Practical 8bis: Working with Text (Part 2)

The basics of Text Mining and NLP

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Part 2 of Practical 8 is *optional* and should only be attempted if Part 1 made sense to you.

1. The first few tasks 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!**
2. The second part is 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

Parts of this practical have been written using `nltk` and `gensim` — both of which I have **removed** from the sds2025 image to keep the size down and because relatively few students used any of this — but it would be *relatively* easy to rework it to use `spacy`. From what I can see, 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. 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` and `nltk`.

Standard libraries we've seen before.

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

# New, but fairly straightforward (for simple things)
from bs4 import BeautifulSoup
```

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

try:
    from nltk.corpus import wordnet as wn
    from nltk.stem.wordnet import WordNetLemmatizer
    from nltk.corpus import stopwords
    stopwords.words('english')
    lemmatizer = WordNetLemmatizer()
    tokenizer = ToktokTokenizer()
except:
    nltk.download("stopwords")
    nltk.download("punkt_tab")
    nltk.download("averaged_perceptron_tagger_eng")
    from nltk.corpus import stopwords
    from nltk.corpus import wordnet as wn
    from nltk.stem.wordnet import WordNetLemmatizer
    stopwords.words('english')

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()
```

```
[nltk_data] Downloading package stopwords to /home/jovyan/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt_tab to /home/jovyan/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger_eng to
[nltk_data]     /home/jovyan/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger_eng is already up-to-
[nltk_data]       date!
```

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.

```
try:
    from wordcloud import WordCloud
except:
    ! pip install wordcloud
import string
import unicodedata
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...")
```

Result!

> Here's my output…

2.2 Loading Data

> **Connections**
>
> Because I generally want each practical to stand on its own (unless I'm trying to make a *point*), I've not moved this to a separate Python file (e.g. `utils.py`, but in line with what we covered back in the lectures on Functions and Packages, 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?

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

def check_cache(f):
    @wraps(f)
    def wrapper(src:str, dst:str, min_size=100) -> Path:
        if src.find('?') == -1:
```

```
            url = Path(src)
        else:
            url = Path(src[:src.find('?')])
        fn  = url.name  # Extract the filename
        dsn = Path(f"{dst}/{fn}") # Destination filename
        if dsn.is_file() and dsn.stat().st_size > min_size:
            print(f"+ {dsn} found locally!")
            return(dsn)
        else:
            print(f"+ {dsn} not found, downloading!")
            return(f(src, dsn))
    return wrapper

@check_cache
def cache_data(src:Path, dst:Path) -> str:
    """Downloads a remote file.

    The function sits between the 'read' step of a pandas or geopandas
    data frame and downloading the file from a remote location. The idea
    is that it will save it locally so that you don't need to remember to
    do so yourself. Subsequent re-reads of the file will return instantly
    rather than downloading the entire file for a second or n-th itme.

    Parameters
    ----------
    src : str
        The remote *source* for the file, any valid URL should work.
    dst : str
        The *destination* location to save the downloaded file.

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

    # Create any missing directories in dest(ination) path
    # -- os.path.join is the reverse of split (as you saw above)
    # but it doesn't work with lists... so I had to google how
    # to use the 'splat' operator! os.makedirs creates missing
    # directories in a path automatically.
    if not dst.parent.exists():
        dst.parent.mkdir(parents=True, exist_ok=True)

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

    print(' + Done downloading...')
```

```
    return dst.resolve()
```

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

Load the main data set:

```
# Load the data sets created in the previous practical
lux    = gpd.read_parquet(Path('data/clean/luxury.geoparquet'))
aff    = gpd.read_parquet(Path('data/clean/affordable.geoparquet'))
bluesp = gpd.read_parquet(Path('data/clean/bluespace.geoparquet'))
```

3 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*. To keep things moving along, we're going to take a small sample from the data set.

