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GDS4AE - *Geographic Data Science for Applied Economists*

- [Dani Arribas-Bel \[@darribas\]](#).
- [Diego Puga \[@ProfDiegoPuga\]](#).

Note

A PDF version of this course is available for download [here](#)

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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 = {\url{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

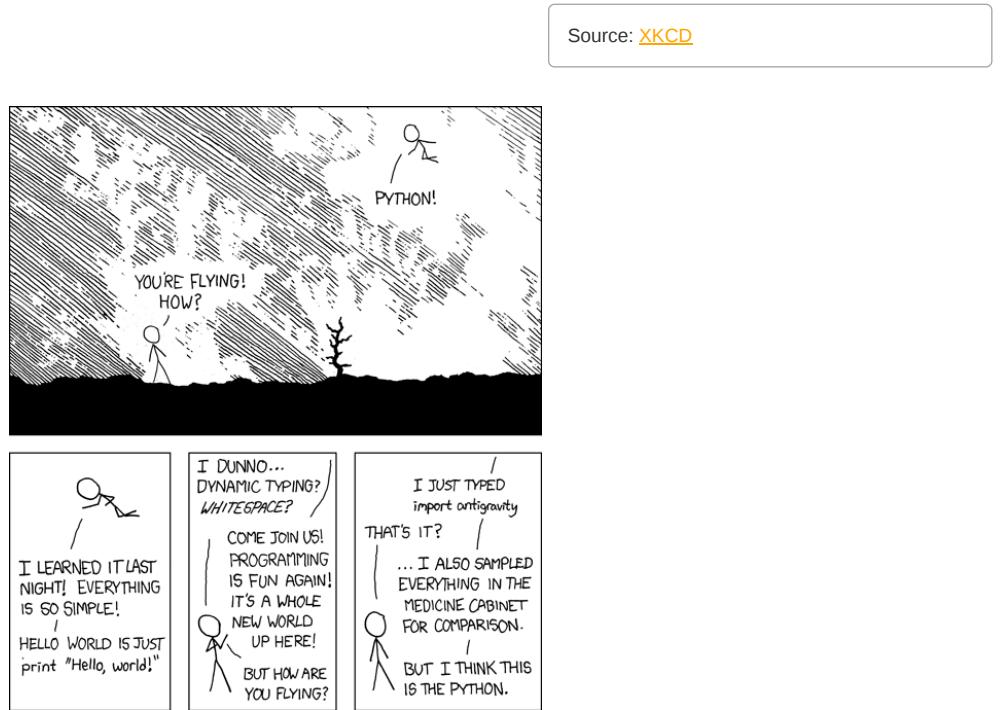
The structure of content is divided in nine blocks:

- [Introduction](#): get familiar with the computational environment 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
- [Spatial Networks](#): understand and work with spatial graphs
- [Transport Costs](#): “getting there” doesn’t always cost the same

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

The materials in this course are published under a [Creative Commons BY-SA 4.0](#) license. This grants you the right to use them freely and (re-)distribute them so long as you give credit to the original creators (see the [Home page](#) for a suggested citation) and license derivative work under the same 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:

Icon made by [Freepik](#) from [www.flaticon.com](#)

https://github.com/darribas/data_science_studio/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 a service that allows you to run scientific projects in the cloud for free. Binder can spin up “ephemeral” instances that allow you to run code on the browser without any local setup. It is possible to run the course on Binder by clicking on the button below:

[launch binder](#)

⚠️ Warning

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

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

Introduction

Geographic Data Science

Note

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

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

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

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.

URL



Source: [The Atlantic](#)

The Atlantic article cover for 'Genomic analysis of elongated skulls: extensive female-biased immigration in early Medieval Bavaria' by Kristina R. Veeramah et al. The cover features a dramatic image of flames and a skull.

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

[URL](#)



EDITORIAL

Ten simple rules for writing and sharing computational analyses in Jupyter Notebooks

Adam Rule¹, Amanda Birmingham², Cristal Zuniga³, Ilkay Attintas⁴, Shih-Cheng Huang⁵, Rob Knight^{1,5}, Niema Moshiri⁶, Mai H. Nguyen¹, Sara Brin Rosenthal², Fernando Pérez⁷, Peter W. Rose⁴

¹ Design Lab, UC San Diego, La Jolla, California, United States of America, ² Center for Computational Biology and Bioinformatics, UC San Diego, La Jolla, California, United States of America, ³ Department of Pediatrics, UC San Diego, La Jolla, California, United States of America, ⁴ Data Science Hub, San Diego Supercomputer Center, UC San Diego, La Jolla, California, United States of America, ⁵ Departments of Bioengineering, and Computer Science and Engineering, and Center for Microbiome Innovation, UC San Diego, La Jolla, California, United States of America, ⁶ Bioinformatics and Systems Biology Graduate Program, UC San Diego, La Jolla, California, United States of America, ⁷ Department of Statistics and Berkeley Institute for Data Science, UC Berkeley, and Lawrence Berkeley National Laboratory, Berkeley, California, United States of America

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

[URL](#)

The screenshot shows the CP-27 - GIS and Computational Notebooks page. The page title is 'CP-27 - GIS and Computational Notebooks'. Below the title, there is a sidebar with links to 'Topic Description', 'References', 'Author and citation info', 'Instructional Resources', 'Additional Resources', 'Related Topics', and 'Keywords'. The main content area discusses the adoption of computational notebooks in various disciplines and introduces the chapter's focus on computational notebooks in geographic context. It includes a brief illustration of a notebook's typical workflow and its benefits. At the bottom, there is an 'Author and Citation Info' section with the following text:

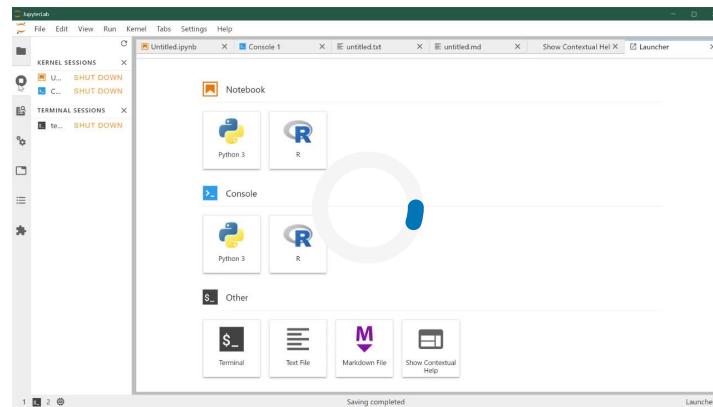
Boeing, G. and Arribas-Bel, D. (2020). GIS and Computational Notebooks. *The Geographic Information Science & Technology Body of Knowledge* (1st Quarter 2021 Edition). John P. Wilson (Ed.). DOI: 10.22224/gistbok/202112/

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.

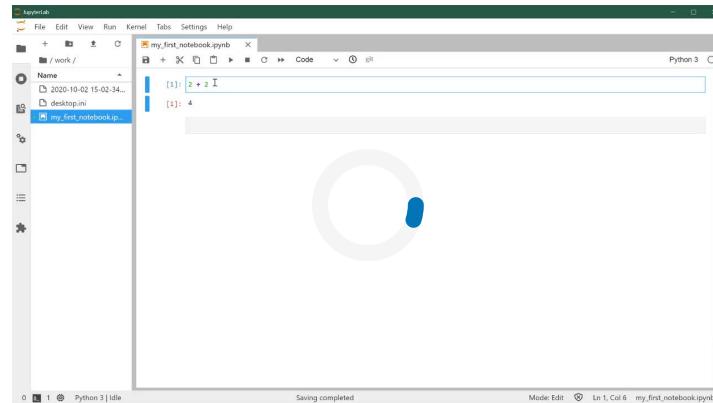
Note

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/madrid_abb.gpkg`:

```
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	bedroom
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/arturo_streets.gpkg`:

```
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	(0)	int64 0	

▼ Attributes:

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	0	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	0	int64 0	

▼ Attributes:

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	0	int64 0	

▼ Attributes:

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.

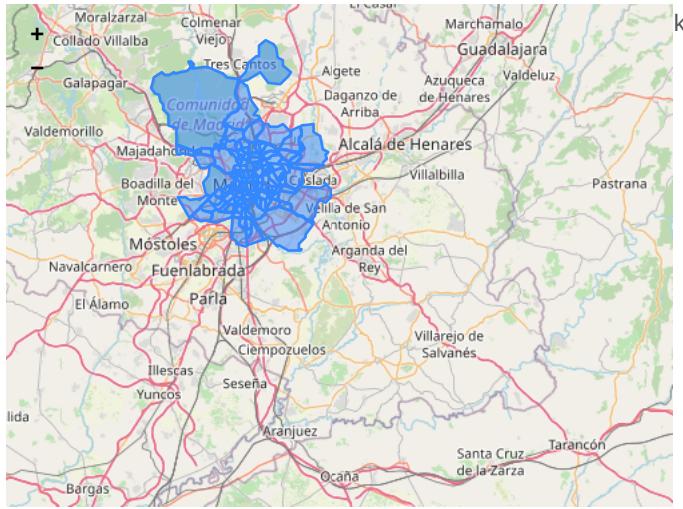
- How many pixels does it contain?
- What if you used bands 1 and 3 instead?

Visualisation

IMPORTANT

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

```
polys.explore()
```



20 km

10 m

Leaflet (<https://leafletjs.com>) | Data by © OpenStreetMap (<http://openstreetmap.org>), under ODbL (<http://www.openstreetmap.org/copyright>).

```
polys.plot()
```

<AxesSubplot:>



```
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 0x7f21c0154100>



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.Stamen.TonerLabels,
    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.Stamen.TonerLabels,
);

```



Centroids

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

```
polys.centroid
```

```
/tmp/ipykernel_104/2101097851.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_104/1054587808.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()
```

```
<AxesSubplot:>
```



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'>
Int64Index: 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:bright")

# 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
)
```



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
)
```

```
/opt/conda/lib/python3.9/site-packages/geopandas/base.py:31: UserWarning:  
The indices of the two GeoSeries are different.  
warn("The indices of the two GeoSeries are different.")
```

```
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

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.

```
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"
);
```



- 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()
```

```
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();
```

```

<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

```

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()
```

	<code>no2_mean</code>	<code>no2_viz</code>
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
);

```



A classification problem

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

```
(198,)
```

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



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 classification  
    ...  
  
    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(lbels=classi.yb).plot(  
        "lbels", 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



- 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



- 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, 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, 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, 2, 1, 2, 1, 1, 1, 2, 2, 1, 3, 1])
```

How many colors?

⚠️ Attention

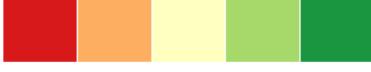
The code used to generate this figure uses more advanced features than planned for this course. If you want to inspect it, toggle the cell below.

