> Geographic Data Science

with

PySAL

and the

pydata stack

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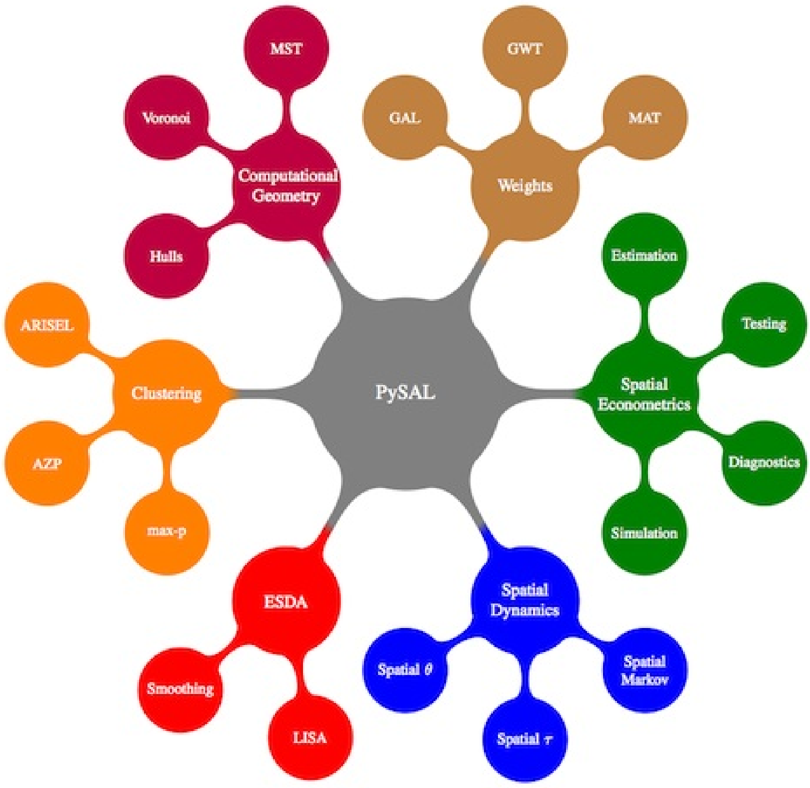
Geographic Data Science with PySAL and the pydata stack

This two-part tutorial will first provide participants with a gentle introduction to Python for geospatial analysis, and an introduction to version `PySAL` 1.11 and the related eco-system of libraries to facilitate common tasks for Geographic Data Scientists. The first part will cover munging geo-data and exploring relations over space. This includes importing data in different formats (e.g. shapefile, GeoJSON), visualizing, combining and tidying them up for analysis, and will use libraries such as `pandas` , `geopandas` , `PySAL` , or `rasterio` . The second part will provide a gentle overview to demonstrate several techniques that allow to extract geospatial insight from the data. This includes spatial clustering and regression and point pattern analysis, and will use libraries such as `PySAL` , `scikit-learn` , or `clusterpy` . A particular emphasis will be set on presenting concepts through visualization, for which libraries such as `matplotlib` , `seaborn` , and `folium` will be used.



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Distribution

> [URL] [PDF] [EPUB] [MOBI] [IPYNB]

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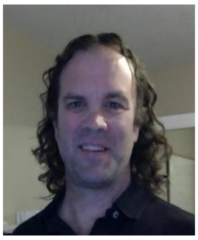
About the authors

 Sergio Rey is professor of geographical sciences and core faculty member of the GeoDa Center for Geospatial Analysis and Computation at the Arizona State University. His research interests include open science, spatial and spatio-temporal data analysis, spatial econometrics, visualization, high performance geocomputation, spatial inequality dynamics, integrated multiregional modeling, and regional science. He co-founded the Python Spatial Analysis Library (PySAL) in 2007 and continues to direct the PySAL project. Rey is a fellow of the spatial econometrics association and editor of the journal Geographical Analysis.

 Dani Arribas-Bel is Lecturer in Geographic Data Science and member of the Geographic Data Science Lab at the University of Liverpool (UK). Dani is interested in undestanding cities as well as in the quantitative and computational methods required to leverage the power of the large amount of urban data increasingly becoming available. He is also part of the team of core developers of PySAL, the open-source library written in Python for spatial analysis. Dani regularly teaches Geographic Data Science and Python courses at the University of Liverpool and has designed and developed several workshops at different levels on spatial analysis and econometrics, Python and open source scientific computing.

Outline

Part I

1. Software and Tools Installation (10 min)
2. Spatial data processing with PySAL (45 min)

   a. Input-output

   b. Visualization and Mapping

   c. Spatial weights
3. Exercise (10 min.)
4. ESDA with PySAL (45 min)

   a. Global Autocorrelation

   b. Local Autocorrelation

   c. Space-Time exploratory analysis
5. Exercise (10 min)

Part II

1. Point Patterns (30 min)

   a. Point visualization

   b. Centrography and distance based statistics
2. Exercise (10 min)
3. Spatial clustering a (30 min)

   a. Geodemographic analysis

   b. Regionalization
4. Exercise (30 min)
5. Spatial Regression (30 min)

   a. Overview

   c. Basic spatial regression: spatial lag and error model
6. Exercise (10 min)

Data

This tutorial makes use of a variety of data sources. Below is a brief description of each dataset as well as the links to the original source where the data was downloaded from. For convenience, we have repackaged the data and included them in the compressed file with the notebooks. You can download it here.

AirBnb listing for Austin (TX)

Source: Inside AirBnb's extract of AirBnb locations in Austin (TX).

Part I

Software and Tools Installation

Dependencies

Participants should have installed the following dependencies:

- Anaconda or MiniConda Python distributions for Python 2.7. See installation instructions on the links.
- `git`
- A `conda` environment loaded with all the dependencies can be installed by running the `pydata.sh` script available as part of the `envs` repository (Github link). To install it, follow these instructions:
    - Clone the repository on your machine:

      `> git clone https://github.com/darribas/envs.git`
    - Navigate into the folder:

      `> cd envs`
    - Run the script:

      `> bash pydata.sh`

Once installed, you need to activate the environment to run the notebooks. In Windows, open up PowerShell and type:

`> activate pydata`

And if you are on GNU/Linux or OSX:

`> source activate pydata`

Get started

Instructions to fire up a notebook here.

Spatial Data Processing

Notebook here.

```
%matplotlib inline

import pysal as ps
```

ESDA with `PySAL`

```
%matplotlib inline

import pysal as ps
```

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

Part II

Point Patterns

IPYNB

This notebook covers a brief introduction on how to visualize and analyze point patterns. To demonstrate this, we will use a dataset of all the AirBnb listings in the city of Austin (check the Data section for more information about the dataset).

Before anything, let us load up the libraries we will use:

```
%matplotlib inline

import numpy as np
import pandas as pd
import geopandas as gpd
import seaborn as sns
import matplotlib.pyplot as plt
import mplleaflet as mpll
```

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

Data preparation

Let us first set the paths to the datasets we will be using:

```
# Adjust this to point to the right file in your computer
listings_link = '/home/dani/Desktop/listings.csv'
```

