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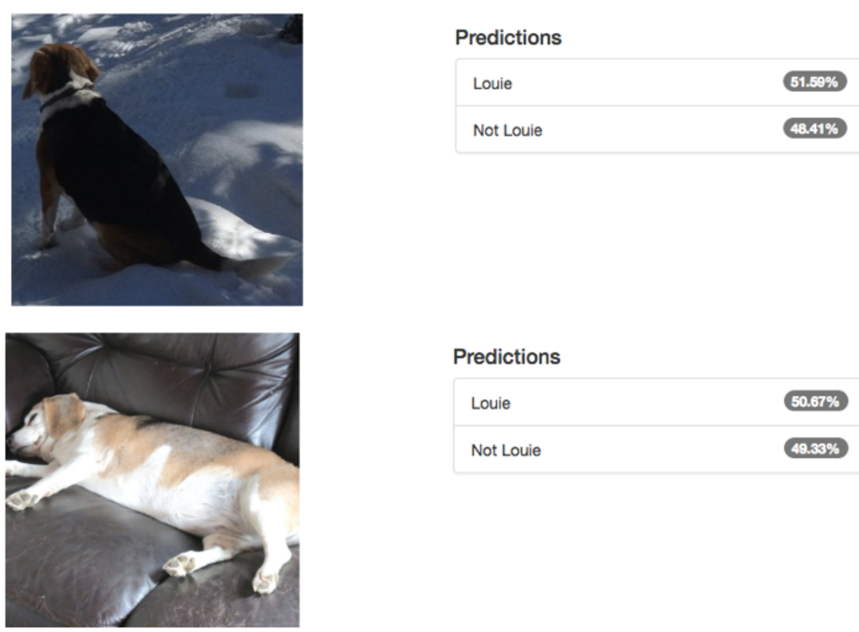
Assignment 2 Individual Part – NVIDIA CNN Course

Summary Table

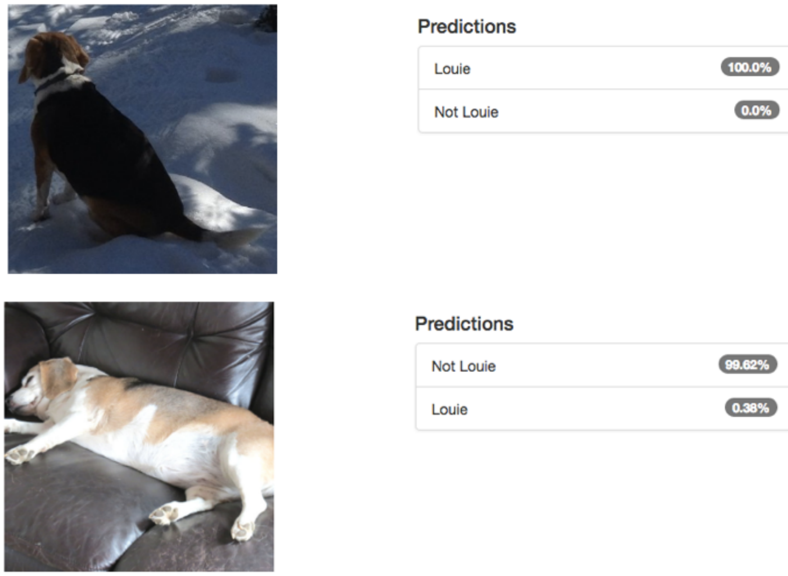
Part	Epochs	Learning Rate	Starting model	Architecture	Train Loss	Validation Accuracy	Validation Loss	mAP
2	5	0.01, stepped	None	AlexNet	0.510573	78.9222	0.444362	n/a
4	3	0.0001, fixed	Part 2	AlexNet	0.417429	80.8514	0.417429	n/a
4	5	0.0001, fixed	Part 2	AlexNet	0.346343	81.2978	0.405009	n/a
4	8	0.0001, fixed	Part 2	AlexNet	0.485231	83.0198	0.377874	n/a
5	5	0.01, stepped	None	Fully Connected CNN	0.383046	79.7353	0.433146	n/a
5	1	1.00E-100	DetectNet	DetectNet	1.08067	n/a	0.804193	13.4135

GPU Task 1

In this task, I completed two experiments. For the first one I trained the Alexnet network for 2 epochs on 16 pictures of beagles, some "Louis" and some "not Louis". After 2 epochs it performs at chance, classifying images of both classes as Louis with slightly above 50% certainty (Figure 1A). For the second one, I trained it for 100 epochs. This time it gets the classifications correct with at or near 100% confidence (Figure 1B). However these tests are with images from the training data rather than images the model has never seen before, and the model is likely overfitting.



A



B

Figure 1: A: Results after 2 epochs. Top image is of Louis, bottom image is not. B: Results after 100 epochs.

GPU Task 2

The purpose of this task was to learn about how validation data can be used to monitor a model's performance with new data while it trains. In this task I trained a neural network to detect dogs versus cats. First the data has to be preprocessed to a size compatible with the AlexNet, and organized into folders where the folder name is the category label, and with 25% of the data set aside as a validation set. Then I trained AlexNet for 5 epochs. The validation data had above 80% accuracy after the 5 epochs as shown in Figure 2, and it categorized a picture of a dog correctly with greater than 90% probability.

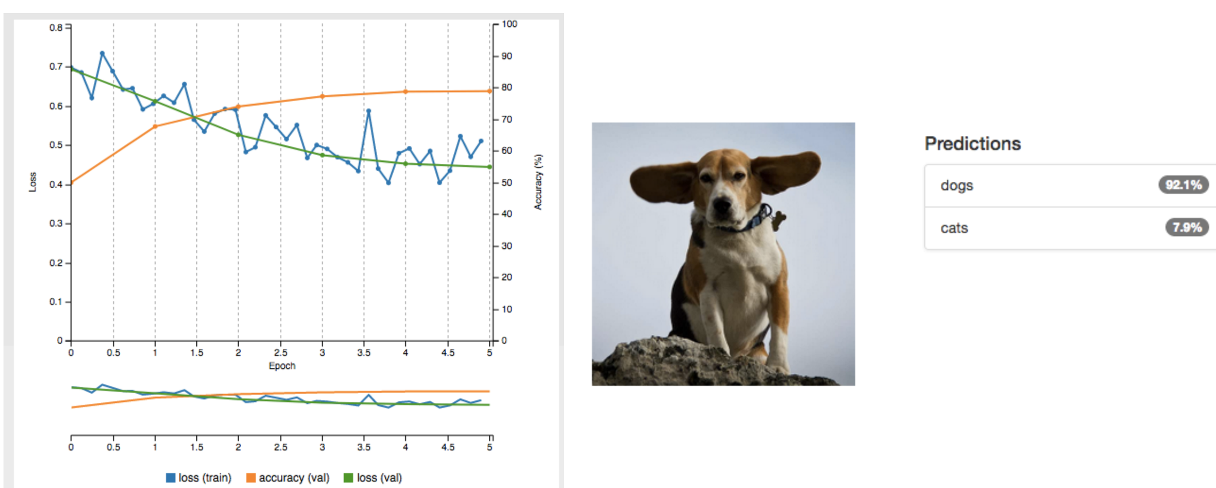


Figure 2: Dogs vs. Cats with 5 epochs. The plot shows the training and validation loss and accuracy. The image of a dog is correctly classified as a dog.

GPU Task 3

The purpose of this task was to deploy a trained model in an application. I imported the architecture and weights from the model from task 2 into a new caffe classifier object in a jupyter notebook. The notebook calculates the predicted probabilities for each class for test images, selects the argmax and prints one statement if it a cat and another if it is a dog as shown in Figure 3. This process can be consolidated into a single script that simply shows the output instead of the image with the output.

Figure 3: Example outputs for images of dogs and cats in the deployment application.

GPU Task 4

For the first part of this task, I took the model from Task 2 and trained it for more epochs to see the effects of training for a longer time. I tested 3, 5, and 8 additional epochs and found they brought only a small improvement to the validation accuracy and loss shown in the summary table. The loss and accuracy curves are in Figure 4. Then I tested using an AlexNet model pretrained on the Imagenet data set. It correctly identified a picture of Louis from Task 1 as a beagle (class 162). This can be used in an application to pair the image with its text label as shown in Figure 5.

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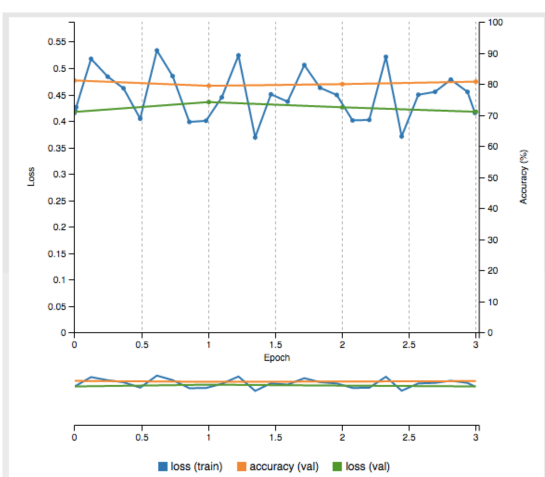

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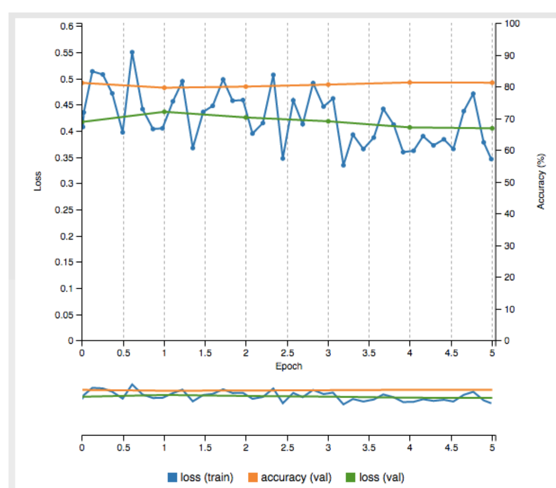

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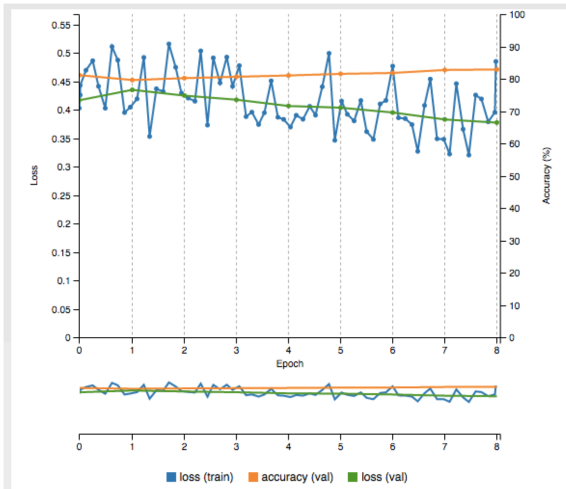

Figure 4: Train and validation loss and accuracy curves for 3, 5, and 8 additional epochs

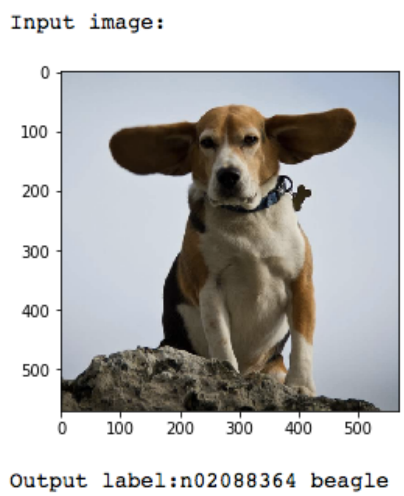

Figure 5: Pretrained AlexNet application output for an image of a beagle

GPU Task 5

For this task I implemented several methods of object localization. I first created an object detector that using a sliding window method to divide the image into a grid of 256x256 sections and for each section predicts whether the image is a dog or a cat. The output is a very imprecise location for the dog in the image as shown in Figure 6.

Next I took the AlexNet architecture and changed it to be a fully connected CNN. This model did a better job of detecting where in the image the dog is, but also had false positives as show in figure 7, which also includes the accuracy and loss curves.

Finally I took a DetectNet architecture and fine-tuned it for one epoch with a very slow learning rate for the dogs and cats data set. Figure 8 contains the mean average precision (mAP) and loss curves, and Figure 9 contains example outputs. This application does a much better job of localizing the dog in the image, but in some images detects multiple overlapping dogs. This is consistent with the mAP of 13%.

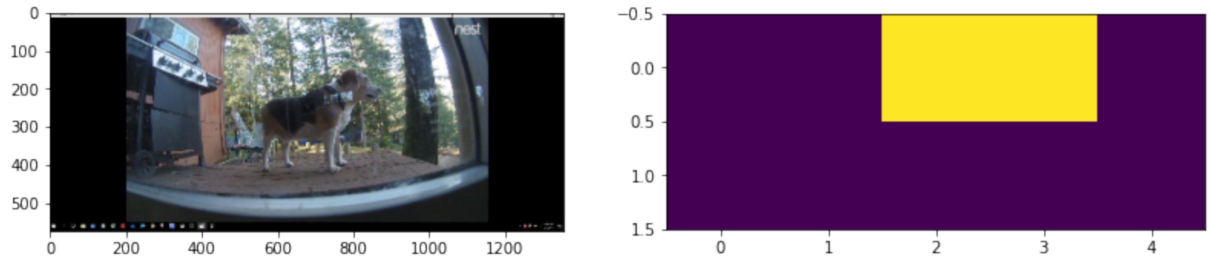

Figure 6: Sliding window prediction as a method of object localization

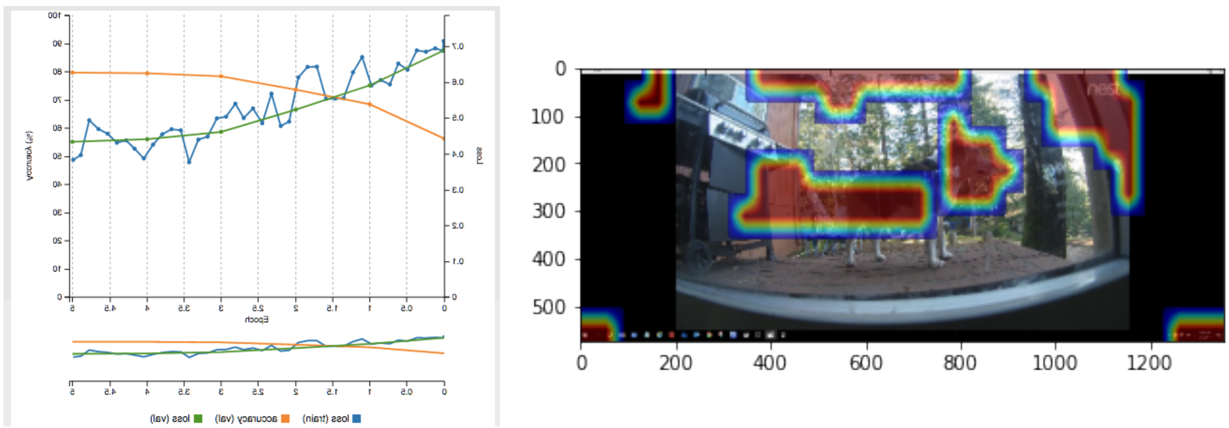

Figure 7: Fully Connected CNN Accuracy and Loss Curves and Example Output

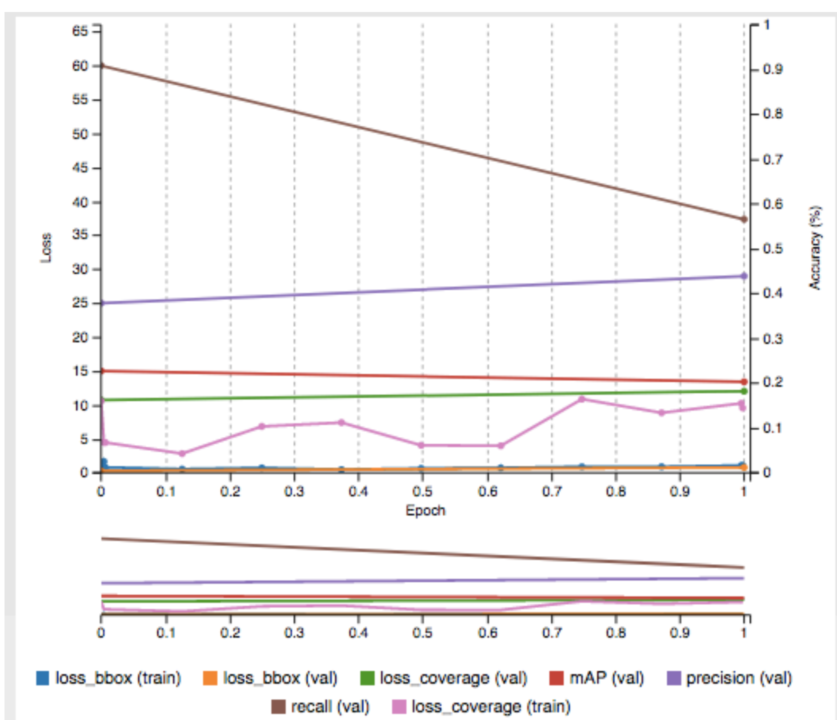

Figure 8: DetectNet Fine-Tuning Accuracy and Loss Curves

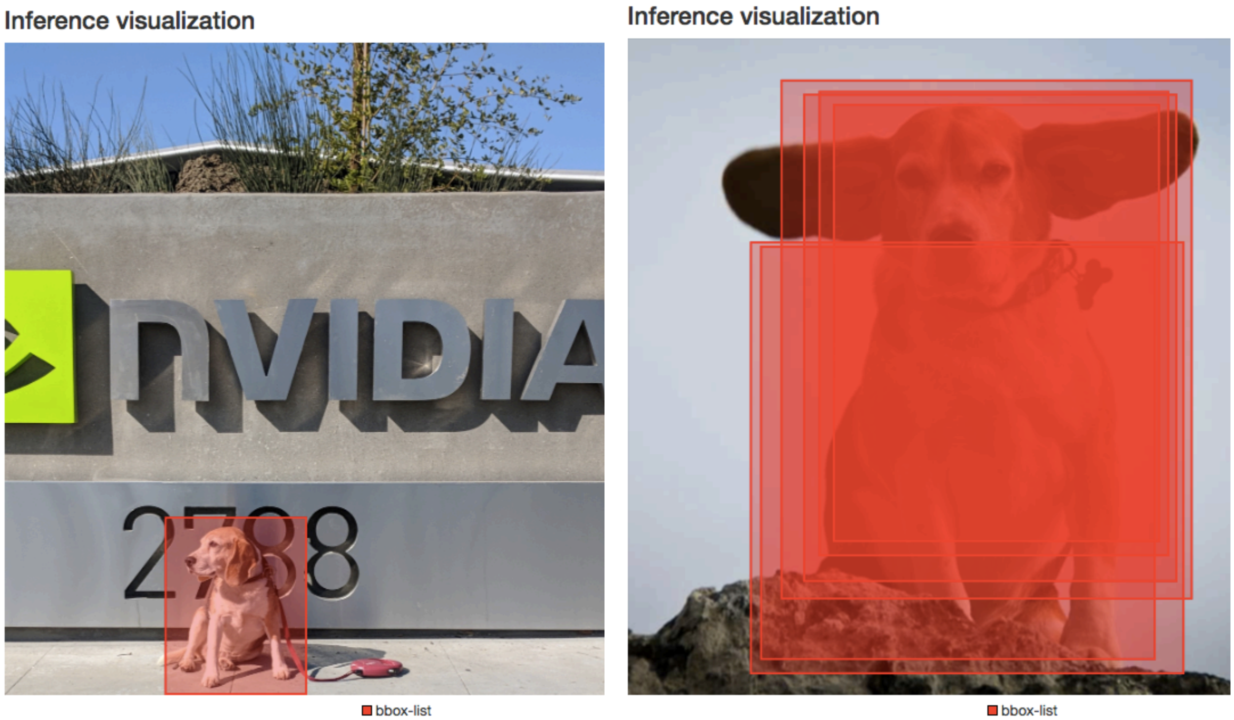

Figure 9: DetectNet Example Outputs