```
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=palmp.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();
```



ℹ Challenge

Give [Task 1](#) 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 0x7f0087843c70>
```



- 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: 10.8+ 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,
 2.438365292698997e-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,
);

```



i 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
)

```



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

Transfer 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 extensive 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 example, 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();

```



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

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
```

Observed Predicted

UC_NM_MN		
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, 1)
p2p_comparison["Observed"].hist()
p2p_comparison["Predicted"].hist()
ax.set_axis_off()
plt.legend(frameon=False)
```

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, 2, 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
)
```

```
/opt/conda/lib/python3.9/site-packages/tobler/util/util.py:151:
FutureWarning: Currently, index_parts defaults to True, but in the
future, it will default to False to be consistent with Pandas. Use
`index_parts=True` to keep the current behavior and True/False to silence
the warning.
    source = source.explode()
```

Not that pollution is expressed as an *intensive* (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 439 ms, sys: 12 ms, total: 451 ms
Wall time: 448 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 analysis using `resolution = 4`. How is the result different? Why?

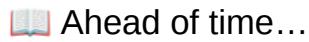
🐾 Next steps

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.

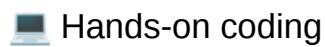
Spatial Feature Engineering (II)

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: (-5.999999999999, 35.265663028, 1.7053025658242e-13, 80.489344496333)
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 214 ms, sys: 13.8 ms, total: 228 ms
Wall time: 226 ms
```

```
/opt/conda/lib/python3.9/site-packages/libpysal/weights/weights.py:172:
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 575 ms, sys: 31.1 ms, total: 606 ms  
Wall time: 602 ms
```

```
/opt/conda/lib/python3.9/site-packages/libpsal/weights/weights.py:172:  
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/lib/python3.9/site-packages/libpsal/weights/weights.py:172:  
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 radius 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
)

```



i 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 [transferring 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/lib/python3.9/site-packages/tobler/util/util.py:151:
FutureWarning: Currently, index_parts defaults to True, but in the
future, it will default to False to be consistent with Pandas. Use
`index_parts=True` to keep the current behavior and True/False to silence
the warning.
    source = source.explode()

```

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");

```



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

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

```
/opt/conda/lib/python3.9/site-packages/esda/getisord.py:636:  
SyntaxWarning: "is" with a literal. Did you mean "=="?  
    if __name__ is "__main__":  
/opt/conda/lib/python3.9/site-packages/spaghetti/network.py:36:  
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(f"\n{dep_msg}\n", FutureWarning)
```

And compute the LISA statistics:

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

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

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



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)
```

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 following will set your mind “on course”:

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

Two Minute Tutorials: What is OpenStreetMap?



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

💡 Tip

Much of the methods covered here rely on the `osmnx.geometries` 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.geometries_from_XXX(  
    <extent>, tags={<key>: True/<value(s)>}, ...  
)
```

The `<extent>` can take several forms:

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

```
['geometries_from_address',
 'geometries_from_bbox',
 'geometries_from_place',
 'geometries_from_point',
 'geometries_from_polygon',
 'geometries_from_xml']
```

The `tags` follow the [official feature spec](#).

Buildings

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

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



```
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   amenity          2 non-null      object  
 1   name              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()
```

		amenity	name	geometry	nodes	building	
	element_type	osmid					
	way	442595762		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.geometries_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.geometries_from_address(  
    "Puerta de Atocha, Madrid", tags={"amenity": "bar"}, dist=1500  
)
```

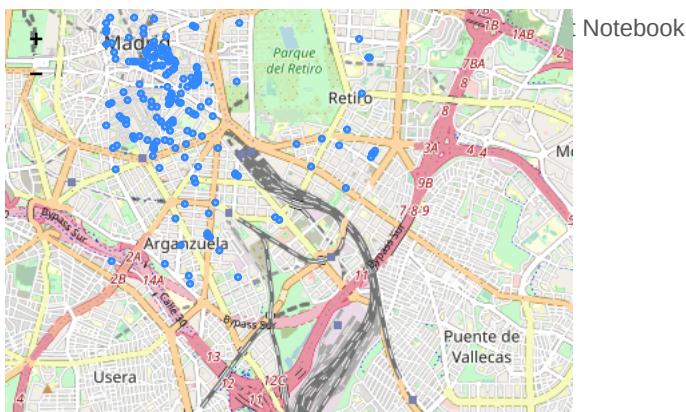
We can quickly explore with **GeoJSON**:

Data

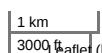
If you have an earlier version of **geopandas** than 0.10, you can obtain a similar map with:

```
GEOJSON(bars.__geo_interface__)
```

```
bars.explore()
```



Notebook



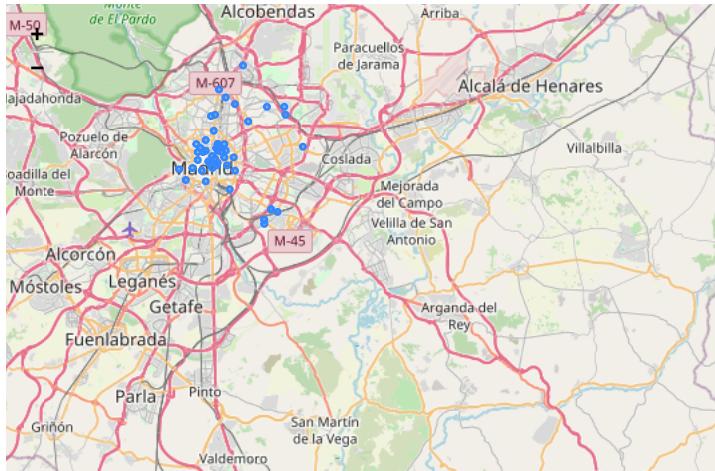
3000 ft Leaflet (<https://leafletjs.com>) | Data by © OpenStreetMap (<http://openstreetmap.org>), under ODbL (<http://www.openstreetmap.org/copyright>).

And stores within Malasaña:

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

We use **geometries_from_place** for delineated areas ("polygonal entities"):

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



10 km
5 mi

Leaflet (<https://leafletjs.com>) | Data by © OpenStreetMap (<http://openstreetmap.org>), under ODbL (<http://www.openstreetmap.org/copyright>).

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

```
bakeries = ox.geometries_from_point(
    (40.418881103417675, -3.692044615745544),
    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.geometries_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
);
```



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 ((-3.70243 40.41716, -3.70242
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,
)
```

```
[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']]
```

Note

For more on graph representations of street networks, see [block 07](#)

```
centro_gr
```

```
<networkx.classes.multidigraph.MultiDiGraph at 0x7fe97aab7dc0>
```

And to visualise it:

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



```
[i for i in dir(ox) if
['plot_graph', 'plot_g
'plot_graph_routes']]
```

```
ox.plot_graph_folium(centro_gr)
```



Leaflet (<https://leafletjs.com>) | © OpenStreetMap (<http://www.openstreetmap.org/copyright>) contributors © CartoDB (<http://cartodb.com/attribution>), CartoDB attributions (<http://cartodb.com/attribution>)

Challenge

How many bookshops are within a 50m radius 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

pyrosm

If you are planning to read full collections of OpenStreetMap entities for a given region, `osmnx` might not be the ideal tool. Instead, it is possible to access extracts of regions and read them in full with [pyrosm](#), which is faster for *these* operations.

More information about the [pyrosm](#) project is available on its [website](#)

```
import pyrosm
```

If you are working on a “popular” place, there are utilities to acquire the data:

```
mad = pyrosm.get_data("Madrid")
mad
```

```
'/tmp/pyrosm/Madrid.osm.pbf'
```

Once downloaded, we can start up the database:

```
mad_osm = pyrosm.OSM(mad)
```

And we can then read parts of all of OpenStreetMap data available for Madrid through queries to `mad_osm`. It is important to note that [pyrosm](#) will return queries as [GeoDataFrame](#) objects, but can also interoperate with graph data structures.

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) [[Boe20a](#)] illustrates how OpenStreetMap can be used to analyse urban form ([Open Access](#))

Spatial Networks

Ahead of time...

Thank you very much to [Martin Fleischmann](#) for providing support and ideas in the development of this block

In this block we cover some of the analytics you can obtain when you consider street networks as spatial graphs rather than as geo-tables.

- A good example of applying concepts and ideas presented in this block is Boeing (2020) [[Boe20b](#)]
- Boeing (2017) [[Boe17](#)] provides a general overview on the `osmnx` project
- A brief overview of `momepy`, the package for urban morphometrics, available in Fleischmann (2019) [[Fle19](#)]

Hands-on coding

```
import pandas
import geopandas
import momepy
import networkx as nx
import contextily
import matplotlib.pyplot as plt
```

[Local files](#) [Online read](#)

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

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

To make things easier later, we “explode” the table so it is made up of `LINESTRINGS` instead of `MULTILINESTRINGS`:

```
db_tab = db.explode().reset_index()
```

```
/tmp/ipykernel_312/1525410135.py:1: FutureWarning: Currently, index_parts
defaults to True, but in the future, it will default to False to be
consistent with Pandas. Use `index_parts=True` to keep the current
behavior and True/False to silence the warning.
db_tab = db.explode().reset_index()
```

```
db_tab.head()
```

 [build/jupyter_execute/co](#)

level_0	level_1	OGC_FID	dm_id	dist_barri	average_quality	population
0	0	0	1	1	1606	3.277406
1	1	0	2	2	1606	3.113298
2	2	0	3	3	1606	3.143822
3	3	0	4	4	1603	5.740980
4	4	0	5	5	1603	5.468163

Analysing street geo-tables

Length

```
length = db_tab.to_crs(
    epsg=32630 # Expressed in metres
).geometry.length
length.head()
```

```
0    118.699481
1    62.210799
2    95.164472
3    23.503065
4    16.090295
dtype: float64
```

```
ax = db_tab.assign(
    length=length
).plot(
    "length",
    scheme="fisherjenkssampled",
    k=9,
    legend=True,
    linewidth=0.5,
    figsize=(12, 12),
    cmap="magma"
)
contextily.add_basemap(
    ax,
    crs=db_tab.crs,
    source=contextily.providers.CartoDB.PositronNoLabels,
    alpha=0.5
)
ax.set_title("Street segment length");
```



Challenge

Create a quantile choropleth of length for the section of the network with `dist_barri` values starting by `01`.

Bonus tip: you can create the subset of the network using the `isin` method:

```
ids = ['0101', '0102', '0103', '0104', '0105', '0106']
subnet = db_tab[db_tab['dist_barri'].isin(ids)]
```

Linearity

```
linearity = momepy.Linearity(db_tab).series
linearity.head()
```

```
0    1.000000
1    0.999999
2    1.000000
3    1.000000
4    1.000000
dtype: float64
```