```
pd.set_option("display.max_colwidth", 250)
sample = bluesp.description.sample(5, random_state=44)
sample
```

```
10390    Stunning & Spacious Air Conditioned 3 bedroom 3BR Apartment on the Ground floo
34253    his charming house boasts a prime location just a 5-minute stroll from iconic
49617    Key features:<br />Three double bedrooms<br />Two bathrooms<br />Close to Wate
56882    Private double ensuite bedroom in a shared home. 8 min walk to Surbiton static
21289    Cosy two bedroom apartment on the ninth floor with an amazing river view, just
Name: description, dtype: object
```

3.1 Removing HTML

> **Difficulty level: Moderate**
>
> You'll have seen that tehre are some things that are *not* text in the sample, most notably this stuff: `<br>` and `<br />`. That is raw HTML, the markup language for web pages. To go any further we will need to strip this out. Depending on what you needed to extract from a web page you *can* select different elements by name, class, or id, and do a whole bunch of other things, but here we're just going to crudely strip the tags out.
> You're also going to see a powerful new method: `apply`. Apply simply runs some function against every row or column in the data set depending on how it's called. In this case, we use a `lambda` function (a function without a formal `def`inition) to create a 'Beautiful Soup' HTML parser and then strip the tags from each row.

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!

Question

```
cleaned = sample.apply(lambda x: BeautifulSoup(??, 'html.parser').??(" "))
cleaned
```

```
10390    Stunning & Spacious Air Conditioned 3 bedroom 3BR Apartment on the Ground floo
34253    his charming house boasts a prime location just a 5-minute stroll from iconic
49617    Key features: Three double bedrooms Two bathrooms Close to Waterloo Excellent
56882    Private double ensuite bedroom in a shared home. 8 min walk to Surbiton static
21289            Cosy two bedroom apartment on the ninth floor with an amazing river vie
Name: description, dtype: object
```

3.2 Lower Case

Difficulty Level: Low.

Question

```
lower = cleaned.??
lower
```

You should get something like the following:

```
10390    stunning & spacious air conditioned 3 bedroom 3br apartment on the ground floo
34253    his charming house boasts a prime location just a 5-minute stroll from iconic
49617    key features: three double bedrooms two bathrooms close to waterloo excellent
56882    private double ensuite bedroom in a shared home. 8 min walk to surbiton static
21289            cosy two bedroom apartment on the ninth floor with an amazing river vie
Name: description, dtype: object
```

3.3 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 its approach to the regex.

3.3.1 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.

Question

```
pat = re.compile(r'[???]+')
subbed = lower.apply(lambda x: pat.sub('',x))
```

Depending on how thorough you are, you should get something like this:

```
10390    stunning  spacious air conditioned 3 bedroom 3br apartment on the ground floor
34253    his charming house boasts a prime location just a 5minute stroll from iconic l
49617    key features: three double bedrooms two bathrooms close to waterloo excellent
56882    private double ensuite bedroom in a shared home 8 min walk to surbiton station
21289                   cosy two bedroom apartment on the ninth floor with an amazing r
Name: description, dtype: object
```

3.3.2 Tokenizer

The other way to do this, which is probably *easier*, 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
tokens = lower.apply(word_tokenize)
tokens
```

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

```
10390    [stunning, &, spacious, air, conditioned, 3, bedroom, 3br, apartment, on, the,
34253    [his, charming, house, boasts, a, prime, location, just, a, 5-
minute, stroll, from, iconic, landmarks, such, as, big, ben, and, the, london, eye, ,,
49617    [key, features, :, three, double, bedrooms, two, bathrooms, close, to, waterlo
56882    [private, double, ensuite, bedroom, in, a, shared, home, ., 8, min, walk, to,
21289    [cosy, two, bedroom, apartment, on, the, ninth, floor, with, an, amazing, rive
Name: description, dtype: object
```

⚠ Not Equivalent!

Notice that these aren't giving you the same result!
For our purposes it is easier in the subsequent stages to work with the `list` output from tokenize rather than the string output from `re.sub`, but if you needed to convert tokenise back to a string you could do it this way:

```
tokens = lower.apply(word_tokenize).apply(lambda x: ' '.join(x))
```

The other way around would be:

```
lower.apply(lambda x: pat.sub('',x)).str.split(' ')
```

3.4 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)
```

```
{"they've", 'have', 'in', "it's", 'when', 'whom', 'these', 'him', 'hadn', 'hasn', 'havi
```

Question

```
passthru = []
for t in tokens[2:4]:
    passthru.append([x for x in t if ?? and len(x) > 1])

for p in passthru:
    as_markdown("Stopwords removed:", p)
```

3.5 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 = 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()
stemmer    = SnowballStemmer(language='english')

# 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.
lemmas  = passthru.apply(lambda x: [lemmatizer.lemmatize(t) for t in x])
stemmed = passthru.apply(lambda x: [stemmer.stem(t) for t in x])

as_markdown("Lemmatised", '\n\n>'.join(lemmas.str.join(' ').to_list()))
print("\n\n")
as_markdown("Stemmed", '\n\n>'.join(stemmed.str.join(' ').to_list()))
```

Lemmatised

> stunning spacious air conditioned bedroom 3br apartment ground floor terrace prime location chelsea perfect place lovely comfortable stay heart chelsea minute walk river thames stamford bridge short journey bus underground south kensington earl court knightsbridge hyde park easy access london attraction perfect choice family group friend
>
> charming house boast prime location 5-minute stroll iconic landmark big ben london eye well conveniently close waterloo station ’ll find bus stop supermarket nearby added convenience inside house comprises three cozy bedroom one luxurious queen-sized bed two two comfortable single bed kitchen equipped basic cooking one toilet sink well full bathroom
>
> key feature three double bedroom two bathroom close waterloo excellent transport link beautiful finish wood flooring throughout full description impressive

1115sqft 104sqm contemporary three double bedroom two bathroom first floor conversion kennington road short walk waterloo lambeth north station cut old vic ’s bar restaurant

private double ensuite bedroom shared home min walk surbiton station 20 min direct waterloo min walk river thames 20 min walk kingston town centre easy bus train wimbledon home shared least two people time sharing kitchen space room bathroom attached room house listed separately 1-2 guest time able see previous review listing one new

cosy two bedroom apartment ninth floor amazing river view minute pimlico station heart city zone bigben buckingham palace hyde park chelsea 15/20 minute walking distance

Stemmed

stun spacious air condit bedroom 3br apart ground floor terrac prime locat chelsea perfect place love comfort stay heart chelsea minut walk river thame stamford bridg short journey bus underground south kensington earl court knightsbridg hyde park easi access london attract perfect choic famili group friend

charm hous boast prime locat 5-minut stroll icon landmark big ben london eye well conveni close waterloo station ll find bus stop supermarket nearbi ad conveni insid hous compris three cozi bedroom one luxuri queen-siz bed two two comfort singl bed kitchen equip basic cook one toilet sink well full bathroom

key featur three doubl bedroom two bathroom close waterloo excel transport link beauti finish wood floor throughout full descript impress 1115sqft 104sqm contemporari three doubl bedroom two bathroom first floor convers kennington road short walk waterloo lambeth north station cut old vic ’s bar restaur

privat doubl ensuit bedroom share home min walk surbiton station 20 min direct waterloo min walk river thame 20 min walk kingston town centr easi bus train wimbledon home share least two peopl time share kitchen space room bathroom attach room hous list separ 1-2 guest time abl see previous review list one new

cosi two bedroom apart ninth floor amaz river view minut pimlico station heart citi zone bigben buckingham palac hyde park chelsea 15/20 minut walk distanc

4 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.

4.1 Downloading the Custom Module

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

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

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`).

```
try:
    from textual import *
except:
    try:
        from unidecode import unidecode
    except:
        ! pip install unidecode
    import urllib.request
    host  = 'https://orca.casa.ucl.ac.uk'
    turl  = f'{host}/~jreades/__textual__.py'
    tdirs = Path('textual')
    tpath = Path(tdirs,'__init__.py')

    if not tpath.exists():
        tdirs.mkdirs(parents=True, exist_ok=True)
        urllib.request.urlretrieve(turl, tpath)
    from textual import *
```

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

4.2 Importing the Custom Module

Difficulty Level: Low.

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

```
normalised = sample.apply(normalise_document, remove_digits=True)
as_markdown('Normalised', '\n\n>'.join(normalised.to_list()))
```

Normalised

> stunning spacious conditioned bedroom apartment ground floor terrace prime location chelsea . perfect place lovely comfortable stay heart chelsea minute walk river thames stamford bridge short journey underground south kensington earls court knightsbridge hyde park easy access london attractions . perfect choice families group friends

charm house boast prime location minute stroll iconic landmark london well conveniently close waterloo station . find stop supermarket nearby added convenience . inside house comprise three cozy bedrooms luxurious queensized comfortable single . kitchen equip basic cooking toilet sink well full bathroom .

feature three double bedroom bathroom close waterloo excellent transport link beautiful finish wood flooring throughout full description impressive sqft . contemporary three double bedroom bathroom first floor conversion kennington road short walk waterloo lambeth north station restaurant .

private double ensuite bedroom share home . walk surbiton station . direct waterloo . walk river thames walk kingston town centre easy train wimbledon . home share least people time share kitchen space . room bathroom attach . room house list separately guest time . able previous review listing

cosy bedroom apartment ninth floor amazing river view minute pimlico station heart city . zone . bigben buckingham palace hyde park chelsea minute walk distance .

```
help(normalise_document)
```

> 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.

5 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)`!

Question

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

5.1 Select and Tokenise

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

5.1.1 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.

```
# This makes it easy to go back and re-run
# the analysis with other data subsets.
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])
```

```
['well decorate sunny garden flat fulham park gardens close putney bridge tube .this co
 'enjoy warm cosy modern apartment . river view gorgeous view city . walk barking stati
 'make memory unique familyfriendly place . near nice bridge minute away harrods londor
```

5.1.2 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: ['well decorate sunny garden flat fulham park gardens close putney bridge

Words 0: [['well', 'decorate', 'sunny', 'garden', 'flat', 'fulham', 'park', 'gardens',
```

6 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`.

6.0.1 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 1839 samples and 13751 outcomes>
<FreqDist with 8022 samples and 13750 outcomes>
<FreqDist with 10517 samples and 13749 outcomes>
```

6.0.2 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                501
london              327
minute              282
river               276
```

```
station             275
view                193
apartment           193
thames              172
room                164
bedroom             162
```

		Ngram Size 2
minute	walk	190
river	view	97
	thames	83
central	london	74
canary	wharf	63
walk	river	46
	waterloo	42
thames	river	41
living	room	37
walk	distance	36

			Ngram Size 3
walk	river	thames	37
station	minute	walk	25
fully	equip	kitchen	23
walk	waterloo	station	20
close	river	thames	18
minute	walk	river	17
within	walk	distance	17
walk	thames	river	17
minute	walk	waterloo	14
thames	river	view	13

Questions

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

7 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 a *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!).

7.1 Fit the Vectoriser

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

input	'content'
encoding	'utf-8'
decode_error	'strict'
strip_accents	None
lowercase	True
preprocessor	None
tokenizer	None
stop_words	None
token_pattern	'(?u)\\b\\w\\w+\\b'
ngram_range	(1, ...)
analyzer	'word'
max_df	1.0
min_df	1
max_features	None
vocabulary	None
binary	False
dtype	<class 'numpy.int64'>

7.2 Brief Demonstration

Once we've fit the vectoriser, we can find the integer associated with any word in the corpus and can also ask how many times it occurs:

```
pd.options.display.max_colwidth=750

# Note that the term can be a unigram, a bigram, or a trigram!
term = 'minute walk'
# 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 '{

# Print the descriptions containing the term
for i, x in enumerate(srcdf[srcdf.description_norm.str.contains(term)].description_n
    as_markdown(f"{term}: {i}",x)
    if i > 4: break
```

```
Vocabulary mapping for 'minute walk' is 10349
Found 115 rows containing 'minute walk'
```

minute walk: 0

make memory unique familyfriendly place . near nice bridge minute away harrods london . cycling area jungle park river view playground available walkable distance . minute walk uxbridge underground station . minute walk shop mall . private parking bike . security service available . security deposit pound . refund hour checkout .

minute walk: 1

nice cozy private room pimlico central london . prime location visit city close river thames minute walk pimlico station walk victoria station . stop local shop within minute walk . apartment basic clean proper picture apartment soon .

minute walk: 2

private quiet bright large double room ensuite bathroom . location stun next thames minute walk stamford brook tube . close riverside great restaurant place historic interest .

minute walk: 3

beautiful modern onebedroom flat heart london . covent garden literally minute walk apartment . charring cross embankment covent garden underground station minute walk . plenty restaurant around minute walk thames river . london .

minute walk: 4

people stay love place quirt private cosy serene culture easy transport link whole london . bedroom double brand suit . hammock relax front room . minute walk canal cafe restaurant near local crown meter walk flat

minute walk: 5

suits couple front room maybe minute elephant castle tube bath shower minikitchen small garden small dining room . minute walk thames minute london bridge

7.3 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
```

```
<Compressed Sparse Row sparse matrix of dtype 'int64'
    with 38238 stored elements and shape (347, 19396)>
```

7.3.1 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
close	3
park	2
flat	2
area	2
bedroom open plan	1
road	1
people	1
situated quiet	1
situated quiet residential	1
putney bridge tube	1

7.3.2 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
cvdf.iloc[0:3,0:7]
```

```
Raw count vectorised data frame has 347 rows and 19,396 columns.
```

	aback	aback spacious	aback spacious apartment	abba	abba voyage	abba voyage walk	abba wa
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0

```
cvdf.iloc[-3:,-7:]
```

	zone public transportation	zone recently	zone recently refurbish	zone tube	zone tube station	z
344	0	0	0	0	0	0
345	0	0	0	0	0	0
346	0	0	0	0	0	0

Questions

1. Why is the single document view a list of terms and counts?
2. Why is the corpus view a table of terms (columns) and integers (rows)?

7.3.3 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 19,396 terms in the data set.
```

```
aback                       1
aback spacious              1
aback spacious apartment    1
abba                        2
abba voyage                 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!

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.
fcvdf.iloc[0:3,0:7]
```

```
Filtered count vectorised data frame has 347 rows and 1,686 columns.
```

	access	access buses	access buses west	access central	access central london	access everything	a
0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0

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

```
access                       68
access buses                  4
access buses west             4
access central                5
access central london         5
                             ..
zone comfortable cosy         7
zone london                   6
zone london warm              4
zone recently                 8
zone recently refurbish       8
Length: 1686, dtype: int64
```

We're going to pick this up again in Task 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`?

8 TF/IDF Vectoriser

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

8.1 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
```

8.2 Single Document

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

	Weights
close	0.243962
area	0.207529
quiet residential	0.203155
putney	0.203155
street close	0.203155
kings road	0.196091

	Weights
residential	0.184943
decorate	0.184943
tennis	0.184943
sunny	0.184943

8.3 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 347 rows and 1,660 columns.
```

	access	access buses	access buses west	access central	access central london	access everything	a
0	0.0	0.0	0.0	0.0	0.0	0.0	0
1	0.0	0.0	0.0	0.0	0.0	0.0	0
2	0.0	0.0	0.0	0.0	0.0	0.0	0
3	0.0	0.0	0.0	0.0	0.0	0.0	0
4	0.0	0.0	0.0	0.0	0.0	0.0	0

Questions

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

9 Word Clouds

9.1 For Counts

Difficulty level: Easy!

