Assignment3 Part1

```
In [4]:
```

```
import torch
import torchvision
import torchvision.transforms as transforms
```

In [5]:

```
#Checking CUDA Availability
train_on_gpu = torch.cuda.is_available()

if not train_on_gpu:
    print('CUDA is not available! Training on CPU...')
else:
    print('CUDA is available! Training on GPU ...')
```

CUDA is available! Training on GPU ...

In [6]:

Files already downloaded and verified Files already downloaded and verified

In [7]:

```
import matplotlib.pyplot as plt
import numpy as np
# functions to show an image
def imshow(img):
   img = img / 2 + 0.5
                         # unnormalize
   npimg = img.numpy()
   plt.imshow(np.transpose(npimg, (1, 2, 0)))
   plt.show()
# get some random training images
dataiter = iter(trainloader)
images, labels = dataiter.next()
# show images
imshow(torchvision.utils.make grid(images))
plt.show()
# print labels
print(' '.join('%5s' % classes[labels[j]] for j in range(4)))
```

```
truck deer bird truck
```

In [8]:

```
import torch.nn as nn
import torch.nn.functional as F
class Net(nn.Module):
    def __init__(self):
        super(Net, self). init
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 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)))
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fcl(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
net = Net()
print(net)
Net.(
  (conv1): Conv2d(3, 6, kernel size=(5, 5), stride=(1, 1))
  (pool): MaxPool2d(kernel size=2, stride=2, padding=0, dilation=1, ceil mode=False)
  (conv2): Conv2d(6, 16, kernel size=(5, 5), stride=(1, 1))
  (fc1): Linear(in features=400, out features=120, bias=True)
  (fc2): Linear(in_features=120, out_features=84, bias=True)
  (fc3): Linear(in features=84, out features=10, bias=True)
In [5]:
import torch.optim as optim
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
In [6]:
for epoch in range(2): # loop over the dataset multiple times
    running loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # get the inputs
        inputs, labels = data
        # zero the parameter gradients
        optimizer.zero grad()
        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        # print statistics
        running_loss += loss.item()
        if i % 2000 == 1999:  # print every 2000 mini-batches
```

print('[%d, %5d] loss: %.3f' %

running loss = 0.0

(epoch + 1, i + 1, running_loss / 2000))

```
print('Finished Training')
[1, 2000] loss: 2.217 [1, 4000] loss: 1.861
[1, 6000] loss: 1.682
[1, 8000] loss: 1.586
[1, 10000] loss: 1.502
[1, 12000] loss: 1.450
[2, 2000] loss: 1.394
[2, 4000] loss: 1.352
[2, 6000] loss: 1.339
[2, 8000] loss: 1.326
[2, 10000] loss: 1.294
[2, 12000] loss: 1.286
Finished Training
Test the Network
In [8]:
dataiter = iter(testloader)
images, labels = dataiter.next()
# print images
imshow(torchvision.utils.make grid(images))
print('GroundTruth: ', ' '.join('%5s' % classes[labels[j]] for j in range(4)))
 20
              40
                    60
                          80
                                100
GroundTruth: cat ship ship plane
In [9]:
_, predicted = torch.max(outputs, 1)
print('Predicted: ', ' '.join('%5s' % classes[predicted[j]]
                              for j in range(4)))
Predicted: plane plane plane
In [15]:
correct = 0
total = 0
confusion matrix = np.zeros([10,10], int)
with torch.no grad():
   for data in testloader:
        images, labels = data
        outputs = net(images)
         _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
        for i, l in enumerate(labels):
            confusion_matrix[l.item(), predicted[i].item()] += 1
print('Accuracy of the network on the 10000 test images: %d %%' % (
```

Accuracy of the network on the 10000 test images: 52 $\mbox{\$}$

100 * correct / total))

In [11]:

```
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
        outputs = net(images)
        _, predicted = torch.max(outputs, 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]))
```

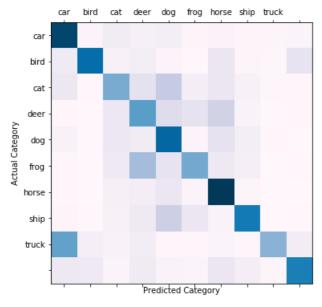
Accuracy of plane : 71 % Accuracy of car : 57 % Accuracy of bird : 37 % Accuracy of cat : 41 % Accuracy of deer : 60 % Accuracy of frog : 75 % Accuracy of horse : 53 % Accuracy of ship : 33 % Accuracy of truck : 52 %

Confusion Matrix

In [41]:

```
import matplotlib.ticker as ticker

fig, ax = plt.subplots(1,1,figsize=(8,6))
    cax=ax.matshow(confusion_matrix,cmap=plt.get_cmap('PuBu'))
#fig.colorbar(cax)
plt.ylabel('Actual Category')
plt.yticks(range(10), classes)
plt.xlabel('Predicted Category')
plt.xticks(range(10), classes)
ax.xaxis.set_major_locator(ticker.MultipleLocator(1))
ax.yaxis.set_major_locator(ticker.MultipleLocator(1))
plt.show()
```



