# GMDL Project

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# 1. Data & Preprocessing

In [1]:

```
import os

import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.utils.data
from torch.utils.data import Dataset

import torchvision
from torchvision import datasets, transforms

import matplotlib.pyplot as plt

from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay

from google.colab import files

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

# Random seed (for reproducibility)
SEED = 42
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed(SEED)
```

In [2]:

```
def imshow(inp, title=None):
    """Imshow for Tensor"""
    inp = inp.numpy().transpose((1, 2, 0))
    mean = np.array([0.485, 0.456, 0.406])
    std = np.array([0.229, 0.224, 0.225])
    inp = std * inp + mean
    inp = np.clip(inp, 0, 1)
    plt.imshow(inp)
    if title is not None:
        plt.title(title)
    plt.pause(0.001)  # pause a bit so that plots are updated
```

## Datasets, dataloaders and transformations

In [3]:

```
BATCH_SIZE = 128
```

In [4]:

```
class data_set(Dataset):
  """for Combined dataset"""
  def __init__(self, dataset, targets):
    self.dataset = dataset
    self.targets = targets

  def __getitem__(self, idx):
    image = self.dataset[idx][0]
    target = self.targets[idx]
    return (image, target)

  def __len__(self):
    return len(self.dataset)
```

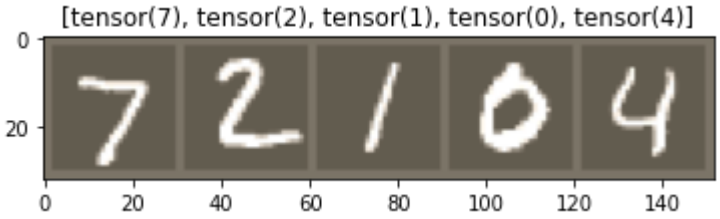
## MNIST - for training

In [5]:

```
mnist_transform = transforms.Compose([transforms.ToTensor(),
                              transforms.Normalize(
                                  (0.1307,),
                                  (0.3081,)), # mnist mean & std
                              transforms.Resize(28)])

mnist_train_set = torchvision.datasets.MNIST(root='./data',
                                              train=True,
                                              download=True,
                                              transform=mnist_transform)

mnist_test_set = torchvision.datasets.MNIST(root='./data',
                                            train=False,
                                            download=True,
                                            transform=mnist_transform)

mnist_train_loader = torch.utils.data.DataLoader(mnist_train_set,
                                              batch_size=BATCH_SIZE,
                                              shuffle=True,
                                              num_workers=2)

mnist_test_loader = torch.utils.data.DataLoader(mnist_test_set,
                                             batch_size=BATCH_SIZE,
                                             shuffle=False,
                                             num_workers=2)
```

In [6]:

```
# Printing 5 MNIST data examples
inputs, classes = next(iter(mnist_test_loader))
out = torchvision.utils.make_grid(inputs[:5])
imshow(out, title=[x for x in classes[:5]])
```




## CIFAR10 as OOD dataset - for evaluation

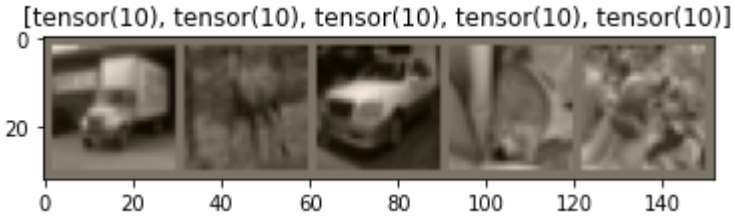
In [7]:

```
CIFAR10_SUBSET_SIZE = 500 # unknown data set

cifar10_transform = transforms.Compose([transforms.ToTensor(),
                              transforms.Normalize(
                                  (0.4914, 0.4822, 0.4465),
                                  (0.247, 0.243, 0.261)), # cifar10 mean & std
                              transforms.Resize(28),
                              transforms.Grayscale(num_output_channels=1)])

cifar10_test_set = torchvision.datasets.CIFAR10(root='./data',
                                                train=False,
                                                download=True,
                                                transform=cifar10_transform)

cifar10_test_subset_data = torch.utils.data.Subset(
    cifar10_test_set,
    np.random.choice(range(len(cifar10_test_set)), size=CIFAR10_SUBSET_SIZE))

sub_cifar10_targets = [10 for i in range(CIFAR10_SUBSET_SIZE)]
cifar10_test_subset = data_set(cifar10_test_subset_data, sub_cifar10_targets)

cifar10_test_loader = torch.utils.data.DataLoader(cifar10_test_subset,
                                                  batch_size=BATCH_SIZE,
                                                  shuffle=False,
                                                  num_workers=2)
```

```
Files already downloaded and verified
```

