COMP47670

Text Mining

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Overview

- Unstructured Text
- Tokenising Text
- Bag-of-Words Representations
- N-Grams
- Term Weighting
- Measuring Similarity
- Challenges in Text Mining
- Pre-Processing Text with Python
- Text Classification

Unstructured Text

Most textual data arrives in an unstructured form without any pre-defined organisation or format, beyond natural language. The vocabulary, formatting, and quality of the text can vary significantly.

United Airlines shares plummet after passenger dragged from plane

Shares plummeted Tuesday, wiping close to $1bn off the holding company's value, after a man was violently removed from a flight by aviation police

Shares in United Airlines' parent company plummeted on Tuesday, wiping close to $1bn off of the company's value, a day after a viral video showing police forcibly dragging a passenger off one of its plane became a global news sensation.

The value of the carrier's holding company, United Continental Holdings, had fallen over 4% before noon, close to $1bn less than the $22.5bn as of Monday's close, according to FactSet data.

AUSTEN'S NOVELS EMMA

LONDON: PBINTED BY SrOTTISWOODE AND CO., NEW-STItEEI SQUASH AND PAflLIAJONT STRELT

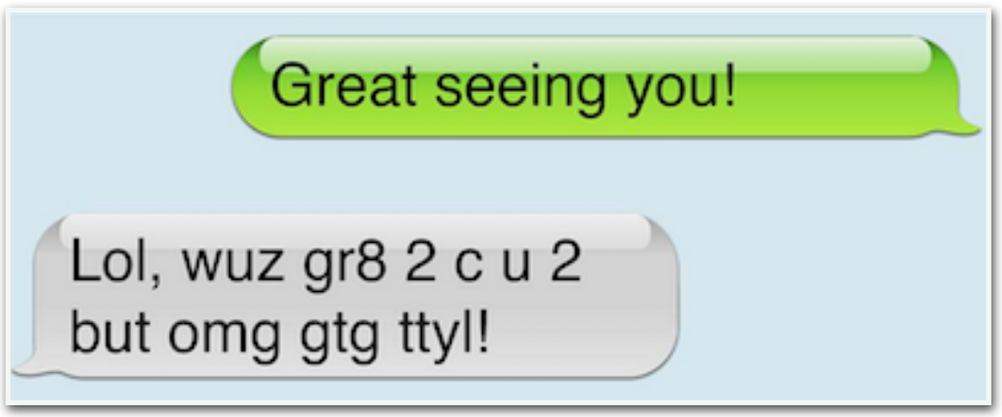
CHAPTER I.

MMA AVOODHOUSE, handsome, clever, and rich, with a comfortable home and happy dis position, seemed to unite some of the best blessings of existence; and had lived nearly twenty-one years in the world with very little to distress or vex her. She was the youngest of the two daughters of a most affec tionate, indulgent father; and had, in consequence of her sister's marriage, been mistress of his house from a very early period. Her mother had died too long ago for her to have more than an indistinct remembrance of her caresses, and her place had been supplied by an excellent woman as gover ness, who had fallen little short of a mother in affection. Sixteen years had Miss Taylor been in Mr. AVoodhouse's family, less as a governess than a friend, very fond of both daughters.

Ai woz lyin on teh stairz n @vorvolak steppd on meh! She sez she noes seez meh buh ai woz dere! 😱😣

Translated from Indonesian by bing Wrong translation?

Could not translate Tweet



Common Tasks in Text Mining

- *Document classification*: e.g. Is a new email spam or non-spam?
- *Topic modelling*: e.g. What are the main subjects being discussed around EU Brexit negotiations?
- *Sentiment analysis*: e.g. Are Twitter users talking positively or negatively about the new iPhone?
- *Review mining*: e.g. Can we extract the most positive and negative features in reviews for a given hotel on TripAdvisor?
- *Authorship attribution*: e.g. Did Shakespeare write all his own dramas?
- *Genre classification*: e.g. Can we automatically assign a new novel to an Amazon genre category?
- *Moderation*: e.g. Can we identify potentially abusive or offensive posts on forums or on social media platforms?
- *Plagiarism detection*: e.g. Are two submitted reports unusually similar?

