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.

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:

```python
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

ℹ Note

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

Standard libraries we've seen before.

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

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

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

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

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

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

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

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

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

from nltk import ngrams, FreqDist

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

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

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

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

```
from IPython.display import display_markdown

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

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

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
from functools import wraps

def check_cache(f):
    @wraps(f)
    def wrapper(src, dst, min_size=100):
        url = urlparse(src) # We assume that this is some kind of valid URL
        fn  = os.path.split(url.path)[-1] # Extract the filename
        dsn = os.path.join(dst,fn) # Destination filename
        if os.path.isfile(dsn) and os.path.getsize(dsn) > 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:str, dst:str) -> 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.
    """

    # Convert the path back into a list (without)
    # the filename -- we need to check that directories
    # exist first.
    path = os.path.split(dst)[0]
    print(f"Path: {path}")

    # 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 path != '':
        os.makedirs(path, exist_ok=True)

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

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

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(os.path.join('data','clean','luxury.geopackage'))
aff    = gpd.read_parquet(os.path.join('data','clean','affordable.geopackage'))
bluesp = gpd.read_parquet(os.path.join('data','clean','bluespace.geopackage'))
```

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*.

3.1 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 G
    'Accept': 'text/html,application/xhtml+xml,application/xml;q=0.9,*/*;q=0.8',
}
url = 'https://www.ucl.ac.uk/bartlett/casa/about-0'
```

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])
```

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/inc
<meta name="description" content="The Centre for Advanced Spatial Analysis (CASA) is an in
<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
```

3.2 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!

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(s
        cleaned += txt

cleaned
```

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(s
        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 institut
 'The Centre for Advanced Spatial Analysis (CASA) was established in 1995 to lead the develo
including physicists, planners, geographers, economists, data scientists, architects, math
united by our mission to tackle the biggest challenges facing cities and societies around th
 'View Map',
 'Contact Address: UCL Centre for Advanced Spatial Analysis First Floor, 90 Tottenham Court
```

3.3 Lower Case

Difficulty Level: Low.

Question

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

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 institut
 'the centre for advanced spatial analysis (casa) was established in 1995 to lead the develo
including physicists, planners, geographers, economists, data scientists, architects, math
united by our mission to tackle the biggest challenges facing cities and societies around th
 'view map',
 'contact address: ucl centre for advanced spatial analysis first floor, 90 tottenham court
```

3.4 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.

3.4.1 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.

Question

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

Answer

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

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

3.4.2 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.

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

```
<function word_tokenize at 0x177fc6200>
```

```
[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!
```

3.4.3 Compare

Look at how these outputs differ in subtle ways:

```python
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)
```

Substituted

> ucl home the bartlett centre for advanced spatial analysis about

Substituted

about

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

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

Substituted

view map

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

Tokenised

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

Tokenised

```
[‘about’]
```

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’, ‘.’]
```

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’, ‘,’, ‘visu-
alisation’, ‘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’, ‘,’, ‘math-
ematicians’, ‘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’, ‘con-
tact’, ‘with’, ‘our’, ‘outstanding’, ‘teachers’, ‘and’, ‘researchers’, ‘.’, ‘location’,
‘the’, ‘ucl’, ‘centre’, ‘for’, ‘advanced’, ‘spatial’, ‘analysis’, ‘is’, ‘located’, ‘at’,
‘90’, ‘tottenham’, ‘court’, ‘road’, ‘,’, ‘london’, ‘,’, ‘w1t’, ‘4tj’, ‘.’]
```

Tokenised

> ['view', 'map']

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']

3.5 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)
```

```
{'a', 'they', 'but', 'few', 'haven', 'those', 'himself', 'do', 'not', 'too', "shan't", 're
```

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)
```

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)
```

Line

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

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’]

3.6 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
```

```python
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)
```

Lemmatised

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

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’]

Stemmed

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

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']

```
# 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',
```

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

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)
```

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...

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)
```

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']

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

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 realworld 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 scientist 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 listing network social activity well continue contact outstanding teacher researcher . 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']

```
help(normalise_document)
```

```
Help on function normalise_document in module textual:

normalise_document(doc: str, html_stripping=True, contraction_expansion=True, accented_c
    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.
```

4.2.1 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.

5 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).

5.1 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)`!

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)
```

Answer

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

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

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


CPU times: user 43.3 s, sys: 886 ms, total: 44.2 s
Wall time: 44.2 s
```

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

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

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


CPU times: user 37 s, sys: 823 ms, total: 37.8 s
Wall time: 37.8 s
```

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

```
CPU times: user 1.58 s, sys: 35.9 ms, total: 1.62 s
Wall time: 1.62 s
```

5.2 Select and Tokenise

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

5.2.1 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 undergr
 'space appartment upper floor modernised secure building near canary wharf  fantastic view
 'newly renovate  totally equipped furnished modern apartment heart london . easily accessi
```

5.2.2 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 .', 'dis

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

5.3 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`.

5.3.1 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>
```

5.3.2 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
```

5.3.3 Questions

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

5.4 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!).

5.4.1 Fit the Vectoriser

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

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

5.4.2 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 {t
# 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
```

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

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 .

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

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

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

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 .

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

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 .

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 .

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 .

5.4.3 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>
```

5.4.4 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

5.4.5 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
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
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

5.4.6 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!

Question

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

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.
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	ac
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.

5.4.7 Questions

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

5.5 TF/IDF Vectoriser

Difficulty level: Moderate

But only if you want to understand how `max_df` and `min_df` work!

5.5.1 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
```

5.5.2 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
gardens	0.414885
stop	0.241659
district line	0.239192
railway	0.232131
underground	0.201738

	Weights
district	0.197221
bridge	0.191983
walk	0.189485
road	0.151163
distance	0.142999

5.5.3 Transformed Corpus

```python
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
0	0.0	0.043972	0.0	0.0	0.11031	0.11031
1	0.0	0.000000	0.0	0.0	0.00000	0.00000
2	0.0	0.000000	0.0	0.0	0.00000	0.00000
3	0.0	0.000000	0.0	0.0	0.00000	0.00000
4	0.0	0.044127	0.0	0.0	0.00000	0.00000

5.5.4 Questions

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

6 Word Clouds

6.1 For Counts

Difficulty level: Easy!

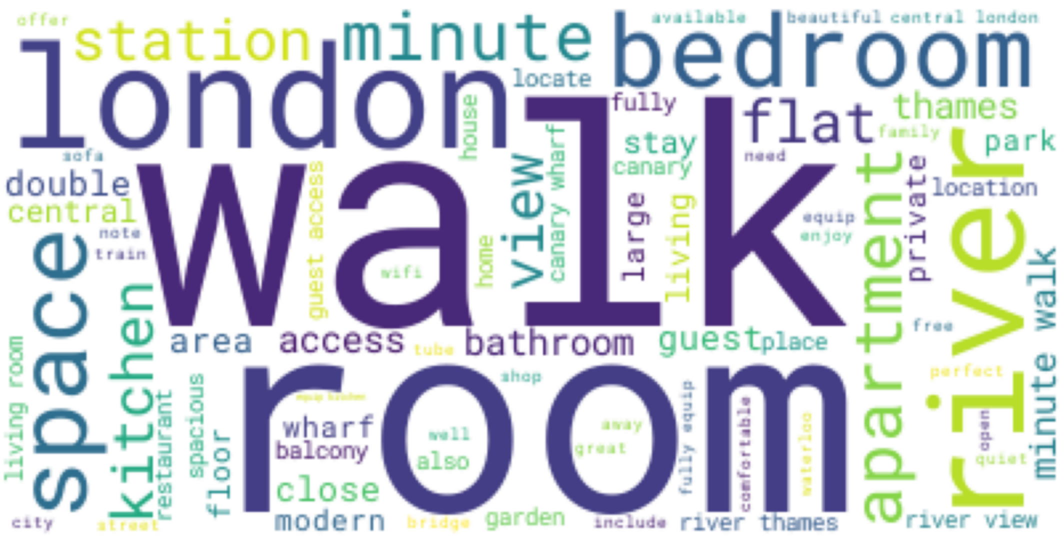
```python
fcvdf.sum().sort_values(ascending=False)
```

```
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")
```



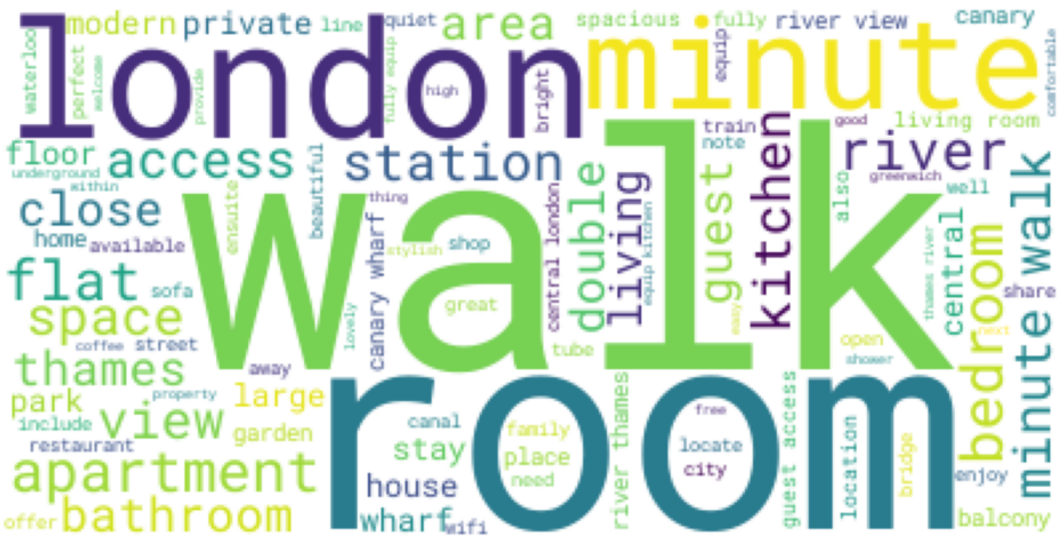
6.2 For TF/IDF Weighting

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")
```



6.2.1 Questions

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

7 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))
```

7.1 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)
```

```
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
```

```python
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

> 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

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

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

7.2 Maximum Likelihood Topic

```python
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()
```

	geometry	listing_url	name	description	ame
19	POINT (519474.79...	https://www.airb...	Townhouse in Ric...	3 Bed House with...	["Bat
71	POINT (537104.16...	https://www.airb...	Rental unit in L...	<b>The space</b>...	["He
713	POINT (530945.88...	https://www.airb...	Rental unit in G...	Newly renovated,...	["Bat
928	POINT (539808.31...	https://www.airb...	Rental unit in L...	Brand new rivers...	["Wa
1397	POINT (538098.29...	https://www.airb...	Rental unit in L...	PLEASE READ OTHE...	["He

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

```
19      house garden close thames river . walk  private road river nearby .  di...
928     brand riverside apartment greenwich peninsula . perfect explore london ...
1424     mint walk thames river  mint tower bridge  mint greenwich bus mint walk...
1644     bright  spacious chill bedroom cosy apartment level friendly quiet bloc...
3887     fabulous bathshower flat modern development east putney  london literal...
3966     large double room river view available large spacious townhouse hampton...
4664     private quiet bright  large double room ensuite bathroom . location stu...
4890     bright  airy bedroom  ground floor apartment quiet street . modernly fu...
5815     perfect claphambattersea modern decor . brand kitchenbathroom minute wa...
6699     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
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=(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')
```

8 Word2Vec

Tip

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

8.1 Configure

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

```python
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
```

```
You've chosen 100 dimensions.
You've chosen a window of size 4.
With a minimum frequency of 0.01 and 408 documents, minimum vocab frequency is 5.
```

8.2 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(..
```

```
CPU times: user 4 s, sys: 94.4 ms, total: 4.09 s
Wall time: 4.07 s
```

8.3 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
```

	Term	V1	V2	V3	Top 7 Similar
0	complimentary	1.524467	1.134316	0.237703	essentials, mbps, toiletry, excel, workspa
1	equip	-1.171649	0.706236	0.676694	equipped, utensil, flatscreen, plan, sofab
2	shower	-0.272218	-2.609626	1.885777	separate, corridor, additional, bathroom
3	smart	1.758183	-0.123735	1.295561	flatscreen, inch, comfy, netflix, kitchen, s
4	design	1.657050	1.763350	-1.095689	chic, beautifully, interior, decor, standar
5	appliance	-0.066985	0.668519	1.304341	essential, necessary, kitchenette, utensil
6	living	0.795928	-1.091040	0.090184	live, separate, lounge, double, come, mo
7	the	0.678621	0.764269	-1.814383	castle, zone, guarantee, cosy, equip, nice
8	directly	-0.485994	-1.765136	-0.389416	docklands, excel, cathedral, undergroun
9	fridgefreezer	-1.023075	-0.408912	-0.379294	cutlery, kettle, toaster, freezer, washer, o
10	bathtub	-1.153225	-0.845233	1.582382	reception, ensuite, bath, walkin, toilet, c
11	train	1.615595	-0.275208	-1.623259	kingston, jubilee, taxi, mudchute, india,
12	palace	-2.354299	-1.162588	-0.131212	buckingham, hyde, min, parliament, sloa
13	shard	0.661091	0.241524	-0.174146	globe, cathedral, shoredich, borough, to

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

8.4 Apply

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

8.4.1 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)?

9 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.

9.1 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!

9.2 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