Practical 8: Working with Text

The basics of Text Mining and NLP

Table of contents

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.

i ? 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.

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

from pathlib import Path
```

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

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][ ]sessions/week3.html#lectures), 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
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()
```

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:

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

```
gdf = gpd.read_parquet( cache_data(url, Path('data/geo')),
          columns=['geometry', 'listing_url', 'name',
                   'description', 'amenities', 'price']).to_crs('epsg:27700')

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

```
+ data/geo/20250615-London-listings.geoparquet found locally!
gdf has 82,856 rows and CRS is OSGB36 / British National Grid.
```

Load supporting Geopackages:

```
ddir  = Path('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.')
```

```
+ data/geo/Boroughs.gpkg found locally!
+ data/geo/Water.gpkg found locally!
+ data/geo/Greenspace.gpkg found locally!
Done.
```

2 Cleaning Text

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

Regardless, 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 boolean NOT (~) applied to a field where the only test we have is *is NA*.

Question

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

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

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)
```

```
56034   ["Dining table", "Paid high chair - available upon request", "Bathtub", "Cooking ba
25066          ["Kitchen", "Elevator", "Bathtub", "Refrigerator", "Microwave", "Stove", "(
12382   ["Dining table", "Free parking on premises", "Cooking basics", "Carbon monoxide al
72986                                                                               ["H
23137                             ["Kitchen", "Refrigerator", "Free parking on premises",
Name: amenities, dtype: object
```

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

```
gdf.amenities.iloc[0][:25]
```

```
'["Kitchen", "Free parking'
```

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

I would be wary of doing what I do below in a 'proper' application without some careful research, but to make our lives easier, we're going to drop rows where one of the two key columns (Description, Amenities) for this practical is `NaN` because 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.

Question

How do you drop all rows where *either* the description or amenities (or both) are `NaN`:

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

You should get that there are `80,917` rows.

3 Regexes in Pandas

ℹ ? 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 below a 'first pass' at the data and would look very carefully at the output of the TF/IDF vectorizer, Count vectorizer and/or LDA to see if I could improve my regexes for further cycles of analysis...

The main gain here 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 Using Strings in Pandas

We've not done much formally with text data in Pandas, so let's have a quick look at what's possible. Most of these operations are accessed by calling on the `.str` accessor and you can read *alllllll about it*.

3.1.1 Trimming

```
# From the pandas documentation
idx = pd.Index([" jack", "jill ", " jesse ", "frank"])

print(idx)
print(idx.str.strip())
print(idx.str.lstrip())
print(idx.str.rstrip())
```

```
Index([' jack', 'jill ', ' jesse ', 'frank'], dtype='object')
Index(['jack', 'jill', 'jesse', 'frank'], dtype='object')
Index(['jack', 'jill ', 'jesse ', 'frank'], dtype='object')
Index([' jack', 'jill', ' jesse', 'frank'], dtype='object')
```

3.1.2 Lower/Upper Case

```
gdf.sample(3, random_state=42).description.str.lower()
```

```
31167    welcome to the stylish 1br 1bath apartment located just few minutes from the bustli
79360    ⊠ lovely house w/ garden nicely nestled in marylebone <br />⊠ 1345 ft2 | 125 m2 <br /
25654    enjoy a stylish experience at this centrally-located flat. supermarkets, a plethora
Name: description, dtype: object
```

```
gdf.sample(3, random_state=42).description.str.upper()
```

```
31167    WELCOME TO THE STYLISH 1BR 1BATH APARTMENT LOCATED JUST FEW MINUTES FROM THE BUSTLI
79360    ⊠ LOVELY HOUSE W/ GARDEN NICELY NESTLED IN MARYLEBONE <BR />⊠ 1345 FT2 | 125 M2 <BR /
25654    ENJOY A STYLISH EXPERIENCE AT THIS CENTRALLY-LOCATED FLAT. SUPERMARKETS, A PLETHORA
Name: description, dtype: object
```

