lab9

April 2, 2025

[1]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score
from sklearn import metrics
from sklearn.model_selection import train_test_split
import torchvision
from torchvision import transforms, datasets
import torch.nn.functional as F
import os
from PIL import Image
```

[14]:
```
df = pd.read_csv('/home/student/Desktop/New Folder 1/220962049_aiml/daily_csv.
↪csv')
device = 'cuda' if torch.cuda.is_available() else 'cpu'
```

[15]:
```
df = df.dropna()

y = df['Price'].values
x = np.arange(1, len(y), 1)

print(len(y))

# Normalize the input range between 0 and 1
minm = y.min()
maxm = y.max()
print(minm, maxm)

y = (y - minm) / (maxm - minm)

Sequence_Length = 10
X = []
Y = []
```

```
for i in range(0, 5900):
    list1 = []
    for j in range(i, i + Sequence_Length):
        list1.append(y[j])
        X.append(list1)
        Y.append(y[j + 1])

#Convert from list to array
X = np.array(X)
Y = np.array(Y)

#Split the data as the train and test set
x_train, x_test, y_train, y_test = train_test_split(X, Y,
test_size=0.10, random_state=42, shuffle=False, stratify=None)
```

```
5952
1.05 18.48
```

[16]:
```
class NGT(Dataset):
    def __init__(self, x, y):
        self.x = torch.tensor(x, dtype=torch.float32)
        self.y = torch.tensor(y, dtype=torch.float32)
        self.len = x.shape[0]

    def __getitem__(self, idx):
        return self.x[idx].to(device), self.y[idx].to(device)

    def __len__(self):
        return self.len

dataset = NGT(x_train,y_train)

from torch.utils.data import DataLoader

train_loader = DataLoader(dataset, shuffle=True, batch_size=256)
```

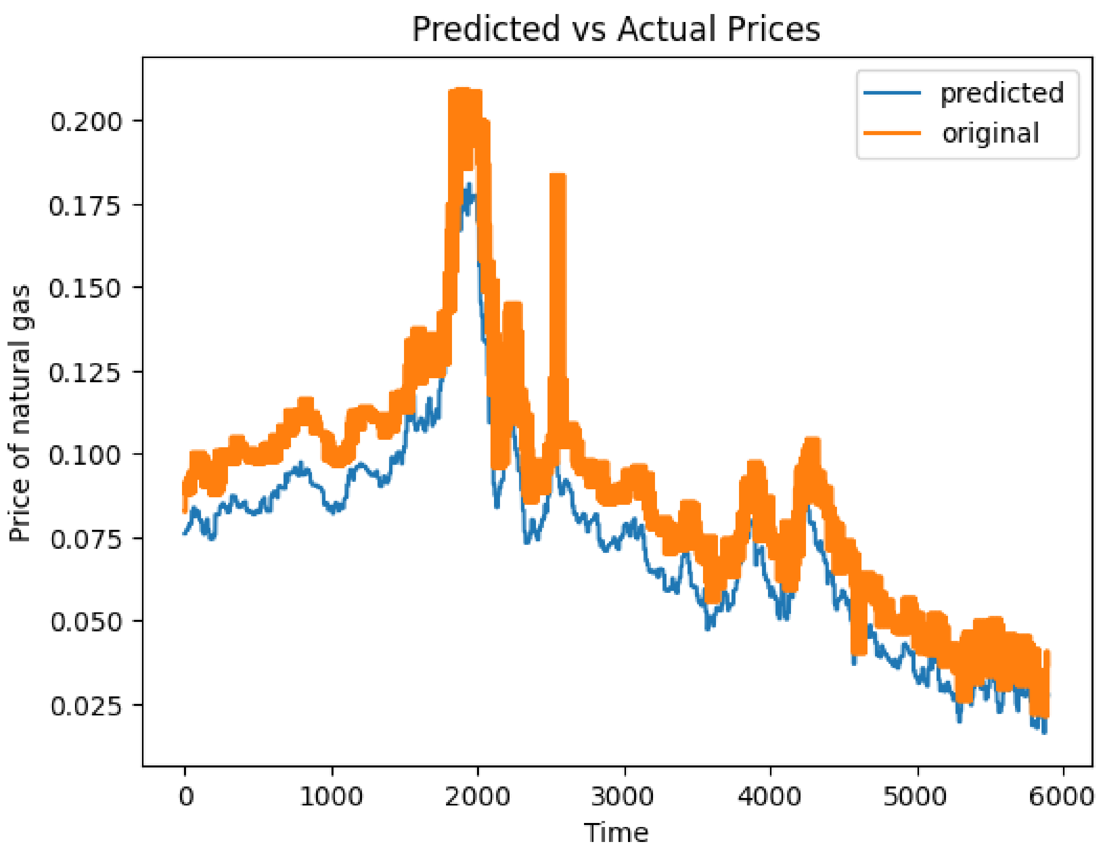
[17]:
```
class LSTMModel(nn.Module):
    def __init__(self):
        super(LSTMModel, self).__init__()
        self.rnn = nn.LSTM(input_size=1, hidden_size=5, num_layers=1,␣
↪batch_first=True)
        self.fc1 = nn.Linear(in_features=5, out_features=1)

    def forward(self, x):
        output, _status = self.rnn(x)
        output = output[:,-1,:]
        output = self.fc1(torch.relu(output))
```

```
        return output
```

[18]:
```
model = LSTMModel().to(device)

criterion = torch.nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.0001)

epochs = 50

for i in range(1, epochs+1):
    for j, data in enumerate(train_loader):
        y_pred = model(data[:][0].view(-1, Sequence_Length, 1)).reshape(-1)
        loss = criterion(y_pred, data[:][1])
        loss.backward()
        optimizer.step()
    if i % 5 == 0:
        print(i, "th iteration : ", loss)
```

```
5 th iteration :  tensor(0.0156, device='cuda:0', grad_fn=<MseLossBackward0>)
10 th iteration :  tensor(0.0028, device='cuda:0', grad_fn=<MseLossBackward0>)
15 th iteration :  tensor(0.0053, device='cuda:0', grad_fn=<MseLossBackward0>)
20 th iteration :  tensor(0.0105, device='cuda:0', grad_fn=<MseLossBackward0>)
25 th iteration :  tensor(0.0009, device='cuda:0', grad_fn=<MseLossBackward0>)
30 th iteration :  tensor(0.0035, device='cuda:0', grad_fn=<MseLossBackward0>)
35 th iteration :  tensor(0.0018, device='cuda:0', grad_fn=<MseLossBackward0>)
40 th iteration :  tensor(0.0017, device='cuda:0', grad_fn=<MseLossBackward0>)
45 th iteration :  tensor(0.0066, device='cuda:0', grad_fn=<MseLossBackward0>)
50 th iteration :  tensor(0.0009, device='cuda:0', grad_fn=<MseLossBackward0>)
```

[19]:
```
test_set = NGT(x_test,y_test)
test_pred = model(test_set[:][0].view(-1,10,1)).view(-1)

plt.title("Predicted vs Actual Prices")
plt.xlabel("Time")
plt.ylabel("Price of natural gas")
plt.plot(test_pred.detach().cpu().numpy(), label='predicted')
plt.plot(test_set[:][1].view(-1).cpu(), label='original')
plt.legend()
plt.show()
```



[20]:
```
from glob import glob
import random
import string

names_dir_path = "/home/student/Desktop/New Folder 1/220962049_aiml/names/names"

class namesDataset(Dataset):
    def __init__(self, dir, train_split=0.9, max_length=None):
        super().__init__()

        self.train = True
        self.data = []

        self.labelToLang = {}

        # Mapping of characters to integers
        all_characters = string.ascii_lowercase
        self.n_characters = len(all_characters)
        self.char_to_index = {ch: i for i, ch in enumerate(all_characters)}
```

```
        file_names = glob(os.path.join(dir, "*.txt"))


        for lang_idx, file_name in enumerate(file_names):
            lang = file_name.split("/")[-1][:-4]
            self.labelToLang[lang_idx] = lang

            f = open(file_name, "r")
            self.data += [([self.char_to_index.get(ch, 0) for ch in name[:-1].
↪lower()], lang_idx) for name in f.readlines()]

        self.max_length = max_length

        if self.max_length is None:
            self.max_length = max([len(data_point[0]) for data_point in self.
↪data])

        random.shuffle(self.data)
        # print(self.data)

        self.train_data, self.test_data = self.data[:int(len(self.data) *␣
↪train_split)], self.data[int(len(self.data) * train_split):]
        print(len(self.train_data), len(self.test_data))
        # print(self.test_data)

    def __len__(self):
        return len(self.train_data) if self.train else len(self.test_data)

    def __getitem__(self, idx):
        name, label = self.train_data[idx] if self.train else self.
↪test_data[idx]

        # Pad name to have fixed length
        name = name[:self.max_length] + [0] * (self.max_length - len(name))

        return torch.Tensor(name).to(device), torch.tensor(label).to(device)
```

[21]:
```
dataset = namesDataset(names_dir_path)

train_loader = DataLoader(dataset, shuffle=False, batch_size=32)
test_loader = DataLoader(dataset, shuffle=True, batch_size=16)
```

18066 2008

[22]:
```
n_characters = dataset.n_characters
n_languages = len(dataset.labelToLang)
```

```
class LanguageModel(nn.Module):
    def __init__(self, n_characters=n_characters, n_languages=n_languages,␣
↪hidden_size=5):
        super(LanguageModel, self).__init__()
        # self.embedding = nn.Embedding(n_characters, hidden_size)
        self.lstm = nn.LSTM(input_size=1, hidden_size=hidden_size,␣
↪num_layers=5, batch_first=True)
        self.fc = nn.Linear(hidden_size, n_languages)

    def forward(self, x):
        # x = self.embedding(x)  # [batch_size, seq_len, hidden_size]
        out, _ = self.lstm(x)  # Get the RNN output
        # print(out.size(), out)
        out = out[:, -1, :]  # Take the output of the last time step
        # print(out.size(), out)
        out = self.fc(out)  # Final linear layer for classification
        return out
```

[23]:
```
learning_rate = 1e-3 * 5

model = LanguageModel(n_characters=n_characters, n_languages=n_languages).
↪to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate)
```

[24]:
```
dataset.train = True
num_epochs = 200

for epoch in range(num_epochs):
    model.train()
    running_loss = 0.0
    correct = 0
    total = 0

    for names, labels in train_loader:
        # Zero gradients
        optimizer.zero_grad()

        names = names.unsqueeze(2)
        # labels = labels.unsqueeze(0)

        # Forward pass
        outputs = model(names)

        # print(labels.size(), outputs.size())
        # outputs = nn.functional.softmax(outputs, dim=1)
```

```
        # Compute loss
        loss = criterion(outputs, labels)
        running_loss += loss.item()

        # Backward pass and optimization
        loss.backward()
        optimizer.step()

        # Track accuracy
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

        # print(predicted, labels)

    epoch_loss = running_loss / len(train_loader)
    accuracy = correct / total * 100
    print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {epoch_loss:.4f}, Accuracy:␣
↪{accuracy:.2f}%")
```

```
Epoch [1/200], Loss: 1.9158, Accuracy: 44.11%
Epoch [2/200], Loss: 1.7577, Accuracy: 47.76%
Epoch [3/200], Loss: 1.6801, Accuracy: 49.33%
Epoch [4/200], Loss: 1.6658, Accuracy: 49.20%
Epoch [5/200], Loss: 1.6532, Accuracy: 49.25%
Epoch [6/200], Loss: 1.6319, Accuracy: 49.96%
Epoch [7/200], Loss: 1.6136, Accuracy: 50.41%
Epoch [8/200], Loss: 1.5953, Accuracy: 51.34%
Epoch [9/200], Loss: 1.5837, Accuracy: 52.04%
Epoch [10/200], Loss: 1.5783, Accuracy: 52.04%
Epoch [11/200], Loss: 1.5771, Accuracy: 52.37%
Epoch [12/200], Loss: 1.5654, Accuracy: 52.55%
Epoch [13/200], Loss: 1.5669, Accuracy: 52.93%
Epoch [14/200], Loss: 1.5928, Accuracy: 52.65%
Epoch [15/200], Loss: 1.6043, Accuracy: 52.03%
Epoch [16/200], Loss: 1.5555, Accuracy: 53.52%
Epoch [17/200], Loss: 1.5450, Accuracy: 53.95%
Epoch [18/200], Loss: 1.5346, Accuracy: 54.85%
Epoch [19/200], Loss: 1.5838, Accuracy: 53.32%
Epoch [20/200], Loss: 1.5647, Accuracy: 53.20%
Epoch [21/200], Loss: 1.5258, Accuracy: 54.38%
Epoch [22/200], Loss: 1.5111, Accuracy: 55.00%
Epoch [23/200], Loss: 1.5059, Accuracy: 55.83%
Epoch [24/200], Loss: 1.4979, Accuracy: 56.52%
Epoch [25/200], Loss: 1.4938, Accuracy: 56.76%
Epoch [26/200], Loss: 1.4949, Accuracy: 56.64%
Epoch [27/200], Loss: 1.4787, Accuracy: 57.28%
Epoch [28/200], Loss: 1.4731, Accuracy: 57.63%
```

```
Epoch [29/200], Loss: 1.4643, Accuracy: 57.67%
Epoch [30/200], Loss: 1.4632, Accuracy: 57.97%
Epoch [31/200], Loss: 1.4496, Accuracy: 58.40%
Epoch [32/200], Loss: 1.4515, Accuracy: 58.64%
Epoch [33/200], Loss: 1.4439, Accuracy: 58.49%
Epoch [34/200], Loss: 1.4737, Accuracy: 57.21%
Epoch [35/200], Loss: 1.4419, Accuracy: 58.65%
Epoch [36/200], Loss: 1.4316, Accuracy: 58.94%
Epoch [37/200], Loss: 1.5177, Accuracy: 55.82%
Epoch [38/200], Loss: 1.4575, Accuracy: 58.35%
Epoch [39/200], Loss: 1.4218, Accuracy: 59.65%
Epoch [40/200], Loss: 1.4241, Accuracy: 59.21%
Epoch [41/200], Loss: 1.4138, Accuracy: 59.73%
Epoch [42/200], Loss: 1.4206, Accuracy: 59.40%
Epoch [43/200], Loss: 1.4145, Accuracy: 59.41%
Epoch [44/200], Loss: 1.4105, Accuracy: 59.48%
Epoch [45/200], Loss: 1.4093, Accuracy: 59.83%
Epoch [46/200], Loss: 1.4130, Accuracy: 59.26%
Epoch [47/200], Loss: 1.4023, Accuracy: 59.80%
Epoch [48/200], Loss: 1.4061, Accuracy: 59.52%
Epoch [49/200], Loss: 1.4055, Accuracy: 59.77%
Epoch [50/200], Loss: 1.3971, Accuracy: 59.93%
Epoch [51/200], Loss: 1.4010, Accuracy: 59.32%
Epoch [52/200], Loss: 1.3910, Accuracy: 59.87%
Epoch [53/200], Loss: 1.3861, Accuracy: 59.95%
Epoch [54/200], Loss: 1.3859, Accuracy: 60.04%
Epoch [55/200], Loss: 1.4089, Accuracy: 59.06%
Epoch [56/200], Loss: 1.3824, Accuracy: 60.27%
Epoch [57/200], Loss: 1.3865, Accuracy: 59.87%
Epoch [58/200], Loss: 1.3910, Accuracy: 59.64%
Epoch [59/200], Loss: 1.3734, Accuracy: 60.23%
Epoch [60/200], Loss: 1.4131, Accuracy: 59.24%
Epoch [61/200], Loss: 1.3678, Accuracy: 60.26%
Epoch [62/200], Loss: 1.3639, Accuracy: 60.59%
Epoch [63/200], Loss: 1.3642, Accuracy: 60.47%
Epoch [64/200], Loss: 1.3651, Accuracy: 60.43%
Epoch [65/200], Loss: 1.3551, Accuracy: 60.46%
Epoch [66/200], Loss: 1.3827, Accuracy: 59.74%
Epoch [67/200], Loss: 1.3580, Accuracy: 60.53%
Epoch [68/200], Loss: 1.3919, Accuracy: 59.63%
Epoch [69/200], Loss: 1.3507, Accuracy: 60.83%
Epoch [70/200], Loss: 1.3667, Accuracy: 60.42%
Epoch [71/200], Loss: 1.3477, Accuracy: 60.79%
Epoch [72/200], Loss: 1.3515, Accuracy: 60.56%
Epoch [73/200], Loss: 1.3419, Accuracy: 61.03%
Epoch [74/200], Loss: 1.3920, Accuracy: 59.35%
Epoch [75/200], Loss: 1.3539, Accuracy: 60.43%
Epoch [76/200], Loss: 1.3774, Accuracy: 59.67%
```

```
Epoch [77/200], Loss: 1.3386, Accuracy: 60.78%
Epoch [78/200], Loss: 1.3329, Accuracy: 61.26%
Epoch [79/200], Loss: 1.3304, Accuracy: 61.23%
Epoch [80/200], Loss: 1.3491, Accuracy: 60.51%
Epoch [81/200], Loss: 1.3338, Accuracy: 60.95%
Epoch [82/200], Loss: 1.3361, Accuracy: 61.18%
Epoch [83/200], Loss: 1.3284, Accuracy: 61.25%
Epoch [84/200], Loss: 1.3317, Accuracy: 60.90%
Epoch [85/200], Loss: 1.3332, Accuracy: 61.14%
Epoch [86/200], Loss: 1.3409, Accuracy: 60.83%
Epoch [87/200], Loss: 1.3201, Accuracy: 61.61%
Epoch [88/200], Loss: 1.3569, Accuracy: 60.56%
Epoch [89/200], Loss: 1.3295, Accuracy: 61.10%
Epoch [90/200], Loss: 1.3926, Accuracy: 60.31%
Epoch [91/200], Loss: 1.6110, Accuracy: 52.46%
Epoch [92/200], Loss: 1.5252, Accuracy: 54.28%
Epoch [93/200], Loss: 1.4827, Accuracy: 55.67%
Epoch [94/200], Loss: 1.4496, Accuracy: 57.20%
Epoch [95/200], Loss: 1.4252, Accuracy: 58.31%
Epoch [96/200], Loss: 1.4216, Accuracy: 58.47%
Epoch [97/200], Loss: 1.4283, Accuracy: 58.35%
Epoch [98/200], Loss: 1.4097, Accuracy: 58.68%
Epoch [99/200], Loss: 1.4158, Accuracy: 58.62%
Epoch [100/200], Loss: 1.4118, Accuracy: 58.57%
Epoch [101/200], Loss: 1.4053, Accuracy: 58.51%
Epoch [102/200], Loss: 1.4070, Accuracy: 58.76%
Epoch [103/200], Loss: 1.3865, Accuracy: 59.45%
Epoch [104/200], Loss: 1.3801, Accuracy: 59.76%
Epoch [105/200], Loss: 1.3748, Accuracy: 60.00%
Epoch [106/200], Loss: 1.3528, Accuracy: 60.78%
Epoch [107/200], Loss: 1.3486, Accuracy: 60.80%
Epoch [108/200], Loss: 1.3407, Accuracy: 60.95%
Epoch [109/200], Loss: 1.3414, Accuracy: 61.11%
Epoch [110/200], Loss: 1.3307, Accuracy: 61.46%
Epoch [111/200], Loss: 1.3295, Accuracy: 61.55%
Epoch [112/200], Loss: 1.3347, Accuracy: 61.09%
Epoch [113/200], Loss: 1.3226, Accuracy: 61.44%
Epoch [114/200], Loss: 1.3523, Accuracy: 60.47%
Epoch [115/200], Loss: 1.3164, Accuracy: 62.04%
Epoch [116/200], Loss: 1.3147, Accuracy: 61.67%
Epoch [117/200], Loss: 1.3268, Accuracy: 61.34%
Epoch [118/200], Loss: 1.3021, Accuracy: 62.27%
Epoch [119/200], Loss: 1.2945, Accuracy: 62.79%
Epoch [120/200], Loss: 1.2927, Accuracy: 62.82%
Epoch [121/200], Loss: 1.2912, Accuracy: 62.86%
Epoch [122/200], Loss: 1.2885, Accuracy: 62.98%
Epoch [123/200], Loss: 1.2939, Accuracy: 62.73%
Epoch [124/200], Loss: 1.2851, Accuracy: 63.09%
```

```
Epoch [125/200], Loss: 1.2803, Accuracy: 63.15%
Epoch [126/200], Loss: 1.2783, Accuracy: 63.24%
Epoch [127/200], Loss: 1.2794, Accuracy: 63.27%
Epoch [128/200], Loss: 1.2744, Accuracy: 63.33%
Epoch [129/200], Loss: 1.2769, Accuracy: 63.46%
Epoch [130/200], Loss: 1.2839, Accuracy: 63.05%
Epoch [131/200], Loss: 1.2665, Accuracy: 63.67%
Epoch [132/200], Loss: 1.2686, Accuracy: 63.58%
Epoch [133/200], Loss: 1.2755, Accuracy: 63.27%
Epoch [134/200], Loss: 1.2634, Accuracy: 63.61%
Epoch [135/200], Loss: 1.2578, Accuracy: 64.02%
Epoch [136/200], Loss: 1.2517, Accuracy: 64.19%
Epoch [137/200], Loss: 1.2524, Accuracy: 64.07%
Epoch [138/200], Loss: 1.2670, Accuracy: 63.47%
Epoch [139/200], Loss: 1.2651, Accuracy: 63.73%
Epoch [140/200], Loss: 1.2545, Accuracy: 64.04%
Epoch [141/200], Loss: 1.2453, Accuracy: 64.27%
Epoch [142/200], Loss: 1.2387, Accuracy: 64.70%
Epoch [143/200], Loss: 1.2532, Accuracy: 64.25%
Epoch [144/200], Loss: 1.2383, Accuracy: 64.74%
Epoch [145/200], Loss: 1.2458, Accuracy: 64.39%
Epoch [146/200], Loss: 1.2449, Accuracy: 64.47%
Epoch [147/200], Loss: 1.2461, Accuracy: 64.25%
Epoch [148/200], Loss: 1.2548, Accuracy: 64.07%
Epoch [149/200], Loss: 1.2316, Accuracy: 64.95%
Epoch [150/200], Loss: 1.2312, Accuracy: 64.97%
Epoch [151/200], Loss: 1.2385, Accuracy: 64.59%
Epoch [152/200], Loss: 1.2479, Accuracy: 64.27%
Epoch [153/200], Loss: 1.2337, Accuracy: 64.62%
Epoch [154/200], Loss: 1.2453, Accuracy: 64.48%
Epoch [155/200], Loss: 1.2350, Accuracy: 64.72%
Epoch [156/200], Loss: 1.2259, Accuracy: 65.06%
Epoch [157/200], Loss: 1.2313, Accuracy: 64.88%
Epoch [158/200], Loss: 1.2500, Accuracy: 64.19%
Epoch [159/200], Loss: 1.2269, Accuracy: 65.12%
Epoch [160/200], Loss: 1.2341, Accuracy: 65.06%
Epoch [161/200], Loss: 1.2356, Accuracy: 64.58%
Epoch [162/200], Loss: 1.2484, Accuracy: 64.31%
Epoch [163/200], Loss: 1.2193, Accuracy: 65.31%
Epoch [164/200], Loss: 1.2240, Accuracy: 65.13%
Epoch [165/200], Loss: 1.2309, Accuracy: 64.80%
Epoch [166/200], Loss: 1.2239, Accuracy: 65.08%
Epoch [167/200], Loss: 1.2615, Accuracy: 63.57%
Epoch [168/200], Loss: 1.2184, Accuracy: 65.29%
Epoch [169/200], Loss: 1.2234, Accuracy: 65.18%
Epoch [170/200], Loss: 1.2120, Accuracy: 65.58%
Epoch [171/200], Loss: 1.2159, Accuracy: 65.55%
Epoch [172/200], Loss: 1.2166, Accuracy: 65.30%
```

```
Epoch [173/200], Loss: 1.2401, Accuracy: 64.82%
Epoch [174/200], Loss: 1.2141, Accuracy: 65.36%
Epoch [175/200], Loss: 1.2099, Accuracy: 65.74%
Epoch [176/200], Loss: 1.2216, Accuracy: 64.91%
Epoch [177/200], Loss: 1.2148, Accuracy: 65.55%
Epoch [178/200], Loss: 1.2260, Accuracy: 64.87%
Epoch [179/200], Loss: 1.2139, Accuracy: 65.46%
Epoch [180/200], Loss: 1.2155, Accuracy: 65.30%
Epoch [181/200], Loss: 1.3559, Accuracy: 61.59%
Epoch [182/200], Loss: 1.2472, Accuracy: 64.42%
Epoch [183/200], Loss: 1.2285, Accuracy: 65.18%
Epoch [184/200], Loss: 1.2414, Accuracy: 64.55%
Epoch [185/200], Loss: 1.2176, Accuracy: 65.43%
Epoch [186/200], Loss: 1.2195, Accuracy: 65.17%
Epoch [187/200], Loss: 1.2202, Accuracy: 64.98%
Epoch [188/200], Loss: 1.2310, Accuracy: 64.66%
Epoch [189/200], Loss: 1.2077, Accuracy: 65.68%
Epoch [190/200], Loss: 1.2078, Accuracy: 65.63%
Epoch [191/200], Loss: 1.2191, Accuracy: 65.26%
Epoch [192/200], Loss: 1.2044, Accuracy: 65.78%
Epoch [193/200], Loss: 1.2033, Accuracy: 65.71%
Epoch [194/200], Loss: 1.2449, Accuracy: 64.20%
Epoch [195/200], Loss: 1.2091, Accuracy: 65.43%
Epoch [196/200], Loss: 1.2114, Accuracy: 65.37%
Epoch [197/200], Loss: 1.2196, Accuracy: 65.02%
Epoch [198/200], Loss: 1.2293, Accuracy: 64.60%
Epoch [199/200], Loss: 1.1890, Accuracy: 65.92%
Epoch [200/200], Loss: 1.2191, Accuracy: 65.26%
```

[25]:

```
dataset.train = False

model.eval()
correct = 0
total = 0

with torch.no_grad():
    for names, labels in test_loader:
        names = names.unsqueeze(2)
        outputs = model(names)
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

accuracy = correct / total * 100
print(f"Validation Accuracy: {accuracy:.2f}%")
```

```
Validation Accuracy: 66.98%
```

[26]:
```
with torch.no_grad():
    for i in range(50):
        name, label = dataset[i]
        name, label = torch.unsqueeze(name, 0), torch.unsqueeze(label, 0)
        name = name.unsqueeze(2)
        #print(name, label)
        outputs = model(name)
        _, predicted = torch.max(outputs, 1)
        # print(predicted)

        print("Actual:", dataset.labelToLang[label.detach().cpu().item()])
        print("Predicted:", dataset.labelToLang[predicted.detach().cpu().
 ↪item()])
        print()
```

```
Actual: Polish
Predicted: English

Actual: Greek
Predicted: Arabic

Actual: English
Predicted: English

Actual: English
Predicted: Russian

Actual: English
Predicted: English

Actual: Russian
Predicted: Russian

Actual: Russian
Predicted: English

Actual: Russian
Predicted: Russian

Actual: Czech
Predicted: Russian

Actual: French
Predicted: English

Actual: Russian
Predicted: Russian
```

```
Actual: English
Predicted: English

Actual: Korean
Predicted: Chinese

Actual: English
Predicted: English

Actual: Scottish
Predicted: English

Actual: Russian
Predicted: Russian

Actual: Arabic
Predicted: English

Actual: Russian
Predicted: Russian

Actual: Russian
Predicted: Russian

Actual: Russian
Predicted: Russian

Actual: Russian
Predicted: Russian

Actual: Irish
Predicted: English

Actual: Scottish
Predicted: English

Actual: Russian
Predicted: Russian

Actual: Arabic
Predicted: Arabic

Actual: Japanese
Predicted: Russian

Actual: Russian
Predicted: Russian
```

```
Actual: Korean
Predicted: English

Actual: Arabic
Predicted: Arabic

Actual: English
Predicted: English

Actual: Russian
Predicted: Russian

Actual: Russian
Predicted: Russian

Actual: Russian
Predicted: Russian

Actual: Russian
Predicted: Russian

Actual: Dutch
Predicted: English

Actual: Japanese
Predicted: English

Actual: Russian
Predicted: Russian

Actual: Japanese
Predicted: Arabic

Actual: Russian
Predicted: Russian

Actual: Arabic
Predicted: Arabic

Actual: Arabic
Predicted: Arabic

Actual: English
Predicted: English

Actual: Spanish
Predicted: Russian
```

```
Actual: Russian
Predicted: Russian

Actual: Japanese
Predicted: English

Actual: Russian
Predicted: Russian

Actual: English
Predicted: Russian

Actual: Czech
Predicted: English

Actual: Russian
Predicted: Russian

Actual: Russian
Predicted: Russian
```

[27]:
```
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import string
```

[28]:
```
text = """In one rearrangement proof, two squares are used whose sides have a␣
↪measure of a + b and which contain four right triangles whose sides are a, b␣
↪and c, with the hypotenuse being c. In the square on the right side, the␣
↪triangles are placed such that the corners of the square correspond to the␣
↪corners of the right angle in the triangles, forming a square in the center␣
↪whose sides are length c. Each outer square has an area of ( a + b ) 2  well␣
↪as 2 a b + c 2, with 2 a b representing the total area of the four triangles.
↪ Within the big square on the left side, the four triangles are moved to␣
↪form two similar rectangles with sides of length a and b. These rectangles␣
↪in their new position have now delineated two new squares, one having side␣
↪length a is formed in the bottom-left corner, and another square of side␣
↪length b formed in the top-right corner. In this new position, this left␣
↪side now has a square of area ( a + b ) 2 as well as 2 a b + a 2 + b 2.␣
↪Since both squares have the area of ( a + b ) 2 {\displaystyle (a+b)^{2}} it␣
↪follows that the other measure of the square area also equal each other such␣
↪that 2 a b + c 2 {\displaystyle 2ab+c^{2}} = 2 a b + a 2 + b 2␣
↪{\displaystyle 2ab+a^{2}+b^{2}}. With the area of the four triangles removed␣
↪from both side of the equation what remains is a 2 + b 2 = c 2 .␣
↪{\displaystyle a^{2}+b^{2}=c^{2}.} [2]
```

```
In another proof rectangles in the second box can also be placed such that both␣
↪have one corner that correspond to consecutive corners of the square. In␣
↪this way they also form two boxes, this time in consecutive corners, with␣
↪areas a 2 {\displaystyle a^{2}} and b 2 {\displaystyle b^{2}}which will␣
↪again lead to a second square of with the area 2 a b + a 2 + b 2␣
↪{\displaystyle 2ab+a^{2}+b^{2}}.

English mathematician Sir Thomas Heath gives this proof in his commentary on␣
↪Proposition I.47 in Euclid's Elements, and mentions the proposals of German␣
↪mathematicians Carl Anton Bretschneider and Hermann Hankel that Pythagoras␣
↪may have known this proof. Heath himself favors a different proposal for a␣
↪Pythagorean proof, but acknowledges from the outset of his discussion "that␣
↪the Greek literature which we possess belonging to the first five centuries␣
↪after Pythagoras contains no statement specifying this or any other␣
↪particular great geometric discovery to him."[3] Recent scholarship has cast␣
↪increasing doubt on any sort of role for Pythagoras as a creator of␣
↪mathematics, although debate about this continues."""
```

```
<>:1: SyntaxWarning: invalid escape sequence '\d'
<>:1: SyntaxWarning: invalid escape sequence '\d'
/tmp/ipykernel_6030/3836106867.py:1: SyntaxWarning: invalid escape sequence '\d'
  text = """In one rearrangement proof, two squares are used whose sides have a
measure of a + b and which contain four right triangles whose sides are a, b and
c, with the hypotenuse being c. In the square on the right side, the triangles
are placed such that the corners of the square correspond to the corners of the
right angle in the triangles, forming a square in the center whose sides are
length c. Each outer square has an area of ( a + b ) 2  well as 2 a b + c 2,
with 2 a b representing the total area of the four triangles. Within the big
square on the left side, the four triangles are moved to form two similar
rectangles with sides of length a and b. These rectangles in their new position
have now delineated two new squares, one having side length a is formed in the
bottom-left corner, and another square of side length b formed in the top-right
corner. In this new position, this left side now has a square of area ( a + b )
2 as well as 2 a b + a 2 + b 2. Since both squares have the area of ( a + b ) 2
{\displaystyle (a+b)^{2}} it follows that the other measure of the square area
also equal each other such that 2 a b + c 2 {\displaystyle 2ab+c^{2}} = 2 a b +
a 2 + b 2 {\displaystyle 2ab+a^{2}+b^{2}}. With the area of the four triangles
removed from both side of the equation what remains is a 2 + b 2 = c 2 .
{\displaystyle a^{2}+b^{2}=c^{2}.} [2]
```

[29]:
```python
chars = sorted(set(text))
vocab_size = len(chars)
char_to_index = {ch: i for i, ch in enumerate(chars)}
index_to_char = {i: ch for i, ch in enumerate(chars)}

# Convert the text into numerical indices
```

```python
encoded_text = [char_to_index[ch] for ch in text]

# Define sequence length (how many characters to look back to predict the next)
sequence_length = 10

# Prepare input-output pairs for training (X, y)
X = []
y = []

for i in range(len(encoded_text) - sequence_length):
    X.append(encoded_text[i:i + sequence_length])
    y.append(encoded_text[i + sequence_length])

X = torch.tensor(X)
y = torch.tensor(y)

# Step 2: Define the RNN model
class NextCharacterRNN(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(NextCharacterRNN, self).__init__()
        self.hidden_size = hidden_size
        self.rnn = nn.RNN(input_size, hidden_size, batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(1, x.size(0), self.hidden_size).to(x.device)

        # Pass input through RNN layer
        out, hn = self.rnn(x, h0)

        # Get the output from the last time step
        out = self.fc(out[:, -1, :])

        return out

# Hyperparameters
input_size = vocab_size  # One-hot encoding of each character
hidden_size = 128  # Number of RNN hidden units
output_size = vocab_size  # Predict next character
learning_rate = 0.001
epochs = 10000

# Model initialization
model = NextCharacterRNN(input_size, hidden_size, output_size)

# Loss and optimizer
```

```
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate)

# Step 3: Train the model
# Convert input sequences to one-hot encoding
X_onehot = torch.zeros(X.size(0), X.size(1), vocab_size)

for i in range(X.size(0)):
    for j in range(X.size(1)):
        X_onehot[i, j, X[i, j]] = 1

# Training loop
for epoch in range(epochs):
    model.train()

    # Forward pass
    outputs = model(X_onehot)

    # Compute loss
    loss = criterion(outputs, y)

    # Backpropagation
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 500 == 0:
        print(f'Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}')

# Step 4: Predict next character
def predict_next_char(model, input_text, char_to_index, index_to_char,
 ↪sequence_length=10):
    model.eval()

    # Prepare the input sequence
    input_indices = [char_to_index[ch] for ch in input_text[-sequence_length:]]
    input_tensor = torch.zeros(1, sequence_length, vocab_size)

    for i in range(sequence_length):
        input_tensor[0, i, input_indices[i]] = 1

    # Make prediction
    with torch.no_grad():
        output = model(input_tensor)
        predicted_index = torch.argmax(output, dim=1).item()

    return index_to_char[predicted_index]
```

```
# Test the model with a sequence of characters
input_text = "Hello, this is a "
predicted_char = predict_next_char(model, input_text, char_to_index,␣
 ↪index_to_char)
print(f'Input text: "{input_text}" -> Predicted next character:␣
 ↪"{predicted_char}"')
```

```
Epoch [500/10000], Loss: 0.1846
Epoch [1000/10000], Loss: 0.0580
Epoch [1500/10000], Loss: 0.0462
Epoch [2000/10000], Loss: 0.0424
Epoch [2500/10000], Loss: 0.0405
Epoch [3000/10000], Loss: 0.0395
Epoch [3500/10000], Loss: 0.0388
Epoch [4000/10000], Loss: 0.0384
Epoch [4500/10000], Loss: 0.0397
Epoch [5000/10000], Loss: 0.0387
Epoch [5500/10000], Loss: 0.0382
Epoch [6000/10000], Loss: 0.0380
Epoch [6500/10000], Loss: 0.0378
Epoch [7000/10000], Loss: 0.0377
Epoch [7500/10000], Loss: 0.0377
Epoch [8000/10000], Loss: 0.0379
Epoch [8500/10000], Loss: 0.0376
Epoch [9000/10000], Loss: 0.0376
Epoch [9500/10000], Loss: 0.0374
Epoch [10000/10000], Loss: 0.0374
Input text: "Hello, this is a " -> Predicted next character: "e"
```

[30]:

```
# Test the model with a sequence of characters
input_text = "other measure of "

for i in range(50):
    predicted_char = predict_next_char(model, input_text, char_to_index,␣
 ↪index_to_char)
    print(f'Input text: "{input_text}" -> Predicted next character:␣
 ↪"{predicted_char}"')
    input_text += predicted_char
```

```
Input text: "other measure of " -> Predicted next character: "a"
Input text: "other measure of a" -> Predicted next character: " "
Input text: "other measure of a " -> Predicted next character: "+"
Input text: "other measure of a +" -> Predicted next character: " "
Input text: "other measure of a + " -> Predicted next character: "b"
Input text: "other measure of a + b" -> Predicted next character: " "
Input text: "other measure of a + b " -> Predicted next character: "a"
Input text: "other measure of a + b a" -> Predicted next character: "n"
```

```
Input text: "other measure of a + b an" -> Predicted next character: "d"
Input text: "other measure of a + b and" -> Predicted next character: " "
Input text: "other measure of a + b and " -> Predicted next character: "w"
Input text: "other measure of a + b and w" -> Predicted next character: "h"
Input text: "other measure of a + b and wh" -> Predicted next character: "i"
Input text: "other measure of a + b and whi" -> Predicted next character: "c"
Input text: "other measure of a + b and whic" -> Predicted next character: "h"
Input text: "other measure of a + b and which" -> Predicted next character: " "
Input text: "other measure of a + b and which " -> Predicted next character: "c"
Input text: "other measure of a + b and which c" -> Predicted next character:
"o"
Input text: "other measure of a + b and which co" -> Predicted next character:
"n"
Input text: "other measure of a + b and which con" -> Predicted next character:
"t"
Input text: "other measure of a + b and which cont" -> Predicted next character:
"a"
Input text: "other measure of a + b and which conta" -> Predicted next
character: "i"
Input text: "other measure of a + b and which contai" -> Predicted next
character: "n"
Input text: "other measure of a + b and which contain" -> Predicted next
character: " "
Input text: "other measure of a + b and which contain " -> Predicted next
character: "f"
Input text: "other measure of a + b and which contain f" -> Predicted next
character: "o"
Input text: "other measure of a + b and which contain fo" -> Predicted next
character: "u"
Input text: "other measure of a + b and which contain fou" -> Predicted next
character: "r"
Input text: "other measure of a + b and which contain four" -> Predicted next
character: " "
Input text: "other measure of a + b and which contain four " -> Predicted next
character: "r"
Input text: "other measure of a + b and which contain four r" -> Predicted next
character: "i"
Input text: "other measure of a + b and which contain four ri" -> Predicted next
character: "g"
Input text: "other measure of a + b and which contain four rig" -> Predicted
next character: "h"
Input text: "other measure of a + b and which contain four righ" -> Predicted
next character: "t"
Input text: "other measure of a + b and which contain four right" -> Predicted
next character: " "
Input text: "other measure of a + b and which contain four right " -> Predicted
next character: "t"
Input text: "other measure of a + b and which contain four right t" -> Predicted
```

```
next character: "r"
Input text: "other measure of a + b and which contain four right tr" ->
Predicted next character: "i"
Input text: "other measure of a + b and which contain four right tri" ->
Predicted next character: "a"
Input text: "other measure of a + b and which contain four right tria" ->
Predicted next character: "n"
Input text: "other measure of a + b and which contain four right trian" ->
Predicted next character: "g"
Input text: "other measure of a + b and which contain four right triang" ->
Predicted next character: "l"
Input text: "other measure of a + b and which contain four right triangl" ->
Predicted next character: "e"
Input text: "other measure of a + b and which contain four right triangle" ->
Predicted next character: "s"
Input text: "other measure of a + b and which contain four right triangles" ->
Predicted next character: " "
Input text: "other measure of a + b and which contain four right triangles " ->
Predicted next character: "a"
Input text: "other measure of a + b and which contain four right triangles a" ->
Predicted next character: "r"
Input text: "other measure of a + b and which contain four right triangles ar"
-> Predicted next character: "e"
Input text: "other measure of a + b and which contain four right triangles are"
-> Predicted next character: " "
Input text: "other measure of a + b and which contain four right triangles are "
-> Predicted next character: "m"
```

[37]:

```
import torch
import torch.nn as nn
import torch.optim as optim

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

class LSTMModel(nn.Module):
    def __init__(self):
        super(LSTMModel, self).__init__()  # Corrected super call
        self.rnn = nn.LSTM(input_size=1, hidden_size=5, num_layers=1,␣
 ↪batch_first=True)
        self.fc = nn.Linear(in_features=5, out_features=1)

    def forward(self, x):
        output, _status = self.rnn(x)
        output = output[:, -1, :]
        output = self.fc(torch.relu(output))
        return output
```

```
data = list(range(25))
x, y = [], []

for i in range(5, 25):
    x.append(data[i-5:i])
    y.append(data[i])

x, y = torch.Tensor(x), torch.Tensor(y)

x, y = x.unsqueeze(2).to(device), y.to(device)  # Add channel dim & move to␣
↪device

model = LSTMModel().to(device)
optimizer = optim.Adam(model.parameters(), lr=1e-2)
criterion = nn.MSELoss()

num_epochs = 200

for epoch in range(num_epochs):
    model.train()
    running_loss = 0.0

    for i in range(x.size(0)):
        optimizer.zero_grad()

        x_data = x[i].unsqueeze(0)  # Add batch dim
        y_data = y[i].unsqueeze(0)

        outputs = model(x_data)
        loss = criterion(outputs, y_data)

        running_loss += loss.item()

        loss.backward()
        optimizer.step()

    epoch_loss = running_loss / x.size(0)  # Fix loss calculation
    print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {epoch_loss:.4f}")
```

```
Epoch [1/200], Loss: 229.8332
Epoch [2/200], Loss: 207.3425
Epoch [3/200], Loss: 187.7792
Epoch [4/200], Loss: 161.3871
Epoch [5/200], Loss: 139.8797
Epoch [6/200], Loss: 123.9630
Epoch [7/200], Loss: 110.7329
Epoch [8/200], Loss: 99.4736
Epoch [9/200], Loss: 89.7901
```

```
Epoch [10/200], Loss: 81.4237
Epoch [11/200], Loss: 74.1824
Epoch [12/200], Loss: 67.9051
Epoch [13/200], Loss: 62.2994
Epoch [14/200], Loss: 56.1175
Epoch [15/200], Loss: 52.4789
Epoch [16/200], Loss: 48.2047
Epoch [17/200], Loss: 43.3130
Epoch [18/200], Loss: 39.2585
Epoch [19/200], Loss: 36.1624
Epoch [20/200], Loss: 33.2499
Epoch [21/200], Loss: 31.8214
Epoch [22/200], Loss: 28.0892
Epoch [23/200], Loss: 26.3870
Epoch [24/200], Loss: 24.7491
Epoch [25/200], Loss: 24.0487
Epoch [26/200], Loss: 20.5353
Epoch [27/200], Loss: 19.0391
Epoch [28/200], Loss: 17.6175
Epoch [29/200], Loss: 16.5821
Epoch [30/200], Loss: 15.2909
Epoch [31/200], Loss: 14.9130
Epoch [32/200], Loss: 13.2505
Epoch [33/200], Loss: 12.9660
Epoch [34/200], Loss: 11.5164
Epoch [35/200], Loss: 11.4066
Epoch [36/200], Loss: 10.1382
Epoch [37/200], Loss: 10.2135
Epoch [38/200], Loss: 8.9713
Epoch [39/200], Loss: 9.0589
Epoch [40/200], Loss: 8.1215
Epoch [41/200], Loss: 8.4079
Epoch [42/200], Loss: 7.3268
Epoch [43/200], Loss: 7.3583
Epoch [44/200], Loss: 6.4463
Epoch [45/200], Loss: 6.5029
Epoch [46/200], Loss: 5.6641
Epoch [47/200], Loss: 5.7577
Epoch [48/200], Loss: 4.8090
Epoch [49/200], Loss: 4.9176
Epoch [50/200], Loss: 4.3398
Epoch [51/200], Loss: 4.6006
Epoch [52/200], Loss: 4.1895
Epoch [53/200], Loss: 4.6025
Epoch [54/200], Loss: 3.5368
Epoch [55/200], Loss: 3.7587
Epoch [56/200], Loss: 3.4969
Epoch [57/200], Loss: 3.9022
```

```
Epoch [58/200], Loss: 2.9077
Epoch [59/200], Loss: 3.1684
Epoch [60/200], Loss: 2.7369
Epoch [61/200], Loss: 3.0902
Epoch [62/200], Loss: 2.8291
Epoch [63/200], Loss: 3.1845
Epoch [64/200], Loss: 2.2581
Epoch [65/200], Loss: 2.5538
Epoch [66/200], Loss: 2.1595
Epoch [67/200], Loss: 2.5002
Epoch [68/200], Loss: 2.3288
Epoch [69/200], Loss: 2.6428
Epoch [70/200], Loss: 1.8367
Epoch [71/200], Loss: 2.1422
Epoch [72/200], Loss: 1.7205
Epoch [73/200], Loss: 2.0695
Epoch [74/200], Loss: 1.9102
Epoch [75/200], Loss: 2.2512
Epoch [76/200], Loss: 1.6704
Epoch [77/200], Loss: 2.0370
Epoch [78/200], Loss: 1.5802
Epoch [79/200], Loss: 1.8751
Epoch [80/200], Loss: 1.6387
Epoch [81/200], Loss: 1.9199
Epoch [82/200], Loss: 1.4897
Epoch [83/200], Loss: 1.7181
Epoch [84/200], Loss: 1.3220
Epoch [85/200], Loss: 1.5305
Epoch [86/200], Loss: 1.3400
Epoch [87/200], Loss: 1.6469
Epoch [88/200], Loss: 1.2373
Epoch [89/200], Loss: 1.4559
Epoch [90/200], Loss: 1.2015
Epoch [91/200], Loss: 1.4374
Epoch [92/200], Loss: 1.3420
Epoch [93/200], Loss: 1.4553
Epoch [94/200], Loss: 0.9508
Epoch [95/200], Loss: 1.2322
Epoch [96/200], Loss: 0.9974
Epoch [97/200], Loss: 1.3308
Epoch [98/200], Loss: 1.2045
Epoch [99/200], Loss: 1.4230
Epoch [100/200], Loss: 1.0770
Epoch [101/200], Loss: 1.2799
Epoch [102/200], Loss: 1.1397
Epoch [103/200], Loss: 1.3454
Epoch [104/200], Loss: 1.1424
Epoch [105/200], Loss: 1.2107
```

```
Epoch [106/200], Loss: 0.8920
Epoch [107/200], Loss: 1.2152
Epoch [108/200], Loss: 1.0158
Epoch [109/200], Loss: 1.1918
Epoch [110/200], Loss: 1.0059
Epoch [111/200], Loss: 1.1090
Epoch [112/200], Loss: 0.8654
Epoch [113/200], Loss: 0.9951
Epoch [114/200], Loss: 0.8953
Epoch [115/200], Loss: 0.9736
Epoch [116/200], Loss: 0.7552
Epoch [117/200], Loss: 0.8531
Epoch [118/200], Loss: 0.7685
Epoch [119/200], Loss: 0.8512
Epoch [120/200], Loss: 0.7923
Epoch [121/200], Loss: 0.8666
Epoch [122/200], Loss: 0.7586
Epoch [123/200], Loss: 0.7789
Epoch [124/200], Loss: 0.6484
Epoch [125/200], Loss: 0.6817
Epoch [126/200], Loss: 0.6517
Epoch [127/200], Loss: 0.6812
Epoch [128/200], Loss: 0.6164
Epoch [129/200], Loss: 0.6283
Epoch [130/200], Loss: 0.5944
Epoch [131/200], Loss: 0.6036
Epoch [132/200], Loss: 0.5557
Epoch [133/200], Loss: 0.5504
Epoch [134/200], Loss: 0.5231
Epoch [135/200], Loss: 0.5171
Epoch [136/200], Loss: 0.4847
Epoch [137/200], Loss: 0.4721
Epoch [138/200], Loss: 0.4483
Epoch [139/200], Loss: 0.4332
Epoch [140/200], Loss: 0.4072
Epoch [141/200], Loss: 0.3949
Epoch [142/200], Loss: 0.3795
Epoch [143/200], Loss: 0.3655
Epoch [144/200], Loss: 0.3484
Epoch [145/200], Loss: 0.3376
Epoch [146/200], Loss: 0.3265
Epoch [147/200], Loss: 0.3161
Epoch [148/200], Loss: 0.3055
Epoch [149/200], Loss: 0.2970
Epoch [150/200], Loss: 0.2891
Epoch [151/200], Loss: 0.2814
Epoch [152/200], Loss: 0.2740
Epoch [153/200], Loss: 0.2674
```

```
Epoch [154/200], Loss: 0.2608
Epoch [155/200], Loss: 0.2548
Epoch [156/200], Loss: 0.2485
Epoch [157/200], Loss: 0.2431
Epoch [158/200], Loss: 0.2368
Epoch [159/200], Loss: 0.2319
Epoch [160/200], Loss: 0.2256
Epoch [161/200], Loss: 0.2209
Epoch [162/200], Loss: 0.2146
Epoch [163/200], Loss: 0.2102
Epoch [164/200], Loss: 0.2036
Epoch [165/200], Loss: 0.1993
Epoch [166/200], Loss: 0.1926
Epoch [167/200], Loss: 0.1884
Epoch [168/200], Loss: 0.1816
Epoch [169/200], Loss: 0.1774
Epoch [170/200], Loss: 0.1703
Epoch [171/200], Loss: 0.1662
Epoch [172/200], Loss: 0.1590
Epoch [173/200], Loss: 0.1549
Epoch [174/200], Loss: 0.1477
Epoch [175/200], Loss: 0.1436
Epoch [176/200], Loss: 0.1365
Epoch [177/200], Loss: 0.1324
Epoch [178/200], Loss: 0.1256
Epoch [179/200], Loss: 0.1217
Epoch [180/200], Loss: 0.1153
Epoch [181/200], Loss: 0.1118
Epoch [182/200], Loss: 0.1064
Epoch [183/200], Loss: 0.1035
Epoch [184/200], Loss: 0.0995
Epoch [185/200], Loss: 0.0977
Epoch [186/200], Loss: 0.0962
Epoch [187/200], Loss: 0.0961
Epoch [188/200], Loss: 0.0987
Epoch [189/200], Loss: 0.1014
Epoch [190/200], Loss: 0.1106
Epoch [191/200], Loss: 0.1164
Epoch [192/200], Loss: 0.1334
Epoch [193/200], Loss: 0.1391
Epoch [194/200], Loss: 0.1524
Epoch [195/200], Loss: 0.1472
Epoch [196/200], Loss: 0.1276
Epoch [197/200], Loss: 0.1069
Epoch [198/200], Loss: 0.0641
Epoch [199/200], Loss: 0.0569
Epoch [200/200], Loss: 0.0889
```

[38]:

```
x = torch.Tensor([1, 2, 3, 4, 5])
x = x.unsqueeze(0).unsqueeze(2).to(device)

with torch.no_grad():
    out = model(x)
    print(out)
```

```
tensor([[5.7834]], device='cuda:0')
```

[ ]:

```

```