

# 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*.

- 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*.

- 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*.

- 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**  
→ 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**
  - 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**

# 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**
  - 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**



# 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.

# 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

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...

## → Document Term Matrix

# 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...

## → Document Term Matrix

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

# 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...

## → Document Term Matrix

## → Operate

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



# 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...

## → Document Term Matrix

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

## → Operate

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

# 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...

## → Document Term Matrix

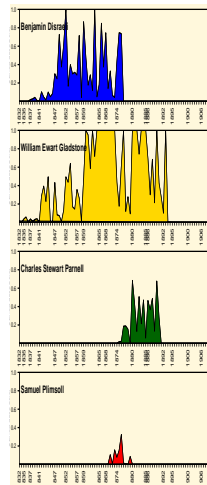
$$\begin{array}{l} MP_{001} \\ MP_{002} \\ MP_i \\ MP_{654} \\ MP_{655} \end{array} \begin{pmatrix} a & an & \dots & ze \\ 2 & 0 & \dots & 1 \\ 0 & 3 & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 2 \end{pmatrix}$$

## → Operate

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

...

## → Inference



# 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.

→ 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.

→ 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.

→ 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.

→ 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.

→ 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.

→ 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.

→ 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.

## 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.

→ 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.

→ 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.

→ 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.

→ 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.

→ 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.

→ 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.

## 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 **boldening**.

# '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 **boldening**.
- **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 underlining or **boldening**.
- **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 **boldening**.
- **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 → 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 → 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.



# 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**.

→ 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.

→ 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.

→ 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.
- annotating in this way is called parts-of-speech tagging.

# Penn POS Tagger

# Penn POS Tagger

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

- 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.

→ 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'.

# 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	↦	abolish
abolished	↦	abolish
abolishing	↦	abolish
abolition	↦	abolit
abortion	↦	abort
abortions	↦	abort
abortive	↦	abort
treasure	↦	treasure
treasured	↦	treasure
treasures	↦	treasure
treasuring	↦	treasure
treasury	↦	treasuri

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

## 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 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.

## 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.

# 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 **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 **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 **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 **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 **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 **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.

*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



The screenshot shows a Google search interface. The search bar contains the text "is obama a citizen of kenya". Below the search bar, the "All" tab is selected. The search results show "About 1,180,000 results (0.75 seconds)". The first result is titled "Obama's Kenyan Citizenship? - FactCheck.org" and includes a URL: [www.factcheck.org/2008/08/obamas-kenyan-citizenship/](http://www.factcheck.org/2008/08/obamas-kenyan-citizenship/). The snippet below the title reads: "Aug 29, 2008 - Q: Does Barack Obama have Kenyan citizenship? A: No. He held both U.S. and Kenyan citizenship as a child, but lost his Kenyan citizenship ...". At the bottom of the page, there are navigation icons for back, forward, and other search functions.

Google

is obama a citizen of kenya

All News Images Videos Shopping More Search tools

About 1,180,000 results (0.75 seconds)

**Obama's Kenyan Citizenship? - FactCheck.org**  
[www.factcheck.org/2008/08/obamas-kenyan-citizenship/](http://www.factcheck.org/2008/08/obamas-kenyan-citizenship/) FactCheck.org  
Aug 29, 2008 - Q: Does Barack Obama have Kenyan citizenship? A: No. He held both U.S. and Kenyan citizenship as a child, but lost his Kenyan citizenship ...

# Very similar documents may not share short $n$ -grams



Google

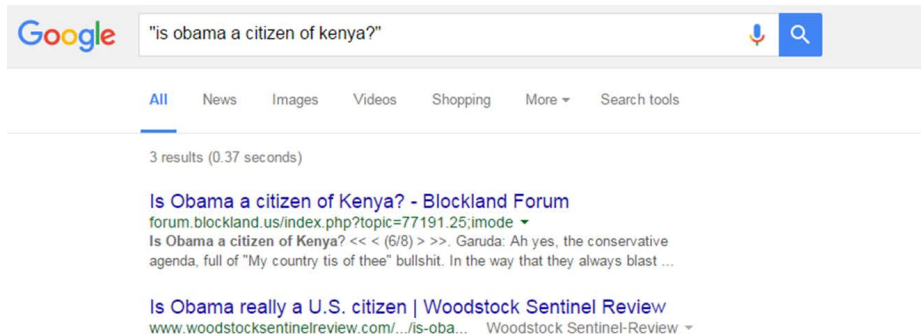
is obama a citizen of kenya

All News Images Videos Shopping More Search tools

About 1,180,000 results (0.75 seconds)

**Obama's Kenyan Citizenship? - FactCheck.org**  
[www.factcheck.org/2008/08/obamas-kenyan-citizenship/](http://www.factcheck.org/2008/08/obamas-kenyan-citizenship/) FactCheck.org  
Aug 29, 2008 - Q: Does Barack Obama have Kenyan citizenship? A: No. He held both U.S. and Kenyan citizenship as a child, but lost his Kenyan citizenship ...

This screenshot shows a Google search for "is obama a citizen of kenya". The search bar contains the text "is obama a citizen of kenya". Below the search bar, the "All" tab is selected. The results show approximately 1,180,000 results in 0.75 seconds. The top result is titled "Obama's Kenyan Citizenship? - FactCheck.org" with a green URL "www.factcheck.org/2008/08/obamas-kenyan-citizenship/". The snippet below the title reads: "Aug 29, 2008 - Q: Does Barack Obama have Kenyan citizenship? A: No. He held both U.S. and Kenyan citizenship as a child, but lost his Kenyan citizenship ...".



Google

"is obama a citizen of kenya?"

All News Images Videos Shopping More Search tools

3 results (0.37 seconds)

**Is Obama a citizen of Kenya? - Blockland Forum**  
[forum.blockland.us/index.php?topic=77191.25;imode](http://forum.blockland.us/index.php?topic=77191.25;imode)  
Is Obama a citizen of Kenya? << < (6/8) > >>. Garuda: Ah yes, the conservative agenda, full of "My country tis of thee" bullshit. In the way that they always blast ...

**Is Obama really a U.S. citizen | Woodstock Sentinel Review**  
[www.woodstocksentinelreview.com/.../is-oba...](http://www.woodstocksentinelreview.com/.../is-oba...) Woodstock Sentinel-Review

This screenshot shows a Google search for "is obama a citizen of kenya?". The search bar contains the text "is obama a citizen of kenya?". Below the search bar, the "All" tab is selected. The results show 3 results in 0.37 seconds. The top result is titled "Is Obama a citizen of Kenya? - Blockland Forum" with a green URL "forum.blockland.us/index.php?topic=77191.25;imode". The snippet below the title reads: "Is Obama a citizen of Kenya? << < (6/8) > >>. Garuda: Ah yes, the conservative agenda, full of "My country tis of thee" bullshit. In the way that they always blast ...". The second result is titled "Is Obama really a U.S. citizen | Woodstock Sentinel Review" with a green URL "www.woodstocksentinelreview.com/.../is-oba...".



# BTW...

# BTW...

Almost all the advice about preprocessing comes from the supervised ('machine-learning') literature,

## BTW...

Almost all the advice about preprocessing comes from the supervised ('machine-learning') literature, and is then applied without thought to unsupervised approaches.

## BTW...

Almost all the advice about preprocessing comes from the supervised ('machine-learning') literature, and is then applied without thought to unsupervised approaches.

Q Does this matter?

# BTW...

Almost all the advice about preprocessing comes from the supervised ('machine-learning') literature, and is then applied without thought to unsupervised approaches.

Q Does this matter?

A Yes, probably (see over)—results are not robust to different preprocessing steps.

## BTW...

Almost all the advice about preprocessing comes from the supervised ('machine-learning') literature, and is then applied without thought to unsupervised approaches.

Q Does this matter?

A Yes, probably (see over)—results are not robust to different preprocessing steps.

Q So just check sensitivity by running multiple models?

## BTW...

Almost all the advice about preprocessing comes from the supervised ('machine-learning') literature, and is then applied without thought to unsupervised approaches.

Q Does this matter?

A Yes, probably (see over)—results are not robust to different preprocessing steps.

Q So just check sensitivity by running multiple models?

A Well, 7 binary steps  $\Rightarrow 2^7 = 128$  possible combinations.

## BTW...

Almost all the advice about preprocessing comes from the supervised ('machine-learning') literature, and is then applied without thought to unsupervised approaches.

Q Does this matter?

A Yes, probably (see over)—results are not robust to different preprocessing steps.

Q So just check sensitivity by running multiple models?

A Well, 7 binary steps  $\Rightarrow 2^7 = 128$  possible combinations. Good luck.



# BTW...

Almost all the advice about preprocessing comes from the supervised ('machine-learning') literature, and is then applied without thought to unsupervised approaches.

Q Does this matter?

A Yes, probably (see over)—results are not robust to different preprocessing steps.

Q So just check sensitivity by running multiple models?

A Well, 7 binary steps  $\Rightarrow 2^7 = 128$  possible combinations. Good luck.

Q What *can* we do?

# BTW...

Almost all the advice about preprocessing comes from the supervised ('machine-learning') literature, and is then applied without thought to unsupervised approaches.

Q Does this matter?

A Yes, probably (see over)—results are not robust to different preprocessing steps.

Q So just check sensitivity by running multiple models?

A Well, 7 binary steps  $\Rightarrow 2^7 = 128$  possible combinations. Good luck.

Q What *can* we do?

A Check how pairwise distances move between texts as we make choices,

# BTW...

Almost all the advice about preprocessing comes from the supervised ('machine-learning') literature, and is then applied without thought to unsupervised approaches.

Q Does this matter?

A Yes, probably (see over)—results are not robust to different preprocessing steps.

Q So just check sensitivity by running multiple models?

A Well, 7 binary steps  $\Rightarrow 2^7 = 128$  possible combinations. Good luck.

Q What *can* we do?

A Check how pairwise distances move between texts as we make choices, esp important when 'theory' is weak. See `preText`.

[Download This Paper](#) [Open PDF in Browser](#) [Share](#) [Email](#) [Add to MyBriefcase](#)

## Text Preprocessing For Unsupervised Learning: Why It Matters, When It Misleads, And What To Do About It

[Matthew James Denny](#)  
Pennsylvania State University

[Arthur Spirling](#)  
New York University

January 25, 2017

**Abstract:**  
Despite the popularity of unsupervised techniques for political science text-as-data research, the importance and implications of preprocessing decisions in this domain have received scant systematic attention. Yet, as we show, such decisions have profound effects on the results of real models for real data. We argue that substantive theory is typically too vague to be of use for feature selection, and that the supervised literature is not necessarily a helpful source of advice. To aid researchers working in unsupervised settings, we introduce a statistical procedure that examines the sensitivity of findings under alternate preprocessing regimes. This approach complements a researcher's substantive understanding of a problem by providing a characterization of the variability changes in preprocessing choices may induce when analyzing a particular dataset. In making scholars aware of the degree to which their results are likely to be sensitive to their preprocessing decisions, it aids replication efforts. We make easy-to-use software available for this purpose.

**Number of Pages in PDF File:** 44

**Keywords:** text-as-data, preprocessing, forking paths

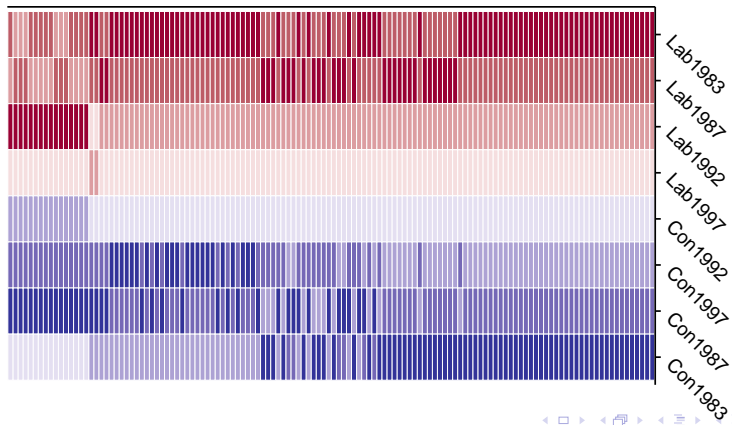




# Denny & Spirling, 2017

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).

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).



# III. Vector Space Model



# III. Vector Space Model

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

# 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*,

### 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

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

# Notation and Terminology

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

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

# Notation and Terminology

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

$w = 1, \dots, W$  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

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

$w = 1, \dots, W$  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

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

$w = 1, \dots, W$  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

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

$w = 1, \dots, W$  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. . .
- stacking those vectors on top of each other gives the **document term matrix** (DTM) or the **document feature matrix** (DFM).



# Notation and Terminology

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

$w = 1, \dots, W$  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. . .
- stacking those vectors on top of each other gives the **document term matrix** (DTM) or the **document feature matrix** (DFM).
- taking the transpose of the DTM gives the **term document matrix** (TDM) or **feature document matrix** (FDM).

# Notation and Terminology

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

$w = 1, \dots, W$  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. . .
- stacking those vectors on top of each other gives the **document term matrix** (DTM) or the **document feature matrix** (DFM).
- 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.

$tf_{dw} \cdot \ln \frac{|D|}{df_w}$ , 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.

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

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

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

→ when a word is common in a given document, but rare in the corpus as whole,

$tf_{dw} \cdot \ln \frac{|D|}{df_w}$ , 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**.

$tf_{dw} \cdot \ln \frac{|D|}{df_w}$ , 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.

$tf_{dw} \cdot \ln \frac{|D|}{df_w}$ , 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.

**and** very low for words occurring in every document:

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

→ 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.

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

→  $tf-idf=0$  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  $\ln \frac{|D|}{df} = \ln \left( \frac{4}{4} \right) = 0$

→  $tf-idf=0$  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  $\ln \frac{|D|}{df} = \ln \left( \frac{4}{4} \right) = 0$

→  $tf-idf=0$  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  $\ln \frac{|D|}{df} = \ln \left( \frac{4}{4} \right) = 0$

→  $tf-idf=0$  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  $\ln \frac{|D|}{df} = \ln \left( \frac{4}{4} \right) = 0$

→  $tf-idf=0$  for 'will' in 1933.

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

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

→  $tf-idf=1.38$  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  $\ln \frac{|D|}{df} = \ln \left( \frac{4}{4} \right) = 0$

→  $tf-idf=0$  for 'will' in 1933.

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

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

→  $tf-idf=1.38$  for 'expect' in 1933.

→ 'expect' helps us discriminate better than 'will'.

# Animals at the Zoo

# Animals at the Zoo

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

# 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**.

→ 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**.

→ 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**.

→ 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**.

→ 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.