# 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. We're also going to look at alternatives to loading the entire data set into memory in Python: using the DuckDB driver we can perform a lot of operations 'outside' of Python's memory and processing limits while still benefiting from reproducibility (the commands are stored in the Python script) and access (we can bring the filtered, linked data into Python when we need to do so).

ℹ 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

```python
ymd  = '20250615'
city = 'London'
host = 'https://orca.casa.ucl.ac.uk'
url  = f'{host}/~jreades/data/{ymd}-{city}-listings.geoparquet'
```

```python
import pandas as pd
import geopandas as gpd
import matplotlib.pyplot as plt

from pathlib import Path
from functools import wraps
from time import time

# A timing decorator courtesy of:
# https://www.geeksforgeeks.org/python/timing-functions-with-decorators-python/
def timing(func):
    def wrap_func(*args, **kwargs):
        t1 = time()
        result = func(*args, **kwargs)
        t2 = time()
        return (t2-t1)
    return wrap_func
```

```python
from pathlib import Path
from requests import get
from functools import wraps

def check_cache(f):
    @wraps(f)
    def wrapper(src:str, dst:str, min_size=100) -> Path:
        if src.find('?') == -1:
            url = Path(src)
        else:
            url = Path(src[:src.find('?')])
        fn  = url.name  # Extract the filename
        dsn = Path(f"{dst}/{fn}") # Destination filename
        if dsn.is_file() and dsn.stat().st_size > 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:Path, dst:Path) -> 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.
    """

    # 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 not dst.parent.exists():
        dst.parent.mkdir(parents=True, exist_ok=True)

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

    print(' + Done downloading...')

    return dst.resolve()
```

```
ddir     = Path('data/geo')
pqt      = url.replace('.geo','.')
```

## 2 Selecting Data in Pandas

In this section we are loading a parquet file using pandas and taking advantage of Python's 'chaining' functionality (`<object>.<method>().<method>()...`) to return the first few rows of a data frame using `head`. The thing to notice is that we're not even bothering to save the result of this command into a variable (thus the lack of a `df =` in the code). We're doing this here *solely* so that you can compare pandas and DuckDB performance and syntax across each of the following steps.

## 2.1 A simple query

```
@timing
def load(n:int):
    for i in range(n):
        pd.read_parquet(f'{pqt}').head(3)

reps = 10
secs = load(reps)
print(f"Average time per call: {secs/reps:.5f}")
```

I get an average time per call of about: 0.44982

## 2.2 Selecting 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 implemented as:

### 2.2.1 Load *then* filter

```
@timing
def load(n:int):
    for i in range(n):
        pd.read_parquet(f'{pqt}')[['listing_url', 'price', 'number_of_reviews', 'pro

reps = 10
secs = load(reps)
print(f"Average time per call of about: {secs/reps:.5f}")
```

I get an average time per call of about: 0.43050

Not bad, not bad…

### 2.2.2 Filter *then* load

```
@timing
def load(n:int):
    for i in range(n):
        pd.read_parquet(f'{pqt}', columns=['listing_url', 'price', 'number_of_review

reps = 10
secs = load(reps)
print(f"Average time per call of about: {secs/reps:.5f}")
```

I get an average time per call of about: 0.32964

Whoa! Notice the difference in the time needed to complete the operation! We just accelerated this step by 0.77 times.!

## 2.3 Adding a constraint

So that is performance for loading data, now let's see what happens when we start subsetting the data by *row* as well as by *column*.

```
@timing
def load(n:int):
    for i in range(n):
        df = pd.read_parquet(f'{pqt}', columns=['listing_url', 'price', 'number_of_r
        df[(df.price < 250) & (df.number_of_reviews > 0) & (df.property_type=='Entir

reps = 10
secs = load(reps)
print(f"Average time per call of about: {secs/reps:.5f}")
```

I get an average time per call of about: 0.33081

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 and performance should have been only slightly slower than doing the column subset in the first place, but things get a bit more complicated when you want to aggregate the return…

## 2.4 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, although we *could* reduce it to two if we really wanted to do so (at the cost of some legibility).

Average time per call of about: 0.32505

I get an average time per call of about: 0.32482

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. That's useful if *non*-observations (i.e. there was no data for this group) is relevant to your data presentation or subsequent modelling/statistical tests[1].

