Practical 7: 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 three parts, not all of which you should expect to complete in this session:

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. **You should feel free to stop here and return to the rest later.**
3. Tasks 6–7: are about finding important vocabulary (think 'keywords' and 'significant terms') in documents so that you can start to think about what is *distinctive* about documents and groups of documents. **This is quite useful and relatively easier to understand than what comes next!**
4. Tasks 8–9: are about fully-fledged NLP using Latent Direclecht Allocation (topic modelling) and Word2Vec (words embeddings for use in clustering or similarity work).

The later parts 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.

> **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 Preamble

This practical has been written using `nltk`, but would be *relatively* easy to rework using `spacy`. Most programmers tend to use one *or* the other, and the switch wouldn't be hard other than having to first load the requisite language models:

```
import spacy

# `...web_md` and `...web_lg` are also options
corp = "en_core_web_sm"

try:
    nlp = spacy.load(corp)
except OSError:
    spacy.cli.download(corp)
    nlp = spacy.load(corp)
```

You can read about the models, and note that they are also available in other languages besides English.

2 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.

2.1 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
```

Vectorisers we will use from the 'big beast' of Python machine learning: Sci-Kit Learn.

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation

# We don't use this but I point out where you *could*
from sklearn.preprocessing import OneHotEncoder
```

NLP-specific libraries that we will use for tokenisation, lemmatisation, and frequency analysis.

```
import nltk
import spacy
from nltk.corpus import wordnet as wn
from nltk.stem.wordnet import WordNetLemmatizer

try:
    from nltk.corpus import stopwords
except:
    nltk.download('stopwords')
    from nltk.corpus import stopwords
stopword_list = set(stopwords.words('english'))

from nltk.tokenize import word_tokenize, sent_tokenize
from nltk.tokenize.toktok import ToktokTokenizer

from nltk.stem.porter import PorterStemmer
from nltk.stem.snowball import SnowballStemmer

from nltk import ngrams, FreqDist
```

```
lemmatizer = WordNetLemmatizer()
tokenizer = ToktokTokenizer()
```

Remaining libraries that we'll use for processing and display text data. Most of this relates to dealing with the various ways that text data cleaning is *hard* because of the myriad formats it comes in.

```
import string
import unicodedata
from bs4 import BeautifulSoup
from wordcloud import WordCloud, STOPWORDS
```

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...")
```

2.1.0.0.1 Result!

> Here's my output...

2.2 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?

```
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:

  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:

```
# Set download URL
ymd  = '2023-09-06'
host = 'https://orca.casa.ucl.ac.uk'
url  = f'{host}/~jreades/data/{ymd}-listings.geoparquet'

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/2023-09-06-listings.geoparquet locally!
	Size is 42 MB (43,985,171 bytes)
gdf has 85,134 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.
```

3 Exploratory Textual Analysis

> 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.

> 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 this currently set to?
pd.options.display.max_colwidth=250   # None = no maximum column width (you probably don't want to leave it at
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
```

3.1 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*.

3.1.0.1 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?

3.1.1 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!)

3.2 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)
```

```
id
23851484
930201284366445056    ["Bathtub", "Hot water kettle", "Shampoo", "Luggage dropoff allowed", "Portable heater", "
19955089              ["Shampoo", "Dryer", "Microwave", "Coffee maker", "Hot water", "Iron", "First aid kit", "Washer", "
886165743387675008
13921898              ["Bathtub", "Indoor fireplace", "Shampoo", "Microwave", "Bed linens", "Hot water", "Iron", "Host g
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", "Essentials"]'
```

3.2.1 Questions

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

3.3 Remove NaN Values

> **ℹ 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:

3.3.0.1 Question

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

You should get that there are 84,273 rows.

4 Using Regular Expressions

> **i** Connections
>
> We're building on the work done in Practical 6, 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.

4.1 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.

4.1.1 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 '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.

4.1.1.1 Question

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

4.1.2 Apply it to Select Data

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

4.1.2.1 Question

```
lux = gdf[gdf.description.str.contains(r'???', regex=True, flags=re.IGNORECASE)].copy()
print(f"Found {lux.shape[0]:,} records for 'luxury' flats")
```

You should get 10,368 rows.

4.1.3 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.

4.1.3.1 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_Jenks_Sampled', ax=ax1)