Tokenising Text

- Raw text documents are textual, not numeric. The first step in analysing unstructured documents is to split the raw text into individual tokens, each corresponding to a single term (word).
- In the simplest case we might split a text string by whitespace:

```
text = "IMF cuts global growth outlook"
text.split(" ")
```

```
['IMF', 'cuts', 'global', 'growth', 'outlook']
```

- In most cases we need to deal with other types of punctuation:

Bad-news ahead? The IMF cuts outlook, says:'growth in doubt…'

- For some types of text, certain characters can have significance:

Discover your #Career pathway with @gradireland! See bit.ly/23aPLZt for pathway graphics & videos #reallife

Tokenising Text

- Scikit-learn provides intelligent tokenisation functions for dealing with English text - i.e. converting a string to a list of tokens.

```
from sklearn.feature_extraction.text import CountVectorizer
tokenize = CountVectorizer().build_tokenizer()
```

```
text = "IMF cuts global growth outlook"
tokenize(text)
```

```
['IMF', 'cuts', 'global', 'growth', 'outlook']
```

```
text = "Bad-news ahead? The IMF cuts outlook, says:Growth in doubt"
tokenize(text)
```

```
['Bad', 'news', 'ahead', 'The', 'IMF', 'cuts', 'outlook', 'says', 'Growth', 'in', 'doubt']
```

- Punctuation and single letter tokens are removed. A standard tokeniser is not always suitable…

```
tweet = "Discover your #Career pathway with @gradireland! See http://bit.ly/23aPLZt"
tokenize(tweet)
```

```
['Discover', 'your', 'Career', 'pathway', 'with', 'gradireland', 'See', 'http', 'bit',
'ly', '23aPLZt']
```

Counting Term Frequencies

- Once we have performed tokenisation, we might then count the frequency of occurrence of terms (tokens) in each document.

Growth forecasts cut as IMF warns of risk. The IMF cut its global growth forecast for 2016. It warned of widespread global stagnation risk and stated the global economy could be vulnerable in 2016.

Term	Frequency
global	3
risk	2
cut	2
IMF	2
2016	2
...	...

- We can repeat this process to compute frequencies across an entire corpus and the sum the frequencies.

Growth forecasts cut as IMF warns of risk. The IMF
c
v
g

IMF chief economist Maurice Obstfeld said in a
sta
efi
the

The Fund called on global policymakers attending the IMF and World Bank meetings, being held in Washington, to take coordinated actions to boost demand with structural economic reforms in 2016.

Term	Frequency
global	5
imf	4
growth	3
2016	3
economy	3
...	...

Bag-of-Words Model for Documents

- How can we go from tokens to numeric features?
- Bag-of-words model: Each document is represented by a vector in a m-dimensional coordinate space, where m is total number of unique terms across all documents (the corpus vocabulary).

Document 1:
Forecasts cut as IMF issues warning

Document 2:
IMF and WBG meet to discuss economy

Document 3:
WBG issues 2016 growth warning

Example:

When we tokenise our corpus of 3 documents, we have a vocabulary of 14 distinct terms (when no filtering is applied).

