# *Introduction to the Course*



Pawan Goyal

CSE, IITKGP

Week 1: Lecture 1

# Course Info

## My Contact


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- **Webpage:** `http://cse.iitkgp.ac.in/~pawang/`

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## Teaching Assistants

- Amrith Krishna
- Mayank Singh

# Books and Materials

### Reference Books

- Daniel Jurafsky and James H. Martin. 2009. Speech and Language Processing: *An Introduction to Natural Language Processing, Speech Recognition, and Computational Linguistics*. 2nd edition. Prentice-Hall.
- Christopher D. Manning and Hinrich Schütze. 1999. *Foundations of Statistical Natural Language Processing*. MIT Press.

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## Lecture Material

- Lecture Slides
- IPython Notebooks

# Course Evaluation Plan

- Assignments : 25% – also include programming assignments in Ipython
- Final Exam : 75%

# *Course Contents: Weeks 1-9*

### *Basic Language Processing Tasks, Tools and Algorithms*

- Basic Text Processing: Tokenization, Stemming, Spelling Correction
- Language Modeling: N-grams, smoothing
- Morphology, Parts of Speech Tagging
- Syntax: PCFGs, Dependency Parsing
- Lexical Semantics, Word Sense Disambiguation
- Distributional Semantics, Word Embeddings
- Topic Models

# Course Contents: Weeks 10-12

## *NLP Applications*

- Entity Linking and Information Extraction
- Text Summarization and Text Classification
- Sentiment Analysis and Opinion Mining

# *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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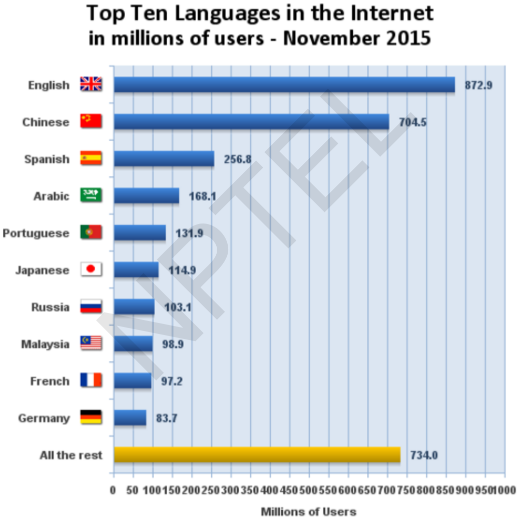
Tweets, Facebook posts, comments, Quora ...

[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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### *Fundamental and Scientific Goal*

*Deep* understanding of *broad* language

### *Engineering Goal*

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

# *What do we do in NLP?*



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Module 1: Lecture 2

# *What is NLP?*

*Fundamental and Scientific Goal*

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# Goals can be very ambitious: Good quality translation

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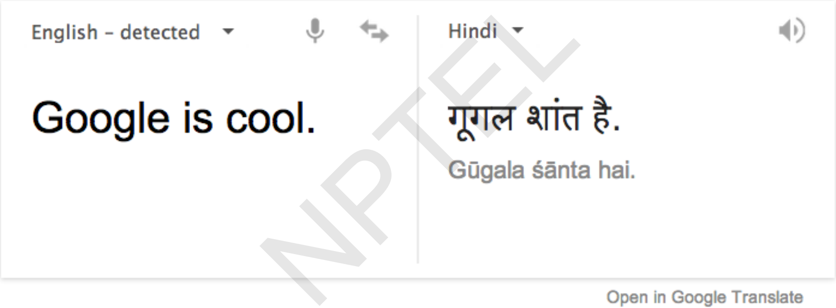

# *Well, even humans have made blunders*

*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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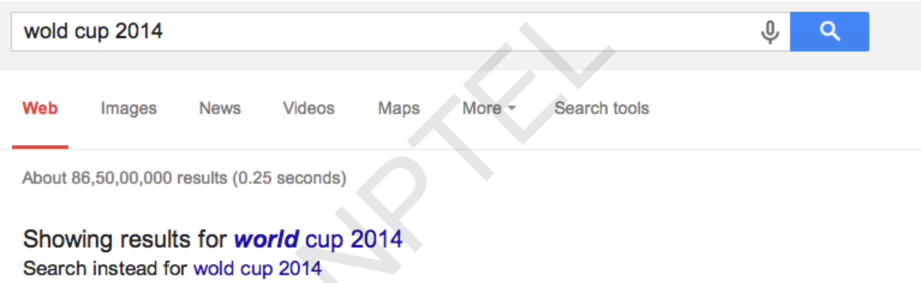
*KFC's Chinese blunder*

KFC's slogan, "Finger lickin' good", when translated into Chinese meant "We'll eat your fingers off."

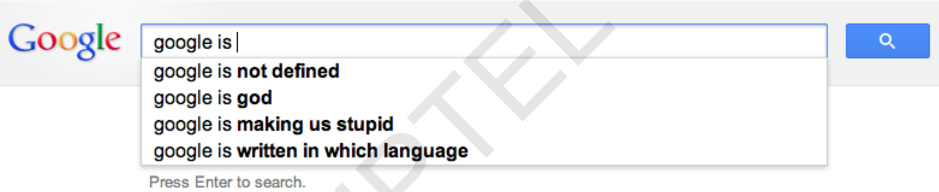
# Well, even humans ...


# *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

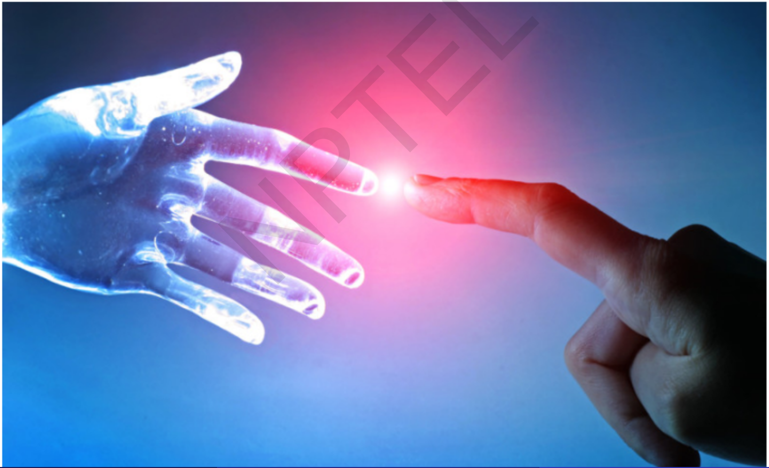
New York Times Co. named Russell T. Lewis, 45, president and general manager of its flagship New York Times newspaper, responsible for all business-side activities. He was executive vice president and deputy general manager. He succeeds Lance R. Primis, who in September was named president and chief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

[1]

[1] 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

# *Why is NLP hard?*

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Week 1: Lecture 3

# Why is NLP hard?

### Lexical Ambiguity

- *Will Will will Will's will?*

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- *Buffalo buffalo Buffalo buffalo buffalo buffalo Buffalo buffalo.*

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## *Lexical Ambiguity*

- *Will Will will Will's will?*
- *Rose rose to put rose roes on her rows of roses.*
- *Buffalo buffalo Buffalo buffalo buffalo buffalo Buffalo buffalo.*
  $\rightarrow$ Buffaloes from Buffalo, NY, whom buffaloes from Buffalo bully, bully buffaloes from Buffalo.

# *Why is NLP hard?*

## *Language ambiguity: Structural*

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

## *Language imprecision and vagueness*

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## Language imprecision and vagueness

- *It is very warm here.*
- *Q: Did your mother call your aunt last night?*
  *A: I'm sure she must have.*

Why is the teacher wearing sun-glasses?

...

Why is the teacher wearing sun-glasses?

...

Because the class is so **bright**.

# Ambiguities

*News Headlines*

- Hospitals Are Sued by 7 Foot Doctors
- Stolen Painting Found by Tree
- 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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### *Syntactic Category*

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

### *Word Meaning*

- ‘make’ can mean ‘create’ or ‘cook’

# Ambiguity is pervasive

## Grammar

make can be

- **Transitive:** (verb with a noun direct object)
- **Ditransitive:** (verb has 2 noun objects)
- **Action-transitive:** (verb has a direct object + verb)

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### Phonetics

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

# Ambiguity is Explosive

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

# *Ambiguity is Explosive*

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- 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. **42 parses**
- 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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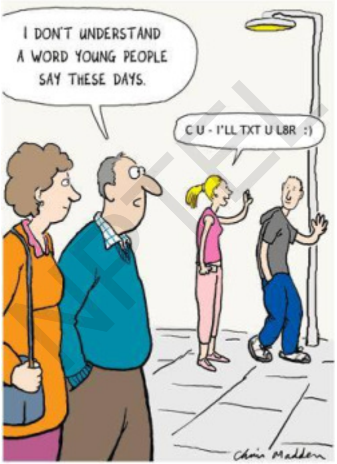
# *Natural Languages vs. Computer Languages*

- 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?



# Why else is NLP hard?

# *Why else is NLP hard?*

### *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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### Segmentation Issues

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# Why else is NLP hard?

## Idioms

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

# *Why else is NLP hard?*

*Idioms*

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

*neologisms*

- unfriend
- retweet
- Google/Skype/photoshop

# Why is NLP hard?

## *New Senses of a word*

- That's *sick* dude!
- Giants

# *Why is NLP hard?*

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### *New Senses of a word*

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### *Tricky Entity Names*

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

# *What we do in NLP?*

### *Tools Required*

- Knowledge about language
- Knowledge about the world
- A way to combine knowledge resources

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- Probabilistic models built from language data
  - $P$(“maison” $\rightarrow$ “house”) is high

# *What we do in NLP?*

## *Tools Required*

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- Knowledge about the world
- A way to combine knowledge resources

## *How is it generally done?*

- Probabilistic models built from language data
  - $P$("maison" $\rightarrow$ "house") is high
  - P(I saw a van) > P(eyes awe of an)
- Extracting rough text features does half the job.

# *Empirical Laws*

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Week 1: Lecture 4

# *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*

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- *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*

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# 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

### 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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### *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.
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*Most words are rare*

- 3993 (50%) word types appear only once
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*But common words are very common*

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

# *Zipf's Law*

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- List the word types in decreasing order of their frequency

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

Let

- $p_r$ denote the probability of word of rank $r$
- $N$ denote the total number of word occurrences

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- $N$ denote the total number of word occurrences

$$p_r = \frac{f}{N} = \frac{A}{r}$$

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

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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.

# Impact of Zipf's Law

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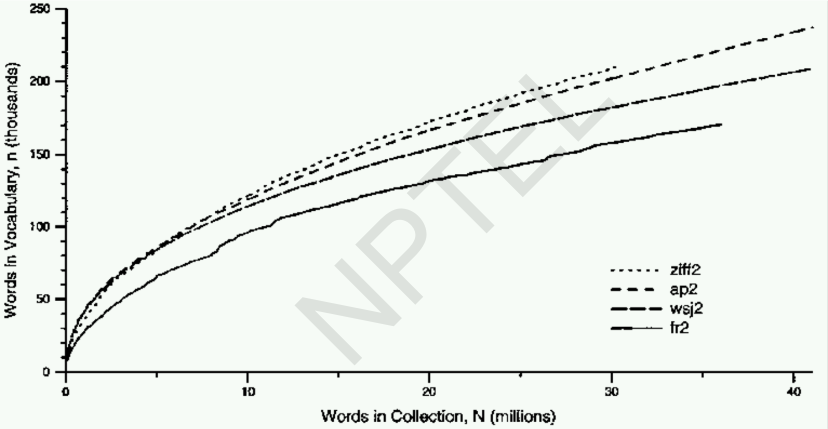
Let $|V|$ be the size of vocabulary and $N$ be the number of tokens.

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

Typically

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

# Heaps' Law: Empirical Evidence



# *Text Processing: Basics*

Pawan Goyal

CSE, IITKGP

Week 1: Lecture 5

*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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## *Approach: build a binary classifier*

For each “.”

