

2. Descriptive Inference I

DS-GA 1015, Text as Data
Arthur Spirling

Feb 12, 2019

Housekeeping

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1 Section in full swing!

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Follow-up: Tokenize Chinese/Arabic



The Stanford Natural Language Processing Group

people publications research blog software teaching local

Software > Stanford Word Segmente

Stanford Word Segmente

[Download](#) | [Questions](#) | [Mailing Lists](#) | [Extensions](#) | [Release history](#) | [FAQ](#)

Tokenization of raw text is a standard pre-processing step for many NLP tasks. For English, tokenization usually involves punctuation splitting and separation of some affixes like possessives. Other languages require more extensive token pre-processing, which is usually called segmentation.

The Stanford Word Segmente currently supports Arabic and Chinese. (The Stanford Tokenizer can be used for English, French, and Spanish.) The provided segmentation schemes have been found to work well for a variety of applications.

The system requires Java 1.8+ to be installed. We recommend at least 1G of memory for documents that contain long sentences. For files with shorter sentences (e.g., 20 tokens),

nltk.tokenize.stanford_segmenter module

```
class nltk.tokenize.stanford_segmenter.StanfordSegmenter(path_to_jar=None, path_to_slf4j=None,  
path_to_sihan_corpora_dict=None, path_to_model=None, path_to_dict=None,  
encoding='UTF-8', options=None, verbose=False, java_options='-mx2g')  
[source]
```

Bases: [nltk.tokenize.api.Tokenizer](#)

```
Interface to the Stanford Segmente >>> from nltk.tokenize.stanford_segmenter import  
StanfordSegmenter >>> segmenter = StanfordSegmenter( ... path_to_jar="stanford-  
segmente-3.6.0.jar", ... path_to_slf4j = "slf4j-api.jar" ...  
path_to_sihan_corpora_dict="./data", ... path_to_model="./data/pku.gz", ...  
path_to_dict="./data/dict-chris6.ser.gz") >>> sentence = u"这是斯坦福中文分词器测试" >>>  
segmenter.segment(sentence) >>> u'u8fd9 u662f u65afu5766u798f u4e2du6587  
u5206u8bcd5668 u6d4bu8bd5n' >>> segmenter.segment_file("test.simp.utf8") >>>  
u'u9762u5bf9 u65b0 u4e16u7eaa uff0c u4e16u754c u5404u56fd ...
```

segment(tokens) [source]

segment_file(input_file_path) [source]

segment_sents(sentences) [source]

tokenize(s) [source]

```
nltk.tokenize.stanford_segmenter.setup_module(module)  
[source]
```

Follow-up: Tokenize Chinese

jieba

"结巴"中文分词：做最好的 Python 中文分词组件

"Jieba" (Chinese for "to stutter") Chinese text segmentation: built to be the best Python Chinese word segmentation module.

- *Scroll down for English documentation.*

特点

- 支持三种分词模式：
 - 精确模式，试图将句子最精确地切开，适合文本分析；
 - 全模式，把句子中所有的可以成词的词语都扫描出来，速度非常快，但是不能解决歧义；
 - 搜索引擎模式，在精确模式的基础上，对长词再次切分，提高召回率，适合用于搜索引擎分词。
- 支持繁体分词
- 支持自定义词典
- MIT 授权协议

在线演示

<https://github.com/fxsjy/jieba>

Follow-up: Tokenize Japanese

rmeCab

RMecab
install
naat-pcを使う
UniDic
旧バージョン
サイトマップ

RMeCab >
install

* Windows (32/64) 用バイナリ

最初に MeCab-0.996.exe を <http://code.google.com/p/mecab/downloads/list> からダウンロードして、ダブルクリックでインストールしておきます。

** Windows (32/64) 用バイナリ

RMeCabをインストールします。Rを起動して、以下のように入力してEnterキーを押してインストールして下さい。

```
install.packages("RMeCab", repos = "http://rmeCab.jp/R")
```

あるいは以下から RMeCab_0.9***.zip をダウンロードしてください。

<http://web.las.tokushima-u.ac.jp/linguistik/win.html>

メニューの「パッケージ」「ローカルなzipファイル」を選んでダウンロードしたRMeCabを選択。

* Mac

以下の手順でMeCabをインストールしてください。

(1) MeCabのインストール 以下の方法でインストールしてください。Homebrewを利用する場合はこちらを参照してください（MacPortsからインストールしたMeCabではエラーになります）。

(A) インストールの準備

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Grammatical gender often removed via stopping.

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“PREPROCESSING”

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

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stemming	322,383	94,516,599

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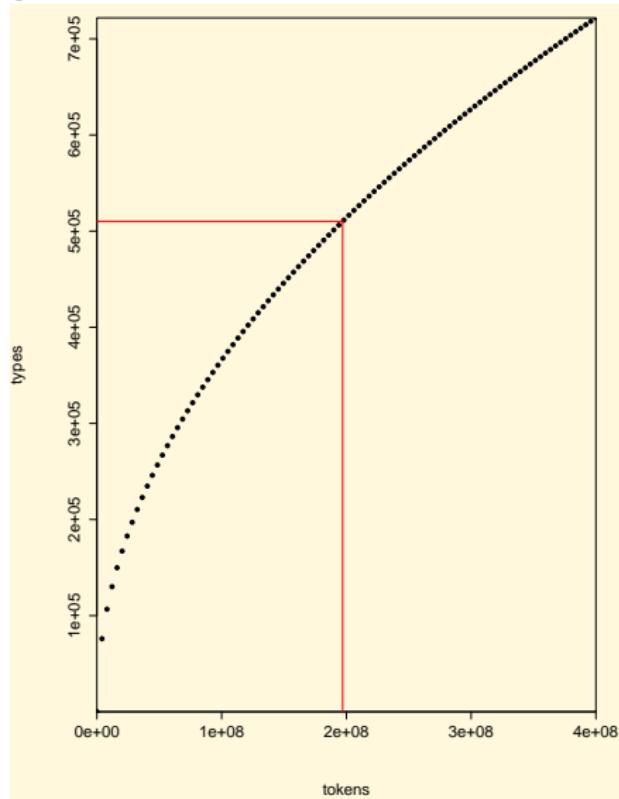
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NB number of types increases rapidly at first, then less rapidly. Need to preprocess, especially for long collections!

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

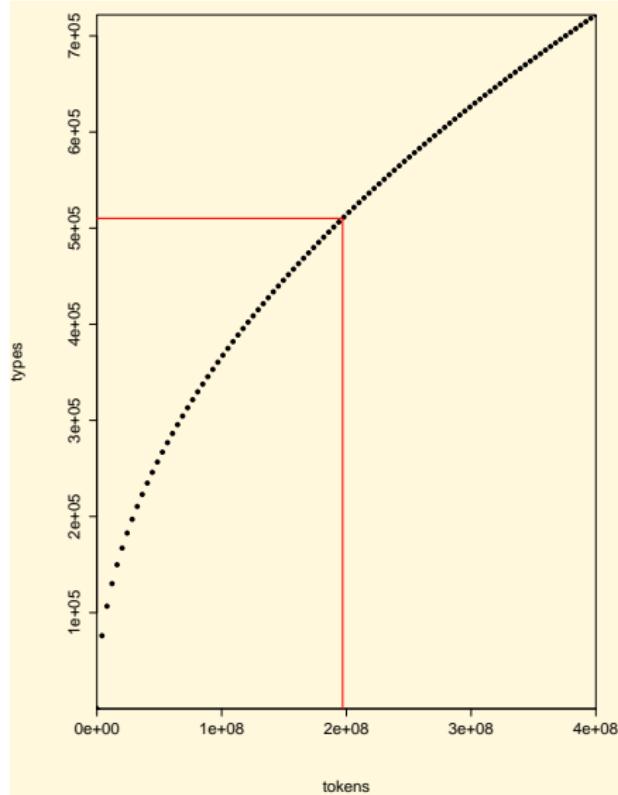
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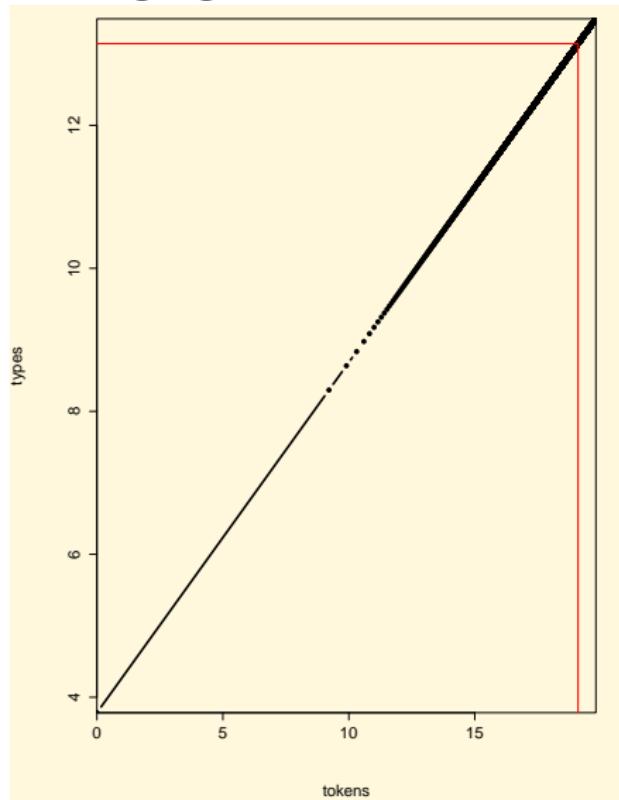
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RCV1, log-log.



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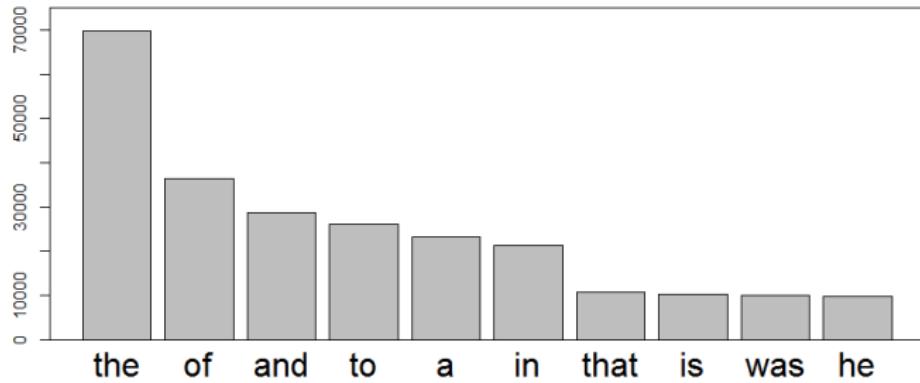
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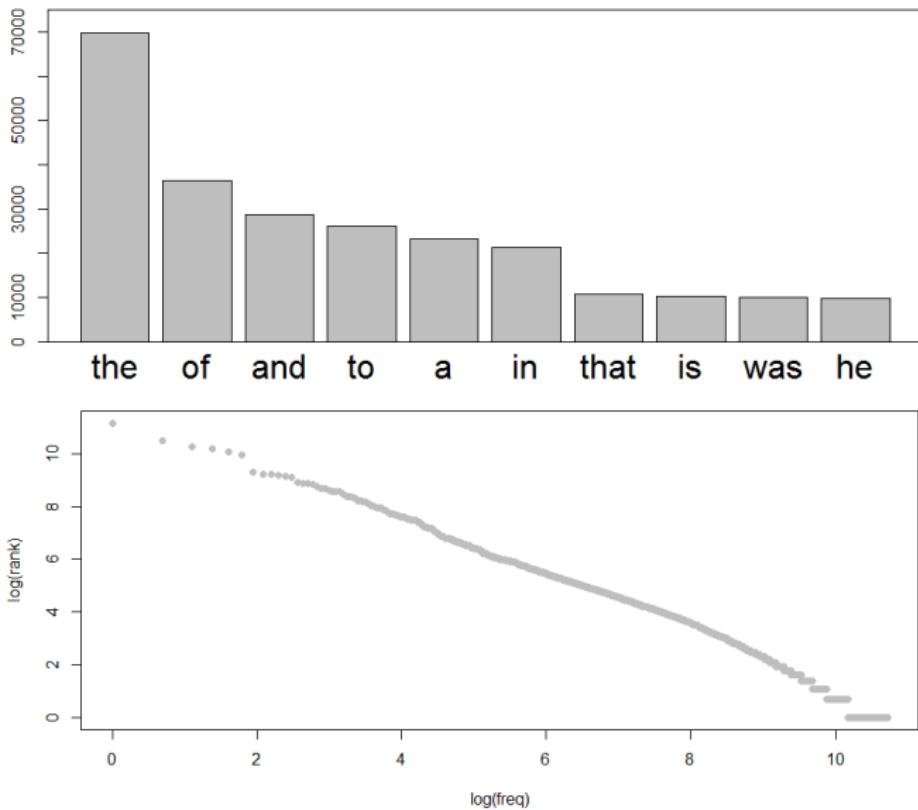
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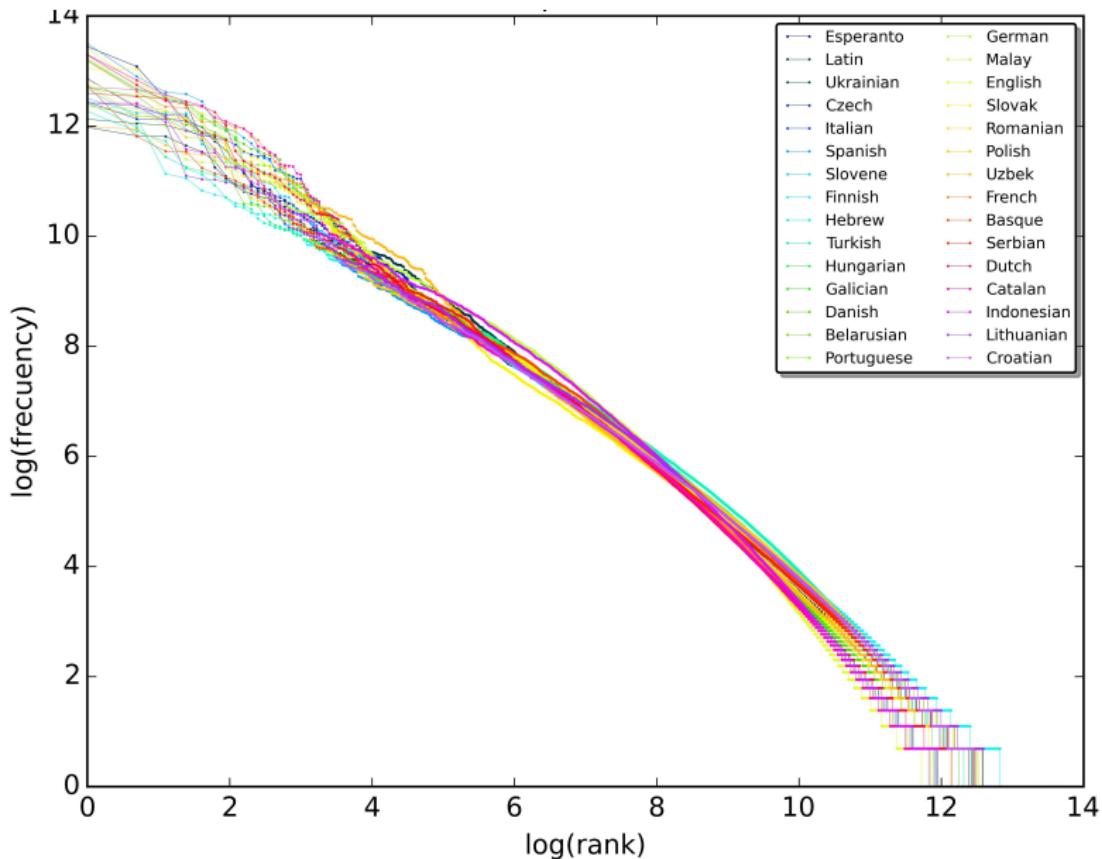
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Other Languages (Wikipedia)

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City Populations in US (Gabaix, 1999)

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740

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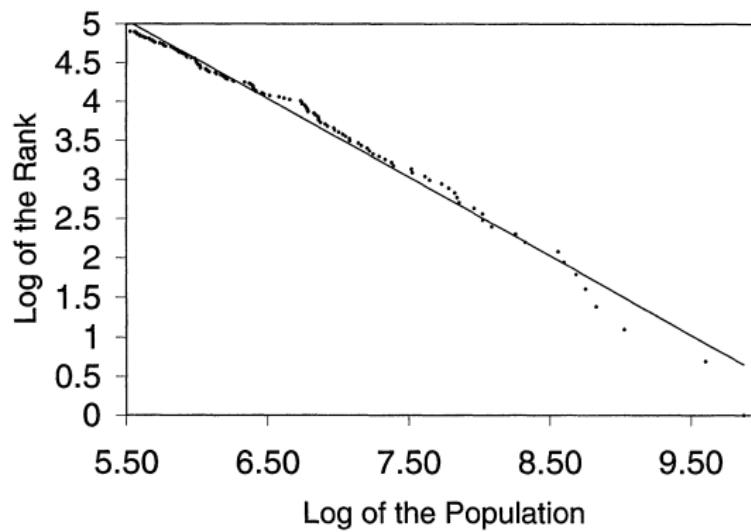


FIGURE I

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

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

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larger distances imply lower similarity.

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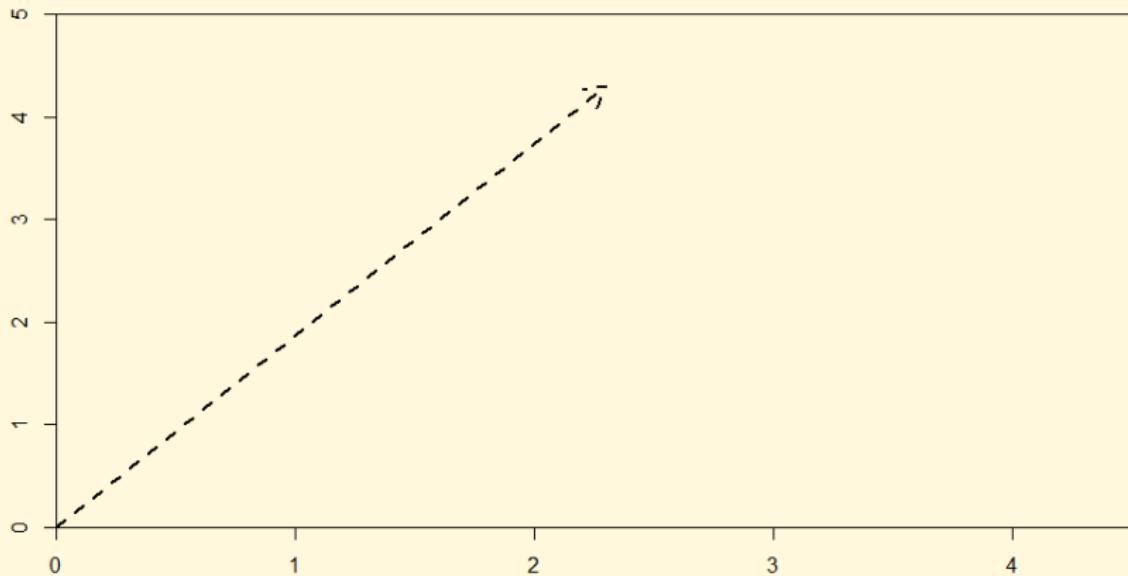
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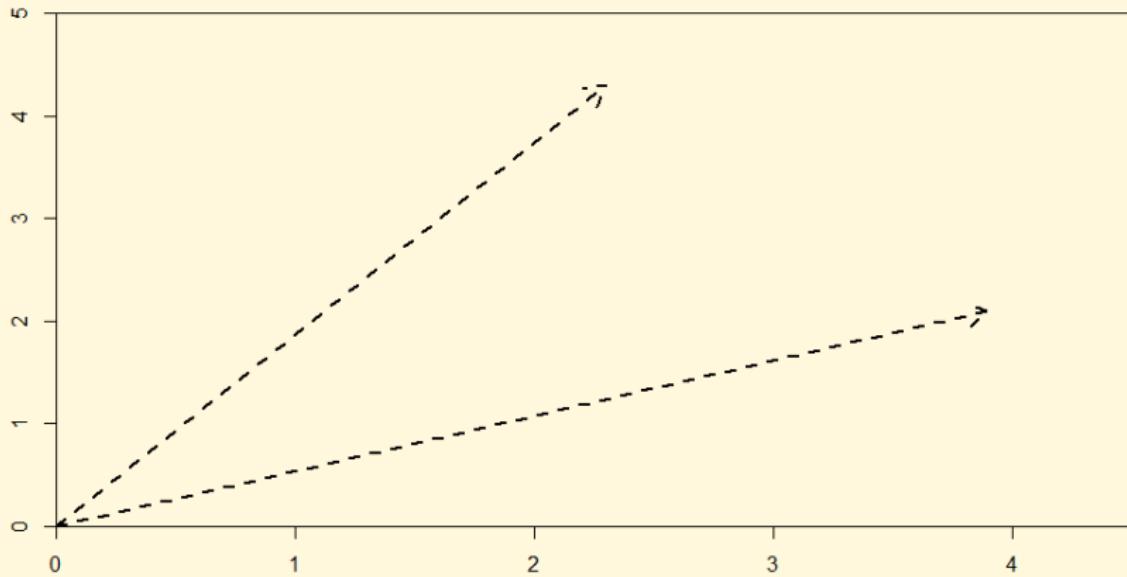
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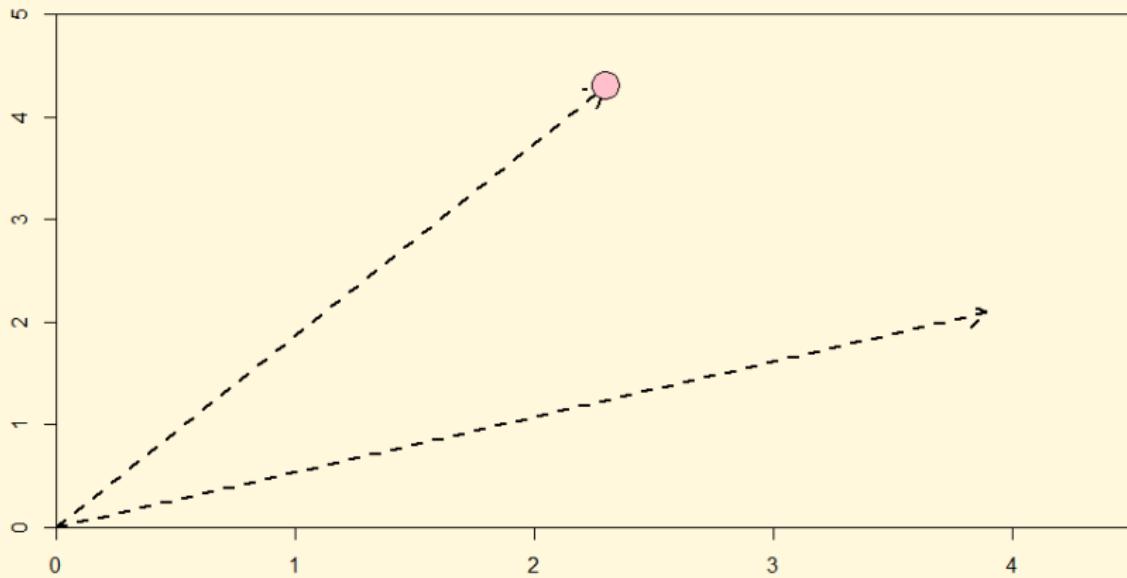
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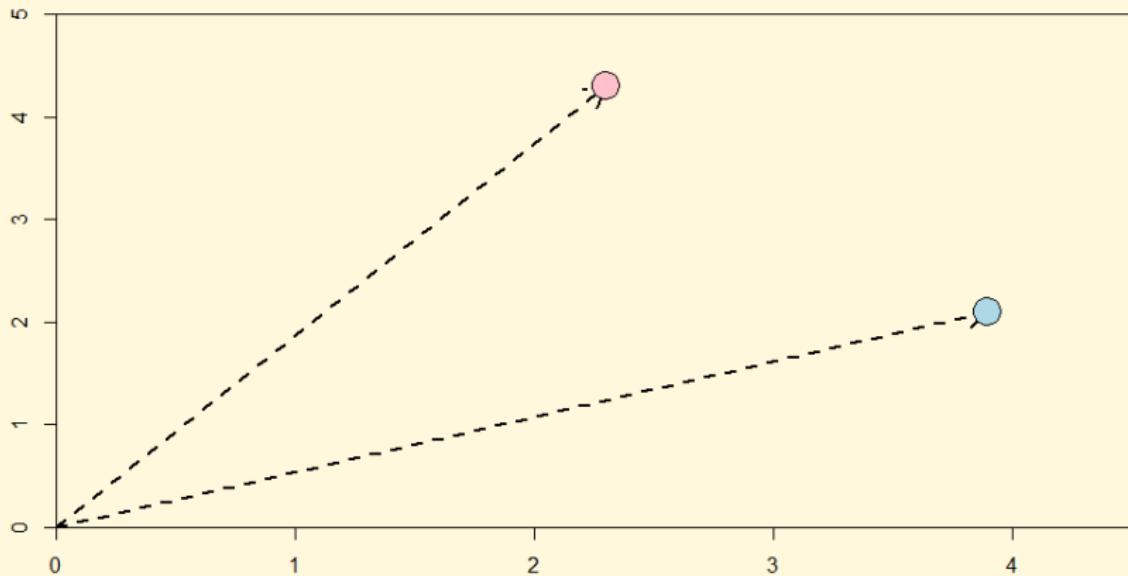
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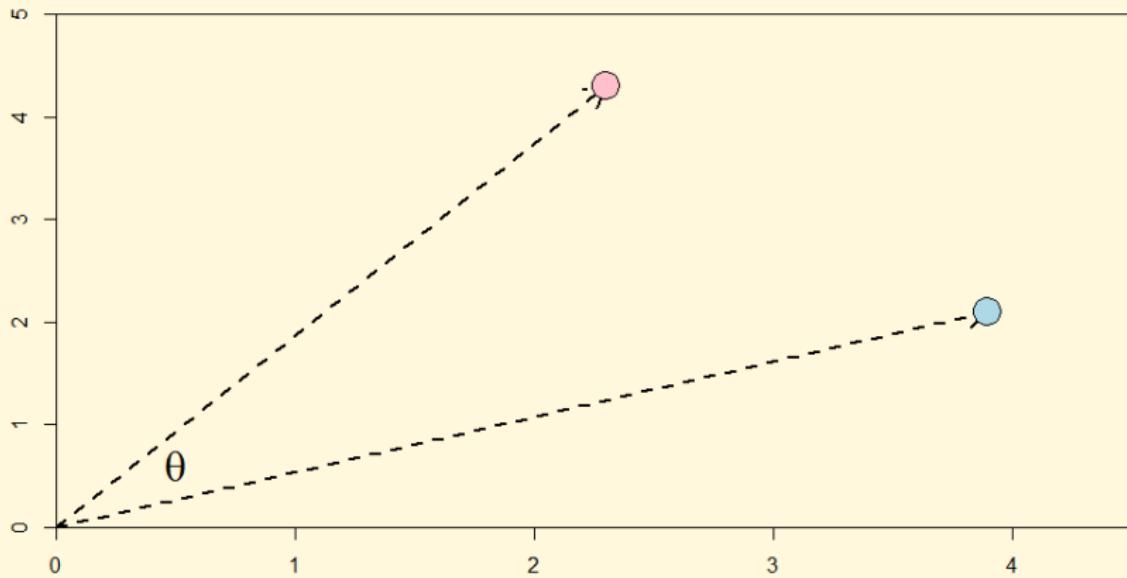
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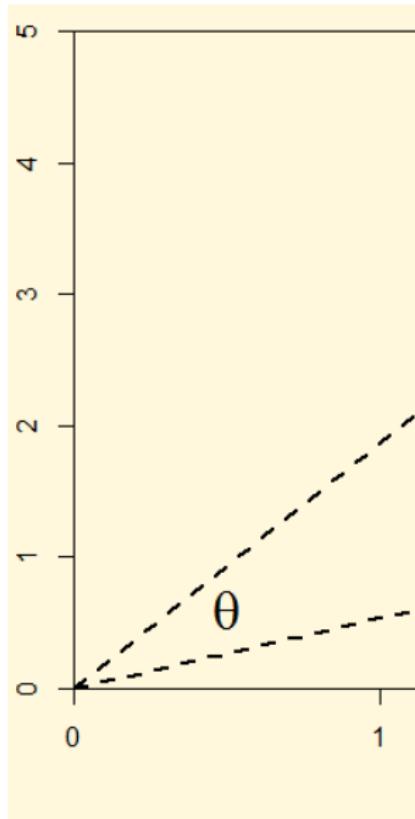
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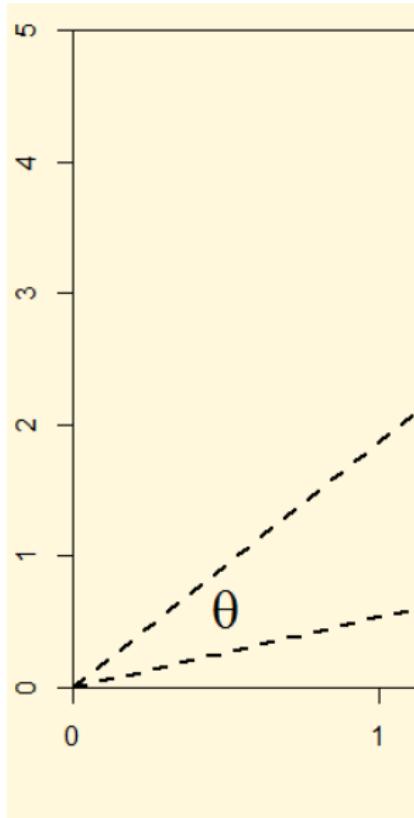


Algebra

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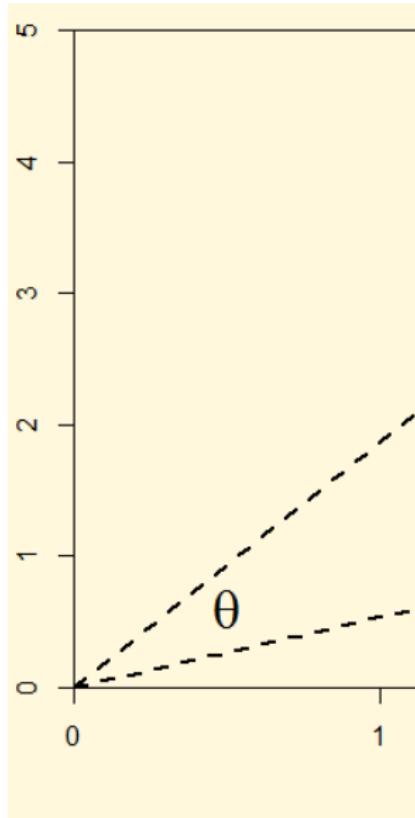


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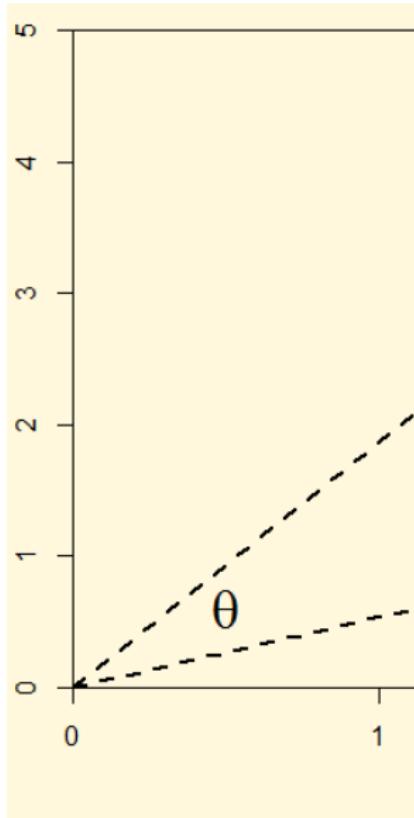
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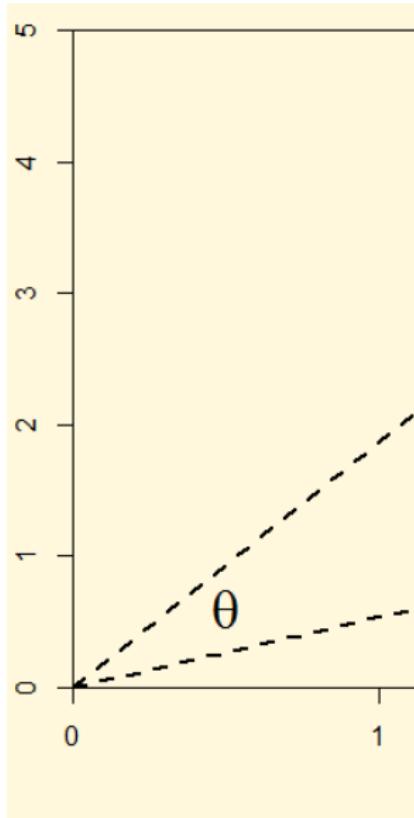
Algebra



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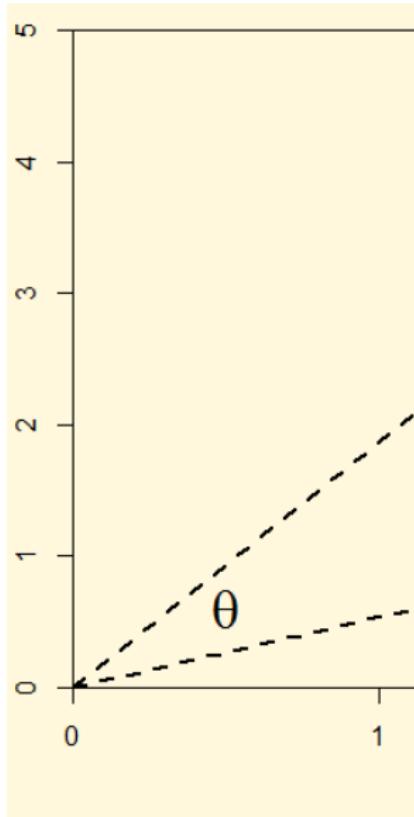
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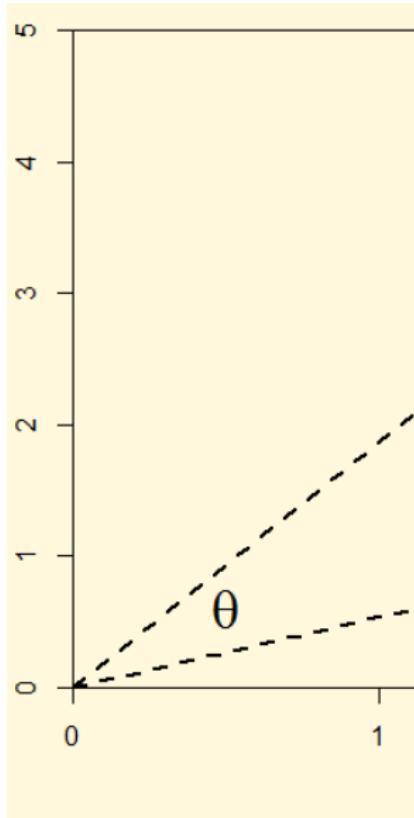
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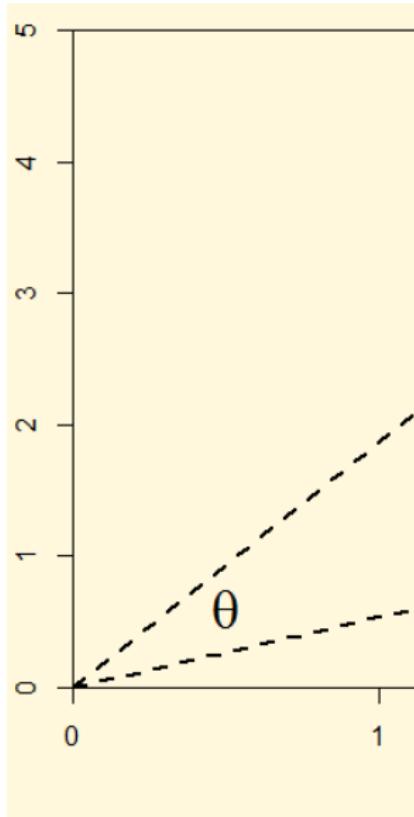
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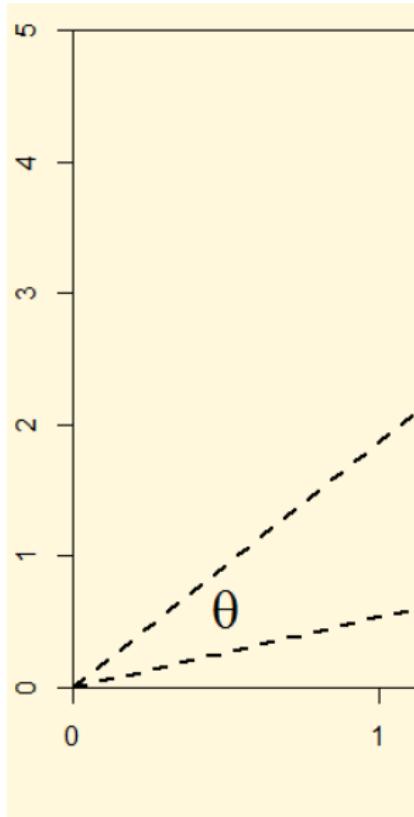
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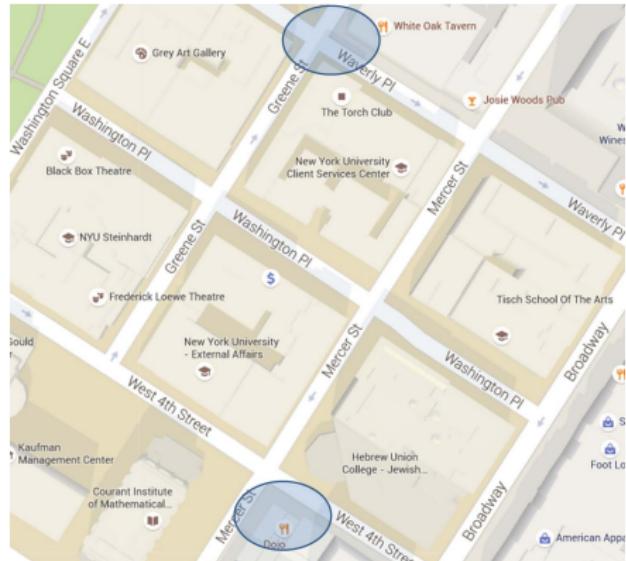
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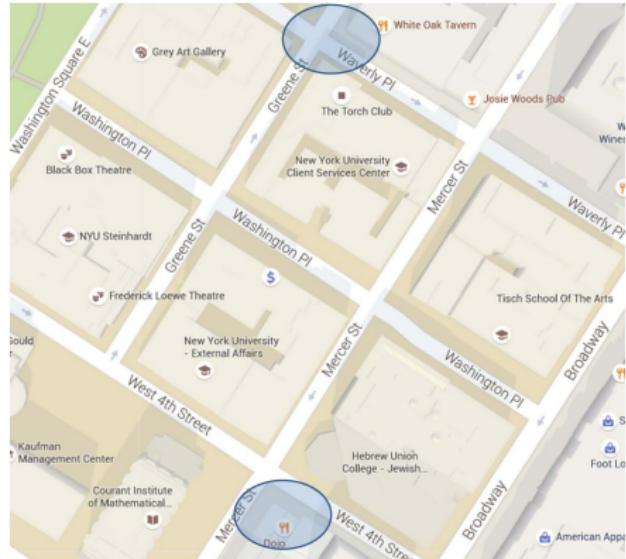
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Partner Exercise

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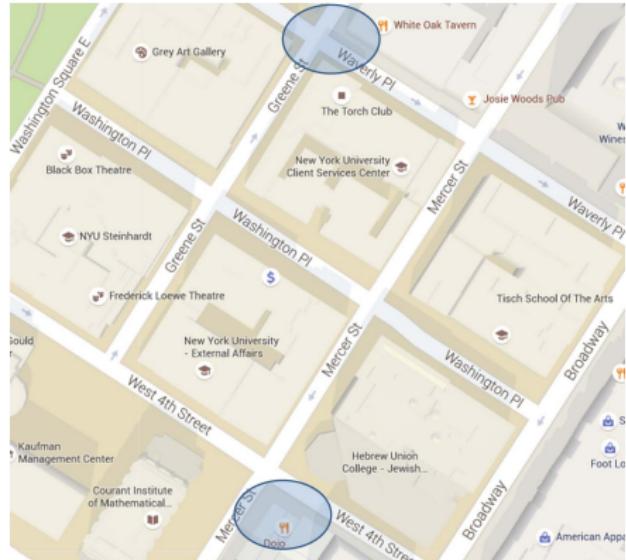


