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GDS4AE - *Geographic Data Science for Applied Economists*

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> **Note**
>
> A PDF version of this course is available for download **here**

Contact

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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 = 2022,
  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)
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:

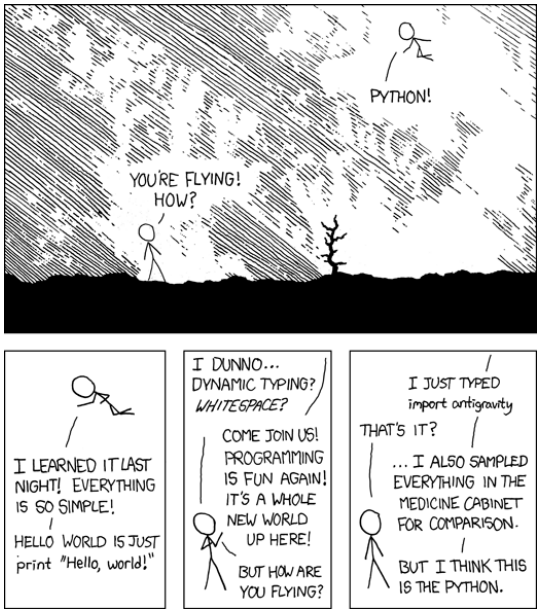
- *Introduction*: get familiar with the computational envirionment of modern data science
- *Spatial Data*: what do spatial data look like in Python?
- *Geovisualisation*: make (good) data maps
- *Spatial Feature Engineering* (Part I and Part II): augment and massage your data using Geography before you feed them into your model
- *OpenStreetMap*: acquire data from the largest geo-table in the world
- *Transport Costs*: “getting there” doesn’t always cost the same
- *CARTO*: explore publishing web maps with CARTO

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:

> https://gdsl-ul.github.io/soft_install/

Github repository

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

> https://github.com/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:

> https://github.com/darribas/gds4ae/archive/master.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:

> https://darribas.org/gds_env/

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:

> **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

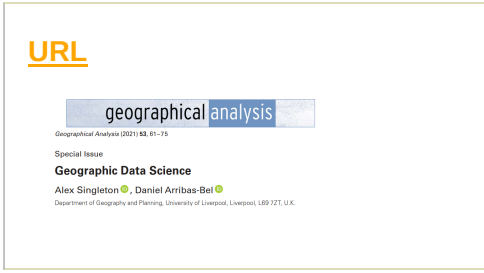
> **Note**
>
> This section is adapted from Block A of the GDS Course [AB19].

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

20:50

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



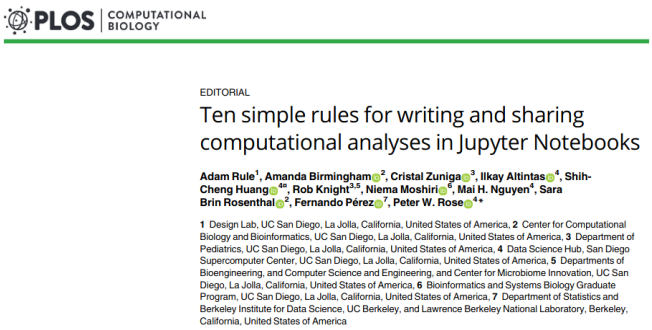
The computational stack

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

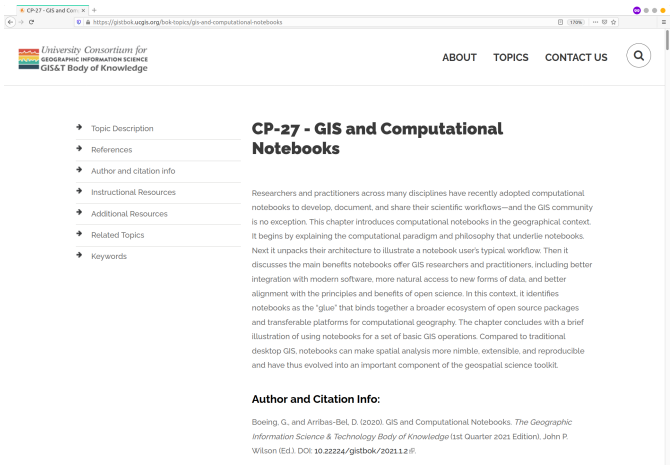
- *Ten simple rules for writing and sharing computational analyses in Jupyter Notebooks*, by Adam Rule et al. [RBZ+19]

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 1 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

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

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

Sometimes, points are provided as separate columns in an otherwise non-spatial table. For example imagine we have an object `cols` which looks like:

```
cols.head()
```

```
          X         Y
0  0.259602  0.854351
1  0.661662  0.782427
2  0.932211  0.319130
3  0.395249  0.469885
4  0.303446  0.008525
```

In this case, we can convert those into proper geometries by:

```
pts = geopandas.GeoSeries(
    geopandas.points_from_xy(cols["X"], cols["Y"])
)
```

```
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	bedroon
0	$60.00	60.0	4.110874	2	1 shared bath	1
1	$31.00	31.0	3.465736	1	1 bath	1
2	$60.00	60.0	4.110874	6	2 baths	3
3	$115.00	115.0	4.753590	4	1.5 baths	2
4	$26.00	26.0	3.295837	1	1 private bath	1

Challenge

Show the top ten values of of `price` and `neighbourhood`

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 9 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   average_quality     66499 non-null  float64
 4   population_density  66499 non-null  float64
 5   X                   66499 non-null  float64
 6   Y                   66499 non-null  float64
 7   value               5465 non-null   float64
 8   geometry            66499 non-null  geometry
dtypes: float64(5), geometry(1), object(3)
memory usage: 4.6+ MB
```

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

Challenge

Print descriptive statistics for `population_density` and `average_quality`

Polygons

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)
```

Challenge

Print the neighborhoods within the “Latina” group

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
```

xarray.DataArray (**band**: 3, **y**: 3681, **x**: 3129)

[34553547 values with dtype=uint8]

▾ Coordinates:

band	(band)	int64	1 2 3
x	(x)	float64	4.248e+05 4.248e+05 ... 4.56e+05
y	(y)	float64	4.499e+06 4.499e+06 ... 4.463e+06
spatial_ref	()	int64	0

▸ Indexes: (3)

▾ Attributes:

AREA_OR_…	Area
scale_factor :	1.0
add_offset :	0.0

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

xarray.DataArray (**y**: 3681, **x**: 3129)

[11517849 values with dtype=uint8]

▾ Coordinates:

band	()	int64	1
x	(x)	float64	4.248e+05 4.248e+05 ... 4.56e+05
y	(y)	float64	4.499e+06 4.499e+06 ... 4.463e+06
spatial_ref	()	int64	0

▸ Indexes: (2)

▾ Attributes:

AREA_OR_…	Area
scale_factor :	1.0
add_offset :	0.0

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

xarray.DataArray (**band**: 3, **y**: 1000, **x**: 1000)

[3000000 values with dtype=uint8]

▾ Coordinates:

band	(band)	int64	1 2 3
x	(x)	float64	4.3e+05 4.3e+05 ... 4.4e+05 4.4e+05
y	(y)	float64	4.48e+06 4.48e+06 ... 4.47e+06
spatial_ref	()	int64	0

▸ Indexes: (3)

▾ Attributes:

AREA_OR_…	Area
scale_factor :	1.0
add_offset :	0.0

Challenge

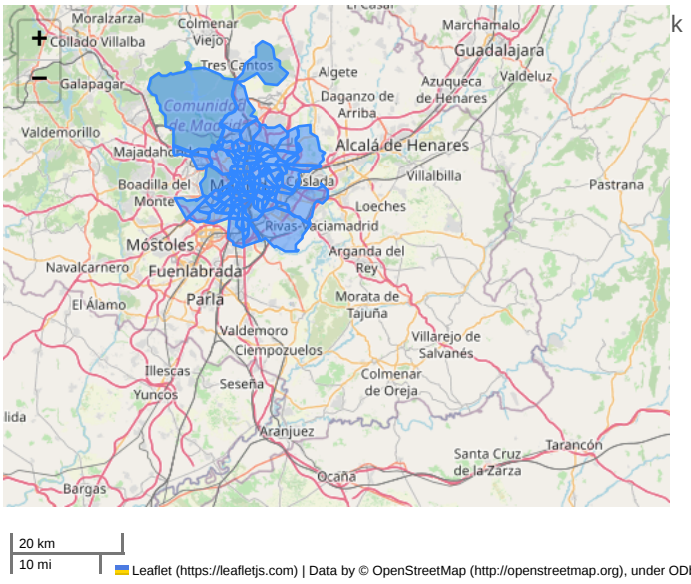
Subset `sat` to band 2 and the section within [444444, 455555] of Easting and [4470000, 4480000] of Northing.

- *How many pixels does it contain?*
- *What if you used bands 1 and 3 instead?*

Visualisation

IMPORTANT
You will need version 0.10.0 or greater of `geopandas` to use `explore`.

```
polys.explore()
```




```
polys.plot()
```

```
<Axes: >
```


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

See more basemap options here.

