

CSC2516: Programming Assignment 2: Convolutional Neural Networks

February 2021

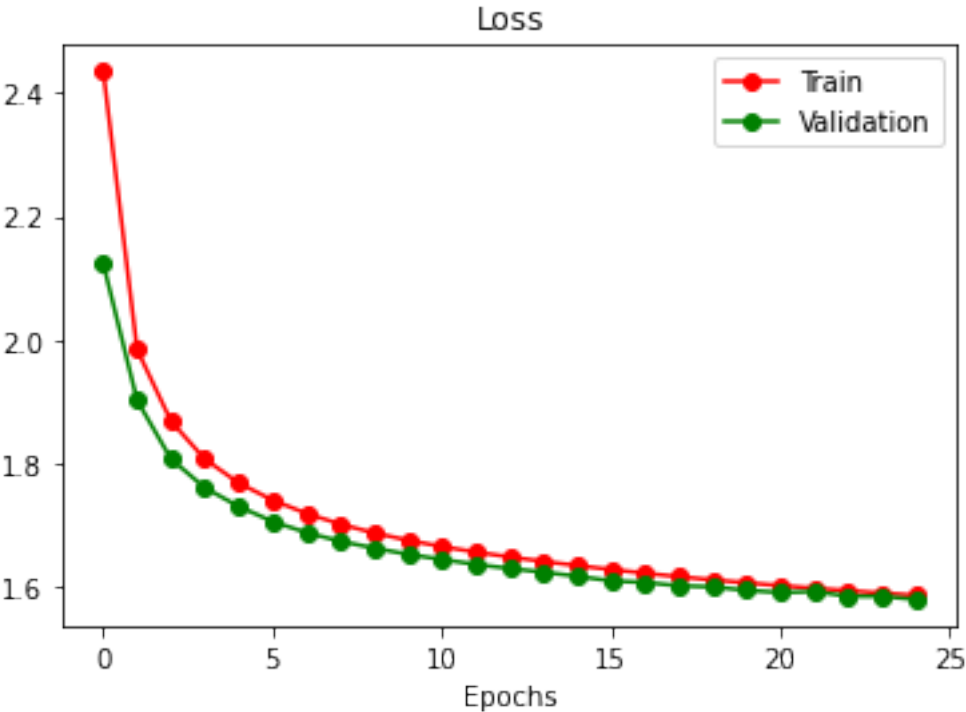
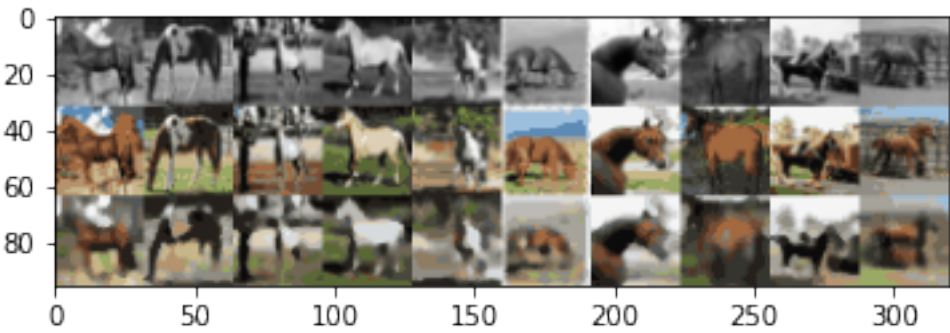
Part A: Pooling and Upsampling

1 Complete the model PoolUpsampleNet

```
1 #V202102171018
2 class PoolUpsampleNet(nn.Module):
3     def __init__(self, kernel, num_filters, num_colours, num_in_channels):
4         super().__init__()
5
6         # Useful parameters
7         padding = kernel // 2
8
9         ##### YOUR CODE GOES HERE #####
10        # Input: [BS, NIC, 32, 32]
11        self.block0 = nn.Sequential(
12            nn.Conv2d(in_channels=num_in_channels,
13                    out_channels=num_filters,
14                    kernel_size=kernel,
15                    padding=padding),
16            nn.MaxPool2d(kernel_size=2),
17            nn.BatchNorm2d(num_features=num_filters),
18            nn.ReLU()
19        )
20        # Output: [BS, NF, 16, 16]
21        self.block1 = nn.Sequential(
22            nn.Conv2d(in_channels=num_filters,
23                    out_channels=2*num_filters,
24                    kernel_size=kernel,
25                    padding=padding),
26            nn.MaxPool2d(kernel_size=2),
27            nn.BatchNorm2d(num_features=2*num_filters),
28            nn.ReLU()
29        )
30        # Output: [BS, 2NF, 8, 8]
31        self.block2 = nn.Sequential(
32            nn.Conv2d(in_channels=2*num_filters,
33                    out_channels=num_filters,
34                    kernel_size=kernel,
35                    padding=padding),
36            nn.Upsample(scale_factor=2),
37            nn.BatchNorm2d(num_features=num_filters),
38            nn.ReLU()
39        )
40        # Output: [BS, NF, 16, 16]
41        self.block3 = nn.Sequential(
42            nn.Conv2d(in_channels=num_filters,
43                    out_channels=num_colours,
44                    kernel_size=kernel,
45                    padding=padding),
46            nn.Upsample(scale_factor=2),
47            nn.BatchNorm2d(num_features=num_colours),
48            nn.ReLU()
49        )
50        # Output: [BS, NC, 32, 32]
51        self.block4 = nn.Sequential(
52            nn.Conv2d(in_channels=num_colours,
53                    out_channels=num_colours,
54                    kernel_size=kernel,
55                    padding=padding)
56        )
57        # Output: [BS, NC, 32, 32]
58        #####
59
60        def forward(self, x):
61            ##### YOUR CODE GOES HERE #####
62            for block in (self.block0, self.block1, self.block2,
63                        self.block3, self.block4):
64                x = block.forward(x)
65            return x
66        #####
```