### 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 do anything further 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* 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

[1] One could imagine, for instance, that you want to present the data in a table in which case you want the zero because there needs to be a value for each cell in the table.

the `ascending` values, and if you wanted to sort *everything* in descending order then it's just `ascending=False`.

# 3 Selecting Data in DuckDB

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.

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

```
import duckdb as db
```

## 3.1 A first query

Let's see a quick demonstration:

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

@timing
def load(n:int):
    for i in range(n):
        db.sql(query)

reps = 25
secs = load(reps)
print(f"Average time per call of about: {secs/reps:.5f}")
```

I get an average time per call of about: 0.00348

The timing code should *already* show a significant improvement over pandas-only code: on my laptop it is 51.77 times faster. Now let's unpack what's happening:

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!

ℹ 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 (`*` == everything>‘)
2. From the parquet file (`<table location>`)
3. Limit the return to 3 rows (`LIMIT <row count>`)

Let’s look at some variations…

## 3.2 Selecting columns

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

@timing
def load(n:int):
    for i in range(n):
        db.sql(query)

reps = 25
secs = load(reps)
print(f"Average time per call of about: {secs/reps:.5f}")
```

I get an average time per call of about: 0.00013

Even though it looked like pandas performed *massively* better when we updated our query to filter then load, DuckDB is **even faster**! I get that DuckDB is 1008.18 faster than pandas.

```
1 SELECT listing_url, price, number_of_reviews, last_review, host_name
2 FROM read_parquet('{pqt}')
3 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>`)

## 3.3 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;
'''

@timing
def load(n:int):
    for i in range(n):
        db.sql(query)

reps = 25
secs = load(reps)
print(f"Average time per call of about: {secs/reps:.5f}")
```

I get an average time per call of about: 0.00013

Performance should still be noteable improvement over pandas, though in my simple tests it's 'only' about 30% faster. IF we wanted to be more rigorous about this we'd want to repeat the same operation many times (e.g. hundreds or thousands of time) to account for the fact that during any given query the computer might be doing other things that impact performance.

Anyway, 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`

## 3.4 Aggregating the return

That's hopefully enough to get you started on *selecting* data, but databases '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) AS 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 5;
'''

@timing
def load(n:int):
    for i in range(n):
        db.sql(query)

reps = 25
secs = load(reps)
print(f"Average time per call of about: {secs/reps:.5f}")
```

I get an average time per call of about: 0.00017

Performance is comparable to pandas in my very basic test, but I find the operation more clearly expressed in SQL than pandas. There are quite a few changes to the query here so it's worth reviewing them in more detail:

```
SELECT property_type, room_type,
    COUNT(*) AS freq, MEDIAN(price) AS 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. We don't need to specify a column here because `*` means 'all rows'.
    - `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.

## 4 Thinking About Joins

We're going to look at joining data by attributes *first* and then look at spatial joins *after* so that you get a sense of how they behave and differ. However, even where you *do* have a spatial problem, it can be worth it to manage it as a non-spatial problem 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 MSOA-level 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(…) |

The *obvious* way to do this is as a spatial join *something* like this:

```
SELECT m."MSOA Code", SUM(<attribute 1>) AS feature_sum, COUNT(<attribute 2>) AS fea
FROM <lsoa data table> AS l, <msoa data table> AS m
WHERE ST_Within(l.<lsoa geom>, m.<msoa geom>)
GROUP BY m."MSOA Code";
```

We'll get to what's happening with `AS l` and `AS lkp` in a bit more detail below, but the term for this is *aliasing* and its saves us having to repeatedly type `<lsoa data table>` by allowing us to use the alias `l`. But you would run this same query *every* time you wanted to aggregate something.

**This is *not* the right way to tackle this problem** even though you can write the query to give you the correct answer. Spatial queries (as I said in the pre-recorded lectures) are *hard*, so if you can 'cache' the result in a *non*-spatial format it will save a lot time in the future.

