Assignment 5,6 + Smoothing 2

(SNLP Tutorial 6)

Vilém Zouhar, Awantee Deshpande, Julius Steuer

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Slides repository

github.com/zouharvi/uds-snlp-tutorial

- Contributions welcome
- "Cheating" allowed

Assignment 5

- Exercise 1: OOV Words
- Exercise 2: Additive smoothing
- Exercise 3: Perplexity, infinite smoothing, interpolation
- Bonus: Other language models

Cross-validation

- Cross-validation is ...
- Train/(valid,test) split
- K-fold cross-validation is ...
- Divide data into k subsets, train on k-1 subsets and test on the remaining 1.
- Leave One Out cross-validation is ...
- N-fold cross-validation (use one point for testing)

Questions

- What is the motivation behind LOOCV?
- What is the main issue of LOOCV?
- Why is k-fold cross-validation better than cross-validation?
- Why is cross-validation better than k-fold cross-validation?
- How does shuffling the dataset affect the LOOV score?
- If two models have same average performance (k-fold cross-validation), are they the same?
- Other usage of k-fold cross-validation (or split in general)?

Smoothing Techniques - Basics

- To keep a language model from assigning 0 or ~0 probabilities to ________
- Generally we can smooth any arbitrary _________
- Different ways to do this...

Floor Discounting

$$P(w|h) = \frac{N(w,h) + \epsilon}{N(h) + \epsilon \cdot V}$$

Variants: Laplace smoothing, Lidstone smoothing, add-α smoothing...

Questions

- What is $N(h)$ for unigram $N(w)$?
- What is $N(h)$ for n-gram $N(w,h)$?
- What is $N(h)$ for zerogram?

Good-Turing

Data: 🍏 🍏 🍏 🍆 🍌 🍌 🍒 🍆 🍌 🍌 🍒 🍆 🍇 🌿

- $N_4 = \{$🍌$\}$
- $N_3 = \{$🍏, 🍆$\}$
- $N_2 = \{$🍒$\}$
- $N_1 = \{$🍇, 🌿$\}$
- $N_0 = \{$🍨$\}$

$$p_r = \frac{(r+1)N_{r+1}}{N_r} \cdot \frac{1}{N}$$

- Nominator: expected total number of occurences of words that occur $r+1$ times
- Denominator-left: previous bucket size
- Fraction-left: expected number of occurences of a single word from that bucket
- Denominator-right: divide by total occurences

Good-Turing - Questions

- Two items have same original frequency. What will be their new probability?
- Let k be the maximum occurence of a word. What's the issue?
- A similar issue related to the one above?
- Do the probabilities sum up to 1?
- How to make it work for anything above unigrams?

Linear Intepolation/Jelinek-Mercer Smoothing

Train: 🍏 🍒 🍌 🍌

Train bigrams: (🍏, 🍒) (🍒, 🍌) (🍌, 🍌)

Test: 🍒 🍏 🍒

$$P(w|h) = \lambda P(w|h) + (1 - \lambda)P(w)$$

Can be generalised to higher order n-grams.

Questions

- What condition must be fulfilled for higher n-grams?
- How is λ_i determined?
- Can you smooth the above probabilities?

Backing-Off models

- What other way can we use the lower-order n-gram distributions?
- Is a lot of context always a good thing?
- Idea behind back-off models: Use information from a lower order n-gram distribution.

$$P(w|h) = \begin{cases} \frac{N(w,h)}{N(h)} + \alpha(h)\beta(w|h) & \text{for N(w,h)} > 0 \\ \alpha(h)\beta(w|h) & \text{otherwise} \end{cases}$$

- How come the coefficient is a function of the history and not a fixed constant?

Absolute Discounting

Corpus

- Train 🍏 🍏 🍏 🍆 🍏 🍌 🍌 🍒 🍏 🍆 🍌 🍌 🍒 🍌 🍏 🍆
- Test 🍫 🍏 🍟 🍌 🍏 🍆 🍆 🍌 🍒 🍟 🍏 🍏

Distribution

- Vocabulary counts

🍏 6 🍌 5 🍆 3 🍒 2 🍟 0 🍫 0

- Decrease all non-zero counts by some parameter d = 0.75

🍏 `6-0.75` 🍌 `5-0.75` 🍆 `3-0.75` 🍒 `2-0.75` 🍟 `0` 🍫 `0`

- Divide by $N = 16$

🍏 `0.33` 🍌 `0.26` 🍆 `0.14` 🍒 `0.11` 🍟 `0` 🍫 `0`

Sum $= 0.33 + 0.26 + 0.14 + 0.11 = 0.84 \neq 1$.

Idea: Utilise this probability mass for zero counts.

Absolute Discounting

$$P(w|h) = \frac{c(w,h) - d}{c(h)}$$

Adjust the probability mass $1 - \sum_h \frac{c(w,h)-d}{c(h)}$

e.g. For bigrams,

$$P_{abs}(w_i|w_{i-1}) = \frac{max\{N(w_{i-1}, w_i) - d, 0\}}{\sum_{w'} N(w_{i-1}, w')} + \lambda(w_{i-1})P_{abs}(w_i)$$

$$P_{abs}(w_i) = \frac{max\{N(w_i) - d, 0\}}{\sum_{w'} N(w')} + \lambda(.)P_{unif}(w_i)$$

$$\text{where } \lambda(w_{i-1}) = \frac{d}{\sum_{w'} N(w_{i-1}, w')} \cdot N_{1+}(w_{i-1}, \bullet)$$

$$\lambda(.) = \frac{d}{\sum_{w'} N(w')} \cdot N_{1+}$$

Absolute Discounting - Questions

- How does the discounting parameter d affect perplexity?
- What values can d take? Why?
- What if we set d to ∞?

Kneser-Ney Smoothing

Idea: Can we use the lower order distributions in a better way?

I WENT TO THE GROCERY ___________ .

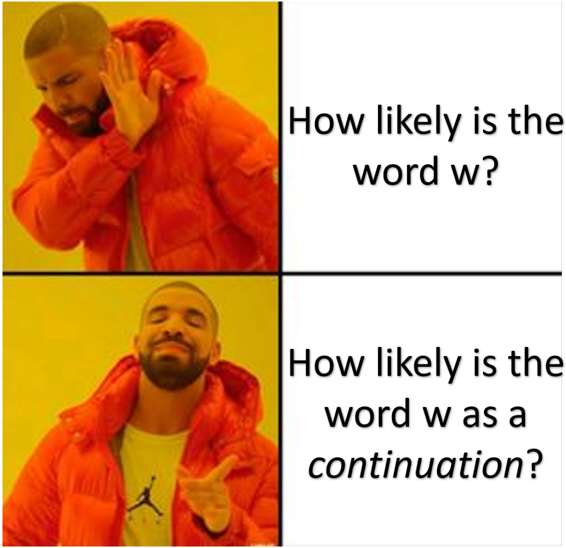
Options:

W_1: STORE

W_2: YORK

Use the fact that YORK generally appears as context or *continuation* of the word NEW.

Kneser-Ney Smoothing



Kneser-Ney Smoothing

$$P_{continuation}(w) \propto |\{w' : C(w', w) > 0\}|$$

Normalize by all bigram types. : $|\{(w_i, w_j) : C(w_i, w_j) > 0\}|$

$$P_{KN}(w_i|w_{i-n+1:i-1}) = \frac{max\{C_{KN}(w_{i-n+1:i-1}, w_i) - d, 0\}}{\sum_{w'} C_{KN}(w_{i-n+1:i-1} w')} + \lambda(w_{i-1})P_{continuation}(w_i)$$

$$\text{where} C_{KN}(\bullet) = \begin{cases} \text{count}(\bullet) & \text{for highest order} \\ \text{continuation\_count}(\bullet) & \text{for lower orders} \end{cases} \tag{1}$$

Will be covered in detail in the next tutorial...

Pruning

- Back-off models and interpolation save n-grams of all orders.

We are storing all $V^n + V^{n-1} + ... + V + 1$ distributions!

- Idea: Store the counts which exceed a threshold $c(\bullet) > K$. Also called a "cut-off".
- Idea: Use some information-theory based approach to determine the nature of the probabilities, and then prune the lower orders. Known as *Stolcke Pruning*.

Questions

- Does pruning assign 0 probability to the pruned n-grams?
- Can we prune an entire branch/subtree? What does this mean?
- What is a good pruning strategy?

Assignment 6

- Exercise 1: MAP and MLE estimates
- Exercise 2: Good Turing Smoothing
- Exercise 3: Cross-Validation

Resources

1. UdS SNLP Class: https://teaching.lsv.uni-saarland.de/snlp/
2. n-gram models: https://web.stanford.edu/~jurafsky/slp3/3.pdf
3. Entropy pruning: https://arxiv.org/pdf/cs/0006025.pdf
4. Twitter emojis
5. Smoothing overview: http://mlwiki.org/index.php/Smoothing_for_Language_Models