

# Natural Language Processing and Machine Translation

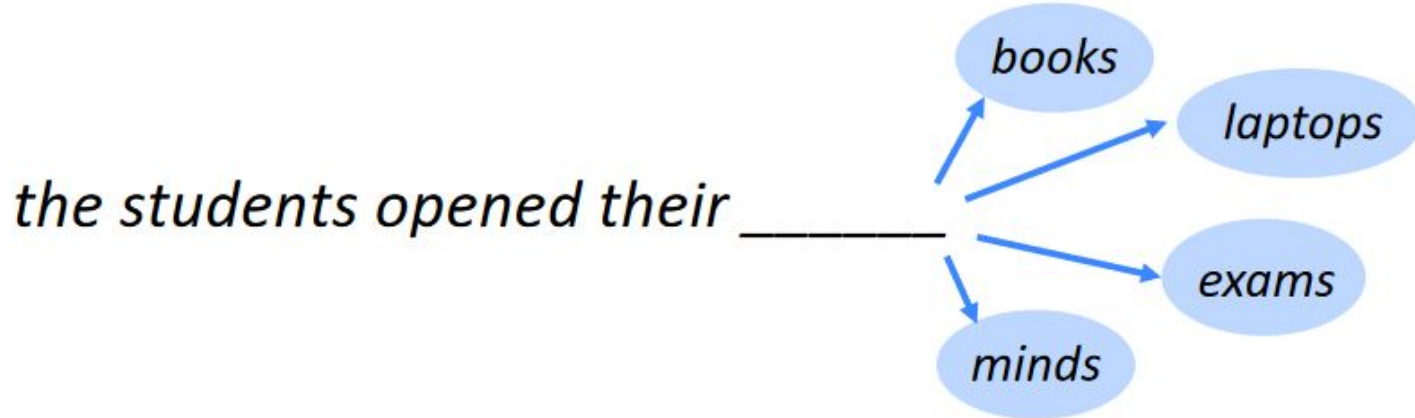
## Language Models

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# Introduction

- Use of various statistical and probabilistic techniques to determine the probability of a given sequence of words occurring in a sentence
- Analyze bodies of text data to provide a base for word predictions



<https://medium.com/@antonio.lopardo/the-basics-of-language-modeling-1c8832f21079>

# N-gram

The cow jumps over the moon

**Unigram/ 1-gram**

The  
cow  
jumps  
over  
the  
moon

**Bigram/2-gram**

The cow  
cow jumps  
jumps over  
over the  
the moon

**3-gram**

The cow jumps  
cow jumps over  
jumps over the  
over the moon

**4-gram**

The cow jumps over  
cow jumps over the  
jumps over the moon

If  $X$  = Num of words in a given sentence  $K$ , the number of  $n$ -grams for sentence  $K$  would be:

$$Ngrams_K = X - (N - 1)$$

# N-gram Language Models

Its water is so transparent that .....

$P(\text{the} | \text{its water is so transparent that})$ .

One approach to calculate this using frequency approach

$$P(\text{the} | \text{its water is so transparent that}) = \frac{C(\text{its water is so transparent that the})}{C(\text{its water is so transparent that})}$$

Will this give us a good estimate in all possible scenarios ??

# N-gram Language Models

Another way to do this is using **chain rule of probability**

$$p(w_1 \dots w_n) = p(w_1) \cdot p(w_2 | w_1) \cdot p(w_3 | w_1 w_2) \cdot p(w_4 | w_1 w_2 w_3) \dots p(w_n | w_1 \dots w_{n-1})$$

But this is again computationally expensive

We make this more simpler with an assumption:

- We approximate the context of the word  $w_k$  by looking at the last word of the context.  
(**Markov Assumption**)

Eg. for bigram

$$p(w) = \prod_{i=1}^{k+1} p(w_i | w_{i-1})$$

# N-gram language models

<s> I am a human </s>  
<s> I am not a stone </s>  
<s> I live in Lahore </s>

$$P(I|<S>) = C(<s>|I) / C(<s>) = 3/3 = 1$$

$$P(am|I) = C(I|am) / C(I) = 2/3$$

$$P(a|am) = C(am|a) / C(a) = 1/2$$

$$P(human|a) = C(a|human) / C(a) = 1/2$$

$$P(</s>|human) = C(human|</s>) / C(human) = 1$$

$$P(not|am) = C(am|not) / C(am) = 1/2$$

$$P(a|not) = C(not|a) / C(not) = 1$$

$$P(stone|a) = C(a|stone) / C(a) = 1/2$$

$$P(</s>|stone) = C(stone|</s>) / C(stone) = 1$$

$$P(live|I) = C(I|live) / C(I) = 1/3$$

$$P(in|live) = C(live|in) / C(live) = 1$$

$$P(Lahore|in) = C(in|Lahore) / C(in) = 1$$

$$P(</s>|Lahore) = C(Lahore|</s>) / C(Lahore) = 1$$

**P(I am a human)**

$$\begin{aligned} &= P(I|<s>) P(am|I) P(a|am) P(human|a) P(</s>|human) \\ &= 1 * 2/3 * 1/2 * 1/2 * 1 \\ &= 1/6 \end{aligned}$$

**P(I am human)**

$$\begin{aligned} &= P(I|<s>) P(am|I) P(human|am) P(</s>|human) \\ &= 1 * 2/3 * 0 * 1 \\ &= 0 \Rightarrow \text{Does this seem correct?} \end{aligned}$$

# Laplace Smoothing

<s> I am a human </s>  
<s> I am not a stone </s>  
<s> I live in Lahore </s>

$$P(I|<S>) = C(<s>|I) / C(<s>) = 3/3 = 1$$

$$P(am|I) = C(I|am) / C(I) = 2/3$$

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$$P(human|a) = C(a|human) / C(a) = 1/2$$

$$P(</s>|human) = C(human|</s>) / C(human) = 1$$

$$P(not|am) = C(am|not) / C(am) = 1/2$$

$$P(a|not) = C(not|a) / C(not) = 1$$

$$P(stone|a) = C(a|stone) / C(a) = 1/2$$

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The solution to the problem of unseen N-grams is to re-distribute some of the probability mass from the observed frequencies to unseen N-grams. This is a general problem in probabilistic modeling called **smoothing**.

$$P_{\text{Laplace}}(w_i) = \frac{c_i + 1}{N + V}$$

Using laplace smoothing (Vocab = 11)

**P(I am human)**

$$\begin{aligned} &= P(I|<s>) P(am|I) P(human|am) P(</s>|human) \\ &= (3+1)/(3+11) * (2+1)/(3+11) * (0+1)/(2+11) * (1+1)/(1+11) \\ &= 4/14 * 3/14 * 1/13 * 2/12 \\ &= 0.00078 \end{aligned}$$

# Good Turing Discounting

- Re-estimate the amount of probability mass to assign N-gram with zero or low counts by looking at the number of N-grams with higher counts
- Use the count of things which are seen once to help estimates the count of things never seen.
- Let  $N_c$  be number of N-grams that occur  $c$  times
  - For bigrams,  $N_0$ , is the number of bigrams of count 0,  $N_1$ , is the number of bigrams with count 1, etc
- Revised count

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



# Kneser Ney Smoothing

- Let the count assigned to each unigram be the number of different words that it follows. Define:

$$N_{1+}(\bullet w_i) = |\{w_{i-1} : c(w_{i-1}w_i) > 0\}|$$

$$N_{1+}(\bullet \bullet) = \sum_{w_i} N_{1+}(\bullet w_i)$$

- Let lower-order distribution be:

$$p_{KN}(w_i) = \frac{N_{1+}(\bullet w_i)}{N_{1+}(\bullet \bullet)}$$

- Put it all together:

$$p_{KN}(w_i | w_{i-n+1}^{i-1}) = \frac{\max\{c(w_{i-n+1}^i) - \delta, 0\}}{\sum_{w_i} c(w_{i-n+1}^i)} + \frac{\delta}{\sum_{w_i} c(w_{i-n+1}^i)} N_{1+}(w_{i-n+1}^{i-1} \bullet) p_{KN}(w_i | w_{i-n+2}^{i-1})$$

# Evaluating Language Models

2 types of evaluation

- Extrinsic evaluation
- Intrinsic evaluation

## Extrinsic Evaluation

- Model metrics compared with respect to applications implemented in

## Intrinsic Evaluation

- Single model evaluation
  - Perplexity

# Perplexity

I always order burger with .....

A good language models with add words like fries, drinks or sausage to the above sentence while a bad language model could add completely random words

fries  
drinks  
sausage

....

....

burgers  
with burgers

A better model of text is the one that assigns a higher probability to the words that actually occurs.

**Perplexity** is the probability of test set normalized by the number of words

$$\begin{aligned} PP(W) &= P(w_1 w_2 \dots w_N)^{-\frac{1}{N}} \\ &= \sqrt[N]{\frac{1}{P(w_1 w_2 \dots w_N)}} \end{aligned}$$

# Perplexity as average branching factor

How hard is the task of recognizing digits '0', '1', '2', '3', '4', '5', '6', '7', '8', '9' ?

There were ..... people in the room.

Assuming that the above space can be filled with any digit from 0-9 and probability of all these digits are equally likely

$$P(\text{any digit}) = 1/10$$

$$PP(\text{any digit}) = (1/10)^{-1}$$

$$= 10$$

**Lower the perplexity, better the model**

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# Backoff

- Non linear method
- Estimate for an n-gram is allowed to back off through progressively shorter histories
- Trigram version

$$\hat{P}(w_i | w_{i-2}w_{i-1}) = \begin{cases} P(w_i | w_{i-2}w_{i-1}), & \text{if } C(w_{i-2}w_{i-1}w_i) > 0 \\ \alpha_1 P(w_i | w_{i-1}), & \text{if } C(w_{i-2}w_{i-1}w_i) = 0 \\ & \text{and } C(w_{i-1}w_i) > 0 \\ \alpha_2 P(w_i), & \text{otherwise.} \end{cases}$$

A word cloud visualization of the phrase "Thank You" in various languages. The central and largest text is "thank you" in red. Other prominent words include "danke" (blue), "gracias" (green), "merci" (orange), and "teşekkür ederim" (pink). The cloud also includes many other languages such as Hindi (शुक्रिया, धन्यवाद), Japanese (ありがとう), Chinese (感谢), and many others. The words are arranged in a circular pattern around the central text.