of tidy datasets is they allow to perform advanced transformations in a more direct way. One of the most common ones is what is called "group-by" operations. Originated in the world of databases, these operations allow you to group observations in a table by one of its labels, index, or category, and apply operations on the data group by group.

For example, given our tidy table with population subgroups, we might want to compute the total sum of population by each group. This task can be split into two different ones:

- Group the table in each of the different subgroups.
- Compute the sum of `Freq` for each of them.

To do this in `pandas`, meet one of its workhorses, and also one of the reasons why the library has become so popular: the `groupby` operator.

```
In [38]: pop_grouped = tidy_subgroupsDF.groupby('Subgroup')
         pop_grouped
```

```
Out[38]: <pandas.core.groupby.DataFrameGroupBy object at 0x112c529d0>
```

The object `pop_grouped` still hasn't computed anything, it is only a convenient way of specifying the grouping. But this allows us then to perform a multitude of operations on it. For our example, the sum is calculated as follows:

```
In [39]: pop_grouped.sum()
```

```
Out[39]:                                    Freq
         Subgroup
         Africa                             8886
         Antarctica and Oceania              581
         Europe                           435790
         Middle East and Asia              18747
         The Americas and the Caribbean     2410
```

Similarly, you can also obtain a summary of each group:

```
In [40]: pop_grouped.describe()
```

```
Out[40]:                                              Freq
         Subgroup
         Africa                         count   298.000000
                                        mean     29.818792
                                        std      51.606065
                                        min       0.000000
                                        25%       7.000000
                                        50%      14.000000
                                        75%      30.000000
                                        max     484.000000
         Antarctica and Oceania         count   298.000000
                                        mean      1.949664
                                        std       2.168216
                                        min       0.000000
                                        25%       0.000000
                                        50%       1.000000
                                        75%       3.000000
                                        max      11.000000
         Europe                         count   298.000000
                                        mean   1462.382550
                                        std     248.673290
                                        min     731.000000
                                        25%    1331.250000
                                        50%    1446.000000
                                        75%    1579.750000
                                        max    2551.000000
         Middle East and Asia           count   298.000000
                                        mean     62.909396
                                        std     102.519614
                                        min       1.000000
                                        25%      16.000000
                                        50%      33.500000
                                        75%      62.750000
                                        max     840.000000
         The Americas and the Caribbean count   298.000000
                                        mean      8.087248
                                        std       9.397638
                                        min       0.000000
                                        25%       2.000000
                                        50%       5.000000
                                        75%      10.000000
                                        max      61.000000
```

Pro-tip: since we only have one variable (`Freq`), a more compact way to display that summary can be obtaine with the counterpart of `stack`, `unstack`:

```
In [41]: pop_grouped.describe().unstack()
```

```
Out[41]:                              Freq                                        \
                                     count         mean         std    min
         Subgroup
         Africa                      298.0    29.818792   51.606065    0.0
         Antarctica and Oceania      298.0     1.949664    2.168216    0.0
         Europe                      298.0  1462.382550  248.673290  731.0
         Middle East and Asia        298.0    62.909396  102.519614    1.0
         The Americas and the Caribbean  298.0     8.087248    9.397638    0.0


                                         25%     50%      75%     max
         Subgroup
         Africa                         7.00    14.0    30.00   484.0
         Antarctica and Oceania         0.00     1.0     3.00    11.0
         Europe                      1331.25  1446.0  1579.75  2551.0
         Middle East and Asia          16.00    33.5    62.75   840.0
         The Americas and the Caribbean   2.00     5.0    10.00    61.0
```

We will not get into it today as it goes beyond the basics we want to conver, but keep in mind that `groupby` allows you to not only call generic functions (like `sum` or `describe`), but also your own functions. This opens the door for virtually any kind of transformation and aggregation possible.

2.4 If you finish early...

Practice your data tidying skills with a different dataset. For example, you can have a look at the Guardian's version of Wikileaks' Afghanistan war logs. The table is stored on a GoogleDoc on the following address:

https://docs.google.com/spreadsheets/d/1EAx8_ksSCmoWW_SlhFyq2QrRn0FNNhcg1TtDFJzZRgc/edit?hl=en#gid=1

And its structure is as follows:

```
In [42]: from IPython.display import IFrame
         url = 'https://docs.google.com/spreadsheets/d/1EAx8_ksSCmoWW_SlhFyq2QrRn0FNNhcg1TtDFJzZRgc/edi
         IFrame(url, 700, 400)
```

```
Out[42]: <IPython.lib.display.IFrame at 0x111e6fb50>
```

Follow these steps:

- Download the table as a `csv` file (File –> Download as –> .csv, current sheet).
- Read it into Python.
- Explore it by creating a few plots.
- Examine its level of tidiness and turn it into a fully tidy dataset.
- Obtain a monthly total count of casualties and create a line or a bar plot of them.
