Autoencoders

Autoencoders

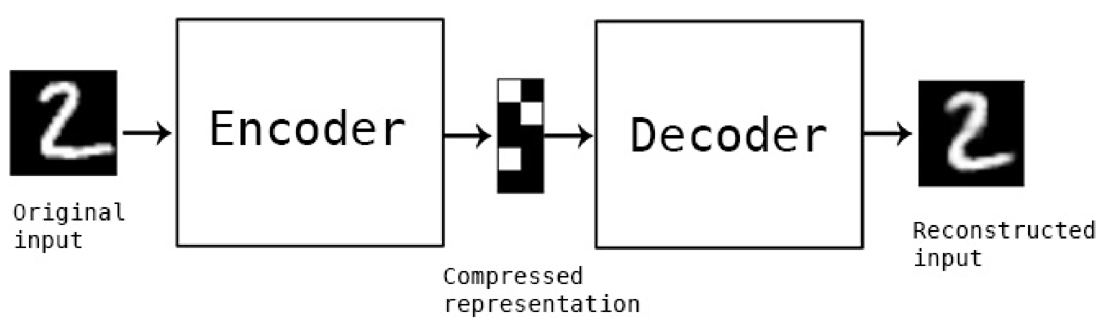
- When training CNNs, one of the problems is that we need a lot of labeled data.

- However, we might want to use raw (unlabeled) data for training CNN feature extractors, which is called **self-supervised learning**.
- Instead of labels, we use training images as both network input and output.

- The main idea of **autoencoder** is that we will have an **encoder network** that converts input image into some **latent space** (normally it is just a vector of some smaller size), and a **decoder network**, whose goal would be to reconstruct the original image.

Autoencoders

- We train autoencoder to capture as much of the information from the original images as possible for accurate reconstruction, the network tries to find best **embedding** of input images to capture the meaning.



Example: Autoencoders with MNIST

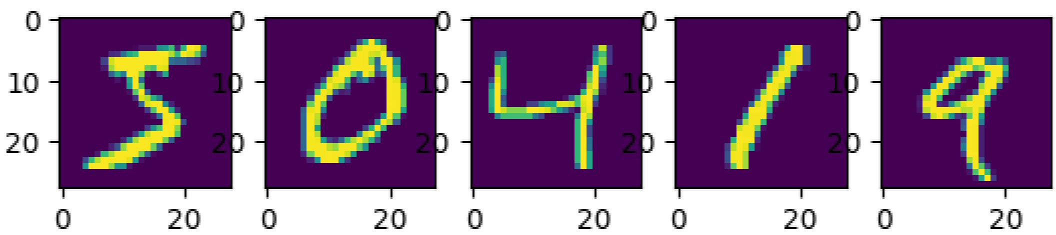
In [37]:
```
import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [38]:
```
import tensorflow as tf
from tensorflow.keras.datasets import mnist
import numpy as np
import matplotlib.pyplot as plt
```

```python
(x_train, y_trainclass), (x_test, y_testclass) = mnist.load_data()
```

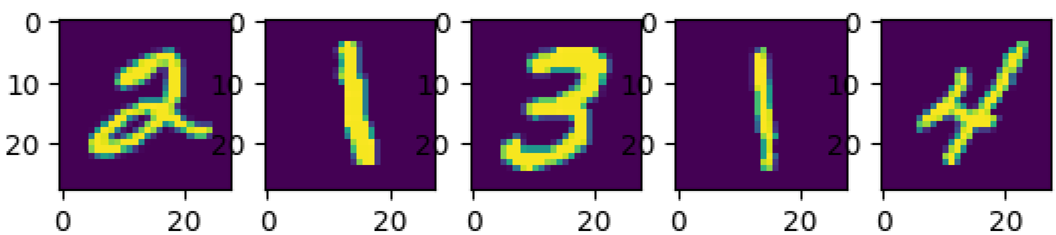
In [39]:

```python
def plotn(n, x):
    fig, ax = plt.subplots(1, n)
    for i, z in enumerate(x[0:n]):
        ax[i].imshow(z.reshape(28,28) if z.size==28*28 else z.reshape(14,14) if z.s
    plt.show()

plotn(5,x_train)
```



In [40]:

```python
def plotidx(indices, x):
    fig, ax = plt.subplots(1, len(indices))
    for i, z in enumerate(x[indices]):
        ax[i].imshow(z.reshape(28,28) if z.size==28*28 else z.reshape(14,14) if z.s
    plt.show()

plotidx([5,6,7,8,9],x_train)
```



Example: Autoencoders with MNIST

In [41]:

```python
from tensorflow.keras.layers import Input, Dense, Conv2D, MaxPooling2D, UpSampling2
from tensorflow.keras.models import Model
from tensorflow.keras.losses import binary_crossentropy, mse
```

In [43]:

```python
input_img = Input(shape=(28,28,1))

x = Conv2D(16, (3,3), activation='relu', padding='same')(input_img)
x = MaxPooling2D((2,2), padding='same')(x)
x = Conv2D(8, (3,3), activation='relu', padding='same')(x)
x = MaxPooling2D((2,2), padding='same')(x)
x = Conv2D(8, (3,3), activation='relu', padding='same')(x)
encoded = MaxPooling2D((2,2), padding='same')(x)

encoder = Model(input_img, encoded)

input_rep = Input(shape=(4,4,8))
```

```python
x = Conv2D(8, (3,3), activation='relu', padding='same')(input_rep)
x = UpSampling2D((2, 2))(x)
x = Conv2D(8, (3,3), activation='relu', padding='same')(x)
x = UpSampling2D((2,2))(x)
x = Conv2D(16, (3,3), activation='relu')(x)
x = UpSampling2D((2,2))(x)
decoded = Conv2D(1, (3,3), activation='sigmoid', padding='same')(x)

decoder = Model(input_rep, decoded)

autoencoder = Model(input_img, decoder(encoder(input_img)))
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
```

Example: Autoencoders with MNIST

In [44]:

```python
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
x_train = np.reshape(x_train, (len(x_train), 28, 28, 1))
x_test = np.reshape(x_test, (len(x_test), 28, 28, 1))
```

In [12]:

```python
autoencoder.fit(x_train, x_train,
                epochs=25,
                batch_size=128,
                shuffle=True,
                validation_data=(x_test, x_test))
```

