

# task-1

March 28, 2023

```
[1]: import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
import numpy as np
from torch.nn.utils.rnn import pad_sequence, pack_padded_sequence,
    pad_packed_sequence
from torch.nn.modules import padding
from torch.optim.lr_scheduler import StepLR
```

## 0.1 Finding the distribution of TAGS

```
[2]: with open('train', "r") as f:
    d={}
    for line in f:
        line = line.strip()
        if len(line) != 0:
            parts = line.split(" ")
            label = parts[2]
            d[label]=1+d.get(label,0)

d
```

```
[2]: {'B-ORG': 6321,
'O': 170524,
'B-MISC': 3438,
'B-PER': 6600,
'I-PER': 4528,
'B-LOC': 7140,
'I-ORG': 3704,
'I-MISC': 1155,
'I-LOC': 1157}
```

## 0.2 Creating Custom Dataset loader for Train and Dev

```
[3]: class NERDataset(Dataset):
    def __init__(self, filename):
        self.data = []
        self.word2idx = {'<unk>':1, '<unkcap>':2}
        self.label2idx = {}
        self.max_sent_len = 0
        self.wordCounter={}

        with open(filename, "r") as f:
            sentence = []
            labels = []
            for line in f:
                line = line.strip()
                if len(line) != 0:
                    parts = line.split(" ")
                    word = parts[1]
                    self.wordCounter[word]=1+self.wordCounter.get(word,0)

            for word,count in self.wordCounter.items():
                if count>1 and word not in self.word2idx:
                    self.word2idx[word]=len(self.word2idx)

            with open(filename, "r") as f:
                sentence = []
                labels = []
                for line in f:
                    line = line.strip()
                    if len(line) == 0:
                        if len(sentence) > self.max_sent_len:
                            self.max_sent_len = len(sentence)

                        self.data.append((sentence, labels))
                        sentence = []
                        labels = []
                    else:
                        parts = line.split(" ")
                        word = parts[1]
                        label = parts[2]
                        if word not in self.word2idx:
                            if word[0].isupper():
                                word='<unkcap>'
                            else:
                                word='<unk>'
```

```

        if label not in self.label2idx:
            self.label2idx[label] = len(self.label2idx)

        sentence.append(self.word2idx[word])
        labels.append(self.label2idx[label])

    if len(sentence) > 0:
        if len(sentence) > self.max_sent_len:
            self.max_sent_len = len(sentence)

        self.data.append((sentence, labels))

    self.word2idx['<PAD>'] = len(self.word2idx)
    self.pad_idx = self.word2idx['<PAD>']

    # Pad sentences
    self.x = [torch.tensor(s) for s, _ in self.data]
    self.x = pad_sequence(self.x, batch_first=True, padding_value=self.
↪pad_idx)

    # Pad labels
    self.y = [torch.tensor(l) for _, l in self.data]
    self.y = pad_sequence(self.y, batch_first=True, padding_value=self.
↪pad_idx)

    # Calculate lengths
    self.lengths = [len(s) for s, _ in self.data]

    def __len__(self):
        return len(self.data)

    def __getitem__(self, index):
        return self.x[index], self.lengths[index], self.y[index]

```

```

[4]: class ValidateNERDataset(Dataset):
    def __init__(self, filename, word2idx, label2idx):
        self.data = []
        self.word2idx = word2idx
        self.label2idx = label2idx
        self.max_sent_len = 0

        with open(filename, "r") as f:
            sentence = []
            labels = []
            for line in f:

```

```

        line = line.strip()
        if len(line) == 0:
            if len(sentence) > self.max_sent_len:
                self.max_sent_len = len(sentence)

            self.data.append((sentence, labels))
            sentence = []
            labels = []
        else:
            parts = line.split(" ")
            word = parts[1]
            label = parts[2]
            if word not in self.word2idx:
                if word[0].isupper():
                    word = '<unkcap>'
                else:
                    word = '<unk>'

            sentence.append(self.word2idx[word])
            labels.append(self.label2idx[label])

    if len(sentence) > 0:
        if len(sentence) > self.max_sent_len:
            self.max_sent_len = len(sentence)

        self.data.append((sentence, labels))

    self.pad_idx = self.word2idx['<PAD>']

    # Pad sentences
    self.x = [torch.tensor(s) for s, _ in self.data]
    self.x = pad_sequence(self.x, batch_first=True, padding_value=self.
↪pad_idx)

    # Pad labels
    self.y = [torch.tensor(l) for _, l in self.data]
    self.y = pad_sequence(self.y, batch_first=True, padding_value=self.
↪pad_idx)

    # Calculate lengths
    self.lengths = [len(s) for s, _ in self.data]

    def __len__(self):
        return len(self.data)

    def __getitem__(self, index):

```

```
return self.x[index], self.lengths[index], self.y[index]
```

### 0.3 BLSTM Model

```
[5]: class BLSTM(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_dim, output_dim,
↳ dropout, label_dim):
        super().__init__()
        self.embedding = nn.Embedding(vocab_size, embedding_dim,
↳ padding_idx=train_dataset.pad_idx)
        self.lstm = nn.LSTM(embedding_dim, hidden_dim, batch_first=True,
↳ ,bidirectional=True)
        self.dropout = nn.Dropout(dropout)
        self.fc = nn.Linear(hidden_dim * 2, output_dim)
        self.act = nn.ELU(alpha=0.75)
        self.classifier = nn.Linear(output_dim, label_dim)

    def forward(self, x, x_lengths):
        embedded = self.embedding(x)
        packed_embedded = nn.utils.rnn.pack_padded_sequence(embedded,
↳ x_lengths, batch_first=True, enforce_sorted=False)
        packed_output, (hidden, cell) = self.lstm(packed_embedded)
        output, output_lengths = nn.utils.rnn.
↳ pad_packed_sequence(packed_output, batch_first=True)
        output = self.dropout(output)
        output = self.fc(output)
        output = self.act(output)
        output = self.classifier(output)
        output = output.permute(0, 2, 1)
        return output
```

### 0.4 Setting the hyperparameter

```
[56]: batch_size = 8
train_dataset = NERDataset('train')

# Hyperparameters
EMBEDDING_DIM = 100
HIDDEN_DIM = 256
OUTPUT_DIM = 128
OUTPUT_LABEL_DIM = len(train_dataset.label2idx)
DROPOUT = 0.33
#learning rate .1 is best
LEARNING_RATE = .005
EPOCHS = 50
STEP_SIZE = 20
```

```
GAMMA = 1
```

```
[57]: device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = BLSTM(len(train_dataset.word2idx), EMBEDDING_DIM, HIDDEN_DIM,
    ↳OUTPUT_DIM, DROPOUT, OUTPUT_LABEL_DIM).to(device)
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True,
    ↳pin_memory=True)
optimizer = optim.SGD(model.parameters(), lr=LEARNING_RATE, momentum=.95)
scheduler = StepLR(optimizer, step_size=STEP_SIZE, gamma=GAMMA)
#freq=list(d.values())
#sum_freq = sum(freq)
#result = [(1.5 - f/sum_freq) for f in freq]
#class_weights = torch.tensor(result).to(device)
#class_weights = torch.tensor([1.6, .5, 1.6, 1.1, 1.4, 1.1, 1.6, 2.1, 2.1]).
    ↳to(device)

#class_weights = torch.tensor([1.6, .7, 1.6, 1.8, 1.7, 1.6, 1.7, 1.6, 1.6]).
    ↳to(device)
class_weights = torch.tensor([1.7, .75, 1.5, 1.8, 1.7, 1.8, 1.7, 1.6, 1.5]).
    ↳to(device)

#class_weights = torch.tensor([2, .5, 2, 1.1, 1.4, 1.1, 1.6, 2.1, 2.1]).
    ↳to(device)

criterion = nn.CrossEntropyLoss(ignore_index=train_dataset.
    ↳pad_idx, weight=class_weights).to(device)
```

```
[8]: train_dataset.label2idx
```

```
[8]: {'B-ORG': 0,
      'O': 1,
      'B-MISC': 2,
      'B-PER': 3,
      'I-PER': 4,
      'B-LOC': 5,
      'I-ORG': 6,
      'I-MISC': 7,
      'I-LOC': 8}
```

```
[9]: dev_dataset = ValidateNERDataset('dev', train_dataset.word2idx, train_dataset.
    ↳label2idx)
dev_loader = DataLoader(dev_dataset)
```

## 0.5 Training the Model

```
[58]: min_val_loss=5
      # Train the model
      for epoch in range(EPOCHS):
          model.train()

          for batch_idx, (x, lengths, y) in enumerate(train_loader):
              optimizer.zero_grad()

              target_packed_embedded = nn.utils.rnn.pack_padded_sequence(y.
→to(device), lengths, batch_first=True, enforce_sorted=False)
              target, target_lengths = nn.utils.rnn.
→pad_packed_sequence(target_packed_embedded, batch_first=True)

              #output = model(x.to(device), lengths.to(device))
              output = model(x.to(device), lengths.cpu())

              loss = criterion(output, target.to(device))
              loss.backward()
              optimizer.step()
              scheduler.step()

              if batch_idx % 100 == 0:
                  print(f"Epoch {epoch}, Batch {batch_idx}, Loss {loss.item()}")

              # Compute and print the validation loss
              if batch_idx % 2000 == 0:
                  model.eval() # Set the model to evaluation mode
                  with torch.no_grad():
                      val_loss = 0
                      for val_x, val_lengths, val_y in dev_loader:
                          val_target_packed_embedded = nn.utils.rnn.
→pack_padded_sequence(val_y.to(device), val_lengths, batch_first=True,
→enforce_sorted=False)
                          val_target, val_target_lengths = nn.utils.rnn.
→pad_packed_sequence(val_target_packed_embedded, batch_first=True)

                          val_output = model(val_x.to(device), val_lengths.cpu())
                          val_loss += criterion(val_output, val_target.to(device)).
→item()

                      print(f"Epoch {epoch}, Batch {batch_idx}, Validation Loss
→{val_loss/len(dev_loader)}")
                      if min_val_loss>val_loss/len(dev_loader):
                          min_val_loss=val_loss/len(dev_loader)
```

```
torch.save(model.state_dict(), 'task_minloss.pt')
```

```
model.train() # Set the model back to training model
```

```
Epoch 0, Batch 0, Loss 2.2467987537384033
Epoch 0, Batch 0, Validation Loss 2.1530335838232024
Epoch 0, Batch 100, Loss 0.5747454166412354
Epoch 0, Batch 200, Loss 0.3972536027431488
Epoch 0, Batch 300, Loss 0.2924852967262268
Epoch 0, Batch 400, Loss 0.27404943108558655
Epoch 0, Batch 500, Loss 0.22460637986660004
Epoch 0, Batch 600, Loss 0.3476652204990387
Epoch 0, Batch 700, Loss 0.21437563002109528
Epoch 0, Batch 800, Loss 0.276003360748291
Epoch 0, Batch 900, Loss 0.2197766900062561
Epoch 0, Batch 1000, Loss 0.32000187039375305
Epoch 0, Batch 1100, Loss 0.2562519609928131
Epoch 0, Batch 1200, Loss 0.8866047263145447
Epoch 0, Batch 1300, Loss 0.19038942456245422
Epoch 0, Batch 1400, Loss 0.16637755930423737
Epoch 0, Batch 1500, Loss 0.738795816898346
Epoch 0, Batch 1600, Loss 0.7032221555709839
Epoch 0, Batch 1700, Loss 0.30590152740478516
Epoch 0, Batch 1800, Loss 0.3025318682193756
Epoch 1, Batch 0, Loss 0.2271697074174881
Epoch 1, Batch 0, Validation Loss 0.9779573119639388
Epoch 1, Batch 100, Loss 0.188228577375412
Epoch 1, Batch 200, Loss 0.25845086574554443
Epoch 1, Batch 300, Loss 0.5732181072235107
Epoch 1, Batch 400, Loss 0.47560781240463257
Epoch 1, Batch 500, Loss 0.3026306927204132
Epoch 1, Batch 600, Loss 0.2636333107948303
Epoch 1, Batch 700, Loss 0.1620873361825943
Epoch 1, Batch 800, Loss 0.13483232259750366
Epoch 1, Batch 900, Loss 0.0808730497956276
Epoch 1, Batch 1000, Loss 0.23824191093444824
Epoch 1, Batch 1100, Loss 0.20465555787086487
Epoch 1, Batch 1200, Loss 0.2690538167953491
Epoch 1, Batch 1300, Loss 0.285736083984375
Epoch 1, Batch 1400, Loss 0.4800832271575928
Epoch 1, Batch 1500, Loss 0.10531609505414963
Epoch 1, Batch 1600, Loss 0.22168803215026855
Epoch 1, Batch 1700, Loss 0.2624880373477936
Epoch 1, Batch 1800, Loss 0.44203421473503113
Epoch 2, Batch 0, Loss 0.13332118093967438
Epoch 2, Batch 0, Validation Loss 0.8257529791659501
```



Epoch 2, Batch 100, Loss 0.21448923647403717  
Epoch 2, Batch 200, Loss 0.2091418206691742  
Epoch 2, Batch 300, Loss 0.22005398571491241  
Epoch 2, Batch 400, Loss 0.13896553218364716  
Epoch 2, Batch 500, Loss 0.15091553330421448  
Epoch 2, Batch 600, Loss 0.17139217257499695  
Epoch 2, Batch 700, Loss 0.19270844757556915  
Epoch 2, Batch 800, Loss 0.13928020000457764  
Epoch 2, Batch 900, Loss 0.25396794080734253  
Epoch 2, Batch 1000, Loss 0.2896393835544586  
Epoch 2, Batch 1100, Loss 0.46319591999053955  
Epoch 2, Batch 1200, Loss 0.13066035509109497  
Epoch 2, Batch 1300, Loss 0.3024241030216217  
Epoch 2, Batch 1400, Loss 0.16198554635047913  
Epoch 2, Batch 1500, Loss 0.1454496681690216  
Epoch 2, Batch 1600, Loss 0.199619323015213  
Epoch 2, Batch 1700, Loss 0.3811242878437042  
Epoch 2, Batch 1800, Loss 0.29208019375801086  
Epoch 3, Batch 0, Loss 0.22863663733005524  
Epoch 3, Batch 0, Validation Loss 0.7131404940856312  
Epoch 3, Batch 100, Loss 0.30172207951545715  
Epoch 3, Batch 200, Loss 0.43450647592544556  
Epoch 3, Batch 300, Loss 0.26929497718811035  
Epoch 3, Batch 400, Loss 0.23557955026626587  
Epoch 3, Batch 500, Loss 0.07875192165374756  
Epoch 3, Batch 600, Loss 0.1882663071155548  
Epoch 3, Batch 700, Loss 0.2585316002368927  
Epoch 3, Batch 800, Loss 0.19841432571411133  
Epoch 3, Batch 900, Loss 0.17867664992809296  
Epoch 3, Batch 1000, Loss 0.2923671007156372  
Epoch 3, Batch 1100, Loss 0.13303512334823608  
Epoch 3, Batch 1200, Loss 0.46129435300827026  
Epoch 3, Batch 1300, Loss 0.2564007639884949  
Epoch 3, Batch 1400, Loss 0.2348671704530716  
Epoch 3, Batch 1500, Loss 0.19420841336250305  
Epoch 3, Batch 1600, Loss 0.45639514923095703  
Epoch 3, Batch 1700, Loss 0.10272443294525146  
Epoch 3, Batch 1800, Loss 0.06176889315247536  
Epoch 4, Batch 0, Loss 0.20407620072364807  
Epoch 4, Batch 0, Validation Loss 0.6374870179891715  
Epoch 4, Batch 100, Loss 0.2765561044216156  
Epoch 4, Batch 200, Loss 0.15558063983917236  
Epoch 4, Batch 300, Loss 0.23321184515953064  
Epoch 4, Batch 400, Loss 0.35759514570236206  
Epoch 4, Batch 500, Loss 0.3848417401313782  
Epoch 4, Batch 600, Loss 0.16536937654018402  
Epoch 4, Batch 700, Loss 0.17327021062374115  
Epoch 4, Batch 800, Loss 0.26535284519195557

Epoch 4, Batch 900, Loss 0.15526174008846283  
Epoch 4, Batch 1000, Loss 0.25845128297805786  
Epoch 4, Batch 1100, Loss 0.2191464602947235  
Epoch 4, Batch 1200, Loss 0.18356741964817047  
Epoch 4, Batch 1300, Loss 0.22480317950248718  
Epoch 4, Batch 1400, Loss 0.31517475843429565  
Epoch 4, Batch 1500, Loss 0.2393524944782257  
Epoch 4, Batch 1600, Loss 0.09737680107355118  
Epoch 4, Batch 1700, Loss 0.07556015253067017  
Epoch 4, Batch 1800, Loss 0.2794700562953949  
Epoch 5, Batch 0, Loss 0.07936917245388031  
Epoch 5, Batch 0, Validation Loss 0.5662990838525181  
Epoch 5, Batch 100, Loss 0.10408347100019455  
Epoch 5, Batch 200, Loss 0.1119004637002945  
Epoch 5, Batch 300, Loss 0.16903828084468842  
Epoch 5, Batch 400, Loss 0.2619238495826721  
Epoch 5, Batch 500, Loss 0.19662462174892426  
Epoch 5, Batch 600, Loss 0.1830054670572281  
Epoch 5, Batch 700, Loss 0.1227228119969368  
Epoch 5, Batch 800, Loss 0.2149682193994522  
Epoch 5, Batch 900, Loss 0.09734497219324112  
Epoch 5, Batch 1000, Loss 0.09554368257522583  
Epoch 5, Batch 1100, Loss 0.20116807520389557  
Epoch 5, Batch 1200, Loss 0.12772580981254578  
Epoch 5, Batch 1300, Loss 0.279792457818985  
Epoch 5, Batch 1400, Loss 0.18832647800445557  
Epoch 5, Batch 1500, Loss 0.06791342794895172  
Epoch 5, Batch 1600, Loss 0.36114272475242615  
Epoch 5, Batch 1700, Loss 0.1210186555981636  
Epoch 5, Batch 1800, Loss 0.11089294403791428  
Epoch 6, Batch 0, Loss 0.18253566324710846  
Epoch 6, Batch 0, Validation Loss 0.5004145449087339  
Epoch 6, Batch 100, Loss 0.2007526308298111  
Epoch 6, Batch 200, Loss 0.10156048834323883  
Epoch 6, Batch 300, Loss 0.2297937124967575  
Epoch 6, Batch 400, Loss 0.06641627103090286  
Epoch 6, Batch 500, Loss 0.1452811360359192  
Epoch 6, Batch 600, Loss 0.19057150185108185  
Epoch 6, Batch 700, Loss 0.06720320135354996  
Epoch 6, Batch 800, Loss 0.15411654114723206  
Epoch 6, Batch 900, Loss 0.21262772381305695  
Epoch 6, Batch 1000, Loss 0.22732232511043549  
Epoch 6, Batch 1100, Loss 0.2630687654018402  
Epoch 6, Batch 1200, Loss 0.15403170883655548  
Epoch 6, Batch 1300, Loss 0.06146189197897911  
Epoch 6, Batch 1400, Loss 0.1427360326051712  
Epoch 6, Batch 1500, Loss 0.06456330418586731  
Epoch 6, Batch 1600, Loss 0.15916569530963898