2016
and
as
cut
discuss
economy
Forecasts
growth
IMF
issues
meet
to
warning
WBG

Bag-of-Words Representation

- Each document can be represented as a term vector, with an entry indicating the number of time a term appears in the document:

Document 1:
Forecasts cut as IMF issues warning

2016	Forecasts	IMF	WBG	and	as	cut	discuss	economy	growth	issues	meet	to	warning
0	1	1	0	0	1	1	0	0	0	1	0	0	1

- By transforming all documents in this way, and stacking them in rows, we create a full document-term matrix:

Document 2:
IMF and WBG meet to discuss economy

Document 3:
2016: WBG issues 2016 growth warning

2016	Forecasts	IMF	WBG	and	as	cut	discuss	economy	growth	issues	meet	to	warning
0	1	1	0	0	1	1	0	0	0	1	0	0	1
0	0	1	1	1	0	0	1	1	0	0	1	1	0
2	0	0	1	0	0	0	0	0	1	1	0	0	1

3 Documents x 14 Terms

Bag-of-Words Representation

- The position (context) of terms within the original document text is lost when using this model.

Document 1:
Forecasts cut as IMF issues warning

2016	Forecasts	IMF	WBG	and	as	cut	discuss	economy	growth	issues	meet	to	warning
0	1	1	0	0	1	1	0	0	0	1	0	0	1

- The size of the vocabulary is often large, meaning that the resulting vectors can be very high dimensional.
- Fortunately, most values in the document-term matrix will be zeros, since for a given document less than a couple thousands of distinct terms will be used.
- We say bag-of-word models are typically high-dimensional sparse datasets. Document-term matrix often has > 98% zero values.

Bag-of-Words in Python

- Scikit-learn includes functionality to easily transform a collection of strings containing documents into a document-term matrix.

Our input, documents, is a list of strings. Each string is a separate document.

```
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(documents)
```

Our output, X, is a sparse NumPy 2D array with rows corresponding to documents and columns corresponding to terms.

- Once the matrix has been created, we can access the list of all terms and an associated dictionary (`vocabulary_`) which maps each unique term to a corresponding column in the matrix.

```
terms = vectorizer.get_feature_names()
len(terms)
```

```
3288
```

How many terms in the vocabulary?

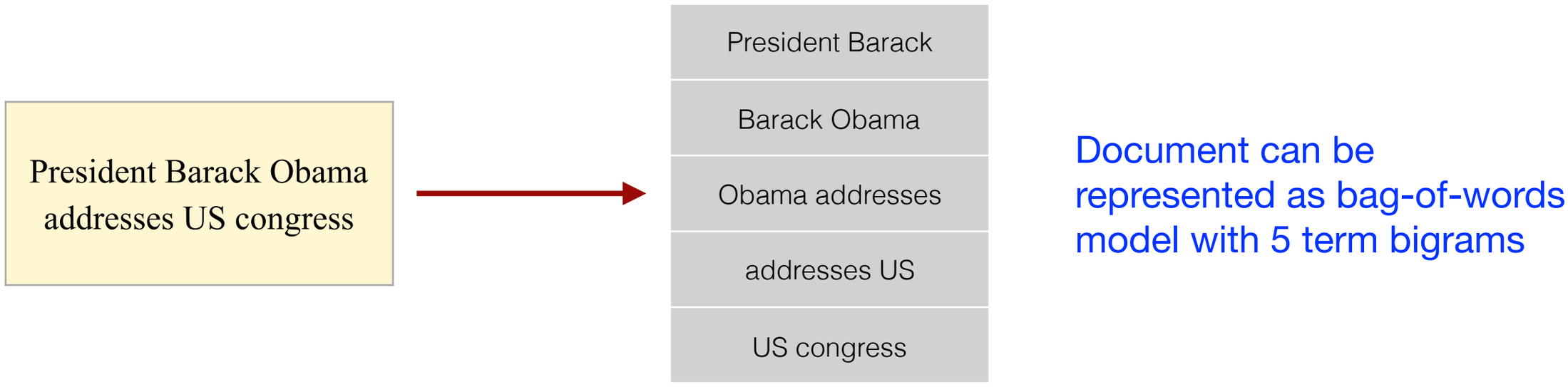
```
vocab = vectorizer.vocabulary_
vocab["world"]
```

```
3246
```

Which column corresponds to term?

