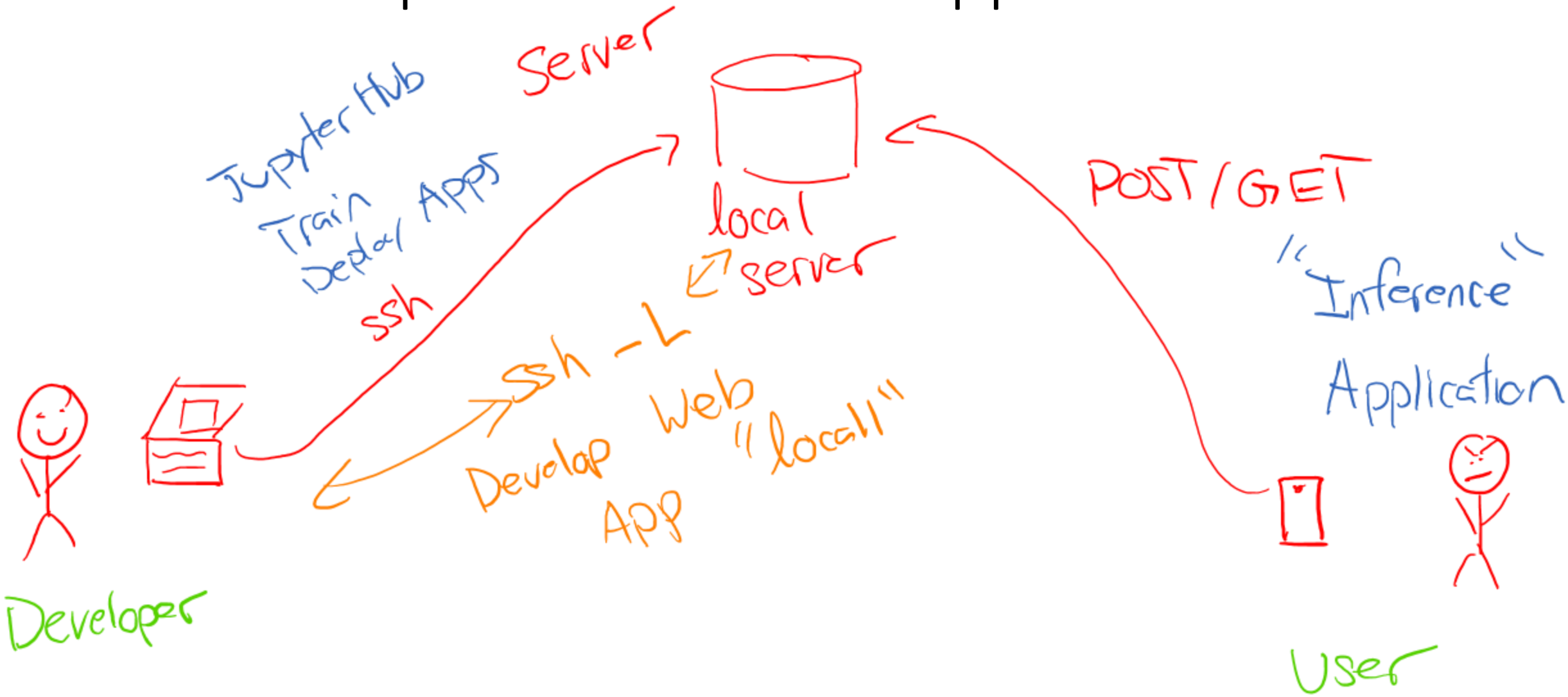
# Attention and Transformers

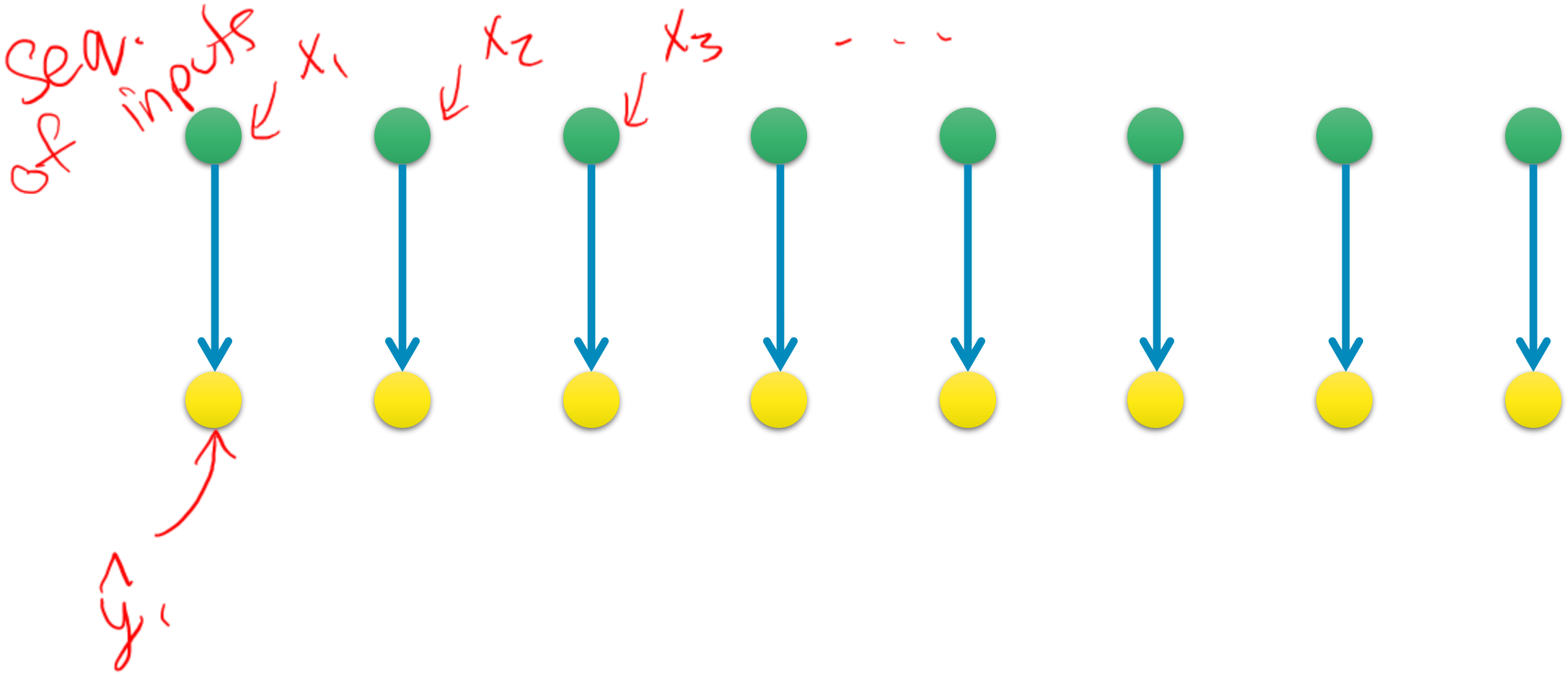
# Recap: Inference and Applications



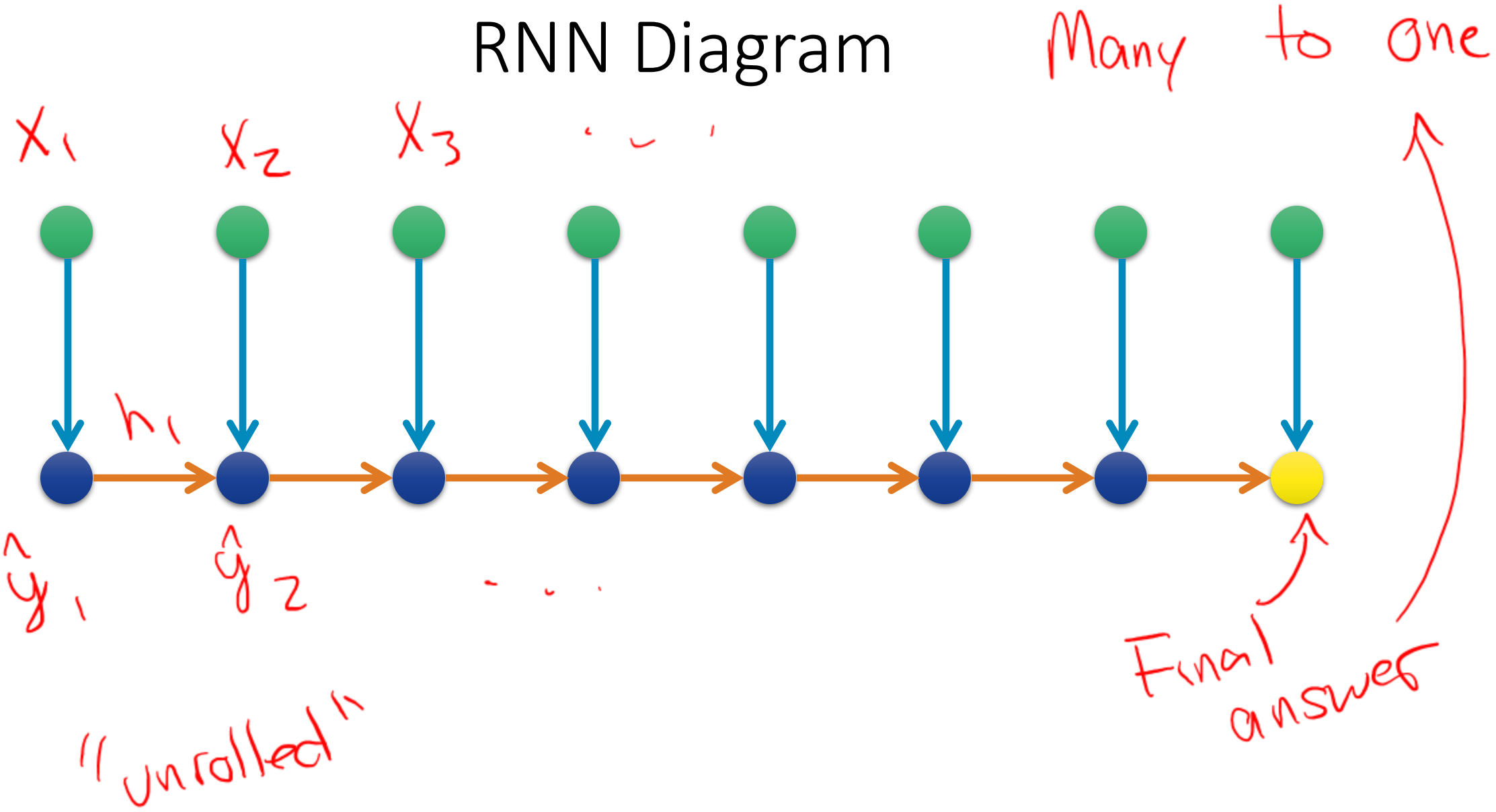
# Outline

- High-level comparison
  - Feed forward networks
  - Recurrent networks
  - Transformer networks
- Remember the RNN encoder/decoder architecture
- Motivate the need for attention
- Explore the transformer architecture

