Practical 7: Working with Text (Part 2)

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.

> **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 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'))
```

```python
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.

```python
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:

```python
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 (44,152,609 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

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']]
```

3.1.0.2 Answer

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

id	description
21898360	A wonderful double room in harrow on the hill.<br /><br />Very quite and secu
40269638	- 3 Bedrooms 2 beds and 1 sofa bed<br />- 2 Bathroom<br />- 0.5 miles Underg
610813289456549376	St George Wharf is a landmark riverside development spanning across 7 acres
917365608608238592	My place is in the Heart of London. It is only 15 mins to KINGS CROSS Unde
6319621	This artsy and cozy small 1 bedroom split level flat is 4 min. from Seven Sister

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

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

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

3.3.0.2 Answer

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

```
Now gdf has 84,273 rows.
```

You should get that there are 84,273 rows.

4 Using Regular Expressions

 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(5, random_state=42)[['description']]
```

4.1.1.2 Answer

```
gdf[
  gdf.description.str.contains(r'(?:luxur(?:y|ious|iat)|prestigious|stunning)', regex=True, flags=re.IGNORECASE)
].sample(5, random_state=42)[['description']]
```

id	description
21052595	NEW 4 BEDROOM HOUSE WITH PRIVATE GARDEN IN WEST HAMPST
3798279	Beautiful home in Kingston upon Thames. Central location - short walk to th
821457432530779648	Stunning spacious one bedroom apartment in one of London's most prime lo
859336290217358976	Well thought out townhouse on a pedestrianised Avenue for families/groups o

id	description
959952321493154432	Perfectly located in Knightsbridge, convenient to most hot spots. This chic ho

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")
```

4.1.2.2 Answer

```
lux = gdf[gdf.description.str.contains(r'(?:luxur(?:y|ious|iat)|prestigious|stunning)', regex=True, flags=re.IGNORECA
print(f"Found {lux.shape[0]:,} records for 'luxury' flats")
```

```
Found 10,368 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).

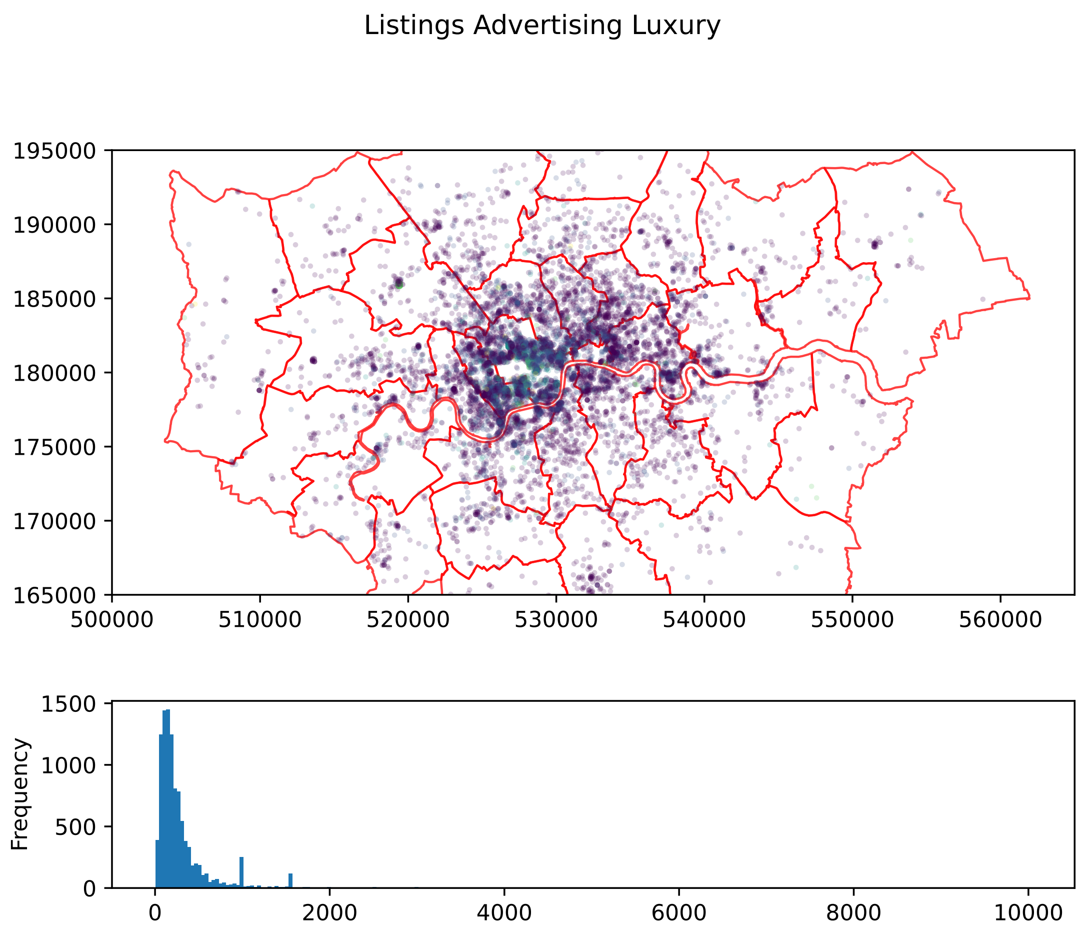
Every time you call subplot2grid you are initialising a new axis-object into which you can then draw with your geopackage or pandas plotting methods.

4.1.3.1 Question

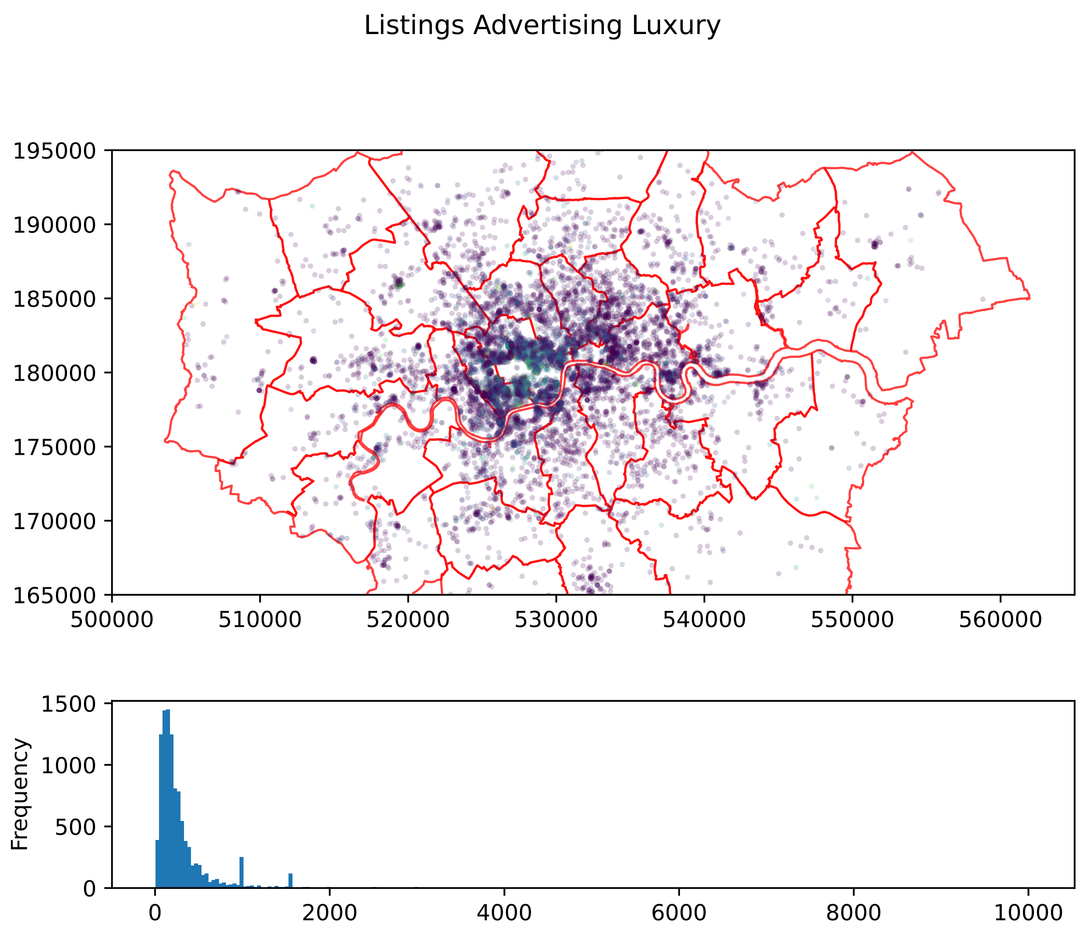
```
f,ax = plt.subplots(1,1,figsize=(9,6))
ax.remove()

# 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()
```

4.1.3.2 Answer

```
f,ax = plt.subplots(1,1,figsize=(7,6))
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)
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((4, 1), (3, 0), 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
```



Your result should look similar to:



4.1.4 Questions

- 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']]
```

4.2.1.2 Answer

```
gdf[
  gdf.description.str.contains(r'\b(?:affordable|budget|cheap|cosy)\b',
  regex=True, flags=re.IGNORECASE)
].sample(5, random_state=42)[['description']]
```

id	description
10466073	This is a charming little flat in crouch end, North London. It is located 10min
679538210387434496	This trendy and spacious 3 bed house in Bow, is ideal for people who want to
7560171	The spacious house offers double bedroom with ensuit bathroom, a large kitc
721518857445429120	Kick back and relax in this calm, stylish one-bedroom, ground-floor flat in Le
731014319309725184	Beautiful 1 bedroom apartment in the heart of Peckham, only 10 minutes wall

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'.")
```

4.2.2.2 Answer

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

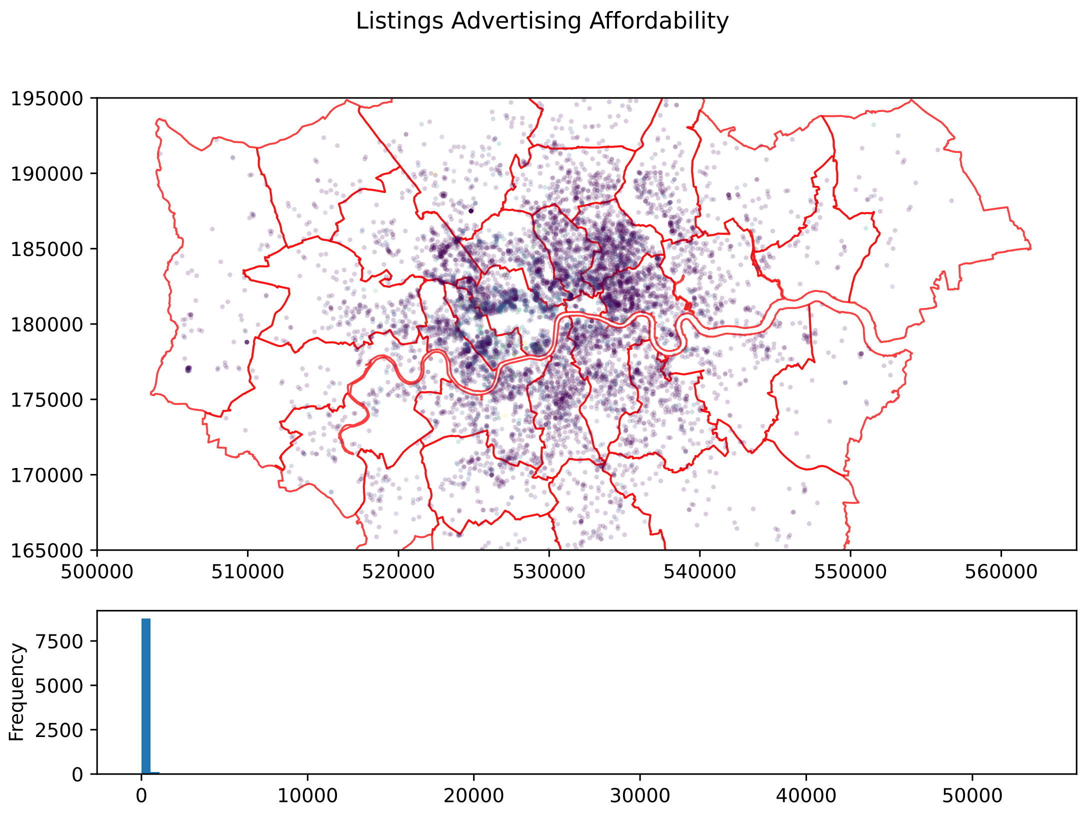
```
There are 8,937 rows flagged as 'affordable'.
```

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']]
```

4.3.1.2 Answer

```
gdf[
  gdf.description.str.contains(r'(?:Thames|river|water|canals?)(?:-|\s+)(?: view|\s?front)\b',
  regex=True, flags=re.IGNORECASE)
].sample(5, random_state=42)[['description']]
```

id	description
906924808902274560	Brand new ultra spacious apartment just one minute walk from the Excel cen
600645213392859136	Are you a woman?<br />We offer a warm and friendly, Home from home, welc
868117243960619264	Just across the street from water front, near shadwell basin. View of Canary V
722937027420061056	There's no better way to experience the beauty of London City than by sleepir
26748596	Welcome to Sunbury Lane in Battersea :)<br /><br />My house is just off the ri

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.")
```

4.3.2.2 Answer

```
bluesp = gdf[
    (gdf.description.str.contains(r'(?:Thames|river|water|canals?)(?:-|\s+)(?:view|front)\b', regex=True, flags=re.IGNO
    (gdf.description.str.contains(r'(?:walk|close|near) to (?:Thames|river|water|canal)', regex=True, flags=re.IGNORE
].copy()
print(f"Found {bluesp.shape[0]:,} rows.")
```