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? Change it and see!
plt.tight_layout() # <-- Try creating the plot *without* this to see what it changes
plt.show()
```

Your result should look similar to:

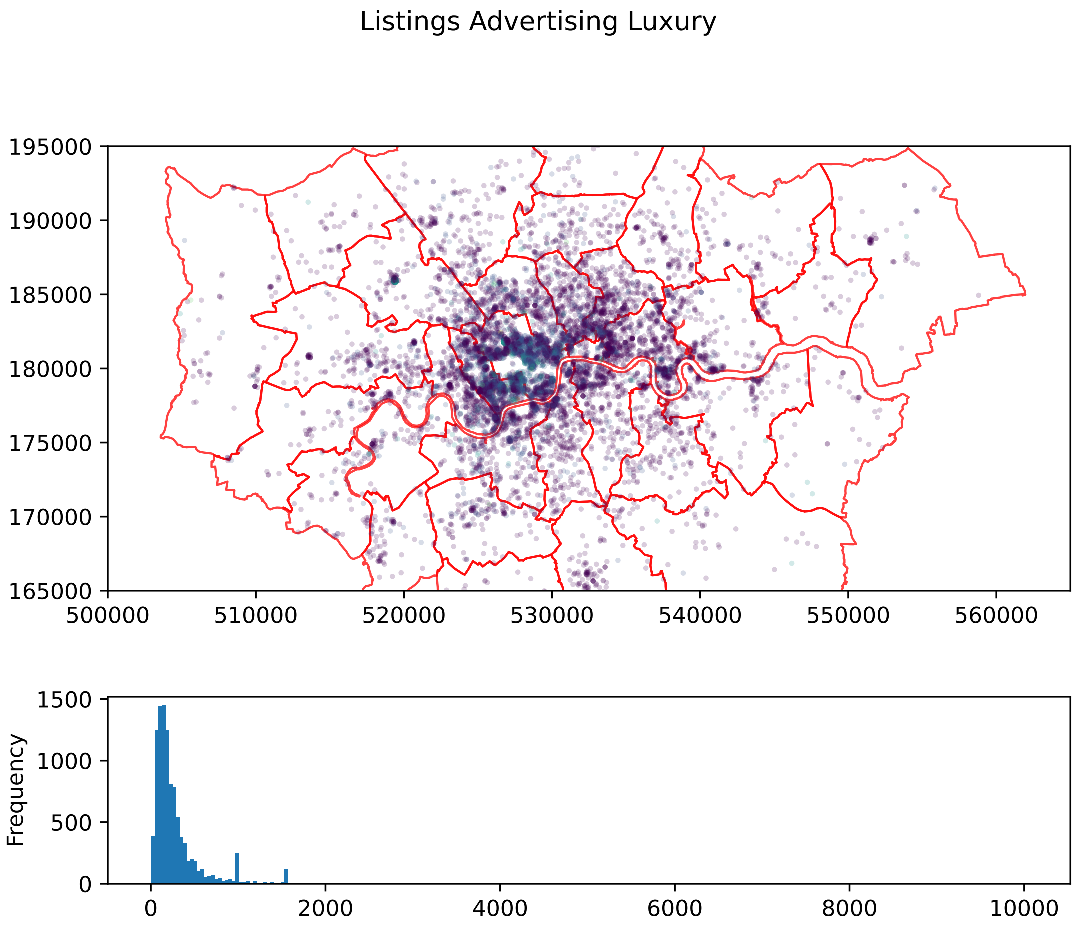


Figure 1: 'Luxury' listings in London

4.1.3.2 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?

4.2 Budget Listings

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

4.2.1 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…

4.2.1.1 Question

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

4.2.2 Apply it to Select Data

4.2.2.1 Question

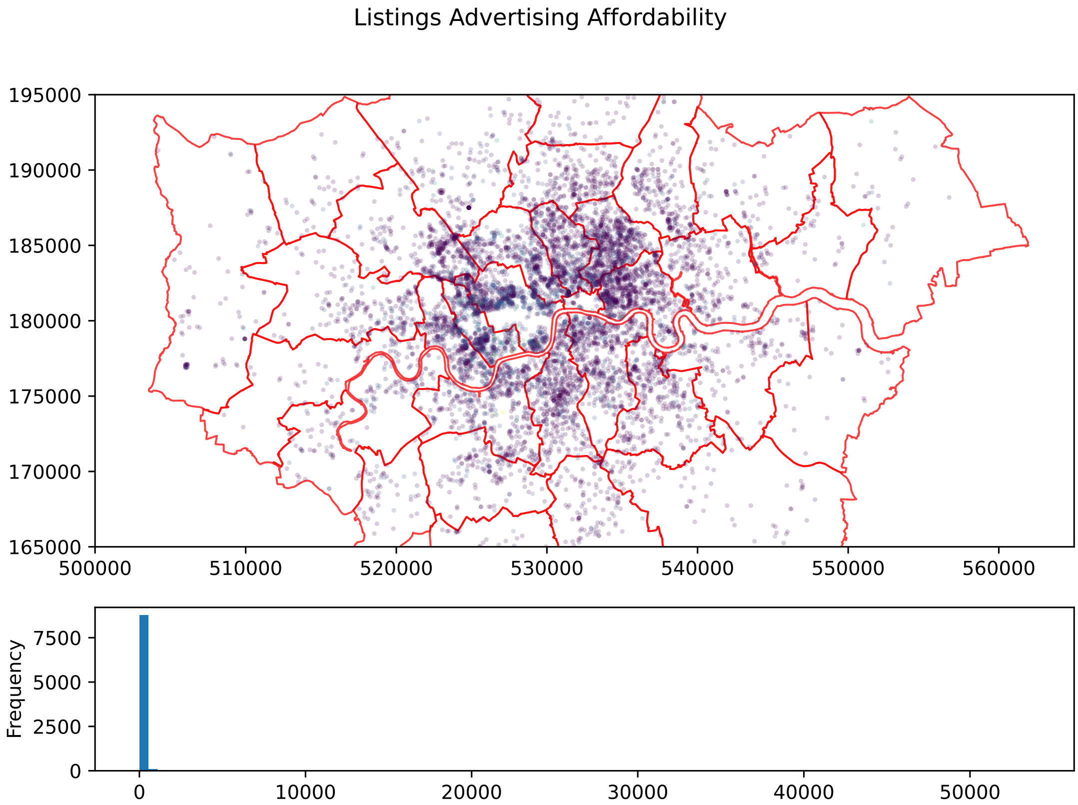
```
aff = gdf[gdf.description.str.contains(???, regex=True, flags=re.IGNORECASE)].copy()
print(f"There are {aff.shape[0]:,} rows flagged as 'affordable'.")
```

You should get {python} f"{aff.shape[0]:,}" rows.

4.2.3 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_Jenks_Sampled', ax=ax1)

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)
```



4.2.4 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.

4.3 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…"

