

8

COMP8730-1-R-2022W Natural Language Processing & Understanding



Lectures

Lec02: Text Segmentation and Normalization



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Lec02: Text Segmentation and Normalization

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Assign 01

Enabled: Statistics Tracking

Attached Files:  [Assignment_01.pdf](#)  (195.82 KB)



Forum: Research Project

Forums are made up of individual discussion threads that can be organized around a particular subject. A thread is a conversation within a forum that includes the initial post and all replies to it. When you access a forum, a list of threads appears. [More Help](#)

(Natural Language
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Weekly Schedule



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Discussion Board



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Create Thread Unsubscribe

Search

Discover Content

Display

Thread Actions ▾
 DATE ▾

Collect

Delete

	THREAD	AUTHOR	STATUS	TAGS	UNREAD POSTS	UNREAD REPLIES TO ME	TOTAL POSTS
<input type="checkbox"/>	1/21/22 1:23 PM Reproducibility Projects	Hossein Fani	Published		0	0	1
<input type="checkbox"/>	1/18/22 12:31 PM Free bootcamps on Python, NLP, ...	Hossein Fani	Published		0	0	1
<input type="checkbox"/>	1/18/22 7:35 AM List of Top Rank NLP-IR Conferences	Hossein Fani	Published		0	0	1

Thread Actions ▾
 Collect Delete

Displaying 1 to 3 of 3 items



The Turing Test
by Alan Turing in 1950

Player C, the interrogator, has the task of trying to determine whether player – A or B – is a machine or which is a human. The interrogator is limited to using the written questions to make his determination.

VOL. LIX. NO. 236.]

[October, 1950]

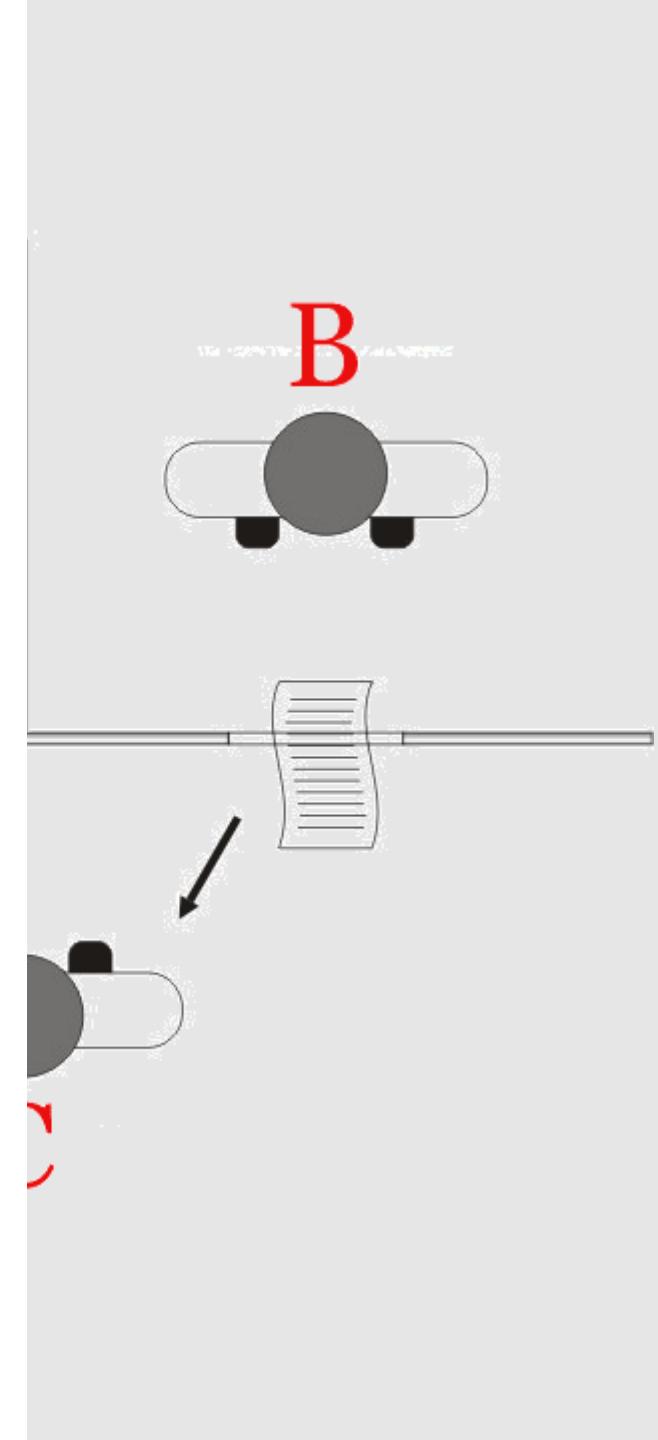
M I N D
A QUARTERLY REVIEW
OF
PSYCHOLOGY AND PHILOSOPHY

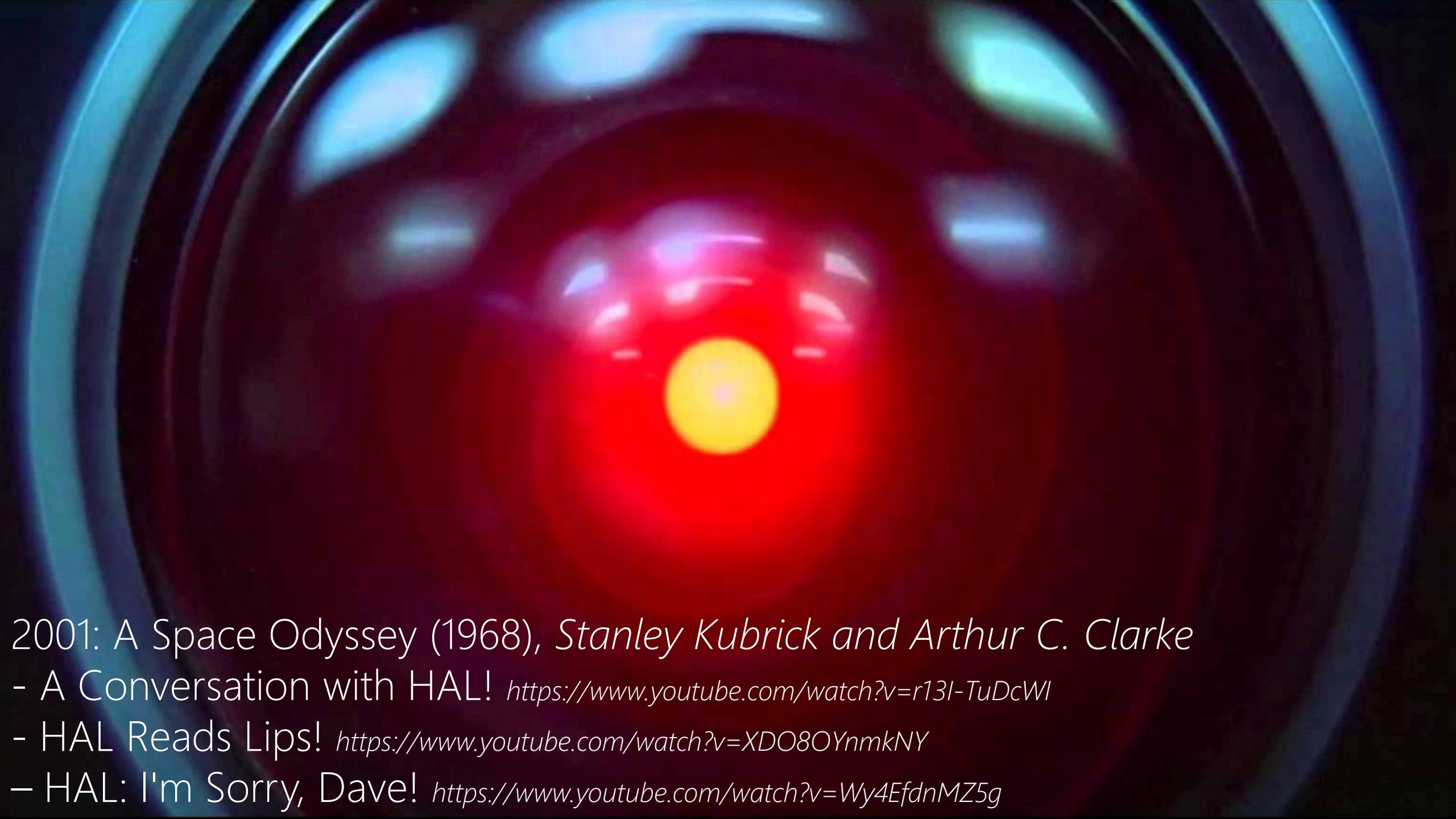
I.—COMPUTING MACHINERY AND
INTELLIGENCE

BY A. M. TURING

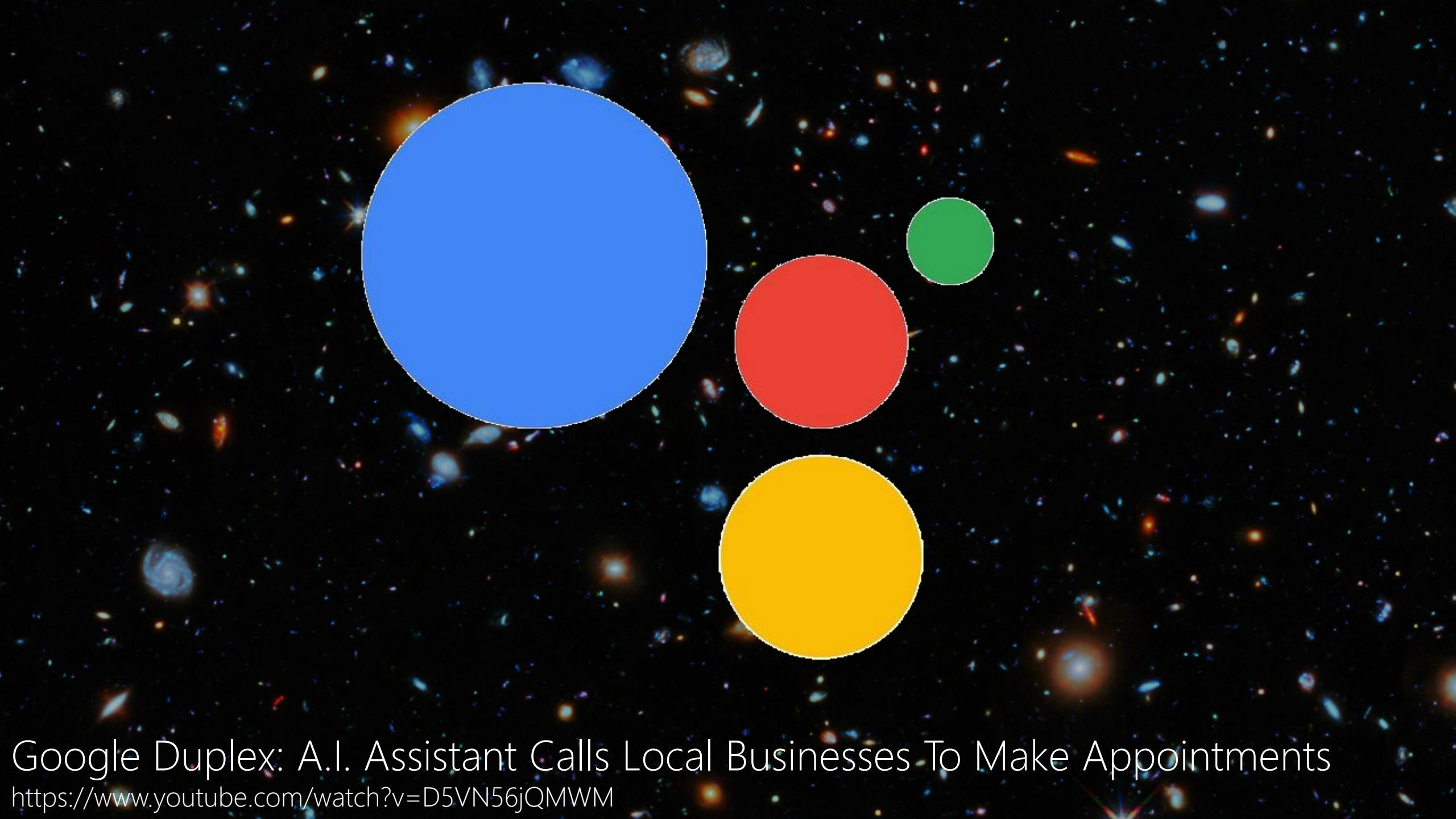
1. *The Imitation Game.*

I PROPOSE to consider the question, ‘Can machines think?’ This should begin with definitions of the meaning of the terms ‘machine’ and ‘think’. The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous. If the meaning of the words ‘machine’ and ‘think’ are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, ‘Can machines think?’ is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.





2001: A Space Odyssey (1968), *Stanley Kubrick and Arthur C. Clarke*
- A Conversation with HAL! <https://www.youtube.com/watch?v=r13I-TuDcWI>
- HAL Reads Lips! <https://www.youtube.com/watch?v=XDO8OYnmkNY>
- HAL: I'm Sorry, Dave! <https://www.youtube.com/watch?v=Wy4EfdnMZ5g>



Google Duplex: A.I. Assistant Calls Local Businesses To Make Appointments
<https://www.youtube.com/watch?v=D5VN56jQMWM>

Research Priorities for Artificial Intelligence

The capacity for language is one of the central features of human intelligence and is therefore a prerequisite for artificial intelligence.

Despite its many practical applications, language is perhaps number 300 in the priority list for AI research. It would be a great achievement if AI could attain the capabilities of an orangutan, which do not include language!