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

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

```
<matplotlib.image.AxesImage at 0x7f7803bc36d0>
```

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

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

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

Challenge

Make three plots of `sat`, plotting one single band in each

Spatial operations

(Re-)Projections

```
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 ensemble
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

```
sat.rio.crs
```

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

```
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
```

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

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

```
# 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.CartoDB.VoyagerOnlyLabels,
);
```

Centroids

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

```
polys.centroid
```

```
/tmp/ipykernel_2058/2101097851.py: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
```

```
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
```

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

```
/tmp/ipykernel_2058/1054587808.py: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(
```

```
<Axes: >
```

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()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
Index: 69420 entries, 0 to 66438
Data columns (total 12 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   average_quality      69420 non-null  float64
 4   population_density   69420 non-null  float64
 5   X                    69420 non-null  float64
 6   Y                    69420 non-null  float64
 7   value                5769 non-null   float64
 8   geometry             69420 non-null  geometry
 9   index_right          69420 non-null  int64
 10  neighbourhood        69420 non-null  object
 11  neighbourhood_group  69420 non-null  object
dtypes: float64(5), geometry(1), int64(1), object(5)
memory usage: 6.9+ MB
```

```
# Subset of lines
ax = sj.query(
    "neighbourhood ==
).plot(color="xkcd:bri

# Subset of line centr
ax = sj.query(
    "neighbourhood ==
).centroid.plot(
    color="xkcd:bright
)

# Local basemap
contextily.add_basemap
    ax,
    crs=sj.crs,
    source="../data/ma
    alpha=0.5
)
```


_build/jupyter_execute/co

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 (441477.245 4473939.537)	5, Calle Casado del Alisal, 28014, Calle Casad...

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

```
/tmp/ipykernel_2058/176561454.py:1: UserWarning: The indices of the two
GeoSeries are different.
  polys.to_crs(
```

```
0      1491.338749
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()
```

```
0    1491.338749
1     565.418135
2     278.121017
3     650.926572
4    1196.771601
dtype: float64
```

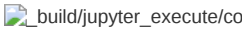
Challenge

Give Task III in this block of the GDS course a go

```
ax = polys.assign(
    dist=d2cemfi/1000
).plot("dist", legend=

cemfi.to_crs(
    polys.crs
).plot(
    marker="*",
    markersize=15,
    color="r",
    label="CEMFI",
    ax=ax
)

ax.legend()
ax.set_title(
    "Distance to CEMFI
);
```



🐾 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
from splot.mapping import vba_choropleth
```

Data

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

Local files | Online read

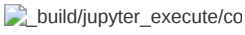
Assuming you have the file locally on the path `../data/`:

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

```
db.info()
```

```
<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
```

```
ax = db.to_crs(
    epsg=3857
).plot(
    edgecolor="red",
    facecolor="none",
    linewidth=2,
    alpha=0.25,
    figsize=(9, 9)
)
contextily.add_basemap
    ax,
    source=contextily.
)
ax.set_axis_off();
```



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

```
ax = db.to_crs(
    epsg=3857
).plot(
    "no2_viz",
    legend=True,
    figsize=(12, 9)
)
contextily.add_basemap(
    ax,
    source=contextily.providers.CartoDB.VoyagerOnlyLabels,
    zoom=7
);
```


_build/jupyter_execute/content/pages/03-Geovisualisation_15_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_18_0.png

How to assign colors?

> **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.

```
def plot_classi(classi, col, db):
    """
    Illustrate a classiffication
    ...

    Arguments
    ---------
    classi : mapclassify.classifiers
             Classification object
    col    : str
             Column name used for `classi`
    db     : geopandas.GeoDataFrame
             Geo-table with data for
             the classification
    """
    f, ax = plt.subplots(figsize=(12, 6))
    ax.set_title(classi.name)
    # KDE
    sns.kdeplot(
        db[col], fill=True, ax=ax
    )
    for i in range(0, len(classi.bins)-1):
        ax.axvline(classi.bins[i], color="red")
    # Map
    aux = f.add_axes([.6, .45, .32, .4])
    db.assign(lbls=classi.yb).plot(
        "lbls", cmap="viridis", ax=aux
    )
    aux.set_axis_off()
    return None
```

- 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_24_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_27_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
```

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])
```

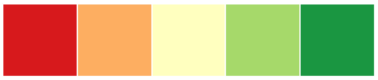
How *many* colors?

> **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.

```
vals = [3, 5, 7, 9, 12, 15]
algos = ["equal_interval", "quantiles", "fisherjenks"]
f, axs = plt.subplots(
    len(algos), len(vals), figsize=(3*len(vals), 3*len(algos))
)
for i in range(len(algos)):
    for j in range(len(vals)):
        db.plot(
            "no2_viz", scheme=algos[i], k=vals[j], ax=axs[i, j]
        )
        axs[i, j].set_axis_off()
        if i==0:
            axs[i, j].set_title(f"k={vals[j]}")
        if j==0:
            axs[i, j].text(
                -0.1,
                0.5,
                algos[i],
                horizontalalignment='center',
                verticalalignment='center',
                transform=axs[i, j].transAxes,
                rotation=90
            )
```

Using the *right* color

> For a safe choice, make sure to visit ColorBrewer

-  **Categories**, non-ordered
-  Graduated, **sequential**
-  Graduated, **divergent**

Choropleths on Geo-Tables

Streamlined

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

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

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

See this tutorial for more details on fine tuning choropleths manually

Challenge

Create an equal interval map with five bins for `no2_viz`

Manual approach

This is valid for any algorithm and provides much more flexibility at the cost of effort.

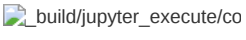
```
classi = mc.Quantiles(db["no2_viz"], k=7)
db.assign(
    classes=classi.yb
).plot("classes");
```

Value by alpha mapping

See here for more examples of VBA mapping.

```
db['area_inv'] = 1 / db.to_crs(epsg=5726).area
```

```
# Set up figure and axis
f, ax = plt.subplots(1, figsize=(12, 9))
# VBA choropleth
vba_choropleth(
    'no2_viz',          # Column for color
    'area_inv',         # Column for transparency (alpha)
    db,                 # Geo-table
    rgb_mapclassify={   # Options for color classification
        'classifier': 'quantiles', 'k':5
    },
    alpha_mapclassify={ # Options for alpha classification
        'classifier': 'quantiles', 'k':5
    },
    legend=True,        # Add legend
    ax=ax               # Axis
)
# Add boundary lines
db.plot(color='none', linewidth=0.05, ax=ax);
```



Legendgrams

Legendgrams are a way to more closely connect the statistical characteristics of your data to the map display.

Warning

Legendgrams are *experimental* at the moment so the code is a bit more involved and less stable. Use at your own risk!

Unfold the cell for an example.

```
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
)
ax.set_axis_off();
```

Challenge

Give Task I in this block of the GDS course a go.

Choropleths on surfaces

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

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

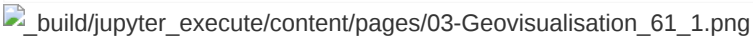
```
grid.where(
    grid != grid.rio.nodata
).plot(cmap="viridis");
```

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

- Discrete equal interval

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

```
<matplotlib.collections.QuadMesh at 0x7fdd6012bcd0>
```



- 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);
```

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

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

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

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

classi = mc.StdMean(
    grid_nona.to_series().dropna().values
)

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

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

classi = mc.BoxPlot(
    grid_nona.to_series().dropna().values
)

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

Challenge

Read the satellite image for Madrid used in the previous section and create three choropleths, one for each band, using the colormaps `Reds`, `Greens`, `Blues`.

Play with different classification algorithms.

- *Do the results change notably?*
- *If so, why do you think that is?*

🐾 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)

Map Matching

📖 Ahead of time…

Feature Engineering is a common term in machine learning that refers to the processes and transformations involved in turning data from the state in which the modeller access them into what is then fed to a model. This can take several forms, from standardisation of the input data, to the derivation of numeric scores that better describe aspects (*features*) of the data we are using.

Spatial Feature Engineering refers to operations we can use to derive "views" or summaries of our data that we can use in models, *using space* as the key medium to create them.

There is only one reading to complete for this block, Chapter 12 of the GDS Book [RABWng]. The first block of Spatial Feature Engineering in this course loosely follows the first part of the chapter (Map Matching), so focus on this first sections for the block.

💻 Hands-on coding

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

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

Local files | Online read

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

```
regions = geopandas.read_file("../data/cambodia_regional.gpkg")
cities = geopandas.read_file("../data/cambodian_cities.geojson")
pollution = rioxarray.open_rasterio(
    "../data/cambodia_s5_no2.tif"
).sel(band=1)
friction = rioxarray.open_rasterio(
    "../data/cambodia_2020_motorized_friction_surface.tif"
).sel(band=1)
```

Check both geo-tables and the surface are in the same CRS:

```
(
    regions.crs.to_epsg() ==
    cities.crs.to_epsg() ==
    pollution.rio.crs.to_epsg()
)
```

```
True
```

Polygons to points

In which region is a city?

```
sj = geopandas.sjoin(cities, regions)
```

```
#   City name | Region name
sj[["UC_NM_MN", "adm2_name"]]
```

	UC_NM_MN	adm2_name
0	Sampov Lun	Sampov Lun
1	Khum Pech Chenda	Phnum Proek
2	Poipet	Paoy Paet
3	Sisophon	Serei Saophoan
4	Battambang	Battambang
5	Siem Reap	Siem Reap
6	Sihanoukville	Preah Sihanouk
7	N/A	Trapeang Prasat
8	Kampong Chhnang	Kampong Chhnang
9	Phnom Penh	Tuol Kouk
10	Kampong Cham	Kampong Cham

Challenge

Using the Madrid AirBnb properties and neighbourhoods dataset, can you determine the neighbourhood group of the first ten properties?

Points to polygons

If we were after the number of cities per region, it is a similar approach, with a (`groupby`) twist at the end:

Note

1. We `set_index` to align both tables
2. We `assign` to create a new column

If you want no missing values, you can `fillna(0)` since you *know* missing data are zeros

```
regions.set_index(
    "adm2_name"
).assign(
    city_count=sj.groupby("adm2_name").size()
).info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
Index: 198 entries, Mongkol Borei to Administrative unit not available
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   adm2_altnm  122 non-null    object
 1   motor_mean  198 non-null    float64
 2   walk_mean   198 non-null    float64
 3   no2_mean    198 non-null    float64
 4   geometry    198 non-null    geometry
 5   city_count  11 non-null     float64
dtypes: float64(4), geometry(1), object(1)
memory usage: 18.9+ KB
```

Challenge

Using the Madrid AirBnb properties, can you compute how many properties each neighbourhood group has?