4.3.1 Create the regular Expression

4.3.1.1 Question

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

4.3.2 Apply it to the Select Data

4.3.2.1 Question

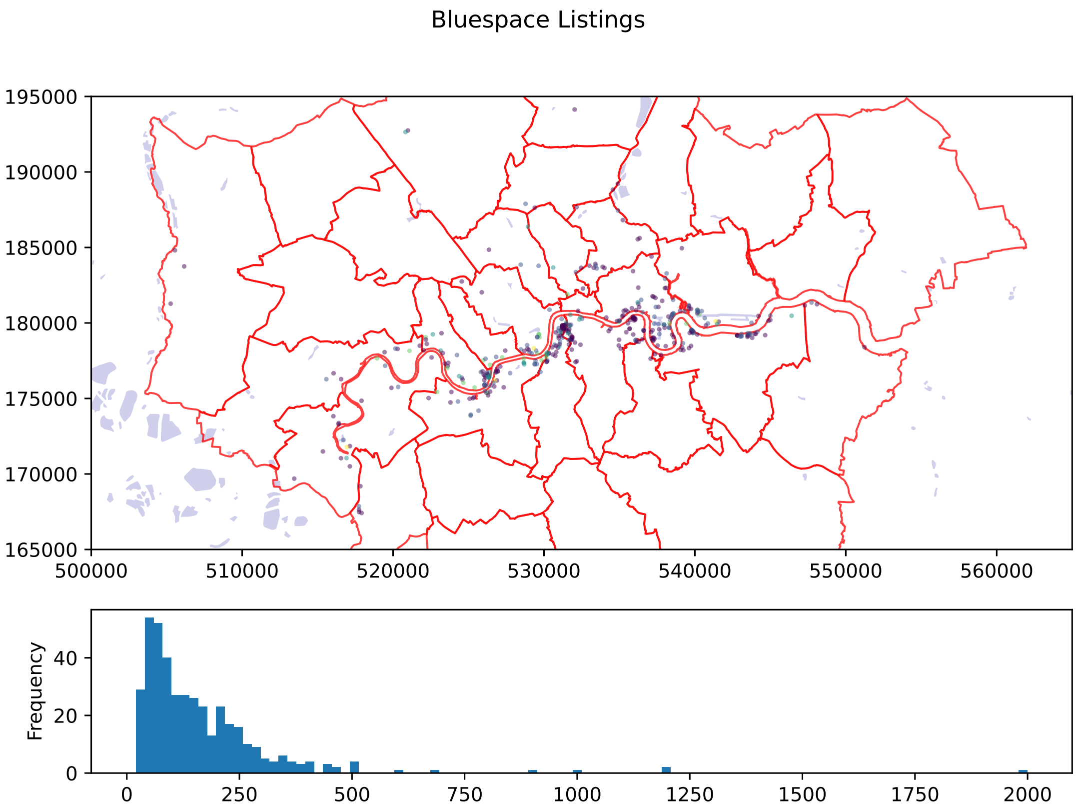
```
bluesp = gdf[
  (gdf.description.str.contains(???, regex=True, flags=re.IGNORECASE)) |
  (gdf.description.str.contains(???, regex=True, flags=re.IGNORECASE))
].copy()
print(f"Found {bluesp.shape[0]:,} rows.")
```

You should get {python} f"{bluesp.shape[0]:,}" rows.

4.3.3 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_Jenks_Sampled', ax=ax1)

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()
```



4.3.4 Questions

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

5 Text Cleaning

Now we're going to step through the *parts* of the process in which we apply to clean and transform text. We'll do this individually before using a function to apply them *all at once*.

5.1 Removing HTML

> ⚠ Difficulty level: Moderate
>
> Because what we're doing will seem really strange and uses some previously unseen libraries that you'll have to google.

Hint: you need to need to **get the text** out of the each returned <p> and <div> element! I'd suggest also commenting this up since there is a *lot* going on on some of these lines of code!

We're going to take a single record to process:

```
sample_row = bluesp.sample(1, random_state=42).description.to_list()[0]
```

Our sample data looks like this:

> An amazing room with equipment you need to make the most of your trip to London. The room has a double size bed, double wardrobe, chest of drawers.We include bedsheets, towels, hand soap, toilet.The house has a bathroom and kitchen that you will share with other roommates.We are 5 min. walk from Canada Water station on zone 2. Central london is 15-20 in tube. You can walk to Tower Bridge, close to river.The spaceA house near the tube station, a 24 hr supermarket, in a quiet area of London, but very close to the center too.Guest accessGuests can use their room and bathroom. Bathroom and kitchen are shared with roommates.During your stayI'm available for questions or tips around the area, through Airbnb messages. Always happy to help!Other things to notePlease do not use shoes inside the houseWe kindly ask to keep noise low from 2

Note, however, that it includes some formatting (bold, line breaks, etc.) that isn't strictly relevant and might actually give us issues downstream because it's 'markup' and not content:

```
An amazing room with equipment you need to make the most of your trip to London. <br />
<br />
The room has a double size bed, double wardrobe, chest of drawers.<br />
<br />
We include bedsheets, towels, hand soap, toilet.<br />
<br />
The house has a bathroom and kitchen that you will share with other roommates.<br />
<br />
We are 5 min. walk from Canada Water station on zone 2. Central london is 15-20 in tube. You can walk to Tower Br
<br />
<b>The space</b><br />
A house near the tube station, a 24 hr supermarket, in a quiet area of London, but very close to the center too.<br />
<br />
<b>Guest access</b><br />
Guests can use their room and bathroom. Bathroom and kitchen are shared with roommates.<br />
<br />
<b>During your stay</b><br />
I'm available for questions or tips around the area, through Airbnb messages. Always happy to help!<br />
<br />
<b>Other things to note</b><br />
Please do not use shoes inside the house<br />
<br />
We kindly ask to keep noise low from 2<br />
```

5.1.0.1 Question

```
cleaned = []

html = sample_row
soup = BeautifulSoup(html)
body = soup.find('body')
```

```
for c in body.findChildren(recursive=False):
  if c.name in ['div','p'] and c.???.strip() != '':
    # \xa0 is a non-breaking space in Unicode (  in HTML)
    txt = [re.sub(r'(?:\u202f|\xa0|\u200b)',' ',x.strip()) for x in c.get_text(separator=" ").split('\n') if x.strip() != '']
    cleaned += txt

# Notice how this has changed from above
print(cleaned)
```

5.2 Lower Case

> Difficulty Level: Low.

5.2.0.1 Question

```
lower = [c.???() for ??? in cleaned]
lower
```

5.3 Stripping 'Punctuation'

> Difficulty level: Hard
>
> This is because you need to understand: 1) why we're *compiling* the regular expression and how to use character classes; and 2) how the NLTK tokenizer differs in approach to the regex.

5.3.1 Regular Expression Approach

We want to clear out punctuation using a regex that takes advantage of the [...] (character class) syntax. The really tricky part is remembering how to specify the 'punctuation' when some of that punctuation has 'special' meanings in a regular expression context. For instance, . means 'any character', while [and] mean 'character class'. So this is another *escaping* problem and it works the *same* way it did when we were dealing with the Terminal...

Hints: some other factors...

1. You will want to match more than one piece of punctuation at a time, so I'd suggest add a + to your pattern.
2. You will need to look into *metacharacters* for creating a kind of 'any of the characters *in this class*' bag of possible matches.

5.3.1.1 Question

```
pattern = re.compile(r'[???]+')
print(pattern)
```

5.3.2 Tokenizer

The other way to do this, which is probably *easier* but produces more complex output, is to draw on the tokenizers already provided by NLTK. For our purposes word_tokenize is probably fine, but depending on your needs there are other options and you can also write your own.

```
nltk.download('punkt')
nltk.download('wordnet')
from nltk.tokenize import word_tokenize
print(word_tokenize)
```

```
<function word_tokenize at 0x3177ee200>
```

```
[nltk_data] Downloading package punkt to /Users/jreades/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /Users/jreades/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

5.3.3 Compare

Look at how these outputs differ in subtle ways:

```
subbed = []
tokens = []
for l in lower:
  subbed.append(re.sub(pattern, ' ', l))
  tokens.append(word_tokenize(l))

for s in subbed:
  as_markdown("Substituted", s)

for t in tokens:
  as_markdown("Tokenised", t)
```

5.3.3.0.1 Substituted

> an amazing room with equipment you need to make the most of your trip to london the room has a double size bed double wardrobe chest of drawers we include bedsheets towels hand soap toilet the house has a bathroom and kitchen that you will share with other roommates we are 5 min walk from canada water station on zone 2 central london is 15 20 in tube you can walk to tower bridge close to river the space a house near the tube station a 24 hr supermarket in a quiet area of london but very close to the center too guest access guests can use their room and bathroom bathroom and kitchen are shared with roommates during your stay i m available for questions or tips around the area through airbnb messages always happy to help other things to note please do not use shoes inside the house we kindly ask to keep noise low from 2

5.3.3.0.2 Tokenised

> ['an', 'amazing', 'room', 'with', 'equipment', 'you', 'need', 'to', 'make', 'the', 'most', 'of', 'your', 'trip', 'to', 'london', '.', 'the', 'room', 'has', 'a', 'double', 'size', 'bed', ',', 'double', 'wardrobe', ',', 'chest', 'of', 'drawers', '.', 'we', 'include', 'bed-sheets', ',', 'towels', ',', 'hand', 'soap', ',', 'toilet', '.', 'the', 'house', 'has', 'a', 'bath-room', 'and', 'kitchen', 'that', 'you', 'will', 'share', 'with', 'other', 'roommates', '.', 'we', 'are', '5', 'min', '.', 'walk', 'from', 'canada', 'water', 'station', 'on', 'zone', '2.', 'central', 'london', 'is', '15-20', 'in', 'tube', '.', 'you', 'can', 'walk', 'to', 'tower', 'bridge', ',', 'close', 'to', 'river', '.', 'the', 'space', 'a', 'house', 'near', 'the', 'tube', 'station', ',', 'a', '24', 'hr', 'supermarket', ',', 'in', 'a', 'quiet', 'area', 'of', 'london', ',', 'but', 'very', 'close', 'to', 'the', 'center', 'too', '.', 'guest', 'access', 'guests', 'can', 'use', 'their', 'room', 'and', 'bathroom', '.', 'bathroom', 'and', 'kitchen', 'are', 'shared', 'with', 'roommates', '.', 'during', 'your', 'stay', 'i', "'m", 'available', 'for', 'questions', 'or', 'tips', 'around', 'the', 'area', ',', 'through', 'airbnb', 'messages', '.', 'always', 'happy', 'to', 'help', '!', 'other', 'things', 'to', 'note', 'please', 'do', 'not', 'use', 'shoes', 'inside', 'the', 'house', 'we', 'kindly', 'ask', 'to', 'keep', 'noise', 'low', 'from', '2']

5.4 Stopword Removal

> **Difficulty Level: Moderate**
>
> You need to remember how list comprehensions work to use the stopword_list.

```
stopword_list = set(stopwords.words('english'))
print(stopword_list)
```

```
{'had', 'only', 'ain', 'ourselves', 'into', 'when', 'are', 'out', 'both', 'that', 've', 'too', 'he', 'doing', "isn't", "you've", 'my', 'for',
```

5.4.0.1 Question

```
stopped = []
for p in tokens: # <-- why do I just take these items from the list?
    stopped.append([x for x in p if x not in ??? and len(x) > 1])

for s in stopped:
    as_markdown("Line", s)
```

5.5 Lemmatisation vs Stemming

> **Difficulty level: Low.**

```
from nltk.stem.porter import PorterStemmer
from nltk.stem.snowball import SnowballStemmer
from nltk.stem.wordnet import WordNetLemmatizer
```

```
lemmatizer = WordNetLemmatizer()
print(lemmatizer.lemmatize('monkeys'))
print(lemmatizer.lemmatize('cities'))
print(lemmatizer.lemmatize('complexity'))
print(lemmatizer.lemmatize('Reades'))
```

```
monkey
city
complexity
Reades
```

```
stemmer = PorterStemmer()
print(stemmer.stem('monkeys'))
print(stemmer.stem('cities'))
print(stemmer.stem('complexity'))
print(stemmer.stem('Reades'))
```

```
monkey
citi
complex
read
```

```
stemmer = SnowballStemmer(language='english')
print(stemmer.stem('monkeys'))
print(stemmer.stem('cities'))
print(stemmer.stem('complexity'))
print(stemmer.stem('Reades'))
```

```
monkey
citi
complex
read
```

```
lemmatizer = WordNetLemmatizer()
lemmas  = []
stemmed = []

# This would be better if we passed in a PoS (Part of Speech) tag as well,
# but processing text for parts of speech is *expensive* and for the purposes
# of this tutorial, not necessary.
for s in stopped:
    lemmas.append([lemmatizer.lemmatize(x) for x in s])

for s in stopped:
    stemmed.append([stemmer.stem(x) for x in s])

for l in lemmas:
    as_markdown('Lemmatised',l)

for s in stemmed:
    as_markdown('Stemmed',s)
```

5.5.0.0.1 Lemmatised

> [‘amazing’, ‘room’, ‘equipment’, ‘need’, ‘make’, ‘trip’, ‘london’, ‘room’, ‘double’, ‘size’, ‘bed’, ‘double’, ‘wardrobe’, ‘chest’, ‘drawer’, ‘include’, ‘bedsheets’, ‘towel’, ‘hand’, ‘soap’, ‘toilet’, ‘house’, ‘bathroom’, ‘kitchen’, ‘share’, ‘roommate’, ‘min’, ‘walk’, ‘canada’, ‘water’, ‘station’, ‘zone’, ‘2.’, ‘central’, ‘london’, ‘15-20’, ‘tube’, ‘walk’, ‘tower’, ‘bridge’, ‘close’, ‘river’, ‘space’, ‘house’, ‘near’, ‘tube’, ‘station’, ‘24’, ‘hr’, ‘supermarket’, ‘quiet’, ‘area’, ‘london’, ‘close’, ‘center’, ‘guest’, ‘access’, ‘guest’, ‘use’, ‘room’, ‘bathroom’, ‘bathroom’, ‘kitchen’, ‘shared’, ‘roommate’, ‘stay’, “ ‘m”, ’available’, ‘question’, ‘tip’, ‘around’, ‘area’, ‘airbnb’, ‘message’, ‘always’, ‘happy’, ‘help’, ‘thing’, ‘note’, ‘please’, ‘use’, ‘shoe’, ‘inside’, ‘house’, ‘kindly’, ‘ask’, ‘keep’, ‘noise’, ‘low’]

5.5.0.0.2 Stemmed

> [‘amaz’, ‘room’, ‘equip’, ‘need’, ‘make’, ‘trip’, ‘london’, ‘room’, ‘doubl’, ‘size’, ‘bed’, ‘doubl’, ‘wardrob’, ‘chest’, ‘drawer’, ‘includ’, ‘bedsheet’, ‘towel’, ‘hand’, ‘soap’, ‘toilet’, ‘hous’, ‘bathroom’, ‘kitchen’, ‘share’, ‘roommat’, ‘min’, ‘walk’, ‘canada’, ‘water’, ‘station’, ‘zone’, ‘2.’, ‘central’, ‘london’, ‘15-20’, ‘tube’, ‘walk’, ‘tower’, ‘bridg’, ‘close’, ‘river’, ‘space’, ‘hous’, ‘near’, ‘tube’, ‘station’, ‘24’, ‘hr’, ‘supermarket’, ‘quiet’, ‘area’, ‘london’, ‘close’, ‘center’, ‘guest’, ‘access’, ‘guest’, ‘use’, ‘room’, ‘bathroom’, ‘bathroom’, ‘kitchen’, ‘share’, ‘roommat’, ‘stay’, “ ‘m”, ’avail’, ‘question’, ‘tip’, ‘around’, ‘area’, ‘airbnb’, ‘messag’, ‘alway’, ‘happi’, ‘help’, ‘thing’, ‘note’, ‘pleas’, ‘use’, ‘shoe’, ‘insid’, ‘hous’, ‘kind’, ‘ask’, ‘keep’, ‘nois’, ‘low’]

5.5.0.1 Compare and Contrast

What are we doing here?

```python
for ix, p in enumerate(stopped):
  stopped_set = set(stopped[ix])
  lemma_set   = set(lemmas[ix])
  print(sorted(stopped_set.symmetric_difference(lemma_set)))
```

```
['drawer', 'drawers', 'guests', 'message', 'messages', 'question', 'questions', 'roommate', 'roommates', 'shoe', 'shoes
```

6 Pandas.Apply

The above approach is fairly hard going since you need to loop through every list element applying these changes one at a time. Instead, we could convert the column to a corpus (or use pandas apply) together with a function imported from a library to do the work.

6.1 Downloading the Custom Module

Difficulty level: Low.

This custom module is not perfect, but it gets the job done… mostly and has some additional features that you could play around with for a final project (e.g. detect_entities and detect_acronyms).

```
import urllib.request
host  = 'https://orca.casa.ucl.ac.uk'
turl  = f'{host}/~jreades/__textual__.py'
tdirs = os.path.join('textual')
tpath = os.path.join(tdirs,'__init__.py')

if not os.path.exists(tpath):
    os.makedirs(tdirs, exist_ok=True)
    urllib.request.urlretrieve(turl, tpath)
```

6.2 Importing the Custom Module

Difficulty Level: Low.

But only because you didn't have to write the module! However, the questions could be hard…

In a Jupyter notebook, this code allows us to edit and reload the library dynamically:

```
%load_ext autoreload
%autoreload 2
```

Now let's import it.

```
from textual import *
```

```
All NLTK libraries installed...
```

```
as_markdown('Input', cleaned)
```

6.2.0.0.1 Input

> ["An amazing room with equipment you need to make the most of your trip to London. The room has a double size bed, double wardrobe, chest of drawers. We include bedsheets, towels, hand soap, toilet. The house has a bathroom and kitchen that you will share with other roommates. We are 5 min. walk from Canada Water station on zone 2. Central london is 15-20 in tube. You can walk to Tower Bridge, close to river. The space A house near the tube station, a 24 hr supermarket, in a quiet area of London, but very close to the center too. Guest access Guests can use their room and bathroom. Bathroom and kitchen are shared with roommates. During your stay I'm available for questions or tips around the area, through Airbnb

messages. Always happy to help! Other things to note Please do not use shoes inside the house We kindly ask to keep noise low from 2”]

```
as_markdown('Normalised', [normalise_document(x, remove_digits=True) for x in cleaned])
```

6.2.0.0.2 Normalised

[‘amazing room equipment need make trip london . room double size double wardrobe chest drawer . include bedsheets towel hand soap toilet . house bathroom kitchen share roommate . walk canada water station zone . central london tube . walk tower bridge close river . space house near tube station supermarket quiet area london close center . guest access guests room bathroom . bathroom kitchen share roommate . stay available question around area airbnb message . always happy help thing note please shoe inside house kindly keep noise’]

```
help(normalise_document)
```

```
Help on function normalise_document in module textual:

normalise_document(doc: str, html_stripping=True, contraction_expansion=True, accented_char_removal=True, te
    Apply all of the functions above to a document using their
    default values so as to demonstrate the NLP process.

    doc: a document to clean.
```

6.2.1 Questions

Let’s assume that you want to analyse web page content…

- Based on the above output, what stopwords do you think are missing?
- Based on the above output, what should be removed but isn’t?
- Based on the above output, how do you think a computer can work with this text?

> Stop!
>
> Beyond this point, we are moving into Natural Language Processing. If you are already struggling with regular expressions, I would recommend *stopping here*. You can come back to revisit the NLP components and creation of word clouds later.

7 Data Normalisation

Now that you’ve seen how the steps are applied to a ‘random’ document, let’s get back to the problem at hand or, as the French would put it, revenons à nos moutons (let’s get back to our sheep).

7.1 Process the Selected Listings

> Difficulty level: Low, but you'll need to be patient!

Notice the use of %%time here – this will tell you how long each block of code takes to complete. It's a really useful technique for reminding *yourself* and others of how long something might take to run. I find that with NLP this is particularly important since you have to do a *lot* of processing on each document in order to normalise it.