- Yann LeCun (computer vision researcher)



Handle: Boston Dynamics' newest design. Jumps 4 feet in the air and zips around at 9 miles per hour. <https://www.youtube.com/watch?v=7h8mX9ZMs7g>

State of AI Report

October 12, 2021

Scaling Language Models: Methods, Analysis & Insights from Training *Gopher*

Jack W. Rae, Sebastian Borgeaud, Trevor Cai, Katie Millican, Jordan Hoffmann, Francis Song, John Aslanides, Sarah Henderson, Roman Ring, Susannah Young, Eliza Rutherford, Tom Hennigan, Jacob Menick, Albin Cassirer, Richard Powell, George van den Driessche, Lisa Anne Hendricks, Maribeth Rauh, Po-Sen Huang, Amelia Glaese, Johannes Welbl, Sumanth Dathathri, Saffron Huang, Jonathan Uesato, John Mellor, Irina Higgins, Antonia Creswell, Nat McAleese, Amy Wu, Erich Elsen, Siddhant Jayakumar, Elena Buchatskaya, David Budden, Esme Sutherland, Karen Simonyan, Michela Paganini, Laurent Sifre, Lena Martens, Xiang Lorraine Li, Adhiguna Kuncoro, Aida Nematzadeh, Elena Gribovskaya, Domenic Donato, Angeliki Lazaridou, Arthur Mensch, Jean-Baptiste Lespiau, Maria Tsimpoukelli, Nikolai Grigorev, Doug Fritz, Thibault Sottiaux, Mantas Pajarskas, Toby Pohlen, Zhitao Gong, Daniel Toyama, Cyprien de Masson d'Autume, Yujia Li, Tayfun Terzi, Vladimir Mikulik, Igor Babuschkin, Aidan Clark, Diego de Las Casas, Aurelia Guy, Chris Jones, James Bradbury, Matthew Johnson, Blake Hechtman, Laura Weidinger, Iason Gabriel, William Isaac, Ed Lockhart, Simon Osindero, Laura Rimell, Chris Dyer, Oriol Vinyals, Kareem Ayoub, Jeff Stanway, Lorrayne Bennett, Demis Hassabis, Koray Kavukcuoglu and Geoffrey Irving



Language modelling provides a step towards intelligent communication systems by harnessing large repositories of written human knowledge to better predict and understand the world. In this paper, we present an analysis of Transformer-based language model performance across a wide range of model

1. Introduction



Natural language communication is core to intelligence, as it allows ideas to be efficiently shared between humans or artificially intelligent systems. The generality of language allows us to express many intelligence tasks as taking in natural language input and producing natural language output.

Artificial intelligence / Machine learning

Training a single AI model can emit as much carbon as five cars in their lifetimes

Deep learning has a terrible carbon footprint.

by Karen Hao

June 6, 2019

Common carbon footprint benchmarks

in lbs of CO₂ equivalent

Roundtrip flight b/w NY and SF (1 passenger)	1,984
Human life (avg. 1 year)	11,023
American life (avg. 1 year)	36,156
US car including fuel (avg. 1 lifetime)	126,000
Transformer (213M parameters) w/ neural architecture search	626,155

Chart: MIT Technology Review • Source: Strubell et al. • [Created with Datawrapper](#)

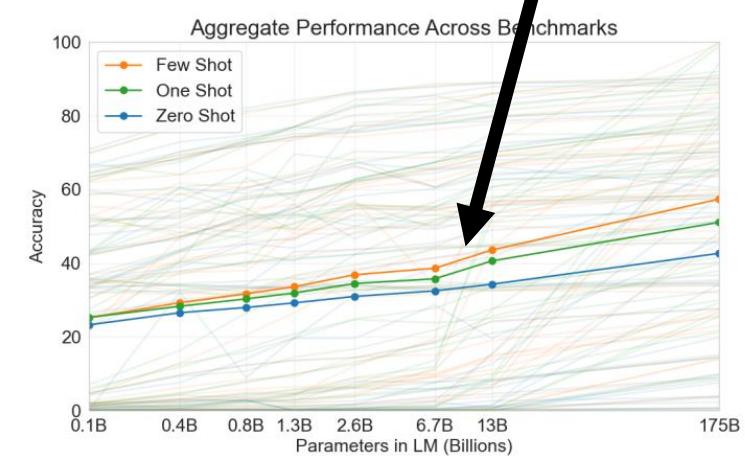


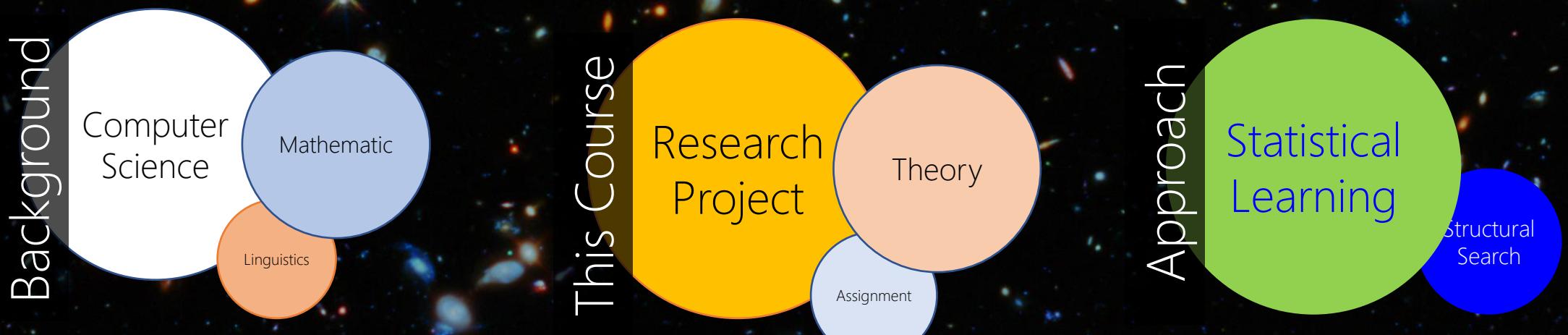
Figure 1.3: Aggregate performance for all 42 accuracy-denominated benchmarks While zero-shot performance improves steadily with model size, few-shot performance increases more rapidly, demonstrating that larger models are more proficient at in-context learning. See Figure 3.8 for a more detailed analysis on SuperGLUE, a standard NLP benchmark suite.



Communication
Understanding

Natural Language Processing

Speech, *Text*, Emotion, ...



Task

NLP is AI-hard (why?)

Pipeline of Understanding

Phonetics and Phonology, Morphology, Syntax, Semantics, Pragmatics, Discourse

Ambiguity

I made her duck

Language is Situated

Rationale, Code Switch, Genre, Time, Place, Dialect, Author

Computational Complexity

Discrete, Compositional, Power-law distribution



Lec02A
11:30am-12:45pm
Text Segmentation

Lec02B
01:00pm-02:20pm
Text Normalization





Natural Language Processing

Phonetics and Phonology, Morphology, Syntax, Semantics, Pragmatics, Discourse

Phonetics and Phonology

knowledge about linguistic sounds
how words are pronounced in terms of sequences of sounds
 how each of these sounds is realized acoustically

Phonetics and Phonology

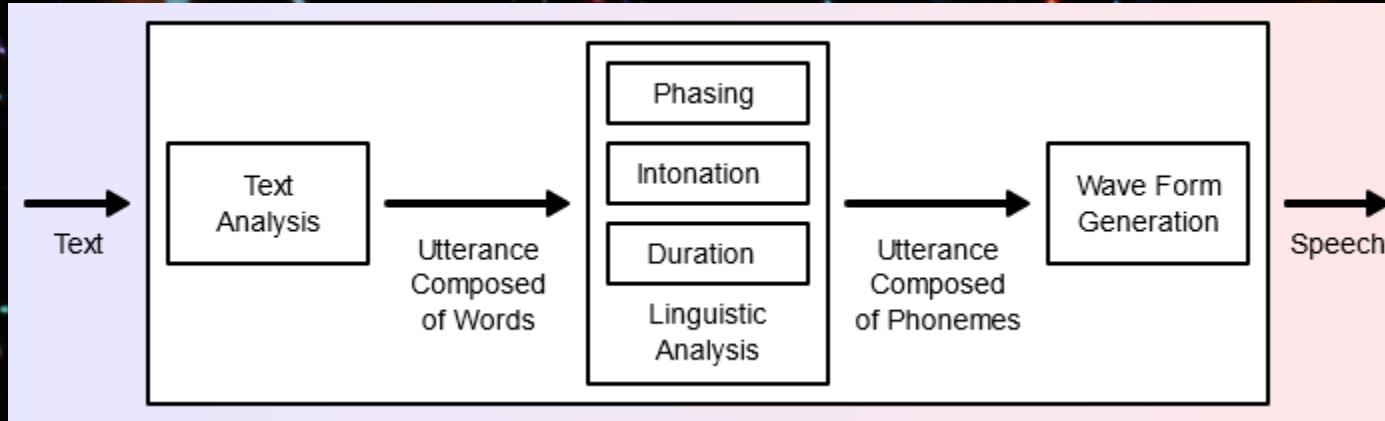
Speech Recognition (SR)

recognize words from an audio signal like in assistants: Alexa, Homepod

Speech Synthesis (Synthesizers)

generate an audio signal from a sequence of words like in Automatic Announcement
Automatic Answering Machine

Phonetics and Phonology



Text-To-Speech System (TTS)

Phone [fəʊn] → Diphones [fə], [əʊ], [ʊn] → much more natural than combining simple phones





Stephen Hawking talks about technology and ACAT (Assistive Context Aware Tool-kit)
<https://www.youtube.com/watch?v=TXY8IKFeKZs>
<https://01.org/acat/>
image: Ted S. Warren/AP



Search Google or type a URL



Search by voice



Natural Language Processing

Phonetics and Phonology, Morphology, Syntax, Semantics, Pragmatics, Discourse

Morphology

knowledge of the meaningful **components** of words
producing and recognizing **variations** of individual words
the way words **break down** into **component parts** that carry different meanings
study of words, how they are formed, their relationships in the same language

Morphology

Lexeme

- Also known as Lemma or citation form
- Refer to a same entity or concept
- Change is called *Inflection*
- Inflection Rules:

Singular vs. Plural: index → indexes, indices

Contractions: cannot → can't

Tenses: do → did, done, does

Wordforms

- Form new lexemes
- Refer to different entities or concepts or ...
- Wordformation Rules:

Compounding: [Dog][catch][er], [Dish][wash][er]

Lemma(Dishwashers) = Dishwasher

Lemma(Dishwashers) ≠ Dish ≠ Wash



CoreNLP

version 4.4.0

— Text to annotate —

Open the Pod bay doors, please, HAL.



lemmas X

— Annotations —

— Language —

English ▾

Submit

Lemmas:

open the Pod bay door ▾ please ▾ HAL ▾

1 Open the Pod bay doors , please , HAL .



Natural Language Processing

Phonetics and Phonology, Morphology, Syntax, Semantics, Pragmatics, Discourse

Syntax

knowledge of the structural relationships between words

knowledge needed to *stream* (order) words
moving beyond individual words

HAL: I'm I do, sorry that afraid Dave I'm can't. ↔ I'm sorry Dave, I'm afraid can't.



version 4.4.0

Pos Tagger

Parser

— Text to annotate —

I'm sorry Dave, I'm afraid can't.

— Annotations —

parts-of-speech dependency parse

— Language —

English

Part-of-Speech:

1 PRP VBP JJ NNP PRP VBP JJ MD RB .
I 'm sorry Dave , I 'm afraid ca n't .

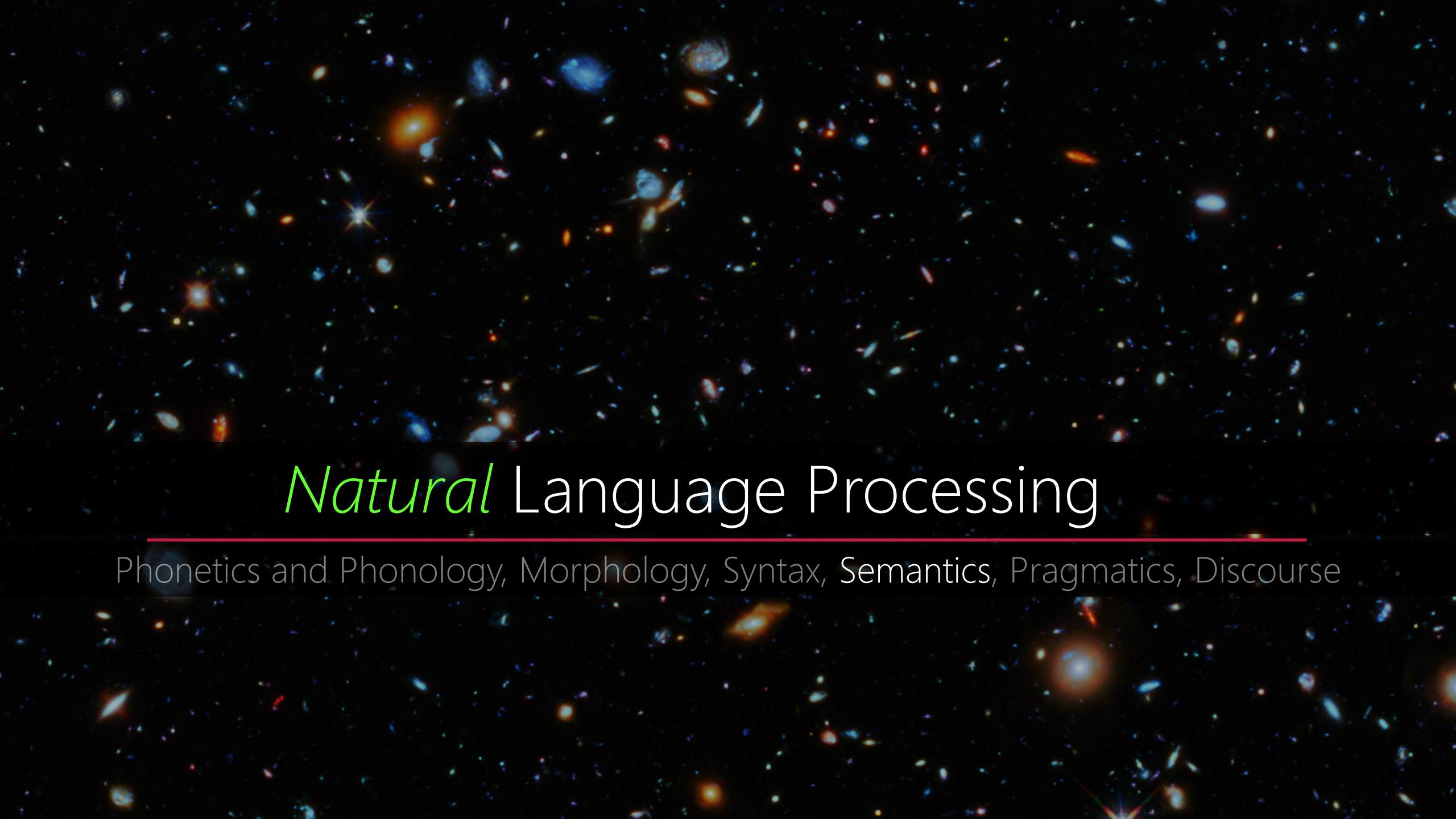
Basic Dependencies:

1 PRP nsubj cop JJ punct NNP nsubj punct PRP cop VBP dep JJ MD advmod RB .
I 'm sorry Dave , I 'm afraid ca n't .

Enhanced++ Dependencies:

1 PRP nsubj cop JJ punct NNP nsubj punct PRP cop VBP dep JJ MD advmod RB .
I 'm sorry Dave , I 'm afraid ca n't .

CC	Coordinating conjunction
CD	Cardinal number
DT	Determiner
EX	Existential there
FW	Foreign word
IN	Preposition or subordinating conjunction
JJ	Adjective
JJR	Adjective, comparative
JJS	Adjective, superlative
LS	List item marker
MD	Modal
NN	Noun, singular or mass
NNS	Noun, plural
NNP	Proper noun, singular
NNPS	Proper noun, plural
PDT	Predeterminer
POS	Possessive ending
PRP	Personal pronoun
PRP\$	Possessive pronoun
RB	Adverb
RBR	Adverb, comparative
RBS	Adverb, superlative
RP	Particle
SYM	Symbol
TO	to
UH	Interjection
VB	Verb, base form
VBD	Verb, past tense
VBG	Verb, gerund or present participle
VBN	Verb, past participle
VBP	Verb, non-3rd person singular present
VBZ	Verb, 3rd person singular present
WDT	Wh-determiner
WP	Wh-pronoun
WP\$	Possessive wh-pronoun
WRB	Wh-adverb



Natural Language Processing

Phonetics and Phonology, Morphology, Syntax, Semantics, Pragmatics, Discourse

Semantics

knowledge of meaning

Lexical

Compositional

- The meaning of the words
cat → *a small domesticated carnivorous mammal ...*
- Polysemy: one word with two or more distinct meanings
polyseme is a word or phrase with multiple meanings
afraid → *Scared*
afraid → *Politely apologetic*
- The meaning of the sentences
I'm afraid of being sorry
sorry, I'm afraid I can't

Named Entity Annotators



version 4.4.0

```
{ 'CARDINAL': 5,  
  'DATE': 29,  
  'EVENT': 1,  
  'GPE': 35,  
  'LOC': 1,  
  'NORP': 5,  
  'ORDINAL': 1,  
  'ORG': 26,  
  'PERSON': 84,  
  'WORK_OF_ART': 1}
```

Open the Pod bay doors, please, HAL.



— Text to annotate —

named entities X

— Annotations —

— Language —

English ▾

Submit

Named Entity Recognition:

1 Open the Pod bay doors , please , HAL .

PERSON

Semantic Annotators



TAGME is a powerful tool that is able to identify *on-the-fly* meaningful short-phrases (called "spots") in an unstructured text and link them to a pertinent [Wikipedia page](#) in a fast and effective way. This annotation process has implications which go far beyond the enrichment of the text with explanatory links because it concerns with the *contextualization* and, in some way, the *understanding* of the text.

Try **TAGME** now!

You can play with the demo interface below or check the documentation to the TAGME RESTful API we are currently supporting.

Currently **TAGME** is available in English, German and in Italian and it is based on Wikipedia snapshots of April, 2016.

NEWS! TAGME is now hosted by the D4Science infrastructure. Check the RESTful API page for details.

Developed by [Paolo Ferragina](#) and Ugo Scaiella at [A³ Lab](#)
[Dipartimento di Informatica, University of Pisa](#)

Input Text

Italiano English Deutsche

On this day 24 years ago Maradona scored his infamous "Hand of God" goal against England in the quarter-final of the 1986

Many links

Few links

[Reset](#)

[TAGME!](#)

Tagged text

Topics

On this day 24 years ago [Maradona](#) scored his infamous "Hand of God" goal against [England](#) in the [quarter-final](#) of the 19

Diego Maradona

Diego Armando Maradona (, born 30 October 1960) is a retired Argentine professional footballer. He has served as a manager and coach at other clubs as well as the national team of Argentina. Many in t...

Argentina v England (1986 FIFA World Cup)

Argentina v England, played on 22 June 1986, was a football match between Argentina and England in the quarter-finals of the 1986 FIFA World Cup at the Estadio Azteca in Mexico City. The game was held...

England national football team

The England national football team represents England in international football and is controlled by The Football Association, the governing body for football in England. England are one of the two ol...



Natural Language Processing

Phonetics and Phonology, Morphology, Syntax, Semantics, Pragmatics, Discourse

Pragmatic

knowledge of the relationship of meaning to the *goals* & *intentions* of the speaker

Syntax: Mono relation between linguistic forms (lexeme)

Semantic: Dyadic relation between lexemes and real-world entities

Pragmatic: Triadic relation between lexemes, world, and the user

Directive: HAL, open the pod bay door.



Pragmatic

knowledge of the relationship of meaning to the *goals* & *intentions* of the speaker

Illocutionary act was introduced into linguistics by the philosopher John Langshaw Austin in his investigation of the various aspects of *speech acts*.

Locution: what was said

"Is there any salt?" at the dinner table, a question about the presence of salt

Illocution: what was meant

"please give me some salt" vs. "Yes" or "No"

Perlocution: what happened as a result, the actual effect.

to cause somebody to pass the salt.



Pragmatic

knowledge of the relationship of meaning to the *goals* & *intentions* of the speaker

John Rogers Searle (/sɜːrl/; born July 31, 1932) is an American philosopher.
Searle, John R. "A Classification of Illocutionary Acts." *Language in Society*, vol. 5, no. 1, Cambridge University Press, 1976, pp. 1–23, <http://www.jstor.org/stable/4166848>.

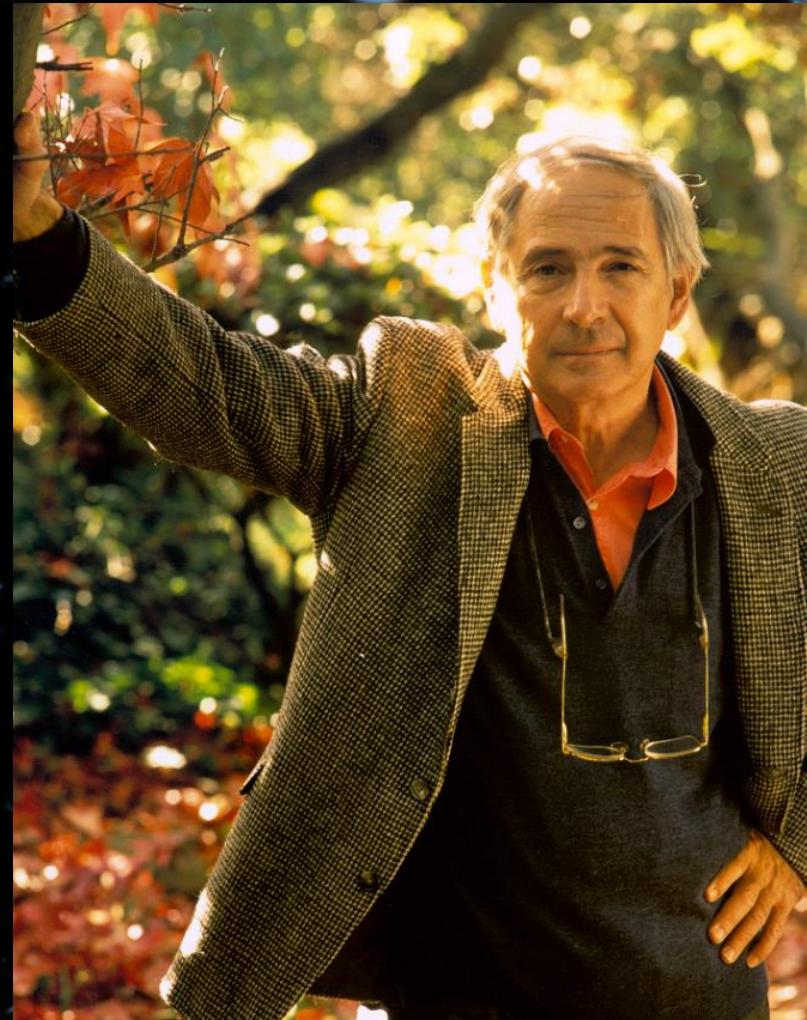
Representative (Assertive) committing the speaker to the truth of the expressed proposition, e.g., asserting, concluding

Directive attempts by the speaker to get the addressee to do something, e.g., advising, requesting

Commissive committing the speaker to a future course of action, e.g., promising, threatening, offering

Expressive expressing a psychological state, e.g., thanking, apologizing, welcoming

Declarative effecting immediate changes in an institutional state of affairs, with extra-linguistic qualities, e.g., declaring war, christening



Pragmatic

knowledge of the relationship of meaning to the *goals* & *intentions* of the speaker



Irony → Sarcasm

<https://en.wikipedia.org/wiki/Irony>

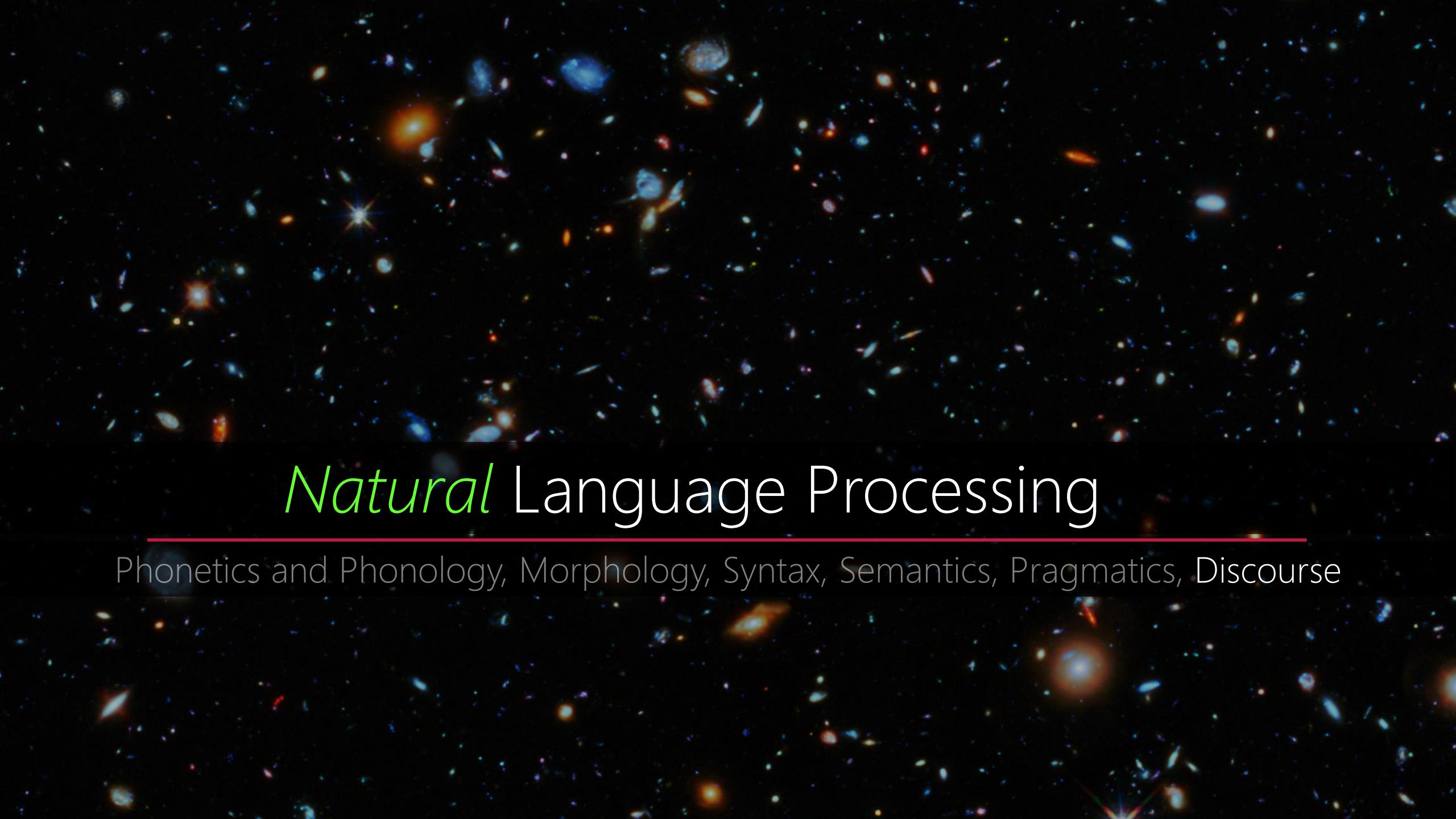
<https://en.wikipedia.org/wiki/Sarcasm>



Sprayed comment below a memorial plaque for Alois Alzheimer who first described Alzheimer's disease - the German text means "Alois, we will never forget you!"

Rhetoric

<https://en.wikipedia.org/wiki/Rhetoric>



Natural Language Processing

Phonetics and Phonology, Morphology, Syntax, Semantics, Pragmatics, Discourse

Discourse

knowledge about linguistic units larger than a single utterance
[discourse structure]

logical flow of events, states, propositions that makes for a coherent idea, argument, or story
another kind of pragmatic knowledge but within a session of communication

Co-reference

*I made *her* duck*

- Answer a question
 - Reading Comprehension
 - Visual Question Answering
 - Annotate a sentence
 - Named Entity Recognition
 - Open Information Extraction
 - Sentiment Analysis
 - Dependency Parsing
 - Constituency Parsing
 - Semantic Role Labeling
-
- Annotate a passage
 - Coreference Resolution
 - Semantic parsing
 - WikiTables Semantic Parsing
 - Cornell NLVR Semantic Parsing

Coreference resolution is the task of finding all expressions that refer to the same entity in a text. It is an important step for many higher-level NLP tasks that involve natural language understanding such as document summarization, question answering, and information extraction.

End-to-end Neural Coreference Resolution (Lee et al, 2017) is a neural model which considers all possible spans in the document as potential mentions and learns distributions over possible antecedents for each span, using aggressive pruning strategies to retain computational efficiency. It achieved state-of-the-art accuracies on the Ontonotes 5.0 dataset in early 2017. The model here is based on that paper, but we have substituted the GloVe embeddings that it uses with SpanBERT embeddings. On Ontonotes this model achieves an F1 score of 78.87% on the test set.

Contributed by: Zhaofeng Wu

Demo Usage

Enter text or



Document

Paul Allen was born on January 21, 1953, in Seattle, Washington, to Kenneth Sam Allen and Edna Faye Allen. Allen attended Lakeside School, a private school in Seattle, where he befriended Bill Gates, two years younger, with whom he shared an enthusiasm for computers. Paul and Bill used a teletype terminal at their high school, Lakeside, to develop their programming skills on several time-sharing computer systems.

Run >

0 Paul Allen was born on January 21 , 1953 , in 1 Seattle , Washington , to Kenneth Sam Allen and Edna Faye Allen . 0 Allen

attended 4 Lakeside School , a private school in 1 Seattle , where 0 he befriended

2 Bill Gates , two years younger , with whom 0 he shared an enthusiasm for computers . 3 0 Paul and 2 Bill used a teletype

terminal at 4 3 their high school , Lakeside , to develop 3 their programming skills on several time - sharing computer systems .

Discourse

knowledge about linguistic units larger than a single utterance
[discourse structure]

logical flow of events, states, propositions that makes for a coherent idea, argument, or story
another kind of pragmatic knowledge but within a session of communication

Discourse Relation

I refused to pay the cobbler the full \$95 because he did poor work. (Contingency)

He knows a tasty meal when he eats one. (Temporal)

IBM's stock price rose, but the overall market fell. (Comparison)

I never gamble too far; in particular, I quit after one try. (Expansion)



Penn Discourse Treebank

PDTB

[Home](#)
[People](#)
[Publications](#)
[Tools](#)
[Bibliography](#)
[Events](#)

The Penn Discourse Treebank Project is an [NSF](#) funded project, supported by NSF grants:

[IIS-14-22186](#) (2014-2017)
[IIS-14-21067](#) (2014-2017)
[CNS-10-59353](#) (2011-2013)
[IIS-07-05671](#) (2007-2012)
[CNS-02-24417](#) (2002-2006)

 **The PDTB 3.0 corpus was released on March 15, 2019 through the [Linguistic Data Consortium](#).** N.B. The corpus was updated on February 4, 2020, to include the final versions of two files of *to clause* annotation that were discovered to not have been loaded earlier, as well as several tokens were inadvertently omitted on the assumption that they were duplicates, when they weren't. Specific changes/additions are recorded in the file [pdtb3-revision-jan-2020.txt](#).

For an introduction to PDTB 3.0 and the PDTB 3.0 Annotation Manual, click [here](#). Please visit the [tools](#) page for technical support.

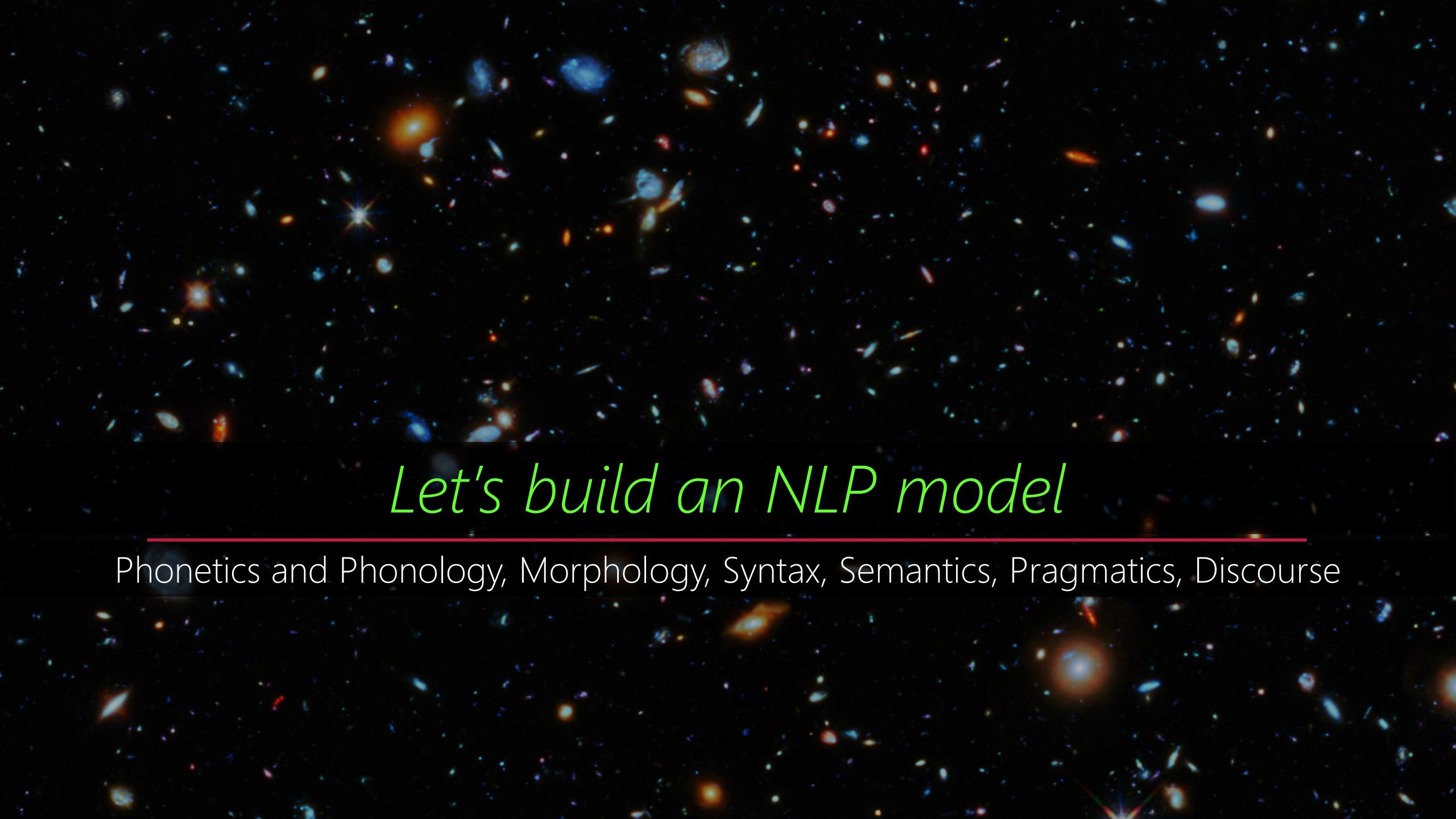
The PDTB 2.0 corpus is still available from this [LDC page](#).

The Penn Discourse Treebank (PDTB) is a large scale corpus annotated with information related to discourse structure and discourse semantics. While there are many aspects of discourse that are crucial to a complete understanding of natural language, the PDTB focuses on encoding *discourse relations*. The annotation methodology follows a lexically-grounded approach. The PDTB has strived to maintain a theory-neutral approach with respect to the nature of high-level

Discourse

due to background knowledge, linguistic elements are *latent* or *implicit!*

great movie by Stanley Kubrick



Let's build an NLP model

Phonetics and Phonology, Morphology, Syntax, Semantics, Pragmatics, Discourse

Lec01B
01:00pm-02:20pm
Text Normalization



Text Segmentation

dividing text into linguistic units, such as words, sentences, or topics

First three words u see are your reality.

JGLDMGKDMMSDOEOVMSCMWOQPRYTLSMLFJOMCES
KOOGJKLMSMIEOPJMLSMVMGKEJSKNMLESSONSJAPO
PEICREATIONJMXLAMFAJFLSMCGJIWLOVEPJFLAMVL
WILFEGMLEMFMEPAVBNZLSNVMJDKUITEWJTKDKNV
MSNGKDSLJGKDLSJGKLSGRATITUDEJGKLSJA~~K~~LGZV
NCNCNSJWUQDLDPWSJGDSKIEMNBKGMMNBAXBDMSII
IMELNGSANVDCONNECTIONKMGEWJNNZCMANHHFL
NQIRPWIQTYIEJCZXNMXZVJSAGKSMZNVLGKELJWJK
TNSNJDQRWADFXCRPWVGCRBYTNMONEYKUMLIMLY
UJVRNWCGEYVOPOWERPUYXDRWKLJDSKLGJKDSLJI
IALIGNMENTJEVMSLJJFLSHAHMLFJELWPORIVMSMM
TGGLDMGKDMMSIOMCHANGEVVMSCMWOQPRYTLSMLFJ
IIMCESKOGJKLMSMIEOPJMLSMVMGKEJSKNMJA~~P~~QE
OOOMXLAMFAHEALTHJFLSMCGJIWPJFLAMVLWILFEGM
NNMFMEPAVBNZLSNVMJDKUISELFCAREVMSNGKDSL
JGKDSLJGKLSJGKLSJA~~K~~LGZVNMCNSJWUQDLDPWSJ
GDSKIEMNBKGMMNBAXBDMSGMELNGSANVDSMGEW
JNNZCMANHHFLSTRENGTHWQIRPWIQTYIEJCZXNMR
ZVJSAGKSMZNVLGKELJWJKCNSNFAMILYJDQRWADE
XCRSWVGCRBYTNKUMLIMLYBJVRNWCGEYVQXDRWS
LJDSKLWPURPOSEJKDSLJEMJGLDMGKDMMSDOEOVM
STMWOQMIRACLESPRYTLSMLFJOMCESKOGJKLMSMI
ELPJMLSMVMGKEJSKNMJAPOBREAKTHROUGHPPEIJM
XLA~~M~~FAJFLSGMDTVNMWURHDKABNPOIUMAFNHAHKJ
JJHJJJDHJSWIIRUMAMBOGEHJAKQWHCSANKNLALADI

What should be considered as word?

- Disfluencies in *utterances*
 - Fragments: broken-off repeated words: miss- misspelled, you- yourself
 - Fillers: non-lexical: huh, uh, erm, um, well, so, like, hmm
- Punctuations , . : ; ? ! Special Chars \$, /, ...
 - part-of-speech tagging
 - parsing
 - speech synthesis
- Morphemes:
 - smallest meaning-bearing unit of a language
 - 'unlikeliest' : morphemes [un-], [likely], [-est]

Word Segmentation → Tokenization

- Word Boundary: Whitespace (natural word delimiter)
Split()

- Exceptions

- New York, rock 'n' roll

- Contractions: I'm

- Languages: Japanese | Chinese | Thai don't have spaces between words

- Emoticons: :)

- Hashtags: #nlproc.

As Chen et al. (2017) point out, this could be treated as 3 words ('Chinese Treebank' segmentation):

(2.5) 姚明 进入 总决赛

YaoMing reaches finals

or as 5 words ('Peking University' segmentation):

(2.6) 姚 明 进 入 总 决 赛

Yao Ming reaches overall finals

Finally, it is possible in Chinese simply to ignore words altogether and use characters as the basic elements, treating the sentence as a series of 7 characters:

(2.7) 姚 明 进 入 总 决 赛

Yao Ming enter enter overall decision| game

Adversarial Multi-Criteria Learning for Chinese Word Segmentation

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Abstract

Different linguistic perspectives causes many diverse segmentation criteria for Chinese word segmentation (CWS). Most existing methods focus on improve the performance for each single criterion. However, it is interesting to exploit these different criteria and mining their common underlying knowledge. In this paper, we propose adversarial multi-criteria learning for CWS. It integrates several underlying

Corpora	Yao	Ming	reaches	the final
CTB	姚明		进入	总决赛
PKU	姚	明	进入	总 决赛

Table 1: Illustration of the different segmentation criteria.

Recently, some efforts have been made to exploit heterogeneous annotation data for Chinese word segmentation or part-of-speech tagging (Jiang et al., 2009; Sun and Wan, 2012; Qiu et al., 2013; Li et al., 2015, 2016). These methods often

As Chen et al. (2017) point out, this could be treated as 3 words ('Chinese Treebank' segmentation):

(2.5) 姚明 进入 总决赛

YaoMing reaches finals

characters are at a reasonable semantic level for most applications
take characters as words!

Not for Japanese and Thai!

(2.7) 姚 明 进 入 总 决 赛
Yao Ming enter enter overall decision game

Adversarial Multi-Criteria Learning for Chinese Word Segmentation

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Abstract

Different linguistic perspectives causes many diverse segmentation criteria for Chinese word segmentation (CWS). Most existing methods focus on improve the performance for each single criterion. However, it is interesting to exploit these different criteria and mining their common underlying knowledge. In this paper, we propose adversarial multi-criteria learning for CWS. It integrates several underlying

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Recently, some efforts have been made to exploit heterogeneous annotation data for Chinese word segmentation or part-of-speech tagging (Jiang et al., 2009; Sun and Wan, 2012; Qiu et al., 2013; Li et al., 2015, 2016). These methods often

Chen, X., Shi, Z., Qiu, X., and Huang, X. (2017). Adversarial multi-criteria learning for Chinese word segmentation. In ACL 2017, 1193–1203.

Word Boundaries → Space

- Regular Expressions (RE): Finite State Automata
 - Alphabetical: [a-zA-Z]*
 - Alpha-numerical: [a-zA-Z0-9]*
 - Punctuations: Ph.D., AT&T, cap'n
 - Special Chars
 - Currency \$45.55
 - Dates (01/02/06)
 - URLs <http://www.stanford.edu>
 - Twitter hashtags #nlproc
 - Email hfani@uwindsor.ca



Learn to Tokenize

Learn to Tokenize

Word → Subword → Word

- Byte-Pair Encoding (BPE)

Sennrich, et al., (2016). Neural machine translation of rare words with subword units. In ACL 2016.

- Wordpiece

Wu et al. (2016) Google's neural machine translation system: Bridging the gap between human and machine translation." arXiv.

- MaxMatch in BERT

Devlin et al. (2019). BERT: Pretraining of deep bidirectional transformers for language understanding. In NAACL HLT.

- SentencePiece

Kudo, T. and Richardson, J. (2018). SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In EMNLP.

Learn to Tokenize

Byte-Pair Encoding (BPE) : Data Compression

Gage, P. (1994). A new algorithm for data compression. *The C Users Journal*, 12(2), 23–38.

aaabd $\textcolor{blue}{aa}$ abac → *pair 'aa' occurs most often* → *replace it with a char (byte) that is not used 'Z'*
→ ZabdZabac; Z=aa

Learn to Tokenize

Byte-Pair Encoding (BPE) : Data Compression

Gage, P. (1994). A new algorithm for data compression. *The C Users Journal*, 12(2), 23–38.

aaabd~~aa~~abac → pair 'aa' occurs most often → replace it with a char (byte) that is not used 'Z'

→ ZabdZabac; Z=aa

→ ZabdZabac → pair 'ab' occurs most often → replace it with 'Y'

→ ZYdZYac; Y=ab, Z=aa

Learn to Tokenize

Byte-Pair Encoding (BPE) : Data Compression

Gage, P. (1994). A new algorithm for data compression. *The C Users Journal*, 12(2), 23–38.

aaabd~~aa~~abac → pair 'aa' occurs most often → replace it with a char (byte) that is not used 'Z'

→ ZabdZabac; Z=aa

→ ZabdZabac → pair 'ab' occurs most often → replace it with 'Y'

→ ZYdZYac; Y=ab, Z=aa

→ ZYdZYac → byte pair 'ZY' with 'X'

→ XdXac; X=ZY, Y=ab, Z=aa

Learn to Tokenize

Byte-Pair Encoding (BPE) : Data Compression

Gage, P. (1994). A new algorithm for data compression. *The C Users Journal*, 12(2), 23–38.

aaabd~~aa~~abac → pair 'aa' occurs most often → replace it with a char (byte) that is not used 'Z'

→ ZabdZabac; Z=aa

→ ZabdZabac → pair 'ab' occurs most often → replace it with 'Y'

→ ZYdZYac; Y=ab, Z=aa

→ ZYdZYac → byte pair 'ZY' with 'X'

→ XdXac; X=ZY, Y=ab, Z=aa

no pairs of bytes that occur more than 1 → no more compression

Learn to Tokenize

Byte-Pair Encoding (BPE) : *Train*

Dictionary ⁽⁰⁾	Vocabulary ⁽⁰⁾	get_stats()	most frequent pair
'l o w </w>'	l	(l, l) → 0	
'l o w e r </w>'	o	(l, o) → 2	
'n e w e s t </w>'	w	(l, w) → 0	
'w i d e s t </w>'	e [all pairs of 'l' with others]	
'e s t e r </w>'	r	(o, l) → 0	
	t	(o, o) → 0	
	n [all pairs of 'o' with others]	
	s	(e, s) → 3	
	d [all pairs of 'e' with others]	
	</w>	(o, </w>) → 0	
		

Learn to Tokenize

Byte-Pair Encoding (BPE) : *Train*

Dictionary ⁽¹⁾	Vocabulary ⁽¹⁾	get_stats()	most frequent pair
'l o w </w>'		(,) → 0	
'l o w e r </w>'	o	(, o) → 2	
'n e w e s t </w>'	w	(, w) → 0	
'w i d e s t </w>'	e [all pairs of 'l' with others]	
'e s t e r </w>'	r	(o,) → 0	
	t	(o, o) → 0	
	n [all pairs of 'o' with others]	
	s	(e, s) → 3 → 0	
	d [all pairs of 'e' with others]	
</w>		(o, </w>) → 0	
	es	
		(es,) → 0	
	 [all pairs of 'es' with others]	
		(es, t) → 3	

Learn to Tokenize

Byte-Pair Encoding (BPE) : *Train*

Dictionary ⁽²⁾	Vocabulary ⁽²⁾	get_stats()	most frequent pair
'l o w </w>' 'l o w e r </w>' 'n e w e st </w>' 'w i d e st </w>' 'e st e r </w>'	l o w e r t n s d </w> es est	(l, l) → 0 (l, o) → 2 (es, l) → 0 [all pairs of 'es' with others] (es, t) → 0 (est, l) → 0[all pairs of 'est' with others] (est, </w>) → 2	(es, t) → ?

Learn to Tokenize

Byte-Pair Encoding (BPE) : *Train*

Dictionary ⁽ⁿ⁾	Vocabulary ⁽ⁿ⁾	get_stats()	most frequent pair
'low</w>' 'lower</w>' 'newest</w>' 'widest</w>' 'ester</w>'	l,o,w,e,r,t,n,s,d,</w>, es est lo low, ... newer wider

Learn to Tokenize

Byte-Pair Encoding (BPE) : *Test*

Vocabulary ⁽ⁿ⁾	Input
lowest	... lowest part of the newer house
lowest	... lowest part of the newer house
lowest	... lowest part of the newer house
lowest	... lowest part of the newer house
lowest	... lowest part of the newer house
lowest	... lowest part of the newer house
lowest	... lowest part of the newer house
lowest	... lowest part of the newer house
newer	... newer wider
wider

Learn to Tokenize

Byte-Pair Encoding (BPE) : *Test*

Vocabulary ⁽ⁿ⁾	Input
lower er t n s d </w> es est lo low lowest part of the newer house lowest part of the newer house lowest part of the newer house low est part of the newer house

What if 'lowest' is not built during training?

Learn to Tokenize

Byte-Pair Encoding (BPE)

1. Help to generalize to produce *unseen* words
2. Rare words into subword units is sufficient for translation
100 rare tokens in German training data and they are translatable from English via smaller units!

<https://github.com/rsennrich/subword-nmt>



```
function BYTE-PAIR ENCODING(strings C, number of merges k) returns vocab V
    V ← all unique characters in C           # initial set of tokens is characters
    for i = 1 to k do                      # merge tokens til k times
         $t_L, t_R \leftarrow$  Most frequent pair of adjacent tokens in C
         $t_{NEW} \leftarrow t_L + t_R$              # make new token by concatenating
        V ← V +  $t_{NEW}$                   # update the vocabulary
        Replace each occurrence of  $t_L, t_R$  in C with  $t_{NEW}$    # and update the corpus
    return V
```

Figure 2.13 The token learner part of the BPE algorithm for taking a corpus broken up into individual characters or bytes, and learning a vocabulary by iteratively merging tokens. Figure adapted from Bostrom and Durrett (2020).

Learn to Tokenize

Wordpiece

Same as BPE but:

- Merging the pairs that *minimizes language model likelihood* of the training data.
- </w> appears at the beginning of words

Google's Neural Machine Translation System: Bridging the Gap
between Human and Machine Translation

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi
yonghui,schuster,zhifengc,qvl,mnorouzi@google.com

Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey,
Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Łukasz Kaiser,
Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens,
George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa,
Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, Jeffrey Dean

Learn to Tokenize

MaxMatch in BERT

Devlin et al. (2019). BERT: Pretraining of deep bidirectional transformers for language understanding. In NAACL HLT.

```
function MAXMATCH(string, dictionary) returns list of tokens T
    if string is empty
        return empty list
    for i ← length(sentence) downto 1
        firstword = first i chars of sentence
        remainder = rest of sentence
        if InDictionary(firstword, dictionary)
            return list(firstword, MaxMatch(remainder,dictionary) )
```

Learn to Tokenize

MaxMatch in BERT

Devlin et al. (2019). BERT: Pretraining of deep bidirectional transformers for language understanding. In NAACL HLT.

unaffable
[u][naffable]
[un][affable]
[una][ffable]
[unaf][fable]
[unaff][able]
[unaffa][ble]
[unaffab][le]
[unaffabl][e]
[unaffable]

```
function MAXMATCH(string, dictionary) returns list of tokens T  
  
if string is empty  
    return empty list  
for i  $\leftarrow$  length(sentence) downto 1  
    firstword = first i chars of sentence  
    remainder = rest of sentence  
    if InDictionary(firstword, dictionary)  
        return list(firstword, MaxMatch(remainder, dictionary))
```

Learn to Tokenize

MaxMatch in BERT

Devlin et al. (2019). BERT: Pretraining of deep bidirectional transformers for language understanding. In NAACL HLT.

unaffable

[u][naffable] return
[un][affable]
[una][ffable]
[unaf][fable]
[unaff][able]
[unaffa][ble]
[unaffab][le]
[unaffabl][e]
[unaffable]

```
function MAXMATCH(string, dictionary) returns list of tokens T  
  
if string is empty  
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    firstword = first i chars of sentence  
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    if InDictionary(firstword, dictionary)  
        return list(firstword, MaxMatch(remainder, dictionary))
```

Learn to Tokenize

MaxMatch in BERT

Devlin et al. (2019). BERT: Pretraining of deep bidirectional transformers for language understanding. In NAACL HLT.

unaffable

[u][naffable] return
[un][affable]
{'un'} U [affable]
[a][ffable]
[af][fable]
[aff][able]

...

[una][ffable]
[unaf][fable]
[unaff][able]
[unaffa][ble]
[unaffab][le]
[unaffabl][e]

```
function MAXMATCH(string, dictionary) returns list of tokens T
    if string is empty
        return empty list
    for i ← length(sentence) downto 1
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            return list(firstword, MaxMatch(remainder,dictionary))
```

Learn to Tokenize

MaxMatch in BERT

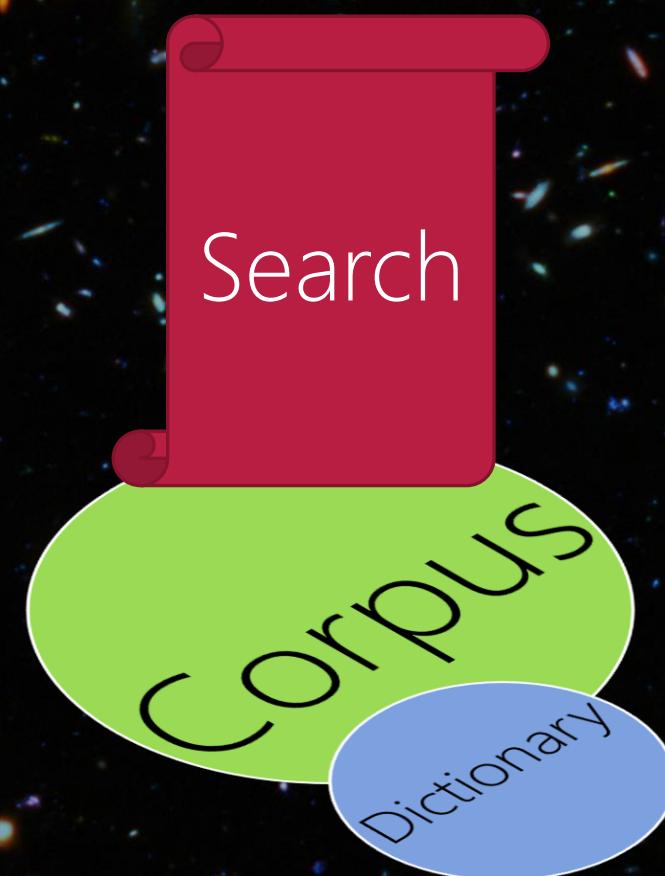
Devlin et al. (2019). BERT: Pretraining of deep bidirectional transformers for language understanding. In NAACL HLT.

unaffable	→	[un, ##aff, ##able]
intention	→	[intent, ##ion]
unwanted running	→	[un, ##want, ##ed, runn, ##ing]

→ marking as internal subwords that do not start words

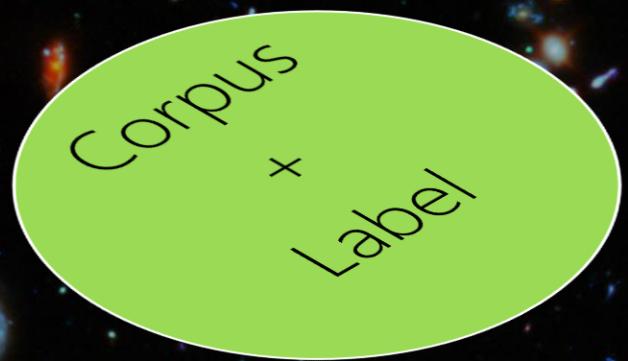
Learn to Tokenize

Unsupervised or Weakly Supervised (Dictionary)



Learn to Tokenize

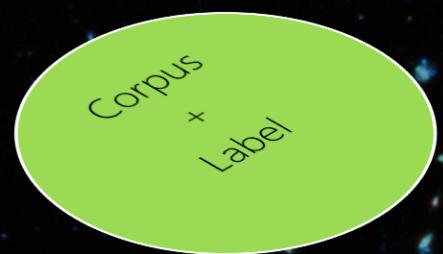
Supervised



Sentence	Word Boundary by Oracle
i_am_sorry.	[0,0], [2,3], [5,9]
open_the_door	[0,3], [5,7], [9, 12]
hello_world!	[0,4], [6, 10]
great_news,_mary!	[0, 4], [6, 9], [12, 15]

Learn to Tokenize

Supervised (Boolean Classifier) : *Train*



Sentence	Word Boundary by Oracle
I_am_sorry.	[0,0], [2,3], [5,9]
Open_the_door	[0,3], [5,7], [9, 12]
Hello_world!	[0,4], [6, 10]
Great_news,_Mary!	[0, 4], [6, 9], [12, 15]



Sentence	Word Boundary by Oracle
_	0 SEP
_a	0 SEP
am	1 APN
m_	0 SEP
_s	1 APN
so	1 APN
or	1 APN
...	...

$$f(x_i, x_{i+1}) \rightarrow \{0, 1\}$$

Learn to Tokenize

Supervised (Boolean Classifier) : *Test*

natural_language



Sentence	$f(x_i, x_{i+1})$	Truth	Error
na	1 APN	1 APN	0
at	1 APN	1 APN	0
tu	1 APN	1 APN	0
ur	1 APN	1 APN	0
ra	0 SEP	1 APN	1
al	1 APN	1 APN	0
l_	1 APN	0 SEP	1
_l	1 APN	0 SEP	1
la	0 SEP	1 APN	1
....	



[natur][al_l][language]

Learn to Tokenize

Supervised (Boolean Classifier)

State	Recognized words	Partial word	Incoming chars	Next Action
state0	[]	φ	[我去过火车站那边]	SEP
state1	[]	我	[去过火车站那边]	SEP
state2	[我]	去	[过火车站那边]	SEP
state3	[我,去]	过	[火车站那边]	SEP
state4	[我,去,过]	火	[车站那边]	APP
state5	[我,去,过]	火车	[站那边]	APP
state6	[我,去,过]	火车站	[那边]	SEP
state7	[我,去,过,火车站]	那	[边]	APP
state8	[我,去,过,火车站]	那边	[]	FIN
state9	[我,去,过,火车站,那边]	φ	[]	--

Table 1: A transition based word segmentation example.

Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, pages 839–849
Vancouver, Canada, July 30 - August 4, 2017. ©2017 Association for Computational Linguistics
<https://doi.org/10.18653/v1/P17-1078>

Neural Word Segmentation with Rich Pretraining

Jie Yang* and **Yue Zhang*** and **Fei Dong**
Singapore University of Technology and Design
{jie.yang, fei.dong}@mymail.sutd.edu.sg
yue.zhang@sutd.edu.sg

Text Segmentation

dividing text into linguistic units, such as words, sentences, or topics

Sentence Segmentation

- Rule-based: Regular Expression
Stanford's CoreNLP
Combined by word segmentation (Tokenizer)

Sentence Segmentation

- Boundary markers
 - Exclamation (!)
 - Question (?)
 - Period (.)
 - Abbreviation: Mr. or Inc.
 - ABS Inc. hold a conference.
 - Both
 - The conference is in ABS Inc.

Sentence Segmentation

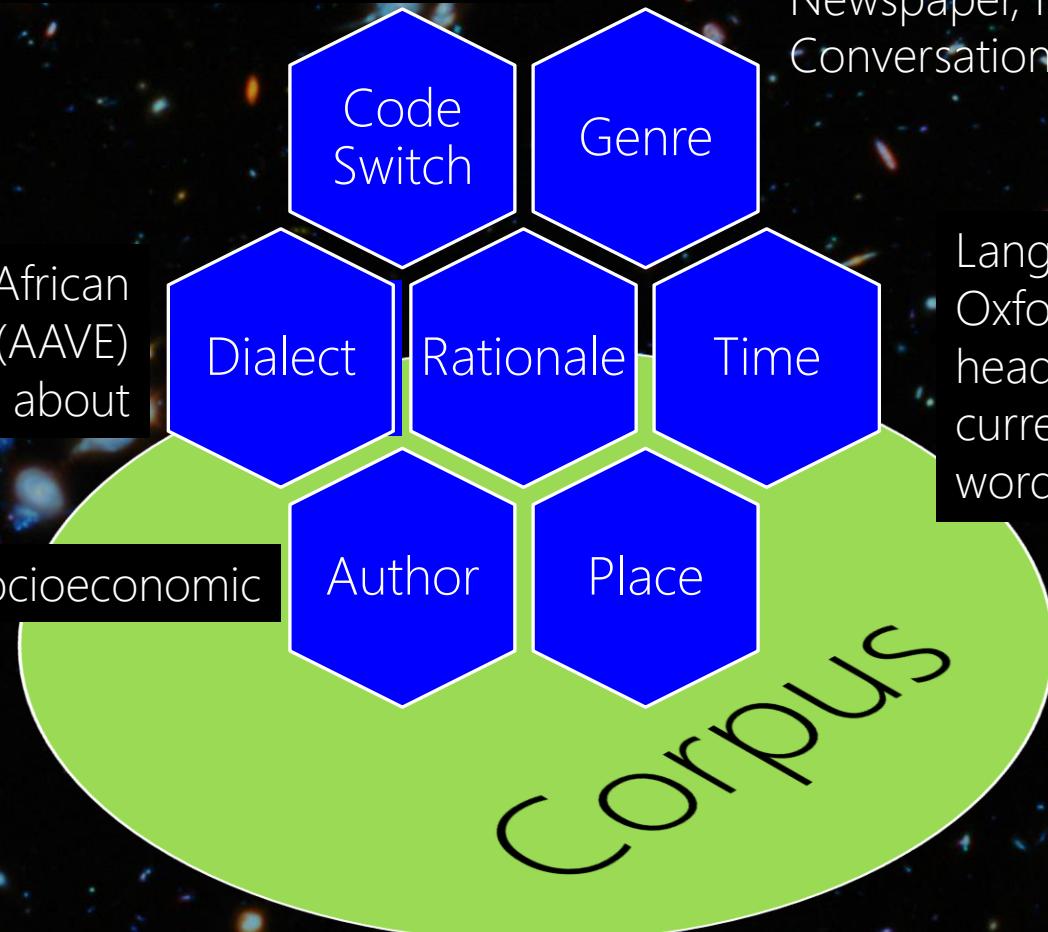
- Learn to Segment
 - Learn to label (.) as sentence marker or abbreviation marker or both

heads up!

dost tha or ra- hega ... dont wory ... but dherya rakhe
[he was and will remain a friend ... don't worry ... but have faith]

Standard American English (SAE) vs. African
American Vernacular English (AAVE)
iont: I don't, talmeabout: talking about

Age, Gender, Race, Socioeconomic



Newspaper, Fiction, non-Fiction, Academic, Social,
Conversation → Disfluencies

Language changes over time
Oxford Dictionary has 273,000
headwords; 171,476 of them being in
current use, 47,156 being obsolete
words

Corpus (*plural Corpora*)

Brown University

English, newspaper, fiction, non-fiction, academic, etc., 1963–64

#Documents = Size = 500, #Tokens = 1 M, #Vocab = Unique Tokens = Types = 38 K

Switchboard

American English, Telephone Conversations between strangers, Early 1990s

#Conversations = Size = 2430, #Tokens = 2.4 M, #Vocab = Unique Tokens = Types = 20 K

Google N-grams

English, Google Books

#Tokens = 1 G, #Vocab = Unique Tokens = Types = 13 M

Datasheets (Data Statements) for Datasets

Emily M. Bender, Batya Friedman, ACL (2018)
Gebru, Timnit, et al. (2018)

direct stakeholders. For example, [Speer \(2017\)](#) found that a sentiment analysis system rated reviews of Mexican restaurants as more negative than other types of food with similar star ratings, because of associations between the word *Mexican* and words with negative sentiment in the larger corpus on which the word embeddings were trained. (See also [Kiritchenko and Mohammad,](#)

Herdan's Law or Heaps' Law

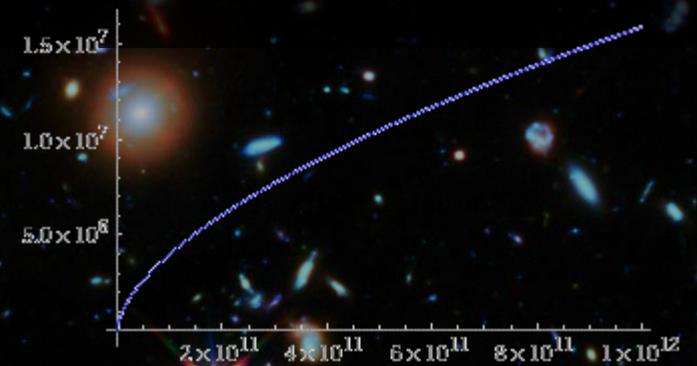
Herdan, G. (1960). Type-token mathematics. The Hague, Mouton.

Heaps, H. S. (1978). Information retrieval. Computational and theoretical aspects. Academic Press.

$$|V| = kN^\beta; \quad 0 < \beta < 1$$

k and β are positive constants.

The value of β depends on the corpus size and the genre, but at least for the large corpora β ranges from 0.67 to 0.75.



Lec02B
01:00pm-02:20pm
Text Normalization



Text Normalization

putting tokens in a *standard format*

choosing a single normal form for tokens with multiple forms

USA → *US*

ain't → *am not*

Text Normalization

- Case Folding
 - mapping everything to lower (upper) case
- Lemmatization
 - converts the word to its meaningful base form (lemma).
 - The same word may have multiple different Lemmas
- Stemming
 - removes or stems the last few characters of a word
 - often leading to incorrect meanings and spelling*
- Autocorrection

Text Normalization

Case Folding

Positive Impact: 'USA' vs. 'usa'

Information Retrieval, Speech Recognition

Negative Impact: 'US' the country vs. 'us' the pronoun

Sentiment Analysis, Text Classification, Information Extraction, Machine Translation

Text Normalization

Lemmatization

Polysemy

the association of one word with two or more distinct meanings
a polyseme is a word or phrase with multiple meanings

saw (noun) vs. *saw* (verb) → see

Text Normalization

Lemmatization : Stemming

crude, chopping off word-final stemming affixes
aim is not to produce a linguistic root, but *to improve performance*

Porter, M. F. (1980). An algorithm for suffix stripping. Program, 14(3), 130–137.

Errors of Commission

organization	organ
doing	doe
numerical	numerous
policy	police

Errors of Omission

European	Europe
analysis	analyzes
noise	noisy
sparse	sparsity

A commission error is an error made due to using an item in the wrong context.

Text Normalization

Spelling Correction
via

Minimum Edit Distance : Word Similarity (Distance)

Text Normalization

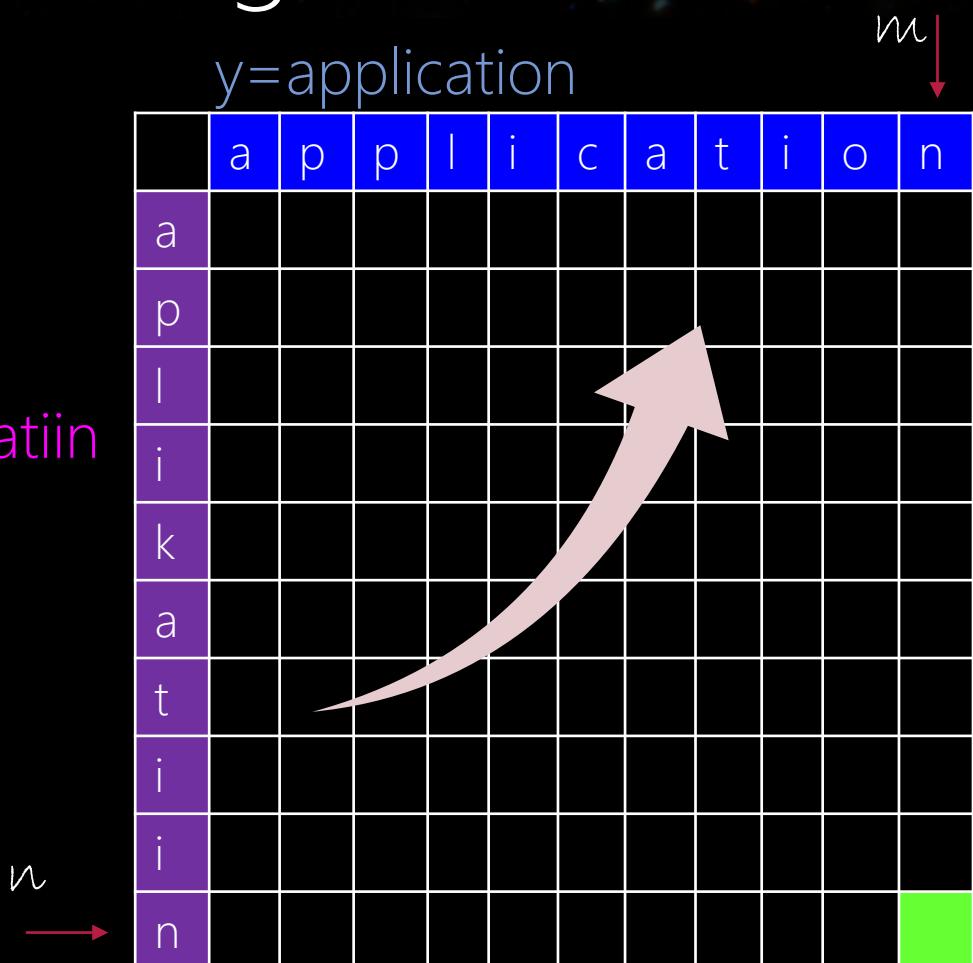
Spelling Correction
via

Minimum Edit Distance : Word Similarity in *Surface*

Text Normalization

Spelling Correction via Minimum Edit Distance

$x = \text{aplikatiin}$

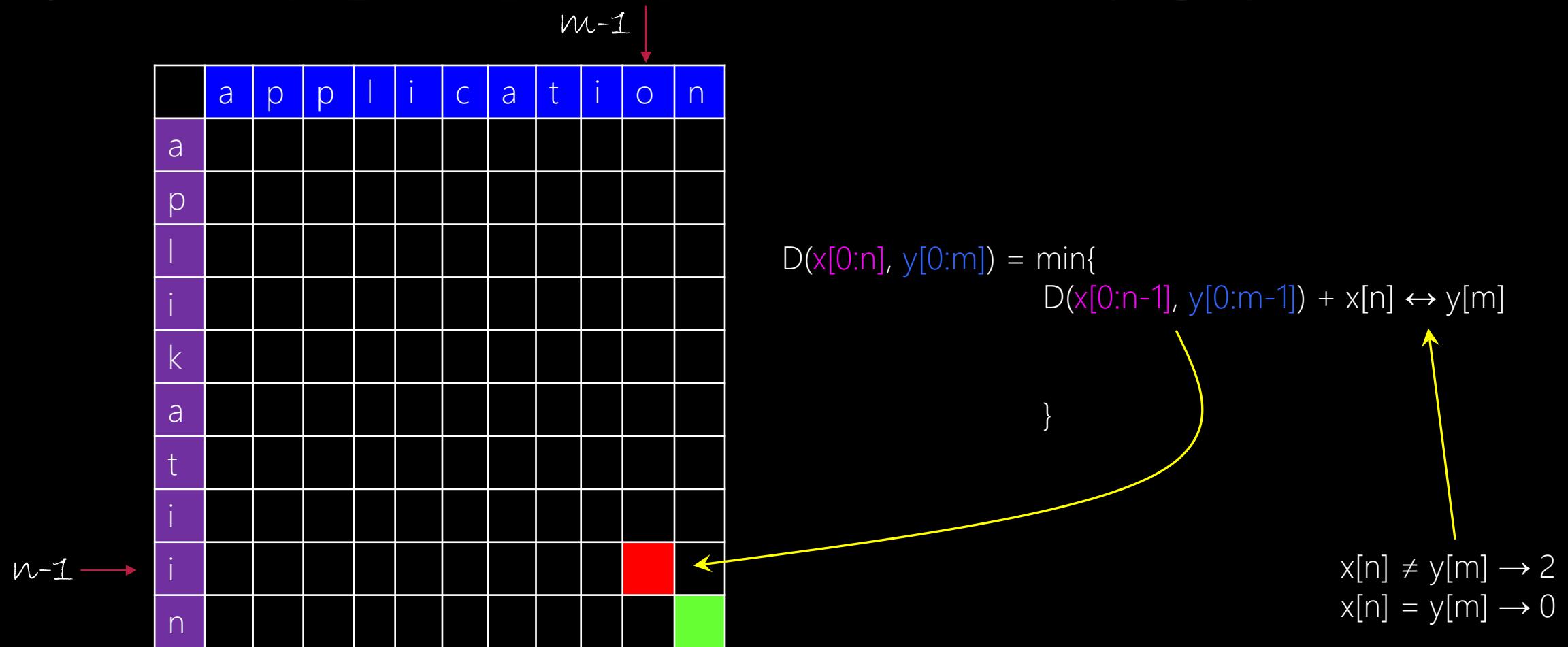


Dynamic Programming (DP)

- Divide to Subproblems and Conquer
- Store Subproblems Solutions
- Aggregate Subproblems Solutions for the Final Solution

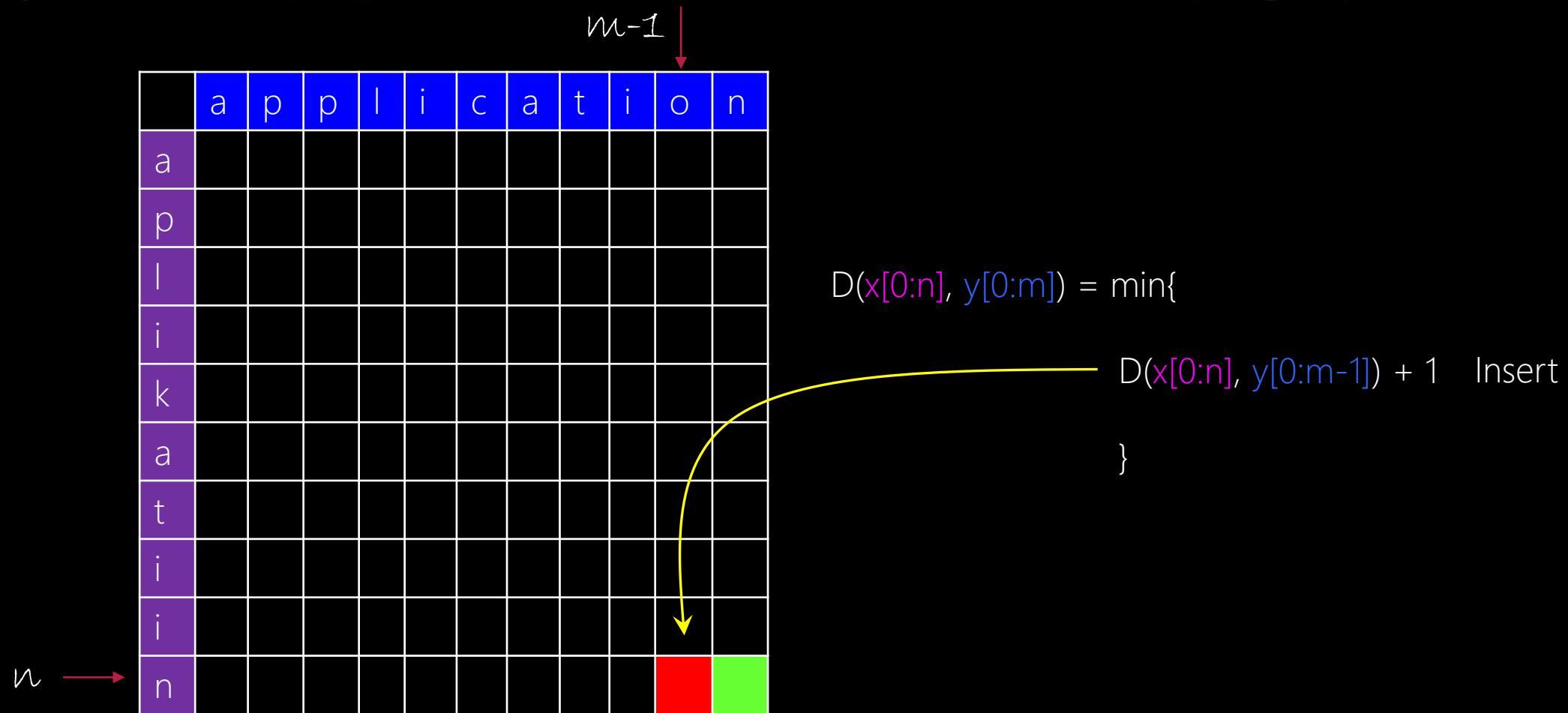
Text Normalization

Spelling Correction via Minimum Edit Distance



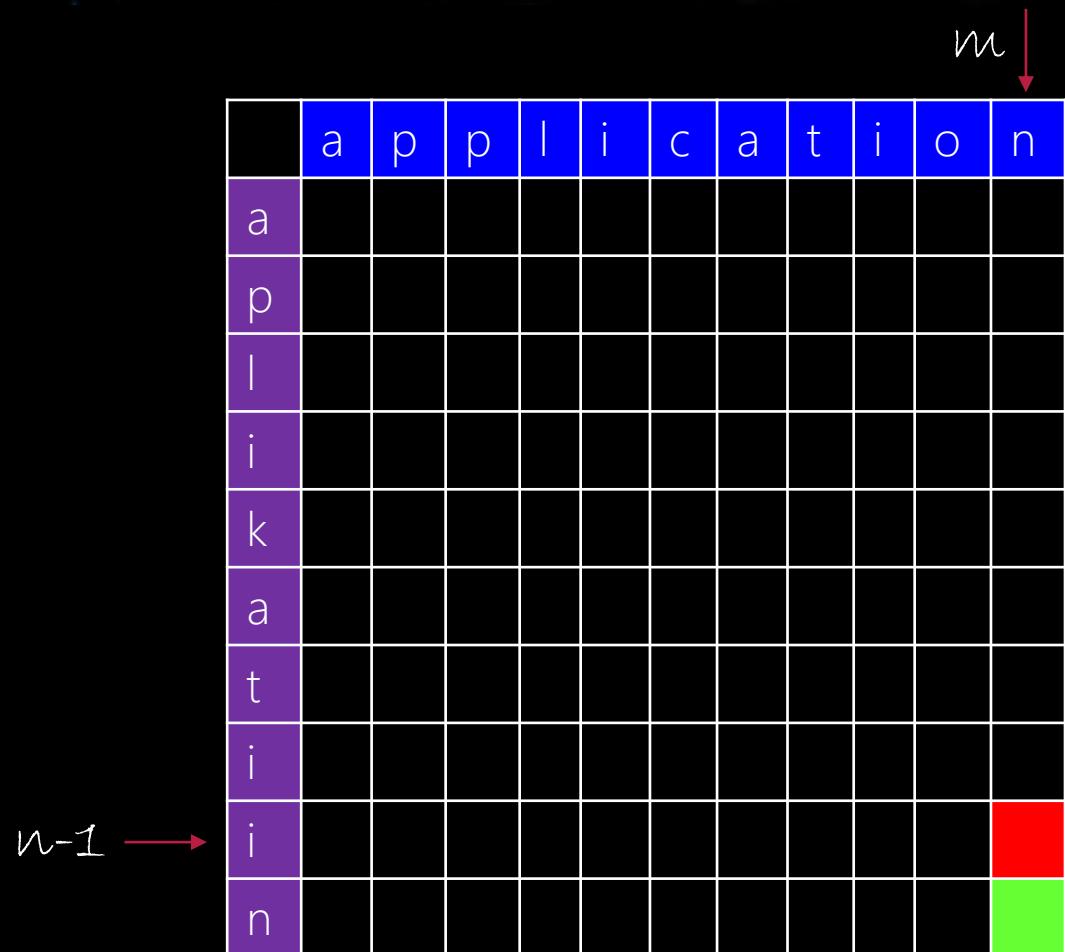
Text Normalization

Spelling Correction via Minimum Edit Distance



Text Normalization

Spelling Correction via Minimum Edit Distance



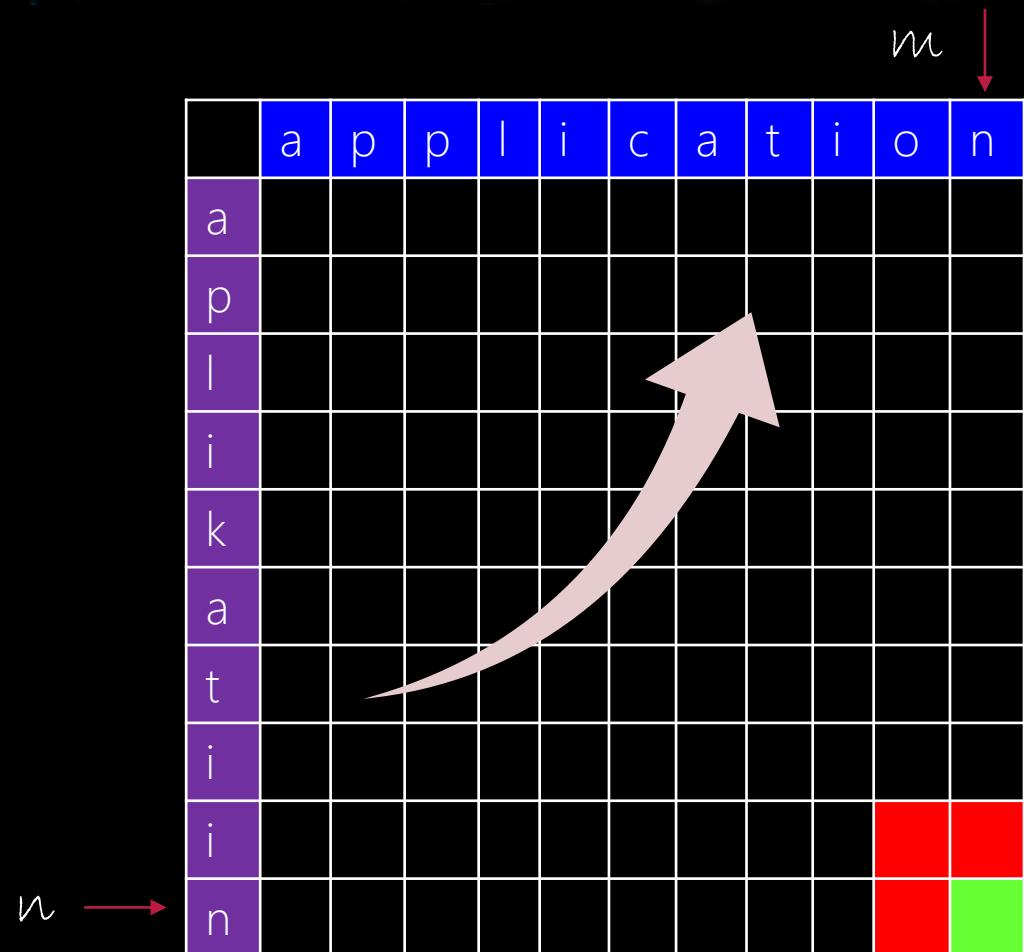
$$D(x[0:n], y[0:m]) = \min\{$$

$$D(x[0:n-1], y[0:m]) + 1 \quad \text{Delete}$$

}

Text Normalization

Spelling Correction via Minimum Edit Distance



$$D(x[0:n], y[0:m]) = \min\{ \begin{array}{ll} D(x[0:n-1], y[0:m-1]) + x[i] \leftrightarrow y[j] & \\ D(x[0:n], y[0:m-1]) + 1 & \text{Insert} \\ D(x[0:n-1], y[0:m]) + 1 & \text{Delete} \\ \} \end{array}$$

Text Normalization

Spelling Correction via Minimum Edit Distance

Levenshtein, V. I. (1966). Binary codes capable of correcting deletions, insertions, and reversals. Cybernetics and Control Theory (1965).

Pioneer in the theory of error correcting codes, Vladimir I. Levenshtein, the father of coding theory in Russia.



```
function MIN-EDIT-DISTANCE(source, target) returns min-distance
    n ← LENGTH(source)
    m ← LENGTH(target)
    Create a distance matrix distance[n+1,m+1]

    # Initialization: the zeroth row and column is the distance from the empty string
    D[0,0] = 0
    for each row i from 1 to n do
        D[i,0] ← D[i-1,0] + del-cost(source[i])
    for each column j from 1 to m do
        D[0,j] ← D[0,j-1] + ins-cost(target[j])

    # Recurrence relation:
    for each row i from 1 to n do
        for each column j from 1 to m do
            D[i,j] ← MIN( D[i-1,j] + del-cost(source[i]),
                           D[i-1,j-1] + sub-cost(source[i],target[j]),
                           D[i,j-1] + ins-cost(target[j]))
    # Termination
    return D[n,m]
```

Text Normalization

Spelling Correction via Minimum Edit Distance

<https://phiresky.github.io/levenshtein-demo/>

	a	p	p	l	i	c	a	t	i	o	n
a	0	1	2	3	4	5	6	7	8	9	10
p	1										
l	2										
i	3										
k	4										
a	5										
t	6										
j	7										
j	8										
n	9										



	a	p	p	l	i	c	a	t	i	o	n
a	0	1	2	3	4	5	6	7	8	9	10
p	1	0	1	2	3	4	5	6	7	8	9



	a	p
a	0	1
p	1	0
l	2	1
i	3	2
k	4	3
a	5	4
t	6	5
j	7	6
j	8	7
n	9	8

	a	p	p
a	0	1	2
p	1	0	1
l	2	1	2

Text Normalization

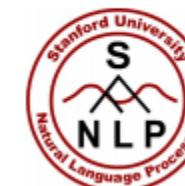
Spelling Correction via Minimum Edit Distance



from (0,0) to (M, N)

corresponds to
an alignment
of the two sequences

Dan Jurafsky



An optimal alignment is composed
of optimal subalignments

Euclidian Distance on Continuous Space

Manhattan Distance on Integer Space

MED on Word Space

+ Code + Text

Spelling Correction via Minimum Edit Distance

```
✓ 0s 1 # https://blog.paperspace.com/implementing-levenshtein-distance-word-autocomplete-autocorrect/
2 # Ahmed Fawzy Gad
3 # AI/ML engineer and a talented technical writer who authors 4 scientific books and more than 80 articles and tutorials. https://www.linkedin.com/in/ahmedfgad
4
5 import numpy
6 def levenshtein(token1, token2):
7     distances = numpy.zeros((len(token1) + 1, len(token2) + 1))
8     for t1 in range(len(token1) + 1): distances[t1][0] = t1
9     for t2 in range(len(token2) + 1): distances[0][t2] = t2
10    a = 0; b = 0; c = 0
11
12    for t1 in range(1, len(token1) + 1):
13        for t2 in range(1, len(token2) + 1):
14            a = distances[t1][t2 - 1]
15            b = distances[t1 - 1][t2]
16            c = distances[t1 - 1][t2 - 1]
17
18            if (a <= b and a <= c): distances[t1][t2] = a + 1
19            elif (b <= a and b <= c): distances[t1][t2] = b + 1
20            else:
21                if (token1[t1 - 1] == token2[t2 - 1]): distances[t1][t2] = c
22                else: distances[t1][t2] = c + 2
23
24    print_matrix(distances, len(token1), len(token2))
25    return distances[len(token1)][len(token2)]
26
27 def print_matrix(distances, token1Length, token2Length):
28     for t1 in range(token1Length + 1):
29         for t2 in range(token2Length + 1):
30             print(str(int(distances[t1][t2])).zfill(2), end=" ")
31         print()
32
33 levenshtein("application", "aplikatiion")
34
```

Text Normalization

Spelling Correction via Minimum Edit Distance

Levenshtein (1966)

Time Complexity: ?

Space Complexity: ?

Text Normalization

Spelling Correction via Minimum Edit Distance

Levenshtein (1966)

Time Complexity: $O(n \times m)$

Space Complexity: $O(n \times m)$

Is it parallelizable? Why?



The Way of the Dragon

Release: June 1, 1972 (Hong Kong)

Director: Bruce Lee

Box office: US\$130 million

Budget: US\$130,000

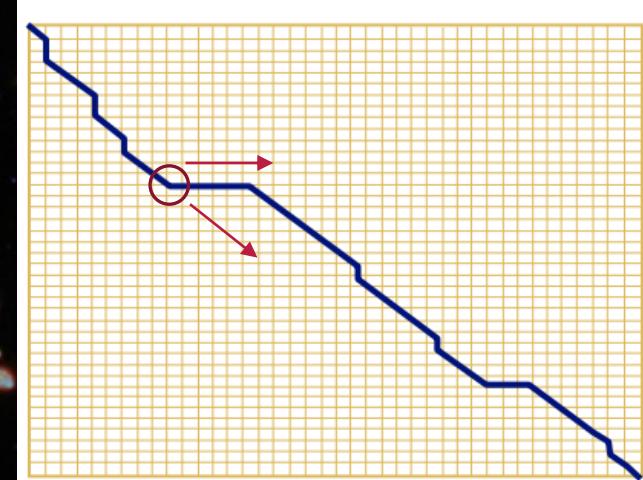
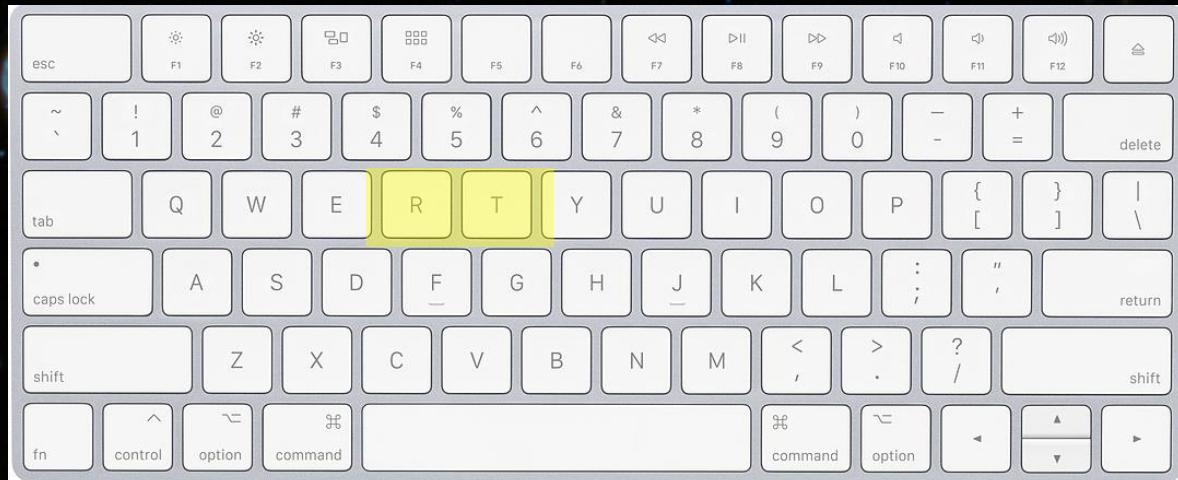
IMDb: 7.3/10

Text Normalization

Learn to Correct Spellings

online texts (e.g., emails) depends on *keyboards*.

Misspells happens more on characters that sit next to each other on the keyboard.
misspell of (r, t) or (t, r) more often → more probable → guide the algorithm toward substitution
Only for [r]→[t] or [t]→[r], less weight!



Text Normalization

Learn to Correct Spellings

online texts (e.g., emails) depends on *keyboards*.

[desi][ng] → [desi][g] (deleting n) → [desig][n] (adding n) → 2

[desi][ng] → [desi][gg] (switch n with g) → [desig][n] (switch g with n) → 2 + 2 = 4

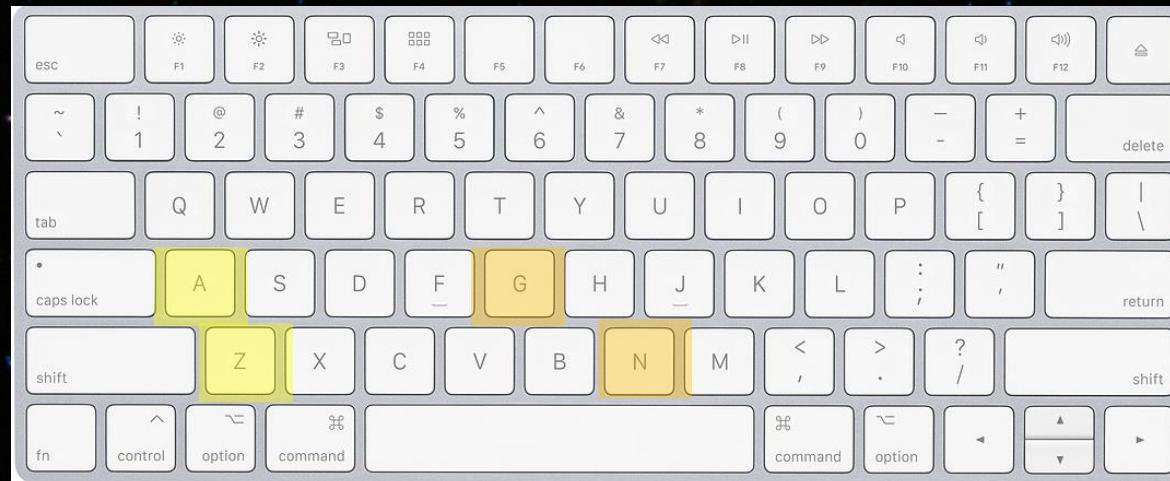


Text Normalization

Learn to Correct Spellings

online texts (e.g., emails) depends on *keyboards*.

Speed of typing is a source of error → Transposition: [desing] → [design]



Text Normalization

Learn to Correct Spellings

*Weighted
Minimum
Edit
Distance*

X	sub[X, Y] = Substitution of X (incorrect) for Y (correct)																										
	Y (correct)																										
a	0	0	7	1	342	0	0	2	118	0	1	0	0	3	76	0	0	1	35	9	9	0	1	0	5	0	
b	0	0	9	9	2	2	3	1	0	0	0	5	11	5	0	10	0	0	2	1	0	0	0	8	0	0	
c	6	5	0	16	0	9	5	0	0	0	1	0	7	9	1	10	2	5	39	40	1	3	7	1	1	0	
d	1	10	13	0	12	0	5	5	0	0	2	3	7	3	0	1	0	43	30	22	0	0	0	4	0	2	
e	388	0	3	11	0	2	2	0	89	0	0	3	0	5	93	0	0	14	12	6	15	0	0	1	0	18	0
f	0	15	0	3	1	0	5	2	0	0	0	3	4	1	0	0	0	6	4	12	0	0	0	2	0	0	
g	4	1	11	11	9	2	0	0	0	1	1	3	0	0	2	1	3	5	13	21	0	0	0	1	0	3	0
h	1	8	0	3	0	0	0	0	0	0	0	2	0	12	14	2	3	0	3	1	11	0	0	0	2	0	0
i	103	0	0	0	146	0	1	0	0	0	0	6	0	0	49	0	0	0	2	1	47	0	0	2	1	15	0
j	0	1	1	9	0	0	1	0	0	0	0	2	1	0	0	0	0	0	5	0	0	0	0	0	0	0	
k	1	2	8	4	1	1	2	5	0	0	0	0	5	0	2	0	0	0	6	0	0	0	0	4	0	0	
l	2	10	1	4	0	4	5	6	13	0	1	0	0	14	2	5	0	11	10	2	0	0	0	0	0	0	
m	1	3	7	8	0	2	0	6	0	0	4	4	0	180	0	6	0	0	9	15	13	3	2	2	3	0	
n	2	7	6	5	3	0	1	19	1	0	4	35	78	0	0	7	0	28	5	7	0	0	1	2	0	2	
o	91	1	1	3	116	0	0	25	0	2	0	0	0	0	14	0	2	4	14	39	0	0	0	0	18	0	
p	0	11	1	2	0	6	5	0	2	9	0	2	7	6	15	0	0	1	3	6	0	4	1	0	0	0	
q	0	0	1	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
r	0	14	0	30	12	2	2	8	2	0	5	8	4	20	1	14	0	0	12	22	4	0	0	1	0	0	
s	11	8	27	33	35	4	0	1	0	1	0	27	0	6	1	7	0	14	0	15	0	0	5	3	20	1	
t	3	4	9	42	7	5	19	5	0	1	0	14	9	5	5	6	0	11	37	0	0	2	19	0	7	6	
u	20	0	0	0	44	0	0	0	64	0	0	0	2	43	0	0	4	0	0	0	0	0	2	0	8	0	
v	0	0	7	0	0	3	0	0	0	0	0	1	0	0	1	0	0	0	8	3	0	0	0	0	0	0	
w	2	2	1	0	1	0	0	2	0	0	1	0	0	0	0	7	0	6	3	3	1	0	0	0	0		
x	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0		
y	0	0	2	0	15	0	1	7	15	0	0	0	2	0	6	1	0	7	36	8	5	0	0	1	0		
z	0	0	0	7	0	0	0	0	0	0	0	7	5	0	0	0	0	2	21	3	0	0	0	0	3		

Text Normalization

Learn to Correct Spellings

Weighted Minimum Edit Distance

$$D(x[0:i], y[0:j]) = \min\{$$

$$D(x[0:i-1], y[0:j-1]) + x[i] \leftrightarrow y[j]$$

$$D(x[0:i], y[0:j-1]) + \text{insert}(y[j])$$

$$D(x[0:i-1], y[0:j]) + \text{delete}(x[i])$$

}

$x[i] \neq y[j] \rightarrow \text{sub}(x[i], y[j])$

$x[i] = y[j] \rightarrow 0$

x	sub[X, Y] = Substitution of X (incorrect) for Y (correct)																									
	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y	z
a	0	0	7	1	342	0	0	2	118	0	1	0	0	3	76	0	0	1	35	9	9	0	1	0	5	6
b	0	0	9	0	23	1	0	0	0	5	11	0	0	10	0	0	10	0	0	0	0	0	8	0	0	0
c	0	5	0	6	0	2	5	0	0	0	7	9	0	10	0	5	39	40	1	0	0	7	0	0	0	0
d	1	10	13	0	12	0	5	5	0	0	2	3	7	3	0	1	0	43	30	22	0	0	4	0	2	1
e	388	0	3	11	0	2	2	0	89	0	0	3	0	5	93	0	0	14	12	6	15	0	1	0	18	0
f	0	15	0	3	1	0	5	2	0	0	0	3	4	1	0	0	0	6	4	12	0	0	2	0	0	0
g	4	1	0	11	9	20	0	0	0	0	3	4	1	0	0	0	0	3	5	13	21	0	0	1	0	3
h	1	8	0	3	0	0	0	0	0	0	2	0	12	14	2	3	0	3	11	0	0	0	0	0	0	0
i	103	0	0	0	146	0	1	0	0	0	0	6	0	0	49	0	0	0	2	1	47	0	2	1	15	0
j	0	1	9	0	0	1	0	0	0	0	6	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0
k	1	2	8	4	1	1	2	5	0	0	0	5	0	2	0	0	0	6	0	0	0	4	0	0	0	3
l	2	10	1	4	0	4	5	0	6	13	0	1	0	0	18	0	2	5	0	0	11	2	0	0	0	
m	1	3	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	9	0	0	13	2	0	0	0	
n	2	7	6	5	3	0	1	19	1	0	4	35	78	0	0	7	0	28	5	7	0	0	1	2	0	
o	91	1	1	3	116	0	0	0	25	0	2	0	0	0	0	14	0	2	4	14	39	0	0	0	18	0
p	0	11	1	2	0	6	5	0	2	9	0	2	7	6	15	0	0	1	3	6	0	4	1	0	0	
q	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
r	0	14	0	30	12	2	8	2	0	0	6	8	0	20	0	0	14	0	0	12	22	4	0	0	1	0
s	11	8	27	33	35	4	0	1	0	1	0	27	0	6	1	7	0	14	0	15	0	0	5	3	20	1
t	3	4	9	42	7	5	19	5	0	1	0	14	9	5	5	6	0	11	37	0	0	2	19	0	7	6
u	20	0	0	0	44	0	0	0	64	0	0	0	2	43	0	0	4	0	0	0	2	0	2	0	8	0
v	0	0	7	0	0	30	0	2	0	0	0	0	0	1	5	0	0	8	0	0	0	8	30	0	0	
w	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	7	0	6	1	0	0	1	0	0	0	
x	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	
y	0	0	0	2	0	15	0	1	7	15	0	0	0	0	2	0	6	1	0	7	36	8	5	0	0	
z	0	0	0	7	0	0	0	0	0	0	0	7	5	0	0	0	0	2	21	3	0	0	0	3	0	

Text Normalization

Learn to Correct Spellings

Weighted Minimum Edit Distance

Applications

Finding the closest word from Dictionary as the **correct spell** (Autocorrection)

Finding the closest word from Dictionary as the **correct meaning!**?

Finding the closest word from Dictionary as the **prediction!**? (Autocompletion)

Computational Biology

Aligning two sequences of protein

Daniel Jurafsky: https://www.youtube.com/watch?v=IL0-bD_e8s4