The answer is to run the spatial query *once* in order to create a 'lookup table' which uses the LSOA and MSOA *codes* (and you can even add Boroughs, Regions, OAs, and so on later if you like!) to tell you if a LSOA falls inside a borough or MSOA. So 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 look like 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 lkp."MSOA Code", SUM(<attribute 1>) AS feature_sum, COUNT(<attribute 2>) AS f
FROM <lsoa data table> AS l, <lookup table> AS lkp
WHERE l."LSOA Code" = lkp."LSOA Code"
GROUP BY lkp."MSOA Code";
```

You can also use this as a foundation for creating a `VIEW` or a `[MATERIALIZED VIEW](https://www.databricks` `views)`, but that's an advanced topic for managing your data more efficiently in an operational environment rather than a research-oriented one.

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-only applications.

## 4.1 Additional Data

For the rest of this notebook we need three data sets about MSOAs (which are statistical neighbourhoods that we'll treat as a proxy for 'real' neighbourhoods). The first two are *non*-spatial:

```
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_nms = pd.read_csv( cache_data(msoa_names_url, 'data') )

# This one can't be cached because we need to access
# an Excel sheet name and the cache_data function isn't
# smart enough to handle this use case.
msoa_pq = Path('data/MSOA_population_estimates.parquet')
if msoa_pq.exists():
    msoa_df = pd.read_parquet(msoa_pq)
else:
    msoa_df = pd.read_excel(msoa_popst_url, sheet_name="Mid-2022 MSOA 2021", header=
    msoa_df.to_parquet(msoa_pq)

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.
```

We also need some geodata:

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

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

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.

# 5 Non-Spatial Joins 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.

### 5.1 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 2.97 ms, sys: 221 µs, total: 3.19 ms
Wall time: 3.15 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.

### 5.2 Constraining the Join

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 2.28 ms, sys: 0 ns, total: 2.28 ms
Wall time: 2.26 ms
```

| | LAD 2021 Code | LAD 2021 Name | MSOA 2021 Code | MSOA 2021 Name | Total | F0 to 4 | F5 to |
|---|---|---|---|---|---|---|---|
| 0 | E09000031 | Waltham Forest | E02000895 | Waltham Forest 001 | 8363 | 208 | 233 |
| 1 | E09000031 | Waltham Forest | E02000896 | Waltham Forest 002 | 9322 | 256 | 278 |
| 2 | E09000031 | Waltham Forest | E02000897 | Waltham Forest 003 | 8438 | 233 | 262 |

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

# 6 Non-Spatial Joins in DuckDB

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

### 6.0.1 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 34.3 ms, sys: 5.3 ms, total: 39.6 ms
Wall time: 41.2 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 |

**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! Another reason is that the files aren't being loaded into memory *first*, but are being read: on small files this allows pandas to outperform DuckDB, but as the file size grows the performance profile will change radically.
Anyway, the download penalty is 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 can now refer to the data from this table using the 'alias' `n.`; e.g. `n.Total`)
4. `LEFT JOIN` as a concept was been covered in the lecture
5. `<table 2 from csv> as m` (we now refer to the data from this table using the alias `m.`; e.g. `m.geometry`)
6. `ON <left table matching column> = <right table matching column>` (here, the unusual thing is the double-quotes around the column name required to deal with the fact that the name 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.

## 6.1 Constraining the Join

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 27.5 ms, sys: 2.73 ms, total: 30.3 ms
Wall time: 31.3 ms
```

| | LAD 2021 Code | LAD 2021 Name | MSOA 2021 Code | MSOA 2021 Name | Total | F0 to 4 | F5 to |
|---|---|---|---|---|---|---|---|
| 0 | E09000031 | Waltham Forest | E02000895 | Waltham Forest 001 | 8363 | 208 | 233 |
| 1 | E09000031 | Waltham Forest | E02000896 | Waltham Forest 002 | 9322 | 256 | 278 |
| 2 | E09000031 | Waltham Forest | E02000897 | Waltham Forest 003 | 8438 | 233 | 262 |

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 28.5 ms, sys: 1.46 ms, total: 29.9 ms
Wall time: 31.5 ms
```

| | LAD 2021 Code | LAD 2021 Name | MSOA 2021 Code | MSOA 2021 Name | Total | F0 to 4 | F5 to |
|---|---|---|---|---|---|---|---|
| 0 | E09000031 | Waltham Forest | E02000895 | Waltham Forest 001 | 8363 | 208 | 233 |
| 1 | E09000031 | Waltham Forest | E02000896 | Waltham Forest 002 | 9322 | 256 | 278 |
| 2 | E09000031 | Waltham Forest | E02000897 | Waltham Forest 003 | 8438 | 233 | 262 |

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.