Surface to points

Consider attaching to each city in `cities` the pollution level, as expressed in `pollution`.

The code for generating this figure is a bit more advanced as it fiddles with text, but if you want to explore it you can toggle it on

```
f, ax = plt.subplots(1, figsize=(9, 9))

pollution.where(
    pollution>0
).plot(
    ax=ax, add_colorbar=False
)

for i, row in cities.iterrows():
    plt.text(
        row.geometry.x,
        row.geometry.y,
        row["UC_NM_MN"],
        fontdict={"color": "white"},
    )

cities.plot(ax=ax, color="r");
```

```
from rasterstats import point_query

city_pollution = point_query(
    cities,
    pollution.values,
    affine=pollution.rio.transform(),
    nodata=pollution.rio.nodata
)
city_pollution
```

```
[3.9397064813333136e-05,
 3.4949825609644426e-05,
 3.825255125820345e-05,
 4.103826573585785e-05,
 3.067677208474005e-05,
 5.108273256655399e-05,
 2.2592785882580366e-05,
 4.050414400882722e-05,
 2.4383652926989897e-05,
 0.0001285838935209779,
 3.258245740282522e-05]
```

And we can map these on the city locations:

```
ax = cities.assign(
    pollution=city_pollution
).plot(
    "pollution",
    cmap="YlOrRd",
    legend=True
)

contextily.add_basemap(
    ax=ax, crs=cities.crs,
);
```


_build/jupyter_execute/content/pages/04-Spatial_feature_eng_i_24_0.png

Challenge

Can you calculate the pollution level at the centroid of each Cambodian region in the regional aggregates dataset? how does it compare to their average value?

Surface to polygons

Instead of transferring to points, we want to aggregate all the information in a surface that falls *within* a polygon.

For this case, we will use the motorised friction surface. The question we are asking thus is: *what is the average degree of friction of each region?* Or, in other words: *what regions are harder to get through with motorised transport?*

```
f, ax = plt.subplots(1, figsize=(9, 9))
friction.plot.imshow(
    add_colorbar=False, ax=ax
)
regions.plot(
    ax=ax, edgecolor="red", facecolor="none"
)
contextily.add_basemap(
    ax,
    crs=regions.crs,
    source=contextily.providers.CartoDB.DarkMatterOnlyLabels,
    zoom=7
)
```


_build/jupyter_execute/content/pages/04-Spatial_feature_eng_i_28_0.png

Again, we can rely on `rasterstats`:

The output is returned from `zonal_stats` as a list of dicts. To make it more manageable, we convert it into a `pandas.DataFrame`.

```
from rasterstats import zonal_stats

regional_friction = pandas.DataFrame(
    zonal_stats(
        regions,
        friction.values,
        affine=friction.rio.transform(),
        nodata=friction.rio.nodata
    ),
    index=regions.index
)
regional_friction.head()
```

	min	max	mean	count
0	0.001200	0.037000	0.006494	979
1	0.001200	0.060000	0.007094	1317
2	0.001200	0.024112	0.006878	324
3	0.001333	0.060000	0.009543	758
4	0.001200	0.060132	0.008619	55

This can then also be mapped onto the polygon geography:

```
f, ax = plt.subplots(1, figsize=(9, 9))
regions.to_crs(
    epsg=3857
).join(
    regional_friction
).plot(
    "mean", scheme="quantiles", ax=ax
)
contextily.add_basemap(
    ax,
    source=contextily.providers.CartoDB.VoyagerOnlyLabels,
    zoom=7
)
```

Challenge

Replicate the analysis above to obtain the average friction for each region using the walking surface (`cambodia_2020_walking_friction_surface.tif`).

Surface to surface

If we want to align the `pollution` surface with that of `friction`, we need to resample them to make them “fit on the same frame”.

```
pollution.shape
```

```
(138, 152)
```

```
friction.shape
```

```
(574, 636)
```

This involves either moving one surface to the frame of the other one, or both into an entirely new one. For the sake of the illustration, we will do the latter and select a frame that is 300 by 400 pixels. Note this involves stretching (upsampling) `pollution`, while compressing (downsampling) `friction`.

```
# Define dimensions
dimX, dimY = 300, 400
minx, miny, maxx, maxy = pollution.rio.bounds()
# Create XY indices
ys = np.linspace(miny, maxy, dimY)
xs = np.linspace(minx, maxx, dimX)
# Set up placeholder array
canvas = xarray.DataArray(
    np.zeros((dimY, dimX)),
    coords=[ys, xs],
    dims=["y", "x"]
).rio.write_crs(4326) # Add CRS
```

```
cvs_pollution = pollution.rio.reproject_match(canvas)
cvs_friction = friction.rio.reproject_match(canvas)
```

```
cvs_pollution.shape
```

```
(400, 300)
```

```
cvs_pollution.shape == cvs_friction.shape
```

```
True
```

Challenge

Trasfer the `pollution` surface to the frame of `friction`, and viceversa.

Attention

The following methods involve modelling and are thus more sophisticated. Take these as a conceptual introduction with an empirical illustration, but keep in mind there are extense literatures on each of them and these cover some of the simplest cases.

Points to points

See this section of Chapter 12 of the GDS Book [RABWng] for more details on the technique

For this exampe, we will assume that, instead of a surface with pollution values, we only have available a sample of points and we would like to obtain estimates for other locations.

For that we will first generate 100 random points within the extent of `pollution` which we will take as the location of our measurement stations:

> **Note**
>
> The code in this cell contains bits that are a bit more advanced, do not despair if not everything makes sense!

```
np.random.seed(123456)

bb = pollution.rio.bounds()
station_xs = np.random.uniform(bb[0], bb[2], 100)
station_ys = np.random.uniform(bb[1], bb[3], 100)
stations = geopandas.GeoSeries(
    geopandas.points_from_xy(station_xs, station_ys),
    crs="EPSG:4326"
)
```

Our station values come from the `pollution` surface, but we assume we do not have access to the latter, and we would like to obtain estimates for the location of the cities:

```
f, ax = plt.subplots(1, figsize=(6, 6))

pollution.where(
    pollution>0
).plot(
    add_colorbar=False, cmap="Blues", ax=ax
)

stations.plot(ax=ax, color="red", label="Stations")
cities.plot(ax=ax, color="lime", label="Cities")

ax.set_title("Pollution sampling")

plt.legend();
```


_build/jupyter_execute/content/pages/04-Spatial_feature_eng_i_50_0.png

We will need the location and the pollution measurements for every station as separate arrays. Before we do that, since we will be calculating distances, we convert our coordinates to a system expressed in metres.

```
stations_mt = stations.to_crs(epsg=5726)
station_xys = np.array(
    [stations_mt.geometry.x, stations_mt.geometry.y]
).T
```

We also need to extract the pollution measurements for each station location:

```
station_measurements = np.array(
    point_query(
        stations,
        pollution.values,
        affine=pollution.rio.transform(),
        nodata=pollution.rio.nodata
    )
)
```

And finally, we will also need the locations of each city expressed in the same coordinate system:

```
cities_mt = cities.to_crs(epsg=5726)
city_xys = np.array(
    [cities_mt.geometry.x, cities_mt.geometry.y]
).T
```

For this illustration, we will use a \(k\)-nearest neighbors regression that estimates the value for each target point (`cities` in our case) as the average weighted by distance of its \(k\) nearest neigbors. In this illustration we will use \(k=10\).

Note how `sklearn` relies only on array data structures, hence why we first had to express all the required information in that format

```
from sklearn.neighbors import KNeighborsRegressor

model = KNeighborsRegressor(
    n_neighbors=10, weights="distance"
).fit(station_xys, station_measurements)
```

Once we have trained the model, we can use it to obtain predictions for each city location:

```
predictions = model.predict(city_xys)
```

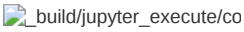
These can be compared with the originally observed values:

```
p2p_comparison = pandas.DataFrame(
    {
        "Observed": city_pollution,
        "Predicted": predictions
    },
    index=cities["UC_NM_MN"]
)
```

```
p2p_comparison
```

UC_NM_MN	Observed	Predicted
Sampov Lun	0.000039	0.000027
Khum Pech Chenda	0.000035	0.000025
Poipet	0.000038	0.000030
Sisophon	0.000041	0.000030
Battambang	0.000031	0.000027
Siem Reap	0.000051	0.000027
Sihanoukville	0.000023	0.000019
N/A	0.000041	0.000028
Kampong Chhnang	0.000024	0.000032
Phnom Penh	0.000129	0.000042
Kampong Cham	0.000033	0.000033

```
f, ax = plt.subplots(1
p2p_comparison["Observ
p2p_comparison["Predic
ax.set_axis_off()
plt.legend(frameon=Fal
```



Challenge

Replicate the analysis above with \(k=15\) and \(k=5\). *Do results change? Why do you think that is?*

Points to surface

Imagine we do not have a surface like `pollution` but we need it. In this context, if you have measurements from some locations, such as in `stations`, we can use the approach reviewed above to generate a surface. The trick to do this is to realise that we can generate a *uniform* grid of target locations that we can then express as a surface.