In [8]:

```
# Printing 5 CIFAR10 data examples
inputs, classes = next(iter(cifar10_test_loader))
out = torchvision.utils.make_grid(inputs[:5])
imshow(out, title=[x for x in classes[:5]])
```

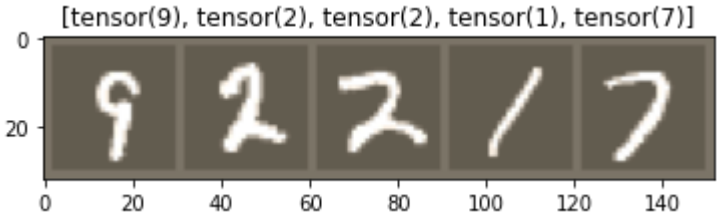



In [9]:

```
combined_test_loader = torch.utils.data.DataLoader(
    torch.utils.data.ConcatDataset([mnist_test_set, cifar10_test_subset]),
        batch_size=BATCH_SIZE, shuffle=True)
```

In [10]:

```
# Printing 5 COMBINED data examples
inputs, classes = next(iter(combined_test_loader))
out = torchvision.utils.make_grid(inputs[:5])
imshow(out, title=[x for x in classes[:5]])
```




# 2. Models

### Baseline model class

In [11]:

```
class CNN(nn.Module):
  def __init__(self):
    super(CNN, self).__init__()
    self.conv1 = nn.Conv2d(1, 32, kernel_size=5)
    self.conv2 = nn.Conv2d(32, 32, kernel_size=5)
    self.conv3 = nn.Conv2d(32,64, kernel_size=5)
    self.fc1 = nn.Linear(3*3*64, 256)
    self.fc2 = nn.Linear(256, 10)

  def forward(self, x):
    x = F.relu(self.conv1(x))
    x = F.dropout(x, p=0.5, training=self.training)

    x = F.relu(F.avg_pool2d(self.conv2(x), 2))
    x = F.dropout(x, p=0.5, training=self.training)

    x = F.relu(F.avg_pool2d(self.conv3(x),2))
    x = F.dropout(x, p=0.5, training=self.training)

    x = x.view(-1, 3*3*64)
    x = F.relu(self.fc1(x))
    x = F.dropout(x, training=self.training)

    x = self.fc2(x)
    return x
```

## OSR model class

In [12]:

```
class OSR(nn.Module):
  def __init__(self, state_dict = None, dropout = 0.3, **kwargs):
    super(OSR, self).__init__()

    self.num_classes = 10
    self.cnn = CNN()
    if state_dict is not None:
      self.cnn.load_state_dict(state_dict)

    self.classify = nn.Linear(self.num_classes, self.num_classes)
    self.anchors = nn.Parameter(torch.diag(
        torch.Tensor([10 for i in range(10)])).double(),
        requires_grad = False)

  def forward(self, x):
    batch_size = len(x)
    x = self.cnn(x)
    outLinear = self.classify(x)
    outDistance = self.distance_classifier(outLinear)

    return outDistance

  def distance_classifier(self, outLinear):
    """ Calculates euclidean distance from outLinear to each class anchor
      Returns n x m array of distance from input of batch_size n
      to anchors of size m """
    n = outLinear.size(0)
    m = self.num_classes
    d = self.num_classes

    outLinear = outLinear.unsqueeze(1).expand(n, m, d).double()
    anchors = self.anchors.unsqueeze(0).expand(n, m, d)
    dists = torch.norm(outLinear-anchors, 2, 2)

    return dists
```