## 7 Spatial Joins in Geopandas

Let's try to find all of the listings that fall within the borough of Waltham Forest.

```
listings = gpd.read_parquet( cache_data(url, ddir) ).to_crs('epsg:27700')
```

```
+ data/geo/20250615-London-listings.geoparquet found locally!
```

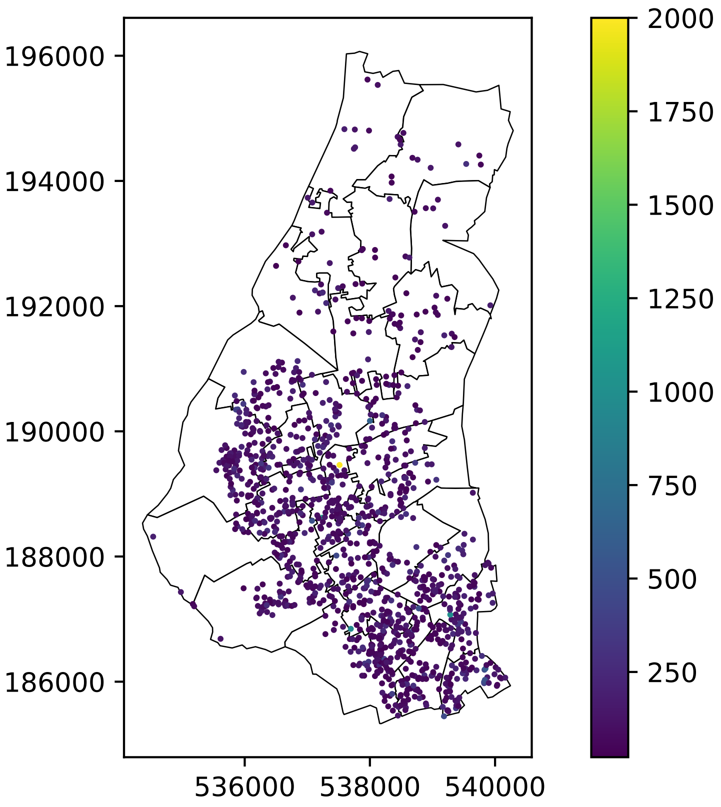
This query implies two steps:

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 `.gpkg` files) then you will need to specify `aspect=1` in the `plot(...)` command.

## 8 Spatial Joins 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 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 example is provided for reference only when you need to work with a geospatial data format and, on the whole, right now I’d recommend using GeoPandas and geoparquet files directly. In fact, if you read closely you’ll realise that this isn’t even a spatial join, it’s just outputting spatially-referenced data!

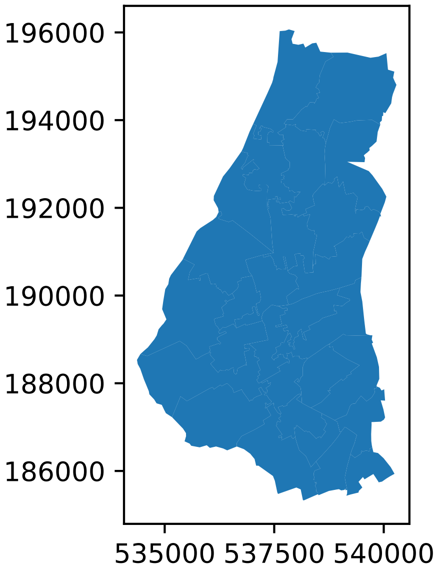
```
%%time

boro = 'Waltham Forest'
```

```
query = f'''
INSTALL SPATIAL;
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 318 ms, sys: 39.9 ms, total: 358 ms
Wall time: 220 ms
```



# 9 Worked Example

Let’s now try work through a practical example that combines everything we’ve just learned.

## 9.1 Load Geodata

A lot of additional geo-data can be accessed from the GeoPortal. And see also my discussion on lookup tables. For demonstration purposes we're going to work the same set of files 'as usual':

```
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!
```

