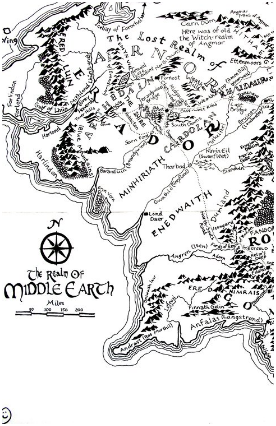
Where Are We?

Where Are We?


Carn Dûm
Here was of old the Witch-realm of Angmar
Angmar
The Lost Realm of
ARNOR
Ettenmoors
RHUDAUR
Fornost
Weather Hills
Weathertop (Amon Sûl)
North Downs
Bree
East-West Road
South Downs
Last Bridge
Bruinen (Loudwater)
Trollshaws
Mitheithel
CARDOLAN
Sarn Ford
Tharbad
Nîn-in-Eilph (Swanfleet)
Glanduin
MINHIRIATH
Baranduin
Eryn Vorn
Gwathlo (Greyflood)
ENEDWAITH
Dunland
Lond Daer
Isengard
FANGORN
Angren
(Isen)
Adorn
Helm's Deep
WESTFOLD
Edoras
ERED NIMRAIS
Pinnath Gelin
Lefnui
Anfalas (Langstrand)
Andrast (Ras Morthil)
Forlindon
Forlond
Gulf of Lhûn
Mithlond
Grey Havens
Tower Hills
Harlond
Harlindon
Blue Mountains
ERED LUIN
ERIADOR
THE SHIRE
Hobbiton
Brandywine Bridge
N
The Realm Of
MIDDLE EARTH
Miles
50 100 150 200

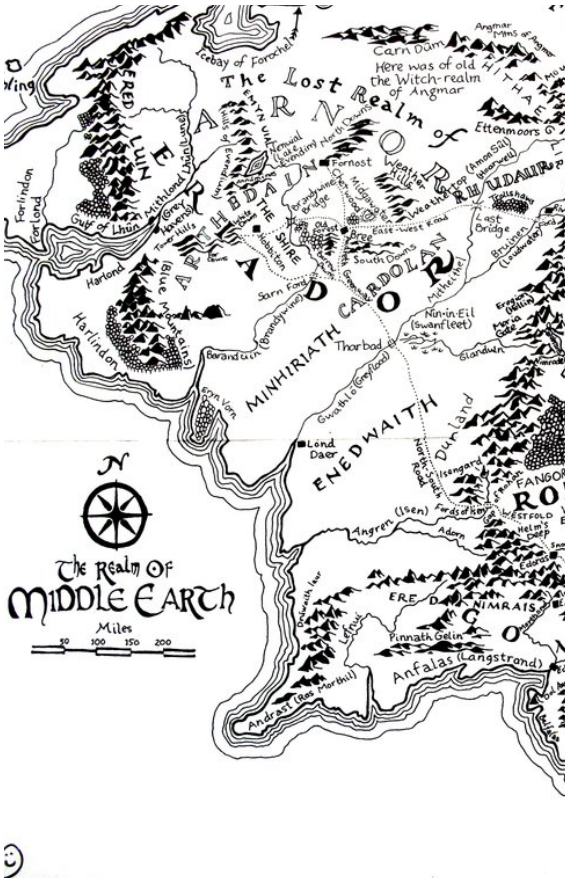
☺

Where Are We?



Our fundamental unit of text analysis is the document term matrix.

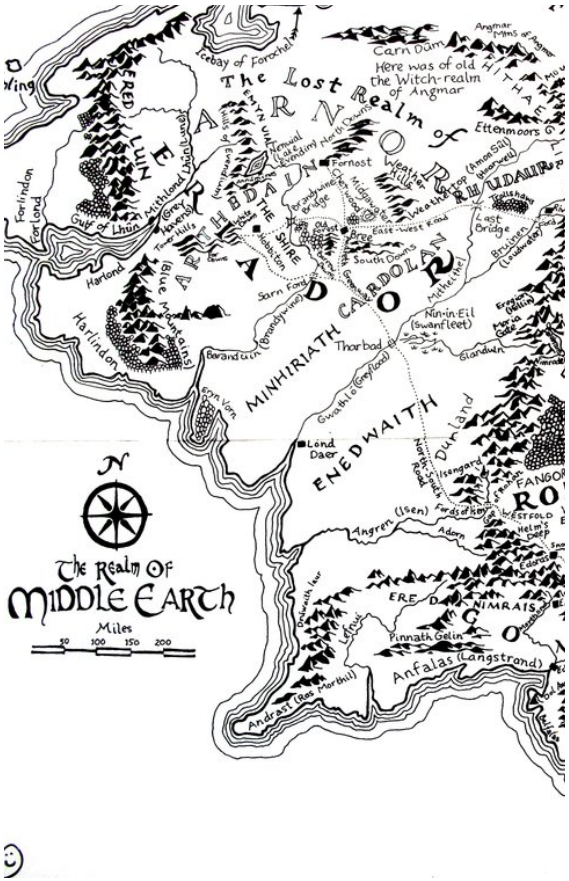
Where Are We?



Our fundamental unit of text analysis is the document term matrix.

This is a set of stacked vectors, with each entry in each vector representing the 'amount' of a particular term.

Where Are We?

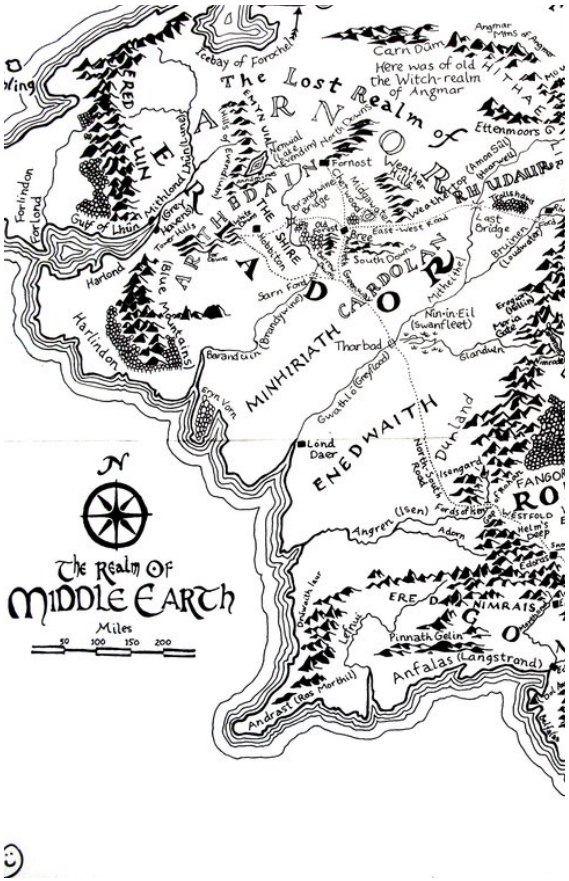


Our fundamental unit of text analysis is the document term matrix.

This is a set of stacked vectors, with each entry in each vector representing the 'amount' of a particular term.

This is could be (re-)weighted in some way (e.g. tfidf).

Where Are We?



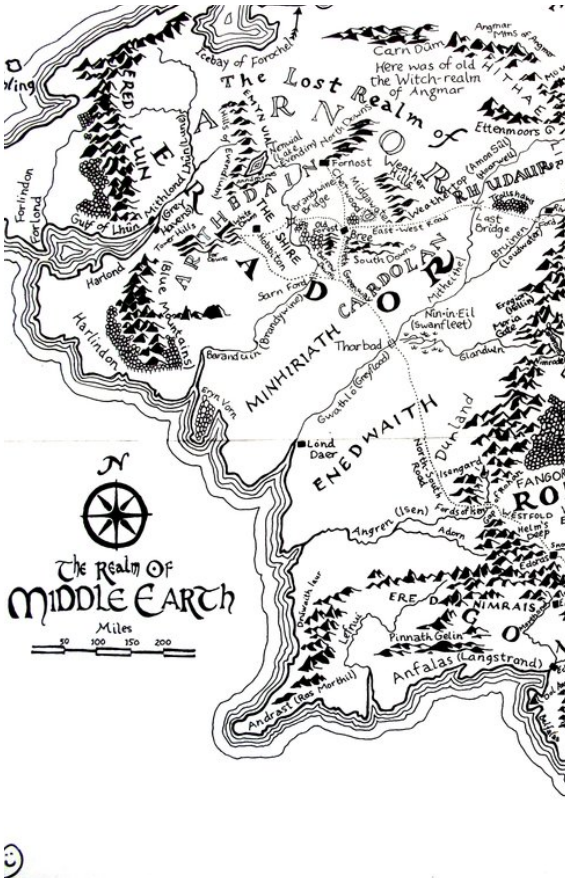
Our fundamental unit of text analysis is the document term matrix.

This is a set of stacked vectors, with each entry in each vector representing the 'amount' of a particular term.

This is could be (re-)weighted in some way (e.g. tfidf).

now cover some fundamental statistical properties of text

Where Are We?



Our fundamental unit of text analysis is the document term matrix.

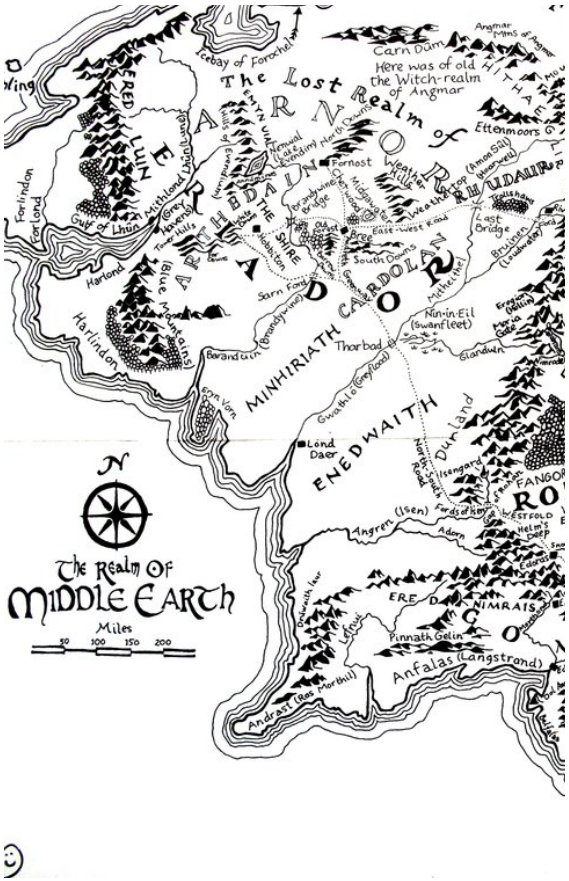
This is a set of stacked vectors, with each entry in each vector representing the 'amount' of a particular term.

This is could be (re-)weighted in some way (e.g. tfidf).

now cover some fundamental statistical properties of text

and think about how to compare documents,

Where Are We?



Our fundamental unit of text analysis is the document term matrix.

This is a set of stacked vectors, with each entry in each vector representing the 'amount' of a particular term.

This is could be (re-)weighted in some way (e.g. tfidf).

now cover some fundamental statistical properties of text

and think about how to compare documents, and summarize their content.

Reminder: From Texts to Numeric Data

Reminder: From Texts to Numeric Data

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

Reminder: 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.

Reminder: 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.

Reminder: 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.

Reminder: 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.

Reminder: 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.

Reminder: From Texts to Numeric Data

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

"PREPROCESSING"

6. operate/model.

Reminder: Quick Note on Terminology

Reminder: Quick Note on Terminology

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

Reminder: 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),

Reminder: 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,

Reminder: 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.

Reminder: 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'

Reminder: 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",

Reminder: 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,

Reminder: 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).

Reminder: 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.

Reminder: 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.

Lossy Compression

Lossy Compression

- when we use the vector space model we remove some information and throw it away

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

$\rightarrow$ this means we cannot restore the original representation of the data:

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

$\rightarrow$ this means we cannot restore the original representation of the data: we have a lossy compression.

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

$\rightarrow$ this means we cannot restore the original representation of the data: we have a lossy compression.

but presumably, life becomes a lot simpler and the tradeoff is worth it.

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

$\rightarrow$ this means we cannot restore the original representation of the data: we have a lossy compression.

but presumably, life becomes a lot simpler and the tradeoff is worth it. How much simpler?

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

$\rightarrow$ this means we cannot restore the original representation of the data: we have a lossy compression.

but presumably, life becomes a lot simpler and the tradeoff is worth it. How much simpler?

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

$\rightarrow$ this means we cannot restore the original representation of the data: we have a lossy compression.

but presumably, life becomes a lot simpler and the tradeoff is worth it. How much simpler?

e.g. Reuters Corpus Volume 1 (RCV1) (2004) is a benchmark text collection of $\sim$ 800000 manually coded news stories.

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

$\rightarrow$ this means we cannot restore the original representation of the data: we have a lossy compression.

but presumably, life becomes a lot simpler and the tradeoff is worth it. How much simpler?

e.g. Reuters Corpus Volume 1 (RCV1) (2004) is a benchmark text collection of $\sim$ 800000 manually coded news stories.

RCV1 has 484,494 types and 197,879,290 tokens (MR&S book, Table 5.1).

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

$\rightarrow$ this means we cannot restore the original representation of the data: we have a lossy compression.

but presumably, life becomes a lot simpler and the tradeoff is worth it. How much simpler?

e.g. Reuters Corpus Volume 1 (RCV1) (2004) is a benchmark text collection of $\sim$ 800000 manually coded news stories.

RCV1 has 484,494 types and 197,879,290 tokens (MR&S book, Table 5.1).

rm numbers	473,723	179,158,204

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

$\rightarrow$ this means we cannot restore the original representation of the data: we have a lossy compression.

but presumably, life becomes a lot simpler and the tradeoff is worth it. How much simpler?

e.g. Reuters Corpus Volume 1 (RCV1) (2004) is a benchmark text collection of $\sim$ 800000 manually coded news stories.

RCV1 has 484,494 types and 197,879,290 tokens (MR&S book, Table 5.1).

rm numbers	473,723	179,158,204
lowercase	391,523	179,158,204

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

→ this means we cannot restore the original representation of the data: we have a lossy compression.

but presumably, life becomes a lot simpler and the tradeoff is worth it. How much simpler?

e.g. Reuters Corpus Volume 1 (RCV1) (2004) is a benchmark text collection of $\sim$ 800000 manually coded news stories.

RCV1 has 484,494 types and 197,879,290 tokens (MR&S book, Table 5.1).

rm numbers	473,723	179,158,204
lowercase	391,523	179,158,204
rm 150 stopwords	391,373	94,516,599

Lossy Compression

- when we use the vector space model we remove some information and throw it away (e.g. word order, numbers, capitals, stop words).

$\rightarrow$ this means we cannot restore the original representation of the data: we have a lossy compression.

but presumably, life becomes a lot simpler and the tradeoff is worth it. How much simpler?

e.g. Reuters Corpus Volume 1 (RCV1) (2004) is a benchmark text collection of $\sim$ 800000 manually coded news stories.

RCV1 has 484,494 types and 197,879,290 tokens (MR&S book, Table 5.1).

rm numbers	473,723	179,158,204
lowercase	391,523	179,158,204
rm 150 stopwords	391,373	94,516,599
stemming	322,383	94,516,599

Heap's Law: Type-Token relationship

Heap's Law: Type-Token relationship

So pre-processing 'works' in the sense that it serves to simplify the problem.

Heap's Law: Type-Token relationship

So pre-processing 'works' in the sense that it serves to simplify the problem.

but how does the total number of types M, change as total number of tokens T increases ?

Heap's Law: Type-Token relationship

So pre-processing 'works' in the sense that it serves to simplify the problem.

but how does the total number of types M, change as total number of tokens T increases ?

Heap's Law:

Heap's Law: Type-Token relationship

So pre-processing 'works' in the sense that it serves to simplify the problem.

but how does the total number of types M, change as total number of tokens T increases ?

Heap's Law: $M = kT^b$

Heap's Law: Type-Token relationship

So pre-processing 'works' in the sense that it serves to simplify the problem.

but how does the total number of types M, change as total number of tokens T increases ?

Heap's Law: $\boxed{M = kT^b}$

where $k \in (30, 100)$ and $b \in (0.4, 0.6)$ for English.

Heap's Law: Type-Token relationship

So pre-processing 'works' in the sense that it serves to simplify the problem.

but how does the total number of types M, change as total number of tokens T increases ?

Heap's Law: $\boxed{M = kT^b}$

where $k \in (30, 100)$ and $b \in (0.4, 0.6)$ for English.

if we preprocess in different ways,

Heap's Law: Type-Token relationship

So pre-processing 'works' in the sense that it serves to simplify the problem.

but how does the total number of types M, change as total number of tokens T increases ?

Heap's Law: $\boxed{M = kT^b}$

where $k \in (30, 100)$ and $b \in (0.4, 0.6)$ for English.

if we preprocess in different ways, we cause k to be different.

Heap's Law: Type-Token relationship

So pre-processing 'works' in the sense that it serves to simplify the problem.

but how does the total number of types M, change as total number of tokens T increases ?

Heap's Law: $\boxed{M = kT^b}$

where $k \in (30, 100)$ and $b \in (0.4, 0.6)$ for English.

if we preprocess in different ways, we cause k to be different.

NB number of types increases rapidly at first,

Heap's Law: Type-Token relationship

So pre-processing 'works' in the sense that it serves to simplify the problem.

but how does the total number of types M, change as total number of tokens T increases ?

Heap's Law: $\boxed{M = kT^b}$

where $k \in (30, 100)$ and $b \in (0.4, 0.6)$ for English.

if we preprocess in different ways, we cause k to be different.

NB number of types increases rapidly at first, then less rapidly.

Heap's Law: Type-Token relationship

So pre-processing 'works' in the sense that it serves to simplify the problem.

but how does the total number of types M, change as total number of tokens T increases ?

Heap's Law: $\boxed{M = kT^b}$

where $k \in (30, 100)$ and $b \in (0.4, 0.6)$ for English.

