Text

Big data: text

- Text is everywhere. It provides a key source of insight in the modern business environment.

- Examples:
  - Product reviews.
  - Internet searches.
  - Social-media activity surrounding a brand.
  - Company earnings calls.
  - Technical documentation.

Big data: text

- Annoying reality: text data is **unstructured**.
- Compare:

Price	Engine	Cylinders	HP	CityMPG
43755	39014	3.5	6	225
46100	41100	3.5	6	225
36945	33337	3.5	6	265
89765	79978	3.2	6	290
23820	21761	2	4	200
33195	30299	3.2	6	270
26990	24647	2.4	4	200
25940	23508	1.8	4	170

vs.

It is not from the benevolence of the butcher, the brewer, or the baker, that we expect our dinner, but from their regard to their own interest. We address ourselves, not to their humanity but to their self-love, and never talk to them of our own necessities but of their advantages. Nobody but a beggar chooses to depend chiefly upon the benevolence of his fellow-citizens.

Text-analysis goals

- Summary/compression:
  - Representing a body of documents as categories
  - Representing a document with a topic or set of topics

- Find similar documents to a given document
  - Showing users items of similar interest
  - Drawing analogies, e.g. from search terms to ads

- Classification of documents
  - Author attribution

Some terminology

- Corpus/corpora: body of documents
  - Wikipedia (each page is a document)
  - All tweets on a given date (each tweet is a document)

- Dictionary: set of all allowable “words”

- n-gram: set of n words in a row
  - “White House”: a bi-gram
  - See Google’s n-gram browser

Some terminology

- NLP: natural language processing
- Text pipeline: how unstructured text becomes tidy data
- Token versus type
  - Token: a string with an identified meaning.
  - Type: a higher-order category representing a concept.
  - Example: “A rose is a rose is a rose.” — Sylvia Plath
    - 9 tokens, 4 types (“a”, “rose”, “is”, “.”)
- Programming analogy: type = class, token = object.

Some terminology

- tokenization: turning a string of symbols into tokens
- metadata: extra information about a document
  - Examples: author, geo-tag
- XML/JSON: two most common file formats for text data
  - More structured than .txt
  - Includes metadata

Information in a document

- Metadata
- Words in a document
  - Can’t describe everything, but can get pretty far
- Sentiment
  - Computers may make mistakes in tagging sentiment
  - Example: I’m having such a great time today at the DMV!
- Main idea/topics
- Grammar/syntax

Tokenization and representation

String of symbols

tokenization

String of tokens

representation

Useful data structure

It ain’t over til it’s over.

“It”, “ain’t”, “over”, “til”, “it’s”, “over”, “.”

(not: “I”, “taint”, “overt”, “tilits”, “over”, “.”

It: 1

ain’t: 1

over: 2

etc

Tokenization: from symbols to tokens

- Tokenization involves many choices of what to do and not do to a raw string of symbols.

- Removing/splitting on white spaces
  - Typically the initial step in tokenization
  - Difficult when words are run together (e.e. cummings poem; “onetwothreefourfive”)

- Removing punctuation
  - But be careful, e.g. :-), ->

Tokenization: from symbols to tokens

- Converting everything to lowercase
- Removing “stop” words
  - the, is, a, of…
  - Take care: one person’s trash is another person’s treasure
- Dropping numbers and mapping to a common symbol (NUM)
- Stemming: drop suffixes
  - acknowledge, acknowledges, acknowledgement
- Deal with misspellings

“Bag of words” (really “bag of types”)

- This shows only the words in a document, and nothing about sentence structure or organization.

> **“There is a tide in the affairs of men, which taken at the flood, leads on to fortune. Omitted, all the voyage of their life is bound in shallows and in miseries. On such a full sea are we now afloat. And we must take the current when it serves, or lose our ventures.”**

- What the data scientist sees:

tide: 1	flood: 1
affairs: 1	the: 4
men: 1	fortune: 1
we: 2	etc.