N-Grams

- A bag-of-words model does not preserve sequence information, so the order of words in a sentence is lost.
- Solution: Build terms using sequences of adjacent tokens. Then construct a document-term matrix in the same way.
- Term Bigrams: Build terms from every pair of adjacent tokens.



- Term *N*-grams: Build terms from *N* adjacent tokens.
- Disadvantage: This approach significantly increases the size of the vocabulary for a given corpus.

N-Grams in Python

- We can use the same Scikit-learn functionality to create a document-term matrix with N-grams.
- We specify an extra parameter `ngram_range` which specifies the shortest and longest token sequences to include. Length 1 is just a single token.

Transform our input documents, extracting single tokens and bigrams:

```
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer(ngram_range = (1,2))
X = vectorizer.fit_transform(documents)
```

Display some sample terms - we see single tokens and bigrams (phrases of length 2):

```
terms = vectorizer.get_feature_names()
print(terms[510:520])
```

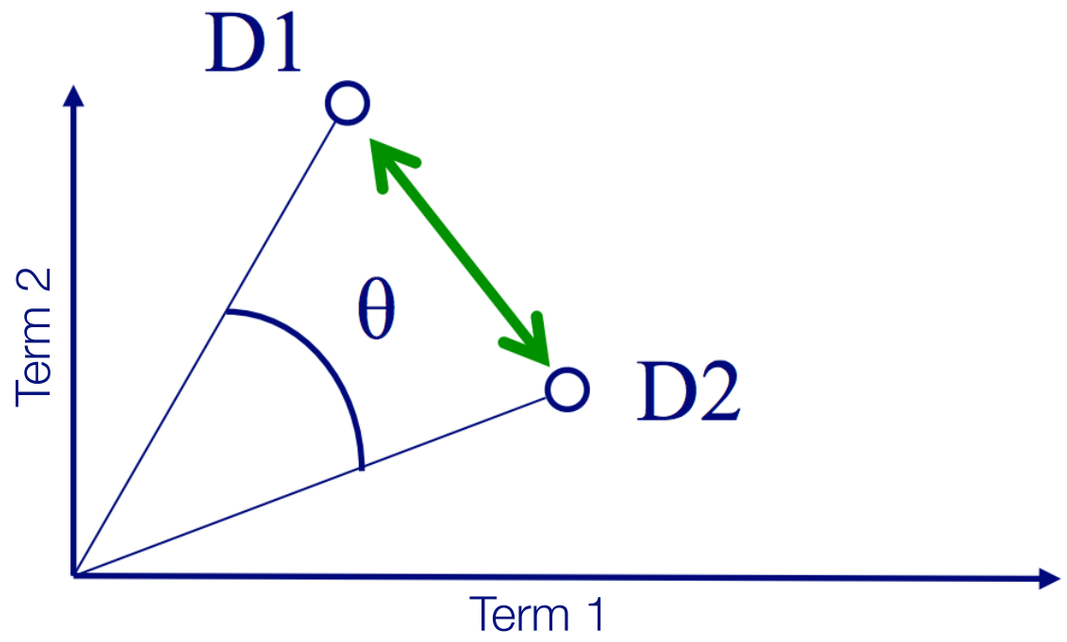
```
['admitted victory', 'adriatic', 'adriatic coast', 'advanced',
'advanced position', 'advantage', 'advantage and', 'advantage
of', 'adverts', 'adverts for']
```

Measuring Similarity

- Cosine similarity: Most common approach for measuring similarity between two documents in a bag-of-words representation is to look at the cosine of the angle between their term vectors.
- Motivation: vectors for documents containing similar terms will point in the same direction in the *m*-dimensional vector space.

$$cos(D1, D2) = \frac{D1 \cdot D2}{||D1||\ ||D2||}$$

$$\text{where } ||D|| = \sqrt{\sum_{i=1}^{m} d_i^2}$$



- Cosine similarity score is 1 if two documents are identical, 0 if two documents share no terms in common.