Epoch 6, Batch 1700, Loss 0.2195957601070404  
Epoch 6, Batch 1800, Loss 0.176566481590271  
Epoch 7, Batch 0, Loss 0.09609535336494446  
Epoch 7, Batch 0, Validation Loss 0.4587673276315663  
Epoch 7, Batch 100, Loss 0.1491001397371292  
Epoch 7, Batch 200, Loss 0.1374945044517517  
Epoch 7, Batch 300, Loss 0.07268303632736206  
Epoch 7, Batch 400, Loss 0.1415235996246338  
Epoch 7, Batch 500, Loss 0.14927378296852112  
Epoch 7, Batch 600, Loss 0.10626259446144104  
Epoch 7, Batch 700, Loss 0.2015487402677536  
Epoch 7, Batch 800, Loss 0.10408079624176025  
Epoch 7, Batch 900, Loss 0.10781732946634293  
Epoch 7, Batch 1000, Loss 0.11697878688573837  
Epoch 7, Batch 1100, Loss 0.2434253841638565  
Epoch 7, Batch 1200, Loss 0.20431847870349884  
Epoch 7, Batch 1300, Loss 0.08505631238222122  
Epoch 7, Batch 1400, Loss 0.10875890403985977  
Epoch 7, Batch 1500, Loss 0.07594679296016693  
Epoch 7, Batch 1600, Loss 0.17256192862987518  
Epoch 7, Batch 1700, Loss 0.11831734329462051  
Epoch 7, Batch 1800, Loss 0.0601741187274456  
Epoch 8, Batch 0, Loss 0.3003526031970978  
Epoch 8, Batch 0, Validation Loss 0.4189145497039828  
Epoch 8, Batch 100, Loss 0.11951681226491928  
Epoch 8, Batch 200, Loss 0.08513219654560089  
Epoch 8, Batch 300, Loss 0.12461874634027481  
Epoch 8, Batch 400, Loss 0.1389780342578888  
Epoch 8, Batch 500, Loss 0.16669906675815582  
Epoch 8, Batch 600, Loss 0.15272685885429382  
Epoch 8, Batch 700, Loss 0.1665341854095459  
Epoch 8, Batch 800, Loss 0.11598549783229828  
Epoch 8, Batch 900, Loss 0.11365815997123718  
Epoch 8, Batch 1000, Loss 0.12409999221563339  
Epoch 8, Batch 1100, Loss 0.11380653083324432  
Epoch 8, Batch 1200, Loss 0.0762694850564003  
Epoch 8, Batch 1300, Loss 0.1557466685771942  
Epoch 8, Batch 1400, Loss 0.13961459696292877  
Epoch 8, Batch 1500, Loss 0.17488205432891846  
Epoch 8, Batch 1600, Loss 0.23938515782356262  
Epoch 8, Batch 1700, Loss 0.0922258123755455  
Epoch 8, Batch 1800, Loss 0.04149429872632027  
Epoch 9, Batch 0, Loss 0.11672808229923248  
Epoch 9, Batch 0, Validation Loss 0.3817907231593344  
Epoch 9, Batch 100, Loss 0.04702385887503624  
Epoch 9, Batch 200, Loss 0.037036698311567307  
Epoch 9, Batch 300, Loss 0.07400259375572205  
Epoch 9, Batch 400, Loss 0.06945805996656418

Epoch 9, Batch 500, Loss 0.13740846514701843  
Epoch 9, Batch 600, Loss 0.0319710373878479  
Epoch 9, Batch 700, Loss 0.098317950963974  
Epoch 9, Batch 800, Loss 0.054491255432367325  
Epoch 9, Batch 900, Loss 0.10119257122278214  
Epoch 9, Batch 1000, Loss 0.09972687065601349  
Epoch 9, Batch 1100, Loss 0.12689277529716492  
Epoch 9, Batch 1200, Loss 0.12201926857233047  
Epoch 9, Batch 1300, Loss 0.11152833700180054  
Epoch 9, Batch 1400, Loss 0.11285129934549332  
Epoch 9, Batch 1500, Loss 0.09939275681972504  
Epoch 9, Batch 1600, Loss 0.06210295110940933  
Epoch 9, Batch 1700, Loss 0.02379193715751171  
Epoch 9, Batch 1800, Loss 0.05130456015467644  
Epoch 10, Batch 0, Loss 0.1037725955247879  
Epoch 10, Batch 0, Validation Loss 0.35519221302909376  
Epoch 10, Batch 100, Loss 0.10573700815439224  
Epoch 10, Batch 200, Loss 0.06455600261688232  
Epoch 10, Batch 300, Loss 0.14859648048877716  
Epoch 10, Batch 400, Loss 0.06176622211933136  
Epoch 10, Batch 500, Loss 0.1025996208190918  
Epoch 10, Batch 600, Loss 0.09285499155521393  
Epoch 10, Batch 700, Loss 0.07364750653505325  
Epoch 10, Batch 800, Loss 0.10379678755998611  
Epoch 10, Batch 900, Loss 0.14991584420204163  
Epoch 10, Batch 1000, Loss 0.14336048066616058  
Epoch 10, Batch 1100, Loss 0.21035981178283691  
Epoch 10, Batch 1200, Loss 0.0723126232624054  
Epoch 10, Batch 1300, Loss 0.029954897239804268  
Epoch 10, Batch 1400, Loss 0.17997696995735168  
Epoch 10, Batch 1500, Loss 0.14095310866832733  
Epoch 10, Batch 1600, Loss 0.062396515160799026  
Epoch 10, Batch 1700, Loss 0.1501711755990982  
Epoch 10, Batch 1800, Loss 0.07771683484315872  
Epoch 11, Batch 0, Loss 0.07938337326049805  
Epoch 11, Batch 0, Validation Loss 0.32758587613347534  
Epoch 11, Batch 100, Loss 0.11992458254098892  
Epoch 11, Batch 200, Loss 0.14211814105510712  
Epoch 11, Batch 300, Loss 0.0521809458732605  
Epoch 11, Batch 400, Loss 0.05556419864296913  
Epoch 11, Batch 500, Loss 0.10300775617361069  
Epoch 11, Batch 600, Loss 0.16305845975875854  
Epoch 11, Batch 700, Loss 0.1770542562007904  
Epoch 11, Batch 800, Loss 0.07335423678159714  
Epoch 11, Batch 900, Loss 0.06437753885984421  
Epoch 11, Batch 1000, Loss 0.08288323879241943  
Epoch 11, Batch 1100, Loss 0.1484157294034958  
Epoch 11, Batch 1200, Loss 0.11262065917253494

Epoch 11, Batch 1300, Loss 0.08042243868112564  
Epoch 11, Batch 1400, Loss 0.10981710255146027  
Epoch 11, Batch 1500, Loss 0.04687344282865524  
Epoch 11, Batch 1600, Loss 0.0801275297999382  
Epoch 11, Batch 1700, Loss 0.07598191499710083  
Epoch 11, Batch 1800, Loss 0.03982032090425491  
Epoch 12, Batch 0, Loss 0.06184924393892288  
Epoch 12, Batch 0, Validation Loss 0.32059952854299256  
Epoch 12, Batch 100, Loss 0.09419762343168259  
Epoch 12, Batch 200, Loss 0.1820274144411087  
Epoch 12, Batch 300, Loss 0.08140411227941513  
Epoch 12, Batch 400, Loss 0.2524007558822632  
Epoch 12, Batch 500, Loss 0.17331774532794952  
Epoch 12, Batch 600, Loss 0.05088638886809349  
Epoch 12, Batch 700, Loss 0.06208612397313118  
Epoch 12, Batch 800, Loss 0.07633735984563828  
Epoch 12, Batch 900, Loss 0.16185401380062103  
Epoch 12, Batch 1000, Loss 0.11430453509092331  
Epoch 12, Batch 1100, Loss 0.11665311455726624  
Epoch 12, Batch 1200, Loss 0.02429070882499218  
Epoch 12, Batch 1300, Loss 0.04413195326924324  
Epoch 12, Batch 1400, Loss 0.1681220978498459  
Epoch 12, Batch 1500, Loss 0.10572013258934021  
Epoch 12, Batch 1600, Loss 0.061557501554489136  
Epoch 12, Batch 1700, Loss 0.09484822303056717  
Epoch 12, Batch 1800, Loss 0.026680175215005875  
Epoch 13, Batch 0, Loss 0.015125062316656113  
Epoch 13, Batch 0, Validation Loss 0.2920546589327014  
Epoch 13, Batch 100, Loss 0.048343636095523834  
Epoch 13, Batch 200, Loss 0.07748477160930634  
Epoch 13, Batch 300, Loss 0.07209204882383347  
Epoch 13, Batch 400, Loss 0.091408871114254  
Epoch 13, Batch 500, Loss 0.07022440433502197  
Epoch 13, Batch 600, Loss 0.19548411667346954  
Epoch 13, Batch 700, Loss 0.13515350222587585  
Epoch 13, Batch 800, Loss 0.07871818542480469  
Epoch 13, Batch 900, Loss 0.15337571501731873  
Epoch 13, Batch 1000, Loss 0.06739784777164459  
Epoch 13, Batch 1100, Loss 0.12133472412824631  
Epoch 13, Batch 1200, Loss 0.023477910086512566  
Epoch 13, Batch 1300, Loss 0.08968847244977951  
Epoch 13, Batch 1400, Loss 0.10570932924747467  
Epoch 13, Batch 1500, Loss 0.08630269020795822  
Epoch 13, Batch 1600, Loss 0.038958046585321426  
Epoch 13, Batch 1700, Loss 0.026231585070490837  
Epoch 13, Batch 1800, Loss 0.17640727758407593  
Epoch 14, Batch 0, Loss 0.07059359550476074  
Epoch 14, Batch 0, Validation Loss 0.28115582251652466

Epoch 14, Batch 100, Loss 0.05106010660529137  
Epoch 14, Batch 200, Loss 0.16798317432403564  
Epoch 14, Batch 300, Loss 0.13460209965705872  
Epoch 14, Batch 400, Loss 0.085304856300354  
Epoch 14, Batch 500, Loss 0.0766729786992073  
Epoch 14, Batch 600, Loss 0.03559689596295357  
Epoch 14, Batch 700, Loss 0.28365713357925415  
Epoch 14, Batch 800, Loss 0.0712871253490448  
Epoch 14, Batch 900, Loss 0.08337335288524628  
Epoch 14, Batch 1000, Loss 0.05842281132936478  
Epoch 14, Batch 1100, Loss 0.03114369325339794  
Epoch 14, Batch 1200, Loss 0.07904843986034393  
Epoch 14, Batch 1300, Loss 0.02817062847316265  
Epoch 14, Batch 1400, Loss 0.05470994859933853  
Epoch 14, Batch 1500, Loss 0.04760793596506119  
Epoch 14, Batch 1600, Loss 0.021784411743283272  
Epoch 14, Batch 1700, Loss 0.04060012102127075  
Epoch 14, Batch 1800, Loss 0.07451733201742172  
Epoch 15, Batch 0, Loss 0.06382890045642853  
Epoch 15, Batch 0, Validation Loss 0.2692164604486669  
Epoch 15, Batch 100, Loss 0.06943883746862411  
Epoch 15, Batch 200, Loss 0.01769212633371353  
Epoch 15, Batch 300, Loss 0.013543208129703999  
Epoch 15, Batch 400, Loss 0.05929357558488846  
Epoch 15, Batch 500, Loss 0.028034809976816177  
Epoch 15, Batch 600, Loss 0.007189398165792227  
Epoch 15, Batch 700, Loss 0.02897472120821476  
Epoch 15, Batch 800, Loss 0.051084261387586594  
Epoch 15, Batch 900, Loss 0.09783235937356949  
Epoch 15, Batch 1000, Loss 0.07343324273824692  
Epoch 15, Batch 1100, Loss 0.07980456203222275  
Epoch 15, Batch 1200, Loss 0.11640782654285431  
Epoch 15, Batch 1300, Loss 0.05187978595495224  
Epoch 15, Batch 1400, Loss 0.14460764825344086  
Epoch 15, Batch 1500, Loss 0.08019427955150604  
Epoch 15, Batch 1600, Loss 0.08387338370084763  
Epoch 15, Batch 1700, Loss 0.01799321174621582  
Epoch 15, Batch 1800, Loss 0.0544838085770607  
Epoch 16, Batch 0, Loss 0.04034394025802612  
Epoch 16, Batch 0, Validation Loss 0.2564718814454204  
Epoch 16, Batch 100, Loss 0.03956501558423042  
Epoch 16, Batch 200, Loss 0.0658891350030899  
Epoch 16, Batch 300, Loss 0.04963094741106033  
Epoch 16, Batch 400, Loss 0.11862848699092865  
Epoch 16, Batch 500, Loss 0.02953493595123291  
Epoch 16, Batch 600, Loss 0.04773204028606415  
Epoch 16, Batch 700, Loss 0.07790886610746384  
Epoch 16, Batch 800, Loss 0.06240898743271828

