Text Preprocessing

COMP90042

Natural Language Processing

Lecture 2

Semester 1 2021 Week 1

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Why are you interested in NLP?

"I want to know how we a d why are processing all the unstructured data / text from basic"

"salary"

"advanced"

"MLB"

"Sexy"

"in need"

"career"

"Intend to do a project with heavy NLP focus"

"linguistics is life"

"MLB"

"Sexy"

"Research Project"

"love language and tech"

Definitions

- Words
  - Sequence of characters with a meaning and/or function
- Sentence
  - “The student is enrolled at the University of Melbourne.”
- Document: one or more sentences.
- Corpus: a collection of documents.
- Word token: each *instance* of a word.
  - E.g. 9 word tokens in the example sentence.
- Word type: *distinct* words.
  - Lexicon (“dictionary”): a group of word types.
  - E.g. 8 word types in the example sentence.

How many words (types) are there in English?

- < 10K
- < 50K
- < 100K
- < 500K
- ???

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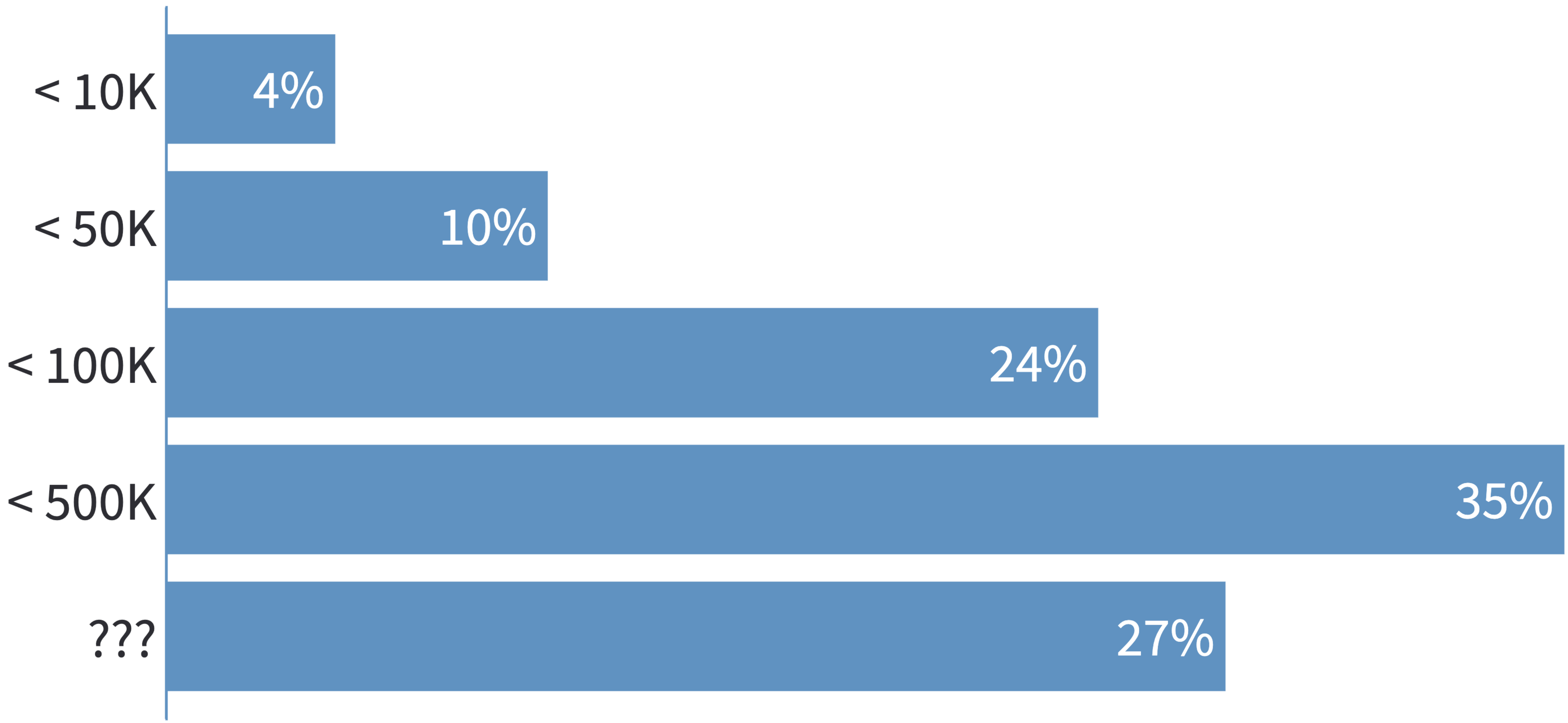
How many words (types) are there in English?