3.1.3 Replacing

```
gdf.sample(3, random_state=42).description.str.replace(r' ','_',regex=False)
```

```
31167    Welcome_to_the_stylish_1BR_1Bath_apartment_located_just_few_minutes_from_the_bu
79360    ⊠_Lovely_house_w/_garden_nicely_nestled_in_Marylebone_<br_/>⊠_1345_ft2_|_125_m2
25654    Enjoy_a_stylish_experience_at_this_centrally-located_flat._Supermarkets,_a_plet
Name: description, dtype: object
```

```
gdf.sample(3, random_state=42).description.str.replace(r'\W','',regex=True)
```

```
31167                           Welcometothestylish1BR1Bathapartmentlocatedjustfewminutes
79360    LovelyhousewgardennicelynestledinMaryleboneb r1345ft2125m2br3bedroomsbr2bathroom
25654                                     Enjoyastylishexperienceatthiscentrallylocatedfla
Name: description, dtype: object
```

3.1.4 Splitting

```
gdf.sample(3, random_state=42).amenities.str.split(r',')
```

```
31167    [["Microwave", "Hot water kettle", "Body soap", "Cleaning products", "Kitchen",
79360    [["Bathtub", "Cooking basics", "First aid kit", "Carbon monoxide alarm", "Bed li
25654    [["Bathtub", "Dishes and silverware", "Carbon monoxide alarm", "Central heating"
Name: amenities, dtype: object
```

```
gdf.sample(3, random_state=42).amenities.str.split(r',', expand=True)
```

	0	1	2	3
31167	["Microwave"	"Hot water kettle"	"Body soap"	"Cleaning products"
79360	["Bathtub"	"Cooking basics"	"First aid kit"	"Carbon monoxide a
25654	["Bathtub"	"Dishes and silverware"	"Carbon monoxide alarm"	"Central heating"

3.1.5 Indexing

```
gdf.sample(3, random_state=42).description.str[:25]
```

```
31167     Welcome to the stylish 1B
79360     ⊠ Lovely house w/ garden
25654     Enjoy a stylish experienc
Name: description, dtype: object
```

3.1.6 Extraction

```
# For some reason this doesn't take regex=True
gdf.sample(3, random_state=42).description.str.extract(r'stylish (?P<detail>\w+)')
```

	detail
31167	1BR
79360	NaN
25654	experience

3.1.7 Putting it Together

```
gdf.sample(3, random_state=42).amenities.str.upper().str.replace(r'(?:\"|\[|\])', ''
```

	0	1	2	3
31167	MICROWAVE	HOT WATER KETTLE	BODY SOAP	CLEANING PRODUC
79360	BATHTUB	COOKING BASICS	FIRST AID KIT	CARBON MONOXIDE
25654	BATHTUB	DISHES AND SILVERWARE	CARBON MONOXIDE ALARM	CENTRAL HEATING

Or you could also tackle it this way:

```
gdf.sample(3, random_state=42).amenities.str.upper().str.replace(r'(?:\"|\[|\])', ''
```

	55 INCH HDTV	BACKYARD	BATHTUB	BED LINENS	BODY SOAP	CARBON MONOXIDE A
31167	0	0	1	1	1	0
79360	0	1	0	1	0	1
25654	1	0	0	0	0	1

Check Your Data!

The `get_dummies` method works better than I expected! I assumed it would struggle with the `[` and `]` at the start and end of the string; however, I *think* what's happening is that these are not allowed characters in a column name so they're simply dropped from the expansion.
What's nice about the `get_dummies` approach from an analytical standpoint is that it deals with the issue that the amenities are not all listed in the same order in every listing. So some might lead with the size of the TV, while other listings (with equally large televisions) lead with the views. Converting all of these to dummies automatically 'sorts' them so that we can ask questions like 'which listings have a TV *and* a great view?'

3.2 Selecting Data

In the same way that we can use operators like `<` and `==` to select rows from a data frame, we also have the output of operations like `contains` available. So here's an example:

```
gdf[
    gdf.description.str.contains(r'Flat', regex=False, flags=re.IGNORECASE)
].sample(3, random_state=42)[['description']]
```

	description
62750	This is my spacious 1 bed flat (approx 50 sqm), kitchen equipped with all appliances you r
35981	Flat is mins walk to tower bridge and many tourist places.. confirm you like dogs when yo
23645	This three bedroom intrior designed flat on the edge of the idyliic Battersea park and mo

4 Selecting 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.

4.0.1 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 'memoized'/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 regex
].sample(3, random_state=42)[['description']]
```

4.0.2 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)
].copy()
lux.to_parquet(os.path.join('data','clean','luxury.geoparquet'))
print(f"Found {lux.shape[0]:,} records for 'luxury' flats")
```

You should get that there are `8,144` rows.

4.0.3 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.

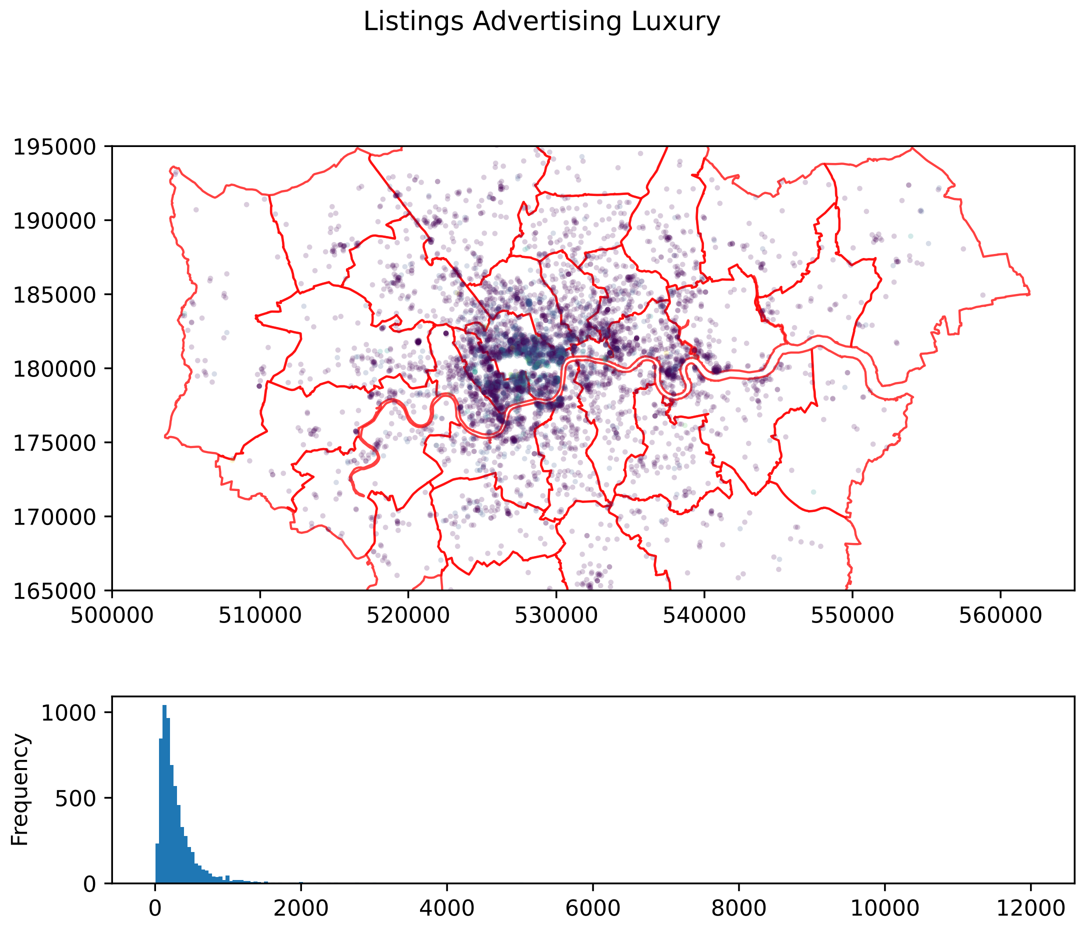
Question

```
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?

5 Selecting Budget Listings

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

5.0.1 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']]
```

5.0.2 Apply it to Select Data

Question

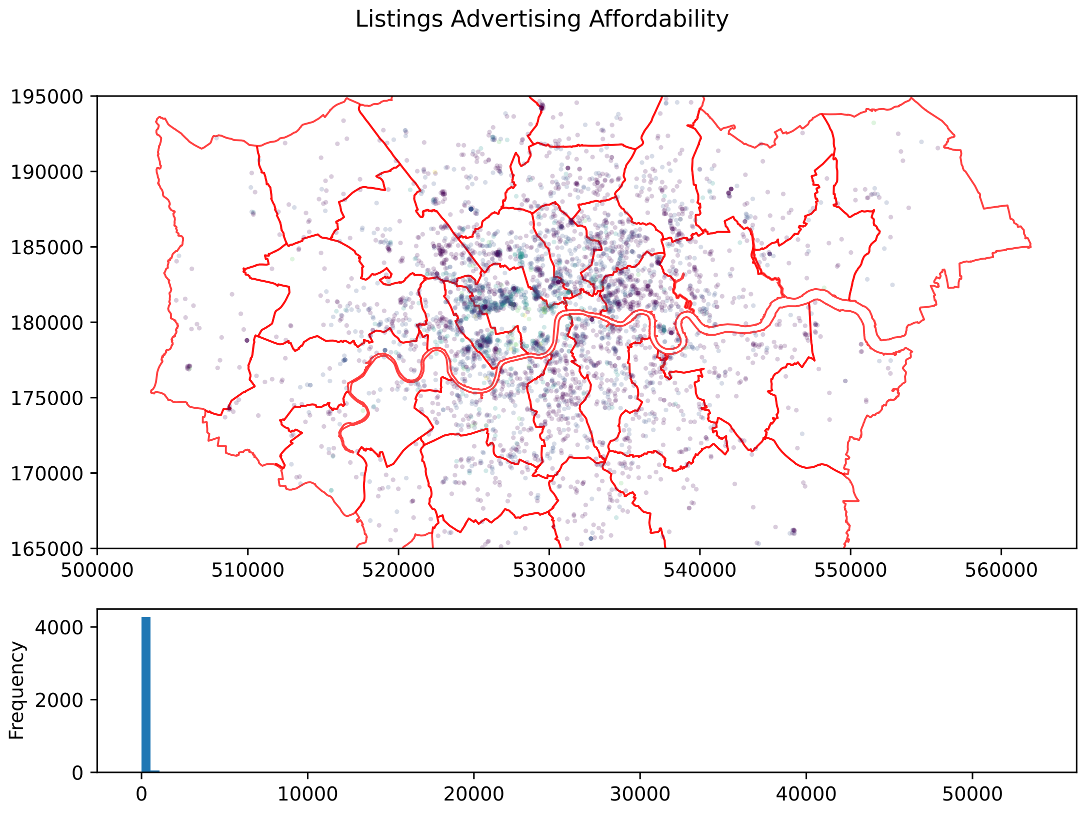
```
aff = gdf[
    gdf.description.str.contains(
        ???,
        regex=True, flags=re.IGNORECASE)
].copy()
aff.to_parquet(os.path.join('data','clean','affordable.geoparquet'))
print(f"There are {aff.shape[0]:,} rows flagged as 'affordable'.")
```

You should get that there are `6,295` rows.

5.0.3 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]);

# 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)
```



5.0.4 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.

