Lecture 11: Computational Efficiency

LING 1340/2340: Data Science for Linguists

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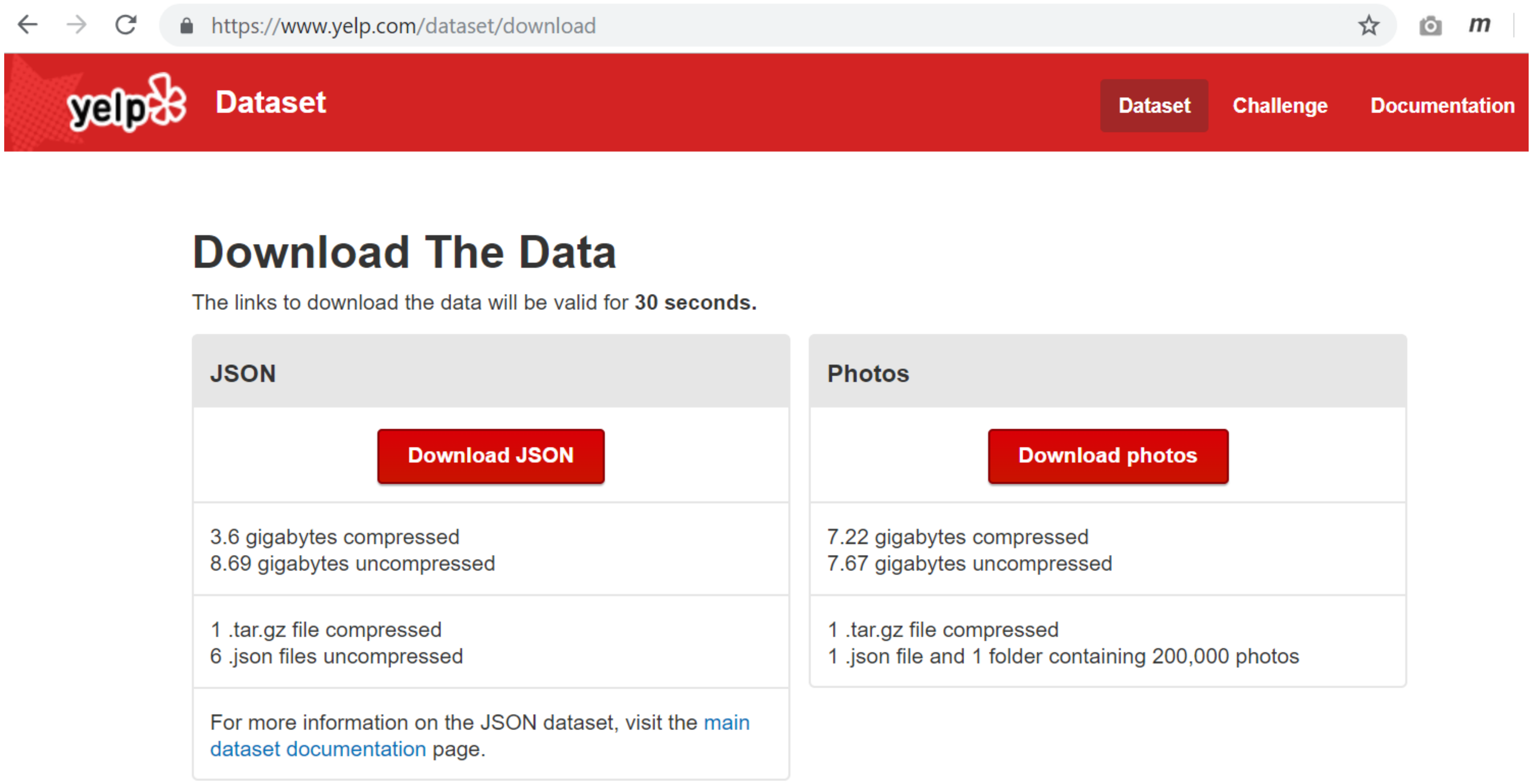
Objectives

- Big data considerations
- Computational efficiency
  - Memory vs. processing time
  - Algorithmic complexity
  - Big O notation
- Word embeddings

The Yelp Dataset Challenge

- https://www.yelp.com/dataset/challenge

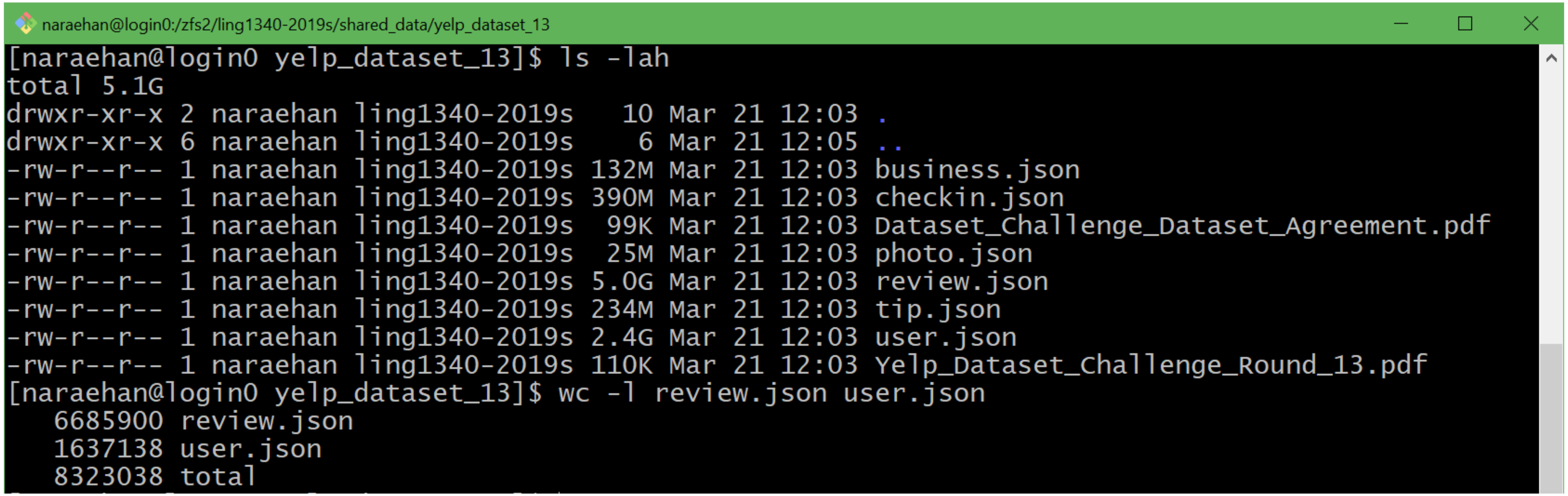

https://www.yelp.com/dataset/download

Download The Data

The links to download the data will be valid for **30 seconds.**

JSON	Photos
Download JSON	Download photos
3.6 gigabytes compressed 8.69 gigabytes uncompressed	7.22 gigabytes compressed 7.67 gigabytes uncompressed
1 .tar.gz file compressed 6 .json files uncompressed	1 .tar.gz file compressed 1 .json file and 1 folder containing 200,000 photos
For more information on the JSON dataset, visit the main dataset documentation page.	

