

GOVERNMENT OF KERALA
DEPARTMENT OF TECHNICAL EDUCATION
RAJIV GANDHI INSTITUTE OF TECHNOLOGY
(GOVT. ENGINEERING COLLEGE)
KOTTAYAM - 686501



RECORD BOOK

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20MCA241 DATA SCIENCE LAB

Name: Vaishnav V

Branch: Master of Computer Applications

Semester: 3

Roll No: 51

CERTIFIED BONAFIDE RECORD WORK DONE BY

Reg No.

STAFF IN CHARGE

INTERNAL EXAMINER

EXTERNAL EXAMINER

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Assignment 1

Review of python programming

Problem Statement

Write Python code to explore and practice with the basic data types, containers, functions, and classes of Python.

1. Start by creating variables of various numeric data types and assigning them values.
2. Print the data types and values of these variables.
3. Perform mathematical operations on these variables.
4. Update the values of these variables.
5. Create boolean variables with True or False values.
6. Print the data types of these boolean variables.
7. Perform Boolean operations on these boolean variables.
8. Create string variables with text values.
9. Print the contents and lengths of these string variables.
10. Concatenate strings.
11. Format strings with variables.
12. Use string methods to manipulate strings by capitalizing, converting to uppercase, justifying, centering, replacing substrings, and stripping whitespace.
13. Create and use Python lists. Perform tasks like appending elements, indexing, slicing, and iterating through the list.
14. Create and use Python tuples. Perform tasks like indexing, slicing, and concatenation.
15. Create and use Python sets. Perform tasks like accessing, adding, deleting set elements.
16. Create and use Python dictionaries. Perform tasks like adding, updating, and removing key-value pairs, and accessing values.
17. Define simple functions with parameters and return values.
18. Call functions with different arguments and use the returned results.
19. Write functions that accept other functions as arguments.

20. Define and use Python classes. Include tasks like creating a class, defining methods, and creating instances.
21. Implement class inheritance and method overriding.
22. Create a class with class variables and instance variables, and demonstrate their usage.

1.1 Basic data types

1.1.1 Numbers

```
1 # Your Python code here
2 print("Hello, world!")
3 print(x + 1)    # Addition
4 print(x - 1)    # Subtraction
5 print(x * 2)    # Multiplication
6 print(x ** 2)   # Exponentiation
```

```
Hello, world! 7    5    14  49
```

1.1.2 Booleans

```
1 t, f = True, False
2 print(type(t))
3 print(t and f) # Logical AND;
4 print(t or f)  # Logical OR;
5 print(not t)   # Logical NOT;
6 print(t != f)  # Logical XOR;
```

```
<class 'bool'>
```

```
False True False True
```

1.1.3 Strings

```
1 hello = 'hello'
2 world = "world"
3 print(hello, len(hello))
4 hw = hello + ' ' + world # String concatenation
5 print(hw)
6 hw12 = '{} {} {}'.format(hello, world, 12) # string formatting
7 print(hw12)
8 s = "hello"
9 print(s.capitalize())
10 print(s.upper())
```

```
hello 5
```

```
hello world
```

```
hello world 12
```

```
Hello
```

```
1 print(s.rjust(7))
2 print(s.center(7))
3 print(s.replace('l', '(ell)'))
4 print(' world '.strip())
```

```
HELLO
  hello
  hello
he(ell)(ell)o
world
```

1.2 Containers

1.2.1 Lists

```
1 xs = [3, 1, 2]
2 print(xs, xs[2])
3 print(xs[-1])
4 xs[2] = 'foo'
5 print(xs)
6 xs.append('bar')
7 print(xs)
8 x = xs.pop()
9 print(x, xs)
```

```
[3, 1, 2] 2
2
[3, 1, 'foo']
[3, 1, 'foo', 'bar']
foo [3, 1]
```

1.2.2 Slicing

```
1 nums = list(range(5))
2 print(nums)
3 print(nums[2:4])
4 print(nums[2:])
5 print(nums[:2])
6 print(nums[:])
7 print(nums[:-1])
8 nums[2:4] = [8, 9] print(nums)
```

```
[0, 1, 2, 3, 4]
[2, 3]
[2, 3, 4]
[0, 1]
[0, 1, 2, 3, 4]
[0, 1, 2, 3]
[0, 1, 8, 9, 4]
```

1.2.3 Loops

```
1 animals = ['cat', 'dog', 'monkey']
2 for animal in animals:
3     print(animal)
```

```
cat
dog
monkey
```

1.2.4 List comprehensions

```
1 nums = [0, 1, 2, 3, 4]
2 squares = []
3 for x in nums:
4     squares.append(x ** 2)
5 print(squares)
```

```
[0, 1, 4, 9, 16]
```

1.2.5 Dictionaries

```
1 d = {'cat': 'cute', 'dog': 'furry'}
2 print(d['cat'])
3 print('cat' in d)
4 d['fish'] = 'wet'
5 print(d['fish'])
```

```
cute
True
wet
```

1.2.6 Sets

```
1 animals = {'cat', 'dog'}
2 print('cat' in animals)
3 print('fish' in animals)
4 animals.add('cat')
5 print(len(animals))
6 animals.remove('cat')
7 print(len(animals))
```

True

False

3

2

1.2.7 Tuples

```
1 d = {(x, x + 1): x for x in range(10)}
2 t = (5, 6)
3 print(type(t))
4 print(d[t])
5 print(d[(1, 2)])
```

<class 'tuple'>

5

1

1.3 Functions

```
1 def sign(x):
2     if x > 0:
3         return 'positive'
4     elif x < 0:
5         return 'negative'
6     else:
7         return 'zero'
8 for x in [-1, 0, 1]:
9     print(sign(x))
```

negative

zero

positive

1.4 Classes

```
1 class Greeter:
2     def __init__(self, name):
3         self.name = name
4     def greet(self, loud=False):
5         if loud:
6             print('HELLO, {}'.format(self.name.upper()))
7         else:
8             print('Hello, {}'.format(self.name))
9 g = Greeter('Fred')
10 g.greet()
11 g.greet(loud=True)
```

Hello, Fred!

HELLO, FRED

1.5 Inheritance

```
1 class Animal:
2     def speak(self):
3         return "Generic animal sound"
4
5 class Dog(Animal):
6     def speak(self):
7         return "Woof!"
8
9 class Cat(Animal):
10    def speak(self):
11        return "Meow!"
12
13 animal = Animal()
14 dog = Dog()
15 cat = Cat()
16
17 print(animal.speak())
18 print(dog.speak())
19 print(cat.speak())
```

Generic animal sound

Woof!

Meow!

1.6 instance variables

```
1 class MyClass:
2     class_var = "I am a class variable" # Class variable
3
4     def __init__(self, instance_val):
5         self.instance_var = instance_val # Instance variable
6
7     def display_vars(self):
8         print(f"Class variable: {MyClass.class_var}")
9         print(f"Instance variable: {self.instance_var}")
10
11 # Demonstrate usage
12 obj1 = MyClass("Value for obj1")
13 obj2 = MyClass("Value for obj2")
14
15 obj1.display_vars()
16 obj2.display_vars()
17
18 # Accessing class variable through the class and instances
19 print(MyClass.class_var)
20 print(obj1.class_var)
21 obj2.class_var
```

Class variable: I am a class variable

Instance variable: Value for obj1

Class variable: I am a class variable

Instance variable: Value for obj2

I am a class variable

I am a class variable

I am a class variable

Assignment 2

Vectorized Computations using Numpy

Problem Statement

Implement the following computations using NumPy:

1. Create a matrix U of shape (m, n) with input values, where m and n are input positive integers.
2. Compute X as the transpose of U .
3. Create a matrix Y of shape $(1, m)$ with random values $\in [0, 1]$.
4. Create a matrix W_1 of shape (p, n) with random values $\in [0, 1]$, where p is an input positive integer.
5. Create a vector B_1 of shape $(p, 1)$ with random values $\in [0, 1]$.
6. Create a vector W_2 of shape $(1, p)$ with all zeros.
7. Create a scalar B_2 with a random value $\in [0, 1]$.
8. Perform the following computations iteratively 15 times:
 - (a) $Z_1 = W_1 \cdot X + B_1$ (Matrix multiplication)
 - (b) $A_1 = f(Z_1)$, where f is a function that returns 0 for negative values and the input value itself otherwise (ReLU)
 - (c) $Z_2 = W_2 \cdot A_1 + B_2$
 - (d) $A_2 = g(Z_2)$, where $g(x) = \frac{1}{1+e^{-x}}$
 - (e) $L = \frac{1}{2}(A_2 - Y)^2$
 - (f) $dA_2 = A_2 - Y$
 - (g) $dZ_2 = dA_2 \circ g'(Z_2)$, where $g'(x) = g(x) \cdot (1 - g(x))$
 - (h) $dA_1 = W_2^\top \cdot dZ_2$
 - (i) $dZ_1 = dA_1 \circ f'(Z_1)$, where:
$$f'(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$
 - (j) $dW_1 = \frac{1}{m} \cdot dZ_1 \cdot X^\top$
 - (k) $dB_1 = \frac{1}{m} \sum dZ_1$ (sum along the columns)

- (l) $dW_2 = \frac{1}{m} \cdot dZ_2 \cdot A_1^\top$
- (m) $dB_2 = \frac{1}{m} \sum dZ_2$ (sum along the columns)
- (n) Update and print W_1 , B_1 , W_2 , and B_2 for $\alpha = 0.01$:
- i. $W_1 = W_1 - \alpha \cdot dW_1$
 - ii. $B_1 = B_1 - \alpha \cdot dB_1$
 - iii. $W_2 = W_2 - \alpha \cdot dW_2$
 - iv. $B_2 = B_2 - \alpha \cdot dB_2$

Code and Outputs

1. Program Code :

```

1 import numpy as np
2 m = int(input("Enter number of rows (m): "))
3 n = int(input("Enter number of columns (n): "))
4 u = []
5 for i in range(m):
6     row = input(f"Enter {n} elements for row {i+1}: ")
7     row_elements = list(map(float, row.strip().split()))
8     u.append(row_elements)
9 U = np.array(u)
10 print(U)

```

Output:

```

Enter number of rows (m): 2
Enter number of columns (n): 2
Enter 2 elements for row 1, separated by spaces: 1 2
Enter 2 elements for row 2, separated by spaces: 3 4
[[1. 2.]
 [3. 4.]]

```

2. Program Code :

```

1 print("transpose of u is:")
2 X=U.T
3 print(X)

```

Output:

```

transpose of u is:
[[1. 3.]

```

[2. 4.]

3. Program Code :

```
1 Y = np.random.rand(1, m)
2 print(Y)
```

Output:

[[0.93419463 0.26522306]]

4. Program Code :

```
1 p=int(input("enter p value:"))
2 W1=np.random.rand(p,n)
3 print(W1)
```

Output:

enter p value: 2
[[0.1101886 0.01550452]
 [0.87842457 0.99378785]]

5. Program Code :

```
1 B1=np.random.rand(p,1)
2 print(B1)
```

Output:

[[0.32971822]
 [0.44886329]]

6. Program Code :

```
1 W2=np.zeros((1,p))
2 print(W2)
```

Output:

```
[[0. 0.]]
```

7. Program Code :

```
1 B2=np.random.rand()
2 print(B2)
```

Output:

0.8918397872420092

8. Program Code :

```
1 def f(x): # ReLU
2     return np.maximum(0, x)
3
4 def fprime(x):
5     return (x > 0).astype(float)
6
7 def g(x): # Sigmoid
8     return 1 / (1 + np.exp(-x))
9
10 def gprime(x):
11     s = g(x)
12     return s * (1 - s)
13
14 # Learning rate
15 alpha = 0.01
16 for iteration in range(15):
17     # (a) Z1 = W1 * X + B1
18     Z1 = W1 @ X + B1 # shape (p, m)
19
20     # (b) A1 = f(Z1)
21     A1 = f(Z1) # ReLU output, shape (p, m)
22
23     # (c) Z2 = W2 * A1 + B2
24     Z2 = W2 @ A1 + B2 # shape (1, m)
25
26     # (d) A2 = g(Z2)
27     A2 = g(Z2) # sigmoid output, shape (1, m)
28
29     # (e) L = 1/2 * (A2 - Y)^2 (Loss per sample)
30     L = 0.5 * np.square(A2 - Y) # shape (1, m)
31
32     # (f) dA2 = A2 - Y
```

```

33     dA2 = A2 - Y # shape (1, m)
34
35     \# (g) dZ2 = dA2 * gprime(Z2)
36     dZ2 = dA2 * gprime(Z2) # element-wise multiplication, shape (1, m)
37
38     \# (h) dA1 = W2.T * dZ2
39     dA1 = W2.T @ dZ2 # shape (p, m)
40
41     \# (i) dZ1 = dA1 . fprime(Z1)
42     dZ1 = dA1 * fprime(Z1) # shape (p, m)
43
44     \# (j) dW1 = 1/m * dZ1 * X.T
45     dW1 = (1 / m) * dZ1 @ X.T # shape (p, n)
46
47     \# (k) dB1 = 1/m * sum of dZ1 along columns
48     dB1 = (1 / m) * np.sum(dZ1, axis=1, keepdims=True) # shape (p, 1)
49
50     \# (l) dW2 = 1/m * dZ2 * A1.T
51     dW2 = (1 / m) * dZ2 @ A1.T # shape (1, p)
52
53     \# (m) dB2 = 1/m * sum of dZ2 along columns
54     dB2 = (1 / m) * np.sum(dZ2, axis=1, keepdims=True) # shape (1, 1), ←
55         scalar but kept as array
56
57     W1 -= alpha * dW1
58     B1 -= alpha * dB1
59     W2 -= alpha * dW2
60     B2 -= alpha * dB2.item() # Convert to scalar
61
62     # Print updated parameters
63     print(f"Iteration {iteration + 1}:")
64     print("W1:\n", W1)
65     print("B1:\n", B1)
66     print("W2:", W2)
67     print("B2:", B2)
68     print("Loss:", np.mean(L))
69     print("-" * 40)

```

Output:

Iteration 1:

W1:

```
[[0.22823926 0.34764299]
 [0.0156025  0.52544597]]
```

B1:

```
[[0.32971266]
 [0.44885914]]
```

W2: [[0.00441104 0.00326981]]

B2: 0.33647478663392744

Loss: 0.04972936057114144

Iteration 2:

W1:

[[0.22824147 0.34764463]

[0.01560414 0.52544719]]

B1:

[[0.3297121]

[0.44885873]]

W2: [[0.00461287 0.0034165]]

B2: 0.3363477117272872

Loss: 0.049721486757244575

Iteration 3:

W1:

[[0.22824377 0.34764635]

[0.01560584 0.52544846]]

B1:

[[0.32971151]

[0.44885829]]

W2: [[0.00481399 0.00356239]]

B2: 0.3362203029438675

Loss: 0.04971365639637108

Iteration 4:

W1:

[[0.22824617 0.34764813]

[0.01560762 0.52544978]]

B1:

[[0.32971089]

[0.44885783]]

W2: [[0.00501439 0.00370751]]

B2: 0.33609256228008216

Loss: 0.04970586898133045

Iteration 5:


```
W1:
[[0.22824866 0.34764998]
 [0.01560946 0.52545115]]
B1:
[[0.32971025]
 [0.44885736]]
W2: [[0.0052141 0.00385186]]
B2: 0.33596449171989246
Loss: 0.049698124011006276
-----

Iteration 6:
W1:
[[0.22825125 0.3476519 ]
 [0.01561137 0.52545257]]
B1:
[[0.32970958]
 [0.44885687]]
W2: [[0.0054131 0.00399543]]
B2: 0.3358360932348894
Loss: 0.049690420990280926
-----

Iteration 7:
W1:
[[0.22825393 0.34765389]
 [0.01561335 0.52545403]]
B1:
[[0.32970889]
 [0.44885635]]
W2: [[0.00561141 0.00413824]]
B2: 0.33570736878437524
Loss: 0.04968275942996133
-----

Iteration 8:
W1:
[[0.22825671 0.34765594]
 [0.0156154 0.52545555]]
B1:
[[0.32970816]
```

```
[0.44885582]]
W2: [[0.00580902 0.00428029]]
B2: 0.33557832031544466
Loss: 0.0496751388467056
-----

Iteration 9:
W1:
[[0.22825958 0.34765806]
[0.01561752 0.52545711]]
B1:
[[0.32970741]
[0.44885526]]
W2: [[0.00600594 0.00442158]]
B2: 0.33544894976306516
Loss: 0.04966755876295083
-----

Iteration 10:
W1:
[[0.22826254 0.34766024]
[0.0156197 0.52545872]]
B1:
[[0.32970663]
[0.44885469]]
W2: [[0.00620218 0.00456213]]
B2: 0.33531925905015725
Loss: 0.04966001870684142
-----

Iteration 11:
W1:
[[0.2282656 0.34766249]
[0.01562194 0.52546037]]
B1:
[[0.32970582]
[0.4488541 ]]
W2: [[0.00639774 0.00470192]]
B2: 0.33518925008767375
Loss: 0.04965251821215874
-----
```

```
Iteration 12:
W1:
  [[0.22826874 0.3476648 ]
   [0.01562426 0.52546207]]
B1:
  [[0.32970499]
   [0.44885348]]
W2: [[0.00659262 0.00484097]]
B2: 0.33505892477467886
Loss: 0.049645056818251515
-----

Iteration 13:
W1:
  [[0.22827198 0.34766718]
   [0.01562663 0.52546381]]
B1:
  [[0.32970413]
   [0.44885285]]
W2: [[0.00678683 0.00497928]]
B2: 0.3349282849984264
Loss: 0.04963763406996691
-----

Iteration 14:
W1:
  [[0.2282753  0.34766962]
   [0.01562907 0.5254656  ]]
B1:
  [[0.32970324]
   [0.4488522  ]]
W2: [[0.00698038 0.00511686]]
B2: 0.33479733263443795
Loss: 0.04963024951758298
-----

Iteration 15:
W1:
  [[0.22827872 0.34767211]
   [0.01563158 0.52546743]]
B1:
```

```
[[0.32970232]
[0.44885153]]
W2: [[0.00717325 0.00525371]]
B2: 0.33466606954657985
Loss: 0.04962290271674142
-----
```

Assignment 3

Vectorized Computations using TensorFlow

Problem Statement

Implement the following computations using NumPy:

1. Create a matrix U of shape (m, n) with input values, where m and n are input positive integers.
2. Compute X as the transpose of U .
3. Create a matrix Y of shape $(1, m)$ with random values $\in [0, 1]$.
4. Create a matrix W_1 of shape (p, n) with random values $\in [0, 1]$, where p is an input positive integer.
5. Create a vector B_1 of shape $(p, 1)$ with random values $\in [0, 1]$.
6. Create a vector W_2 of shape $(1, p)$ with all zeros.
7. Create a scalar B_2 with a random value $\in [0, 1]$.
8. Perform the following computations iteratively 15 times:
 - (a) $Z_1 = W_1 \cdot X + B_1$ (Matrix multiplication)
 - (b) $A_1 = f(Z_1)$, where f is a function that returns 0 for negative values and the input value itself otherwise (ReLU)
 - (c) $Z_2 = W_2 \cdot A_1 + B_2$
 - (d) $A_2 = g(Z_2)$, where $g(x) = \frac{1}{1+e^{-x}}$
 - (e) $L = \frac{1}{2}(A_2 - Y)^2$
 - (f) $dA_2 = A_2 - Y$
 - (g) $dZ_2 = dA_2 \circ g'(Z_2)$, where $g'(x) = g(x) \cdot (1 - g(x))$
 - (h) $dA_1 = W_2^\top \cdot dZ_2$
 - (i) $dZ_1 = dA_1 \circ f'(Z_1)$, where:
$$f'(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$
 - (j) $dW_1 = \frac{1}{m} \cdot dZ_1 \cdot X^\top$
 - (k) $dB_1 = \frac{1}{m} \sum dZ_1$ (sum along the columns)

- (l) $dW_2 = \frac{1}{m} \cdot dZ_2 \cdot A_1^\top$
- (m) $dB_2 = \frac{1}{m} \sum dZ_2$ (sum along the columns)
- (n) Update and print W_1 , B_1 , W_2 , and B_2 for $\alpha = 0.01$:
- i. $W_1 = W_1 - \alpha \cdot dW_1$
 - ii. $B_1 = B_1 - \alpha \cdot dB_1$
 - iii. $W_2 = W_2 - \alpha \cdot dW_2$
 - iv. $B_2 = B_2 - \alpha \cdot dB_2$

Code and Outputs

1. Program Code :

```

1 import tensorflow as tf
2 m = int(input("enter row:"))
3 n = int(input("enter column:"))
4 U=tf.random.uniform([m,n],minval=1,maxval=10)
5 print(U)

```

Output:

```

enter row:3
enter column:4
tf.Tensor(
[[3.1435356 4.676051 9.81332 1.7113744]
 [4.332196 8.284798 9.341486 3.9649148]
 [8.549854 6.2711954 4.6171894 8.232712 ]], shape=(3, 4), dtype=float32)

```

2. Program Code :

```

1 X = tf.transpose(U)
2 print(X)

```

Output:

```

tf.Tensor(
[[3.1435356 4.332196 8.549854 ]
 [4.676051 8.284798 6.2711954]
 [9.81332 9.341486 4.6171894]
 [1.7113744 3.9649148 8.232712 ]], shape=(4, 3), dtype=float32)

```

3. Program Code :

```
1 Y = np.random.rand(1, m)
2 printY = tf.random.uniform(shape=(1, m), minval=0, maxval=10, dtype=tf.↵
    int32)
3 print(Y)
```

Output:

```
tf.Tensor([[1 5 9]], shape=(1, 3), dtype=int32)
```

4. Program Code :

```
1 W1 = tf.Variable(tf.random.uniform(shape=(p, n), minval=0, maxval=1, ↵
    dtype=tf.float32))
2 print(W1)
```

Output:

```
<tf.Variable 'Variable:0' shape=(6, 4) dtype=float32, numpy=
array([[0.5436977 , 0.72874427, 0.68472576, 0.94835377],
       [0.96630347, 0.9926599 , 0.03001082, 0.14628553],
       [0.05960095, 0.17020118, 0.12600875, 0.8665062 ],
       [0.46588528, 0.23078609, 0.10589218, 0.2996155 ],
       [0.31661344, 0.59627604, 0.35098183, 0.4152949 ],
       [0.20630908, 0.14224207, 0.982635 , 0.02675736]], dtype=float32)>
```

5. Program Code :

```
1 B1 = tf.Variable(tf.random.uniform(shape=(p, 1), minval=0, maxval=1, ↵
    dtype=tf.float32))
2 print(B1)
```

Output:

```
<tf.Variable 'Variable:0' shape=(6, 1) dtype=float32, numpy=
array([[0.8493881 ],
       [0.08162391],
       [0.31380033],
       [0.9507289 ],
       [0.2724731 ],
```

```
[0.89534795]], dtype=float32)>
```

