AutoEncoder

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Autoencoder

- An **autoencoder** is a type of artificial neural network designed to:
- **Learn Efficient Representations**: It compresses data into a smaller form (encoding) and reconstructs it back to the original form (decoding).
- **Self-supervised Learning**: It uses input data as both the input and output, training itself without labeled data.
- **Key Goal**: To capture the most important features or patterns in data while minimizing reconstruction error.

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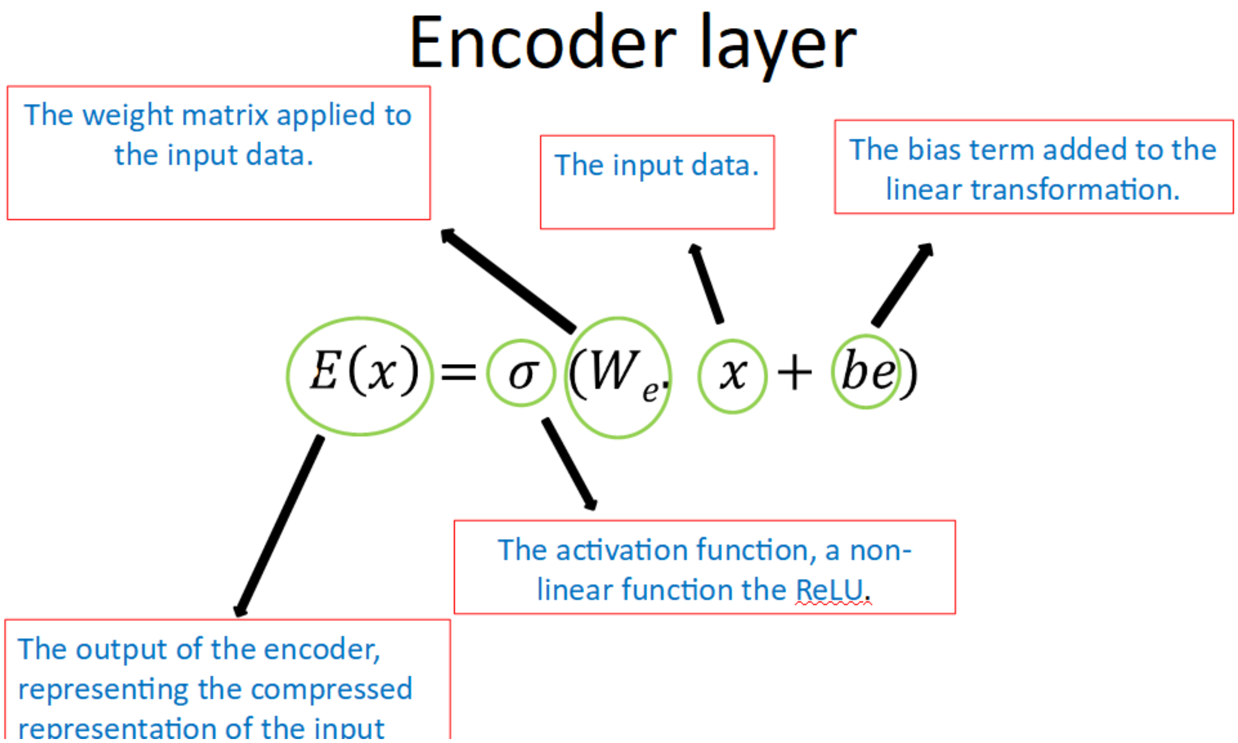
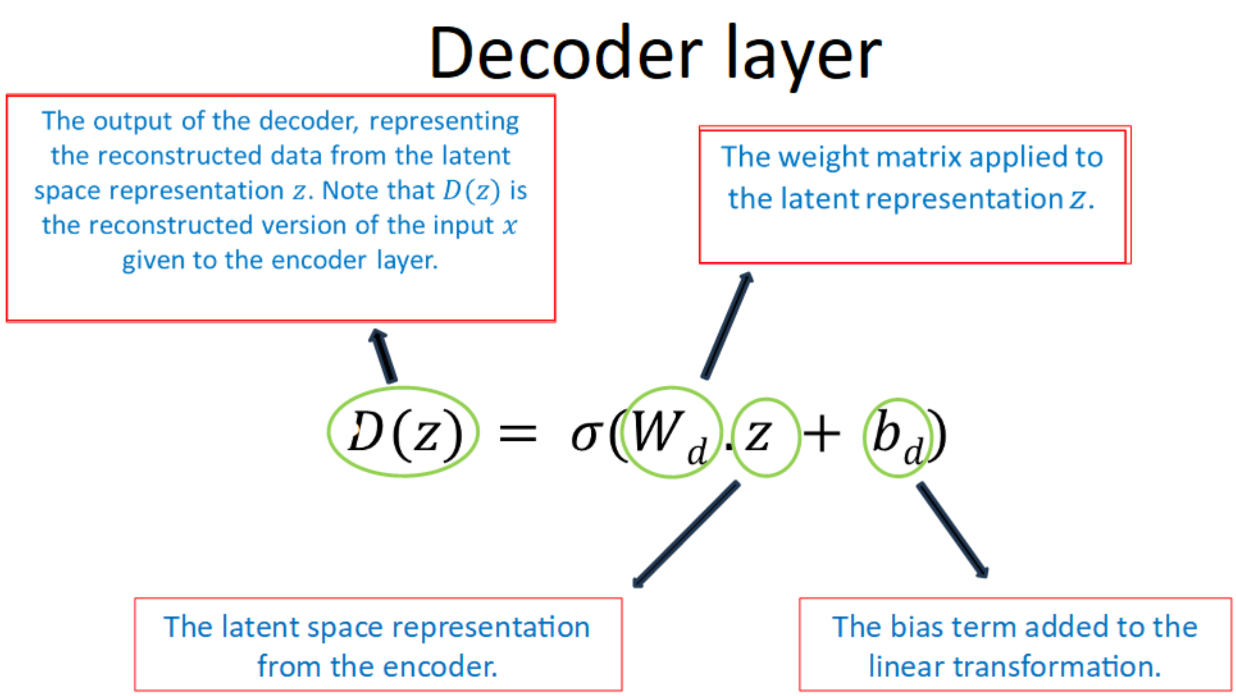
Encoder Layer



Decoder Layer



Mean Squared Error (MSE)

Autoencoder loss function

The reconstructed output from the autoencoder.

$$L_{MSE}(x_i) = \frac{1}{n}\sum_{i=1}^{n}(x_i - D(E(x_i)))^2$$

Mean square error based loss function

The number of samples

is the element of the input data

Autoendoer Implementation from Scratch (Base Concept + Practice Pupose Only)

Steps: The basics of "AutoEncoder" with it's implementaion using "Numpy" only.

Explanation of Components:

1. x_i: The original input data point.
2. $E(x_i)$: The encoded representation of the input data through the encoder.
3. $D(E(x_i))$: The reconstructed output after passing the encoded data through the decoder.
4. $(x_i - D(E(x_i)))^2$: The squared difference (error) between the original data and the reconstructed data for each dimension.
5. $\frac{1}{n}$: The average is taken over all dimensions n in the data.

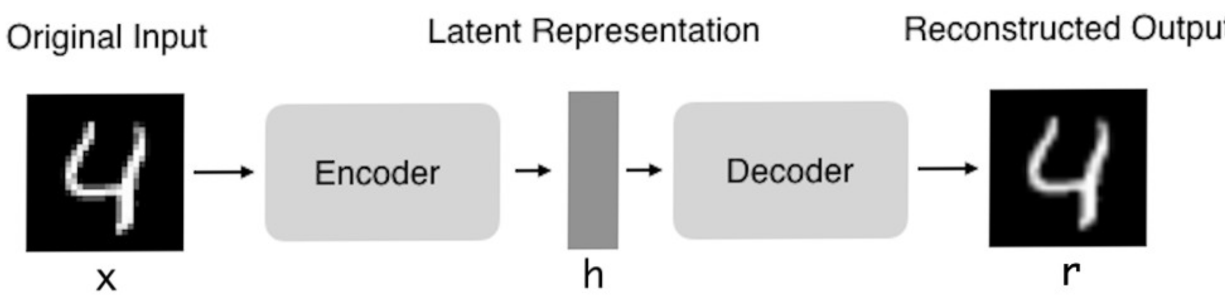
1. Numpy library
2. input -> xi (Self Defined Weights)
3. Encoder/Decoder Weights (Self Defined Weights)

4. Main AutoEncoder_Decoder(): Function that performs the following
- Encoder Calculations
- Decoder Calculations
- Mean Squared Error
1. Display_Data() that displays Encoder, Decoder,and MSE

```
import numpy as np  # type: ignore

xi = np.array([1.0, 0.8, 0.5])          # Input data


wEncoder = np.array([[0.8, 0.3, 0.5],   # Encoder weights
                    [0.4, 0.7, 0.2]])

wDecoder = np.array([[0.9, 0.4],        # Decoder Weights
                     [0.2, 0.7],
                     [0.5, 0.3]])



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


def Autoencoder_Decoder(wEncoder,wDecoder, xi):
# ---Encoder---
    z = np.dot(wEncoder, xi)
    activated_z = relu(z)

# ---Decoder---
    x_reconstructed = np.dot(wDecoder, activated_z)
    activated_reconstructed_x = relu(x_reconstructed)

# ---Mean Squared Error---
    diffrences = []
    for i,j in zip(xi, activated_reconstructed_x):
       squeare_errors = pow((i - j),2)
       diffrences.append(squeare_errors)

    return ("Encoder :", activated_z),  ("Decoder :
",activated_reconstructed_x), ("Mean Squared Error :",

sum(np.array(diffrences)) / len(diffrences))


def Display_Data(): # Display the Data
   for i,j in Autoencoder_Decoder(wEncoder, wDecoder, xi): # Function
Autoencoder_Decoder()
       print(i,j)
```

```
Display_Data() # Call the function

Encoder : [1.29 1.06]
Decoder :  [1.585 1.    0.963]
Mean Squared Error : 0.19886466666666677
```

Level 2: Implementation of AutoEncoder on image

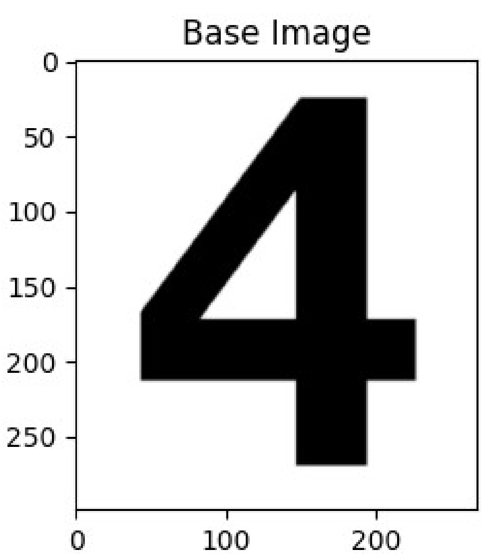


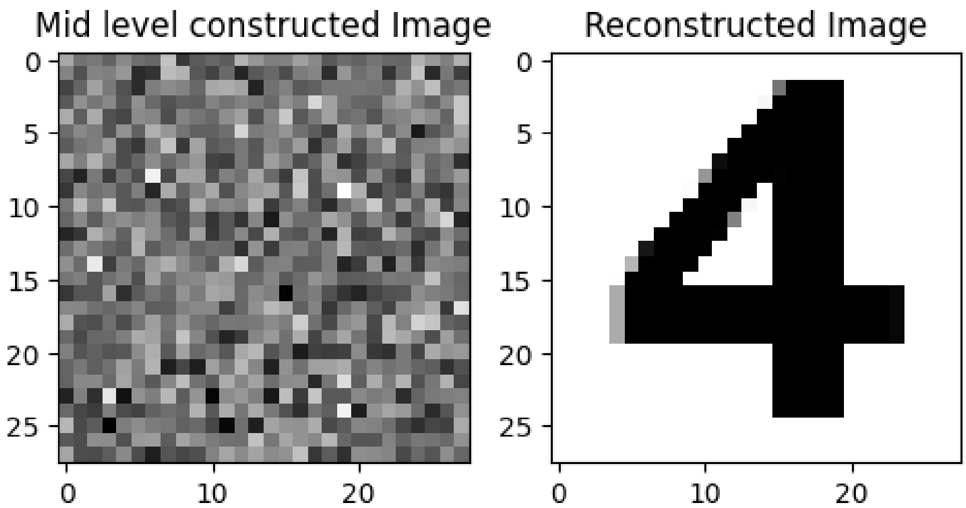
Steps:

1. Dependecies (Libraries)
2. ReLU Activation Function
3. Load grayscale image and resize
4. Flatten image into 1D array
5. Encoder Weights and calculations
6. Decoder Weights and calculations
7. Finally, Show original and reconstructed images

```
import numpy as np                # type: ignore
import cv2                        # type: ignore
import matplotlib.pyplot as plt # type: ignore

def relu(x):
    return np.maximum(0, x)  # ReLU Activation Function

# Load grayscale image and resize
img = cv2.imread('image.png')
image = cv2.imread("image.png", cv2.IMREAD_GRAYSCALE)  # Change image 
path
image = cv2.resize(image, (28, 28))  # Resize to 28x28
image = image / 255.0  # Normalize pixel values (0-1)

# Flatten image into 1D array
x = image.flatten()
```

```
# Encoder Weights
wencoder = np.random.rand(100, x.shape[0])  # Random weights
z = np.dot(wencoder, x)
activated_z = relu(z)

# Decoder Weights and calculations
wdecoder = np.random.rand(x.shape[0], 100)
x_reconstructed = np.dot(wdecoder, activated_z)
activated_reconstructed_x = relu(x_reconstructed)

# Reshape to original image size
x_reconstructed_image = activated_reconstructed_x.reshape(28, 28)

# Show original and reconstructed images
plt.figure(figsize=(6,3))
plt.subplot(1, 2, 1)
plt.imshow(img, cmap="gray")
plt.title("Base Image")

plt.figure(figsize=(6,3))
plt.subplot(1, 2, 2)
plt.imshow(image, cmap="gray")
plt.title("Reconstructed Image")

plt.subplot(1, 2, 1)
plt.imshow(x_reconstructed_image, cmap="gray")
plt.title("Mid level constructed Image")
plt.show()
```





Mid level constructed Image
Reconstructed Image
0
5
10
15
20
25
0
10
20