

- Regression layer
- The backbone of the network was taken from a pretrained model resnet50.
- Separate Train, Validation & Test datasets.
- Images and model were trained using CUDA
- Different batch sizes were tested (batch_size = 8 showed the best result in terms of trending loss)
- Adam optimizer was used; used learning rate and weight decay values recommended by many people on the web and other papers (Ir=1e-3, weight_decay=1e-5)
- Dropout (p=0.2) of the weights was used between the backbone layer and fully-connected layers to prevent overfitting
- CrossEntropyLoss for classification, MSEloss for regression
- If the model doesn't train better after the next Epoch, the previous one is maintained (i.e., lower accuracy and higher loss)

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- This assignment is not complete in some ways
- First, the issue was that the test inputs varied in size and shape when using dataloader
 - For instance, if the batch size was 16, the training and validation inputs were all
 of tensor (16*7*7*2048). However, for the test inputs that wasn't the case. There
 were different numbers of candidate regions, different numbers of ground truths

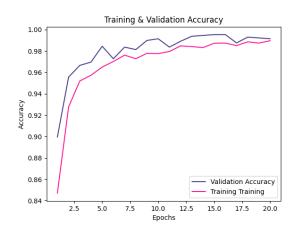
and so on. So, computing losses for the test set was not successfully implemented.

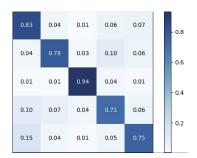
- Also, the regression layer does not "learn"
 - It's because I could not figure out how to correctly find where in the 4C output I should be looking to compute the losses given the ground truth regions and classes. Using Dataloader made things a lot harder because now the output tensor had an extra dimension n (output tensor = n * 4C)
 - Without learning, bounding box prediction was meaningless. Therefore, it failed at getting the IOU between the predicted and correct bounding box rectangles.
- Different batch sizes (=8, 16) and number of epochs (=20, 50) were tested, and more testing could be done using different learning rates, dropout rates, and also extra hidden layer(s) in the fully connected part of the network.
- Batch size of 8 had a much better result than 16 in terms of accuracy and loss.

Test result (batchsize = 8)

batch size: 8						
Epoch	Training accuracy	Training loss	Validation accuracy	Validation loss		
(01/20)	0.8471	0.4819	0.8995	0.4304		
(02/20)	0.9277	0.2907	0.9556	0.1801		
(03/20)	0.9519	0.2021	0.9665	0.1111		
(04/20)	0.9573	0.2220	0.9696	0.1732		
(05/20)	0.9649	0.2017	0.9844	0.0677		
(06/20)	0.9702	0.1670	0.9727	0.1314		
(07/20)	0.9761	0.1392	0.9836	0.0793		
(08/20)	0.9728	0.2011	0.9813	0.0845		
(09/20)	0.9778	0.1260	0.9899	0.0667		
(10/20)	0.9776	0.1498	0.9914	0.0296		
(11/20)	0.9795	0.1612	0.9836	0.1321		
(12/20)	0.9848	0.1290	0.9891	0.0508		
(13/20)	0.9841	0.1155	0.9938	0.0246		
(14/20)	0.9832	0.1147	0.9945	0.0269		
(15/20)	0.9873	0.0962	0.9953	0.0295		
(16/20)	0.9874	0.0933	0.9953	0.0128		
(17/20)	0.9850	0.1066	0.9875	0.0740		
(18/20)	0.9886	0.1036	0.9930	0.0624		
(19/20)	0.9874	0.0908	0.9922	0.0608		
(20/20)	0.9896	0.0760	0.9914	0.0346		







(batchsize = 16)

batch size: 16							
Epoch	Training accuracy	Training loss	Validation accuracy	Validation loss			
(01/20)	0.8648	0.1742	0.9003	0.1424			
(02/20)	0.9403	0.0847	0.9564	0.0682			
(03/20)	0.9600	0.0508	0.9852	0.0247			
(04/20)	0.9659	0.0584	0.9338	0.1839			
(05/20)	0.9718	0.0461	0.9899	0.0167			
(06/20)	0.9799	0.0361	0.9860	0.0261			
(07/20)	0.9808	0.0335	0.9891	0.0128			
(08/20)	0.9869	0.0233	0.9891	0.0147			
(09/20)	0.9837	0.0295	0.9860	0.0201			
(10/20)	0.9812	0.0453	0.9899	0.0367			
(11/20)	0.9860	0.0307	0.9914	0.0170			
(12/20)	0.9899	0.0222	0.9907	0.0218			
(13/20)	0.9873	0.0251	0.9891	0.0159			
(14/20)	0.9841	0.0444	0.9938	0.0077			
(15/20)	0.9887	0.0272	0.9922	0.0195			
(16/20)	0.9871	0.0320	0.9735	0.0867			
(17/20)	0.9909	0.0214	0.9961	0.0053			
(18/20)	0.9917	0.0418	0.9836	0.0604			
(19/20)	0.9881	0.0325	0.9969	0.0043			
(20/20)	0.9923	0.0204	0.9984	0.0040			