Practical 9: Selecting Data

Selecting & Linking Data

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> **Important**
>
> This practical focusses on data linkage! You will have seen quite a bit of this of these across the preceding three to four weeks, but they were picked up in an *ad-hoc* way, here we try to systematise things a bit.

> **Connections**
>
> We're going to look at how data can be joined (linked) to other data using a range of techniques: pure Python (spatial and non-spatial) and SQL (non-spatial only).

1 Preamble

```
ymd  = '20240614'
city = 'London'
host = 'https://orca.casa.ucl.ac.uk'
url  = f'{host}/~jreades/data/{ymd}-{city}-listings.geoparquet'
```

```
import os
import numpy as np
import pandas as pd
import geopandas as gpd
import seaborn as sns
```

```python
import matplotlib.cm as cm
import matplotlib.pyplot as plt
```

```python
import os
from requests import get
from urllib.parse import urlparse
from functools import wraps

def check_cache(f):
    @wraps(f)
    def wrapper(src, dst, min_size=100):
        url = urlparse(src) # We assume that this is some kind of valid URL
        fn  = os.path.split(url.path)[-1] # Extract the filename
        dsn = os.path.join(dst,fn) # Destination filename
        if os.path.isfile(dsn) and os.path.getsize(dsn) > min_size:
            print(f"+ {dsn} found locally!")
            return(dsn)
        else:
            print(f"+ {dsn} not found, downloading!")
            return(f(src, dsn))
    return wrapper

@check_cache
def cache_data(src:str, dst:str) -> str:
    """Downloads a remote file.

    The function sits between the 'read' step of a pandas or geopandas
    data frame and downloading the file from a remote location. The idea
    is that it will save it locally so that you don't need to remember to
    do so yourself. Subsequent re-reads of the file will return instantly
    rather than downloading the entire file for a second or n-th itme.

    Parameters
    ----------
    src : str
        The remote *source* for the file, any valid URL should work.
    dst : str
        The *destination* location to save the downloaded file.

    Returns
    -------
    str
        A string representing the local location of the file.
    """

    # Convert the path back into a list (without)
    # the filename -- we need to check that directories
    # exist first.
    path = os.path.split(dst)[0]
    print(f"Path: {path}")
```

```python
    # Create any missing directories in dest(ination) path
    # -- os.path.join is the reverse of split (as you saw above)
    # but it doesn't work with lists... so I had to google how
    # to use the 'splat' operator! os.makedirs creates missing
    # directories in a path automatically.
    if path != '':
        os.makedirs(path, exist_ok=True)

    # Download and write the file
    with open(dst, "wb") as file:
        response = get(src)
        file.write(response.content)

    print(' + Done downloading...')

    return dst
```

```python
ddir = os.path.join('data','geo') # destination directory
pqt  = cache_data(url, ddir)
```

```
+ data/geo/20240614-London-listings.geoparquet found locally!
```

2 Selecting Data

2.1 In Pandas

2.1.1 Recap: A First Query

```python
pd.read_parquet(f'{pqt}').head(3)
```

	id	listing_url	last_scraped	name
0	92644	https://www.airbnb.com/rooms/92644	2023-09-06	Rental unit in Earlsfield · ?4.57
1	93015	https://www.airbnb.com/rooms/93015	2023-09-06	Rental unit in Hammersmith ·
2	13913	https://www.airbnb.com/rooms/13913	2023-09-06	Rental unit in Islington · ?4.80

This should (I hope) be trivial to read now: we are loading a parquet file using pandas and taking advantage of Python's 'chaining' functionality (`<object>.<method>().<method>()...`) to return the first three rows using `head`. It is worth noticing that we're not even bothering to save the result of this command to a data frame (thus the lack of a `df =` in the code) and We're doing this here solely so that you can compare pandas and SQL/DuckDB syntax across each of the following steps.

2.1.2 Recap: Selecting some columns

To load a columnar subset of the data we have two options:

1. Load all the data and *then* subset (which always happens with CSV files but is optional with other formats)
2. Load only the columns we care about (which is possible with parquet files)

And in code these are:

Load then filter

```
%%time
pd.read_parquet(f'{pqt}')[['listing_url', 'price', 'number_of_reviews', 'property_ty
```

```
CPU times: user 133 ms, sys: 44.9 ms, total: 178 ms
Wall time: 133 ms
```

	listing_url	price	number_of_reviews	property_type
0	https://www.airbnb.com/rooms/92644	42.0	216.0	Private room in rental u
1	https://www.airbnb.com/rooms/93015	175.0	38.0	Entire rental unit
2	https://www.airbnb.com/rooms/13913	79.0	41.0	Private room in rental u
3	https://www.airbnb.com/rooms/15400	150.0	94.0	Entire rental unit
4	https://www.airbnb.com/rooms/93734	46.0	180.0	Private room in condo

Filter then load

```
%%time
pd.read_parquet(f'{pqt}', columns=['listing_url', 'price', 'number_of_reviews', 'pro
```

```
CPU times: user 14 ms, sys: 1.83 ms, total: 15.8 ms
Wall time: 13 ms
```

	listing_url	price	number_of_reviews	property_type
0	https://www.airbnb.com/rooms/92644	42.0	216.0	Private room in rental u
1	https://www.airbnb.com/rooms/93015	175.0	38.0	Entire rental unit
2	https://www.airbnb.com/rooms/13913	79.0	41.0	Private room in rental u
3	https://www.airbnb.com/rooms/15400	150.0	94.0	Entire rental unit
4	https://www.airbnb.com/rooms/93734	46.0	180.0	Private room in condo

Notice the difference in time!!!

2.1.3 Recap: Adding a constraint

```
df = pd.read_parquet(f'{pqt}', columns=['listing_url', 'price', 'number_of_reviews',
df[(df.price < 250) & (df.number_of_reviews > 0) & (df.property_type=='Entire home/a
```

	listing_url	price	number_of_reviews	prop
18922	https://www.airbnb.com/rooms/20296839	96.0	7.0	Entir
18975	https://www.airbnb.com/rooms/20349067	99.0	1.0	Entir
22319	https://www.airbnb.com/rooms/22959348	100.0	3.0	Entir
38944	https://www.airbnb.com/rooms/42969992	173.0	1.0	Entir
52418	https://www.airbnb.com/rooms/649784743352942906	91.0	9.0	Entir

For improved legibility you can also write this as:

```
df = pd.read_parquet(f'{pqt}', columns=['listing_url', 'price', 'number_of_reviews',
df[
    (df.price < 250) &
    (df.number_of_reviews > 0) &
    (df.property_type=='Entire home/apt')
].head(5)
```

Notice here that we are using three conditions to filter the data *as well as* a column filter on loading to minimise the amount of data loaded into memory. Applying the filters simultaneously will also make it easy to see what you've done (you aren't applying each one separately) and to adjust the overall cleaning process.

