МИНОБРНАУКИ РОССИИ

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Кафедра КБ-4 «Интеллектуальные системы информационной безопасности»

Практическая работа №6 – лабораторная работа №4

по дисципилне

«Анализ зазищенности систем искусственного интеллекта»

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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
```

Зададим нормализующие преобразования, 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)
```

Настроим использование графического ускорителя.

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

Создадим класс НС на основе фреймворка torch.

```
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.Dropout(0.25)
    self.dropout2 = nn.Dropout(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.

```
model = Net().to(device)
```

Создадим оптимизатор, функцию потерь и трейнер сети.

```
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)
```

Определили функцию обучения сети.

```
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
```

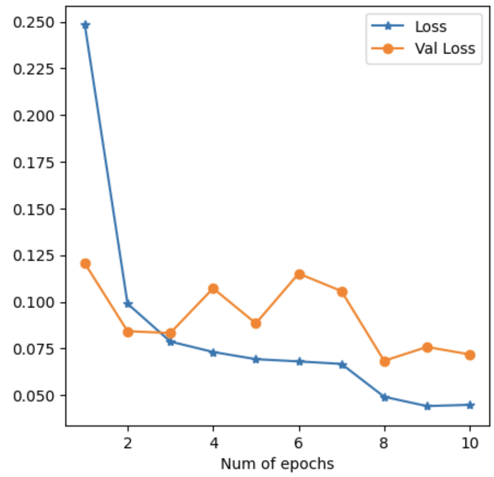
Обучим модель.

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

```
Fitting the model...
Epoch: 1 Loss: 0.24841752398738037 Val_Loss: 0.12061824470002139
Epoch: 2 Loss: 0.09896987803633864 Val_Loss: 0.08424650834364011
Epoch: 3 Loss: 0.07869950483775712 Val_Loss: 0.08328769305922769
Epoch: 4 Loss: 0.07311822975879405 Val_Loss: 0.10720105448503194
Epoch: 5 Loss: 0.06926371024317246 Val_Loss: 0.0884460765918882
Epoch: 6 Loss: 0.06806250782961033 Val_Loss: 0.11510764005056094
Epoch: 7 Loss: 0.06674116253729839 Val_Loss: 0.10574276480031856
Epoch: 8 Loss: 0.04912241660950879 Val_Loss: 0.0683882074708118
Epoch: 9 Loss: 0.044145967845800285 Val_Loss: 0.07580555725895 81
Epoch: 10 Loss: 0.044831771374373657 Val_Loss: 0.07181386937930914
```

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

```
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.

```
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
```

```
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
```

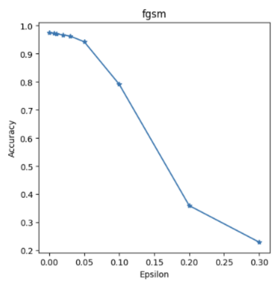
```
def mifgsm_attack(input,epsilon,data_grad):
  iter=10
  decay_factor=1.0
  pert_out = input
  alpha = epsilon/iter
  g=0
  for i in range(iter-1):
    g = decay_factor*g + data_grad/torch.norm(data_grad,p=1)
    pert_out = pert_out + alpha*torch.sign(g)
    pert_out = torch.clamp(pert_out, 0, 1)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

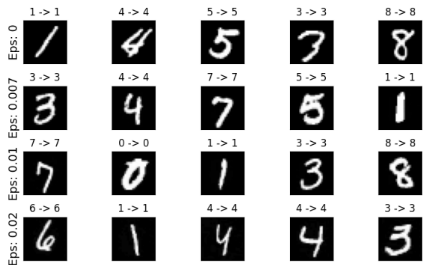
Создадим функцию проверки.

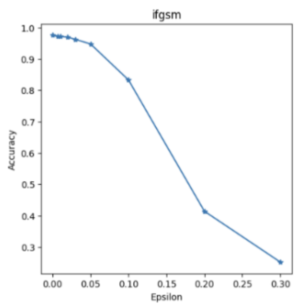
```
def test(model,device,test_loader,epsilon,attack):
  correct = 0
  adv_examples = []
  for data, target in test_loader:
    data, target = data.to(device), target.to(device)
    data.requires_grad = True
    output = model(data)
    init_pred = output.max(1, keepdim=True)[1]
    if init_pred.item() != 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
```

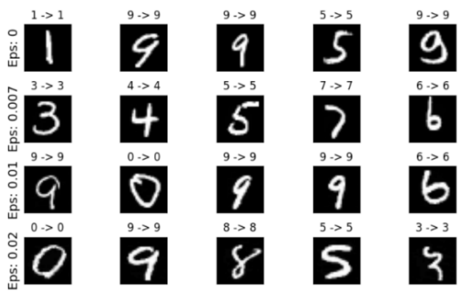
Построим графики успешности атак(Accuracy/эпсилон) и примеры выполненных атак в зависимости от степени возмущения epsilon.

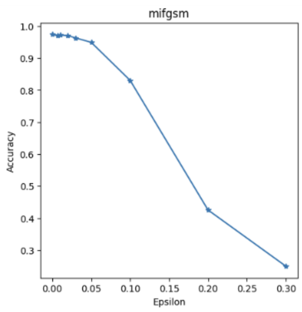
```
epsilons = [0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
for attack in ("fgsm","ifgsm","mifgsm"):
  accuracies = []
  examples = []
  for eps in epsilons:
    acc, ex = test(model, device,test_loader,eps,attack)
    accuracies.append(acc)
    examples.append(ex)
  plt.figure(figsize=(5,5))
  plt.plot(epsilons, 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()
```

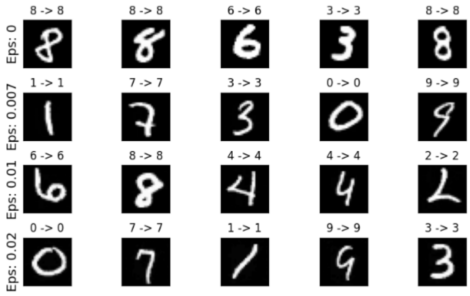












Создадим 2 класса НС.

```
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
```

```
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.

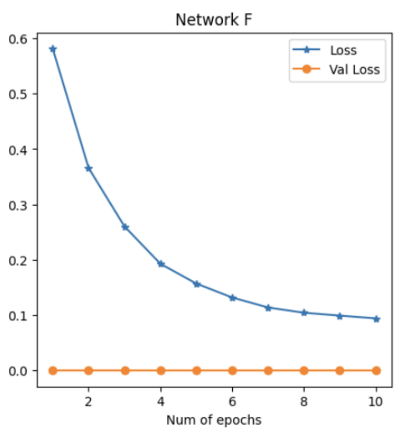
```
def fit(model,device,optimizer,scheduler,criterion,train_loader,val_loader,Temp,epochs):
  data_loader = {'train':train_loader,'val':val_loader}
  print("Fitting the model...")
  train_loss,val_loss=[],[]
  for epoch in range(epochs):
    loss_per_epoch,val_loss_per_epoch=0,0
    for phase in ('train','val'):
      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()
        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
```

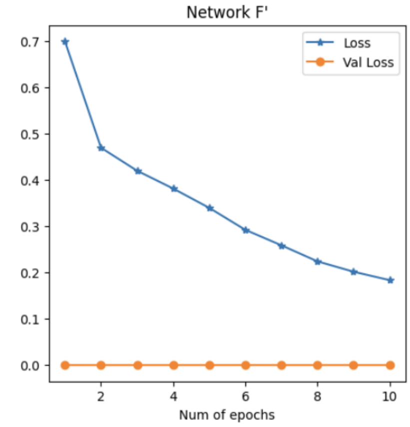
Создадим функцию защиты методом дистилляции.

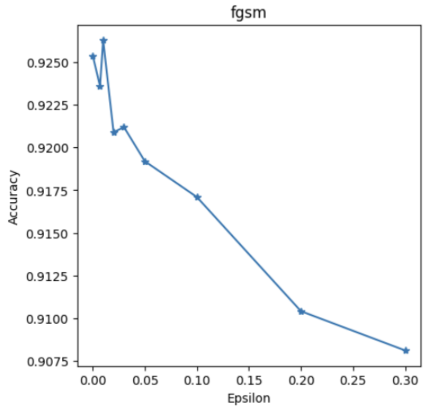
```python
def defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilons):
  modelF = NetF().to(device)
  optimizerF = optim.Adam(modelF.parameters(),lr=0.0001, betas=(0.9, 0.999))
  schedulerF = optim.lr_scheduler.ReduceLROnPlateau(optimizerF, mode='min', factor=0.1, patience=3)
  modelF1 = 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,1,"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()
  plt.show()
```

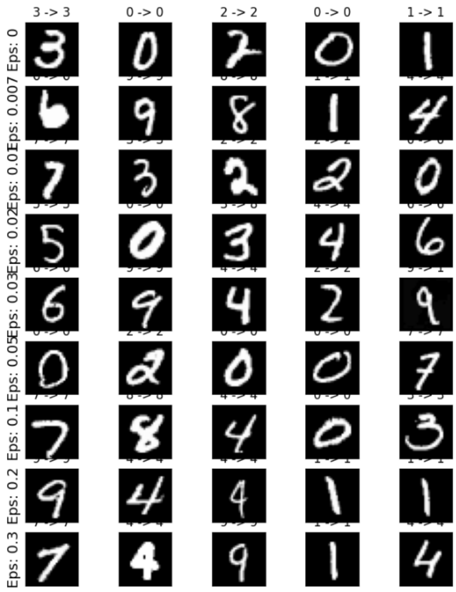
Получим результаты оценки защищенных сетей.

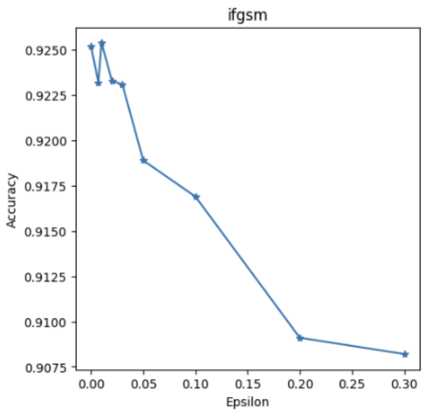
```python
Temp=100
epochs=10
epsilons=[0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
defense(device,train_loader,val_loader,test_loader,epochs,Temp,epsilons)
```

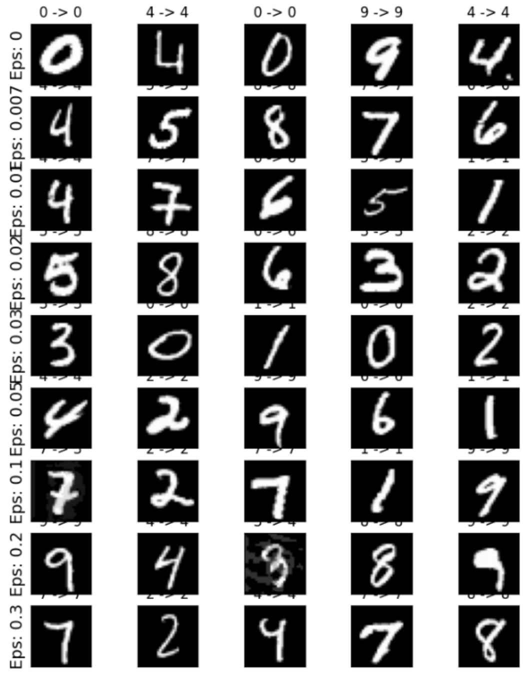


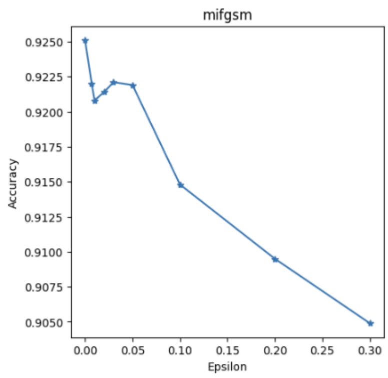

Network F'
Loss
Val Loss
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
2
4
6
8
10
Num of epochs

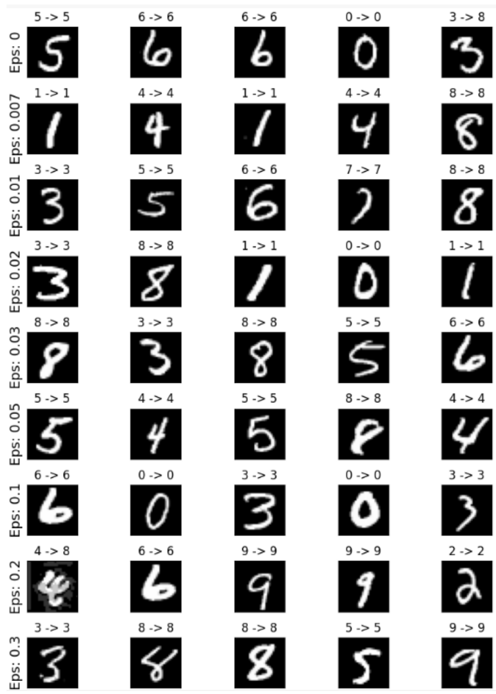

fgsm
Accuracy
0.9250
0.9225
0.9200
0.9175
0.9150
0.9125
0.9100
0.9075
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Epsilon


3 -> 3
0 -> 0
2 -> 2
0 -> 0
1 -> 1
Eps: 0
Eps: 0.007
Eps: 0.1
Eps: 0.2
Eps: 0.3


ifgsm
Accuracy
0.9250
0.9225
0.9200
0.9175
0.9150
0.9125
0.9100
0.9075
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Epsilon







Вывод: 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.

Итог по увеличению стойкости модели:

атака fgsm снизила точность не защищенных данных до - 14%, защищенных - до - 91%;

атака ifgsm снизила точность не защищенных данных до - 15%, защищенных - до - 91%;

атака mifgsm снизила точность не защищенных данных до - 15%, защищенных - до - 91%.

Модель, которая обучалась на метках учителя имеет большее значение потерь после обучения, но это невилируется стойкостью к атакам FGSM.