2 Run main training loop of PoolUpsampleNet

```
1 ...
2 Epoch [25/25], Loss: 1.5852, Time (s): 33
3 Epoch [25/25], Val Loss: 1.5785, Val Acc: 41.6%, Time(s): 34.18
```



Do these results look good to you? Why or why not?

The images appear blurry because in the network they were up-sampled from 8x8 back to 32x32. The background and saddles also appear poorly coloured.

3 Compute the number of weights, outputs, and connections in the model

For 32x32 inputs:

Kernel Size	K	3				
Number of Input Channels	NIC	3				
Number of Filters	NF	32				
Number of Colours	NC	24				
Image Width	W	32				
Image Height	H	32				
PoolUpsampleNet		Weights	Outputs		Connections	
Image						
0 Conv2d	$NF \cdot NIC \cdot K \cdot K + NF$	= 896	$NF \cdot H \cdot W$	= 32768	$(NF \cdot NIC \cdot K \cdot K + NF) \cdot H \cdot W$	= 917504
MaxPool2d			$NF \cdot H / 2 \cdot W / 2$	= 8192	$NF \cdot H \cdot W$	= 32768
BatchNorm2d	$NF + NF$	= 64	$NF \cdot H / 2 \cdot W / 2$	= 8192	$(H / 2 \cdot W / 2) \cdot (H / 2 \cdot W / 2)$	= 65536
ReLU			$NF \cdot H / 2 \cdot W / 2$	= 8192		
1 Conv2d	$(2 \cdot NF) \cdot NF \cdot K \cdot K + (2 \cdot NF)$	= 18496	$(2 \cdot NF) \cdot H / 2 \cdot W / 2$	= 16384	$((2 \cdot NF) \cdot NF \cdot K \cdot K + (2 \cdot NF)) \cdot H / 2 \cdot W / 2$	= 4734976
MaxPool2d			$(2 \cdot NF) \cdot H / 4 \cdot W / 4$	= 4096	$(2 \cdot NF) \cdot H / 2 \cdot W / 2$	= 16384
BatchNorm2d	$(2 \cdot NF) + (2 \cdot NF)$	= 128	$(2 \cdot NF) \cdot H / 4 \cdot W / 4$	= 4096	$(H / 4 \cdot W / 4) \cdot (H / 4 \cdot W / 4)$	= 4096
ReLU			$(2 \cdot NF) \cdot H / 4 \cdot W / 4$	= 4096		
2 Conv2d	$NF \cdot (2 \cdot NF) \cdot K \cdot K + NF$	= 18464	$NF \cdot H / 4 \cdot H / 4$	= 2048	$(NF \cdot (2 \cdot NF) \cdot K \cdot K + NF) \cdot H / 4 \cdot W / 4$	= 1181696
Upsample			$NF \cdot H / 2 \cdot W / 2$	= 8192	$NF \cdot H / 2 \cdot W / 2$	= 8192
BatchNorm2d	$NF + NF$	= 64	$NF \cdot H / 2 \cdot W / 2$	= 8192	$(H / 2 \cdot W / 2) \cdot (H / 2 \cdot W / 2)$	= 65536
ReLU			$NF \cdot H / 2 \cdot W / 2$	= 8192		
3 Conv2d	$NC \cdot NF \cdot K \cdot K$	= 6912	$NC \cdot H / 2 \cdot W / 2$	= 6144	$(NC \cdot NF \cdot K \cdot K) \cdot H / 2 \cdot W / 2$	= 1769472
Upsample			$NC \cdot H \cdot W$	= 24576	$NC \cdot H \cdot W$	= 24576
BatchNorm2d	$NC + NC$	= 48	$NC \cdot H \cdot W$	= 24576	$(H \cdot W) \cdot (H \cdot W)$	= 1048576
ReLU			$NC \cdot H \cdot W$	= 24576		
4 Conv2d	$NC \cdot NC \cdot K \cdot K + NC$	= 5208	$NC \cdot H \cdot W$	= 24576	$(NC \cdot NC \cdot K \cdot K + NC) \cdot H \cdot W$	= 5332992
Total		50280		217088		15202304

For 64x64 inputs:

Kernel Size	K	3				
Number of Input Channels	NIC	3				
Number of Filters	NF	32				
Number of Colours	NC	24				
Image Width	W	64				
Image Height	H	64				
PoolUpsampleNet	Weights		Outputs		Connections	
Image						
0 Conv2d	$NF * NIC * K * K + NF$	= 896	$NF * H * W$	= 131072	$(NF * NIC * K * K + NF) * H * W$	= 3670016
MaxPool2d			$NF * H / 2 * W / 2$	= 32768	$NF * H * W$	= 131072
BatchNorm2d	$NF + NF$	= 64	$NF * H / 2 * W / 2$	= 32768	$(H / 2 * W / 2) * (H / 2 * W / 2)$	= 1048576
ReLU			$NF * H / 2 * W / 2$	= 32768		
1 Conv2d	$(2 * NF) * NF * K * K + (2 * NF)$	= 18496	$(2 * NF) * H / 2 * W / 2$	= 65536	$((2 * NF) * NF * K * K + (2 * NF)) * H / 2 * W / 2$	= 18939904
MaxPool2d			$(2 * NF) * H / 4 * W / 4$	= 16384	$(2 * NF) * H / 2 * W / 2$	= 65536
BatchNorm2d	$(2 * NF) + (2 * NF)$	= 128	$(2 * NF) * H / 4 * W / 4$	= 16384	$(H / 4 * W / 4) * (H / 4 * W / 4)$	= 65536
ReLU			$(2 * NF) * H / 4 * W / 4$	= 16384		
2 Conv2d	$NF * (2 * NF) * K * K + NF$	= 18464	$NF * H / 4 * H / 4$	= 8192	$(NF * (2 * NF) * K * K + NF) * H / 4 * W / 4$	= 4726784
Upsample			$NF * H / 2 * W / 2$	= 32768	$NF * H / 2 * W / 2$	= 32768
BatchNorm2d	$NF + NF$	= 64	$NF * H / 2 * W / 2$	= 32768	$(H / 2 * W / 2) * (H / 2 * W / 2)$	= 1048576
ReLU			$NF * H / 2 * W / 2$	= 32768		
3 Conv2d	$NC * NF * K * K$	= 6912	$NC * H / 2 * W / 2$	= 24576	$(NC * NF * K * K) * H / 2 * W / 2$	= 7077888
Upsample			$NC * H * W$	= 98304	$NC * H * W$	= 98304
BatchNorm2d	$NC + NC$	= 48	$NC * H * W$	= 98304	$(H * W) * (H * W)$	= 16777216
ReLU			$NC * H * W$	= 98304		
4 Conv2d	$NC * NC * K * K + NC$	= 5208	$NC * H * W$	= 98304	$(NC * NC * K * K + NC) * H * W$	= 21331968
Total		50280		868352		75014144

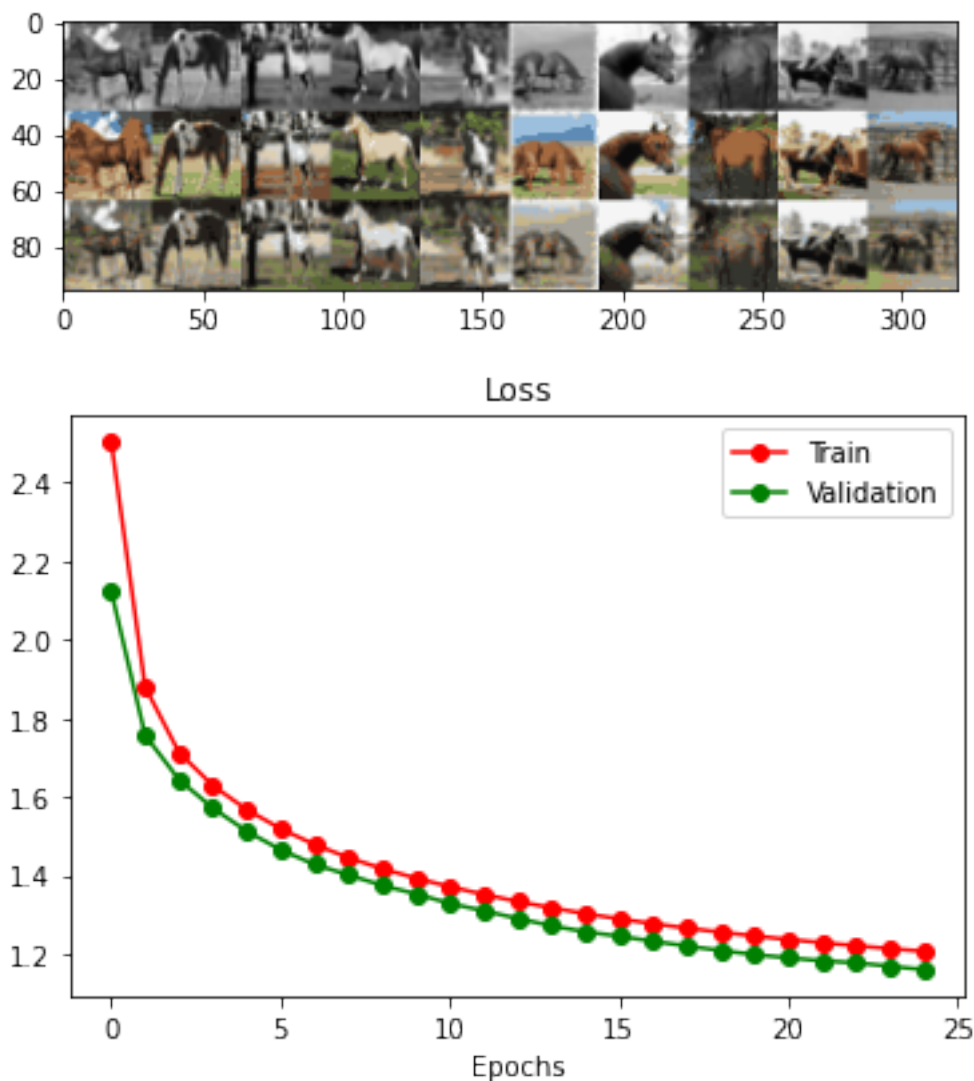
Part B: Strided and Transposed Convolutions

