2. Descriptive Inference I (Flipped)

DS-GA 1015, Text as Data
Arthur Spirling

Feb 16, 2021

Housekeeping

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1 Lab straight after this lecture

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2. Please do federal engagement survey

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3. HW 1 out soon.

Where Are We?

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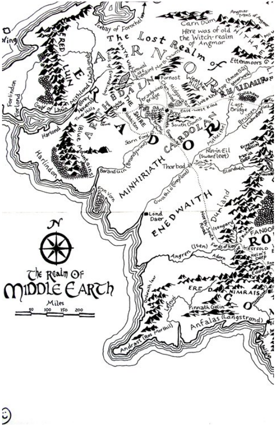
The Realm of
Middle Earth
Miles
50
100
150
200
Icebay of Forochel
The Lost Realm of
ARNOR
Carn Dûm
Here was of old
the Witch-realm
of Angmar
Ettenmoors
Fornost
North Downs
Weather Hills
Weathertop (Amon Sûl)
RHUDAUR
Trollshaws
Last Bridge
Bruinen (Loudwater)
Ered Luin
Forlindon
Forlond
Gulf of Lhûn
Mithlond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

Where Are We?



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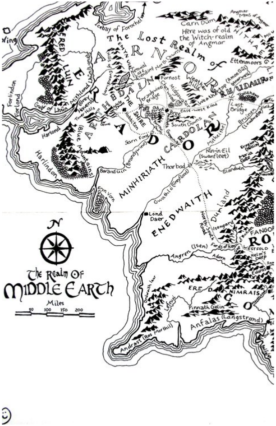

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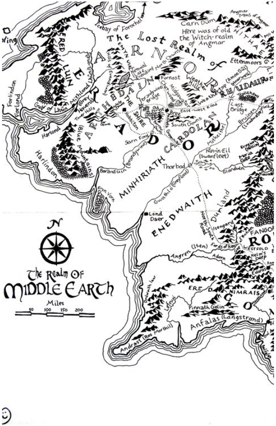

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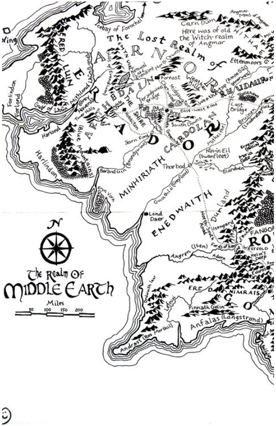

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Zipf's Law tells us about the rank-frequency distribution. What does it say?

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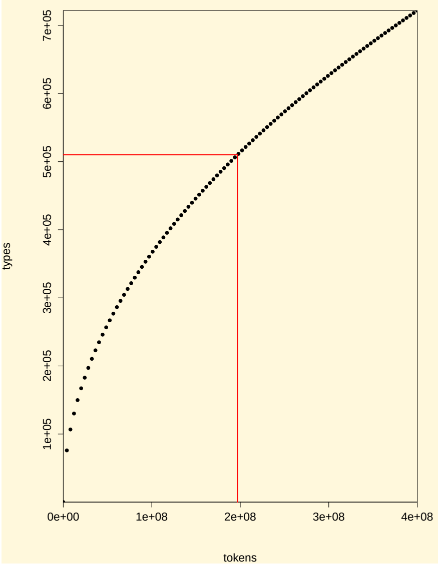

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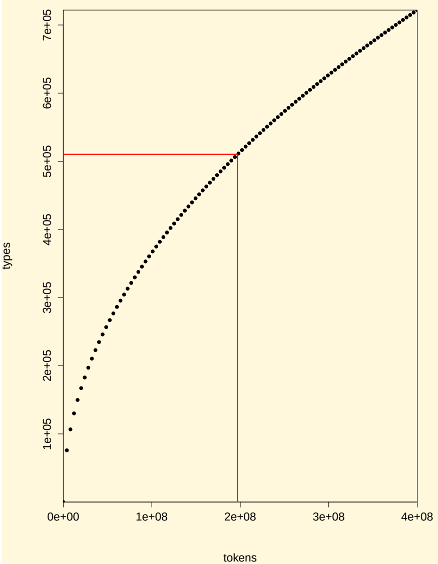
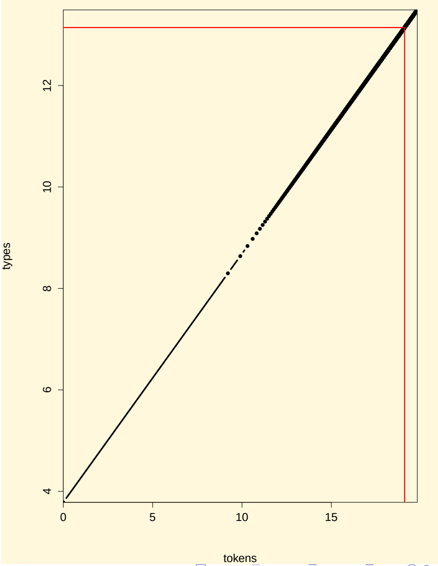


RCV1, log-log.



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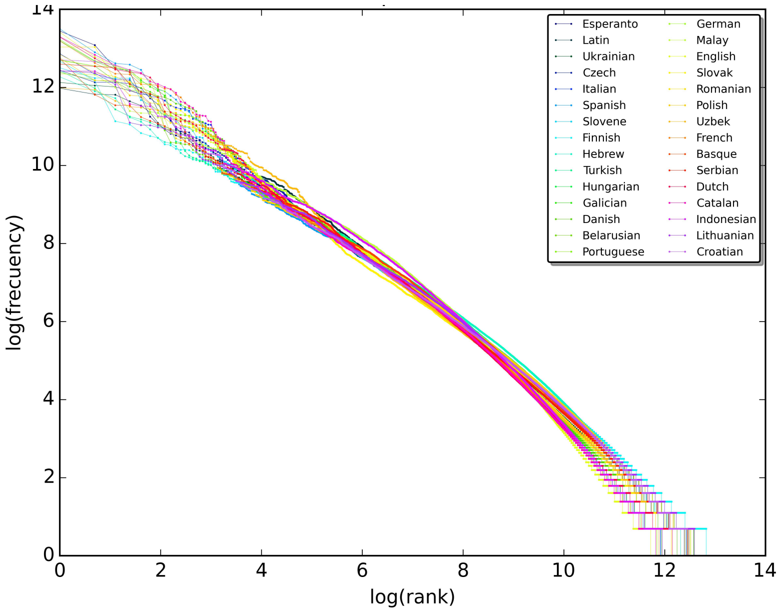

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2 Astrophysicists study extraterrestrial signals looking for Zipf's law in the patterns. Why?

NAUTILUS | cosmos

Listening for Extraterrestrial Blah Blah

At the cosmic dinner party, intelligence is the loudest thing in the room.

By Laurance R. Doyle
Illustrations by Tianhua Mao

Euclidean Distance

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

larger distances imply lower similarity.

Partner exercise

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$\boxed{c_{ij} \approx 0.90}$

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$\boxed{c_{ij} \approx 0.90}$ Why are the numbers in general so ‘high’?

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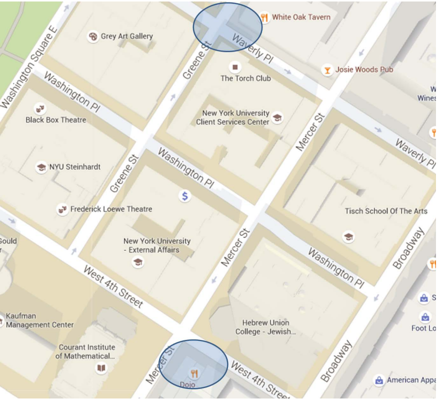

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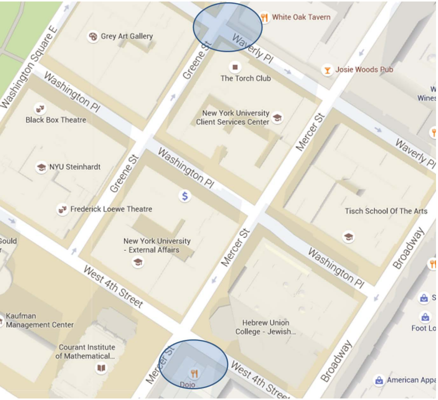

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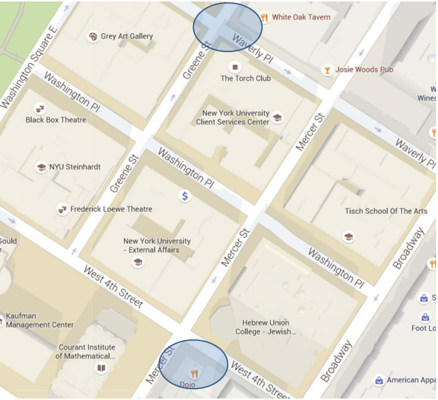

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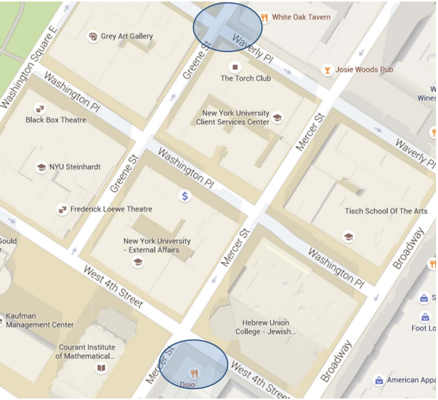

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- what is Manhattan distance between Dojo and White Oak Tavern?

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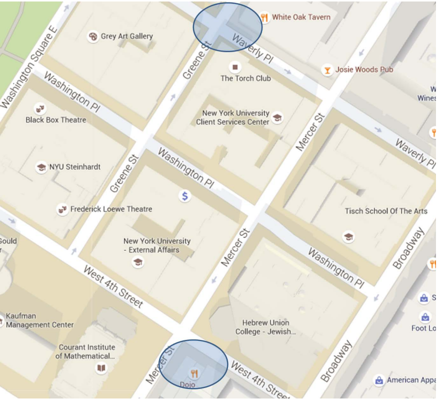

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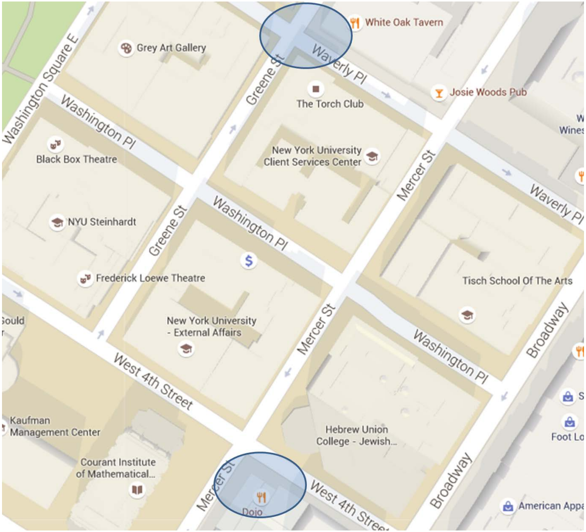

White Oak Tavern
Grey Art Gallery
Waverly Pl
Greene St
The Torch Club
Josie Woods Pub
Washington Square E
Washington Pl
Black Box Theatre
New York University
Client Services Center
Mercer St
Waverly Pl
NYU Steinhardt
Greene St
Washington Pl
Frederick Loewe Theatre
Tisch School Of The Arts
New York University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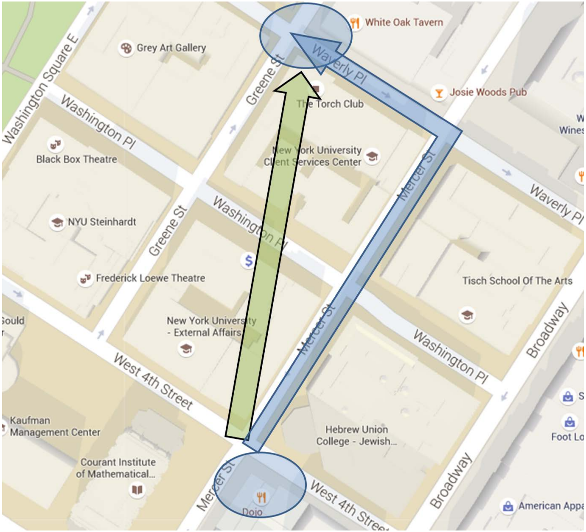

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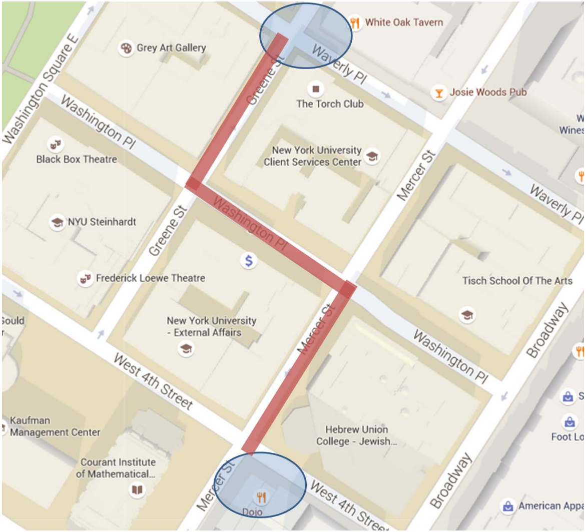

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Edit Distance: An Example

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The smallest number of operations taking us from s_1 to s_2 is the **Levenshtein distance** between those strings.

Levenshtein in Action

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$s_1 = \texttt{easternmost}$

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$s_1 = $ `easternmost`

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1 delete `m`, delete `o`, delete `s`, delete `t`.

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$s_1 =$ easternmost

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1 delete m, delete o, delete s, delete t. $\longrightarrow$ eastern

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$s_1 =$ `easternmost`

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1. delete `m`, delete `o`, delete `s`, delete `t`. $\longrightarrow$ `eastern`
2. insert `h`. $\longrightarrow$ `easthern`

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How many operations?

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How many operations? $4 + 1$

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How many operations? $4 + 1 + 3$

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How many operations? $4 + 1 + 3 = 8$.

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How many operations? $4 + 1 + 3 = 8$. **Levenshtein distance** is 8.

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Brown Corpus: 'New York'

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		Second Word		
		York	¬ York	total
First Word	New	303 New York	240 (e.g. 'new day')	543
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→ ‘york’ doesn't occur often in the corpus, but when it does, it's almost always proceeded by ‘new’

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$\Rightarrow$ reject the null hypothesis of independence: this word is a good choice as a collocation.

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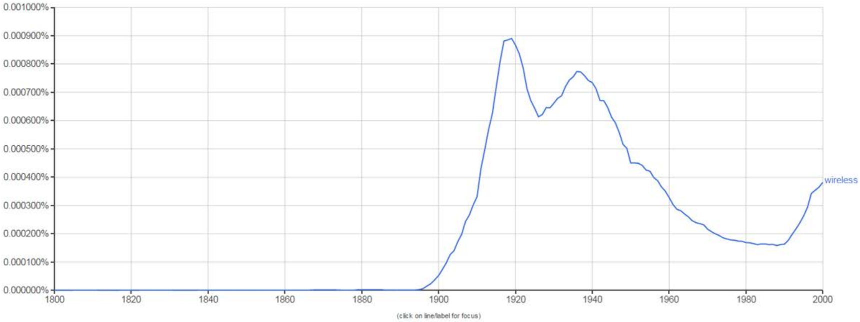
3. location code —document details.

Use of 'Wireless' changes by context



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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.