Text normalisation, units and edit distance

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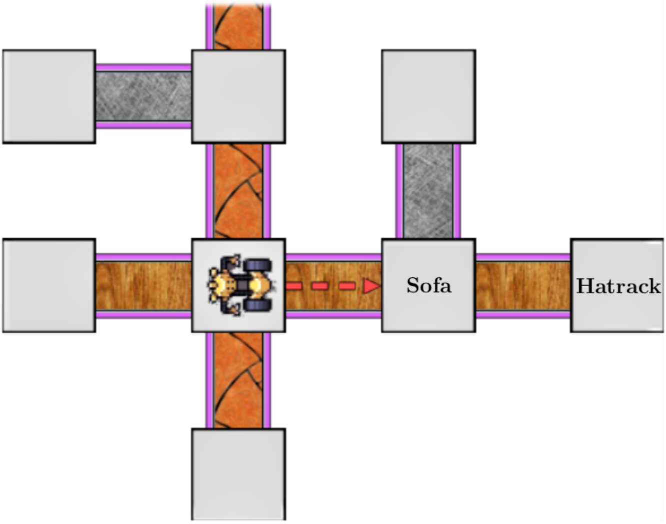
Robotic instruction following



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

[1]Figure by Ryan Eloff.

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.

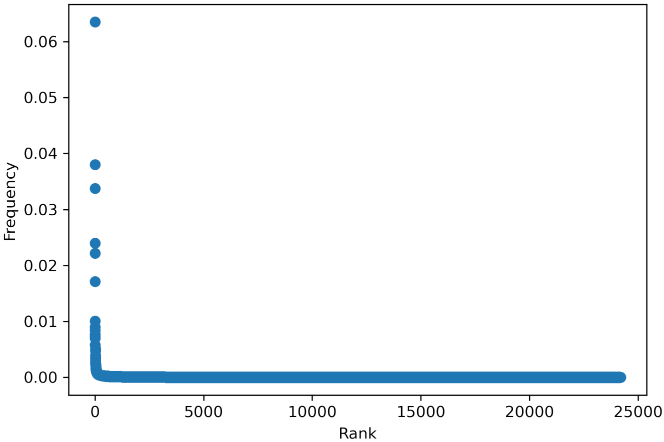
This is linear on a plot with the frequency and rank axes on log scales. Why? Because

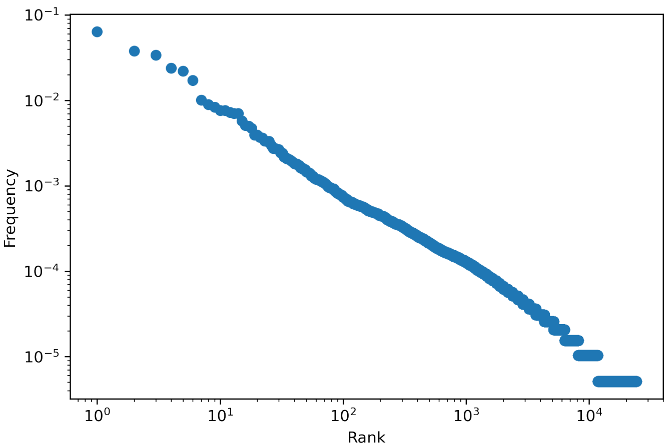
$$\log f \approx \log c - \log r$$

which looks like

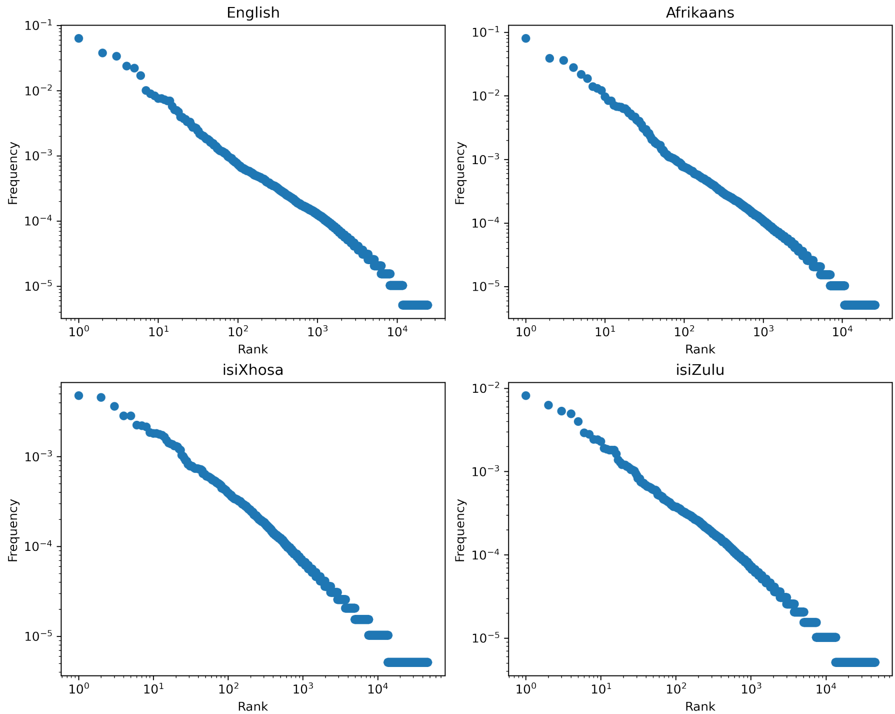
$$y \approx k - x$$

On English:


0.06
0.05
0.04
0.03
0.02
0.01
0.00
Frequency
0
5000
10000
15000
20000
25000
Rank


10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
Frequency
10^{0}
10^{1}
10^{2}
10^{3}
10^{4}
Rank

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 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 _ 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 _
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_
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, all with a cost of 4.

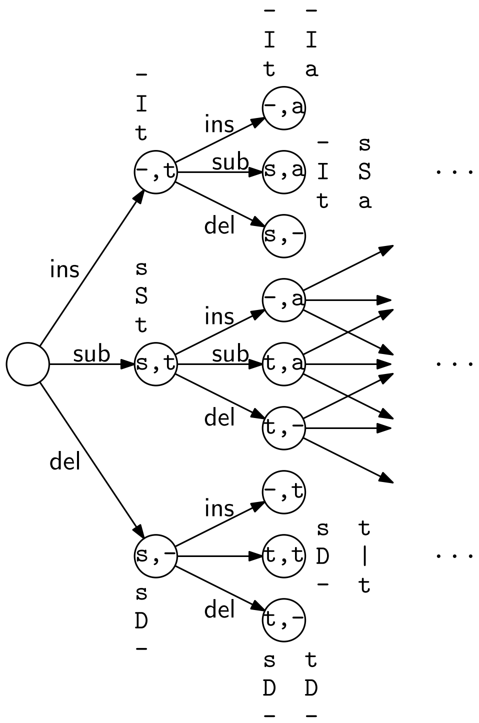
Converting $x_{1:N} =$ `stall` into $y_{1:N} =$ `table`:

```
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:

$$\begin{aligned} D_{0,0} &= 0 \\ D_{i,0} &= D_{i-1,0} + w_{\text{del}} \qquad \text{for } i = 1, 2, \ldots, N \\ D_{0,j} &= D_{0,j-1} + w_{\text{ins}} \qquad \text{for } j = 1, 2, \ldots, M \end{aligned}$$

- Recursion:

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

$$\text{for } i = 1, 2, \ldots, M \text{ and } j = 1, 2, \ldots, N$$

- 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:

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

		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	$\uparrow 5$	$\uparrow 4$	$\uparrow 3$	$\leftarrow\nwarrow\uparrow 4$	$\nwarrow\uparrow 3$	$\leftarrow\nwarrow\uparrow 4$

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

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

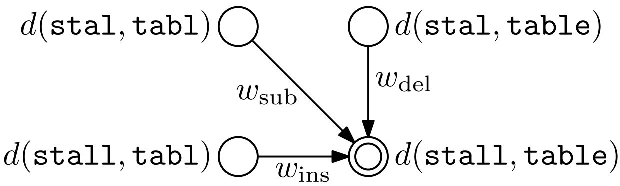
Why is this guaranteed to give the optimal alignment?

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:

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

Then I could get the edit distance of $d(\texttt{stall}, \texttt{table})$. 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).

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

More on the edit distance

Advanced edit distance

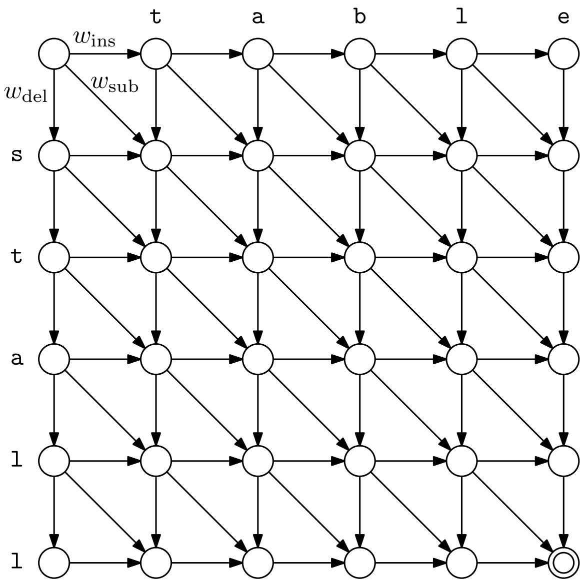
- Can give different weight w depending on the symbols involved
- Local alignment variants: Find subsequences that align well
- Dynamic time warping: Align continuous signals

Applications of edit distance

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

Dynamic programming in general

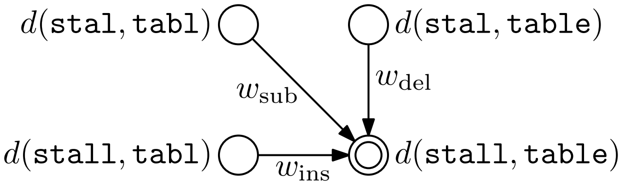
The edit distance algorithm is an instance of dynamic programming – a more general class of algorithms. Dynamic programming can always be reduced to finding the optimal path through a directed acyclic graph. The graph for the edit distance algorithm:



Common misconceptions

Deletions in calculating the edit distance

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 covert `stal` into `table` takes 3 edits (acting optimally). Now I ask you to covert `stall` into `table`. Here's one way (it might not be the optimal way):

- Delete the last `l` 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 $d(\texttt{stal}, \texttt{table}) = 3$, then we know that $d(\texttt{stall}, \texttt{table})$ 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 more generally.

Acknowledgements

This note uses content from:

- Jan Buys' NLP course at the University of Cape Town
- Sharon Goldwater's NLP course at the University of Edinburgh