“Bag of words” (really “bag of types”)

- Advantage: easy to work with and calculate with
- Disadvantage: it destroys other important sources of information (syntax, structure)
- We can get surprisingly far with the BoW representation
- Two common options for data structures:
  - Hash table/key-value store (dictionary in Python)
  - Vectors

“Bag of words” as a hash table (Python dictionary)

- Keys: words (really types)
- Values: counts in the document
- Easy to add new entry to hash table
- Useful for open-ended vocabulary
- Generally preferred for storage/manipulation

```
tide: 1          flood: 1
affairs: 1       the: 4
men: 1           fortune: 1
we: 2            ...
```

“Bag of words” as a vector

- Each index in a vector corresponds to a word; each entry is word count

- Can be difficult to update if a new word is encountered

- Easier to do math with

- Two examples of document vectors

tide	affairs	the	. . .	bacteria	cars	ain’t	over	til
1	1	4	. . .	0	0	0	0	0
0	0	0	. . .	0	0	1	2	2

(most entries not shown)

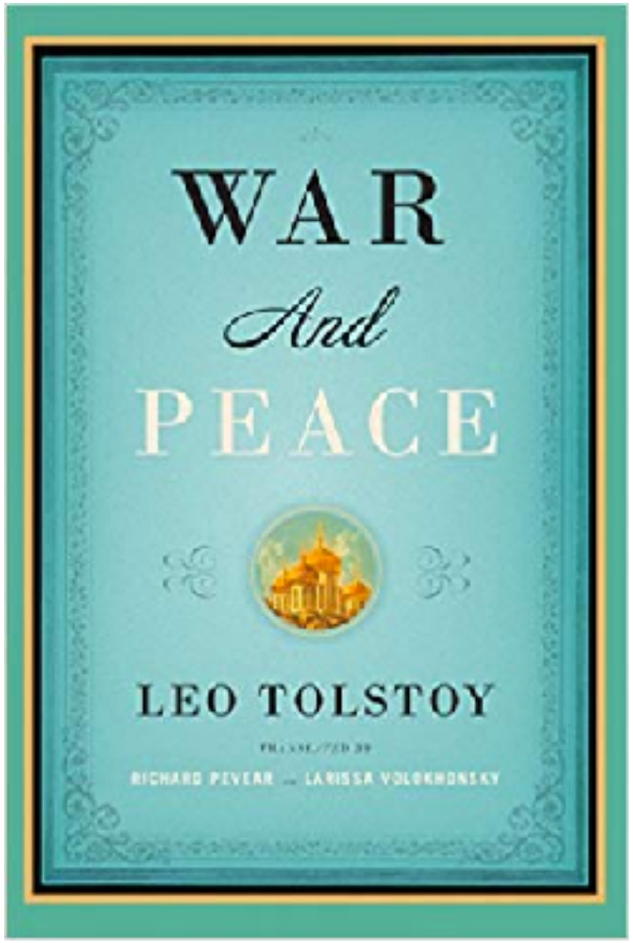
Document-term matrix (DTM)

- N = number of documents, D = size of dictionary
- X_{ij} = number of times term j appears in document i.
- The document-term matrix X for a corpus puts each document's vector as a row of the matrix:

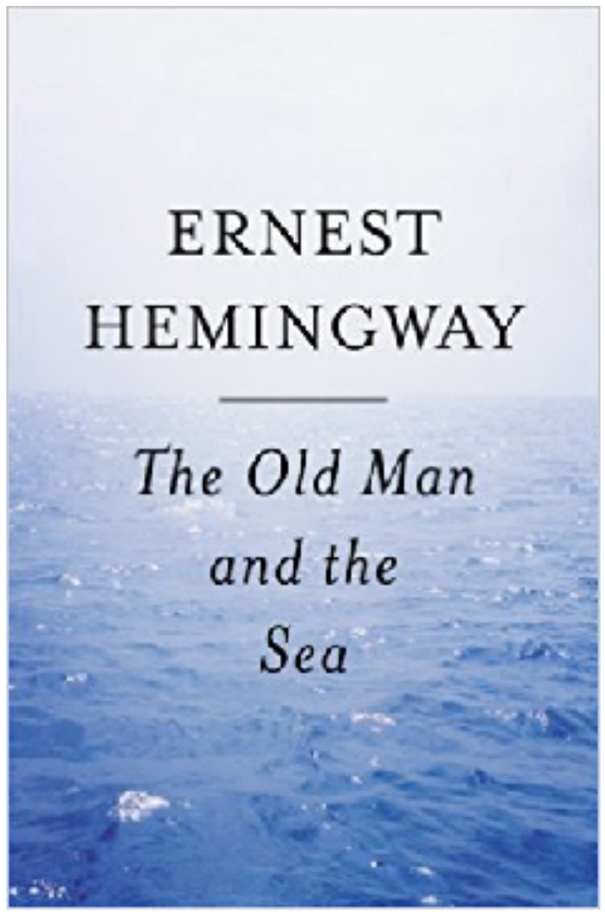
$$\begin{pmatrix} X_{11} & X_{12} & \dots & X_{1D} \\ X_{21} & X_{22} & \dots & X_{2D} \\ X_{31} & X_{32} & \dots & X_{3D} \\ & \vdots & & \\ X_{N1} & X_{N2} & \dots & X_{ND} \end{pmatrix}$$

