

Assignment 2: Weakly Supervised Object Localization

- [Visual Learning and Recognition \(16-824\) Spring 2018](#)

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Task 0

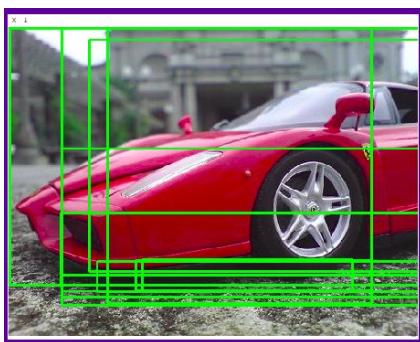
Q 0.1: WHAT CLASSES DOES THE IMAGE AT INDEX 2018 CONTAIN?

Class: car

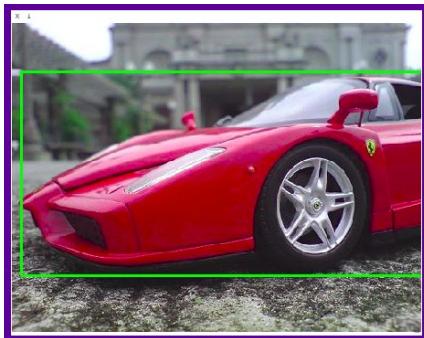
Q 0.2: WHAT IS THE FILENAME OF THE IMAGE AT INDEX 2018?

File name: 003998.jpg

Q 0.3 USE VISDOM+CV2 TO VISUALIZE THE TOP 10 BOUNDING BOX PROPOSALS FOR IMAGE AT INDEX 2018. YOU WOULD NEED TO FIRST PLOT THE IMAGE AND THEN PLOT THE RECTANGLES FOR EACH BOUNDING BOX PROPOSAL.



Q 0.4 USE VISDOM+CV2 TO VISUALIZE THE GROUND TRUTH BOXES FOR IMAGE AT INDEX 2018.



Task 1

Q1.1

Custom.py -> find_classes

This function creates a mapping from classes to index.

Custom.py -> Make_dataset

Reads images and and corresponding labels

Custom.py -> LocalizerAlexNet(nn.Module): __init__

Architecture definition for the Localizer AlexNet Model.

Custom.py -> LocalizerAlexNet(nn.Module): forward

Forward propagation for LocalizerAlexNet

Custom.py -> LocalizerAlexNetRobust(nn.Module): __init__

Architecture definition for the Localizer AlexNet Robust Model.

Custom.py -> LocalizerAlexNetRobust(nn.Module): forward

Forward propagation for LocalizerAlexNetRobust

Custom.py -> localizer_alexnet(pretrained=False, **kwargs):

Creates the Alex Net architecture and loads the pretrained weights

Custom.py -> localizer_alexnet_robust(pretrained=False, **kwargs):

Creates the Alex Net Robust architecture and loads the pretrained weights

Custom.py -> IMDBDataset

Getting data (images and the ground truth labels) from the class IMDB

Main.py ->

Defined loss function and optimizer

Created loggers for visdom and tboard

Added output from model

Global Max pooled output and also upscaled it to get the heatmaps

Computed gradient and do SGD step

Added Visualizations

Defined Metric 1

Defined Metric 2

Q1.2

Output resolution of the model is 20x29x29 for an input image of size 512x512, where 29x29 is the spatial dimension and 20 is the number of classes more generally it is batch_size x no_classes x spatial resolution

Q1.4

Initially we observe a very steep drop in loss because there is imbalance of number of labels/class of objects present in the images, as in most images have very few (less than 3) classes of objects present and so initially the network tries to optimize the loss by predicting everything as zero, that is no class is present in the images. This results in a very steep decrease in loss. But of course after that the network starts to learn the actual objects present in the images.

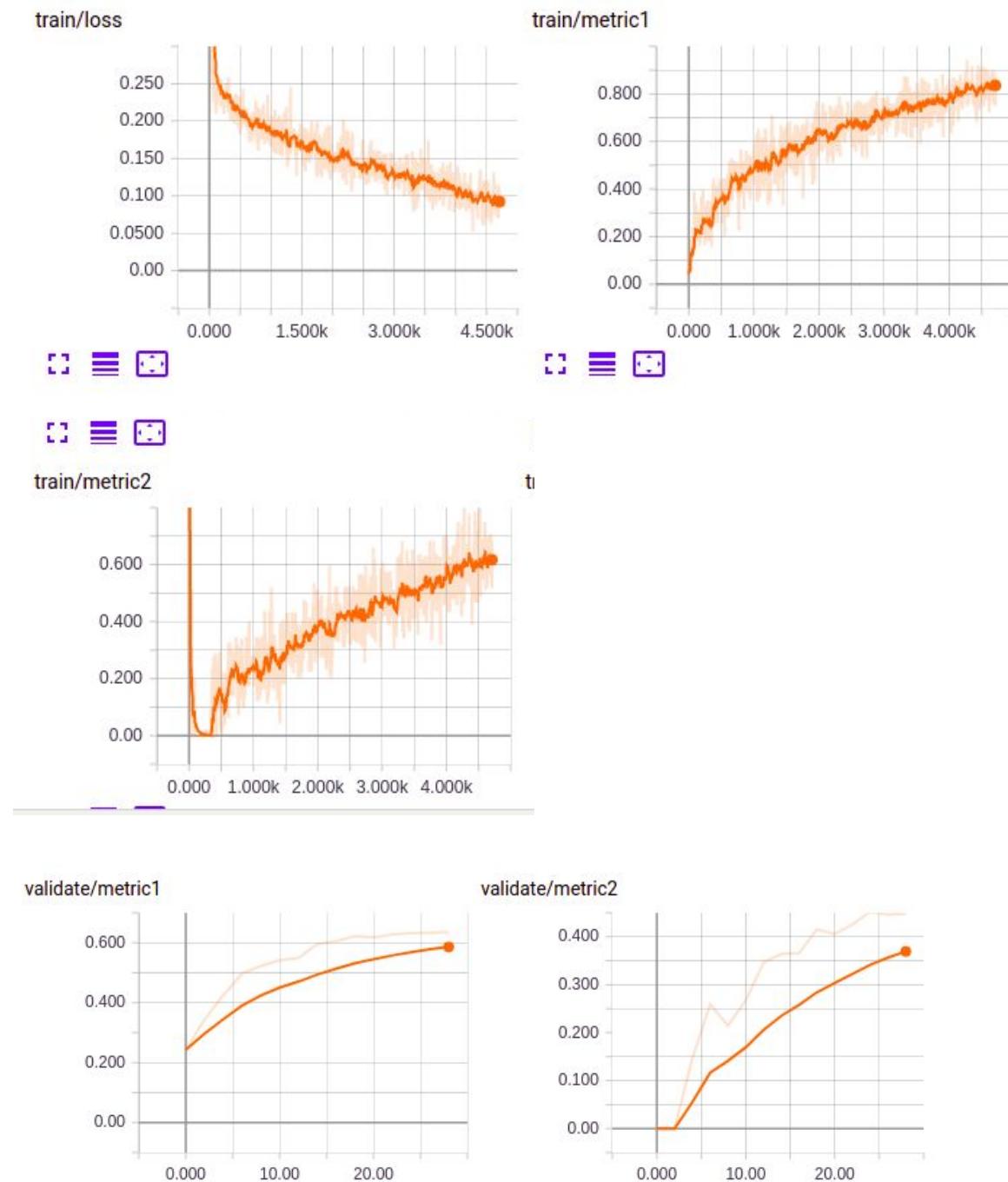
Q1.5

I am using the following:

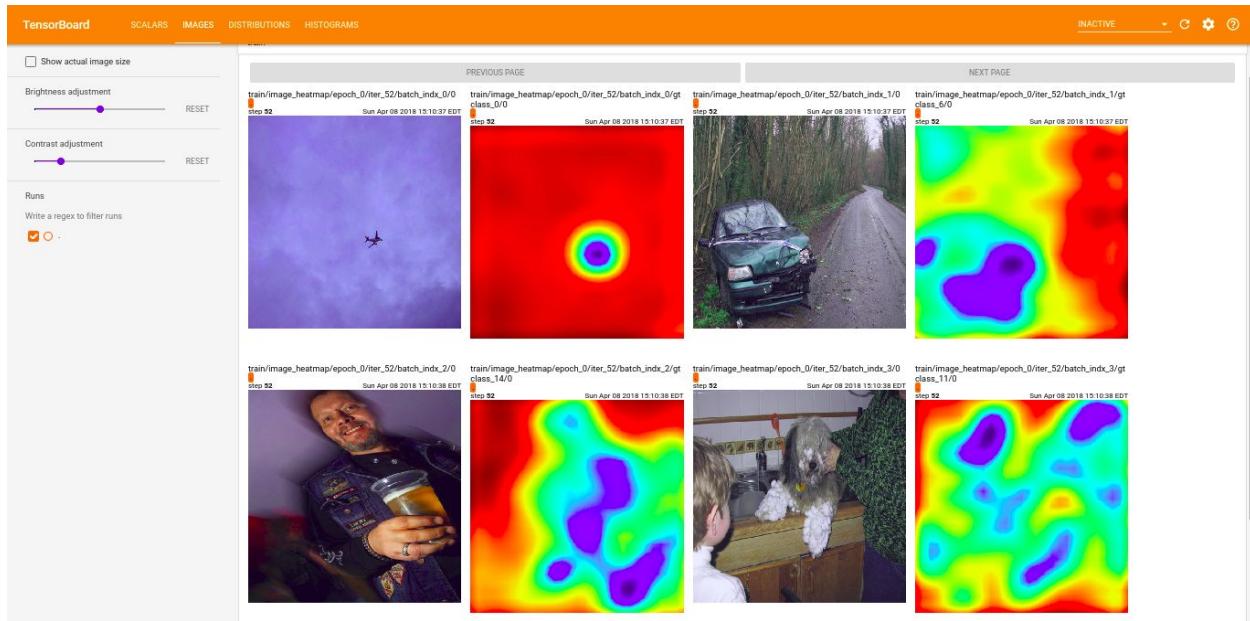
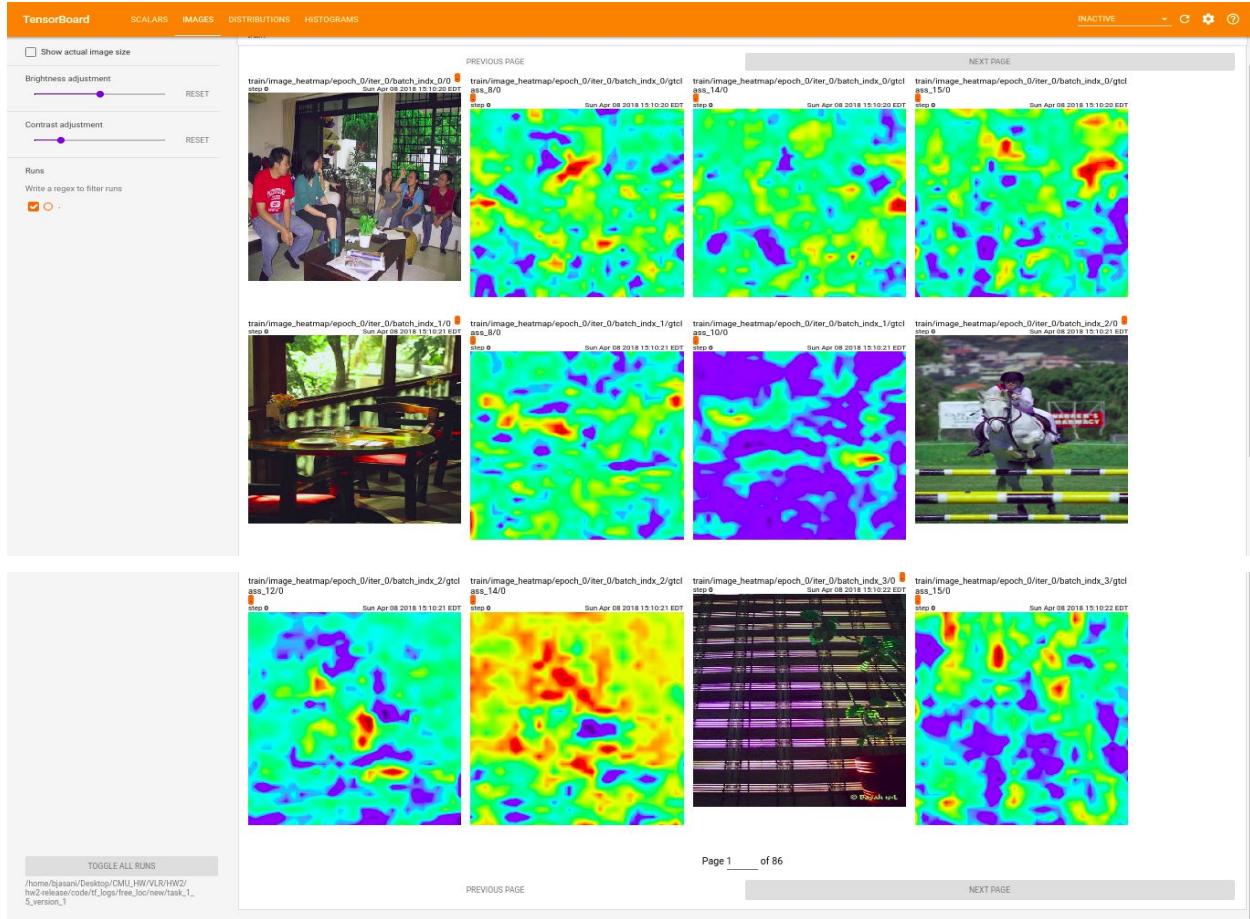
Metric 1: mean average precision (mAP), as was used in HW1

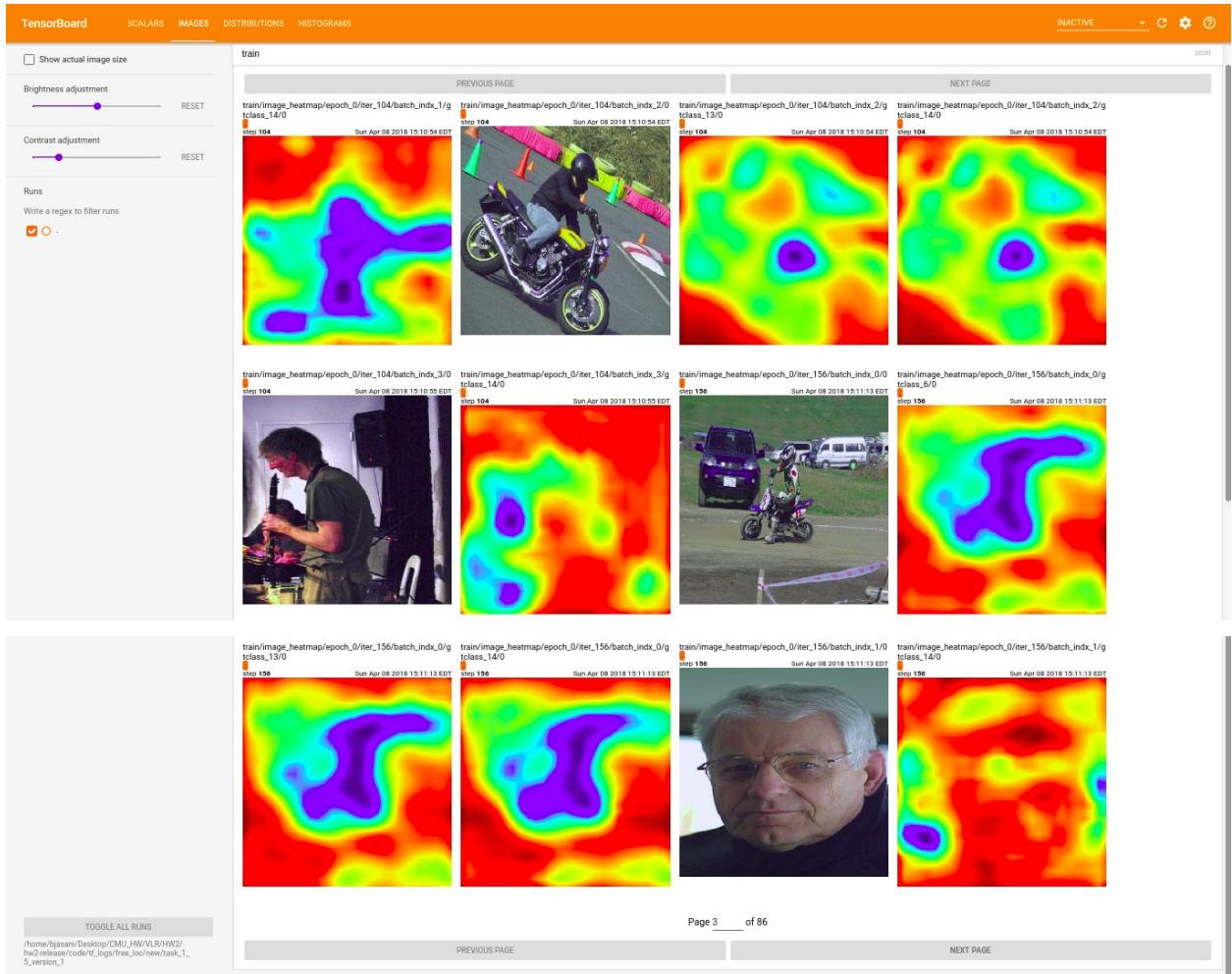
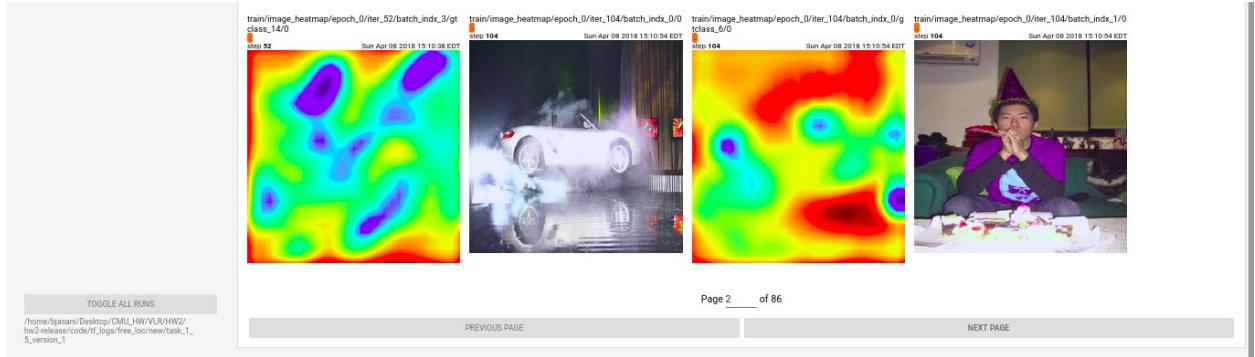
Metric 2: recall with a threshold of 0.5 (if the activation is above 0.5 then the class is considered to be present or else absent). Recall would only count the true positive for the classes which have ground truth labels present and so would be more robust.

