Natural Language Processing

Lecture 3 : Text Normalization

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Lecture based on material originally developed by :
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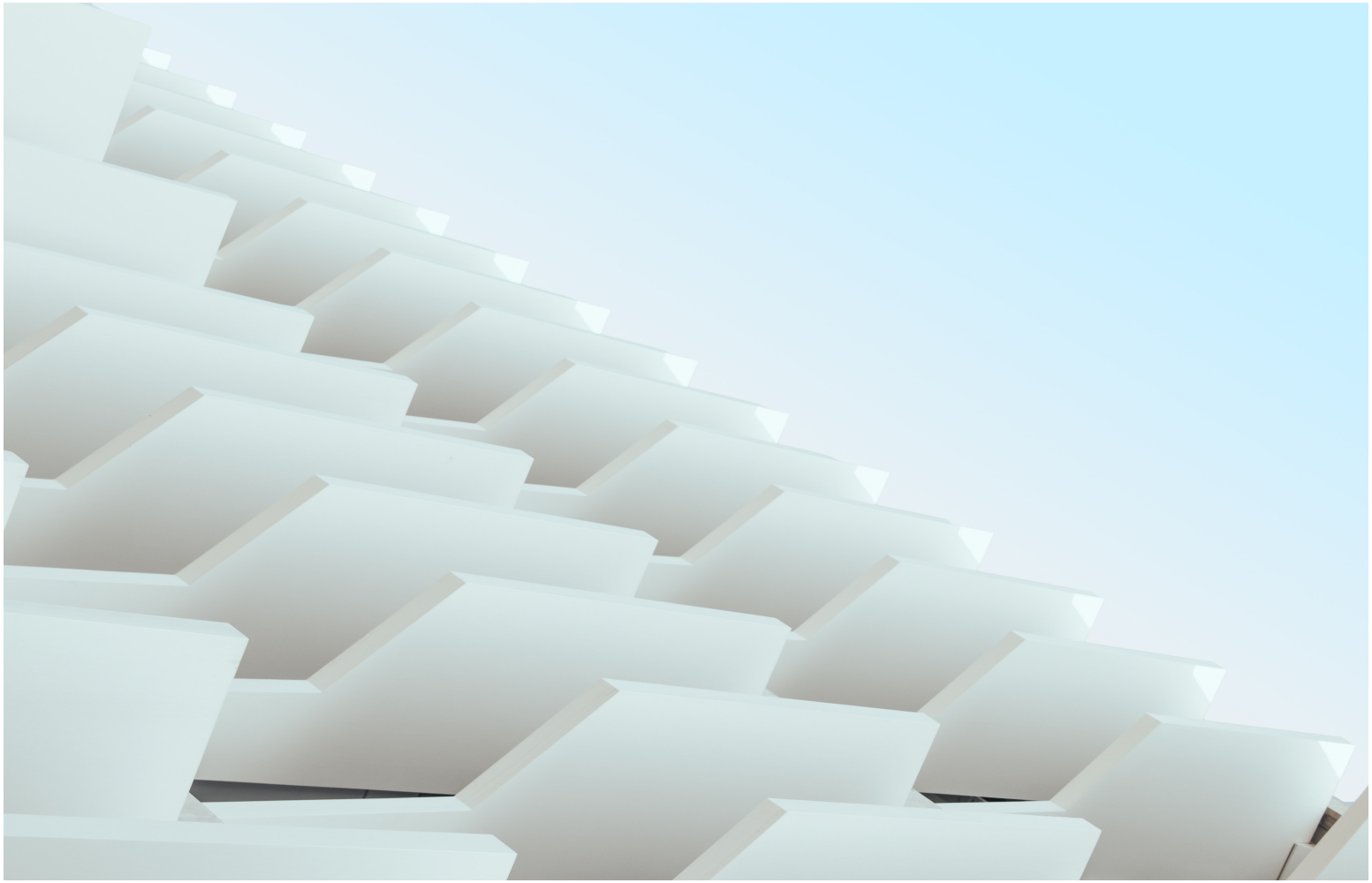
Regular expressions



Jordi Moncasi on Unsplash

Regular expressions

Cleaning up a text data set requires the use of specialized **regular expressions**.

Most programming languages have facilities for

- compiling regular expressions into efficient finite automata
- running these automata on input text

Regular expressions come in many variants. We describe here the so-called **extended** regular expressions.

