

# Deep Architectures for POS Tagging and NER

Quang-Vinh Dinh  
Ph.D. in Computer Science

# Outline

- Quick Review
- POS Tagging Using Different Models
- Named Entity Recognition
- Step-by-step Examples
- PyTorch Implementation

# Quiz 1

❖ Choose the correct code segment?

```
import torch
import torch.nn as nn
import torch.nn.functional as F

class MyModel(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(5, 4)
        self.fc2 = nn.Linear(4, 3)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x

model = MyModel()
```

```
from torchinfo import summary
```

```
input_x = torch.randn((32, 5))
model = MyModel()
```

```
summary(model, input_data=input_x)
```

```
from torchinfo import summary
```

```
input_x = torch.randn((32, 8, 5))  
model = MyModel()
```

```
summary(model, input_data=input_x)
```

```
=====
```

Layer (type:depth-idx)	Output Shape
MyModel	[32, 3]
─Linear: 1-1	[32, 4]
─Linear: 1-2	[32, 3]

```
=====
```

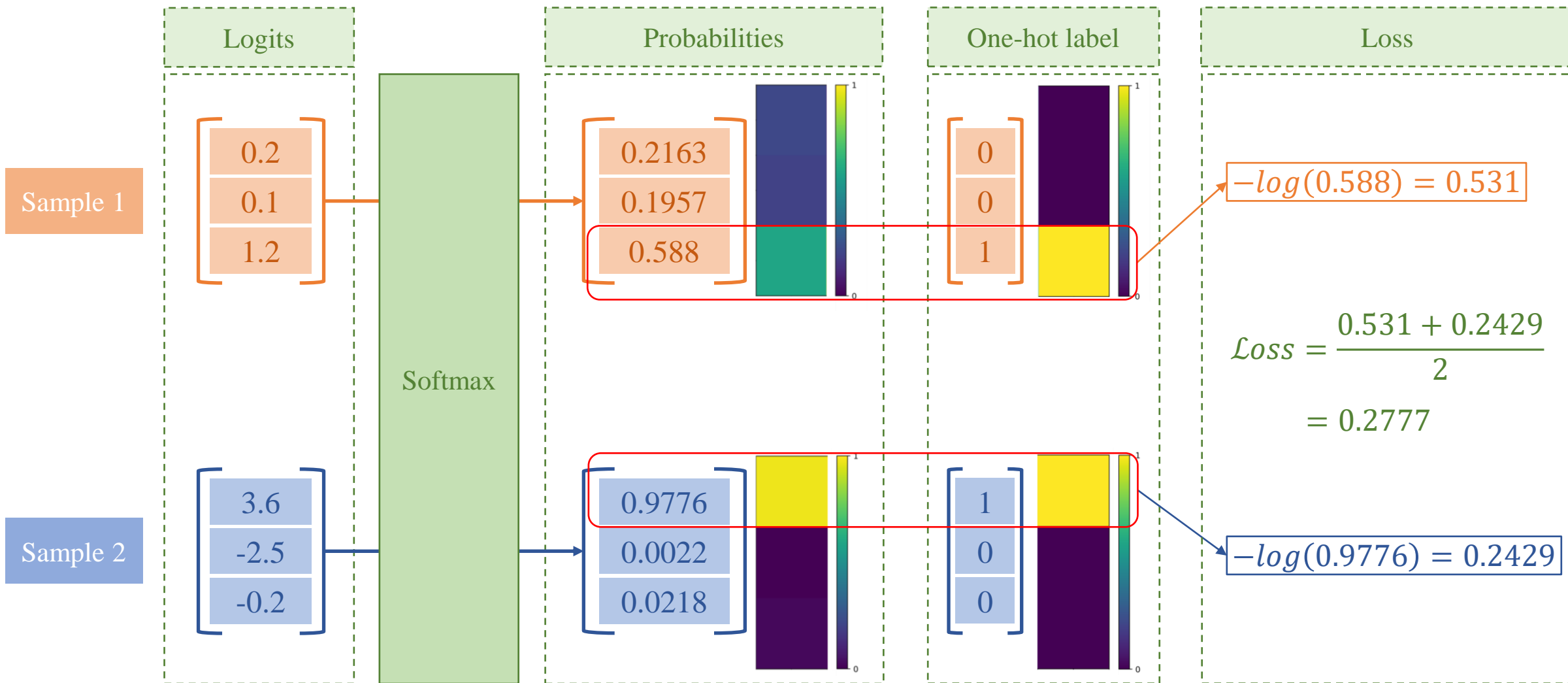
Total params: 39 | =====

[illegible]

# Cross Entropy Loss

N\_classes = 3

$$L = - \sum_i y_i \log(\hat{y}_i)$$

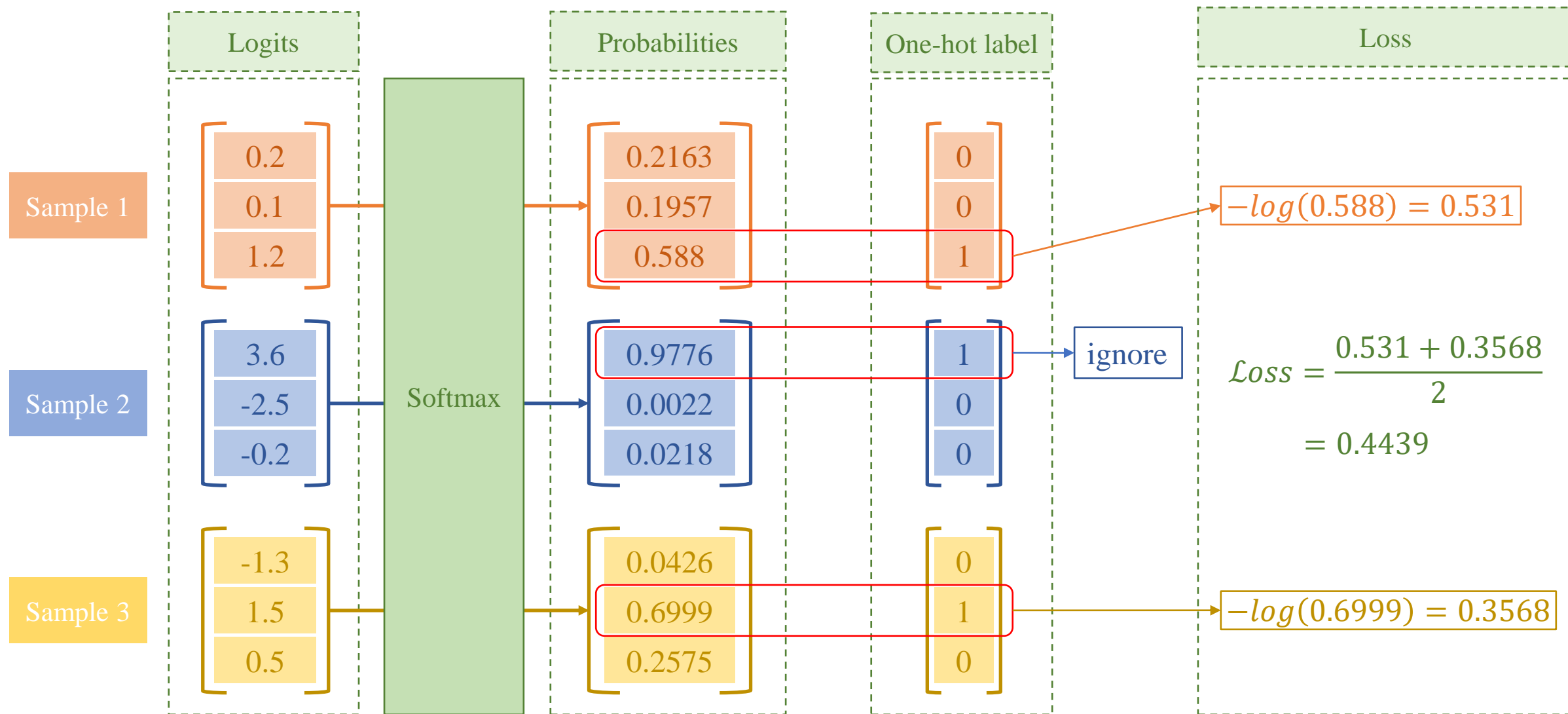


# Cross Entropy Loss

N\_classes = 3

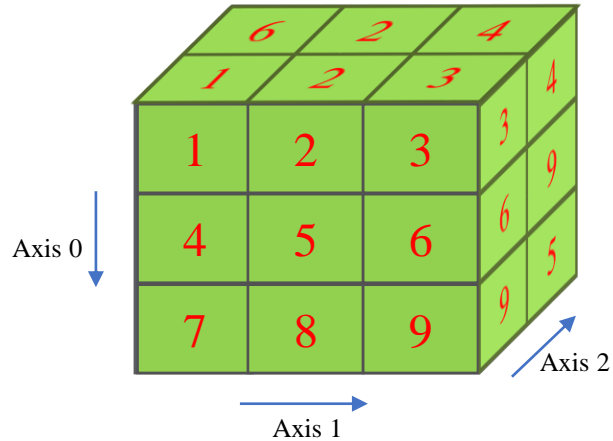
$$L = - \sum_i y_i \log(\hat{y}_i)$$

**Ignore\_index = 0**



# Quiz 2

## ❖ Loss function



Three dimensions includes

- batch\_size  $N$
- sequence\_length  $L$
- num\_classes  $C$

```
PyTorch
criterion = nn.CrossEntropyLoss()
loss = criterion(Z, y)
```

if the  $y$  shape is  $(N,)$

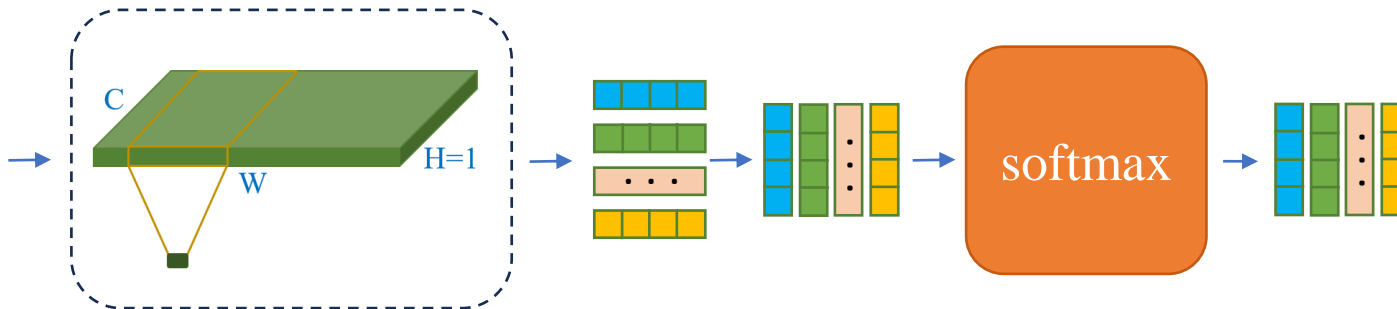
the  $Z$  shape is  $(?)$

if the  $y$  shape is  $(N, C)$

the  $Z$  shape is  $(?)$

if the  $Z$  shape is  $(N, L, C)$

the  $y$  shape is  $(?)$



# Outline

- Quick Review
- POS Tagging Using Different Models
- Named Entity Recognition
- Step-by-step Examples
- PyTorch Implementation

# Designing a Model for POS Tagging

Doc	Label
i want a dog	[0, 1, 2, 0]
books are expensive	[0, 1, 2]

Label	Meaning
0	Noun/Pronoun
1	Verb
2	Others

building  
dictionary  
→  
vocab size = 9  
sequence length = 4

index	word
0	[UNK]
1	[pad]
2	a
3	are
4	books
5	dog
6	expensive
7	i
8	want

Dictionary

0	[-0.1882, 0.5530, ..., 0.7013]
1	[1.7840, -0.8278, ..., 1.3586]
2	[1.0281, -1.9094, ..., 0.4211]
3	[-1.3083, -0.0987, ..., -0.3680]
4	[0.2293, 1.3255, ..., 2.0501]
5	[0.4058, -0.6624, ..., 0.7203]
6	[0.5582, 0.0786, ..., 0.6902]
7	[0.4309, -1.3067, ..., 1.5977]
8	[0.3058, -0.7624, ..., 0.6203]

Embedding

i	7	[0.4058, -0.6624, ..., 0.7203]
want	8	[0.3058, -0.7624, ..., 0.6203]
a	2	[1.0281, -1.9094, ..., 0.4211]
dog	5	[0.4058, -0.6624, ..., 0.7203]

sample 1

sample 1 \_ Embedding

Vectorization and Embedding

shape=(1, 4, 4)  
(N, seq\_len, embed\_dim)

A  
sample

Vectorization  
&  
Embedding

shape=(1, 4, 4)  
(N, C, seq\_len)

???

Output

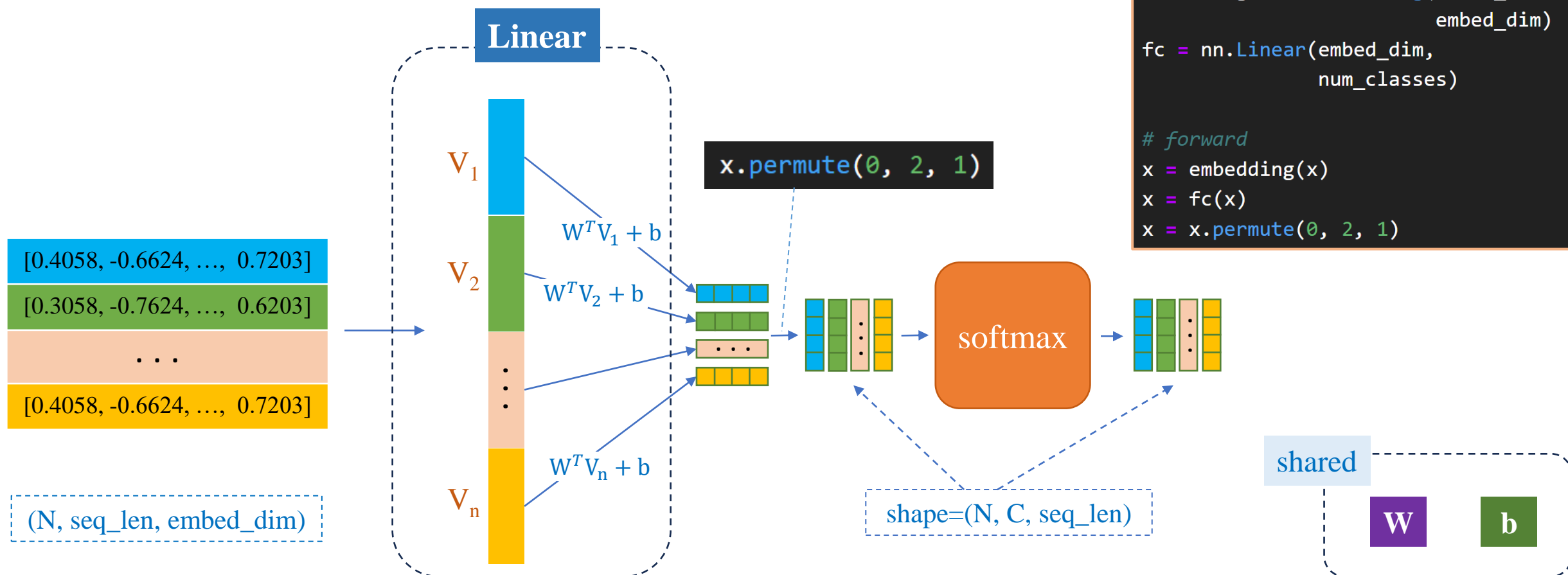
Model

Model Pipeline



# Designing a Model for POS Tagging

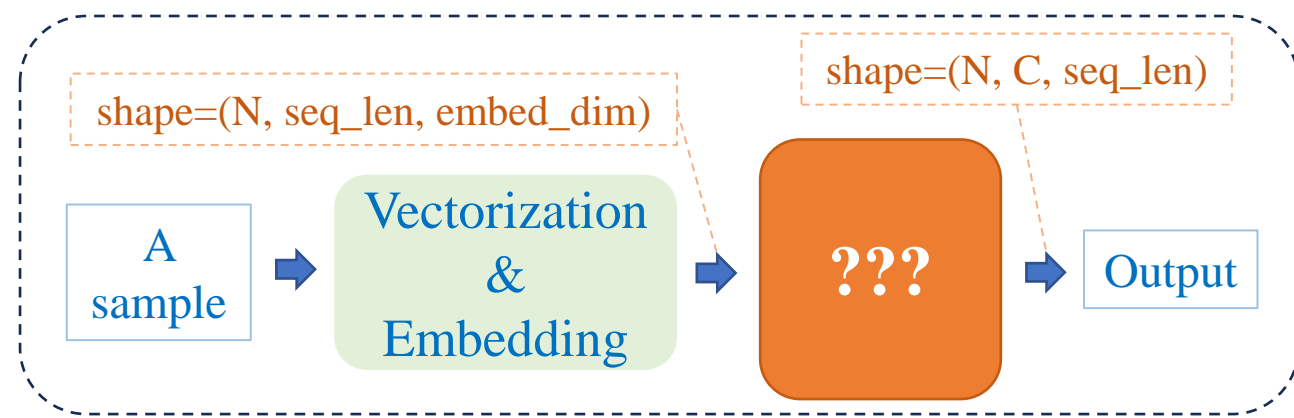
Using MLP



# Designing a Model for POS Tagging

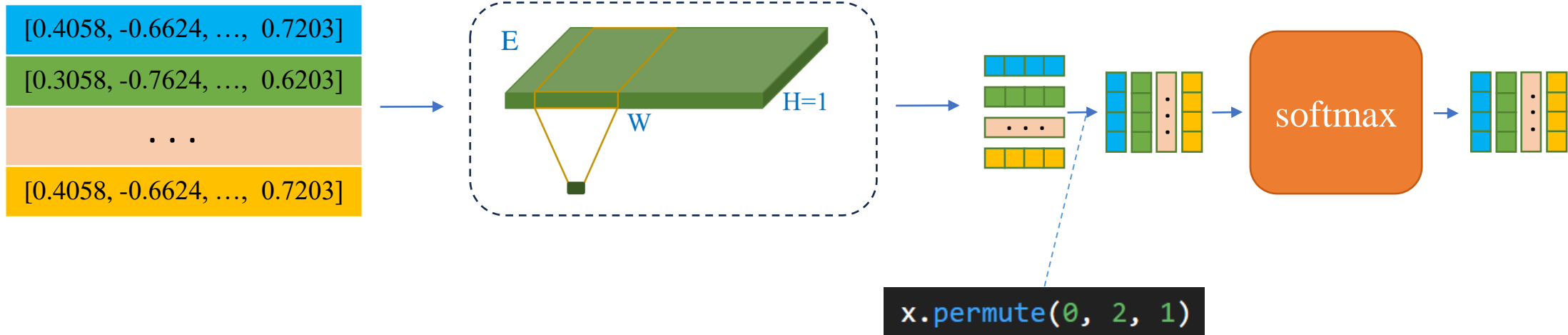
Using CNN

This pipeline is wrong.  
Let's find out!



```
embedding = nn.Embedding(vocab_size, 3)
conv1d = nn.Conv1d(3, num_classes,
                   kernel_size=2, padding='same')

# forward
x = self.embedding(x)
x = self.conv1d(x)
x = x.permute(0, 2, 1)
```



# Designing a Model for POS Tagging

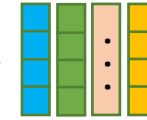
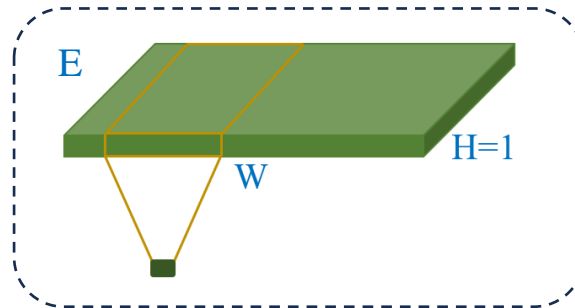
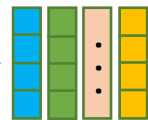
## Using CNN

input size  $(N, C_{in}, L)$  and output  $(N, C_{out}, L_{out})$

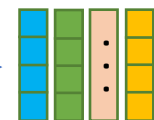
<https://pytorch.org/docs/stable/generated/torch.nn.Conv1d.html>

```
x.permute(0, 2, 1)
```

[0.4058, -0.6624, ..., 0.7203]
[0.3058, -0.7624, ..., 0.6203]
...
[0.4058, -0.6624, ..., 0.7203]



softmax



$(N, \text{seq\_len}, \text{embed\_dim } E)$

$(N, \text{embed\_dim } E, \text{seq\_len})$

$\text{shape}=(N, C, \text{seq\_len})$

$\text{shape}=(N, \text{seq\_len}, \text{embed\_dim})$

A  
sample

Vectorization  
&  
Embedding

???

Output

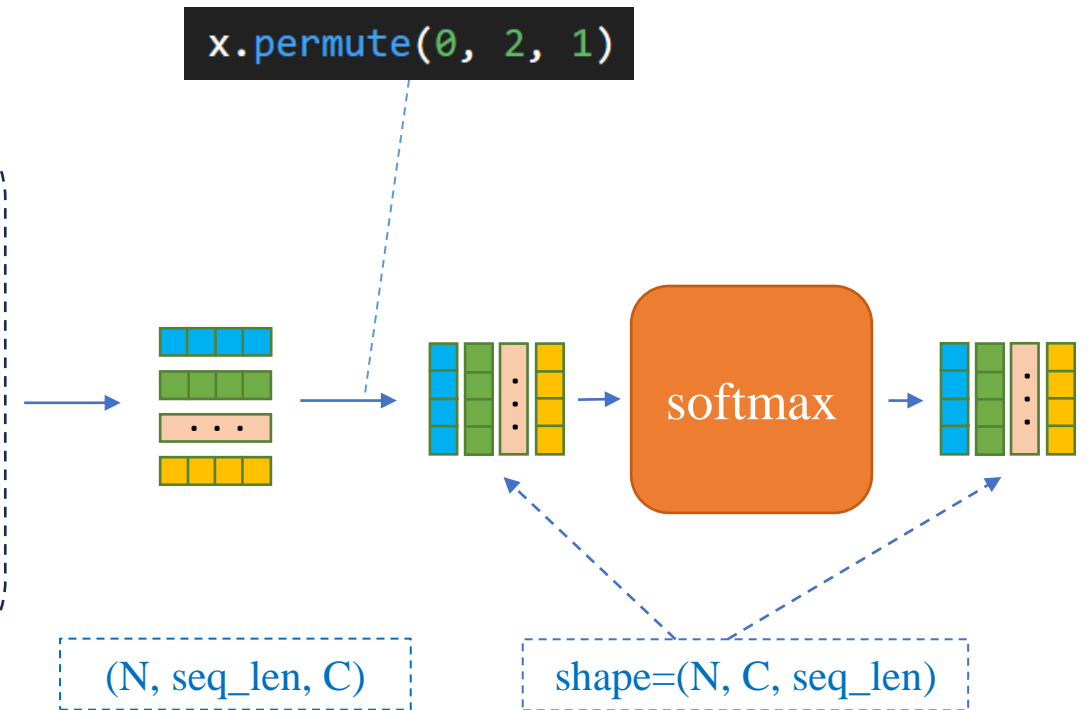
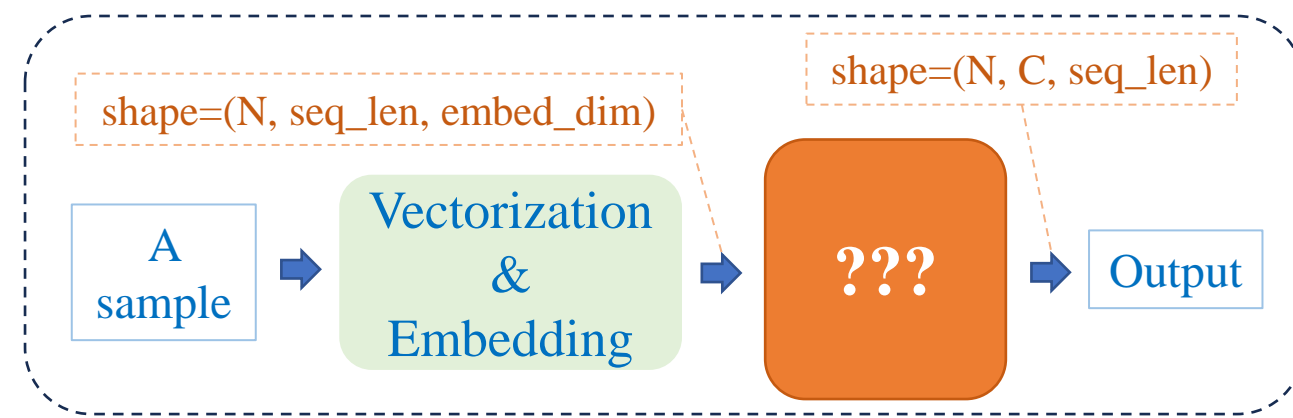
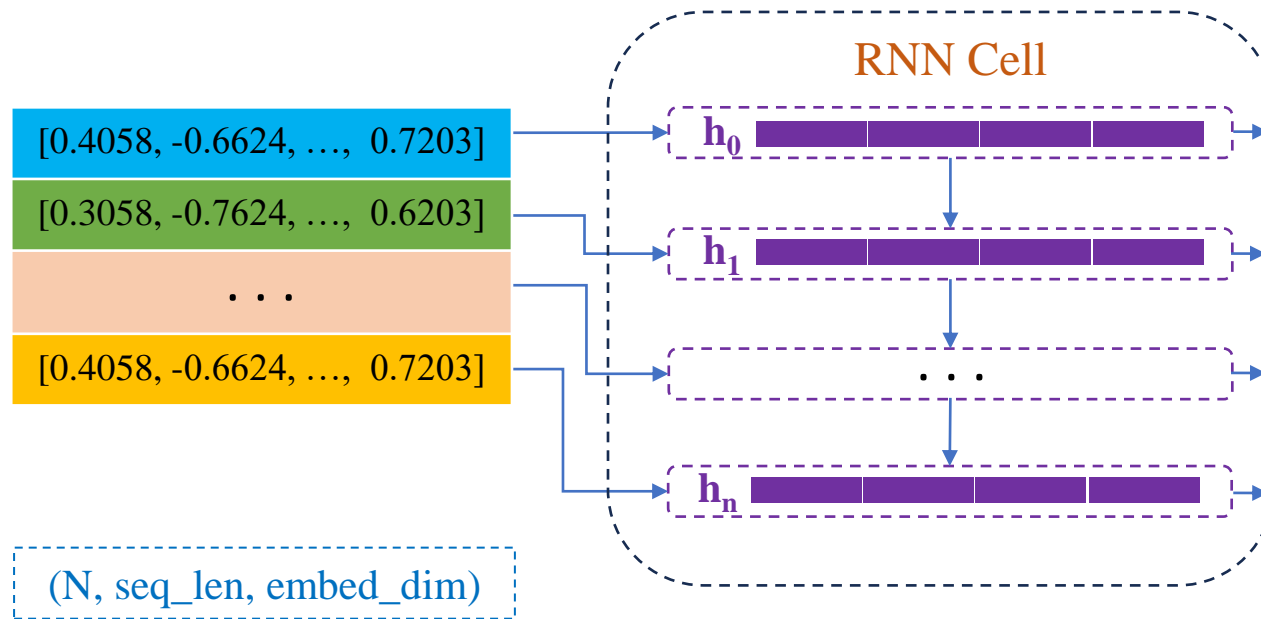
$\text{shape}=(N, C, \text{seq\_len})$

```
embedding = nn.Embedding(vocab_size, 3)
conv1d = nn.Conv1d(3, num_classes,
                   kernel_size=2, padding='same')

# forward
x = self.embedding(x)
x = x.permute(0, 2, 1)
x = self.conv1d(x)
```

# Designing a Model for POS Tagging

Using RNN

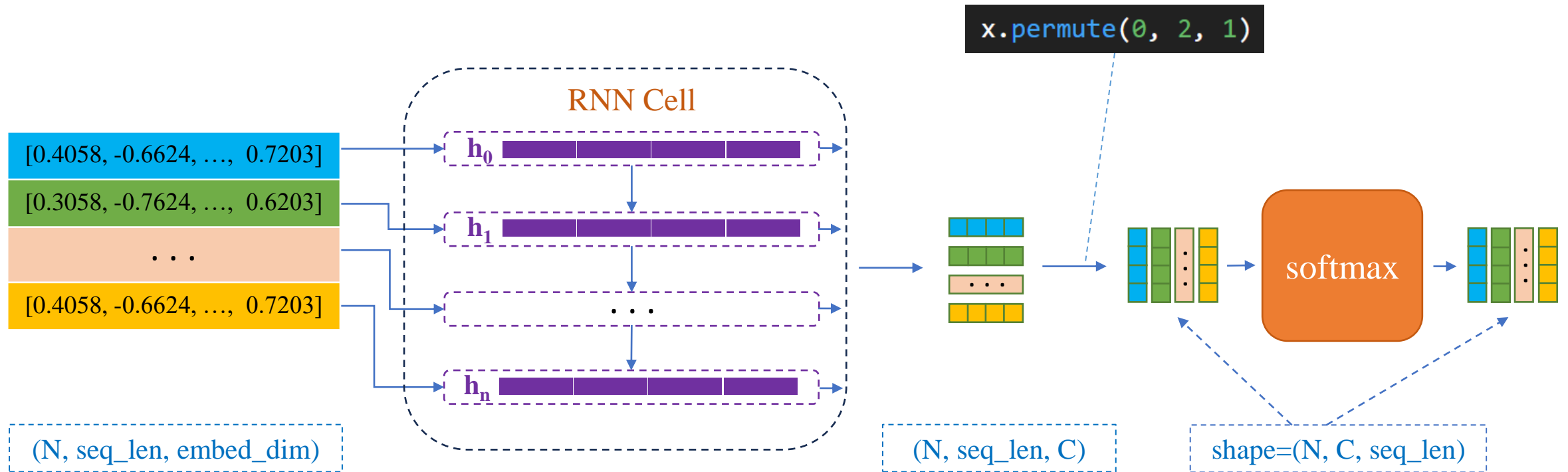


# Designing a Model for POS Tagging

## Using RNN: Implementation

```
embedding = nn.Embedding(vocab_size, emb_dim)
recurrent = nn.RNN(emb_dim, num_classes, batch_first=True)

# forward
x = embedding(x)
output, _ = recurrent(x)
x = output.permute(0, 2, 1)
```



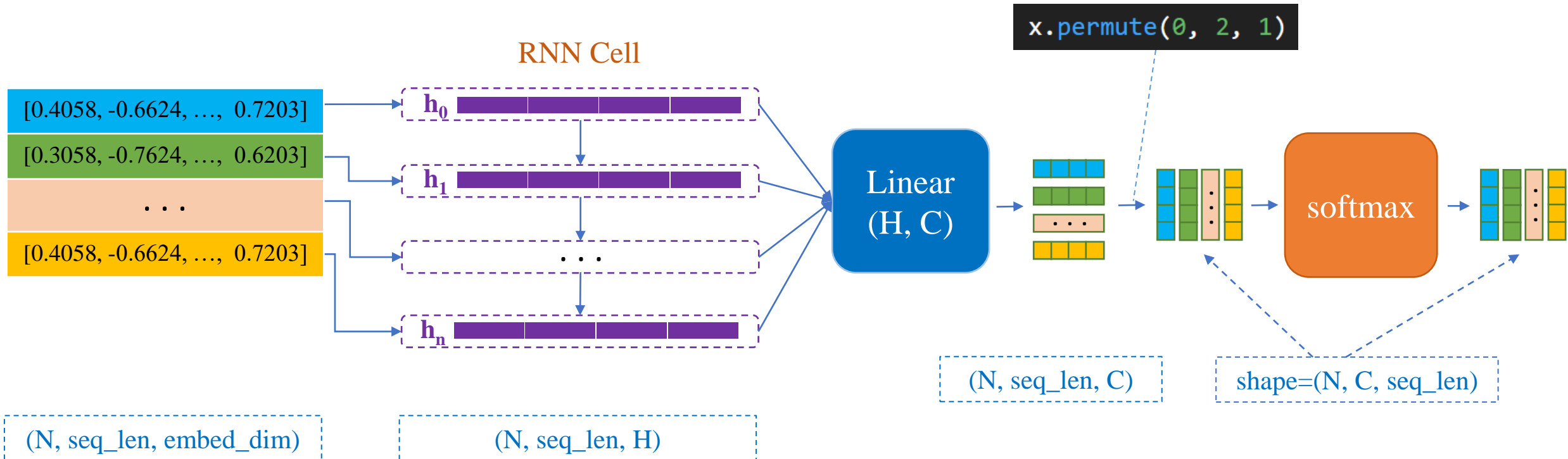
# Designing a Model for POS Tagging

Using RNN + Linear

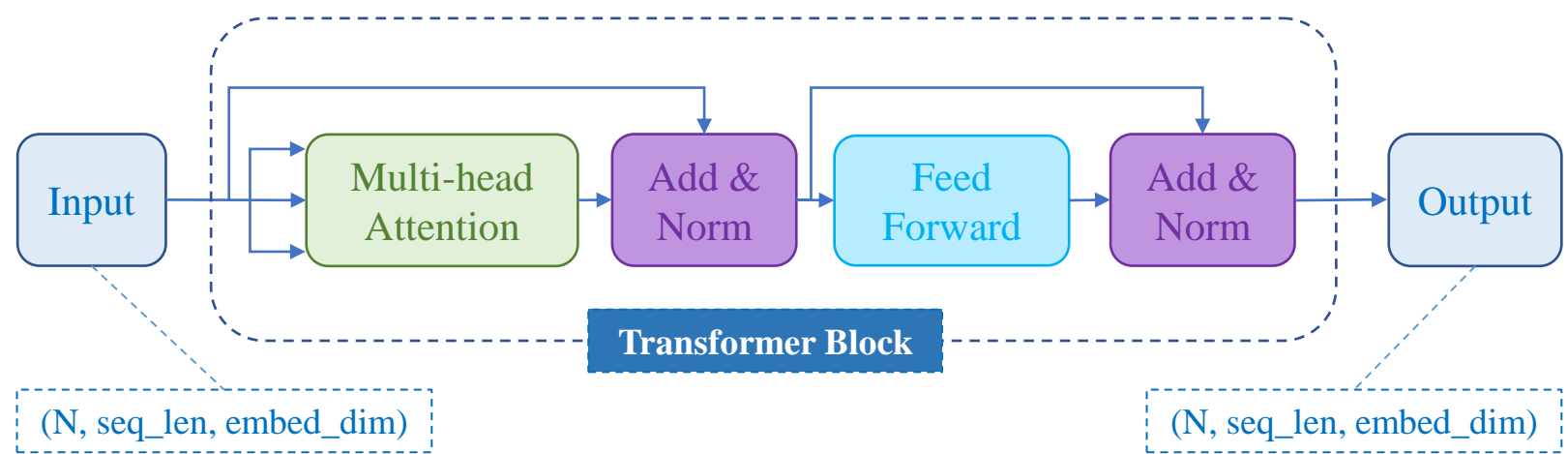
Similar to LSTM/GRU

```
embedding = nn.Embedding(vocab_size, emb_dim)
recurrent = nn.RNN(emb_dim, hidden_size, batch_first=True)
fc = nn.Linear(hidden_size, num_classes)

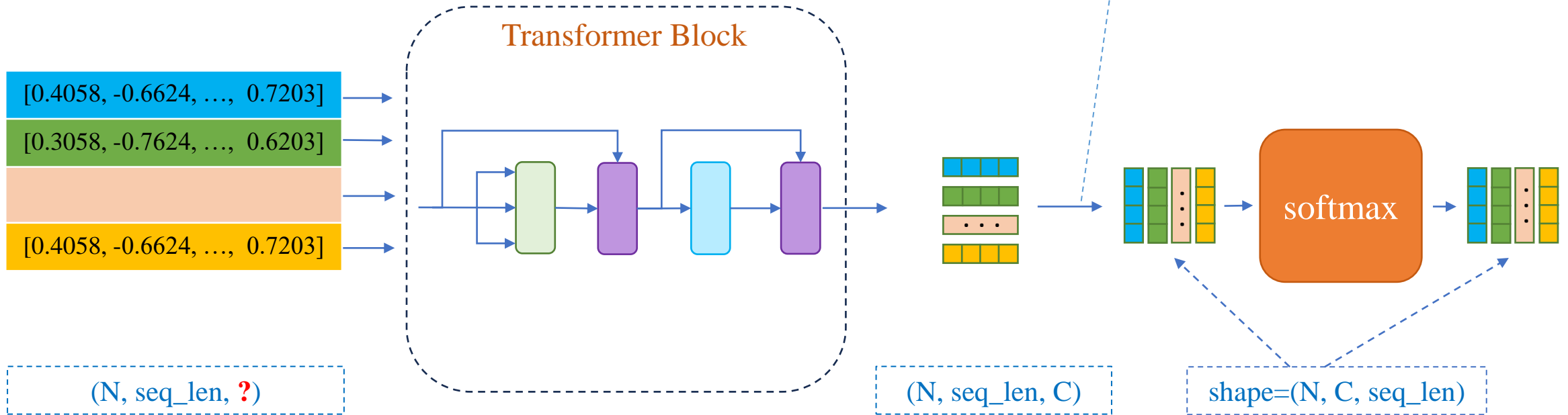
# forward
x = embedding(x)
output, _ = recurrent(x)
x = fc(output)
x = x.permute(0, 2, 1)
```



# Designing a Model for POS Tagging

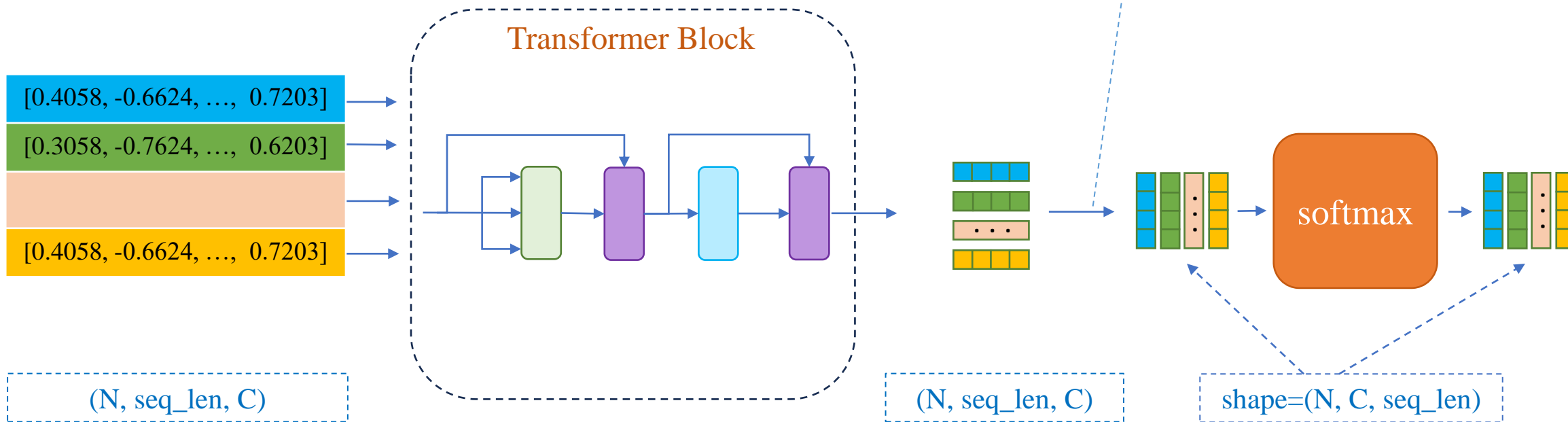


## Using Transformer



# Designing a Model for POS Tagging

## Using Transformer



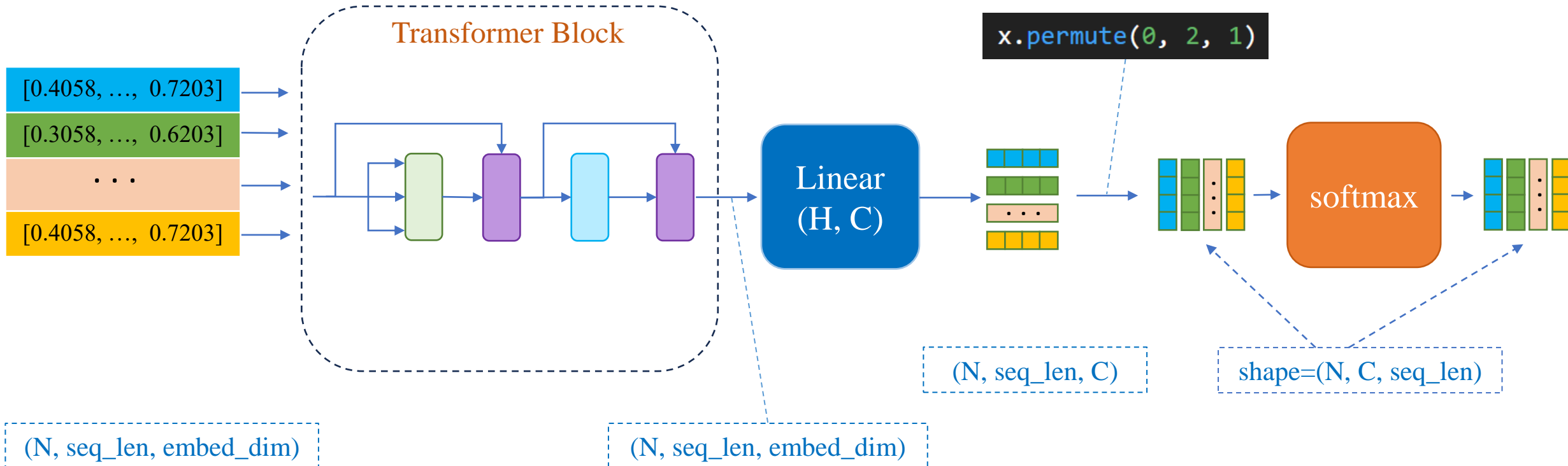


# Designing a Model for POS Tagging

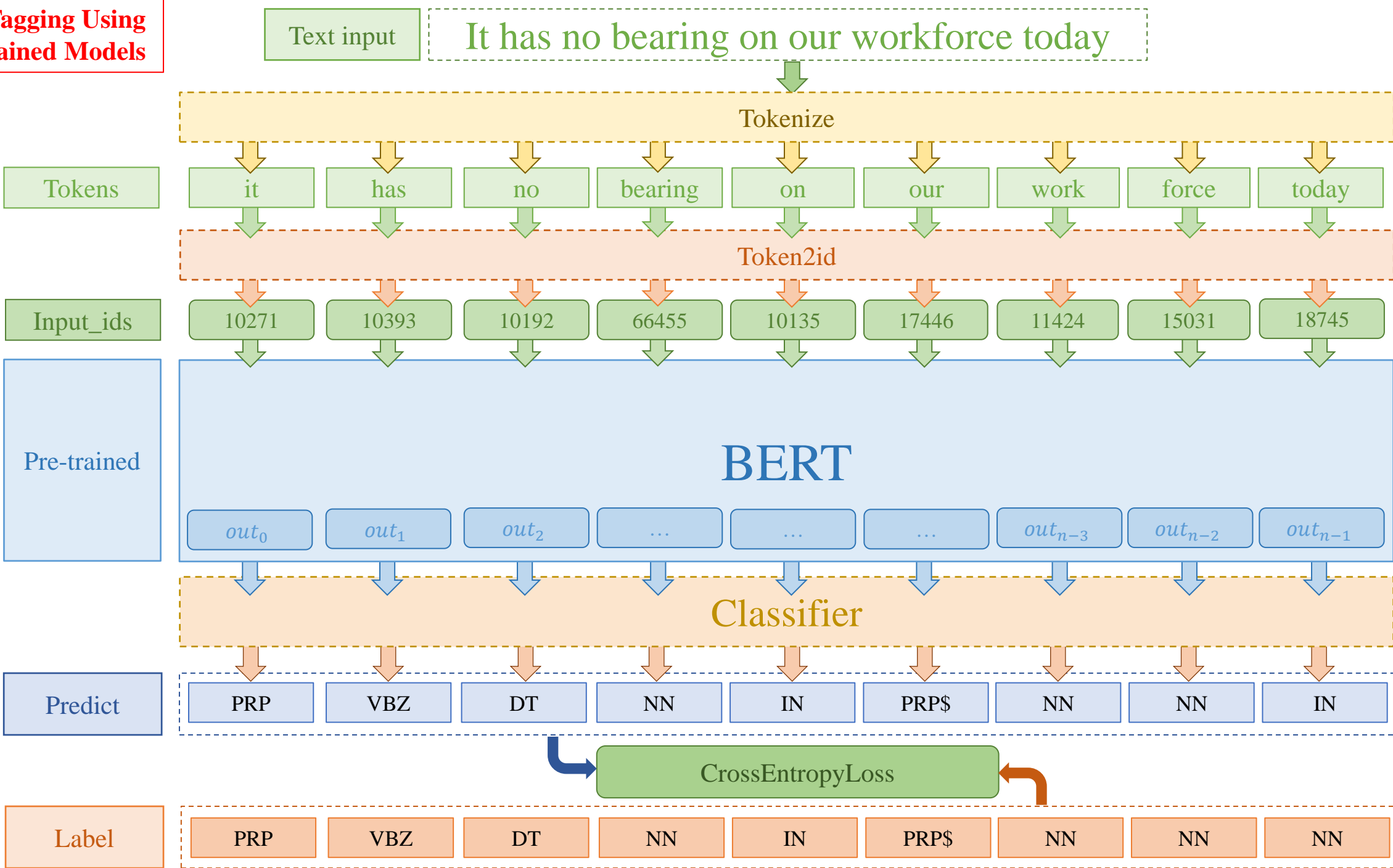
Using Transformer + Linear

```
embedding = nn.Embedding(vocab_size, embed_dim)
transformer = TransformerBlock(embed_dim, 1, embed_dim)
fc = nn.Linear(embed_dim, num_classes)

# forward
x = self.embedding(x)
x = self.transformer(x, x, x)
x = self.fc(x)
x = x.permute(0, 2, 1)
```



**POS Tagging Using  
Pre-trained Models**



# Outline

- Quick Review
- POS Tagging Using Different Models
- Named Entity Recognition
- Step-by-step Examples
- PyTorch Implementation

# Conll2003 Dataset for Part-of-Speech Tagging

Num\_classes = 47

Train

14041

Val

3250

Test

3453

0	“	Quotation mask
1		space
2	#	Hash
3	\$	Dolla
4	(	Opening parenthesis
5	)	Closing parenthesis
6	,	Comma
7	.	Dot
8	:	Colon
9	``	Apostrophe

10	CC	Coordinating conjunction
11	CD	Cardinal number
12	DT	Determiner
13	EX	Existential <i>there</i>
14	FW	Foreign word
15	IN	Preposition or subordinating conjunction
16	JJ	Adjective
17	JJR	Adjective, comparative
18	JJS	Adjective, superlative
19	LS	List item marker

20	MD	Modal
21	NN	Noun, singular or mass
22	NNP	Proper noun, singular
23	NNP S	Proper noun, plural
24	NNS	Noun, plural
25	NN S YM	Noun or Symbol
26	PDT	Predeterminer
27	POS	Possessive ending
28	PRP	Personal pronoun
29	PRP\$	Possessive pronoun

# Conll2003 Dataset for Part-of-Speech Tagging

Num\_classes = 47

## Example

### Input tokens

[ "Cup", "qualifying", "round", ",", "second", "leg", "soccer", "matches", "on", "Thursday" ]

### Label

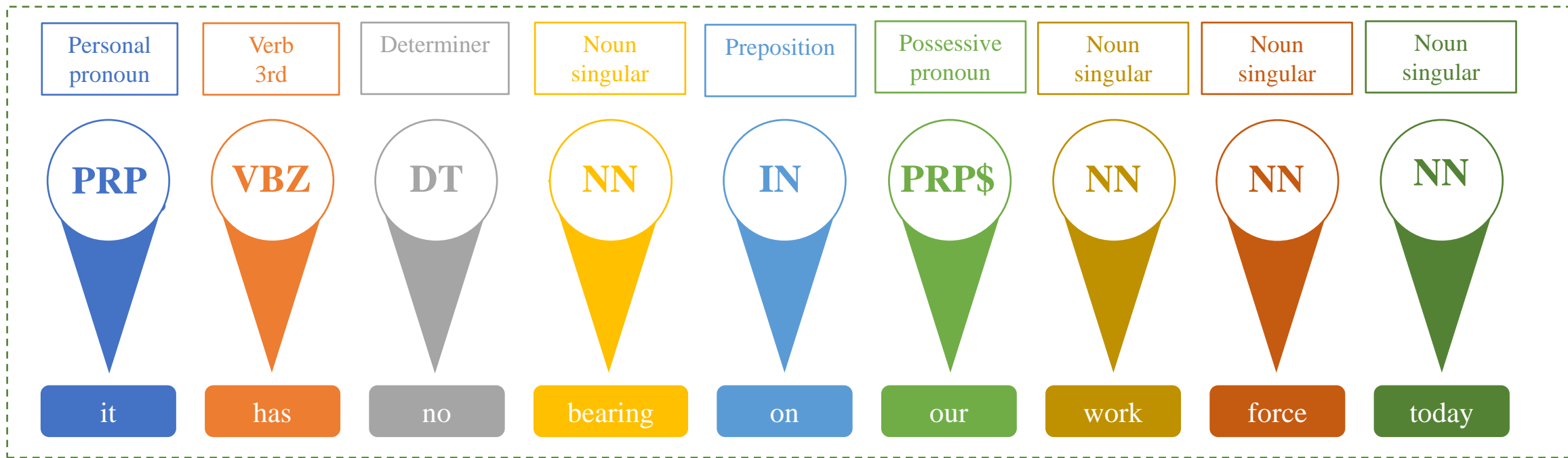
[ "NNP", "VBG", "RB", ",", "JJ", "NN", "NN", "NNS", "IN", "NNP" ]

### Label-encoded

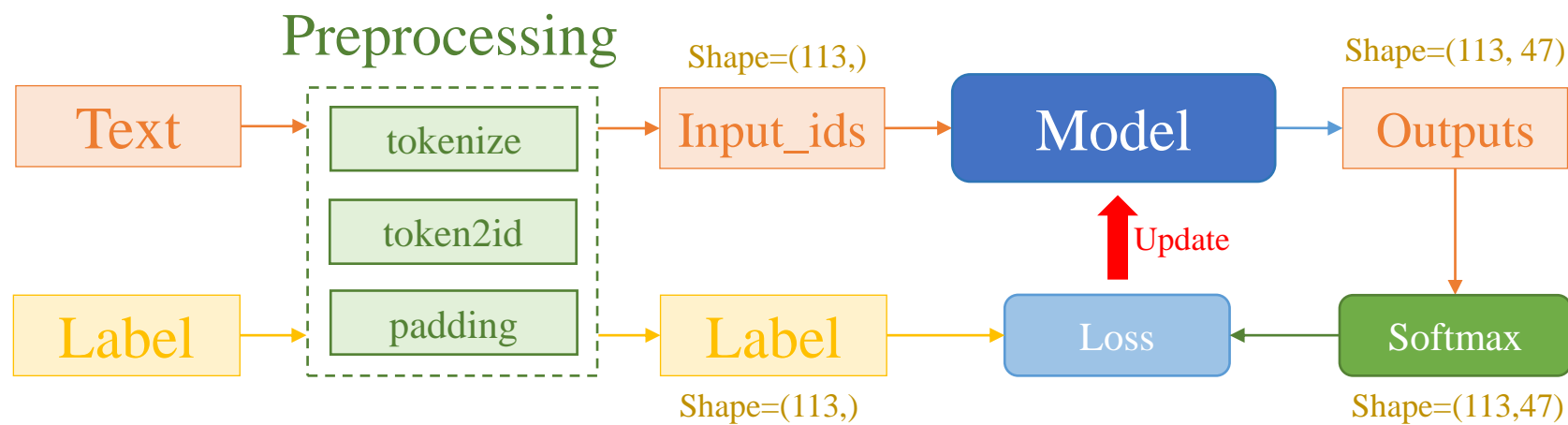
[ 22, 39, 30, 6, 16, 21, 21, 24, 15, 22, ]

30	RB	Adverb
31	RBR	Adverb, comparative
32	RBS	Adverb, superlative
33	RP	Particle
34	SYM	Symbol
35	TO	to
36	UH	Interjection
37	VB	Verb, base form
38	VBD	Verb, past tense
39	VBG	Verb, gerund or present participle
40	VBN	Verb, past participle
41	VBP	Verb, non-3rd person singular present
42	VBZ	Verb, 3rd person singular present
43	WDT	Wh-determiner
44	WP	Wh-pronoun
45	WP\$	Possessive wh-pronoun
46	WRB	Wh-adverb

# Part-of-speed Tagging



Index	Label
0	<unk>
1	NN
2	IN
3	NNP
...	...
43	LS
44	FW
45	UH
46	SYM



# Custom Dataset in Pytorch

Create a Custom Dataset



`__init__(self, ...)` function:  
Khởi tạo các thuộc tính/biến



`__len__(self)` function:  
Trả về độ dài của dataset



`__getitem__(self, idx)` function:  
Xử lý một sample và trả về x và y

```
from transformers import AutoTokenizer
```

```
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
```

```
sequence_length = 5
```

```
sample1 = 'We are learning AI'
```

```
sample2 = 'AI is a CS topic'
```

```
sentences = [sample1, sample2]
```

```
labels = [0, 1]
```

```
from torch.utils.data import Dataset
```

```
class MyDataset(Dataset):
```

```
    def __init__(self, sentences, labels, tokenizer, max_len):  
        super().__init__()  
        #...
```

```
    def __len__(self):  
        return len(self.sentences)
```

```
    def __getitem__(self, idx):  
        #...  
  
        return tokens, sentence_label
```

# Outline

- Quick Review
- POS Tagging Using Different Models
- Named Entity Recognition
- Step-by-step Examples
- PyTorch Implementation



# Named Entity Recognition

## ❖ Introduction

Conll2003 dataset for Named-Entity Recognition

Num\_classes = 9

Train

14041

Val

3250

Test

3453

0	O	Out-of-class
1	B-PER	Begin-Person
2	I-PER	In-Person
3	B-ORG	Begin-Organization
4	I-ORG	In-Organization
5	B-LOC	Begin-Location
6	I-LOC	In-Location
7	B-MISC	Begin-Miscellaneous
8	I-MISC	In-Miscellaneous

Example

Input tokens

["BCH", "in", "the", "hive", "of", "Chilean", "pensions" ]

Label

["B-ORG", "O", "O", "O", "O", "B-MISC", "O" ]

Label-encoded

[ 3, 0, 0, 0, 0, 7, 0 ]

## POS Tagging

We are exploring the topic of deep learning

2057 2024 11131 ... 1997 2784 4083

out\_0 out\_1 ... out\_6 out\_7

12 41 40 12 15 16 24

mapping

We (DT) are (VBP) exploring (VPN) the (DT)  
topic (NN) of (IN) deep (JJ) learning (NNS)

## Named Entity Recognition

France won the World Cup in Russia in 2018

2065 2180 1996 ... 3607 1999 2760

out\_0 out\_1 ... out\_7 out\_8

6 0 0 7 8 0 6 0 0

mapping

France (LOC) won the World Cup (MISC)  
in Russia (LOC) in 2018

Tokenizer

BERT

Classifier

## Step-by-step Examples

# Named Entity Recognition

Doc	Label
karpathy is working in openai	[0, 4, 4, 4, 2]
geoffrey hinton is from canada	[0, 1, 4, 4, 2]

building  
dictionary

index	word
0	[UNK]
1	[pad]
2	is
3	canada
4	from
5	geoffrey
6	hinton
7	in
8	karpathy
9	openai
10	working

Dictionary

karpathy	8	[0.7109, -1.2178, -1.5470, -1.2587]
is	2	[0.5303, 0.7931, -1.1894, 0.1906]
working	10	[-0.2059, 1.3111, -1.2398, -1.0455]
in	7	[-0.1117, 1.2757, -0.3398, 0.5976]
openai	9	[-0.4392, 0.5843, -0.7790, 0.2032]

Sample 1

Sample 1 \_ Embedding

0	[-1.5755, 0.0146, 0.2361, 0.3852]
1	[0.2267, -1.1683, 0.0791, -1.3988]
2	[0.5303, 0.7931, -1.1894, 0.1906]
3	[0.0649, -0.0649, 2.3004, 0.3508]
4	[0.4401, -0.1977, 1.1706, -0.4241]
5	[-0.9880, 1.1651, -0.7740, -0.5781]
6	[-0.1220, 0.3313, 0.6327, -0.3742]
7	[-0.1117, 1.2757, -0.3398, 0.5976]
8	[0.7109, -1.2178, -1.5470, -1.2587]
9	[-0.4392, 0.5843, -0.7790, 0.2032]
10	[-0.2059, 1.3111, -1.2398, -1.0455]

Embedding

vocab size = 11  
sequence length = 5  
num of classes = 5+1

ID	Meaning
0	B-Person
1	I-Person
2	B-Org./Location
3	I-Org./Location
4	Others
5	<padding>

Label Codes

# Named Entity Recognition

Doc	Label
karpthy is working in openai	[0, 4, 4, 4, 2]
geoffrey hinton is from canada	[0, 1, 4, 4, 2]

vocab size = 12  
 sequence length = 5  
 num of classes = 5+1

ID	Meaning
0	B-Person
1	I-Person
2	B-Org./Location
3	I-Org./Location
4	Others
5	<padding>

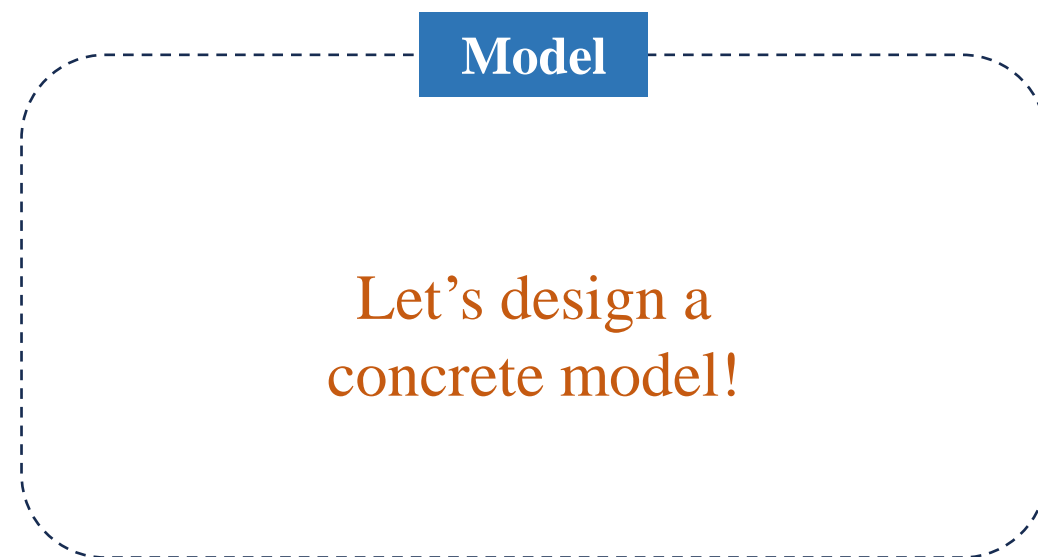
Label Codes

karpthy	8	[0.7109, -1.2178, -1.5470, -1.2587]
is	2	[0.5303, 0.7931, -1.1894, 0.1906]
working	10	[-0.2059, 1.3111, -1.2398, -1.0455]
in	7	[-0.1117, 1.2757, -0.3398, 0.5976]
openai	9	[-0.4392, 0.5843, -0.7790, 0.2032]

Sample 1

Sample 1 \_ Embedding  
 (N, seq\_len, embed\_dim)

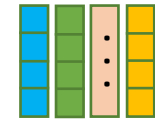
→



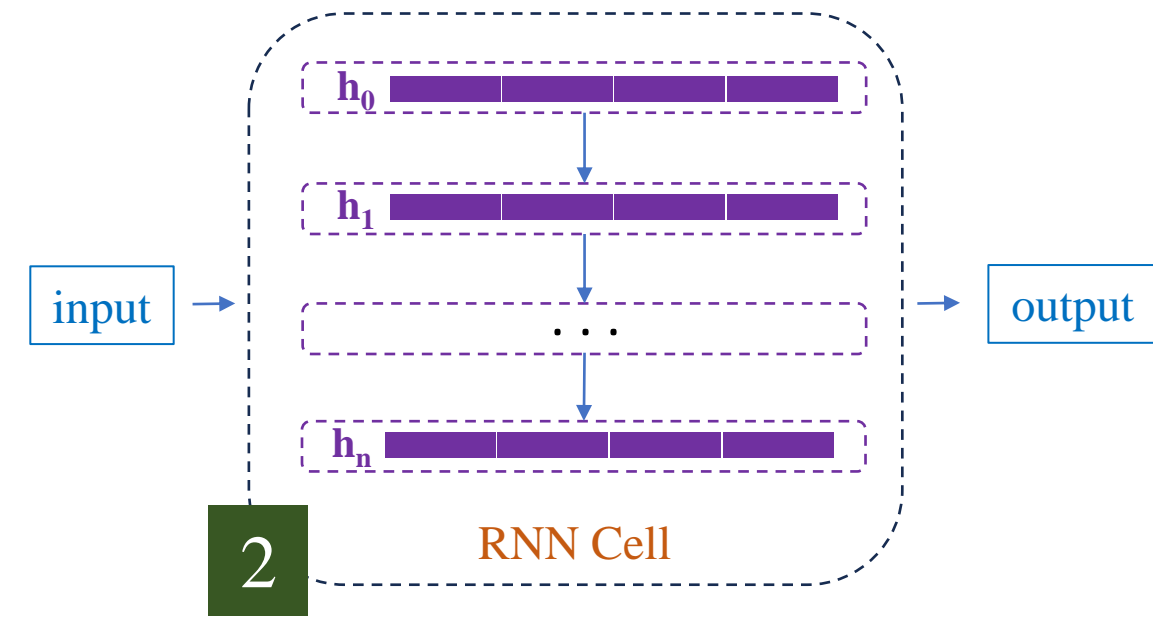
(CNN, RNN, Transformer, ...)

[0.7109, -1.2178, -1.5470, -1.2587]
[0.5303, 0.7931, -1.1894, 0.1906]
[-0.2059, 1.3111, -1.2398, -1.0455]
[-0.1117, 1.2757, -0.3398, 0.5976]
[-0.4392, 0.5843, -0.7790, 0.2032]

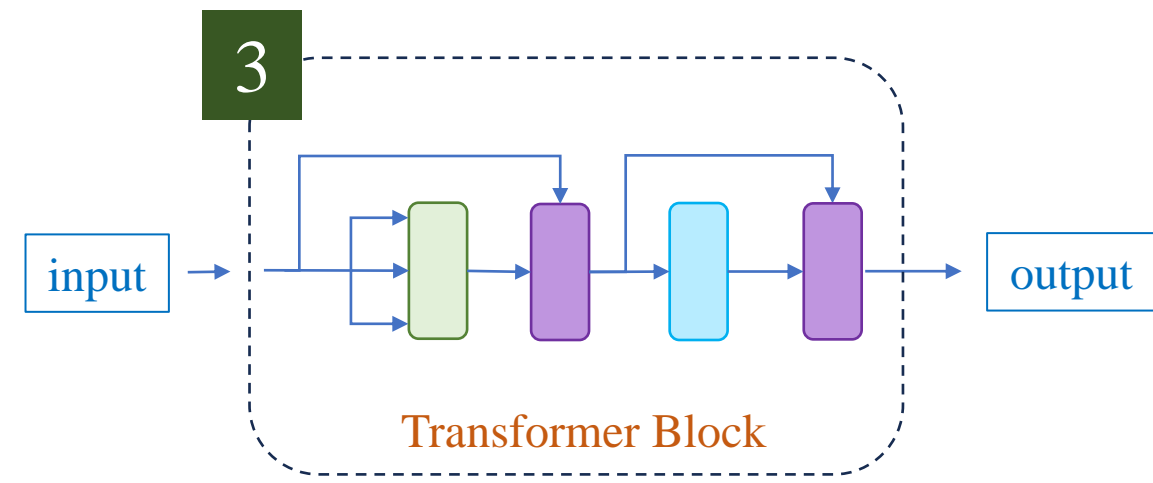
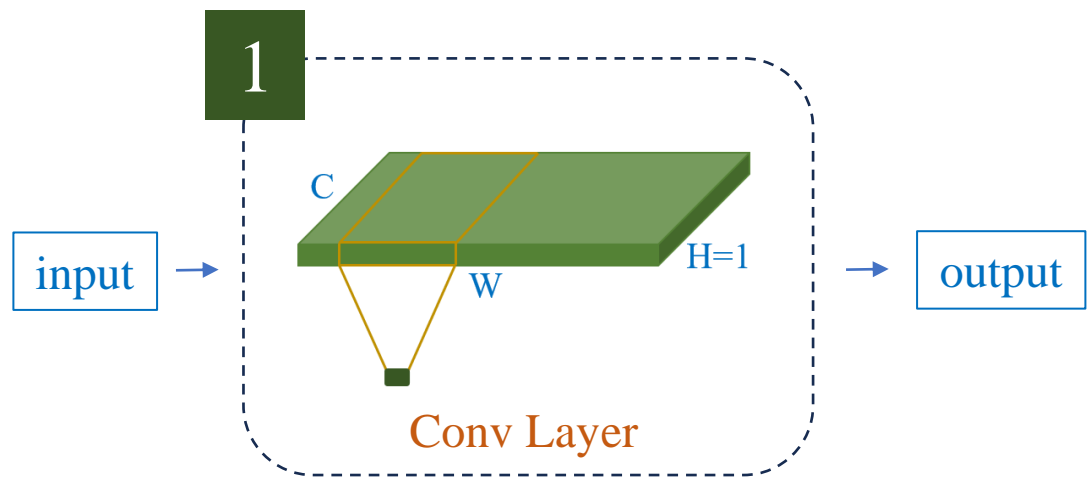
Input: Sample 1 \_ Embedding  
(N, seq\_len, embed\_dim)

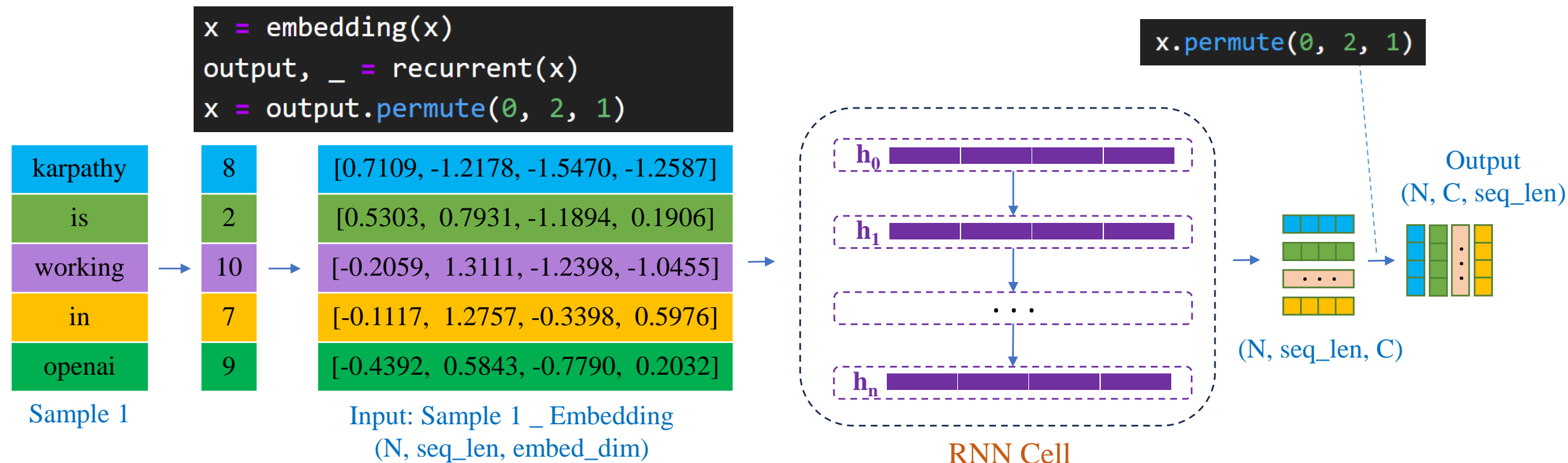
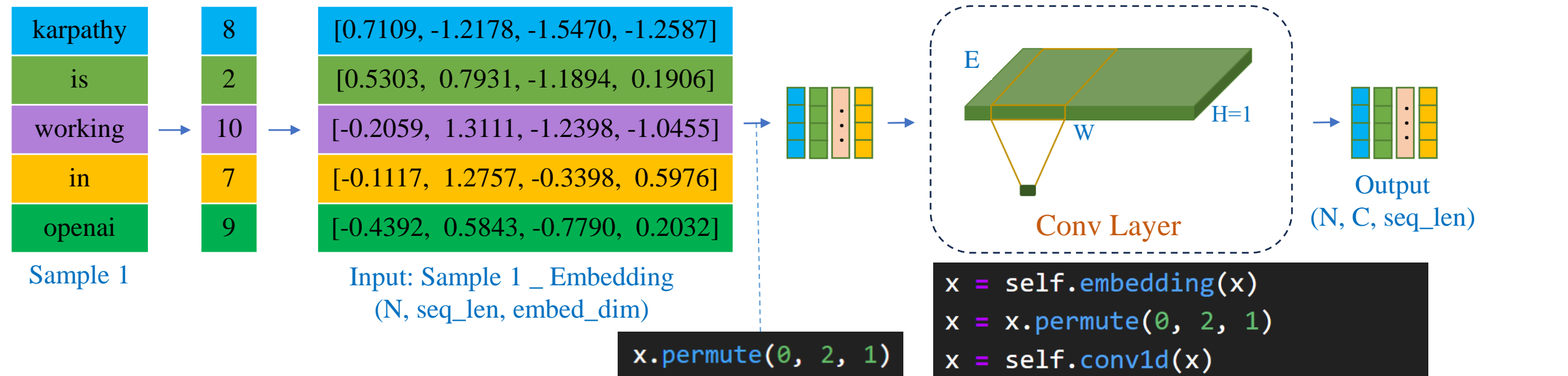


Output  
shape=(N, C, seq\_len)



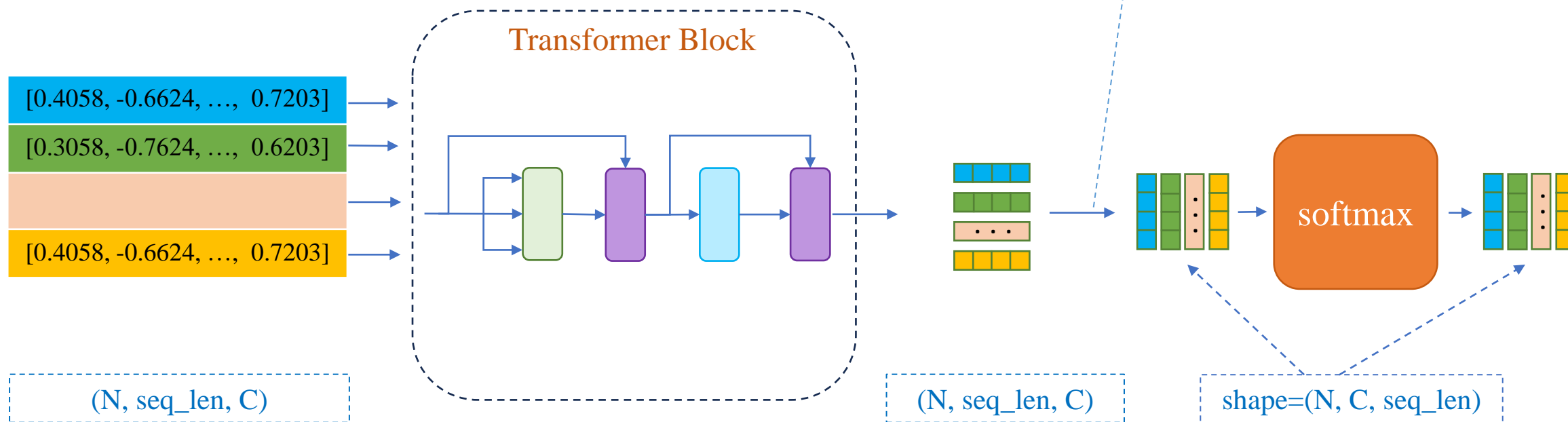
Which ones are feasible?





# Designing a Model for POS Tagging

## Using Transformer



```
embedding = nn.Embedding(vocab_size, 4)
transformer = TransformerBlock(4, 1, 4)
# embed_dim, num_heads, ff_dim

# forward
x = self.embedding(x)
x = self.transformer(x, x, x)
x = x.permute(0, 2, 1)
```



