Home

`GDS4AE` - *Geographic Data Science for Applied Economists*

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Citation

If you use materials from this resource in your own work, we recommend the following citation:

```
@article{darribas_gds_course,
  author = {Dani Arribas-Bel and Diego Puga},
  title = {Geographic Data Science for Applied Economists},
  year = 2021,
  annote = {\href{https://darribas.org/gds4ae}}
}
```

Overview

This resource provides an introduction to Geographic Data Science for applied economists using Python. It has been designed to be delivered within 15 hours of teaching, split into ten sessions of 1.5h each.

How to follow along

`GDS4AE` is best followed if you can interactively tinker with its content. To do that, you will need two things:

1. A computer set up with the Jupyter Lab environment and all the required libraries (please see the Software stack part in the Infrastructure section for instructions)

Contents

2. A local copy of the materials that you can run on your own computer (see the repository section in the Infrastructure section for instructions)

Blocks have different components:

- *Ahead of time...*: materials to go on your own ahead of the live session
- *Hands-on coding*: content for the live session
- *Next steps*: a few pointers to continue your journey on the area the block covers

Content

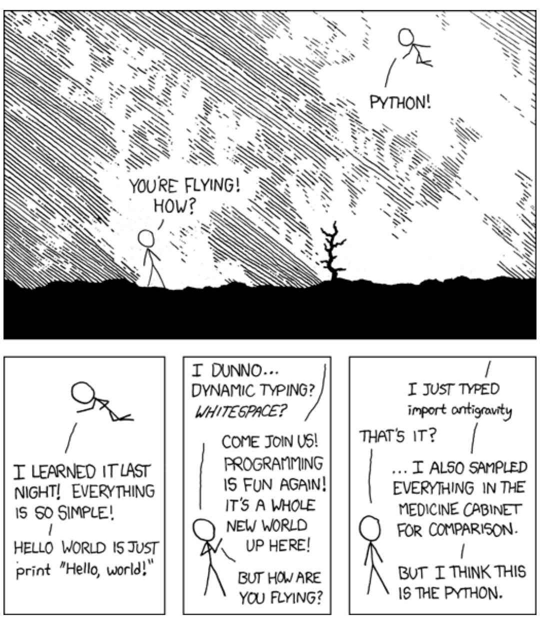
The structure of content is divided in nine blocks:

- *Introduction*: get familiar with the computational envirionment of modern data science
- *Spatial Data*: what do spatial data look like in Python?
- *Geovisualisation*: make (good) data maps
- *Spatial Feature Engineering* (Part I and Part II): augment and massage your data using Geography before you feed them into your model
- *Spatial Networks* (Part I and Part II): understand, acquire and work with spatial graphs
- *Transport Costs*: "getting there" doesn't always cost the same
- *Visual challenges*: all the details nobody told you (but should have) about visualising geographic data

Each block has its own section and is designed to be delivered in 1.5 hours approximately. The content of some of these blocks relies on external resources, all of them freely available. When that is the case, enough detail is provided in the to understand how additional material fits in.

Why Python?

There are several reasons why we have made this choice. Many of them are summarised nicely in this article by The Economist (paywalled).:w



Source: XKCD

Data

All the datasets used in this resource is freely available. Some of them have been developed in the context of the resource, others are borrowed from other resources. A full list of the datasets used, together with links to the original source, or to reproducible code to generate the data used is available in the Datasets page.

License

Infrastructure

This page covers a few technical aspects on how the course is built, kept up to date, and how you can create a computational environment to run all the code it includes.

Software stack

This course is best followed if you can not only read its content but also interact with its code and even branch out to write your own code and play on your own. For that, you will need to have installed on your computer a series of interconnected software packages; this is what we call a *stack*.

Instructions on how to install a software stack that allows you to run the materials of this course depend on the operating system you are using. Detailed guides are available for the main systems on the following resource, provided by the Geographic Data Science Lab:

@gdsl-ul/soft_install

Github repository

All the materials for this course and this website are available on the following Github repository:

@darribas/gds4ae

If you are interested, you can download a compressed `.zip` file with the most up-to-date version of all the materials, including the HTML for this website at:

Icon made by Freepik from www.flaticon.com

@darribas/gds4ae_zip

Containerised backend

The course is developed, built and tested using the `gds_env`, a containerised platform for Geographic Data Science. You can read more about the `gds_env` project at:

Binder

Binder is service that allows you to run scientific projects in the cloud for free. Binder can spin up *"ephemeral"* instances that allow you to run code on the browser without any local setup. It is possible to run the course on Binder by clicking on the button below:

launch binder

Warning

It is important to note Binder instances are *ephemeral* in the sense that the data and content created in a session is **NOT** saved anywhere and is deleted as soon as the browser tab is closed.

Binder is also the backend this website relies on when you click on the rocket icon (🚀) on a page with code. Remember, you can play with the code interactively but, once you close the tab, all the changes are lost.

Introduction

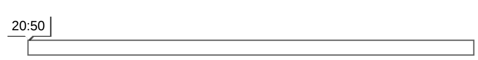
Geographic Data Science

Note

This section is adapted from [Block A](#) of the GDS Course [AB19].

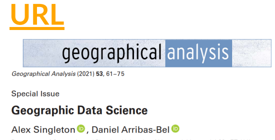
Before we learn *how* to do Geographic Data Science or even *why* you would want to do it, let's start with *what* it is. We will rely on two resources:

- First, in this video, Dani Arribas-Bel covers the building blocks at the First [Spatial Data Science Conference](#), organised by [CARTO](#)



- Second, *Geographic Data Science*, by Alex Singleton and Dani Arribas-Bel [SAB19]

URL


geographical analysis

Geographical Analysis (2021) 53, 61–75

Special Issue

Geographic Data Science

Alex Singleton, Daniel Arribas-Bel

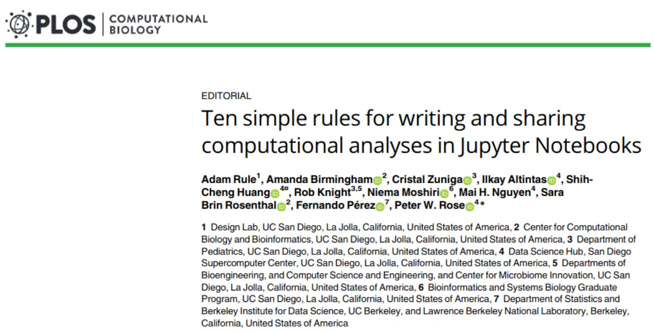
Department of Geography and Planning, University of Liverpool, Liverpool, L69 7ZT, U.K.

The computational stack

One of the core learning outcomes of this course is to get familiar with the modern computational environment that is used across industry and science to "do" Data Science. In this section, we will learn about ecosystem of concepts and tools that come together to provide the building blocks of much computational work in data science these days.

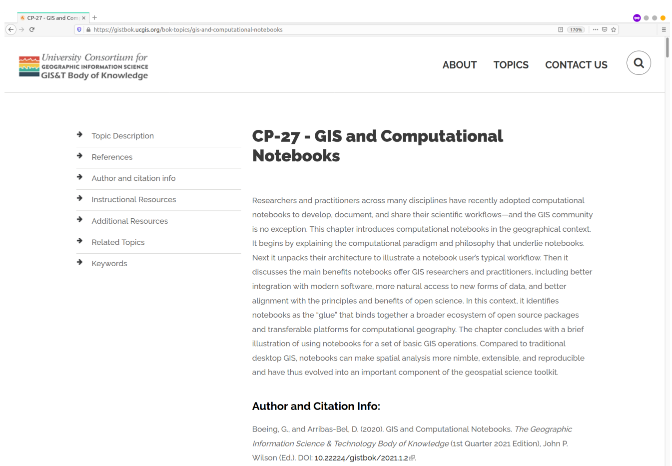
Source: [The Atlantic]

- *Ten simple rules for writing and sharing computational analyses in Jupyter Notebooks*, by Adam Rule et al. [RBZ+19]



[URL]

- *GIS and Computational Notebooks*, by Geoff Boeing and Dani Arribas-Bel [BAB20]



[URL]

Now we are familiar with the conceptual pillars on top of which we will be working, let's switch gears into a more practical perspective. The following two clips cover the basics of Jupyter Lab, the frontend that glues all the pieces together, and Jupyter Notebooks, the file format, application, and protocol that allows us to record, store and share workflows.

> **Note**
>
> The clips are sourced from [Block A] of the GDS Course [AB19]

Jupyter Lab

Jupyter Notebooks

Spatial Data

Ahead of time...

This block is all about understanding spatial data, both conceptually and practically. Before your fingers get on the keyboard, the following readings will help you get going and familiar with core ideas:

- Chapter 2 of the GDS Book [RABWng], which provides a conceptual overview of representing Geography in data
- Chapter 3 of the GDS Book [RABWng], a sister chapter with a more applied perspective on how concepts are implemented in computer data structures

Additionally, parts of this block are based and source from Block C in the GDS Course [AB19].

