Practical 8: Working with Text

The basics of Text Mining and NLP

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A lot of the content here is provided to help you *understand* what text-cleaning does and how it generates tokens that can be processed by the various analytical approaches commonly-used in NLP. The best way to think about this is as a practical in two parts, with a bonus 'Part 2' that you should not expect to complete unless you probably shouldn't be taking CASA0013 in the first place:

1. Tasks 1–3: these are largely focussed on the basics: exploring text and using regular expressions to find and select text.
2. Tasks 4–5: this might seem like a *bit* of a detour, but it's intended to show you in a more tangible way how 'normalisation' works when we're working with text.

The later parts in Part 2 are largely complete and ready to run; however, that *doesn't* mean you should just skip over them and think you've grasped what's happening and it will be easy to apply in your own analyses. I would *not* pay as much attention to LDA topic mining since I don't think it's results are that good, but I've included it here as it's still commonly-used in the Digital Humanities and by Marketing folks. Word2Vec is much more powerful and forms the basis of the kinds of advances seen in ChatGPT and other LLMs.

> **i Connections**
>
> Working with text is unquestionably *hard*. In fact, *conceptually* this is probaly the most challenging practical of the term! But data scientists are *always* dealing with text because so much of the data that we collect (even more so thanks to the web) is not only text-based (URLs are text!) but, increasingly, unstructured (social media posts, tags, etc.). So while getting to grips with text is a challenge, it also uniquely positions you with respect to the skills and knowledge that other graduates are offering to employers.

1 Setup

Difficulty Level: Low

But this is only because this has been worked out for you. Starting from sctach in NLP is *hard* so people try to avoid it as much as possible.

1.1 Required Modules

Note

Notice that the number of modules and functions that we import is steadily increasing week-on-week, and that for text processing we tend to draw on quite a wide range of utilies! That said, the three most commonly used are: `sklearn`, `nltk`, and `spacy`.

Standard libraries we've seen before.

```
import os
import numpy as np
import pandas as pd
import geopandas as gpd
import re
import math
import matplotlib.pyplot as plt
```

This next is just a small utility function that allows us to output Markdown (like this cell) instead of plain text:

```
from IPython.display import display_markdown

def as_markdown(head='', body='Some body text'):
    if head != '':
        display_markdown(f"##### {head}\n\n>{body}\n", raw=True)
    else:
        display_markdown(f">{body}\n", raw=True)

as_markdown('Result!', "Here's my output...")
```

Result!

> Here's my output...

1.2 Loading Data

> **ℹ Connections**
>
> Because I generally want each practical to stand on its own (unless I'm trying to make a *point*), I've not moved this to a separate Python file (e.g. `utils.py`, but in line with what we covered back in the lectures on Functions and Packages, this sort of thing is a good candidate for being split out to a separate file to simplify re-use.

Remember this function from last week? We use it to save downloading files that we already have stored locally. But notice I've made some small changes... what do these do to help the user?

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

def cache_data(src:str, dest:str) -> str:
    """Downloads and caches a remote file locally.

    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.
    dest : str
        The *destination* location to save the downloaded file.

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

    url = urlparse(src) # We assume that this is some kind of valid URL
    fn  = os.path.split(url.path)[-1] # Extract the filename
    dfn = os.path.join(dest,fn) # Destination filename

    # Check if dest+filename does *not* exist --
    # that would mean we have to download it! We
    # also check for *very* small files that are
    # likely to represent an incomplete download.
    if not os.path.isfile(dfn) or os.stat(dfn).st_size < 250:
```

```python
        print(f"{dfn} not found, downloading!")

        # Convert the path back into a list (without)
        # the filename -- we need to check that directories
        # exist first.
        path = os.path.split(dest)

        # 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 len(path) >= 1 and path[0] != '':
            os.makedirs(os.path.join(*path), exist_ok=True)

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

        print("\tDone downloading...")

