Recitation 8: Attention

Jingwei Zhang & Bharat Gaind

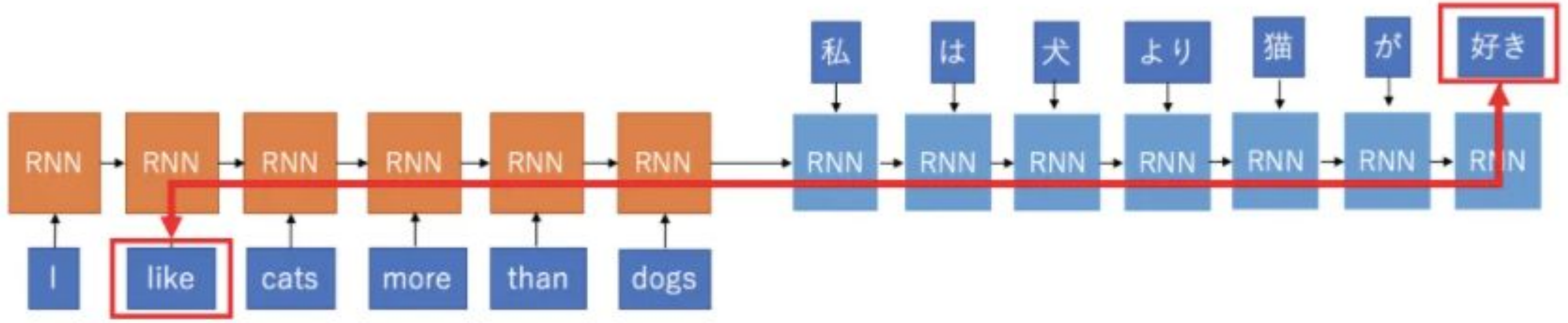
RNN Tasks

(HW3P2) Speech frame sequence -> Phoneme sequence

- Order-correspondence
- Each output corresponds to a small segment of input sequence

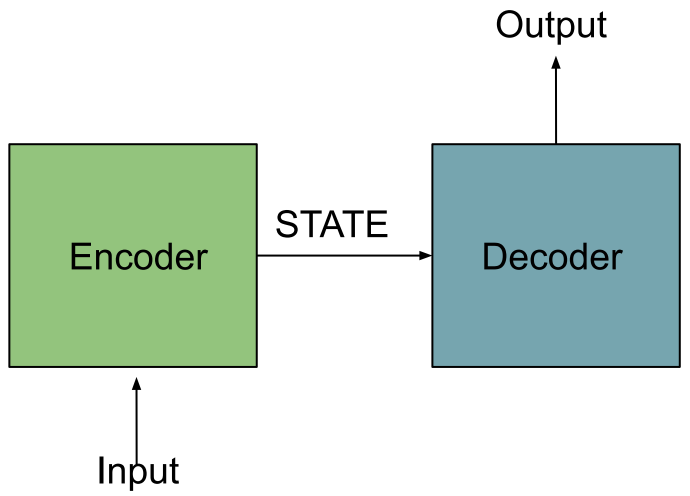
RNN Tasks

- Text -> Translation of text
- Image -> A caption describing the image
- Document, Question -> Answer selected from the document



Generative Architecture

- The output sequence can only be built after seeing the entire input sequence
- The output is itself a sequence, generated from the input sequence



Decoder = Conditional Generator

In Math:

$$P(y_t | x_1, \dots, x_T, y_1, \dots, y_{t-1})$$

Each item in the output sequence must be conditioned on:

- The entire input sequence
- All the past output items

In Deep Learning:

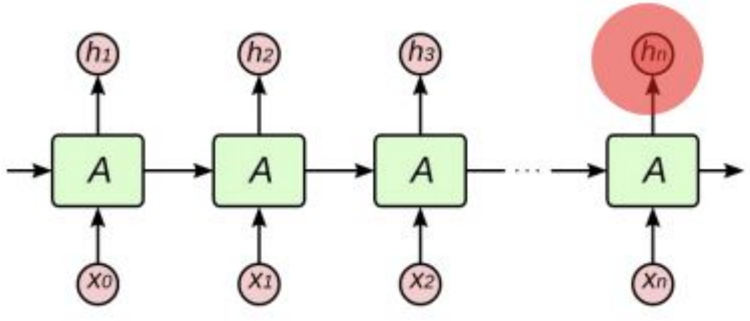
The decoder must have access to:

- Some kind of encoding of the entire input sequence
- The past states of the decoder

How to encode the input sequence

Recall the “many-to-many” Architecture (HW3P2)

Hidden states only encode information about the history of inputs
Ideally the last hidden state is an encoding of the entire input sequence
Let’s consider the last hidden state first



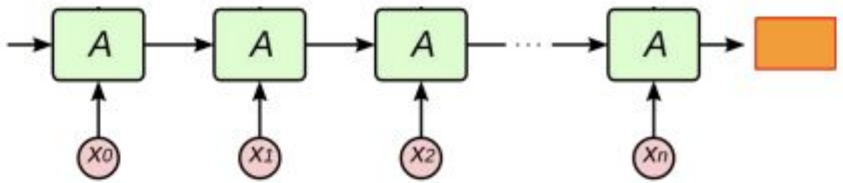
How to inform the decoder of the input encoding

- Pass the last hidden state of the input sequence at
  - the first time step
  - every time step

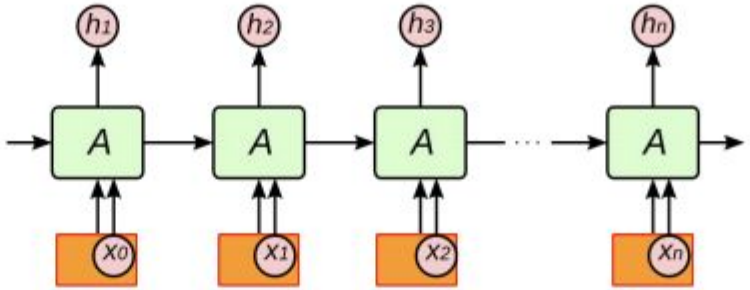
- Pass a more flexible input encoding at every time step
  - determined by the current decoder state

Network Prototype 1

Produce an encoding of the entire input.



Repeatedly pass the encoding to the output network.



Problems?

Using one fixed vector to encode an entire sequence, hoping that the last hidden state could compress all the information

- Hard to train. Input encoding vector is overloaded with information, and earlier inputs tends to get forgotten
- Hard for the decoder to focus. Each time it's seeing the same thing

How to inform the decoder of the input encoding

- Pass the last hidden state of the input sequence at
  - the first time step
  - every time step

- Pass a more flexible input encoding at every time step
  - determined by the current decoder state

Let the decoder decide the input encoding

Intuition:
At each time step, the decoder focuses on a specific segment of the input sequence to produce the current output

Formulation:

- Compute a time-varying input encoding that focuses on the part of input that matters to the current time step in the output
- Therefore, this input encoding should be a function of:
  - The decoder hidden state at current time step
  - The encoder hidden states at each input time step

General Attention Mechanism

- Construct a **query** $\mathbf{q}_i$ from the decoder state $\mathbf{h}_i^{dec}$
  - Represents the decoder's interest
- Construct a **key** $\mathbf{k}_j$ from the encoder state $\mathbf{h}_j^{enc}$
- Calculate an **attention score** $\mathbf{att}(\mathbf{q}_i, \mathbf{k}_j)$
  - Tells how much at output time step i the decoder should focus on the j-th input item
- Construct a **value** $\mathbf{v}_j$ from the encoder state $\mathbf{h}_j^{enc}$
- Then construct the encoding by computing a weighted sum of values using attention scores as weights:
  - $\sum_{j=1}^{T} \mathbf{att}(\mathbf{q}_i, \mathbf{k}_j)\, \mathbf{v}_j$