This filter is fairly straightforward, but things get more complicated when you want to aggregate the return…

2.1.4 Aggregating the return

There is a *lot* to unpack here, and notice that it takes three steps to achieve our goal of selecting, grouping, aggregating, sorting, and printing out the ten most frequent combinations of room and property type.

```
df = pd.read_parquet(f'{pqt}', columns=['property_type','room_type','number_of_revie
df = df[
    (df.price < 1050) &
    (df.number_of_reviews > 0)
]
df.groupby(
        by=['room_type','property_type'],
        observed=True
    ).agg(
        freq = ("property_type", "count"),
        median_price = ("price", "median"),
).reset_index().sort_values(
        by=['freq','room_type','property_type'], ascending=[False,True,True]
    ).head(10)
```

	room_type	property_type	freq	median_price
18	Entire home/apt	Entire rental unit	24662	136.0
68	Private room	Private room in rental unit	9763	52.0
59	Private room	Private room in home	7800	49.0
10	Entire home/apt	Entire condo	7542	156.0
14	Entire home/apt	Entire home	5243	200.0
52	Private room	Private room in condo	2883	67.0
19	Entire home/apt	Entire serviced apartment	1565	200.0
72	Private room	Private room in townhouse	1205	55.0
20	Entire home/apt	Entire townhouse	967	235.0
45	Private room	Private room in bed and breakfast	412	78.0

Hopefully the first two steps are fairly clear, so let's focus on the final one:

Group By

This is a *reasonably* intelligible step in which we group the data loaded by room and property:

```
dfg = df.groupby(
        by=['room_type','property_type'],
        observed=True
    )
dfg
```

The *order* here matters: `groupby(by=[<A>,<B>])` does not return the same result as `groupby(by=[<B>,<A>])`. Try it:

```
df.groupby(
        by=['property_type','room_type'],
        observed=True
    )
```

The other thing to note here is the `observed=True`. This is a nice bit of additional functionality that, if you set it to `False` will return a number for all possible combinations, inserting a zero if that combintaion is *not* observed in the data.

Agg

The `agg` step aggregates the data specified in the functions:

```
dfg.agg(
        freq = ("property_type", "count"),
        median_price = ("price", "median"),
)
```

Pandas offers a *lot* of different ways to do this, but the above approach is perhaps the most flexible since we are telling Pandas to apply the `count` function to the `property_type` field and assign it to a column called `freq`, and to apply the `median` function to the `price` field and assign that to a column called `median_price`.

'Degroup'

In order to work with the aggregated data you will *almost* always want to convert your `GroupedDataFrame` back to a regular `DataFrame` and that means resetting the index `reset_index()` – this is just one of those things to learn about grouped data in Pandas.

Sort

Finally, to sort the *data* (which is usually what you want) you need to `sort_values`, where `by` specifies the fields you want to sort on and `ascending` is a matching (optional) list that specifies the sort order for each sort column. If you just want to sort everything in ascending order then you don't need to specify the `ascending` values, and if you wanted to sort *everything* in descending order then it's just `ascending=False`.

2.2 In SQL

That last example may have left you despairing of every being able to select/filter/aggregate/derive your data, but there *is* another way that is often far simpler *if* you are: a) willing to learn a different language, and b) willing to work with data in different formats. And that's all thanks to Parquet and DuckDB.

2.2.1 Parquet and DuckDB

One of the recent technical *revolutions* that has fundamentally reshaped my workflow is the combination of parquet files and in-memory databases. Parquet and Apache Arrow are closely related but, in short, when you want to save large data sets in an easy-to-access format then Parquet should be your default choice. DuckDB gives you a way to treat Parquet files *as* a database **table** and run queries against it using standard SQL. You can install DuckDB on the command-line, but you can also query it from within Python using the appropriate module.

2.2.2 A First Query

Let's see a quick demonstration:

```
import duckdb as db

query = f'''
SELECT *
FROM read_parquet('{pqt}')
LIMIT 3;
'''

db.sql(query).to_df()
```

	id	listing_url	last_scraped	name
0	92644	https://www.airbnb.com/rooms/92644	2023-09-06	Rental unit in Earlsfield · ?4.57
1	93015	https://www.airbnb.com/rooms/93015	2023-09-06	Rental unit in Hammersmith ·
2	13913	https://www.airbnb.com/rooms/13913	2023-09-06	Rental unit in Islington · ?4.80

And now let's unpack this:

1. We import the `duckdb` library as `db`.
2. We set up a SQL `query` using a multi-line f-string
3. We use DuckDb to execute the query and return a pandas dataframe (`df`)

What's particularly elegant here (and quite different from trying to talk to a Postres or MySQL database) is that there's no connect-execute-collect pattern; we just build the query and execute it!

2.2.3 Deciphering SQL

I *do* declare...

Now let's take a look at the SQL query... SQL is what's called a declarative language, meaning that it is about the logic we want the program to follow rather than the 'flow' of execution. Python supports *some* declarative elements but is more commonly seen as an imperative language supporting procedural or functional approaches. This is a long way of saying: SQL won't look like Python even though we're executing SQL from *within* Python.

So our query (with added line numbers for clarity) looked liked this:

```
1 SELECT *
2 FROM read_parquet('{pqt}')
3 LIMIT 3
```

Line-by-line this means:

1. Select all columns (`SELECT <* == everything>`)
2. From the parquet file (`FROM <table location>`)
3. Limit the return to 3 rows (`LIMIT <row count>`)

Let's look at some variations...

2.2.4 Choosing some columns

```
query = f'''
SELECT listing_url, price, number_of_reviews, last_review, host_name
FROM read_parquet('{pqt}')
LIMIT 5;
'''
```

```
db.sql(query).to_df()
```

	listing_url	price	number_of_reviews	last_review	host_nam
0	https://www.airbnb.com/rooms/92644	42.0	216.0	2022-10-29	Dee Dee
1	https://www.airbnb.com/rooms/93015	175.0	38.0	2022-09-30	Sarah
2	https://www.airbnb.com/rooms/13913	79.0	41.0	2022-12-11	Alina
3	https://www.airbnb.com/rooms/15400	150.0	94.0	2023-05-01	Philippa
4	https://www.airbnb.com/rooms/93734	46.0	180.0	2023-09-02	William

```sql
SELECT listing_url, price, number_of_reviews, last_review, host_name
FROM read_parquet('{pqt}')
LIMIT 5;
```

It should be fairly easy to see how the query has changed from last time, but line-by-line this means:

1. Select a set of columns from the table in the order specified (`SELECT <column 1>, <column 30>, <column 5>...`)
2. From the parquet file (`FROM <table location>`)
3. Limit the return to 5 rows (`LIMIT <row count>`)

2.2.5 Adding a constraint

```
query = f'''
SELECT listing_url, price, number_of_reviews, last_review, host_name
FROM read_parquet('{pqt}')
WHERE price < 250
AND number_of_reviews > 0
AND property_type='Entire home/apt'
LIMIT 5;
'''

db.sql(query).to_df()
```

	listing_url	price	number_of_reviews	last_revie
0	https://www.airbnb.com/rooms/20296839	96.0	7.0	2017-10-0
1	https://www.airbnb.com/rooms/20349067	99.0	1.0	2017-11-12
2	https://www.airbnb.com/rooms/22959348	100.0	3.0	2018-02-0
3	https://www.airbnb.com/rooms/42969992	173.0	1.0	2021-10-2
4	https://www.airbnb.com/rooms/649784743352942906	91.0	9.0	2023-03-2

In this query we've added *three* constraints using a `WHERE`, which is asking DuckDB to find all of the rows *where* the following things are true:

4. The `price` must be less than ($)250/night
5. The `number_of_reviews` must be more than 0
6. The `property_type` must be `Entire home/apt`

2.2.6 Aggregating the return

So far, we've seen a few ways (and hopefully enough to get you started) to *select* data, but databases also 'excel' at aggregating data in various ways. We aren't going to get into things like windowing functions or stored procedures here, but even simple aggregates done in DuckDB can vastly improve on the performance of pandas.