## 9.2 Select London MSOAs

Connections

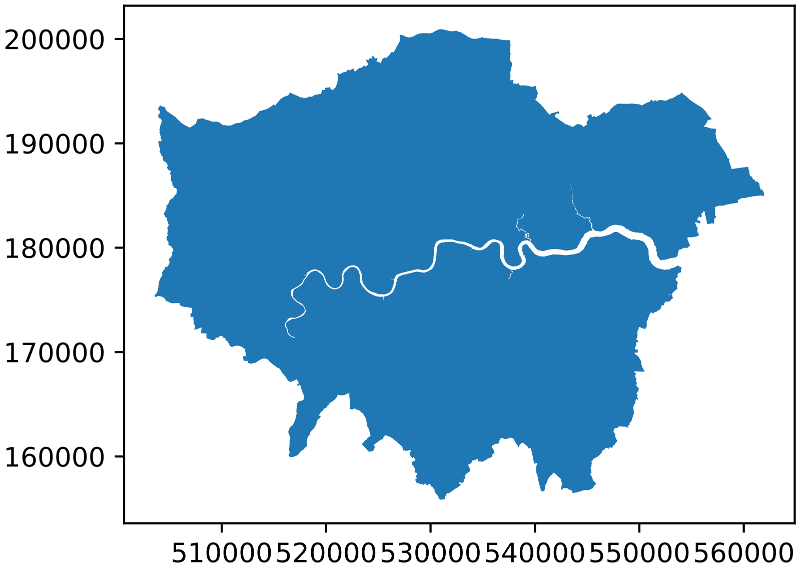
One thing to remember here is that computers are *exact*. So if you say that the selection should only be of MSOAs *within* London then you actually need to think about whether a shared border qualifies as 'within'. Watch the lectures again if you're unsure, but that's why here we take this slightly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

### 9.2.1 Union

As we don't have a boundary file for London, we can *generate* use using the `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 legibility.

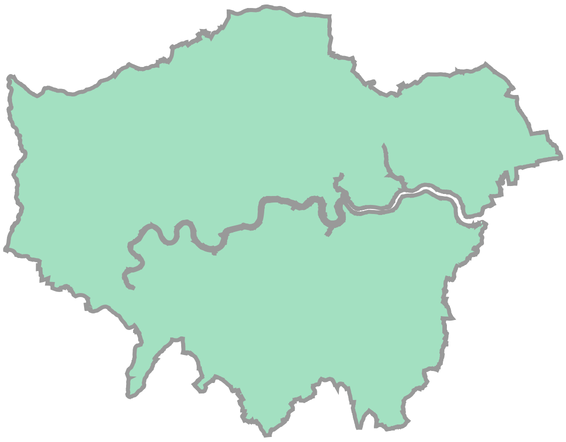
So here's approach 1, which is a method call returning a GeoDataFrame (which is why we can call `plot`):

```
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.union_all()
```

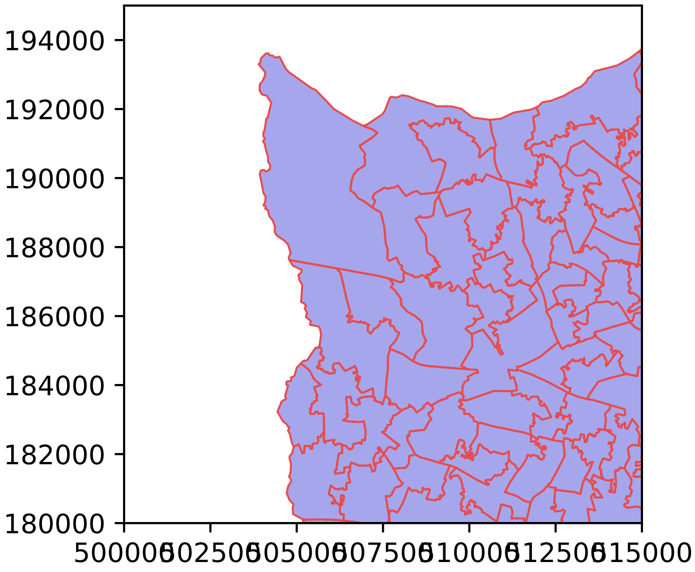


ℹ Connections

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.