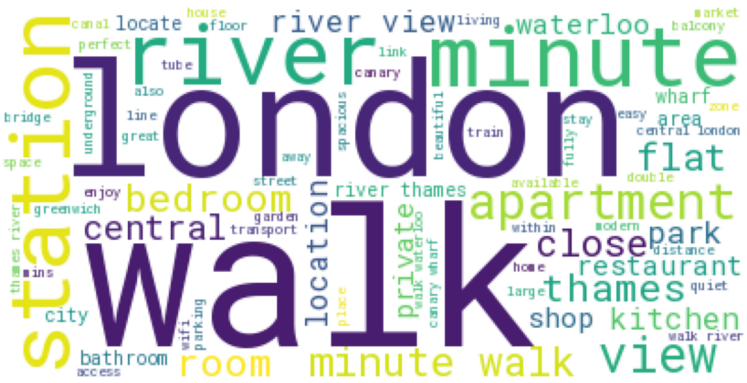
```
fcvdf.sum().sort_values(ascending=False)
```

```
walk                  501
london                327
minute                282
river                 276
station               275
                     ...
capital stay london     4
```

```
small garden              4
capital stay              4
smart bedroom             4
highgate                  4
Length: 1686, dtype: int64
```

```
ff = Path('RobotoMono-VariableFont_wght.ttf')
dp = Path('/home/jovyan/fonts/')
tp = Path(Path.home(),'Library','Fonts')
if tp.exists():
    fp = tp / ff
else:
    fp = dp / ff
```

```
f,ax = plt.subplots(1,1,figsize=(5,5))
plt.gcf().set_dpi(300)
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")
```



9.2 For TF/IDF Weighting

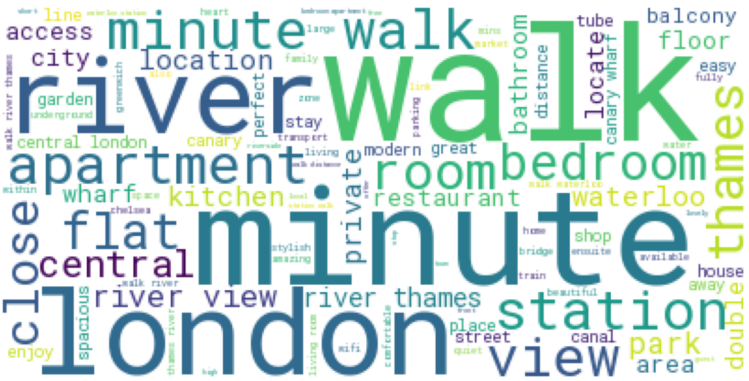
> Difficulty level: Low, but you'll need to be patient!

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

```
walk                    23.946637
minute                  17.656652
london                  17.114220
```

```
river                          15.518695
apartment                      14.149614
                                  ...
smart bedroom                   0.332017
smart bedroom battersea         0.332017
smart netflixs close            0.332017
terrace overlooking             0.332017
netflixs close                  0.332017
Length: 1660, dtype: float64
```

```
f,ax = plt.subplots(1,1,figsize=(5,5))
plt.gcf().set_dpi(300)
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")
```



Questions

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

10 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))
```

10.1 Calculate Topics

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

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

n_components	3
doc_topic_prior	None
topic_word_prior	None
learning_method	'batch'
learning_decay	0.7
learning_offset	10.0
max_iter	10
batch_size	128
evaluate_every	-1
total_samples	1000000.0
perp_tol	0.1
mean_change_tol	0.001
max_doc_update_iter	100
n_jobs	None
verbose	0
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])
```

```
waterloo
quiet
floor
city
park
kitchen
house
easy
space
access
canal
minute
```

```
street
locate
river view
close
apartment
room
bedroom
flat
station
river
view
london
walk
```

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

Top 10 words for topic #0

waterloo, quiet, floor, city, park, kitchen, house, easy, space, access, canal, minute, street, locate, river view, close, apartment, room, bedroom, flat, station, river, view, london, walk

Top 10 words for topic #1

shop, double, restaurant, location, great, bathroom, stay, minute walk, city, thames, waterloo, river view, kitchen, central, flat, close, bedroom, room, view, minute, station, river, london, apartment, walk

Top 10 words for topic #2

house, central london, locate, restaurant, distance, wharf, shop, location, river thames, private, bedroom, flat, room, central, park, close, view, apartment, thames, minute walk, river, station, london, minute, walk

