6.S079 FROM EMBEDDINGS TO LANGUAGE

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THANKS TO MIKEY SHULMAN FOR SOME SLIDE IDEAS

The Core Thing

- We need a model that can compute P(someSentence)
- We can use it to build a sequence model
  - Input: a sequence of tokens
  - Output: a sequence of tokens
- Lots of applications can be built this way

Translation

INPUT: “J’ai vu un chat noir”

OUTPUT A: “I saw a cat black”

vs

OUTPUT B: “I saw a black cat”

Can we compute that $P(A) < P(B)$?

Speech Recognition

*

INPUT: <some waveform>

OUTPUT A: “Yesterday I met Prince Harry”

vs

OUTPUT B: “Yesterday I met prints hairy”

Can we compute that P(A) > P(B)?

*The GPT image for “prints hairy” is too weird and alarming to put onscreen

Naive Text Generation

- If you can compute P(nextWord | precedingWords)…

- P(nextWord | “My favorite food is”):
  – nextWord = “pizza”
  – nextWord = “love”
  – nextWord = “antagonist”

- Just try every possible word, pick the best

Computing Sentence Probability

- For a sequence with n words
  $w^n{}_1 = w_1, w_2, \ldots, w_n$

- Every word w is drawn from a fixed vocabulary

- $P(w^n{}_1) = P(w_1)P(w_2|w_1)P(w_3|w^2{}_1)\ldots P(w_n|w^{n-1}{}_1)$

$$= \prod_{k=1}^{n} P(w_k|w_1^{k-1})$$

The Simplest Model

- Where do we get evidence for $P(w_k|w^{k-1}_1)$?

- If you want to be really basic, just ignore the context (that is, a k-gram model where k=1)

  Or, put another way, assume that
  $P(w_k|w^{k-1}_1) = P(w_k)$

- Compute as
  $P(w_k) = Count(w_k) / TotalTrainingWords$

Expanding Context

- We can do better with more context

- For k=2 ("bigrams"), we model $P(w_k|w^{k-1}_1) = P(w_k|w_{k-1})$

- Count the bigram $P(w_k|w_{k-1})$, divide by count of all bigrams starting with w_{k-1}

  $$P(w_k|w_{k-1}) = \frac{C(w_{k-1}w_k)}{\sum_{w'} C(w_{k-1}w'_k)}$$

- Use special tokens for start/end sentence

Discussion

- Why does a larger corpus help?
- How big does your corpus have to be?
- How could we tell if corpus was too small?
- Why word-grams? Why not characters?

Evaluation

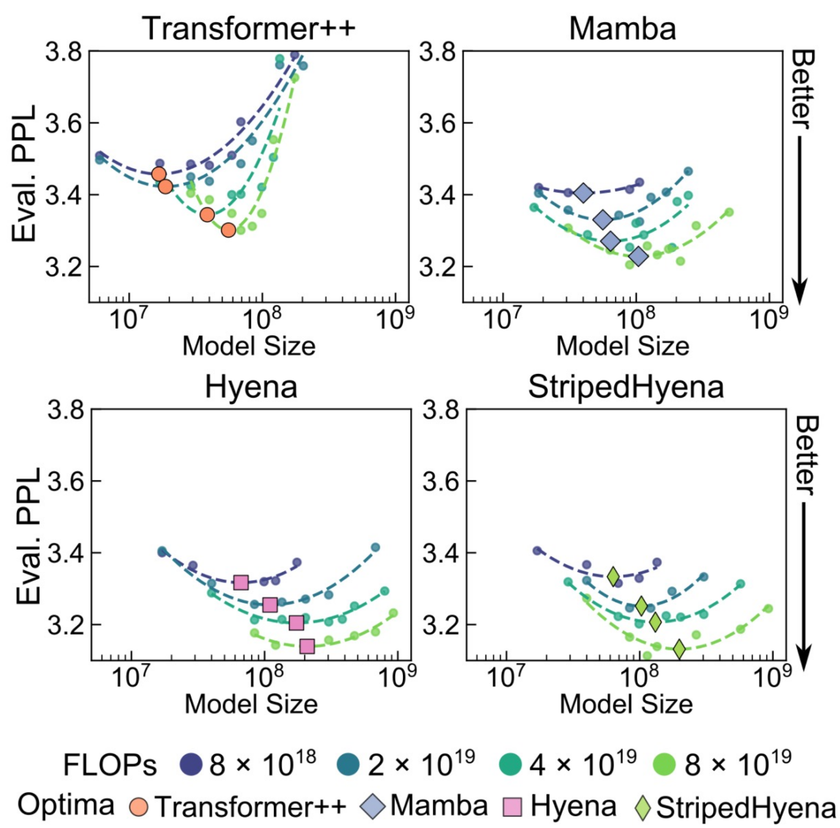
- How can we tell if the model is good?
  - Maybe it helps with a downstream task
  - A general-purpose metric would be nice

- "Perplexity" measures the inverse probability of an unseen test corpus with a particular language model
  - If text is real, then its probability should be high
  - Lower is better

$$PP(W) = P(w_1 \ldots w_N)^{-\frac{1}{N}}$$

Perplexity

- What's nice about Perplexity?
  - It's easy to compute
  - You don't need a concrete task
  - You don't need to understand the language!



Measures of Perplexity on different language models' predictions of single-nucleotide sequences from prokaryotic genomes

From Ngyuen et al, "Sequence modeling and design from molecular to genome scale with Evo", 2024

Perplexity

- What's bad about Perplexity?
  - It only works if your model gives a real probability (so: no rule-based methods)
  - Can't compare language models with different vocabularies
  - What is a "good" Perplexity number?
- Discussion: is a bigram language model an example of supervised or unsupervised learning?
- Discussion: when might you see overfitting in this setting?

Data, Models, Features

- More context is better
- …but we will run out of data for statistics when k-grams get big enough

- We need some combination of:
  - More informative features
  - Constrained models to avoid overfitting
- …but feature engineering for language is extremely hard
- …and expressivity of the model is hard to engineer

Neural Methods

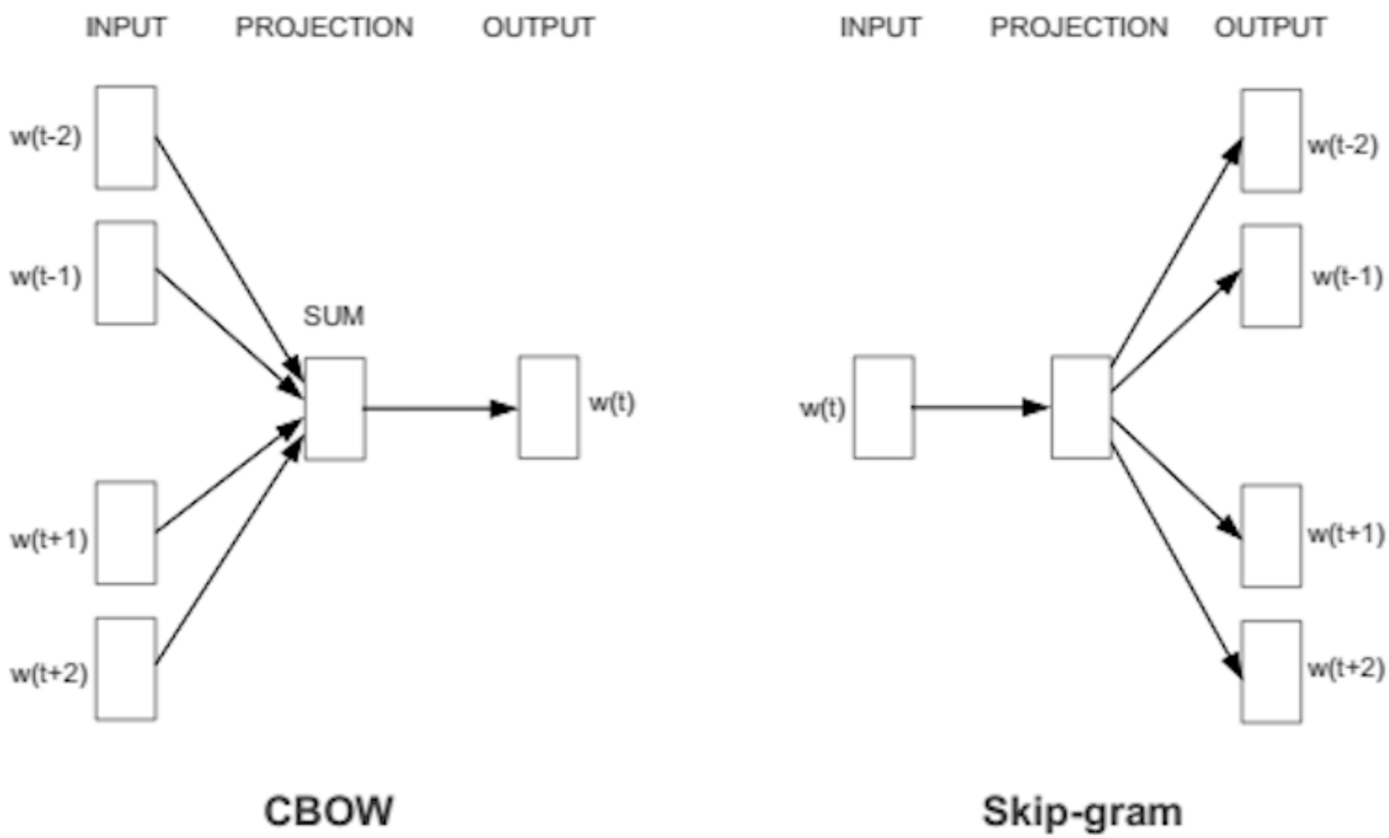
- Neural methods like CBOW let us avoid feature engineering
- Managing overfitting is poorly-understood but works in practice through model architecture, dropout, and other methods

Encoder-Decoders

- Most sequence models use Encoder-Decoder architecture
  - The encoder converts the input into a compressed embedding-style representation
  - The decoder converts an encoded representation back into the target language
- Nice qualities:
  - You can train them separately
  - You can mix/match them them for different input and output types
- word2vec has encoder/decoder architecture

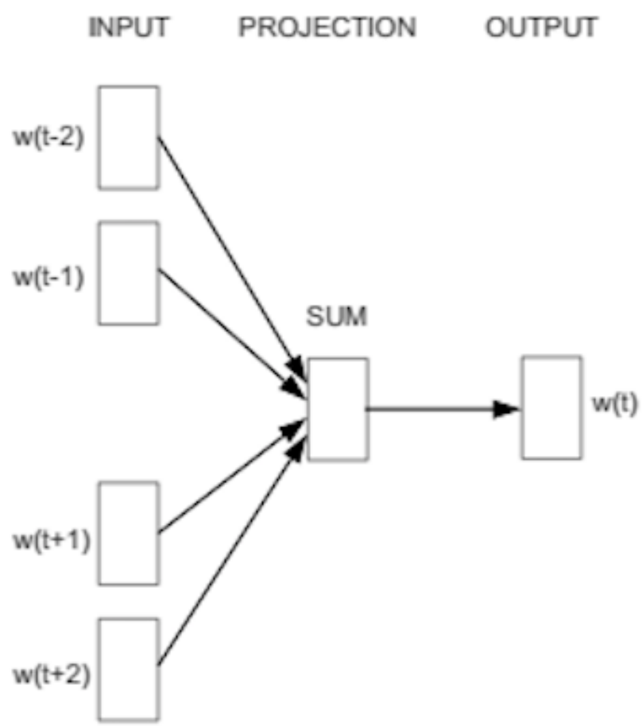
Beyond w2v

- For a chatbot, what's bad about the w2v encoder/decoder architecture?



Beyond w2v

- (Focus on CBOW for now)
- What's bad about this for chat?



CBOW

Weaknesses of w2v for chat

- Input architecture “looks into the future” (this is easy to fix)
- Each word has a single embedding, regardless of usage
  - “I am going to **stick** to it”
  - “I am going to throw the **stick**”
  - The w2v embedding for stick will reflect both senses, even though in some contexts the correct sense is obvious to a human
- Can’t handle truly huge vocabularies
- Sentence modeling is very primitive

BERT, ELMO, and the Transformer

- Ideas in these papers led to incredible improvements in the last 7 years
- We'll cover these after break