```
Epoch 1/25
469/469 [==============================] - 7s 16ms/step - loss: 0.1455 - val_loss:
0.1335
Epoch 2/25
469/469 [==============================] - 7s 16ms/step - loss: 0.1290 - val_loss:
0.1229
Epoch 3/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1205 - val_loss:
0.1163
Epoch 4/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1148 - val_loss:
0.1113
Epoch 5/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1107 - val_loss:
0.1083
Epoch 6/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1080 - val_loss:
0.1057
Epoch 7/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1061 - val_loss:
0.1042
Epoch 8/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1046 - val_loss:
0.1029
Epoch 9/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1035 - val_loss:
0.1019
Epoch 10/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1024 - val_loss:
0.1011
Epoch 11/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1014 - val_loss:
0.0999
Epoch 12/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1006 - val_loss:
0.0993
Epoch 13/25
469/469 [==============================] - 7s 15ms/step - loss: 0.0999 - val_loss:
0.0986
Epoch 14/25
469/469 [==============================] - 7s 15ms/step - loss: 0.0993 - val_loss:
0.0980
Epoch 15/25
469/469 [==============================] - 7s 15ms/step - loss: 0.0987 - val_loss:
0.0976
Epoch 16/25
469/469 [==============================] - 7s 15ms/step - loss: 0.0983 - val_loss:
0.0971
Epoch 17/25
469/469 [==============================] - 7s 15ms/step - loss: 0.0978 - val_loss:
0.0966
Epoch 18/25
469/469 [==============================] - 7s 16ms/step - loss: 0.0975 - val_loss:
0.0963
Epoch 19/25
469/469 [==============================] - 8s 16ms/step - loss: 0.0971 - val_loss:
```

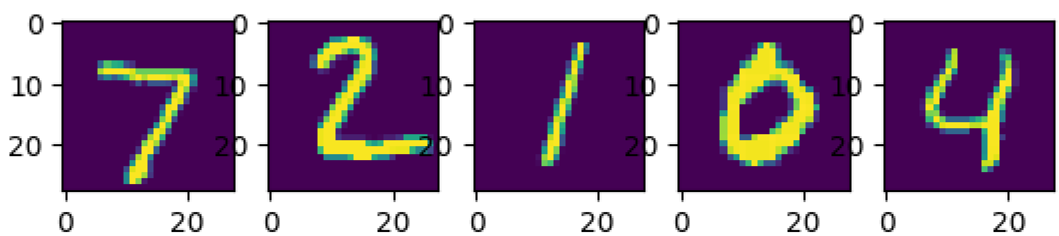
```
0.0962
Epoch 20/25
469/469 [==============================] - 8s 17ms/step - loss: 0.0968 - val_loss:
0.0957
Epoch 21/25
469/469 [==============================] - 8s 17ms/step - loss: 0.0965 - val_loss:
0.0954
Epoch 22/25
469/469 [==============================] - 8s 17ms/step - loss: 0.0963 - val_loss:
0.0952
Epoch 23/25
469/469 [==============================] - 8s 17ms/step - loss: 0.0960 - val_loss:
0.0950
Epoch 24/25
469/469 [==============================] - 8s 17ms/step - loss: 0.0957 - val_loss:
0.0944
Epoch 25/25
469/469 [==============================] - 8s 17ms/step - loss: 0.0955 - val_loss:
0.0945
```

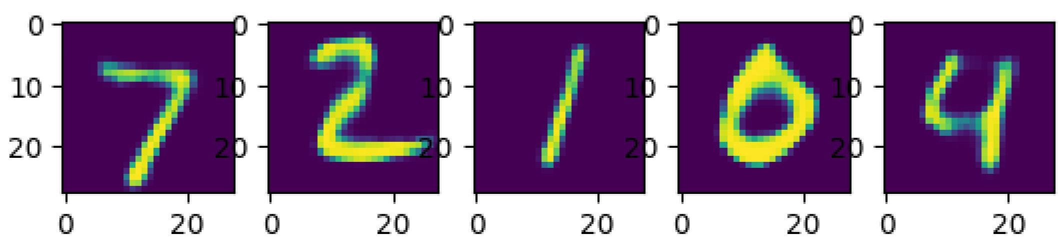
Out[12]: <keras.src.callbacks.History at 0x1c8c195fa60>

Example: Autoencoders with MNIST

In [13]:
```
y_test = autoencoder.predict(x_test[0:5])
plotn(5,x_test)
plotn(5,y_test)
```

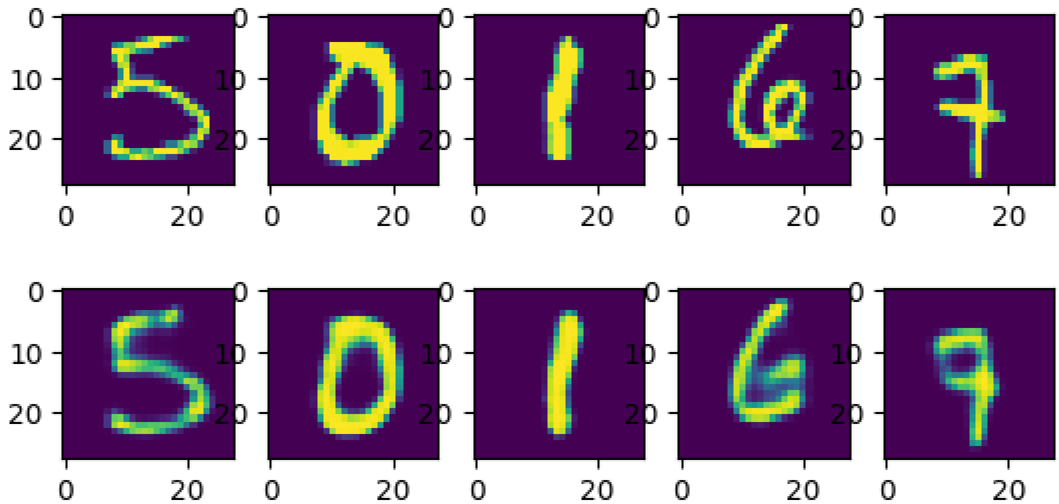
```
1/1 [==============================] - 0s 100ms/step
```





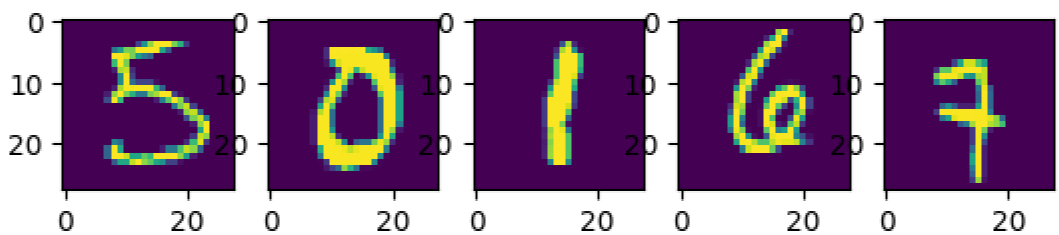
In [14]:
```
indices = [15, 28, 39, 123, 1012]
y_test = autoencoder.predict(x_test[indices])
plotidx(indices, x_test)
plotn(len(indices), y_test)
```

```
1/1 [==============================] - 0s 16ms/step
```



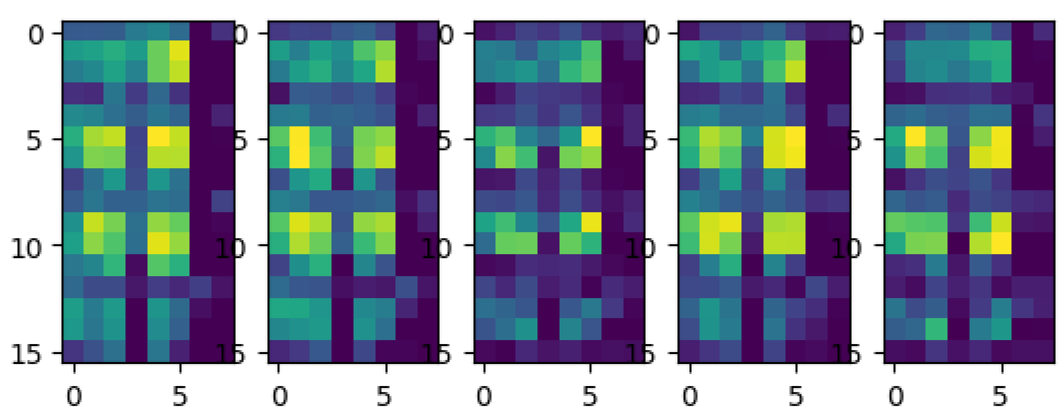
We consider some example inputs

```
In [23]: indices = [15, 28, 39, 123, 1012]
         plotidx(indices, x_test)
```



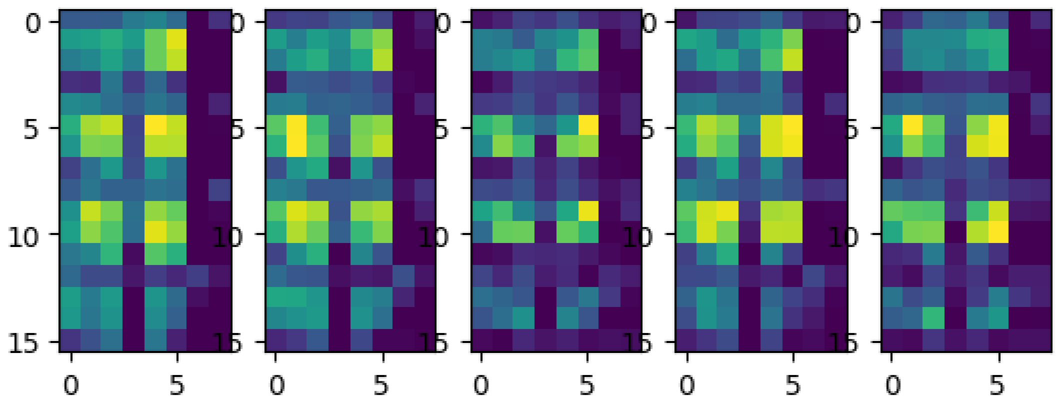
We use the (trained) encoder to convert the input images into some latent space vectors.

```
In [24]: encoder = Model(input_img, encoded);
         encoded_imgs = encoder.predict(x_test[indices], verbose=False);
         plotn(len(indices),encoded_imgs.reshape(5,-1,8))
```

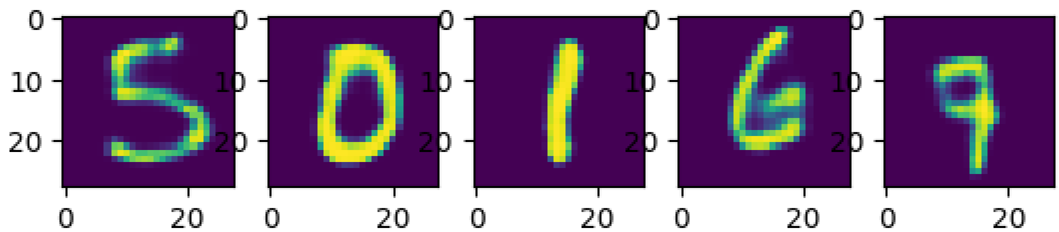


Let's decode the latent space vectors into images.

```
In [26]: plotn(len(indices),encoded_imgs.reshape(5,-1,8))
```



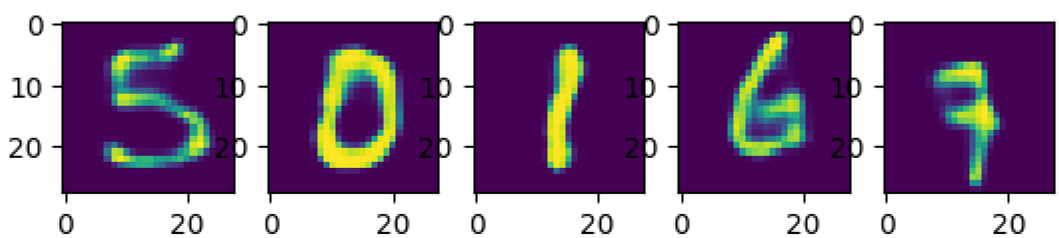
In [27]:
```
res = decoder.predict(encoded_imgs, verbose=False)
plotn(len(indices), res)
```



Example: Autoencoder with MNIST

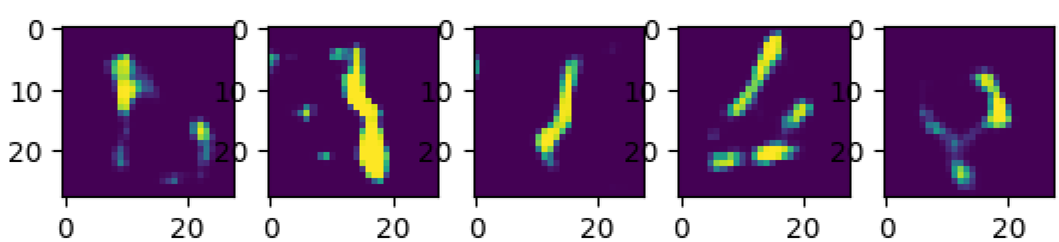
If we add some small noise to the latent space representations.

In [29]:
```
res = decoder.predict(encoded_imgs + 0.1*np.random.randn(len(indices),4,4,8), verbo
plotn(len(indices), res)
```



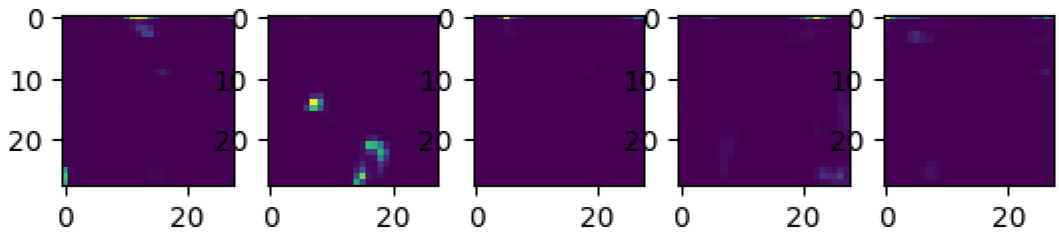
If we add a lot of noise to the latent space representations.

In [30]:
```
res = decoder.predict(encoded_imgs + np.random.randn(len(indices),4,4,8), verbose=F
plotn(len(indices), res)
```



If we just pass noises to the decoder.

In [38]:
```
res = decoder.predict(np.random.rand(5,4,4,8), verbose=False)
plotn(5,res)
```



Denoising

Denoising

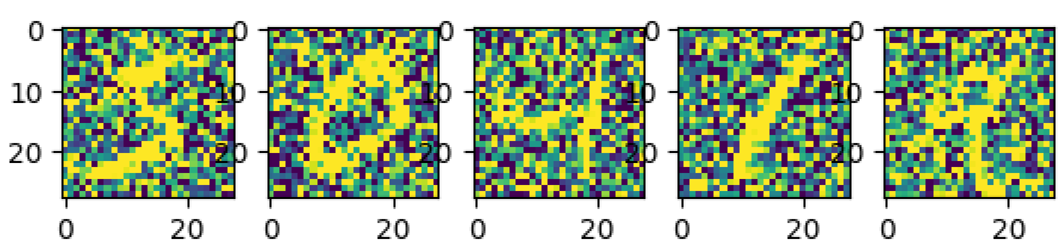
- Autoencoders can be used to remove noise from images.

- To train **denoiser**, we start with noise-free images, and add artificial noise to them.
- We feed autoencoder with **noisy images as input**, and **noise-free images as output**.

Example: Denoising for MNIST

We create a noisy dataset from the original noise-free MNIST dataset.

In [39]:
```
def noisify(data):
  return np.clip(data+np.random.normal(loc=0.5,scale=0.5,size=data.shape),0.,1.)

x_train_noise = noisify(x_train)
x_test_noise = noisify(x_test)

plotn(5,x_train_noise)
```



Example: Denoising for MNIST

We train an autoencoder for the denoising task with noisy images as input and noise-free images as output.

```
In [40]: autoencoder.fit(x_train_noise, x_train,
                         epochs=25,
                         batch_size=128,
                         shuffle=True,
                         validation_data=(x_test_noise, x_test))
```

```
Epoch 1/25
469/469 [==============================] - 7s 15ms/step - loss: 0.2232 - val_loss:
0.1877
Epoch 2/25
469/469 [==============================] - 7s 16ms/step - loss: 0.1801 - val_loss:
0.1718
Epoch 3/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1674 - val_loss:
0.1612
Epoch 4/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1599 - val_loss:
0.1560
Epoch 5/25
469/469 [==============================] - 7s 16ms/step - loss: 0.1554 - val_loss:
0.1523
Epoch 6/25
469/469 [==============================] - 7s 16ms/step - loss: 0.1521 - val_loss:
0.1495
Epoch 7/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1494 - val_loss:
0.1472
Epoch 8/25
469/469 [==============================] - 7s 16ms/step - loss: 0.1471 - val_loss:
0.1444
Epoch 9/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1452 - val_loss:
0.1431
Epoch 10/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1436 - val_loss:
0.1415
Epoch 11/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1425 - val_loss:
0.1406
Epoch 12/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1413 - val_loss:
0.1393
Epoch 13/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1403 - val_loss:
0.1387
Epoch 14/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1395 - val_loss:
0.1376
Epoch 15/25
469/469 [==============================] - 7s 15ms/step - loss: 0.1387 - val_loss:
0.1369
Epoch 16/25
469/469 [==============================] - 7s 16ms/step - loss: 0.1381 - val_loss:
0.1362
Epoch 17/25
469/469 [==============================] - 8s 17ms/step - loss: 0.1374 - val_loss:
0.1356
Epoch 18/25
469/469 [==============================] - 9s 19ms/step - loss: 0.1369 - val_loss:
0.1356
Epoch 19/25
469/469 [==============================] - 8s 17ms/step - loss: 0.1365 - val_loss:
```

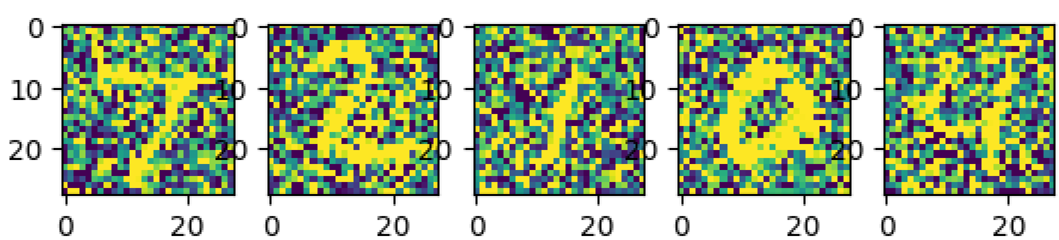
```
0.1346
Epoch 20/25
469/469 [==============================] - 8s 17ms/step - loss: 0.1359 - val_loss:
0.1343
Epoch 21/25
469/469 [==============================] - 8s 17ms/step - loss: 0.1356 - val_loss:
0.1342
Epoch 22/25
469/469 [==============================] - 8s 17ms/step - loss: 0.1350 - val_loss:
0.1340
Epoch 23/25
469/469 [==============================] - 8s 17ms/step - loss: 0.1346 - val_loss:
0.1333
Epoch 24/25
469/469 [==============================] - 8s 17ms/step - loss: 0.1342 - val_loss:
0.1328
Epoch 25/25
469/469 [==============================] - 8s 18ms/step - loss: 0.1338 - val_loss:
0.1327
```

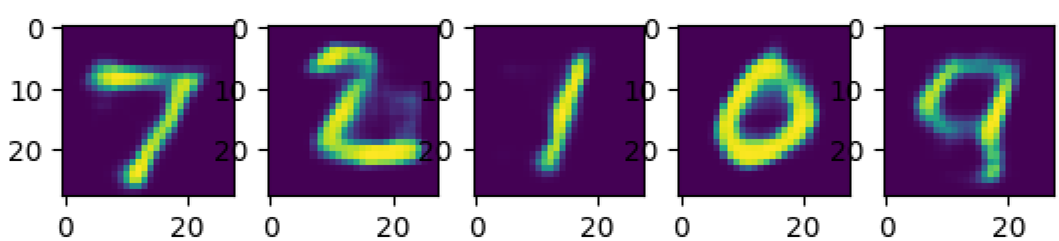
Out[40]:
```
<keras.src.callbacks.History at 0x1c8e1749a80>
```

Example: Denoising for MNIST

We test the trained autoencoder to denoise some noisy images.

In [41]:
```
y_test = autoencoder.predict(x_test_noise[0:5], verbose=False)
plotn(5,x_test_noise)
plotn(5,y_test)
```





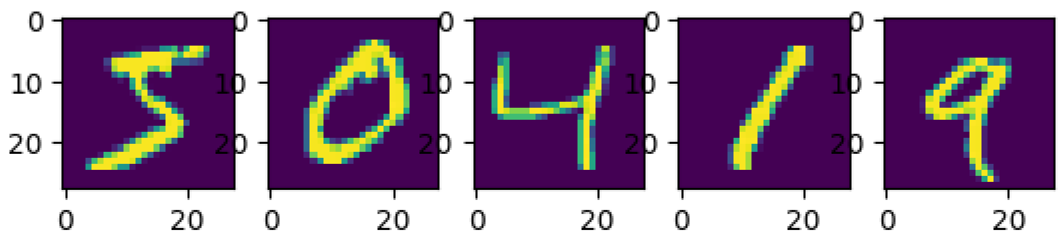
Exercises: *The Fashion-MNIST dataset has the same image size. Let's try an autoencoder trained on MNIST to denoise Fashion-MNIST images, and vice versa.*

Super-resolution

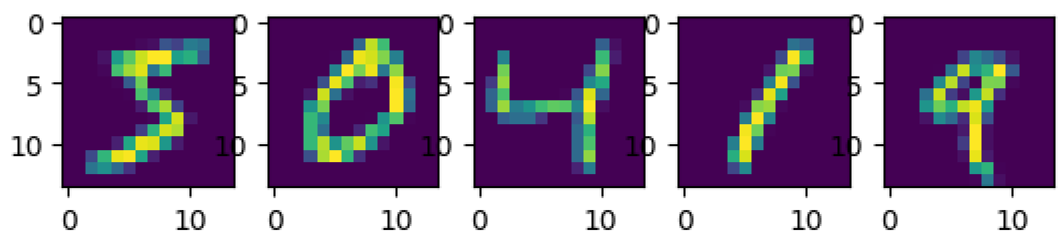
- Similarly to denoiser, we can train autoencoders to increase the resolution of images.

- To train super-resolution network, we start with high-resolution images, and automatically downscale them to produce network inputs.
- We feed the autoencoder with small images as inputs and high-res images as outputs.

In [42]:
```
plotn(5, x_train)
```



In [43]:
```
x_train_lr = tf.keras.layers.AveragePooling2D()(x_train).numpy()
x_test_lr = tf.keras.layers.AveragePooling2D()(x_test).numpy()
plotn(5, x_train_lr)
```



Example: Super-resolution on MNIST

In [2]:
```
from tensorflow.keras.layers import Input, Dense, Conv2D, MaxPooling2D, UpSampling2
from tensorflow.keras.models import Model
from tensorflow.keras.losses import binary_crossentropy, mse
```