In [29]:

```
print(c.ijust(iu), ena=··)
print()
for i,r in enumerate(confusion_matrix):
    print(classes[i].ljust(16), end='')
    for idx, p in enumerate(r):
      print(str(p).ljust(10), end='')
    print()
    r = r/np.sum(r)
    print(''.ljust(16), end='')
    for idx, p in enumerate(r):
       print(str(p).ljust(10), end='')
    print()
                                                                     dog
actual/pred
                                     bird
                                                           deer
                                                                                frog
                                                                                          horse
                                                                                                     shi
                plane
                           car
                                                cat
truck
                717
                           19
                                      69
                                                4.3
                                                           58
                                                                     12
                                                                                26
                                                                                          17
                                                                                                     17
plane
22
                 0.717
                           0.019
                                      0.069
                                                0.043
                                                           0.058
                                                                     0.012
                                                                                0.026
                                                                                          0.017
                                                                                                     0.0
0.022
                 74
                           576
                                      39
                                                58
                                                           19
                                                                                95
                                                                                          16
                                                                                                     8
car
111
                 0.074
                           0.576
                                      0.039
                                                0.058
                                                                     0.004
                                                                                0.095
                                                          0.019
                                                                                          0.016
                                                                                                     0.0
0.111
                 89
                           3
                                      370
                                                                                100
                                                                                                     8
bird
                                                116
                                                           215
                                                                     54
                                                                                          37
8
                 0.089
                           0.003
                                      0.37
                                                0.116
                                                           0.215
                                                                     0.054
                                                                                0.1
                                                                                          0.037
                                                                                                     0.0
0.008
cat
                 9
                           2
                                      92
                                                419
                                                           138
                                                                     114
                                                                                185
                                                                                          27
                                                                                                     3
11
                 0.009
                           0.002
                                      0.092
                                                0.419
                                                           0.138
                                                                     0.114
                                                                                0.185
                                                                                          0.027
                                                                                                     0.0
0.011
                           2
                                                                                                     9
deer
                 33
                                      94
                                                66
                                                           605
                                                                     19
                                                                                113
                                                                                          58
1
                 0.033
                           0.002
                                      0.094
                                                0.066
                                                           0.605
                                                                     0.019
                                                                                0.113
                                                                                          0.058
                                                                                                     0.0
0.001
                 7
                           2
                                      78
                                                285
                                                           112
                                                                     378
                                                                                85
                                                                                          48
                                                                                                     1
dog
                 0.007
                           0.002
                                      0.078
                                                0.285
                                                           0.112
                                                                     0.378
                                                                                0.085
                                                                                          0.048
                                                                                                     0.0
0.004
frog
                                      46
                                                56
                                                           98
                                                                     18
                                                                                758
                                                                                          12
                                                                                                     0
2
                 0.009
                           0.001
                                      0.046
                                                0.056
                                                           0.098
                                                                     0.018
                                                                                0.758
                                                                                          0.012
                                                                                                     0.0
0.002
                 14
                           4
                                      37
                                                78
                                                           198
                                                                     99
                                                                                29
horse
                                                                                          537
                                                                                                     1
                                      0.037
                                                0.078
                           0.004
                                                           0.198
                                                                                0.029
                 0.014
                                                                     0.099
                                                                                          0.537
                                                                                                     0.0
0.003
ship
                 406
                           48
                                      33
                                                64
                                                           11
                                                                     10
                                                                                23
                                                                                          9
                                                                                                     336
60
                 0.406
                           0.048
                                      0.033
                                                0.064
                                                           0.011
                                                                     0.01
                                                                                0.023
                                                                                          0.009
                                                                                                     0.3
0.06
                           82
                                      22
                                                75
                                                           27
                                                                     22
truck
                 83
                                                                                96
                                                                                          54
                                                                                                     14
525
                 0.083
                           0.082
                                      0.022
                                                0.075
                                                           0.027
                                                                     0.022
                                                                                0.096
                                                                                          0.054
                                                                                                     0.0
0.525
4
                                                                                                     Þ
```

Assignment3 Part2

```
In [1]:
```

```
import torch
import torchvision
import torchvision.transforms as transforms
```

In [2]:

```
#Checking CUDA Availability
train_on_gpu = torch.cuda.is_available()

if not train_on_gpu:
    print('CUDA is not available! Training on CPU...')
else:
    print('CUDA is available! Training on GPU ...')
```

CUDA is available! Training on GPU ...