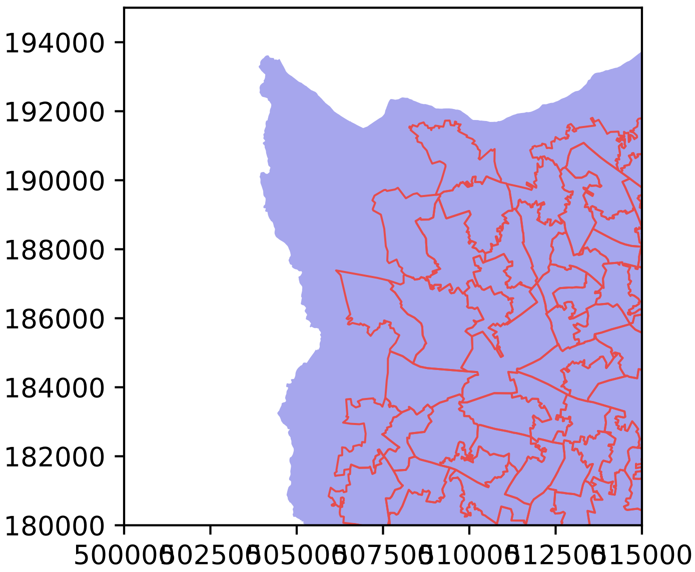
## 9.3 Selecting London MSOAs

```
ldn = gpd.GeoDataFrame(gpd.GeoSeries(data=boros.union_all())).rename(columns={0:'geo
ldn = ldn.set_crs(epsg=27700)
ax  = ldn.plot(facecolor=(.5, .5, .9, .7))
msoas.plot(ax=ax, facecolor='none', edgecolor=(.9, .3, .3), linewidth=0.75)
ax.set_xlim(500000, 515000)
ax.set_ylim(180000, 195000);
```



### 9.3.1 A (Bad) First Join

```
ldn_msoas = gpd.sjoin(msoas, ldn, predicate='within', how='inner')
ax = ldn.plot(facecolor=(.5, .5, .9, .7))
ldn_msoas.plot(ax=ax, facecolor='none', edgecolor=(.9, .3, .3), 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 why this hasn't worked as you might (sensibly) have expected? This is another reason that you need to pay close attention to the differences between spatial and non-spatial joins.

### 9.3.2 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

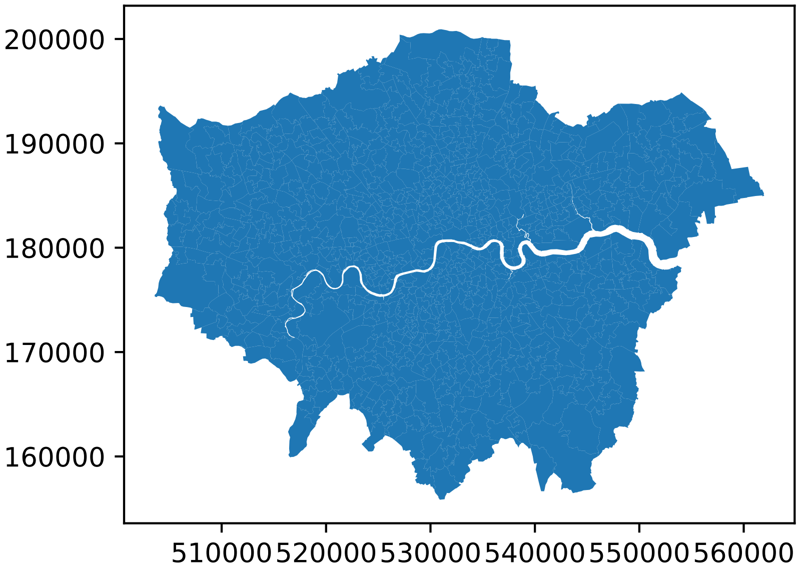
```
ldn['buffered'] = ldn.geometry.???(???)
ldn = ldn.set_geometry('buffered').set_crs(epsg=27700)
ax  = ldn.plot(facecolor=(.5, .5, .9, .5))
msoas.plot(ax=ax, facecolor='none', edgecolor=(.6, .6, .6, .6))
ax.set_xlim(500000, 515000)
ax.set_ylim(180000, 195000);
```

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()
```

Your result should be:



### 9.3.3 Important Note

If your plot above looks like the output from `pandas` and not `geopandas` then the list of columns and the documentation for `set_geometry` might help you to understand what is going wrong:

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

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

It's important to recognise that `join` and `sjoin` are *not* the same even though they may effectively perform the same function. An issue can arise if we join two *geodata* frames using the join function from `pandas`. The latter doesn't know anything about spatial data and we can therefore 'lose track' of the geometry column. *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. Here's the code to use if you have a `geometry_left` column and aren't able to show a map:

```
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 `union_all` *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

## 9.4 Create Borough and Regional Mappings

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 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.

### 9.4.1 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]
```

### 9.4.2 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(???)
```

### 9.4.3 And Save

```
ldn_msoas.to_parquet(ddir / 'London_MSOA_Names.geoparquet')
```

## 9.5 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())
```

