University of Tokyo: Text-as-Data
Day 1, Part I

Arthur Spirling

June 3, 2017

Boring but important sanity check

Boring but important sanity check

https://github.com/ArthurSpirling/UTokyo-TextAsData

What this class is about...

What this class is about...

What this class is about...

Text as the new frontier of...

What this class is about...

Text as the new frontier of...

data:

What this class is about...

Text as the new frontier of...

data: lots of it (literally petabytes) on the web... not to mention archives.

What this class is about...

Text as the new frontier of...

data: lots of it (literally petabytes) on the web... not to mention archives.

methods:

Text as the new frontier of. . .

data: lots of it (literally petabytes) on the web. . . not to mention archives.

methods: unstructured data needs to be harvested and modeled.

What this class is about...

Text as the new frontier of...

> data: lots of it (literally petabytes) on the web...not to mention archives.
>
> methods: unstructured data needs to be harvested and modeled.
>
> social science:

What this class is about...

Text as the new frontier of...

data: lots of it (literally petabytes) on the web...not to mention archives.

methods: unstructured data needs to be harvested and modeled.

social science: politicians give speeches,

What this class is about. . .

Text as the new frontier of. . .

data: lots of it (literally petabytes) on the web. . . not to mention archives.

methods: unstructured data needs to be harvested and modeled.

social science: politicians give speeches, thinkers write articles,

What this class is about...

Text as the new frontier of...

data: lots of it (literally petabytes) on the web... not to mention archives.

methods: unstructured data needs to be harvested and modeled.

social science: politicians give speeches, thinkers write articles, nations sign treaties,

What this class is about. . .

Text as the new frontier of. . .

- data: lots of it (literally petabytes) on the web. . . not to mention archives.

- methods: unstructured data needs to be harvested and modeled.

- social science: politicians give speeches, thinkers write articles, nations sign treaties, users connect on Facebook etc.

What this class is about. . .

Text as the new frontier of. . .

data: lots of it (literally petabytes) on the web. . . not to mention archives.

methods: unstructured data needs to be harvested and modeled.

social science: politicians give speeches, thinkers write articles, nations sign treaties, users connect on Facebook etc.

Introduction to quantitative 'text-as-data' approaches as strategies to learn more about social scientific phenomena of interest.

Overview

Overview


since
stand
responsibility
parents
live
law
together
matter
south
need
research
form

Overview

- Descriptive inference:

Overview

- Descriptive inference: how to characterize text,

Overview

- Descriptive inference: how to characterize text, vector space model,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style, bursts.

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style, bursts.

- Basic supervised techniques:

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style, bursts.
- Basic supervised techniques: dictionaries,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style, bursts.

- Basic supervised techniques: dictionaries, sentiment,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style, bursts.

- Basic supervised techniques: dictionaries, sentiment, events,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style, bursts.
- Basic supervised techniques: dictionaries, sentiment, events, scaling.

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style, bursts.
- Basic supervised techniques: dictionaries, sentiment, events, scaling.
- Basic unsupervised techniques:

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style, bursts.
- Basic supervised techniques: dictionaries, sentiment, events, scaling.
- Basic unsupervised techniques: clusters,

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style, bursts.
- Basic supervised techniques: dictionaries, sentiment, events, scaling.
- Basic unsupervised techniques: clusters, scaling

Overview

- Descriptive inference: how to characterize text, vector space model, collocations, bag-of-words, (dis)similarity measures, diversity, complexity, style, bursts.
- Basic supervised techniques: dictionaries, sentiment, events, scaling.
- Basic unsupervised techniques: clusters, scaling, topics.

Quantitative vs Qualitative

Quantitative vs Qualitative

Quantitative vs Qualitative

- For most of its history text analysis was qualitative.

Quantitative vs Qualitative

- For most of its history text analysis was qualitative.
- Partly still is:

Quantitative vs Qualitative

- For most of its history text analysis was qualitative.
- Partly still is: need to make qualitative judgements about what the text reveals,

Quantitative vs Qualitative

- For most of its history text analysis was qualitative.
- Partly still is: need to make qualitative judgements about what the text reveals, and validation requires substantive knowledge

Quantitative vs Qualitative

- For most of its history text analysis was qualitative.
- Partly still is: need to make qualitative judgements about what the text reveals, and validation requires substantive knowledge
- ‘Distant reading’ instead of ‘close reading’

Quantitative vs Qualitative

- For most of its history text analysis was qualitative.
- Partly still is: need to make qualitative judgements about what the text reveals, and validation requires substantive knowledge
- 'Distant reading' instead of 'close reading'—not focussed on interpretation in light of norms or belief systems.

Quantitative vs Qualitative

- For most of its history text analysis was qualitative.
- Partly still is: need to make qualitative judgements about what the text reveals, and validation requires substantive knowledge
- ‘Distant reading’ instead of ‘close reading’—not focussed on interpretation in light of norms or belief systems.
- Important: quantitative work is reliable and replicable (easily)

Quantitative vs Qualitative

- For most of its history text analysis was qualitative.
- Partly still is: need to make qualitative judgements about what the text reveals, and validation requires substantive knowledge
- 'Distant reading' instead of 'close reading'—not focussed on interpretation in light of norms or belief systems.
- Important: quantitative work is reliable and replicable (easily) and can cope with large volume of material.

What this class is not about. . .

What this class is not about...

What this class is not about...

- Data acquisition:

What this class is not about…

- Data acquisition: many source of text,

What this class is not about. . .

- Data acquisition: many source of text, but web-scraping better taught elsewhere.

What this class is not about...

- Data acquisition: many source of text, but web-scraping better taught elsewhere.

e.g. `http://www.crummy.com/software/BeautifulSoup/`

What this class is not about...

- Data acquisition: many source of text, but web-scraping better taught elsewhere.

e.g. `http://www.crummy.com/software/BeautifulSoup/`

- Regular expressions and basic text manipulation:

What this class is not about. . .

- Data acquisition: many source of text, but web-scraping better taught elsewhere.

e.g. `http://www.crummy.com/software/BeautifulSoup/`

- Regular expressions and basic text manipulation: won't generally be required,

What this class is not about...

- Data acquisition: many source of text, but web-scraping better taught elsewhere.

e.g. `http://www.crummy.com/software/BeautifulSoup/`

- Regular expressions and basic text manipulation: won't generally be required, though helpful if known.

What this class is not about. . .

- Data acquisition: many source of text, but web-scraping better taught elsewhere.

e.g. `http://www.crummy.com/software/BeautifulSoup/`

- Regular expressions and basic text manipulation: won't generally be required, though helpful if known.

- CS 'stuff' like machine translation, OCR, algorithm design etc.

What this class is not about...

- Data acquisition: many source of text, but web-scraping better taught elsewhere.

e.g. `http://www.crummy.com/software/BeautifulSoup/`

- Regular expressions and basic text manipulation: won't generally be required, though helpful if known.

- CS 'stuff' like machine translation, OCR, algorithm design etc.

→ excellent options elsewhere.

Software

Software

Software

https://www.r-project.org/

Software

https://www.r-project.org/

Contrary to (un)popular opinion,

Software

https://www.r-project.org/

Contrary to (un)popular opinion, R has excellent text handling/modeling capabilities.

Software

Contrary to (un)popular opinion, `R` has excellent text handling/modeling capabilities.

Free, and massive online community writing packages and extending modeling abilities.

`https://www.r-project.org/`

Software

https://www.r-project.org/

Contrary to (un)popular opinion, R has excellent text handling/modeling capabilities.

Free, and massive online community writing packages and extending modeling abilities.

We will use quanteda and other packages.

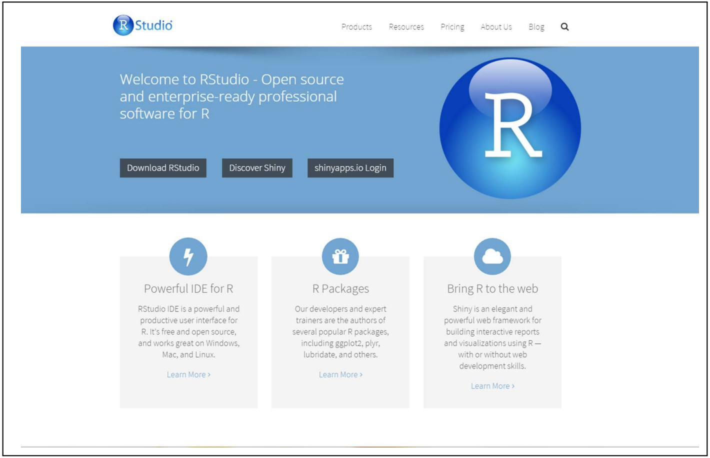
Writing R: RStudio

Writing R: RStudio

https://www.rstudio.com/

Writing R: RStudio

`https://www.rstudio.com/`



Goal of Text Analysis

Goal of Text Analysis

In many (most?) social science applications of text as data, we are trying to make an inference about a *latent variable*.

Goal of Text Analysis

In many (most?) social science applications of text as data, we are trying to make an inference about a *latent variable*.

$\rightarrow$ something which we cannot observe directly but which we can make inferences about from things we can observe.

Goal of Text Analysis

In many (most?) social science applications of text as data, we are trying to make an inference about a *latent variable*.

$\rightarrow$ something which we cannot observe directly but which we can make inferences about from things we can observe. Examples include ideology, ambition, narcissism, propensity to vote etc.

Goal of Text Analysis

In many (most?) social science applications of text as data, we are trying to make an inference about a *latent variable*.

→ something which we cannot observe directly but which we can make inferences about from things we can observe. Examples include ideology, ambition, narcissism, propensity to vote etc.

In traditional social science research, we might observe roll call votes,

Goal of Text Analysis

In many (most?) social science applications of text as data, we are trying to make an inference about a *latent variable*.

$\rightarrow$ something which we cannot observe directly but which we can make inferences about from things we can observe. Examples include ideology, ambition, narcissism, propensity to vote etc.

In traditional social science research, we might observe roll call votes, donation decisions,

Goal of Text Analysis

In many (most?) social science applications of text as data, we are trying to make an inference about a *latent variable*.

→ something which we cannot observe directly but which we can make inferences about from things we can observe. Examples include ideology, ambition, narcissism, propensity to vote etc.

In traditional social science research, we might observe roll call votes, donation decisions, responses to survey questions, etc.

Goal of Text Analysis

In many (most?) social science applications of text as data, we are trying to make an inference about a *latent variable*.

→ something which we cannot observe directly but which we can make inferences about from things we can observe. Examples include ideology, ambition, narcissism, propensity to vote etc.

In traditional social science research, we might observe roll call votes, donation decisions, responses to survey questions, etc.

Here, the thing we can observe are the words spoken, the passages written, the issues debated or whatever.

Goal of Text Analysis

In many (most?) social science applications of text as data, we are trying to make an inference about a *latent variable*.

→ something which we cannot observe directly but which we can make inferences about from things we can observe. Examples include ideology, ambition, narcissism, propensity to vote etc.

In traditional social science research, we might observe roll call votes, donation decisions, responses to survey questions, etc.

Here, the thing we can observe are the words spoken, the passages written, the issues debated or whatever.

And. . .

And. . .

And. . .

- the latent variable of interest may pertain to the. . .

And. . .

- the latent variable of interest may pertain to the. . .

author ‘what does this Senator prioritize?’,

And. . .

- the latent variable of interest may pertain to the. . .

author ‘what does this Senator prioritize?’,
‘where is this party in ideological space?’

And. . .

- the latent variable of interest may pertain to the. . .

author ‘what does this Senator prioritize?’, ‘where is this party in ideological space?’

doc ‘does this treaty represent a fair deal for American Indians?’,

And. . .

- the latent variable of interest may pertain to the. . .

author ‘what does this Senator prioritize?’, ‘where is this party in ideological space?’

doc ‘does this treaty represent a fair deal for American Indians?’, ‘how did the discussion of lasers change over time?’

And. . .

- the latent variable of interest may pertain to the. . .

author ‘what does this Senator prioritize?’, ‘where is this party in ideological space?’

doc ‘does this treaty represent a fair deal for American Indians?’, ‘how did the discussion of lasers change over time?’

both ‘how does the way Japanese politicians talk about national defence change in response to electoral system shift?’

We need to think carefully about. . .

We need to think carefully about...

