# Assignment 5 + Smoothing 2

## (SNLP Tutorial 6)

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# Assignment 5

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

# Cross-validation

- K-fold cross-validation: Divide data into k subsets, train on k-1 subsets and test on the remaining 1.
- Leave One Out cross-validation: Train on all data points except one. Do this N times.

## Questions

- Why is cross-validation beneficial?
- How does shuffling the dataset affect the LOOV score?
- When is k-fold cross-validation beneficial over standard cross-validation?

# Smoothing Techniques

Remember the basics!

We perform smoothing to keep a language model from assigning 0 or ∼0 probabilities to rare/unseen events.

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-$\alpha$ smoothing...

# Good-Turing

Data: 🍏 🍏 🍏 🍆 🍏 🍌 🍌 🍒 🍏 🍆 🍌 🍌 🍒 🍆 🍇 🌿

# Good-Turing

Data: 🍏 🍏 🍏 🍆 🍏 🍌 🍌 🍒 🍏 🍆 🍌 🍌 🍒 🍆 🍇 🌿

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

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

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

- 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

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- 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

$B_1$: (FROZEN YOGHURT)

$B_2$: (FROZEN RED)

What will floor discounting do here? Can we interpolate our bigram model with a unigram model?

$$P(w|h) = \lambda_1 P(w|h) + (1 - \lambda_1) P(w)$$

Can be generalised to higher order n-grams.

## Questions

- What condition must be fulfilled for higher n-grams?
- How is $\lambda_i$ 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.

A "recursion" strategy...

$$P(w|h) = \begin{cases} \frac{N(w,h)-d}{N(h)} + \alpha(h)\beta(w|h) & \text{for N(w,h)} > 0 \\ \alpha(h)\beta(w|h) & \text{otherwise} \end{cases} \tag{1}$$

# Absolute Discounting

## Corpus

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

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## Distribution

- Vocabulary counts

🍏 6 🍌 5 🍆 3 🍒 2 🍟 0 🍫 0

- Decrease all non-zero counts by some parameter $\mathrm{d} = 0.75$

🍏 `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`

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

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- Divide by $N = 16$

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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 $1 - \sum_h \frac{c(w,h)-d}{c(h)}$

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e.g. For bigrams,

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

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

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

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

# Absolute Discounting - Questions

- How does the discounting parameter $d$ affect perplexity?
- What values can $d$ take? Why?
- What problems does Absolute Discounting have?

# 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

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Options:

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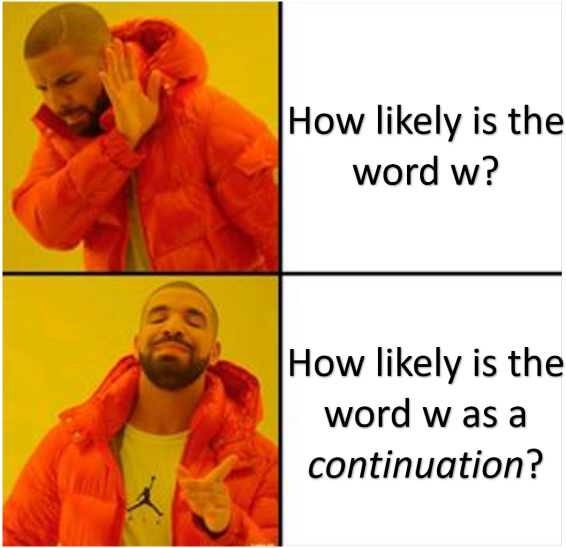
$W_2$: YORK

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

# Kneser-Ney Smoothing



# Kneser-Ney Smoothing

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

```
**Don't forget to normalise!**
```

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

$$\text{where} C_{KN}(\bullet) = \begin{cases} count(\bullet) & \text{for highest order} \\ continuationcount(\bullet) & \text{for lower orders} \end{cases} \quad (2)$$

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

# Pruning

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

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

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

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## Questions

- Does pruning assign 0 probability to the pruned n-grams?
- Can you 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