Problem_1

April 27, 2024

[ ]:
```
'''
Patrick Ballou
ID: 801130521
ECGR 4106
Homework 5
Problem 1
'''
```

[ ]: '\nPatrick Ballou\nID: 801130521\nECGR 4106\nHomework 5\nProblem 1\n'

[ ]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torch import cuda
import matplotlib.pyplot as plt
from torch.utils.data import DataLoader, Dataset
from sklearn.model_selection import train_test_split
import numpy as np
import time
```

[ ]:
```
#check if GPU is available and set the device accordingly
#device = 'torch.device("cuda:0" if torch.cuda.is_available() else "cpu")'
device = 'cuda'
print("Using GPU: ", cuda.get_device_name())

gpu_info = !nvidia-smi
gpu_info = '\n'.join(gpu_info)
if gpu_info.find('failed') >= 0:
  print('Not connected to a GPU')
else:
  print(gpu_info)
```

```
Using GPU:  NVIDIA L4
Thu Apr 25 14:48:27 2024
+-----------------------------------------------------------------------------
--------+
| NVIDIA-SMI 535.104.05             Driver Version: 535.104.05   CUDA Version:
12.2     |
```

```
|-----------------------------------------+----------------------+--------------
--------+
| GPU  Name                 Persistence-M | Bus-Id        Disp.A | Volatile
Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |         Memory-Usage | GPU-Util
Compute M. |
|                                         |                      |
MIG M. |
|=========================================+======================+==============
========|
|   0  NVIDIA L4                      Off | 00000000:00:03.0 Off |
0 |
| N/A   52C    P8              13W /  72W |      4MiB / 23034MiB |      0%
Default |
|                                         |                      |
N/A |
+-----------------------------------------+----------------------+--------------
--------+

+-------------------------------------------------------------------------------
--------+
| Processes:
|
|  GPU   GI   CI        PID   Type   Process name                            GPU
Memory |
|        ID   ID
Usage      |
|===============================================================================
========|
|  No running processes found
|
+-------------------------------------------------------------------------------
--------+
```

[ ]:
```
text = """Next character prediction is a fundamental task in the field of␣
↪natural language processing (NLP) that involves predicting the next␣
↪character in a sequence of text based on the characters that precede it.␣
↪This task is essential for various applications, including text␣
↪auto-completion, spell checking, and even in the development of␣
↪sophisticated AI models capable of generating human-like text.

At its core, next character prediction relies on statistical models or deep␣
↪learning algorithms to analyze a given sequence of text and predict which␣
↪character is most likely to follow. These predictions are based on patterns␣
↪and relationships learned from large datasets of text during the training␣
↪phase of the model.
```

```
One of the most popular approaches to next character prediction involves the␣
↪use of Recurrent Neural Networks (RNNs), and more specifically, a variant␣
↪called Long Short-Term Memory (LSTM) networks. RNNs are particularly␣
↪well-suited for sequential data like text, as they can maintain information␣
↪in 'memory' about previous characters to inform the prediction of the next␣
↪character. LSTM networks enhance this capability by being able to remember␣
↪long-term dependencies, making them even more effective for next character␣
↪prediction tasks.

Training a model for next character prediction involves feeding it large␣
↪amounts of text data, allowing it to learn the probability of each␣
↪character's appearance following a sequence of characters. During this␣
↪training process, the model adjusts its parameters to minimize the␣
↪difference between its predictions and the actual outcomes, thus improving␣
↪its predictive accuracy over time.

Once trained, the model can be used to predict the next character in a given␣
↪piece of text by considering the sequence of characters that precede it.␣
↪This can enhance user experience in text editing software, improve␣
↪efficiency in coding environments with auto-completion features, and enable␣
↪more natural interactions with AI-based chatbots and virtual assistants.

In summary, next character prediction plays a crucial role in enhancing the␣
↪capabilities of various NLP applications, making text-based interactions␣
↪more efficient, accurate, and human-like. Through the use of advanced␣
↪machine learning models like RNNs and LSTMs, next character prediction␣
↪continues to evolve, opening new possibilities for the future of text-based␣
↪technology."""
```

[ ]:
```
# Creating character vocabulary
chars = sorted(list(set(text)))
ix_to_char = {i: ch for i, ch in enumerate(chars)}
char_to_ix = {ch: i for i, ch in enumerate(chars)}
```

[ ]:
```
def prepare_dataset(max_length):
    X = []
    y = []
    for i in range(len(text) - max_length):
        sequence = text[i:i + max_length]
        label = text[i + max_length]
        X.append([char_to_ix[char] for char in sequence])
        y.append(char_to_ix[label])