Both of these are implementates using sklearn in the TODO blocks

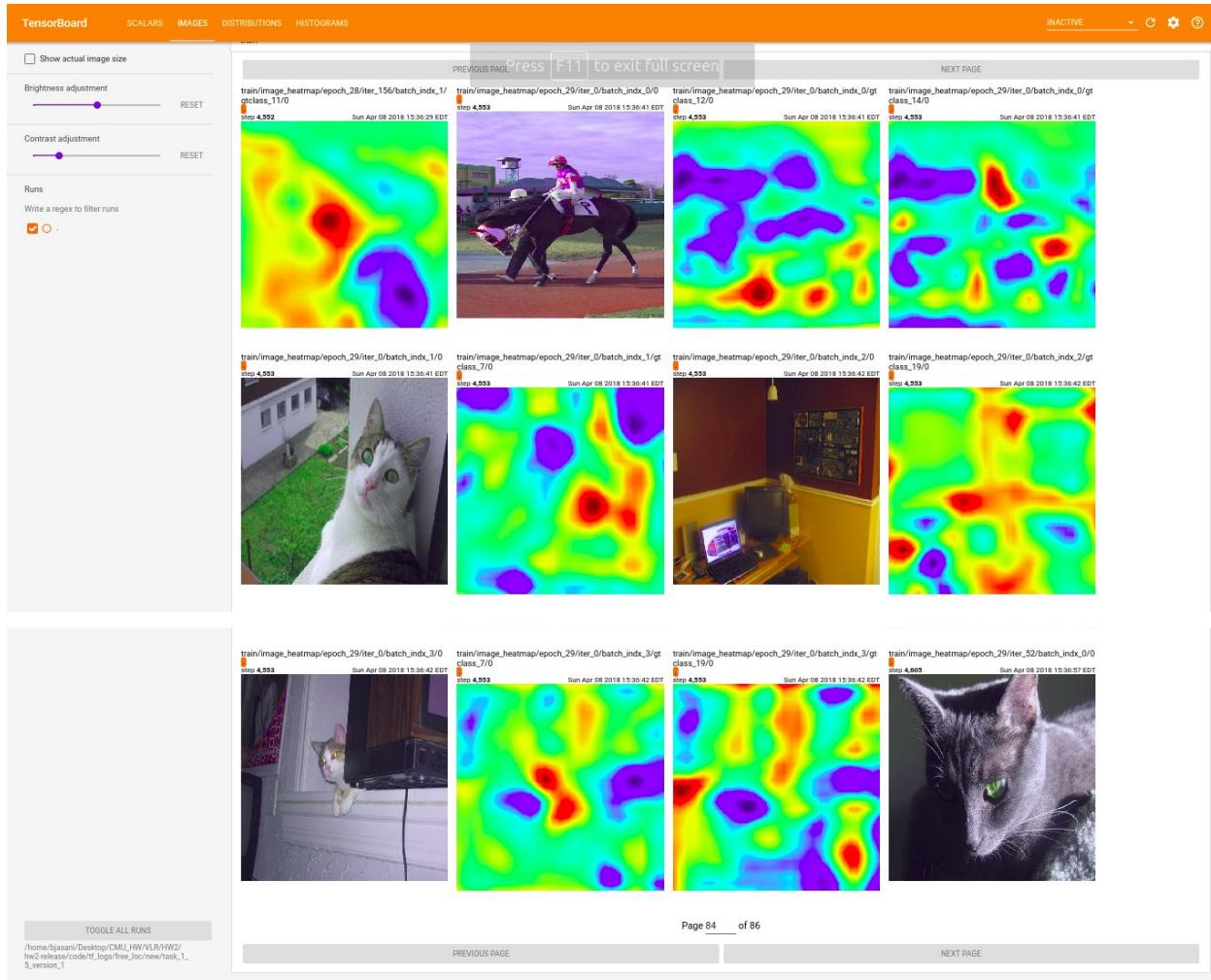


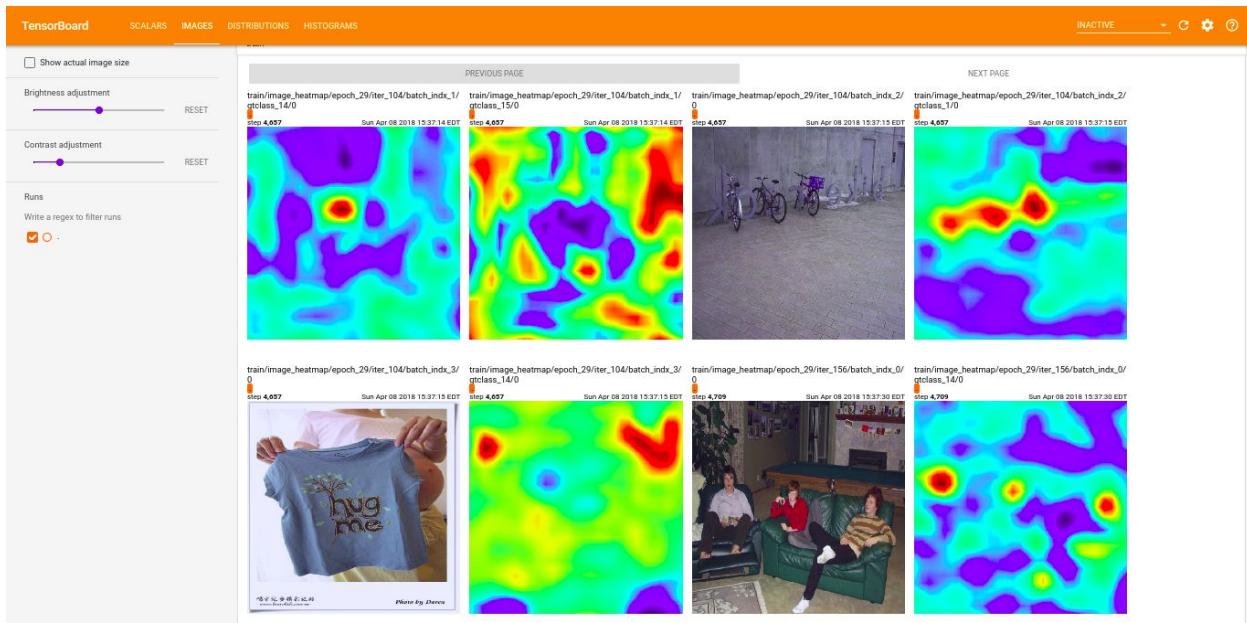
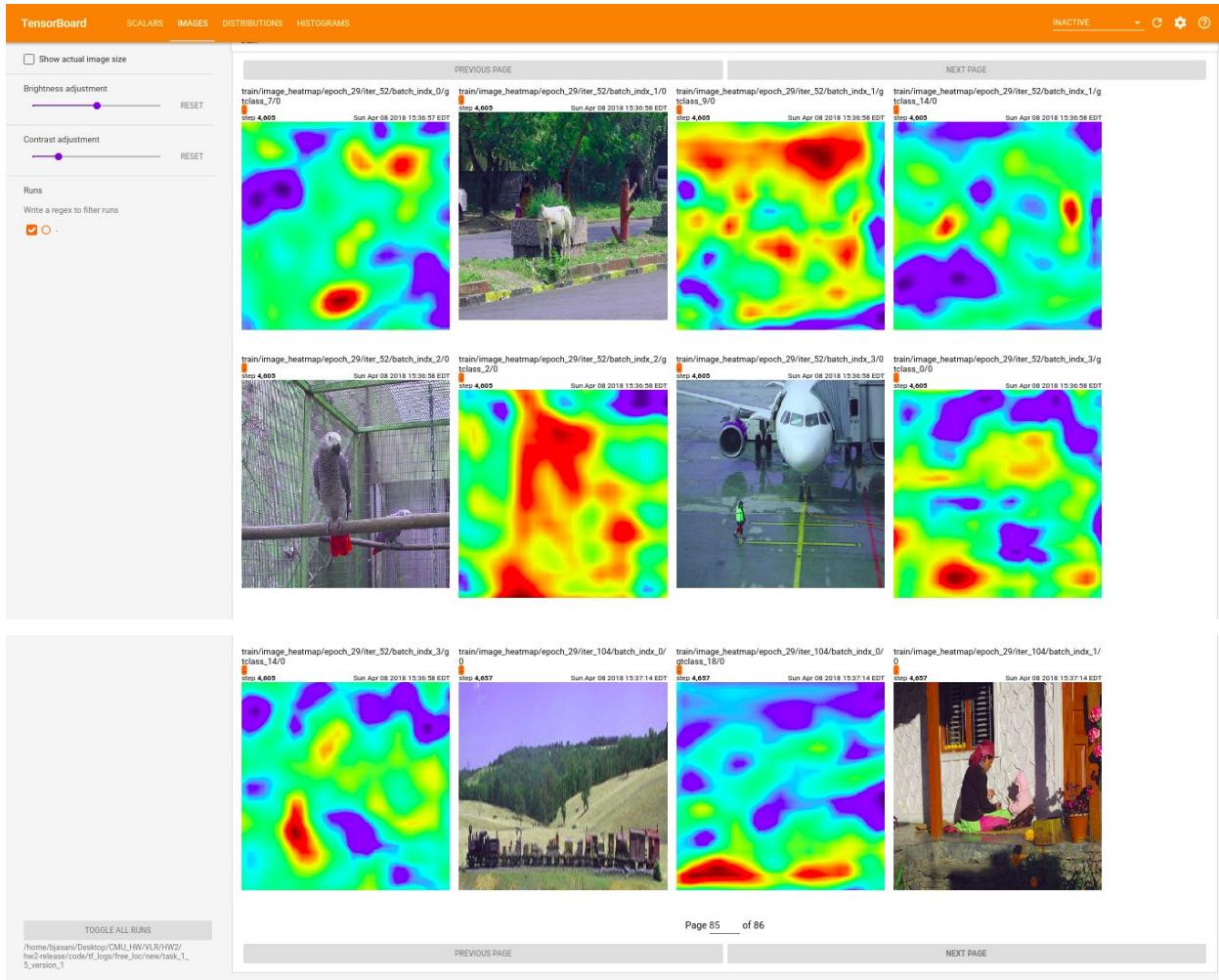
Tensorboard images and heatmap for first logged epoch



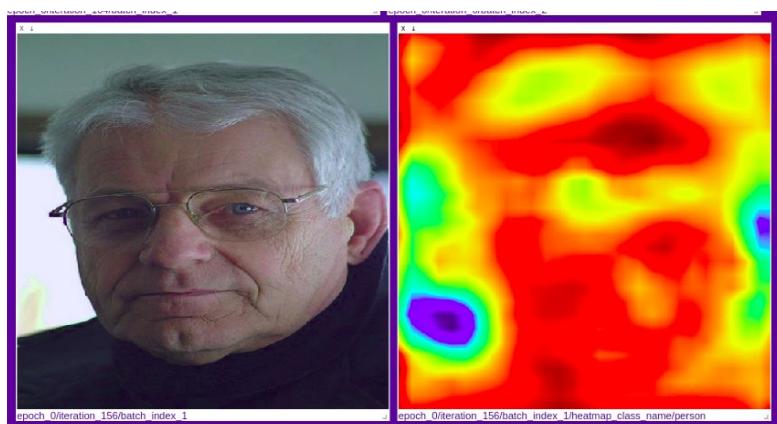
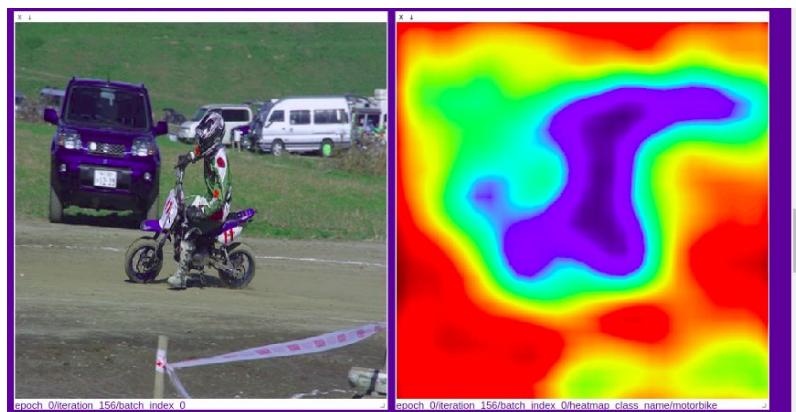
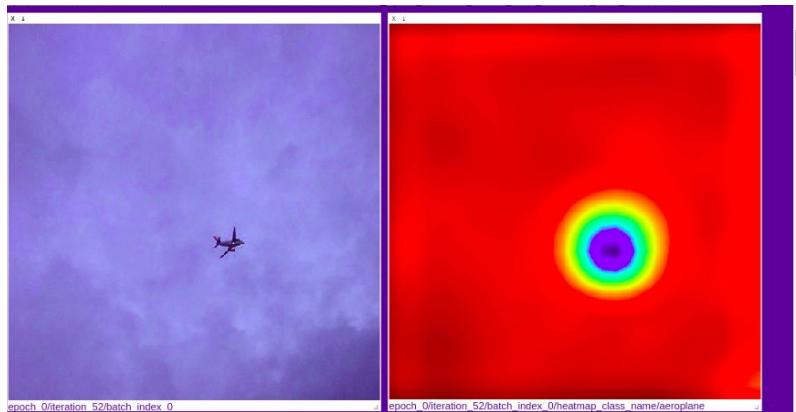


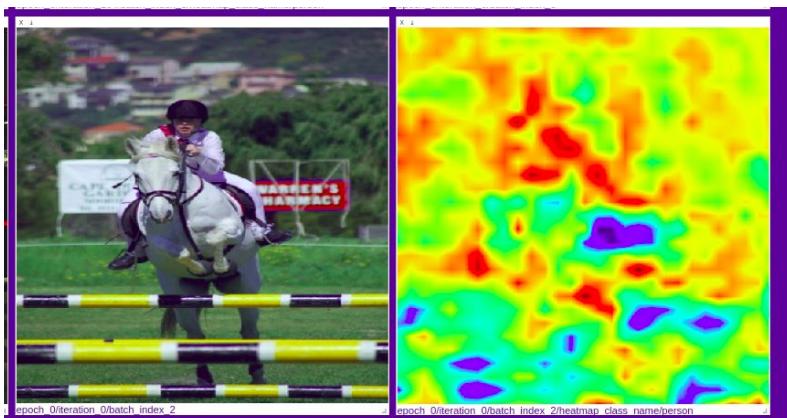
Tensorboard images and heatmap for last logged epoch

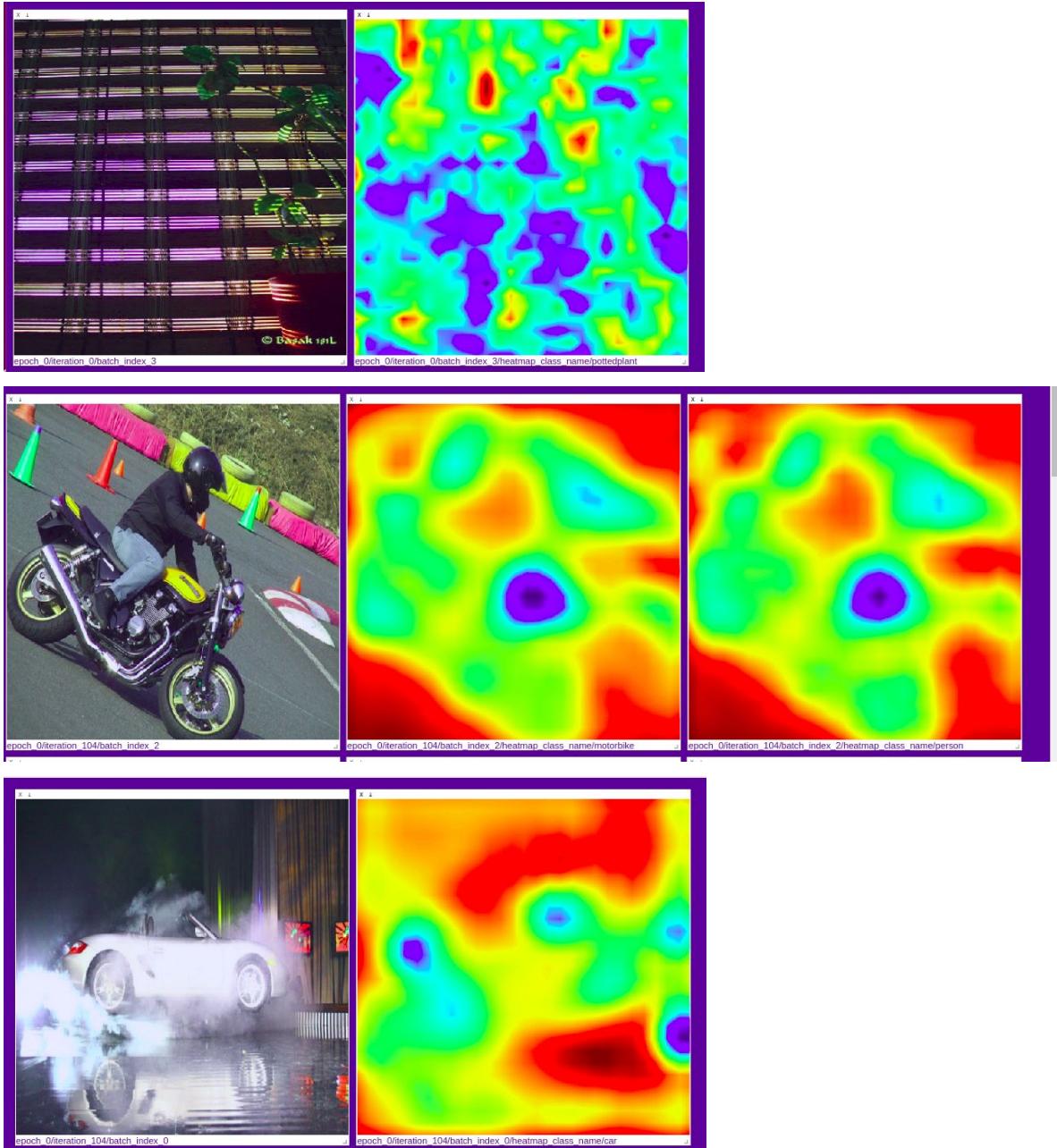




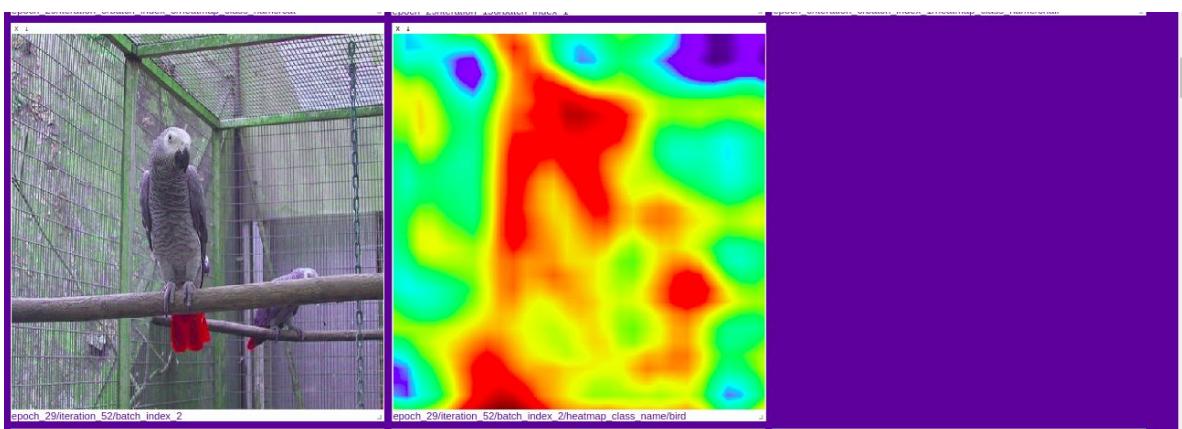
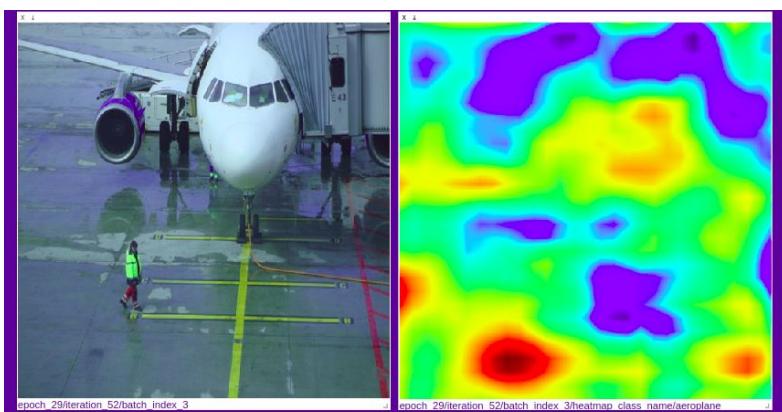
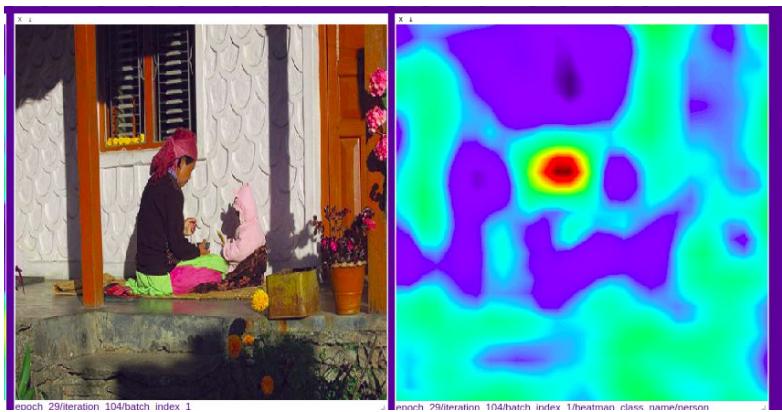
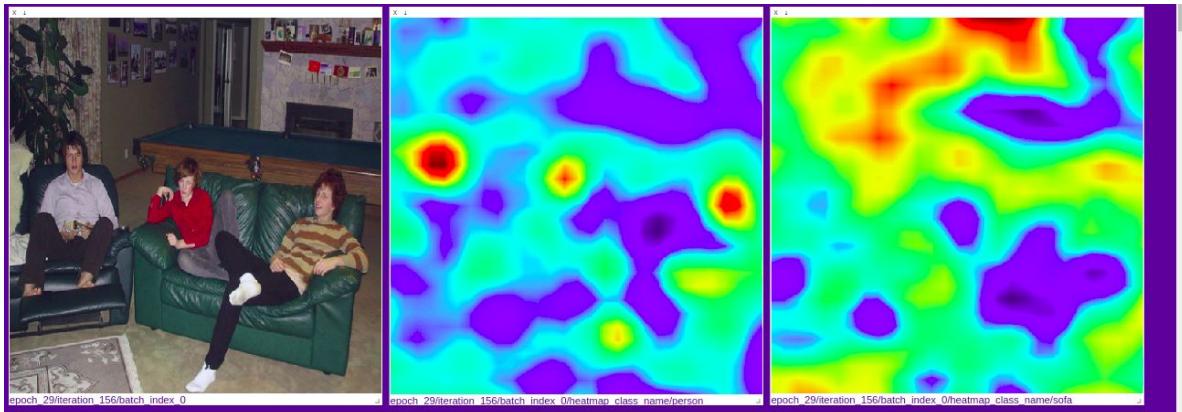
Visdom images and heatmap for first logged epoch

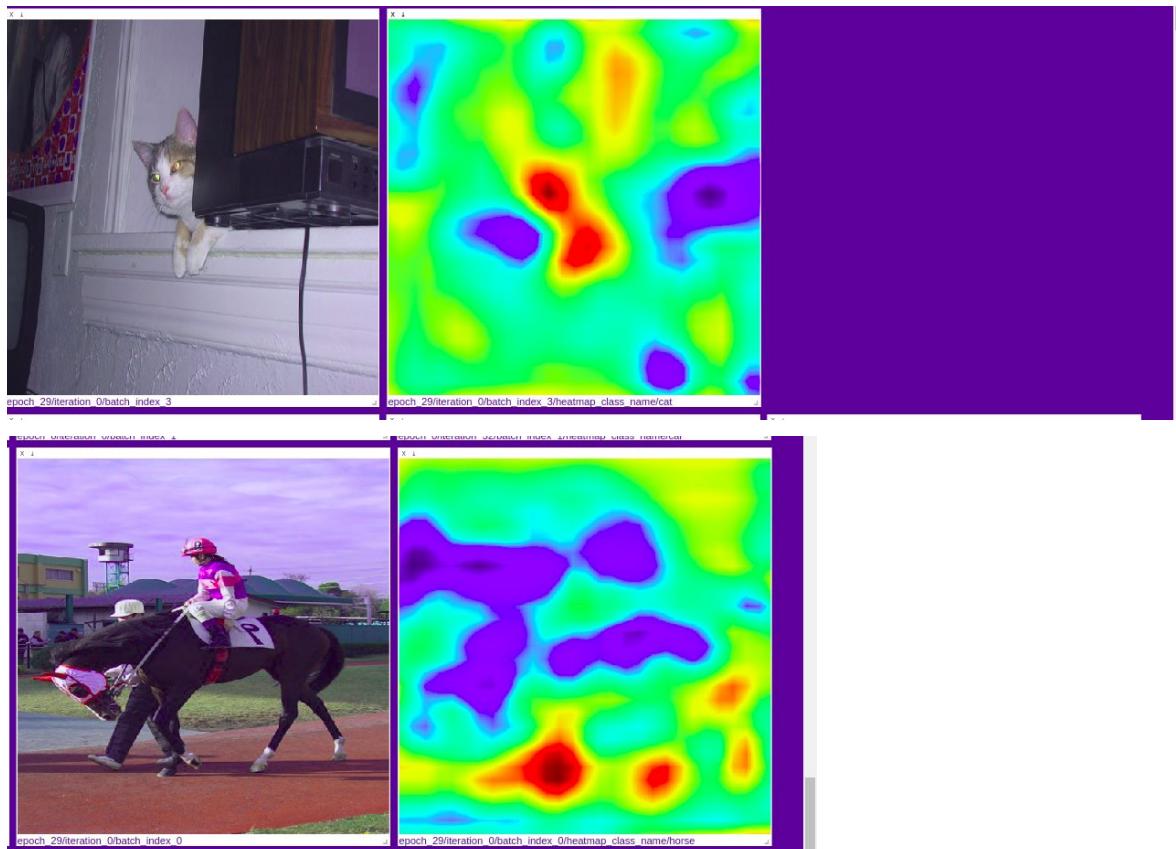




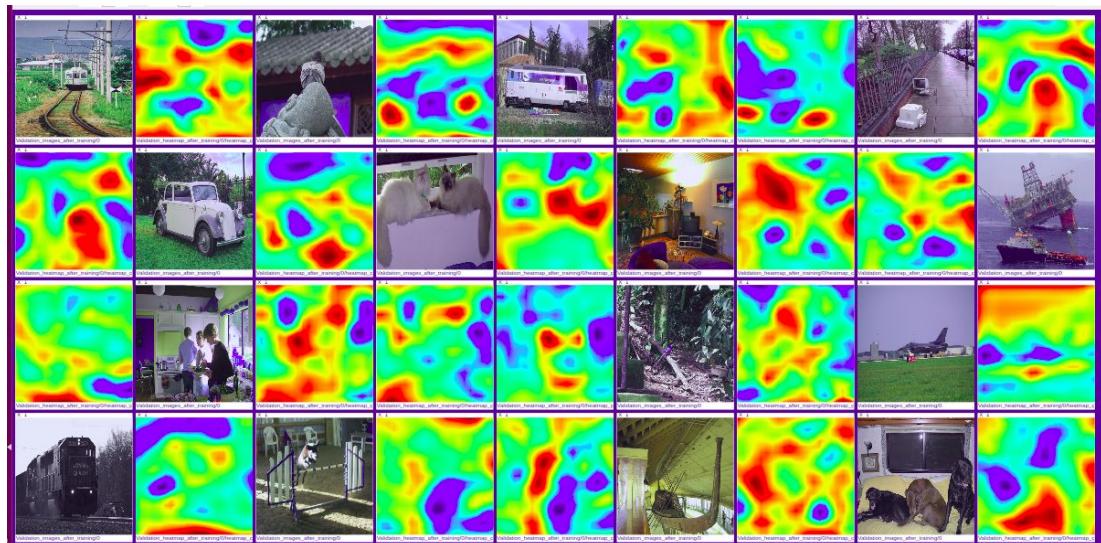


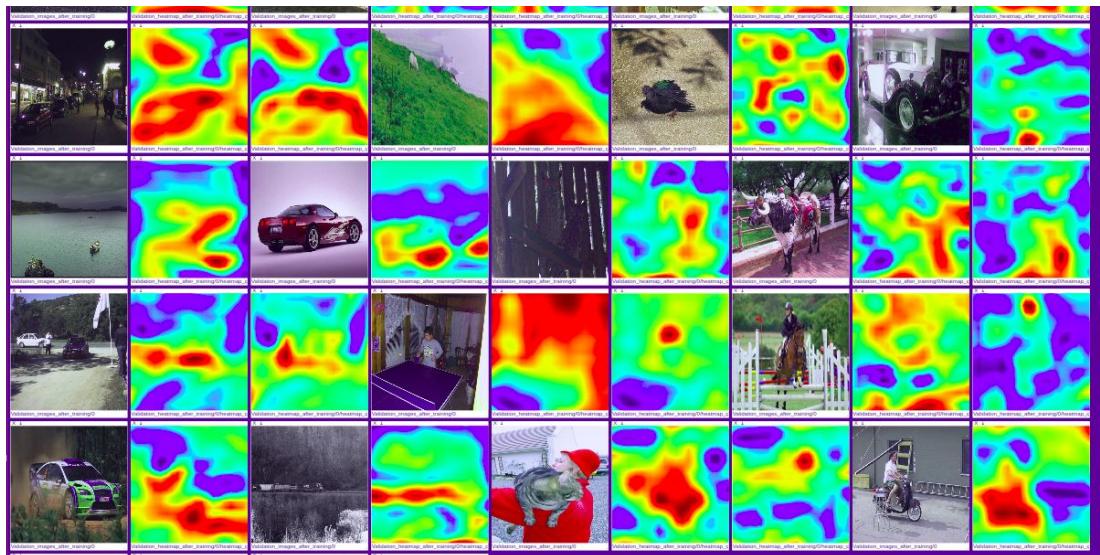
Visdom images and heatmap for last logged epoch





Visdom screenshot for 20 randomly chosen validation images and heat maps





At the end of training:

Training loss: 0.1104

Train metric 1: 0.7474

Train metric 2: 0.5185

Validation metric 1: 0.6345

Validation metric 2: 0.4486

Q 1.6 IN THE HEATMAP VISUALIZATIONS YOU OBSERVE THAT THERE ARE USUALLY PEAKS ON SALIENT FEATURES OF THE OBJECTS BUT NOT ON THE ENTIRE OBJECTS. HOW CAN YOU FIX THIS IN THE ARCHITECTURE OF THE MODEL?

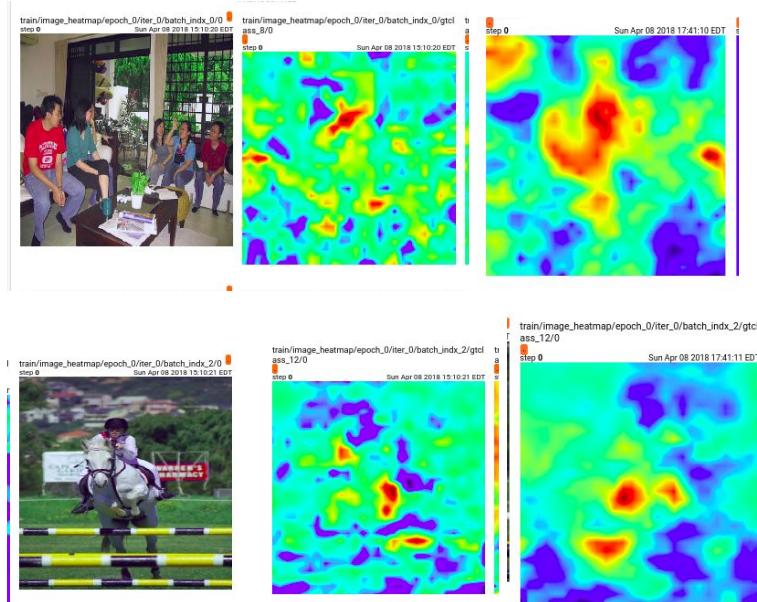
So I am doing two things for this

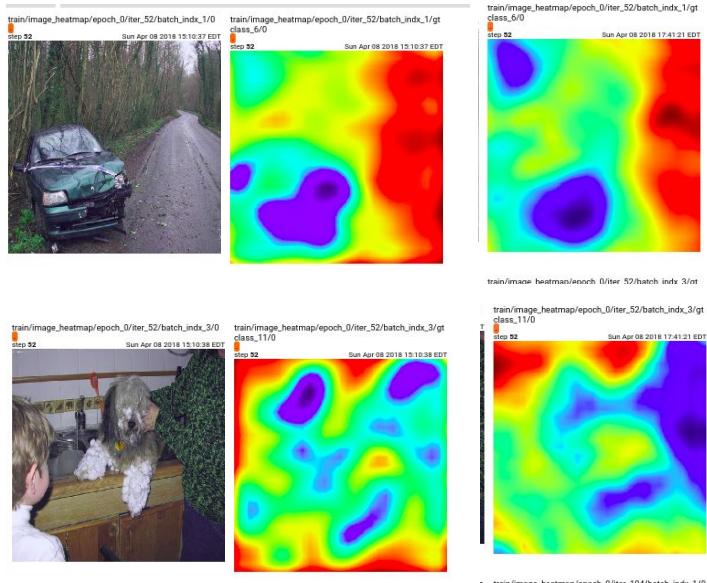
- 1) Apply dropout to randomly suppress the activations just after the output of the classifier
- 2) Use a multiple average pooling after the dropout to get a more spreaded version of activations and then take an average of them

This is implemented as below:

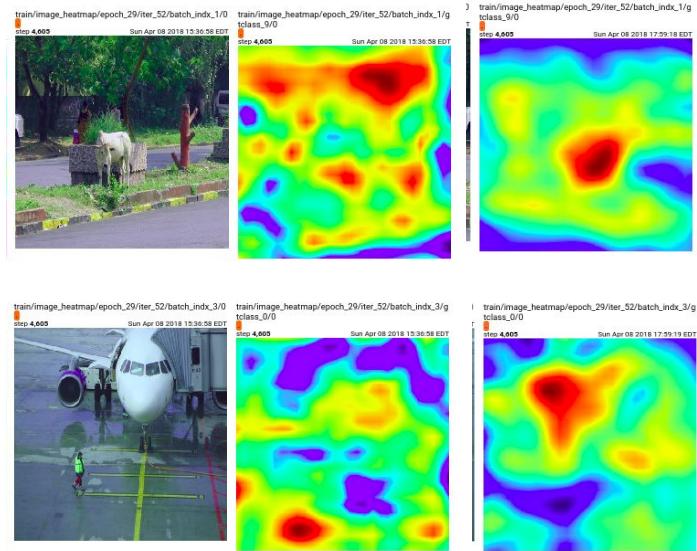
```
x = self.classifier(x)
x = F.dropout2d(x, p=0.5)
x1 = F.avg_pool2d(x, kernel_size = 3 , stride = 1, padding = 1 )
x2 = F.avg_pool2d(x, kernel_size = 5, stride = 1, padding = 2 )
x3 = F.avg_pool2d(x, kernel_size = 7, stride = 1, padding = 3 )
X = (x + x1 + x2 + x3)/4.0
```

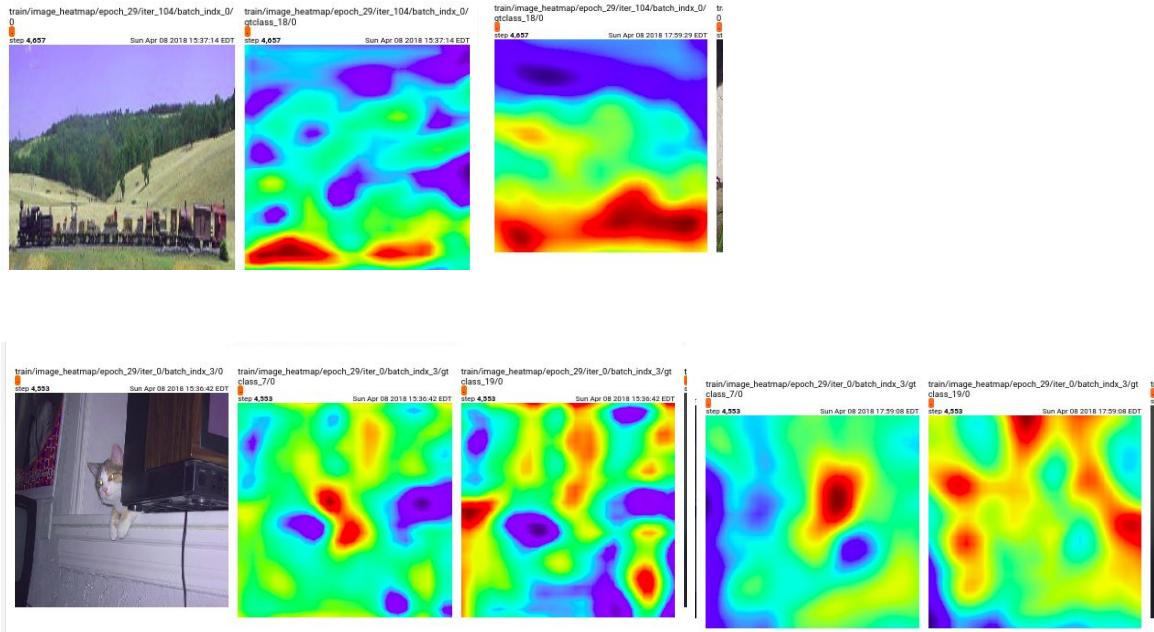
Screenshot of tensor board showing images and heat maps for the first logged epoch *for Q1.5 and Q1.6 side-by-side*.



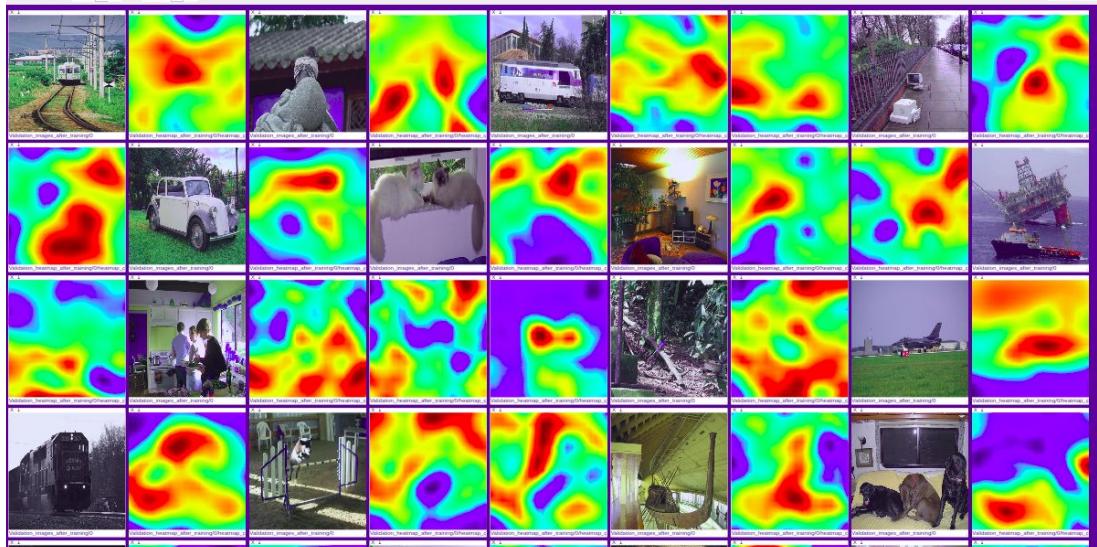


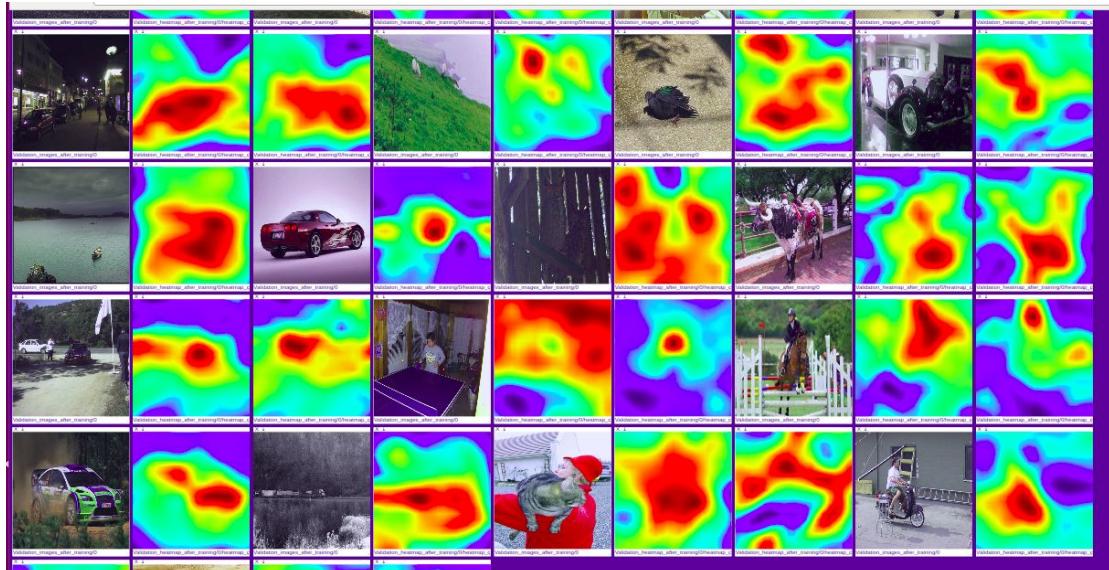
Screenshot of tensor board showing images and heat maps for the last logged epoch *for Q1.5 and Q1.6 side-by-side*.





Visdom screenshot for 20 randomly chosen validation images (but same images as Q1.5) and heat maps





Report training loss, validation metric1, validation metric2 at the end of training

At the end of the training:

Training Loss : 0.3873

Validation metric 1 : 0.713

Validation metric 2 :0.505

Task 2

- visdom downloaded image of training loss vs iterations

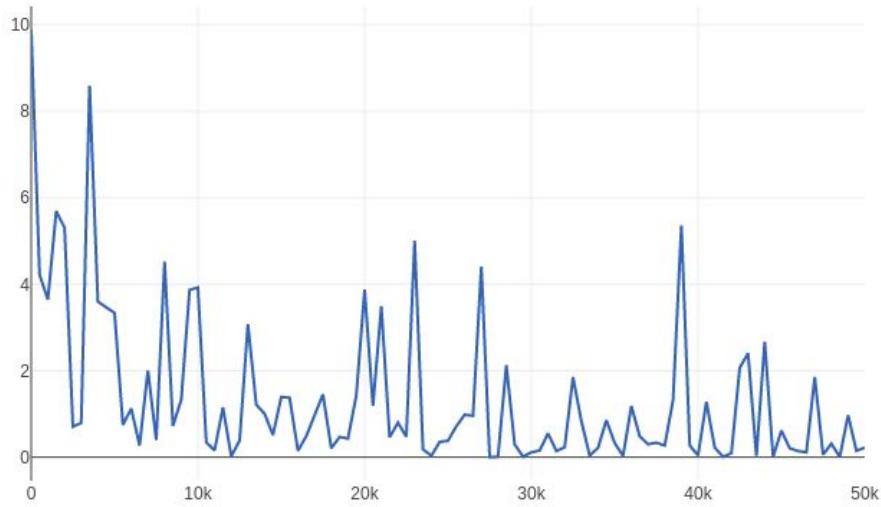
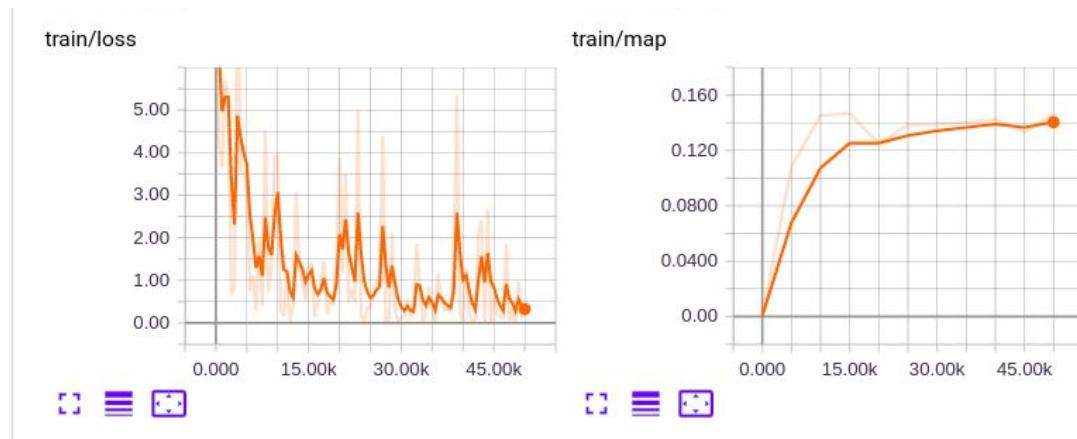


Figure: Training loss vs iterations

- tensor board screenshot of training loss vs iterations



- tensor board screenshot histogram of gradients of weights for conv1, conv2 and fc7

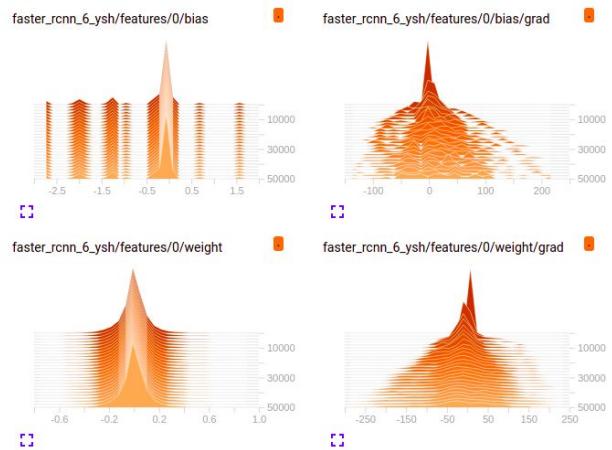


Figure: Conv1 plots

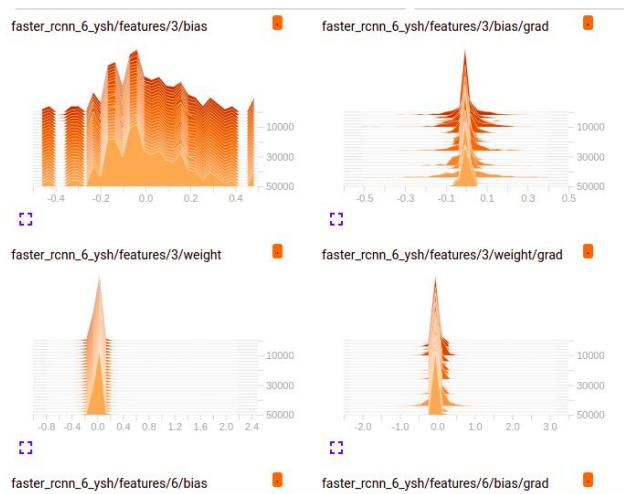


Figure: Conv2 plots

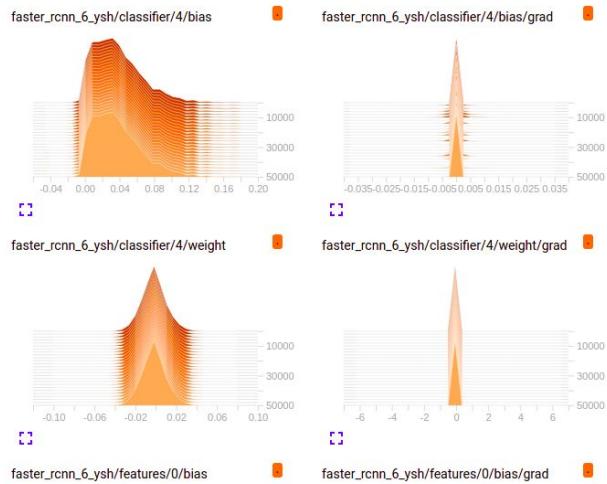


Figure: FC7 plots

- visdom downloaded image of test mAP vs iterations plot

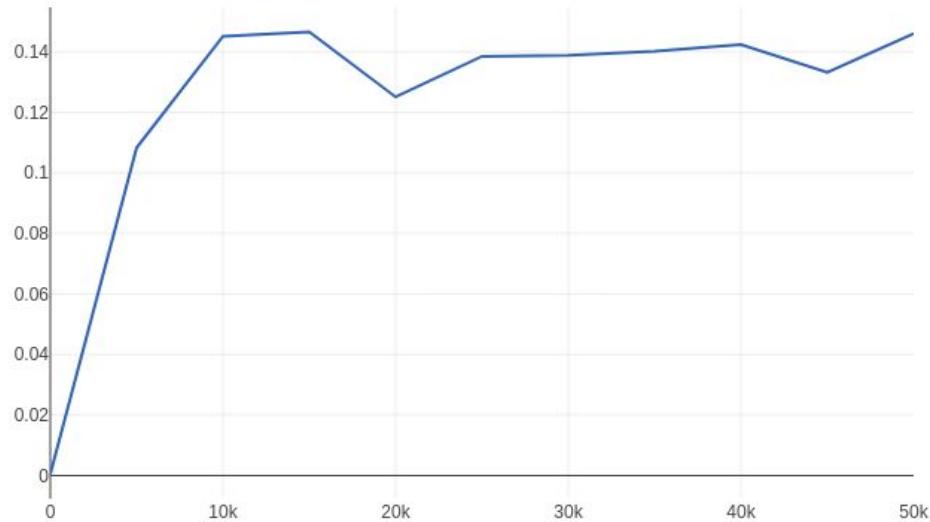
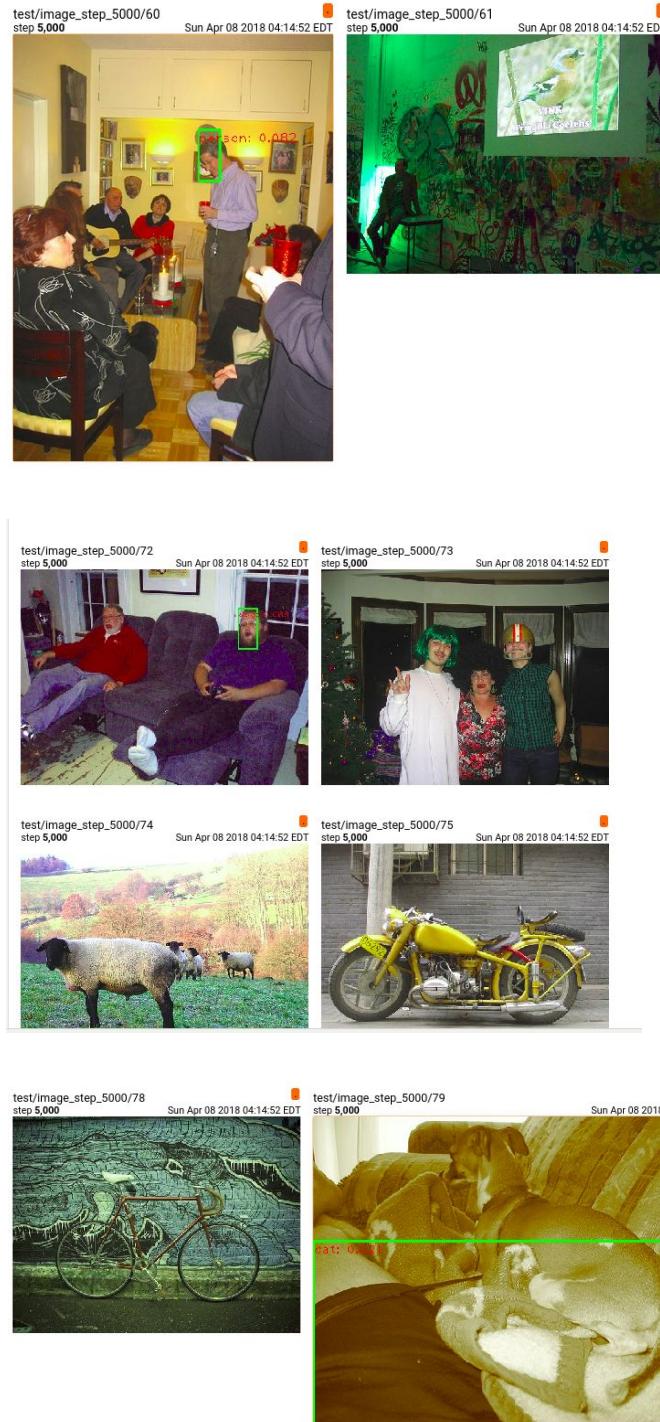


Figure: Test mAP vs iterations

- tensorboard screenshot for class-wise APs vs iterations showing 3 or more classes

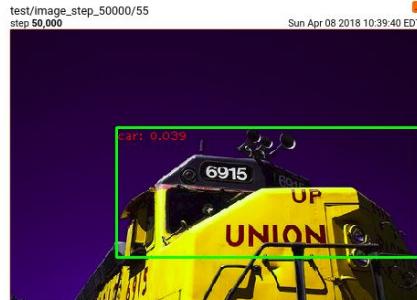
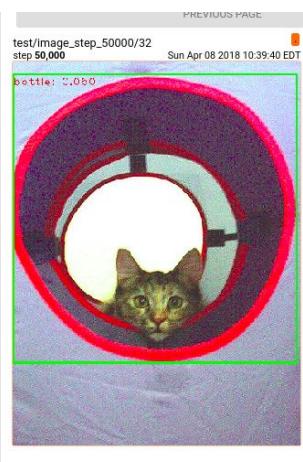
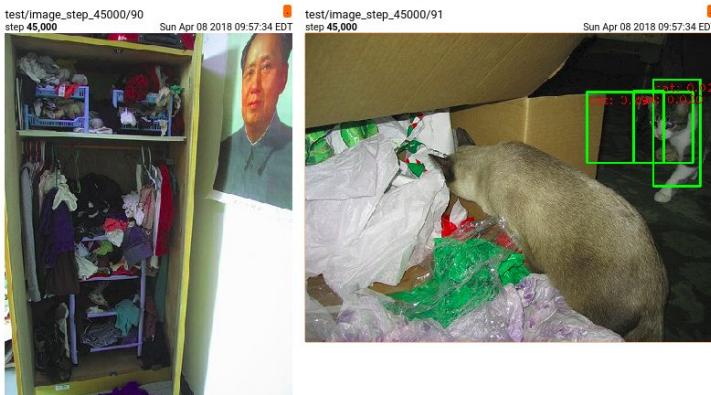


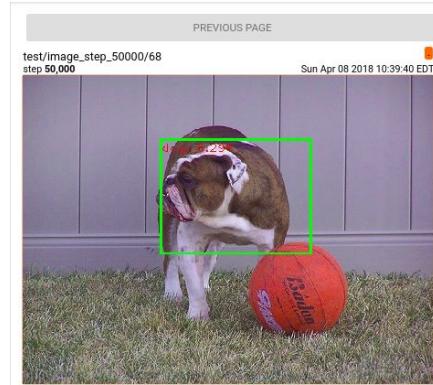
- tensor board screenshot of images with predicted boxes for the first logged iteration (5000)



- tensor board screenshot of images with predicted boxes for the last logged iteration (50000 or 45000)







- report final classwise APs on the test set and mAP on the test set

AP for aeroplane = 0.2485

AP for bicycle = 0.2866

AP for bird = 0.1879

AP for boat = 0.1146

AP for bottle = 0.0529

AP for bus = 0.2384

AP for car = 0.2324

AP for cat = 0.1684

AP for chair = 0.0195

AP for cow = 0.1182

AP for diningtable = 0.0223

AP for dog = 0.0962

AP for horse = 0.1883

AP for motorbike = 0.2202

AP for person = 0.0128

AP for pottedplant = 0.0749

AP for sheep = 0.0862

AP for sofa = 0.0802

AP for train = 0.3000

AP for tvmonitor = 0.1725

Mean AP = 0.1461