Preprocessing, vectorizing, and comparing text

CS 780/880 Natural Language Processing Lecture 3

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Representing text numerically

Before we try to do anything computational with text, we need to create a representation our computer can actually work with

We often want this to include preprocessing and normalization that makes it easier to treat similar texts similarly

E.g.

- Case
- Stemming
- Tokenization
- Synonymy

Case study: text similarity

Very frequent basic NLP task: how similar are these two texts?

Especially in comparison to these other two texts?

Why might we want to do this?

- Web search
- Classification based on similar labeled examples
- Plagiarism detection
- Etc.

I will use text similarity as a motivating task for preprocessing and vectorizing text.

Our corpus

Four short movie reviews:

Review 0: "The film was a delight--I was riveted."
Review 1: "It's the most delightful and riveting movie."
Review 2: "It was a terrible flick, the worst I have ever seen."
Review 3: "I have a feeling the film was recut poorly.“

Question: Which review is most similar to review 0?

Our corpus

Four short movie reviews:

Review 0: "The film was a delight--I was riveted."
Review 1: "It's the most delightful and riveting movie."
Review 2: "It was a terrible flick, the worst I have ever seen."
Review 3: "I have a feeling the film was recut poorly.“

Answer: review 1.

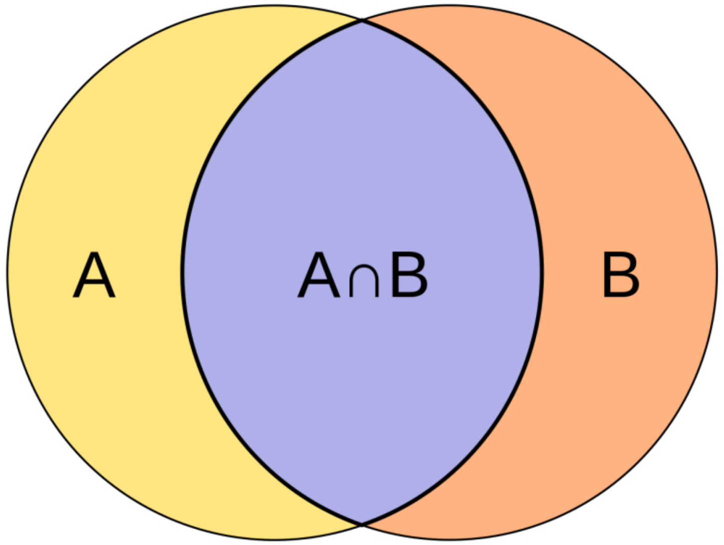
- But can we come up with a similarity metric that reflects that fact?

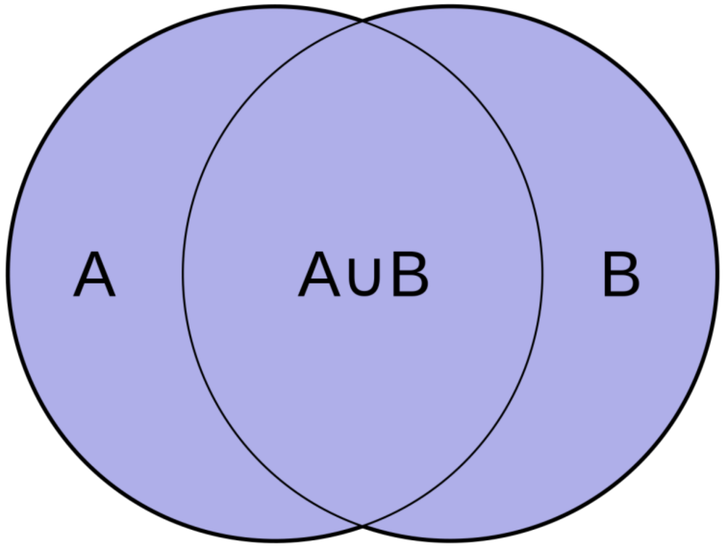
Jaccard similarity

Very basic discrete similarity metric.

Given two sets, divide size of intersection by size of union

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}.$$





https://en.wikipedia.org/wiki/Jaccard_index

Bag-of-words representations

Simplest representation of text is as a **“bag-of-words”** without respect to order

This is also called a **unigram** or **1-gram** representation.

But how to identify distinct unigrams in text?

- Naïve solution: split on whitespaces
- We’ll improve on this in a bit

Example:

"The film was a delight--I was riveted.“ →

```
['The', 'film', 'was', 'a', 'delight--I', 'was', 'riveted.']
```

Jaccard similarity for reviews 0 and 2

Review 0: "The film was a delight--I was riveted.“ →

```
['The', 'film', 'was', 'a', 'delight--I', 'was', 'riveted.’]
```

Review 2: "It was a terrible flick, the worst I have ever seen." →

```
['It', 'was', 'a', 'terrible', 'flick,', 'the', 'worst', 'I', 'have',
'ever', 'seen.’]
```

Intersection: `{'was', 'a’}`

Union:

```
{'terrible', 'flick,', 'seen.', 'riveted.', 'worst', 'I', 'The', 'a',
'delight--I', 'the', 'It', 'have', 'was', 'film', 'ever’}
```

Jaccard similarity: 0.133

Jaccard similarity for reviews 0 and 1

Review 0: "The film was a delight--I was riveted.“ →

```
['The', 'film', 'was', 'a', 'delight--I', 'was', 'riveted.’]
```

Review 1: "It's the most delightful and riveting movie.“ →

```
["It's", 'the', 'most', 'delightful', 'and', 'riveting', 'movie.’]
```

Intersection: [none]

Union:

```
{"It's", 'delightful', 'and', 'the', 'most', 'was', 'film',
'riveted.', 'movie.', 'The', 'riveting', 'a', 'delight--I’}
```

Jaccard similarity: 0

What went wrong here?

Preprocessing text

Various transformations we can perform on text in order to iron out superficial differences and home in on the types of similarity we are interested in

What preprocessing you do depends on your application

Basics include:

- **Lower-casing**
- Removing punctuation
- Removing common words, aka “stopwords”
- Removing unicode characters
  - Often needed for web text
- And a bunch of other stuff. Often some trial-and-error here

Lower-casing

Very simple and obvious thing to do, but smooths out some differences

Review 0: "The film was a delight--I was riveted.“ →

```
['the', 'film', 'was', 'a', 'delight--i', 'was', 'riveted.']
```

Review 1: "It's the most delightful and riveting movie.“ →

```
["it's", 'the', 'most', 'delightful', 'and', 'riveting', 'movie.']
```

Intersection: `{'the'}`

Union:

```
{"it's", 'delightful', 'and', 'the', 'most', 'was', 'film',
'riveted.', 'movie.', 'riveting', 'a', 'delight--i'}
```

Jaccard similarity: 0.083

Better, but we’re still not beating .133

Lower-casing

Simplest way to do it in Python is just to use `str.lower()`

Not always appropriate!

- **Semantic differences**: “I told Frank to close up the shop” vs. “I have to be frank with you.”
- **Syntactic differences:** “The ….” vs. “the …”

Rule of thumb:

- Until we get to Transformer-based models, lower-casing should be a standard part of your preprocessing pipeline.

