TEXT SIMILARITY

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Admin

Assignment 4a
- Solutions posted
- If you're still unsure about questions 3 and 4, come talk to me.

Assignment 4b

Quiz #2 next Thursday
- Cover material from 9/17 – 9/26 (syntax, grammars, parsing)
- 45 minute take-home
- Will have a short class (~30 minutes)

Course feeback

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parse.sh

Put in your **code** directory

Java:

```
#! /bin/bash

javac -cp . nlp/parser/*.java
java -Xmx1G -cp . nlp.parser.CKYParser $1 $2
```

python:

```
#! /bin/bash

python3 ckyparser.py $1 $2
```

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Text Similarity

A common question in NLP is how similar are texts

score: sim(,) = ?

rank: ?

How could these be useful? Applications?

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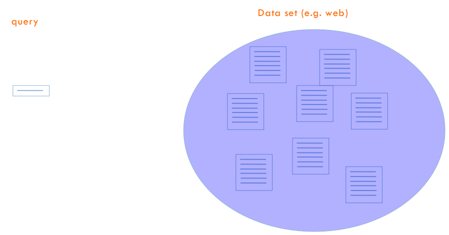
Text similarity: applications

Information retrieval (search)



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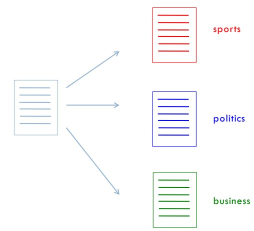
Text similarity: applications

Text classification



These "documents" could be actual documents, for example using k-means or pseudo-documents, like a class centroid/average

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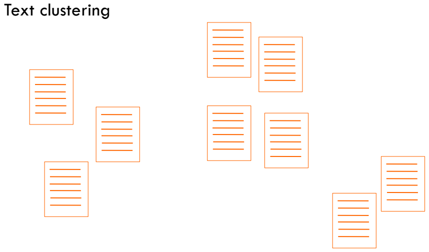
Text similarity: applications

Text clustering



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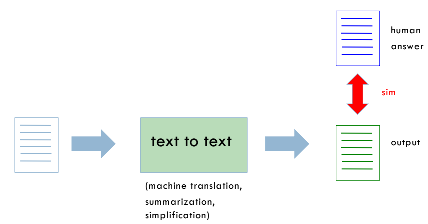
Text similarity: applications

Automatic evaluation



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Text similarity: applications

Word similarity

sim(*banana*, apple) = ?

Word-sense disambiguation

I went to the *bank* to get some money.

financial bank river bank

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Text similarity: application

Automatic grader

Question: what is a variable?
Answer: a location in memory that can store a value

How good are:

- a variable is a location in memory where a value can be stored
- a named object that can hold a numerical or letter value
- it is a location in the computer 's memory where it can be stored for use by a program
- a variable is the memory address for a specific type of stored data or from a mathematical perspective a symbol representing a fixed definition with changing values
- a location in memory where data can be stored and retrieved

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Text similarity

There are many different notions of similarity depending on the domain and the application

Today, we'll look at some different tools

There is no one single tool that works in all domains

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Text similarity approaches

sim(,) = ?

A: When the defendant and his lawyer walked into the court, some of the victim supporters turned their backs to him.

B: When the defendant walked into the courthouse with his attorney, the crowd truned their backs on him.

How can we do this?

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The basics: text overlap

Texts that have overlapping words are more similar

A: When the defendant and his lawyer walked into the court, some of the victim supporters turned their backs to him.

B: When the defendant walked into the courthouse with his attorney, the crowd truned their backs on him.

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Word overlap: a numerical score

Idea 1: number of overlapping words

A: When the defendant and his lawyer walked into the court, some of the victim supporters turned their backs to him.

B: When the defendant walked into the courthouse with his attorney, the crowd truned their backs on him.

sim(T1, T2) = 11

problems?

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Word overlap problems

- Doesn't take into account word order
- Related: doesn't reward longer overlapping sequences

A: defendant his the When lawyer into walked backs him the court, of supporters and some the victim turned their backs him to.