In [3]:

Files already downloaded and verified Files already downloaded and verified

In [4]:

```
import matplotlib.pyplot as plt
import numpy as np
# functions to show an image
def imshow(img):
   img = img / 2 + 0.5
                         # unnormalize
   npimg = img.numpy()
   plt.imshow(np.transpose(npimg, (1, 2, 0)))
   plt.show()
# get some random training images
dataiter = iter(trainloader)
images, labels = dataiter.next()
# show images
imshow(torchvision.utils.make grid(images))
plt.show()
# print labels
print(' '.join('%5s' % classes[labels[j]] for j in range(4)))
```

Selecting mask size of 3x3

In [8]:

```
import torch.nn as nn
import torch.nn.functional as F
class Net(nn.Module):
    def init (self):
        super(Net, self).__init__()
        #3 Convolutional layers
        self.conv1 = nn.Conv2d(3, 6, 3)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 3)
       self.fc1 = nn.Linear(16 * 6 * 6, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)
        #Add dropout if data is overfitting
        #self.dropout=nn.Dropout(.15)
    def forward(self, x):
       x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        \#x = self.pool(F.relu(self.conv3(x)))
        x = x.view(-1, 16 * 6 * 6)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x
net = Net()
print(net)
#if train on gpu:
   net.cuda()
Net. (
  (conv1): Conv2d(3, 6, kernel size=(3, 3), stride=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv2): Conv2d(6, 16, kernel_size=(3, 3), stride=(1, 1))
  (fc1): Linear(in_features=576, out_features=120, bias=True)
  (fc2): Linear(in features=120, out features=84, bias=True)
  (fc3): Linear(in features=84, out features=10, bias=True)
In [9]:
import torch.optim as optim
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
In [10]:
for epoch in range(2): # loop over the dataset multiple times
```

```
running_loss = 0.0
net.train()
for i, data in enumerate(trainloader, 0):
   # get the inputs
   inputs, labels = data
   # zero the parameter gradients
   optimizer.zero_grad()
    # forward + backward + optimize
    outputs = net(inputs)
    loss = criterion(outputs, labels)
```

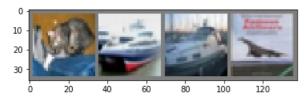
```
loss.backward()
        optimizer.step()
        # print statistics
        running loss += loss.item()
        if i \% 2000 == 1999: # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' %
                 (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0
print('Finished Training')
[1, 2000] loss: 2.253
[1, 4000] loss: 1.806
[1, 6000] loss: 1.612
    8000] loss: 1.497
[1, 10000] loss: 1.451
[1, 12000] loss: 1.408
[2, 2000] loss: 1.326
[2, 4000] loss: 1.287
    6000] loss: 1.282
[2,
[2, 8000] loss: 1.230
[2, 10000] loss: 1.226
[2, 12000] loss: 1.231
Finished Training
```

Test the Network

In [11]:

```
dataiter = iter(testloader)
images, labels = dataiter.next()

# print images
imshow(torchvision.utils.make_grid(images))
print('GroundTruth: ', ' '.join('%5s' % classes[labels[j]] for j in range(4)))
```



GroundTruth: cat ship ship plane

In [12]:

Predicted: ship deer ship deer

In [13]:

```
correct = 0
total = 0
confusion_matrix = np.zeros([10,10], int)
with torch.no_grad():
    for data in testloader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
    for i, l in enumerate(labels):
        confusion_matrix[l.item(), predicted[i].item()] += 1
```

```
print('Accuracy of the network on the 10000 test images: %d %%' % (
   100 * correct / total))
```

Accuracy of the network on the 10000 test images: 57 $\mbox{\%}$

In [1]:

```
##Increase in accuracy by 5% by changing the mask size
```

In [14]:

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

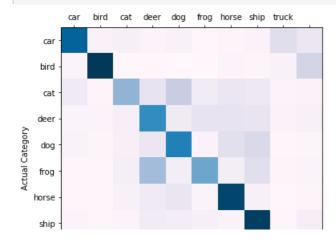
for i in range(10):
    print('Accuracy of %5s : %2d %%' % (
        classes[i], 100 * class_correct[i] / class_total[i]))
```

Accuracy of plane : 60 % Accuracy of car : 73 % Accuracy of bird : 31 % Accuracy of cat : 46 % Accuracy of deer : 49 % Accuracy of frog : 69 % Accuracy of horse : 71 % Accuracy of ship : 66 % Accuracy of truck : 70 %

In [15]:

```
import matplotlib.ticker as ticker
```

```
fig, ax = plt.subplots(1,1,figsize=(8,6))
cax=ax.matshow(confusion_matrix,cmap=plt.get_cmap('PuBu'))
#fig.colorbar(cax)
plt.ylabel('Actual Category')
plt.yticks(range(10), classes)
plt.xlabel('Predicted Category')
plt.xticks(range(10), classes)
ax.xaxis.set_major_locator(ticker.MultipleLocator(1))
ax.yaxis.set_major_locator(ticker.MultipleLocator(1))
plt.show()
```



```
truck - Predicted Category'
```

In [16]:

```
print('actual/pred'.ljust(16), end='')
for i,c in enumerate(classes):
    print(c.ljust(10), end='')
print()
for i,r in enumerate(confusion_matrix):
    print(classes[i].ljust(16), end='')
    for idx, p in enumerate(r):
        print(str(p).ljust(10), end='')
    print(''.ljust(16), end='')
    for idx, p in enumerate(r):
        print(str(p).ljust(10), end='')
    for idx, p in enumerate(r):
        print(str(p).ljust(10), end='')
    print()
```

actual/pred truck	plane	car	bird	cat	deer	dog	frog	horse	shi
plane 93	600	32	46	19	32	4	18	26	130
	0.6	0.032	0.046	0.019	0.032	0.004	0.018	0.026	0.1
0.093 car 170	20	730	5	6	1	2	19	16	31
	0.02	0.73	0.005	0.006	0.001	0.002	0.019	0.016	0.0
0.17 bird 26	72	15	312	109	200	64	97	86	19
	0.072	0.015	0.312	0.109	0.2	0.064	0.097	0.086	0.0
0.026 cat 37	21	19	41	465	74	108	109	102	24
37	0.021	0.019	0.041	0.465	0.074	0.108	0.109	0.102	0.0
0.037 deer 13	28	14	44	96	498	26	121	151	9
	0.028	0.014	0.044	0.096	0.498	0.026	0.121	0.151	0.0
0.013 dog 21	12	7	51	278	57	375	56	127	16
	0.012	0.007	0.051	0.278	0.057	0.375	0.056	0.127	0.0
0.021 frog	7	12	36	71	99	21	692	39	6
17									
0.017	0.007	0.012	0.036	0.071	0.099	0.021	0.692	0.039	0.0
horse	19	8	19	64	55	43	26	712	7
	0.019	0.008	0.019	0.064	0.055	0.043	0.026	0.712	0.0
0.047 ship 87	99	77	10	13	9	9	10	17	669
	0.099	0.077	0.01	0.013	0.009	0.009	0.01	0.017	0.6
0.087 truck	24	136	6	19	4	7	25	46	32
701									
0.701	0.024	0.136	0.006	0.019	0.004	0.007	0.025	0.046	0.0
4									Þ

Assignment3 Question3

```
In [1]:
```

```
import torch
import torchvision
import torchvision.transforms as transforms
```

In [2]:

```
#Checking CUDA Availability
train_on_gpu = torch.cuda.is_available()

if not train_on_gpu:
    print('CUDA is not available! Training on CPU...')
else:
    print('CUDA is available! Training on GPU ...')
```

CUDA is available! Training on GPU ...

In [3]:

Files already downloaded and verified Files already downloaded and verified

In [4]:

```
import matplotlib.pyplot as plt
import numpy as np
# functions to show an image
def imshow(img):
   img = img / 2 + 0.5
                         # unnormalize
   npimg = img.numpy()
   plt.imshow(np.transpose(npimg, (1, 2, 0)))
   plt.show()
# get some random training images
dataiter = iter(trainloader)
images, labels = dataiter.next()
# show images
imshow(torchvision.utils.make grid(images))
plt.show()
# print labels
print(' '.join('%5s' % classes[labels[j]] for j in range(4)))
```

Increasing no. of filters in conv1

```
In [11]:
```

```
import torch.nn as nn
import torch.nn.functional as F
class Net(nn.Module):
    def init (self):
        super(Net, self).__init__()
        #3 Convolutional layers changing no of filters to 12 from 6 for conv1
        self.conv1 = nn.Conv2d(3, 12, 3)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(12, 16, 3)
        self.fc1 = nn.Linear(16 * 6 * 6, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)
        #Add dropout if data is overfitting
        #self.dropout=nn.Dropout(.15)
    def forward(self, x):
       x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        \#x = self.pool(F.relu(self.conv3(x)))
        x = x.view(-1, 16 * 6 * 6)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x
net = Net()
print(net)
#if train on gpu:
   net.cuda()
Net. (
  (conv1): Conv2d(3, 12, kernel size=(3, 3), stride=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv2): Conv2d(12, 16, kernel_size=(3, 3), stride=(1, 1))
  (fc1): Linear(in_features=576, out_features=120, bias=True)
  (fc2): Linear(in features=120, out features=84, bias=True)
  (fc3): Linear(in features=84, out features=10, bias=True)
In [12]:
import torch.optim as optim
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
In [13]:
for epoch in range(2): # loop over the dataset multiple times
```

```
running_loss = 0.0
net.train()
for i, data in enumerate(trainloader, 0):
   # get the inputs
   inputs, labels = data
   # zero the parameter gradients
   optimizer.zero_grad()
    # forward + backward + optimize
    outputs = net(inputs)
    loss = criterion(outputs, labels)
```

```
loss.backward()
        optimizer.step()
        # print statistics
        running loss += loss.item()
        if i % 2000 == 1999: # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' %
                 (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0
print('Finished Training')
[1, 2000] loss: 2.225
[1, 4000] loss: 1.751
[1, 6000] loss: 1.603
    8000] loss: 1.516
[1, 10000] loss: 1.423
[1, 12000] loss: 1.400
[2, 2000] loss: 1.303
[2, 4000] loss: 1.282
    6000] loss: 1.256
[2,
[2, 8000] loss: 1.216
[2, 10000] loss: 1.168
[2, 12000] loss: 1.166
Finished Training
```

Test the Network

In [14]:

```
dataiter = iter(testloader)
images, labels = dataiter.next()

# print images
imshow(torchvision.utils.make_grid(images))
print('GroundTruth: ', ' '.join('%5s' % classes[labels[j]] for j in range(4)))
```



GroundTruth: cat ship ship plane

In [15]:

Predicted: ship ship dog car

In [16]:

```
correct = 0
total = 0
confusion_matrix = np.zeros([10,10], int)
with torch.no_grad():
    for data in testloader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
    for i, l in enumerate(labels):
        confusion_matrix[l.item(), predicted[i].item()] += 1
```

```
print('Accuracy of the network on the 10000 test images: %d %%' % (
    100 * correct / total))
```

Accuracy of the network on the 10000 test images: 60 $\mbox{\%}$

Increase in accuracy with increase in conv1 filters is seen by 3%

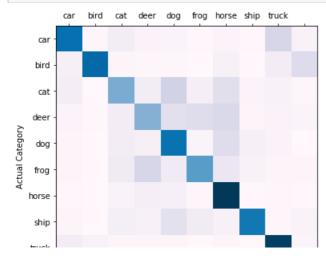
In [17]:

Accuracy of plane : 61 %
Accuracy of car : 64 %
Accuracy of bird : 39 %
Accuracy of cat : 37 %
Accuracy of deer : 60 %
Accuracy of dog : 45 %
Accuracy of frog : 82 %
Accuracy of horse : 59 %
Accuracy of ship : 80 %
Accuracy of truck : 68 %

In [18]:

```
import matplotlib.ticker as ticker

fig, ax = plt.subplots(1,1,figsize=(8,6))
    cax=ax.matshow(confusion_matrix,cmap=plt.get_cmap('PuBu'))
#fig.colorbar(cax)
plt.ylabel('Actual Category')
plt.yticks(range(10), classes)
plt.xlabel('Predicted Category')
plt.xticks(range(10), classes)
ax.xaxis.set_major_locator(ticker.MultipleLocator(1))
ax.yaxis.set_major_locator(ticker.MultipleLocator(1))
plt.show()
```



In [19]:

```
print('actual/pred'.ljust(16), end='')
for i,c in enumerate(classes):
    print(c.ljust(10), end='')
print()
for i,r in enumerate(confusion_matrix):
    print(classes[i].ljust(16), end='')
    for idx, p in enumerate(r):
        print(str(p).ljust(10), end='')
    print()

r = r/np.sum(r)
    print(''.ljust(16), end='')
    for idx, p in enumerate(r):
        print(str(p).ljust(10), end='')
    print(str(p).ljust(10), end='')
    print()
```

actual/pred truck	plane	car	bird	cat	deer	dog	frog	horse	shi
plane 34	613	13	70	27	25	6	23	7	182
	0.613	0.013	0.07	0.027	0.025	0.006	0.023	0.007	0.1
0.034 car 152	51	645	20	8	8	4	42	4	66
	0.051	0.645	0.02	0.008	0.008	0.004	0.042	0.004	0.0
0.152 bird 13	62	4	399	70	202	54	141	21	34
	0.062	0.004	0.399	0.07	0.202	0.054	0.141	0.021	0.0
0.013 cat 25	22	5	68	374	137	151	169	20	29
	0.022	0.005	0.068	0.374	0.137	0.151	0.169	0.02	0.0
0.025 deer 3	16	3	67	50	607	25	150	52	27
	0.016	0.003	0.067	0.05	0.607	0.025	0.15	0.052	0.0
0.003 dog 20	15	1	84	181	81	459	105	37	17
	0.015	0.001	0.084	0.181	0.081	0.459	0.105	0.037	0.0
0.02 frog 7	5	3	33	54	47	11	823	7	10
	0.005	0.003	0.033	0.054	0.047	0.011	0.823	0.007	0.0
0.007 horse 32	17	3	56	44	130	75	41	591	11
	0.017	0.003	0.056	0.044	0.13	0.075	0.041	0.591	0.0
0.032 ship 24	66	36	16	19	15	3	17	3	801
	0.066	0.036	0.016	0.019	0.015	0.003	0.017	0.003	8.0
0.024	56	82	14	21	13	6	34	14	71
truck 689	36	02	14	21	13	О	34	14	/ 1
0.689	0.056	0.082	0.014	0.021	0.013	0.006	0.034	0.014	0.C

Assignment3 Question4 Part1 with test subset of 100 images

```
In [55]:
```

```
import torch
import torchvision
import torchvision.transforms as transforms
```

In [56]:

```
#Checking CUDA Availability
train_on_gpu = torch.cuda.is_available()

if not train_on_gpu:
    print('CUDA is not available! Training on CPU...')
else:
    print('CUDA is available! Training on GPU ...')
```

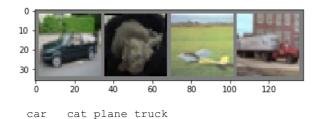
CUDA is available! Training on GPU ...

In [57]:

Files already downloaded and verified Files already downloaded and verified

In [58]:

```
import matplotlib.pyplot as plt
import numpy as np
# functions to show an image
def imshow(img):
   img = img / 2 + 0.5
                       # unnormalize
   npimg = img.numpy()
  plt.imshow(np.transpose(npimg, (1, 2, 0)))
   plt.show()
# get some random training images
dataiter = iter(trainloader)
images, labels = dataiter.next()
# show images
imshow(torchvision.utils.make grid(images))
plt.show()
# print labels
```



In [59]:

```
import torch.nn as nn
import torch.nn.functional as F
class Net(nn.Module):
   def __init_ (self):
        super(Net, self).__init__()
        #3 Convolutional layers
       self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
        self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
        self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
        #Max Pooling Layer
        self.pool = nn.MaxPool2d(2, 2)
       #Fully Connected Linear Layer
       self.fc1 = nn.Linear(64 * 4 * 4, 800)
       self.fc2 = nn.Linear(800, 400)
        self.fc3=nn.Linear(400,10)
        self.dropout = nn.Dropout(0.20)
        #Add dropout if data is overfitting
        #self.dropout=nn.Dropout(.15)
    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))
        x = x.view(-1, 64 * 4 * 4)
       x = F.relu(self.fcl(x))
       x = self.dropout(x)
        x = F.relu(self.fc2(x))
       x = self.dropout(x)
       x = self.fc3(x)
       return x
net = Net()
#if train on gpu:
   net.cuda()
```

In [60]:

```
import torch.optim as optim

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
```

In [61]:

```
for epoch in range(2): # loop over the dataset multiple times

running_loss = 0.0
net.train()
for i, data in enumerate(trainloader, 0):
    # get the inputs
    inputs, labels = data

# zero the parameter gradients
    optimizer.zero_grad()

# forward + backward + optimize
    outputs = net(inputs)
```

```
loss = criterion(outputs, labels)
        loss, backward()
        optimizer.step()
        # print statistics
        running loss += loss.item()
        if i % 2000 == 1999: # print every 2000 mini-batches
             print('[%d, %5d] loss: %.3f' %
                   (epoch + 1, i + 1, running_loss / 2000))
             running_loss = 0.0
print('Finished Training')
[1, 2000] loss: 2.252
[1, 4000] loss: 1.963
[1, 6000] loss: 1.734
[1, 8000] loss: 1.602
[1, 10000] loss: 1.508
[1, 12000] loss: 1.451
[2, 2000] loss: 1.356
[2, 4000] loss: 1.328
[2, 6000] loss: 1.255
[2, 8000] loss: 1.249
[2, 10000] loss: 1.184
[2, 12000] loss: 1.180
```

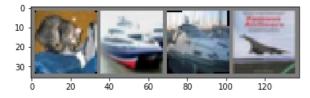
Test the Network

Finished Training

In [62]:

```
dataiter = iter(testloader)
images, labels = dataiter.next()

# print images
imshow(torchvision.utils.make_grid(images))
print('GroundTruth: ', ' '.join('%5s' % classes[labels[j]] for j in range(4)))
```



GroundTruth: cat ship ship plane

In [63]:

Predicted: frog dog truck horse

In [64]:

```
from torch.utils.data.sampler import SubsetRandomSampler
num_test=len(testset)
indices = list(range(num_test))
np.random.shuffle(indices)
split = int(np.floor(.01 * num_test))
test_idx, subset_idx = indices[split:], indices[:split]

print(len(subset_idx), "Test subset created")

#test_sampler = SubsetRandomSampler(test_idx)
subset_sampler = SubsetRandomSampler(subset_idx)
```

100 Test subset created

In [65]:

```
correct = 0
total = 0
confusion matrix = np.zeros([10,10], int)
with torch.no grad():
    for data in subsetloader:
       images, labels = data
       outputs = net(images)
         _, predicted = torch.max(outputs.data, 1)
        _
labels=labels
       #print(len(labels))
        total += labels.size(0)
       correct += ((predicted == labels).sum().item())
        for i, l in enumerate(labels):
           confusion matrix[l.item(), predicted[i].item()] += 1
#print(correct, total)
print('Accuracy of the network on the 100 test images: %d %%' % (
   100 * correct / total))
```

Accuracy of the network on the 100 test images: 60 %

In [66]:

```
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 subsetloader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs, 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 %%' % (
            classs_correct[i] / class_total[i]))
```

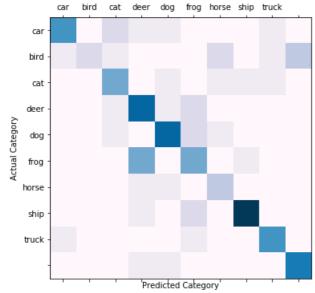
Accuracy of plane : 63 %
Accuracy of car : 20 %
Accuracy of bird : 33 %
Accuracy of cat : 50 %
Accuracy of deer : 58 %
Accuracy of dog : 45 %
Accuracy of frog : 80 %
Accuracy of horse : 53 %
Accuracy of ship : 87 %
Accuracy of truck : 55 %

In [67]:

```
import matplotlib.ticker as ticker

fig, ax = plt.subplots(1,1,figsize=(8,6))
cax=ax.matshow(confusion_matrix,cmap=plt.get_cmap('PuBu'))
#fig.colorbar(cax)
```

```
plt.ylabel('Actual Category')
plt.yticks(range(10), classes)
plt.xlabel('Predicted Category')
plt.xticks(range(10), classes)
ax.xaxis.set_major_locator(ticker.MultipleLocator(1))
ax.yaxis.set_major_locator(ticker.MultipleLocator(1))
plt.show()
```



Assignment3 Question4 Part2 with flip and additional conv layer

```
In [37]:
```

```
import torch
import torchvision
import torchvision.transforms as transforms
```

In [38]:

```
#Checking CUDA Availability
train_on_gpu = torch.cuda.is_available()

if not train_on_gpu:
    print('CUDA is not available! Training on CPU...')
else:
    print('CUDA is available! Training on GPU ...')
```

CUDA is available! Training on GPU ...

In [63]:

```
#Adding random flipping & rotation
```

In [39]:

```
transform = transforms.Compose([
   transforms.RandomHorizontalFlip(), # randomly flip
   transforms.RandomRotation(10),
   transforms.ToTensor(),
   transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
   1)
trainset = torchvision.datasets.CIFAR10(root='./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='./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')
```

Files already downloaded and verified Files already downloaded and verified

In [40]:

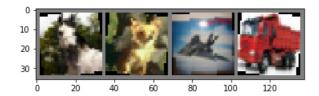
```
import matplotlib.pyplot as plt
import numpy as np

# functions to show an image

def imshow(img):
    img = img / 2 + 0.5  # unnormalize
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()

# get some random training images
dataiter = iter(trainloader)
images, labels = dataiter.next()
```

```
# show images
imshow(torchvision.utils.make_grid(images))
plt.show()
# print labels
print(' '.join('%5s' % classes[labels[j]] for j in range(4)))
```



horse dog plane truck

In []:

#Network achitecture is modified with increasing the depth and adding 3 convolutional layers and #3 fully connected layers along with droput

In [54]:

```
import torch.nn as nn
import torch.nn.functional as F
class Net(nn.Module):
   def __init__(self):
       super(Net, self). init ()
       #3 Convolutional layers
       self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
       self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
       self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
       #Max Pooling Layer
       self.pool = nn.MaxPool2d(2, 2)
       #Fully Connected Linear Layer
       self.fc1 = nn.Linear(64 * 4 * 4, 800)
       self.fc2 = nn.Linear(800, 400)
       self.fc3=nn.Linear(400,10)
       self.dropout = nn.Dropout(0.25)
       #Add dropout if data is overfitting
       #self.dropout=nn.Dropout(.15)
   def forward(self, x):
       x = self.pool(F.relu(self.conv1(x)))
       x = self.pool(F.relu(self.conv2(x)))
       x = self.pool(F.relu(self.conv3(x)))
       x = x.view(-1, 64 * 4 * 4)
       x = F.relu(self.fc1(x))
       x = self.dropout(x)
       x = F.relu(self.fc2(x))
       x = self.dropout(x)
       x = self.fc3(x)
       return x
net = Net()
#if train on qpu:
   net.cuda()
```

In [55]:

```
import torch.optim as optim

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
```

In [56]:

```
for epoch in range(5): # loop over the dataset multiple times
```

```
running_loss = 0.0
    net.train()
    for i, data in enumerate(trainloader, 0):
       # get the inputs
       inputs, labels = data
        # zero the parameter gradients
        optimizer.zero_grad()
        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
       loss.backward()
       optimizer.step()
        # print statistics
        running loss += loss.item()
       if i % 2000 == 1999: # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' %
                 (epoch + 1, i + 1, running loss / 2000))
            running_loss = 0.0
print('Finished Training')
[1, 2000] loss: 2.283
[1, 4000] loss: 1.991
```

```
[1, 6000] loss: 1.742
[1, 8000] loss: 1.601
[1, 10000] loss: 1.524
[1, 12000] loss: 1.454
[2, 2000] loss: 1.381
[2, 4000] loss: 1.338
[2, 6000] loss: 1.292
[2, 8000] loss: 1.250
[2, 10000] loss: 1.199
[2, 12000] loss: 1.192
[3, 2000] loss: 1.122
[3, 4000] loss: 1.093
[3, 6000] loss: 1.098
[3, 8000] loss: 1.057
[3, 10000] loss: 1.067
[3, 12000] loss: 1.027
[4, 2000] loss: 0.994
[4, 4000] loss: 0.980
[4, 6000] loss: 0.960
[4, 8000] loss: 0.945
[4, 10000] loss: 0.946
[4, 12000] loss: 0.936
[5, 2000] loss: 0.901
[5, 4000] loss: 0.879
[5, 6000] loss: 0.881
[5, 8000] loss: 0.876
[5, 10000] loss: 0.889
[5, 12000] loss: 0.866
Finished Training
```

Test the Network

```
In [57]:
```

```
dataiter = iter(testloader)
images, labels = dataiter.next()

# print images
imshow(torchvision.utils.make_grid(images))
print('GroundTruth: ', ' '.join('%5s' % classes[labels[j]] for j in range(4)))
```



```
40
                                   120
       20
                   60
                        80
                               100
GroundTruth: cat ship ship plane
In [58]:
_, predicted = torch.max(outputs, 1)
print('Predicted: ', ' '.join('%5s' % classes[predicted[j]]
                              for j in range(4)))
Predicted:
           frog frog car
                              doa
In [59]:
correct = 0
total = 0
confusion matrix = np.zeros([10,10], int)
with torch.no_grad():
    for data in testloader:
       images, labels = data
       outputs = net(images)
         , predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
       correct += (predicted == labels).sum().item()
        for i, l in enumerate(labels):
            confusion_matrix[1.item(), predicted[i].item()] += 1
print('Accuracy of the network on the 10000 test images: %d %%' % (
   100 * correct / total))
Accuracy of the network on the 10000 test images: 69 %
```

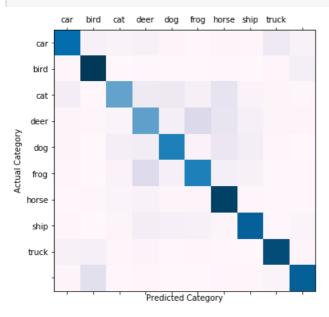
Accuracy achieved is 69% which is 9% higher than the last best case with smaller subset of test images

```
In [60]:
```

```
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
       outputs = net(images)
        _, predicted = torch.max(outputs, 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 : 65 %
Accuracy of car: 89 %
Accuracy of bird: 47 %
Accuracy of
            cat : 48 %
Accuracy of deer: 61
Accuracy of
             dog : 60 %
Accuracy of frog: 86 %
Accuracy of horse : 74 %
Accuracy of ship: 81 %
Accuracy of truck : 74 %
In [61]:
```

```
import matplotlib.ticker as ticker

fig, ax = plt.subplots(1,1,figsize=(8,6))
    cax=ax.matshow(confusion_matrix,cmap=plt.get_cmap('PuBu'))
#fig.colorbar(cax)
plt.ylabel('Actual Category')
plt.yticks(range(10), classes)
plt.xlabel('Predicted Category')
plt.xticks(range(10), classes)
ax.xaxis.set_major_locator(ticker.MultipleLocator(1))
ax.yaxis.set_major_locator(ticker.MultipleLocator(1))
plt.show()
```



In [62]:

```
print('actual/pred'.ljust(16), end='')
for i,c in enumerate(classes):
    print(c.ljust(10), end='')
print()
for i,r in enumerate(confusion_matrix):
    print(classes[i].ljust(16), end='')
    for idx, p in enumerate(r):
        print(str(p).ljust(10), end='')
    print(''.ljust(16), end='')
    for idx, p in enumerate(r):
        print(str(p).ljust(10), end='')
        print(str(p).ljust(10), end='')
        print(str(p).ljust(10), end='')
        print()
```

actual/pred truck	plane	car	bird	cat	deer	dog	frog	horse	shi
plane 41	678	47	35	48	21	7	16	9	98
0.041	0.678	0.047	0.035	0.048	0.021	0.007	0.016	0.009	0.0
car 63	12	890	2	7	2	2	7	4	11
0.063	0.012	0.89	0.002	0.007	0.002	0.002	0.007	0.004	0.0
bird 13	65	7	474	96	105	57	132	31	20
0.013	0.065	0.007	0.474	0.096	0.105	0.057	0.132	0.031	0.0
cat 17	16	12	29	482	63	182	128	53	18
0.017	0.016	0.012	0.029	0.482	0.063	0.182	0.128	0.053	0.0
deer 3	18	3	58	77	611	32	114	71	13
0.003	0.018	0.003	0.058	0.077	0.611	0.032	0.114	0.071	0.0

dog	9	4	30	168	54	611	62	47	7
8	0.009	0.004	0.03	0.168	0.054	0.611	0.062	0.047	0.0
0.008									
frog 7	7	9	29	38	17	18	857	10	8
	0.007	0.009	0.029	0.038	0.017	0.018	0.857	0.01	0.0
0.007									
horse	9	5	21	67	51	50	18	743	8
28									
	0.009	0.005	0.021	0.067	0.051	0.05	0.018	0.743	0.0
0.028									
ship	45	53	9	23	8	9	8	4	824
17									
	0.045	0.053	0.009	0.023	0.008	0.009	0.008	0.004	0.8
0.017									
truck	20	147	7	15	4	4	14	15	29
745									
	0.02	0.147	0.007	0.015	0.004	0.004	0.014	0.015	0.0
0.745									100000
4									Þ