Hands-on coding

(Geographic) tables

```
import pandas
import geopandas
import xarray, rioxarray
import contextily
import matplotlib.pyplot as plt
```

Points

Local files   Online read

Assuming you have the file locally on the path `../data/`:

```
pts = geopandas.read_file("../data/madrid_abb.gpkg")
```

Point geometries from columns

```
pts.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 18399 entries, 0 to 18398
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   price            18399 non-null  object
 1   price_usd        18399 non-null  float64
 2   log1p_price_usd  18399 non-null  float64
 3   accommodates     18399 non-null  int64
 4   bathrooms        18399 non-null  object
 5   bedrooms         18399 non-null  float64
 6   beds             18399 non-null  float64
 7   neighbourhood    18399 non-null  object
 8   room_type        18399 non-null  object
 9   property_type    18399 non-null  object
 10  WiFi             18399 non-null  object
 11  Coffee           18399 non-null  object
 12  Gym              18399 non-null  object
 13  Parking          18399 non-null  object
 14  km_to_retiro     18399 non-null  float64
 15  geometry         18399 non-null  geometry
dtypes: float64(5), geometry(1), int64(1), object(9)
memory usage: 2.2+ MB
```

```
pts.head()
```

	price	price_usd	log1p_price_usd	accommodates	bathrooms	bedrooms
0	$60.00	60.0	4.110874	2	1 shared bath	1.0
1	$31.00	31.0	3.465736	1	1 bath	1.0
2	$60.00	60.0	4.110874	6	2 baths	3.0
3	$115.00	115.0	4.753590	4	1.5 baths	2.0
4	$26.00	26.0	3.295837	1	1 private bath	1.0

Lines

Local files Online read

Assuming you have the file locally on the path `../data/`:

```
pts = geopandas.read_file("../data/arturo_streets.gpkg")
```

```
lines.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 66499 entries, 0 to 66498
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   OGC_FID     66499 non-null  object
 1   dm_id       66499 non-null  object
 2   dist_barri  66483 non-null  object
 3   X           66499 non-null  float64
 4   Y           66499 non-null  float64
 5   value       5465 non-null   float64
 6   geometry    66499 non-null  geometry
dtypes: float64(3), geometry(1), object(3)
memory usage: 3.6+ MB
```

```
lines.loc[0, "geometry"]
```

_build/jupyter_execute/content/pages/02-Spatial_data_16_0.svg

Polygons

```
<IPython.display.GeoJSON object>
```

Local files Online read

Assuming you have the file locally on the path `../data/`:

```
polys = geopandas.read_file("../data/neighbourhoods.geojson")
```

```
polys.head()
```

	neighbourhood	neighbourhood_group	geometry
0	Palacio	Centro	MULTIPOLYGON (((-3.70584 40.42030, -3.70625 40...
1	Embajadores	Centro	MULTIPOLYGON (((-3.70384 40.41432, -3.70277 40...
2	Cortes	Centro	MULTIPOLYGON (((-3.69796 40.41929, -3.69645 40...
3	Justicia	Centro	MULTIPOLYGON (((-3.69546 40.41898, -3.69645 40...
4	Universidad	Centro	MULTIPOLYGON (((-3.70107 40.42134, -3.70155 40...

```
polys.query("neighbourhood_group == 'Retiro'")
```

	neighbourhood	neighbourhood_group	geometry
13	Pacífico	Retiro	MULTIPOLYGON (((-3.67015 40.40654, -3.67017 40...
14	Adelfas	Retiro	MULTIPOLYGON (((-3.67283 40.39468, -3.67343 40...
15	Estrella	Retiro	MULTIPOLYGON (((-3.66506 40.40647, -3.66512 40...
16	Ibiza	Retiro	MULTIPOLYGON (((-3.66916 40.41796, -3.66927 40...
17	Jerónimos	Retiro	MULTIPOLYGON (((-3.67874 40.40751, -3.67992 40...
18	Niño Jesús	Retiro	MULTIPOLYGON (((-3.66994 40.40850, -3.67012 40...

```
polys.neighbourhood_group.unique()
```

```
array(['Centro', 'Arganzuela', 'Retiro', 'Salamanca', 'Chamartín',
       'Moratalaz', 'Tetuán', 'Chamberí', 'Fuencarral - El Pardo',
       'Moncloa - Aravaca', 'Puente de Vallecas', 'Latina', 'Carabanchel',
       'Usera', 'Ciudad Lineal', 'Hortaleza', 'Villaverde',
       'Villa de Vallecas', 'Vicálvaro', 'San Blas - Canillejas',
       'Barajas'], dtype=object)
```

Surfaces

Local files Online read

Assuming you have the file locally on the path `../data/`:

```
sat = xarray.open_rasterio("../data/madrid_scene_s2_10_tc.tif")
```

```
sat
```

```
sat.sel(band=1)
```

```
sat.sel(
    x=slice(430000, 440000),  # x is ascending
    y=slice(4480000, 4470000) # y is descending
)
```

