

Lecture 21

Advanced smoothing techniques (N-gram models)

N-gram probability calculation

eg. Of next word prediction (bigram model) : this **is** ...?....

- Probability of the Nth word given the previous N-1 words

(bigram : N=2)
$$P(w_n | w_{n-1}) = \frac{C(w_{n-1} w_n)}{C(w_{n-1})}$$

(N-gram)
$$P(w_n | w_{n-N+1}^{n-1}) = \frac{C(w_{n-N+1}^{n-1} w_n)}{C(w_{n-N+1}^{n-1})}$$

- max probability → winner among all candidate words = next word
- Probability of the whole sentence containing n words (eg. for bigrams)

$$P(w_1^n) \approx \prod_{k=1}^n P(w_k | w_{k-1})$$

OOV (Out of Vocabulary) words and why do you require smoothing?

- Formula 1 (prob of next word)

$$P(w_n | w_{n-1}) = \frac{C(w_{n-1} w_n)}{C(w_{n-1})}$$

- Count of denom=0
- 0/0 (avoid divide by zero)
- Count of denom in non zero
- Count of num=0 (prob in Formula
- Even if 1 prob in chain is 0 the whole sent. prob=0

- Formula 2 (prob of whole sentence)

$$P(w_1^n) \approx \prod_{k=1}^n P(w_k | w_{k-1})$$

- wk-2wk-1wk (trigram)
- This is...wk...

Laplace Smoothing (recap)

- **Laplace smoothing** (of last slide probability formula)
- Also called add-one smoothing
- To prevent 0/0 situation
- Add 1 to numerator and V to the denominator

$$p_i^* = \frac{c_i + 1}{N + V}$$

Let c^* be the modified count in the numerator

V =size of the vocabulary = number of unique unigram (denominator) in the training corpus

Class Assignment (deadline 5 pm on 21/10/20)

Training corpus \rightarrow build a probabilistic model (N-gram) \rightarrow Test input \rightarrow prediction of the next word \rightarrow prob(sentence) [LM: Language modelling]

Training corpus:

$N=2$ (bigram) $V=13$

$\langle s \rangle$ the start of the day was good $\langle /s \rangle \langle s \rangle$ if the start is good the who day is good $\langle /s \rangle \langle s \rangle$ the goodness of the day matters $\langle /s \rangle$

Text prediction (LM):

$\langle s \rangle$ the $\langle /s \rangle \langle s \rangle$ the.....

Advanced smoothing techniques

1. Good-Turing discounting

- Proposed by Good (1953)
- Ques: How to handle OOV (Out of Vocabulary) words whose count in the training corpus is zero?
- Let N_c be the number of N-grams that occur c times (in the training corpus)
- (EXCEPT N_0)

$$c^* = (c + 1) \frac{N_{c+1}}{N_c}$$

- $N_2=6$ $N_1=14$ $N_0=0$ $N=20$
- For N_0 case (OOV), $c^*=N_1/N=14/20$

2. Knesser-Ney smoothing

$$P_{\text{KN}}(w_i | w_{i-1}) = \begin{cases} \frac{\frac{C(w_{i-1} w_i) - D}{C(w_{i-1})}}{\alpha(w_i) \sum_{w_i'} |\{w_{i-1} : C(w_{i-1} w_i) > 0\}|} & \text{if } C(w_{i-1} w_i) > 0 \\ \text{otherwise.} & \end{cases}$$

3. Interpolation

$$P_{\text{base}}(w_i | w_{i-n+1}^{i-1}) = \lambda_n P_{\text{ML}}(w_i | w_{i-n+1}^{i-1}) + (1 - \lambda_n) P_{\text{base}}(w_i | w_{i-n+2}^{i-1})$$

4. Katz backoff

- Similar to interpolation
- Backoff to lower N-grams in case higher N-grams not present in training corpus

$$P_{\text{katz}}(z|x,y) = \begin{cases} P^*(z|x,y), & \text{if } C(x,y,z) > 0 \\ \alpha(x,y)P_{\text{katz}}(z|y), & \text{else if } C(x,y) > 0 \\ P^*(z), & \text{otherwise,} \end{cases}$$
$$P_{\text{katz}}(z|y) = \begin{cases} P^*(z|y), & \text{if } C(y,z) > 0 \\ \alpha(y)P^*(z), & \text{otherwise.} \end{cases}$$