task2_autoencoder

March 14, 2025

[1]:
```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
from nn.nn import NeuralNetwork
```

[2]:
```python
random_seed = 37
```

[3]:
```python
digits = load_digits()
X = digits.data
y = digits.target

X = X / 16.0 # Normalize the data to range [0, 1]

X_train, X_val, y_train, y_val = train_test_split(
    X,
    y,
    test_size=0.2,
    random_state=random_seed
   )

print(X_val.shape)
```

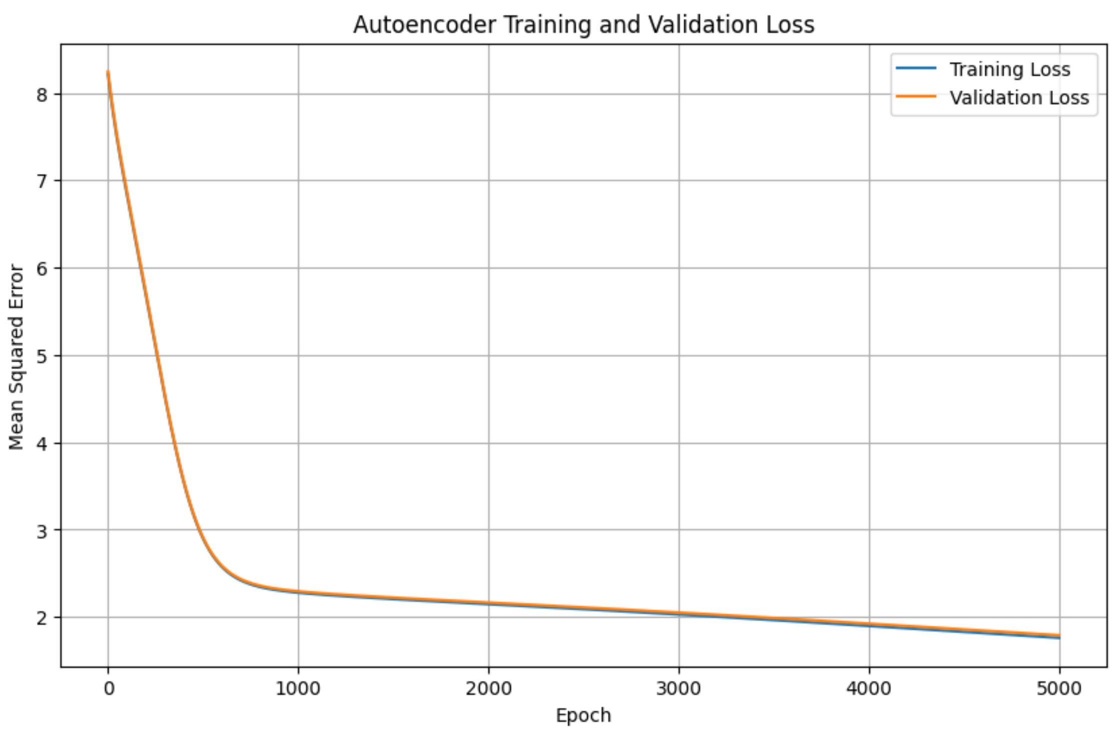
```
(360, 64)
```

[4]:
```python
nn_architecture = [
    {'input_dim': 64, 'output_dim': 16, 'activation': 'relu'},
    {'input_dim': 16, 'output_dim': 64, 'activation': 'none'},
]

# Hyperparameters
learning_rate = 0.0001 # looked like an L at lr=0.01, and was way too slow at␣
 ↪lr=0.001
seed = random_seed # 37 is a cool number
batch_size = 16 # data easily fits in memory
epochs = 5000 # shite model won't overfit shit
loss_function = 'mean_squared_error' # classic
```

```python
autoencoder = NeuralNetwork(
    nn_arch=nn_architecture,
    lr=learning_rate,
    seed=seed,
    batch_size=batch_size,
    epochs=epochs,
    loss_function=loss_function
)
```

[5]:

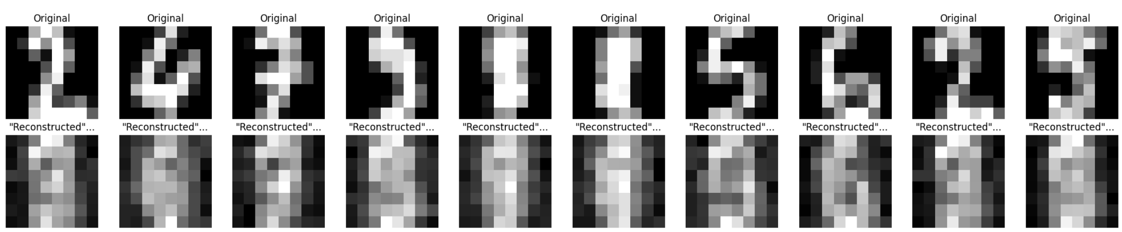
```python
# Train the autoencoder
train_losses, val_losses = autoencoder.fit(X_train, X_train, X_val, X_val)

plt.figure(figsize=(10, 6))
plt.plot(train_losses, label='Training Loss')
plt.plot(val_losses, label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Mean Squared Error')
plt.title('Autoencoder Training and Validation Loss')
plt.legend()
plt.grid(True)
plt.show()
```



[6]:
```
# Evaluate the autoencoder on validation data
reconstructed_val, _ = autoencoder.forward(X_val)
reconstructed_val = reconstructed_val.T  # Convert to original shape

mse = np.mean((X_val - reconstructed_val) ** 2)
print(f"Average reconstruction error (MSE) on validation set: {mse:.6f}")
```

```
Average reconstruction error (MSE) on validation set: 0.055931
```

[9]:
```
# Visualize original images and their reconstructions
n = 10  # Number of digits to display
plt.figure(figsize=(20, 4))

for i in range(n):
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(X_val[i].reshape(8, 8), cmap='gray') #plot originals
    plt.title("Original")
    plt.axis('off')

    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(reconstructed_val[i].reshape(8, 8), cmap='gray') #plot␣
 ↪"reconstructions"... oof
    plt.title('"Reconstructed"')
    plt.axis('off')

plt.tight_layout()
plt.show()
```



0.0.1 Hyperparameter Choices:

1. Architecture (64x16x64):
    - required by assignment
2. Learning Rate (0.0001):
    - looked like an L at lr=0.01, and was way too slow at lr=0.001
    - I had the computational power to train for a while, so I went with a smaller learning rate bc larger ones were just not improving the loss
    - still a little high based on the l-shaped loss curve
3. Batch Size (16):

- Provides good balance between computation efficiency and gradient accuracy
- Started with 32, but found the batch size needed to be small enough to update parameters frequently

4. Epochs (5000):
   - found that a low LR and high epochs minimized validation loss on this dataset
   - modern computers can handle this well
5. Loss Function (MSE):
   - Mean squared error is the standard for reconstruction tasks

[ ]:

```

```