Working with big data files



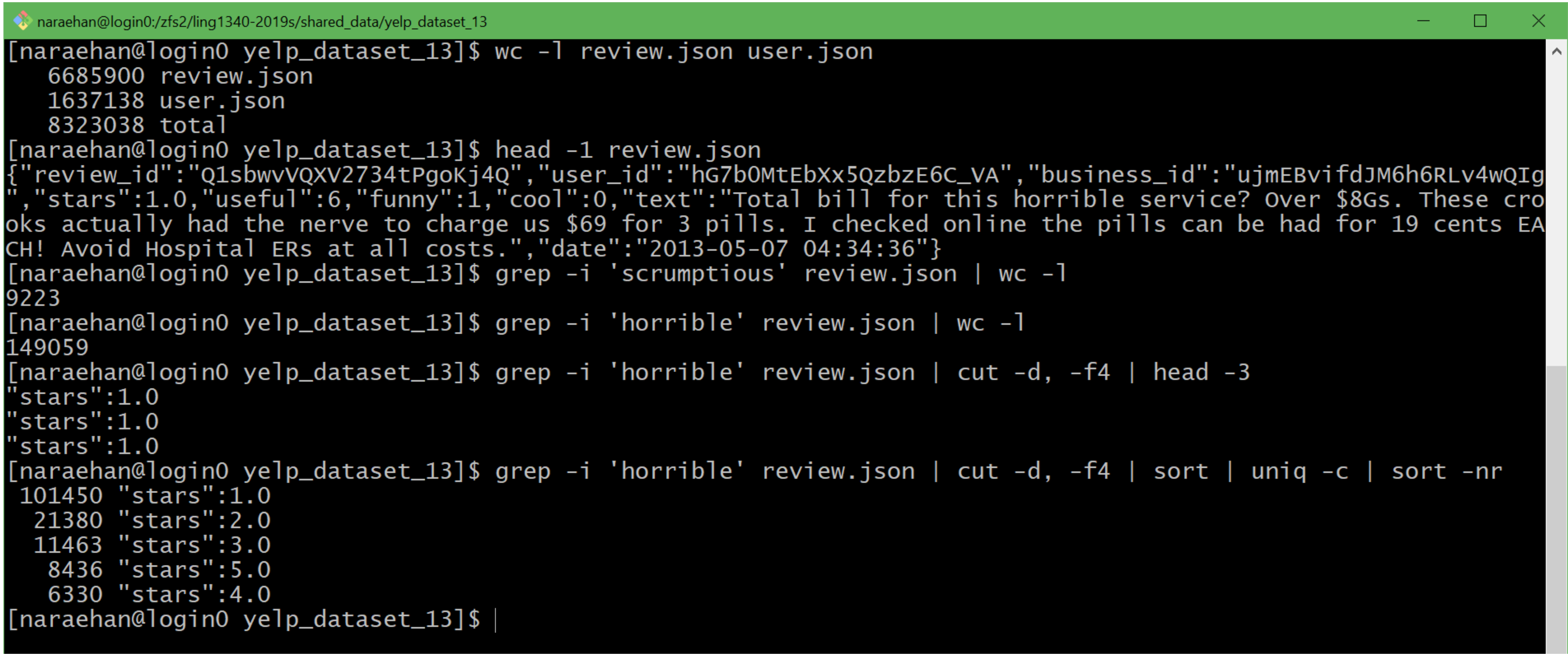
naraehan@login0:/zfs2/ling1340-2019s/shared_data/yelp_dataset_13

```
[naraehan@login0 yelp_dataset_13]$ ls -lah
total 5.1G
drwxr-xr-x 2 naraehan ling1340-2019s   10 Mar 21 12:03 .
drwxr-xr-x 6 naraehan ling1340-2019s    6 Mar 21 12:05 ..
-rw-r--r-- 1 naraehan ling1340-2019s 132M Mar 21 12:03 business.json
-rw-r--r-- 1 naraehan ling1340-2019s 390M Mar 21 12:03 checkin.json
-rw-r--r-- 1 naraehan ling1340-2019s  99K Mar 21 12:03 Dataset_Challenge_Dataset_Agreement.pdf
-rw-r--r-- 1 naraehan ling1340-2019s  25M Mar 21 12:03 photo.json
-rw-r--r-- 1 naraehan ling1340-2019s 5.0G Mar 21 12:03 review.json
-rw-r--r-- 1 naraehan ling1340-2019s 234M Mar 21 12:03 tip.json
-rw-r--r-- 1 naraehan ling1340-2019s 2.4G Mar 21 12:03 user.json
-rw-r--r-- 1 naraehan ling1340-2019s 110K Mar 21 12:03 Yelp_Dataset_Challenge_Round_13.pdf
[naraehan@login0 yelp_dataset_13]$ wc -l review.json user.json
   6685900 review.json
   1637138 user.json
   8323038 total
```

- Each file is in JSON format, and they are huge:
  - review.json is 5.0GB with 6.7 million records
  - user.json is 2.4GB with 1.6 million records
  - ← Too big to open in most text editors (Notepad++ couldn't.)
  - ← How to explore them?

In command line. head/tail, grep and regular expression-based searching.

Command line exploration

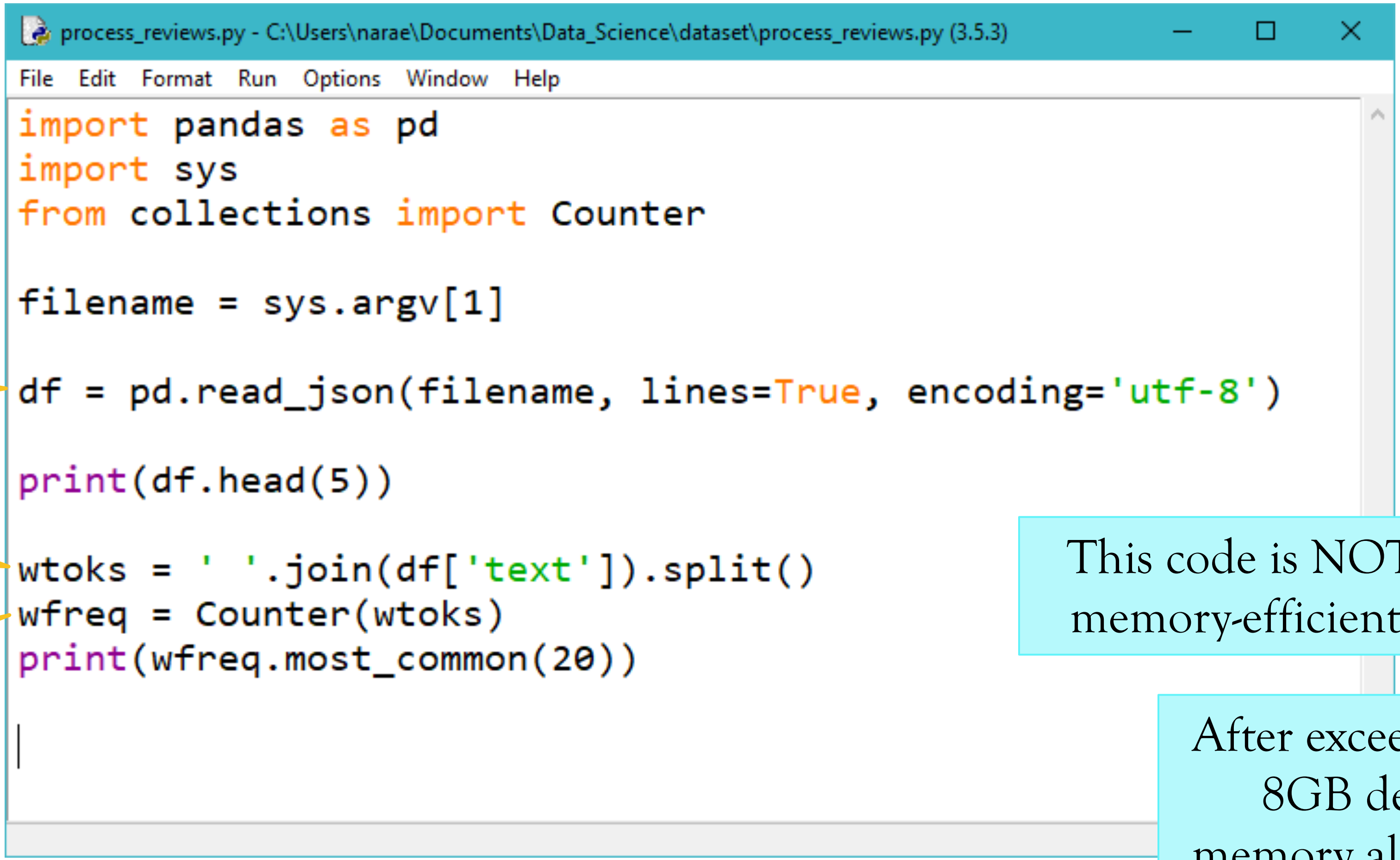


naraehan@login0:/zfs2/ling1340-2019s/shared_data/yelp_dataset_13

```
[naraehan@login0 yelp_dataset_13]$ wc -l review.json user.json
   6685900 review.json
   1637138 user.json
   8323038 total
[naraehan@login0 yelp_dataset_13]$ head -1 review.json
{"review_id":"Q1sbwvVQXV2734tPgoKj4Q","user_id":"hG7b0MtEbXx5QzbzE6C_VA","business_id":"ujmEBvifdJM6h6RLv4wQIg
","stars":1.0,"useful":6,"funny":1,"cool":0,"text":"Total bill for this horrible service? Over $8Gs. These cro
oks actually had the nerve to charge us $69 for 3 pills. I checked online the pills can be had for 19 cents EA
CH! Avoid Hospital ERs at all costs.","date":"2013-05-07 04:34:36"}
[naraehan@login0 yelp_dataset_13]$ grep -i 'scrumptious' review.json | wc -l
9223
[naraehan@login0 yelp_dataset_13]$ grep -i 'horrible' review.json | wc -l
149059
[naraehan@login0 yelp_dataset_13]$ grep -i 'horrible' review.json | cut -d, -f4 | head -3
"stars":1.0
"stars":1.0
"stars":1.0
[naraehan@login0 yelp_dataset_13]$ grep -i 'horrible' review.json | cut -d, -f4 | sort | uniq -c | sort -nr
 101450 "stars":1.0
  21380 "stars":2.0
  11463 "stars":3.0
   8436 "stars":5.0
   6330 "stars":4.0
[naraehan@login0 yelp_dataset_13]$ |
```

Opening + processing big files

- How much resource does it take to process review.json file (5.0GB)?


process_reviews.py - C:\Users\narae\Documents\Data_Science\dataset\process_reviews.py (3.5.3)
File Edit Format Run Options Window Help

```
import pandas as pd
import sys
from collections import Counter

filename = sys.argv[1]

df = pd.read_json(filename, lines=True, encoding='utf-8')

print(df.head(5))

wtoks = ' '.join(df['text']).split()
wfreq = Counter(wtoks)
print(wfreq.most_common(20))
```

There's 5 GB

Another ~4 GB

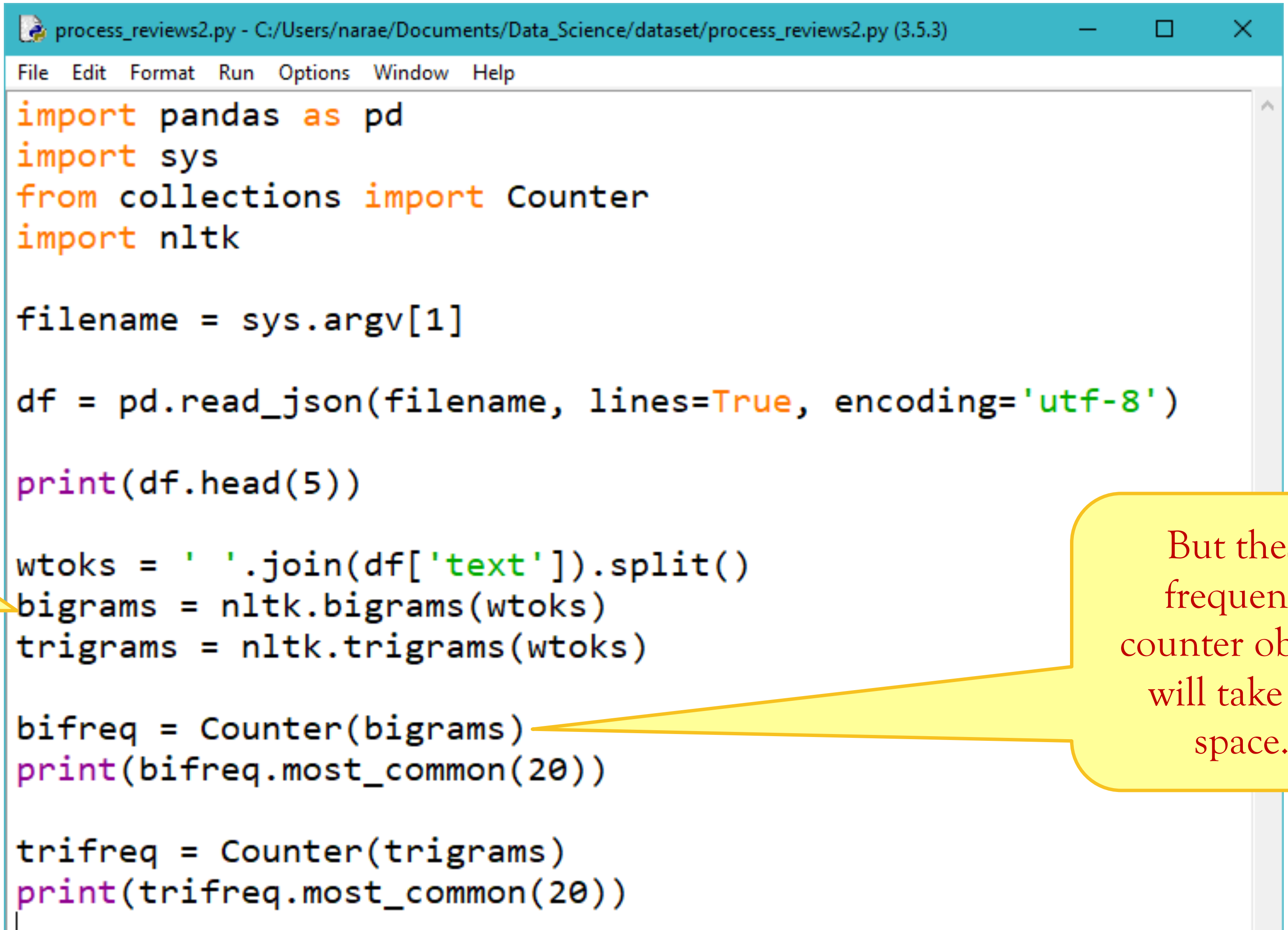
Not as big

This code is NOT memory-efficient.

After exceeding the 8GB default memory allocation, the job gets killed.

Memory consideration

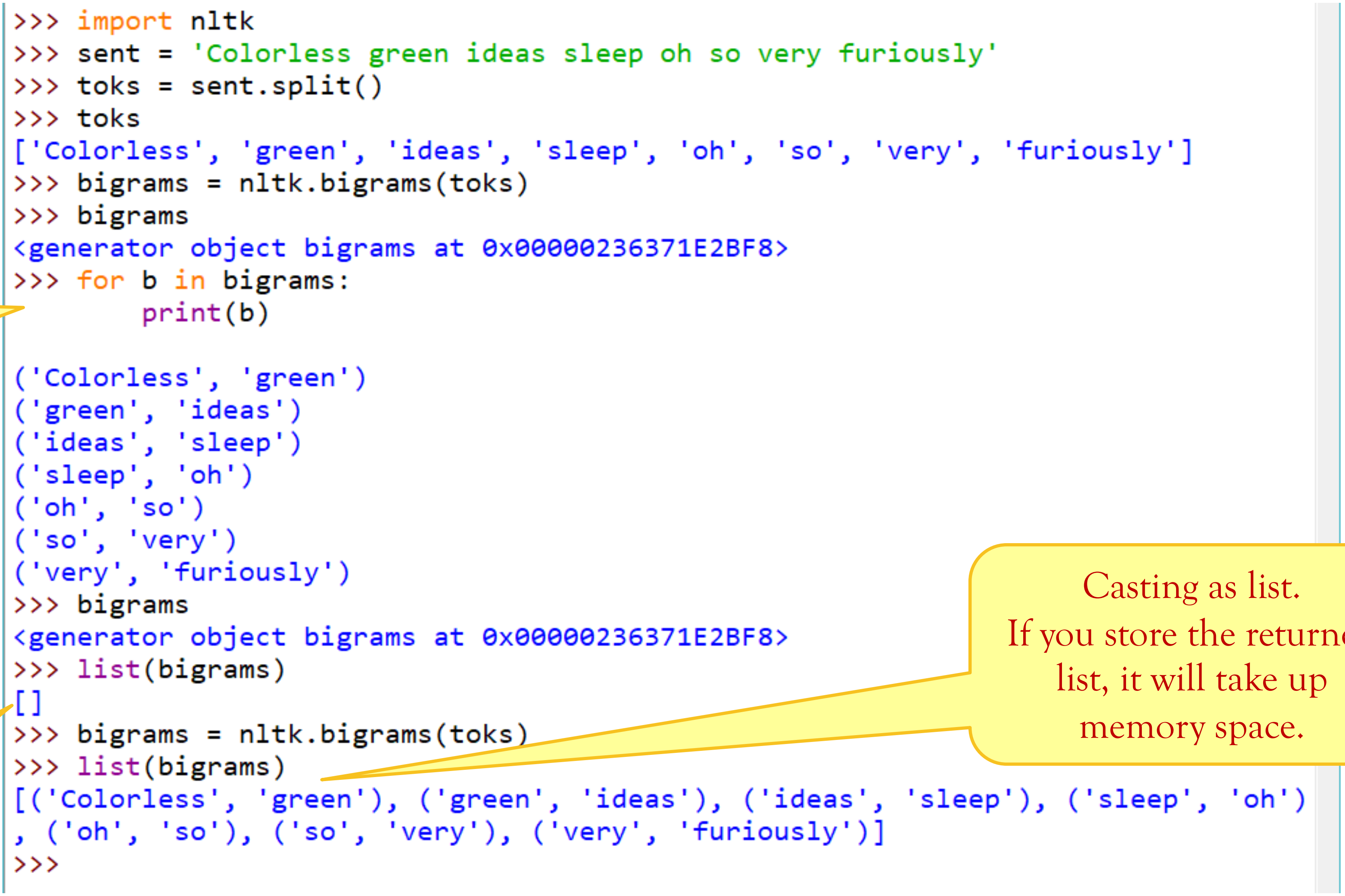
- How much space needed for bigrams? Trigrams?


process_reviews2.py - C:/Users/narae/Documents/Data_Science/dataset/process_reviews2.py (3.5.3)
File Edit Format Run Options Window Help

```
import pandas as pd
import sys
from collections import Counter
import nltk

filename = sys.argv[1]

df = pd.read_json(filename, lines=True, encoding='utf-8')

print(df.head(5))

wtoks = ' '.join(df['text']).split()
bigrams = nltk.bigrams(wtoks)
trigrams = nltk.trigrams(wtoks)

bifreq = Counter(bigrams)
print(bifreq.most_common(20))

trifreq = Counter(trigrams)
print(trifreq.most_common(20))
```

Good news! These are built as generator objects and take up almost zero space.

But these frequency counter objects will take up space.



```
>>> import nltk
>>> sent = 'Colorless green ideas sleep oh so very furiously'
>>> toks = sent.split()
>>> toks
['Colorless', 'green', 'ideas', 'sleep', 'oh', 'so', 'very', 'furiously']
>>> bigrams = nltk.bigrams(toks)
>>> bigrams
<generator object bigrams at 0x00000236371E2BF8>
>>> for b in bigrams:
        print(b)

('Colorless', 'green')
('green', 'ideas')
('ideas', 'sleep')
('sleep', 'oh')
('oh', 'so')
('so', 'very')
('very', 'furiously')
>>> bigrams
<generator object bigrams at 0x00000236371E2BF8>
>>> list(bigrams)
[]
>>> bigrams = nltk.bigrams(toks)
>>> list(bigrams)
[('Colorless', 'green'), ('green', 'ideas'), ('ideas', 'sleep'), ('sleep', 'oh')
, ('oh', 'so'), ('so', 'very'), ('very', 'furiously')]
>>>
```

Generator type objects take up little memory space; meant to be used in a loop-like environment.

Content has been exhausted

Casting as list. If you store the returned list, it will take up memory space.

File opening & closing methods

```
f = open('review.json')
lines = f.readlines()
for l in lines:
    if 'horrible' in l:
        print(l)
f.close()
```

```
f = open('review.json')
for l in f:
    if 'horrible' in l:
        print(l)
f.close()
```

```
lines = open('review.json').readlines()
for l in lines :
    if 'horrible' in l:
        print(l)
```

Python will close up this file handle.

```
with open('review.json') as f:
    for l in f:
        if 'horrible' in l:
            print(l)
```

No need to close f later. Some folks swear by using `with`.

Which methods are memory-efficient?

Handling files in chunks

```
f = open('review.json')
lines1 = f.readlines(1000000000)
lines2 = f.readlines(1000000000)
lines3 = f.readlines(1000000000)
lines4 = f.readlines(1000000000)
lines5 = f.readlines()
f.close()
```

Optional # of bytes to read. (When used like this without a loop, offers no memory advantage.)

```
dfs = pd.read_json('review.json', lines=True, chunksize=10000, encoding='utf8')

wfreq = Counter()

for df in dfs:
    wtoks = ' '.join(df['text']).split()
    temp = Counter(wtoks)
    wfreq.update(temp)

print(wfreq.most_common(20))
```

Generator object. Takes up zero space.

`chunksize` optional parameter in pandas' `read_json` method reads in 10,000 lines at a time...

then, iterate through each small df.

Memory-efficient! This code uses only 290MB of memory!!

Pandas vs. large data: tips

- "Why and How to Use Pandas with Large (but not big) Data"
  - https://towardsdatascience.com/why-and-how-to-use-pandas-with-large-data-9594dda2ea4c

1. Read CSV file data in chunk size
2. Filter out unimportant columns in `df` to save memory
3. Change `dtypes` for columns
   - float64 takes up more space than float32.

Vectorizing and training in chunks

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_extraction.text import HashingVectorizer
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)

filename = 'review_10k.json'
length = 10000
chunk_size = 1000
chunks = length/chunk_size

df_chunks = pd.read_json(filename, lines=True, chunksize=chunk_size, encoding="utf-8")

clf = MultinomialNB()
vectorizer = HashingVectorizer(non_negative=True)

for i, df in enumerate(df_chunks):
    if i < 0.8 * chunks:
        clf.partial_fit(vectorizer.transform(df['text']), df['stars'], classes=[1,2,3,4,5])
    else:
        pred = clf.predict(vectorizer.transform(df['text']))
        print('batch {}, {} accuracy'.format(i, np.mean(pred == df['stars'])))
```

If vectorizer/ML model depends only on individual row of data, it can be implemented in chunks.

(Caveat: TF-IDF vectorizer and most ML models can't.)

Hashing vectorizer skips the IDF part of TF/IDF, can be implemented in chunks!

NB classifier can be trained in partial bits!