Different regular expression parsers may treat some expressions slightly differently.

Search

/d/ matches **d** in **woodchuck**.

/a/ does not match anything in **woodchuck**.

/ck/ matches the last two letters in **woodchuck**.

Sets of characters

`/[abc]/` matches **a**, **b** or **c**.

`/[^abc]/` matches any character other than **a**, **b** and **c**.

`/[a-z]/` matches any character from **a** to **z**.

`/./` matches any character; also called **wildcard**.

Aliases

`\d` stands for any **digit**; same as `[0-9]`.

`\D` stands for any **character** other than a **digit**; same as `[^0-9]`.

`\w` stands for any **alphanumeric** or **underscore**.

`\W` converse of above.

`\s` stands for any **whitespace** character.

`\S` converse of above.

`\.` stands for **period**.

`\n` stands for **newline**.

Repetition

`/\d{2,5}/` matches between 2 and 5 **digits**.

`/\d{3,}/` matches 3 or more **digits**.

`/\d{4}\w?/` matches exactly 4 **digits** and one optional **alphanumeric** or **underscore**.

`/[a-z]+/` matches one or more **lowercase letters** (positive closure).

`/\s+java\s+/` matches **java** with one or more **whitespace** characters before and after.

`/[^\+]*/` matches zero or more **characters** other than + (Kleene star).

Longest match

Tools generally return the **leftmost** occurrence of a match in text.

Example : `/\$\d+/` returns **$4** rather than **$6** in string **How many is $4 plus $6?**

By POSIX (Portable Operating System Interface, IEEE standard) the returned substring should be the **longest** match.

Example : `/\d+/` returns **64000** in **The $64000 question**, rather than **6** or **64** or **640**, etc.

Regrettably, many tools are not POSIX and some tools apply a 'greedy' search strategy.

Anchors

/^/ matches **beginning** of input string or line.

/$/ matches **end** of input string or line.

/\b/ matches word **boundary**.

/^The/ matches occurrence of **The** at the beginning of a string.

Example : /\bthe\b/ would not match any occurrence of **the** in word **other**, as there is no word boundary before **t** and after **e**.

Disjunctions and groups

`/the|any/` matches **the** or **any**.

`/gupp(y|ies)/` matches **guppy** or **guppies**.

Example : `/(^|[^a-zA-Z])[tT]he([^a-zA-Z]|$)/` matches any occurrences of **the** and **The** as isolated words.

Substitution & back-reference

We can replace matches of a regular expression by a given pattern using the **substitute** operator.

Example : `s/colour/color/` changes UK spelling to US spelling.

We can use matches of a regular expression through the **back-reference** operator.

Example : `s/([0-9]+)/<\1>/` where `\1` is replaced by contents of first parenthesis pair, so replace e.g. **a123b** by **a<123>b**.

Words

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Words and punctuation marks

We need to distinguish between **words** and **punctuation marks**.

Example :

> *He stepped out into the hall, was delighted to encounter a water brother.*

The above sentence has 13 words and 2 punctuation symbols.

Punctuation is critical

- for finding sentence boundaries (period, colon, etc.)
- for identifying some aspects of meaning (question mark, etc.).

Tokens vs. types

There are two ways of talking about words

- **types** are the **distinct** words appearing in a document
- **tokens** are the **individual** occurrences of words in a document

Example :

> *They picnicked by the pool, then lay back on the grass and looked at the stars.*

Ignoring punctuation marks, the above sentence has 16 tokens and 14 types.

Vocabulary

The set of all types in a corpus is the **vocabulary** V.

More about corpora in later slides.

The vocabulary size $|V|$ is the number of types in the corpus.

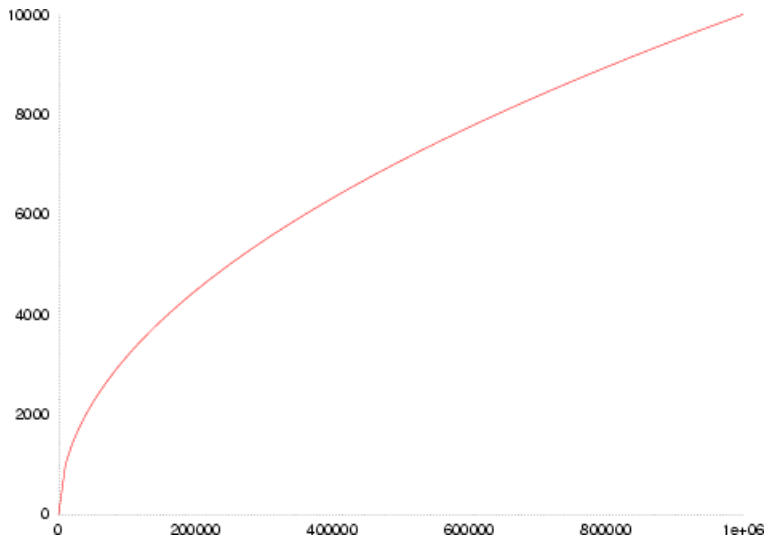
The size of the corpus N is the number of tokens, if we ignore punctuation marks.

Vocabulary

Example : N vs. $|V|$ for a few English corpora

Corpus	Tokens = N	Types = $\|V\|$
Shakespeare	884 thousand	31 thousand
Brown corpus	1 million	38 thousand
Switchboard telephone conversations	2.4 million	20 thousand
COCA	440 million	2 million
Google n-grams	1 trillion	13 million

Herdan/Heaps law

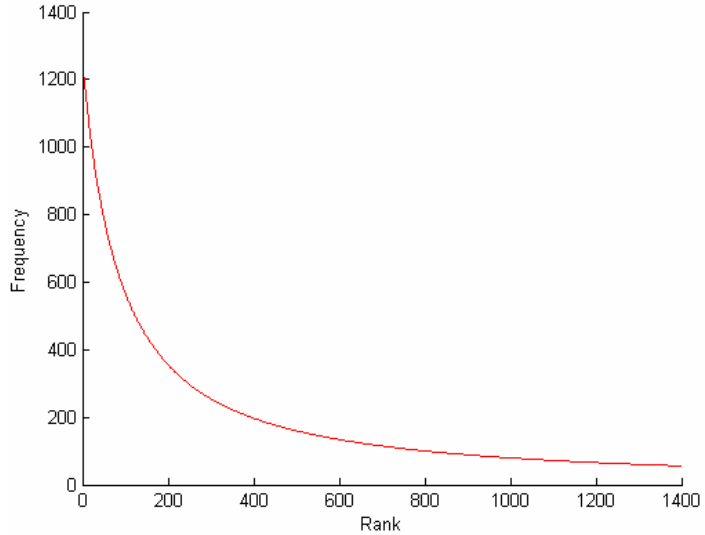


In very large corpora, the relation between N and $|V|$ can be expressed as

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

where $k \in [10, 100]$ and $\beta \in [0.4, 0.75]$.

Zipf/Mandelbrot law



In very large corpora, the r-th most frequent type has frequency $f(r)$ that scales according to

$$f(r) \quad \propto \quad \frac{1}{(r+\beta)^{\alpha}}$$

with $\alpha \simeq 1$ and $\beta \simeq 2.7$

Word-forms and lemmas

The **word-form** is the full inflected or derived form of the word.

Each word-form is associated with a single **lemma**, the citation form used in **dictionaries**.

Example : Word-forms **sing**, **sang**, **sung** are associated with the lemma **sing**.

Alternatively to $|V|$, another measure of the number of words in a corpus is the number of lemmas.

Multi-element word-forms

A word-form can be made of several separated elements
Example : English: San Francisco; French: *sine die* (from Latin).

A word-form can be made of several merged elements
Example : English: don't = do + not; Spanish: damélo = da + me + lo (give + to me + it).

There is no one-to-one correspondence between tokens and word-forms

Corpora

Corpora

Corpus (plural corpora): large collection of text, in computer-readable form.

Several dimensions of variation for corpora should be taken into account: language, genre, etc.

Language: It is important to test NLP algorithms on more than one language.

There is an unfortunate current tendency to developed corpora mainly for English.

Languages lacking large corpora are considered **low-resource languages**.