# 3. Training

### Training procedure for baseline model

In [13]:

```
def train(model, criterion, train_loader):
  optimizer = torch.optim.Adam(model.parameters())#,lr=0.001, betas=(0.9,0.999))
  EPOCHS = 5 # return to 5 at the end
  model.train()

  for epoch in range(EPOCHS):
    print('--------------- Epoch : {} -------------'.format(epoch + 1))
    correct = 0
    loss = 0
    for batch_idx, (inputs, targets) in enumerate(train_loader):
      inputs = inputs.to(device)
      targets = targets.to(device)
      optimizer.zero_grad()

      outputs = model(inputs)

      loss = criterion(outputs, targets)
      loss.backward()
      optimizer.step()

      if batch_idx % 100 == 0:
        print('[{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
              batch_idx*len(inputs),
              len(train_loader.dataset),
              100.*batch_idx / len(train_loader),
              loss.data))
```

In [14]:

```
cnn = CNN()
if torch.cuda.is_available():
    cnn.cuda()

criterion = nn.CrossEntropyLoss()
train(cnn, criterion, mnist_train_loader)
```

```
--------------- Epoch : 1 -------------
[0/60000 (0%)]  Loss: 2.308709
[12800/60000 (21%)]     Loss: 0.373247
[25600/60000 (43%)]     Loss: 0.293713
[38400/60000 (64%)]     Loss: 0.184874
[51200/60000 (85%)]     Loss: 0.199000
--------------- Epoch : 2 -------------
[0/60000 (0%)]  Loss: 0.116369
[12800/60000 (21%)]     Loss: 0.127072
[25600/60000 (43%)]     Loss: 0.101849
[38400/60000 (64%)]     Loss: 0.255822
[51200/60000 (85%)]     Loss: 0.088009
--------------- Epoch : 3 -------------
[0/60000 (0%)]  Loss: 0.073958
[12800/60000 (21%)]     Loss: 0.100053
[25600/60000 (43%)]     Loss: 0.097226
[38400/60000 (64%)]     Loss: 0.098851
[51200/60000 (85%)]     Loss: 0.161452
--------------- Epoch : 4 -------------
[0/60000 (0%)]  Loss: 0.041486
[12800/60000 (21%)]     Loss: 0.089241
[25600/60000 (43%)]     Loss: 0.078540
[38400/60000 (64%)]     Loss: 0.121775
[51200/60000 (85%)]     Loss: 0.030553
--------------- Epoch : 5 -------------
[0/60000 (0%)]  Loss: 0.052053
[12800/60000 (21%)]     Loss: 0.077292
[25600/60000 (43%)]     Loss: 0.110536
[38400/60000 (64%)]     Loss: 0.038515
[51200/60000 (85%)]     Loss: 0.080671
```

In [15]:

```
torch.save(cnn.state_dict(), "cnn_weights.pt")
files.download("cnn_weights.pt")
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.Javascript object>
```

## Training procedure for OSR model

$$\mathbf{Loss}_T(\boldsymbol{x}, y) = \log\left(1 + \sum_{j \neq y}^{N} \exp\left(d_y - d_j\right)\right)$$

$$\mathbf{Loss}_A(\boldsymbol{x}, y) = d_y$$

$$\mathbf{Loss}_{CAC}(\boldsymbol{x}, y) = \mathbf{Loss}_T(\boldsymbol{x}, y) + \lambda \cdot \mathbf{Loss}_A(\boldsymbol{x}, y)$$

In [16]:

```
def Loss_CAC(distances, targets, lmbda=0.1):
    true_distances = torch.gather(distances, 1, targets.view(-1, 1)).view(-1)
    non_true_distances = torch.Tensor(
            [[i for i in range(10) if targets[x] != i]
             for x in range(len(distances))]).long().to(device)
    other_distances = torch.gather(distances, 1, non_true_distances)

    loss_A = torch.mean(true_distances)

    loss_T = torch.exp(true_distances.unsqueeze(1) - other_distances)
    loss_T = torch.mean(torch.log(1+torch.sum(loss_T, dim = 1)))

    loss_CAC = loss_T + lmbda * loss_A

    return loss_CAC
```

In [17]:

```
osr = OSR(cnn.state_dict())

if torch.cuda.is_available():
  osr.cuda()

criterion = Loss_CAC
train(osr, criterion, mnist_train_loader)
```

```
--------------- Epoch : 1 -------------
[0/60000 (0%)]  Loss: 7.114793
[12800/60000 (21%)]     Loss: 0.848866
[25600/60000 (43%)]     Loss: 0.594756
[38400/60000 (64%)]     Loss: 0.444379
[51200/60000 (85%)]     Loss: 0.475413
--------------- Epoch : 2 -------------
[0/60000 (0%)]  Loss: 0.446922
[12800/60000 (21%)]     Loss: 0.478245
[25600/60000 (43%)]     Loss: 0.407595
[38400/60000 (64%)]     Loss: 0.423709
[51200/60000 (85%)]     Loss: 0.475037
--------------- Epoch : 3 -------------
[0/60000 (0%)]  Loss: 0.360406
[12800/60000 (21%)]     Loss: 0.360602
[25600/60000 (43%)]     Loss: 0.439699
[38400/60000 (64%)]     Loss: 0.309769
[51200/60000 (85%)]     Loss: 0.371988
--------------- Epoch : 4 -------------
[0/60000 (0%)]  Loss: 0.285697
[12800/60000 (21%)]     Loss: 0.374239
[25600/60000 (43%)]     Loss: 0.374600
[38400/60000 (64%)]     Loss: 0.331799
[51200/60000 (85%)]     Loss: 0.311298
--------------- Epoch : 5 -------------
[0/60000 (0%)]  Loss: 0.325274
[12800/60000 (21%)]     Loss: 0.343488
[25600/60000 (43%)]     Loss: 0.281393
[38400/60000 (64%)]     Loss: 0.384812
[51200/60000 (85%)]     Loss: 0.335081
```

In [18]:

```
torch.save(osr.state_dict(), "osr_weights.pt")
files.download("osr_weights.pt")
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.Javascript object>
```

# 4. Evaluation

In [19]:

```
def get_cnn_prediction(outputs):
  return torch.max(outputs, 1)[1]
```

In [20]:

```
def get_osr_prediction(outputs, threshold=0.5):
  softmin = torch.nn.Softmin(dim=1)
  invScores = 1 - softmin(outputs)
  scores = torch.Tensor(outputs * invScores).detach().cpu()
  pred_value, prediction = torch.min(scores, axis=1)
  prediction[pred_value > threshold] = 10
  return torch.Tensor(prediction).to(device)
```

In [21]:

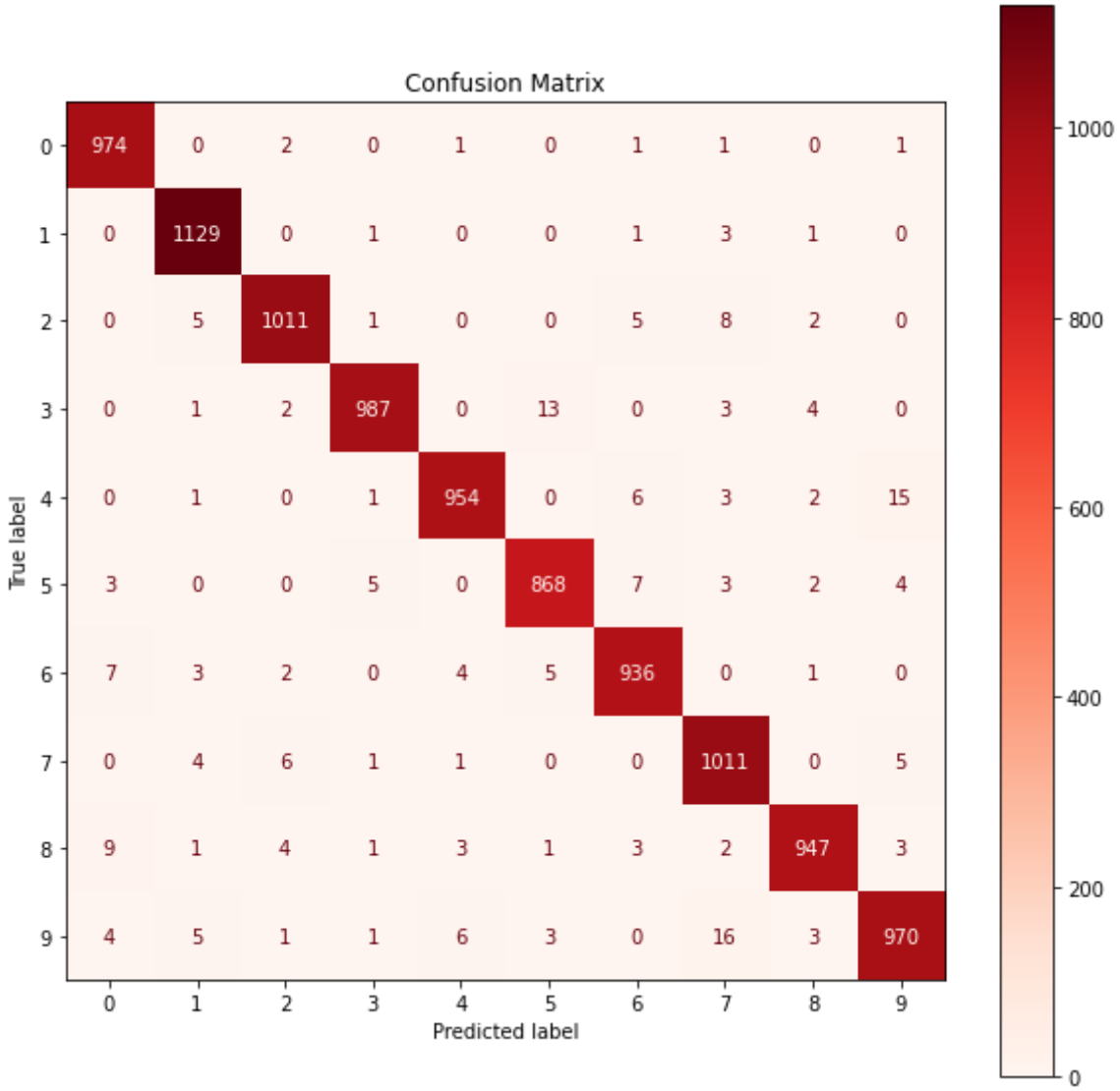
```
dictionary = {0:0, 1:0, 2:0, 3:0, 4:0, 5:0, 6:0, 7:0, 8:0, 9:0, 10:1}

def evaluate(model, labels, get_prediction, test_loader, binary=False):
  y_true = []
  y_pred = []
  correct = 0
  with torch.no_grad():
    for inputs, targets in test_loader:
      inputs = inputs.to(device)
      targets = targets.to(device)

      outputs = model(inputs)

      predicted = get_prediction(outputs)

      correct += (predicted == targets).sum()

      y_true += list(targets.detach().cpu())
      y_pred += list(predicted.detach().cpu())

    if binary:
      y_true = [dictionary[int(y)] for y in y_true]
      y_pred = [dictionary[int(y)] for y in y_pred]

    print("Evaluation accuracy on the testing set: {:.3f}% ".format(
        float(correct*100) / (len(test_loader)*BATCH_SIZE)))

    cm = confusion_matrix(y_true, y_pred, labels=range(len(labels)))

    disp = ConfusionMatrixDisplay(cm, display_labels=labels)
    fig, ax = plt.subplots(figsize=(10,10))
    ax.set_title("Confusion Matrix")
    disp.plot(cmap='Reds', ax=ax)
    plt.show()

    return cm
```

## Baseline results

In [22]:

```
baseline_c_matrix = evaluate(cnn, range(10), get_cnn_prediction,
                             mnist_test_loader)
```

```
Evaluation accuracy on the testing set: 96.786%
```




## OSR rational

To solve the OSR problem, a distance based method that will create finite and closed clusters, felt the most natural for us. This is since we both feel quite comfortable with their concepts (from other courses & mini project). In a distance based method, zones that represent clusters can be created, with a set radius threshold that determines where the zones ends. Any input that wouldn't be mapped to a zone will be classified as 'unknown'.

The problem that we encountered was that the initially formed clusters we received weren't "tight" clusters (around their centres) as we wished for. That caused the samples of the OOD testing set (random images from the CIFAR10 dataset in our example) to easily slip in and be classified to some of those clusters (some of them even got high confidence!). Consequently, the idea of finding whether the data is from OOD based on it's distance from all the clusters that the trained model had, encountered difficulties.

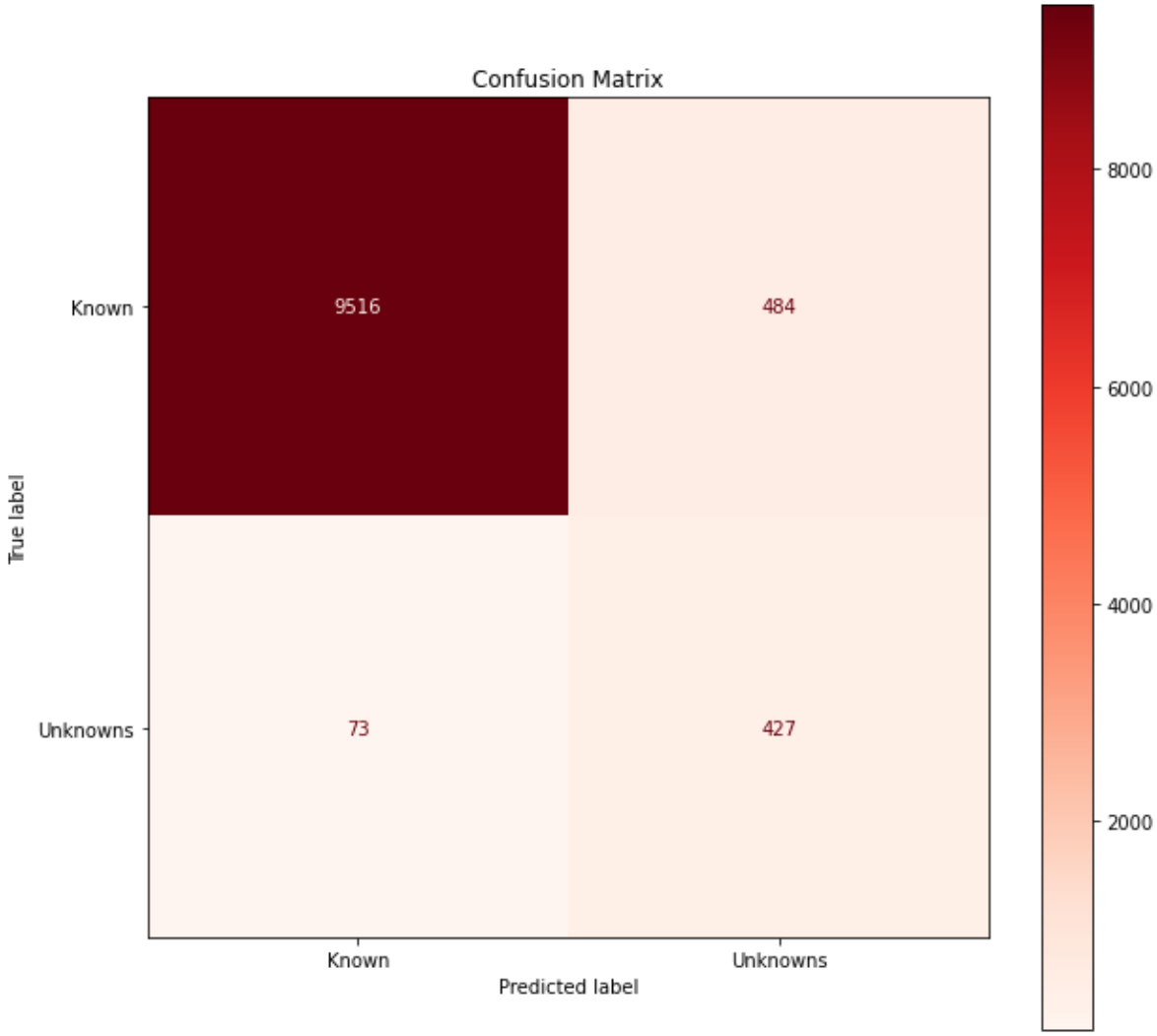
Ultimately, we found the referenced paper [1] on anchor clustering. With that method, we can learn to gather the desired inputs from the known dataset around specific (nearby) points in space, and hopefully send the unknown unlearned OOD inputs to distant, far away points. Implementing this method resulted in a major improvement for our OSR problem, and gave us the desired behaviour we were looking for.

## OOD results

In [23]:

```
ood_c_matrix = evaluate(osr, ['Known', 'Unknowns'], get_osr_prediction,
                        combined_test_loader, True)
```

```
Evaluation accuracy on the testing set: 93.251%
```



In [24]:

```
success_on_known = (ood_c_matrix[0,0] / len(mnist_test_set)) * 100
print("We recieved {:.2f}% success rate on the {} MNIST samples".format(
    success_on_known, len(mnist_test_set)))
success_on_unknown = (ood_c_matrix[1,1] / CIFAR10_SUBSET_SIZE) * 100
print("We recieved {:.2f}% success rate on the {} OOD samples".format(
    success_on_unknown, CIFAR10_SUBSET_SIZE))
```

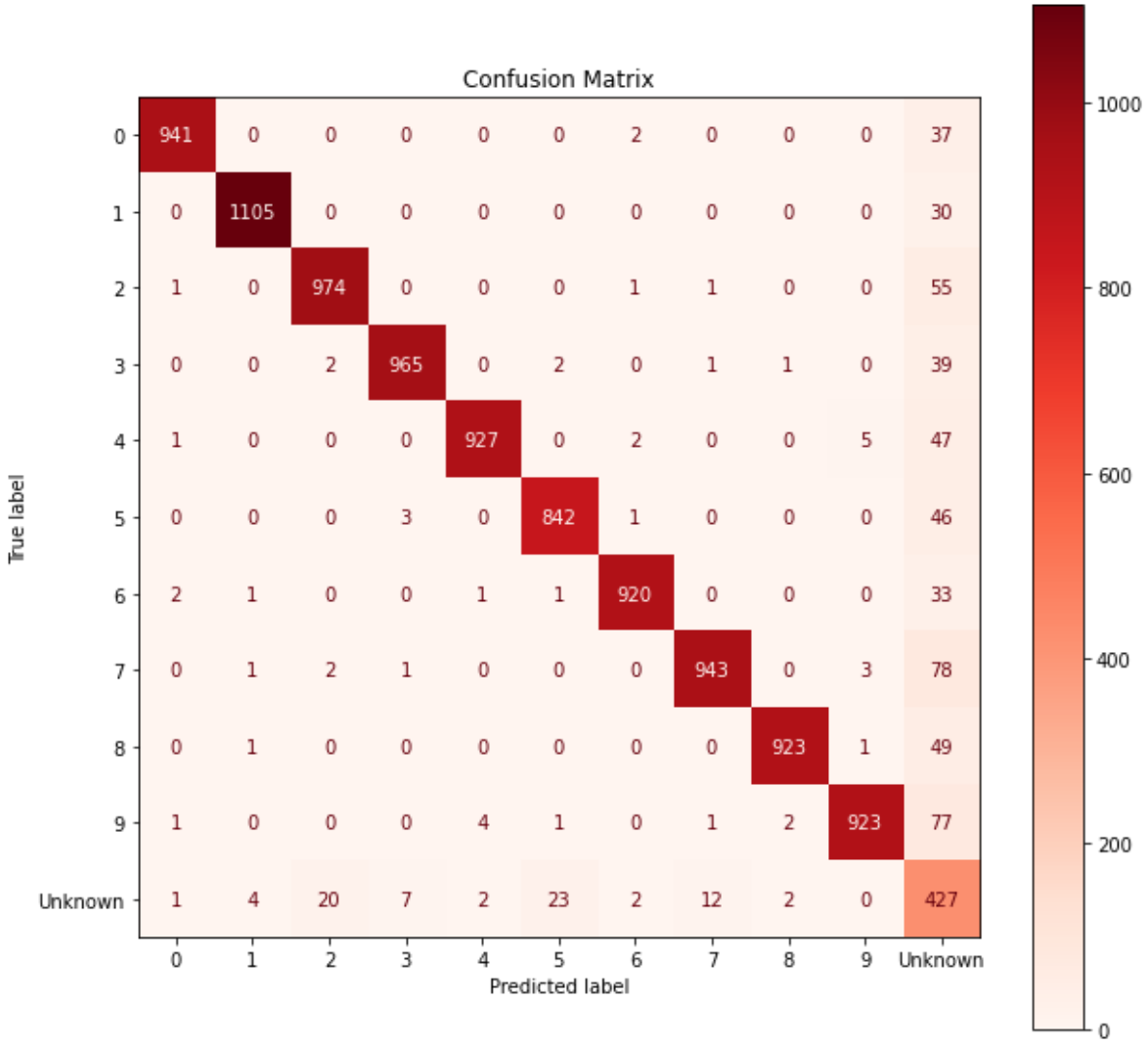
```
We recieved 95.16% success rate on the 10000 MNIST samples
We recieved 85.40% success rate on the 500 OOD samples
```

### OSR results

In [25]:

```
osr_c_matrix = evaluate(osr, list(range(10)) + ['Unknown'], get_osr_prediction,
                        combined_test_loader)
```

```
Evaluation accuracy on the testing set: 93.091%
```



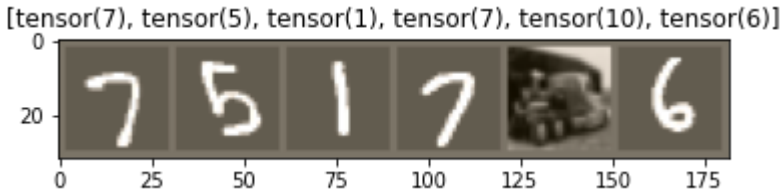

# 5. Visualization

In [26]:

```
def visualize_model(model, get_prediction, num_images=6):
  model.eval()
  images_so_far = 0
  fig = plt.figure()

  with torch.no_grad():
    for i, (inputs, labels) in enumerate(combined_test_loader):
      inputs = inputs.to(device)
      labels = labels.to(device)

      outputs = model(inputs)
      predicted = get_prediction(outputs)

      out_inputs = []
      out_labels = []
      for j in range(inputs.size()[0]):
        out_inputs.append(inputs.cpu().data[j])
        out_labels.append(predicted.cpu().data[j])
        images_so_far += 1

        if images_so_far == num_images:
            out_inputs = torchvision.utils.make_grid(out_inputs)
            imshow(out_inputs, title=out_labels)
            return
```

In [27]:

```
visualize_model(osr, get_osr_prediction, 6)
```




# 6. Reference

[1] Miller, Dimity and Suenderhauf, Niko and Milford, Michael and Dayoub, Feras. Class Anchor Clustering: A Loss for Distance-Based Open Set Recognition. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 3,570-3,578 https://openaccess.thecvf.com/content/WACV2021/papers/Miller_Class_Anchor_Clustering_A_Loss_for_Distance_Based_Open_Set_Recognition_WACV_2021_paper.pdf (https://openaccess.thecvf.com/content/WACV2021/papers/Miller_Class_Anchor_Clustering_A_Loss_for_Distance_Based_Open_Set_Recognition_WACV_2021_paper.pdf)