

自然語言處理與應用

Natural Language Processing and Applications

PyTorch Modeling

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2025/03/17





Steps for building your first PyTorch program

Step 1 (Data):

- Prepare the dataset
- Overwrite PyTorch
 Dataset
- Define DataLoader

Step 2 (Model):

- Construct the model
- Define the loss function
- Define the optimizer

Step 3 (Training):

Write the training process

Step 4 (Evaluation):

Write the evaluation process



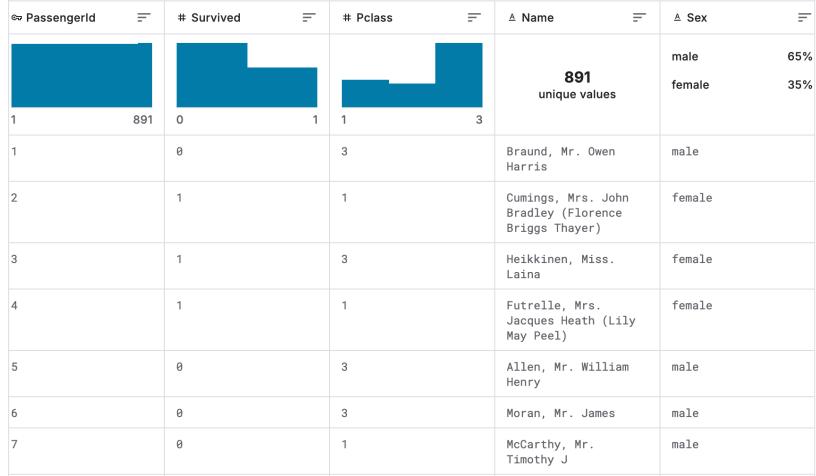
Step 1: Prepare the dataset

Step 1 (Data)

- From torchvision (image data) or torchtext (text data)
 - You may skip Step 1-2.
- User-defined dataset
 - Download from the Internet
 - Your own dataset



What is a dataset?



data / instance /example



dataset

- 為了符合我們載入資料的需求
 - 例如:適合我們資料的前處理過程
- 簡潔且容易維護的資料存取介面:

```
sent, label = dataset[0] # `dataset` 是透過 PyTorch Dataset 所建立的
index
```



Step 1 (Data)

• 我們需要繼承 torch.utils.data.Dataset,並改寫三個項目 (__init__, __getitem__, __len__):

```
import torch
class CustomDataset(torch.utils.data.Dataset):
   def __init__(self, parameter_1, parameter_2, ...):
       # Prepare some things
       # that you are going to use in `__getitem__` and `__len__`
   def getitem (self, index):
       # do something
       return data, label
   def len (self):
       return len(data variable)
```

- __init___: 初始化 class 中的變數
- __getitem__: 讓PyTorch Dataset 可 以透過 index 來取 得任一筆資料
- __len__: 取得資料 集的總數



Step 1 (Data)

```
class WaimaiDataset(torch.utils.data.Dataset):
    # 繼承 torch.utils.data.Dataset
    def __init__(self, data, max_seq_len, use_jieba):
        self.df = data
        self.max_seq_len = max_seq_len
        # 可以選擇要不要使用結巴進行斷詞
        self.use_jieba = use_jieba

# 改寫繼承的 __len__ function
    def __len__(self):
        return len(self.df)
```



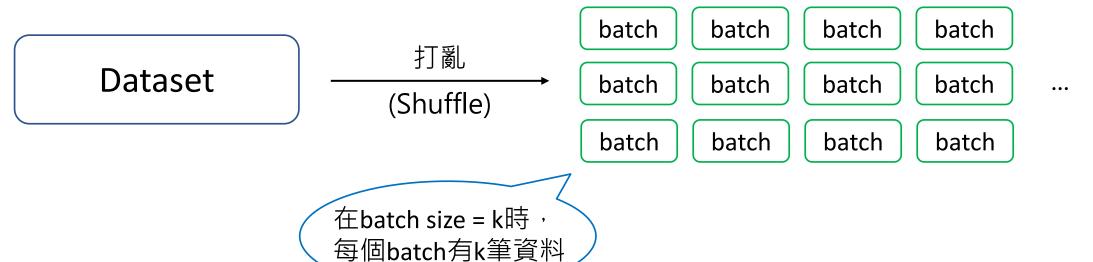
```
# 改寫繼承的 getitem function
def __getitem__(self, idx):
   # dataframe 的第一個 column 是 label
   # dataframe 的第一個 column 是 評論的句子
   label, sent = self.df.iloc[idx, 0:2]
   # 先將 label 轉為 float32 以方便後面進行 loss function 的計算
   label tensor = torch.tensor(label, dtype=torch.float32)
   if self.use jieba:
       # 使用 lcut 可以 return list
       tokens = jieba.lcut(sent, cut all=False)
   else:
   # 每個字都斷詞
   tokens = list(sent)
   # 控制最大的序列長度
   tokens = tokens[:self.max seq len]
   # 根據 vocab 轉換 word id
   # vocab 是一個 list
   tokens id = [vocab[word] for word in tokens]
   tokens tensor = torch.LongTensor(tokens id)
   # 所以 第 0 個index是句子,第 1 個index是 label
   return tokens_tensor, label_tensor
```

Step 1 (Data)



Step 1-3: Define DataLoader

Step 1 (Data)



We should split the dataset into train / validation / test sets first.
train_loader = torch.utils.data.DataLoader(trainset, batch_size=TRAIN_BS, shuffle=True,
collate_fn=collate_batch)
test_loader = torch.utils.data.DataLoader(testset, batch_size=TEST_BS, shuffle=False,
collate_fn=collate_batch)



Advantages of batching

- Training:
 - mini-batch gradient descent 有機會避免模型陷入局部最小值
- Inference (validation or test):
 - 省記憶體
 - 不需要累積梯度,所以 inference 時期的 batch size (bs) 通常可以比 training 時期的 bs 還大



Step 1-4: Padding

• 每個 batch 中的資料長度可能不同,我們需要進行 padding (補齊)

<s></s>	Recite	the	first	law	<s></s>	<pad></pad>	<pad></pad>	<pad></pad>	Datah tangar siza.
<s></s>	How	are	you	<s></s>	<pad></pad>	<pad></pad>	<pad></pad>	<pad></pad>	Batch tensor size: (batch size, seq length)
<s></s>	Who	is	the	first	president	of	U.S.	<s></s>	(_ / 1_ 0 /

```
def collate_batch(batch):
    # 抽每一個 batch 的第 0 個(注意順序)
    text = [i[0] for i in batch]
    # 進行 padding
    text = pad_sequence(text, batch_first=True)
```



Step 2-1: Construct the model

Step 2 (Model)

- 我們需要:
 - 1. 繼承 torch.nn.Module,
 - 2. 初始化 torch.nn.Module 原本定義的內容
 - 3. 改寫兩個項目 (__init___, forward)

```
class MyModel(torch.nn.Module):
    def __init__(self):
        super().__init__() # 初始化torch.nn.Module原本定義的內容
        # Define our new variables
        # Define our model layers

def forward(self, x):
    # Do something (forward pass)
    return output
```



為什麼需要 super().___init___()?

模型需要繼承 torch.nn.Module,並且透過 super().__init__() 初始化原本在 nn.Module 中被定義
 好的內容,如下圖所示:

```
206 • • •
            def __init__(self):
                                                                                                                        83 •
207
                Initializes internal Module state, shared by both nn.Module and ScriptModule.
208
209
210
                torch._C._log_api_usage_once("python.nn_module")
211
212
                self.training = True
                self._parameters = OrderedDict()
213
                self._buffers = OrderedDict()
214
215
                self._non_persistent_buffers_set = set()
216
                self. backward hooks = OrderedDict()
217
                self._forward_hooks = OrderedDict()
218
                self._forward_pre_hooks = OrderedDict()
219
                self._state_dict_hooks = OrderedDict()
220
                self._load_state_dict_pre_hooks = OrderedDict()
221
                self._modules = OrderedDict()
```



Step 2-2: Define the loss function

Step 2 (Model)

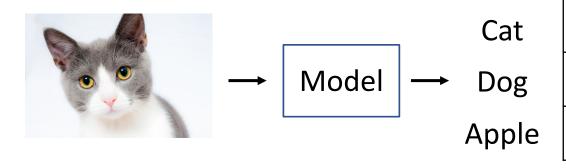
Loss functions	Usage
torch.nn.CrossEntropyLoss	Classification
torch.nn.MSELoss	Regression
torch.nn.BCELoss	Binary classification

loss_function = torch.nn.CrossEntropyLoss()



模型輸出的後處理

Cross-entropy:
$$\mathcal{L}_i = -\log P(Y = y_i | X = x_i)$$



Unnormalized log-probabilities / logits	Unnormalized probabilities	Probabilities	
0.5	1.6487	0.225	
0.7	2.0138	0.275	
1.3	3.6693	0.500	

Model → Exponential → Softmax

Cross-entropy (交叉熵)

Cross-entropy: $\mathcal{L}_i = -\log P(Y = y_i | X = x_i)$

其中i代表第i筆資料

交叉」(Cross) 代表的是 兩個機率分布之間的關係,特別是用一個分布來衡量 與另一個分布的相似程度

- 量測模型輸出的負對數機率,代表模型預測該類別的信心程度
 - 模型預測該類別的信心程度越大時, \mathcal{L}_i 就會越小
 - 模型預測該類別的信心程度越小時, \mathcal{L}_i 就會越大

$P(Y = y_i X = x_i)$	$\mathcal{L}_i = -\log P(Y = y_i X = x_i)$
0.9	-log0.9 ≈ 0.105
0.1	-log0.1 ≈ 2.302



Step 2-3: Define the optimizer

Step 2 (Model)

Loss functions	Meaning		
torch.optim.SGD	Stochastic gradient descent (with momentum)		
torch.optim.RMSprop	RMSProp (Root Mean Square Propagation)		
torch.optim.Adam	Adam (Adaptive Moment Estimation)		
torch.optim.AdamW	AdamW (Adam with decoupled weight decay)		

```
learning_rate = 1e-3 # 代表 0.001
optimizer = optim.Adam(model.parameters(), lr=learning_rate)
```



Step 3: Write the training process

Step 3 (Training)

- Clear gradients optimizer.zero grad()
- 2. Input data to the model
- Computer loss
- Computer gradients
- 5. Update model parameters
- 6. (Repeat 1. to 5. until the end of training)

- output = model(**batch)
- loss = loss function(gold, output)
- loss.backward()
- optimizer.step()



** in Python

• **dict 可以展開字典,轉換成關鍵字參數傳遞給函式

```
def greet(age, name):
    print(f"My name is {name} and I am {age} years old.")

person_info = {"name": "Alex", "age": 25}
greet(**person_info) # 等同於 greet(name="Alex", age=25)
```



Step 3: Write the training process

Step 3 (Training)

- 1. Clear gradients
- 2. Input data to the model
- 3. Computer loss
- 4. Computer gradients
- 5. Update model parameters
- 6. (Repeat 1. to 5. until the end of training)

```
optimizer.zero_grad()
```

```
output = model(**batch)
```

```
loss = loss_function(gold, output)
```

loss.backward()

optimizer.step()



Step 3: Write the training process

Step 3 (Training)

```
for batch in train_loader:
   output = model(**batch)
   ...
```

output = model(**batch)

```
# Get x, y from your dataloader
for batch_x, batch_y in train_loader:
    output = model(batch_x)
    loss = criterion(output, target)
    ...
```



Step 4: Write the evaluation process

Step 4 (Evaluation)

```
from sklearn.metrics import accuracy_score

with torch.no_grad():
    for batch in val_loader: # or test_loader
        output = model(**batch)
        pred = outputs.argmax(dim=1)
        ...
        predictions.append(pred)

accuracy_score(test_labels, predictions)
```



Thank you!

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