        # What's this doing???
        f_size = os.stat(dfn).st_size
        print(f"\tSize is {f_size/1024**2:,.0f} MB ({f_size:,} bytes)")

    else:
        print(f"Found {dfn} locally!")

        # And why is it here as well???
        f_size = os.stat(dfn).st_size
        print(f"\tSize is {f_size/1024**2:,.0f} MB ({f_size:,} bytes)")

    return dfn
```

Tip

For very large *non*-geographic data sets, remember that you can `use_cols` (or `columns` depending on the file type) to specify a subset of columns to load.

Load the main data set:

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

```python
gdf = gpd.read_parquet( cache_data(url, os.path.join('data','geo')),
                        columns=['geometry', 'listing_url', 'name',
                                 'description', 'amenities', 'price'])
```

```
gdf = gdf.to_crs('epsg:27700')

print(f"gdf has {gdf.shape[0]:,} rows and CRS is {gdf.crs.name}.")
```

```
Found data/geo/20240614-London-listings.geoparquet locally!
    Size is 42 MB (44,000,824 bytes)
gdf has 85,127 rows and CRS is OSGB36 / British National Grid.
```

Load supporting Geopackages:

```
ddir  = os.path.join('data','geo') # destination directory
spath = 'https://github.com/jreades/fsds/blob/master/data/src/' # source path

boros = gpd.read_file( cache_data(spath+'Boroughs.gpkg?raw=true', ddir) )
water = gpd.read_file( cache_data(spath+'Water.gpkg?raw=true', ddir) )
green = gpd.read_file( cache_data(spath+'Greenspace.gpkg?raw=true', ddir) )

print('Done.')
```

```
Found data/geo/Boroughs.gpkg locally!
    Size is 1 MB (905,216 bytes)
Found data/geo/Water.gpkg locally!
    Size is 0 MB (208,896 bytes)
Found data/geo/Greenspace.gpkg locally!
    Size is 1 MB (1,146,880 bytes)
Done.
```

2 Exploratory Textual Analysis

Connections

If you plan to work with data post-graduation then you will *need* to become comfortable with Regular Expressions (aka. regexes). These are the focus of the Patterns in Text lecture but they barely even scratch the surface of what regexes can do. They are *hard*, but they are powerful.

Tip

In a full text-mining application I would spend a lot more time on this stage: sampling, looking at descriptions in full, performing my analysis (the rest of the steps) and then coming back with a deeper understanding of the data to make further changes to the analysis.

It's helpful to have a sense of what data look like before trying to do something with them, but by default pandas truncates quite a lot of output to keep it from overwhelming the display. For text processing, however, you should probably change the amount of preview text provided by pandas using the available options. *Note*: there are lots of other options that you can tweak in pandas.

```
print(f"Default maximum column width: {pd.options.display.max_colwidth}") # What's t
pd.options.display.max_colwidth=250   # None = no maximum column width (you probably
print(f"Now maximum column width set to: {pd.options.display.max_colwidth}")
```

```
Default maximum column width: 50
Now maximum column width set to: 250
```

2.1 The Description Field

⚠ Difficulty level: Moderate, because of the questions.

To explore the description field properly you'll need to filter out any NA/NaN descriptions before sampling the result. *Hint*: you'll need to think about negation (~) of a method output that tells you if a field *is NA*.

Question

```
gdf[???].sample(5, random_state=42)[['description']]
```

Stop

What do you notice about the above? Are they simple text? Are there patterns of problems? Are there characters that represent things other than words and simple punctuation?

2.1.1 Questions

- What patterns can you see that might need 'dealing with' for text-mining to work?
- What non-text characters can you see? (Things *other* than A-Z, a-z, and simple punctuation!)

2.2 The Amenities Field

⚠ Difficulty level: Moderate, because of the questions.

This field presents a subtle issue that might not be obvious here:

```
gdf.amenities.sample(5, random_state=42)
```

```
17638    ["Free dryer \u2013 In unit", "Hot water kettle", "Shampoo", "Luggage dropoff allow
84107    ["Bathtub", "Clothing storage: closet", "Portable heater", "Microwave", "Hot water
53166                                        ["Hot water", "Iron", "Outdoor dining area", "
72159    ["Free dryer \u2013 In unit", "Clothing storage: closet", "Hot water kettle", "Sham
84441    ["Bathtub", "Clothing storage: closet", "Elevator", "Hot water", "Carbon monoxide
Name: amenities, dtype: object
```

But look what happens now, can you see the issue a little more easily?