```
batch 8, 0.444 accuracy
batch 9, 0.439 accuracy
```

Computational efficiency: space vs. time

SPACE: **memory** footprint

- Do not create duplicate data objects.
- Avoid creating a data object that does not need to be stored in its entirety.
- In code, delete large data objects that will no longer be used
  - Do not simply rely on Python's garbage collection

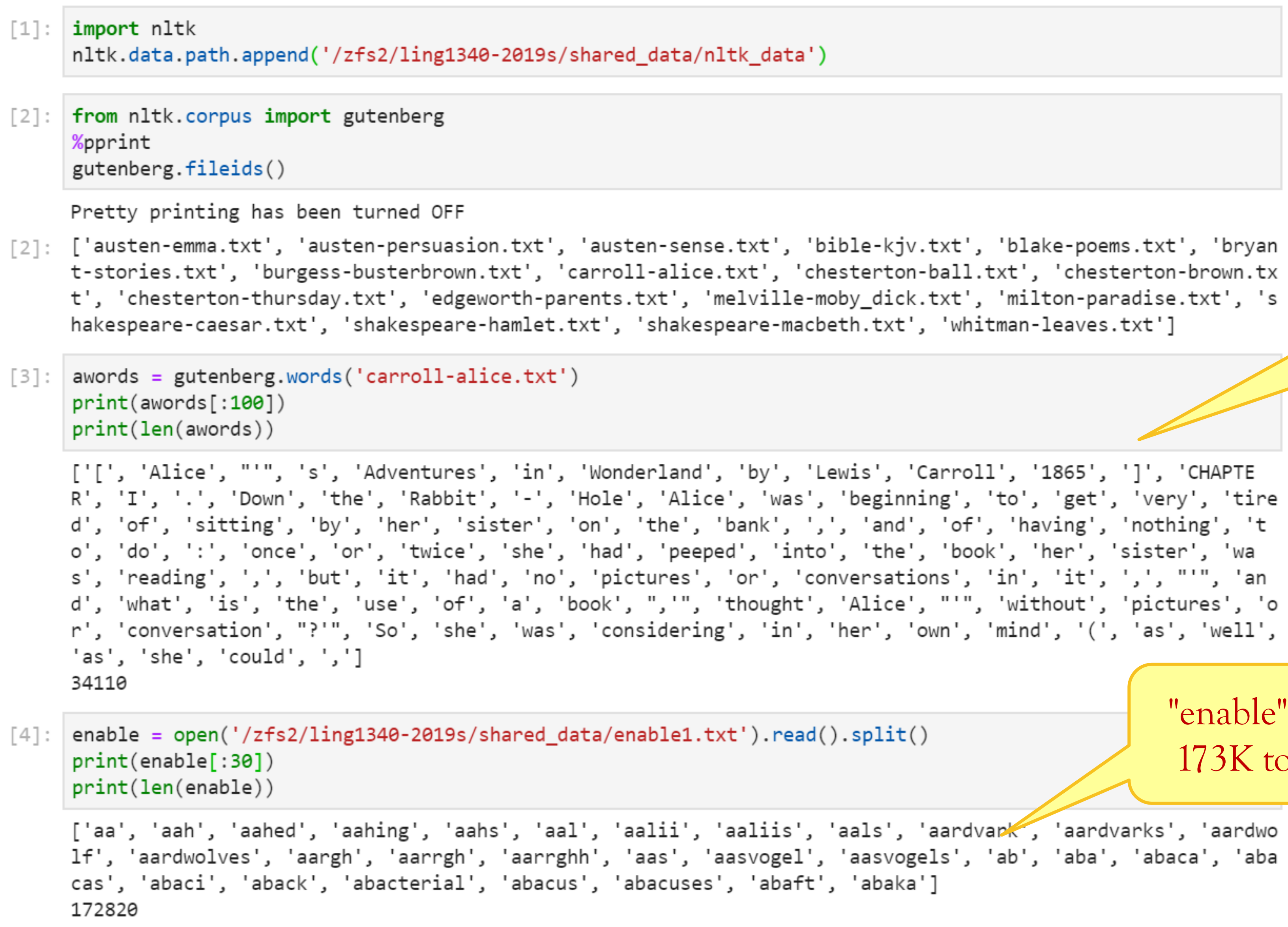
TIME: **processor** runtime

- Avoid duplicating an expensive processing step: process once, store result as an object, then reuse.
- Use an efficient algorithm.
- Use the data type optimal for the task at hand.

Optimize both.

Trade-off relationship sometimes: manage available computational resources, achieve balance & goal!

Data types and optimization



```
[1]: import nltk
     nltk.data.path.append('/zfs2/ling1340-2019s/shared_data/nltk_data')
```

```
[2]: from nltk.corpus import gutenberg
     %pprint
     gutenberg.fileids()
```

```
     Pretty printing has been turned OFF

[2]: ['austen-emma.txt', 'austen-persuasion.txt', 'austen-sense.txt', 'bible-kjv.txt', 'blake-poems.txt', 'bryan
     t-stories.txt', 'burgess-busterbrown.txt', 'carroll-alice.txt', 'chesterton-ball.txt', 'chesterton-brown.tx
     t', 'chesterton-thursday.txt', 'edgeworth-parents.txt', 'melville-moby_dick.txt', 'milton-paradise.txt', 's
     hakespeare-caesar.txt', 'shakespeare-hamlet.txt', 'shakespeare-macbeth.txt', 'whitman-leaves.txt']
```

```
[3]: awords = gutenberg.words('carroll-alice.txt')
     print(awords[:100])
     print(len(awords))
```

```
     ['[', 'Alice', "'", 's', 'Adventures', 'in', 'Wonderland', 'by', 'Lewis', 'Carroll', '1865', ']', 'CHAPTE
     R', 'I', '.', 'Down', 'the', 'Rabbit', '-', 'Hole', 'Alice', 'was', 'beginning', 'to', 'get', 'very', 'tire
     d', 'of', 'sitting', 'by', 'her', 'sister', 'on', 'the', 'bank', ',', 'and', 'of', 'having', 'nothing', 't
     o', 'do', ':', 'once', 'or', 'twice', 'she', 'had', 'peeped', 'into', 'the', 'book', 'her', 'sister', 'wa
     s', 'reading', ',', 'but', 'it', 'had', 'no', 'pictures', 'or', 'conversations', 'in', 'it', ',', "'", 'an
     d', 'what', 'is', 'the', 'use', 'of', 'a', 'book', ",'", 'thought', 'Alice', "'", 'without', 'pictures', 'o
     r', 'conversation', "?'", 'So', 'she', 'was', 'considering', 'in', 'her', 'own', 'mind', '(', 'as', 'well',
     'as', 'she', 'could', ',']
     34110
```

```
[4]: enable = open('/zfs2/ling1340-2019s/shared_data/enable1.txt').read().split()
     print(enable[:30])
     print(len(enable))
```

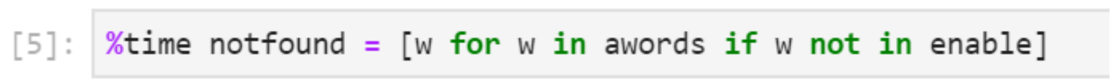
```
     ['aa', 'aah', 'aahed', 'aahing', 'aahs', 'aal', 'aalii', 'aaliis', 'aals', 'aardvark', 'aardvarks', 'aardwo
     lf', 'aardwolves', 'aargh', 'aarrgh', 'aarrghh', 'aas', 'aasvogel', 'aasvogels', 'ab', 'aba', 'abaca', 'aba
     cas', 'abaci', 'aback', 'abacterial', 'abacus', 'abacuses', 'abaft', 'abaka']
     172820
```

"Alice in Wonderland", 34K tokens

Task: find Alice words that are not found in enable list

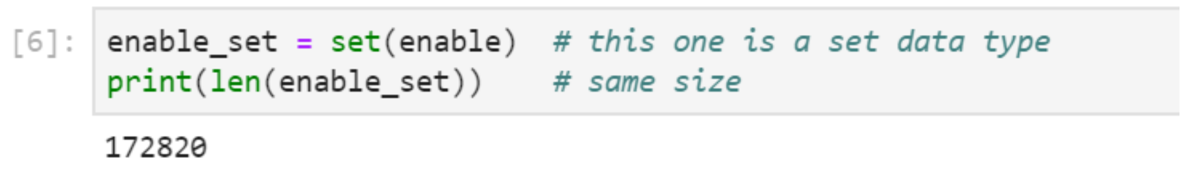
"enable" word list, 173K total words

- Try 1: list-comprehend through awords (list), filter against enable (list)

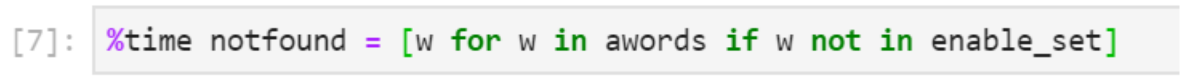