Visualisation

```
polys.plot()
```

```
<AxesSubplot:>
```

_build/jupyter_execute/content/pages/02-Spatial_data_31_1.png

```
ax = lines.plot(linewidth=0.1, color="black")
contextily.add_basemap(ax, crs=lines.crs)
```

_build/jupyter_execute/content/pages/02-Spatial_data_32_0.png

See more basemap options here.

```python
ax = pts.plot(color="red", figsize=(12, 12), markersize=0.1)
contextily.add_basemap(
    ax,
    crs = pts.crs,
    source = contextily.providers.CartoDB.DarkMatter
);
```

_build/jupyter_execute/content/pages/02-Spatial_data_34_0.png

```python
sat.plot.imshow(figsize=(12, 12))
```

```
<matplotlib.image.AxesImage at 0x7feeb28d8130>
```

_build/jupyter_execute/content/pages/02-Spatial_data_35_1.png

```python
f, ax = plt.subplots(1, figsize=(12, 12))
sat.plot.imshow(ax=ax)
contextily.add_basemap(
    ax,
    crs=sat.rio.crs,
    source=contextily.providers.Stamen.TonerLabels,
    zoom=11
);
```

IMPORTANT

You will need version 1.1.0 of `contextily` to use label layers. Install it with:

```
pip install \
    -U --no-deps \
    contextily
```

_build/jupyter_execute/content/pages/02-Spatial_data_37_0.png

Spatial operations

(Re-)Projections

```python
pts.crs
```

```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: World
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

```python
sat.rio.crs
```

```
CRS.from_epsg(32630)
```

```python
pts.to_crs(sat.rio.crs).crs
```

```
<Projected CRS: EPSG:32630>
Name: WGS 84 / UTM zone 30N
Axis Info [cartesian]:
- [east]: Easting (metre)
- [north]: Northing (metre)
Area of Use:
- undefined
Coordinate Operation:
- name: UTM zone 30N
- method: Transverse Mercator
Datum: World Geodetic System 1984
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

```python
sat.rio.reproject(pts.crs).rio.crs
```

```
CRS.from_epsg(4326)
```

```python
# All into Web Mercator (EPSG:3857)
f, ax = plt.subplots(1, figsize=(12, 12))
## Satellite image
sat.rio.reproject(
    "EPSG:3857"
).plot.imshow(
    ax=ax
)
## Neighbourhoods
polys.to_crs(epsg=3857).plot(
    linewidth=2,
    edgecolor="xkcd:lime",
    facecolor="none",
    ax=ax
)
## Labels
contextily.add_basemap( # No need to reproject
    ax,
    source=contextily.providers.Stamen.TonerLabels,
);
```

_build/jupyter_execute/content/pages/02-Spatial_data_44_0.png

Centroids

Note the warning that geometric operations with non-project CRS object result in biases.

```python
polys.centroid
```

```
<ipython-input-46-5ec1eefde6d0>:1: UserWarning: Geometry is in a geographic CRS.
Results from 'centroid' are likely incorrect. Use 'GeoSeries.to_crs()' to re-project
geometries to a projected CRS before this operation.

  polys.centroid
```

```
0      POINT (-3.71398 40.41543)
1      POINT (-3.70237 40.40925)
2      POINT (-3.69674 40.41485)
3      POINT (-3.69657 40.42367)
4      POINT (-3.70698 40.42568)
                 ...
123    POINT (-3.59135 40.45656)
124    POINT (-3.59723 40.48441)
125    POINT (-3.55847 40.47613)
126    POINT (-3.57889 40.47471)
127    POINT (-3.60718 40.46415)
Length: 128, dtype: geometry
```

```python
lines.centroid
```

```
0        POINT (444133.737 4482808.936)
1        POINT (444192.064 4482878.034)
2        POINT (444134.563 4482885.414)
3        POINT (445612.661 4479335.686)
4        POINT (445606.311 4479354.437)
                      ...
66494    POINT (451980.378 4478407.920)
66495    POINT (436975.438 4473143.749)
66496    POINT (442218.600 4478415.561)
66497    POINT (442213.869 4478346.700)
66498    POINT (442233.760 4478278.748)
Length: 66499, dtype: geometry
```

```python
ax = polys.plot(color="purple")
polys.centroid.plot(
    ax=ax, color="lime", markersize=1
)
```

```
<ipython-input-52-47fdeef35535>:2: UserWarning: Geometry is in a geographic CRS.
Results from 'centroid' are likely incorrect. Use 'GeoSeries.to_crs()' to re-project
geometries to a projected CRS before this operation.

  polys.centroid.plot(
```

```
<AxesSubplot:>
```

