AI VIETNAM
All-in-One Course

From Text Generation to Machine Translation

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Ph.D. in Computer Science

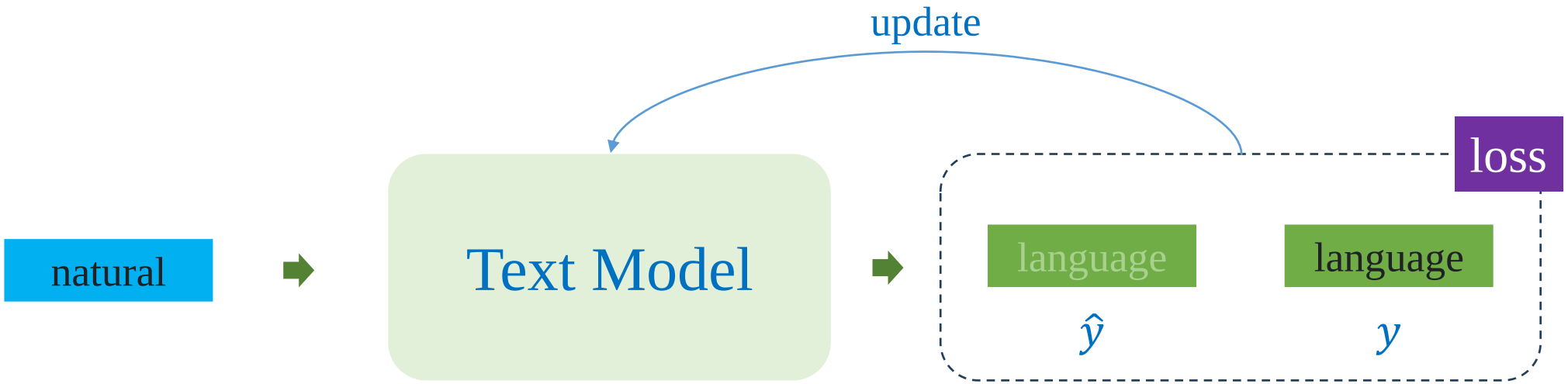
Year 2024

Outline

- Text Generation Using Transformer
- An improved Approach to Text Generation
- Machine Translation Using RNN
- Machine Translation Using Transformer

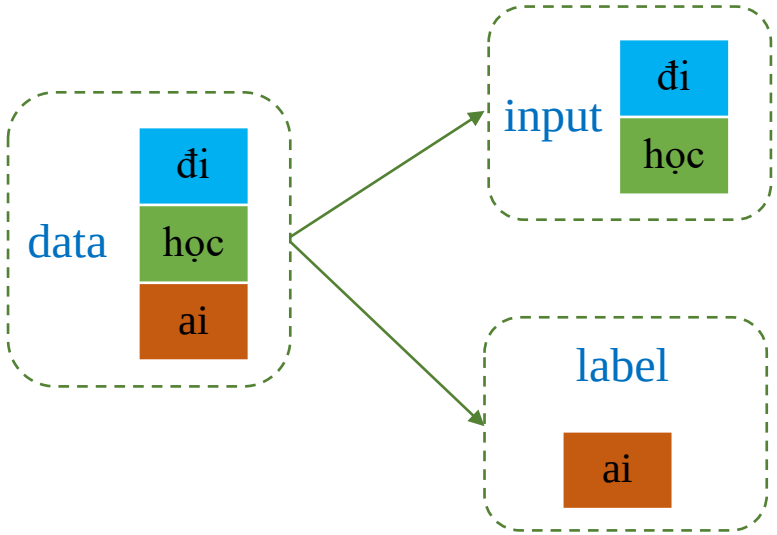
Self-Supervision Using Text Data

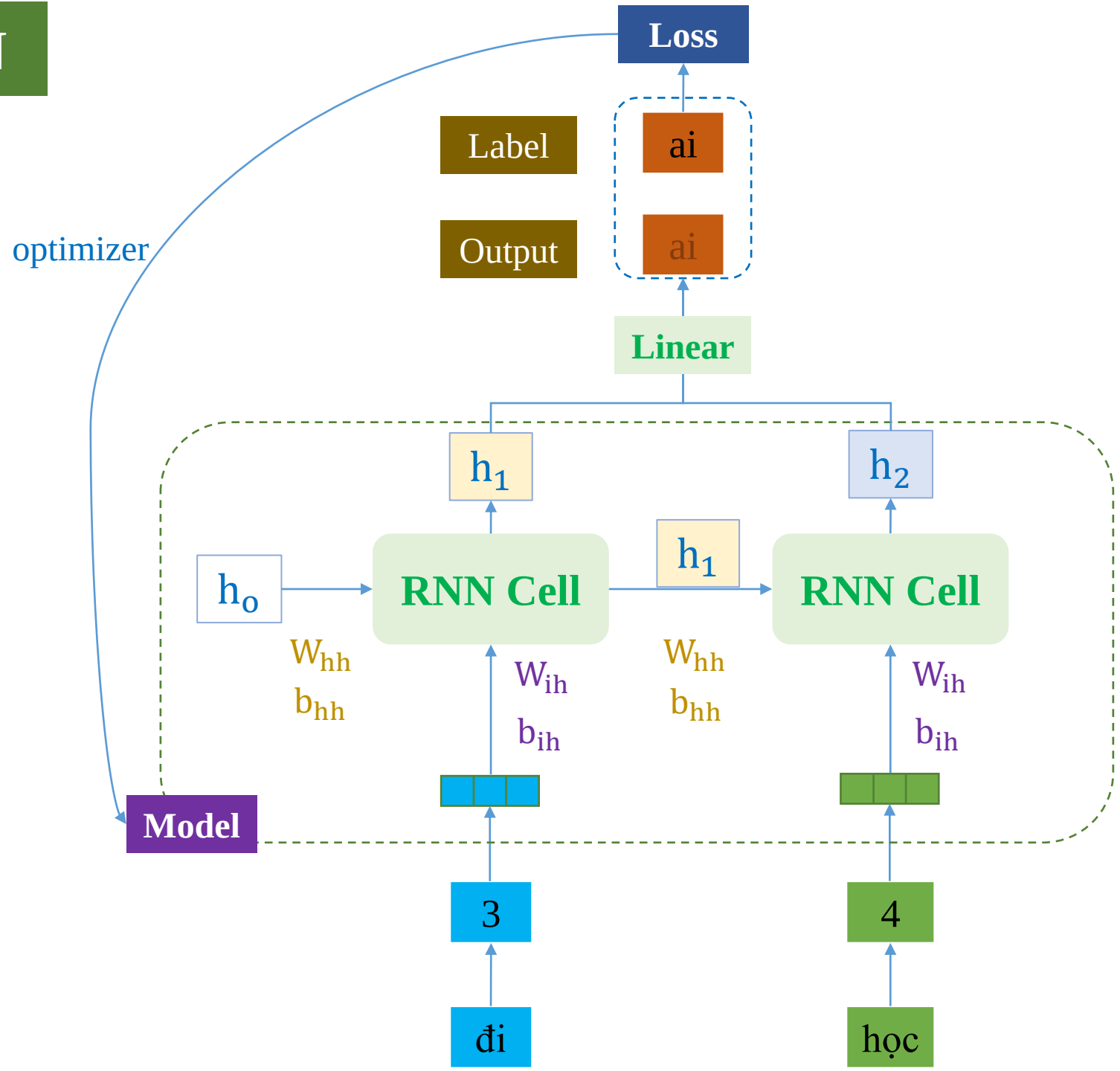
❖ **Encode the sequential relationship**



Implementation Using RNN

Using all the features





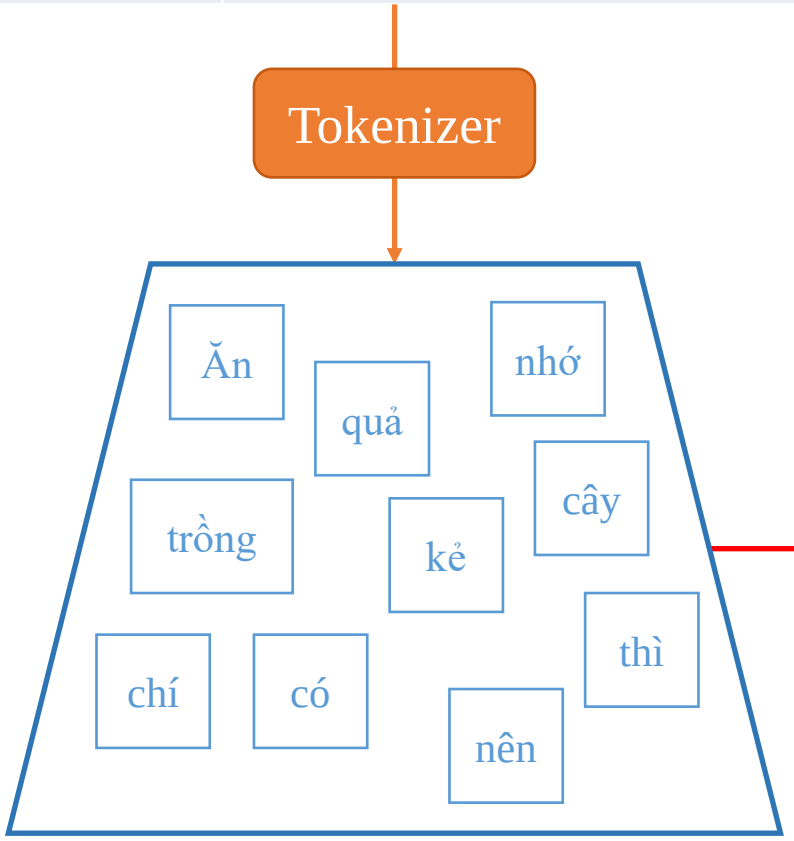
Example

Copus

Id	Text
0	Ăn quả nhớ kẻ trồng cây
1	Có chí thì nên

```
tokenizer = get_tokenizer('basic_english')
def yield_tokens(examples):
    for text in examples:
        yield tokenizer(text)

# Create vocabulary
vocab_size = 13
build_vocab_from_iterator(yield_tokens(corpus),
          max_tokens=vocab_size,
          specials=["<unk>", "<pad>", "<sos>"])
```



Build vocab

Add

vocab_size = 13

Vocab

Token	Id
<unk>	0
<pad>	1
<sos>	2
chí	3
cây	4
có	5
kẻ	6
nhớ	7
nên	8
quả	9
thì	10
trồng	11
ăn	12

Id	Text
0	Ăn quả nhớ kẻ trồng cây
1	Có chí thì nên

Input tokens	Target token
<sos>	Ăn
<sos> Ăn	quả
<sos> Ăn quả	nhớ
<sos> Ăn quả nhớ	kẻ
<sos> Ăn quả nhớ kẻ	trồng
<sos> Ăn quả nhớ kẻ trồng	cây
<sos>	Có
<sos> Có	chí
<sos> Có chí	thì
<sos> Có chí thì	nên

Next token prediction dataset

```python
# create the next-token-prediction dataset
corpus = [
    "ăn quả nhớ kẻ trồng cây",
    "có chí thì nên"
]

data_x = []
data_y = []
for vector in corpus:
    vector = vector.split()

    for i in range(len(vector)):
        data_x.append(['<sos>'] + vector[:i])
        data_y.append(vector[i])
```

Token	Id
<unk>	0
<pad>	1
<sos>	2
chí	3
cây	4
có	5
kẻ	6
nhớ	7
nên	8
quả	9
thì	10
trồng	11
ăn	12

vocab_size = 13

Example

Id	Text
0	Ăn quả nhớ kẻ trồng cây
1	Có chí thì nên

Input tokens	Target token
<sos>	Ăn
<sos> Ăn	quả
<sos> Ăn quả	nhớ
<sos> Ăn quả nhớ	kẻ
<sos> Ăn quả nhớ kẻ	trồng
<sos> Ăn quả nhớ kẻ trồng	cây
<sos>	Có
<sos> Có	chí
<sos> Có chí	thì
<sos> Có chí thì	nên

Next token prediction dataset

Token	Id
<unk>	0
<pad>	1
<sos>	2
chí	3
cây	4
có	5
kẻ	6
nhớ	7
nên	8
quả	9
thì	10
trồng	11
ăn	12

Vocab

padding

sequence_length = 6

data_x_ids	data_y_ids
[2, 1, 1, 1, 1, 1]	12
[2, 12, 1, 1, 1, 1]	9
[2, 12, 9, 1, 1, 1]	7
[2, 12, 9, 7, 1, 1]	6
[2, 12, 9, 7, 6, 1]	11
[2, 12, 9, 7, 6, 11]	4
[2, 1, 1, 1, 1, 1]	5
[2, 5, 1, 1, 1, 1]	3
[2, 5, 3, 1, 1, 1]	10
[2, 5, 3, 10, 1, 1]	8

Training data

Example

Id	Text
0	Ăn quả nhớ kẻ trồng cây
1	Có chí thì nên

Input tokens	Target token
<sos>	Ăn
<sos> Ăn	quả
<sos> Ăn quả	nhớ
<sos> Ăn quả nhớ	kẻ
<sos> Ăn quả nhớ kẻ	trồng
<sos> Ăn quả nhớ kẻ trồng	cây
<sos>	Có
<sos> Có	chí
<sos> Có chí	thì
<sos> Có chí thì	nên

Next token prediction dataset

```
data_x_ids = []
data_y_ids = []
def vectorize(x, y, vocab, sequence_length):
    x_ids = [vocab[token] for token in x][:sequence_length]
    x_ids = x_ids + [vocab["<pad>"]]*(sequence_length - len(x))
    return x_ids, vocab[y]
for x, y in zip(data_x, data_y):
    x_ids, y_ids = vectorize(x, y, vocab, sequence_length)
    data_x_ids.append(x_ids)
    data_y_ids.append(y_ids)
```

Vocab

padding

sequence_length = 6

Training data

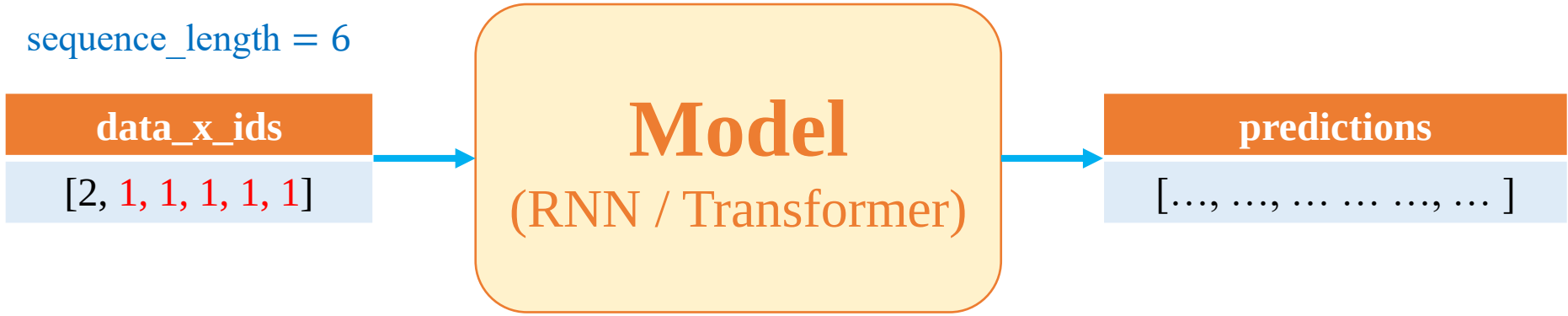
data_x_ids	data_y_ids
[2, 1, 1, 1, 1, 1]	12
[2, 12, 1, 1, 1, 1]	9
[2, 12, 9, 1, 1, 1]	7
[2, 12, 9, 7, 1, 1]	6
[2, 12, 9, 7, 6, 1]	11
[2, 12, 9, 7, 6, 11]	4
[2, 1, 1, 1, 1, 1]	5
[2, 5, 1, 1, 1, 1]	3
[2, 5, 3, 1, 1, 1]	10
[2, 5, 3, 10, 1, 1]	8

Example

Token	Id
<unk>	0
<pad>	1
<sos>	2
chí	3
cây	4
có	5
kẻ	6
nhớ	7
nên	8
quả	9
thì	10
trồng	11
ăn	12

vocab_size = 13

sequence_length = 6




```python
class TG_Model(nn.Module):
    def __init__(self, vocab_size, sequence_length):
        super().__init__()
        self.recurrent = nn.RNN(4, 4, batch_first=True)
        self.linear = nn.Linear(sequence_length*4, vocab_size)

    def forward(self, x):
        x,_ = self.recurrent(x) # [n, sequence_length, 4]
        x = nn.Flatten()(x)     # [n, 24]
        x = self.linear(x)      # [n, 13]
        return x

model = TG_Model(vocab_size, sequence_length)
outputs = model(data_x_ids)
```

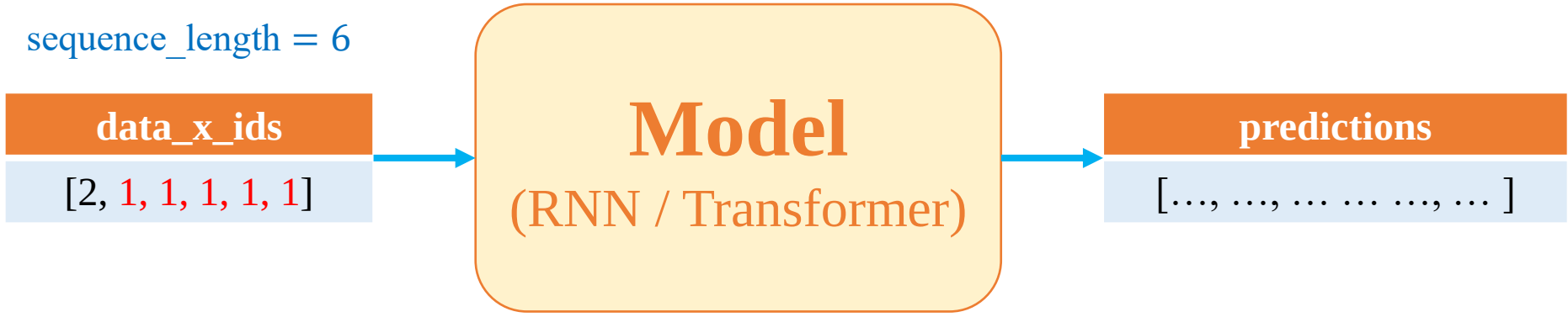
?