> **Tip**
>
> When you aggregate data you need to retrieve *every* column in the `SELECT` portion that you `GROUP BY` in the `WHERE` portion of the query. This will make sense when you see the examples below… (and should also make sense based on the Pandas equivalent above)

```
query = f'''
SELECT property_type, room_type, COUNT(*) AS frequency, MEDIAN(price)
FROM read_parquet('{pqt}')
WHERE price < 1000
AND number_of_reviews > 0
GROUP BY room_type, property_type
ORDER BY frequency DESC, room_type, property_type
LIMIT 10;
'''

db.sql(query).to_df()
```

	property_type	room_type	frequency	median(price)
0	Entire rental unit	Entire home/apt	24634	136.0
1	Private room in rental unit	Private room	9754	52.0
2	Private room in home	Private room	7797	49.0
3	Entire condo	Entire home/apt	7532	155.0
4	Entire home	Entire home/apt	5228	200.0
5	Private room in condo	Private room	2880	67.0
6	Entire serviced apartment	Entire home/apt	1565	200.0
7	Private room in townhouse	Private room	1204	55.0
8	Entire townhouse	Entire home/apt	964	234.5
9	Private room in bed and breakfast	Private room	412	78.0

There are quite a few changes to the query here so it's worth reviewing them in more detail:

```sql
SELECT property_type, room_type, COUNT(*) AS frequency, MEDIAN(price)
FROM read_parquet('{pqt}')
WHERE price < 1000
AND number_of_reviews > 0
GROUP BY room_type, property_type
ORDER BY frequency DESC, room_type, property_type
LIMIT 10;
```

Key things to note:

1. We have two new aggregate *functions*:

   - `COUNT(*)` returns a count of the number of rows in each group specified in the `GROUP BY` clause.
   - `MEDIAN(price)` returns, unsurprisingly, the median value of the `price` column for each group specified in the `GROUP BY` clause.
   - *Note* also the `AS frequency` which 'renames' the column returned by the query; it's the same concept as the `import x as y` in Python.

2. `GROUP BY` is where the aggregation happens, and here we're asking DuckDB to take all of the rows selected (`WHERE price < 1000 AND number_of_reviews > 0`) and group them using the `room_type` and `property_type` fields.
3. `ORDER BY` orders the returned records by the columns we specify, and they can be either `ASC`ending (the default) or `DESC`ending (descending).

What you should also be noting here is that:

- This query returns *very* quickly compared to the pandas equivalent.
- We have been able to express our selection, grouping, and organising criteria very succinctly.

In terms of both speed and intelligibility, there can be quite substantial advantages to moving *some* of your workflow into a database or a database-like format such as Parquet and then querying that from Python. Databases are *designed* for the kind of application that Pandas struggles with, and if you get to windowing functions and stored procedures you'll see how there are situations where something is far easier to express in Python/Pandas than in SQL.

So the trick here is to recognise when you are facing a problem that: a) will benefit from being expressed/tackled in a different language; and b) won't create undue overhead on your technology 'stack'. In working with environmental and built environment data I was able to cut the processing time by 80% when I moved the bulk of the data linkage work from Pandas into Parquet+DuckDB. *But*, by the same token, what's the point of using Postgres and managing a spatial database to perform a single step in a much longer workflow *unless* the performance considerations are so massive they outweigh any other issue.

3 Non-Spatial Joins

We're going to look at joining data by attributes *first* and then look at spatial joins so that you get a sense of how they behave and differ.

For non-spatial joins we only need two data sets relating to MSOAs:

```
msoa_names_url = 'https://houseofcommonslibrary.github.io/msoanames/MSOA-Names-1.20.
msoa_popst_url = 'https://orca.casa.ucl.ac.uk/~jreades/data/sapemsoaquinaryagetablef

msoa_df = pd.read_excel(msoa_popst_url, sheet_name="Mid-2022 MSOA 2021", header=3)
msoa_nms = pd.read_csv( cache_data(msoa_names_url, 'data') )

# For DuckDB
if not os.path.exists('data/MSOA_population_estimates.parquet'):
```

```
    msoa_df.to_parquet('data/MSOA_population_estimates.parquet')

print(f"msoa_df  has {msoa_df.shape[0]:,} rows and {msoa_df.shape[1]:,} columns.")
print(f"msoa_nms has {msoa_nms.shape[0]:,} rows and {msoa_nms.shape[1]:,} columns.")
```

```
+ data/MSOA-Names-1.20.csv found locally!
msoa_df  has 7,264 rows and 43 columns.
msoa_nms has 7,201 rows and 6 columns.
```

The preferred solution

To keep it simple: you should assume that non-spatial joins are *always* going to be faster than spatial ones, even in a performant spatial database. Asking if one number is less than another, or if a piece of text is found in another piece of text, is *much* simpler than asking if one object falls within the boundaries of another. Spatial databases are fast and very cool, but if you can express your problem non-spatially it will be faster to solve it that way too.

3.1 In Pandas

Pandas distinguishes between several types of what SQL would call a 'join': the process of linking two data sets. Depending on what you want to do, this will fall into one of the merge, join, concatenate, or compare functions:

- `concat` simply appends one data frame to another and won't be discussed further, but keep in mind that you can concatenate horizontally and vertically (across and down), and that having named indexes can cause consternation. You would find it most useful for appending columns to a data set (appending rows should be approached differently) or extending a data set for year n with data from year $n+1$...
- `merge` is what we normally want when we want to do something similar to a SQL join. You should refer back to the lecture for the differences between 'one-to-one', 'one-to-many', and 'many-to-many'. Note too that merging is a function of the pandas library and *not* a method of a data frame.

3.1.1 Joining by attribute

So in our case, to join the two MSOA data sets we're going to need to match the MSOA codes which have (slightly) different names in the two datasets:

```
%%time

rs = pd.merge(msoa_df, msoa_nms[['msoa11cd','msoa11hclnm','Laname']], left_on='MSOA
print(f"Result set has {rs.shape[0]:,} rows and {rs.shape[1]:,} columns.")
rs.head(3)
```

```
Result set has 7,264 rows and 46 columns.
CPU times: user 2.43 ms, sys: 369 µs, total: 2.8 ms
Wall time: 2.65 ms
```

	LAD 2021 Code	LAD 2021 Name	MSOA 2021 Code	MSOA 2021 Name	Total	F0 to 4	F5 to
0	E06000001	Hartlepool	E02002483	Hartlepool 001	10323	265	296
1	E06000001	Hartlepool	E02002484	Hartlepool 002	10460	325	349
2	E06000001	Hartlepool	E02002485	Hartlepool 003	8040	238	287

But wait! There's an issue lurking in the data!

```
print(f"There are {rs.msoa11hclnm.isna().sum()} missing MSOA Names!")
```

```
There are 184 missing MSOA Names!
```

Can you work out why this has happened? There is a clue in the column names!

There's no way to solve this problem except by changing the code to use this URL instead for the MSOA Names.

We can also try to constrain the result set to one LA thanks to data in the MSOA Names database:

```
%%time

la_nm = 'Waltham Forest'
sdf   = msoa_nms[msoa_nms.Laname==la_nm][['msoa11cd','msoa11hclnm','Laname']].copy()

rs = pd.merge(msoa_df, sdf, left_on='MSOA 2021 Code', right_on='msoa11cd', how='inne
print(f"Result set has {rs.shape[0]:,} rows and {rs.shape[1]:,} columns.")
rs.head(3)
```

```
Result set has 28 rows and 46 columns.
CPU times: user 1.8 ms, sys: 207 µs, total: 2 ms
Wall time: 1.94 ms
```

	LAD 2021 Code	LAD 2021 Name	MSOA 2021 Code	MSOA 2021 Name	Total	F0 to 4	F5
0	E09000031	Waltham Forest	E02000895	Waltham Forest 001	8363	208	23
1	E09000031	Waltham Forest	E02000896	Waltham Forest 002	9322	256	27
2	E09000031	Waltham Forest	E02000897	Waltham Forest 003	8438	233	26

Without the `how=inner`, the result set would still have all of the rows but some of the columns would be nearly completely empty.

3.2 In SQL

SQL-based joins use very similar keywords (since Pandas is copying SQL), but how we put together the query is quite different.

