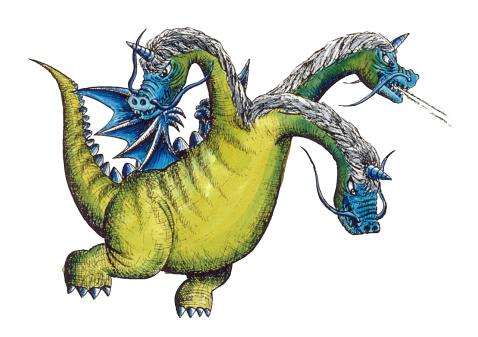
# Transformer Model (2/2): From Shallow to Deep

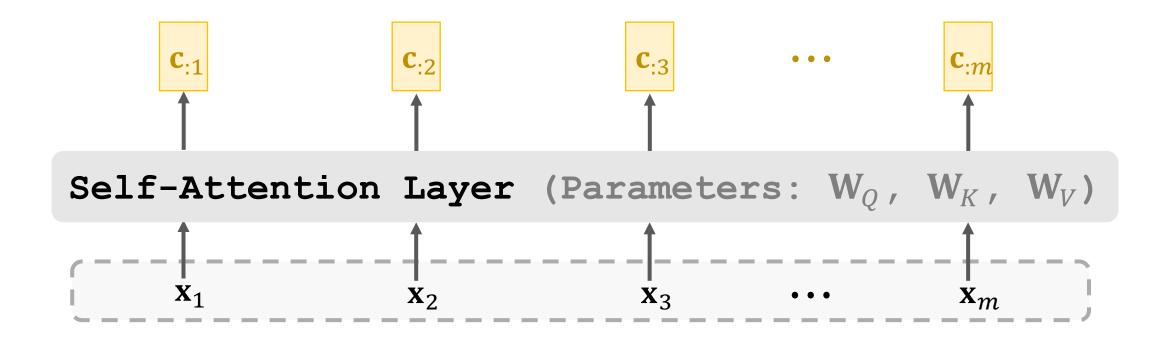
Shusen Wang

# **Multi-Head Attention**



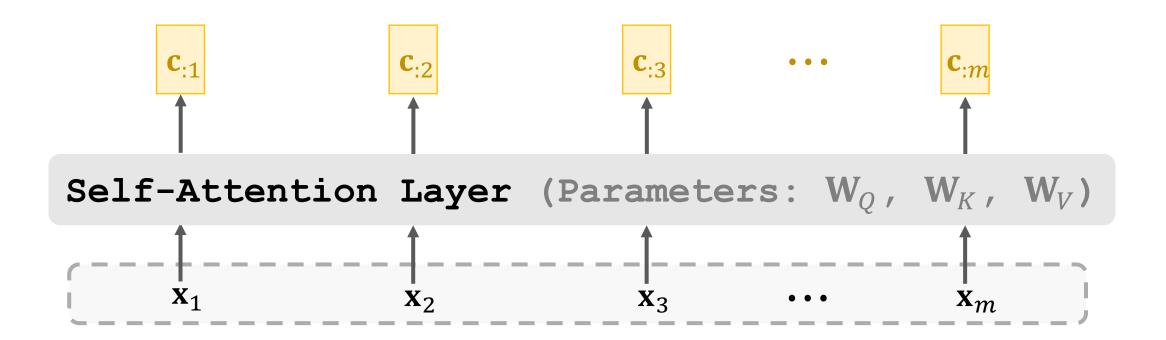
## **Single-Head Self-Attention**

- Self-attention layer: C = Attn(X, X).
- This is called "single-head self-attention".



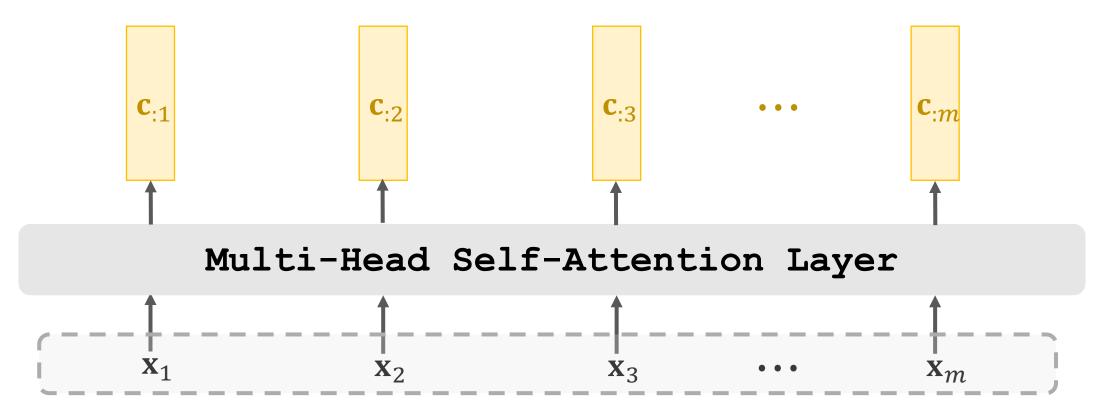
#### **Multi-Head Self-Attention**

- Using l single-head self-attentions (which do not share parameters.)
  - A single-head self-attention has 3 parameter matrices:  $\mathbf{W}_O$ ,  $\mathbf{W}_K$ ,  $\mathbf{W}_V$ .
  - Totally 3l parameters matrices.



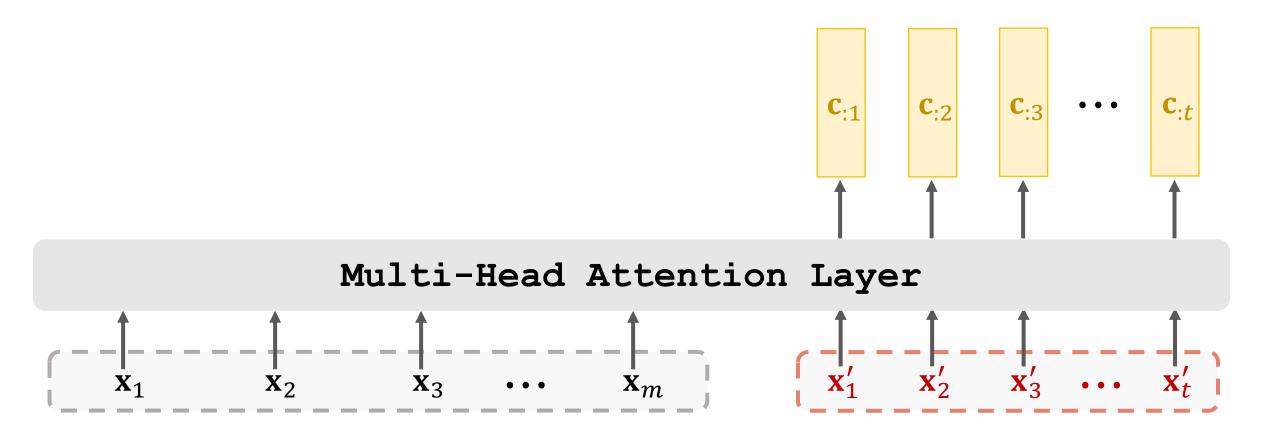
#### **Multi-Head Self-Attention**

- Using l single-head self-attentions (which do not share parameters.)
- Concatenating outputs of single-head self-attentions.
  - Suppose single-head self-attentions' outputs are  $d \times m$  matrices.
  - Multi-head's output shape:  $(ld) \times m$ .



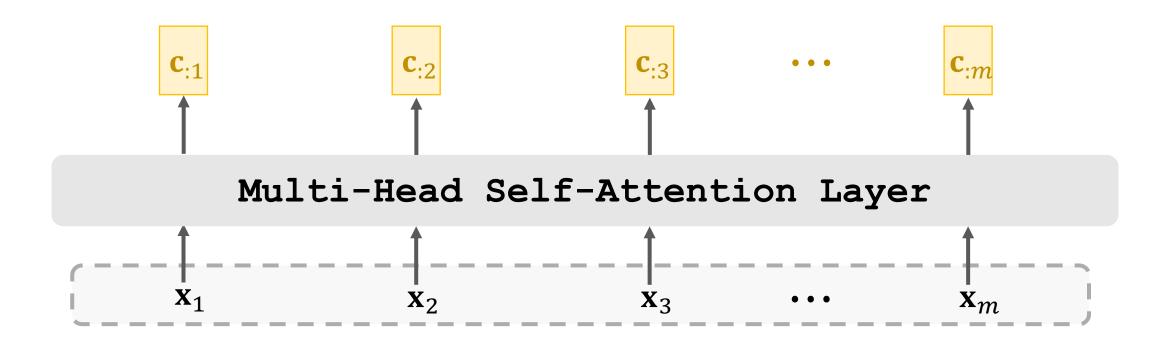
#### **Multi-Head Attention**

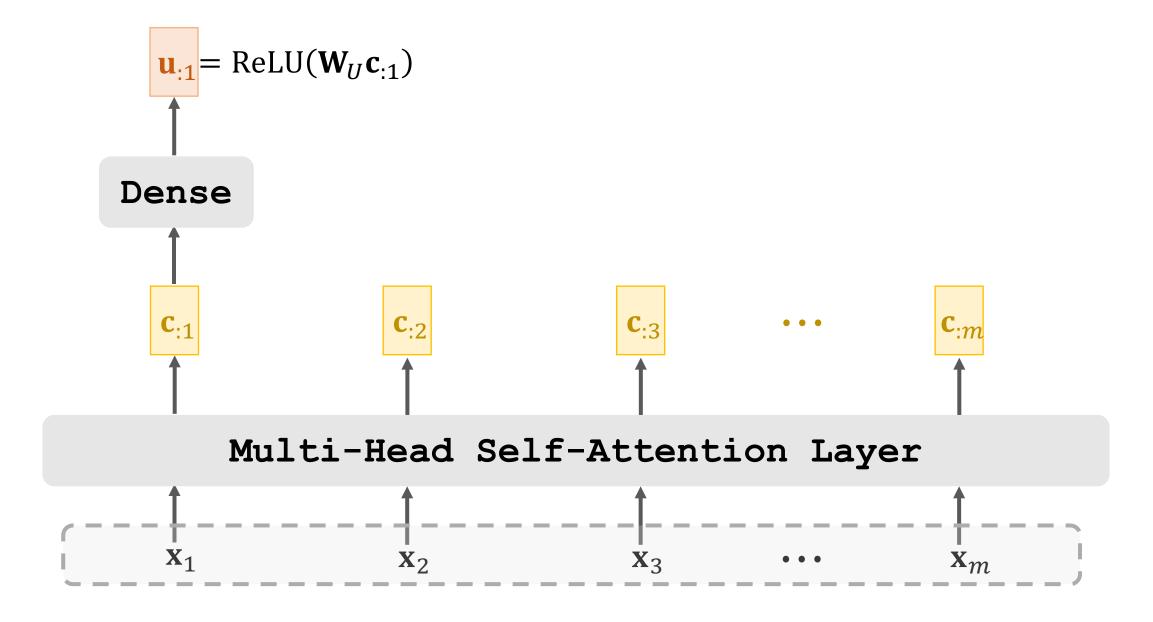
- Using *l* single-head attentions (which do not share parameters.)
- Concatenating single-head attentions' outputs.

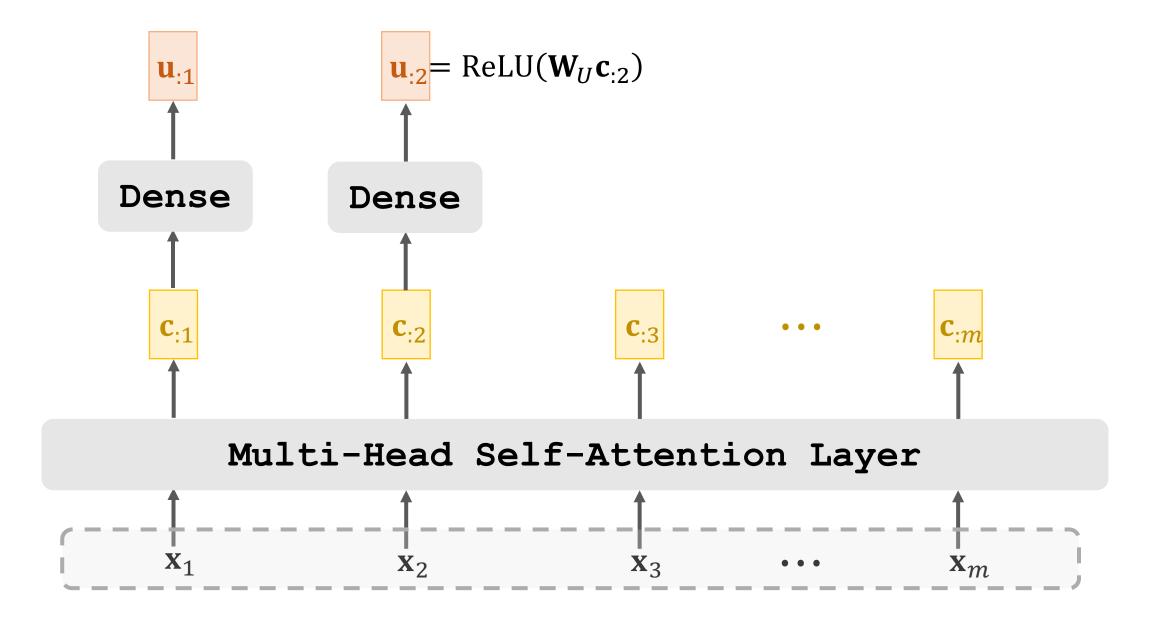


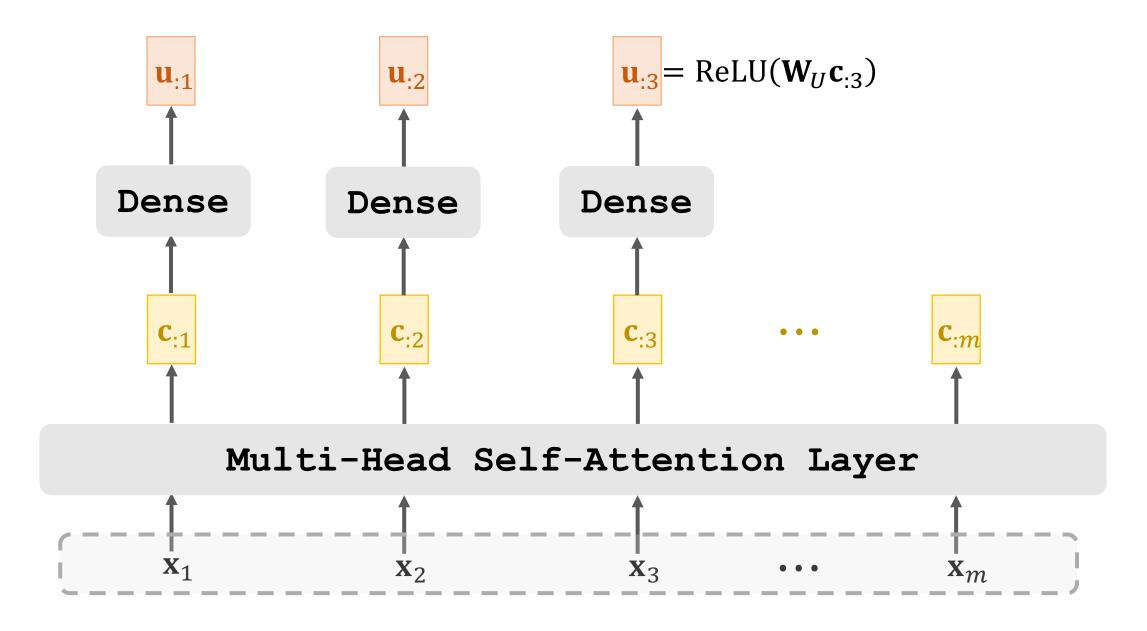
# **Stacked Self-Attention Layers**

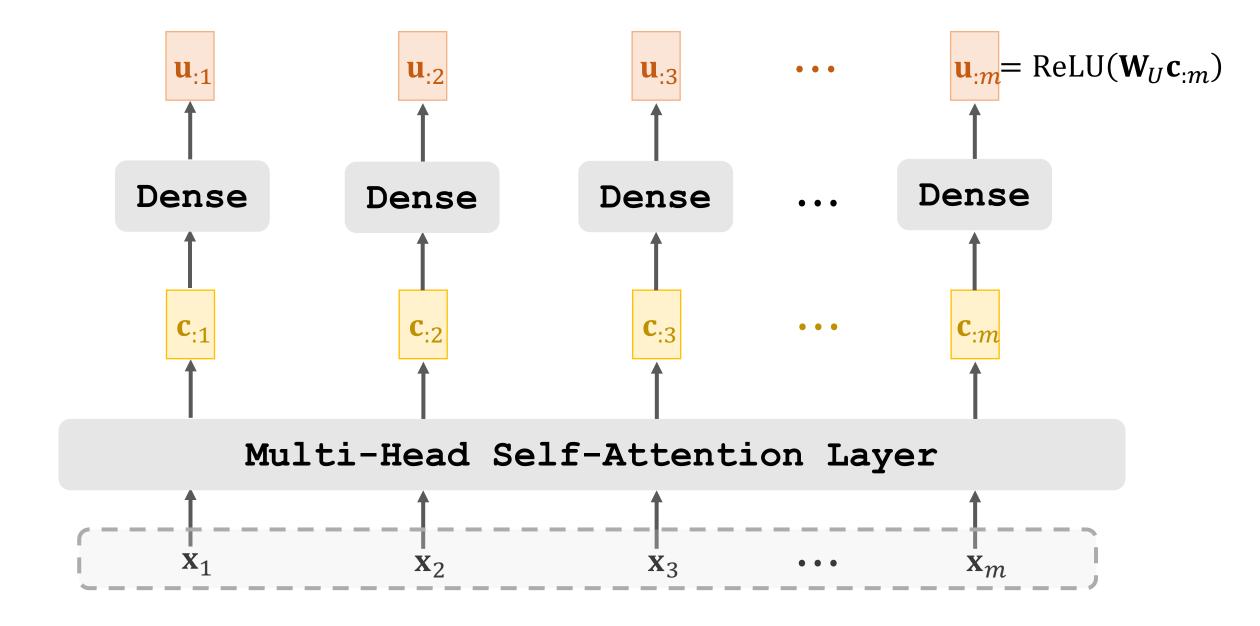
# **Self-Attention Layer**



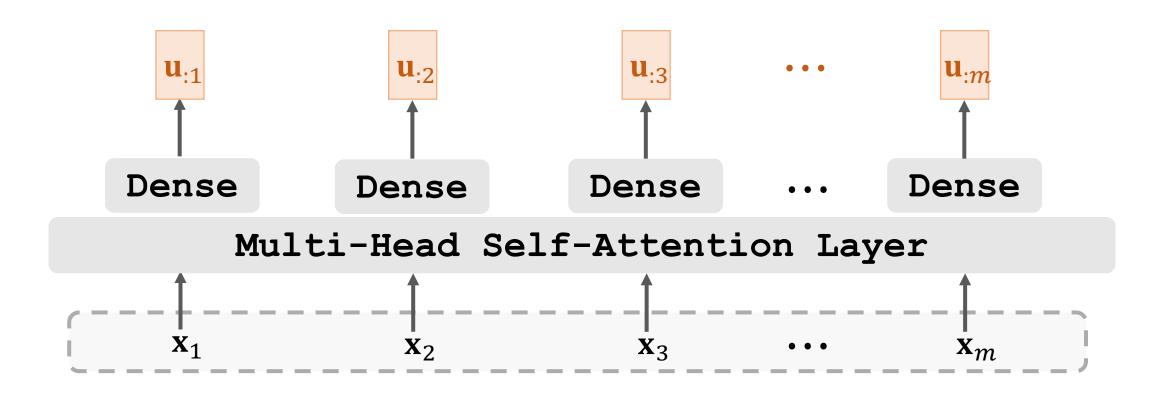




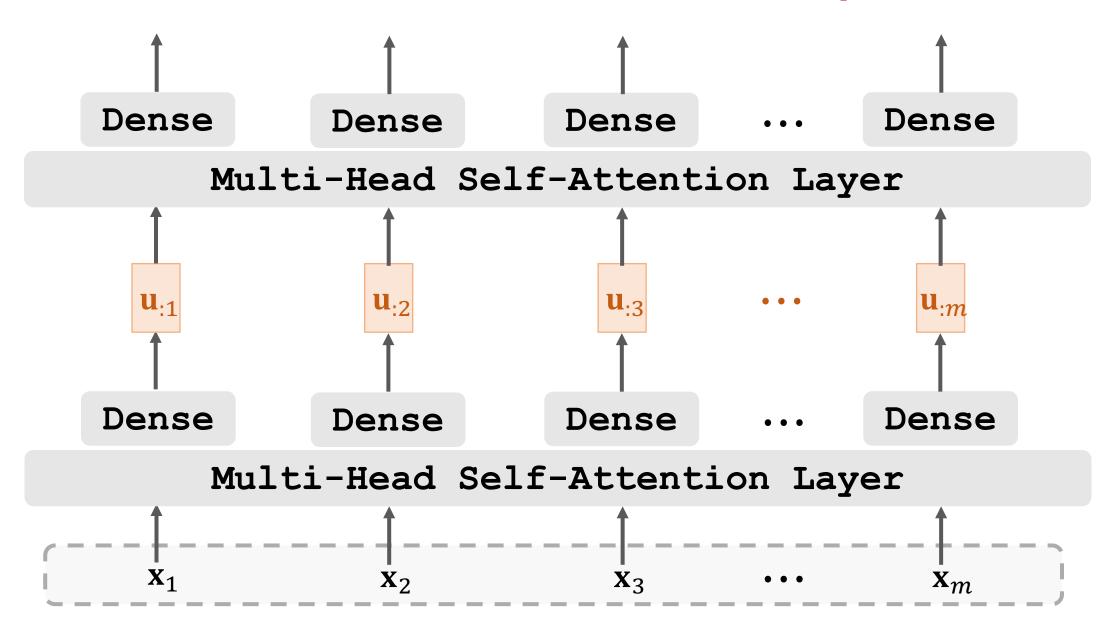




# **Stacked Self-Attention Layers**

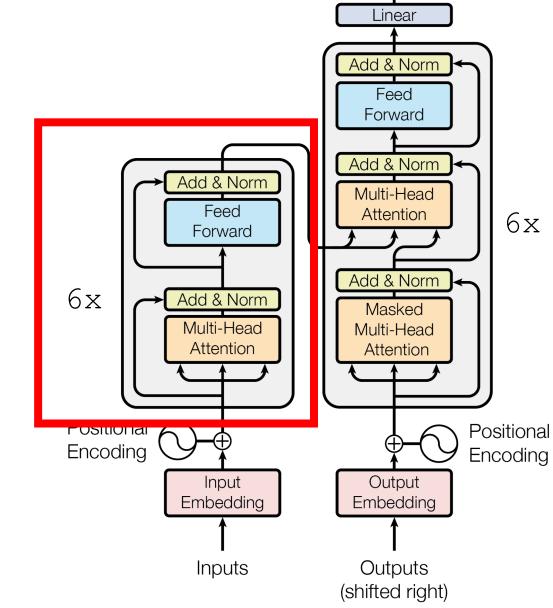


# **Stacked Self-Attention Layers**



# **Encoder of Transformer**

- 1 block = self-attention + dense.
- Encoder is a stack of 6 such blocks.
- Other tricks:
  - Skip connection.
  - Normalization.

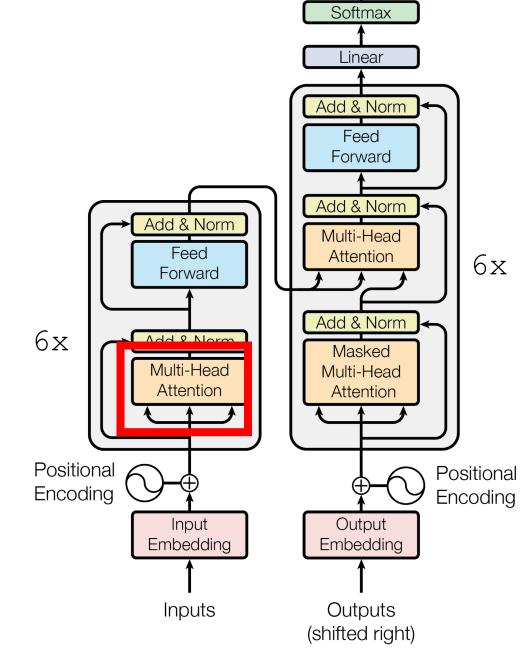


Output Probabilities

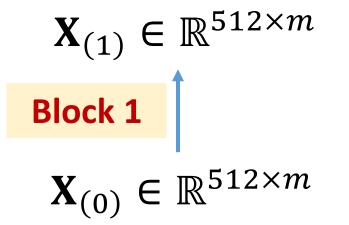
Softmax

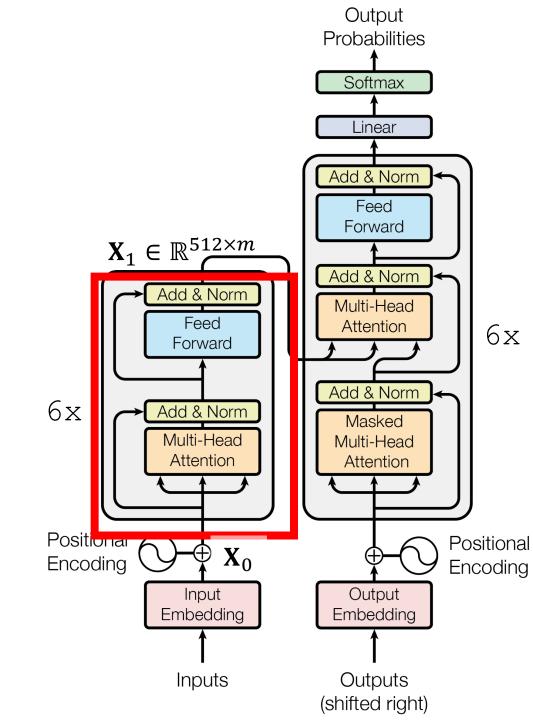
#### Multi-head self-attention:

- Input shape:  $512 \times m$ .
- Use 8 single-head attentions.
- Every single-head attention outputs a  $64 \times m$  matrix.
- Thus the output shape is  $512 \times m$ .

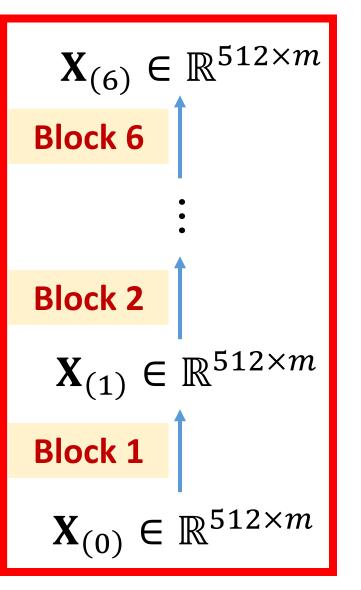


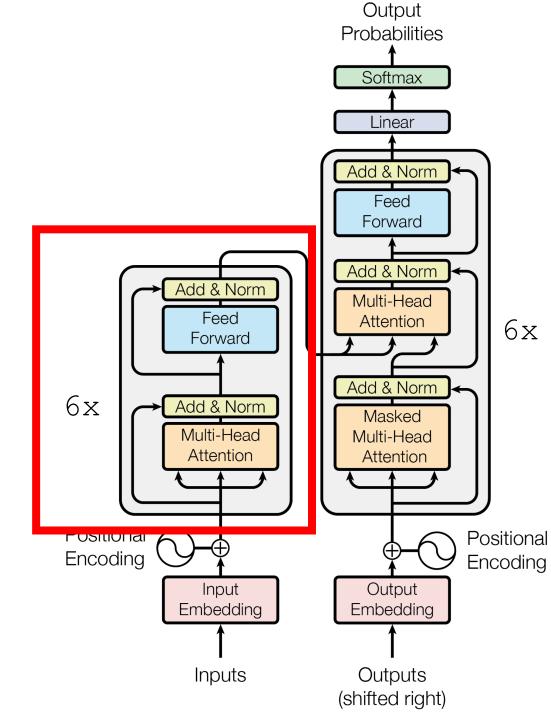
Output Probabilities





#### **Encoder**





# **Stacked Attention Layers**

- Transformer is a Seq2Seq model (encoder + decoder).
- Encoder's inputs are vectors  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_m$ .
- Decoder's inputs are vectors  $\mathbf{x}'_1, \mathbf{x}'_2, \cdots, \mathbf{x}'_t$ .

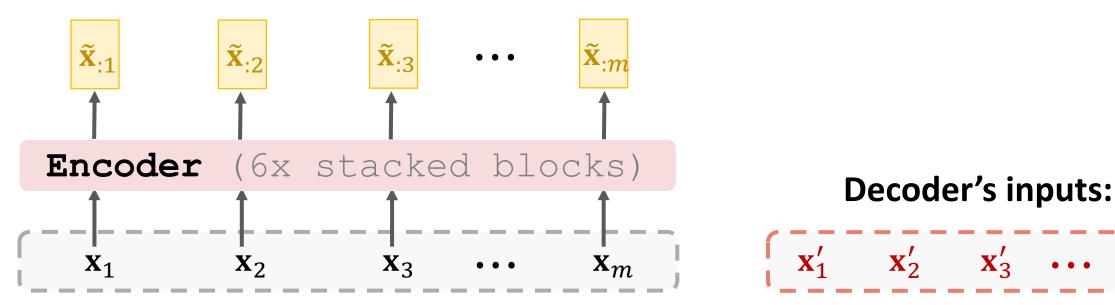
#### **Encoder's inputs:**

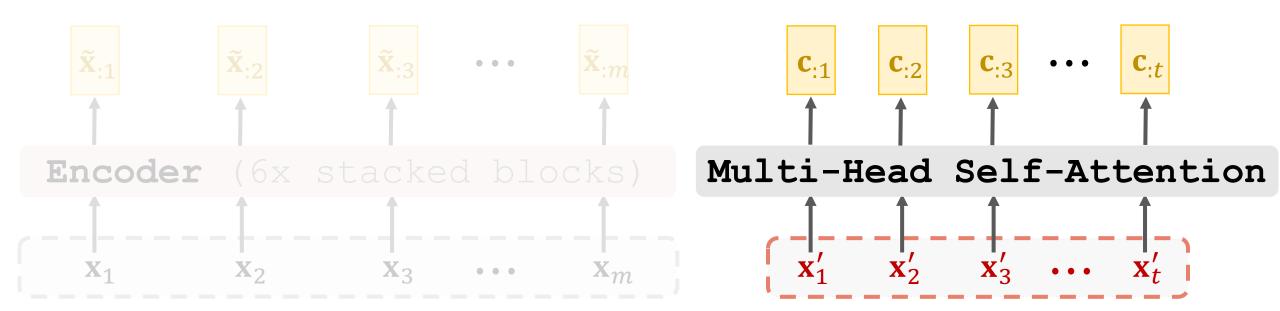
**Decoder's inputs:** 

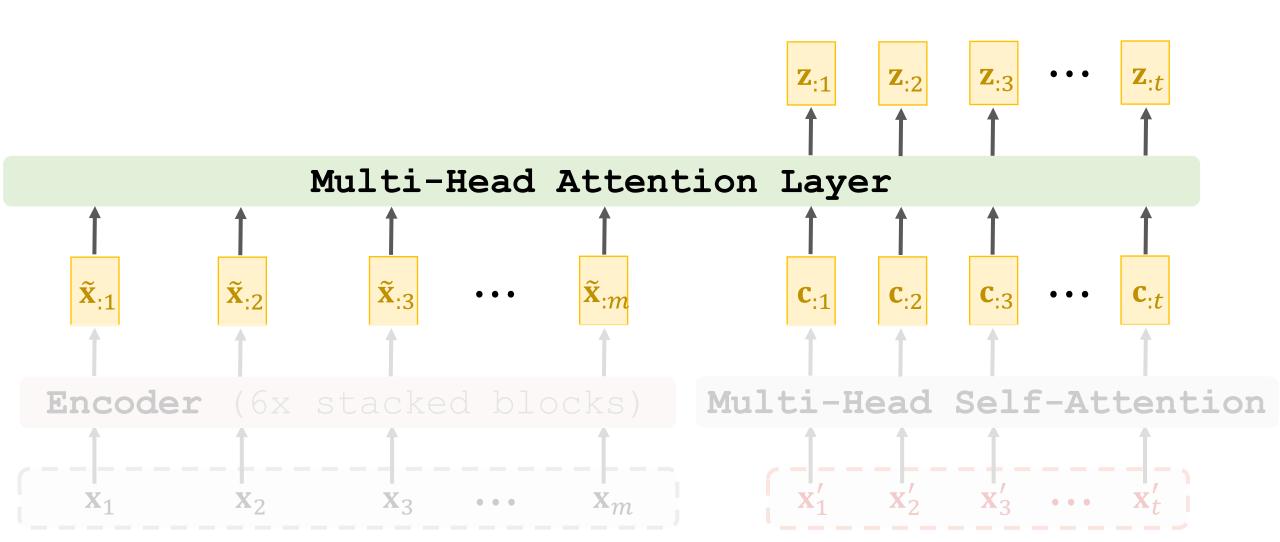
 $\mathbf{x}_1 \qquad \mathbf{x}_2 \qquad \mathbf{x}_3 \qquad \cdots \qquad \mathbf{x}_m$ 

 $\mathbf{x}_1'$   $\mathbf{x}_2'$   $\mathbf{x}_3'$  ···  $\mathbf{x}_t'$ 

- Transformer's encoder contains 6 stacked blocks.
- 1 block  $\approx$  1 multi-head attention layer + 1 dense layer.

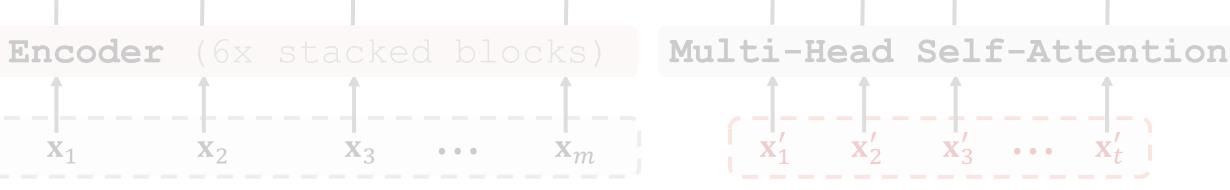






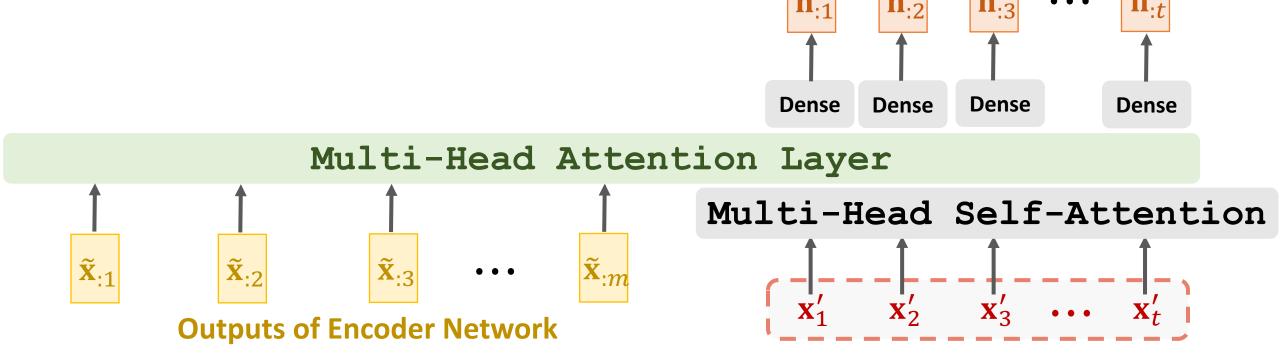
# $\mathbf{h}_{\cdot 1} = \text{ReLU}(\mathbf{W}_H \mathbf{Z}_{:1})$ **Stacked Attentions Dense Z**:2 Multi-Head Attention Layer Multi-Head Self-Attention Encoder (6x stacked blocks)

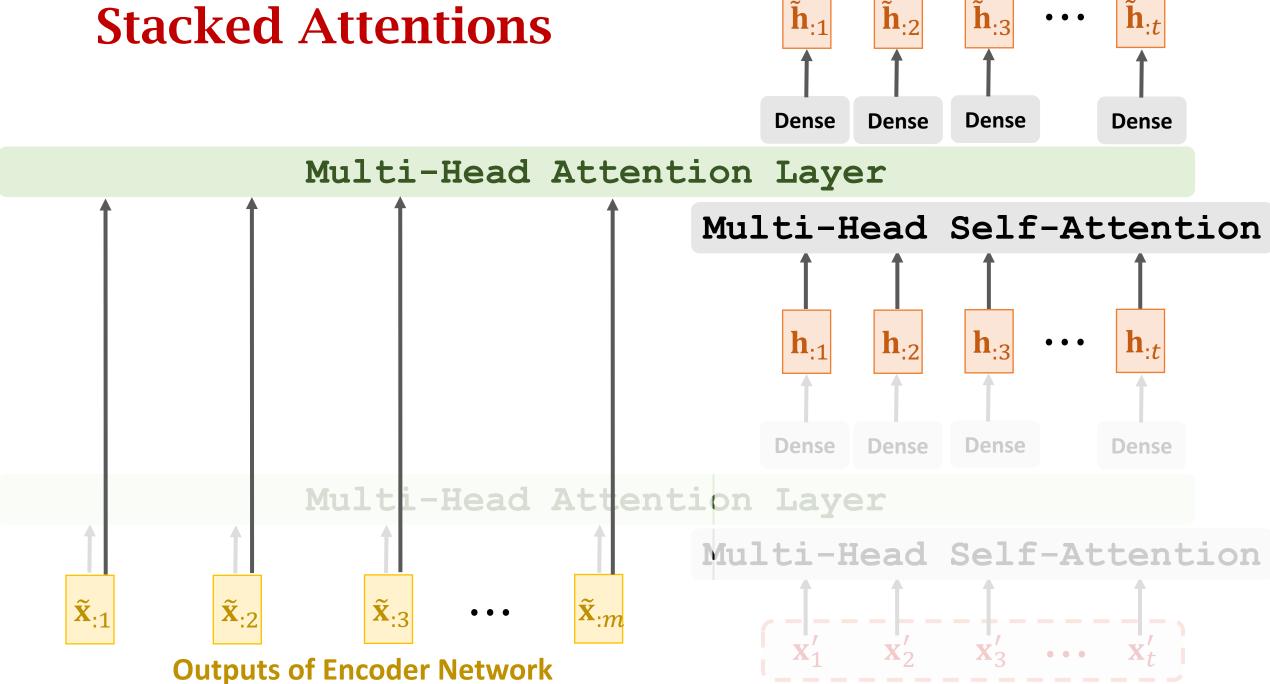
# $\mathbf{h}_{:2} = \text{ReLU}(\mathbf{W}_H \mathbf{z}_{:2})$ **Stacked Attentions** Dense **Dense Z**:2 **Z**:1 Multi-Head Attention Layer



# h:2 **h**:3 **Stacked Attentions** Dense Dense **Dense** Dense **Z**:2 Multi-Head Attention Layer Multi-Head Self-Attention Encoder (6x stacked blocks)

- We have stacked 3 layers: self-attention + attention + dense.
- They together map  $(\widetilde{X}, X')$  to H.
- One block of Transformer's decoder is the stack of the 3 layer.

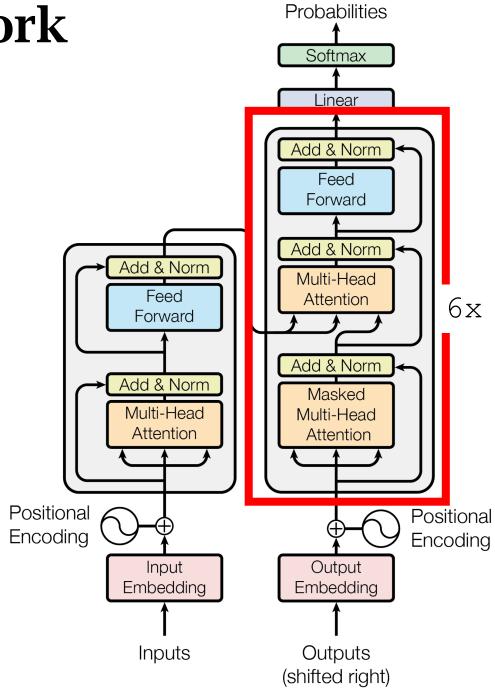




# **Decoder of Transformer**

### **Decoder Network**

- 1 block = self-attention + attention layer + dense.
- Decoder is a stack of 6 such blocks.



Output

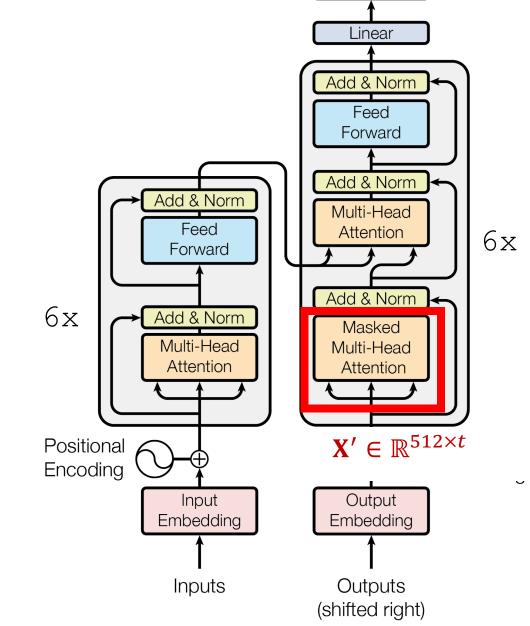
## Decoder Network: One Block

#### Multi-head self-attention.

- Input shape:  $512 \times t$ .
- Use 8 single-head self-attentions:

$$C = Attn(X', X').$$

- Each outputs  $64 \times t$  matrix.
- Output shape:  $512 \times t$ .



Output Probabilities

Softmax

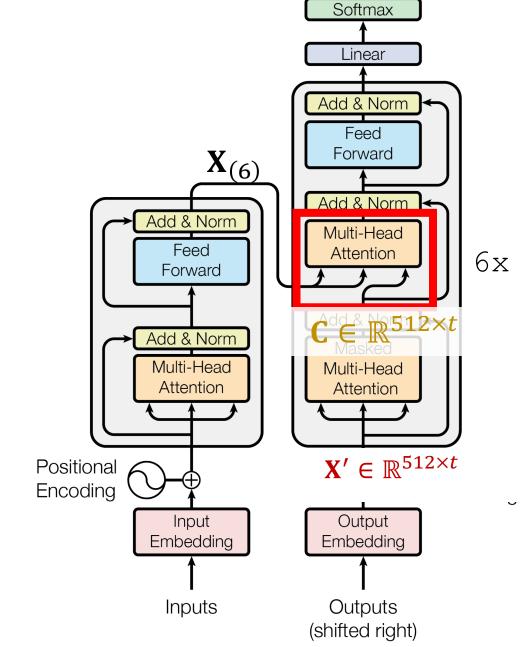
### Decoder Network: One Block

#### Multi-head attention.

Use 8 single-head attentions:

Attn
$$(X_{(6)}, C)$$
.

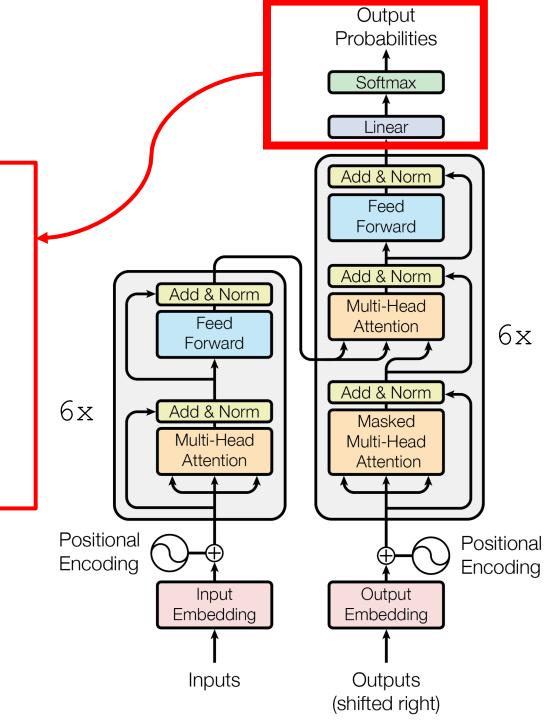
- Each outputs  $64 \times t$  matrix.
- Output shape:  $512 \times t$ .



Output Probabilities

### **Decoder Network**

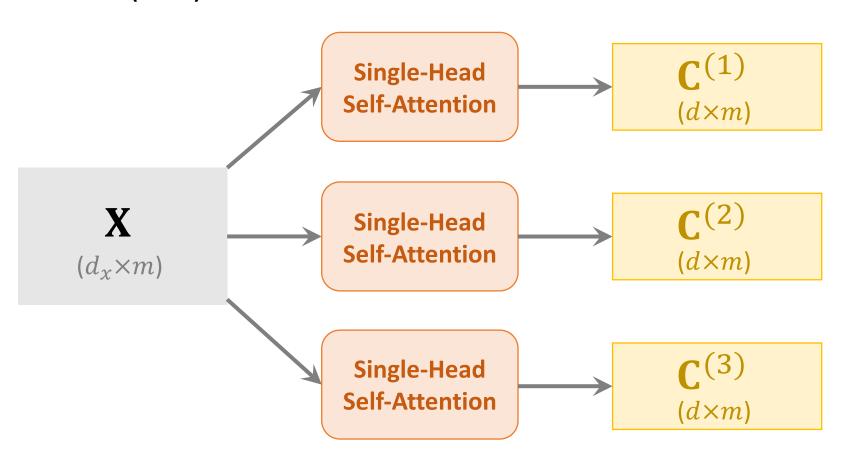
- Output a distribution over the vocabulary.
- Compare the distribution with the one-hot encode of the label.
- Loss, e.g., cross-entropy.
- Gradient.
- Dpdate model parameters.



# Summary

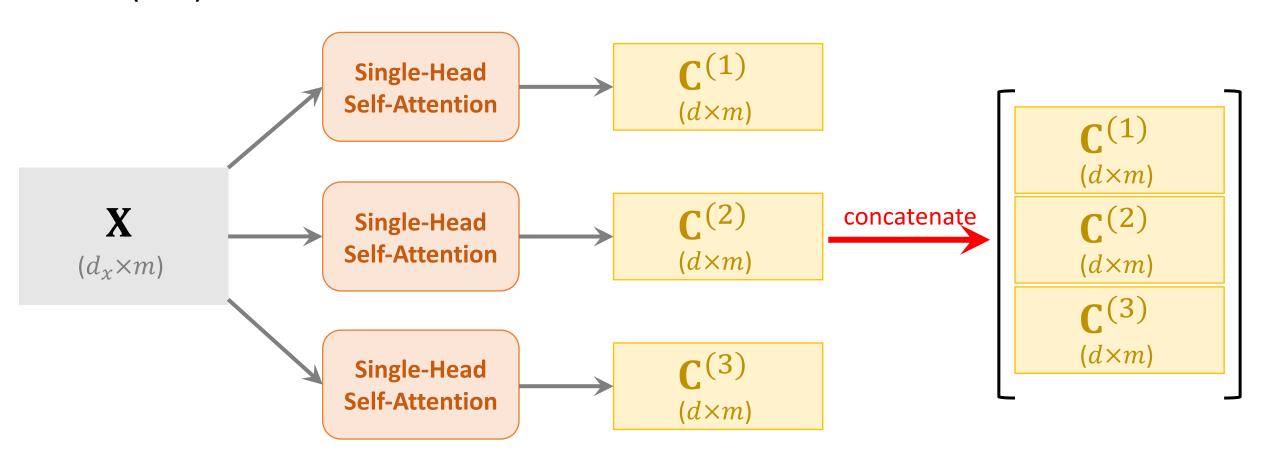
# From Single-Head to Multi-Head

• Single-head (self) attention can be combined to form a multi-head (self) attention.



# From Single-Head to Multi-Head

• Single-head (self) attention can be combined to form a multi-head (self) attention.



#### **Encoder Network of Transformer**

- 1 encoder block  $\approx$  8-head self-attention + dense.
- Encoder network is a stack of 6 such blocks.
- Input shape:  $512 \times m$ .
- Output shape:  $512 \times m$ .

#### **Decoder Network of Transformer**

- 1 decoder block  $\approx$  8-head self-attention + 8-head attention + dense.
- Encoder network is a stack of 6 such blocks.
- Input shape:  $512 \times t$ .
- Output shape:  $512 \times t$ .

## Summary

- Transformer model is not RNN.
- Transformer is based on attention and self-attention.
- Upside: Outperform all the state-of-the-art RNN models.
- Downside: Much more expensive than RNN models.

# Thank you!