Example

Token	Id
<unk>	0
<pad>	1
<sos>	2
chí	3
cây	4
có	5
kẻ	6
nhớ	7
nên	8
quả	9
thì	10
trồng	11
ăn	12

vocab_size = 13

sequence_length = 6




```python
class TG_Model(nn.Module):
    def __init__(self, vocab_size, sequence_length):
        super().__init__()
        self.embedding = nn.Embedding(vocab_size, 4)
        self.recurrent = nn.RNN(4, 4, batch_first=True)
        self.linear = nn.Linear(sequence_length*4, vocab_size)

    def forward(self, x):
        x = self.embedding(x)    # [n, sequence_length, 4]
        x,_ = self.recurrent(x) # [n, sequence_length, 4]
        x = nn.Flatten()(x)      # [n, 24]
        x = self.linear(x)       # [n, 13]
        return x

model = TG_Model(vocab_size, sequence_length)
outputs = model(data_x_ids)
```

Example

Training

data_x_ids
[2, 1, 1, 1, 1, 1]
[2, 12, 1, 1, 1, 1]
[2, 12, 9, 1, 1, 1]
[2, 12, 9, 7, 1, 1]
[2, 12, 9, 7, 6, 1]
[2, 12, 9, 7, 6, 11]
[2, 1, 1, 1, 1, 1]
[2, 5, 1, 1, 1, 1]
[2, 5, 3, 1, 1, 1]
[2, 5, 3, 10, 1, 1]

predicted ids
12
9
7
6
12
4
5
3
9
8

data_y_ids
12
9
7
6
11
4
5
3
10
8

Update params

Feed Forward

sequence_length = 4

hidden_dim = 4

Input tokens	Target token
<sos> Có chí thì	nên

Input ids	Target ids
[2, 5, 3, 10]	[8]

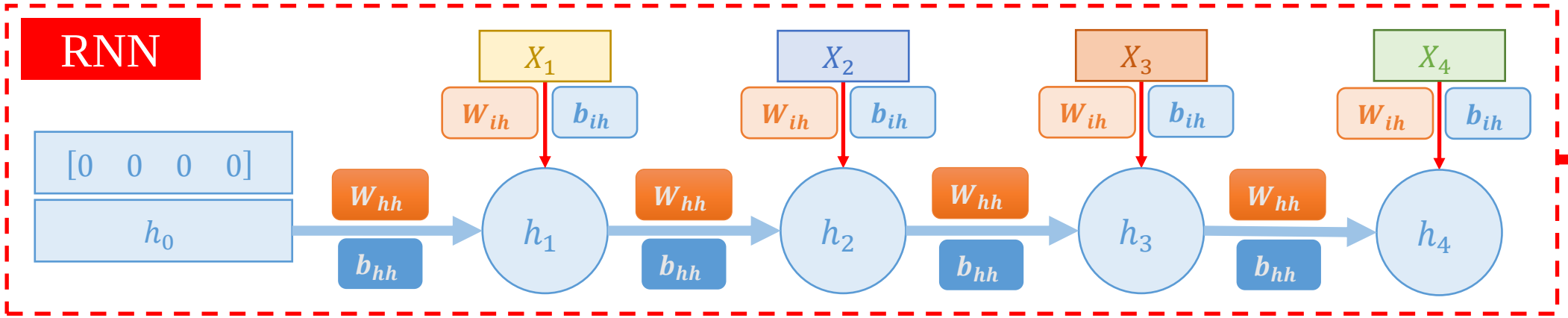
[2 5 3 10] → Embedding layer →

$X_1 = [-0.7521 \quad 1.6487 \quad -0.3925 \quad -1.4036]$

$X_2 = [-0.7581 \quad 1.0783 \quad 0.8008 \quad 1.6806]$

$X_3 = [-0.7279 \quad -0.5594 \quad -0.7688 \quad 0.7624]$

$X_4 = [-0.8371 \quad -0.9224 \quad 1.8113 \quad 0.1606]$



W_{hh}

$$\begin{bmatrix} 0.3035 & -0.1187 & 0.2860 & -0.3885 \\ -0.2523 & 0.1524 & 0.1057 & -0.1275 \\ 0.2980 & 0.3399 & -0.3626 & -0.2669 \\ 0.4578 & -0.1687 & -0.1773 & -0.4838 \end{bmatrix}$$

W_{ih}

$$\begin{bmatrix} -0.2982 & -0.2982 & 0.4497 & 0.1666 \\ 0.4811 & -0.4126 & -0.4959 & -0.3912 \\ -0.3363 & 0.2025 & 0.1790 & 0.4155 \\ -0.2582 & -0.3409 & 0.2653 & -0.2021 \end{bmatrix}$$

b_{hh}

$[0.0117 \quad -0.3415 \quad -0.4242 \quad -0.2753]$

b_{ih}

$[-0.2863 \quad 0.1249 \quad -0.0660 \quad -0.3629]$

$h_1 = [-0.7409 \quad -0.4739 \quad -0.5055 \quad -0.6786]$

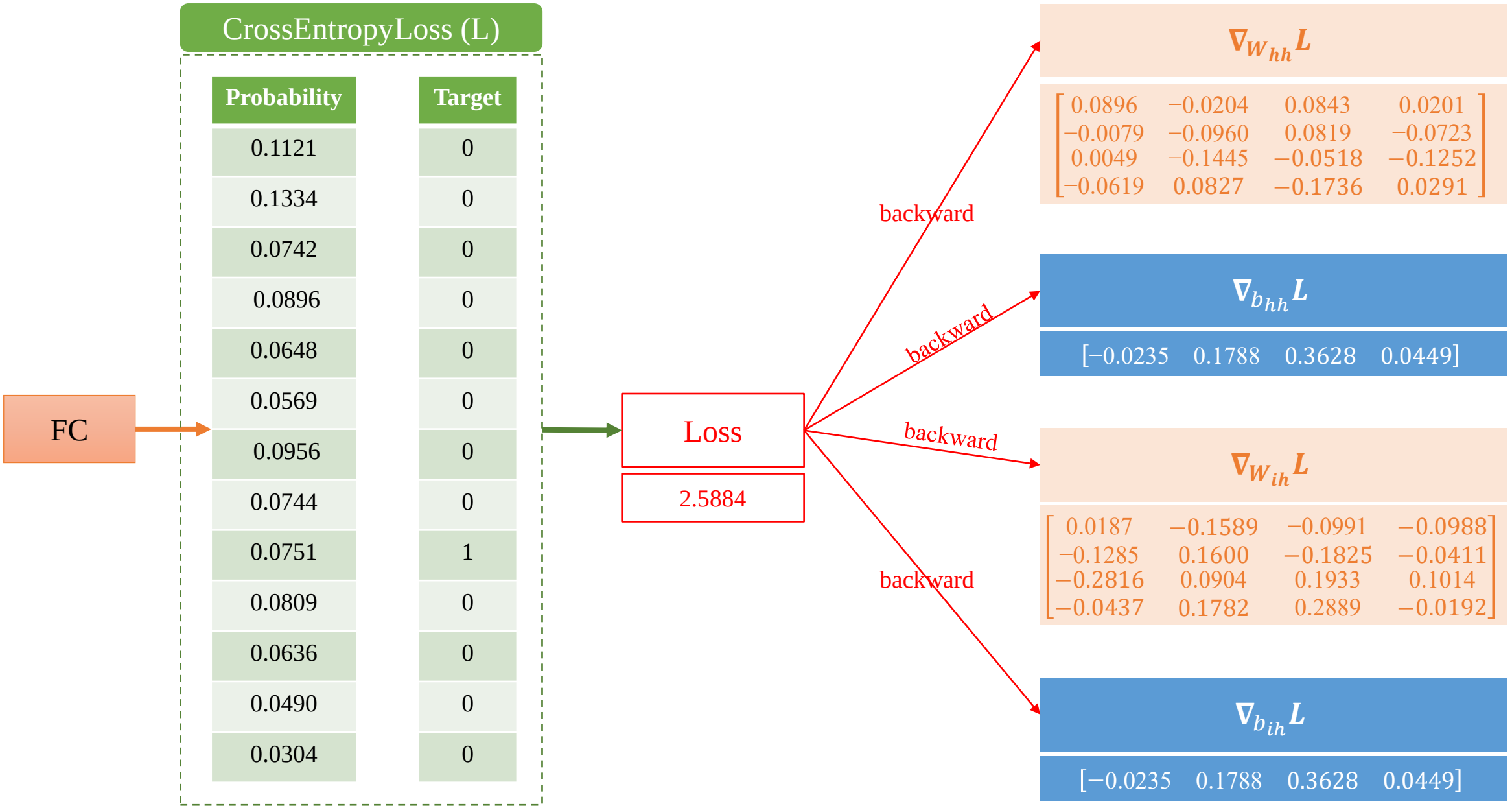
$h_2 = [0.2170 \quad -0.9590 \quad 0.6681 \quad -0.6519]$

$h_3 = [0.4735 \quad -0.2915 \quad -0.4692 \quad -0.1583]$

$h_4 = [0.8327 \quad -0.8839 \quad 0.2449 \quad 0.6446]$

Flatten → Linear (16, 13)

Back-Propagation



Example

Token	Id
<unk>	0
<pad>	1
<sos>	2
chí	3
cây	4
có	5
kẻ	6
nhớ	7
nên	8
quả	9
thì	10
trồng	11
ăn	12

vocab_size = 13

data_x_ids

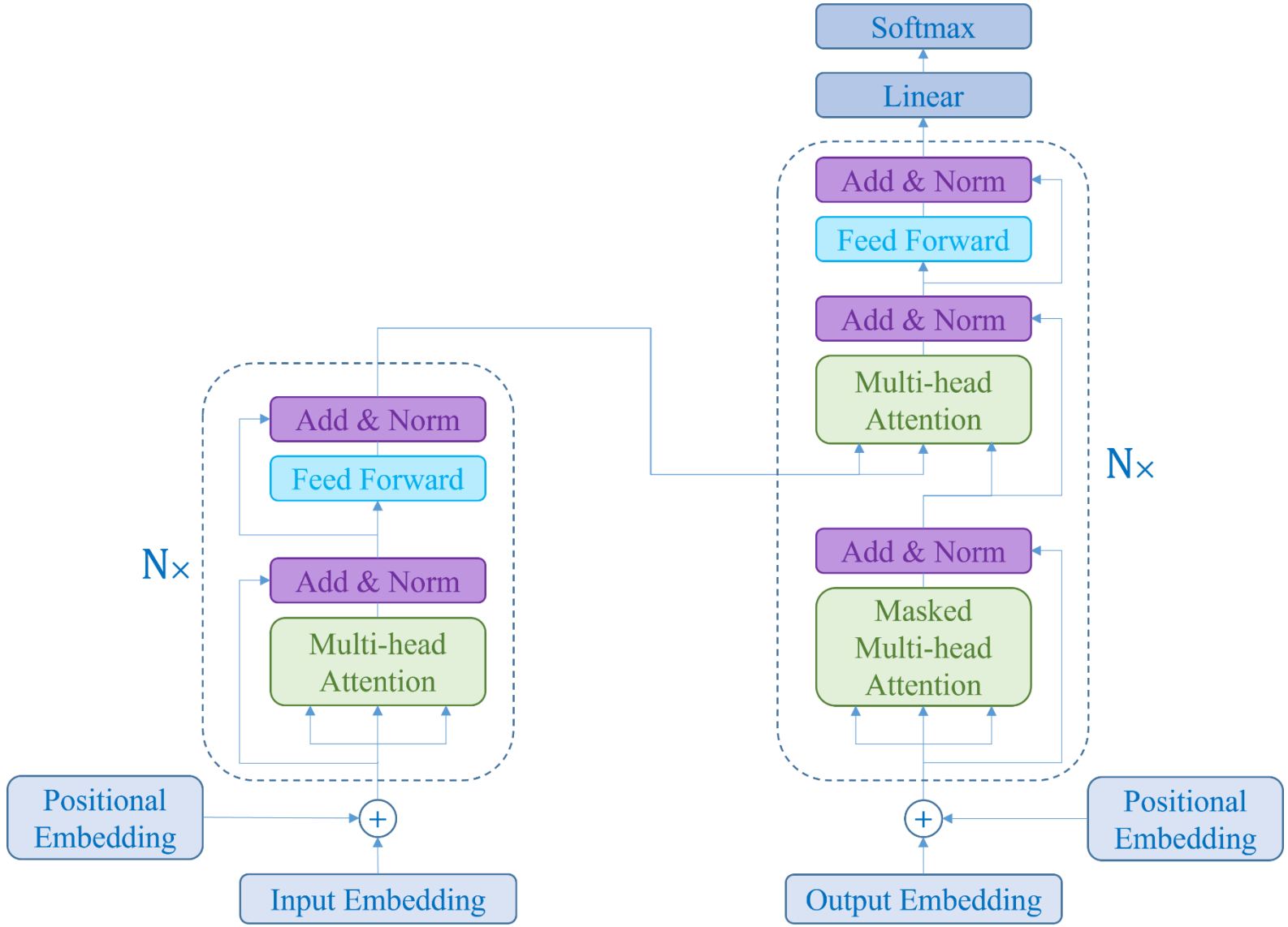
[2, 1, 1, 1, 1, 1]

sequence_length = 6

Model (Transformer)

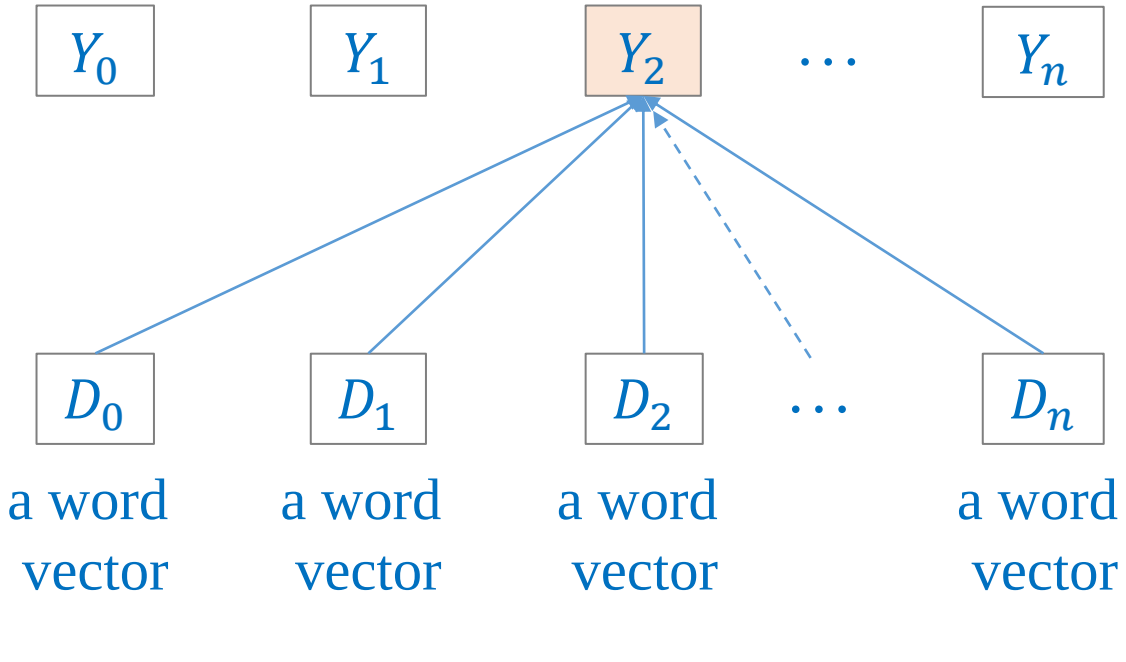
predictions

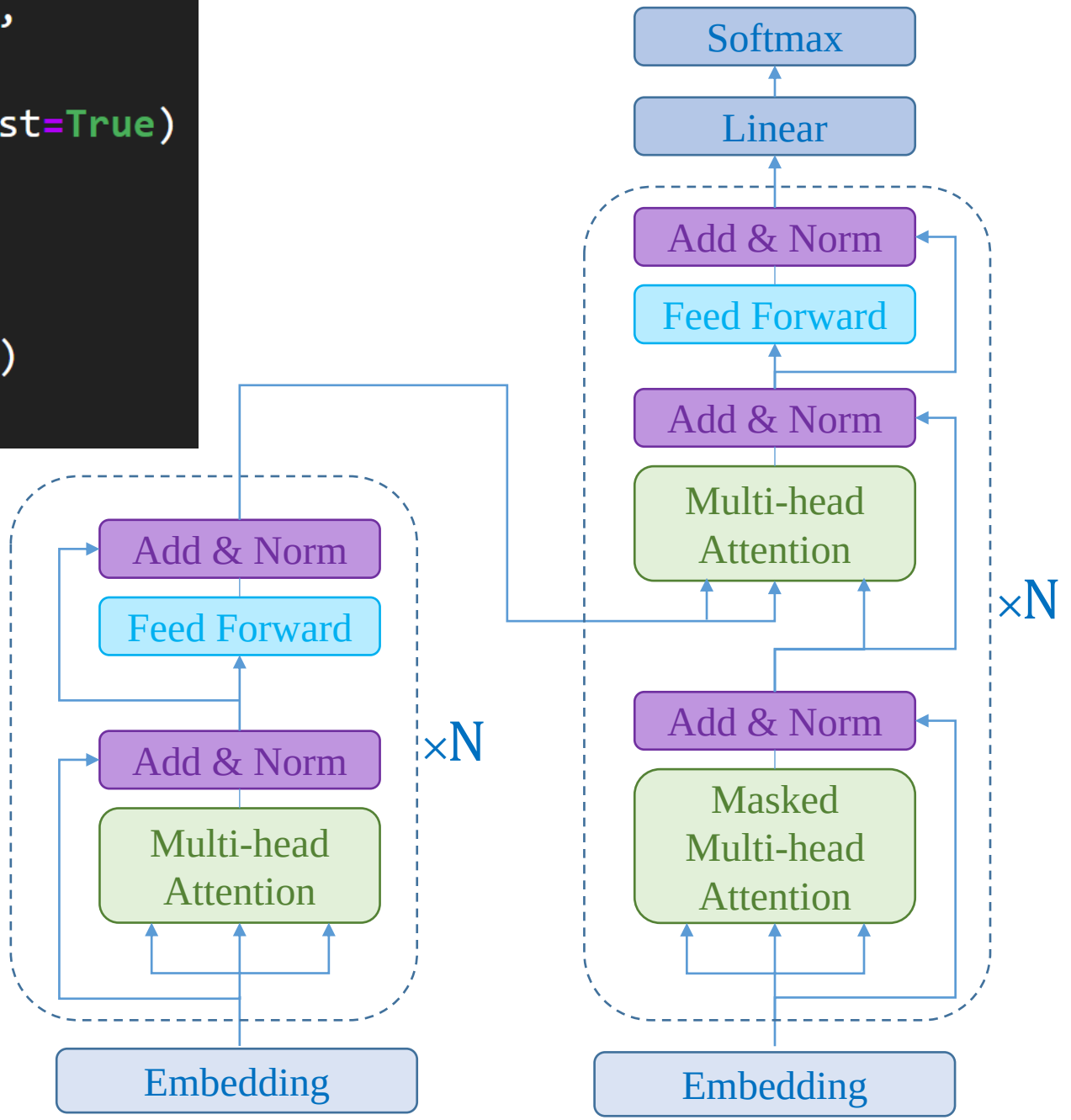
[…, …, … … …, …]



```python
layer = nn.TransformerEncoderLayer(d_model=3,
                                   nhead=1,
                                   batch_first=True)

# feed forward
src = torch.Tensor([[[ 0.69,  0.72, -1.41],
                     [ 0.21,  1.10, -1.31]]])
out = layer(src)
```

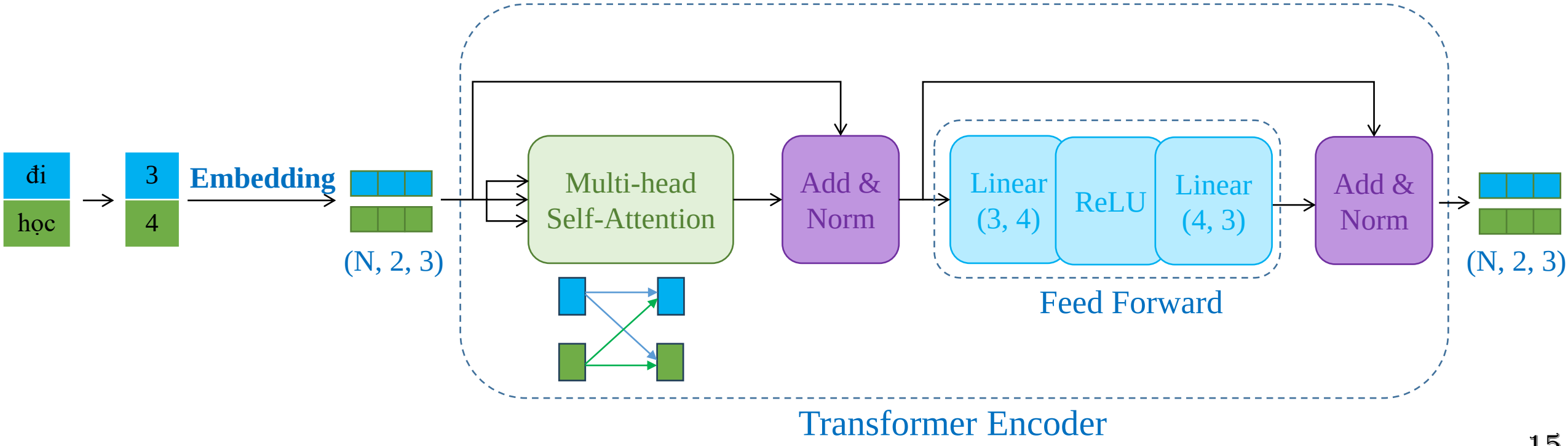




Encoder in Pytorch

index	word
0	[UNK]
1	[pad]
2	ai
3	đi
4	học
…	…

index	Embedding
0	[-0.188, …, 0.7013]
1	[1.7840…, 1.3586]
2	[1.0281, …, 0.4211]
3	[-1.308, …, -0.3680]
4	[0.2293, …, 2.0501]
…	…



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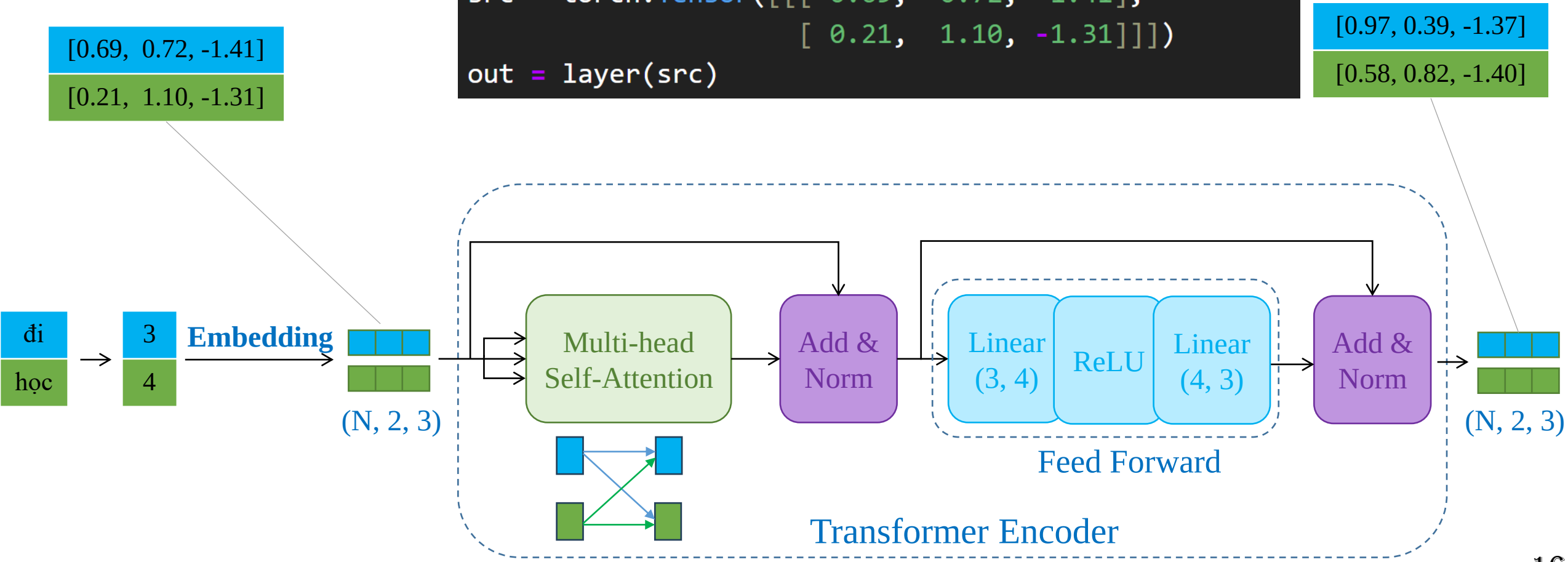
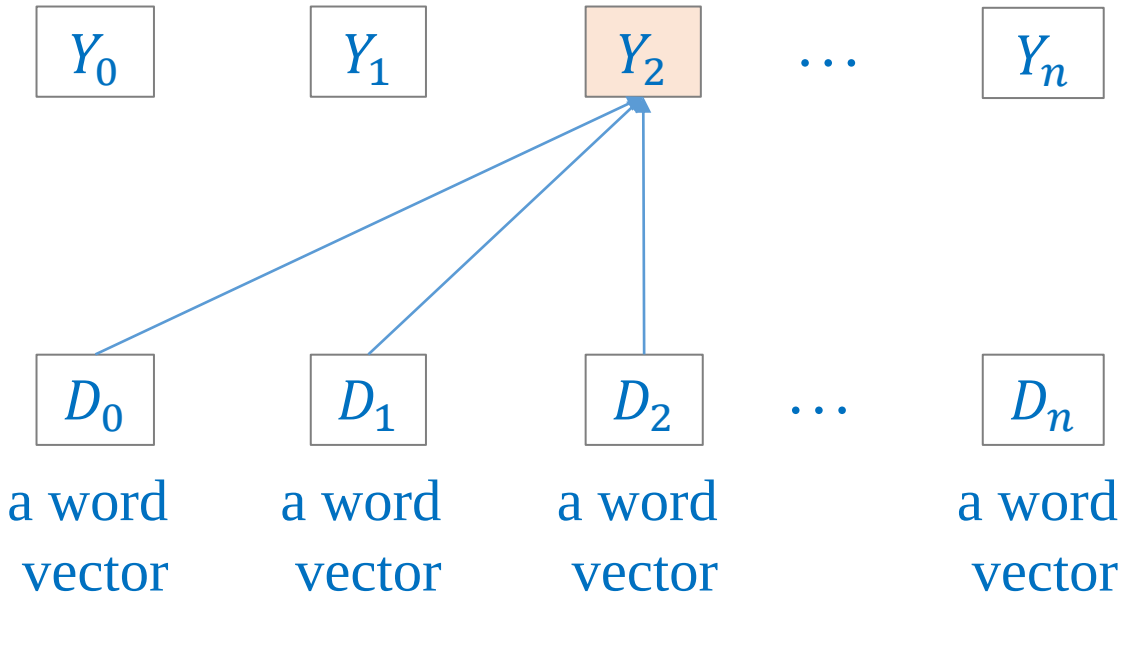
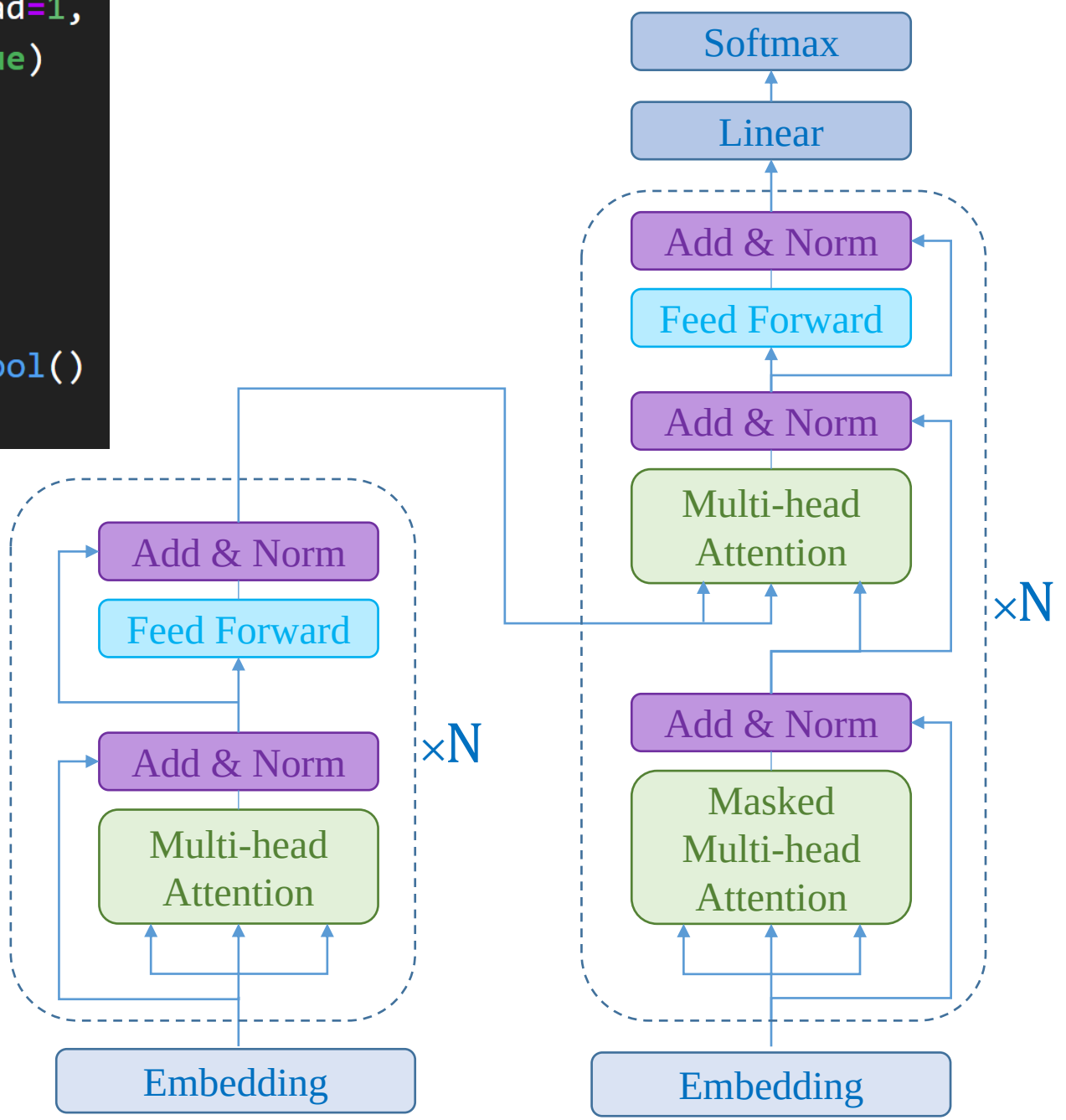


```python
layer = nn.TransformerEncoderLayer(d_model=3, nhead=1,
                                   batch_first=True)

# feed forward
src = torch.Tensor([[[ 0.69,  0.72, -1.41],
                     [ 0.21,  1.10, -1.31],
                     [-0.88,  0.60, -0.31]]])
mask = torch.triu(torch.ones(3, 3), diagonal=1).bool()
out = layer(src, src_mask=mask)
```

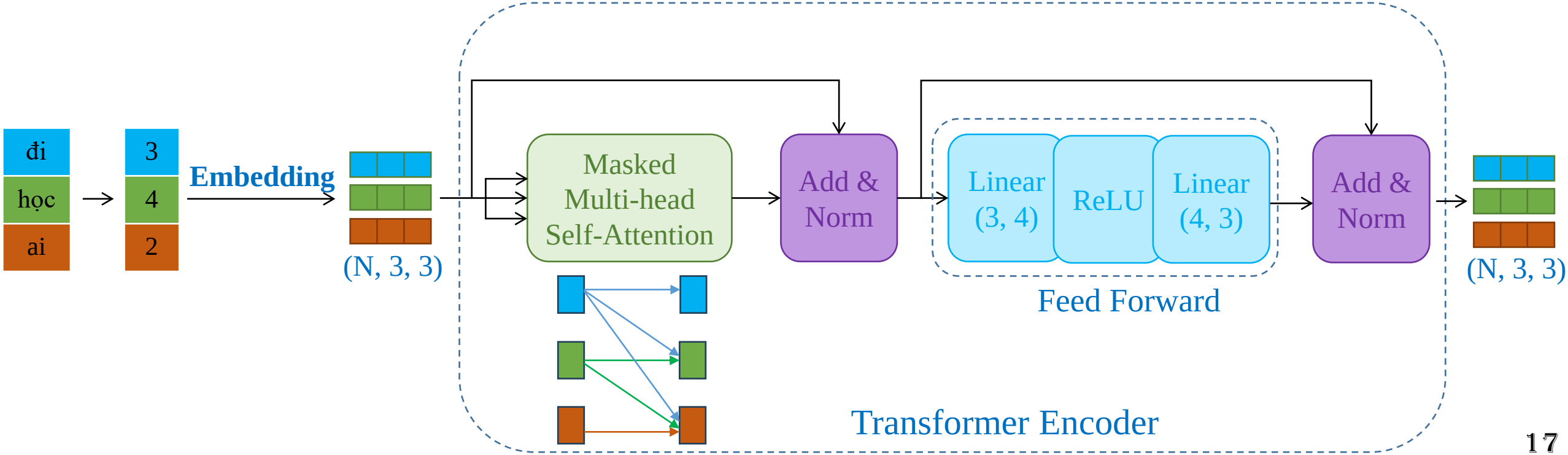




Masked Encoder in Pytorch

index	word
0	[UNK]
1	[pad]
2	ai
3	đi
4	học
…	…

index	Embedding
0	[-0.188, …, 0.7013]
1	[1.7840…, 1.3586]
2	[1.0281, …, 0.4211]
3	[-1.308, …, -0.3680]
4	[0.2293, …, 2.0501]
…	…



