МИНОБРНАУКИ РОССИИ
Федеральное государственное бюджетное образовательное учреждение высшего образования
«МИРЭА – Российский технологический университет»
РТУ МИРЭА

Институт кибербезопасности и цифровых технологий

КБ-4 «Интеллектуальные системы информационной безопасности»

Отчет по практической и лабораторной работе

по дисциплине: «Анализ защищенности систем искусственного интеллекта»

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Москва, 2023

Выполним импорт необходимых библиотек.

```
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import transforms,datasets
```

Загрузим набор данных (MNIST), разобьем данные на подвыборки.

```
transform = transforms.Compose([transforms.ToTensor(),
transforms.Normalize((0.0,), (1.0,))])
dataset = datasets.MNIST(root = './data', train=True, transform = transform, download=True)
train_set, val_set = torch.utils.data.random_split(dataset, [50000, 10000])
test_set = datasets.MNIST(root = './data', train=False, transform = transform, download=True)
train_loader = torch.utils.data.DataLoader(train_set,batch_size=1,shuffle=True)
val_loader = torch.utils.data.DataLoader(val_set,batch_size=1,shuffle=True)
test_loader = torch.utils.data.DataLoader(test_set,batch_size=1,shuffle=True)
print("Training data:",len(train_loader),"Validation data:",len(val_loader),"Test data:",len(test_loader))
```

```
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/MNIST/raw/train-images-idx3-ubyte.gz
100%|██████████| 9912422/9912422 [00:00<00:00, 118647742.08it/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/MNIST/raw/train-labels-idx1-ubyte.gz
100%|██████████| 28881/28881 [00:00<00:00, 47993539.55it/s]
Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/raw
```

Настроим использование графического ускорителя.

```
[3] use_cuda=True
    device = torch.device("cuda" if (use_cuda and torch.cuda.is_available()) else "cpu")
```

1 Создание атак на модель НС

Создадим класс НС на основе фреймворка torch

```
[4] class Net(nn.Module):
      def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, 3, 1)
        self.conv2 = nn.Conv2d(32, 64, 3, 1)
        self.dropout1 = nn.Dropout2d(0.25)
        self.dropout2 = nn.Dropout2d(0.5)
        self.fc1 = nn.Linear(9216, 128)
        self.fc2 = nn.Linear(128, 10)
      def forward(self, x):
        x = self.conv1(x)
        x = F.relu(x)
        x = self.conv2(x)
        x = F.relu(x)
        x = F.max_pool2d(x, 2)
        x = self.dropout1(x)
        x = torch.flatten(x, 1)
        x = self.fc1(x)
        x = F.relu(x)
        x = self.dropout2(x)
        x = self.fc2(x)
        output = F.log_softmax(x, dim=1)
        return output
```

Проверим работоспособность созданного класса НС.

```
[5] model = Net().to(device)
```

Создадим оптимизатор, функцию потерь и трейнер сети.

```
[6] optimizer = optim.Adam(model.parameters(),lr=0.0001, betas=(0.9, 0.999))
    criterion = nn.NLLLoss()
    scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='min', factor=0.1, patience=3)
```

Определим функцию обучения сети.

```
[7] def fit(model,device,train_loader,val_loader,epochs):
      data_loader = {'train':train_loader,'val':val_loader}
      print("Fitting the model...")
      train_loss,val_loss=[],[]
      for epoch in range(epochs):
        loss_per_epoch,val_loss_per_epoch=0,0
        for phase in ('train','val'):
          for i,data in enumerate(data_loader[phase]):
            input,label = data[0].to(device),data[1].to(device)
            output = model(input)
            #calculating loss on the output
            loss = criterion(output,label)
            if phase == 'train':
              optimizer.zero_grad()
              #grad calc w.r.t Loss func
              loss.backward()
              #update weights
              optimizer.step()
              loss_per_epoch+=loss.item()
            else:
              val_loss_per_epoch+=loss.item()
        scheduler.step(val_loss_per_epoch/len(val_loader))
        print("Epoch: {} Loss: {} Val_Loss: {}".format(epoch+1,loss_per_epoch/len(train_loader),val_loss_per_epoch/len(val_loader)))
        train_loss.append(loss_per_epoch/len(train_loader))
        val_loss.append(val_loss_per_epoch/len(val_loader))
      return train_loss,val_loss
```

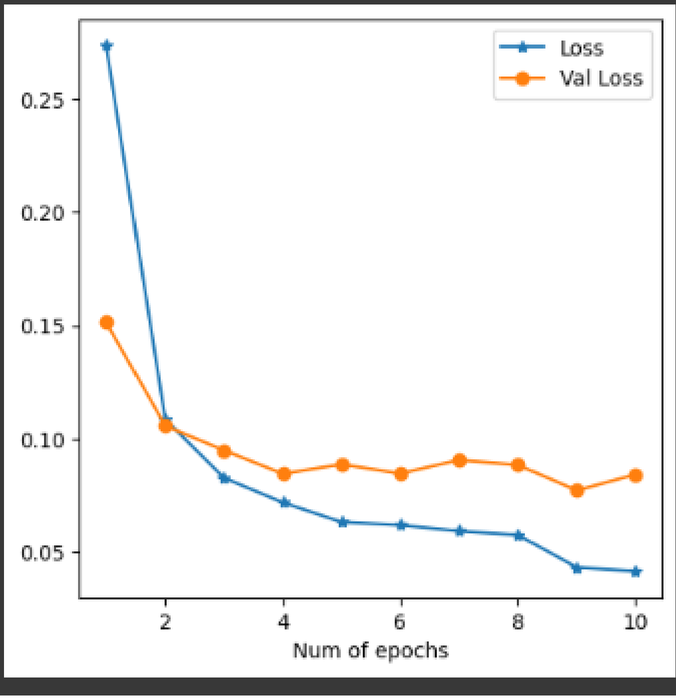
Обучим модель.

```
[8] loss, val_loss = fit(model, device, train_loader, val_loader, 10)

    Fitting the model...
    /usr/local/lib/python3.10/dist-packages/torch/nn/functional.py:1345: UserWarni
      warnings.warn(warn_msg)
    Epoch: 1 Loss: 0.27364798618042624 Val_Loss: 0.1514760968370528
    Epoch: 2 Loss: 0.1085534713517188 Val_Loss: 0.10566764865441187
    Epoch: 3 Loss: 0.08270403996756964 Val_Loss: 0.09490188534468656
    Epoch: 4 Loss: 0.07184107978025048 Val_Loss: 0.08452242758264042
    Epoch: 5 Loss: 0.06318974395321775 Val_Loss: 0.08870745507981724
    Epoch: 6 Loss: 0.06183685142550104 Val_Loss: 0.08463778928197853
    Epoch: 7 Loss: 0.05919382139317826 Val_Loss: 0.09058659238292247
    Epoch: 8 Loss: 0.05746152144902565 Val_Loss: 0.0884336885243108
    Epoch: 9 Loss: 0.04317616631293602 Val_Loss: 0.07717185551352328
    Epoch: 10 Loss: 0.04143624664735127 Val_Loss: 0.08422930549846026
```

Построим графики потерь при обучении и валидации в зависимости от эпохи.

```
[9]  fig = plt.figure(figsize=(5,5))
     plt.plot(np.arange(1,11), loss, "*-",label="Loss")
     plt.plot(np.arange(1,11), val_loss,"o-",label="Val Loss")
     plt.xlabel("Num of epochs")
     plt.legend()
     plt.show()
```



Создадим функции атак FGSM, I-FGSM, MI-FGSM.

```
[10] def fgsm_attack(input,epsilon,data_grad):
       pert_out = input + epsilon*data_grad.sign()
       pert_out = torch.clamp(pert_out, 0, 1)
       return pert_out
```

```
[11] def ifgsm_attack(input,epsilon,data_grad):
       iter = 10
       alpha = epsilon/iter
       pert_out = input
       for i in range(iter-1):
         pert_out = pert_out + alpha*data_grad.sign()
         pert_out = torch.clamp(pert_out, 0, 1)
         if torch.norm((pert_out-input),p=float('inf')) > epsilon:
           break
       return pert_out
```

```
[12] def mifgsm_attack(input,epsilon,data_grad):
       iter=10
       decay_factor=1.0
       pert_out = input
       alpha = epsilon/iter
       g=0
       for i in range(iter-1):
         g = decay_factor*g + data_grad/torch.norm(data_grad,p=1)
         pert_out = pert_out + alpha*torch.sign(g)
         pert_out = torch.clamp(pert_out, 0, 1)
         if torch.norm((pert_out-input),p=float('inf')) > epsilon:
           break
       return pert_out
```

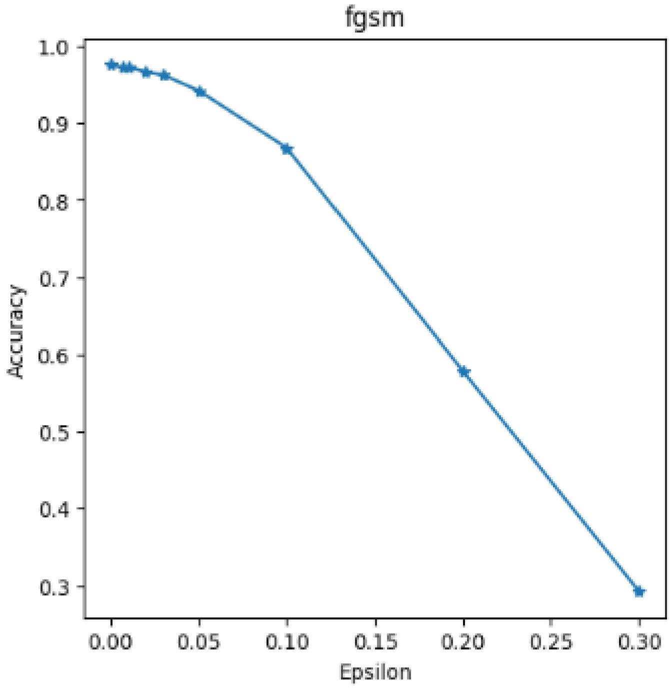
Создадим функцию проверки.

