The Markov approximation

• From previous slide, notice that can estimate **some** of the factors of the joint distribution:

$$P(sentence) = P(\mathbf{x}^{(1)}, ..., \mathbf{x}^{(T)}) = P(\mathbf{x}^{(1)}) \cdot P(\mathbf{x}^{(2)} | \mathbf{x}^{(1)}) \cdot P(\mathbf{x}^{(3)} | \mathbf{x}^{(1)}, \mathbf{x}^{(2)}) ... P(\mathbf{x}^{(T)} | \mathbf{x}^{(1)}, ..., \mathbf{x}^{(T-1)})$$
yes yes yes No!

- The Markov assumption: $P(\mathbf{x}^{(t)}|\mathbf{x}^{(1)},...,\mathbf{x}^{(t-1)}) = P(\mathbf{x}^{(t)}|\mathbf{x}^{(t-n)},...,\mathbf{x}^{(t-1)})$
- Example: $P(dog \mid the, quick, brown, fox, jumped, over, the, lazy) = P(dog) \leftarrow (n = 1)$ $P(dog \mid the, quick, brown, fox, jumped, over, the, lazy) = P(dog \mid lazy) \leftarrow (n = 2)$ $P(dog \mid the, quick, brown, fox, jumped, over, the, lazy) = P(dog \mid the, lazy) \leftarrow (n = 3)$ $P(dog \mid the, quick, brown, fox, jumped, over, the, lazy) = P(dog \mid over, the, lazy) \leftarrow (n = 4)$

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.