```
ax = db_tab.assign(
    linearity=linearity
).plot(
    "linearity",
    scheme="fisherjenkssampled",
    k=9,
    legend=True,
    linewidth=0.5,
    figsize=(12, 12),
    cmap="magma"
)
contextily.add_basemap(
    ax,
    crs=db_tab.crs,
    source=contextily.providers.CartoDB.PositronNoLabels,
    alpha=0.5
)
ax.set_title("Street segment linearity");
```



Challenge

Create a choropleth of linearity for the `subnet` table you have created above

Streets as spatial graphs

From geo-table to spatial graph:

```
db_graph = momepy.gdf_to_nx(db_tab)
db_graph
```

```
<networkx.classes.multigraph.Multigraph at 0x7fd9843d4b80>
```

Now `db_graph` is a different animal than `db` that emphasizes *connections* rather than attributes.

```
db_graph.is_directed()
```

```
False
```

```
db_graph.is_multigraph()
```

```
True
```

The (first and last) coordinates of each street segment become the ID for each segment in the graph:

```
print(db_tab.loc[0, "geometry"])
```

```
LINestring (444096.3161762458 4482762.870216271, 444171.158127317  
4482855.001910598)
```

```
l = db_tab.loc[0, "geometry"]  
l.coords
```

```
<shapely.coords.CoordinateSequence at 0x7fd974ab4940>
```

```
node0a, node0b = edge0 = list(  
    db_tab.loc[0, "geometry"].coords  
)  
edge0
```

```
[(444096.3161762458, 4482762.870216271),  
(444171.15812731703, 4482855.001910598)]
```

We can use those to extract adjacencies to each node:

```
db_graph[node0a]
```

```
AdjacencyView({(444171.15812731703, 4482855.001910598): {0: {'level_0':  
0, 'level_1': 0, 'OGC_FID': '1', 'dm_id': '1', 'dist_barri': '1606',  
'average_quality': 3.277406, 'population_density': 1149.981915, 'X':  
444133.736820226, 'Y': 4482808.89166328, 'value': nan, 'geometry':  
<shapely.geometry.linestring.LineString object at 0x7fd97668bbe0>,  
'mm_len': 118.69948078964639}}, (444083.8275243509, 4482747.422611062):  
{538: {'level_0': 538, 'level_1': 0, 'OGC_FID': '539', 'dm_id': '539',  
'dist_barri': '1606', 'average_quality': 3.225291, 'population_density':  
2833.605516, 'X': 444090.105664431, 'Y': 4482755.13506047, 'value': nan,  
'geometry': <shapely.geometry.linestring.LineString object at  
0x7fd985c4ad30>, 'mm_len': 19.864413729824115}}})
```

We can access edge information for each pair of nodes with a concatenated dict query:

```
db_graph[node0a][node0b]
```

```
AtlasView({0: {'level_0': 0, 'level_1': 0, 'OGC_FID': '1', 'dm_id': '1',  
'dist_barri': '1606', 'average_quality': 3.277406, 'population_density':  
1149.981915, 'X': 444133.736820226, 'Y': 4482808.89166328, 'value': nan,  
'geometry': <shapely.geometry.linestring.LineString object at  
0x7fd97668bbe0>, 'mm_len': 118.69948078964639}})
```

```
db_graph[node0a][node0b][0]
```

```
{'level_0': 0,
 'level_1': 0,
 'OGC_FID': '1',
 'dm_id': '1',
 'dist_barri': '1606',
 'average_quality': 3.277406,
 'population_density': 1149.981915,
 'X': 444133.736820226,
 'Y': 4482808.89166328,
 'value': nan,
 'geometry': <shapely.geometry.linestring.LineString at 0x7fd97668bbe0>,
 'mm_len': 118.69948078964639}
```

```
db_graph[node0a][node0b][0]["geometry"]
```



If we need all the node IDs:

```
list(
    db_graph.nodes
)[:5] # Limit to the first five elements
```

```
[(444096.3161762458, 4482762.870216271),
 (444171.15812731703, 4482855.001910598),
 (444212.942998509, 4482901.090971609),
 (444097.96831143444, 4482915.825653204),
 (445608.8837672261, 4479346.814511424)]
```

And same for edges:

 Note

`edges` returns a triplet with the origin and destination node IDs, and the ID of the edge, which is linked to the ID of the segment in the geo-table

```
list(
    db_graph.edges
)[:5] # Limit to the first five elements
```

```
[((444096.3161762458, 4482762.870216271),
 (444171.15812731703, 4482855.001910598),
 0),
 ((444096.3161762458, 4482762.870216271),
 (444083.8275243509, 4482747.422611062),
 538),
 ((444171.15812731703, 4482855.001910598),
 (444212.942998509, 4482901.090971609),
 1),
 ((444171.15812731703, 4482855.001910598),
 (444097.96831143444, 4482915.825653204),
 2),
 ((444212.942998509, 4482901.090971609),
 (444254.9705938099, 4482866.143285849),
 10886)]
```

Or:

```
db_graph.edges[node0a, node0b, 0]
```

```

{'level_0': 0,
 'level_1': 0,
 'OGC_FID': '1',
 'dm_id': '1',
 'dist_barri': '1606',
 'average_quality': 3.277406,
 'population_density': 1149.981915,
 'X': 444133.736820226,
 'Y': 4482808.89166328,
 'value': nan,
 'geometry': <shapely.geometry.linestring.LineString at 0x7fd97668bbe0>,
 'mm_len': 118.69948078964639}

```

If you want fast access to adjacencies:

```
db_graph.adj[node0a]
```

```

AdjacencyView({(444171.15812731703, 4482855.001910598): {0: {'level_0': 0, 'level_1': 0, 'OGC_FID': '1', 'dm_id': '1', 'dist_barri': '1606', 'average_quality': 3.277406, 'population_density': 1149.981915, 'X': 444133.736820226, 'Y': 4482808.89166328, 'value': nan, 'geometry': <shapely.geometry.linestring.LineString object at 0x7fd97668bbe0>, 'mm_len': 118.69948078964639}, (444083.8275243509, 4482747.422611062): {538: {'level_0': 538, 'level_1': 0, 'OGC_FID': '539', 'dm_id': '539', 'dist_barri': '1606', 'average_quality': 3.225291, 'population_density': 2833.605516, 'X': 444090.105664431, 'Y': 4482755.13506047, 'value': nan, 'geometry': <shapely.geometry.linestring.LineString object at 0x7fd985c4ad30>, 'mm_len': 19.864413729824115}}})

```

Challenge

Create the graph version of [subnet](#) and consider the street segment indexed in the table as [53271](#). Check the adjacencies on both ends of the segment using [db_graph](#) and [subnet](#). Are they the same in both graphs? Why?

Analysing graphs

There are *many* ways to extract information and descriptives from a graph. In this section we will explore a few that can tell us important information about the position of a node or edge in the network and about the broader characteristics of sections of the graph.

Degree

Degree tells us the number of neighbors of every edge, that is how many other nodes it is directly connected to.

```
degree = list(db_graph.degree)
degree[:5]
```

```

[((444096.3161762458, 4482762.870216271), 2),
 ((444171.15812731703, 4482855.001910598), 3),
 ((444212.942998509, 4482901.090971609), 3),
 ((444097.96831143444, 4482915.825653204), 3),
 ((445608.8837672261, 4479346.814511424), 2)]

```

Node centrality

Fraction of nodes a node is connected to:

```
nc = pandas.Series(
    nx.degree_centrality(db_graph)
)
nc.head()
```

```
444096.316176 4.482763e+06 0.00004
444171.158127 4.482855e+06 0.00006
444212.942999 4.482901e+06 0.00006
444097.968311 4.482916e+06 0.00006
445608.883767 4.479347e+06 0.00004
dtype: float64
```

```
nc.plot.hist(bins=100, figsize=(6, 3));
```



💡 Tip

Other variations of centrality measures are available in [networkx](#). They are computationally demanding but relatively straightforward to calculate using the library. For a few of those, you can check:

- [This networkx example](#)
- [The momepy documentation on centrality](#)

ℹ️ Challenge

Create a histogram of degree for `db_graph`. Now replicate the figure for the case of `subnet`. *What can you learn about the two graphs by doing this exercise?*

Meshedness

The [meshedness](#) of a graph captures the degree of node edge density as compared to that of nodes. Higher meshedness is related to denser, more inter-connected grids.

```
%time meshd = momepy.meshedness(db_graph, distance=500)
```

```
CPU times: user 1min 9s, sys: 353 ms, total: 1min 10s
Wall time: 1min 9s
```

```
meshd.nodes[node0a]
```

```
{'meshedness': 0.058823529411764705}
```

```
pandas.Series(
    {i: meshd.nodes[i]['meshedness'] for i in meshd.nodes}
).plot.hist(bins=100, figsize=(9, 4));
```



ℹ️ Challenge

Replicate the computation of meshedness for `sub_graph` using a threshold of 250m and 500m. How do the distributions of both compare with each other?

Betweenness centrality

How often do shortest-path routes pass through a given node?

This is computationally very demanding, so we will work on a subset of the full graph:

```

ids = ['0101', '0102', '0103', '0104', '0105', '0106']
subnet = db_tab[db_tab['dist_barri'].isin(ids)]
sub_graph = momepy.gdf_to_nx(subnet)
node_sub = subnet.loc[53271, 'geometry'].coords[0]

```

Calculating it is trivial with [momepy](#):

```

%%time
betweenness = momepy.betweenness_centrality(sub_graph)

```

```

CPU times: user 18.6 s, sys: 0 ns, total: 18.6 s
Wall time: 18.6 s

```

As with meshedness, we obtain another graph in return with the information attached to it:

```

betweenness.nodes[node_sub]

```

```

{'betweenness': 0.0011679130514459708}

```

Attaching information to street segments

The trick here is to be able to transfer back the information stored as graphs into geo-tables so we can apply everything we already know about manipulating and mapping data in that structure. With [momepy](#), we can bring a graph back into a geo-table:

```

nodes = momepy.nx_to_gdf(
    meshd, points=True, lines=False
)

```

```

nodes.head()

```

	meshedness	nodeID	geometry
0	0.058824	0	POINT (444096.316 4482762.870)
1	0.092308	1	POINT (444171.158 4482855.002)
2	0.101449	2	POINT (444212.943 4482901.091)
3	0.065574	3	POINT (444097.968 4482915.826)
4	0.000000	4	POINT (445608.884 4479346.815)

```

ax = nodes.plot(
    "meshedness",
    scheme="fisherjenkssampled",
    markersize=0.1,
    legend=True,
    figsize=(12, 12)
)
contextily.add_basemap(
    ax,
    crs=nodes.crs,
    source=contextily.providers.CartoDB.DarkMatterNoLabels
)
ax.set_title("Meshedness");

```



With other measures index on node IDs, we can use joining machinery in [pandas](#):