1 Complete the model ConvTransposeNet

```
1 #V202102171234
2 class ConvTransposeNet(nn.Module):
3     def __init__(self, kernel, num_filters, num_colours, num_in_channels):
4         super().__init__()
5
6         # Useful parameters
7         stride = 2
8         padding = kernel // 2
9         output_padding = 1
10
11         ##### YOUR CODE GOES HERE #####
12         # Input: [BS, NIC, 32, 32]
13         self.block0 = nn.Sequential(
14             nn.Conv2d(in_channels=num_in_channels,
15                      out_channels=num_filters,
16                      kernel_size=kernel,
17                      padding=padding,
18                      stride=stride),
19             nn.BatchNorm2d(num_features=num_filters),
20             nn.ReLU()
21         )
22         # Output: [BS, NF, 16, 16]
23         self.block1 = nn.Sequential(
24             nn.Conv2d(in_channels=num_filters,
25                      out_channels=2*num_filters,
26                      kernel_size=kernel,
27                      padding=padding,
28                      stride=stride),
29             nn.BatchNorm2d(num_features=2*num_filters),
30             nn.ReLU()
31         )
32         # Output: [BS, 2NF, 8, 8]
33         self.block2 = nn.Sequential(
34             nn.ConvTranspose2d(in_channels=2*num_filters,
35                               out_channels=num_filters,
36                               kernel_size=kernel,
37                               padding=padding,
38                               output_padding=output_padding,
39                               stride=stride),
40             nn.BatchNorm2d(num_features=num_filters),
41             nn.ReLU()
42         )
43         # Output: [BS, NF, 16, 16]
44         self.block3 = nn.Sequential(
45             nn.ConvTranspose2d(in_channels=num_filters,
46                               out_channels=num_colours,
47                               kernel_size=kernel,
48                               padding=padding,
49                               output_padding=output_padding,
50                               stride=stride),
51             nn.BatchNorm2d(num_features=num_colours),
52             nn.ReLU()
53         )
54         # Output: [BS, NC, 32, 32]
55         self.block4 = nn.Sequential(
56             nn.Conv2d(in_channels=num_colours,
57                      out_channels=num_colours,
58                      kernel_size=kernel,
59                      padding=padding)
60         )
61         # Output: [BS, NC, 32, 32]
62         #####
63
64         def forward(self, x):
65             ##### YOUR CODE GOES HERE #####
66             for block in (self.block0, self.block1, self.block2,
67                           self.block3, self.block4):
68                 x = block.forward(x)
69             return x
70         #####
```

Train the model

```
1 ...
2 Epoch [25/25], Loss: 1.2070, Time (s): 104
3 Epoch [25/25], Val Loss: 1.1603, Val Acc: 54.7%, Time(s): 105.78
```



3 How do the result compare to Part A?

The result qualitatively appear similar as before. The current `ConvTransposeNet` model seems to be worse at colouring brown horses.

The current model resulted in *lower* validation loss (1.2) compared to the previous model (1.6). The `ConvTranspose2d` layers produce lower loss than `Upsample` because the transposed convolutions fits additional weights to “reverse” the previous skipping done by the convolution, resulting in a better numeric fitting and lower loss.

4 padding parameter

	<code>nn.Conv2d</code>	<code>nn.ConvTranspose2d</code>
if kernel size = 4	<code>padding=1</code>	<code>padding=1</code> <code>output_padding=0</code>
if kernel size = 5	<code>padding=2</code>	<code>padding=2</code> <code>output_padding=1</code>

5 Describe the effect of batch sizes on the training/validation loss, and the final image output quality.

Smaller batch sizes were associated with lower training/validation loss and the output quality was better with smaller batch sizes.