- Decides EndOfSentence/NotEndOfSentence
- 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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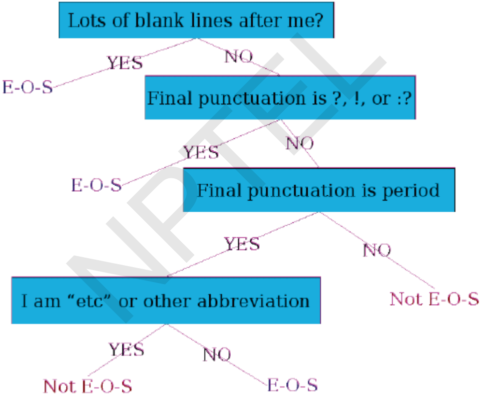

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*Basic Idea*

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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- Support Vector Machines
- Logistic regression
- Neural Networks

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

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

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### *End-of-Line Hyphen*

Used for splitting whole words into part for text justification.

*This paper describes MIMIC, an adaptive mixed initia-tive spoken dialogue system that provides movie show-time information.*

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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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### *French*

**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

Sharapova now lives in US southeastern Florida

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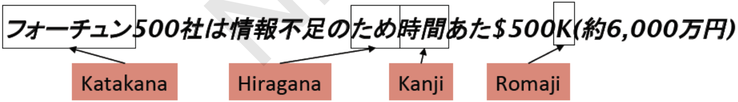
**Japanese:** further complications with multiple alphabets intermingled.



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*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.

# Text Segmentation for Sanskrit

### General assumption behind the design

Sentences from Classical Sanskrit may be generated by a regular relation $R$ of the Kleene closure $W^*$ of a regular set $W$ of *words* over a finite alphabet $\Sigma$.

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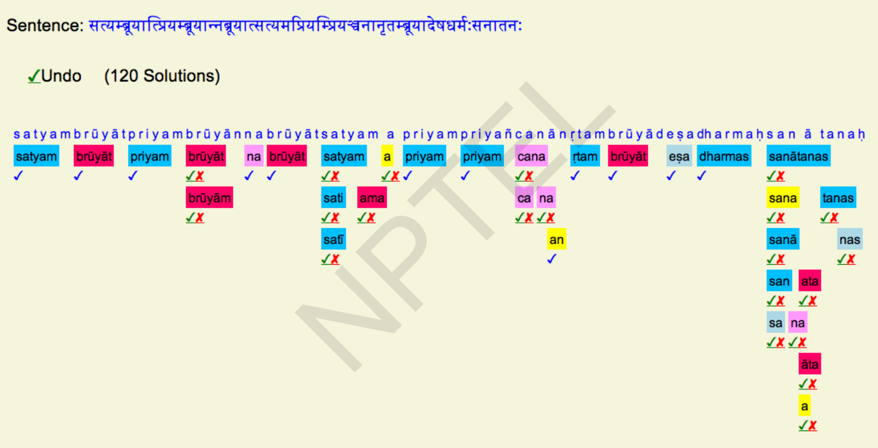
### Analysis of a sentence

A candidate sentence $w$ is analyzed by inverting relation $R$ to produce a finite sequence $w_1, w_2, ...w_n$ of word forms, together with a proof that $w \in R(w_1 \cdot w_2 ... \cdot w_n)$.

# Word Segmentation in Sanskrit



# *Normalization*

*Why to "normalize"?*

Indexed text and query terms must have the same form.

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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

# *Case Folding*

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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 inforamtion 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.*

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# Porter's algorithm

### Step 1a

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

# *Porter's algorithm*

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### *Step 1b*

- (*v*)ing $\rightarrow$ $\phi$ (walking $\rightarrow$ walk, king $\rightarrow$

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### Step 1b

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

# *Porter's algorithm*

### *Step 2*

- ational $\rightarrow$ ate (relational $\rightarrow$ relate)
- izer $\rightarrow$ ize (digitizer $\rightarrow$ digitize)
- ator $\rightarrow$ ate (operator $\rightarrow$ operate)

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### Step 3

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