

Für $k = 2$ bekommen wir:

$p(\text{Er ölt}) =$

$p(E|\langle s \rangle, \langle s \rangle) \quad p(r|\langle s \rangle, E) \quad p(-|E, r) \quad p(\ddot{o}|r, -) \quad p(l|-, \ddot{o}) \quad p(t|\ddot{o}, l) \quad p(\langle s \rangle|l, t)$

$$p(w_i | w_{i-k}^{i-1}) = \frac{\max(0, f(w_{i-k}^i) - \delta_k)}{f(w_{i-k}^{i-1})} + \alpha(w_{i-k}^{i-1}) p(w_i | w_{i-k+1}^{i-1})$$

$p(\text{Buch} | \text{das}, \text{rote}) = p^*(\text{Buch} | \text{das}, \text{rote}) + \alpha(\text{das}, \text{rote}) \cdot p_{\text{backoff}}(\text{Buch} | \text{das}, \text{rote})$

$p_{\text{backoff}}(\text{Buch} | \text{rote}) = (p^*(\text{Buch} | \text{rote}) + \alpha(\text{rote}) \cdot p_{\text{backoff}}(\text{Buch} | \text{rote}))$

$p_{\text{backoff}}(\text{Buch}) = p^*(\text{Buch} | \text{rote})$
 $= f(\text{Buch}) / f() \text{ oder } N$

$p^*(\text{Buch} | \text{das}, \text{rote}) = (f(\text{das}, \text{rote}, \text{Buch}) - \delta_2) / f(\text{das}, \text{rote})$

$p^*(\text{Buch} | \text{rote}) = (f(\text{rote}, \text{Buch}) - \delta_1) / f(\text{rote})$

.....

$$p(w_i | w_{i-k}^{i-1}) = \frac{\max(0, f(w_{i-k}^i) - \delta_k)}{f(w_{i-k}^{i-1})} + \alpha(w_{i-k}^{i-1}) p(w_i | w_{i-k+1}^{i-1})$$

$p(w_3 | w_1, w_2) = (f(w_1, w_2, w_3) - \delta_2) / f(w_1, w_2) + \alpha(w_1, w_2) \cdot p_{\text{backoff}}(w_3 | w_2)$

3-gram-freq

('das', 'rote', 'buch')	:	5
('dieses', 'rote', 'buch')	:	2
('gute', 'rote', 'buch')	:	4
('das', 'gelbe', 'buch')	:	1
('das', 'rote', 'kleid')	:	2
('dieses', 'rote', 'kleid')	:	2
('das', 'rote', 'haus')	:	8

We read the training corpus and get this 3-gram freq.

Next we want to compute $p_{\text{smoothed}}(\text{ngram})$ for all ngrams.

These will be our trained parameters.

When we have a new text. We convert the text in to a seq of ngram and compute the product of $p_{\text{smoothed}}(\text{ngram})$.

Goal

3-gram-smoothed_prob

('das', 'rote', 'buch')	:	0.001
('dieses', 'rote', 'buch')	:	0.002
('gute', 'rote', 'buch')	:	0.0004
('das', 'gelbe', 'buch')	:	0.0231
('das', 'rote', 'kleid')	:	0.33
('dieses', 'rote', 'kleid')	:	0.002
('das', 'rote', 'haus')	:	0.0018

p^*

$$p(w_i | w_{i-k}^{i-1}) = \frac{\max(0, f(w_{i-k}^{i-1}) - \delta_k)}{f(w_{i-k}^{i-1})} + \alpha(w_{i-k}^{i-1}) p(w_i | w_{i-k+1}^{i-1})$$

$$p(w_3 | w_1, w_2) = (f(w_1, w_2, w_3) - \delta_2) / f(w_1, w_2) + \alpha(w_1, w_2) \cdot p_{\text{backoff}}(w_3 | _ w_2)$$

3-gram-freq

('das', 'rote', 'buch')	:	5
('dieses', 'rote', 'buch')	:	2
('gute', 'rote', 'buch')	:	4
('das', 'gelbe', 'buch')	:	1
('das', 'rote', 'kleid')	:	2
('dieses', 'rote', 'kleid')	:	2
('das', 'rote', 'haus')	:	8

How to get $f(w_1, w_2, w_3)$?

look up at the 3-gram-freq

How to get $f(w_1, w_2)$?

$$f(w_{i-k}^{i-1}) = \sum_w f(w_{i-k}^{i-1} w)$$

Folien 80

to get the freq of the context “das, rote” of a 3-gram, you look at the 3-gram-freq. Go through all 3-gram, and ask if does this 3-gram has the context “das, rote”?

It does not matter what word the 3-gram has. We only look at the context of it.

Then you take the freq of those 3-gram and sum them up.

This is how we compute the context of each 3-gram.

(do it for all 3 gram and store the context freq in a dict)

how to compute the discount (3-gram /k = 2) ?

$$\delta = \frac{N_1}{N_1 + 2N_2}$$

You look up in the 3-gram-freq again. ...

Now we can compute $p^*(\text{das rote Buch})$

3-gram-freq

('das', 'rote', 'buch')	:	5
('dieses', 'rote', 'buch')	:	2
('gute', 'rote', 'buch')	:	4
('das', 'gelbe', 'buch')	:	1
('das', 'rote', 'kleid')	:	2
('dieses', 'rote', 'kleid')	:	2
('das', 'rote', 'haus')	:	8

$$p(w_i | w_{i-k}^{i-1}) = \frac{\max(0, f(w_{i-k}^{i-1}) - \delta_k)}{f(w_{i-k}^{i-1})} + \alpha(w_{i-k}^{i-1}) p(w_i | w_{i-k+1}^{i-1})$$

How can you compute the backoff of the context “das, rote”?

$$\alpha(C) = 1 - \sum_{w: f(C, w) > 0} \frac{f(C, w) - \delta}{f(C)}$$

You need $p^*(3\text{-gram})$ of all 3-gram.

We first will compute p^* for all 3-grams from the training corpus.

3-gram-freq

('das', 'rote', 'buch')	:	5
('dieses', 'rote', 'buch')	:	2
('gute', 'rote', 'buch')	:	4
('das', 'gelbe', 'buch')	:	1
('das', 'rote', 'kleid')	:	2
('dieses', 'rote', 'kleid')	:	2
('das', 'rote', 'haus')	:	8

now that we already have $f(3\text{gram})$, $f(\text{context})$, discount (3-gram), we can compute p^*

for each 3-gram, we compute p^* and store it in a new dictionary.
In Übung4 solution, p^* is “prob”.

p^*

('das', 'rote', 'buch')	:	0.001
('dieses', 'rote', 'buch')	:	0.001
('gute', 'rote', 'buch')	:	0.005
('das', 'gelbe', 'buch')	:	0.006
('das', 'rote', 'kleid')	:	0.022
('dieses', 'rote', 'kleid')	:	0.003
('das', 'rote', 'haus')	:	0.042

Now we can compute p^* .

We have all p^* , now we can compute the backoff factor (context)
-we will compute the backoff factor for all context

$C = \text{“das rote”}$

$$\alpha(C) = 1 - \sum_{w: f(C, w) > 0} \frac{f(C, w) - \delta}{f(C)}$$

(Note: In the original image, the fraction $\frac{f(C, w) - \delta}{f(C)}$ is circled in blue, and a blue arrow points from the label p^ above it to the numerator $f(C, w) - \delta$.)*

For each context, for example “das rote”, look in p^* dict, for 3-gram that has this exact context.

Sum up p^* of such 3-gram and subtract the result from 1

p^*

('das', 'rote', 'buch')	:	0.001
('dieses', 'rote', 'buch')	:	0.001
('gute', 'rote', 'buch')	:	0.005
('das', 'gelbe', 'buch')	:	0.006
('das', 'rote', 'kleid')	:	0.022
('dieses', 'rote', 'kleid')	:	0.003
('das', 'rote', 'haus')	:	0.042

backoff(context 3-gram)

('das', 'rote')	:	$1 - [p^*(\text{das, rote, buch}) + p^*(\text{das rote kleid}) + p^*(\text{das rote haus})]$
('dieses', 'rote')	:	$1 - [p^*(\text{dieses, rote, buch}) + p^*(\text{dieses rote kleid})]$
('gute', 'rote')	:	$1 - [p^*(\text{gute, rote, buch})]$
('das', 'gelbe')	:	$1 - [p^*(\text{das, gelbe, buch})]$

$$p(w_i | w_{i-k}^{i-1}) = \frac{\max(0, f(w_{i-k}^i) - \delta_k)}{f(w_{i-k}^{i-1})} + \alpha(w_{i-k}^{i-1}) p(w_i | w_{i-k+1}^{i-1})$$

$$p(w_3 | w_1, w_2) = (f(w_1, w_2, w_3) - \delta_2) / f(w_1, w_2) + \alpha(w_1, w_2) \cdot \mathbf{p_backoff}(w_3 | _ w_2)$$

$$\mathbf{p_backoff}(w_3 | _ w_2) = f(w_2, w_3) - \text{discount}(k=1) / f(w_2) + \text{backoff}(w_2) * p(w_3)$$

3-gram-freq

('das', 'rote', 'buch')	:	5
('dieses', 'rote', 'buch')	:	2
('gute', 'rote', 'buch')	:	4
('das', 'gelbe', 'buch')	:	1
('das', 'rote', 'kleid')	:	2
('dieses', 'rote', 'kleid')	:	2
('das', 'rote', 'haus')	:	8

How to compute $f(w_1, w_2)$?

$$p_{\text{backoff}}(w | C) = \frac{f_{\text{rot}}^*(C, w)}{\sum_{w'} f^*(C, w')} \quad \text{Folie 87}$$

We need a 2-gram freq which we will derive from the existing 3-gram freq

hier we have 2 options for how to compute the freq

For example, $f(\text{rote}, \text{buch})$

$$f(C, w) = \sum_{w'} f(w', C, w)$$

$$f^*(C, w) = \sum_{w'} \mathbf{1}_{f(w', C, w) > 0}$$

0.

2-gram-freq (standard)

('rote', 'buch')	:	5+2+4
('gelbe', 'buch')	:	1
('rote', 'kleid')	:	2+2
('rote', 'haus')	:	8

2-gram-freq (kneser-ney)

('rote', 'buch')	:	1+1+1
('gelbe', 'buch')	:	1
('rote', 'kleid')	:	1+1
('rote', 'haus')	:	1

Now that we have the 2-gram freq, to compute $f(\text{rote buch})$, we can simply look up in the 2-gram freq dict.

Next, how can we compute the context freq $f(\text{rote})$?

$$p_{\text{backoff}}(w | C) = \frac{f_{\text{rot}}^*(C, w)}{\sum_{w'} f^*(C, w')}$$

To compute $f(\text{rote})$, we look up in the 2-gram freq dict, and look for those with context rote. Sum the freq of them up. Below we will use the standard 2-gram-freq to compute this.

2-gram-freq (standard)

('rote', 'buch')	:	11
('gelbe', 'buch')	:	1
('rote', 'kleid')	:	4
('rote', 'haus')	:	8

2-gram context

rote : 11 + 4 + 8
gelb : 1

Übung

- compute discount for the bigram (the same method as shown in 3-gram step)
- then compute $p^*(\text{bigram})$
- then compute $\text{backoff_factor}(\text{bigram_context})$

Do the same for unigram

(To check your solution, run the file “Example_code_markov_model” in the tutorial website)

p^*

backoff (context 2gram)