We will set as our target locations those of the pixels in the target surface we have seen above:

```
canvas_mt = canvas.rio.reproject(5726)
```

```
xy_pairs = canvas_mt.to_series().index
xys = np.array(
    [
        xy_pairs.get_level_values("x"),
        xy_pairs.get_level_values("y")
    ]
).T
```

To obtain pollution estimates at each location, we can `predict` with `model`:

```
predictions_grid = model.predict(xys)
```

And with these at hand, we can convert them into a surface:

```
predictions_series = pandas.DataFrame(
    {"predictions_grid": predictions_grid}
).join(
    pandas.DataFrame(xys, columns=["x", "y"])
).set_index(["y", "x"])

predictions_surface = xarray.DataArray().from_series(
    predictions_series["predictions_grid"]
).rio.write_crs(canvas_mt.rio.crs)
```

```
f, axs = plt.subplots(1, 2, figsize=(16, 6))

cvs_pollution.where(
    cvs_pollution>0
).plot(ax=axs[0])
axs[0].set_title("Observed")

predictions_surface.where(
    predictions_surface>0
).rio.reproject_match(
    cvs_pollution
).plot(ax=axs[1])
axs[1].set_title("Predicted")

plt.show()
```


```
f, ax = plt.subplots(1, figsize=(9, 4))
cvs_pollution.where(
    cvs_pollution>0
).plot.hist(
    bins=100, alpha=0.5, ax=ax, label="Observed"
)
predictions_surface.rio.reproject_match(
    cvs_pollution
).plot.hist(
    bins=100, alpha=0.5, ax=ax, color="g", label="predicted"
)
plt.legend()
plt.show()
```

Room for improvement but, remember this was a rough first pass!

> **Challenge**
>
> Train a model with pollution measurements from each city location and generate a surface from it. *How does the output compare to the one above? Why do you think that is?*

Polygons to polygons

In this final example, we transfer data from a polygon geography to *another* polygon geography. Effectively, we re-apportion values from one set of areas to another based on the extent of shared area.

Our illustration will cover how to move pollution estimates from `regions` into a uniform hexagonal grid we will first create.

> **Important**
>
> This code requires `tobler` 0.7.0 or above

```
import tobler

hex_grid = tobler.util.h3fy(
    regions, resolution=5
)
```

Not that pollution is expressed as an *intesive* (rate) variable. We need to recognise this when specifying the interpolation model:

> **Attention**
>
> This feature requires `tobler` 6.0 or above

```
%%time
pollution_hex = tobler.area_weighted.area_interpolate(
    regions.assign(geometry=regions.buffer(0)).to_crs(epsg=5726),
    hex_grid.to_crs(epsg=5726),
    intensive_variables=["no2_mean"]
)
```

```
CPU times: user 440 ms, sys: 4.92 ms, total: 445 ms
Wall time: 447 ms
```

And the results look like:

```
f, axs = plt.subplots(1, 3, figsize=(12, 4))

regions.plot(
    "no2_mean", scheme="quantiles", k=12, ax=axs[0]
)
axs[0].set_axis_off()

hex_grid.plot(
    facecolor="none", edgecolor="red", ax=axs[1]
)
axs[1].set_axis_off()

pollution_hex.to_crs(epsg=4326).plot(
    "no2_mean", scheme="quantiles", k=12, ax=axs[2]
)
axs[2].set_axis_off()

plt.show()
```

Challenge

Replicate the analytis using `resolution = 4`. *How is the result different? Why?*

🐾 Next steps

If you are interested in learning more about spatial feature engineering through map matching, the following pointers might be useful to delve deeper into specific types of "data transfer":

- The **`datashader`** library is a great option to transfer geo-tables into surfaces, providing tooling to perform these operations in a highly efficient and performant way.
- When aggregating surfaces into geo-tables, the library **`rasterstats`** contains most if not all of the machinery you will need.
- For transfers from polygon to polygon geographies, **`tobler`** is your friend. Its official documentation contains examples for different use cases.

Spatial Feature Engineering (II)

Map Synthesis

📖 Ahead of time…

In this second part of Spatial Feature Engineering, we turn to Map Synthesis. There is only one reading to complete for this block, Chapter 12 of the GDS Book [RABWng]. This block of Spatial Feature Engineering in this course loosely follows the second part of the chapter (Map Synthesis).

💻 Hands-on coding

```
import pandas, geopandas
import numpy as np
import contextily
import tobler
```

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

Local files | Online read

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

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

We will be working with a modified version of `pts`:

- Since we will require distance calculations, we will switch to the Spanish official projection
- To make calculations in the illustration near-instantaneous, we will work with a smaller (random) sample of Airbnb properties (10% of the total)

```
db = pts.sample(
    frac=0.1, random_state=123
).to_crs(epsg=25830)
```

As you can see in the description, the new CRS is expressed in metres:

```
db.crs
```

```
<Projected CRS: EPSG:25830>
Name: ETRS89 / UTM zone 30N
Axis Info [cartesian]:
- E[east]: Easting (metre)
- N[north]: Northing (metre)
Area of Use:
- name: Europe between 6°W and 0°W: Faroe Islands offshore; Ireland -
offshore; Jan Mayen - offshore; Norway including Svalbard - offshore;
Spain - onshore and offshore.
- bounds: (-6.0, 35.26, 0.01, 80.49)
Coordinate Operation:
- name: UTM zone 30N
- method: Transverse Mercator
Datum: European Terrestrial Reference System 1989 ensemble
- Ellipsoid: GRS 1980
- Prime Meridian: Greenwich
```

Distance buffers

How many Airbnb's are within 500m of each Airbnb?

```
from pysal.lib import weights
```

Using `DistanceBand`, we can build a spatial weights matrix that assigns `1` to each observation within 500m, and `0` otherwise.

```
%%time
w500m = weights.DistanceBand.from_dataframe(
    db, threshold=500, binary=True
)
```

```
CPU times: user 283 ms, sys: 16.8 ms, total: 300 ms
Wall time: 303 ms
```

```
/opt/conda/envs/gds/lib/python3.9/site-
packages/libpysal/weights/weights.py:224: UserWarning: The weights matrix
is not fully connected:
 There are 86 disconnected components.
 There are 47 islands with ids: 6878, 16772, 15006, 1336, 3168, 15193,
1043, 5257, 4943, 12849, 10609, 11309, 10854, 10123, 3388, 9380, 10288,
13071, 3523, 15316, 3856, 205, 7720, 10454, 18307, 3611, 12405, 10716,
14813, 15467, 1878, 16597, 14329, 7933, 16215, 13525, 13722, 11932,
14456, 8848, 15197, 8277, 9922, 13072, 13852, 5922, 17151.
  warnings.warn(message)
```

The number of neighbors can be accessed through the `cardinalities` attribute:

```
n_neis = pandas.Series(w500m.cardinalities)
n_neis.head()
```

```
11297    213
2659       5
16242     21
15565      9
14707    159
dtype: int64
```

```
db.assign(
    n_neis=n_neis
).plot("n_neis", markersize=0.1);
```

Challenge

Calculate the number of AirBnb properties within 250m of each other property. *What is the average?*

Distance rings

How many Airbnb's are between 500m and 1km of each Airbnb?

```
%%time
w1km = weights.DistanceBand.from_dataframe(
    db, threshold=1000, binary=True
)
```

```
CPU times: user 915 ms, sys: 67.5 ms, total: 982 ms
Wall time: 995 ms
```

```
/opt/conda/envs/gds/lib/python3.9/site-
packages/libpysal/weights/weights.py:224: UserWarning: The weights matrix
is not fully connected:
 There are 20 disconnected components.
 There are 5 islands with ids: 4943, 12849, 15467, 13525, 11932.
  warnings.warn(message)
```

Now, we could do simply a subtraction:

```
n_ring_neis = pandas.Series(w1km.cardinalities) - n_neis
```

Or, if we need to know *which is which*, we can use set operations on weights:

```
w_ring = weights.w_difference(w1km, w500m, constrained=False)
```

```
/opt/conda/envs/gds/lib/python3.9/site-
packages/libpysal/weights/weights.py:224: UserWarning: The weights matrix
is not fully connected:
 There are 34 disconnected components.
 There are 23 islands with ids: 3744, 4143, 4857, 4943, 6986, 8345, 8399,
9062, 10592, 10865, 11574, 11613, 11785, 11840, 11932, 12015, 12635,
12714, 12849, 13091, 13317, 13525, 15467.
  warnings.warn(message)
```

And we can confirm they're both the same:

```
(pandas.Series(w_ring.cardinalities) - n_ring_neis).sum()
```

```
0
```

Challenge

Can you create a plot with the following two lines?

- One depicting the average number of properties within a range of 50m, 100m, 250m, 500m, 750m
- Another one with the *increase* of average neighbors for the same distances above

Cluster membership (points)

We can use the spatial configuration of observations to classify them as part of clusters or not, which can then be encoded, for example, as dummy variables in a model.

These *magic* numbers need to be pre-set and you can play with both `min_pct` (or `min_pts` directly) and `eps` to see how they affect the results (spoiler: a lot!)

```
from sklearn.cluster import DBSCAN

min_pct = 2
min_pts = len(db) * min_pct // 100
eps = 500
```

We will illustrate it with a minimum number of points of `min_pct` % of the sample and a maximum radious of `eps` metres.

```
model = DBSCAN(min_samples=min_pts, eps=eps)
model.fit(
    db.assign(
        x=db.geometry.x
    ).assign(
        y=db.geometry.y
    )[['x', 'y']]
);
```

We will attach the labels to `db` for easy access:

```
db["labels"] = model.labels_
```

We can define boundaries to turn point clusters into polygons if that fits our needs better:

> **Attention**
>
> The code in this cell is a bit more advanced than expected for this course, but is used here as an illustration.

```
from pysal.lib import cg

boundaries = []
cl_ids = [i for i in db["labels"].unique() if i!=-1]
for cl_id in cl_ids:
    sub = db.query(f"labels == {cl_id}")
    cluster_boundaries = cg.alpha_shape_auto(
        np.array(
            [sub.geometry.x, sub.geometry.y]
        ).T,
    )
    boundaries.append(cluster_boundaries)
boundaries = geopandas.GeoSeries(
    boundaries, index=cl_ids, crs=db.crs
)
```

And we can see what the clusters look like:

```
ax = db.to_crs(
    epsg=3857
).plot(
    markersize=0.1, color="lime"
)
boundaries.to_crs(
    epsg=3857
).plot(
    ax=ax, edgecolor="red", facecolor="none"
)
contextily.add_basemap(
    ax,
    source=contextily.providers.CartoDB.DarkMatterNoLabels
)
```


_build/jupyter_execute/content/pages/05-Spatial_feature_eng_ii_41_0.png

> **Challenge**
>
> *How does the map above change if you require 5% of points instead of 2% for a candidate cluster to be considered so?*

Cluster membership (polygons)

We can take a similar approach as above if we have polygon geographies instead of points. Rather than using DBSCAN, here we can rely on local indicators of spatial association (LISAs) to pick up spatial concentrations of high or low values.

