

Text normalisation, units and edit distance

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Text normalisation

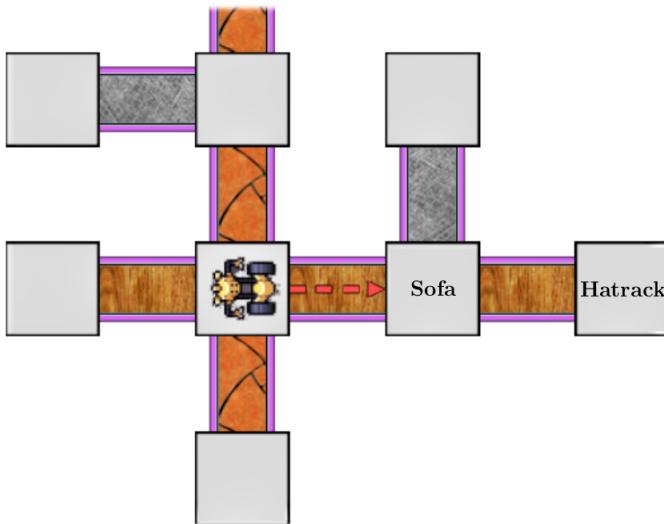
Tokenisation and units

Words

Subword units

Edit distance

Robotic instruction following



We want to instruct the robot with natural language commands like:¹

1. Move forward to the chair and then turn left.
2. Go 2 spaces and check if there is a coat stand.

The dumbest NLP solution

- Collect dataset of (X, y) pairs, each $X = x_{1:T}$ an input instruction and y the command the robot should execute
- Gives set of training pairs: $\{(X^{(n)}, y^{(n)})\}_{n=1}^N$
- For new input, find the closest input in the training set and predict its label y , i.e. one-nearest neighbour classification

¹Figure by Ryan Elof.

To do this, we need to figure out:

- How should we preprocess the data?
 - Should we map 2 to two or the other way around in input sentences?
 - Is punctuation important?
 - Can we lowercase everything?
- What is our basic modelling unit?
 - What is each x_t in the input sequence $x_{1:T}$?
 - Words, characters or maybe something in between?
- How do we measure the distance between two sequences?
 - Is the input word `forward` more similar to `forwds` or to `reverse`?

Text normalisation

Text normalisation is the task of converting text to a consistent, standardised form appropriate for the task at hand.

Normalisation rules have to deal with things like:

- Punctuation: Can often remove, but sometimes it is useful, e.g. full stops indicating the end of a sentence. Need to decide whether we keep punctuation in abbreviations, numbers, dates, hyphenated words, etc.
- Abbreviations: m.p.h. or miles per hour? Ph.D. or PhD? USA or US?
- Numbers and prices: R55,000.50 or R55 000.50 or R55000.50 or R55000,50 or fifty-five-thousand rand and fifty cents?
- Dates: 13/04/22 or 13 April 2022?
- URLs (<http://www.kamperh.com>), email addresses (someone@ed.ac.uk), hashtags (#nlproc), and emoticons :)
- Clitic contractions: what're or what are or what 're?
- Casing: We might want to lowercase everything, but it could also be useful to keep capitalisation, e.g. to identify names like Stellenbosch or San Francisco.
- Multi-word expressions: New York-based, \$37-a-share

Text normalisation rules are often implemented with regular expressions (J&M3, Sec. 2.1).

Task-specific

Unfortunately there isn't a single set of text normalisation rules that can be applied across all settings. The normalisation scheme should match your specific task. There are some standards, e.g. the Penn Treebank tokenisation or [NIST's tools for ASR text normalisation](#), but you can't apply these blindly without regard to the NLP task at hand.

Tokenisation and units

Tokenisation involves breaking up the input stream into the units we will model, i.e. constructing $x_{1:T}$ from the (normalised) input.

Say we have the following input:

```
turn right at the door
```

One obvious tokenisation would be to just split at spaces between words:

```
["turn", "right", "at", "the", "door"]
```

But we could also just use characters as our modelling unit:

```
["t", "u", "r", "n", " ", "r", "i", "g", "h", ...]
```

Let us first talk about words and then return to the question of which units to use.