> **Tip**
>
> Notice how we can change the default parameters for normalise_document even when using apply, but that the syntax is different. So whereas we'd use normalise_document(doc, remove_digits=True) if calling the function directly, here it's .apply(normalise_document, remove_digits=True)!

7.1.0.1 Question

```
%%time
# I get about 1 minute on a M2 Mac
lux['description_norm'] = lux.???.apply(???, remove_digits=True)
```

```
%%time
# I get about 1 minute on a M2 Mac
aff['description_norm'] = aff.???.apply(???, remove_digits=True)
```

```
%%time
# I get about 2 seconds on a M2 Mac
bluesp['description_norm'] = bluesp.???.apply(???, remove_digits=True)
```

7.2 Select and Tokenise

> Difficulty level: Low, except for the double list-comprehension.

7.2.1 Select and Extract Corpus

See useful tutorial here. Although we shouldn't have any empty descriptions, by the time we've finished normalising the textual data we may have *created* some empty values and we need to ensure that we don't accidentally pass a NaN to the vectorisers and frequency distribution functions.

```
# The data set to which we want to apply
# the data normalisation code... feel free
# to change (though so will your results)
srcdf = bluesp
```

Coding Tip

Notice how you only need to change the value of the variable here to try any of the different selections we did above? This is a simple kind of parameterisation somewhere between a function and hard-coding everything.

```
corpus = srcdf.description_norm.fillna(' ').values
print(corpus[0:3])
```

```
['house garden close thames river . walk  private road river nearby .  district line underground . walk . direct access
 'space appartment upper floor modernised secure building near canary wharf  fantastic view river thames london .
 'newly renovate  totally equipped furnished modern apartment heart london . easily accessible kind transport . wall
```

7.2.2 Tokenise

There are different forms of tokenisation and different algorithms will expect differing inputs. Here are two:

```
sentences = [nltk.sent_tokenize(text) for text in corpus]
words     = [[nltk.tokenize.word_tokenize(sentence)
             for sentence in nltk.sent_tokenize(text)]
             for text in corpus]
```

Notice how this has turned every sentence into an array and each document into an array of arrays:

```
print(f"Sentences 0: {sentences[0]}")
print()
print(f"Words 0: {words[0]}")
```

```
Sentences 0: ['house garden close thames river .', 'walk  private road river nearby .', 'district line underground .', 'wa

Words 0: [['house', 'garden', 'close', 'thames', 'river', '.'], ['walk', 'private', 'road', 'river', 'nearby', '.'], ['district', 'line', 'u
```

7.3 Frequencies and Ngrams

Difficulty level: Moderate.

One new thing you'll see here is the `ngram`: ngrams are 'simply' pairs, or triplets, or quadruplets of words. You may come across the terms unigram (`ngram(1,1)`), bigram (`ngram(2,2)`), trigram (`ngram(3,3)`)... typically, you will rarely find anything beyond trigrams, and these present real issues for text2vec algorithms because the embedding for `geographical`, `information`, and `systems` is *not* the same as for `geographical information systetms`.

7.3.1 Build Frequency Distribution

Build counts for ngram range 1..3:

```
fcounts = dict()

# Here we replace all full-stops... can you think why we might do this?
data = nltk.tokenize.word_tokenize(' '.join([text.replace('.','') for text in corpus]))

for size in 1, 2, 3:
    fdist = FreqDist(ngrams(data, size))
    print(fdist)
    # If you only need one note this: https://stackoverflow.com/a/52193485/4041902
    fcounts[size] = pd.DataFrame.from_dict({f'Ngram Size {size}': fdist})
```

```
<FreqDist with 2692 samples and 26245 outcomes>
<FreqDist with 14173 samples and 26244 outcomes>
<FreqDist with 19540 samples and 26243 outcomes>
```

7.3.2 Output Top-n Ngrams

And output the most common ones for each ngram range:

```
for dfs in fcounts.values():
    print(dfs.sort_values(by=dfs.columns.values[0], ascending=False).head(10))
    print()
```

```
           Ngram Size 1
walk                594
room                472
london              469
river               418
bedroom             412
space               391
minute              382
apartment           373
station             307
flat                303

                Ngram Size 2
minute  walk             252
river   thames           138
        view             138
living  room             134
canary  wharf            112
guest   access           110
central london           107
fully   equip             76
equip   kitchen           71
thames  river             65
```

```
                    Ngram Size 3
fully  equip  kitchen          68
walk   river  thames            37
close  river  thames            35
walk   thames river             27
minute walk   river             23
open   plan   kitchen           20
thames river  view              20
sofa   living room              19
within walk   distance          19
open   plan   live              18
```

7.3.3 Questions

- Can you think why we don't care about punctuation for frequency distributions and n-grams?
- Do you understand what n-grams *are*?

7.4 Count Vectoriser

> Difficulty level: Low, but the output needs some thought!

This is a big foray into sklearn (sci-kit learn) which is the main machine learning and clustering module for Python. For processing text we use *vectorisers* to convert terms to a vector representation. We're doing this on the smallest of the derived data sets because these processes can take a while to run and generate *huge* matrices (remember: one row and one column for each term!).

7.4.1 Fit the Vectoriser

```
cvectorizer = CountVectorizer(ngram_range=(1,3))
cvectorizer.fit(corpus)
```

```
CountVectorizer(ngram_range=(1, 3))
```

7.4.2 Brief Demonstration

Find the number associated with a word in the vocabulary and how many times it occurs in the original corpus:

```
term = 'stratford'
pd.options.display.max_colwidth=750
# Find the vocabulary mapping for the term
print(f"Vocabulary mapping for {term} is {cvectorizer.vocabulary_[term]}")
# How many times is it in the data
print(f"Found {srcdf.description_norm.str.contains(term).sum():,} rows containing {term}")
# Print the descriptions containing the term
```

```
for x in srcdf[srcdf.description_norm.str.contains(term)].description_norm:
  as_markdown('Stratford',x)
```

Vocabulary mapping for stratford is 29373
Found 10 rows containing stratford

7.4.2.0.1 Stratford

> house garden close thames river . walk private road river nearby . district line underground . walk . direct access central london near gardens . kids playground walk distance along thames path . space residential neighborhood english corporate expat family . house culdesac private road river thames . river foot away . walking distance subway . central london underground district line . gardens stop walk zone . addition overground stratford also stop gardens underground station . gardens stop walk . overland railway station bridge . walk . take waterloo railway station minute . bicycle follow towpath hammersmith bridge continue putney bridge . lastly several stree

7.4.2.0.2 Stratford

> please read things note comfortable clean bright brand flat east london minute central london tube quite central great transport link major london attraction minute walk river park undergroundtubedlr station supermarket docklands stratford olympic stadium westfield shopping centre . enjoy brick lane indian restaurant spitalfields market colombian flower market historical whitechapel . space please read things note nice clean fresh bright airy . space perfect professional single person couple . make feel like home choice anything like wake relaxing cooking . guest access please read things note entire flat . please treat home away . please treat .