```
[5]: %time notfound = [w for w in awords if w not in enable]
```

- Try 2: same, but filter against enable list as a SET

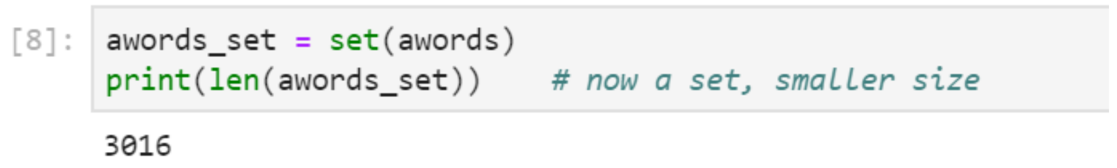


```
[6]: enable_set = set(enable)  # this one is a set data type
     print(len(enable_set))     # same size

     172820
```

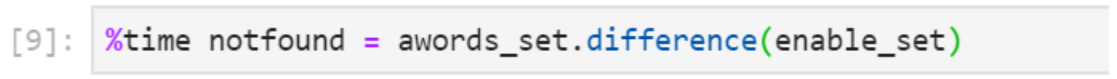


```
[7]: %time notfound = [w for w in awords if w not in enable_set]
```

- Try 3: compute the SET difference

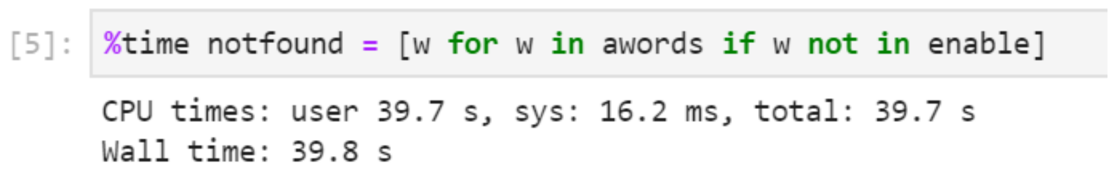


```
[8]: awords_set = set(awords)
     print(len(awords_set))     # now a set, smaller size

     3016
```



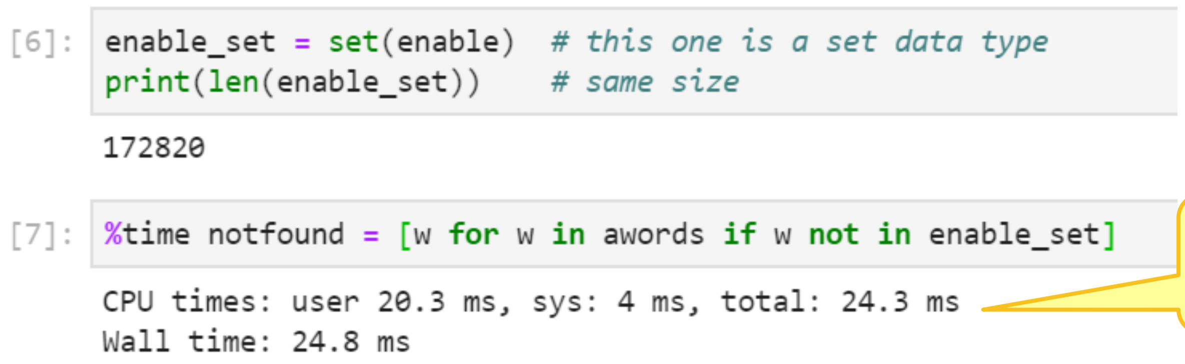
```
[9]: %time notfound = awords_set.difference(enable_set)
```

- Try 1: list-comprehend through awords (list), filter against enable (list)



```
[5]: %time notfound = [w for w in awords if w not in enable]

CPU times: user 39.7 s, sys: 16.2 ms, total: 39.7 s
Wall time: 39.8 s
```

- Try 2: same, but filter against enable list as a SET



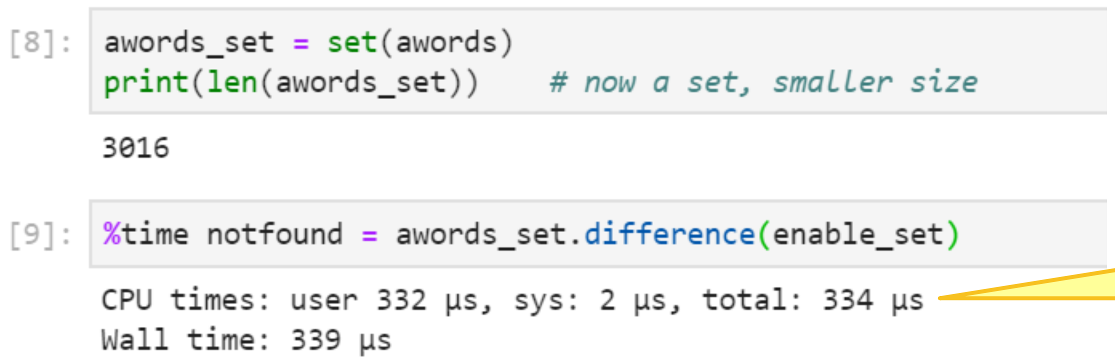
```
[6]: enable_set = set(enable)   # this one is a set data type
     print(len(enable_set))     # same size

172820

[7]: %time notfound = [w for w in awords if w not in enable_set]

CPU times: user 20.3 ms, sys: 4 ms, total: 24.3 ms
Wall time: 24.8 ms
```

much faster

Lists as a data type are NOT optimized for membership operations…

but sets are!

- Try 3: compute the SET difference



```
[8]: awords_set = set(awords)
     print(len(awords_set))     # now a set, smaller size

3016

[9]: %time notfound = awords_set.difference(enable_set)

CPU times: user 332 µs, sys: 2 µs, total: 334 µs
Wall time: 339 µs
```

blazing fast

Keep efficiency in mind: pick the right combination of data structure and operation

Algorithmic complexity and the Big O

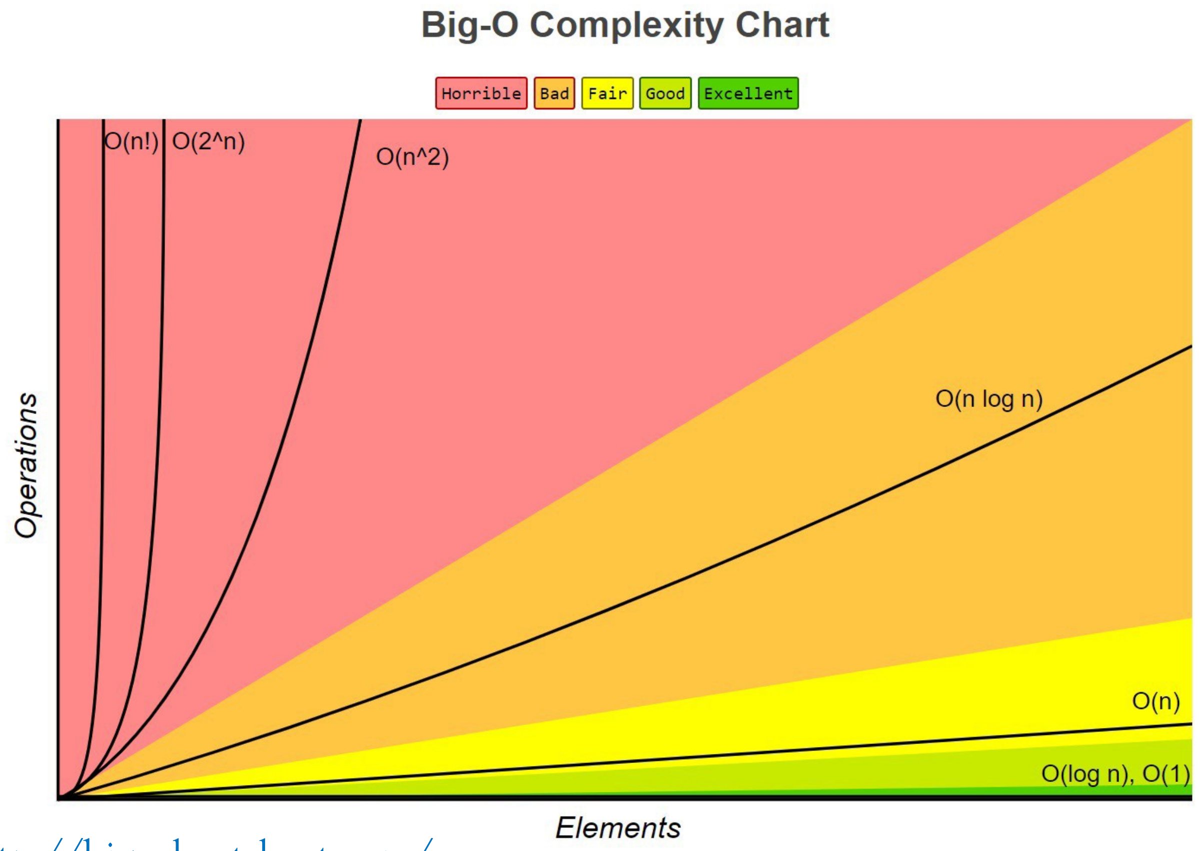
- https://rob-bell.net/2009/06/a-beginners-guide-to-big-o-notation/
- We have a **list of *n* items**. Imagine *n* is 100, 1000 or even 1 million.

1. Is the first element an even number?
   - Can be implemented in O(1): an algorithm that executes in a **constant** time regardless of the size of the input dataset.
2. Does the list contain value 42?
   - Can be implemented in O(n): an algorithm whose performance will grow **linearly** in proportion to the size of the input data.
3. Does the list contain duplicate values?
   - Can be implemented in O(n^2):an algorithm whose performance is directly proportional to the square of the size of the input data set (**quadratic**).

Algorithmic complexity and the Big O

- https://rob-bell.net/2009/06/a-beginners-guide-to-big-o-notation/
- We have a **list of *n* items**. Imagine *n* is 100, 1000 or even 1 million.

4. Sort the list (ascending or descending)
   - Can be implemented in O(n log n): an algorithm that executes in loglinear time.
   - See: https://brilliant.org/wiki/sorting-algorithms/



http://bigocheatsheet.com/

Algorithmic efficiency: summary

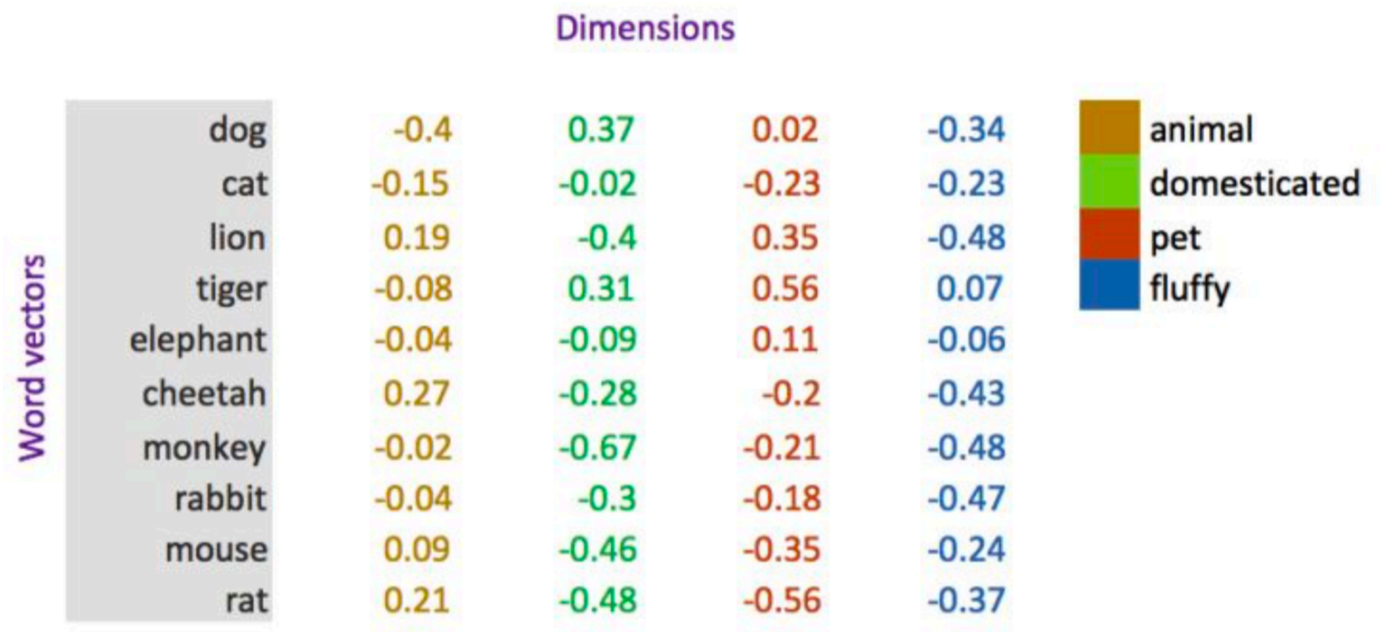
- A problem can be implemented with varying degrees of algorithmic efficiency.
- A problem comes with its own inherent algorithmic complexity limit.
  - **Big O notation** is a mathematical notation that encapsulates the relationship between the processing time and the input data size.
  - Example: the most efficient known sorting algorithm bottoms out at O(n log n).
- In a nutshell…
  - Compose the most efficient algorithm that you can.
  - Understand the relationship between the data size growth and the processing time growth. O(n) has fair scalability, O(n^2) becomes intractable.
  - Efficiency of an algorithm can lead to dramatic runtime difference when dealing with big data.

Word representations

- We've seen Count Vectorizer and TF-IDF
- These don't account for:
  - Word meaning
  - Word context
- How can we capture things like:
  - "apple" and "orange" are fruits
  - *king* – *man* + *woman* = *queen*

Word embeddings (simplified)

- An embedding of a word is a vector representing that word
  - Example 4-dimensional embedding for *dog*: [–0.4, 0.37, 0.02, –0.34]
- Each dimension of the vector represents some meaning or concept



Word vectors	Dimensions			
dog	-0.4	0.37	0.02	-0.34
cat	-0.15	-0.02	-0.23	-0.23
lion	0.19	-0.4	0.35	-0.48
tiger	-0.08	0.31	0.56	0.07
elephant	-0.04	-0.09	0.11	-0.06
cheetah	0.27	-0.28	-0.2	-0.43
monkey	-0.02	-0.67	-0.21	-0.48
rabbit	-0.04	-0.3	-0.18	-0.47
mouse	0.09	-0.46	-0.35	-0.24
rat	0.21	-0.48	-0.56	-0.37

🟧 animal
🟩 domesticated
🟥 pet
🟦 fluffy

Word embeddings (less simple)

- In reality, what each dimension represents is much harder to define
- Words with similar meanings have similar representations
- While TF-IDF focuses on word relevance, word embeddings focus on word meaning
- Many different ways to produce word embeddings…

Word2Vec

- First major model of word embeddings
  - Introduced by Google Research in 2013
- Given some text, for each word, take the word and some context
