NUS | Computing
National University of Singapore

CS4248: Natural Language Processing

Lecture 2 — Strings & Words

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

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:
  ~ ! @ # $ % ^ & * _ - + = ` | \ ( ) { } [ ] : ; " ' < > , . ? /

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

word boundary

```
(\b([a-zA-Z])\w*\2\b)
```

1 letter

0..* letters, digits, or underscores

Backreference to the 2nd group (➜ must be 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.

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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

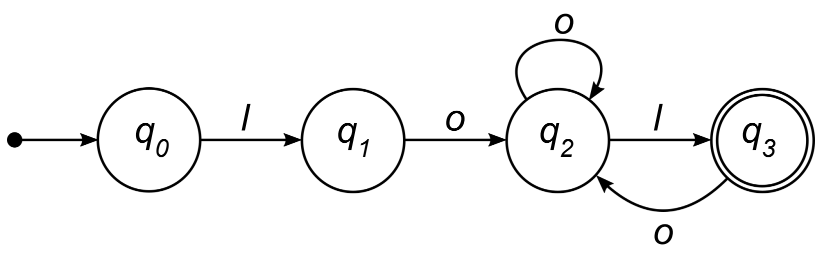
Regular Expression

l(o+l)+

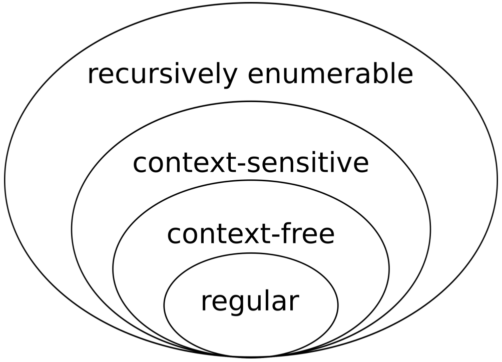
Regular Language

{lol, loool, lolol, looolol, …}

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



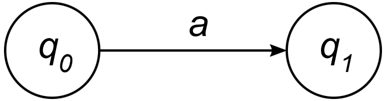
Chomsky Hierarchy
(Source: Wikipedia)



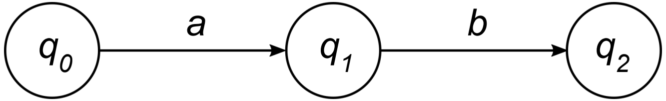
Relationship to Finite State Automata

- Basic equivalences

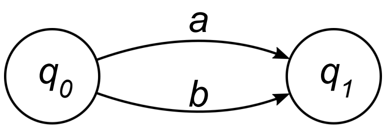
a



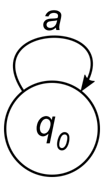
ab



a | b

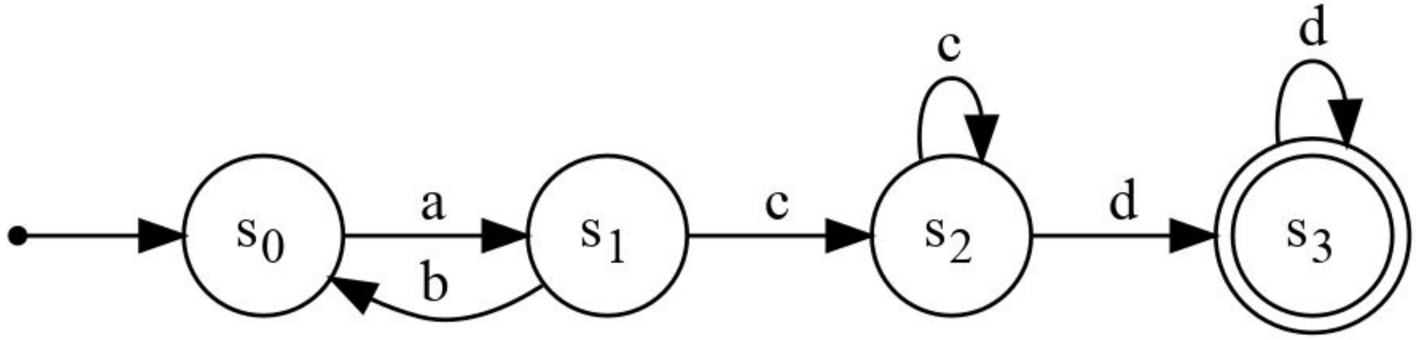


a*



In-Lecture Activity (10 mins)

- Task: Find a RegEx describing the FSA below
  - Post your RegEx to Canvas > Discussions
    (individually or as a group; include all group members' names in the post)
  - Optional: There are more than one correct answer ➜ Why?



