



**МИНОБРНАУКИ РОССИИ**  
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**РТУ МИРЭА**

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ИКБ направление «Киберразведка и противодействие угрозам с применением технологий искусственного интеллекта» 10.04.01

Кафедра КБ-4 «Интеллектуальные системы информационной безопасности»

**Практическая работа №6**

по дисциплине

«Анализ защищенности систем искусственного интеллекта»

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## 1. Выполнить 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
```

2. Задать нормализующие преобразования? загрузить набор данных (MNIST), разбить 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, 105207821.42it/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, 24275690.15it/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/MNIST/raw/t10k-images-idx3-ubyte.gz  
100%|██████████| 1648877/1648877 [00:00<00:00, 26633591.34it/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/MNIST/raw/t10k-labels-idx1-ubyte.gz  
100%|██████████| 4542/4542 [00:00<00:00, 18993548.12it/s]  
Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw

Training data: 50000 Validation data: 10000 Test data: 10000

## 3. Настроить использование графического ускорителя (если возможно)

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

#### 4. Создать 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.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
```

#### 5. Проверить работоспособность созданного класса НС

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

#### 6. Создать 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)
```

## 7. Определить 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
```

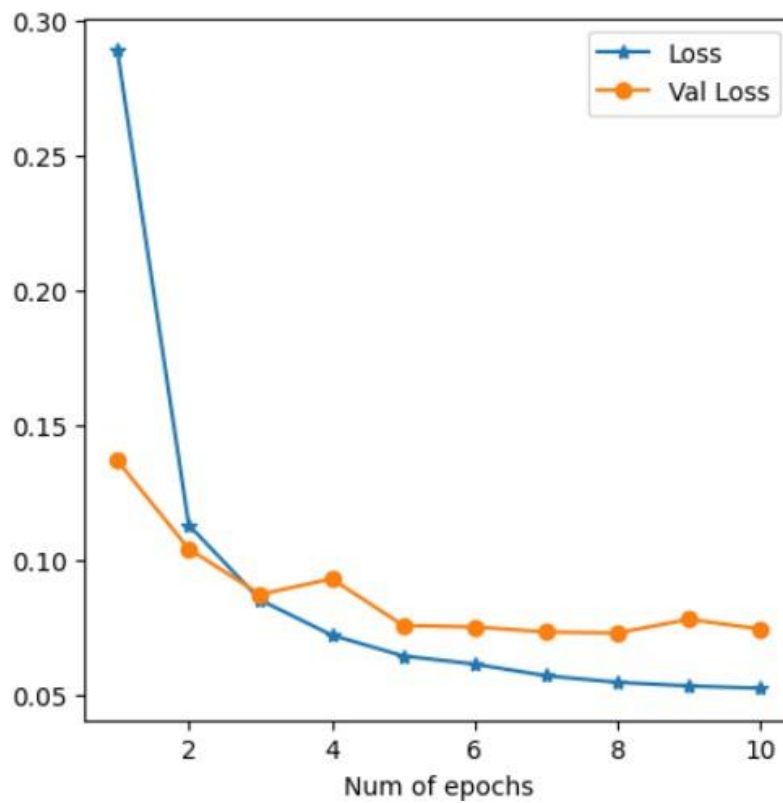
## 8. Обучить модель

```
[ ] 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: UserWarning: dropout2d: Received a 2-D input to dropout2d, which is deprecated and will result in an error in a future release. To retain
warnings.warn(warn_msg)
Epoch: 1 Loss: 0.2888022748806934 Val_Loss: 0.13686765499146245
Epoch: 2 Loss: 0.11297931097731007 Val_Loss: 0.10411850843998495
Epoch: 3 Loss: 0.0851646830555988 Val_Loss: 0.08724210682397247
Epoch: 4 Loss: 0.07216926405874084 Val_Loss: 0.09303551193967913
Epoch: 5 Loss: 0.06446179831371818 Val_Loss: 0.07576892791402166
Epoch: 6 Loss: 0.061423064131789176 Val_Loss: 0.07517019388235097
Epoch: 7 Loss: 0.05710774980605556 Val_Loss: 0.07333107345493659
Epoch: 8 Loss: 0.0546891696877841 Val_Loss: 0.07294204704767313
Epoch: 9 Loss: 0.0533269792951741 Val_Loss: 0.0780563005981545
Epoch: 10 Loss: 0.052500439544574236 Val_Loss: 0.07439602900140584
```

9. Построить 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()
```



## 10. Создать 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):  
    pert_out = input + epsilon*data_grad.sign()  
    pert_out = torch.clamp(pert_out, 0, 1)  
    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
```



## 11. Создать функцию проверки

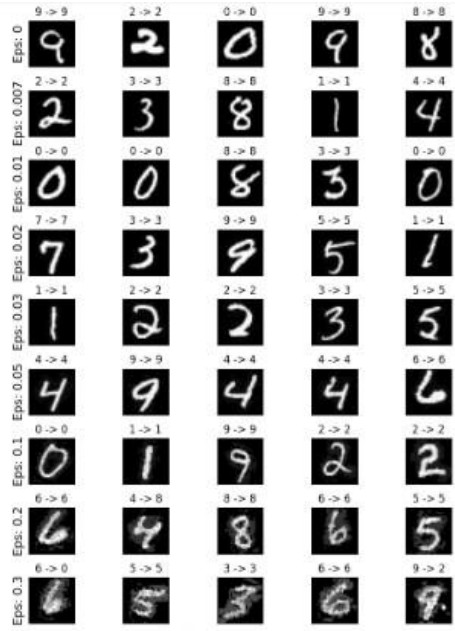
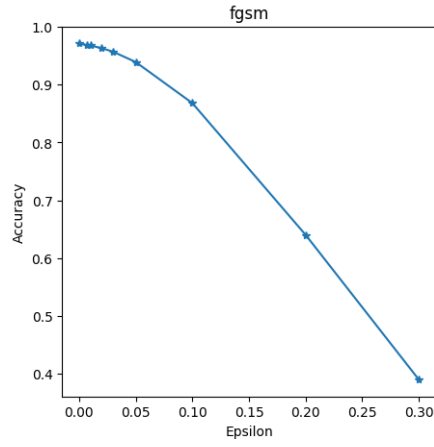
```
[ ] def test(model,device,test_loader,epsilon,attack):
    correct = 0
    adv_examples = []
    for data, target in test_loader:
        data, target = data.to(device), target.to(device)
        data.requires_grad = True
        output = model(data)
        init_pred = output.max(1, keepdim=True)[1]
        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: {} \t Test Accuracy = {} / {} = {}".format(epsilon, correct, len(test_loader), final_acc))
    return final_acc, adv_examples
```

## 12. Построить графики успешности атак (Ассигура/эпсилон) и примеры выполненных атак в зависимости от степени возмущения epsilon

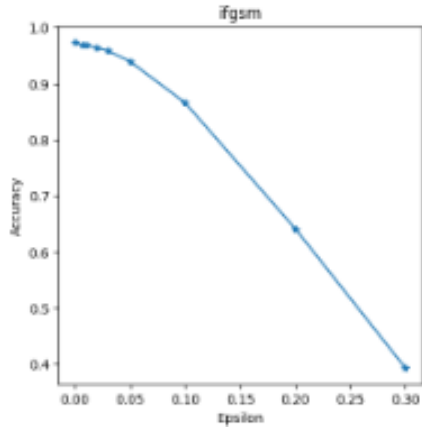
```
[ ] epsilons = [0,0.007,0.01,0.02,0.03,0.05,0.1,0.2,0.3]
for attack in ("fgsm","ifgsm","mifgsm"):
    accuracies = []
    examples = []
    for eps in epsilons:
        acc, ex = test(model, device, test_loader, eps, attack)
        accuracies.append(acc)
        examples.append(ex)
    plt.figure(figsize=(5,5))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

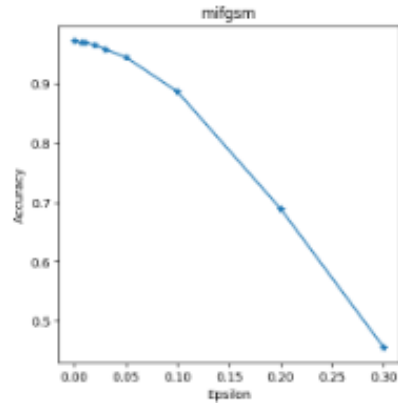
Epsilon: 0 Test Accuracy = 9715 / 10000 = 0.9715  
 Epsilon: 0.007 Test Accuracy = 9684 / 10000 = 0.9684  
 Epsilon: 0.01 Test Accuracy = 9678 / 10000 = 0.9678  
 Epsilon: 0.02 Test Accuracy = 9630 / 10000 = 0.963  
 Epsilon: 0.03 Test Accuracy = 9570 / 10000 = 0.957  
 Epsilon: 0.05 Test Accuracy = 9391 / 10000 = 0.9391  
 Epsilon: 0.1 Test Accuracy = 8681 / 10000 = 0.8681  
 Epsilon: 0.2 Test Accuracy = 6403 / 10000 = 0.6403  
 Epsilon: 0.3 Test Accuracy = 3900 / 10000 = 0.39



Epsilon: 0 Test Accuracy = 9734 / 10000 = 0.9734  
 Epsilon: 0.007 Test Accuracy = 9684 / 10000 = 0.9684  
 Epsilon: 0.01 Test Accuracy = 9683 / 10000 = 0.9683  
 Epsilon: 0.02 Test Accuracy = 9635 / 10000 = 0.9635  
 Epsilon: 0.03 Test Accuracy = 9581 / 10000 = 0.9581  
 Epsilon: 0.05 Test Accuracy = 9391 / 10000 = 0.9391  
 Epsilon: 0.1 Test Accuracy = 8657 / 10000 = 0.8657  
 Epsilon: 0.2 Test Accuracy = 6416 / 10000 = 0.6416  
 Epsilon: 0.3 Test Accuracy = 3936 / 10000 = 0.3936



Epsilon: 0 Test Accuracy = 9717 / 10000 = 0.9717  
 Epsilon: 0.007 Test Accuracy = 9688 / 10000 = 0.9688  
 Epsilon: 0.01 Test Accuracy = 9696 / 10000 = 0.9696  
 Epsilon: 0.02 Test Accuracy = 9643 / 10000 = 0.9643  
 Epsilon: 0.03 Test Accuracy = 9573 / 10000 = 0.9573  
 Epsilon: 0.05 Test Accuracy = 9440 / 10000 = 0.944  
 Epsilon: 0.1 Test Accuracy = 8860 / 10000 = 0.886  
 Epsilon: 0.2 Test Accuracy = 6891 / 10000 = 0.6891  
 Epsilon: 0.3 Test Accuracy = 4558 / 10000 = 0.4558





## 13. Создать 2 класса NC

```

class NetF(nn.Module):
    def __init__(self):
        super(NetF, self).__init__()
        self.conv1 = nn.Conv2d(1, 12, 3, 1)
        self.conv2 = nn.Conv2d(12, 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 NetFl(nn.Module):
    def __init__(self):
        super(NetFl, 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(4096, 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

```

```

| | 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 == "mitgsm":
| |             perturbed_data = mitgsm_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: {} \t Test Accuracy = {} / {} = {}".format(epsilon, correct, len(test_loader), final_acc))
| |     return final_acc, adv_examples

```

## 15. Создать 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()

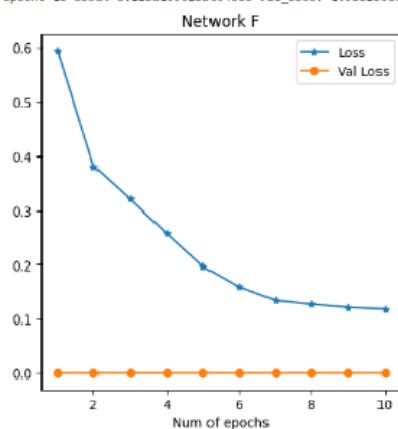
    cnt = 0
    plt.figure(figsize=(8,10))
    for i in range(len(epsilons)):
        for j in range(len(examples[i])):
            cnt += 1
            plt.subplot(len(epsilons),len(examples[0]),cnt)
            plt.xticks([], [])
            plt.yticks([], [])
            if j == 0:
                plt.ylabel("Eps: {}".format(epsilons[i]), fontsize=14)
            orig,adv,ex = examples[i][j]
            plt.title("{} -> {}".format(orig, adv))
            plt.imshow(ex, cmap="gray")
    plt.tight_layout()
    plt.show()
```

## 16. Получить результаты оценки защищенных сетей

```
[ ] 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)
```

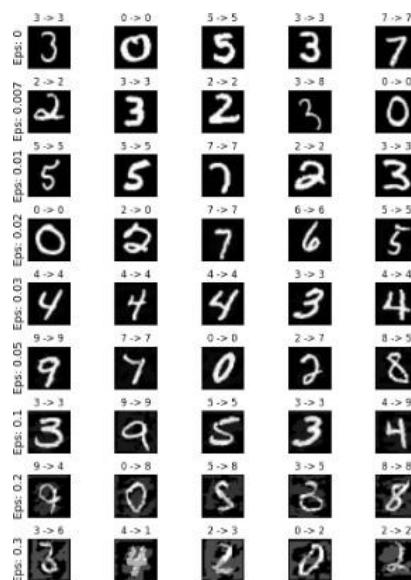
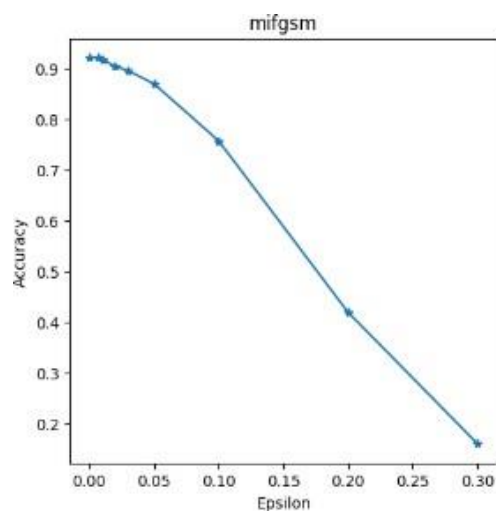
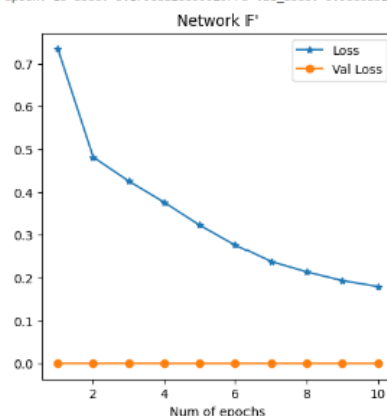
Fitting the model...

Epoch	Loss	Val_Loss
1	0.5942301008338612	6.0455070436000826e-05
2	0.38111651549537273	2.4114381754770875e-06
3	0.320571732473624	6.321442797780037e-05
4	0.2577987575996458	2.792829507961869e-06
5	0.19696446680835042	1.4604850858449936e-05
6	0.15930642053022293	7.717136144328833e-05
7	0.1342266594754222	2.9667984144180082e-05
8	0.12708058400267552	7.098467671312392e-07
9	0.1213777249197193	4.831489892676473e-05
10	0.11831995268594063	1.9881098924088291e-07



Fitting the model...

Epoch	Loss	Val_Loss
1	0.7341860436542259	7.3816833156161e-05
2	0.4814861043057221	3.793086782097816e-05
3	0.4257214840258858	8.835125323385001e-05
4	0.37636658081239927	6.181324065821245e-06
5	0.32302982872449076	1.2494549414259382e-05
6	0.2764673140686783	9.581387130310759e-07
7	0.23765527697519806	8.918157815060113e-07
8	0.21359191702052588	2.9410405620458126e-06
9	0.19335069339717906	9.855865697318223e-07
10	0.17966826599925775	9.933583205565811e-08



Вывод: применение защитной дистилляции обеспечивает безопасность и надежность нейронных сетей. Атаки на защищенные классы НС оказывают меньшее влияние в сравнении с атаками на незащищенную модель.