Homework 4 - Dario Placencio

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1 Homework 4 - Dario Placencio

```python
# import the necessary packages
import numpy as np
import pandas as pd
import os
import torch
import torchvision
import torchvision.transforms as transforms
import torch.nn as nn
import torch.optim as optim
import matplotlib
matplotlib.use('Agg')
import matplotlib.pyplot as plt
from IPython.display import Image
import plotly.io as pio
```

1.0.1 3 - Language Identification with Naive Bayes

1. Use files 0.txt to 9.txt in each language as the training data. Estimate the prior probabilities $\hat{p}(y = e)$, $\hat{p}(y = j)$, $\hat{p}(y = s)$ using additive smoothing with parameter $\frac{1}{2}$. Give the formula for additive smoothing with parameter $\frac{1}{2}$ in this case. Print and include in final report the prior probabilities. (Hint: Store all probabilities here and below in log() internally to avoid underflow. This also means you need to do arithmetic in log-space. But answer questions with probability, not log probability.)

```python
# Adjust the extract_path to point directly to the languageID folder
extract_path = 'languageID'
```

```python
# Read the contents of the training files
def read_files(lang, start, end):
    """Read files for a given language between start and end indices."""
    contents = ""
    for i in range(start, end + 1):
        with open(os.path.join(extract_path, f"{lang}{i}.txt"), 'r',
    errors='ignore') as f:
            contents += f.read()
    return contents
```

```
# Extract training data for each language
english_train = read_files('e', 0, 9)
spanish_train = read_files('s', 0, 9)
japanese_train = read_files('j', 0, 9)

len(english_train), len(spanish_train), len(japanese_train)
```

[ ]: (15339, 16500, 15496)

```
# Given data and smoothing parameters
N_y = 10   # Number of English training documents
N = 30     # Total number of training documents
alpha = 0.5  # Smoothing parameter
V = 3   # Number of classes (languages)

# Compute smoothed prior probability for English
p_e_smoothed = (N_y + alpha) / (N + alpha * V)
p_e_smoothed
```

[ ]: 0.3333333333333333

```
# Store as log probabilities
p_e_smoothed = np.log(p_e_smoothed)
```

```
# Compute smoothed prior probability for Spanish
p_s_smoothed = (N_y + alpha) / (N + alpha * V)
p_s_smoothed
```

[ ]: 0.3333333333333333

```
# Store as log probabilities
p_s_smoothed = np.log(p_s_smoothed)
```

```
# Compute smoothed prior probability for Japanese
p_j_smoothed = (N_y + alpha) / (N + alpha * V)
p_j_smoothed
```

[ ]: 0.3333333333333333

```
# Store as log probabilities
p_j_smoothed = np.log(p_j_smoothed)
```

2. Using the same training data, estimate the class conditional probability (multinomial parameter) for English $\theta_{i,e} := \hat{p}(c_i \mid y = e)$ where c_i is the i-th character. That is, $c_1 = a, ..., c_{26} = z, c_{27} = space$.

Again use additive smoothing with parameter $\frac{1}{2}$. Give the formula for additive smoothing with parameter $\frac{1}{2}$ in this case.

Print θ_e and include in final report which is a vector with 27 elements.

```python
from collections import defaultdict

# Function to count the frequency of each character in a given text
def char_frequencies(text):
    freq = defaultdict(int)
    for char in text:
        # Only consider lowercase alphabets and space
        if char in 'abcdefghijklmnopqrstuvwxyz ':
            freq[char] += 1
    return freq

# Assuming english_train contains the combined content of English training files
english_freq = char_frequencies(english_train)

# Compute the total number of characters in the English training data
total_english_chars = sum(english_freq.values())

# Vocabulary
vocabulary = 'abcdefghijklmnopqrstuvwxyz '

# Smoothing parameter
alpha = 0.5

# Compute the class conditional probabilities for English
theta_e = {}
for char in vocabulary:
    theta_e[char] = (english_freq[char] + alpha) / (total_english_chars + alpha
    * len(vocabulary))

print(theta_e)
```

```
{'a': 0.0601685114819098, 'b': 0.011134974392863043, 'c': 0.021509995043779945,
'd': 0.021972575582355856, 'e': 0.1053692383941847, 'f': 0.018932760614571286,
'g': 0.017478936064761277, 'h': 0.047216256401784236, 'i': 0.055410540227986124,
'j': 0.001420783082768875, 'k': 0.0037336857756484387, 'l':
0.028977366595076822, 'm': 0.020518751032545846, 'n': 0.057921691723112505, 'o':
0.06446390219725756, 'p': 0.01675202378985627, 'q': 0.0005617049396993227, 'r':
0.053824549810011564, 's': 0.06618205848339666, 't': 0.08012555757475633, 'u':
0.026664463902197257, 'v': 0.009284652238559392, 'w': 0.015496448042293078, 'x':
0.001156451346439782, 'y': 0.013844374690236246, 'z': 0.0006277878737815959, '
': 0.1792499586981662}
```

```python
# Store as log probabilities
for char in vocabulary:
    theta_e[char] = np.log(theta_e[char])
```

