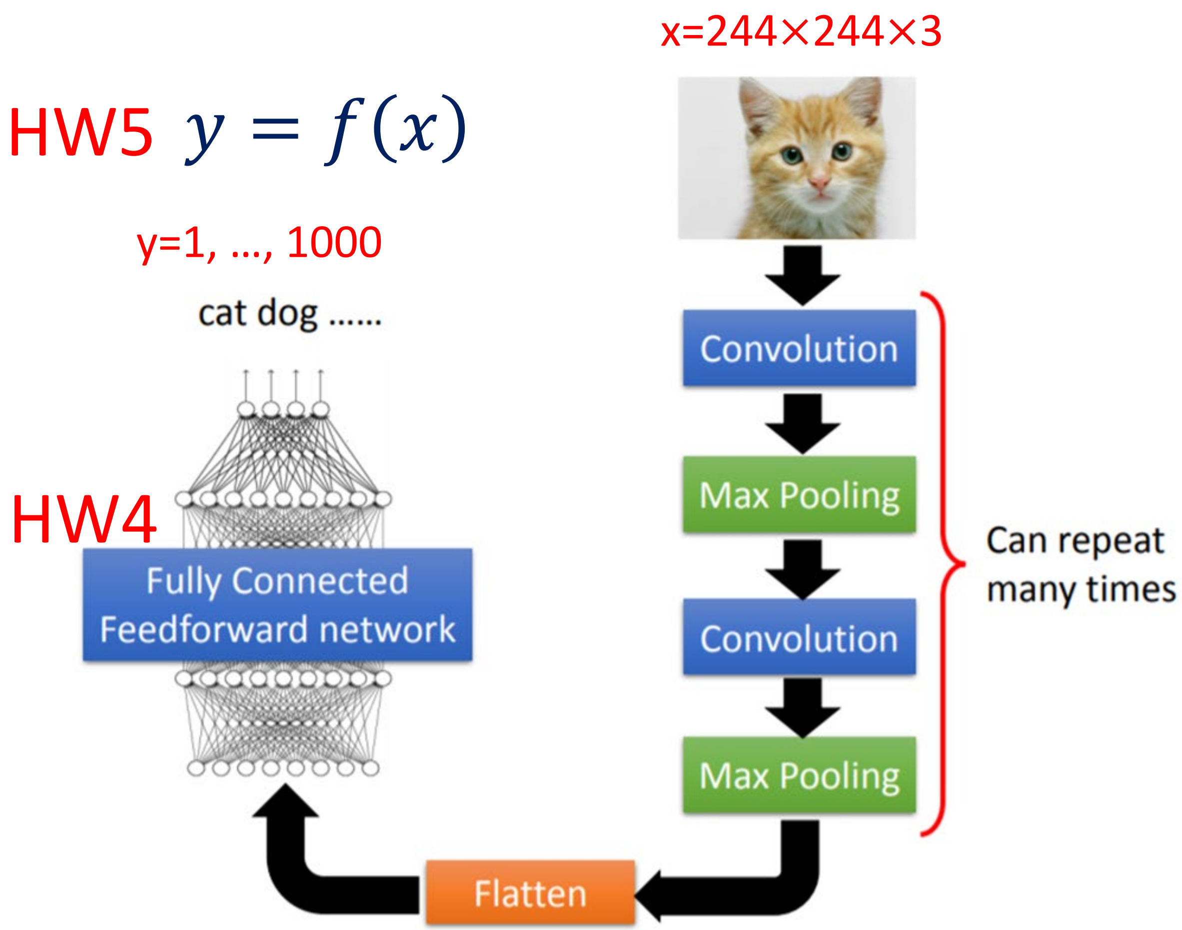
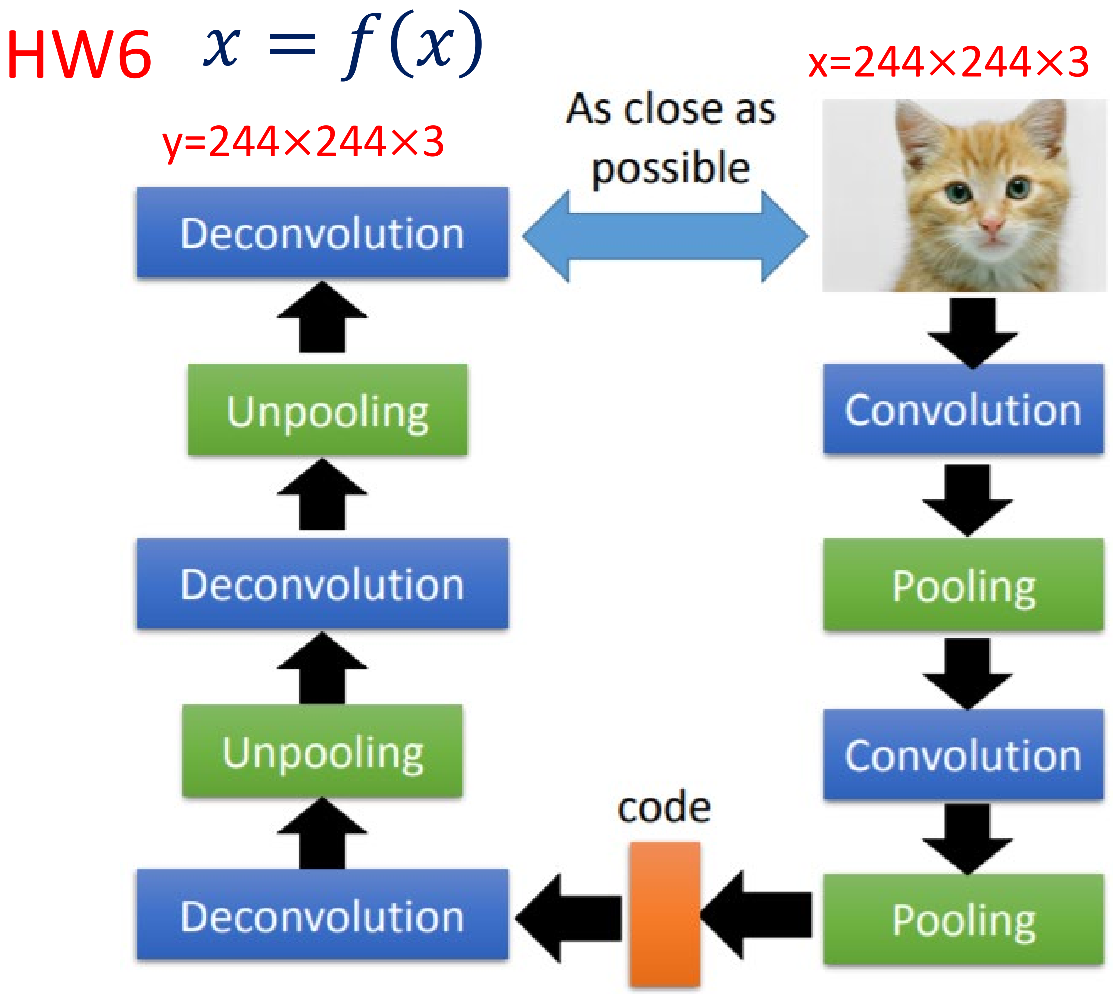
Auto-encoder

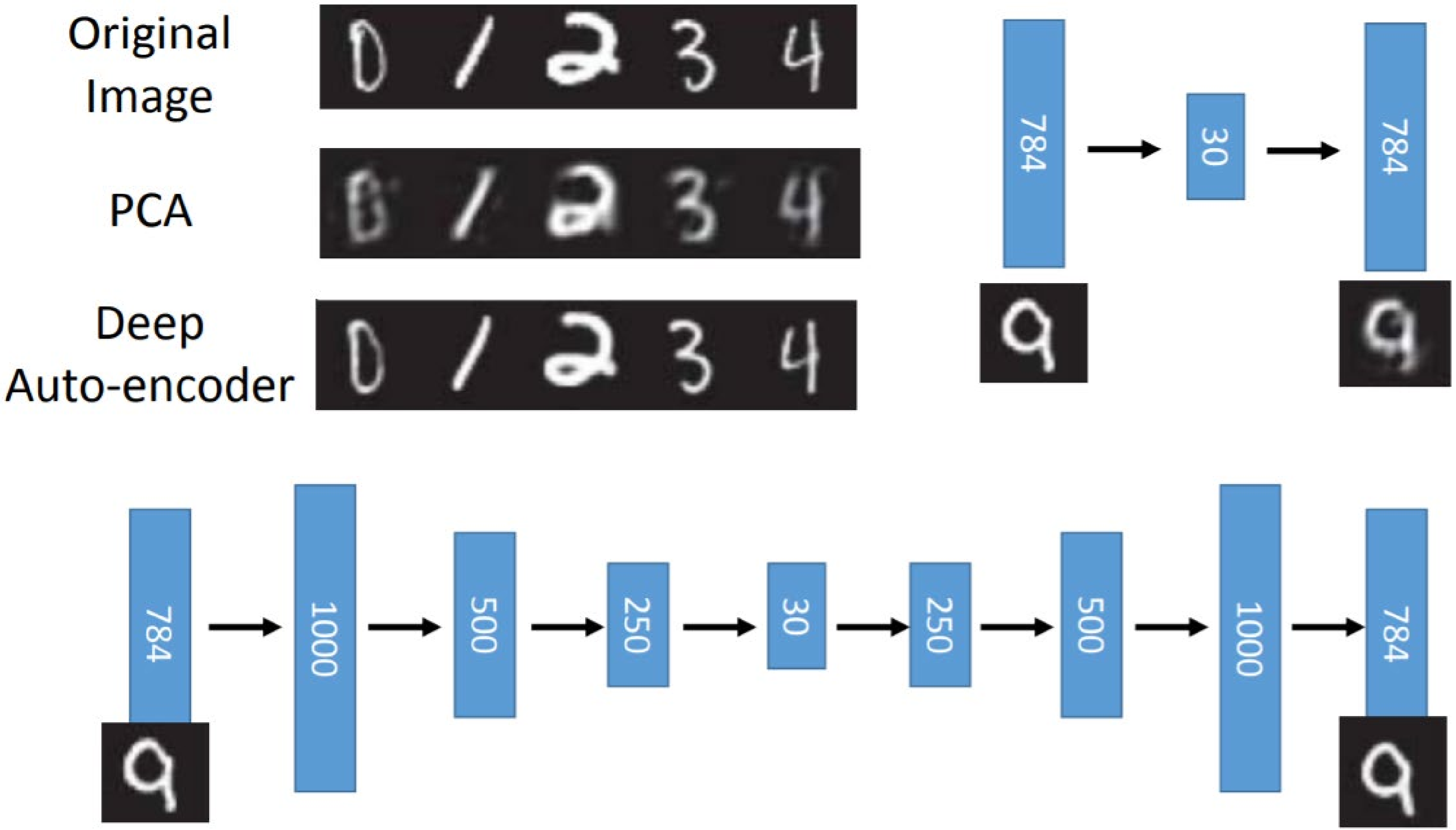
- CNN Image Classifier – Convolution section + MLP classifier
- CNN Autoencoder – Convolution section + Deconvolution section to recover the input image





Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

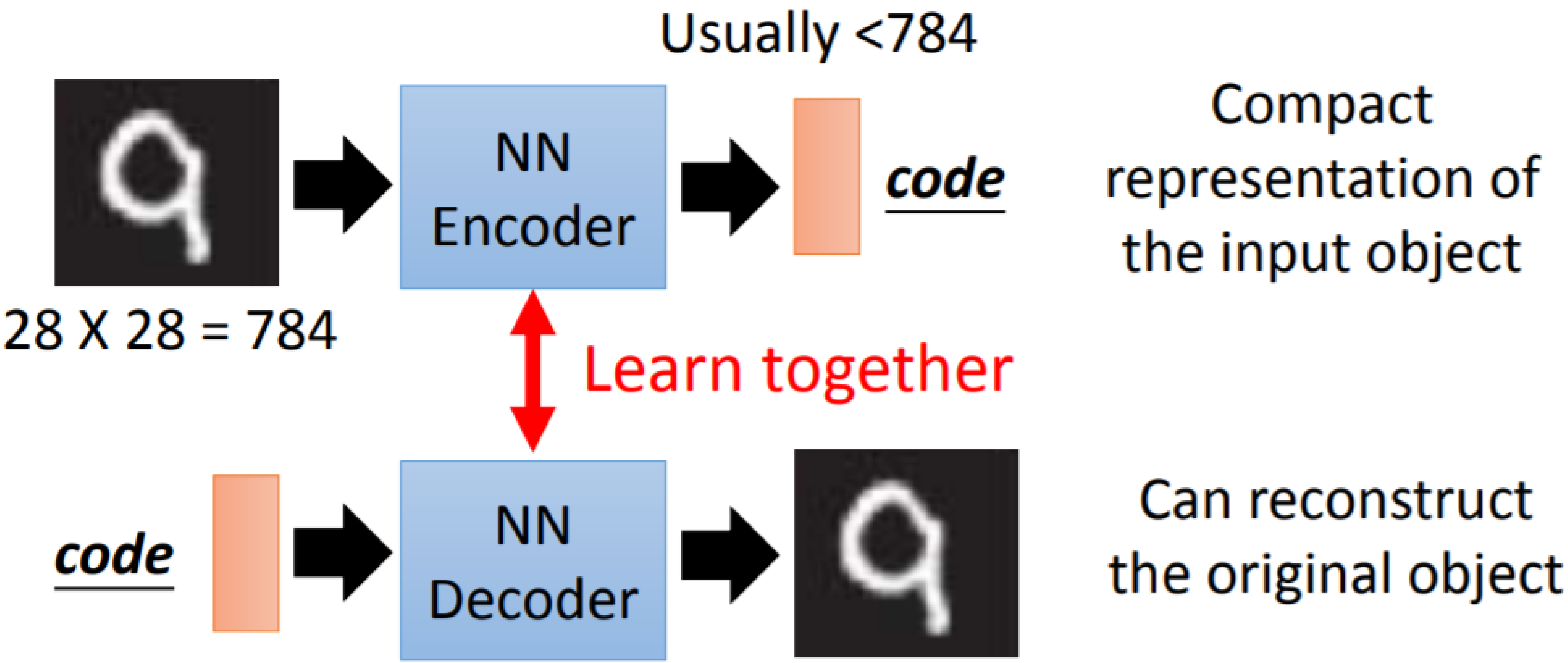
MLP based autoencoder



Reference: Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. "Reducing the dimensionality of data with neural networks." *Science* 313.5786 (2006): 504-507

Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Autoencoder learns a compact representation of the input image

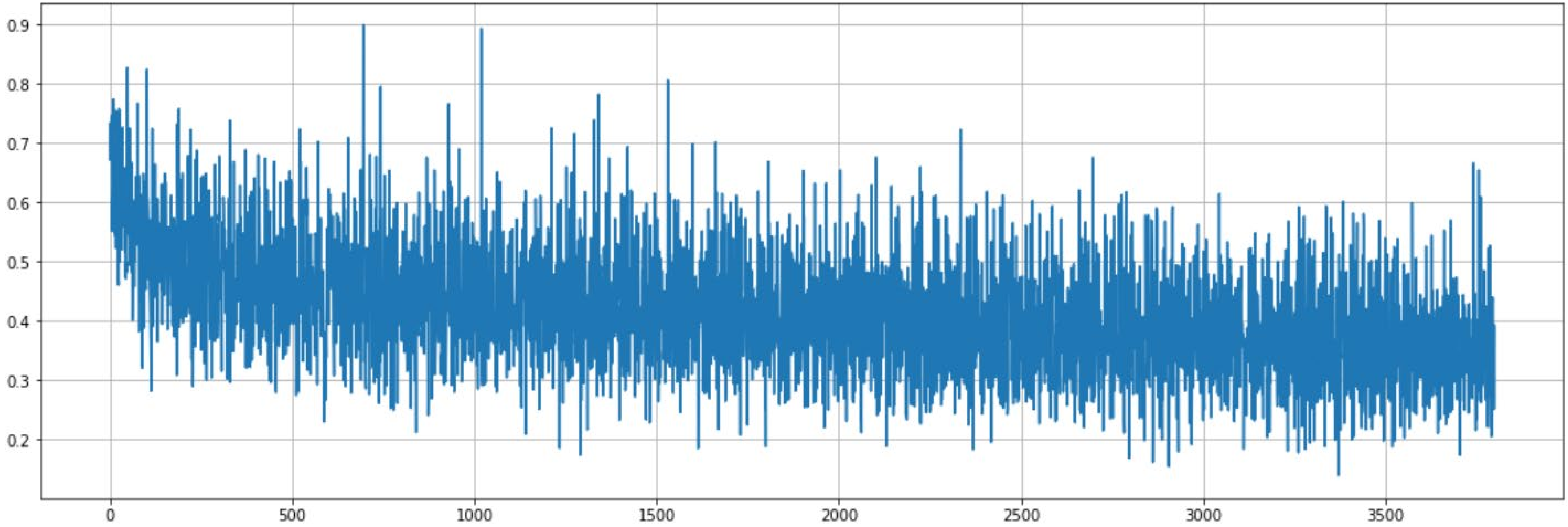


Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Practice

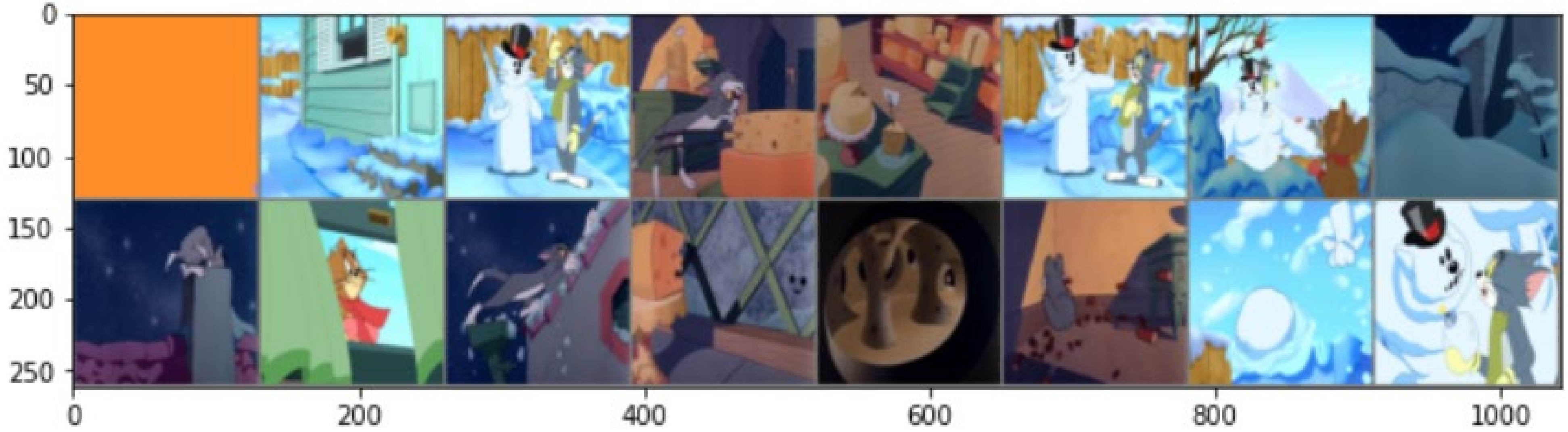
- Run “7.1.Conv_AE.ipynb"

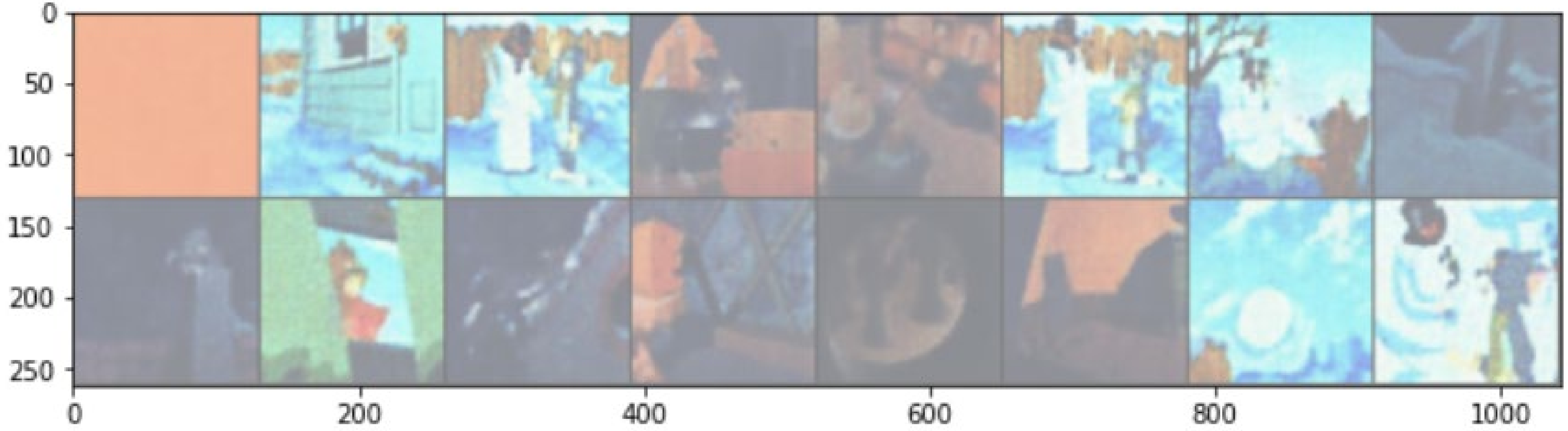
Train 200 epochs



Train 200 epochs

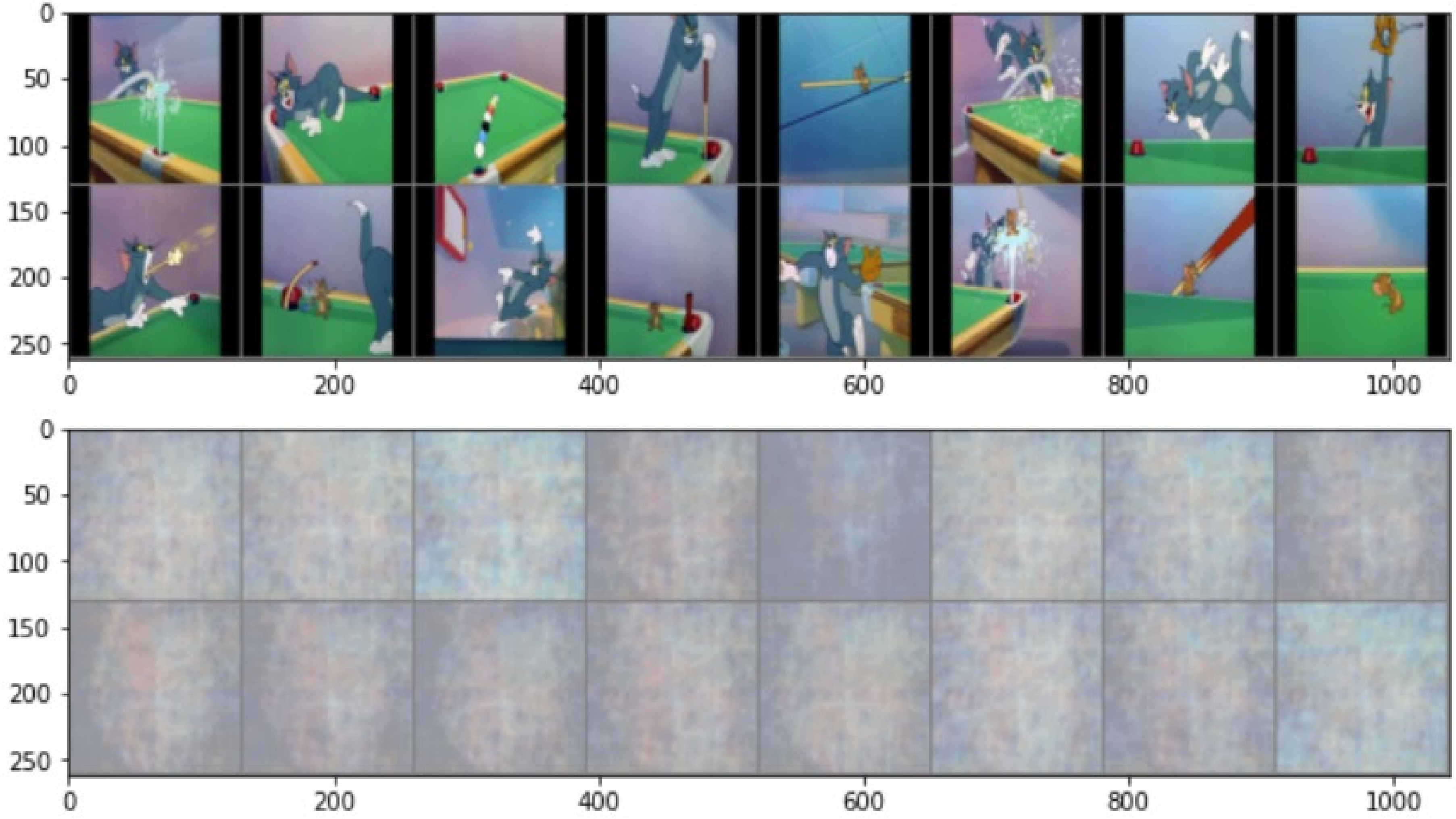
Test on training images – the NN is able to recover more from the input images



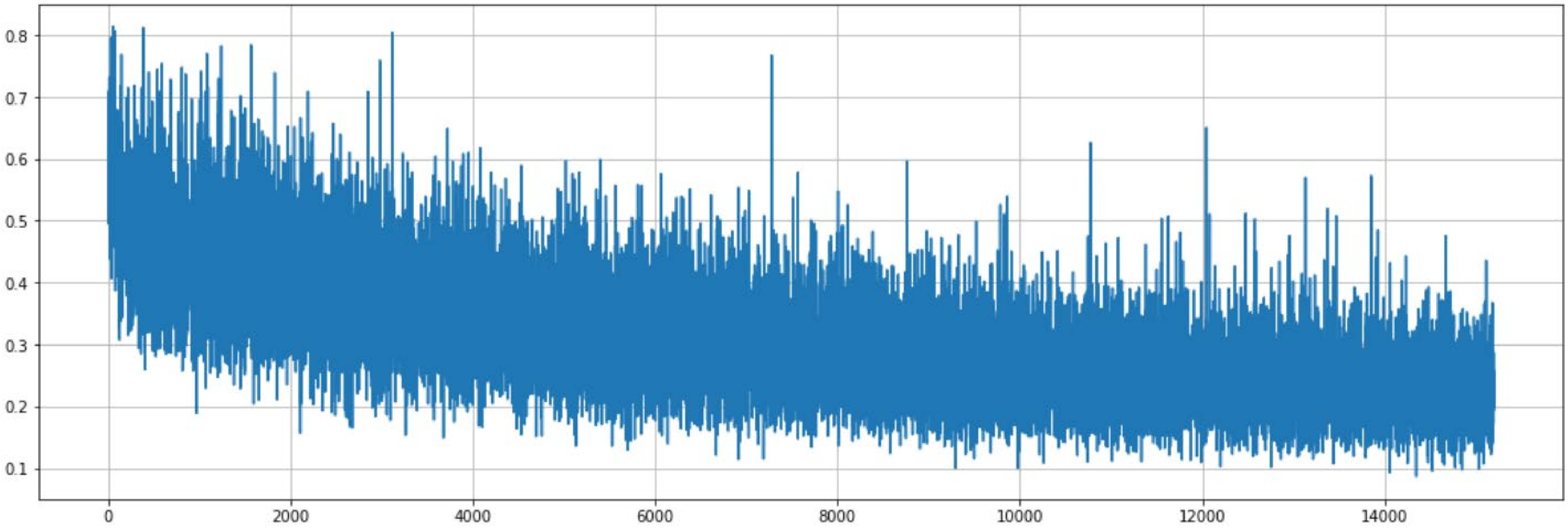


Train 200 epochs

Test on un-seen images – fails to reconstruct the input images

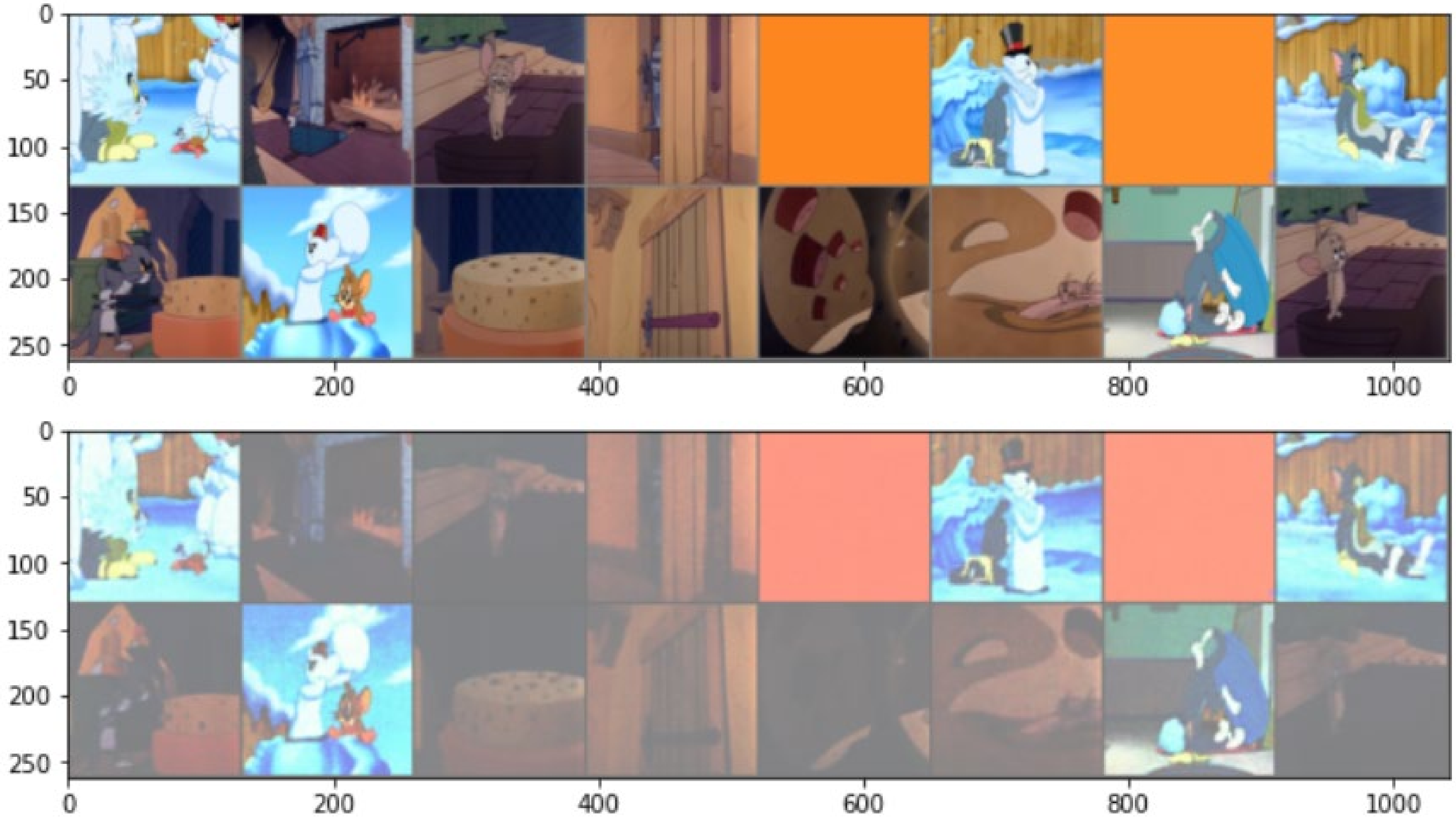


Train 800 epochs



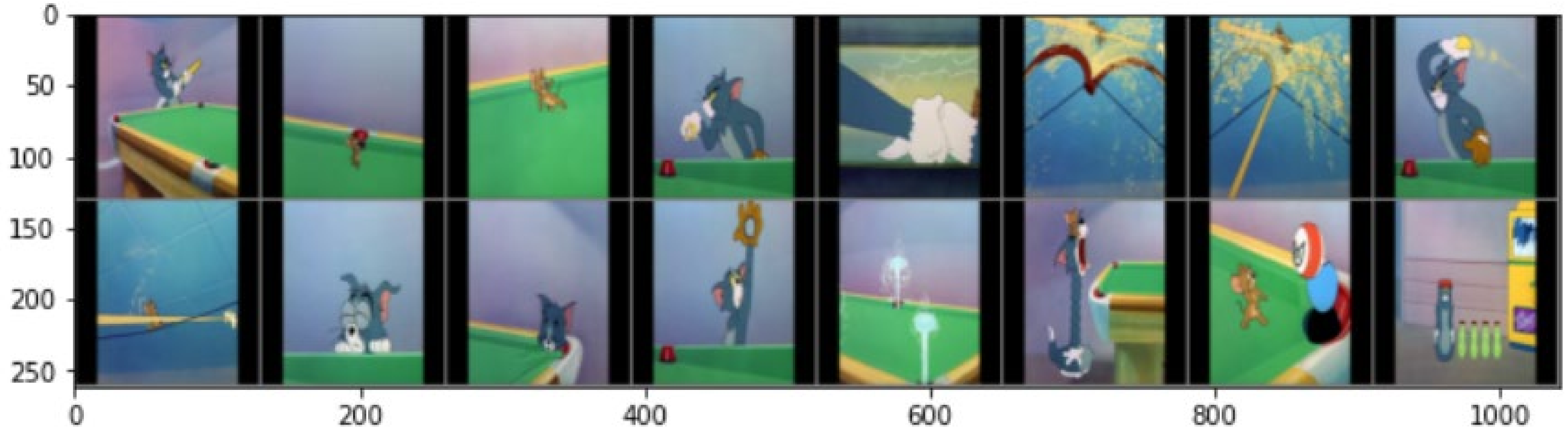
Train 800 epochs

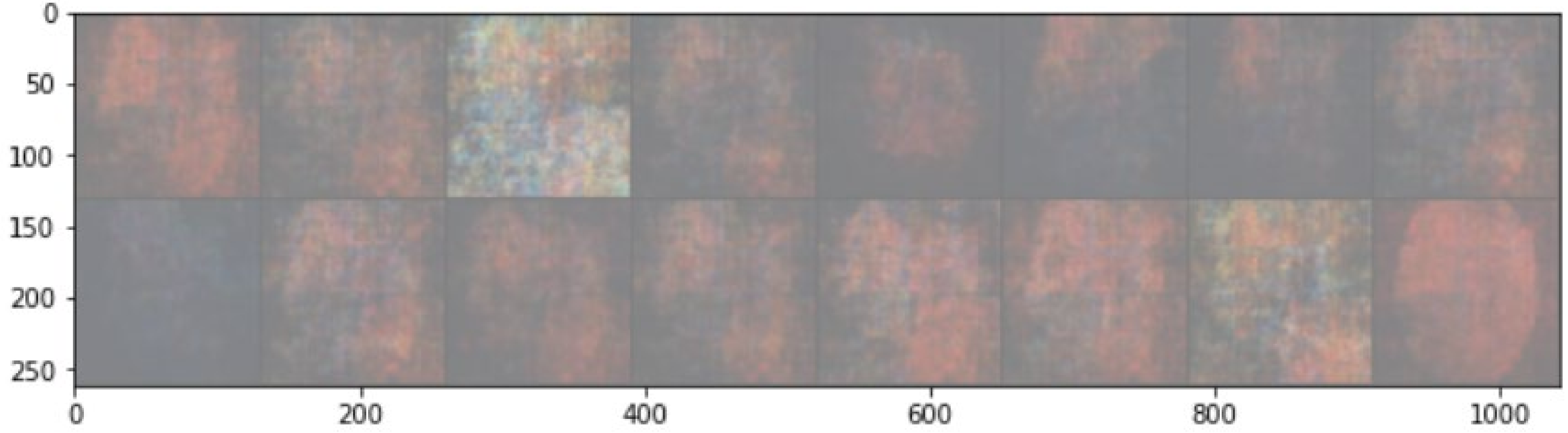
Test on training images



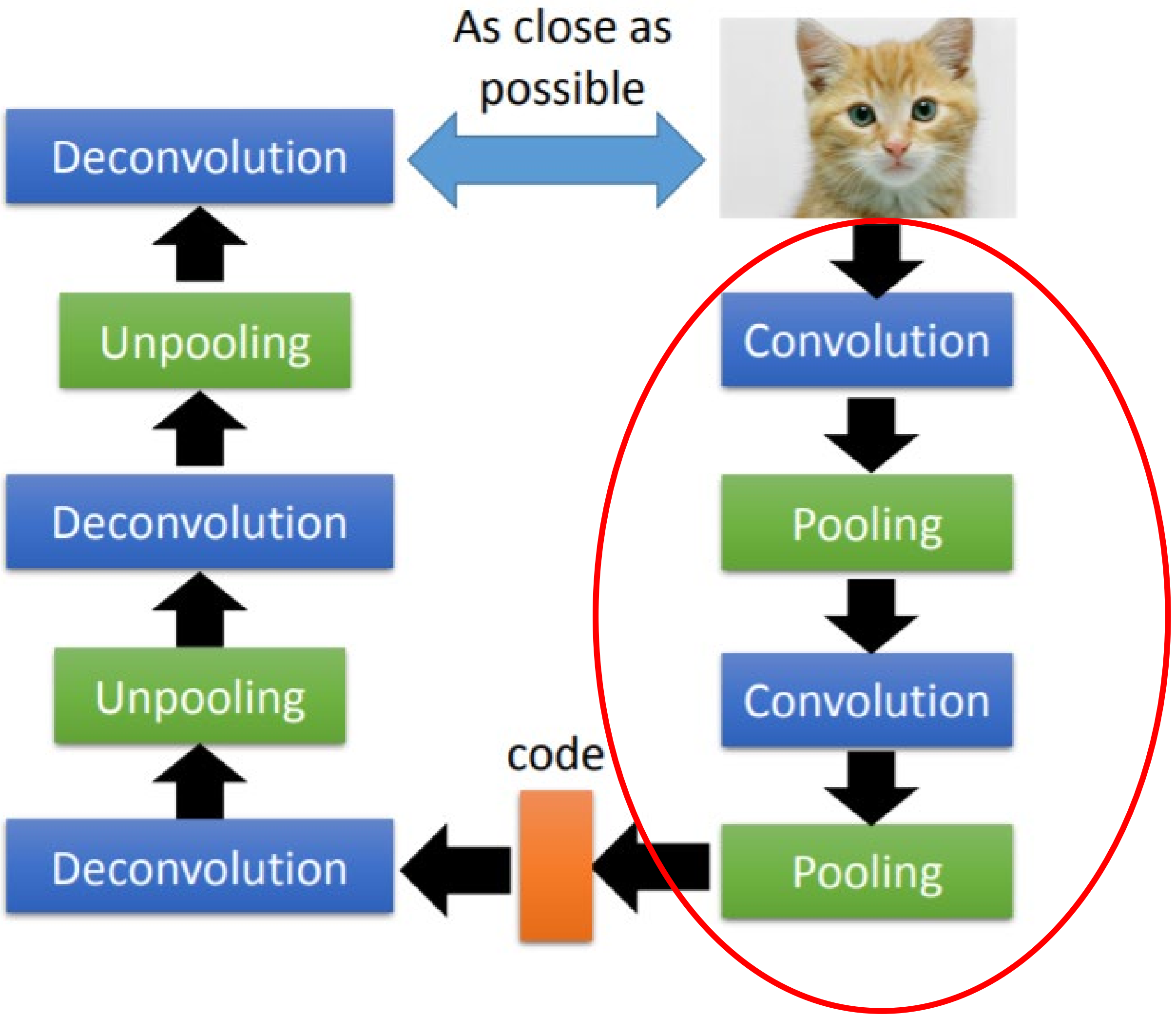
Train 800 epochs

Test on un-seen images – fails to reconstruct the input images





Encoder




```
self.encoder = nn.Sequential(
  nn.Conv2d(3, 32, kernel_size=2, stride=2),
  nn.BatchNorm2d(32, eps=1e-05, momentum=0.1, af
  nn.ReLU(),
  nn.Conv2d(32, 64, kernel_size=2, stride=2),
  nn.BatchNorm2d(64, eps=1e-05, momentum=0.1, af
  nn.ReLU(),
  nn.Conv2d(64, 128, kernel_size=2, stride=2),
  nn.BatchNorm2d(128, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(128, 256, kernel_size=2, stride=2),
  nn.BatchNorm2d(256, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(256, 512, kernel_size=2, stride=2),
  nn.BatchNorm2d(512, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(512, 1024, kernel_size=2, stride=2),
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1,
  nn.ReLU(),
  nn.Conv2d(1024, 1024, kernel_size=2, stride=2)
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1,
  nn.ReLU(),
  Flatten(),
  nn.Linear(in_features=i, out_features=o),
)
```

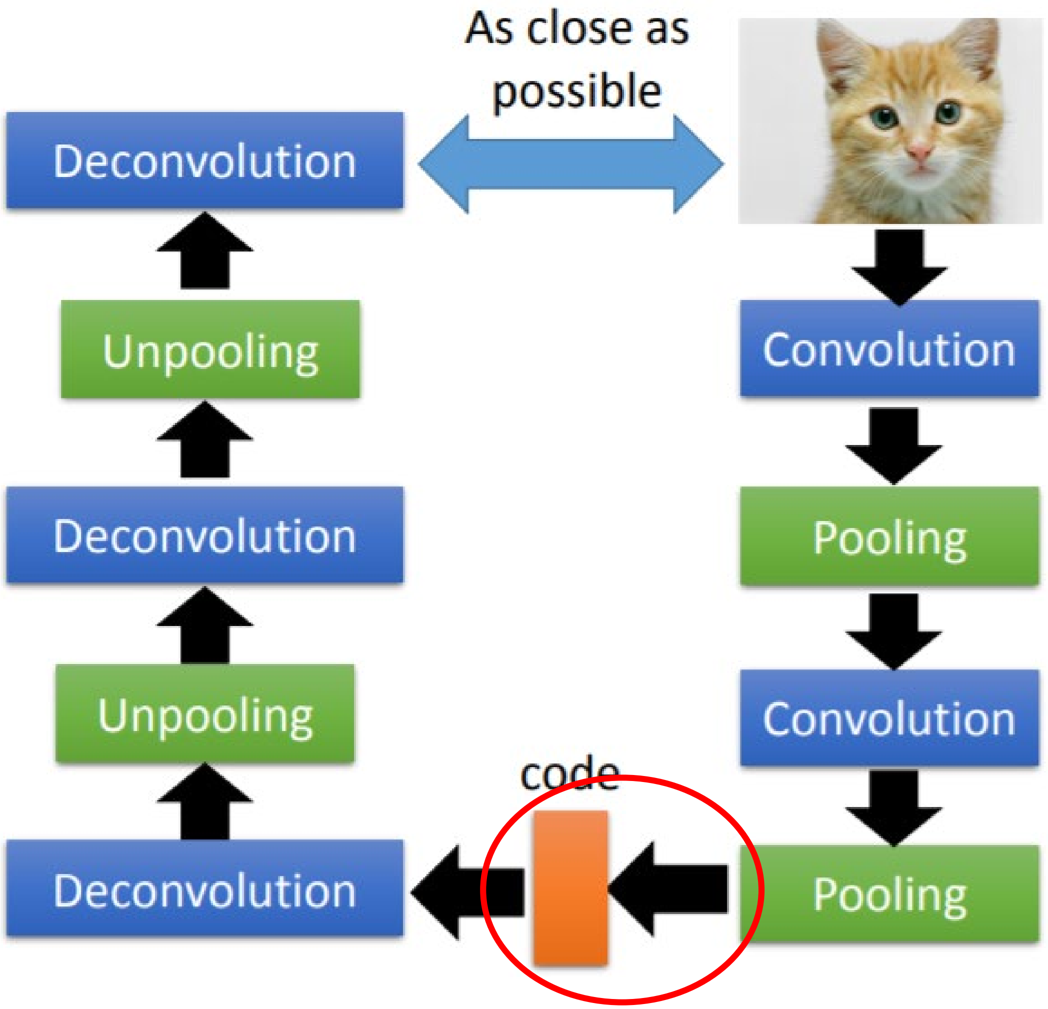
Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Practice: Draw the feature maps of encoder

- Let input image = 224x224x3
- Draw the feature maps (H, W, depth) after each convolution and max pooling
- What is the number of nodes after flatten?

PYTORCH

Latent vector




```
class autoencoder(nn.Module):
  def __init__(self,i=1024,o=64):
    super(autoencoder, self).__init__()
    self.encoder = nn.Sequential(
      nn.Conv2d(3, 32, kernel_size=2, stride=
      nn.BatchNorm2d(32, eps=1e-05, momentum=
      nn.ReLU(),
```

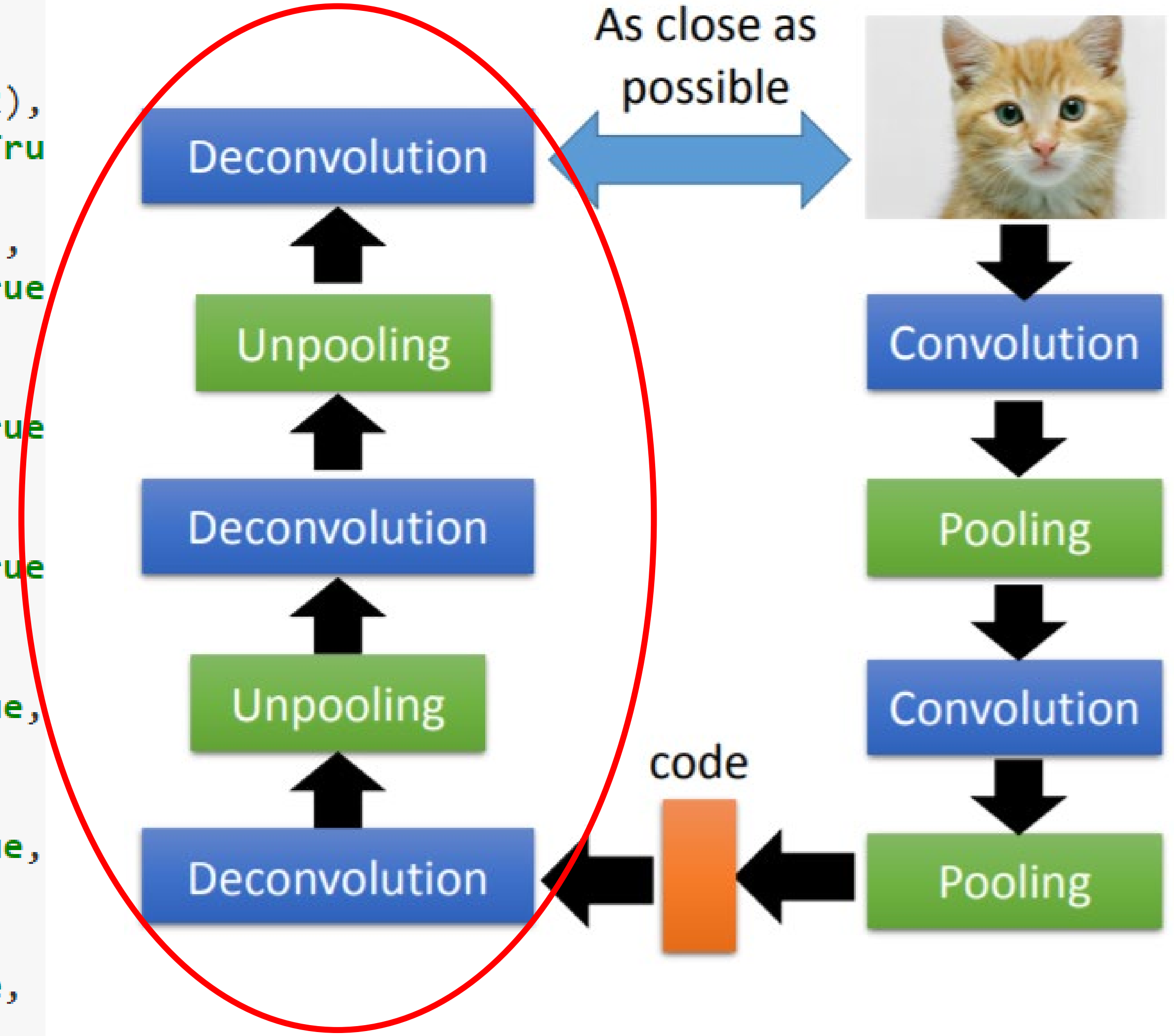
```
      nn.BatchNorm2d(1024, eps=1e-05, momentum=0.
      nn.ReLU(),
      nn.Conv2d(1024, 1024, kernel_size=2, stride
      nn.BatchNorm2d(1024, eps=1e-05, momentum=0.
      nn.ReLU(),
      Flatten(),
      nn.Linear(in_features=i, out_features=o),
    )
```

```
      Flatten-22                [-1, 1024]
       Linear-23                  [-1, 64]
       Linear-24                [-1, 1024]
   UnFlatten-25          [-1, 1024, 1, 1]
```

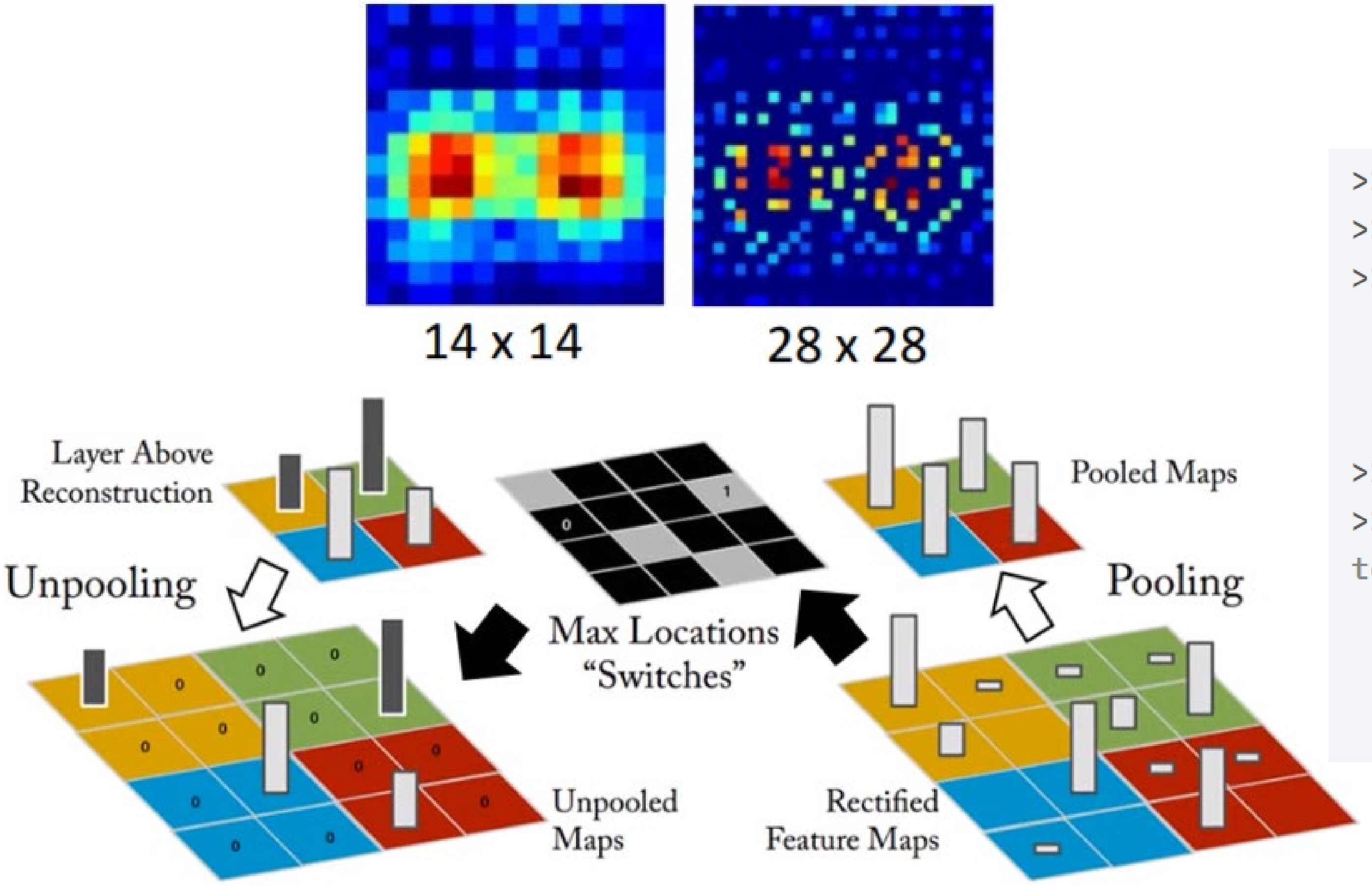
Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Decoder

```
self.decoder = nn.Sequential(
  nn.Linear(in_features=o, out_features=i),
  UnFlatten(),
  nn.ConvTranspose2d(1024, 1024, kernel_size=2, stride=2),
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=Tru
  nn.ReLU(),
  nn.ConvTranspose2d(1024, 512, kernel_size=2, stride=2),
  nn.BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(512, 256, kernel_size=2, stride=2),
  nn.BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(256, 128, kernel_size=2, stride=2),
  nn.BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(128, 64, kernel_size=2, stride=2),
  nn.BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
  nn.ReLU(),
  nn.ConvTranspose2d(64, 32, kernel_size=2, stride=2),
  nn.BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
  nn.ReLU(),
  nn.ConvTranspose2d(32, 3, kernel_size=2, stride=2),
  nn.BatchNorm2d(3, eps=1e-05, momentum=0.1, affine=True,
  nn.Sigmoid(),
)
```



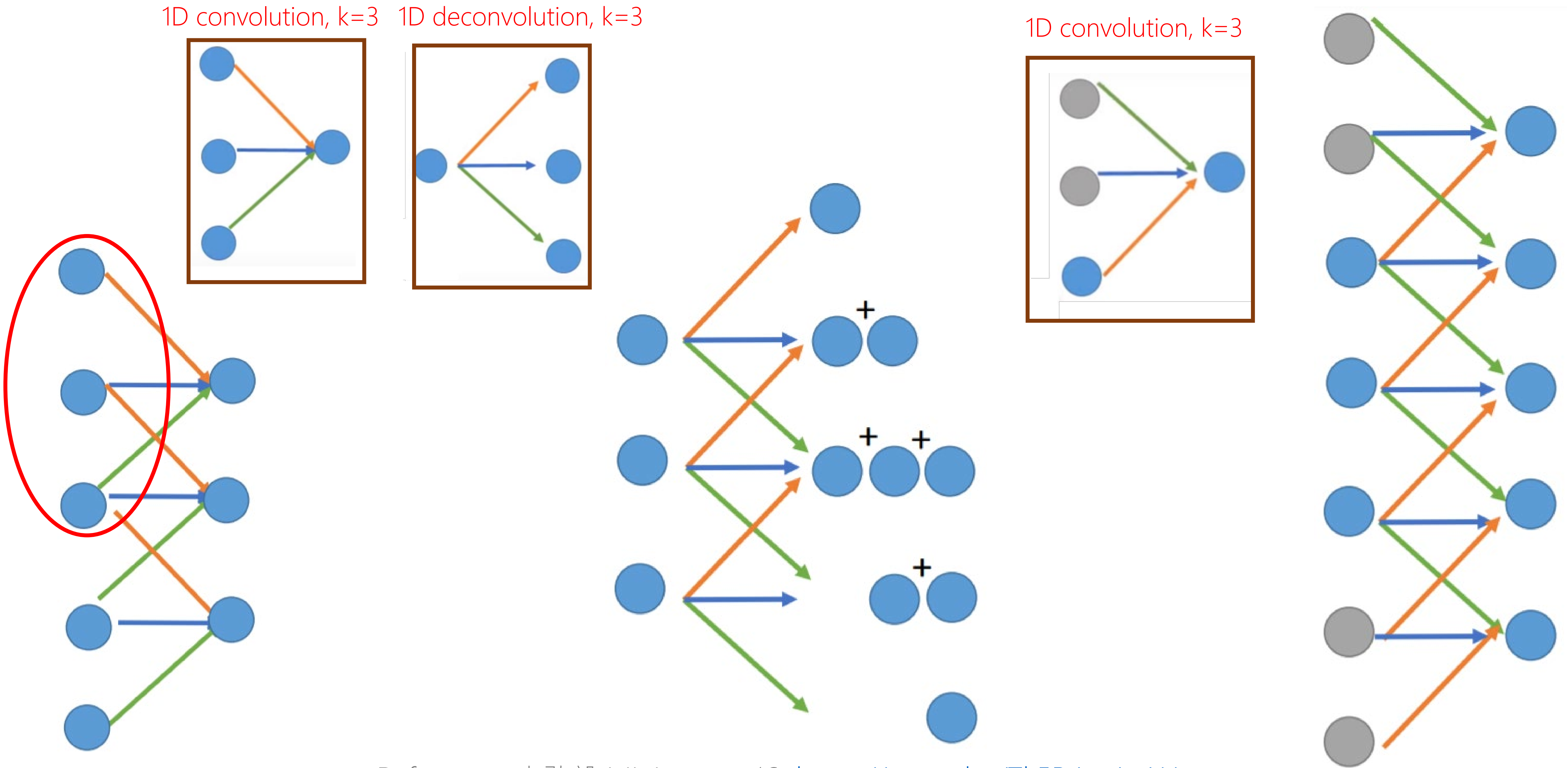
Unpooling




```
>>> pool = nn.MaxPool2d(2, stride=2, return_indices=True)
>>> unpool = nn.MaxUnpool2d(2, stride=2)
>>> input = torch.tensor([[[[ 1.,  2,  3,  4],
                            [ 5,  6,  7,  8],
                            [ 9, 10, 11, 12],
                            [13, 14, 15, 16]]]])
>>> output, indices = pool(input)
>>> unpool(output, indices)
tensor([[[[  0.,   0.,   0.,   0.],
          [  0.,   6.,   0.,   8.],
          [  0.,   0.,   0.,   0.],
          [  0.,  14.,   0.,  16.]]]])
```

Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

Deconvolution



Reference: 李弘毅 ML Lecture 16 https://youtu.be/Tk5B4seA-AU

In this ConvAE example, we only use deconvolution for up sampling, no un-pooling is used.

```
self.decoder = nn.Sequential(
  nn.Linear(in_features=o, out_features=i),
  UnFlatten(),
  nn.ConvTranspose2d(1024, 1024, kernel_size=2, stride=2),
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=Tru
  nn.ReLU(),
  nn.ConvTranspose2d(1024, 512, kernel_size=2, stride=2),
  nn.BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(512, 256, kernel_size=2, stride=2),
  nn.BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(256, 128, kernel_size=2, stride=2),
  nn.BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True
  nn.ReLU(),
  nn.ConvTranspose2d(128, 64, kernel_size=2, stride=2),
  nn.BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
  nn.ReLU(),
  nn.ConvTranspose2d(64, 32, kernel_size=2, stride=2),
  nn.BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True,
  nn.ReLU(),
  nn.ConvTranspose2d(32, 3, kernel_size=2, stride=2),
  nn.BatchNorm2d(3, eps=1e-05, momentum=0.1, affine=True,
  nn.Sigmoid(),
)
```

Practice: Draw the feature maps of decoder

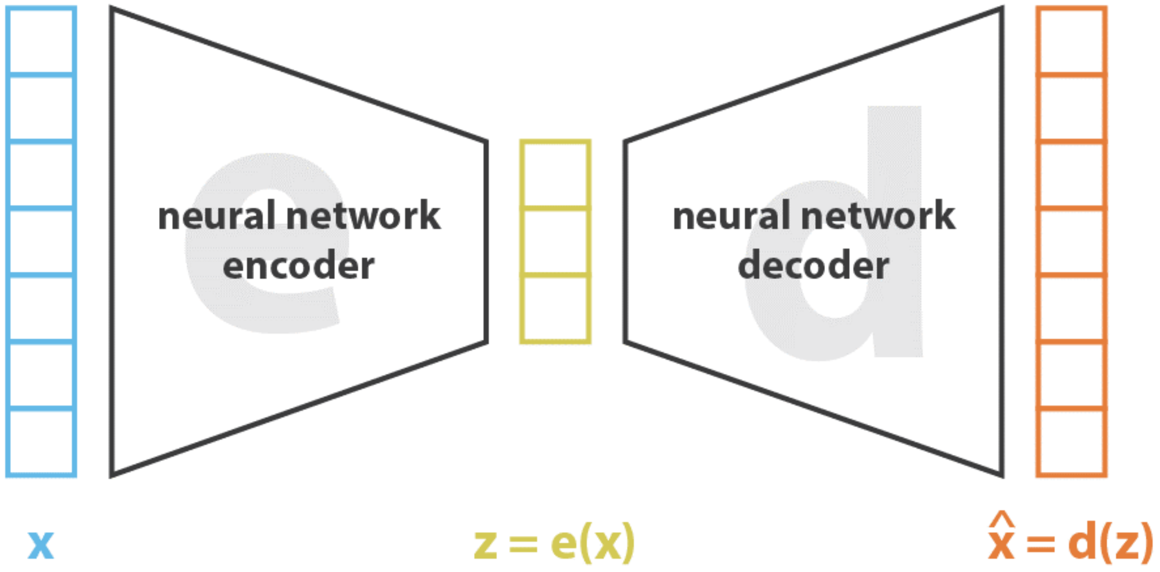
- Input – the number of nodes after un-flattern
- Draw feature maps (H, W, depth) after each de-convolution and un-max pooling

Deconvolution

```
(2): ConvTranspose2d(1024, 1024, kernel_size=(2, 2), stride=(2, 2))
(3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_r
(4): ReLU()
(5): ConvTranspose2d(1024, 512, kernel_size=(2, 2), stride=(2, 2))
(6): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_ru
(7): ReLU()
(8): ConvTranspose2d(512, 256, kernel_size=(2, 2), stride=(2, 2))
(9): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_ru
(10): ReLU()
```

```
   ConvTranspose2d-26          [-1, 1024, 2, 2]
       BatchNorm2d-27          [-1, 1024, 2, 2]
              ReLU-28          [-1, 1024, 2, 2]
   ConvTranspose2d-29           [-1, 512, 4, 4]
       BatchNorm2d-30           [-1, 512, 4, 4]
              ReLU-31           [-1, 512, 4, 4]
   ConvTranspose2d-32           [-1, 256, 8, 8]
       BatchNorm2d-33           [-1, 256, 8, 8]
              ReLU-34           [-1, 256, 8, 8]
   ConvTranspose2d-35         [-1, 128, 16, 16]
       BatchNorm2d-36         [-1, 128, 16, 16]
              ReLU-37         [-1, 128, 16, 16]
   ConvTranspose2d-38          [-1, 64, 32, 32]
       BatchNorm2d-39          [-1, 64, 32, 32]
              ReLU-40          [-1, 64, 32, 32]
```

Loss function



$$\text{loss} = \| x - \hat{x} \|^2 = \| x - d(z) \|^2 = \| x - d(e(x)) \|^2$$

Source: https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73

```
[13]: for batchX, _ in loader:
        break;
      print(batchX.shape)

      torch.Size([16, 3, 128, 128])

[14]: tensorY=model(batchX.to(device))
      print(tensorY.shape)

      torch.Size([16, 3, 128, 128])

[15]: loss = loss_func(tensorY, batchX.to(device))
      print(loss)

      tensor(0.6961, device='cuda:0', grad_fn=<Msel
```

Save and load PyTorch model

```
[27]: torch.save(model.state_dict(), "AE800.pt")
```

```
[28]: model=autoencoder() #build NN architecture
      model.load_state_dict(torch.load("AE800.pt")) #load model weights
      model.to(device)
      model.eval()
```

PYTORCH

Save and load PyTorch model

Get latent vectors of all training images

[37]:

```
for step, (batchX, batchY) in enumerate(loader):
  tensorY = model.encoder(batchX.to(device))
  if(step==0):
    arrayX = np.array(tensorY.cpu().detach().numpy())
    arrayY = batchY.cpu().detach().numpy()
  else:
    arrayX = np.concatenate((arrayX, tensorY.cpu().detach().numpy()))
    arrayY = np.concatenate((arrayY, batchY.cpu().detach().numpy()))
print(arrayX.shape, arrayY.shape)
```

```
(298, 64) (298,)
```

PYTORCH

Use *t*-SNE to reduce dimensions from 64 to 2

```
[38]: from sklearn.manifold import TSNE
      tsne = TSNE(perplexity=5, n_components=2, init='pca', n_iter=5000)
      # try perlexity = 5, 10, 30, 50
```

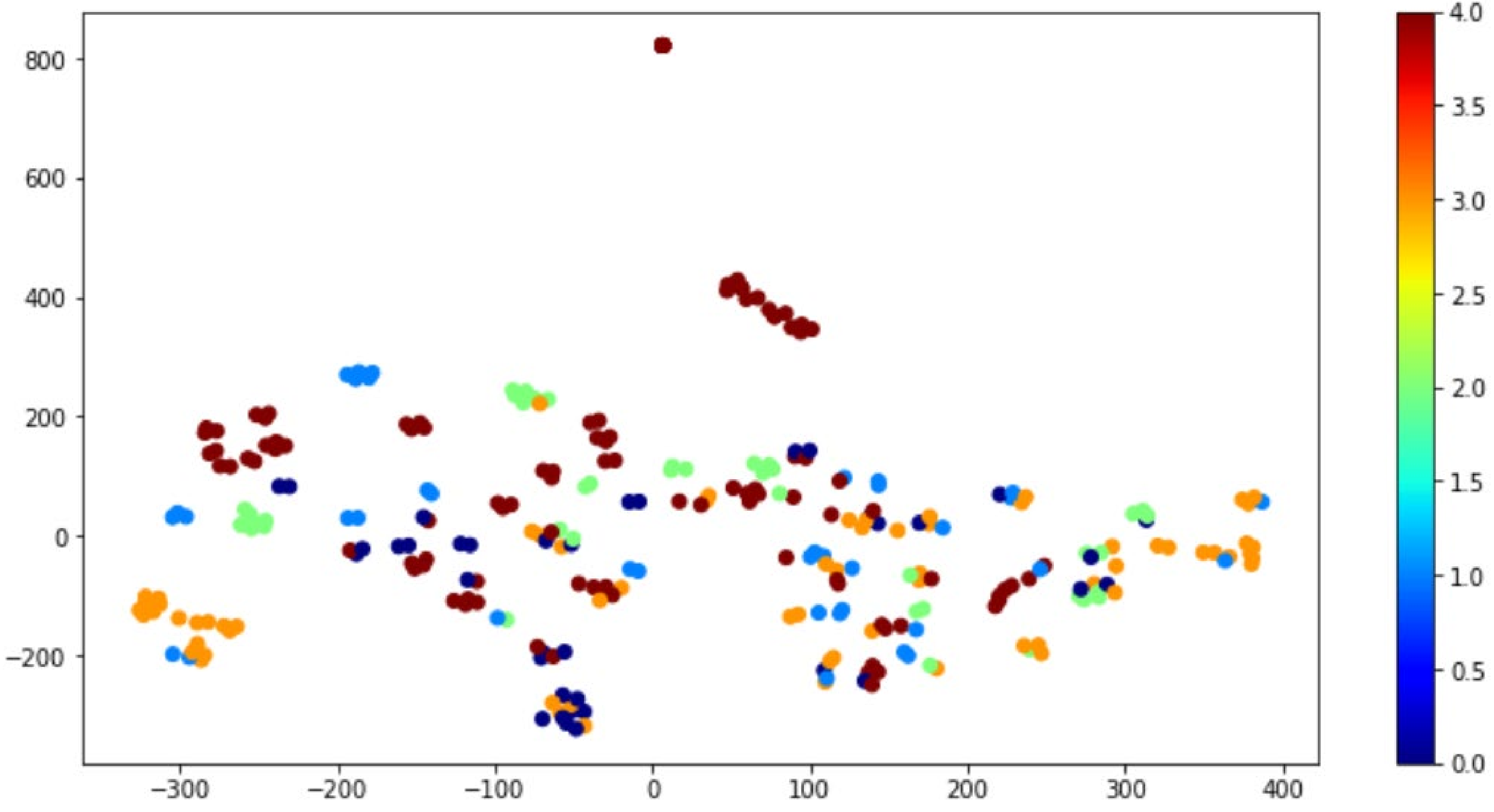
```
[39]: x=tsne.fit_transform(arrayX)
      print(x.shape)
```

```
(298, 2)
```

```
[40]: plt.figure(figsize=(18,9))
      plt.scatter(x[:, 0], x[:, 1], c= arrayY)
      plt.show()
```

PYTORCH

Use *t*-SNE to reduce dimensions from 64 to 2

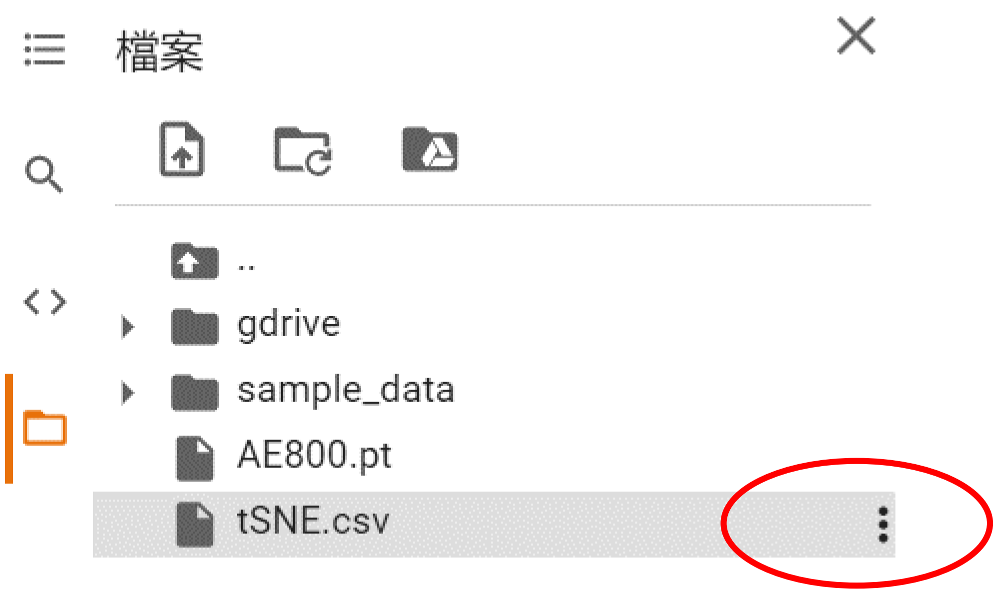


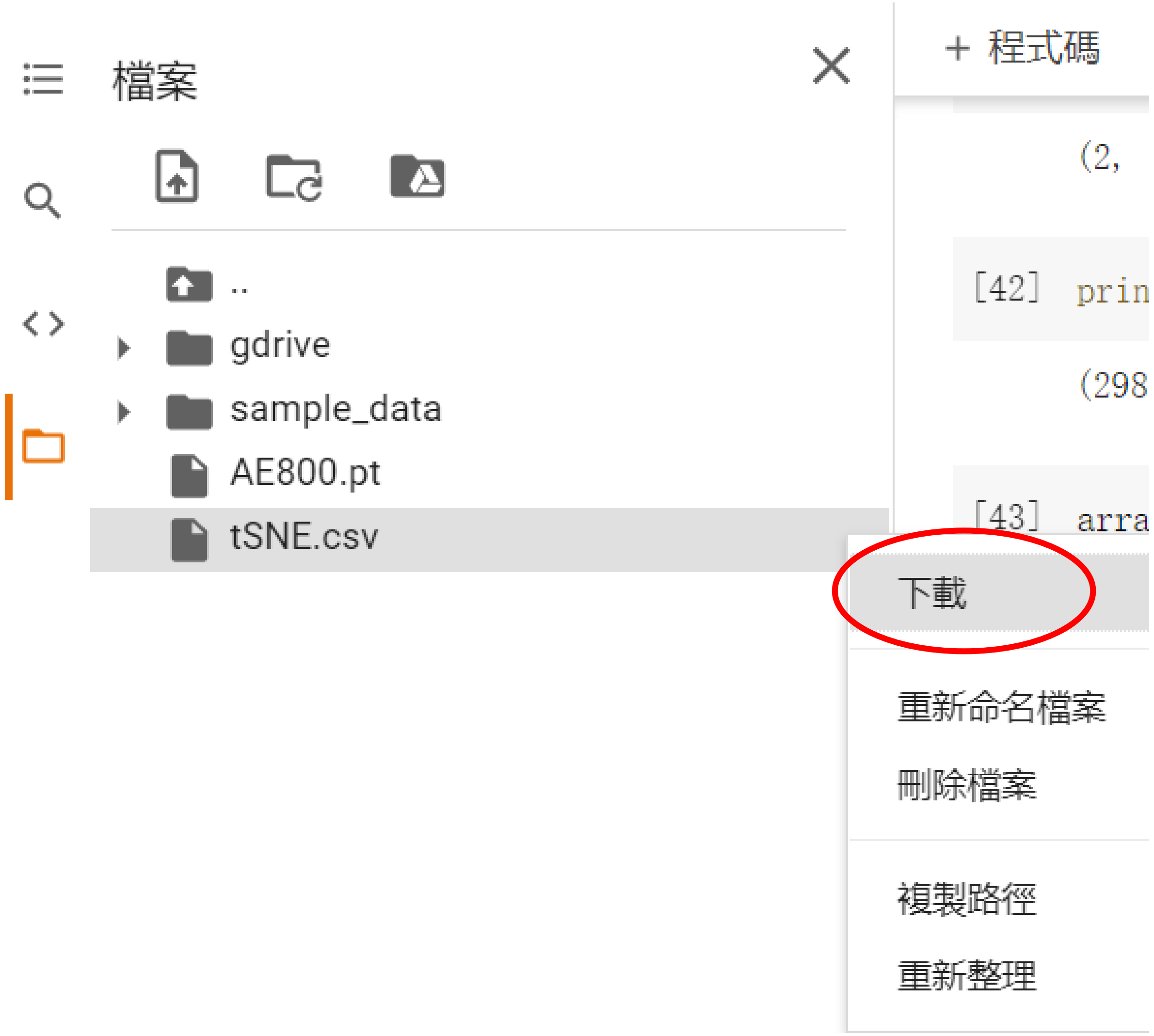
Save data to csv file

```
[42] print(x.shape, arrayY.shape)

     (298, 2) (298,)

[43] arrayY1 = arrayY.reshape(arrayY.shape[0], 1)
     print(arrayY1.shape)

     (298, 1)

[44] XYArray = np.hstack((x, arrayY1))
     print(XYArray.shape)

     (298, 3)

[45] # Save data to excel for further Tableau visualization
     import pandas as pd
     pd.DataFrame(XYArray).to_csv("tSNE.csv")
```

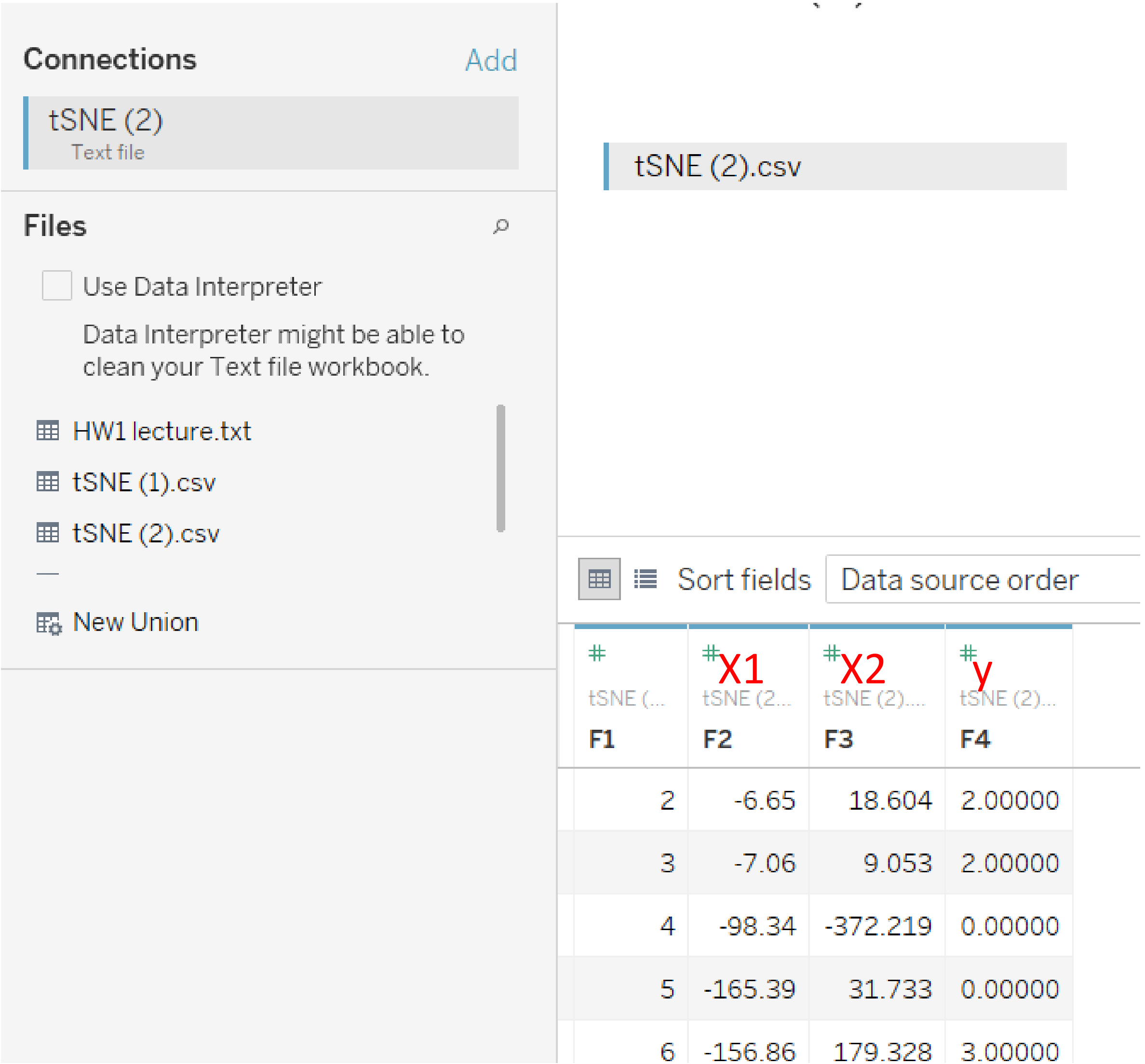
Save data to csv file

Download csv file

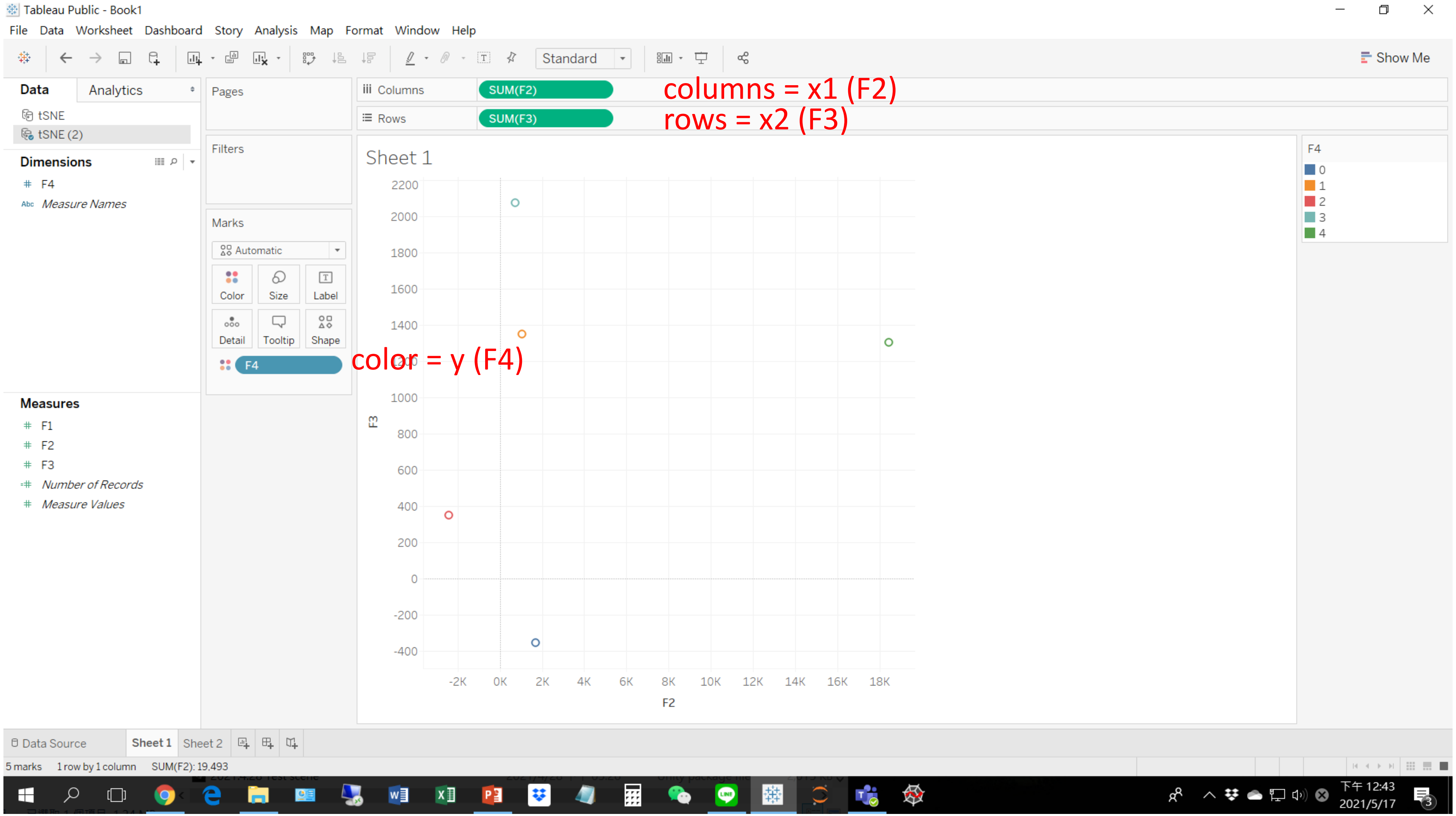




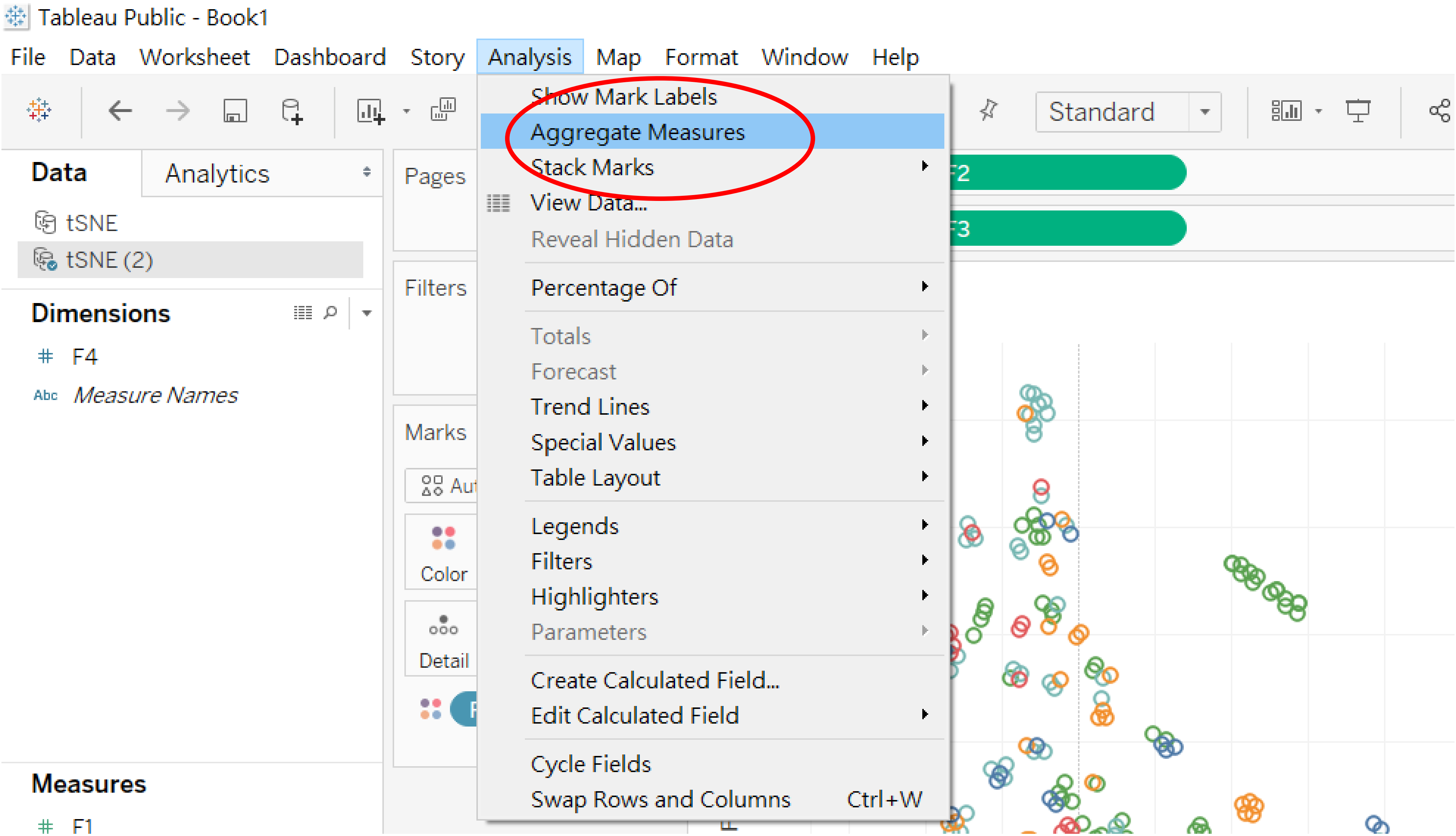
Visualize in Tableau public



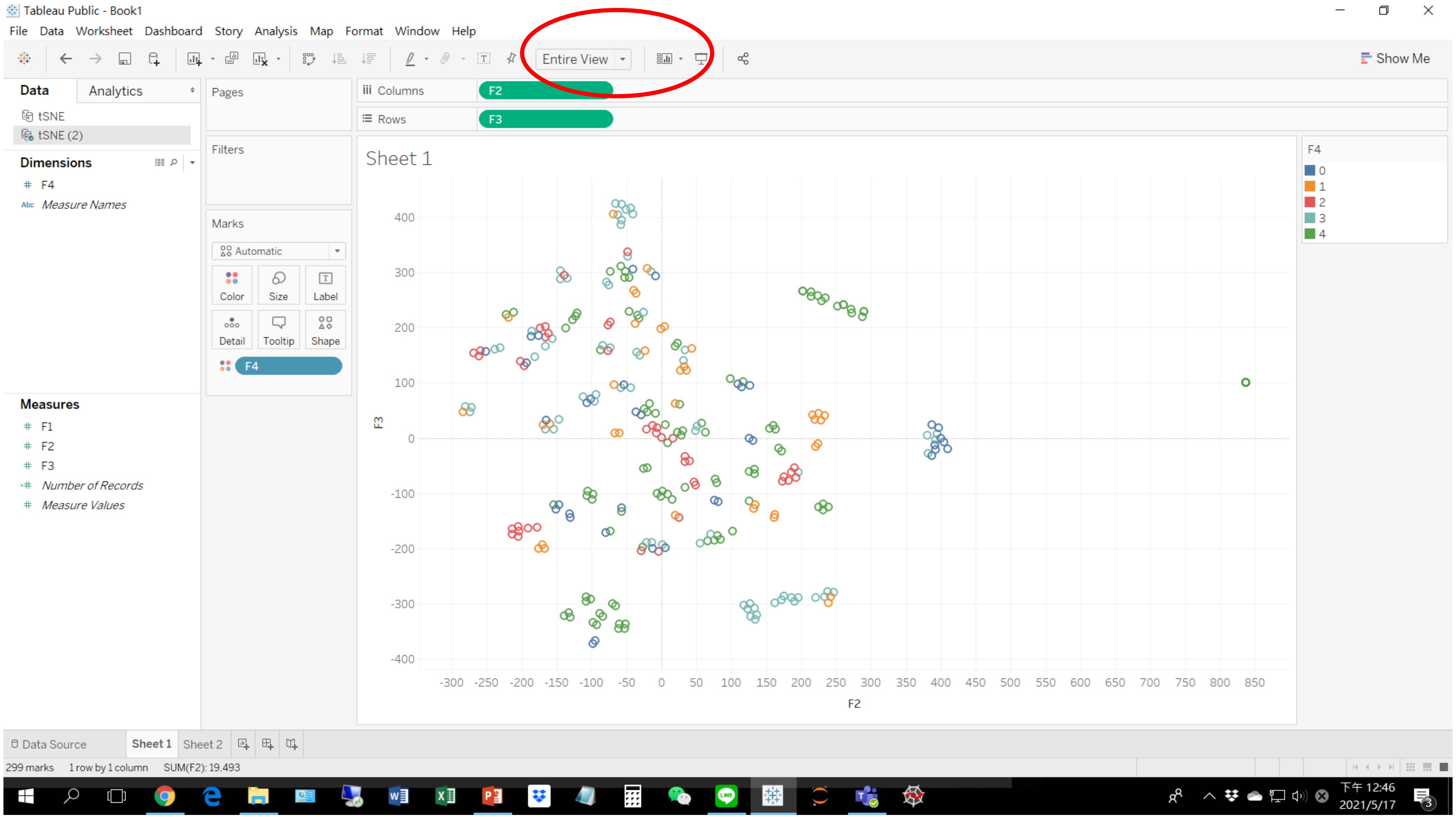
Visualize in Tableau public



Visualize in Tableau public



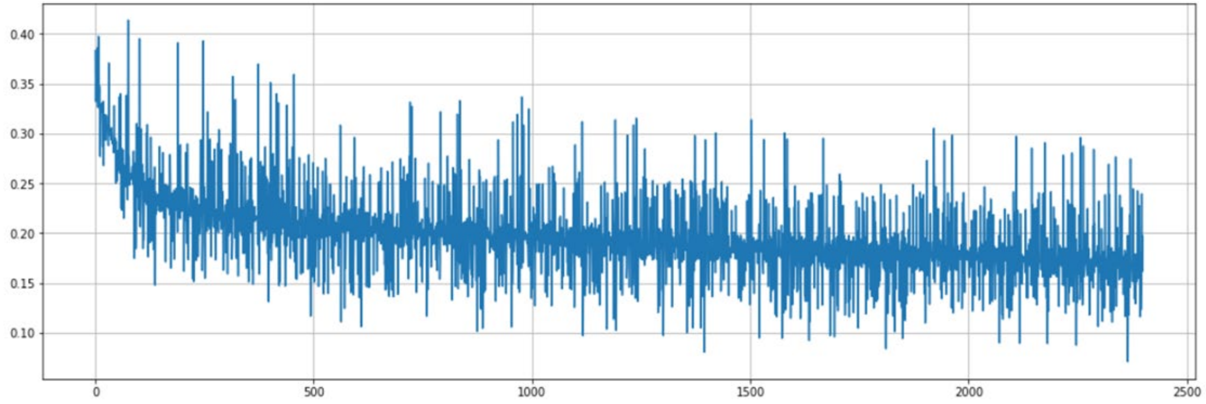
Visualize in Tableau public



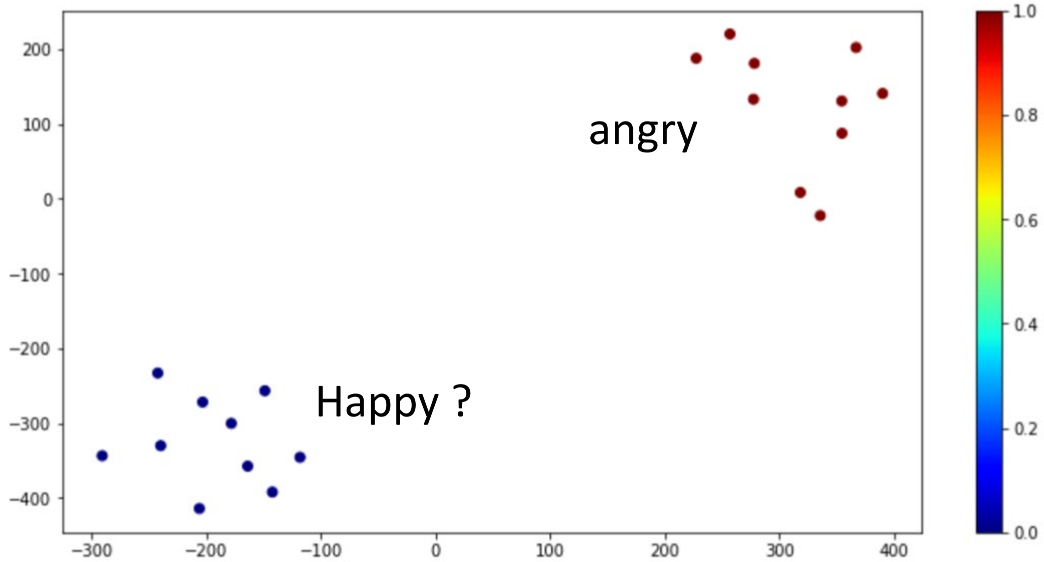
HW6 (1)

- Train an AE to learn a compact representation (try latent vector of size 20, 30, 50) of your facial expression. Test with 10 happy and 10 angry faces.
- Show the recovered image.
- Send the latent vectors to *t*-SNE to see whether they form clusters.

Happy = ?, Angry = ?, Latent vector size = ?, 1160 epochs

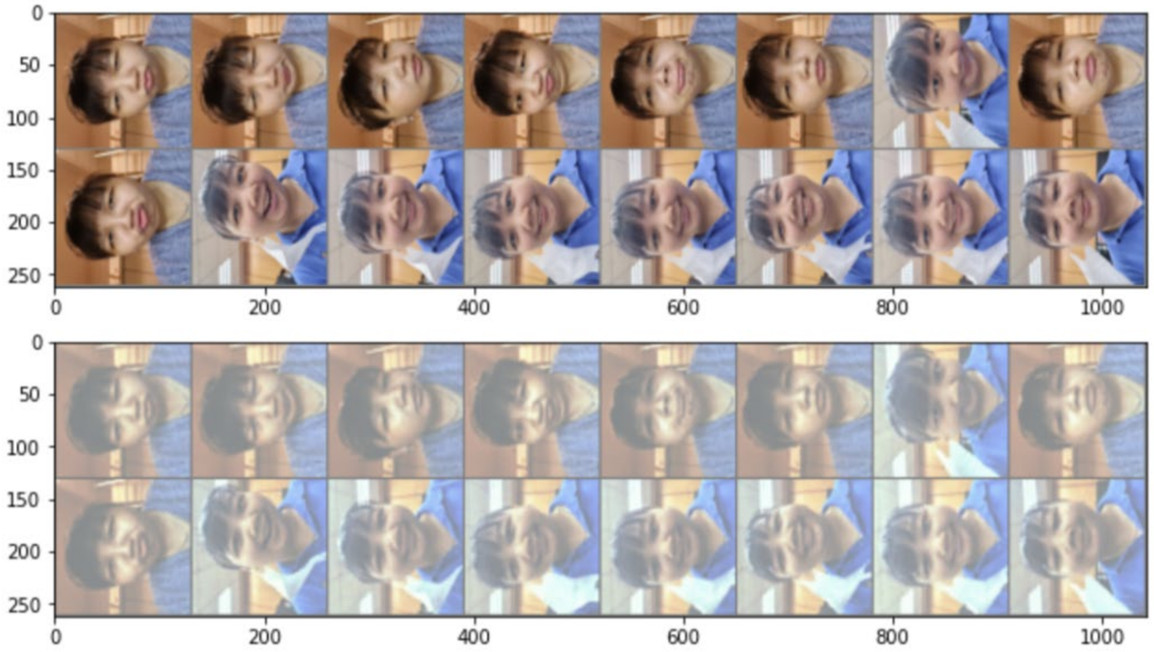


t-SNE (perplexity=?) results of training images

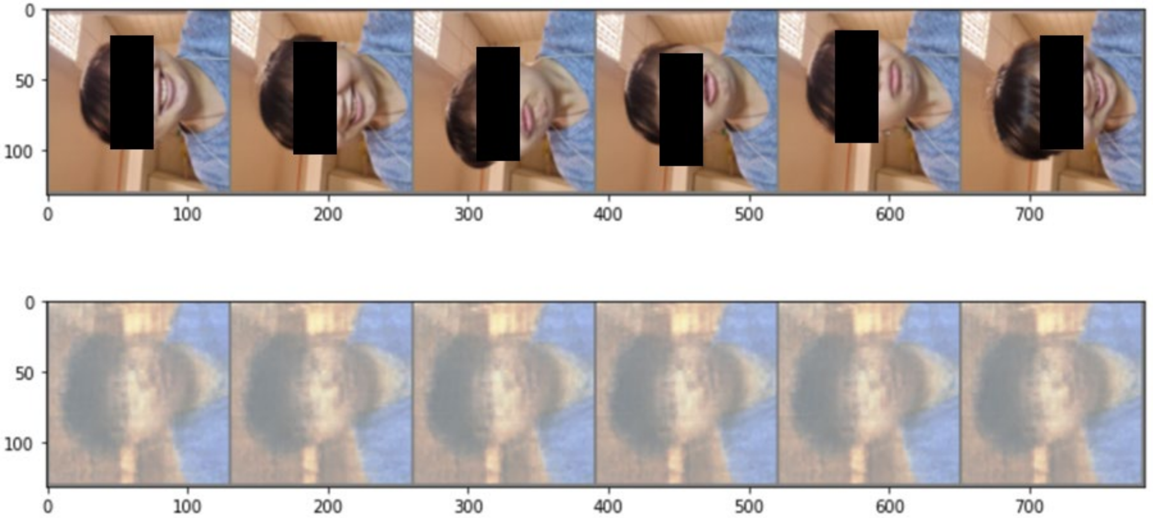


1061259 Keren

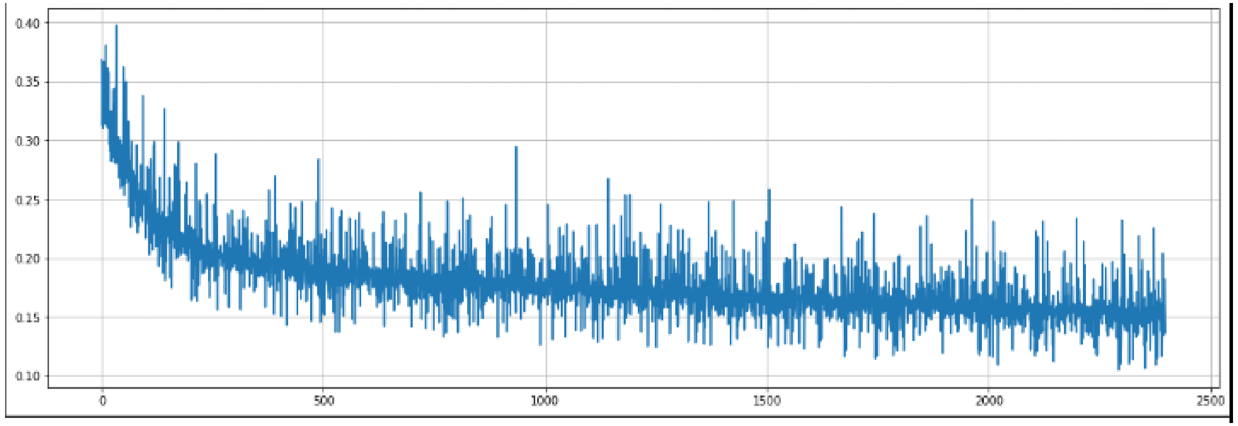
Recovered training images



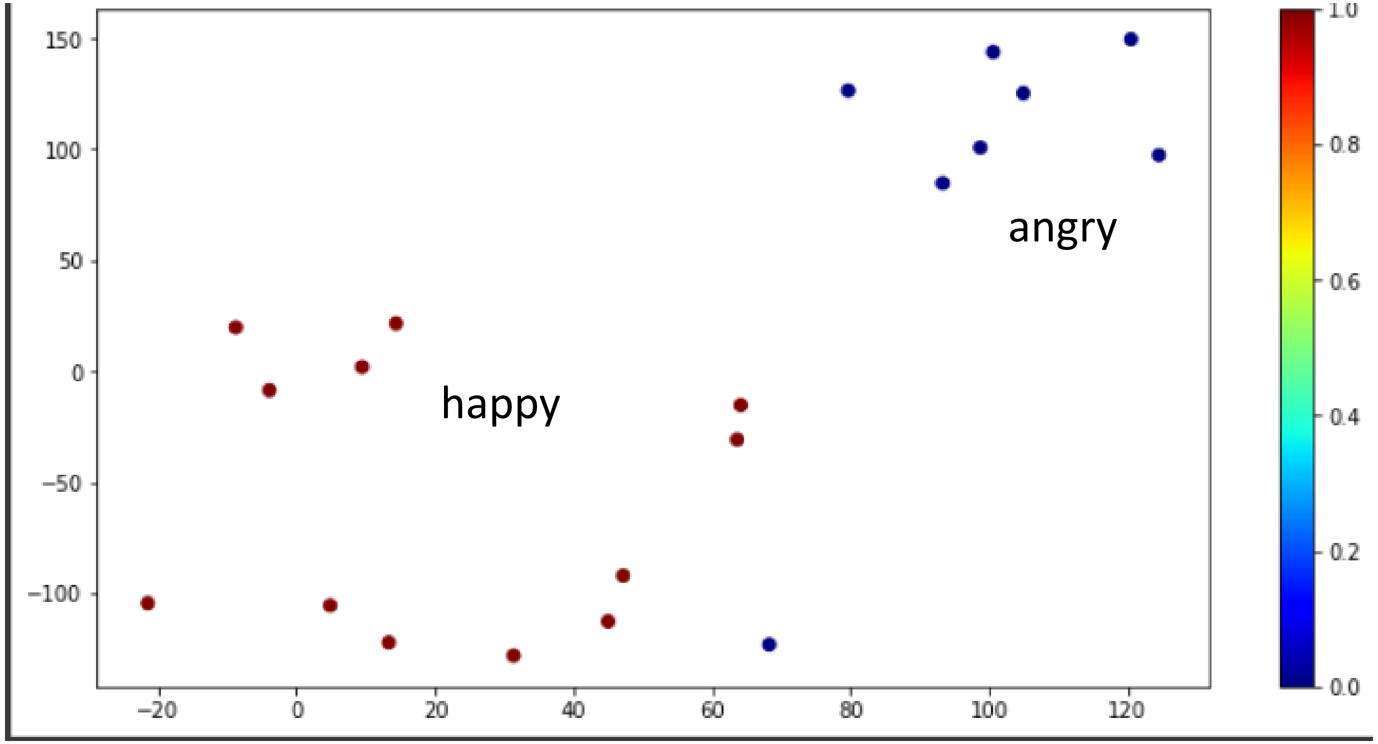
Recovered un-seen test images



Happy = 12, Angry = 8, Latent vector size = 20, 1200 epochs



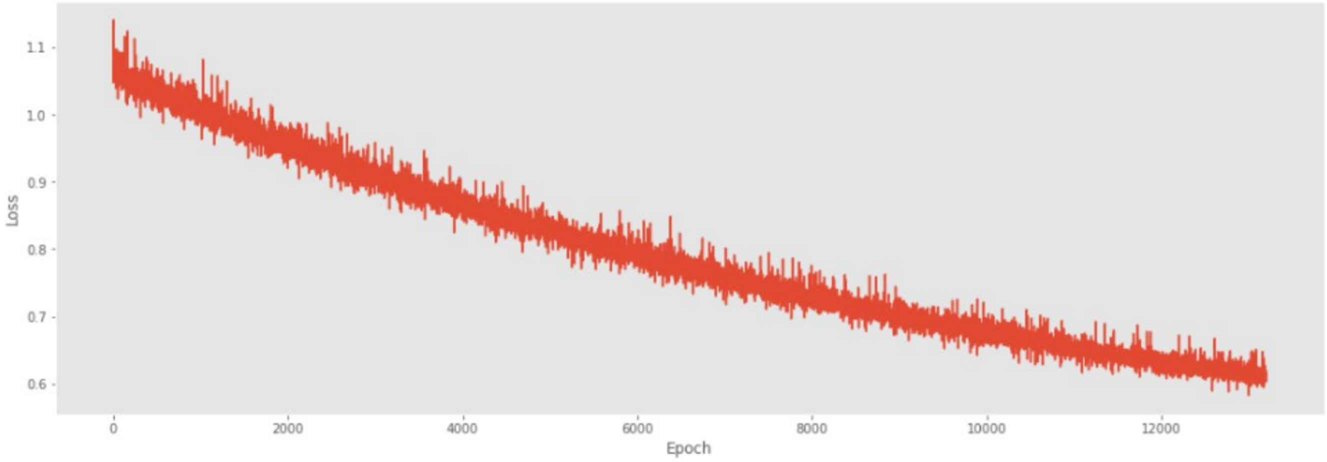
t-SNE (perplexity=?) results of training images



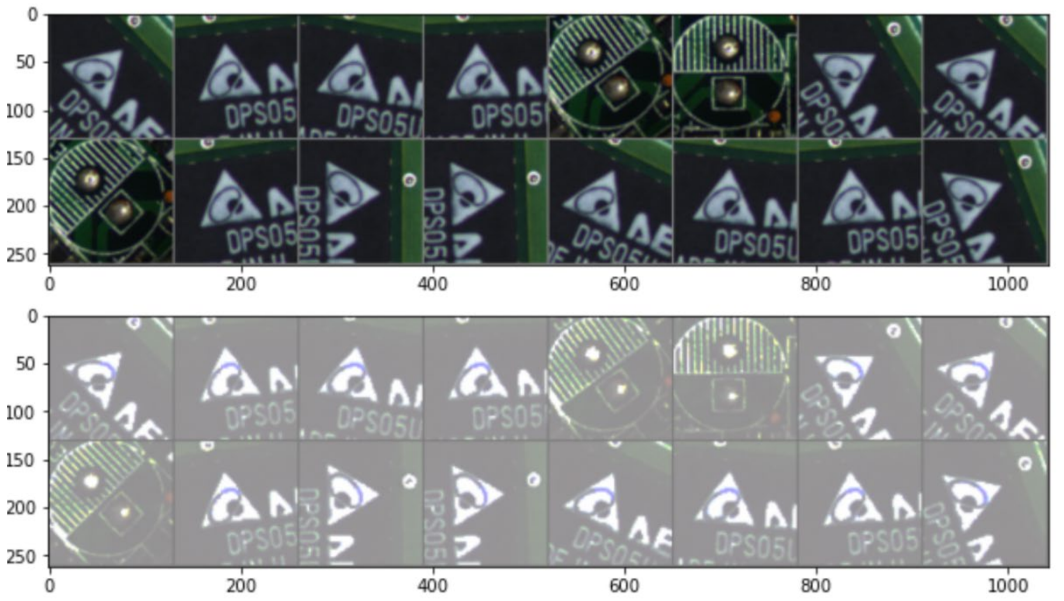
Recovered training images

Recovered un-seen test images

Class 1 = ?, Class 2 = ?, Latent vector size = ?, ? epochs

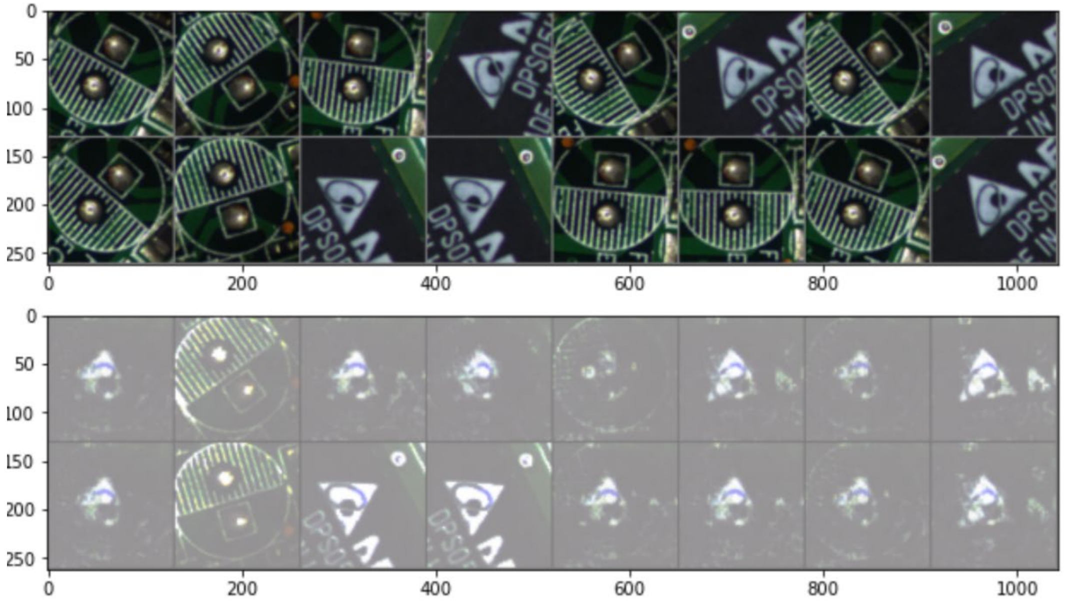


Recovered training images



t-SNE (perplexity=?) results of training images

Recovered test images

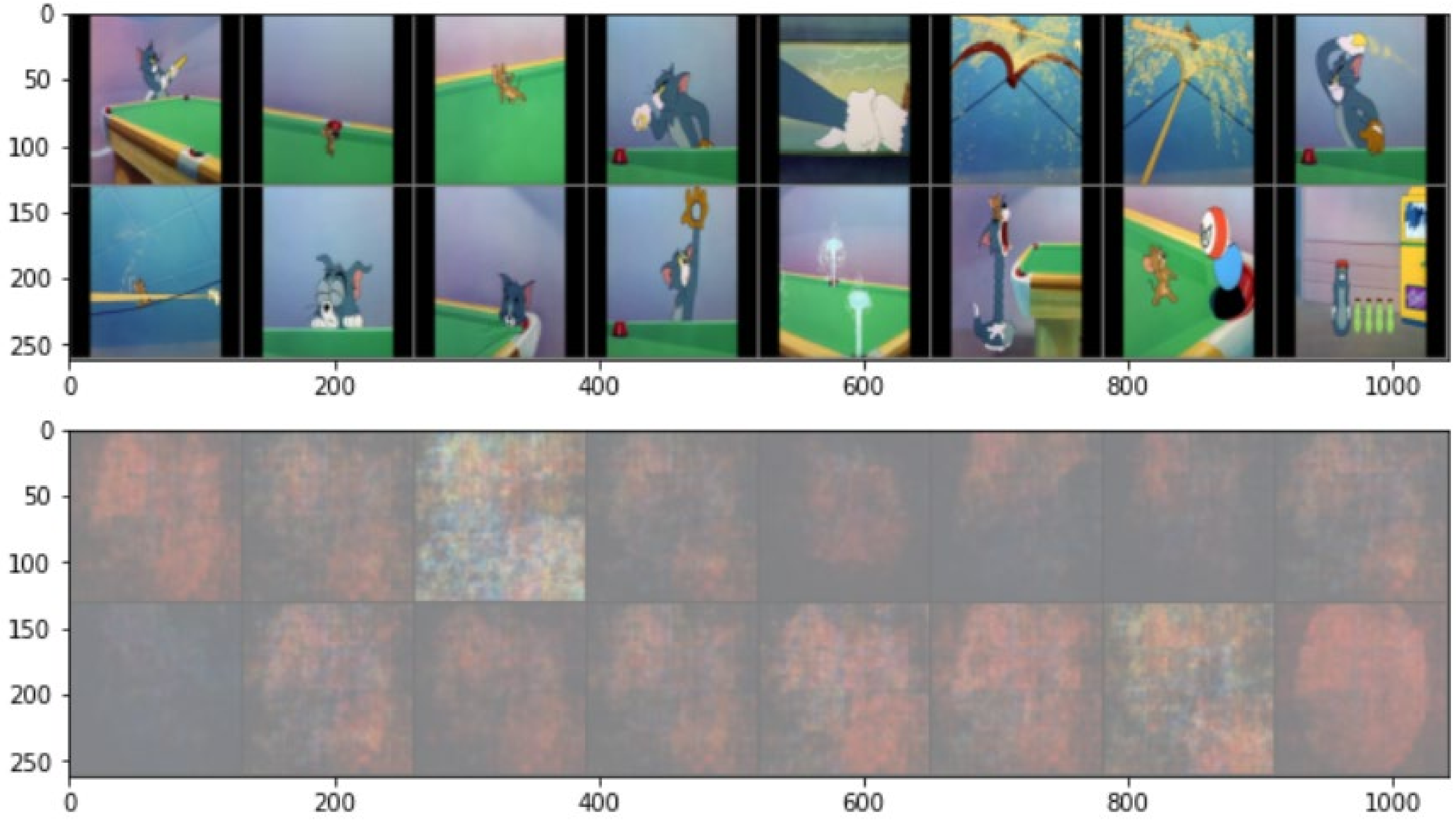


1085442 Carlos

How about Tom & Jerry?

Results are still not good after 1200 epochs

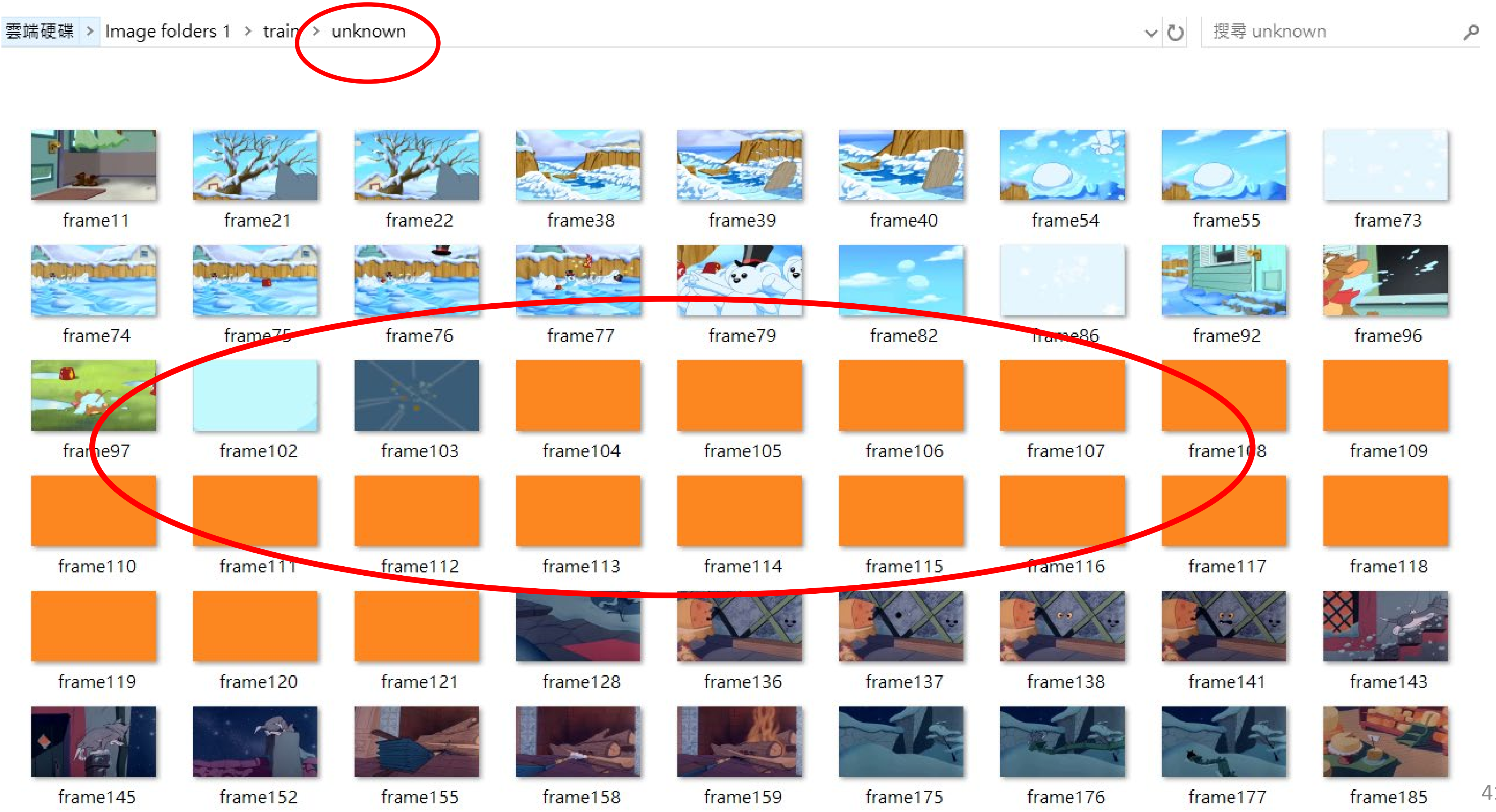
Test on un-seen images – fails to reconstruct the input images



What to do if training is not successful?

- Check if the training data is too diversified? Your AI model is as good as your data, and as bad as your data too.
- Examine loss plot to understand the gradient decent process. Train with more epochs if the trend of the optimization process is good.
- Tune other hyper-parameters, e.g., batch size?

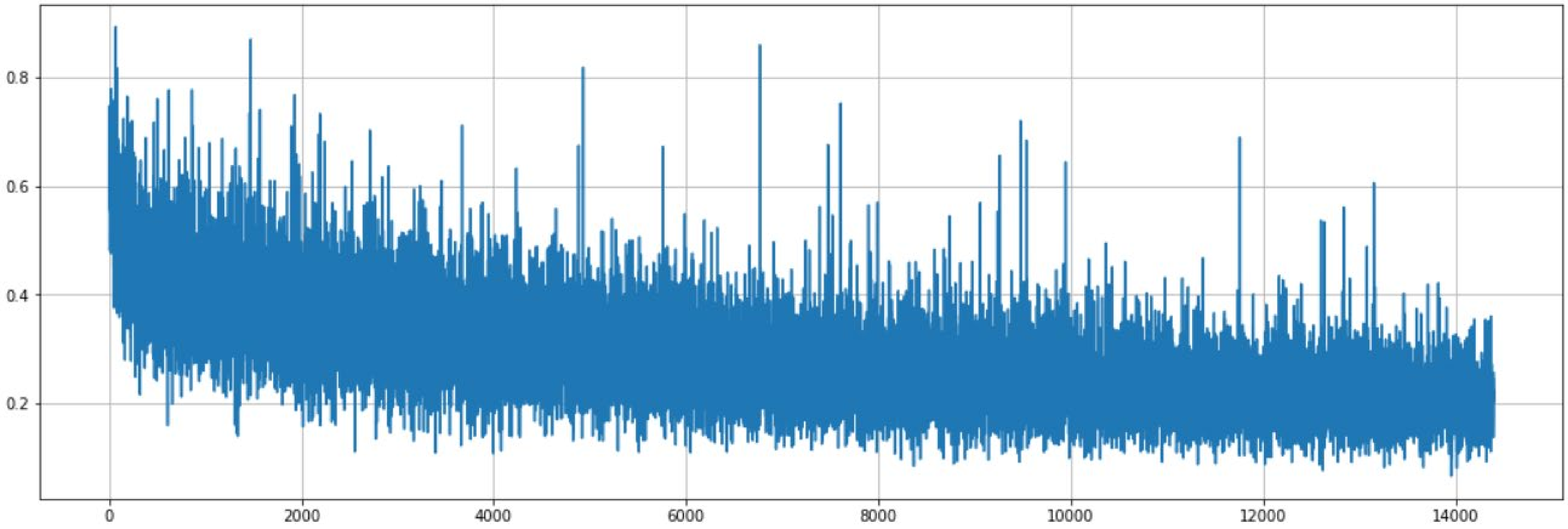
Your AI model is as good as your data, and as bad as your data too



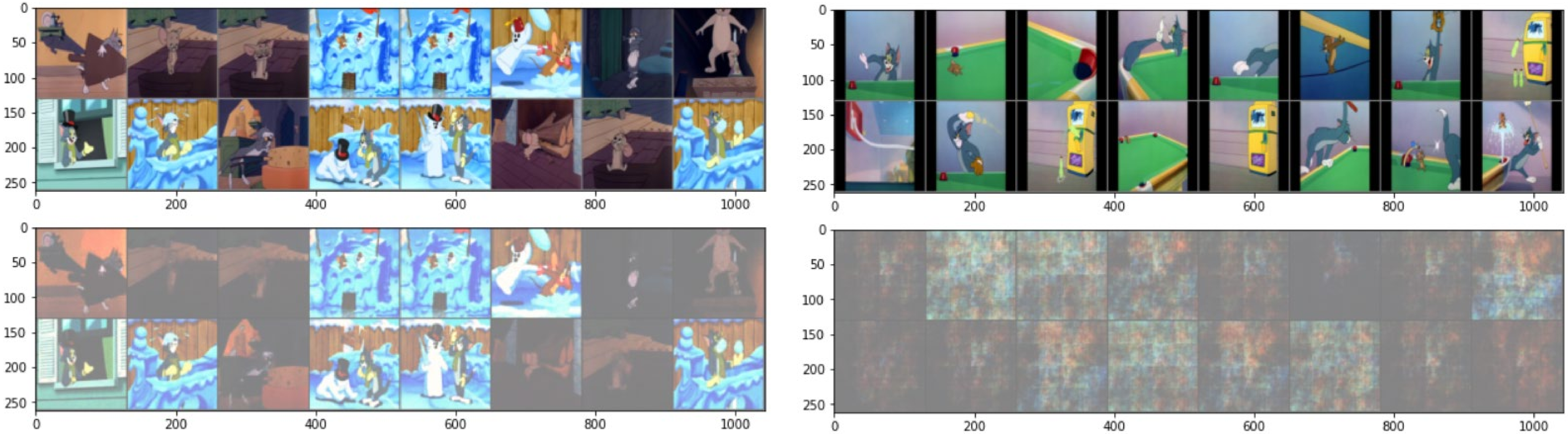
Create a new folder "Image folder 1", remove the "Unknown" sub-folder

Test folder remains the same

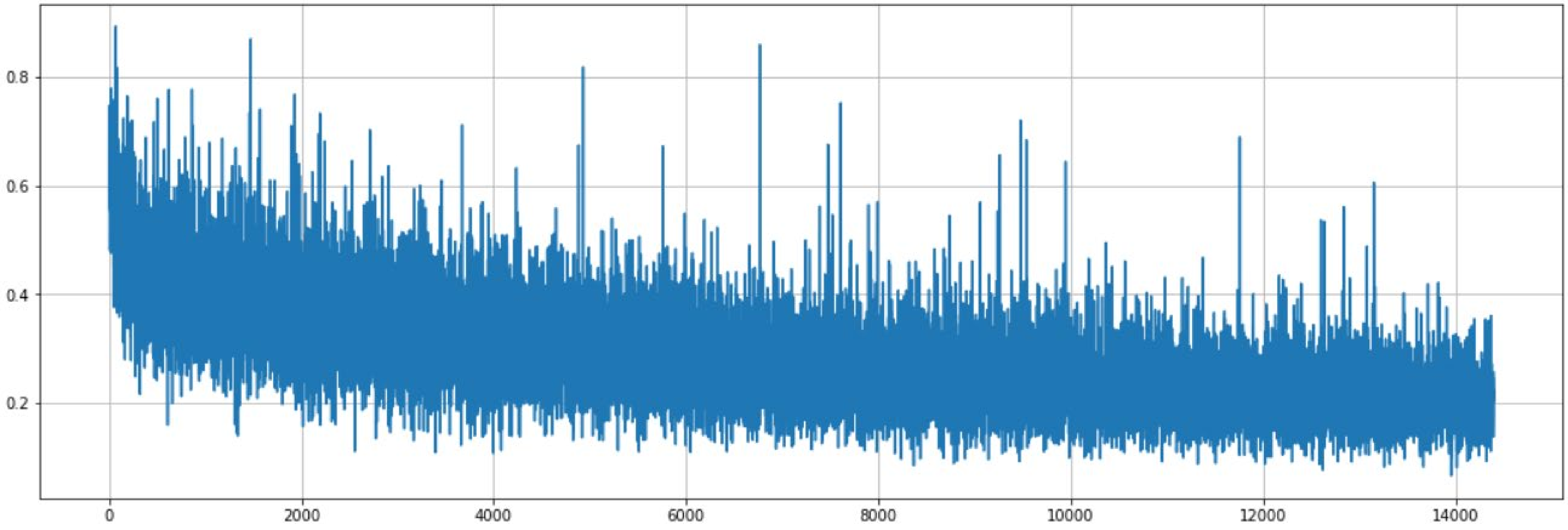
Train 1200 epochs after removing the "unknown" folder



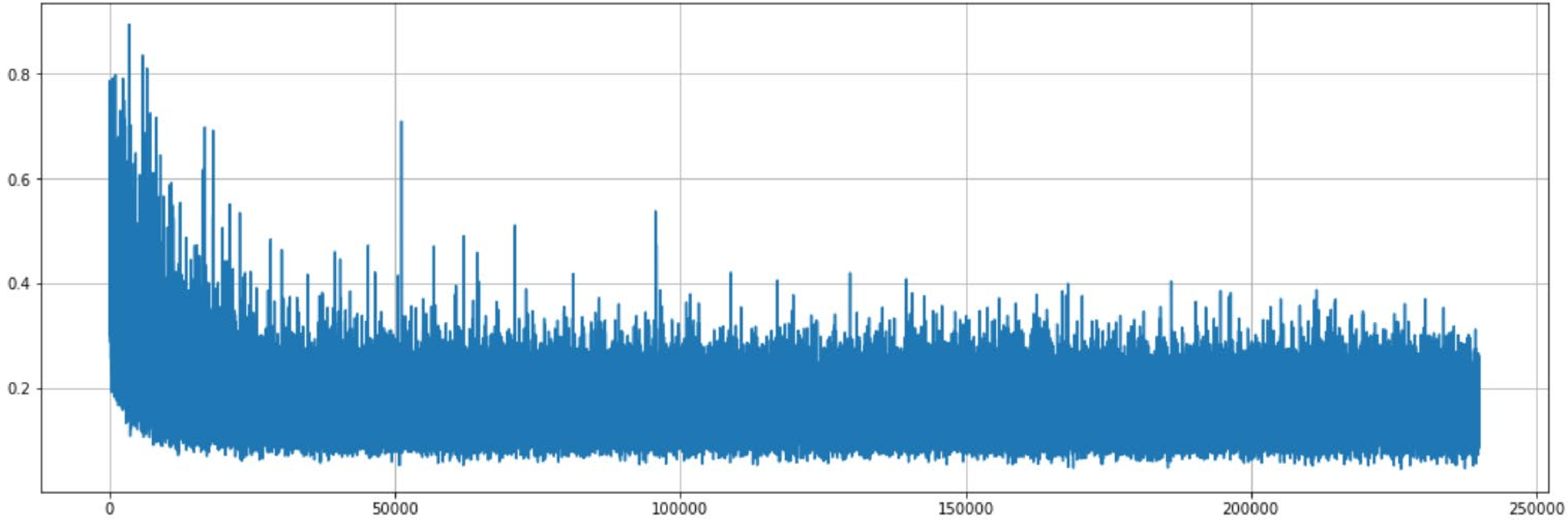
Train 1200 epochs after removing the "unknown" folder



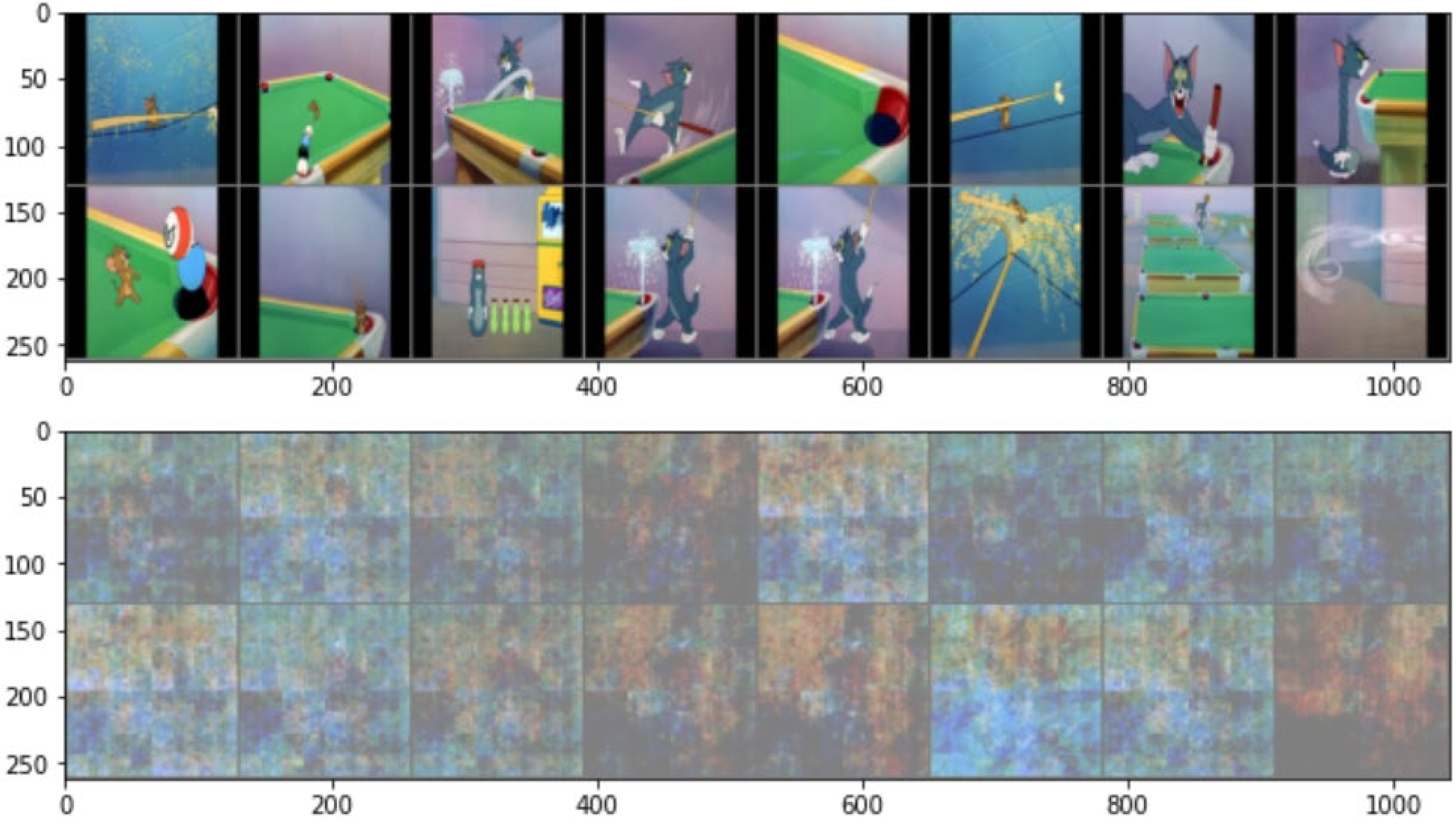
Examine the loss plot to understand the gradient decent process.



Results after training 20,000 epochs



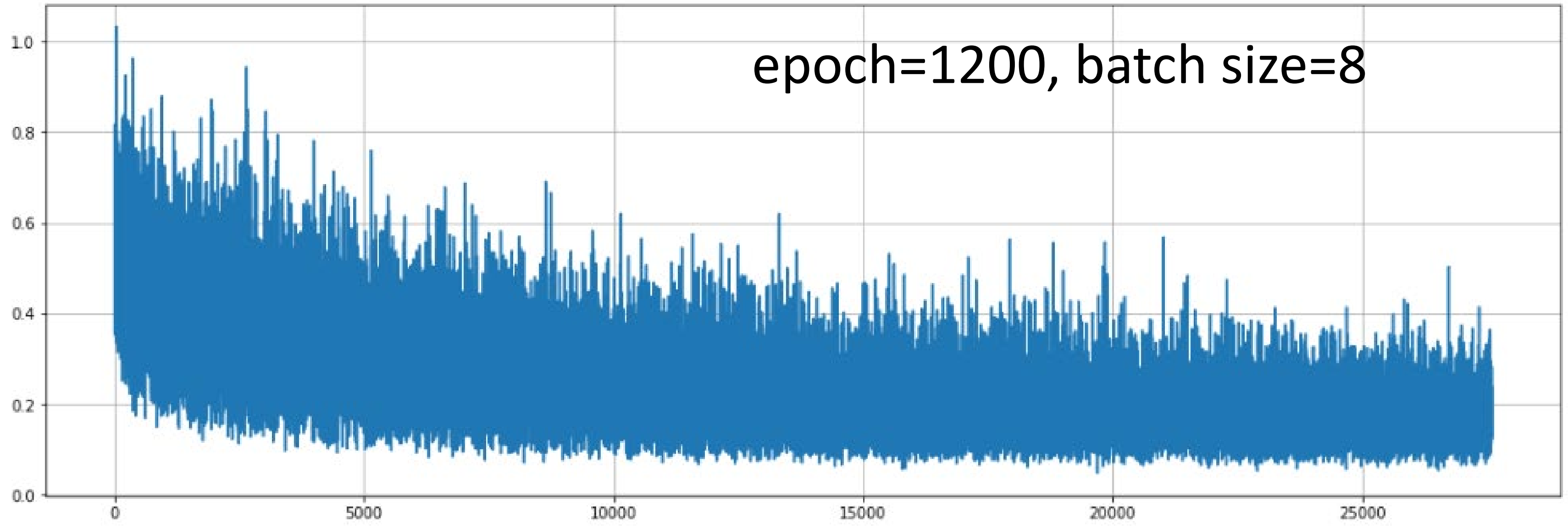
Results after training 20,000 epochs

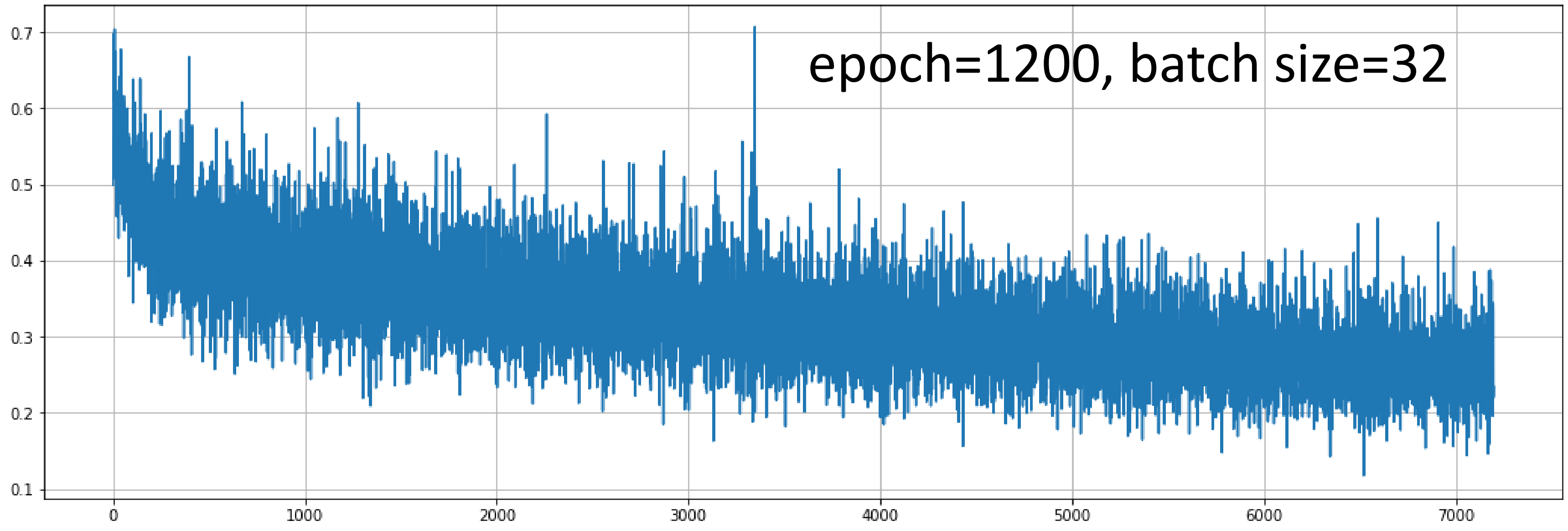


How about batch size? Increase or decrees ?

```
self.encoder = nn.Sequential(
  nn.Conv2d(3, 32, kernel_size=2, stride=2),
  nn.BatchNorm2d(32, eps=1e-05, momentum=0.1, af
  nn.ReLU(),
  nn.Conv2d(32, 64, kernel_size=2, stride=2),
  nn.BatchNorm2d(64, eps=1e-05, momentum=0.1, af
  nn.ReLU(),
  nn.Conv2d(64, 128, kernel_size=2, stride=2),
  nn.BatchNorm2d(128, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(128, 256, kernel_size=2, stride=2),
  nn.BatchNorm2d(256, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(256, 512, kernel_size=2, stride=2),
  nn.BatchNorm2d(512, eps=1e-05, momentum=0.1, a
  nn.ReLU(),
  nn.Conv2d(512, 1024, kernel_size=2, stride=2),
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1,
  nn.ReLU(),
  nn.Conv2d(1024, 1024, kernel_size=2, stride=2)
  nn.BatchNorm2d(1024, eps=1e-05, momentum=0.1,
  nn.ReLU(),
  Flatten(),
  nn.Linear(in_features=i, out_features=o),
)
```

```
[12]: import torch.utils.data as Data
loader = Data.DataLoader(
    dataset=train_dataset,
    batch_size=16,
    shuffle=True)
```


epoch=1200, batch size=8
1.0
0.8
0.6
0.4
0.2
0.0
0
5000
10000
15000
20000
25000


epoch=1200, batch size=32
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1000
2000
3000
4000
5000
6000
7000

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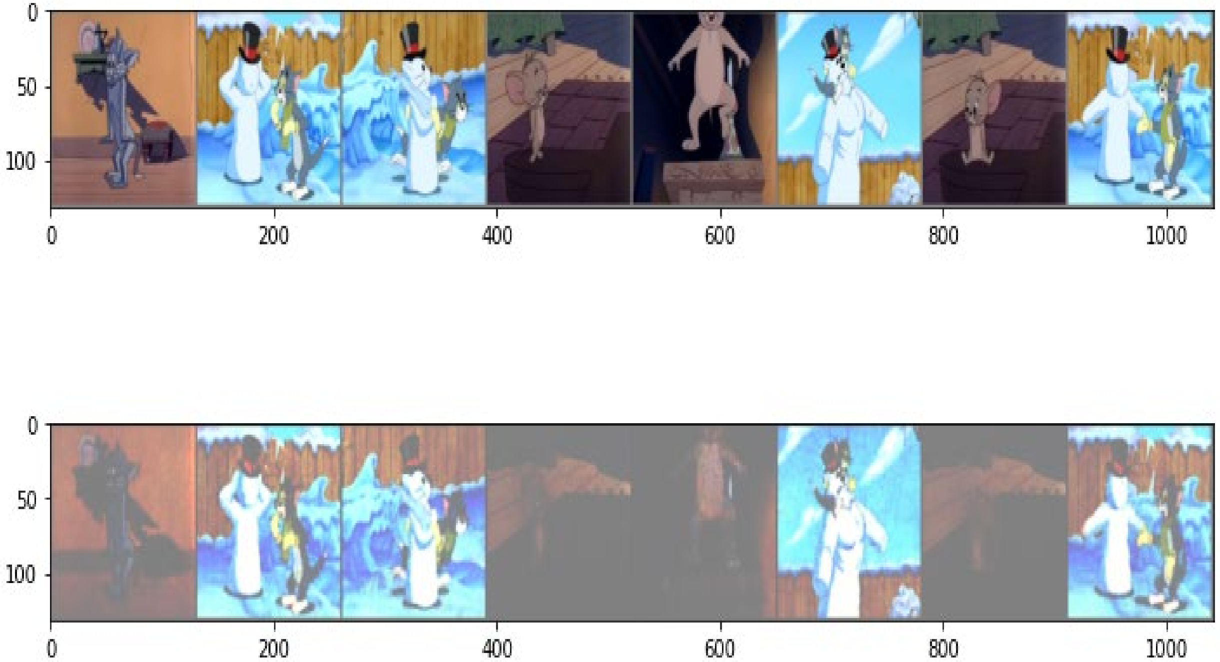
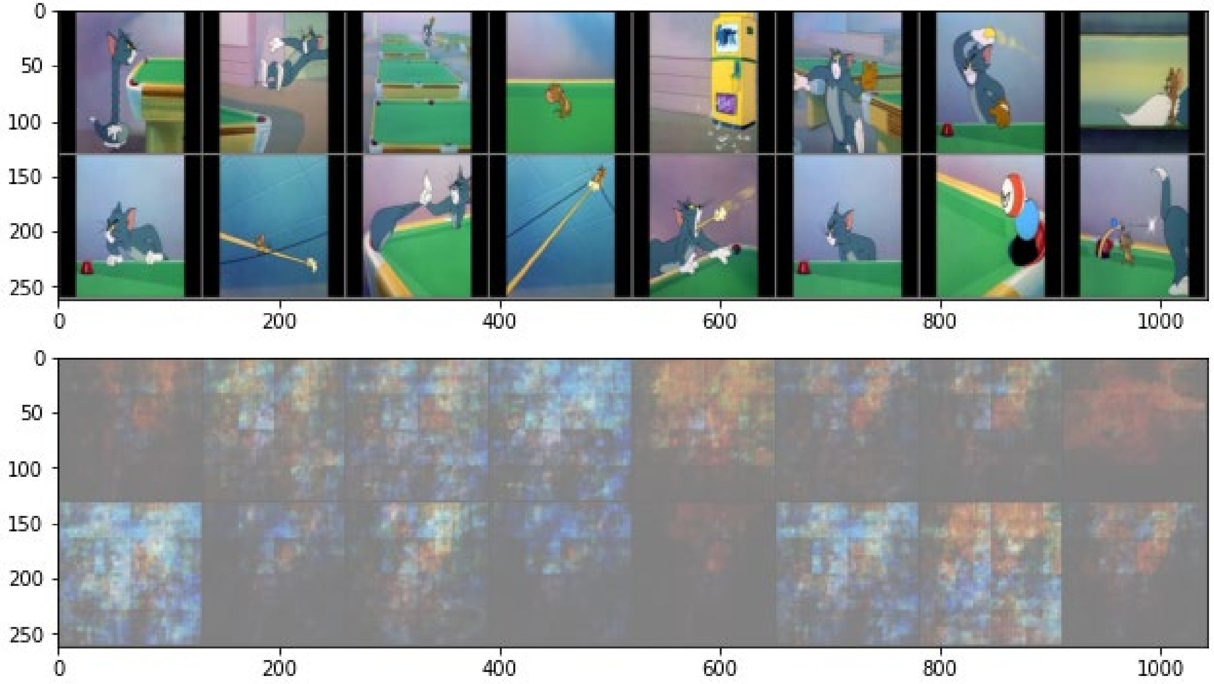
epoch=1200, batch size=8

Train:

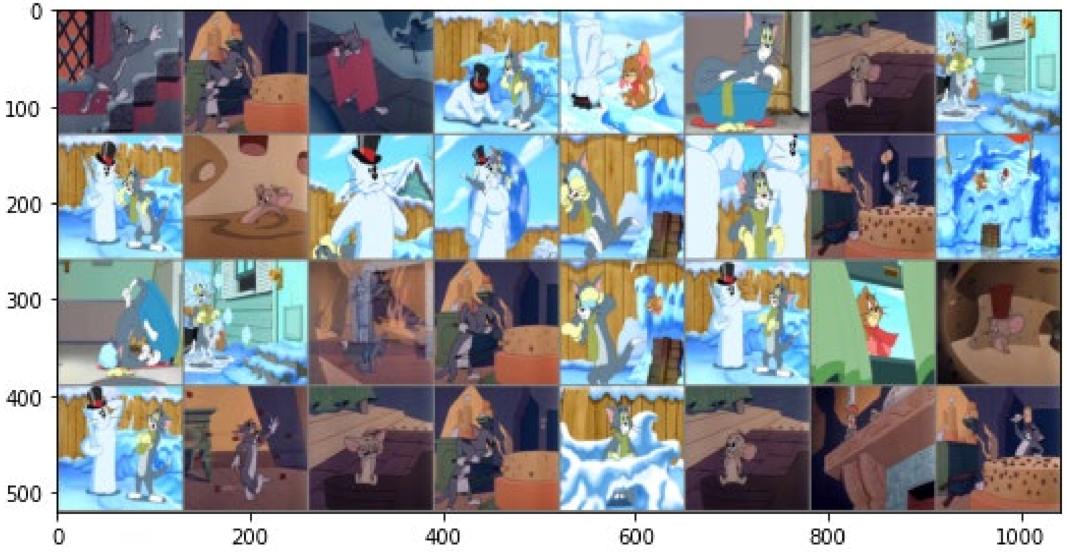


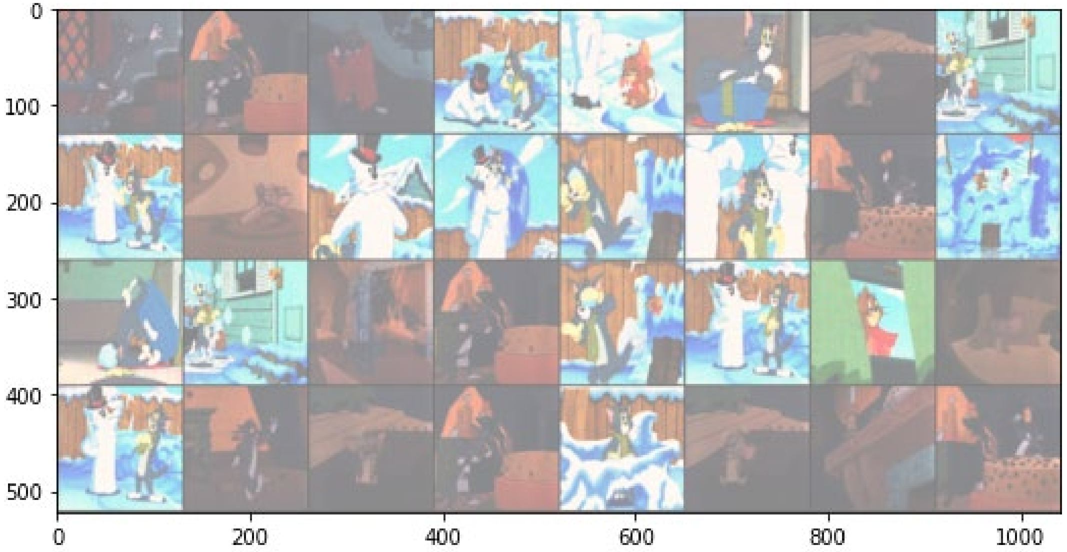
Test:



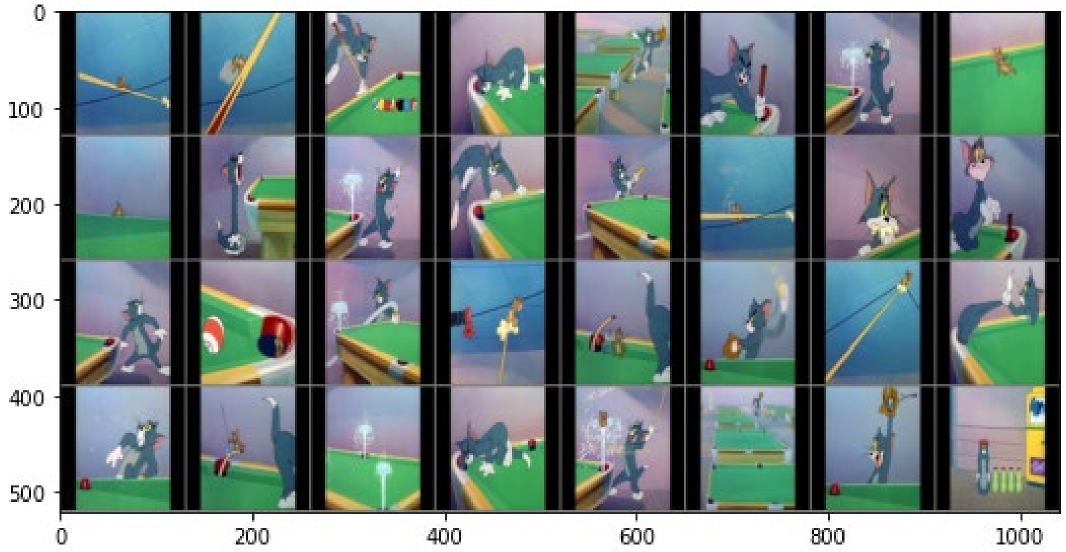
epoch=1200, batch size=32

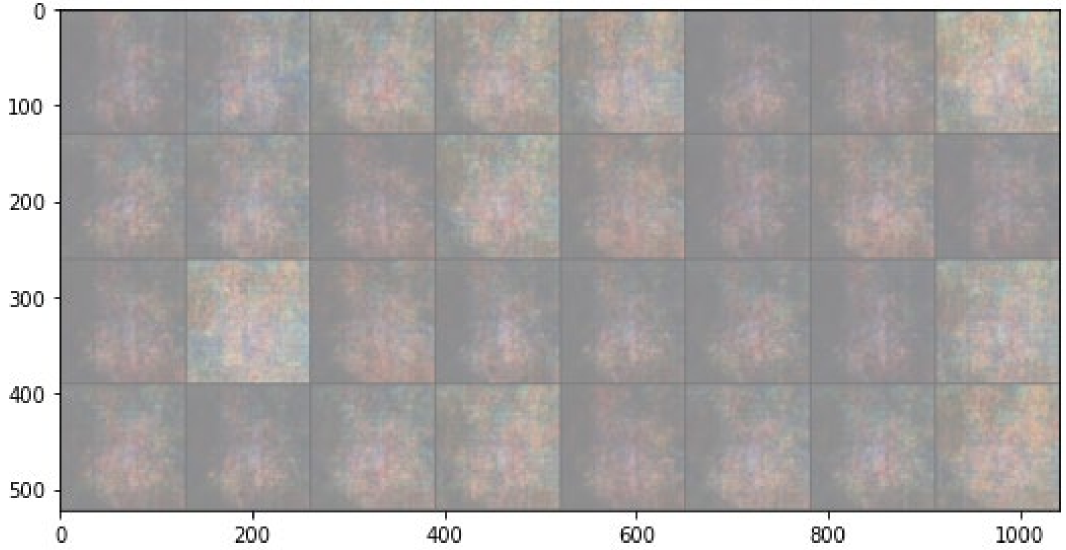
Train:





Test:





Training images are too diversified?

2000 epochs using new training images