10.2 Maximum Likelihood Topic

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

```
(347, 3)
```

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

	geometry	listing_url	name	description	amenities
5	POINT (524555.52...	https://www.airb...	Fulham Garden Flat	Well decorated s...	[”Dining
426	POINT (543953.65...	https://www.airb...	Cosy London Flat...	Enjoy my warm an...	[”Bed lin
516	POINT (506207.28...	https://www.airb...	Furnished Apartment	Make some memori...	[”Kitche
725	POINT (536247.17...	https://www.airb...	Comfortable room...	My place is clos...	[”Hange
1492	POINT (528407.92...	https://www.airb...	Modern, bright, ...	Luxury canal sid...	[”Dining

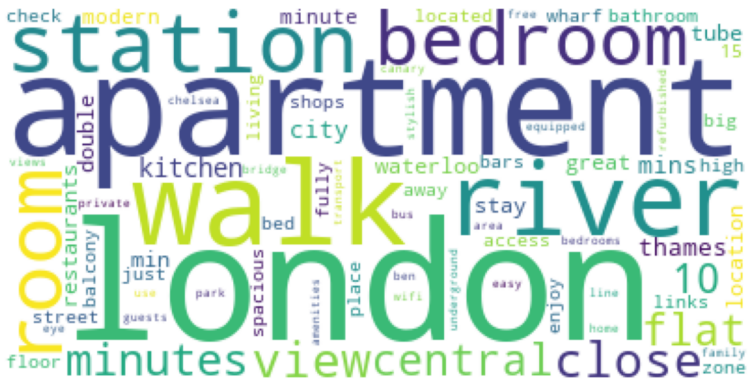
```
pd.options.display.max_colwidth=75
srcdf[srcdf.Topic==1].description_norm.head(10)
```

```
426     enjoy warm cosy modern apartment . river view gorgeous view city . walk...
725     place close mile tube station  brick lane shoreditch  queen mary univer...
1957    beautifully refurbish fully equip flat pimlico . lovely zone neighborho...
3536    private quiet bright  large double room ensuite bathroom . location stu...
4149    spacious bed flat city center river thames view . walk waterloo  blackf...
5414    fabulous riverside flat  balcony great view thames canary wharf . next ...
5868    whole family stylish place . river viewings bedroom apartment hour conc...
7024    elegant master bedroom king size ensuite bathroom charming  quiet road ...
7581    bedroom manhattan apartment stylish chelsea creek development  locate l...
7646    luxury retreat breathtaking canal views welcome enchant canal view flat...
Name: description_norm, dtype: object
```

```
vectorizer = CountVectorizer(ngram_range=(1,1), stop_words='english', analyzer='word
topic_corpus = vectorizer.fit_transform(srcdf[srcdf.Topic==1].description.values) #
```

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

```
f,ax = plt.subplots(1,1,figsize=(5,5))
plt.gcf().set_dpi(300)
Cloud = WordCloud(
            background_color="white",
            max_words=75).generate_from_frequencies(topicdf.sum())
ax.imshow(Cloud)
ax.axis("off");
# plt.savefig('Wordcloud 3.png')
```



11 Word2Vec

> **Tip**
>
> This algorithm works almost like magic. You should play with the configuration parameters and see how it changes your results. **However**, at this time I've not preinstalled `gensim` as it bloated the image substantially.

11.1 Configure

```
from gensim.models.word2vec import Word2Vec
```

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

window = 4
print(f"You've chosen a window of size {window}.")

min_v_freq  = 0.01 # Don't keep words appearing less than 1% 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, m
```

11.2 Train

```
%%time

corpus      = srcdf.description_norm.fillna(' ').values
#corpus_sent = [nltk.sent_tokenize(text) for text in corpus] # <-- with more formal
corpus_sent = [d.replace('.',' ').split(' ') for d in corpus] # <-- deals better wit
model       = Word2Vec(sentences=corpus_sent, vector_size=dims, window=window, epoch
                min_count=min_v_count, seed=42, workers=1)

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

11.3 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_s

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
```

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

11.4 Apply

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

11.4.1 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)?

12 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=Tr
```

```
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.

12.1 Applications

The above is *still* only the results for the one of the subsets of 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 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!

12.2 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