_build/jupyter_execute/content/pages/02-Spatial_data_49_2.png

Spatial joins

More information about spatial joins in `geopandas` is available on its documentation page

```
sj = geopandas.sjoin(
    lines,
    polys.to_crs(lines.crs)
)
```

```
sj.info()
```

_build/jupyter_execute/content/pages/02-Spatial_data_53_0.png

```
<class 'geopandas.geodataframe.GeoDataFrame'>
Int64Index: 69420 entries, 0 to 66438
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   OGC_FID             69420 non-null  object
 1   dm_id               69420 non-null  object
 2   dist_barri          69414 non-null  object
 3   X                   69420 non-null  float64
 4   Y                   69420 non-null  float64
 5   value               5769 non-null   float64
 6   geometry            69420 non-null  geometry
 7   index_right         69420 non-null  int64
 8   neighbourhood       69420 non-null  object
 9   neighbourhood_group  69420 non-null  object
dtypes: float64(3), geometry(1), int64(1), object(5)
memory usage: 5.8+ MB
```

Areas

```
areas = polys.to_crs(
    epsg=25830
).area * 1e-6 # Km2
areas.head()
```

```
0    1.471037
1    1.033253
2    0.592049
3    0.742031
4    0.947616
dtype: float64
```

Distances

```
cemfi = geopandas.tools.geocode(
    "Calle Casado del Alisal, 5, Madrid"
).to_crs(epsg=25830)
cemfi
```

	geometry	address
0	POINT (441473.624 4473943.520)	Calle de Casado del Alisal 5, 28014 Madrid, Sp...

```
polys.to_crs(
    cemfi.crs
).distance(
    cemfi.geometry
)
```

```
/opt/conda/lib/python3.8/site-packages/geopandas/base.py:39: UserWarning: The indices
of the two GeoSeries are different.
  warn("The indices of the two GeoSeries are different.")
```

```
0      1487.894214
1              NaN
2              NaN
3              NaN
4              NaN
          ...
123            NaN
124            NaN
125            NaN
126            NaN
127            NaN
Length: 128, dtype: float64
```

```
d2cemfi = polys.to_crs(
    cemfi.crs
).distance(
    cemfi.geometry[0] # NO index
)
d2cemfi.head()
```

_build/jupyter_execute/content/pages/02-Spatial_data_60_0.png

```
0    1487.894214
1     567.196279
2     275.166923
3     645.807884
4    1191.537001
dtype: float64
```

Next steps

If you are interested in following up on some of the topics explored in this block, the following pointers might be useful:

- Although we have seen here `geopandas` only, all non-geographic operations on geo-tables are really thanks to `pandas`, the workhorse for tabular data in Python. Their official documentation is an excellent first stop. If you prefer a book, McKinney (2012) [McK12] is a great one.
- For more detail on geographic operations on geo-tables, the Geopandas official documentation is a great place to continue the journey.
- Surfaces, as covered here, are really an example of multi-dimensional labelled arrays. The library we use, `xarray` represents the cutting edge for working with these data structures in Python, and their documentation is a great place to wrap your head around how data of this type can be manipulated. For geographic extensions (CRS handling, reprojections, etc.), we have used `rioxarray` under the hood, and its documentation is also well worth checking.

Geovisualisation

Ahead of time...

This block is all about visualising statistical data on top of a geography. Although this task looks simple, there are a few technical and conceptual building blocks that it helps to understand before we try to make our own maps. Aim to complete the following readings by the time we get our hands on the keyboard:

- Block D of the GDS course [AB19], which provides an introduction to choropleths (statistical maps)
- Chapter 5 of the GDS Book [RABWng], discussing choropleths in more detail

Hands-on coding

```
import geopandas
import xarray, rioxarray
import contextily
import seaborn as sns
from pysal.viz import mapclassify as mc
from legendgram import legendgram
import matplotlib.pyplot as plt
import palettable.matplotlib as palmpl
```

Local files Online read

Assuming you have the file locally on the path `../data/`:

```
db = geopandas.read_file("../data/cambodia_regional.gpkg")
```

```
db.info()
```

Data

If you want to read more about the data sources behind this dataset, head to the Datasets section

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 198 entries, 0 to 197
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   adm2_name   198 non-null    object
 1   adm2_altnm  122 non-null    object
 2   motor_mean  198 non-null    float64
 3   walk_mean   198 non-null    float64
 4   no2_mean    198 non-null    float64
 5   geometry    198 non-null    geometry
dtypes: float64(3), geometry(1), object(2)
memory usage: 9.4+ KB
```

_build/jupyter_execute/content/pages/03-Geovisualisation_7_0.png

We will use the average measurement of nitrogen dioxide (`no2_mean`) by region throughout the block.

To make visualisation a bit easier below, we create an additional column with values rescaled:

```
db["no2_viz"] = db["no2_mean"] * 1e5
```

This way, numbers are larger and will fit more easily on legends:

```
db[["no2_mean", "no2_viz"]].describe()
```

	no2_mean	no2_viz
count	198.000000	198.000000
mean	0.000032	3.236567
std	0.000017	1.743538
min	0.000014	1.377641
25%	0.000024	2.427438
50%	0.000029	2.922031
75%	0.000034	3.390426
max	0.000123	12.323324

Choropleths

_build/jupyter_execute/content/pages/03-Geovisualisation_14_0.png

A classiffication problem

```
db["no2_viz"].unique().shape
```

```
(198,)
```

```
sns.displot(
    db, x="no2_viz", kde=True, aspect=2
);
```

_build/jupyter_execute/content/pages/03-Geovisualisation_17_0.png

Attention

To build an intuition behind each classification algorithm more easily, we create a helper method (`plot_classi`) that generates a visualisation of a given classification.

Toggle the cell below if you are interested in the code behind it.

- Equal intervals

```
classi = mc.EqualInterval(db["no2_viz"], k=7)
classi
```

```
EqualInterval

   Interval      Count
----------------------
[ 1.38,  2.94] |   103
( 2.94,  4.50] |    80
( 4.50,  6.07] |     6
( 6.07,  7.63] |     1
( 7.63,  9.20] |     3
( 9.20, 10.76] |     0
(10.76, 12.32] |     5
```

_build/jupyter_execute/content/pages/03-Geovisualisation_22_0.png

- Quantiles

```
classi = mc.Quantiles(db["no2_viz"], k=7)
classi
```

```
Quantiles

   Interval      Count
----------------------
[ 1.38,  2.24] |    29
( 2.24,  2.50] |    28
( 2.50,  2.76] |    28
( 2.76,  3.02] |    28
( 3.02,  3.35] |    28
( 3.35,  3.76] |    28
( 3.76, 12.32] |    29
```

_build/jupyter_execute/content/pages/03-Geovisualisation_25_0.png

- Fisher-Jenks

```
classi = mc.FisherJenks(db["no2_viz"], k=7)
classi
```

```
FisherJenks

   Interval      Count
----------------------
[ 1.38,  2.06] |    20
( 2.06,  2.69] |    58
( 2.69,  3.30] |    62
( 3.30,  4.19] |    42
( 4.19,  5.64] |     7
( 5.64,  9.19] |     4
( 9.19, 12.32] |     5
```

_build/jupyter_execute/content/pages/03-Geovisualisation_28_0.png

- Fisher-Jenks

```
classi = mc.FisherJenks(db["no2_viz"], k=7)
classi
```

```
FisherJenks

   Interval      Count
----------------------
[ 1.38,  2.06] |    20
( 2.06,  2.69] |    58
( 2.69,  3.30] |    62
( 3.30,  4.19] |    42
( 4.19,  5.64] |     7
( 5.64,  9.19] |     4
( 9.19, 12.32] |     5
```

_build/jupyter_execute/content/pages/03-Geovisualisation_31_0.png

---

Now let's dig into the internals of `classi`:

```
classi
```

```
FisherJenks

   Interval      Count
----------------------
[ 1.38,  2.06] |    20
( 2.06,  2.69] |    58
( 2.69,  3.30] |    62
( 3.30,  4.19] |    42
( 4.19,  5.64] |     7
( 5.64,  9.19] |     4
( 9.19, 12.32] |     5
```

```
classi.k
```

```
7
```

```
classi.bins
```

```
array([ 2.05617382,  2.6925931 ,  3.30281182,  4.19124954,  5.63804861,
        9.19190206, 12.32332434])
```