3. Print θ_j, θ_s and include in final report the class conditional probabilities for Japanese and

3

Spanish.

```python
# Compute character frequencies for Japanese and Spanish
japanese_freq = char_frequencies(japanese_train)
spanish_freq = char_frequencies(spanish_train)

# Compute the total number of characters in the Japanese and Spanish training␣
 ↪data
total_japanese_chars = sum(japanese_freq.values())
total_spanish_chars = sum(spanish_freq.values())

# Compute the class conditional probabilities for Japanese
theta_j = {}
for char in vocabulary:
    theta_j[char] = (japanese_freq[char] + alpha) / (total_japanese_chars +␣
 ↪alpha * len(vocabulary))

# Compute the class conditional probabilities for Spanish
theta_s = {}
for char in vocabulary:
    theta_s[char] = (spanish_freq[char] + alpha) / (total_spanish_chars + alpha␣
 ↪* len(vocabulary))

print("Theta_j:", theta_j)
print("Theta_s:", theta_s)
```

```
Theta_j: {'a': 0.1317656102589189, 'b': 0.010866906600510151, 'c':
0.005485866033054963, 'd': 0.01722631818022992, 'e': 0.06020475907613823, 'f':
0.003878542227191726, 'g': 0.014011670568503443, 'h': 0.03176211607673224, 'i':
0.09703343932352633, 'j': 0.0023411020650616725, 'k': 0.05740941332681086, 'l':
0.001432614696530277, 'm': 0.03979873510604843, 'n': 0.05671057688947902, 'o':
0.09116321324993885, 'p': 0.0008735455466648031, 'q': 0.00010482546559977637,
'r': 0.04280373178657535, 's': 0.0421747789929767, 't': 0.056990111464411755,
'u': 0.07061742199238269, 'v': 0.0002445927530661449, 'w': 0.01974212935462455,
'x': 3.4941821866592126e-05, 'y': 0.01415143785596981, 'z': 0.00772214263251686,
' ': 0.12344945665466997}
Theta_s: {'a': 0.10456045141993771, 'b': 0.008232863618143134, 'c':
0.03752582405722919, 'd': 0.039745922111559924, 'e': 0.1138108599796491, 'f':
0.00860287996053159, 'g': 0.0071844839813758445, 'h': 0.0045327001942585795,
'i': 0.049859702136844375, 'j': 0.006629459467793161, 'k':
0.0002775122567913416, 'l': 0.052943171656748174, 'm': 0.02580863988159477, 'n':
0.054176559464709693, 'o': 0.07249236841293824, 'p': 0.02426690512164287, 'q':
0.007677839104560451, 'r': 0.05929511886774999, 's': 0.06577040485954797, 't':
0.03561407295488884, 'u': 0.03370232185254849, 'v': 0.00588942678301625, 'w':
9.250408559711388e-05, 'x': 0.0024976103111220747, 'y': 0.007862847275754679,
'z': 0.0026826184823163022, ' ': 0.16826493170115014}
```

```python
# Store as log probabilities
for char in vocabulary:
    theta_j[char] = np.log(theta_j[char])
    theta_s[char] = np.log(theta_s[char])
```

4. Treat e10.txt as a test document x. Represent x as a bag-of-words count vector (Hint: the vocabulary has size 27).

Print the bag-of-words vector x and include in final report.

```python
# Read the content of e10.txt
with open('languageID/e10.txt', 'r', errors='ignore') as f:
    test_content = f.read()

# Compute character frequencies for the test content
test_freq = char_frequencies(test_content)

# Create the bag-of-words vector
bow_vector = [test_freq[char] for char in vocabulary]

print("Bag-of-Words Vector:", bow_vector)
```

Bag-of-Words Vector: [164, 32, 53, 57, 311, 55, 51, 140, 140, 3, 6, 85, 64, 139, 182, 53, 3, 141, 186, 225, 65, 31, 47, 4, 38, 2, 498]

5. Compute $\hat{p}(x \mid y)$ for $y = e, j, s$ under the multinomial model assumption, respectively. Use the formula $\hat{p}(x \mid y) = \prod_{i=1}^{d} \theta_{i,y}^{x_i}$ where $x = (x_1, \ldots, x_d)$.

Show the three values: $\hat{p}(x \mid y = e), \hat{p}(x \mid y = j), \hat{p}(x \mid y = s)$.

Hint: you may notice that we omitted the multinomial coefficient. This is ok for classification because it is a constant w.r.t. y.

```python
import math

# Function to compute the log-probability log(p(x|y)) for a given language and
# →its log(theta) values
def compute_log_probability(bow_vector, log_theta_values):
    log_prob = 0
    for xi, char in zip(bow_vector, vocabulary):
        log_prob += xi * log_theta_values[char]
    return log_prob

# Compute log(p(x|y)) for each language
log_p_x_given_e = compute_log_probability(bow_vector, theta_e)
log_p_x_given_j = compute_log_probability(bow_vector, theta_j)
log_p_x_given_s = compute_log_probability(bow_vector, theta_s)

print("log(p(x|y=e)):", log_p_x_given_e)
print("log(p(x|y=j)):", log_p_x_given_j)
```

```
print("log(p(x|y=s)):", log_p_x_given_s)
```

```
log(p(x|y=e)): -7841.865447060635
log(p(x|y=j)): -8771.433079075032
log(p(x|y=s)): -8467.282044010557
```

```python
[ ]: # Convert the log probabilities back to regular probabilities
     p_x_given_e = math.exp(log_p_x_given_e)
     p_x_given_j = math.exp(log_p_x_given_j)
     p_x_given_s = math.exp(log_p_x_given_s)

     print("p(x|y=e):", p_x_given_e)
     print("p(x|y=j):", p_x_given_j)
     print("p(x|y=s):", p_x_given_s)
```

```
p(x|y=e): 0.0
p(x|y=j): 0.0
p(x|y=s): 0.0
```

```python
[ ]: # Print p_x_given_e, p_x_given_j, and p_x_given_s with 10 decimal places
     print("p(x|y=e): {:.10f}".format(p_x_given_e))
     print("p(x|y=j): {:.10f}".format(p_x_given_j))
     print("p(x|y=s): {:.10f}".format(p_x_given_s))
```

```
p(x|y=e): 0.0000000000
p(x|y=j): 0.0000000000
p(x|y=s): 0.0000000000
```

6. Use Bayes rule and your estimated prior and likelihood, compute the posterior $\hat{p}(y \mid x)$.

Show the three values: $\hat{p}(y = e \mid x), \hat{p}(y = j \mid x), \hat{p}(y = s \mid x)$.

Show the predicted class label of x.

```python
[ ]: # Compute log posterior for each language using the log priors
     log_posterior_e = log_p_x_given_e + p_e_smoothed
     log_posterior_j = log_p_x_given_j + p_j_smoothed
     log_posterior_s = log_p_x_given_s + p_s_smoothed

     # Normalize log posteriors by subtracting the max value among them
     max_log_posterior = max(log_posterior_e, log_posterior_j, log_posterior_s)

     # Convert normalized log posteriors back to regular probabilities
     posterior_e = math.exp(log_posterior_e - max_log_posterior)
     posterior_j = math.exp(log_posterior_j - max_log_posterior)
     posterior_s = math.exp(log_posterior_s - max_log_posterior)

     # Normalize the posteriors to sum to 1
     normalizing_factor = posterior_e + posterior_j + posterior_s
     normalized_posterior_e = posterior_e / normalizing_factor
```

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```
normalized_posterior_j = posterior_j / normalizing_factor
normalized_posterior_s = posterior_s / normalizing_factor

# Determine the predicted class label
predicted_class_label = max([('e', normalized_posterior_e), ('j',␣
 ↪normalized_posterior_j), ('s', normalized_posterior_s)], key=lambda x:␣
 ↪x[1])[0]

print("p(y=e|x):", normalized_posterior_e)
print("p(y=j|x):", normalized_posterior_j)
print("p(y=s|x):", normalized_posterior_s)
print("Predicted class label:", predicted_class_label)
```

```
p(y=e|x): 1.0
p(y=j|x): 0.0
p(y=s|x): 2.4267389118368303e-272
Predicted class label: e
```

7. Evaluate the performance of your classifier on the test set (files 10.txt to 19.txt in three languages).

Present the performance using a confusion matrix. A confusion matrix summarizes the types of errors your classifier makes, as shown in the table below. The columns are the true language a document is in, and the rows are the classified outcome of that document. The cells are the number of test documents in that situation. For example, the cell with row = English and column = Spanish contains the number of test documents that are really Spanish, but misclassified as English by your classifier.

