Deep Learning

Autonomous Robotics Lab

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Timeline

- Where we will do it
- How we will do it
- What we will do

Before we start

- There are two GPU servers for students

  cantor.felk.cvut.cz

  taylor.felk.cvut.cz

- You can access them using ssh command

GPU servers

- Important command: “nvidia-smi” – shows actual load on GPUs

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 410.48                 Driver Version: 410.48                    |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  GeForce GTX 108...  On   | 00000000:04:00.0 Off |                  N/A |
| 43%   64C    P2   310W / 250W |  10366MiB / 11178MiB |     51%      Default |
+-------------------------------+----------------------+----------------------+
|   1  GeForce GTX 108...  On   | 00000000:05:00.0 Off |                  N/A |
| 52%   68C    P2   208W / 250W |   8227MiB / 11178MiB |     40%      Default |
+-------------------------------+----------------------+----------------------+
|   2  GeForce GTX 108...  On   | 00000000:08:00.0 Off |                  N/A |
| 29%   37C    P8    15W / 250W |      0MiB / 11178MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+
|   3  GeForce GTX 108...  On   | 00000000:09:00.0 Off |                  N/A |
| 29%   31C    P8    15W / 250W |      0MiB / 11178MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+
|   4  GeForce GTX 108...  On   | 00000000:84:00.0 Off |                  N/A |
| 29%   31C    P8    15W / 250W |      0MiB / 11178MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+
|   5  GeForce GTX 108...  On   | 00000000:85:00.0 Off |                  N/A |
| 29%   35C    P8    15W / 250W |      0MiB / 11178MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+
|   6  GeForce GTX 108...  On   | 00000000:88:00.0 Off |                  N/A |
| 29%   32C    P8    14W / 250W |      0MiB / 11178MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+
```

GPU servers

- Always choose the card with enough memory with command:

  export CUDA_VISIBLE_DEVICES=X

  where X is the number of selected card

Working environment on GPU servers

- You have to activate virtual environment to use pytorch on GPU servers

```
source /opt/torchenv/bin/activate
```

PyTorch

Tensors

Tensors are similar to NumPy's ndarrays, with the addition being that Tensors can also be used on a GPU to accelerate computing.

```
x = torch.tensor([5.5, 3])
print(x)
```

PyTorch

From numpy to tensor

```
nparr = np.array([5.5, 3])
x = torch.from_numpy(nparr)
```

From tensor to numpy

```
nparr = x.numpy()
```

PyTorch

Computation graph

a = torch.tensor(1)

b = torch.tensor(3.)

c = a + b or c = torch.add(a, b)

c = a * b or c = torch.mul(a, b)

PyTorch

Tensors has attribute .requires_grad

-> if it is set to True pytorch tracks all operations on this tensor

x = torch.rand(2, 2, requires_grad=True)

-> then we can use backward() function to compute gradients

Training

```
import numpy as np                                              # Imports
import torch

X = np.random.rand(30, 1)*2.0                                   # Create data as numpy arrays
w = np.random.rand(2, 1)                                        # Randomly select weights
y = (X*w[0] + w[1]/(X+1)**2) + np.random.randn(30, 1) * 0.05         # Create targets
print('target w1 {} w2 {}'.format(w[0], w[1]))
Xt = torch.from_numpy(X).float()                                # Convert numpy arrays to torch tensors
yt = torch.from_numpy(y).float()
W1 = torch.rand(1, requires_grad=True)                          # Initialize weights randomly with parameter requires_grad=True
W2 = torch.rand(1, requires_grad=True)

lr = 0.005                                                      # set up learning rate
for epoch in range(2500):
    y_pred = (torch.mul(W1,Xt), torch.div(W2, torch.add(Xt,torch.tensor(1))**2)) # Compute predictions
    loss = torch.mean((y_pred - yt) ** 2)                       # Compute cost function
    loss.backward()                                             # Run back-propagation
    W1.data = W1.data - lr*W1.grad.data                         # Update parameters
    W2.data = W2.data - lr*W2.grad.data
    W1.grad.data.zero_()                                        # Reset gradients
    W2.grad.data.zero_()

print('found w {} b {}'.format(W1.data ,W2.data))
```

Training

Model with parameters

```
import numpy as np                                            # Imports
import torch