```
gdf.amenities.iloc[0]
```

```
'["Heating", "TV with standard cable", "Wifi", "Smoke alarm", "Dryer", "Kitchen", "Washer"
```

2.2.1 Questions

- What's the implicit format of the Amenities columns?
- How could you represent the data contained in the column?

2.3 Remove NaN Values

> **Note**
>
> I would be wary of doing the below in a 'proper' application without doing some careful research first, but to make our lives easier, we're going to drop rows where one of these values is NaN *now* so it will simplify the steps below. In reality, I would spend quite a bit more time investigating which values are NaN and why before simply dropping them.

Anyway, drop all rows where *either* the description or amenities (or both) are NA:

Question

```
gdf = gdf.dropna(???)
print(f"Now gdf has {gdf.shape[0]:,} rows.")
```

You should get that there are `84,266` rows.

3 Using Regular Expressions

> **Connections**
>
> We're building on the work done in Practical 7, but making use now of the lecture on Patterns in Text) to quickly sort through the listings.

There is a *lot* that can be done with Regular Expressions to identify relevant records in textual data and we're going to use this as a starting point for the rest of the analysis. I would normally consider the regexes here a 'first pass' at the data, but would look very carefully at the output of the TF/IDF vectorizer, Count vectorizer, and LDA to see if I could improve my regexes for further cycles of analysis... the main gain there is that regexes are *much* faster than using the full NLP (Natural Language Processing) pipeline on the *full* data set each time. As an alternative, you could develop the pipeline using a random subsample of the data and then process the remaining records sequentially – in this context there is no justification for doing that, but with a larger corpus it might make sense.

3.1 Luxury Listings

Difficulty level: Hard, because of the regular expression and questions.

I would like you to find listings that *might* (on the basis of word choice) indicate 'luxury' accommodation.

3.1.1 Create the Regular Expression

You should start with variations on 'luxury' (i.e. luxurious, luxuriate, ...) and work out a **single regular expression** that works for variations on this *one* word. **Later**, I would encourage you to come back to this and consider what other words might help to signal 'luxury'... perhaps words like 'stunning' or 'prestigious'? Could you add those to the regex as well?

Hints: this is a toughy, but...

1. All regular expressions work best using the `r'...'` (which means raw string) syntax.
2. You need to be able to *group* terms. Recall, however, that in Python a 'group' of the form `r'(some text)'` refers to matching (`some text` will be 'memo-ized'/remembered), whereas what you need here is a "non-capturing group" of the **positive lookahead** type. That's a Google clue right there, but you've also seen this in the lecture.

In fact, in my real-world applications you might even need more than one group/non-capturing group in a *nested* structure.

Question

```
gdf[
    gdf.description.str.contains(r'???', regex=True, flags=re.IGNORECASE) # <-- The
].sample(3, random_state=42)[['description']]
```

3.1.2 Apply it to Select Data

Assign it to a new data frame called `lux`:

Question

```
lux = gdf[gdf.description.str.contains(r'???', regex=True, flags=re.IGNORECASE)].cop
lux.to_parquet(os.path.join('data','clean','luxury.geopackage'))
print(f"Found {lux.shape[0]:,} records for 'luxury' flats")
```

You should get that there are `10,367` rows.

3.1.3 Plot the Data

Now we are going to create a more complex plot that will give space to both the spatial and price distributions using `subplot2grid`.

