IN5550: Neural Methods in Natural Language Processing
Sub-lecture 4.3
Pre-neural language models

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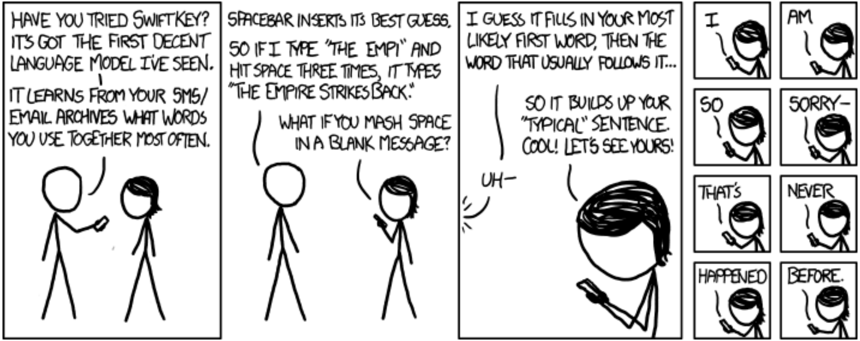
Contents

Language modeling (LM)

Predicting the next word in the text given the previous words:



(XKCD)

Language modeling task definition

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- These two tasks are mathematically equivalent.

$$P(w_{1:n}) = P(w_1)P(w_2|w_1)P(w_3|w_{1:2})P(w_4|w_{1:3})...P(w_n|w_{1:n-1}) \tag{1}$$

- Any system able to yield $P(x)$ given S is a language model (LM).

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We'll see examples in this course.

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Language modeling is widely used: text messaging, machine translation, chat-bots, summarization...., representation learning!

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- exponentiated negative log-likelihoods per token
- For corpus perplexity, you simply average token perplexities.

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7. if the previous bigram is unknown, fall back to the frequency-based method.

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Deep learning comes to help in the next sub-lecture 4.4!