Tokenization

Tokenization: splitting up a string sequence like into its component tokens

- **Token**: whatever pieces we are dividing text into
    - Often equates to individual words and pieces of punctuation
    - But transformer-based models use pieces of words
- Not as trivial as just splitting on whitespace

Naïve example:

Review 0: "The film was a delight--I was riveted.“ →

```
[‘the', 'film', 'was', 'a', 'delight--i', 'was', 'riveted.’]
```

More sophisticated example:

Review 0: “the film was a delight--I was riveted.“ → `['the', 'film', 'was', 'a', 'delight', '--', 'i', 'was', 'riveted', '.’]`

NLTK

Natural Language ToolKit (NLTK): https://www.nltk.org/index.html

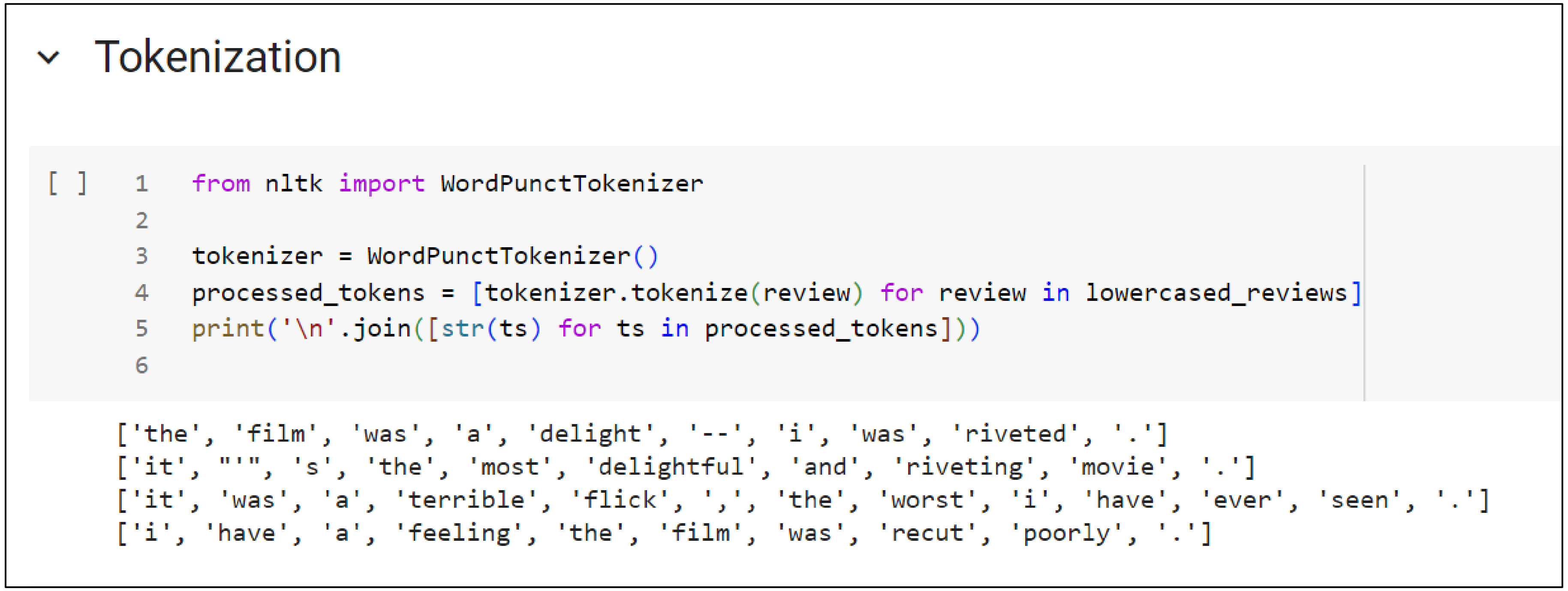
Most popular Python text processing package

Competes with SpacY, which is also good

Has lots of basic NLP functionality: tokenization, stemming, parsing, etc.

- We’ll only be doing tokenization and stemming

NLTK tokenization



Tokenization

```
[ ]
from nltk import WordPunctTokenizer

tokenizer = WordPunctTokenizer()
processed_tokens = [tokenizer.tokenize(review) for review in lowercased_reviews]
print('\n'.join([str(ts) for ts in processed_tokens]))

```

```
['the', 'film', 'was', 'a', 'delight', '--', 'i', 'was', 'riveted', '.']
['it', "'", 's', 'the', 'most', 'delightful', 'and', 'riveting', 'movie', '.']
['it', 'was', 'a', 'terrible', 'flick', ',', 'the', 'worst', 'i', 'have', 'ever', 'seen', '.']
['i', 'have', 'a', 'feeling', 'the', 'film', 'was', 'recut', 'poorly', '.']
```

https://colab.research.google.com/drive/1wkRxJvA8GPuoSXwJmlNTBcaKzxzXYTo3#scrollTo=jpRpAdf6PQYw

Full documentation: https://www.nltk.org/api/nltk.tokenize.html

Tokenization

Review 0: "The film was a delight--I was riveted.“ →

```
['the', 'film', 'was', 'a', 'delight', '--', 'i', 'was', 'riveted',
'.’]
```

Review 1: "It's the most delightful and riveting movie.“ →

```
[“it's", 'the', 'most', 'delightful', 'and', 'riveting', 'movie.’]
```

Intersection: `{‘the’, ‘.'}`

Union:

```
{‘it', "'s", 'delightful', 'and', 'most', 'was', 'film', 'riveted',
‘.', 'movie', 'riveting', 'a', 'delight’, ‘--', ‘i’}
```

Jaccard similarity: 0.133

So now we’ve matched .133… are we done?

Stemming

Stemming: chop off affixes that distinguish plural versus singular and different tenses of words

- So we can match e.g. ‘delight’ with ‘delightful’, ‘riveting’ with ‘riveted’

Example:

“the film was a delight--I was riveted.“

tokenization → `['the', 'film', 'was', 'a', 'delight', '--', 'i', 'was', 'riveted', '.’]`