```
```

6 Selecting '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..."

6.0.1 Create the regular Expression

Question

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

6.0.2 Apply it to the Select Data

Question

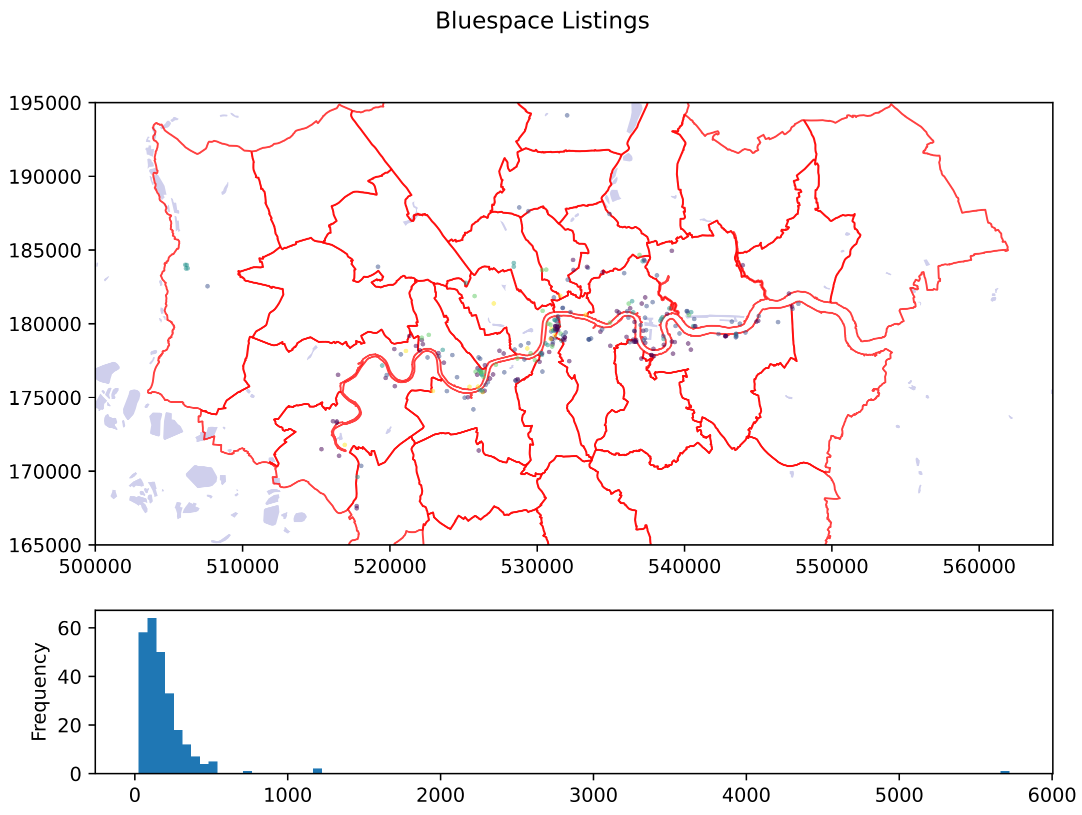
```
bluesp = gdf[
    (gdf.description.str.contains(???, regex=True, flags=re.IGNORECASE)) |
    (gdf.description.str.contains(???, regex=True, flags=re.IGNORECASE))
].copy()
bluesp.to_parquet(os.path.join('data','clean','bluespace.geoparquet'))
print(f"Found {bluesp.shape[0]:,} rows.")
```

You should get that there are `347` rows.

6.0.3 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()
```



6.0.4 Questions

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

7 Real-World Examples

Here are some *parts* of real-world regex code that I'm using to extract the main elements of addresses in a data set that I'm working on. There are four *more* regular expressions that I then compile into one monster regex, but see if you can make sense of what kinds of text they will match.

```
alocation = re.compile(r'''
  \b(?P<flat>
      (?:The)?
      (?:
          (?:Basement|Lower|Ground|Upper|First|Second|Third|Fourth|Fifth|And)
          \b\s*
      )+
      (?:Floors?)?
  )\b\s*
''', re.X | re.IGNORECASE)

# Regex to match ranges in addresses
# This regex matches ranges like '1-5', '2 to 4', '3–7', '10/12', etc.
is_range = re.compile(r'''
    \b(
        (?:
            \d+[A-Ha-h]|  # Note that the order of the conditions
            [A-Ha-h]\d+|  # here matters. If you put \d+ *first*
            \d+|          # then '2b' will never match because '2'
            [A-Ha-h]      # will always be pulled out before.
        )
        \s*
        (?:-|–|—|[Tt]o|/)
        \s*
        (?:
            \d+[A-Ha-h]|
            [A-Ha-h]\d+|
            \d+|
            [A-Ha-h]
        )
    )\b
''', re.X)
```

One way to do that is write some simple 'test cases' and see what happens! Notice that, in the `alocation` regex we have a "named capture group". See if you can *add* this to the `is_range` regular expression... you might want to duplicate the code block above so that you have a 'clean' copy to revert to if you break the regular expressions and aren't sure why.

```
cases = [
    'Lower Ground Floor Flat', 'Flat 2b',
    '#34', 'Basement and Ground Floor',
    '1b-3c Hoxton Square']

for c in cases:
    print(f"Case: {c}")
    m1 = alocation.search(c)
    m2 = is_range.search(c)
    if m1:
        print("\tGot a match on alocation.")
        print(f"\tMatch was: '{m1.group('flat')}'")
    if m2:
        print("\tGot a match on is_range")
        print(f"\tMatch was: '{m2.group(1)}'")
    if not(m1 or m2):
        print("\tNo match.")
    print()
```

```
Case: Lower Ground Floor Flat
	Got a match on alocation.
	Match was: 'Lower Ground Floor'

Case: Flat 2b
	No match.

Case: #34
	No match.

Case: Basement and Ground Floor
	Got a match on alocation.
	Match was: 'Basement and Ground Floor'

Case: 1b-3c Hoxton Square
	Got a match on is_range
	Match was: '1b-3c'
```

8 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