For the illustration, we will aggregate the location of Airbnb properties to a regular hexagonal grid, similar to how we generated it when transfering from polygons to polygons. First we create a polygon covering the extent of points:

```
one = geopandas.GeoSeries(
    [cg.alpha_shape_auto(
        np.array(
            [db.geometry.x, db.geometry.y]
        ).T,
    )],
    crs=db.crs
)
```

Then we can tessellate:

```
abb_hex = tobler.util.h3fy(
    one, resolution=8
)
```

```
/opt/conda/envs/gds/lib/python3.9/site-packages/pyproj/crs/crs.py:1293:
UserWarning: You will likely lose important projection information when
converting to a PROJ string from another format. See:
https://proj.org/faq.html#what-is-the-best-format-for-describing-
coordinate-reference-systems
  proj = self._crs.to_proj4(version=version)
```

And obtain a count of points in each polygon:

```
counts = geopandas.sjoin(
    db, abb_hex
).groupby(
    "index_right"
).size()

abb_hex["count"] = counts
abb_hex["count"] = abb_hex["count"].fillna(0)

abb_hex.plot("count", scheme="fisherjenks");
```


_build/jupyter_execute/content/pages/05-Spatial_feature_eng_ii_49_0.png

To identify spatial clusters, we rely on `esda`:

```
from pysal.explore import esda
```

```
/opt/conda/envs/gds/lib/python3.9/site-
packages/numba/core/decorators.py:262: NumbaDeprecationWarning:
numba.generated_jit is deprecated. Please see the documentation at:
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-of-generated-jit for more information and advice on a suitable replacement.
  warnings.warn(msg, NumbaDeprecationWarning)
/opt/conda/envs/gds/lib/python3.9/site-
packages/numba/core/decorators.py:262: NumbaDeprecationWarning:
numba.generated_jit is deprecated. Please see the documentation at:
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-of-generated-jit for more information and advice on a suitable replacement.
  warnings.warn(msg, NumbaDeprecationWarning)
/opt/conda/envs/gds/lib/python3.9/site-packages/quantecon/lss.py:20:
NumbaDeprecationWarning: The 'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The implicit default value for this argument is currently False, but it will be changed to True in Numba 0.59.0. See https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-of-object-mode-fall-back-behaviour-when-using-jit for details.
  def simulate_linear_model(A, x0, v, ts_length):
/opt/conda/envs/gds/lib/python3.9/site-packages/spaghetti/network.py:40:
FutureWarning: The next major release of pysal/spaghetti (2.0.0) will
drop support for all ``libpysal.cg`` geometries. This change is a first
step in refactoring ``spaghetti`` that is expected to result in
dramatically reduced runtimes for network instantiation and operations.
Users currently requiring network and point pattern input as
``libpysal.cg`` geometries should prepare for this simply by converting
to ``shapely`` geometries.
  warnings.warn(dep_msg, FutureWarning, stacklevel=1)
```

And compute the LISA statistics:

```
w = weights.Queen.from_dataframe(abb_hex)
lisa = esda.Moran_Local(abb_hex["count"], w)
```

```
/tmp/ipykernel_2683/2473509840.py:1: FutureWarning: `use_index` defaults
to False but will default to True in future. Set True/False directly to
control this behavior and silence this warning
  w = weights.Queen.from_dataframe(abb_hex)
```

For a visual inspection of the clusters, `splot`:

```
from pysal.viz import splot
from splot.esda import lisa_cluster
```

```
lisa_cluster(lisa, abb_hex, p=0.01);
```

And, if we want to extract the labels for each polygon, we can do so from the `lisa` object:

```
lisa.q * (lisa.p_sim < 0.01)
```

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0, 3, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3,
       0, 3, 0, 0, 0, 0, 0, 0, 3, 3, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 3, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 3, 0, 0, 0,
       1, 0, 0, 3, 0, 0, 0, 3, 0, 0, 0, 0, 0, 3, 0, 0, 0, 3, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0, 0,
       0, 0, 0, 3, 3, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0, 0, 0,
       3, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 3, 0, 3,
       0, 0, 0, 0, 0, 0, 3, 3, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 3, 0, 0, 0, 0, 0, 0, 3, 0, 0, 3, 0, 0, 3, 3, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 1, 0, 0, 3, 0, 1, 0, 0, 1, 0, 0])
```

🐾 Next steps

If you want a bit more background into some of the techniques reviewed in this block, the following might be of interest:

- Block E of the GDS Course [AB19] will introduce you to more techniques like the LISAs seen above to explore the spatial dimension of the statistical properties of your data. If you want a more detailed read, Chapter 4 of the GDS Book [RABWng] will do just that.
- Block F of the GDS Course [AB19] will introduce you to more techniques like the LISAs seen above to explore the spatial dimension of the statistical properties of your data. If you want a more detailed read, Chapter 7 of the GDS Book [RABWng] will do just that.
- Block H of the GDS Course [AB19] will introduce you to more techniques for exploring point patterns. If you want a more comprehensive read, Chapter 8 of the GDS Book [RABWng] will do just that.

OpenStreetMap

📖 Ahead of time…

This session is all about OpenStreetMap. To provide an overview of what the project is, whether you have never heard of it or you are somewhat familiar, the followring will set your mind “on course”:

- The following short clip provides a general overview of what OpenStreetMap is

- This recent piece contains several interesting points about how OpenStreetMap is currently being created and some of the implications this model may have.
- Anderson et al. (2019) [ASP19] provides some of the academic underpinnings to the views expressed in Morrison's piece

💻 Hands-on coding

```
import geopandas
import contextily
from IPython.display import GeoJSON
```

Since some of the query options we will discuss involve pre-defined extents, we will read the Madrid neighbourhoods dataset first:

Local files | Online read

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

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

To make some of the examples below *easy* on OpenStreetMap servers, we will single out the smallest neighborhood:

```
areas = neis.to_crs(
    epsg=32630
).area

smallest = neis[areas == areas.min()]
smallest
```

	neighbourhood	neighbourhood_group	geometry
98	Atalaya	Ciudad Lineal	MULTIPOLYGON (((-3.66195 40.46338, -3.66364 40...

```
ax = smallest.plot(
    facecolor="none", edgecolor="blue", linewidth=2
)
contextily.add_basemap(
    ax,
    crs=smallest.crs,
    source=contextily.providers.OpenStreetMap.Mapnik
);
```

`osmnx`

```
import osmnx as ox
```

Here is a trick to pin all your queries to OpenStreetMap to a specific date, so results are always reproducible, even if the map changes in the meantime.
Tip courtesy of Martin Fleischmann.

```
ox.settings.overpass_settings = (
    '[out:json][timeout:90][date:"2021-03-07T00:00:00Z"]'
)
```

Tip

Much of the methods covered here rely on the `osmnx.features` module. Check out its reference here

There are two broad areas to keep in mind when querying data on OpenStreetMap through `osmnx`:

- The interface to specify the *extent* of the search
- The *nature* of the entities being queried. Here, the interface relies entirely on OpenStreetMap's tagging system. Given the distributed nature of the project, this is variable, but a good place to start is:

> https://wiki.openstreetmap.org/wiki/Tags

Generally, the interface we will follow involves the following:

```
received_entities = ox.features_from_XXX(
    <extent>, tags={<key>: True/<value(s)>}, ...
)
```

The `<extent>` can take several forms:

```
[i for i in dir(ox) if "features_from_" in i]
```

```
['features_from_address',
 'features_from_bbox',
 'features_from_place',
 'features_from_point',
 'features_from_polygon',
 'features_from_xml']
```

The `tags` follow the official feature spec.

Buildings

```
blgs = ox.features_from_polygon(
    smallest.squeeze().geometry, tags={"building": True}
)
```

```
blgs.plot();
```


_build/jupyter_execute/content/pages/06-OpenStreetMap_25_0.png

```
blgs.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
MultiIndex: 115 entries, ('way', 442595762) to ('way', 577690922)
Data columns (total 27 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   name              2 non-null      object
 1   amenity           2 non-null      object
 2   geometry          115 non-null    geometry
 3   nodes             115 non-null    object
 4   building          115 non-null    object
 5   addr:housenumber  21 non-null     object
 6   addr:postcode     3 non-null      object
 7   addr:street       9 non-null      object
 8   denomination      1 non-null      object
 9   phone             2 non-null      object
 10  religion          1 non-null      object
 11  source            1 non-null      object
 12  source:date       1 non-null      object
 13  url               1 non-null      object
 14  wheelchair        1 non-null      object
 15  building:levels   11 non-null     object
 16  addr:city         8 non-null      object
 17  addr:country      6 non-null      object
 18  wikidata          1 non-null      object
 19  website           1 non-null      object
 20  country           1 non-null      object
 21  diplomatic        1 non-null      object
 22  name:en           1 non-null      object
 23  name:fr           1 non-null      object
 24  name:ko           1 non-null      object
 25  office            1 non-null      object
 26  target            1 non-null      object
dtypes: geometry(1), object(26)
memory usage: 29.7+ KB
```