6. Program Code :

```
1 W2 = tf.Variable(tf.zeros(shape=(10, p), dtype=tf.float32))
2 print(W2)
```

Output:

```
<tf.Variable 'Variable:0' shape=(10, 6) dtype=float32, numpy=
array([[0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0.]], dtype=float32)>
```

7. Program Code :

```
1 B2=np.random.rand()
2 printB2 = tf.Variable(tf.random.uniform(shape=(), minval=0, maxval=1, ↵
      dtype=tf.float32))
3 print(B2)
```

Output:

```
<tf.Variable 'Variable:0' shape=() dtype=float32, numpy=0.9369667768478394>
```

8. Program Code :

```
1 alpha = 0.01 # Learning rate
2 epochs = 15 # Iterations
3 for i in range(epochs):
4     # a. Z1 = W1 X + B1
5     Z1 = tf.matmul(W1, X) + B1
6
7     # b. A1 = ReLU(Z1)
```

```

8     A1 = tf.nn.relu(Z1)
9
10    # c. Z2 = W2      A1 + B2
11    Z2 = tf.matmul(W2, A1) + B2
12
13    # d. A2 = softmax(Z2) along axis=0
14    A2 = tf.nn.softmax(Z2, axis=0)
15
16    # e. One-hot encode Y (shape (10, m))
17    Y_one_hot = tf.one_hot(tf.squeeze(Y), depth=10, axis=0)
18
19    # f. dZ2 = A2 - one_hot(Y)
20    dZ2 = A2 - Y_one_hot
21
22    # g. dA2 = W2^T      dZ2
23    dA2 = tf.matmul(tf.transpose(W2), dZ2)
24
25    # h. dW2 = 1/m * dZ2      A1^T
26    dW2 = (1/m) * tf.matmul(dZ2, tf.transpose(A1))
27
28    # i. dB2 = 1/m * sum(dZ2)
29    dB2 = (1/m) * tf.reduce_sum(dZ2)
30
31    # j. ReLU derivative
32    relu_derivative = tf.cast(Z1 > 0, tf.float32)
33    dZ1 = dA2 * relu_derivative
34
35    # k. dA1 = W1^T      dZ1
36    dA1 = tf.matmul(tf.transpose(W1), dZ1)
37
38    # l. dB1 = 1/m * sum over columns
39    dB1 = (1/m) * tf.reduce_sum(dZ1, axis=1, keepdims=True)
40
41    # m. dW1 = 1/m * dZ1      X^T
42    dW1 = (1/m) * tf.matmul(dZ1, tf.transpose(X))
43
44    # Gradient descent update
45    W1.assign_sub(alpha * dW1)
46    B1.assign_sub(alpha * dB1)
47    W2.assign_sub(alpha * dW2)
48    B2.assign_sub(alpha * dB2)
49
50    # Print updates
51    print(f"\nIteration {i + 1}")
52    print("W1:\n", W1.numpy())
53    print("B1:\n", B1.numpy())
54    print("W2:\n", W2.numpy())
55    print("B2:\n", B2.numpy())

```

Output:

Iteration 1

W1:

```
[[0.5436977  0.72874427 0.68472576 0.94835377]
 [0.96630347 0.9926599  0.03001082 0.14628553]
 [0.05960095 0.17020118 0.12600875 0.8665062 ]
 [0.46588528 0.23078609 0.10589218 0.2996155 ]
 [0.31661344 0.59627604 0.35098183 0.4152949 ]
 [0.20630908 0.14224207 0.982635   0.02675736]]
```

B1:

```
[[0.8493881 ]
 [0.08162391]
 [0.31380033]
 [0.9507289 ]
 [0.2724731 ]
 [0.89534795]]
```

W2:

```
[[ -0.01824814 -0.01252315 -0.00673919 -0.00714713 -0.01049294 -0.01081975]
 [ 0.02944714  0.01516291  0.00664917  0.00967398  0.01687705  0.02883933]
 [ -0.01824814 -0.01252315 -0.00673919 -0.00714713 -0.01049294 -0.01081975]
 [ -0.01824814 -0.01252315 -0.00673919 -0.00714713 -0.01049294 -0.01081975]
 [ -0.01824814 -0.01252315 -0.00673919 -0.00714713 -0.01049294 -0.01081975]
 [ 0.04641449  0.03198412  0.01524353  0.01638018  0.02787183  0.03002335]
 [ -0.01824814 -0.01252315 -0.00673919 -0.00714713 -0.01049294 -0.01081975]
 [ -0.01824814 -0.01252315 -0.00673919 -0.00714713 -0.01049294 -0.01081975]
 [ -0.01824814 -0.01252315 -0.00673919 -0.00714713 -0.01049294 -0.01081975]
 [ 0.05187537  0.04051497  0.02528163  0.02397573  0.02870169  0.01687554]]
```

B2:

0.9369668

Iteration 2

W1:

```
[[0.5440847  0.7291323  0.68503964 0.9487317 ]
 [0.96658623 0.99287343 0.0300517  0.14658767]
 [0.05977688 0.170277   0.12593713 0.86670125]
 [0.46606034 0.23089719 0.10591274 0.29979736]
 [0.3168252  0.59651226 0.35118473 0.41550112]
```

[0.20647387 0.1426236 0.9832724 0.02685763]]

B1:

[[0.8494403]

[0.08164761]

[0.313808]

[0.95074356]

[0.27250382]

[0.8954082]]

W2:

[[-0.02150786 -0.01467208 -0.00786347 -0.00838606 -0.01236975 -0.01295926]

[0.04989494 0.02434149 0.01017301 0.01592855 0.02855928 0.05185796]

[-0.02150786 -0.01467208 -0.00786347 -0.00838606 -0.01236975 -0.01295926]

[-0.02150786 -0.01467208 -0.00786347 -0.00838606 -0.01236975 -0.01295926]

[-0.02150786 -0.01467208 -0.00786347 -0.00838606 -0.01236975 -0.01295926]

[0.05202485 0.03580823 0.01530089 0.01673463 0.0322702 0.03618712]

[-0.02150786 -0.01467208 -0.00786347 -0.00838606 -0.01236975 -0.01295926]

[-0.02150786 -0.01467208 -0.00786347 -0.00838606 -0.01236975 -0.01295926]

[-0.02150786 -0.01467208 -0.00786347 -0.00838606 -0.01236975 -0.01295926]

[0.04863521 0.04255482 0.02957039 0.02603926 0.02575875 0.00266969]]

B2:

0.9369668

Iteration 3

W1:

[[0.54436487 0.7295368 0.6856369 0.94895]

[0.9669562 0.99322605 0.03033764 0.14694698]

[0.06009676 0.17048019 0.12601657 0.8670231]

[0.46629772 0.23107494 0.10606664 0.30002058]

[0.31694847 0.596751 0.35154873 0.41559023]

[0.20614487 0.14270681 0.983958 0.02642284]]

B1:

[[0.8495066]

[0.08169664]

[0.3138382]

[0.95077336]

[0.27254036]

[0.89543575]]

W2:

```

[[-0.02378823 -0.01616677 -0.00864297 -0.0092498 -0.01368246 -0.01447512]
[ 0.0420111  0.01402709  0.00322986  0.01110312  0.02392759  0.05813773]
[-0.02378823 -0.01616677 -0.00864297 -0.0092498 -0.01368246 -0.01447512]
[-0.02378823 -0.01616677 -0.00864297 -0.0092498 -0.01368246 -0.01447512]
[-0.02378823 -0.01616677 -0.00864297 -0.0092498 -0.01368246 -0.01447512]
[ 0.05502487  0.03782367  0.0143731  0.01605421  0.0351713  0.04085137]
[-0.02378823 -0.01616677 -0.00864297 -0.0092498 -0.01368246 -0.01447512]
[-0.02378823 -0.01616677 -0.00864297 -0.0092498 -0.01368246 -0.01447512]
[-0.02378823 -0.01616677 -0.00864297 -0.0092498 -0.01368246 -0.01447512]
[ 0.0694816  0.06131657  0.04289781  0.03759124  0.03667834  0.00233668]]