3.2.1 Joining by attribute

```
%%time

query = f'''
SELECT *
FROM
    read_parquet('data/MSOA_population_estimates.parquet') as n
LEFT JOIN
    read_csv('{cache_data(msoa_names_url, 'data')}', header=true) as m
ON
    n."MSOA 2021 Code"=m.msoa11cd;
'''

db.sql(query).to_df().head(3)
```

```
+ data/MSOA-Names-1.20.csv found locally!
CPU times: user 27.2 ms, sys: 3.32 ms, total: 30.6 ms
Wall time: 30 ms
```

	LAD 2021 Code	LAD 2021 Name	MSOA 2021 Code	MSOA 2021 Name	Tota
0	E09000001	City of London	E02000001	City of London 001	108
1	E09000002	Barking and Dagenham	E02000002	Barking and Dagenham 001	838
2	E09000002	Barking and Dagenham	E02000003	Barking and Dagenham 002	118(

> **Slower???**
>
> *Without* the data caching function, the query above may *appear* slower than the Pandas one but if you look at the timing information you'll see that the actual time spent processing the data was less. How can that be? Notice that above we're reading the CSV file from the House of Commons library as *part* of the join, so most of that delay is spent waiting for the CSV file to download! That's why I prefer to download a file *once* and save it locally rather than downloading the same file again and again. Plus it's friendlier (and cheaper!) to the person or organisation providing the data to you.

Let's take a look at the SQL:

```sql
SELECT *
FROM
    read_parquet('data/MSOA_population_estimates.parquet') as n
LEFT JOIN
```

```
    read_csv(msoa_names_url, header=true) as m
ON
    n."MSOA 2021 Code"=m.msoa11cd;
```

Line-by-line:

1. `SELECT` every column (this is the `*`, change this if you want to only pull a subset of columns)
2. `FROM` the following tables (it doesn't really matter if the tables are on this line or the next for legibility)
3. `<table 1 from parquet> as n` (we now refer to the data from this table using the prefix `n.`; e.g. `n.Total`)
4. `LEFT JOIN` is the SQL way of saying to keep all of the rows in the first table (`n`, which is the first, and therefore 'left' table)
5. `<table 2 from csv> as m` (we now refer to the data from this table using the prefix `m.`; e.g. `m.geometry`)
6. `ON <left table matching column> = <right table matching column>` (here, the unusual thin is the double-quotes around the column name required to deal with the fact that the label contains spaces).

Notice how there are parallels between even quite different languages here: if you have spaces or special characters or whatever in your column name then you're going to need to handle that a little differently, and if you have two tables to join you have a left (aka first) one and a right (aka second) one and the order matters.

Now, running the same query to get the Waltham Forest data can be done two ways:

```
%%time

boro = 'Waltham Forest'
query = f'''
SELECT *
FROM
    read_parquet('data/MSOA_population_estimates.parquet') as n
INNER JOIN
    read_csv('{cache_data(msoa_names_url, 'data')}', header=true) as m
ON
    n."MSOA 2021 Code"=m.msoa11cd
WHERE
    m.Laname='{boro}';
'''

db.sql(query).to_df().head(3)
```

```
+ data/MSOA-Names-1.20.csv found locally!
CPU times: user 22.5 ms, sys: 2.17 ms, total: 24.7 ms
Wall time: 24.2 ms
```

	LAD 2021 Code	LAD 2021 Name	MSOA 2021 Code	MSOA 2021 Name	Total	F0 to 4	F5
0	E09000031	Waltham Forest	E02000895	Waltham Forest 001	8363	208	23

	LAD 2021 Code	LAD 2021 Name	MSOA 2021 Code	MSOA 2021 Name	Total	F0 to 4	F5
1	E09000031	Waltham Forest	E02000896	Waltham Forest 002	9322	256	27
2	E09000031	Waltham Forest	E02000897	Waltham Forest 003	8438	233	26

Everything here is *basically* the same except for:

1. We changed the `LEFT JOIN` to an `INNER JOIN` – this should make sense to you if you've watched the lectures.
2. We added a `WHERE m.Laname=<borough name>` which restricts the match to only those rows where the Local Authority name is Waltham Forest.

However, note that this query can *also* be written this way:

```
%%time

boro = 'Waltham Forest'
query = f'''
SELECT *
FROM
    read_parquet('data/MSOA_population_estimates.parquet') as n,
    read_csv('{cache_data(msoa_names_url, 'data')}', header=true) as m
WHERE m.Laname='{boro}'
AND n."MSOA 2021 Code"=m.msoa11cd;
'''

db.sql(query).to_df().head(3)
```

```
+ data/MSOA-Names-1.20.csv found locally!
CPU times: user 22.2 ms, sys: 2.01 ms, total: 24.2 ms
Wall time: 23.9 ms
```

	LAD 2021 Code	LAD 2021 Name	MSOA 2021 Code	MSOA 2021 Name	Total	F0 to 4	F5
0	E09000031	Waltham Forest	E02000895	Waltham Forest 001	8363	208	23
1	E09000031	Waltham Forest	E02000896	Waltham Forest 002	9322	256	27
2	E09000031	Waltham Forest	E02000897	Waltham Forest 003	8438	233	26

The second way is a little easier to read, but it *only* allows you to do **inner joins** where attributes need to match in both tables for a row to be kept. This situation is such a common 'use case' that it makes sense to have this simpler syntax, but the previous code will work for inner, left, right, and outer joins.

4 Spatial Joins

Spatial DuckDB

DuckDB also now supports spatial queries via the `SPATIAL` extension. Performance is *not* that of a tuned Postgres+PostGIS database, but the overhead of *creating* such a tuned database often exceeds the benefit for ad-hoc querying. Basically, Postgres+PostGIS is great if you're a company such as Booking.com, Airbnb, or OpenStreetMap, but it's most likely overkill for offline read-oriented applications.

4.1 Why obvious is not always right (Part 432)

Building on what I said above in Section 3, even where you *do* have a spatial challenge, it can be worth it to convert it to a non-spatial solution to improve the overall performance of your code. For instance, say you have data from LSOAs and want to be able to aggregate it up to MSOAs and Boroughs to perform various analyses.

LSOA Table

LSOA Code	Polygon
LSOA1	WKT(...)
LSOA2	WKT(...)
LSOA3	WKT(...)

MSOA Table

MSOA Code	Polygon
MSOA1	WKT(...)
MSOA2	WKT(...)
MSOA3	WKT(...)

Borough Table

Borough Code	Polygon
BORO1	WKT(...)
BORO2	WKT(...)
BORO3	WKT(...)

The *obvious* way to do this is as a spatial join: `select all LSOAs within an MSOA and aggregate them`. And you would then run this same query for every dimension you want to aggregate. **This is *not* the right way to tackle this problem** even though you can write the query to give you the correct answer.

The *right* way when you are going to repeatedly run an expensive spatial query is to work out if you can 'cache' the result to save time in the future. In this case the answer is to create a 'lookup table' which uses the LSOA and MSOA and Borough codes to tell you if a LSOA falls inside a borough or MSOA. You perform the hard spatial query *just once* to create the lookup table, and thereafter you are using a fast non-spatial query.

In this case your lookup table will be this…

Lookup Table

LSOA Code	MSOA Code	Borough Code
LSOA1	MSOA1	BORO1
LSOA2	MSOA1	BORO1
LSOA3	MSOA2	BORO1

Now you can do any kind of *spatial aggregation* you want without having to incur the costs of running a *spatial query* using something like:

```
SELECT m."MSOA Code", SUM(<attribute>) as feature_sum, COUNT(<attribute 2>) as featu
FROM <lsoa data table> as l, <lookup table> as lkp
WHERE l."LSOA Code" = lkp."LSOA Code"
GROUP BY lkp."MSOA Code";
```

See, no need for a spatial query and you can run the same query easily for many features. You can also use this as a foundation for creating a `VIEW` or a `MATERIALIZED VIEW`, but that's an advanced topic for managing your data more efficiently in an operational environment rather than a research-oriented one.

