Свёрточные нейронные сети: **CIFAR10</h3>**

В этом ноутбке мы посмотрим, насколько хорошо **CNN** будут предсказывать классы на более сложном датасете картинок **-- CIFAR10.**

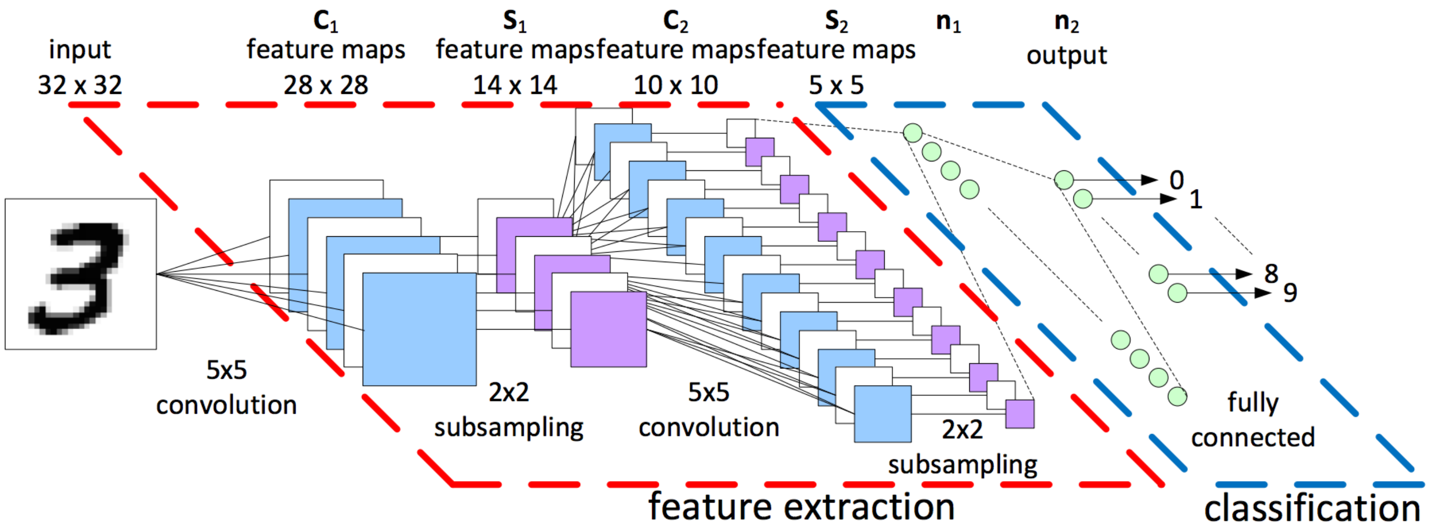
Внимание: Рассматривается *задача классификации изображений*.

Свёрточная нейросеть (Convolutional Neural Network, CNN) **-** это многослойная нейросеть, имеющая в своей архитектуре помимо *полносвязных слоёв* (а иногда их может и не быть) ещё и **свёрточные слои (Conv Layers)** и **pooling-слои (Pool Layers)**.

Собственно, название такое эти сети получили потому, что в основе их работы лежит операция **свёртки.**

Сразу же стоит сказать, что свёрточные нейросети **были придуманы прежде всего для задач, связанных с изображениями** , следовательно, на вход они тоже "ожидают" изображение.

- Например, вот так выглядит неглубокая свёрточная нейросеть, имеющая такую архитектуру:
  `Input -> Conv 5x5 -> Pool 2x2 -> Conv 5x5 -> Pool 2x2 -> FC -> Output`



Свёрточные нейросети (простые, есть и намного более продвинутые) почти всегда строятся по следующему правилу:

`INPUT -> [[CONV -> RELU]*N -> POOL?]*M -> [FC -> RELU]*L -> FC`

то есть:

1). ***Входной слой***: **batch** картинок **--** тензор размера `(batch_size, H, W, C)` или `(batch_size, C, H, W)`

2). M блоков (**M** $\geq$ **0**) из свёрток и **pooling**-ов, причём именно в том порядке, как в формуле выше. Все эти M блоков вместе называют ***feature extractor*** свёрточной нейросети, потому что эта часть сети отвечает непосредственно за формирование новых, более сложных признаков поверх тех, которые подаются (то есть, по аналогии с **MLP**, мы опять же переходим к новому признаковому пространству, однако здесь оно строится сложнее, чем в обычных многослойных сетях, поскольку используется операция свёртки)

3). L штук **FullyConnected**-слоёв (с активациями). Эту часть из L **FC**-слоёв называют ***classificator***, поскольку эти слои отвечают непосредственно за предсказание нужно класса (сейчас рассматривается задача классификации изображений).

Свёрточная нейросеть на **PyTorch**

Ещё раз напомним про основные компоненты нейросети:

- непосредственно, сама **архитектура** нейросети (сюда входят типы функций активации у каждого нейрона);
- начальная **инициализация** весов каждого слоя;
- метод **оптимизации** нейросети (сюда ещё входит метод изменения `learning_rate`);
- размер **батчей** (`batch_size`);
- количетсво **эпох** обучения (`num_epochs`);
- **функция потерь** (`loss`);
- тип **регуляризации** нейросети (`weight_decay`, для каждого слоя можно свой);

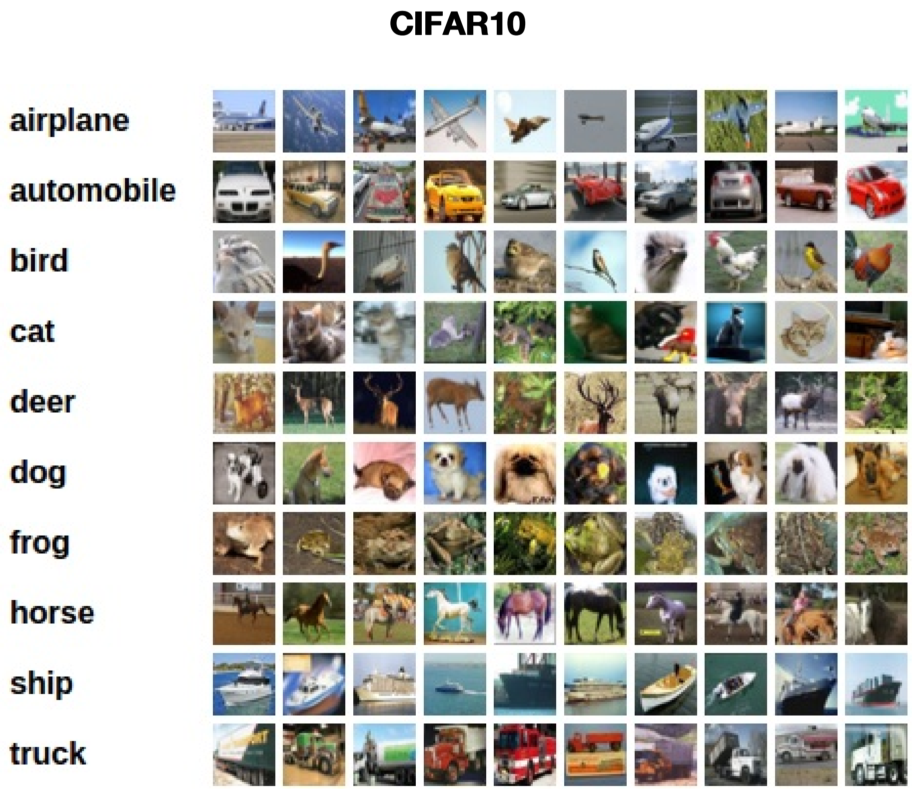
То, что связано с ***данными и задачей***:

- само **качество** выборки (непротиворечивость, чистота, корректность постановки задачи);
- **размер** выборки;

Так как мы сейчас рассматриваем **архитектуру CNN**, то, помимо этих компонент, в свёрточной нейросети можно настроить следующие вещи:

- (в каждом **ConvLayer**) **размер фильтров (окна свёртки)** (`kernel_size`)
- (в каждом **ConvLayer**) **количество фильтров** (`out_channels`)
- (в каждом **ConvLayer**) размер **шага окна свёртки (stride)** (`stride`)
- (в каждом **ConvLayer**) тип **padding'а** (`padding`)

- (в каждом **PoolLayer**) размер окна **pooling'а** (`kernel_size`)
- (в каждом **PoolLayer**) шаг окна **pooling'а** (`stride`)
- (в каждом **PoolLayer**) тип **pooling'а** (`pool_type`)
- (в каждом **PoolLayer**) тип **padding'а** (`padding`)



CIFAR10: это набор из **60k** картинок **32**x**32**x**3**, **50k** которых составляют обучающую выборку, и оставшиеся **10k -** тестовую**.** Классов в этом датасете **10:** `'plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck'`**.**

In [1]:

```
# !pip install torch torchvision
```

In [2]:

```
import torch
import torchvision
from torchvision import transforms

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

In [3]:

```python
from tqdm import tqdm_notebook
```

In [4]:

```python
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

trainset = torchvision.datasets.CIFAR10(root='../pytorch_data', train=True,
                                        download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=4,
                                          shuffle=True, num_workers=2)

testset = torchvision.datasets.CIFAR10(root='../pytorch_data', train=False,
                                       download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=4,
                                         shuffle=False, num_workers=2)

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

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ../pytorch_data\cifar-10-python.tar.gz


Extracting ../pytorch_data\cifar-10-python.tar.gz to ../pytorch_data
Files already downloaded and verified
```

In [5]:

```python
# trainset.data
```

Out[5]:

```
array([[[[ 59,  62,  63],
         [ 43,  46,  45],
         [ 50,  48,  43],
         ...,
         [158, 132, 108],
         [152, 125, 102],
         [148, 124, 103]],

        [[ 16,  20,  20],
         [  0,   0,   0],
         [ 18,   8,   0],
         ...,
         [123,  88,  55],
         [119,  83,  50],
         [122,  87,  57]],

        [[ 25,  24,  21],
         [ 16,   7,   0],
```

```
  [ 49,  27,   8],
  ...,
  [118,  84,  50],
  [120,  84,  50],
  [109,  73,  42]],

 ...,

 [[208, 170,  96],
  [201, 153,  34],
  [198, 161,  26],
  ...,
  [160, 133,  70],
  [ 56,  31,   7],
  [ 53,  34,  20]],

 [[180, 139,  96],
  [173, 123,  42],
  [186, 144,  30],
  ...,
  [184, 148,  94],
  [ 97,  62,  34],
  [ 83,  53,  34]],

 [[177, 144, 116],
  [168, 129,  94],
  [179, 142,  87],
  ...,
  [216, 184, 140],
  [151, 118,  84],
  [123,  92,  72]]],


[[[154, 177, 187],
  [126, 137, 136],
  [105, 104,  95],
  ...,
  [ 91,  95,  71],
  [ 87,  90,  71],
  [ 79,  81,  70]],

 [[140, 160, 169],
  [145, 153, 154],
  [125, 125, 118],
  ...,
  [ 96,  99,  78],
  [ 77,  80,  62],
  [ 71,  73,  61]],

 [[140, 155, 164],
  [139, 146, 149],
```

```
  [115, 115, 112],
  ...,
  [ 79,  82,  64],
  [ 68,  70,  55],
  [ 67,  69,  55]],

 ...,

 [[175, 167, 166],
  [156, 154, 160],
  [154, 160, 170],
  ...,
  [ 42,  34,  36],
  [ 61,  53,  57],
  [ 93,  83,  91]],

 [[165, 154, 128],
  [156, 152, 130],
  [159, 161, 142],
  ...,
  [103,  93,  96],
  [123, 114, 120],
  [131, 121, 131]],

 [[163, 148, 120],
  [158, 148, 122],
  [163, 156, 133],
  ...,
  [143, 133, 139],
  [143, 134, 142],
  [143, 133, 144]]],


[[[255, 255, 255],
  [253, 253, 253],
  [253, 253, 253],
  ...,
  [253, 253, 253],
  [253, 253, 253],
  [253, 253, 253]],

 [[255, 255, 255],
  [255, 255, 255],
  [255, 255, 255],
  ...,
  [255, 255, 255],
  [255, 255, 255],
  [255, 255, 255]],

 [[255, 255, 255],
```

```
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  [254, 254, 254],
  ...,
  [254, 254, 254],
  [254, 254, 254],
  [254, 254, 254]],

 ...,

 [[113, 120, 112],
  [111, 118, 111],
  [105, 112, 106],
  ...,
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  [ 72,  80,  79],
  [ 72,  80,  79]],

 [[111, 118, 110],
  [104, 111, 104],
  [ 99, 106,  98],
  ...,
  [ 68,  75,  73],
  [ 70,  76,  75],
  [ 78,  84,  82]],

 [[106, 113, 105],
  [ 99, 106,  98],
  [ 95, 102,  94],
  ...,
  [ 78,  85,  83],
  [ 79,  85,  83],
  [ 80,  86,  84]]],


...,


[[[ 35, 178, 235],
  [ 40, 176, 239],
  [ 42, 176, 241],
  ...,
  [ 99, 177, 219],
  [ 79, 147, 197],
  [ 89, 148, 189]],

 [[ 57, 182, 234],
  [ 44, 184, 250],
  [ 50, 183, 240],
  ...,
  [156, 182, 200],
  [141, 177, 206],
```

```
  [116, 149, 175]],

 [[ 98, 197, 237],
  [ 64, 189, 252],
  [ 69, 192, 245],
  ...,
  [188, 195, 206],
  [119, 135, 147],
  [ 61,  79,  90]],

 ...,

 [[ 73,  79,  77],
  [ 53,  63,  68],
  [ 54,  68,  80],
  ...,
  [ 17,  40,  64],
  [ 21,  36,  51],
  [ 33,  48,  49]],

 [[ 61,  68,  75],
  [ 55,  70,  86],
  [ 57,  79, 103],
  ...,
  [ 24,  48,  72],
  [ 17,  35,  53],
  [  7,  23,  32]],

 [[ 44,  56,  73],
  [ 46,  66,  88],
  [ 49,  77, 105],
  ...,
  [ 27,  52,  77],
  [ 21,  43,  66],
  [ 12,  31,  50]]],


[[[189, 211, 240],
  [186, 208, 236],
  [185, 207, 235],
  ...,
  [175, 195, 224],
  [172, 194, 222],
  [169, 194, 220]],

 [[194, 210, 239],
  [191, 207, 236],
  [190, 206, 235],
  ...,
  [173, 192, 220],
  [171, 191, 218],
```

```
  [171, 191, 216],
  [167, 190, 216]],

 [[208, 219, 244],
  [205, 216, 240],
  [204, 215, 239],
  ...,
  [175, 191, 217],
  [172, 190, 216],
  [169, 191, 215]],

 ...,

 [[207, 199, 181],
  [203, 195, 175],
  [203, 196, 173],
  ...,
  [135, 132, 127],
  [162, 158, 150],
  [168, 163, 151]],

 [[198, 190, 170],
  [189, 181, 159],
  [180, 172, 147],
  ...,
  [178, 171, 160],
  [175, 169, 156],
  [175, 169, 154]],

 [[198, 189, 173],
  [189, 181, 162],
  [178, 170, 149],
  ...,
  [195, 184, 169],
  [196, 189, 171],
  [195, 190, 171]]],


[[[229, 229, 239],
  [236, 237, 247],
  [234, 236, 247],
  ...,
  [217, 219, 233],
  [221, 223, 234],
  [222, 223, 233]],

 [[222, 221, 229],
  [239, 239, 249],
  [233, 234, 246],
  ...,
  [223, 223, 236],
```

```
         [227, 228, 238],
         [210, 211, 220]],

        [[213, 206, 211],
         [234, 232, 239],
         [231, 233, 244],
         ...,
         [220, 220, 232],
         [220, 219, 232],
         [202, 203, 215]],

        ...,

        [[150, 143, 135],
         [140, 135, 127],
         [132, 127, 120],
         ...,
         [224, 222, 218],
         [230, 228, 225],
         [241, 241, 238]],

        [[137, 132, 126],
         [130, 127, 120],
         [125, 121, 115],
         ...,
         [181, 180, 178],
         [202, 201, 198],
         [212, 211, 207]],

        [[122, 119, 114],
         [118, 116, 110],
         [120, 116, 111],
         ...,
         [179, 177, 173],
         [164, 164, 162],
         [163, 163, 161]]]], dtype=uint8)
```

In [6]:

```
trainloader.dataset.train_list[0]
```

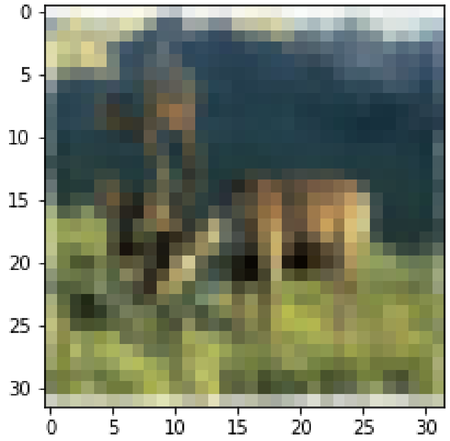
Out[6]:

```
['data_batch_1', 'c99cafc152244af753f735de768cd75f']
```

In [7]:

```
# случайный индекс от 0 до размера тренировочной выборки
i = np.random.randint(low=0, high=50000)
```

```
plt.imshow(trainloader.dataset.data[i]);
```



Напишем свёрточную нейросеть для предсказания на **CIFAR10.**

In [8]:

```
import torch.nn as nn
import torch.nn.functional as F
```

In [9]:

```
class SimpleConvNet(torch.nn.Module):
    def __init__(self):
        # вызов конструктора класса nn.Module()
        super(SimpleConvNet, self).__init__()
        # feature extractor
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=6, kernel_size=5)
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)
        self.conv2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5)
        # classificator
        self.fc1 = nn.Linear(5 * 5 * 16, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        # print(x.shape)
        x = x.view(-1, 5 * 5 * 16)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

Обучим:

In [10]:

```
from tqdm import tqdm_notebook
```

In [11]:

```
net = SimpleConvNet()

loss_fn = torch.nn.CrossEntropyLoss()

learning_rate = 1e-4
optimizer = torch.optim.Adam(net.parameters(), lr=learning_rate)

# итерируемся
for epoch in tqdm_notebook(range(3)):

    running_loss = 0.0
    for i, batch in enumerate(tqdm_notebook(trainloader)):
        # так получаем текущий батч
        X_batch, y_batch = batch

        # обнуляем веса
        optimizer.zero_grad()

        # forward + backward + optimize
        y_pred = net(X_batch)
        loss = loss_fn(y_pred, y_batch)
        loss.backward()
        optimizer.step()

        running_loss += loss.item()
        # выводим качество каждые 2000 батчей
        if i % 2000 == 1999:
            print('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0

print('Обучение закончено')
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/3477602096.py:9: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for epoch in tqdm_notebook(range(3)):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/3477602096.py:12: TqdmDeprecationWarning: This function will be removed in tqdm
==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
```

```
for i, batch in enumerate(tqdm_notebook(trainloader)):
```

```
[1,  2000] loss: 2.028
[1,  4000] loss: 1.774
[1,  6000] loss: 1.697
[1,  8000] loss: 1.639
[1, 10000] loss: 1.599
[1, 12000] loss: 1.588


[2,  2000] loss: 1.535
[2,  4000] loss: 1.515
[2,  6000] loss: 1.501
[2,  8000] loss: 1.478
[2, 10000] loss: 1.470
[2, 12000] loss: 1.433


[3,  2000] loss: 1.423
[3,  4000] loss: 1.416
[3,  6000] loss: 1.389
[3,  8000] loss: 1.373
[3, 10000] loss: 1.356
[3, 12000] loss: 1.373
Обучение закончено
```

Посмотрим на **accuracy** на тестовом датасете**:**

In [12]:

```
class_correct = list(0. for i in range(10))
class_total = list(0. for i in range(10))

with torch.no_grad():
    for data in testloader:
        images, labels = data
        y_pred = net(images)
        _, predicted = torch.max(y_pred, 1)
        c = (predicted == labels).squeeze()
        for i in range(4):
            label = labels[i]
            class_correct[label] += c[i].item()
            class_total[label] += 1

for i in range(10):
    print('Accuracy of %5s : %2d %%' % (
        classes[i], 100 * class_correct[i] / class_total[i]))
```

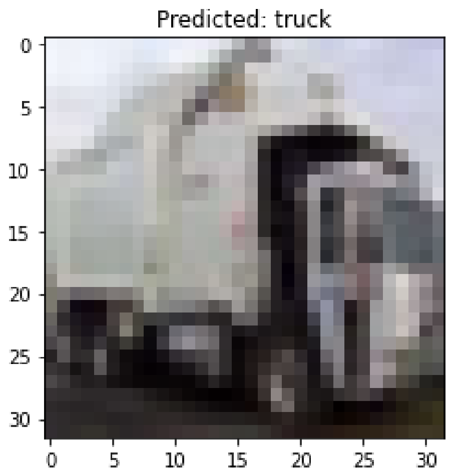
```
Accuracy of plane : 34 %
Accuracy of   car : 63 %
Accuracy of  bird : 24 %
```

```
Accuracy of  bird : 24 %
Accuracy of   cat : 32 %
Accuracy of  deer : 35 %
Accuracy of   dog : 47 %
Accuracy of  frog : 74 %
Accuracy of horse : 53 %
Accuracy of  ship : 79 %
Accuracy of truck : 54 %
```

Проверим работу нейросети визуально (позапускайте ячейку несколько раз):

In [13]:

```python
i = np.random.randint(low=0, high=10000)

def visualize_result(index):
    image = testloader.dataset.data[index]
    plt.imshow(image)

    image = transform(image)  # не забудем отмасштабировать!

    y_pred = net(image.view(1, 3, 32, 32))
    _, predicted = torch.max(y_pred, 1)

    plt.title(f'Predicted: {classes[predicted.numpy()[0]]}')

visualize_result(i)
```



Улучшим свёрточную нейросеть: поэкспериментируем с архитектурой (количество слоёв, порядок слоёв), с гиперпараметрами слоёв (размеры **kernel_size**, размеры **pooling**'а, количество **kernel**'ов в свёрточном слое) и с гиперпараметрами, указанными в "Компоненты нейросети" (см. памятку выше).

In [14]:

```
class BetterConvNet(nn.Module):
    def __init__(self):
        # вызов конструктора класса nn.Module()
        super(BetterConvNet, self).__init__()

        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)

        self.conv1 = nn.Conv2d(in_channels=3, out_channels=6, kernel_size=5)
        self.conv2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5)
        self.conv3 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=5)

        self.fc1 = nn.Linear(3 * 3 * 32, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(self.conv3(F.relu(self.conv2(x))))
#          print(x.shape)
        x = x.view(-1, 3 * 3 * 32)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

Обучим:

In [15]:

```
from tqdm import tqdm_notebook
```

In [16]:

```
net = BetterConvNet()

loss_fn = torch.nn.CrossEntropyLoss()

learning_rate = 1e-3
optimizer = torch.optim.Adam(net.parameters(), lr=learning_rate)

# итерируемся
for epoch in tqdm_notebook(range(5)):

    running_loss = 0.0
    for i, batch in enumerate(tqdm_notebook(trainloader)):
        # так получаем текущий батч
        X_batch, y_batch = batch

        # обнуляем веса
```

```python
        optimizer.zero_grad()

        # forward + backward + optimize
        y_pred = net(X_batch)
        loss = loss_fn(y_pred, y_batch)
        loss.backward()
        optimizer.step()

        # выведем текущий loss
        running_loss += loss.item()
        # выведем качество каждые 2000 батчей
        if i % 2000 == 1999:
            print('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0

print('Обучение закончено')
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/4107937569.py:9: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for epoch in tqdm_notebook(range(5)):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/4107937569.py:12: TqdmDeprecationWarning: This function will be removed in tqdm
==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for i, batch in enumerate(tqdm_notebook(trainloader)):
```

```
[1,  2000] loss: 1.905
[1,  4000] loss: 1.639
[1,  6000] loss: 1.569
[1,  8000] loss: 1.526
[1, 10000] loss: 1.514
[1, 12000] loss: 1.489


[2,  2000] loss: 1.408
[2,  4000] loss: 1.425
[2,  6000] loss: 1.393
[2,  8000] loss: 1.387
[2, 10000] loss: 1.375
[2, 12000] loss: 1.346


[3,  2000] loss: 1.294
[3,  4000] loss: 1.308
[3,  6000] loss: 1.322
[3,  8000] loss: 1.280
[3, 10000] loss: 1.270
[3, 12000] loss: 1.284
```

```
[4,  2000] loss: 1.226
[4,  4000] loss: 1.242
[4,  6000] loss: 1.233
[4,  8000] loss: 1.210
[4, 10000] loss: 1.234
[4, 12000] loss: 1.225


[5,  2000] loss: 1.174
[5,  4000] loss: 1.160
[5,  6000] loss: 1.204
[5,  8000] loss: 1.175
[5, 10000] loss: 1.192
[5, 12000] loss: 1.220
Обучение закончено
```

In [17]:

```
class_correct = list(0. for i in range(10))
class_total = list(0. for i in range(10))

with torch.no_grad():
    for data in testloader:
        images, labels = data
        y_pred = net(images)
        _, predicted = torch.max(y_pred, 1)
        c = (predicted == labels).squeeze()
        for i in range(4):
            label = labels[i]
            class_correct[label] += c[i].item()
            class_total[label] += 1

for i in range(10):
    print('Accuracy of %5s : %2d %%' % (
        classes[i], 100 * class_correct[i] / class_total[i]))
```

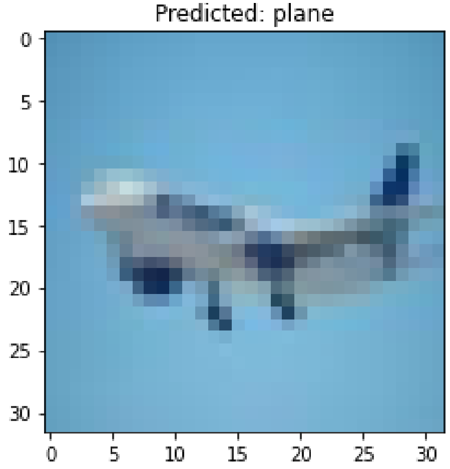
```
Accuracy of plane : 69 %
Accuracy of   car : 80 %
Accuracy of  bird : 29 %
Accuracy of   cat : 52 %
Accuracy of  deer : 37 %
Accuracy of   dog : 22 %
Accuracy of  frog : 72 %
Accuracy of horse : 76 %
Accuracy of  ship : 58 %
Accuracy of truck : 55 %
```

Если качество **~70%** в среднем, то текущая нейросеть вполне неплоха (однако на этом датасете известны архитектуры, дающие **95+%** качества).

Посмотрим визуально на работу нейросети:

In [18]:

```
i = np.random.randint(low=0, high=10000)

def visualize_result(index):
    image = testloader.dataset.data[index]
    plt.imshow(image)

    image = transform(image)  # не забудем отмасштабировать!

    y_pred = net(image.view(1, 3, 32, 32))
    _, predicted = torch.max(y_pred, 1)

    plt.title(f'Predicted: {classes[predicted.numpy()[0]]}')

visualize_result(i)
```



Попробуем обучить ещё более сильную нейросеть:

In [19]:

```
class StrongConvNet(nn.Module):
    def __init__(self):
        # вызов конструктора класса nn.Module()
        super(StrongConvNet, self).__init__()

        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)

        self.dropout = nn.Dropout(p=0.2)

        self.conv1 = nn.Conv2d(in_channels=3, out_channels=8, kernel_size=5)
```

```python
        self.bn1 = nn.BatchNorm2d(8)
        self.conv2 = nn.Conv2d(in_channels=8, out_channels=16, kernel_size=1)
        self.bn2 = nn.BatchNorm2d(16)
        self.conv3 = nn.Conv2d(in_channels=16, out_channels=16, kernel_size=3)
        self.bn3 = nn.BatchNorm2d(16)
        self.conv4 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=1)
        self.bn4 = nn.BatchNorm2d(32)
        self.conv5 = nn.Conv2d(in_channels=32, out_channels=32, kernel_size=3)
        self.bn5 = nn.BatchNorm2d(32)

        self.fc1 = nn.Linear(4 * 4 * 32, 128)
        self.fc2 = nn.Linear(128, 10)

    def forward(self, x):
        x = self.bn1(F.relu(self.conv1(x)))
        x = self.pool(x)
        x = self.bn2(F.relu(self.conv2(x)))
        x = self.bn3(F.relu(self.conv3(x)))
        x = self.pool(x)
        x = self.bn4(F.relu(self.conv4(x)))
        x = self.bn5(F.relu(self.conv5(x)))
#         print(x.shape)
        x = x.view(-1, 4 * 4 * 32)
        x = F.relu(self.fc1(x))
        x = self.dropout(x)
        x = self.fc2(x)
        return x
```

Обучим:

In [20]:

```python
from tqdm import tqdm_notebook
```

In [21]:

```python
from torch.optim import lr_scheduler
```

In [22]:

```python
net = StrongConvNet()

loss_fn = torch.nn.CrossEntropyLoss()

num_epochs = 5

optimizer = torch.optim.Adam(net.parameters(), lr=learning_rate)
learning_rate = 1e-3
# новая фишка -- динамически изменяем LR
```

```
scheduler = lr_scheduler.CosineAnnealingLR(optimizer, T_max=num_epochs)

for epoch in tqdm_notebook(range(num_epochs)):

    scheduler.step()

    running_loss = 0.0
    for i, batch in enumerate(tqdm_notebook(trainloader)):
        X_batch, y_batch = batch

        optimizer.zero_grad()

        y_pred = net(X_batch)
        loss = loss_fn(y_pred, y_batch)
        loss.backward()
        optimizer.step()

        running_loss += loss.item()
        if i % 2000 == 1999:
            print('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0

print('Обучение закончено')
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/3687784610.py:12: TqdmDeprecationWarning: This function will be removed in tqdm
==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for epoch in tqdm_notebook(range(num_epochs)):
```

```
C:\Users\koshi8bit\anaconda3\lib\site-packages\torch\optim\lr_scheduler.py:129: UserWarning: Detected call of `lr_scheduler.step()
` before `optimizer.step()`. In PyTorch 1.1.0 and later, you should call them in the opposite order: `optimizer.step()` before `lr
_scheduler.step()`.  Failure to do this will result in PyTorch skipping the first value of the learning rate schedule. See more det
ails at https://pytorch.org/docs/stable/optim.html#how-to-adjust-learning-rate
  warnings.warn("Detected call of `lr_scheduler.step()` before `optimizer.step()`. "
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/3687784610.py:17: TqdmDeprecationWarning: This function will be removed in tqdm
==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for i, batch in enumerate(tqdm_notebook(trainloader)):
```

```
[1,  2000] loss: 1.849
[1,  4000] loss: 1.651
[1,  6000] loss: 1.576
[1,  8000] loss: 1.513
[1, 10000] loss: 1.438
[1, 12000] loss: 1.439


[2,  2000] loss: 1.310
[2,  4000] loss: 1.280
```

```
[2,  6000] loss: 1.282
[2,  8000] loss: 1.257
[2, 10000] loss: 1.216
[2, 12000] loss: 1.229


[3,  2000] loss: 1.118
[3,  4000] loss: 1.100
[3,  6000] loss: 1.099
[3,  8000] loss: 1.104
[3, 10000] loss: 1.076
[3, 12000] loss: 1.069


[4,  2000] loss: 1.027
[4,  4000] loss: 0.987
[4,  6000] loss: 0.961
[4,  8000] loss: 0.968
[4, 10000] loss: 0.974
[4, 12000] loss: 0.977


[5,  2000] loss: 0.958
[5,  4000] loss: 0.950
[5,  6000] loss: 0.961
[5,  8000] loss: 0.944
[5, 10000] loss: 0.944
[5, 12000] loss: 0.953
Обучение закончено
```

In [23]:

```
class_correct = list(0. for i in range(10))
class_total = list(0. for i in range(10))

with torch.no_grad():
    for data in testloader:
        images, labels = data
        y_pred = net(images)
        _, predicted = torch.max(y_pred, 1)
        c = (predicted == labels).squeeze()
        for i in range(4):
            label = labels[i]
            class_correct[label] += c[i].item()
            class_total[label] += 1

for i in range(10):
    print('Accuracy of %5s : %2d %%' % (
        classes[i], 100 * class_correct[i] / class_total[i]))
```

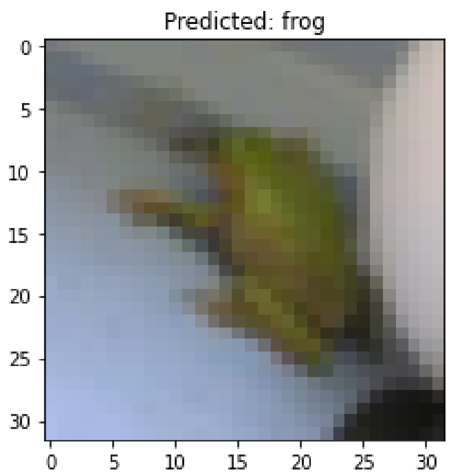
```
Accuracy of plane : 67 %
Accuracy of   car : 72 %
Accuracy of  bird : 52 %
```

```
Accuracy of  bird : 52 %
Accuracy of   cat : 37 %
Accuracy of  deer : 55 %
Accuracy of   dog : 51 %
Accuracy of  frog : 69 %
Accuracy of horse : 65 %
Accuracy of  ship : 73 %
Accuracy of truck : 72 %
```

Посмотрим визуально на работу нейросети:

In [24]:

```
i = np.random.randint(low=0, high=10000)

def visualize_result(index):
    image = testloader.dataset.data[index]
    plt.imshow(image)

    image = transform(image)  # не забудем отмасштабировать!

    y_pred = net(image.view(1, 3, 32, 32))
    _, predicted = torch.max(y_pred, 1)

    plt.title(f'Predicted: {classes[predicted.numpy()[0]]}')

visualize_result(i)
```



Даже обучив более глубокую и прокаченную **(BatchNorm, Dropout)** нейросеть на этих данных мы видим, что качество нас всё ещё не устраивает, в реальной жизни необходимо ошибаться не больше, чем на **5%**, а часто и это уже много. Как же быть, ведь свёрточные нейросети должны хорошо классифицировать изображения?

К сожалению, обучение нейросети с нуля на не очень большой выборке (а здесь она именно такая) часто приводит к переобучению, что плохо сказывается на

К сожалению, обучение нейросети с нуля на не очень большой выборке (а здесь она именно такая) часто приводит к переобучению, что плохо сказывается на тестовом качестве.

Для того, чтобы получить более качественную модель, часто **до**обучают сильную нейросеть, обученную на **ImageNet,** то есть используют технику **Transfer Learning.** О ней речь пойдёт далее в нашем курсе.

Полезные ссылки

1). *Примеры написания нейросетей на* ***PyTorch*** *(официальные туториалы)* ***(****на английском****):***
https://pytorch.org/tutorials/beginner/pytorch_with_examples.html#examples
https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html

2). Курс Стэнфорда**:** **http://cs231n.github.io/**

3). Практически исчерпывающая информация по основам свёрточных нейросетей **(**из **cs231n) (**на английском**):**

http://cs231n.github.io/convolutional-networks/
http://cs231n.github.io/understanding-cnn/
http://cs231n.github.io/transfer-learning/

4). Видео о **Computer Vision** от **Andrej Karpathy:** **https://www.youtube.com/watch?v=u6aEYuemt0M**

In [27]:

```
def print_res(df):
    return df.sort_values(by=['avg'], ascending=False)
```

In [28]:

```
def get_f_name(f):
  arr = str(f).split(' ')
  name = arr[1]
  if name == 'method':
    name = arr[2]
  return name #  + f'<{str(f)}>'
```

In [82]:

```
import pandas as pd
global_res = pd.DataFrame(columns=['channels1', 'channels2', 'channels3', 'kernel_size1', 'kernel_size2', 'kernel_size3', 'fc1', 'fc2', 'fc3', 'is_max_pool', 'activation', 'avg', 'max', 'min', 'ch_c', 'conv_c', 'fc_c', 'num_epochs', 'lr'])
```

In [34]:

```
# device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
device = torch.device("cpu")
print(str(device))
```

```
cpu
```

In [74]:

```
class SimpleConvNet_my(nn.Module):
    def __init__(self, channels1, channels2, kernel_size1, kernel_size2, fc1, fc2, is_max_pool = True, activation=F.relu):
        # вызов конструктора предка
        super(SimpleConvNet_my, self).__init__()
        # необходмо заранее знать, сколько каналов у картинки (сейчас = 1),
        # которую будем подавать в сеть, больше ничего
        # про входящие картинки знать не нужно
        self.channels1 = channels1
        self.channels2 = channels2
        self.kernel_size1 = kernel_size1
        self.kernel_size2 = kernel_size2
        self.fc1_c = fc1
        self.fc2_c = fc2
        self.is_max_pool = is_max_pool
        self.activation = activation
        self.num_epochs = 0

        self.conv1 = nn.Conv2d(in_channels=3, out_channels=channels1, kernel_size=kernel_size1)
        new_size = 32 - kernel_size1 + 1
        if is_max_pool:
          self.pool = nn.MaxPool2d(kernel_size=2, stride=2)
        else:
          self.pool = nn.AvgPool2d(kernel_size=2, stride=2)
        new_size = new_size // 2
        self.conv2 = nn.Conv2d(in_channels=channels1, out_channels=channels2, kernel_size=kernel_size2)
        new_size = new_size - kernel_size2 + 1
        new_size = new_size // 2

        self.fc1_size = new_size * new_size * channels2

        self.fc1 = nn.Linear(new_size * new_size * channels2, fc1)  # !!!
        self.fc2 = nn.Linear(fc1, fc2)
        self.fc3 = nn.Linear(fc2, 10)

    def forward(self, x):
        x = self.pool(self.activation(self.conv1(x)))
        #print(x.shape)
        x = self.pool(self.activation(self.conv2(x)))
        #print(x.shape)
        x = x.view(-1, self.fc1_size)  # !!!
```

```
        x = self.activation(self.fc1(x))
        x = self.activation(self.fc2(x))
        x = self.fc3(x)
        return x

    def train(self, learning_rate = 1e-4, num_epochs = 3):
        self.num_epochs = num_epochs
        self.learning_rate = learning_rate
        loss_fn = torch.nn.CrossEntropyLoss()
        optimizer = torch.optim.Adam(self.parameters(), lr=learning_rate)
        # итерируемся
        for epoch in tqdm_notebook(range(num_epochs)):
            running_loss = 0.0
            for i, batch in enumerate(tqdm_notebook(trainloader)):
                # так получаем текущий батч
                X_batch, y_batch = batch
                global device
                X_batch, y_batch = X_batch.to(device), y_batch.to(device)

                # обнуляем веса
                optimizer.zero_grad()

                # forward + backward + optimize
                y_pred = self(X_batch)
                loss = loss_fn(y_pred, y_batch)
                loss.backward()
                optimizer.step()

                # выведем текущий loss
                running_loss += loss.item()
                # выведем качество каждые 2000 батчей
                if i % 2000 == 1999:
                    print('[%d, %5d] loss: %.3f' %
                          (epoch + 1, i + 1, running_loss / 2000))
                    running_loss = 0.0

        print('fin')

    def validatee(self):
        class_correct = list(0. for i in range(10))
        class_total = list(0. for i in range(10))

        with torch.no_grad():
            for data in testloader:
                images, labels = data
                y_pred = self(images)
                _, predicted = torch.max(y_pred, 1)
                c = (predicted == labels).squeeze()
                for i in range(4):
                    label = labels[i]
```

```
                    class_correct[label] += c[i].item()
                    class_total[label] += 1
        res = []
        for i in range(10):
            tmp = 100 * class_correct[i] / class_total[i]
            res.append(tmp)
            print('Accuracy of %2s : %2d %%' % (
                classes[i], tmp))

        class_correct_t = sum(class_correct)
        class_total_t = sum(class_total)

        rrr = (100. * class_correct_t / class_total_t)
        print('\nTotal accuracy AVG:', rrr)
        print(f'max={max(res)}; min={min(res)}')
        rezzz = [
              self.channels1,
              self.channels2,
              0,
              self.kernel_size1,
              self.kernel_size2,
              0,
              self.fc1_c,
              self.fc2_c,
              0,
              self.is_max_pool,
              get_f_name(self.activation),
              rrr,
              round(max(res), 2),
              round(min(res), 2),
              2,
              2,
              2,
              self.num_epochs,
              self.learning_rate
        ]
        print(len(rezzz), rezzz)
        global_res.loc[len(global_res)] = rezzz
```

In [31]:

```
functions = [F.elu, F.softsign, torch.tanh]
kernels = [[5, 5], [7, 3]]
fcs = [[120, 84], [200, 100]]
is_max_pools = [True]
```

In [39]:

```
for function in tqdm_notebook(functions):
    for kernel in tqdm_notebook(kernels):
```

```python
        for fc in tqdm_notebook(fcs):
            for is_max_pool in tqdm_notebook(is_max_pools):
                net = SimpleConvNet_my(6, 16, kernel[0], kernel[1], fc[0], fc[1], is_max_pool, function)
                net.to(device)
                net.train()
                net.validatee()
                print_res(global_res)
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2248802741.py:1: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for function in tqdm_notebook(functions):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2248802741.py:2: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for kernel in tqdm_notebook(kernels):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2248802741.py:3: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for fc in tqdm_notebook(fcs):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2248802741.py:4: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for is_max_pool in tqdm_notebook(is_max_pools):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/332785600.py:49: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for epoch in tqdm_notebook(range(num_epochs)):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/332785600.py:51: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for i, batch in enumerate(tqdm_notebook(trainloader)):
```

```
[1,  2000] loss: 1.976
[1,  4000] loss: 1.733
[1,  6000] loss: 1.621
[1,  8000] loss: 1.553
[1, 10000] loss: 1.517
[1, 12000] loss: 1.490


[2,  2000] loss: 1.456
[2,  4000] loss: 1.452
```

```
[2,  6000] loss: 1.409
[2,  8000] loss: 1.395
[2, 10000] loss: 1.394
[2, 12000] loss: 1.371

[3,  2000] loss: 1.322
[3,  4000] loss: 1.349
[3,  6000] loss: 1.325
[3,  8000] loss: 1.325
[3, 10000] loss: 1.294
[3, 12000] loss: 1.303
fin
Accuracy of plane : 59 %
Accuracy of car : 70 %
Accuracy of bird : 34 %
Accuracy of cat : 31 %
Accuracy of deer : 39 %
Accuracy of dog : 51 %
Accuracy of frog : 64 %
Accuracy of horse : 63 %
Accuracy of ship : 65 %
Accuracy of truck : 54 %

Total accuracy AVG: 53.58
max=70.7; min=31.8



[1,  2000] loss: 1.964
[1,  4000] loss: 1.723
[1,  6000] loss: 1.615
[1,  8000] loss: 1.540
[1, 10000] loss: 1.512
[1, 12000] loss: 1.473

[2,  2000] loss: 1.422
[2,  4000] loss: 1.425
[2,  6000] loss: 1.388
[2,  8000] loss: 1.372
[2, 10000] loss: 1.350
[2, 12000] loss: 1.330

[3,  2000] loss: 1.305
[3,  4000] loss: 1.289
[3,  6000] loss: 1.282
[3,  8000] loss: 1.263
[3, 10000] loss: 1.241
[3, 12000] loss: 1.242
fin
Accuracy of plane : 57 %
```

```
Accuracy of car : 77 %
Accuracy of bird : 28 %
Accuracy of cat : 39 %
Accuracy of deer : 63 %
Accuracy of dog : 43 %
Accuracy of frog : 66 %
Accuracy of horse : 54 %
Accuracy of ship : 67 %
Accuracy of truck : 55 %

Total accuracy AVG: 55.33
max=77.1; min=28.9
```

```
[1,  2000] loss: 1.985
[1,  4000] loss: 1.797
[1,  6000] loss: 1.676
[1,  8000] loss: 1.622
[1, 10000] loss: 1.576
[1, 12000] loss: 1.550

[2,  2000] loss: 1.500
[2,  4000] loss: 1.487
[2,  6000] loss: 1.483
[2,  8000] loss: 1.454
[2, 10000] loss: 1.443
[2, 12000] loss: 1.409

[3,  2000] loss: 1.398
[3,  4000] loss: 1.391
[3,  6000] loss: 1.370
[3,  8000] loss: 1.355
[3, 10000] loss: 1.323
[3, 12000] loss: 1.318
fin
Accuracy of plane : 49 %
Accuracy of car : 67 %
Accuracy of bird : 31 %
Accuracy of cat : 40 %
Accuracy of deer : 39 %
Accuracy of dog : 41 %
Accuracy of frog : 61 %
Accuracy of horse : 62 %
Accuracy of ship : 67 %
Accuracy of truck : 60 %

Total accuracy AVG: 52.2
max=67.8; min=31.5
```

```
[1,  2000] loss: 1.933
[1,  4000] loss: 1.681
[1,  6000] loss: 1.595
[1,  8000] loss: 1.540
[1, 10000] loss: 1.517
[1, 12000] loss: 1.497

[2,  2000] loss: 1.456
[2,  4000] loss: 1.439
[2,  6000] loss: 1.399
[2,  8000] loss: 1.374
[2, 10000] loss: 1.385
[2, 12000] loss: 1.359

[3,  2000] loss: 1.321
[3,  4000] loss: 1.333
[3,  6000] loss: 1.313
[3,  8000] loss: 1.325
[3, 10000] loss: 1.308
[3, 12000] loss: 1.291
fin
Accuracy of plane : 55 %
Accuracy of car : 63 %
Accuracy of bird : 37 %
Accuracy of cat : 43 %
Accuracy of deer : 32 %
Accuracy of dog : 42 %
Accuracy of frog : 67 %
Accuracy of horse : 64 %
Accuracy of ship : 69 %
Accuracy of truck : 57 %

Total accuracy AVG: 53.24
max=69.2; min=32.4
```

```
[1,  2000] loss: 2.020
[1,  4000] loss: 1.856
[1,  6000] loss: 1.754
[1,  8000] loss: 1.677
[1, 10000] loss: 1.617
[1, 12000] loss: 1.569

[2,  2000] loss: 1.515
```

```
[2,  4000] loss: 1.489
[2,  6000] loss: 1.451
[2,  8000] loss: 1.459
[2, 10000] loss: 1.445
[2, 12000] loss: 1.407

[3,  2000] loss: 1.375
[3,  4000] loss: 1.380
[3,  6000] loss: 1.373
[3,  8000] loss: 1.353
[3, 10000] loss: 1.318
[3, 12000] loss: 1.333
fin
Accuracy of plane : 53 %
Accuracy of car : 67 %
Accuracy of bird : 39 %
Accuracy of cat : 34 %
Accuracy of deer : 31 %
Accuracy of dog : 49 %
Accuracy of frog : 63 %
Accuracy of horse : 61 %
Accuracy of ship : 62 %
Accuracy of truck : 55 %

Total accuracy AVG: 51.88
max=67.0; min=31.1



[1,  2000] loss: 2.041
[1,  4000] loss: 1.858
[1,  6000] loss: 1.742
[1,  8000] loss: 1.653
[1, 10000] loss: 1.606
[1, 12000] loss: 1.569

[2,  2000] loss: 1.513
[2,  4000] loss: 1.507
[2,  6000] loss: 1.454
[2,  8000] loss: 1.447
[2, 10000] loss: 1.428
[2, 12000] loss: 1.416

[3,  2000] loss: 1.364
[3,  4000] loss: 1.367
[3,  6000] loss: 1.347
[3,  8000] loss: 1.353
[3, 10000] loss: 1.331
[3, 12000] loss: 1.324
fin
```

```
fin
Accuracy of plane : 54 %
Accuracy of car : 55 %
Accuracy of bird : 41 %
Accuracy of cat : 30 %
Accuracy of deer : 38 %
Accuracy of dog : 51 %
Accuracy of frog : 64 %
Accuracy of horse : 65 %
Accuracy of ship : 68 %
Accuracy of truck : 61 %

Total accuracy AVG: 53.17
max=68.6; min=30.7
```

```
[1,  2000] loss: 2.051
[1,  4000] loss: 1.891
[1,  6000] loss: 1.756
[1,  8000] loss: 1.680
[1, 10000] loss: 1.640
[1, 12000] loss: 1.600

[2,  2000] loss: 1.570
[2,  4000] loss: 1.558
[2,  6000] loss: 1.509
[2,  8000] loss: 1.501
[2, 10000] loss: 1.489
[2, 12000] loss: 1.488

[3,  2000] loss: 1.448
[3,  4000] loss: 1.440
[3,  6000] loss: 1.438
[3,  8000] loss: 1.413
[3, 10000] loss: 1.408
[3, 12000] loss: 1.402
fin
Accuracy of plane : 53 %
Accuracy of car : 57 %
Accuracy of bird : 41 %
Accuracy of cat : 26 %
Accuracy of deer : 32 %
Accuracy of dog : 49 %
Accuracy of frog : 56 %
Accuracy of horse : 59 %
Accuracy of ship : 68 %
Accuracy of truck : 51 %

Total accuracy AVG: 49.7
```

```
Total accuracy AVG: 49.7
max=68.1; min=26.9



[1,  2000] loss: 2.028
[1,  4000] loss: 1.840
[1,  6000] loss: 1.722
[1,  8000] loss: 1.654
[1, 10000] loss: 1.603
[1, 12000] loss: 1.598

[2,  2000] loss: 1.566
[2,  4000] loss: 1.535
[2,  6000] loss: 1.506
[2,  8000] loss: 1.469
[2, 10000] loss: 1.465
[2, 12000] loss: 1.457

[3,  2000] loss: 1.432
[3,  4000] loss: 1.397
[3,  6000] loss: 1.395
[3,  8000] loss: 1.398
[3, 10000] loss: 1.409
[3, 12000] loss: 1.368
fin
Accuracy of plane : 48 %
Accuracy of car : 60 %
Accuracy of bird : 29 %
Accuracy of cat : 32 %
Accuracy of deer : 41 %
Accuracy of dog : 49 %
Accuracy of frog : 66 %
Accuracy of horse : 59 %
Accuracy of ship : 63 %
Accuracy of truck : 52 %

Total accuracy AVG: 50.12
max=66.1; min=29.3




[1,  2000] loss: 2.007
[1,  4000] loss: 1.830
[1,  6000] loss: 1.668
[1,  8000] loss: 1.590
[1, 10000] loss: 1.579
[1, 12000] loss: 1.529
```

```
[2,  2000] loss: 1.490
[2,  4000] loss: 1.450
[2,  6000] loss: 1.447
[2,  8000] loss: 1.429
[2, 10000] loss: 1.418
[2, 12000] loss: 1.381

[3,  2000] loss: 1.371
[3,  4000] loss: 1.357
[3,  6000] loss: 1.336
[3,  8000] loss: 1.347
[3, 10000] loss: 1.321
[3, 12000] loss: 1.315
fin
Accuracy of plane : 52 %
Accuracy of car : 65 %
Accuracy of bird : 30 %
Accuracy of cat : 30 %
Accuracy of deer : 48 %
Accuracy of dog : 50 %
Accuracy of frog : 60 %
Accuracy of horse : 64 %
Accuracy of ship : 65 %
Accuracy of truck : 61 %

Total accuracy AVG: 52.98
max=65.3; min=30.8



[1,  2000] loss: 1.973
[1,  4000] loss: 1.761
[1,  6000] loss: 1.642
[1,  8000] loss: 1.565
[1, 10000] loss: 1.515
[1, 12000] loss: 1.492

[2,  2000] loss: 1.459
[2,  4000] loss: 1.416
[2,  6000] loss: 1.415
[2,  8000] loss: 1.391
[2, 10000] loss: 1.390
[2, 12000] loss: 1.369

[3,  2000] loss: 1.345
[3,  4000] loss: 1.338
[3,  6000] loss: 1.307
[3,  8000] loss: 1.310
[3, 10000] loss: 1.288
```

```
[3, 12000] loss: 1.302
fin
Accuracy of plane : 62 %
Accuracy of car : 69 %
Accuracy of bird : 42 %
Accuracy of cat : 39 %
Accuracy of deer : 28 %
Accuracy of dog : 43 %
Accuracy of frog : 75 %
Accuracy of horse : 62 %
Accuracy of ship : 62 %
Accuracy of truck : 53 %

Total accuracy AVG: 54.04
max=75.9; min=28.4
```

```
[1,  2000] loss: 2.006
[1,  4000] loss: 1.840
[1,  6000] loss: 1.752
[1,  8000] loss: 1.654
[1, 10000] loss: 1.579
[1, 12000] loss: 1.545

[2,  2000] loss: 1.504
[2,  4000] loss: 1.478
[2,  6000] loss: 1.437
[2,  8000] loss: 1.453
[2, 10000] loss: 1.427
[2, 12000] loss: 1.397

[3,  2000] loss: 1.366
[3,  4000] loss: 1.374
[3,  6000] loss: 1.375
[3,  8000] loss: 1.352
[3, 10000] loss: 1.345
[3, 12000] loss: 1.351
fin
Accuracy of plane : 51 %
Accuracy of car : 70 %
Accuracy of bird : 33 %
Accuracy of cat : 29 %
Accuracy of deer : 40 %
Accuracy of dog : 45 %
Accuracy of frog : 65 %
Accuracy of horse : 62 %
Accuracy of ship : 67 %
Accuracy of truck : 50 %
```

```
Total accuracy AVG: 51.67
max=70.8; min=29.0



[1,  2000] loss: 1.944
[1,  4000] loss: 1.727
[1,  6000] loss: 1.685
[1,  8000] loss: 1.609
[1, 10000] loss: 1.573
[1, 12000] loss: 1.558


[2,  2000] loss: 1.526
[2,  4000] loss: 1.484
[2,  6000] loss: 1.467
[2,  8000] loss: 1.462
[2, 10000] loss: 1.460
[2, 12000] loss: 1.432


[3,  2000] loss: 1.397
[3,  4000] loss: 1.392
[3,  6000] loss: 1.389
[3,  8000] loss: 1.356
[3, 10000] loss: 1.370
[3, 12000] loss: 1.368
fin
Accuracy of plane : 55 %
Accuracy of car : 59 %
Accuracy of bird : 28 %
Accuracy of cat : 29 %
Accuracy of deer : 42 %
Accuracy of dog : 44 %
Accuracy of frog : 65 %
Accuracy of horse : 66 %
Accuracy of ship : 66 %
Accuracy of truck : 63 %

Total accuracy AVG: 52.05
max=66.9; min=28.2
```

In [68]:

```
print_res(global_res)
```

Out[68]:

	channels1	channels2	channels3	kernel_size1	kernel_size2	kernel_size3	fc1	fc2	fc3	is_max_pool	activation	avg	max	min	ch_c	conv_c	fc_c	num_epochs	lr
14	6	16	0	5	5	0	200	100	0	True	elu	64.77	77.9	43.8	2	2	2	13	0.0001

	channels1	channels2	channels3	kernel_size1	kernel_size2	kernel_size3	fc1	fc2	fc3	is_max_pool	activation	avg	max	min	ch_c	conv_c	fc_c	num_epochs	lr
13	6	16	0	5	5	0	200	100	0	True	elu	61.26	78.5	37.7	2	2	2	7	0.0001
1	6	16	0	5	5	0	200	100	0	True	elu	55.33	77.1	28.9	2	2	2	3	0.0001
12	6	16	0	5	5	0	200	100	0	True	elu	54.68	70.1	32.2	2	2	2	3	0.0001
9	6	16	0	5	5	0	200	100	0	True	tanh	54.04	75.9	28.4	2	2	2	3	0.0001
0	6	16	0	5	5	0	120	84	0	True	elu	53.58	70.7	31.8	2	2	2	3	0.0001
3	6	16	0	7	3	0	200	100	0	True	elu	53.24	69.2	32.4	2	2	2	3	0.0001
5	6	16	0	5	5	0	200	100	0	True	softsign	53.17	68.6	30.7	2	2	2	3	0.0001
8	6	16	0	5	5	0	120	84	0	True	tanh	52.98	65.3	30.8	2	2	2	3	0.0001
2	6	16	0	7	3	0	120	84	0	True	elu	52.20	67.8	31.5	2	2	2	3	0.0001
11	6	16	0	7	3	0	200	100	0	True	tanh	52.05	66.9	28.2	2	2	2	3	0.0001
4	6	16	0	5	5	0	120	84	0	True	softsign	51.88	67.0	31.1	2	2	2	3	0.0001
10	6	16	0	7	3	0	120	84	0	True	tanh	51.67	70.8	29.0	2	2	2	3	0.0001
7	6	16	0	7	3	0	200	100	0	True	softsign	50.12	66.1	29.3	2	2	2	3	0.0001
6	6	16	0	7	3	0	120	84	0	True	softsign	49.70	68.1	26.9	2	2	2	3	0.0001

In [62]:

```
# global_res.to_csv('2-2-2--13-epoch--cifar10.csv', sep='\t', encoding='utf-8')
```

In [67]:

```
# global_res['num_epochs'] = 3
# global_res['lr'] = 1e-4
```

In [59]:

```
# global_res.loc[13,'num_epochs'] = 7
```

Лучашя сеть из прошлой лабы показала удручающий результат **55%.** Пробую увеличить кол-во эпох и изменить **learning_rates**

In [83]:

```
# functions = [F.elu, F.leaky_relu]
functions = [F.elu]
num_epochssss = [3, 7, 13]
learning_rates = [5e-3, 5e-4, 5e-5]
```

In [84]:

```
for function in tqdm_notebook(functions):
```

```python
    for num_epochs in tqdm_notebook(num_epochssss):
        for learning_rate in tqdm_notebook(learning_rates):
            net = SimpleConvNet_my(6, 16, 5, 5, 200, 100, True, function)
            net.to(device)
            net.train(num_epochs=num_epochs, learning_rate=learning_rate)
            net.validatee()
            # print_res(global_res)
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2095501102.py:1: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for function in tqdm_notebook(functions):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2095501102.py:2: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for num_epochs in tqdm_notebook(num_epochssss):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2095501102.py:3: TqdmDeprecationWarning: This function will be removed in tqdm=
=5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for learning_rate in tqdm_notebook(learning_rates):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2477625818.py:52: TqdmDeprecationWarning: This function will be removed in tqdm
==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for epoch in tqdm_notebook(range(num_epochs)):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2477625818.py:54: TqdmDeprecationWarning: This function will be removed in tqdm
==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for i, batch in enumerate(tqdm_notebook(trainloader)):
```

```
[1,  2000] loss: 2.432
[1,  4000] loss: 2.486
[1,  6000] loss: 2.487
[1,  8000] loss: 2.483
[1, 10000] loss: 2.486
[1, 12000] loss: 2.493


[2,  2000] loss: 2.491
[2,  4000] loss: 2.479
[2,  6000] loss: 2.485
[2,  8000] loss: 2.483
[2, 10000] loss: 2.487
[2, 12000] loss: 2.487


[3,  2000] loss: 2.485
```

```
[3,  2000] loss: 2.485
[3,  4000] loss: 2.481
[3,  6000] loss: 2.480
[3,  8000] loss: 2.498
[3, 10000] loss: 2.489
[3, 12000] loss: 2.477
fin
Accuracy of plane :  0 %
Accuracy of car :  0 %
Accuracy of bird :  0 %
Accuracy of cat :  0 %
Accuracy of deer : 100 %
Accuracy of dog :  0 %
Accuracy of frog :  0 %
Accuracy of horse :  0 %
Accuracy of ship :  0 %
Accuracy of truck :  0 %

Total accuracy AVG: 10.0
max=100.0; min=0.0
19 [6, 16, 0, 5, 5, 0, 200, 100, 0, True, 'elu', 10.0, 100.0, 0.0, 2, 2, 2, 3, 0.005]


[1,  2000] loss: 1.784
[1,  4000] loss: 1.575
[1,  6000] loss: 1.473
[1,  8000] loss: 1.413
[1, 10000] loss: 1.368
[1, 12000] loss: 1.311


[2,  2000] loss: 1.226
[2,  4000] loss: 1.218
[2,  6000] loss: 1.208
[2,  8000] loss: 1.202
[2, 10000] loss: 1.159
[2, 12000] loss: 1.148


[3,  2000] loss: 1.058
[3,  4000] loss: 1.052
[3,  6000] loss: 1.033
[3,  8000] loss: 1.044
[3, 10000] loss: 1.045
[3, 12000] loss: 1.011
fin
Accuracy of plane : 54 %
Accuracy of car : 69 %
Accuracy of bird : 48 %
Accuracy of cat : 53 %
Accuracy of deer : 55 %
Accuracy of dog : 46 %
```

```
Accuracy of frog : 65 %
Accuracy of horse : 68 %
Accuracy of ship : 83 %
Accuracy of truck : 69 %

Total accuracy AVG: 61.42
max=83.0; min=46.9
19 [6, 16, 0, 5, 5, 0, 200, 100, 0, True, 'elu', 61.42, 83.0, 46.9, 2, 2, 2, 3, 0.0005]


[1,  2000] loss: 2.049
[1,  4000] loss: 1.880
[1,  6000] loss: 1.777
[1,  8000] loss: 1.695
[1, 10000] loss: 1.647
[1, 12000] loss: 1.609


[2,  2000] loss: 1.559
[2,  4000] loss: 1.547
[2,  6000] loss: 1.494
[2,  8000] loss: 1.489
[2, 10000] loss: 1.475
[2, 12000] loss: 1.455


[3,  2000] loss: 1.435
[3,  4000] loss: 1.421
[3,  6000] loss: 1.399
[3,  8000] loss: 1.387
[3, 10000] loss: 1.381
[3, 12000] loss: 1.378
fin
Accuracy of plane : 55 %
Accuracy of car : 62 %
Accuracy of bird : 37 %
Accuracy of cat : 30 %
Accuracy of deer : 36 %
Accuracy of dog : 36 %
Accuracy of frog : 71 %
Accuracy of horse : 60 %
Accuracy of ship : 59 %
Accuracy of truck : 57 %

Total accuracy AVG: 50.85
max=71.6; min=30.3
19 [6, 16, 0, 5, 5, 0, 200, 100, 0, True, 'elu', 50.85, 71.6, 30.3, 2, 2, 2, 3, 5e-05]



[1,  2000] loss: 2.303
[1,  4000] loss: 2.461
```

```
[1,  6000] loss: 2.488
[1,  8000] loss: 2.485
[1, 10000] loss: 2.486
[1, 12000] loss: 2.486

[2,  2000] loss: 2.483
[2,  4000] loss: 2.481
[2,  6000] loss: 2.475
[2,  8000] loss: 2.494
[2, 10000] loss: 2.493
[2, 12000] loss: 2.489

[3,  2000] loss: 2.488
[3,  4000] loss: 2.478
[3,  6000] loss: 2.487
[3,  8000] loss: 2.480
[3, 10000] loss: 2.480
[3, 12000] loss: 2.504

[4,  2000] loss: 2.488
[4,  4000] loss: 2.494
[4,  6000] loss: 2.495
[4,  8000] loss: 2.486
[4, 10000] loss: 2.493
[4, 12000] loss: 2.480

[5,  2000] loss: 2.488
[5,  4000] loss: 2.474
[5,  6000] loss: 2.498
[5,  8000] loss: 2.484
[5, 10000] loss: 2.485
[5, 12000] loss: 2.484

[6,  2000] loss: 2.496
[6,  4000] loss: 2.478
[6,  6000] loss: 2.496
[6,  8000] loss: 2.476
[6, 10000] loss: 2.484
[6, 12000] loss: 2.482

[7,  2000] loss: 2.478
[7,  4000] loss: 2.484
[7,  6000] loss: 2.496
[7,  8000] loss: 2.490
[7, 10000] loss: 2.482
[7, 12000] loss: 2.486
fin
```

```
Accuracy of plane :  0 %
Accuracy of car : 100 %
Accuracy of bird :  0 %
Accuracy of cat :  0 %
Accuracy of deer :  0 %
Accuracy of dog :  0 %
Accuracy of frog :  0 %
Accuracy of horse :  0 %
Accuracy of ship :  0 %
Accuracy of truck :  0 %

Total accuracy AVG: 10.0
max=100.0; min=0.0
19 [6, 16, 0, 5, 5, 0, 200, 100, 0, True, 'elu', 10.0, 100.0, 0.0, 2, 2, 2, 7, 0.005]


[1,  2000] loss: 1.779
[1,  4000] loss: 1.556
[1,  6000] loss: 1.455
[1,  8000] loss: 1.390
[1, 10000] loss: 1.310
[1, 12000] loss: 1.279

[2,  2000] loss: 1.212
[2,  4000] loss: 1.175
[2,  6000] loss: 1.159
[2,  8000] loss: 1.142
[2, 10000] loss: 1.130
[2, 12000] loss: 1.086

[3,  2000] loss: 1.027
[3,  4000] loss: 1.011
[3,  6000] loss: 1.001
[3,  8000] loss: 0.994
[3, 10000] loss: 0.996
[3, 12000] loss: 0.982

[4,  2000] loss: 0.872
[4,  4000] loss: 0.887
[4,  6000] loss: 0.896
[4,  8000] loss: 0.892
[4, 10000] loss: 0.899
[4, 12000] loss: 0.898

[5,  2000] loss: 0.772
[5,  4000] loss: 0.800
[5,  6000] loss: 0.808
[5,  8000] loss: 0.814
[5, 10000] loss: 0.813
```

```
[5, 12000] loss: 0.821


[6,  2000] loss: 0.692
[6,  4000] loss: 0.695
[6,  6000] loss: 0.740
[6,  8000] loss: 0.744
[6, 10000] loss: 0.747
[6, 12000] loss: 0.738


[7,  2000] loss: 0.609
[7,  4000] loss: 0.642
[7,  6000] loss: 0.644
[7,  8000] loss: 0.686
[7, 10000] loss: 0.687
[7, 12000] loss: 0.673
fin
Accuracy of plane : 73 %
Accuracy of car : 78 %
Accuracy of bird : 58 %
Accuracy of cat : 46 %
Accuracy of deer : 65 %
Accuracy of dog : 59 %
Accuracy of frog : 66 %
Accuracy of horse : 65 %
Accuracy of ship : 77 %
Accuracy of truck : 73 %

Total accuracy AVG: 66.46
max=78.1; min=46.7
19 [6, 16, 0, 5, 5, 0, 200, 100, 0, True, 'elu', 66.46, 78.1, 46.7, 2, 2, 2, 7, 0.0005]



[1,  2000] loss: 2.018
[1,  4000] loss: 1.791
[1,  6000] loss: 1.678
[1,  8000] loss: 1.660
[1, 10000] loss: 1.591
[1, 12000] loss: 1.581


[2,  2000] loss: 1.528
[2,  4000] loss: 1.514
[2,  6000] loss: 1.454
[2,  8000] loss: 1.481
[2, 10000] loss: 1.469
[2, 12000] loss: 1.443


[3,  2000] loss: 1.409
[3,  4000] loss: 1.409
[3,  6000] loss: 1.401
```

```
[3,  6000] loss: 1.401
[3,  8000] loss: 1.376
[3, 10000] loss: 1.363
[3, 12000] loss: 1.386


[4,  2000] loss: 1.330
[4,  4000] loss: 1.334
[4,  6000] loss: 1.325
[4,  8000] loss: 1.333
[4, 10000] loss: 1.314
[4, 12000] loss: 1.309


[5,  2000] loss: 1.264
[5,  4000] loss: 1.282
[5,  6000] loss: 1.279
[5,  8000] loss: 1.279
[5, 10000] loss: 1.257
[5, 12000] loss: 1.264


[6,  2000] loss: 1.216
[6,  4000] loss: 1.235
[6,  6000] loss: 1.239
[6,  8000] loss: 1.229
[6, 10000] loss: 1.233
[6, 12000] loss: 1.209


[7,  2000] loss: 1.210
[7,  4000] loss: 1.199
[7,  6000] loss: 1.182
[7,  8000] loss: 1.175
[7, 10000] loss: 1.182
[7, 12000] loss: 1.178
fin
Accuracy of plane : 61 %
Accuracy of car : 73 %
Accuracy of bird : 32 %
Accuracy of cat : 36 %
Accuracy of deer : 33 %
Accuracy of dog : 50 %
Accuracy of frog : 80 %
Accuracy of horse : 66 %
Accuracy of ship : 69 %
Accuracy of truck : 60 %

Total accuracy AVG: 56.36
max=80.4; min=32.2
19 [6, 16, 0, 5, 5, 0, 200, 100, 0, True, 'elu', 56.36, 80.4, 32.2, 2, 2, 2, 7, 5e-05]
```

```
[1,  2000] loss: 2.439
[1,  4000] loss: 2.479
[1,  6000] loss: 2.493
[1,  8000] loss: 2.485
[1, 10000] loss: 2.488
[1, 12000] loss: 2.490

[2,  2000] loss: 2.497
[2,  4000] loss: 2.483
[2,  6000] loss: 2.485
[2,  8000] loss: 2.499
[2, 10000] loss: 2.480
[2, 12000] loss: 2.527

[3,  2000] loss: 2.487
[3,  4000] loss: 2.488
[3,  6000] loss: 2.479
[3,  8000] loss: 2.473
[3, 10000] loss: 2.486
[3, 12000] loss: 2.490

[4,  2000] loss: 2.489
[4,  4000] loss: 2.480
[4,  6000] loss: 2.498
[4,  8000] loss: 2.481
[4, 10000] loss: 2.491
[4, 12000] loss: 2.489

[5,  2000] loss: 2.487
[5,  4000] loss: 2.490
[5,  6000] loss: 2.492
[5,  8000] loss: 2.490
[5, 10000] loss: 2.487
[5, 12000] loss: 2.495

[6,  2000] loss: 2.483
[6,  4000] loss: 2.483
[6,  6000] loss: 2.494
[6,  8000] loss: 2.491
[6, 10000] loss: 2.487
[6, 12000] loss: 2.496

[7,  2000] loss: 2.492
[7,  4000] loss: 2.503
[7,  6000] loss: 2.481
[7,  8000] loss: 2.483
[7, 10000] loss: 2.495
```

```
[7, 12000] loss: 2.487

[8,  2000] loss: 2.487
[8,  4000] loss: 2.490
[8,  6000] loss: 2.491
[8,  8000] loss: 2.484
[8, 10000] loss: 2.485
[8, 12000] loss: 2.478

[9,  2000] loss: 2.482
[9,  4000] loss: 2.477
[9,  6000] loss: 2.480
[9,  8000] loss: 2.499
[9, 10000] loss: 2.485
[9, 12000] loss: 2.484

[10,  2000] loss: 2.492
[10,  4000] loss: 2.493
[10,  6000] loss: 2.492
[10,  8000] loss: 2.490
[10, 10000] loss: 2.481
[10, 12000] loss: 2.494

[11,  2000] loss: 2.493
[11,  4000] loss: 2.484
[11,  6000] loss: 2.488
[11,  8000] loss: 2.482
[11, 10000] loss: 2.487
[11, 12000] loss: 2.478

[12,  2000] loss: 2.492
[12,  4000] loss: 2.498
[12,  6000] loss: 2.500
[12,  8000] loss: 2.487
[12, 10000] loss: 2.486
[12, 12000] loss: 2.490

[13,  2000] loss: 2.489
[13,  4000] loss: 2.480
[13,  6000] loss: 2.477
[13,  8000] loss: 2.491
[13, 10000] loss: 2.484
[13, 12000] loss: 2.497
fin
Accuracy of plane :  0 %
Accuracy of car :  0 %
Accuracy of bird : 100 %
Accuracy of cat :  0 %
```

```
Accuracy of deer :  0 %
Accuracy of dog :  0 %
Accuracy of frog :  0 %
Accuracy of horse :  0 %
Accuracy of ship :  0 %
Accuracy of truck :  0 %

Total accuracy AVG: 10.0
max=100.0; min=0.0
19 [6, 16, 0, 5, 5, 0, 200, 100, 0, True, 'elu', 10.0, 100.0, 0.0, 2, 2, 2, 13, 0.005]


[1,  2000] loss: 1.765
[1,  4000] loss: 1.516
[1,  6000] loss: 1.425
[1,  8000] loss: 1.346
[1, 10000] loss: 1.325
[1, 12000] loss: 1.269

[2,  2000] loss: 1.195
[2,  4000] loss: 1.165
[2,  6000] loss: 1.176
[2,  8000] loss: 1.133
[2, 10000] loss: 1.131
[2, 12000] loss: 1.130

[3,  2000] loss: 1.026
[3,  4000] loss: 1.020
[3,  6000] loss: 1.015
[3,  8000] loss: 1.029
[3, 10000] loss: 1.025
[3, 12000] loss: 1.014

[4,  2000] loss: 0.911
[4,  4000] loss: 0.909
[4,  6000] loss: 0.906
[4,  8000] loss: 0.924
[4, 10000] loss: 0.924
[4, 12000] loss: 0.923

[5,  2000] loss: 0.799
[5,  4000] loss: 0.812
[5,  6000] loss: 0.832
[5,  8000] loss: 0.852
[5, 10000] loss: 0.823
[5, 12000] loss: 0.836

[6,  2000] loss: 0.726
```

```
[6,  4000] loss: 0.720
[6,  6000] loss: 0.752
[6,  8000] loss: 0.752
[6, 10000] loss: 0.761
[6, 12000] loss: 0.767

[7,  2000] loss: 0.622
[7,  4000] loss: 0.647
[7,  6000] loss: 0.668
[7,  8000] loss: 0.692
[7, 10000] loss: 0.721
[7, 12000] loss: 0.695

[8,  2000] loss: 0.553
[8,  4000] loss: 0.591
[8,  6000] loss: 0.599
[8,  8000] loss: 0.619
[8, 10000] loss: 0.637
[8, 12000] loss: 0.643

[9,  2000] loss: 0.479
[9,  4000] loss: 0.539
[9,  6000] loss: 0.551
[9,  8000] loss: 0.588
[9, 10000] loss: 0.572
[9, 12000] loss: 0.587

[10,  2000] loss: 0.444
[10,  4000] loss: 0.464
[10,  6000] loss: 0.500
[10,  8000] loss: 0.524
[10, 10000] loss: 0.541
[10, 12000] loss: 0.535

[11,  2000] loss: 0.397
[11,  4000] loss: 0.440
[11,  6000] loss: 0.459
[11,  8000] loss: 0.483
[11, 10000] loss: 0.479
[11, 12000] loss: 0.482

[12,  2000] loss: 0.364
[12,  4000] loss: 0.389
[12,  6000] loss: 0.416
[12,  8000] loss: 0.435
[12, 10000] loss: 0.433
[12, 12000] loss: 0.455
```

```
[13,  2000] loss: 0.306
[13,  4000] loss: 0.355
[13,  6000] loss: 0.380
[13,  8000] loss: 0.396
[13, 10000] loss: 0.417
[13, 12000] loss: 0.449
fin
Accuracy of plane : 71 %
Accuracy of car : 76 %
Accuracy of bird : 53 %
Accuracy of cat : 43 %
Accuracy of deer : 54 %
Accuracy of dog : 54 %
Accuracy of frog : 78 %
Accuracy of horse : 74 %
Accuracy of ship : 77 %
Accuracy of truck : 71 %

Total accuracy AVG: 65.48
max=78.9; min=43.2
19 [6, 16, 0, 5, 5, 0, 200, 100, 0, True, 'elu', 65.48, 78.9, 43.2, 2, 2, 2, 13, 0.0005]


[1,  2000] loss: 2.026
[1,  4000] loss: 1.857
[1,  6000] loss: 1.735
[1,  8000] loss: 1.655
[1, 10000] loss: 1.626
[1, 12000] loss: 1.536

[2,  2000] loss: 1.505
[2,  4000] loss: 1.514
[2,  6000] loss: 1.494
[2,  8000] loss: 1.455
[2, 10000] loss: 1.446
[2, 12000] loss: 1.452

[3,  2000] loss: 1.426
[3,  4000] loss: 1.410
[3,  6000] loss: 1.404
[3,  8000] loss: 1.397
[3, 10000] loss: 1.388
[3, 12000] loss: 1.363

[4,  2000] loss: 1.356
[4,  4000] loss: 1.354
[4,  6000] loss: 1.328
[4,  8000] loss: 1.331
```

```
[4, 10000] loss: 1.332
[4, 12000] loss: 1.301

[5,  2000] loss: 1.299
[5,  4000] loss: 1.289
[5,  6000] loss: 1.283
[5,  8000] loss: 1.289
[5, 10000] loss: 1.260
[5, 12000] loss: 1.260

[6,  2000] loss: 1.253
[6,  4000] loss: 1.245
[6,  6000] loss: 1.235
[6,  8000] loss: 1.242
[6, 10000] loss: 1.212
[6, 12000] loss: 1.226

[7,  2000] loss: 1.200
[7,  4000] loss: 1.192
[7,  6000] loss: 1.194
[7,  8000] loss: 1.196
[7, 10000] loss: 1.177
[7, 12000] loss: 1.224

[8,  2000] loss: 1.171
[8,  4000] loss: 1.171
[8,  6000] loss: 1.161
[8,  8000] loss: 1.169
[8, 10000] loss: 1.150
[8, 12000] loss: 1.155

[9,  2000] loss: 1.151
[9,  4000] loss: 1.132
[9,  6000] loss: 1.124
[9,  8000] loss: 1.139
[9, 10000] loss: 1.118
[9, 12000] loss: 1.126

[10,  2000] loss: 1.114
[10,  4000] loss: 1.083
[10,  6000] loss: 1.107
[10,  8000] loss: 1.121
[10, 10000] loss: 1.089
[10, 12000] loss: 1.102

[11,  2000] loss: 1.063
[11,  4000] loss: 1.072
```

```
[11,  6000] loss: 1.070
[11,  8000] loss: 1.078
[11, 10000] loss: 1.086
[11, 12000] loss: 1.081


[12,  2000] loss: 1.062
[12,  4000] loss: 1.060
[12,  6000] loss: 1.051
[12,  8000] loss: 1.056
[12, 10000] loss: 1.038
[12, 12000] loss: 1.054


[13,  2000] loss: 1.001
[13,  4000] loss: 1.025
[13,  6000] loss: 1.050
[13,  8000] loss: 1.016
[13, 10000] loss: 1.041
[13, 12000] loss: 1.034
fin
Accuracy of plane : 63 %
Accuracy of car : 75 %
Accuracy of bird : 42 %
Accuracy of cat : 30 %
Accuracy of deer : 55 %
Accuracy of dog : 48 %
Accuracy of frog : 73 %
Accuracy of horse : 70 %
Accuracy of ship : 77 %
Accuracy of truck : 64 %

Total accuracy AVG: 60.17
max=77.4; min=30.7
19 [6, 16, 0, 5, 5, 0, 200, 100, 0, True, 'elu', 60.17, 77.4, 30.7, 2, 2, 2, 13, 5e-05]
```

In [79]:

```
# net = SimpleConvNet_my(6, 16, 5, 5, 200, 100, True, F.elu)
# net.to(device)
# net.train(num_epochs=13)
# net.validatee()
# print_res(global_res)
```

In [89]:

```
# global_res.to_csv('elu-ne-3-7-13--lr-3-4-5.csv', sep='\t', encoding='utf-8')
```

Увеличение кол-ва эпох с **3** до **13** увеличело предсказание на **10% (**Лучшее **64%)** Пробую уменьшить **learning_rate**

In [80]:

In [80]:

```
# net = SimpleConvNet_my(6, 16, 5, 5, 200, 100, True, F.leaky_relu)
# net.to(device)
# net.train(num_epochs=2) #, learning_rate=5e-5)
# net.validatee()
# print_res(global_res)
```

In [85]:

```
print_res(global_res)
```

Out[85]:

	channels1	channels2	channels3	kernel_size1	kernel_size2	kernel_size3	fc1	fc2	fc3	is_max_pool	activation	avg	max	min	ch_c	conv_c	fc_c	num_epochs	lr
4	6	16	0	5	5	0	200	100	0	True	elu	66.46	78.1	46.7	2	2	2	7	0.00050
7	6	16	0	5	5	0	200	100	0	True	elu	65.48	78.9	43.2	2	2	2	13	0.00050
1	6	16	0	5	5	0	200	100	0	True	elu	61.42	83.0	46.9	2	2	2	3	0.00050
8	6	16	0	5	5	0	200	100	0	True	elu	60.17	77.4	30.7	2	2	2	13	0.00005
5	6	16	0	5	5	0	200	100	0	True	elu	56.36	80.4	32.2	2	2	2	7	0.00005
2	6	16	0	5	5	0	200	100	0	True	elu	50.85	71.6	30.3	2	2	2	3	0.00005
0	6	16	0	5	5	0	200	100	0	True	elu	10.00	100.0	0.0	2	2	2	3	0.00500
3	6	16	0	5	5	0	200	100	0	True	elu	10.00	100.0	0.0	2	2	2	7	0.00500
6	6	16	0	5	5	0	200	100	0	True	elu	10.00	100.0	0.0	2	2	2	13	0.00500

In [ ]:

```
лучший результат с 2 conv и 2 fc получился 66.46%
```

Пробую другую архитектуру с дропаутом**, 3 FC** и **4 conv**

In [129]:

```
from torch.nn import Dropout
class SimpleConvNet_my2(nn.Module):
    def __init__(self, channels1, channels2, channels3, channels4, kernel_size1, kernel_size2, kernel_size3, kernel_size4, fc1, f
c2, dropout, is_max_pool = True, activation=F.relu):
        # вызов конструктора предка
        super(SimpleConvNet_my2, self).__init__()
        # необходмо заранее знать, сколько каналов у картинки (сейчас = 1),
        # которую будем подавать в сеть, больше ничего
        # про входящие картинки знать не нужно
        self.channels1 = channels1
```

```
        self.channels2 = channels2
        self.kernel_size1 = kernel_size1
        self.kernel_size2 = kernel_size2
        self.fc1_c = fc1
        self.fc2_c = fc2
        self.is_max_pool = is_max_pool
        self.activation = activation
        self.num_epochs = 0

        if is_max_pool:
          self.pool = nn.MaxPool2d(kernel_size=2, stride=2)
        else:
          self.pool = nn.AvgPool2d(kernel_size=2, stride=2)

        self.conv1 = nn.Conv2d(in_channels=3, out_channels=channels1, kernel_size=kernel_size1)
        new_size = 32 - kernel_size1 + 1
        #new_size = new_size // 2

        self.conv2 = nn.Conv2d(in_channels=channels1, out_channels=channels2, kernel_size=kernel_size2)
        new_size = new_size - kernel_size2 + 1
        new_size = new_size // 2 #тут нет пулинга

        self.conv3 = nn.Conv2d(in_channels=channels2, out_channels=channels3, kernel_size=kernel_size3)
        new_size = new_size - kernel_size3 + 1
        #new_size = new_size // 2

        self.conv4 = nn.Conv2d(in_channels=channels3, out_channels=channels4, kernel_size=kernel_size4)
        new_size = new_size - kernel_size4 + 1
        new_size = new_size // 2

        #print(new_size)

        self.fc1_size = new_size * new_size * channels4

        self.fc1 = nn.Linear(self.fc1_size, fc1)  # !!!
        self.fc2 = nn.Linear(fc1, fc2)
        self.fc3 = nn.Linear(fc2, 10)

        # self.fc1 = nn.Linear(self.fc1_size, fc1)
        # self.fc3 = nn.Linear(fc1, 10)

        self.dropout1 = Dropout(dropout)
        self.dropout2 = Dropout(dropout)


    def forward(self, x):
        x = self.pool(self.activation(self.conv2(self.activation(self.conv1(x)))))
        x = self.pool(self.conv4(self.activation(self.conv3(x))))
        x = x.view(-1, self.fc1_size)
        x = self.dropout1(self.activation(self.fc1(x)))
```

```python
        x = self.dropout2(self.activation(self.fc2(x)))
        x = self.fc3(x)

        return x

    def train(self, learning_rate = 1e-4, num_epochs = 3):
        self.num_epochs = num_epochs
        self.learning_rate = learning_rate
        loss_fn = torch.nn.CrossEntropyLoss()
        optimizer = torch.optim.Adam(self.parameters(), lr=learning_rate)
        # итерируемся
        for epoch in tqdm_notebook(range(num_epochs)):
            running_loss = 0.0
            for i, batch in enumerate(tqdm_notebook(trainloader)):
                # так получаем текущий батч
                X_batch, y_batch = batch
                global device
                X_batch, y_batch = X_batch.to(device), y_batch.to(device)

                # обнуляем веса
                optimizer.zero_grad()

                # forward + backward + optimize
                y_pred = self(X_batch)
                loss = loss_fn(y_pred, y_batch)
                loss.backward()
                optimizer.step()

                # выведем текущий loss
                running_loss += loss.item()
                # выведем качество каждые 2000 батчей
                if i % 2000 == 1999:
                    print('[%d, %5d] loss: %.3f' %
                          (epoch + 1, i + 1, running_loss / 2000))
                    running_loss = 0.0

        print('fin')

    def validatee(self):
        class_correct = list(0. for i in range(10))
        class_total = list(0. for i in range(10))

        with torch.no_grad():
            for data in testloader:
                images, labels = data
                global device
                images, labels = images.to(device), labels.to(device)
                y_pred = self(images)
                _, predicted = torch.max(y_pred, 1)
                c = (predicted == labels).squeeze()
```

```
            for i in range(4):
                label = labels[i]
                class_correct[label] += c[i].item()
                class_total[label] += 1
    res = []
    for i in range(10):
        tmp = 100 * class_correct[i] / class_total[i]
        res.append(tmp)
        print('Accuracy of %2s : %2d %%' % (
            classes[i], tmp))

    class_correct_t = sum(class_correct)
    class_total_t = sum(class_total)

    rrr = (100. * class_correct_t / class_total_t)
    print('\nTotal accuracy AVG:', rrr)
    print(f'max={max(res)}; min={min(res)}')
    rezzz = [
          self.channels1,
          self.channels2,
          0,
          self.kernel_size1,
          self.kernel_size2,
          0,
          self.fc1_c,
          self.fc2_c,
          0,
          self.is_max_pool,
          get_f_name(self.activation),
          rrr,
          round(max(res), 2),
          round(min(res), 2),
          4,
          4,
          2,
          self.num_epochs,
          self.learning_rate
    ]
    print(len(rezzz), rezzz)
    global_res.loc[len(global_res)] = rezzz
```

In [113]:

```
# device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
device = torch.device("cpu")
print(str(device))
```

cpu

In [131]:

```python
net = SimpleConvNet_my2(20, 30, 40, 50, 3, 3, 3, 3, 120, 84, 0.1, True)
net.to(device)
net.train(num_epochs=10, learning_rate=5e-3)
net.validatee()
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/4023883281.py:71: TqdmDeprecationWarning: This function will be removed in tqdm
==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for epoch in tqdm_notebook(range(num_epochs)):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/4023883281.py:73: TqdmDeprecationWarning: This function will be removed in tqdm
==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for i, batch in enumerate(tqdm_notebook(trainloader)):
```

```
[1,  2000] loss: 2.306
[1,  4000] loss: 2.307
[1,  6000] loss: 2.305
[1,  8000] loss: 2.304
[1, 10000] loss: 2.305
[1, 12000] loss: 2.305

[2,  2000] loss: 2.305
[2,  4000] loss: 2.304
[2,  6000] loss: 2.305
[2,  8000] loss: 2.304
[2, 10000] loss: 2.304
[2, 12000] loss: 2.304

[3,  2000] loss: 2.305
[3,  4000] loss: 2.305
[3,  6000] loss: 2.304
[3,  8000] loss: 2.305
[3, 10000] loss: 2.305
[3, 12000] loss: 2.304

[4,  2000] loss: 2.305
[4,  4000] loss: 2.304
[4,  6000] loss: 2.305
[4,  8000] loss: 2.305
[4, 10000] loss: 2.305
[4, 12000] loss: 2.305

[5,  2000] loss: 2.309
[5,  4000] loss: 2.305
[5,  6000] loss: 2.305
[5,  8000] loss: 2.306
```

```
[5, 10000] loss: 2.305
[5, 12000] loss: 2.304

[6,  2000] loss: 2.304
[6,  4000] loss: 2.309
[6,  6000] loss: 2.306
[6,  8000] loss: 2.305
[6, 10000] loss: 2.304
[6, 12000] loss: 2.308

[7,  2000] loss: 2.305
[7,  4000] loss: 2.304
[7,  6000] loss: 2.304
[7,  8000] loss: 2.305
[7, 10000] loss: 2.304
[7, 12000] loss: 2.305

[8,  2000] loss: 2.305
[8,  4000] loss: 2.304
[8,  6000] loss: 2.305
[8,  8000] loss: 2.305
[8, 10000] loss: 2.305
[8, 12000] loss: 2.305

[9,  2000] loss: 2.305
[9,  4000] loss: 2.304
[9,  6000] loss: 2.304
[9,  8000] loss: 2.304
[9, 10000] loss: 2.304
[9, 12000] loss: 2.304

[10,  2000] loss: 2.305
[10,  4000] loss: 2.305
[10,  6000] loss: 2.304
[10,  8000] loss: 2.305
[10, 10000] loss: 2.304
[10, 12000] loss: 2.305
fin
Accuracy of plane :   0 %
Accuracy of car :   0 %
Accuracy of bird :   0 %
Accuracy of cat :   0 %
Accuracy of deer :   0 %
Accuracy of dog :   0 %
Accuracy of frog :   0 %
Accuracy of horse :   0 %
Accuracy of ship : 100 %
Accuracy of truck :   0 %
```

```
Total accuracy AVG: 10.0
max=100.0; min=0.0
19 [20, 30, 0, 3, 3, 0, 120, 84, 0, True, 'relu', 10.0, 100.0, 0.0, 4, 4, 2, 10, 0.005]
```

ООЧень забавный результат.

Сеть обучилась только на рыбках

Убираю один **fc** слой

In [123]:

```
from torch.nn import Dropout
class SimpleConvNet_my3(nn.Module):
    def __init__(self, channels1, channels2, channels3, channels4, kernel_size1, kernel_size2, kernel_size3, kernel_size4, fc1, d
ropout, is_max_pool = True, activation=F.relu):
        # вызов конструктора предка
        super(SimpleConvNet_my3, self).__init__()
        # необходимо заранее знать, сколько каналов у картинки (сейчас = 1),
        # которую будем подавать в сеть, больше ничего
        # про входящие картинки знать не нужно
        self.channels1 = channels1
        self.channels2 = channels2
        self.kernel_size1 = kernel_size1
        self.kernel_size2 = kernel_size2
        self.fc1_c = fc1
        self.fc2_c = 0
        self.is_max_pool = is_max_pool
        self.activation = activation
        self.num_epochs = 0

        if is_max_pool:
          self.pool = nn.MaxPool2d(kernel_size=2, stride=2)
        else:
          self.pool = nn.AvgPool2d(kernel_size=2, stride=2)

        self.conv1 = nn.Conv2d(in_channels=3, out_channels=channels1, kernel_size=kernel_size1)
        new_size = 32 - kernel_size1 + 1
        #new_size = new_size // 2

        self.conv2 = nn.Conv2d(in_channels=channels1, out_channels=channels2, kernel_size=kernel_size2)
        new_size = new_size - kernel_size2 + 1
        new_size = new_size // 2 #тут нет пулинга

        self.conv3 = nn.Conv2d(in_channels=channels2, out_channels=channels3, kernel_size=kernel_size3)
        new_size = new_size - kernel_size3 + 1
        #new_size = new_size // 2

        self.conv4 = nn.Conv2d(in_channels=channels3, out_channels=channels4, kernel_size=kernel_size4)
```

```python
        new_size = new_size - kernel_size4 + 1
        new_size = new_size // 2

        #print(new_size)

        self.fc1_size = new_size * new_size * channels4

        self.fc1 = nn.Linear(self.fc1_size, fc1)   # !!!
        # self.fc2 = nn.Linear(fc1, fc2)
        self.fc3 = nn.Linear(fc1, 10)

        # self.fc1 = nn.Linear(self.fc1_size, fc1)
        # self.fc3 = nn.Linear(fc1, 10)

        self.dropout1 = Dropout(dropout)
        # self.dropout2 = Dropout(dropout)


    def forward(self, x):
        x = self.pool(self.activation(self.conv2(self.activation(self.conv1(x)))))
        x = self.pool(self.conv4(self.activation(self.conv3(x))))
        x = x.view(-1, self.fc1_size)
        x = self.dropout1(self.activation(self.fc1(x)))
        # x = self.dropout2(self.activation(self.fc2(x)))
        x = self.fc3(x)

        return x

    def train(self, learning_rate = 1e-4, num_epochs = 3):
        self.num_epochs = num_epochs
        self.learning_rate = learning_rate
        loss_fn = torch.nn.CrossEntropyLoss()
        optimizer = torch.optim.Adam(self.parameters(), lr=learning_rate)
        # итерируемся
        for epoch in tqdm_notebook(range(num_epochs)):
            running_loss = 0.0
            for i, batch in enumerate(tqdm_notebook(trainloader)):
                # так получаем текущий батч
                X_batch, y_batch = batch
                global device
                X_batch, y_batch = X_batch.to(device), y_batch.to(device)

                # обнуляем веса
                optimizer.zero_grad()

                # forward + backward + optimize
                y_pred = self(X_batch)
                loss = loss_fn(y_pred, y_batch)
                loss.backward()
                optimizer.step()
```

```
            # выведем текущий loss
            running_loss += loss.item()
            # выведем качество каждые 2000 батчей
            if i % 2000 == 1999:
                print('[%d, %5d] loss: %.3f' %
                      (epoch + 1, i + 1, running_loss / 2000))
                running_loss = 0.0

    print('fin')

def validatee(self):
    class_correct = list(0. for i in range(10))
    class_total = list(0. for i in range(10))

    with torch.no_grad():
        for data in testloader:
            images, labels = data
            global device
            images, labels = images.to(device), labels.to(device)
            y_pred = self(images)
            _, predicted = torch.max(y_pred, 1)
            c = (predicted == labels).squeeze()
            for i in range(4):
                label = labels[i]
                class_correct[label] += c[i].item()
                class_total[label] += 1
    res = []
    for i in range(10):
        tmp = 100 * class_correct[i] / class_total[i]
        res.append(tmp)
        print('Accuracy of %2s : %2d %%' % (
            classes[i], tmp))

    class_correct_t = sum(class_correct)
    class_total_t = sum(class_total)

    rrr = (100. * class_correct_t / class_total_t)
    print('\nTotal accuracy AVG:', rrr)
    print(f'max={max(res)}; min={min(res)}')
    rezzz = [
          self.channels1,
          self.channels2,
          0,
          self.kernel_size1,
          self.kernel_size2,
          0,
          self.fc1_c,
          self.fc2_c,
          0,
```

```
            self.is_max_pool,
            get_f_name(self.activation),
            rrr,
            round(max(res), 2),
            round(min(res), 2),
            4,
            4,
            2,
            self.num_epochs,
            self.learning_rate
        ]
        print(len(rezzz), rezzz)
        global_res.loc[len(global_res)] = rezzz
```

In [127]:

```
net = SimpleConvNet_my3(20, 30, 40, 50, 3, 3, 3, 3, 120, 0.1, True, F.relu)
net.to(device)
net.train(num_epochs=10, learning_rate=5e-3)
net.validatee()
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2322862002.py:71: TqdmDeprecationWarning: This function will be removed in tqdm
==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for epoch in tqdm_notebook(range(num_epochs)):
```

```
C:\Users\KOSHI8~1\AppData\Local\Temp/ipykernel_4672/2322862002.py:73: TqdmDeprecationWarning: This function will be removed in tqdm
==5.0.0
Please use `tqdm.notebook.tqdm` instead of `tqdm.tqdm_notebook`
  for i, batch in enumerate(tqdm_notebook(trainloader)):
```

```
[1,  2000] loss: 1.972
[1,  4000] loss: 1.671
[1,  6000] loss: 1.579
[1,  8000] loss: 1.510
[1, 10000] loss: 1.466
[1, 12000] loss: 1.420


[2,  2000] loss: 1.377
[2,  4000] loss: 1.350
[2,  6000] loss: 1.330
[2,  8000] loss: 1.310
[2, 10000] loss: 1.278
[2, 12000] loss: 1.284


[3,  2000] loss: 1.213
[3,  4000] loss: 1.204
[3,  6000] loss: 1.193
[3,  8000] loss: 1.154
```

```
[3, 10000] loss: 1.150
[3, 12000] loss: 1.133

[4,  2000] loss: 1.077
[4,  4000] loss: 1.083
[4,  6000] loss: 1.047
[4,  8000] loss: 1.045
[4, 10000] loss: 1.035
[4, 12000] loss: 1.022

[5,  2000] loss: 0.971
[5,  4000] loss: 0.992
[5,  6000] loss: 0.952
[5,  8000] loss: 0.957
[5, 10000] loss: 0.950
[5, 12000] loss: 0.907

[6,  2000] loss: 0.902
[6,  4000] loss: 0.886
[6,  6000] loss: 0.873
[6,  8000] loss: 0.858
[6, 10000] loss: 0.837
[6, 12000] loss: 0.898

[7,  2000] loss: 0.806
[7,  4000] loss: 0.810
[7,  6000] loss: 0.808
[7,  8000] loss: 0.815
[7, 10000] loss: 0.803
[7, 12000] loss: 0.804

[8,  2000] loss: 0.740
[8,  4000] loss: 0.755
[8,  6000] loss: 0.749
[8,  8000] loss: 0.746
[8, 10000] loss: 0.773
[8, 12000] loss: 0.761

[9,  2000] loss: 0.690
[9,  4000] loss: 0.720
[9,  6000] loss: 0.703
[9,  8000] loss: 0.709
[9, 10000] loss: 0.702
[9, 12000] loss: 0.710

[10,  2000] loss: 0.655
[10,  4000] loss: 0.660
```

```
[10,  6000] loss: 0.650
[10,  8000] loss: 0.677
[10, 10000] loss: 0.682
[10, 12000] loss: 0.683
fin
Accuracy of plane : 79 %
Accuracy of car : 84 %
Accuracy of bird : 51 %
Accuracy of cat : 56 %
Accuracy of deer : 68 %
Accuracy of dog : 65 %
Accuracy of frog : 79 %
Accuracy of horse : 80 %
Accuracy of ship : 76 %
Accuracy of truck : 80 %

Total accuracy AVG: 72.26
max=84.8; min=51.1
19 [20, 30, 0, 3, 3, 0, 120, 0, 0, True, 'relu', 72.26, 84.8, 51.1, 4, 4, 2, 10, 0.0001]
```

In [ ]:

```
import IPython
IPython.display.Audio("https://freesound.org/data/previews/80/80921_1022651-lq.ogg", autoplay=True)
# from js2py import eval_js
# eval_js('new Audio("https://freesound.org/data/previews/80/80921_1022651-lq.ogg").play()')
```

In [ ]:

```
ОГО! Отличный результат в 72%, думаю на нем стоит остановиться.

Итог увеличение конволюшен слоев дало хороший результат. В связке с дропаутом и 2 слоями fc получилось за 3 дня работы получить 7
2 %!

Кошкарев Алексей 20223
```