

Machine Learning

Home Assignment 6

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Contents

1 Logistic regression in PyTorch	1
2 Convolutional Neural Networks	2
2.1 Sobel filter	2
2.2 Convolutional neural networks	4
2.3 Augmentation	5

1 Logistic regression in PyTorch

```
class LogisticRegressionPytorch(nn.Module):
    def __init__(self, d, m):
        """
        d: input dimensionality
        m: number of classes (output dimensionality)
        """
        super(LogisticRegressionPytorch, self).__init__()
        self.fc = nn.Linear(d, m)          # added
        self.activation_fn = nn.Sigmoid()  # added

    def forward(self, x):
        """
        x: input data
        """
```

```

        return self.activation_fn(self.fc(x)) # added

# definition of the loss function
criterion = nn.MultiMarginLoss() # added

# definition of the training
for epoch in range(no_epochs): # Loop over the dataset multiple times
    # Zero the parameter gradients
    optimizer.zero_grad()

    # Forward + backward + optimize
    outputs = logreg_pytorch(X_train_T) # added
    loss = criterion(outputs, y_train_T) # added
    loss.backward() # added
    optimizer.step()

# getting the biases
bs_torch = logreg_pytorch.fc.bias.detach().numpy() # added

```

While I don't get the same accuracy on the training and test data, I think the implementation is correct, because the losses aren't too different and the weights are initialized to random values.

2 Convolutional Neural Networks

2.1 Sobel filter

```

# define convolutional layer
conv = nn.Conv2d(1, 2, W, padding = 0, bias=False)

# define the weights
simmetry = np.array([1, 0, -1])
g_x = torch.from_numpy(np.array([simmetry, 2 * simmetry, simmetry]))
params = torch.from_numpy(np.array([g_x, g_x.T])).reshape((2, 1, W, W))
conv.weight = torch.nn.Parameter(params.float(), requires_grad=False)

# apply the convolution
c = conv(x)

```

```
# combine the two channels to the final feature map
x2 = torch.sqrt(torch.sum(torch.square(c), dim=1))
```

So I defined the convolutional layer with 2 output channels. Considering the input image Figure 1, applying the convolutional layer results in two feature maps, one for each channel, respectively Figure 2 and Figure 3. Finally, I combined the two channels to obtain the final feature map Figure 4, and thus the Sobel filter.

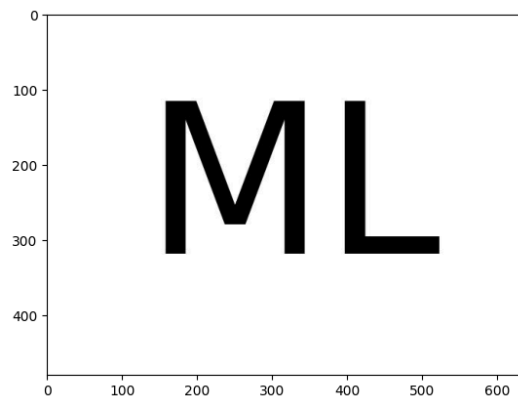


Figure 1: Input image

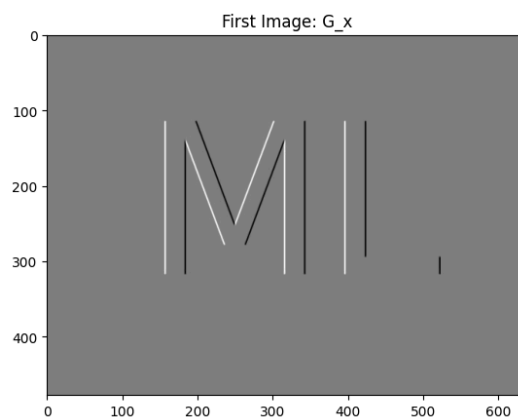


Figure 2: First channel of the feature map

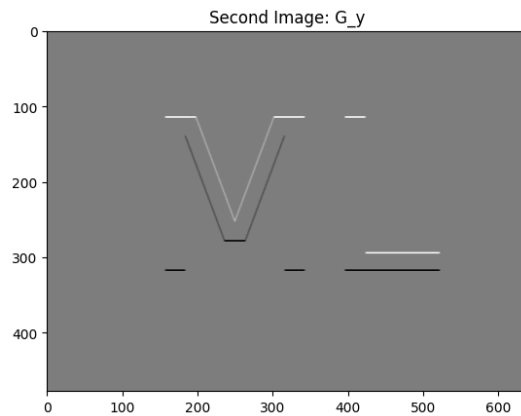


Figure 3: Second channel of the feature map

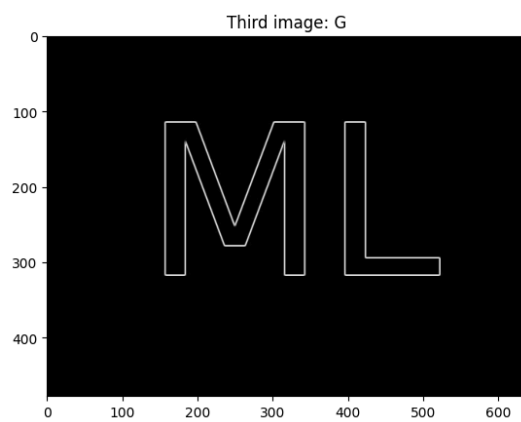


Figure 4: Combined feature map

2.2 Convolutional neural networks

```
class Net(nn.Module):
    def __init__(self, img_size=28):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 64, 5)
        self.pool1 = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(64, 64, 5)
        self.pool2 = nn.MaxPool2d(2, 2)
        self.fc1 = nn.Linear(1024, 43)

    def forward(self, x):
        x = self.pool1(F.elu(self.conv1(x)))
        x = self.pool2(F.elu(self.conv2(x)))
        x = torch.flatten(x, 1)
```

```
x = F.elu(self.fc1(x))  
return x
```

2.3 Augmentation

Which transformations are applied to the input images during training?

The Data class in `GTSRBTrafficSigns.py` applies the following transformations to augment the dataset:

1. **Resize**: which makes all images the same size, 32x32 pixels.
2. **RandomAffine**: applies slight random rotation to the images.
3. **RandomCrop**: extracts random sections of the images.
4. **CenterCrop**: focuses on the center of the images.
5. **ColorJitter**: adjusts the brightness and contrast of the images.
6. **RandomHorizontalFlip**: flips the images horizontally.