Term frequency (TF) weighting

- Some documents are longer than others. Maybe we don’t care about raw word counts — only frequency of a occurrence of each word.



VS



Term frequency (TF) weighting

- Some documents are longer than others. Maybe we don't care about raw word counts — only frequency of a occurrence of each word.
- In this case, we might normalize the document term matrix row to sum to 1 along each row:

$$\text{TF}_{ij} = \frac{X_{ij}}{\sum_{j=1}^{D} X_{ij}} \quad (\text{“term frequency”})$$

Inverse-document frequency (IDF) weighting

- Similarly, some words occur frequently across all documents but aren't that interesting or useful.
  - "Brisket" in a corpus of documents about Texas BBQ.
  - "Rome" in a corpus of travel narratives about Rome.
  - "Congress" in a corpus of political news stories.

- The rarer/more specific words might be much more helpful for a given NLP task (classification, summary, matching, etc). **Specificity is inversely proportional to how common a word is across the whole corpus.**

Inverse-document frequency (IDF) weighting

- IDF weights measure the specificity of a term:

$$\text{IDF}_j = \log(1 + N/M_j)$$

$$N$$

$$M_j = \sum_{i=1} \mathbf{1}(X_{ij} > 0)$$

$$= \text{Number of docs where term } j \text{ appears}$$

TF-IDF weights

- We can combine these to define TF-IDF weights

$$\begin{aligned}\tilde{X}_{ij} &= \text{TF-IDF}_{ij} \\ &= \text{TF}_{ij} \cdot \text{IDF}_j \\ &= \frac{X_{ij}}{\sum_{j=1}^{D} X_{ij}} \cdot \log(1 + N/M_j)\end{aligned}$$

- We then use the TF-IDF weights instead of the actual document-term matrix.

- Words that are frequent in a document but rare in the whole corpus get high TF-IDF weights.

OK, now what?

- Compare documents (rows of the matrix)
- Compare words (columns of the matrix)
- Cluster documents
- Find low-dimensional summaries, e.g. via PCA
- Classify documents
- Etc.

Comparing documents

- A standard measure of similarity is cosine similarity. Intuitively, two documents are similar if their vectors point in the same direction. (Recall that each row of our document-term matrix is a vector x_i).

$$
\begin{aligned}
\text{sim}(x_1, x_2) &= \frac{x_1 \cdot x_2}{\|x_1\| \cdot \|x_2\|} \\
&= \frac{\sum_{j=1}^{D} x_{1j} x_{2j}}{\left(\sum_{j=1}^{D} X_{1j}^2\right)^{-1/2} \cdot \left(\sum_{j=1}^{D} X_{2j}^2\right)^{-1/2}} \\
&= \text{Cosine of angle b/t } x_1 \text{ and } x_2
\end{aligned}
$$

Cosine distance

- Cosine similarity can also be used to define cosine distance between two nonnegative vectors.

$$\begin{aligned}\text{dist}(x_1, x_2) &= 1 - \text{sim}(x_1, x_2) \\ &= 1 - \frac{x_1 \cdot x_2}{\|x_1\| \cdot \|x_2\|}\end{aligned}$$

- TF weights and TF-IDF weights are nonnegative.

- Remember, as long as we can measure distances, we can cluster documents (see `proxy` package in R).