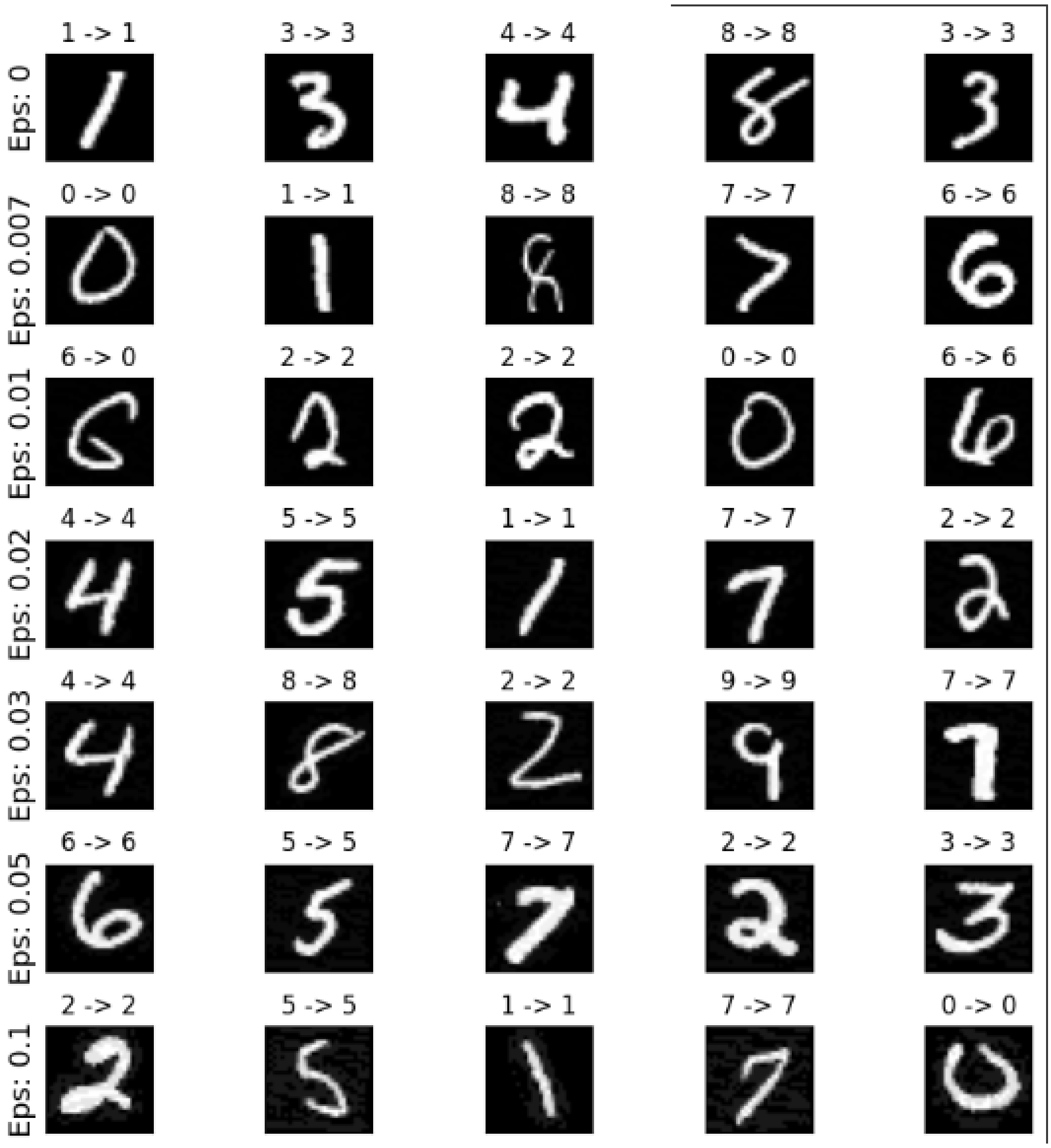
```
[13] def test(model,device,test_loader,epsilon,attack):
       correct = 0
       adv_examples = []
       for data, target in test_loader:
         data, target = data.to(device), target.to(device)
         data.requires_grad = True
         output = model(data)
         init_pred = output.max(1, keepdim=True)[1]
         if init_pred.item() != target.item():
           continue
         loss = F.nll_loss(output, target)
         model.zero_grad()
         loss.backward()
         data_grad = data.grad.data
         if attack == "fgsm":
           perturbed_data = fgsm_attack(data,epsilon,data_grad)
         elif attack == "ifgsm":
           perturbed_data = ifgsm_attack(data,epsilon,data_grad)
         elif attack == "mifgsm":
           perturbed_data = mifgsm_attack(data,epsilon,data_grad)
         output = model(perturbed_data)
         final_pred = output.max(1, keepdim=True)[1]
         if final_pred.item() == target.item():
           correct += 1
         if (epsilon == 0) and (len(adv_examples) < 5):
           adv_ex = perturbed_data.squeeze().detach().cpu().numpy()
           adv_examples.append( (init_pred.item(), final_pred.item(), adv_ex) )
         else:
           if len(adv_examples) < 5:
             adv_ex = perturbed_data.squeeze().detach().cpu().numpy()
             adv_examples.append( (init_pred.item(), final_pred.item(), adv_ex) )
       final_acc = correct/float(len(test_loader))
       print("Epsilon: {}\tTest Accuracy = {} / {} = {}".format(epsilon, correct, len(test_loader), final_acc))
       return final_acc, adv_examples
```

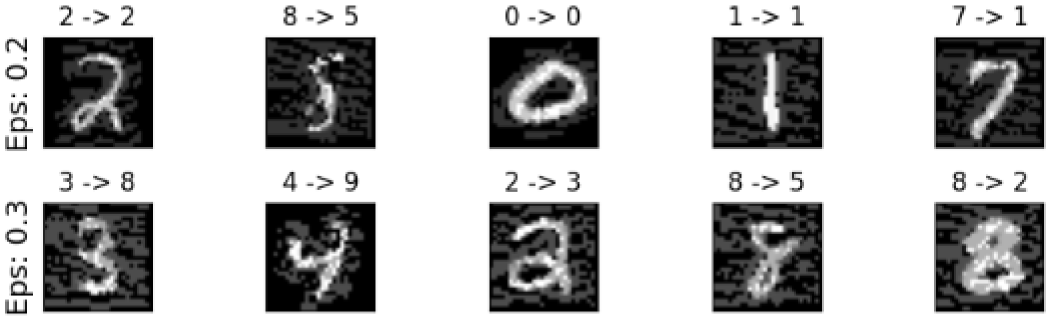
Построим графики успешности атак(Accuracy/эпсилон) и примеры выполненных атак в зависимости от степени возмущения epsilon.

```
epsilons = [0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
for attack in ("fgsm","ifgsm","mifgsm"):
  accuracies = []
  examples = []
  for eps in epsilons:
    acc, ex = test(model, device,test_loader,eps,attack)
    accuracies.append(acc)
    examples.append(ex)
  plt.figure(figsize=(5,5))
  plt.plot(epsilons, accuracies, "*-")
  plt.title(attack)
  plt.xlabel("Epsilon")
  plt.ylabel("Accuracy")
  plt.show()
  cnt = 0
  plt.figure(figsize=(8,10))
  for i in range(len(epsilons)):
    for j in range(len(examples[i])):
      cnt += 1
      plt.subplot(len(epsilons),len(examples[0]),cnt)
      plt.xticks([], [])
      plt.yticks([], [])
      if j == 0:
        plt.ylabel("Eps: {}".format(epsilons[i]), fontsize=14)
      orig,adv,ex = examples[i][j]
      plt.title("{} -> {}".format(orig, adv))
      plt.imshow(ex, cmap="gray")
  plt.tight_layout()
  plt.show()
```

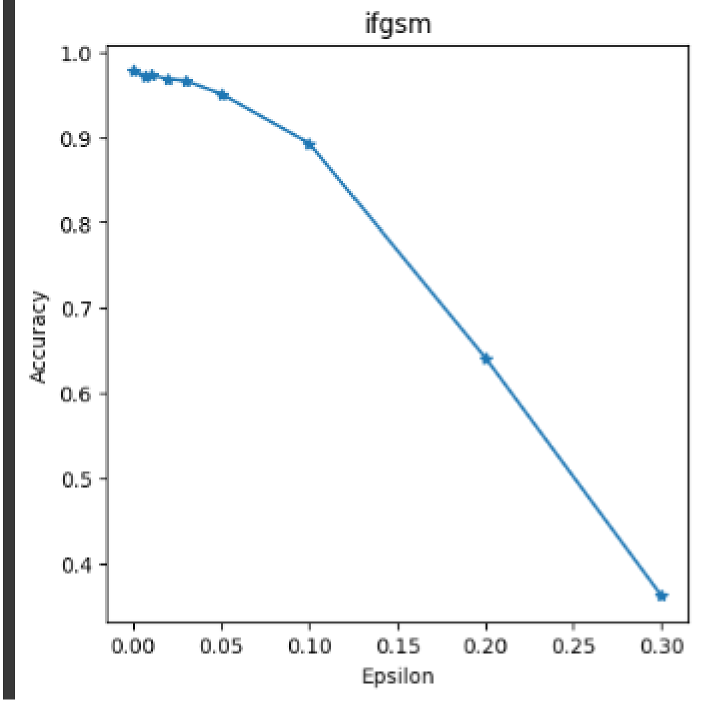
```
Epsilon: 0      Test Accuracy = 9761 / 10000 = 0.9761
Epsilon: 0.007  Test Accuracy = 9721 / 10000 = 0.9721
Epsilon: 0.01   Test Accuracy = 9730 / 10000 = 0.973
Epsilon: 0.02   Test Accuracy = 9665 / 10000 = 0.9665
Epsilon: 0.03   Test Accuracy = 9624 / 10000 = 0.9624
Epsilon: 0.05   Test Accuracy = 9423 / 10000 = 0.9423
Epsilon: 0.1    Test Accuracy = 8680 / 10000 = 0.868
Epsilon: 0.2    Test Accuracy = 5786 / 10000 = 0.5786
Epsilon: 0.3    Test Accuracy = 2929 / 10000 = 0.2929
```

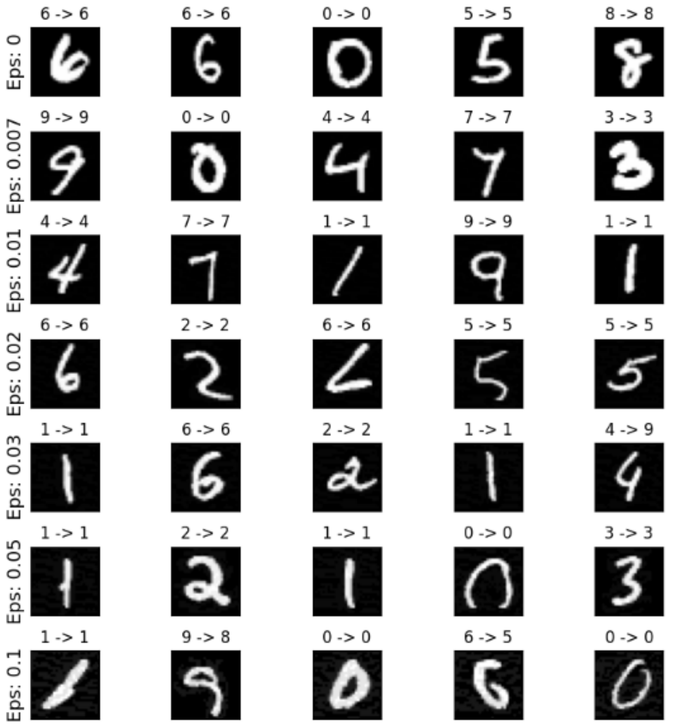

fgsm
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
Accuracy
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Epsilon

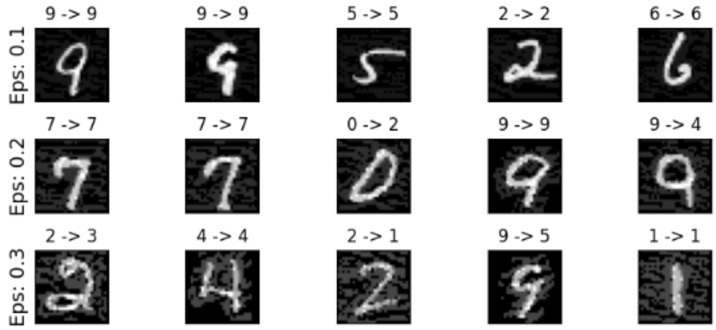

1 -> 1
3 -> 3
4 -> 4
8 -> 8
3 -> 3
Eps: 0
0 -> 0
1 -> 1
8 -> 8
7 -> 7
6 -> 6
Eps: 0.007
6 -> 0
2 -> 2
2 -> 2
0 -> 0
6 -> 6
Eps: 0.01
4 -> 4
5 -> 5
1 -> 1
7 -> 7
2 -> 2
Eps: 0.02
4 -> 4
8 -> 8
2 -> 2
9 -> 9
7 -> 7
Eps: 0.03
6 -> 6
5 -> 5
7 -> 7
2 -> 2
3 -> 3
Eps: 0.05
2 -> 2
5 -> 5
1 -> 1
7 -> 7
0 -> 0
Eps: 0.1




```
Epsilon: 0      Test Accuracy = 9780 / 10000 = 0.978
Epsilon: 0.007  Test Accuracy = 9722 / 10000 = 0.9722
Epsilon: 0.01   Test Accuracy = 9725 / 10000 = 0.9725
Epsilon: 0.02   Test Accuracy = 9687 / 10000 = 0.9687
Epsilon: 0.03   Test Accuracy = 9660 / 10000 = 0.966
Epsilon: 0.05   Test Accuracy = 9510 / 10000 = 0.951
Epsilon: 0.1    Test Accuracy = 8931 / 10000 = 0.8931
Epsilon: 0.2    Test Accuracy = 6417 / 10000 = 0.6417
Epsilon: 0.3    Test Accuracy = 3627 / 10000 = 0.3627
```




Eps: 0
6 -> 6
6 -> 6
0 -> 0
5 -> 5
8 -> 8
Eps: 0.007
9 -> 9
0 -> 0
4 -> 4
7 -> 7
3 -> 3
Eps: 0.01
4 -> 4
7 -> 7
1 -> 1
9 -> 9
1 -> 1
Eps: 0.02
6 -> 6
2 -> 2
6 -> 6
5 -> 5
5 -> 5
Eps: 0.03
1 -> 1
6 -> 6
2 -> 2
1 -> 1
4 -> 9
Eps: 0.05
1 -> 1
2 -> 2
1 -> 1
0 -> 0
3 -> 3
Eps: 0.1
1 -> 1
9 -> 8
0 -> 0
6 -> 5
0 -> 0


Eps: 0.1
9 -> 9
9 -> 9
5 -> 5
2 -> 2
6 -> 6
Eps: 0.2
7 -> 7
7 -> 7
0 -> 2
9 -> 9
9 -> 4
Eps: 0.3
2 -> 3
4 -> 4
2 -> 1
9 -> 5
1 -> 1

2 Защита от атак

Создадим 2 класса НС.

```python
class NetF(nn.Module):
  def __init__(self):
    super(NetF, self).__init__()
    self.conv1 = nn.Conv2d(1, 32, 3, 1)
    self.conv2 = nn.Conv2d(32, 64, 3, 1)
    self.dropout1 = nn.Dropout2d(0.25)
    self.dropout2 = nn.Dropout2d(0.5)
    self.fc1 = nn.Linear(9216, 128)
    self.fc2 = nn.Linear(128, 10)

  def forward(self, x):
    x = self.conv1(x)
    x = F.relu(x)
    x = self.conv2(x)
    x = F.relu(x)
    x = F.max_pool2d(x, 2)
    x = self.dropout1(x)
    x = torch.flatten(x, 1)
    x = self.fc1(x)
    x = F.relu(x)
    x = self.dropout2(x)
    x = self.fc2(x)
    return x
```

```python
class NetF1(nn.Module):
  def __init__(self):
    super(NetF1, self).__init__()
    self.conv1 = nn.Conv2d(1, 16, 3, 1)
    self.conv2 = nn.Conv2d(16, 32, 3, 1)
    self.dropout1 = nn.Dropout2d(0.25)
    self.dropout2 = nn.Dropout2d(0.5)
    self.fc1 = nn.Linear(4608, 64)
    self.fc2 = nn.Linear(64, 10)

  def forward(self, x):
    x = self.conv1(x)
    x = F.relu(x)
    x = self.conv2(x)
    x = F.relu(x)
    x = F.max_pool2d(x, 2)
    x = self.dropout1(x)
    x = torch.flatten(x, 1)
    x = self.fc1(x)
    x = F.relu(x)
    x = self.dropout2(x)
    x = self.fc2(x)
    return x
```

Переопределим функцию обучения и тестирования.

```
def fit(model,device,optimizer,scheduler,criterion,train_loader,val_loader,Temp,epochs):
  data_loader = {'train':train_loader,'val':val_loader}
  print("Fitting the model...")
  train_loss,val_loss=[],[]
  for epoch in range(epochs):
    loss_per_epoch,val_loss_per_epoch=0,0
    for phase in ('train','val'):
      for i,data in enumerate(data_loader[phase]):
        input,label = data[0].to(device),data[1].to(device)
        output = model(input)
        output = F.log_softmax(output/Temp,dim=1)
        #calculating loss on the output
        loss = criterion(output,label)
        if phase == 'train':
          optimizer.zero_grad()
          #grad calc w.r.t Loss func
          loss.backward()
          #update weights
          optimizer.step()
          loss_per_epoch+=loss.item()
      else:
        val_loss_per_epoch+=loss.item()
    scheduler.step(val_loss_per_epoch/len(val_loader))
    print("Epoch: {} Loss: {} Val_Loss: {}".format(epoch+1,loss_per_epoch/len(train_loader),val_loss_per_epoch/len(val_loader)))
    train_loss.append(loss_per_epoch/len(train_loader))
    val_loss.append(val_loss_per_epoch/len(val_loader))
  return train_loss,val_loss

  def test(model,device,test_loader,epsilon,Temp,attack):
    correct=0
    adv_examples = []
    for data, target in test_loader:
      data, target = data.to(device), target.to(device)
      data.requires_grad = True
      output = model(data)
      output = F.log_softmax(output/Temp,dim=1)
      init_pred = output.max(1, keepdim=True)[1]
      if init_pred.item() != target.item():
        continue
      loss = F.nll_loss(output, target)
      model.zero_grad()
      loss.backward()
      data_grad = data.grad.data
      if attack == "fgsm":
        perturbed_data = fgsm_attack(data,epsilon,data_grad)
      elif attack == "ifgsm":
        perturbed_data = ifgsm_attack(data,epsilon,data_grad)
      elif attack == "mifgsm":
        perturbed_data = mifgsm_attack(data,epsilon,data_grad)
      output = model(perturbed_data)
      final_pred = output.max(1, keepdim=True)[1]
      if final_pred.item() == target.item():
        correct += 1
        if (epsilon == 0) and (len(adv_examples) < 5):
          adv_ex = perturbed_data.squeeze().detach().cpu().numpy()
          adv_examples.append( (init_pred.item(), final_pred.item(), adv_ex) )
        else:
          if len(adv_examples) < 5:
            adv_ex = perturbed_data.squeeze().detach().cpu().numpy()
```

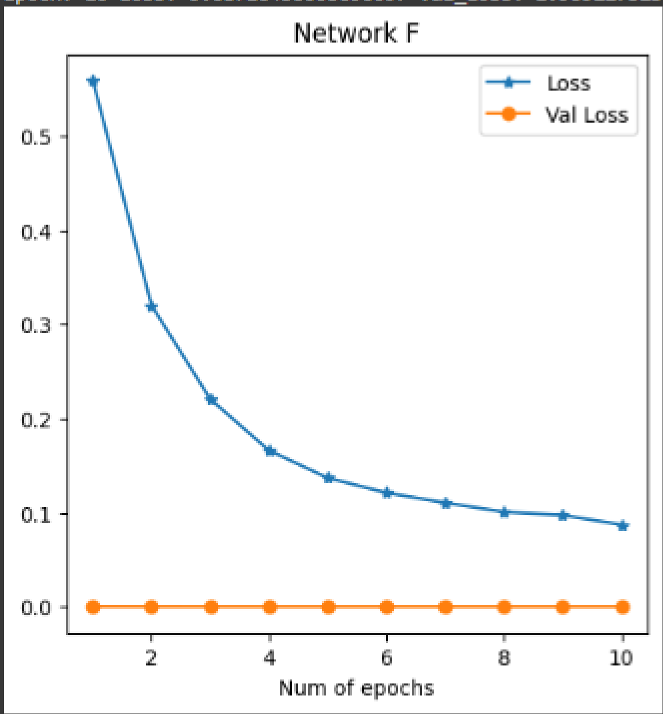
Создадим функцию защиты методом дистилляции.

```
def defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilons):
  modelF = NetF().to(device)
  optimizerF = optim.Adam(modelF.parameters(),lr=0.0001, betas=(0.9, 0.999))
  schedulerF = optim.lr_scheduler.ReduceLROnPlateau(optimizerF, mode='min', factor=0.1, patience=3)
  modelF1 = NetF1().to(device)
  optimizerF1 = optim.Adam(modelF1.parameters(),lr=0.0001, betas=(0.9, 0.999))
  schedulerF1 = optim.lr_scheduler.ReduceLROnPlateau(optimizerF1, mode='min', factor=0.1, patience=3)
  criterion = nn.NLLLoss()
  lossF,val_lossF=fit(modelF,device,optimizerF,schedulerF,criterion,train_loader,val_loader,Temp,epochs)
  fig = plt.figure(figsize=(5,5))
  plt.plot(np.arange(1,epochs+1), lossF, "*-",label="Loss")
  plt.plot(np.arange(1,epochs+1), val_lossF,"o-",label="Val Loss")
  plt.title("Network F")
  plt.xlabel("Num of epochs")
  plt.legend()
  plt.show()
  #converting target labels to soft labels
  for data in train_loader:
    input, label = data[0].to(device),data[1].to(device)
    softlabel = F.log_softmax(modelF(input),dim=1)
    data[1] = softlabel
  lossF1,val_lossF1=fit(modelF1,device,optimizerF1,schedulerF1,criterion,train_loader,val_loader,Temp,epochs)
  fig = plt.figure(figsize=(5,5))
  plt.plot(np.arange(1,epochs+1), lossF1, "*-",label="Loss")
  plt.plot(np.arange(1,epochs+1), val_lossF1,"o-",label="Val Loss")
  plt.title("Network F'")
  plt.xlabel("Num of epochs")
  plt.legend()
  plt.show()
  model = NetF1().to(device)
  model.load_state_dict(modelF1.state_dict())
  for attack in ("fgsm","ifgsm","mifgsm"):
    accuracies = []
    examples = []
    for eps in epsilons:
      acc, ex = test(model,device,test_loader,eps,"fgsm")
      accuracies.append(acc)
      examples.append(ex)
  plt.figure(figsize=(5,5))
  plt.plot(epsilons, accuracies, "*-")
  plt.title(attack)
  plt.xlabel("Epsilon")
  plt.ylabel("Accuracy")
  plt.show()
  cnt = 0
  plt.figure(figsize=(8,10))
  for i in range(len(epsilons)):
    for j in range(len(examples[i])):
      cnt += 1
      plt.subplot(len(epsilons),len(examples[0]),cnt)
      plt.xticks([], [])
      plt.yticks([], [])
      if j == 0:
        plt.ylabel("Eps: {}".format(epsilons[i]), fontsize=14)
      orig,adv,ex = examples[i][j]
      plt.title("{} -> {}".format(orig, adv))
      plt.imshow(ex, cmap="gray")
  plt.tight_layout()
```

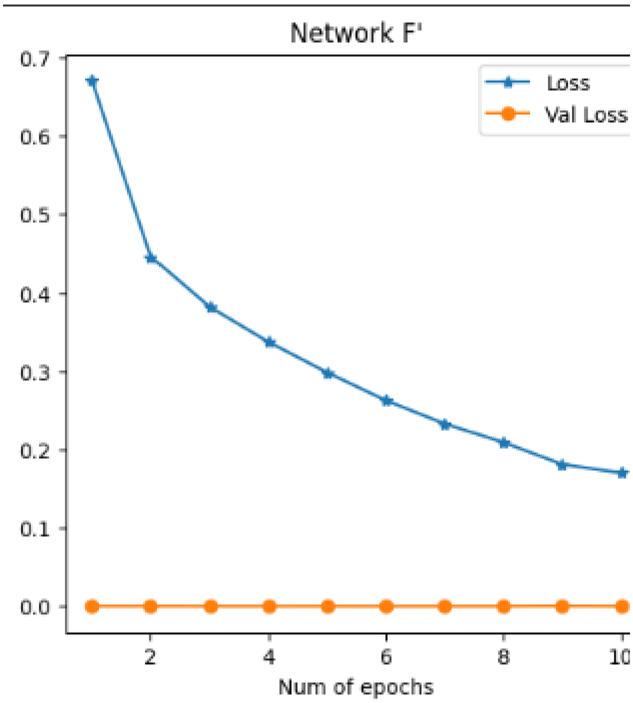
Получим результаты оценки защищенных

```
Temp=100
epochs=10
epsilons=[0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilons)
```

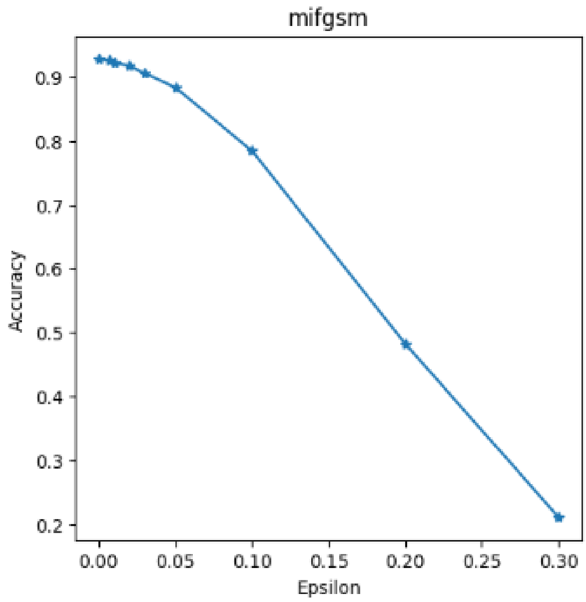
```
Fitting the model...
Epoch: 1 Loss: 0.5586636638233529 Val_Loss: 0.0001373449472710490З
Epoch: 2 Loss: 0.32000435114445375 Val_Loss: 3.885443676263094e-05
Epoch: 3 Loss: 0.22065452498864171 Val_Loss: 2.6573986560106278e-05
Epoch: 4 Loss: 0.166122699417228 Val_Loss: 2.089180740586016e-06
Epoch: 5 Loss: 0.13697167539701155 Val_Loss: 2.0265563023258437e-10
Epoch: 6 Loss: 0.12113108773361844 Val_Loss: 1.0716508119367063e-05
Epoch: 7 Loss: 0.11046593322182684 Val_Loss: 1.7166009683933225e-09
Epoch: 8 Loss: 0.10070784397399411 Val_Loss: 1.8325391924008726e-06
Epoch: 9 Loss: 0.09728810295630186 Val_Loss: 6.29195295914542e-06
Epoch: 10 Loss: 0.08716456005690097 Val_Loss: 1.969227523659356e-08
```



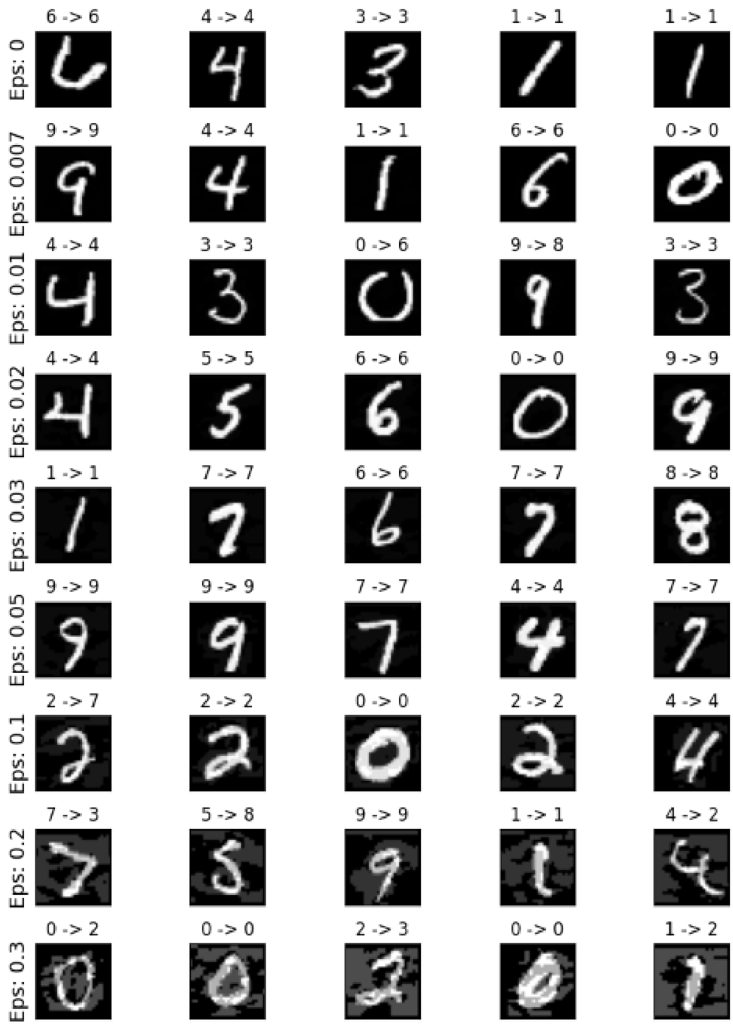

```
Fitting the model...
Epoch: 1 Loss: 0.6708522244577682 Val_Loss: 8.905845731496811e-05
Epoch: 2 Loss: 0.4460383526137011 Val_Loss: 8.857200965285301e-05
Epoch: 3 Loss: 0.38187247984231215 Val_Loss: 2.3023875430226327e-06
Epoch: 4 Loss: 0.33720084358059105 Val_Loss: 2.4729261049287745e-06
Epoch: 5 Loss: 0.29825992335180374 Val_Loss: 1.5593550726771354e-05
Epoch: 6 Loss: 0.2625956706629719 Val_Loss: 2.759788396360818e-07
Epoch: 7 Loss: 0.23289492150114827 Val_Loss: 3.2116492511704563e-07
Epoch: 8 Loss: 0.20901024173459745 Val_Loss: 1.4200437907129527e-05
Epoch: 9 Loss: 0.18101272500992469 Val_Loss: 0.0003574684738783617
Epoch: 10 Loss: 0.17011370223791447 Val_Loss: 7.655074005015194e-08
```




```
Epsilon: 0      Test Accuracy = 9282 / 10000 = 0.9282
Epsilon: 0.007  Test Accuracy = 9266 / 10000 = 0.9266
Epsilon: 0.01   Test Accuracy = 9253 / 10000 = 0.9253
Epsilon: 0.02   Test Accuracy = 9186 / 10000 = 0.9186
Epsilon: 0.03   Test Accuracy = 9065 / 10000 = 0.9065
Epsilon: 0.05   Test Accuracy = 8850 / 10000 = 0.885
Epsilon: 0.1    Test Accuracy = 7835 / 10000 = 0.7835
Epsilon: 0.2    Test Accuracy = 4814 / 10000 = 0.4814
Epsilon: 0.3    Test Accuracy = 2124 / 10000 = 0.2124
Epsilon: 0      Test Accuracy = 9285 / 10000 = 0.9285
Epsilon: 0.007  Test Accuracy = 9264 / 10000 = 0.9264
Epsilon: 0.01   Test Accuracy = 9239 / 10000 = 0.9239
Epsilon: 0.02   Test Accuracy = 9177 / 10000 = 0.9177
Epsilon: 0.03   Test Accuracy = 9107 / 10000 = 0.9107
Epsilon: 0.05   Test Accuracy = 8819 / 10000 = 0.8819
Epsilon: 0.1    Test Accuracy = 7839 / 10000 = 0.7839
Epsilon: 0.2    Test Accuracy = 4839 / 10000 = 0.4839
Epsilon: 0.3    Test Accuracy = 2130 / 10000 = 0.213
Epsilon: 0      Test Accuracy = 9280 / 10000 = 0.928
Epsilon: 0.007  Test Accuracy = 9262 / 10000 = 0.9262
Epsilon: 0.01   Test Accuracy = 9225 / 10000 = 0.9225
Epsilon: 0.02   Test Accuracy = 9172 / 10000 = 0.9172
Epsilon: 0.03   Test Accuracy = 9056 / 10000 = 0.9056
Epsilon: 0.05   Test Accuracy = 8834 / 10000 = 0.8834
Epsilon: 0.1    Test Accuracy = 7843 / 10000 = 0.7843
Epsilon: 0.2    Test Accuracy = 4825 / 10000 = 0.4825
Epsilon: 0.3    Test Accuracy = 2111 / 10000 = 0.2111
```



mifgsm
Accuracy
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Epsilon



Eps: 0
6 -> 6
4 -> 4
3 -> 3
1 -> 1
1 -> 1
Eps: 0.007
9 -> 9
4 -> 4
1 -> 1
6 -> 6
0 -> 0
Eps: 0.01
4 -> 4
3 -> 3
0 -> 6
9 -> 8
3 -> 3
Eps: 0.02
4 -> 4
5 -> 5
6 -> 6
0 -> 0
9 -> 9
Eps: 0.03
1 -> 1
7 -> 7
6 -> 6
7 -> 7
8 -> 8
Eps: 0.05
9 -> 9
9 -> 9
7 -> 7
4 -> 4
7 -> 7
Eps: 0.1
2 -> 7
2 -> 2
0 -> 0
2 -> 2
4 -> 4
Eps: 0.2
7 -> 3
5 -> 8
9 -> 9
1 -> 1
4 -> 2
Eps: 0.3
0 -> 2
0 -> 0
2 -> 3
0 -> 0
1 -> 2

Заключение

В данной лабораторной работе по изучению защиты от атак на модели НС, использовался набор данных MNIST.Далее были созданы атаки на модель НС. Созданы функции атак FGSM, I-FGMS, MI-FGSM.Также были созданы графики успешности атак и примеры выполненных атак. Помимо этого, была создан защитный метод дистилляции, а также проведена оценка результата работы. Основная идея защитной дистиляции заключается в обучении устойчивой модели, путем передачи знаний от базовой модели, подверженной атакам, к новой модели, которая спроектирована для устойчивости к различным атакам.Дистилляция дает более плоские локальные минимумы. Следовательно, небольшие изменения во входных данных с меньшей вероятностью изменят прогнозируемые значения.