Partner Exercise



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

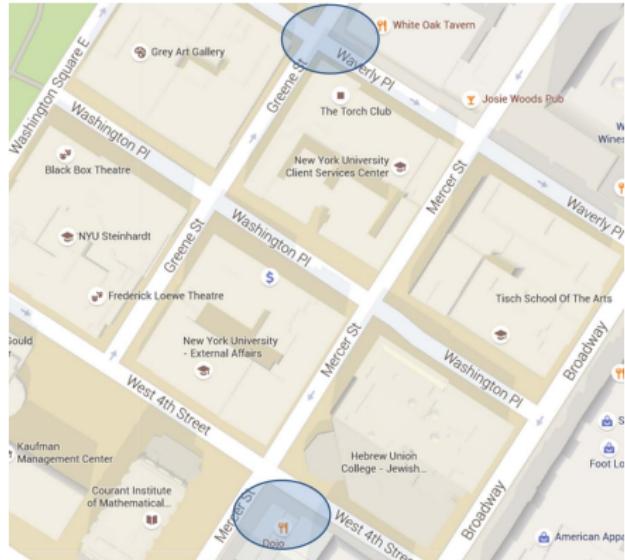
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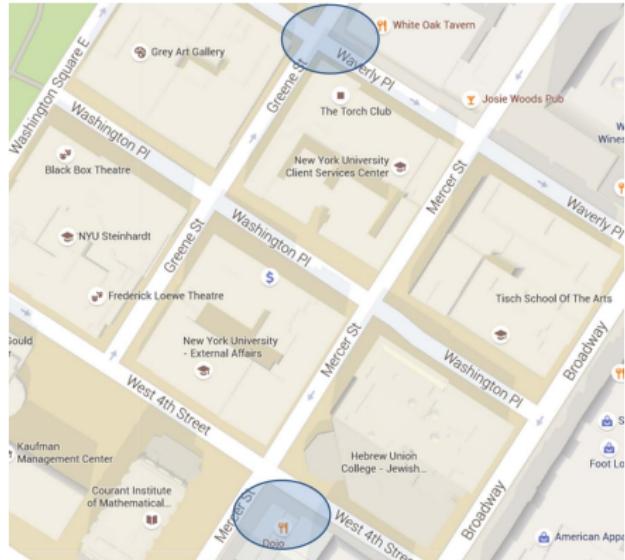
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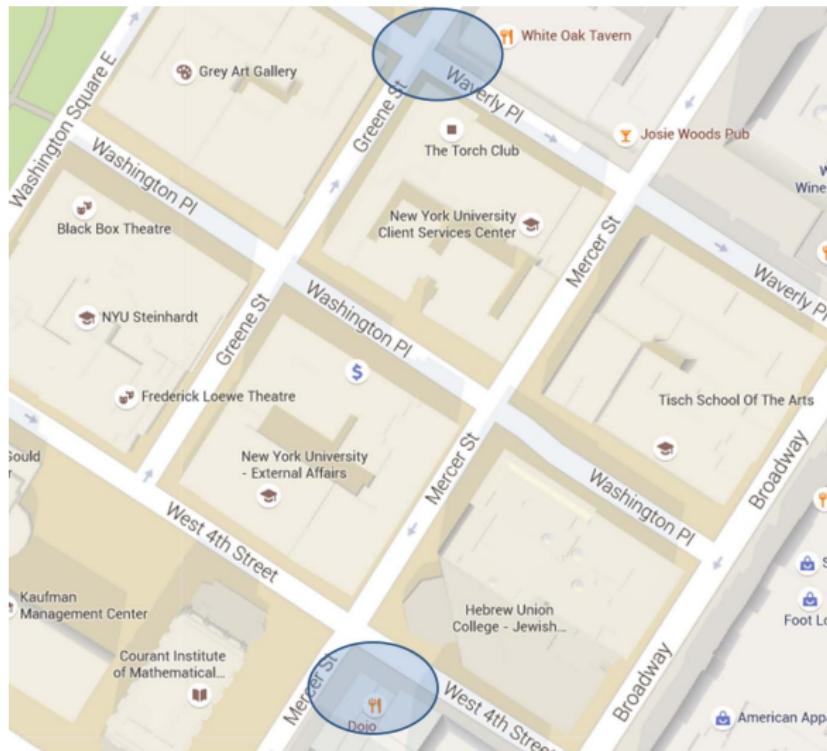


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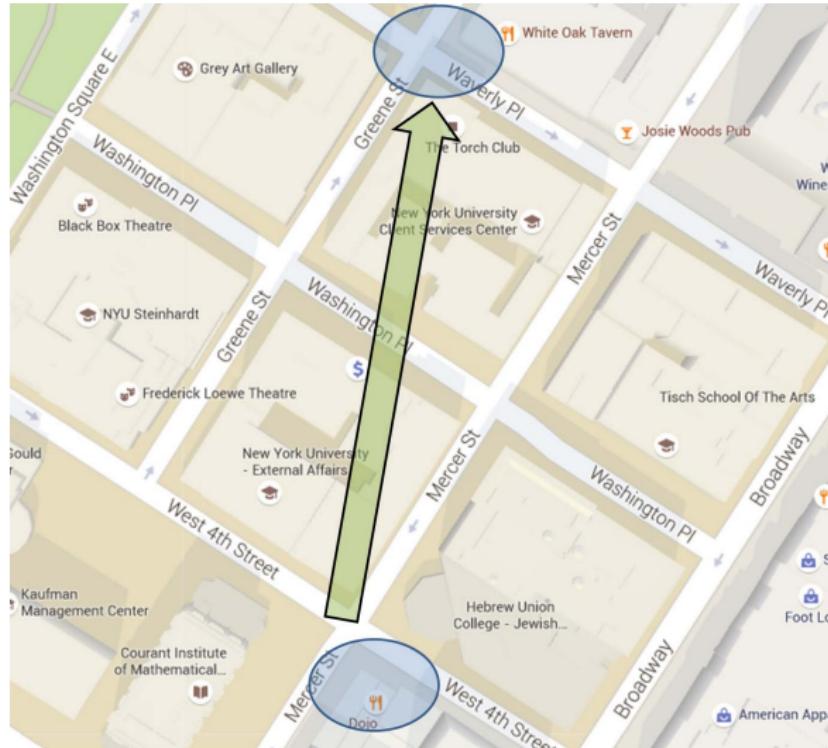
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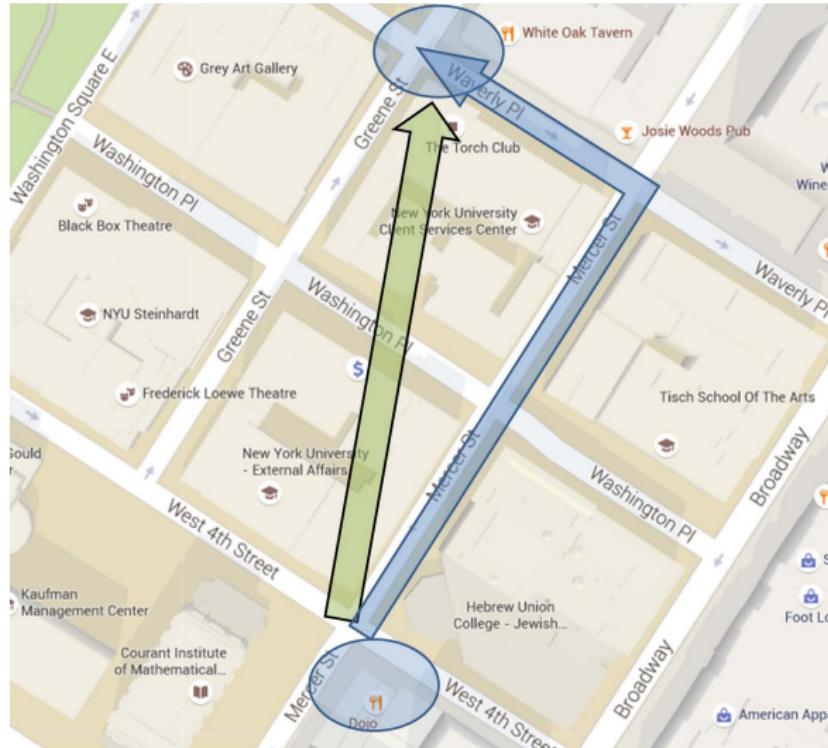


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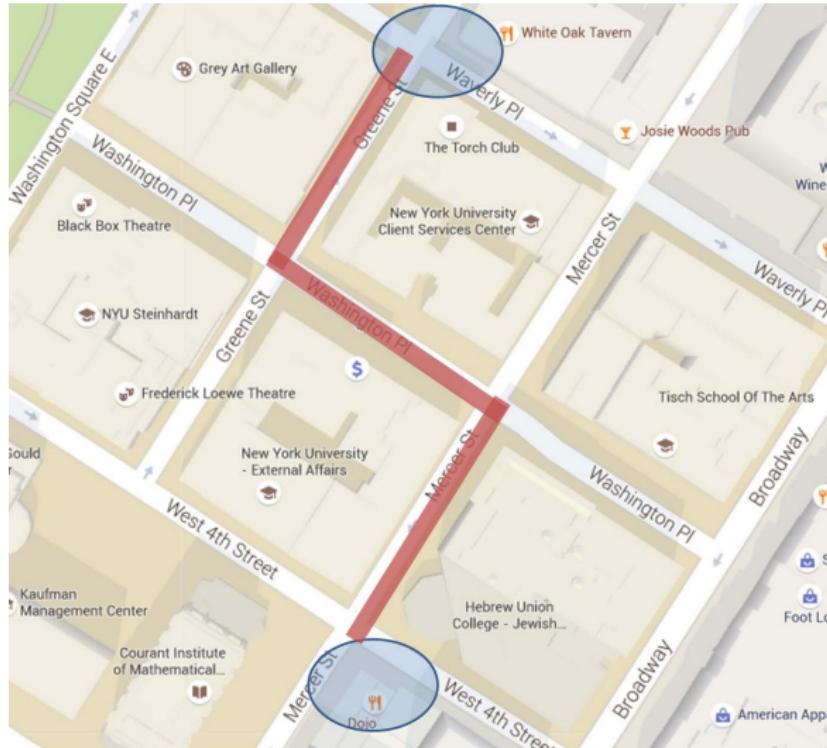
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21842	on	the
21839	for	the
18568	and	the
16121	that	the
15630	at	the
15494	to	be
13899	in	a
13689	of	a
13361	by	the
13183	with	the
12622	from	the
11428	New	York
10007	he	said
9775	as	a
9231	is	a
8753	has	been
8573	for	a

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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

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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
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can construct 2×2 table, and consider **expected** vs **observed** frequency...

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		Second Word		total
		w_2	$\neg w_2$	
First Word	w_1	O_{11}	O_{12}	$O_{11} + O_{12}$
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Example: 'democratic' and the Second Reform Act

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



A LEAP IN THE DARK.

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

The Original Speaker and Speech

The Original Speaker and Speech

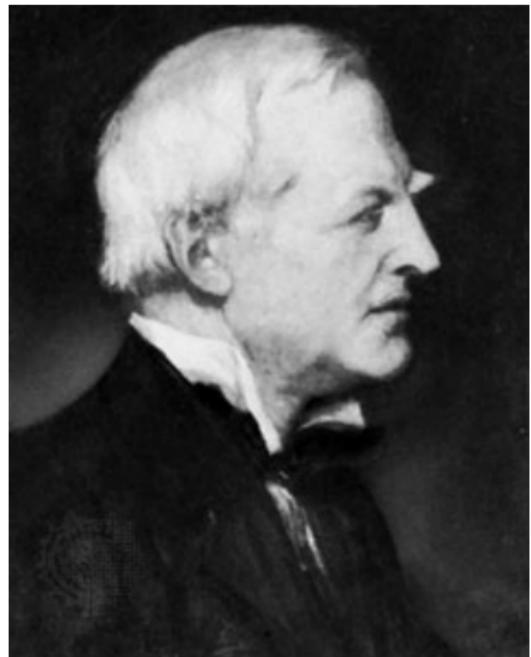


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You cannot trust to a majority elected by men just above the status of paupers. The experiment has been tried; it has answered nowhere; it has failed in America, and it will not answer here.

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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

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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?

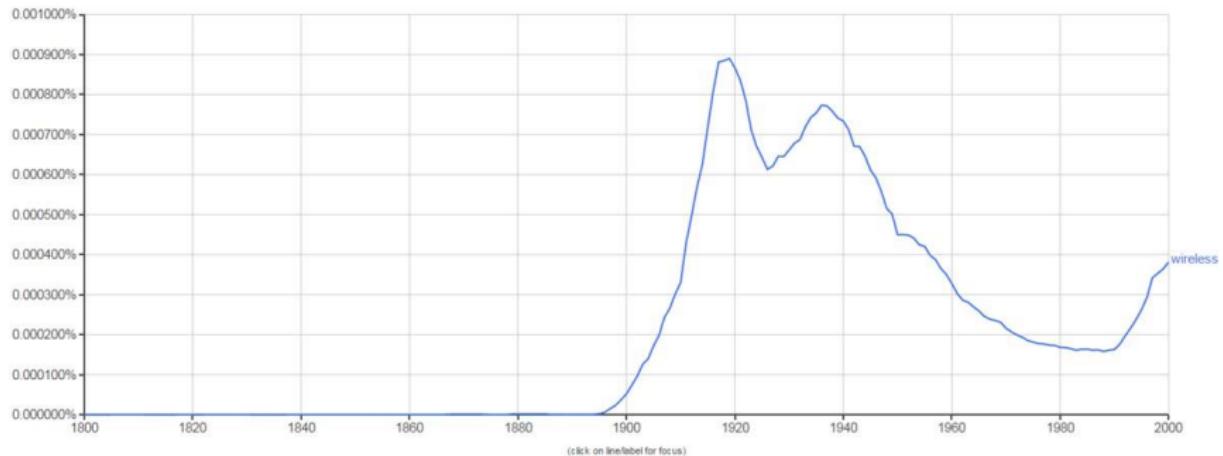
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Give an example of a **political** key word that might appear in a different *context* if we study the US vs some other country.

Use of 'Wireless'



(click on line/label for focus)