ITCS 4111/5111: Introduction to NLP

Tokenization: From text to sentences and tokens

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Tokenization: From Text to Tokens

- **Tokenization** = segmenting text into tokens:
  - **token** = a sequence of characters, in a particular document at a particular position.
  - **type** = the class of all tokens that contain the same character sequence.
    - “... to be or not to be ...”
    - “... so be it, he said ...”  \(3 \text{ tokens, 1 type}\)
  - **term** = a (normalized) type that is included in the dictionary.
    - **text** = “to sleep perchance to dream”, “US ambassador dreams”
    - **tokens** = to, sleep, perchance, to, dream, US, ambassador, dreams
    - **types** = to, sleep, perchance, dream, US, ambassador, dreams
    - **terms** = sleep, perchance, dream, USA, ambassador (lemmas, norm)
Tokenization: From Text to Tokens

- Split on whitespace and non-alphanumerics?
  - Good as a starting point, but complicated by many tricky cases:
    - **Appostrophes** are ambiguous:
      - *possessive* constructions:
        » the books’s cover => the book s cover
      - *contractions*:
        » he’s happy => he is happy
        » aren’t => are not
      - *quotations*:
        » ‘let it be’ => let it be
Tokenization: From Text to Tokens

• Split on whitespace and non-alphanumeric?
  – Good as a starting point, but complicated by many tricky cases:
    • **Whitespaces** in proper names or collocations:
      – San Francisco => San_Francisco
        » how do we determine it should be a single token?
    • **Hyphenations**:
      – co-education => co-education
      – state-of-the-art => state of the art? state_of_the_art?
      – lowercase, lower-case, lower case => lower_case
      – Hewlett-Packard => Hewlett_Packard? Hewlett Packard?
    • **Whitespaces and Hyphenations**:
      – San Francisco-Los Angeles => San_Francisco Los_Angeles
Tokenization: From Text to Tokens

• Split on whitespace and non-alphanumeric?
  – Good as a starting point, but complicated by many tricky cases:
    • Whitespaces and Hyphenations:
      – split on hyphens and whitespaces, but use a phrase index.
    • Unusual strings that should be recognized as tokens:
      – C++, C#, B-52, C4.5, M*A*S*H.
    • URLs, IP addresses, email addresses, tracking numbers.
      – exclude numbers, monetary amounts, URLs from indexing?

• Use same tokenization rules for all documents:
  – e.g. training vs. testing.
Tokenization is Language Dependent

- Need to know the language of document/query:
  - **Language Identification**, based on classifiers trained on short character subsequences as features, is highly effective.
  - **French** (reduced definite article, postposed clitic pronouns):
    - l’ensemble, un ensemble, donne-moi.
  - **German** (compound nouns), need *compound splitter*:
    - Computerlinguistik
    - Lebensversicherungsgesellschaftsangestellter
  - **East Asian languages**, need *word segmenter*:
    - 莎拉波娃现在居住在美国东南部的佛罗里达。
    - Not always guaranteed a unique tokenization
    - Complicated in Japanese, with multiple alphabets intermingled.
Tokenization is Language Dependent

- Need to know the language of the document/query:
  - Arabic and Hebrew:
    - Written right to left, but with certain items like numbers written left to right.
    - Words are separated, but letter forms within a word form complex ligatures

Algeria achieved its independence in 1962 after 132 years of French occupation.
Language Dependent Processing

• **Compound Splitting for German:**
  – usually implemented by finding segments that match against dictionary entries.

• **Word Segmentation for Chinese:**
  – ML sequence tagging models trained on manually segmented text:
    • *Logistic Regression, HMMs, Conditional Random Fields.*
  – Multiple segmentations are possible:

![Figure 2.4](image-url) Ambiguities in Chinese word segmentation. The two characters can be treated as one word meaning ‘monk’ or as a sequence of two words meaning ‘and’ and ‘still’.
From Tokens to Terms: Normalization

- **Token Normalization** = reducing multiple tokens to the same canonical term, such that matches occur despite superficial differences.