```
[ ]: def predict_language(document):
         bow_vector = [document.count(char) for char in vocabulary]
         log_p_x_given_e = compute_log_probability(bow_vector, theta_e)
         log_p_x_given_j = compute_log_probability(bow_vector, theta_j)
         log_p_x_given_s = compute_log_probability(bow_vector, theta_s)
         log_posterior_e = log_p_x_given_e + p_e_smoothed
         log_posterior_j = log_p_x_given_j + p_j_smoothed
         log_posterior_s = log_p_x_given_s + p_s_smoothed
         predicted_class_label = max([('e', log_posterior_e), ('j',␣
     ↪log_posterior_j), ('s', log_posterior_s)], key=lambda x: x[1])[0]
         return predicted_class_label

     # Confusion matrix evaluation
     languages = ['e', 'j', 's']
     confusion_matrix = {lang1: {lang2: 0 for lang2 in languages} for lang1 in␣
      ↪languages}

     base_path = "languageID/"
     for lang in languages:
         for i in range(10, 20):
```

```
        filename = os.path.join(base_path, f"{lang}{i}.txt")
        with open(filename, 'r', encoding='utf-8', errors='ignore') as file:
            document = file.read().lower()
        predicted_label = predict_language(document)
        confusion_matrix[predicted_label][lang] += 1  # Rows: Predicted,␣
 ↪Columns: True


print(confusion_matrix)
```

{'e': {'e': 10, 'j': 0, 's': 0}, 'j': {'e': 0, 'j': 10, 's': 0}, 's': {'e': 0,
'j': 0, 's': 10}}

1.0.2   4 - Simple Feed-Forward Network

2. Implement it in NumPy or PyTorch using basic linear algebra operations. (e.g. You are
   not allowed to use auto-grad, built-in optimizer, model, etc. in this step. You can use
   library functions for data loading, processing, etc.). Evaluate your implementation on MNIST
   dataset, report test errors and learning curve. (10 pts)

```
[ ]: # Load the MNIST dataset

     # Transform the data to torch tensors and normalize it
     transform = transforms.Compose([transforms.ToTensor(),
                                     transforms.Normalize((0.5,), (0.5,))])

     # Load the training and test datasets
     train_dataset = torchvision.datasets.MNIST(root='./data', train=True,␣
      ↪transform=transform, download=True)
     test_dataset = torchvision.datasets.MNIST(root='./data', train=False,␣
      ↪transform=transform, download=True)


     train_loader = torch.utils.data.DataLoader(dataset=train_dataset,␣
      ↪batch_size=100, shuffle=True)
     test_loader = torch.utils.data.DataLoader(dataset=test_dataset, batch_size=100,␣
      ↪shuffle=False)
```

```
[ ]: # Define the Network Architecture

     input_size = 28*28   # MNIST images are 28x28
     hidden_size1 = 300   # First hidden layer
     hidden_size2 = 200   # Second hidden layer
     output_size = 10    # Number of output classes (digits 0-9)

     # Initialize weights and biases with Xavier initialization
     W1 = torch.randn(input_size, hidden_size1) * torch.sqrt(torch.tensor(2. /␣
      ↪(input_size + hidden_size1)))
     W1.requires_grad_()
     b1 = torch.randn(hidden_size1, requires_grad=True)
```

```python
W2 = torch.randn(hidden_size1, hidden_size2) * torch.sqrt(torch.tensor(2. /␣
 ↪(hidden_size1 + hidden_size2)))
W2.requires_grad_()
b2 = torch.randn(hidden_size2, requires_grad=True)

W3 = torch.randn(hidden_size2, output_size) * torch.sqrt(torch.tensor(2. /␣
 ↪(hidden_size2 + output_size)))
W3.requires_grad_()
b3 = torch.randn(output_size, requires_grad=True)
```

```python
# Implement Forward and Backward Passes

def sigmoid(x):
    return 1 / (1 + torch.exp(-x))

def softmax(x):
    return torch.exp(x) / torch.sum(torch.exp(x), dim=1).view(-1, 1)

def forward(x):
    z1 = torch.mm(x, W1) + b1
    a1 = sigmoid(z1)
    z2 = torch.mm(a1, W2) + b2
    a2 = sigmoid(z2)
    z3 = torch.mm(a2, W3) + b3
    y_hat = softmax(z3)
    return y_hat, a1
```

```python
# Train the Network

learning_rate = 1e-5
num_epochs = 10
batch_size = 64
train_loader = torch.utils.data.DataLoader(dataset=train_dataset,␣
 ↪batch_size=batch_size, shuffle=True)
loss_list = []

for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):
        images = images.view(-1, 28*28)

        # Forward pass
        y_hat, a1 = forward(images)

        # Convert labels to one-hot encoding
        labels_onehot = torch.zeros(labels.size(0), 10)
        labels_onehot.scatter_(1, labels.view(-1, 1), 1)
```

```python
        # Compute the loss
        epsilon = 1e-7
        loss = -torch.sum(labels_onehot * torch.log(y_hat + epsilon))

        # Backward pass
        # Compute gradients
        loss.backward()

        # Update weights and biases
        with torch.no_grad():
            W1 -= learning_rate * W1.grad
            b1 -= learning_rate * b1.grad
            W2 -= learning_rate * W2.grad
            b2 -= learning_rate * b2.grad
            W3 -= learning_rate * W3.grad
            b3 -= learning_rate * b3.grad

            # Set gradients to zero for the next iteration
            W1.grad.zero_()
            b1.grad.zero_()
            W2.grad.zero_()
            b2.grad.zero_()
            W3.grad.zero_()
            b3.grad.zero_()

        if (i+1) % 100 == 0:
            print(f'Epoch [{epoch+1}/{num_epochs}], Step [{i+1}/
 ↪{len(train_loader)}], Loss: {loss.item()}')
            loss_list.append(loss.item())
```