But first, we need some actual geodata to work with:

```
msoa_gpkg = gpd.read_file( cache_data(f'{host}/~jreades/data//MSOA-2011.gpkg', ddir)
listings  = gpd.read_parquet( cache_data(f'{host}/~jreades/data/{ymd}-{city}-listing
```

```
+ data/geo/MSOA-2011.gpkg found locally!
+ data/geo/20240614-London-listings.geoparquet found locally!
```

4.2 In Geopandas

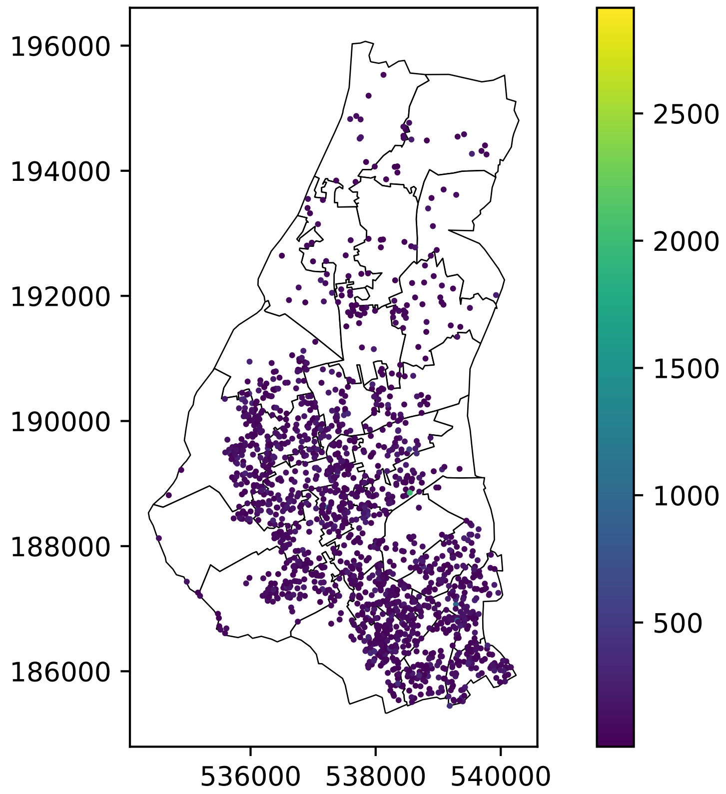
Let's try to find all of the listings that fall within the borough of Waltham Forest, so that implies two steps:

1. Subset the MSOA geo-data so that it only includes the Waltham Forest MSOAs.
2. Run a spatial query to find the listings that are within those MSOAs (we could, optionally, `union` the MSOAs to get the outline of the borough)

```
boro = 'Waltham Forest'
boro_gdf = msoa_gpkg[msoa_gpkg.LAD11NM==boro].copy()
```

```
# Do the spatial join
boro_listings = gpd.sjoin(listings, boro_gdf, predicate='within', rsuffix='_r')

# Layer the plots
f, ax = plt.subplots(1,1,figsize=(8,5))
boro_gdf.plot(color="white", edgecolor="black", linewidth=0.5, ax=ax)
boro_listings.plot(column='price', cmap='viridis', legend=True, s=1.5, aspect=1, ax=
```



> **Warning**
>
> If you get `ValueError: aspect must be finite and positive` when you try to make a plot (this seems fairly common with GeoPackages (`.gpkg` files) then you will need to specify `aspect=1` in the `plot(...)` command.

4.3 In SQL

After quite a bit of faff my conclusion is that, while you *can* do spatial queries in DuckDB it is a lot of work and *probably* not worth the effort *at this time*. The 'issue' is that spatial support (as well as Excel supprt) is provided via the `GDAL` framework and this takes quite a different approach. After working it out, spatial queries do work *fairly* well if you do them *entirely* within DuckDB (reading, merging, and writing the data) and then load the results in a separate step using GeoPandas; however, you *cannot* get a GeoDataFrame back via `db.query(<query>).to_df()` since that only returns a Pandas data frame and the geometry column is unreadable. In addition, geoparquet support seems limited while GeoPackage performance is *poor*, so you're basically losing all the advantages of a parquet-based workflow.

So the examples below are provided for reference only and, on the whole, right now I'd recommend using GeoPandas and geoparquet files directly.

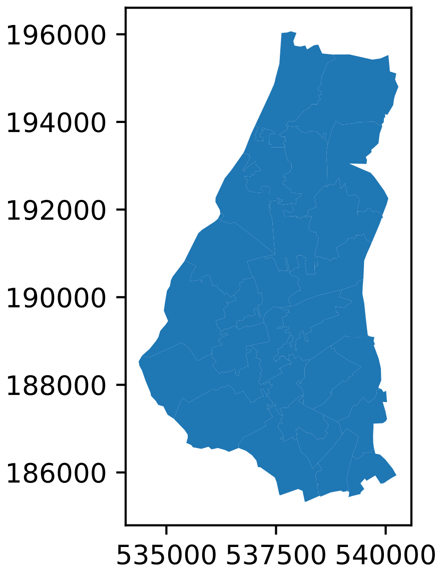
```
%%time

boro = 'Waltham Forest'

query = f'''
LOAD SPATIAL;
COPY(
  SELECT m.MSOA11CD, n.msoa11nm, n.Laname, m.geom
  FROM
      (SELECT MSOA11CD, geom FROM ST_Read("{cache_data(f'{host}/~jreades/data/MSOA-2
      read_csv("{cache_data(msoa_names_url, 'data')}") AS n
  WHERE m.MSOA11CD=n.msoa11cd
  AND n.Laname='{boro}'
) TO 'data/geo/merged.gpkg' WITH (FORMAT GDAL, DRIVER 'GPKG', LAYER_CREATION_OPTIONS
'''

db.sql(query)
rs = gpd.read_file('data/geo/merged.gpkg')
print(f"Result set has {rs.shape[0]:,} rows and {rs.shape[1]:,} columns.")
rs.head(5)
rs.plot(aspect=1)
```

```
+ data/geo/MSOA-2011.gpkg found locally!
+ data/MSOA-Names-1.20.csv found locally!
Result set has 28 rows and 4 columns.
CPU times: user 308 ms, sys: 41.7 ms, total: 350 ms
Wall time: 101 ms
```



5 Worked Example

With that background material, let's now work through a practical example.

5.1 Load Geodata

A lot of useful geo-data can be accessed from the GeoPortal. And see also my discussion on lookup tables.

```
spath = 'https://github.com/jreades/fsds/blob/master/data/src/' # source path
water = gpd.read_file( cache_data(spath+'Water.gpkg?raw=true', ddir) )
boros = gpd.read_file( cache_data(spath+'Boroughs.gpkg?raw=true', ddir) )
green = gpd.read_file( cache_data(spath+'Greenspace.gpkg?raw=true', ddir) )
msoas = gpd.read_file( cache_data(f'{host}/~jreades/data/MSOA-2011.gpkg', ddir) ).to
```

```
+ data/geo/Water.gpkg found locally!
+ data/geo/Boroughs.gpkg found locally!
+ data/geo/Greenspace.gpkg found locally!
+ data/geo/MSOA-2011.gpkg found locally!
```

5.2 Select London MSOAs

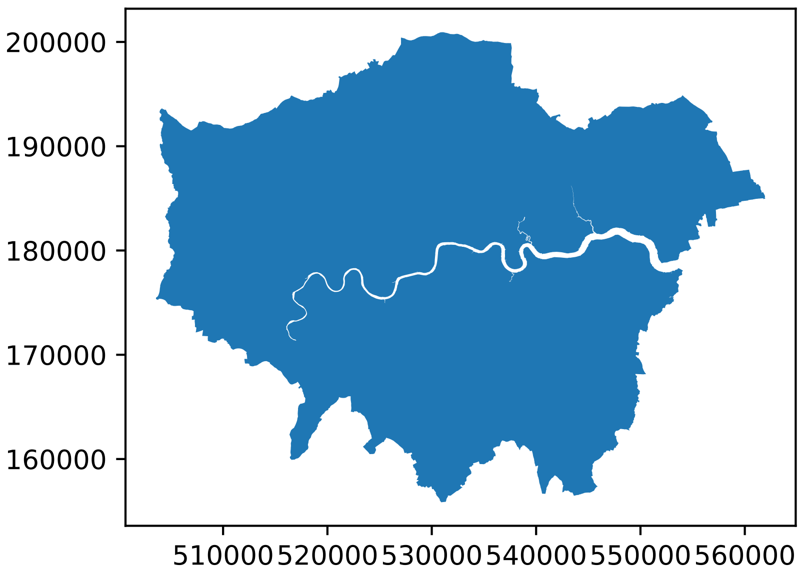
> **ℹ Connections**
>
> One thing to remember here is that computers are *exact*. So if you say that the selection should only be of MSOAs *within* London then you actually need to think about whether a shared border qualifies as 'within'. Watch the lectures again if you're unsure, but that's why here we take this slightly clunk approach of buffering the London boundary *before* doing the selection.

5.2.1 Union

As we don't have a boundary file for London, we can *generate* use using the `unary_union` operator (as we do here) or using the dissolve() approach. Consider the pros and cons of each approach in terms of performance, output format, and leigibility.

So here's approach 1, which is a method call returning a GeoDataFrame (which is why we can call `plot`):

```
boros.dissolve().plot();
```



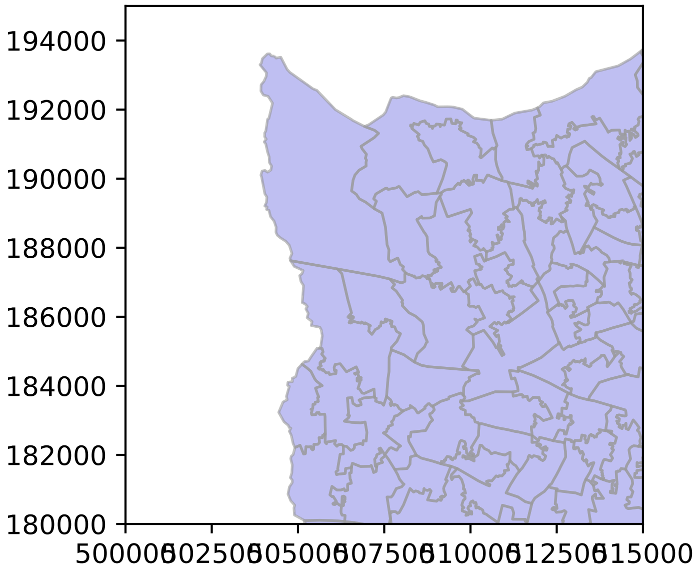
And here's approach 2, which is an *attribute* and returns a raw polygon (so no reason to call `plot`, but it's come back without the rest of the data frame!):

```
boros.unary_union
```

> **ℹ Connections**
>
> Notice how we're also demonstrating some additional ways of plotting 'on the fly' (without generating a data frame) as well as (below) showing you how to zoom in/out.

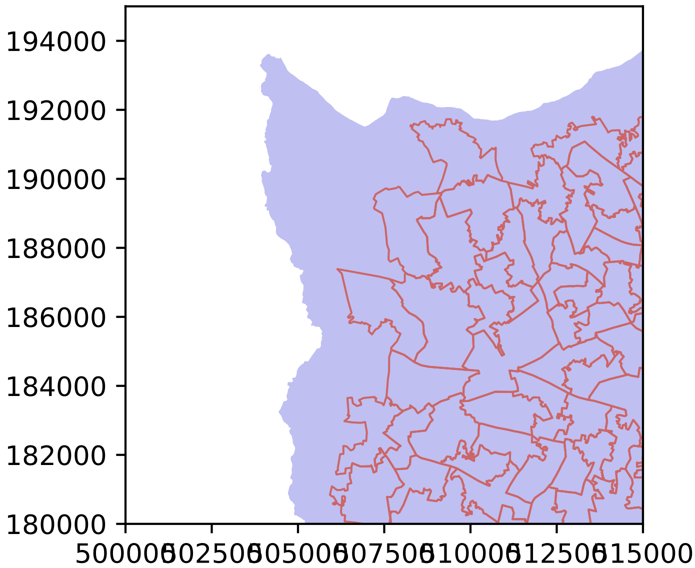
```
ldn = gpd.GeoDataFrame(gpd.GeoSeries(data=boros.unary_union)).rename(columns={0:'geo
ldn = ldn.set_crs(epsg=27700)
ax  = ldn.plot(facecolor=(.5, .5, .9, .5))
msoas.plot(ax=ax, facecolor='none', edgecolor=(.6, .6, .6, .6))
```

```
ax.set_xlim(500000, 515000)
ax.set_ylim(180000, 195000);
```



5.2.2 A (Bad) First Join

```
ldn_msoas = gpd.sjoin(msoas, ldn, predicate='within', how='inner')
ax = ldn.plot(facecolor=(.5, .5, .9, .5))
ldn_msoas.plot(ax=ax, facecolor='none', edgecolor=(.8, .4, .4), linewidth=0.75)
ax.set_xlim(500000, 515000)
ax.set_ylim(180000, 195000);
```



What has gone wrong???

Before you move on to the solution, stop and actually *think* about what this hasn't done what you would have expected? THis is another reason that you need to pay attention to the differences between spatial and non-spatial joins.

5.2.3 Buffer and Join

In order to ensure that we get all the MSOAs *within* London we need to buffer the boundary by some amount to ensure that `within` returns what we want. If *cover* were easier to use then that option might be preferable.

Question

```
ldn['buffered'] = ldn.geometry.???(???)
ldn = ldn.set_geometry('buffered').set_crs(epsg=27700)
ax  = ldn.plot(facecolor=(.5, .5, .9, .5))
msoas.plot(ax=ax, facecolor='none', edgecolor=(.6, .6, .6, .6))
ax.set_xlim(500000, 515000)
ax.set_ylim(180000, 195000);
```

By default we want do an *inner* join because we want to drop everything that doesn't line up between the two data sets (i.e. don't keep the thousands of *other* non-London MSOAs).

Question

```
ldn_msoas = gpd.sjoin(msoas, ldn, predicate='???', how='inner')
ldn_msoas.plot()
```

Question

Hmmmm, not quite what you were expecting? See if you can figure out from the list of columns and the documentation for `set_geometry` what is going wrong? This might also help:

```
print(", ".join(ldn_msoas.columns.to_list()))
```

```
MSOA11CD, MSOA11NM, LAD11CD, LAD11NM, RGN11CD, RGN11NM, USUALRES, HHOLDRES, COMESTRES, POP
```

The issue arises because we've joined two geo-data frames but the join function comes from pandas, which doesn't know anything about spatial data and we have therefore 'lost track' of the column in which the geometry is stored. *Worse*, there are actually two geometry columns now, so we need to tell Geopandas which one to use!