```
help(plt.subplot2grid)
```

Notice that there are two ways to create the plot specified above. I chose route 1, but in some ways route 2 (where you specify a `gridspec` object and *then* add the axes might be a bit simpler to work out if you're starting from scratch.

The critical thing here is to understand how we'er initialising a plot that has **4 rows** and **1 column** even though it is only showing **2 plots**. What we're going to do is set the *first* plot to span **3 rows** so that it takes up 75% of the plot area (3/4), while the *second* plot only takes up 25% (1/4). They will appear one above the other, so there's only 1 column. Here's how to read the key parts of `subplot2grid`:

- `nrows` – how many rows *of plots* in the figure.
- `ncols` – how many columns *of plots* in the figure.
- `row` – what row of the figure does *this* plot start on (0-indexed like a list in Python).
- `col` – what column of the figure does *this* plot start on (0-indexed like a list in Python).
- `rowspan` – how many rows of the figure does *this* plot span (*not* 0-indexed because it's not list-like).
- `colspan` – how many columns of the figure does *this* plot span (*not* 0-indexed because it's not list-like).

Every time you call `subplot2grid` you are initialising a new axis-object into which you can then draw with your geopackage or pandas plotting methods.

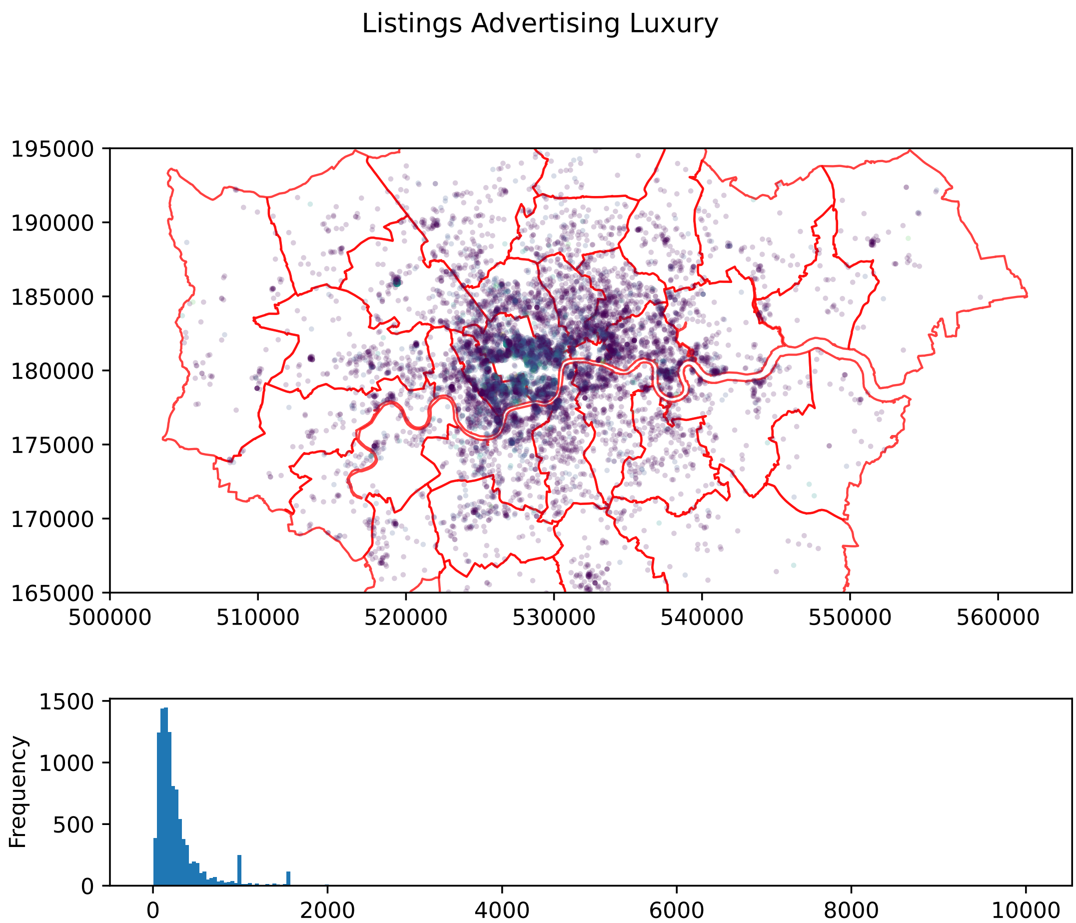
Question

```
f,ax = plt.subplots(1,1,figsize=(9,6))
ax.remove()

# The first plot
```

```
ax1 = plt.subplot2grid((4, 1), (???), rowspan=???)
boros.plot(edgecolor='red', facecolor='none', linewidth=1, alpha=0.75, ax=ax1)
lux.plot(markersize=2, column='price', cmap='viridis', alpha=0.2, scheme='Fisher_Jen

ax1.set_xlim([500000, 565000])
ax1.set_ylim([165000, 195000]);

# The second plot
ax2 = plt.subplot2grid((???), (???), rowspan=1)
lux.price.plot.hist(bins=250, ax=ax2)

plt.suptitle("Listings Advertising Luxury") # <-- How does this differ from title? C
plt.tight_layout() # <-- Try creating the plot *without* this to see what it changes
plt.show()
```

Your result should look similar to:

Figure 1: 'Luxury' listings in London



Question

- What does suptitle do and how is it different from title? Could you use this as part of your plot-making process?
- What does tight_layout do?

3.2 Budget Listings

Difficulty level: Easy, because you've worked out the hard bits already.

3.2.1 Create the Regular Expression

What words can you think of that might help you to spot affordable and budget accommodation? Start with just a couple of words and then I would encourage you to consider what *other* words might help to signal 'affordability'... perhaps words like 'cosy' or 'charming' and then think about how you could you add those to the regex?

Hints: this just builds on what you did above with one exception:

1. I'd try adding word boundary markers to the regex (`\b`) where appropriate...

Question

```
gdf[
    gdf.description.str.contains(???, regex=True, flags=re.IGNORECASE)
].sample(5, random_state=42)[['description']]
```

3.2.2 Apply it to Select Data

Question

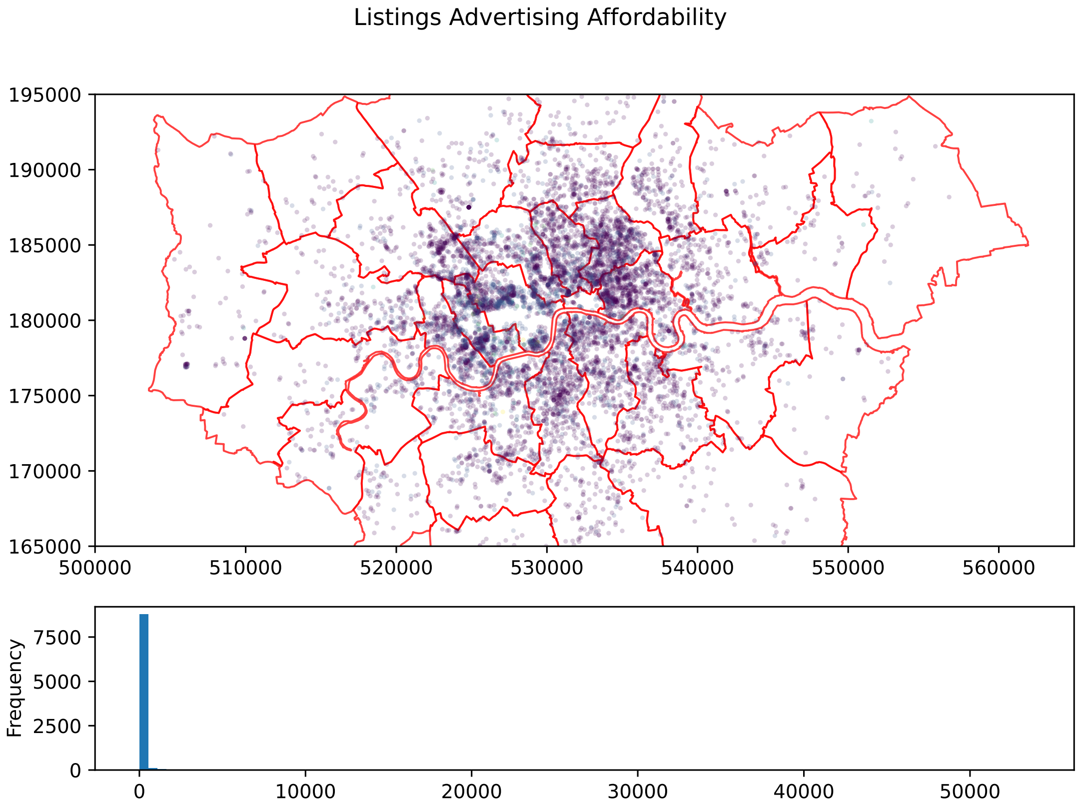
```
aff = gdf[gdf.description.str.contains(???, regex=True, flags=re.IGNORECASE)].copy()
aff.to_parquet(os.path.join('data','clean','affordable.geopackage'))
print(f"There are {aff.shape[0]:,} rows flagged as 'affordable'.")
```

You should get that there are `8,937` rows.

3.2.3 Plot the Data

```
f,ax = plt.subplots(1,1,figsize=(8,6))
ax.remove()

# The first plot
ax1 = plt.subplot2grid((4, 1), (0, 0), rowspan=3)
boros.plot(edgecolor='red', facecolor='none', linewidth=1, alpha=0.75, ax=ax1)
aff.plot(markersize=2, column='price', cmap='viridis', alpha=0.2, scheme='Fisher_Jen

ax1.set_xlim([500000, 565000])
ax1.set_ylim([165000, 195000]);
```

```python
# The second plot
ax2 = plt.subplot2grid((4, 1), (3, 0), rowspan=1)
aff.price.plot.hist(bins=100, ax=ax2)

plt.suptitle("Listings Advertising Affordability")
plt.tight_layout()
#plt.savefig("Affordable_Listings.png", dpi=150)
```



3.2.4 Questions

- Do you think that this is a *good* way to select affordable options?
- Do you understand what `dpi` means and how `savefig` works?
- Copy the code from above but modify it to constrain the histogram on a more limited distribution by *filtering* out the outliers *before* drawing the plot. I would copy the cell above to one just below here so that you keep a working copy available and can undo any changes that break things.

```python

```

3.3 Near Bluespace

> ⚠ Difficulty level: Medium, because you're still learning about regexes.

Now see if you can work out a regular expression to find accommodation that emphasises accessibility to the Thames and other 'blue spaces' as part of the description? One thing you'll need to tackle is that some listings seem to say something about Thameslink and you wouldn't want those be returned as part of a regex looking for *rivers*. So by way of a hint:

- You probably need to think about the Thames, rivers, and water.
- These will probably be *followed* by a qualifier like a 'view' (e.g. Thames-view) or a front (e.g. water-front).
- But you need to rule out things like "close the Thameslink station…"

3.3.1 Create the regular Expression

Question