- the appropriate population and sample

We need to think carefully about...

- the appropriate population and sample

→ document selection, stochastic view of text

We need to think carefully about...

- the appropriate population and sample

$\rightarrow$ document selection, stochastic view of text

- what we actually care about in the observed data, how to get at it, how to characterize it.

We need to think carefully about...

- the appropriate population and sample

$\rightarrow$ document selection, stochastic view of text

- what we actually care about in the observed data, how to get at it, how to characterize it.

$\rightarrow$ feature selection, feature representation, description

We need to think carefully about...

- the appropriate population and sample

→ document selection, stochastic view of text

- what we actually care about in the observed data, how to get at it, how to characterize it.

→ feature selection, feature representation, description

- exactly how to aggregate/mine/model the observed data—the texts with their relevant features measured/coded—that we have.

We need to think carefully about...

- the appropriate population and sample

$\rightarrow$ document selection, stochastic view of text

- what we actually care about in the observed data, how to get at it, how to characterize it.

$\rightarrow$ feature selection, feature representation, description

- exactly how to aggregate/mine/model the observed data—the texts with their relevant features measured/coded—that we have.

$\rightarrow$ statistical choices

We need to think carefully about...

- the appropriate population and sample

$\rightarrow$ document selection, stochastic view of text

- what we actually care about in the observed data, how to get at it, how to characterize it.

$\rightarrow$ feature selection, feature representation, description

- exactly how to aggregate/mine/model the observed data—the texts with their relevant features measured/coded—that we have.

$\rightarrow$ statistical choices

- what we can infer about the latent variables.

We need to think carefully about...

- the appropriate population and sample

→ document selection, stochastic view of text

- what we actually care about in the observed data, how to get at it, how to characterize it.

→ feature selection, feature representation, description

- exactly how to aggregate/mine/model the observed data—the texts with their relevant features measured/coded—that we have.

→ statistical choices

- what we can infer about the latent variables.

→ comparing, testing, validating.

In general, we will...

In general, we will...

Get Texts

In general, we will...

Get Texts

An expert hospital consultant has written to my hon. Friend...

Order. The Minister must be allowed to reply without interruption.

I am grateful to my hon. Friend for her question. I pay tribute to her work with the International Myeloma Foundation...

My constituent, Brian Jago, was fortunate enough to receive a course of Velcade, as a result of which he does not have to...

In general, we will. . .

Get Texts $\rightarrow$ Document Term Matrix

```
An expert hospital
consultant has written
to my hon. Friend…
```

```
Order. The Minister
must be allowed to
reply without
interruption.
```

```
I am grateful to my
hon. Friend for her
question. I pay tribute
to her work with the
International Myeloma
Foundation…
```

```
My constituent, Brian
Jago, was fortunate
enough to receive a
course of Velcade, as a
result of which he does
not have to…
```

In general, we will. . .

Get Texts

```
An expert hospital
consultant has written
to my hon. Friend…
```

```
Order. The Minister
must be allowed to
reply without
interruption.
```

```
I am grateful to my
hon. Friend for her
question. I pay tribute
to her work with the
International Myeloma
Foundation…
```

```
My constituent, Brian
Jago, was fortunate
enough to receive a
course of Velcade, as a
result of which he does
not have to…
```

$\rightarrow$ Document Term Matrix

$$\begin{array}{c} \\ MP_{001} \\ MP_{002} \\ \\ MP_i \\ \\ MP_{654} \\ MP_{655} \end{array} \begin{array}{c} \begin{array}{cccc} a & an & \ldots & ze \end{array} \\ \begin{pmatrix} 2 & 0 & \ldots & 1 \\ 0 & 3 & \ldots & 0 \\ \vdots & \vdots & \ldots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 2 \end{pmatrix} \end{array}$$

In general, we will. . .

Get Texts → Document Term Matrix → Operate

An expert hospital consultant has written to my hon. Friend…

Order. The Minister must be allowed to reply without interruption.

I am grateful to my hon. Friend for her question. I pay tribute to her work with the International Myeloma Foundation…

My constituent, Brian Jago, was fortunate enough to receive a course of Velcade, as a result of which he does not have to…

$$\begin{array}{c} \\ MP_{001} \\ MP_{002} \\ MP_i \\ MP_{654} \\ MP_{655} \end{array} \begin{array}{c} \begin{array}{cccc} a & an & \ldots & ze \end{array} \\ \begin{pmatrix} 2 & 0 & \ldots & 1 \\ 0 & 3 & \ldots & 0 \\ \vdots & \vdots & \ldots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 2 \end{pmatrix} \end{array}$$

In general, we will...

Get Texts → Document Term Matrix → Operate

```
An expert hospital
consultant has written
to my hon. Friend…
```

```
Order. The Minister
must be allowed to
reply without
interruption.
```

```
I am grateful to my
hon. Friend for her
question. I pay tribute
to her work with the
International Myeloma
Foundation…
```

```
My constituent, Brian
Jago, was fortunate
enough to receive a
course of Velcade, as a
result of which he does
not have to…
```

$$
\begin{array}{r}
\\ MP_{001} \\ MP_{002} \\ \\ MP_i \\ \\ MP_{654} \\ MP_{655}
\end{array}
\begin{array}{c}
\begin{array}{cccc} a & an & \dots & ze \end{array} \\
\begin{pmatrix}
2 & 0 & \dots & 1 \\
0 & 3 & \dots & 0 \\
\vdots & \vdots & \dots & \vdots \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \dots & 2
\end{pmatrix}
\end{array}
$$

- (dis)similarity
- diversity
- readability
- scale
- classify
- topic model
- burstiness
- sentiment
- ...

In general, we will...

Get Texts → Document Term Matrix → Operate → Inference

An expert hospital consultant has written to my hon. Friend…

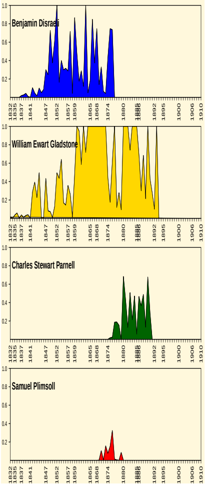
Order. The Minister must be allowed to reply without interruption.

I am grateful to my hon. Friend for her question. I pay tribute to her work with the International Myeloma Foundation…

My constituent, Brian Jago, was fortunate enough to receive a course of Velcade, as a result of which he does not have to…

$$
\begin{array}{c} \\ MP_{001} \\ MP_{002} \\ MP_i \\ MP_{654} \\ MP_{655} \end{array}
\begin{array}{c}
\begin{array}{cccc} a & an & \dots & ze \end{array} \\
\begin{pmatrix} 2 & 0 & \dots & 1 \\ 0 & 3 & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 2 \end{pmatrix}
\end{array}
$$

- (dis)similarity
- diversity
- readability
- scale
- classify
- topic model
- burstiness
- sentiment
- ...



I. Defining the Corpus

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

$\longrightarrow$ how large? if small enough to read in reasonable time, you should probably just do that.

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

→ how large? if small enough to read in reasonable time, you should probably just do that.

'structured', in the sense that you know what the documents are, where they begin and end, who authored them etc.

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

→ how large? if small enough to read in reasonable time, you should probably just do that.

‘structured’, in the sense that you know what the documents are, where they begin and end, who authored them etc.

‘unstructured data’ in sense that what is wanted (e.g. ideological position) may not be directly observable.

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

→ how large? if small enough to read in reasonable time, you should probably just do that.

'structured', in the sense that you know what the documents are, where they begin and end, who authored them etc.

'unstructured data' in sense that what is wanted (e.g. ideological position) may not be directly observable.

may be annotated in sense that metadata —data that is not part of the document itself—is available.

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

$\longrightarrow$ how large? if small enough to read in reasonable time, you should probably just do that.

- 'structured', in the sense that you know what the documents are, where they begin and end, who authored them etc.
- 'unstructured data' in sense that what is wanted (e.g. ideological position) may not be directly observable.

- may be annotated in sense that metadata —data that is not part of the document itself—is available. Examples include markup, authorship and date information, linguistic tagging (more below)

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

→ how large? if small enough to read in reasonable time, you should probably just do that.

'structured', in the sense that you know what the documents are, where they begin and end, who authored them etc.

'unstructured data' in sense that what is wanted (e.g. ideological position) may not be directly observable.

may be annotated in sense that metadata —data that is not part of the document itself—is available. Examples include markup, authorship and date information, linguistic tagging (more below)

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

→ how large? if small enough to read in reasonable time, you should probably just do that.

'structured', in the sense that you know what the documents are, where they begin and end, who authored them etc.

'unstructured data' in sense that what is wanted (e.g. ideological position) may not be directly observable.

may be annotated in sense that metadata —data that is not part of the document itself—is available. Examples include markup, authorship and date information, linguistic tagging (more below)

e.g. court transcripts,

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

→ how large? if small enough to read in reasonable time, you should probably just do that.

'structured', in the sense that you know what the documents are, where they begin and end, who authored them etc.

'unstructured data' in sense that what is wanted (e.g. ideological position) may not be directly observable.

may be annotated in sense that metadata —data that is not part of the document itself—is available. Examples include markup, authorship and date information, linguistic tagging (more below)

e.g. court transcripts, legislative records,

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

→ how large? if small enough to read in reasonable time, you should probably just do that.

'structured', in the sense that you know what the documents are, where they begin and end, who authored them etc.

'unstructured data' in sense that what is wanted (e.g. ideological position) may not be directly observable.

may be annotated in sense that metadata —data that is not part of the document itself—is available. Examples include markup, authorship and date information, linguistic tagging (more below)

e.g. court transcripts, legislative records, Twitter feeds,

I. Defining the Corpus

defn (typically) large set of texts or documents which we wish to analyze.

→ how large? if small enough to read in reasonable time, you should probably just do that.

'structured', in the sense that you know what the documents are, where they begin and end, who authored them etc.

'unstructured data' in sense that what is wanted (e.g. ideological position) may not be directly observable.

may be annotated in sense that metadata —data that is not part of the document itself—is available. Examples include markup, authorship and date information, linguistic tagging (more below)

e.g. court transcripts, legislative records, Twitter feeds, Brown Corpus etc.

Sampling

Sampling

The corpus is made up of the documents within it,

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim 1\%$ of all their tweets,

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim 1\%$ of all their tweets, but it would presumably be prohibitively expensive to store 100%.

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim 1\%$ of all their tweets, but it would presumably be prohibitively expensive to store 100%.

Often,

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim 1\%$ of all their tweets, but it would presumably be prohibitively expensive to store 100%.

Often, authors claim to have the universe of cases in their corpus: *all* press releases,

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim 1\%$ of all their tweets, but it would presumably be prohibitively expensive to store 100%.

Often, authors claim to have the universe of cases in their corpus: *all* press releases, *all* treaties,

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim 1\%$ of all their tweets, but it would presumably be prohibitively expensive to store 100%.

Often, authors claim to have the universe of cases in their corpus: *all* press releases, *all* treaties, *all* debate speeches.

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim 1\%$ of all their tweets, but it would presumably be prohibitively expensive to store 100%.

Often, authors claim to have the universe of cases in their corpus: *all* press releases, *all* treaties, *all* debate speeches.

$\longrightarrow$ depending on your philosophical position,

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim$ 1% of all their tweets, but it would presumably be prohibitively expensive to store 100%.

Often, authors claim to have the universe of cases in their corpus: *all* press releases, *all* treaties, *all* debate speeches.

$\rightarrow$ depending on your philosophical position, you still need to think about sampling error.

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim 1\%$ of all their tweets, but it would presumably be prohibitively expensive to store 100%.

Often, authors claim to have the universe of cases in their corpus: *all* press releases, *all* treaties, *all* debate speeches.

$\rightarrow$ depending on your philosophical position, you still need to think about sampling error. This is because there exists a superpopulation of populations from which the universe you observed came from.

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim 1\%$ of all their tweets, but it would presumably be prohibitively expensive to store 100%.

Often, authors claim to have the universe of cases in their corpus: *all* press releases, *all* treaties, *all* debate speeches.

$\rightarrow$ depending on your philosophical position, you still need to think about sampling error. This is because there exists a superpopulation of populations from which the universe you observed came from.

Random error may not be the only concern:

Sampling

The corpus is made up of the documents within it, but these may be a sample of the total population of documents available.

We sample for reasons of time, resources or (legal) necessity.

e.g. Twitter gives you $\sim 1\%$ of all their tweets, but it would presumably be prohibitively expensive to store 100%.

Often, authors claim to have the universe of cases in their corpus: *all* press releases, *all* treaties, *all* debate speeches.

$\longrightarrow$ depending on your philosophical position, you still need to think about sampling error. This is because there exists a superpopulation of populations from which the universe you observed came from.

Random error may not be the only concern: corpus should be representative in some well defined sense for inferences to be meaningful.

Partner Exercise

Partner Exercise

Partner Exercise

- You are consulting for a company who want to know what the world thinks of their product, a shampoo that slows balding in men.

Partner Exercise

- You are consulting for a company who want to know what the world thinks of their product, a shampoo that slows balding in men. They tell you to scrape Facebook data (timelines) as your corpus, and to analyze who is using it, and what they think of it.

Partner Exercise

- You are consulting for a company who want to know what the world thinks of their product, a shampoo that slows balding in men. They tell you to scrape Facebook data (timelines) as your corpus, and to analyze who is using it, and what they think of it.
- Excluding any technical issues with the scraping,

Partner Exercise

- You are consulting for a company who want to know what the world thinks of their product, a shampoo that slows balding in men. They tell you to scrape Facebook data (timelines) as your corpus, and to analyze who is using it, and what they think of it.
- Excluding any technical issues with the scraping, give three concerns about the validity of inferences from such a project.

II. Reducing Complexity

II. Reducing Complexity

- language is extraordinarily complex,

II. Reducing Complexity

- language is extraordinarily complex, and involves great subtlety and nuanced interpretation.

II. Reducing Complexity

- language is extraordinarily complex, and involves great subtlety and nuanced interpretation.

but remarkably, we can do very well by simplifying, and representing documents as straightforward mathematical objects.

II. Reducing Complexity

- language is extraordinarily complex, and involves great subtlety and nuanced interpretation.

but remarkably, we can do very well by simplifying, and representing documents as straightforward mathematical objects.

$\rightarrow$ makes the modeling problem much more tractable.

II. Reducing Complexity

- language is extraordinarily complex, and involves great subtlety and nuanced interpretation.

but remarkably, we can do very well by simplifying, and representing documents as straightforward mathematical objects.

$\rightarrow$ makes the modeling problem much more tractable.

by ‘do very well’, we mean that much more complicated representations add (almost) nothing to the quality of our inferences,

II. Reducing Complexity

- language is extraordinarily complex, and involves great subtlety and nuanced interpretation.

but remarkably, we can do very well by simplifying, and representing documents as straightforward mathematical objects.

$\rightarrow$ makes the modeling problem much more tractable.

by 'do very well', we mean that much more complicated representations add (almost) nothing to the quality of our inferences, our ability to predict outcomes,

II. Reducing Complexity

- language is extraordinarily complex, and involves great subtlety and nuanced interpretation.

but remarkably, we can do very well by simplifying, and representing documents as straightforward mathematical objects.

$\rightarrow$ makes the modeling problem much more tractable.

by 'do very well', we mean that much more complicated representations add (almost) nothing to the quality of our inferences, our ability to predict outcomes, and the fit of our models.

II. Reducing Complexity

- language is extraordinarily complex, and involves great subtlety and nuanced interpretation.

but remarkably, we can do very well by simplifying, and representing documents as straightforward mathematical objects.

$\rightarrow$ makes the modeling problem much more tractable.

by 'do very well', we mean that much more complicated representations add (almost) nothing to the quality of our inferences, our ability to predict outcomes, and the fit of our models.

NB inevitably, the degree to which one simplifies is dependent on the particular task at hand.

II. Reducing Complexity

- language is extraordinarily complex, and involves great subtlety and nuanced interpretation.

but remarkably, we can do very well by simplifying, and representing documents as straightforward mathematical objects.

$\rightarrow$ makes the modeling problem much more tractable.

by 'do very well', we mean that much more complicated representations add (almost) nothing to the quality of our inferences, our ability to predict outcomes, and the fit of our models.

NB inevitably, the degree to which one simplifies is dependent on the particular task at hand.

$\rightarrow$ there is no 'one best way' to go from texts to numeric data.

II. Reducing Complexity

- language is extraordinarily complex, and involves great subtlety and nuanced interpretation.

but remarkably, we can do very well by simplifying, and representing documents as straightforward mathematical objects.

→ makes the modeling problem much more tractable.

by 'do very well', we mean that much more complicated representations add (almost) nothing to the quality of our inferences, our ability to predict outcomes, and the fit of our models.

NB inevitably, the degree to which one simplifies is dependent on the particular task at hand.

→ there is no 'one best way' to go from texts to numeric data. Good idea to check sensitivity.

From Texts to Numeric Data

From Texts to Numeric Data

1. collect raw text in machine readable/electronic form. Decide what constitutes a document.

From Texts to Numeric Data

1. collect raw text in machine readable/electronic form. Decide what constitutes a document.

2. strip away 'superfluous' material: HTML tags, capitalization, punctuation, stop words etc.

From Texts to Numeric Data

1. collect raw text in machine readable/electronic form. Decide what constitutes a document.
2. strip away 'superfluous' material: HTML tags, capitalization, punctuation, stop words etc.
3. cut document up into useful elementary pieces: tokenization.

From Texts to Numeric Data

1. collect raw text in machine readable/electronic form. Decide what constitutes a document.
2. strip away 'superfluous' material: HTML tags, capitalization, punctuation, stop words etc.
3. cut document up into useful elementary pieces: tokenization.
4. add descriptive annotations that preserve context: tagging.

From Texts to Numeric Data

1. collect raw text in machine readable/electronic form. Decide what constitutes a document.
2. strip away ‘superfluous’ material: HTML tags, capitalization, punctuation, stop words etc.
3. cut document up into useful elementary pieces: tokenization.
4. add descriptive annotations that preserve context: tagging.
5. map tokens back to common form: lemmatization, stemming.

From Texts to Numeric Data

1. collect raw text in machine readable/electronic form. Decide what constitutes a document.

2. strip away ‘superfluous’ material: HTML tags, capitalization, punctuation, stop words etc.
3. cut document up into useful elementary pieces: tokenization.
4. add descriptive annotations that preserve context: tagging.
5. map tokens back to common form: lemmatization, stemming.

6. operate/model.

From Texts to Numeric Data

1. collect raw text in machine readable/electronic form. Decide what constitutes a document.

“PREPROCESSING”

6. operate/model.

‘superfluous’ material: control characters and punctuation

‘superfluous’ material: control characters and punctuation

- generally think control characters—non-printing, but cause the document to look different—like `\n`,

‘superfluous’ material: control characters and punctuation

- generally think control characters—non-printing, but cause the document to look different—like `\n`, do not connote much that is of substantive importance.

‘superfluous’ material: control characters and punctuation

- generally think control characters—non-printing, but cause the document to look different—like `\n`, do not connote much that is of substantive importance.

→ remove them.

‘superfluous’ material: control characters and punctuation

- generally think control characters—non-printing, but cause the document to look different—like `\n`, do not connote much that is of substantive importance.

→ remove them. Same for underlining or **emboldening**.

‘superfluous’ material: control characters and punctuation

- generally think control characters—non-printing, but cause the document to look different—like `\n`, do not connote much that is of substantive importance.

→ remove them. Same for underlining or **emboldening**.

- punctuation may also be unhelpful

‘superfluous’ material: control characters and punctuation

- generally think control characters—non-printing, but cause the document to look different—like `\n`, do not connote much that is of substantive importance.

→ remove them. Same for <u>underlining</u> or **emboldening**.

- punctuation may also be unhelpful

  are `wash`, `wash.`, `wash,`, `wash)` really different words?

‘superfluous’ material: control characters and punctuation

- generally think control characters—non-printing, but cause the document to look different—like `\n`, do not connote much that is of substantive importance.

→ remove them. Same for underlining or **emboldening**.

- punctuation may also be unhelpful

  are `wash`, `wash.`, `wash,`, `wash)` really different words?

→ convert everything to whitespace (?)

Well. . .

Well. . .

what to do depends on what language features you are most interested in.

Well. . .

what to do depends on what language features you are most interested in.

if the grammatical structure of sentences matters, makes sense to keep most, if not all, punctuation.

Well. . .

what to do depends on what language features you are most interested in.

if the grammatical structure of sentences matters, makes sense to keep most, if not all, punctuation.

e.g. social media:

Well. . .

what to do depends on what language features you are most interested in.

if the grammatical structure of sentences matters, makes sense to keep most, if not all, punctuation.

e.g. social media: does use of `!` differ by age group?

Well. . .

what to do depends on what language features you are most interested in.

if the grammatical structure of sentences matters, makes sense to keep most, if not all, punctuation.

e.g. social media: does use of `!` differ by age group?

but mostly just interested in coarse features (such as word frequencies); converting most punctuation to whitespace is quick and better than keeping it.

Well. . .

what to do depends on what language features you are most interested in.

if the grammatical structure of sentences matters, makes sense to keep most, if not all, punctuation.

e.g. social media: does use of `!` differ by age group?

but mostly just interested in coarse features (such as word frequencies); converting most punctuation to whitespace is quick and better than keeping it.

NB ‘dictionaries’ can be used to map contractions back to their component parts

Well. . .

what to do depends on what language features you are most interested in.

if the grammatical structure of sentences matters, makes sense to keep most, if not all, punctuation.

e.g. social media: does use of `!` differ by age group?

but mostly just interested in coarse features (such as word frequencies); converting most punctuation to whitespace is quick and better than keeping it.

NB 'dictionaries' can be used to map contractions back to their component parts

e.g. tell us that `won't` could be `will not`

Well...

what to do depends on what language features you are most interested in.

if the grammatical structure of sentences matters, makes sense to keep most, if not all, punctuation.

e.g. social media: does use of `!` differ by age group?

but mostly just interested in coarse features (such as word frequencies); converting most punctuation to whitespace is quick and better than keeping it.

NB 'dictionaries' can be used to map contractions back to their component parts

e.g. tell us that `won't` could be `will not`

but may not be as important as you think.

‘superfluous’ material: capitalization

‘superfluous’ material: capitalization

Federalist 1

`The subject speaks its own importance; comprehending in its consequences nothing less than the existence of the UNION, the safety and welfare of the parts of which it is composed, the fate of an empire in many respects the most interesting in the world.`

‘superfluous’ material: capitalization

Federalist 1

`The subject speaks its own importance; comprehending in its consequences nothing less than the existence of the UNION, the safety and welfare of the parts of which it is composed, the fate of an empire in many respects the most interesting in the world.`

is the one use of ‘`The`’ the same word as the seven uses of ‘`the`’?

‘superfluous’ material: capitalization

Federalist 1

`The subject speaks its own importance; comprehending in its consequences nothing less than the existence of the UNION, the safety and welfare of the parts of which it is composed, the fate of an empire in many respects the most interesting in the world.`

- is the one use of ‘`The`’ the same word as the seven uses of ‘`the`’?
- is ‘`UNION`’ the same word as ‘`union`’ and ‘`Union`’ as used elsewhere in this essay?