The core dataset we will use is `listings.csv`, which contains a lot of information about each individual location listed at AirBnb within Austin:

```
lst = pd.read_csv(listings_link)
lst.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5835 entries, 0 to 5834
Data columns (total 92 columns):
id                                    5835 non-null int64
listing_url                           5835 non-null object
scrape_id                             5835 non-null int64
last_scraped                          5835 non-null object
name                                  5835 non-null object
```

```
summary                         5373 non-null object
space                           4475 non-null object
description                     5832 non-null object
experiences_offered             5835 non-null object
neighborhood_overview           3572 non-null object
notes                           2413 non-null object
transit                         3492 non-null object
thumbnail_url                   5542 non-null object
medium_url                      5542 non-null object
picture_url                     5835 non-null object
xl_picture_url                  5542 non-null object
host_id                         5835 non-null int64
host_url                        5835 non-null object
host_name                       5820 non-null object
host_since                      5820 non-null object
host_location                   5810 non-null object
host_about                      3975 non-null object
host_response_time              4177 non-null object
host_response_rate              4177 non-null object
host_acceptance_rate            3850 non-null object
host_is_superhost               5820 non-null object
host_thumbnail_url              5820 non-null object
host_picture_url                5820 non-null object
host_neighbourhood              4977 non-null object
host_listings_count             5820 non-null float64
host_total_listings_count       5820 non-null float64
host_verifications              5835 non-null object
host_has_profile_pic            5820 non-null object
host_identity_verified          5820 non-null object
street                          5835 non-null object
neighbourhood                   4800 non-null object
neighbourhood_cleansed          5835 non-null int64
neighbourhood_group_cleansed    0 non-null float64
city                            5835 non-null object
state                           5835 non-null object
zipcode                         5810 non-null float64
market                          5835 non-null object
smart_location                  5835 non-null object
country_code                    5835 non-null object
country                         5835 non-null object
latitude                        5835 non-null float64
longitude                       5835 non-null float64
is_location_exact               5835 non-null object
property_type                   5835 non-null object
room_type                       5835 non-null object
accommodates                    5835 non-null int64
bathrooms                       5789 non-null float64
bedrooms                        5829 non-null float64
beds                            5812 non-null float64
bed_type                        5835 non-null object
amenities                       5835 non-null object
square_feet                     302 non-null float64
price                           5835 non-null object
```

```
weekly_price                        2227 non-null object
monthly_price                       1717 non-null object
security_deposit                    2770 non-null object
cleaning_fee                        3587 non-null object
guests_included                     5835 non-null int64
extra_people                        5835 non-null object
minimum_nights                      5835 non-null int64
maximum_nights                      5835 non-null int64
calendar_updated                    5835 non-null object
has_availability                    5835 non-null object
availability_30                     5835 non-null int64
availability_60                     5835 non-null int64
availability_90                     5835 non-null int64
availability_365                    5835 non-null int64
calendar_last_scraped               5835 non-null object
number_of_reviews                   5835 non-null int64
first_review                        3827 non-null object
last_review                         3829 non-null object
review_scores_rating                3789 non-null float64
review_scores_accuracy              3776 non-null float64
review_scores_cleanliness           3778 non-null float64
review_scores_checkin               3778 non-null float64
review_scores_communication         3778 non-null float64
review_scores_location              3779 non-null float64
review_scores_value                 3778 non-null float64
requires_license                    5835 non-null object
license                             1 non-null float64
jurisdiction_names                  0 non-null float64
instant_bookable                    5835 non-null object
cancellation_policy                 5835 non-null object
require_guest_profile_picture       5835 non-null object
require_guest_phone_verification    5835 non-null object
calculated_host_listings_count      5835 non-null int64
reviews_per_month                   3827 non-null float64
dtypes: float64(20), int64(14), object(58)
memory usage: 4.1+ MB
```

It turns out that one record displays a very odd location and, for the sake of the illustration, we will remove it:

```
odd = lst.loc[lst.longitude>-80, ['longitude', 'latitude']]
odd
```