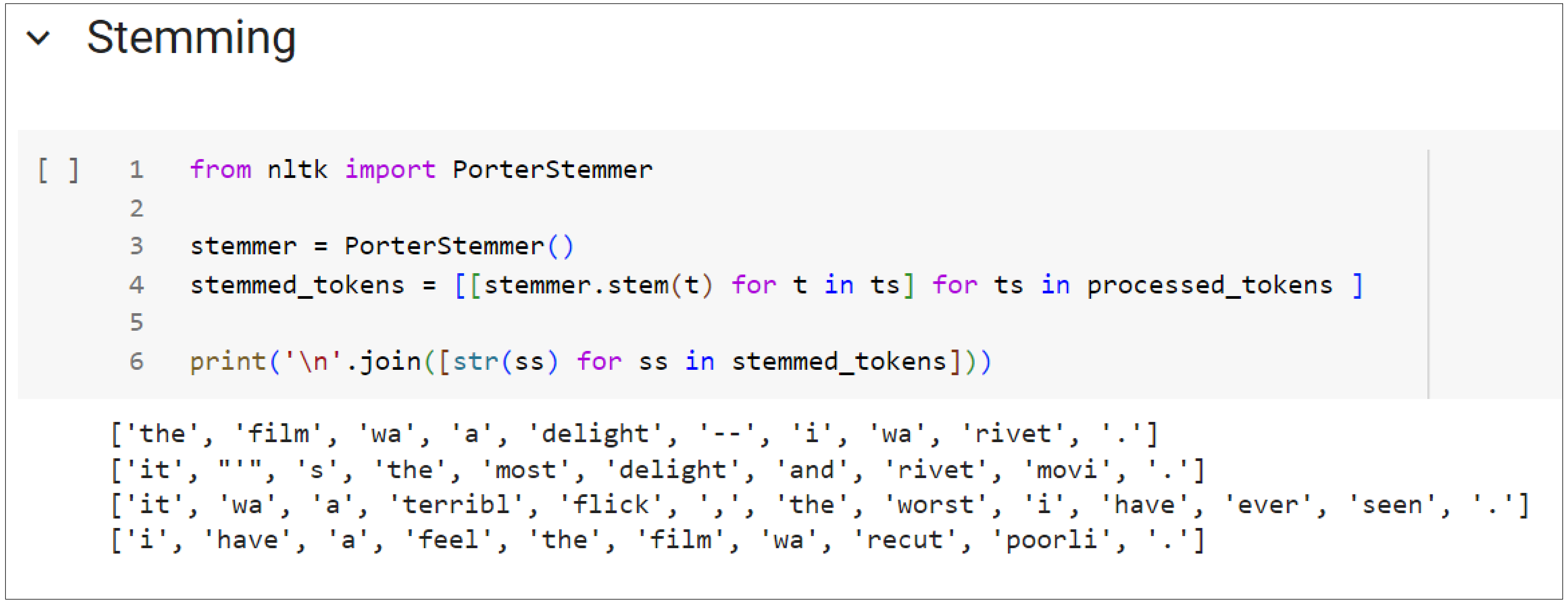
stemming → `['the', 'film', 'wa', 'a', 'delight', '--', 'i', 'wa', 'rivet', '.’]`

Contrast with **lemmatization**, which would recover the dictionary versions of the words

- But if all we’re doing is comparing, why would we care?
- So in practice, lemmatization is hardly ever done

NLTK stemming

Again, very simple



Stemming

```
[ ]
from nltk import PorterStemmer

stemmer = PorterStemmer()
stemmed_tokens = [[stemmer.stem(t) for t in ts] for ts in processed_tokens ]

print('\n'.join([str(ss) for ss in stemmed_tokens]))
```

```
['the', 'film', 'wa', 'a', 'delight', '--', 'i', 'wa', 'rivet', '.']
['it', "'", 's', 'the', 'most', 'delight', 'and', 'rivet', 'movi', '.']
['it', 'wa', 'a', 'terribl', 'flick', ',', 'the', 'worst', 'i', 'have', 'ever', 'seen', '.']
['i', 'have', 'a', 'feel', 'the', 'film', 'wa', 'recut', 'poorli', '.']
```

https://colab.research.google.com/drive/1wkRxJvA8GPuoSXwJmlNTBcaKzxzXYTo3#scrollTo=IALw4yPRffmY

How do NLTK tokenization & stemming work

Default options for NLTK are Punkt tokenizer and Porter stemmer

- But there other options

Punkt tokenizer

- Uses a trained ML model to recognize where to split up sentences
- Trained on a big corpus of English-language text
- https://www.nltk.org/api/nltk.tokenize.punkt.html

Porter stemmer

- Uses a bunch of hand-written rules that are specific to the English language
- Old algorithm (1979)
- https://tartarus.org/martin/PorterStemmer/

You can treat these as black boxes for now, though we'll learn more about modeling as we move forward.

Jaccard similarity (after preprocessing)

Review 0: "The film was a delight--I was riveted." →

```
['the', 'film', 'wa', 'a', 'delight', '--', 'i', 'wa', 'rivet', '.']
```

Review 1: "It's the most delightful and riveting movie." →

```
['it', "'", 's', 'the', 'most', 'delight', 'and', 'rivet', 'movi',
'.']
```

Intersection: `{'delight', 'rivet', '.', 'the'}`

Union:

```
{"'", 'movi', 'most', 'delight', '--', '.', 'the', 'a', 'it', 'and',
'rivet', 'film', 'i', 's', 'wa'}
```

Jaccard similarity: .267 **Yay!**

Jaccard similarity (after preprocessing)

Review 0: "The film was a delight--I was riveted.“ →

```
['the', 'film', 'wa', 'a', 'delight', '--', 'i', 'wa', 'rivet', '.’]
```

Review 2: "It was a terrible flick, the worst I have ever seen." →

```
['it', 'wa', 'a', 'terribl', 'flick', ',', 'the', 'worst', 'i',
'have', 'ever', 'seen', '.’]
```

Intersection: `{'the', 'wa', 'i', '.', 'a’}`

Union:

```
{'flick', 'delight', 'seen', 'worst', '--', '.', 'the', 'a', 'it',
'rivet', 'have', ',', 'film', 'terribl', 'i', 'ever', 'wa’}
```

Jaccard similarity: .294 **…dang.**

Problem

"The film was a delight--I was riveted."

vs.

"It's the most delightful and riveting movie."

→Jaccard similarity .267

Intersection: `{'delight', 'rivet', '.', 'the'}`

"The film was a delight--I was riveted."

vs.

"It was a terrible flick, the worst I have ever seen."

→ Jaccard similarity .294

Intersection: `{'the', 'wa', 'i', '.', 'a'}`

What's the problem?

Vectors

To go beyond very simple preprocessing, you really need to **vectorize** your text.

A **vector** is a 1-dimensional set of values, usually numeric.

Examples:

[0.1 8.2 11.7 0.5]

[1 2 3 4 5]

[True False True True False]

[1 0 0 1 1 0]

Different from a list because you are generally operating on the whole vector at once rather than iterating through it.

Vector operations

In many ways can be treated a single number

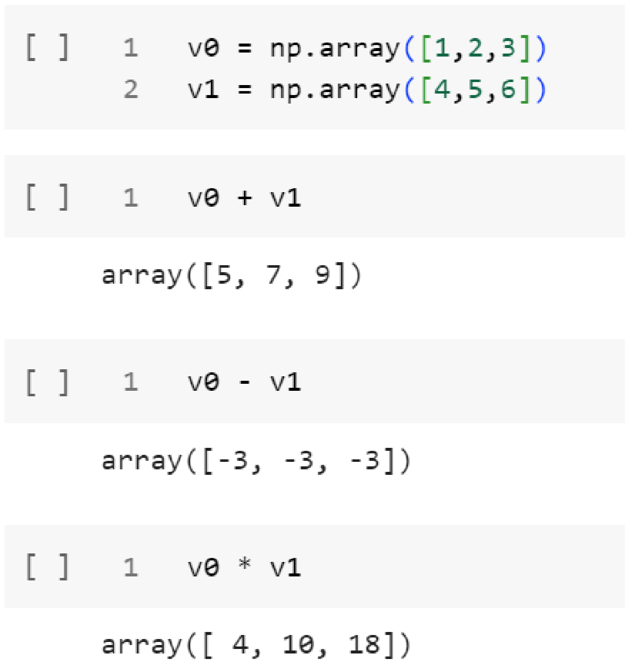
Addition: [1 2 3] + [4 5 6] = [5 7 9]
Subtraction: [1 2 3] - [4 5 6] = [-3 -3 -3]
Division: [1 2 3] / [4 5 6] = [0.25 0.4 0.5]
Multiplication: [1 2 3] * [4 5 6] = [4 10 18]
Power:[1 2 3] ^ 2 = [1 4 9]