‘superfluous’ material: capitalization

Federalist 1

`The subject speaks its own importance; comprehending in its consequences nothing less than the existence of the UNION, the safety and welfare of the parts of which it is composed, the fate of an empire in many respects the most interesting in the world.`

is the one use of ‘`The`’ the same word as the seven uses of ‘`the`’?

is ‘`UNION`’ the same word as ‘`union`’ and ‘`Union`’ as used elsewhere in this essay?

yes $\rightarrow$ lowercase (uppercase) everything

'superfluous' material: capitalization

Federalist 1

```
The subject speaks its own importance; comprehending in its
consequences nothing less than the existence of the UNION, the
safety and welfare of the parts of which it is composed, the fate
of an empire in many respects the most interesting in the world.
```

- is the one use of '`The`' the same word as the seven uses of '`the`'?
- is '`UNION`' the same word as '`union`' and '`Union`' as used elsewhere in this essay?
- yes $\rightarrow$ lowercase (uppercase) everything
- or keep lists (dictionary) of proper nouns, lowercase everything else

‘superfluous’ material: capitalization

Federalist 1

`The subject speaks its own importance; comprehending in its consequences nothing less than the existence of the UNION, the safety and welfare of the parts of which it is composed, the fate of an empire in many respects the most interesting in the world.`

- is the one use of ‘`The`’ the same word as the seven uses of ‘`the`’?
- is ‘`UNION`’ the same word as ‘`union`’ and ‘`Union`’ as used elsewhere in this essay?
- yes → lowercase (uppercase) everything
- or keep lists (dictionary) of proper nouns, lowercase everything else
- or lowercase words at the beginning of a sentence (how do we know where a sentence begins?) leave everything else as is

‘superfluous’ material: capitalization

Federalist 1

`The subject speaks its own importance; comprehending in its consequences nothing less than the existence of the UNION, the safety and welfare of the parts of which it is composed, the fate of an empire in many respects the most interesting in the world.`

- is the one use of ‘`The`’ the same word as the seven uses of ‘`the`’?
- is ‘`UNION`’ the same word as ‘`union`’ and ‘`Union`’ as used elsewhere in this essay?
- yes → lowercase (uppercase) everything
- or keep lists (dictionary) of proper nouns, lowercase everything else
- or lowercase words at the beginning of a sentence (how do we know where a sentence begins?) leave everything else as is

Quick Note on Terminology

Quick Note on Terminology

a type is a unique sequence of characters that are grouped together in some meaningful way.

Quick Note on Terminology

a type is a unique sequence of characters that are grouped together in some meaningful way. Mostly a word (for us),

Quick Note on Terminology

a type is a unique sequence of characters that are grouped together in some meaningful way. Mostly a word (for us), but might also be a word plus punctuation,

Quick Note on Terminology

a type is a unique sequence of characters that are grouped together in some meaningful way. Mostly a word (for us), but might also be a word plus punctuation, or a number etc.

Quick Note on Terminology

a type is a unique sequence of characters that are grouped together in some meaningful way. Mostly a word (for us), but might also be a word plus punctuation, or a number etc.

e.g. ‘`France`’, ‘`American Revolution`’, ‘`1981`’

Quick Note on Terminology

a type is a unique sequence of characters that are grouped together in some meaningful way. Mostly a word (for us), but might also be a word plus punctuation, or a number etc.

e.g. ‘`France`’, ‘`American Revolution`’, ‘`1981`’

a token is a particular *instance* of type.

e.g. “`Dog eat dog world`”,

Quick Note on Terminology

a type is a unique sequence of characters that are grouped together in some meaningful way. Mostly a word (for us), but might also be a word plus punctuation, or a number etc.

e.g. ‘`France`’, ‘`American Revolution`’, ‘`1981`’

a token is a particular *instance* of type.

e.g. “`Dog eat dog world`”, contains three types,

Quick Note on Terminology

a type is a unique sequence of characters that are grouped together in some meaningful way. Mostly a word (for us), but might also be a word plus punctuation, or a number etc.

e.g. ‘`France`’, ‘`American Revolution`’, ‘`1981`’

a token is a particular *instance* of type.

e.g. “`Dog eat dog world`”, contains three types, but four tokens (for most purposes).

Quick Note on Terminology

a type is a unique sequence of characters that are grouped together in some meaningful way. Mostly a word (for us), but might also be a word plus punctuation, or a number etc.

e.g. ‘`France`’, ‘`American Revolution`’, ‘`1981`’

a token is a particular *instance* of type.

e.g. “`Dog eat dog world`”, contains three types, but four tokens (for most purposes).

a term is a type that is part of the system’s ‘dictionary’ (i.e. what the quantitative analysis technique recognizes as a type to be recorded etc). Could be different from the tokens, but often closely related.

Quick Note on Terminology

a type is a unique sequence of characters that are grouped together in some meaningful way. Mostly a word (for us), but might also be a word plus punctuation, or a number etc.

e.g. '`France`', '`American Revolution`', '`1981`'

a token is a particular *instance* of type.

e.g. "`Dog eat dog world`", contains three types, but four tokens (for most purposes).

a term is a type that is part of the system's 'dictionary' (i.e. what the quantitative analysis technique recognizes as a type to be recorded etc). Could be different from the tokens, but often closely related.

e.g. stemmed word like '`treasuri`', which doesn't appear in the document itself.

Tokens and tokenization

Tokens and tokenization

The text is now ‘clean’,

Tokens and tokenization

The text is now ‘clean’, and we want to pull out the meaningful subunits

Tokens and tokenization

The text is now ‘clean’, and we want to pull out the meaningful subunits—the tokens.

Tokens and tokenization

The text is now ‘clean’, and we want to pull out the meaningful subunits—the tokens. We will use a tokenizer.

Tokens and tokenization

The text is now ‘clean’, and we want to pull out the meaningful subunits—the tokens. We will use a tokenizer.

$\rightarrow$ usually the tokens are words,

Tokens and tokenization

The text is now 'clean', and we want to pull out the meaningful subunits—the tokens. We will use a tokenizer.

→ usually the tokens are words, but might include numbers or punctuation too.

Tokens and tokenization

The text is now ‘clean’, and we want to pull out the meaningful subunits—the tokens. We will use a tokenizer.

→ usually the tokens are words, but might include numbers or punctuation too.

Common rule for a tokenizer is to use whitespace as the marker.

Tokens and tokenization

The text is now ‘clean’, and we want to pull out the meaningful subunits—the tokens. We will use a tokenizer.

→ usually the tokens are words, but might include numbers or punctuation too.

Common rule for a tokenizer is to use whitespace as the marker.

but given application might require something more subtle

Tokens and tokenization

The text is now 'clean', and we want to pull out the meaningful subunits—the tokens. We will use a tokenizer.

→ usually the tokens are words, but might include numbers or punctuation too.

Common rule for a tokenizer is to use whitespace as the marker.

but given application might require something more subtle

e.g. "`Brown vs Board of Education`" may not be usefully tokenized as '`Brown`', '`vs`', '`Board`', '`of`', '`Education`'

Exceptions and Other Ideas

Exceptions and Other Ideas

In some languages,

Exceptions and Other Ideas

In some languages, tokenizing is a non-trivial problem because whitespace may not be used:

Exceptions and Other Ideas

In some languages, tokenizing is a non-trivial problem because whitespace may not be used:

问世间情是何物，直教生死相许。
天南地北双飞客，老翅几回寒暑。

Exceptions and Other Ideas

In some languages, tokenizing is a non-trivial problem because whitespace may not be used:

问世间情是何物，直教生死相许。
天南地北双飞客，老翅几回寒暑。

We may want to deal directly with multiword expressions in some contexts.

Exceptions and Other Ideas

In some languages, tokenizing is a non-trivial problem because whitespace may not be used:

问世间情是何物，直教生死相许。
天南地北双飞客，老翅几回寒暑。

We may want to deal directly with multiword expressions in some contexts.There are rules which help us identify them relatively quickly and accurately.

Exceptions and Other Ideas

In some languages, tokenizing is a non-trivial problem because whitespace may not be used:

问世间情是何物，直教生死相许。
天南地北双飞客，老翅几回寒暑。

We may want to deal directly with multiword expressions in some contexts. There are rules which help us identify them relatively quickly and accurately.

e.g. ‘`White House`’ , ‘`traffic light`’

Exceptions and Other Ideas

In some languages, tokenizing is a non-trivial problem because whitespace may not be used:

问世间情是何物，直教生死相许。
天南地北双飞客，老翅几回寒暑。

We may want to deal directly with multiword expressions in some contexts.There are rules which help us identify them relatively quickly and accurately.

e.g. ‘`White House`’ , ‘`traffic light`’

NB these words mean something ‘special’ (and slightly opaque) when combined. Related to idea of collocations: words that appear together more often than we'd predict based on random sampling.

Removing Stop Words

Removing Stop Words

There are certain words that serve as linguistic connectors (‘function words’) which we can remove.

Removing Stop Words

There are certain words that serve as linguistic connectors (‘function words’) which we can remove.

$\rightarrow$ this simplifies our document considerably, with little loss of substantive ‘content’.

Removing Stop Words

There are certain words that serve as linguistic connectors ('function words') which we can remove.

→ this simplifies our document considerably, with little loss of substantive 'content'. Indeed, search engines often ignore them.

Removing Stop Words

There are certain words that serve as linguistic connectors ('function words') which we can remove.

→ this simplifies our document considerably, with little loss of substantive 'content'. Indeed, search engines often ignore them.

There are many lists available,

Removing Stop Words

There are certain words that serve as linguistic connectors ('function words') which we can remove.

→ this simplifies our document considerably, with little loss of substantive 'content'. Indeed, search engines often ignore them.

There are many lists available, and we may add to them in an application specific way.

Removing Stop Words

There are certain words that serve as linguistic connectors ('function words') which we can remove.

→ this simplifies our document considerably, with little loss of substantive 'content'. Indeed, search engines often ignore them.

There are many lists available, and we may add to them in an application specific way.

e.g. working with Congressional speech data, '`representative`' might be a stop word; in *Hansard* data, '`honourable`' might be.

Removing Stop Words

There are certain words that serve as linguistic connectors ('function words') which we can remove.

$\rightarrow$ this simplifies our document considerably, with little loss of substantive 'content'. Indeed, search engines often ignore them.

There are many lists available, and we may add to them in an application specific way.

e.g. working with Congressional speech data, '`representative`' might be a stop word; in *Hansard* data, '`honourable`' might be.

NB in some specific applications,

Removing Stop Words

There are certain words that serve as linguistic connectors ('function words') which we can remove.

→ this simplifies our document considerably, with little loss of substantive 'content'. Indeed, search engines often ignore them.

There are many lists available, and we may add to them in an application specific way.

e.g. working with Congressional speech data, '`representative`' might be a stop word; in *Hansard* data, '`honourable`' might be.

NB in some specific applications, function word usage **is** important

Removing Stop Words

There are certain words that serve as linguistic connectors ('function words') which we can remove.

→ this simplifies our document considerably, with little loss of substantive 'content'. Indeed, search engines often ignore them.

There are many lists available, and we may add to them in an application specific way.

e.g. working with Congressional speech data, '`representative`' might be a stop word; in *Hansard* data, '`honourable`' might be.

NB in some specific applications, function word usage **is** important—we'll discuss this when we deal with authorship attribution.

Some stop words

Some stop words

a	about	above	after	again	against	all
am	an	and	any	are	aren't	as
at	be	because	been	before	being	below
between	both	but	by	can't	cannot	could
couldn't	did	didn't	do	does	doesn't	doing
don't	down	during	each	few	for	from
further	had	hadn't	has	hasn't	have	haven't
having	he	he'd	he'll	he's	her	here
here's	hers	herself	him	himself	his	how
how's	i	i'd	i'll	i'm	i've	if
in	into	is	isn't	it	it's	its
itself	let's	me	more	most	mustn't	my
myself	no	nor	not	of	off	on
once	only	or	other	ought	our	ours
ourselves	out	over	own	same	shan't	she
she'd	she'll	she's	should	shouldn't	so	some
such	than	that	that's	the	their	theirs
them	themselves	then	there	there's	these	they
they'd	they'll	they're	they've	this	those	through
to	too	under	until	up	very	was
wasn't	we	we'd	we'll	we're	we've	were
weren't	what	what's	when	when's	where	where's
which	while	who	who's	whom	why	why's
with	won't	would	wouldn't	you	you'd	you'll
you're	you've	your	yours	yourself	yourselves	

Tagging

Tagging

so far tokens are on even footing—no distinctions drawn between nouns, verbs, nouns acting as subjects, nouns acting as objects, etc.

Tagging

so far
: tokens are on even footing—no distinctions drawn between nouns, verbs, nouns acting as subjects, nouns acting as objects, etc.

and
: for many applications, this information doesn't help very much (e.g. for classification).

Tagging

so far tokens are on even footing—no distinctions drawn between nouns, verbs, nouns acting as subjects, nouns acting as objects, etc.

and for many applications, this information doesn't help very much (e.g. for classification).

but in other applications we may really want to know information about the part-of-speech this word represents

Tagging

so far tokens are on even footing—no distinctions drawn between nouns, verbs, nouns acting as subjects, nouns acting as objects, etc.

and for many applications, this information doesn't help very much (e.g. for classification).

but in other applications we may really want to know information about the part-of-speech this word represents. We want to disambiguate in what sense a term is being used.

