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- 1. Define N gram, examples for unigram, bigram, trigram
 - a. N-gram is a contiguous sequence of N words in a text.
 - b. Examples for unigram, bigram, trigram
 - i. Unigram: ['I', 'love', 'natural', 'language', 'processing']
 - ii. Bigram: [('l', 'love'), ('love', 'natural'), ('natural', 'language'), ('language', 'processing')]
 - iii. Trigram: [('I', 'love', 'natural'), ('love', 'natural', 'language'), ('natural', 'language', 'processing')]
 - c. Concept of BOS, EOS, UNK
 - i. BOS is Beginning of Sentence. Ex: ['<BOS>', 'I', 'love', 'NLP']
 - ii. EOS is End of Sentence. Ex. ['I', 'love', 'NLP', 'EOS>']
 - iii. UNK is unknown token, words not in vocabulary. Ex: ['1', 'love', '<UNK>'] where NLP is not in vocab
- 2. Probability and smoothing
 - a. Count("cat sat") = 1Count("cat") = 1

MLE Formula: Count("cat sat")/Count("cat") = 1/1 = 1.0

- Smoothing prevents zero probabilities when an unseen N-gram appears, ensuring the model can generalize better
 Laplace smoothing: adds 1 to all counts to avoid zero probabilities
- c. $P(\text{``sat''} \mid \text{``cat''}) = (\text{Count}(\text{``cat sat''}) + 1)/(\text{Count}(\text{``cat''}) + V) = (1+1)/(1+7) = 0.25$
- 3. Intrinsic and Extrinsic Evaluation
 - a. Intrinsic evaluation: tests a model on an isolated task
 Extrinsic evaluation: tests a model's effectiveness in a real world task
 - b. Perplexity measures how well a model predicts unseen text. Lower perplexity = better language model
 - c. $PP = (0.01)^{(-1/10)} = 10^{0.1} = 1.2589$