Measuring Similarity

Document 1:
Forecasts cut as IMF issues warning

Document 2:
IMF and WBG meet to discuss economy

Document 3:
IMF and WBG meet to discuss growth

and	as	cut	discuss	economy	Forecasts	growth	IMF	issues	meet	to	warning	WBG
0	1	1	0	0	1	0	1	1	0	0	1	0
1	0	0	1	1	0	0	1	0	1	1	0	1
1	0	0	1	0	0	1	1	0	1	1	0	1

$cos(D1, D2) = 0.15 \quad cos(D1, D3) = 0.15$

$cos(D2, D3) = 0.86$

We can perform the same calculations in Python...

```
from sklearn.metrics.pairwise import cosine_similarity
print( "cos(D1,D2) = %.2f" % cosine_similarity( X[0], X[1] ) )
print( "cos(D1,D3) = %.2f" % cosine_similarity( X[0], X[2] ) )
print( "cos(D2,D3) = %.2f" % cosine_similarity( X[1], X[2] ) )
```

```
cos(D1,D2) = 0.15
cos(D1,D3) = 0.15
cos(D2,D3) = 0.86
```

Measure similarity between rows of the document-term matrix X

Challenges in Text Mining

- The Sparsity Problem: Natural language use often involves huge vocabularies, so most documents will share very few words.
- The use of N-grams also increases sparsity, as even fewer documents will share the same phrases.
- This problem is exacerbated due to…
  - Synonymy: languages often use many different words to refer to identical or closely related concepts (e.g. ‘residence’,‘abode’).
  - Homonymy: a single word can have either multiple unrelated meanings (e.g. ‘jaguar’ - car or animal?).
  - Polysemy: a single word can have multiple related meanings (e.g. ‘bank’ - a financial institution or the building housing it?).
- This applies when analysing a monolingual corpus. Text analysis becomes far more difficult when working with a multilingual corpus.

Challenges in Text Mining

- The Sparsity Problem has several practical consequences...
  - Additional memory and processing requirements due to more dimensions (terms).
  - Analytical problems related to sparsity - e.g. when using a bag-of-words representation, we can fail to identify documents which are related to the same concepts.

Document 1:
jaguars are expensive cars

Document 2:
a jaguar is a costly vehicle

Document 3:
the jaguar, a feline animal

a	animal	are	cars	costly	expensive	feline	is	jaguar	jaguars	the	vehicle
0	0	1	1	0	1	0	0	0	1	0	0
1	0	0	0	1	0	0	1	1	0	0	1
1	1	0	0	0	0	1	0	1	0	1	0

$$cos(D1, D2) = 0.0 \qquad cos(D2, D3) = 0.4$$

Text Preprocessing

- The number of terms used to represent documents (and hence the sparsity) is often reduced by applying a number of simple preprocessing techniques before building a document-term matrix:
  - Minimum term length: Exclude terms of length < 2
  - Case conversion: Converting all terms to lowercase.
  - Stemming: Process by which endings are removed from terms in order to remove things like tense or plurals:
    e.g. `compute, computing, computer = comput`
  - Lemmatisation: Process to reduce a term to its canonical form. This is a more advanced form of stemming.
  - Stop-word filtering: Remove terms that appear on a pre-defined filter list of terms that are highly frequent and do not convey useful information (e.g. `and, the, while`)
  - Low frequency filtering: Remove terms that appear in very few documents.