The easiest way to do this is to simply rename the geometry we *want* and then set is as the active geometry:

```
ldn_msoas = ldn_msoas.rename(columns={'geometry_left':'geometry'}).set_geometry('geo
ldn_msoas.drop(columns='geometry_right', inplace=True)
```

We also no longer really need to keep the full MSOA data set hanging about.

```
try:
    del(msoas)
except NameError:
    print("msoas already deleted.")
```

Question

- Can you explain *why* the outputs of the `dissolve` and `unary_union` *look* differnet? And use that as the basis for explaining why they *are* different?

  Answer 1

- How do you know that the units for the buffering operation are metres? 250 could be *anything* right?

  Answer 2

- Why do we need to buffer the London geometry *before* performing the *within* spatial join?

  Answer 3

5.3 Append or Derive Names

We don't actually make use of these in this session, but *both* operations could be relevant to your final reports:

1. The Borough-to-Subregion mapping could help you to group your data into larger sets so that your resulst become more reobust. it also connects us to long-run patterns of socio-economic development in London.
2. The MSOA Names data set (which you used above) gives you something that you could use to label one or more 'neighbourhoods' on a map with names that are *relevant*. So rather than talking about "As you can see, Sutton 003, is…", you can write "The Wrythe neighbourhood [or area] of Sutton is significantly different from the surrounding areas…"

They also usefully test your understanding of regular expressions and a few other aspects covered in previous weeks.

5.3.1 Replace

You've done this before: notice that the MSOA Name *contains* the Borough name **with a space and some digits at the end**. Use a regex (in `str.replace()`) to extract the LA name from the MSOA name. See if you do this *without* having to find your previous answer!

Question

```
ldn_msoas['Borough'] = ldn_msoas.MSOA11NM.str.replace(r'???','',regex=True)

# Just check results look plausible; you should have:
# - 33 boroughs
# - A df shape of 983 x 13
print(ldn_msoas.Borough.unique())
print(f"There are {len(ldn_msoas.Borough.unique())} boroughs.")
print(f"Overall shape of data frame is {' x '.join([str(x) for x in ldn_msoas.shape]
```

5.3.2 Map

Now that we've got the borough names we can set up a `mapping` dict here so that we can apply it as part of the `groupby` operation below (you should have 33 keys when done):

```
mapping = {}
for b in ['Enfield','Waltham Forest','Redbridge','Barking and Dagenham','Havering','
    mapping[b]='Outer East and North East'
for b in ['Haringey','Islington','Hackney','Tower Hamlets','Newham','Lambeth','South
    mapping[b]='Inner East'
for b in ['Bromley','Croydon','Sutton','Merton','Kingston upon Thames']:
    mapping[b]='Outer South'
for b in ['Wandsworth','Kensington and Chelsea','Hammersmith and Fulham','Westminste
    mapping[b]='Inner West'
for b in ['Richmond upon Thames','Hounslow','Ealing','Hillingdon','Brent','Harrow','
    mapping[b]='Outer West and North West'
print(len(mapping.keys()))
```

```
33
```

Question

```
ldn_msoas['Subregion'] = ldn_msoas.Borough.map(???)
```

5.3.3 And Save

```
ldn_msoas.to_parquet(os.path.join('data','geo','London_MSOA_Names.geoparquet'))
```

5.4 Load InsideAirbnb Data

```
listings = gpd.read_parquet( cache_data(f'{host}/~jreades/data/{ymd}-{city}-listings
print(f"Data frame is {listings.shape[0]:,} x {listings.shape[1]}")
```

```
+ data/geo/20240614-London-listings.geoparquet found locally!
Data frame is 85,127 x 32
```

5.4.1 Spatial Join

Associate LA (Local Authority) names to the listings using a spatial join, but **notice** the `how` here:

Question

```
gdf_la = gpd.sjoin(listings, ???, predicate='???', how='left')
print(gdf_la.columns.to_list())
```

5.4.2 Tidy Up

```
gdf_la.drop(columns=['index_right','HECTARES','NONLD_AREA','ONS_INNER'], inplace=Tru
```

You'll need to look closely to check that the `value_counts` output squares with your expectations. If you don't get `33` then there's an issue and you'll need to run the code in Section 5.4.3:

```
if len(gdf_la.NAME.unique()) == 33:
    print("All good...")
else:
    print("Need to run the next section of code...")
    print(f"Now there are... {len(gdf_la.NAME.unique())} boroughs?")
    gdf_la.NAME.value_counts(dropna=False)
```

```
All good...
```

5.4.3 Find Problematic Listings

If you were told that you need to run the next sectin of code then see if you can work out what happened...

```python
try:
    print(gdf_la[gdf_la.NAME.isna()].sample(2)[['name', 'NAME']])
    ax = gdf_la[gdf_la.NAME.isna()].plot(figsize=(9,6), markersize=5, alpha=0.5)
    boros.plot(ax=ax, edgecolor='r', facecolor='None', alpha=0.5);
except ValueError as e:
   pass
```

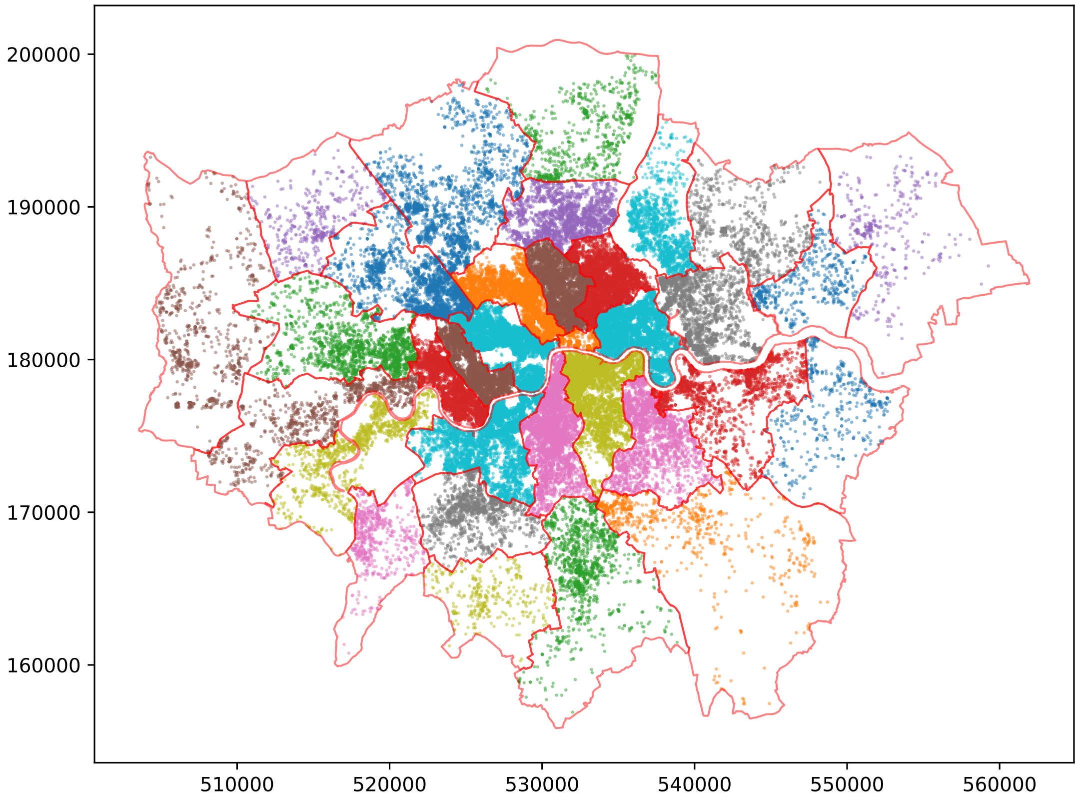
In short: in some cases there may be records that fall outside of London because of Airbnb's shuffling approach:

```python
gdf_la.drop(index=gdf_la[gdf_la.NAME.isna()].index, axis=1, inplace=True)
print(f"Data frame is {gdf_la.shape[0]:,} x {gdf_la.shape[1]}")
```

5.4.4 Check and Save

```python
ax = gdf_la.plot(column='NAME', markersize=0.5, alpha=0.5, figsize=(9,7))
boros.plot(ax=ax, edgecolor='r', facecolor='None', alpha=0.5);
```

You should get the following:




```python
gdf_la.to_parquet(os.path.join('data','geo','Listings_with_LA.geoparquet'))
```

Question

- Do you understand the difference between `how='inner'` and `how='left'`?