How Many Unique Words?

	#Tokens (N)	#Type (|V|)
Switchboard phone conversation	2.4 million	20 thousand
Shakespeare	800 thousand	31 thousand
Google N-gram	1 trillion	13 million

Church and Gale (1990): $|V| > O(N^{1/2})$

Why Preprocess?

- Most NLP applications have documents as inputs:
  - “This movie is so great!!! U should definitely watch it in the theater! Best sci-fi eva!” → 😀
  - “Eu estive em Melbourne no ano passado.” → “I was in Melbourne last year.”
- **Key point:** language is compositional. As humans, we can break these documents into individual components. To understand language, a computer should do the same.
- **Preprocessing** is the first step.

Preprocessing Steps

1. Remove unwanted formatting (e.g. HTML)
2. **Sentence segmentation**: break documents into sentences
3. **Word tokenisation**: break sentences into words
4. **Word normalisation**: transform words into canonical forms
5. **Stopword removal**: delete unwanted words

“<p> Hi there. I’m TARS. </p>”

“Hi there. I’m TARS.”

[“Hi there.”, “I’m TARS.”]

[[“Hi”, “there”, “.”], [“I”, “’m”, “TARS”, “.”]]

[[“hi”, “there”, “.”], [“i”, “am”, “tars”, “.”]]

[[],[“tars”]]

Sentence Segmentation

“Hi there. I’m TARS.” → [“Hi there.”, “I’m TARS.”]

Sentence Segmentation

- Naïve approach: break on sentence punctuation ([.?!])
  - But periods are used for abbreviations! (U.S. dollar, …, Yahoo! as a word)
- Second try: use regex to require capital ([.?!] [A-Z])
  - But abbreviations often followed by names (Mr. Brown)
- Better yet: have lexicons
  - But difficult to enumerate all names and abbreviations
- State-of-the-art uses machine learning, not rules

Binary Classifier

- Looks at every “.” and decides whether it is the end of a sentence.
    - Decision trees, logistic regression
- Features
    - Look at the words before and after “.”
    - Word shapes:
        - Uppercase, lowercase, ALL_CAPS, number
        - Character length
    - Part-of-speech tags:
        - Determiners tend to start a sentence

Word Tokenisation

[“Hi there.”,
“I’m TARS.”] → [[“Hi”, “there”, “.”],
[“I”, “’m”, “TARS”, “.”]]

Word Tokenisation: English

- Naïve approach: separate out alphabetic strings (\w+)
- Abbreviations (*U.S.A.*)
- Hyphens (*merry-go-round vs. well-respected* vs. *yes-but*)
- Numbers (*1,000,00.01*)
- Dates (3/1/2016)
- Clitics (*n't* in *can't*)
- Internet language (http://www.google.com, #metoo, :-))
- Multiword units (New Zealand)

Word Tokenisation: Chinese

- Some Asian languages are written without spaces between words
- In Chinese, words often correspond to more than one character

墨大	的	学生	与众不同
Unimelb	’s	students (are)	special

Word Tokenisation: Chinese

- Standard approach assumes an existing vocabulary
- MaxMatch algorithm
  - Greedily match longest word in the vocabulary

V = {墨,大,的,学,生,与,众,不,同, 墨大,学生,不同,与众不同}

墨大的学生与众不同

match 墨大, move to 的
match 的, move to 学
match 学生, move to 与
match与众不同, done

Word Tokenisation: Chinese

- But how do we know what the vocabulary is
- And doesn’t always work

去	买	新西兰	花
go	buy	New Zealand	flowers

去	买	新	西兰花
go	buy	new	broccoli

Word Tokenisation: German

- *Lebensversicherungsgesellschaftsangestellter*
- = *life insurance company employee*
- Requires compound splitter

Subword Tokenisation

- *Colourless green ideas sleep furiously* → *[colour] [less] [green] [idea] [s] [sleep] [furious] [ly]*
- One popular algorithm: byte-pair encoding (BPE)
- Core idea: iteratively merge frequent pairs of characters
- Advantage:
    - Data-informed tokenisation
    - Works for different languages
    - Deals better with unknown words

Byte-Pair Encoding

- Corpus
  - [5] l o w _
  - [2] l o w e s t _
  - [6] n e w e r _
  - [3] w i d e r _
  - [2] n e w _
- Vocabulary
  - _, d, e, i, l, n, o, r, s, t, w

Byte-Pair Encoding

- Corpus
  - [5] l o w _
  - [2] l o w e s t _
  - [6] n e w e r_
  - [3] w i d e r_
  - [2] n e w _
- Vocabulary
  - _, d, e, i, l, n, o, r, s, t, w, r_

Byte-Pair Encoding

- Corpus
  - [5] l o w _
  - [2] l o w e s t _
  - [6] n e w er_
  - [3] w i d er_
  - [2] n e w _
- Vocabulary
  - _, d, e, i, l, n, o, r, s, t, w, r_, er_

Byte-Pair Encoding

- Corpus
  - [5] l o w _
  - [2] l o w e s t _
  - [6] n ew er_
  - [3] w i d er_
  - [2] n ew _
- Vocabulary
  - _, d, e, i, l, n, o, r, s, t, w, r_, er_, ew

Byte-Pair Encoding

- Corpus
  - [5] l o w _
  - [2] l o w e s t _
  - [6] new er_
  - [3] w i d er_
  - [2] new _
- Vocabulary
  - _, d, e, i, l, n, o, r, s, t, w, r_, er_, ew, new

Byte-Pair Encoding

- Vocabulary
  - _, d, e, i, l, n, o, r, s, t, w, r_, er_, ew, new
  - _, d, e, i, l, n, o, r, s, t, w, r_, er_, ew, new, lo
  - _, d, e, i, l, n, o, r, s, t, w, r_, er_, ew, new, lo, low
  - _, d, e, i, l, n, o, r, s, t, w, r_, er_, ew, new, lo, low, newer_
  - _, d, e, i, l, n, o, r, s, t, w, r_, er_, ew, new, lo, low, newer_, low_

Byte-Pair Encoding

- In practice BPE will run with thousands of merges, creating a large vocabulary
- Most frequent words will be represented as full words
- Rarer words will be broken into subwords
- In the worst case, unknown words in test data will be broken into individual letter

What are the disadvantages of subword tokenisation?

- Language-dependent
- Larger vocabulary
- Creates non-sensical subwords
- Unable to handle misspellings

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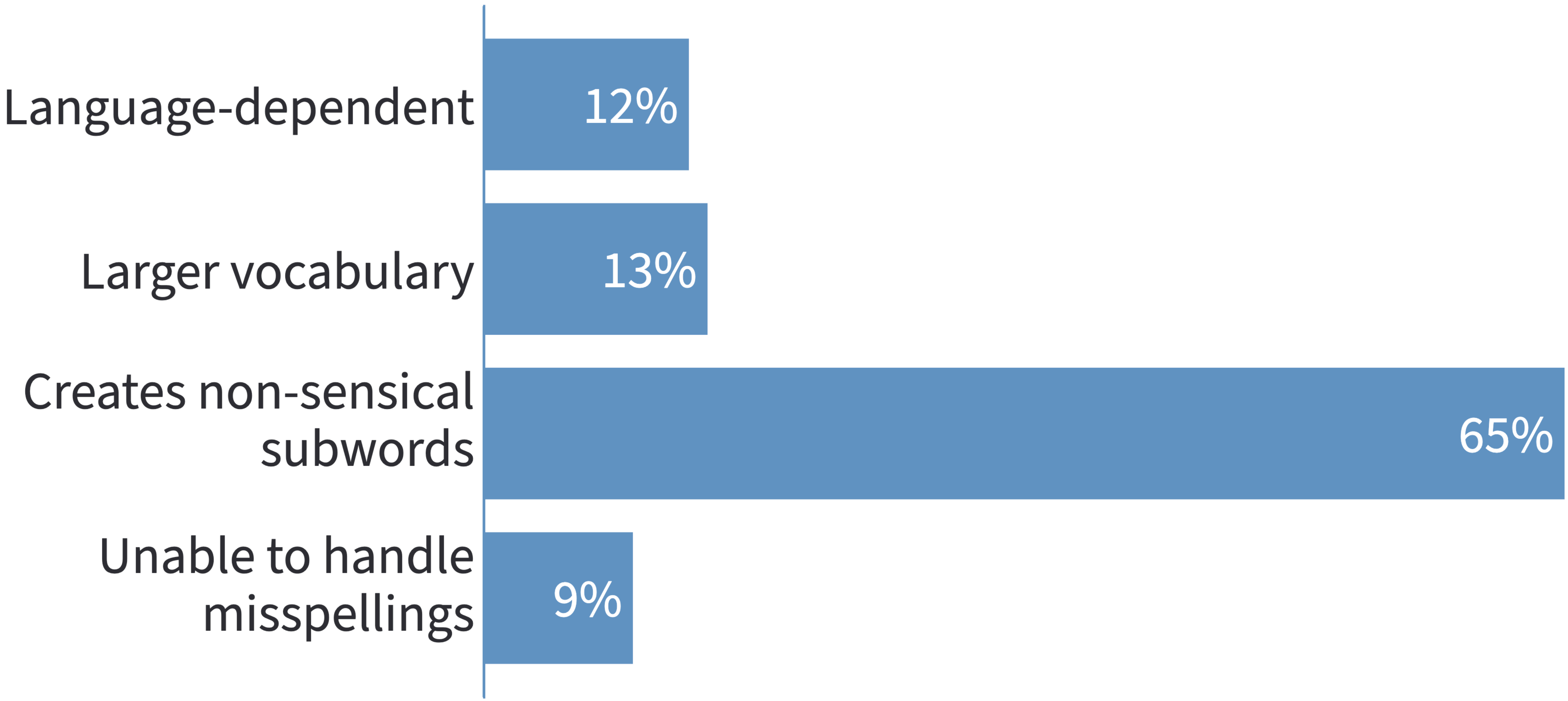
What are the disadvantages of subword tokenisation?



Word Normalisation

[["Hi", "there", "."],
["I", "'m", "TARS", "."]] $\longrightarrow$ [["hi", "there", "."],
["i", "am", "tars", "."]]

Word Normalisation

- Lower casing (Australia → australia)
- Removing morphology (cooking → cook)
- Correcting spelling (definately → definitely)
- Expanding abbreviations (U.S.A → USA)
- Goal:
  - Reduce vocabulary
  - Maps words into the same type

Inflectional Morphology

- Inflectional morphology creates grammatical variants
- English inflects nouns, verbs, and adjectives
  - Nouns: *number* of the noun (*-s*)
  - Verbs: *number* of the subject *(-s), the* *aspect* (*-ing*) of the action and the *tense (-ed*) of the action
  - Adjectives: *comparatives* (*-er*) and *superlatives* (*-est*)
- Many languages have much richer inflectional morphology than English
  - E.g. French inflects nouns for gender (*un chat*, *une chatte*)

Lemmatisation

- Lemmatisation means removing any inflection to reach the uninflected form, the *lemma*
  - speaking → speak
- In English, there are irregularities that prevent a trivial solution:
  - poked → poke (not pok)
  - stopping → stop (not stopp)
  - watches → watch (not watche)
  - was → be (not *wa*)
- A lexicon of lemmas needed for accurate lemmatisation

Derivational Morphology

- Derivational morphology creates distinct words
- English derivational *suffixes* often change the lexical category, e.g.
  - -ly (personal → personally)
  - -ise (final → finalise)
  - -er (write → writer)
- English derivational *prefixes* often change the meaning without changing the lexical category
  - write → rewrite
  - healthy → unhealthy

Stemming

- Stemming strips off all suffixes, leaving a *stem*
  - E.g. automate, automatic, automation → automat
  - Often not an actual lexical item
- Even less lexical sparsity than lemmatisation
- Popular in information retrieval
- Stem not always interpretable

The Porter Stemmer

- Most popular stemmer for English
- Applies rewrite rules in stages
  - First strip inflectional suffixes,
    - E.g. *-ies* → *-i*
  - Then derivational suffixes
    - E.g *-isation* → *-ise* → *-i*

The Porter Stemmer

- c (lowercase) = consonant; e.g. ‘b’, ‘c’, ‘d’
- v (lowercase) = vowel; e.g. ‘a’, ‘e’, ‘i’, ‘o’, ‘u’
- C = a sequence of consonants
  - s, ss, tr, bl
- V = a sequence of vowels
  - o, oo, ee, io

The Porter Stemmer

- A word has one of the four forms:
  - CVCV … C
  - CVCV … V
  - VCVC … C
  - VCVC … V
- Which can be represented as:
  - [C]VCVC … [V]
  - [C] $(VC)^m$ [V]
  - m = measure

$[C]\ (VC)^m\ [V]$

- TREE
  - $= CV$
  - $= C(VC)^0V$
  - $[m=0]$
- TREES
  - $= CVC$
  - $= C(VC)^1$
  - $[m=1]$
- TROUBLES
  - $= CVCVC$
  - $= C(VC)^2$
  - $[m=2]$

Examples

- m=0: TR, EE, TREE, Y, BY
- m=1: TROUBLE, OATS, TREES, IVY
- m=2: TROUBLES, PRIVATE, OATEN, ORRERY

The Porter Stemmer

- Rules format: (condition) S1 → S2
- e.g. (m > 1) EMENT → null
  - REPLACEMENT
  - → REPLAC

CVCVC = $C(VC)^2$ = [m=2]

- Always use the longest matching S1
  - CARESSES → CARESS
  - CARESS → CARESS
  - CARES → CARE

Rules:
SSES → SS
IES → I
SS → SS
S → null

The Porter Stemmer

- Step 1: plurals and inflectional morphology

	Rule	Positive Example	Negative Example
a	SSES → SS	caresses → caress	
	IES → I	ponies → poni	
	SS → SS	caress → caress	
	S → null	cats → cat	$(VC)^1$ $C(VC)^0$
b	(m>0) EED → EE	agreed → agree	feed → feed
	(*v*) ED → null *v* = stem has vowel	plastered → plaster	bled → bled
	(*v*) ING →	motoring → motor	sing → sing
b+	AT → ATE	conflat(ed) → conflate	
c	(*v*) Y → I	happy → happi	

The Porter Stemmer

- Step 2, 3, 4: derivational inflections

	Rule	Positive Example
2	(m>0) ATIONAL → ATE	relational → relate
	(m>0) TIONAL → TION	conditional → condition
	(m>0) ENCI → ENCE	valenci → valence
	(m>0) ANCI → ANCE	hesitanci → hesitance
3	(m>0) ICATE → IC	triplicate → triplic
	(m>0) ATIVE → null	formative → form
	(m>0) ALIZE → AL	formalize → formal
4	(m>1) AL → null	revival → reviv
	(m>1) ER → null	airliner → airlin
	(m>1) ATE → null	activate → activ

The Porter Stemmer

- Step 5: tidying up

	Rule	Positive Example
5	(m>1) E → null	probate → probat
	(m>1 and *d and *L) null → single letter *d = stem ends with double consonant (e.g. -TT) *L = stem ends with 'l'	controll → control

The Porter Stemmer

- computational → comput
  - step 2: ATIONAL → ATE: computate
  - step 4: ATE → null: comput
- computer → comput
  - step 4: ER → null: comput

Fixing Spelling Errors

- Why fix them?
  - Spelling errors create new, rare types
  - Disrupt various kinds of linguistic analysis
  - Very common in internet corpora
  - In web search, particularly important in queries
- How?
  - String distance (Levenshtein, etc.)
  - Modelling of error types (phonetic, typing etc.)
  - Use an *n*-gram language model (next lecture!)

Other Word Normalisation

- Normalising spelling variations
  - Normalize → Normalise (or vice versa)
  - U r so coool! → *you are so cool*
- Expanding abbreviations
  - US, U.S. → United States
  - imho → in my humble opinion

Stopword Removal

[["hi", "there", "."],
 ["i", "am", "tars", "."]] → [[],["tars"]]

Stop Words

- Definition: a list of words to be removed from the document
  - Typical in bag-of-word (BOW) representations
  - Not appropriate when sequence is important
- How to choose them?
  - All *closed-class* or *function* words
    - E.g. *the, a, of, for, he, …*
  - Any high frequency words
  - NLTK, spaCy NLP toolkits

A Final Word

- Preprocessing unavoidable in text analysis
- Can have a major effect on downstream applications
- Exact steps may vary depending on corpus, task
- Simple rule-based systems work well, but rarely perfectly
- Language-dependent

Further Reading

- J&M3 Ch 2.4
- Details on the Porter Stemmer algorithm http://snowball.tartarus.org/algorithms/porter/stemmer.html