Tagging

so far tokens are on even footing—no distinctions drawn between nouns, verbs, nouns acting as subjects, nouns acting as objects, etc.

and for many applications, this information doesn't help very much (e.g. for classification).

but in other applications we may really want to know information about the part-of-speech this word represents. We want to disambiguate in what sense a term is being used.

e.g. in 'events' studies,

Tagging

so far tokens are on even footing—no distinctions drawn between nouns, verbs, nouns acting as subjects, nouns acting as objects, etc.

and for many applications, this information doesn't help very much (e.g. for classification).

but in other applications we may really want to know information about the part-of-speech this word represents. We want to disambiguate in what sense a term is being used.

e.g. in 'events' studies, when we are recording who did what to whom: '`the UK bombing will force ISIS to surrender`'. Here `force` is a verb, not a noun.

Tagging

so far tokens are on even footing—no distinctions drawn between nouns, verbs, nouns acting as subjects, nouns acting as objects, etc.

and for many applications, this information doesn't help very much (e.g. for classification).

but in other applications we may really want to know information about the part-of-speech this word represents. We want to disambiguate in what sense a term is being used.

e.g. in 'events' studies, when we are recording who did what to whom: '`the UK bombing will force ISIS to surrender`'. Here `force` is a verb, not a noun.

$\rightarrow$ annotating in this way is called parts-of-speech tagging.

Penn POS Tagger

Penn POS Tagger

Number	Tag	Description
1.	CC	Coordinating conjunction
2.	CD	Cardinal number
3.	DT	Determiner
4.	EX	Existential *there*
5.	FW	Foreign word
6.	IN	Preposition or subordinating conjunction
7.	JJ	Adjective
8.	JJR	Adjective, comparative
9.	JJS	Adjective, superlative
10.	LS	List item marker
11.	MD	Modal
12.	NN	Noun, singular or mass
13.	NNS	Noun, plural
14.	NNP	Proper noun, singular
15.	NNPS	Proper noun, plural
16.	PDT	Predeterminer
17.	POS	Possessive ending
18.	PRP	Personal pronoun
19.	PRP$	Possessive pronoun
20.	RB	Adverb
21.	RBR	Adverb, comparative
22.	RBS	Adverb, superlative
23.	RP	Particle
24.	SYM	Symbol
25.	TO	*to*
26.	UH	Interjection
27.	VB	Verb, base form
28.	VBD	Verb, past tense
29.	VBG	Verb, gerund or present participle
30.	VBN	Verb, past participle
31.	VBP	Verb, non-3rd person singular present
32.	VBZ	Verb, 3rd person singular present
33.	WDT	Wh-determiner
34.	WP	Wh-pronoun
35.	WP$	Possessive wh-pronoun
36.	WRB	Wh-adverb

Stemming and Lemmatization

Stemming and Lemmatization

Documents may use different forms of words

Stemming and Lemmatization

Documents may use different forms of words (‘`jumped`’, ‘`jumping`’, ‘`jump`’),

Stemming and Lemmatization

Documents may use different forms of words (‘`jumped`’, ‘`jumping`’, ‘`jump`’), or words which are similar in concept (‘`bureaucratic`’, ‘`bureaucrat`’, ‘`bureaucratization`’) as if they are different tokens.

Stemming and Lemmatization

Documents may use different forms of words (‘`jumped`’, ‘`jumping`’, ‘`jump`’), or words which are similar in concept (‘`bureaucratic`’, ‘`bureaucrat`’, ‘`bureaucratization`’) as if they are different tokens.

→ we can simplify considerably by mapping these variants (back) to the same word.

Stemming and Lemmatization

Documents may use different forms of words ('`jumped`', '`jumping`', '`jump`'), or words which are similar in concept ('`bureaucratic`', '`bureaucrat`', '`bureaucratization`') as if they are different tokens.

$\rightarrow$ we can simplify considerably by mapping these variants (back) to the same word.

- Stemming does this using a crude (heuristic) which just 'chops off' the affixes. It returns a stem which might not be a dictionary word.

Stemming and Lemmatization

Documents may use different forms of words (`jumped`, `jumping`, `jump`), or words which are similar in concept (`bureaucratic`, `bureaucrat`, `bureaucratization`) as if they are different tokens.

$\rightarrow$ we can simplify considerably by mapping these variants (back) to the same word.

- Stemming does this using a crude (heuristic) which just 'chops off' the affixes. It returns a stem which might not be a dictionary word.
- Lemmatization does this using a vocabulary, parts of speech context and mapping rules. It returns a word in the dictionary: a lemma (which is a canonical form of a 'lexeme').

Stemming and Lemmatization

Documents may use different forms of words (`jumped`, `jumping`, `jump`), or words which are similar in concept (`bureaucratic`, `bureaucrat`, `bureaucratization`) as if they are different tokens.

→ we can simplify considerably by mapping these variants (back) to the same word.

- Stemming does this using a crude (heuristic) which just 'chops off' the affixes. It returns a stem which might not be a dictionary word.
- Lemmatization does this using a vocabulary, parts of speech context and mapping rules. It returns a word in the dictionary: a lemma (which is a canonical form of a 'lexeme').

e.g. depending on context, lemmatization would return `see` or `saw` if it came across `saw`.

Stemming and Lemmatization

Documents may use different forms of words ('`jumped`', '`jumping`', '`jump`'), or words which are similar in concept ('`bureaucratic`', '`bureaucrat`', '`bureaucratization`') as if they are different tokens.

→ we can simplify considerably by mapping these variants (back) to the same word.

- Stemming does this using a crude (heuristic) which just 'chops off' the affixes. It returns a stem which might not be a dictionary word.
- Lemmatization does this using a vocabulary, parts of speech context and mapping rules. It returns a word in the dictionary: a lemma (which is a canonical form of a 'lexeme').

e.g. depending on context, lemmatization would return '`see`' or '`saw`' if it came across '`saw`'.

Stemming

Stemming

Though technically incorrect,

Stemming

Though technically incorrect, ‘stemming’ and ‘lemmatization’ often used interchangeably.

Stemming

Though technically incorrect, ‘stemming’ and ‘lemmatization’ often used interchangeably.

For small examples,

Stemming

Though technically incorrect, ‘stemming’ and ‘lemmatization’ often used interchangeably.

For small examples, one can use a ‘look up’ table:

Stemming

Though technically incorrect, ‘stemming’ and ‘lemmatization’ often used interchangeably.

For small examples, one can use a ‘look up’ table: table listing what a given realization of a word should be mapped to.

Stemming

Though technically incorrect, ‘stemming’ and ‘lemmatization’ often used interchangeably.

For small examples, one can use a ‘look up’ table: table listing what a given realization of a word should be mapped to.

btw we sometimes use ‘equivalency classes’

Stemming

Though technically incorrect, 'stemming' and 'lemmatization' often used interchangeably.

For small examples, one can use a 'look up' table: table listing what a given realization of a word should be mapped to.

btw we sometimes use 'equivalency classes' meaning that an internal thesaurus maps different words back to the same type of word:

Stemming

Though technically incorrect, ‘stemming’ and ‘lemmatization’ often used interchangeably.

For small examples, one can use a ‘look up’ table: table listing what a given realization of a word should be mapped to.

btw we sometimes use ‘equivalency classes’ meaning that an internal thesaurus maps different words back to the same type of word: e.g. ‘`rightwing`’ and ‘`republican`’ to ‘`conservative`’.

Stemming

Though technically incorrect, 'stemming' and 'lemmatization' often used interchangeably.

For small examples, one can use a 'look up' table: table listing what a given realization of a word should be mapped to.

btw we sometimes use 'equivalency classes' meaning that an internal thesaurus maps different words back to the same type of word: e.g. '`rightwing`' and '`republican`' to '`conservative`'.

In practice, need something faster (and cruder), so software implements the Porter Stemmer using algorithms like `Snowball`.

Snowball examples

Snowball examples

Original Word		Stemmed Word
abolish	$\mapsto$	`abolish`
abolished	$\mapsto$	`abolish`
abolishing	$\mapsto$	`abolish`
abolition	$\mapsto$	`abolit`

Snowball examples

Original Word		Stemmed Word
abolish	$\mapsto$	`abolish`
abolished	$\mapsto$	`abolish`
abolishing	$\mapsto$	`abolish`
abolition	$\mapsto$	`abolit`
abortion	$\mapsto$	`abort`
abortions	$\mapsto$	`abort`
abortive	$\mapsto$	`abort`

Snowball examples

Original Word		Stemmed Word
abolish	$\mapsto$	abolish
abolished	$\mapsto$	abolish
abolishing	$\mapsto$	abolish
abolition	$\mapsto$	abolit
abortion	$\mapsto$	abort
abortions	$\mapsto$	abort
abortive	$\mapsto$	abort
treasure	$\mapsto$	treasure
treasured	$\mapsto$	treasure
treasures	$\mapsto$	treasure
treasuring	$\mapsto$	treasure
treasury	$\mapsto$	treasuri

NYT

Emergency measures adopted for Beijing's first ``red alert" over air pollution left millions of schoolchildren cooped up at home, forced motorists off the roads and shut down factories across the region on Tuesday, but they failed to dispel the toxic air that shrouded the Chinese capital in a soupy, metallic haze.

NYT

`Emergency measures adopted for Beijing's first ''red alert" over air pollution left millions of schoolchildren cooped up at home, forced motorists off the roads and shut down factories across the region on Tuesday, but they failed to dispel the toxic air that shrouded the Chinese capital in a soupy, metallic haze.`

marked up

Emergenc $\boxed{\texttt{y}}$ measur $\boxed{\texttt{es}}$ adopt $\boxed{\texttt{ed}}$ for Beij $\boxed{\texttt{ing}}$ s first red alert over air pollut $\boxed{\texttt{ion}}$ left million $\boxed{\texttt{s}}$ of schoolchildren coop $\boxed{\texttt{ed}}$ up at home, forc $\boxed{\texttt{ed}}$ motorist $\boxed{\texttt{s}}$ off the road $\boxed{\texttt{s}}$ and shut down factor $\boxed{\texttt{ies}}$ across the region on Tuesday, but they fail $\boxed{\texttt{ed}}$ to dispel the toxic air that shroud $\boxed{\texttt{ed}}$ the Chines $\boxed{\texttt{e}}$ capit $\boxed{\texttt{al}}$ in a soupy, metal $\boxed{\texttt{lic}}$ haze.

NYT

Emergency measures adopted for Beijing's first ''red alert" over air pollution left millions of schoolchildren cooped up at home, forced motorists off the roads and shut down factories across the region on Tuesday, but they failed to dispel the toxic air that shrouded the Chinese capital in a soupy, metallic haze.

marked up

Emergenc$\boxed{\text{y}}$ measur$\boxed{\text{es}}$ adopt$\boxed{\text{ed}}$ for Beij$\boxed{\text{ing}}$ s first red alert over air pollut$\boxed{\text{ion}}$ left million$\boxed{\text{s}}$ of schoolchildren coop$\boxed{\text{ed}}$ up at home, forc$\boxed{\text{ed}}$ motorist$\boxed{\text{s}}$ off the road$\boxed{\text{s}}$ and shut down factor$\boxed{\text{ies}}$ across the region on Tuesday, but they fail$\boxed{\text{ed}}$ to dispel the toxic air that shroud$\boxed{\text{ed}}$ the Chines$\boxed{\text{e}}$ capit$\boxed{\text{al}}$ in a soupy, metal$\boxed{\text{lic}}$ haze.

NYT

Emergency measures adopted for Beijings first red alert over air pollution left millions of schoolchildren cooped up at home, forced motorists off the roads and shut down factories across the region on Tuesday, but they failed to dispel the toxic air that shrouded the Chinese capital in a soupy, metallic haze.

Stemmed

Emergenc measur adopt for Beij s first red alert over air pollut left million of schoolchildren coop up at home forc motorist off the road and shut down factori across the region on Tuesdai but thei fail to dispel the toxic air that shroud the Chines capit in a soupi metal haze.

NYT

Emergency measures adopted for Beijings first red alert over air pollution left millions of schoolchildren cooped up at home, forced motorists off the roads and shut down factories across the region on Tuesday, but they failed to dispel the toxic air that shrouded the Chinese capital in a soupy, metallic haze.

Stemmed

Emergenc measur adopt for Beij s first red alert over air pollut left million of schoolchildren coop up at home forc motorist off the road and shut down factori across the region on Tuesdai but thei fail to dispel the toxic air that shroud the Chines capit in a soupi metal haze.

Partner Exercise

Partner Exercise

Consider these elements of a document. Suppose we change all punctuation to whitespace, de-capitalize, remove stop words, and stem what remains.

Partner Exercise

Consider these elements of a document. Suppose we change all punctuation to whitespace, de-capitalize, remove stop words, and stem what remains. What do we get?

Partner Exercise

Consider these elements of a document. Suppose we change all punctuation to whitespace, de-capitalize, remove stop words, and stem what remains. What do we get? Is the original meaning intact?

Partner Exercise

Consider these elements of a document. Suppose we change all punctuation to whitespace, de-capitalize, remove stop words, and stem what remains. What do we get? Is the original meaning intact?

1. `The mountains are beautiful in Ore. and Wash.`
2. `http://www.wsj.com/articles/son-of-saul-not-about-the-survivors-1449590175`
3. `I can’t go with him to Beijing.`

We Don't Care about Word Order

We Don't Care about Word Order

We have now pre-processed our texts.

We Don't Care about Word Order

We have now pre-processed our texts.

Generally,

We Don't Care about Word Order

We have now pre-processed our texts.

Generally, we are willing to ignore the order of the words in a document.

We Don't Care about Word Order

We have now pre-processed our texts.

Generally, we are willing to ignore the order of the words in a document. This considerably simplifies things.

We Don't Care about Word Order

We have now pre-processed our texts.

Generally, we are willing to ignore the order of the words in a document. This considerably simplifies things. And we do (almost) as well without that information as when we retain it.

We Don't Care about Word Order

We have now pre-processed our texts.

Generally, we are willing to ignore the order of the words in a document. This considerably simplifies things. And we do (almost) as well without that information as when we retain it.

NB we are treating a document as a

We Don't Care about Word Order

We have now pre-processed our texts.

Generally, we are willing to ignore the order of the words in a document. This considerably simplifies things. And we do (almost) as well without that information as when we retain it.

NB we are treating a document as a $\boxed{\text{bag-of-words}}$ (BOW).

We Don't Care about Word Order

We have now pre-processed our texts.

Generally, we are willing to ignore the order of the words in a document. This considerably simplifies things. And we do (almost) as well without that information as when we retain it.

NB we are treating a document as a $\boxed{\text{bag-of-words}}$ (BOW).

btw, we keep multiplicity—i.e. multiple uses of same token

We Don't Care about Word Order

We have now pre-processed our texts.

Generally, we are willing to ignore the order of the words in a document. This considerably simplifies things. And we do (almost) as well without that information as when we retain it.

NB we are treating a document as a $\boxed{\text{bag-of-words}}$ (BOW).

btw, we keep multiplicity—i.e. multiple uses of same token

We Don't Care about Word Order

We have now pre-processed our texts.

Generally, we are willing to ignore the order of the words in a document. This considerably simplifies things. And we do (almost) as well without that information as when we retain it.

NB we are treating a document as a $\boxed{\text{bag-of-words}}$ (BOW).

btw, we keep multiplicity—i.e. multiple uses of same token

e.g. "The leading Republican presidential candidate has said Muslims should be banned from entering the US."

We Don't Care about Word Order

We have now pre-processed our texts.

Generally, we are willing to ignore the order of the words in a document. This considerably simplifies things. And we do (almost) as well without that information as when we retain it.

NB we are treating a document as a $\boxed{\text{bag-of-words}}$ (BOW).

btw, we keep multiplicity—i.e. multiple uses of same token

e.g. "`The leading Republican presidential candidate has said Muslims should be banned from entering the US.`"

→ "`lead republican presidenti candid said muslim ban enter us`"

We Don't Care about Word Order

We have now pre-processed our texts.

Generally, we are willing to ignore the order of the words in a document. This considerably simplifies things. And we do (almost) as well without that information as when we retain it.

NB we are treating a document as a $\boxed{\text{bag-of-words}}$ (BOW).

btw, we keep multiplicity—i.e. multiple uses of same token

e.g. "The leading Republican presidential candidate has said Muslims should be banned from entering the US."

→ "lead republican presidenti candid said muslim ban enter us"

= "us lead said candid presidenti ban muslim republican enter"

Could we retain Word Order?

Could we retain Word Order?

for some applications,

Could we retain Word Order?

for some applications, we might retaining word order is very important.

Could we retain Word Order?

- for some applications, we might retaining word order is very important.
- e.g. we have a large number of multiword expressions or named entities like ‘`Bill Gates`’

Could we retain Word Order?

- for some applications, we might retaining word order is very important.
- e.g. we have a large number of multiword expressions or named entities like '`Bill Gates`'
- e.g. we think some important subtlety of expression is lost:

Could we retain Word Order?

for some applications, we might retaining word order is very important.

e.g. we have a large number of multiword expressions or named entities like '`Bill Gates`'

e.g. we think some important subtlety of expression is lost: negation perhaps—

Could we retain Word Order?

for some applications, we might retaining word order is very important.

e.g. we have a large number of multiword expressions or named entities like '`Bill Gates`'

e.g. we think some important subtlety of expression is lost: negation perhaps—"`I want coffee, not tea`"

Could we retain Word Order?

- **for** some applications, we might retaining word order is very important.
- **e.g.** we have a large number of multiword expressions or named entities like ‘`Bill Gates`’
- **e.g.** we think some important subtlety of expression is lost: negation perhaps—“`I want coffee, not tea`”might be interpreted very differently without word order.

Could we retain Word Order?

- for some applications, we might retaining word order is very important.
- e.g. we have a large number of multiword expressions or named entities like ‘`Bill Gates`’
- e.g. we think some important subtlety of expression is lost: negation perhaps—“`I want coffee, not tea`”might be interpreted very differently without word order.

→ can use *n*-grams, which are (sometimes contiguous) sequences of two (bigrams) or three (trigrams) tokens.

Could we retain Word Order?

- for some applications, we might retaining word order is very important.
- e.g. we have a large number of multiword expressions or named entities like ‘`Bill Gates`’
- e.g. we think some important subtlety of expression is lost: negation perhaps—“`I want coffee, not tea`”might be interpreted very differently without word order.

- → can use *n*-grams, which are (sometimes contiguous) sequences of two (bigrams) or three (trigrams) tokens. This makes computations considerably more complex.

Could we retain Word Order?

for some applications, we might retaining word order is very important.

e.g. we have a large number of multiword expressions or named entities like ‘`Bill Gates`’

e.g. we think some important subtlety of expression is lost: negation perhaps—“`I want coffee, not tea`”might be interpreted very differently without word order.

→ can use *n*-grams, which are (sometimes contiguous) sequences of two (bigrams) or three (trigrams) tokens. This makes computations considerably more complex.

also can use *substrings* which are groups of *n* contiguous characters.

Using String Kernels instead. . .

Using String Kernels instead...

1. `peace not war between`
2. `brothers not warfare now`
3. `be war not friendship`

documents are similar in word use terms...

Using String Kernels instead...

1. `peace not war between`
2. `brothers not warfare now`
3. `be war not friendship`

Using String Kernels instead...

1. `peace not war between`
2. `brothers not warfare now`
3. `be war not friendship`

not w,

Using String Kernels instead...

1. `peace not war between`
2. `brothers not warfare now`
3. `be war not friendship`

not w,

Using String Kernels instead...

1. `peace |not w|ar between`
2. `brothers |not w|arfare now`
3. `be war not friendship`

not w,

Using String Kernels instead...

1. peace n|ot wa|r between
2. brothers n|ot wa|rfare now
3. be war not friendship

ot wa,

Using String Kernels instead...

1. `peace no|t war|between`
2. `brothers no|t war|fare now`
3. `be war not friendship`

t war

original/some pre-processing

`a military patrol boat rescued three of the kayakers on general carrera lake and a helicopter lifted out the other three the chilean army said`

original/some pre-processing

```
a military patrol boat rescued three of the kayakers on general carrera
lake and a helicopter lifted out the other three the chilean army said
```

bigrams

```
"a military" "military patrol" "patrol boat" "boat rescued" "rescued
three" "three of" "of the" "the kayakers" "kayakers on" "on general"
"general carrera" "carrera lake" "lake and" "and a" "a helicopter"
"helicopter lifted" "lifted out" "out the" "the other" "other three"
"three the" "the chilean" "chilean army" "army said"
```

original/some pre-processing

```
a military patrol boat rescued three of the kayakers on general carrera
lake and a helicopter lifted out the other three the chilean army said
```

bigrams

```
"a military" "military patrol" "patrol boat" "boat rescued" "rescued
three" "three of" "of the" "the kayakers" "kayakers on" "on general"
"general carrera" "carrera lake" "lake and" "and a" "a helicopter"
"helicopter lifted" "lifted out" "out the" "the other" "other three"
"three the" "the chilean" "chilean army" "army said"
```

trigrams

```
"a military patrol" "military patrol boat" "patrol boat rescued" "boat
rescued three" "rescued three of" "three of the" "of the kayakers" "the
kayakers on" "kayakers on general" "on general carrera" "general carrera
lake" "carrera lake and" "lake and a" "and a helicopter" "a helicopter
lifted" "helicopter lifted out" "lifted out the" "out the other" "the
other three" "other three the" "three the chilean" "the chilean army"
"chilean army said"
```

Very similar documents may not share short n-grams

Very similar documents may not share short *n*-grams

Very similar documents may not share short *n*-grams

Denny & Spirling: Cautionary Tale

Denny & Spirling: Cautionary Tale

Political scientists often use text-as-data in an exploratory or unsupervised way.

Denny & Spirling: Cautionary Tale

Political scientists often use text-as-data in an exploratory or unsupervised way. In that world, the metric isn't really 'prediction'.

Denny & Spirling: Cautionary Tale

Political scientists often use text-as-data in an exploratory or unsupervised way. In that world, the metric isn't really 'prediction'. Yet most advice about pre-processing comes from the supervised literature.

Denny & Spirling: Cautionary Tale

Political scientists often use text-as-data in an exploratory or unsupervised way. In that world, the metric isn't really 'prediction'. Yet most advice about pre-processing comes from the supervised literature.

so generally hope that our inferences are pretty much the same substantively, regardless of the (common) pre-processing steps we take.

Denny & Spirling: Cautionary Tale

Political scientists often use text-as-data in an exploratory or unsupervised way. In that world, the metric isn't really 'prediction'. Yet most advice about pre-processing comes from the supervised literature.

so generally hope that our inferences are pretty much the same substantively, regardless of the (common) pre-processing steps we take.

Well is that true?

Denny & Spirling: Cautionary Tale

Political scientists often use text-as-data in an exploratory or unsupervised way. In that world, the metric isn't really 'prediction'. Yet most advice about pre-processing comes from the supervised literature.

so generally hope that our inferences are pretty much the same substantively, regardless of the (common) pre-processing steps we take.

Well is that true? Rarely (never) checked . . . and maybe not.

Denny & Spirling: Cautionary Tale

Political scientists often use text-as-data in an exploratory or unsupervised way. In that world, the metric isn't really 'prediction'. Yet most advice about pre-processing comes from the supervised literature.

so generally hope that our inferences are pretty much the same substantively, regardless of the (common) pre-processing steps we take.

Well is that true? Rarely (never) checked ... and maybe not.

Denny & Spirling look at (Wordfish) scaling of four sets of UK election manifestos (1983, 1987, 1992, 1997).

Hmm...

Hmm. . .

If preprocessing makes no difference to ‘results’, it shouldn’t matter which we do—punctuation, numbers, lowercase, stem, stops, infrequent terms, *n*-grams—in terms of manifesto estimated to be most left (or right).

Hmm. . .

If preprocessing makes no difference to ‘results’, it shouldn’t matter which we do—punctuation, numbers, lowercase, stem, stops, infrequent terms, *n*-grams—in terms of manifesto estimated to be most left (or right).

P	N	L	M	S	I	G	Most Left	Most Right

Hmm. . .

If preprocessing makes no difference to 'results', it shouldn't matter which we do—punctuation, numbers, lowercase, stem, stops, infrequent terms, *n*-grams—in terms of manifesto estimated to be most left (or right).

