

# CS 378 Lecture 24

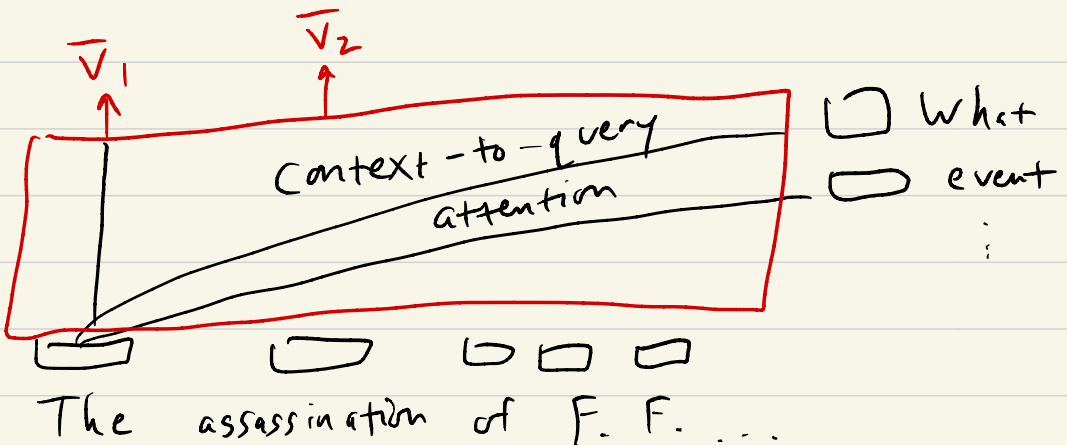
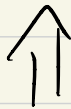
Today

- ① Self-attention for language modeling
- ② Transformers
- ③ BERT
- ④ Analysis + results of BERT

Recap

QA

rest of the model



ELMo: train a RNN LM on lots of data, use it to produce "contextualized" embeddings

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## Announcements

- FP: updated models
  - AU back soon
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## Self-attention

Lang modeling:  $P(\bar{w}) = P(w_1) P(w_2 | w_1) P(w_3 | w_1 w_2) \dots$

n-grams: look at past  $n-1$  words only

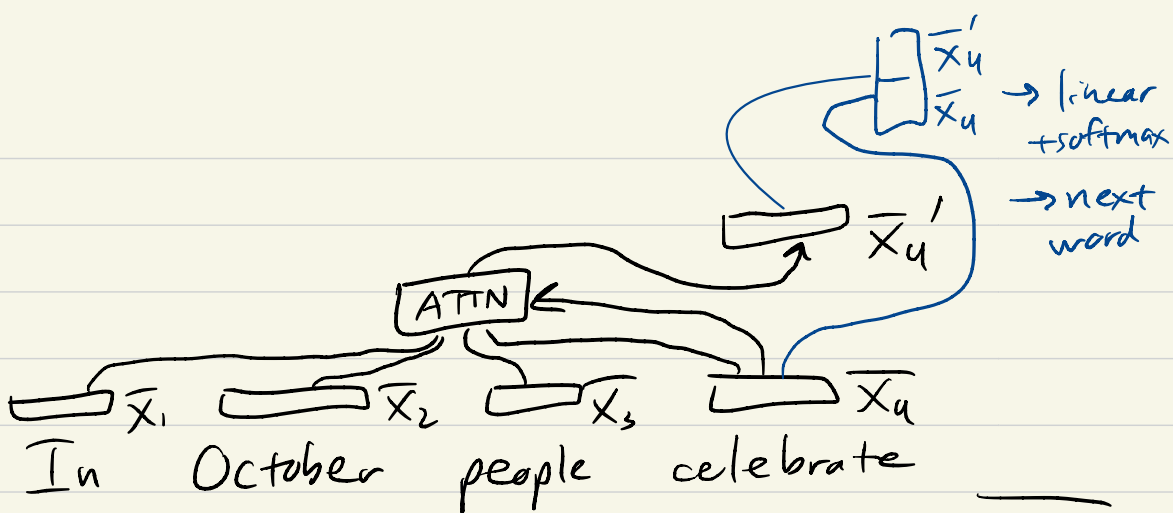
RNNs: look at everything, but they can forget stuff

In October, people in the US  
celebrate \_\_\_\_\_  
Halloween

Predicting the next word requires  
looking back a long way, but  
sparsely

Alice really likes to go to the movies  
with me. She likes horror movies,  
I'm good friends with \_\_\_\_\_.  
her  
Alice

Self-attention: look back at the sequence  
so far to predict the next word



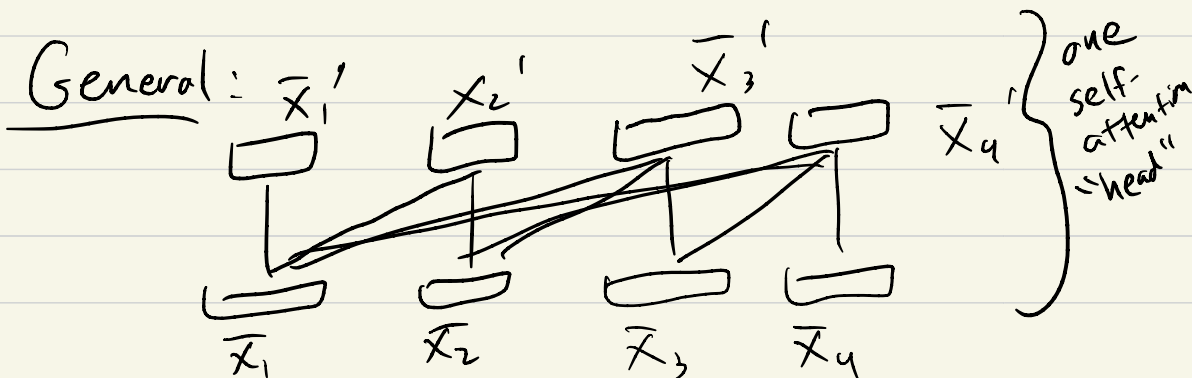
$$\alpha_u = \text{softmax}_i(\bar{x}_4^T W \bar{x}_i)$$

Bar chart showing attention weights for the words "oct" and "celebr.". The weight for "oct" is approximately 0.8, and the weight for "celebr." is approximately 0.2.

$\bar{x}_4$  "key"

$\bar{x}_1, \dots, \bar{x}_4$  "values" the attention is over

$$\bar{x}_u' = \sum_i \alpha_{u,i} \bar{x}_i$$



Follows same abstraction as RNN:

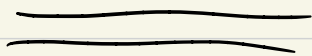
Sequence of vectors  $\bar{x}_1, \dots, \bar{x}_n$

$\Rightarrow$  new sequence of vectors where

$\bar{x}_i$  "knows about"  $\bar{x}_1, \dots, \bar{x}_{i-1}$

Advantages: easy access to past words  
parallelizable

Disadvantages: not as powerful as LSTMs  
(so far)



We want to look back at lots of  
things in the context

Multi-head self-attention:  $K$  "heads"  
which each do an attn computation

Alice likes going...)

Movies with me

Combine  
(average)

ATTN

In October people celebrate

$\alpha^{(1)}$  1111

$\alpha^{(2)}$  1111

$$\alpha_y^{(k)} = \text{softmax}_i (\bar{x}_y^T W^{(k)} \bar{x}_i)$$

$$\bar{X}'^{(k)}_q = \sum_i \alpha_{u,i}^{(k)} V^{(k)} \bar{x}_i$$

↖ new param matrix

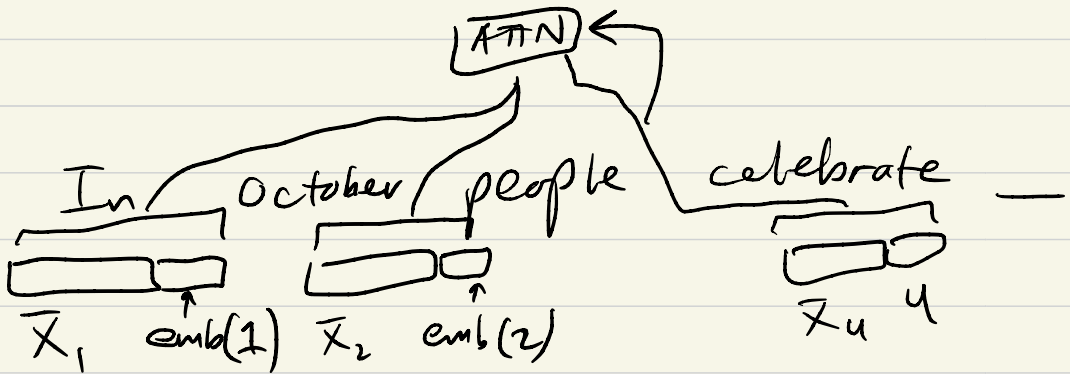
$K=1 \dots K$ , do independent  
copies of the computation

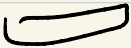
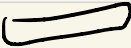


$(w^{(k)}, v^{(k)})$  is a head

## Positional encoding

Attention doesn't know the order of the words

Solution: encode position into  $\bar{X}_i$



- 1 
  - 2 
  - 3 
- 

50-dim embs, trained with the rest of the model

# Transformer