But there are certain operations that are only defined for vectors:
Dot product: [1 2 3] · [4 5 6] = sum([1 2 3] * [4 5 6]) = 32

There is a **lot** of stuff that can be done with vectors (see: all of linear algebra)
We will focus on just what we need to know to do the things we want to do

Vectors in Python

- Not implemented in standard Python
- Implemented in popular and ubiquitous **numpy** library
- numpy typically imported as np



```
v0 = np.array([1,2,3])
v1 = np.array([4,5,6])
```

```
v0 + v1
```

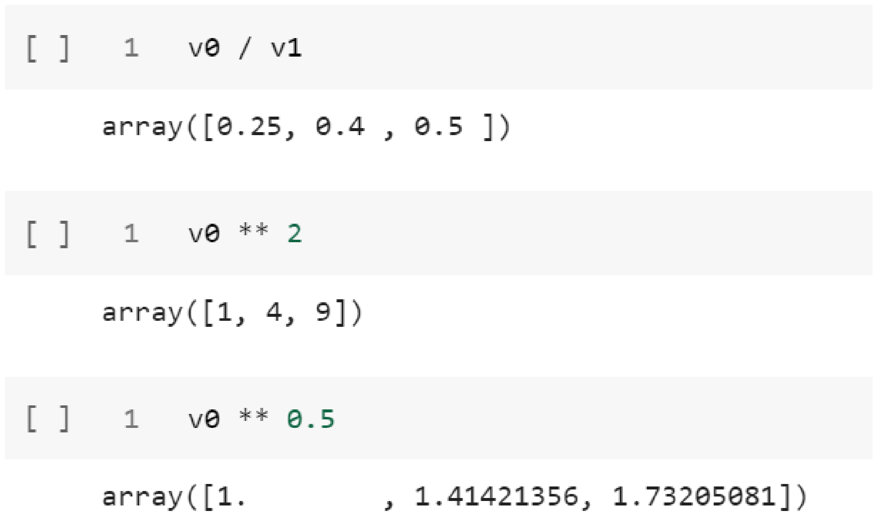
```
array([5, 7, 9])
```

```
v0 - v1
```

```
array([-3, -3, -3])
```

```
v0 * v1
```

```
array([ 4, 10, 18])
```



```
v0 / v1
```

```
array([0.25, 0.4 , 0.5 ])
```

```
v0 ** 2
```

```
array([1, 4, 9])
```

```
v0 ** 0.5
```

```
array([1.        , 1.41421356, 1.73205081])
```

https://colab.research.google.com/drive/1wkRxJvA8GPuoSXwJmlNTBcaKzxzXYTo3#scrollTo=sVTukDn_YyXD

Representing bag-of-words as a vector

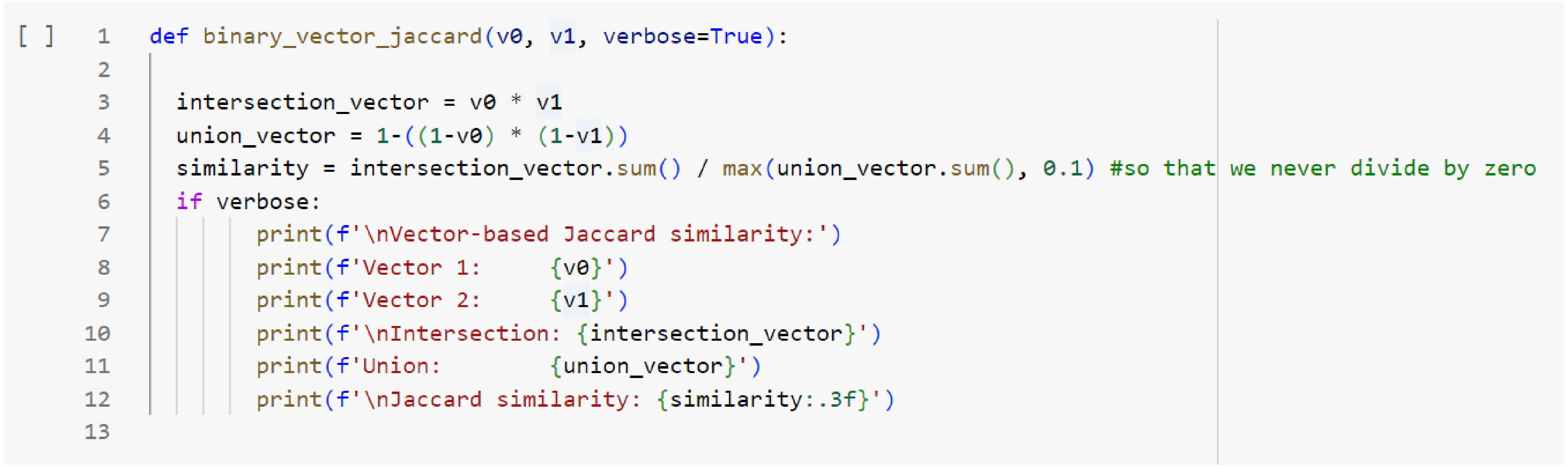
Basic idea: each text is a vector the size of the vocabulary, with the number in each slot representing the count of that word in that text

"The film was a delight--I was riveted.” →

the	1.0
film	1.0
wa	2.0
a	1.0
delight	1.0
--	1.0
i	1.0
rivet	1.0
.	1.0
it	0.0
'	0.0
s	0.0
most	0.0
and	0.0
movi	0.0
terribl	0.0
flick	0.0
,	0.0
worst	0.0
have	0.0
ever	0.0
seen	0.0
feel	0.0
recut	0.0
poorli	0.0

Jaccard similarity for (binary) vectors

We can (hackily) still do Jaccard similarity if we binarize our vectors to be only 0 and 1



```
[ ]  def binary_vector_jaccard(v0, v1, verbose=True):

       intersection_vector = v0 * v1
       union_vector = 1-((1-v0) * (1-v1))
       similarity = intersection_vector.sum() / max(union_vector.sum(), 0.1) #so that we never divide by zero
       if verbose:
             print(f'\nVector-based Jaccard similarity:')
             print(f'Vector 1:     {v0}')
             print(f'Vector 2:     {v1}')
             print(f'\nIntersection: {intersection_vector}')
             print(f'Union:        {union_vector}')
             print(f'\nJaccard similarity: {similarity:.3f}')

```

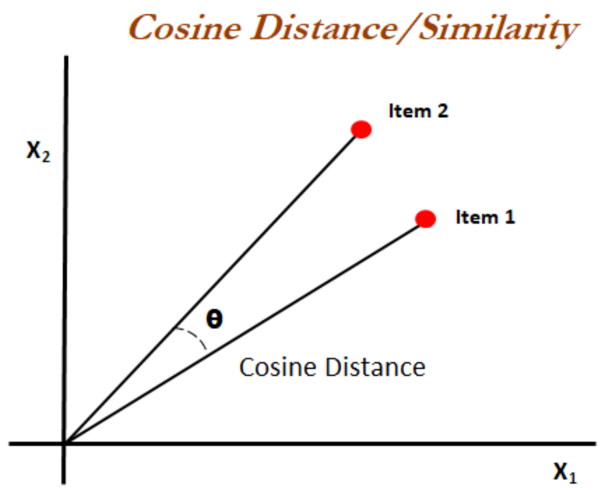
But it’s probably good to learn a similarity metric that can handle continuous values