7.4.2.0.3 Stratford

> comfortable fairly flat east london travel zone minute central london quite central great transport link major london attraction minute walk river park undergroundtube station minute supermarket minute docklands stratford olympic stadium westfield shopping centre . enjoy brick lane indian restaurant spitalfields market colombian flower market historical whitechapel . space spacious comfortable tidy clean airy relaxing . live flat sleep open plan lounge balcony . guest access bathroom share . welcome microwave ready meal toaster make drink till fridge store food . please make sure clean clear immediately . dining table . stay present morning evening weekend . also

7.4.2.0.4 Stratford

entire appartment double bedroom large living area.the apartment feature kitchen come free wifi flat screen tv.to make exicting luxurious even free free sauna well . space stunning apartment london docklands bank thames river close thames barrier park canary wharf . apartment floor spacious living room balcony . nearest station pontoon dock walkable distance direct train stratford . mins . bank . excel centre . walk . arena canary wharf mins train mins central london . world heritage sitethames barrier thames barrier park walk appartment . london city airport train station away . fully kitchen bathroom broadband internet underground secure parking onsite . attract

7.4.2.0.5 Stratford

luxurious bedroom apartment zone love hidden secret part town minute away everywhere river view slow pace main artery town right doorstep well hidden beauty park waterway . easy . walk tube route center town well stratford olympic park canary wharf much much right doorstep space welcome home place love bedroom hold personal belonging bedroom give guest idea size . bedroom large double accommodate comfortably . sofa chair accommodate guest extra extra charge . welcome guest personally wish know . therefore important check time convenient . midnight arrival . time ehich discuss good

7.4.2.0.6 Stratford

place close mile tube station brick lane shoreditch queen mary university london stratford westfield minute tube central london . love place newly renovate flat amazing canal view guest bedroom clean friendly environment . place good couple solo adventurer business traveller .

7.4.2.0.7 Stratford

locate high street give amazing water view stadium sight amazing architectural structure walk pudding mill lane walk abba walk stratford westfield walk stratfordstratford international station mins walk mins train ride central london

7.4.2.0.8 Stratford

modern spacious bedroom suite apartment close river thames wimbledon . situate wandsworth district london england lawn tennis club centre court .km clapham junction . stratford bridge chelsea . city view free wifi throughout property . apartment feature bedroom kitchen fridge oven wash machine flat screen seating area bathroom shower . eventim .km away .

7.4.2.0.9 Stratford

perfect group trip . modern spacious suite apartment close river thames wimbledon . situated wandsworth district london england lawn tennis club centre court .km clapham junction . stratford bridge chelsea . city view free wifi throughout property . apartment feature bedroom kitchen wfridge oven wash machine flat screen seating area bathroom wshower . eventim .km away .

7.4.2.0.10 Stratford

flat locate zone east london near canary wharf . nice quiet residential area canal . flat amazing canal view balcony . enjoy morning coffee swan goose everyday . huge park opposite flat picnic . canary wharf shop mall . mins bank stratford westfield . mins central oxford circus tube . locate convenient transportation link .

7.4.3 Transform the Corpus

You can only *tranform* the entire corpus *after* the vectoriser has been fitted. There is an option to fit_transform in one go, but I wanted to demonstrate a few things here and some vectorisers are don't support the one-shot fit-and-transform approach. **Note the type of the transformed corpus**:

```
cvtcorpus = cvectorizer.transform(corpus)
cvtcorpus # cvtcorpus for count-vectorised transformed corpus
```

```
<408x35278 sparse matrix of type '<class 'numpy.int64'>'
  with 71420 stored elements in Compressed Sparse Row format>
```

7.4.4 Single Document

Here is the **first** document from the corpus:

```
doc_df = pd.DataFrame(cvtcorpus[0].T.todense(),
              index=cvectorizer.get_feature_names_out(), columns=["Counts"]
             ).sort_values('Counts', ascending=False)
doc_df.head(10)
```

	Counts
walk	6
gardens	4
river	4
bridge	3
stop	3
thames	3
station	3
underground	3
railway	2

	Counts
central london	2

7.4.5 Transformed Corpus

```
cvdf = pd.DataFrame(data=cvtcorpus.toarray(),
                    columns=cvectorizer.get_feature_names_out())
print(f"Raw count vectorised data frame has {cvdf.shape[0]:,} rows and {cvdf.shape[1]:,} columns.")
cvdf.iloc[0:5,0:10]
```

Raw count vectorised data frame has 408 rows and 35,278 columns.

	aaathe	aaathe apartment	aaathe apartment quiet	aand	aand comfy	aand comfy sofa	ab
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0

7.4.6 Filter Low-Frequency Words

These are likely to be artefacts of text-cleaning or human input error. As well, if we're trying to look across an entire corpus then we might not want to retain words that only appear in a couple of documents.

Let's start by getting the *column* sums:

```
sums = cvdf.sum(axis=0)
print(f"There are {len(sums):,} terms in the data set.")
sums.head()
```

There are 35,278 terms in the data set.

```
aaathe                    1
aaathe apartment          1
aaathe apartment quiet    1
aand                      1
aand comfy                1
dtype: int64
```

Remove columns (i.e. terms) appearing in **less than 1% of documents**. You can do this by thinking about what the shape of the data frame means (rows and/or columns) and how you'd get 1% of that!

7.4.6.1 Question

```
filter_terms = sums >= cvdf.shape[0] * ???
```

Now see how we can use this to strip out the columns corresponding to low-frequency terms:

```
fcvdf = cvdf.drop(columns=cvdf.columns[~filter_terms].values)
print(f"Filtered count vectorised data frame has {fcvdf.shape[0]:,} rows and {fcvdf.shape[1]:,} columns.")
fcvdf.iloc[0:5,0:10]
```

```
Filtered count vectorised data frame has 408 rows and 2,043 columns.
```

	able	access	access access	access bathroom	access central	access central london	access
0	0	1	0	0	1	1	0
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	1	0	0	0	0	0

```
fcvdf.sum(axis=0)
```

```
able                      8
access                  242
access access             7
access bathroom           5
access central            8
                       ...
zone comfortable cosy     7
zone near                 5
zone near underground     5
zone recently            10
zone recently refurbish  10
Length: 2043, dtype: int64
```

7.4.7 Questions

- Can you explain what doc_df contains?
- What does cvdf contain? Explain the rows and columns.
- What is the function of filter_terms?

7.5 TF/IDF Vectoriser

> ⚠ Difficulty level: Moderate
>
> But only if you want to understand how max_df and min_df work!

7.5.1 Fit and Transform

```
tfvectorizer = TfidfVectorizer(use_idf=True, ngram_range=(1,3),
                    max_df=0.75, min_df=0.01) # <-- these matter!
tftcorpus    = tfvectorizer.fit_transform(corpus) # TF-transformed corpus
```

7.5.2 Single Document

```
doc_df = pd.DataFrame(tftcorpus[0].T.todense(), index=tfvectorizer.get_feature_names_out(), columns=["Weights"]
doc_df.sort_values('Weights', ascending=False).head(10)
```

	Weights
gardens	0.414885
stop	0.241659
district line	0.239192
railway	0.232131
underground	0.201738
district	0.197221
bridge	0.191983
walk	0.189485
road	0.151163
distance	0.142999

7.5.3 Transformed Corpus

```
tfidf = pd.DataFrame(data=tftcorpus.toarray(),
                columns=tfvectorizer.get_feature_names_out())
print(f"TF/IDF data frame has {tfidf.shape[0]:,} rows and {tfidf.shape[1]:,} columns.")
tfidf.head()
```

TF/IDF data frame has 408 rows and 1,911 columns.

	able	access	access access	access bathroom	access central	access central london	acce
0	0.0	0.043972	0.0	0.0	0.11031	0.11031	0.0
1	0.0	0.000000	0.0	0.0	0.00000	0.00000	0.0
2	0.0	0.000000	0.0	0.0	0.00000	0.00000	0.0
3	0.0	0.000000	0.0	0.0	0.00000	0.00000	0.0
4	0.0	0.044127	0.0	0.0	0.00000	0.00000	0.0

7.5.4 Questions

- What does the TF/IDF score *represent*?
- What is the role of max_df and min_df?

8 Word Clouds

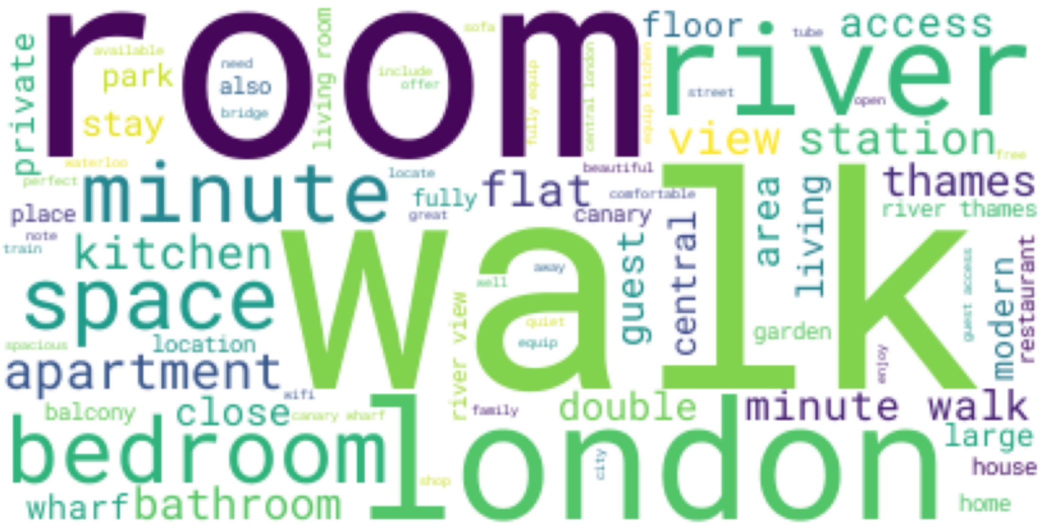
8.1 For Counts

Difficulty level: Easy!

```
fcvdf.sum().sort_values(ascending=False)
```

```
walk                     595
room                     472
london                   471
river                    418
bedroom                  412
                        ...
chic                       5
term                       5
choice                     5
teddington                 5
london aquarium minute     5
Length: 2043, dtype: int64
```

```
ff = 'RobotoMono-VariableFont_wght.ttf'
dp = '/home/jovyan/.local/share/fonts/'
tp = os.path.join(os.path.expanduser('~'),'Library','Fonts')
if os.path.exists(tp):
    fp = os.path.join(tp,ff)
else:
    fp = os.path.join(dp,ff)

f,ax = plt.subplots(1,1,figsize=(7, 7))
plt.gcf().set_dpi(150)
Cloud = WordCloud(
    background_color="white",
    max_words=75,
    font_path=fp
).generate_from_frequencies(fcvdf.sum())
ax.imshow(Cloud)
ax.axis("off");
#plt.savefig("Wordcloud 1.png")
```



8.2 For TF/IDF Weighting

> 💡 Difficulty level: Low, but you'll need to be patient!

```
tfidf.sum().sort_values(ascending=False)
```

```
walk                  23.037285
room                  19.135852
london                18.744519
minute                18.650909
apartment             18.082855
                        ...
station apartment one     0.401426
station also close        0.401426
apartment one benefit     0.401426
apartment one             0.401426
also close station        0.401426
Length: 1911, dtype: float64
```

```
f,ax = plt.subplots(1,1,figsize=(7, 7))
plt.gcf().set_dpi(150)
Cloud = WordCloud(
    background_color="white",
    max_words=100,
    font_path=fp
).generate_from_frequencies(tfidf.sum())
ax.imshow(Cloud)
ax.axis("off");
#plt.savefig("Wordcloud 2.png")
```

8.2.1 Questions

- What does the sum represent for the count vectoriser?
- What does the sum represent for the TF/IDF vectoriser?

8.3 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