5.5 Create LA Data

Now that we've assigned every listing to a borough, we can derive aggregate values for different groups of zones.

5.5.1 Select LA

Select a LA that is relevant to *you* to explore further…

```
LA = 'Waltham Forest'
```

5.5.2 Spatial Join

The first thing we want to do is join MSOA identifiers to each listing. In both cases we want to constrain the data to only be for 'our' LA of interest since that will speed up the process substantially:

```
gdf_msoa = gpd.sjoin(
            gdf_la[gdf_la.NAME==LA].reset_index(),
            ldn_msoas[ldn_msoas.Borough==LA][['MSOA11CD','MSOA11NM','USUALRES','HHOL
gdf_msoa.head(2)
```

	index	id	listing_url	last_scraped	name
0	37	41870	https://www.airbnb.com/rooms/41870	2023-09-07	Home in Walthamstow
1	90	78606	https://www.airbnb.com/rooms/78606	2023-09-07	Rental unit in Walthar

5.5.3 Aggregate

Now aggregate the data by MSOA, deriving median price and a count of the listings:

```
grdf_msoa = gdf_msoa.groupby('MSOA11NM').agg(
    listing_count = ('price','count'),
    median_price = ('price','median')
).reset_index()
print(f"Have {grdf_msoa.shape[0]:,} rows and {grdf_msoa.shape[1]:,} columns")
grdf_msoa.head(2)
```

```
Have 28 rows and 3 columns
```

	MSOA11NM	listing_count	median_price

	MSOA11NM	listing_count	median_price
0	Waltham Forest 001	17	97.0
1	Waltham Forest 002	14	58.0

5.5.4 Join (Again)

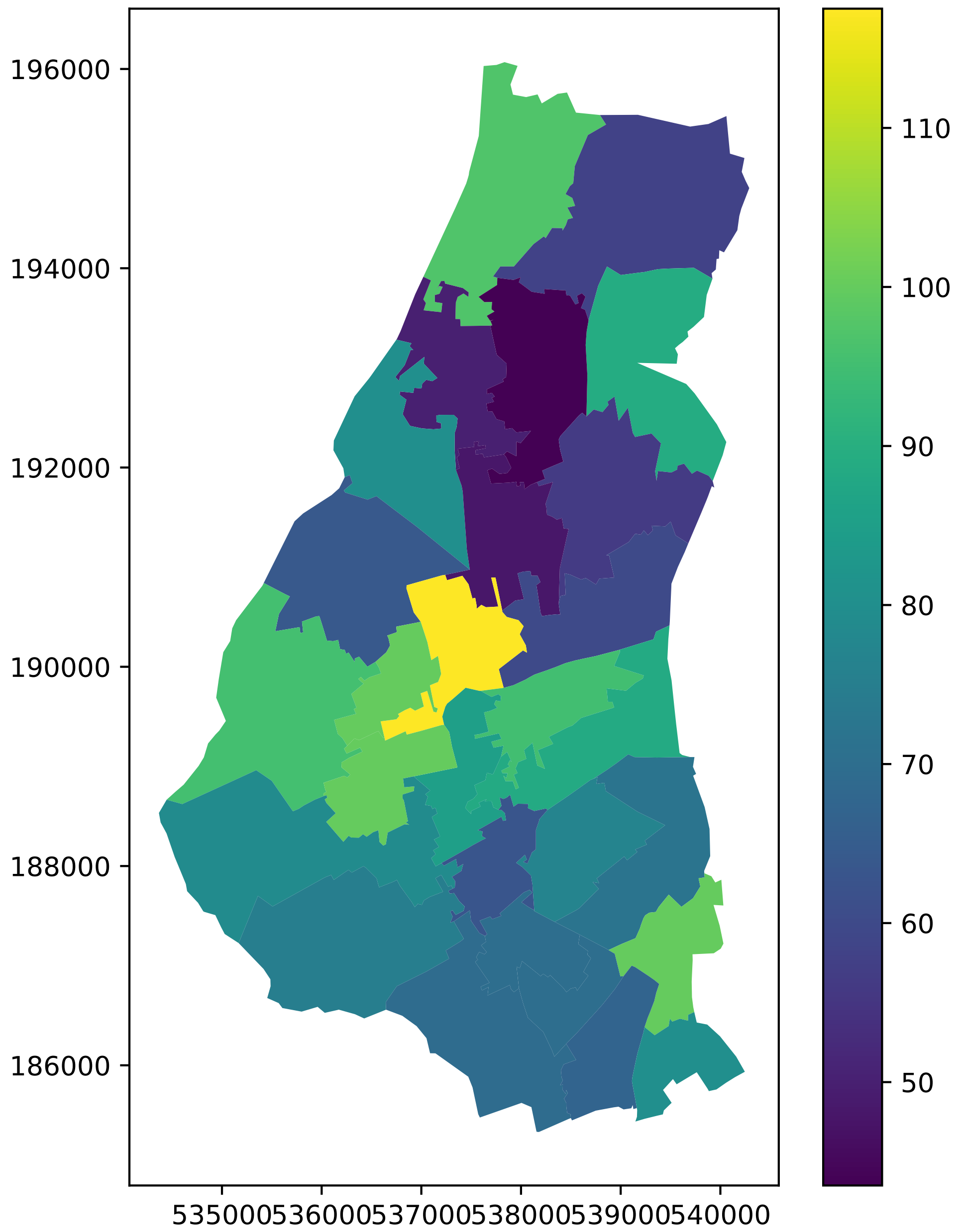
Here we see the **difference between merge and join**. You'll notice that `join` operates by taking one data frame as the implicit '*left*' table (the one which *calls* join) while the one that is passed to the join function is, implicitly, the '*right*' table. Join operates only using indexes, so you'll need to insert the code to specify the same index on both data frames, but this can be done **on-the-fly** as part of the joining operation:

```
msoa_gdf = grdf_msoa.set_index('MSOA11NM').join(
                ldn_msoas[ldn_msoas.Borough==LA].set_index('MSOA11NM'),
                rsuffix='_r').set_geometry('geometry')
msoa_gdf.head(3)
```

MSOA11NM	listing_count	median_price	MSOA11CD	LAD11CD	LAD11NM
Waltham Forest 001	17	97.0	E02000895	E09000031	Waltham Forest
Waltham Forest 002	14	58.0	E02000896	E09000031	Waltham Forest
Waltham Forest 003	7	89.0	E02000897	E09000031	Waltham Forest

```
msoa_gdf.plot(column='median_price', legend=True, figsize=(8,8));
```

You should get something like:



5.5.5 Save

Just so that we can pick up here without having to re-run all the preceding cells.

```
msoa_gdf.to_parquet(os.path.join('data','geo',f'{LA}-MSOA_data.geoparquet'))
```

Question

- Do you understand the differences between `pd.merge` and `df.join`? and `gpd.sjoin`?
- Do you understand why it may be necessary to `set_geometry` in some cases?