Corpora

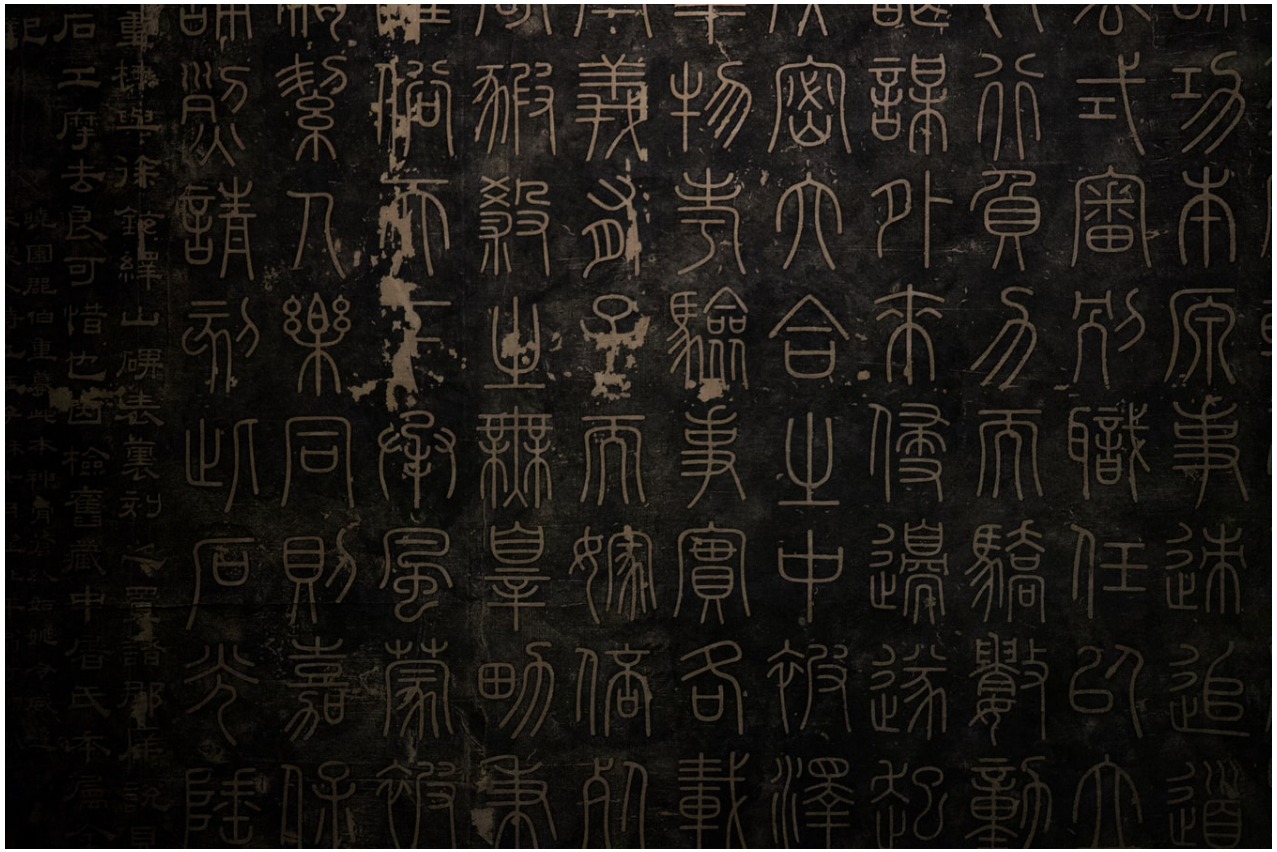
Genre: Text documents might come from newswire, fiction, scientific articles, Wikipedia, etc.

Time: Language changes over time. For some languages we have good corpora of texts from different historical periods.

Collection process: How big is the data and how was it sampled? How was the data pre-processed, and what metadata is available?

Annotation: What are the specifics of the used annotation? How was the data annotated? How were the annotators trained?

Text Normalization



Text Normalization

Text normalization is the process of transforming a text into some predefined standard form. This consists of several tasks.

There is **no all-purpose** normalization procedure: text normalization depends on

- what type of text is being normalized
- what type of NLP task needs to be carried out afterwards

Text normalization is also important for applications other than NLP, such as text mining and WEB search engines.

Text Normalization

In this lecture we briefly overview the most common tasks involved in text normalization

- language identification
- spell checking
- contraction
- punctuation
- special characters
- tokenization
- sentence segmentation
- case folding
- stop words
- stemming
- lemmatization

Ordering of the above modules is important. Some modules are optional.

