n-gram models

- The Markov assumption: $P(\mathbf{x}^{(t)}|\mathbf{x}^{(1)},...,\mathbf{x}^{(t-1)}) = P(\mathbf{x}^{(t)}|\mathbf{x}^{(t-n)},...,\mathbf{x}^{(t-1)})$
- n-gram models are language models that use the Markov assumption with a specific selection of n.

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P(dog \mid the, quick, brown, fox, jumped, over, the, lazy) = P(dog) \leftarrow (n = 1) Unigram P(dog \mid the, quick, brown, fox, jumped, over, the, lazy) = P(dog \mid lazy) \leftarrow (n = 2) Bigram P(dog \mid the, quick, brown, fox, jumped, over, the, lazy) = P(dog \mid the, lazy) \leftarrow (n = 3) Trigram P(dog \mid the, quick, brown, fox, jumped, over, the, lazy) = P(dog \mid over, the, lazy) \leftarrow (n = 4) 4-gram
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• This should look familiar to Lecture-03 (Word2Vec)! Skip-gram modeling generalizes *n*-grams by not considering the sequence order of the *context* words.

Estimating *n*-gram probabilities

• The maximum likelihood estimate of an *n*-gram model:

$$P(\mathbf{x}^{(t)} | \mathbf{x}^{(t-n)}, ..., \mathbf{x}^{(t-1)}) \stackrel{MLE}{=} \frac{count(\mathbf{x}^{(t-n)}, ..., \mathbf{x}^{(t)})}{\sum_{j=1}^{N} count(\mathbf{x}^{(t-n)}, ..., \mathbf{x}^{(t)})}$$

Example from Jurafsky & Martin

Here are the calculations for some of the bigram probabilities from this corpus

$$P(I|~~) = \frac{2}{3} = .67~~$$
 $P(Sam|~~) = \frac{1}{3} = .33~~$ $P(am|I) = \frac{2}{3} = .67$ $P(|Sam) = \frac{1}{2} = 0.5$ $P(Sam|am) = \frac{1}{2} = .5$ $P(do|I) = \frac{1}{3} = .33$