Autoencoders

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- They work by compressing the input into a latent-space representation, and then reconstructing the output from this representation.

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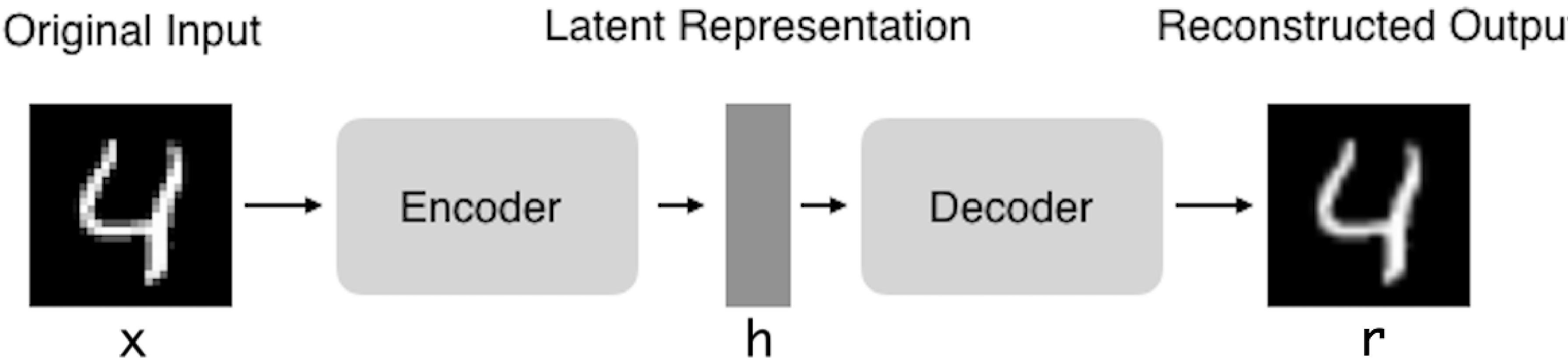

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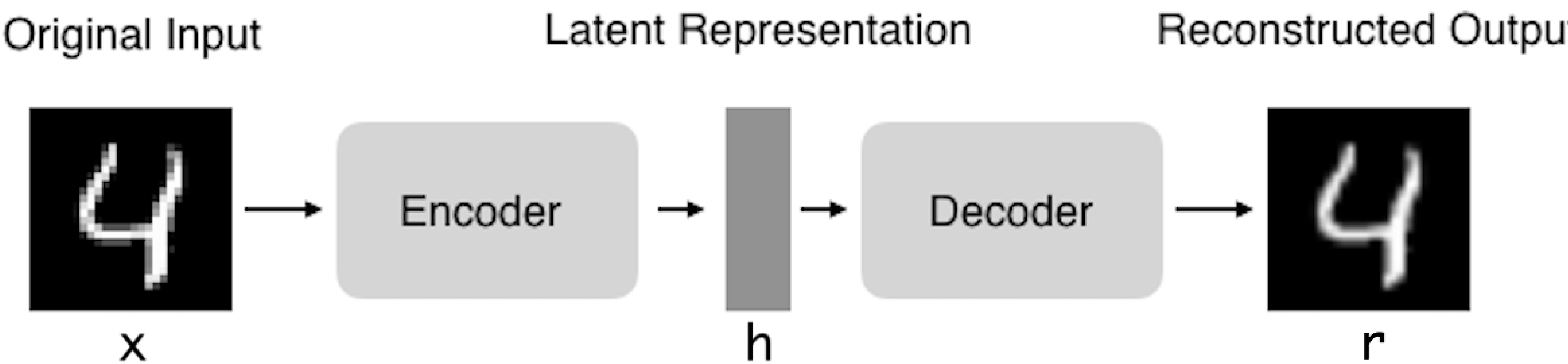

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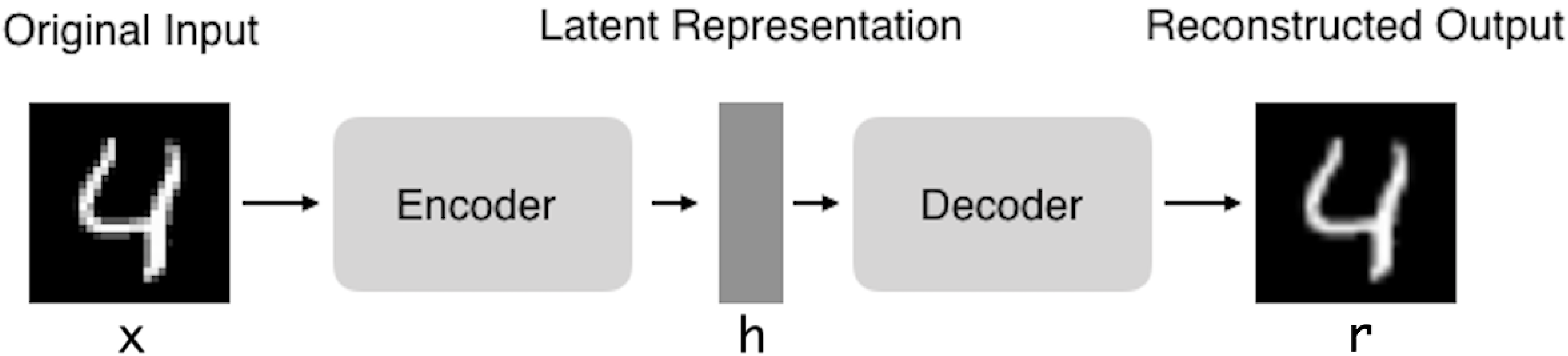

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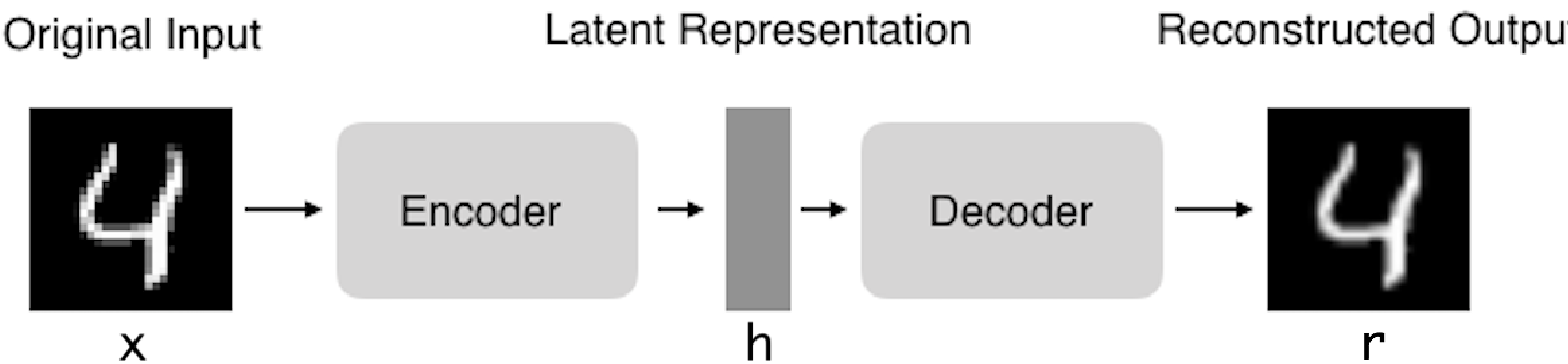

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➢The autoencoder as a whole can thus be described by the function g(f(x)) = r where you want r as close as the original input x.

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- Indeed, we hope that, by training the autoencoder to copy the input to the output, the latent representation 'h' will take on useful properties.

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- By training an undercomplete representation, we force the autoencoder to learn the most salient features of the training data.

- If the autoencoder is given too much capacity, it can learn to perform the copying task without extracting any useful information about the distribution of the data.

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- In these cases, even a linear encoder and linear decoder can learn to copy the input to the output without learning anything useful about the data distribution.

- Ideally, one could train any architecture of autoencoder successfully, choosing the code dimension and the capacity of the encoder and decoder based on the complexity of distribution to be modelled.

Types of Autoencoders [1]

- Vanilla autoencoder
- Multilayer autoencoder
- Convolutional autoencoder
- Regularized autoencoder

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  - The input and output are the same, and we learn how to reconstruct the input, for example using the adam optimizer and the mean squared error loss function.

Types of Autoencoders [1]

- Vanilla autoencoder

```
input_size = 784
hidden_size = 64
output_size = 784

x = Input(shape=(input_size,))

# Encoder
h = Dense(hidden_size, activation='relu')(x)

# Decoder
r = Dense(output_size, activation='sigmoid')(h)

autoencoder = Model(input=x, output=r)
autoencoder.compile(optimizer='adam', loss='mse')
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autoencoder.fit(x_train, x_train, epochs=5)
reconstructed = autoencoder.predict(x_test)
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    - But we should be careful to not make it too powerful.
    - Otherwise the autoencoder will simply learn to copy its inputs to the output, without learning any meaningful representation.
    - It will just mimic the identity function.
    - The autoencoder will reconstruct the training data perfectly, but it will be overfitting without being able to generalize to new instances, which is not what we want.

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    - If the input data has a pattern, for example the digit "1" usually contains a somewhat straight line and the digit "0" is circular, it will learn this fact and encode it in a more compact form.
    - **If the input data was completely random without any internal correlation or dependency, then an undercomplete autoencoder won't be able to recover it perfectly.**
    - **But luckily, in the real-world there is a lot of dependency.**

Types of Autoencoders [1]

➢ Multilayer autoencoder

```
input_size = 784
hidden_size = 128
code_size = 64

x = Input(shape=(input_size,))

# Encoder
hidden_1 = Dense(hidden_size, activation='relu')(x)
h = Dense(code_size, activation='relu')(hidden_1)

# Decoder
hidden_2 = Dense(hidden_size, activation='relu')(h)
r = Dense(input_size, activation='sigmoid')(hidden_2)

autoencoder = Model(input=x, output=r)
autoencoder.compile(optimizer='adam', loss='mse')
```

```
autoencoder.fit(x_train, x_train, epochs=5)
reconstructed = autoencoder.predict(x_test)
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  - Any of the hidden layers can be picked as the feature representation but we will make the network symmetrical and use the middle-most layer.

Types of Autoencoders [1]

- Convolutional autoencoder

```
x = Input(shape=(28, 28,1))

# Encoder
conv1_1 = Conv2D(16, (3, 3), activation='relu', padding='same')(x)
pool1 = MaxPooling2D((2, 2), padding='same')(conv1_1)
conv1_2 = Conv2D(8, (3, 3), activation='relu', padding='same')(pool1)
pool2 = MaxPooling2D((2, 2), padding='same')(conv1_2)
conv1_3 = Conv2D(8, (3, 3), activation='relu', padding='same')(pool2)
h = MaxPooling2D((2, 2), padding='same')(conv1_3)


# Decoder
conv2_1 = Conv2D(8, (3, 3), activation='relu', padding='same')(h)
up1 = UpSampling2D((2, 2))(conv2_1)
conv2_2 = Conv2D(8, (3, 3), activation='relu', padding='same')(up1)
up2 = UpSampling2D((2, 2))(conv2_2)
conv2_3 = Conv2D(16, (3, 3), activation='relu')(up2)
up3 = UpSampling2D((2, 2))(conv2_3)
r = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(up3)

autoencoder = Model(input=x, output=r)
autoencoder.compile(optimizer='adam', loss='mse')
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Notice: padding="valid"

```
autoencoder.fit(x_train, x_train, epochs=5)
reconstructed = autoencoder.predict(x_test)
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  - Rather than limiting the model capacity by keeping the encoder and decoder shallow and the code size small, regularized autoencoders use a loss function that encourages the model to have other properties besides the ability to copy its input to its output.
  - In practice, we usually find two types of regularized autoencoder:
    - the sparse autoencoder and
    - the denoising autoencoder.

Types of Autoencoders

- Sparse autoencoder
  - Please recall, when we apply weight regularizer, it is like adding a term in loss function like $\sum_i \sum_j |w_{ij}|$ for L1 regularization and $\sum_i \sum_j w_{ij}^2$ for L2 regularization. This ensures that weights are very small and therefore our model is simple and we can avoid overfitting.

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  - Here, in sparse autoencoder, we regularize output (that is activations) of neurons and therefore they are small and many are zero leading to a sparse representation.

Types of Autoencoders [1]

