

МИНОБРНАУКИ РОССИИ

Федеральное государственное бюджетное образовательное учреждение

высшего образования

«МИРЭА – Российский технологический университет»

Институт кибербезопасности и цифровых технологий Кафедра КБ-4 «Интеллектуальные системы информационной безопасности»

Отчёт по лабораторной работе № 1

По дисциплине

«Анализ защищенности систем искусственного интеллекта»

Выполнил:

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Каждый фрагмент кода начинается с краткого комментария, описывающего процесс, в целях которого этот фрагмент и написан.

Вывод для каждого фрагмента кода для наглядности будет написан на сером фоне.

```
# Сначала скопируем проект по ссылке в локальную среду Google Colab !git
clone https://github.com/ewatson2/EEL6812 DeepFool Project.git
Cloning into 'EEL6812 DeepFool Project'...
remote: Enumerating objects: 96, done. remote:
Counting objects: 100% (3/3), done. remote:
Compressing objects: 100% (2/2), done.
remote: Total 96 (delta 2), reused 1 (delta 1), pack-reused 93 Receiving
objects: 100% (96/96), 33.99 MiB | 11.54 MiB/s, done. Resolving deltas:
100% (27/27), done.
# Меняем дирректорию исполнения на папку проекта
%cd /content/EEL6812 DeepFool Project
/content/EEL6812 DeepFool Project
# Импортируем необходимые библиотеки
import numpy as np import json,
from torch.utils.data import DataLoader, random split
from torchvision import datasets, models from
torchvision.transforms import transforms
# Импортируем вспомогательные библиотеки из файлов проекта
from models.project models import FC 500 150, LeNet CIFAR, LeNet MNIST,
from utils.project utils import get clip bounds, evaluate attack,
display attack
# Установим случайное рандомное значение в виде переменной
rand seed={"Порядковый номер ученика группы в Гугл-таблице"}, укажем
значение для np.random.seed и torch.manual seed rand seed = 22
np.random.seed(rand seed) torch.manual seed(rand seed)
<torch. C.Generator at 0x7ce54824a550>
# Используем в качестсве устройства видеокарту use cuda
= torch.cuda.is available()
device = torch.device('cuda' if use cuda else 'cpu')
# Загрузим датасет MNIST с параметрами mnist mean = 0.5, mnist std = 0.5,
mnist dim = 28 mnist mean = 0.5 mnist std = 0.5
mnist dim = 28
mnist min, mnist max =
get clip bounds (mnist mean,
mnist std,
mnist dim) mnist min = mnist min.to(device)
mnist max = mnist max.to(device)
```

```
mnist tf =
transforms.Compose([
transforms.ToTensor(),
transforms.Normalize(
mean=mnist mean,
std=mnist_std)])
mnist tf train = transforms.Compose([
transforms.RandomHorizontalFlip(),
transforms.ToTensor(),
transforms.Normalize(
mean=mnist mean,
std=mnist std)])
mnist tf inv = transforms.Compose([
transforms.Normalize(
mean=0.0,
        std=np.divide(1.0, mnist std)),
transforms.Normalize(
        mean=np.multiply(-1.0, mnist std),
std=1.0)])
mnist temp = datasets.MNIST(root='datasets/mnist', train=True,
download=True, transform=mnist_tf_train) mnist_train, mnist_val =
random split(mnist temp, [50000, 10000])
mnist test = datasets.MNIST(root='datasets/mnist',
train=False,
                                          download=True,
transform=mnist tf)
cifar classes = ['airplane', 'automobile', 'bird', 'cat', 'deer',
                 'dog', 'frog', 'horse', 'ship', 'truck']
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 da
tasets/mnist/MNIST/raw/train-images-idx3-ubyte.gz
100%| 9912422/9912422 [00:00<00:00, 122629555.19it/s]
Extracting datasets/mnist/MNIST/raw/train-images-idx3-ubyte.gz to datasets/mn
ist/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 da
tasets/mnist/MNIST/raw/train-labels-idx1-ubyte.gz
              | 28881/28881 [00:00<00:00, 39677593.78it/s]
Extracting datasets/mnist/MNIST/raw/train-labels-idx1-ubyte.gz to datasets/mn
ist/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.qz to dat
asets/mnist/MNIST/raw/t10k-images-idx3-ubyte.gz
        | 1648877/1648877 [00:00<00:00, 47687909.56it/s]
Extracting datasets/mnist/MNIST/raw/t10k-images-idx3-ubyte.gz to datasets/mni
st/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 dat
asets/mnist/MNIST/raw/t10k-labels-idx1-ubyte.gz
       4542/4542 [00:00<00:00, 19012503.76it/s]
Extracting datasets/mnist/MNIST/raw/t10k-labels-idx1-ubyte.gz to datasets/mni
st/MNIST/raw
# Загрузим датасет CIFAR-10 с параметрами cifar mean = [0.491, 0.482,
```

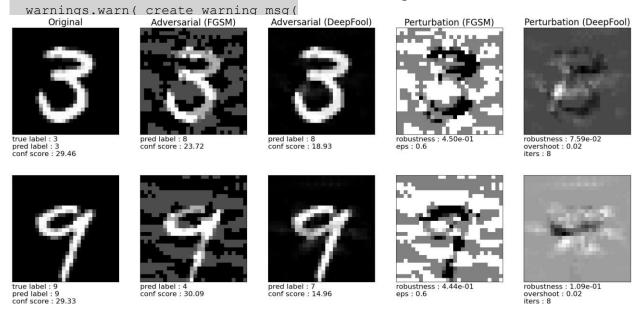
```
0.447] cifar std = [0.202, 0.199, 0.201] cifar dim = 32
cifar mean = [0.491, 0.482, 0.447] cifar std = [0.202,
0.199, 0.201] cifar dim = 32
cifar min,
                         cifar max
get clip bounds (cifar mean,
cifar std,
                                        cifar dim)
cifar min = cifar min.to(device) cifar max
cifar max.to(device)
cifar tf =
transforms.Compose([
transforms.ToTensor(),
transforms.Normalize(
mean=cifar mean,
std=cifar std)])
cifar tf train = transforms.Compose([
transforms.RandomCrop(
size=cifar dim,
                       padding=4),
    transforms.RandomHorizontalFlip(),
transforms.ToTensor(),
transforms.Normalize(
mean=cifar mean,
                        std=cifar std)])
cifar tf inv = transforms.Compose([
transforms.Normalize(
mean=[0.0, 0.0, 0.0],
std=np.divide(1.0, cifar std)),
transforms.Normalize(
        mean=np.multiply(-1.0, cifar mean),
std=[1.0, 1.0, 1.0])
cifar temp = datasets.CIFAR10(root='datasets/cifar-10', train=True,
download=True, transform=cifar_tf_train) cifar_train, cifar_val =
random split(cifar temp, [40000, 10000])
cifar test = datasets.CIFAR10(root='datasets/cifar-10',
train=False,
                                           download=True,
transform=cifar tf)
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to datase
ts/cifar-10/cifar-10-python.tar.gz
              | 170498071/170498071 [00:03<00:00, 43315076.71it/s]
Extracting datasets/cifar-10/cifar-10-python.tar.gz to datasets/cifar-10
Files already downloaded and verified
# Выполним настройку и загрузку DataLoader batch size = 64 workers = 4
batch size = 64 workers = 4
mnist loader train = DataLoader (mnist train, batch size=batch size,
shuffle=True, num workers=workers)
                                           mnist loader val
                                            batch size=batch size,
DataLoader (mnist val,
                                            mnist loader test =
shuffle=False, num workers=workers)
DataLoader (mnist test,
                                            batch size=batch size,
shuffle=False, num_workers=workers)
cifar_loader_train = DataLoader(cifar_train, batch_size=batch_size,
                                         cifar loader_val
shuffle=True, num workers=workers)
DataLoader(cifar val,
                                            batch size=batch size,
shuffle=False,
               num workers=workers)
                                           cifar loader test =
DataLoader(cifar test,
                                            batch size=batch size,
shuffle=False, num workers=workers)
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: U
serWarning: This DataLoader will create 4 worker processes in total. Our sugg
ested max number of worker in current system is 2, which is smaller than what
this DataLoader is going to create. Please be aware that excessive worker cre
```

```
ation might get DataLoader running slow or even freeze, lower the worker numb
er to avoid potential slowness/freeze if necessary.
 warnings.warn( create warning msg(
import os
train model = True
epochs = 50
epochs nin = 100
lr = 0.004
lr nin = 0.01
lr scale = 0.5
momentum = 0.9
print step = 5
deep batch size = 64
deep num classes = 10
deep overshoot = 0.02
deep max iters = 50
deep_args = [deep_batch_size,
deep num classes,
                               deep overshoot,
deep_max_iters]
if not
os.path.isdir('weights/deepfool'):
    os.makedirs('weights/deepfool', exist ok=True)
 if not
os.path.isdir('weights/fgsm'):
    os.makedirs('weights/fgsm', exist ok=True)
# Загрузим и оценим стойкость модели Network-In-Network Model к FGSM и
DeepFool атакам на основе датасета CIFAR-10 fgsm eps
= 0.6
model = LeNet MNIST().to(device)
model.load state dict(torch.load('weights/clean/mnist lenet.pth', map locat
ion=torch.device('cpu')))
evaluate_attack('mnist lenet fgsm.csv',
                'results', device, model, mnist loader test,
mnist min, mnist max,fgsm eps, is fgsm=True) print('')
evaluate attack('mnist lenet deepfool.csv', 'results', device, model,
mnist loader test, mnist min, mnist max, deep args, is fgsm=False) if
device.type == 'cuda': torch.cuda.empty_cache()
FGSM Test Error: 87.89%
FGSM Robustness: 4.58e-01
FGSM Time (All Images) : 0.29 s
FGSM Time (Per Image) : 28.86 us
DeepFool Test Error: 98.74%
DeepFool Robustness: 9.64e-02
DeepFool Time (All Images): 193.32 s
DeepFool Time (Per Image): 19.33 ms
# Загрузим и оценим стойкость модели LeNet к FGSM и DeepFool атакам на
основе датасета CIFAR-10 fgsm eps = 0.2
model = FC 500 150().to(device)
model.load state dict(torch.load('weights/clean/mnist fc.pth',
map location=torch.device('cpu')))
```

```
evaluate attack('mnist fc fgsm.csv', 'results', device, model,
mnist loader test, mnist min, mnist max, fgsm eps, is fgsm=True)
print('') evaluate attack('mnist fc deepfool.csv', 'results',
device, model, mnist loader test, mnist min, mnist max, deep args,
is fgsm=False) if device.type == 'cuda': torch.cuda.empty cache()
FGSM Test Error: 87.08%
FGSM Robustness: 1.56e-01
FGSM Time (All Images): 0.15 s
FGSM Time (Per Image): 14.99 us
DeepFool Test Error: 97.92%
DeepFool Robustness: 6.78e-02
DeepFool Time (All Images) : 141.81 s
DeepFool Time (Per Image) : 14.18 ms
# Загрузим и оценим стойкость модели LeNet к FGSM и DeepFool атакам на
основе датасета CIFAR-10 fgsm eps = 0.1
model = LeNet CIFAR().to(device)
model.load state dict(torch.load('weights/clean/cifar lenet.pth',
map location=torch.device('cpu')))
evaluate attack('cifar lenet fgsm.csv', 'results', device,
model, cifar loader test, cifar min, cifar max, fgsm eps,
is_fgsm=True) print('')
evaluate_attack('cifar_lenet_deepfool.csv', 'results', device, model,
cifar loader test, cifar min, cifar max, deep args, is fgsm=False)
if device.type == 'cuda':
torch.cuda.empty cache()
FGSM Test Error: 91.71%
FGSM Robustness: 8.90e-02
FGSM Time (All Images): 0.40 s
FGSM Time (Per Image): 40.08 us
DeepFool Test Error: 87.81%
DeepFool Robustness: 1.78e-02
DeepFool Time (All Images): 73.27 s
DeepFool Time (Per Image) : 7.33 ms
```

Выполним оценку атакующих примеров для сетей

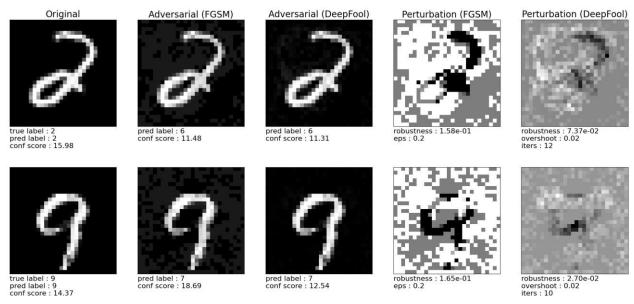
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: U serWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.



FCNet на датасете MNIST fgsm_eps = 0.2 model = FC_500_150().to(device) model.load_state_dict(torch.load('weights/clean/mnist_fc.pth')) display_attack(device, model, mnist_test, mnist_tf_inv, mnist_min, mnist_max, fgsm_eps, deep_args, has_labels=False, 12_norm=True, pert_scale=1.0, fig_rows=2, fig_width=25,

if device.type == 'cuda': torch.cuda.empty cache()

fig height=11)

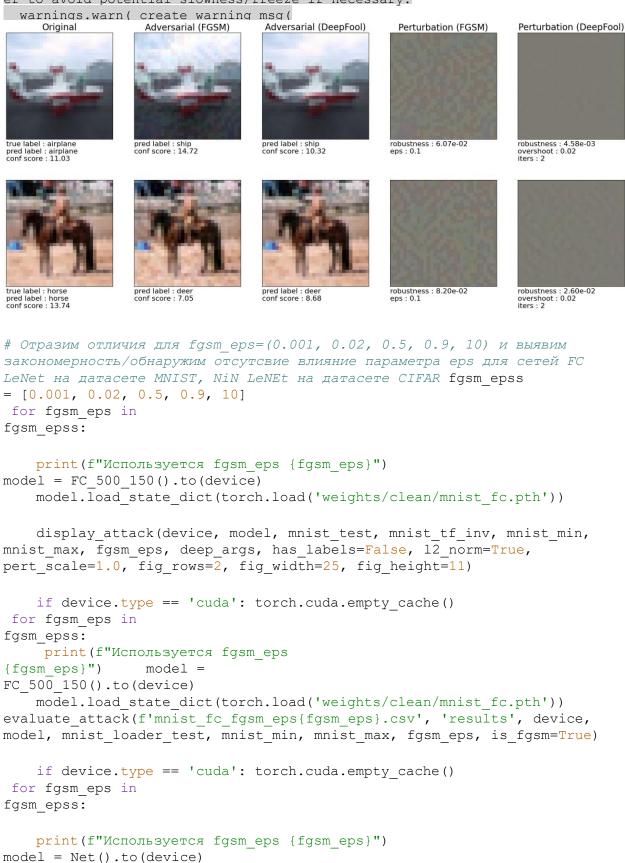


```
fgsm eps = 0.2 model =
Net().to(device)
model.load_state_dict(torch.load('weights/clean/cifar nin.pth'))
 display_attack(device, model, cifar_test, cifar_tf_inv,
cifar min, cifar max, fgsm eps, deep args, has labels=False,
12 norm=True, pert scale=1.0, fig rows=2, fig width=25,
fig height=11, label map=cifar classes)
if device.type == 'cuda': torch.cuda.empty cache()
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: U
serWarning: This DataLoader will create 4 worker processes in total. Our sugg
ested max number of worker in current system is 2, which is smaller than what
this DataLoader is going to create. Please be aware that excessive worker cre
ation might get DataLoader running slow or even freeze, lower the worker numb
er to avoid potential slowness/freeze if necessary.
  warnings.warn( create warning msg(
                                        Adversarial (DeepFool)
                                                             Perturbation (FGSM)
                                                                                Perturbation (DeepFool)
                      Adversarial (FGSM)
      Original
true label : horse
pred label : horse
conf score : 36.05
                                                                                robustness : 2.28e-02
overshoot : 0.02
iters : 2
                                                            robustness: 1.84e-01
eps: 0.2
                    pred label : dog
conf score : 22.90
                                        pred label : dog
conf score : 28.38
                                                                                robustness : 2.17e-02
overshoot : 0.02
iters : 2
```

Network-in-Network на датасете CIFAR

LeNet Ha Matacete CIFAR fgsm_eps = 0.1 model = LeNet_CIFAR().to(device) model.load_state_dict(torch.load('weights/clean/cifar_lenet.pth')) display_attack(device, model, cifar_test, cifar_tf_inv, cifar_min, cifar_max, fgsm_eps, deep_args, has_labels=False, 12_norm=True, pert_scale=1.0, fig_rows=2, fig_width=25, fig_height=11, label_map=cifar_classes) if device.type == 'cuda': torch.cuda.empty cache()

/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: U serWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.



model.load state dict(torch.load('weights/clean/cifar nin.pth'))

```
display_attack(device, model, cifar_test, cifar_tf_inv,
cifar_min, cifar_max, fgsm_eps, deep_args, has_labels=False,
l2_norm=True, pert_scale=1.0, fig_rows=2, fig_width=25, fig_height=11,
label_map=cifar_classes)

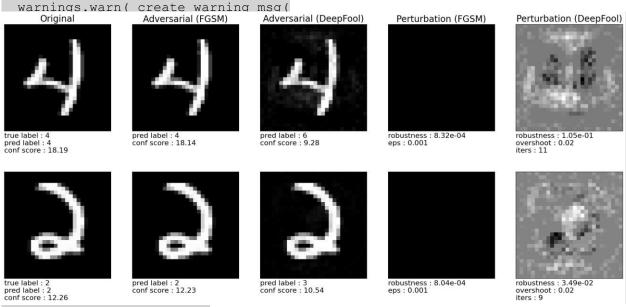
if device.type == 'cuda': torch.cuda.empty_cache()
for fgsm_eps in
fgsm_epss:

print(f"Используется fgsm_eps {fgsm_eps}")
model = Net().to(device)
   model.load_state_dict(torch.load('weights/clean/cifar_nin.pth'))
   evaluate_attack(f'cifar_nin_fgsm_eps{fgsm_eps}.csv',
'results', device, model, cifar_loader_test, cifar_min, cifar_max,
fgsm_eps, is_fgsm=True)

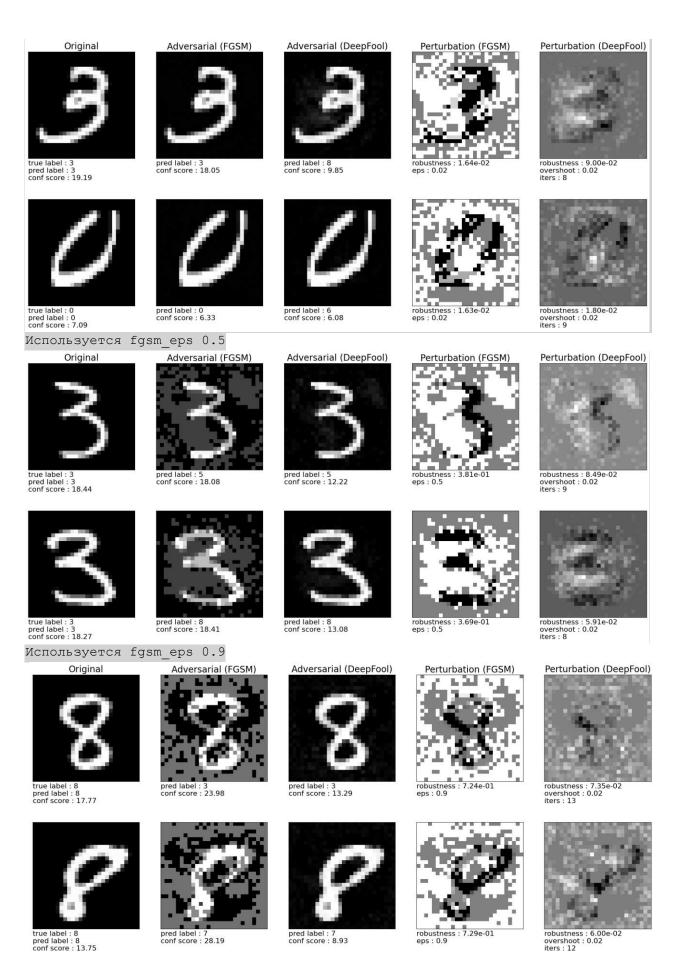
if device.type == 'cuda': torch.cuda.empty cache()
```

Используется fgsm eps 0.001

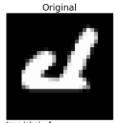
/usr/local/lib/pvthon3.10/dist-packages/torch/utils/data/dataloader.pv:557: U serWarning: This DataLoader will create 4 worker processes in total. Our suggested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker creation might get DataLoader running slow or even freeze, lower the worker number to avoid potential slowness/freeze if necessary.



Используется fgsm eps 0.02



Используется fgsm eps 10

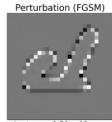


true label : 4 pred label : 4 conf score : 17.02

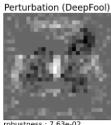




pred label : 6 conf score : 11.74



robustness : 1.50e+00 eps : 10



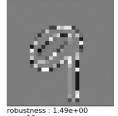
robustness : 7.63e-02 overshoot : 0.02 iters : 11



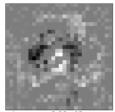




pred label : 3 conf score : 8.28



robustness: 1.49e+00 eps: 10



robustness : 3.98e-02 overshoot : 0.02 iters : 10

Используется fgsm_eps 0.001

FGSM Test Error: 3.07% FGSM Robustness: 8.08e-04

FGSM Time (All Images): 0.72 s

FGSM Time (Per Image) : 72.00 us

Используется $fgsm_eps 0.02$

FGSM Test Error: 5.54%

FGSM Robustness: 1.60e-02

FGSM Time (All Images): 0.54 s

FGSM Time (Per Image) : 53.68 us

Используется fgsm eps 0.5

FGSM Test Error: 99.21%

FGSM Robustness: 3.86e-01

FGSM Time (All Images): 0.56 s

FGSM Time (Per Image) : 56.40 us

Используется fgsm eps 0.9

FGSM Test Error: 99.87%

FGSM Robustness: 6.86e-01

FGSM Time (All Images): 0.60 s

FGSM Time (Per Image) : 60.29 us

Используется fgsm eps 10

FGSM Test Error: 99.87%

FGSM Robustness : 1.47e+00

FGSM Time (All Images): 0.55 s

FGSM Time (Per Image) : 55.18 us

Используется fgsm eps 0.001

/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: U serWarning: This DataLoader will create 4 worker processes in total. Our sugg ested max number of worker in current system is 2, which is smaller than what this DataLoader is going to create. Please be aware that excessive worker cre ation might get DataLoader running slow or even freeze, lower the worker numb er to avoid potential slowness/freeze if necessary.

warnings.warn(create warning msg(















true label : truck pred label : truck conf score : 58.46

pred label : truck conf score : 58.73

pred label : automobile conf score : 34.72

robustness: 7.67e-04 eps: 0.001

robustness : 5.45e-02 overshoot : 0.02 iters : 4

Используется fasm eps 0.02 Adversarial (FGSM)

Original

Adversarial (DeepFool)

Perturbation (FGSM) robustness: 1.89e-02 eps: 0.02



true label : automobile pred label : automobile conf score : 44.48







pred label : deer conf score : 45.05

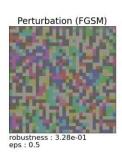
pred label : horse conf score : 43.39

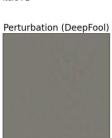
robustness: 1.92e-02 eps: 0.02

robustness : 2.38e-02 overshoot : 0.02 iters : 2

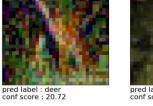








true label : frog pred label : frog conf score : 25.01



pred label : deer conf score : 19.51

robustness : 9.53e-03 overshoot : 0.02 iters : 2







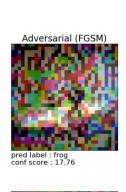
robustness: 3.05e-01 eps: 0.5

true label : truck pred label : truck conf score : 37.62

robustness: 1.50e-02 overshoot: 0.02 iters: 3

Используется fgsm eps 0.9







Perturbation (FGSM)







true label : bird pred label : bird conf score : 26.85

pred label : deer conf score : 20.08

robustness : 2.00e-02 overshoot : 0.02 iters : 2 robustness: 8.14e-01 eps: 0.9



Adversarial (DeepFool) pred label : ship conf score : 23.05

robustness: 2.94e+00 eps: 10

Perturbation (FGSM)

Perturbation (DeepFool)

true label : ship pred label : airplane conf score : 25.37









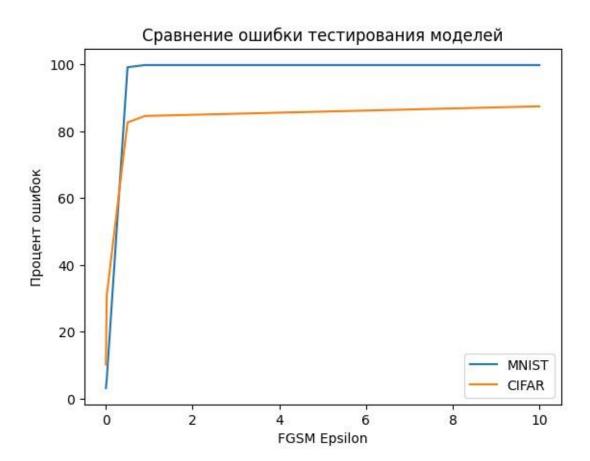
robustness : 3.94e-02 overshoot : 0.02 iters : 5

