Лабортаторная работа №7

По курсу "нейроинформатика"

студент: Гаврилов М.С.
группа: М8О-406Б-19

Цель работы:

Исследование свойств автоэнкодеров

In [1]:
```
import numpy as np
import pylab
import copy
import sklearn as skl

import torch
import torch.nn as nn
from tqdm import tqdm

import matplotlib.pyplot as plt
import numpy as np
```

In [2]:
```
import torch
import torchvision
import torchvision.transforms as transforms
```

Загрузка cifar-10 и формирование датасета из одного класса

In [3]:
```
def imshow(img):
    img = img / 2 + 0.5
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()

def normalize(img):
    res = copy.deepcopy(img)
    for i in range(len(img)):
        res[i] = img[i] / img[i].abs().max()
    return res

def print_imgs(dataloader,cnt,net = None):
    imgs = next(iter(dataloader))
    imshow(torchvision.utils.make_grid(
        normalize(imgs.reshape([imgs.shape[0]] + list(imgs.shape[2:]))[0:cnt].detach())
    ))

    if(net != None):
        imshow(torchvision.utils.make_grid(
            normalize(net(imgs).reshape([imgs.shape[0]] + list(imgs.shape[2:]))[0:cnt].d
        ))
```

In [4]:
```
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

cifarset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                        download=True, transform=transform)
cifarloader = torch.utils.data.DataLoader(cifarset, batch_size=1,
                                          shuffle=True, num_workers=2)


classes = ('plane', 'car', 'bird', 'cat',
           'deer', 'dog', 'frog', 'horse', 'ship', 'truck')
```

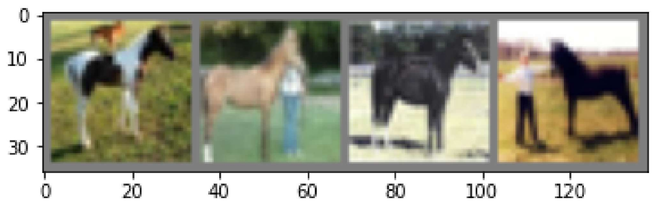
```
Files already downloaded and verified
```

In [5]:
```
class_to_extract = 7

single_class_set = []
for data,label in tqdm(cifarloader):
    if label[0] == class_to_extract:
        single_class_set.append(data)
sc_loader = torch.utils.data.DataLoader(single_class_set, batch_size=64,
                                          shuffle=True, num_workers=2)
```

```
100%|██████████| 5000
0/50000 [01:10<00:00, 706.68it/s]
```

Пример изображений выбранного класса

In [252]:
```
print_imgs(sc_loader,4)
```



Класс автоэнкодера

Две ступени, латентне пространство размером 512

In [82]:
```
class Autoencoder(torch.nn.Module):
    def __init__(self,linear_size):
        super(Autoencoder,self).__init__()

        self.EDN = torch.nn.Sequential(
        torch.nn.Linear(linear_size,1024),
        torch.nn.Linear(1024,512),
        torch.nn.Linear(512,1024),
        torch.nn.Linear(1024,linear_size))

    def forward(self,x):
        im_shape = x.shape
        x = x.flatten(1)
        res = self.EDN(x).reshape(im_shape)
        return res
```

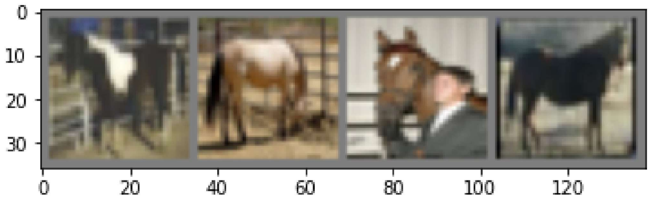
Функция оучения

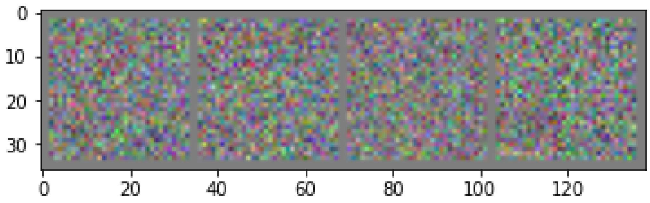
In [83]:
```
def train(model,dataloader,n_epochs,lr,
          optimiser = torch.optim.Adam,
          criterion = torch.nn.MSELoss()
          ):

    optim = optimiser(model.parameters(),lr=lr)

    arr = []
    for i in tqdm(range(n_epochs)):
        for elm in dataloader:
            optim.zero_grad()
            loss = ((model(elm) - elm)**2).sum()
            loss.backward()
            optim.step()

        arr.append([i,
                    loss.detach().numpy(),
                   ])

    return np.array(arr)
```

Построение и обучение первой сети

In [84]:
```
tst_net = Autoencoder(single_class_set[0].flatten().shape[0])
```

In [85]:
```
print_imgs(sc_loader,4,tst_net)
```

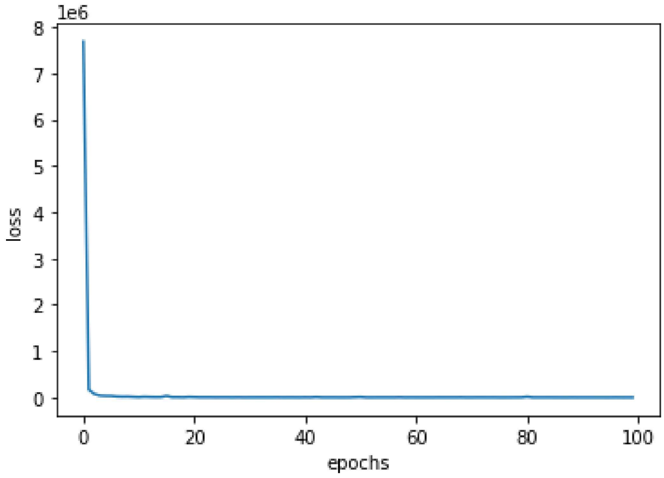




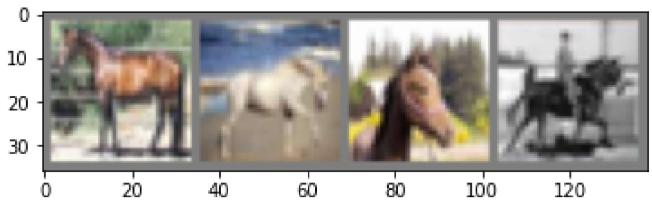
In [86]:
```
arr = train(tst_net,sc_loader,100,0.01)
```

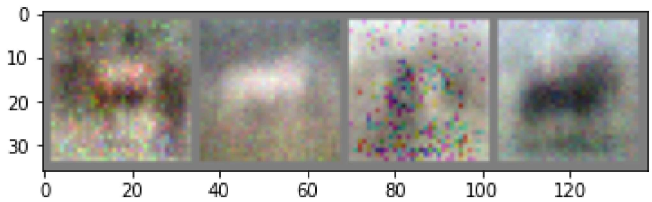
```
100%|██████████████████████████████████████████████████|
100/100 [33:49<00:00, 20.30s/it]
```

In [87]:
```
pylab.ylabel("loss")
pylab.xlabel("epochs")
pylab.plot(arr[:,0],arr[:,1])
pylab.show()
```

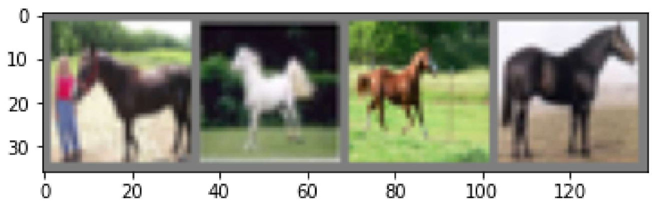


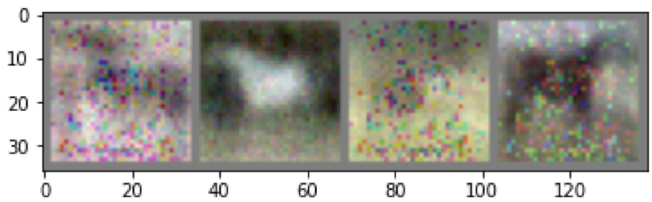
In [88]:
```
print_imgs(sc_loader,4,tst_net)
```



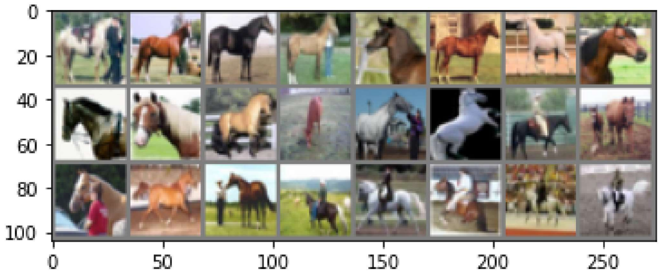


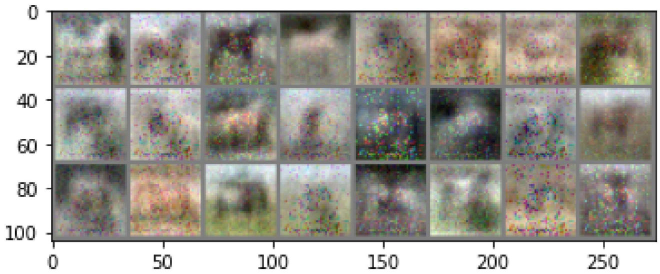
In [90]:
```
print_imgs(sc_loader,4,tst_net)
```





In [89]:
```
print_imgs(sc_loader,24,tst_net)
```





Более простой автоэнкодер

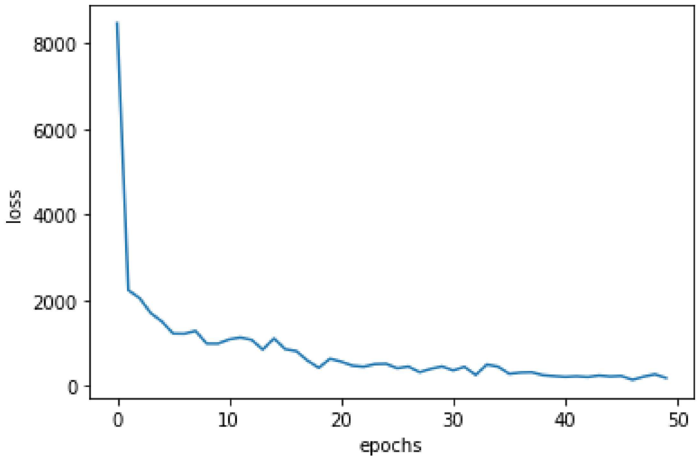
In [8]:
```
class Autoencoder(torch.nn.Module):
    def __init__(self,linear_size):
        super(Autoencoder,self).__init__()

        self.EDN = torch.nn.Sequential(
        torch.nn.Linear(linear_size,1024),
        torch.nn.Linear(1024,linear_size))

    def forward(self,x):
        im_shape = x.shape
        x = x.flatten(1)
        res = self.EDN(x).reshape(im_shape)
        return res
```

In [9]:
```
repl_net = Autoencoder(single_class_set[0].flatten().shape[0])
```

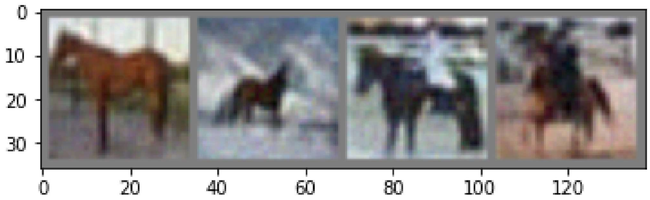
In [13]:
```
arr = train(repl_net,sc_loader,50,0.01)
```

```
100%|
| 50/50 [11:34<00:00, 13.89s/it]
```

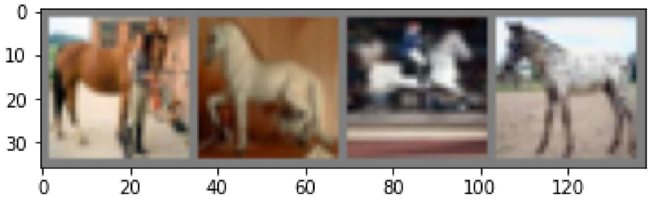
In [14]:
```
pylab.ylabel("loss")
pylab.xlabel("epochs")
pylab.plot(arr[:,0],arr[:,1])
pylab.show()
```

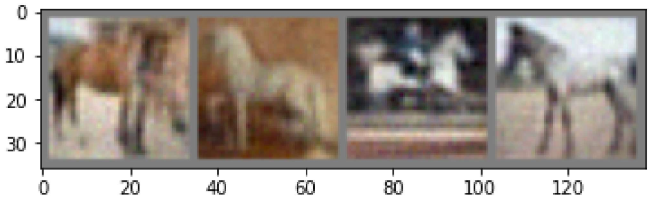


In [15]:
```
print_imgs(sc_loader,4,repl_net)
```

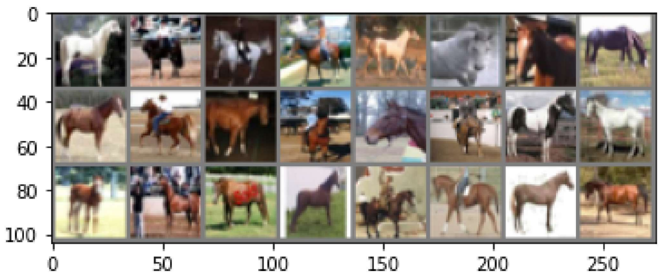


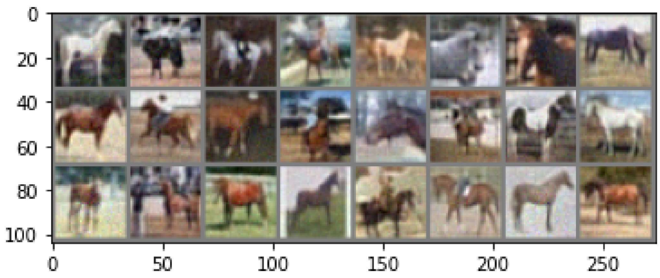
In [16]:
```
print_imgs(sc_loader,4,repl_net)
```





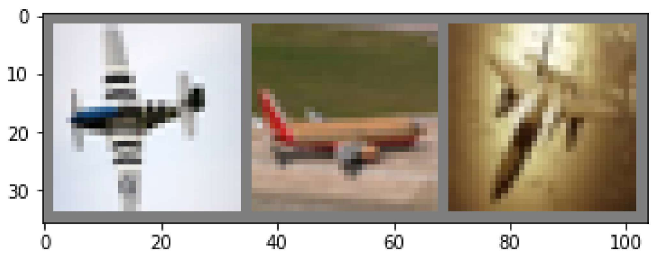
In [17]:
```
print_imgs(sc_loader,24,repl_net)
```



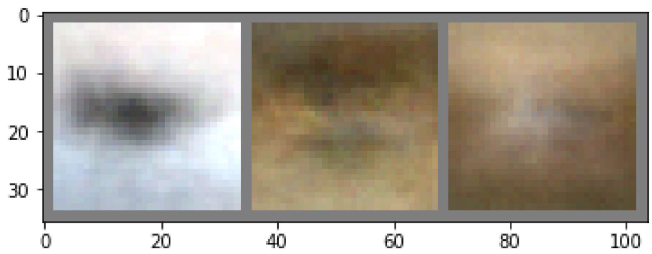


Примеры интересных результатов

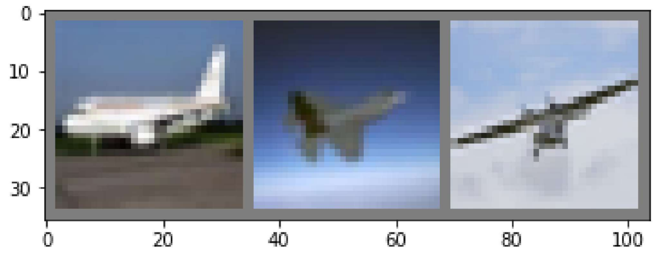
In [145]:
```
imgs = next(iter(scd_loader))
imshow(torchvision.utils.make_grid(
    imgs.reshape([imgs.shape[0]] + list(imgs.shape[2:]))[0:3]
).detach())
imshow(torchvision.utils.make_grid(
    tst_net(imgs).reshape([imgs.shape[0]] + list(imgs.shape[2:]))[0:3]
).detach())
```



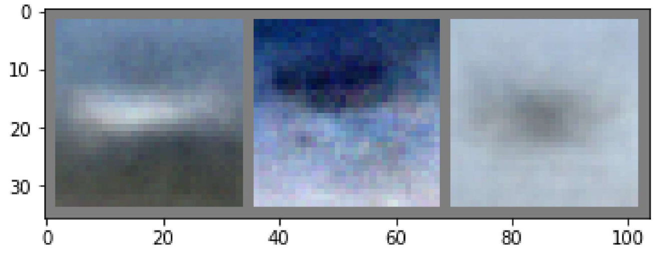
```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or
[0..255] for integers).
```



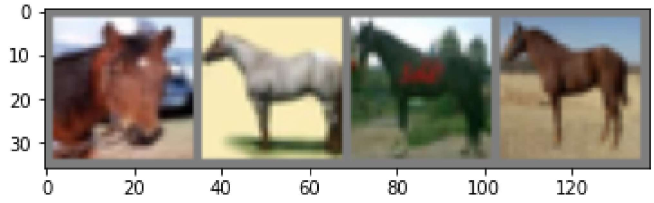
In [148]:
```
imgs = next(iter(scd_loader))
imshow(torchvision.utils.make_grid(
    imgs.reshape([imgs.shape[0]] + list(imgs.shape[2:]))[0:3]
).detach())
imshow(torchvision.utils.make_grid(
    tst_net(imgs).reshape([imgs.shape[0]] + list(imgs.shape[2:]))[0:3]
).detach())
```

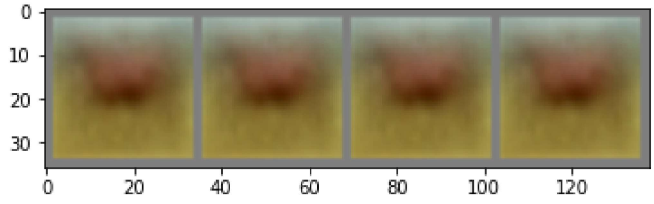


```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or
[0..255] for integers).
```



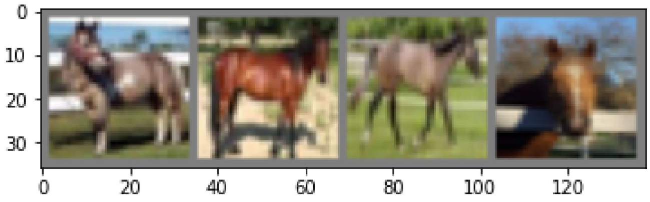
In [80]:
```
print_imgs(sc_loader,4,tst_net)
```

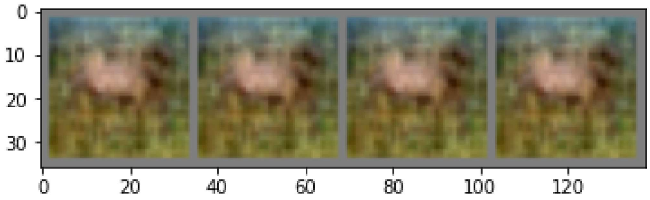




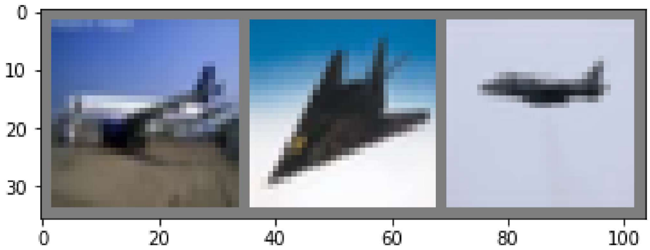
In [ ]:

In [69]:
```
print_imgs(sc_loader,4,tst_net)
```

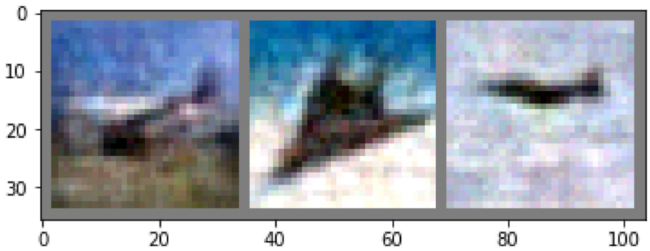




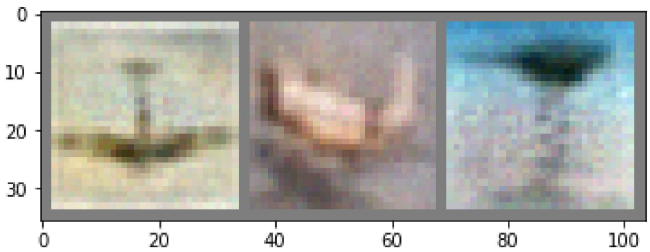
In [159]:
```
imgs = next(iter(scd_loader))
imshow(torchvision.utils.make_grid(
    imgs.reshape([imgs.shape[0]] + list(imgs.shape[2:]))[0:3]
).detach())
imshow(torchvision.utils.make_grid(
    repl_net(imgs).reshape([imgs.shape[0]] + list(imgs.shape[2:]))[0:3]
).detach())
```



```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or
[0..255] for integers).
```



In [197]:
```
imshow(torchvision.utils.make_grid(normalize(repl_net(imgs).reshape([imgs.shape[0]] + li
```



Вывод

В ходе выполнения этой лабораторной работы я ознакомился с принипами работы автоэнкодера и получил опыт в реализации простых автоэнкодеров. К сожалению, во время выполнения этой работы у меня не было доступа к cuda, и я не смог обучить более сложные сети