Cosine similarity

Given two vectors, defined as the **dot product** of the vectors divided by the product of the magnitudes of the two vectors

$$\text{cosine similarity} = S_C(A,B) := \cos(\theta) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum\limits_{i=1}^{n} A_i B_i}{\sqrt{\sum\limits_{i=1}^{n} A_i^2}\sqrt{\sum\limits_{i=1}^{n} B_i^2}},$$

https://en.wikipedia.org/wiki/Cosine_similarity



https://www.oreilly.com/library/view/statistics-for-machine/9781788295758/eb9cd609-e44a-40a2-9c3a-f16fc4f5289a.xhtml

Jaccard vs cosine similarity

```
Text 1: The film was a delight--I was riveted.
Text 2: It's the most delightful and riveting movie.

Count vector 1: [1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
Count vector 2: [1. 0. 0. 0. 1. 0. 0. 1. 1. 1. 1. 1. 1. 1. 1.
0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]

Jaccard similarity: 0.267
Cosine similarity: 0.365
```

Jaccard vs cosine similarity

```
Text 1: The film was a delight--I was riveted.
Text 2: It was a terrible flick, the worst I have ever seen.

Count vector 1: [1. 1. 2. 1. 1. 1. 1. 1. 1. 0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
Count vector 2: [1. 0. 1. 1. 0. 0. 1. 0. 1. 1. 0. 0. 0. 0. 0.
1. 1. 1. 1. 1. 1. 1. 0. 0. 0.]

Jaccard similarity: 0.294
Cosine similarity: 0.480
```

Are we done? (still no)

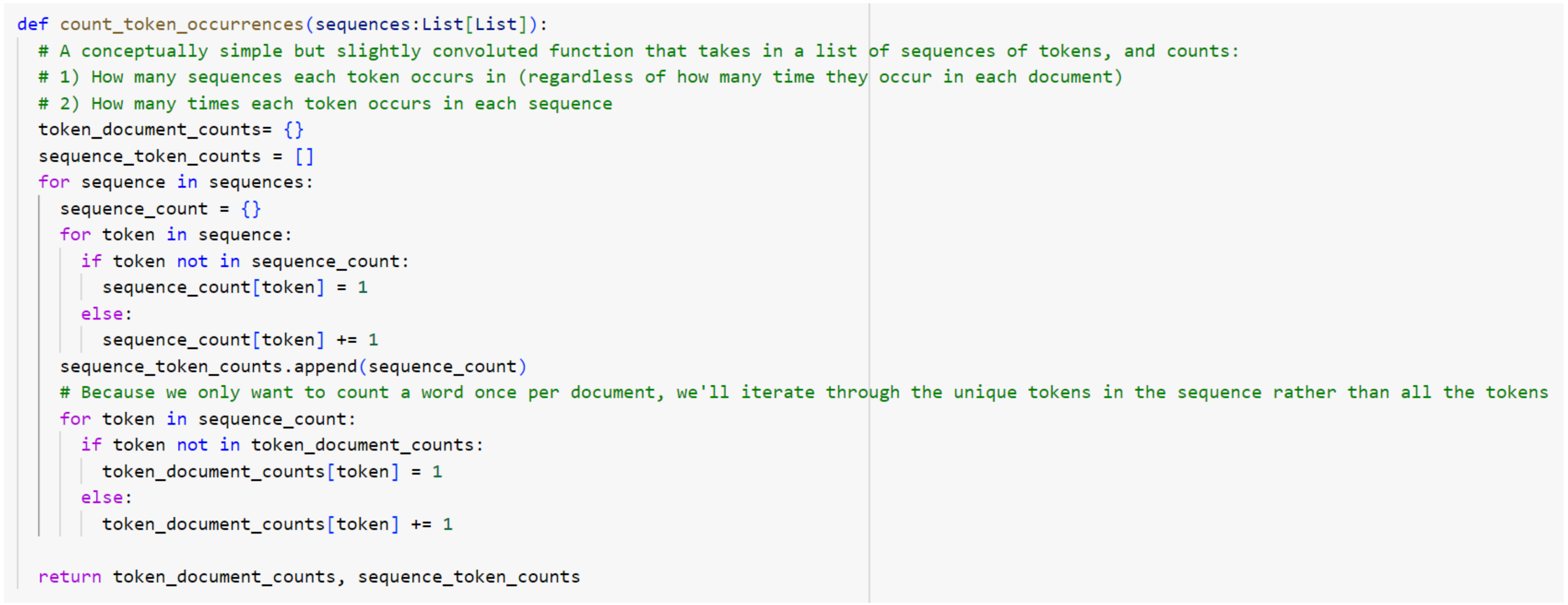
TF-IDF

TF-IDF: Term Frequency – Inverse Document Frequency

Basic idea: When we make a vector representation of a bag of words, **upweight** rare words and **downweight** common words

The value at slot *i* for a given sequence *s* should be the **term frequency** of word *i* within *s*, divided by the **document frequency** of word *i* in the corpus as a whole

Manual TF-IDF: counting tokens



```python
def count_token_occurrences(sequences:List[List]):
  # A conceptually simple but slightly convoluted function that takes in a list of sequences of tokens, and counts:
  # 1) How many sequences each token occurs in (regardless of how many time they occur in each document)
  # 2) How many times each token occurs in each sequence
  token_document_counts= {}
  sequence_token_counts = []
  for sequence in sequences:
    sequence_count = {}
    for token in sequence:
      if token not in sequence_count:
        sequence_count[token] = 1
      else:
        sequence_count[token] += 1
    sequence_token_counts.append(sequence_count)
    # Because we only want to count a word once per document, we'll iterate through the unique tokens in the sequence rather than all the tokens
    for token in sequence_count:
      if token not in token_document_counts:
        token_document_counts[token] = 1
      else:
        token_document_counts[token] += 1

  return token_document_counts, sequence_token_counts
```

https://colab.research.google.com/drive/1wkRxJvA8GPuoSXwJmlNTBcaKzxzXYTo3#scrollTo=qOs8zZqmQxC8

