

Natural Language Processing with Probabilistic Model

- Autocorrect
- Part of Speech Tagging and Hidden Markov Models
- Autocomplete and Language Models
- Word embeddings with neural networks

Autocorrect

- Learning objectives
 - What is autocorrect?
 - Building the model
 - Minimum edit distance
 - Minimum edit distance algorithm

deah → dear ✓

yeah
dear
dean
... etc

	#	s	t	a	y
#	0	1	2	3	4
p	1	2	3	4	5
l	2	3	4	5	6
a	3	4	5	4	5
y	4	5	6	5	4

What is autocorrect?

Happy birthday deah friend!



Happy birthday deer friend!



??

Happy birthday ☒ dear friend!



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Autocorrect is an application that changes misspelled words into the correct ones.

How it works

1. Identify a misspelled word deah

2. Find strings n edit distance away deah

_eah

3. Filter candidates

d_ar

deah

de_r

yeah

4. Calculate word probabilities

... etc

dear

deah

dean

yeah

... etc

dear

dean

... etc

Building the model

1. Identify a misspelled word

```
if word not in vocab:  
    misspelled = True
```

deah

Happy birthday deer !



- If word not in vocabulary then its misspelled
- More sophisticated techniques for identifying words that are probably incorrect by looking at the words surrounding them

Building the model

2. Find strings n edit distance away: find all possible strings that are n edit distance away using

- Edit: an operation performed on a string to change it
 - how many operations away one string is from another
 - Insert (add a letter)
 - Add a letter to a string at any position: to ==> top, two,...
 - Delete (remove a letter)
 - Remove a letter from a string : hat ==> ha, at, ht
 - Switch (swap 2 adjacent letters)
 - Example: eta=> eat, tea
 - Replace (change 1 letter to another): Example: jaw ==> jar,paw,saw,...
 - By combining the 4 edit operations, we get list of all possible strings that are n edit

deah

_eah
d_ar
de_r
... etc

Building the model

3. Filter candidates

- From the list from step 2, consider only real and correct spelled word
- if the edit word not in vocabulary ==> remove it from list of candidates

<u>deah</u>		<u>deah</u>
_eah		yeah
d_ar	→	dear
de_r		dean
... etc		... etc

Building the model

- Calculate word probabilities: the word candidate is the one with the highest probability
word probability in a corpus is: number of times the word appears divided by the total number of words.

Example: "I am happy because I am learning"

$$P(w) = \frac{C(w)}{V}$$

$$P(\text{am}) = \frac{C(\text{am})}{V} = \frac{2}{7}$$

$P(w)$ Probability of a word

$C(w)$ Number of times the word appears

V Total size of the corpus

Word	Count
I	2
am	2
happy	1
because	1
learning	1

Total : 7

Minimum edit distance

- How to evaluate similarity between 2 strings?
- Minimum number of edits needed to transform 1 string to the other
- Applications
 - Spelling correction,
 - Document similarity,
 - Machine translation,
 - DNA sequencing, and more

Minimum edit distance

- Example:

Source:

p	l	a	y
---	---	---	---



Source:

s	t	a	y
---	---	---	---

p → s : replace
l → t : replace

} edits = 2

Edit cost:

Insert 1

Delete 1

Replace 2

edit distance = 2 * 2 = 4

Minimum edit distance algorithm

- The source word layed on the column
- The target word layed on the row
- Empty string at the start of each word at (0,0)
- $D[i,j]$ is the minimum editing distance between the beginning of the source word to index i and the beginning of the target word to index j

Minimum edit distance

- Source: play → Target: stay
 - Have the source wordplay here down the left column
 - Targets were to transform into stay along the top row
 - The goal is to fill out this distance matrix $D[]$
 - $D[i, j] = \text{source}[: i] \text{ target } [:j]$
 - $D[m, n] = \text{source} \rightarrow \text{target}$

		0	1	2	3	4
		#	s	t	a	y
0	#					
1	p					
2	l					
3	a					
4	y					

Minimum edit distance

Source: play → Target: stay

Cost: insert: 1, delete: 1, replace: 2

p → s

insert + delete: p → ps → s:
2

delete + insert: p → # → s
 2

replace: p → s:
 2

		0	1	2	3	4
		#	s			
0	#	0	1			
1	p	1	2			
2						
3						
4						

Minimum edit distance II

Source: play → Target: stay

Cost: insert: 1, delete: 1, replace: 2

play → #

$$D[i, j] = D[i-1, j] + del_cost$$

$$D[4, 0] = \text{play} \rightarrow \# \\ = \text{source}[:4] \rightarrow \text{target } 0]$$

		0	1	2	3	4
		#	s	t	a	y
0	#	0	1			
1	p	1	2			
2	l	2				
3	a	3				
4	y	4				

		0	1	2	3	4
		#	s	t	a	y
0	#	0	1	2	3	4
1	p	1	2			
2	l	2				
3	a	3				
4	y	4				

- $D[4, 0]$, you have the minimum edit distance for play to the empty string
- same idea in the first row by transforming the empty string to stay by inserting one letter at a time

Minimum edit distance

Source: play → Target: stay

Cost: insert: 1, delete: 1, replace: 2

p → s

$$D[i, j] = \min \begin{cases} D[i-1, j] + del_cost \\ D[i, j-1] + ins_cost \\ D[i-1, j-1] + \begin{cases} rep_cost; & \text{if } src[i] \neq tar[j] \\ 0; & \text{if } src[i] = tar[j] \end{cases} \end{cases}$$

		0	1	2	3	4
		#	s	t	a	y
0	#	0	1	2	3	4
1	p	1	2			
2	l	2				
3	a	3				
4	y	4				

Minimum edit distance

- Source: play \rightarrow Target: stay
 - Cost: insert: 1, delete: 1, replace: 2 play \rightarrow stay
 - $D[m, n] = 4$

		0	1	2	3	4
		#	s	t	a	y
0	#	0	1	2	3	4
1	p	1	2	3	4	5
2	l	2	3	4	5	6
3	a	3	4	5	4	5
4	y	4	5	6	5	4

Minimum edit distance

Source: play → Target: stay

Cost: insert: 1, delete: 1, replace: 2

- Levenshtein distance

		0	1	2	3	4
		#	s	t	a	y
0	#	0	1	2	3	4
1	p	1	2	3	4	5
2	l	2	3	4	5	6
3	a	3	4	5	4	5
4	y	4	5	6	5	4

- The Levenshtein distance between two sequences is the simplest weighting factor in which each of the three operations has a cost of 1 (Levenshtein, 1966)—we assume that the substitution of a letter for itself, for example, t for t, has zero cost.

Minimum edit distance III

Source: play → Target: stay

Cost: insert: 1, delete: 1, replace: 2

- Levenshtein distance
- Backtrace: a pointer in each cell letting you know where character came from

		0	1	2	3	4
		#	s	t	a	y
0	#	0	1	2	3	4
1	p	1	2	3	4	5
2	l	2	3	4	5	6
3	a	3	4	5	4	5
4	y	4	5	6	5	4

Minimum edit distance

- Source: play → Target: stay
- Cost: insert: 1, delete: 1, replace: 2
- Levenshtein distance
- Backtrace
- Dynamic programming:
 - solving the smallest subproblem first and then reusing that result to solve the next biggest subproblem

		0	1	2	3	4
		#	s	t	a	y
0	#	0	1	2	3	4
1	p	1	2	3	4	5
2	l	2	3	4	5	6
3	a	3	4	5	4	5
4	y	4	5	6	5	4

Summary

- What is autocorrect?
- Building the model
- Minimum edit distance
- Minimum edit distance algorithm

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