```
blgs.head()
```

		name	amenity	geometry	nodes	building
element_type	**osmid**					
way	**442595762**	NaN	NaN	POLYGON ((-3.66377 40.46317, -3.66363 40.46322...	[4402722774, 4402722775, 4402722776, 440272277...	yes
	442595763	NaN	NaN	POLYGON ((-3.66394 40.46346, -3.66415 40.46339...	[4402722778, 4402722779, 4402722780, 440272278...	yes
	442595764	NaN	NaN	POLYGON ((-3.66379 40.46321, -3.66401 40.46314...	[4402722782, 4402722783, 4402722784, 440272278...	yes
	442595765	NaN	NaN	POLYGON ((-3.66351 40.46356, -3.66294 40.46371...	[4402722786, 4402722787, 4402722788, 440272278...	yes
	442596830	NaN	NaN	POLYGON ((-3.66293 40.46289, -3.66281 40.46294...	[4402729658, 4402729659, 4402729660, 440272966...	yes

5 rows × 27 columns

If you want to visit the entity online, you can do so at:

```
https://www.openstreetmap.org/<unique_id>
```

Challenge

Extract the building footprints for the Sol neighbourhood in `neis`

Other polygons

```
park = ox.features_from_place(
    "Parque El Retiro, Madrid", tags={"leisure": "park"}
)
```

```
ax = park.plot(
    facecolor="none", edgecolor="blue", linewidth=2
)
contextily.add_basemap(
    ax,
    crs=smallest.crs,
    source=contextily.providers.OpenStreetMap.Mapnik
);
```

Points of interest

Bars around Atocha station:

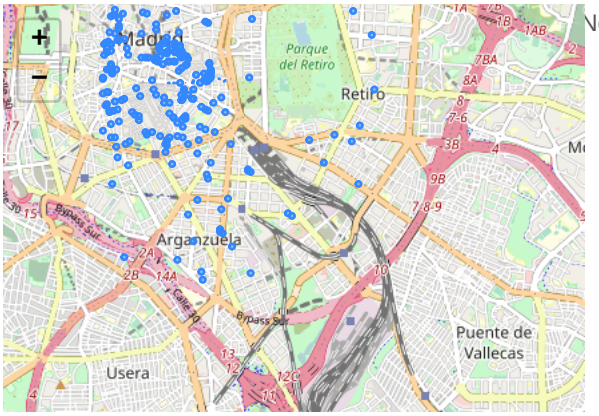
```
bars = ox.features_from_address(
    "Puerta de Atocha, Madrid", tags={"amenity": "bar"}, dist=1500
)
```

We can quickly explore with `GeoJSON`:

Data
If you have an earlier version of `geopandas` than 0.10, you can obtain a similar map with:

```
GeoJSON(bars.__geo_interface__)
```

```
bars.explore()
```



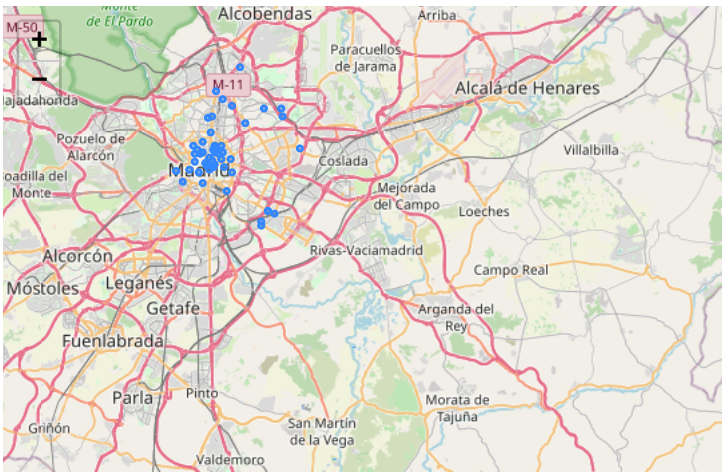
Notebook

And stores within Malasaña:

```
shops = ox.features_from_address(
    "Malasaña, Madrid, Spain", # Boundary to search within
    tags={
        "shop": True,
        "landuse": ["retail", "commercial"],
        "building": "retail"
    },
    dist=1000
)
```

We use `features_from_place` for delineated areas (“polygonal entities”):

```
cs = ox.features_from_place(
    "Madrid, Spain",
    tags={"amenity": "charging_station"}
)
cs.explore()
```



Similarly, we can work with location data. For example, searches around a given point:

```
bakeries = ox.features_from_point(
    (40.418881103417675, -3.6920446157455444),
    tags={"shop": "bakery", "craft": "bakery"},
    dist=500
)
GeoJSON(bakeries.__geo_interface__)
```

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

Challenge

- *How many music shops does OSM record within 750 metres of Puerta de Alcalá?*
- *Are there more restaurants or clothing shops within the polygon that represents the Pacífico neighbourhood in `neis` table?*

Streets

Street data can be obtained as another type of entity, as above; or as a graph object.

Geo-tables

```
centro = ox.features_from_polygon(
    neis.query("neighbourhood == 'Sol'").squeeze().geometry,
    tags={"highway": True}
)
```

We can get a quick peak into what is returned (grey), compared to the region we used for the query:

```
ax = neis.query(
    "neighbourhood == 'Sol'"
).plot(color="k")
centro.plot(
    ax=ax,
    color="0.5",
    linewidth=0.2,
    markersize=0.5
);
```


_build/jupyter_execute/content/pages/06-OpenStreetMap_51_0.png

This however will return all sorts of things:

```
centro.geometry
```

```
element_type  osmid
node          21734214                                POINT (-3.70427
40.41662)
              21734250                                POINT (-3.70802
40.41612)
              21734252                                POINT (-3.70847
40.41677)
              21968134                                POINT (-3.69945
40.41786)
              21968197                                POINT (-3.70054
40.41645)
                                                      ...
way           907553665    LINESTRING (-3.70686 40.41380, -3.70719
40.41369)
              909056211    LINESTRING (-3.70705 40.42021, -3.70680
40.42020)
relation      5662178      POLYGON ((-3.70948 40.41551, -3.70952
40.41563...
              7424032      POLYGON ((-3.70263 40.41712, -3.70253
40.41714...
              8765884      POLYGON ((-3.70636 40.41475, -3.70635
40.41481...
Name: geometry, Length: 609, dtype: geometry
```

Spatial graphs

This returns clean, processed *graph* objects for the street network:

```
centro_gr = ox.graph_from_polygon(
    neis.query("neighbourhood == 'Sol'").squeeze().geometry,
)
```

```
centro_gr
```

```
<networkx.classes.multidigraph.MultiDiGraph at 0x7fb37850c610>
```

```
[i for i in dir(ox) if
```

```
['graph_from_address',
 'graph_from_bbox',
 'graph_from_gdfs',
 'graph_from_place',
 'graph_from_point',
 'graph_from_polygon',
 'graph_from_xml']
```

And to visualise it:

```
ox.plot_figure_ground(centro_gr);
```


_build/jupyter_execute/content/pages/06-OpenStreetMap_61_0.png

```
(
    ox.graph_to_gdfs(centro_gr, nodes=False)
    .explore()
)
```

```
[i for i in dir(ox) if
```

```
['plot_graph', 'plot_g
'plot_graph_routes']
```

Challenge

How many bookshops are within a 50m radious of the Paseo de la Castellana?

Bonus tip: this one involves the following steps:

- Extracting the street segment for Paseo de la Castellana
- Drawing a 50m buffer around it
- Querying OSM for bookshops

🐾 Next steps

If you found the content in this block useful, the following resources represent some suggestions on where to go next:

- Parts of the block are inspired and informed by Geoff Boeing's excellent course on Urban Data Science
- More in depth content about `osmnx` is available in the official examples collection
- Boeing (2020) [Boe20] illustrates how OpenStreetMap can be used to analyse urban form (Open Access)

Transport costs

📖 Ahead of time…

💻 Hands-on coding

```
import momepy
import geopandas
import contextily
import xarray, rioxarray
import osmnx as ox
import numpy as np
import matplotlib.pyplot as plt
```

```
ox.settings.overpass_settings = (
    '[out:json][timeout:90][date:"2021-03-07T00:00:00Z"]'
)
```

Local files | Online read

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

```
streets = geopandas.read_file("../data/arturo_streets.gpkg")
abbs = geopandas.read_file("../data/madrid_abb.gpkg")
neis = geopandas.read_file("../data/neighbourhoods.geojson")
```

`pandana` graphs

```
import pandana
```

Before building the routing network, we convert to graph and back in `momepy` to "clean" the network and ensure it complies with requirements for routing.

```
%%time
nodes, edges = momepy.nx_to_gdf( # Convert back to geo-table
    momepy.gdf_to_nx(            # Convert to a clean NX graph
        streets.explode(index_parts='True')        # We "explode" to
avoid multi-part rows
    )
)
nodes = nodes.set_index("nodeID")# Reindex nodes on ID
```

```
CPU times: user 3.2 s, sys: 76.5 ms, total: 3.27 s
Wall time: 3.24 s
```

Once we have nodes and edges "clean" from the graph representation, we can build a `pandana.Network` object we will use for routing:

```
streets_pdn = pandana.Network(
    nodes.geometry.x,
    nodes.geometry.y,
    edges["node_start"],
    edges["node_end"],
    edges[["mm_len"]]
)

streets_pdn
```

```
Generating contraction hierarchies with 16 threads.
Setting CH node vector of size 49985
Setting CH edge vector of size 66499
Range graph removed 444 edges of 132998
. 10% . 20% . 30% . 40% . 50% . 60% . 70% . 80% . 90% . 100%
```

```
<pandana.network.Network at 0x7fbbc3db5d00>
```

Shortest-path routing

How do I go from A to B?

For example, from the first Airbnb in the geo-table…

```
first = abbs.loc[[0], :].to_crs(streets.crs)
```

…to Puerta del Sol.

```
import geopy
geopy.geocoders.options.default_user_agent = "gds4ae"
sol = geopandas.tools.geocode(
    "Puerta del Sol, Madrid", geopy.Nominatim
).to_crs(streets.crs)
sol
```

	geometry	address
0	POINT (440247.314 4474264.131)	Puerta del Sol, Barrio de los Austrias, Sol, C...

First we *snap* locations to the network:

```
pt_nodes = streets_pdn.get_node_ids(
    [first.geometry.x.iloc[0], sol.geometry.x.iloc[0]],
    [first.geometry.y.iloc[0], sol.geometry.y.iloc[0]]
)
pt_nodes
```

```
0     3071
1    35731
Name: node_id, dtype: int64
```

Then we can route the shortest path:

```
route_nodes = streets_pdn.shortest_path(
    pt_nodes[0], pt_nodes[1]
)
route_nodes
```

```
array([ 3071,  3476,  8268,  8266,  8267, 18695, 18693,  1432,  1430,
         353,  8175,  8176, 18121, 17476, 16858, 14322, 16857, 17810,
       44795, 41220, 41217, 41221, 41652, 18924, 18928, 48943, 18931,
       21094, 21095, 23219, 15398, 15399, 15400, 47446, 47447, 23276,
       47448, 23259, 23260, 23261, 27951, 27952, 27953, 48327, 11950,
       11949, 11944, 19475, 19476, 27333, 30088, 43294, 11940, 11941,
       11942, 48325, 37484, 48316, 15893, 15890, 15891, 29954, 25453,
        7341, 34991, 23608, 28217, 21648, 21649, 21651, 39075, 25108,
       25102, 25101, 25100, 48518, 47287, 34623, 31187, 29615, 48556,
       22844, 48553, 48555, 40922, 40921, 40923, 48585, 46372, 46371,
       46370, 45675, 45676, 38778, 38777, 19144, 20498, 20497, 20499,
       47737, 42303, 42302, 35730, 35727, 35729, 35731])
```

With this information, we can build the route line manually:

Attention

The code to generate the route involves writing a function and is a bit more advanced than expected for this course. If this looks too complicated, do not despair.
Also, please note this builds a *simplified* line for the route, not one that is based on the original geometries (distance calculations *are* based on the original network).

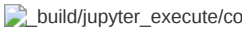
```
from shapely.geometry import LineString

def route_nodes_to_line(nodes, network):
    pts = network.nodes_df.loc[nodes, :]
    s = geopandas.GeoDataFrame(
        {"src_node": [nodes[0]], "tgt_node": [nodes[1]]},
        geometry=[LineString(pts.values)],
        crs=streets.crs
    )
    return s
```

We can calculate the route:

```
route = route_nodes_to_line(route_nodes, streets_pdn)
```

And we get it back as a geo-table (with one row):



```
route
```

	src_node	tgt_node	geometry
0	3071	3476	LINESTRING (442606.507 4478714.516, 442597.100...

If we wanted to obtain the length of the route:

```
route_len = streets_pdn.shortest_path_length(
    pt_nodes[0], pt_nodes[1]
)
round(route_len / 1000, 3) # Dist in Km
```

```
5.514
```

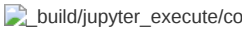
Challenge

- What is the network distance between CEMFI and Puerta del Sol?
- BONUS I: how much longer is it than if you could fly in a straight line?
- BONUS II: if one walks at a speed of 5 Km/h, how long does the walk take you?

Weighted routing

How do I go from A to B passing by the "best" buildings?

This is really an extension of standard routing that takes advantage of the flexibility of `pandana.Network` objects.



The overall process is the same; the main difference is, when we build the `Network` object, to replace distance (`mm_len`) with a measure that *combines* distance and building quality. Note that we want to *maximise* building quality, but the routing algorithms use a *minimisation* function. Hence, our composite index will need to reflect that.

The strategy is divided in the following steps:

1. Re-scale distance between 0 and 1
2. Build a measure inverse to building quality in the $[0, 1]$ range
3. Generate a combined measure (`wdist`) by picking a weighting parameter
4. Build a new `Network` object that incorporates `wdist` instead of distance
5. Compute route between the two points of interest

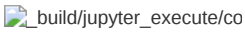
For 1., we can use the scaler in `scikit-learn`:

```
from sklearn.preprocessing import minmax_scale
```

Then generate and attach to `edges` a scaled version of `mm_len`:

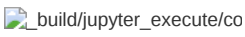
```
edges["scaled_dist"] = minmax_scale(edges["mm_len"])
```

We move on to 2., with a similar approach. We will use the negative of the building quality average (`average_quality`):



```
edges["scaled_inv_bquality"] = minmax_scale(
    -edges["average_quality"]
)
```

Taking 1. and 2. into 3. we can build `wdist`. For this example, we will give each dimension the same weight (0.5), but this is at discretion of the researcher.



```
w = 0.5
edges["wdist"] = (
    edges["scaled_dist"] * w +
    edges["scaled_inv_bquality"] * (1-w)
)
```

Now we can recreate the `Network` object based on our new measure (4.) and provide routing. Since it is the same process as with distance, we will do it all in one go:

```
# Build new graph object
w_graph = pandana.Network(
    nodes.geometry.x,
    nodes.geometry.y,
    edges["node_start"],
    edges["node_end"],
    edges[["wdist"]]
)
# Snap locations to their nearest node
pt_nodes = w_graph.get_node_ids(
    [first.geometry.x.iloc[0], sol.geometry.x.iloc[0]],
    [first.geometry.y.iloc[0], sol.geometry.y.iloc[0]]
)
# Generate route
w_route_nodes = w_graph.shortest_path(
    pt_nodes[0], pt_nodes[1]
)
# Build LineString
w_route = route_nodes_to_line(
    w_route_nodes, w_graph
)
```

```
Generating contraction hierarchies with 16 threads.
Setting CH node vector of size 49985
Setting CH edge vector of size 66499
Range graph removed 444 edges of 132998
. 10% . 20% . 30% . 40% . 50% . 60% . 70% . 80% . 90% . 100%
```

Now we are ready to display it on a map:

```
# Building quality
ax = streets.plot(
    "average_quality",
    scheme="quantiles",
    cmap="magma",
    linewidth=0.5,
    figsize=(9, 9)
)
# Shortest route
route.plot(
    color="xkcd:orange red", linewidth=3, ax=ax, label="Shortest"
)
# Weighted route
w_route.plot(
    color="xkcd:easter green", linewidth=3, ax=ax, label="Weighted"
)
# Styling
ax.set_axis_off()
plt.legend();
```


_build/jupyter_execute/content/pages/07-Transport_costs_49_0.png

Challenge

1. Explore the differences in the output of weighted routing if you change the weight between distance and the additional constrain.
2. Recreate weighted routing using the linearity of street segments. How can you go from A to B avoiding long streets?

Proximity

What is the nearest internet cafe for Airbnb's without WiFi?

First we identify Airbnb's without WiFi:

```
no_wifi = abbs.query(
    "WiFi == '0'"
).to_crs(streets.crs)
```

Then pull WiFi spots in Madrid from OpenStreetMap:

```
icafes = ox.features_from_place(
    "Madrid, Spain", tags={"amenity": "internet_cafe"}
).to_crs(streets.crs).reset_index()
```

```
ax = no_wifi.plot(
    color="red",
    markersize=1,
    alpha=0.5,
    label="Airbnb no WiFi",
    figsize=(9, 9)
)
icafes.plot(
    ax=ax, color="lime", label="Internet cafes"
)
contextily.add_basemap(
    ax,
    crs=no_wifi.crs,
    source=contextily.providers.CartoDB.Voyager
)
ax.set_axis_off()
plt.legend()
plt.show()
```


_build/jupyter_execute/content/pages/07-Transport_costs_57_0.png

The logic for this operation is the following:

1. Add the points of interest (POIs, the internet cafes) to the network object (`streets_pdn`)
2. Find the nearest node to each POI
3. Find the nearest node to each Airbnb without WiFi
4. Connect each Airbnb to its nearest internet cafe

We can add the internet cafes to the network object (1.) with the `set_pois` method:

Note we set `maxitems=1` because we are only going to query for the nearest cafe. This will make computations much faster

```
streets_pdn.set_pois(
    category="Internet cafes", # Our name for the layer in the `Network`
object
    maxitems=1,               # Use to count only nearest cafe
    maxdist=100000,           # 100km so everything is included
    x_col=icafes.geometry.x,  # X coords of cafes
    y_col=icafes.geometry.y,  # Y coords of cafes
)
```

Once the cafes are added to the network, we can find the nearest one to each node (2.):

Note there are some nodes for which we can't find a nearest cafe. These are related to disconnected parts of the network

```
cafe2nnode = streets_pdn.nearest_pois(
    100000,              # Max distance to look for
    "Internet cafes",    # POIs to look for
    num_pois=1,          # No. of POIs to include
    include_poi_ids=True # Store POI ID
).join(# Then add the internet cafee IDs and name
    icafes[['osmid', 'name']],
    on="poi1"
).rename(# Rename the distance from node to cafe
    columns={1: "dist2icafe"}
)
cafe2nnode.head()
```

nodeID	dist2icafe	poi1	osmid	name
0	5101.421875	9.0	3.770327e+09	Silver Envíos 2
1	5190.265137	9.0	3.770327e+09	Silver Envíos 2
2	5252.475098	9.0	3.770327e+09	Silver Envíos 2
3	5095.101074	9.0	3.770327e+09	Silver Envíos 2
4	5676.117188	9.0	3.770327e+09	Silver Envíos 2

Note that, to make things easier down the line, we can link `cafe2nnode` to the cafe IDs.

And we can also link Airbnb's to nodes (3.) following a similar approach as we have seen above:

```
abbs_nnode = streets_pdn.get_node_ids(
    no_wifi.geometry.x, no_wifi.geometry.y
)
abbs_nnode.head()
```

```
26      8872
50     10905
62     41158
63     34257
221    32215
Name: node_id, dtype: int64
```

Finally, we can bring together both to find out what is the nearest internet cafe for each Airbnb (4.):

```
abb_icafe = no_wifi[
    ["geometry"]     # Keep only geometries of ABBs w/o WiFi
].assign(
    nnode=abbs_nnode # Attach to thse ABBs the nearest node in the
network
).join(              # Join to each ABB the nearest cafe using node IDs
    cafe2nnode,
    on="nnode"
)
abb_icafe.head()
```

	geometry	nnode	dist2icafe	poi1	osmid	name
26	POINT (443128.256 4483599.841)	8872	4926.223145	9.0	3.770327e+09	Silver Envíos 2
50	POINT (441885.677 4475916.602)	10905	1876.392944	19.0	6.922981e+09	Locutorio
62	POINT (440439.640 4476480.771)	41158	1164.812988	17.0	5.573414e+09	NaN
63	POINT (438485.311 4471714.377)	34257	1466.537964	5.0	2.304485e+09	NaN
221	POINT (439941.104 4473117.914)	32215	354.268005	15.0	5.412145e+09	NaN

Challenge

Calculate distances to nearest internet cafe for ABBs *with* WiFi. On average, which of the two groups (with and without WiFi) are closer to internet cafes?

Accessibility

This flips the previous question on its head and, instead of asking what is the nearest POI to a given point, along the network (irrespective of distance), it asks *how many POIs can I access within a network-based distance radious?*

```
%%time
parks = ox.features_from_place(
    "Madrid, Spain", tags={"leisure": "park"}
).to_crs(streets.crs)
```

```
CPU times: user 382 ms, sys: 461 µs, total: 382 ms
Wall time: 385 ms
```

How many parks are within 500m(-euclidean) of an Airbnb?

We draw a radious of 500m around each AirBnb:

```
buffers = geopandas.GeoDataFrame(
    geometry=abbs.to_crs(
        streets.crs
    ).buffer(
        500
    )
)
```

Then intersect it with the location of parks, and count by buffer (ie. Airbnb):

```
park_count = geopandas.sjoin(
    parks, buffers
).groupby(
    "index_right"
).size()
```

How many parks are within 500m(-network) of an Airbnb?

We need to approach this as a calculation *within* the network. The logic of steps thus looks like:

1. Use the aggregation module in `pandana` to count the number of parks within 500m of each node in the network
2. Extract the counts for the nodes nearest to Airbnb properties
3. Assign park counts to each Airbnb

We can set up the aggregate engine (1.). This involves three steps:

a. Obtain nearest node for each park

```
parks_nnode = streets_pdn.get_node_ids(
    parks.centroid.x, parks.centroid.y
)
```

b. Insert the parks' nearest node through `set` so it can be "aggregated"

```
streets_pdn.set(
    parks_nnode, name="Parks"
)
```

c. "Aggregate" for a distance of 500m, effectively counting the number of parks within 500m of each node

```
parks_by_node = streets_pdn.aggregate(
    distance=500, type="count", name="Parks"
)
parks_by_node.head()
```

```
nodeID
0    5.0
1    5.0
2    6.0
3    8.0
4    1.0
dtype: float64
```

At this point, we have the number of parks within 500m of *every* node in the network. To identify those that correspond to each Airbnb (3.), we first pull out the nearest nodes to each ABB:

```
abbs_xys = abbs.to_crs(streets.crs).geometry
abbs_nnode = streets_pdn.get_node_ids(
    abbs_xys.x, abbs_xys.y
)
```

And use the list to asign the count of the nearest node to each Airbnb:

```
park_count_network = abbs_nnode.map(
    parks_by_node
)
park_count_network.head()
```

```
0     4.0
1     9.0
2     5.0
3     0.0
4    12.0
Name: node_id, dtype: float64
```

For which areas do both differ most?

We can compare the two counts above to explore to what extent the street layout is constraining access to nearby parks.

```
park_comp = geopandas.GeoDataFrame(
    {
        "Euclidean": park_count,
        "Network": park_count_network
    },
    geometry=abbs.geometry,
    crs=abbs.crs
)
```

```
ax = park_comp.plot.scatter("Euclidean", "Network")
ax.axline([0, 0], [1, 1], color='red');# 45deg line
```


_build/jupyter_execute/content/pages/07-Transport_costs_91_0.png

And, geographically:

Note there are a few cases where there are more network counts than Euclidean. These are due to the slight inaccuracies introduced by calculating network distances from nodes rather than the locations themselves

```
f, axs = plt.subplots(1, 3, figsize=(15, 5))

# Euclidean count
abbs.to_crs(
    streets.crs
).assign(
    n_parks=park_count
).fillna(0).plot(
    "n_parks",
    scheme="fisherjenkssampled",
    alpha=0.5,
    markersize=1,
    figsize=(9, 9),
    legend=True,
    ax=axs[0]
)
contextily.add_basemap(
    axs[0],
    crs=streets.crs,
    source=contextily.providers.CartoDB.PositronNoLabels
)
axs[0].set_axis_off()
axs[0].set_title("Euclidean Distances")

# Count difference
with_parks = park_comp.query(
    "(Network > 0) & (Euclidean > 0)"
)
count_diff = 100 * (
    with_parks["Euclidean"] -
    with_parks["Network"]
) / with_parks["Euclidean"]
abbs.to_crs(
    streets.crs
).assign(
    n_parks=count_diff
).dropna().plot(
    "n_parks",
    scheme="fisherjenkssampled",
    alpha=0.5,
    markersize=1,
    figsize=(9, 9),
    legend=True,
    ax=axs[1]
)
contextily.add_basemap(
    axs[1],
    crs=streets.crs,
    source=contextily.providers.CartoDB.PositronNoLabels
)
axs[1].set_axis_off()
axs[1].set_title("Count Difference (%)")

# Network count
abbs.to_crs(
    streets.crs
).assign(
    n_parks=park_count_network
).fillna(0).plot(
    "n_parks",
    scheme="fisherjenkssampled",
    alpha=0.5,
    markersize=1,
    figsize=(9, 9),
    legend=True,
    ax=axs[2]
)
contextily.add_basemap(
    axs[2],
    crs=streets.crs,
    source=contextily.providers.CartoDB.PositronNoLabels
)
axs[2].set_axis_off()
axs[2].set_title("Network Distances")

plt.show()
```

Challenge

Calculate accessibility to *other* ABBs from each ABB through the network. *How many ABBs can you access within 500m of each ABB?*

Note you will need to use the locations of ABBs both as the source and the target for routing in this case.

🐾 Next steps

If you found the content in this block useful, the following resources represent some suggestions on where to go next:

- The **pandana** tutorial and documentation are excellent places to get a more detailed and comprehensive view into the functionality of the library

Web mapping with CARTO

📖 Ahead of time…

Important

REQUIRED You will need to have a (free) account with CARTO to complete this session.

There are several ways of obtaining a free account. The recommended one is to sign up for CARTO for education. Follow the steps provided in the link, which boil down to:

1. Sign up for Github (if you do not have an account already)
2. Apply for the Github Education Pack
3. Wait for verification and confirm. **This could take from 1h to several days**.
4. Claim your CARTO student account

Danger

IMPORTANT Do *not* sign up for a free trial, as this is limited to a couple of weeks

💻 Hands-on

Note

Please refer to the lecture demo for details on how to do achieve the goals outlined in this page.

In this session, we will explore the CARTO platform. This will be a whirlwind tour of some of the main things you can do within the platform, and its potential.

Data

You can access the data file here.

For this overview, we will use the dataset of Cambodian regions we have used earlier in the course.

Workflow

Data ingestion

- Data Explorer
- Import data (remote link)
  - Regions
  - Cities

My first map

- Map Vs data pages
- Create a map
- Parts of Builder
  - Map view
  - Sources
  - Layers
- Control tabs
  - Layer properties
  - Widgets
  - Interactions
  - Legend
  - Basemap
- Perspective

Interactivity

- Pan, zoom
- Tooltips
- Widgets

Choropleths

- Color palettes
- Algorithms

3D

- Enable 3D

Publishing and sharing

- Publish
- Publish updates

Challenge

You can find the datasets from the book at the bottom of the side bar. Each dataset includes a direct link to the file at the bottom of its page.

Pick a dataset from the GDS Book (or an alternative dataset you're familiar with) and replicate the workflow above to make a map.

🐾 Next steps

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]`
- ℹ️ Furhter information `[URL]`


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

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`
- ℹ️ 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]`
- ℹ️ Furhter information `[URL]`

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]`
- ℹ️ Furhter information `[URL]`

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]`
- ℹ️ 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]`
- ℹ️ 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]`
- ℹ️ 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]`
- ℹ️ 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

Bibliography

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RABWng Sergio J. Rey, Daniel Arribas-Bel, and Levi J. Wolf. *Geographic Data Science with PySAL and the PyData stack*. CRC press, forthcoming.

RBZ+19 Adam Rule, Amanda Birmingham, Cristal Zuniga, Ilkay Altintas, Shih-Cheng Huang, Rob Knight, Niema Moshiri, Mai H Nguyen, Sara Brin Rosenthal, Fernando Pérez, and others. Ten simple rules for writing and sharing computational analyses in jupyter notebooks. *PLoS Comput Biol*, 2019. doi:https://doi.org/10.1371/journal.pcbi.1007007.

SAB19 Alex Singleton and Daniel Arribas-Bel. Geographic data science. *Geographical Analysis*, 2019.

WNVR+20 DJ Weiss, A Nelson, CA Vargas-Ruiz, K Gligorić, S Bavadekar, E Gabrilovich, A Bertozzi-Villa, J Rozier, HS Gibson, T Shekel, and others. Global maps of travel time to healthcare facilities. *Nature Medicine*, 26(12):1835–1838, 2020.

By Dani Arribas-Bel & Diego Puga