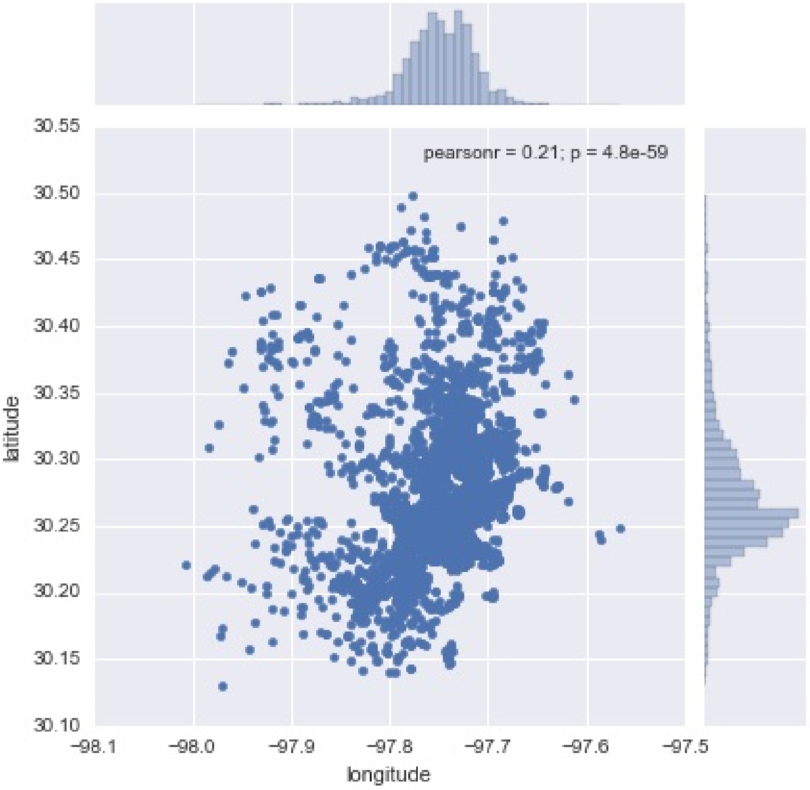
	longitude	latitude
5832	-5.093682	43.214991

```
lst = lst.drop(odd.index)
```

Point Visualization

The most straighforward way to get a first glimpse of the distribution of the data is to plot their latitude and longitude:

```
sns.jointplot(x="longitude", y="latitude", data=lst);
```



Now this does not neccesarily tell us much about the dataset or the distribution of locations within Austin. There are two main challenges in interpreting the plot: one, there is lack of context, which means the points are not identifiable over space (unless you are so familiar with lon/lat pairs that they have a clear meaning to you); and two, in the center of the plot, there are so many points that it is hard to tell any patter other than a big blurb of blue.

Let us first focus on the first problem, geographical context. The quickest and easiest way to provide context to this set of points is to overlay a general map. If we had an image with the map or a set of several data sources that we could aggregate to create a map, we could build it from scratch. But in the XXI Century, the easiest is to overlay our point dataset on top of a web map. In this case, we will use Leaflet, and we will convert our underlying `matplotlib` points with `mplleaflet`. The full dataset (+5k observations) is a bit too much for leaflet to plot it directly on screen, so we will obtain a random sample of 100 points:

```
rids = np.arange(lst.shape[0])
np.random.shuffle(rids)
f, ax = plt.subplots(1, figsize=(6, 6))
lst.iloc[rids[:100], :].plot(kind='scatter', x='longitude', y='latitude', \
                      s=30, linewidth=0, ax=ax)
mpll.display(fig=f,)
```

This map allows us to get a much better sense of where the points are and what type of location they might be in. For example, now we can see that the bigh blue blurb has to do with the urbanized core of Austin.

`bokeh` alternative

Leaflet is not the only technology to display data on maps, although it is probably the default option in many cases. When the data is larger than "acceptable", we need to resort to more technically sophisticated alternatives. One option is provided by `bokeh` and its `datashaded` submodule (see here for a very nice introduction to the library, from where this example has been adapted).

Before we delve into `bokeh`, let us reproject our original data (lon/lat coordinates) into Web Mercator, as `bokeh` will expect them. To do that, we turn the coordinates into a `GeoSeries`:

```
from shapely.geometry import Point
xys_wb = gpd.GeoSeries(lst[['longitude', 'latitude']].apply(Point, axis=1), \
                      crs="+init=epsg:4326")
xys_wb = xys_wb.to_crs(epsg=3857)
x_wb = xys_wb.apply(lambda i: i.x)
y_wb = xys_wb.apply(lambda i: i.y)
```

Now we are ready to setup the plot in `bokeh`:

```
from bokeh.plotting import figure, output_notebook, show
from bokeh.tile_providers import STAMEN_TERRAIN
output_notebook()

minx, miny, maxx, maxy = xys_wb.total_bounds
y_range = miny, maxy
x_range = minx, maxx

def base_plot(tools='pan,wheel_zoom,reset',plot_width=600, plot_height=400, **plot_args)
:
    p = figure(tools=tools, plot_width=plot_width, plot_height=plot_height,
        x_range=x_range, y_range=y_range, outline_line_color=None,
        min_border=0, min_border_left=0, min_border_right=0,
        min_border_top=0, min_border_bottom=0, **plot_args)

    p.axis.visible = False
    p.xgrid.grid_line_color = None
    p.ygrid.grid_line_color = None
    return p

options = dict(line_color=None, fill_color='#800080', size=4)
```

```
<div class="bk-banner">
    <a href="http://bokeh.pydata.org" target="_blank" class="bk-logo bk-logo-small bk-l
ogo-notebook"></a>
    <span id="a0125a61-aa40-4d88-9db2-d2b800c39acb">Loading BokehJS ...</span>
</div>
```

And good to go for mapping!

```
# NOTE: `show` turned off to be able to compile the website,
#       comment out the last line of this cell for rendering.
p = base_plot()
p.add_tile(STAMEN_TERRAIN)
p.circle(x=x_wb, y=y_wb, **options)
#show(p)
```

```
<bokeh.models.renderers.GlyphRenderer at 0x7f6cf6ce8c90>
```

As you can quickly see, `bokeh` is substantially faster at rendering larger amounts of data.

The second problem we have spotted with the first scatter is that, when the number of points grows, at some point it becomes impossible to discern anything other than a big blur of color. To some extent, interactivity gets at that problem by allowing the user to zoom in until every point is an entity on its own. However, there exist techniques that allow to summarize the data to be able to capture the overall pattern at once. Traditionally, kernel density estimation (KDE) has been one of the most common solutions by approximating a continuous surface of point intensity. In this context, however, we will explore a more recent alternative suggested by the `datashader` library (see the paper if interested in more details).

Arguably, our dataset is not large enough to justify the use of a reduction technique like datashader, but we will create the plot for the sake of the illustration. Keep in mind, the usefulness of this approach increases the more points you need to be plotting.

```
# NOTE: `show` turned off to be able to compile the website,
#       comment out the last line of this cell for rendering.

import datashader as ds
from datashader.callbacks import InteractiveImage
from datashader.colors import viridis
from datashader import transfer_functions as tf
from bokeh.tile_providers import STAMEN_TONER

p = base_plot()
p.add_tile(STAMEN_TONER)

pts = pd.DataFrame({'x': x_wb, 'y': y_wb})
pts['count'] = 1
def create_image90(x_range, y_range, w, h):
    cvs = ds.Canvas(plot_width=w, plot_height=h, x_range=x_range, y_range=y_range)
    agg = cvs.points(pts, 'x', 'y',  ds.count('count'))
    img = tf.interpolate(agg.where(agg > np.percentile(agg,90)), \
                         cmap=viridis, how='eq_hist')
    return tf.dynspread(img, threshold=0.1, max_px=4)

#InteractiveImage(p, create_image90)
```

The key advandage of `datashader` is that is decouples the point processing from the plotting. That is the bit that allows it to be scalable to truly large datasets (e.g. millions of points). Essentially, the approach is based on generating a very fine grid, counting points within pixels, and encoding the count into a color scheme. In our map, this is not particularly effective because we do not have too many points (the previous plot is probably a more effective one) and esssentially there is a pixel per location of every point. However, hopefully this example shows how to create this kind of scalable maps.

Centrography and distance based statistics

Spatial Clustering

```
%matplotlib inline

import pandas as pd
```

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

```
link = '/home/dani/Desktop/listings.csv'
db = pd.read_csv(link)
db.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5835 entries, 0 to 5834
Data columns (total 92 columns):
id                                    5835 non-null int64
listing_url                           5835 non-null object
scrape_id                             5835 non-null int64
last_scraped                          5835 non-null object
name                                  5835 non-null object
summary                               5373 non-null object
space                                 4475 non-null object
description                           5832 non-null object
experiences_offered                   5835 non-null object
neighborhood_overview                 3572 non-null object
notes                                 2413 non-null object
transit                               3492 non-null object
thumbnail_url                         5542 non-null object
medium_url                            5542 non-null object
picture_url                           5835 non-null object
xl_picture_url                        5542 non-null object
host_id                               5835 non-null int64
host_url                              5835 non-null object
host_name                             5820 non-null object
host_since                            5820 non-null object
host_location                         5810 non-null object
host_about                            3975 non-null object
host_response_time                    4177 non-null object
host_response_rate                    4177 non-null object
host_acceptance_rate                  3850 non-null object
host_is_superhost                     5820 non-null object
host_thumbnail_url                    5820 non-null object
host_picture_url                      5820 non-null object
```

```
host_neighbourhood                  4977 non-null object
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host_total_listings_count           5820 non-null float64
host_verifications                  5835 non-null object
host_has_profile_pic                5820 non-null object
host_identity_verified              5820 non-null object
street                              5835 non-null object
neighbourhood                       4800 non-null object
neighbourhood_cleansed              5835 non-null int64
neighbourhood_group_cleansed        0 non-null float64
city                                5835 non-null object
state                               5835 non-null object
zipcode                             5810 non-null float64
market                              5835 non-null object
smart_location                      5835 non-null object
country_code                        5835 non-null object
country                             5835 non-null object
latitude                            5835 non-null float64
longitude                           5835 non-null float64
is_location_exact                   5835 non-null object
property_type                       5835 non-null object
room_type                           5835 non-null object
accommodates                        5835 non-null int64
bathrooms                           5789 non-null float64
bedrooms                            5829 non-null float64
beds                                5812 non-null float64
bed_type                            5835 non-null object
amenities                           5835 non-null object
square_feet                         302 non-null float64
price                               5835 non-null object
weekly_price                        2227 non-null object
monthly_price                       1717 non-null object
security_deposit                    2770 non-null object
cleaning_fee                        3587 non-null object
guests_included                     5835 non-null int64
extra_people                        5835 non-null object
minimum_nights                      5835 non-null int64
maximum_nights                      5835 non-null int64
calendar_updated                    5835 non-null object
has_availability                    5835 non-null object
availability_30                     5835 non-null int64
availability_60                     5835 non-null int64
availability_90                     5835 non-null int64
availability_365                    5835 non-null int64
calendar_last_scraped               5835 non-null object
number_of_reviews                   5835 non-null int64
first_review                        3827 non-null object
last_review                         3829 non-null object
review_scores_rating                3789 non-null float64
review_scores_accuracy              3776 non-null float64
review_scores_cleanliness           3778 non-null float64
review_scores_checkin               3778 non-null float64
review_scores_communication         3778 non-null float64
```

```
review_scores_location            3779 non-null float64
review_scores_value               3778 non-null float64
requires_license                  5835 non-null object
license                           1 non-null float64
jurisdiction_names                0 non-null float64
instant_bookable                  5835 non-null object
cancellation_policy               5835 non-null object
require_guest_profile_picture     5835 non-null object
require_guest_phone_verification  5835 non-null object
calculated_host_listings_count    5835 non-null int64
reviews_per_month                 3827 non-null float64
dtypes: float64(20), int64(14), object(58)
memory usage: 4.1+ MB
```

Spatial Regression