1. Create equivalence classes, named after one member of the class:
   - {anti-discriminatory, antidiscriminatory}
   - {U.S.A., USA}
     - but what about C.A.T vs. CAT?

2. Can complicate later processing tasks is annotation already done on original, unnormalized version of text:
   - Need to maintain positional correspondence between normalized token and its original, unnormalized version
From Tokens to Terms: Normalization

• Accents and diacritics in French:
  – résumé vs. resume.

• Umlauts in German:
  – Tuebingen vs. Tübingen

• British vs. American spellings:
  – colour vs. color.

• Multiple formats for dates, times:
  – 09/30/2013 vs. Sep 30, 2013.
From Tokens to Terms: Normalization

• **Case-Folding** = reduce all letters to lower case:
  – change *Automobile* at beginning of sentences to *automobile*.
  • how about *Ferrari*?
  – but may lead to unintended matches:
    • the Fed vs. fed.
    • Bush, Black, General Motors, Associated Press, ...

• **Heuristic** = lowercase only some tokens:
  – words at beginning of sentences.
  – all words in a title where most words are capitalized.

• **Truecasing** = use a classifier to decide when to fold:
  – trained on many heuristic features.
Lemmatization and Stemming

- **Lemmatization** = reduce a word to its base/dictionary form, i.e. its lemma:
  - is, am, are => be
  - car, cars => car

- Lemmatization commonly only collapses the different *inflectional* forms of a lemma:
  - saw => see (if verb), or saw (if noun).


From Tokens to Terms: Stemming

- **Stemming** = reduce *inflectional* and sometimes *derivationally* related forms of a word to a common base form i.e. the *stem*.
  - automate, automates, automatic, automation => automat
  - see, saw => s

- Crude affix chopping that is language dependent:

  *for example compressed and compression are both accepted as equivalent to compress.*

  *for example compress and compress are both accepted as equivalent to compress.*
Porter’s Algorithm

http://www.tartarus.org/~martin/PorterStemmer/

• The most common stemmer for English:
  – at least as good as other stemming options.
  – 5 phases of word reductions, applied sequentially.
  – conventions for rule selection and application:
    • select the reduction rule that applies to the longest suffix:

      | Rule | Example   |
      |------|-----------|
      | SSES | caresses  |
      |  I   | ponies    |
      | SS   | caress    |
      | S    | cats      |
      |  →   | caress    |
      |  →   | poni      |
      |  →   | caress    |
      |  →   | cat       |

• check the number of syllables, for suffix determination:

\[(m > 1) \quad \text{EMENT} \quad \rightarrow\]

would map *replacement* to *replac*, but not *cement* to *c.*
Other Stemming Algorithms

- **Lovins** stemmer, **Paice/Husk** stemmer, **Snowball**:
  - http://www.comp.lancs.ac.uk/computing/research/stemming/

- Stemming is language- and often application-specific:
  - open source and commercial plug-ins.

- **Does it improve IR performance?**
  - mixed results for English: improves recall, but hurts precision.
    - operative (dentistry) ⇒ oper
  - definitely useful for languages with richer morphology:
    - Spanish, German, Finish (30% gains).
Sentence Segmentation

• Generally based on punctuation marks: ? ! .
  – Periods are ambiguous, as sentence boundary markers and abbreviation/acronym markers:
    • Mr., Inc., m.p.h.
  – Sometimes they mark both:
    • SAN FRANCISCO (MarketWatch) – Technology stocks were mostly in positive territory on Monday, powered by gains in shares of Microsoft Corp. and IBM Corp.

• Tokenization approaches:
  – Regular Expressions.
  – Machine Learning (state of the art).
Extracting Linguistic Features with spaCy

```python
import spacy

nlp = spacy.load("en_core_web_sm")
doc = nlp("Apple is looking at buying U.K. startup for $11.1 million.")

for token in doc:
    print(token.text, token.lemma_, token.pos_, token.tag_, token.dep_,
           token.shape_, token.is_alpha, token.is_stop)
```

<table>
<thead>
<tr>
<th>Term</th>
<th>Form</th>
<th>Lemma</th>
<th>POS</th>
<th>Tag</th>
<th>Dep</th>
<th>Shape</th>
<th>Is Alpha</th>
<th>Is Stop</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>Apple</td>
<td>PROPN</td>
<td>NNP</td>
<td>nsubj</td>
<td>Xxxxx</td>
<td>True</td>
<td>False</td>
<td></td>
</tr>
<tr>
<td>is</td>
<td>be</td>
<td>AUX</td>
<td>VBZ</td>
<td>aux</td>
<td>xx</td>
<td>True</td>
<td>True</td>
<td></td>
</tr>
<tr>
<td>looking</td>
<td>look</td>
<td>VERB</td>
<td>VBG</td>
<td>ROOT</td>
<td>xxxx</td>
<td>True</td>
<td>False</td>
<td></td>
</tr>
<tr>
<td>at</td>
<td>at</td>
<td>ADP</td>
<td>IN</td>
<td>prep</td>
<td>xx</td>
<td>True</td>
<td>True</td>
<td></td>
</tr>
<tr>
<td>buying</td>
<td>buy</td>
<td>VERB</td>
<td>VBG</td>
<td>pcomp</td>
<td>xxxx</td>
<td>True</td>
<td>False</td>
<td></td>
</tr>
<tr>
<td>U.K.</td>
<td>U.K.</td>
<td>PROPN</td>
<td>NNP</td>
<td>compound</td>
<td>X.X.</td>
<td>False</td>
<td>False</td>
<td></td>
</tr>
<tr>
<td>startup</td>
<td>startup</td>
<td>NOUN</td>
<td>NN</td>
<td>dobj</td>
<td>xxx</td>
<td>True</td>
<td>False</td>
<td></td>
</tr>
<tr>
<td>for</td>
<td>for</td>
<td>ADP</td>
<td>IN</td>
<td>prep</td>
<td>xxx</td>
<td>True</td>
<td>True</td>
<td></td>
</tr>
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<td>$</td>
<td>$</td>
<td>SYM</td>
<td>$</td>
<td>quantmod</td>
<td>$</td>
<td>False</td>
<td>False</td>
<td></td>
</tr>
<tr>
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<td>11.1</td>
<td>NUM</td>
<td>CD</td>
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<td>dd.d</td>
<td>False</td>
<td>False</td>
<td></td>
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<td>pobj</td>
<td>xxxx</td>
<td>True</td>
<td>False</td>
<td></td>
</tr>
<tr>
<td>.</td>
<td>.</td>
<td>PUNCT</td>
<td>.</td>
<td>punct</td>
<td>.</td>
<td>False</td>
<td>False</td>
<td></td>
</tr>
</tbody>
</table>
Tokenization and Sentence Segmentation

```python
import spacy

nlp = spacy.load("en_core_web_sm")
doc = nlp("Apple is looking at buying U.K. startup for $1 billion. "
          "The deal is unlikely to go through."")

for token in doc:
    print(token, end = ' ')
print()

```

Apple is looking at buying U.K. startup for $1 billion. The deal is unlikely to go through.

```python
for sent in doc.sents:
    for token in sent:
        print(token, end = ' ')
    print()

```

Apple is looking at buying U.K. startup for $1 billion. The deal is unlikely to go through.
By default, spaCy’s nlp() function runs an entire linguistic pipeline:

- But this is inefficient if we only need to tokenize …
• Run only the pipeline component(s) that are needed. Two options:
  1. Call the component directly.
  2. Use the default pipeline but disable components that are not needed.

```python
from spacy.lang.en import English
nlp = English()
tokenizer = nlp.tokenizer
tokens = tokenizer("U.S. economy is healing, but there’s a long way to go. "
  "The spread of Covid-19 led to surge in orders for factory robots")
for token in tokens:
    print(token, end = ' ')
print()
```

U.S. economy is healing, but there’s a long way to go. The spread of Covid-19 led to surge in orders for factory robots.
Tokenization in spaCy

https://spacy.io/usage/processing-pipelines

- Run only the pipeline component(s) that are needed. Two options:
  1. Call the component directly.
  2. Use the default pipeline but disable components that are not needed.

```python
import spacy

# Load the tagger, ner, and parser but don't enable them.
nlp = spacy.load("en_core_web_sm", disable=['tagger', 'ner', 'parser'])
nlp.remove_pipe("parser")
nlp.remove_pipe("tagger")
nlp.remove_pipe("ner")

doc = nlp("U.S. economy is healing, but there’s a long way to go. "
  "The spread of Covid-19 led to surge in orders for factory robots.")

for token in doc:
    print(token, end = ' ')
print()
```

U.S. economy is healing, but there’s a long way to go. The spread of Covid-19 led to surge in orders for factory robots.
Sentence Segmentation in spaCy

• Run only the pipeline component(s) that are needed:
  – But spaCy by default uses the parser for sentence segmentation!
  • Use a rule-based (but not as accurate) Sentencizer.

```python
from spacy.lang.en import English
	nlp = English()

sentencizer = nlp.create_pipe("sentencizer")

nlp.add_pipe(sentencizer)

doc = nlp("U.S. economy is healing, but there's a long way to go. "
          "The spread of Covid-19 led to surge in orders for factory robots.")

for sent in doc.sents:
    for token in sent:
        print(token, end = ' ')

print()
```

U.S. economy is healing, but there’s a long way to go.
The spread of Covid-19 led to surge in orders for factory robots.
Statistical Properties of Text
Statistical Properties of Text

• **Zipf’s Law** models the distribution of terms in a corpus:
  – How many times does the $k^{\text{th}}$ most frequent word appears in a corpus of size $N$ words?
  – Important for determining index terms and properties of compression algorithms.

• **Heap’s Law** models the number of words in the vocabulary as a function of the corpus size:
  – What is the number of unique words appearing in a corpus of size $N$ words?
  – This determines how the size of the inverted index will scale with the size of the corpus.
Word Distribution

- **A few words are very common:**
  - The 2 most frequent words (e.g. “the”, “of”) can account for about 10% of word occurrences.

- **Most words are very rare:**
  - Half the words in a corpus appear only once, called *hapax legomena* (Greek for “read only once”)

- **A “heavy tailed” or “long tailed” distribution:**
  - Since most of the probability mass is in the “tail” compared to an exponential distribution.
Zipf’s Law

12.5% of the planets have 71% of the mass

#OCCUPYJUPITER
Word Distribution

Frequency vs. rank for all words in Moby Dick
Moby Dick:
- 44% hapax legomena
- 17% dis legomena

“Honorificabilitudinitatibus”:
- Shakespeare’s *hapax legomenon*
- longest word with alternating vowels and consonants
Zipf’s Law

• Rank all the words in the vocabulary by their frequency, in decreasing order.
  – Let $r(w)$ be the rank of word $w$.
  – Let $f(w)$ be the frequency of word $w$.

• Zipf (1949) postulated that frequency and rank are related by a power law:

$$f(w) = \frac{c}{r(w)}$$

  – $c$ is a normalization constant that depends on the corpus.
Zipf’s Law

- If the most frequent term (the) occurs $f_1$ times:
  - Then the second most frequent term (of) occurs $f_1 / 2$ times.
  - The third most frequent term (and) occurs $f_1 / 3$ times, …

- **Power Laws**: $y = cx^k$
  - Zipf’s Law is a power law with $k = -1$.
  - Linear relationship between log($y$) and log($x$):
    - log($y$) = log $c + k$ log($x$)
    - on a log scale, power laws give a straight line with slope $k$.

- Zipf is quite accurate, except for very high and low rank.
Zipf’s Law Fit to Brown Corpus

\[ f(w) = \frac{100000}{r(w)} \]
Mandelbrot’s Distribution

• The following more general form gives a bit better fit:

\[ f = \frac{c}{(r + \rho)^K} \]

• When fit to Brown corpus:
  • \( c = 105.4 \)
  • \( K = –1.15 \)
  • \( \rho = 100 \)
Mandelbrot’s Law Fit to Brown Corpus

Mandelbrot’s function on Brown corpus
Vocabulary vs. Collection Size

• How big is the term vocabulary?
  – That is, how many distinct words are there?

• Can we assume an upper bound?
  – Not really upper-bounded due to proper names, typos, etc.

• In practice, the vocabulary will keep growing with the collection size.
Heap’s Law

• Given:
  – $M$ is the size of the vocabulary.
  – $T$ is the number of tokens in the collection.

• Then:
  – $M = kT^b$
  – $k, b$ depend on the collection type:
    • typical values: $30 \leq k \leq 100$ and $b \approx 0.5$ (square root).
    • in a log-log plot of $M$ vs. $T$, Heaps’ law predicts a line with slope of about $\frac{1}{2}$. 
For RCV1, the dashed line $\log_{10} M = 0.49 \log_{10} T + 1.64$ is the best least squares fit.

Thus, $M = 10^{1.64} T^{0.49}$ so $k = 10^{1.64} \approx 44$ and $b = 0.49$.

For first 1,000,020 tokens:
- Law predicts 38,323 terms;
- Actually, 38,365 terms.

$\Rightarrow$ Good empirical fit for RCV1!
Explanations

- **Zipf’s Law:**
  - Zipf’s explanation was his “principle of least effort”:
    - Balance between speaker’s desire for a small vocabulary and hearer’s desire for a large one.
  - Herbert Simon’s explanation is “rich get richer.”
  - Li (1992) shows that just random typing of letters including a space will generate “words” with a Zipfian distribution.

- **Heaps’ Law:**
  - Can be derived from Zipf’s law by assuming documents are generated by randomly sampling words from a Zipfian distribution.
Homework Assignment 1

- **Distributions of Words & Sentences:**

  1. The first task is to compute the frequency vs. rank distribution of the words in Moby Dick.
     - For this, you will need to tokenize the document and create a vocabulary mapping word types to their document frequency.
  2. The second task is to segment the document into sentences and compute the sentence length distribution.
     - Here you will experiment with spaCy's default sentence segmenter as well as the simple rule-based Sentencizer.
def tokenizer_pseudo_code:
    special_cases, prefix_search, suffix_search, infix_finditer, token_match, url_match

    tokens = []
    for substring in text.split():
        suffixes = []
        while substring:
            while prefix_search(substring) or suffix_search(substring):
                if token_match(substring):
                    tokens.append(substring)
                    substring = ''
                    break
                if substring in special_cases:
                    tokens.extend(special_cases[substring])
                    substring = ''
                    break
                if prefix_search(substring):
                    split = prefix_search(substring).end()
                    tokens.append(substring[:split])
                    substring = substring[split:]
                if substring in special_cases:
                    continue
                if suffix_search(substring):
                    split = suffix_search(substring).start()
                    suffixes.append(substring[split:])
                    substring = substring[:split]
                if token_match(substring):
                    tokens.append(substring)
                    substring = ''
                elif url_match(substring):
                    tokens.append(substring)
                    substring = ''
                elif substring in special_cases:
                    tokens.extend(special_cases[substring])
                    substring = ''
                elif list(infix_finditer(substring)):
                    infixes = infix_finditer(substring)
                    offset = 0
                    for match in infixes:
                        tokens.append(substring[offset : match.start()])
                        tokens.append(substring[match.start() : match.end()])
                        offset = match.end()
                    if substring[offset:] != ''
                        tokens.append(substring[offset:])
                        substring = ''
                    elif substring:
                        tokens.append(substring)
                        substring = ''
                tokens.extend(reversed(suffixes))

    return tokens

https://spacy.io/usage/linguistic-features#tokenization
Tokenization in NLTK

Default word tokenizer in NLTK:

```python
>>> import nltk, re, pprint
>>> from nltk import word_tokenize
>>> from urllib import request
>>> url = http://www.gutenberg.org/files/2554/2554-0.txt
>>> response = request.urlopen(url)
>>> raw = response.read().decode('utf8')
>>> tokens = word_tokenize(raw)
>>> len(tokens)
254354
>>> tokens[:10]
['The', 'Project', 'Gutenberg', 'EBook', 'of', 'Crime', 'and', 'Punishment', '!', 'by']
```

Custom tokenization through regular expressions in NLTK:

```python
>>> text = 'That U.S.A. poster-print costs $12.40...
>>> pattern = r''''(?x) # set flag to allow verbose regexps
... ([A-Z].)+ # abbreviations, e.g. U.S.A.
... | \w+-\w+* # words with optional internal hyphens
... | $\d+($\d+)?%? # currency and percentages, e.g. $12.40, 82%
... | .\.\.\. # ellipsis
... | []\\,;"'\?\(\?:-\' # these are separate tokens; includes ], [
... ',

>>> nltk.regexp_tokenize(text, pattern)
['That', 'U.S.A.', 'poster-print', 'costs', '$12.40', '...']
```
Word segmentation: Subwords

- Use the data to tell us how to tokenize:
  - Instead of manually designed rules.
  - Instead of training on manually tokenized examples.

- Called **Subword tokenization**:
  - Because tokens are often parts of words.

- Can include common morphemes like -est or -er.
  - (A morpheme is the smallest meaning-bearing unit of a language; unlikeliest has morphemes un-, likely, and -est.)
Subword Tokenization

• Three common algorithms:
  1. **Byte-Pair Encoding (BPE)** (Sennrich et al., 2016)
  2. **Unigram language modeling tokenization** (Kudo, 2018)
  3. **WordPiece** (Schuster and Nakajima, 2012)

• All have 2 parts:
  1. A token **learner** that takes a raw training corpus and induces a vocabulary, e.g. a set of tokens.
  2. A token **segmenter** that takes a raw test sentence and tokenizes it according to that vocabulary.
Byte Pair Encoding (BPE)

Let vocabulary be the set of all individual characters
   = \{A, B, C, D,…, a, b, c, d….\}

• Repeat:
  – Choose the two symbols that are most frequently adjacent in training corpus (say ‘A’, ‘B’),
  – Add a new merged symbol ‘AB’ to the vocabulary
  – Replace every adjacent ’A’ ’B’ in corpus with ‘AB’.
• Until $k$ merges have been done.
BPE token learner algorithm

function BYTE-PAIR ENCODING(strings C, number of merges k) returns vocab V

V ← all unique characters in C  # initial set of tokens is characters
for i = 1 to k do  # merge tokens til k times
    t_L, t_R ← Most frequent pair of adjacent tokens in C
    t_NEW ← t_L + t_R  # make new token by concatenating
    V ← V + t_NEW  # update the vocabulary
    Replace each occurrence of t_L, t_R in C with t_NEW  # and update the corpus
return V

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

from the training data, greedily, in the order we learned them. (Thus the frequencies in the test data don’t play a role, just the frequencies in the training data). So first we segment each test sentence word into characters. Then we apply the first rule: replace every instance of er in the test corpus with r, and then the second rule: replace every instance of er in the test corpus with er, and so on. By the end, if the test corpus contained the word newer, it would be tokenized as a full word. But a new (unknown) word like lower would be merged into the two tokens lower.

Of course in real algorithms BPE is run with many thousands of merges on a very large input corpus. The result is that most words will be represented as full symbols, and only the very rare words (and unknown words) will have to be represented by their parts.

2.4.4 Word Normalization, Lemmatization and Stemming

Word normalization is the task of putting words/tokens in a standard format, choosing a single normal form for words with multiple forms like USA and US or uh-huh and uhhuh. This standardization may be valuable, despite the spelling information that is lost in the normalization process. For information retrieval or information extraction about the US, we might want to see information from documents whether they mention the US or the USA.

Case folding is another kind of normalization. Mapping everything to lower case means that Woodchuck and woodchuck are represented identically, which is very helpful for generalization in many tasks, such as information retrieval or speech recognition. For sentiment analysis and other text classification tasks, information extraction, and machine translation, by contrast, case can be quite helpful and case folding is generally not done. This is because maintaining the difference between, for example, US the country and us the pronoun can outweigh the advantage in generalization that case folding would have provided for other words.

For many natural language processing situations we also want two morphologically different forms of a word to behave similarly. For example in web search, someone may type the string woodchucks but a useful system might want to also return pages that mention woodchuck with no s. This is especially common in morphologically complex languages like Russian, where for example the word Moscow has different endings in the phrases Moscow, of Moscow, to Moscow, and so on.

Lemmatization is the task of determining that two words have the same root, despite their surface differences. The words am, are, and is have the shared lemma...
Byte Pair Encoding (BPE)

- Most subword algorithms are run inside white-space separated tokens.
- So first add a special end-of-word symbol '__' before whitespace in training corpus:
  - Homework exercise:
    - Design a RE and write Python code to do this substitution.
- Next, separate into letters.
The algorithm is usually run inside words (not merging across word boundaries), so the input corpus is first white-space-separated to give a set of strings, each corresponding to the characters of a word, plus a special end-of-word symbol, and its counts. Let’s see its operation on the following tiny input corpus of 18 word tokens with counts for each word (the word *low* appears 5 times, the word *newer* 6 times, and so on), which would have a starting vocabulary of 11 letters:

<table>
<thead>
<tr>
<th>corpus</th>
<th>vocabulary</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 low</td>
<td>_, d, e, i, l, n, o, r, s, t, w</td>
</tr>
<tr>
<td>2 lowest</td>
<td></td>
</tr>
<tr>
<td>6 newer</td>
<td></td>
</tr>
<tr>
<td>3 wider</td>
<td></td>
</tr>
<tr>
<td>2 new</td>
<td></td>
</tr>
</tbody>
</table>

Once we’ve learned our vocabulary, the token parser is used to tokenize a test sentence. The token parser just runs on the test data the merges we have learned.

Note that there can be ties; we could have instead chosen to merge *r* first, since that also has a frequency of 9.

Original (very fascinating 😳) corpus:

low low low low low lowest lowest newer newer newer newer newer newer newer wider wider wider wider wider new new

Add end-of-word tokens and segment:
BPE token learner

<table>
<thead>
<tr>
<th>corpus</th>
<th>vocabulary</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>low_</td>
</tr>
<tr>
<td>2</td>
<td>lowest_</td>
</tr>
<tr>
<td>6</td>
<td>newer_</td>
</tr>
<tr>
<td>3</td>
<td>wider_</td>
</tr>
<tr>
<td>2</td>
<td>new_</td>
</tr>
</tbody>
</table>

Merge er to er

<table>
<thead>
<tr>
<th>corpus</th>
<th>vocabulary</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>low_</td>
</tr>
<tr>
<td>2</td>
<td>lowest_</td>
</tr>
<tr>
<td>6</td>
<td>newer_</td>
</tr>
<tr>
<td>3</td>
<td>wider_</td>
</tr>
<tr>
<td>2</td>
<td>new_</td>
</tr>
<tr>
<td></td>
<td>_, d, e, i, l, n, o, r, s, t, w, er</td>
</tr>
</tbody>
</table>
**Byte Pair Encoding (BPE)**

<table>
<thead>
<tr>
<th>corpus</th>
<th>vocabulary</th>
</tr>
</thead>
<tbody>
<tr>
<td>low _</td>
<td>__, d, e, i, l, n, o, r, s, t, w, er</td>
</tr>
<tr>
<td>lowest _</td>
<td></td>
</tr>
<tr>
<td>newer _</td>
<td></td>
</tr>
<tr>
<td>wider _</td>
<td></td>
</tr>
<tr>
<td>new _</td>
<td></td>
</tr>
</tbody>
</table>

Merge `er _` to `er _`

<table>
<thead>
<tr>
<th>corpus</th>
<th>vocabulary</th>
</tr>
</thead>
<tbody>
<tr>
<td>low _</td>
<td>_<em>, d, e, i, l, n, o, r, s, t, w, er, er</em></td>
</tr>
<tr>
<td>lowest _</td>
<td></td>
</tr>
<tr>
<td>newer _</td>
<td></td>
</tr>
<tr>
<td>wider _</td>
<td></td>
</tr>
<tr>
<td>new _</td>
<td></td>
</tr>
</tbody>
</table>
Byte Pair Encoding (BPE)

<table>
<thead>
<tr>
<th>corpus</th>
<th>vocabulary</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 low _</td>
<td><strong>, d, e, i, l, n, o, r, s, t, w, er, er</strong></td>
</tr>
<tr>
<td>2 lowest _</td>
<td></td>
</tr>
<tr>
<td>6 newer</td>
<td></td>
</tr>
<tr>
<td>3 wider</td>
<td></td>
</tr>
<tr>
<td>2 new</td>
<td></td>
</tr>
</tbody>
</table>

Merge **new** to **ne**

<table>
<thead>
<tr>
<th>corpus</th>
<th>vocabulary</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 low _</td>
<td><strong>, d, e, i, l, n, o, r, s, t, w, er, er</strong>, ne</td>
</tr>
<tr>
<td>2 lowest _</td>
<td></td>
</tr>
<tr>
<td>6 newer</td>
<td></td>
</tr>
<tr>
<td>3 wider</td>
<td></td>
</tr>
<tr>
<td>2 new</td>
<td></td>
</tr>
</tbody>
</table>
The next merges are:

<table>
<thead>
<tr>
<th>Merge</th>
<th>Current Vocabulary</th>
</tr>
</thead>
<tbody>
<tr>
<td>(ne, w)</td>
<td><strong>, d, e, i, l, n, o, r, s, t, w, er, er</strong>, ne, new</td>
</tr>
<tr>
<td>(l, o)</td>
<td><strong>, d, e, i, l, n, o, r, s, t, w, er, er</strong>, ne, new, lo</td>
</tr>
<tr>
<td>(lo, w)</td>
<td><strong>, d, e, i, l, n, o, r, s, t, w, er, er</strong>, ne, new, lo, low</td>
</tr>
<tr>
<td>(new, er__)</td>
<td><strong>, d, e, i, l, n, o, r, s, t, w, er, er</strong>, ne, new, lo, low, newer__</td>
</tr>
<tr>
<td>(low, __)</td>
<td><strong>, d, e, i, l, n, o, r, s, t, w, er, er</strong>, ne, new, lo, low, newer__, low__</td>
</tr>
</tbody>
</table>
Using BPE on a new text

- On the test corpus, run each merge learned from the training data:
  - Greedily
  - In the order we learned them
  - (test frequencies don't play a role)

- So: merge every \texttt{e r} to \texttt{er}, then merge \texttt{er_} to \texttt{er_}, etc.

- Result:
  - Test set "\texttt{n e w e r_}" would be tokenized as a full word
  - Test set "\texttt{l o w e r_}" would be two tokens: "\texttt{low er_}"