X = np.random.rand(30, 1)*2.0                                 # Create data as numpy arrays
w = np.random.rand(2, 1)                                      # Randomly select weights
y = (X*w[0] + w[1]/(X+1)**2) + np.random.randn(30, 1) * 0.05          # Create targets
print('target w1 {} w2 {}'.format(w[0], w[1]))
Xt = torch.from_numpy(X).float()                              # Convert numpy arrays to torch tensors
yt = torch.from_numpy(y).float()
W1 = torch.rand(1, requires_grad=True)                        # Initialize weights randomly with parameter requires_grad=True
W2 = torch.rand(1, requires_grad=True)

lr = 0.005                                                    # set up learning rate
for epoch in range(2500):
    y_pred = (torch.mul(W1,Xt), torch.div(W2, torch.add(Xt,torch.tensor(1))**2)) # Compute predictions
    loss = torch.mean((y_pred - yt) ** 2)                     # Compute cost function
    loss.backward()                                           # Run back-propagation
    W1.data = W1.data - lr*W1.grad.data                       # Update parameters
    W2.data = W2.data - lr*W2.grad.data
    W1.grad.data.zero_()                                      # Reset gradients
    W2.grad.data.zero_()

print('found w {} b {}'.format(W1.data ,W2.data))
```

Training

Loss computation

```
import numpy as np                                              # Imports
import torch

X = np.random.rand(30, 1)*2.0                                   # Create data as numpy arrays
w = np.random.rand(2, 1)                                        # Randomly select weights
y = (X*w[0] + w[1]/(X+1)**2) + np.random.randn(30, 1) * 0.05         # Create targets
print('target w1 {} w2 {}'.format(w[0], w[1]))
Xt = torch.from_numpy(X).float()                                # Convert numpy arrays to torch tensors
yt = torch.from_numpy(y).float()
W1 = torch.rand(1, requires_grad=True)                          # Initialize weights randomly with parameter requires_grad=True
W2 = torch.rand(1, requires_grad=True)

lr = 0.005                                                      # set up learning rate
for epoch in range(2500):
    y_pred = (torch.mul(W1,Xt), torch.div(W2, torch.add(Xt,torch.tensor(1))**2)) # Compute predictions
    loss = torch.mean((y_pred - yt) ** 2)                       # Compute cost function
    loss.backward()                                             # Run back-propagation
    W1.data = W1.data - lr*W1.grad.data                         # Update parameters
    W2.data = W2.data - lr*W2.grad.data
    W1.grad.data.zero_()                                        # Reset gradients
    W2.grad.data.zero_()

print('found w {} b {}'.format(W1.data ,W2.data))
```

Training

Backward pass (gradient computation)

```
import numpy as np                                   # Imports
import torch

X = np.random.rand(30, 1)*2.0                        # Create data as numpy arrays
w = np.random.rand(2, 1)                             # Randomly select weights
y = (X*w[0] + w[1]/(X+1)**2) + np.random.randn(30, 1) * 0.05         # Create targets
print('target w1 {} w2 {}'.format(w[0], w[1]))
Xt = torch.from_numpy(X).float()                     # Convert numpy arrays to torch tensors
yt = torch.from_numpy(y).float()
W1 = torch.rand(1, requires_grad=True)               # Initialize weights randomly with parameter requires_grad=True
W2 = torch.rand(1, requires_grad=True)

lr = 0.005                                           # set up learning rate
for epoch in range(2500):
    y_pred = (torch.mul(W1,Xt), torch.div(W2, torch.add(Xt,torch.tensor(1))**2)) # Compute predictions
    loss = torch.mean((y_pred - yt) ** 2)            # Compute cost function
    loss.backward()                                  # Run back-propagation
    W1.data = W1.data - lr*W1.grad.data              # Update parameters
    W2.data = W2.data - lr*W2.grad.data
    W1.grad.data.zero_()                             # Reset gradients
    W2.grad.data.zero_()

print('found w {} b {}'.format(W1.data ,W2.data))
```

Training

Optimization step

```
import numpy as np                                              # Imports
import torch

X = np.random.rand(30, 1)*2.0                                   # Create data as numpy arrays
w = np.random.rand(2, 1)                                        # Randomly select weights
y = (X*w[0] + w[1]/(X+1)**2) + np.random.randn(30, 1) * 0.05          # Create targets
print('target w1 {} w2 {}'.format(w[0], w[1]))
Xt = torch.from_numpy(X).float()                                # Convert numpy arrays to torch tensors
yt = torch.from_numpy(y).float()
W1 = torch.rand(1, requires_grad=True)                          # Initialize weights randomly with parameter requires_grad=True
W2 = torch.rand(1, requires_grad=True)

lr = 0.005                                                      # set up learning rate
for epoch in range(2500):
    y_pred = (torch.mul(W1,Xt), torch.div(W2, torch.add(Xt,torch.tensor(1))**2)) # Compute predictions
    loss = torch.mean((y_pred - yt) ** 2)                       # Compute cost function
    loss.backward()                                             # Run back-propagation
    W1.data = W1.data - lr*W1.grad.data                         # Update parameters
    W2.data = W2.data - lr*W2.grad.data
    W1.grad.data.zero_()                                        # Reset gradients
    W2.grad.data.zero_()

print('found w {} b {}'.format(W1.data ,W2.data))
```

Training

Optimization step

This could be replaced by optimizer

```
optimizer = torch.optim.SGD(parameters, lr, momentum, weight_decay)
optimizer.step()                                    # Update parameters
optimizer.zero_grad()                               # Reset gradients
```

```
W1.data = W1.data - lr*W1.grad.data                 # Update parameters
W2.data = W2.data - lr*W2.grad.data
W1.grad.data.zero_()                                # Reset gradients
W2.grad.data.zero_()
```

Barbie detector

- Our goal is to implement program that will detect barbie in image and gives us a 3d coordinates of that barbie.

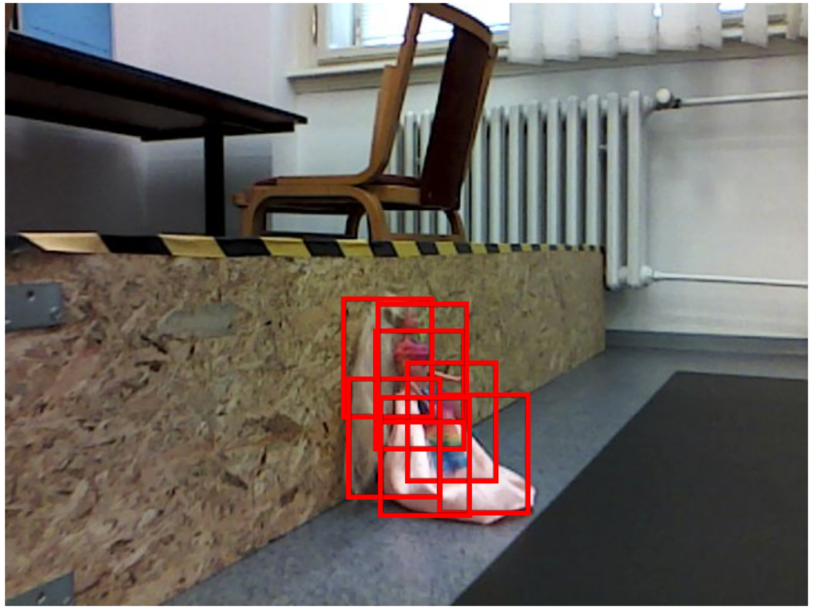
X, Y, Z, according to robot

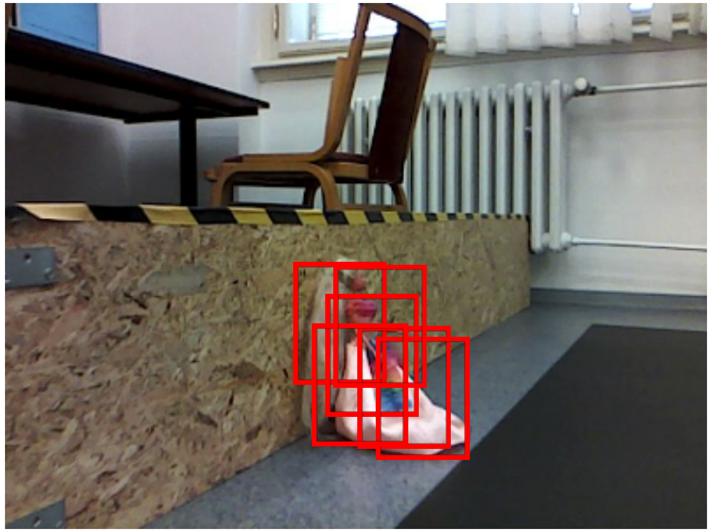
Model

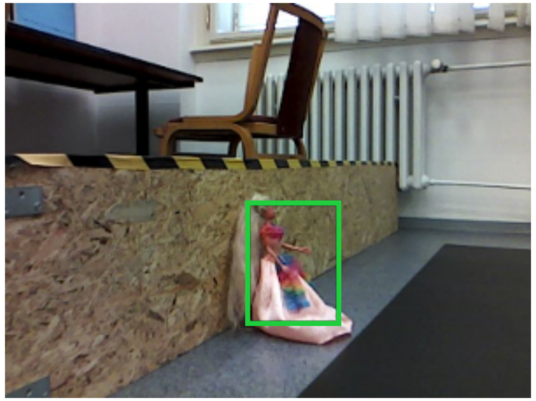
- We use feature extractor part of the network called YOLO V2 TINY