  - One way to do this is a *skip-gram model*: Given a “center” word, use a neural network to predict the probabilities that it will be surrounded by some context words
  - Another way is to train a model to “fill in” the “center” word given some context
    - “the cat _ on the mat” > high probability for “sat”
  - Embeddings are produced by an intermediate “hidden” layer in the network

Why do this?

- Vector arithmetic with words! (*king – man + woman = queen*)
- Show relationships between concepts in 2D

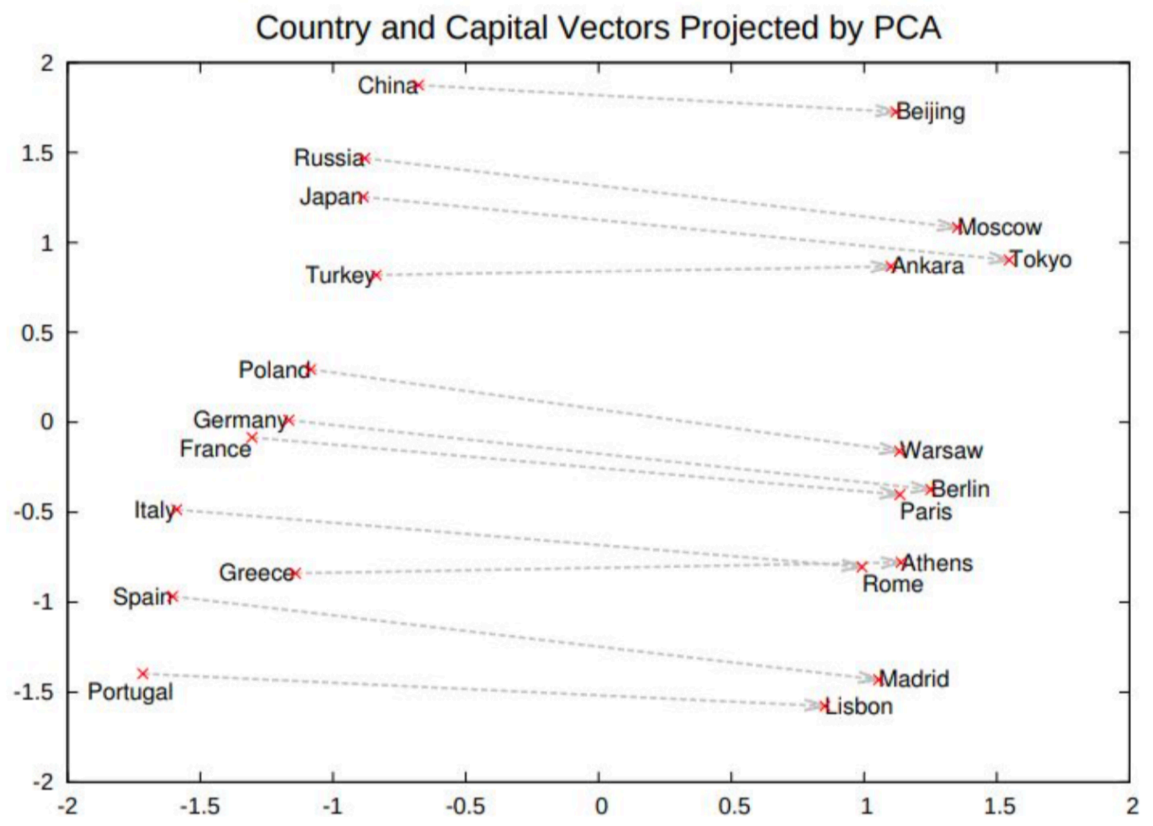
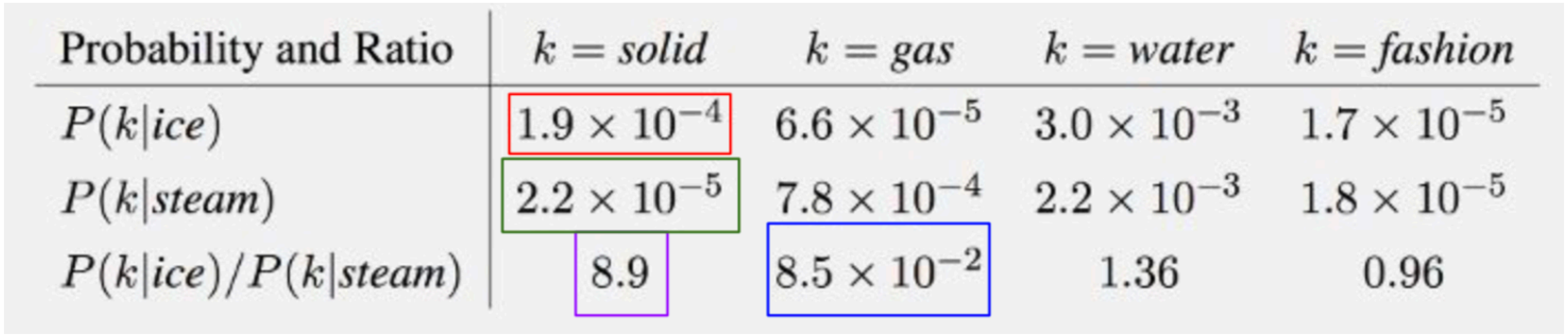


Figure 2: Two-dimensional PCA projection of the 1000-dimensional Skip-gram vectors of countries and their capital cities. The figure illustrates ability of the model to automatically organize concepts and learn implicitly the relationships between them, as during the training we did not provide any supervised information about what a capital city means.

GloVe: Global Vectors for Word Representation

- Not training a model to predict stuff; rather, using co-occurrence ratios
  - P(*k* | *w*) = probability that *k* appears in the context of *w*.
  - *solid* is related to *ice* but not to *steam*, so P(*solid* | *ice*) should be high and P(*solid* | *steam*) low.
  - So the ratio of P(*solid* | *ice*) / P(*solid* | *steam*) is large.
  - *gas* is related to *steam* but not *ice*, so the ratio of P(*gas* | *ice*) / P(*gas* | *steam*) is small.
  - Words related to both (e.g. *water*) or neither (e.g. *fashion*) should have a ratio close to 1.
  - The dot product of two vectors equals the log of the words' probability of co-occurrence.



Probability and Ratio	$k = solid$	$k = gas$	$k = water$	$k = fashion$
$P(k\|ice)$	$\boxed{1.9 \times 10^{-4}}$	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(k\|steam)$	$\boxed{2.2 \times 10^{-5}}$	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
$P(k\|ice)/P(k\|steam)$	$\boxed{8.9}$	$\boxed{8.5 \times 10^{-2}}$	1.36	0.96

FastText

- Basically an extension of Word2Vec
  - Facebook's AI Research lab, 2015
- Uses character ngrams, e.g. *apple* > *ap*, *app*, *appl*, *apple*, *pp*, *ppl*, *pple*, etc.
- Benefits:
  - Can generate word embeddings for new words, as long as it has the right character ngrams
  - Supposedly better performance than other models for certain downstream tasks
- Drawbacks:
  - More hyperparameters to tweak (including ngram sizes)
  - Requires more resources in both time and space

More on word embeddings

- Word embeddings (usually pretrained) are the standard features to start with for basically any NLP research task
  - image captioning, question answering, machine translation, what-have-you
- Steps for text classification using word embeddings:
  - Tokenize text
  - Map each token to its word embedding to create 2D matrix of features
  - Add more features if desired
  - Train classifier
- Fixed-length input models can average our word embeddings to create a single feature vector
- Variable-length input models (e.g., recurrent neural networks) lose less information

Wrapping up

- Homework 4
  - Fun with CRC!
  - Make sure to check out the list of tips at the bottom of the page…
  - As a class we have 10000 Service Units, which is 10k hours of computing time (not that much).
    - Don't let your jobs run infinitely! Test on small samples of data and make sure they work before you run large jobs.
- Next class
  - Clustering, HW review