    X = np.array(X)
    y = np.array(y)

    # Splitting the dataset into training and validation sets
```

```
    X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

    # Converting data to PyTorch tensors
    X_train = torch.tensor(X_train, dtype=torch.long)
    y_train = torch.tensor(y_train, dtype=torch.long)
    X_val = torch.tensor(X_val, dtype=torch.long)
    y_val = torch.tensor(y_val, dtype=torch.long)

    return X_train, y_train, X_val, y_val
```

[ ]:
```
# Defining the Transformer model
class CharTransformer(nn.Module):
    def __init__(self, input_size, hidden_size, output_size, num_layers, nhead):
        super(CharTransformer, self).__init__()
        self.embedding = nn.Embedding(input_size, hidden_size)
        encoder_layers = nn.TransformerEncoderLayer(hidden_size, nhead,␣
↪batch_first=True)
        self.transformer_encoder = nn.TransformerEncoder(encoder_layers,␣
↪num_layers)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        embedded = self.embedding(x)
        transformer_output = self.transformer_encoder(embedded)
        output = self.fc(transformer_output[:, -1, :])  # Get the output of the␣
↪last Transformer block
        return output
```

[ ]:
```
def training_loop(model, criterion, optimizer, epochs, X_train, y_train, X_val,␣
↪y_val, max_length):

    train_history = []
    val_history = []
    init_time = time.time()
    print(f"{max_length} sequence transformer results:")

    for epoch in range(epochs):
        model.train()
        optimizer.zero_grad()
        output = model(X_train)
        loss = criterion(output, y_train)
        loss.backward()
        optimizer.step()

        # Validation
        model.eval()
```

```
        with torch.no_grad():
            val_output = model(X_val)
            val_loss = criterion(val_output, y_val)
            _, predicted = torch.max(val_output, 1)
            val_accuracy = (predicted == y_val).float().mean()

        train_history.append(loss.item())
        val_history.append(val_accuracy.item())

        if (epoch+1) % 10 == 0:
            print(f'Epoch {epoch+1}, Loss: {train_history[-1]}, Validation Loss: {val_loss.item()}, Validation Accuracy: {val_history[-1]}')

    print(f"Training time: {time.time() - init_time} seconds")
    save_path = f'../../Models/hw5_1_{max_length}.pth'
    #torch.save(model.state_dict(), save_path)

    return train_history, val_history

# Prediction function
def predict_next_char(model, initial_str, max_length):
    model.eval()
    with torch.no_grad():
        initial_input = torch.tensor([char_to_ix[c] for c in initial_str[-max_length:]], dtype=torch.long).unsqueeze(0)
        prediction = model(initial_input)
        predicted_index = torch.argmax(prediction, dim=1).item()
        return ix_to_char[int(predicted_index)]

def next_char_test(model, max_length):
    test_str = "This is a simple example to demonstrate how to predict the next char"
    predicted_char = predict_next_char(model, test_str, max_length)
    print(f"Predicted next character: '{predicted_char}'")
```

[ ]:

```
# Hyperparameters
hidden_size = 256
num_layers = 4
nhead = 4

max_lengths = [10, 20, 30]
learning_rate = .0005
epochs = 100
```

[ ]:

```
train_histories = []
val_histories = []
```

```
for window_size in max_lengths:
    model = CharTransformer(len(chars), hidden_size, len(chars), num_layers,␣
 ↪nhead)
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=learning_rate)

    X_train, y_train, X_val, y_val = prepare_dataset(window_size)

    train_history, val_history = training_loop(model, criterion, optimizer,␣
 ↪epochs, X_train, y_train, X_val, y_val, window_size)
    train_histories.append(train_history)
    val_histories.append(val_history)
    print("\n")

    next_char_test(model, window_size)
    print("\n\n") if window_size != 30 else None
```

```
10 sequence transformer results:
Epoch 10, Loss: 2.4080586433410645, Validation Loss: 2.5051023960113525,
Validation Accuracy: 0.2704402506351471
Epoch 20, Loss: 2.0444071292877197, Validation Loss: 2.4036715030670166,
Validation Accuracy: 0.33752620220184326
Epoch 30, Loss: 1.6987130641937256, Validation Loss: 2.373068332672119,
Validation Accuracy: 0.3668763041496277
Epoch 40, Loss: 1.3319175243377686, Validation Loss: 2.4580023288726807,
Validation Accuracy: 0.3731656074523926
Epoch 50, Loss: 0.9410110116004944, Validation Loss: 2.65513277053833,
Validation Accuracy: 0.36477985978126526
Epoch 60, Loss: 0.6164496541023254, Validation Loss: 2.9696104526519775,
Validation Accuracy: 0.3542976975440979
Epoch 70, Loss: 0.4114442467689514, Validation Loss: 3.1755635738372803,
Validation Accuracy: 0.3731656074523926
Epoch 80, Loss: 0.22664591670036316, Validation Loss: 3.445261240005493,
Validation Accuracy: 0.3689727485179901
Epoch 90, Loss: 0.17504791915416718, Validation Loss: 3.696992874145508,
Validation Accuracy: 0.36477985978126526
Epoch 100, Loss: 0.13712351024150848, Validation Loss: 3.8674631118774414,
Validation Accuracy: 0.36477985978126526
Training time: 182.34048581123352 seconds


Predicted next character: 'a'



20 sequence transformer results:
Epoch 10, Loss: 2.6871519088745117, Validation Loss: 2.7132623195648193,
```

```
Validation Accuracy: 0.21684210002422333
Epoch 20, Loss: 2.321113109588623, Validation Loss: 2.5463039875030518,
Validation Accuracy: 0.25473684072494507
Epoch 30, Loss: 2.103867292404175, Validation Loss: 2.503826141357422,
Validation Accuracy: 0.269473671913147
Epoch 40, Loss: 1.8689113855361938, Validation Loss: 2.532803773880005,
Validation Accuracy: 0.2757894694805145
Epoch 50, Loss: 1.5970028638839722, Validation Loss: 2.6253719329833984,
Validation Accuracy: 0.2926315665245056
Epoch 60, Loss: 1.316619873046875, Validation Loss: 2.818438768386841,
Validation Accuracy: 0.28421053290367126
Epoch 70, Loss: 0.9813405871391296, Validation Loss: 3.059547185897827,
Validation Accuracy: 0.2947368323802948
Epoch 80, Loss: 0.6918473243713379, Validation Loss: 3.256744861602783,
Validation Accuracy: 0.2800000011920929
Epoch 90, Loss: 0.4566172659397125, Validation Loss: 3.5641286373138428,
Validation Accuracy: 0.2905263304710388
Epoch 100, Loss: 0.3032119870185852, Validation Loss: 3.799943685531616,
Validation Accuracy: 0.2926315665245056
Training time: 419.69847226142883 seconds
```

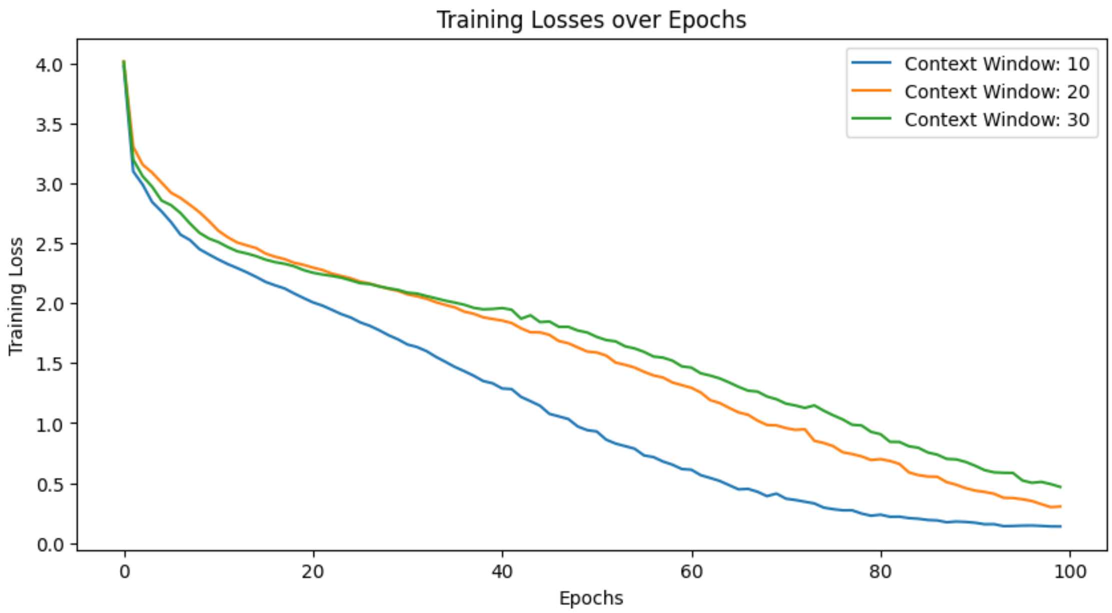
```
Predicted next character: 'a'
```

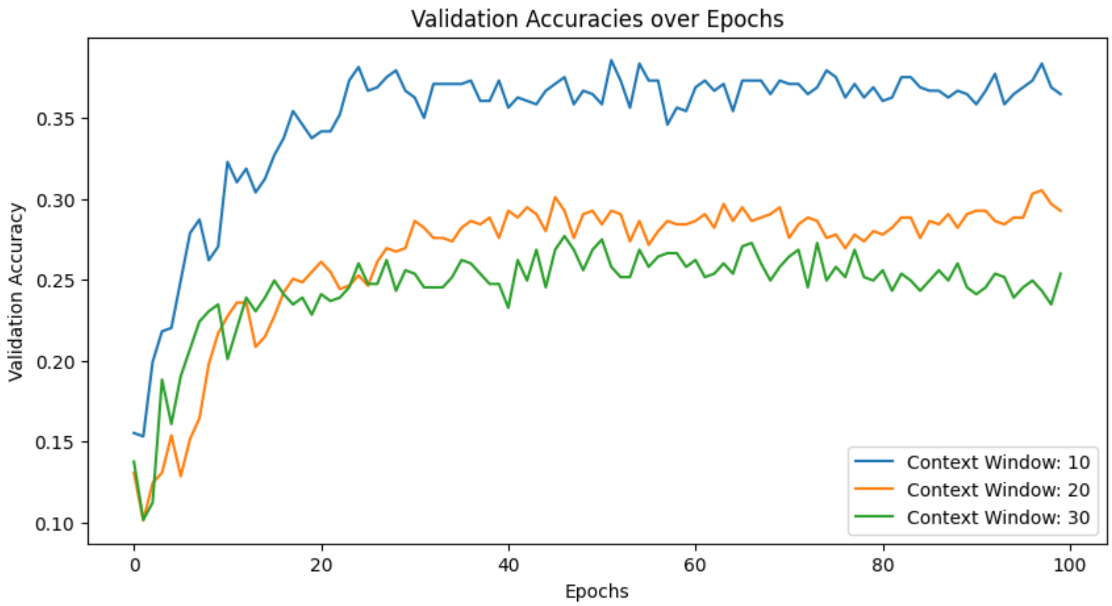
```
30 sequence transformer results:
Epoch 10, Loss: 2.540902614593506, Validation Loss: 2.7158145904541016,
Validation Accuracy: 0.23467230796813965
Epoch 20, Loss: 2.2777161598205566, Validation Loss: 2.582134962081909,
Validation Accuracy: 0.22832980751991272
Epoch 30, Loss: 2.111842155456543, Validation Loss: 2.5371346473693848,
Validation Accuracy: 0.25581395626068115
Epoch 40, Loss: 1.952932596206665, Validation Loss: 2.6494176387786865,
Validation Accuracy: 0.2473572939634323
Epoch 50, Loss: 1.7562140226364136, Validation Loss: 2.642242431640625,
Validation Accuracy: 0.268498957157135
Epoch 60, Loss: 1.4736355543136597, Validation Loss: 2.824350118637085,
Validation Accuracy: 0.25792813301086426
Epoch 70, Loss: 1.1992594003677368, Validation Loss: 3.067345142364502,
Validation Accuracy: 0.25792813301086426
Epoch 80, Loss: 0.9267798066139221, Validation Loss: 3.3158175945281982,
Validation Accuracy: 0.24947145581245422
Epoch 90, Loss: 0.6758770942687988, Validation Loss: 3.6170268058776855,
Validation Accuracy: 0.2452431321144104
Epoch 100, Loss: 0.4670465886592865, Validation Loss: 3.9806814193725586,
Validation Accuracy: 0.25369977951049805
Training time: 665.9915945529938 seconds
```

Predicted next character: 'e'

```
[ ]: # Plotting training losses
plt.figure(figsize=(10, 5))
for i, max_length in enumerate(max_lengths):
    plt.plot(train_histories[i], label=f"Context Window: {max_length}")
plt.xlabel("Epochs")
plt.ylabel("Training Loss")
plt.title("Training Losses over Epochs")
plt.legend()
plt.show()

# Plotting validation accuracies
plt.figure(figsize=(10, 5))
for i, max_length in enumerate(max_lengths):
    plt.plot(val_histories[i], label=f"Context Window: {max_length}")
plt.xlabel("Epochs")
plt.ylabel("Validation Accuracy")
plt.title("Validation Accuracies over Epochs")
plt.legend()
plt.show()
```




Validation Accuracies over Epochs
Validation Accuracy
Epochs
0.10
0.15
0.20
0.25
0.30
0.35
0
20
40
60
80
100
Context Window: 10
Context Window: 20
Context Window: 30