Classification

- Suppose we have a training set of documents N documents with raw word/phrase counts X_{ij}.

- Suppose we have a class label Y_i for each document. Each Y_i is an integer from 1, …, M.

- Now new test documents arrive without labels. How do we classify them?

Common approaches to classification

- KNN based on cosine distance.
- Cluster the training set, assign test documents to nearest cluster
- Fit a classifier (mlogit, trees, BART, etc) using features derived from the text
- Naive Bayes on counts
- etc!

KNN, clustering, classification…

- There are lots of choices here
  - What pre-processing should I apply? (Removing super-rare words, stop words, weight scheme, smoothing, etc…)
  - What dimensionality reduction, if any, should I do on the resulting matrix of features?
  - What distance measure should I use?

Naive Bayes

- Test document i consists of a set of N_i words:

$$(w_1, w_2, \ldots, w_{N_i}) \text{ where } \quad w_k \in \{1, \ldots, D\}$$

- E.g. (“the”, “BBQ”, “at” “Franklin” … “super”, “delicious”)

- Goal: compute the probability that this new document falls into each class:

$$P(Y = m \mid w_1, \ldots, w_{N_i}) \quad \text{for} \quad m = 1, \ldots, M$$

Naive Bayes

- The underlying statistical model in Naive Bayes classification is “bag of words”: it assumes that each word is drawn independently from a bag with a class-specific probability:

$$P(w_k = i \mid Y = m) = \pi_{im}$$

- π_{im}: probability that a random word from the bag is word i, given that the class is m.

- E.g. maybe if class m is about BBQ, $\pi_{\text{"brisket", m}}$ is high, but $\pi_{\text{"Lionel Messi", m}}$ is low.

Naive Bayes

- Under the assumption that each word is independent (the “naive” part), we can just compound up the probabilities for each occurrence of observed word.

- So if we let $X_i = (X_{i1}, X_{i2}, \ldots, X_{iD})$ be our vector of word counts in test document i, we have

$$P(X_i \mid Y = m) = \pi_{1m}^{X_{i1}} \cdot \pi_{2m}^{X_{i2}} \cdots \pi_{Dm}^{X_{iD}}$$
$$= \prod_{j=1}^{D} \pi_{jm}^{X_{ij}}$$

Naive Bayes

- Now use Bayes rule:

$$P(Y = m \mid X_i) \propto P(Y = m) \cdot P(X_i \mid Y = m)$$

$$= P(Y = m) \cdot \prod_{j=1}^{D} \pi_{jm}^{X_{ij}}$$

- Note 1: it's easy to estimate the prior probabilities P(Y = m) from the fraction of each class on the training data.

- Note 2: for classification, we can ignore the denominator $P(X_i)$ in Bayes rule, since it is the same for all classes.

Naive Bayes

- Now use Bayes rule:

$$P(Y = m \mid X_i) \propto P(Y = m) \cdot P(X_i \mid Y = m)$$

$$= P(Y = m) \cdot \prod_{j=1}^{D} \pi_{jm}^{X_{ij}}$$

- Note 3: it's also easy to estimate the probability vectors π from the training data.

$$\hat{\pi}_{jm} = \frac{\sum_{i:Y_i=m} X_{ij}}{\sum_{i:Y_i=m} \sum_{j=1}^{D} X_{ij}} = \frac{\text{Count of word } j \text{ in class } m}{\text{Count of all words in class } m}$$

Laplace smoothing

- Note 4: sometimes we add a “pseudocount” to the raw term frequencies

$$\tilde{\pi}_{jm} = \frac{\alpha + \sum_{i:Y_i=m} X_{ij}}{\alpha D + \sum_{i:Y_i=m} \sum_{j=1}^{D} X_{ij}}$$

- This is called “smoothing”. alpha = 1: Laplace smoothing, but other choices are possible.

Log scale

- Note 5: usually we work with log probabilities to avoid numerical underflow:

$$P(Y = m \mid X_i) \propto P(Y = m) \prod_{j=1}^{D} \pi_{jm}^{X_{ij}}$$

$$\log P(Y = m \mid X_i) = \log P(Y = m) + \sum_{j=1}^{D} X_{ij} \cdot \log \pi_{jm} + \text{constant}$$