Manual TF-IDF: counting tokens

Term counts

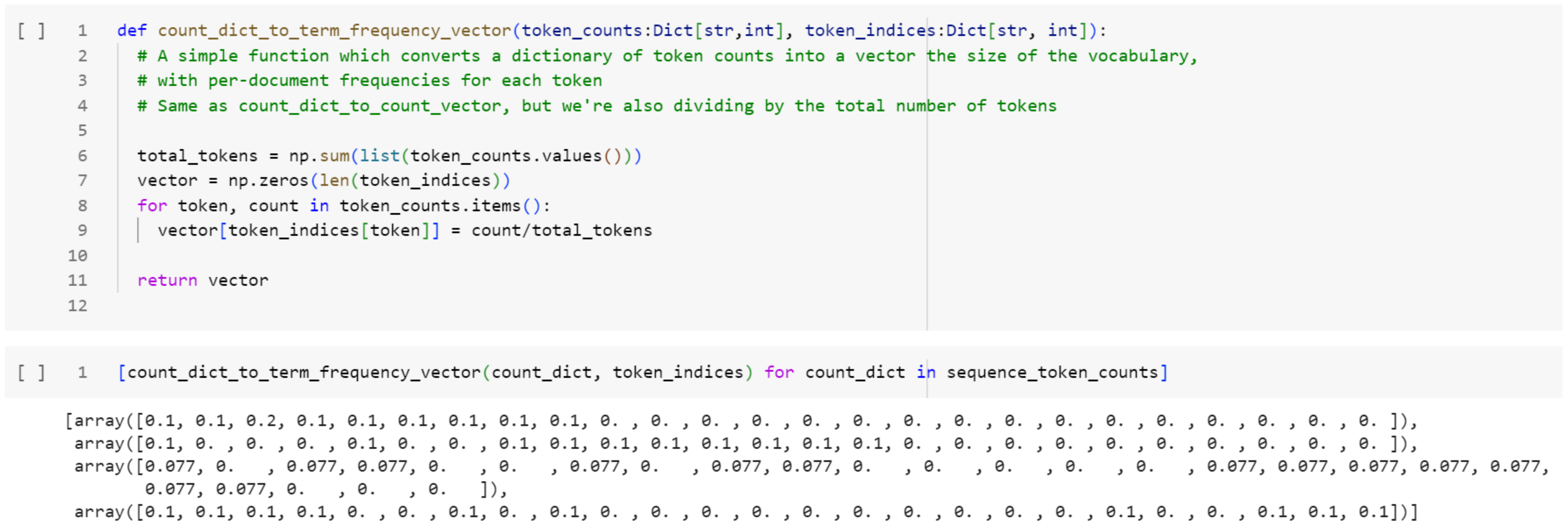
```
Review 0:
 {'--': 1,
 '.': 1,
 'a': 1,
 'delight': 1,
 'film': 1,
 'i': 1,
 'rivet': 1,
 'the': 1,
 'wa': 2}

Review 1:
 {"'": 1,
 '.': 1,
 'and': 1,
 'delight': 1,
 'it': 1,
 'most': 1,
 'movi': 1,
 'rivet': 1,
 's': 1,
 'the': 1}
```

```
Review 2:
 {',': 1,
 '.': 1,
 'a': 1,
 'ever': 1,
 'flick': 1,
 'have': 1,
 'i': 1,
 'it': 1,
 'seen': 1,
 'terribl': 1,
 'the': 1,
 'wa': 1,
 'worst': 1}

Review 3:
 {'.': 1,
 'a': 1,
 'feel': 1,
 'film': 1,
 'have': 1,
 'i': 1,
 'poorli': 1,
 'recut': 1,
 'the': 1,
 'wa': 1}
```

Document counts

```
{'the': 4,
 'film': 2,
 'wa': 3,
 'a': 3,
 'delight': 2,
 '--': 1,
 'i': 3,
 'rivet': 2,
 '.': 4,
 'it': 2,
 "'": 1,
 's': 1,
 'most': 1,
 'and': 1,
 'movi': 1,
 'terribl': 1,
 'flick': 1,
 ',': 1,
 'worst': 1,
 'have': 2,
 'ever': 1,
 'seen': 1,
 'feel': 1,
 'recut': 1,
 'poorli': 1}
```

Manual TF-IDF: converting to frequencies



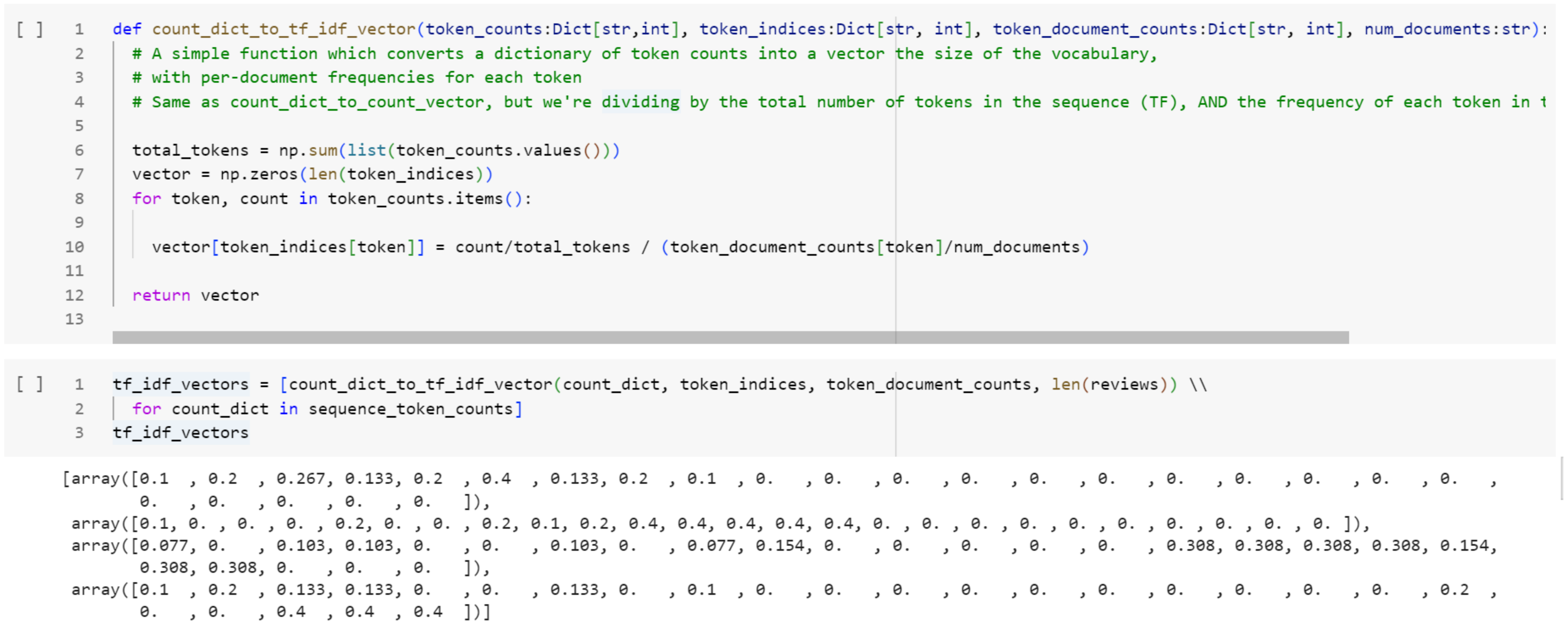
```
[ ]  def count_dict_to_term_frequency_vector(token_counts:Dict[str,int], token_indices:Dict[str, int]):
       # A simple function which converts a dictionary of token counts into a vector the size of the vocabulary,
       # with per-document frequencies for each token
       # Same as count_dict_to_count_vector, but we're also dividing by the total number of tokens

       total_tokens = np.sum(list(token_counts.values()))
       vector = np.zeros(len(token_indices))
       for token, count in token_counts.items():
         vector[token_indices[token]] = count/total_tokens

       return vector

```

```
[ ]  [count_dict_to_term_frequency_vector(count_dict, token_indices) for count_dict in sequence_token_counts]
```

```
[array([0.1, 0.1, 0.2, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ]),
 array([0.1, 0. , 0. , 0. , 0.1, 0. , 0. , 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ]),
 array([0.077, 0.   , 0.077, 0.077, 0.   , 0.   , 0.077, 0.   , 0.077, 0.077, 0.   , 0.   , 0.   , 0.   , 0.   , 0.077, 0.077, 0.077, 0.077, 0.077,
        0.077, 0.077, 0.   , 0.   , 0.   ]),
 array([0.1, 0.1, 0.1, 0.1, 0. , 0. , 0.1, 0. , 0.1, 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0.1, 0. , 0. , 0.1, 0.1, 0.1])]
```

https://colab.research.google.com/drive/1wkRxJvA8GPuoSXwJmlNTBcaKzxzXYTo3#scrollTo=o7bdFZ2-VEsy&line=3&uniqifier=1

