ECE 57000 Assignment 8 Exercise

Your Name:

Exercise 1: Define classifier that extracts latent representations and visualize representations (**40 points**)

The latent (i.e., hidden) representations generated by a deep neural network are very important concept in deep learning since the latent space is where the most significant features of the dataset are learned and extracted. In this homework, we will explore the latent representations of a classifier using clustering and nearest neighbor methods.

We provide the code for a simple residual CNN with batchnorm and data loaders.

- Here, we define a neural network block architecture that does batch normalization after each convolution layer and has a skip connection. You can read more about batch normalization and skip connections in these papers https://arxiv.org/pdf/1502.03167.pdf and https://arxiv.org/pdf/1512.03385.pdf, respectively.
- In this neural network, the block networks are designed so that the input dimension and the output dimension stay the same. This may not be an optimal design, but it will help us visualize the latent representation later.

In [1]:
```
import torch
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(device)
```

```
cuda
```

In [2]:
```
import torchvision
import torchvision.transforms as transforms
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import numpy as np

class SimpleResidualBlock(nn.Module):
    def __init__(self, ch_in, mult=4):
        super().__init__()
        self.conv1 = nn.Conv2d(ch_in, mult * ch_in, kernel_size=3, stride=1, padding=1
        self.bn1 = nn.BatchNorm2d(mult * ch_in)

        self.conv2 = nn.Conv2d(mult * ch_in, mult * ch_in, kernel_size=3, stride=1, pa
        self.bn2 = nn.BatchNorm2d(mult * ch_in)

        self.conv3 = nn.Conv2d(mult * ch_in, ch_in, kernel_size=3, stride=1, padding=1
        self.bn3 = nn.BatchNorm2d(ch_in)
```

```
    def forward(self, x):
        x_ = x.clone()
        x_ = torch.relu(self.bn1(self.conv1(x_)))
        x_ = torch.relu(self.bn2(self.conv2(x_)))
        x_ = torch.relu(self.bn3(self.conv3(x_)))
        x = x + x_
        return x

class SimpleResNet(nn.Module):
    def __init__(self, ch_in, n_blocks=3):
        super().__init__()
        self.residual_layers = nn.ModuleList([SimpleResidualBlock(ch_in) for i in rang
        self.maxpool = nn.MaxPool2d((2, 2))
        self.fc = nn.Linear(9, 10)

    def forward(self, x):
        for residual in self.residual_layers:
          x = residual(x)
          x = self.maxpool(x)
        x = x.view(x.shape[0], -1)  # Unravel tensor dimensions
        out = self.fc(x)
        return out
```

In [3]:
```
import torchvision.transforms as transforms
import matplotlib.pyplot as plt

# Create MNIST datasets
classes = np.arange(10)
transform = torchvision.transforms.Compose(
  [torchvision.transforms.ToTensor(),
   torchvision.transforms.Normalize((0.1307,),(0.3081,))])
train_dataset = torchvision.datasets.MNIST('./data', train=True, download=True, transf
test_dataset = torchvision.datasets.MNIST('./data', train=False, download=True, transf

# Create dataloaders
batch_size_train, batch_size_test = 64, 128
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_size_train,
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size_test, sh

# Show sample images
batch_idx, (images, targets) = next(enumerate(train_loader))
fig, ax = plt.subplots(3,3,figsize = (5,5))
for i in range(3):
  for j in range(3):
    image = images[i*3+j].permute(1,2,0)
    image = image/2 + 0.5
    ax[i,j].imshow(image.squeeze(2))
    ax[i,j].set_title(f'{classes[targets[i*3+j]]}')
    ax[i,j].axis('off')
fig.show()
```

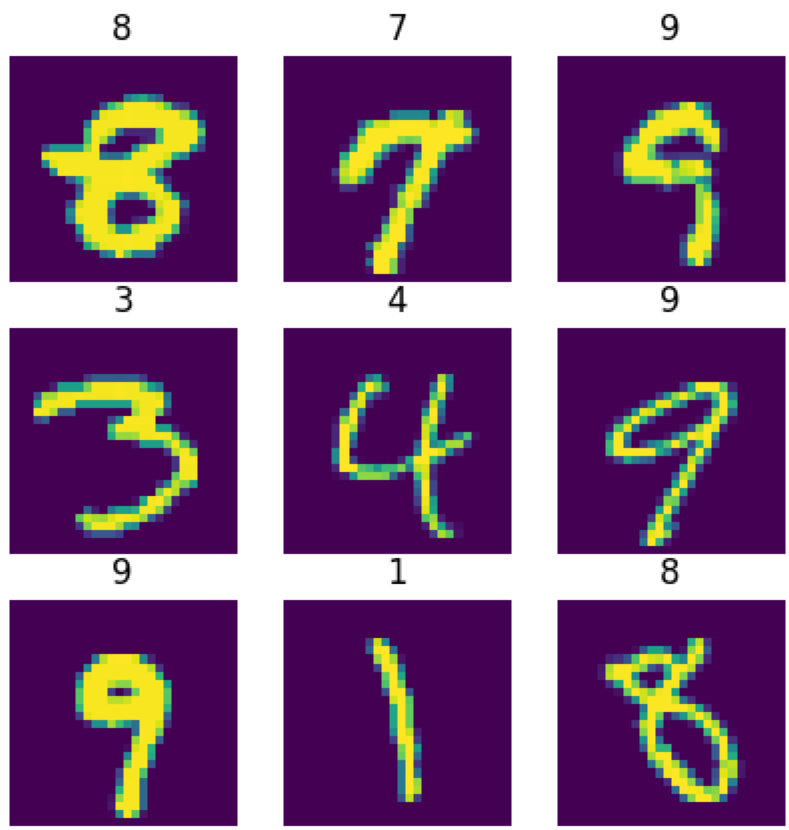
```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to ./data/MNI
ST/raw/train-images-idx3-ubyte.gz
100%|██████████| 9912422/9912422 [00:00<00:00, 155088113.33it/s]
```

```
Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to ./data/MNI
ST/raw/train-labels-idx1-ubyte.gz
100%|██████████| 28881/28881 [00:00<00:00, 113105222.99it/s]
Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to ./data/MNIS
T/raw/t10k-images-idx3-ubyte.gz
100%|██████████| 1648877/1648877 [00:00<00:00, 41264022.27it/s]
Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to ./data/MNIS
T/raw/t10k-labels-idx1-ubyte.gz
100%|██████████| 4542/4542 [00:00<00:00, 16437039.49it/s]
Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
```



Task 1: Inherit the original model class and define a new function returning the same output with the parent's forward function as well as intermediate representations (including the original input)

Specifically, the function below should return the original output from `forward` function of the parent's class and a list of intermediate representations `z_list`. `z_list` should be a Python list with 4 entries corresponding to the original batch and the batch **after each maxpool layer.**

Hints:

- Because of inheritance, you do not need to implement another `__init__` function. For those who are not familiar with inheritance, here is the link to get to know what Inheritance in Python is: https://www.geeksforgeeks.org/inheritance-in-python/.
- You will want to do the same computation as the original `forward` function but add some code to save intermediate representations, i.e., the code should output exactly the same thing as the original `forward` function but also return intermediate outputs.
- The output of this exercise should be:
  ```
  Representation z0 batch shape = torch.Size([128, 1, 28, 28])
  Representation z1 batch shape = torch.Size([128, 1, 14, 14])
  Representation z2 batch shape = torch.Size([128, 1, 7, 7])
  Representation z3 batch shape = torch.Size([128, 1, 3, 3])
  ```
- We provide a simple example for a linear model below.

In [4]:
```
# Trivial example below
class AffineModel(nn.Module):
    def __init__(self, A, b):
        super().__init__()
        self.A, self.b = A, b
    def forward(self, x):
        x = torch.matmul(x, self.A)
        return x + self.b
class ExtractAffineModel(AffineModel):
    def compute_and_extract_representations(self, x):
        z_list = [x]
        x = torch.matmul(x, self.A)
        z_list.append(x)
        return x + self.b, z_list
```

In [7]:
```
class SimpleResNetWithRepresentations(SimpleResNet):
  def compute_and_extract_representations(self, x):
    # ---------- Your code ----------

        # Extract representations at different layers (assuming there are 4 layers in
    z_list = [x]  # The first entry is the original data

        # Extract representations from intermediate layers
    for residual in self.residual_layers:
          x = residual(x)
          x=self.maxpool(x)
          z_list.append(x)
    x=x.view(x.shape[0],-1)
    out=self.fc(x)
    # ---------- End your code ----------
    return out, z_list

model = SimpleResNetWithRepresentations(ch_in=1)
model.to(device)
images, labels = next(iter(test_loader)) # get a batch
images = images.to(device)
# Check that outputs match
out, z_list = model.compute_and_extract_representations(images)
assert torch.all(model(images) == out), 'Outputs should be the same'
# Check shapes of representations
```

```
assert len(z_list) == 4, 'Should have length of 4'
assert torch.all(z_list[0] == images), 'First entry should be original data'
for zi, z in enumerate(z_list):
  print(f'Representation z{zi} batch shape = {z.shape}')
```

```
Representation z0 batch shape = torch.Size([128, 1, 28, 28])
Representation z1 batch shape = torch.Size([128, 1, 14, 14])
Representation z2 batch shape = torch.Size([128, 1, 7, 7])
Representation z3 batch shape = torch.Size([128, 1, 3, 3])
```

Task 2: Train the model

Using the train and test functions given above, train `model` for 4 epochs using the Adam optimizer with a learning rate of 0.01.

In [10]:

```
def train(epoch, model, optimizer):
    model.train() # we need to set the mode for our model
    for batch_idx, (images, targets) in enumerate(train_loader):
      images = images.to(device)
      targets = targets.to(device)
      optimizer.zero_grad()
      output = model(images)
      loss = F.cross_entropy(output, targets) # Here is a typical loss function (negat
      loss.backward()
      optimizer.step()
      if batch_idx % 100 == 0: # We visulize our output every 10 batches
        print(f'Epoch {epoch}: [{batch_idx*len(images)}/{len(train_loader.dataset)}] L

def test(epoch, model):
  model.eval() # we need to set the mode for our model
  test_loss = 0
  correct = 0
  with torch.no_grad():
    for images, targets in test_loader:
      images = images.to(device)
      targets = targets.to(device)
      output = model(images)
      test_loss += F.cross_entropy(output, targets, reduction='sum').item()
      pred = output.data.max(1, keepdim=True)[1] # we get the estimate of our result b
      correct += pred.eq(targets.data.view_as(pred)).sum() # sum up the corrected samp
  test_loss /= len(test_loader.dataset)
  print(f'Test result on epoch {epoch}: Avg loss is {test_loss}, Accuracy: {100.*corre

# ----------- <Your code> ---------------
optimizer=optim.Adam(model.parameters(),lr=0.01)
max_epoch=4
for epoch in range(1,max_epoch+1):
    train(epoch,model,optimizer)
    test(epoch,model)

# ----------- <End Your code> ---------------
```

```
Epoch 0: [0/60000] Loss: 4.661559104919434
Epoch 0: [6400/60000] Loss: 0.8535533547401428
Epoch 0: [12800/60000] Loss: 0.60825115442276
Epoch 0: [19200/60000] Loss: 0.6422501802444458
Epoch 0: [25600/60000] Loss: 0.4122356176376343
Epoch 0: [32000/60000] Loss: 0.5739757418632507
Epoch 0: [38400/60000] Loss: 0.3638189435005188
Epoch 0: [44800/60000] Loss: 0.23391728103160858
Epoch 0: [51200/60000] Loss: 0.4162711203098297
Epoch 0: [57600/60000] Loss: 0.3185249865055084
Test result on epoch 0: Avg loss is 0.3705607275009155, Accuracy: 88.20999908447266%
Epoch 1: [0/60000] Loss: 0.16119764745235443
Epoch 1: [6400/60000] Loss: 0.3084009289741516
Epoch 1: [12800/60000] Loss: 0.34214890003204346
Epoch 1: [19200/60000] Loss: 0.2937931418418884
Epoch 1: [25600/60000] Loss: 0.15202787518501282
Epoch 1: [32000/60000] Loss: 0.45756465196609497
Epoch 1: [38400/60000] Loss: 0.4194618761539459
Epoch 1: [44800/60000] Loss: 0.1697075068950653
Epoch 1: [51200/60000] Loss: 0.28948891162872314
Epoch 1: [57600/60000] Loss: 0.1376608908176422
Test result on epoch 1: Avg loss is 0.24180054202079773, Accuracy: 92.38999938964844%
Epoch 2: [0/60000] Loss: 0.2027958631515503
Epoch 2: [6400/60000] Loss: 0.4729873239994049
Epoch 2: [12800/60000] Loss: 0.38184696435928345
Epoch 2: [19200/60000] Loss: 0.0629521831870079
Epoch 2: [25600/60000] Loss: 0.35338377952575684
Epoch 2: [32000/60000] Loss: 0.09703244268894196
Epoch 2: [38400/60000] Loss: 0.2685605585575104
Epoch 2: [44800/60000] Loss: 0.33888861536979675
Epoch 2: [51200/60000] Loss: 0.07997147738933563
Epoch 2: [57600/60000] Loss: 0.2698926031589508
Test result on epoch 2: Avg loss is 0.35157323929071427, Accuracy: 88.5%
Epoch 3: [0/60000] Loss: 0.284807950258255
Epoch 3: [6400/60000] Loss: 0.30175134539604187
Epoch 3: [12800/60000] Loss: 0.20445431768894196
Epoch 3: [19200/60000] Loss: 0.251637727022171
Epoch 3: [25600/60000] Loss: 0.26431718468666077
Epoch 3: [32000/60000] Loss: 0.1378180831670761
Epoch 3: [38400/60000] Loss: 0.2066544145345688
Epoch 3: [44800/60000] Loss: 0.2693553864955902
Epoch 3: [51200/60000] Loss: 0.31202319264411926
Epoch 3: [57600/60000] Loss: 0.14130142331123352
Test result on epoch 3: Avg loss is 0.19844129675626754, Accuracy: 93.97999572753906%
Epoch 4: [0/60000] Loss: 0.2590074837207794
Epoch 4: [6400/60000] Loss: 0.09117928147315979
Epoch 4: [12800/60000] Loss: 0.18191583454608917
Epoch 4: [19200/60000] Loss: 0.27295583486557007
Epoch 4: [25600/60000] Loss: 0.21356874704360962
Epoch 4: [32000/60000] Loss: 0.18775004148483276
Epoch 4: [38400/60000] Loss: 0.12970665097236633
Epoch 4: [44800/60000] Loss: 0.29271620512008667
Epoch 4: [51200/60000] Loss: 0.229395791888237
Epoch 4: [57600/60000] Loss: 0.2794577479362488
Test result on epoch 4: Avg loss is 0.28021553959846496, Accuracy: 91.15999603271484%
```

Task 3: Visualize the intermediate latent representations

- Plot the representations of 20 images from the test dataset in a supblots grid of shape (20, 4) (code already given for setting up these subplots) where the rows correspond to samples in the dataset and columns correspond to the representations produced by `compute_and_extract_representations`

Notes:

- We give code below for normalizing the image and plotting on an axis with a title.
- Make sure to set `model.eval()` when computing because of the batchnorm layers
- No title or ylabel is needed in this case.
- `z_list` is a list of 4 tensors of shape ([B, 1, 28, 28]). **Figure out how to pass through the assertion error and think why the batch dimension cannot be processed together.**

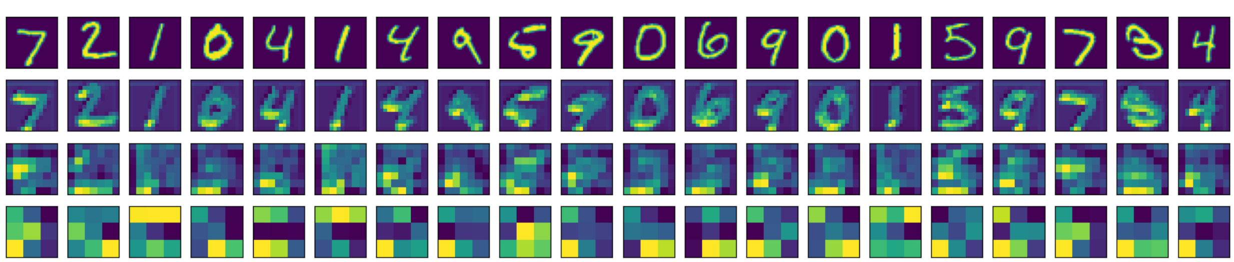
In [11]:

```python
def plot_representation(z, ax):
  # Normalize image for visualization
  assert z.ndim == 3, 'Should be 3 dimensional tensor with C x H x W'
  z = (z - z.min())/(z.max() - z.min())
  if torch.is_tensor(z):  # Convert torch tensor to numpy if needed
    z = z.detach().cpu().numpy()
  ax.imshow(z.transpose((1,2,0)).squeeze(2))
  # Remove ticks and ticklabels to make plot clean
  ax.set_xticks([])
  ax.set_yticks([])
  ax.set_xticklabels([])
  ax.set_yticklabels([])

n_show = 20
fig, axes_mat = plt.subplots(4, n_show, figsize=[n_show, 4])
# ----------- <Your code> ---------------

for dat in test_loader:
  image=dat[0]
  image=image.to(device)
  nn,z_out=model.compute_and_extract_representations(image[:20])
  first_batch=z_out[0]
  second_batch=z_out[1]
  third_batch=z_out[2]
  fourth_batch=z_out[3]
  for i in range(20):
    plot_representation(first_batch[i],axes_mat[0,i])
    plot_representation(second_batch[i],axes_mat[1,i])
    plot_representation(third_batch[i],axes_mat[2,i])
    plot_representation(fourth_batch[i],axes_mat[3,i])
  break

# ----------- End your code ---------------
```



Notice how the representations become more and more abstract as the depth increases.

Exercise 2: Clustering with different representations (50 points)

Task 1: Create simple numpy arrays of the representations

To perform further manipulations in numpy and scikit-learn, we will need to create simple numpy arrays for each representation. We provide the code for merging multiple batches. You will need to provide the code for extracting from the given data loader.

- Loop through the data loader and extract representations for each batch
- Append the labels and z_list to corresponding lists
- Break out of loop when the number extracted is n_extract or greater

The output of the merged lists should print the following for both train and test:

```
Types of merged lists
    [<class 'numpy.ndarray'>, <class 'numpy.ndarray'>, <class
'numpy.ndarray'>, <class 'numpy.ndarray'>]
Shapes of merged lists
    [(200, 1, 28, 28), (200, 1, 14, 14), (200, 1, 7, 7), (200, 1, 3,
3)]
Shape of merged labels
    (200,)
```

In [13]:

```
def extract_numpy_representations(model, data_loader, n_extract):
  # ------------- Your code ---------------
  extracted_z_lists = []
  labels_list = []
# ------------- Your code ---------------
  n=0
  for data in data_loader:
    images, labels = data
    labels_list.append(labels)
    images = images.to(device)
    out, z_list = model.compute_and_extract_representations(images)
    extracted_z_lists.append(z_list)
    n= n+1
    if n>= n_extract:
      break



  # ------------- End your code ---------------
  # Check extracted_z_lists (type should be tensor)
  print(f'Types of first batch\n    {[type(z) for z in extracted_z_lists[0]]}')
  print(f'Shapes of first batch\n    {[z.shape for z in extracted_z_lists[0]]}')

  # Merge extracted z_lists and labels and make numpy arrays
  z_list_merge_np = [
    np.vstack([
```

```
      z_list[i].detach().cpu().numpy()
      for z_list in extracted_z_lists
    ])[:n_extract]  # Extract up to n_extract
    for i in range(len(extracted_z_lists[0]))
  ]
  print(f'Types of merged lists\n    {[type(z) for z in z_list_merge_np]}')
  print(f'Shapes of merged lists\n    {[z.shape for z in z_list_merge_np]}')
  labels_merged_np = np.concatenate([
    labels.detach().cpu().numpy()
    for labels in labels_list
  ])[:n_extract]  # Extract up to n_extract
  print(f'Shape of merged labels\n    {labels_merged_np.shape}')
  return z_list_merge_np, labels_merged_np

# Extract train and test samples
z_list_train, labels_train = extract_numpy_representations(model, train_loader, n_extr
z_list_test, labels_test = extract_numpy_representations(model, test_loader, n_extract
# Extract regular train and test
x_test = z_list_test[0]
x_train = z_list_train[0]
```

```
Types of first batch
    [<class 'torch.Tensor'>, <class 'torch.Tensor'>, <class 'torch.Tensor'>, <class
'torch.Tensor'>]
Shapes of first batch
    [torch.Size([64, 1, 28, 28]), torch.Size([64, 1, 14, 14]), torch.Size([64, 1, 7,
7]), torch.Size([64, 1, 3, 3])]
Types of merged lists
    [<class 'numpy.ndarray'>, <class 'numpy.ndarray'>, <class 'numpy.ndarray'>, <clas
s 'numpy.ndarray'>]
Shapes of merged lists
    [(200, 1, 28, 28), (200, 1, 14, 14), (200, 1, 7, 7), (200, 1, 3, 3)]
Shape of merged labels
    (200,)
Types of first batch
    [<class 'torch.Tensor'>, <class 'torch.Tensor'>, <class 'torch.Tensor'>, <class
'torch.Tensor'>]
Shapes of first batch
    [torch.Size([128, 1, 28, 28]), torch.Size([128, 1, 14, 14]), torch.Size([128, 1,
7, 7]), torch.Size([128, 1, 3, 3])]
Types of merged lists
    [<class 'numpy.ndarray'>, <class 'numpy.ndarray'>, <class 'numpy.ndarray'>, <clas
s 'numpy.ndarray'>]
Shapes of merged lists
    [(200, 1, 28, 28), (200, 1, 14, 14), (200, 1, 7, 7), (200, 1, 3, 3)]
Shape of merged labels
    (200,)
```

Task 2: Perform K-means clustering on different representations

In this task, we will perform kmeans clustering on each of the latent representations of the test set and then evaluate the clustering based on the true class labels. A good discussion of clustering metrics can be found in scikit-learn's documentation on clustering metrics.

- Using scikit-learn's `sklearn.cluster.KMeans` estimator, perform kmeans with $k = 10$ and `random_state=0` on the latent representations and extract the cluster labels.

- Use `sklearn.metrics.adjusted_rand_score` to compute a score to evaluate the clustering based on the true class labels.

Notes:

- You will need to reshape the tensors into matrices immediately before passing into sklearn functions (you should keep the original data as is so that the images can be plotted, but just reshape immediately before passing into scikit-learn functions). Specifically, the arrays will have shape (B, C, H, W) and you should reshape to (B, C*H*W) before passing to scikit-learn functions.
- We provide code for plotting and evaluating your clustering.
- Note that clustering is unsupervised. What we're plotting here is the ten different clusters, not the ten different categories of true labels. Thus, the cluster index in the plotted image is not necessarily matched to the true label.
- Sometimes the `plot_cluster` will have white boxes if there are less than 5 samples in that cluster. Generally, if you use `n_clusters=10` for the clustering tasks, you will have none or only a few white boxes, which is okay.

In [14]:

```
def plot_cluster(cluster_labels, z_test, title):
  # Plot the top images in each cluster both in original space and latent representati
  n_samples_show, n_clusters = 5, 10
  nr, nc = n_samples_show, 2*n_clusters
  fig, axes_mat = plt.subplots(nr, nc, figsize=np.array([nc, nr])/2)
  axes_mat_list = np.split(axes_mat, n_clusters, axis=1)
  for ci, axes_mat in enumerate(axes_mat_list): # Loop over clusters
    sel = cluster_labels==ci
    z_cluster = z_test[sel][:n_samples_show]
    x_cluster = x_test[sel][:n_samples_show]
    for test_i, (z, x, axes) in enumerate(zip(z_cluster, x_cluster, axes_mat)):
      plot_representation(x, axes[0])
      plot_representation(z, axes[1])
      if ci == 0:
        axes[0].set_ylabel(test_i)
      if test_i == len(axes_mat)-1:
        axes[0].set_xlabel(f'C{ci}x')
        axes[1].set_xlabel(f'C{ci}z')
  fig.suptitle(title)
  plt.show()
```

In [16]:

```
from sklearn.cluster import KMeans
from sklearn.metrics import adjusted_rand_score

def cluster_and_score(z, true_labels):
  # ----------- <Your code> ---------------
  b,c,h,w = z.shape
  z = np.reshape(z,(b,c*h*w) )
  kmeans = KMeans(n_clusters=10, random_state=0).fit(z)
  cluster_labels = kmeans.labels_
  score = adjusted_rand_score(cluster_labels,true_labels)
  #kmeans_ score = KMeans(n_clusters=10, random_state=0).score(z)
  # ----------- End your code ---------------
  return cluster_labels, score
```

```
fig = plt.figure(figsize=(2,2))
plt.bar([f'z{zi}' for zi in range(len(z_list_test))],
        [cluster_and_score(z_test, labels_test)[1] for z_test in z_list_test])
plt.ylabel('Score')
for zi, z_test in enumerate(z_list_test):
  cluster_labels, score = cluster_and_score(z_test, labels_test)
  plot_cluster(cluster_labels, z_test, f'Clustering with z{zi}, Score={score:.4f}')
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarnin
g: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
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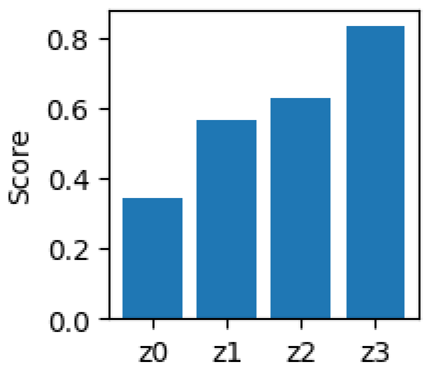

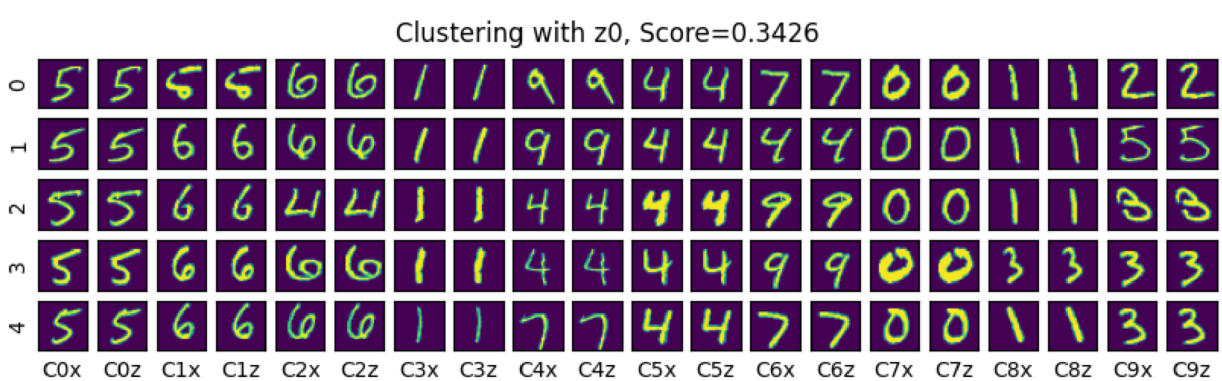


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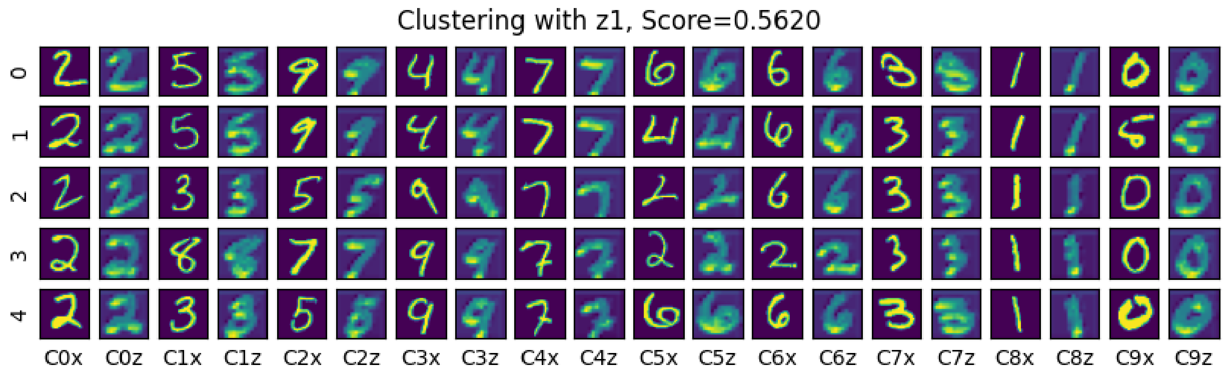


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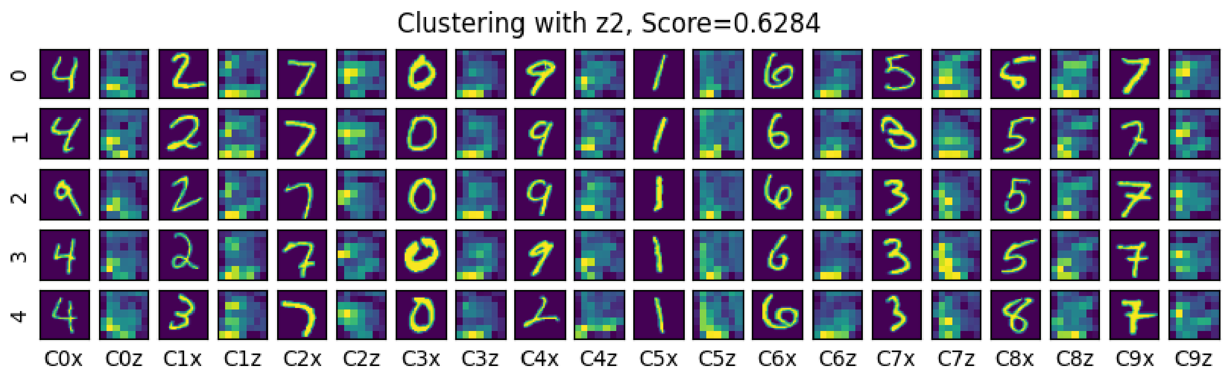


```
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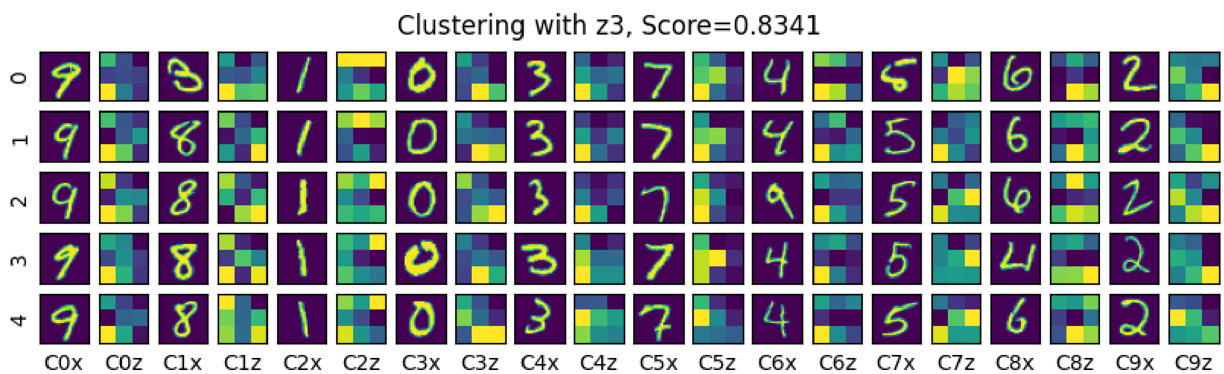


Notice how the 3x3 pattern for the last representation looks similar across the samples.

Exercise 3: Nearest neigbhors methods using representations (10 points)

Task 1: Compute and plot nearest neigbhors in different representations

We will now compute the 1 nearest neighbor (i.e., `n_neighbors=1`) of test points compared to train points in different representations.

- Loop through the representations for the train and test numpy arrays (i.e., `z_list_train` and `z_list_test`).
- For each representaiton from the different layers, compute the *training* indices corresponding to the nearest neighbor of first 15 *testing* indices.
- Plot the neighbors by passing the test indices and corresponding nearest neighbor training indices along with the corresponding train and test representations and a title that describes which representation into `plot_neighbor`.

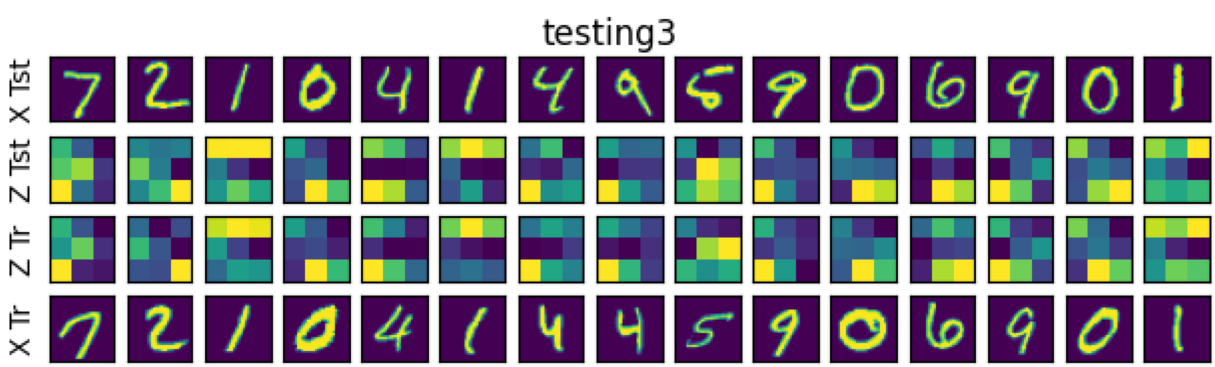
Notes:

- See note above about reshaping tensors immediately before passing to scikit-learn functions which expect a matrix.
- The `sklearn.neighbors.NearestNeighbors` class and the `kneighbors` method may be very helpful. The data that is passed to `fit` will be the training data and the data passed to `kneighbors` should be the new test data.
- The test indices should just be `np.arange(15)` assuming that you find the nearest training points for the first 15 points in the test dataset.

In [17]:
```
def plot_neigbhor(test_ind, nearest_train_ind, z_test, z_train, title):
  '''
  Plots the original test image, the test image representation,
    the nearest train image representation, the nearest original train image.
  '''
  assert len(test_ind) == len(nearest_train_ind), 'Test and train indices should be th
  n_test = len(test_ind)
  fig, axes_mat = plt.subplots(4, n_test, figsize=np.array([n_test, 4])/2)
  for test_i, nearest_train_i, axes in zip(test_ind, nearest_train_ind, axes_mat.T):
    plot_representation(x_test[test_i], axes[0])
    plot_representation(z_test[test_i], axes[1])
    plot_representation(z_train[nearest_train_i], axes[2])
    plot_representation(x_train[nearest_train_i], axes[3])
    if test_i == 0:
      for lab, ax in zip(['X Tst', 'Z Tst', 'Z Tr', 'X Tr'], axes):
        ax.set_ylabel(lab)
  fig.suptitle(title)

# --------- Your code ---------
from sklearn.neighbors import NearestNeighbors as nn
for btach_ind, (z_train, z_test) in enumerate(zip(z_list_train,z_list_test)):
#for i in range(15):
  X = z_train.reshape(z_train.shape[0],-1)
  neigh = nn(n_neighbors=1)
  modelx = neigh. fit(X)
  test_temp = z_test[:15].reshape(z_test[:15].shape[0],-1)
  distance, train_ind = modelx.kneighbors(test_temp)
  #print(neares_ train ind)
  test_ind = np.arange(15)
  plot_neigbhor(test_ind, train_ind.ravel(), z_test, z_train, f'testing{btach_ind}' )
```

```
# --------- End your code ---------
```



In [ ]: