CMSC 473/673
Natural Language Processing

Instructor: Lara J. Martin (she/they)

TA: Duong Ta (he)

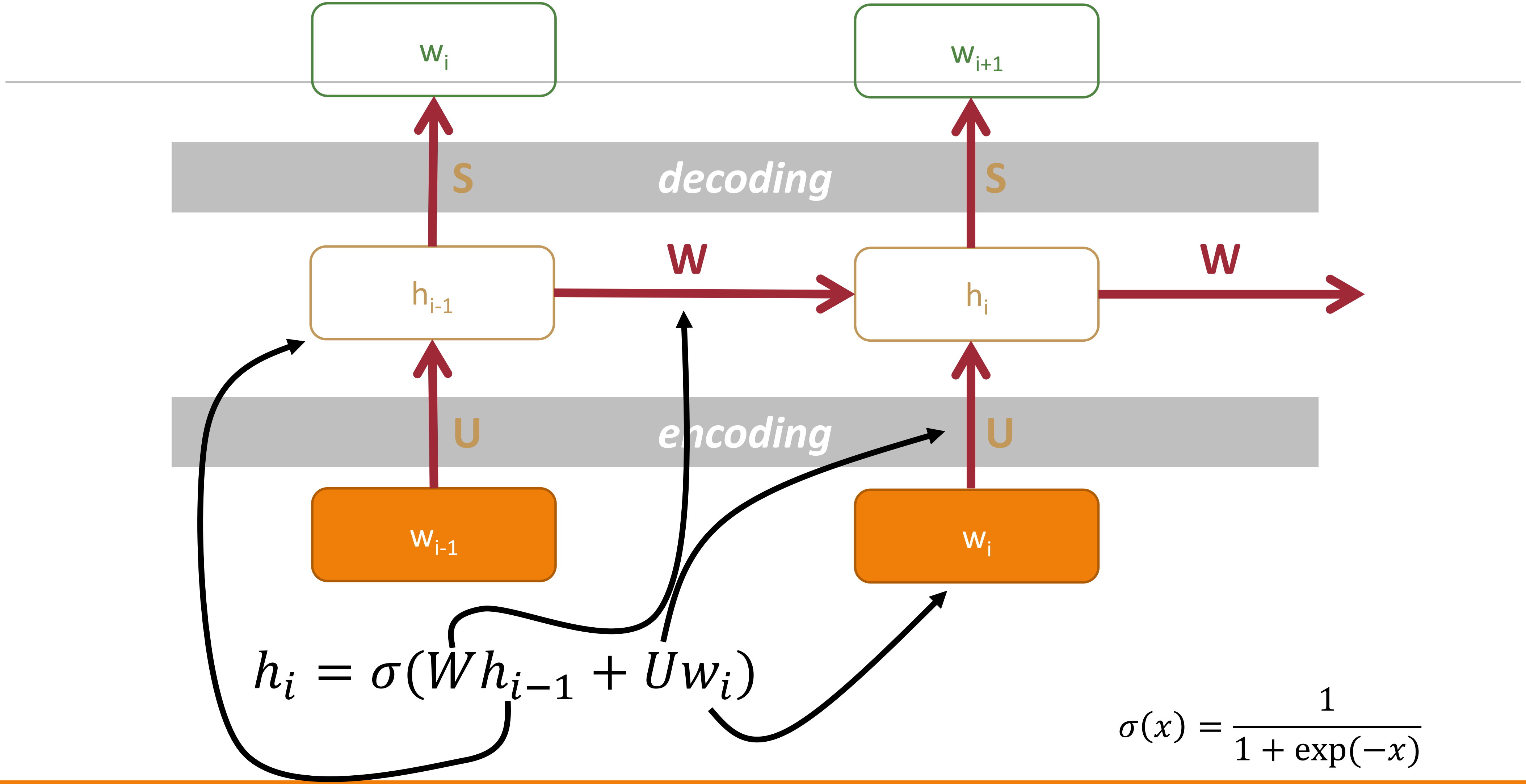
Slides modified from Dr. Frank Ferraro & Dr. Daphne Ippolito

Learning Objectives

Compare sequence-to-sequence RNNs to simple NNs & non-neural LMs

Compare sequence-to-sequence RNNs to transformers

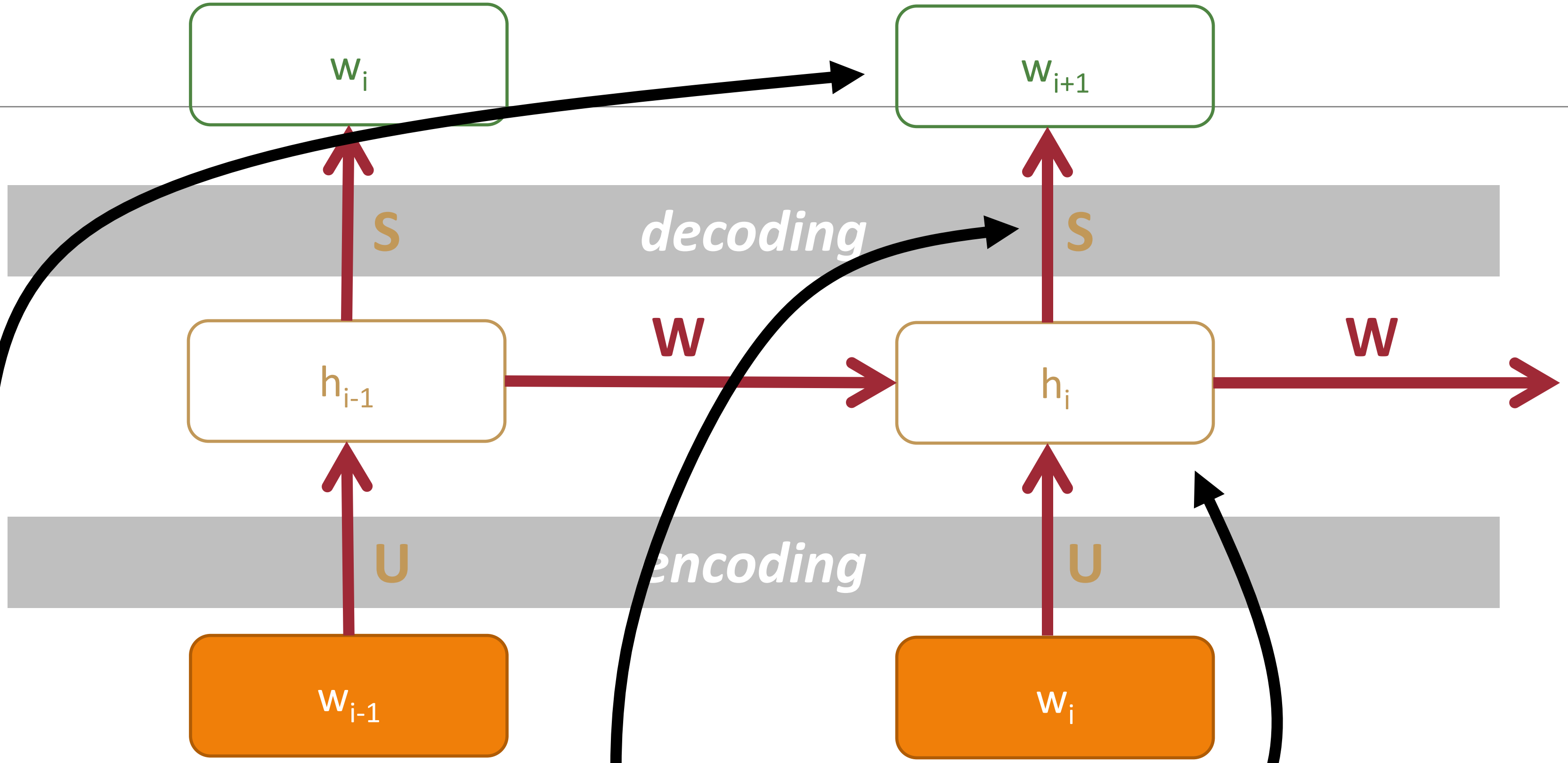
Review:
A *Simple* Recurrent Neural Network Cell



$$h_i = \sigma(W h_{i-1} + U w_i)$$

$$\sigma(x) = \frac{1}{1 + \exp(-x)}$$

Review:
A *Simple* Recurrent Neural Network Cell

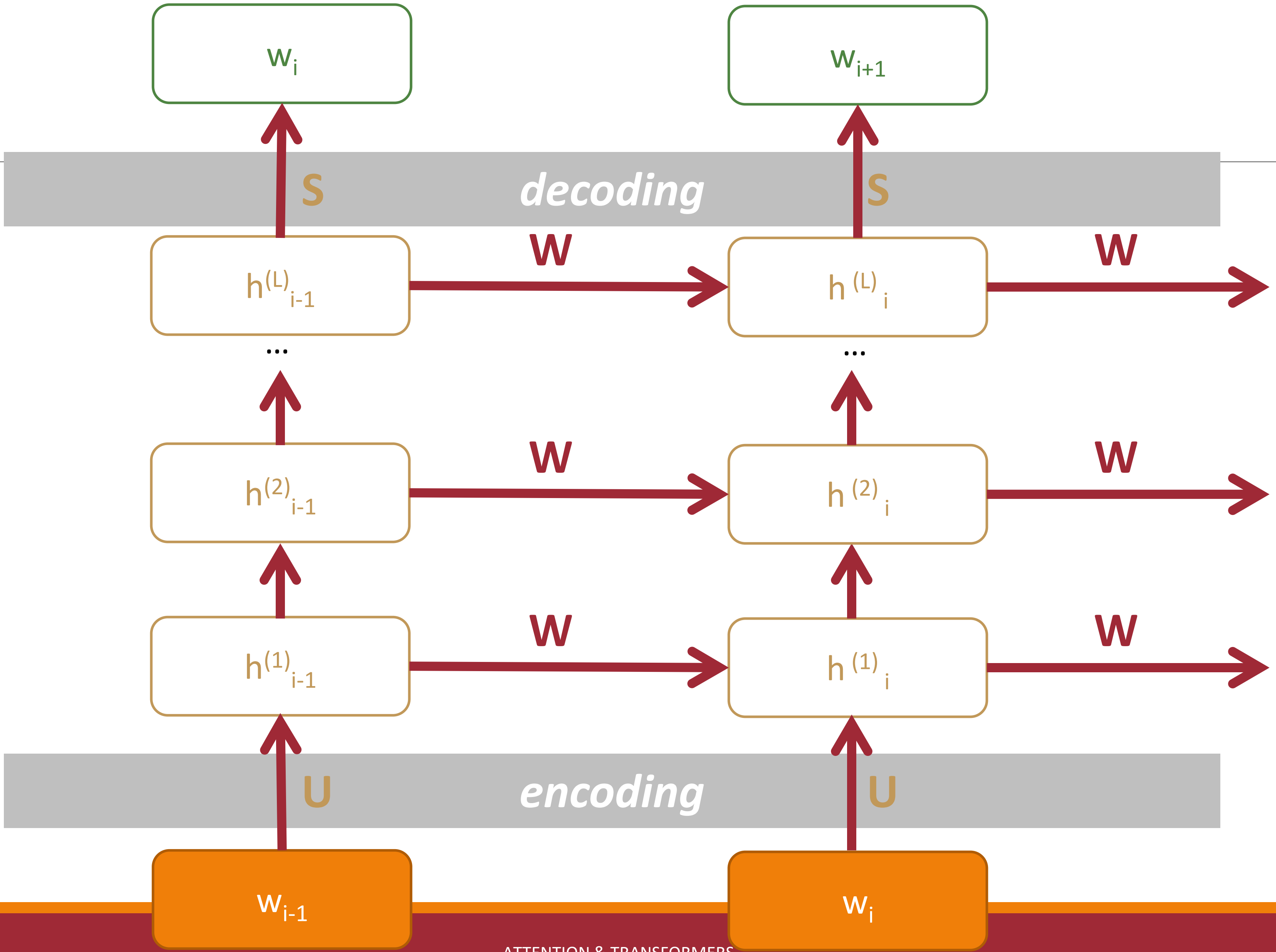


$$h_i = \sigma(W h_{i-1} + U w_i)$$

$$\sigma(x) = \frac{1}{1 + \exp(-x)}$$

$$\widehat{w}_{i+1} = \text{softmax}(S h_i)$$

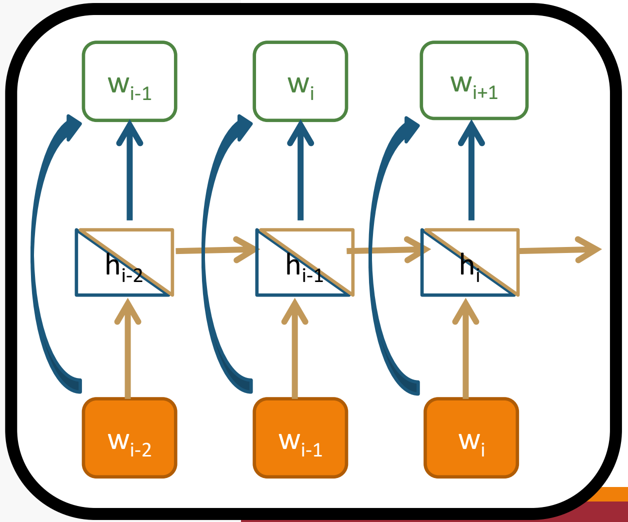
Review: A Multi-Layer *Simple* Recurrent Neural Network Cell



Review:
Defining A Simple RNN in Python

http://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

```
import torch.nn as nn

class RNN(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(RNN, self).__init__()

        self.hidden_size = hidden_size

        self.i2h = nn.Linear(input_size + hidden_size, hidden_size)
        self.h2o = nn.Linear(hidden_size, output_size)
        self.softmax = nn.LogSoftmax(dim=1)

    def forward(self, input, hidden):
        combined = torch.cat((input, hidden), 1)
        hidden = self.i2h(combined)
        output = self.h2o(hidden)
        output = self.softmax(output)
        return output, hidden

    def initHidden(self):
        return torch.zeros(1, self.hidden_size)

n_hidden = 128
rnn = RNN(n_letters, n_hidden, n_categories)
```



Review:
Training A Simple RNN in Python

http://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

Negative log-likelihood

```
criterion = nn.NLLLoss()


learning_rate = 0.005 # If you set this too high, it might explode. If too low, it might not learn

def train(category_tensor, line_tensor):
    hidden = rnn.initHidden()

    rnn.zero_grad()

    for i in range(line_tensor.size()[0]):
        output, hidden = rnn(line_tensor[i], hidden)

    loss = criterion(output, category_tensor)
    loss.backward()

    # Add parameters' gradients to their values, multiplied by learning rate
    for p in rnn.parameters():
        p.data.add_(-learning_rate, p.grad.data)

    return output, loss.data[0]
```

get predictions

eval predictions

compute gradient

perform SGD

Set t = 0
Pick a starting value θ_t
Until converged:
  for example(s) sentence i:
  1. Compute loss l on x_i
  2. Get gradient $g_t = l'(x_i)$
  3. Get scaling factor ρ_t
  4. Set $\theta_{t+1} = \theta_t - \rho_t * g_t$
  5. Set t += 1

Sequence-to-Sequence RNNs

Up until 2017 or so, neural language models were mostly built using recurrent neural networks.

Sequence to Sequence Learning with Neural Networks

Ilya Sutskever
Google
ilyasu@google.com

Oriol Vinyals
Google
vinyals@google.com

Quoc V. Le
Google
qvl@google.com

Abstract

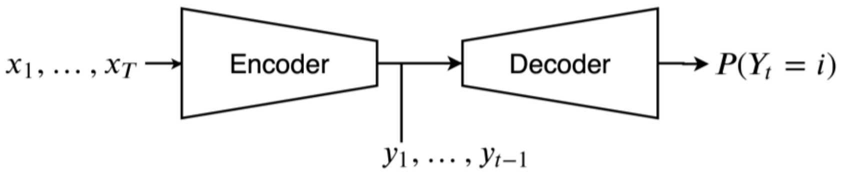
Deep Neural Networks (DNNs) are powerful models that have achieved excellent performance on difficult learning tasks. Although DNNs work well whenever large labeled training sets are available, they cannot be used to map sequences to sequences. In this paper, we present a general end-to-end approach to sequence learning that makes minimal assumptions on the sequence structure. Our method uses a multilayered Long Short-Term Memory (LSTM) to map the input sequence to a vector of a fixed dimensionality, and then another deep LSTM to decode the target sequence from the vector. Our main result is that on an English to French translation task from the WMT'14 dataset, the translations produced by the LSTM achieve a BLEU score of 34.8 on the entire test set, where the LSTM's BLEU score was penalized on out-of-vocabulary words. Additionally, the LSTM did not have difficulty on long sentences. For comparison, a phrase-based SMT system achieves a BLEU score of 33.3 on the same dataset. When we used the LSTM to rerank the 1000 hypotheses produced by the aforementioned SMT system, its BLEU score increases to 36.5, which is close to the previous best result on this task. The LSTM also learned sensible phrase and sentence representations that are sensitive to word order and are relatively invariant to the active and the passive voice. Finally, we found that reversing the order of the words in all source sentences (but not target sentences) improved the LSTM's performance markedly, because doing so introduced many short term dependencies between the source and the target sentence which made the optimization problem easier.

Generating Sequences With Recurrent Neural Networks

Alex Graves
Department of Computer Science
University of Toronto
graves@cs.toronto.edu

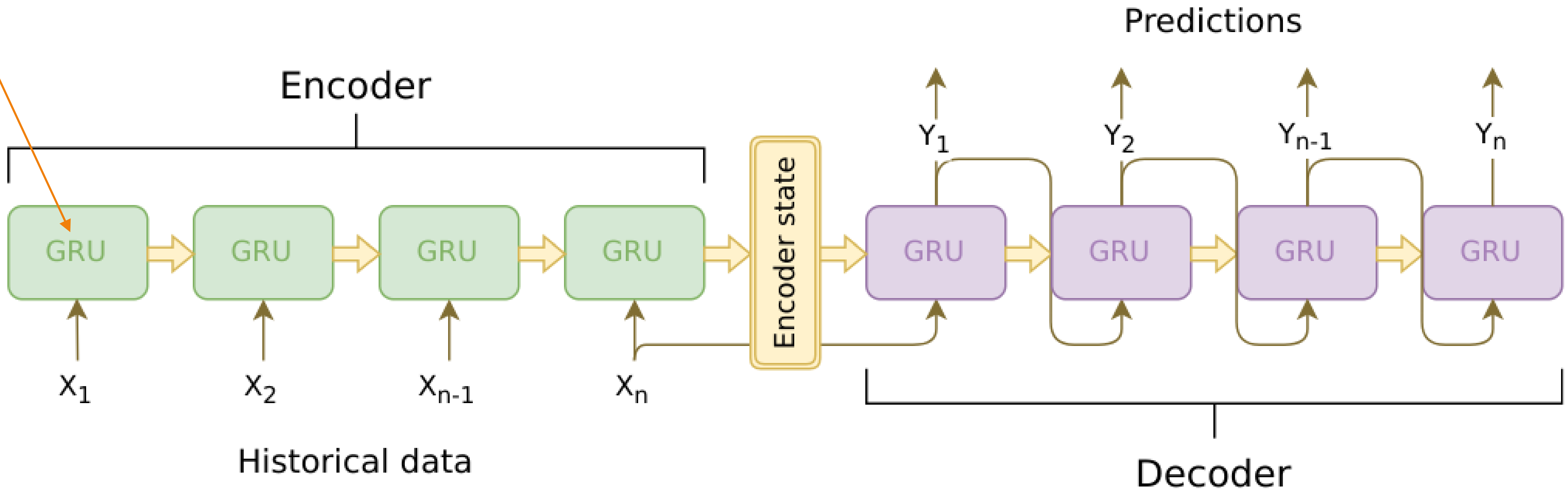
Abstract

This paper shows how Long Short-term Memory recurrent neural networks can be used to generate complex sequences with long-range structure, simply by predicting one data point at a time. The approach is demonstrated for text (where the data are discrete) and online handwriting (where the data are real-valued). It is then extended to handwriting synthesis by allowing the network to condition its predictions on a text sequence. The resulting system is able to generate highly realistic cursive handwriting in a wide variety of styles.



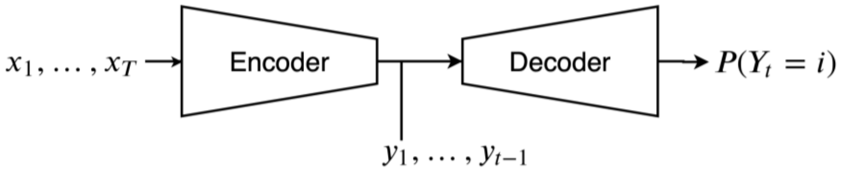
Sequence-to-Sequence / Encoder-Decoder Models

Can be LSTM



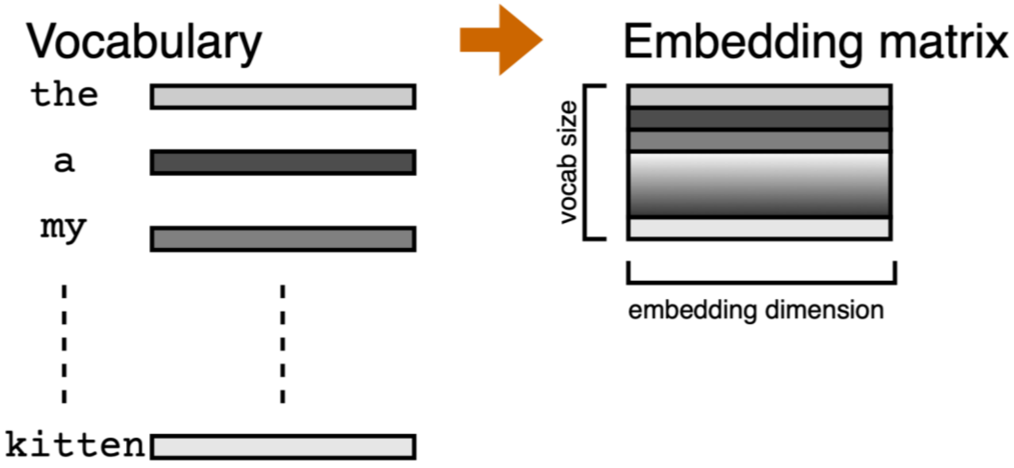
https://jeddy92.github.io/JEddy92.github.io/ts_seq2seq_intro/

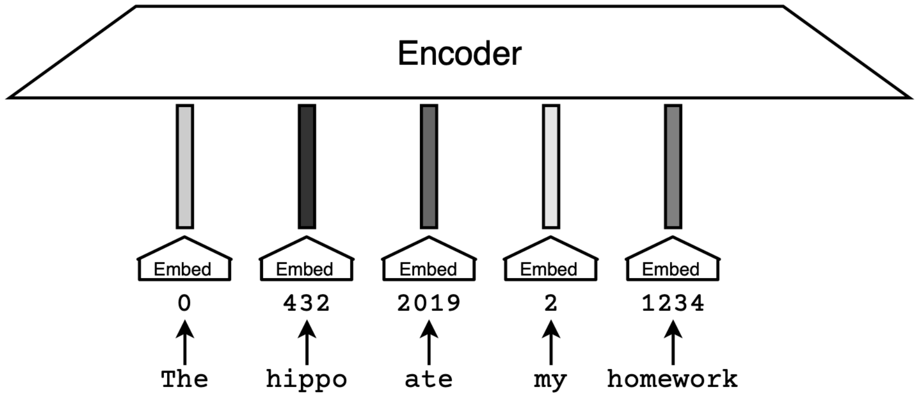
I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to Sequence Learning with Neural Networks," in *Conference on Advances in Neural Information Processing Systems (NeurIPS)*, Montréal, Canada, 2014, pp. 3104–3112. https://proceedings.neurips.cc/paper_files/paper/2014/hash/a14ac55a4f27472c5d894ec1c3c743d2-Abstract.html

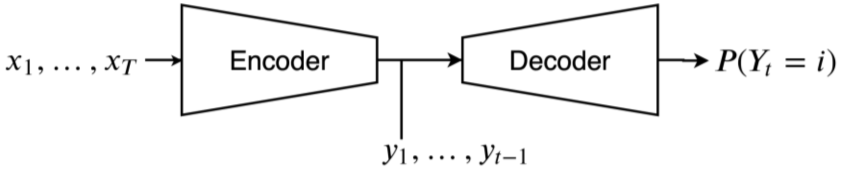


Inputs to the Encoder

The encoder takes as input the embeddings corresponding to each token in the sequence.

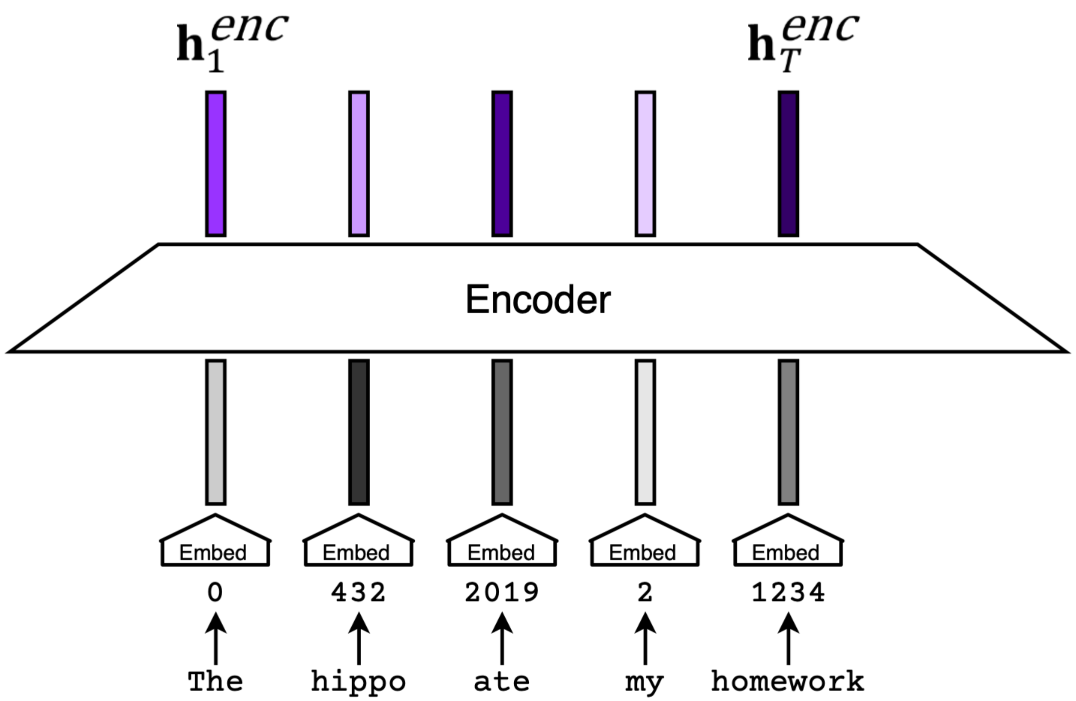


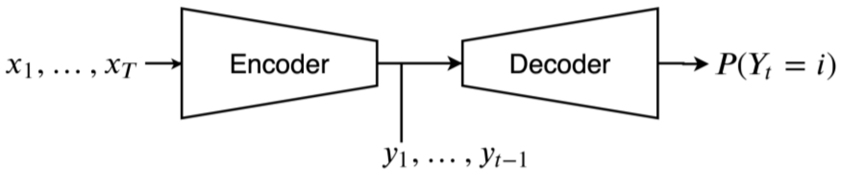




Outputs from the Encoder

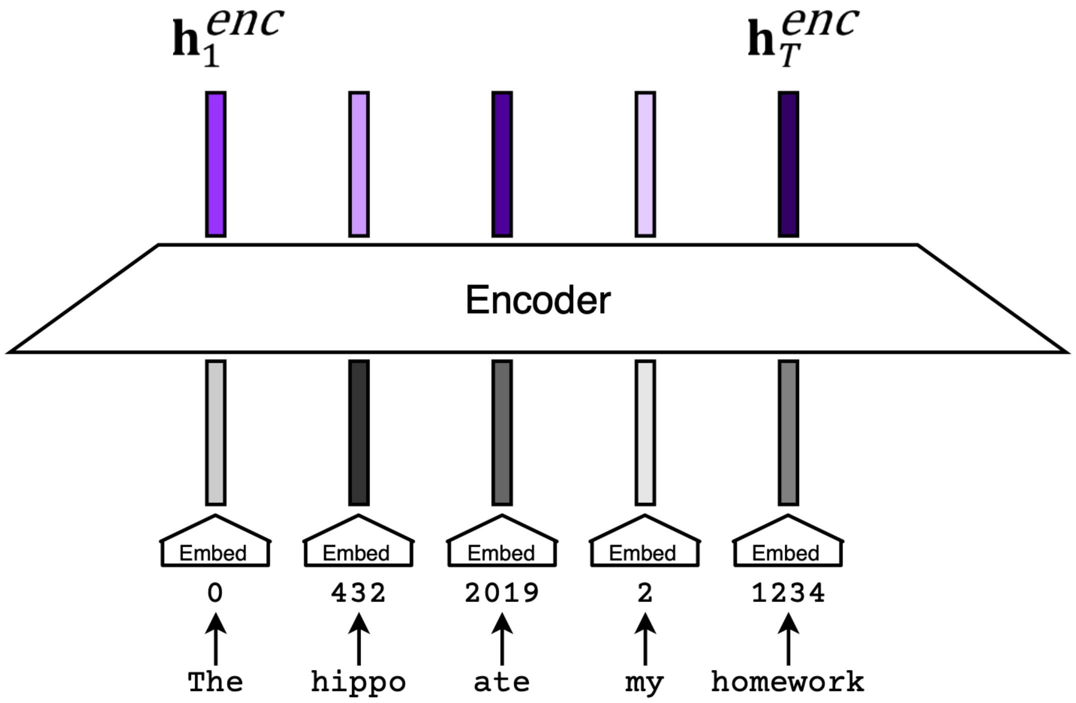
The encoder outputs a sequence of vectors. These are called the hidden state of the encoder.

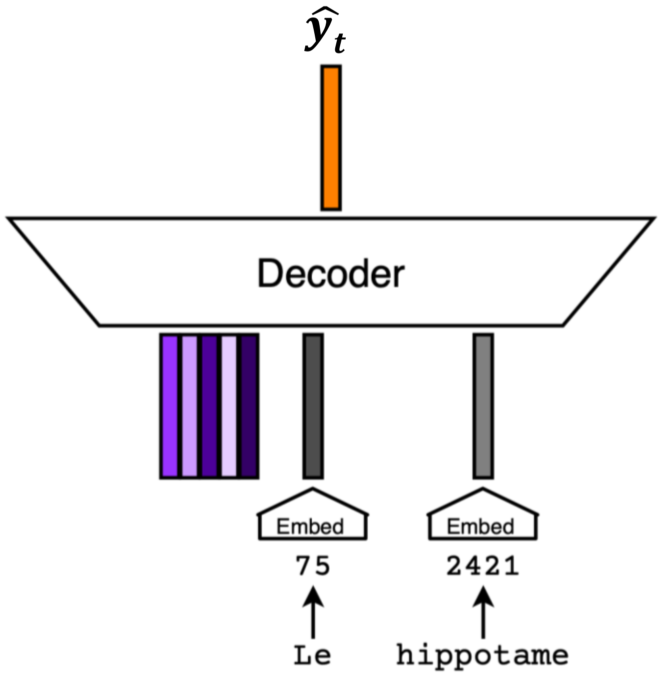


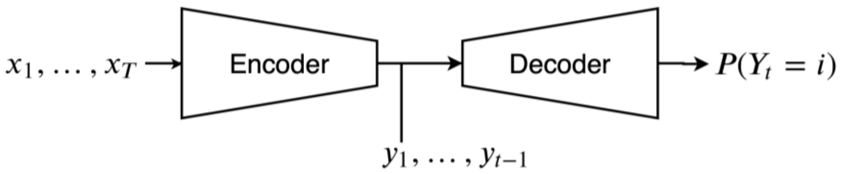


Inputs to the Decoder

The decoder takes as input the hidden states from the encoder as well as the embeddings for the tokens seen so far in the target sequence.

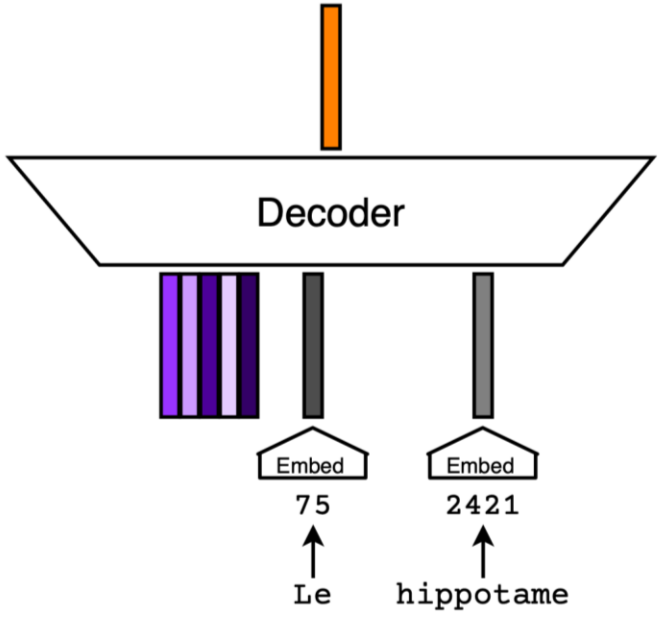






Outputs from the Decoder

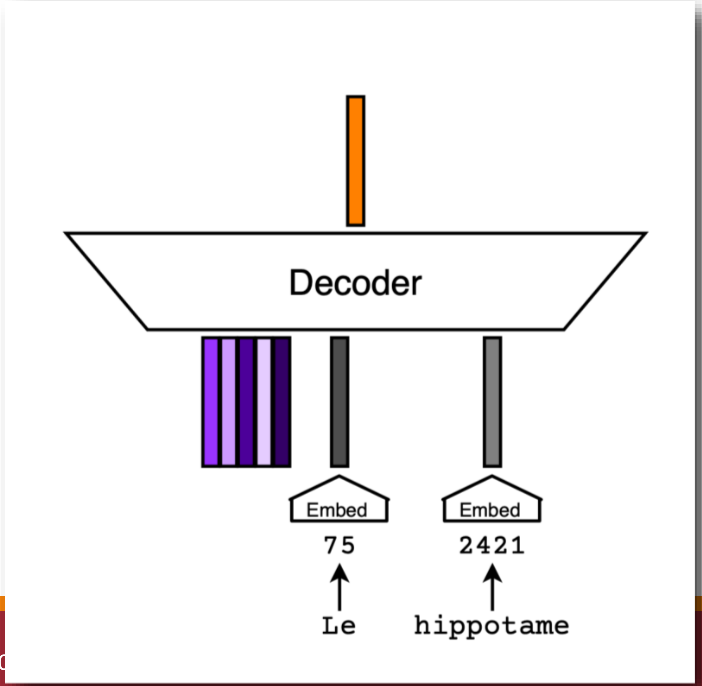
The decoder outputs an embedding $\widehat{yt}$. The goal is for this embedding to be as close as possible to the embedding of the true next token.

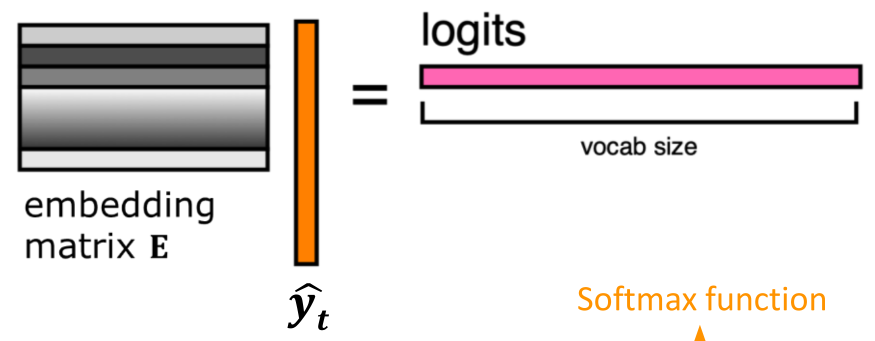


Turning $\widehat{yt}$ into a Probability Distribution

We can multiply the predicted embedding $\widehat{yt}$ by our vocabulary embedding matric to get a score for each vocabulary word. These scores are referred to as logits.

The softmax function then lets us turn the logits into probabilities.





$$P(Y_t = i | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1}) = \boxed{\frac{\exp(\mathbf{E}\hat{\boldsymbol{y}}_{t[i]})}{\sum_j \exp(\mathbf{E}\hat{\boldsymbol{y}}_{t[i]})}}$$

Review: Loss Function

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(Y_t = \boxed{i^*} | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})$$

The index of the true tth word in the target sequence.

Review: Loss Function

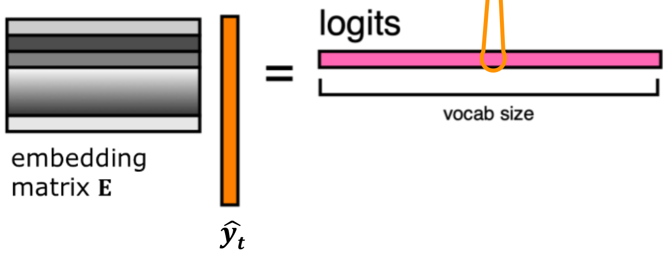
$$\mathcal{L} = -\sum_{t=1}^{T} \log \boxed{P(Y_t = i^* | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})}$$

The probability the language model assigns to the true tth word in the target sequence.

Loss Function

Score for word at index i^*

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(Y_t = i^* | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})$$



$$= -\sum_{t=1}^{T} \log \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_t[i^*])}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}$$

$$P(Y_t = i | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1}) = \frac{\exp(\mathbf{E}\hat{\boldsymbol{y}}_{t[i]})}{\sum_j \exp(\mathbf{E}\hat{\boldsymbol{y}}_{t[i]})}$$

Loss Function

$$\mathcal{L} = -\sum_{t=1}^{T} \log P(Y_t = i^* | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1})$$

$$= -\sum_{t=1}^{T} \cancel{\log} \frac{\cancel{\exp}(\mathbf{E}\mathbf{y}_t[i^*])}{\cancel{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_t[j])}}$$

$$= -\sum_{t=1}^{T} \mathbf{E}\hat{\mathbf{y}}_t[i^*]$$

Generating Text

Also sometimes called decoding

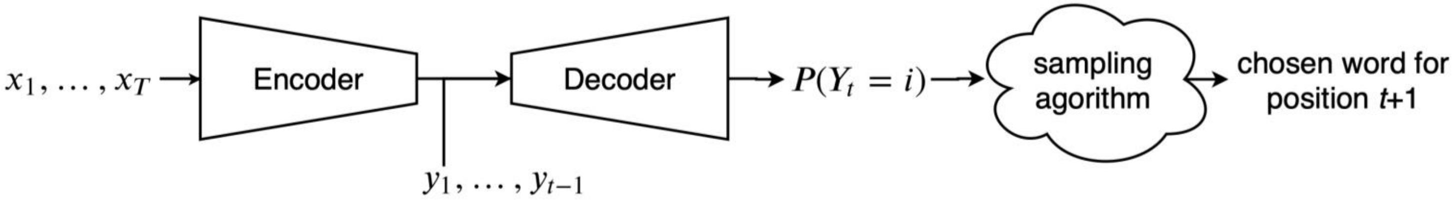
To generate text, we need an algorithm that selects tokens given the predicted probability distributions.

Examples:

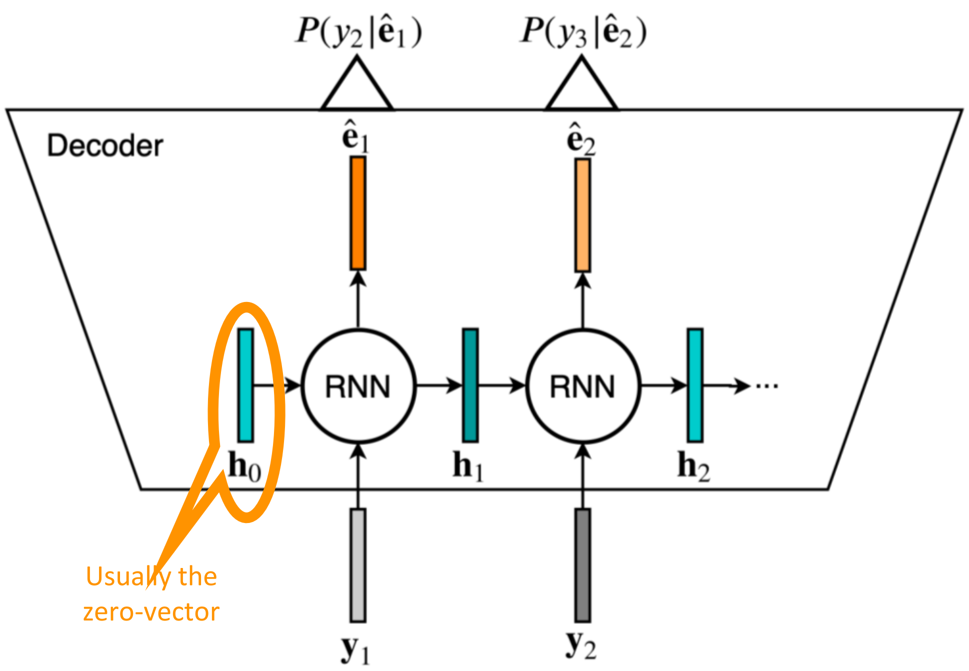
Argmax

Random sampling

Beam search



RNNs - Single Layer Decoder



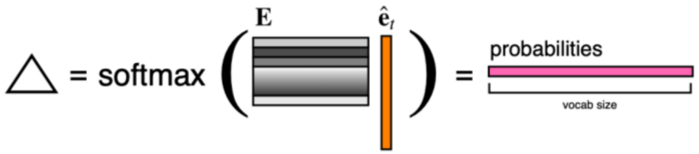
The current hidden state is computed as a function of the previous hidden state and the embedding of the current word in the target sequence.

$$\mathbf{h}_t = \mathrm{RNN}(\mathbf{W}_{ih}\mathbf{y}_t + \mathbf{W}_{hh}\mathbf{h}_{t-1} + \mathbf{b}_h)$$

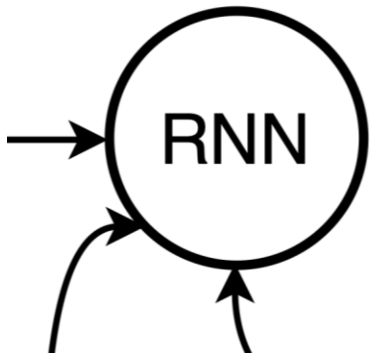
The current hidden state is used to predict an embedding for the next word in the target sequence.

$$\hat{\mathbf{e}}_t = \mathbf{b}_e + \mathbf{W}_{he}\mathbf{h}_t$$

This predicted embedding is used in the loss function:



What is the “RNN” unit?



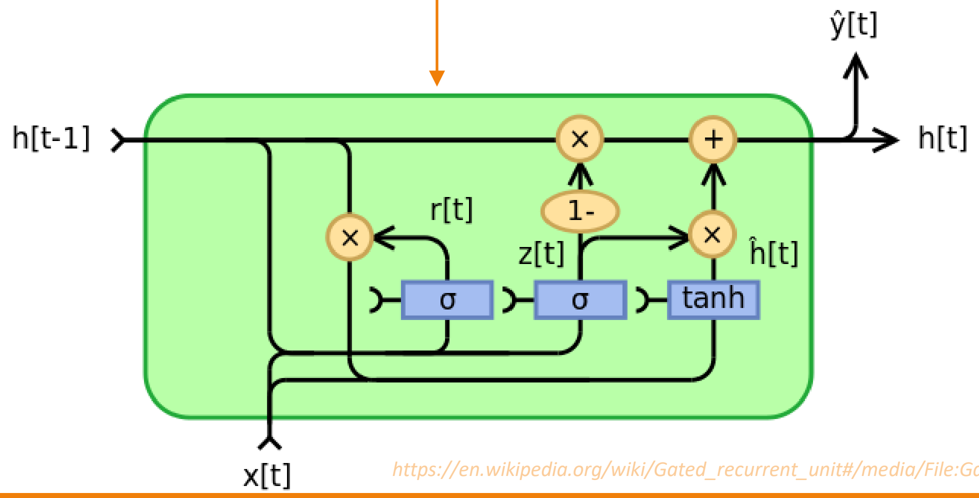
?

Review: LSTMs/GRUs

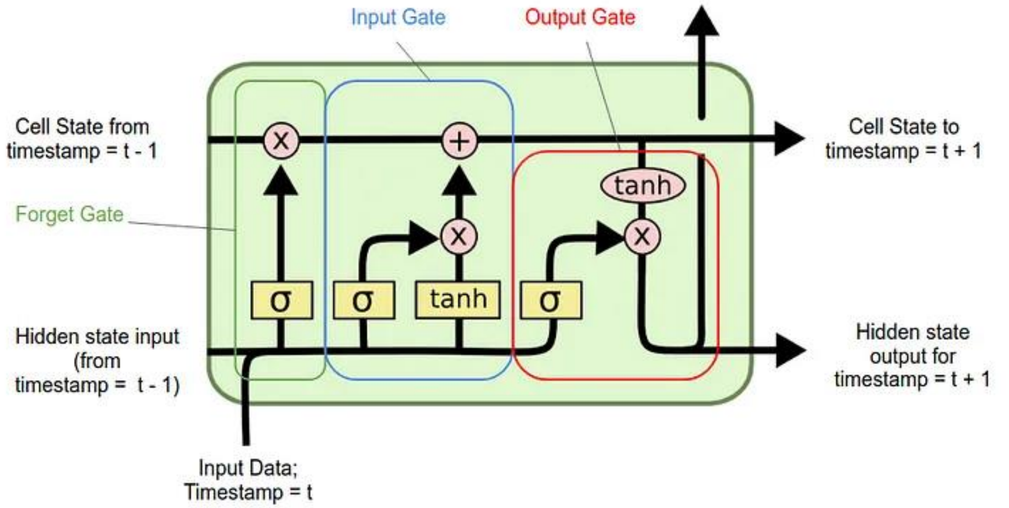
LSTM: Long Short-Term Memory (Hochreiter & Schmidhuber, 1997)

LSTMs were originally designed to keep around information for longer in the hidden state as it gets repeatedly updated.

GRU: Gated Recurrent Unit (Cho et al., 2014)

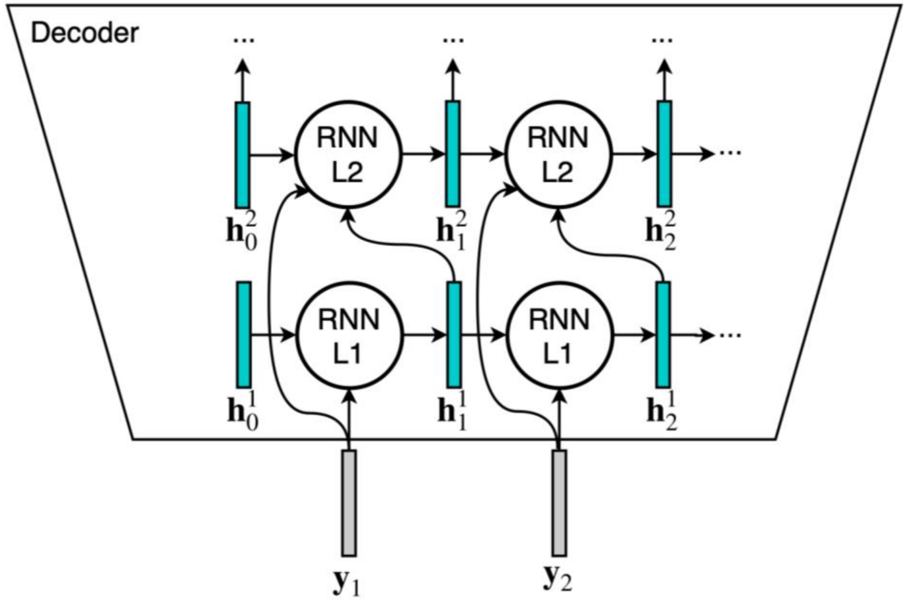


https://en.wikipedia.org/wiki/Gated_recurrent_unit#/media/File:Gated_Recurrent_Unit,_base_type.svg



https://medium.com/analytics-vidhya/lstms-explained-a-complete-technically-accurate-conceptual-guide-with-keras-2a650327e8f2

RNN Multi-Layer Decoder Architecture



Computing the next hidden state:

For the first layer:

$$\mathbf{h}_t^1 = \mathrm{RNN}(\mathbf{W}_{ih^1}\mathbf{y}_t + \mathbf{W}_{h^1h^1}\mathbf{h}_{t-1}^1 + \mathbf{b}_h^1)$$

For subsequent layers:

$$\mathbf{h}_t^l = \mathrm{RNN}(\mathbf{W}_{ih^l}\mathbf{y}_t + \mathbf{W}_{h^{l-1}h^l}\mathbf{h}_t^{l-1} + \mathbf{W}_{h^lh^l}\mathbf{h}_{t-1}^l + \mathbf{b}_h^l)$$

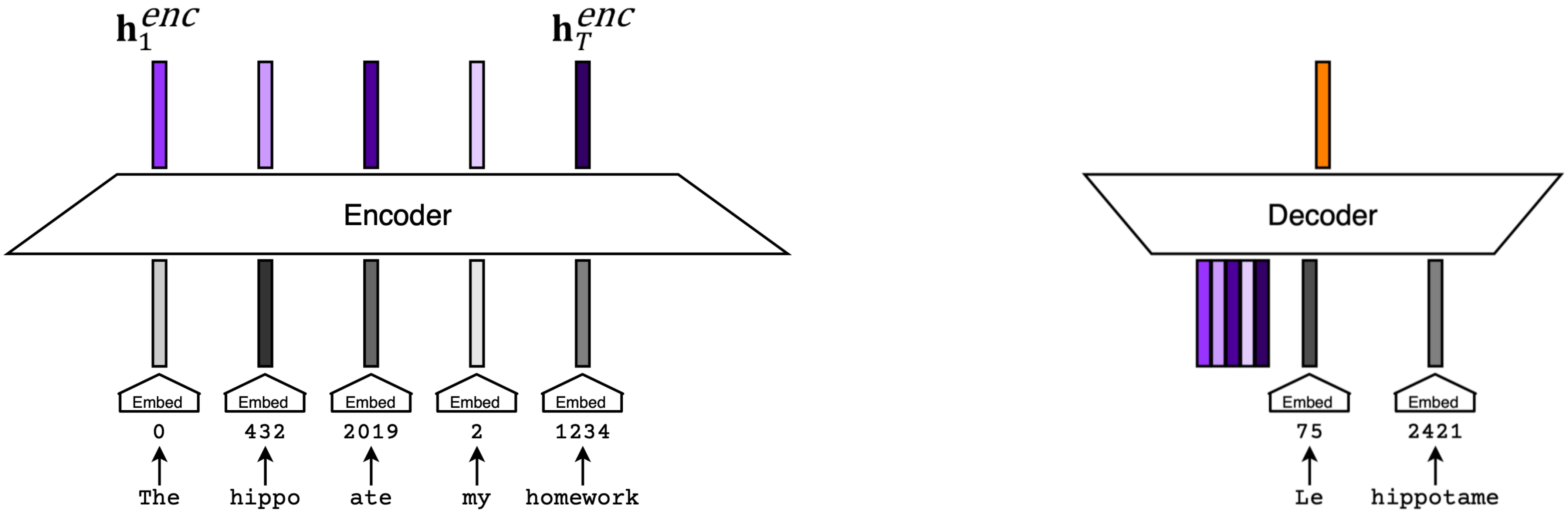
Predicting an embedding for the next token in the sequence:

$$\hat{\mathbf{e}}t = \mathbf{b}_e + \sum_{l=1}^{L}\mathbf{W}_{h^le}\mathbf{h}_t^l$$

Each of the b and W are learned bias and weight matrices.

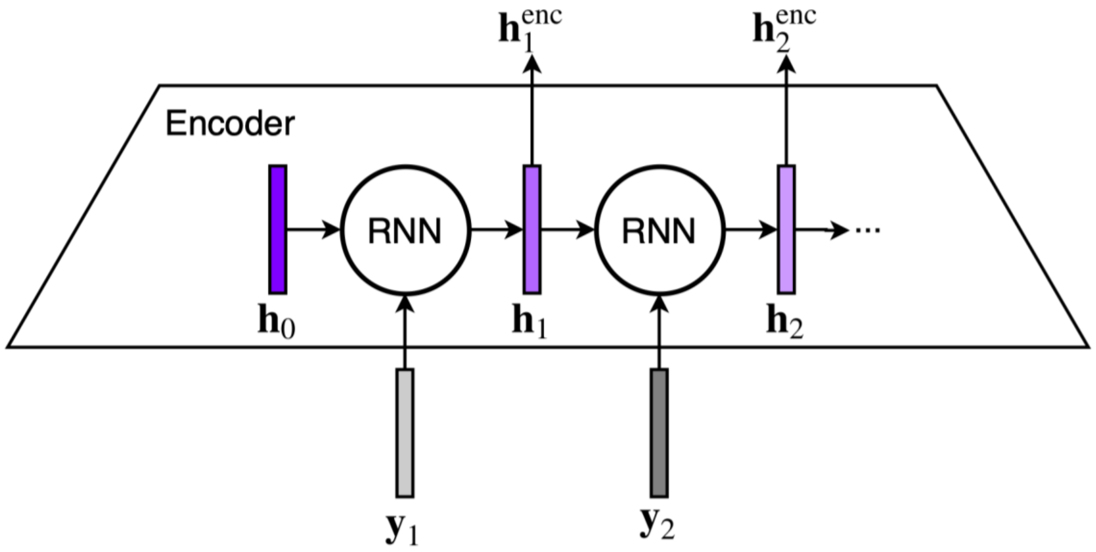
RNN Encoder-Decoder Architectures

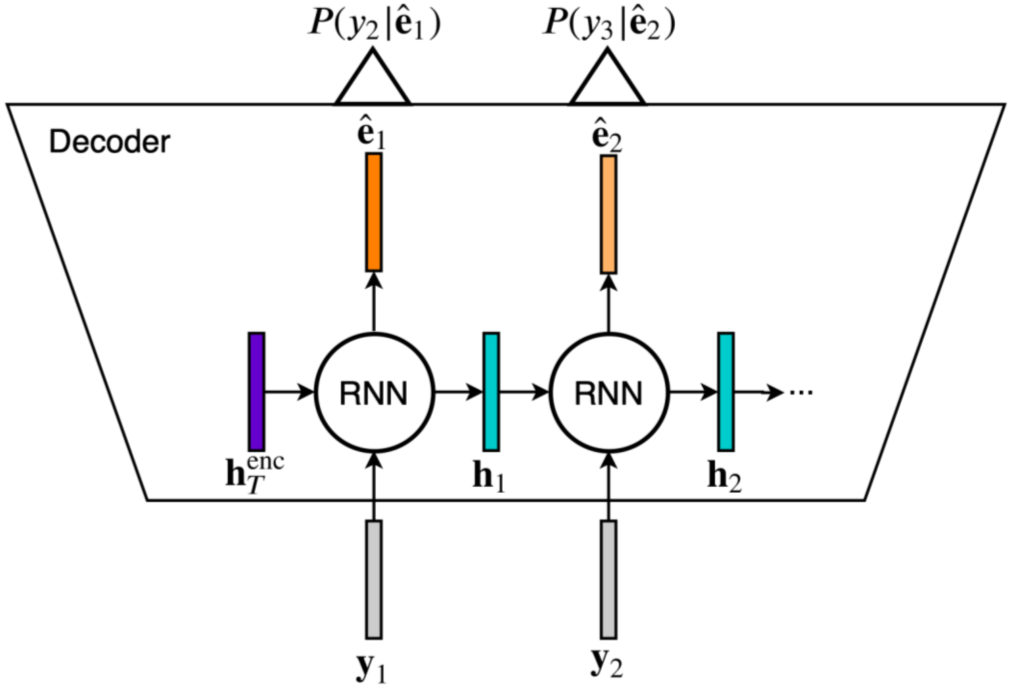
How do we implement an encoder-decoder model?



RNN Encoder-Decoder Architectures

Simplest approach: Use the final hidden state from the encoder to initialize the first hidden state of the decoder.





RNN Encoder-Decoder Architectures

[The, hippopotamus, …

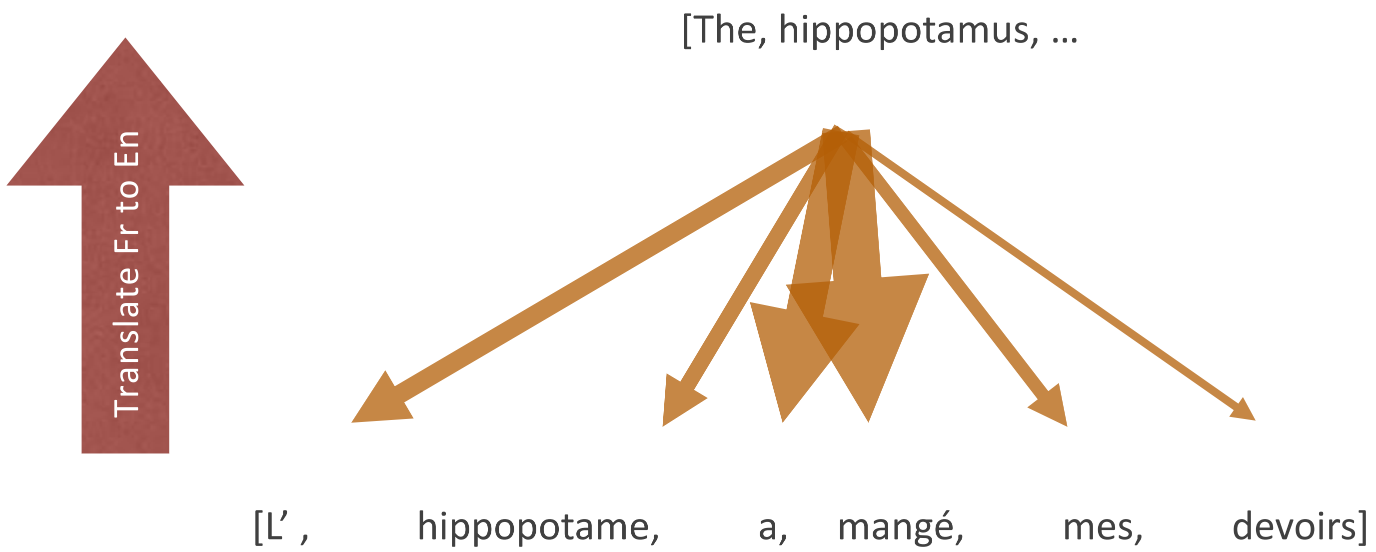
Translate Fr to En

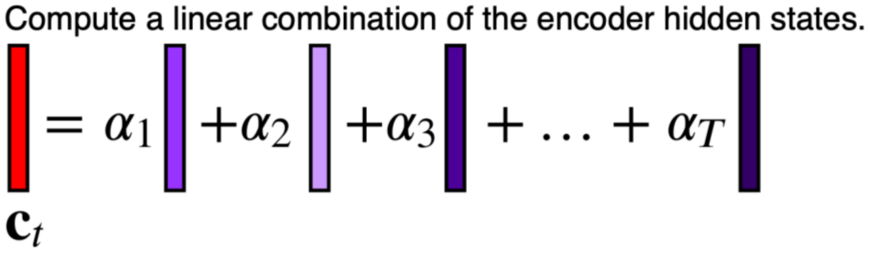
When predicting the next English word, how much weight should the model put on each French word in the source sequence?

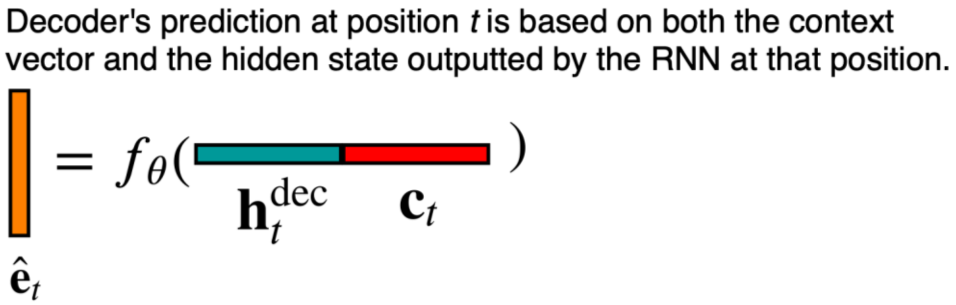
[L’ , hippopotame, a, mangé, mes, devoirs]

Attention

Better approach: an attention mechanism







RNN Encoder-Decoder Architectures

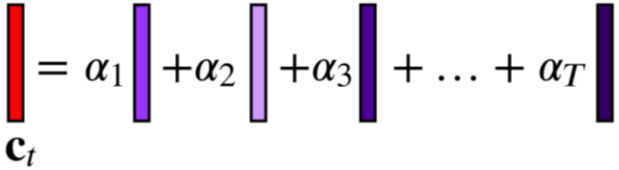
The tth context vector is computed as $\mathbf{c}t = \mathbf{H}^{\text{enc}} at$

at[i] = softmax(att_score($\mathbf{h}_t^{\text{dec}}$, $\mathbf{h}i^{\text{enc}}$))

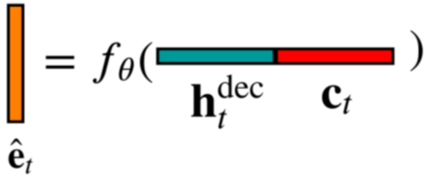
There are a few different options for the attention score:

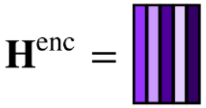
$$\text{att\_score}(\mathbf{h}_t^{\text{dec}}, \mathbf{h}_i^{\text{enc}}) = \begin{cases} \mathbf{h}_t^{\text{dec}} \cdot \mathbf{h}_{\boldsymbol{i}}^{\text{enc}} & \text{dot product} \\ \mathbf{h}_t^{\text{dec}}\, \mathbf{W}a\, \mathbf{h}_{\boldsymbol{i}}^{\text{enc}} & \text{bilinear function} \\ w_{a1}^{\top} \tanh(\mathbf{W}a\mathbf{2}[\mathbf{h}_t^{\text{dec}}, \mathbf{h}_{\boldsymbol{i}}^{\text{enc}}]) & \text{MLP} \end{cases}$$

Compute a linear combination of the encoder hidden states.

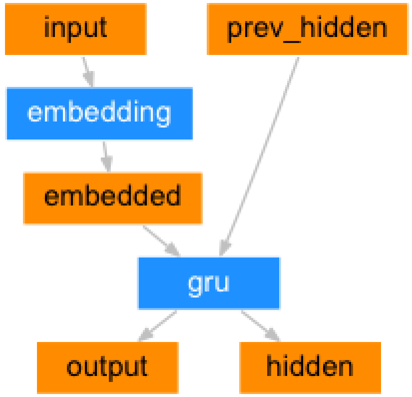


Decoder's prediction at position t is based on both the context vector and the hidden state outputted by the RNN at that position.





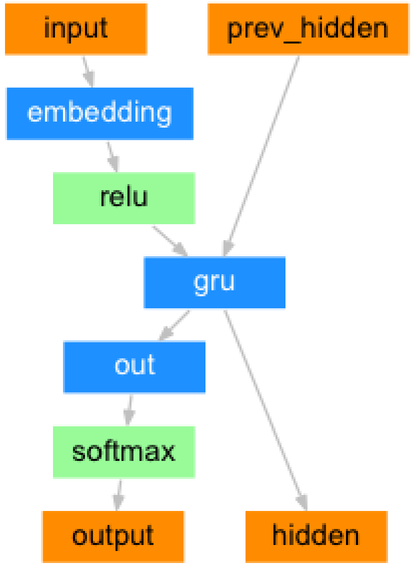
Review: Encoder Code




```
class EncoderRNN(nn.Module):
    def __init__(self, input_size, hidden_size, dropout_p=0.1):
        super(EncoderRNN, self).__init__()
        self.hidden_size = hidden_size

        self.embedding = nn.Embedding(input_size, hidden_size)
        self.gru = nn.GRU(hidden_size, hidden_size, batch_first=True)
        self.dropout = nn.Dropout(dropout_p)

    def forward(self, input):
        embedded = self.dropout(self.embedding(input))
        output, hidden = self.gru(embedded)
        return output, hidden
```

https://pytorch.org/tutorials/intermediate/seq2seq_translation_tutorial.html

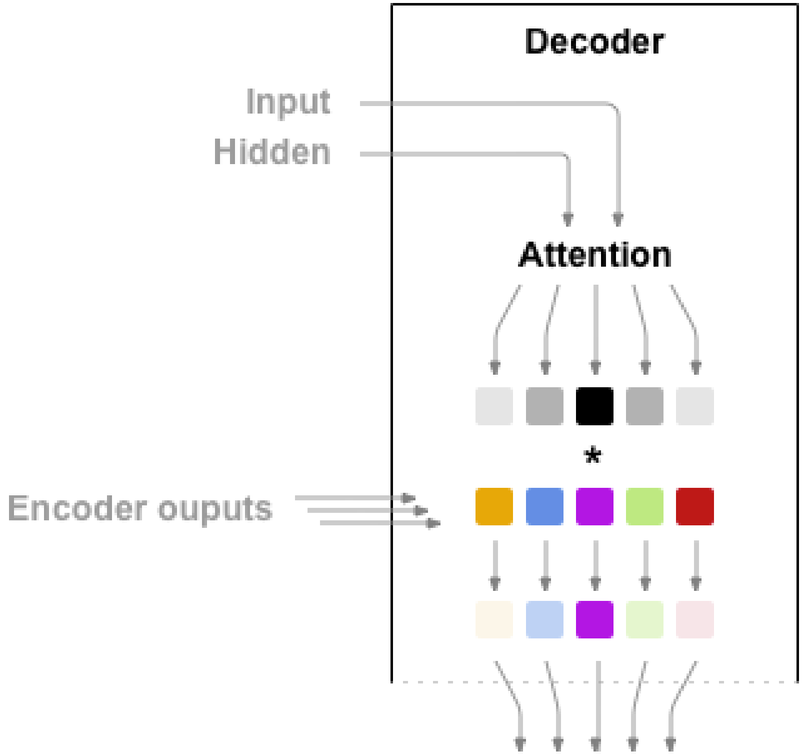
Review: Decoder Code



https://pytorch.org/tutorials/intermediate/seq2seq_translation_tutorial.html

```
class DecoderRNN(nn.Module):
    def __init__(self, hidden_size, output_size):
        super(DecoderRNN, self).__init__()
        self.embedding = nn.Embedding(output_size, hidden_size)
        self.gru = nn.GRU(hidden_size, hidden_size, batch_first=True)
        self.out = nn.Linear(hidden_size, output_size)

    def forward(self, encoder_outputs, encoder_hidden, target_tensor=None):
        batch_size = encoder_outputs.size(0)
        decoder_input = torch.empty(batch_size, 1, dtype=torch.long,
device=device).fill_(SOS_token)
        decoder_hidden = encoder_hidden
        decoder_outputs = []

        for i in range(MAX_LENGTH):
            decoder_output, decoder_hidden  = self.forward_step(decoder_input, decoder_hidden)
            decoder_outputs.append(decoder_output)

            if target_tensor is not None:
                # Teacher forcing: Feed the target as the next input
                decoder_input = target_tensor[:, i].unsqueeze(1) # Teacher forcing
            else:
                # Without teacher forcing: use its own predictions as the next input
                _, topi = decoder_output.topk(1)
                decoder_input = topi.squeeze(-1).detach()  # detach from history as input

        decoder_outputs = torch.cat(decoder_outputs, dim=1)
        decoder_outputs = F.log_softmax(decoder_outputs, dim=-1)
        return decoder_outputs, decoder_hidden, None # We return `None` for consistency in the
training loop

    def forward_step(self, input, hidden):
        output = self.embedding(input)
        output = F.relu(output)
        output, hidden = self.gru(output, hidden)
        output = self.out(output)
        return output, hidden
```

Attention Decoder



https://pytorch.org/tutorials/intermediate/seq2seq_translation_tutorial.html

Think-Pair-Share

What are some of the strengths of seq2seq models (compared to some of the earlier LMs we talked about)?

What are some of its weaknesses?

Transformers

Since 2018, the field has rapidly standardized on the Transformer architecture

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com

Noam Shazeer* Google Brain noam@google.com

Niki Parmar* Google Research nikip@google.com

Jakob Uszkoreit* Google Research usz@google.com

Llion Jones* Google Research llion@google.com

Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu

Łukasz Kaiser* Google Brain lukaszkaiser@google.com

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

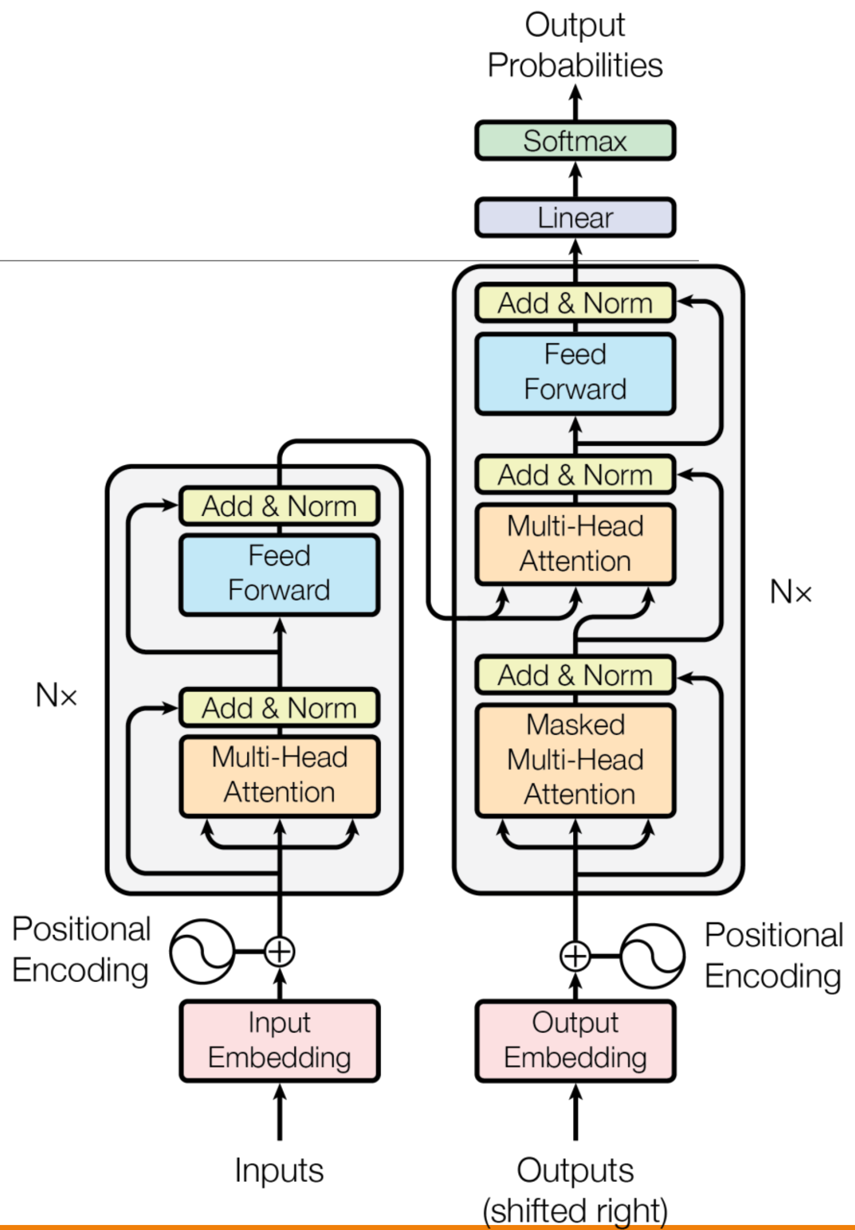
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to

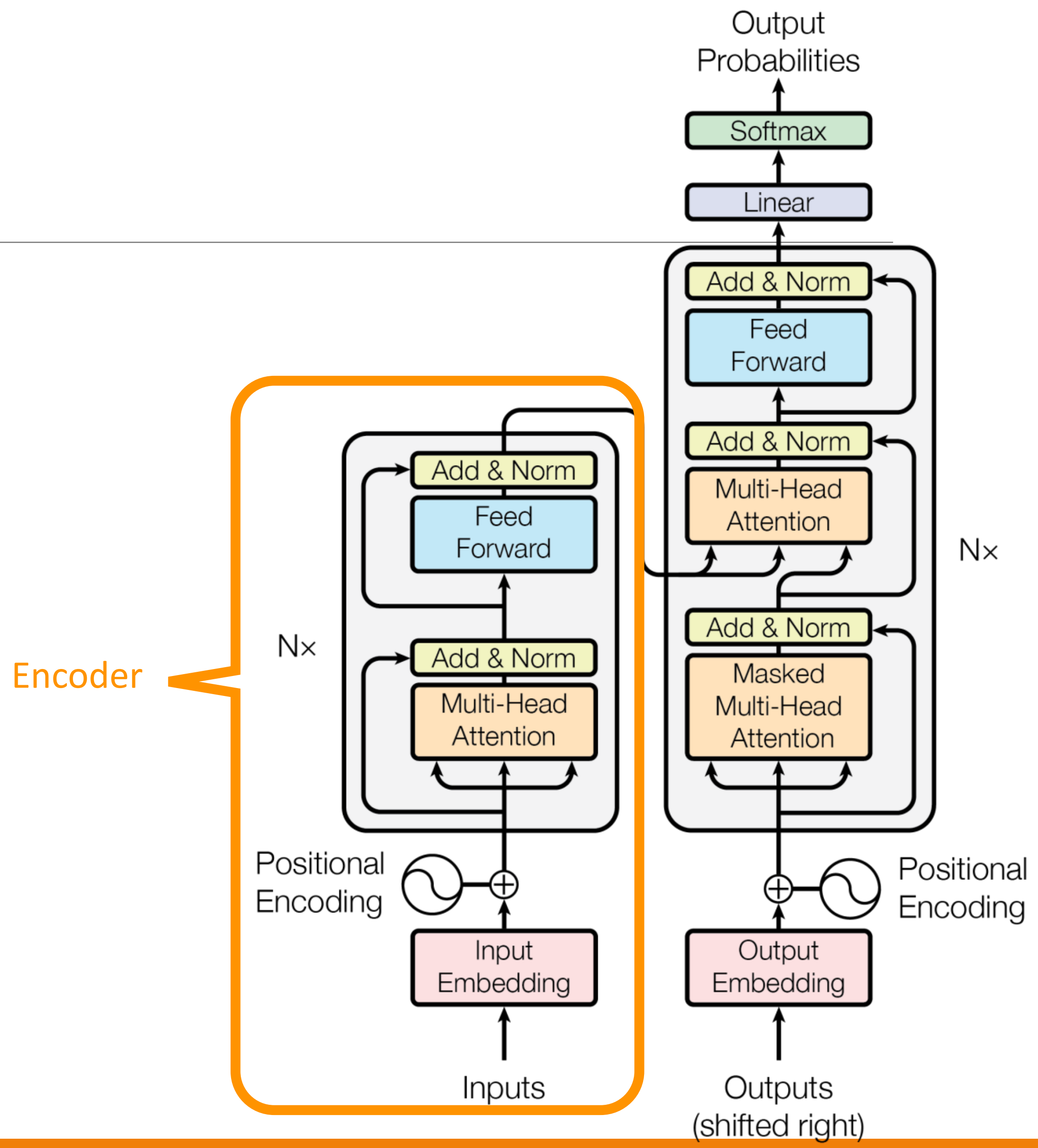
Transformers

The Transformer is a **non-recurrent** non-convolutional (feed-forward) neural network designed for language understanding

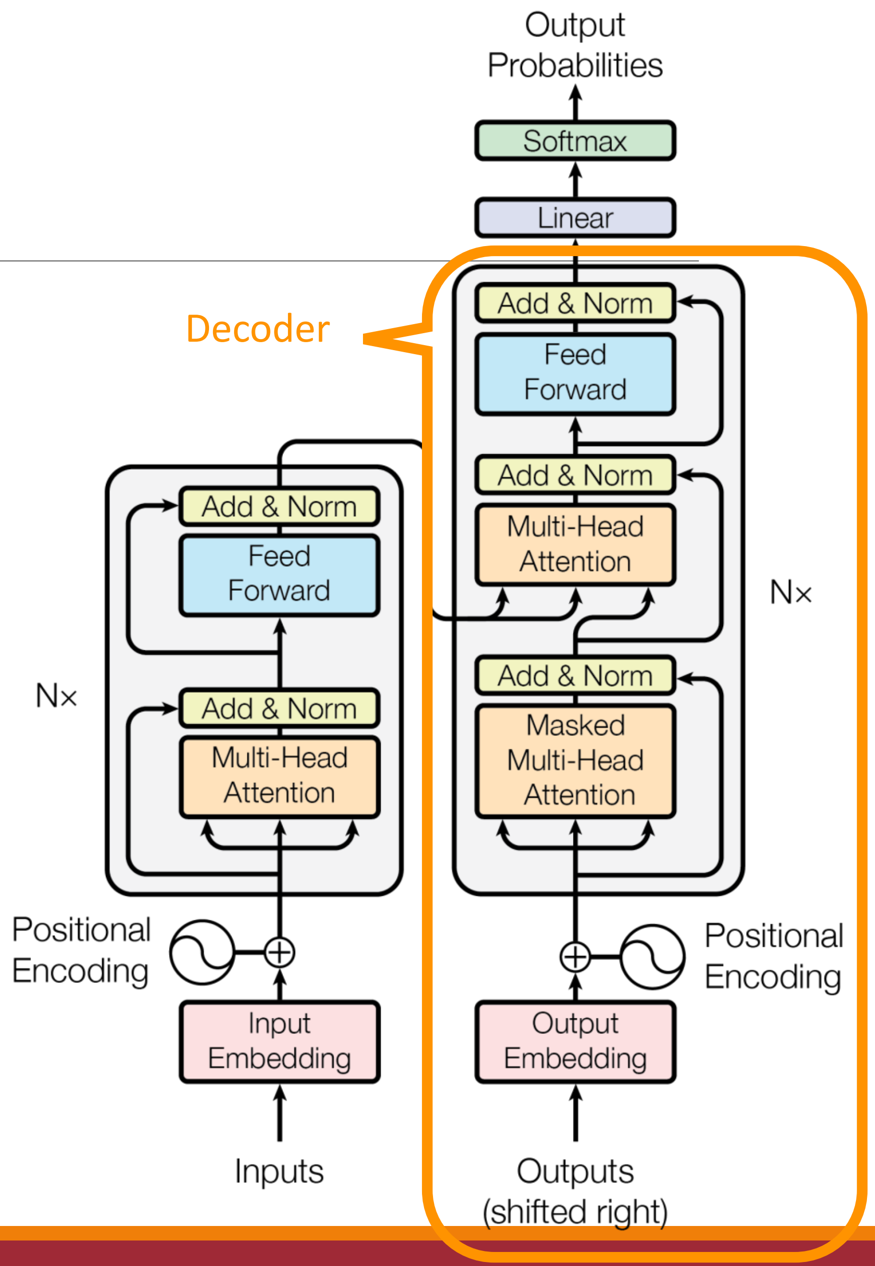
- introduces self-attention in addition to encoder-decoder attention