```

nc.head()

```

```
444096.316176 4.482763e+06 0.00004
444171.158127 4.482855e+06 0.00006
444212.942999 4.482901e+06 0.00006
444097.968311 4.482916e+06 0.00006
445608.883767 4.479347e+06 0.00004
dtype: float64
```

```
degree_tab = pandas.DataFrame(
    degree, columns=["id", "degree"]
)
degree_tab.index = pandas.MultiIndex.from_tuples(
    degree_tab["id"]
)
degree_tab = degree_tab["degree"]
degree_tab.head()
```

```
444096.316176 4.482763e+06 2
444171.158127 4.482855e+06 3
444212.942999 4.482901e+06 3
444097.968311 4.482916e+06 3
445608.883767 4.479347e+06 2
Name: degree, dtype: int64
```

```
net_stats = pandas.DataFrame(
    {"degree": degree_tab, "centrality": nc},
)
net_stats.index.names = ["x", "y"]
net_stats.head()
```

		degree	centrality
x	y		
444096.316176	4.482763e+06	2	0.00004
444171.158127	4.482855e+06	3	0.00006
444212.942999	4.482901e+06	3	0.00006
444097.968311	4.482916e+06	3	0.00006
445608.883767	4.479347e+06	2	0.00004

```
net_stats_geo = nodes.assign(
    x=nodes.geometry.x
).assign(
    y=nodes.geometry.y
).set_index(
    ["x", "y"]
).join(net_stats)

net_stats_geo.head()
```

	x	y	meshedness	nodeID	geometry	degree	ce
444096.316176	4.482763e+06	0.058824	0	POINT (444096.316 4482762.870)		2	(
444171.158127	4.482855e+06	0.092308	1	POINT (444171.158 4482855.002)		3	(
444212.942999	4.482901e+06	0.101449	2	POINT (444212.943 4482901.091)		3	(
444097.968311	4.482916e+06	0.065574	3	POINT (444097.968 4482915.826)		3	(
445608.883767	4.479347e+06	0.000000	4	POINT (445608.884 4479346.815)		2	(

```
f, axs = plt.subplots(1, 2, figsize=(18, 9))
vars_to_plot = ["degree", "centrality"]
for i in range(2):
    net_stats_geo.plot(
        vars_to_plot[i],
        scheme="fisherjenkssampled",
        markersize=0.2,
        legend=True,
        ax=axs[i]
    )
    contextily.add_basemap(
        axs[i],
        crs=nodes.crs,
        source=contextily.providers.CartoDB.DarkMatterNoLabels
    )
    axs[i].set_title(f"Node {vars_to_plot[i]}")
```



Challenge

Create choropleths for node and betweenness centrality for `sub_graph`. How do they compare?

Next steps

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

- The [NetworkX tutorial](#) is a great place to get a better grasp of the data structures we use to represent (spatial) graphs
- Parts of the block benefit from the section on [urban networks](#) in Geoff Boeing's excellent [course on Urban Data Science](#)
- If you are interested in urban morphometric analysis (the study of the shape of different elements making up cities), the [momepy](#) library is an excellent reference to absorb, including its [user guide](#)

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
```

Moving along (street) networks

[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()      # We "explode" to avoid multi-part rows
    )
)
nodes = nodes.set_index("nodeID")# Reindex nodes on ID
```

```
<timed exec>:3: FutureWarning: Currently, index_parts defaults to True,
but in the future, it will default to False to be consistent with Pandas.
Use `index_parts=True` to keep the current behavior and True/False to
silence the warning.
```

```
CPU times: user 3.96 s, sys: 48.2 ms, total: 4.01 s
Wall time: 4.01 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 8 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 0x7f00bd5cfbe0>
```

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 (440247.814 4474264.648)	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, sol.geometry.x],
    [first.geometry.y, sol.geometry.y]
)
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):



	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, sol.geometry.x],  
    [first.geometry.y, sol.geometry.y])  
)  
# 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 8 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();

```



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.geometries_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()

```



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
)
```

```
/opt/conda/lib/python3.9/site-packages/pandana/network.py:660:
DeprecationWarning: The default dtype for empty Series will be 'object' instead of 'float64' in a future version. Specify a dtype explicitly to silence this warning.
    elif isinstance(maxitems, type(pd.Series())):
/opt/conda/lib/python3.9/site-packages/pandana/network.py:668:
DeprecationWarning: The default dtype for empty Series will be 'object' instead of 'float64' in a future version. Specify a dtype explicitly to silence this warning.
    elif isinstance(maxdist, type(pd.Series())):
```

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  
    nnode=abbs_nnode # Attach to these 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 radius?*

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

```
CPU times: user 1.07 s, sys: 19.7 ms, total: 1.09 s  
Wall time: 1.09 s
```

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

We draw a radius 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 assign 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
```



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.

Shortest-path along surfaces

[Local files](#) [Online read](#)

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

```
friction_walk = rioxarray.open_rasterio(  
    "../data/cambodia_2020_walking_friction_surface.tif"  
)  
friction_motor = rioxarray.open_rasterio(  
    "../data/cambodia_2020_motorized_friction_surface.tif"  
)  
cities = geopandas.read_file("../data/cambodian_cities.geojson")
```

```
main_roads = ox.geometries_from_place(  
    "Cambodia", tags={"highway": "trunk"}  
)
```

```
# Try read locally  
try:  
    main_roads = geopandas.read_file("../data/cambodia_roads_cache.gpkg")  
# Download/write otherwise  
except:  
    main_roads = ox.geometries_from_place(  
        "Cambodia", tags={"highway": "trunk"})  
    main_roads.to_file(  
        "../data/cambodia_roads_cache.gpkg", driver="GPKG")  
    )
```

From the geo-table of roads, we can generate a surface that has a value of 1 on cells where a road crosses, and 0 otherwise (*rasterisation*).

```
from geocube.api.core import make_geocube  
  
roads_surface = make_geocube(  
    main_roads.assign(  
        one=1  
    ).to_crs(epsg=3148),  
    measurements=["one"],  
    resolution=(500, 500)  
)["one"]
```

Now we turn it into a binary mask:

```
road_mask = xarray.where(  
    roads_surface.isnull(), 0, 1  
)
```

```
road_mask
```

```
xarray.DataArray 'one' (y: 745, x: 847)
```

```
█ array([[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, 0]])
```

▼ Coordinates:

y	float64 1.167e+06 1.168e+06 ... 1.539e+06	
x	float64 2.348e+05 2.352e+05 ... 6.578e+05	
spatial_ref	int64 0	

► Attributes: (0)

Then we can generate the routing from, say Phnom Penh to Poipet, using `xarray-spatial`'s A* algorithm:

```
from xrspatial import a_star_search  
  
# Pull out starting point  
start = cities.query(  
    "UC_NM_MN == 'Phnom Penh'"  
).to_crs(  
    epsg=3148  
) .squeeze().geometry  
  
# Pull out ending point  
end = cities.query(  
    "UC_NM_MN == 'Poipet'"  
).to_crs(  
    epsg=3148  
) .squeeze().geometry  
  
# Routing  
route = a_star_search(  
    road_mask,           # Road surface  
    (start.y, start.x), # Starting point  
    (end.y, end.x),    # Destination point  
    barriers=[0],        # Cell values that cannot be crossed  
    snap_start=True,     # Snap starting point to valid cells  
    snap_goal=True       # Snap ending point to valid cells  
)
```

```
route
```

<matplotlib.collection

```
xarray.DataArray (y: 745, x: 847)
```

```
█ array([[nan, nan, nan, ..., nan, nan, nan],  
       [nan, nan, nan, ..., nan, nan, nan],  
       [nan, nan, nan, ..., nan, nan, nan],  
       ...,  
       [nan, nan, nan, ..., nan, nan, nan],  
       [nan, nan, nan, ..., nan, nan, nan],  
       [nan, nan, nan, ..., nan, nan, nan]])
```

▼ Coordinates:

y	float64 1.167e+06 1.168e+06 ... 1.539e+06	
x	float64 2.348e+05 2.352e+05 ... 6.578e+05	
spatial_ref	int64 0	

► Attributes: (0)

And we can turn the route surface into a line that connects the pixels in the route:

```
from shapely.geometry import LineString

route_line = LineString(
    route.to_series().dropna().reset_index().rename(
        columns={0: "order"})
    .sort_values(
        "order"
    )[
        ["x", "y"]
    ].values
)
route_line
```



Challenge

Calculate the route between Battambang and Sihanoukville. *What is the distance?*

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
- More about [xarray-spatial](#), the library that provides geospatial techniques on top of surfaces is available at the project's [documentation](#)

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_abn.gpkg](#)
- Code used to generate the file [\[URL\]](#).
- Furhter information [\[URL\]](#).



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Airbnb neighbourhoods

Source

This dataset has been directly sourced from the website [Inside Airbnb](#). The file was imported on February 10th 2021.

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

-  Data file [neighbourhoods.geojson](#)
-  Furhter information [\[URL\]](#)



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Arturo

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

-  Data file [arturo_streets.gpkg](#)
-  Code used to generate the file [\[Page\]](#)
-  Furhter information [\[URL\]](#)



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Sentinel 2 - 120m mosaic

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

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

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

-  Data files ([Jan 1st](#), [Apr 1st](#), [Jul 10th](#), [Nov 27th](#))
-  Code used to generate the file [\[Page\]](#)
-  Furhter information [\[URL\]](#)



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Sentinel 2 - 10m GHS composite

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

-  Data file [madrid_scene_s2_10_tc.tif](#)
-  Code used to generate the file [\[Page\]](#)
-  Furhter information [\[URL\]](#)



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Cambodia

Pollution

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

-  Data file [cambodia_s5_no2.tif](#)
-  Code used to generate the file [\[Page\]](#).
-  Furhter information [\[URL\]](#).

Friction surfaces

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

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

Each is provided on a separate file.

-  Data files ([Motorized](#) and [Walking](#))
-  Code used to generate the file [\[Page\]](#).
-  Furhter information [\[URL\]](#).

Regional aggregates

Source

This dataset relies on boundaries from the [Humanitarian Data Exchange](#). The file is provided by the World Food Programme through the Humanitarian Data Exchange and was accessed on February 15th 2021.

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

-  Data file [cambodia Regional.gpkg](#)
-  Code used to generate the file [\[Page\]](#).



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Cambodian cities

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

-  Data file [cambodian_cities.geojson](#)
-  Code used to generate the file [\[Page\]](#).
-  Furhter information [\[URL\]](#).



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Further Resources

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

Courses

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

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

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

https://darribas.org/gds_course

Books

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

<https://pythongis.org/>

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

<https://geographicdata.science>

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By Dani Arribas-Bel & Diego Puga



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