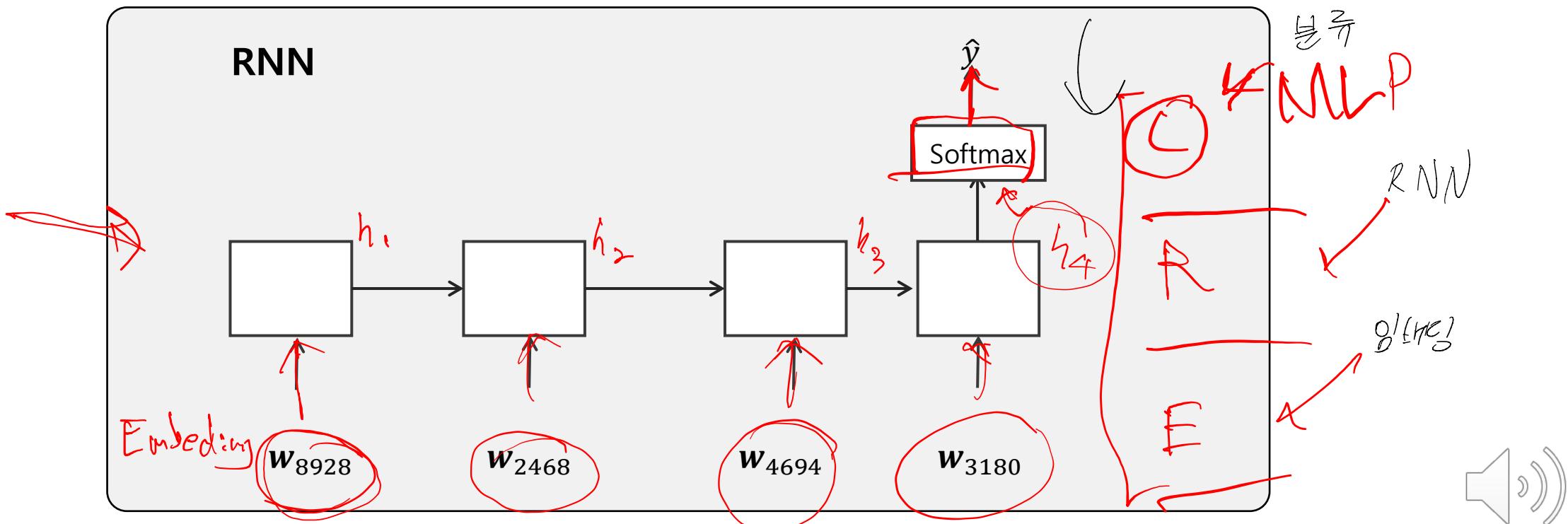
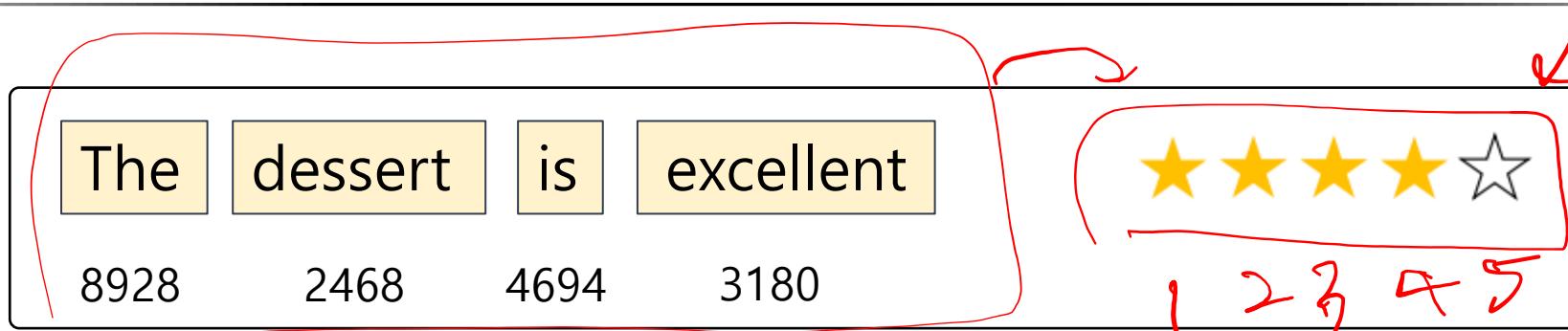


Text classification using PyTorch

Deep Learning

Woohwan Jung

Sentiment Classification



RNN



torch.nn.RNN

CLASS `torch.nn.RNN(*args, **kwargs)`

[SOURCE] 

Applies a multi-layer Elman RNN with tanh or ReLU non-linearity to an input sequence.

For each element in the input sequence, each layer computes the following function:

$$h_t = \tanh(W_{ih}x_t + b_{ih} + W_{hh}h_{(t-1)} + b_{hh})$$

where h_t is the hidden state at time t , x_t is the input at time t , and $h_{(t-1)}$ is the hidden state of the previous layer at time $t-1$ or the initial hidden state at time 0. If `nonlinearity` is 'relu', then ReLU is used instead of tanh.

Parameters

- **input_size** – The number of expected features in the input x
- **hidden_size** – The number of features in the hidden state h
- **num_layers** – Number of recurrent layers. E.g., setting `num_layers=2` would mean stacking two RNNs together to form a stacked RNN, with the second RNN taking in outputs of the first RNN and computing the final results. Default: 1
- **nonlinearity** – The non-linearity to use. Can be either 'tanh' or 'relu'. Default: 'tanh'
- **bias** – If `False`, then the layer does not use bias weights b_{ih} and b_{hh} . Default: `True`
- **batch_first** – If `True`, then the input and output tensors are provided as $(batch, seq, feature)$. Default: `False`
- **dropout** – If non-zero, introduces a Dropout layer on the outputs of each RNN layer except the last layer, with dropout probability equal to `dropout`. Default: 0
- **bidirectional** – If `True`, becomes a bidirectional RNN. Default: `False`

Examples:

Parameters

```
>>> rnn = nn.RNN(10, 20, 2)
>>> input = torch.randn(5, 3, 10)
>>> h0 = torch.randn(2, 3, 20)
>>> output, hn = rnn(input, h0)
```



torch.nn.RNN

Inputs: input, h_0

SL

- **input** of shape $(\text{seq_len}, \text{batch}, \text{input_size})$: tensor containing the features of the input sequence. The input can also be a packed variable length sequence. See [torch.nn.utils.rnn.pack_padded_sequence\(\)](#) or [torch.nn.utils.rnn.pack_sequence\(\)](#) for details.
- **h_0** of shape $(\text{num_layers} * \text{num_directions}, \text{batch}, \text{hidden_size})$: tensor containing the initial hidden state for each element in the batch. Defaults to zero if not provided. If the RNN is bidirectional, num_directions should be 2, else it should be 1.

Outputs: output, h_n

- **output** of shape $(\text{seq_len}, \text{batch}, \text{num_directions} * \text{hidden_size})$: tensor containing the output features (h_t) from the last layer of the RNN, for each t . If a [torch.nn.utils.rnn.PackedSequence](#) has been given as the input, the output will also be a packed sequence.
For the unpacked case, the directions can be separated using `output.view(seq_len, batch, num_directions, hidden_size)`, with forward and backward being direction 0 and 1 respectively. Similarly, the directions can be separated in the packed case.
- **h_n** of shape $(\text{num_layers} * \text{num_directions}, \text{batch}, \text{hidden_size})$: tensor containing the hidden state for $t = \text{seq_len}$.

Like `output`, the layers can be separated using `h_n.view(num_layers, num_directions, batch, hidden_size)`.

SL = 5
 $\text{BS} = 3$ input 21×10

Examples:

```
>>> rnn = nn.RNN(10, 20, 2)
>>> input = torch.randn(5, 3, 10)
>>> h0 = torch.randn(2, 3, 20)
>>> output, hn = rnn(input, h0)
```

BS 5×3
SL: 10 X 3 X 2
ND \times HF

torch.nn.LSTM

CLASS `torch.nn.LSTM(*args, **kwargs)`

Applies a multi-layer long short-term memory (LSTM) RNN to an input sequence.

For each element in the input sequence, each layer computes the following function:

$$\begin{aligned} i_t &= \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \\ f_t &= \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \\ g_t &= \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg}) \\ o_t &= \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \\ c_t &= f_t \odot c_{t-1} + i_t \odot g_t \\ h_t &= o_t \odot \tanh(c_t) \end{aligned}$$

Parameters

- **input_size** – The number of expected features in the input x
- **hidden_size** – The number of features in the hidden state h
- **num_layers** – Number of recurrent layers. E.g., setting `num_layers=2` would mean stacking two LSTMs together to form a stacked LSTM, with the second LSTM taking in outputs of the first LSTM and computing the final results. Default: 1
- **bias** – If `False`, then the layer does not use bias weights b_{ih} and b_{hh} . Default: `True`
- **batch_first** – If `True`, then the input and output tensors are provided as (batch, seq, feature). Default: `False`
- **dropout** – If non-zero, introduces a Dropout layer on the outputs of each LSTM layer except the last layer, with dropout probability equal to `dropout`. Default: 0
- **bidirectional** – If `True`, becomes a bidirectional LSTM. Default: `False`
- **proj_size** – If > 0 , will use LSTM with projections of corresponding size. Default: 0

Parameters

```
>>> rnn = nn.LSTM(10, 20, 2) Z131
>>> input = torch.randn(5, 3, 10)
>>> h0 = torch.randn(2, 3, 20)
>>> c0 = torch.randn(2, 3, 20)
>>> output, (hn, cn) = rnn(input, (h0, c0))
```



torch.nn.LSTM

Inputs: input, (h_0, c_0)

- **input** of shape $(seq_len, batch, input_size)$: tensor containing the features of the input sequence. The input can also be a packed variable length sequence. See [torch.nn.utils.rnn.pack_padded_sequence\(\)](#) or [torch.nn.utils.rnn.pack_sequence\(\)](#) for details.
- **h_0** of shape $(num_layers * num_directions, batch, hidden_size)$: tensor containing the initial hidden state for each element in the batch. If the LSTM is bidirectional, num_directions should be 2, else it should be 1. If $proj_size > 0$ was specified, the shape has to be $(num_layers * num_directions, batch, proj_size)$.
- **c_0** of shape $(num_layers * num_directions, batch, hidden_size)$: tensor containing the initial cell state for each element in the batch.
If (h_0, c_0) is not provided, both **h_0** and **c_0** default to zero.

Outputs: output, (h_n, c_n)

- **output** of shape $(seq_len, batch, num_directions * hidden_size)$: tensor containing the output features (h_t) from the last layer of the LSTM, for each t . If a [torch.nn.utils.rnn.PackedSequence](#) has been given as the input, the output will also be a packed sequence. If $proj_size > 0$ was specified, output shape will be $(seq_len, batch, num_directions * proj_size)$.
For the unpacked case, the directions can be separated using `output.view(seq_len, batch, num_directions, hidden_size)`, with forward and backward being direction 0 and 1 respectively. Similarly, the directions can be separated in the packed case.
- **h_n** of shape $(num_layers * num_directions, batch, hidden_size)$: tensor containing the hidden state for $t = seq_len$. If $proj_size > 0$ was specified, **h_n** shape will be $(num_layers * num_directions, batch, proj_size)$. Like **output**, the layers can be separated using `h_n.view(num_layers, num_directions, batch, hidden_size)` and similarly for **c_n**.
- **c_n** of shape $(num_layers * num_directions, batch, hidden_size)$: tensor containing the cell state for $t = seq_len$.

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```
>>> rnn = nn.LSTM(10, 20, 2)
>>> input = torch.randn(5, 3, 10)
>>> h0 = torch.randn(2, 3, 20)
>>> c0 = torch.randn(2, 3, 20)
>>> output, (hn, cn) = rnn(input, (h0, c0))
```

○ ၂

→ short term state

설 수 있

→ long term state



Embedding layer



EMBEDDING

```
CLASS torch.nn.Embedding(num_embeddings, embedding_dim, padding_idx=None,  
    max_norm=None, norm_type=2.0, scale_grad_by_freq=False, sparse=False,  
    _weight=None, device=None, dtype=None) [SOURCE]
```

A simple lookup table that stores embeddings of a fixed dictionary and size.

This module is often used to store word embeddings and retrieve them using indices. The input to the module is a list of indices, and the output is the corresponding word embeddings.

Parameters

- **num_embeddings** (*int*) – size of the dictionary of embeddings *421 371*
- **embedding_dim** (*int*) – the size of each embedding vector *4 214*
- **padding_idx** (*int, optional*) – If specified, the entries at `padding_idx` do not contribute to the gradient; therefore, the embedding vector at `padding_idx` is not updated during training, i.e. it remains as a fixed “pad”. For a newly constructed Embedding, the embedding vector at `padding_idx` will default to all zeros, but can be updated to another value to be used as the padding vector.

```
>>> # an Embedding module containing 10 tensors of size 3x4  
>>> embedding = nn.Embedding(10, 3)  
>>> # a batch of 2 samples of 4 indices each  
>>> input = torch.LongTensor([[1,2,4,5],[4,3,2,9]])  
>>> embedding(input)  
tensor([[[ -0.0251, -1.6902,  0.7172],  
        [-0.6431,  0.0748,  0.6969],  
        [ 1.4970,  1.3448, -0.9685],  
        [-0.3677, -2.7265, -0.1685]],  
  
       [[ 1.4970,  1.3448, -0.9685],  
        [ 0.4362, -0.4004,  0.9400],  
        [-0.6431,  0.0748,  0.6969],  
        [ 0.9124, -2.3616,  1.1151]]])
```



CLASSEMTHOD from_pretrained(*embeddings*, *freeze=True*, *padding_idx=None*, *max_norm=None*, *norm_type=2.0*, *scale_grad_by_freq=False*, *sparse=False*) [SOURCE]

5

Creates Embedding instance from given 2-dimensional FloatTensor.

Parameters

- **embeddings** (*Tensor*) – FloatTensor containing weights for the Embedding. First dimension is being passed to Embedding as `num_embeddings`, second as `embedding_dim`.
 - **freeze** (*boolean, optional*) – If `True`, the tensor does not get updated in the learning process. Equivalent to `embedding.weight.requires_grad = False`.

Default: True

`padding_idx` (*int*, optional) – If specified, the entries at `padding_idx` do not

```
>>> # FloatTensor containing pretrained weights
>>> weight = torch.FloatTensor([[1, 2.3, 3], [4, 5.1, 6.3]])
>>> embedding = nn.Embedding.from_pretrained(weight)
>>> # Get embeddings for index 1
>>> input = torch.LongTensor([1])
>>> embedding(input)
tensor([[ 4.0000,  5.1000,  6.3000]])
```



Text classification

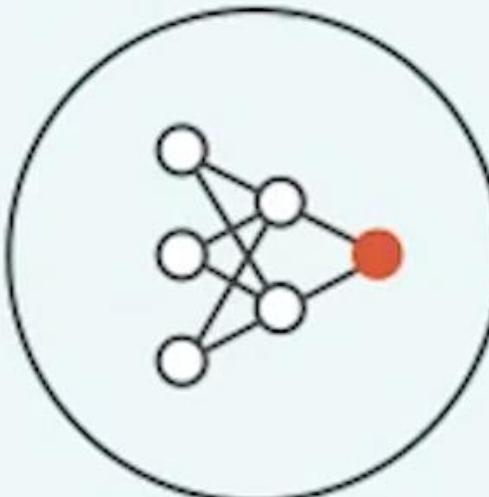


torchtext ≈ torchvision of

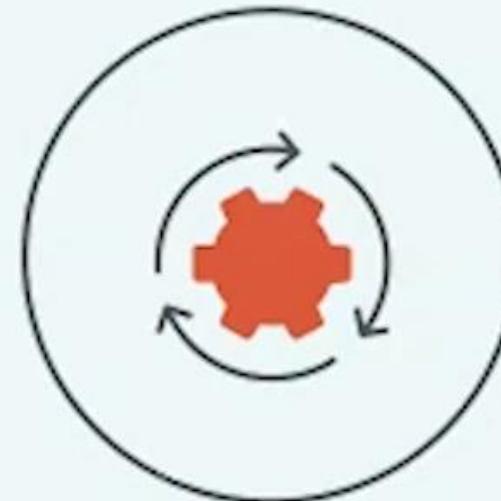
NLP by 22



NLP DATASETS



TEXT
PROCESSING
PIPELINES



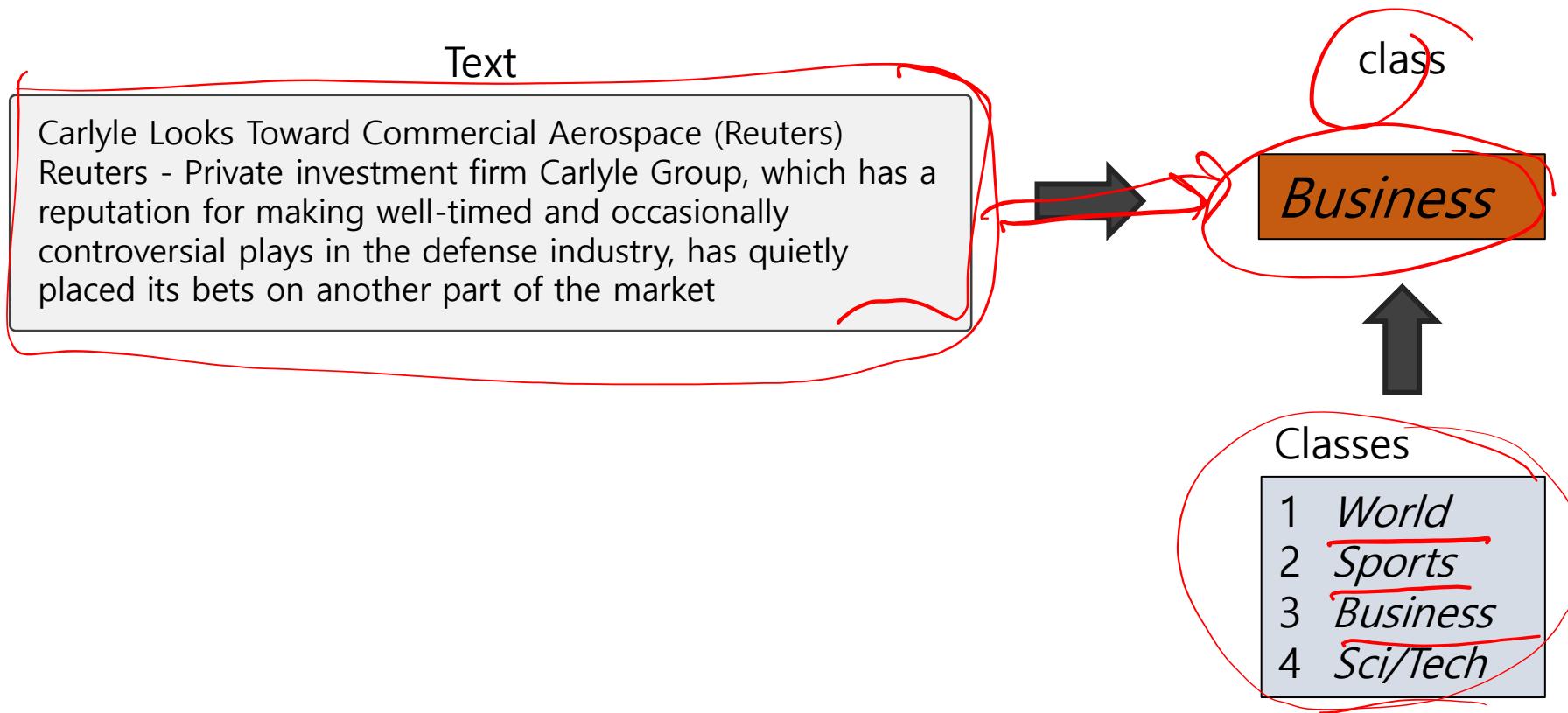
BASIC NLP
OPERATORS



torchtext.datasets.AG_NEWS

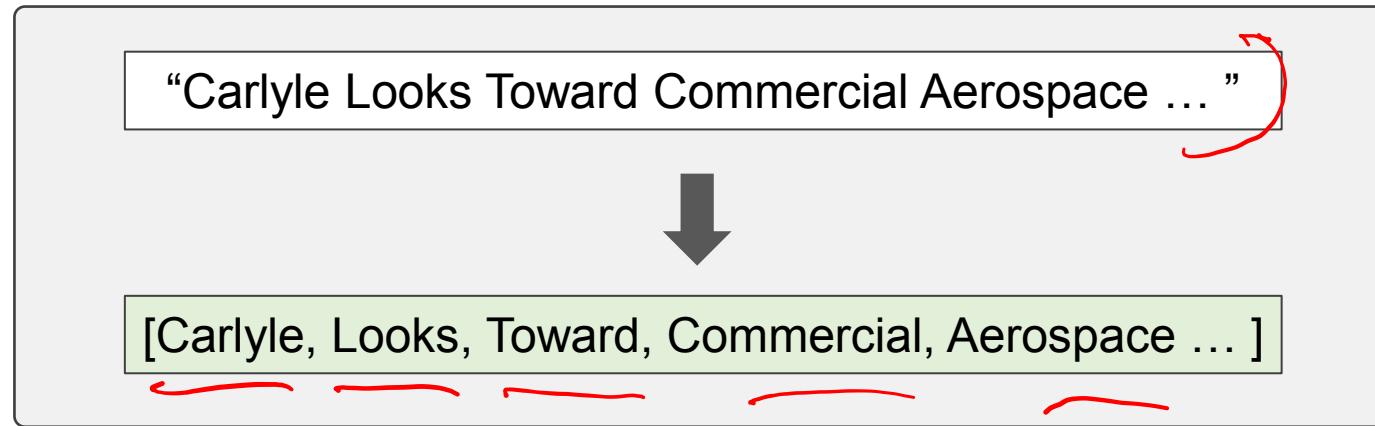
- News classification dataset

自然語言
NLP
Classification



Prepare Data Processing Pipelines

Tokenize



Build vocabulary

```
{<PAD>:0, <UNK>:1, ':': 2, 'the': 3, ...}
```



Prepare Data Processing Pipelines

G10/E1 20/

1

```
import torch
from torchtext.datasets import AG_NEWS
import random
from torchtext.vocab import Vectors

SEED = 5
random.seed(SEED)
torch.manual_seed(SEED)

<torch._C.Generator at 0x16aaad85390>

train_data, test_data = AG_NEWS()
```

3

```
train_iter = AG_NEWS(split='train')
counter = Counter()
MAX_LEN = 0

labels = []
for (label, line) in train_iter:
    tokens = tokenizer(line)
    counter.update(tokens)
    MAX_LEN = max(MAX_LEN, len(tokens))
    labels.append(label)

num_class = len(set(labels))
vocab = Vocab(counter, specials = ["<pad>", "<unk>"], min_freq=10)
PAD = vocab["<pad>"]
print(len(vocab))
```

반복문이 있는 경우

X17

20645

2

```
from torchtext.data.utils import get_tokenizer
from collections import Counter
from torchtext.vocab import Vocab

tokenizer = get_tokenizer('basic_english')

tokenizer("A tokenizer is in charge of preparing the inputs for a model.")

['a',
 'tokenizer',
 'is',
 'in',
 'charge',
 'of',
 'preparing',
 'the',
 'inputs',
 'for',
 'a',
 'model',
 '.']
```

4

```
# The vocabulary block converts a list of tokens into integers,
[vocab[token] for token in ['here', 'is', 'an', 'example']]

[476, 22, 31, 5298]

text_pipeline = lambda x: [vocab[token] for token in tokenizer(x)]
label_pipeline = lambda x: int(x) - 1

text_pipeline('here is the an example')

[476, 22, 31, 5298]
```



Generate data batch and iterator

```
from torch.utils.data import DataLoader
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

def collate_batch(batch):
    label_list, text_list = [], []
    max_len = 0
    for (_label, _text) in batch:
        label_list.append(label_pipeline(_label))
        token_ids = text_pipeline(_text)
        text_list.append(token_ids)
        max_len = max(max_len, len(token_ids))

    text_list = [tokens + [PAD] * (max_len - len(tokens)) for tokens in text_list]
    label_list = torch.tensor(label_list, dtype=torch.int64)
    text_list = torch.tensor(text_list, dtype=torch.int64)
    return label_list.to(device), text_list.to(device)
```



Define the Model

```
from torch import nn
from torch.nn.utils.rnn import pack_padded_sequence

class TextClassificationModel(nn.Module):
    def __init__(self, vocab, num_class, embed_dim, hidden_dim, num_rnn_layers=1):
        super(TextClassificationModel, self).__init__()
        self.embedding = nn.Embedding.from_pretrained(vocab.vectors)
        self.rnn = nn.RNN(embed_dim, hidden_dim, num_layers=num_rnn_layers, batch_first=True)
        self.fc = nn.Linear(hidden_dim, num_class)
        #self.init_weights(vocab)

    def init_weights(self, vocab):
        initrange = 0.5
        self.embedding.weight.data.uniform_(-initrange, initrange)
        self.fc.weight.data.uniform_(-initrange, initrange)
        self.fc.bias.data.zero_()

    def forward(self, input_text):
        embedded = self.embedding(input_text)
        packed_input = pack_padded_sequence(embedded, input_lengths.tolist(), batch_first=True)
        output_h = self.rnn(packed_input)[0]
        h_n = output_h[:, -1, :]
        pred = self.fc(h_n)
        return pred
```

vocab.load_vectors("glove.6B.100d")

emsize = 100

model = TextClassificationModel(vocab, num_class, emsize, 128, num_rnn_layers = 1)



Training

```
import time

def train(dataloader, model, criterion, optimizer):
    model.train()
    total_acc, total_count = 0, 0
    log_interval = 500
    start_time = time.time()

    loss_cum = 0.0
    for idx, (label, text) in enumerate(dataloader):
        #input_lengths = torch.LongTensor([torch.max(text[i], :).nonzero()[-1] for i in range(len(text))])
        #input_lengths, sorted_idx = input_lengths.sort(0, descending=True)
        #text = text[sorted_idx]
        #label = label[sorted_idx]
        optimizer.zero_grad()
        predicted_label = model(text)

        loss = criterion(predicted_label, label)
        loss.backward()
        loss_cum += loss.item()

        optimizer.step()
        total_acc += (predicted_label.argmax(1) == label).sum().item()
        total_count += label.size(0)
        if idx % log_interval == 0 and idx > 0:
            elapsed = time.time() - start_time
            print('| epoch {:3d} | {:5d}/{:5d} batches '
                  '| loss {:.3f} | accuracy {:.3f}'.format(epoch, idx, len(dataloader),
                  loss_cum/total_count, total_acc/total_count))
    total_acc, total_count, loss_cum = 0, 0, 0.0
    start_time = time.time()
```

```
def evaluate(dataloader, model):
    model.eval()
    total_acc, total_count = 0, 0

    with torch.no_grad():
        for idx, (label, text) in enumerate(dataloader):
            predicted_label = model(text)
            loss = criterion(predicted_label, label)
            total_acc += (predicted_label.argmax(1) == label).sum().item()
            total_count += label.size(0)
    return total_acc/total_count
```



Training

```
LR = 1e-4
EPOCHS = 5
BATCH_SIZE = 8
criterion = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=LR)

from torch.utils.data import random_split

train_iter, test_iter = AG_NEWS()
train_dataset = list(train_iter)
test_dataset = list(test_iter)
num_train = int(len(train_dataset) * 0.95)
split_train_, split_valid_ = random_split(train_dataset, [num_train, len(train_dataset) - num_train])

train_dataloader = DataLoader(split_train_, batch_size=BATCH_SIZE,
                             shuffle=True, collate_fn=collate_batch)
valid_dataloader = DataLoader(split_valid_, batch_size=BATCH_SIZE,
                             shuffle=False, collate_fn=collate_batch)
test_dataloader = DataLoader(test_dataset, batch_size=BATCH_SIZE,
                             shuffle=False, collate_fn=collate_batch)

for epoch in range(1, EPOCHS + 1):
    epoch_start_time = time.time()
    train(train_dataloader, model, criterion, optimizer)
    accu_val = evaluate(valid_dataloader, model)

    print('-' * 59)
    print(f'| end of epoch {epoch} | time: {time.time() - epoch_start_time:.2f}s | '
          f'valid accuracy {accu_val:.3f}')
    print('-' * 59)
```

epoch	1	500/14250 batches	loss	0.173	accuracy	0.262
epoch	1	1000/14250 batches	loss	0.164	accuracy	0.368
epoch	1	1500/14250 batches	loss	0.170	accuracy	0.308
epoch	1	2000/14250 batches	loss	0.162	accuracy	0.364
epoch	1	2500/14250 batches	loss	0.145	accuracy	0.446
epoch	1	3000/14250 batches	loss	0.144	accuracy	0.430
epoch	1	3500/14250 batches	loss	0.142	accuracy	0.461
epoch	1	4000/14250 batches	loss	0.141	accuracy	0.448
epoch	1	4500/14250 batches	loss	0.143	accuracy	0.469
epoch	1	5000/14250 batches	loss	0.157	accuracy	0.398
epoch	1	5500/14250 batches	loss	0.154	accuracy	0.415
epoch	1	6000/14250 batches	loss	0.147	accuracy	0.441
epoch	1	6500/14250 batches	loss	0.145	accuracy	0.430
epoch	1	7000/14250 batches	loss	0.141	accuracy	0.450
epoch	1	7500/14250 batches	loss	0.140	accuracy	0.478
epoch	1	8000/14250 batches	loss	0.150	accuracy	0.414
epoch	1	8500/14250 batches	loss	0.140	accuracy	0.453
epoch	1	9000/14250 batches	loss	0.132	accuracy	0.471
epoch	1	9500/14250 batches	loss	0.129	accuracy	0.503
epoch	1	10000/14250 batches	loss	0.133	accuracy	0.488
epoch	1	10500/14250 batches	loss	0.132	accuracy	0.482
epoch	1	11000/14250 batches	loss	0.154	accuracy	0.392
epoch	1	11500/14250 batches	loss	0.163	accuracy	0.378
epoch	1	12000/14250 batches	loss	0.134	accuracy	0.480
epoch	1	12500/14250 batches	loss	0.123	accuracy	0.492
epoch	1	13000/14250 batches	loss	0.115	accuracy	0.584
epoch	1	13500/14250 batches	loss	0.104	accuracy	0.638
epoch	1	14000/14250 batches	loss	0.121	accuracy	0.543
end of epoch 1 time: 147.70s valid accuracy 0.580						

epoch	3	12000/14250 batches	loss	0.118	accuracy	0.572
epoch	3	12500/14250 batches	loss	0.103	accuracy	0.677
epoch	3	13000/14250 batches	loss	0.104	accuracy	0.661
epoch	3	13500/14250 batches	loss	0.143	accuracy	0.523
epoch	3	14000/14250 batches	loss	0.126	accuracy	0.612

end of epoch 3 time: 162.01s valid accuracy 0.646						
-------------------------------------------------------	--	--	--	--	--	--

epoch	5	12000/14250 batches	loss	0.145	accuracy	0.402
epoch	5	12500/14250 batches	loss	0.136	accuracy	0.507
epoch	5	13000/14250 batches	loss	0.131	accuracy	0.553
epoch	5	13500/14250 batches	loss	0.126	accuracy	0.563
epoch	5	14000/14250 batches	loss	0.116	accuracy	0.603

end of epoch 5 time: 170.73s valid accuracy 0.662						
-------------------------------------------------------	--	--	--	--	--	--



Testing

```
: accu_val = evaluate(test_dataloader, model)
:     print(f"Test accuracy {accu_val:.3f}")
```

Test accuracy 0.658

f

0.658

0.25

한국어로



Question

DL-21 At SEZ

Truck 4

```
def forward(self, input_text):
    embedded = self.embedding(input_text)
    #packed_input = pack_padded_sequence(em
    output, _ = self.rnn(embedded)
    h_n = output[:, -1, :] # This line will
    pred = self.fc(h_n)
    return pred
```

Friendly	against	Scotland	at	Murray	.
Nadim	Ladki	<PAD>	<PAD>	<PAD>	<PAD>
AL-AIN	United	Arab	Emirates	<PAD>	<PAD>
ROME	1996-12	<PAD>	<PAD>	<PAD>	<PAD>
Two	goals	in	the	last	minutes



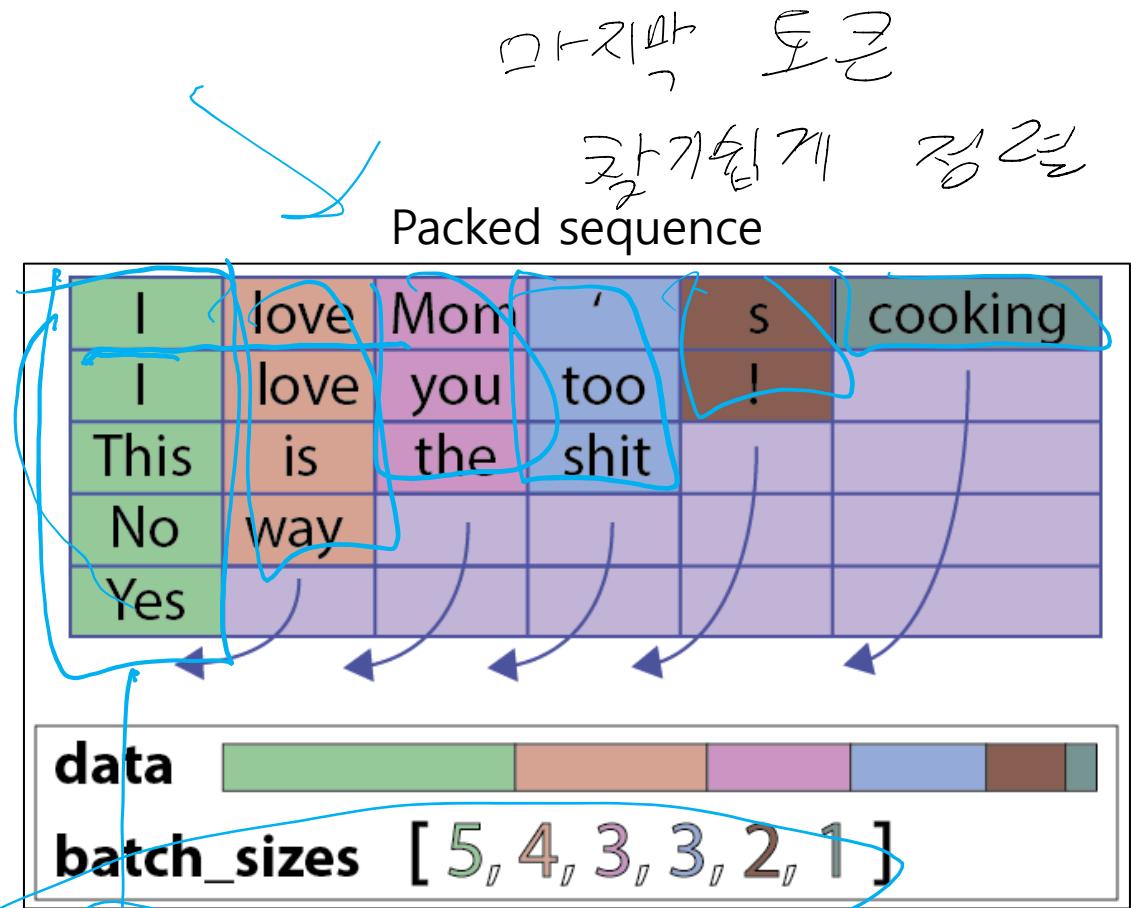
Packed Sequence



Packed Sequence

Normal tensor

I	love	Mom	'	s	cooking
I	love	you	too	!	
No	way				
This	is	the	shit		
Yes					



Source: [Understanding emotions — from Keras to pyTorch](#)



Packed Sequence – Pytorch

Input sequences

```
input_seq2idx  
=====  
tensor([[ 1, 16, 7, 11, 13, 2],  
       [ 1, 16, 6, 15, 8, 0],  
       [ 12, 9, 0, 0, 0, 0],  
       [ 5, 14, 3, 17, 0, 0],  
       [ 10, 0, 0, 0, 0, 0]])
```

Sort inputs by lengths

```
input_lengths = torch.LongTensor([torch.max(input_seq2idx[i, :].data.nonzero())+1 for i in range(input_seq2idx.size(0))])  
input_lengths, sorted_idx = input_lengths.sort(0, descending=True)  
input_seq2idx = input_seq2idx[sorted_idx]
```

Sorted inputs

```
input_seq2idx, input_lengths  
=====  
tensor([[ 1, 16, 7, 11, 13, 2],  
       [ 1, 16, 6, 15, 8, 0],  
       [ 5, 14, 3, 17, 0, 0],  
       [ 12, 9, 0, 0, 0, 0],  
       [ 10, 0, 0, 0, 0, 0]])  
tensor([ 6, 5, 4, 2, 1])
```



Packed Sequence with RNN

Define layers

```
embed = nn.Embedding(vocab_size, embedding_size, padding_idx=0)
rnn = nn.RNN(input_size=embedding_size, hidden_size=hidden_size, batch_first=True)
```

Using RNNs with packed sequences

```
embedded = embed(input_seq2idx)
packed_input = pack_padded_sequence(embedded, input_lengths.tolist(), batch_first=True)
packed_output, hidden = rnn(packed_input)
```

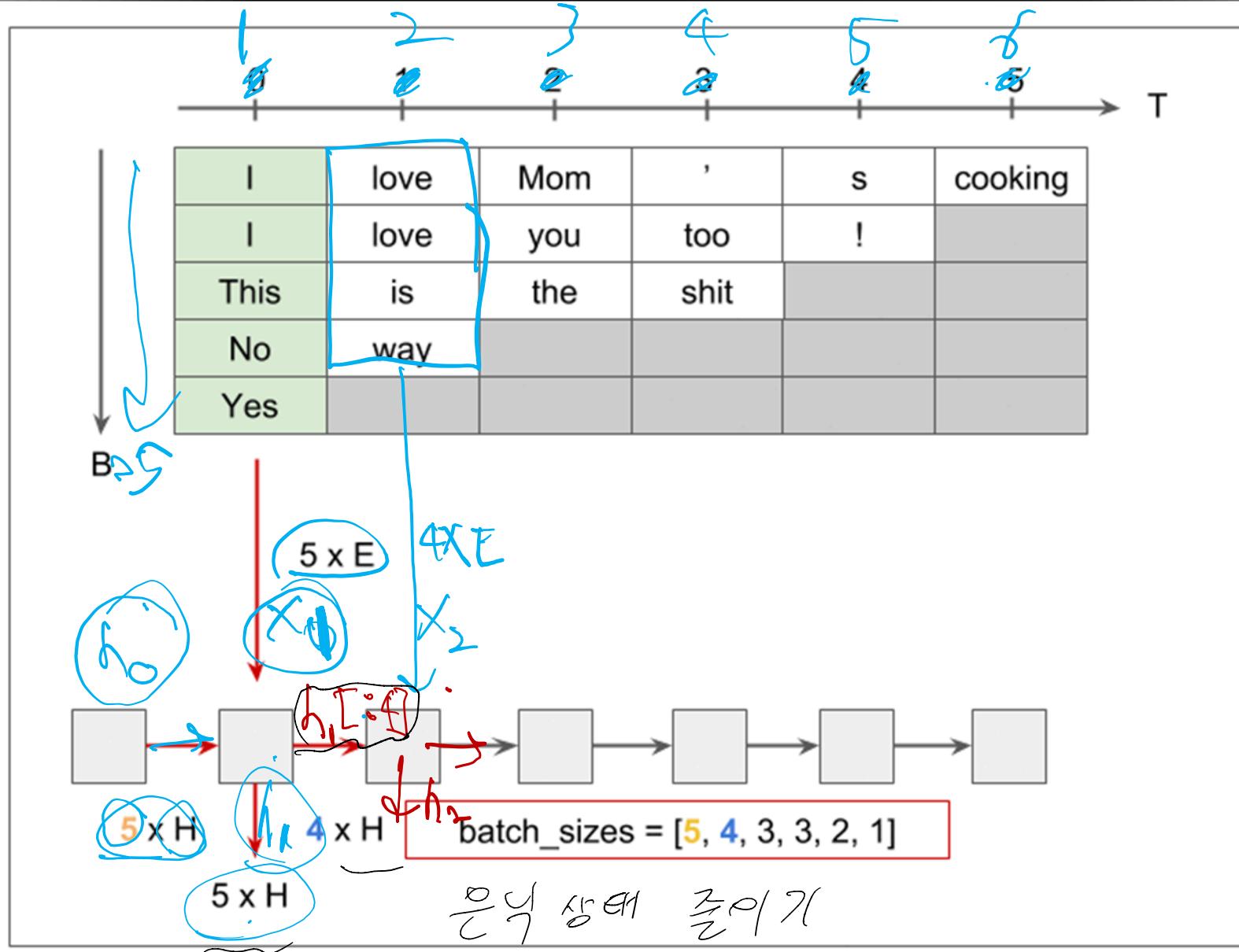
Padded Seq

Pack

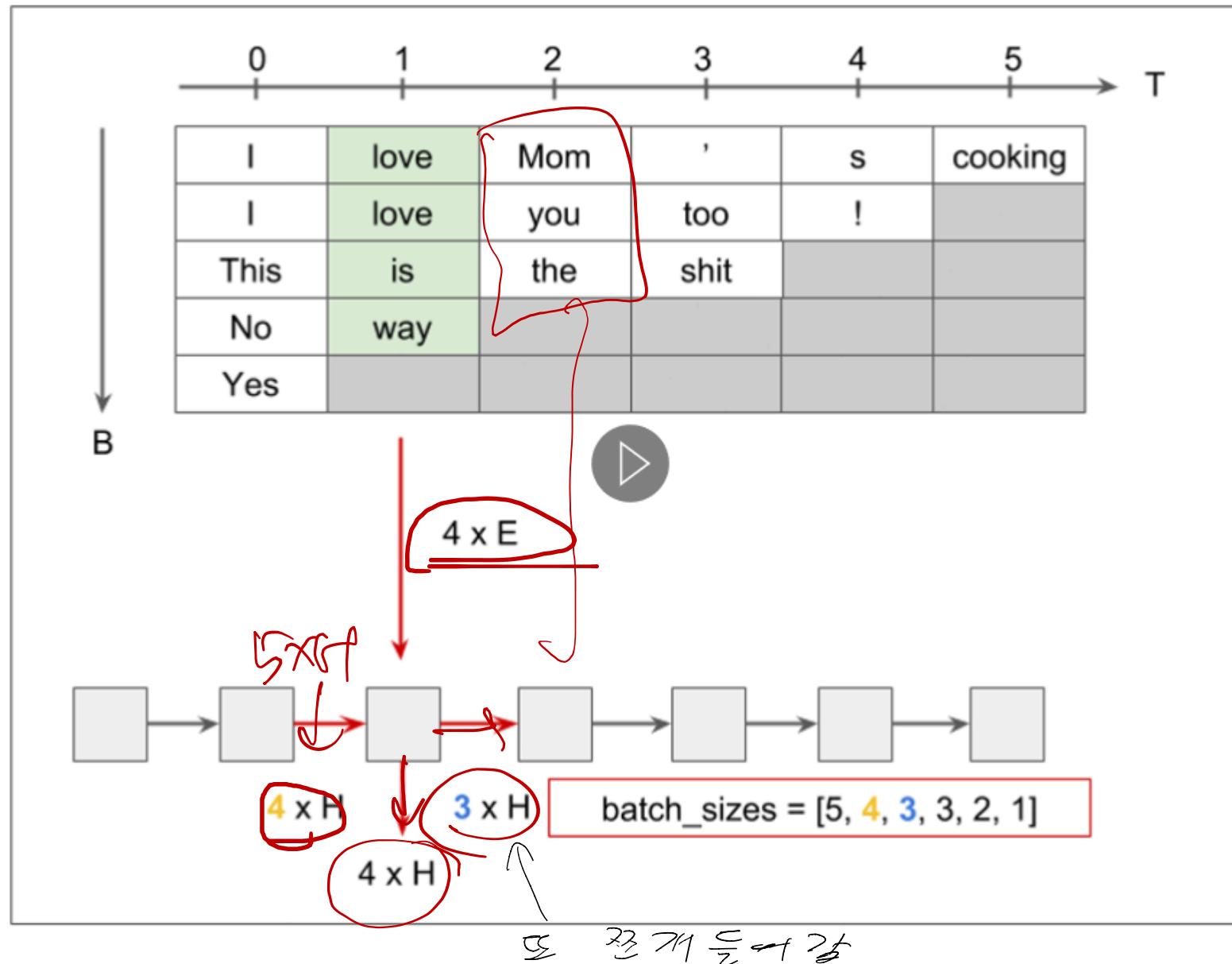
Packed Seq



Packed Sequence with RNN



Packed Sequence with RNN



Text classification

With packed sequences



Define the Model

```
from torch import nn
from torch.nn.utils.rnn import pack_padded_sequence

class TextClassificationModel(nn.Module):
    def __init__(self, vocab, num_class, embed_dim, hidden_dim, num_rnn_layers=1):
        super(TextClassificationModel, self).__init__()
        self.embedding = nn.Embedding.from_pretrained(vocab.vectors)

        self.rnn = nn.RNN(embed_dim, hidden_dim, num_layers = num_rnn_layers, batch_first = True)
        self.fc = nn.Linear(hidden_dim, num_class)
        #self.init_weights(vocab)

    def init_weights(self, vocab):
        initrange = 0.5
        self.embedding.weight.data.uniform_(-initrange, initrange)
        self.fc.weight.data.uniform_(-initrange, initrange)
        self.fc.bias.data.zero_()

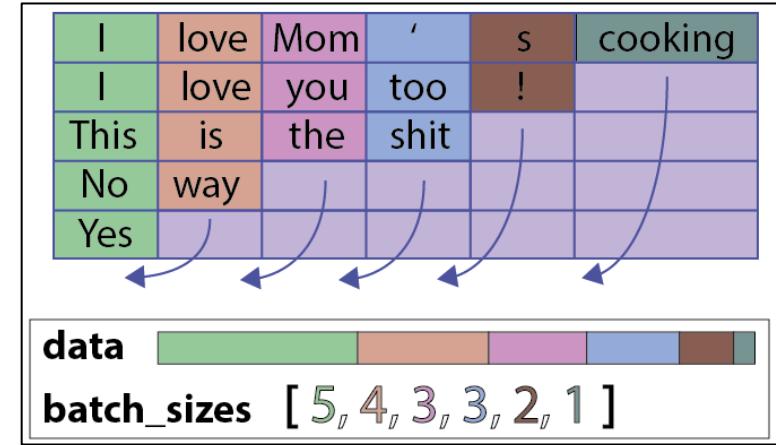
    def forward(self, input_text, input_lengths):
        embedded = self.embedding(input_text)
        packed_input = pack_padded_sequence(embedded, input_lengths.tolist(), batch_first=True)

        packed_output, hidden = self.rnn(packed_input)
        #output, _ = self.rnn(embedded)
        #h_n = output[-1, :].view(1, -1) # This line will be improved in the next class
        h_n = hidden[0]
        pred = self.fc(h_n)

        return pred
```

Last hidden states

OK
Right?



Output [o : g : - :]
Right?



Training

```
import time

def train(dataloader, model, criterion, optimizer):
    model.train()
    total_acc, total_count = 0, 0
    log_interval = 100
    start_time = time.time()

    loss_cum = 0.0
    for idx, (label, text) in enumerate(dataloader):
        input_lengths = torch.LongTensor([torch.max(text[i, :].nonzero())+1 for i in range(text.size(0))])
        input_lengths, sorted_idx = input_lengths.sort(0, descending=True)
        text = text[sorted_idx]
        label = label[sorted_idx]

        optimizer.zero_grad()
        predicted_label = model(text, input_lengths)

        loss = criterion(predicted_label, label)
        loss.backward()
        loss_cum += loss.item()

        optimizer.step()
        total_acc += (predicted_label.argmax(1) == label).sum().item()
        total_count += label.size(0)
        if idx % log_interval == 0 and idx > 0:
            elapsed = time.time() - start_time
            print('| epoch {:3d} | {:5d}/{:5d} batches '
                  '| loss {:.3f} | accuracy {:.3f}'.format(epoch, idx, len(dataloader),
                                                          loss_cum/total_count, total_acc/total_count))
            total_acc, total_count, loss_cum = 0, 0, 0.0
            start_time = time.time()
```



Batchsize 4

Packed sequence

epoch	1	500/14250 batches loss	0.139 accuracy	0.539
epoch	1	1000/14250 batches loss	0.094 accuracy	0.698
epoch	1	1500/14250 batches loss	0.077 accuracy	0.761
epoch	1	2000/14250 batches loss	0.073 accuracy	0.785
epoch	1	2500/14250 batches loss	0.064 accuracy	0.825
epoch	1	3000/14250 batches loss	0.063 accuracy	0.840
epoch	1	3500/14250 batches loss	0.054 accuracy	0.864
epoch	1	4000/14250 batches loss	0.067 accuracy	0.816
epoch	1	4500/14250 batches loss	0.058 accuracy	0.857
epoch	1	5000/14250 batches loss	0.055 accuracy	0.861
epoch	1	5500/14250 batches loss	0.058 accuracy	0.849
epoch	1	6000/14250 batches loss	0.055 accuracy	0.859
epoch	1	6500/14250 batches loss	0.055 accuracy	0.868
epoch	1	7000/14250 batches loss	0.056 accuracy	0.855
epoch	1	7500/14250 batches loss	0.057 accuracy	0.856
epoch	1	8000/14250 batches loss	0.052 accuracy	0.870
epoch	1	8500/14250 batches loss	0.055 accuracy	0.858
epoch	1	9000/14250 batches loss	0.054 accuracy	0.863
epoch	1	9500/14250 batches loss	0.076 accuracy	0.746
epoch	1	10000/14250 batches loss	0.080 accuracy	0.766
epoch	1	10500/14250 batches loss	0.062 accuracy	0.831
epoch	1	11000/14250 batches loss	0.055 accuracy	0.857
epoch	1	11500/14250 batches loss	0.055 accuracy	0.857
epoch	1	12000/14250 batches loss	0.055 accuracy	0.854
epoch	1	12500/14250 batches loss	0.052 accuracy	0.867
epoch	1	13000/14250 batches loss	0.054 accuracy	0.866
epoch	1	13500/14250 batches loss	0.052 accuracy	0.864
epoch	1	14000/14250 batches loss	0.052 accuracy	0.869

end of epoch	1	time: 165.30s valid accuracy	0.861	

Padded Seq

```
def forward(self, input_text):
    embedded = self.embedding(input_text)
    #packed_input = pack_padded_sequence(embedded, batch_size=4, padding_value=0)
    output, _ = self.rnn(embedded)
    h_n = output[:, -1, :]
    pred = self.fc(h_n)
    return pred
```

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epoch	1	500/14250 batches loss	0.173 accuracy	0.262
epoch	1	1000/14250 batches loss	0.164 accuracy	0.368
epoch	1	1500/14250 batches loss	0.170 accuracy	0.308
epoch	1	2000/14250 batches loss	0.162 accuracy	0.364
epoch	1	2500/14250 batches loss	0.145 accuracy	0.446
epoch	1	3000/14250 batches loss	0.144 accuracy	0.430
epoch	1	3500/14250 batches loss	0.142 accuracy	0.461
epoch	1	4000/14250 batches loss	0.141 accuracy	0.448
epoch	1	4500/14250 batches loss	0.143 accuracy	0.469
epoch	1	5000/14250 batches loss	0.157 accuracy	0.398
epoch	1	5500/14250 batches loss	0.154 accuracy	0.415
epoch	1	6000/14250 batches loss	0.147 accuracy	0.441
epoch	1	6500/14250 batches loss	0.145 accuracy	0.430
epoch	1	7000/14250 batches loss	0.141 accuracy	0.450
epoch	1	7500/14250 batches loss	0.140 accuracy	0.478
epoch	1	8000/14250 batches loss	0.150 accuracy	0.414
epoch	1	8500/14250 batches loss	0.140 accuracy	0.453
epoch	1	9000/14250 batches loss	0.132 accuracy	0.471
epoch	1	9500/14250 batches loss	0.129 accuracy	0.503
epoch	1	10000/14250 batches loss	0.133 accuracy	0.488
epoch	1	10500/14250 batches loss	0.132 accuracy	0.482
epoch	1	11000/14250 batches loss	0.154 accuracy	0.392
epoch	1	11500/14250 batches loss	0.163 accuracy	0.378
epoch	1	12000/14250 batches loss	0.134 accuracy	0.480
epoch	1	12500/14250 batches loss	0.123 accuracy	0.492
epoch	1	13000/14250 batches loss	0.115 accuracy	0.584
epoch	1	13500/14250 batches loss	0.104 accuracy	0.638
epoch	1	14000/14250 batches loss	0.121 accuracy	0.543

end of epoch	1	time: 147.70s valid accuracy	0.580	



Batchsize 32

정상 학습 + 정상 예측

Packed sequence

epoch	1	900/ 3563 batches	loss	0.015	accuracy	0.832
epoch	1	1000/ 3563 batches	loss	0.014	accuracy	0.849
epoch	1	1100/ 3563 batches	loss	0.014	accuracy	0.863
epoch	1	1200/ 3563 batches	loss	0.014	accuracy	0.854
epoch	1	1300/ 3563 batches	loss	0.013	accuracy	0.864
epoch	1	1400/ 3563 batches	loss	0.014	accuracy	0.860
epoch	1	1500/ 3563 batches	loss	0.012	accuracy	0.870
epoch	1	1600/ 3563 batches	loss	0.013	accuracy	0.878
epoch	1	1700/ 3563 batches	loss	0.013	accuracy	0.870
epoch	1	1800/ 3563 batches	loss	0.014	accuracy	0.858
epoch	1	1900/ 3563 batches	loss	0.013	accuracy	0.866
epoch	1	2000/ 3563 batches	loss	0.012	accuracy	0.876
epoch	1	2100/ 3563 batches	loss	0.013	accuracy	0.871
epoch	1	2200/ 3563 batches	loss	0.013	accuracy	0.869
epoch	1	2300/ 3563 batches	loss	0.013	accuracy	0.868
epoch	1	2400/ 3563 batches	loss	0.012	accuracy	0.876
epoch	1	2500/ 3563 batches	loss	0.013	accuracy	0.864
epoch	1	2600/ 3563 batches	loss	0.012	accuracy	0.875
epoch	1	2700/ 3563 batches	loss	0.013	accuracy	0.863
epoch	1	2800/ 3563 batches	loss	0.012	accuracy	0.871
epoch	1	2900/ 3563 batches	loss	0.013	accuracy	0.871
epoch	1	3000/ 3563 batches	loss	0.012	accuracy	0.874
epoch	1	3100/ 3563 batches	loss	0.012	accuracy	0.885
epoch	1	3200/ 3563 batches	loss	0.012	accuracy	0.880
epoch	1	3300/ 3563 batches	loss	0.012	accuracy	0.870
epoch	1	3400/ 3563 batches	loss	0.012	accuracy	0.873
epoch	1	3500/ 3563 batches	loss	0.012	accuracy	0.880
end of epoch 1 time: 77.12s valid accuracy 0.871						

```
def forward(self, input_text):  
    embedded = self.embedding(input_text)  
    #packed_input = pack_padded_sequence(em  
    output, _ = self.rnn(embedded)  
    h_n = output[-1, :] # This line will  
    pred = self.fc(h_n)  
    return pred
```

epoch	1	900/ 3563 batches	loss	0.037	accuracy	0.458
epoch	1	1000/ 3563 batches	loss	0.035	accuracy	0.459
epoch	1	1100/ 3563 batches	loss	0.039	accuracy	0.403
epoch	1	1200/ 3563 batches	loss	0.039	accuracy	0.419
epoch	1	1300/ 3563 batches	loss	0.037	accuracy	0.441
epoch	1	1400/ 3563 batches	loss	0.044	accuracy	0.273
epoch	1	1500/ 3563 batches	loss	0.040	accuracy	0.393
epoch	1	1600/ 3563 batches	loss	0.035	accuracy	0.475
epoch	1	1700/ 3563 batches	loss	0.034	accuracy	0.464
epoch	1	1800/ 3563 batches	loss	0.037	accuracy	0.431
epoch	1	1900/ 3563 batches	loss	0.036	accuracy	0.450
epoch	1	2000/ 3563 batches	loss	0.044	accuracy	0.316
epoch	1	2100/ 3563 batches	loss	0.043	accuracy	0.280
epoch	1	2200/ 3563 batches	loss	0.043	accuracy	0.284
epoch	1	2300/ 3563 batches	loss	0.043	accuracy	0.264
epoch	1	2400/ 3563 batches	loss	0.043	accuracy	0.291
epoch	1	2500/ 3563 batches	loss	0.042	accuracy	0.287
epoch	1	2600/ 3563 batches	loss	0.042	accuracy	0.316
epoch	1	2700/ 3563 batches	loss	0.042	accuracy	0.317
epoch	1	2800/ 3563 batches	loss	0.042	accuracy	0.318
epoch	1	2900/ 3563 batches	loss	0.042	accuracy	0.306
epoch	1	3000/ 3563 batches	loss	0.042	accuracy	0.316
epoch	1	3100/ 3563 batches	loss	0.042	accuracy	0.325
epoch	1	3200/ 3563 batches	loss	0.041	accuracy	0.318
epoch	1	3300/ 3563 batches	loss	0.038	accuracy	0.394
epoch	1	3400/ 3563 batches	loss	0.038	accuracy	0.389
epoch	1	3500/ 3563 batches	loss	0.038	accuracy	0.396
end of epoch 1 time: 71.57s valid accuracy 0.394						



References

- <https://github.com/bentrevett/pytorch-sentiment-analysis>