Epoch 16, Batch 900, Loss 0.14063061773777008  
Epoch 16, Batch 1000, Loss 0.0967077687382698  
Epoch 16, Batch 1100, Loss 0.11914514750242233  
Epoch 16, Batch 1200, Loss 0.04061715304851532  
Epoch 16, Batch 1300, Loss 0.1021168902516365  
Epoch 16, Batch 1400, Loss 0.12035612761974335  
Epoch 16, Batch 1500, Loss 0.08280784636735916  
Epoch 16, Batch 1600, Loss 0.05092557892203331  
Epoch 16, Batch 1700, Loss 0.04994342103600502  
Epoch 16, Batch 1800, Loss 0.046034075319767  
Epoch 17, Batch 0, Loss 0.020493028685450554  
Epoch 17, Batch 0, Validation Loss 0.26769391427657657  
Epoch 17, Batch 100, Loss 0.03184641897678375  
Epoch 17, Batch 200, Loss 0.03654196113348007  
Epoch 17, Batch 300, Loss 0.07983583211898804  
Epoch 17, Batch 400, Loss 0.022982247173786163  
Epoch 17, Batch 500, Loss 0.01884744130074978  
Epoch 17, Batch 600, Loss 0.02702292613685131  
Epoch 17, Batch 700, Loss 0.1271274834871292  
Epoch 17, Batch 800, Loss 0.04350189119577408  
Epoch 17, Batch 900, Loss 0.012059426866471767  
Epoch 17, Batch 1000, Loss 0.08355630934238434  
Epoch 17, Batch 1100, Loss 0.0287178922444582  
Epoch 17, Batch 1200, Loss 0.03311901539564133  
Epoch 17, Batch 1300, Loss 0.025597194209694862  
Epoch 17, Batch 1400, Loss 0.06106317788362503  
Epoch 17, Batch 1500, Loss 0.035822298377752304  
Epoch 17, Batch 1600, Loss 0.01658862829208374  
Epoch 17, Batch 1700, Loss 0.04815424606204033  
Epoch 17, Batch 1800, Loss 0.08082082122564316  
Epoch 18, Batch 0, Loss 0.047724124044179916  
Epoch 18, Batch 0, Validation Loss 0.24336735726034317  
Epoch 18, Batch 100, Loss 0.05029311403632164  
Epoch 18, Batch 200, Loss 0.07585671544075012  
Epoch 18, Batch 300, Loss 0.05090991035103798  
Epoch 18, Batch 400, Loss 0.060030341148376465  
Epoch 18, Batch 500, Loss 0.04509042948484421  
Epoch 18, Batch 600, Loss 0.043469928205013275  
Epoch 18, Batch 700, Loss 0.024189133197069168  
Epoch 18, Batch 800, Loss 0.024078277871012688  
Epoch 18, Batch 900, Loss 0.03480019047856331  
Epoch 18, Batch 1000, Loss 0.04319576919078827  
Epoch 18, Batch 1100, Loss 0.06482231616973877  
Epoch 18, Batch 1200, Loss 0.029589364305138588  
Epoch 18, Batch 1300, Loss 0.06785007566213608  
Epoch 18, Batch 1400, Loss 0.027589142322540283  
Epoch 18, Batch 1500, Loss 0.10919898748397827  
Epoch 18, Batch 1600, Loss 0.08309780061244965

Epoch 18, Batch 1700, Loss 0.3154008686542511  
Epoch 18, Batch 1800, Loss 0.1869318187236786  
Epoch 19, Batch 0, Loss 0.022147124633193016  
Epoch 19, Batch 0, Validation Loss 0.2515422634323856  
Epoch 19, Batch 100, Loss 0.03195851668715477  
Epoch 19, Batch 200, Loss 0.14917011559009552  
Epoch 19, Batch 300, Loss 0.0751456543803215  
Epoch 19, Batch 400, Loss 0.06457994878292084  
Epoch 19, Batch 500, Loss 0.05236239358782768  
Epoch 19, Batch 600, Loss 0.043905019760131836  
Epoch 19, Batch 700, Loss 0.044727351516485214  
Epoch 19, Batch 800, Loss 0.018075378611683846  
Epoch 19, Batch 900, Loss 0.0703897476196289  
Epoch 19, Batch 1000, Loss 0.07296272367238998  
Epoch 19, Batch 1100, Loss 0.029996061697602272  
Epoch 19, Batch 1200, Loss 0.015745095908641815  
Epoch 19, Batch 1300, Loss 0.07263316959142685  
Epoch 19, Batch 1400, Loss 0.03136203810572624  
Epoch 19, Batch 1500, Loss 0.08526603132486343  
Epoch 19, Batch 1600, Loss 0.10125400871038437  
Epoch 19, Batch 1700, Loss 0.035910602658987045  
Epoch 19, Batch 1800, Loss 0.07193384319543839  
Epoch 20, Batch 0, Loss 0.03766849637031555  
Epoch 20, Batch 0, Validation Loss 0.2500736036043265  
Epoch 20, Batch 100, Loss 0.03092874214053154  
Epoch 20, Batch 200, Loss 0.044215478003025055  
Epoch 20, Batch 300, Loss 0.06352640688419342  
Epoch 20, Batch 400, Loss 0.03769572079181671  
Epoch 20, Batch 500, Loss 0.025049179792404175  
Epoch 20, Batch 600, Loss 0.041472576558589935  
Epoch 20, Batch 700, Loss 0.015519369393587112  
Epoch 20, Batch 800, Loss 0.02234438993036747  
Epoch 20, Batch 900, Loss 0.0745508149266243  
Epoch 20, Batch 1000, Loss 0.06227707117795944  
Epoch 20, Batch 1100, Loss 0.055607642978429794  
Epoch 20, Batch 1200, Loss 0.11382174491882324  
Epoch 20, Batch 1300, Loss 0.05170445516705513  
Epoch 20, Batch 1400, Loss 0.05761825293302536  
Epoch 20, Batch 1500, Loss 0.033323176205158234  
Epoch 20, Batch 1600, Loss 0.06411397457122803  
Epoch 20, Batch 1700, Loss 0.08200991898775101  
Epoch 20, Batch 1800, Loss 0.029899684712290764  
Epoch 21, Batch 0, Loss 0.07027751207351685  
Epoch 21, Batch 0, Validation Loss 0.24055116087238243  
Epoch 21, Batch 100, Loss 0.038375526666641235  
Epoch 21, Batch 200, Loss 0.009299498051404953  
Epoch 21, Batch 300, Loss 0.17514976859092712  
Epoch 21, Batch 400, Loss 0.0664982795715332



Epoch 21, Batch 500, Loss 0.11762002855539322  
Epoch 21, Batch 600, Loss 0.023351864889264107  
Epoch 21, Batch 700, Loss 0.01207203883677721  
Epoch 21, Batch 800, Loss 0.013243654742836952  
Epoch 21, Batch 900, Loss 0.01635531708598137  
Epoch 21, Batch 1000, Loss 0.03615470603108406  
Epoch 21, Batch 1100, Loss 0.006064609158784151  
Epoch 21, Batch 1200, Loss 0.10970988124608994  
Epoch 21, Batch 1300, Loss 0.026377998292446136  
Epoch 21, Batch 1400, Loss 0.09144935011863708  
Epoch 21, Batch 1500, Loss 0.04512413963675499  
Epoch 21, Batch 1600, Loss 0.059807635843753815  
Epoch 21, Batch 1700, Loss 0.028757546097040176  
Epoch 21, Batch 1800, Loss 0.02803198993206024  
Epoch 22, Batch 0, Loss 0.06002616509795189  
Epoch 22, Batch 0, Validation Loss 0.2223017852466536  
Epoch 22, Batch 100, Loss 0.07384287565946579  
Epoch 22, Batch 200, Loss 0.03794955089688301  
Epoch 22, Batch 300, Loss 0.01844317652285099  
Epoch 22, Batch 400, Loss 0.028159143403172493  
Epoch 22, Batch 500, Loss 0.074176125228405  
Epoch 22, Batch 600, Loss 0.02365902066230774  
Epoch 22, Batch 700, Loss 0.08676757663488388  
Epoch 22, Batch 800, Loss 0.017303530126810074  
Epoch 22, Batch 900, Loss 0.024258412420749664  
Epoch 22, Batch 1000, Loss 0.09329210221767426  
Epoch 22, Batch 1100, Loss 0.015339972451329231  
Epoch 22, Batch 1200, Loss 0.06369661539793015  
Epoch 22, Batch 1300, Loss 0.05142686888575554  
Epoch 22, Batch 1400, Loss 0.07871433347463608  
Epoch 22, Batch 1500, Loss 0.044672779738903046  
Epoch 22, Batch 1600, Loss 0.016383422538638115  
Epoch 22, Batch 1700, Loss 0.0887053832411766  
Epoch 22, Batch 1800, Loss 0.012844324111938477  
Epoch 23, Batch 0, Loss 0.03212219104170799  
Epoch 23, Batch 0, Validation Loss 0.22330913183041715  
Epoch 23, Batch 100, Loss 0.09102480113506317  
Epoch 23, Batch 200, Loss 0.04293946549296379  
Epoch 23, Batch 300, Loss 0.019177811220288277  
Epoch 23, Batch 400, Loss 0.085164375603199  
Epoch 23, Batch 500, Loss 0.031235672533512115  
Epoch 23, Batch 600, Loss 0.09302211552858353  
Epoch 23, Batch 700, Loss 0.028801361098885536  
Epoch 23, Batch 800, Loss 0.04089367389678955  
Epoch 23, Batch 900, Loss 0.007014173548668623  
Epoch 23, Batch 1000, Loss 0.05244547501206398  
Epoch 23, Batch 1100, Loss 0.02504034712910652  
Epoch 23, Batch 1200, Loss 0.024365397170186043

