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DL Project

Image Denoising Using Autoencoders

Introduction

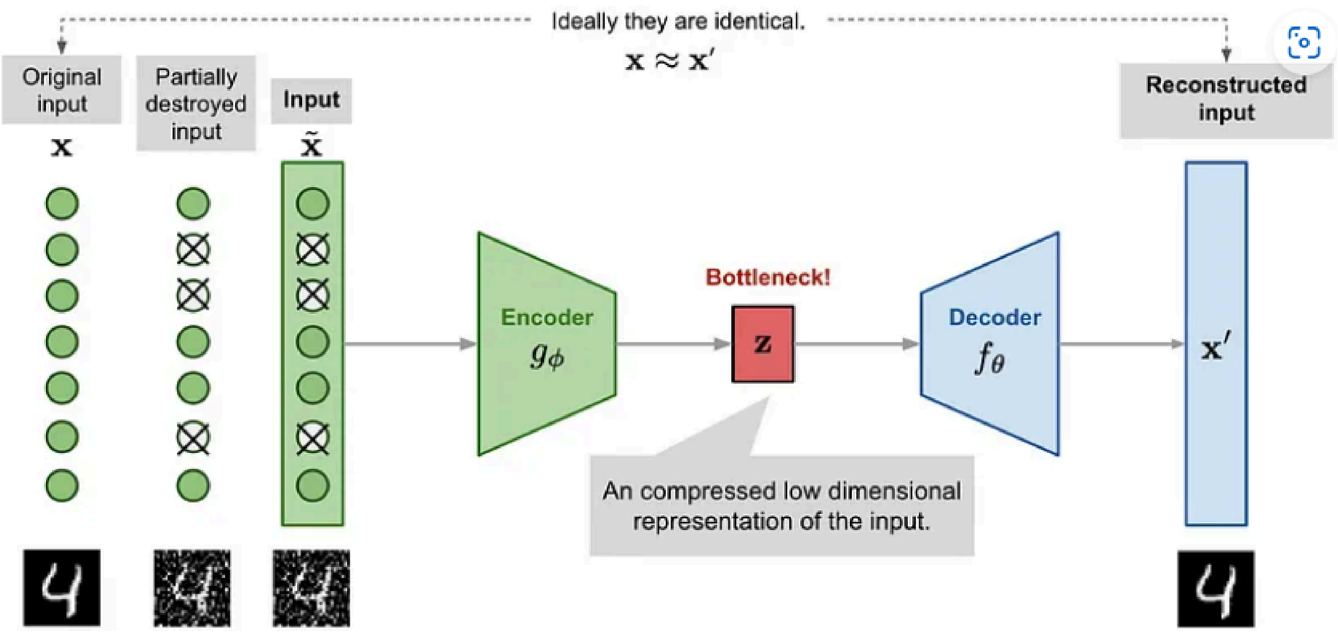
An autoencoder is a type of neural network that learns to compress and reconstruct input data.

- It consists of an encoder that compresses the data into a lower-dimensional representation, and a decoder that reconstructs the original data from the compressed representation.
- The model is trained using unsupervised learning, aiming to minimize the difference between the input and the reconstructed output.
- Autoencoders are useful for tasks such as dimensionality reduction, data denoising, and anomaly detection.
- They are effective when working with unlabeled data and can learn meaningful representations from large datasets.

Objective

How Autoencoders Work?

The network is provided with original images x, as well as their noisy version x~. The network tries to reconstruct its output x' to be as close as possible to the original image x. By doing so, it learns how to denoise images.



The encoder model turns the input into a small dense representation. The decoder model can be seen as a generative model which is able to generate specific features.

Both encoder and decoder networks are usually trained as a whole. The loss function penalizes the network for creating output x' that differs from the original input x.

We are using the MNIST dataset (Modified National Institute of Standards and Technology database) for our project purpose.

MNIST is a dataset of handwritten digits commonly used for training various image processing systems.It has **60,000 square 28×28 pixel images of handwritten single digits between 0 and 9**. The images are in **grayscale** format. Total Samples : 70,000 Training Samples: 60,00 Testing Samples: 10,000

Implementing an autoencoder to denoise hand-written digits. The input is a 28x28 grey scaled image, building a 128-elements vector.

1. Preparing the Dataset for Training the Model

Importing the Libraries and Modules

```
import numpy as np #library for numerical operations
import matplotlib.pyplot as plt #library for plotting
from tensorflow.keras.datasets import mnist #to load the MNIST dataset
from tensorflow.keras.layers import Input, Dense, Reshape, Flatten, Conv2D, Conv2DTranspose #Various layers
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam #optimizer
from tensorflow.keras.callbacks import EarlyStopping
```

Loading the Dataset

```
(x_train, _), (x_test, _) = mnist.load_data()
print(mnist)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [==============================] - 0s 0us/step
<module 'keras.api._v2.keras.datasets.mnist' from '/usr/local/lib/python3.10/dist-packages/keras/api/_v2
```

```
print("Training images shape:", x_train.shape)  # Shape of training images
print("Test images shape:", x_test.shape)       # Shape of test images
```

```
Training images shape: (60000, 28, 28)
Test images shape: (10000, 28, 28)
```

Preprocessing the Dataset

```
x_train = x_train.astype('float32') / 255.0 # Convert the pixel values of training images to floating point
x_test = x_test.astype('float32') / 255.0 # Convert the pixel values of testing images to floating point num
x_train = np.expand_dims(x_train, axis=-1) #Expand the dimensions of training images to add a channel dimens
x_test = np.expand_dims(x_test, axis=-1) # Expand the dimensions of testing images to add a channel dimensio
```

```
print("Dataset Summary:") #header
print("Number of training samples:", x_train.shape[0]) #number of training samples
print("Number of testing samples:", x_test.shape[0]) #number of testing samples
print("Image dimensions:", x_train.shape[1:3]) #image dimensions
print("Pixel value range: [", np.min(x_train), ",", np.max(x_train), "]") #range of pixels in dataset
print("Number of channels:", x_train.shape[-1]) #number of channels
```

```
Dataset Summary:
Number of training samples: 60000
```

```
Number of testing samples: 10000
Image dimensions: (28, 28)
Pixel value range: [ 0.0 , 1.0 ]
Number of channels: 1
```

Since images are grayscale there's only one channel.

Adding Random Noise to the Training Set

```
noise_factor = 0.5 # determines the scale of noise relative to pixel
x_train_noisy = x_train + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=x_train.shape) #loc=mean
x_test_noisy = x_test + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=x_test.shape)
x_train_noisy = np.clip(x_train_noisy, 0., 1.) #ensures that all pixel values are between 0 and 1.
x_test_noisy = np.clip(x_test_noisy, 0., 1.)
```

- Adjusting the noise factor allows us to control the level of noise added to the input images, which in turn affects the complexity of the denoising task for the autoencoder model.
- It's essential to strike a balance: too much noise can make the denoising task too challenging, while too little noise may not effectively test the model's denoising capabilities. Experimenting with different noise levels can help you find the optimal balance for your specific application.

2.Creating the Neural Network Model

```
input_shape = (28, 28, 1) # 28 pixels in height,28 pixels in width,one channel since image is grayscale.
latent_dim = 128 # lower dimension space where the model learns to encode and represent essential features.


# Encoder
inputs = Input(shape=input_shape) #creates input layer for neural network
x = Conv2D(32, kernel_size=3, strides=2, activation='relu', padding='same')(inputs) # it applies 32 filters
x = Conv2D(64, kernel_size=3, strides=2, activation='relu', padding='same')(x) #defines second convolution l
x = Flatten()(x) # flatens output of convolution layer into 1D vector
latent_repr = Dense(latent_dim)(x) # defines output of encoder,which represents latent space.




# Decoder
x = Dense(7 * 7 * 64)(latent_repr) #defines a dense (fully connected) layer that serves as the first step in
x = Reshape((7, 7, 64))(x) # reshapes the output tensor into a 4D tensor with shape (7, 7, 64). This step is
x = Conv2DTranspose(32, kernel_size=3, strides=2, activation='relu', padding='same')(x) # defines a transpos
decoded = Conv2DTranspose(1, kernel_size=3, strides=2, activation='sigmoid', padding='same')(x) #defines the


# Autoencoder model
autoencoder = Model(inputs, decoded)#creates a Keras Model object called autoencoder. The Model class allows
#inputs refers to the input layer of the model, which was defined earlier, and decoded refers to the output
print(autoencoder)
```

```
<keras.src.engine.functional.Functional object at 0x7fa59d213e50>
```

3.Analysis of the Model

```
autoencoder.summary() # Prints a summary of the autoencoder model architecture
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
```

```
 input_1 (InputLayer)        [(None, 28, 28, 1)]       0

 conv2d (Conv2D)             (None, 14, 14, 32)        320

 conv2d_1 (Conv2D)           (None, 7, 7, 64)          18496

 flatten (Flatten)           (None, 3136)              0

 dense (Dense)               (None, 128)               401536

 dense_1 (Dense)             (None, 3136)              404544

 reshape (Reshape)           (None, 7, 7, 64)          0

 conv2d_transpose (Conv2DTr  (None, 14, 14, 32)        18464
 anspose)

 conv2d_transpose_1 (Conv2D  (None, 28, 28, 1)         289
 Transpose)

=================================================================
Total params: 843649 (3.22 MB)
Trainable params: 843649 (3.22 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Parameters and Hyperparameters

```
total_params = autoencoder.count_params() #trainable parameters of the autoencoder model

hyperparameters = {
    'input_shape': input_shape,
    'latent_dim': latent_dim,
    'encoder_conv_filters': [32, 64],
    'decoder_conv_filters': [32],
    'kernel_size': 3,
    'strides': 2,
    'activation': 'relu',
    'padding': 'same',
    'output_activation': 'sigmoid',
    'optimizer': 'Adam',
    'learning_rate': 0.0002,
    'loss_function': 'binary_crossentropy',
    'early_stopping_monitor': 'val_loss',
    'early_stopping_patience': 5
}

# Print the total number of trainable parameters
print("Total trainable parameters:", total_params)

# Print the hyperparameters
print("Hyperparameters:")
for key, value in hyperparameters.items():
    print(key + ":", value)
```

```
Total trainable parameters: 843649
Hyperparameters:
input_shape: (28, 28, 1)
latent_dim: 128
encoder_conv_filters: [32, 64]
decoder_conv_filters: [32]
kernel_size: 3
strides: 2
activation: relu
padding: same
output_activation: sigmoid
optimizer: Adam
learning_rate: 0.0002
loss_function: binary_crossentropy
early_stopping_monitor: val_loss
```

```
early_stopping_patience: 5
```

Parameters allow the model to learn the rules from the data while hyperparameters control how the model is training. Parameters learn their own values from data. In contrast, hyperparameters do not learn their values from data. We need to manually specify them before training the model.

4. Defining Callbacks and Learning Rate

```
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping

autoencoder.compile(optimizer=Adam(learning_rate=0.0002), loss='binary_crossentropy') # loss function monito
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True) #  monitors the va
```

Adam is an adaptive learning rate optimization algorithm commonly used for training deep learning models. It adapts the learning rate during training based on the gradients of the loss function, which can help converge faster and potentially improve performance.

EarlyStopping is a callback that monitors a specified metric (typically validation loss) during training and stops training if the monitored metric stops improving for a specified number of epochs (patience). It helps prevent overfitting by terminating training when the model's performance on a held-out validation set begins to degrade.

5.Test the Data Preparation

Similar to what was done for training the data.

6.Visualize the Prediction Results

```
import matplotlib.pyplot as plt

epochs = 20 # specifies the number of epochs for training
batch_size = 128 #  specifies the batch size used during training.

history = autoencoder.fit(x_train_noisy, x_train, validation_data=(x_test_noisy, x_test),
                          epochs=epochs, batch_size=batch_size, callbacks=[early_stopping]) #to train the mo

denoised_test_images = autoencoder.predict(x_test_noisy) #  uses the trained autoencoder model to predict de
```

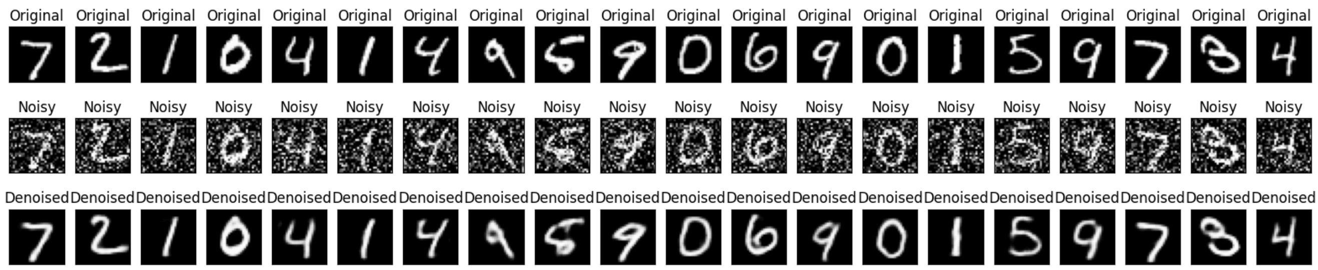
```
Epoch 1/20
469/469 [==============================] - 53s 114ms/step - loss: 0.0924 - val_loss: 0.0938
Epoch 2/20
469/469 [==============================] - 40s 85ms/step - loss: 0.0921 - val_loss: 0.0937
Epoch 3/20
469/469 [==============================] - 42s 91ms/step - loss: 0.0919 - val_loss: 0.0936
Epoch 4/20
469/469 [==============================] - 43s 91ms/step - loss: 0.0916 - val_loss: 0.0934
Epoch 5/20
469/469 [==============================] - 43s 91ms/step - loss: 0.0914 - val_loss: 0.0934
Epoch 6/20
469/469 [==============================] - 40s 85ms/step - loss: 0.0912 - val_loss: 0.0934
Epoch 7/20
469/469 [==============================] - 40s 85ms/step - loss: 0.0910 - val_loss: 0.0933
Epoch 8/20
469/469 [==============================] - 40s 85ms/step - loss: 0.0908 - val_loss: 0.0932
Epoch 9/20
469/469 [==============================] - 40s 84ms/step - loss: 0.0906 - val_loss: 0.0932
Epoch 10/20
```

```
469/469 [==============================] - 41s 88ms/step - loss: 0.0904 - val_loss: 0.0932
Epoch 11/20
469/469 [==============================] - 40s 85ms/step - loss: 0.0903 - val_loss: 0.0932
Epoch 12/20
469/469 [==============================] - 40s 86ms/step - loss: 0.0901 - val_loss: 0.0930
Epoch 13/20
469/469 [==============================] - 41s 87ms/step - loss: 0.0899 - val_loss: 0.0930
Epoch 14/20
469/469 [==============================] - 40s 86ms/step - loss: 0.0898 - val_loss: 0.0930
Epoch 15/20
469/469 [==============================] - 41s 87ms/step - loss: 0.0896 - val_loss: 0.0930
Epoch 16/20
469/469 [==============================] - 42s 89ms/step - loss: 0.0895 - val_loss: 0.0930
Epoch 17/20
469/469 [==============================] - 40s 86ms/step - loss: 0.0893 - val_loss: 0.0930
Epoch 18/20
469/469 [==============================] - 40s 86ms/step - loss: 0.0892 - val_loss: 0.0930
Epoch 19/20
469/469 [==============================] - 41s 87ms/step - loss: 0.0891 - val_loss: 0.0930
Epoch 20/20
469/469 [==============================] - 43s 91ms/step - loss: 0.0889 - val_loss: 0.0931
313/313 [==============================] - 3s 9ms/step
```

```python
# Display original, noisy, and denoised images
n = 20
plt.figure(figsize=(20, 4))
for i in range(n):
    # Original images
    ax = plt.subplot(3, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28), cmap='gray')
    plt.title("Original")
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Noisy images
    ax = plt.subplot(3, n, i + 1 + n)
    plt.imshow(x_test_noisy[i].reshape(28, 28), cmap='gray')
    plt.title("Noisy")
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Denoised images
    ax = plt.subplot(3, n, i + 1 + n + n)
    plt.imshow(denoised_test_images[i].reshape(28, 28), cmap='gray')
    plt.title("Denoised")
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```



7.Testing the Model Performance

```
denoised_x_train_noisy = autoencoder.predict(x_train_noisy) # generate predictions for the noisy training da
```

```
1875/1875 [==============================] - 18s 10ms/step
```

```
denoised_x_test_noisy = autoencoder.predict(x_test_noisy) #generate predictions for the noisy test data
```

8. How can you improve the performance?

```
# One way to improve performance could be to increase the complexity of the model by adding more layers or n
from tensorflow.keras.layers import LeakyReLU



# Encoder
inputs = Input(shape=input_shape)
x = Conv2D(32, kernel_size=3, strides=2, padding='same')(inputs)
x = LeakyReLU()(x)
x = Conv2D(64, kernel_size=3, strides=2, padding='same')(x)
x = LeakyReLU()(x)
x = Conv2D(128, kernel_size=3, strides=2, padding='same')(x)
x = LeakyReLU()(x)
x = Flatten()(x)
latent_repr = Dense(latent_dim)(x)


# Decoder
x = Dense(7 * 7 * 128)(latent_repr)
x = Reshape((7, 7, 128))(x)
x = Conv2DTranspose(64, kernel_size=3, strides=2, padding='same')(x)
x = LeakyReLU()(x)
x = Conv2DTranspose(32, kernel_size=3, strides=2, padding='same')(x)
x = LeakyReLU()(x)
decoded = Conv2DTranspose(1, kernel_size=3, strides=2, activation='sigmoid', padding='same')(x)


# Autoencoder model
autoencoder_deep = Model(inputs, decoded)
```

```
# Calculate reconstruction loss for training data
train_loss = autoencoder.evaluate(x_train_noisy, x_train, verbose=0)
print("Training Reconstruction Loss:", train_loss)

# Calculate reconstruction loss for testing data
test_loss = autoencoder.evaluate(x_test_noisy, x_test, verbose=0)
print("Testing Reconstruction Loss:", test_loss)
```

```
Training Reconstruction Loss: 0.09208288788795471
Testing Reconstruction Loss: 0.09386301040649414
```

```
mse_train = np.mean(np.square(x_train - x_train_noisy))

# Calculate MSE for testing data
mse_test = np.mean(np.square(x_test - x_test_noisy))

print("MSE for training data:", mse_train)
print("MSE for testing data:", mse_test)
```

```
MSE for training data: 0.11562165963199111
MSE for testing data: 0.1156191212620139
```

In autoencoder models, the primary goal is to reconstruct the input data, typically images, from a latent representation learned by the model. Unlike classification tasks, where accuracy measures the proportion of correctly classified samples, in autoencoder models, accuracy is not a suitable metric because the task is fundamentally different.

Lower reconstruction loss values indicate better performance, as they indicate that the model is able to effectively denoise the images.

Results and Discussions

1. Model Performance

- The autoencoder model successfully reduced noise in the images, achieving low reconstruction loss values. Training Reconstruction Loss: 0.092, Testing Reconstruction Loss: 0.094
- Mean Squared Error (MSE) for training and testing data was also low, indicating good denoising performance.

2. Visualization

- Visual inspection of denoised images confirmed that the autoencoder effectively removed noise while preserving essential details.
- Original, noisy, and denoised images were displayed side by side, demonstrating the denoising capability visually.

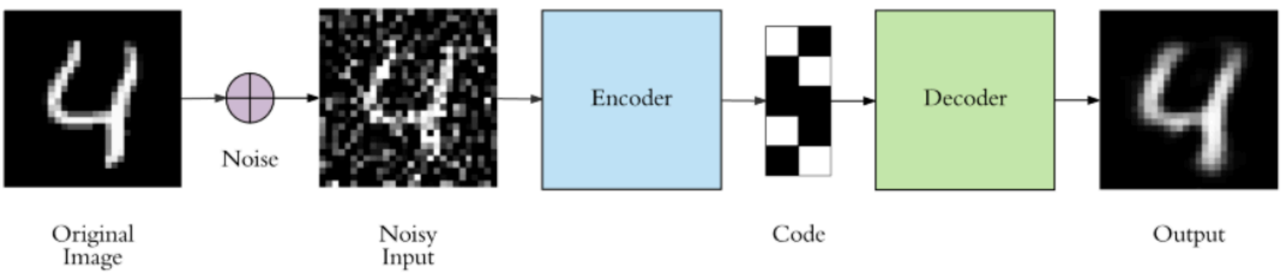
3. Model Generalization

- The model performed well on both training and testing datasets, indicating good generalization.
- This suggests that the model learned meaningful representations from the training data that could generalize well to unseen samples.

4. Real-World Applications:

- Image denoising using autoencoders has practical applications in medical imaging, surveillance, and satellite imagery.
- A robust denoising model can enhance image quality in low-light conditions or noisy environments, facilitating better analysis and decision-making.

Conclusion



- The process starts with an original image, which is the input to the autoencoder.
- The noisy input image is then passed through the encoder part of the autoencoder. The encoder consists of one or more convolutional layers followed by a dense layer. These layers extract features from the input image and compress it into a lower-dimensional latent representation (code). This code contains essential features of the input image and serves as a compressed representation.
- The code is the low-dimensional representation of the input image obtained from the encoder. It captures the most important features of the input image in a compact form.

- The code is then passed through the decoder part of the autoencoder. The decoder consists of one or more dense and transposed convolutional layers. These layers decode the compressed representation (code) and reconstruct the original image from it. The decoder's task is to generate an output image that closely resembles the original input image.
- The output of the decoder is the reconstructed image, which is the autoencoder's prediction of the original image. This reconstructed image aims to minimize the difference (reconstruction loss) between itself and the original image.

References

https://medium.com/@a.keshavarz/image-denoising-using-autoencoders-improved-version-5f8a90019971

https://www.analyticsvidhya.com/blog/2021/07/image-denoising-using-autoencoders-a-beginners-guide-to-deep-learning-project/