B: When the defendant walked into the courthouse with his attorney, the crowd truned their backs on him.

sim(T1, T2) = 11

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Word overlap problems

Doesn't take into account length

A: When the defendant and his lawyer walked into the court, some of the victim supporters turned their backs to him.

B: When the defendant walked into the courthouse with his attorney, the crowd truned their backs on him. *I ate a large banana at work today and thought it was great!*

sim(T1, T2) = 11

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Word overlap problems

Doesn't take into account synonyms

A: When the defendant and his *lawyer* walked into the *court*, some of the victim supporters turned their backs to him.

B: When the defendant walked into the *courthouse* with his *attorney*, the crowd truned their backs on him.

sim(T1, T2) = 11

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Word overlap problems

Doesn't take into account spelling mistakes

A: When the defendant and his lawyer walked into the court, some of the victim supporters *turned* their backs to him.

B: When the defendant walked into the courthouse with his attorney, the crowd *truned* their backs on him.

sim(T1, T2) = 11

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Word overlap problems

Treats all words the same

A: When the defendant and his lawyer walked into the court, some of the victim supporters turned their backs to him.

B: When the defendant walked into the courthouse with his attorney, the crowd truned their backs on him.

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Word overlap problems

May not handle frequency properly

A: When the defendant and his lawyer walked into the court, some of the victim supporters turned their backs to him. I ate a *banana* and then another *banana* and it was good!

B: When the defendant walked into the courthouse with his attorney, the crowd truned their backs on him. I ate a large *banana* at work today and thought it was great!

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Word overlap: sets

A: When the defendant and his lawyer walked into the court, some of the victim supporters turned their backs to him.

A
and
backs
court
defendant
him
…

B: When the defendant walked into the courthouse with his attorney, the crowd truned their backs on him.

B
and
backs
courthouse
defendant
him
…

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Word overlap: sets

What is the overlap, using set notation?

- |A ∩ B| the size of the intersection

How can we incorporate length/size into this measure?

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Word overlap: sets

What is the overlap, using set notation?

- |A ∩ B| the size of the intersection

How can we incorporate length/size into this measure?

Jaccard index (Jaccard similarity coefficient)

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

Dice's coefficient

$$Dice(A,B) = \frac{2\,|A \cap B|}{|A| + |B|}$$

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Word overlap: sets

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \qquad Dice(A,B) = \frac{2\,|A \cap B|}{|A| + |B|}$$

How are these related?

Hint: break them down in terms of

$|A - B|$ words in A but not B

$|B - A|$ words in B but not A

$|A \cap B|$ words in both A and B

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Word overlap: sets

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

$$= \frac{|A \cap B|}{\underbrace{|A-B|}_{\text{in A but not B}} + \underbrace{|B-A|}_{\text{in B but not A}} + |A \cap B|}$$

$$Dice(A,B) = \frac{2\,|A \cap B|}{|A| + |B|}$$

$$= \frac{2\,|A \cap B|}{|A-B| + |B-A| + 2\,|A \cap B|}$$

Dice's coefficient gives twice the weight to overlapping words

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Set overlap

Our problems:

- word order
- length
- synonym
- spelling mistakes
- word importance
- word frequency

Set overlap measures can be good in some situations, but often we need more general tools

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Bag of words representation

When the defendant and his lawyer walked into the court, some of the victim supporters turned their backs to him.

When|the|defendant|and|his|lawyer|walked|into|the|court, |some|of|the|victim|supporters|turned|their|backs|to|him.

What information do we lose?

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Bag of words representation

For now, let's ignore word order:

Obama said banana repeatedly last week on tv, "banana, banana, banana"

(4, 1, 1, 0, 0, 1, 0, 0, …)

banana obama said california across tv wrong capital

"Bag of words representation": multi-dimensional vector, one dimension per word in our vocabulary

Frequency of word occurrence

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Bag of words representation

http://membercentral.aaas.org/blogs/member-spotlight/tom-mitchell-studies-human-language-both-man-and-machine

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Vector based word

A

a1: When	1
a2: the	2
a3: defendant	1
a4: and	1
a5: courthouse	0
…	

B

b1: When	1
b2: the	2
b3: defendant	1
b4: and	0
b5: courthouse	1
…	

Multi-dimensional vectors, one dimension per word in our vocabulary

How do we calculate the similarity based on these vectors?

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Vector based similarity

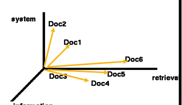
We have a |V|-dimensional vector space

Terms are axes of the space

Documents are points or vectors in this space

Very high-dimensional

This is a very sparse vector - most entries are zero



What question are we asking in this space for similarity?

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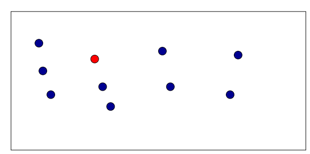
Vector based similarity

Similarity relates to distance

We'd like to measure the similarity of documents in the |V| dimensional space

What are some distance measures?



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Distance measures

Euclidean (L2)

$$dist(A,B) = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2}$$

Manhattan (L1)

$$dist(A,B) = \sum_{i=1}^{n} |a_i - b_i|$$

What do these mean for our bag of word vectors?

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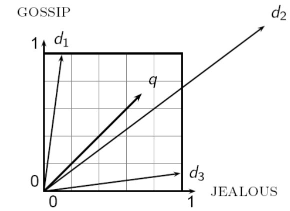
Distance can be problematic

Which d is closest to q using one of the previous distance measures?

Which do you think should be closer?



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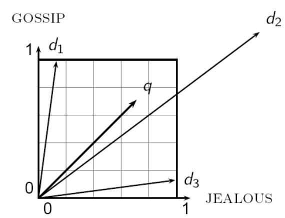
Distance can be problematic

The Euclidean (or L1) distance between q and d_2 is large even though the distribution of words is similar



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Use angle instead of distance

Thought experiment:

- take a document d
- make a new document d' by concatenating two copies of d
- "Semantically" d and d' have the same content

What is the Euclidean distance between d and d'?
What is the angle between them?

- The Euclidean distance can be large
- The angle between the two documents is 0

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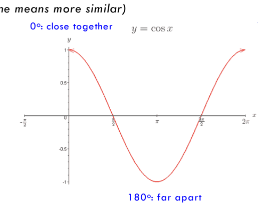
From angles to cosines

Cosine is a monotonically decreasing function for the interval [0º, 180º]

decreasing angle is equivalent to *increasing* cosine of that angle
(larger cosine means more similar)



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Near and far

https://youtu.be/E9IuXEwpU7U

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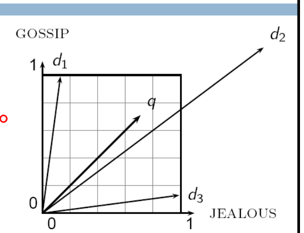
cosine

How do we calculate the cosine between two vectors?



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Cosine of two vectors

Dot product

$$A \cdot B = \|A\|\|B\|\cos\theta$$

$$\cos\theta = \frac{A \cdot B}{\|A\|\|B\|} = \frac{A}{\|A\|} \cdot \frac{B}{\|B\|}$$

Dot product between unit length vectors

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Cosine as a similarity

$$sim_{\cos'}(A,B) = A \cdot B = \sum_{i=1}^{n} a_i b_i$$

ignoring length normalization

Just another distance measure, like the others:

$$dist_{L2}(A,B) = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2}$$

$$dist_{L1}(A,B) = \sum_{i=1}^{n} |a_i - b_i|$$

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Cosine as a similarity

$$sim_{\cos'}(A,B) = A \cdot B = \sum_{i=1}^{n} a_i b_i$$

ignoring length normalization

For bag of word vectors, what does this do?

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Cosine as a similarity

$$sim_{\cos'}(A,B) = A \cdot B = \sum_{i=1}^{n} a_i b_i$$

ignoring length normalization

Only words that occur in *both* documents count towards similarity

Words that occur more frequently in both receive more weight

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Length normalization

A vector can be length-normalized by dividing each of its components by its length

Often, we'll use L_2 norm (could also normalize by other norms):

$$\|\vec{x}\|_2 = \sqrt{\sum_i x_i^2}$$

Dividing a vector by its L_2 norm makes it a unit (length) vector

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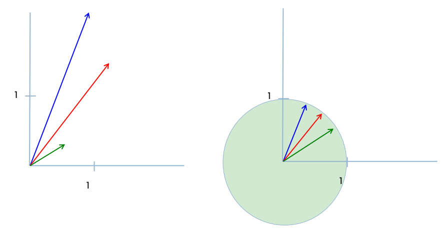
Unit length vectors



In many situations, normalization improves similarity, but not in all situations

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Normalized distance measures

Cosine

$$sim_{\cos}(A,B) = A \cdot B = \sum_{i=1}^{n} a_i' b_i' = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^2}\sqrt{\sum_{i=1}^{n} b_i^2}}$$

L2

$$dist_{L2}(A,B) = \sqrt{\sum_{i=1}^{n} (a_i' - b_i')^2}$$

L1

$$dist_{L1}(A,B) = \sum_{i=1}^{n} |a_i' - b_i'|$$

a' and b' are length normalized versions of the vectors

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Distance measures

Cosine

$$sim_{\cos}(A,B) = A \cdot B = \sum_{i=1}^{n} a_i' b_i'$$

L2

$$dist_{L2}(A,B) = \sqrt{\sum_{i=1}^{n} (a_i' - b_i')^2}$$

L1

$$dist_{L1}(A,B) = \sum_{i=1}^{n} |a_i' - b_i'|$$

Cosine is the most common measure. Why do you think?

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Distance measures

Cosine

$$sim_{\cos}(A,B) = A \cdot B = \sum_{i=1}^{n} a_i' b_i'$$

L2

$$dist_{L2}(A,B) = \sqrt{\sum_{i=1}^{n} (a_i' - b_i')^2}$$

L1

$$dist_{L1}(A,B) = \sum_{i=1}^{n} |a_i' - b_i'|$$

- L1 and L2 penalize sentences for not having words, i.e. if a has it but b doesn't
- Cosine can be significantly faster since it only calculates over the intersection

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Our problems

Which of these have we addressed?

- word order
- length
- synonym
- spelling mistakes
- word importance
- word frequency

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Our problems

Which of these have we addressed?

- word order
- length
- synonym
- spelling mistakes
- word importance
- word frequency

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Word overlap problems

Treats all words the same

A: When the defendant and his lawyer walked into the court, some of the victim supporters turned their backs to him.

B: When the defendant walked into the courthouse with his attorney, the crowd truned their backs on him.

Ideas?

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Word importance

Include a weight for each word/feature

A

a1: When	1	w1
a2: the	2	w2
a3: defendant	1	w3
a4: and	1	w4
a5: courthouse	0	w5
...		...

B

b1: When	1	w1
b2: the	2	w2
b3: defendant	1	w3
b4: and	0	w4
b5: courthouse	1	w5
...		...

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Distance + weights

We can incorporate the weights into the distances

Think of it as either (*both work out the same*):

- preprocessing the vectors by multiplying each dimension by the weight
- incorporating it directly into the similarity measure

$$sim_{\cos}(A,B) = A \cdot B = \frac{\sum_{i=1}^{n} w_i a_i w_i b_i}{\sqrt{\sum_{i=1}^{n}(w_i a_i)^2}\sqrt{\sum_{i=1}^{n}(w_i b_i)^2}}$$

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Idea: use corpus statistics

the

defendant

What would be a quantitative measure of word importance?

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Document frequency

document frequency (DF) is one measure of word importance

Terms that occur in many documents are weighted less, since overlapping with these terms is very likely

- In the extreme case, take a word like the that occurs in almost EVERY document

Terms that occur in only a few documents are weighted more

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Document vs. overall frequency

The overall frequency of a word is the number of occurrences in a dataset, counting multiple occurrences

Example:

Word	Overall frequency	Document frequency
insurance	10440	3997
try	10422	8760

Which word is a more informative (and should get a higher weight)?

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Document frequency

Word	Collection frequency	Document frequency
insurance	10440	3997
try	10422	8760

Document frequency is often related to word importance, but we want an actual weight. Problems?

$$sim_{\cos}(A,B) = A \cdot B = \frac{\sum_{i=1}^{n} w_i a_i w_i b_i}{\sqrt{\sum_{i=1}^{n} (w_i a_i)^2} \sqrt{\sum_{i=1}^{n} (w_i b_i)^2}}$$

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From document frequency to weight

Word	Collection frequency	Document frequency
insurance	10440	3997
try	10422	8760

weight and document frequency are **inversely** related
- higher document frequency should have lower weight and vice versa

document frequency is unbounded

document frequency will change depending on the size of the data set (i.e. the number of documents)

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Inverse document frequency

$$\text{idf}_w = \log \frac{N}{\text{df}_w}$$

N: # of documents in dataset

df_w: document frequency of w

IDF is inversely correlated with DF
- higher DF results in lower IDF

N incorporates a dataset dependent normalizer

log dampens the overall weight

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IDF example, suppose *N*=1 million

term	df$_t$	idf$_t$
calpurnia	1	
animal	100	
sunday	1,000	
fly	10,000	
under	100,000	
the	1,000,000	

What are the IDFs assuming log base 10?

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IDF example, suppose N=1 million

term	df_t	idf_t
calpurnia	1	6
animal	100	4
sunday	1,000	3
fly	10,000	2
under	100,000	1
the	1,000,000	0

There is one idf value/weight for each word

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IDF example, suppose N=1 million

term	df_t	idf_t
calpurnia	1	
animal	100	
sunday	1,000	
fly	10,000	
under	100,000	
the	1,000,000	

What if we didn't use the log to dampen the weighting?

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IDF example, suppose N=1 million

term	df_t	idf_t
calpurnia	1	1,000,000
animal	100	10,000
sunday	1,000	1,000
fly	10,000	100
under	100,000	10
the	1,000,000	1

What if we didn't use the log to dampen the weighting?

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TF-IDF

One of the most common weighting schemes

TF = term frequency

IDF = inverse document frequency

$$a'_i = \underbrace{a_i}_{\text{TF}} \times \underbrace{\log N / \mathrm{df}_i}_{\text{IDF (word importance weight)}}$$

We can then use this with any of our similarity measures!

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Stoplists: extreme weighting

Some words like ‘a’ and ‘the’ will occur in almost every document

- IDF will be 0 for any word that occurs in all documents
- For words that occur in almost all of the documents, they will be nearly 0

A ***stoplist*** is a list of words that should **not** be considered (in this case, similarity calculations)

- Sometimes this is the *n* most frequent words
- Often, it's a list of a few hundred words manually created

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Stoplist

I	all-over	around	beneath	due	go
a	almost	as	beside	durin	goddamn
aboard	along	aside	besides	during	goody
about	alongside	astride	between	each	gosh
above	altho	at	bewteen	eh	half
across	although	atop	beyond	either	have
after	amid	avec	bi	en	he
afterwards	amidst	away	both	every	hell
against	among	back	but	ever	her
agin	amongst	be	by	everyone	herself
ago	an	because	ca.	everything	hey
agreed-upon	and	before	de	except	him
ah	another	beforehand	des	far	himself
alas	any	behind	despite	fer	his
albeit	anyone	behynde	do	for	ho
all	anything	below	down	from	how

If most of these end up with low weights anyway, why use a stoplist?

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Stoplists

Two main benefits

- More fine grained control: some words may not be frequent, but may not have any content value (alas, teh, gosh)
- Often does contain many frequent words, which can drastically reduce our storage and computation

Any downsides to using a stoplist?

- For some applications, some stop words may be important

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Text similarity so far…

Set based – easy and efficient to calculate

- word overlap
- Jaccard
- Dice

Vector based

- create a feature vector based on word occurrences (or other features)
- Can use any distance measures
  - L1 (Manhattan)
  - L2 (Euclidean)
  - Cosine (*most common*)
- Normalize the length
- Feature/dimension weighting
  - inverse document frequency (IDF)

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