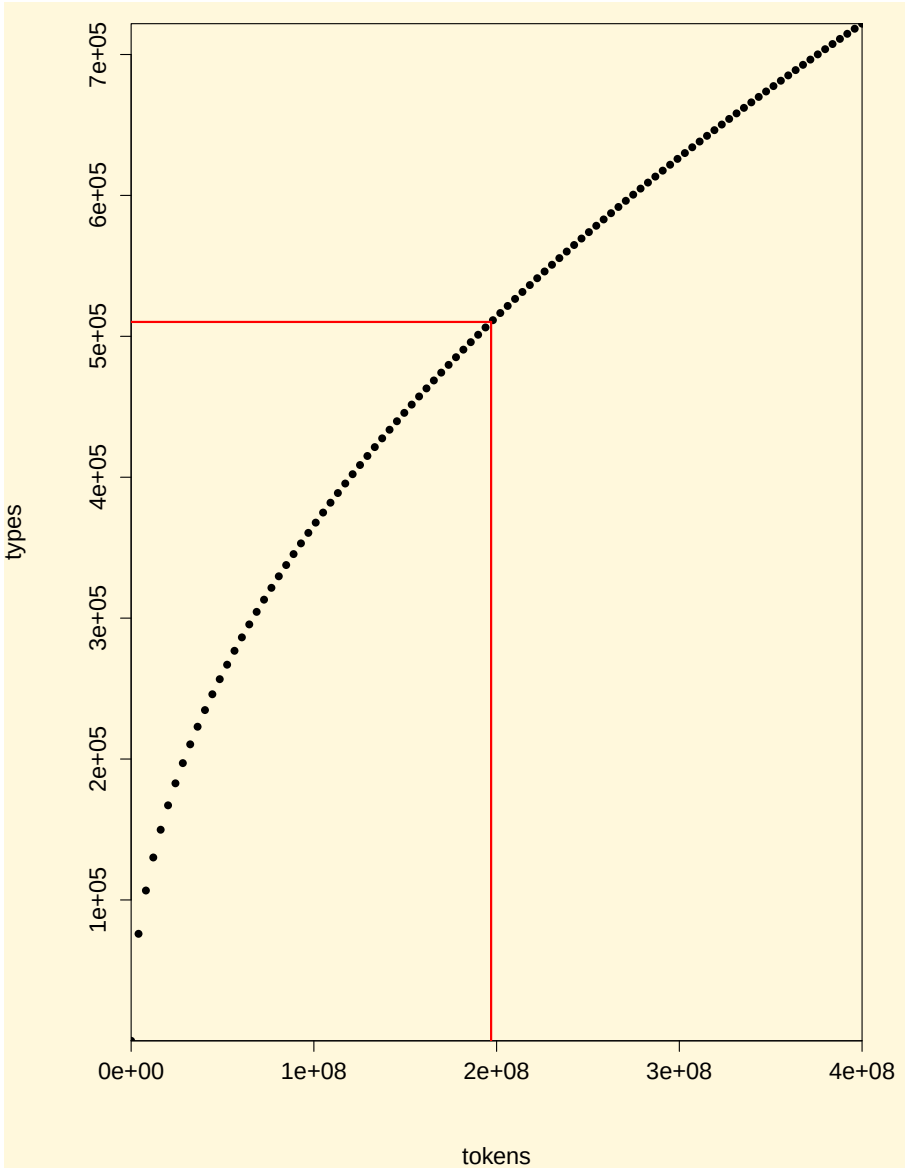
if we preprocess in different ways, we cause k to be different.

NB number of types increases rapidly at first, then less rapidly. Need to preprocess, especially for long collections!

$k = 44, b = 0.49, T = 400,000$

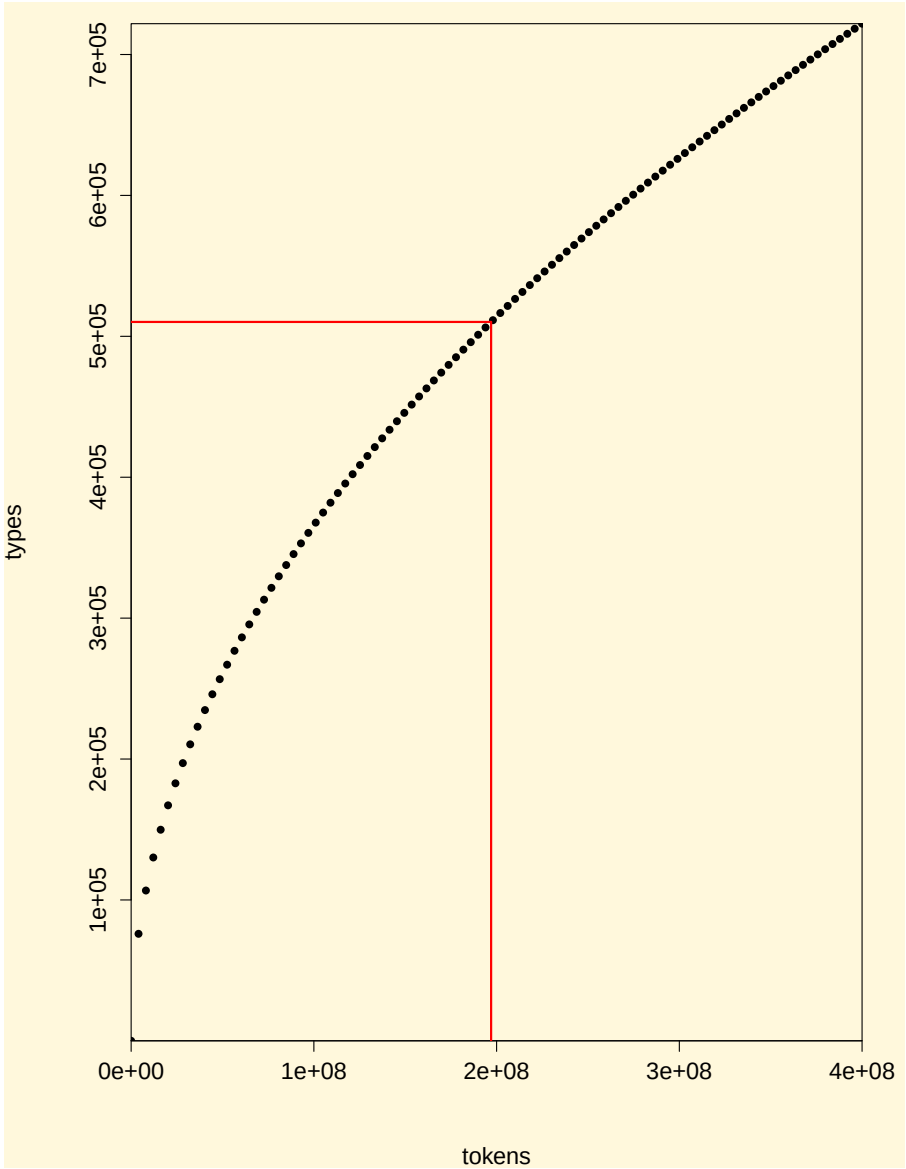
$k = 44, b = 0.49, T = 400,000$

RCV1.

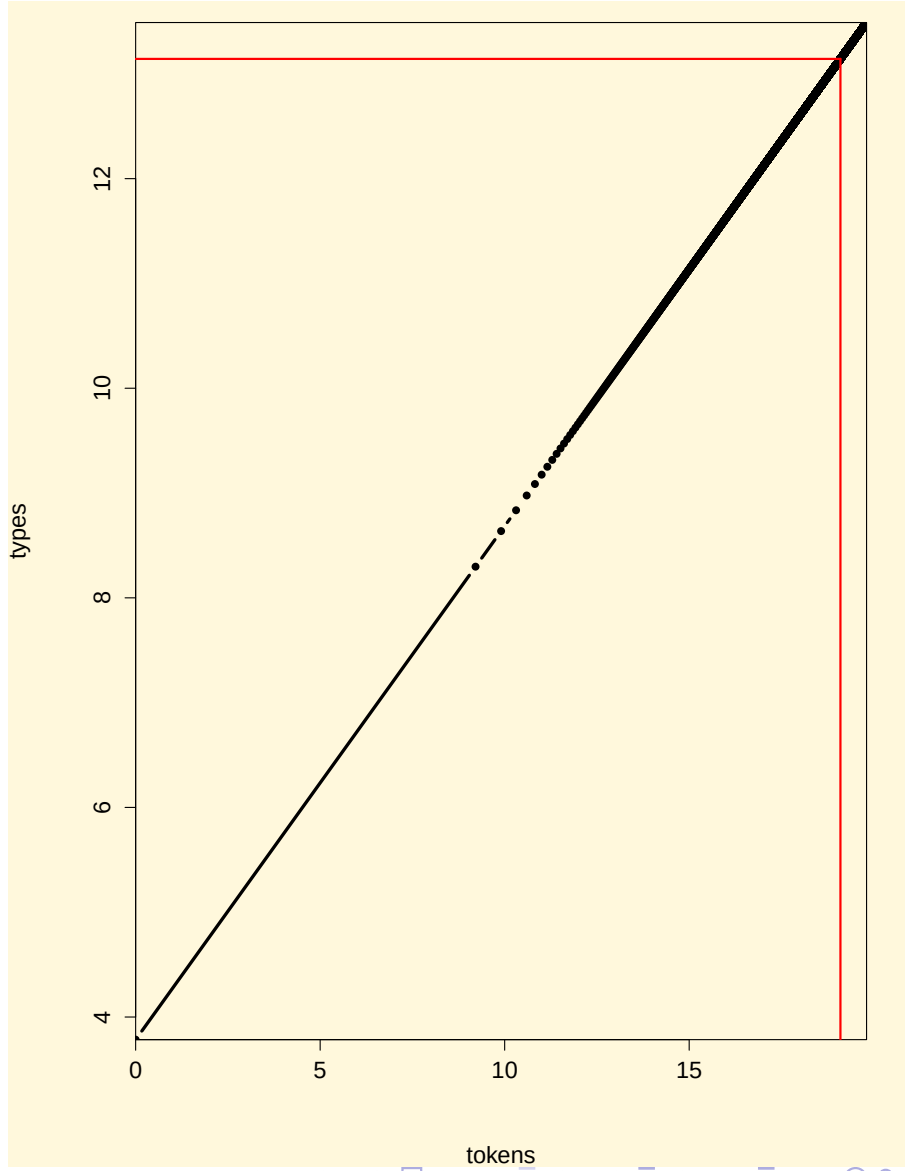


$k = 44, b = 0.49, T = 400,000$

RCV1.



RCV1, log-log.



Zipf's Law

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

→ how much more common is the most common term relative to the second common term?

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

→ how much more common is the most common term relative to the second common term? What about relative to the the third most common term? And the fourth...

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

→ how much more common is the most common term relative to the second common term? What about relative to the the third most common term? And the fourth...

Zipf's Law: corpus frequency of ith most common term is $\propto \frac{1}{i}$

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

→ how much more common is the most common term relative to the second common term? What about relative to the the third most common term? And the fourth...

Zipf's Law: corpus frequency of ith most common term is $\propto \frac{1}{i}$

so second most common term is half as common as most common,

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

→ how much more common is the most common term relative to the second common term? What about relative to the the third most common term? And the fourth...

Zipf's Law: corpus frequency of ith most common term is $\propto \frac{1}{i}$

so second most common term is half as common as most common,

and third most common term is one third as common as most common,

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

→ how much more common is the most common term relative to the second common term? What about relative to the the third most common term? And the fourth...

Zipf's Law: corpus frequency of ith most common term is $\propto \frac{1}{i}$

so second most common term is half as common as most common,

and third most common term is one third as common as most common,

and fourth most common term is one quarter as common as most common,

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

→ how much more common is the most common term relative to the second common term? What about relative to the the third most common term? And the fourth...

Zipf's Law: corpus frequency of ith most common term is $\propto \frac{1}{i}$

so second most common term is half as common as most common,

and third most common term is one third as common as most common,

and fourth most common term is one quarter as common as most common,

etc Can rewrite as:

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

→ how much more common is the most common term relative to the second common term? What about relative to the the third most common term? And the fourth...

Zipf's Law: corpus frequency of ith most common term is $\propto \frac{1}{i}$

so second most common term is half as common as most common,

and third most common term is one third as common as most common,

and fourth most common term is one quarter as common as most common,

etc Can rewrite as: corpus frequency of $i = ci^k$ or

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

→ how much more common is the most common term relative to the second common term? What about relative to the the third most common term? And the fourth...

Zipf's Law: corpus frequency of ith most common term is $\propto \frac{1}{i}$

so second most common term is half as common as most common,

and third most common term is one third as common as most common,

and fourth most common term is one quarter as common as most common,

etc Can rewrite as: corpus frequency of $i = ci^k$ or $\log(\text{corpus frequency}) = \log c + k \log i$,

Zipf's Law

Heap's Law tells us about the relationship between tokens and types.

but what about the relationship between the relative frequency of terms in the corpus?

→ how much more common is the most common term relative to the second common term? What about relative to the the third most common term? And the fourth...

Zipf's Law: corpus frequency of ith most common term is $\propto \frac{1}{i}$

so second most common term is half as common as most common,

and third most common term is one third as common as most common,

and fourth most common term is one quarter as common as most common,

etc Can rewrite as: corpus frequency of $i = ci^k$ or
$\log(\text{corpus frequency}) = \log c + k \log i$, where i is the rank, $k = -1$.

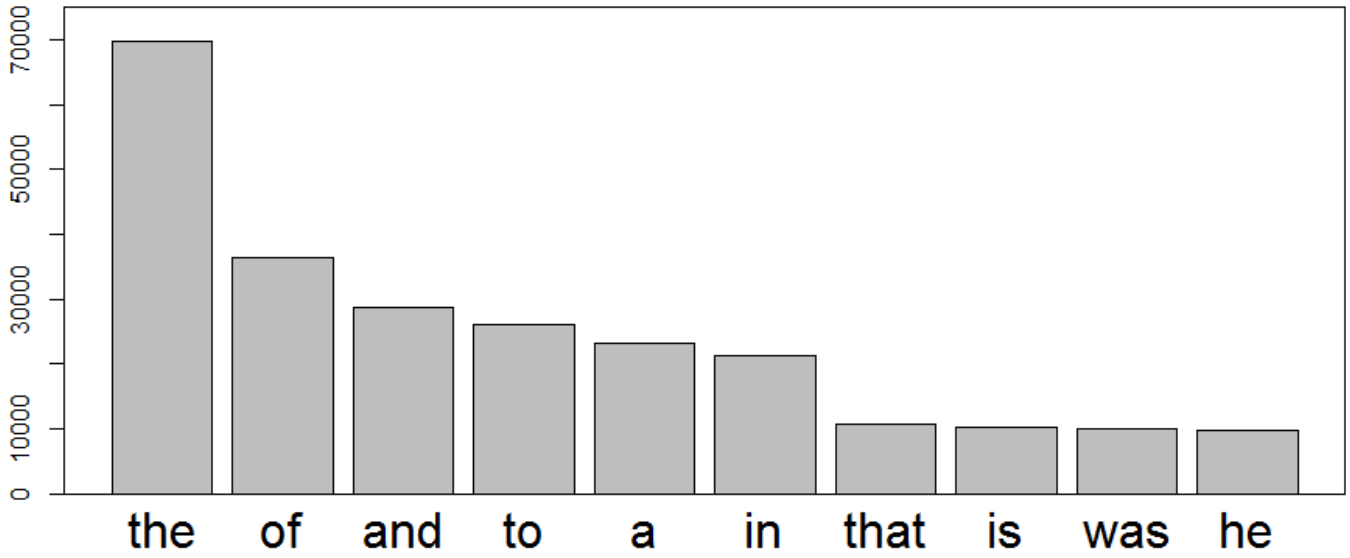
Brown Corpus (1961)

Brown Corpus (1961)

term	freq
the	69836
of	36365
and	28826
to	26126
a	23157
in	21314
that	10777
is	10182
was	9968
he	9801

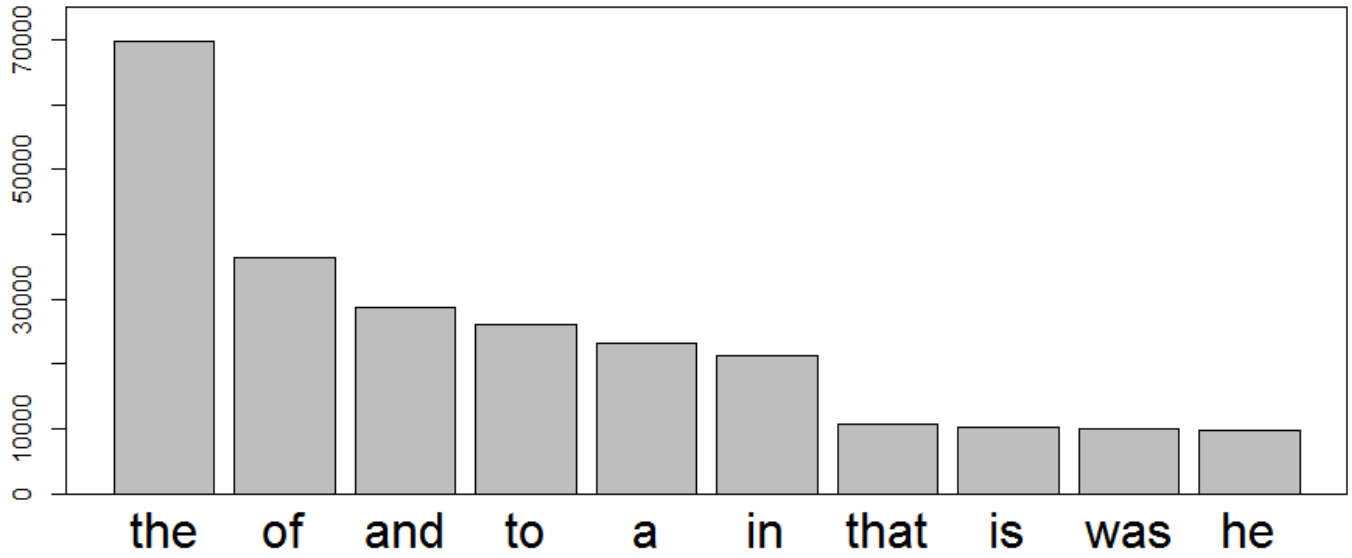
Brown Corpus (1961)

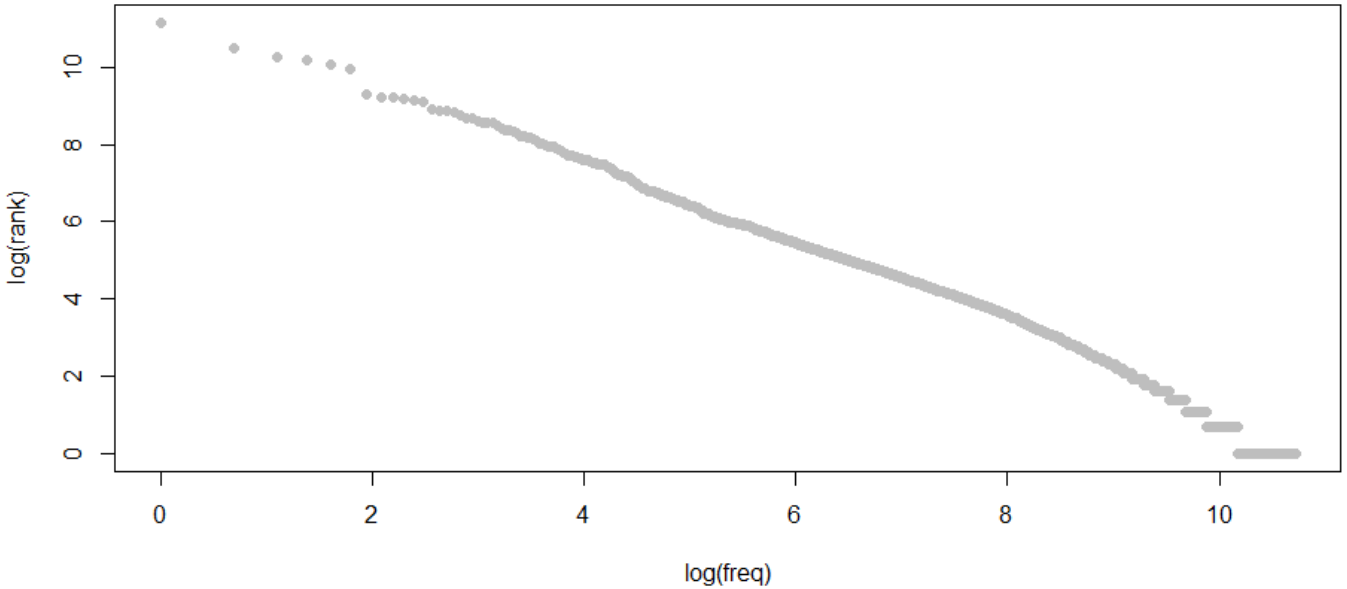
term	freq
the	69836
of	36365
and	28826
to	26126
a	23157
in	21314
that	10777
is	10182
was	9968
he	9801



Brown Corpus (1961)

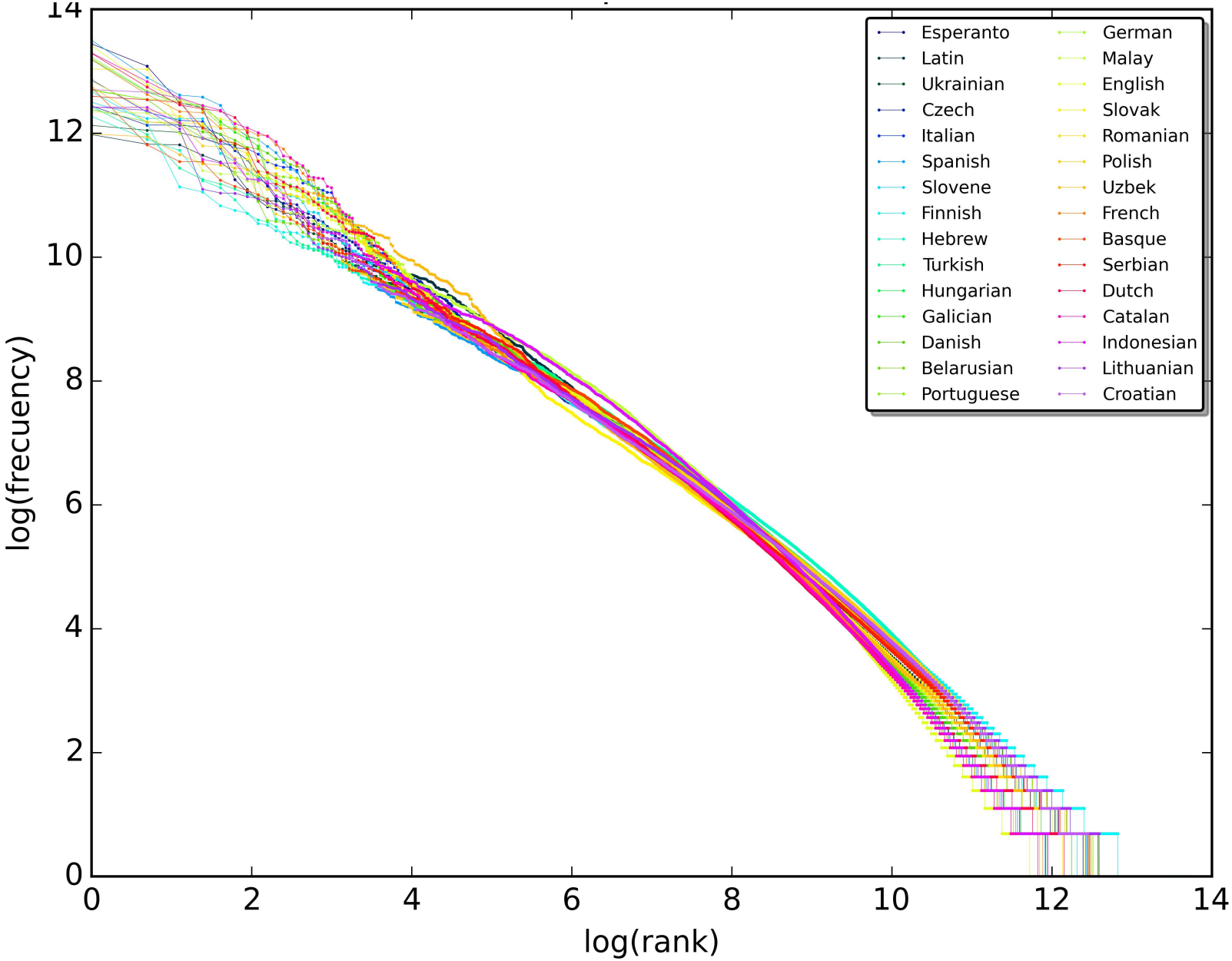
term	freq
the	69836
of	36365
and	28826
to	26126
a	23157
in	21314
that	10777
is	10182
was	9968
he	9801





Other Languages (Wikipedia)

Other Languages (Wikipedia)



City Populations in US (Gabaix, 1999)

City Populations in US (Gabaix, 1999)

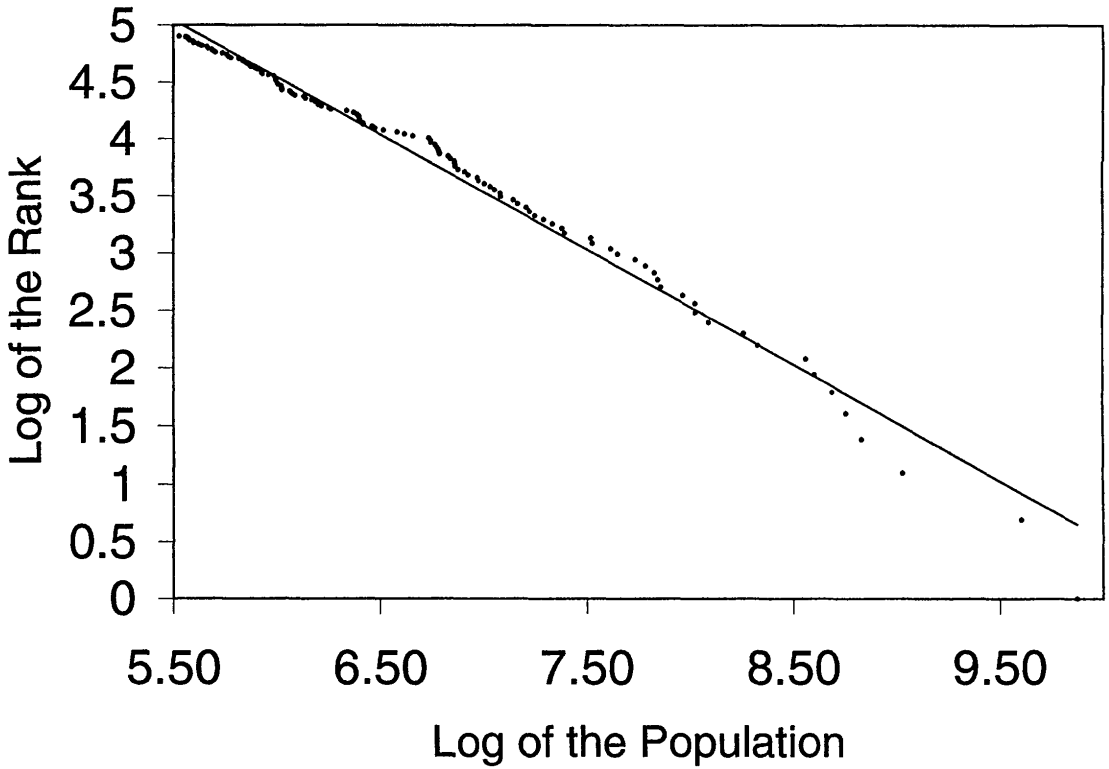


FIGURE I
Log Size versus Log Rank of the 135 largest U. S. Metropolitan Areas in 1991
Source: Statistical Abstract of the United States [1993].

Comparing Texts: Distance

Comparing Texts: Distance

Recall that the vector space model represents a document as a point in the feature space.

Comparing Texts: Distance

Recall that the vector space model represents a document as a point in the feature space.

i.e. $\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d.

Comparing Texts: Distance

Recall that the vector space model represents a document as a point in the feature space.

i.e. $\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d.

q how 'far' is that document from some other document (in the same space)?

Comparing Texts: Distance

Recall that the vector space model represents a document as a point in the feature space.

i.e. $\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d.

q how 'far' is that document from some other document (in the same space)?

$\rightarrow$ tells us about similarity of documents

Comparing Texts: Distance

Recall that the vector space model represents a document as a point in the feature space.

i.e. $\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d.

q how 'far' is that document from some other document (in the same space)?

$\rightarrow$ tells us about similarity of documents

and is typically required for application of multivariate techniques, anyway

Comparing Texts: Distance

Recall that the vector space model represents a document as a point in the feature space.

i.e. $\mathbf{y}_d \in \mathbb{R}^W$ is a representation of document d.

q how 'far' is that document from some other document (in the same space)?

$\rightarrow$ tells us about similarity of documents

and is typically required for application of multivariate techniques, anyway

e.g. principal components analysis operates on distance matrix.

Metrics vs Measures

Metrics vs Measures

NB not all measures of distance or similarity are metrics.

Metrics vs Measures

NB not all measures of distance or similarity are metrics. To be a metric, the measure of *distance* between documents i and j, s_{ij} must have certain properties:

Metrics vs Measures

NB not all measures of distance or similarity are metrics. To be a metric, the measure of *distance* between documents i and j, s_{ij} must have certain properties:

1. no negative distances: $s_{ij} \geq 0$

Metrics vs Measures

NB not all measures of distance or similarity are metrics. To be a metric, the measure of *distance* between documents i and j, s_{ij} must have certain properties:

1. no negative distances: $s_{ij} \geq 0$

2. distance between documents is zero $\iff$ documents are identical

Metrics vs Measures

NB not all measures of distance or similarity are metrics. To be a metric, the measure of *distance* between documents i and j, s_{ij} must have certain properties:

1. no negative distances: $s_{ij} \geq 0$
2. distance between documents is zero $\iff$ documents are identical
3. distance between documents is symmetric:

Metrics vs Measures

NB not all measures of distance or similarity are metrics. To be a metric, the measure of *distance* between documents i and j, s_{ij} must have certain properties:

1. no negative distances: $s_{ij} \geq 0$
2. distance between documents is zero $\iff$ documents are identical
3. distance between documents is symmetric: $s_{ij} = s_{ji}$

Metrics vs Measures

NB not all measures of distance or similarity are metrics. To be a metric, the measure of *distance* between documents i and j, s_{ij} must have certain properties:

1. no negative distances: $s_{ij} \geq 0$
2. distance between documents is zero $\iff$ documents are identical
3. distance between documents is symmetric: $s_{ij} = s_{ji}$
4. measures satisfy triangle inequality. $s_{ik} \leq s_{ij} + s_{jk}$

Metrics vs Measures

NB not all measures of distance or similarity are metrics. To be a metric, the measure of *distance* between documents i and j, s_{ij} must have certain properties:

1. no negative distances: $s_{ij} \geq 0$
2. distance between documents is zero $\iff$ documents are identical
3. distance between documents is symmetric: $s_{ij} = s_{ji}$
4. measures satisfy triangle inequality. $s_{ik} \leq s_{ij} + s_{jk}$

i.e. if doc i is similar to doc j *and* doc j is similar to doc k,

Metrics vs Measures

NB not all measures of distance or similarity are metrics. To be a metric, the measure of *distance* between documents i and j, s_{ij} must have certain properties:

1. no negative distances: $s_{ij} \geq 0$
2. distance between documents is zero $\iff$ documents are identical
3. distance between documents is symmetric: $s_{ij} = s_{ji}$
4. measures satisfy triangle inequality. $s_{ik} \leq s_{ij} + s_{jk}$

i.e. if doc i is similar to doc j *and* doc j is similar to doc k, then doc i is similar to doc k

Metrics vs Measures

NB not all measures of distance or similarity are metrics. To be a metric, the measure of *distance* between documents i and j, s_{ij} must have certain properties:

1. no negative distances: $s_{ij} \geq 0$
2. distance between documents is zero $\iff$ documents are identical
3. distance between documents is symmetric: $s_{ij} = s_{ji}$
4. measures satisfy triangle inequality. $s_{ik} \leq s_{ij} + s_{jk}$

i.e. if doc i is similar to doc j *and* doc j is similar to doc k, then doc i is similar to doc k (we have an upper bound on how far apart they can be)

Euclidean Distance

Euclidean Distance

The 'ordinary', 'straight line' distance between two points in space.

Recall that $\mathbf{y}_i$ and $\mathbf{y}_j$ are documents,

Euclidean Distance

The 'ordinary', 'straight line' distance between two points in space.

Recall that $\mathbf{y}_i$ and $\mathbf{y}_j$ are documents,

$$\|\mathbf{y}_i - \mathbf{y}_j\| = \sqrt{(\mathbf{y}_i - \mathbf{y}_j) \cdot (\mathbf{y}_i - \mathbf{y}_j)} = \sqrt{\sum (\mathbf{y}_i - \mathbf{y}_j)^2}$$

Euclidean Distance

The 'ordinary', 'straight line' distance between two points in space.

Recall that $\mathbf{y}_i$ and $\mathbf{y}_j$ are documents,

$$\|\mathbf{y}_i - \mathbf{y}_j\| = \sqrt{(\mathbf{y}_i - \mathbf{y}_j) \cdot (\mathbf{y}_i - \mathbf{y}_j)} = \sqrt{\sum (\mathbf{y}_i - \mathbf{y}_j)^2}$$

e.g. $\mathbf{y}_i = [0.00, 0.00, 1.38, 1.52, 0.00]$ and $\mathbf{y}_j = [0.00, 2.13, 3.24, 0.01, 0.06]$

Euclidean Distance

The 'ordinary', 'straight line' distance between two points in space.

Recall that $\mathbf{y}_i$ and $\mathbf{y}_j$ are documents,

$$\|\mathbf{y}_i - \mathbf{y}_j\| = \sqrt{(\mathbf{y}_i - \mathbf{y}_j) \cdot (\mathbf{y}_i - \mathbf{y}_j)} = \sqrt{\sum (\mathbf{y}_i - \mathbf{y}_j)^2}$$

e.g. $\mathbf{y}_i = [0.00, 0.00, 1.38, 1.52, 0.00]$ and $\mathbf{y}_j = [0.00, 2.13, 3.24, 0.01, 0.06]$

well $(\mathbf{y}_i - \mathbf{y}_j) = [0.00, -2.13, -1.86, 1.51, -0.06]$

Euclidean Distance

The 'ordinary', 'straight line' distance between two points in space.

Recall that $\mathbf{y}_i$ and $\mathbf{y}_j$ are documents,

$$\|\mathbf{y}_i - \mathbf{y}_j\| = \sqrt{(\mathbf{y}_i - \mathbf{y}_j) \cdot (\mathbf{y}_i - \mathbf{y}_j)} = \sqrt{\sum (\mathbf{y}_i - \mathbf{y}_j)^2}$$

e.g. $\mathbf{y}_i = [0.00, 0.00, 1.38, 1.52, 0.00]$ and $\mathbf{y}_j = [0.00, 2.13, 3.24, 0.01, 0.06]$

well $(\mathbf{y}_i - \mathbf{y}_j) = [0.00, -2.13, -1.86, 1.51, -0.06]$

and $(\mathbf{y}_i - \mathbf{y}_j) \cdot (\mathbf{y}_i - \mathbf{y}_j) =$

Euclidean Distance

The 'ordinary', 'straight line' distance between two points in space.

Recall that $\mathbf{y}_i$ and $\mathbf{y}_j$ are documents,

$$\|\mathbf{y}_i - \mathbf{y}_j\| = \sqrt{(\mathbf{y}_i - \mathbf{y}_j) \cdot (\mathbf{y}_i - \mathbf{y}_j)} = \sqrt{\sum (\mathbf{y}_i - \mathbf{y}_j)^2}$$

e.g. $\mathbf{y}_i = [0.00, 0.00, 1.38, 1.52, 0.00]$ and $\mathbf{y}_j = [0.00, 2.13, 3.24, 0.01, 0.06]$

well $(\mathbf{y}_i - \mathbf{y}_j) = [0.00, -2.13, -1.86, 1.51, -0.06]$

and $(\mathbf{y}_i - \mathbf{y}_j) \cdot (\mathbf{y}_i - \mathbf{y}_j) = (0 \times 0) + (-2.13 \times -2.13) + (-1.86 \times -1.86) + (1.51 \times 1.51) + (-0.06 \times -0.06) = 10.2802$

Euclidean Distance

The 'ordinary', 'straight line' distance between two points in space.

Recall that $\mathbf{y}_i$ and $\mathbf{y}_j$ are documents,

$$\|\mathbf{y}_i - \mathbf{y}_j\| = \sqrt{(\mathbf{y}_i - \mathbf{y}_j) \cdot (\mathbf{y}_i - \mathbf{y}_j)} = \sqrt{\sum (\mathbf{y}_i - \mathbf{y}_j)^2}$$

e.g. $\mathbf{y}_i = [0.00, 0.00, 1.38, 1.52, 0.00]$ and $\mathbf{y}_j = [0.00, 2.13, 3.24, 0.01, 0.06]$

well $(\mathbf{y}_i - \mathbf{y}_j) = [0.00, -2.13, -1.86, 1.51, -0.06]$

and $(\mathbf{y}_i - \mathbf{y}_j) \cdot (\mathbf{y}_i - \mathbf{y}_j) = (0 \times 0) + (-2.13 \times -2.13) + (-1.86 \times -1.86) + (1.51 \times 1.51) + (-0.06 \times -0.06) = 10.2802$

and $\sqrt{(\mathbf{y}_i - \mathbf{y}_j) \cdot (\mathbf{y}_i - \mathbf{y}_j)} = 3.206275$

larger distances imply lower similarity.

Better Approach

Better Approach

Euclidean distance rewards magnitude, rather than direction.

Better Approach

Euclidean distance rewards magnitude, rather than direction.

i.e. doesn't reward being close in relative use of terms.

Better Approach

Euclidean distance rewards magnitude, rather than direction.

i.e. doesn't reward being close in relative use of terms. Instead, rewards documents that are similarly 'far' from the origin.

Better Approach

Euclidean distance rewards magnitude, rather than direction.

i.e. doesn't reward being close in relative use of terms. Instead, rewards documents that are similarly 'far' from the origin.

We can do better by normalizing document length,

Better Approach

Euclidean distance rewards magnitude, rather than direction.

i.e. doesn't reward being close in relative use of terms. Instead, rewards documents that are similarly 'far' from the origin.

We can do better by normalizing document length, and rewarding relatively similar uses of terms.

Better Approach

Euclidean distance rewards magnitude, rather than direction.

i.e. doesn't reward being close in relative use of terms. Instead, rewards documents that are similarly 'far' from the origin.

We can do better by normalizing document length, and rewarding relatively similar uses of terms.

$\rightarrow$ divide out each of the components (the documents) by their length:

Better Approach

Euclidean distance rewards magnitude, rather than direction.

i.e. doesn't reward being close in relative use of terms. Instead, rewards documents that are similarly 'far' from the origin.

We can do better by normalizing document length, and rewarding relatively similar uses of terms.

$\rightarrow$ divide out each of the components (the documents) by their length: the L^2 norm, $||\mathbf{y}_i|| = \sqrt{\sum w^2}$,

Better Approach

Euclidean distance rewards magnitude, rather than direction.

i.e. doesn't reward being close in relative use of terms. Instead, rewards documents that are similarly 'far' from the origin.

We can do better by normalizing document length, and rewarding relatively similar uses of terms.

→ divide out each of the components (the documents) by their length: the L^2 norm, $||\mathbf{y}_i|| = \sqrt{\sum w^2}$, where w refers to the (weighted) frequency of a feature in the document vector.

Better Approach

Euclidean distance rewards magnitude, rather than direction.

i.e. doesn't reward being close in relative use of terms. Instead, rewards documents that are similarly 'far' from the origin.

We can do better by normalizing document length, and rewarding relatively similar uses of terms.

→ divide out each of the components (the documents) by their length: the L^2 norm, $||\mathbf{y}_i|| = \sqrt{\sum w^2}$, where w refers to the (weighted) frequency of a feature in the document vector.

so when the document has generally high term frequencies (because it is longer),

Better Approach

Euclidean distance rewards magnitude, rather than direction.

i.e. doesn't reward being close in relative use of terms. Instead, rewards documents that are similarly 'far' from the origin.

We can do better by normalizing document length, and rewarding relatively similar uses of terms.

→ divide out each of the components (the documents) by their length: the L^2 norm, $||\mathbf{y}_i|| = \sqrt{\sum w^2}$, where w refers to the (weighted) frequency of a feature in the document vector.

so when the document has generally high term frequencies (because it is longer), w^2 will be larger,

Better Approach

Euclidean distance rewards magnitude, rather than direction.

i.e. doesn't reward being close in relative use of terms. Instead, rewards documents that are similarly 'far' from the origin.

We can do better by normalizing document length, and rewarding relatively similar uses of terms.

→ divide out each of the components (the documents) by their length: the L^2 norm, $||\mathbf{y}_i|| = \sqrt{\sum w^2}$, where w refers to the (weighted) frequency of a feature in the document vector.

so when the document has generally high term frequencies (because it is longer), w^2 will be larger, which makes $||\mathbf{y}_i||$ larger.

Cosine Similarity

Cosine Similarity

$$c_{ij} = \boxed{\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{\|\mathbf{y}_i\| \ \|\mathbf{y}_j\|}}$$

Cosine Similarity

$$c_{ij} = \boxed{\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{\|\mathbf{y}_i\| \ \|\mathbf{y}_j\|}}$$

$\rightarrow$ we have a measure of similarity, which (since $\mathbf{y}_i$ and $\mathbf{y}_j$ are non-negative) must be between 0 and 1.

Cosine Similarity

$$c_{ij} = \boxed{\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{\|\mathbf{y}_i\| \ \|\mathbf{y}_j\|}}$$

→ we have a measure of similarity, which (since $\mathbf{y}_i$ and $\mathbf{y}_j$ are non-negative) must be between 0 and 1.

If $\mathbf{y}_i$ and $\mathbf{y}_j$ are vectors, c_{ij} is the cosine of the angle between them.

Cosine Similarity

$$c_{ij} = \boxed{\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{\|\mathbf{y}_i\| \ \|\mathbf{y}_j\|}}$$

→ we have a measure of similarity, which (since $\mathbf{y}_i$ and $\mathbf{y}_j$ are non-negative) must be between 0 and 1.

If $\mathbf{y}_i$ and $\mathbf{y}_j$ are vectors, c_{ij} is the cosine of the angle between them.

and document length is controlled for.

Cosine Similarity

$$c_{ij} = \boxed{\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{\|\mathbf{y}_i\| \ \|\mathbf{y}_j\|}}$$

→ we have a measure of similarity, which (since $\mathbf{y}_i$ and $\mathbf{y}_j$ are non-negative) must be between 0 and 1.

If $\mathbf{y}_i$ and $\mathbf{y}_j$ are vectors, c_{ij} is the cosine of the angle between them.

and document length is controlled for.

so intuitively,

Cosine Similarity

$$c_{ij} = \boxed{\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{\|\mathbf{y}_i\| \ \|\mathbf{y}_j\|}}$$

→ we have a measure of similarity, which (since $\mathbf{y}_i$ and $\mathbf{y}_j$ are non-negative) must be between 0 and 1.

If $\mathbf{y}_i$ and $\mathbf{y}_j$ are vectors, c_{ij} is the cosine of the angle between them.

and document length is controlled for.

so intuitively, cosine similarity captures some notion of relative 'direction' (e.g. style or topics in the document)

Cosine Similarity

$$c_{ij} = \boxed{\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{\|\mathbf{y}_i\| \ \|\mathbf{y}_j\|}}$$

→ we have a measure of similarity, which (since $\mathbf{y}_i$ and $\mathbf{y}_j$ are non-negative) must be between 0 and 1.

If $\mathbf{y}_i$ and $\mathbf{y}_j$ are vectors, c_{ij} is the cosine of the angle between them.

and document length is controlled for.

so intuitively, cosine similarity captures some notion of relative 'direction' (e.g. style or topics in the document) rather than 'magnitude' (distance from origin).

Cosine Similarity

$$c_{ij} = \boxed{\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{\|\mathbf{y}_i\| \ \|\mathbf{y}_j\|}}$$

→ we have a measure of similarity, which (since $\mathbf{y}_i$ and $\mathbf{y}_j$ are non-negative) must be between 0 and 1.

If $\mathbf{y}_i$ and $\mathbf{y}_j$ are vectors, c_{ij} is the cosine of the angle between them.

and document length is controlled for.

so intuitively, cosine similarity captures some notion of relative 'direction' (e.g. style or topics in the document) rather than 'magnitude' (distance from origin). Is the Pearson correlation between two vectors that have been demeaned.

Example

Example

$\mathbf{y}_i = [2.3, 4.3]$; $\mathbf{y}_j = [3.9, 2.1]$

Example

$$\mathbf{y}_i = [2.3, 4.3];\ \mathbf{y}_j = [3.9, 2.1]$$

then $\mathbf{y}_i \cdot \mathbf{y}_j = [2.3 \times 3.9] + [4.3 \times 2.1] = 18.$

Example

$$\mathbf{y}_i = [2.3, 4.3];\ \mathbf{y}_j = [3.9, 2.1]$$

then $\mathbf{y}_i \cdot \mathbf{y}_j = [2.3 \times 3.9] + [4.3 \times 2.1] = 18.$

and $||\mathbf{y}_i|| = \sqrt{2.3^2 + 4.3^2} = 4.88;\ ||\mathbf{y}_j|| = \sqrt{3.9^2 + 2.1^2} = 4.43$

Example

$$\mathbf{y}_i = [2.3, 4.3];\ \mathbf{y}_j = [3.9, 2.1]$$

then $\mathbf{y}_i \cdot \mathbf{y}_j = [2.3 \times 3.9] + [4.3 \times 2.1] = 18.$

and $||\mathbf{y}_i|| = \sqrt{2.3^2 + 4.3^2} = 4.88;\ ||\mathbf{y}_j|| = \sqrt{3.9^2 + 2.1^2} = 4.43$

so $c_{ij} = \frac{18}{4.88 \times 4.43} =$

Example

$$\mathbf{y}_i = [2.3, 4.3];\ \mathbf{y}_j = [3.9, 2.1]$$

then $\mathbf{y}_i \cdot \mathbf{y}_j = [2.3 \times 3.9] + [4.3 \times 2.1] = 18.$

and $||\mathbf{y}_i|| = \sqrt{2.3^2 + 4.3^2} = 4.88;\ ||\mathbf{y}_j|| = \sqrt{3.9^2 + 2.1^2} = 4.43$

so $c_{ij} = \frac{18}{4.88 \times 4.43} = 0.83.$

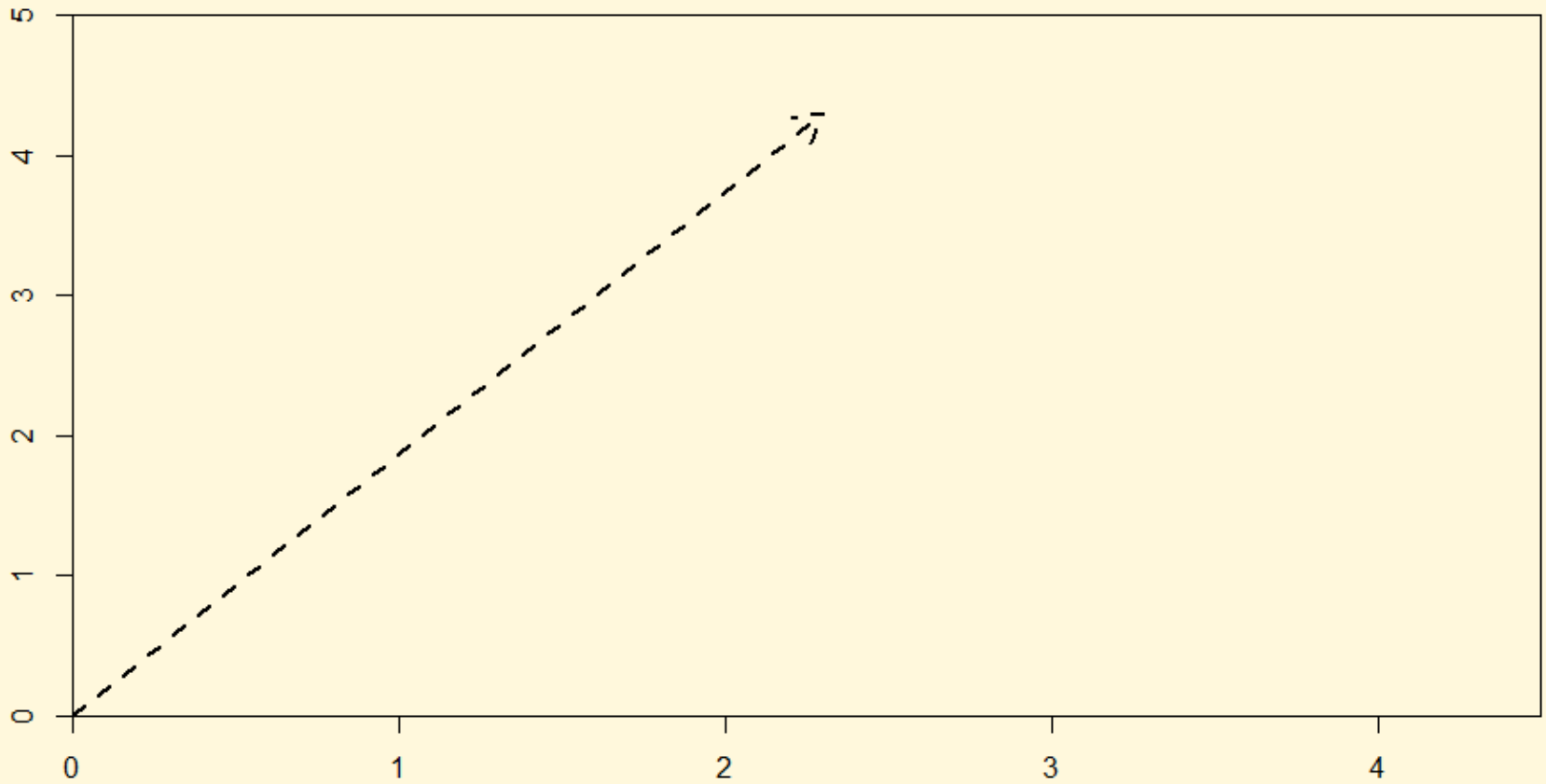
Graphically

Graphically

$$y_i = [2.3, 4.3]; \; y_j = [3.9, 2.1]$$

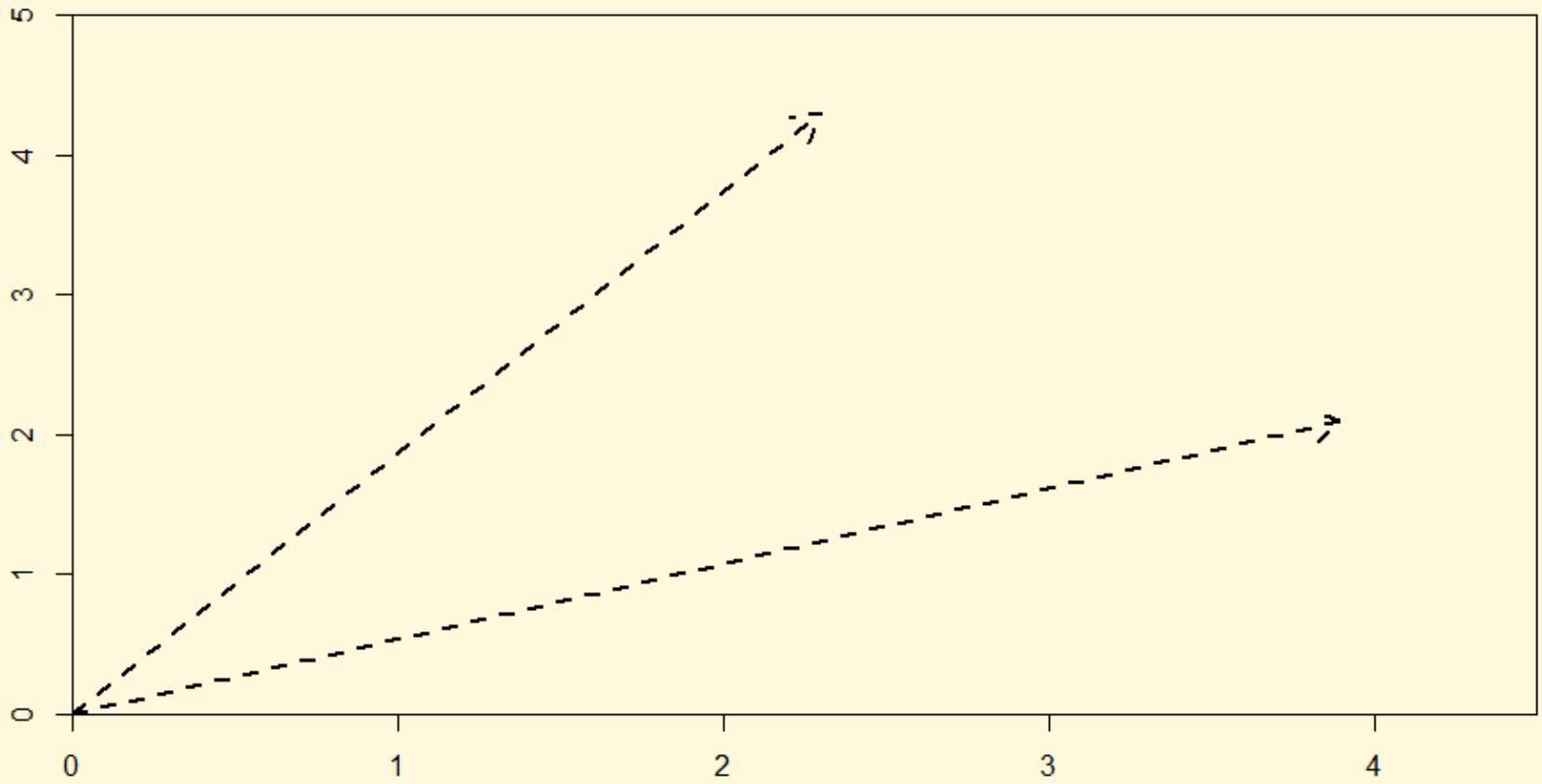
Graphically

$\mathbf{y_i} = [2.3, 4.3]$; $\mathbf{y_j} = [3.9, 2.1]$



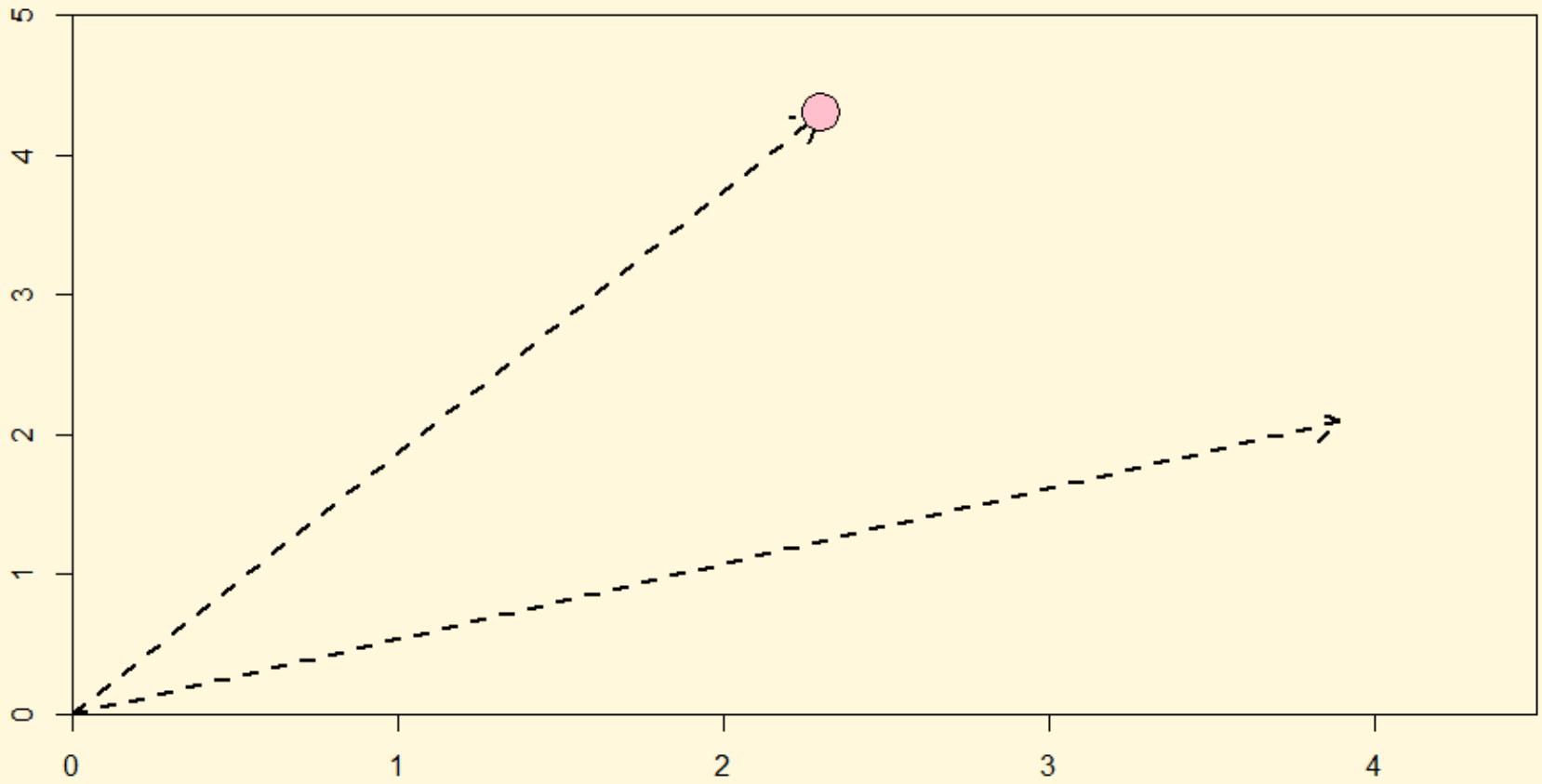
Graphically

$y_i = [2.3, 4.3]$; $y_j = [3.9, 2.1]$



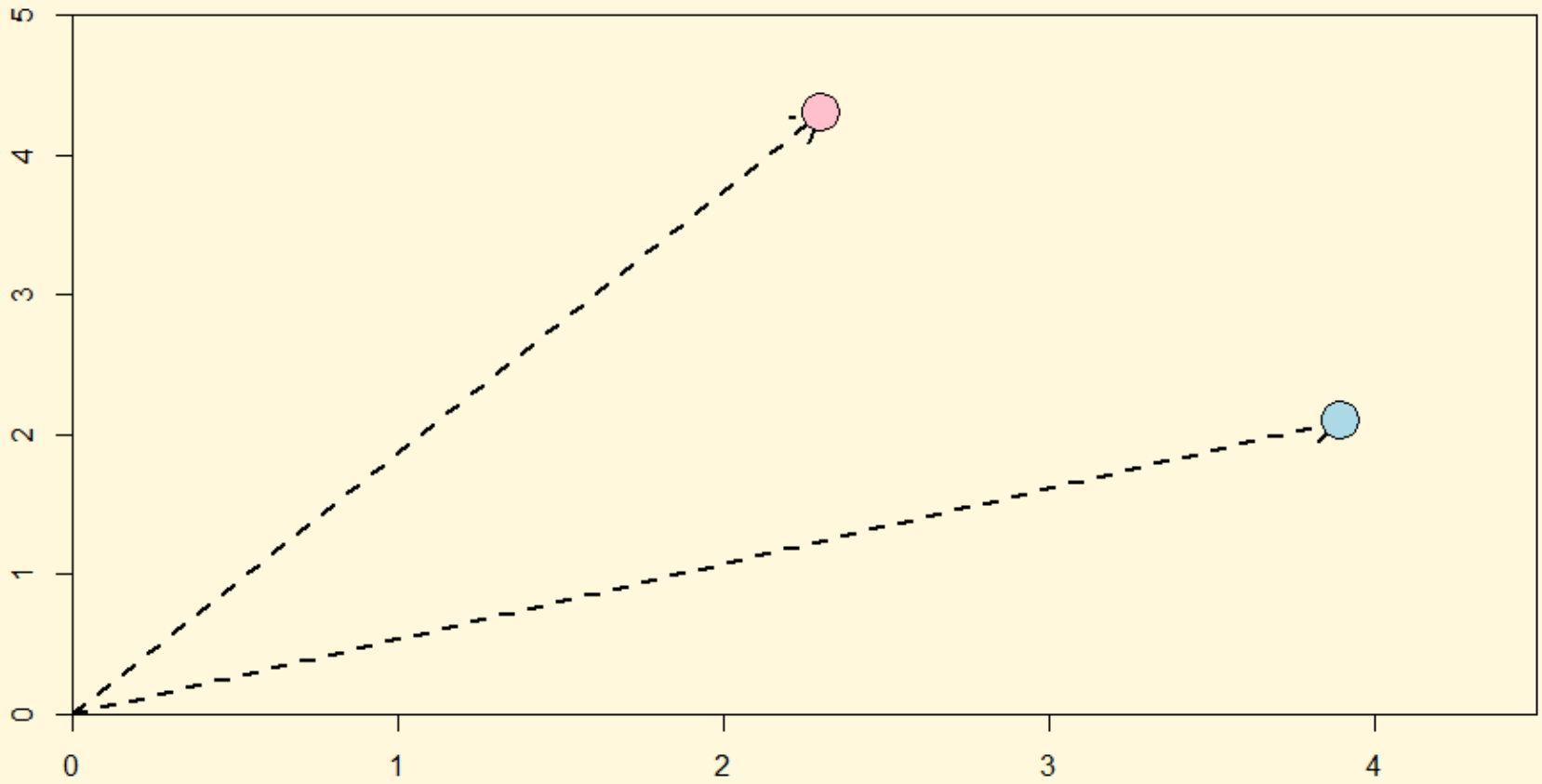
Graphically

$y_i = [2.3, 4.3]$; $y_j = [3.9, 2.1]$



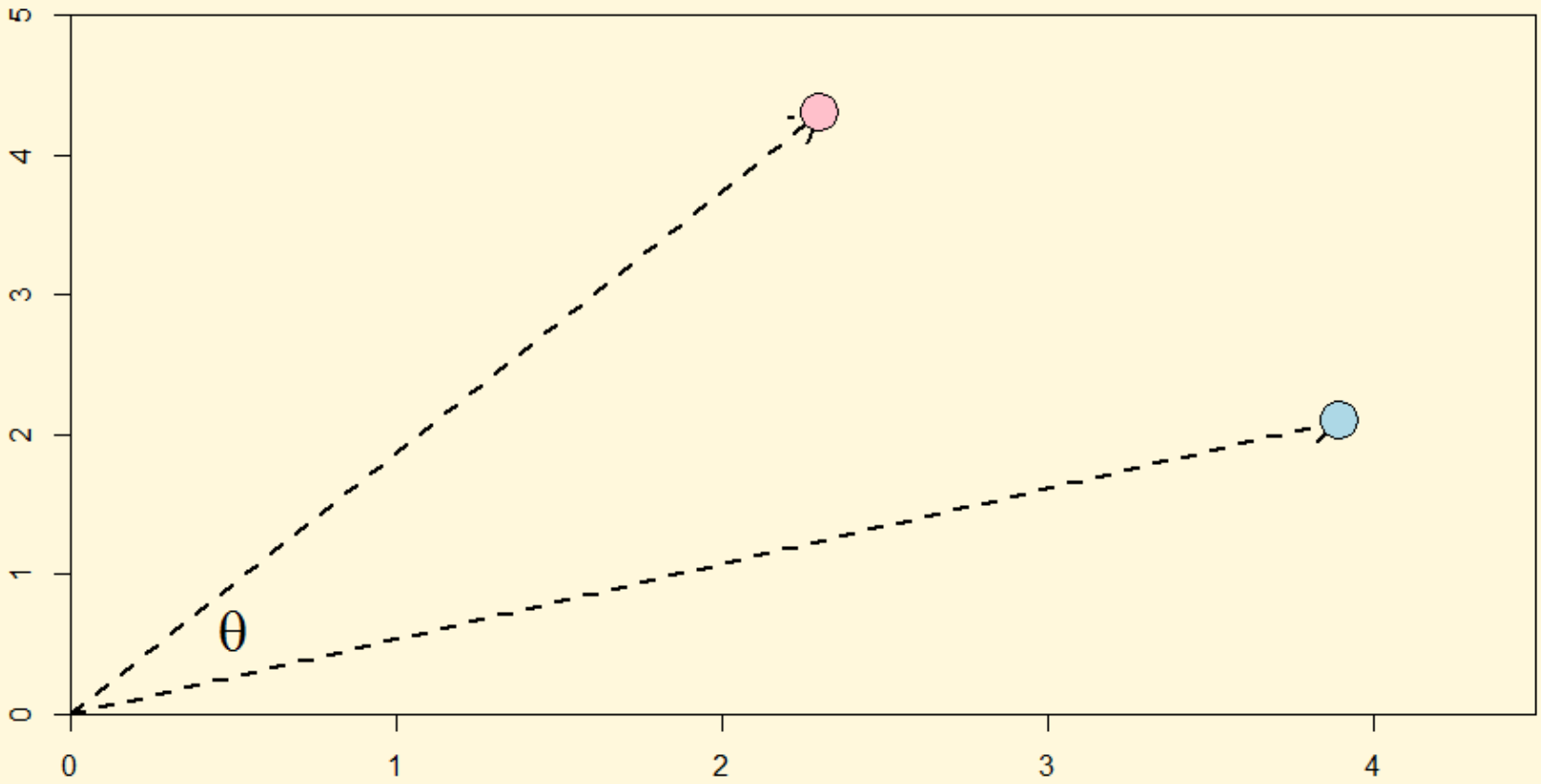
Graphically

$y_i = [2.3, 4.3]$; $y_j = [3.9, 2.1]$



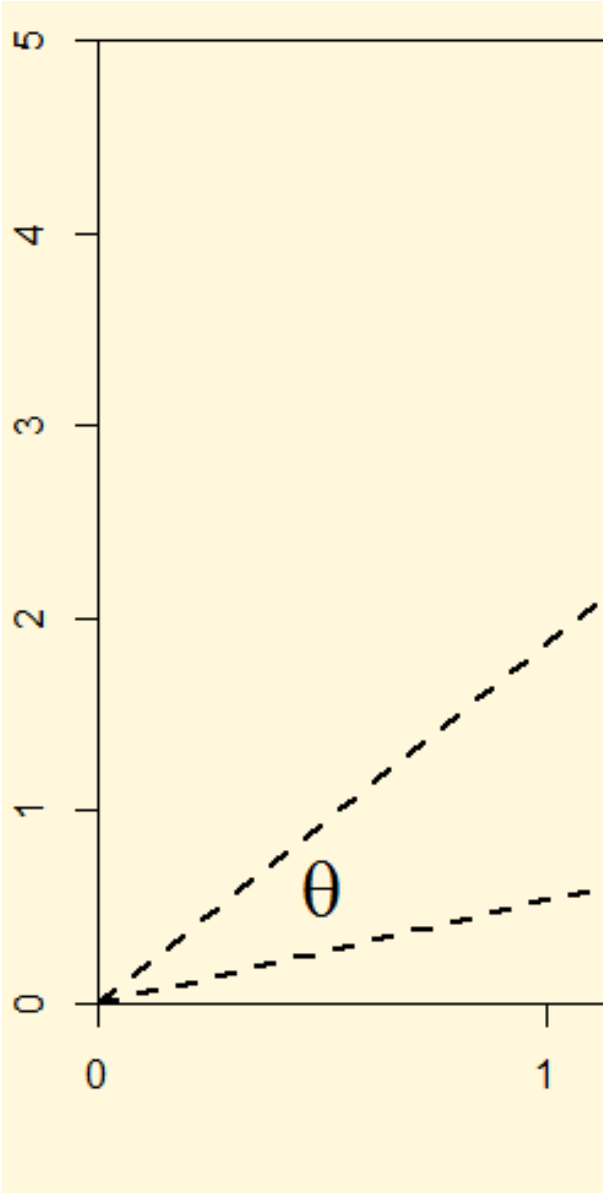
Graphically

$y_i = [2.3, 4.3]$; $y_j = [3.9, 2.1]$

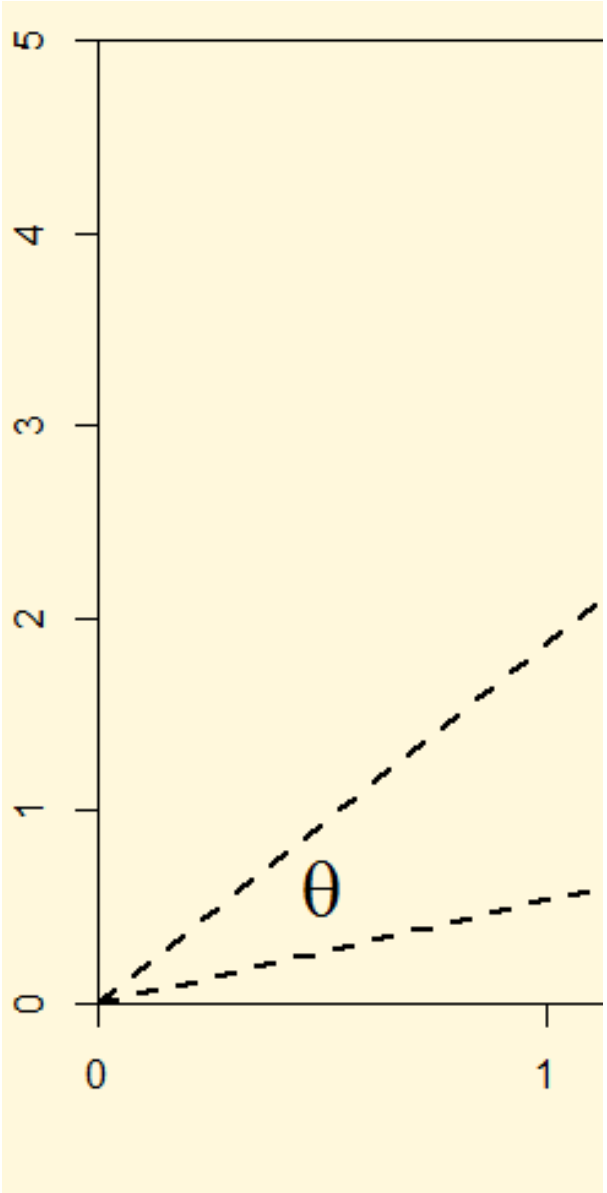


Algebra

Algebra

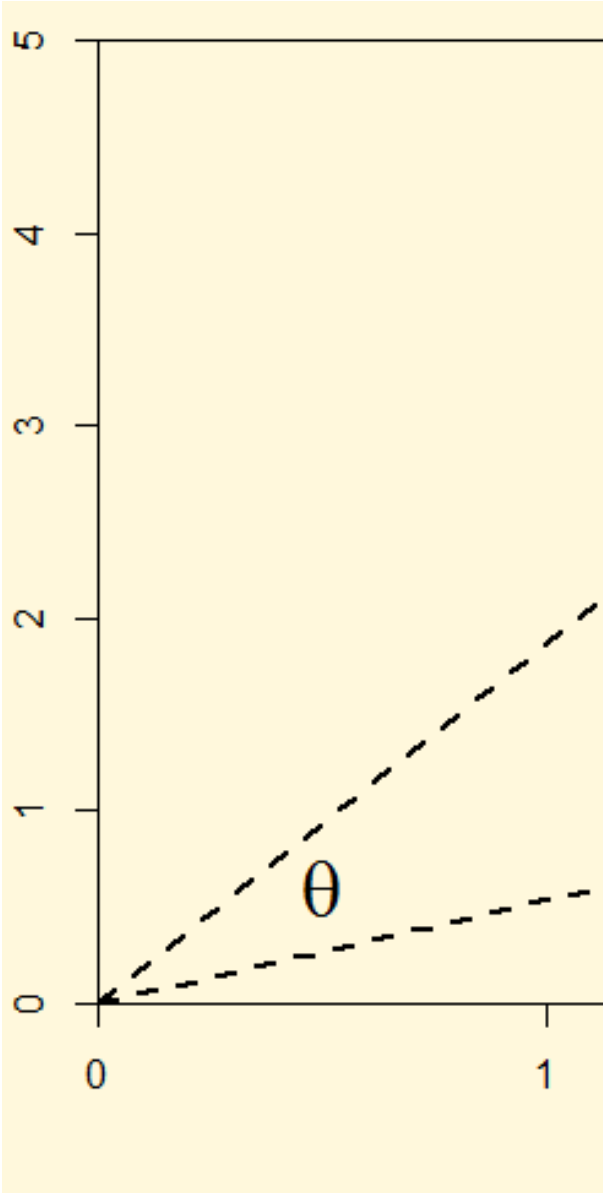


Algebra



know dot product of vectors:

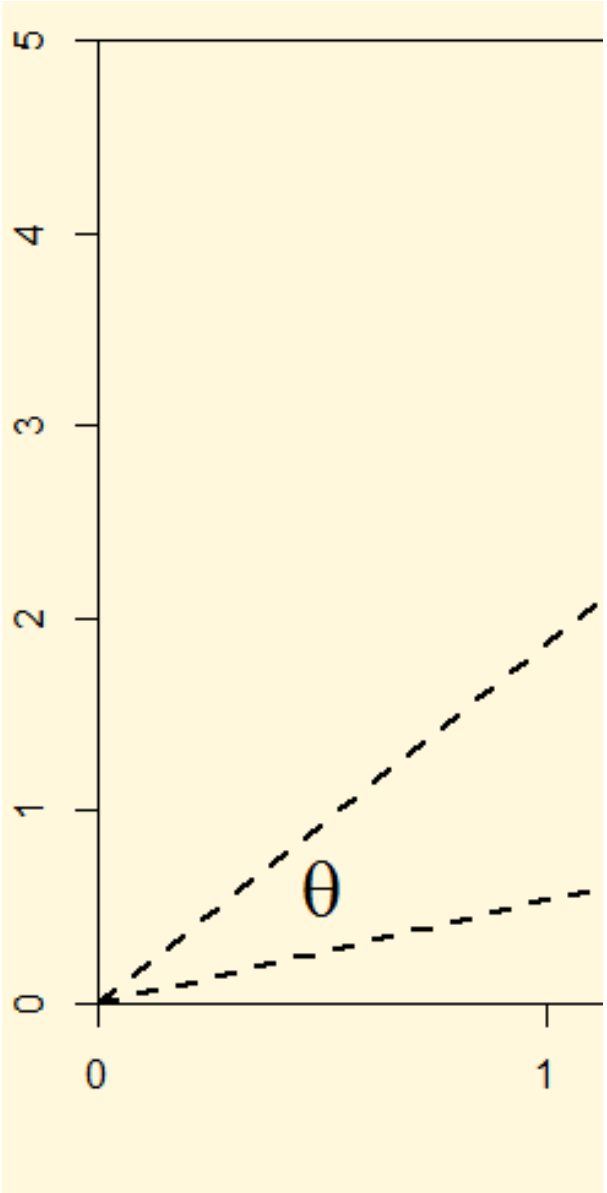
Algebra



know dot product of vectors:

$$\mathbf{y}_i \cdot \mathbf{y}_j = ||\mathbf{y}_i|| ||\mathbf{y}_j|| \cos\theta$$

Algebra

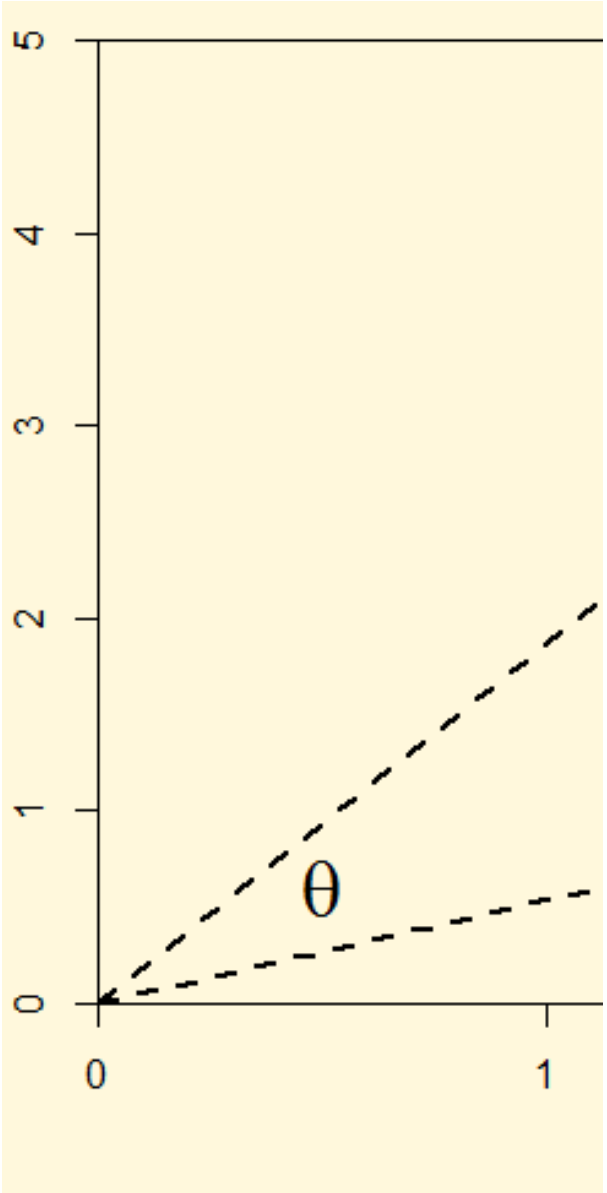


know dot product of vectors:

$$\mathbf{y}_i \cdot \mathbf{y}_j = ||\mathbf{y}_i|| ||\mathbf{y}_j|| \cos\theta$$

then $\cos\theta = \frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i|| ||\mathbf{y}_j||}$

Algebra



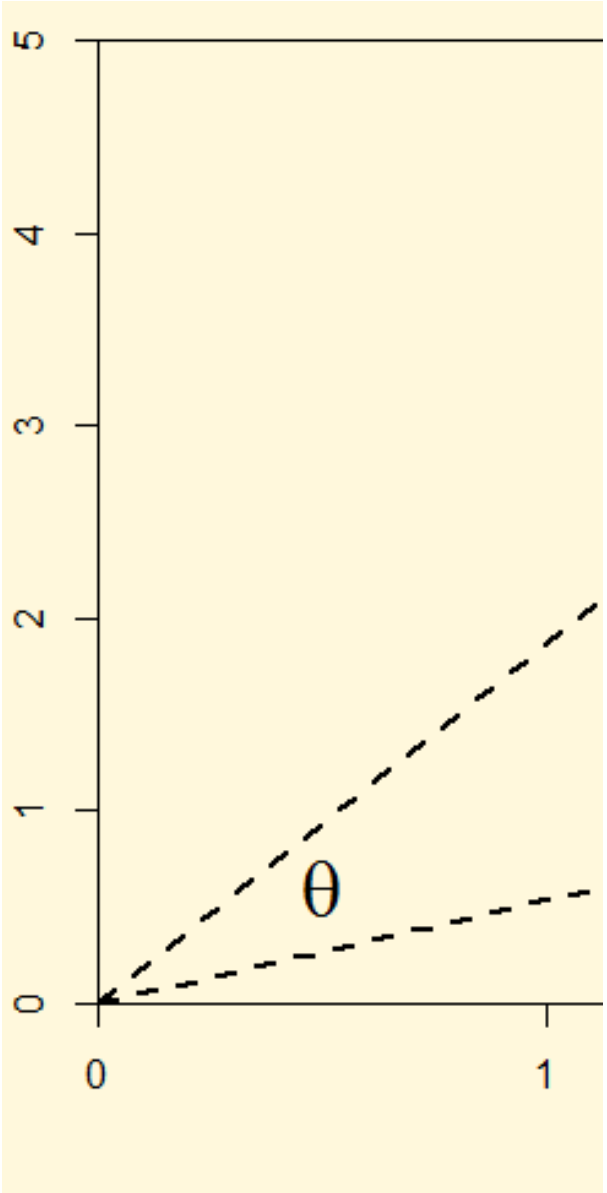
know dot product of vectors:

$$\mathbf{y}_i \cdot \mathbf{y}_j = ||\mathbf{y}_i|| ||\mathbf{y}_j|| \cos\theta$$

then $\cos\theta = \frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i|| ||\mathbf{y}_j||}$

and $\theta = \arccos\left(\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i|| ||\mathbf{y}_j||}\right)$.

Algebra



know dot product of vectors:

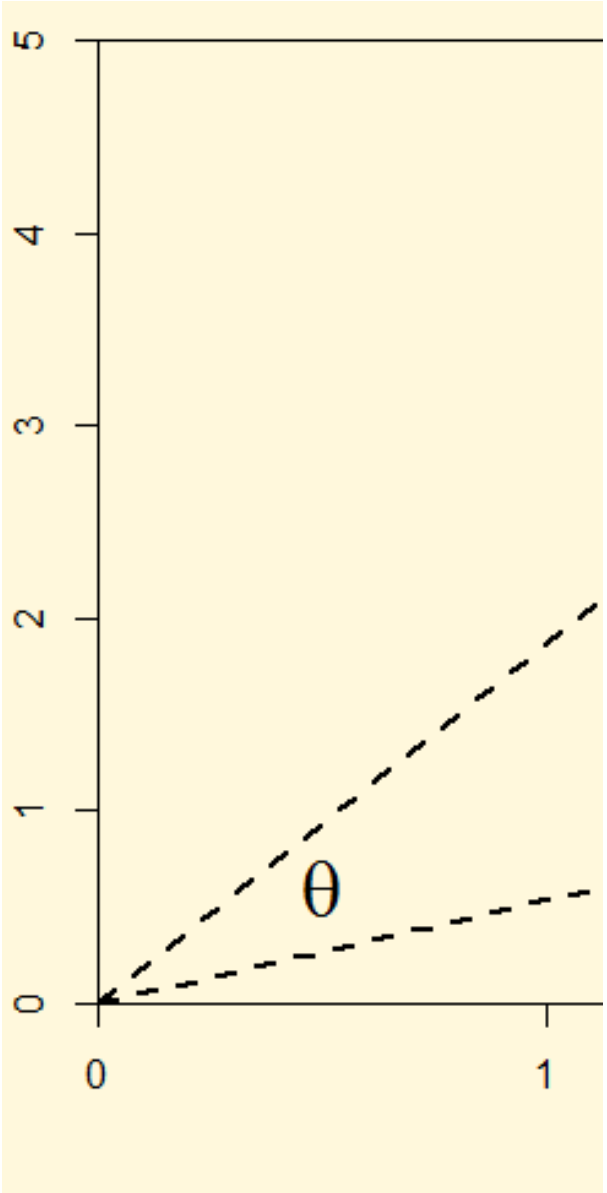
$$\mathbf{y}_i \cdot \mathbf{y}_j = ||\mathbf{y}_i|| ||\mathbf{y}_j|| \cos\theta$$

then $\cos\theta = \frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i|| ||\mathbf{y}_j||}$

and $\theta = \arccos\left(\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i|| ||\mathbf{y}_j||}\right)$.

so $\theta = \arccos\left(\frac{18}{21.62}\right)$

Algebra



know dot product of vectors:

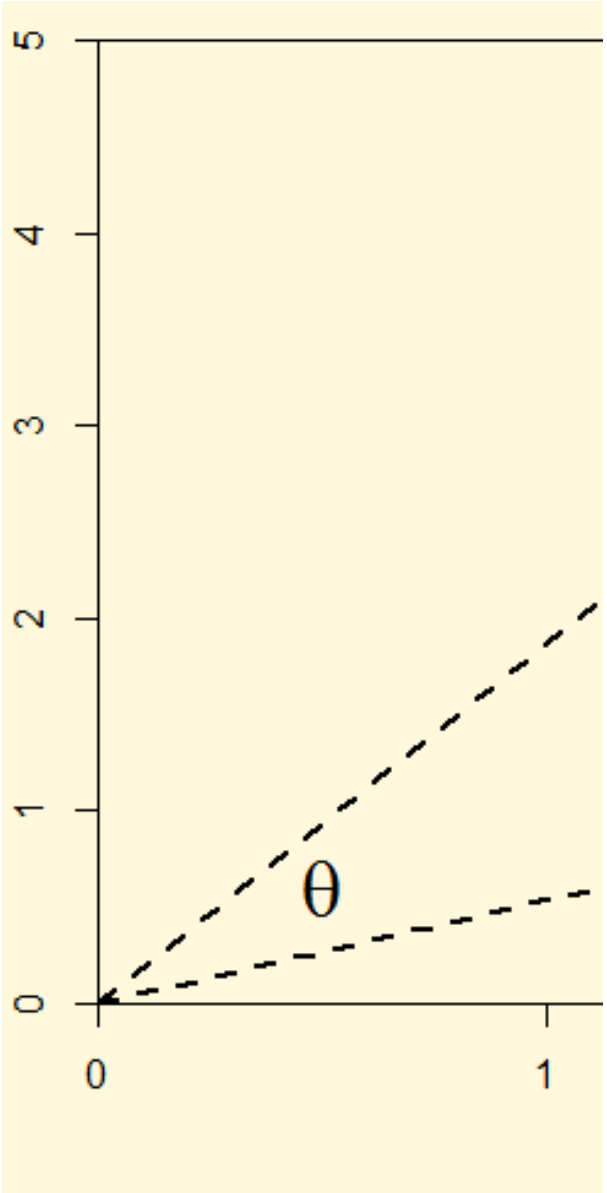
$$\mathbf{y}_i \cdot \mathbf{y}_j = ||\mathbf{y}_i|| ||\mathbf{y}_j|| \cos\theta$$

then $\cos\theta = \frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i|| ||\mathbf{y}_j||}$

and $\theta = \arccos\left(\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i|| ||\mathbf{y}_j||}\right)$.

so $\theta = \arccos\left(\frac{18}{21.62}\right) = 0.58$

Algebra



know dot product of vectors:

$$\mathbf{y}_i \cdot \mathbf{y}_j = ||\mathbf{y}_i||||\mathbf{y}_j|| \cos\theta$$

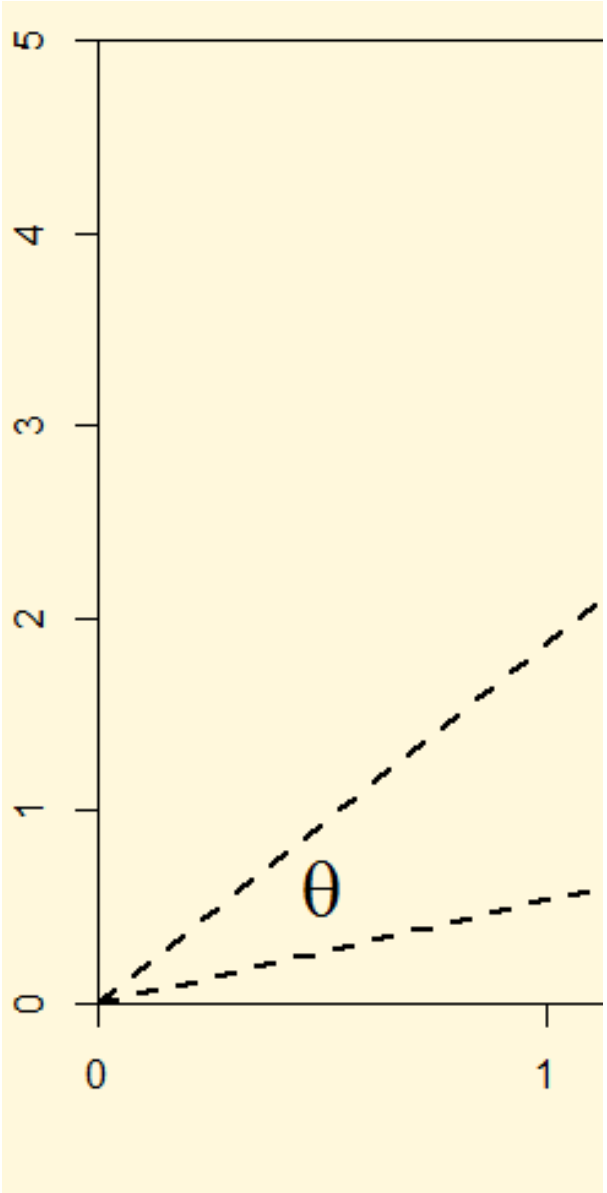
then $\cos\theta = \frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i||||\mathbf{y}_j||}$

and $\theta = \arccos\left(\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i||||\mathbf{y}_j||}\right)$.

so $\theta = \arccos\left(\frac{18}{21.62}\right) = 0.58$

$$\rightarrow 0.58 \times \frac{180}{\pi} = 33.63°.$$

Algebra



know dot product of vectors:

$$\mathbf{y}_i \cdot \mathbf{y}_j = ||\mathbf{y}_i|| ||\mathbf{y}_j|| \cos\theta$$

then $\cos\theta = \frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i|| ||\mathbf{y}_j||}$

and $\theta = \arccos\left(\frac{\mathbf{y}_i \cdot \mathbf{y}_j}{||\mathbf{y}_i|| ||\mathbf{y}_j||}\right)$.

so $\theta = \arccos\left(\frac{18}{21.62}\right) = 0.58$

$\rightarrow 0.58 \times \frac{180}{\pi} = 33.63°$.

Looks about right.

1983 General Election Manifestos

1983 General Election Manifestos

1983 General Election Manifestos

- Labour manifesto as ‘longest suicide note in history’

1983 General Election Manifestos

- Labour manifesto as 'longest suicide note in history'
- unilateral nuclear disarmament, withdrawal from the EEC, abolition of the Lords, re-nationalisation

1983 General Election Manifestos

- Labour manifesto as 'longest suicide note in history'
- unilateral nuclear disarmament, withdrawal from the EEC, abolition of the Lords, re-nationalisation

1983 General Election Manifestos

- Labour manifesto as 'longest suicide note in history'
- unilateral nuclear disarmament, withdrawal from the EEC, abolition of the Lords, re-nationalisation

- Conservative manifesto promised trade union curbs, deflation etc.

1983 General Election Manifestos

- Labour manifesto as 'longest suicide note in history'
- unilateral nuclear disarmament, withdrawal from the EEC, abolition of the Lords, re-nationalisation

- Conservative manifesto promised trade union curbs, deflation etc.

$$c_{ij} \approx 0.70$$

1997 General Election Manifestos

1997 General Election Manifestos

1997 General Election Manifestos

- Conservative manifesto promised continuation of moderate Major years.

1997 General Election Manifestos

- Conservative manifesto promised continuation of moderate Major years.

1997 General Election Manifestos

- Conservative manifesto promised continuation of moderate Major years.

- ‘New Labour’ and ‘Third Way’

1997 General Election Manifestos

- Conservative manifesto promised continuation of moderate Major years.

- 'New Labour' and 'Third Way'
- committed to Conservative spending plans (for next two years),

1997 General Election Manifestos

- Conservative manifesto promised continuation of moderate Major years.

- 'New Labour' and 'Third Way'
- committed to Conservative spending plans (for next two years), no income tax rises.

1997 General Election Manifestos

- Conservative manifesto promised continuation of moderate Major years.

- 'New Labour' and 'Third Way'
- committed to Conservative spending plans (for next two years), no income tax rises.

$$c_{ij} \approx 0.90$$

Animals at the Zoo

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan:

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan: known as 'taxicab' distance or 'city block' distance.

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan: known as 'taxicab' distance or 'city block' distance. Absolute difference between coordinates: $||\mathbf{y}_i - \mathbf{y}_j|| = \sum |\mathbf{y}_i - \mathbf{y}_j|$.

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan: known as 'taxicab' distance or 'city block' distance. Absolute difference between coordinates: $||\mathbf{y}_i - \mathbf{y}_j|| = \sum |\mathbf{y}_i - \mathbf{y}_j|$. As we go from $\mathbf{y}_i$ to $\mathbf{y}_j$,

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan: known as 'taxicab' distance or 'city block' distance. Absolute difference between coordinates: $||\mathbf{y}_i - \mathbf{y}_j|| = \sum |\mathbf{y}_i - \mathbf{y}_j|$. As we go from $\mathbf{y}_i$ to $\mathbf{y}_j$, have to do so at right angles: travel along, turn 90° and then up (or down), then turn 90° and go along, turn 90° etc.

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan: known as 'taxicab' distance or 'city block' distance. Absolute difference between coordinates: $||\mathbf{y}_i - \mathbf{y}_j|| = \sum |\mathbf{y}_i - \mathbf{y}_j|$. As we go from $\mathbf{y}_i$ to $\mathbf{y}_j$, have to do so at right angles: travel along, turn 90° and then up (or down), then turn 90° and go along, turn 90° etc.

Canberra:

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan: known as 'taxicab' distance or 'city block' distance. Absolute difference between coordinates: $||\mathbf{y}_i - \mathbf{y}_j|| = \sum |\mathbf{y}_i - \mathbf{y}_j|$. As we go from $\mathbf{y}_i$ to $\mathbf{y}_j$, have to do so at right angles: travel along, turn 90° and then up (or down), then turn 90° and go along, turn 90° etc.

Canberra: weighted version of Manhattan distance.

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan: known as 'taxicab' distance or 'city block' distance. Absolute difference between coordinates: $||\mathbf{y}_i - \mathbf{y}_j|| = \sum |\mathbf{y}_i - \mathbf{y}_j|$. As we go from $\mathbf{y}_i$ to $\mathbf{y}_j$, have to do so at right angles: travel along, turn 90° and then up (or down), then turn 90° and go along, turn 90° etc.

Canberra: weighted version of Manhattan distance. $\sum \frac{|\mathbf{y}_i - \mathbf{y}_j|}{|\mathbf{y}_i| + |\mathbf{y}_j|}$

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan: known as 'taxicab' distance or 'city block' distance. Absolute difference between coordinates: $||\mathbf{y}_i - \mathbf{y}_j|| = \sum |\mathbf{y}_i - \mathbf{y}_j|$. As we go from $\mathbf{y}_i$ to $\mathbf{y}_j$, have to do so at right angles: travel along, turn 90° and then up (or down), then turn 90° and go along, turn 90° etc.

Canberra: weighted version of Manhattan distance. $\sum \frac{|\mathbf{y}_i - \mathbf{y}_j|}{|\mathbf{y}_i| + |\mathbf{y}_j|}$

Minowski: generalized version of Euclidean and Manhattan.

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan: known as 'taxicab' distance or 'city block' distance. Absolute difference between coordinates: $||\mathbf{y}_i - \mathbf{y}_j|| = \sum |\mathbf{y}_i - \mathbf{y}_j|$. As we go from $\mathbf{y}_i$ to $\mathbf{y}_j$, have to do so at right angles: travel along, turn 90° and then up (or down), then turn 90° and go along, turn 90° etc.

Canberra: weighted version of Manhattan distance. $\sum \frac{|\mathbf{y}_i - \mathbf{y}_j|}{|\mathbf{y}_i| + |\mathbf{y}_j|}$

Minowski: generalized version of Euclidean and Manhattan. $\left(\sum |\mathbf{y}_i - \mathbf{y}_j|^c\right)^{\frac{1}{c}}$.

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

Manhattan: known as 'taxicab' distance or 'city block' distance. Absolute difference between coordinates: $||\mathbf{y}_i - \mathbf{y}_j|| = \sum |\mathbf{y}_i - \mathbf{y}_j|$. As we go from $\mathbf{y}_i$ to $\mathbf{y}_j$, have to do so at right angles: travel along, turn 90° and then up (or down), then turn 90° and go along, turn 90° etc.

Canberra: weighted version of Manhattan distance. $\sum \frac{|\mathbf{y}_i - \mathbf{y}_j|}{|\mathbf{y}_i| + |\mathbf{y}_j|}$

Minowski: generalized version of Euclidean and Manhattan. $(\sum |\mathbf{y}_i - \mathbf{y}_j|^c)^{\frac{1}{c}}$. If c is 1, this is Manhattan. If c is 2, this is Euclidean.

Animals at the Zoo

- we can produce a cosine dissimilarity measure via $1 - c_{ij}$ (though not a metric)

but there are a large number of other distance measures on offer:

Jaccard: size of the intersection of the two documents (number of common words between the documents) divided by the size of the union of the two documents (total number of unique words in docs).

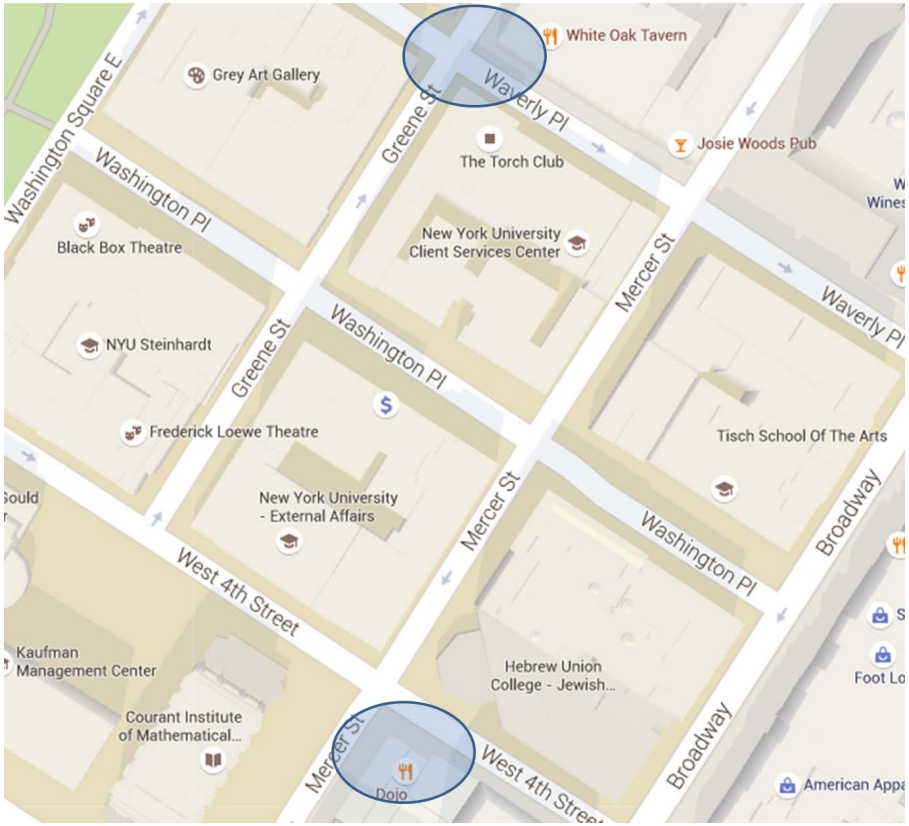
Manhattan: known as 'taxicab' distance or 'city block' distance. Absolute difference between coordinates: $||\mathbf{y}_i - \mathbf{y}_j|| = \sum |\mathbf{y}_i - \mathbf{y}_j|$. As we go from $\mathbf{y}_i$ to $\mathbf{y}_j$, have to do so at right angles: travel along, turn 90° and then up (or down), then turn 90° and go along, turn 90° etc.

Canberra: weighted version of Manhattan distance. $\sum \frac{|\mathbf{y}_i - \mathbf{y}_j|}{|\mathbf{y}_i| + |\mathbf{y}_j|}$

Minowski: generalized version of Euclidean and Manhattan. $(\sum |\mathbf{y}_i - \mathbf{y}_j|^c)^{\frac{1}{c}}$. If c is 1, this is Manhattan. If c is 2, this is Euclidean.

etc

Exercise

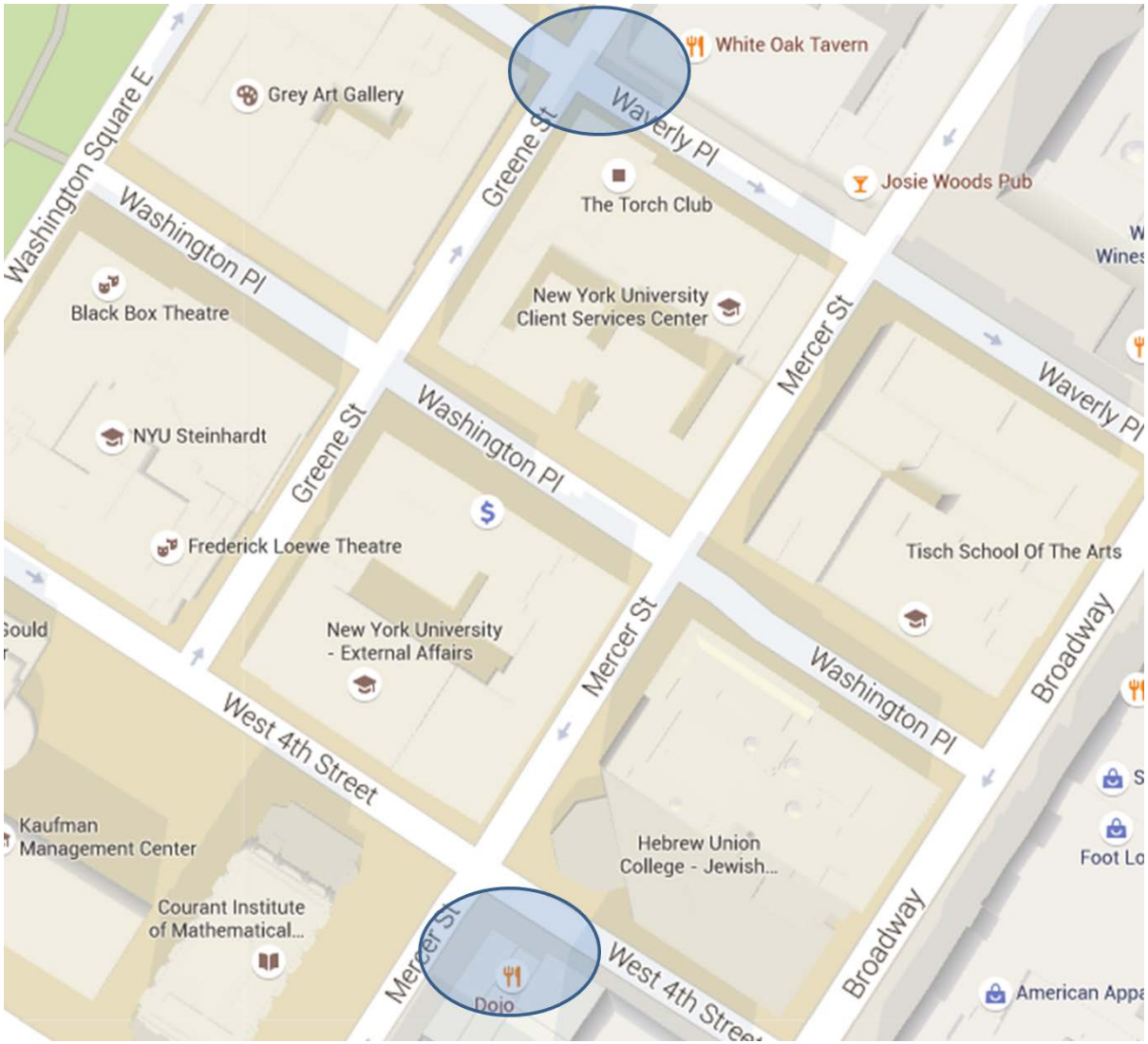


Suppose a block is one unit long and one unit wide.

- what is Euclidean distance between Dojo and White Oak Tavern?
- what is Manhattan distance between Dojo and White Oak Tavern?

Solution

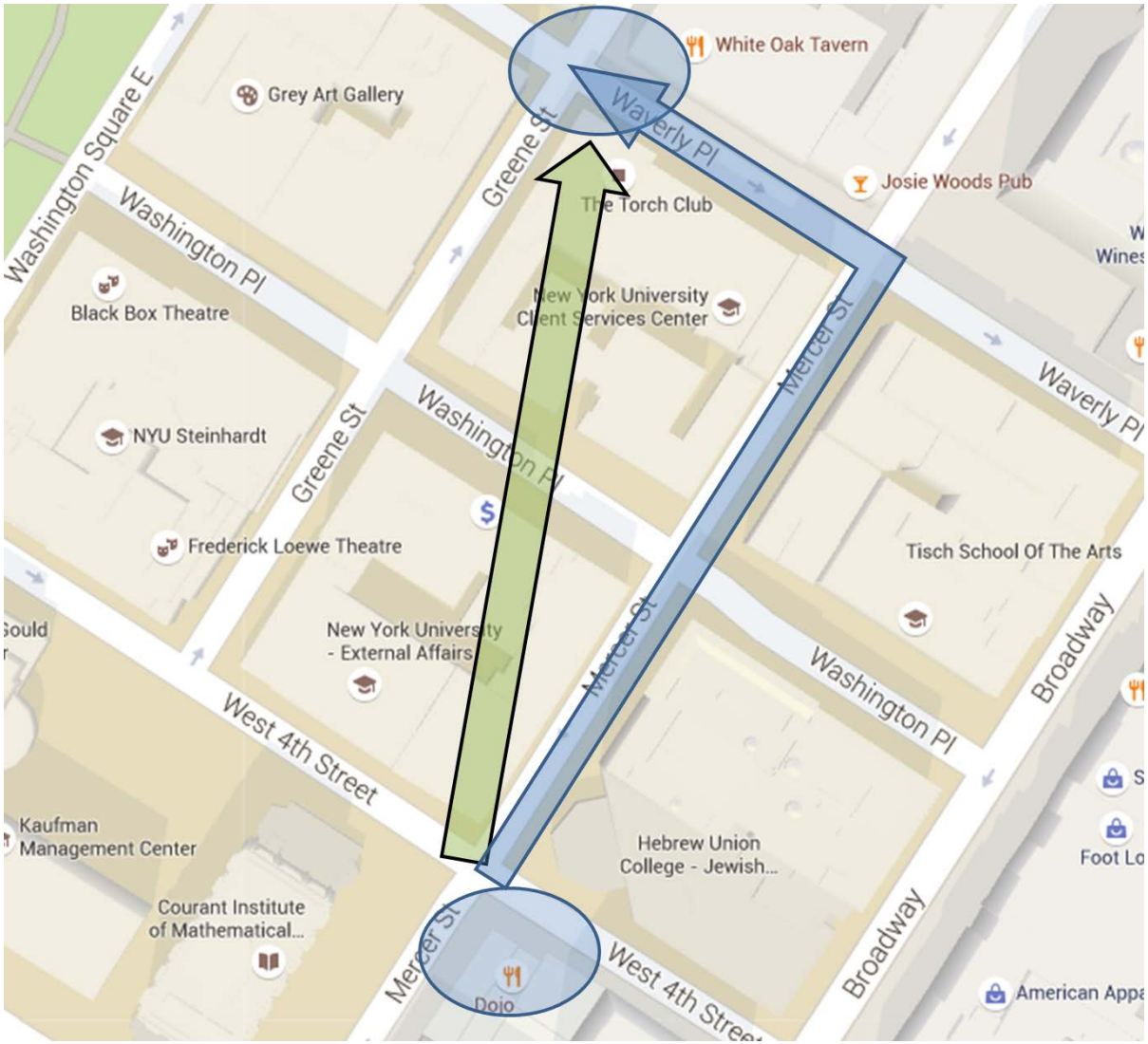
Solution


White Oak Tavern
Grey Art Gallery
Waverly Pl
Washington Square E
Washington Pl
Greene St
The Torch Club
Josie Woods Pub
Black Box Theatre
New York University
Client Services Center
Mercer St
NYU Steinhardt
Greene St
Washington Pl
Waverly Pl
Frederick Loewe Theatre
Tisch School Of The Arts
New York University
- External Affairs
Mercer St
Broadway
West 4th Street
Washington Pl
Kaufman
Management Center
Hebrew Union
College - Jewish...
Courant Institute
of Mathematical...
Mercer St
Dojo
West 4th Street
Broadway

Solution

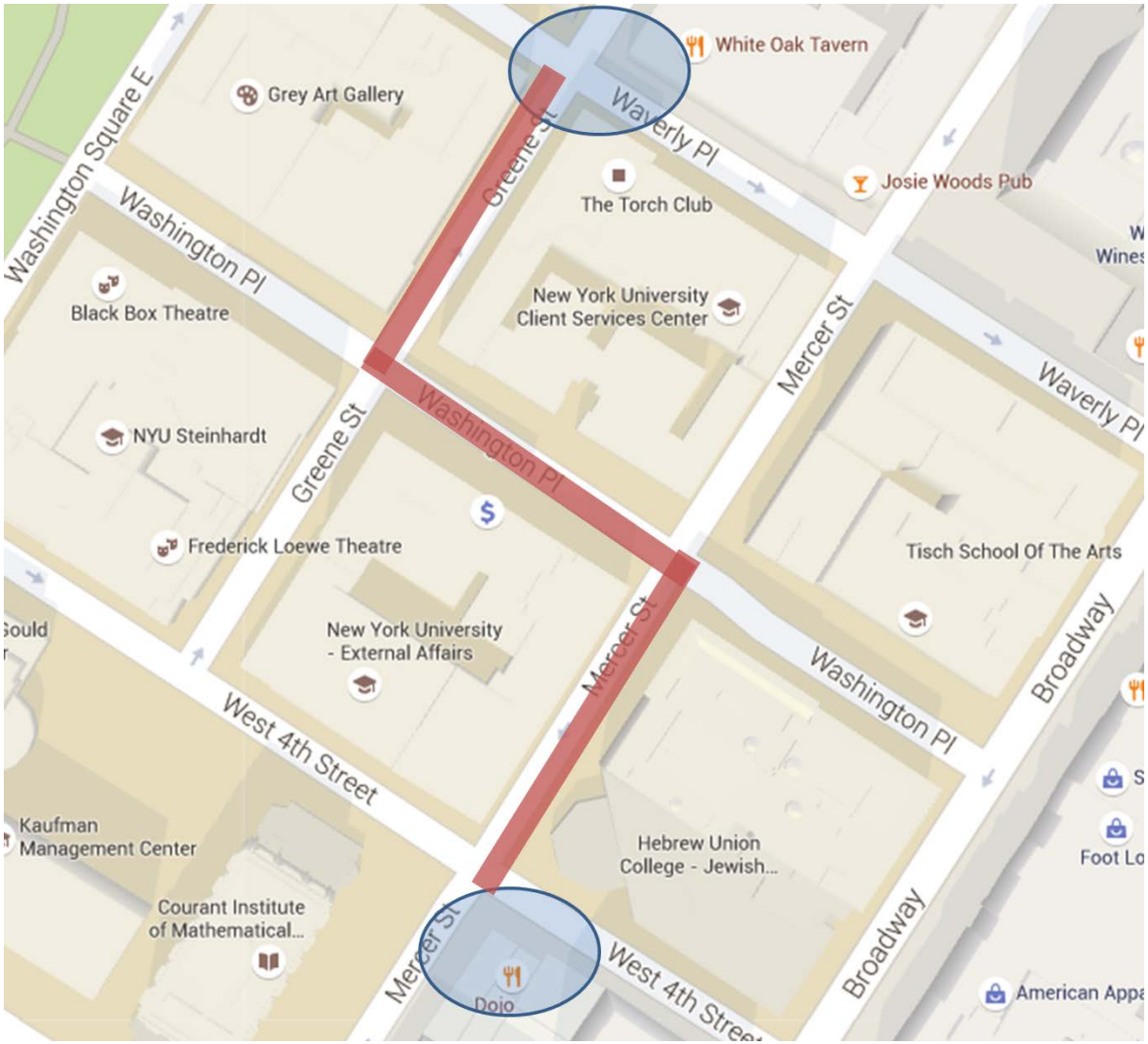
- Euclidean ($\sqrt{5}$)

Solution



- Euclidean ($\sqrt{5}$)
- Manhattan (3)

Solution



- Euclidean ($\sqrt{5}$)
- Manhattan (3)
- Manhattan (3)

Collocations, phrasemes and co-occurrence

Collocations, phrasemes and co-occurrence

So far,

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style.

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style. In some cases, may also want to think seriously about collocations:

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style. In some cases, may also want to think seriously about collocations: words that co-occur in a document,

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style. In some cases, may also want to think seriously about collocations: words that co-occur in a document, adjacent (or close to adjacent) to one another.

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style. In some cases, may also want to think seriously about collocations: words that co-occur in a document, adjacent (or close to adjacent) to one another.

defn group of two or more adjacent words that are seen together more often than we would 'expect' were words placed in document independent of the others.

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style. In some cases, may also want to think seriously about collocations: words that co-occur in a document, adjacent (or close to adjacent) to one another.

defn group of two or more adjacent words that are seen together more often than we would 'expect' were words placed in document independent of the others. Mean something specific. Describe as strong collocation if the link between the words is fixed and restrictive.

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style. In some cases, may also want to think seriously about collocations: words that co-occur in a document, adjacent (or close to adjacent) to one another.

defn group of two or more adjacent words that are seen together more often than we would 'expect' were words placed in document independent of the others. Mean something specific. Describe as strong collocation if the link between the words is fixed and restrictive.

e.g. 'do business' (not 'make business'),

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style. In some cases, may also want to think seriously about collocations: words that co-occur in a document, adjacent (or close to adjacent) to one another.

defn group of two or more adjacent words that are seen together more often than we would 'expect' were words placed in document independent of the others. Mean something specific. Describe as strong collocation if the link between the words is fixed and restrictive.

e.g. 'do business' (not 'make business'), 'save money' (not 'preserve money').

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style. In some cases, may also want to think seriously about collocations: words that co-occur in a document, adjacent (or close to adjacent) to one another.

defn group of two or more adjacent words that are seen together more often than we would 'expect' were words placed in document independent of the others. Mean something specific. Describe as strong collocation if the link between the words is fixed and restrictive.

e.g. 'do business' (not 'make business'), 'save money' (not 'preserve money'). Note that one of the terms is chosen freely (e.g. money),

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style. In some cases, may also want to think seriously about collocations: words that co-occur in a document, adjacent (or close to adjacent) to one another.

defn group of two or more adjacent words that are seen together more often than we would 'expect' were words placed in document independent of the others. Mean something specific. Describe as strong collocation if the link between the words is fixed and restrictive.

e.g. 'do business' (not 'make business'), 'save money' (not 'preserve money'). Note that one of the terms is chosen freely (e.g. money), but the other is constrained by language.

Collocations, phrasemes and co-occurrence

So far, we've treated the features in a 'bag of words' style. In some cases, may also want to think seriously about collocations: words that co-occur in a document, adjacent (or close to adjacent) to one another.

defn group of two or more adjacent words that are seen together more often than we would 'expect' were words placed in document independent of the others. Mean something specific. Describe as strong collocation if the link between the words is fixed and restrictive.

e.g. 'do business' (not 'make business'), 'save money' (not 'preserve money'). Note that one of the terms is chosen freely (e.g. money), but the other is constrained by language.

Why study?

Why study?

Collocations are a type of phraseme: an idiomatic, ‘set phrase’ in a language.

Why study?

Collocations are a type of phraseme: an idiomatic, 'set phrase' in a language. Has *at least* one word or part that is constrained.

Why study?

Collocations are a type of phraseme: an idiomatic, 'set phrase' in a language. Has *at least* one word or part that is constrained. In the extreme, the meaning may not be implied by any of the lexical components.

Why study?

Collocations are a type of phraseme: an idiomatic, 'set phrase' in a language. Has *at least* one word or part that is constrained. In the extreme, the meaning may not be implied by any of the lexical components.

e.g. 'He was pulling my leg'

Why study?

Collocations are a type of phraseme: an idiomatic, 'set phrase' in a language. Has *at least* one word or part that is constrained. In the extreme, the meaning may not be implied by any of the lexical components.

e.g. 'He was pulling my leg', 'At the drop of a hat.'

Why study?

Collocations are a type of phraseme: an idiomatic, 'set phrase' in a language. Has *at least* one word or part that is constrained. In the extreme, the meaning may not be implied by any of the lexical components.

e.g. 'He was pulling my leg', 'At the drop of a hat.'

Phrasemes are interesting in that they tell us something about history or culture of language.

Why study?

Collocations are a type of phraseme: an idiomatic, 'set phrase' in a language. Has *at least* one word or part that is constrained. In the extreme, the meaning may not be implied by any of the lexical components.

e.g. 'He was pulling my leg', 'At the drop of a hat.'

Phrasemes are interesting in that they tell us something about history or culture of language.

Why do we talk of 'strong tea' but 'powerful drugs'?

Why study?

Collocations are a type of phraseme: an idiomatic, 'set phrase' in a language. Has *at least* one word or part that is constrained. In the extreme, the meaning may not be implied by any of the lexical components.

e.g. 'He was pulling my leg', 'At the drop of a hat.'

Phrasemes are interesting in that they tell us something about history or culture of language.

Why do we talk of 'strong tea' but 'powerful drugs'?

\+ Very important when studying named entities, like people or cities

Why study?

Collocations are a type of phraseme: an idiomatic, 'set phrase' in a language. Has *at least* one word or part that is constrained. In the extreme, the meaning may not be implied by any of the lexical components.

e.g. 'He was pulling my leg', 'At the drop of a hat.'

Phrasemes are interesting in that they tell us something about history or culture of language.

Why do we talk of 'strong tea' but 'powerful drugs'?

\+ Very important when studying named entities, like people or cities

e.g. 'Prime Minister'

How to Find Them?

How to Find Them?

Frequency? Typically not enough to look for (say) common bigrams (NYT corpus):

How to Find Them?

Frequency? Typically not enough to look for (say) common bigrams (NYT corpus):

frequency	w_1	w_2
80871	of	the
58841	in	the
26430	to	the
21842	on	the
21839	for	the
18568	and	the
16121	that	the
15630	at	the
15494	to	be
13899	in	a
13689	of	a
13361	by	the
13183	with	the
12622	from	the
11428	New	York
10007	he	said
9775	as	a
9231	is	a
8753	has	been
8573	for	a

How to Find Them?

Frequency? Typically not enough to look for (say) common bigrams (NYT corpus):

frequency	w_1	w_2
80871	of	the
58841	in	the
26430	to	the
21842	on	the
21839	for	the
18568	and	the
16121	that	the
15630	at	the
15494	to	be
13899	in	a
13689	of	a
13361	by	the
13183	with	the
12622	from	the
11428	New	York
10007	he	said
9775	as	a
9231	is	a
8753	has	been
8573	for	a

$\rightarrow$ most of these are uninteresting pairs of function words

How to Find Them?

Frequency? Typically not enough to look for (say) common bigrams (NYT corpus):

frequency	w_1	w_2
80871	of	the
58841	in	the
26430	to	the
21842	on	the
21839	for	the
18568	and	the
16121	that	the
15630	at	the
15494	to	be
13899	in	a
13689	of	a
13361	by	the
13183	with	the
12622	from	the
11428	New	York
10007	he	said
9775	as	a
9231	is	a
8753	has	been
8573	for	a

→ most of these are uninteresting pairs of function words (except 'New York')

How to Find Them?

Frequency? Typically not enough to look for (say) common bigrams (NYT corpus):

frequency	w_1	w_2
80871	of	the
58841	in	the
26430	to	the
21842	on	the
21839	for	the
18568	and	the
16121	that	the
15630	at	the
15494	to	be
13899	in	a
13689	of	a
13361	by	the
13183	with	the
12622	from	the
11428	New	York
10007	he	said
9775	as	a
9231	is	a
8753	has	been
8573	for	a

→ most of these are uninteresting pairs of function words (except 'New York')

Justeson and Katz (1995) improve performance considerably by applying parts-of-speech tagger,

How to Find Them?

Frequency? Typically not enough to look for (say) common bigrams (NYT corpus):

frequency	w_1	w_2
80871	of	the
58841	in	the
26430	to	the
21842	on	the
21839	for	the
18568	and	the
16121	that	the
15630	at	the
15494	to	be
13899	in	a
13689	of	a
13361	by	the
13183	with	the
12622	from	the
11428	New	York
10007	he	said
9775	as	a
9231	is	a
8753	has	been
8573	for	a

→ most of these are uninteresting pairs of function words (except 'New York')

Justeson and Katz (1995) improve performance considerably by applying parts-of-speech tagger, and only keeping those bigrams and trigrams that fulfill certain criteria...

Justeson and Katz (1995)

Justeson and Katz (1995)

N noun.

Justeson and Katz (1995)

N noun.

A adjective.

Justeson and Katz (1995)

N noun.

A adjective.

P preposition.

Justeson and Katz (1995)

N noun.

A adjective.

P preposition.

then following offers marked improvement:

Justeson and Katz (1995)

N noun.

A adjective.

P preposition.

then following offers marked improvement:

pattern	example
A N	Prime Minister
N N	surface area
A A N	little green men
A N N	real estate agent
N A N	home sweet home
N N N	term document matrix
N P N	Secretary of State

Reanalyzing NYT corpus: top ranked bi-grams

Reanalyzing NYT corpus: top ranked bi-grams

frequency	$w_1 w_2$	
11487	New York	A N
7261	United States	A N
5412	Los Angeles	N N
3301	last year	A N
3191	Saudi Arabia	N N
2699	last week	A N
2514	vice president	A N
2378	Persian Gulf	A N
2161	San Francisco	N N
2106	President Bush	N N
2001	Middle East	A N
1942	Saddam Hussein	N N
1867	Soviet Union	A N
1850	White House	A N
1633	United Nations	A N
1337	York City	N N
1328	oil prices	N N
1210	next year	A N
1074	chief executive	A N
1073	real estate	A N

Key Words in Context

Key Words in Context

In Information Retrieval it is often extremely helpful to know how and where a particular token of interest appears,

Key Words in Context

In Information Retrieval it is often extremely helpful to know how and where a particular token of interest appears, in terms of the words around it.

Key Words in Context

In Information Retrieval it is often extremely helpful to know how and where a particular token of interest appears, in terms of the words around it.

→ quick overview of general use,

Key Words in Context

In Information Retrieval it is often extremely helpful to know how and where a particular token of interest appears, in terms of the words around it.

→ quick overview of general use, and allows for easy, follow up inspection of the document in question.

Key Words in Context

In Information Retrieval it is often extremely helpful to know how and where a particular token of interest appears, in terms of the words around it.

$\rightarrow$ quick overview of general use, and allows for easy, follow up inspection of the document in question.

also true in social science applications where we might want to understand how a given concept appears,

Key Words in Context

In Information Retrieval it is often extremely helpful to know how and where a particular token of interest appears, in terms of the words around it.

$\rightarrow$ quick overview of general use, and allows for easy, follow up inspection of the document in question.

also true in social science applications where we might want to understand how a given concept appears, or when we are looking for prototypical examples.

Key Words in Context

In Information Retrieval it is often extremely helpful to know how and where a particular token of interest appears, in terms of the words around it.

→ quick overview of general use, and allows for easy, follow up inspection of the document in question.

also true in social science applications where we might want to understand how a given concept appears, or when we are looking for prototypical examples.

1 keyword of interest.

Key Words in Context

In Information Retrieval it is often extremely helpful to know how and where a particular token of interest appears, in terms of the words around it.

→ quick overview of general use, and allows for easy, follow up inspection of the document in question.

also true in social science applications where we might want to understand how a given concept appears, or when we are looking for prototypical examples.

1. keyword of interest.
2. context —typically the sentence in which it appears.

Key Words in Context

In Information Retrieval it is often extremely helpful to know how and where a particular token of interest appears, in terms of the words around it.

→ quick overview of general use, and allows for easy, follow up inspection of the document in question.

also true in social science applications where we might want to understand how a given concept appears, or when we are looking for prototypical examples.

1. keyword of interest.
2. context —typically the sentence in which it appears.
3. location code —document details.

Example: 'democratic' and the Second Reform Act

Example: 'democratic' and the Second Reform Act

DERBY, 1867. DIZZY WINS WITH "REFORM BILL."

A LEAP IN THE DARK.

Example: 'democratic' and the Second Reform Act

1867 House of Commons considers extending suffrage to urban working class men,

Example: 'democratic' and the Second Reform Act

1867 House of Commons considers extending suffrage to urban working class men, via 'Representation of the People Act'

Example: 'democratic' and the Second Reform Act

1867 House of Commons considers extending suffrage to urban working class men, via 'Representation of the People Act'

$\rightarrow$ represents approximate doubling of electorate.

Example: 'democratic' and the Second Reform Act

1867 House of Commons considers extending suffrage to urban working class men, via 'Representation of the People Act'

→ represents approximate doubling of electorate.

Debates of the time are lively and long.

Example: 'democratic' and the Second Reform Act

1867 House of Commons considers extending suffrage to urban working class men, via 'Representation of the People Act'

→ represents approximate doubling of electorate.

Debates of the time are lively and long. Normative notions of extending 'rights' on one hand (and pragmatic politics) vs fear of mob rule.

Example: 'democratic' and the Second Reform Act

1867 House of Commons considers extending suffrage to urban working class men, via 'Representation of the People Act'

→ represents approximate doubling of electorate.

Debates of the time are lively and long. Normative notions of extending 'rights' on one hand (and pragmatic politics) vs fear of mob rule.

q What role did 'democratic' play in the debate?

Some KWIC from the debates: `kwic()` in quanteda

	preword	word	postword
.	.	.	.
.	.	.	.
.	.	.	.
[s267549.txt, 994]	evil that attends a purely	democratic	form of Government. There could be
[s267549.txt, 1015]	here, not possibly towards a	democratic	form of government, but in
[s267738.txt, 1492]	swept away in some further	democratic	change. And it is for
[s267738.txt, 1560]	throne. When you get a	democratic	basis for your institutions, you
[s267738.txt, 1952]	differences between ourselves and other	democratic	legislatures? Where is the democratic
[s267738.txt, 1957]	democratic legislatures? Where is the	democratic	legislature which enjoys the powers
[s267738.txt, 2243]	almost utterly useless against a	democratic	Chamber, and the question to
[s267738.txt, 2286]	to the violence of the	democratic	Chamber you are creating, and,
[s267738.txt, 2294]	are creating, and, as the	democratic	principle brooks no rival, this
[s267738.txt, 2374]	spirit of democracy that the	democratic	Chamber itself would become an
[s267738.txt, 2678]	power is given to the	democratic	majority, that majority does not
[s267738.txt, 2767]	job? In accordance with the	democratic	principle the army would demand
[s267744.txt, 204]	Conservative patronage, of the most	democratic	Reform Bill ever brought in.

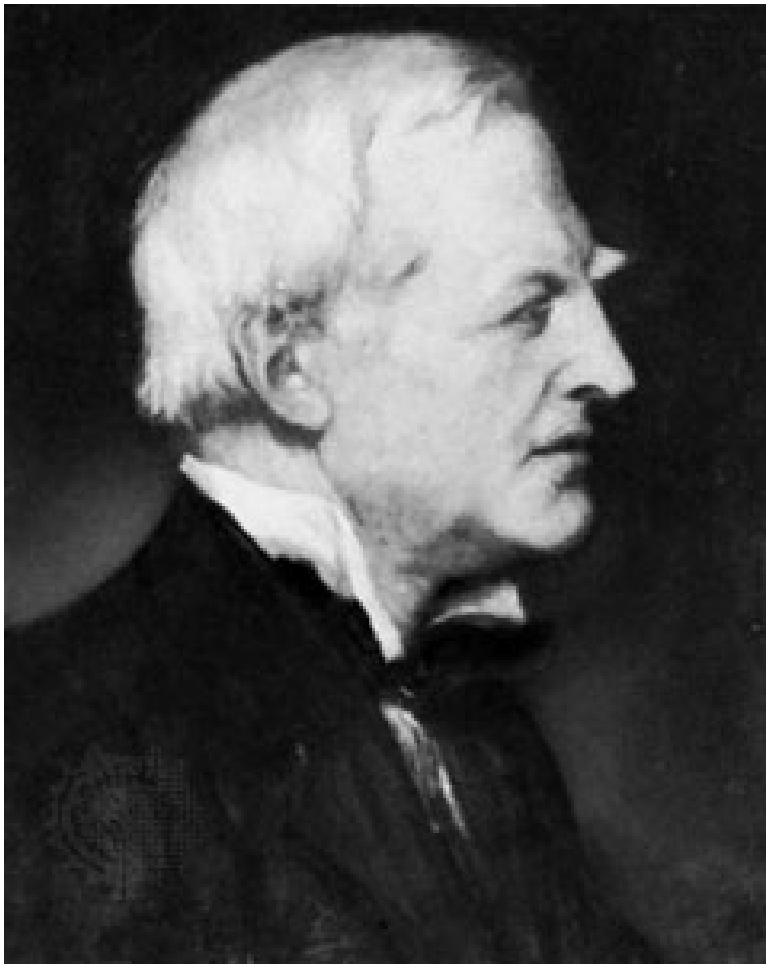
Detail: s267738.txt

Detail: s267738.txt

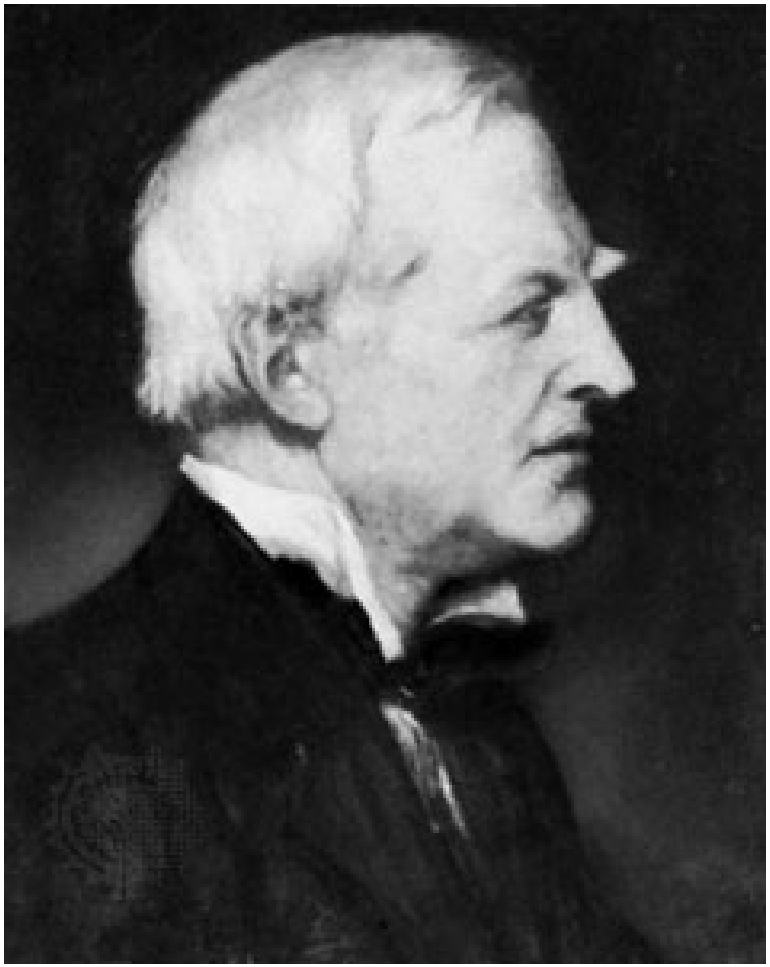
preword	word	postword
swept away in some further	democratic	change. And it is for
throne. When you get a	democratic	basis for your institutions, you
differences between ourselves and other	democratic	legislatures? Where is the democratic
democratic legislatures? Where is the	democratic	legislature which enjoys the powers
almost utterly useless against a	democratic	Chamber, and the question to
to the violence of the	democratic	Chamber you are creating, and,
are creating, and, as the	democratic	principle brooks no rival, this
spirit of democracy that the	democratic	Chamber itself would become an
power is given to the	democratic	majority, that majority does not
job? In accordance with the	democratic	principle the army would demand

The Original Speaker and Speech

The Original Speaker and Speech

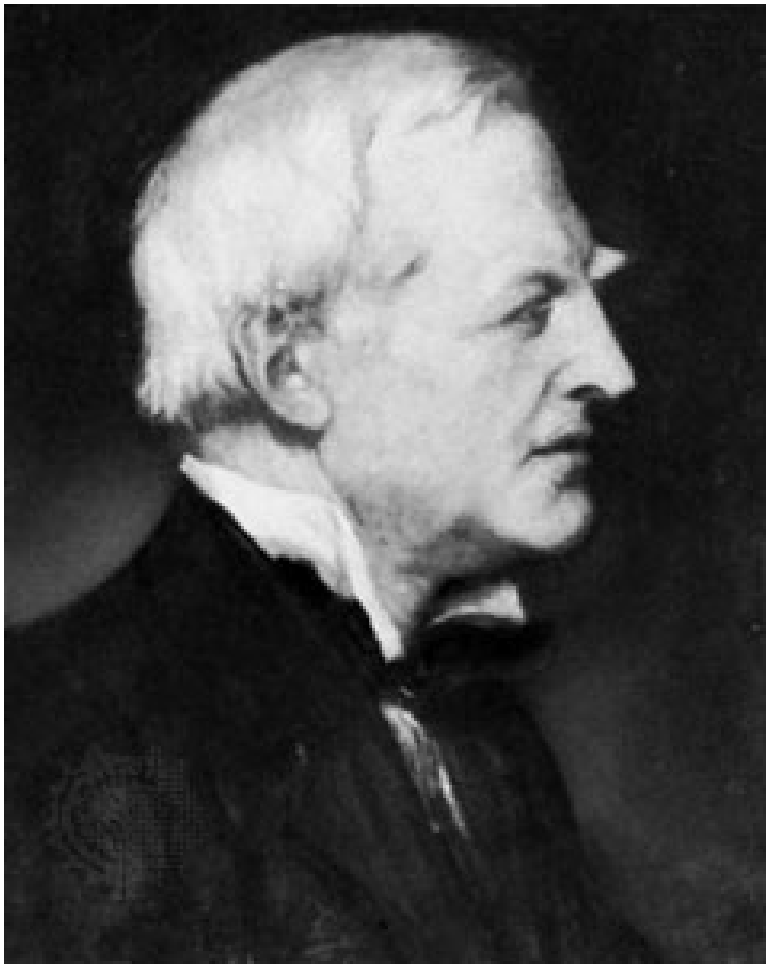


The Original Speaker and Speech



You cannot trust to a majority elected by men just above the status of paupers. The experiment has been tried; it has answered nowhere; it has failed in America, and it will not answer here.

The Original Speaker and Speech



You cannot trust to a majority elected by men just above the status of paupers. The experiment has been tried; it has answered nowhere; it has failed in America, and it will not answer here.

In accordance with the democratic principle the army would demand to elect their own officers, and there would be endless change in the Constitution arising out of the present Bill, which, so far from being an end to our evils, is only the first step to them.

Partner Exercise

Exercise

The context of key words is especially important when comparing usage across time and space.

Exercise

The context of key words is especially important when comparing usage across time and space.

Suppose you were studying the history of entertainment technology. Consider the key word '`wireless`'. How has the frequency of this term changed over time? How has the context changed?

Exercise

The context of key words is especially important when comparing usage across time and space.

Suppose you were studying the history of entertainment technology. Consider the key word '`wireless`'. How has the frequency of this term changed over time? How has the context changed?

Give an example of a political key word that might appear in a different *context* if we study the US vs some other country.

Use of ‘Wireless’