Manual TF-IDF: converting to frequencies



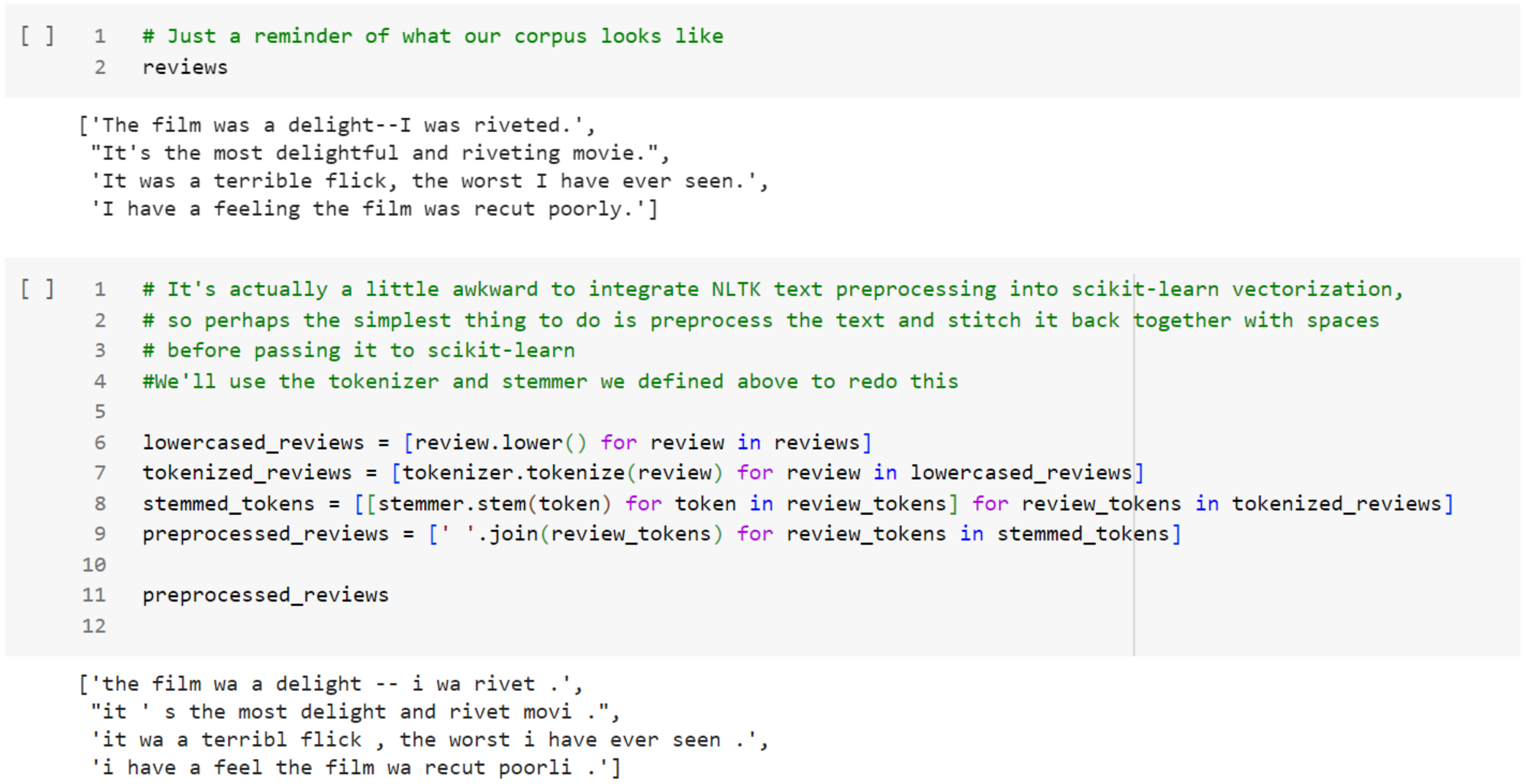
```
[ ]
def count_dict_to_tf_idf_vector(token_counts:Dict[str,int], token_indices:Dict[str, int], token_document_counts:Dict[str, int], num_documents:str):
  # A simple function which converts a dictionary of token counts into a vector the size of the vocabulary,
  # with per-document frequencies for each token
  # Same as count_dict_to_count_vector, but we're dividing by the total number of tokens in the sequence (TF), AND the frequency of each token in t

  total_tokens = np.sum(list(token_counts.values()))
  vector = np.zeros(len(token_indices))
  for token, count in token_counts.items():

    vector[token_indices[token]] = count/total_tokens / (token_document_counts[token]/num_documents)

  return vector

```

```
[ ]
tf_idf_vectors = [count_dict_to_tf_idf_vector(count_dict, token_indices, token_document_counts, len(reviews)) \\
  for count_dict in sequence_token_counts]
tf_idf_vectors
```

```
[array([0.1  , 0.2  , 0.267, 0.133, 0.2  , 0.4  , 0.133, 0.2  , 0.1  , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   ,
        0.   , 0.   , 0.   , 0.   , 0.   ]),
 array([0.1, 0. , 0. , 0. , 0.2, 0. , 0. , 0.2, 0.1, 0.2, 0.4, 0.4, 0.4, 0.4, 0.4, 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ]),
 array([0.077, 0.   , 0.103, 0.103, 0.   , 0.   , 0.103, 0.   , 0.077, 0.154, 0.   , 0.   , 0.   , 0.   , 0.   , 0.308, 0.308, 0.308, 0.308, 0.154,
        0.308, 0.308, 0.   , 0.   , 0.   ]),
 array([0.1  , 0.2  , 0.133, 0.133, 0.   , 0.   , 0.133, 0.   , 0.1  , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.   , 0.2  ,
        0.   , 0.   , 0.4  , 0.4  , 0.4  ])]
```

Easy TF-IDF: Scikit-Learn

Repeat all the preprocessing



```
[ ]
# Just a reminder of what our corpus looks like
reviews
```

```
['The film was a delight--I was riveted.',
 "It's the most delightful and riveting movie.",
 'It was a terrible flick, the worst I have ever seen.',
 'I have a feeling the film was recut poorly.']
```

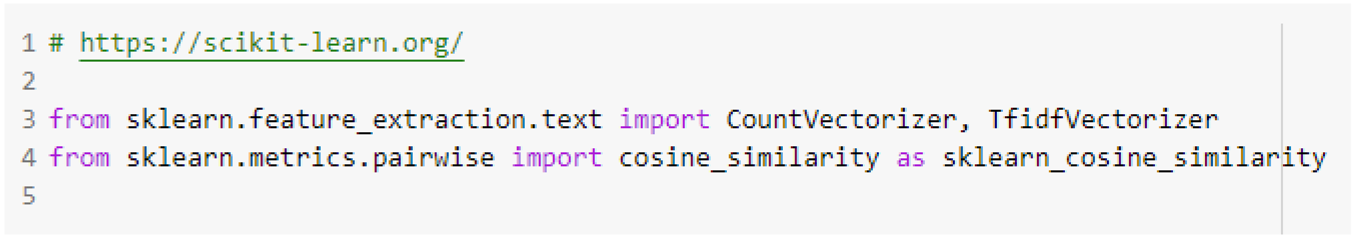
```
[ ]
# It's actually a little awkward to integrate NLTK text preprocessing into scikit-learn vectorization,
# so perhaps the simplest thing to do is preprocess the text and stitch it back together with spaces
# before passing it to scikit-learn
#We'll use the tokenizer and stemmer we defined above to redo this

lowercased_reviews = [review.lower() for review in reviews]
tokenized_reviews = [tokenizer.tokenize(review) for review in lowercased_reviews]
stemmed_tokens = [[stemmer.stem(token) for token in review_tokens] for review_tokens in tokenized_reviews]
preprocessed_reviews = [' '.join(review_tokens) for review_tokens in stemmed_tokens]

preprocessed_reviews

```

```
['the film wa a delight -- i wa rivet .',
 "it ' s the most delight and rivet movi .",
 'it wa a terribl flick , the worst i have ever seen .',
 'i have a feel the film wa recut poorli .']
```

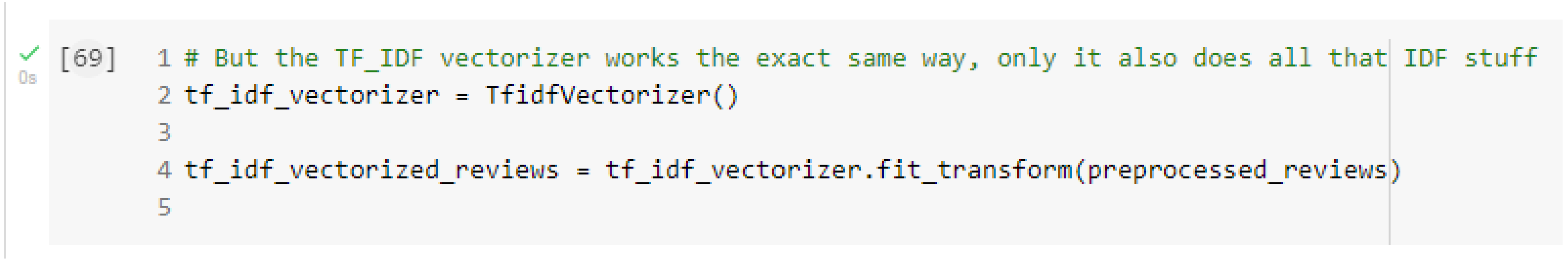
https://colab.research.google.com/drive/1wkRxJvA8GPuoSXwJmlNTBcaKzxzXYTo3#scrollTo=epXg1HS9Staq

Easy TF-IDF: Scikit-Learn

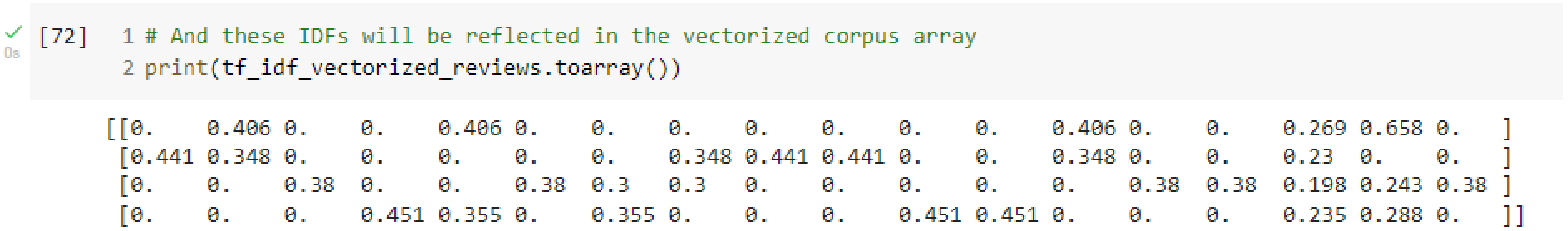
Then create and use a TfidfVectorizor (or a CountVectorizer if you just want counts)



```python
# https://scikit-learn.org/

from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity as sklearn_cosine_similarity

```



```python
[69]
# But the TF_IDF vectorizer works the exact same way, only it also does all that IDF stuff
tf_idf_vectorizer = TfidfVectorizer()

tf_idf_vectorized_reviews = tf_idf_vectorizer.fit_transform(preprocessed_reviews)

```



```python
[72]
# And these IDFs will be reflected in the vectorized corpus array
print(tf_idf_vectorized_reviews.toarray())
```

```
[[0.    0.406 0.    0.    0.406 0.    0.    0.    0.    0.    0.    0.    0.406 0.    0.    0.269 0.658 0.   ]
 [0.441 0.348 0.    0.    0.    0.    0.    0.348 0.441 0.441 0.    0.    0.348 0.    0.    0.23  0.    0.   ]
 [0.    0.    0.38  0.    0.    0.38  0.3   0.3   0.    0.    0.    0.    0.    0.38  0.38  0.198 0.243 0.38 ]
 [0.    0.    0.    0.451 0.355 0.    0.355 0.    0.    0.    0.451 0.451 0.    0.    0.    0.235 0.288 0.   ]]
```

Cosine similarity revisited

```
Text 1: The film was a delight--I was riveted.

Text 2: It's the most delightful and riveting movie.

Vector 1: [0.1 0.2 0.267 0.133 0.2 0.4 0.133 0.2 0.1 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. ]

Vector 2: [0.1 0. 0. 0. 0.2 0. 0. 0.2 0.1 0.2 0.4 0.4 0.4 0.4 0.4 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. ]

Cosine similarity: 0.162


Text 1: The film was a delight--I was riveted.

Text 3: It was a terrible flick, the worst I have ever seen.

Vector 1: [0.1 0.2 0.267 0.133 0.2 0.4 0.133 0.2 0.1 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. ]

Vector 2: [0.077 0. 0.103 0.103 0. 0. 0.103 0. 0.077 0.154 0. 0. 0. 0. 0. 0.308 0.308 0.308 0.308 0.154
0.308 0.308 0. 0. 0. ]

Cosine similarity: 0.135
```

So now we've finally (finally!) come up with a similarity metric that captures our intuitions

Other similarity/distance metrics

Euclidean: Euclidean (l2) distance between the two vectors in vector space

- https://en.wikipedia.org/wiki/Euclidean_distance
- https://docs.scipy.org/doc/scipy/reference/generated/scipy.spatial.distance.euclidean.html (scipy implementation)

Manhattan distance: L1 distance between the two vectors in vector space

- https://en.wikipedia.org/wiki/Taxicab_geometry
- https://docs.scipy.org/doc/scipy/reference/generated/scipy.spatial.distance.cityblock.html#scipy.spatial.distance.cityblock

Others: https://docs.scipy.org/doc/scipy/reference/spatial.distance.html#module-scipy.spatial.distance

- But really, 95% of people use Jaccard, Euclidean or cosine distance

Concluding thoughts

Review 0: "The film was a delight--I was riveted."
Review 1: "It's the most delightful and riveting movie."
Review 2: "It was a terrible flick, the worst I have ever seen.“

With preprocessing and frequency normalization, we conquered several of the problems we identified at the beginning.

But what about synonymy (e.g. “film” versus “flick”)?

And what about word order?

And what if we’re more interested in sentence structure than lexical similarity?