Introduction to Neural Networks and Deep Learning

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1. Introduction to Neural Networks

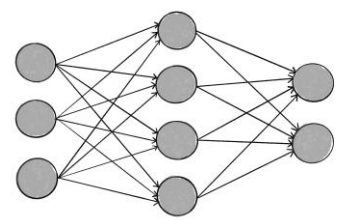
Basic concepts of neural networks.

What is a Neural Network?

- Inspired by the human brain.
- Composed of layers (input, hidden, and output).
- Learn patterns from data using weights and activation functions.

Structure of a Neural Network

- **Input Layer:** Receives input data.
- **Hidden Layers (Dense):** Extracts patterns & features.
- **Output Layer (Dense):** Produces final predictions.



Where are Neural Networks Used?

- Image recognition (e.g., face detection, medical imaging).
- Natural language processing (e.g., chatbots, language translation).
- Self-driving cars, fraud detection, etc.

Basic Structure of a Neural Network

- **Neurons:** Mathematical functions that process inputs.
- **Weights & Biases:** Control the importance of inputs.
- **Activation Functions:** Transform input values (ReLU, Sigmoid, etc.).
- **Forward Propagation:** Computes output.
- **Backpropagation:** Adjusts weights to improve learning.

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2. Setting Up the Practical Environment

Install Required Libraries

pip install jupyterlab numpy pandas matplotlib tensorflow keras torch torchvision

```
Anaconda Prompt

(base) C:\Users\A.Eldemoksy>pip install jupyterlab numpy pandas matplotlib tensorflow keras torch torchvision
```

```
Anaconda Prompt - pip insta

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```

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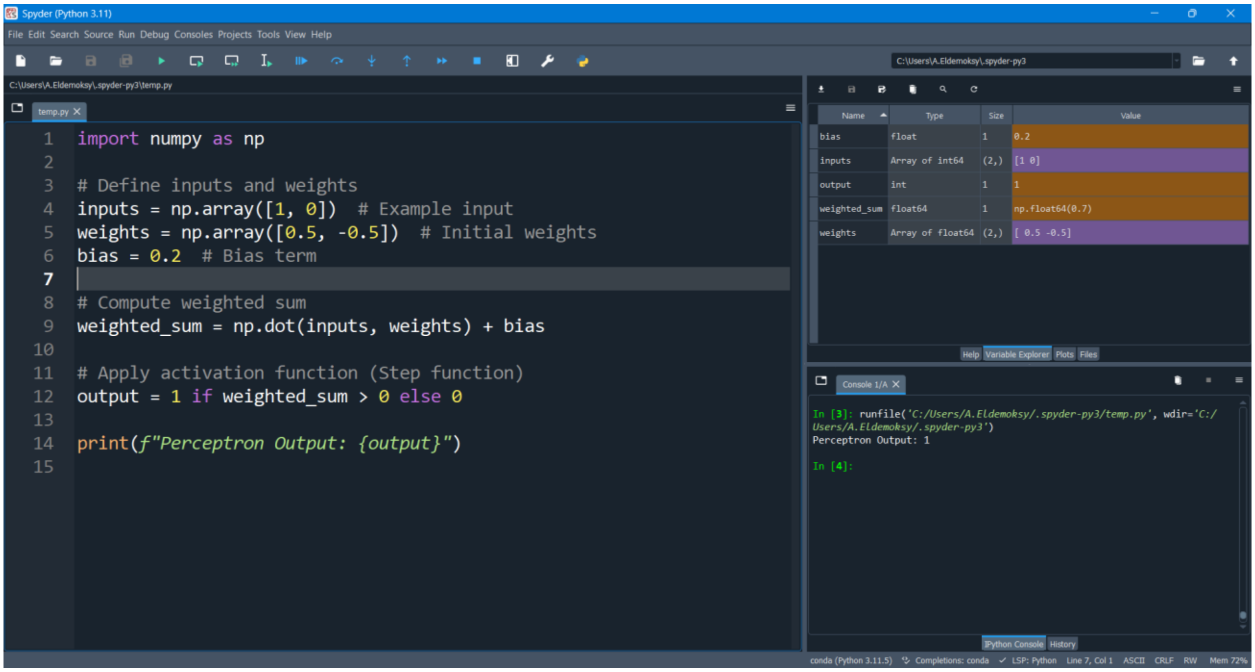
3. Implementing a Simple Perceptron

Example1: Implement a Perceptron using NumPy

```
import numpy as np

# Define inputs and weights

inputs = np.array([1, 0])  # Example input

weights = np.array([0.5, -0.5])  # Initial weights

bias = 0.2  # Bias term

# Compute weighted sum

weighted_sum = np.dot(inputs, weights) + bias

# Apply activation function (Step function)

output = 1 if weighted_sum > 0 else 0

print(f"Perceptron Output: {output}")
```



Key Takeaways:

- Adjusting weights and bias impacts learning.
- Activation functions determine neuron output.

What is Bias in Neural Networks?

Bias is an additional parameter in a **neural network** that helps adjust the output along with the weighted sum of inputs. It ensures that the model can **shift** the activation function, allowing it to learn patterns more effectively.

Why Do We Need Bias?

- Without bias, a neural network might be too rigid and unable to **fit complex data**.
- It allows the model to **generalize better** by shifting activation functions.
- Helps prevent **underfitting**, especially when data doesn't pass through the origin (0,0).

python code for the activation functions

```
import numpy as np

def binary_step(x):
    return np.where(x >= 0, 1, 0)

def linear(x):
    return x

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

def relu(x):
    return np.maximum(0, x)

def tanh(x):
    return np.tanh(x)

def softmax(x):
    exp_x = np.exp(x - np.max(x))  # Stability improvement
    return exp_x / exp_x.sum(axis=0)
```

Binary Classification on a Linearly Separable Dataset

Here, we are going to process of building, training, and evaluating a **Perceptron model** for binary classification using a synthetic, linearly separable dataset. It covers data preprocessing, model training, and performance evaluation. We will follow these steps:

1. Import Libraries
2. Generate Dataset using **make_blobs()**
3. Train-Test Split with **train_test_split()**
4. Scale Features using **StandardScaler()**
5. Initialize Perceptron with appropriate input size
6. Train the Model with **fit()** over 100 epochs
7. Predict on test data and evaluate accuracy by comparing predictions with actual labels
8. Visualize Results using a scatter plot

```python
# Import the necessary library
import numpy as np
from sklearn.datasets import make_blobs
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Generate a linearly separable dataset with two classes
X, y = make_blobs(n_samples=1000,
                  n_features=2,
                  centers=2,
                  cluster_std=3,
                  random_state=23)

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.2,
                                                    random_state=23,
                                                    shuffle=True
                                                   )

# Scale the input features to have zero mean and unit variance
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```python
# Set the random seed legacy
np.random.seed(23)

# Initialize the Perceptron with the appropriate number of inputs
perceptron = Perceptron(num_inputs=X_train.shape[1])

# Train the Perceptron on the training data
perceptron.fit(X_train, y_train, num_epochs=100)

# Prediction
pred = perceptron.predict(X_test)

# Test the accuracy of the trained Perceptron on the testing data
accuracy = np.mean(pred != y_test)
print("Accuracy:", accuracy)

# Plot the dataset
plt.scatter(X_test[:, 0], X_test[:, 1], c=pred)
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()
```

Output:

```
Accuracy: 0.975
```