Variation: Dot Product Attention

- **Query** $\mathbf{q}_i = \mathbf{h}_i^{dec}$
- **Key** $\mathbf{k}_j = \mathbf{h}_j^{enc}$
- **Value** $\mathbf{v}_j = \mathbf{h}_j^{enc}$
- **Attention score** att$(\mathbf{q}_i, \mathbf{k}_j)$ = softmax$(\mathbf{q}_i \cdot \mathbf{k}_j)$ (over all j)
  - Simplest similarity calculation (but works well in practice)
  - Does not introduce new parameters

Variation: Bilinear Attention

- **Query** $\mathbf{q}_i = \mathbf{h}_i^{dec}$
- **Key** $\mathbf{k}_j = \mathbf{h}_j^{enc}$
- **Value** $\mathbf{v}_j = \mathbf{h}_j^{enc}$
- **Attention score** $\text{att}(\mathbf{q}_i, \mathbf{k}_j) = \text{softmax}(\mathbf{q}_i^T \mathbf{W} \mathbf{k}_j)$ (over all j)
  - Queries and keys do not have to be in the same space
  - Introduces new parameters

Variation: Additive Attention

- **Query** $\mathbf{q}_i = \mathbf{h}_i^{dec}$
- **Key** $\mathbf{k}_j = \mathbf{h}_j^{enc}$
- **Value** $\mathbf{v}_j = \mathbf{h}_j^{enc}$
- **Attention score** $\mathrm{att}(\mathbf{q}_i, \mathbf{k}_j) = \mathrm{softmax}(\mathbf{W}_a^T \tanh(\mathbf{W}_q \mathbf{q}_i + \mathbf{W}_k \mathbf{k}_j))$ (over all j)

Variation: Scaled Dot Product Attention

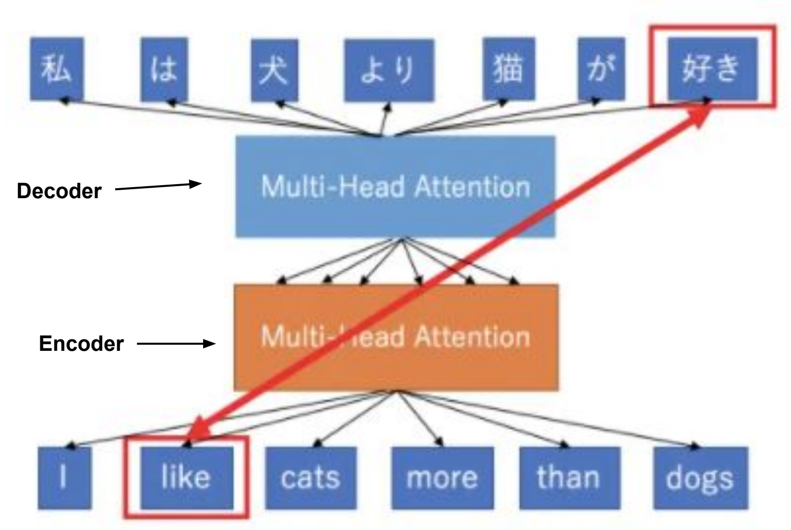
- **Query** $\mathbf{q}_i = \mathrm{MLP}_\mathrm{q}(\mathbf{h}_i^{dec})$
- **Key** $\mathbf{k}_j = \mathrm{MLP}_\mathrm{k}(\mathbf{h}_j^{enc})$
- **Value** $\mathbf{v}_j = \mathrm{MLP}_\mathrm{v}(\mathbf{h}_j^{enc})$
- **Attention score** $\mathrm{att}(\mathbf{q}_i, \mathbf{k}_j) = \mathrm{softmax}\left(\frac{\mathbf{q}_i \cdot \mathbf{k}_j}{\sqrt{H}}\right)$ (over all j)
  - Use the dot product to calculate similarity for projected key value representation
  - Scaled by the sqrt of hidden size in order not to saturate the gradient of softmax

Problems of RNN-based Attention

- Sequential nature of RNNs make them impossible to fully parallelize
  - Step-by-step computation relies on the output of the previous time-step
  - Cannot leverage parallelism of GPUs
- They struggle with long-term dependencies
  - What about LSTMs? Still cannot hold information across very long sequences
  - In NLP tasks, the same word may have very different meanings based on the context

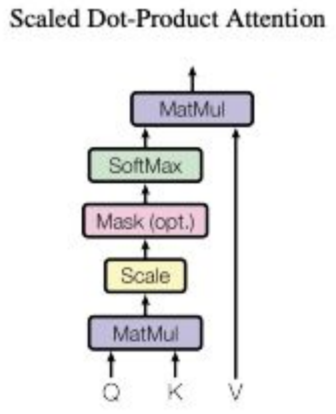
Transformer Nets

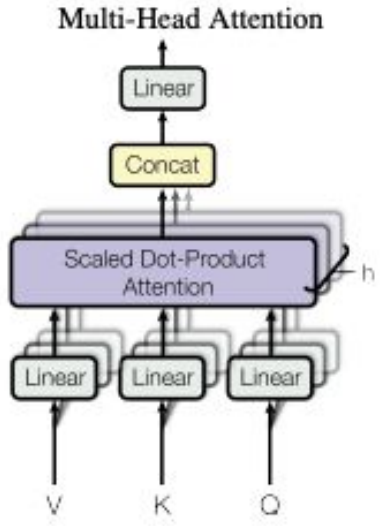
- Revolutionary sequence to sequence architecture from Google (2017)
- Forget about RNNs, **capture dependencies across the sequences using attention**
- This allows the encoder and decoder see the entire sequence at once
- Parallelism



Multi-Head Attention

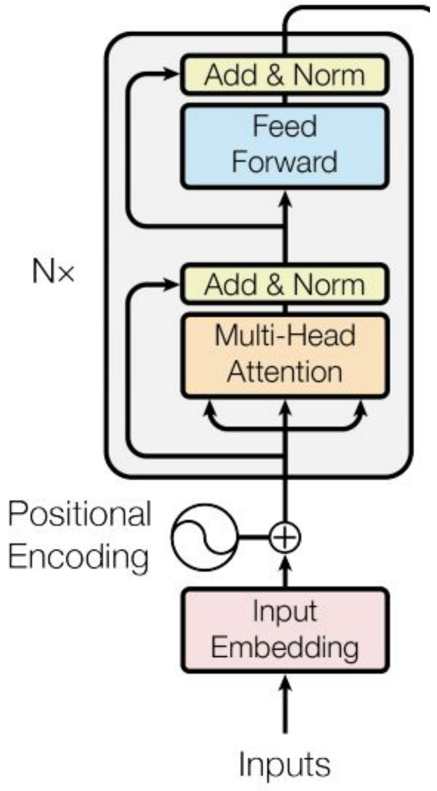
- Attention can be interpreted as a way of computing the relevance of a set of **values**, based on some **keys** and **queries**.
- Attention is applied multiple times to capture more complex input dependencies
- Each attention ‘head’ has unique weights
- Each attention ‘head’ can focus on different parts of the input sequence (and probably serve different purposes)





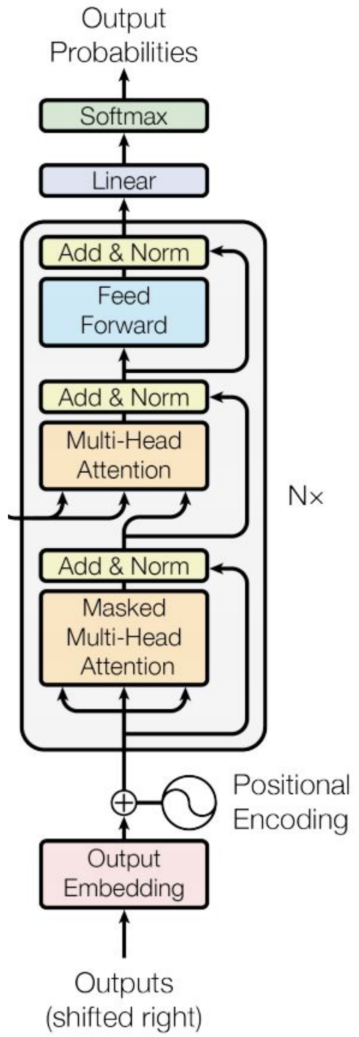
Transformer Encoder

- Contains multiple ‘blocks’ (~6 blocks)
- Residual connections between the multi-head attention blocks
- Positional encodings explicitly encode the relative and absolute positions of the inputs as vectors
- These encodings are then added to the input embeddings
- Without them the output for “I like 11-785 more than 10-707” would be identical to the output for “I like 10-707 more than 11-785”



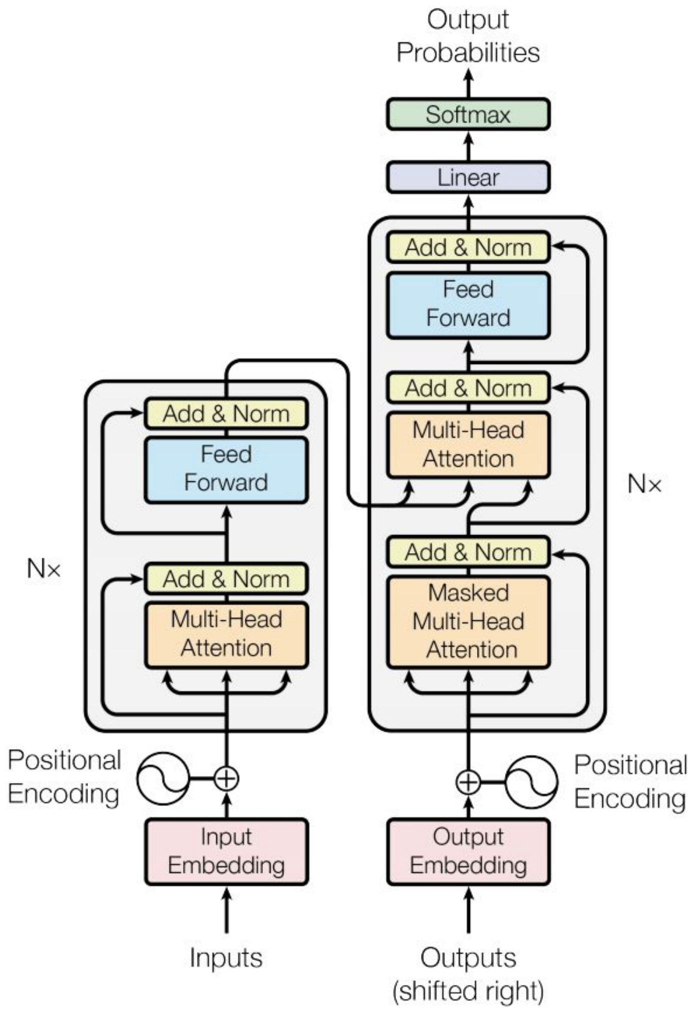
Transformer Decoder

- Very similar to the encoder
- ‘Masked’ Multi-Head Attention block to hide future output values during training
- The query from the decoder is used with the keys/values from the encoder
- Final output probabilities are computed using a projection layer followed by a softmax



Putting together

- Input sequence is used to compute the keys and values in the encoder
- Masked-attention blocks in the decoder transform the output sequence until the current time-step into the queries
- Multi-head attention in the decoder combines the keys, queries and values
- The result is projected into output probabilities for the current time step



More resources

1. The original paper: Attention Is All You Need
2. Detailed explanation