```

B2:

0.9369668

Iteration 4

W1:

```

[[0.54456615 0.7296166 0.6855571 0.9491705 ]
[0.9670649 0.9930576 0.02972147 0.1471456 ]
[0.06015258 0.17020564 0.12535027 0.8671558 ]
[0.46637133 0.23091623 0.1056752 0.30013505]
[0.3170603 0.5968633 0.35159475 0.4157107 ]
[0.20632197 0.14342077 0.9854092 0.02643069]]

```

B1:

```

[[0.8495157 ]
[0.08165764]
[0.31379238]
[0.9507499 ]
[0.27255175]
[0.8955589 ]]

```

W2:

```

[[-0.02536496 -0.01718486 -0.00916773 -0.00984013 -0.01459073 -0.01555978]
[ 0.06067901  0.02228434  0.00641039  0.01682881  0.03455279  0.07933678]
[-0.02536496 -0.01718486 -0.00916773 -0.00984013 -0.01459073 -0.01555978]
[-0.02536496 -0.01718486 -0.00916773 -0.00984013 -0.01459073 -0.01555978]
[-0.02536496 -0.01718486 -0.00916773 -0.00984013 -0.01459073 -0.01555978]
[ 0.06793095  0.047042  0.01752629  0.01947974  0.04372374  0.05035991]
[-0.02536496 -0.01718486 -0.00916773 -0.00984013 -0.01459073 -0.01555978]
[-0.02536496 -0.01718486 -0.00916773 -0.00984013 -0.01459073 -0.01555978]
[-0.02536496 -0.01718486 -0.00916773 -0.00984013 -0.01459073 -0.01555978]

```

[0.04894472 0.05096768 0.04023744 0.03257233 0.0238586 -0.02077828]]
B2:
0.9369668

Iteration 5

W1:
[[0.54446983 0.7297462 0.68589073 0.94904184]
[0.9674453 0.99343157 0.029893 0.14754917]
[0.06071552 0.17058392 0.12548393 0.8677301]
[0.46670476 0.23115642 0.10583855 0.30045897]
[0.3168777 0.59688705 0.35175148 0.41551864]
[0.20494483 0.14272706 0.98565483 0.02495259]]

B1:
[[0.84953296]
[0.0816977]
[0.31384468]
[0.95078754]
[0.27254885]
[0.89547443]]

W2:
[[-0.02663331 -0.01800724 -0.00959386 -0.01031731 -0.01532073 -0.01642304]
[0.04898913 0.00964089 -0.00164447 0.01066934 0.02770217 0.08264242]
[-0.02663331 -0.01800724 -0.00959386 -0.01031731 -0.01532073 -0.01642304]
[-0.02663331 -0.01800724 -0.00959386 -0.01031731 -0.01532073 -0.01642304]
[-0.02663331 -0.01800724 -0.00959386 -0.01031731 -0.01532073 -0.01642304]
[0.0490137 0.03380131 0.0082994 0.01011308 0.03403436 0.04254838]
[-0.02663331 -0.01800724 -0.00959386 -0.01031731 -0.01532073 -0.01642304]
[-0.02663331 -0.01800724 -0.00959386 -0.01031731 -0.01532073 -0.01642304]
[-0.02663331 -0.01800724 -0.00959386 -0.01031731 -0.01532073 -0.01642304]
[0.08843033 0.08260843 0.06050207 0.05143874 0.04550854 -0.01022954]]

B2:
0.9369668

Iteration 6

W1:
[[0.54421353 0.7290388 0.6848433 0.9488654]
[0.96697074 0.9923117 0.02798015 0.14727342]
[0.06020464 0.16939694 0.1235977 0.8673955]

```
[0.46634153 0.23028271 0.10452887 0.3002042 ]
[0.31682476 0.5967054 0.3514299 0.4154978 ]
[0.20569806 0.14428818 0.9884229 0.02539183]]
```

B1:

```
[[0.8494365 ]
[0.08151804]
[0.3136653 ]
[0.9506631 ]
[0.2725208 ]
[0.89574105]]
```

W2:

```
[[-0.02758269 -0.01860692 -0.00989785 -0.0106671 -0.01586794 -0.01710733]
[ 0.07026246 0.02002005 0.00282962 0.01758609 0.03979877 0.10456118]
[-0.02758269 -0.01860692 -0.00989785 -0.0106671 -0.01586794 -0.01710733]
[-0.02758269 -0.01860692 -0.00989785 -0.0106671 -0.01586794 -0.01710733]
[-0.02758269 -0.01860692 -0.00989785 -0.0106671 -0.01586794 -0.01710733]
[ 0.08831793 0.06144477 0.02147724 0.02400715 0.05775957 0.06698877]
[-0.02758269 -0.01860692 -0.00989785 -0.0106671 -0.01586794 -0.01710733]
[-0.02758269 -0.01860692 -0.00989785 -0.0106671 -0.01586794 -0.01710733]
[-0.02758269 -0.01860692 -0.00989785 -0.0106671 -0.01586794 -0.01710733]
[ 0.03449841 0.04878358 0.04497809 0.03307643 0.01351726 -0.05179865]]
```

B2:

```
0.9369668
```

Iteration 7

W1:

```
[[0.54302347 0.72829604 0.684333 0.9477258 ]
[0.96689343 0.9923197 0.02767759 0.14728399]
[0.06092195 0.16992201 0.12380151 0.86813194]
[0.4666424 0.23051909 0.10467075 0.30050385]
[0.3158323 0.59606874 0.35092968 0.41456085]
[0.20257539 0.14217022 0.98752165 0.02224048]]
```

B1:

```
[[0.8493061 ]
[0.08148628]
[0.313734 ]
[0.9506963 ]
[0.27240613]
```

[0.89543796]]

W2:

```
[[ -0.02824281 -0.01902939 -0.010115   -0.01091341 -0.01624781 -0.01756909]
 [  0.06654714  0.01310556 -0.00205909  0.01465033  0.03753265  0.11200816]
 [ -0.02824281 -0.01902939 -0.010115   -0.01091341 -0.01624781 -0.01756909]
 [ -0.02824281 -0.01902939 -0.010115   -0.01091341 -0.01624781 -0.01756909]
 [ -0.02824281 -0.01902939 -0.010115   -0.01091341 -0.01624781 -0.01756909]
 [  0.03471732  0.02397028 -0.0009962   0.00082714  0.02816684  0.03969237]
 [ -0.02824281 -0.01902939 -0.010115   -0.01091341 -0.01624781 -0.01756909]
 [ -0.02824281 -0.01902939 -0.010115   -0.01091341 -0.01624781 -0.01756909]
 [ -0.02824281 -0.01902939 -0.010115   -0.01091341 -0.01624781 -0.01756909]
 [  0.09643514  0.09612986  0.07386026  0.06091638  0.04803514 -0.02871693]]
```

B2:

0.9369668

Iteration 8

W1:

```
[[0.54246366 0.72703856 0.6828151  0.94723463]
 [0.9662355  0.99081403 0.02535841 0.14683256]
 [0.06019149 0.16829821 0.12139438 0.8676032 ]
 [0.46605137 0.22921829 0.10289096 0.3000379 ]
 [0.31568065 0.5957041  0.35049978 0.41442525]
 [0.2032713  0.14374001 0.9905854  0.02255804]]
```