Text Preprocessing in Python

- By default Scikit-learn converts tokens to lowercase and removes tokens of length 1 (i.e. single letters).
- Scikit-learn allows us to perform other simple preprocessing steps by adapting the `CountVectorizer`.

```
vectorizer = CountVectorizer(stop_words="english")
X = vectorizer.fit_transform(documents)
```

Use built-in stop-words by specifying the language

```
mywords = [ "and", "the", "am", "pm" ]
vectorizer = CountVectorizer(stop_words=mywords)
X = vectorizer.fit_transform(documents)
```

Use a custom list of stopwords

Filter terms appearing in less than 5 documents:

```
vectorizer = CountVectorizer(min_df = 5)
X = vectorizer.fit_transform(documents)
```

Multiple preprocessing steps...

```
vectorizer = CountVectorizer(stop_words="english", min_df = 5)
X = vectorizer.fit_transform(documents)
```

Text Preprocessing in Python

- To stem or lemmatise tokens, we need to use functionality from another text analysis library: NLTK (http://www.nltk.org)

Install via command line:

```
conda install nltk
```

- Apply stemming to individual words:

```
from nltk.stem.porter import PorterStemmer
words = ['cycles', 'insists', 'computer', 'flying', ‘cars’, ’is’, ‘are’]
stemmer = PorterStemmer()
for w in words:
    print( stemmer.stem(w) )
```

```
cycl insist comput fli car is are
```

- Apply lemmatisation to individual words:

```
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()
for w in words:
    print( lemmatizer.lemmatize(w) )
```

```
cycle insists computer flying car is are
```

Try

```
for w in words:
    print( lemmatizer.lemmatize(w. 'v') )
```

Term Weighting

- As well as including or excluding terms, we can also modify or weight the frequency values themselves.
- We can improve the usefulness of the document-term matrix by giving higher weights to more "important" terms.
- TF-IDF: Common approach for weighting the score for a term in a document. Several different formulations, but always consist of:
  - Term Frequency (TF): Number of times a given term appears in a single document.
  - Inverse Document Frequency (IDF): Function of total number of distinct documents containing a term. Effect is to penalise common terms that appear in almost every document.

Common version is log-based TF-IDF

$$w(t,d) = \underbrace{tf(t,d)}_{\text{TF}} \times \underbrace{(log\left(\frac{n}{df(t)}\right) + 1)}_{\text{IDF}}$$

n = total number of documents

Term Weighting

- **Example:** In a dataset of n=1000 documents, for a document *D*...

  Term 'cat' appears in the document *D* 3 times, and appears in 50 documents in total.

  Term 'dog' appears in the document *D* 4 times, and appears in 250 documents in total.

$$w(\text{cat}, D) = 3 \times (log(\tfrac{1000}{50}) + 1) = 11.987$$

$$w(\text{dog}, D) = 4 \times (log(\tfrac{1000}{250}) + 1) = 9.545$$

Term 'cat' is more "important"

- In Scikit-learn, we can generate a TF-IDF weighted document-term matrix by using `TfidfVectorizer` in place of `CountVectorizer`:

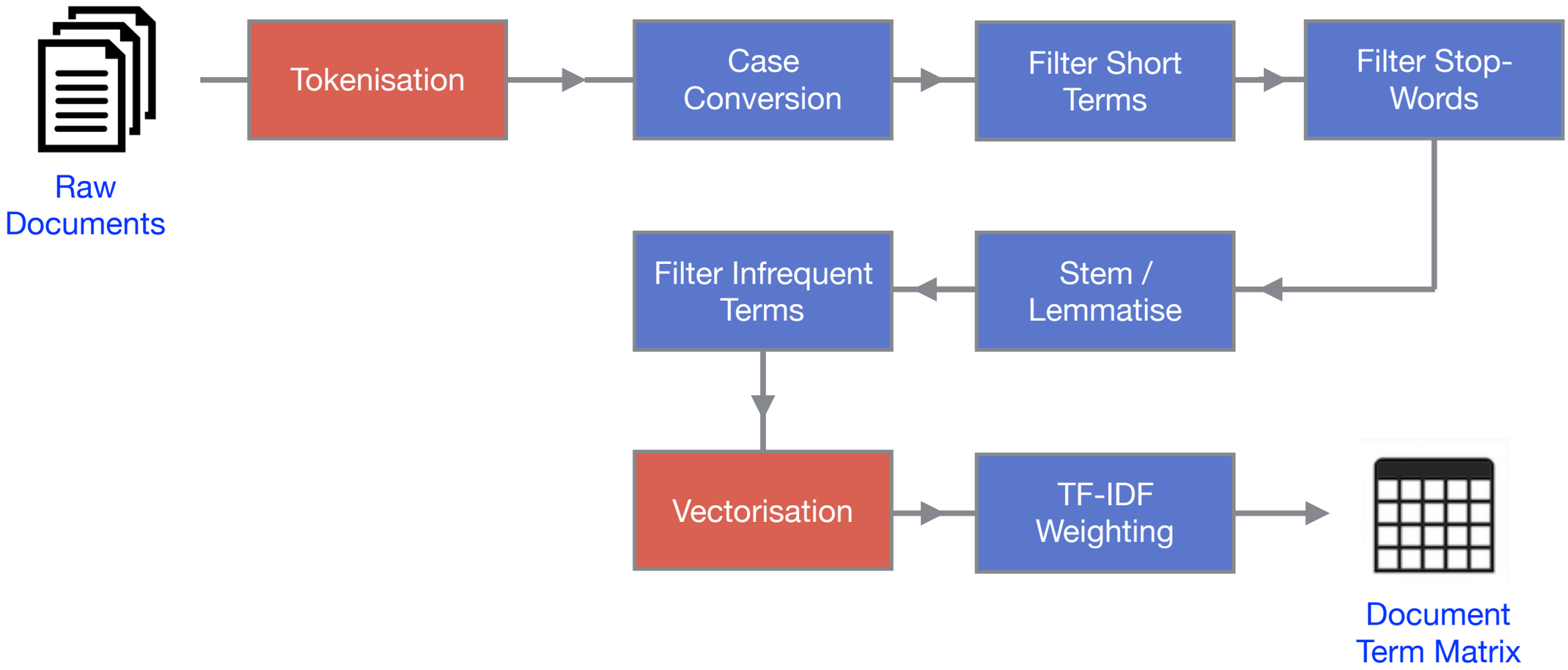
```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(documents)
```

```
vectorizer = TfidfVectorizer(stop_words="english", min_df = 5)
X = vectorizer.fit_transform(documents)
```