Language identification

Language identification is the task of detecting the source language for the input text.

This is preliminary to spell checking, tokenization, acronym expansion, etc.

Several **statistical** techniques for this task: functional word frequency, *N*-gram language models (some later lecture), distance measure based on mutual information, etc.

Explore the following libraries

- Python **langdetect**
- Apache OpenNLP **LanguageDetector**

Spell checker

Spell checkers correct grammatical mistakes in text.

Especially useful for quickly written text, such as Twitter and Amazon reviews.

Spell checkers use approximate string matching algorithms such as **Levenshtein distance** to find correct spellings.

Difficult cases: a misspelled word might still be in the language (English: than vs. then, their vs. there). To deal with these cases, more sophisticated algorithms analyze the **context** formed by the surrounding words.

Explore the following libraries

- Python **TextBlob**, based on the Natural Language Toolkit (NLTK) library
- Resources for fuzzy string matching
  - `https://github.com/seatgeek/fuzzywuzzy`
  - `https://pypi.org/project/fuzzywuzzy/`

Contractions

The following should be managed before further normalization (all examples in English language)

- **contracted forms**: we'll, don't
- **abbreviations**: inc., Mr.
- **slang**: IMHO, LOL, tl;dr

Difficult cases: ambiguity with apostrophe which is also used as

- genitive marker (book's cover)
- quotative ('The other class', she said)

The most straightforward technique is to create a **dictionary** of contractions and abbreviations with their corresponding expansions.

Punctuation

Punctuation marks in text need to be isolated and treated as if they were separate words. This is critical for finding sentence boundaries and for identifying some aspects of meaning (question marks, exclamation marks, quotation marks).

Difficult cases: many punctuation symbols also used in abbreviations (period), company names (Yahoo!), compound words (-), etc.

Explore the following libraries

- Python **string.punctuation**
- NLTK **nltk.punkt**

Special characters

Special care for

- **emoticons**: :) ;) etc., use regular expressions
- **emoji**: 😀 😅 etc., use specialized libraries

Explore the following library

- `https://github.com/NeelShah18/emot`

Tokenization

Tokenization is the process of segmenting text into units called tokens.

Tokenization techniques can be grouped into three families

- word tokenization
- character tokenization
- subword tokenization

Tokens are then organized into a **vocabulary** and, depending on the specific NLP application, may later be mapped into **natural numbers**.

Token indexing is very common when using neural networks.

Word tokenization

Glen Carrie on Unsplash

Word tokenization

Word tokenization is a very common approach for European languages.

For English, most of the text is already (word) tokenized after previous steps, with the following important exceptions

- special compound names (white space vs. whitespace)
- city names (San Francisco, Los Angeles), companies, etc.

  This requires named entity recognition, presented in some later lecture.

Explore the following libraries

- NLTK **word.tokenize**
- SpaCy **Tokenization**

  `https://spacy.io/usage/linguistic-features#tokenization`

Word tokenization

German writes compound nouns without spaces.

Example : Computerlinguistik, 'computational linguistics'.

Several compound-splitter tools available.

Italian and Spanish incorporate verbs and **clitics**, which are special type of pronouns.

Example : comprarlo $>$ comprare $+$ lo, 'to buy it'.

This process can be iterated on the same word.

Word tokenization

There are certain language-independent tokens that require **specialized** processing

- phone numbers: (800) 234-2333
- dates: Mar 11, 1983

  `https://dateparser.readthedocs.io/en/latest/`
- email addresses: jblack@mail.yahoo.com
- web URLs: http://stuff.big.com/new/specials.html
- hashtags: #nlproc

Use of **regular expressions** is recommended in these cases.

Character tokenization

Raphael Schaller on Unsplash

Character tokenization

Major east Asian languages (e.g., Chinese, Japanese, Korean, and Thai) write text without any spaces between words.

For most Chinese NLP tasks, character tokenization works better than word tokenization

- each character generally represents a single unit of meaning
- word tokenization results in huge vocabulary, with large number of very rare words

Character tokenization

Example : Consider the following Chinese sentence and possible tokenizations

姚明进入总决赛
"Yao Ming reaches the finals"

姚 明 进入 总 决赛
Yao Ming reaches overall finals

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

Character tokenization

For Japanese and Thai the character is too small a unit, and algorithms for word segmentation are required.

Standard segmentation algorithms for these languages use neural sequence models.

This is related to sequence labelling, presented in some later lecture.

Subword tokenization

Brett Jordan from Unsplash

Subword tokenization

Many NLP systems need to deal with **unknown words**, that is, words that are not in the vocabulary of the system.

Example :
If the training corpus contains the words **foot** and **ball**, but not the word **football**, then if football appears in the test set the system does not know what to do.

Example :
If the training corpus contains the words **low**, **new**, **newer** but not **lower**, then if lower appears in the test set the system does not know what to do.

Subword tokenization

To deal with the problem of unknown words, modern tokenizers automatically induce sets of tokens that include tokens smaller than words, called **subwords**.

Subword tokenization reduces vocabulary size, and has become the **most common** tokenization method for large language modelling and neural models in general (see future lectures).

Subword tokenization is inspired by algorithms originally developed in information theory as a simple and fast form of **data compression** alternative to Lempel-Ziv-Welch.

Data compression provides more interesting results than morphemes.

Subword tokenization

Subword tokenization schemes consists of three different algorithms

- the **token learner** takes a raw training corpus and induces a set of tokens, called **vocabulary**
- the **token segmenter** (encoder) takes a vocabulary and a raw test sentence, and segments the sentence into the tokens in the vocabulary
- the **token merger** (decoder) takes a token sequence and reconstructs the original sentence

Subword tokenization

Example :
Given the sample sentence 'GPT-3 can be used for linguistics'

- learner constructs the vocabulary:
  { -, 3, be, can, for, G, istics, lingu, PT, used }
- encoder translates sample sentence into token sequence:
  G, PT, -, 3, can, be, used, for, lingu, istics
- decoder translates back to the original sentence, including white spaces:
  GPT-3 can be used for linguistics

Subword tokenization

Three algorithms are widely used for subword tokenization

- byte-pair encoding (BPE) tokenization
- unigram tokenization
- WordPiece tokenization

Explore the following library

- **SentencePiece**

  Includes implementations of BPE and unigram tokenization

BPE: learner

The BPE **token learner** is usually run inside words, not merging across word boundaries. To this end, use a special end-of-word marker.

The algorithm iterates through the following steps

- begin with a vocabulary composed by all individual characters
- choose the two symbols A, B that are most frequently adjacent
- add a new merged symbol AB to the vocabulary
- replace every adjacent A, B in the corpus with AB

The algorithm follows a greedy approach.

Stop when the vocabulary reaches size k, a **hyperparameter**.

Stopping criterion can alternatively be the number of iterations (merges).

BPE: learner

Example : Underscore is the end-of-word marker

corpus	vocabulary
5 l o w _	_, d, e, i, l, n, o, r, s, t, w
2 l o w e s t _	
6 n e w e r _	
3 w i d e r _	
2 n e w _	

Most frequent pair is **e**, **r** with a total of 9 occurrences (we arbitrarily break ties).

corpus	vocabulary
5 l o w _	_, d, e, i, l, n, o, r, s, t, w, er
2 l o w e s t _	
6 n e w er _	
3 w i d er _	
2 n e w _	

BPE: learner

The algorithm now learns the word-final token **er_**

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er, er_
2	l o w e s t _	
6	n e w er_	
3	w i d er_	
2	n e w _	

The next merge produces token **ne**

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne
2	l o w e s t _	
6	ne w er_	
3	w i d er_	
2	ne w _	

BPE: learner

If we continue, the next merges are

Merge	Current Vocabulary
(ne, w)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new
(l, o)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo
(lo, w)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low
(new, er_)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_
(low, _)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_, low_

After several iterations, BPE learns

- entire words
- most frequent units, useful for tokenizing unknown words

BPE: encoder

Two versions of **BPE token segmenter** (encoder)

- apply merge rules in **frequency order** all over the data set
- for each word, **left-to-right**, match longest token from vocabulary (eager)

Not clear whether the two algorithms always provide the same encoding.

Example :
Assume training corpus contained words **newer**, **low**, but not **lower**. Typically, the test word `[lower]` will be encoded by means of tokens `[low, er_]`.

BPE: encoder

Encoding is **computationally expensive**.

