Problem_2

April 27, 2024

[ ]:
```
'''
Patrick Ballou
ID: 801130521
ECGR 4106
Homework 5
Problem 2
'''
```

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[ ]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torch import cuda
import requests
import matplotlib.pyplot as plt
from torch.utils.data import DataLoader, Dataset
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
Fri Apr 26 05:27:25 2024
+-------------------------------------------------------------------------------
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| 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   33C    P8              12W /  72W |      4MiB / 23034MiB |      0%
Default |
|                                         |                      |
N/A |
+-----------------------------------------+----------------------+--------------
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+-------------------------------------------------------------------------------
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| Processes:
|
|  GPU   GI   CI        PID   Type   Process name                            GPU
Memory |
|        ID   ID
Usage      |
|===============================================================================
========|
|  No running processes found
|
+-------------------------------------------------------------------------------
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```

[ ]:

```python
# Pred dataset for training
url = "https://raw.githubusercontent.com/karpathy/char-rnn/master/data/
 ↪tinyshakespeare/input.txt"
response = requests.get(url)
text = response.text  # This is the entire text data

chars = sorted(list(set(text)))
char_to_int = {ch: i for i, ch in enumerate(chars)}
int_to_char = {i: ch for i, ch in enumerate(chars)}

# Encode the text into integers
encoded_text = [char_to_int[ch] for ch in text]
```

[ ]:
```python
class CharDataset(Dataset):
    def __init__(self, sequences, targets):
        self.sequences = sequences
        self.targets = targets

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

    def __getitem__(self, index):
        return self.sequences[index], self.targets[index]

def prepare_dataset(sequence_length):
    sequences = []
    targets = []
    for i in range(0, len(encoded_text) - sequence_length):
        seq = encoded_text[i:i+sequence_length]
        target = encoded_text[i+sequence_length]
        sequences.append(seq)
        targets.append(target)

    # Convert lists to PyTorch tensors
    sequences = torch.tensor(sequences, dtype=torch.long)
    targets = torch.tensor(targets, dtype=torch.long)

    # Instantiate the dataset
    dataset = CharDataset(sequences, targets)

    # Create data loaders
    batch_size = 64
    train_size = int(len(dataset) * 0.8)
    test_size = len(dataset) - train_size
    train_dataset, test_dataset = torch.utils.data.random_split(dataset,
 ↪[train_size, test_size])

    train_loader = DataLoader(train_dataset, shuffle=True,
 ↪batch_size=batch_size)
    test_loader = DataLoader(test_dataset, shuffle=False, batch_size=batch_size)

    return train_loader, test_loader

# 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, train_loader,␣
↪test_loader, max_length):

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

    # Training the model
    for epoch in range(epochs):
        model.train()
        running_loss = 0.0

        for data, target in train_loader:
            data, target = data.to(device), target.to(device)
            optimizer.zero_grad()
            output = model(data)
            loss = criterion(output, target)
            loss.backward()
            running_loss += loss.item()
            optimizer.step()

        # Validation
        model.eval()
        correct = 0
        total = 0
        with torch.no_grad():
            for data, target in test_loader:
                data, target = data.to(device), target.to(device)
                output = model(data)
                _, predicted = torch.max(output, 1)
                total += target.size(0)
                correct += (predicted == target).sum().item()

        train_history.append(running_loss / len(train_loader))
        val_history.append(correct / total * 100)
```

```
        print(f'Epoch {epoch+1}, Loss: {train_history[-1]}, Validation Accuracy:
↪ {val_history[-1]}')

    print(f"Training time: {(time.time() - init_time)/60} minutes")
    save_path = f'../../Models/hw5_2_{max_length}.pth'
    #torch.save(model.state_dict(), save_path)

    return train_history, val_history

# Prediction function
def predict_next_char(model, char_to_ix, ix_to_char, 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).to(device)
        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, char_to_int, int_to_char,␣
↪test_str, max_length)
    print(f"Predicted next character: '{predicted_char}'")
```

1 Problem 2A: 20, 30, 50 sequence lengths

[ ]:
```
# Hyperparameters
hidden_size = 256
num_layers = 3
nhead = 2

max_lengths = [20, 30, 50]
learning_rate = .0005
epochs = 10
```

[ ]:
```
train_histories = []
val_histories = []
models = []

for window_size in max_lengths:
    model = CharTransformer(len(chars), hidden_size, len(chars), num_layers,␣
↪nhead).to(device)
    criterion = nn.CrossEntropyLoss()
```

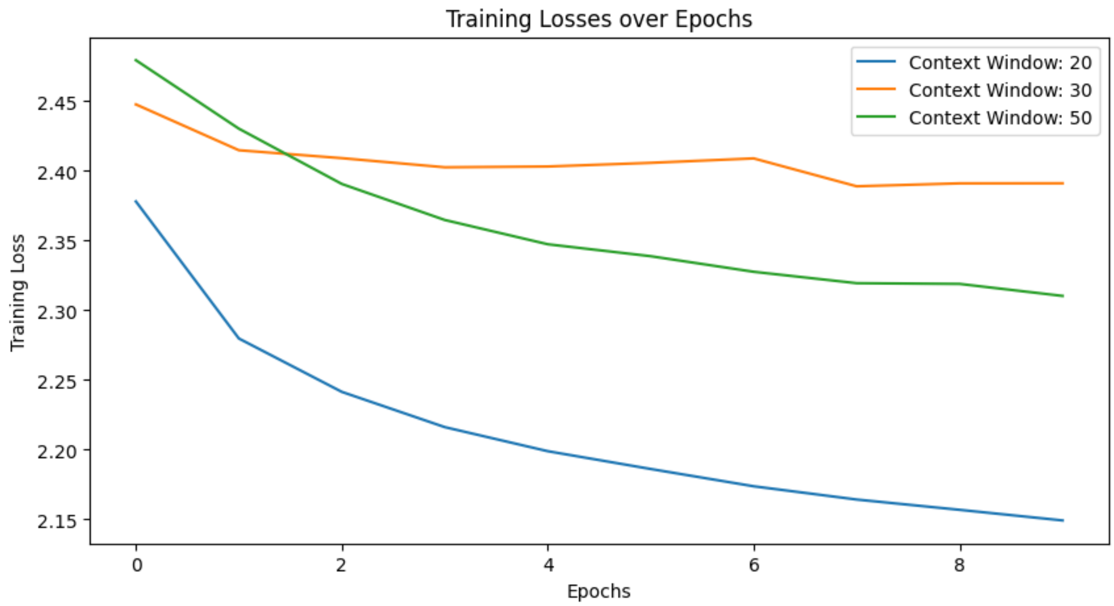
```python
    optimizer = optim.Adam(model.parameters(), lr=learning_rate)

    train_loader, test_loader = prepare_dataset(window_size)

    train_history, val_history = training_loop(model, criterion, optimizer, epochs, train_loader, test_loader, 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 != 50 else None
    models.append(model)
```