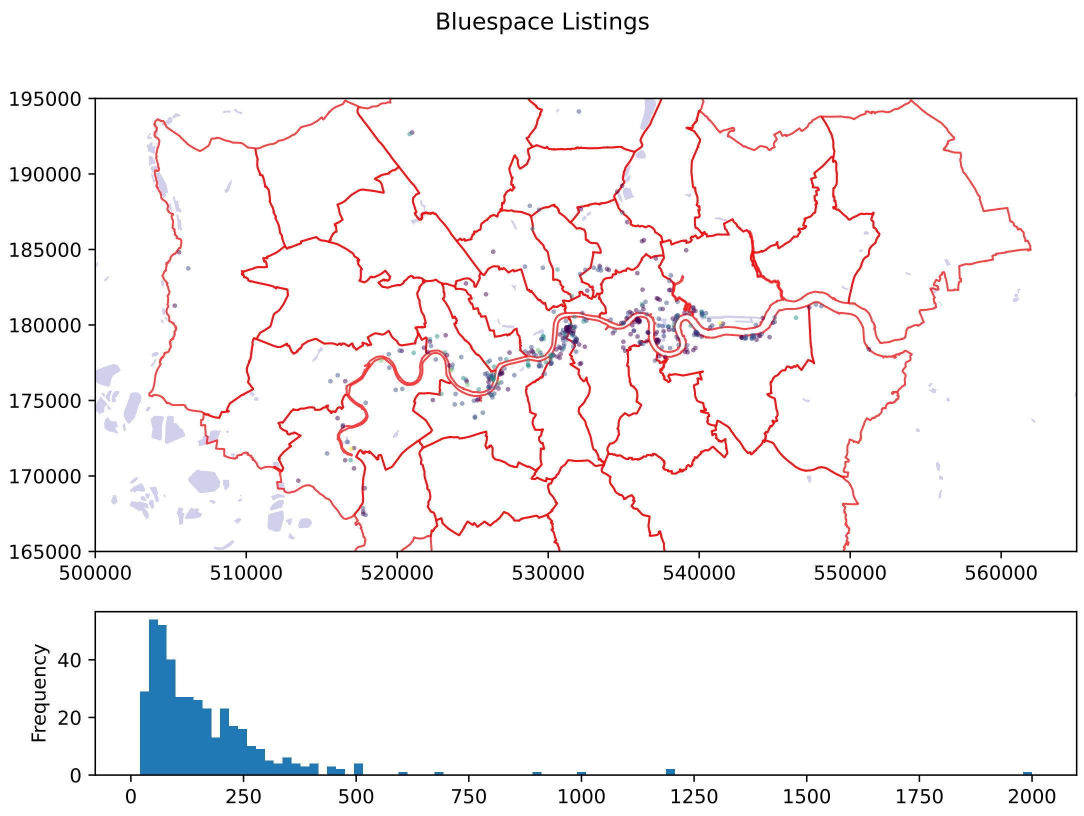
```
Found 408 rows.
```

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()
```

Bluespace Listings



4.3.4 Questions

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

5 Illustrative Text Cleaning

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

5.1 Downloading a Web Page

Difficulty Level: Low.

There is plenty of good economic geography research being done using web pages. Try using Google Scholar to look for work using the British Library's copy of the *Internet Archive*.

```
from urllib.request import urlopen, Request

# We need this so that the Bartlett web site 'knows'
# what kind of browser it is deasling with. Otherwise
# you get a Permission Error (403 Forbidden) because
# the site doesn't know what to do.
hdrs = {
  'User-Agent': 'Mozilla/5.0 (X11; Linux x86_64) AppleWebKit/537.11 (KHTML, like Gecko) Chrome/23.0.1271.64 S
  'Accept': 'text/html,application/xhtml+xml,application/xml;q=0.9,*/*;q=0.8',
}
url = 'https://www.ucl.ac.uk/bartlett/casa/about-0'
```

5.1.0.1 Question

```
# Notice that here we have to assemble a request and
# then 'open' it so that the request is properly issued
# to the web server. Normally, we'd just use `urlopen`,
# but that doesn't give you the ability to set the headers.
request  = Request(url, None, hdrs) #The assembled request
response = urlopen(request)
html     = response.???.decode('utf-8') # The data you need

print(html[:1000])
```

5.1.0.2 Answer

```
# Notice that here we have to assemble a request and
# then 'open' it so that the request is properly issued
# to the web server. Normally, we'd just use `urlopen`,
# but that doesn't give you the ability to set the headers.
request  = Request(url, None, hdrs) #The assembled request
response = urlopen(request)
html     = response.read().decode('utf-8') # The data you need

print(html[:1000])
```

```
<!DOCTYPE html>
<!--[if IE 7]>
<html lang="en" class="lt-ie9 lt-ie8 no-js"> <![endif]-->
<!--[if IE 8]>
<html lang="en" class="lt-ie9 no-js"> <![endif]-->
<!--[if gt IE 8]><!-->
<html lang="en" class="no-js"> <!--<![endif]-->
<head>
  <meta name="viewport" content="width=device-width, initial-scale=1.0"/>
  <meta name="author" content="UCL"/>
  <meta property="og:profile_id" content="uclofficial"/>
  <meta http-equiv="Content-Type" content="text/html; charset=utf-8" />
<link rel="shortcut icon" href="https://www.ucl.ac.uk/bartlett/casa/sites/all/themes/indigo/favicon.ico" type="image/
<meta name="description" content="The Centre for Advanced Spatial Analysis (CASA) is an interdisciplinary researc
<link rel="canonical" href="https://www.ucl.ac.uk/bartlett/casa/about-0" />
<meta name="ucl:faculty" content="Bartlett" />
<meta name="ucl:org_unit" content="Cent
```

5.2 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!

5.2.0.1 Question

```
cleaned = []

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 (&nbsp; 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

cleaned
```

5.2.0.2 Answer

```
cleaned = []

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

for c in body.findChildren(recursive=False):
    if c.name in ['div','p'] and c.get_text().strip() != '':
        # \xa0 is a non-breaking space in Unicode (&nbsp; 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

cleaned
```

```
['UCL Home The Bartlett Centre for Advanced Spatial Analysis About',
 'About',
 'The Centre for Advanced Spatial Analysis (CASA) is an interdisciplinary research institute focusing on the science
 'The Centre for Advanced Spatial Analysis (CASA) was established in 1995 to lead the development of a science of
including physicists, planners, geographers, economists, data scientists, architects, mathematicians and compute
united by our mission to tackle the biggest challenges facing cities and societies around the world.  We work acros
 'View Map',
 'Contact Address: UCL Centre for Advanced Spatial Analysis First Floor, 90 Tottenham Court Road London W1T 4T
 'Tweets by CASAUCL']
```

5.3 Lower Case

Difficulty Level: Low.

5.3.0.1 Question

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

5.3.0.2 Answer

```
lower = [s.lower() for s in cleaned]
lower
```

```
['ucl home the bartlett centre for advanced spatial analysis about',
 'about',
 'the centre for advanced spatial analysis (casa) is an interdisciplinary research institute focusing on the science of
 'the centre for advanced spatial analysis (casa) was established in 1995 to lead the development of a science of ci
including physicists, planners, geographers, economists, data scientists, architects, mathematicians and compute
united by our mission to tackle the biggest challenges facing cities and societies around the world.  we work acros
 'view map',
 'contact address: ucl centre for advanced spatial analysis first floor, 90 tottenham court road london w1t 4tj teleph
 'tweets by casaucl']
```

5.4 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.

5.4.1 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.

5.4.1.1 Question

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

5.4.1.2 Answer

```
pattern = re.compile(r'[,\.!\-><=\(\)\[\]V&\'\'";\+\–\—]+')
print(pattern)
```

```
re.compile('[,\\.!\\-><=\\(\\)\\[\\]V&\\\'\\'";\\+\\–\\—]+')
```

5.4.2 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 0x17ff462a0>
```

```
[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!
```

5.4.3 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)
```

5.4.3.0.1 Substituted

> ucl home the bartlett centre for advanced spatial analysis about

5.4.3.0.2 Substituted

about

5.4.3.0.3 Substituted

the centre for advanced spatial analysis casa is an interdisciplinary research institute focusing on the science of cities within the bartlett faculty of the built environment at ucl

5.4.3.0.4 Substituted

the centre for advanced spatial analysis casa was established in 1995 to lead the development of a science of cities drawing upon methods and ideas in modelling and data science sensing the urban environment visualisation and computation today casa s research is still pushing boundaries to create better cities for everyone both leading the intellectual agenda and working closely with government and industry partners to make real world impact our teaching reflects this making the most of our cutting edge research tools new forms of data and long standing non academic partnerships to train the next generation of urban scientists with the skills and ideas they ll need to have an impact in industry government academia and the third sector the casa community is closely connected but strongly interdisciplinary we bring together people from around the world with a unique variety of backgrounds including physicists planners geographers economists data scientists architects mathematicians and computer scientists united by our mission to tackle the biggest challenges facing cities and societies around the world we work across multiple scales: from the hyper local environment of the low powered sensor all the way up to satellite remote sensing of whole countries and regions studying at casa brings lifelong value with our students poised to take on leadership and integration roles at the forefront of urban and spatial data science by studying with us you will become part of our active and engaged alumni community with access to job listings networking and social activities as well as continued contact with our outstanding teachers and researchers location the ucl centre for advanced spatial analysis is located at 90 tottenham court road london w1t 4tj

5.4.3.0.5 Substituted

view map

5.4.3.0.6 Substituted

contact address: ucl centre for advanced spatial analysis first floor 90 tottenham court road london w1t 4tj telephone: 44 0 20 3108 3877 email: casa@ucl ac uk

5.4.3.0.7 Substituted

tweets by casaucl

5.4.3.0.8 Tokenised

[‘ucl’, ‘home’, ‘the’, ‘bartlett’, ‘centre’, ‘for’, ‘advanced’, ‘spatial’, ‘analysis’, ‘about’]

5.4.3.0.9 Tokenised

[‘about’]

5.4.3.0.10 Tokenised

[‘the’, ‘centre’, ‘for’, ‘advanced’, ‘spatial’, ‘analysis’, ‘(’, ‘casa’, ‘)’, ‘is’, ‘an’, ‘interdisciplinary’, ‘research’, ‘institute’, ‘focusing’, ‘on’, ‘the’, ‘science’, ‘of’, ‘cities’, ‘within’, ‘the’, ‘bartlett’, ‘faculty’, ‘of’, ‘the’, ‘built’, ‘environment’, ‘at’, ‘ucl’, ‘.’]

5.4.3.0.11 Tokenised

[‘the’, ‘centre’, ‘for’, ‘advanced’, ‘spatial’, ‘analysis’, ‘(’, ‘casa’, ‘)’, ‘was’, ‘established’, ‘in’, ‘1995’, ‘to’, ‘lead’, ‘the’, ‘development’, ‘of’, ‘a’, ‘science’, ‘of’, ‘cities’, ‘drawing’, ‘upon’, ‘methods’, ‘and’, ‘ideas’, ‘in’, ‘modelling’, ‘and’, ‘data’, ‘science’, ‘,’, ‘sensing’, ‘the’, ‘urban’, ‘environment’, ‘,’, ‘visualisation’, ‘and’, ‘computation’, ‘.’, ‘today’, ‘,’, ‘casa’, ’ ’ ‘, ’s’, ‘research’, ‘is’, ‘still’, ‘pushing’, ‘boundaries’, ‘to’, ‘create’, ‘better’, ‘cities’, ‘for’, ‘everyone’, ‘,’, ‘both’, ‘leading’, ‘the’, ‘intellectual’, ‘agenda’, ‘and’, ‘working’, ‘closely’, ‘with’, ‘government’, ‘and’, ‘industry’, ‘partners’, ‘to’, ‘make’, ‘real-world’, ‘impact’, ‘.’, ‘our’, ‘teaching’, ‘reflects’, ‘this’, ‘,’, ‘making’, ‘the’, ‘most’, ‘of’, ‘our’, ‘cutting-edge’, ‘research’, ‘,’, ‘tools’, ‘,’, ‘new’, ‘forms’, ‘of’, ‘data’, ‘,’, ‘and’, ‘long-standing’, ‘non-academic’, ‘partnerships’, ‘to’, ‘train’, ‘the’, ‘next’, ‘generation’, ‘of’, ‘urban’, ‘scientists’, ‘with’, ‘the’, ‘skills’, ‘and’, ‘ideas’, ‘they’, ’ ’ ‘, ’ll’, ‘need’, ‘to’, ‘have’, ‘an’, ‘impact’, ‘in’, ‘industry’, ‘,’, ‘government’, ‘,’, ‘academia’, ‘,’, ‘and’, ‘the’, ‘third’, ‘sector’, ‘.’, ‘the’, ‘casa’, ‘community’, ‘is’, ‘closely’, ‘connected’, ‘,’, ‘but’, ‘strongly’, ‘interdisciplinary’, ‘.’, ‘we’, ‘bring’, ‘together’, ‘people’, ‘from’, ‘around’, ‘the’, ‘world’, ‘with’, ‘a’, ‘unique’, ‘variety’, ‘of’, ‘backgrounds’, ‘–’, ‘including’, ‘physicists’, ‘,’, ‘planners’, ‘,’, ‘geographers’, ‘,’, ‘economists’, ‘,’, ‘data’, ‘scientists’, ‘,’, ‘architects’, ‘,’, ‘mathematicians’, ‘and’, ‘computer’, ‘scientists’, ‘–’, ‘united’, ‘by’, ‘our’, ‘mission’, ‘to’, ‘tackle’, ‘the’, ‘biggest’, ‘challenges’, ‘facing’, ‘cities’, ‘and’, ‘societies’, ‘around’, ‘the’, ‘world’, ‘.’, ‘we’, ‘work’, ‘across’, ‘multiple’, ‘scales’, ‘:’, ‘from’, ‘the’, ‘hyper-local’, ‘environment’, ‘of’, ‘the’, ‘low-powered’, ‘sensor’, ‘all’, ‘the’, ‘way’, ‘up’, ‘to’, ‘satellite’, ‘remote’, ‘sensing’, ‘of’, ‘whole’, ‘countries’, ‘and’, ‘regions’, ‘.’, ‘studying’, ‘at’, ‘casa’, ‘brings’, ‘lifelong’, ‘value’, ‘,’, ‘with’, ‘our’, ‘students’, ‘poised’, ‘to’, ‘take’, ‘on’, ‘leadership’, ‘and’, ‘integration’, ‘roles’, ‘at’, ‘the’, ‘forefront’, ‘of’, ‘urban’, ‘and’, ‘spatial’, ‘data’, ‘science’, ‘.’, ‘by’, ‘studying’, ‘with’, ‘us’, ‘you’, ‘will’, ‘become’, ‘part’, ‘of’, ‘our’, ‘active’, ‘and’, ‘engaged’, ‘alumni’, ‘community’, ‘,’, ‘with’, ‘access’, ‘to’, ‘job’, ‘listings’, ‘,’, ‘networking’, ‘and’, ‘social’, ‘activities’, ‘,’, ‘as’, ‘well’, ‘as’, ‘continued’, ‘contact’, ‘with’, ‘our’, ‘outstanding’, ‘teachers’, ‘and’, ‘researchers’, ‘.’, ‘location’, ‘the’, ‘ucl’, ‘centre’, ‘for’, ‘advanced’, ‘spatial’, ‘analysis’, ‘is’, ‘located’, ‘at’, ‘90’, ‘tottenham’, ‘court’, ‘road’, ‘,’, ‘london’, ‘,’, ‘w1t’, ‘4tj’, ‘.’]

5.4.3.0.12 Tokenised

[‘view’, ‘map’]

5.4.3.0.13 Tokenised

[‘contact’, ‘address’, ‘:’, ‘ucl’, ‘centre’, ‘for’, ‘advanced’, ‘spatial’, ‘analysis’, ‘first’, ‘floor’, ‘,’, ‘90’, ‘tottenham’, ‘court’, ‘road’, ‘london’, ‘w1t’, ‘4tj’, ‘telephone’, ‘:’, ‘+44’, ‘(’, ‘0’, ‘)’, ‘20’, ‘3108’, ‘3877’, ‘email’, ‘:’, ‘casa’, ‘@’, ‘ucl.ac.uk’]

5.4.3.0.14 Tokenised

[‘tweets’, ‘by’, ‘casaucl’]

5.5 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)
```

```
{'very', 'some', "don't", 'at', 'he', 'theirs', 'for', "shan't", 'because', 'wouldn', 'd', 'off', 'with', 'against', 'hadn', 'doing', 'the
```

5.5.0.1 Question

```
stopped = []
for p in tokens[2:4]: # <-- 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)
```

5.5.0.2 Answer

```
stopped = []
for p in tokens[2:4]: # <-- why do I just take these items from the list?
  stopped.append([x for x in p if x not in stopword_list and len(x) > 1])

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

5.5.0.2.1 Line

[‘centre’, ‘advanced’, ‘spatial’, ‘analysis’, ‘casa’, ‘interdisciplinary’, ‘research’, ‘institute’, ‘focusing’, ‘science’, ‘cities’, ‘within’, ‘bartlett’, ‘faculty’, ‘built’, ‘environment’, ‘ucl’]

5.5.0.2.2 Line

['centre', 'advanced', 'spatial', 'analysis', 'casa', 'established', '1995', 'lead', 'development', 'science', 'cities', 'drawing', 'upon', 'methods', 'ideas', 'modelling', 'data', 'science', 'sensing', 'urban', 'environment', 'visualisation', 'computation', 'today', 'casa', 'research', 'still', 'pushing', 'boundaries', 'create', 'better', 'cities', 'everyone', 'leading', 'intellectual', 'agenda', 'working', 'closely', 'government', 'industry', 'partners', 'make', 'real-world', 'impact', 'teaching', 'reflects', 'making', 'cutting-edge', 'research', 'tools', 'new', 'forms', 'data', 'long-standing', 'non-academic', 'partnerships', 'train', 'next', 'generation', 'urban', 'scientists', 'skills', 'ideas', 'need', 'impact', 'industry', 'government', 'academia', 'third', 'sector', 'casa', 'community', 'closely', 'connected', 'strongly', 'interdisciplinary', 'bring', 'together', 'people', 'around', 'world', 'unique', 'variety', 'backgrounds', 'including', 'physicists', 'planners', 'geographers', 'economists', 'data', 'scientists', 'architects', 'mathematicians', 'computer', 'scientists', 'united', 'mission', 'tackle', 'biggest', 'challenges', 'facing', 'cities', 'societies', 'around', 'world', 'work', 'across', 'multiple', 'scales', 'hyper-local', 'environment', 'low-powered', 'sensor', 'way', 'satellite', 'remote', 'sensing', 'whole', 'countries', 'regions', 'studying', 'casa', 'brings', 'lifelong', 'value', 'students', 'poised', 'take', 'leadership', 'integration', 'roles', 'forefront', 'urban', 'spatial', 'data', 'science', 'studying', 'us', 'become', 'part', 'active', 'engaged', 'alumni', 'community', 'access', 'job', 'listings', 'networking', 'social', 'activities', 'well', 'continued', 'contact', 'outstanding', 'teachers', 'researchers', 'location', 'ucl', 'centre', 'advanced', 'spatial', 'analysis', 'located', '90', 'tottenham', 'court', 'road', 'london', 'w1t', '4tj']

5.6 Lemmatisation vs Stemming

Difficulty level: Low.

```python
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
```

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

```
monkey
citi
complex
read
```

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

```
monkey
citi
complex
read
```

```python
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)
```

5.6.0.0.1 Lemmatised

[‘centre’, ‘advanced’, ‘spatial’, ‘analysis’, ‘casa’, ‘interdisciplinary’, ‘research’, ‘institute’, ‘focusing’, ‘science’, ‘city’, ‘within’, ‘bartlett’, ‘faculty’, ‘built’, ‘environment’, ‘ucl’]

5.6.0.0.2 Lemmatised

[‘centre’, ‘advanced’, ‘spatial’, ‘analysis’, ‘casa’, ‘established’, ‘1995’, ‘lead’, ‘development’, ‘science’, ‘city’, ‘drawing’, ‘upon’, ‘method’, ‘idea’, ‘modelling’, ‘data’, ‘science’, ‘sensing’, ‘urban’, ‘environment’, ‘visualisation’, ‘computation’, ‘today’, ‘casa’, ‘research’, ‘still’, ‘pushing’, ‘boundary’, ‘create’, ‘better’, ‘city’, ‘everyone’, ‘leading’, ‘intellectual’, ‘agenda’, ‘working’, ‘closely’, ‘government’, ‘industry’, ‘partner’, ‘make’, ‘real-world’, ‘impact’, ‘teaching’, ‘reflects’, ‘making’, ‘cutting-edge’, ‘research’, ‘tool’, ‘new’, ‘form’, ‘data’, ‘long-standing’, ‘non-academic’, ‘partnership’, ‘train’, ‘next’, ‘generation’, ‘urban’, 'scientist', 'skill', 'idea', 'need', 'impact', 'industry', 'government', 'academia', 'third', 'sector', 'casa', 'community', 'closely', 'connected', 'strongly', 'interdisciplinary', 'bring', 'together', 'people', 'around', 'world', 'unique', 'variety', 'background', 'including', 'physicist', 'planner', 'geographer', 'economist', 'data', 'scientist', 'architect', 'mathematician', 'computer', 'scientist', 'united', 'mission', 'tackle', 'biggest', 'challenge', 'facing', 'city', 'society', 'around', 'world', 'work', 'across', 'multiple', 'scale', 'hyper-local', 'environment', 'low-powered', 'sensor', 'way', 'satellite', 'remote', 'sensing', 'whole', 'country', 'region', 'studying', 'casa', 'brings', 'lifelong', 'value', 'student', 'poised', 'take', 'leadership', 'integration', 'role', 'forefront', 'urban', 'spatial', 'data', 'science', 'studying', 'u', 'become', 'part', 'active', 'engaged', 'alumnus', 'community', 'access', 'job', 'listing', 'networking', 'social', 'activity', 'well', 'continued', 'contact', 'outstanding', 'teacher', 'researcher', 'location', 'ucl', 'centre', 'advanced', 'spatial', 'analysis', 'located', '90', 'tottenham', 'court', 'road', 'london', 'w1t', '4tj']

5.6.0.0.3 Stemmed

['centr', 'advanc', 'spatial', 'analysi', 'casa', 'interdisciplinari', 'research', 'institut', 'focus', 'scienc', 'citi', 'within', 'bartlett', 'faculti', 'built', 'environ', 'ucl']

5.6.0.0.4 Stemmed

['centr', 'advanc', 'spatial', 'analysi', 'casa', 'establish', '1995', 'lead', 'develop', 'scienc', 'citi', 'draw', 'upon', 'method', 'idea', 'model', 'data', 'scienc', 'sens', 'urban', 'environ', 'visualis', 'comput', 'today', 'casa', 'research', 'still', 'push', 'boundari', 'creat', 'better', 'citi', 'everyon', 'lead', 'intellectu', 'agenda', 'work', 'close', 'govern', 'industri', 'partner', 'make', 'real-world', 'impact', 'teach', 'reflect', 'make', 'cutting-edg', 'research', 'tool', 'new', 'form', 'data', 'long-stand', 'non-academ', 'partnership', 'train', 'next', 'generat', 'urban', 'scientist', 'skill', 'idea', 'need', 'impact', 'industri', 'govern', 'academia', 'third', 'sector', 'casa', 'communiti', 'close', 'connect', 'strong', 'interdisciplinari', 'bring', 'togeth', 'peopl', 'around', 'world', 'uniqu', 'varieti', 'background', 'includ', 'physicist', 'planner', 'geograph', 'economist', 'data', 'scientist', 'architect', 'mathematician', 'comput', 'scientist', 'unit', 'mission', 'tackl', 'biggest', 'challeng', 'face', 'citi', 'societi', 'around', 'world', 'work', 'across', 'multipl', 'scale', 'hyper-loc', 'environ', 'low-pow', 'sensor', 'way', 'satellit', 'remot', 'sens', 'whole', 'countri', 'region', 'studi', 'casa', 'bring', 'lifelong', 'valu', 'student', 'pois', 'take', 'leadership', 'integr', 'role', 'forefront', 'urban', 'spatial', 'data', 'scienc', 'studi', 'us', 'becom', 'part', 'activ', 'engag', 'alumni', 'communiti', 'access', 'job', 'list', 'network', 'social', 'activ', 'well', 'continu', 'contact', 'outstand', 'teacher', 'research', 'locat', 'ucl', 'centr', 'advanc', 'spatial', 'analysi', 'locat', '90', 'tottenham', 'court', 'road', 'london', 'w1t', '4tj']

```python
# What are we doing here?
for ix, p in enumerate(stopped):
    stopped_set = set(stopped[ix])
    lemma_set   = set(lemmas[ix])
    print(sorted(stopped_set.symmetric_difference(lemma_set)))
```

```
['cities', 'city']
['activities', 'activity', 'alumni', 'alumnus', 'architect', 'architects', 'background', 'backgrounds', 'boundaries', 'bounda
```

6 Applying Normalisation

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

[‘UCL Home The Bartlett Centre for Advanced Spatial Analysis About’, ‘About’, ‘The Centre for Advanced Spatial Analysis (CASA) is an interdisciplinary research institute focusing on the science of cities within The Bartlett Faculty of the Built Environment at UCL.’, ‘The Centre for Advanced Spatial Analysis (CASA) was established in 1995 to lead the development of a science of cities drawing upon methods and ideas in modelling and data science, sensing the urban environment, visualisation and computation. Today, CASA’s research is still pushing boundaries to create better cities for everyone, both leading the intellectual agenda and working closely with government and industry partners to make real-world impact. Our teaching reflects this, making the most of our cutting-edge research, tools, new forms of data, and long-standing non-academic partnerships to train the next generation of urban scientists with the skills and ideas they’ll need to have an impact in industry, government, academia, and the third sector. The CASA community is closely connected, but strongly interdisciplinary. We bring together people from around the world with a unique variety of backgrounds – including physicists, planners, geographers, economists, data scientists, architects, mathematicians and computer scientists – united by our mission to tackle the biggest challenges facing cities and societies around the world. We work across multiple scales: from the hyper-local environment of the low-powered sensor all the way up to satellite remote sensing of whole countries and regions. Studying at CASA brings lifelong value, with our students poised to take on leadership and integration roles at the forefront of urban and spatial data science. By studying with us you will become part of our active and engaged alumni community, with access to job listings, networking and social activities, as well as continued contact with our outstanding teachers and researchers. Location The UCL Centre for Advanced Spatial Analysis is located at 90 Tottenham Court Road, London, W1T 4TJ.’, ‘View Map’, ‘Contact Address: UCL Centre for Advanced Spatial Analysis First Floor, 90 Tottenham Court Road London W1T 4TJ Telephone: +44 (0)20 3108 3877 Email: casa@ucl.ac.uk’, ‘Tweets by CASAUCL’]

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

6.2.0.0.2 Normalised

[‘home bartlett centre advanced spatial analysis’, ’ ‘, ’centre advanced spatial analysis . casa . interdisciplinary research institute focus science city within bartlett faculty built environment .’, ‘centre advanced spatial analysis . casa . establish lead development science city draw upon method idea modelling data science sense urban environment visualisation computation . today research still push boundary create good city everyone lead intellectual agenda work closely government industry partner make real-world impact . teaching reflect make cuttingedge research tool form data longstanding nonacademic partnership train next generation urban scientist skill idea need impact industry government academia third sector . casa community closely connect strongly interdisciplinary . bring together people around world unique variety background include physicist planner geographer economist data scientist architect mathematician computer sci-

```
entist unite mission tackle challenge face city society around world . work
across multiple scale hyperlocal environment lowpowered sensor satellite
remote sensing whole country region . studying casa bring lifelong value
student poise take leadership integration role forefront urban spatial data
science . study become part active engage alumnus community access list-
ing network social activity well continue contact outstanding teacher re-
searcher . location centre advanced spatial analysis locate tottenham court
road london .', 'view', 'contact address centre advanced spatial analysis first
floor tottenham court road london telephone . email casa ucl.ac.uk', 'tweets
casaucl']
```

```python
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 Revenons à Nos Moutons

Now that you've seen how the steps are applied to a 'random' HTML document, let's get back to the problem at hand (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)
```

7.1.0.2 Answer

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

```
/Users/jreades/Documents/git/fsds/practicals/textual/__init__.py:606: MarkupResemblesLocatorWarning:

The input looks more like a filename than markup. You may want to open this file and pass the filehandle into Beaut

CPU times: user 44 s, sys: 613 ms, total: 44.6 s
Wall time: 44.6 s
```

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

```
/Users/jreades/Documents/git/fsds/practicals/textual/__init__.py:606: MarkupResemblesLocatorWarning:

The input looks more like a filename than markup. You may want to open this file and pass the filehandle into Beaut

CPU times: user 36.9 s, sys: 609 ms, total: 37.5 s
Wall time: 37.6 s
```

```
%%time
# I get about 1 seconds on a M2 Mac
bluesp['description_norm'] = bluesp.description.apply(normalise_document, remove_digits=True)
```

```
CPU times: user 1.58 s, sys: 29.4 ms, total: 1.61 s
Wall time: 1.61 s
```

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.

```
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 . wal
```

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
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] * ???
```

7.4.6.2 Answer

```
filter_terms = sums >= cvdf.shape[0] * 0.01
```

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
```

We're going to pick this up again in Task 7.

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

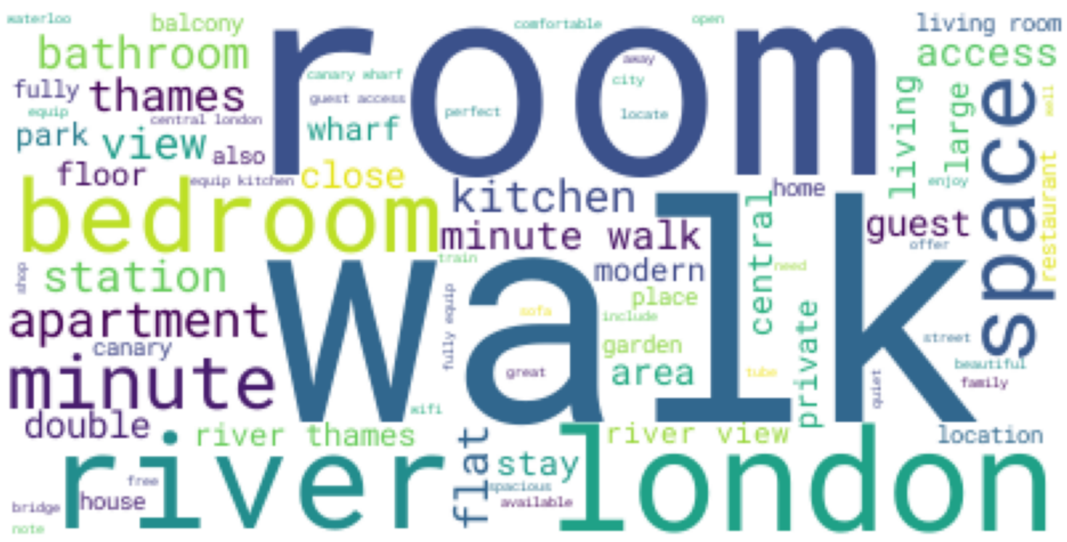
8.1 For Counts

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=(8, 8))
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")
```



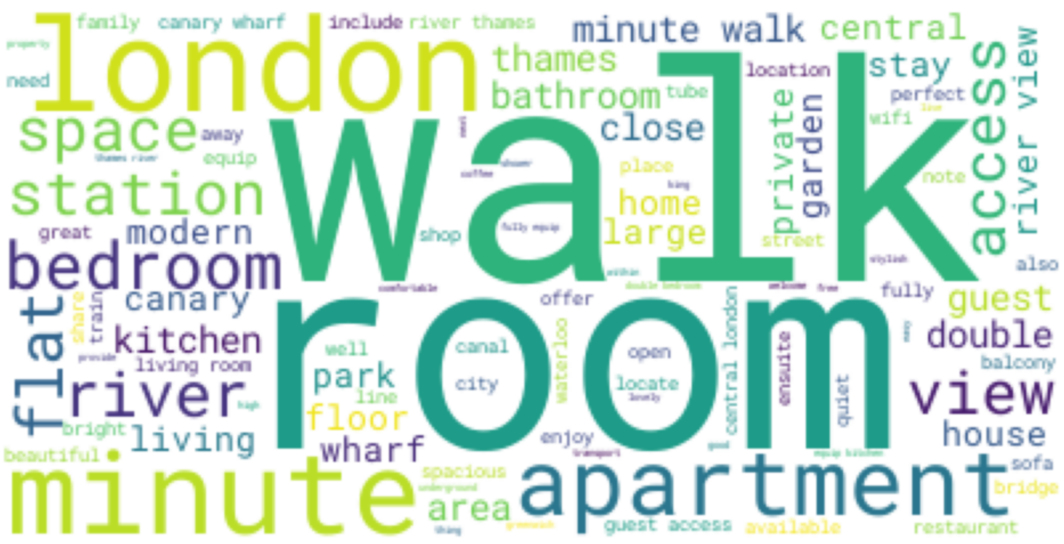
8.2 For TF/IDF Weighting

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=(8, 8))
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?

9 Latent Dirchlet Allocation

Tip

I would give this a *low* priority. It's a commonly-used method, but on small data sets it really isn't much use and I've found its answers to be… unclear… even on large data sets.

Adapted from this post on doing LDA using sklearn. Most other examples use the gensim library.

```
# Notice change to ngram range
# (try 1,1 and 1,2 for other options)
vectorizer = CountVectorizer(ngram_range=(1,2))
```

9.1 Calculate Topics

```
vectorizer.fit(corpus)
tcorpus = vectorizer.transform(corpus) # tcorpus for transformed corpus

LDA = LatentDirichletAllocation(n_components=3, random_state=42) # Might want to experiment with n_compone
LDA.fit(tcorpus)
```

```
LatentDirichletAllocation(n_components=3, random_state=42)
```

```
first_topic = LDA.components_[0]
top_words = first_topic.argsort()[-25:]

for i in top_words:
    print(vectorizer.get_feature_names_out()[i])
```

```
river thames
modern
area
wharf
flat
access
bathroom
guest
house
minute
private
kitchen
large
thames
living
view
station
floor
bedroom
apartment
walk
london
river
room
space
```

```
for i,topic in enumerate(LDA.components_):
    as_markdown(f'Top 10 words for topic #{i}', ', '.join([vectorizer.get_feature_names_out()[i] for i in topic.argsort()[
```

9.1.0.0.1 Top 10 words for topic #0

> river thames, modern, area, wharf, flat, access, bathroom, guest, house, minute, private, kitchen, large, thames, living, view, station, floor, bedroom, apartment, walk, london, river, room, space

9.1.0.0.2 Top 10 words for topic #1

> park, fully, modern, private, living, guest, view, double, close, access, area, flat, thames, bathroom, station, apartment, kitchen, space, minute walk, room, london, river, bedroom, minute, walk

9.1.0.0.3 Top 10 words for topic #2

living, river view, canary wharf, canary, central, wharf, stay, close, bathroom, guest, kitchen, double, minute, thames, access, station, flat, space, view, bedroom, apartment, river, walk, london, room

9.2 Maximum Likelihood Topic

```
topic_values = LDA.transform(tcorpus)
topic_values.shape
```

```
(408, 3)
```

```
pd.options.display.max_colwidth=20
srcdf['Topic'] = topic_values.argmax(axis=1)
srcdf.head()
```

id	geometry	listing_url	name	description
36299	POINT (519476.34...	https://www.airb...	Townhouse in Ric...	3 Bed House with...
170702	POINT (537106.00...	https://www.airb...	Rental unit in L...	<b>The space</b>...
608438	POINT (530947.63...	https://www.airb...	Rental unit in G...	Newly renovated,...
827436	POINT (539810.14...	https://www.airb...	Rental unit in L...	Brand new rivers...
1580666	POINT (538100.19...	https://www.airb...	Rental unit in L...	PLEASE READ OTHE...

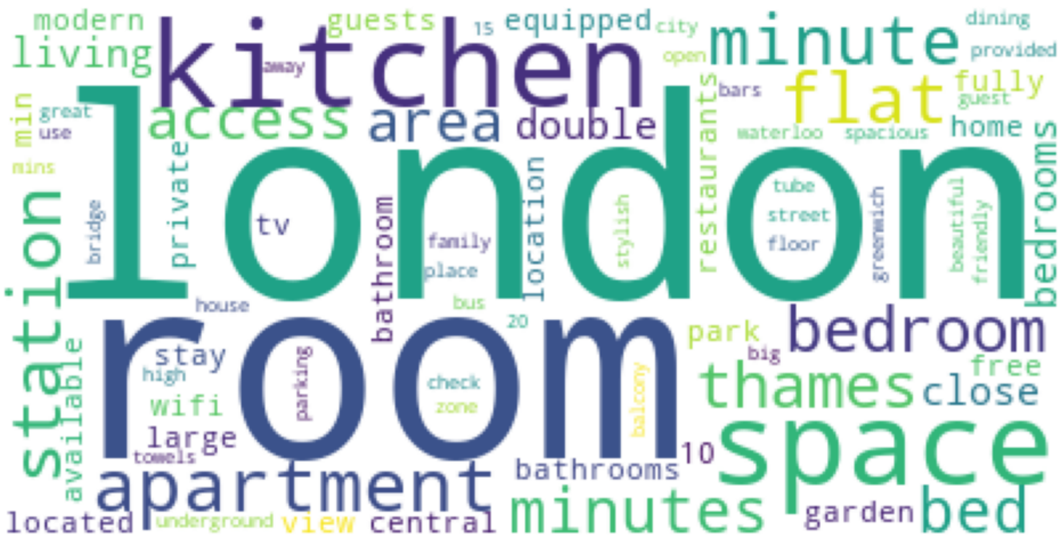
```
pd.options.display.max_colwidth=75
srcdf[srcdf.Topic==1].description_norm.head(10)
```

```
id
36299     house garden close thames river . walk  private road river nearby .  di...
827436     brand riverside apartment greenwich peninsula . perfect explore london ...
1611173    mint walk thames river  mint tower bridge  mint greenwich bus mint walk...
1910741    bright  spacious chill bedroom cosy apartment level friendly quiet bloc...
5284354    fabulous bathshower flat modern development east putney  london literal...
5498948    large double room river view available large spacious townhouse hampton...
6479011    private quiet bright  large double room ensuite bathroom . location stu...
6619558    bright  airy bedroom  ground floor apartment quiet street . modernly fu...
7495122    perfect claphambattersea modern decor . brand kitchenbathroom minute wa...
8352150    room front house overlook balcony  road river . bright sunny house view...
Name: description_norm, dtype: object
```

```
vectorizer = CountVectorizer(ngram_range=(1,1), stop_words='english', analyzer='word', max_df=0.7, min_df=0.05)
topic_corpus = vectorizer.fit_transform(srcdf[srcdf.Topic==1].description.values) # tcorpus for transformed corpus
```

```
topicdf = pd.DataFrame(data=topic_corpus.toarray(),
                        columns=vectorizer.get_feature_names_out())
```

```
f,ax = plt.subplots(1,1,figsize=(8,8))
plt.gcf().set_dpi(150)
Cloud = WordCloud(
        background_color="white",
        max_words=75).generate_from_frequencies(topicdf.sum())
ax.imshow(Cloud)
ax.axis("off");
# plt.savefig('Wordcloud 3.png')
```



10 Word2Vec

Tip

This algorithm works almost like magic. You should play with the configuration parameters and see how it changes your results.

10.1 Configure

```
from gensim.models.word2vec import Word2Vec

dims = 100
print(f"You've chosen {dims} dimensions.")

window = 3
print(f"You've chosen a window of size {window}.")

min_v_freq  = 0.005 # Don't keep words appearing less than 0.5% frequency
min_v_count = math.ceil(min_v_freq * srcdf.shape[0])
print(f"With a minimum frequency of {min_v_freq} and {srcdf.shape[0]:,} documents, minimum vocab frequency is
```

```
You've chosen 100 dimensions.
You've chosen a window of size 3.
With a minimum frequency of 0.005 and 408 documents, minimum vocab frequency is 3.
```

10.2 Train

```
%%time

corpus      = srcdf.description_norm.fillna(' ').values
#corpus_sent = [nltk.sent_tokenize(text) for text in corpus] # <-- with more formal writing this would work well
corpus_sent = [d.replace('.',' ').split(' ') for d in corpus] # <-- deals better with many short sentences though context
model       = Word2Vec(sentences=corpus_sent, vector_size=dims, window=window, epochs=200,
                min_count=min_v_count, seed=42, workers=1)

#model.save(f"word2vec-d{dims}-w{window}.model") # <-- You can then Word2Vec.load(...) which is useful with l
```

```
CPU times: user 4.2 s, sys: 70.8 ms, total: 4.27 s
Wall time: 4.25 s
```

10.3 Explore Similarities

This next bit of code only runs if you have calculated the frequencies above in the Frequencies and Ngrams section.

```
pd.set_option('display.max_colwidth',150)

df = fcounts[1] # <-- copy out only the unigrams as we haven't trained anything else

n    = 14 # number of words
topn  = 7  # number of most similar words

selected_words = df[df['Ngram Size 1'] > 5].reset_index().level_0.sample(n, random_state=42).tolist()

words = []
v1   = []
v2   = []
v3   = []
sims  = []

for w in selected_words:
    try:
        vector = model.wv[w]  # get numpy vector of a word
        #print(f"Word vector for '{w}' starts: {vector[:5]}...")

        sim = model.wv.most_similar(w, topn=topn)
        #print(f"Similar words to '{w}' include: {sim}.")

        words.append(w)
        v1.append(vector[0])
        v2.append(vector[1])
        v3.append(vector[2])
        sims.append(", ".join([x[0] for x in sim]))
    except KeyError:
        print(f"Didn't find {w} in model. Can happen with low-frequency terms.")
```

```
vecs = pd.DataFrame({
  'Term':words,
  'V1':v1,
  'V2':v2,
  'V3':v3,
  f'Top {topn} Similar':sims
})

vecs
```

	Term	V1	V2	V3	Top 7 Similar
0	complimentary	-0.957243	-1.486986	-1.123290	professionally, sustainable, considerate, ha
1	equip	-1.839925	0.654449	-0.097641	equipped, diner, fullyequipped, flatscreen,
2	shower	0.048209	0.343932	2.158660	separate, corridor, toilet, shared, bathroom
3	smart	1.519984	-1.943256	-0.310231	flatscreen, wireless, oled, inch, netflix, stre
4	design	0.511491	1.845216	-1.068899	interior, beautifully, comfort, standout, chi
5	appliance	0.281022	0.608689	-1.014925	functional, essential, necessary, kitchenett
6	living	-1.026039	0.176004	-1.438652	live, separate, room, modern, table, double
7	the	-3.042268	-3.073883	1.338165	londonelephant, furnished, both, equip, zo
8	directly	0.288156	-1.780736	-0.016401	pick, excel, crossharbour, incredible, them
9	fridgefreezer	-0.665757	0.406782	0.152970	cutlery, americanstyle, refrigerator, kettle,
10	bathtub	-1.493979	1.130018	0.971623	bath, walkin, ensuite, mirror, toilet, fridge,
11	train	-1.821561	-1.496900	-0.311242	taxi, elizabeth, district, tube, crossharbour
12	palace	1.628689	1.310075	-1.671952	buckingham, hyde, sloane, min, parliamen
13	shard	0.224605	-0.295689	-1.599193	globe, cathedral, shoredich, borough, towe

```
#print(model.wv.index_to_key) # <-- the full vocabulary that has been trained
```

10.4 Apply

We're going to make *use* of this further next week…

10.4.1 Questions

- What happens when *dims* is very small (e.g. 25) or very large (e.g. 300)?
- What happens when *window* is very small (e.g. 2) or very large (e.g. 8)?

#0. Processing the Full File

Caution

This code can take *some time* (> **5 minutes on a M2 Mac**) to run, so **don't run this** until you've understood what we did before!

You will get a warning about "." looks like a filename, not markup — this looks a little scary, but is basically suggesting that we have a description that consists only of a '.' or that looks like some kind of URL (which the parser thinks means you're trying to pass it something to download).

```
%%time
# This can take up to 8 minutes on a M2 Mac
gdf['description_norm'] = ''
gdf['description_norm'] = gdf.description.apply(normalise_document, remove_digits=True, special_char_removal=T

gdf.to_parquet(os.path.join('data','geo',f'{fn.replace(".","-with-nlp.")}'))
```

Tip

Saving an intermediate file at this point is useful because you've done quite a bit of *expensive* computation. You *could* restart-and-run-all and then go out for the day, but probably easier to just save this output and then, if you need to restart your analysis at some point in the future, just remember to deserialise amenities back into a list format.

10.5 Applications

The above is *still* only the results for the 'luxury' apartments *alone*. At this point, you would probably want to think about how your results might change if you changed any of the following:

1. Using one of the other data sets that we created, or even the entire data set!
2. Applying the CountVectorizer or TfidfVectorizer *before* selecting out any of our 'sub' data sets.
3. Using the visualisation of information from #2 to improve our regex selection process.
4. Reducing, increasing, or constraining (i.e. `ngrams=(2,2)`) the size of the ngrams while bearing in mind the impact on processing time and interpretability.
5. Filtering by type of listing or host instead of keywords found in the description (for instance, what if you applied TF/IDF to the entire data set and then selected out 'Whole Properties' before splitting into those advertised by hosts with only one listing vs. those with multiple listings?).
6. Linking this back to the geography.

Over the next few weeks we'll also consider alternative means of visualising the data!

10.6 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