```
gdf[
    gdf.description.str.contains(???, regex=???, flags=???)
].sample(5, random_state=42)[['description']]
```

3.3.2 Apply it to the Select Data

Question

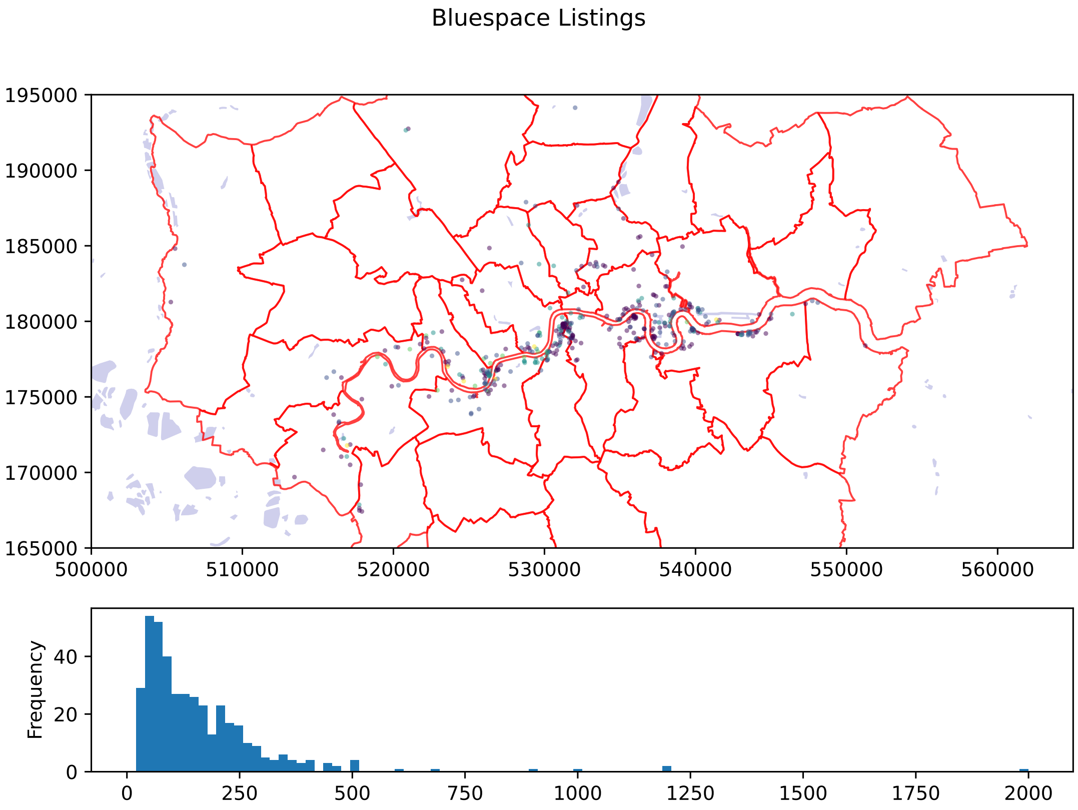
```
bluesp = gdf[
    (gdf.description.str.contains(???, regex=True, flags=re.IGNORECASE)) |
    (gdf.description.str.contains(???, regex=True, flags=re.IGNORECASE))
].copy()
bluesp.to_parquet(os.path.join('data','clean','bluespace.geopackage'))
print(f"Found {bluesp.shape[0]:,} rows.")
```

You should get that there are `408` rows.

3.3.3 Plot the Data

```
f,ax = plt.subplots(1,1,figsize=(8,6))
ax.remove()

# The first plot
ax1 = plt.subplot2grid((4, 1), (0, 0), rowspan=3)
water.plot(edgecolor='none', facecolor=(.25, .25, .7, .25), ax=ax1)
boros.plot(edgecolor='red', facecolor='none', linewidth=1, alpha=0.75, ax=ax1)
bluesp.plot(markersize=2, column='price', cmap='viridis', alpha=0.5, scheme='Fisher_

ax1.set_xlim([500000, 565000])
ax1.set_ylim([165000, 195000]);

# The second plot
ax2 = plt.subplot2grid((4, 1), (3, 0), rowspan=1)
```

```
bluesp.price.plot.hist(bins=100, ax=ax2)

plt.suptitle("Bluespace Listings")
plt.tight_layout()
plt.show()
```



3.3.4 Questions

- How else might you select listings with a view of the Thames or other bluespaces?

3.4 Resources

There is a lot more information out there, including a whole book and your standard O'Reilly text.

And some more useful links:

- Pandas String Contains Method
- Using Regular Expressions with Pandas
- Summarising Chapters from Frankenstein using TF/IDF