Words

Word tokens and types

- Word type: A unique word class
- Word token: Instance of a word of a specific type

Can have multiple word tokens of the same type occurring in a text.

How many word types and tokens are in this sentence?

a cat and a brown dog chase a black dog

Answer: 7 types and 10 tokens

Word counts

In 10k sentences from the English [Wikipedia dump](#), there are 194 207 word tokens from 24 183 types. The most frequent words are listed below.

Any word:

Count	Word	Rank
12 336	the	1
7384	of	2
6561	and	3
4655	in	4
4305	to	5
3322	a	6
1959	is	7
1743	as	8
1627	The	9
1483	that	10

Nouns:

Count	Word
419	Apollo
379	state
276	Lincoln
240	Alaska
231	time
230	Agassi
215	Alabama
179	century
170	use
153	anthropology

Zipf's law

The frequency of a word is inversely proportional to its rank:

$$f \approx \frac{c}{r}$$

where f is the word frequency, r the rank, and c some constant.

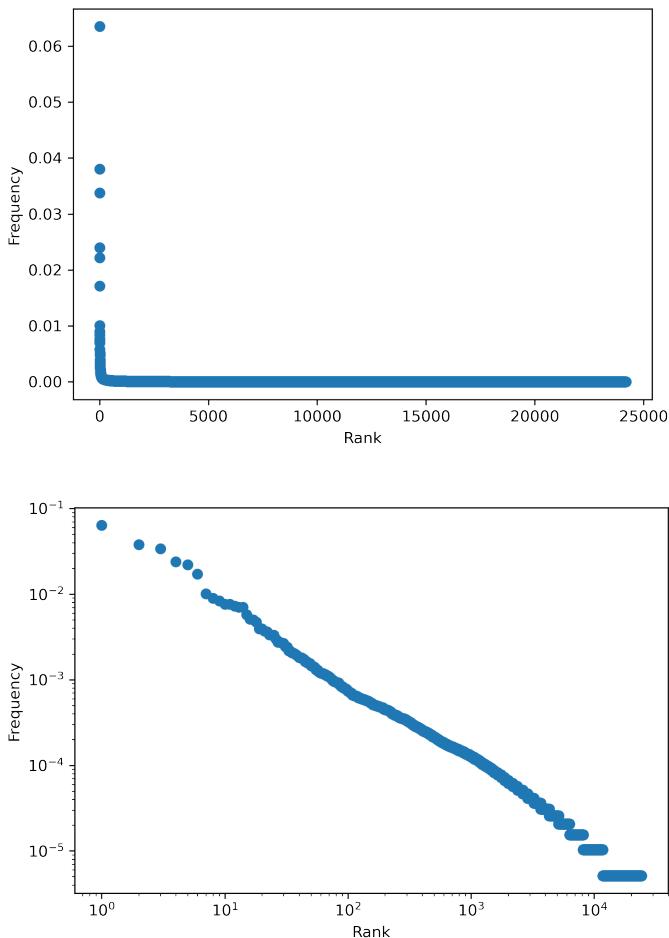
This is linear on a plot with the frequency and rank axes on log scales.
Why? Because

$$\log f \approx \log c - \log r$$

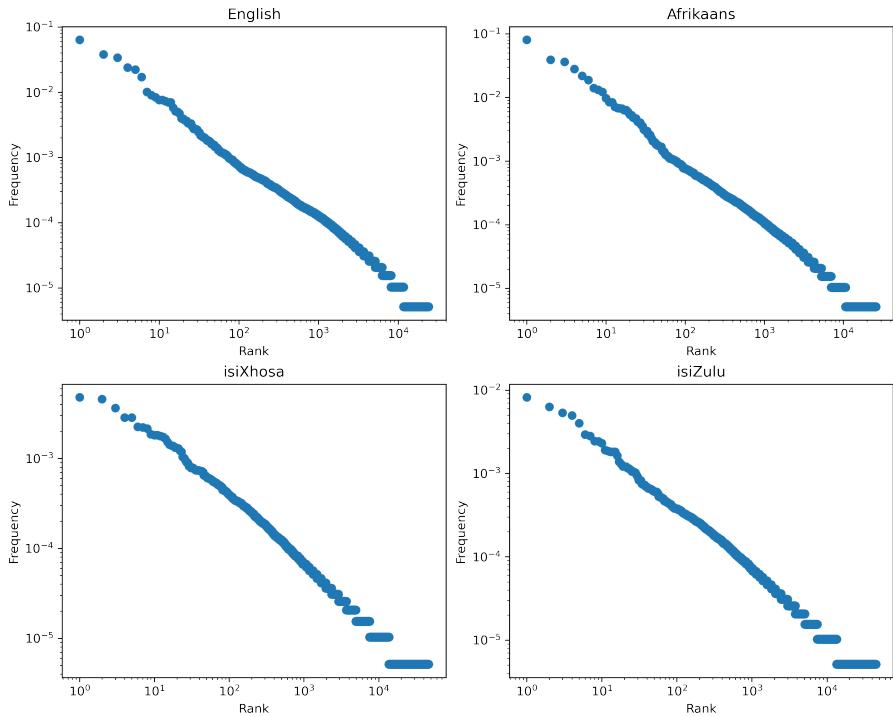
which looks like

$$y \approx k - x$$

On English:



An empirical law that holds for all languages. On different languages from the [Wikipedia dumps](#):



NLP challenge: Sparsity

Most words will be used infrequently, but we still need to be able to deal with them. This is a challenge when using machine learning since your training data might only have one or two occurrences of most words (or maybe even zero!), but we still need to be able to handle these words at test time.

What's so special about words?

You might think that the idea of a “word” is pretty obvious. But this is not really the case.

English: How many words in didn't, New York, high-risk, @stellenboschuniversity?

Afrikaans and German: Form words using agglutination

- satellietnavigasiestelsels (af)
- K-gemiddeldestrosvormingalgoritme (af)
- computerlinguistikvorlesung (de)

isiZulu: Morphologically rich

- wukutholakala = wu+u+ku+thol+akal+a

Chinese: Written without spaces

Chinese characters are meaning-bearing units (normally morphemes) that combine into words, but there is no standard definition of a word.

姚明进入总决赛

Yao Ming reaches the finals

姚明 进入 总决赛

YaoMing reaches 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

So which units should we use in our NLP system?

- Looked at using words or characters as units
- Words have sparsity problems but also a lot of structure (a single word gives meaning)
- Characters don't have structure (a single Latin script character gives no meaning) but don't suffer from sparsity (why not?)
- Maybe there is something in between these two extremes with some structure but less sparsity?

Subword units: Morphology

Morpheme: The smallest meaning-bearing unit of a language

unlikeliest = un+likely+est

Morphology: Study of how words are built up from morphemes

de+salin+ate+ion and not ate+salin+ion+de

In some languages, morphology matters a lot:

ru: zhenshina devochke dala knigu

en: the woman gave the girl a book

ru: zhenshine devochka dala knigu

en: the girl gave the woman a book

Types of morphemes

- Stems: Central morpheme giving a word its main meaning, e.g. fox, cat, small, walk
- Affixes: Added on to give additional meaning, e.g.
 - Suffix: +s, +ed
 - Prefix: un+
 - Inflex: +bloody+, uit+ge+eet (af)
 - Circumfix: ge+sag+t (de)

Example: isiXhosa children's book



Stems vs lemmas

- Lemma: Canonical form (dictionary form) of a set of words
 - am, are, is have the lemma be.
 - fly, flies, flew, flying have the lemma fly.
 - walk, walks, walked, walking have the lemma walk.
 - walker, walkers have the lemma walker.
- Stem: Part of the word that is common to all its variants (there are also other definitions)
 - produce, production have the stem produc.
 - walk, walks, walked, walking, walker, walkers have the stem walk.
 - Do fly, flies, flew, flying have a common stem fl?
Or maybe only fly and flying share the stem fly? The decision will depend on the application.
- Lemmatisation and stemming are both NLP tasks
 - Porter stemmer: Rule-based and fast but crude (J&M3, Sec. 2.4.4)

Byte-pair encoding (BPE)

Instead of morphemes, subword units can also be learned automatically from a text corpus. There are several approaches including SentencePiece and byte-pair encoding (BPE).

We will look at BPE, probably one of the most popular approaches. BPE first learns the units and then applies them to new data.

Neural Machine Translation of Rare Words with Subword Units

Rico Sennrich and Barry Haddow and Alexandra Birch

School of Informatics, University of Edinburgh

{rico.sennrich,a.birch}@ed.ac.uk, bhaddow@inf.ed.ac.uk

Token learner algorithm

- Initialisation:
 - Vocabulary $\mathcal{V} \leftarrow$ unique characters in text
 - Tokenise text into separate characters
- for iteration $i = 1$ to K :
 - Find most frequent pair of adjacent tokens: t_L, t_R
 - Merge tokens: $t_{\text{new}} = t_L t_R$
 - Add to vocabulary: $\mathcal{V} \leftarrow \mathcal{V} \cup \{t_{\text{new}}\}$
 - Replace all occurrences of t_L, t_R in text with t_{new}

Token segmenter

Apply on the data the merges we learned on the training data in the order we learned them.

BPE example

Corpus:

```
low low low low low  
lower lower  
newer newer newer newer newer  
wider wider wider  
new new new
```

The corpus has 19 word tokens from 5 word types.

- iteration $i = 1$:
 - Find most frequent pair of adjacent tokens: t_L, t_R
 - Merge tokens: $t_{\text{new}} = t_L t_R$
 - Add to vocabulary: $\mathcal{V} \leftarrow \mathcal{V} \cup \{t_{\text{new}}\}$
 - Replace all occurrences of t_L, t_R in text with t_{new} .

```

l o w _ l o w _ l o w _ l o w _ l o w _
l o w e r _ l o w e r _
n e w e r _ n e w e r _ n e w e r _ n e w e r _ n e w e r -
n e w e r -
w i d e r _ w i d e r _ w i d e r -
n e w _ n e w _ n e w -

```

- iteration $i = 2$:
 - Find most frequent pair of adjacent tokens: t_L, t_R
 - Merge tokens: $t_{\text{new}} = t_L t_R$
 - Add to vocabulary: $\mathcal{V} \leftarrow \mathcal{V} \cup \{t_{\text{new}}\}$
 - Replace all occurrences of t_L, t_R in text with t_{new} .

l o w _
 l o w er _ l o w er _
 n e w er _ n e w er _ n e w er _ n e w er _ n e w er _
 n e w er _
 w i d er _ w i d er _ w i d er _
 n e w _ n e w _ n e w _

- iteration $i = 3$:
 - Find most frequent pair of adjacent tokens: t_L, t_R
 - Merge tokens: $t_{\text{new}} = t_L t_R$
 - Add to vocabulary: $\mathcal{V} \leftarrow \mathcal{V} \cup \{t_{\text{new}}\}$
 - Replace all occurrences of t_L, t_R in text with t_{new} .

```

l o w _ l o w _ l o w _ l o w _ l o w _
l o w er_ l o w er_
n e w er_ n e w er_ n e w er_ n e w er_
n e w er_
w i d er_ w i d er_ w i d er_
n e w _ n e w _ n e w _

```

Iteration: 1
5: l o w </w>
2: l o w e r </w>
6: n e w e r </w>
3: w i d e r </w>
3: n e w </w>
Merge: ("e", "r")

Iteration: 2
5: l o w </w>
2: l o w er </w>
6: n e w er </w>
3: w i d er </w>
3: n e w </w>
Merge: ("er", "</w>")

Iteration: 3
5: l o w </w>
2: l o w er</w>
6: n e w er</w>
3: w i d er</w>
3: n e w </w>
Merge: ("n", "e")

...

Iteration: 7
5: low </w>
2: low er</w>
6: new er</w>
3: w i d er</w>
3: new </w>
Merge: ("new", "er</w>")

Edit distance

Given two symbolic sequences, how similar are they?

The edit distance is the **minimum** number of changes needed to convert one sequence to the other.

It is also called the Levenshtein distance.

Edit distance between stall and table:

```
s t a l l  
t a l l      # deletion  
t a b l      # substitution  
t a b l e   # insertion
```

The edit distance between stall and table is therefore 3, if we let deletions, substitutions and insertions all cost 1.

We often use a higher penalty for substitutions. (Why?) If we use a penalty of 2 for substitutions and 1 for deletions and insertions, the edit distance would be 4.

One way to determine the edit distance is to find the best alignment between the sequences.

Example: Alignment costs between stall and table

Let $w_{\text{del}} = w_{\text{ins}} = 1$ and $w_{\text{sub}} = 2$. Below are example alignments between stall and table with their alignment costs. The edit distance is the optimal alignment: a cost of 4 in this case. There are a few optimal alignments in this case, all with a cost of 4.

Converting $x_{1:N} = \text{stall}$ into $y_{1:N} = \text{table}$:

s	t	a	-	l	-	l
S	D		I		I	D
t	-	a	b	l	e	-

cost: 6

s	t	a	l	-	l	-
D	D	S	S	I		I
-	-	t	a	b	l	e

cost: 8

s	t	a	l	l	-
D			S		I
-	t	a	b	l	e

cost: 4

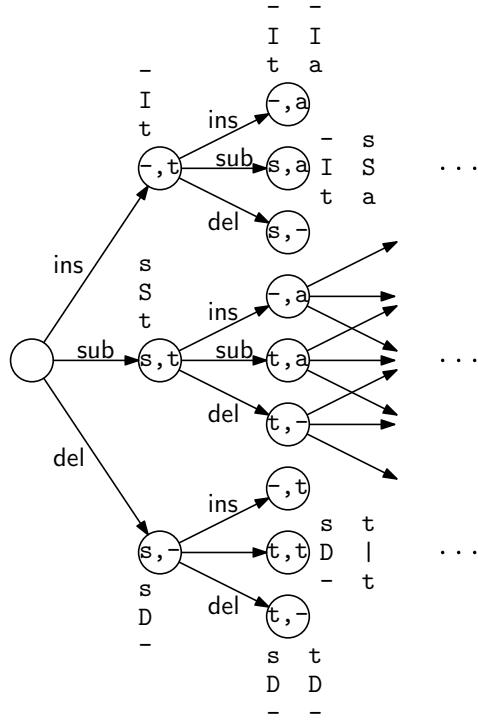
s	t	a	-	l	l
D			I		S
-	t	a	b	l	e

cost: 4

Brute force alignment

One solution to calculating the edit distance is to consider all possible alignments and pick the one with the lowest cost out of all the options.

But how many possible alignments are there?



Roughly $\mathcal{O}(3^N)$ -ish. The number of alignments grows exponentially with the length of the sequences!

So rather than brute force, we use a **dynamic programming** algorithm: Break the problem down into simpler sub-problems and then solve recursively ([Wikipedia](#)). Note that the algorithm below is guaranteed to give the optimal alignment: there are no approximations.

Edit distance algorithm

- Inputs: $x_{1:N}$ to be converted into $y_{1:M}$
- Cost matrix: $\mathbf{D} \in \mathbb{R}^{(N+1) \times (M+1)}$
- Initialisation:

$$D_{0,0} = 0$$

$$D_{i,0} = D_{i-1,0} + w_{\text{del}} \quad \text{for } i = 1, 2, \dots, N$$

$$D_{0,j} = D_{0,j-1} + w_{\text{ins}} \quad \text{for } j = 1, 2, \dots, M$$

- Recursion:

$$D_{i,j} = \begin{cases} D_{i-1,j-1} & \text{if } x_i = y_j \\ \min \begin{cases} D_{i-1,j} + w_{\text{del}} \\ D_{i,j-1} + w_{\text{ins}} \\ D_{i-1,j-1} + w_{\text{sub}} \end{cases} & \text{if } x_i \neq y_j \end{cases}$$

for $i = 1, 2, \dots, M$ and $j = 1, 2, \dots, N$

- Backtracking: From $D_{N,M}$ to $D_{0,0}$

Sometimes referred to as the [Wagner-Fischer algorithm](#).

Example: Align stall to table

$w_{\text{del}} = 1$, $w_{\text{ins}} = 1$ and $w_{\text{sub}} = 2$

Cost matrix:

		t	a	b	l	e
	0	$\leftarrow 1$	$\leftarrow 2$	$\leftarrow 3$	$\leftarrow 4$	$\leftarrow 5$
s	$\uparrow 1$	$\leftarrow \nwarrow \uparrow 2$	$\leftarrow \nwarrow \uparrow 3$	$\leftarrow \nwarrow \uparrow 4$	$\leftarrow \nwarrow \uparrow 5$	$\leftarrow \nwarrow \uparrow 6$
t	$\uparrow 2$	$\nwarrow 1$	$\leftarrow 2$	$\leftarrow 3$	$\leftarrow 4$	$\leftarrow 5$
a	$\uparrow 3$	$\uparrow 2$	$\nwarrow 1$	$\leftarrow 2$	$\leftarrow 3$	$\leftarrow 4$
l	$\uparrow 4$	$\uparrow 3$	$\uparrow 2$	$\leftarrow \nwarrow \uparrow 3$	$\nwarrow 2$	$\leftarrow 3$
l	$\uparrow 5$	$\uparrow 4$	$\uparrow 3$	$\leftarrow \nwarrow \uparrow 4$	$\nwarrow \uparrow 3$	$\leftarrow \nwarrow \uparrow 4$

Backtrace path:

		t	a	b	l	e
		$\leftarrow 1$	$\leftarrow 2$	$\leftarrow 3$	$\leftarrow 4$	$\leftarrow 5$
s	$\uparrow 1$	$\leftarrow \nwarrow \uparrow 2$	$\leftarrow \nwarrow \uparrow 3$	$\leftarrow \nwarrow \uparrow 4$	$\leftarrow \nwarrow \uparrow 5$	$\leftarrow \nwarrow \uparrow 6$
t	$\uparrow 2$	$\nwarrow 1$	$\leftarrow 2$	$\leftarrow 3$	$\leftarrow 4$	$\leftarrow 5$
a	$\uparrow 3$	$\uparrow 2$	$\nwarrow 1$	$\leftarrow 2$	$\leftarrow 3$	$\leftarrow 4$
l	$\uparrow 4$	$\uparrow 3$	$\uparrow 2$	$\leftarrow \nwarrow \uparrow 3$	$\nwarrow 2$	$\leftarrow 3$
l	$\uparrow 5$	$\uparrow 4$	$\uparrow 3$	$\leftarrow \nwarrow \uparrow 4$	$\nwarrow \uparrow 3$	$\leftarrow \nwarrow \uparrow 4$

$D_{2,2} = d(\text{st}, \text{ta})$ $D_{2,3} = d(\text{st}, \text{tab})$
 $D_{3,2} = d(\text{sta}, \text{ta})$ $D_{3,3} = d(\text{sta}, \text{tab})$

Time complexity: Calculate $\mathcal{O}(NM)$ values in cost matrix

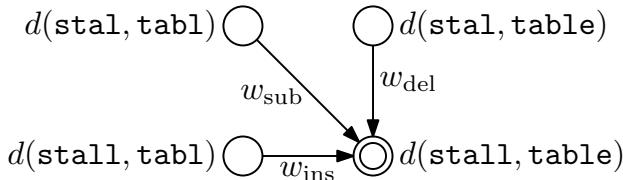
Why is this guaranteed to give the optimal alignment?

Each cell $D_{i,j}$ is the smallest cost to align $x_{1:i}$ to $y_{1:j}$. Why?

Let's say I knew the edit distances for:

- $d(\text{stall}, \text{tabl})$
- $d(\text{stal}, \text{table})$
- $d(\text{stal}, \text{tabl})$

Then I could get the edit distance of $d(\text{stall}, \text{table})$. This would be exact, without any approximation!²



This also holds for the non-final steps. The edit distance algorithm uses this as its smallest subproblem. The solution to each subproblem is stored, and then used to solve and store the solutions to larger subproblems until we get the final solution (the best overall alignment).

²Substitutions and insertions are sometimes easier to see than deletions. I unpack deletions specifically under [common misconceptions](#).

More on the edit distance

Advanced edit distance

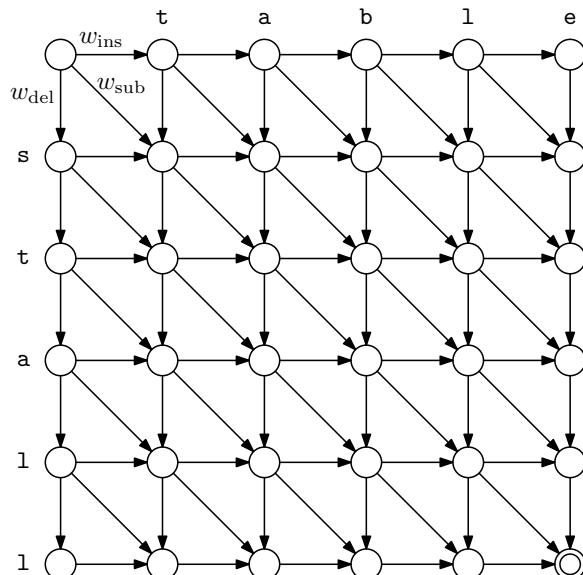
- Can give different weight w depending on the symbols involved
- Local alignment variants: Find subsequences that align well
- Dynamic time warping: Align continuous signals

Applications of edit distance

- Computational biology: Aligning sequences of nucleotides
- Spelling correction
- Speech recognition: Calculating word error rate

Dynamic programming in general

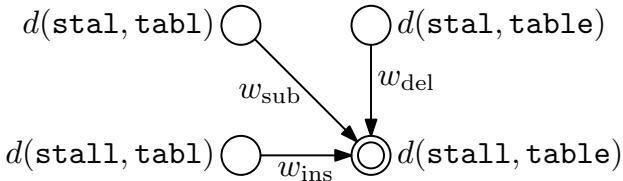
The edit distance algorithm is an instance of dynamic programming – a more general class of algorithms. Dynamic programming can always be reduced to finding the optimal path through a directed acyclic graph. The graph for the edit distance algorithm:



Common misconceptions

Deletions in dynamic programming

Students (and I myself) sometime struggle to understand the deletion edge in the dynamic programming graph fragment:



Forget about the graph for a second. Imagine I told you that to convert stal into table takes 3 edits (acting optimally). Now I ask you to convert stall into table. Here's one way (it might not be the optimal way):

- Delete the last 1 in stall: stal (1 deletion)
- Now convert stal into table (I told you this will take 3 edits)

So I know I convert stall to table with $1 + 3 = 4$ edits, by just adding one deletion.

There might be a better way to convert stall to table, but if $d(\text{stal}, \text{table}) = 3$, then we know that $d(\text{stall}, \text{table})$ will at worst be 4.

This is what the w_{del} edge corresponds to in the graph fragment.

Videos covered in this note

- A first NLP example (8 min)
- Text normalisation and tokenisation (8 min)
- Words (12 min)
- Morphology (5 min)
- Stems and lemmas (3 min)
- Byte-pair encoding (BPE) (9 min)
- Edit distance (20 min)

Further reading

I have a separate note that describes [dynamic programming](#) in a more general sense.

Acknowledgements

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