Используется fasm eps 0.001 FGSM Test Error: 10.12% FGSM Robustness: 8.92e-04 FGSM Time (All Images) : 1.09 s FGSM Time (Per Image): 108.82 us Используется fgsm eps 0.02 FGSM Test Error: 30.76% FGSM Robustness: 1.78e-02 FGSM Time (All Images): 1.31 s FGSM Time (Per Image): 131.25 us Используется fasm eps 0.5 FGSM Test Error: 82.65% FGSM Robustness: 4.40e-01 FGSM Time (All Images): 1.12 s FGSM Time (Per Image) : 112.16 us Используется fgsm eps 0.9 FGSM Test Error: 84.60%

FGSM Robustness: 7.79e-01 FGSM Time (All Images) : 1.16 s FGSM Time (Per Image): 116.42 us Используется fgsm eps 10 FGSM Test Error: 87.53% FGSM Robustness : 2.46e+00 FGSM Time (All Images): 1.15 s

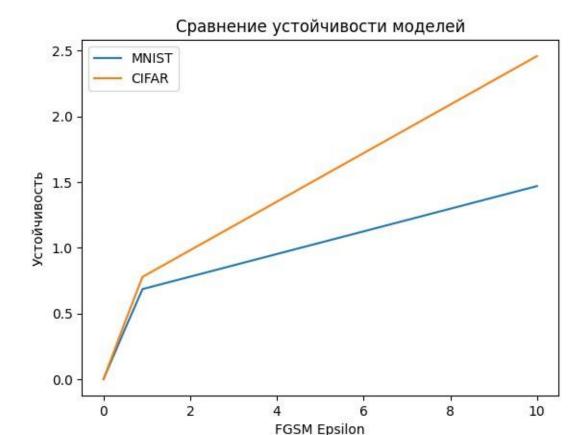
```
import matplotlib.pyplot as plt
```

```
fgsm_eps = [0.001, 0.02, 0.5, 0.9, 10]
fgsm_test_error_MNIST = [3.07, 5.54, 99.21, 99.87, 99.87]
fgsm_robustness_MNIST = [8.08e-04, 1.60e-02, 3.86e-01, 6.86e-01, 1.47e+00]
fgsm_test_error_CIFAR = [10.12, 30.76, 82.67, 84.62, 87.50]
fgsm_robustness_CIFAR = [8.92e-04, 1.78e-02, 4.40e-01, 7.79e-01, 2.46e+00]
plt.plot(fgsm_eps, fgsm_test_error_MNIST,
label='MNIST') plt.plot(fgsm_eps, fgsm_test_error_CIFAR,
label='CIFAR')
plt.xlabel('FGSM Epsilon')
plt.ylabel('Процент ошибок')
plt.title('Сравнение ошибки тестирования моделей')
plt.legend()
plt.show()
```



In [24]:

```
plt.plot(fgsm_eps, fgsm_robustness_MNIST, label='MNIST')
plt.plot(fgsm_eps, fgsm_robustness_CIFAR, label='CIFAR')
plt.xlabel('FGSM
Epsilon')
plt.ylabel('Устойчивость')
plt.title('Сравнение устойчивости моделей') plt.legend()
plt.show()
```



По картинкам понятно что от параметра fgsm_eps зависит степень шума. Параметр fgsm_eps имеет значительное влияние на производительность модели и ее устойчивость к атакам.

При увеличении значения fgsm_eps увеличивается ошибка тестирования модели, что указывает на снижение ее производительности.

В то же время, устойчивость модели также увеличивается с увеличением fgsm_eps, что указывает на то, что модель становится менее устойчивой к атакам. Это означает, что модель более подвержена ошибкам при обработке входных данных, которые были зашумлены.

Время вычислений не показывает последовательной тенденции с увеличением fgsm_eps. Это говорит о том, что величина возмущений не оказывает существенного влияния на время обработки изображений.