### 9.5.1 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 9.5.2:

```
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...
```

### 9.5.2 Find Problematic Listings

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

```
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
```

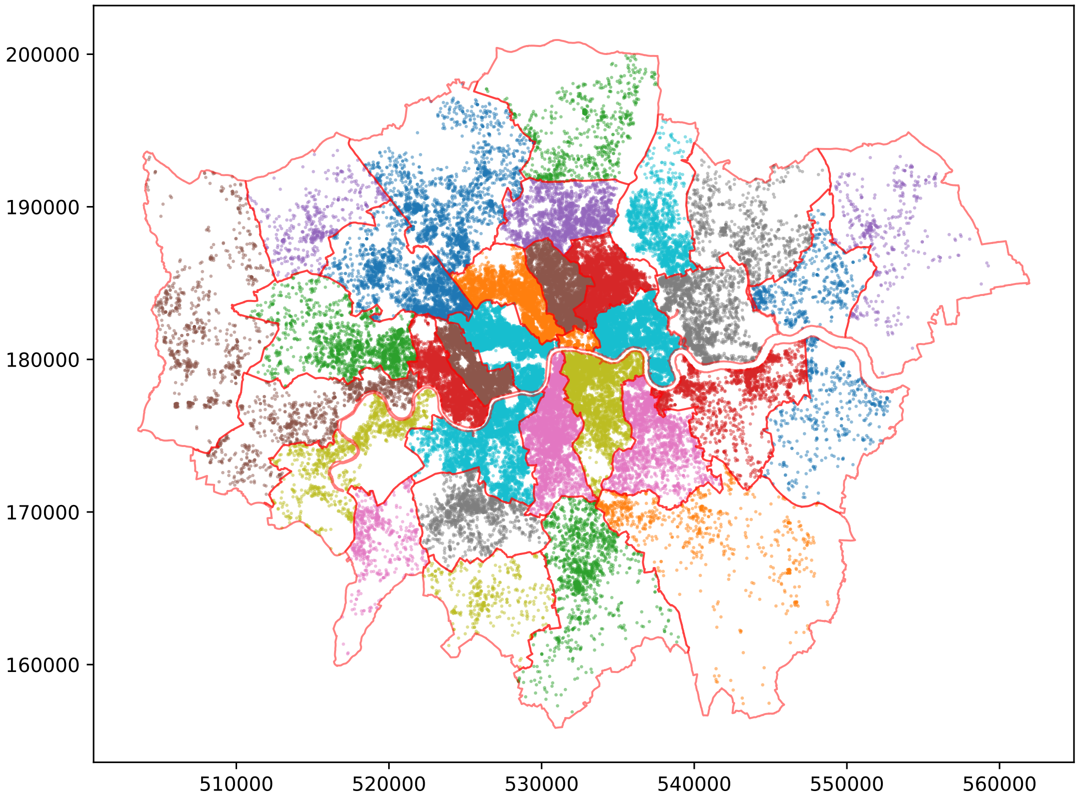
In short: in some cases there may be records that fall outside of London because of Airbnb's shuffling approach:

```
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]}")
```