```
WARNING:tensorflow:From C:\Users\HoangLN\AppData\Local\Programs\Python\Python310\lib
\site-packages\keras\src\losses.py:2976: The name tf.losses.sparse_softmax_cross_ent
ropy is deprecated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy inst
ead.
```

In [45]:
```
input_img = Input(shape=(14, 14, 1))

x = Conv2D(16, (3,3), activation='relu', padding='same')(input_img)
x = MaxPooling2D((2,2), padding='same')(x)
x = Conv2D(8, (3,3), activation='relu', padding='same')(x)
encoded = MaxPooling2D((2,2), padding='same')(x)

encoder = Model(input_img, encoded)

input_rep = Input(shape=(4,4,8))
```

```python
x = Conv2D(8, (3,3), activation='relu', padding='same')(input_rep)
x = UpSampling2D((2,2))(x)
x = Conv2D(8, (3,3), activation='relu', padding='same')(x)
x = UpSampling2D((2,2))(x)
x = Conv2D(16, (3,3), activation='relu')(x)
x = UpSampling2D((2,2))(x)
decoded = Conv2D(1, (3,3), activation='sigmoid', padding='same')(x)

decoder = Model(input_rep, decoded)

autoencoder = Model(input_img, decoder(encoder(input_img)))
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
```

We feed the autoencoder with small images as inputs and high-res images as outputs.

In [46]:

```python
autoencoder.fit(x_train_lr, x_train,
               epochs=25,
               batch_size=128,
               shuffle=True,
               validation_data=(x_test_lr, x_test))
```

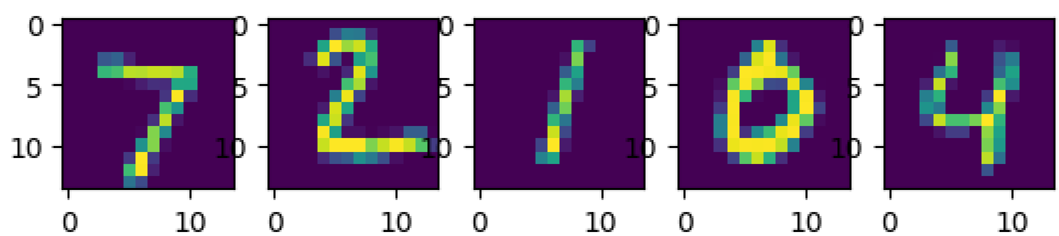
```
Epoch 1/25
469/469 [==============================] - 6s 12ms/step - loss: 0.2228 - val_loss:
0.1549
Epoch 2/25
469/469 [==============================] - 6s 12ms/step - loss: 0.1420 - val_loss:
0.1308
Epoch 3/25
469/469 [==============================] - 6s 12ms/step - loss: 0.1268 - val_loss:
0.1212
Epoch 4/25
469/469 [==============================] - 6s 12ms/step - loss: 0.1197 - val_loss:
0.1163
Epoch 5/25
469/469 [==============================] - 6s 12ms/step - loss: 0.1152 - val_loss:
0.1123
Epoch 6/25
469/469 [==============================] - 6s 12ms/step - loss: 0.1119 - val_loss:
0.1100
Epoch 7/25
469/469 [==============================] - 6s 12ms/step - loss: 0.1094 - val_loss:
0.1068
Epoch 8/25
469/469 [==============================] - 6s 13ms/step - loss: 0.1074 - val_loss:
0.1050
Epoch 9/25
469/469 [==============================] - 6s 12ms/step - loss: 0.1057 - val_loss:
0.1037
Epoch 10/25
469/469 [==============================] - 6s 12ms/step - loss: 0.1043 - val_loss:
0.1025
Epoch 11/25
469/469 [==============================] - 6s 12ms/step - loss: 0.1031 - val_loss:
0.1012
Epoch 12/25
469/469 [==============================] - 6s 12ms/step - loss: 0.1021 - val_loss:
0.1007
Epoch 13/25
469/469 [==============================] - 6s 14ms/step - loss: 0.1012 - val_loss:
0.0996
Epoch 14/25
469/469 [==============================] - 6s 13ms/step - loss: 0.1005 - val_loss:
0.0996
Epoch 15/25
469/469 [==============================] - 6s 13ms/step - loss: 0.0998 - val_loss:
0.0981
Epoch 16/25
469/469 [==============================] - 6s 12ms/step - loss: 0.0991 - val_loss:
0.0977
Epoch 17/25
469/469 [==============================] - 6s 12ms/step - loss: 0.0985 - val_loss:
0.0970
Epoch 18/25
469/469 [==============================] - 6s 12ms/step - loss: 0.0980 - val_loss:
0.0964
Epoch 19/25
469/469 [==============================] - 6s 12ms/step - loss: 0.0975 - val_loss:
```

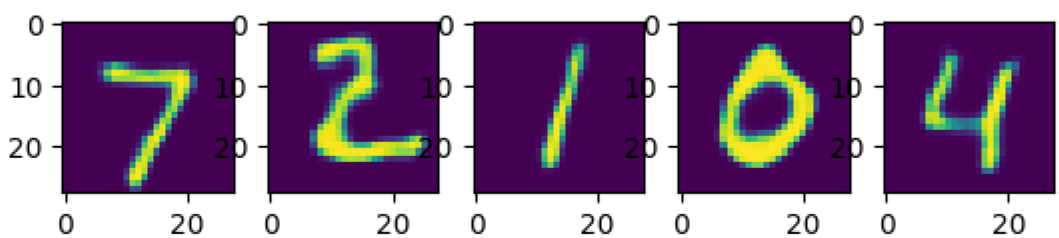
```
0.0958
Epoch 20/25
469/469 [==============================] - 6s 12ms/step - loss: 0.0971 - val_loss:
0.0957
Epoch 21/25
469/469 [==============================] - 6s 12ms/step - loss: 0.0966 - val_loss:
0.0952
Epoch 22/25
469/469 [==============================] - 6s 13ms/step - loss: 0.0963 - val_loss:
0.0948
Epoch 23/25
469/469 [==============================] - 6s 13ms/step - loss: 0.0959 - val_loss:
0.0944
Epoch 24/25
469/469 [==============================] - 6s 13ms/step - loss: 0.0956 - val_loss:
0.0942
Epoch 25/25
469/469 [==============================] - 6s 14ms/step - loss: 0.0953 - val_loss:
0.0943
```

Out[46]:
```
<keras.src.callbacks.History at 0x1c8e3fa8fd0>
```

Example: Super-resolution on MNIST

In [48]:
```
y_test_lr = autoencoder.predict(x_test_lr[0:5], verbose=False)
plotn(5, x_test_lr)
plotn(5, y_test_lr)
```





Exercise:

- *Try to train similarly a super-resolution network on Fashion-MNIST.*
- *Try to train super-resolution networks on CIFAR-10 for 2x and 4x upscaling.*

Variational Auto-Encoders (VAE)

Variational Auto-Encoders (VAE)

- Traditional autoencoders reduce the dimension of the input data somehow, figuring out the important features of input images. However, latent vectors often do not make much sense

- Taking MNIST dataset as an example, figuring out which digits correspond to different latent vectors is not an easy task, because *close latent vectors would not necessarily correspond to the same digits*.

- To train **generative models**, it is better to have some understanding of the latent space. This idea leads to **variational auto-encoder (VAE)**.

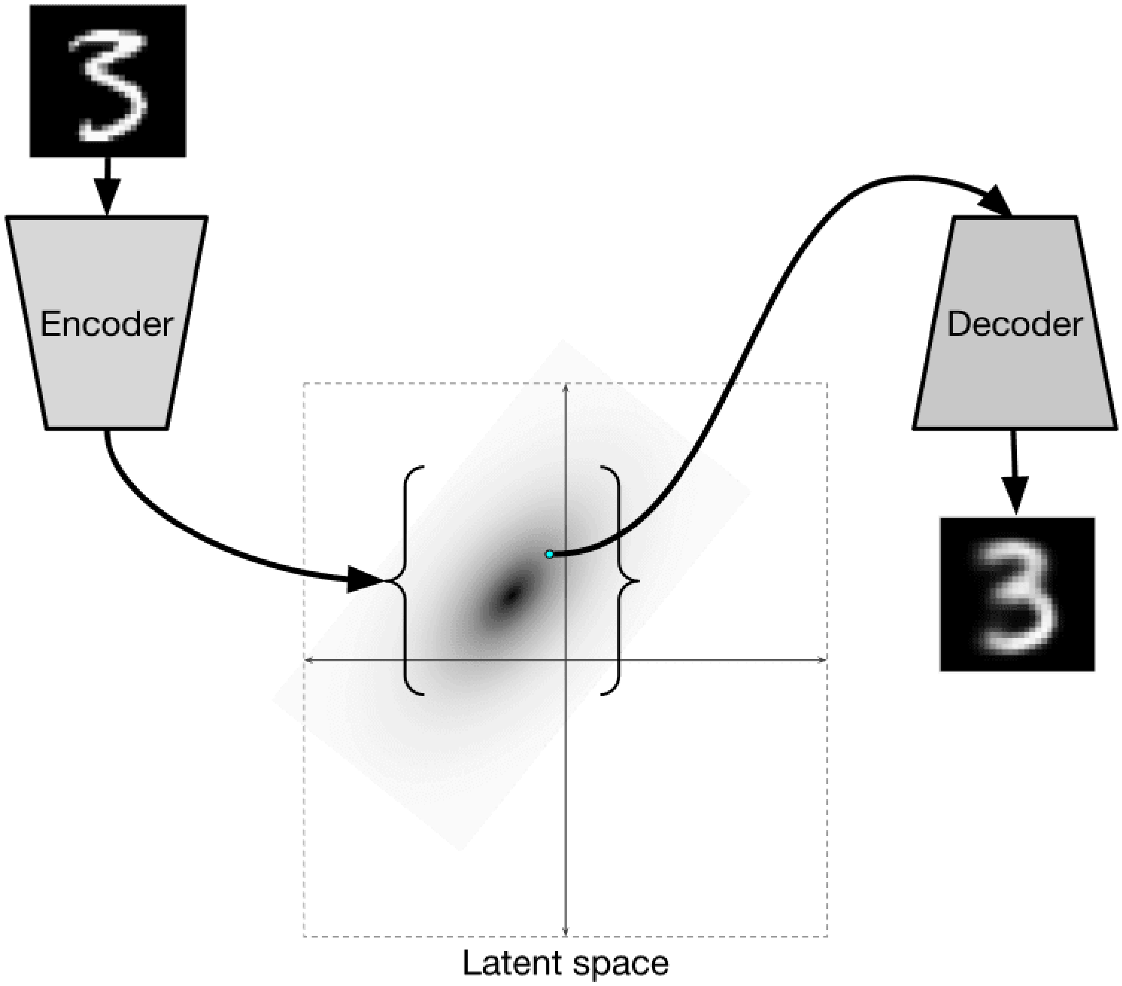
Variational Auto-Encoders (VAE)

- VAE is the autoencoder that learns to predict *statistical distribution of the latent parameters*, so-called **latent distribution**.

- For example, we assume that latent vectors would be distributed as $\mathcal{N}(z_{\text{mean}}, e^{\text{z\_log\_sigma}})$, where $z_{\text{mean}}, z\_\text{log\_sigma} \in \mathbb{R}^d$.

- Encoder in VAE learns to predict those parameters, and then decoder takes a random vector from this distribution to reconstruct the object.

Variational Auto-Encoders (VAE)



Variational Auto-Encoders (VAE)

- From input vector, we predict `z_mean` and `z_log_sigma` (instead of predicting the standard deviation itself, we predict its logarithm).
- We sample a vector `sample` from the distribution $\mathcal{N}(\mathrm{z\_mean}, \mathrm{z\_log\_sigma})$.
- Decoder tries to decode the original image using `sample` as an input vector.

Example: VAE on MNIST

In [45]:
```
intermediate_dim = 512
latent_dim = 2
batch_size = 128

tf.compat.v1.disable_eager_execution()

inputs = Input(shape=(784,))
h = Dense(intermediate_dim, activation='relu')(inputs)
```

```
z_mean = Dense(latent_dim)(h)
z_log_sigma = Dense(latent_dim)(h)
```

In [46]:
```
@tf.function
def sampling(args):
    z_mean, z_log_sigma = args
    bs = tf.shape(z_mean)[0]
    epsilon = tf.random.normal(shape=(bs, latent_dim))
    return z_mean + tf.exp(z_log_sigma) * epsilon

z = Lambda(sampling)([z_mean, z_log_sigma])
```

Example: VAE on MNIST

In [47]:
```
encoder = Model(inputs, [z_mean, z_log_sigma, z])

latent_inputs = Input(shape=(latent_dim,))
x = Dense(intermediate_dim, activation='relu')(latent_inputs)
outputs = Dense(784, activation='sigmoid')(x)

decoder = Model(latent_inputs, outputs)

outputs = decoder(encoder(inputs)[2])

vae = Model(inputs, outputs)
```

Example: VAE on MNIST

VAEs use a loss function consisting of two parts:

- **Reconstruction loss:** shows how close reconstructed image is to the target (can be `MSE`). It is the same loss function as in normal autoencoders.
- **KL loss**: based on Kullback-Leibler divergence - a metric to estimate how similar two statistical distributions are. KL loss ensures that latent variable distributions tays close to normal distribution.

Reference: https://kvfrans.com/deriving-the-kl/

In [48]:
```
@tf.function
def vae_loss(x1, x2):
    reconstruction_loss = mse(x1, x2)*784
    tmp = 1 + z_log_sigma - tf.square(z_mean) - tf.exp(z_log_sigma)
    kl_loss = -0.5*tf.reduce_sum(tmp, axis=-1)
    return tf.convert_to_tensor(tf.reduce_mean(reconstruction_loss + kl_loss))

vae.compile(optimizer='rmsprop', loss=vae_loss)
```

Example: VAE on MNIST

In [49]:
```
x_train_flat = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test_flat = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))

vae.fit(x_train_flat, x_train_flat,
        shuffle=True,
        epochs=25,
        batch_size=batch_size,
        validation_data=(x_test_flat, x_test_flat))
```

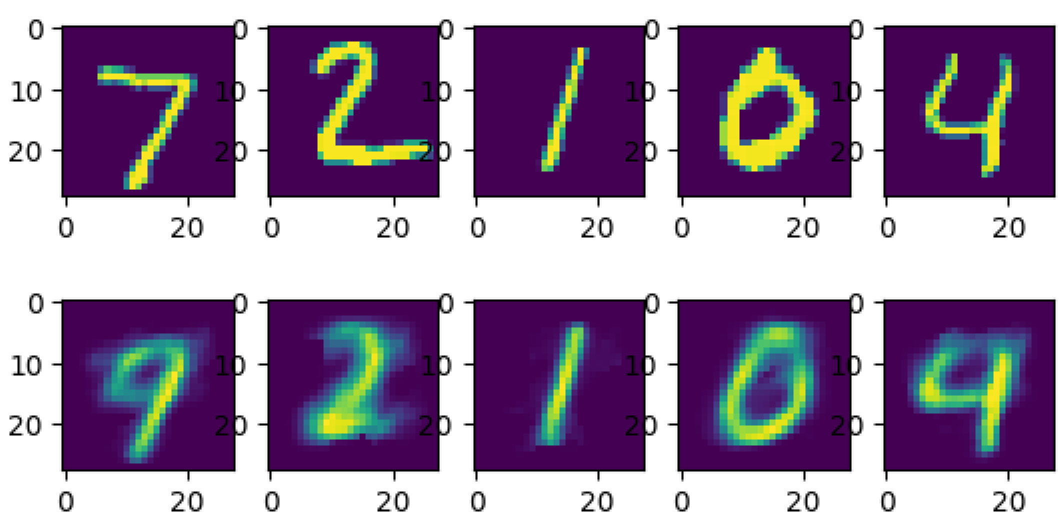
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/25
60000/60000 [==============================] - 3s 55us/sample - loss: 48.4083 - val_
loss: 42.4046
Epoch 2/25
60000/60000 [==============================] - 3s 47us/sample - loss: 41.6079 - val_
loss: 40.8550
Epoch 3/25
60000/60000 [==============================] - 3s 45us/sample - loss: 40.4213 - val_
loss: 40.1389
Epoch 4/25
60000/60000 [==============================] - 3s 46us/sample - loss: 39.6158 - val_
loss: 39.3001
Epoch 5/25
60000/60000 [==============================] - 3s 48us/sample - loss: 38.9903 - val_
loss: 38.7456
Epoch 6/25
60000/60000 [==============================] - 3s 47us/sample - loss: 38.4941 - val_
loss: 38.3061
Epoch 7/25
60000/60000 [==============================] - 3s 47us/sample - loss: 38.0835 - val_
loss: 37.9434
Epoch 8/25
60000/60000 [==============================] - 3s 47us/sample - loss: 37.7461 - val_
loss: 37.9262
Epoch 9/25
60000/60000 [==============================] - 3s 47us/sample - loss: 37.4914 - val_
loss: 37.4126
Epoch 10/25
60000/60000 [==============================] - 3s 47us/sample - loss: 37.2672 - val_
loss: 37.4081
Epoch 11/25
60000/60000 [==============================] - 3s 46us/sample - loss: 37.0633 - val_
loss: 37.2256
Epoch 12/25
60000/60000 [==============================] - 3s 47us/sample - loss: 36.8881 - val_
loss: 36.9466
Epoch 13/25
60000/60000 [==============================] - 3s 46us/sample - loss: 36.7350 - val_
loss: 36.8332
Epoch 14/25
60000/60000 [==============================] - 3s 49us/sample - loss: 36.5696 - val_
loss: 36.5917
Epoch 15/25
60000/60000 [==============================] - 3s 48us/sample - loss: 36.4263 - val_
loss: 36.6288
Epoch 16/25
60000/60000 [==============================] - 3s 49us/sample - loss: 36.3121 - val_
loss: 36.5753
Epoch 17/25
60000/60000 [==============================] - 3s 49us/sample - loss: 36.2043 - val_
loss: 36.4585
Epoch 18/25
60000/60000 [==============================] - 3s 48us/sample - loss: 36.0779 - val_
loss: 36.3772
Epoch 19/25
```

```
60000/60000 [==============================] - 3s 51us/sample - loss: 35.9897 - val_
loss: 36.1943
Epoch 20/25
60000/60000 [==============================] - 3s 51us/sample - loss: 35.8826 - val_
loss: 36.2304
Epoch 21/25
60000/60000 [==============================] - 3s 50us/sample - loss: 35.7994 - val_
loss: 36.1639
Epoch 22/25
60000/60000 [==============================] - 3s 51us/sample - loss: 35.7109 - val_
loss: 35.9932
Epoch 23/25
60000/60000 [==============================] - 3s 48us/sample - loss: 35.6301 - val_
loss: 36.1477
Epoch 24/25
60000/60000 [==============================] - 3s 50us/sample - loss: 35.5530 - val_
loss: 35.9552
Epoch 25/25
60000/60000 [==============================] - 3s 51us/sample - loss: 35.4919 - val_
loss: 36.0094
```

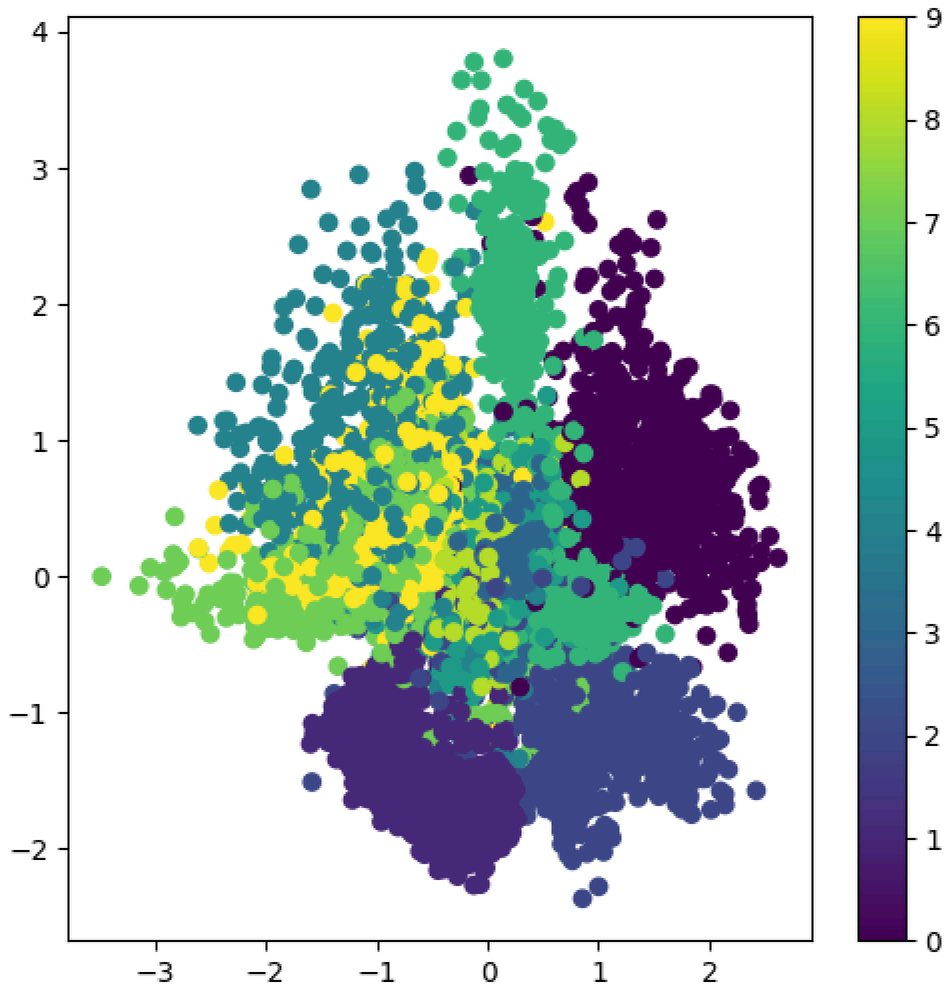
Out[49]: <keras.src.callbacks.History at 0x1a4fb03d690>

Example: VAE on MNIST

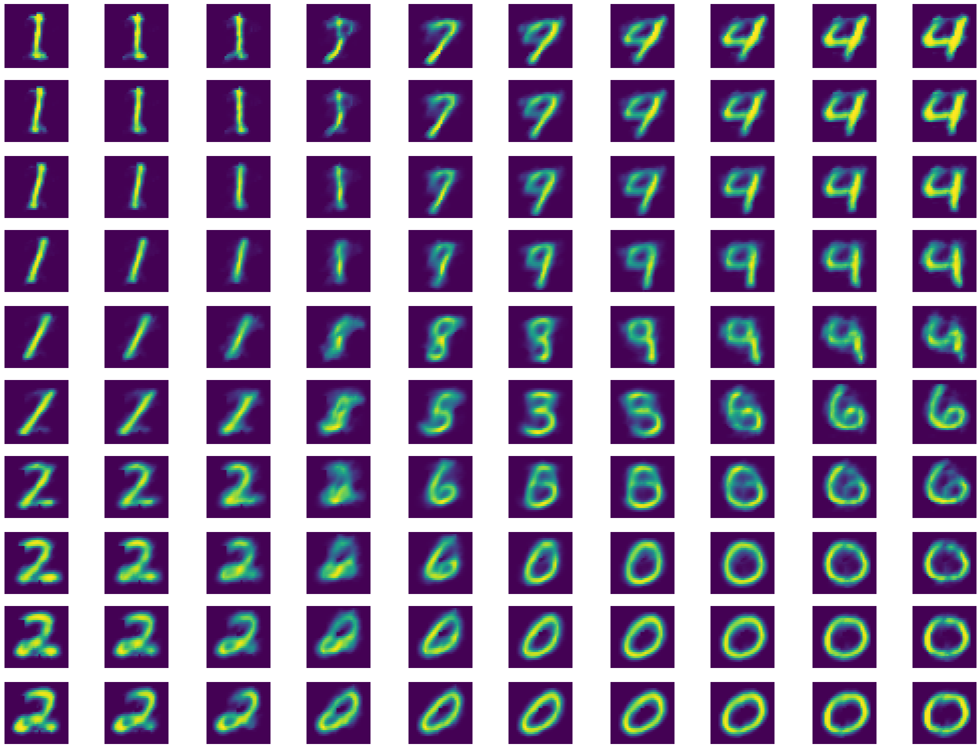
In [50]:
```
y_test = vae.predict(x_test_flat[0:5])
plotn(5,x_test_flat)
plotn(5,y_test)
```



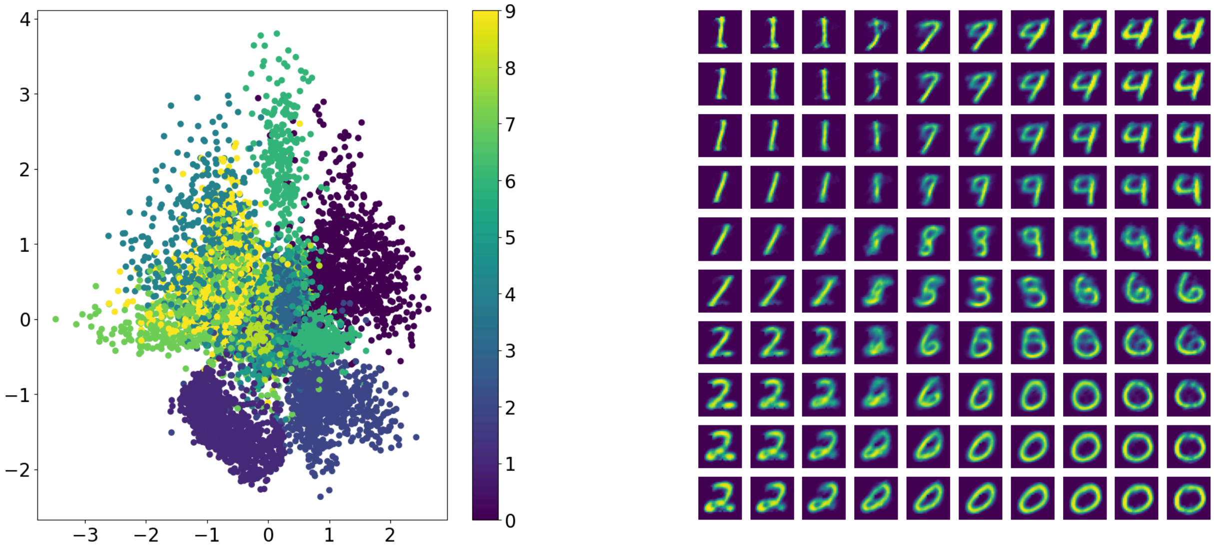
In [51]:
```
x_test_encoded = encoder.predict(x_test_flat)[0]
plt.figure(figsize=(6,6))
plt.scatter(x_test_encoded[:,0], x_test_encoded[:,1], c=y_testclass)
plt.colorbar()
plt.show()
```



In [52]:
```
def plotsample(n):
    dx = np.linspace(-2,2,n)
    dy = np.linspace(-2,2,n)
    fig,ax = plt.subplots(n,n)
    for i,xi in enumerate(dx):
        for j,xj in enumerate(dy):
            res = decoder.predict(np.array([xi,xj]).reshape(-1,2))[0]
            ax[i,j].imshow(res.reshape(28,28))
            ax[i,j].axis('off')
    plt.show()

plotsample(10)
```



In [94]:
```
fig = plt.figure(figsize=(20, 10))
subfigs = fig.subfigures(1, 2)

axsLeft = subfigs[0].subplots(1,1)
x_test_encoded = encoder.predict(x_test_flat)[0]
im = axsLeft.scatter(x_test_encoded[:,0], x_test_encoded[:,1], c=y_testclass);
axsLeft.tick_params(labelsize=20)
cbar = fig.colorbar(im, ax=axsLeft)
cbar.ax.tick_params(labelsize=20)

n = 10
dx = np.linspace(-2,2,n)
dy = np.linspace(-2,2,n)
axRight = subfigs[1].subplots(n,n)
for i,xi in enumerate(dx):
    for j,xj in enumerate(dy):
        res = decoder.predict(np.array([xi,xj]).reshape(-1,2))[0]
        axRight[i,j].imshow(res.reshape(28,28));
        axRight[i,j].axis('off')
```



In [95]:
```
fig.tight_layout()
plt.show()
```

In [ ]: