NUS | Computing
National University of Singapore

CS4248: Natural Language Processing

Lecture 2 — Strings & Words

Recap of Week 01

Communication with Machines

Humans

Machines

Natural Language

Analysis →

← Generation

R ← Some abstract internal representation / model of language and the world

Source: Wiki Common (CC BY-SA 4.0): gpu

NLP in One Slide

"shallower" ↕ "deeper"

Units	Analysis	Tasks
characters, morphemes, words	**Lexical Analysis** (understanding structure & meaning of words)	• Tokenization • Stemming • Normalization • Lemmatization
	Syntactic Analysis (organization of words into sentences)	• Part-of-Speech Tagging • Syntactic parsing (constituents, dependencies)
phrases, clauses, sentences	**Semantic Analysis** (meaning of words and sentences)	• Word Sense Disambiguation • Named Entity Recognition • Semantic Role Labeling
paragraphs, documents	**Discourse Analysis** (meaning of sentences in documents)	• Coreference / anaphora resolution • Ellipsis resolution • Stance detection
world knowledge, common sense	**Pragmatic Analysis** (understanding & interpreting language in context)	• Textual Entailment • Intent recognition

14

🏃‍♀️🏃🏃‍♂️DYI Winograd Schema

(5 minutes)

Find and post your own examples for Winograd Schema(s)

Explain what is ambiguous about it.

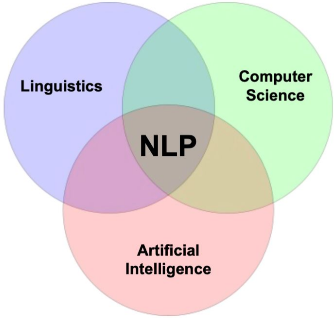
Go wild! Find good interesting ones.

Give kudos and upvote your peers!

40

What is NLP? — The Bigger Picture

Human Language
- Speech
- Writing



Algorithms, e.g.:
- Indexing / search
- Pattern matching

Machine Learning
Deep Learning

53

Outline

- **Regular Expressions**
  - **Basic Concepts**
  - Relationship to FSA
  - Error Types
- Corpus Preprocessing
  - Tokenization
  - Normalization
  - Stemming / Lemmatization
  - Segmentation
- Word error handling
  - Spelling Errors
  - Minimum Edit Distance
  - Noisy Channel Model

Regular Expressions

- ## Regular Expression — Definition
  - Search pattern used to match character combinations in a string
  - Pattern = sequence of characters

- ## Common applications
  - Parse text documents to find specific character patterns
  - Validate text to ensure it matches predefined patterns
  - Extract, edit, replace, delete substrings matching a pattern

Example: password validation

* Must have a minimum of 8 characters
* Must not contain username
* Must include at least 1 uppercase
* Must include at least 1 lowercase
* Must include at least 1 digit or 1 special character:
  ~ ! @ # $ % ^ & * _ - + = ` | \ ( ) { } [ ] : ; " ' < > , . ? /

- ## Two basic search approaches
  - Default: match only first occurrence of pattern
  - Global search: match all occurrences of pattern (assumed in most following examples)

Basic Patterns

- Fixed patterns

`floor` ➜ *My block has 15 floors, and I live on floor 5.*

`5` ➜ *My block has 15 floors, and I live on floor 5.*

`blocks` ➜ *My block has 15 floors, and I live on floor 5.*

- Special characters (metacharacters)

Character	Explanation
`.`	matches any character except line breaks
`^`	match the start of a string
`$`	match the end of a string
`|`	matches RegEx either before or after the symbol (e.g., `floor|floors`)
`\b`	matches boundary between word and non-word

Character Classes

- Character class
  - Defines set of valid characters
  - Enclosed using "`[...]`"
  - Can be negated: "`[^...]`"

`[0-9][0-9]` ➜ *My block has 15 floors, and I live on floor 5.*

(match all sequences of 2 digits)

`[.,;:]` ➜ *My block has 15 floors, and I live on floor 5.*

(match all sequences of length 1 that are either a period, comma, etc.)

`[^a-z]` ➜ *My block has 15 floors, and I live on floor 5.*

(match all sequences of length 1 that are not a lowercase letter)

Predefined Character Classes

- Common character classes with their own shorthand notation (i.e., metacharacters)

Class	Alternative	Explanation
`\d`	`[0-9]`	matches any digit
`\D`	`[^0-9]`	matches any non-digit
`\s`	`[ \n\r\t\f]`	matches any whitespace character
`\S`	`[^ \n\r\t\f]`	matches any non-whitespace character
`\w`	`[a-zA-Z0-9_]`	matches any word character
`\W`	`[^a-zA-Z0-9_]`	matches any non-word character

Repetition Patterns

- Very common: patterns with flexible lengths, e.g.:
  - All numbers with more than 2 digits
  - All words with less than 5 characters

- Repetition patterns — metacharacters

Pattern	Explanation
`+`	1 or more occurrences
`*`	0 or more occurrences
`?`	0 or 1 occurrences
`{n}`	exactly `n` occurrences
`{l,u}`	between `l` and u occurrences; can be unbounded: `{l,}` or `{,u}`

Repetition Patterns — Examples

`\d{2,}` ➜ *My block has 15 floors, and I live on floor 5.*

(match all numbers with 2 or more digits)

`\d+` ➜ *My block has 15 floors, and I live on floor 5.*

(match all numbers with 1 or more digits)

`\b\w{2,4}\b` ➜ *My block has 15 floors, and I live on floor 5.*

(match words with 2 to 4 characters)

`\b[Ff]loor[s]?\b` ➜ *My block has 15 floors, and I live on floor 5.*

(match occurrences of "floor", either capitalized or not, either in singular or plural)

Groups

Quick quiz: In which case(s) would the RegEx below fail to correctly match an email address?

- Groups: Organizing patterns into parts
  - Groups are enclosed using "(...)"
  - While whole expression must match, groups are captures individually
    (a match is no longer a string but a tuple of strings, on for each group)
  - Groups can be nested, e.g., (...(...)...((...))...)
    (order of groups depends on the order in which the groups "open")

Send an email to alice@example.org for more information.

Match @-symbol

```
([\w.-]+)@([\w.-]+)
```

Match 1 or more letters, digits, underscores, or periods

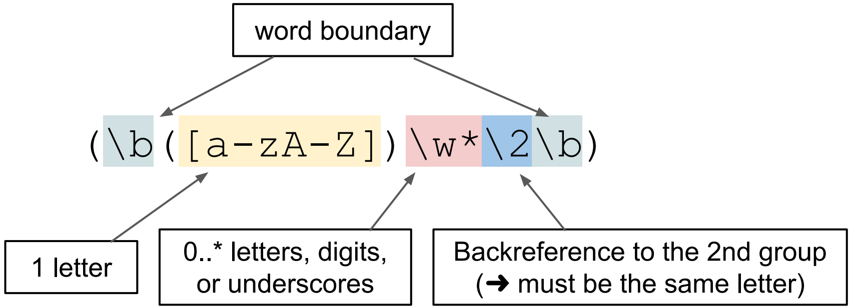
Match:	*user@example.org*
Group #1:	*alice*
Group #2:	*example.org*

Backreferences

Quick quiz: Can the same be achieved using only 1 group?

- Reference groups within a RegEx
  - Find repeated patterns (see example below)
  - Support only partial replacement of matches

- Example:
  - *"My mom said I need to pass this test."*
  - Goal: Find all words that start and end with the same letter



Match:	*mom*
Group #1:	*mom*
Group #2:	*m*

Match:	*test*
Group #1:	*test*
Group #2:	*t*

Lookarounds

- Special groups — assertions
  - Match like any other group, but do not capture the match
  - 2 types: lookaheads and lookbehinds
  - 2 forms of assertion: positive and negative

	Type	Example
`(?=)`	positive lookahead	`A(?=B)` ➜ finds expr. A but only when followed by expr. B
`(?!)`	negative lookahead	`A(?!B)` ➜ finds expr. A but only when not followed by expr. B
`(?<=)`	positive lookbehind	`(?<=B)A` ➜ finds expr. A but only when preceded by expr. B
`(?<!)`	negative lookbehind	`(?<!B)A` ➜ finds expr. A but only when not preceded by expr. B

Lookarounds — Example

- Positive lookahead
  - *"Paying 10 SGD for 1 kg of chicken seems fair."*
  - Goal: Extract all *kg* values (numbers followed by the unit *kg*)

`\d+(?=\s*kg)` ➜

"Paying 10 SGD for 1 kg of chicken seems fair.
"Paying 10 SGD for 1.5 kg of chicken seems fair.
"Paying 10 SGD for 1,500.00 kg of chicken seems fair.

`[0-9.,]*[0-9]+(?=\s*kg)` ➜

"Paying 10 SGD for 1 kg of chicken seems fair.
"Paying 10 SGD for 1.5 kg of chicken seems fair.
"Paying 10 SGD for 1,500.00 kg of chicken seems fair.