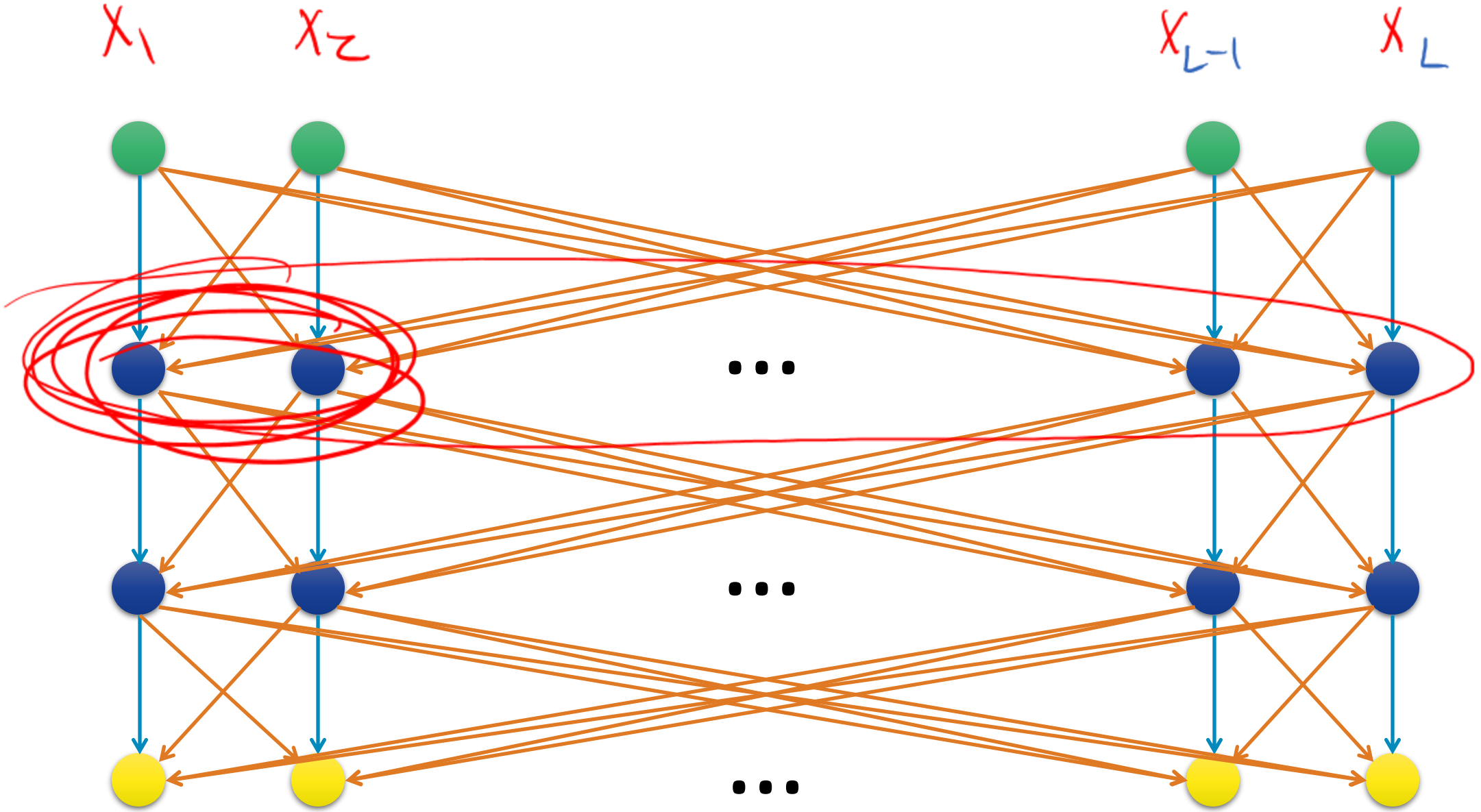
# Feed Forward NN Diagram



# RNN Diagram



# Transformer Diagram



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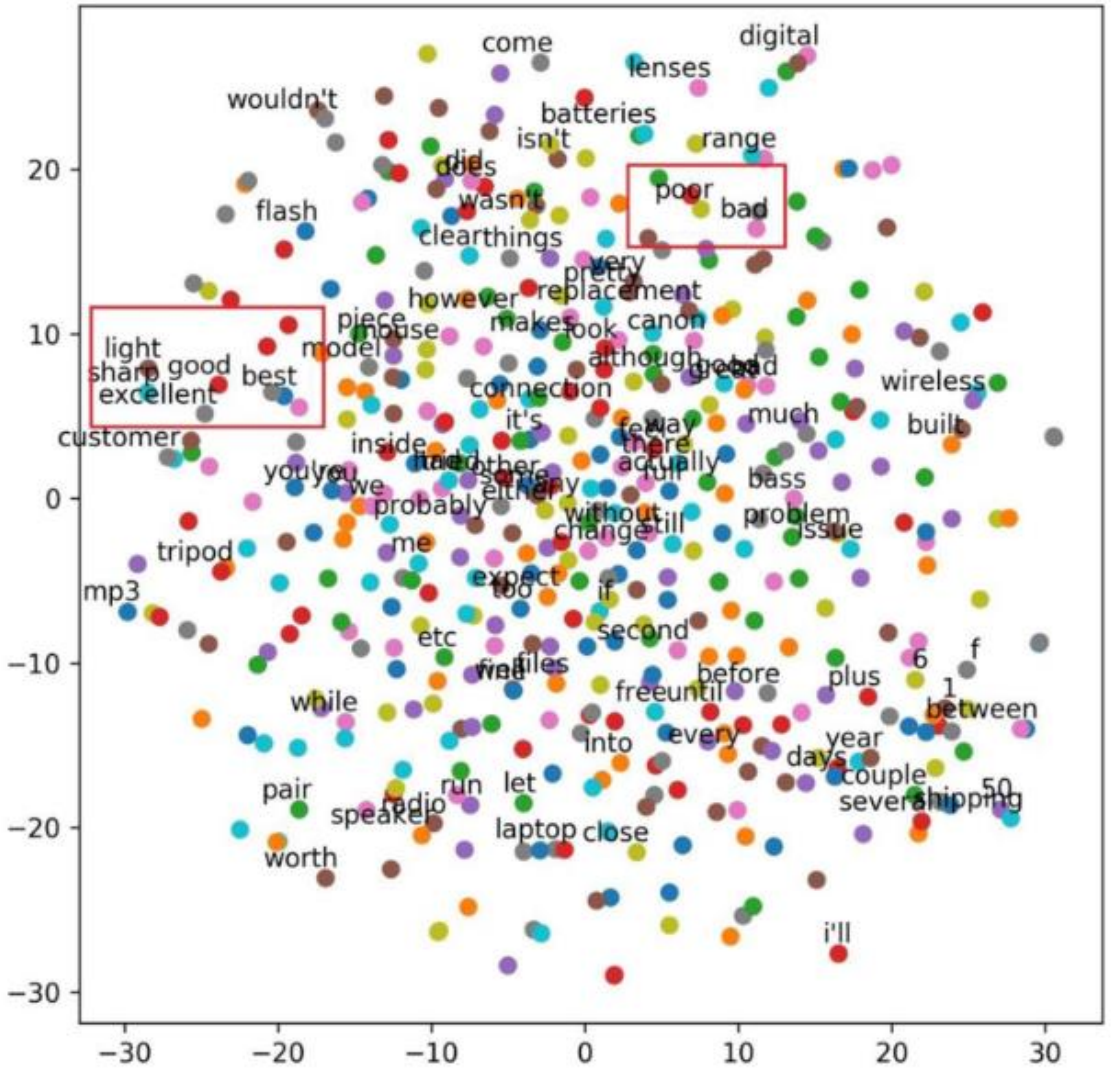
# Translation Encoder/Decoder RNN

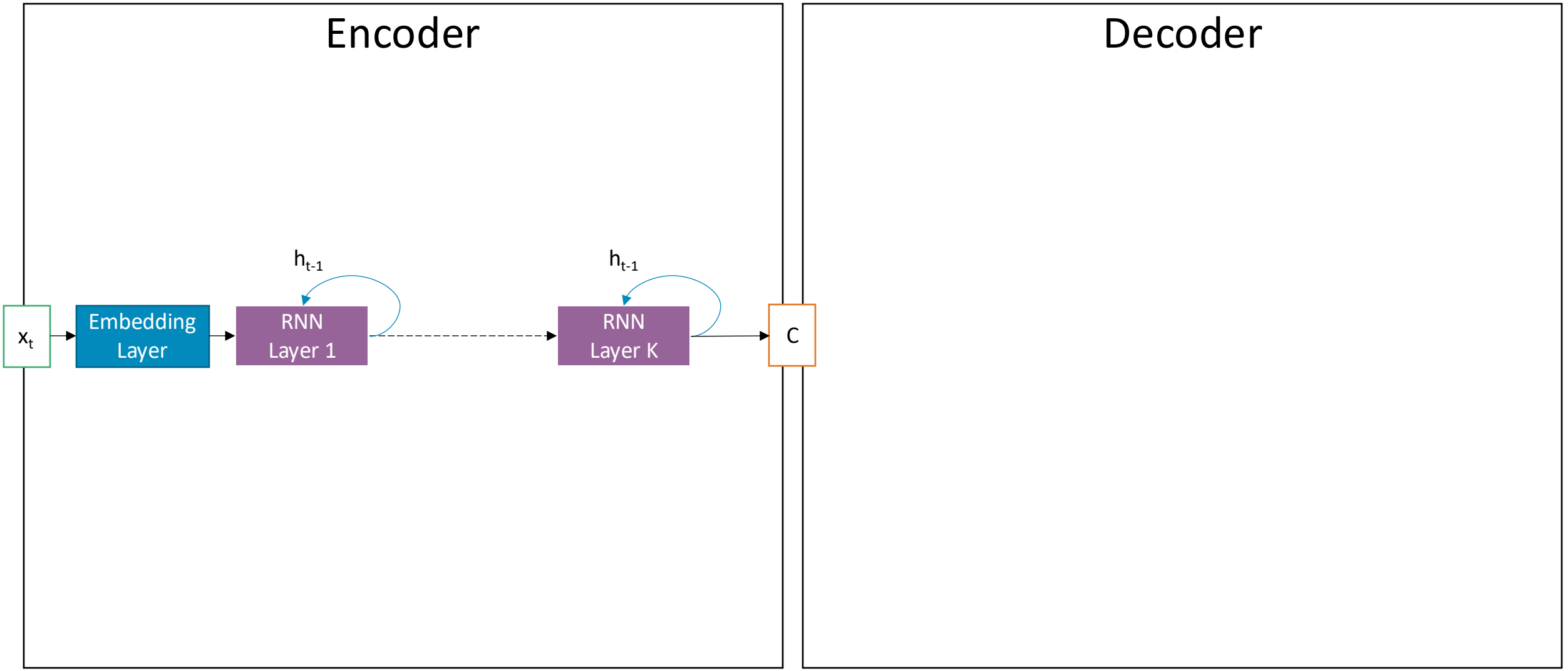
# Embedding Space




**Cross-domain sentiment aware word embeddings for review sentiment analysis**

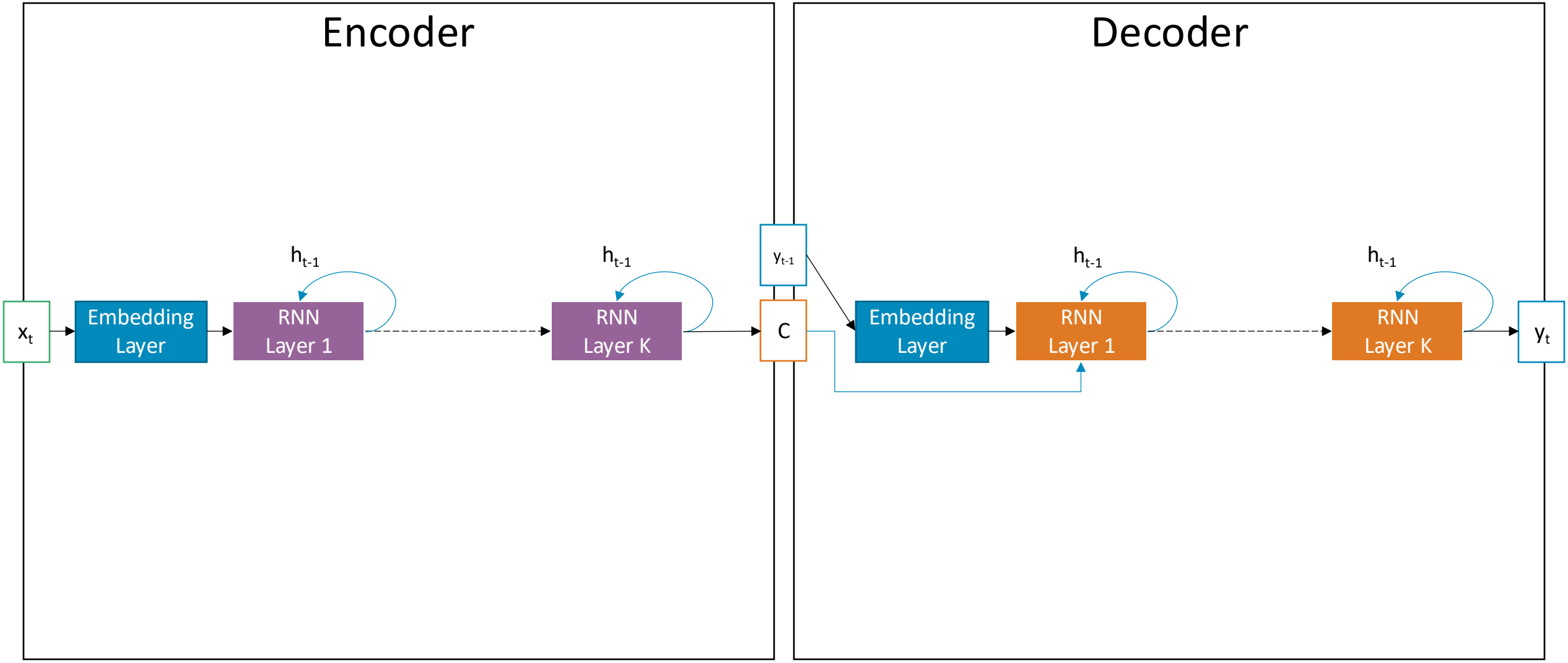
Jun Liu[1] · Shuang Zheng[1] · Guangxia Xu[1,2,3] · Mingwei Lin[4]

# Translation Encoder/Decoder RNN




These RNN layers are not show as “unrolled” (we have multiple layers)

# Translation Encoder/Decoder RNN

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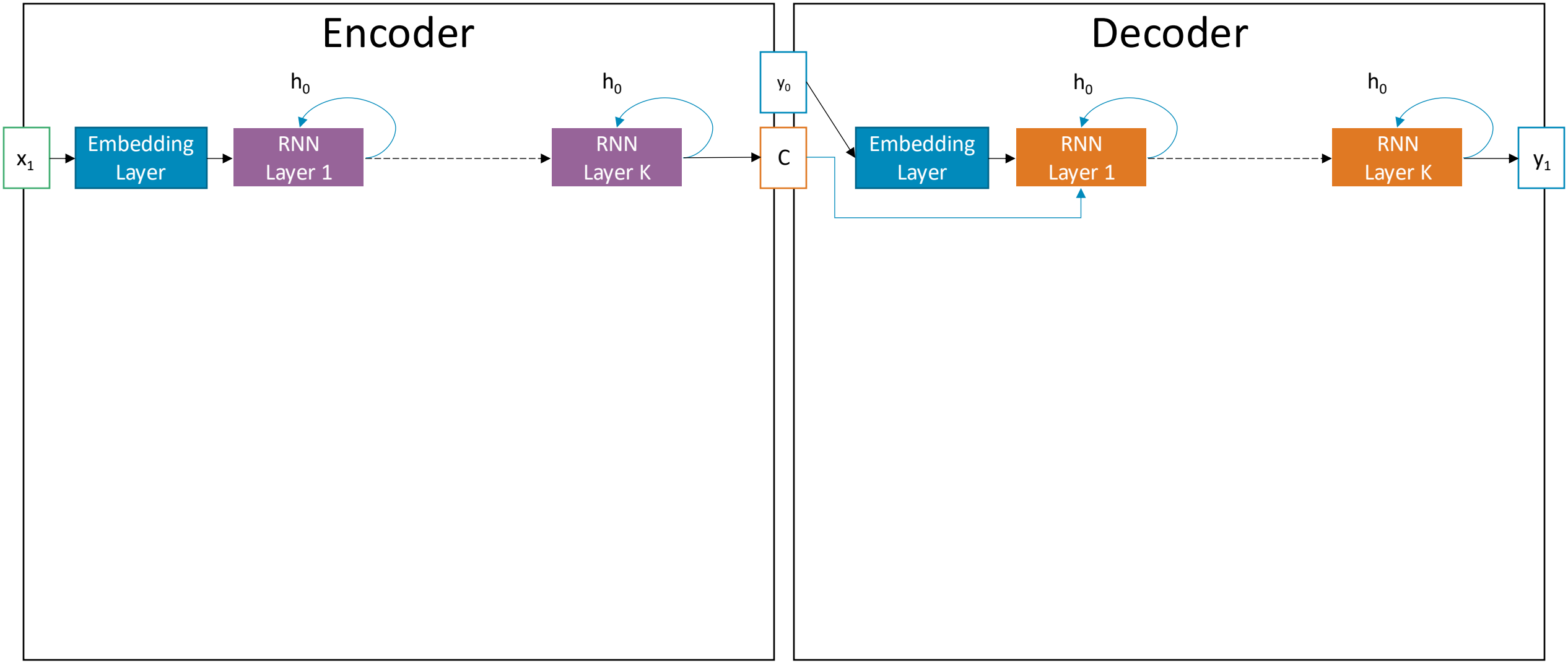
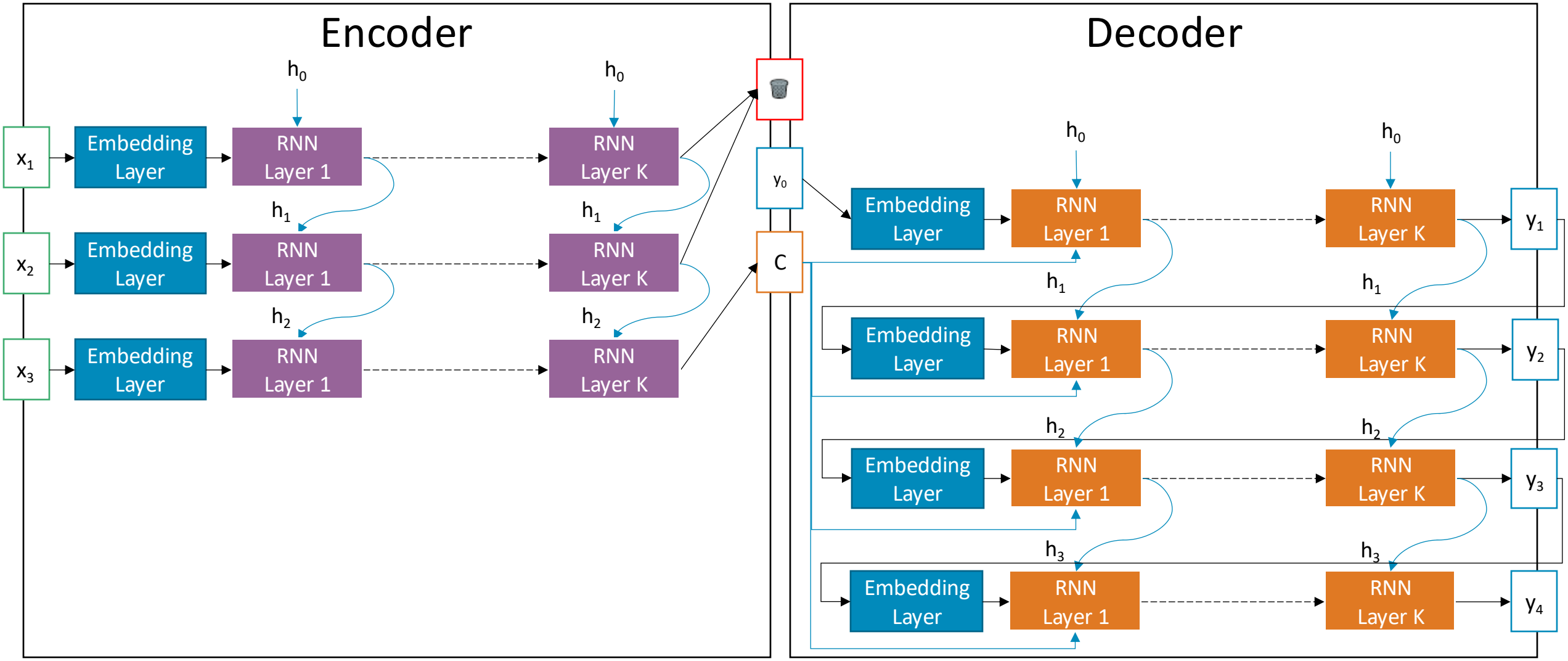


# Translation Encoder/Decoder RNN

Unrolled Version



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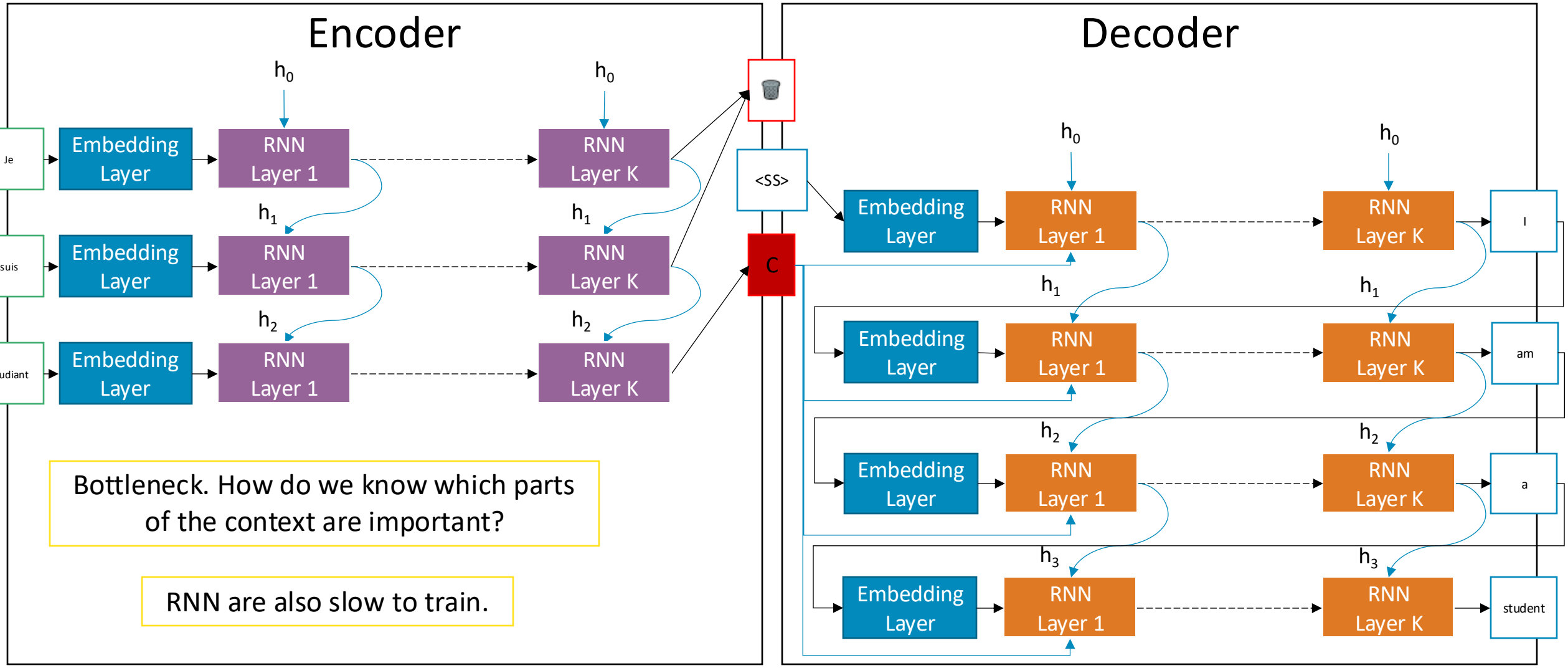
Unrolled Version



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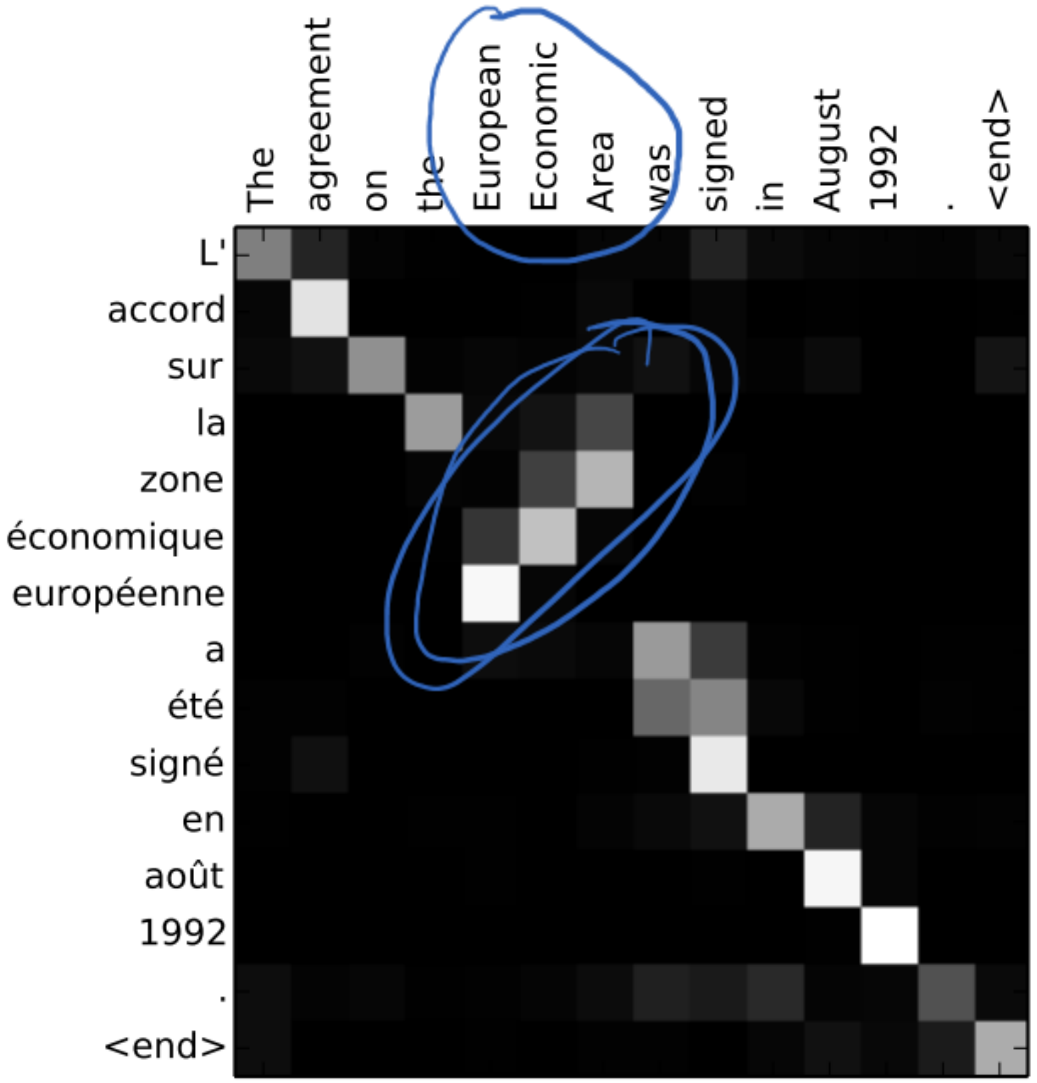
# Attention




The agreement on the European Economic Area was signed in August 1992.

L’ accord sur la zone économique européenne a été signé en août 1992.

[Submitted on 1 Sep 2014 (v1), last revised 19 May 2016 (this version, v7)]

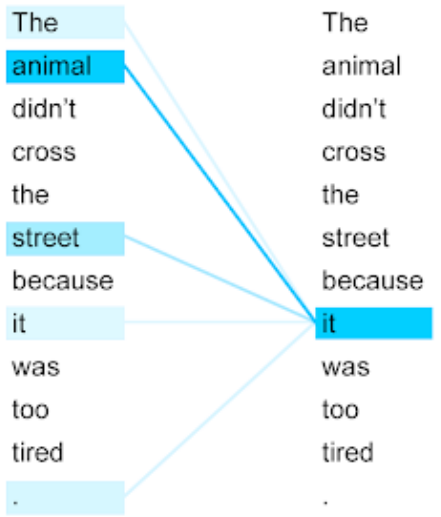
**Neural Machine Translation by Jointly Learning to Align and Translate**

Dzmitry Bahdanau, Kyunghyun Cho, Yoshua Bengio

# Coreference Resolution

The animal didn’t cross the street because it was too tired.

L’animal n’a pas traverse la rue parce qu’il était trop fatigue.



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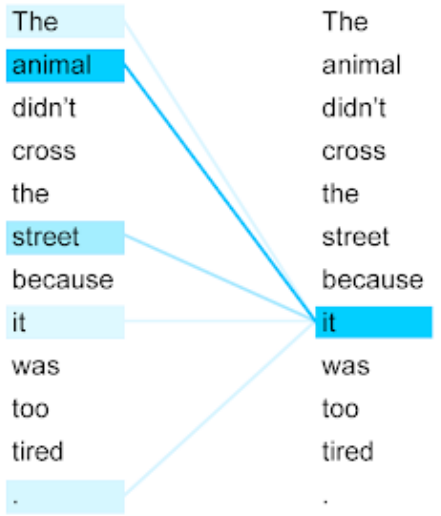


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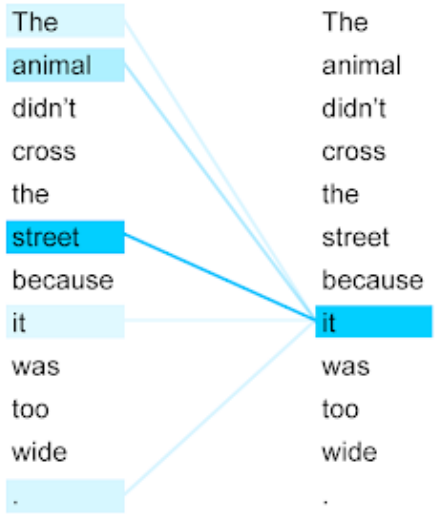
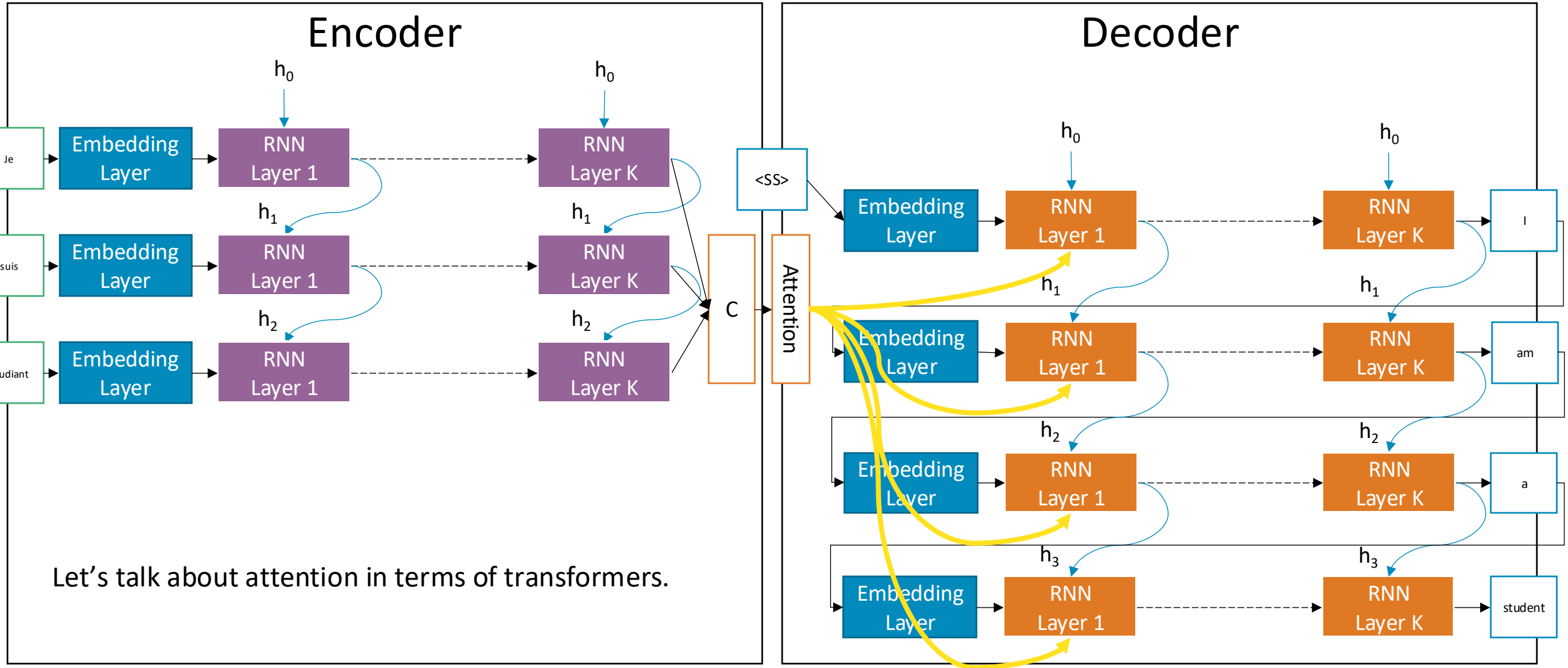


# Translation Encoder/Decoder RNN

Unrolled Version




Let's talk about attention in terms of transformers.

# Transformer Model Introduced In…

2017

**Attention Is All You Need**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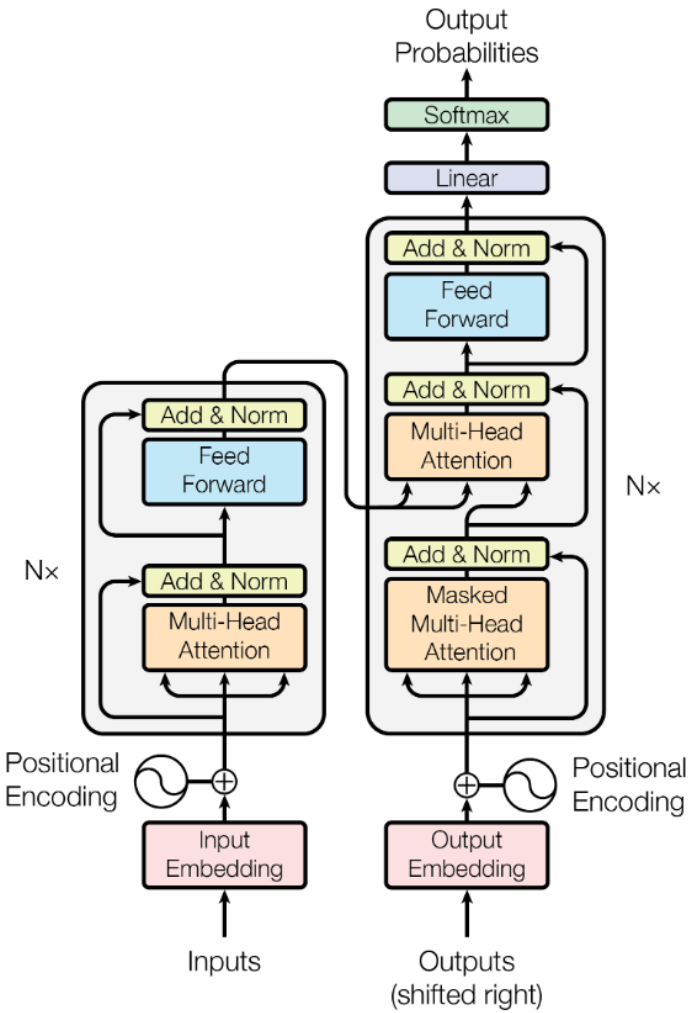
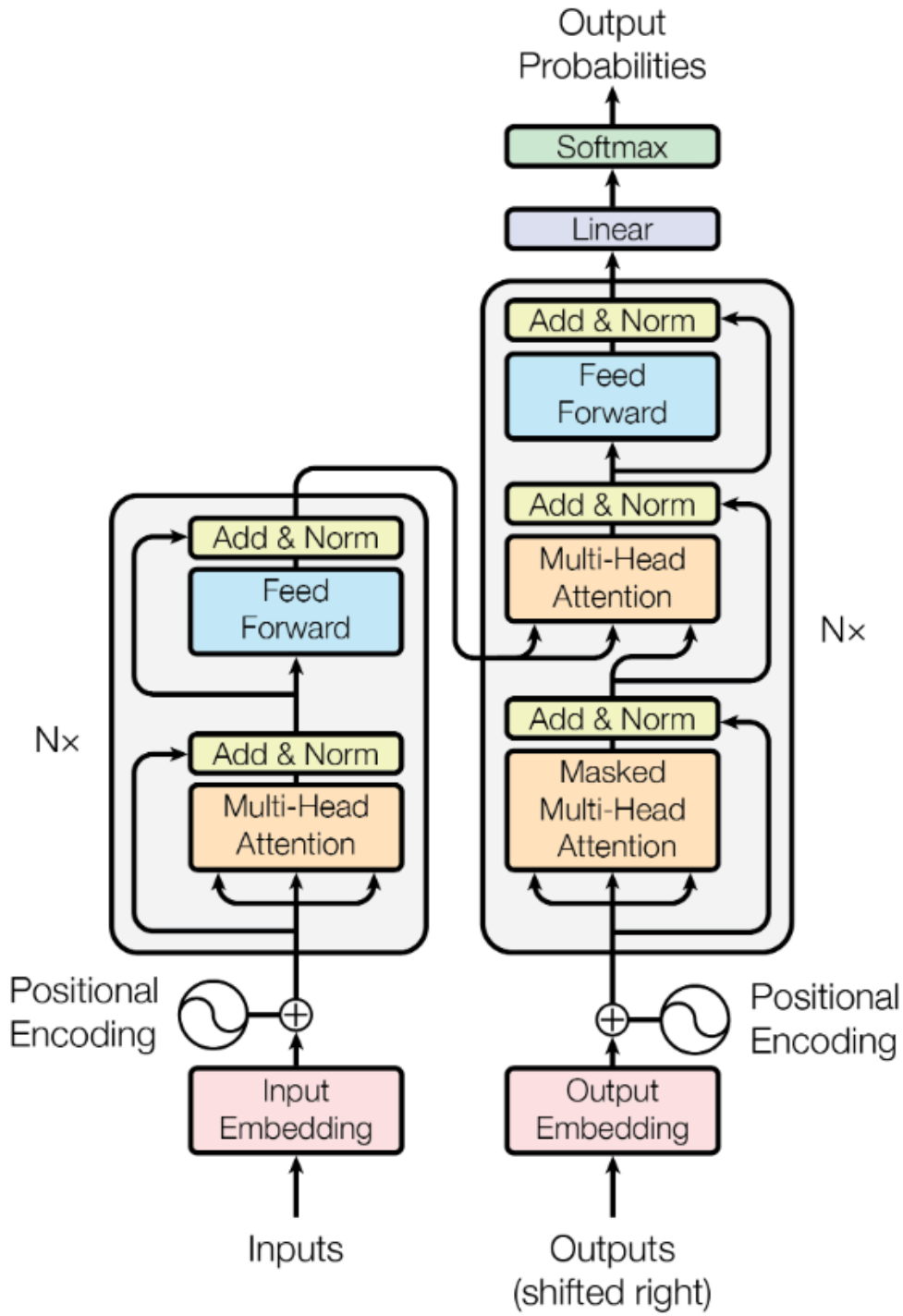



No recurrence. No convolutions.

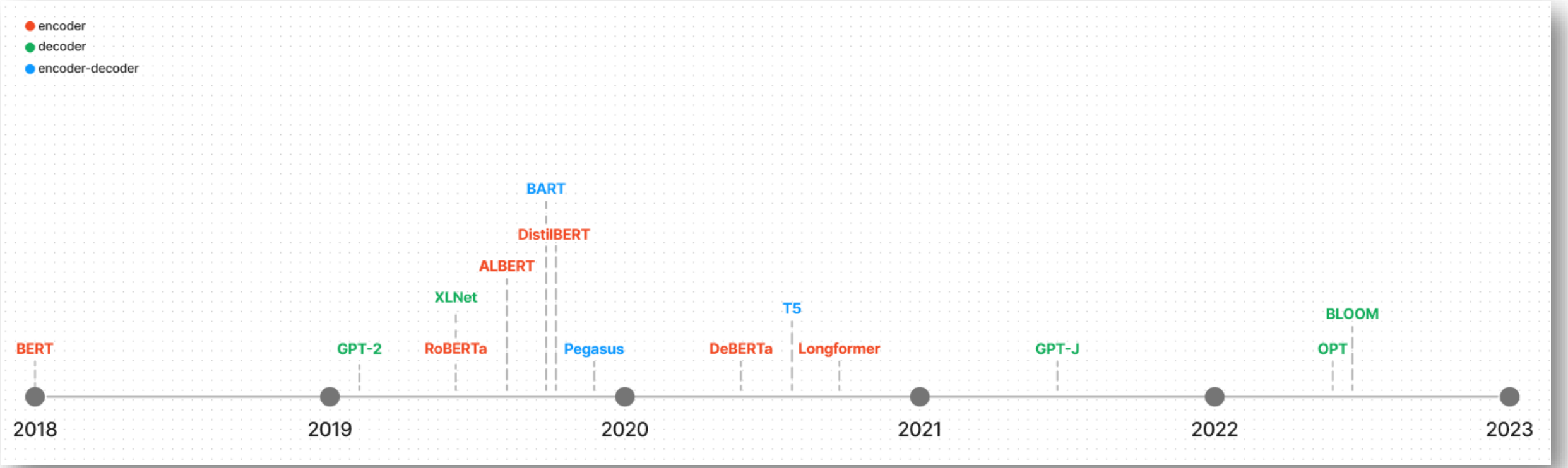
Better output. Faster to train.


Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
N×
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
N×
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Inputs
Outputs (shifted right)

# A Lot Happened All at Once

**Attention is All you Need**

Part of Advances in Neural Information Processing Systems 30 (NIPS 2017)




https://huggingface.co/docs/transformers/model_summary

# Common Transformer Applications

- Audio
  - Classification
  - Speech to text
- Vision
  - Classification
  - Object detection
  - Segmentation
  - Depth estimation
  - Captioning
- Text (NLP)
  - Classification
  - Question answering
  - Summarization
  - Translation
  - Named entity recognition
  - Language modeling
    - Masked (fill in the blank)
    - Generation
    - Completion

# Outline

- High-level comparison
  - Feed forward networks
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  - Transformer networks
- Remember the RNN encoder/decoder architecture
- Motivate the need for attention
- Explore the transformer architecture
  - Start with an example: Dialogue completion
  - Start with word indices as input
  - Dig through the transformer architecture
    - Embeddings (take indices as input)
    - Encoder
    - Decoder

# PyTorch Transformer Layers

| | |
|---|---|
| nn.Transformer | A transformer model. |
| nn.TransformerEncoder | TransformerEncoder is a stack of N encoder layers. |
| nn.TransformerDecoder | TransformerDecoder is a stack of N decoder layers. |
| nn.TransformerEncoderLayer | TransformerEncoderLayer is made up of self-attn and feedforward network. |
| nn.TransformerDecoderLayer | TransformerDecoderLayer is made up of self-attn, multi-head-attn and feedforward network. |

# torch.nn.Transformer

Transformer: A Novel Neural Network Architecture for Language Understanding

```
class Transformer(Module):
    def __init__(
        self,
        d_model: int = 512,
        nhead: int = 8,
        num_encoder_layers: int = 6,
        num_decoder_layers: int = 6,
        dim_feedforward: int = 2048,
        dropout: float = 0.1,
        activation: Union[str, Callable[[Tensor], Tensor]] = F.relu,
        custom_encoder: Optional[Any] = None,
        custom_decoder: Optional[Any] = None,
        layer_norm_eps: float = 1e-5,
        batch_first: bool = False,
        norm_first: bool = False,
        bias: bool = True,
        device=None,
        dtype=None,
    ) -> None:
```

the number of expected features in the encoder/decoder inputs

the number of heads in the multiheadattention models

the dimension of the feedforward network model

Default input and output tensor shapes (seq, batch, feature)

Batch Size

seq length

```
transformer_model = nn.Transformer(nhead=16, num_encoder_layers=12)
src = torch.rand((10, 32, 512))
tgt = torch.rand((20, 32, 512))
out = transformer_model(src, tgt)
```

# Example Application: Dialogue Completer

TRAIN: *But that is not for them to decide. All we have to decide is what to do with the time that is given us.*

INPUT: *But that is not for them to decide. All we have*

OUTPUT: *to decide is what to do with the time that is given us.*

*"But that is not for them to decide. All we have to decide is what to do with the time that is given us."*

# Transformer Procedure

1. Tokenization (convert input into tokens with arbitrary unique identifiers)
2. Transform tokens into embeddings (each token has a learned “meaning”)
3. Augment embeddings into positional embeddings
4. For each positional embedding

# Words to Vocabulary Indices

INPUT: <START>*But that is not for them to decide. All we have*<END>

OUTPUT: <START>*to decide is what to do with the time that is given us.*<END>

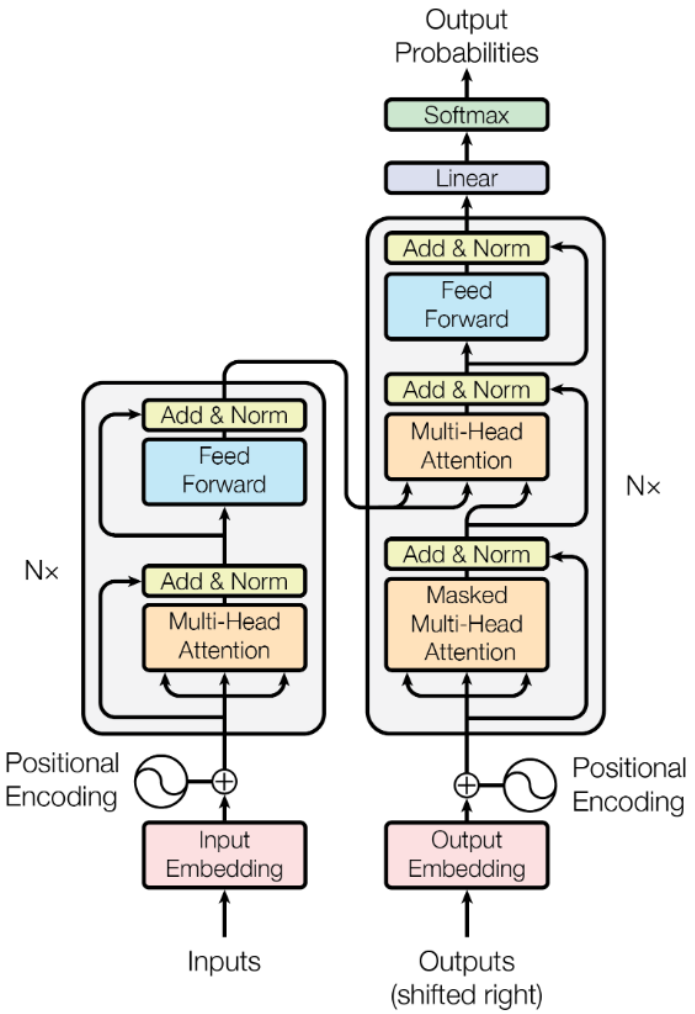
Input and output indices don’t always have to be the same.

# Constructing a Transformer

```
def make_transformer(
    src_vocab_size: int,
    tgt_vocab_size: int,
    d_model: int = 512,
    num_head: int = 8,
    num_layers: int = 6,
    d_feedforward: int = 2048,
    dropout_prob: float = 0.1,
    max_len: int = 5000,
):
    model = Transformer(
        PositionalEmbedding(src_vocab_size, d_model, dropout_prob, max_len),
        Encoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
        PositionalEmbedding(tgt_vocab_size, d_model, dropout_prob, max_len),
        Decoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
        Generator(d_model, tgt_vocab_size),
    )


    for p in model.parameters():
        if p.dim() > 1:
            nn.init.xavier_uniform_(p)


    return model
```




https://github.com/anthonyjclark/cs152sp23/blob/main/Lectures/13-Transformer.py

Adapted from: The Annotated Transformer

# Constructing a Transformer

```
def make_transformer(
    src_vocab_size: int,
    tgt_vocab_size: int,
    d_model: int = 512,
    num_head: int = 8,
    num_layers: int = 6,
    d_feedforward: int = 2048,
    dropout_prob: float = 0.1,
    max_len: int = 5000,
):
    model = Transformer(
        PositionalEmbedding(src_vocab_size, d_model, dropout_prob, max_len),
        Encoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
        PositionalEmbedding(tgt_vocab_size, d_model, dropout_prob, max_len),
        Decoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
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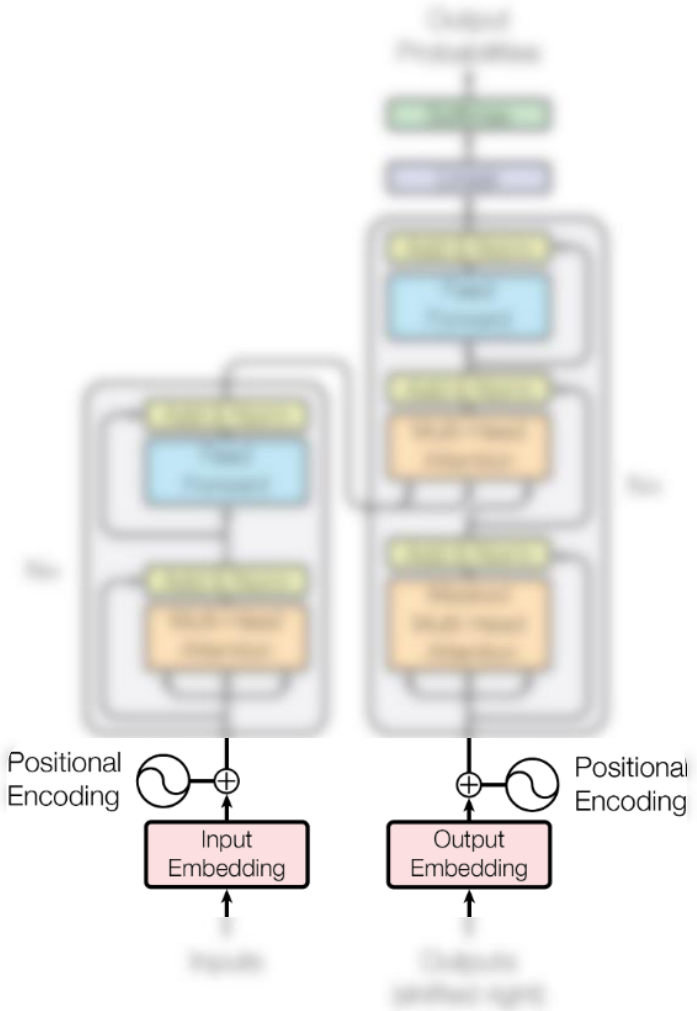


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# PositionalEmbedding

```python
class PositionalEncoding(nn.Module):
    def __init__(self, d_model: int, dropout_prob: float, max_len: int):
        super().__init__()
        self.dropout = nn.Dropout(dropout_prob)

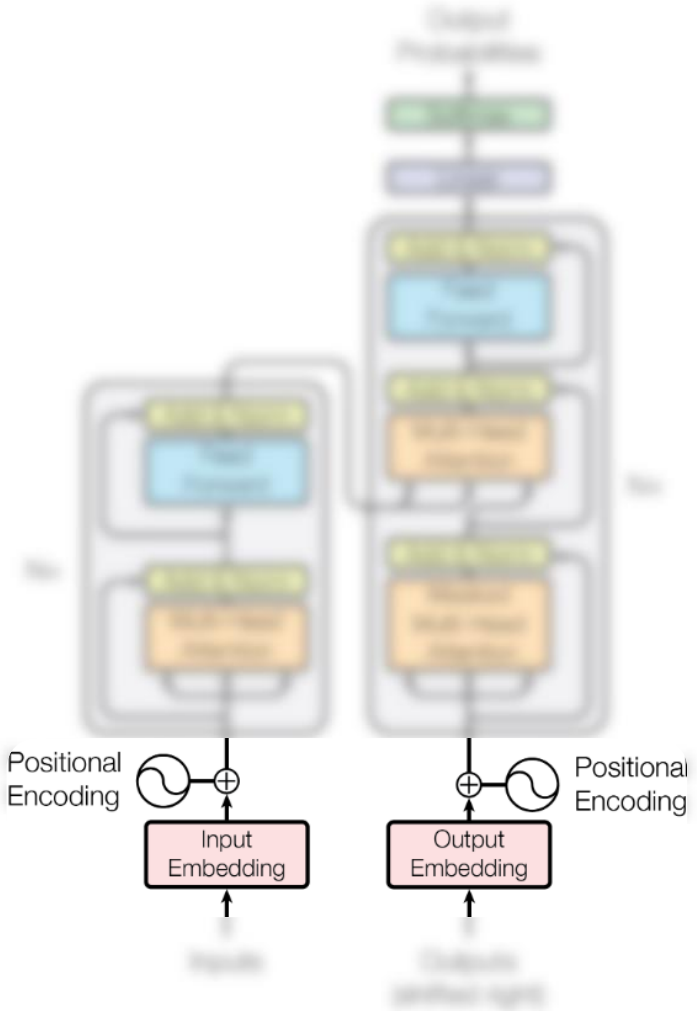
        # Compute the positional encodings once in log space
        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len).unsqueeze(1)
        div_term = torch.exp(torch.arange(0, d_model, 2) * -(log(10000.0) / d_model))
        pe[:, 0::2] = torch.sin(position * div_term)
        pe[:, 1::2] = torch.cos(position * div_term)
        pe = pe.unsqueeze(0)
        self.register_buffer("pe", pe)

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        x = x + self.pe[:, : x.size(1)].requires_grad_(False)
        return self.dropout(x)


class PositionalEmbedding(nn.Module):
    "Scaled embedding followed by a positional encoding."

    def __init__(self, vocab_size: int, d_model: int, dropout_prob: float, max_len: int):
        super().__init__()
        self.embed = ScaledEmbedding(d_model, vocab_size)
        self.positional_encoding = PositionalEncoding(d_model, dropout_prob, max_len)

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        return self.positional_encoding(self.embed(x))
```



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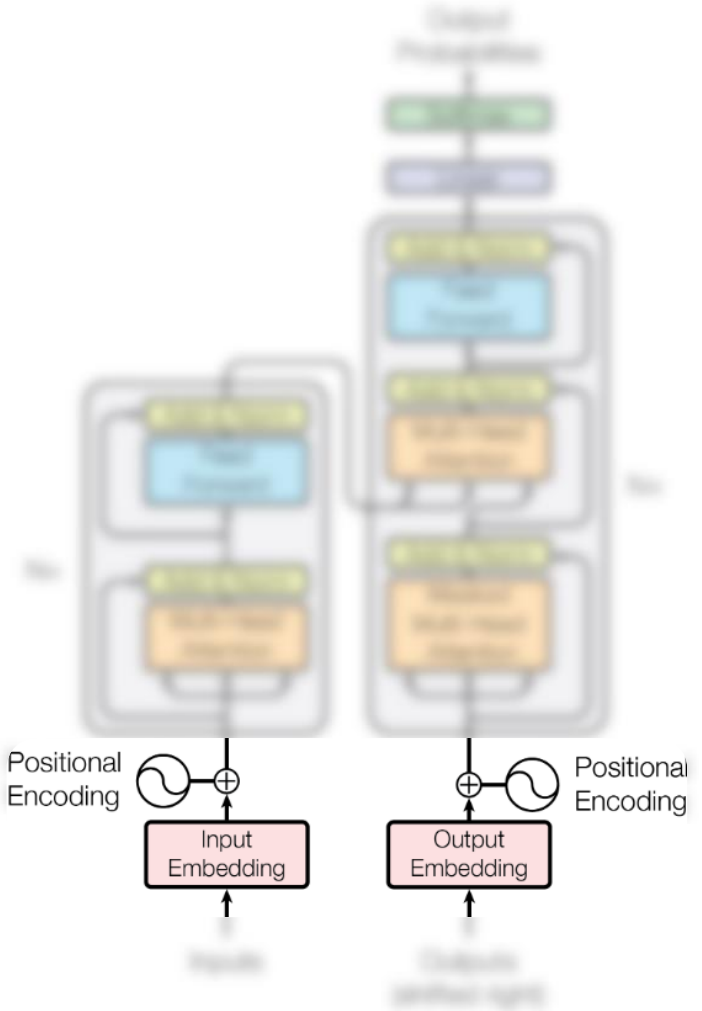


$$p_i = \sin\left(\frac{i}{10000^{\frac{2i}{d}}}\right) \forall \text{ even numbers}$$

$$p_i = \cos\left(\frac{i}{10000^{\frac{2i}{d}}}\right) \forall \text{ odd numbers}$$

# Constructing a Transformer

```
def make_transformer(
    src_vocab_size: int,
    tgt_vocab_size: int,
    d_model: int = 512,
    num_head: int = 8,
    num_layers: int = 6,
    d_feedforward: int = 2048,
    dropout_prob: float = 0.1,
    max_len: int = 5000,
):
    model = Transformer(
        PositionalEmbedding(src_vocab_size, d_model, dropout_prob, max_len),
        Encoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
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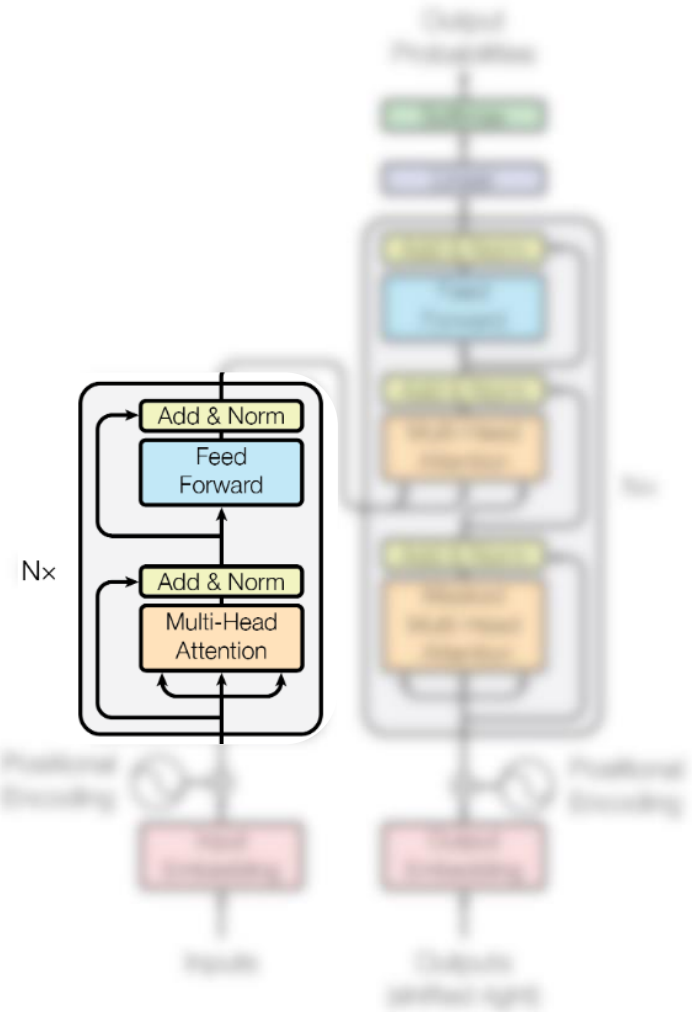


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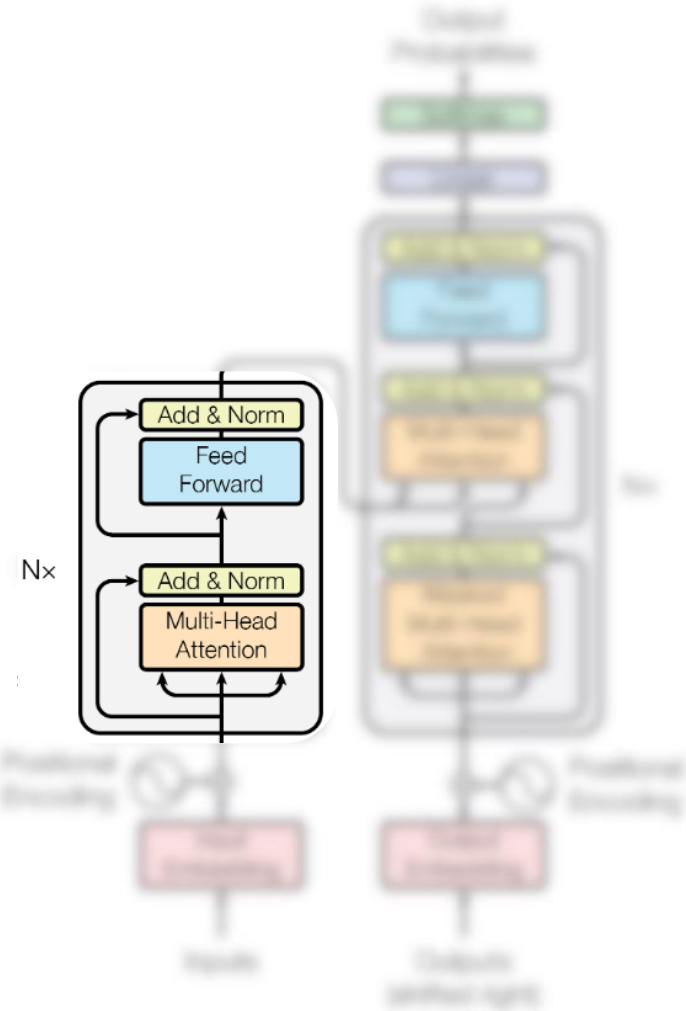
Adapted from: The Annotated Transformer

# Encoder

```python
class EncoderLayer(nn.Module):
    "An encoder layer is composed of self-attention and feed forward components."

    def __init__(self, d_model: int, num_head: int, ff_dim: int, dropout_prob: float):
        super().__init__()
        self.self_attention = MultiHeadedAttention(d_model, num_head, dropout_prob)
        self.feed_forward = PositionWiseFeedForward(d_model, ff_dim, dropout_prob)
        self.sublayer1 = SublayerConnection(d_model, dropout_prob)
        self.sublayer2 = SublayerConnection(d_model, dropout_prob)

    def forward(self, x: torch.Tensor, mask: torch.Tensor) -> torch.Tensor:
        x = self.sublayer1(x, lambda x: self.self_attention(x, x, x, mask))
        return self.sublayer2(x, self.feed_forward)


class Encoder(nn.Module):
    "An encoder block comprising N encoder layers."

    def __init__(self, d_model: int, num_head: int, num_layers: int, ff_dim: int, dropout_pr
        super().__init__()

        self.layers = nn.ModuleList()
        for _ in range(num_layers):
            self.layers.append(EncoderLayer(d_model, num_head, ff_dim, dropout_prob))

        self.norm = nn.LayerNorm(d_model)

    def forward(self, x: torch.Tensor, mask: torch.Tensor) -> torch.Tensor:
        for layer in self.layers:
            x = layer(x, mask)
        return self.norm(x)
```



# Coreference Resolution

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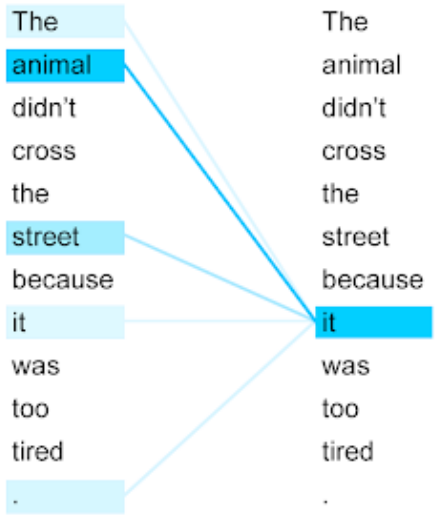


The animal didn’t cross the street because it was too wide.

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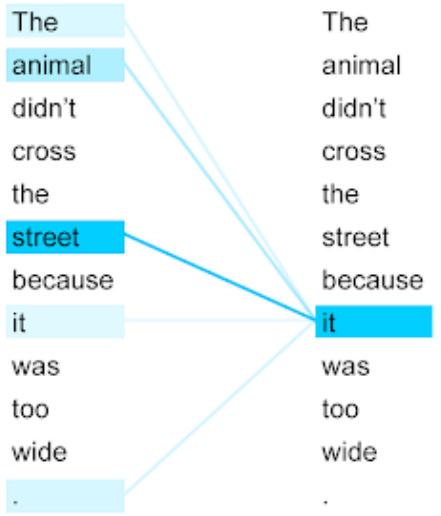
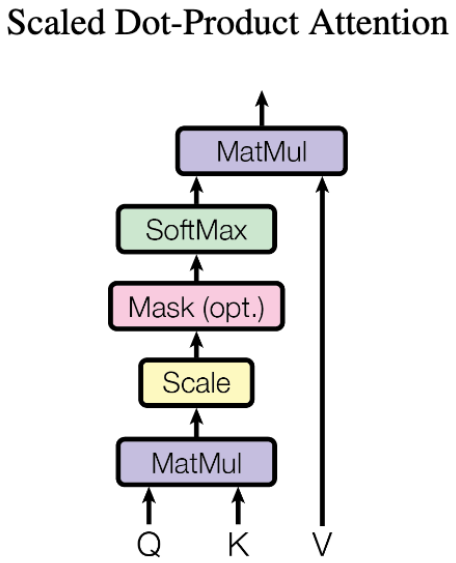
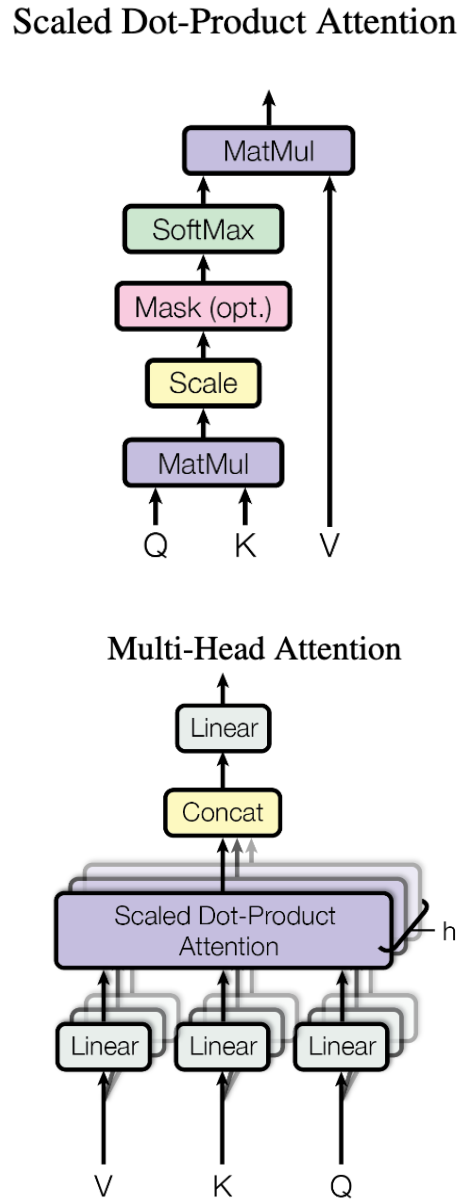


# Self-Attention

- Self-attention processes the entire sequence at once (not one at a time like an RNN)



# MultiHeadedAttention



```python
class MultiHeadedAttention(nn.Module):
    "Multi-Head Attention module."

    def __init__(self, d_model: int, num_head: int, dropout_prob: float):
        super().__init__()
        assert d_model % num_head == 0

        self.d_per_head = d_model // num_head
        self.num_head = num_head

        self.linear_layers = nn.ModuleList()
        for _ in range(4):
            self.linear_layers.append(nn.Linear(d_model, d_model))

        self.dropout = nn.Dropout(dropout_prob)

    def forward(
        self,
        query: torch.Tensor,
        key: torch.Tensor,
        value: torch.Tensor,
        mask: torch.Tensor | None = None,
    ) -> torch.Tensor:

        if mask is not None:
            mask = mask.unsqueeze(1)
```

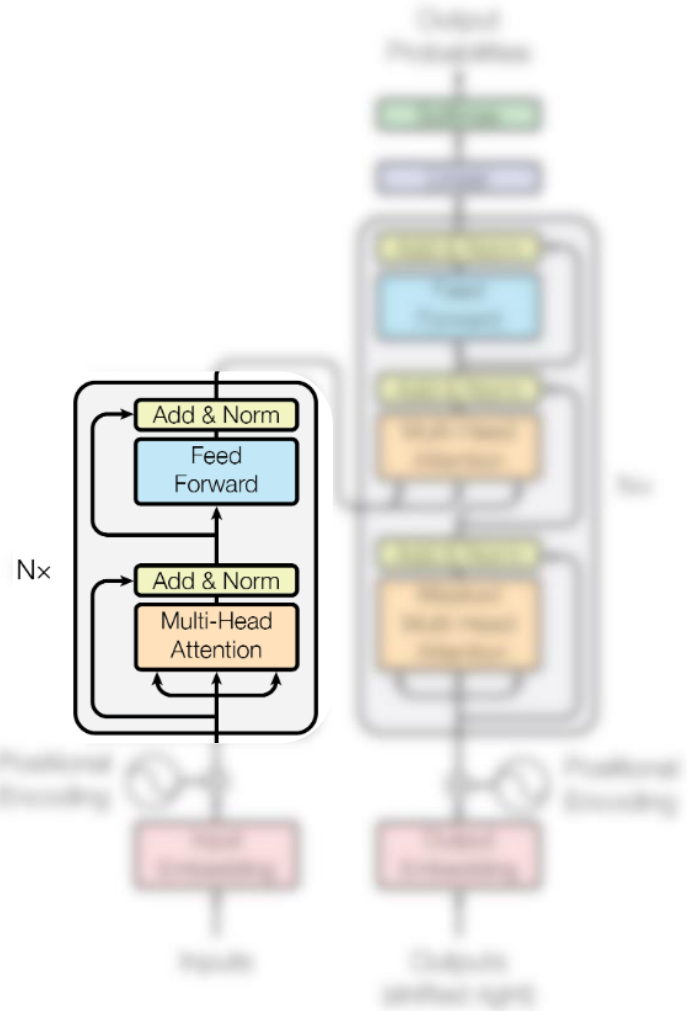
```
def forward(
    self,
    query: torch.Tensor,
    key: torch.Tensor,
    value: torch.Tensor,
    mask: torch.Tensor | None = None,
) -> torch.Tensor:

    if mask is not None:
        mask = mask.unsqueeze(1)
    num_batches = query.size(0)

    # (1) Do all the linear projections in batch from d_model => h x d_k
    query, key, value = [
        lin(x).view(num_batches, -1, self.num_head, self.d_per_head).transpose(1, 2)
        for lin, x in zip(self.linear_layers, (query, key, value))
    ]

    # (2) Apply attention on all the projected vectors in batch.
    # "Compute 'Scaled Dot Product Attention'"
    d_k = query.size(-1)
    scores = torch.matmul(query, key.transpose(-2, -1)) / sqrt(d_k)
    if mask is not None:
        scores = scores.masked_fill(mask == 0, -1e9)
    attention = scores.softmax(dim=-1)
    if self.dropout is not None:
```

```
# (2) Apply attention on all the projected vectors in batch.
# "Compute 'Scaled Dot Product Attention'"
d_k = query.size(-1)
scores = torch.matmul(query, key.transpose(-2, -1)) / sqrt(d_k)
if mask is not None:
    scores = scores.masked_fill(mask == 0, -1e9)
attention = scores.softmax(dim=-1)
if self.dropout is not None:
    attention = self.dropout(attention)
x = torch.matmul(attention, value)

# (3) "Concat" using a view and apply a final linear.
x = (
    x.transpose(1, 2)
    .contiguous()
    .view(num_batches, -1, self.num_head * self.d_per_head)
)
del query
del key
del value
return self.linear_layers[-1](x)
```

# PositionWiseFeedForward

```python
class PositionWiseFeedForward(nn.Module):
    "Implements feedforward neural network equation."

    def __init__(self, d_model: int, ff_dim: int, dropout_prob: float):
        super().__init__()
        self.w1 = nn.Linear(d_model, ff_dim)
        self.w2 = nn.Linear(ff_dim, d_model)
        self.dropout = nn.Dropout(dropout_prob)


    def forward(self, x: torch.Tensor) -> torch.Tensor:
        return self.w2(self.dropout(self.w1(x).relu()))
```

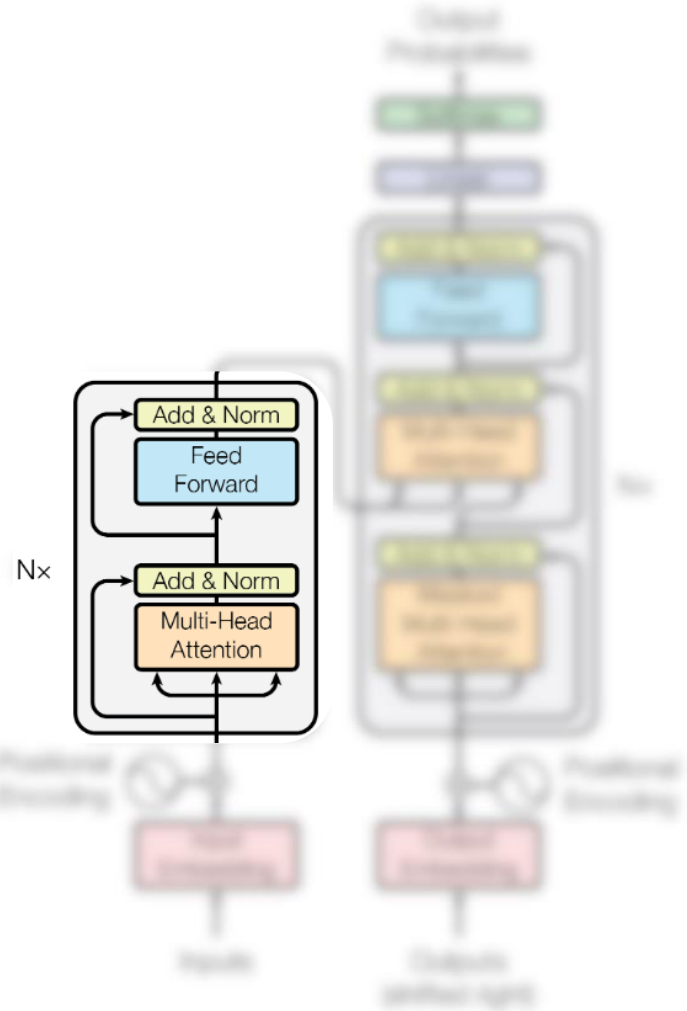
```python
class EncoderLayer(nn.Module):
    "An encoder layer is composed of self-attention and feed forward components."

    def __init__(self, d_model: int, num_head: int, ff_dim: int, dropout_prob: float):
        super().__init__()
        self.self_attention = MultiHeadedAttention(d_model, num_head, dropout_prob)
        self.feed_forward = PositionWiseFeedForward(d_model, ff_dim, dropout_prob)
        self.sublayer1 = SublayerConnection(d_model, dropout_prob)
        self.sublayer2 = SublayerConnection(d_model, dropout_prob)

    def forward(self, x: torch.Tensor, mask: torch.Tensor) -> torch.Tensor:
        x = self.sublayer1(x, lambda x: self.self_attention(x, x, x, mask))
        return self.sublayer2(x, self.feed_forward)
```



# SublayerConnection

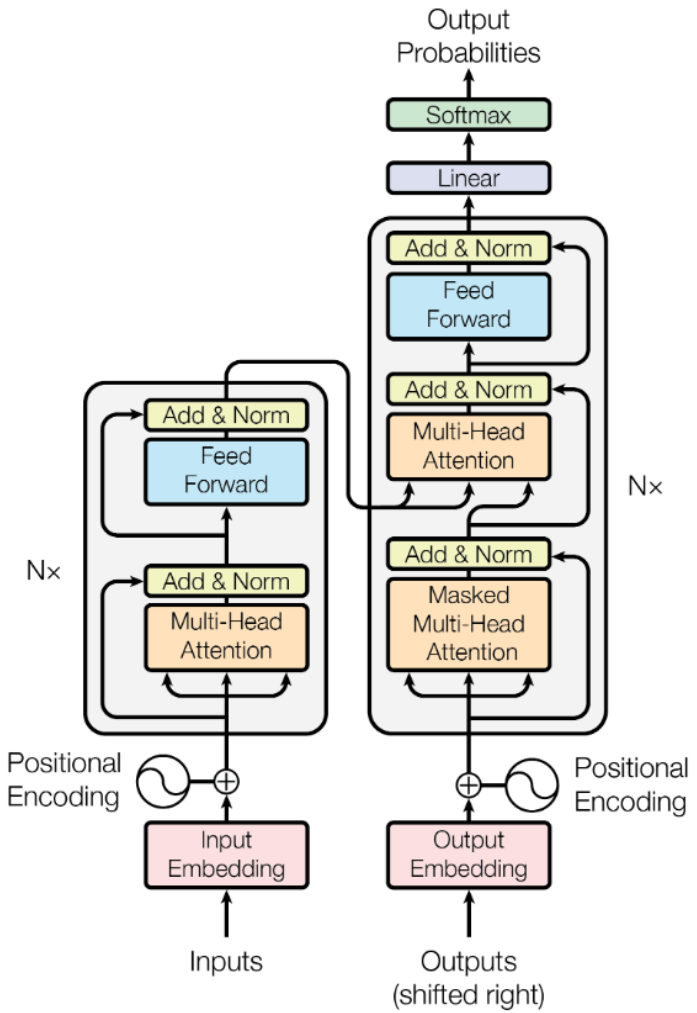
```python
class SublayerConnection(nn.Module):
    "A residual connection followed by a LayerNorm."


    def __init__(self, d_model: int, dropout_prob: float):
        super().__init__()
        self.layernorm = nn.LayerNorm(d_model)
        self.dropout = nn.Dropout(dropout_prob)


    def forward(self, x: torch.Tensor, sublayer: nn.Module) -> torch.Tensor:
        return x + self.dropout(sublayer(self.layernorm(x)))
```

```python
class EncoderLayer(nn.Module):
    "An encoder layer is composed of self-attention and feed forward components."

    def __init__(self, d_model: int, num_head: int, ff_dim: int, dropout_prob: float):
        super().__init__()
        self.self_attention = MultiHeadedAttention(d_model, num_head, dropout_prob)
        self.feed_forward = PositionWiseFeedForward(d_model, ff_dim, dropout_prob)
        self.sublayer1 = SublayerConnection(d_model, dropout_prob)
        self.sublayer2 = SublayerConnection(d_model, dropout_prob)

    def forward(self, x: torch.Tensor, mask: torch.Tensor) -> torch.Tensor:
        x = self.sublayer1(x, lambda x: self.self_attention(x, x, x, mask))
        return self.sublayer2(x, self.feed_forward)
```



# Constructing a Transformer

```
def make_transformer(
    src_vocab_size: int,
    tgt_vocab_size: int,
    d_model: int = 512,
    num_head: int = 8,
    num_layers: int = 6,
    d_feedforward: int = 2048,
    dropout_prob: float = 0.1,
    max_len: int = 5000,
):
    model = Transformer(
        PositionalEmbedding(src_vocab_size, d_model, dropout_prob, max_len),
        Encoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
        PositionalEmbedding(tgt_vocab_size, d_model, dropout_prob, max_len),
        Decoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
        Generator(d_model, tgt_vocab_size),
    )


    for p in model.parameters():
        if p.dim() > 1:
            nn.init.xavier_uniform_(p)


    return model
```

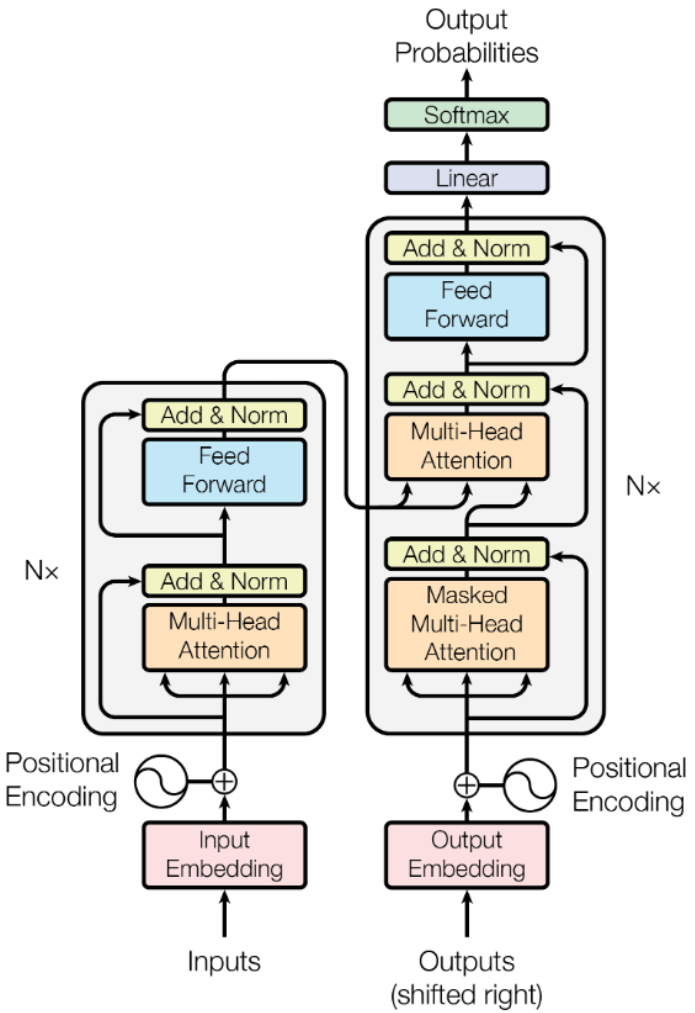



https://github.com/anthonyjclark/cs152sp23/blob/main/Lectures/13-Transformer.py

Adapted from: The Annotated Transformer

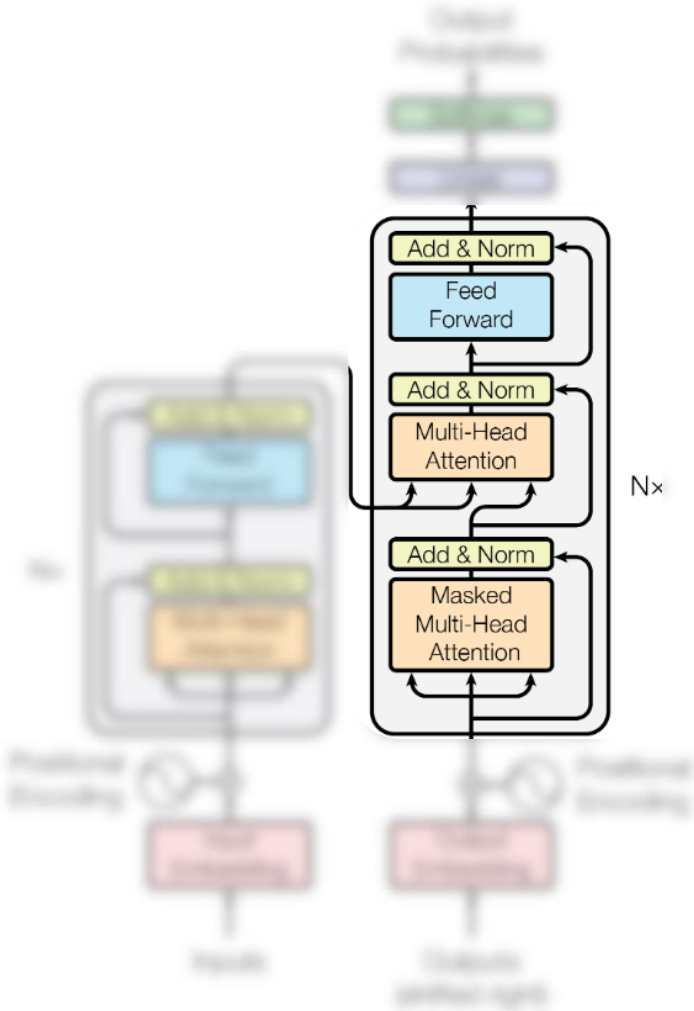
# Decoder

```python
class DecoderLayer(nn.Module):
    "A decode layer comprises self and source attention and feed forward components."
    def __init__(self, d_model: int, num_head: int, ff_dim: int, dropout_prob: float):
        super().__init__()
        self.self_attention = MultiHeadedAttention(d_model, num_head, dropout_prob)
        self.src_attention = MultiHeadedAttention(d_model, num_head, dropout_prob)
        self.feed_forward = PositionWiseFeedForward(d_model, ff_dim, dropout_prob)
        self.sublayer1 = SublayerConnection(d_model, dropout_prob)
        self.sublayer2 = SublayerConnection(d_model, dropout_prob)
        self.sublayer3 = SublayerConnection(d_model, dropout_prob)

    def forward(self, x: torch.Tensor, memory: torch.Tensor, src_mask: torch.Tensor, tgt_ma
        m = memory
        x = self.sublayer1(x, lambda x: self.self_attention(x, x, x, tgt_mask))
        x = self.sublayer2(x, lambda x: self.src_attention(x, m, m, src_mask))
        return self.sublayer3(x, self.feed_forward)

class Decoder(nn.Module):
    "A decoder block comprising N layers with masking."
    def __init__(self, d_model: int, num_head: int, num_layers: int, ff_dim: int, dropout_
        super().__init__()
        self.layers = nn.ModuleList()
        for _ in range(num_layers):
            self.layers.append(DecoderLayer(d_model, num_head, ff_dim, dropout_prob))

        self.norm = nn.LayerNorm(d_model)

    def forward(self, x: torch.Tensor, memory: torch.Tensor, src_mask: torch.Tensor, tgt_ma
        for layer in self.layers:
            x = layer(x, memory, src_mask, tgt_mask)
        return self.norm(x)
```



# Decoder

```python
class DecoderLayer(nn.Module):
    "A decode layer comprises self and source attention and feed forward components."
    def __init__(self, d_model: int, num_head: int, ff_dim: int, dropout_prob: float):
        super().__init__()
        self.self_attention = MultiHeadedAttention(d_model, num_head, dropout_prob)
        self.src_attention = MultiHeadedAttention(d_model, num_head, dropout_prob)
        self.feed_forward = PositionWiseFeedForward(d_model, ff_dim, dropout_prob)
        self.sublayer1 = SublayerConnection(d_model, dropout_prob)
        self.sublayer2 = SublayerConnection(d_model, dropout_prob)
        self.sublayer3 = SublayerConnection(d_model, dropout_prob)

    def forward(self, x: torch.Tensor, memory: torch.Tensor, src_mask: torch.Tensor, tgt_ma
        m = memory
        x = self.sublayer1(x, lambda x: self.self_attention(x, x, x, tgt_mask))
        x = self.sublayer2(x, lambda x: self.src_attention(x, m, m, src_mask))
        return self.sublayer3(x, self.feed_forward)

class Decoder(nn.Module):
    "A decoder block comprising N layers with masking."
    def __init__(self, d_model: int, num_head: int, num_layers: int, ff_dim: int, dropout_
        super().__init__()
        self.layers = nn.ModuleList()
        for _ in range(num_layers):
            self.layers.append(DecoderLayer(d_model, num_head, ff_dim, dropout_prob))

        self.norm = nn.LayerNorm(d_model)

    def forward(self, x: torch.Tensor, memory: torch.Tensor, src_mask: torch.Tensor, tgt_ma
        for layer in self.layers:
            x = layer(x, memory, src_mask, tgt_mask)
        return self.norm(x)
```



# Example Application: Dialogue Completer

TRAIN: *But that is not for them to decide. All we have to decide is what to do with the time that is given us.*

INPUT: *But that is not for them to decide. All we have*

OUTPUT: *to decide is what to do with the time that is given us.*

*"But that is not for them to decide. All we have to decide is what to do with the time that is given us."*

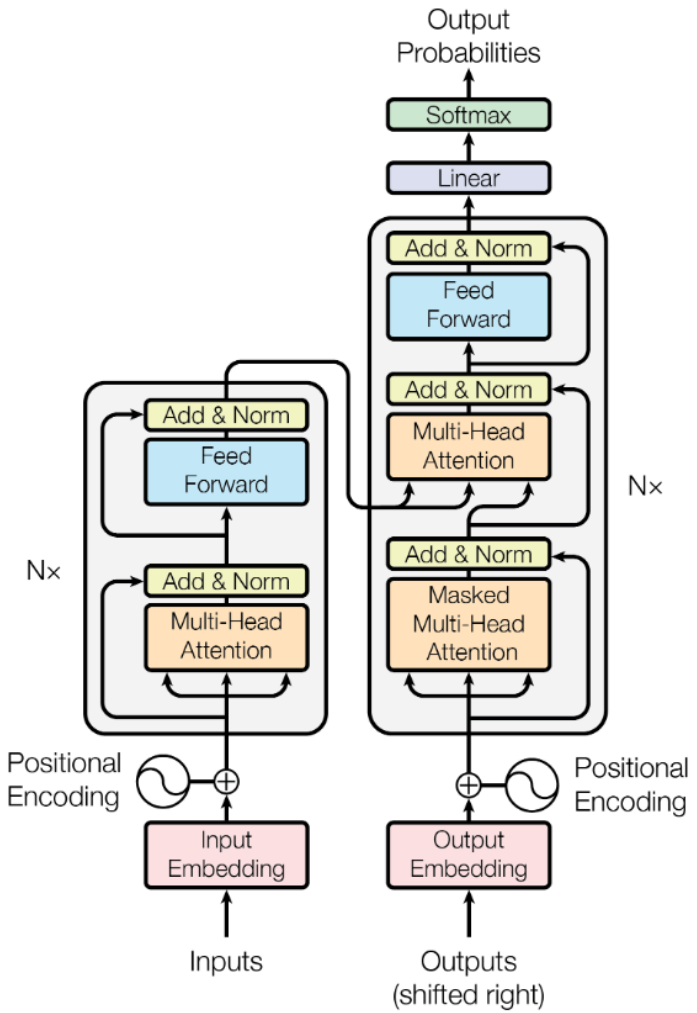
# Masking

INPUT: <START>*But that is not for them to decide. All we have*<END>

OUTPUT: <START>*to decide is what to do with the time that is given us.*<END>

# Constructing a Transformer

```
def make_transformer(
    src_vocab_size: int,
    tgt_vocab_size: int,
    d_model: int = 512,
    num_head: int = 8,
    num_layers: int = 6,
    d_feedforward: int = 2048,
    dropout_prob: float = 0.1,
    max_len: int = 5000,
):
    model = Transformer(
        PositionalEmbedding(src_vocab_size, d_model, dropout_prob, max_len),
        Encoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
        PositionalEmbedding(tgt_vocab_size, d_model, dropout_prob, max_len),
        Decoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
        Generator(d_model, tgt_vocab_size),
    )


    for p in model.parameters():
        if p.dim() > 1:
            nn.init.xavier_uniform_(p)


    return model
```

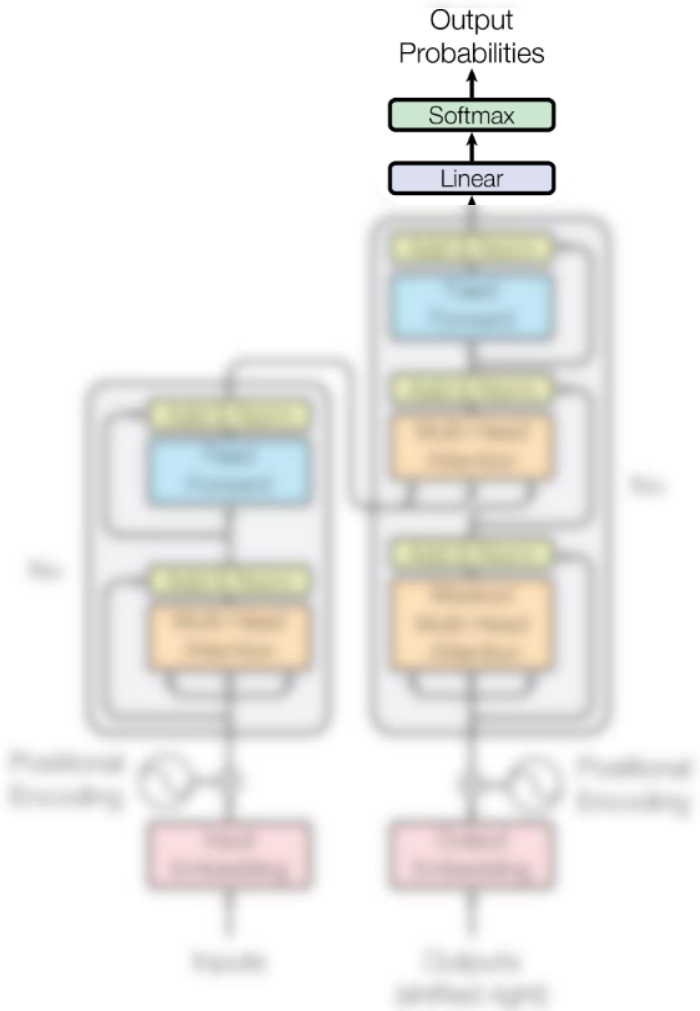



https://github.com/anthonyjclark/cs152sp23/blob/main/Lectures/13-Transformer.py

Adapted from: The Annotated Transformer

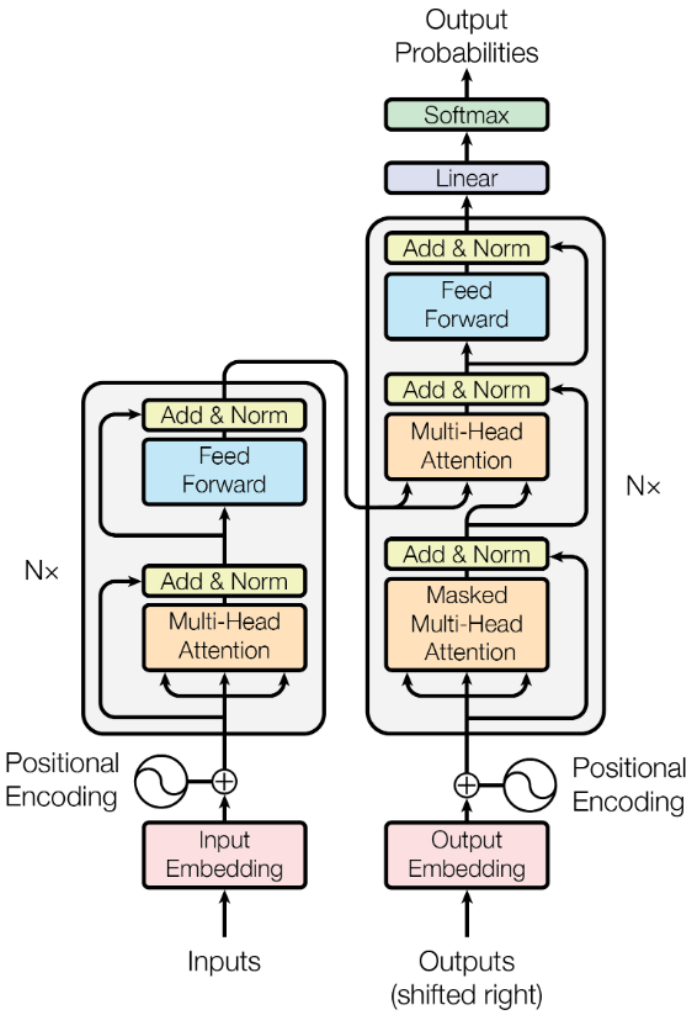
# Generator

```python
class Generator(nn.Module):
    "Define standard linear + softmax generation step."

    def __init__(self, d_model: int, vocab_size: int):
        super().__init__()
        self.linear = nn.Linear(d_model, vocab_size)

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        return log_softmax(self.linear(x), dim=-1)
```



# Constructing a Transformer

```
def make_transformer(
    src_vocab_size: int,
    tgt_vocab_size: int,
    d_model: int = 512,
    num_head: int = 8,
    num_layers: int = 6,
    d_feedforward: int = 2048,
    dropout_prob: float = 0.1,
    max_len: int = 5000,
):
    model = Transformer(
        PositionalEmbedding(src_vocab_size, d_model, dropout_prob, max_len),
        Encoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
        PositionalEmbedding(tgt_vocab_size, d_model, dropout_prob, max_len),
        Decoder(d_model, num_head, num_layers, d_feedforward, dropout_prob),
        Generator(d_model, tgt_vocab_size),
    )


    for p in model.parameters():
        if p.dim() > 1:
            nn.init.xavier_uniform_(p)


    return model
```




https://github.com/anthonyjclark/cs152sp23/blob/main/Lectures/13-Transformer.py

Adapted from: The Annotated Transformer

# Summary

- Recurrent neural networks were the best performing for sequence tasks.
- They have an advantage of arbitrary input and output sequence lengths.
- Transformers have fixed input and output sequence lengths (with padding).
- But, transformers outperform RNNs on (probably) all sequence tasks.
- Transformers do not maintain any internal memory.
- Most (if not all) large language models (LLMs) are built on transformers.

# Resources

- Visualizing A Neural Machine Translation Model
- Transformer: A Novel Neural Network Architecture for Language Understanding
- A Visual Guide to Transformers Neural Networks: step by step explanation - YouTube
- L19.4.1 Using Attention Without the RNN -- A Basic Form of Self-Attention - YouTube
- karpathy/nanoGPT: The simplest, fastest repository for training/finetuning medium-sized GPTs.
- karpathy/minGPT: A minimal PyTorch re-implementation of the OpenAI GPT (Generative Pretrained Transformer) training
- karpathy/minGPT: A minimal PyTorch re-implementation of the OpenAI GPT (Generative Pretrained Transformer) training
- The Annotated Transformer