```
classi.yb
```

```
array([2, 3, 3, 1, 1, 2, 1, 1, 1, 0, 0, 3, 2, 1, 1, 1, 3, 1, 1, 1, 2, 0,
       0, 4, 2, 1, 3, 1, 0, 0, 0, 1, 2, 2, 6, 5, 4, 2, 1, 3, 2, 3, 2, 1,
       2, 3, 2, 3, 1, 1, 3, 1, 2, 3, 3, 1, 3, 3, 1, 0, 1, 1, 3, 2, 0, 0,
       2, 1, 0, 0, 0, 2, 0, 1, 3, 3, 3, 2, 3, 2, 3, 1, 2, 3, 1, 1, 1, 1,
       2, 1, 2, 2, 1, 2, 2, 2, 1, 3, 2, 3, 2, 2, 2, 1, 2, 3, 3, 2, 0, 3,
       1, 0, 1, 2, 1, 1, 2, 1, 2, 6, 5, 6, 2, 2, 3, 6, 3, 4, 3, 4, 2, 3,
       0, 2, 5, 6, 4, 5, 2, 2, 2, 1, 1, 1, 2, 1, 2, 3, 3, 2, 2, 2, 3, 2,
       1, 1, 3, 4, 2, 1, 3, 1, 2, 3, 4, 0, 1, 1, 2, 1, 2, 2, 2, 2, 1, 2,
       2, 2, 0, 0, 1, 2, 3, 3, 3, 3, 3, 2, 1, 2, 1, 1, 1, 2, 2, 1, 3, 1])
```

How *many* colors?

> **Attention**
>
> The code used to generate this figure uses more advanced features than planned for this course.
>
> If you want to inspect it, toggle the cell below.

_build/jupyter_execute/content/pages/03-Geovisualisation_39_0.png

Using the *right* color

- Qualitative **Categories**, non-ordered
- Sequential Graduated, **sequential**
- Divergent Graduated, **divergent**

For a safe choice, make sure to visit ColorBrewer

Choropleths on Geo-Tables

How can we create classifications from data on geo-tables? Two ways:

- Directly within `plot` (only for some algorithms)

```python
db.plot(
    "no2_viz", scheme="quantiles", k=7, legend=True
);
```

_build/jupyter_execute/content/pages/03-Geovisualisation_44_0.png

- Manually attaching the data (for any algorithm)

See this tutorial for more details on fine tuning choropleths manually

```python
classi = mc.Quantiles(db["no2_viz"], k=7)
db.assign(
    classes=classi.yb
).plot("classes");
```

_build/jupyter_execute/content/pages/03-Geovisualisation_46_0.png

---

Legendgrams:

```python
f, ax = plt.subplots(figsize=(9, 9))

classi = mc.Quantiles(db["no2_viz"], k=7)

db.assign(
    classes=classi.yb
).plot("classes", ax=ax)

legendgram(
    f,                    # Figure object
    ax,                   # Axis object of the map
    db["no2_viz"],        # Values for the histogram
    classi.bins,          # Bin boundaries
    pal=palmpl.Viridis_7,# color palette (as palettable object)
    legend_size=(.5,.2), # legend size in fractions of the axis
    loc = 'lower right', # matplotlib-style legend locations
    clip = (2,10)        # clip the displayed range of the histogram
)
ax.set_axis_off();
```

_build/jupyter_execute/content/pages/03-Geovisualisation_48_0.png

Surface visualisation

Local files Online read

Assuming you have the file locally on the path `../data/`:

```
grid = xarray.open_rasterio(
    "../data/cambodia_s5_no2.tif"
).sel(band=1)
```

- (Implicit) continuous equal interval

```
grid.where(
    grid != grid.rio.nodata
).plot(cmap="viridis");
```

_build/jupyter_execute/content/pages/03-Geovisualisation_53_0.png

```
grid.where(
    grid != grid.rio.nodata
).plot(cmap="viridis", robust=True);
```

_build/jupyter_execute/content/pages/03-Geovisualisation_54_0.png

- Discrete equal interval

```
grid.where(
    grid != grid.rio.nodata
).plot(cmap="viridis", levels=7)
```

```
<matplotlib.collections.QuadMesh at 0x7f47b175f610>
```

_build/jupyter_execute/content/pages/03-Geovisualisation_56_1.png

- Combining with `mapclassify`

```
grid_nona = grid.where(
    grid != grid.rio.nodata
)

classi = mc.Quantiles(
    grid_nona.to_series().dropna(), k=7
)

grid_nona.plot(
    cmap="viridis", levels=classi.bins
)
plt.title(classi.name);
```

_build/jupyter_execute/content/pages/03-Geovisualisation_58_0.png

_build/jupyter_execute/content/pages/03-Geovisualisation_59_0.png

_build/jupyter_execute/content/pages/03-Geovisualisation_60_0.png

Data

If you want to read more about the data sources behind this dataset, head to the Datasets section _build/jupyter_execute/content/pages/03-Geovisualisation_61_0.png

Next steps

If you are interested in statistical maps based on classification, here are two recommendations to check out next:

- On the technical side, the documentation for `mapclassify` (including its tutorials) provides more detail and illustrates more classification algorithms than those reviewed in this block
- On a more conceptual note, Cynthia Brewer's "Designing better maps" [Bre15] is an excellent blueprint for good map making.

Spatial Feature Engineering (I)

Spatial Feature Engineering (II)

Spatial Networks (I)

Spatial Networks (II)

Transport costs

Visual challenges and opportunities

Datasets

This section covers the datasets required to run the course interactively. For archival reasons, all of those listed here have been mirrored in the repository for this course so, if you have downloaded the course, you already have a local copy of them.

Madrid

Airbnb properties

> **Source**
>
> This dataset has been sourced from the course "Spatial Modelling for Data Scientists". The file imported here corresponds to the `v0.1.0` version.

This dataset contains a pre-processed set of properties advertised on the AirBnb website within the region of Madrid (Spain), together with house characteristics.

- Data file `madrid_abb.gpkg`
- Code used to generate the file `[URL]`
- Furhter information `[URL]`

Airbnb neighbourhoods

> **Source**
>
> This dataset has been directly sourced from the website Inside Airbnb. The file was imported on February 10th 2021.

This dataset contains neighbourhood boundaries for the city of Madrid, as provided by Inside Airbnb.

- Data file `neighbourhoods.geojson`
- Furhter information `[URL]`

This dataset is licensed under a CC0 1.0 Universal Public Domain Dedication.

Arturo

This dataset contains the street layout of Madrid as well as scores of habitability, where available, associated with street segments. The data originate from the Arturo Project, by 300,000Km/s, and the available file here is a slimmed down version of their official street layout distributed by the project.

- Data file `arturo_streets.gpkg`
- Code used to generate the file `[Page]`
- Furhter information `[URL]`

This dataset is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Sentinel 2 - 120m mosaic

This dataset contains four scenes for the region of Madrid (Spain) extracted from the Digital Twin Sandbox Sentinel-2 collection, by the SentinelHub. Each scene corresponds to the following dates in 2019:

- January 1st
- April 1st
- July 10th
- November 17th

Each scene includes red, green, blue and near-infrared bands.

- Data files (`Jan_1st`, `Apr_1st`, `Jul_10th`, `Nov_27th`)
- Code used to generate the file `[Page]`
- Furhter information `[URL]`

This dataset is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Sentinel 2 - 10m GHS composite

This dataset contains a scene for the region of Madrid (Spain) extracted from the GHS Composite S2, by the European Commission.

- Data file `madrid_scene_s2_10_tc.tif`
- Code used to generate the file `[Page]`

- Furhter information [URL]

Cambodia

Pollution

Surface with NO_2 measurements (tropospheric column) information attached from Sentinel 5.

- Data file `cambodia_s5_no2.tif`
- Code used to generate the file [Page]
- Furhter information [URL]

Friction surfaces

This dataset is an extraction of the following two data products by Weiss et al. (2020) [WNVR+20] and distributed through the Malaria Atlas Project:

- Global friction surface enumerating land-based travel walking-only speed without access to motorized transport for a nominal year 2019 (Minutes required to travel one metre)
- Global friction surface enumerating land-based travel speed with access to motorized transport for a nominal year 2019 (Minutes required to travel one metre)

Each is provided on a separate file.

- Data files (`Motorized` and `Walking`
- Code used to generate the file [Page]
- Furhter information [URL]

Regional aggregates

> **Source**
>
> This dataset relies on boundaries from the Humanitarian Data Exchange. The file is provided by the World Food Programme through the Humanitarian Data Exchange and was accessed on February 15th 2021.

Pollution and friction aggregated at Level 2 (municipality) administrative boundaries for Cambodia.

- Data file `cambodia_regional.gpkg`
- Code used to generate the file [Page]

Cambodian cities

Extract from the Urban Centre Database (UCDB), version 1.2, of the centroid for Cambodian cities.

- Data file `cambodian_cities.geojson`
- Code used to generate the file [Page]
- Furhter information [URL]

Further Resources

If this course is successful, it will leave you wanting to learn more about using Python for (Geographic) Data Science. See below a few resources that are good "next steps".

Courses

- The "Automating GIS processes", by Vuokko Heikinheimo and Henrikki Tenkanen is a great overview of GIS with a modern Python stack:

> https://autogis-site.readthedocs.io/

- The "GDS Course" by Dani Arribas-Bel [AB19] is an introductory level overview of Geographic Data Science, including notebooks, slides and video clips.

> https://darribas.org/gds_course

Books

- *"Python for Geographic Data Analysis"*, by Henrikki Tenkanen, Vuokko Heikinheimo and David Whipp:

> https://pythongis.org/

- *"Geographic Data Science in Python"*, by Sergio J. Rey, Dani Arribas-Bel and Levi J. Wolf:

> https://geographicdata.science

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Wes McKinney. *Python for data analysis: Data wrangling with Pandas, NumPy, and IPython*. O'Reilly Media, Inc., 2012.

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By Dani Arribas-Bel & Diego Puga