- Sparse autoencoder

```
input_size = 784
hidden_size = 64
output_size = 784

x = Input(shape=(input_size,))

# Encoder
h = Dense(hidden_size, activation='relu', activity_regularizer=regularizers.l1(10e-5))(x)

# Decoder
r = Dense(output_size, activation='sigmoid')(h)

autoencoder = Model(input=x, output=r)
autoencoder.compile(optimizer='adam', loss='mse')
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autoencoder.fit(x_train, x_train, epochs=5)
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  - There is another way to force the autoencoder to learn useful features, which is adding random noise to its inputs and making it recover the original noise-free data.
  - This way the autoencoder can't simply copy the input to its output because the input also contains random noise.
  - We are asking it to subtract the noise and produce the underlying meaningful data. This is called a denoising autoencoder.

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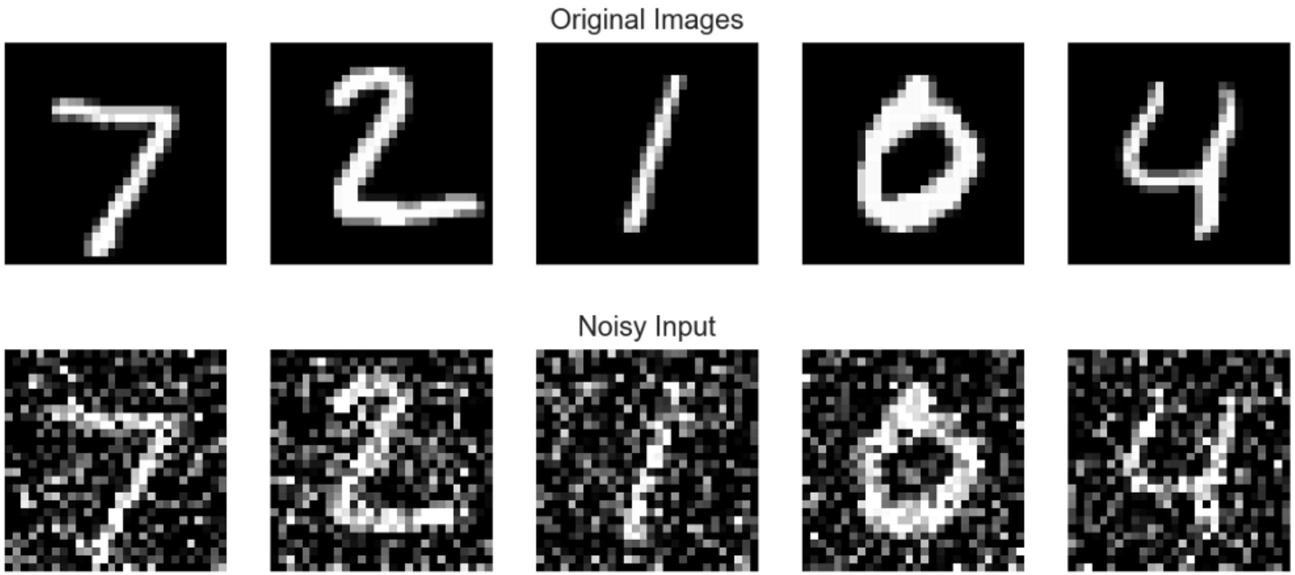
- Denoising autoencoder



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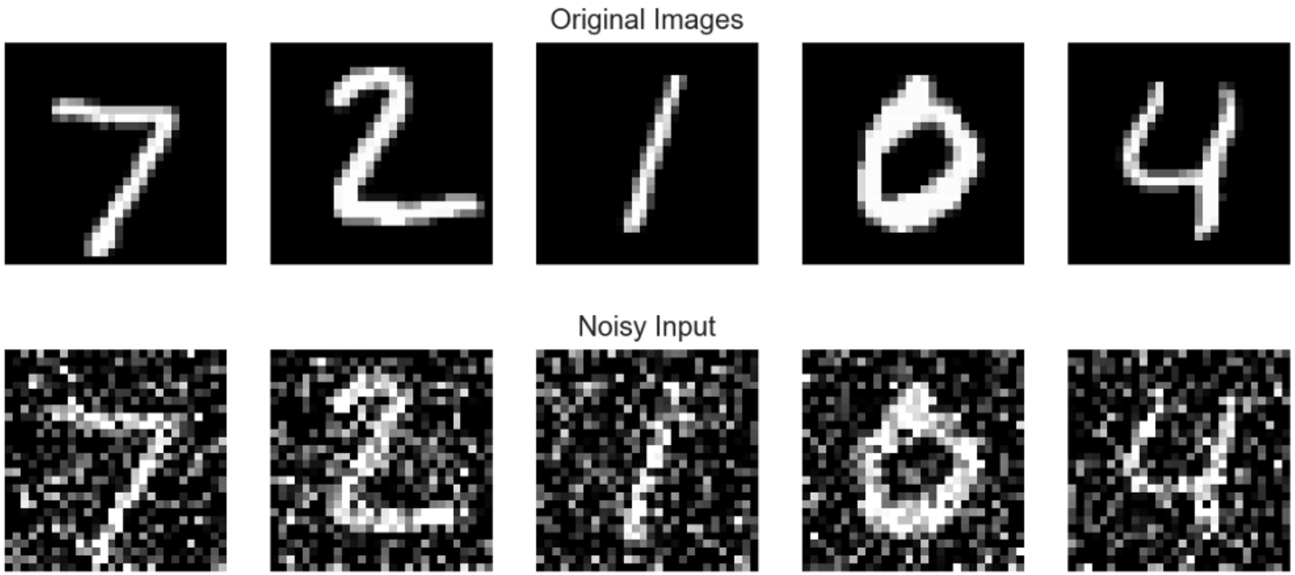

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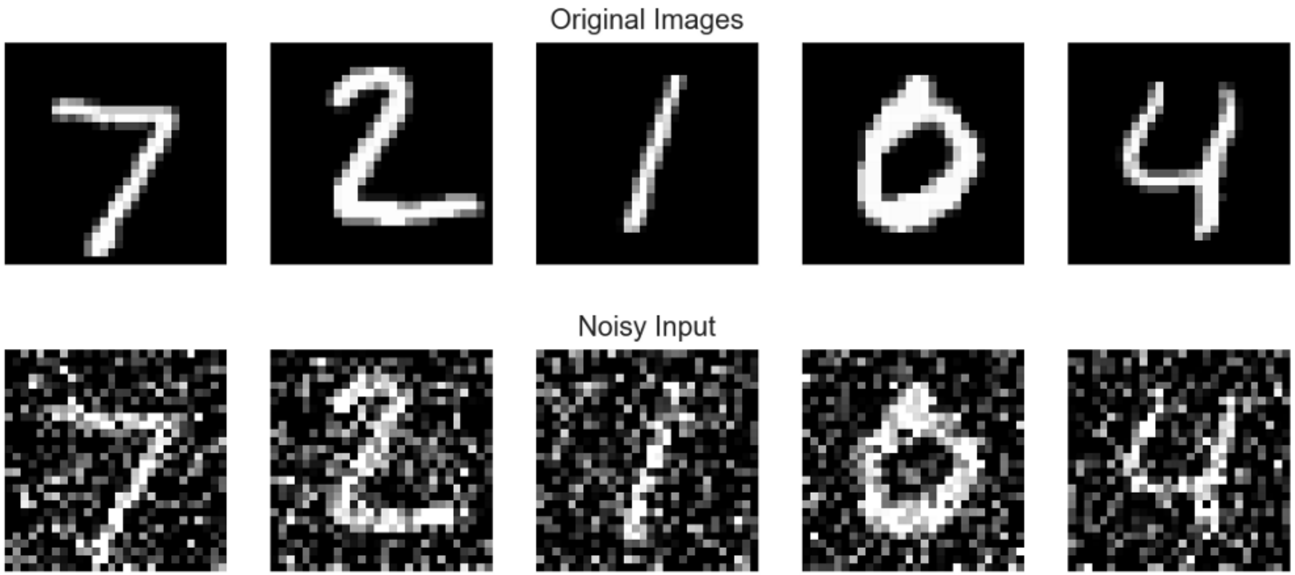

➢ The top row contains the original images.

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➢ The autoencoder doesn't see the original image at all.

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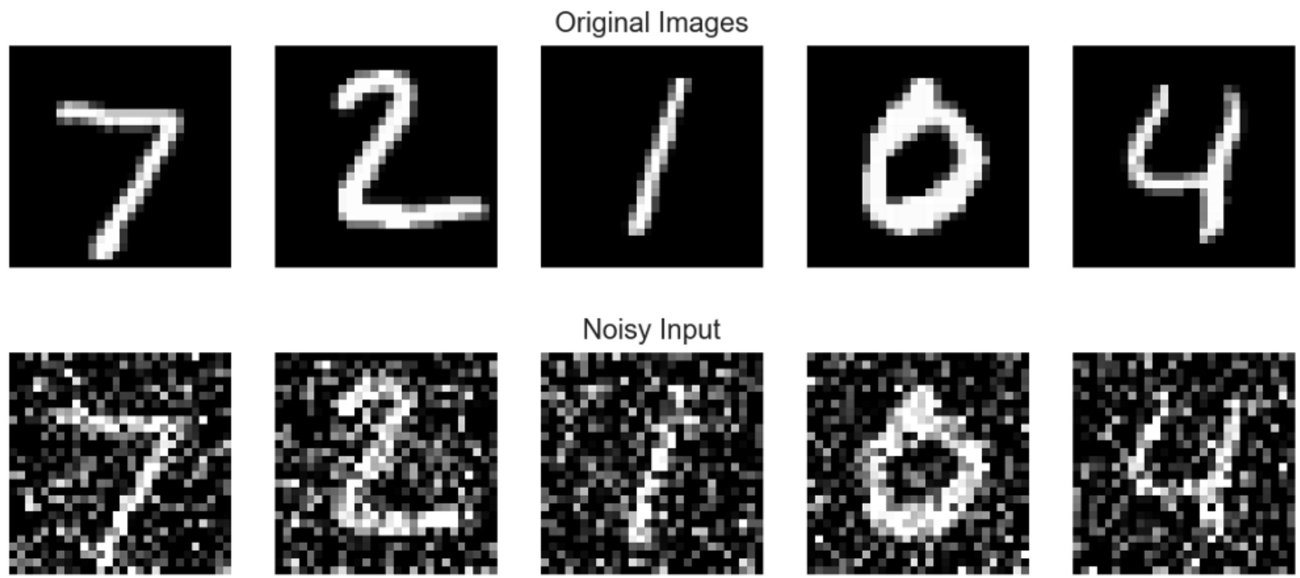

- The top row contains the original images.
- We add random Gaussian noise to them and the noisy data becomes the input to the autoencoder.
- The autoencoder doesn't see the original image at all.
- But then we expect the autoencoder to regenerate the noise-free original image.

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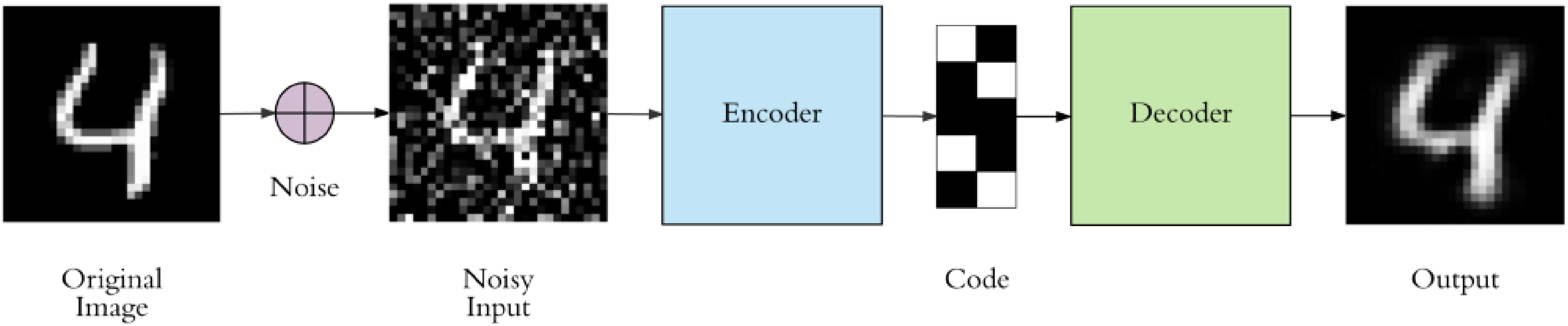

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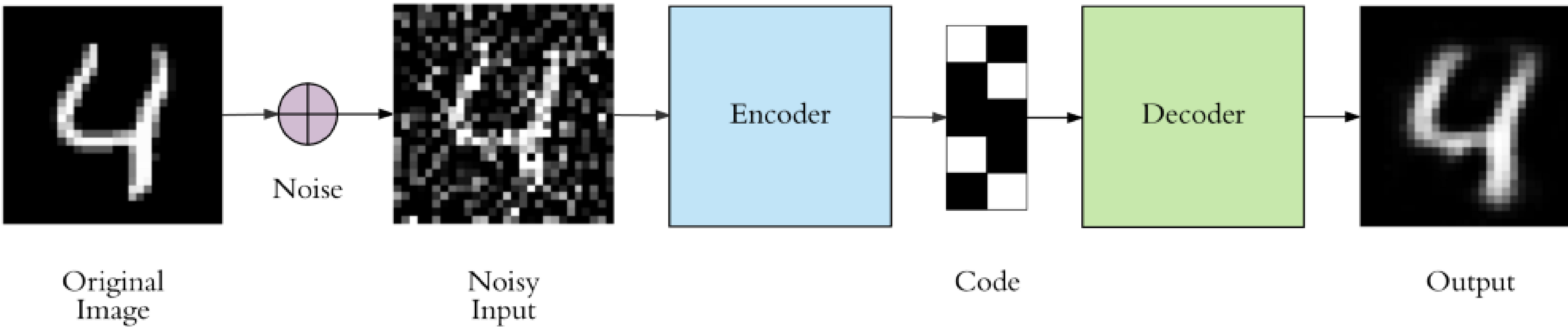

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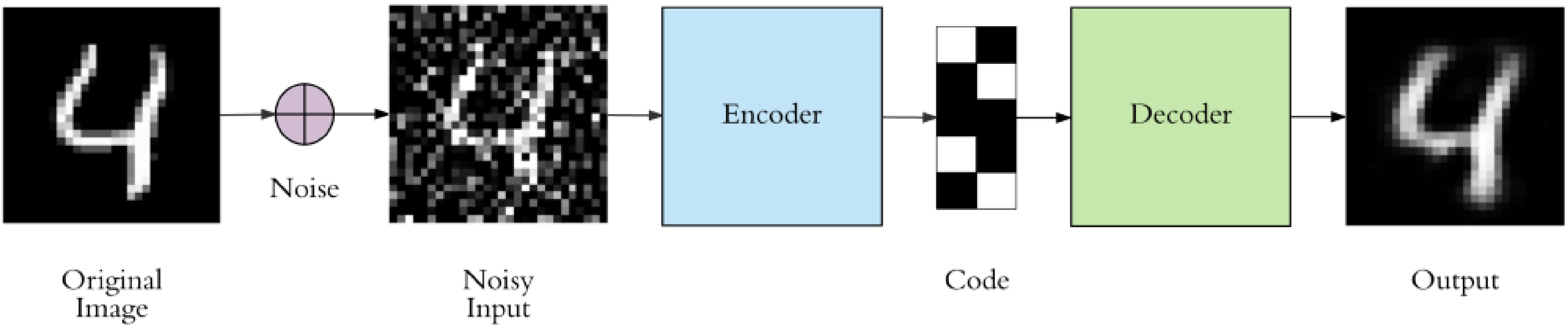

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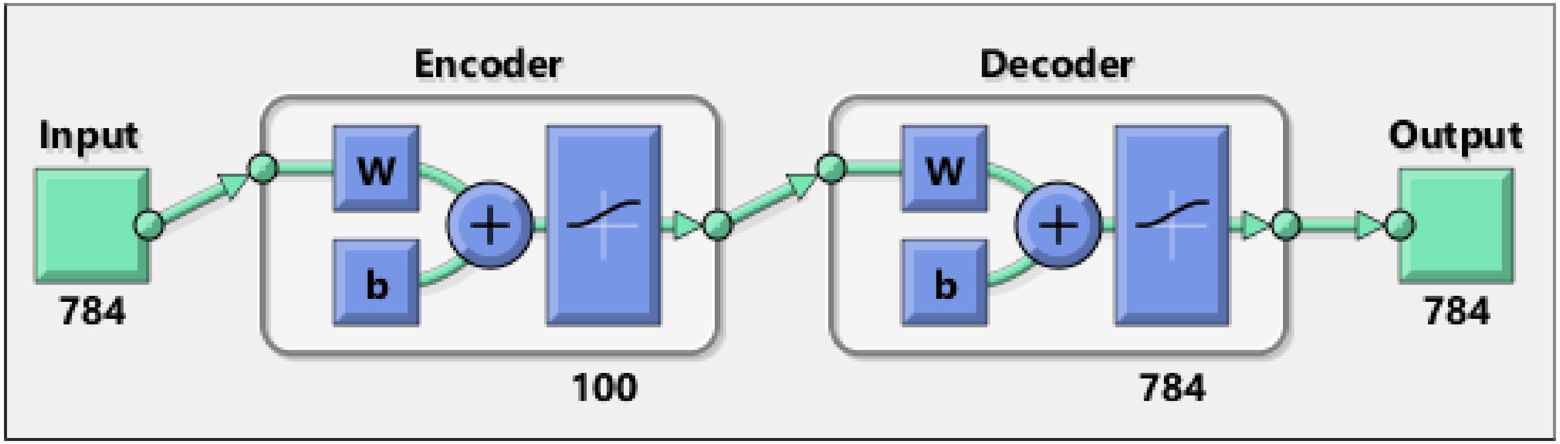
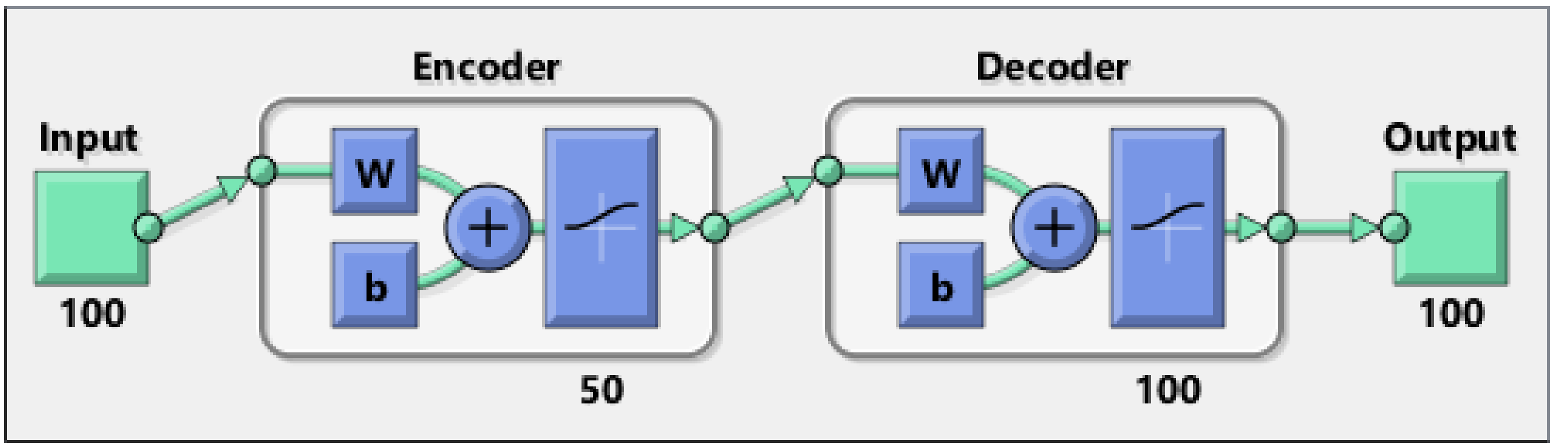
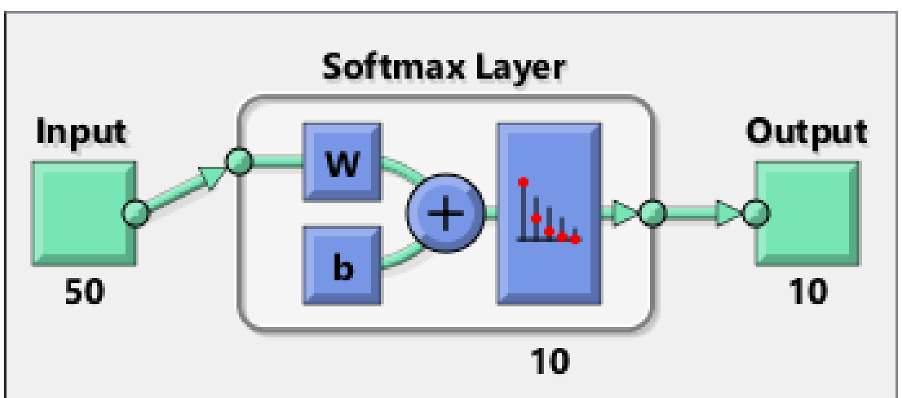
- Denoising autoencoder is trained as:

  - autoencoder.fit(x_train_noisy, x_train)

Stacked Autoencoders [4]

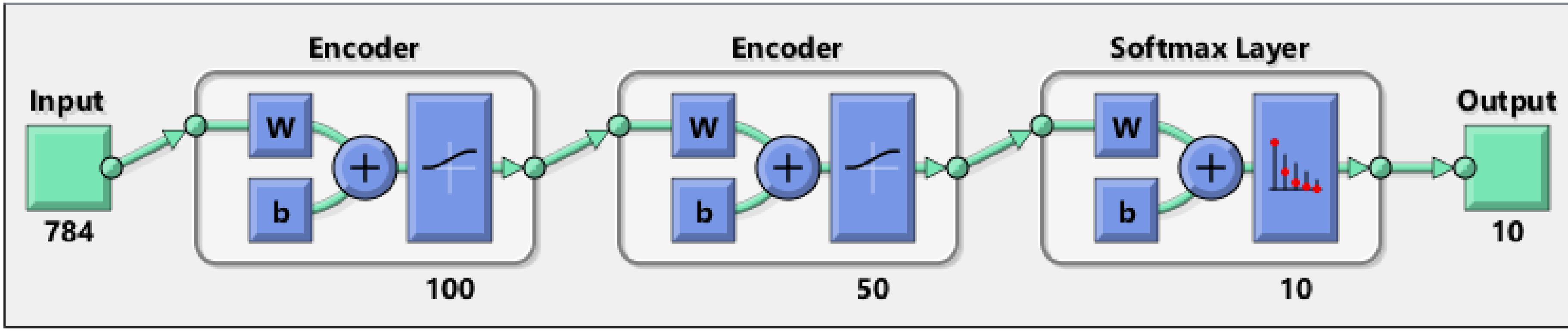






model1.fit(x_train_784, x_train_784)
model2.fit(h_100, h_100)
model3.fit(h_50, y_train_10)

Stacked Autoencoders [4]



Fine Tuning Stacked Autoencoders [4]

```
model.fit(x_train, y_train)
```

References

1. https://towardsdatascience.com/deep-inside-autoencoders-7e41f319999f
2. https://towardsdatascience.com/applied-deep-learning-part-3-autoencoders-1c083af4d798
3. http://ufldl.stanford.edu/wiki/index.php/Stacked_Autoencoders
4. https://in.mathworks.com/help/deeplearning/examples/train-stacked-autoencoders-for-image-classification.html

Disclaimer

- These slides are not original and have been prepared from various sources for teaching purpose.