Outline

- **Regular Expressions**
  - Basic Concepts
  - **Relationship to FSA**
  - Error Types
- Corpus Preprocessing
  - Tokenization
  - Normalization
  - Stemming / Lemmatization
  - Segmentation
- Word error handling
  - Spelling Errors
  - Minimum Edit Distance
  - Noisy Channel Model

Pre-Lecture Activity for Next Week

- Assigned Task (due before Jan 20)
  - Post a 1-2 sentence answer to the following question into the L1 Discussion forum
    (you will find the thread on Canvas > Discussion > Week 2 (L1))

"What is the relationship between a Finite State Machine and Regular Expressions?"

Side notes:
- This task is meant as a warm-up to provide some context for the next lecture
- No worries if you get lost; we will talk about this in the next lecture
- You can just copy-&-paste others' answers but this won't help you learn better


CONFIDENTIAL
TOP SECRET
CONFIDENTIAL

Relationship to Finite State Automata

- Equivalence
  - Regular Expressions describe **Regular Languages**
    (most restricted types of languages w.r.t Chomsky Hierarchy)
  - Regular Language = language accepted by a FSA

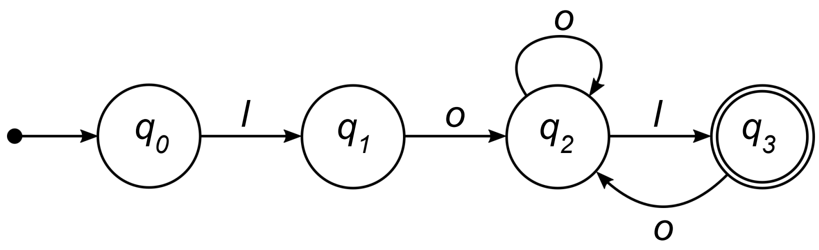
Regular Expression

l(o+l)+

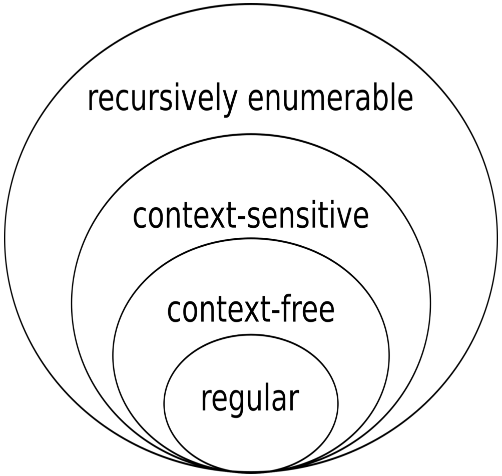
Regular Language

{lol, loool, lolol, looolol, …}

Example: FSA that accepts the Regular Language described by the Regular Expression **l(o+l)+**



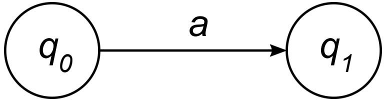
Chomsky Hierarchy
(Source: Wikipedia)



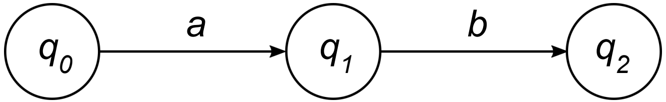
Relationship to Finite State Automata

- Basic equivalences

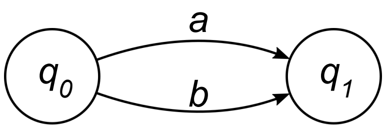
a



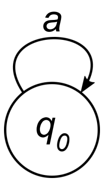
ab



a | b



a*



🏃‍♀️ 🏃 🏃‍♂️ In-Lecture Activity (5 mins)

Outline

- **Regular Expressions**
  - Basic Concepts
  - Relationship to FSA
  - **Error Types**
- Corpus Preprocessing
  - Tokenization
  - Normalization
  - Stemming / Lemmatization
  - Segmentation
- Word error handling
  - Spelling Errors
  - Minimum Edit Distance
  - Noisy Channel Model

Error Types — What Can Go Wrong

Quick quiz: What would be a better RegEx for this task?

- Example: Find all occurrences of article "the"
  - Naive approach: "`the`" (fixed pattern)

incorrect matches

correct matches

There's no other way to learn the power of Regular Expressions than to use them regularly. The productivity is worth the effort.

missing match

Error Types

- 2 basic types of errors

Matching strings that we should not have matched
(e.g., *other*, *theology*, *weather*, *bathe*, *mother*) → **False Positives** (Type I Errors)

Not matching things that we should have matched
(e.g., *THE*) → **False Negatives** (Type II Errors)

Error Types — Observations

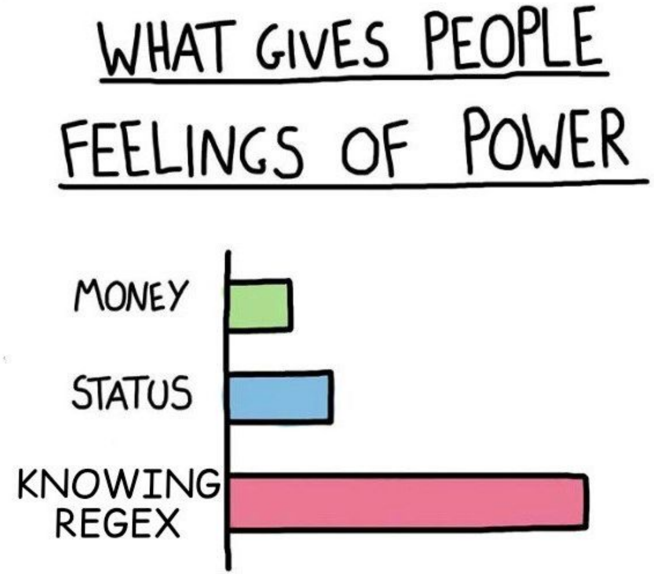
- Many contexts deal with these 2 types of errors, e.g.:
  - Medical testing (e.g., ART test is positive but person is not infected with COVID ➜ false positive)
  - Information retrieval (e.g., a Web search is missing a relevant page ➜ false negative)
  - Document classification (e.g., an abusive tweet has be classified as positive ➜ false positive)

- Reducing errors
  - Both error types not always equally bad ($\overbrace{\text{infected person tests negative}}^{\textbf{false negative}}$ vs. $\overbrace{\text{healthy person test positive}}^{\textbf{false positive}}$)
  - Reducing False Positives and False Negatives often in conflict
    (reducing False Positives often increases False Negatives, and vice versa)

Regular Expressions — Summary

- Know their powers
  - Extremely useful tool for many (low-level) text processing tasks (e.g., data preprocessing, tokenization, normalization)
  - Important skill for anyone working with strings or text
- Know their limitations
  - Regular Expressions represent hard rules
  - Higher-level text processing task generally require statistical models ("soft" rules)

➜ Machine Learning classifiers



Outline

- **Regular Expressions**
  - Basic Concepts
  - Relationship to FSA
  - Error Types
- Corpus Preprocessing
  - **Tokenization**
  - Normalization
  - Stemming / Lemmatization
  - Segmentation
- Word error handling
  - Spelling Errors
  - Minimum Edit Distance
  - Noisy Channel Model

Tokenization

- Tokenization: splitting a string into **tokens ➜ vocabulary** (set of all unique tokens)
  - Token = character sequence with a semantic meaning
    (typically: words, numbers, punctuation — but may differ depending on applications)
  - Very important for step for most NLP algorithms
    (tokenization errors quickly propagate up ➜ "garbage in, garbage out")

Character-based tokenization trivial (e.g., using Regex: .)

- 3 basic approaches

character-based	*S h e*	*' s*	*d r i v*	*i n g*	*f a s t*	*e r*	*t h a n*	*a l l o w*	*e d*	.
subword-based	*She*	*'s*	*driv*	*ing*	*fast*	*er*	*than*	*allow*	*ed*	.
word-based	*She*	*'s*	*driving*		*faster*		*than*	*allowed*		.

Tokenization — Word-Based

Quick quiz: What is an important assumption for the 2 approaches?

- 2 intuitive approaches (solved using RegEx)
  - Match all words, numbers and punctuation marks ➜ `\w+|\d+|[,.;:]`
  - Match boundaries between "words" and "non-words" ➜ `(?=\W)|(?<=\W)`

`\w+|\d+|[,.;:]` ➜ *NLP is fun, and there is so much to learn in 13 weeks.*

`(?=\W)|(?<=\W)` ➜ *NLP | |is| |fun|,| |and| |there| |is| |so| |much| |to| |learn| |in| |13| |weeks|.|*

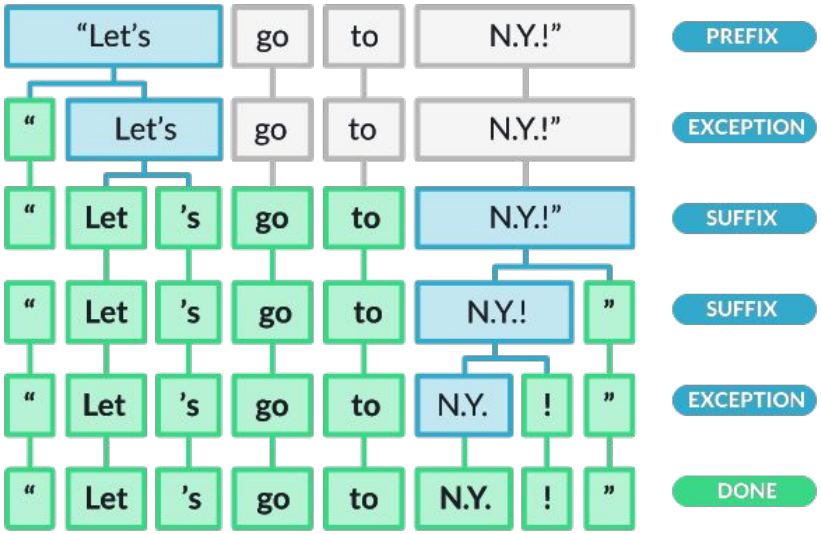
Tokenization — It Quickly Gets Tricky

Multiword phrases	➜	*I just came back from New York City.*
Common contractions	➜	*I'm not home, so don't call.*
Hyphenations	➜	*NLP is a well-defined but non-trivial topic.*
Acronyms, names, etc.	➜	*I watched a C++ documentary on T.V.*
Special tokens	➜	*My email is chris@nus.comp.nus.sg :o)*

RegEx used:

```
\w+|\d+|[,.;:]
```

Example: spaCy Tokenizer



(1) Split string on whitespace characters

(2) From left to right, recursively check substrings:

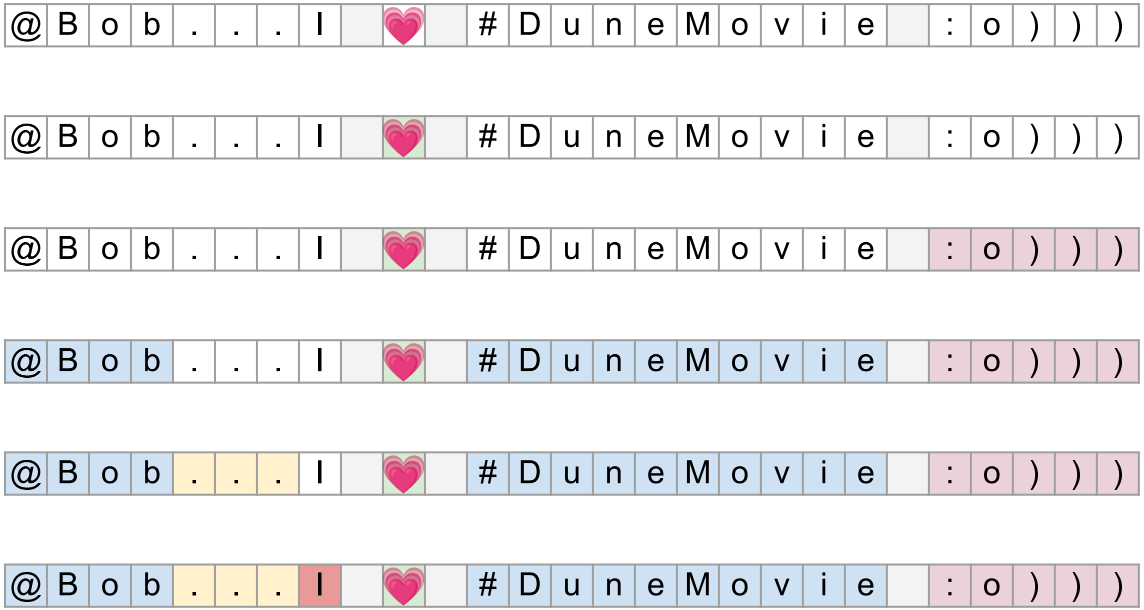
- Does substring match an exception rule?
  (e.g., *"don't"* → *"do"*, *"n't"*, but keep *"U.K."*)
- Can a prefix, suffix or infix be split of?
  (e.g., commas, periods, quotes, hyphens)

Substring checks based on
- Regular Expressions
- Hand-crafted rules / patterns

Source: https://spacy.io/usage/spacy-101

Example: Chris's Tokenizer

Sequential labeling of characters



Label all whitespace characters

Label all unicode characters

Label all emoticons

Label all special token types

Label all punctuation marks

Label all all alphanumeric characters

➜ Tokens = Substrings with adjacent characters with the same labels

Tokenization — Language Issues

- French
  - Different uses of apostrophes and hyphens (compared to English)

direct article — *l'ensemble* — *"the whole" / "all"*

indicates imperative — *donne-moi* — *"give me!"*

➜ 1 token or 2 tokens?

- German
  - Very common: compound nouns

Arbeiterunfallversicherungsgesetz
"worker injury insurance act"

➜ important: **compound splitter**

Tokenization — Language Issues

- Languages without whitespaces separating words

Chinese

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 "

Japanese

フォーチュン500社は情報不足のため時間あた$500K(約6,000万円)

Katakana **Hiragana** **Kanji** **Romanji**

- multiple syllabaries
- multiple formats for dates and amounts

Tokenization — Word Segmentation of Chinese Text

- Baseline algorithm: **Maximum Matching**

莎拉波娃现在居住在美国东南部的佛罗里达

(1) Place a pointer at the beginning of the string

莎拉波娃现在居住在美国东南部的佛罗里达

Sharapova

(2) Find longest word in dictionary that matches string starting the pointer

莎拉波娃|现在居住在美国东南部的佛罗里达

(3) Mover the pointer over the word in the string

莎拉波娃|**现在**居住在美国东南部的佛罗里达

now

(4) Goto #2 to process the whole string

Tokenization — Maximum Matching

- Surprisingly good performance on Chinese text
  (even better performance with probabilistic methods or extensions)

- Generally does not work for English text

thetabledownthere

correct → *the table down there*

Maximum Matching → *theta bled own there*

Tokenization — Subword-Based

- Subword-based tokenization
  - So far: a priori specification of rules (e.g., RegEx) what constitutes valid tokens
  - Now: use data to specify how to tokenize

- Why do we want to do this?
  - **Out Of Vocabulary (OOV)** words
    (word/token an NLP model has not seen before)
  - Very rare words in corpus

➜ problematic when building statistical models

Examples: *Obamacare* *kiasuism* *chillax*

frequent tokens

➜ **Goal:** Split OOV and rare words into (some) known & frequent tokens

Tokenization — Subword-Based

- Different algorithms for subword tokenization
  - Byte-Pair Encoding (BPE), Unigram Language Model Tokenization, WordPiece, etc.

- Different approaches, similar 2-parts setup

(1) **Token Learner**
Takes raw training corpus and induces a vocabulary (i.e., set of tokens)

(2) **Token Segmenter**
Takes a raw text and tokenizes it according to vocabulary

Tokenization — BPE Token Learner

Quick quiz: What happens if k=0 or k=∞ ?

Corpus: *"low low low low low lower lower newest newest newest newest newest newest widest widest widest longer"*

special end-of-word token

Initialize vocabulary (e.g., {*'d', 'e', 'g', 'i', 'l', 'n', 'o', 'r', 's', 't', 'w',* $\boxed{\text{'\_'}}$})

REPEAT

Find the 2 tokens most frequently adjacent to each other (e.g., *'e', 's'*)

Add a new merged token *'es'* to vocabulary

Replace every adjacent '*e' 's'* in corpus with *'es'*

UNTIL $\boxed{k}$ merges have been done

parameter of algorithm

Tokenization — BPE Token Learner

corpus representation

6	n e w e s t _
5	l o w _
3	w i d e s t _
2	l o w e r _
1	l o n g e r _

vocabulary

d, e, g, i, l, n, o, r, s, t, w, _

merges

most frequent pair: **e** & **s** (9 occurrences)

corpus representation

6	n e w **es** t _
5	l o w _
3	w i d **es** t _
2	l o w e r _
1	l o n g e r _

vocabulary

d, e, g, i, l, n, o, r, s, t, w, _, **es**

merges

(e, s)

most frequent pair: **es** & **t** (9 occurrences)

Tokenization — BPE Token Learner

corpus representation

6	n e w **est** _
5	l o w _
3	w i d **est** _
2	l o w e r _
1	l o n g e r _

vocabulary

d, e, g, i, l, n, o, r, s, t, w, _, es, **est**

merges

(e, s), **(es, t)**

most frequent pair: **est** & **_** (9 occurrences)

corpus representation

6	n e w **est_**
5	l o w _
3	w i d **est_**
2	l o w e r _
1	l o n g e r _

vocabulary

d, e, g, i, l, n, o, r, s, t, w, _, es, est, **est_**

merges

(e, s), (es, t), **(est, _)**

most frequent pair: **l** & **o** (8 occurrences)

Tokenization — BPE Token Learner

corpus representation

6	n e w est_
5	lo w _
3	w i d est_
2	lo w e r _
1	lo n g e r _

vocabulary

d, e, g, i, l, n, o, r, s, t, w, _, es, est, est_, lo

merges

(e, s), (es, t), (est, _), (l, o)

most frequent pair: lo & w (7 occurrences)

corpus representation

6	n e w est_
5	low _
3	w i d est_
2	low e r _
1	lo n g e r _

vocabulary

d, e, g, i, l, n, o, r, s, t, w, _, es, est, est_, lo, low

merges

(e, s), (es, t), (est, _), (l, o), (lo, w)

most frequent pair: n & e (6 occurrences)

Tokenization — BPE Token Learner

vocabulary d, e, g, i, l, n, o, r, s, t, w, _, es, est, est_, lo, low, **ne**

merges (e, s), (es, t), (est, _), (l, o), (lo, w), **(n, e)**

⇩

vocabulary d, e, g, i, l, n, o, r, s, t, w, _, es, est, est_, lo, low, ne, **new**

merges (e, s), (es, t), (est, _), (l, o), (lo, w), (n, e), **(ne, w)**

⇩

vocabulary d, e, g, i, l, n, o, r, s, t, w, _, es, est, est_, lo, low, ne, new, **newest_**

merges (e, s), (es, t), (est, _), (l, o), (lo, w), (n, e), (ne, w), **(new, est_)**

⇩

...

Tokenization — BPE Token Segmenter

vocabulary d, e, g, i, l, n, o, r, s, t, w, _, es, est, est_, lo, low, ne, new, newest_, low_, er, er_, wi, wid, widest_, lower_, lon, long, longer_

merges (e, s), (es, t), (est, _), (l, o), (lo, w), (n, e), (ne, w), (new, est_), (low, _), (e, r), (er, _), (w, i), (wi, d), (wid, est_), (low, er_), (lo, n), (lon, g), (long, er_)

Tokenize/segment *"newer"*

Run each merge in order they have been learned

```
n e w e r _
              (n, e)
ne w e r _
              (ne, w)
new e r _
              (e, r)
new er _
              (er, _)
new er_
```

➜ tokens: *"new"*, *"er_"*

Tokenization — Summary

- Tokenization as low-level NLP task
  - Challenges: important, non-trivial, language-dependent
  - Particularly tricky for informal language (e.g., social media)

- 3 basic approaches
  - Character-based (trivial to do but often not suitable — individual characters generally carry no semantic meaning)
  - Word-based (a priori specification of rules; language-dependent; problem: OOV/rare words)
  - Subword-based (tokenization learned from data — tokens are often morphemes!)

- Practical consideration (when using off-the-shell word-based tokenizers)
  - What is my type of text (e.g., formal or informal)? Are there special tokens (e.g., URLs, hashtags)?
  - Try and assess different tokenizers — very, very last resort: write your own tokenizer

Outline

- Regular Expressions
  - Basic Concepts
  - Relationship to FSA
  - Error Types
- **Corpus Preprocessing**
  - Tokenization
  - **Normalization**
  - Stemming / Lemmatization
  - Segmentation
- Word error handling
  - Spelling Errors
  - Minimum Edit Distance
  - Noisy Channel Model

Normalization

- Goal: Convert text into a canonical (standard) form
  - Remove noise / "randomness" from text
  - Affects characters, words, sentences, documents
- Implicit definition of equivalence classes
  - Suitable normalization steps depend on task/application

Raw	Normalized
Germany GERMANY	germany
USA U.S.A US of A	USA
tonight tonite 2N8	tonight
connect connects connected connecting connection	connect
:) :-) :o)	smile

Alternative to equivalence classes: **asymmetric expansion**

Example: Web Search (utilize case of search terms)

Entered term		**Searched terms**
window	➜	window, windows
windows	➜	Windows, windows, window
Windows	➜	Windows

Normalization — Case Folding

- When to fold?
  - Common application: Information Retrieval
    (e.g., Web search where must users type only in lowercase anyway)
  - Potential problems: *Bush* vs. *bush*, *MOM* vs. *mom*, *Cloud* vs. *cloud*, etc.
    (potential exception: upper case word in mid sentence?)

- When NOT to fold?
  - NLP tasks where case of letters or words are important features
  - Examples: Named Entity Recognition, Machine Translation

They sent ***us*** *a card from the* ***US*** *during their vacation.*

Distinction important for NER and MT!

Outline

- Regular Expressions
  - Basic Concepts
  - Relationship to FSA
  - Error Types
- **Corpus Preprocessing**
  - Tokenization
  - Normalization
  - **Stemming / Lemmatization**
  - Segmentation
- Word error handling
  - Spelling Errors
  - Minimum Edit Distance
  - Noisy Channel Model

Normalization — Stemming & Lemmatization

- Motivating example:

"dogs make the best friends" vs. *"a dog makes a good friend"*

➜ Very similar semantics but (very) different syntax

- Common reasons for variations of the same word
  - Singular vs. plural form (mainly of nouns)
  - Different tenses of verbs
  - Comparative/superlative of adjectives

➜ Can we normalize words to abstract from such variations?

Normalization — Stemming

- Idea of Stemming
  - Reduce words to their stem
  - Approach: crude chopping of affixes based on rules (➜ language dependent)
  - Different stemmers apply different rules
- Characteristics
  - Pro: fast + no lexicon required
  - Con: stemmed word not necessarily a proper word (i.e., not in dictionary)

Examples
(alternatives reflect results from different stemmers)

Raw	Stemmed
cats	*cat*
running	*run*
phones	*phon(e)*
presumably	*presum*
crying	*cry/cri*
went	*went*
worse	*wors*
best	*best*
mice	*mic(e)*

Normalization — Stemming: Porter Stemmer

- Porter Stemmer — most common stemmer for English text
  - Simple, efficient + very good results in practice

- Series of rewrite rules that run in a cascade
  - Output of each pass is fed is input to the next pass
  - Stemming steps if a pass yields no more changes

	sses ➝ ss	e.g.: *possesses* ➝ *possess*, *classes* ➝ *class*
	tional ➝ tion	e.g., *optional* ➝ *option*, *fictional* ➝ *function*
	ies ➝ i	e.g., *cries* ➝ *cri*, *tries* ➝ *tri*
stem must contain vowel	(*v*)ing ➝ ε	e.g.: *sing* ➝ *sing*, singing ➝ *sing*, *talking* ➝ *talk*
stem must contain >1 chars	(m>1)ement ➝ ε	e.g., *replacement* ➝ *replac*, *cement* ➝ *cement*

More details: https://tartarus.org/martin/PorterStemmer/

Normalization — Lemmatization

- Idea of Lemmatization
  - Reduce inflections or variant forms to base form
  - Find the correct dictionary headword form
  - Differentiates between word forms: nouns (N), verbs (V), adjectives (A)

Raw	Lemmatized (N)	Lemmatized (V)	Lemmatized (A)
running	*running*	*run*	*running*
phones	*phone*	*phone*	*phones*
went	*went*	*go*	*went*
worse	*worse*	*worse*	*bad*
mice	*mouse*	*mice*	*mice*

Normalization — Lemmatization: Characteristics

- Pros
  - Lemmatized words are proper words (i.e., dictionary words)
  - Can normalize irregular forms (e.g., *went* → *go*, *worst* → *bad*)

- Cons
  - Requires curated lexicons / lookup tables + rules (typically)
  - Requires Part-of-Speech tags for correct results
  - Generally slower as stemming

Normalization — Stemming & Lemmatization

- Back to our motivating example

Raw:	*"dogs make the best friends"*	*"a dog makes a good friend"*
Stemmed:	*"dog make the best friend"*	*"a dog make a good friend"*
Lemmatized:	*"dog make the good friend"*	*"a dog make a good friend"*

Normalization — Final Words

- Canonical form also effects tokenization, e.g.: Penn Treebank Tokenizer
  - Separate out clitics (e.g., *doesn't* ➜ *does n't*; *John's* ➜ *John 's*)
  - Keep hyphenated words together
  - Separate out all punctuation symbols
- Other common normalization steps
  - Removal of stopwords (e.g., *a*, *an*, *the*, *not*, *and*, *or*, *but*, *to*, *from*, *at*)
  - Removal of non-standard tokens (e.g., URs, emojis, emoticons)
  - ...

🏃‍♀️🏃🏃‍♂️ Quick Quiz

Outline

- Regular Expressions
  - Basic Concepts
  - Relationship to FSA
  - Error Types
- **Corpus Preprocessing**
  - Tokenization
  - Normalization
  - Stemming / Lemmatization
  - **Segmentation**
- Word error handling
  - Spelling Errors
  - Minimum Edit Distance
  - Noisy Channel Model

Sentence Segmentation

- Sound like a simple task but…
  - Period "." can be quite ambiguous (e.g., "1.25", "U.S.A.", "Dr.") — "?", "!" relatively unambiguous
  - Poor punctuation in informal text (common: missing whitespaces, missing capitalization)

  ➜ RegEx for segmenting sentences quickly become very complex

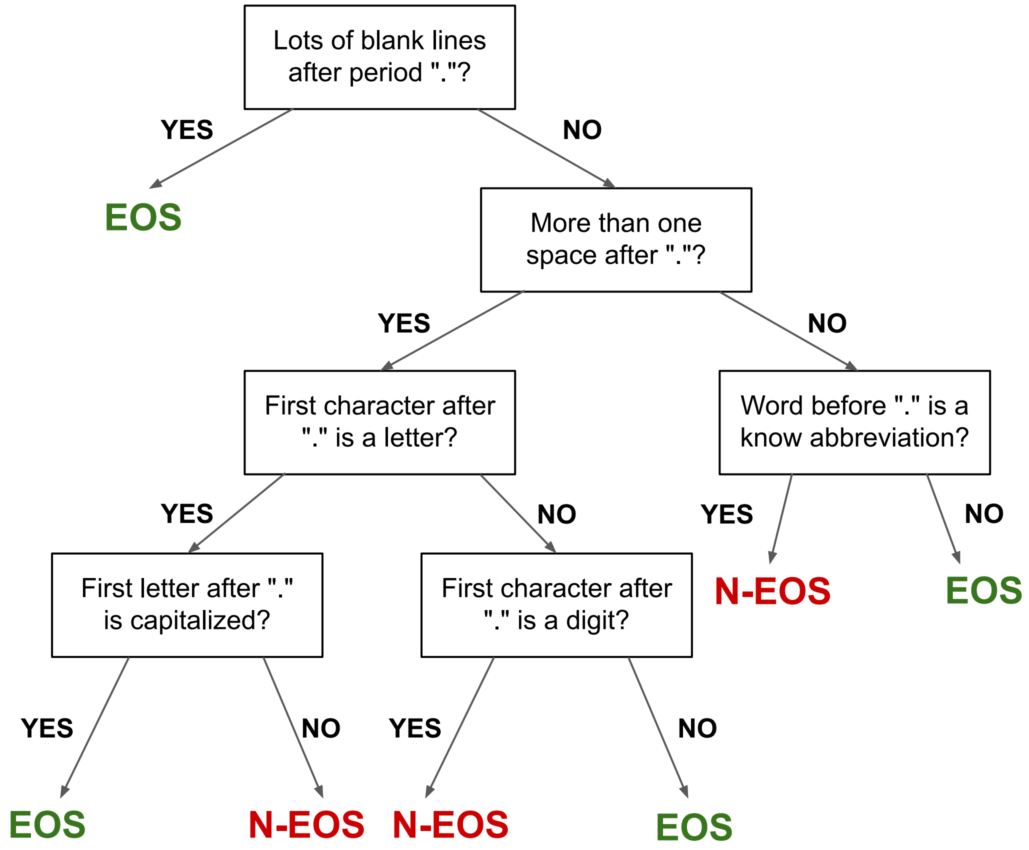
  Example RegEx: `(?<!\w\.\w.)(?<![A-Z][a-z]\.)(?<=\.|\?)\s`
  (Source: Stackoverflow)

- Alternative: binary classifier
  - Consider each period "." in a text
  - Classify: EndOfSentence or NotEndOfSentence

  ➜ Possible approaches: handwritten rules, set of RegEx, machine learning

Example: Simple Rules (represented as a binary Decision Tree)

Quick quiz: What are some common cases where this classifier would fail?

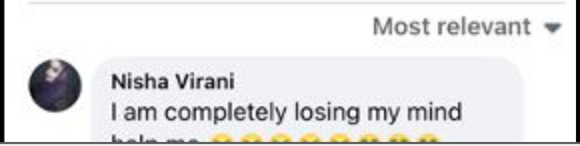


Many Other Features Conceivable

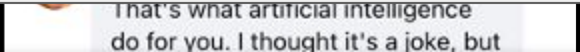
- Example: numerical features
  - length of word before / after period "."
  - Distance (in #chars) to next punctuation mark
  - Probabilities derived from a dataset
    (e.g., probability of with "." occurs at the end of sentence)

Side note: In informal text (e.g., social media) people often use emoticons or emojis to separate sentences, making this task even more complicated.

Break


Most relevant
Nisha Virani
I am completely losing my mind


CONFIDENTIAL
TOP SECRET
CONFIDENTIAL

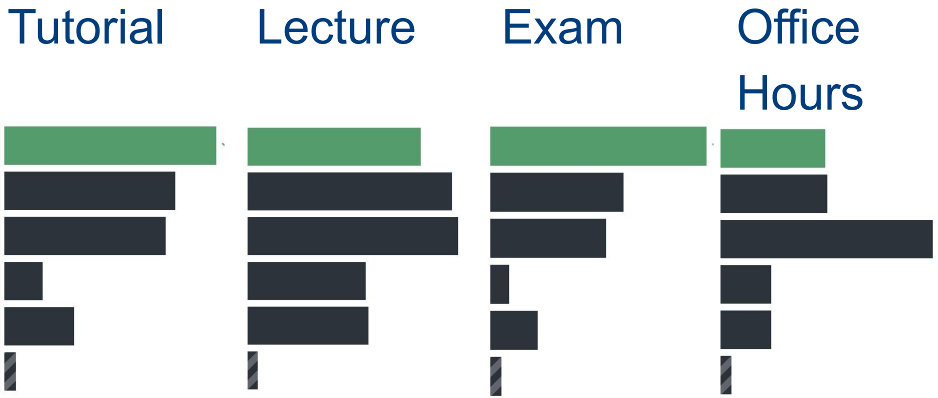

That's what artificial intelligence
do for you. I thought it's a joke, but

Why are you taking this module?

It's a core requirement of my programme.	23 respondents	9 %
It's an elective course (one of a basket) requirement for my programme.	103 respondents	40 %
I need this course to graduate this coming semester.	55 respondents	21 %
I'm taking a related focus area, minor or track that has this as part of the possible fulfilling courses.	139 respondents	54 %
I'm a student doing research, and NLP is my research area or related to my research area.	24 respondents	9 %
It looked interesting.	214 respondents	83 %
I have friends that are taking this course.	70 respondents	27 %
It fits well in my timetable.	52 respondents	20 %
Someone referred me to take this course because of its content.	29 respondents	11 %
Someone referred me to take this course because of its instruction staff.	26 respondents	10 %
I like project courses.	40 respondents	16 %
I saw that it was popular.	30 respondents	12 %
I have fulfilled all the prerequisites for the course, so why not?	38 respondents	15 %
Others, I've mentioned in the next question.	5 respondents	2 %

Venues

Strongly prefer physical venue	85 respondents	**33 %**
Rrefer physical venue	68 respondents	26 %
Neutral	64 respondents	25 %
Disprefer physical venue	13 respondents	5 %
Strongly disprefer physical venue	26 respondents	10 %
No Answer	2 respondents	1 %



Major or Programme

Arts		0 %
Business	9 respondents	3 %
Computer Engineering	20 respondents	8 %
Computer Sciences	175 respondents	68 %
Data Science	51 respondents	20 %
English Language, Foreign Language		0 %
Linguistics		0 %
Math / Statistics	22 respondents	9 %
Masters	42 respondents	16 %
Ph.D. Candidate		0 %
SCALE / Continuing Education Learner		0 %
Other	6 respondents	2 %

Overseas?

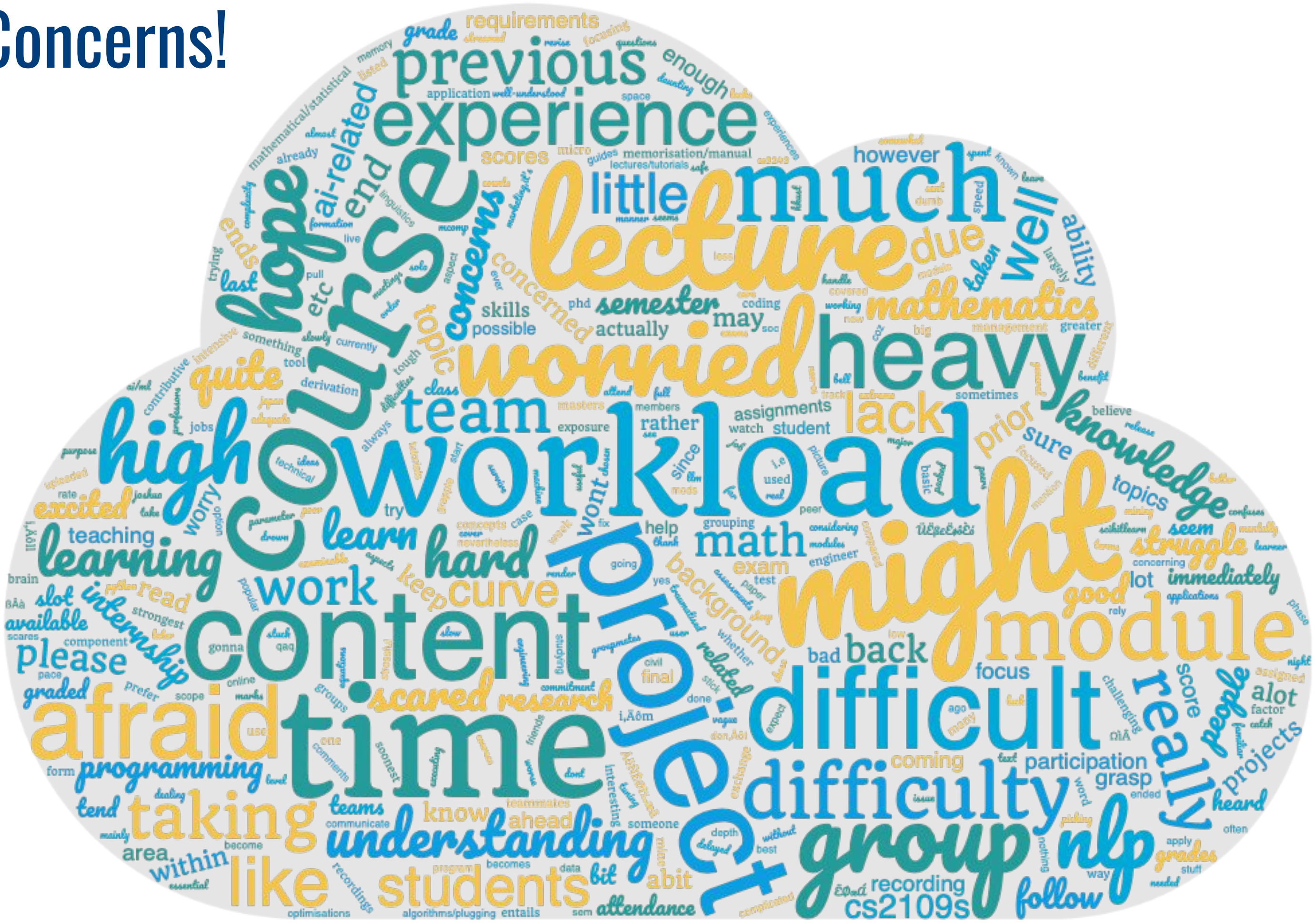
Yes, abroad on exchange or NOC.	1 respondent	0 %
Yes, on internship.	25 respondents	10 %
Considering one of the two above.	13 respondents	5 %
No, full-time local student (most students).	219 respondents	85 %

NLP Career Path

No idea.	16 respondents	6 %
Unlikely.	9 respondents	3 %
Somewhat Unlikely.	29 respondents	11 %
So-So.	72 respondents	28 %
Somewhat Likely.	100 respondents	39 %
Likely.	31 respondents	12 %
No Answer	1 respondent	0 %

What do you want to learn?

Your Concerns!



Outline

- Regular Expressions
  - Basic Concepts
  - Relationship to FSA
  - Error Types
- Corpus Preprocessing
  - Tokenization
  - Normalization
  - Stemming / Lemmatization
  - Segmentation
- **Word error handling**
  - **Spelling Errors**
  - Minimum Edit Distance
  - Noisy Channel Model

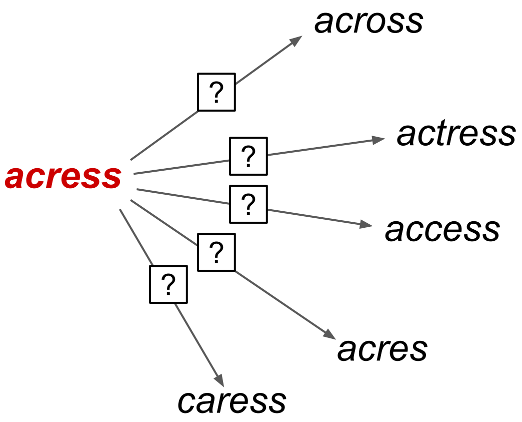
Spelling Errors

Increasing Complexity

1. **Non-word error detections**
   - Basically, word is not found in dictionary
   - Example: detecting *graffe* (misspelling of giraffe)

2. **Isolated-word error correction**
   - Consider word in isolation (i.e., without surrounding words)
   - Example: correcting *graffe* to *giraffe*

3. **Context-sensitive error detection & correction**
   - Consider surrounding words to detect and correct errors
   - Important for "wrong" words that a spelled correctly
   - Examples: *there* vs. *three*, *dessert* vs. *desert*, *son* vs. *song*



Spelling Errors — Common Patterns

- Observation
  - Most misspelled words in typewritten text are **single-error**
  - Damerau (1964): 80%, Peterson (1986): 93-95%

- Single-error misspellings
  - Insertion (e.g., *acress* vs. *acres*)
  - Deletion (e.g., *acress* vs. *actress*)
  - Substitution (e.g., *acress* vs. *access*)
  - Transposition (e.g., *acress* vs. *caress*)

For non-word errors:

➜ Good candidates are orthographically similar

➜ **Minimum Edit Distance**

Outline

- Regular Expressions
  - Basic Concepts
  - Relationship to FSA
  - Error Types
- Corpus Preprocessing
  - Tokenization
  - Normalization
  - Stemming / Lemmatization
  - Segmentation
- **Word error handling**
  - Spelling Errors
  - **Minimum Edit Distance**
  - Noisy Channel Model

Minimum Edit Distance (MED)

- Minimum Edit Distance between 2 strings s_1 and s_2
  - Minimum number of allowed edit operations to transform s_1 into s_2
  - Allowed edit operations: **Insertion**, **Deletion**, **Substitution**, Transposition

Not covered here to keep examples simple

- Example
  - s_1 = *"LANGUAGE"*
  - s_2 = *"SAUSAGE"*

➜ **Alignment** of MED:

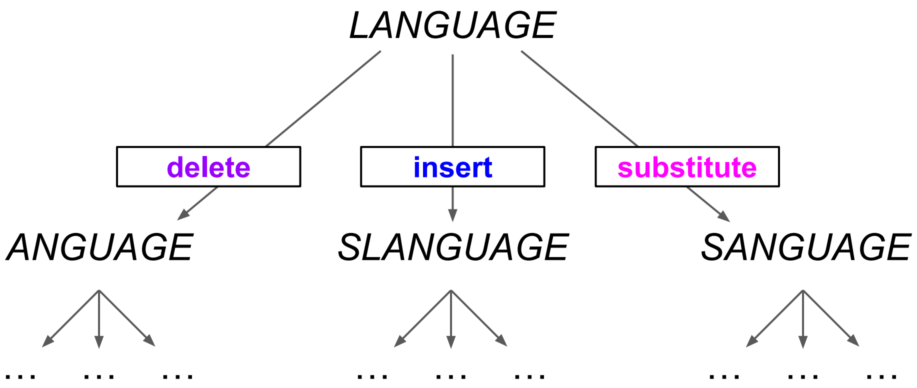
L	A	N	G	U	*	A	G	E
|	|	|	|	|	|	|	|	|
S	A	*	*	U	S	A	G	E

MED if all operations cost 1 ➜ 4

MED if Substitution costs 2, Insertion 1, Deletion 1 ➜ 5

Minimum Edit Distance — Calculation

- Problem formulation: Find a path (i.e., sequence of edits) from start string to final string
  - **Initial state**: the word being transformed (e.g., *"LANGUAGE"*)
  - **Target state**: the word being transformed into (e.g., *"SAUSAGE"*)
  - **Operators**: **insert**, **delete**, **substitute**
  - **Path cost**: aggregated costs of all edits

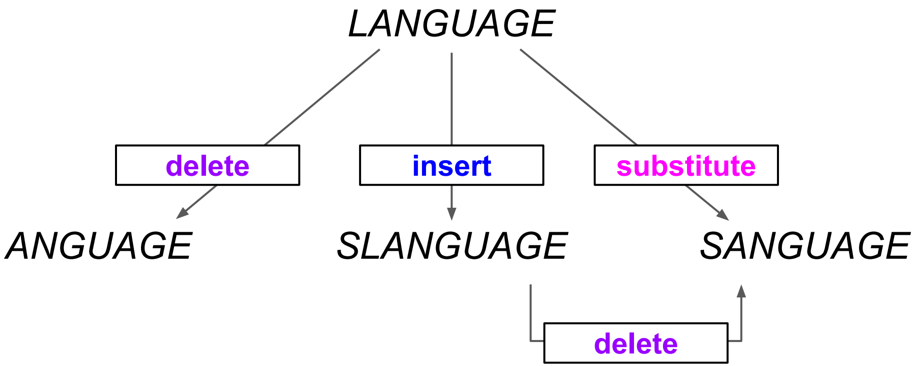


➜ Potentially huge search space

➜ Naive navigation of all path impractical

Minimum Edit Distance — Calculation

- Observations
  - Many distinct paths end up in the same state



➜ No need to keep track of all paths

➜ Only important: "cheapest" path to each revisited state
(best in terms of costs, not just number of operations!)

➜ Solve using **Dynamic Programming**
solving problems by combining solutions to subproblems

Minimum Edit Distance — Calculation

- Input: 2 strings
  - Source string X of length n
  - Target string Y of length m
- Define $D(i, j)$ as MED between $\underbrace{X[0..i]}_{\text{first } i \text{ chars of } X}$ and $\underbrace{Y[0..j]}_{\text{first } j \text{ chars of } Y}$

$$\boxed{\rightarrow \text{MED between } X \text{ and } Y \text{ is thus } D(n, m)}$$

- Bottom-up approach of Dynamic Programming
  - Compute $D(i, j)$ for small i , j (base cases)
  - Compute $D(i, j)$ for larger i, j based on previously computes $D(i, j)$ for smaller i, j

Minimum Edit Distance — Calculation

- Initialization of bases cases
  - $D(i,0) = i$ (getting from $X[0..i]$ to empty target string requires i deletions)
  - $D(0,j) = j$ (getting from empty source string to $Y[0..j]$ requires j insertions)

- For $0 < i \leq n$ and $0 < j \leq m$

$$D(i,j) = min \begin{cases} D(i-1,j)+1 & \textbf{Delete} \\ D(i,j-1)+1 & \textbf{Insert} \\ D(i-1,j-1) + \begin{cases} 2, & if\, X[i] \neq Y[j] \\ 0, & if\, X[i] = Y[j] \end{cases} & \textbf{Substitute} \end{cases}$$

Assumptions for costs

Insert: **1**

Delete: **1**

Substitute: **2**

➜ Levenshtein MED

Complexity analysis

Space: O(nm)

Time: O(nm)

Minimum Edit Distance — Calculation Example

E	8							
G	7							
A	6							
U	5							
G	4							
N	3							
A	2							
L	1							
#	0	1	2	3	4	5	6	7
	#	S	A	U	S	A	G	E

$$D(i,j) = min \begin{cases} D(i-1,j)+1 & \text{Delete} \\ D(i,j-1)+1 & \text{Insert} \\ D(i-1,j-1)+\begin{cases} 2, & if\, X[i] \neq Y[i] \\ 0, & if\, X[i] = Y[i] \end{cases} & \text{Substitute} \end{cases}$$

Minimum Edit Distance — Calculation Example

E	8	9	8	7	8	7	6	5
G	7	8	7	6	7	6	5	6
A	6	7	6	5	6	5	6	7
U	5	6	5	4	5	6	7	8
G	4	5	4	5	6	7	6	7
N	3	4	3	4	5	6	7	8
A	2	3	2	3	4	5	6	7
L	1	2	3	4	5	6	7	8
#	0	1	2	3	4	5	6	7
	#	**S**	**A**	**U**	**S**	**A**	**G**	**E**

Minimum Edit Distance — Backtrace & Alignments

- Current limitation
  - Base algorithm only returns the MED
  - Often important: alignment between strings

```
L A N G U * A G E
| | | | | | | | |
S A * * U S A G E
```

How do we get this?

- Keep track of backtrace
  - Remember from which "direction" we entered a new cell
  - At the end, trace path from upper right corner to read of alignment

Keep set of pointers for each i, j

Small extension to base algorithm:

$$PTR(i,j) = \begin{cases} \texttt{LEFT} & \textbf{Insert} \\ \texttt{DOWN} & \textbf{Delete} \\ \texttt{DIAG} & \textbf{Substitute} \end{cases}$$

Note: Backtraces are generally not unique ➜ different alignments for the same MED possible

Minimum Edit Distance — Backtrace & Alignments

E	8	↙←↓ 9	↓ 8	↓ 7	↙←↓ 8	↓ 7	↓ 6	↙ 5
G	7	↙←↓ 8	↓ 7	↓ 6	↙←↓ 7	↓ 6	↙ 5	← 6
A	6	↙←↓ 7	↙↓ 6	↓ 5	↙←↓ 6	↙ 5	← 6	← 7
U	5	↙←↓ 6	↓ 5	↙ 4	← 5	← 6	←↓ 7	↙←↓ 8
G	4	↙←↓ 5	↓ 4	↙←↓ 5	↙←↓ 6	↙←↓ 7	↙ 6	← 7
N	3	↙←↓ 4	↓ 3	↙←↓ 4	↙←↓ 5	↙←↓ 6	↙←↓ 7	↙←↓ 8
A	2	↙←↓ 3	↙ 2	← 3	← 4	↙← 5	← 6	← 7
L	1	↙←↓ 2	↙←↓ 3	↙←↓ 4	↙←↓ 5	↙←↓ 6	↙←↓ 7	↙←↓ 8
#	0	1	2	3	4	5	6	7
	#	**S**	**A**	**U**	**S**	**A**	**G**	**E**

L A N G U * A G E
| | | | | | | | |
S A * * U S A G E

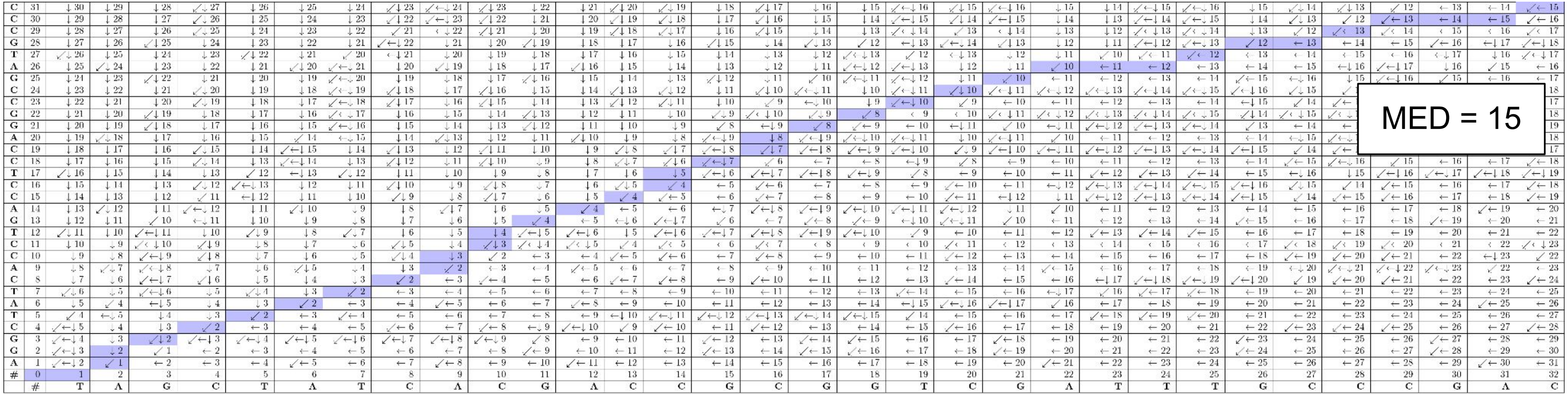
Quick quiz: Why do we choose the diagonal path here?

Complexity analysis
Time: O(n+m)

Minimum Edit Distance — More Examples

- Biology: Align 2 sequences of nucleotides

```
AGGCTATCACCTGACCTCCAGGCCGATGCCC
TAGCTATCACGACCGCGGTCGATTTGCCCGAC
```




```
* A G G C T A T C A C C T G A C C T C C A G G C C G A * * T G * C C * * C
| | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
T A * G C T A T C A * C * G A C C * G C * G G T C G A T T T G C C C G A C
```

🏃‍♀️🏃🏃‍♂️ In-Lecture Activity (5 mins)

🏃‍♀️ 🏃 🏃‍♂️ In-Lecture Activity (5 mins)

Minimum Edit Distance — Other Uses in NLP

- Evaluating Machine Translation and speech recognition

  e.g., How similar are 2 translations?

Reference:	*Spokesman*	***confirms***	*****	*senior*	***government***	*adviser*	*was*	*shot*	*****
	|	|	|	|	|	|	|	|	|
Prediction:	*Spokesman*	***said***	***the***	*senior*	*	*adviser*	*was*	*shot*	***dead***

- Named Entity Extraction and Entity Coreference

"We stayed at the	***	*Merchant*	*Court*	*prior to a cruise"*
		|	|	
"The	***Swissotel***	*Merchant*	*Court*	*is a great place to stay in Singapore"*

Referring to the same entity?

Minimum Edit Distance — Efficiency

- Time:

- Space:

- Backtrace:

Minimum Edit Distance — Efficiency

Minimum Edit Distance — Extensions

- Weighted Minimum Edit Distance, e.g.:
  - Spell Correction: some letters are more likely to be mistyped than others
  - Biology: certain kinds of deletions or insertions are more likely than others

➜ Generalization of algorithm
  - Application-dependent weights (i.e., costs for edit operations)

Initialization of base cases:

$$D(0,0) = 0$$
$$D(i,0) = D(i-1,0) + del(X[i]), \quad \text{for } 1 < i \leq n$$
$$D(0,j) = D(0,j-1) + ins(Y[i]), \quad \text{for } 1 < i \leq m$$

Recurrence relation:

$$D(i,j) = min \begin{cases} D(i-1,j) & + \, del(X[i]) \\ D(i,j-1) & + \, ins(Y[j]) \\ D(i-1,j-1) & + \, sub(X[i],Y[i]) \end{cases}$$

Minimum Edit Distance — Extensions

- Needleman-Wunsch
  - No penalty for gaps (*) at the beginning or the end of an alignment
  - Good if strings have very different lengths
- Smith-Wasserman
  - Ignore badly aligned regions
  - Find optimal <u>local</u> alignments within substrings
    (Levenshtein finds the best global distance and alignment)

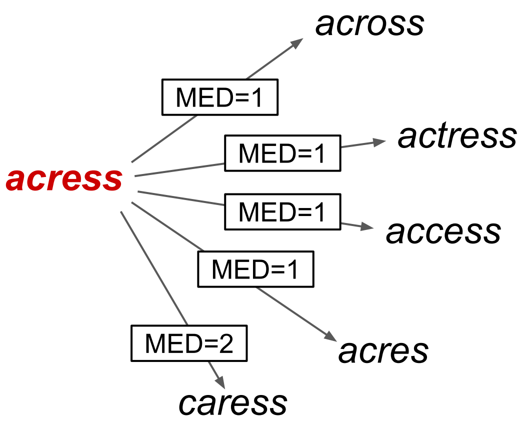
Common application:
Alignment of nucleotides sequences

Outline

- Regular Expressions
  - Basic Concepts
  - Relationship to FSA
  - Error Types
- Corpus Preprocessing
  - Tokenization
  - Normalization
  - Stemming / Lemmatization
  - Segmentation
- **Word error handling**
  - Spelling Errors
  - Minimum Edit Distance
  - **Noisy Channel Model**

Where We are Right Now

- Given a misspelled word, generate suitable candidates for error correction
  - 80% of errors are within minimum edit distance 1
  - Almost all errors within minimum edit distance 2
  - Covers also missing spaces and hyphens
    (e.g., *thisidea* vs. *this idea*; *inlaw* vs. *in-law*)

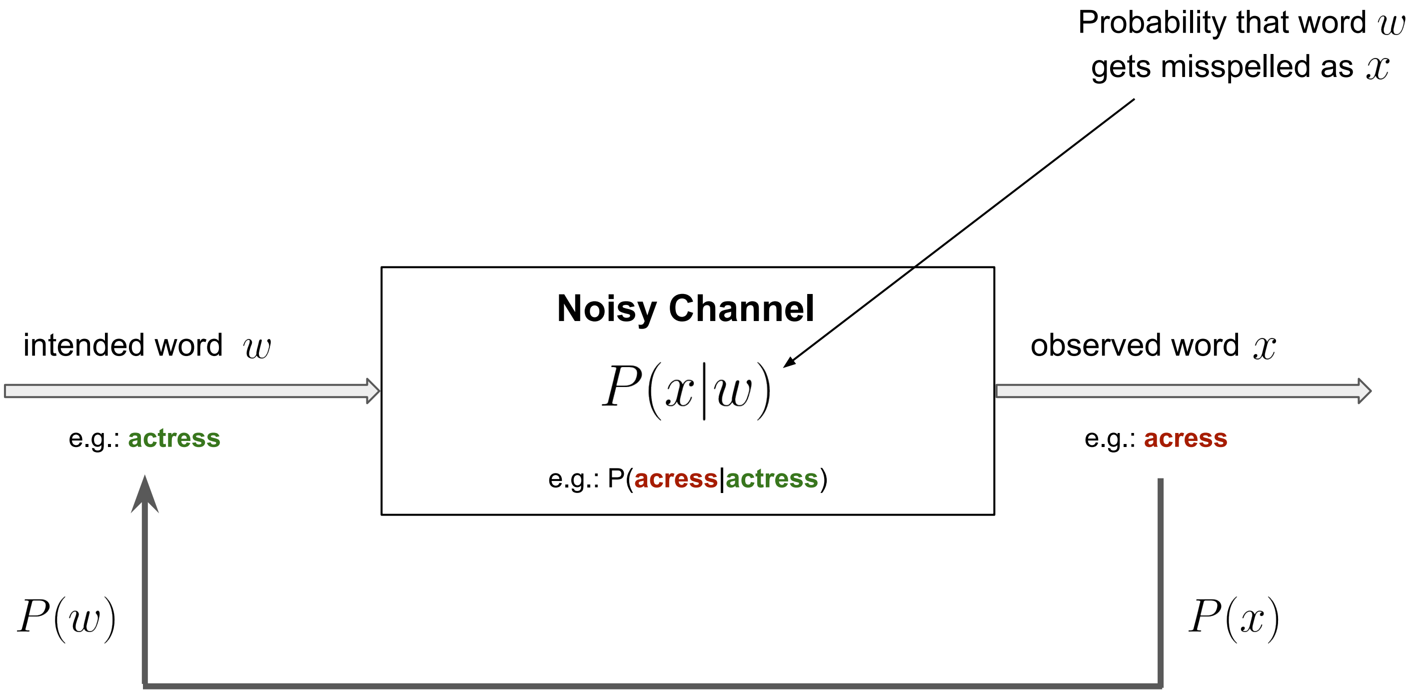


- Still missing: Which is the most likely candidate?
  - Ranking of candidates to show top candidates first
  - Support for automated spelling correction

➜ Noisy Channel Model

Idea: Assign each candidate a probability

Noisy Channel Model — Intuition



Decoding: Observing error x, can we predict correct word w?

Noisy Channel Model — Bayesian Inferencing

Given an observation x of a misspelled word,

find the correct word w:

$$\widehat{w} = \underset{w \in V}{\operatorname{argmax}}\ P(w|x)$$

$$\widehat{w} = \underset{w \in V}{\operatorname{argmax}}\ \frac{P(x|w)P(w)}{P(x)}$$

$$\widehat{w} = \underset{w \in V}{\operatorname{argmax}}\ P(x|w)P(w)$$

➜ How to calculate $P(x|w)$ and $P(w)$?

Quick refresher: Bayes' Theorem

$$P(A, B) = P(A|B)P(B)$$

$$P(A, B) = P(B|A)P(A)$$

➜ $P(A|B)P(B) = P(B|A)P(A)$

➜ $P(A|B) = \dfrac{P(B|A)P(A)}{P(B)}$

Noisy Channel Model — Calculating/Estimating $P(w)$

- Approach using Maximum Likelihood Estimate (MLE)
  - Required: Large text corpus with N words
  - Calculate/estimate $P(w)$ with $P(w) = \dfrac{freq(w)}{N}$

- Example
  - 100 MB Wikipedia dump
  - Total of 14.4M+ words

w	*freq(w)*	*P(w)*
actress	1,135	0.0000784
cress	1	0.00000…
caress	3	0.00000…
access	1,670	0.0001153
across	1,756	0.0001213
acres	177	0.0000122

Note: The frequencies can widely different across different corpora (e.g. Wikipedia articles vs. English Literature).

Noisy Channel Model — Calculating/Estimating $P(x|w)$

- In general, $P(x|w)$ almost impossible to predict
  - Predictions depends on arbitrary factors
    (e.g., proficiency of typist, lighting conditions, input device)

- Estimate $P(x|w)$ based on simplifying assumptions (Kernighan et al., 1990)
  - Most misspelled words in typewritten text are single-error
  - Consider only single-error misspellings: **Insertion**, **Deletion**, **Substitution**, **Transposition**

Noisy Channel Model — Calculating/Estimating $P(x|w)$

- Definition of 4 confusion matrices (1 for each single-error type)
  - Each confusion matrix lists the number of times one "thing" was confused with another
  - e.g., for substitution, an entry represents the number of times one letter was incorrectly used

- Underlying definitions for generate confusion matrices

$ins[x, y]$	number of times x was typed as xy
$del[x, y]$	number of times xy was typed as x
$sub[x, y]$	number of times x is substituted for y
$trans[x, y]$	number of times xy was typed as yx
$count[x]$	number of times that x appeared in the training set
$count[x, y]$	number of times that xy appeared in the training set

$$x, y \in \{a, b, c, ..., z\}$$

Noisy Channel Model — Calculating/Estimating $P(x|w)$

$$P(x|w) = \begin{cases} \dfrac{ins[w_{i-1},x_i]}{count[w_i]} & \text{, if insertion} \\ \dfrac{del[w_{i-1},w_i]}{count[w_{i-1},w_i]} & \text{, if deletion} \\ \dfrac{sub[x_i,w_i]}{count[w_i]} & \text{, if substitution} \\ \dfrac{trans[w_i,w_{i+1}]}{count[w_i,w_{i+1}]} & \text{, if transposition} \end{cases}$$

w_i = i-th character in the correct word w

x_i = i-th character in the misspelled word x

Noisy Channel Model — Calculating/Estimating $P(x|w)$

sub[X, Y] = Substitution of X (incorrect) for Y (correct)

X \ 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	0
b	0	0	9	9	2	2	3	1	0	0	0	5	11	5	0	10	0	0	2	1	0	0	8	0	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	4	0	2	0
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	11	11	9	2	0	0	0	1	1	3	0	0	2	1	3	5	13	21	0	0	1	0	3	0
h	1	8	0	3	0	0	0	0	0	0	2	0	12	14	2	3	0	3	1	11	0	0	2	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	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	4	0	0	3
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	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	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	0	2	43	0	0	4	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	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	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	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	0

Source: A Spelling Correction Program Based on a Noisy Channel Model (Kernighan et al., 1990)

Noisy Channel Model — Example

- Noisy channel probabilities for *"acress"*

Candidate Correction	Correct Letter	Error Letter	x|w	P(x|w)	P(w)	10^9*P(x|w)P(w)	%
actress	t		c|ct	.000117	.0000231	2.7	35.9
cress		a	a|#	.00000144	.00000054	.00078	~0
caress	ca	ac	ac|ca	.00000164	.00000170	.0028	~0
access	c	r	r|c	.00000021	.0000916	.019	~0
across	**o**	**e**	**e|o**	**.0000093**	**.000299**	**2.8**	**37.2**
acres		s	es|e	.0000321	.0000318	1.0	13.3
acres		s	ss|s	.0000342	.0000318	1.0	13.3

➜ Choice of candidate for correction: *across*

Noisy Channel Model — Discussion

- Basic limitation: No consideration of additional context
  - Model only applicable for non-word errors
  - Basic model will always suggest "across" to correct "acress"

"The role was played by an ***acress*** *famous for her comedic timing."*

"actress" here the better candidate

➜ **Language Models** (next lecture)

Summary

- RegEx — fundamental and useful tool

- Text Preprocessing — getting your data ready for analysis
  - Tokenization
  - Stemming / Lemmatization
  - Normalization

  typical very task-dependent!

- Error Handling (so far)
  - Focus on single-error misspellings
  - Focus on isolated-word error correction

  already very non-trivial!

Outlook for Next Week: Language Models

Image from Da Nina @ Unsplash

Pre-Lecture Activity for Next Week