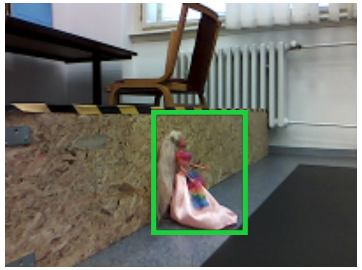
- We run the network on the multiple input image scales to detect barbies of all sizes

Network will find barbies size are near to 64x48 pixels

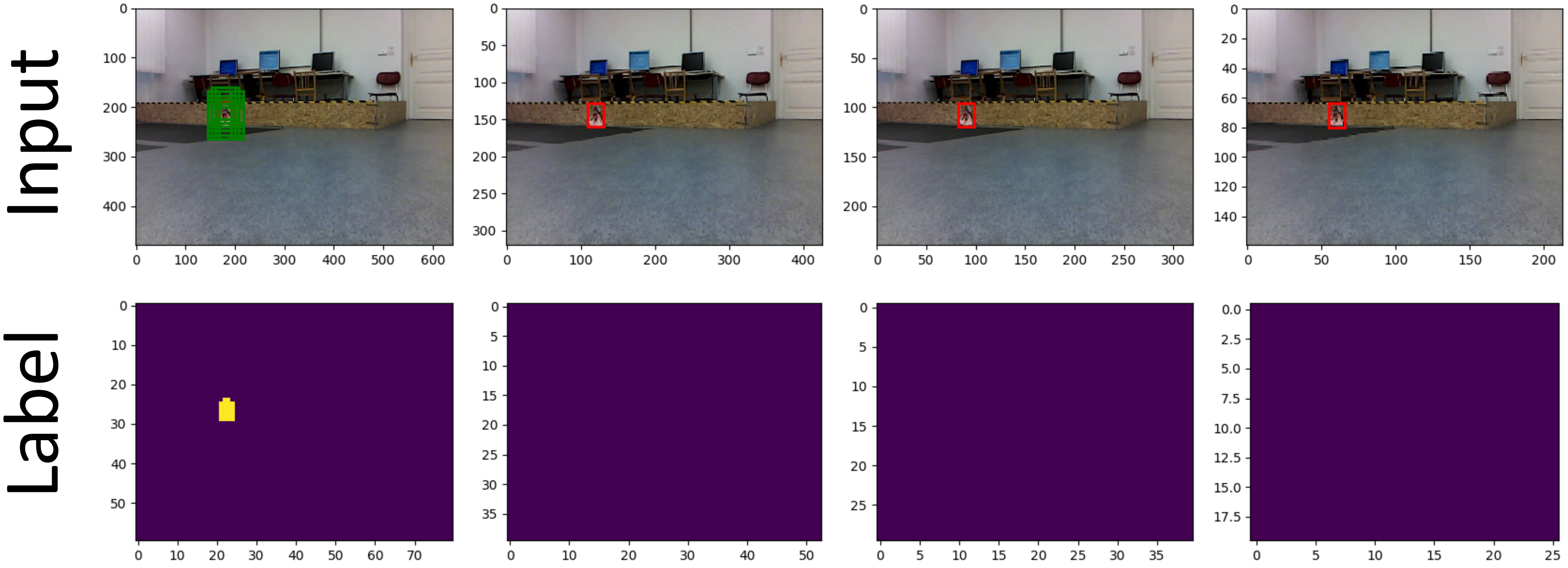




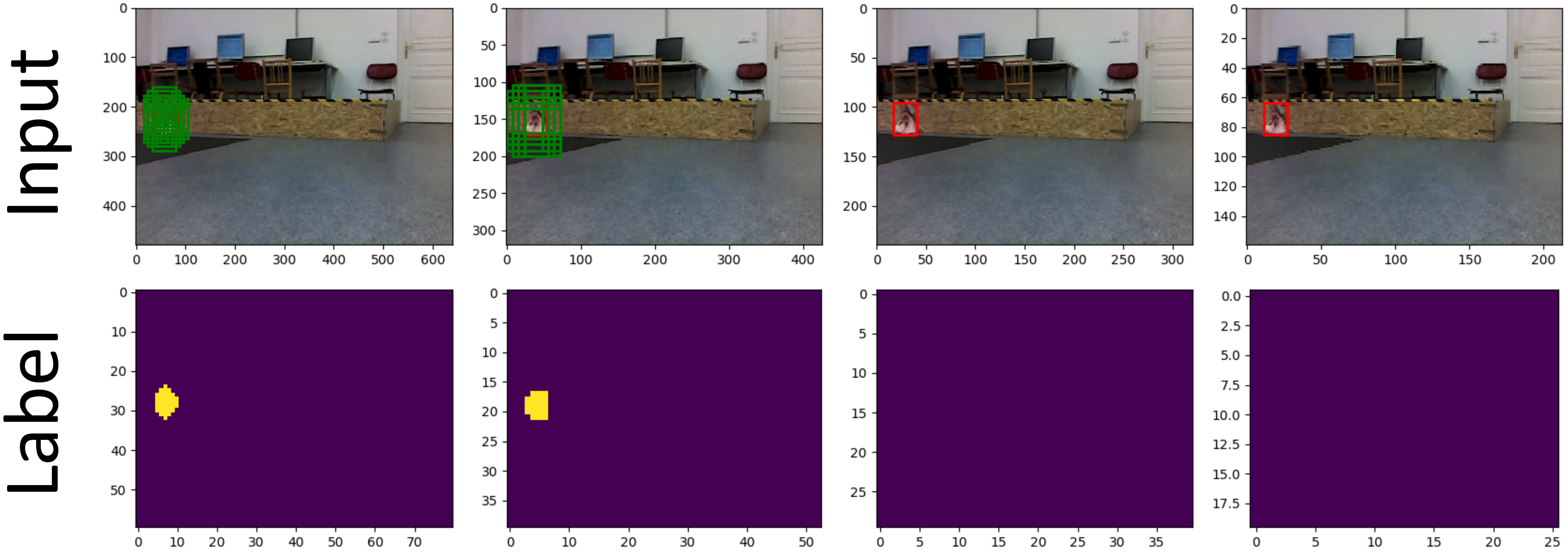




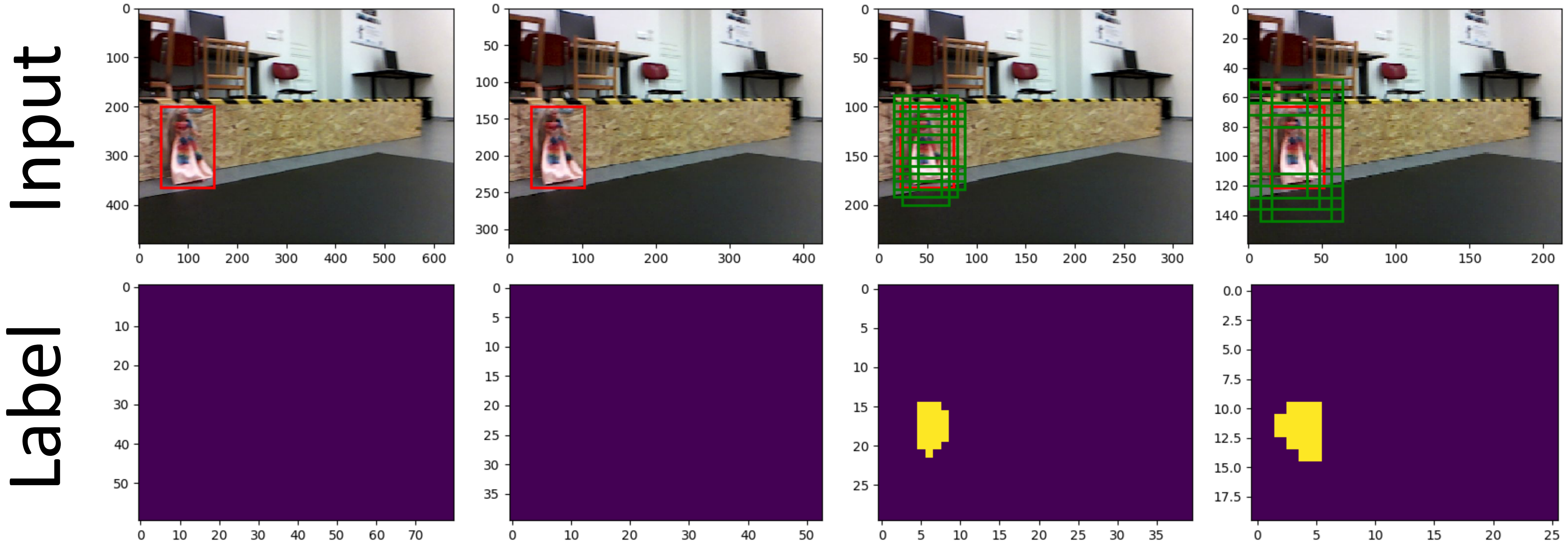
Training dataset



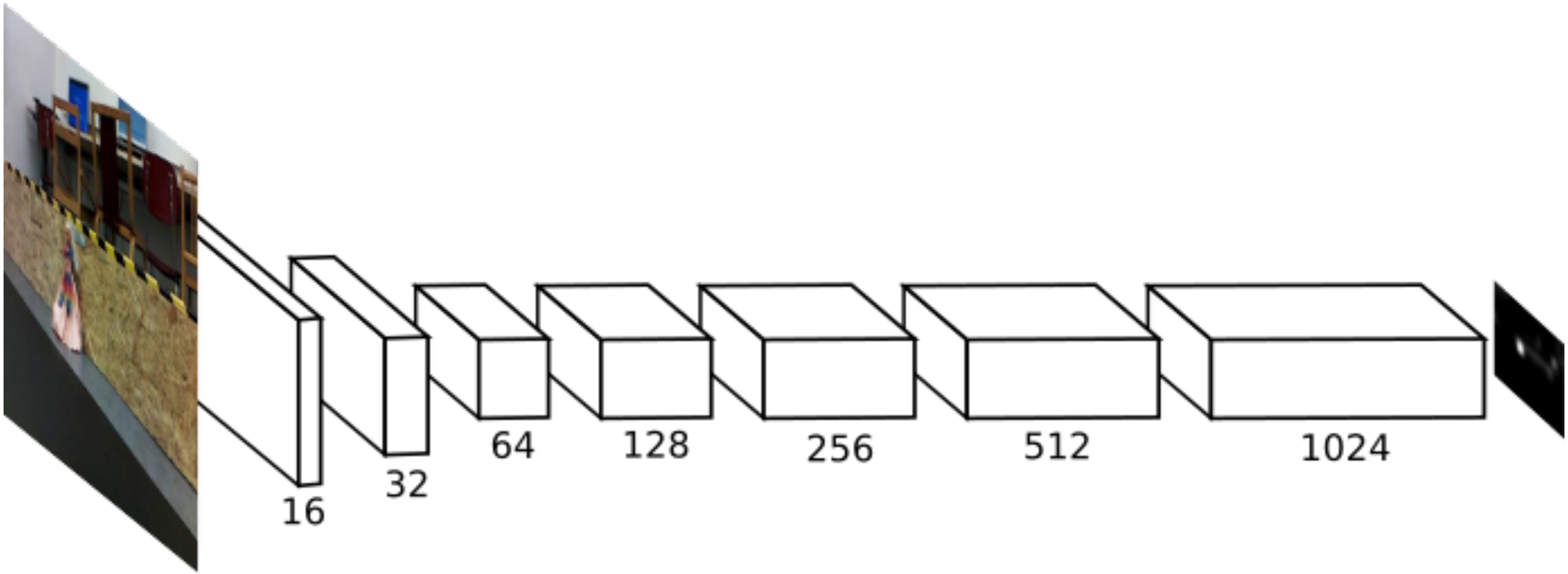
Training dataset



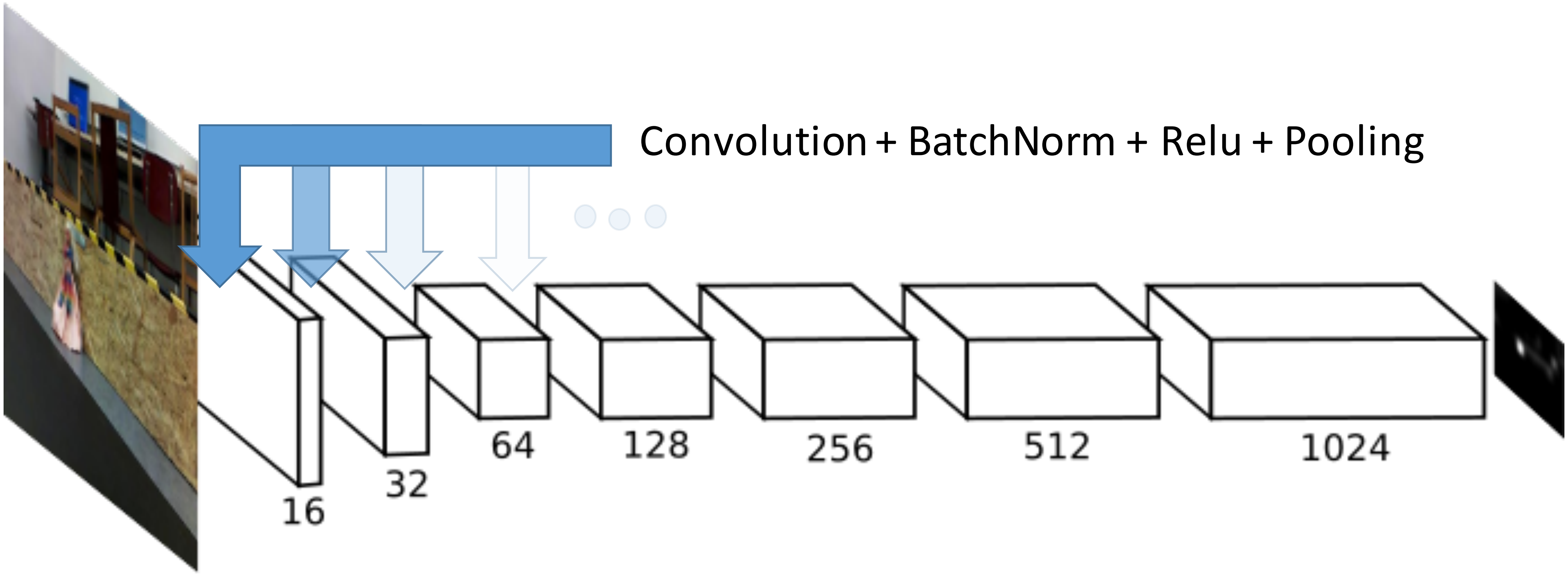
Training dataset



Network architecture



Network architecture



Network class

- Class Net(nn.module) has two main functions

    __init__()

        defines neural network blocks and their parameters

    forward

        defines computation graph of neural network

def __init__(self):

```
super(Net, self).__init__()
self.relu = nn.LeakyReLU(0.1, inplace=True)
self.pool1 = nn.MaxPool2d(2, 2)
self.pool2 = nn.MaxPool2d(3, 1, 1)
self.conv1 = nn.Conv2d(3, 16, 3, 1, 1, bias=False)
self.bn1 = nn.BatchNorm2d(16)
self.conv2 = nn.Conv2d(16, 32, 3, 1, 1, bias=False)
self.bn2 = nn.BatchNorm2d(32)
self.conv3 = nn.Conv2d(32, 64, 3, 1, 1, bias=False)
self.bn3 = nn.BatchNorm2d(64)
self.conv4 = nn.Conv2d(64, 128, 3, 1, 1, bias=False)
self.bn4 = nn.BatchNorm2d(128)
self.conv5 = nn.Conv2d(128, 256, 3, 1, 1, bias=False)
self.bn5 = nn.BatchNorm2d(256)
self.conv6 = nn.Conv2d(256, 512, 3, 1, 1, bias=False)
self.bn6 = nn.BatchNorm2d(512)
self.conv7 = create a convolutional layer without bias with input_channels = 512, output_channels = 1024, kernel_size = 3, stride = 1, padding = 1
self.bn7 = nn.BatchNorm2d(1024)
self.conv8 = nn.Conv2d(1024, 1, 1, 1)
```

def forward(self, input):

```
x = self.pool1(self.relu(self.bn1(self.conv1(input))))
x = self.pool1(self.relu(self.bn2(self.conv2(x))))
x = self.pool1(self.relu(self.bn3(self.conv3(x))))
x = self.pool2(self.relu(self.bn4(self.conv4(x))))
x = self.pool2(self.relu(self.bn5(self.conv5(x))))
x = self.pool2(self.relu(self.bn6(self.conv6(x))))
x = self.relu(self.bn7(self.conv7(x)))
x = (self.conv8(x))
return x
```

Training script

- Training script is prepared for you!

  You only need to set paths for training and validation data

  They are shared on the GPU servers in

  /opt/barbie/barbie_validation_data

  /opt/barbie/barbie_training_data

  and set training parameters properly: batch_size

  number of epochs

  learning_rate

  freeze_pretrained_layers

Training script

- When you lost a connection the running script will be terminated

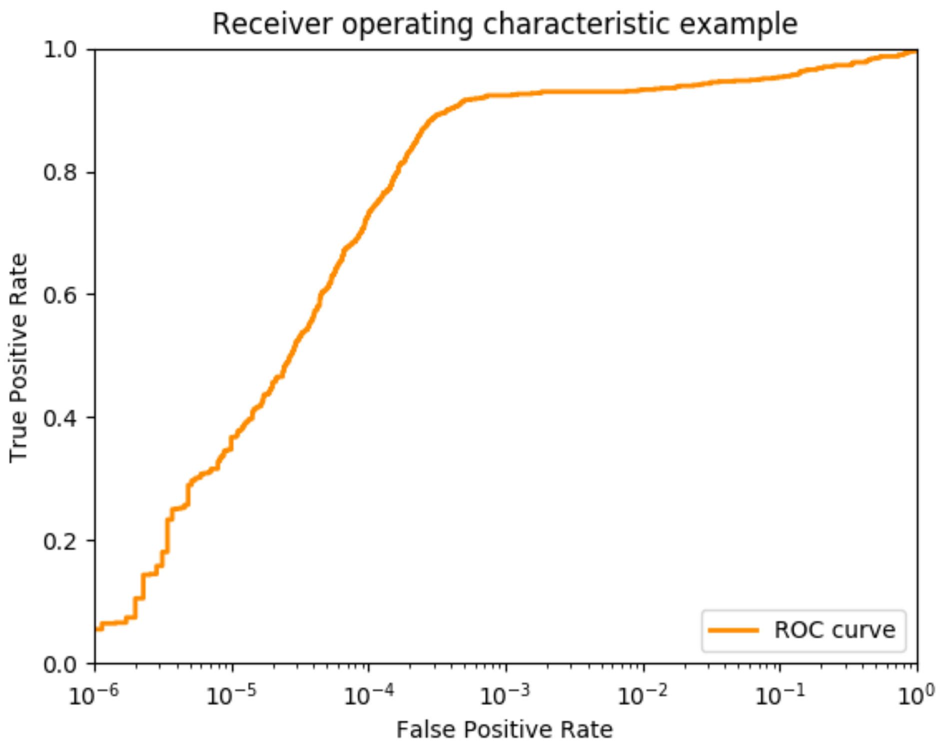
  -> use ”screen” when running the training script

Basic Linux Screen Usage

1. On the command prompt, type **screen** .
2. Run the desired program.
3. Use the key sequence Ctrl-a + Ctrl-d to detach from the **screen** session.
4. Reattach to the **screen** session by typing **screen** -r .

HOMEWORK

- Train the network:
  1) Fill in the Net class in network.py
  2) Train the network using the train.py
     - try different training parameters to train the network
  3) Plot roc curve using the script roc.py
     (use ssh with +X parameter to allow graphic)



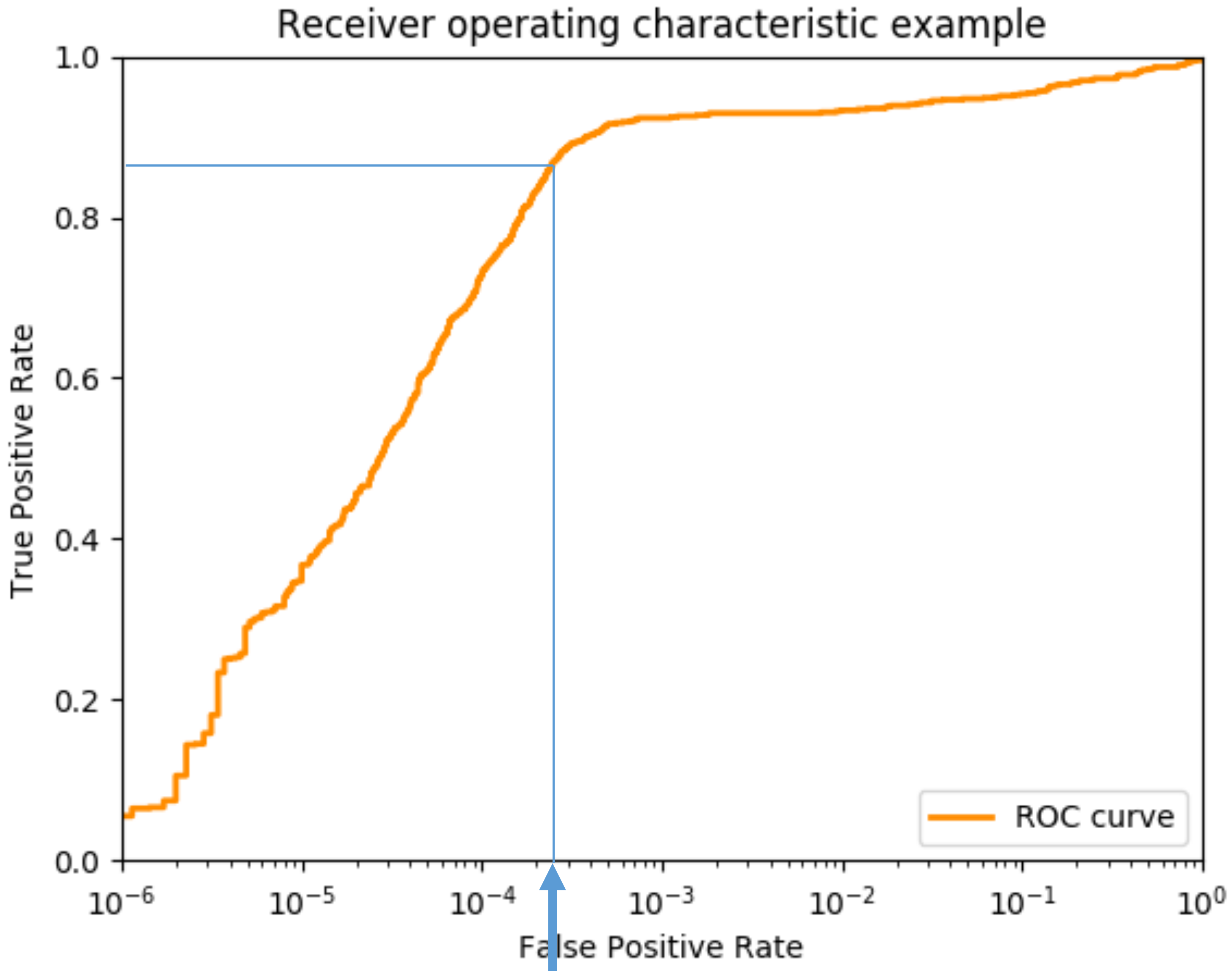
DEADLINE next week! (9. 4. 2020)

ROC

TPR = TP/(TP+FN)

FPR = FP/(FP+TN)

Highlighted point:
One overlooked
barbie pixel per image,
87% of barbie pixels
correctly detected.
(take a look at the training
data, to survey
a quality of the detector)



Number of pixels on all scales
= 4800+2120+1200+520 = 8640