Assignment 4+Smoothing (SNLP tutorial 4)

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Overview

- Task, Metrics
- Differential Privacy
- Homework

Assignment 4

- Exercise 1: Huffman encoding
- Exercise 2: Conditional entropy of DNA
- Bonus: Huffman encoding adaptations

OOV words

Corpus

- Train set:
- Test set:



OOV words

Corpus

- Train set:
 - Test set:



Accumulate counts

OOV words

Corpus

- Train set:



































- 6 2 5 3 2









OOV words

- What about and •?
- OOV rate: 2 + 1/4 + 2 + 2 + 1 + 1 + 1 = 27%
- Solutions? character-level subword units.

Additive smoothing (add- α -smoothing)

Unigrams

Add zero counts to frequency table















ullet Increase all counts by lpha=1



















• Divide by N = 22



















Perplexity

• Relative frequencies on test corpus:

















Additive smoothing (add- α -smoothing)

Unigrams

- Add zero counts to frequency table

- $6 \geq 5 \qquad 3 \qquad 2 \qquad \bigcirc 0$

- ullet Increase all counts by lpha=1
- 6+1 > 5+1 3+1 2+1 0+1

- Divide by N = 22

- 0.32 \geqslant 0.27 \triangleright 0.18 $\stackrel{\triangleright}{\triangleright}$ 0.13 $\stackrel{\bigcirc}{\square}$ 0.05

Perplexity

• Relative frequencies on test corpus:















 $PP = 2^{(0.33 \cdot 0.32 + 0.27 \cdot 0.17 + 0.18 \cdot 0.17 + 0.13 \cdot 0.17 + 2 \cdot (0.05 \cdot 0.08))} = 1.4$

Recall the additive smoothing formula for unigrams:

$$p_{smoothed}(w_i) = \frac{C(w_i) + \alpha}{N + \alpha |V|}$$
(1)

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• What is *N*? What is *V*?

Remember from Assignment 2 that:

$$p(w_i|w_{i-1}) = \frac{C(w_{i-1}, w_i)}{C(w_{i-1})}$$
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- Smoothe the bigram count: $C(w_{i-1}, w_i) \rightarrow C(w_{i-1}, w_i) + \alpha$
- Normalization: $p_{smoothed}(w_i|w_{i-1}) = \frac{C(w_{i-1},w_i) + \alpha}{?}$



Additive smoothing: Bigrams: bigram counts

• Collect bigram counts & condtional probabilities for history A

Bigram	$C(w_i, w_{i-1})$	$C(w_{i-1})$	$\frac{C(w_{i-1},w_i)}{C(w_{i-1})}$
AE	3	6	1/2
AA	2	6	1/3
AB	1	6	1/6

Additive smoothing: Bigrams: add alpha

• We encounter an unknown bigram AF

Bigram	$C_{\alpha}(w_{i-1},w_i)$	$C_{\alpha}(w_{i-1})$	$\frac{C_{\alpha}(w_{i-1},w_i)}{C_{\alpha}(w_{i-1})}$
AE	3+1	6 + 1	4/7
AA	2+1	6+1	3/7
AB	1+1	6+1	2/7
ightarrow AF	$0\!+\!1$	6 + 1	1/7

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- Solution: We need to adjust the divisor a tiny bit. But how tiny?

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- Pretend that we have seen the history |V| = 3 times more.

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Bigram	$C_{\alpha}(w_{i-1}) + \alpha V $	$rac{C_{lpha}(w_{i-1},w_i)}{C_{lpha}(w_{i-1})+lpha V }$
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• Now the probabilities sum up to 1: 4/10 + 3/10 + 2/10 + 1/10 = 1

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AE	7 + 4	4/11
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$\rightarrow AF$	7 + 4	1/11
ightarrow AD	7 + 4	1/11

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AE	7 + 4	4/11
AA	7 + 4	3/11
AB	7 + 4	2/11
ightarrow AF	7 + 4	1/11
ightarrow AD	7 + 4	1/11

- $C_{\alpha}(A)$ is constant
- Probabilities sum up to 1: 4/11 + 3/11 + 2/11 + 1/11 + 1/11 = 1

• General formula for smoothed bigram Probabilities:

$$p(w_i|w_{i-1}) = \frac{C(w_{i-1}, w_i) + \alpha}{C(w_{i-1}) + \alpha|V|}$$
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• For n-grams of length n:

$$p(w_i|w_{i-1}:w_{i-n+1}) = \frac{C(w_{i-n+1}:w_i) + \alpha}{C(w_{i-n+1}:w_{i-1}) + \alpha |V_{(w_{i-n+1}:w_{i-1},\bullet)}|}$$
(5)

Kneser-Ney Smoothing

TODO

absolute discounting

Cross-Validation

TODO

Estimating LOO Parameters

TODO ??

Laplace Smoothing

add epsilon

TODO

Linear Discounting

• linear interpolation

Good-Turing Discounting

TODO

Count Trees

• remove infrequent nodes

TODO

Privacy

TODO differential privacy

Resources

- UdS SNLP Class, WSD: https://teaching.lsv.uni-saarland.de/snlp/
- Classical Statistical WSD: https://www.aclweb.org/anthology/P91-1034.pdf
- on-gram count trees: http://ssli.ee.washington.edu/WS07/notes/ngrams.pdf