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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 <u>not</u> have matched
(e.g., *other*, *theology*, *weather*, *bathe*, *mother*) → **False Positives** (Type I Errors)

<u>Not</u> 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)

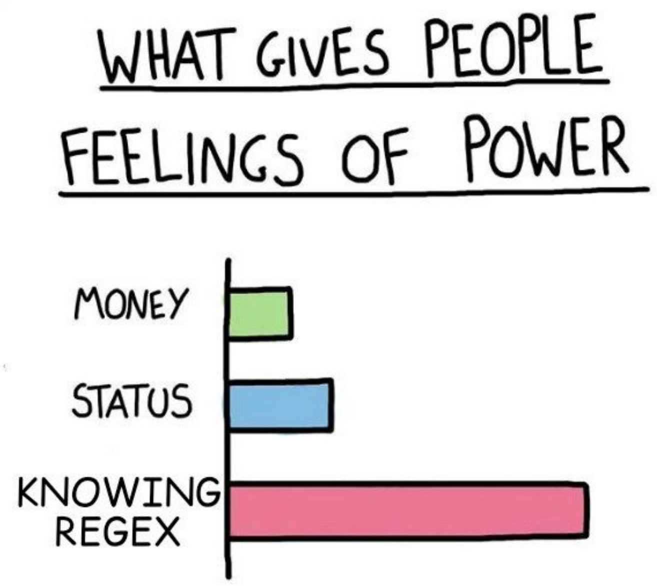
- Reducing errors
  - Both error types not always equally bad ($\overbrace{\text{infected person tests negative}}^{\textbf{false negative}}$ vs. $\overbrace{\text{healthy person test positive}}^{\textbf{false positive}}$)
  - Reducing False Positives and False Negatives often in conflict
    (reducing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



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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")
- 3 basic approaches

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

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.*

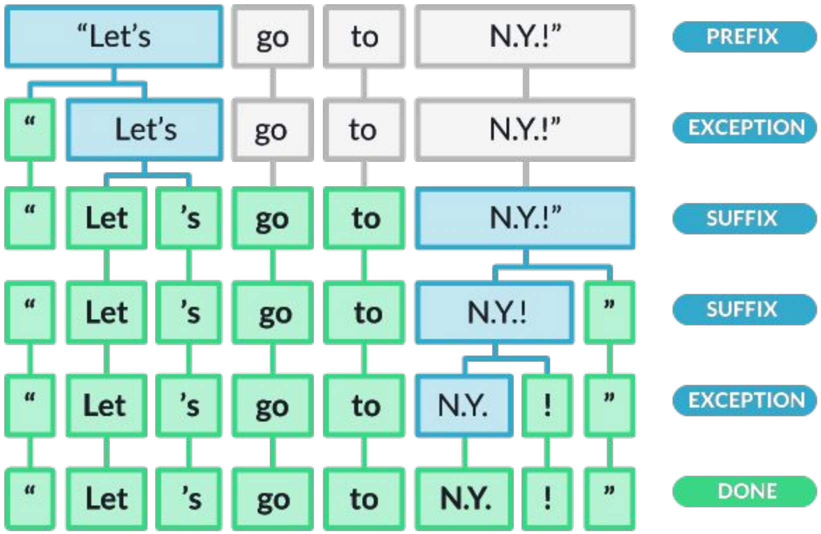
Tokenization — It Quickly Gets Tricky

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:

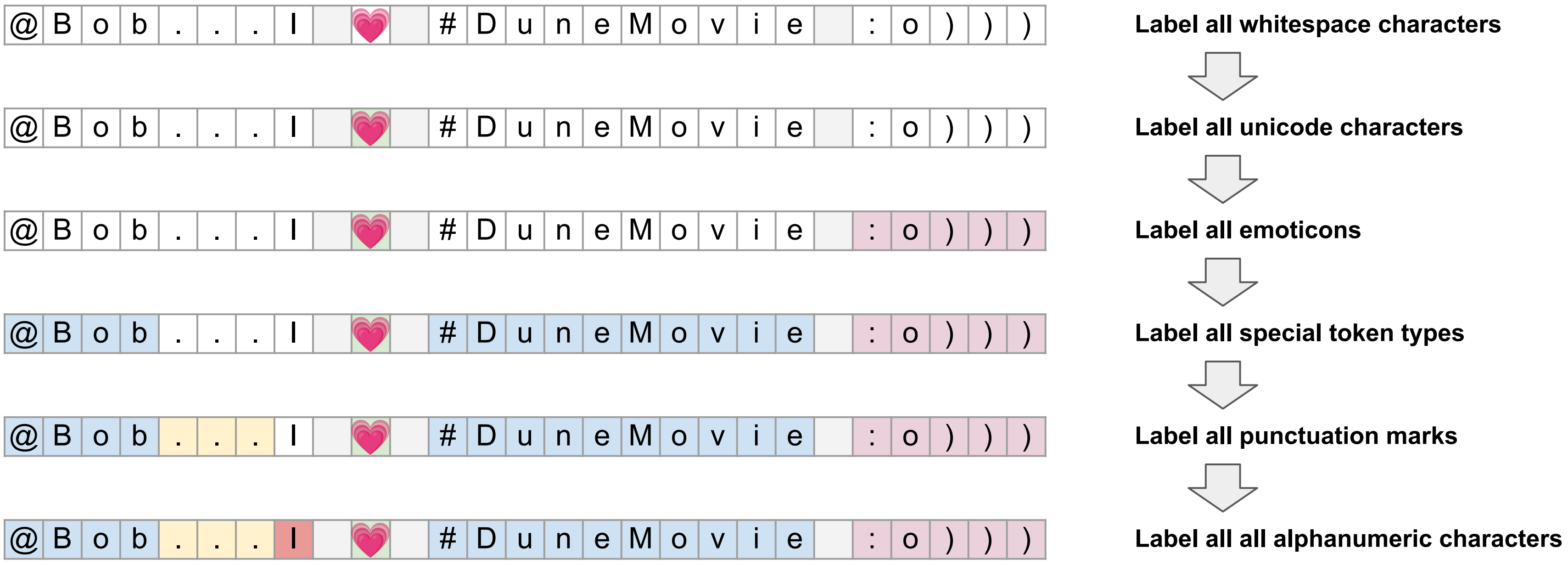
- Does substring match an exception rule?
  (e.g., *"don't"* → *"do"*, *"n't"*, but keep *"U.K."*)
- Can a prefix, suffix or infix be split of?
  (e.g., commas, periods, quotes, hyphens)

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



➜ Tokens = Substrings with adjacent characters with the same labels

Tokenization — Language Issues

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

direct article

indicates imperative

l'ensemble

donne-moi

"the whole" / "all"

"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

- multiple syllabaries
- multiple formats for dates and amounts

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**

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

莎拉波娃现在居住在美国东南部的佛罗里达

Sharapova

莎拉波娃 | 现在居住在美国东南部的佛罗里达

莎拉波娃 | **现在**居住在美国东南部的佛罗里达

now

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

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

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

(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*

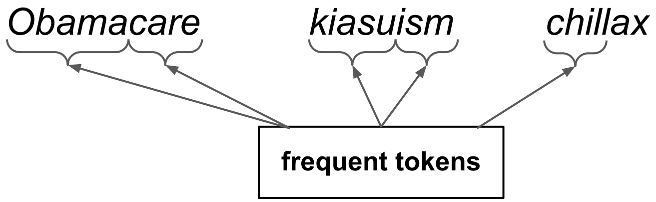
Tokenization — Subword-Based

- 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:



➜ **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', '_'*})

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 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

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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

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

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

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!

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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

Which preprocessing step would negatively affect **sentiment analysis** most obviously (arguably)?

A Case-folding

B Stemming

C Lemmatization

D Stop word removal

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

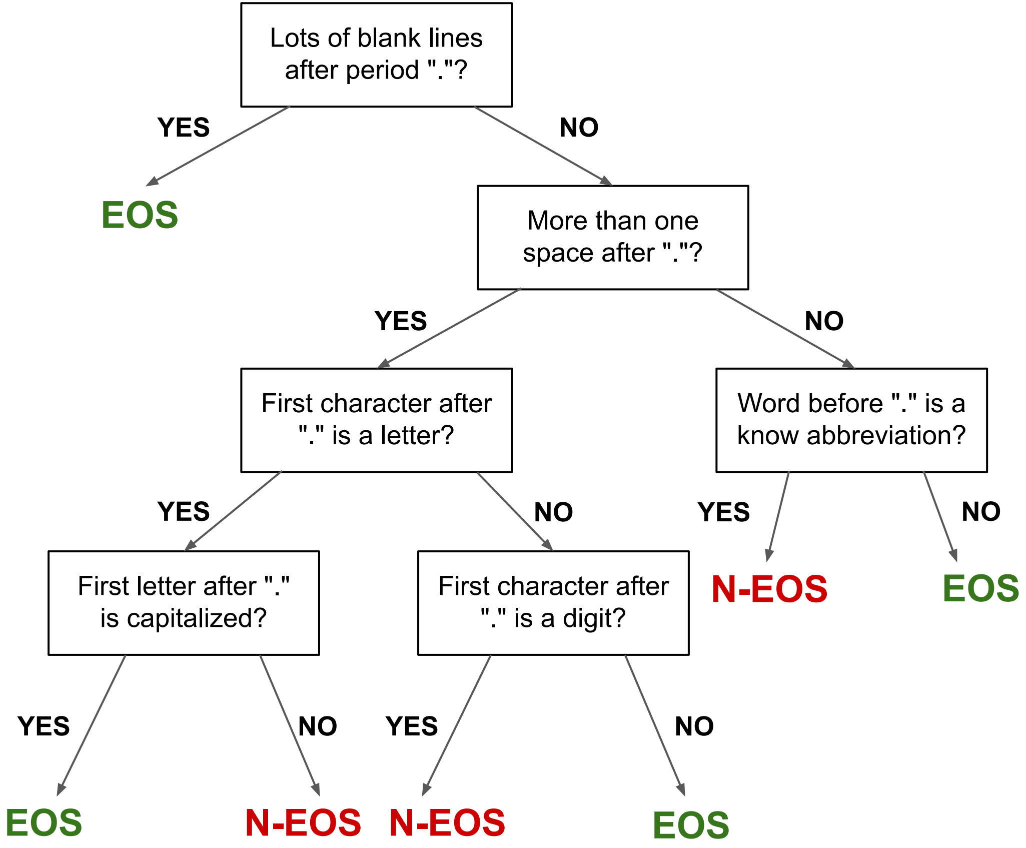
  Example RegEx: `(?<!\w\.\w.)(?<![A-Z][a-z]\.)(?<=\.|\?)\s`
  (Source: Stackoverflow)

- 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.

Outline

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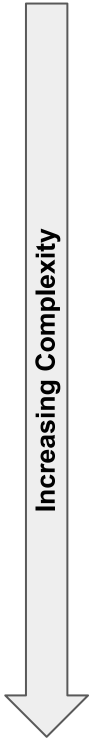
Spelling Errors



1. Non-word error detections

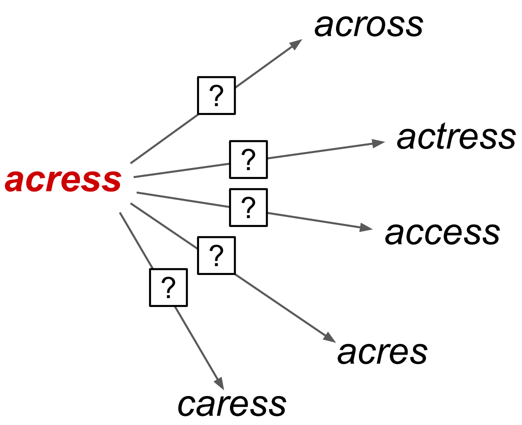
- Basically, word is not found in dictionary
- Example: detecting *graffe* (misspelling of giraffe)

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
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- **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:

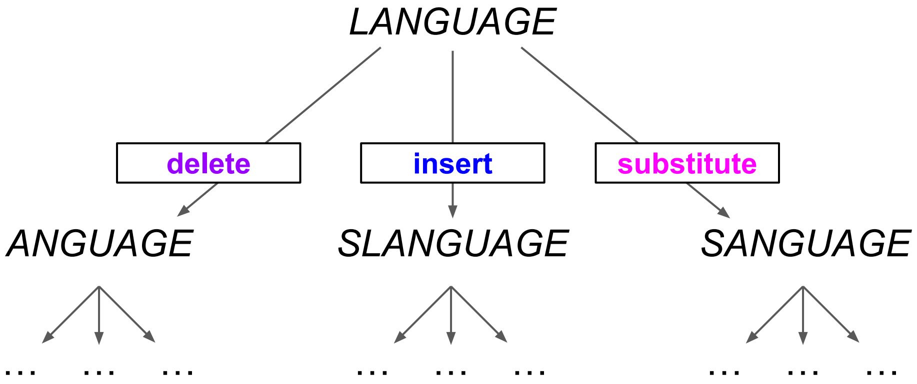
L	**A**	**N**	**G**	**U**	*****	**A**	**G**	**E**
|	|	|	|	|	|	|	|	|
S	**A**	*****	*****	**U**	**S**	**A**	**G**	**E**

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

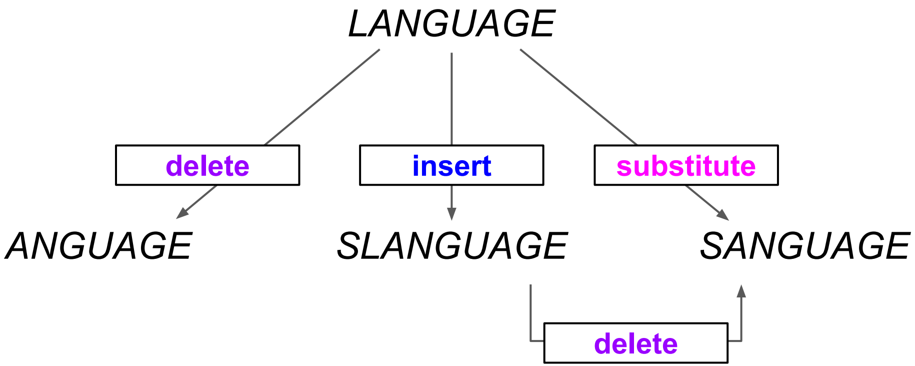


➜ Potentially huge search space

➜ 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

first *i* chars of *X*

first *j* chars of *Y*

- Define $D(i, j)$ as MED between $X[0..i]$ and $Y[0..j]$

➜ MED between X and Y 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:

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

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?

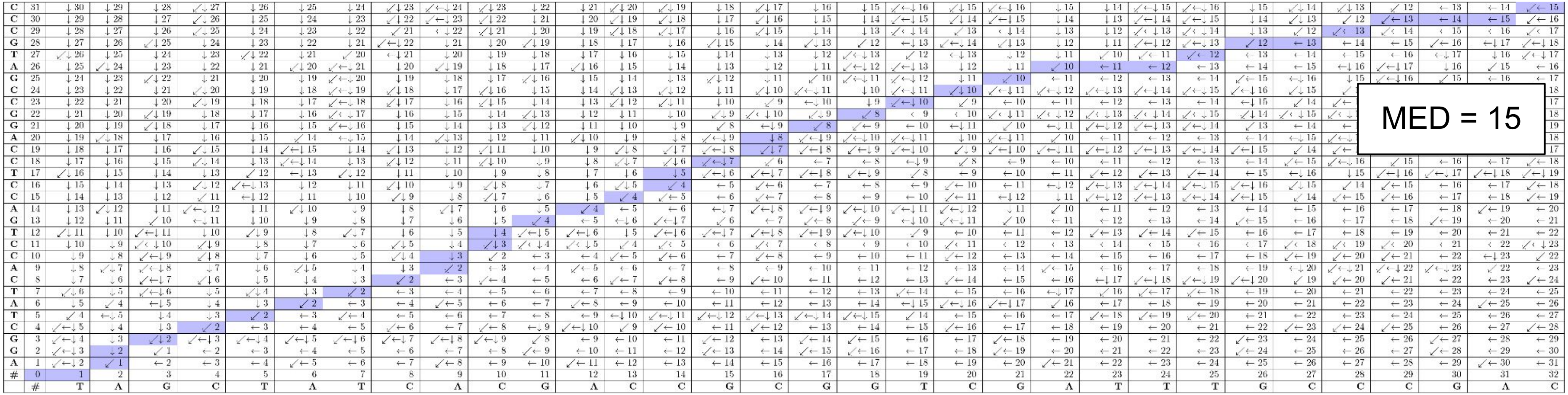
Complexity analysis

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 (10 mins)

- Task: Compute the MED and alignment between "NUS" and "TRUST"
  - Post your MED (Levenshtein) and alignment to Canvas > Discussions
    (individually or as a group – add all group members' names to the post)

S	3					
U	2					
N	1					
#	0	1	2	3	4	5
	#	T	R	U	S	T

- Try to complete the table for this task
  (probably not needed as the words are very short)
- Some of you can share their solution

Example alignment (but bad one!)

```
NUS*****
***TRUST
```

In-Lecture Activity (10 mins)

- Solution

S	3	↙←↓ 4	↙←↓ 5	↓ 4	↙ 3	← 4
U	2	↙←↓ 3	↙←↓ 4	↙ 3	← 4	← 5
N	1	↙←↓ 2	↙←↓ 3	↙←↓ 4	↙←↓ 5	↙←↓ 6
#	0	1	2	3	4	5
	#	T	R	U	S	T

* N U S *

| | | | |

T R U S T

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 — 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
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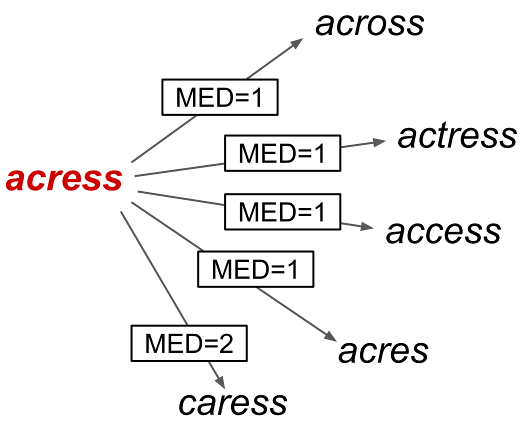
  - Stemming / Lemmatization
  - Segmentation
- **Word error handling**
  - Spelling Errors
  - Minimum Edit Distance
  - **Noisy Channel Model**

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*)

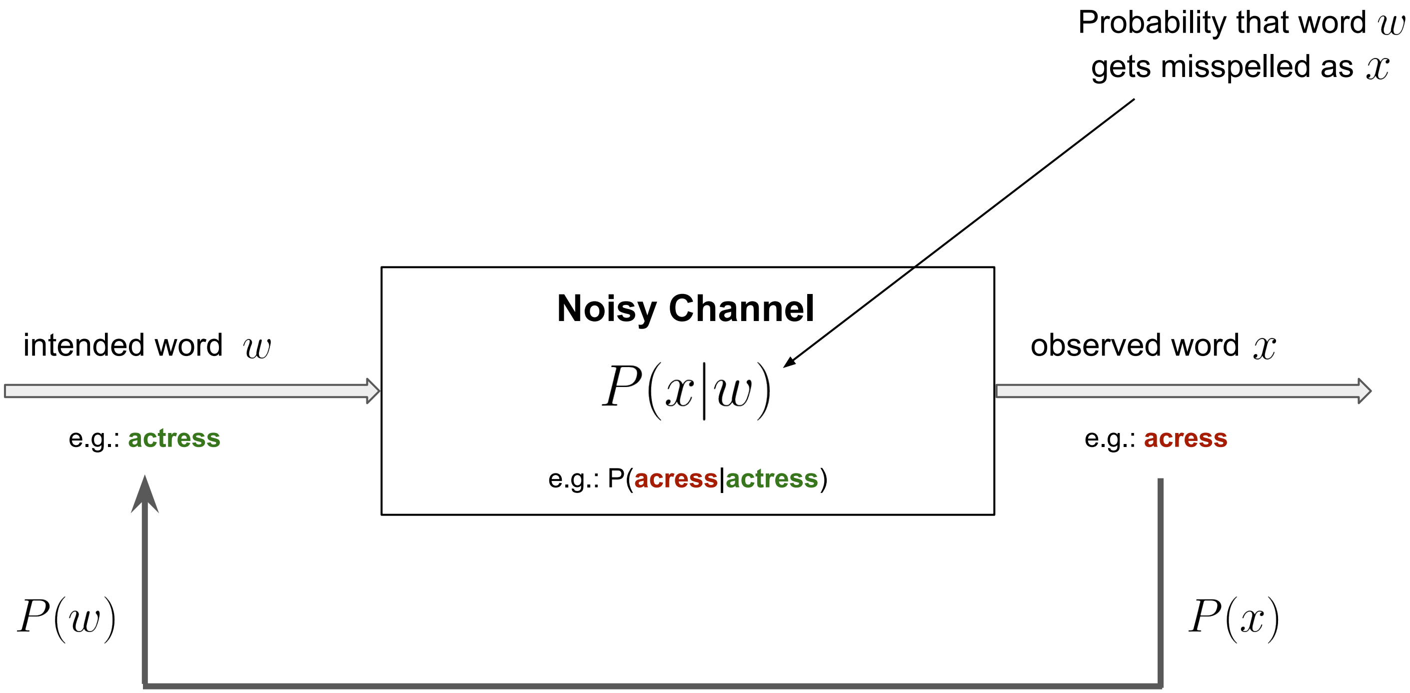


- Still missing: Which is the most likely candidate?
  - Ranking of candidates to show top candidates first
  - Support for automated spelling correction

➜ 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 $P(x|w)$

$$P(x|w) = \begin{cases} \dfrac{ins[w_{i-1}, x_i]}{count[w_i]} & \text{, if insertion} \\[2ex] \dfrac{del[w_{i-1}, w_i]}{count[w_{i-1}, w_i]} & \text{, if deletion} \\[2ex] \dfrac{sub[x_i, w_i]}{count[w_i]} & \text{, if substitution} \\[2ex] \dfrac{trans[w_i, w_{i+1}]}{count[w_i, w_{i+1}]} & \text{, if transposition} \end{cases}$$

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)

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

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!

Pre-Lecture Activity for Next Week

- Assigned Task
    - Post a 1-2 sentence answer to the following question into the Canvas Discussion
      (you will find the thread on Canvas > Discussions)

"What do we mean when we talk about the probability of a sentence?"

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 his won't help you learn better

Solutions to Quick Quizzes

- Slide 9
  - The given RegEx is very simple and would match substrings that are not email addresses
  - Examples: a@b, …@---
- Slide 10
  - The outer group is not needed and can be removed
  - However, we then need to change the numbering: `\b([a-zA-Z])\w*\1\b`
- Slide 18
  - For example: `\b[Tt]he\b` or `\b(the|The)\b`
  - Note that this would fail to match "THE" which might or might not be a good thing
- Slide 24
  - Words/tokens are generally separated by whitespace characters
  - OK-ish assumption for English but not for many other languages

Solutions to Quick Quizzes

- Slide 34
  - k=0 ➜ BPE "degenerates" to character-based tokenization
  - k=∞ ➜ BPE "degenerates" to word-based tokenization
- Slide 52: D
  - Words such as *"not"*, *"n't"*, *"never"*, etc. are typically considered stop words
  - However, these word often flip the sentiment polarity, e.g., *"I'm happy."* vs *"I'm not happy."*
- Slide 55
  - Obvious cases: unknown abbreviations (maybe *"etc."*)
  - More informal writing style, e.g., using ellipses: *"I think…well…the movie was good."*
- Slide 69
  - Choosing the "diagonal path" yields the shortest alignment (typically preferred)