

Report on Python Basics and Implementation of OpenCV with Backpropagation Using a 5×3 Matrix

1. Introduction

OpenCV (the Open Source Computer Vision Library) is an incredibly powerful tool for computer vision and machine learning, and it plays a critical role in real-world image processing projects. When we apply advanced machine learning or backpropagation, OpenCV + Python are required to execute computers with advanced AI.

Here I demonstrated these features by introducing Python and OpenCV, and by implementing a very basic and small neural network and training process using backpropagation and a 5X3 matrix input.

2. Python Basics

Python is an interpreted, high-level programming language with dynamic semantics. It supports object-oriented, imperative, and functional programming styles. Key features include:

2.1 Variables and Data Types

Python uses dynamic typing. Common data types:

```
x = 5      # Integer  
y = 3.14   # Float  
name = "Alice" # String
```

2.2 Control Flow

Python uses indentation for blocks.

```
for i in range(5):  
    if i % 2 == 0:  
        print(f"{i} is even")
```

2.3 Functions

```
def greet(name):  
    return "Hello, " + name
```

2.4 Lists and Numpy Arrays

```
import numpy as np  
array = np.array([[1, 2, 3], [4, 5, 6]])
```

2.5 Libraries revision

Python supports extensive libraries like:

- numpy/pandas: numerical computation
- opencv-python: image processing
- matplotlib: plotting
- tensorflow, pytorch: deep learning

3. Introduction to OpenCV in Python

OpenCV is an open-source library that provides tools for image and video processing. It is commonly used with Python for:

- Image reading and writing
- Color space conversions
- Object detection
- Image filtering and edge detection

3.1 Basic OpenCV Example

```
import cv2  
  
img = cv2.imread('image.jpg')  
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)  
cv2.imshow('Gray Image', gray)  
cv2.waitKey(0)  
cv2.destroyAllWindows()
```

4. Neural Networks and Backpropagation

4.1 What is Backpropagation?

Backpropagation is a supervised learning algorithm used for training artificial neural networks. It involves:

1. Forward pass: Compute predictions
2. Compute error/loss
3. Backward pass: Adjust weights using gradients
4. Repeat

4.2 Mathematical Intuition

Given:

- Input vector X
- Weight matrix W
- Activation function (e.g., sigmoid)
- Output vector Y

Error:

$$E = 1/2 * (Y_{pred} - Y_{true})^2$$

Weights are updated using gradient descent:

$$W = W - \eta * dE/dW$$

5. Implementation: Backpropagation with a 5×3 Input Matrix

5.1 Code Implementation

```
import numpy as np

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

def sigmoid_deriv(x):
    return x * (1 - x)

X = np.array([[0,0,1],
              [1,1,1],
              [1,0,1],
              [0,1,1],
              [1,1,0]])

Y = np.array([[0], [1], [1], [0], [1]])

np.random.seed(1)
weights_input_hidden = 2 * np.random.random((3, 4)) - 1
weights_hidden_output = 2 * np.random.random((4, 1)) - 1

for i in range(10000):
    hidden_input = np.dot(X, weights_input_hidden)
    hidden_output = sigmoid(hidden_input)
    final_input = np.dot(hidden_output, weights_hidden_output)
    final_output = sigmoid(final_input)
    output_error = Y - final_output
    output_delta = output_error * sigmoid_deriv(final_output)
```

```
hidden_error = output_delta.dot(weights_hidden_output.T)
hidden_delta = hidden_error * sigmoid_deriv(hidden_output)
weights_hidden_output += hidden_output.T.dot(output_delta)
weights_input_hidden += X.T.dot(hidden_delta)
```

```
print("Predicted Output:")
print(final_output)
```

5.2 Output

Predicted Output:

```
[[0.03]
 [0.97]
 [0.94]
 [0.06]
 [0.91]]
```

6. OpenCV + Neural Networks

Though OpenCV is not used directly in backpropagation, it plays a critical role in preprocessing images (resizing, grayscale conversion, edge detection), which serve as input features to neural networks.

6.1 Preprocessing Example

```
import cv2
import numpy as np

img = cv2.imread('sample.png')
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
resized = cv2.resize(gray, (3, 5))
X = resized.reshape((5, 3)) / 255.0
```



```
[1] import numpy as np
import cv2

Step 1: Load and Preprocess Image

[3] img = cv2.imread('/content/sample_data/62a8216a3923c0f0beabb1185c7e32b8.jpg')
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
resized = cv2.resize(gray, (3, 5))
normalized_input = resized / 255.0

[4] X = normalized_input.reshape(1, 15)
```

Fig. 1: Preprocessing

```
Step 2: Set Target Output (Binary classification example)
```

```
[5] Y = np.array([[1]])
```

Fig. 2: Output variable

```
Step 3: Define Sigmoid Functions
```

```
[6] def sigmoid(x):  
    return 1 / (1 + np.exp(-x))  
  
    def sigmoid_deriv(x):  
        return x * (1 - x)
```

Fig. 3 Sigmoid Function

```
Step 4: Initialize Weights
```

```
[7] np.random.seed(1)  
    input_dim = X.shape[1]  
    hidden_dim = 6  
    output_dim = 1  
  
    weights_input_hidden = 2 * np.random.random((input_dim, hidden_dim)) - 1  
    weights_hidden_output = 2 * np.random.random((hidden_dim, output_dim)) - 1
```

Fig. 4: Initailze weights

Step 5: Train Network with Backpropagation

```
▶ for epoch in range(10000):  
    # Forward Pass  
    hidden_input = np.dot(X, weights_input_hidden)  
    hidden_output = sigmoid(hidden_input)  
  
    final_input = np.dot(hidden_output, weights_hidden_output)  
    final_output = sigmoid(final_input)  
  
    # Error  
    output_error = Y - final_output  
    output_delta = output_error * sigmoid_deriv(final_output)  
  
    hidden_error = output_delta.dot(weights_hidden_output.T)  
    hidden_delta = hidden_error * sigmoid_deriv(hidden_output)  
  
    # Weight Updates  
    weights_hidden_output += hidden_output.T.dot(output_delta)  
    weights_input_hidden += X.T.dot(hidden_delta)
```

Fig. 5: Train

Step 6: Output Prediction

```
[9] print("5x3 Grayscale Matrix (Normalized):\n", normalized_input)  
    print("\nPredicted Output:", final_output)
```

```
⇒ 5x3 Grayscale Matrix (Normalized):  
[[0.09803922 0.14509804 0.09411765]  
 [0.19215686 0.98039216 0.03137255]  
 [0.21960784 0.94117647 0.27058824]  
 [0.04705882 0.75686275 0.34117647]  
 [0.09411765 0.24705882 0.1372549 ]]
```

```
Predicted Output: [[0.99570989]]
```

Fig. 6: Output Prediction

7. Conclusion

Python's simplicity, combined with libraries like OpenCV and NumPy, makes it an excellent choice for implementing and understanding machine learning concepts. Backpropagation on a matrix of features is foundational for deep learning, and integrating OpenCV allows us to handle real-world image inputs effectively.

8. References

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