B1:

```
[[0.8491543 ]
 [0.08126398]
 [0.3135003 ]
 [0.9505209 ]
 [0.27236387]
 [0.8957241 ]]
```

W2:

```
[[ -0.02892415 -0.01945556 -0.0103295  -0.01116276 -0.01664057 -0.01806988]
 [  0.07020423  0.01201735 -0.00340854  0.01504506  0.03941161  0.12185399]
 [ -0.02892415 -0.01945556 -0.0103295  -0.01116276 -0.01664057 -0.01806988]
 [ -0.02892415 -0.01945556 -0.0103295  -0.01116276 -0.01664057 -0.01806988]
 [ -0.02892415 -0.01945556 -0.0103295  -0.01116276 -0.01664057 -0.01806988]
 [  0.08880774  0.06156588  0.01743004  0.02039561  0.06042088  0.07340805]
 [ -0.02892415 -0.01945556 -0.0103295  -0.01116276 -0.01664057 -0.01806988]]
```

```

[-0.02892415 -0.01945556 -0.0103295 -0.01116276 -0.01664057 -0.01806988]
[-0.02892415 -0.01945556 -0.0103295 -0.01116276 -0.01664057 -0.01806988]
[ 0.04345703  0.06260569  0.05828495  0.04269861  0.0166515 -0.06877295]]

```

B2:

0.9369668

Iteration 9

W1:

```

[[0.5415247  0.7264723  0.68241304 0.9463413 ]
[0.9665      0.99105006 0.02511411 0.14719701]
[0.06129592 0.1690763  0.12172379 0.86872387]
[0.46665335 0.22965361 0.10316045 0.3006296 ]
[0.31474468 0.59511226 0.3500033  0.41355047]
[0.19970281 0.14134848 0.9896464  0.01894275]]

```

B1:

```

[[0.8490511 ]
[0.0812621 ]
[0.31360787]
[0.9505868 ]
[0.27225354]
[0.8953848 ]]

```

W2:

```

[[-0.029511  -0.01983119 -0.01052256 -0.01138173 -0.01697828 -0.01848031]
[ 0.06822014  0.00642733 -0.00751743  0.01286176  0.03812703  0.1299833 ]
[-0.029511  -0.01983119 -0.01052256 -0.01138173 -0.01697828 -0.01848031]
[-0.029511  -0.01983119 -0.01052256 -0.01138173 -0.01697828 -0.01848031]
[-0.029511  -0.01983119 -0.01052256 -0.01138173 -0.01697828 -0.01848031]
[ 0.03646701  0.02498666 -0.00453142 -0.0022603  0.03154057  0.04676023]
[-0.029511  -0.01983119 -0.01052256 -0.01138173 -0.01697828 -0.01848031]
[-0.029511  -0.01983119 -0.01052256 -0.01138173 -0.01697828 -0.01848031]
[-0.029511  -0.01983119 -0.01052256 -0.01138173 -0.01697828 -0.01848031]
[ 0.10188979  0.1074043  0.08570674  0.06907065  0.04918036 -0.04738141]]

```

B2:

0.9369668

Iteration 10

W1:

```

[[0.5408759  0.72508544 0.6807365  0.94577277]

```



```
[0.96565    0.98924756 0.0223654  0.14659499]
[0.06032266 0.16704345 0.11877286 0.8679947 ]
[0.46588698 0.22805344 0.10100104 0.30001444]
[0.31459942 0.594781   0.3496062  0.41342235]
[0.2007812  0.14357159 0.9936414  0.01955996]]
```

B1:

```
[[0.8488808 ]
[0.080993   ]
[0.31331548]
[0.9503702  ]
[0.27221397]
[0.89576936]]
```

W2:

```
[[-0.03008321 -0.02018627 -0.01070006 -0.01158985 -0.01730827 -0.01890765]
[ 0.07295451  0.00633978 -0.00821404  0.01380793  0.04060707  0.1398281 ]
[-0.03008321 -0.02018627 -0.01070006 -0.01158985 -0.01730827 -0.01890765]
[-0.03008321 -0.02018627 -0.01070006 -0.01158985 -0.01730827 -0.01890765]
[-0.03008321 -0.02018627 -0.01070006 -0.01158985 -0.01730827 -0.01890765]
[ 0.09076723  0.06275165  0.01399934  0.01740499  0.06391215  0.080535  ]
[-0.03008321 -0.02018627 -0.01070006 -0.01158985 -0.01730827 -0.01890765]
[-0.03008321 -0.02018627 -0.01070006 -0.01158985 -0.01730827 -0.01890765]
[-0.03008321 -0.02018627 -0.01070006 -0.01158985 -0.01730827 -0.01890765]
[ 0.0468607   0.07221244  0.0691151   0.04991601  0.01663865 -0.0880096 ]]
```

B2:

0.9369668

Iteration 11

W1:

```
[[0.5399688  0.72453207 0.68033326 0.94491154]
[0.9661409  0.9896521  0.02218279 0.14719337]
[0.06176664 0.1680632  0.11925951 0.8694467 ]
[0.46672073 0.2286476  0.10139   0.30082735]
[0.31359196 0.5941376  0.34904775 0.41248482]
[0.19655208 0.14068383 0.9924138  0.01528791]]
```

B1:

```
[[0.84878   ]
[0.08101254]
[0.31346074]
```

[0.95046294]
[0.2720933]
[0.8953586]]

W2:

[[-3.0577136e-02 -2.0502195e-02 -1.0862343e-02 -1.1774052e-02
-1.7592518e-02 -1.9253636e-02]
[6.9718137e-02 1.8911436e-05 -1.2650739e-02 1.1206380e-02
3.8587943e-02 1.4688736e-01]
[-3.0577136e-02 -2.0502195e-02 -1.0862343e-02 -1.1774052e-02
-1.7592518e-02 -1.9253636e-02]
[-3.0577136e-02 -2.0502195e-02 -1.0862343e-02 -1.1774052e-02
-1.7592518e-02 -1.9253636e-02]
[-3.0577136e-02 -2.0502195e-02 -1.0862343e-02 -1.1774052e-02
-1.7592518e-02 -1.9253636e-02]
[3.9565910e-02 2.6947603e-02 -7.5424276e-03 -4.8029479e-03
3.5684243e-02 5.4571651e-02]
[-3.0577136e-02 -2.0502195e-02 -1.0862343e-02 -1.1774052e-02
-1.7592518e-02 -1.9253636e-02]
[-3.0577136e-02 -2.0502195e-02 -1.0862343e-02 -1.1774052e-02
-1.7592518e-02 -1.9253636e-02]
[-3.0577136e-02 -2.0502195e-02 -1.0862343e-02 -1.1774052e-02
-1.7592518e-02 -1.9253636e-02]
[1.0475588e-01 1.1654881e-01 9.6229553e-02 7.6014899e-02
4.8875418e-02 -6.6683590e-02]]]

B2:

0.9369668

Iteration 12

W1:

[[0.5393303 0.7231805 0.67871255 0.9443487]
[0.9652373 0.98777163 0.01930565 0.14655292]
[0.06067017 0.16580652 0.11602376 0.8686132]
[0.46586597 0.22688438 0.09903852 0.3001335]
[0.31349677 0.5939145 0.3487785 0.41240132]
[0.19787967 0.14336914 0.9970492 0.01610302]]]

B1:

[[0.8486146]
[0.08072957]

[0.31313813]
[0.9502257]
[0.2720667]
[0.89580953]]

W2:

[[-0.03108736 -0.02081736 -0.01101914 -0.01195885 -0.01788689 -0.0196383]
[0.07292172 -0.00087409 -0.01366197 0.01168513 0.0401637 0.15520842]
[-0.03108736 -0.02081736 -0.01101914 -0.01195885 -0.01788689 -0.0196383]
[-0.03108736 -0.02081736 -0.01101914 -0.01195885 -0.01788689 -0.0196383]
[-0.03108736 -0.02081736 -0.01101914 -0.01195885 -0.01788689 -0.0196383]
[0.09279409 0.06401701 0.01063557 0.01446605 0.06743419 0.08760698]
[-0.03108736 -0.02081736 -0.01101914 -0.01195885 -0.01788689 -0.0196383]
[-0.03108736 -0.02081736 -0.01101914 -0.01195885 -0.01788689 -0.0196383]
[-0.03108736 -0.02081736 -0.01101914 -0.01195885 -0.01788689 -0.0196383]
[0.05189565 0.08257857 0.08016034 0.05756071 0.01761032 -0.10534731]]

B2:

0.9369668

Iteration 13

W1:

[[0.53850067 0.72266775 0.67829555 0.9435711]
[0.9658835 0.988254 0.01905915 0.14732693]
[0.06238842 0.16700055 0.11658952 0.8703384]
[0.46691504 0.22762088 0.09952141 0.3011546]
[0.31244072 0.59322596 0.34813514 0.41142884]
[0.19324295 0.14022903 0.99575526 0.01141409]]

B1:

[[0.8485185]
[0.08075564]
[0.3133102]
[0.95034206]
[0.27193567]
[0.8953631]]

W2:

[[-0.03151779 -0.02109226 -0.01116013 -0.01211914 -0.01813465 -0.01994086]
[0.07308393 -0.00476204 -0.01675039 0.01045995 0.04009466 0.1640435]
[-0.03151779 -0.02109226 -0.01116013 -0.01211914 -0.01813465 -0.01994086]
[-0.03151779 -0.02109226 -0.01116013 -0.01211914 -0.01813465 -0.01994086]

```

[-0.03151779 -0.02109226 -0.01116013 -0.01211914 -0.01813465 -0.01994086]
[ 0.03972107  0.02697465 -0.01152234 -0.00842446  0.03810911  0.06037893]
[-0.03151779 -0.02109226 -0.01116013 -0.01211914 -0.01813465 -0.01994086]
[-0.03151779 -0.02109226 -0.01116013 -0.01211914 -0.01813465 -0.01994086]
[-0.03151779 -0.02109226 -0.01116013 -0.01211914 -0.01813465 -0.01994086]
[ 0.1078195   0.12543316  0.10639361  0.08279843  0.04873872 -0.08483642]]

```

B2:

0.9369668

Iteration 14

W1:

```

[[0.5378311  0.72126913 0.6766497  0.9429732 ]
[0.9649589  0.98634005 0.01615   0.146666  ]
[0.06120392 0.16457646 0.1131702  0.869423  ]
[0.46597752 0.2257017  0.09700566 0.30038217]
[0.31237292 0.59306353 0.34794652 0.4113675  ]
[0.19465855 0.14309706 1.0006347  0.0123005  ]]

```

B1:

```

[[0.8483492 ]
[0.08046882]
[0.31296778]
[0.95008683]
[0.27191707]
[0.89583856]]

```

W2:

```

[[-0.0319625  -0.02136588 -0.01129568 -0.01227961 -0.01839134 -0.02027887]
[ 0.0722108  -0.00814562 -0.01894066  0.00951892  0.03928887  0.16915812]
[-0.0319625  -0.02136588 -0.01129568 -0.01227961 -0.01839134 -0.02027887]
[-0.0319625  -0.02136588 -0.01129568 -0.01227961 -0.01839134 -0.02027887]
[-0.0319625  -0.02136588 -0.01129568 -0.01227961 -0.01839134 -0.02027887]
[ 0.09346053  0.06436759  0.00681808  0.01103149  0.07015482  0.09378393]
[-0.0319625  -0.02136588 -0.01129568 -0.01227961 -0.01839134 -0.02027887]
[-0.0319625  -0.02136588 -0.01129568 -0.01227961 -0.01839134 -0.02027887]
[-0.0319625  -0.02136588 -0.01129568 -0.01227961 -0.01839134 -0.02027887]
[ 0.05806613  0.09333915  0.09119229  0.06540683  0.01929564 -0.12098998]]

```

B2:

0.9369668

Iteration 15

W1:

```
[[0.53716016 0.72086126 0.67627966 0.9423546 ]  
[0.96575385 0.9868942  0.01584487 0.14760675]  
[0.06312533 0.16588475 0.11377048 0.8713521 ]  
[0.4672057  0.22654887 0.0975593  0.301576  ]  
[0.31134313 0.5923907  0.34727433 0.41043004]  
[0.18987103 0.13991404 0.9994435  0.00744072]]
```

B1:

```
[[0.8482687 ]  
[0.08050141]  
[0.31315798]  
[0.9502223 ]  
[0.2717856 ]  
[0.8953886 ]]
```

W2:

```
[[ -0.03235386 -0.02161551 -0.01142349 -0.01242512 -0.01861667 -0.02055485]  
[ 0.07504897 -0.0101071  -0.02095571  0.00938393  0.04075382  0.17936324]  
[ -0.03235386 -0.02161551 -0.01142349 -0.01242512 -0.01861667 -0.02055485]  
[ -0.03235386 -0.02161551 -0.01142349 -0.01242512 -0.01861667 -0.02055485]  
[ -0.03235386 -0.02161551 -0.01142349 -0.01242512 -0.01861667 -0.02055485]  
[ 0.04136546  0.02813231 -0.01479971 -0.011366   0.04135526  0.0667384 ]  
[ -0.03235386 -0.02161551 -0.01142349 -0.01242512 -0.01861667 -0.02055485]  
[ -0.03235386 -0.02161551 -0.01142349 -0.01242512 -0.01861667 -0.02055485]  
[ -0.03235386 -0.02161551 -0.01142349 -0.01242512 -0.01861667 -0.02055485]  
[ 0.1100626   0.13328335  0.1157198   0.08895791  0.0482076  -0.10221774]]
```

B2:

0.9369668

Implementing a Fully Connected Neural Network (FCNN) from Scratch Using TensorFlow

Problem Statement

Implement the following computations using TensorFlow on the MNIST dataset:

1. Load the MNIST dataset, consisting of 60,000 training and 10,000 test grayscale images of size 28×28 pixels and labels from 0 to 9.
2. Flatten each image into a 784-dimensional vector and form matrix U of shape (m, n) with $m = 60000$ and $n = 784$.
3. Compute $X = U^T$ and normalize pixel values to $[0, 1]$.
4. Form label matrix Y of shape $(1, m)$ from training labels.
5. Similarly, prepare X_{test} and Y_{test} from the test dataset.
6. Display one training image and its label.
7. Define hyperparameters: hidden layer size $p = 10$, output size $q = 10$, learning rate $\alpha = 0.01$, and epochs = 1000.
8. Initialize weights and biases:
 - $W_1 \in \mathbb{R}^{p \times n} \sim \mathcal{N}(0, 1) \times \frac{\sqrt{q}}{n}$
 - $B_1 \in \mathbb{R}^{p \times 1} = 0$
 - $W_2 \in \mathbb{R}^{q \times p} \sim \mathcal{N}(0, 1) \times \frac{\sqrt{q}}{p}$
 - $B_2 \in \mathbb{R}^{q \times 1} = 0$
9. Perform forward and backward propagation with ReLU and softmax activations for 1000 epochs:
 - (a) $Z_1 = W_1 X + B_1$
 - (b) $A_1 = \text{ReLU}(Z_1)$
 - (c) $Z_2 = W_2 A_1 + B_2$
 - (d) $A_2 = \text{softmax}(Z_2)$
 - (e) Compute cross-entropy loss and accuracy every 100 epochs.
 - (f) Backpropagate errors to compute gradients dW_1, dB_1, dW_2, dB_2 .
 - (g) Update parameters using learning rate α .

10. Repeat training using TensorFlow's `GradientTape` for automatic differentiation.
11. Test the trained model on one test image and display the prediction.
12. Evaluate overall accuracy on the entire test dataset.

4.1 Implementation and Computations

```
1 import tensorflow as tf
2 import numpy as np
3 import matplotlib.pyplot as plt
4
5 # Load MNIST data
6 (x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()
7
8 # Prepare training data
9 m_train = x_train.shape[0]
10 n = 28 * 28
11 U = tf.reshape(x_train, shape=(m_train, n))
12 X = tf.transpose(U)
13 X = tf.cast(X, tf.float32) / 255.0
14 Y = tf.reshape(y_train, shape=(1, m_train))
15
16 # Prepare test data
17 m_test = x_test.shape[0]
18 V = tf.reshape(x_test, shape=(m_test, n))
19 Xtest = tf.transpose(V)
20 Xtest = tf.cast(Xtest, tf.float32) / 255.0
21 Ytest = tf.reshape(y_test, shape=(1, m_test))
22
23 # Display one training image and label
24 idx = 0
25 image = tf.reshape(X[:, idx], shape=(28, 28))
26 plt.imshow(image, cmap='gray')
27 plt.title(f"Label: {Y[0, idx].numpy()}")
28 plt.show()
29
30 # Hyperparameters
31 p = 10 # hidden neurons
32 q = 10 # output neurons (digits 0-9)
33 alpha = 0.01
34 epochs = 1000
35
36 # Initialize weights and biases
37 W1 = tf.Variable(tf.random.normal(shape=(p, n), mean=0.0, stddev=1.0) * (q ** ←
    0.5 / n))
38 B1 = tf.Variable(tf.zeros(shape=(p, 1)))
39 W2 = tf.Variable(tf.random.normal(shape=(q, p), mean=0.0, stddev=1.0) * (q ** ←
    0.5 / p))
```

```

40 B2 = tf.Variable(tf.zeros(shape=(q, 1)))
41
42 # Activation functions
43 def relu(Z):
44     return tf.maximum(Z, 0)
45
46 def relu_derivative(Z):
47     return tf.cast(Z > 0, tf.float32)
48
49 def softmax(Z):
50     exp_Z = tf.exp(Z - tf.reduce_max(Z, axis=0, keepdims=True))
51     return exp_Z / tf.reduce_sum(exp_Z, axis=0, keepdims=True)
52
53 def one_hot_T(Y, num_classes=10):
54     Y_flat = tf.reshape(Y, [-1])
55     oh = tf.one_hot(Y_flat, depth=num_classes)
56     return tf.transpose(oh)
57
58 m = m_train
59
60 # Training loop (manual gradients)
61 for epoch in range(1, epochs + 1):
62     with tf.GradientTape() as tape:
63         Z1 = tf.matmul(W1, X) + B1
64         A1 = relu(Z1)
65         Z2 = tf.matmul(W2, A1) + B2
66         A2 = softmax(Z2)
67         Y_onehot = one_hot_T(Y, q)
68         loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(labels=↔
        tf.transpose(Y_onehot), logits=tf.transpose(Z2)))
69
70 # Backprop manually
71 dZ2 = A2 - Y_onehot
72 dW2 = (1/m) * tf.matmul(dZ2, A1, transpose_b=True)
73 dB2 = (1/m) * tf.reduce_sum(dZ2, axis=1, keepdims=True)
74 dA1 = tf.matmul(W2, dZ2, transpose_a=True)
75 dZ1 = dA1 * relu_derivative(Z1)
76 dW1 = (1/m) * tf.matmul(dZ1, X, transpose_b=True)
77 dB1 = (1/m) * tf.reduce_sum(dZ1, axis=1, keepdims=True)
78
79 # Update weights
80 W1.assign_sub(alpha * dW1)
81 B1.assign_sub(alpha * dB1)
82 W2.assign_sub(alpha * dW2)
83 B2.assign_sub(alpha * dB2)
84
85 if epoch % 100 == 0:
86     preds = tf.argmax(A2, axis=0, output_type=tf.int32)
87     correct = tf.equal(preds, tf.cast(Y[0], tf.int32))

```



```

88         accuracy = tf.reduce_mean(tf.cast(correct, tf.float32))
89         print(f"Epoch {epoch}, Loss: {loss.numpy():.4f}, Accuracy: {accuracy.↵
            numpy()*100:.2f}%")
90
91     print("\nTraining with GradientTape automatic differentiation...")
92
93     # Re-initialize weights for GradientTape training
94     W1.assign(tf.random.normal(shape=(p, n), mean=0.0, stddev=1.0) * (q ** 0.5 / n↵
        ))
95     B1.assign(tf.zeros(shape=(p, 1)))
96     W2.assign(tf.random.normal(shape=(q, p), mean=0.0, stddev=1.0) * (q ** 0.5 / p↵
        ))
97     B2.assign(tf.zeros(shape=(q, 1)))
98
99     for epoch in range(1, epochs + 1):
100         with tf.GradientTape() as tape:
101             Z1 = tf.matmul(W1, X) + B1
102             A1 = relu(Z1)
103             Z2 = tf.matmul(W2, A1) + B2
104             A2 = softmax(Z2)
105             Y_onehot = one_hot_T(Y, q)
106             loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(labels=↵
                tf.transpose(Y_onehot), logits=tf.transpose(Z2)))
107
108             grads = tape.gradient(loss, [W1, B1, W2, B2])
109             W1.assign_sub(alpha * grads[0])
110             B1.assign_sub(alpha * grads[1])
111             W2.assign_sub(alpha * grads[2])
112             B2.assign_sub(alpha * grads[3])
113
114             if epoch % 100 == 0:
115                 preds = tf.argmax(A2, axis=0, output_type=tf.int32)
116                 correct = tf.equal(preds, tf.cast(Y[0], tf.int32))
117                 accuracy = tf.reduce_mean(tf.cast(correct, tf.float32))
118                 print(f"Epoch {epoch}, Loss: {loss.numpy():.4f}, Accuracy: {accuracy.↵
                    numpy()*100:.2f}%")
119
120     # Test on one test image
121     test_idx = 0
122     test_image = tf.reshape(Xtest[:, test_idx], (n,1))
123     plt.imshow(tf.reshape(test_image, (28,28)), cmap='gray')
124     plt.title(f"True Label: {Ytest[0, test_idx].numpy()}")
125     plt.show()
126
127     Z1_test = tf.matmul(W1, test_image) + B1
128     A1_test = relu(Z1_test)
129     Z2_test = tf.matmul(W2, A1_test) + B2
130     A2_test = softmax(Z2_test)
131     pred_label = tf.argmax(A2_test, axis=0).numpy()

```

```

132 print(f"Predicted Label: {pred_label}")
133 print("Correct prediction!" if pred_label == Ytest[0, test_idx].numpy() else "↔
      Incorrect prediction.")
134
135 # Test accuracy on full test set
136 Z1_test_all = tf.matmul(W1, Xtest) + B1
137 A1_test_all = relu(Z1_test_all)
138 Z2_test_all = tf.matmul(W2, A1_test_all) + B2
139 A2_test_all = softmax(Z2_test_all)
140 preds_test = tf.argmax(A2_test_all, axis=0, output_type=tf.int32)
141 correct_test = tf.equal(preds_test, tf.cast(Ytest[0], tf.int32))
142 accuracy_test = tf.reduce_mean(tf.cast(correct_test, tf.float32))
143 print(f"Test Set Accuracy: {accuracy_test.numpy()*100:.2f}%")

```

```

Epoch 100, Loss: 1.7792, Accuracy: 53.91%
Epoch 200, Loss: 1.4631, Accuracy: 65.27%
Epoch 300, Loss: 1.2204, Accuracy: 71.58%
Epoch 400, Loss: 1.0432, Accuracy: 75.02%
Epoch 500, Loss: 0.9166, Accuracy: 77.23%
Epoch 600, Loss: 0.8239, Accuracy: 79.22%
Epoch 700, Loss: 0.7536, Accuracy: 80.71%
Epoch 800, Loss: 0.6985, Accuracy: 81.88%
Epoch 900, Loss: 0.6540, Accuracy: 82.86%
Epoch 1000, Loss: 0.6172, Accuracy: 83.88%

```

```

Predicted Label: 7
Correct prediction!
Test Set Accuracy: 84.88%

```