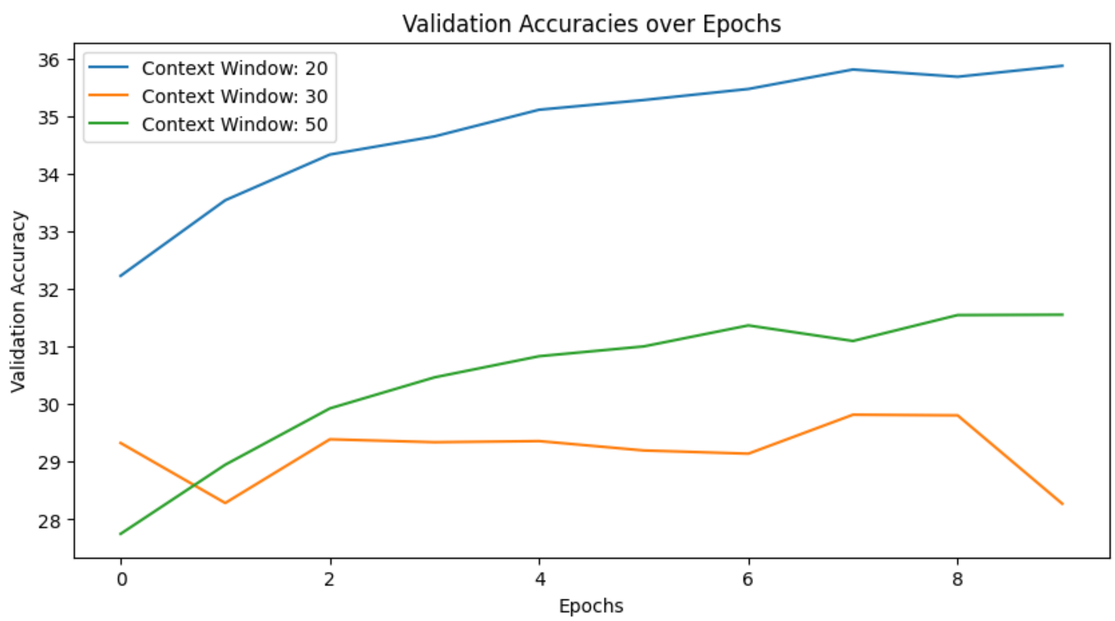
```
20 sequence transformer results:
Epoch 1, Loss: 2.3781242570840826, Validation Accuracy: 32.22817438081363
Epoch 2, Loss: 2.279810735718178, Validation Accuracy: 33.539840860697076
Epoch 3, Loss: 2.241520992432059, Validation Accuracy: 34.3328476969629
Epoch 4, Loss: 2.2162290881390225, Validation Accuracy: 34.64754006500056
Epoch 5, Loss: 2.1989653752505554, Validation Accuracy: 35.11061302252605
Epoch 6, Loss: 2.18619710241612, Validation Accuracy: 35.27916619970862
Epoch 7, Loss: 2.1737852297989937, Validation Accuracy: 35.47102992267175
Epoch 8, Loss: 2.1642856603030247, Validation Accuracy: 35.80903283648997
Epoch 9, Loss: 2.156897004832413, Validation Accuracy: 35.6830662333296
Epoch 10, Loss: 2.14928344218912, Validation Accuracy: 35.872688557659984
Training time: 20.495648515224456 minutes


Predicted next character: 'e'




30 sequence transformer results:
Epoch 1, Loss: 2.4477557629498605, Validation Accuracy: 29.327170926109392
Epoch 2, Loss: 2.4148842569557893, Validation Accuracy: 28.28580778489553
Epoch 3, Loss: 2.4091973809697302, Validation Accuracy: 29.391275501741582
Epoch 4, Loss: 2.402650372853608, Validation Accuracy: 29.34106772222546
Epoch 5, Loss: 2.4032119405771493, Validation Accuracy: 29.360343923289683
Epoch 6, Loss: 2.4058402947884314, Validation Accuracy: 29.197616923607967
Epoch 7, Loss: 2.4090153984519747, Validation Accuracy: 29.142029739143688
Epoch 8, Loss: 2.389019610139173, Validation Accuracy: 29.818041627628624
Epoch 9, Loss: 2.391117018349653, Validation Accuracy: 29.80683453398663
Epoch 10, Loss: 2.3911717040530407, Validation Accuracy: 28.27370412376218
Training time: 24.676496263345083 minutes


Predicted next character: ' '
```

```
50 sequence transformer results:
Epoch 1, Loss: 2.4794675380166815, Validation Accuracy: 27.75060631463807
Epoch 2, Loss: 2.430350461891641, Validation Accuracy: 28.95023512904079
Epoch 3, Loss: 2.3906916719805884, Validation Accuracy: 29.927511218501902
Epoch 4, Loss: 2.3648410472495707, Validation Accuracy: 30.466357943057975
Epoch 5, Loss: 2.347435210616769, Validation Accuracy: 30.83306062249797
Epoch 6, Loss: 2.33885371223308, Validation Accuracy: 31.00341150047743
Epoch 7, Loss: 2.3276846634146304, Validation Accuracy: 31.367872720996644
Epoch 8, Loss: 2.319504162063388, Validation Accuracy: 31.097552775150287
Epoch 9, Loss: 2.3189843632948826, Validation Accuracy: 31.547189434659227
Epoch 10, Loss: 2.3103705315418215, Validation Accuracy: 31.55346551963742
Training time: 36.899282876650496 minutes


Predicted next character: ' '
```

[ ]:

```
# 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()
```





2 Problem 2B: Adjusting hyperparameters

[ ]:
```
# Hyperparameters
hidden_size = 256
num_layers = 4
```

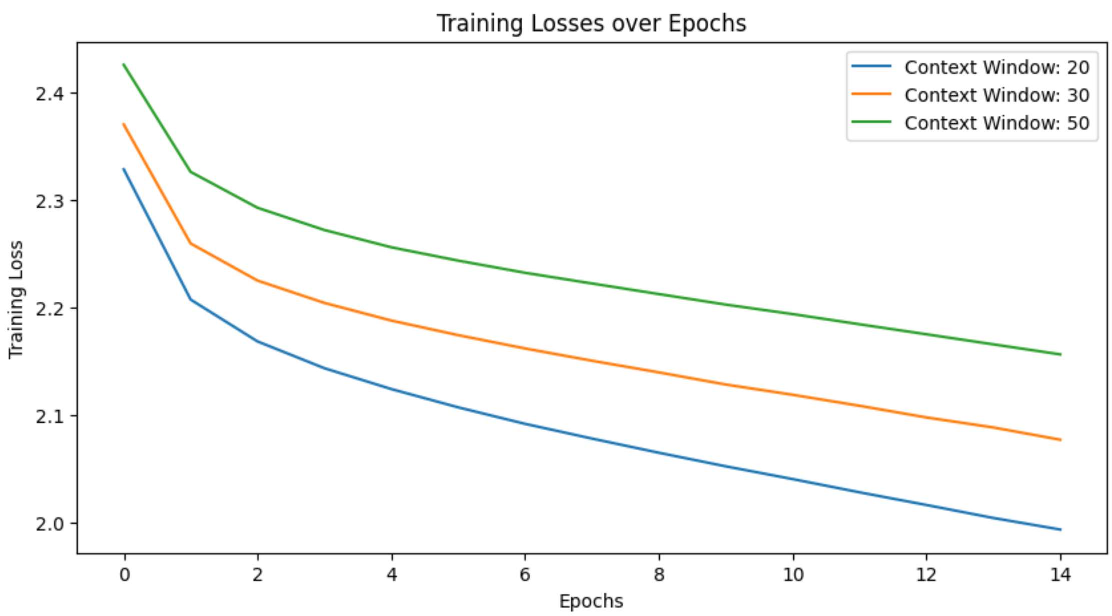
```
nhead = 4

max_lengths = [20, 30, 50]
learning_rate = .0001
epochs = 15
```

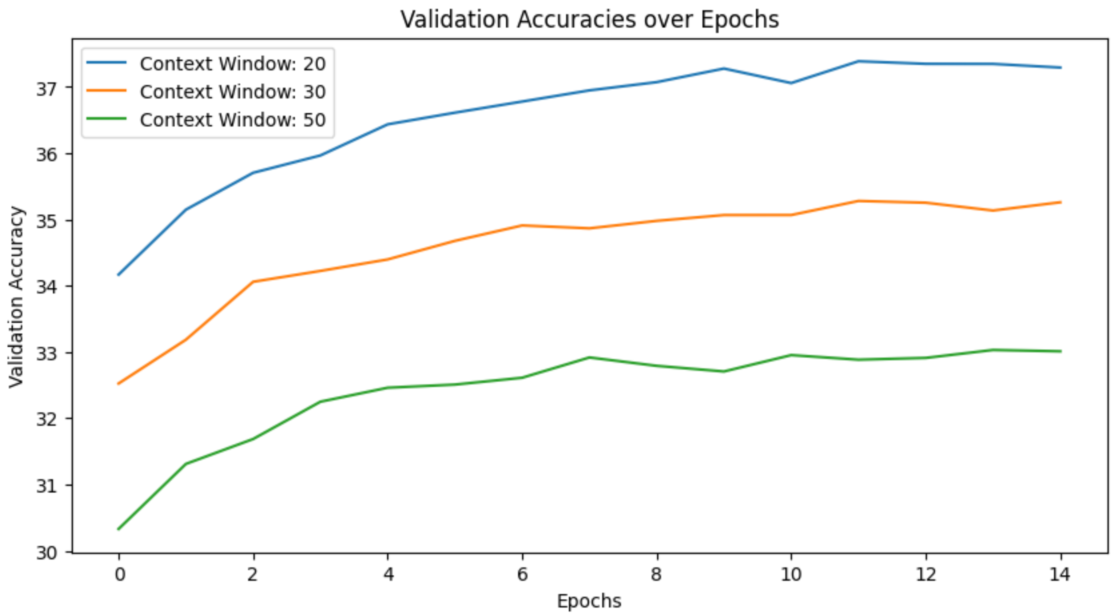
[ ]:
```
train_histories = []
val_histories = []
models_b = []

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

    train_loader, test_loader = prepare_dataset(window_size)

    train_history, val_history = training_loop(model, criterion, optimizer,
 ↪epochs, train_loader, test_loader, 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 != 50 else None
    models_b.append(model)
```

```
20 sequence transformer results:
Epoch 1, Loss: 2.328511470831134, Validation Accuracy: 34.16832903731929
Epoch 2, Loss: 2.2072384393959865, Validation Accuracy: 35.147820239829656
Epoch 3, Loss: 2.168260598186098, Validation Accuracy: 35.704583660203966
Epoch 4, Loss: 2.14332148995947, Validation Accuracy: 35.966379020508796
Epoch 5, Loss: 2.1239149742657233, Validation Accuracy: 36.43572789420598
Epoch 6, Loss: 2.1068844257960198, Validation Accuracy: 36.61190182673988
Epoch 7, Loss: 2.091532752074941, Validation Accuracy: 36.78000672419589
Epoch 8, Loss: 2.0778255151777247, Validation Accuracy: 36.94855990137846
Epoch 9, Loss: 2.064630270619855, Validation Accuracy: 37.07273338563263
Epoch 10, Loss: 2.0519855890743943, Validation Accuracy: 37.278045500392246
Epoch 11, Loss: 2.0401073334284274, Validation Accuracy: 37.0588367141096
Epoch 12, Loss: 2.0277804503830383, Validation Accuracy: 37.38787403339684
Epoch 13, Loss: 2.0159855133439124, Validation Accuracy: 37.34932197691359
Epoch 14, Loss: 2.00389172188189, Validation Accuracy: 37.34797713773395
Epoch 15, Loss: 1.9931346984126086, Validation Accuracy: 37.293287011094925
Training time: 39.17643499771754 minutes


Predicted next character: 'e'
```

```
30 sequence transformer results:
Epoch 1, Loss: 2.370202120173091, Validation Accuracy: 32.524330600296764
Epoch 2, Loss: 2.259460325281444, Validation Accuracy: 33.185100841428586
Epoch 3, Loss: 2.22491579308688, Validation Accuracy: 34.059254145503935
Epoch 4, Loss: 2.204130405479581, Validation Accuracy: 34.223325996422695
Epoch 5, Loss: 2.187697753266386, Validation Accuracy: 34.39681180600073
Epoch 6, Loss: 2.174122049879807, Validation Accuracy: 34.67698914705052
Epoch 7, Loss: 2.1617202574285264, Validation Accuracy: 34.909648411058264
Epoch 8, Loss: 2.1503024566364215, Validation Accuracy: 34.86616488772734
Epoch 9, Loss: 2.1394327329459015, Validation Accuracy: 34.979132391638615
Epoch 10, Loss: 2.128141408533292, Validation Accuracy: 35.066547722046145
Epoch 11, Loss: 2.118585914875696, Validation Accuracy: 35.06699600579183
Epoch 12, Loss: 2.108340448905019, Validation Accuracy: 35.27948250124398
Epoch 13, Loss: 2.0974821834732467, Validation Accuracy: 35.25303376024888
Epoch 14, Loss: 2.088149030795272, Validation Accuracy: 35.13513513513514
Epoch 15, Loss: 2.0767420101890792, Validation Accuracy: 35.25930973268841
Training time: 48.42438319524129 minutes


Predicted next character: 'e'



50 sequence transformer results:
Epoch 1, Loss: 2.4257603373970094, Validation Accuracy: 30.329180657106097
Epoch 2, Loss: 2.326111007054829, Validation Accuracy: 31.310043080840455
Epoch 3, Loss: 2.292701094192611, Validation Accuracy: 31.68615988774774
Epoch 4, Loss: 2.2719903020721275, Validation Accuracy: 32.24921436864827
Epoch 5, Loss: 2.2559081604825835, Validation Accuracy: 32.46035979898597
Epoch 6, Loss: 2.2434825767593156, Validation Accuracy: 32.50787872810655
Epoch 7, Loss: 2.232165393562916, Validation Accuracy: 32.61098583846254
Epoch 8, Loss: 2.2222212722150654, Validation Accuracy: 32.917169127041404
Epoch 9, Loss: 2.212358854068709, Validation Accuracy: 32.79075084390929
Epoch 10, Loss: 2.202563408294618, Validation Accuracy: 32.70557540491955
Epoch 11, Loss: 2.193719099633681, Validation Accuracy: 32.95258417798977
Epoch 12, Loss: 2.1842322063965907, Validation Accuracy: 32.88354724322967
Epoch 13, Loss: 2.174923464251871, Validation Accuracy: 32.91044475027906
Epoch 14, Loss: 2.1655380646513143, Validation Accuracy: 33.03013865664884
Epoch 15, Loss: 2.1562034023439094, Validation Accuracy: 33.0099655263618
Training time: 73.8289006392161 minutes


Predicted next character: '
'
```

[ ]:
```python
# 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
Context Window: 20
Context Window: 30
Context Window: 50
Validation Accuracy
Epochs
37
36
35
34
33
32
31
30
0
2
4
6
8
10
12
14