CS378: Natural Language Processing
Lecture 17: Transformers for Language Modeling, Implementation

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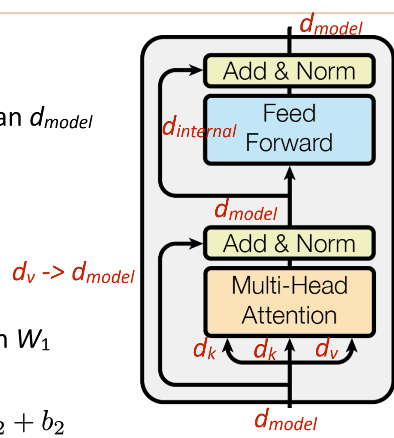
Transformers

Dimensions

- Vectors: d_{model}
- Queries/keys: d_k , always smaller than d_{model}
- Values: separate dimension d_v , output is multiplied by W^O which is d_v x d_{model} so we can get back to d_{model} before the residual
- FFN can explode the dimension with W_1 and collapse it back with W_2

$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$



Vaswani et al. (2017)

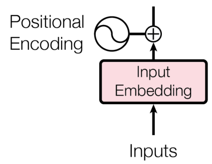
Transformers: Position Sensitivity

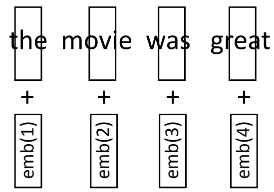
The ballerina is very excited that she will dance in the show.

- If this is in a longer context, we want words to attend *locally*
- But transformers have *no notion of position* by default

Vaswani et al. (2017)

Transformers: Position Sensitivity



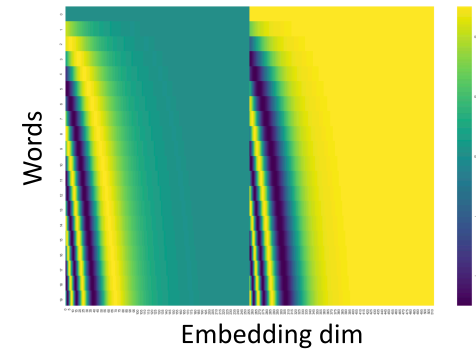


- Encode each sequence position as an integer, add it to the word embedding vector
- Why does this work?

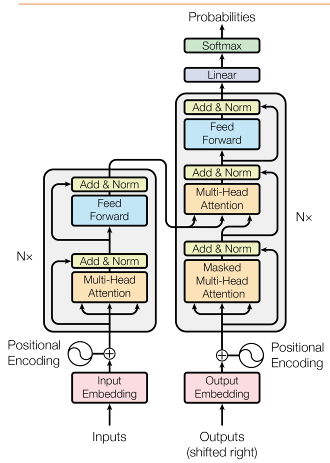
Transformers

Alammar, *The Illustrated Transformer*

- Alternative from Vaswani et al.: sines/cosines of different frequencies (closer words get higher dot products by default)



Transformers: Complete Model

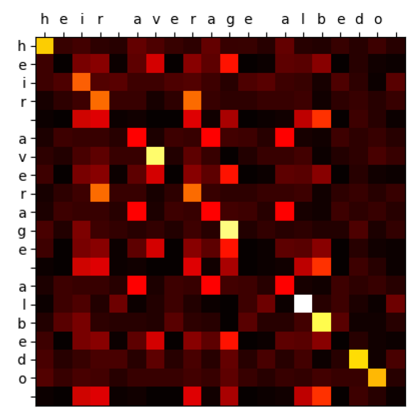


- Original Transformer paper presents an **encoder-decoder** model
- Right now we don't need to think about both of these parts — will return in the context of MT
- Decoder differs because each token only attends to those coming before it. Can do this with an **attention mask**

Vaswani et al. (2017)

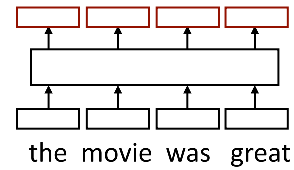
Attention Maps

- Example visualization of attention matrix A (from assignment)
- Each row: distribution over what that token attends to. E.g., the first "v" attends very heavily to itself (bright yellow box)
- **Your task on the HW: assess if the attentions make sense**



Using Transformers

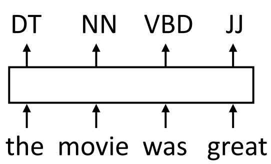
What do Transformers produce?



- Encoding of each word — can pass this to another layer to make a prediction (like predicting the next word for language modeling)
- Like RNNs, Transformers can be viewed as a transformation of a sequence of vectors into a sequence of context-dependent vectors

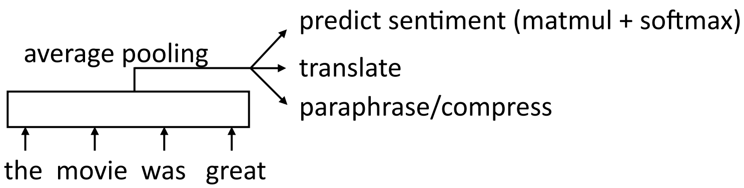
Transformer Uses

- Transducer: make some prediction for each element in a sequence

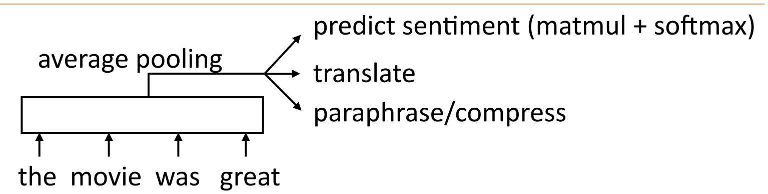


output **y** = score for each tag, then softmax

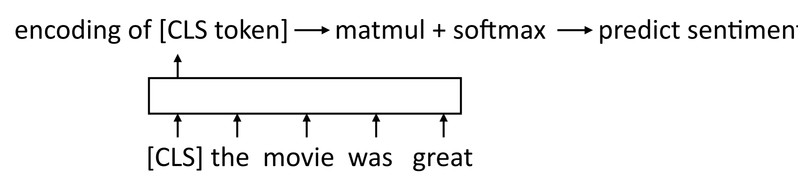
- Classifier: encode a sequence into a fixed-sized vector and classify that



Transformer Uses

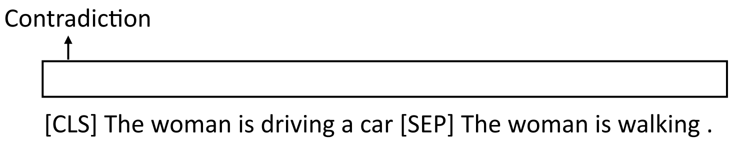


- Alternative: use a placeholder [CLS] token at the start of the sequence. Because [CLS] attends to everything with self-attention, it can do the pooling for you!



Transformer Uses

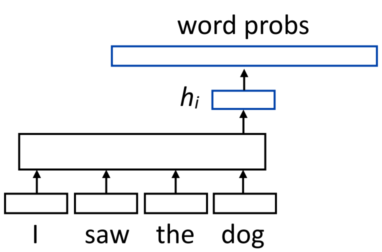
- Sentence **pair** classifier: feed in two sentences and classify something about their relationship



- Why might Transformers be particularly good at sentence **pair** tasks compared to something like a DAN?

Transformer Language Modeling

Transformer Language Modeling



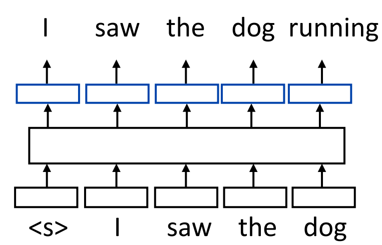
$$P(w|\text{context}) = \frac{\exp(\mathbf{w} \cdot \mathbf{h_i})}{\sum_{w'} \exp(\mathbf{w'} \cdot \mathbf{h_i})}$$

equivalent to

$$P(w|\text{context}) = \text{softmax}(W\mathbf{h}_i)$$

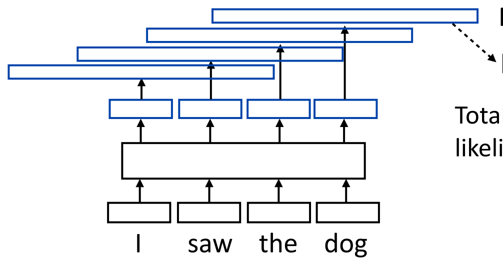
- *W* is a (vocab size) x (hidden size) matrix; linear layer in PyTorch (rows are word embeddings)

Training Transformer LMs



- Input is a sequence of words, output is those words shifted by one,
- Allows us to train on predictions across several timesteps simultaneously (similar to batching but this is NOT what we refer to as batching)

Training Transformer LMs



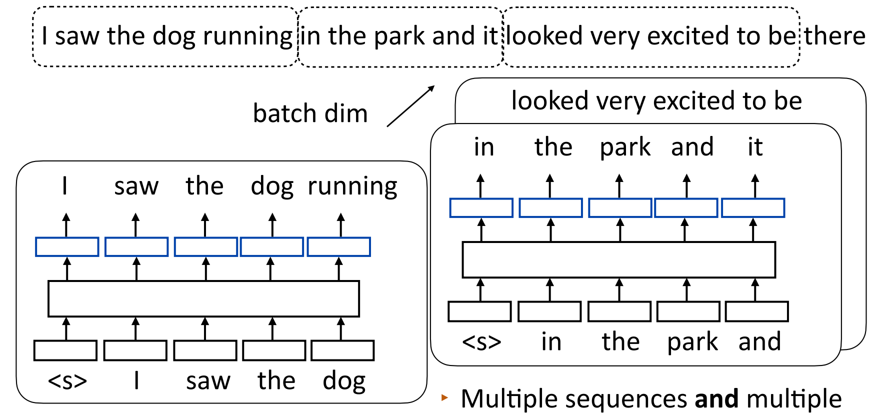
Total loss = sum of negative log likelihoods at each position

```
loss_fcn = nn.NLLLoss()
loss += loss_fcn(log_probs, ex.output_tensor)
```

[seq len, num output classes] [seq len]

- Batching is a little tricky with NLLLoss: need to collase [batch, seq len, num classes] to [batch * seq len, num classes]. You do not need to batch

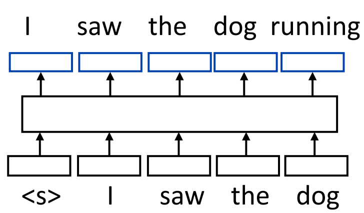
Batched LM Training



- Multiple sequences **and** multiple timesteps per sequence

A Small Problem with Transformer LMs

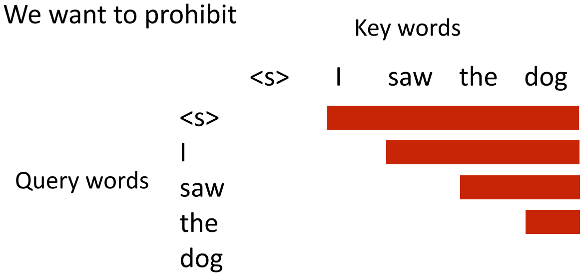
- This Transformer LM as we've described it will *easily* achieve perfect accuracy. Why?



- With standard self-attention: "I" attends to "saw" and the model is "cheating". How do we ensure that this doesn't happen?

Attention Masking

- We want to prohibit



- We want to mask out everything in red (an upper triangular matrix)

Implementing in PyTorch

- nn.TransformerEncoder can be built out of nn.TransformerEncoderLayers, can accept an input and a mask for language modeling:

```
# Inside the module; need to fill in size parameters
layers = nn.TransformerEncoderLayer([...])
transformer_encoder = nn.TransformerEncoder(encoder_layers, num_layers=[...])
[. . .]
# Inside forward(): puts negative infinities in the red part
mask = torch.triu(torch.ones(len, len) * float('-inf'), diagonal=1)
output = transformer_encoder(input, mask=mask)
```

- **You cannot use these for Part 1, only for Part 2**

LM Evaluation

- Accuracy doesn't make sense — predicting the next word is generally impossible so accuracy values would be very low
- Evaluate LMs on the likelihood of held-out data (averaged to normalize for length)

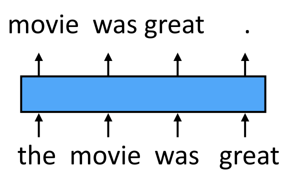
$$\frac{1}{n}\sum_{i=1}^{n}\log P(w_i|w_1,\ldots,w_{i-1})$$

- Perplexity: exp(average negative log likelihood). Lower is better
  - Suppose we have probs 1/4, 1/3, 1/4, 1/3 for 4 predictions
  - Avg NLL (base e) = 1.242 Perplexity = 3.464 <== geometric mean of denominators

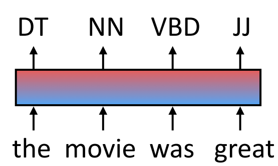
Preview: Pre-training and BERT

- Transformers are usually large and you don't want to train them for each new task

Train on language modeling…



then "fine-tune" that model on your target task with a new classification layer



Transformer Extensions

Scaling Laws

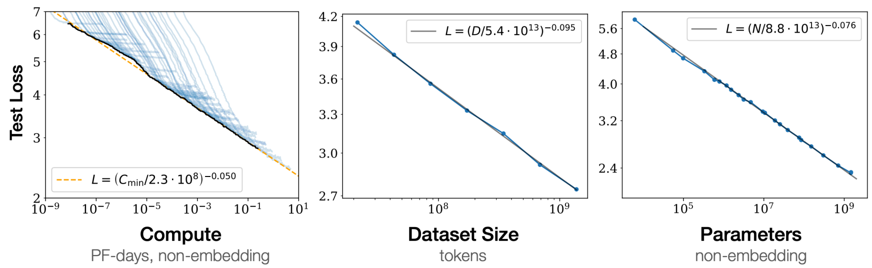


Figure 1 Language modeling performance improves smoothly as we increase the model size, datasetset size, and amount of compute[2] used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.

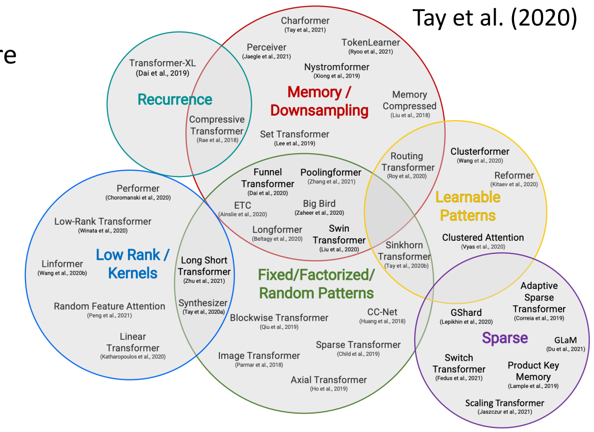
- Transformers scale really well!

Kaplan et al. (2020)

Transformer Runtime

- Even though most parameters and FLOPs are in feedforward layers, Transformers are still limited by quadratic complexity of self-attention
- Many ways proposed to handle this

Tay et al. (2020)



Performers

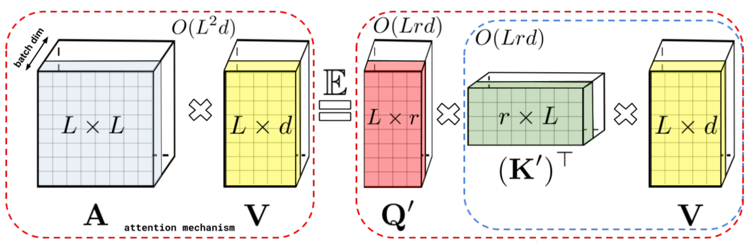
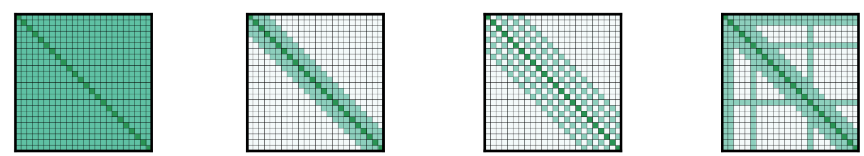


Figure 1: Approximation of the regular attention mechanism $\mathbf{AV}$ (before $\mathbf{D}^{-1}$-renormalization) via (random) feature maps. Dashed-blocks indicate order of computation with corresponding time complexities attached.

- No more len² term, but we are fundamentally approximating the self-attention mechanism (cannot form **A** and take the softmax)

Choromanski et al. (2020)

Longformer



(a) Full n^2 attention (b) Sliding window attention (c) Dilated sliding window (d) Global+sliding window

Figure 2: Comparing the full self-attention pattern and the configuration of attention patterns in our Longformer.

- Use several pre-specified self-attention patterns that limit the number of operations while still allowing for attention over a reasonable set of things
- Scales to 4096-length sequences

Beltagy et al. (2021)

Vision and RL

- DALL-E 1: learns a discrete "codebook" and treats an image as a sequence of visual tokens which can be modeled autoregressively, then decoded back to an image
- Decision Transformer: does reinforcement learning by Transformer-based modeling over a series of actions
- Transformers are now being used all over AI

Ramesh et al. (2021), Chen et al. (2021)

Takeaways

- Transformers are going to be the foundation for the much of the rest of this class and are a ubiquitous architecture nowadays
- Many details to get right, many ways to tweak and extend them, but core idea is the multi-head self attention and their ability to contextualize items in sequences
- Next: machine translation and seq2seq models (conditional language modeling)