Masked Encoder in Pytorch

```
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# feed forward
src = torch.Tensor([[[ 0.69,  0.72, -1.41],
                     [ 0.21,  1.10, -1.31],
                     [-0.88,  0.60, -0.31]]])
mask = torch.triu(torch.ones(3, 3), diagonal=1).bool()
out = layer(src, src_mask=mask)
```
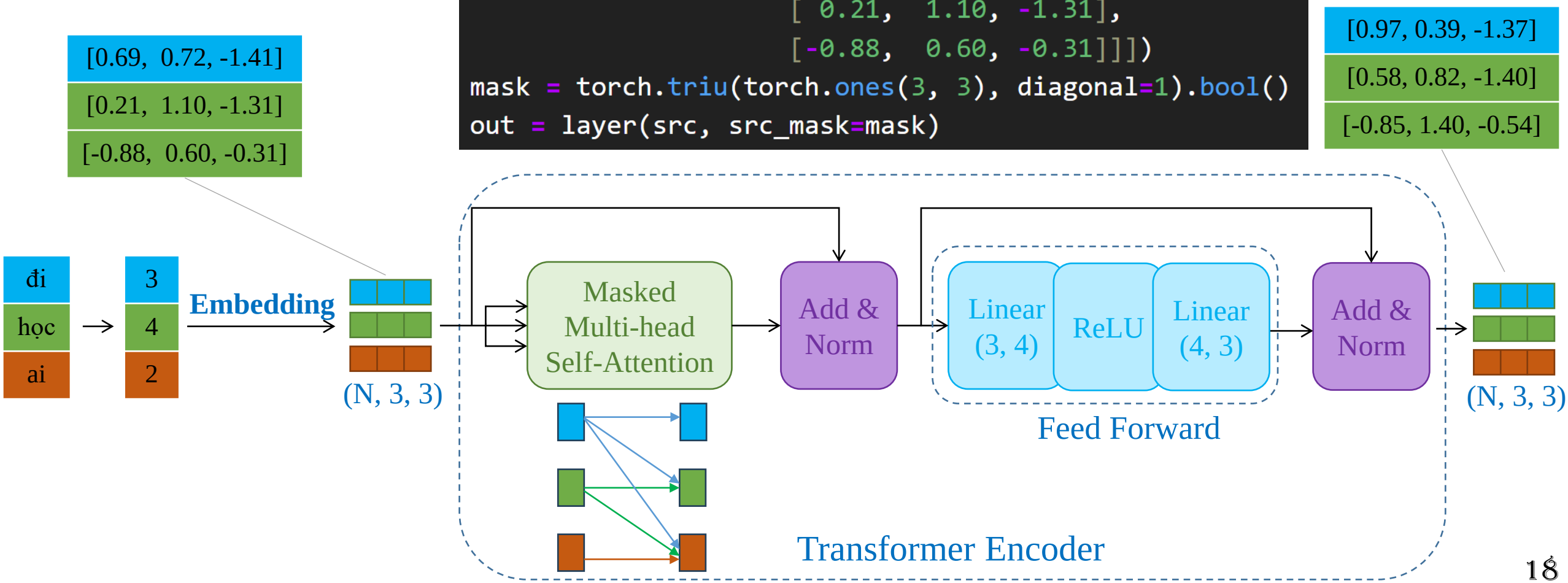



Masked Multi-head Attention

head = 1

$$W_Q = \begin{bmatrix} -0.35 & 0.51 & 0.50 \\ 0.36 & -0.47 & -0.29 \\ -0.51 & -0.14 & -0.56 \end{bmatrix}$$

$$W_K = \begin{bmatrix} -0.49 & -0.68 & 0.18 \\ -0.44 & -0.46 & 0.18 \\ 0.07 & -0.10 & 0.44 \end{bmatrix}$$

$$W_V = \begin{bmatrix} -0.41 & 0.39 & -0.65 \\ -0.40 & -0.07 & -0.34 \\ -0.55 & -0.13 & -0.29 \end{bmatrix}$$

$$W_O = \begin{bmatrix} -0.36 & -0.08 & 0.32 \\ 0.27 & 0.05 & 0.15 \\ -0.05 & -0.28 & 0.05 \end{bmatrix}$$

$$X = \begin{bmatrix} -0.1 & 0.1 & 0.3 \\ 0.4 & -1.1 & -0.3 \end{bmatrix}$$

$$Q = XW_Q = \begin{bmatrix} -0.1 & 0.1 & 0.3 \\ 0.4 & -1.1 & -0.3 \end{bmatrix} \begin{bmatrix} -0.35 & 0.51 & 0.50 \\ 0.36 & -0.47 & -0.29 \\ -0.51 & -0.14 & -0.56 \end{bmatrix}$$

$$= \begin{bmatrix} -0.08 & -0.14 & -0.24 \\ -0.39 & 0.77 & 0.69 \end{bmatrix}$$

$$K = XW_K = \begin{bmatrix} -0.1 & 0.1 & 0.3 \\ 0.4 & -1.1 & -0.3 \end{bmatrix} \begin{bmatrix} -0.49 & -0.68 & 0.18 \\ -0.44 & -0.46 & 0.18 \\ 0.07 & -0.10 & 0.44 \end{bmatrix}$$

$$= \begin{bmatrix} 0.02 & -0.01 & 0.13 \\ 0.27 & 0.27 & -0.26 \end{bmatrix}$$

$$V = XW_V = \begin{bmatrix} -0.1 & 0.1 & 0.3 \\ 0.4 & -1.1 & -0.3 \end{bmatrix} \begin{bmatrix} -0.41 & 0.39 & -0.65 \\ -0.40 & -0.07 & -0.34 \\ -0.55 & -0.13 & -0.29 \end{bmatrix}$$

$$= \begin{bmatrix} -0.16 & -0.08 & -0.05 \\ -0.02 & -0.02 & 0.05 \end{bmatrix}$$

$$M = \begin{bmatrix} 0 & -\infty \\ 0 & 0 \end{bmatrix}$$

Masked Multi-head Attention

❖ Example

approximately

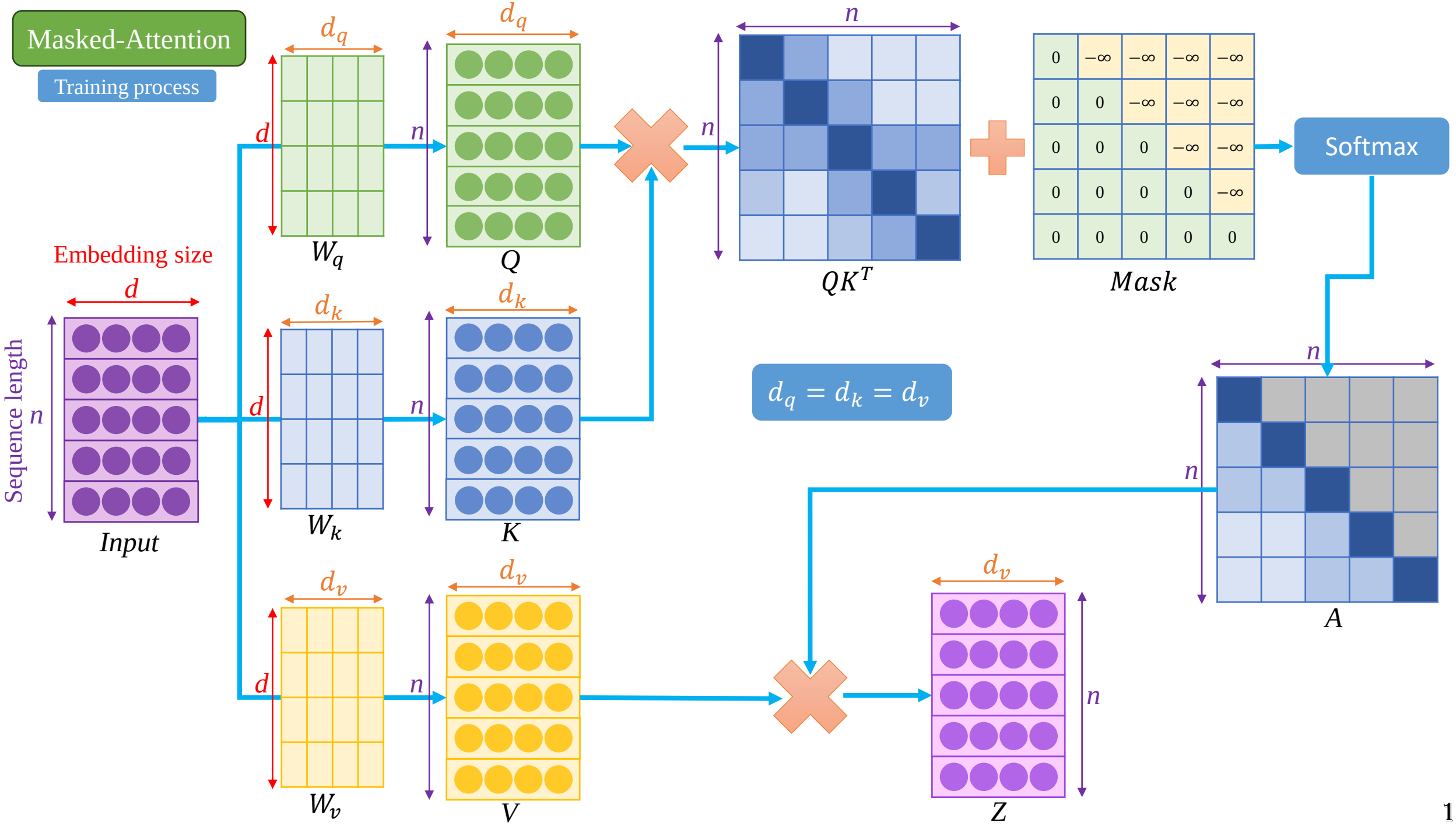
$$A = softmax\left(\frac{QK^T}{\sqrt{d}} + M\right)V$$

$$= softmax\left(\begin{bmatrix} -0.08 & -0.14 & -0.24 \\ -0.39 & 0.77 & 0.69 \end{bmatrix}\begin{bmatrix} 0.02 & 0.27 \\ -0.01 & 0.27 \\ 0.13 & -0.26 \end{bmatrix}\frac{1}{\sqrt{d}} + \begin{bmatrix} 0 & -\infty \\ 0 & 0 \end{bmatrix}\right)\begin{bmatrix} -0.16 & -0.08 & -0.05 \\ -0.02 & -0.02 & 0.05 \end{bmatrix}$$

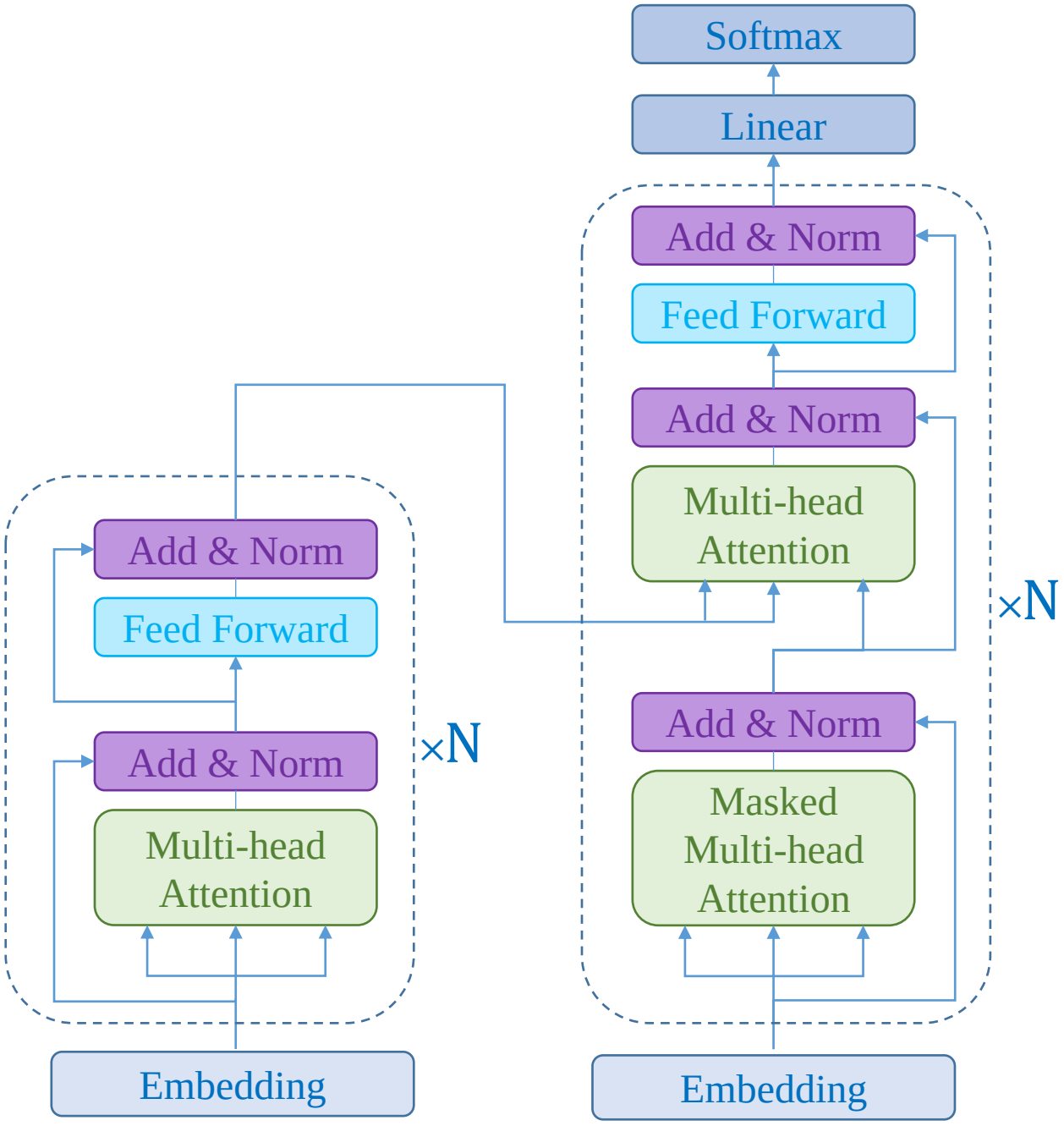
$$= softmax\left(\begin{bmatrix} -0.019 & 0.002 \\ 0.043 & -0.046 \end{bmatrix} + \begin{bmatrix} 0 & -\infty \\ 0 & 0 \end{bmatrix}\right)\begin{bmatrix} -0.16 & -0.08 & -0.05 \\ -0.02 & -0.02 & 0.05 \end{bmatrix}$$

$$= \begin{bmatrix} 1.0 & 0.0 \\ 0.52 & 0.48 \end{bmatrix}\begin{bmatrix} -0.16 & -0.08 & -0.05 \\ -0.02 & -0.02 & 0.05 \end{bmatrix} = \begin{bmatrix} -0.16 & -0.08 & -0.05 \\ 0.12 & 0.08 & 0.06 \end{bmatrix}$$

$$Y = AW_O = \begin{bmatrix} -0.16 & -0.08 & -0.05 \\ 0.12 & 0.08 & 0.06 \end{bmatrix}\begin{bmatrix} -0.36 & -0.08 & 0.32 \\ 0.27 & 0.05 & 0.15 \\ -0.05 & -0.28 & 0.05 \end{bmatrix} = \begin{bmatrix} 0.03 & 0.02 & -0.06 \\ -0.02 & -0.02 & 0.05 \end{bmatrix}$$

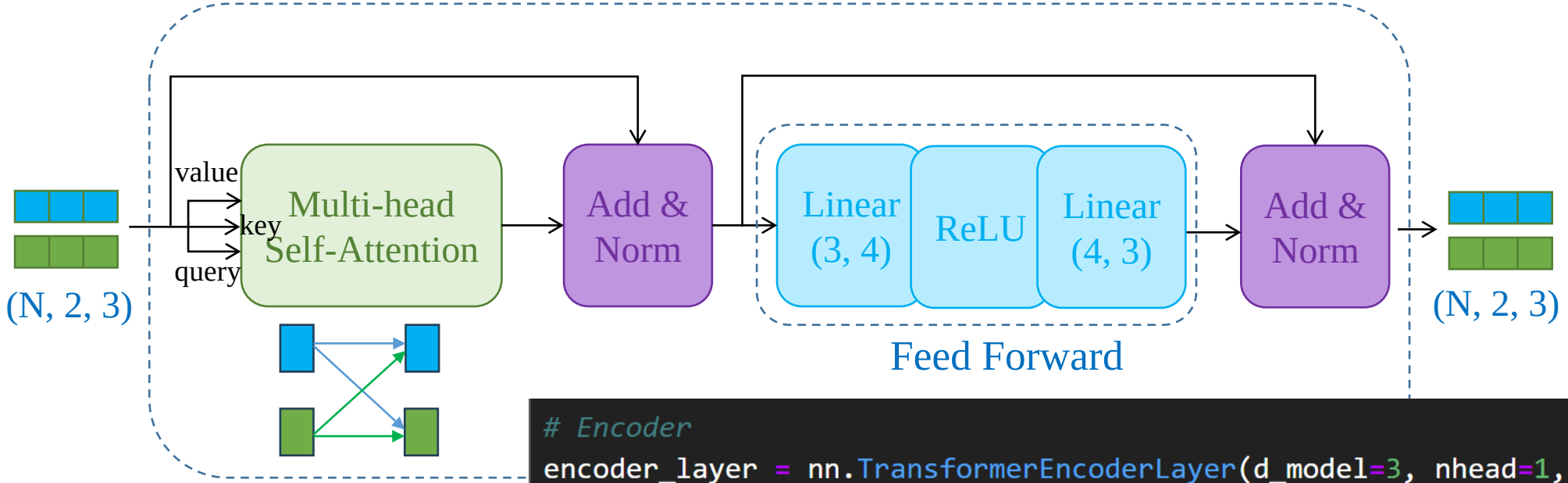

Masked-Attention
Training process
Embedding size
Sequence length
Input
W_q
W_k
W_v
Q
K
V
QK^T
$Mask$
Softmax
A
Z
$d_q = d_k = d_v$

```python
nn.TransformerEncoderLayer(d_model=3,
                           nhead=1,
                           batch_first=True)
nn.TransformerDecoderLayer(d_model=3,
                           nhead=1,
                           batch_first=True)


# feed forward
src = torch.Tensor([[[0.48, 0.44, 0.71],
                     [0.65, 0.80, 0.79]]])

tgt = torch.Tensor([[[0.3516, 0.9509, 0.2771],
                     [0.1993, 0.0177, 0.2628],
                     [0.0774, 0.5253, 0.6413],
                     [0.6749, 0.5501, 0.1641]]])

context = encoder_layer(src)
mask = torch.triu(torch.ones(4, 4),
                  diagonal=1).bool()
out = decoder_layer(tgt, context,
                    tgt_mask=mask)
```



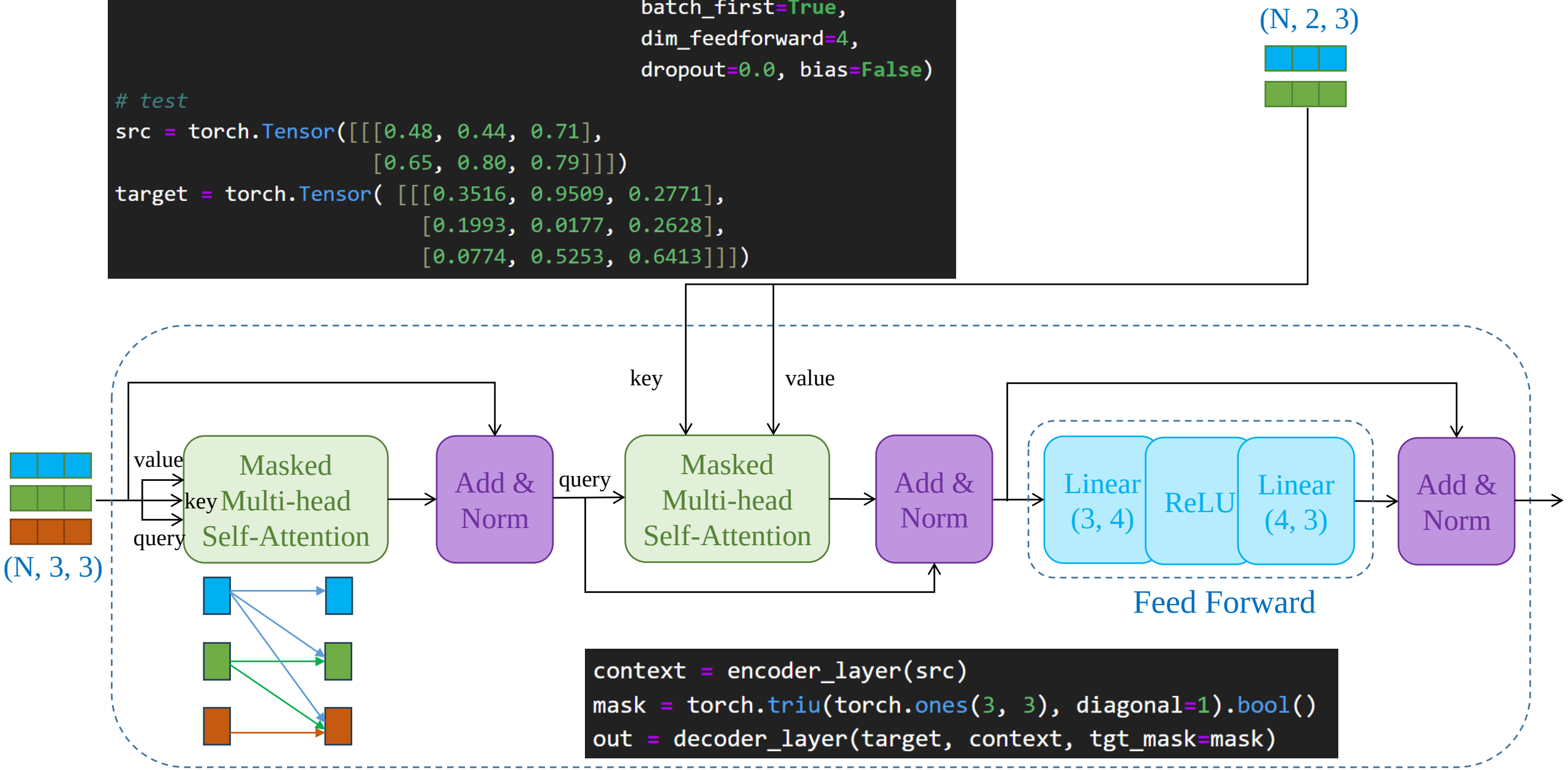
Transformer in PyTorch

❖ Transformer Encoder

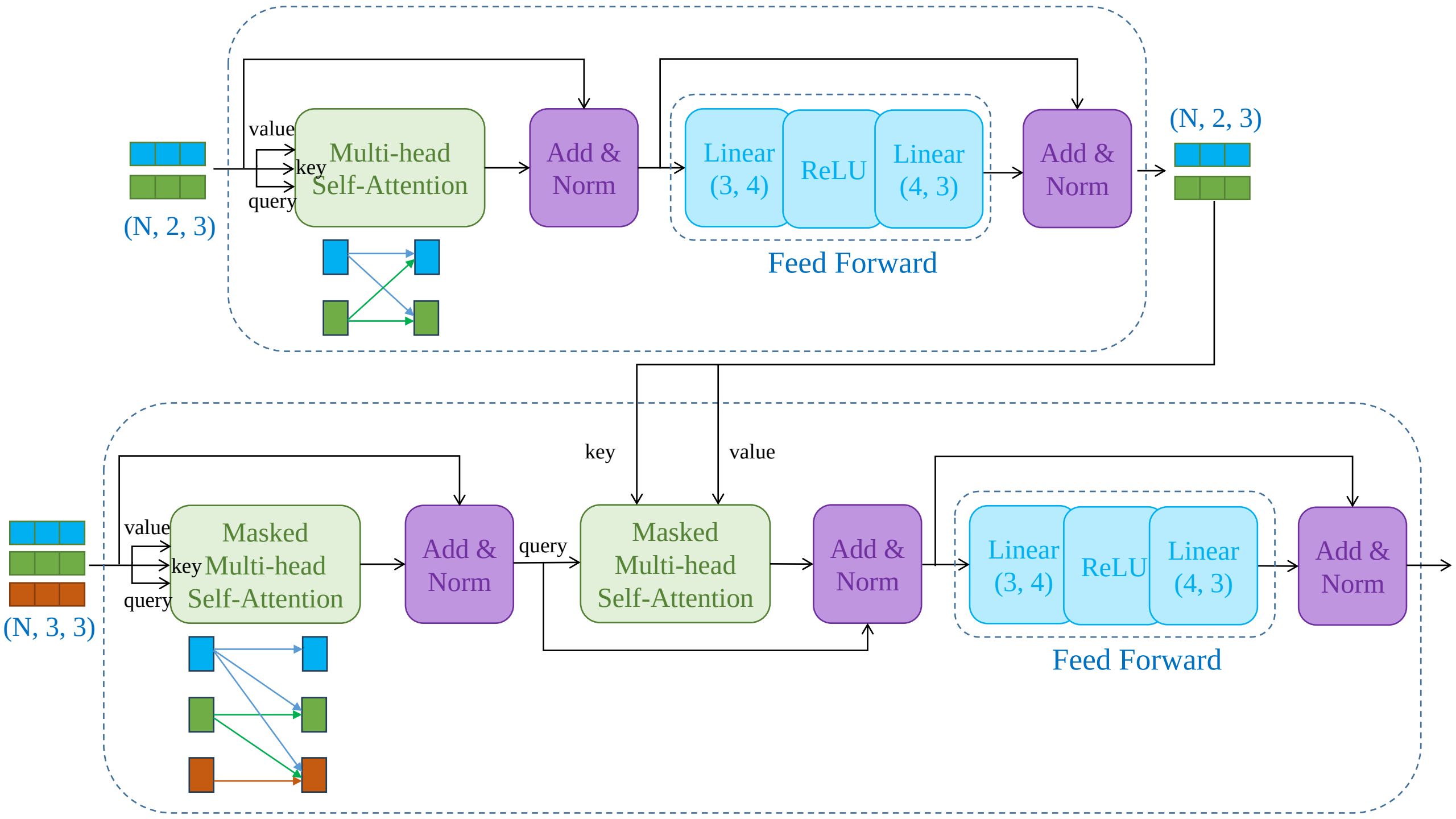



```python
# Encoder
encoder_layer = nn.TransformerEncoderLayer(d_model=3, nhead=1,
                                           batch_first=True,
                                           dim_feedforward=4,
                                           dropout=0.0, bias=False)


# test
src = torch.Tensor([[[0.48, 0.44, 0.71],
                     [0.65, 0.80, 0.79]]])
context = encoder_layer(src)
```

```python
# layers
encoder_layer = nn.TransformerEncoderLayer(...)
decoder_layer = nn.TransformerDecoderLayer(d_model=3, nhead=1,
                                           batch_first=True,
                                           dim_feedforward=4,
                                           dropout=0.0, bias=False)
# test
src = torch.Tensor([[[0.48, 0.44, 0.71],
                     [0.65, 0.80, 0.79]]])
target = torch.Tensor( [[[0.3516, 0.9509, 0.2771],
                         [0.1993, 0.0177, 0.2628],
                         [0.0774, 0.5253, 0.6413]]])
```

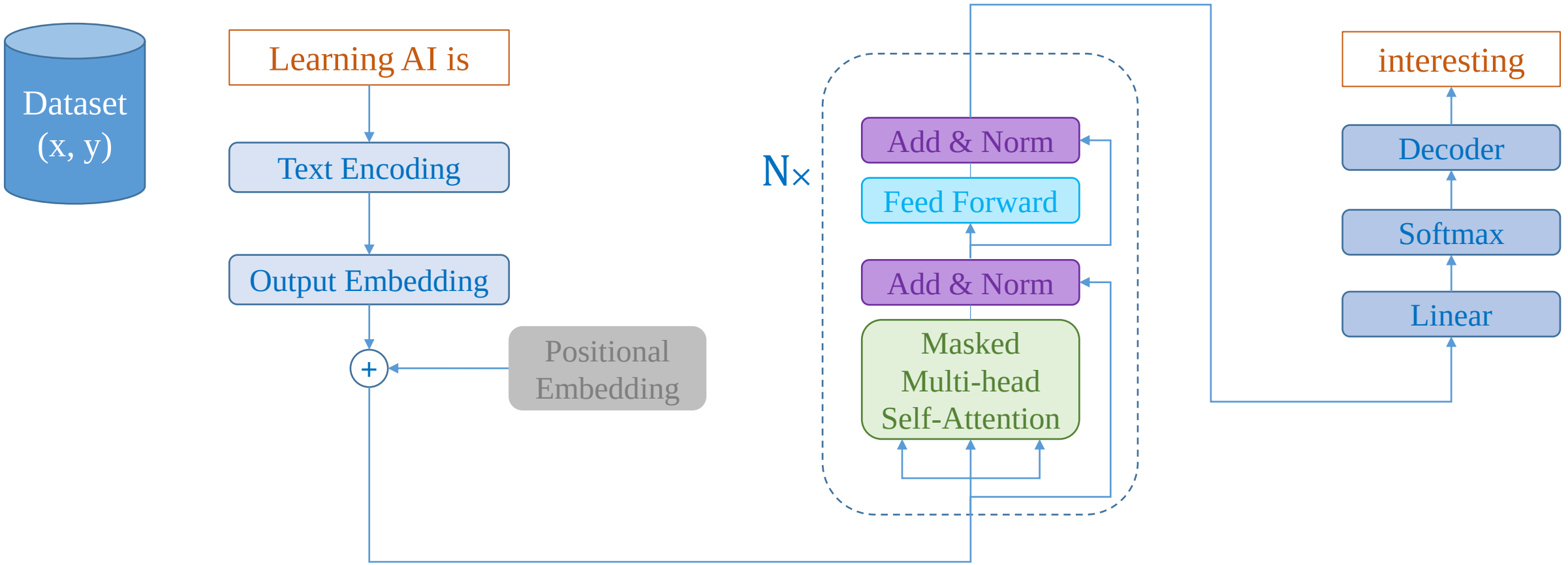



```python
context = encoder_layer(src)
mask = torch.triu(torch.ones(3, 3), diagonal=1).bool()
out = decoder_layer(target, context, tgt_mask=mask)
```


(N, 2, 3)
value
key
query
Multi-head Self-Attention
Add & Norm
Linear (3, 4)
ReLU
Linear (4, 3)
Feed Forward
Add & Norm
(N, 2, 3)
(N, 3, 3)
value
key
query
Masked Multi-head Self-Attention
Add & Norm
key
value
query
Masked Multi-head Self-Attention
Add & Norm
Linear (3, 4)
ReLU
Linear (4, 3)
Feed Forward
Add & Norm

Text Generation

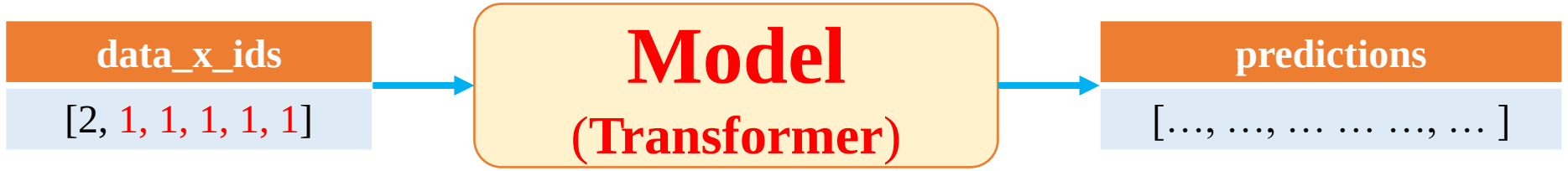
❖ Architecture



Example

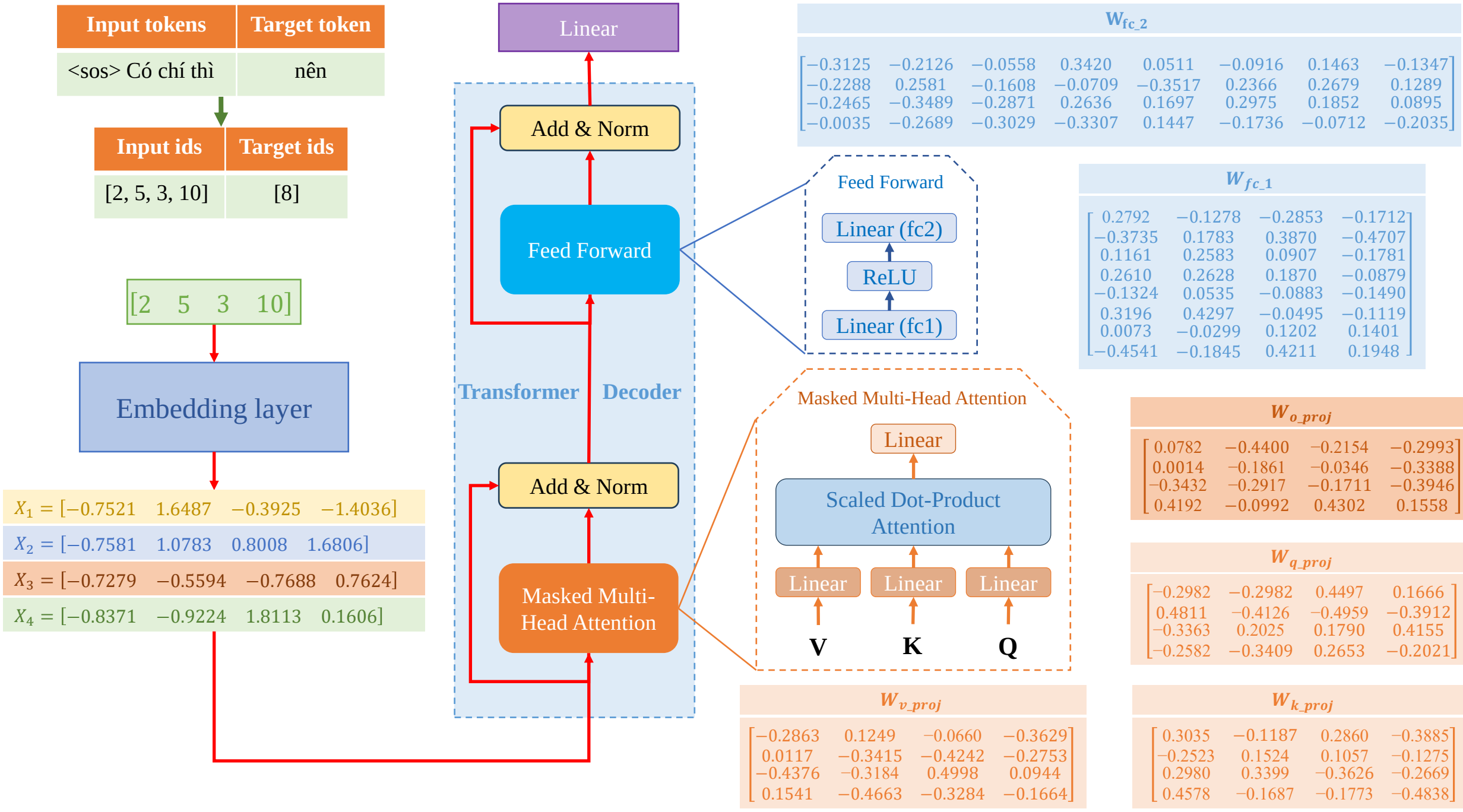
Token	Id
<unk>	0
<pad>	1
<sos>	2
chí	3
cây	4
có	5
kẻ	6
nhớ	7
nên	8
quả	9
thì	10
trồng	11
ăn	12

vocab_size = 13



sequence_length = 6

```python
class TG_Model(nn.Module):
    def __init__(self, vocab_size, embed_dim, num_heads, sequence_length):
        super().__init__()
        self.embedding = nn.Embedding(vocab_size, embed_dim)
        self.mask = torch.triu(torch.ones(sequence_length, sequence_length),
                               diagonal=1).bool()
        self.transformer =  nn.TransformerEncoderLayer(d_model=embed_dim,
                                                       nhead=num_heads,
                                                       batch_first=True,
                                                       dim_feedforward=4)
        self.linear = nn.Linear(sequence_length*embed_dim, vocab_size)

    def forward(self, x):
        x = self.embedding(x)                          # [n, seq_len, embed_dim]
        x = self.transformer(x, src_mask=self.mask)    # [n, seq_len, embed_dim]
        x = nn.Flatten()(x)                            # [n, seq_len*embed_dim]
        x = self.linear(x)                             # [n, vocab_size]
        return x

model = TG_Model(vocab_size, 8, 2, sequence_length)
```

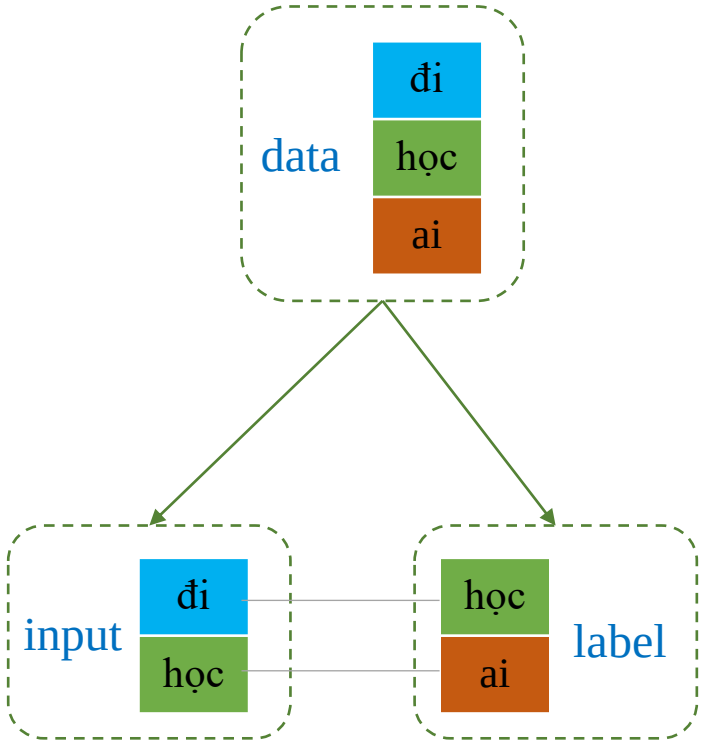

Input tokens
Target token
<sos> Có chí thì
nên
Input ids
Target ids
[2, 5, 3, 10]
[8]
[2 5 3 10]
Embedding layer
$X_1 = [-0.7521 \quad 1.6487 \quad -0.3925 \quad -1.4036]$
$X_2 = [-0.7581 \quad 1.0783 \quad 0.8008 \quad 1.6806]$
$X_3 = [-0.7279 \quad -0.5594 \quad -0.7688 \quad 0.7624]$
$X_4 = [-0.8371 \quad -0.9224 \quad 1.8113 \quad 0.1606]$
Transformer Decoder
Masked Multi-Head Attention
Add & Norm
Feed Forward
Add & Norm
Linear
Feed Forward
Linear (fc2)
ReLU
Linear (fc1)
Masked Multi-Head Attention
Linear
Scaled Dot-Product Attention
Linear
Linear
Linear
V
K
Q
W_{fc_2}
$\begin{bmatrix} -0.3125 & -0.2126 & -0.0558 & 0.3420 & 0.0511 & -0.0916 & 0.1463 & -0.1347 \\ -0.2288 & 0.2581 & -0.1608 & -0.0709 & -0.3517 & 0.2366 & 0.2679 & 0.1289 \\ -0.2465 & -0.3489 & -0.2871 & 0.2636 & 0.1697 & 0.2975 & 0.1852 & 0.0895 \\ -0.0035 & -0.2689 & -0.3029 & -0.3307 & 0.1447 & -0.1736 & -0.0712 & -0.2035 \end{bmatrix}$
W_{fc_1}
$\begin{bmatrix} 0.2792 & -0.1278 & -0.2853 & -0.1712 \\ -0.3735 & 0.1783 & 0.3870 & -0.4707 \\ 0.1161 & 0.2583 & 0.0907 & -0.1781 \\ 0.2610 & 0.2628 & 0.1870 & -0.0879 \\ -0.1324 & 0.0535 & -0.0883 & -0.1490 \\ 0.3196 & 0.4297 & -0.0495 & -0.1119 \\ 0.0073 & -0.0299 & 0.1202 & 0.1401 \\ -0.4541 & -0.1845 & 0.4211 & 0.1948 \end{bmatrix}$
W_{o_proj}
$\begin{bmatrix} 0.0782 & -0.4400 & -0.2154 & -0.2993 \\ 0.0014 & -0.1861 & -0.0346 & -0.3388 \\ -0.3432 & -0.2917 & -0.1711 & -0.3946 \\ 0.4192 & -0.0992 & 0.4302 & 0.1558 \end{bmatrix}$
W_{q_proj}
$\begin{bmatrix} -0.2982 & -0.2982 & 0.4497 & 0.1666 \\ 0.4811 & -0.4126 & -0.4959 & -0.3912 \\ -0.3363 & 0.2025 & 0.1790 & 0.4155 \\ -0.2582 & -0.3409 & 0.2653 & -0.2021 \end{bmatrix}$
W_{v_proj}
$\begin{bmatrix} -0.2863 & 0.1249 & -0.0660 & -0.3629 \\ 0.0117 & -0.3415 & -0.4242 & -0.2753 \\ -0.4376 & -0.3184 & 0.4998 & 0.0944 \\ 0.1541 & -0.4663 & -0.3284 & -0.1664 \end{bmatrix}$
W_{k_proj}
$\begin{bmatrix} 0.3035 & -0.1187 & 0.2860 & -0.3885 \\ -0.2523 & 0.1524 & 0.1057 & -0.1275 \\ 0.2980 & 0.3399 & -0.3626 & -0.2669 \\ 0.4578 & -0.1687 & -0.1773 & -0.4838 \end{bmatrix}$

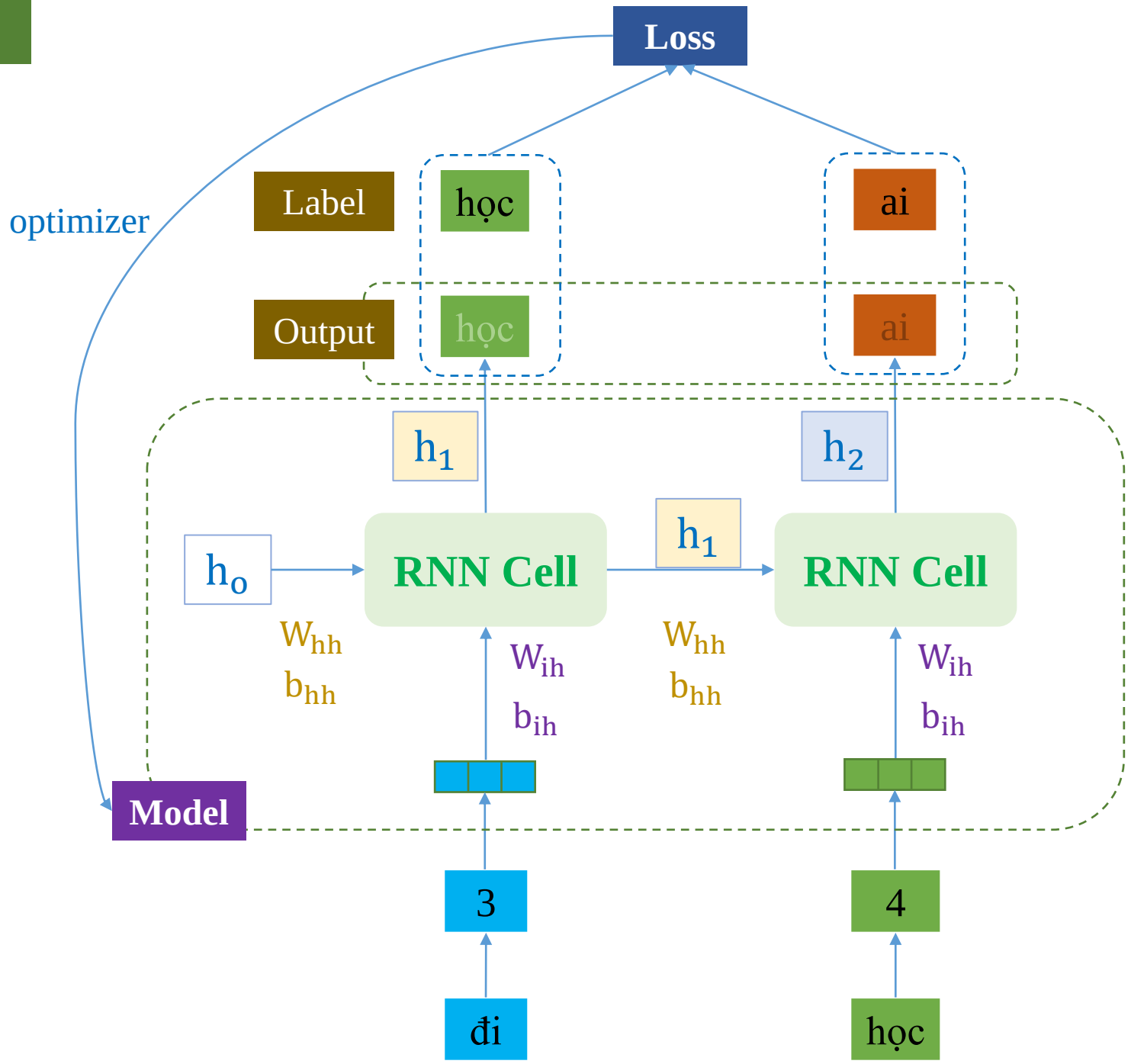
Outline

- Text Generation Using Transformer
- An improved Approach to Text Generation
- Machine Translation Using RNN
- Machine Translation Using Transformer

An improved approach

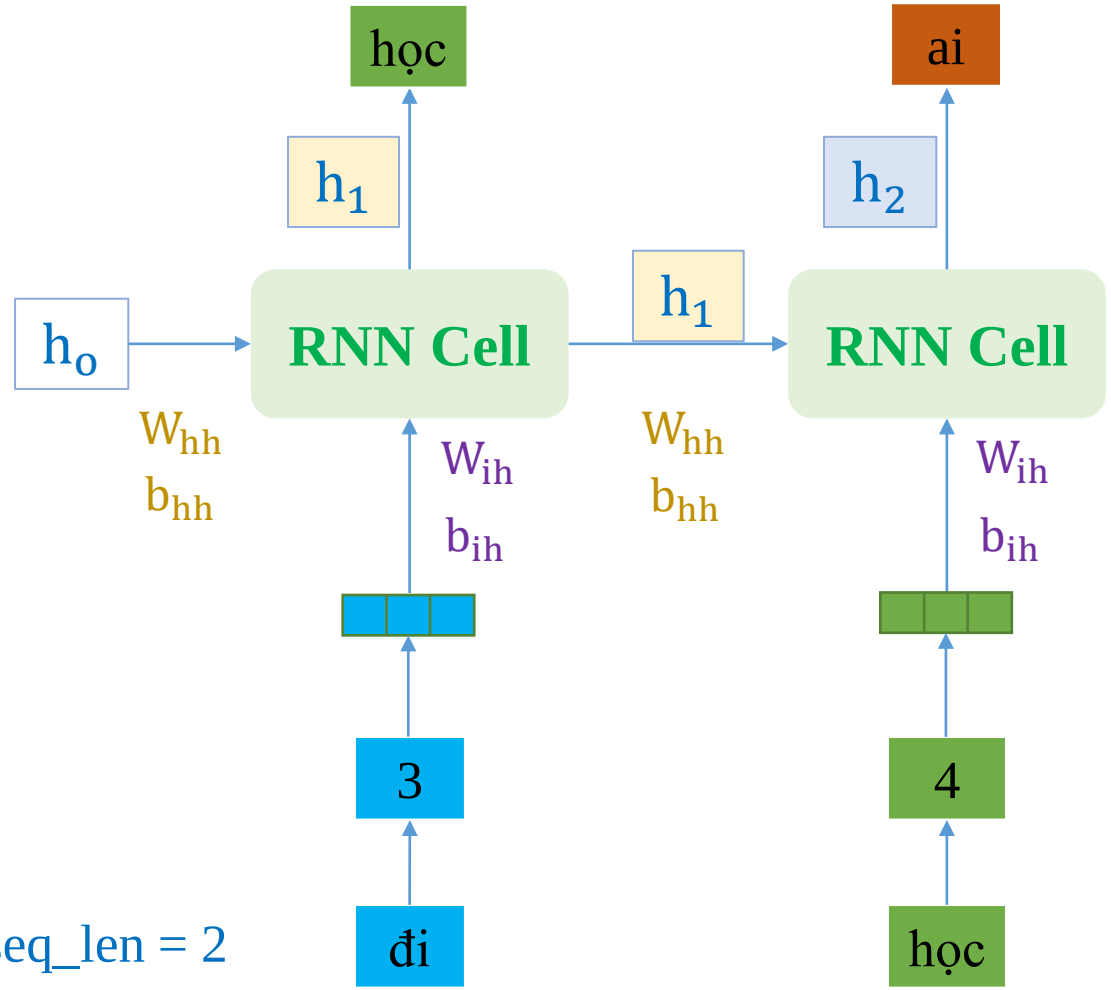
*Linear can be added (where?)





An improved approach

hidden_dim = vocab_size = 4



seq_len = 2

[-0.88, 0.81, 0.77]

[-1.27, 0.84, 0.04]

Embedded Input

*Linear can be added

W_{ih}

[0.25, 0.05, 0.17]

[-0.11, 0.35, 0.22]

[0.44, -0.22, -0.42]

[0.38, 0.36, -0.01]

b_{ih} [-0.47, 0.13, 0.46, -0.15]

W_{hh}

[0.38, -0.06, 0.37, -0.19]

[-0.16, 0.42, 0.08, -0.02]

[-0.36, -0.01, 0.17, 0.39]

[-0.43, 0.09, 0.33, 0.03]

b_{hh} [0.43, 0.16, 0.34, -0.39]

Output

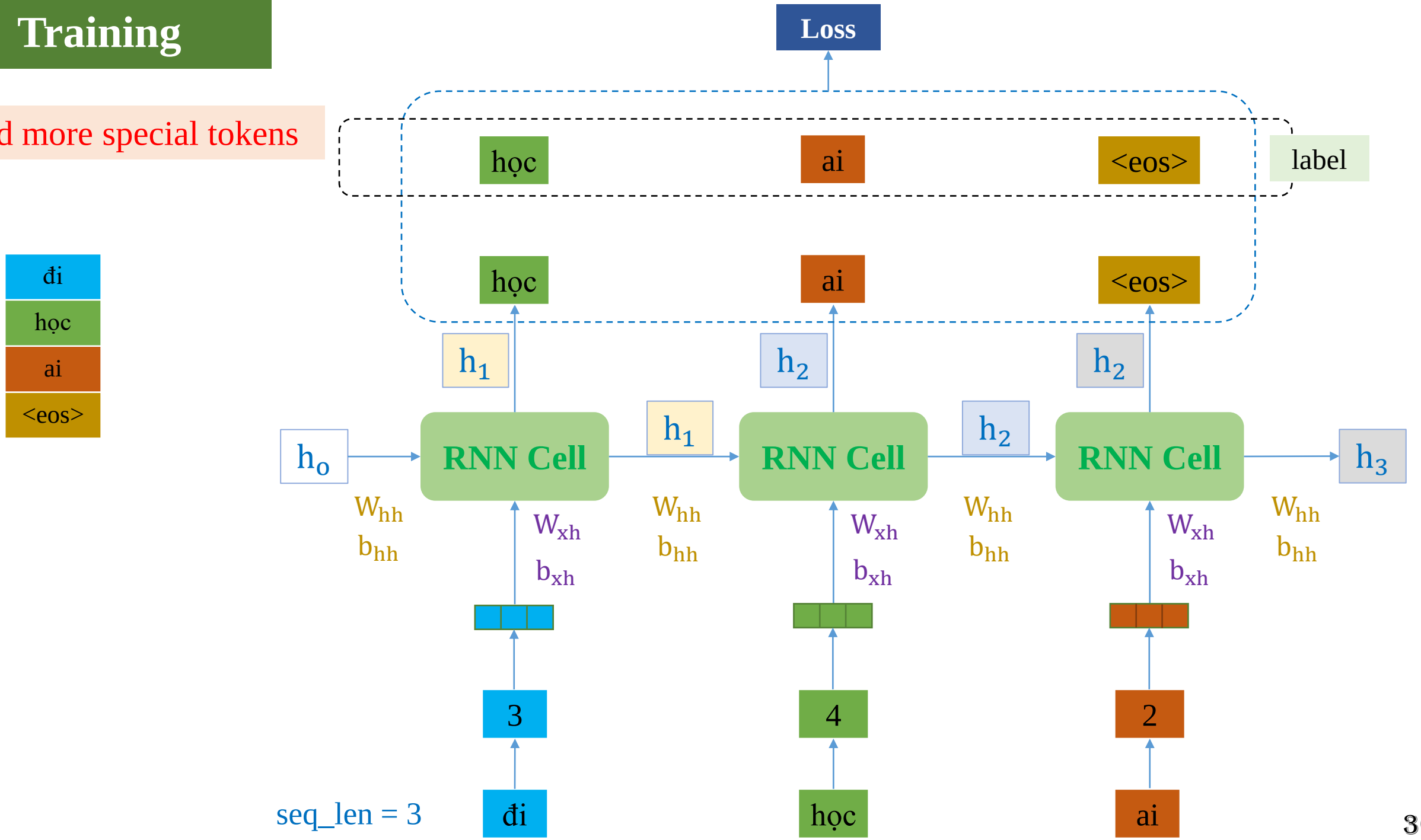
[-0.08, 0.68, -0.08, -0.53]

[-0.30, 0.77, -0.15, -0.58]

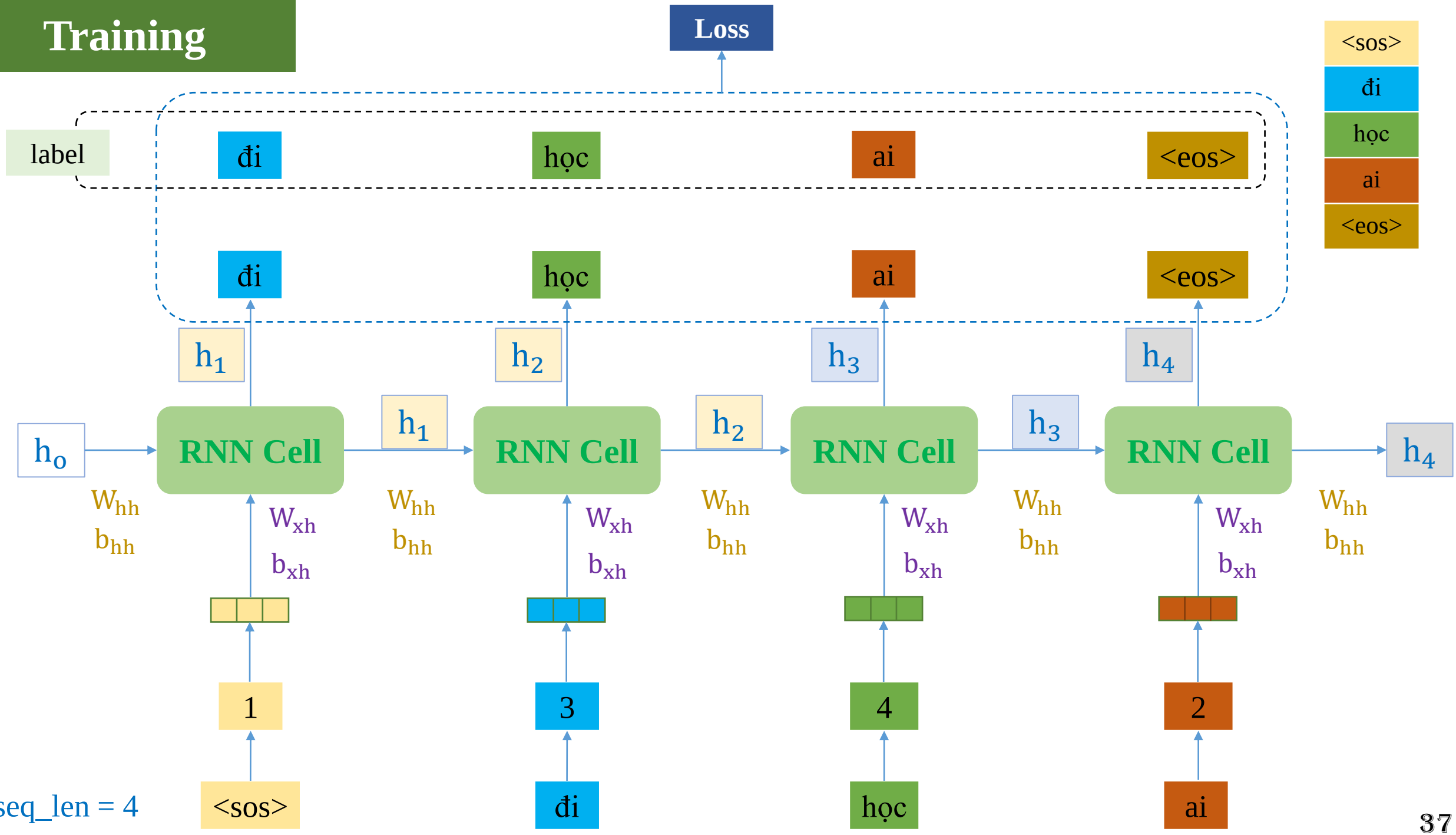
Hidden [-0.30, 0.77, -0.15, -0.58]

Training

Add more special tokens



Training


Loss
label
đi
học
ai
<eos>
<sos>
đi
học
ai
<eos>
h1
h2
h3
h4
ho
RNN Cell
RNN Cell
RNN Cell
RNN Cell
h1
h2
h3
h4
Whh
bhh
Wxh
bxh
1
3
4
2
<sos>
đi
học
ai
seq_len = 4

Outline

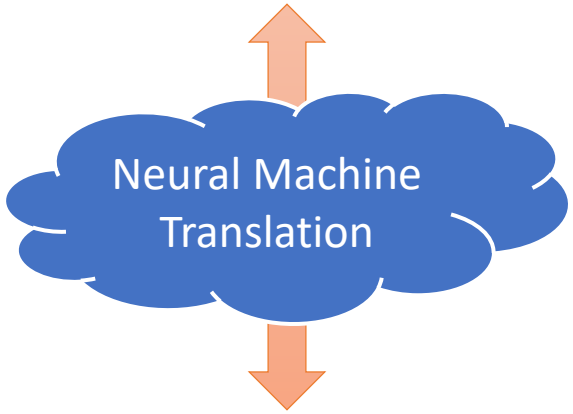
- Text Generation Using Transformer
- An improved Approach to Text Generation
- Machine Translation Using RNN
- Machine Translation Using Transformer

Dataset

IWSLT'15 English-Vietnamese data

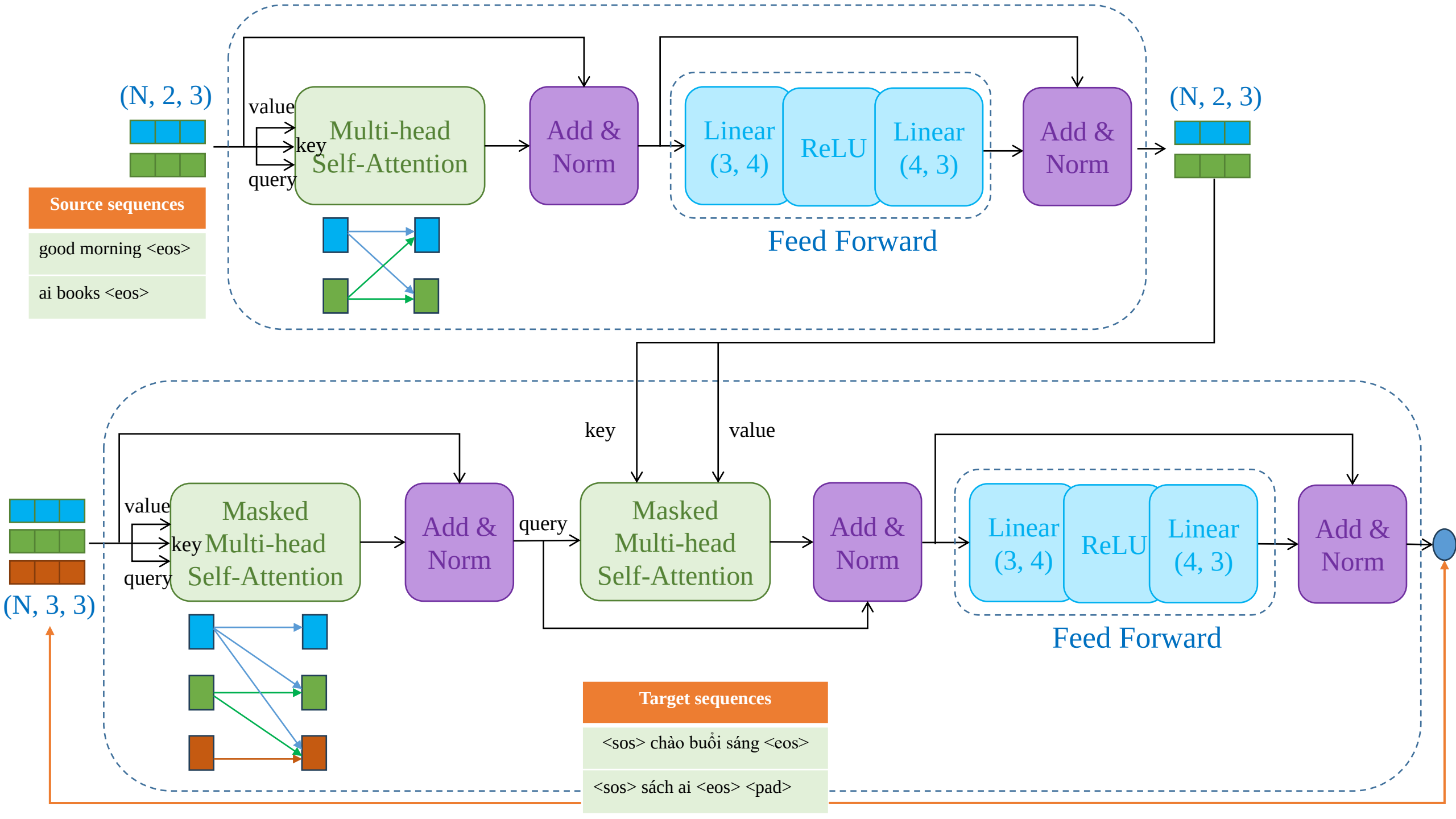
Train	Val	Test
133K sentences	1K3 sentences	1K3 sentences

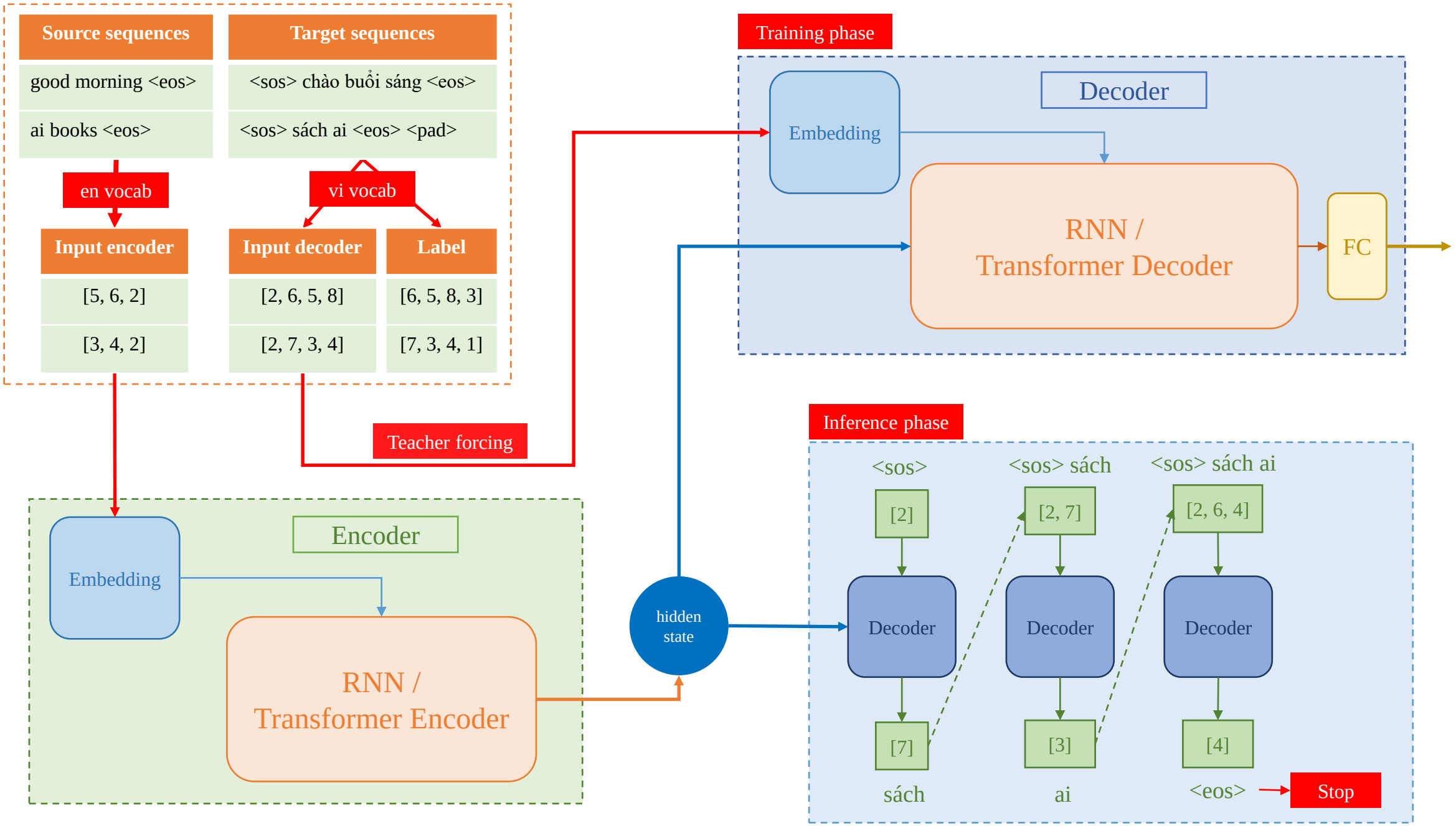
En - sequence	Over 15,000 scientists go to San Francisco every year for that .

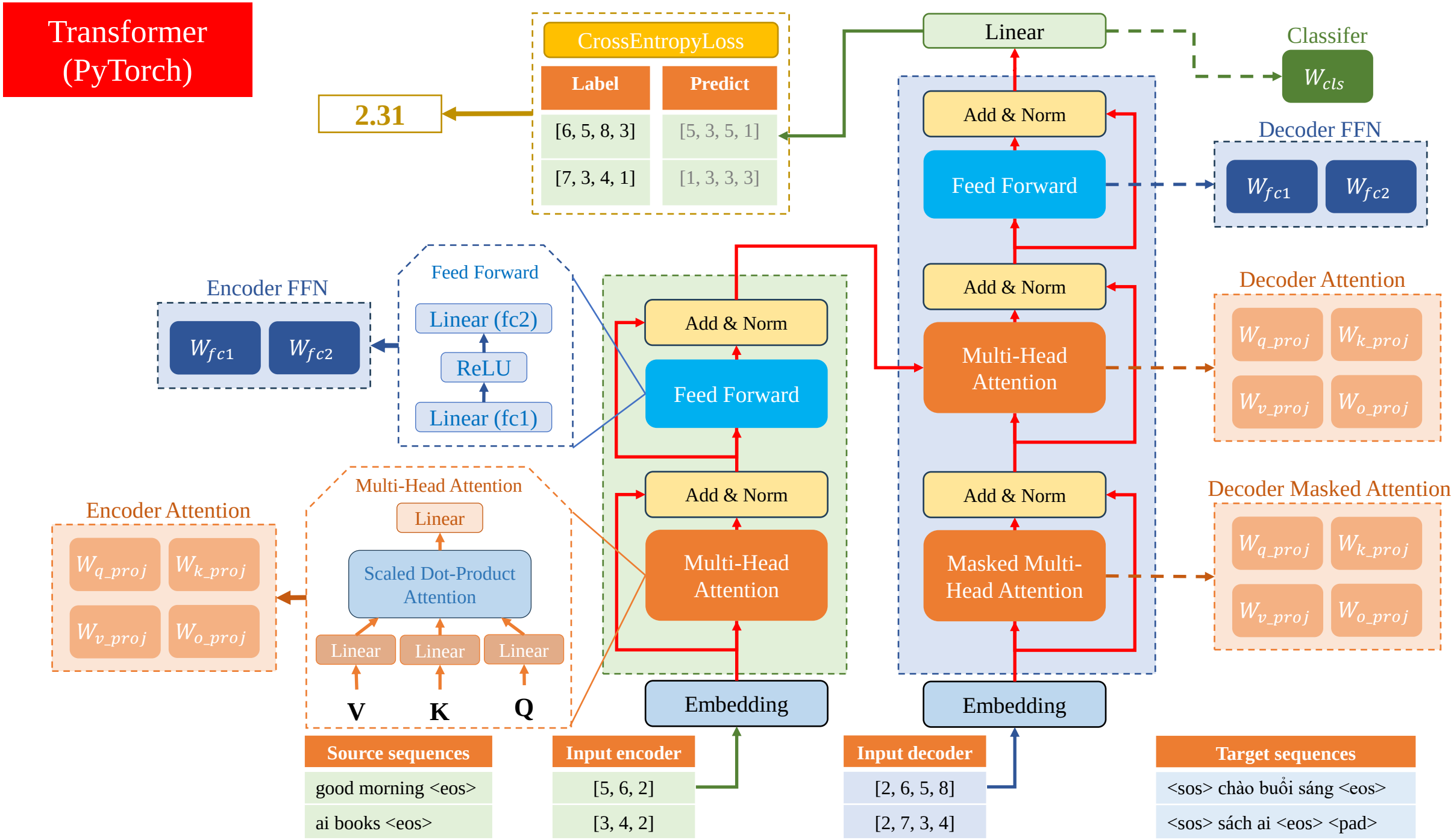


Vi - sequence	Mỗi năm , hơn 15,000 nhà khoa học đến San Francisco để tham dự hội nghị này .

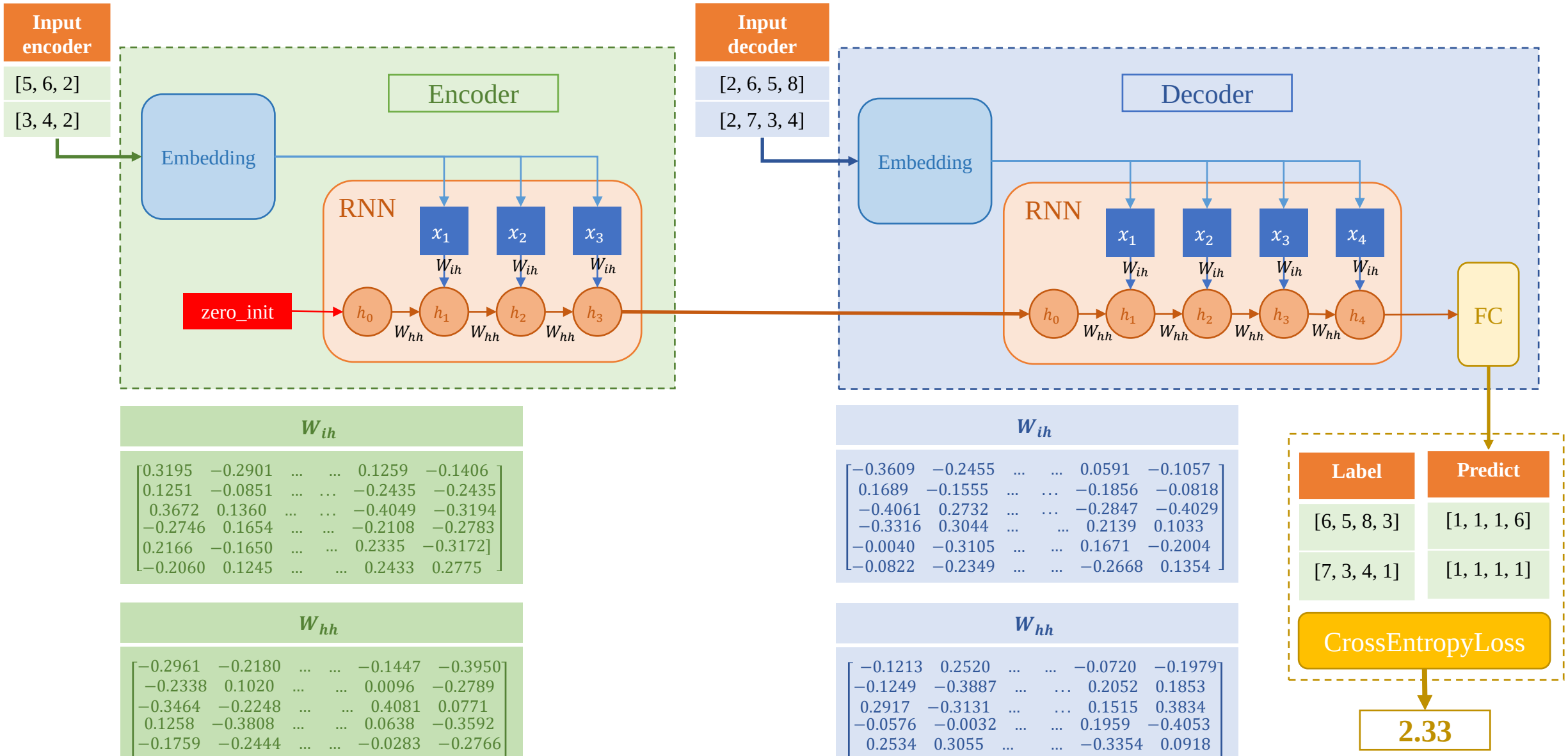
Ref: https://nlp.stanford.edu/projects/nmt/


(N, 2, 3)
value
key
query
Multi-head Self-Attention
Add & Norm
Linear (3, 4)
ReLU
Linear (4, 3)
Feed Forward
Add & Norm
(N, 2, 3)
Source sequences
good morning <eos>
ai books <eos>
key
value
(N, 3, 3)
value
key
query
Masked Multi-head Self-Attention
Add & Norm
query
Masked Multi-head Self-Attention
Add & Norm
Linear (3, 4)
ReLU
Linear (4, 3)
Feed Forward
Add & Norm
Target sequences
<sos> chào buổi sáng <eos>
<sos> sách ai <eos> <pad>


Source sequences
Target sequences
good morning <eos>
<sos> chào buổi sáng <eos>
ai books <eos>
<sos> sách ai <eos> <pad>
en vocab
vi vocab
Input encoder
Input decoder
Label
[5, 6, 2]
[2, 6, 5, 8]
[6, 5, 8, 3]
[3, 4, 2]
[2, 7, 3, 4]
[7, 3, 4, 1]
Teacher forcing
Training phase
Embedding
Decoder
RNN / Transformer Decoder
FC
Encoder
Embedding
RNN / Transformer Encoder
hidden state
Inference phase
<sos>
<sos> sách
<sos> sách ai
[2]
[2, 7]
[2, 6, 4]
Decoder
Decoder
Decoder
[7]
[3]
[4]
sách
ai
<eos>
Stop

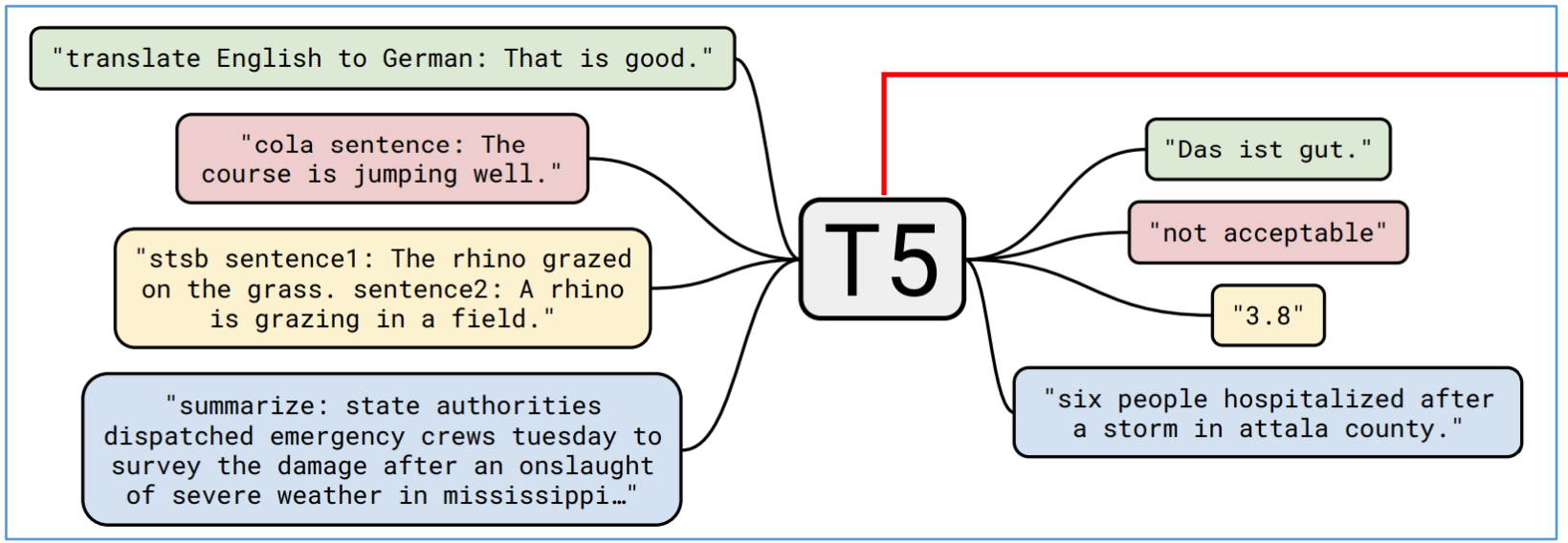

Transformer (PyTorch)
CrossEntropyLoss
Label
Predict
[6, 5, 8, 3]
[5, 3, 5, 1]
[7, 3, 4, 1]
[1, 3, 3, 3]
2.31
Linear
Classifer
W_{cls}
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Embedding
Decoder FFN
W_{fc1}
W_{fc2}
Decoder Attention
W_{q_proj}
W_{k_proj}
W_{v_proj}
W_{o_proj}
Decoder Masked Attention
W_{q_proj}
W_{k_proj}
W_{v_proj}
W_{o_proj}
Feed Forward
Linear (fc2)
ReLU
Linear (fc1)
Encoder FFN
W_{fc1}
W_{fc2}
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Embedding
Multi-Head Attention
Linear
Scaled Dot-Product Attention
Linear
Linear
Linear
V
K
Q
Encoder Attention
W_{q_proj}
W_{k_proj}
W_{v_proj}
W_{o_proj}
Source sequences
good morning <eos>
ai books <eos>
Input encoder
[5, 6, 2]
[3, 4, 2]
Input decoder
[2, 6, 5, 8]
[2, 7, 3, 4]
Target sequences
<sos> chào buổi sáng <eos>
<sos> sách ai <eos> <pad>

RNN

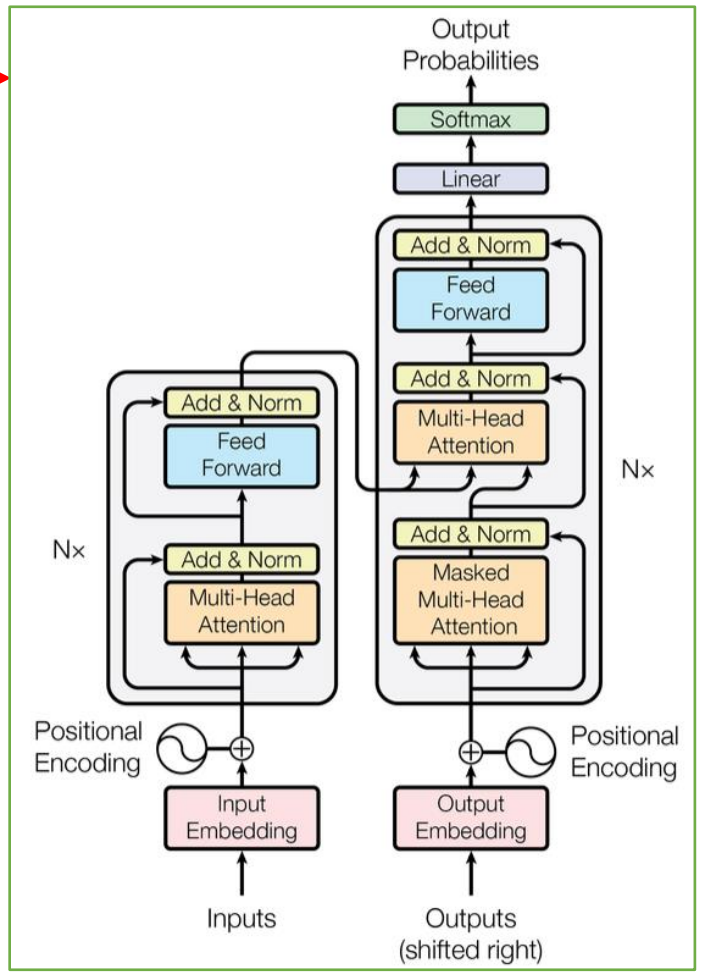

Input encoder
[5, 6, 2]
[3, 4, 2]
Embedding
Encoder
RNN
x_1 x_2 x_3
W_{ih}
zero_init
h_0 h_1 h_2 h_3
W_{hh}
Input decoder
[2, 6, 5, 8]
[2, 7, 3, 4]
Embedding
Decoder
RNN
x_1 x_2 x_3 x_4
W_{ih}
h_0 h_1 h_2 h_3 h_4
W_{hh}
FC
W_{ih}
0.3195 −0.2901 ... ... 0.1259 −0.1406
0.1251 −0.0851 ... ... −0.2435 −0.2435
0.3672 0.1360 ... ... −0.4049 −0.3194
−0.2746 0.1654 ... ... −0.2108 −0.2783
0.2166 −0.1650 ... ... 0.2335 −0.3172]
−0.2060 0.1245 ... ... 0.2433 0.2775
W_{hh}
−0.2961 −0.2180 ... ... −0.1447 −0.3950
−0.2338 0.1020 ... ... 0.0096 −0.2789
−0.3464 −0.2248 ... ... 0.4081 0.0771
0.1258 −0.3808 ... ... 0.0638 −0.3592
−0.1759 −0.2444 ... ... −0.0283 −0.2766
−0.2802 −0.2382 ... ... 0.3423 −0.0810
W_{ih}
−0.3609 −0.2455 ... ... 0.0591 −0.1057
0.1689 −0.1555 ... ... −0.1856 −0.0818
−0.4061 0.2732 ... ... −0.2847 −0.4029
−0.3316 0.3044 ... ... 0.2139 0.1033
−0.0040 −0.3105 ... ... 0.1671 −0.2004
−0.0822 −0.2349 ... ... −0.2668 0.1354
W_{hh}
−0.1213 0.2520 ... ... −0.0720 −0.1979
−0.1249 −0.3887 ... ... 0.2052 0.1853
0.2917 −0.3131 ... ... 0.1515 0.3834
−0.0576 −0.0032 ... ... 0.1959 −0.4053
0.2534 0.3055 ... ... −0.3354 0.0918
0.2255 −0.4063 ... ... −0.0357 −0.2009
Label
Predict
[6, 5, 8, 3]
[1, 1, 1, 6]
[7, 3, 4, 1]
[1, 1, 1, 1]
CrossEntropyLoss
2.33

Model

T5: Text-to-Text Transfer Transformer



Original transformer



Encoder-Decoder model pre-trained on a **multi-task mixture** of **unsupervised** and **supervised** tasks

Unsupervised

Predict masked spans

Supervised

seq2seq
input-output mapping

Ref: https://arxiv.org/pdf/1910.10683.pdf