Many systems use some form of **caching**:

- pre-tokenize all the words and save how a word should be tokenized in a dictionary
- when an unknown word (not in dictionary) is seen
  - apply the encoder to tokenize the word
  - add the tokenization to the dictionary for future reference

BPE: decoder

BPE token merger: To decode, we have to

- concatenate all the tokens together to get the whole word
- use the end-of-word marker to solve possible ambiguities

Example :
The encoded sequence

```
[the_, high, est_, range_, in_, Seattle_]
```

will be decoded as

```
[the, highest, range, in, Seattle]
```

as opposed to

```
[the, high, estrange, in, Seattle]
```

WordPiece

WordPiece is a subword tokenization algorithm used by the large language model BERT.

BERT will be presented in a later lecture.

Like BPE, WordPiece starts from the initial alphabet and learns merge rules.

The main difference is the way pair A, B is selected to be merged ($f(X)$ is the frequency of token X)

$$\frac{f(A, B)}{f(A) \times f(B)}$$

The algorithm **prioritizes** the merging of pairs where the individual parts are less frequent in the vocabulary.

Sentence segmentation

Text normalization also includes **sentence segmentation**: breaking up a text into individual sentences

This can be done using cues like periods, question marks, or exclamation points.

Case folding

Lower casing is very useful to standardize words and before stop words removal.

After this step, you can perform word statistics, such as Zip's law.

Difficult cases: if some words must be capitalized (proper names, cities), specialized pre-processing is needed.

Sometimes it might be useful to keep both versions of the text data.

Most programming languages have facilities for string lowercasing.

Stop words

Stop word removal includes getting rid of

- common articles
- pronouns
- prepositions
- coordinations

Stop word removal heavily depends on the task at hand, since it can wipe out relevant information.

This is more of a dimensionality reduction technique than normalization. Much more common in IR than in NLP.

Stemming

Stemming refers to the process of slicing a word with the intention of removing affixes.

Stemming is **problematic** in the linguistic perspective, since it sometimes produces words that are not in the language, or else words that have a different meaning.

Example :

- arguing $>$ argu, flies $>$ fli
- playing $>$ play, caring $>$ car
- news $>$ new

Much more commonly used in IR than in NLP. Porter and Snowball stemmers very popular (rule based). For low-resource languages statistical stemmers are also an option.

Lemmatization

Lemmatization has the objective of reducing a word to its base form, also called **lemma**, therefore grouping together different forms of the same word.

Example :

- am, are, is $>$ be
- car, cars, car's, cars' $>$ car

Lemmatization and stemming are mutually exclusive, and the former is much more resource-intensive than the latter.

Explore the following library

- TextBlob, word inflection and lemmatization

  `https://textblob.readthedocs.io/en/dev/`

Should we always normalize?

We need to ask ourselves

- is important information being lost?
- is noisy information being removed?

Research papers

Research papers

Title: Neural Machine Translation of Rare Words with Subword Units
Authors: Rico Sennrich, Barry Haddow, Alexandra Birch
Conference: ACL 2016
Content: In this work we introduce an effective approach making NMT models capable of open-vocabulary translation by encoding rare and unknown words as sequences of subword units.

https://aclanthology.org/P16-1162/

Research papers

Title: SentencePiece: A simple and language independent subword tokenizer and detokenizer for Neural Text Processing
Authors: Taku Kudo, John Richardson
Conference: EMNLP 2018
Content: This work describes SentencePiece, a language-independent subword tokenizer and detokenizer designed for Neural-based text processing, including Neural Machine Translation.

https://aclanthology.org/D18-2012/

Research papers

Title: Between words and characters: A Brief History of Open-Vocabulary Modeling and Tokenization in NLP
Authors: Sabrina J. Mielke, Zaid Alyafeai, Elizabeth Salesky, Colin Raffel, Manan Dey, Matthias Gallé, Arun Raja, Chenglei Si, Wilson Y. Lee, Benoît Sagot, Samson Tan
Repository: arXiv.org.cs.Computation and Language, 20 Dec 2021
Content: Subword-based approaches have become dominant in many areas, enabling small vocabularies while still allowing for fast inference. This survey connects several lines of work from the pre-neural and neural era, showing how hybrid approaches based on words, subword and characters have been proposed and evaluated.

https://arxiv.org/abs/2112.10508