Epoch 23, Batch 1300, Loss 0.026884768158197403  
Epoch 23, Batch 1400, Loss 0.03908161818981171  
Epoch 23, Batch 1500, Loss 0.03296460956335068  
Epoch 23, Batch 1600, Loss 0.026263831183314323  
Epoch 23, Batch 1700, Loss 0.012914319522678852  
Epoch 23, Batch 1800, Loss 0.02029886655509472  
Epoch 24, Batch 0, Loss 0.009594548493623734  
Epoch 24, Batch 0, Validation Loss 0.23475190515789154  
Epoch 24, Batch 100, Loss 0.0162326879799366  
Epoch 24, Batch 200, Loss 0.012115662917494774  
Epoch 24, Batch 300, Loss 0.01312224566936493  
Epoch 24, Batch 400, Loss 0.011339096352458  
Epoch 24, Batch 500, Loss 0.02177335135638714  
Epoch 24, Batch 600, Loss 0.02012052573263645  
Epoch 24, Batch 700, Loss 0.0142291858792305  
Epoch 24, Batch 800, Loss 0.01342003047466278  
Epoch 24, Batch 900, Loss 0.02970913052558899  
Epoch 24, Batch 1000, Loss 0.04884859174489975  
Epoch 24, Batch 1100, Loss 0.01493280753493309  
Epoch 24, Batch 1200, Loss 0.017438434064388275  
Epoch 24, Batch 1300, Loss 0.01638597995042801  
Epoch 24, Batch 1400, Loss 0.06789017468690872  
Epoch 24, Batch 1500, Loss 0.03567858785390854  
Epoch 24, Batch 1600, Loss 0.053938113152980804  
Epoch 24, Batch 1700, Loss 0.010747894644737244  
Epoch 24, Batch 1800, Loss 0.055236056447029114  
Epoch 25, Batch 0, Loss 0.02104882337152958  
Epoch 25, Batch 0, Validation Loss 0.2289459264197563  
Epoch 25, Batch 100, Loss 0.023696009069681168  
Epoch 25, Batch 200, Loss 0.11626526713371277  
Epoch 25, Batch 300, Loss 0.015039042569696903  
Epoch 25, Batch 400, Loss 0.01393035240471363  
Epoch 25, Batch 500, Loss 0.016573501750826836  
Epoch 25, Batch 600, Loss 0.02557813934981823  
Epoch 25, Batch 700, Loss 0.01160935964435339  
Epoch 25, Batch 800, Loss 0.021962786093354225  
Epoch 25, Batch 900, Loss 0.043071337044239044  
Epoch 25, Batch 1000, Loss 0.12397047132253647  
Epoch 25, Batch 1100, Loss 0.024386947974562645  
Epoch 25, Batch 1200, Loss 0.020234987139701843  
Epoch 25, Batch 1300, Loss 0.013508175499737263  
Epoch 25, Batch 1400, Loss 0.016674106940627098  
Epoch 25, Batch 1500, Loss 0.011822172440588474  
Epoch 25, Batch 1600, Loss 0.03068116493523121  
Epoch 25, Batch 1700, Loss 0.04285630211234093  
Epoch 25, Batch 1800, Loss 0.0337807722389698  
Epoch 26, Batch 0, Loss 0.03447393700480461  
Epoch 26, Batch 0, Validation Loss 0.23305978778016526

Epoch 26, Batch 100, Loss 0.02335200086236  
Epoch 26, Batch 200, Loss 0.05359356477856636  
Epoch 26, Batch 300, Loss 0.0064874067902565  
Epoch 26, Batch 400, Loss 0.016202975064516068  
Epoch 26, Batch 500, Loss 0.06036576256155968  
Epoch 26, Batch 600, Loss 0.01143350824713707  
Epoch 26, Batch 700, Loss 0.022988740354776382  
Epoch 26, Batch 800, Loss 0.015551374293863773  
Epoch 26, Batch 900, Loss 0.014839943498373032  
Epoch 26, Batch 1000, Loss 0.04904180392622948  
Epoch 26, Batch 1100, Loss 0.05041860416531563  
Epoch 26, Batch 1200, Loss 0.049235302954912186  
Epoch 26, Batch 1300, Loss 0.011540563777089119  
Epoch 26, Batch 1400, Loss 0.049782004207372665  
Epoch 26, Batch 1500, Loss 0.045186225324869156  
Epoch 26, Batch 1600, Loss 0.03804987296462059  
Epoch 26, Batch 1700, Loss 0.03537118434906006  
Epoch 26, Batch 1800, Loss 0.11591817438602448  
Epoch 27, Batch 0, Loss 0.016130270436406136  
Epoch 27, Batch 0, Validation Loss 0.21464871791369264  
Epoch 27, Batch 100, Loss 0.020431818440556526  
Epoch 27, Batch 200, Loss 0.03330223634839058  
Epoch 27, Batch 300, Loss 0.03659454733133316  
Epoch 27, Batch 400, Loss 0.014270336367189884  
Epoch 27, Batch 500, Loss 0.031160306185483932  
Epoch 27, Batch 600, Loss 0.05548519268631935  
Epoch 27, Batch 700, Loss 0.012917321175336838  
Epoch 27, Batch 800, Loss 0.0394771546125412  
Epoch 27, Batch 900, Loss 0.008940689265727997  
Epoch 27, Batch 1000, Loss 0.04150766134262085  
Epoch 27, Batch 1100, Loss 0.03223249688744545  
Epoch 27, Batch 1200, Loss 0.047836847603321075  
Epoch 27, Batch 1300, Loss 0.06125517189502716  
Epoch 27, Batch 1400, Loss 0.020187586545944214  
Epoch 27, Batch 1500, Loss 0.04836105555295944  
Epoch 27, Batch 1600, Loss 0.035843655467033386  
Epoch 27, Batch 1700, Loss 0.04289904981851578  
Epoch 27, Batch 1800, Loss 0.0067330156452953815  
Epoch 28, Batch 0, Loss 0.03127161040902138  
Epoch 28, Batch 0, Validation Loss 0.22118662916143922  
Epoch 28, Batch 100, Loss 0.09726354479789734  
Epoch 28, Batch 200, Loss 0.02083716168999672  
Epoch 28, Batch 300, Loss 0.009205899201333523  
Epoch 28, Batch 400, Loss 0.021908175200223923  
Epoch 28, Batch 500, Loss 0.021502695977687836  
Epoch 28, Batch 600, Loss 0.008907283656299114  
Epoch 28, Batch 700, Loss 0.03906087204813957  
Epoch 28, Batch 800, Loss 0.006622492801398039

Epoch 28, Batch 900, Loss 0.015664050355553627  
Epoch 28, Batch 1000, Loss 0.005002114921808243  
Epoch 28, Batch 1100, Loss 0.031496454030275345  
Epoch 28, Batch 1200, Loss 0.04989632964134216  
Epoch 28, Batch 1300, Loss 0.05210838094353676  
Epoch 28, Batch 1400, Loss 0.021234074607491493  
Epoch 28, Batch 1500, Loss 0.012320706620812416  
Epoch 28, Batch 1600, Loss 0.03423824533820152  
Epoch 28, Batch 1700, Loss 0.022662203758955002  
Epoch 28, Batch 1800, Loss 0.023352550342679024  
Epoch 29, Batch 0, Loss 0.005789414048194885  
Epoch 29, Batch 0, Validation Loss 0.22687598357926084  
Epoch 29, Batch 100, Loss 0.01682494767010212  
Epoch 29, Batch 200, Loss 0.021590564399957657  
Epoch 29, Batch 300, Loss 0.007807399146258831  
Epoch 29, Batch 400, Loss 0.00891093909740448  
Epoch 29, Batch 500, Loss 0.006915247067809105  
Epoch 29, Batch 600, Loss 0.006497984752058983  
Epoch 29, Batch 700, Loss 0.047029364854097366  
Epoch 29, Batch 800, Loss 0.007562939543277025  
Epoch 29, Batch 900, Loss 0.006956795696169138  
Epoch 29, Batch 1000, Loss 0.015389258041977882  
Epoch 29, Batch 1100, Loss 0.014137116260826588  
Epoch 29, Batch 1200, Loss 0.01305637788027525  
Epoch 29, Batch 1300, Loss 0.013023742474615574  
Epoch 29, Batch 1400, Loss 0.1125974953174591  
Epoch 29, Batch 1500, Loss 0.016047457233071327  
Epoch 29, Batch 1600, Loss 0.006781259551644325  
Epoch 29, Batch 1700, Loss 0.046499405056238174  
Epoch 29, Batch 1800, Loss 0.003988121636211872  
Epoch 30, Batch 0, Loss 0.017821136862039566  
Epoch 30, Batch 0, Validation Loss 0.2239960567037369  
Epoch 30, Batch 100, Loss 0.00921498704701662  
Epoch 30, Batch 200, Loss 0.020388484001159668  
Epoch 30, Batch 300, Loss 0.030651062726974487  
Epoch 30, Batch 400, Loss 0.02791127935051918  
Epoch 30, Batch 500, Loss 0.0008404291002079844  
Epoch 30, Batch 600, Loss 0.02933233231306076  
Epoch 30, Batch 700, Loss 0.030362505465745926  
Epoch 30, Batch 800, Loss 0.055886730551719666  
Epoch 30, Batch 900, Loss 0.022554436698555946  
Epoch 30, Batch 1000, Loss 0.02014904096722603  
Epoch 30, Batch 1100, Loss 0.0403021015226841  
Epoch 30, Batch 1200, Loss 0.016655882820487022  
Epoch 30, Batch 1300, Loss 0.0080352071672678  
Epoch 30, Batch 1400, Loss 0.053731102496385574  
Epoch 30, Batch 1500, Loss 0.038543201982975006  
Epoch 30, Batch 1600, Loss 0.02766658365726471

Epoch 30, Batch 1700, Loss 0.011750585399568081  
Epoch 30, Batch 1800, Loss 0.016138043254613876  
Epoch 31, Batch 0, Loss 0.009082704782485962  
Epoch 31, Batch 0, Validation Loss 0.2135197534924718  
Epoch 31, Batch 100, Loss 0.014770773239433765  
Epoch 31, Batch 200, Loss 0.004622797016054392  
Epoch 31, Batch 300, Loss 0.0013009392423555255  
Epoch 31, Batch 400, Loss 0.03950627148151398  
Epoch 31, Batch 500, Loss 0.017171377316117287  
Epoch 31, Batch 600, Loss 0.07481458783149719  
Epoch 31, Batch 700, Loss 0.08210770785808563  
Epoch 31, Batch 800, Loss 0.0075347390957176685  
Epoch 31, Batch 900, Loss 0.030306875705718994  
Epoch 31, Batch 1000, Loss 0.04766792804002762  
Epoch 31, Batch 1100, Loss 0.04811003804206848  
Epoch 31, Batch 1200, Loss 0.061667945235967636  
Epoch 31, Batch 1300, Loss 0.034620948135852814  
Epoch 31, Batch 1400, Loss 0.0287628173828125  
Epoch 31, Batch 1500, Loss 0.014785492792725563  
Epoch 31, Batch 1600, Loss 0.040404368191957474  
Epoch 31, Batch 1700, Loss 0.016607236117124557  
Epoch 31, Batch 1800, Loss 0.014207564294338226  
Epoch 32, Batch 0, Loss 0.0707070529460907  
Epoch 32, Batch 0, Validation Loss 0.21605437942413902  
Epoch 32, Batch 100, Loss 0.06759537756443024  
Epoch 32, Batch 200, Loss 0.03468044102191925  
Epoch 32, Batch 300, Loss 0.02191278338432312  
Epoch 32, Batch 400, Loss 0.052886202931404114  
Epoch 32, Batch 500, Loss 0.05177924409508705  
Epoch 32, Batch 600, Loss 0.03621060401201248  
Epoch 32, Batch 700, Loss 0.010839192196726799  
Epoch 32, Batch 800, Loss 0.024717478081583977  
Epoch 32, Batch 900, Loss 0.019296281039714813  
Epoch 32, Batch 1000, Loss 0.023161303251981735  
Epoch 32, Batch 1100, Loss 0.05835309997200966  
Epoch 32, Batch 1200, Loss 0.00605830829590559  
Epoch 32, Batch 1300, Loss 0.019510747864842415  
Epoch 32, Batch 1400, Loss 0.01223570853471756  
Epoch 32, Batch 1500, Loss 0.07565198093652725  
Epoch 32, Batch 1600, Loss 0.02693234384059906  
Epoch 32, Batch 1700, Loss 0.0030180765315890312  
Epoch 32, Batch 1800, Loss 0.013708816841244698  
Epoch 33, Batch 0, Loss 0.016312940046191216  
Epoch 33, Batch 0, Validation Loss 0.21739109464335196  
Epoch 33, Batch 100, Loss 0.01797451078891754  
Epoch 33, Batch 200, Loss 0.05382939800620079  
Epoch 33, Batch 300, Loss 0.067205511033535  
Epoch 33, Batch 400, Loss 0.030369851738214493

Epoch 33, Batch 500, Loss 0.024280229583382607  
Epoch 33, Batch 600, Loss 0.01141324732452631  
Epoch 33, Batch 700, Loss 0.030450452119112015  
Epoch 33, Batch 800, Loss 0.03574267402291298  
Epoch 33, Batch 900, Loss 0.021793203428387642  
Epoch 33, Batch 1000, Loss 0.028540894389152527  
Epoch 33, Batch 1100, Loss 0.005354049149900675  
Epoch 33, Batch 1200, Loss 0.05382648855447769  
Epoch 33, Batch 1300, Loss 0.019543413072824478  
Epoch 33, Batch 1400, Loss 0.00940735824406147  
Epoch 33, Batch 1500, Loss 0.02412489242851734  
Epoch 33, Batch 1600, Loss 0.028409695252776146  
Epoch 33, Batch 1700, Loss 0.010648876428604126  
Epoch 33, Batch 1800, Loss 0.009466582909226418  
Epoch 34, Batch 0, Loss 0.01625082641839981  
Epoch 34, Batch 0, Validation Loss 0.22444544755171297  
Epoch 34, Batch 100, Loss 0.01606122963130474  
Epoch 34, Batch 200, Loss 0.034541986882686615  
Epoch 34, Batch 300, Loss 0.01583649031817913  
Epoch 34, Batch 400, Loss 0.00415912177413702  
Epoch 34, Batch 500, Loss 0.04341466352343559  
Epoch 34, Batch 600, Loss 0.01797505095601082  
Epoch 34, Batch 700, Loss 0.015490432269871235  
Epoch 34, Batch 800, Loss 0.00789731740951538  
Epoch 34, Batch 900, Loss 0.0008832168532535434  
Epoch 34, Batch 1000, Loss 0.026465829461812973  
Epoch 34, Batch 1100, Loss 0.022448522970080376  
Epoch 34, Batch 1200, Loss 0.03811817616224289  
Epoch 34, Batch 1300, Loss 0.029843194410204887  
Epoch 34, Batch 1400, Loss 0.010980761609971523  
Epoch 34, Batch 1500, Loss 0.011593558825552464  
Epoch 34, Batch 1600, Loss 0.041880056262016296  
Epoch 34, Batch 1700, Loss 0.010156296193599701  
Epoch 34, Batch 1800, Loss 0.011181908659636974  
Epoch 35, Batch 0, Loss 0.03413408622145653  
Epoch 35, Batch 0, Validation Loss 0.21897112691982087  
Epoch 35, Batch 100, Loss 0.02827370911836624  
Epoch 35, Batch 200, Loss 0.002395821735262871  
Epoch 35, Batch 300, Loss 0.026660721749067307  
Epoch 35, Batch 400, Loss 0.05002279579639435  
Epoch 35, Batch 500, Loss 0.05217396095395088  
Epoch 35, Batch 600, Loss 0.013744880445301533  
Epoch 35, Batch 700, Loss 0.013757020235061646  
Epoch 35, Batch 800, Loss 0.002319274703040719  
Epoch 35, Batch 900, Loss 0.017252763733267784  
Epoch 35, Batch 1000, Loss 0.016607271507382393  
Epoch 35, Batch 1100, Loss 0.008374662138521671  
Epoch 35, Batch 1200, Loss 0.002358641941100359

Epoch 35, Batch 1300, Loss 0.014974637888371944  
Epoch 35, Batch 1400, Loss 0.007057132199406624  
Epoch 35, Batch 1500, Loss 0.018898656591773033  
Epoch 35, Batch 1600, Loss 0.025922391563653946  
Epoch 35, Batch 1700, Loss 0.023603463545441628  
Epoch 35, Batch 1800, Loss 0.011669328436255455  
Epoch 36, Batch 0, Loss 0.0474419891834259  
Epoch 36, Batch 0, Validation Loss 0.22736590598198708  
Epoch 36, Batch 100, Loss 0.04773088917136192  
Epoch 36, Batch 200, Loss 0.010980311781167984  
Epoch 36, Batch 300, Loss 0.041111059486866  
Epoch 36, Batch 400, Loss 0.013363029807806015  
Epoch 36, Batch 500, Loss 0.011670216917991638  
Epoch 36, Batch 600, Loss 0.054316673427820206  
Epoch 36, Batch 700, Loss 0.027227673679590225  
Epoch 36, Batch 800, Loss 0.011728753335773945  
Epoch 36, Batch 900, Loss 0.04917406290769577  
Epoch 36, Batch 1000, Loss 0.0018234903691336513  
Epoch 36, Batch 1100, Loss 0.008921720087528229  
Epoch 36, Batch 1200, Loss 0.01726468652486801  
Epoch 36, Batch 1300, Loss 0.06769486516714096  
Epoch 36, Batch 1400, Loss 0.008666829206049442  
Epoch 36, Batch 1500, Loss 0.028160270303487778  
Epoch 36, Batch 1600, Loss 0.06178351491689682  
Epoch 36, Batch 1700, Loss 0.02191794477403164  
Epoch 36, Batch 1800, Loss 0.022437062114477158  
Epoch 37, Batch 0, Loss 0.050000112503767014  
Epoch 37, Batch 0, Validation Loss 0.23254970738774994  
Epoch 37, Batch 100, Loss 0.021646203473210335  
Epoch 37, Batch 200, Loss 0.005000113509595394  
Epoch 37, Batch 300, Loss 0.021814744919538498  
Epoch 37, Batch 400, Loss 0.0011640748707577586  
Epoch 37, Batch 500, Loss 0.009087457321584225  
Epoch 37, Batch 600, Loss 0.008609138429164886  
Epoch 37, Batch 700, Loss 0.007998541928827763  
Epoch 37, Batch 800, Loss 0.05303807556629181  
Epoch 37, Batch 900, Loss 0.0421777069568634  
Epoch 37, Batch 1000, Loss 0.05112447217106819  
Epoch 37, Batch 1100, Loss 0.007525376044213772  
Epoch 37, Batch 1200, Loss 0.045740339905023575  
Epoch 37, Batch 1300, Loss 0.004570935852825642  
Epoch 37, Batch 1400, Loss 0.026136178523302078  
Epoch 37, Batch 1500, Loss 0.028172140941023827  
Epoch 37, Batch 1600, Loss 0.004412894602864981  
Epoch 37, Batch 1700, Loss 0.016333702951669693  
Epoch 37, Batch 1800, Loss 0.014088512398302555  
Epoch 38, Batch 0, Loss 0.028460128232836723  
Epoch 38, Batch 0, Validation Loss 0.22355960320242127

Epoch 38, Batch 100, Loss 0.015058749355375767  
Epoch 38, Batch 200, Loss 0.010151134803891182  
Epoch 38, Batch 300, Loss 0.01736038364470005  
Epoch 38, Batch 400, Loss 0.04923202097415924  
Epoch 38, Batch 500, Loss 0.026548050343990326  
Epoch 38, Batch 600, Loss 0.004588425625115633  
Epoch 38, Batch 700, Loss 0.029016554355621338  
Epoch 38, Batch 800, Loss 0.032920125871896744  
Epoch 38, Batch 900, Loss 0.01658175140619278  
Epoch 38, Batch 1000, Loss 0.05139727517962456  
Epoch 38, Batch 1100, Loss 0.03522685915231705  
Epoch 38, Batch 1200, Loss 0.01051418948918581  
Epoch 38, Batch 1300, Loss 0.0025606004055589437  
Epoch 38, Batch 1400, Loss 0.016237720847129822  
Epoch 38, Batch 1500, Loss 0.028176199644804  
Epoch 38, Batch 1600, Loss 0.010847735218703747  
Epoch 38, Batch 1700, Loss 0.03084947168827057  
Epoch 38, Batch 1800, Loss 0.011472279205918312  
Epoch 39, Batch 0, Loss 0.003028921550139785  
Epoch 39, Batch 0, Validation Loss 0.2294476413134289  
Epoch 39, Batch 100, Loss 0.016418687999248505  
Epoch 39, Batch 200, Loss 0.005587361287325621  
Epoch 39, Batch 300, Loss 0.024447612464427948  
Epoch 39, Batch 400, Loss 0.029123825952410698  
Epoch 39, Batch 500, Loss 0.013793873600661755  
Epoch 39, Batch 600, Loss 0.03025314025580883  
Epoch 39, Batch 700, Loss 0.0019018735038116574  
Epoch 39, Batch 800, Loss 0.010202368721365929  
Epoch 39, Batch 900, Loss 0.06564696878194809  
Epoch 39, Batch 1000, Loss 0.01048697717487812  
Epoch 39, Batch 1100, Loss 0.009900406934320927  
Epoch 39, Batch 1200, Loss 0.025957664474844933  
Epoch 39, Batch 1300, Loss 0.015273735858500004  
Epoch 39, Batch 1400, Loss 0.020473193377256393  
Epoch 39, Batch 1500, Loss 0.012155474163591862  
Epoch 39, Batch 1600, Loss 0.008043992333114147  
Epoch 39, Batch 1700, Loss 0.002077685669064522  
Epoch 39, Batch 1800, Loss 0.029997387900948524  
Epoch 40, Batch 0, Loss 0.04170982912182808  
Epoch 40, Batch 0, Validation Loss 0.2175917953129447  
Epoch 40, Batch 100, Loss 0.021800190210342407  
Epoch 40, Batch 200, Loss 0.022950049489736557  
Epoch 40, Batch 300, Loss 0.023555375635623932  
Epoch 40, Batch 400, Loss 0.008792600594460964  
Epoch 40, Batch 500, Loss 0.0215973611921072  
Epoch 40, Batch 600, Loss 0.020399631932377815  
Epoch 40, Batch 700, Loss 0.026895571500062943  
Epoch 40, Batch 800, Loss 0.006660579238086939



Epoch 40, Batch 900, Loss 0.029485095292329788  
Epoch 40, Batch 1000, Loss 0.010005602613091469  
Epoch 40, Batch 1100, Loss 0.009246445260941982  
Epoch 40, Batch 1200, Loss 0.002656296594068408  
Epoch 40, Batch 1300, Loss 0.02469390444457531  
Epoch 40, Batch 1400, Loss 0.04131625220179558  
Epoch 40, Batch 1500, Loss 0.010904927738010883  
Epoch 40, Batch 1600, Loss 0.02806035242974758  
Epoch 40, Batch 1700, Loss 0.011936861090362072  
Epoch 40, Batch 1800, Loss 0.002219732850790024  
Epoch 41, Batch 0, Loss 0.020030410960316658  
Epoch 41, Batch 0, Validation Loss 0.2151000677479132  
Epoch 41, Batch 100, Loss 0.02035657875239849  
Epoch 41, Batch 200, Loss 0.020746266469359398  
Epoch 41, Batch 300, Loss 0.04799213632941246  
Epoch 41, Batch 400, Loss 0.011125502176582813  
Epoch 41, Batch 500, Loss 0.018331114202737808  
Epoch 41, Batch 600, Loss 0.012210732325911522  
Epoch 41, Batch 700, Loss 0.0050561134703457355  
Epoch 41, Batch 800, Loss 0.018073316663503647  
Epoch 41, Batch 900, Loss 0.02022239938378334  
Epoch 41, Batch 1000, Loss 0.012112726457417011  
Epoch 41, Batch 1100, Loss 0.007135792635381222  
Epoch 41, Batch 1200, Loss 0.03733742609620094  
Epoch 41, Batch 1300, Loss 0.04745831713080406  
Epoch 41, Batch 1400, Loss 0.03829367831349373  
Epoch 41, Batch 1500, Loss 0.020368823781609535  
Epoch 41, Batch 1600, Loss 0.022236455231904984  
Epoch 41, Batch 1700, Loss 0.02272457629442215  
Epoch 41, Batch 1800, Loss 0.010846358723938465  
Epoch 42, Batch 0, Loss 0.008309673517942429  
Epoch 42, Batch 0, Validation Loss 0.22294877016292566  
Epoch 42, Batch 100, Loss 0.01778329536318779  
Epoch 42, Batch 200, Loss 0.039093244820833206  
Epoch 42, Batch 300, Loss 0.005404260009527206  
Epoch 42, Batch 400, Loss 0.0031859686132520437  
Epoch 42, Batch 500, Loss 0.026301676407456398  
Epoch 42, Batch 600, Loss 0.041803181171417236  
Epoch 42, Batch 700, Loss 0.02488560415804386  
Epoch 42, Batch 800, Loss 0.004194892942905426  
Epoch 42, Batch 900, Loss 0.02569451555609703  
Epoch 42, Batch 1000, Loss 0.02610929124057293  
Epoch 42, Batch 1100, Loss 0.01463839691132307  
Epoch 42, Batch 1200, Loss 0.028183121234178543  
Epoch 42, Batch 1300, Loss 0.0201349388808012  
Epoch 42, Batch 1400, Loss 0.008212345652282238  
Epoch 42, Batch 1500, Loss 0.027702324092388153  
Epoch 42, Batch 1600, Loss 0.02144547365605831

Epoch 42, Batch 1700, Loss 0.022460628300905228  
Epoch 42, Batch 1800, Loss 0.005238496232777834  
Epoch 43, Batch 0, Loss 0.009879386983811855  
Epoch 43, Batch 0, Validation Loss 0.23644515110686318  
Epoch 43, Batch 100, Loss 0.00421792920678854  
Epoch 43, Batch 200, Loss 0.0023862957023084164  
Epoch 43, Batch 300, Loss 0.0031851311214268208  
Epoch 43, Batch 400, Loss 0.01840435527265072  
Epoch 43, Batch 500, Loss 0.03169188275933266  
Epoch 43, Batch 600, Loss 0.0031649312004446983  
Epoch 43, Batch 700, Loss 0.04572496563196182  
Epoch 43, Batch 800, Loss 0.02471069060266018  
Epoch 43, Batch 900, Loss 0.008848386816680431  
Epoch 43, Batch 1000, Loss 0.01370218861848116  
Epoch 43, Batch 1100, Loss 0.036556046456098557  
Epoch 43, Batch 1200, Loss 0.023128440603613853  
Epoch 43, Batch 1300, Loss 0.025090724229812622  
Epoch 43, Batch 1400, Loss 0.08232662826776505  
Epoch 43, Batch 1500, Loss 0.009486147202551365  
Epoch 43, Batch 1600, Loss 0.01595039665699005  
Epoch 43, Batch 1700, Loss 0.01621733233332634  
Epoch 43, Batch 1800, Loss 0.0034627215936779976  
Epoch 44, Batch 0, Loss 0.01245071366429329  
Epoch 44, Batch 0, Validation Loss 0.22512916487719184  
Epoch 44, Batch 100, Loss 0.006794607732445002  
Epoch 44, Batch 200, Loss 0.012590298429131508  
Epoch 44, Batch 300, Loss 0.005458304192870855  
Epoch 44, Batch 400, Loss 0.020930763334035873  
Epoch 44, Batch 500, Loss 0.019667495042085648  
Epoch 44, Batch 600, Loss 0.0037080857437103987  
Epoch 44, Batch 700, Loss 0.046513043344020844  
Epoch 44, Batch 800, Loss 0.0023037875071167946  
Epoch 44, Batch 900, Loss 0.019203919917345047  
Epoch 44, Batch 1000, Loss 0.015336127020418644  
Epoch 44, Batch 1100, Loss 0.007009715307503939  
Epoch 44, Batch 1200, Loss 0.03142821416258812  
Epoch 44, Batch 1300, Loss 0.017926152795553207  
Epoch 44, Batch 1400, Loss 0.005407337099313736  
Epoch 44, Batch 1500, Loss 0.031701985746622086  
Epoch 44, Batch 1600, Loss 0.027504438534379005  
Epoch 44, Batch 1700, Loss 0.007208304479718208  
Epoch 44, Batch 1800, Loss 0.032364048063755035  
Epoch 45, Batch 0, Loss 0.004071938339620829  
Epoch 45, Batch 0, Validation Loss 0.2244538157030533  
Epoch 45, Batch 100, Loss 0.00445753475651145  
Epoch 45, Batch 200, Loss 0.0008771125576458871  
Epoch 45, Batch 300, Loss 0.01119028590619564  
Epoch 45, Batch 400, Loss 0.014727558009326458

Epoch 45, Batch 500, Loss 0.021048787981271744  
Epoch 45, Batch 600, Loss 0.019548995420336723  
Epoch 45, Batch 700, Loss 0.059151869267225266  
Epoch 45, Batch 800, Loss 0.007170002907514572  
Epoch 45, Batch 900, Loss 0.01928052492439747  
Epoch 45, Batch 1000, Loss 0.025201085954904556  
Epoch 45, Batch 1100, Loss 0.007651932071894407  
Epoch 45, Batch 1200, Loss 0.0457867793738842  
Epoch 45, Batch 1300, Loss 0.01372334361076355  
Epoch 45, Batch 1400, Loss 0.014320624060928822  
Epoch 45, Batch 1500, Loss 0.04621375352144241  
Epoch 45, Batch 1600, Loss 0.02030172199010849  
Epoch 45, Batch 1700, Loss 0.010361701250076294  
Epoch 45, Batch 1800, Loss 0.001801633508875966  
Epoch 46, Batch 0, Loss 0.029311925172805786  
Epoch 46, Batch 0, Validation Loss 0.22731977877510287  
Epoch 46, Batch 100, Loss 0.007622121833264828  
Epoch 46, Batch 200, Loss 0.004921257961541414  
Epoch 46, Batch 300, Loss 0.017603883519768715  
Epoch 46, Batch 400, Loss 0.023500224575400352  
Epoch 46, Batch 500, Loss 0.0036390521563589573  
Epoch 46, Batch 600, Loss 0.02162461169064045  
Epoch 46, Batch 700, Loss 0.009351593442261219  
Epoch 46, Batch 800, Loss 0.0037467379588633776  
Epoch 46, Batch 900, Loss 0.005208058748394251  
Epoch 46, Batch 1000, Loss 0.003975552041083574  
Epoch 46, Batch 1100, Loss 0.010219247080385685  
Epoch 46, Batch 1200, Loss 0.0055900984443724155  
Epoch 46, Batch 1300, Loss 0.026305370032787323  
Epoch 46, Batch 1400, Loss 0.0031137452460825443  
Epoch 46, Batch 1500, Loss 0.0499301478266716  
Epoch 46, Batch 1600, Loss 0.005335706286132336  
Epoch 46, Batch 1700, Loss 0.005113305523991585  
Epoch 46, Batch 1800, Loss 0.011909027583897114  
Epoch 47, Batch 0, Loss 0.013606727123260498  
Epoch 47, Batch 0, Validation Loss 0.23514153281929248  
Epoch 47, Batch 100, Loss 0.009694558568298817  
Epoch 47, Batch 200, Loss 0.0008799670031294227  
Epoch 47, Batch 300, Loss 0.0045702457427978516  
Epoch 47, Batch 400, Loss 0.011648732237517834  
Epoch 47, Batch 500, Loss 0.014090859331190586  
Epoch 47, Batch 600, Loss 0.005326614249497652  
Epoch 47, Batch 700, Loss 0.0049874866381287575  
Epoch 47, Batch 800, Loss 0.005757666192948818  
Epoch 47, Batch 900, Loss 0.028723308816552162  
Epoch 47, Batch 1000, Loss 0.010574491694569588  
Epoch 47, Batch 1100, Loss 0.009217663668096066  
Epoch 47, Batch 1200, Loss 0.011303622275590897

Epoch 47, Batch 1300, Loss 0.01190020889043808  
Epoch 47, Batch 1400, Loss 0.006005876697599888  
Epoch 47, Batch 1500, Loss 0.054156314581632614  
Epoch 47, Batch 1600, Loss 0.021413074806332588  
Epoch 47, Batch 1700, Loss 0.007578665390610695  
Epoch 47, Batch 1800, Loss 0.010973572731018066  
Epoch 48, Batch 0, Loss 0.014238303527235985  
Epoch 48, Batch 0, Validation Loss 0.2401193021447972  
Epoch 48, Batch 100, Loss 0.000610014540143311  
Epoch 48, Batch 200, Loss 0.0032523085828870535  
Epoch 48, Batch 300, Loss 0.0021348586305975914  
Epoch 48, Batch 400, Loss 0.015746187418699265  
Epoch 48, Batch 500, Loss 0.0032548820599913597  
Epoch 48, Batch 600, Loss 0.028263505548238754  
Epoch 48, Batch 700, Loss 0.007368424441665411  
Epoch 48, Batch 800, Loss 0.0027619535103440285  
Epoch 48, Batch 900, Loss 0.005785462912172079  
Epoch 48, Batch 1000, Loss 0.01696121133863926  
Epoch 48, Batch 1100, Loss 0.0037246025167405605  
Epoch 48, Batch 1200, Loss 0.006658997852355242  
Epoch 48, Batch 1300, Loss 0.00108896114397794  
Epoch 48, Batch 1400, Loss 0.03176086023449898  
Epoch 48, Batch 1500, Loss 0.0015489544020965695  
Epoch 48, Batch 1600, Loss 0.010621435940265656  
Epoch 48, Batch 1700, Loss 0.024879368022084236  
Epoch 48, Batch 1800, Loss 0.0026517354417592287  
Epoch 49, Batch 0, Loss 0.008922647684812546  
Epoch 49, Batch 0, Validation Loss 0.2216287234797767  
Epoch 49, Batch 100, Loss 0.012714230455458164  
Epoch 49, Batch 200, Loss 0.06724872440099716  
Epoch 49, Batch 300, Loss 0.0019235273357480764  
Epoch 49, Batch 400, Loss 0.00276759872213006  
Epoch 49, Batch 500, Loss 0.011271637864410877  
Epoch 49, Batch 600, Loss 0.008156250230967999  
Epoch 49, Batch 700, Loss 0.011254837736487389  
Epoch 49, Batch 800, Loss 0.022814592346549034  
Epoch 49, Batch 900, Loss 0.012635491788387299  
Epoch 49, Batch 1000, Loss 0.004061373881995678  
Epoch 49, Batch 1100, Loss 0.0018113936530426145  
Epoch 49, Batch 1200, Loss 0.0007626957958564162  
Epoch 49, Batch 1300, Loss 0.01150959450751543  
Epoch 49, Batch 1400, Loss 0.0006476319395005703  
Epoch 49, Batch 1500, Loss 0.009181187488138676  
Epoch 49, Batch 1600, Loss 0.004751368425786495  
Epoch 49, Batch 1700, Loss 0.005318129435181618  
Epoch 49, Batch 1800, Loss 0.026920044794678688

## 1 Model Saving and Loading

```
[61]: torch.save(model.state_dict(), 'blstm1.pt')
```

```
[62]: model2 = BLSTM(len(train_dataset.word2idx), EMBEDDING_DIM, HIDDEN_DIM,   
    ↪ OUTPUT_DIM, DROPOUT, OUTPUT_LABEL_DIM).to(device)
```

```
[63]: model2.load_state_dict(torch.load('blstm1.pt'))  
    #model2.load_state_dict(torch.load('task_minloss.pt'))
```

```
[63]: <All keys matched successfully>
```

## 2 Dev Prediction

```
[64]: from sklearn.metrics import precision_recall_fscore_support  
  
model2.eval()  
predicted_labels = []  
true_labels = []  
  
with torch.no_grad():  
    for x, lengths, y in dev_loader:  
        x = x.to(device)  
        y = y.to(device)  
        target_packed_embedded = nn.utils.rnn.pack_padded_sequence(y, lengths,   
    ↪ batch_first=True, enforce_sorted=False)  
        target, target_lengths = nn.utils.rnn.  
    ↪ pad_packed_sequence(target_packed_embedded, batch_first=True)  
  
        output = model2(x, lengths)  
  
        predicted = torch.argmax(output, dim=1)  
        predicted_labels.extend(predicted.cpu().numpy().tolist())  
        true_labels.extend(target.cpu().numpy().tolist())
```

```
[66]: y_pred = [element for sub_list in predicted_labels for element in sub_list]  
    y_true=[element for sub_list in true_labels for element in sub_list]  
  
list1 = y_true.copy()  
list2 = y_pred.copy()  
value_to_remove = train_loader.dataset.pad_idx  
i = 0  
while i < len(list1):  
    if list1[i] == value_to_remove:  
        # remove the element from list1  
        list1.pop(i)
```

```

        # remove the corresponding element from list2 by using its index
        list2.pop(i)
    else:
        # only increment the loop counter if an element wasn't removed
        i += 1

print(list1)
print(list2)

```

```

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```

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[illegible]



















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[illegible]







[illegible]







[illegible]

```
[67]: precision, recall, f1_score, _ = precision_recall_fscore_support(list1, list2,
    ↪ average='weighted')
print(f'Precision: {precision:.4f}, Recall: {recall:.4f}, F1 score: {f1_score:.4f}')
```

Precision: 0.9598, Recall: 0.9607, F1 score: 0.9598

## 2.1 dev.out file for evaluating on PERL

```
[68]: devOutput = open("dev.out", "w")
k=0
i=0
idx2label = {value: key for key, value in train_dataset.label2idx.items()}

with open('/content/dev', 'r') as f:
    for line in f:

        line = line.strip().split(' ')
        #print(line)
        if len(line)>1:
            idx,word,gold = line[0], line[1],line[2]
            pred=predicted_labels[k][i]
            i=i+1
            key = idx2label[pred]
            devOutput.write(f"{idx} {word} {gold} {key}\n")
        else:
            devOutput.write(f"\n")
            k=k+1
            i=0
f.close()
devOutput.close()
```

```
[68]:
```

## 2.2 dev1.out file for submission (in same format as train)

```
[69]: devOutput = open("dev1.out", "w")
k=0
i=0

with open('/content/dev', 'r') as f:
    for line in f:
        line = line.strip().split(' ')
        if len(line)>1:
            idx,word,gold = line[0], line[1],line[2]
            pred=predicted_labels[k][i]
            i=i+1
            key = idx2label[pred]
            devOutput.write(f"{idx} {word} {key}\n")
        else:
            devOutput.write(f"\n")
            k=k+1
```

```

        i=0
    f.close()
    devOutput.close()

```

### 3 Test Predictions

```

[70]: class TestNERDataset(Dataset):
    def __init__(self, filename, word2idx):
        self.data = []
        self.word2idx = word2idx
        self.max_sent_len = 0

        with open(filename, "r") as f:
            sentence = []
            for line in f:
                line = line.strip()
                if len(line) == 0:
                    if len(sentence) > self.max_sent_len:
                        self.max_sent_len = len(sentence)

                    self.data.append(sentence)
                    sentence = []
                else:
                    parts = line.split(" ")
                    word = parts[1]
                    if word not in self.word2idx:
                        if word[0].isupper():
                            word = '<unkcap>'
                        else:
                            word = '<unk>'

                    sentence.append(self.word2idx[word])

            if len(sentence) > 0:
                if len(sentence) > self.max_sent_len:
                    self.max_sent_len = len(sentence)

                self.data.append(sentence)

        self.pad_idx = self.word2idx['<PAD>']

        # Pad sentences
        self.x = [torch.tensor(s) for s in self.data]
        self.x = pad_sequence(self.x, batch_first=True, padding_value=self.
↪ pad_idx)

```

```

        # Calculate lengths
        self.lengths = [len(s) for s in self.data]

    def __len__(self):
        return len(self.data)

    def __getitem__(self, index):
        return self.x[index], self.lengths[index]

```

[70]:

```

[71]: test_dataset = TestNERDataset('test', train_dataset.word2idx)
      test_loader = DataLoader(test_dataset)

```

```

[72]: from sklearn.metrics import precision_recall_fscore_support

      model2.eval()
      predicted_labels = []
      true_labels = []

      with torch.no_grad():
          for x, lengths in test_loader:
              x = x.to(device)

              output = model2(x, lengths)

              predicted = torch.argmax(output, dim=1)
              predicted_labels.extend(predicted.cpu().numpy().tolist())

```

### 3.1 test1.out file for submission

```

[73]: testOutput = open("test1.out", "w")
      k=0
      i=0

      with open('/content/test', 'r') as f:
          for line in f:
              line = line.strip().split(' ')
              if len(line)>1:
                  idx,word = line[0], line[1]
                  pred=predicted_labels[k][i]
                  i=i+1
                  key = idx2label[pred]
                  testOutput.write(f"{idx} {word} {key}\n")
              else:
                  testOutput.write(f"\n")

```



```
        k=k+1
        i=0
f.close()
testOutput.close()
```

[73]: