

CS371N Lecture 10

LM2: Self-attention, Transformers

Announcements

- A2 due
- A3 out, due in 2 weeks
- Bias in embs response due

Recap Language models:

$$P(\bar{w}) = \prod_{i=1}^l P(w_i | w_1 \dots w_{i-1})$$

$$n\text{-gram LMs: } P(\bar{w}) = \prod_{i=1}^l P(w_i | w_{i-n+1} \dots w_{i-1})$$

Store probabilities explicitly (model as categorical distributions)

Estimation: count + normalize

Neural LMs:

predict w_i | w_1, \dots, w_{i-1}

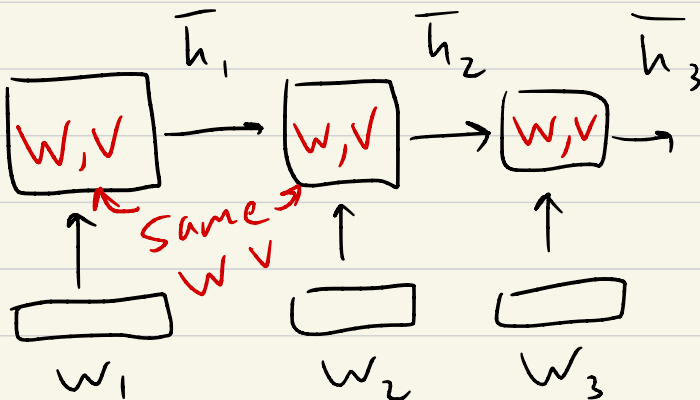
DANs? FFNNs?

Today

- RNNs and their shortcomings
- (Self)-attention

RNNs encode a sequence of vectors sequentially by tracking a "hidden state"

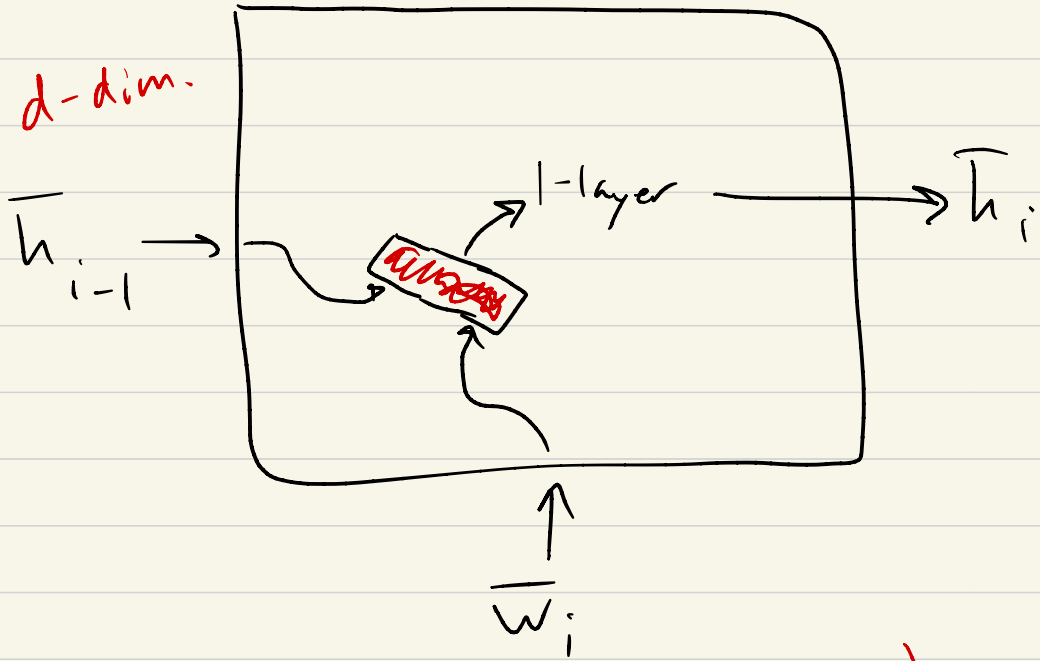
"summary" of the seq.



$$P(w_4 | w_1, \dots, w_3) = \text{softmax}(U \bar{h}_3)$$

Elman network

RNN cell



$$\bar{h}_i = \tanh(W\bar{w}_i + V\bar{h}_{i-1})$$

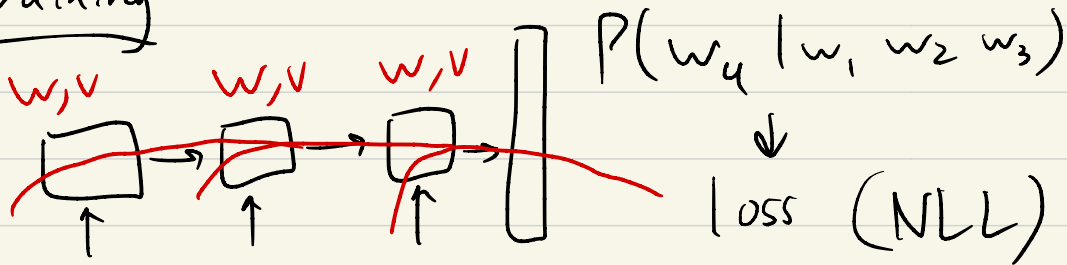
W : $d \times |\text{word emb}|$ matrix
 V : $d \times d$] parameters

Key property: params don't depend on sequence length

⇒ can scale to arbitrarily long inputs

However, it's position-sensitive!

Training



backprop

updates to w, v accumulate over whole sequence

Hard to learn! ⇒ Long short-term memory net (LSTM)

Shortcomings of RNNs

"Forgetfulness" - hard to track information over many steps

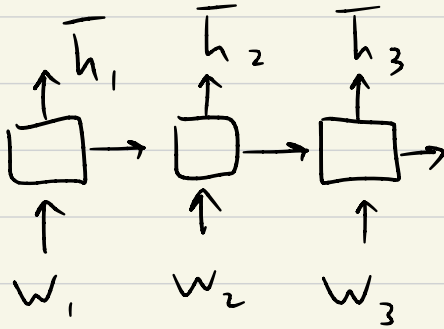
$$\bar{h}_i = \tanh(\sim + V\bar{h}_{i-1})$$

$$\bar{h}_i = V\bar{h}_{i-1} \quad h_i \approx \sum_{j=1}^i V^{(i-j)} W w_j$$

LSTM: "gates" to control what parts of the vector change

$O(n)$ sequential dependence

RNN "API"

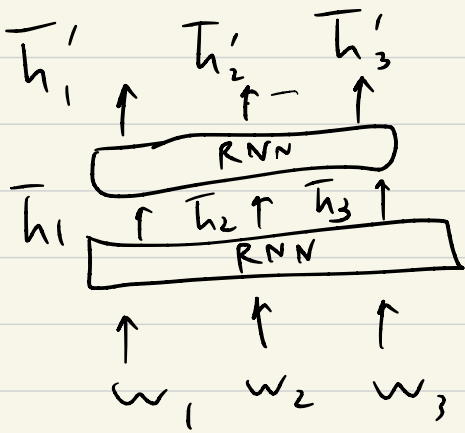


h_3 "context-aware" word embedding
for word w_3

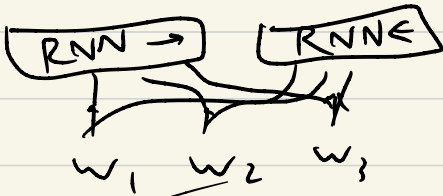
h_3 blends h_2 (context) w/ w_3
(word 3)

RNN (seq of vectors) \Rightarrow seq of vectors
aware of context

Stack these layers



Can increase depth



Transformer: layer that contextualize words based on other words in the sequence

$$(e'_1, e'_2, e'_3) = \text{Transformer}(e_1, e_2, e_3)$$

Running example:

Suppose we have seqs of As
and Bs of length 4

if all As \rightarrow next is A

if any B \rightarrow next is B

AAAA A

ABAA B

BAAA B

predict next char
using this sequence
that came before

BAAAA ... A B
1000

hard for RNNs
to predict

Attention = allows us to do

"random access" on the context
to retrieve info we need

"Souped up" DAN, will add order
information next time

k_i e_i
Keys: embedding of the sequence

query: vector representing what
we want to find

Assume key $A = \begin{bmatrix} 1 \\ 0 \end{bmatrix}^{e_A}$ $B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}^{e_B}$
(word embeddings)

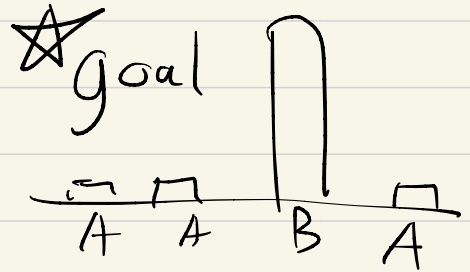
$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$ $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$ $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$ $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$

A A B A

query: what we want to find

find Bs!

$$q = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad \text{"B"}$$



Attention will compute a distribution over the tokens so far with higher weight for things that match q

Steps (1) Compute score for each key based on query

$$s_i = k_i^T q$$

$$s: \begin{matrix} 0 & 0 & 1 & 0 \end{matrix} \quad q = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\begin{matrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} & \begin{bmatrix} 1 \\ 0 \end{bmatrix} & \begin{bmatrix} 0 \\ 1 \end{bmatrix} & \begin{bmatrix} 1 \\ 0 \end{bmatrix} \\ A & A & B & A \end{matrix}$$

② Softmax scores to get probs.

$$\bar{\alpha} = \text{softmax}(\bar{S})$$

$[0 \ 0 \ 1 \ 0]$ Assume $e=3$

\downarrow $\rightarrow \frac{e^1}{e^0 + e^0 + e^1 + e^0} \approx \frac{1}{2}$

$[\frac{1}{6} \ \frac{1}{6} \ \frac{1}{2} \ \frac{1}{6}]$



③ Compute the output

$$\text{output} = \sum \alpha_i e_i \quad \text{weighted sum of } e_i$$

$$= \frac{1}{6} \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \frac{1}{6} \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} 0 \\ 1 \end{bmatrix} + \frac{1}{6} \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}$$

Compare to DAN:

$$\frac{1}{4} \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \frac{1}{4} \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \frac{1}{4} \begin{bmatrix} 0 \\ 1 \end{bmatrix} + \frac{1}{4} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 3/4 \\ 1/4 \end{bmatrix}$$

$\begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}$ weights the B more highly

Ideally want:

$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$ if all A_s ✓

$\begin{bmatrix} 0 \\ 1 \end{bmatrix}$ if any B $\begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}$ ✗

Let $q = [0 \ 10]$

Softmax $[0 \ 0 \ 10 \ 0]$

↓
0 0 1 0 probs.

Decouple keys + queries from embeddings

Embedding matrix $E = \begin{matrix} A \\ A \\ B \\ A \end{matrix} \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}$

target e

$$\underbrace{\left(E^T W^K \right)}_{W^K = I} \left(W^Q e \right) \quad B \quad e = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

\downarrow

$$W^Q = 10 \cdot I \quad \downarrow$$

(keep $\begin{bmatrix} 1 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$) $q = \begin{bmatrix} 0 \\ 10 \end{bmatrix}$

Parameters W^K and W^Q will let us learn how to query

Self-attention

every word is a key and query simultaneously

do one attention computation per word \Rightarrow contextualized embeddings for each word

E : same embs, seq len $\times d$ ($d=2$)

K : same, seq len $\times d$

Q : seq len $\times d$ (rather than $1 \times d$)

