Why do we study Natural Language Processing

Niloy Ganguly

IITKGP, LUH

Week 1: Module 1

Why study NLP?

Text is the largest repository of human knowledge

news articles, web pages, scientific articles, patents, emails, government documents ....

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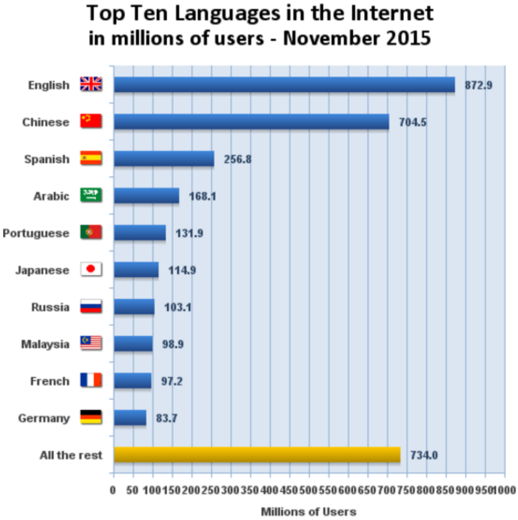
Tweets, Facebook posts, comments, Quora ...

[1] You could not understand the majority of the world's data



[1] Source: Internet world statistics

What is NLP?

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Fundamental and Scientific Goal

Deep understanding of *broad* language

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Engineering Goal

Design, implement, and test systems that process natural languages for practical applications

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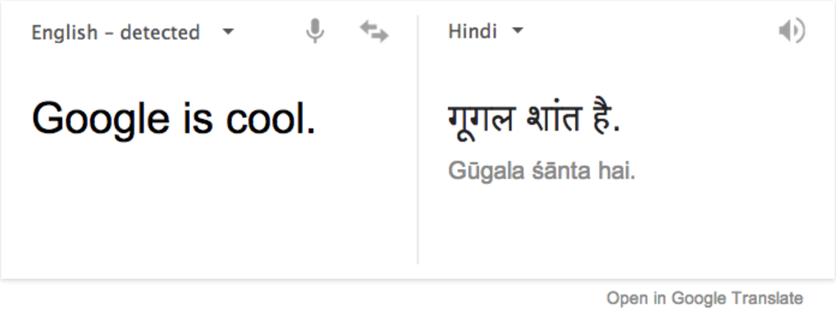
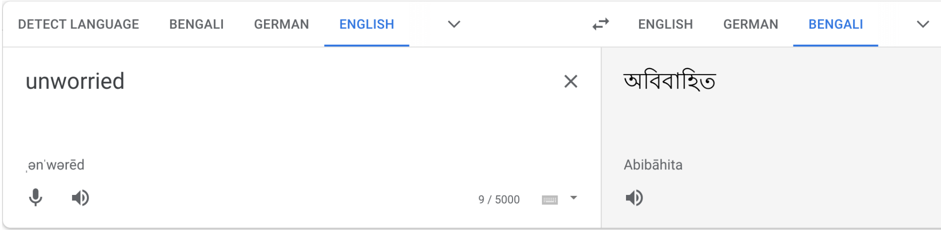
Goals can be very ambitious: Good quality translation



Santa → calm

Goals can be very ambitious: Good quality translation



Abibhahita → unmarried

Well, even humans have made blunders

Pepsi Chinese blunder

“Come alive with the Pepsi Generation”, when translated into Chinese meant, “Pepsi brings your relatives back from the dead.”

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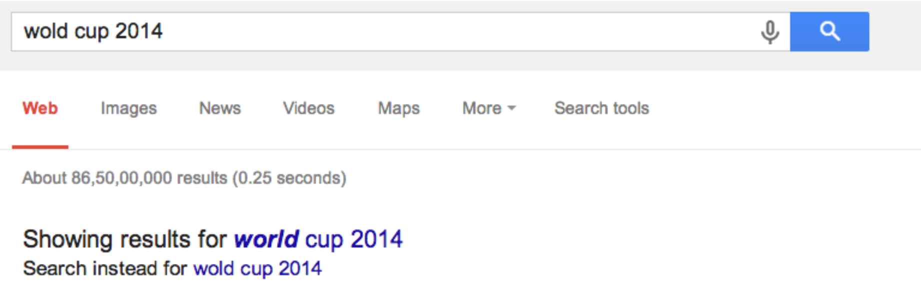
KFC’s Chinese blunder

KFC’s slogan, “Finger lickin’ good”, when translated into Chinese meant “We’ll eat your fingers off.”

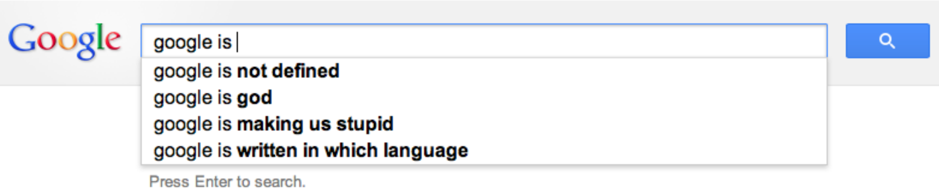
Well, even humans ...

Goals can be very ambitious: Open Domain Chatbots

And Goals Can be Practical: Auto Completion



And Goals can be Practical: Search Engines



And Goals can be Practical: Information Extraction

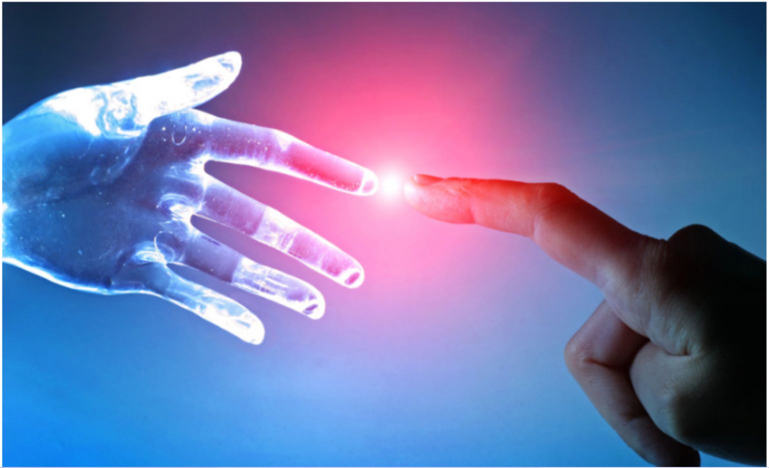
New York Times Co. named Russell T. Lewis, 45, president and general manager of its flagship New York Times newspaper, responsible for all business-side activities. He was executive vice president and deputy general manager. He succeeds Lance R. Primis, who in September was named president and chief operating officer of the parent.

Person	Company	Post	State
Russell T. Lewis	New York Times newspaper	president and general manager	start
Russell T. Lewis	New York Times newspaper	executive vice president	end
Lance R. Primis	New York Times Co.	president and CEO	start

And Goals can be Practical: Domain-specific Chatbots

Computer science class fails to notice their TA was actually an AI chatbot

by NAPIER LOPEZ — 9 weeks ago in SHAREABLES



And Goals can be Practical: Domain-specific Chatbots

Jill wasn't very good for the first few weeks after she started in January, often giving odd and irrelevant answers. Her responses were posted in a forum that wasn't visible to students.

"Initially her answers weren't good enough because she would get stuck on keywords," said Lalith Polepeddi, one of the graduate students who co-developed the virtual TA. "For example, a student asked about organizing a meet-up to go over video lessons with others, and Jill gave an answer referencing a textbook that could supplement the video lessons — same keywords — but different context. So we learned from mistakes like this one, and gradually made Jill smarter."

After some tinkering by the research team, Jill found her groove and soon was answering questions with 97 percent certainty. When she did, the human TAs would upload her responses to the students. By the end of March, Jill didn't need any assistance: She wrote the class directly if she was 97 percent positive her answer was correct.

[2]

[2] http://www.news.gatech.edu/2016/05/09/artificial-intelligence-course-creates-ai-teaching-assist

And Goals can be Practical: Sentiment Analysis

Other Goals

- Spam detection
- Machine Translation services on the Web
- Text Summarization
- ...

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Natural Language Technology not yet perfect

But still good enough for several useful applications

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Week 1: Module 1

Why is NLP hard?

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  $\rightarrow$ Modal Verb, Name of a person, Verb, Name of a person, Noun

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  $\rightarrow$ Buffalo $\rightarrow$ animal, Buffalo $\rightarrow$ city, Buffalo $\rightarrow$ bully
- *[Buffalo buffalo] [Buffalo buffalo buffalo] [buffalo Buffalo buffalo].*
  $\rightarrow$ Buffaloes from Buffalo, NY, whom buffaloes from Buffalo bully, bully buffaloes from Buffalo.

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Language ambiguity: Structural

- *The man saw the boy with the binoculars.*

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- *The man saw the boy with the binoculars.*
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- *Hole found in the room wall; police are looking into it.*

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- *Q: Did your mother call your aunt last night?*
  A: I'm sure she must have.
  $\rightarrow$ Probably I dont know, I am making a guess but using the term **sure**.

But that's the fun part of it

Why is the teacher wearing sun-glasses?

...

But that's the fun part of it

Why is the teacher wearing sun-glasses?

...

Because the class is so **bright**.

Ambiguities

News Headlines

- Hospitals Are Sued by 7 Foot Doctors

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  $\rightarrow$ 7 Feet or 7 Different Foot doctor
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- Teacher Strikes Idle Kids
  $\rightarrow$ Teacher Strikes; Idle Kids

Ambiguity is pervasive

- Find at least 5 meanings of this sentence:
  - I made her duck

Ambiguity is pervasive

- Find at least 5 meanings of this sentence:
  - I made her duck
- I cooked duck for her
- I cooked duck belonging to her
- I created the (artificial) duck, she owns
- I caused her to quickly lower her head or body
- I waved my magic wand and turned her into a duck

Ambiguity is pervasive

Syntactic Category

- ‘Duck’ can be a noun or verb
- ‘her’ can be a possessive (‘of her’) or dative (‘for her’) pronoun

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Word Meaning

- 'make' can mean 'create' or 'cook'

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Grammar

make can be

- **Transitive:** (verb with a noun direct object)

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- **Transitive:** (verb with a noun direct object) $\rightarrow$ I cooked duck belonging to her
- **Ditransitive:** (verb has 2 noun objects)

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- **Transitive:** (verb with a noun direct object) → I cooked duck belonging to her
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Phonetics

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- I'm eight or duck
- I'm aid her duck

Ambiguity is Explosive

- I saw the man with the telescope. **2 parses**

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- I saw the man with the telescope. **2 parses**
- I saw the man on the hill with the telescope. **5 parses**

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- I saw the man on the hill in Texas with the telescope. **14 parses**

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- I saw the man on the hill in Texas with the telescope at noon on Monday. **132 parses**

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  - avoids language being overly complex
- Language relies on people's ability to use their knowledge and inference abilities to properly resolve ambiguities

Natural Languages vs. Computer Languages

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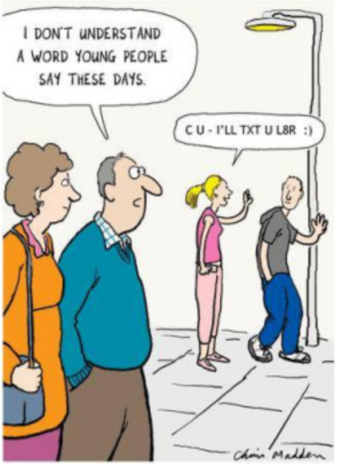
Natural Languages vs. Computer Languages

- Ambiguity is the primary difference between natural and computer languages.
- Formal programming languages are designed to be unambiguous
  - *Formal programming languages can be defined by a grammar that produces a unique parse for each sentence in the language.*
- Programming languages are also designed for efficient (deterministic) parsing.

Why else is NLP hard?



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Non-standard English

Great job @justinbieber! Were SOO PROUD of what youve accomplished! U taught us 2 #neversaynever & you yourself should never give up either

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the [New York]-[New Haven] [Railroad]

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Idioms

- dark horse
- Ball in your court
- Burn the midnight oil

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neologisms

- unfriend
- retweet
- Google/Skype/photoshop

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New Senses of a word

- That's *sick* dude!
- Giants

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- Giants ... *multinationals, conglomerates, manufacturers*

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Tricky Entity Names

- Where is *A Bug's Life* playing ...
- *Let It Be* was recorded ...

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Tools Required

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- A way to combine knowledge resources

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  - P(“maison” $\rightarrow$ “house”) is high
  - P(I saw a van) > P(eyes awe of an)

Empirical Laws

Niloy Ganguly

IITKGP, LUH

Week 1: Module 2

Function Words vs. Content Words

Function words have little lexical meaning but serve as important elements to the structure of sentences.

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Example

- The *winfy prunkilmonger* from the *glidgement mominkled* and *brangified* all his *levensers vederously*.
- *Glop* angry investigator *larm blonk* government harassed *gerfritz* infuriated *sutbor pumrog* listeners thoroughly.

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Function words are closed-class words

prepositions, pronouns, auxiliary verbs, conjunctions, grammatical articles, particles etc.

Most Common Words in Tom Sawyer

Word	Freq.	Use
the	3332	determiner (article)
and	2972	conjunction
a	1775	determiner
to	1725	preposition, verbal infinitive marker
of	1440	preposition
was	1161	auxiliary verb
it	1027	(personal/expletive) pronoun
in	906	preposition
that	877	complementizer, demonstrative
he	877	(personal) pronoun
I	783	(personal) pronoun
his	772	(possessive) pronoun
you	686	(personal) pronoun
Tom	679	proper noun
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The list is dominated by the little words of English, having important grammatical roles.

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These are usually referred to as *function words*, such as determiners, prepositions, complementizers etc.

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The one really exceptional word is *Tom*, whose frequency reflects the text chosen.

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How many words are there in this text?

Type vs. Tokens

Type-Token distinction

Type-token distinction is a distinction that separates a concept from the objects which are particular instances of the concept

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Type/Token Ratio

- The type/token ratio (TTR) is the ratio of the number of different words (types) to the number of running words (tokens) in a given text or corpus.
- This index indicates how often, on average, a new ‘word form’ appears in the text or corpus.

Comparison Across Texts

Mark Twain's Tom Sawyer

- 71,370 word tokens
- 8,018 word types
- TTR = 0.112

Complete Shakespeare work

- 884,647 word tokens
- 29,066 word types
- TTR = 0.032

Empirical Observations on Various Texts

Comparing Conversation, academic prose, news, fiction

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- Academic prose writing has the second lowest TTR.

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Not a valid measure of ‘text complexity’ by itself

- The value varies with the size of the text.
- For a valid measure, a running average is computed on consecutive 1000-word chunks of the text.

Word Distribution from Tom Sawyer

Word Frequency	Frequency of Frequency
1	3993
2	1292
3	664
4	410
5	243
6	199
7	172
8	131
9	82
10	91
11-50	540
51-100	99
> 100	102

- TTR = 0.11 $\Rightarrow$ Words occur on average 9 times each.
- But words have a very uneven distribution.

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Most words are rare

- 3993 (50%) word types appear only once
- They are called *happax legomena* (Greek for ‘read only once’)

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51-100	99
> 100	102

- TTR = 0.11 ⇒ Words occur on average 9 times each.
- But words have a very uneven distribution.

Most words are rare

- 3993 (50%) word types appear only once
- They are called *happax legomena* (Greek for 'read only once')

But common words are very common

- 100 words account for 51% of all tokens of all text

Zipf's Law

- Count the frequency of each word type in a large corpus
- List the word types in decreasing order of their frequency

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i.e. the 50th most common word should occur with 3 times the frequency of the 150th most common word.

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- p_r denote the probability of word of rank r
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The value of A is found closer to 0.1 for corpus

Empirical Evaluation from Tom Sawyer

Word	Freq. (f)	Rank (r)	$f \cdot r$	Word	Freq. (f)	Rank (r)	$f \cdot r$
the	3332	1	3332	turned	51	200	10200
and	2972	2	5944	you'll	30	300	9000
a	1775	3	5235	name	21	400	8400
he	877	10	8770	comes	16	500	8000
but	410	20	8400	group	13	600	7800
be	294	30	8820	lead	11	700	7700
there	222	40	8880	friends	10	800	8000
one	172	50	8600	begin	9	900	8100
about	158	60	9480	family	8	1000	8000
more	138	70	9660	brushed	4	2000	8000
never	124	80	9920	sins	2	3000	6000
Oh	116	90	10440	Could	2	4000	8000
two	104	100	10400	Applausive	1	8000	8000

Zipf's Other Laws

Correlation: Number of meanings and word frequency

The number of meanings m of a word obeys the law:

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Empirical Support

- Rank $\approx$ 10000, average 2.1 meanings
- Rank $\approx$ 5000, average 3 meanings
- Rank $\approx$ 2000, average 4.6 meanings

Zipf's Other Laws

Correlation: Word length and word frequency

Word frequency is inversely proportional to their length.

Impact of Zipf's Law

The Good part

Stopwords account for a large fraction of text, thus eliminating them greatly reduces the number of tokens in a text.

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Stopwords account for a large fraction of text, thus eliminating them greatly reduces the number of tokens in a text.

The Bad part

Most words are extremely rare and thus, gathering sufficient data for meaningful statistical analysis is difficult for most words.

Vocabulary Growth

How does the size of the overall vocabulary (number of unique words) grow with the size of the corpus?

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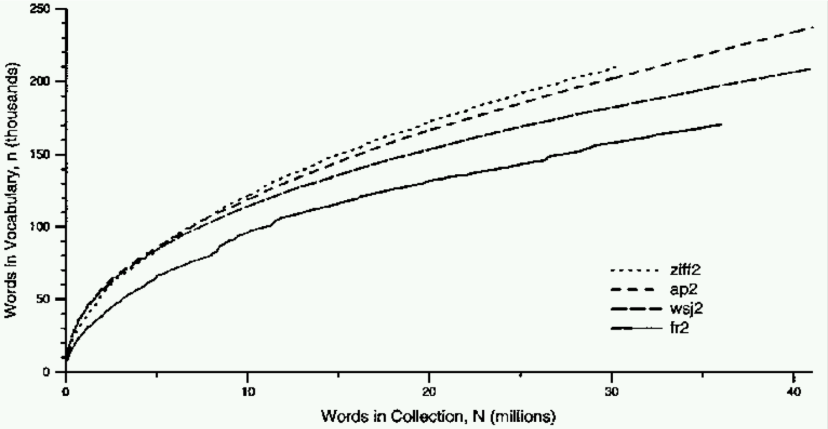
Let $|V|$ be the size of vocabulary and N be the number of tokens.

$$|V| = KN^{\beta}$$

Typically

- K $\approx$ 10-100
- $\beta \approx$ 0.4 - 0.6 (roughly square root)

Heaps' Law: Empirical Evidence



Text Processing: Basics

Niloy Ganguly

IITKGP, LUH

Week 1: Lecture 5

Text processing: tokenization

What is Tokenization?

Tokenization is the process of segmenting a string of characters into words.

Depending on the application in hand, you might have to perform *sentence segmentation* as well.

Sentence Segmentation

The problem of deciding where the sentences begin and end.

Challenges Involved

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Approach: build a binary classifier

For each "."

- Decides EndOfSentence/NotEndOfSentence

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- Classifiers can be: hand-written rules, regular expressions, or machine learning

Sentence Segmentation: Decision Tree Example

Decision Tree: Is this word the end-of-sentence (E-O-S)?

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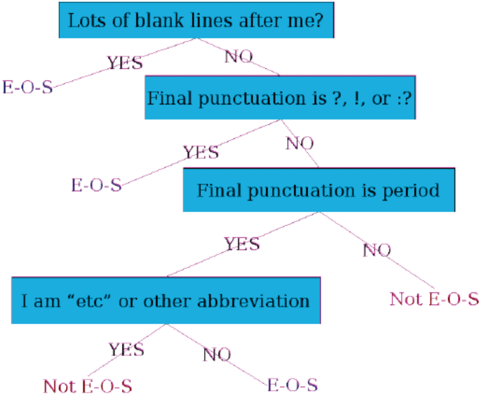

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Implementing Decision Trees

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- Just an if-then-else statement

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Basic Idea

Usually works top-down, by choosing a variable at each step that best splits the set of items.
Popular algorithms: ID3, C4.5, CART

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The questions in the decision tree can be thought of as features, that could be exploited by any other classifier:

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- Support Vector Machines
- Logistic regression
- Neural Networks

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I have a can opener; but I can't open these cans.

Word Token

- An occurrence of a word
- For the above sentence, 11 word tokens.

Word Type

- A different realization of a word
- For the above sentence, 10 word types.

Tokenization in practice

- NLTK Toolkit (Python)
- Stanford CoreNLP (Java)
- Unix Commands

Word Tokenization

Word Tokenization

Issues in Tokenization

- Finland's $\rightarrow$ Finland Finlands Finland's ?
- What're, I'm, shouldn't $\rightarrow$ What are, I am, should not ?
- San Francisco $\rightarrow$ one token or two?
- m.p.h. $\rightarrow$??

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- m.p.h. $\rightarrow$??

For information retrieval, use the same convention for documents and queries

Handling Hyphenation

Hyphens can be

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End-of-Line Hyphen

Used for splitting whole words into part for text justification.

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Sententially Determined Hyphenation

Mainly to prevent incorrect parsing of the phrase. Some possible usages:

- Noun modified by an 'ed'-verb: *case-based, hand-delivered*
- Entire expression as a modifier in a noun group: *three-to-five-year direct marketing plan*

Language Specific Issues: French and German

French

l'ensemble: want to match with un ensemble

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l'ensemble: want to match with un ensemble

German

Noun coumpounds are not segmented

- Lebensversicherungsgesellschaftsangestellter
- 'life insurance company employee'
- Compound splitter required for German information retrieval

Language Specific Issues: Chinese and Japanese

No space between words

莎拉波娃现在居住在美国东南部的佛罗里达。

莎拉波娃 现在 居住 在 美国 东南部 的 佛罗里达

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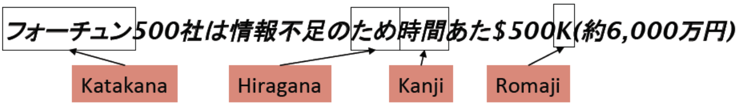
Japanese: further complications with multiple alphabets intermingled.



सत्यम्ब्रूयात्प्रियम्ब्रूयान्नब्रूयात्सत्यमप्रियम्प्रियश्चनानृतम्ब्रूयादेषधर्मःसनातनः

satyaṃbrūyātpriyaṃbrūyānnabrūyātsatyamapriyaṃpriyaṃcanānṛtambrūyād-eṣadharmaḥsanātanaḥ.

"One should tell the truth, one should say kind words; one should neither tell harsh truths, nor flattering lies; this is a rule for all times."

Language Specific Issues: Sanskrit

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Segmented Text:

satyam brūyāt priyam brūyāt na brūyāt satyam apriyam priyam ca na anṛtam brūyāt eṣaḥ dharmaḥ sanātanaḥ.

Longest Words

Max	Language (non scientific)
431	**Sanskrit** *(Longest)*
173	Greek
136	Afrikaans
85	Māori
79	German
74	Turkish
64	Icelandic
56	Hungarian
54	Spanish
49	Dutch
46	Malay
45	English
44	Romanian
42	Georgian
41	Czech
39	Bulgarian
39	Lithuanian
36	Kazakh
33	Norwegian
32	Tagalog
32	Polish
30	Serbian
30	Montenegrin
30	Italian
30	Croatian

Longest Words

Compound word composed of 431 letters, from the Varadāmbikā Pariṅaya Campū by Tirumalāmba

निरन्तरान्धकारिता-दिगन्तर-कन्दलदमन्द-सुधारस-बिन्दु-सान्द्रतर-घनाघन-वृन्द-सन्देहकर-
स्यन्दमान-मकरन्द-बिन्दु-बन्धुरतर-माकन्द-तरु-कुल-तल्प-कल्प-मृदुल-सिकता-जाल-जटिल-
मूल-तल-मरुवक-मिलदलघु-लघु-लय-कलित-रमणीय-पानीय-शालिका-बालिका-करार-विन्द-
गलन्तिका-गलदेला-लवङ्ग-पाटल-घनसार-कस्तूरिकातिसौरभ-मेदुर-लघुतर-मधुर-शीतलतर-
सलिलधारा-निराकरिष्णु-तदीय-विमल-विलोचन-मयूख-रेखापसारित-पिपासायास-पथिक-
लोकान्

Word Tokenization in Chinese or Sanskrit

Also called '**Word Segmentation**'.

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Greedy Algorithm for Chinese

Maximum Matching (Greedy Algorithm)

- Start a pointer at the beginning of the string
- Find the largest word in dictionary that matches the string starting at pointer
- Move the pointer over the word in string

Think of the cases when word segmentation would be required for English Text.

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Think of the cases when word segmentation would be required for English Text.
Finding constituent words in a compound hashtags: #ThankYouSachin, #musicmonday etc.

Normalization

Why to "normalize"?

Indexed text and query terms must have the same form.

- U.S.A. and USA should be matched

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Indexed text and query terms must have the same form.

- U.S.A. and USA should be matched
- We implicitly define equivalence classes of terms

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- Reduce all letters to lower case

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- Possible exceptions (Task dependent):
  - Upper case in mid sentence, may point to named entities (e.g. General Motors)
  - For MT and information extraction, some cases might be helpful (*US* vs. *us*)

Lemmatization

- Reduce inflections or variant forms to base form:
  - am, are, is $\rightarrow$ be
  - car, cars, car's, cars' $\rightarrow$ car
- Have to find the correct dictionary headword form

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  - Infix: '*n*' in '*vindati*' (he knows), as contrasted with *vid* (to know).

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  - *automate(s), automatic, automation* all reduced to *automat*

for example compressed and compression are both accepted as equivalent to compress.

for exampl compress and compress ar both accept as equival to compress

Porter's algorithm

Step 1a

- sses $\rightarrow$ ss (caresses $\rightarrow$ caress)
- ies $\rightarrow$ i (ponies $\rightarrow$ poni)
- ss $\rightarrow$ ss (caress $\rightarrow$ caress)
- s $\rightarrow$ ϕ (cats $\rightarrow$ cat)

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Step 1b

- (*v*)ing → ϕ (walking → walk, king →

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- s $\rightarrow$ ϕ (cats $\rightarrow$ cat)

Step 1b

- (*v*)ing $\rightarrow$ ϕ (walking $\rightarrow$ walk, king $\rightarrow$ king)
- (*v*)ed $\rightarrow$ ϕ (played $\rightarrow$ play)

Porter's algorithm

Step 2

- ational $\rightarrow$ ate (relational $\rightarrow$ relate)
- izer $\rightarrow$ ize (digitizer $\rightarrow$ digitize)
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Step 3

- al $\rightarrow$ ϕ (revival $\rightarrow$ reviv)
- able $\rightarrow$ ϕ (adjustable $\rightarrow$ adjust)
- ate $\rightarrow$ ϕ (activate $\rightarrow$ activ)