Can include preprocessing steps as before

Text Processing Pipeline Overview

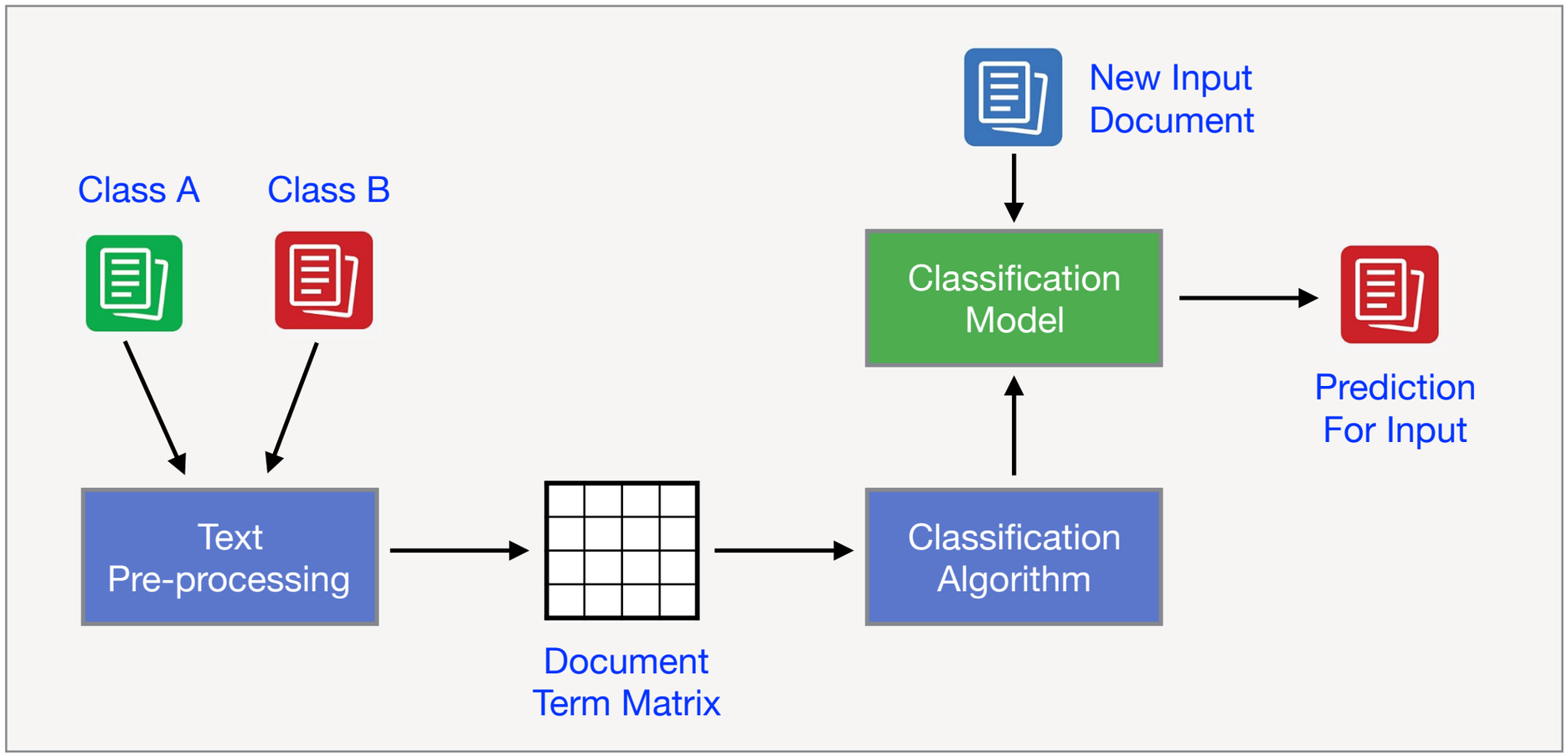
Typical text preprocessing steps for processing a corpus...



Subsequent modelling steps can then be applied to the document-term matrix - e.g. document classification, documenter clustering.

Text Classification

- **Goal:** To learn a model from the training set so that we can accurately predict classes for new unlabeled documents.
- **Input:** Training set of labelled text documents, annotated with two or more class labels (categories).



Text Classification

- When we have labelled documents to use as training data, we can apply many standard classifiers to a document-term matrix, using the functionality from Scikit-learn that we saw previously.
- As before, we will need to split training and test data for evaluations, with 2 sets of documents: `train_documents`, `test_documents`

```
vectorizer = TfidfVectorizer()
train_X = vectorizer.fit_transform(train_documents)
```

Create document-term matrix from training documents by calling `fit_transform()`

```
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier(n_neighbors=3)
model.fit(train_X, train_target)
```

Build a KNN model on it

```
test_X = vectorizer.transform(test_documents)
```

Create document-term matrix from test documents. We call `transform()` to use the same vocabulary as before.

```
predicted = model.predict(test_X)
```

We can now make predictions for our test documents using the KNN model and the test document-term matrix

Text Classification

- A number of general purpose classification algorithms are frequently used for classifying text documents:
  - **kNN:** Standard nearest neighbour classifier, using an appropriate similarity measure (e.g. Cosine).
  - **Naive Bayes:** Classification based on term frequency counts. Incorrectly assumes all terms are independent, but can still be effective in practice.
  - **Support Vector Machines:** Often apply SVMs with a linear kernel to calculate document similarity.
- To compare the performance of different algorithms and/or different parameter settings on the same corpus, we use standard classifier evaluation methods - e.g. measure each classifier's mean accuracy in a k-fold cross-validation experiment.