### 9.5.3 Check and Save

```
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:



```
gdf_la.to_parquet(ddir / 'Listings_with_LA.geoparquet')
```

**Question**

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

## 9.6 Create LA Data

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

### 9.6.1 Select LA

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

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

### 9.6.2 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 | n |
|---|---|---|---|---|---|
| 0 | 4 | 809481748064671744 | https://www.airbnb.com/rooms/809481748064671711 | 2024-06-15 | 4 |
| 1 | 6 | 738113134161127040 | https://www.airbnb.com/rooms/738113134161127067 | 2024-06-14 | V |

### 9.6.3 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 |
|---|---|---|---|
| 0 | Waltham Forest 001 | 11 | 110.0 |
| 1 | Waltham Forest 002 | 11 | 90.0 |

### 9.6.4 Join (Again)

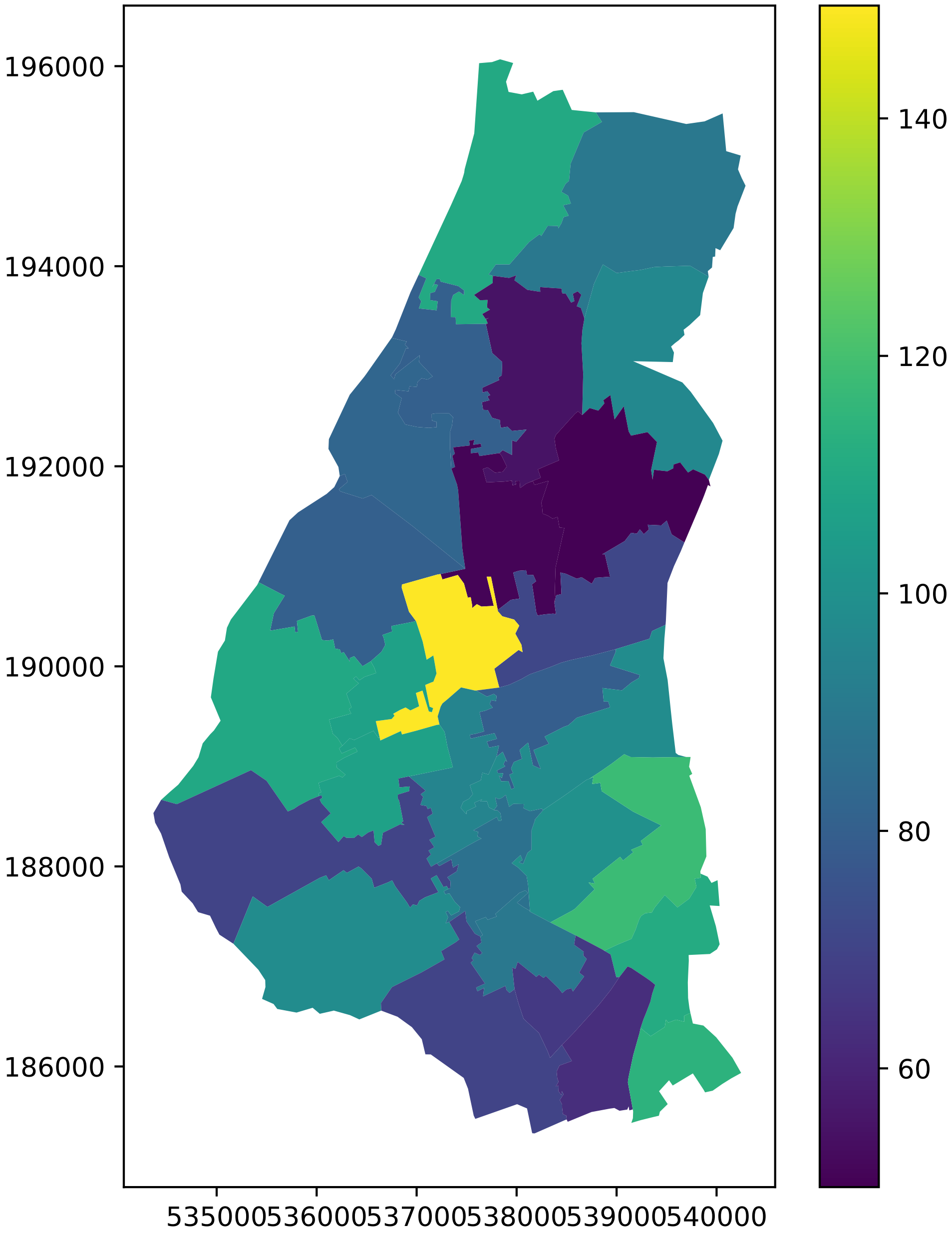
Here we see the **difference between merge and join**. You'll notice that `join` operates by taking one data frame as the implicit '*left*' table (the one which *calls* join) while the one that is passed to the join function is, implicitly, the '*right*' table. Join operates only using indexes, so you'll 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)
```

| | listing_count | median_price | MSOA11CD | LAD11CD | LAD11NM | RGN1 |
|---|---|---|---|---|---|---|
| MSOA11NM | | | | | | |
| Waltham Forest 001 | 11 | 110.0 | E02000895 | E09000031 | Waltham Forest | E1200 |
| Waltham Forest 002 | 11 | 90.0 | E02000896 | E09000031 | Waltham Forest | E1200 |
| Waltham Forest 003 | 6 | 96.5 | E02000897 | E09000031 | Waltham Forest | E1200 |

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

You should get something like:



### 9.6.5 Save

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

```
msoa_gdf.to_parquet(ddir / 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?