P	N	L	M	S	I	G	Most Left	Most Right
T	T	T	T	T	T	T	Lab 1983	Con 1997
T	T	F	F	T	T	T	Lab 1983	Con 1983
F	T	F	F	F	T	T	Lab 1992	Con 1992

Hmm...

If preprocessing makes no difference to 'results', it shouldn't matter which we do—punctuation, numbers, lowercase, stem, stops, infrequent terms, *n*-grams—in terms of manifesto estimated to be most left (or right).

P	N	L	M	S	I	G	Most Left	Most Right
T	T	T	T	T	T	T	Lab 1983	Con 1997
T	T	F	F	T	T	T	Lab 1983	Con 1983
F	T	F	F	F	T	T	Lab 1992	Con 1992
F	F	T	T	T	F	T	Lab 1997	Con 1987

Hmm...

If preprocessing makes no difference to 'results', it shouldn't matter which we do—punctuation, numbers, lowercase, stem, stops, infrequent terms, *n*-grams—in terms of manifesto estimated to be most left (or right).

P	N	L	M	S	I	G	Most Left	Most Right
T	T	T	T	T	T	T	Lab 1983	Con 1997
T	T	F	F	T	T	T	Lab 1983	Con 1983
F	T	F	F	F	T	T	Lab 1992	Con 1992
F	F	T	T	T	F	T	Lab 1997	Con 1987

$\rightarrow$ more variance than we would like!

III. Vector Space Model

III. Vector Space Model

We can think about a document as being a collection of W features (tokens, words etc)

We can think about a document as being a collection of W features (tokens, words etc)

if each feature can be placed on the real line,

III. Vector Space Model

We can think about a document as being a collection of W features (tokens, words etc)

if each feature can be placed on the real line, then the document can be thought of as a point $\mathbb{R}^W$.

III. Vector Space Model

We can think about a document as being a collection of W features (tokens, words etc)

if each feature can be placed on the real line, then the document can be thought of as a point $\mathbb{R}^W$.

e.g. "`Bob goes home`" can be thought of a vector in 3 dimensions:

III. Vector Space Model

We can think about a document as being a collection of W features (tokens, words etc)

if each feature can be placed on the real line, then the document can be thought of as a point $\mathbb{R}^W$.

e.g. "`Bob goes home`" can be thought of a vector in 3 dimensions: one corresponds to how '`Bob`'-ish it is, one corresponds to how '`goes`'-ish it is, one corresponds to how '`home`'-ish it is.

III. Vector Space Model

We can think about a document as being a collection of W features (tokens, words etc)

if each feature can be placed on the real line, then the document can be thought of as a point $\mathbb{R}^W$.

e.g. "`Bob goes home`" can be thought of a vector in 3 dimensions: one corresponds to how '`Bob`'-ish it is, one corresponds to how '`goes`'-ish it is, one corresponds to how '`home`'-ish it is.

Features will typically be the *n*-gram (mostly unigram) frequencies of the tokens in the document,

III. Vector Space Model

We can think about a document as being a collection of W features (tokens, words etc)

if each feature can be placed on the real line, then the document can be thought of as a point $\mathbb{R}^W$.

e.g. "`Bob goes home`" can be thought of a vector in 3 dimensions: one corresponds to how '`Bob`'-ish it is, one corresponds to how '`goes`'-ish it is, one corresponds to how '`home`'-ish it is.

Features will typically be the *n*-gram (mostly unigram) frequencies of the tokens in the document, or some function of those frequencies.

III. Vector Space Model

We can think about a document as being a collection of W features (tokens, words etc)

if each feature can be placed on the real line, then the document can be thought of as a point $\mathbb{R}^W$.

e.g. "`Bob goes home`" can be thought of a vector in 3 dimensions: one corresponds to how '`Bob`'-ish it is, one corresponds to how '`goes`'-ish it is, one corresponds to how '`home`'-ish it is.

Features will typically be the *n*-gram (mostly unigram) frequencies of the tokens in the document, or some function of those frequencies.

e.g. '`the cat sat on the mat`' becomes `(2,1,1,1,1)`

III. Vector Space Model

We can think about a document as being a collection of W features (tokens, words etc)

if each feature can be placed on the real line, then the document can be thought of as a point $\mathbb{R}^W$.

e.g. "`Bob goes home`" can be thought of a vector in 3 dimensions: one corresponds to how '`Bob`'-ish it is, one corresponds to how '`goes`'-ish it is, one corresponds to how '`home`'-ish it is.

Features will typically be the *n*-gram (mostly unigram) frequencies of the tokens in the document, or some function of those frequencies.

e.g. '`the cat sat on the mat`' becomes `(2,1,1,1,1)` if we define the dimensions as `(the, cat, sat, on, mat)` and use simple counts.

Notation and Terminology

Notation and Terminology

$d = 1, \ldots, D$ indexes documents in the corpus

Notation and Terminology

$d = 1, \ldots, D$ indexes documents in the corpus

$w = 1, \ldots, W$ indexes features found in documents

Notation and Terminology

$d = 1, \ldots, D$ indexes documents in the corpus

$w = 1, \ldots, W$ indexes features found in documents

$\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d in a particular feature space

Notation and Terminology

$d = 1, \ldots, D$ indexes documents in the corpus

$w = 1, \ldots, W$ indexes features found in documents

$\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d in a particular feature space

so each document is now a vector,

Notation and Terminology

$d = 1, \ldots, D$ indexes documents in the corpus

$w = 1, \ldots, W$ indexes features found in documents

$\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d in a particular feature space

so each document is now a vector, with each entry representing the frequency of a particular token or feature...

Notation and Terminology

$d = 1, \ldots, D$ indexes documents in the corpus

$w = 1, \ldots, W$ indexes features found in documents

$\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d in a particular feature space

so each document is now a vector, with each entry representing the frequency of a particular token or feature...

$\rightarrow$ stacking those vectors on top of each other gives the document term matrix (DTM) or the document feature matrix (DFM).

Notation and Terminology

$d = 1, \ldots, D$ indexes documents in the corpus

$w = 1, \ldots, W$ indexes features found in documents

$\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d in a particular feature space

so each document is now a vector, with each entry representing the frequency of a particular token or feature...

$\rightarrow$ stacking those vectors on top of each other gives the document term matrix (DTM) or the document feature matrix (DFM).

$\rightarrow$ taking the transpose of the DTM gives the term document matrix (TDM) or feature document matrix (FDM).

Notation and Terminology

$d = 1, \ldots, D$ indexes documents in the corpus

$w = 1, \ldots, W$ indexes features found in documents

$\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d in a particular feature space

so each document is now a vector, with each entry representing the frequency of a particular token or feature...

$\rightarrow$ stacking those vectors on top of each other gives the document term matrix (DTM) or the document feature matrix (DFM).

$\rightarrow$ taking the transpose of the DTM gives the term document matrix (TDM) or feature document matrix (FDM).

partial DTM from Roosevelt's Inaugural Addresses

partial DTM from Roosevelt's Inaugural Addresses

```
                 features
docs              american expect induct presid will
  1933-Roosevelt         2      1      1      1   12
  1937-Roosevelt         4      0      0      2   16
  1941-Roosevelt         4      0      0      1    4
  1945-Roosevelt         1      0      0      1    7
```

partial TDM from Roosevelt's Inaugural Addresses

partial TDM from Roosevelt's Inaugural Addresses

```
            docs
features     1933-Roosevelt 1937-Roosevelt 1941-Roosevelt 1945-Roosevelt
  american                2              4              4              1
  expect                  1              0              0              0
  induct                  1              0              0              0
  presid                  1              2              1              1
  will                   12             16              4              7
```

IV. Weighting

IV. Weighting

To this point,

IV. Weighting

To this point, we have been constructing the document vectors as counts.

IV. Weighting

To this point, we have been constructing the document vectors as counts. More formally, this is term frequency, since it simply records the number of occurrences of a given term.

IV. Weighting

To this point, we have been constructing the document vectors as counts. More formally, this is term frequency, since it simply records the number of occurrences of a given term.

but this implies that all words are of ‘equal importance’.

IV. Weighting

To this point, we have been constructing the document vectors as counts. More formally, this is term frequency, since it simply records the number of occurrences of a given term.

but this implies that all words are of 'equal importance'. This is a problem in some domains

IV. Weighting

To this point, we have been constructing the document vectors as counts. More formally, this is term frequency, since it simply records the number of occurrences of a given term.

but this implies that all words are of 'equal importance'. This is a problem in some domains

e.g. almost every article in political science will mention 'politics',

IV. Weighting

To this point, we have been constructing the document vectors as counts. More formally, this is term frequency, since it simply records the number of occurrences of a given term.

but this implies that all words are of 'equal importance'. This is a problem in some domains

e.g. almost every article in political science will mention 'politics', but that suggests they are all more similar than they really are (and makes it hard to find 'different' ones).

IV. Weighting

To this point, we have been constructing the document vectors as counts. More formally, this is term frequency, since it simply records the number of occurrences of a given term.

but this implies that all words are of 'equal importance'. This is a problem in some domains

e.g. almost every article in political science will mention 'politics', but that suggests they are all more similar than they really are (and makes it hard to find 'different' ones).

so we may want to do something that throws certain feature relationships into starker relief.

IV. Weighting

To this point, we have been constructing the document vectors as counts. More formally, this is term frequency, since it simply records the number of occurrences of a given term.

but this implies that all words are of 'equal importance'. This is a problem in some domains

e.g. almost every article in political science will mention 'politics', but that suggests they are all more similar than they really are (and makes it hard to find 'different' ones).

so we may want to do something that throws certain feature relationships into starker relief.

along with term frequency, we may want to consider document frequency: the number of documents in which this word appears.

Introducing tf-idf

Introducing tf-idf

- tf_{dw}, term frequency: number of times word w appears in document d

Introducing tf-idf

- tf_{dw}, term frequency: number of times word w appears in document d
- df_w, document frequency: number of documents in the collection of documents that contain word w

Introducing tf-idf

- tf_{dw}, term frequency: number of times word w appears in document d
- df_w, document frequency: number of documents in the collection of documents that contain word w

Introducing tf-idf

- tf_{dw}, term frequency: number of times word w appears in document d
- df_w, document frequency: number of documents in the collection of documents that contain word w

- $\ln \frac{|D|}{df_w}$, inverse document frequency: (natural) log of the total size of the corpus $|D|$ divided by the number of documents in the collection of documents that contain word w.

Introducing tf-idf

- tf_{dw}, term frequency: number of times word w appears in document d
- df_w, document frequency: number of documents in the collection of documents that contain word w

- $\ln \frac{|D|}{df_w}$, inverse document frequency: (natural) log of the total size of the corpus $|D|$ divided by the number of documents in the collection of documents that contain word w. When the word is common in the corpus,

Introducing tf-idf

- tf_{dw}, term frequency: number of times word w appears in document d
- df_w, document frequency: number of documents in the collection of documents that contain word w

- $\ln \frac{|D|}{df_w}$, inverse document frequency: (natural) log of the total size of the corpus $|D|$ divided by the number of documents in the collection of documents that contain word w. When the word is common in the corpus, this will be a small number. When the word is rare,

Introducing tf-idf

- tf_{dw}, term frequency: number of times word w appears in document d
- df_w, document frequency: number of documents in the collection of documents that contain word w

- $\ln \frac{|D|}{df_w}$, inverse document frequency: (natural) log of the total size of the corpus $|D|$ divided by the number of documents in the collection of documents that contain word w. When the word is common in the corpus, this will be a small number. When the word is rare, this will be a large number.

Introducing tf-idf

- tf_{dw}, term frequency: number of times word w appears in document d
- df_w, document frequency: number of documents in the collection of documents that contain word w

- $\ln \frac{|D|}{df_w}$, inverse document frequency: (natural) log of the total size of the corpus $|D|$ divided by the number of documents in the collection of documents that contain word w. When the word is common in the corpus, this will be a small number. When the word is rare, this will be a large number.

$\boxed{tf_{dw} \cdot \ln \frac{|D|}{df_w}}$, term frequency-inverse document frequency: tf-idf.

Introducing tf-idf

- tf_{dw}, term frequency: number of times word w appears in document d
- df_w, document frequency: number of documents in the collection of documents that contain word w

- $\ln \frac{|D|}{df_w}$, inverse document frequency: (natural) log of the total size of the corpus $|D|$ divided by the number of documents in the collection of documents that contain word w. When the word is common in the corpus, this will be a small number. When the word is rare, this will be a large number.

