Natural Language Processing

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Contents

1 Basic text processing

Text normalization Operations such as:

Tokenization Split a sentence in tokens. Tokenization

> **Remark.** Depending on the approach, a token is not always a word.

Lemmatization/stemming Convert words to their canonical form. Lemmatization/stemming

> **Example.** {`sang`, `sung`, `sings`} $\mapsto$ `sing`

Sentence segmentation Split a text in sentences. Sentence segmentation

> **Remark.** A period does not always signal the end of a sentence.

1.1 Regular expressions

Regular expression (regex) Formal language to describe string patterns. Regular expression (regex)

1.1.1 Basic operators

Disjunction (brackets) Match a single character between square brackets `[]`.

> **Example.** `/[wW]oodchuck/` matches `Woodchuck` and `woodchuck`.

Range Match a single character from a range of characters or digits.

> **Example.**
> - `/[A-Z]/` matches a single upper case letter.
> - `/[a-z]/` matches a single lower case letter.
> - `/[0-9]/` matches a single digit.

Negation Match the negation of a pattern.

> **Example.** `/[^A-Z]/` matches a single character that is not an upper case letter.

Disjunction (pipe) Disjunction of regular expressions separated by `|`.

> **Example.** `/groundhog|woodchuck/` matches `groundhog` and `woodchuck`.

Wildcards

Optional A character followed by `?` can be matched optionally.

> **Example.** `/woodchucks?/` matches `woodchuck` and `woodchucks`.

Any `.` matches any character.

Kleene `*` A character followed by `*` can be matched zero or more times.

Kleene `+` A character followed by `+` must be matched at least once.

Counting A character followed by `{n,m}` must be matched from n to m times.

Example.

- `{n}` matches exactly n instances of the previous character.
- `{n,m}` matches from n to m instances of the previous character.
- `{n,}` matches at least n instances of the previous character.
- `{,m}` matches at most m instances of the previous character.

Anchors

Start of line `^` matches only at the start of line.

Example. `/^a/` matches a but not `ba`.

End of line `$` matches only at the end of line.

Example. `/a$/` matches a but not `ab`.

Word boundary `\b` matches a word boundary character.

Word non-boundary `\B` matches a word non-boundary character.

Aliases

- `\d` matches a single digit (same as `[0-9]`).
- `\D` matches a single non-digit (same as `[^\d]`).
- `\w` matches a single alphanumeric or underscore character (same as `[a-zA-Z0-9_]`).
- `\w` matches a single non-alphanumeric and non-underscore character (same as `[^\w]`).
- `\s` matches a single whitespace (space or tab).
- `\S` matches a single non-whitespace.

Capture group Operator to refer to previously matched substrings.

Example. In the regex `/the (.*)er they were, the \1er they will be/`, `\1` should match the same content matched by `(.*)`.

1.2 Tokenization

Lemma Words with the same stem and roughly the same semantic meaning. Lemma

Example. `cat` and `cats` are the same lemma.

Wordform Orthographic appearance of a word. Wordform

Example. `cat` and `cats` do not have the same wordform.

Vocabulary Collection of text elements, each indexed by an integer. Vocabulary

Remark. To reduce the size of a vocabulary, words can be reduced to lemmas.

Type / Wordtype Element of a vocabulary (i.e., wordforms in the vocabulary). Type / Wordtype

Token Instance of a type in a text. Token

Genre Topic of a text corpus (e.g., short social media comments, books, Wikipedia pages, . . .). Genre

Remark (Herdan's law)**.** Given a corpus with N tokens, a vocabulary V over that corpus roughly have size:

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

where the typical values are $10 \leq k \leq 100$ and $0.4 \leq \beta \leq 0.6$.

Stopwords Frequent words that can be dropped. Stopwords

Remark. If semantics is important, stopwords should be kept. LLMs keep stopwords.

Rule-based tokenization Hand-defined rules for tokenization. Rule-based tokenization

Remark. For speed, simple tokenizers use regex.

Data-driven tokenization Determine frequent tokens from a large text corpus. Data-driven tokenization

1.2.1 Data-driven tokenization

Tokenization is done by two components:

Token learner Learns a vocabulary from a given corpus (i.e., training). Token learner

Token segmenter Segments a given input into tokens based on a vocabulary (i.e., inference). Token segmenter

Byte-pair encoding (BPE) Based on the most frequent n-grams. Byte-pair encoding (BPE)

Token learner Given a training corpus C, BPE determines the vocabulary as follows:

1. Start with a vocabulary V containing all the 1-grams of C and an empty set of merge rules M.
2. While the desired size of the vocabulary has not been reached:
   a) Determine the pair of tokens $t_1 \in V$ and $t_2 \in V$ such that, among all the possible pairs, the n-gram $t_1 + t_2 = t_1t_2$ obtained by merging them is the most frequent in the corpus C.
   b) Add t_1t_2 to V and the merge rule $t_1 + t_2$ to M.

Example. Given the following corpus:

Occurrences	Tokens
5	`l o w $`
2	`l o w e r $`
6	`n e w e s t $`
6	`w i d e s t $`

The initial vocabulary is: $V = \{\texttt{\$}, \texttt{l}, \texttt{o}, \texttt{w}, \texttt{e}, \texttt{r}, \texttt{n}, \texttt{w}, \texttt{s}, \texttt{t}, \texttt{i}, \texttt{d}\}$.
At the first iteration, $\texttt{e} + \texttt{s} = \texttt{es}$ is the most frequent n-gram. Corpus and vocabulary are updated as:

Occurrences	Tokens
5	`l o w $`
2	`l o w e r $`
6	`n e w es t $`
6	`w i d es t $`

$$V = \{\texttt{\$}, \texttt{l}, \texttt{o}, \texttt{w}, \texttt{e}, \texttt{r}, \texttt{n}, \texttt{w}, \texttt{s}, \texttt{t}, \texttt{i}, \texttt{d}\} \cup \{\texttt{es}\}$$

At the second iteration, $\texttt{es} + \texttt{t} = \texttt{est}$ is the most frequent n-gram:

Occurrences	Tokens
5	`l o w $`
2	`l o w e r $`
6	`n e w est $`
6	`w i d est $`

$$V = \{\texttt{\$}, \texttt{l}, \texttt{o}, \texttt{w}, \texttt{e}, \texttt{r}, \texttt{n}, \texttt{w}, \texttt{s}, \texttt{t}, \texttt{i}, \texttt{d}, \texttt{es}\} \cup \{\texttt{est}\}$$

And so on…

Token segmenter Given the vocabulary V and the merge rules M, the BPE segmenter does the following:

1. Split the input into 1-grams.
2. Iteratively scan the input and do the following:
   a) Apply a merge rule if possible.
   b) If no merge rules can be applied, lookup the (sub)word in the vocabulary. Tokens out-of-vocabulary are marked with a special unknown token `[UNK]`.

WordPiece Similar to BPE with the addition of merge rules ranking and a special leading/tailing set of characters (usually `##`) to identify subwords (e.g., `new##`, `##est` are possible tokens). WordPiece

Unigram Starts with a big vocabulary and remove tokens following a loss function. Unigram

1.3 Normalization

Normalization Convert tokens into a standard form. Normalization

Example. `U.S.A.` and `USA` should be encoded using the same index.

Case folding Map every token to upper/lower case. Case folding

Remark. Depending on the task, casing might be important (e.g., `US` vs `us`).

Lemmatization Reduce inflections and variant forms to their base form. Lemmatization

Example. $\{\texttt{am}, \texttt{are}, \texttt{is}\} \mapsto \texttt{be}$

Remark. Accurate lemmatization requires complete morphological parsing.

Stemming Reduce terms to their stem. Stemming

Remark. Stemming is a simpler approach to lemmatization.

Porter stemmer Simple stemmer based on cascading rewrite rules.

> **Example.** `ational` $\mapsto$ `ate`, `ing` $\mapsto \varepsilon$, `sses` $\mapsto$ `ss`.

1.4 Edit distance

Minimum edit distance Minimum number of edit operations (insertions, deletions, and substitutions) needed to transform a string into another one.

Minimum edit distance

> **Remark.** Dynamic programming can be used to efficiently determine the minimum edit distance.

Levenshtein distance Edit distance where:

Levenshtein distance

- Insertions cost 1;
- Deletions cost 1;
- Substitutions cost 2.

> **Example.** The Levenshtein distance between `intention` and `execution` is 8.

I	N	T	E	*	N	T	I	O	N
|	|	|	|	|	|	|	|	|	|
*	E	X	E	C	U	T	I	O	N
$-$	$\pm$	$\pm$		$+$	$\pm$				
1	2	2		1	2				

2 Language models

2.1 Spelling correction

Spelling correction

Spelling correction Spelling errors can be of two types:

Non-word spelling Typos that result in non-existing words. Possible candidates can be determined though a dictionary lookup.

Real-word spelling Can be:

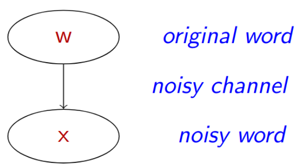
Typographical error Typos that result in existing words.

Cognitive error Due to words similarity (e.g., `piece` vs `peace`).

Noisy channel model

Noisy channel model Assumes that the observable input is a distorted form of the original word. A decoder tests word hypotheses and selects the best match.

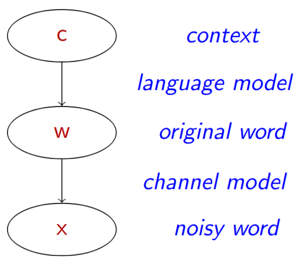
More formally, we want a model of the channel that, similarly to Bayesian inference, determines the likelihood that a word $w \in V$ is the original word for a noisy one x. From there, we can estimate the correct word $\hat{w}$:



$$\hat{w} = \arg\max_{w \in V} \mathcal{P}(w|x)$$

By applying (i) Bayes' rule, (ii) the fact that $\hat{w}$ is independent of $\mathcal{P}(x)$, and (iii) that a subset $C \subseteq V$ of the vocabulary can be used, the estimate becomes:

$$\hat{w} = \arg\max_{w \in C} \underbrace{\mathcal{P}(x|w)}_{\text{channel model}} \underbrace{\mathcal{P}(w)}_{\text{prior}}$$



Moreover, it is reasonable to include a context c when computing the prior:

$$\hat{w} = \arg\max_{w \in C} \underbrace{\mathcal{P}(x|w)}_{\text{channel model}} \underbrace{\mathcal{P}(w|c)}_{\text{language model}}$$

Noisy channel spelling method Spelling correction in a noisy channel model can be done as follows:

1. Find candidate words with similar spelling to the input based on a distance metric (e.g., Damerau-Levenshtein which is the Levenshtein distance with the addition of adjacent transpositions).
2. Score each candidate based on the language and channel model:
   - Use typing features of the user.
   - Use local context.
   - Use a confusion matrix with common mistakes.

Example. Consider the sentence:

> [...] *was called a "stellar and versatile* `acress` *whose combination of sass and glamour has defined her* [...]*"*

By using the Corpus of Contemporary English (COCA), we can determine the following words as candidates:

`actress` · `cress` · `caress` · `access` · `across` · `acres`

Language model By considering a language model without context, the priors are computed as $\mathcal{P}(w) = \frac{\texttt{count}(w)}{|\texttt{COCA}|}$ (where $|\texttt{COCA}| = 404\,253\,213$):

w	$\texttt{count}(w)$	$\mathcal{P}(w)$
`actress`	9321	0.0000231
`cress`	220	0.000000544
`caress`	686	0.00000170
`access`	37 038	0.0000916
`across`	120 844	0.000299
`acres`	12 874	0.0000318

Channel model By using a confusion matrix of common typos, the channel model is:

w	$x\|w$	$\mathcal{P}(x\|w)$
`actress`	`c|ct`	0.000117
`cress`	`a|#`	0.00000144
`caress`	`ac|ca`	0.00000164
`access`	`r|c`	0.000000209
`across`	`e|o`	0.0000093
`acres`	`es|e`	0.0000321
`acres`	`ss|s`	0.0000342

The ranking is the obtained as:

w	$\mathcal{P}(x\|w)\mathcal{P}(w)$
`actress`	$2.7 \cdot 10^9$
`cress`	$0.00078 \cdot 10^9$
`caress`	$0.0028 \cdot 10^9$
`access`	$0.019 \cdot 10^9$
`across`	$2.8 \cdot 10^9$
`acres`	$1.02 \cdot 10^9$
`acres`	$1.09 \cdot 10^9$

Therefore, the most likely correction of `acress` for this model is `across`.
If the previous word is considered in the context, the relevant tokens of the new language model are:

w_{i-1}	w_i	$\mathcal{P}(w_i\|w_{i-1})$
`versatile`	`actress`	0.000021
`versatile`	`across`	0.000021
`actress`	`whose`	0.001
`across`	`whose`	0.000006

This allows to measure the likelihood of a sentence as:

$$\mathcal{P}(\texttt{versatile }\underline{\texttt{actress}}\texttt{ whose}) = \mathcal{P}(\texttt{actress}|\texttt{versatile})\mathcal{P}(\texttt{whose}|\texttt{actress}) = 210 \cdot 10^{-10}$$
$$\mathcal{P}(\texttt{versatile }\underline{\texttt{across}}\texttt{ whose}) = \mathcal{P}(\texttt{across}|\texttt{versatile})\mathcal{P}(\texttt{whose}|\texttt{across}) = 1 \cdot 10^{-10}$$

Finally, we have that:

$$\mathcal{P}(\texttt{versatile }\underline{\texttt{actress}}\texttt{ whose}|\texttt{versatile acress whose}) = 2.7 \cdot 210 \cdot 10^{-19}$$
$$\mathcal{P}(\texttt{versatile }\underline{\texttt{across}}\texttt{ whose}|\texttt{versatile acress whose}) = 2.8 \cdot 10^{-19}$$

So `actress` is the most likely correction for `acress` in this model.

Remark. In practice, log-probabilities are used to avoid underflows and to make computation faster (i.e., sums instead of products).

2.2 Language models

(Probabilistic) language model Model to determine the probability of a word w in a given context c: Language model

$$\mathcal{P}(w|c)$$

Usually, it is based on counting statistics and uses as context the sequence of previous tokens:

$$\mathcal{P}(w_i|w_1, \dots, w_{i-1})$$

This is equivalent to computing the probability of the whole sentence, which expanded using the chain rule becomes:

$$\begin{aligned}\mathcal{P}(w_1, \dots, w_{i-1}w_i) &= \mathcal{P}(w_1)\mathcal{P}(w_2|w_1)\mathcal{P}(w_3|w_{1..2}) \dots \mathcal{P}(w_n|w_{1..n-1}) \\ &= \prod_{i=1}^{n} \mathcal{P}(w_i|w_{1..i-1})\end{aligned}$$

Remark. Simply counting the number of occurrences of a sentence as $\mathcal{P}(w_i|w_{1..i-1}) = w_{1..i}/w_{1..i-1}$ is not ideal as there are too many possible sentences.

Markov assumption Limit the length of the context to a window of k previous tokens: Markov assumption in language models

$$\mathcal{P}(w_i|w_{1..i-1}) \approx \mathcal{P}(w_i|w_{i-k..i-1})$$

$$\mathcal{P}(w_{1..n}) \approx \prod_{i=1}^{n} \mathcal{P}(w_i|w_{i-k..i-1})$$

Unigram model Model without context ($k = 0$):

$$\mathcal{P}(w_{1..n}) \approx \prod_{i} \mathcal{P}(w_i)$$

Bigram model Model with a single token context ($k = 1$):

$$\mathcal{P}(w_{1..n}) \approx \prod_{i} \mathcal{P}(w_i|w_{i-1})$$

N-gram model Model with a context of $k = N - 1$ tokens: N-gram model

$$\mathcal{P}(w_{1..n}) \approx \prod_{i} \mathcal{P}(w_i|w_{i-N+1..i-1})$$

Remark. N-gram models cannot capture long-range dependencies.

Estimating N-gram probabilities Consider the bigram case, the probability that a token w_i follows w_{i-1} can be determined by counting:

$$\mathcal{P}(w_i | w_{i-1}) = \frac{\texttt{count}(w_{i-1}w_i)}{\texttt{count}(w_{i-1})}$$

Remark. N-gram models cannot handle unknown tokens.

Remark. N-gram models capture knowledge about:

- Grammar and syntax.
- Some information about the dataset (e.g., domain, genre of corpus, cultural aspects, ...).

Generation by sampling Randomly sample tokens from the distribution of a language model.

Generation by sampling

Remark. In N-gram models ($N \geq 2$), the distribution changes depending on the previously sampled tokens.