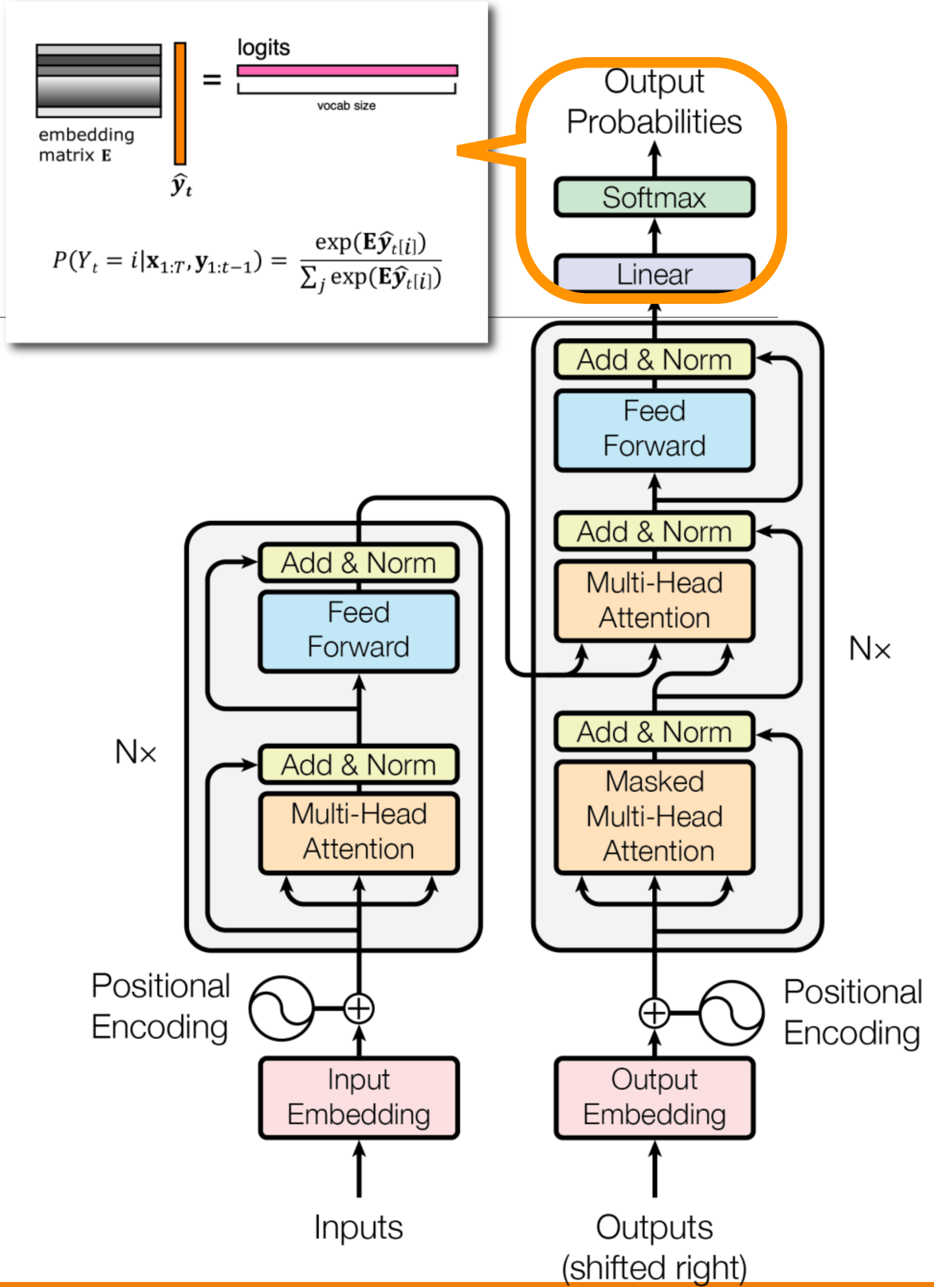
Transformers



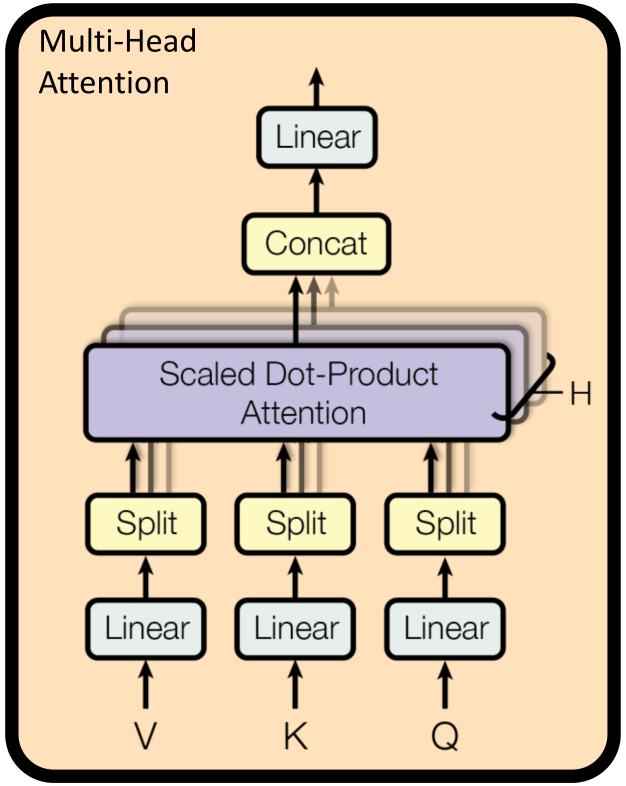
Transformers

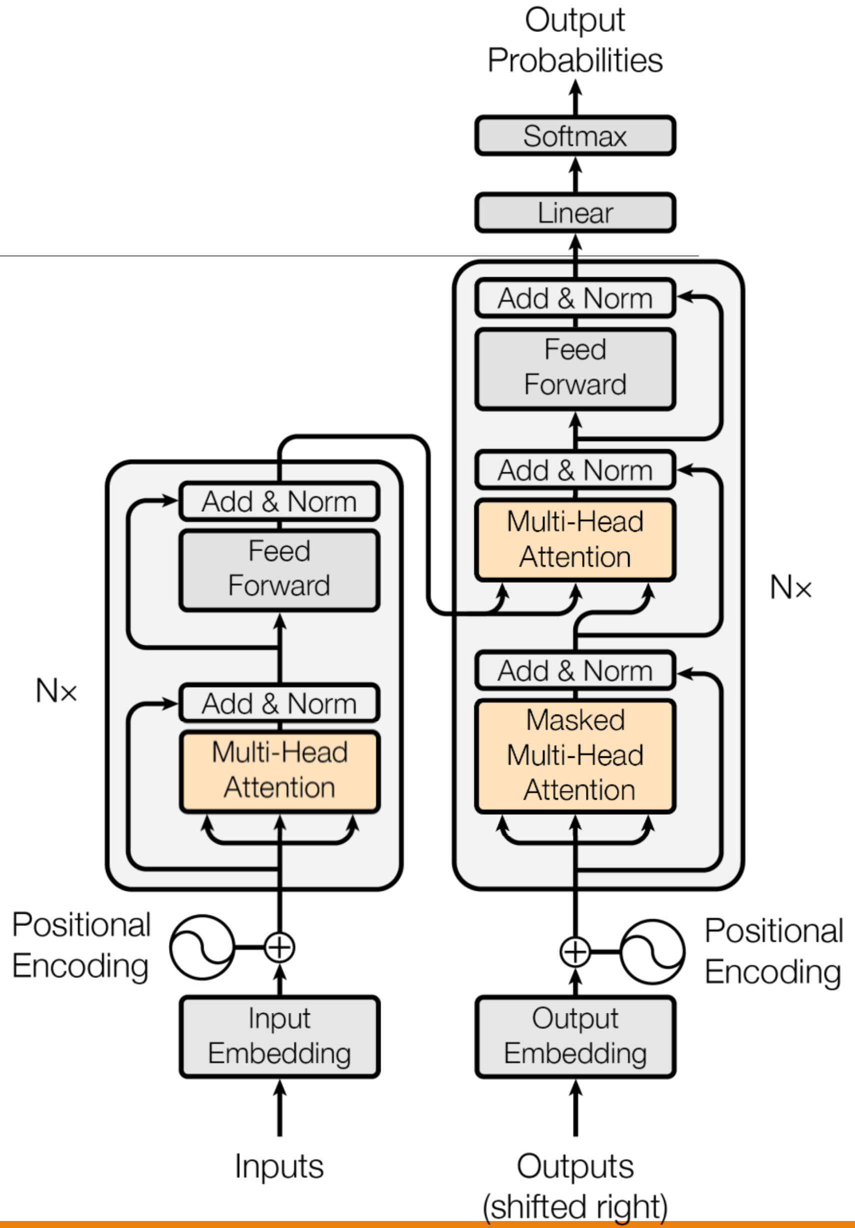


Transformers

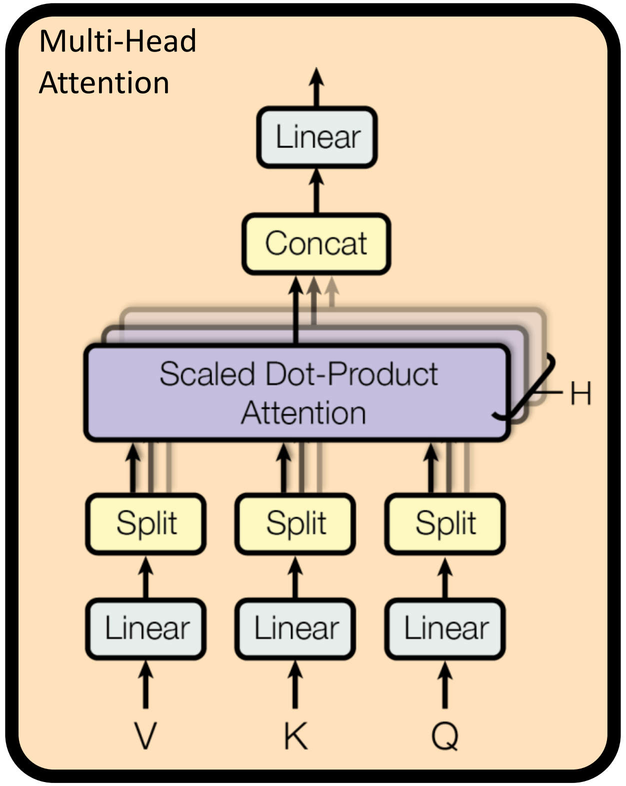


Attention Mechanism

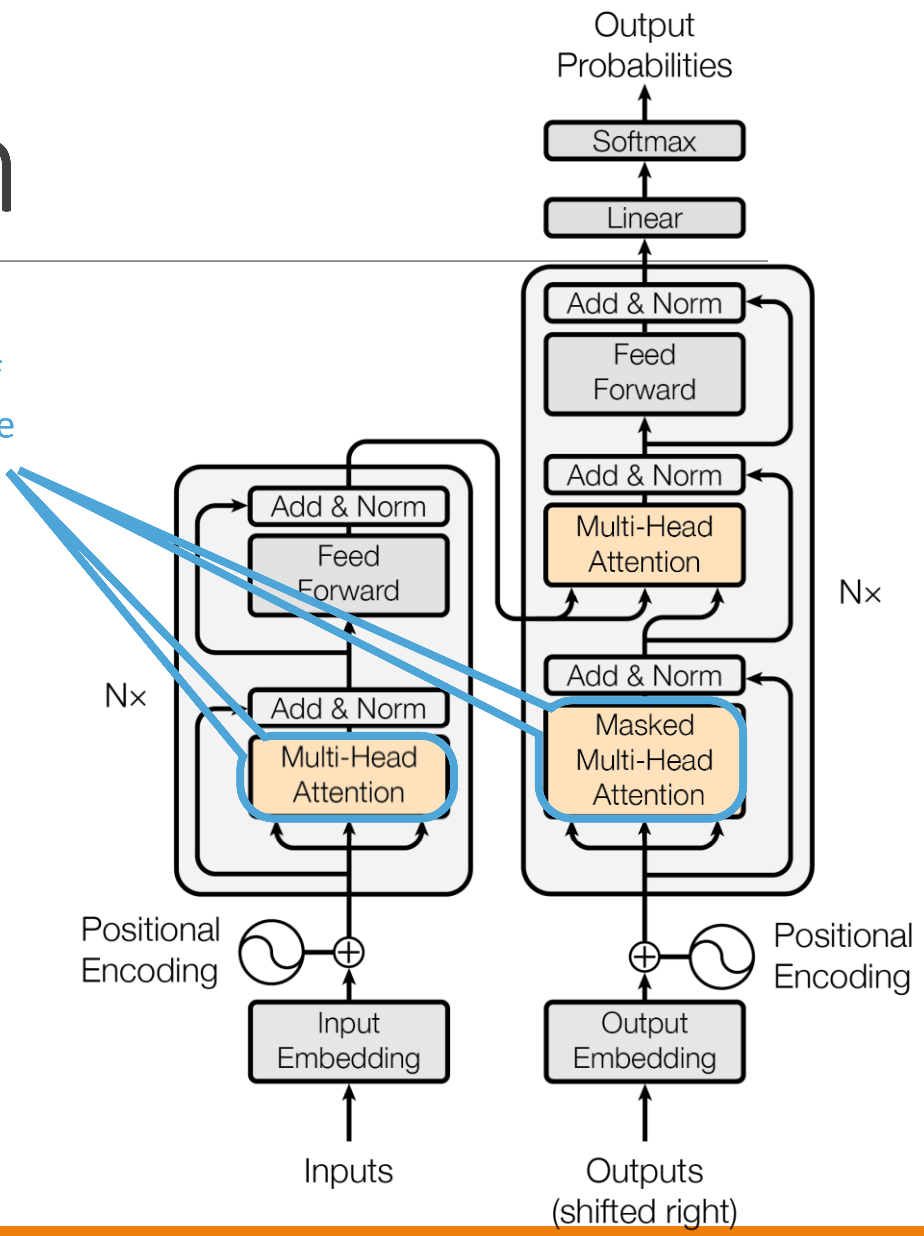




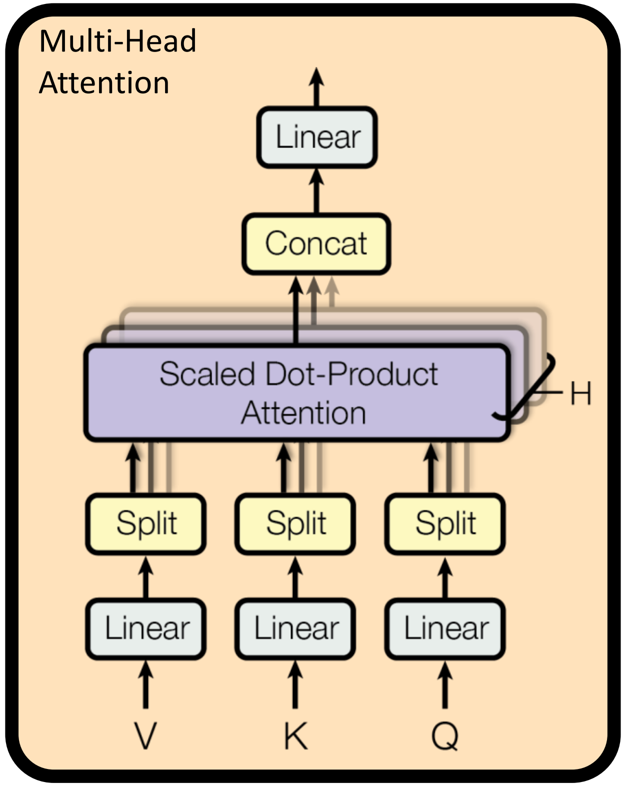
Multi-Head Attention



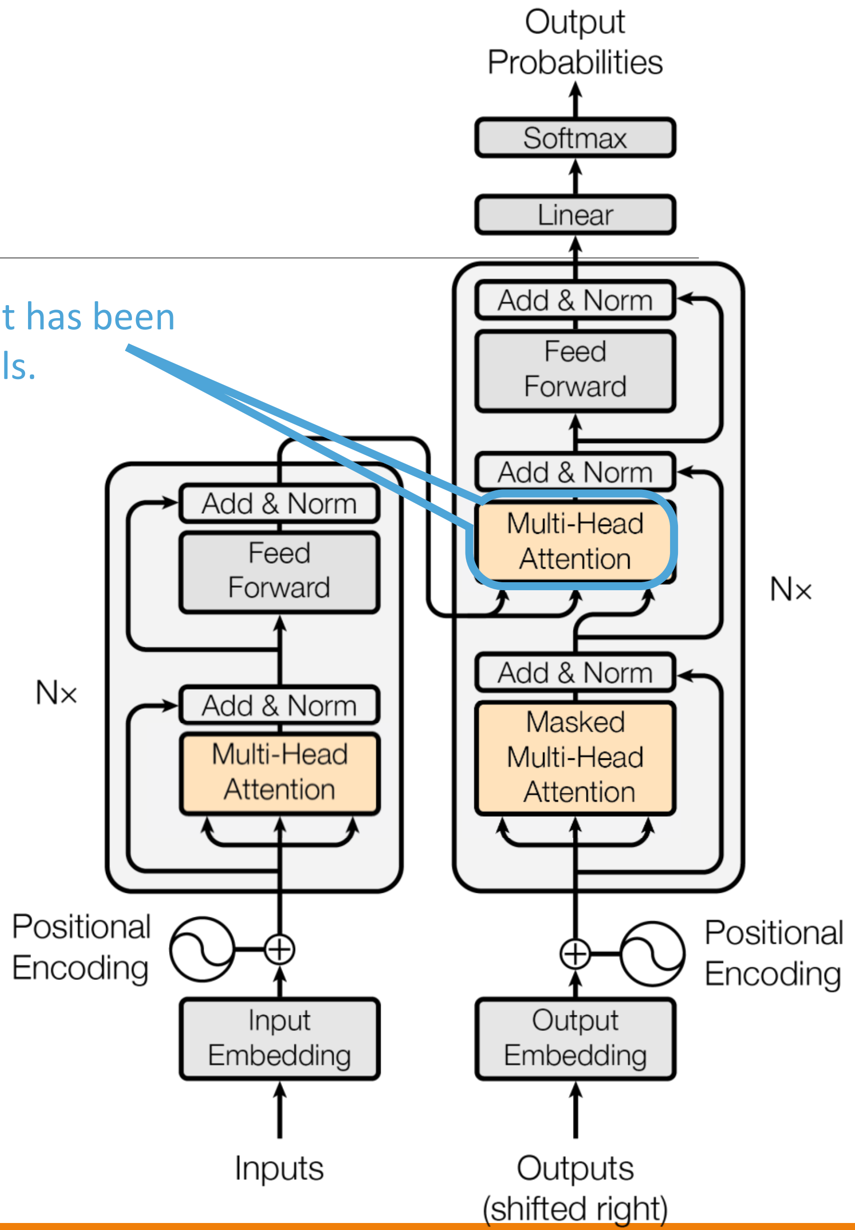
Self-attention between a sequence of hidden states and that same sequence of hidden states.



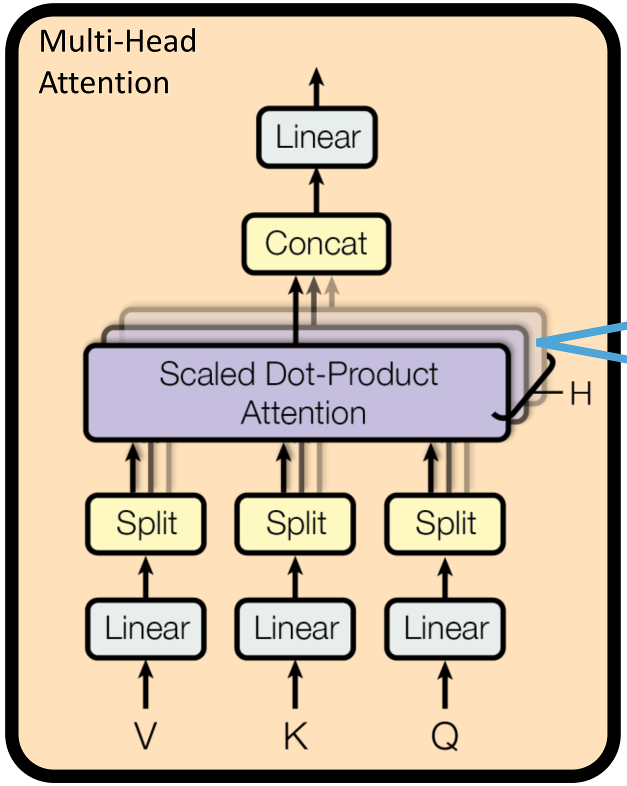
Multi-Head Attention

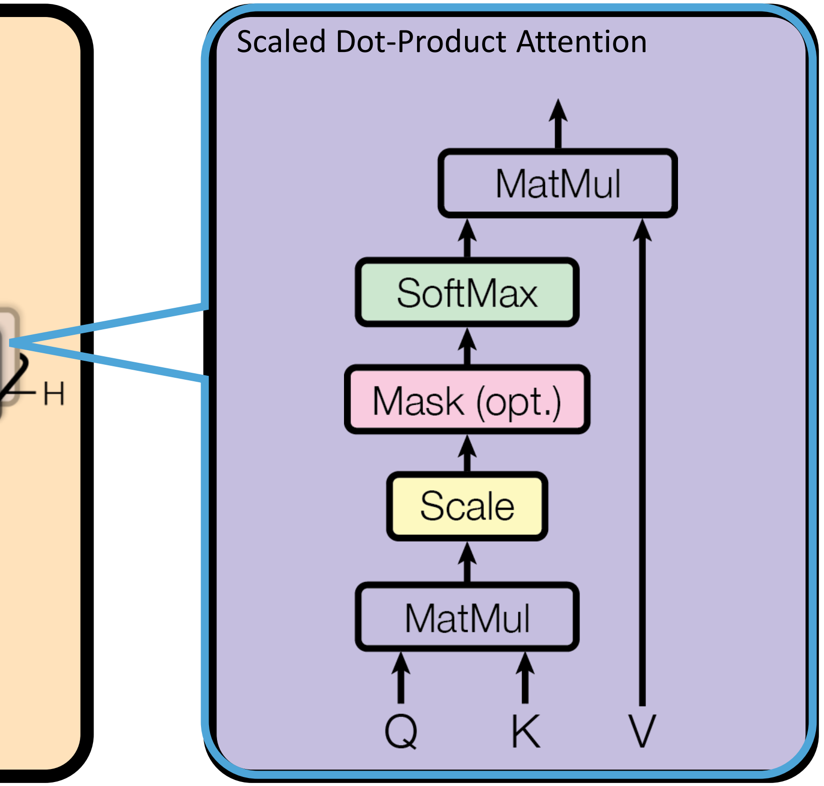


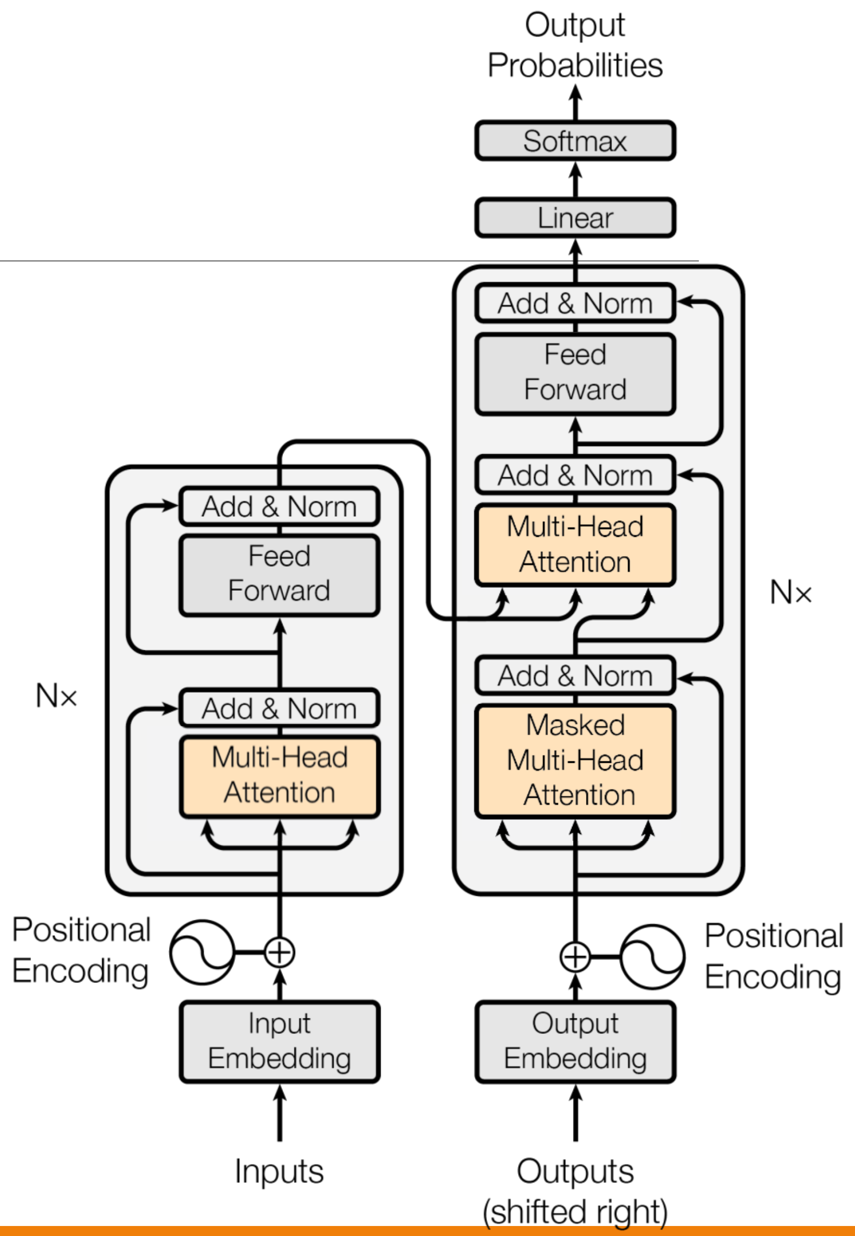
Encoder-decoder attention, like what has been standard in recurrent seq2seq models.



Attention Mechanism

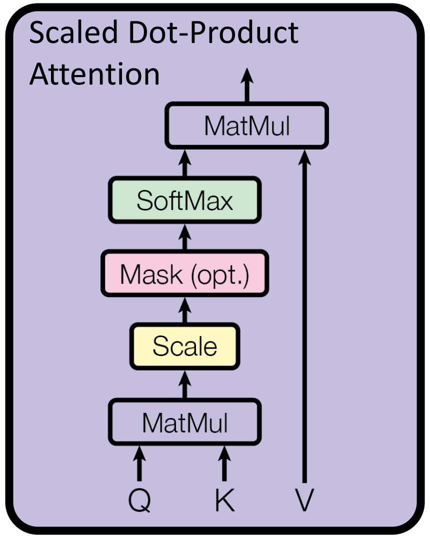






Scaled Dot-Product Attention

The scaled dot-product attention mechanism is almost identical to the one we looked at, but let's turn it into matrix multiplications.



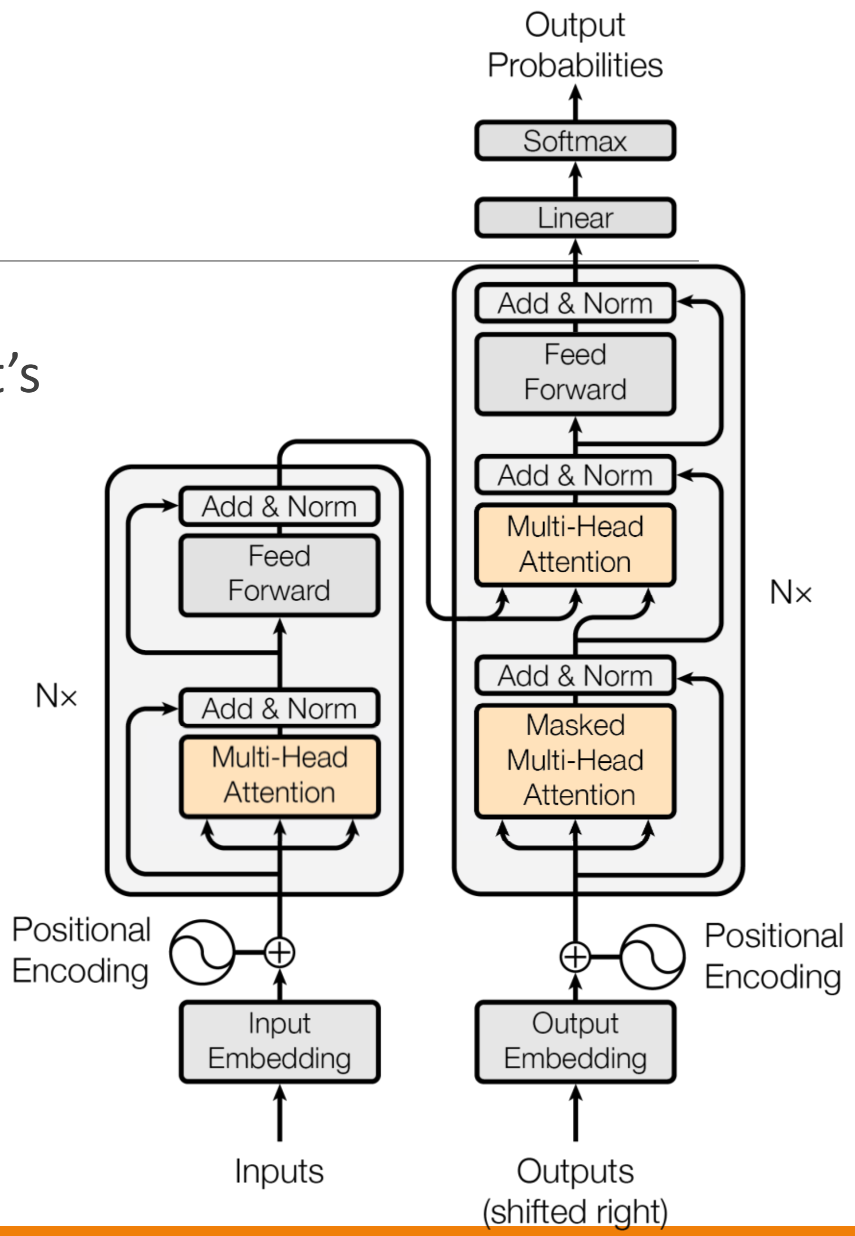
The query: Q ∈ R^{Txdk}

The key: K ∈ $R^{T'xdk}$

The value: V ∈ R^{Txdk}

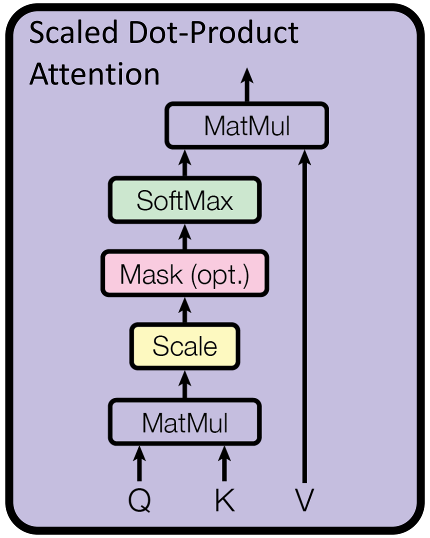
This is the α vector we learned about before.

$$\text{Attention}(Q,K,V) = \boxed{\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)} V$$



Scaled Dot-Product Attention

The scaled dot-product attention mechanism is almost identical to the one we looked at, but let's turn it into matrix multiplications.



The query: Q ∈ R^{Txdk}

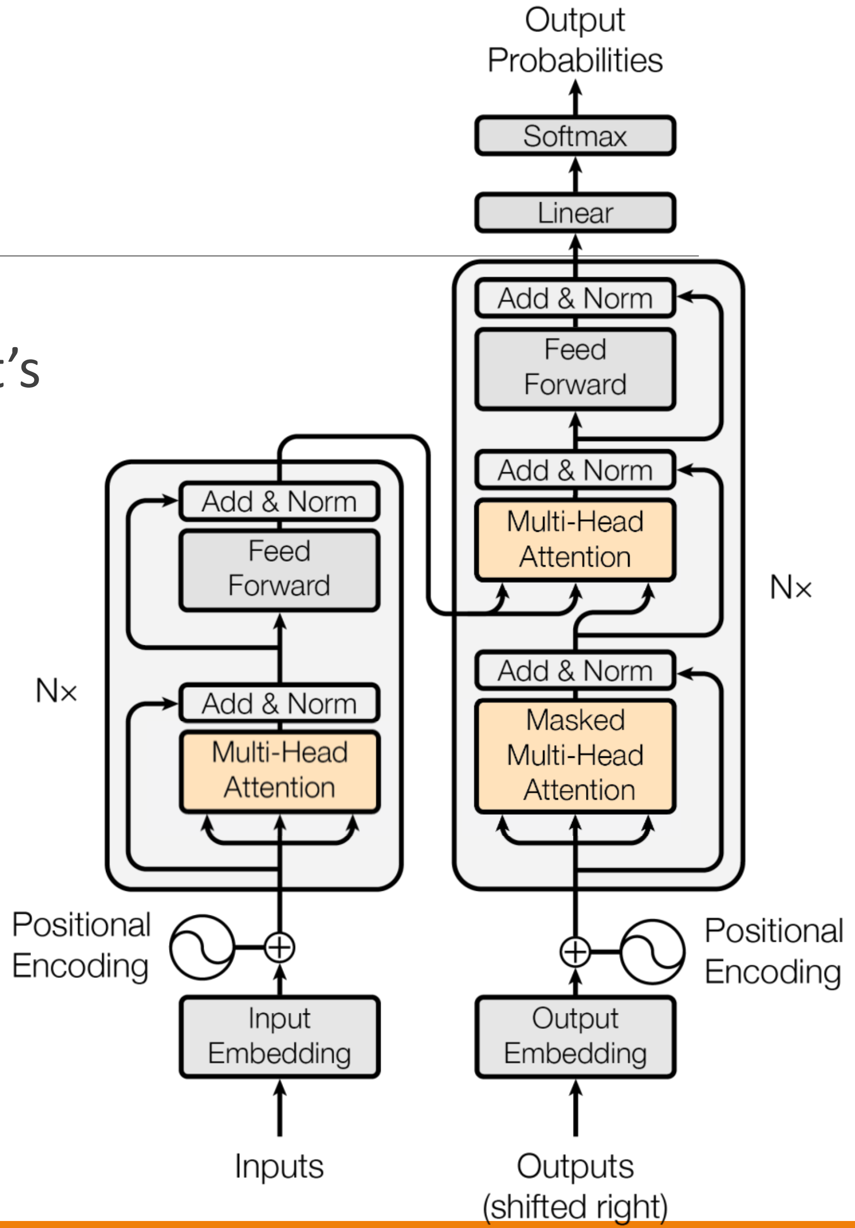
The key: K ∈ $R^{T'xdk}$

The value: V ∈ R^{Txdk}

This is the dot-product scoring function from previous slides

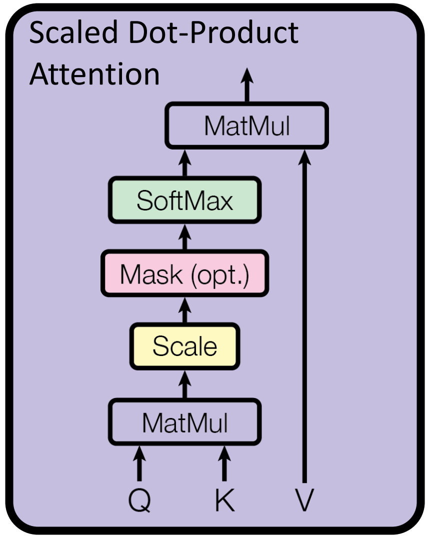
$$\text{Attention(Q,K,V)} = \text{softmax}\left(\frac{\mathbf{QK}^T}{\sqrt{d_k}}\right)\mathbf{V}$$

The $\sqrt{d_k}$ in the denominator prevents the dot product from getting too big



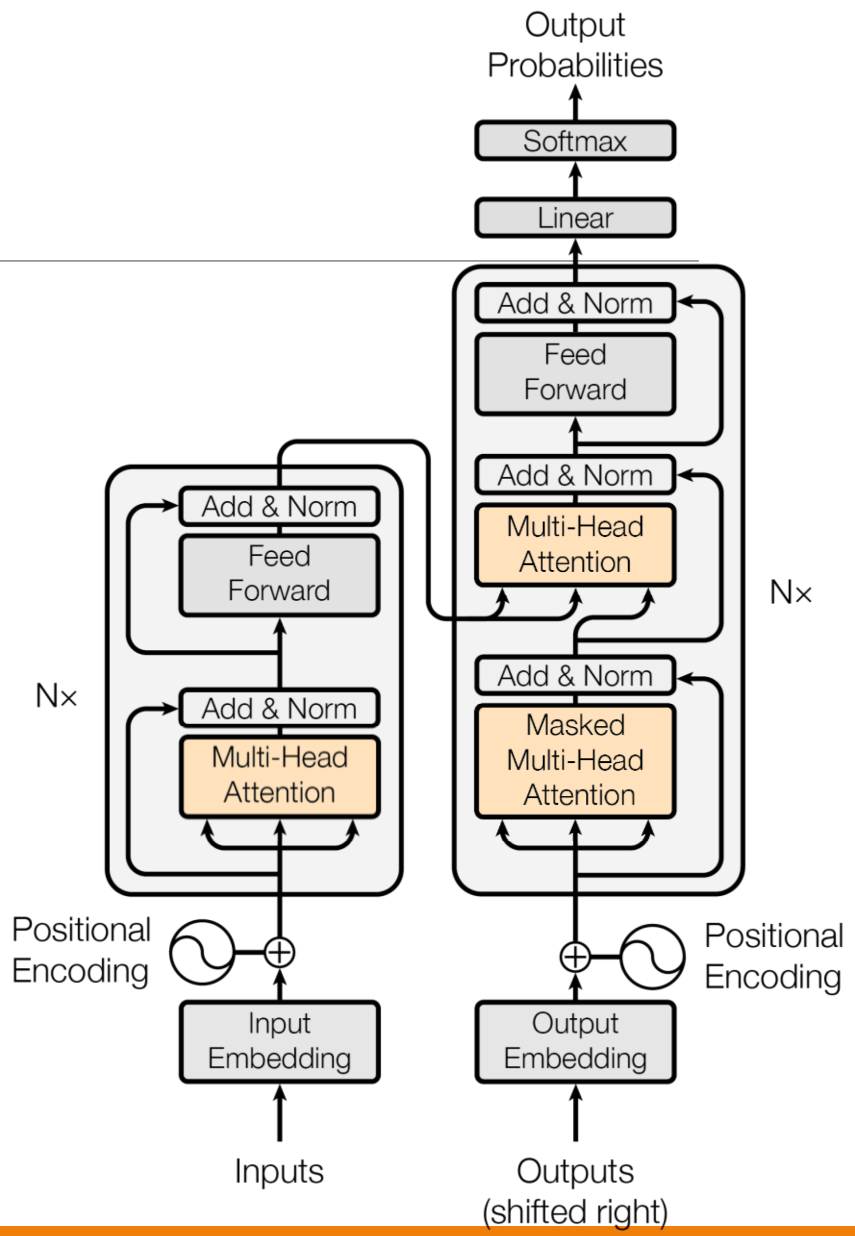
Scaled Dot-Product Attention

Attention(Q,K,V) = softmax$\left(\frac{\mathbf{QK}^T}{\sqrt{d_k}}\right)\mathbf{V}$



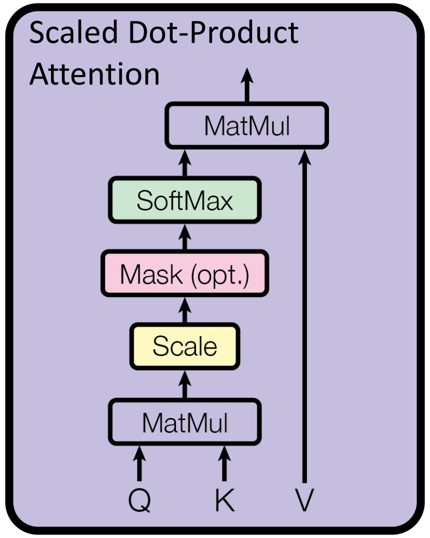
<u>The rough algorithm:</u>

- For each vector in Q (query matrix), take the linear sum of the vectors in V (value matrix)
- The amount to weigh each vector in V is dependent on how “similar” that vector is to the query vector
- “Similarity” is measured in terms of the dot product between the vectors



Scaled Dot-Product Attention

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{\mathbf{QK}^T}{\sqrt{d_k}}\right)\mathbf{V}$$

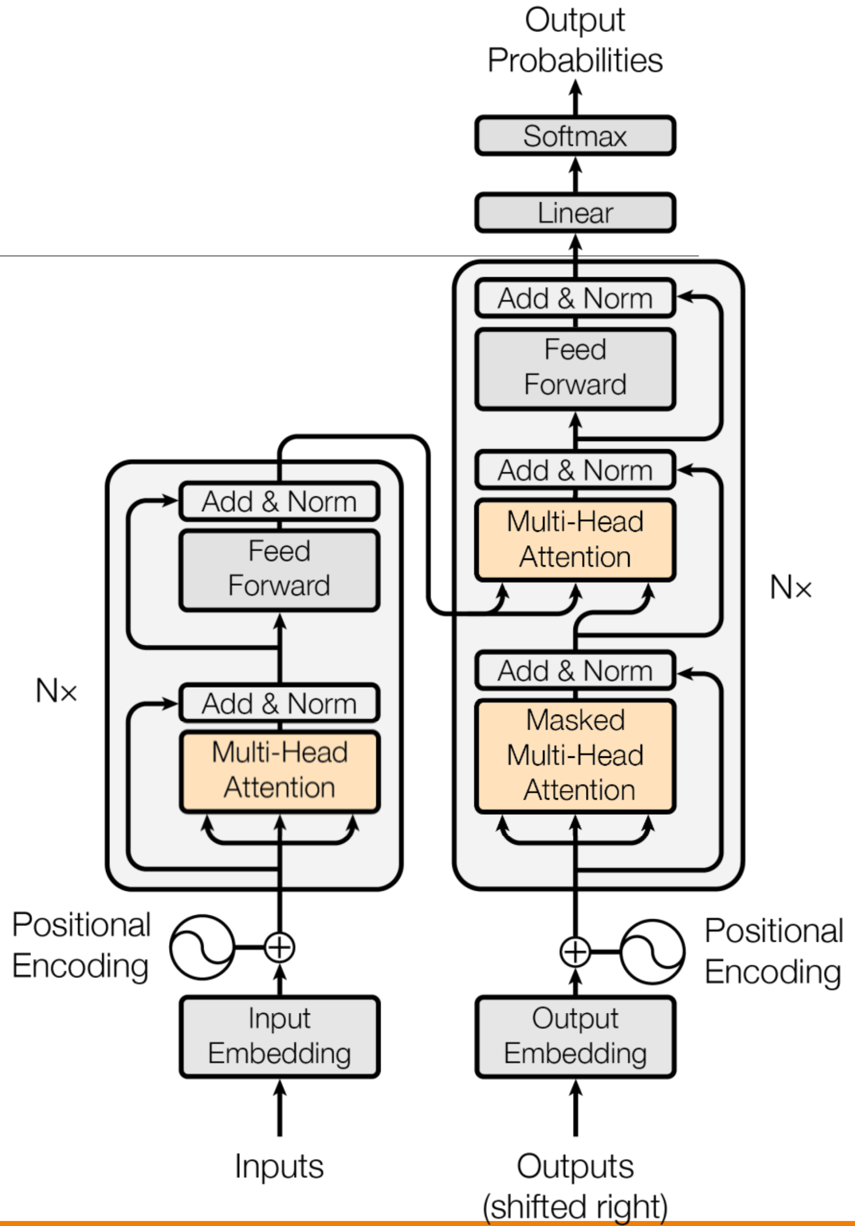


For self-attention:

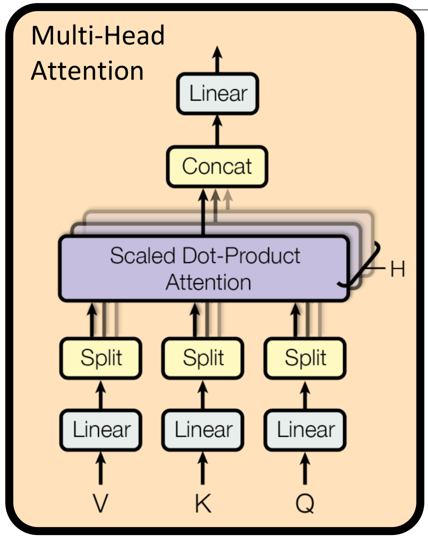
Keys, queries, and values all come from the outputs of the previous layer

For encoder-decoder attention:

Keys and values come from encoder's final output. Queries come from the previous decoder layer's outputs.



Multi-Head Attention



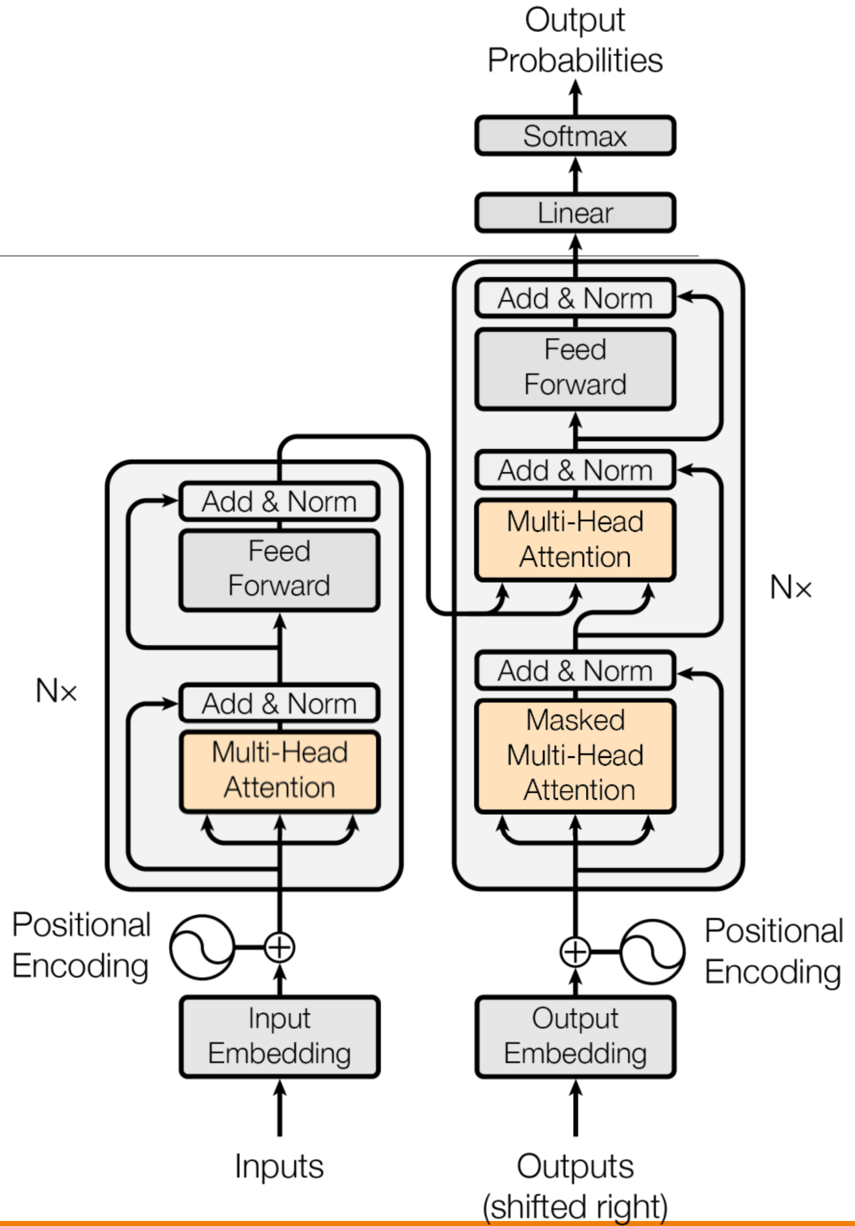
$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{\mathbf{QK}^T}{\sqrt{d_k}}\right)\mathbf{V}$$

$$\text{MultiHeadAtt}(\mathbf{Q,K,V}) = \text{Concat}(\text{head}_1, \ldots \text{head}_h)\mathbf{W}^O$$

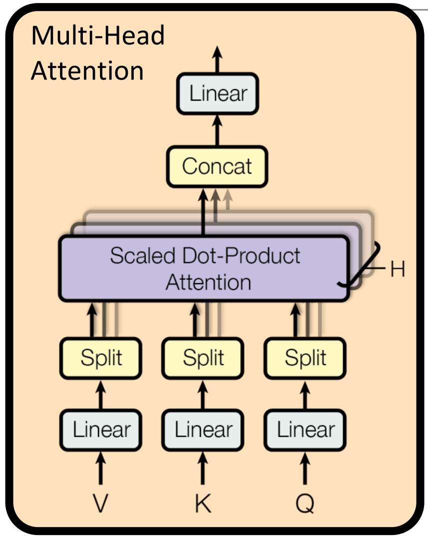
Instead of operating on **Q**, **K**, and **V** mechanism projects each input into a smaller dimension. This is done h times.

The attention operation is performed on each of these “heads,” and the results are concatenated.

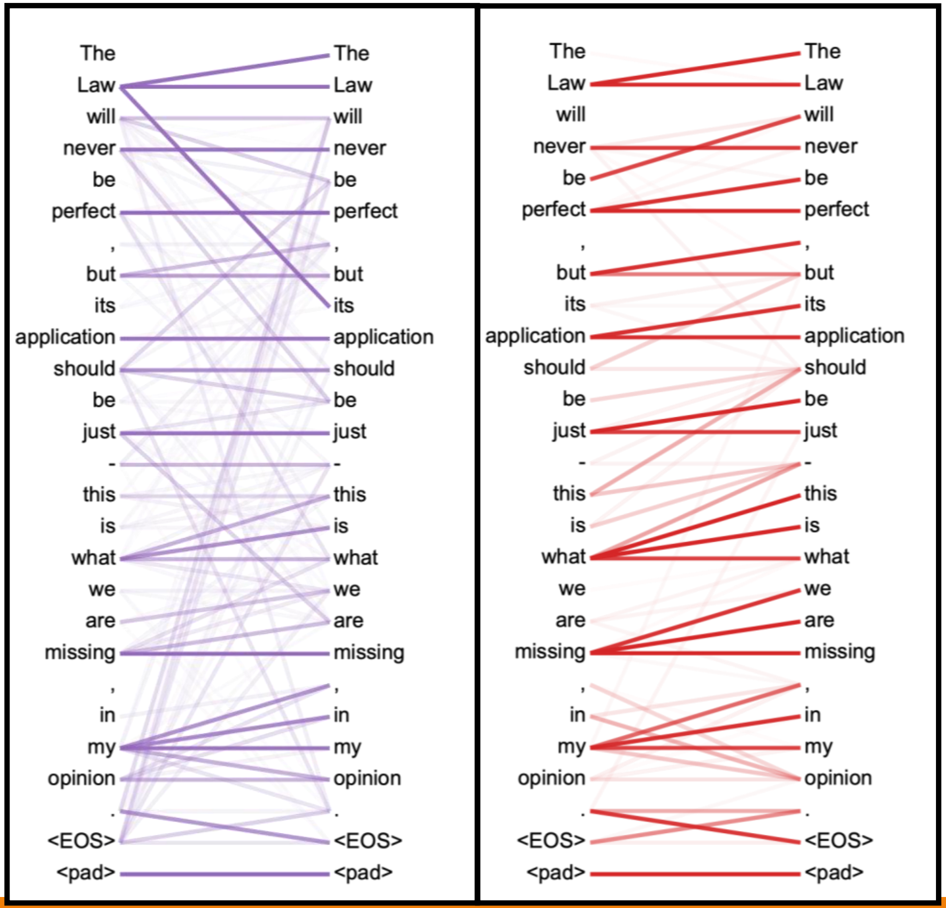
Multi-head attention allows the model to jointly attend to information from different representation subspaces at different positions.

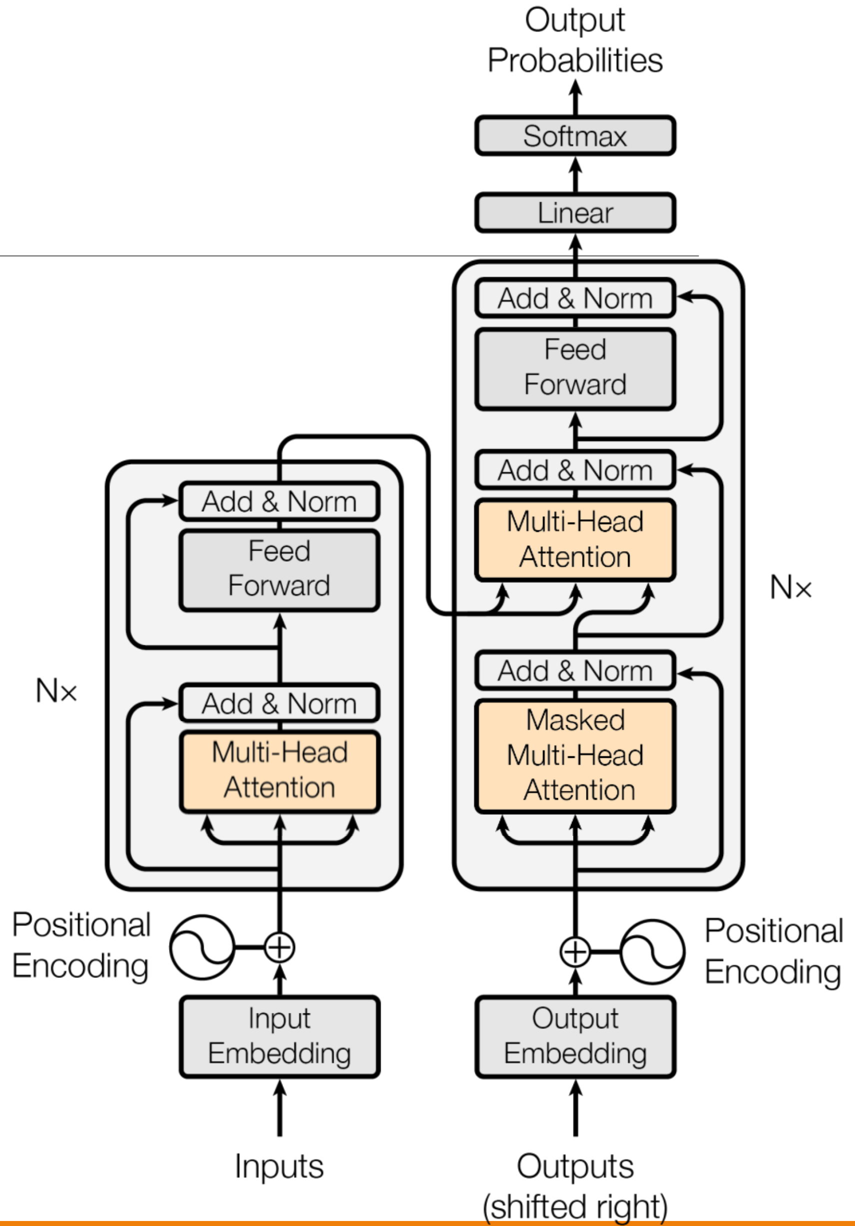


Multi-Head Attention



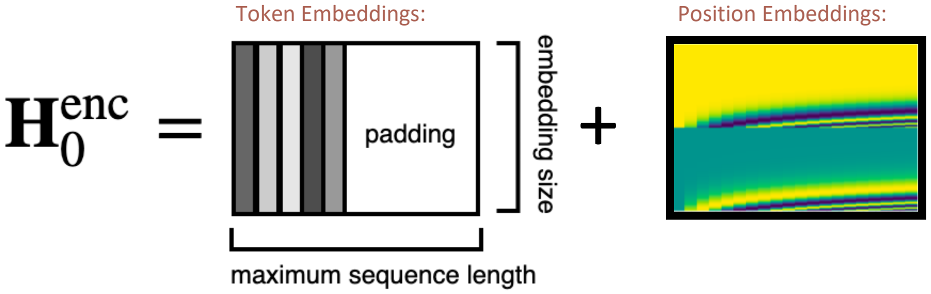
Two different self-attention heads:



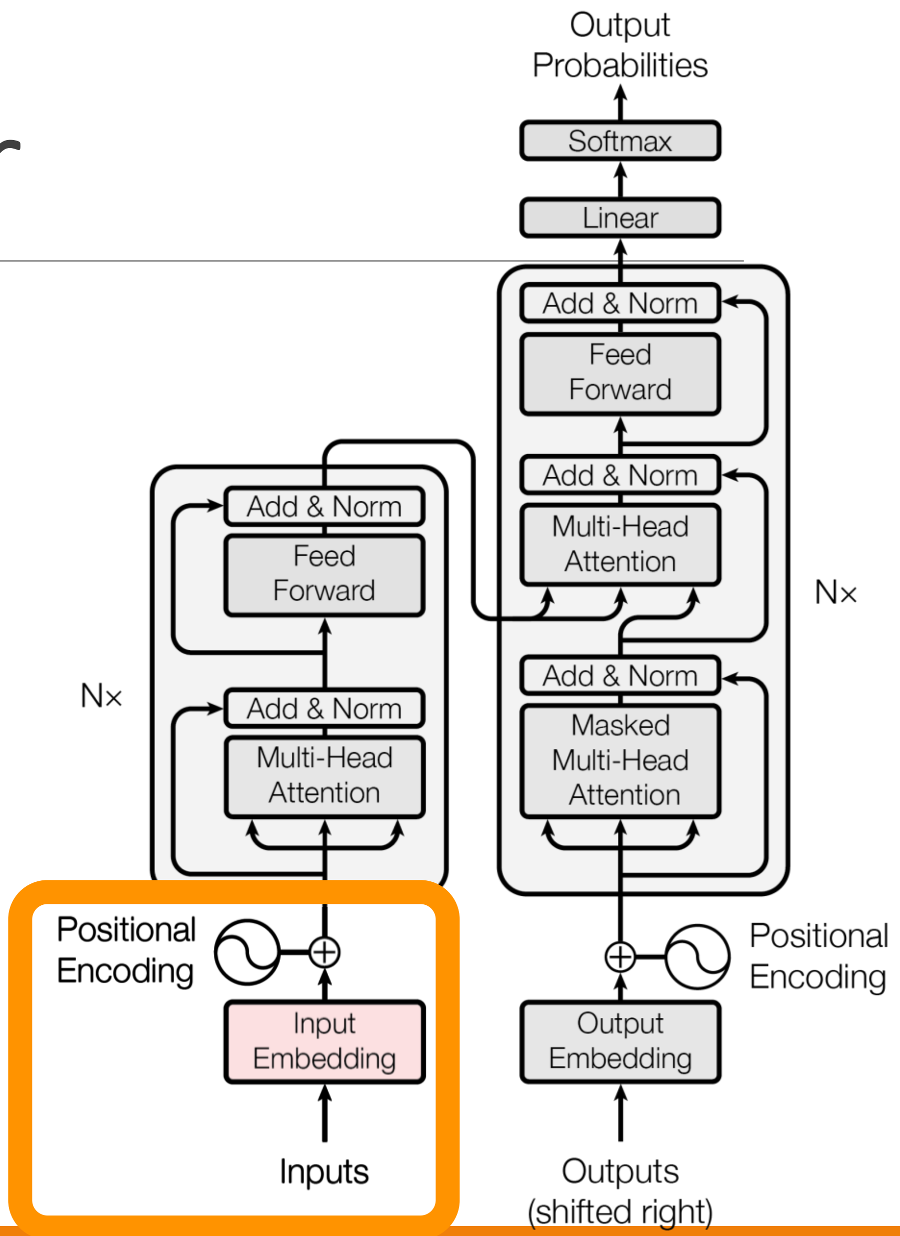


Inputs to the Encoder

The input into the encoder looks like:

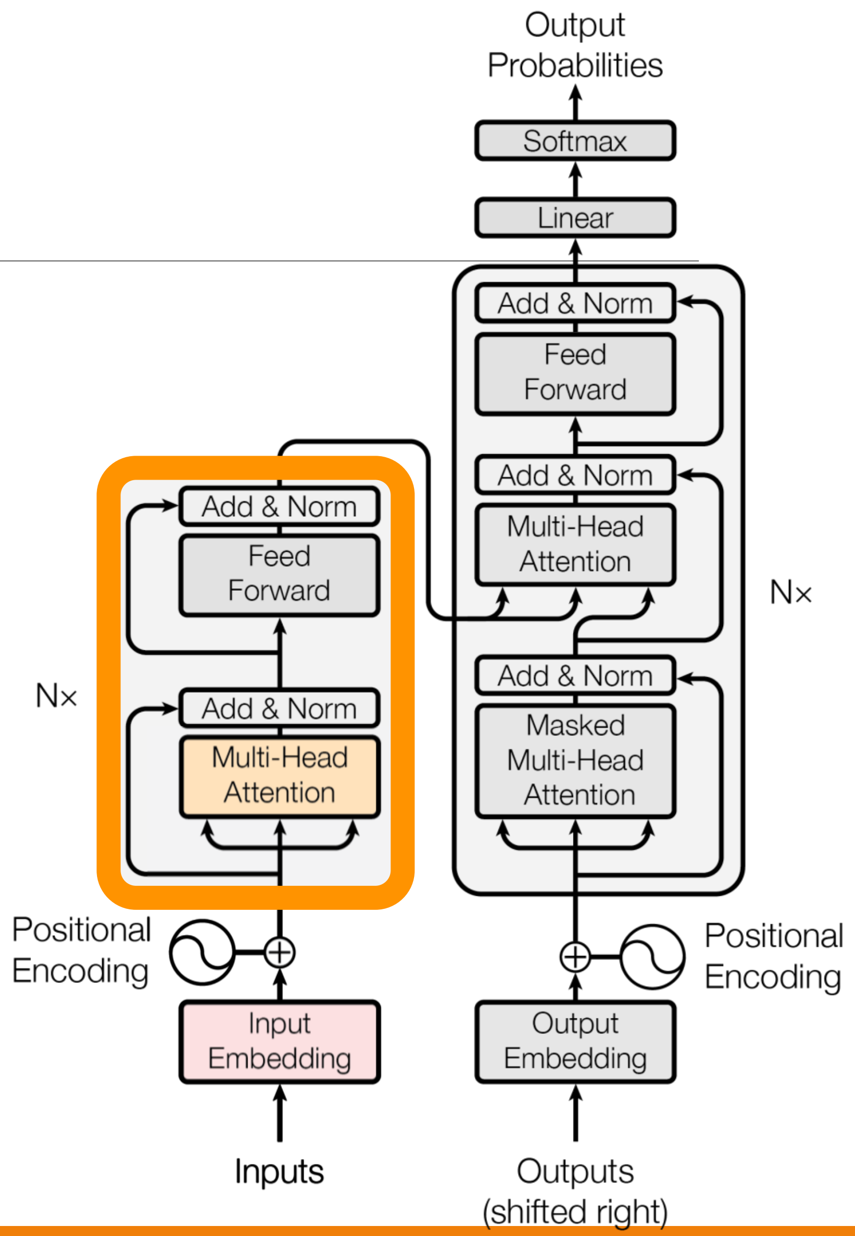


= token embeddings + position embeddings



The Encoder

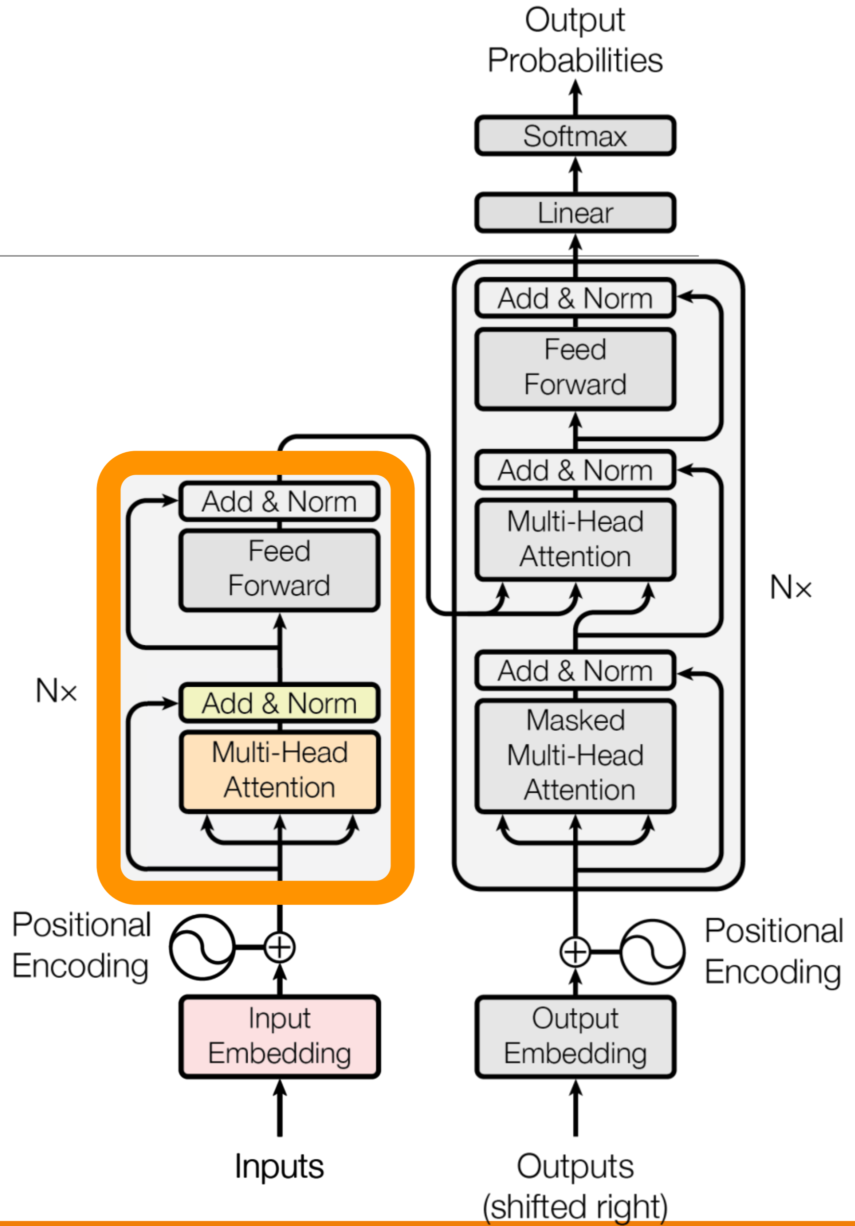
Multi-Head Attention $= \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$



The Encoder

$\boxed{\text{Multi-Head Attention}} = \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$

$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{enc})$

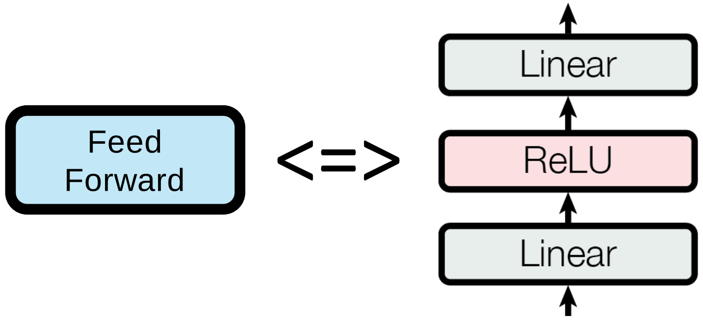


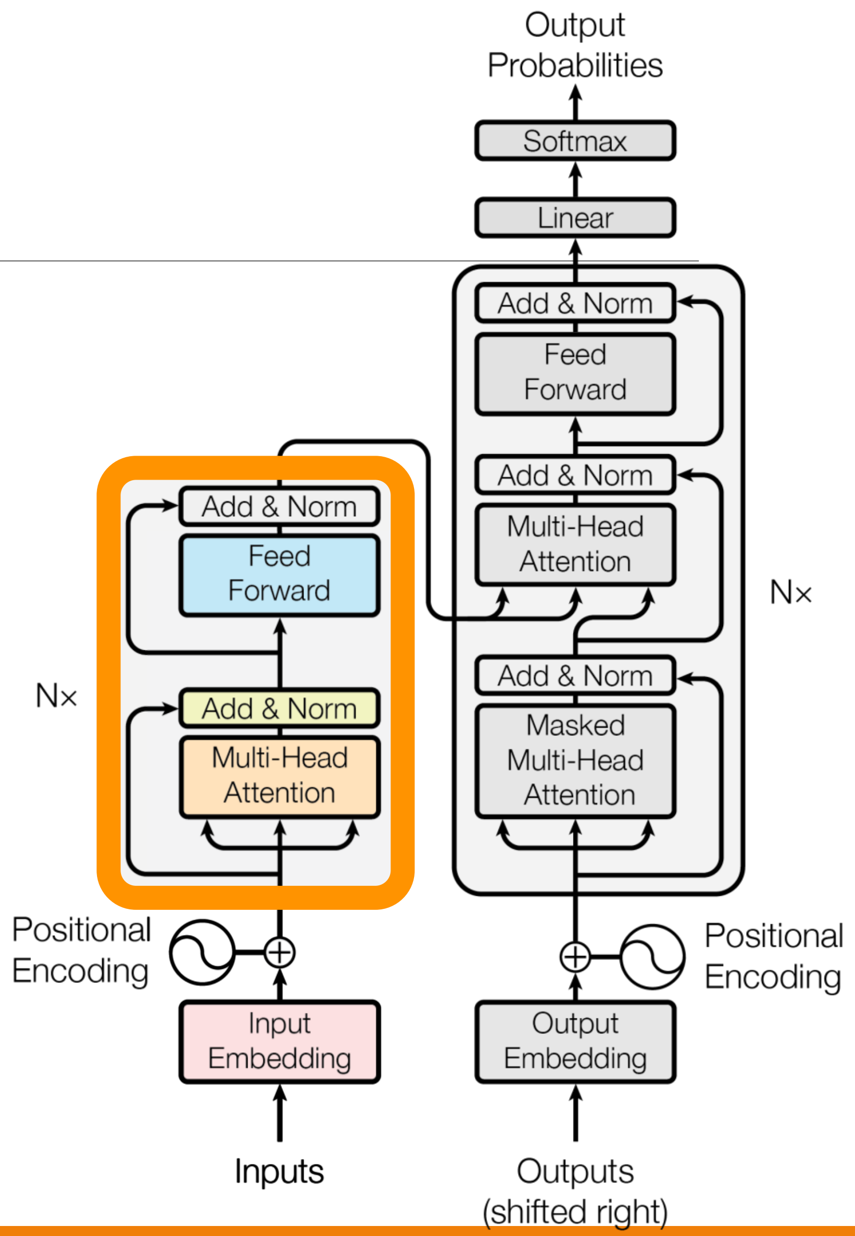
The Encoder

$\boxed{\text{Multi-Head Attention}} = \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$

$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{enc})$

$\boxed{\text{Feed Forward}} = max(0, \boxed{\text{Add \& Norm}}\,\mathbf{W}_1 + b_1)\mathbf{W}_2 + b_2$





The Encoder

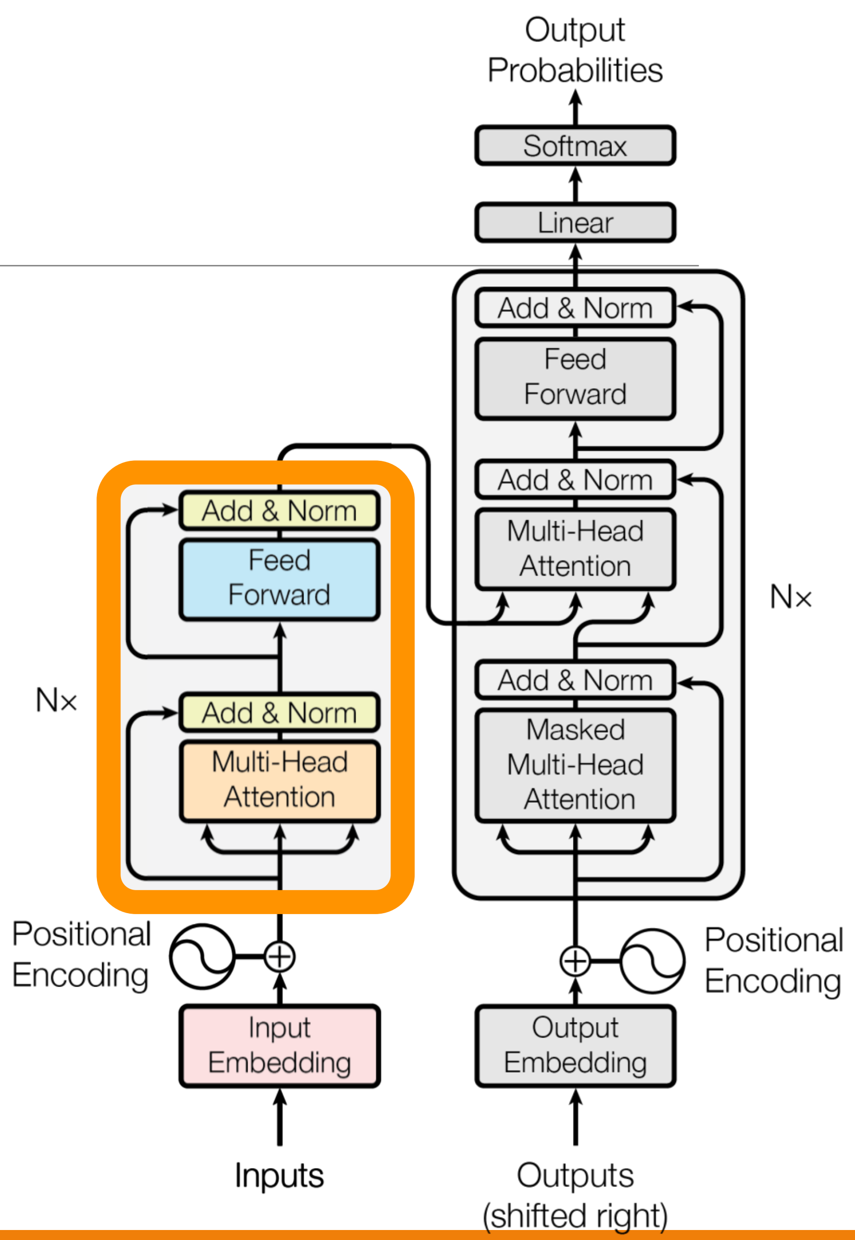
$$\boxed{\text{Multi-Head Attention}} = \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$$

$$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{enc})$$

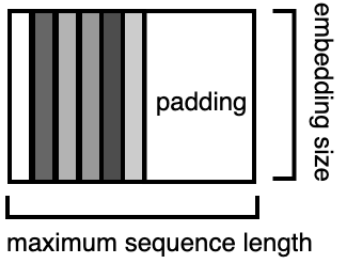
$$\boxed{\text{Feed Forward}} = max(0, \boxed{\text{Add \& Norm}}\mathbf{W}_1 + b_1)\mathbf{W}_2 + b_2$$

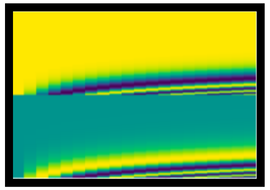
$$\boxed{\text{Add \& Norm (2)}} = \text{LayerNorm}(\boxed{\text{Feed Forward}} + \mathbf{H}_i^{enc})$$

$$\mathbf{H}_{i+1}^{enc} = \boxed{\text{Add \& Norm (2)}}$$

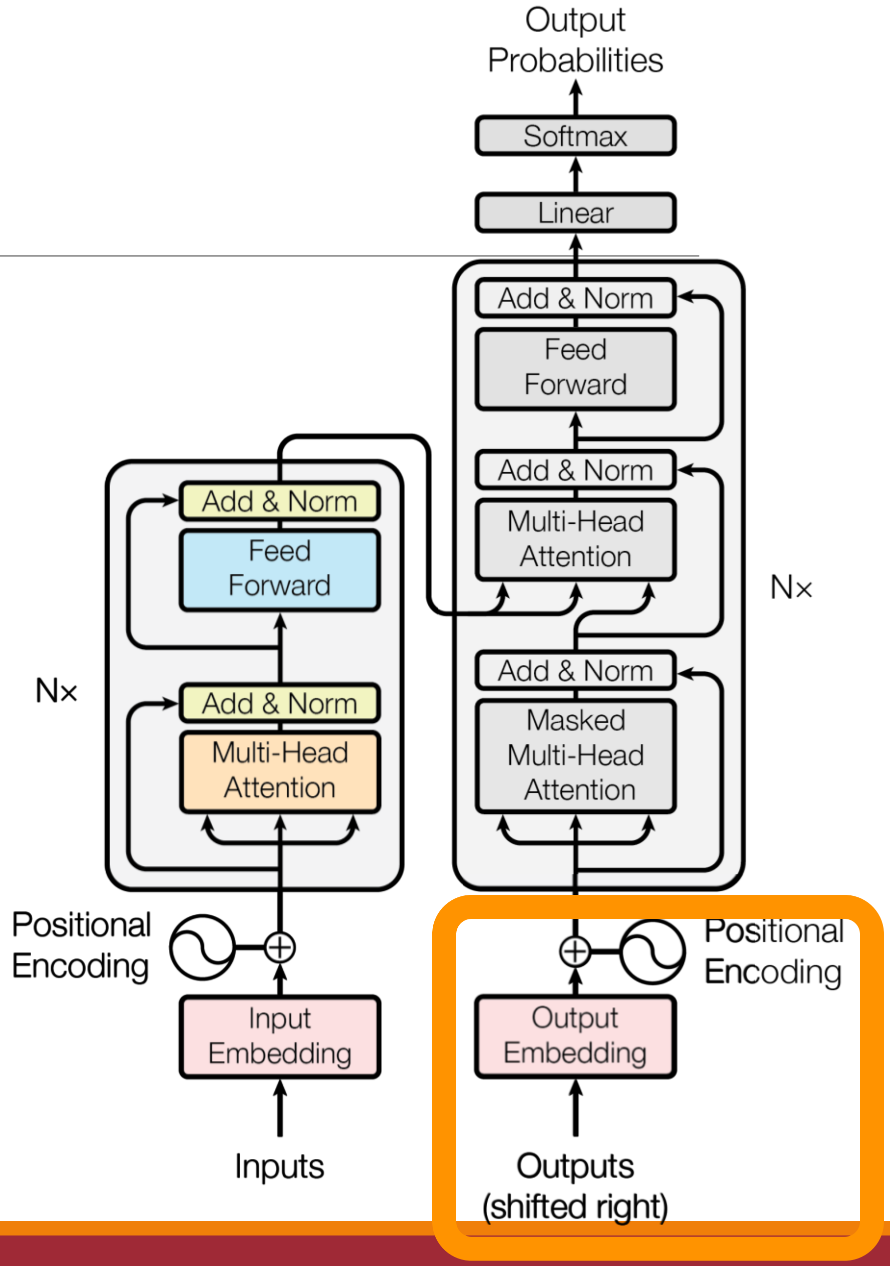


The Decoder

$\mathbf{H}_0^{\text{dec}} =$ 

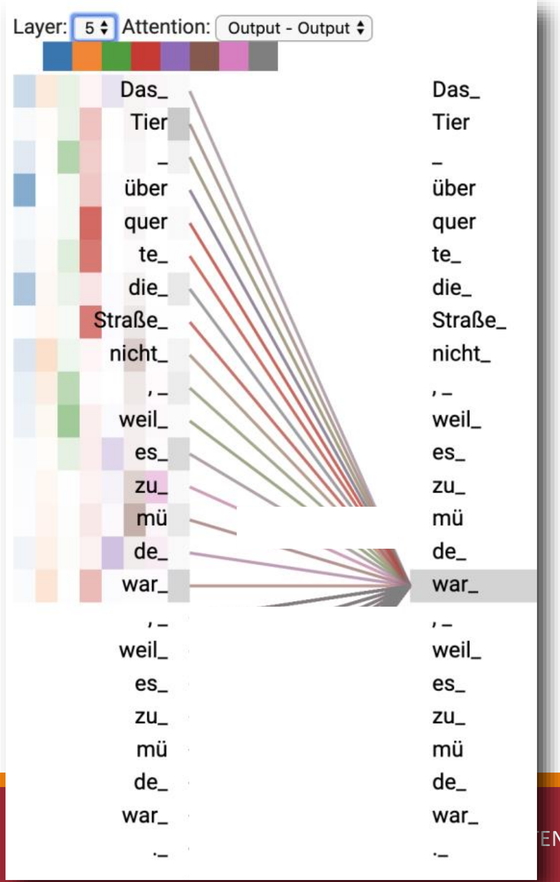
$+$ 

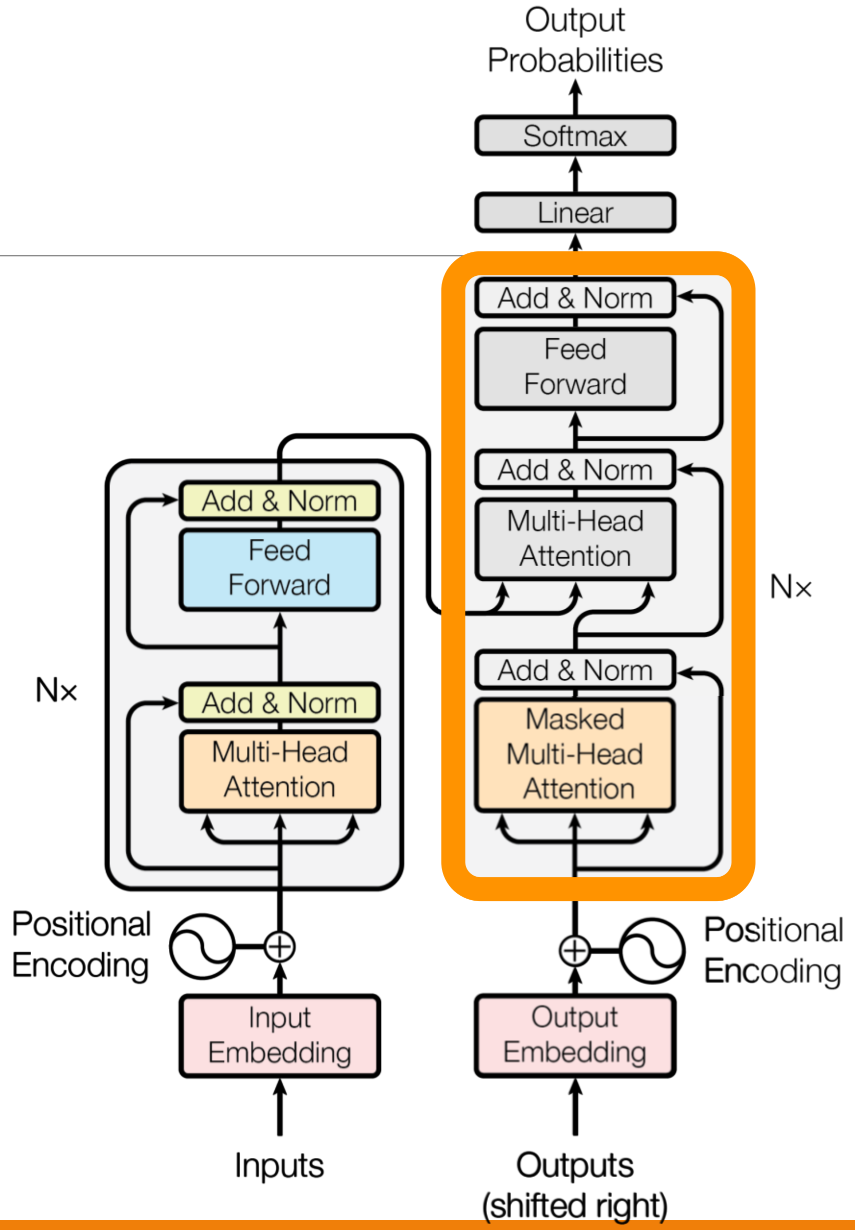
= token embeddings + position embeddings



The Decoder

Masked Multi-Head Attention $= \text{MaskedMultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec})$

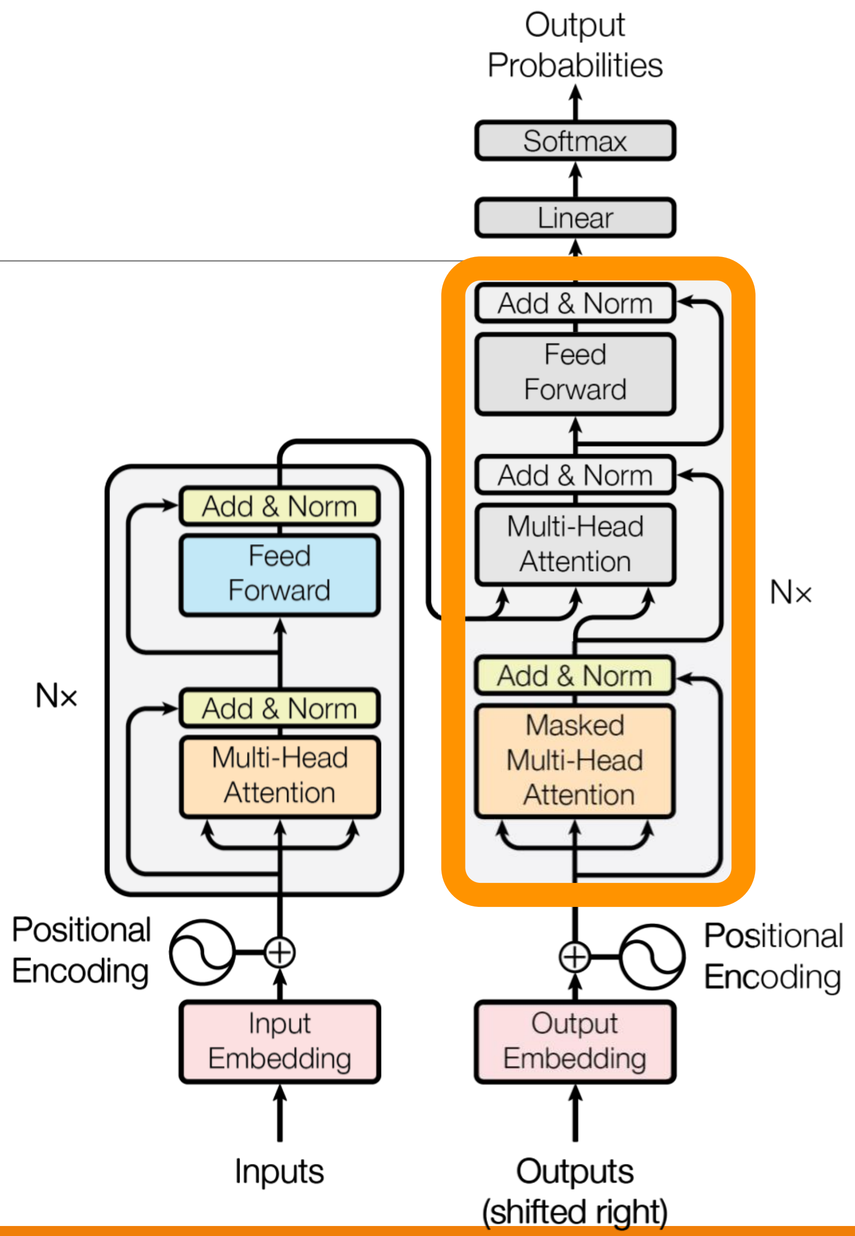




The Decoder

$$\boxed{\text{Masked Multi-Head Attention}} = \text{MaskedMultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec})$$

$$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{dec})$$

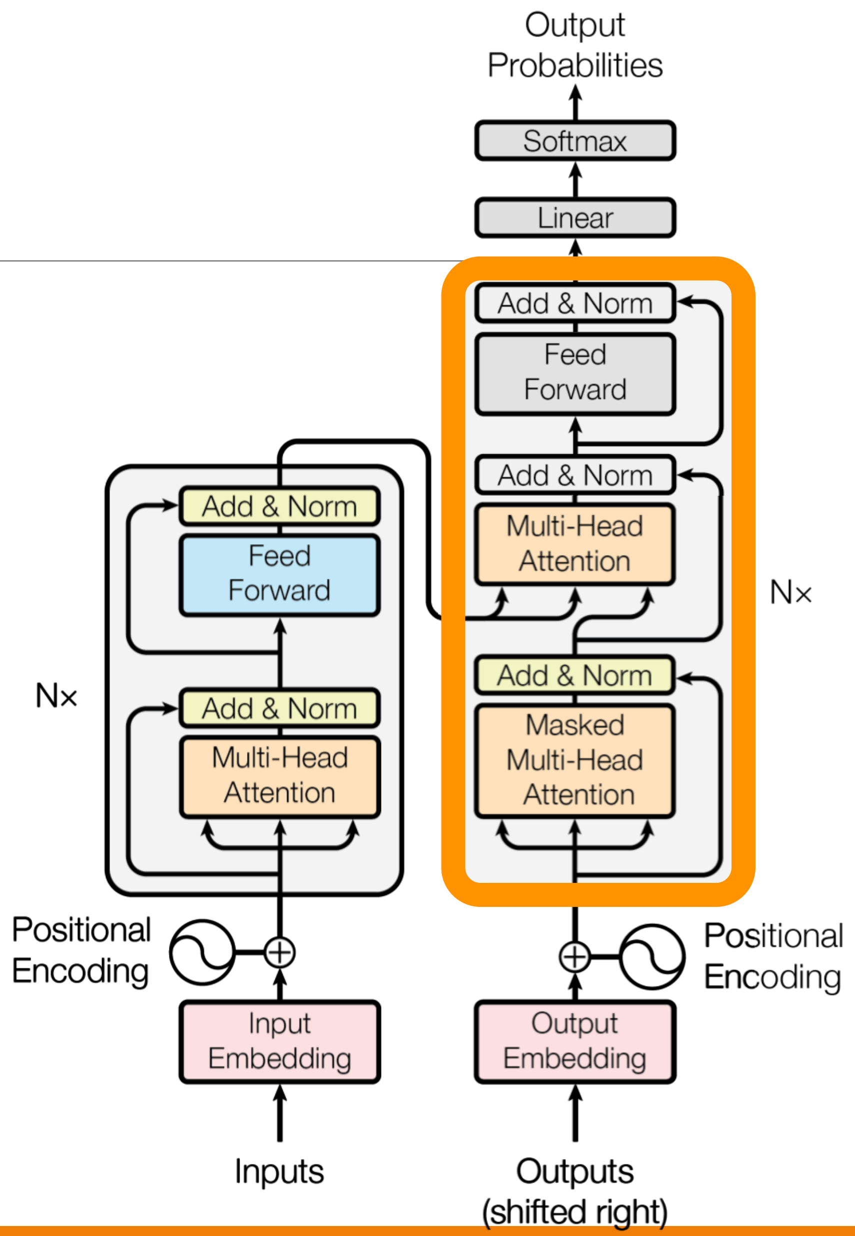


The Decoder

$\boxed{\text{Masked Multi-Head Attention}} = \text{MaskedMultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec})$

$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{dec})$

$\boxed{\text{Enc-Dec Multi-Head Attention}} = \text{MultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$



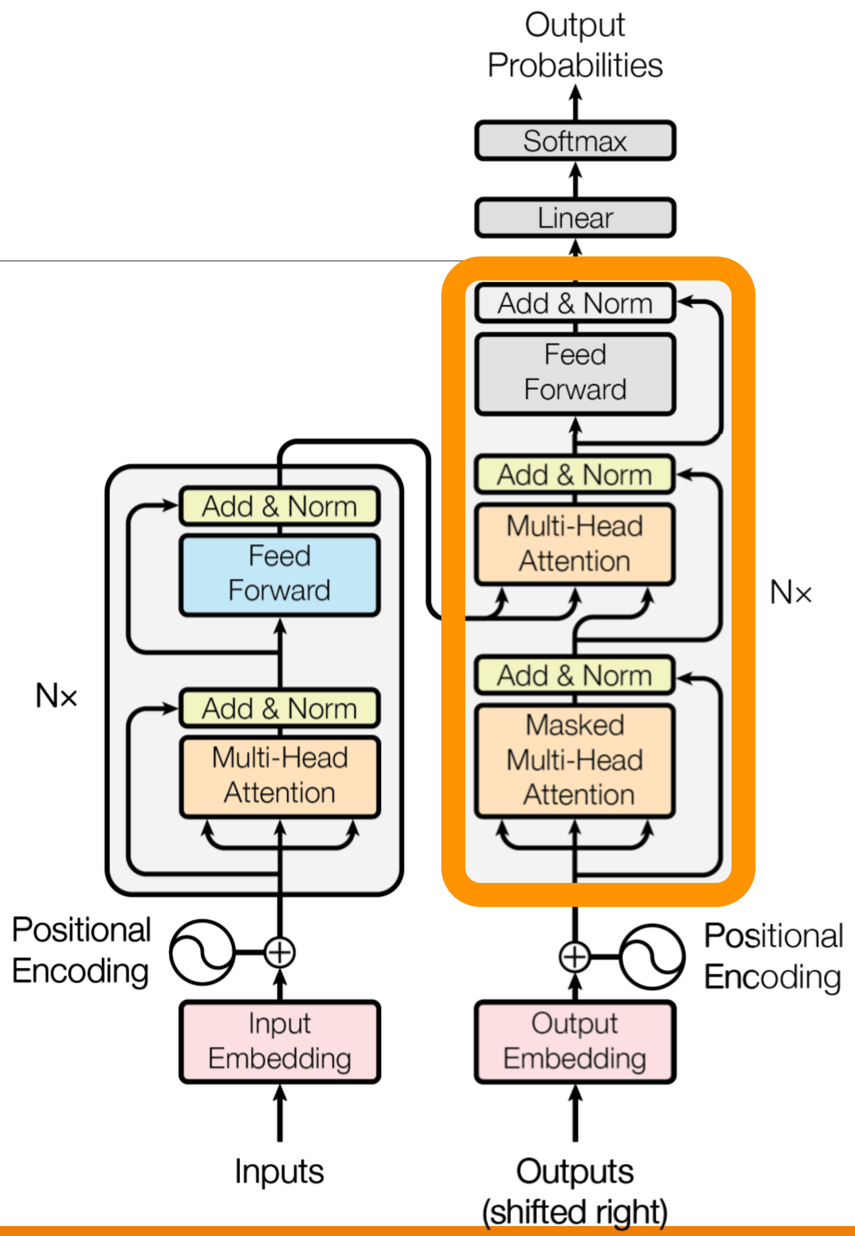
The Decoder

Masked Multi-Head Attention = MaskedMultiHeadAtt($\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}$)

Add & Norm = LayerNorm(Multi-Head Attention $+ \mathbf{H}_i^{dec}$)

Enc-Dec Multi-Head Attention = MultiHeadAtt($\mathbf{H}_i^{dec}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}$)

Add & Norm (2) = LayerNorm(Multi-Head Attention + Add & Norm)



The Decoder

$$\boxed{\text{Masked Multi-Head Attention}} = \text{MaskedMultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec})$$

$$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{dec})$$

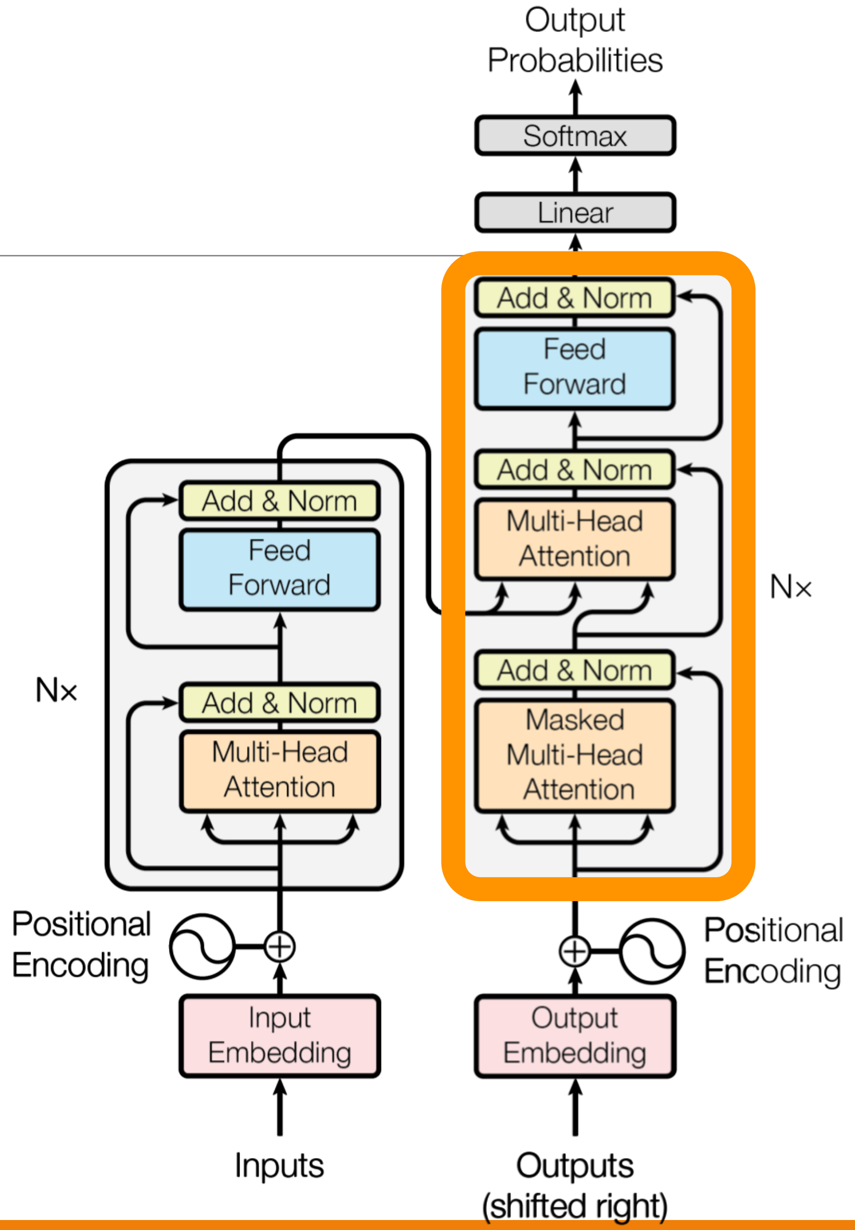
$$\boxed{\text{Enc-Dec Multi-Head Attention}} = \text{MultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$$

$$\boxed{\text{Add \& Norm (2)}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \boxed{\text{Add \& Norm}})$$

$$\boxed{\text{Feed Forward}} = max(0, \boxed{\text{Add \& Norm (2)}}\,\mathbf{W}_1 + b_1)\mathbf{W}_2 + b_2$$

$$\boxed{\text{Add \& Norm (3)}} = \text{LayerNorm}(\boxed{\text{Feed Forward}} + \boxed{\text{Add \& Norm (2)}})$$

$$\mathbf{H}_{i+1}^{dec} = \boxed{\text{Add \& Norm (3)}}$$



Strengths of the Transformer Architecture

Training is easily parallelizable

- Larger models can be trained efficiently.

Does not “forget” information from earlier in the sequence.

- Any position can attend to any position.

What are some of its weaknesses?

Knowledge Check

Draw a map comparing & contrasting the following LMs that we talked about:

Count-based LMs

Maxent/Logistic Regression LMs

Simple NNs

Simple RNNs

Seq2Seq RNNs

Transformers

Submit on Google Classroom after class