$\boxed{tf_{dw} \cdot \ln \frac{|D|}{df_w}\text{, term frequency-inverse document frequency: tf-idf.}}$

tf-idf

$\boxed{tf_{dw} \cdot \ln \frac{|D|}{df_w}\text{, term frequency-inverse document frequency: tf-idf.}}$

tf-idf

$$\boxed{tf_{dw} \cdot \ln \frac{|D|}{df_w}, \text{ term frequency-inverse document frequency: tf-idf.}}$$

$\rightarrow$ when a word is common in a given document, but rare in the corpus as whole,

tf-idf

$\boxed{tf_{dw} \cdot \ln \frac{|D|}{df_w}\text{, term frequency-inverse document frequency: tf-idf.}}$

$\rightarrow$ when a word is common in a given document, but rare in the corpus as whole, this means tf is high and idf is high. So presence of that word is indicative of difference, and it is weighted up.

tf-idf

$\boxed{tf_{dw} \cdot \ln \frac{|D|}{df_w}\text{, term frequency-inverse document frequency: tf-idf.}}$

→ when a word is common in a given document, but rare in the corpus as whole, this means tf is high and idf is high. So presence of that word is indicative of difference, and it is weighted up.

but if word is common in a given document, and common in the corpus, tf is high, but idf are low. So term is weighted down, and filtered out.

tf-idf

$\boxed{tf_{dw} \cdot \ln \frac{|D|}{df_w}\text{, term frequency-inverse document frequency: tf-idf.}}$

$\rightarrow$ when a word is common in a given document, but rare in the corpus as whole, this means tf is high and idf is high. So presence of that word is indicative of difference, and it is weighted up.

but if word is common in a given document, and common in the corpus, tf is high, but idf are low. So term is weighted down, and filtered out.

and very low for words occurring in every document:

tf-idf

$$\boxed{tf_{dw} \cdot \ln \frac{|D|}{df_w}, \text{ term frequency-inverse document frequency: tf-idf.}}$$

$\rightarrow$ when a word is common in a given document, but rare in the corpus as whole, this means tf is high and idf is high. So presence of that word is indicative of difference, and it is weighted up.

but if word is common in a given document, and common in the corpus, tf is high, but idf are low. So term is weighted down, and filtered out.

and very low for words occurring in every document: least discriminative words.

Example: FDR corpus

Example: FDR corpus

FDR used ‘`will`’ 12 times in his 1933 speech.

Example: FDR corpus

FDR used '`will`' 12 times in his 1933 speech. So, $tf = 12$.

Example: FDR corpus

FDR used ‘`will`’ 12 times in his 1933 speech. So, $tf = 12$.

and in his 4 speeches (our corpus),

Example: FDR corpus

FDR used '`will`' 12 times in his 1933 speech. So, $tf = 12$.

and in his 4 speeches (our corpus), he used it (at least once) in *every* speech. So, $|D| = 4$ and $df = 4$

Example: FDR corpus

FDR used '`will`' 12 times in his 1933 speech. So, $tf = 12$.

and in his 4 speeches (our corpus), he used it (at least once) in *every* speech. So, $|D| = 4$ and $df = 4$

so the *idf* is $\ln \frac{|D|}{df} = \ln\left(\frac{4}{4}\right)$

Example: FDR corpus

FDR used '`will`' 12 times in his 1933 speech. So, $tf = 12$.

and in his 4 speeches (our corpus), he used it (at least once) in *every* speech. So, $|D| = 4$ and $df = 4$

so the *idf* is $\ln \frac{|D|}{df} = \ln\left(\frac{4}{4}\right) = 0$

Example: FDR corpus

FDR used '`will`' 12 times in his 1933 speech. So, tf=12.

and in his 4 speeches (our corpus), he used it (at least once) in *every* speech. So, $|D| = 4$ and $df = 4$

so the idf is $\ln \frac{|D|}{df} = \ln \left(\frac{4}{4}\right) = 0$

$\rightarrow$ tf-idf=0 for '`will`' in 1933.

Example: FDR corpus

FDR used '`will`' 12 times in his 1933 speech. So, tf=12.

and in his 4 speeches (our corpus), he used it (at least once) in *every* speech. So, $|D| = 4$ and $df = 4$

so the *idf* is $\ln \frac{|D|}{df} = \ln\left(\frac{4}{4}\right) = 0$

$\rightarrow$ tf-idf=0 for '`will`' in 1933.

but he used '`expect`' once in 1933, and he didn't use it any other speech.

Example: FDR corpus

FDR used '`will`' 12 times in his 1933 speech. So, $tf = 12$.

and in his 4 speeches (our corpus), he used it (at least once) in *every* speech. So, $|D| = 4$ and $df = 4$

so the *idf* is $\ln \frac{|D|}{df} = \ln \left(\frac{4}{4}\right) = 0$

$\rightarrow$ tf-idf=0 for '`will`' in 1933.

but he used '`expect`' once in 1933, and he didn't use it any other speech.

so *idf* is $\ln \frac{|D|}{df} = \ln \left(\frac{4}{1}\right)$

Example: FDR corpus

FDR used '`will`' 12 times in his 1933 speech. So, tf=12.

and in his 4 speeches (our corpus), he used it (at least once) in *every* speech. So, $|D| = 4$ and $df = 4$

so the *idf* is $\ln \frac{|D|}{df} = \ln\left(\frac{4}{4}\right) = 0$

$\rightarrow$ tf-idf=0 for '`will`' in 1933.

but he used '`expect`' once in 1933, and he didn't use it any other speech.

so *idf* is $\ln \frac{|D|}{df} = \ln\left(\frac{4}{1}\right) = 1.38$

Example: FDR corpus

FDR used '`will`' 12 times in his 1933 speech. So, $tf = 12$.

and in his 4 speeches (our corpus), he used it (at least once) in *every* speech. So, $|D| = 4$ and $df = 4$

so the *idf* is $\ln \frac{|D|}{df} = \ln\left(\frac{4}{4}\right) = 0$

$\rightarrow$ tf-idf=0 for '`will`' in 1933.

but he used '`expect`' once in 1933, and he didn't use it any other speech.

so *idf* is $\ln \frac{|D|}{df} = \ln\left(\frac{4}{1}\right) = 1.38$

$\rightarrow$ tf-idf=1.38 for '`expect`' in 1933.

Example: FDR corpus

FDR used '`will`' 12 times in his 1933 speech. So, tf=12.

and in his 4 speeches (our corpus), he used it (at least once) in *every* speech. So, $|D| = 4$ and $df = 4$

so the *idf* is $\ln \frac{|D|}{df} = \ln\left(\frac{4}{4}\right) = 0$

$\rightarrow$ tf-idf=0 for '`will`' in 1933.

but he used '`expect`' once in 1933, and he didn't use it any other speech.

so *idf* is $\ln \frac{|D|}{df} = \ln\left(\frac{4}{1}\right) = 1.38$

$\rightarrow$ tf-idf=1.38 for '`expect`' in 1933.

$\rightarrow$ '`expect`' helps us discriminate better than '`will`'.

Animals at the Zoo

Animals at the Zoo

Term frequency		Document frequency	
n (natural)	$\text{tf}_{t,d}$	n (no)	1
l (logarithm)	$1 + \log(\text{tf}_{t,d})$	t (idf)	$\log \frac{N}{\text{df}_t}$
a (augmented)	$0.5 + \frac{0.5 \times \text{tf}_{t,d}}{\max_t(\text{tf}_{t,d})}$	p (prob idf)	$\max\{0, \log \frac{N - \text{df}_t}{\text{df}_t}\}$
b (boolean)	$\begin{cases} 1 & \text{if } \text{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$		
L (log ave)	$\frac{1+\log(\text{tf}_{t,d})}{1+\log(\text{ave}_{t \in d}(\text{tf}_{t,d}))}$		

Notes on a DTM

Notes on a DTM

the way we construct the DTM—

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

→ in some cases, we won't need a DTM at all.

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

$\rightarrow$ in some cases, we won't need a DTM at all.

NB DTM tends to be sparse

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

$\rightarrow$ in some cases, we won't need a DTM at all.

NB DTM tends to be sparse: contains lots of (mostly) zeros.

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

→ in some cases, we won't need a DTM at all.

NB DTM tends to be sparse: contains lots of (mostly) zeros.

- partly a consequence of language itself:

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

→ in some cases, we won't need a DTM at all.

NB DTM tends to be sparse: contains lots of (mostly) zeros.

- partly a consequence of language itself: people say things in idiosyncratic ways.

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

→ in some cases, we won't need a DTM at all.

NB DTM tends to be sparse: contains lots of (mostly) zeros.

- partly a consequence of language itself: people say things in idiosyncratic ways.
- partly a consequence of reweighting:

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

$\rightarrow$ in some cases, we won't need a DTM at all.

NB DTM tends to be sparse: contains lots of (mostly) zeros.

- partly a consequence of language itself: people say things in idiosyncratic ways.
- partly a consequence of reweighting: taking log(1).

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

$\rightarrow$ in some cases, we won't need a DTM at all.

NB DTM tends to be sparse: contains lots of (mostly) zeros.

- partly a consequence of language itself: people say things in idiosyncratic ways.
- partly a consequence of reweighting: taking log(1).

in some applications,

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

→ in some cases, we won't need a DTM at all.

NB DTM tends to be sparse: contains lots of (mostly) zeros.

- partly a consequence of language itself: people say things in idiosyncratic ways.
- partly a consequence of reweighting: taking log(1).

in some applications, we might remove sparse terms

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

→ in some cases, we won't need a DTM at all.

NB DTM tends to be sparse: contains lots of (mostly) zeros.

- partly a consequence of language itself: people say things in idiosyncratic ways.
- partly a consequence of reweighting: taking log(1).

in some applications, we might remove sparse terms—tokens that occur in very few docs.

Notes on a DTM

the way we construct the DTM—including order/nature of pre-processing—is application specific.

→ in some cases, we won't need a DTM at all.

NB DTM tends to be sparse: contains lots of (mostly) zeros.

- partly a consequence of language itself: people say things in idiosyncratic ways.
- partly a consequence of reweighting: taking log(1).

in some applications, we might remove sparse terms—tokens that occur in very few docs.

NB there are efficient ways to store and manipulate sparse matrices.

Partner Exercise

Partner Exercise

- Why do we log the idf part in tf-idf?

Partner Exercise

- Why do we log the idf part in tf-idf? (hint: think about how we'd like idf to react to very rare vs fairly rare words)

Partner Exercise

- Why do we log the idf part in tf-idf? (hint: think about how we'd like idf to react to very rare vs fairly rare words)
- Does the base of the logarithm matter?

Partner Exercise

- Why do we log the idf part in tf-idf? (hint: think about how we'd like idf to react to very rare vs fairly rare words)
- Does the base of the logarithm matter?
- Consider comparing two novels from Tolstoy in terms of the common (weighted) terms they contain. Now consider comparing two tweets.

Partner Exercise

- Why do we log the idf part in tf-idf? (hint: think about how we'd like idf to react to very rare vs fairly rare words)
- Does the base of the logarithm matter?
- Consider comparing two novels from Tolstoy in terms of the common (weighted) terms they contain. Now consider comparing two tweets. Which set of documents will, on average, have more elements in common?

Partner Exercise

- Why do we log the idf part in tf-idf? (hint: think about how we'd like idf to react to very rare vs fairly rare words)
- Does the base of the logarithm matter?
- Consider comparing two novels from Tolstoy in terms of the common (weighted) terms they contain. Now consider comparing two tweets. Which set of documents will, on average, have more elements in common? Why?

Partner Exercise

- Why do we log the idf part in tf-idf? (hint: think about how we'd like idf to react to very rare vs fairly rare words)
- Does the base of the logarithm matter?
- Consider comparing two novels from Tolstoy in terms of the common (weighted) terms they contain. Now consider comparing two tweets. Which set of documents will, on average, have more elements in common? Why? What should we do about this?

Partner Exercise

- Why do we log the idf part in tf-idf? (hint: think about how we'd like idf to react to very rare vs fairly rare words)
- Does the base of the logarithm matter?
- Consider comparing two novels from Tolstoy in terms of the common (weighted) terms they contain. Now consider comparing two tweets. Which set of documents will, on average, have more elements in common? Why? What should we do about this?