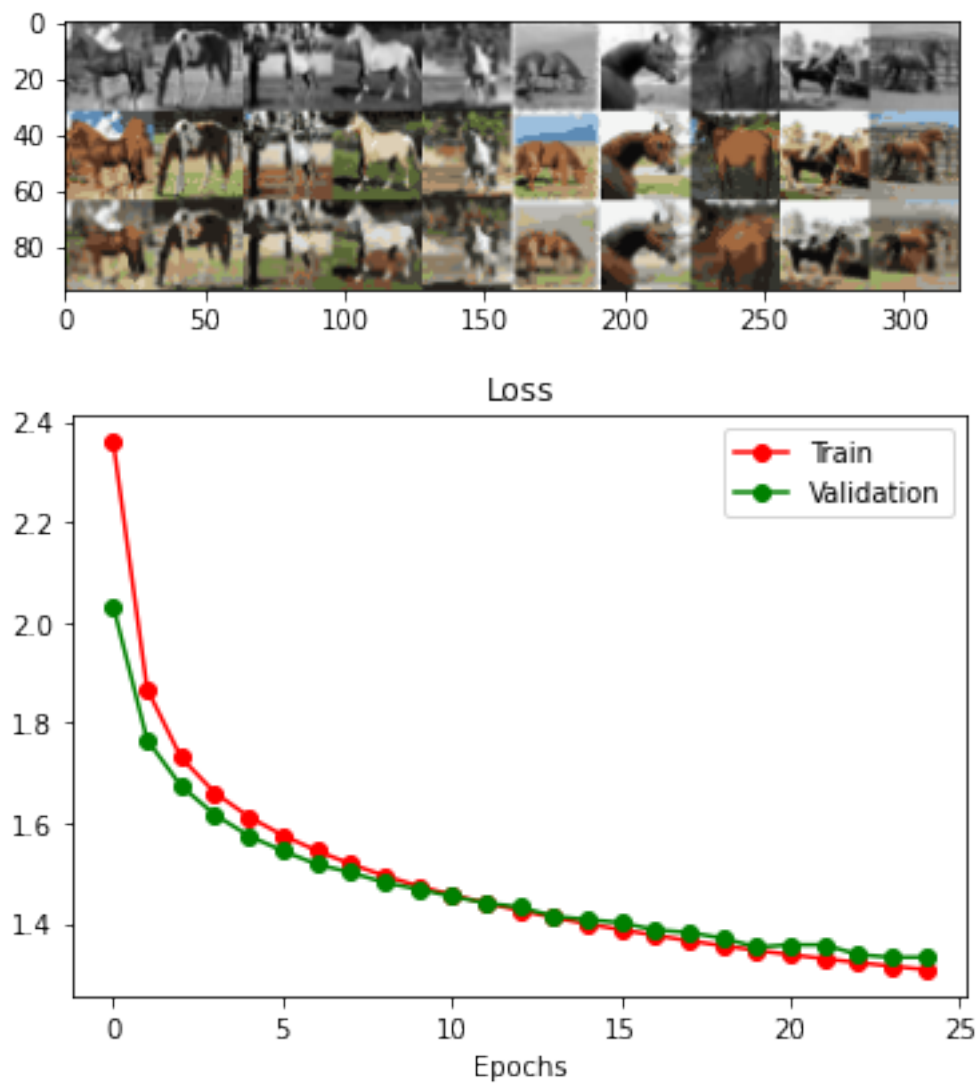
Part C: Skip Connections

1 Add a skip connection...

```
1  #V202102200047
2  class UNet(nn.Module):
3      def __init__(self, kernel, num_filters, num_colours, num_in_channels):
4          super().__init__()
5
6          # Useful parameters
7          stride = 2
8          padding = kernel // 2
9          output_padding = 1
10
11         ##### YOUR CODE GOES HERE #####
12         # Input: [BS, NIC, 32, 32]
13         self.block0 = nn.Sequential(
14             nn.Conv2d(in_channels=num_in_channels,
15                       out_channels=num_filters,
16                       kernel_size=kernel,
17                       padding=padding),
18             nn.MaxPool2d(kernel_size=2),
19             nn.BatchNorm2d(num_features=num_filters),
20             nn.ReLU()
21         )
22         # Output: [BS, NF, 16, 16]
23         self.block1 = nn.Sequential(
24             nn.Conv2d(in_channels=num_filters,
25                       out_channels=2*num_filters,
26                       kernel_size=kernel,
27                       padding=padding),
28             nn.MaxPool2d(kernel_size=2),
29             nn.BatchNorm2d(num_features=2*num_filters),
30             nn.ReLU()
31         )
32         # Output: [BS, 2NF, 8, 8]
33         self.block2 = nn.Sequential(
34             nn.Conv2d(in_channels=2*num_filters,
35                       out_channels=num_filters,
36                       kernel_size=kernel,
37                       padding=padding),
38             nn.Upsample(scale_factor=2),
39             nn.BatchNorm2d(num_features=num_filters),
40             nn.ReLU()
41         )
42         # Concatenate
43         # Output: [BS, NF+NF, 16, 16]
44         self.block3 = nn.Sequential(
45             nn.Conv2d(in_channels=num_filters+num_filters,
46                       out_channels=num_colours,
47                       kernel_size=kernel,
48                       padding=padding),
49             nn.Upsample(scale_factor=2),
50             nn.BatchNorm2d(num_features=num_colours),
51             nn.ReLU()
52         )
53         # Concatenate
54         # Output: [BS, NC+NIC, 32, 32]
55         self.block4 = nn.Sequential(
56             nn.Conv2d(in_channels=num_colours+num_in_channels,
57                       out_channels=num_colours,
58                       kernel_size=kernel,
59                       padding=padding)
60         )
61         # Output: [BS, NC, 32, 32]
62         #####
63
64         def forward(self, x):
65             ##### YOUR CODE GOES HERE #####
66             x_input = x
67             x = self.block0(x)
68             x_1 = x
69             x = self.block1(x)
70             x = self.block2(x)
71             x = torch.cat((x_1, x), dim=1)
72             x = self.block3(x)
73             x = torch.cat((x_input, x), dim=1)
74             x = self.block4(x)
75             return x
76         #####
```

2 Train the model

```
1  ...
2  Epoch [25/25], Loss: 1.3075, Time (s): 33
3  Epoch [25/25], Val Loss: 1.3323, Val Acc: 48.2%, Time(s): 34.52
```



3 How does the result compare to the previous mode

The skip connections did not improve validation loss as compared to the previous model, but improved the output qualitatively. The brown horses were coloured closer to the actual brown colour. The improvements come from:

1. The skip connections allows high resolution, low level features that did not need convolution operation or only one convolution to be directly passed down to the final layers.
2. More channels in the final two layers increased the complexity and parameters of the model.

Part D.1. Fine tune Semantic Segmentation Model with Cross Entropy Loss

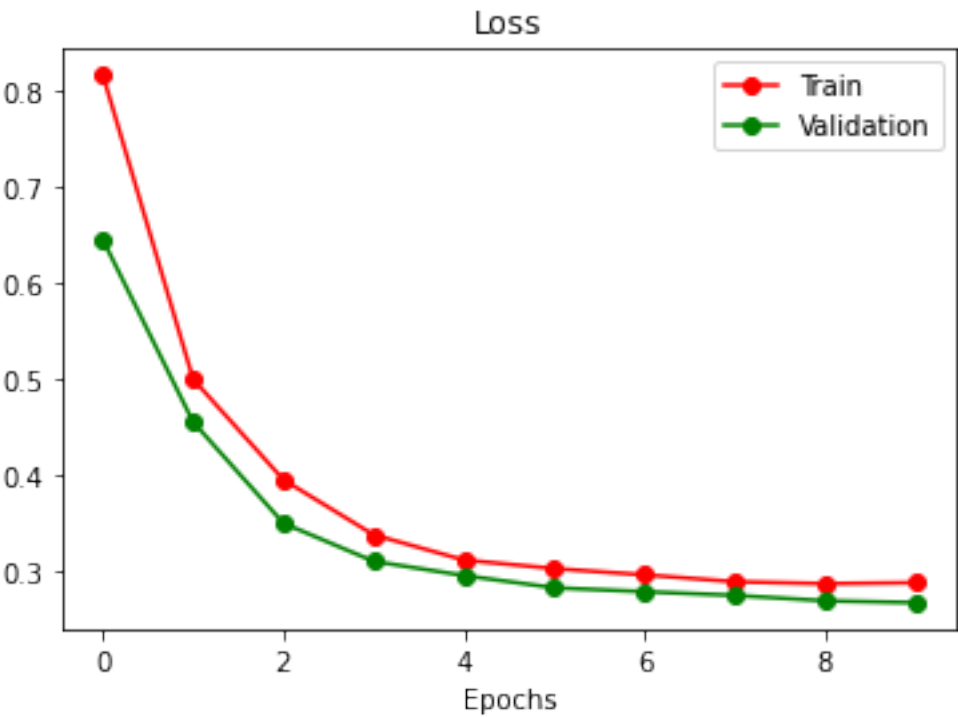
1 Complete the train function

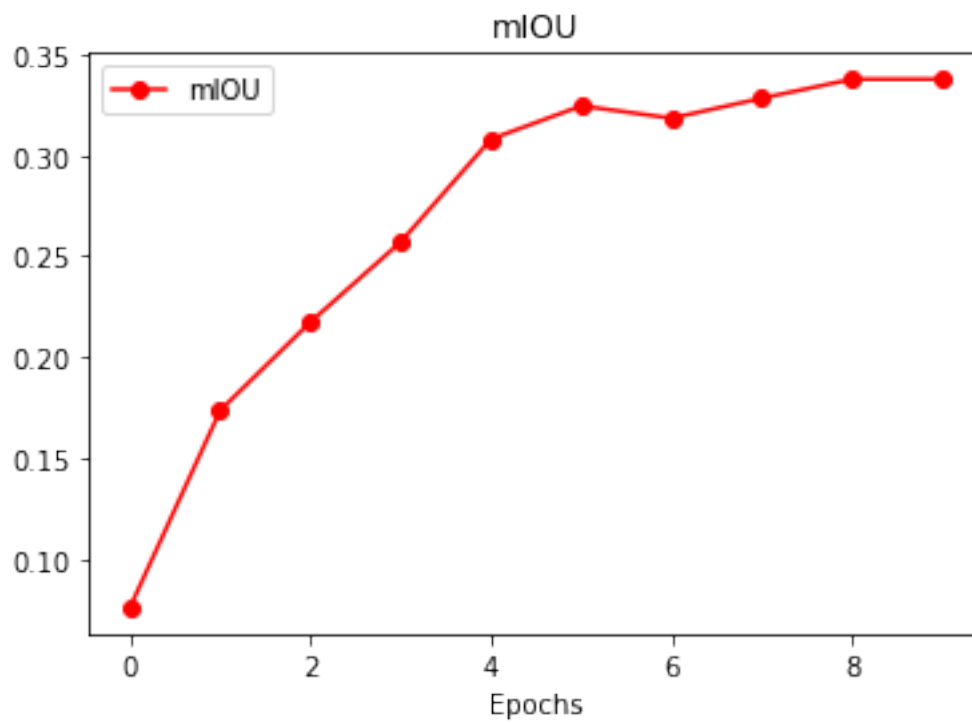
```
1 # We only learn the last layer and freeze all the other weights
2 ##### Code goes here #####
3 # Around 2-3 lines of code
4 for name, param in model.named_parameters():
5     if name.startswith("classifier.4"):
6         print("Appending " + name + " to learned_parameters")
7         learned_parameters.append(param)
8 #####
```

2 Complete the script

```
1 # Truncate the last layer and replace it with the new one.
2 # To avoid 'CUDA out of memory' error, you might find it useful (sometimes required)
3 #   to set the 'requires_grad'=False for some layers
4 ##### YOUR CODE GOES HERE #####
5 # Around 2 lines of code
6 for param in model.parameters():
7     param.requires_grad = False
8 model.classifier[-1] = nn.Conv2d(256, 2, kernel_size=(1, 1), stride=(1, 1))
9 #####

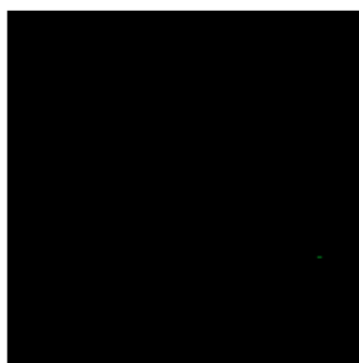
1 ...
2 Epoch [10/10], Loss: 0.2869, Time (s): 44
3 Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or
  [0..255] for integers).
4 Epoch [10/10], Loss: 0.2661, mIOU: 0.3377, Validation time (s): 12
5 Saving model...
6 Best model achieves mIOU: 0.3377
```





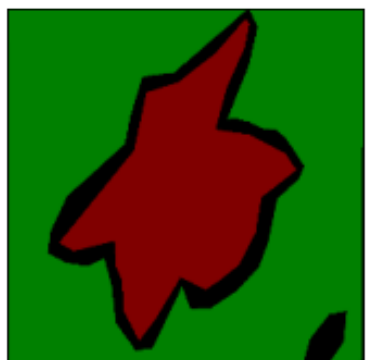
3 Visualize Predictions

```
1 plot_prediction(args, model, is_train=True, index_list=[0, 1, 2, 3])
```





```
1 plot_prediction(args, model, is_train=False, index_list=[0, 1, 2, 3])
```



Part D.2. Finetune Semantic Segmentation Model with IoU Loss

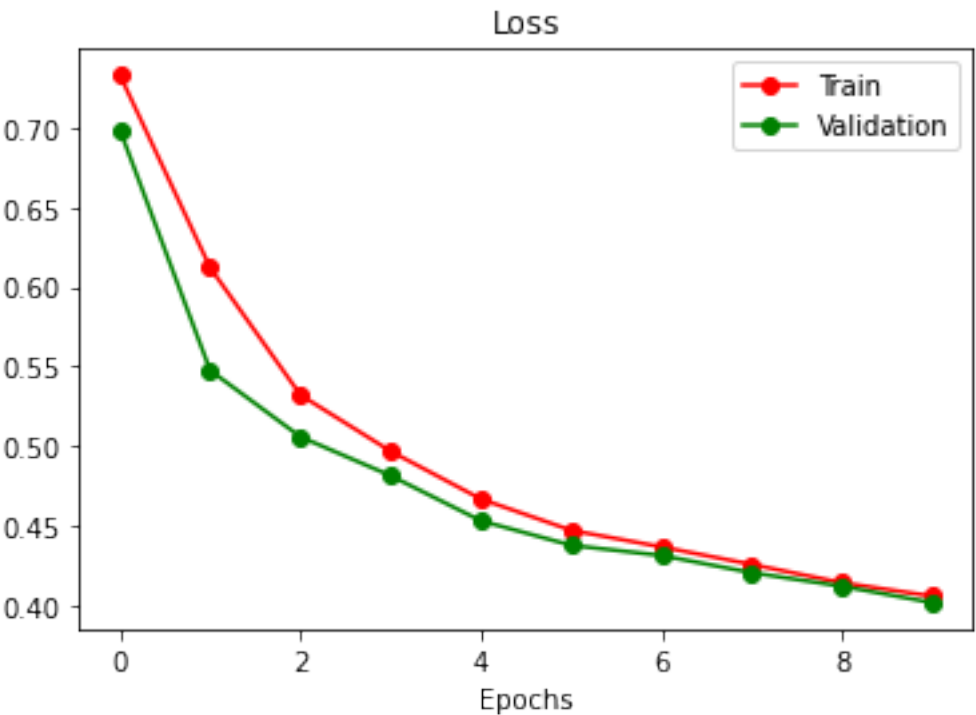
1 Change the loss function from cross entropy used in part D.1 to the (soft) IoU loss

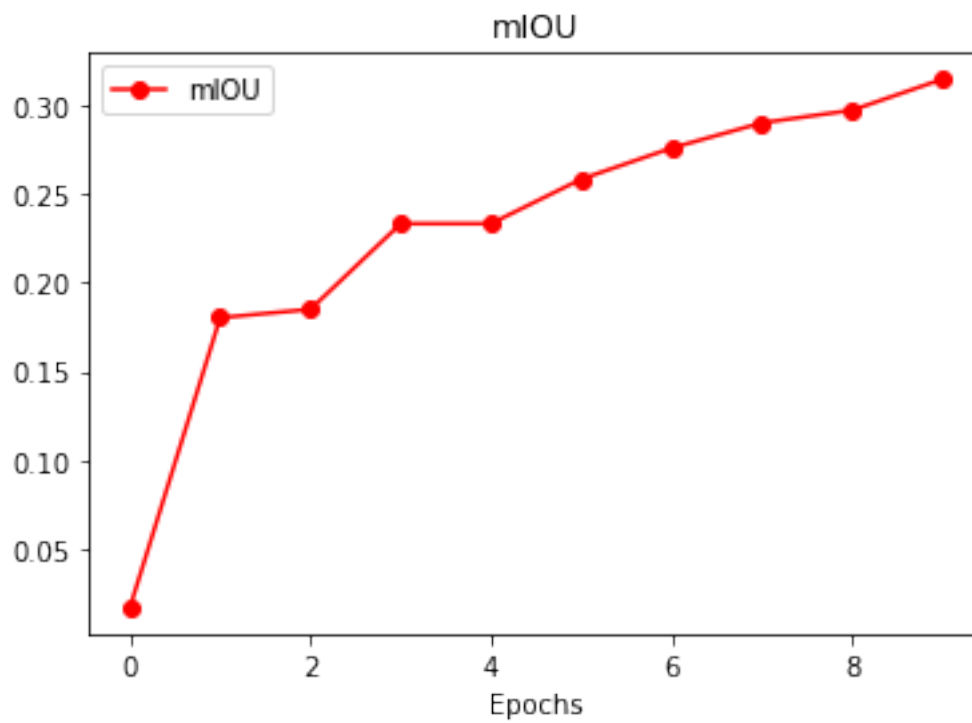
```
1 # def compute_IoU_loss(pred, gt):
2 def compute_iou_loss(pred, gt):
3     # Compute the IoU between the pred and the gt (ground truth)
4     ##### YOUR CODE GOES HERE #####
5     # Around 2-3 lines of code
6
7     # - apply softmax on pred along the channel dimension (dim=1)
8     softmaxed_pred = nn.functional.softmax(pred, dim=1)
9
10    # - only have to compute IoU between gt and the foreground channel of pred
11    # - no need to consider IoU for the background channel of pred
12    # - extract foreground from the softmaxed pred (e.g., softmaxed_pred[:, 1, :, :])
13    softmaxed_pred_fg = softmaxed_pred[:, 1, :, :]
14
15    # - compute intersection between foreground and gt
16    intersection = (softmaxed_pred_fg * gt).sum()
17
18    # - compute union between foreground and gt
19    union = (softmaxed_pred_fg + gt - softmaxed_pred_fg * gt).sum()
20
21    # - compute loss using the computed intersection and union
22    loss = 1.0 - intersection / union
23
24    #####
25    return loss
26
27 ...
28
29 # Truncate the last layer and replace it with the new one.
30 # To avoid 'CUDA out of memory' error, you might find it useful (sometimes required)
31 # to set the 'requires_grad'=False for some layers
32 ##### YOUR CODE GOES HERE #####
33 # Around 2 lines of code
34 for param in model.parameters():
35     param.requires_grad = False
36 model.classifier[-1] = nn.Conv2d(256, 2, kernel_size=(1, 1), stride=(1, 1))
37 #####
```

What is the validation mIoU (mean IoU)? How does this compare with the mIoU when training with the cross entropy?

Best model achieves mIOU: 0.3142. Previously with cross entropy the best model mIOU was 0.3377. The current method achieved a better model than the previous best model. See below:

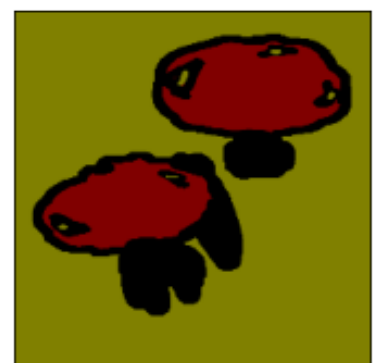
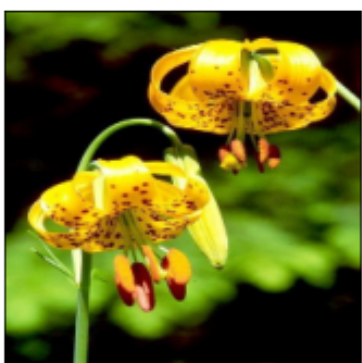
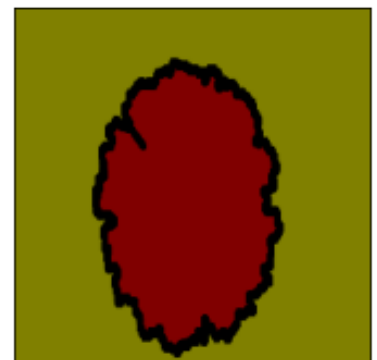
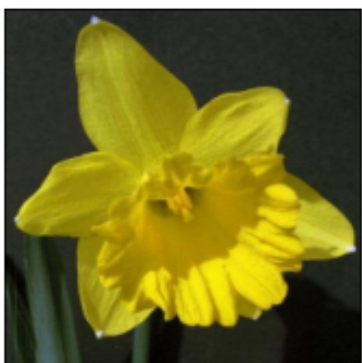
```
1 ...
2 Epoch [10/10], Loss: 0.4062, Time (s): 46
3 Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or
  [0..255] for integers).
4 Epoch [10/10], Loss: 0.4022, mIOU: 0.3142, Validation time (s): 12
5 Saving model...
6 Best model achieves mIOU: 0.3142
```





2 Visualize the predictions

```
1 plot_prediction(args, model, is_train=True, index_list=[0, 1, 2, 3])
```





```
1 plot_prediction(args, model, is_train=False, index_list=[0, 1, 2, 3])
```