```
Epoch [1/10], Step [100/938], Loss: 150.44065856933594
Epoch [1/10], Step [200/938], Loss: 158.19175720214844
Epoch [1/10], Step [300/938], Loss: 152.0260009765625
Epoch [1/10], Step [400/938], Loss: 149.39987182617188
Epoch [1/10], Step [500/938], Loss: 150.20960998535156
Epoch [1/10], Step [600/938], Loss: 150.26626586914062
Epoch [1/10], Step [700/938], Loss: 147.4139862060547
Epoch [1/10], Step [800/938], Loss: 144.841796875
Epoch [1/10], Step [900/938], Loss: 145.0714569091797
Epoch [2/10], Step [100/938], Loss: 144.92933654785156
Epoch [2/10], Step [200/938], Loss: 145.10665893554688
Epoch [2/10], Step [300/938], Loss: 145.93634033203125
Epoch [2/10], Step [400/938], Loss: 144.9344482421875
Epoch [2/10], Step [500/938], Loss: 145.16329956054688
Epoch [2/10], Step [600/938], Loss: 145.87161254882812
Epoch [2/10], Step [700/938], Loss: 144.6089324951172
Epoch [2/10], Step [800/938], Loss: 145.76742553710938
```

```
Epoch [2/10], Step [900/938], Loss: 145.1107177734375
Epoch [3/10], Step [100/938], Loss: 144.79183959960938
Epoch [3/10], Step [200/938], Loss: 144.9639892578125
Epoch [3/10], Step [300/938], Loss: 144.24851989746094
Epoch [3/10], Step [400/938], Loss: 144.83367919921875
Epoch [3/10], Step [500/938], Loss: 144.0528106689453
Epoch [3/10], Step [600/938], Loss: 143.10714721679688
Epoch [3/10], Step [700/938], Loss: 143.80262756347656
Epoch [3/10], Step [800/938], Loss: 144.7071533203125
Epoch [3/10], Step [900/938], Loss: 144.11297607421875
Epoch [4/10], Step [100/938], Loss: 144.13900756835938
Epoch [4/10], Step [200/938], Loss: 144.18218994140625
Epoch [4/10], Step [300/938], Loss: 143.67921447753906
Epoch [4/10], Step [400/938], Loss: 144.0732879638672
Epoch [4/10], Step [500/938], Loss: 143.0061492919922
Epoch [4/10], Step [600/938], Loss: 143.6227569580078
Epoch [4/10], Step [700/938], Loss: 142.7310333251953
Epoch [4/10], Step [800/938], Loss: 142.706787109375
Epoch [4/10], Step [900/938], Loss: 143.005859375
Epoch [5/10], Step [100/938], Loss: 142.14376831054688
Epoch [5/10], Step [200/938], Loss: 142.5039825439453
Epoch [5/10], Step [300/938], Loss: 143.33448791503906
Epoch [5/10], Step [400/938], Loss: 142.2433319091797
Epoch [5/10], Step [500/938], Loss: 141.51812744140625
Epoch [5/10], Step [600/938], Loss: 141.9885711669922
Epoch [5/10], Step [700/938], Loss: 143.1004638671875
Epoch [5/10], Step [800/938], Loss: 141.04580688476562
Epoch [5/10], Step [900/938], Loss: 140.5126190185547
Epoch [6/10], Step [100/938], Loss: 141.87103271484375
Epoch [6/10], Step [200/938], Loss: 140.72235107421875
Epoch [6/10], Step [300/938], Loss: 140.95265197753906
Epoch [6/10], Step [400/938], Loss: 141.5476837158203
Epoch [6/10], Step [500/938], Loss: 140.26698303222656
Epoch [6/10], Step [600/938], Loss: 140.1280517578125
Epoch [6/10], Step [700/938], Loss: 140.3040313720703
Epoch [6/10], Step [800/938], Loss: 141.64251708984375
Epoch [6/10], Step [900/938], Loss: 140.82797241210938
Epoch [7/10], Step [100/938], Loss: 139.7085723876953
Epoch [7/10], Step [200/938], Loss: 140.82366943359375
Epoch [7/10], Step [300/938], Loss: 138.39443969726562
Epoch [7/10], Step [400/938], Loss: 141.16297912597656
Epoch [7/10], Step [500/938], Loss: 140.764801025390 62
Epoch [7/10], Step [600/938], Loss: 140.22271728515625
Epoch [7/10], Step [700/938], Loss: 139.89588928222656
Epoch [7/10], Step [800/938], Loss: 139.31581115722656
Epoch [7/10], Step [900/938], Loss: 139.6656951904297
Epoch [8/10], Step [100/938], Loss: 139.0992889404297
Epoch [8/10], Step [200/938], Loss: 139.98033142089844
```

```
Epoch [8/10], Step [300/938], Loss: 138.3582763671875
Epoch [8/10], Step [400/938], Loss: 138.02357482910156
Epoch [8/10], Step [500/938], Loss: 140.56471252441406
Epoch [8/10], Step [600/938], Loss: 136.2198486328125
Epoch [8/10], Step [700/938], Loss: 137.43252563476562
Epoch [8/10], Step [800/938], Loss: 135.9687957763672
Epoch [8/10], Step [900/938], Loss: 138.53297424316406
Epoch [9/10], Step [100/938], Loss: 137.4494171142578
Epoch [9/10], Step [200/938], Loss: 138.25155639648438
Epoch [9/10], Step [300/938], Loss: 137.78530883789062
Epoch [9/10], Step [400/938], Loss: 138.82151794433594
Epoch [9/10], Step [500/938], Loss: 138.03427124023438
Epoch [9/10], Step [600/938], Loss: 139.8271942138672
Epoch [9/10], Step [700/938], Loss: 138.09976196289062
Epoch [9/10], Step [800/938], Loss: 136.7034912109375
Epoch [9/10], Step [900/938], Loss: 138.18231201171875
Epoch [10/10], Step [100/938], Loss: 139.20860290527344
Epoch [10/10], Step [200/938], Loss: 135.65049743652344
Epoch [10/10], Step [300/938], Loss: 138.6070556640625
Epoch [10/10], Step [400/938], Loss: 134.47235107421875
Epoch [10/10], Step [500/938], Loss: 132.58444213867188
Epoch [10/10], Step [600/938], Loss: 135.80419921875
Epoch [10/10], Step [700/938], Loss: 135.9111328125
Epoch [10/10], Step [800/938], Loss: 135.47509765625
Epoch [10/10], Step [900/938], Loss: 134.71739196777344
```

```python
# Test the Network and Report Test Errors

correct = 0
total = 0

with torch.no_grad():
    for images, labels in test_loader:
        images = images.view(-1, 28*28)
        y_hat, _ = forward(images)
        _, predicted = torch.max(y_hat.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum()

print(f'Accuracy of the network on the 10000 test images: {100 * correct /
 ↪total} %')
```

```
Accuracy of the network on the 10000 test images: 54.40999984741211 %
```

```python
import plotly.graph_objects as go

# Create the figure
fig = go.Figure()
```

```python
# Add the loss curve data
fig.add_trace(go.Scatter(y=loss_list, mode='lines', name='Loss'))

# Set the layout for the figure
fig.update_layout(
    title='Training Loss over Time',
    xaxis_title='Iteration',
    yaxis_title='Loss',
    xaxis=dict(showgrid=True, showline=True, showticklabels=True),
    yaxis=dict(showgrid=True, showline=True, showticklabels=True)
)

# Display the figure
fig.show()
```

```python
[ ]: img_bytes = pio.to_image(fig, format="png")
     Image(img_bytes)
```
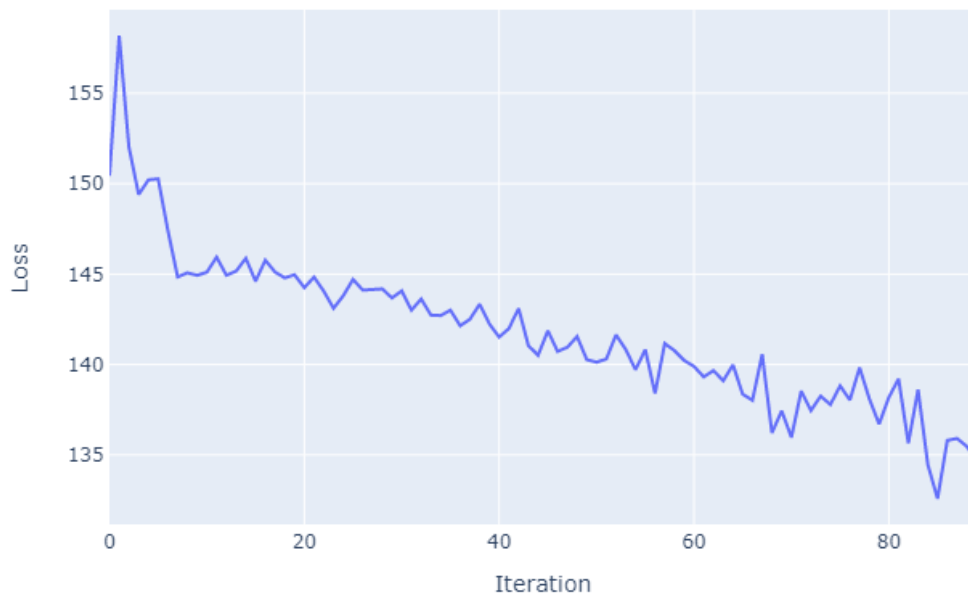
[ ]:

Training Loss over Time

3. Implement the same network in PyTorch (or any other framework). You can use all the features of the framework e.g. auto-grad etc. Evaluate it on MNIST dataset, report test errors, and learning curve. (2 pts)

```python
# Load the training and test datasets
transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.
 ↪5,), (0.5,))])
train_dataset = torchvision.datasets.MNIST(root='./data', train=True,␣
 ↪transform=transform, download=True)
test_dataset = torchvision.datasets.MNIST(root='./data', train=False,␣
 ↪transform=transform)
train_loader = torch.utils.data.DataLoader(dataset=train_dataset,␣
 ↪batch_size=64, shuffle=True)
test_loader = torch.utils.data.DataLoader(dataset=test_dataset, batch_size=64,␣
 ↪shuffle=False)
```

```python
# Define the Network Architecture with Sigmoid for hidden layers
class NeuralNetworkSigmoid(nn.Module):
    def __init__(self, input_size, hidden_size1, hidden_size2, output_size):
        super(NeuralNetworkSigmoid, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size1)
        self.fc2 = nn.Linear(hidden_size1, hidden_size2)
        self.fc3 = nn.Linear(hidden_size2, output_size)
        self.sigmoid = nn.Sigmoid()

        # Xavier (Glorot) Initialization for Sigmoid
        nn.init.xavier_uniform_(self.fc1.weight)
        nn.init.xavier_uniform_(self.fc2.weight)

    def forward(self, x):
        x = self.sigmoid(self.fc1(x))
        x = self.sigmoid(self.fc2(x))
        x = self.fc3(x)   # removed softmax here
        return x

# Initialize the network with the specified dimensions
model_sigmoid = NeuralNetworkSigmoid(28*28, 300, 200, 10)
```

```python
# Set Loss Function and Optimizer
learning_rate = 0.01
optimizer = optim.SGD(model_sigmoid.parameters(), lr=learning_rate)   # SGD␣
 ↪without momentum
```

```python
# Train the Network
num_epochs = 10
loss_list_sigmoid = []
criterion = nn.CrossEntropyLoss()

for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):
        images = images.view(-1, 28*28)
```

```python
        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model_sigmoid(images)

        # Calculate loss
        loss = criterion(outputs, labels)

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

        if (i+1) % 100 == 0:
            print(f'Epoch [{epoch+1}/{num_epochs}], Step [{i+1}/
  ↪{len(train_loader)}], Loss: {loss.item()}')
            loss_list_sigmoid.append(loss.item())
```

```
Epoch [1/10], Step [100/938], Loss: 2.292510747909546
Epoch [1/10], Step [200/938], Loss: 2.2745885848999023
Epoch [1/10], Step [300/938], Loss: 2.236137866973877
Epoch [1/10], Step [400/938], Loss: 2.2385945320129395
Epoch [1/10], Step [500/938], Loss: 2.246877431869507
Epoch [1/10], Step [600/938], Loss: 2.2270617485046387
Epoch [1/10], Step [700/938], Loss: 2.2525980472564697
Epoch [1/10], Step [800/938], Loss: 2.221071243286133
Epoch [1/10], Step [900/938], Loss: 2.1858716011047363
Epoch [2/10], Step [100/938], Loss: 2.1568338871002197
Epoch [2/10], Step [200/938], Loss: 2.119809150695801
Epoch [2/10], Step [300/938], Loss: 2.0830423831939697
Epoch [2/10], Step [400/938], Loss: 2.0672149658203125
Epoch [2/10], Step [500/938], Loss: 1.9432536363601685
Epoch [2/10], Step [600/938], Loss: 1.9893263578414917
Epoch [2/10], Step [700/938], Loss: 1.715041160583496
Epoch [2/10], Step [800/938], Loss: 1.8554497957229614
Epoch [2/10], Step [900/938], Loss: 1.6881569623947144
Epoch [3/10], Step [100/938], Loss: 1.6012632846832275
Epoch [3/10], Step [200/938], Loss: 1.6248172521591187
Epoch [3/10], Step [300/938], Loss: 1.4931164979934692
Epoch [3/10], Step [400/938], Loss: 1.423913836479187
Epoch [3/10], Step [500/938], Loss: 1.5174356698989868
Epoch [3/10], Step [600/938], Loss: 1.3259869813919067
Epoch [3/10], Step [700/938], Loss: 1.2630555629730225
Epoch [3/10], Step [800/938], Loss: 1.1542565822601318
Epoch [3/10], Step [900/938], Loss: 1.1549248695373535
Epoch [4/10], Step [100/938], Loss: 1.037700891494751
Epoch [4/10], Step [200/938], Loss: 1.0694125890731812
```

```
Epoch [4/10], Step [300/938], Loss: 0.9972710013389587
Epoch [4/10], Step [400/938], Loss: 1.0252350568771362
Epoch [4/10], Step [500/938], Loss: 1.0819385051727295
Epoch [4/10], Step [600/938], Loss: 1.0091618299484253
Epoch [4/10], Step [700/938], Loss: 0.8767440319061279
Epoch [4/10], Step [800/938], Loss: 0.7152828574180603
Epoch [4/10], Step [900/938], Loss: 0.8610665798187256
Epoch [5/10], Step [100/938], Loss: 0.9560669660568237
Epoch [5/10], Step [200/938], Loss: 0.7160088419914246
Epoch [5/10], Step [300/938], Loss: 0.8273577690124512
Epoch [5/10], Step [400/938], Loss: 0.7674003839492798
Epoch [5/10], Step [500/938], Loss: 0.82974773645401
Epoch [5/10], Step [600/938], Loss: 0.7529183030128479
Epoch [5/10], Step [700/938], Loss: 0.6722601652145386
Epoch [5/10], Step [800/938], Loss: 0.7306991815567017
Epoch [5/10], Step [900/938], Loss: 0.7301172614097595
Epoch [6/10], Step [100/938], Loss: 0.7639034390449524
Epoch [6/10], Step [200/938], Loss: 0.76024520397186628
Epoch [6/10], Step [300/938], Loss: 0.5960515141487122
Epoch [6/10], Step [400/938], Loss: 0.9589837789535522
Epoch [6/10], Step [500/938], Loss: 0.6737836003303528
Epoch [6/10], Step [600/938], Loss: 0.6552358865737915
Epoch [6/10], Step [700/938], Loss: 0.4662915766239166
Epoch [6/10], Step [800/938], Loss: 0.6583096981048584
Epoch [6/10], Step [900/938], Loss: 0.523502767086029
Epoch [7/10], Step [100/938], Loss: 0.7014241218566895
Epoch [7/10], Step [200/938], Loss: 0.6115772128105164
Epoch [7/10], Step [300/938], Loss: 0.722679853439331
Epoch [7/10], Step [400/938], Loss: 0.5301729440689087
Epoch [7/10], Step [500/938], Loss: 0.5377673506736755
Epoch [7/10], Step [600/938], Loss: 0.8452486991882324
Epoch [7/10], Step [700/938], Loss: 0.512640118598938
Epoch [7/10], Step [800/938], Loss: 0.41439181566238403
Epoch [7/10], Step [900/938], Loss: 0.4587152898311615
Epoch [8/10], Step [100/938], Loss: 0.5379469394683838
Epoch [8/10], Step [200/938], Loss: 0.4712846875190735
Epoch [8/10], Step [300/938], Loss: 0.4268187880516052
Epoch [8/10], Step [400/938], Loss: 0.4376557171344757
Epoch [8/10], Step [500/938], Loss: 0.505620002746582
Epoch [8/10], Step [600/938], Loss: 0.43054917454719543
Epoch [8/10], Step [700/938], Loss: 0.6603127121925354
Epoch [8/10], Step [800/938], Loss: 0.4829855263233185
Epoch [8/10], Step [900/938], Loss: 0.43703171610832214
Epoch [9/10], Step [100/938], Loss: 0.4643995463848114
Epoch [9/10], Step [200/938], Loss: 0.7232795357704163
Epoch [9/10], Step [300/938], Loss: 0.39175742864608765
Epoch [9/10], Step [400/938], Loss: 0.6205026507377625
Epoch [9/10], Step [500/938], Loss: 0.5583638548851013
```

```
Epoch [9/10], Step [600/938], Loss: 0.3877916932106018
Epoch [9/10], Step [700/938], Loss: 0.5199547410011292
Epoch [9/10], Step [800/938], Loss: 0.38301512598991394
Epoch [9/10], Step [900/938], Loss: 0.4598042368888855
Epoch [10/10], Step [100/938], Loss: 0.5218845009803772
Epoch [10/10], Step [200/938], Loss: 0.39239010214805603
Epoch [10/10], Step [300/938], Loss: 0.5380221605300903
Epoch [10/10], Step [400/938], Loss: 0.48484063148498535
Epoch [10/10], Step [500/938], Loss: 0.47320041060447693
Epoch [10/10], Step [600/938], Loss: 0.474805623292923
Epoch [10/10], Step [700/938], Loss: 0.6889896392822266
Epoch [10/10], Step [800/938], Loss: 0.4263448417186737
Epoch [10/10], Step [900/938], Loss: 0.3722385764122009
```

```python
# Test the Network
correct_sigmoid = 0
total_sigmoid = 0

with torch.no_grad():
    for images, labels in test_loader:
        images = images.view(-1, 28*28)
        outputs = model_sigmoid(images)
        _, predicted = torch.max(outputs.data, 1)
        total_sigmoid += labels.size(0)
        correct_sigmoid += (predicted == labels).sum().item()

print(f'Accuracy of the network on the 10000 test images: {100 *␣
 ↪correct_sigmoid / total_sigmoid} %')
print(f'Number of parameters in the network: {sum(p.numel() for p in␣
 ↪model_sigmoid.parameters())}')
print(f'Hyperparameters: {num_epochs}, {batch_size}, {learning_rate}')
```

```
Accuracy of the network on the 10000 test images: 88.89 %
Number of parameters in the network: 297710
Hyperparameters: 10, 64, 0.01
```

```python
# Create the figure
fig = go.Figure()

# Add the loss curve data
fig.add_trace(go.Scatter(y=loss_list_sigmoid, mode='lines', name='Loss'))

# Set the layout for the figure
fig.update_layout(
    title='Training Loss over Time',
    xaxis_title='Iteration',
    yaxis_title='Loss',
    xaxis=dict(showgrid=True, showline=True, showticklabels=True),
```

```
        yaxis=dict(showgrid=True, showline=True, showticklabels=True)
)

# Display the figure
fig.show()
```

```
[ ]: img_bytes = pio.to_image(fig, format="png")
     Image(img_bytes)
```
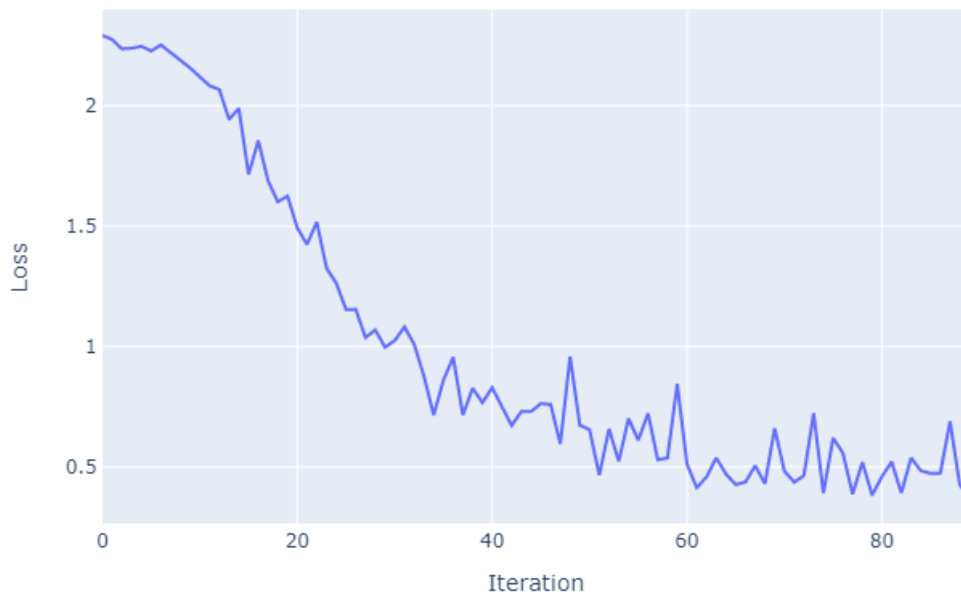
[ ]:

Training Loss over Time

4. Try different weight initialization a) all weights initialized to 0, and b) initialize the weights randomly between -1 and 1. Report test error and learning curves for both. (You can use either of the implementations) (3 pts)

```
[ ]: # Load the training and test datasets
     transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.
      ↪5,), (0.5,))])
     train_dataset = torchvision.datasets.MNIST(root='./data', train=True,␣
      ↪transform=transform, download=True)
     test_dataset = torchvision.datasets.MNIST(root='./data', train=False,␣
      ↪transform=transform)
     train_loader = torch.utils.data.DataLoader(dataset=train_dataset,␣
      ↪batch_size=64, shuffle=True)
```

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```python
test_loader = torch.utils.data.DataLoader(dataset=test_dataset, batch_size=64,
  ↪shuffle=False)
```

```python
# Define the Network Architecture with Sigmoid for hidden layers
class NeuralNetworkSigmoid(nn.Module):
    def __init__(self, input_size, hidden_size1, hidden_size2, output_size):
        super(NeuralNetworkSigmoid, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size1)
        self.fc2 = nn.Linear(hidden_size1, hidden_size2)
        self.fc3 = nn.Linear(hidden_size2, output_size)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        x = self.sigmoid(self.fc1(x))
        x = self.sigmoid(self.fc2(x))
        x = self.fc3(x)
        return x
```

```python
# Define custom weight initializations
def zero_weights_initialization(model):
    for m in model.modules():
        if isinstance(m, nn.Linear):
            nn.init.constant_(m.weight, 0)
            nn.init.constant_(m.bias, 0)

def random_weights_initialization(model):
    for m in model.modules():
        if isinstance(m, nn.Linear):
            nn.init.uniform_(m.weight, -1, 1)
            nn.init.uniform_(m.bias, -1, 1)

# Initialize models and apply custom weight initializations
model_zero = NeuralNetworkSigmoid(28*28, 300, 200, 10)
model_random = NeuralNetworkSigmoid(28*28, 300, 200, 10)

zero_weights_initialization(model_zero)
random_weights_initialization(model_random)
```

```python
# Training function
def train_model(model, num_epochs=10):
    learning_rate = 0.01
    optimizer = optim.SGD(model.parameters(), lr=learning_rate)
    criterion = nn.CrossEntropyLoss()
    loss_list = []

    for epoch in range(num_epochs):
        for i, (images, labels) in enumerate(train_loader):
```

```python
            images = images.view(-1, 28*28)
            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            if (i+1) % 100 == 0:
                print(f'Epoch [{epoch+1}/{num_epochs}], Step [{i+1}/
  {len(train_loader)}], Loss: {loss.item()}')
                loss_list.append(loss.item())

    return loss_list

# Testing function
def test_model(model):
    correct = 0
    total = 0
    with torch.no_grad():
        for images, labels in test_loader:
            images = images.view(-1, 28*28)
            outputs = model(images)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    return 100 * correct / total
```

```python
# Train and test functions remain the same ...

loss_list_zero = train_model(model_zero)
loss_list_random = train_model(model_random)

accuracy_zero = test_model(model_zero)
accuracy_random = test_model(model_random)

print(f'Accuracy with Zero Initialization: {accuracy_zero} %')
print(f'Number of parameters in the network: {sum(p.numel() for p in model_zero.
  parameters())}')
print(f'Hyperparameters: {num_epochs}, {batch_size}, {learning_rate}')
```

```
Epoch [1/10], Step [100/938], Loss: 2.2959036827087402
Epoch [1/10], Step [200/938], Loss: 2.3098185062408447
Epoch [1/10], Step [300/938], Loss: 2.2983412742614746
Epoch [1/10], Step [400/938], Loss: 2.300004243850708
Epoch [1/10], Step [500/938], Loss: 2.324035882949829
Epoch [1/10], Step [600/938], Loss: 2.2947351932525635
Epoch [1/10], Step [700/938], Loss: 2.300985813140869
```

```
Epoch [1/10], Step [800/938], Loss: 2.2945473194122314
Epoch [1/10], Step [900/938], Loss: 2.2986879348754883
Epoch [2/10], Step [100/938], Loss: 2.2957682609558105
Epoch [2/10], Step [200/938], Loss: 2.3193600177764893
Epoch [2/10], Step [300/938], Loss: 2.3031725883483887
Epoch [2/10], Step [400/938], Loss: 2.308579444885254
Epoch [2/10], Step [500/938], Loss: 2.313770055770874
Epoch [2/10], Step [600/938], Loss: 2.291682481765747
Epoch [2/10], Step [700/938], Loss: 2.3063442707061768
Epoch [2/10], Step [800/938], Loss: 2.308854103088379
Epoch [2/10], Step [900/938], Loss: 2.3122706413269043
Epoch [3/10], Step [100/938], Loss: 2.3091959953308105
Epoch [3/10], Step [200/938], Loss: 2.3086392879486084
Epoch [3/10], Step [300/938], Loss: 2.2995505332946777
Epoch [3/10], Step [400/938], Loss: 2.315145969390869
Epoch [3/10], Step [500/938], Loss: 2.2901668548583984
Epoch [3/10], Step [600/938], Loss: 2.297959327697754
Epoch [3/10], Step [700/938], Loss: 2.3273708820343018
Epoch [3/10], Step [800/938], Loss: 2.282715082168579
Epoch [3/10], Step [900/938], Loss: 2.2930617332458496
Epoch [4/10], Step [100/938], Loss: 2.3076090812683105
Epoch [4/10], Step [200/938], Loss: 2.3027360439300537
Epoch [4/10], Step [300/938], Loss: 2.294618844985962
Epoch [4/10], Step [400/938], Loss: 2.286463499069214
Epoch [4/10], Step [500/938], Loss: 2.3102128505706787
Epoch [4/10], Step [600/938], Loss: 2.3031625747680664
Epoch [4/10], Step [700/938], Loss: 2.2965002059936523
Epoch [4/10], Step [800/938], Loss: 2.3000760078430176
Epoch [4/10], Step [900/938], Loss: 2.2989449501037598
Epoch [5/10], Step [100/938], Loss: 2.287170171737671
Epoch [5/10], Step [200/938], Loss: 2.313420057296753
Epoch [5/10], Step [300/938], Loss: 2.2981622219085693
Epoch [5/10], Step [400/938], Loss: 2.293731451034546
Epoch [5/10], Step [500/938], Loss: 2.299309730529785
Epoch [5/10], Step [600/938], Loss: 2.298801898956299
Epoch [5/10], Step [700/938], Loss: 2.2951977252960205
Epoch [5/10], Step [800/938], Loss: 2.304935932159424
Epoch [5/10], Step [900/938], Loss: 2.288813591003418
Epoch [6/10], Step [100/938], Loss: 2.3064780235290527
Epoch [6/10], Step [200/938], Loss: 2.309649705886841
Epoch [6/10], Step [300/938], Loss: 2.2970387935638428
Epoch [6/10], Step [400/938], Loss: 2.306081771850586
Epoch [6/10], Step [500/938], Loss: 2.301093101501465
Epoch [6/10], Step [600/938], Loss: 2.316398859024048
Epoch [6/10], Step [700/938], Loss: 2.2961008548736572
Epoch [6/10], Step [800/938], Loss: 2.3125345706939697
Epoch [6/10], Step [900/938], Loss: 2.3104517459869385
Epoch [7/10], Step [100/938], Loss: 2.284198522567749
```

```
Epoch [7/10], Step [200/938], Loss: 2.28190279006958
Epoch [7/10], Step [300/938], Loss: 2.2970802783966064
Epoch [7/10], Step [400/938], Loss: 2.292177438735962
Epoch [7/10], Step [500/938], Loss: 2.3092918395996094
Epoch [7/10], Step [600/938], Loss: 2.3049864768981934
Epoch [7/10], Step [700/938], Loss: 2.289271593093872
Epoch [7/10], Step [800/938], Loss: 2.294886350631714
Epoch [7/10], Step [900/938], Loss: 2.3200173377990723
Epoch [8/10], Step [100/938], Loss: 2.28857421875
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Epoch [8/10], Step [300/938], Loss: 2.3046154975891113
Epoch [8/10], Step [400/938], Loss: 2.3181662559509277
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Epoch [8/10], Step [800/938], Loss: 2.3037962913513184
Epoch [8/10], Step [900/938], Loss: 2.3151023387908936
Epoch [9/10], Step [100/938], Loss: 2.300825357437134
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Epoch [9/10], Step [800/938], Loss: 2.289113759994507
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Epoch [1/10], Step [900/938], Loss: 0.9693819880485535
Epoch [2/10], Step [100/938], Loss: 0.8525758981704712
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Epoch [2/10], Step [400/938], Loss: 0.7700785994529724
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Epoch [2/10], Step [900/938], Loss: 1.30469810962677
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Epoch [6/10], Step [900/938], Loss: 0.5193513035774231
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Epoch [7/10], Step [700/938], Loss: 0.4811353385448456
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Epoch [7/10], Step [800/938], Loss: 0.5643269419670105
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Epoch [9/10], Step [100/938], Loss: 0.48117464780807495
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Epoch [9/10], Step [900/938], Loss: 0.407464861869812
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Epoch [10/10], Step [600/938], Loss: 0.28651031851768494
Epoch [10/10], Step [700/938], Loss: 0.4751476049423218
Epoch [10/10], Step [800/938], Loss: 0.5462862253189087
Epoch [10/10], Step [900/938], Loss: 0.4771941006183624
Accuracy with Zero Initialization: 10.28 %
Number of parameters in the network: 297710
Hyperparameters: 10, 64, 0.01
```

```python
print(f'Accuracy with Random Initialization: {accuracy_random} %')
print(f'Number of parameters in the network: {sum(p.numel() for p in
    model_random.parameters())}')
print(f'Hyperparameters: {num_epochs}, {batch_size}, {learning_rate}')
```

```
Accuracy with Random Initialization: 85.8 %
Number of parameters in the network: 297710
Hyperparameters: 10, 64, 0.01
```

```python
# Create the figure
fig = go.Figure()

# Add the loss curve data for both initializations
fig.add_trace(go.Scatter(y=loss_list_zero, mode='lines', name='Zero
    Initialization'))
```

```
fig.add_trace(go.Scatter(y=loss_list_random, mode='lines', name='Random␣
  ↪Initialization'))

# Set the layout for the figure
fig.update_layout(
    title='Training Loss over Time',
    xaxis_title='Iteration',
    yaxis_title='Loss',
    xaxis=dict(showgrid=True, showline=True, showticklabels=True),
    yaxis=dict(showgrid=True, showline=True, showticklabels=True)
)

# Display the figure
fig.show()
```

```
[ ]: img_bytes = pio.to_image(fig, format="png")
     Image(img_bytes)
```

[ ]: