Airbus Ship Detection

Christopher Broll
Zachary Stein
Shilpa Rajbhandari

Introduction

- Airbus is an aerospace defense company based in Europe, posted a challenge to build a model to classify ships in satellite imagery.

- The model will be useful to prevent privacy, illegal fishing, drug trafficking, illegal cargo movement. It will be beneficial to insurance companies and environmental agencies as well.

Objective

- Our objective is to classify ships whether ships appear in satellite imagery (binary classification)

- Based on Kaggle competition below:
(https://www.kaggle.com/c/airbus-ship-detection)

Project Data

	ImageId	EncodedPixels
0	00003e153.jpg	NaN
1	0001124c7.jpg	NaN
2	000155de5.jpg	264661 17 265429 33 266197 33 266965 33 267733...
3	000194a2d.jpg	360486 1 361252 4 362019 5 362785 8 363552 10 ...
4	000194a2d.jpg	51834 9 52602 9 53370 9 54138 9 54906 9 55674 ...

source:https://www.kaggle.com/inversion/run-length-decoding-quick-start

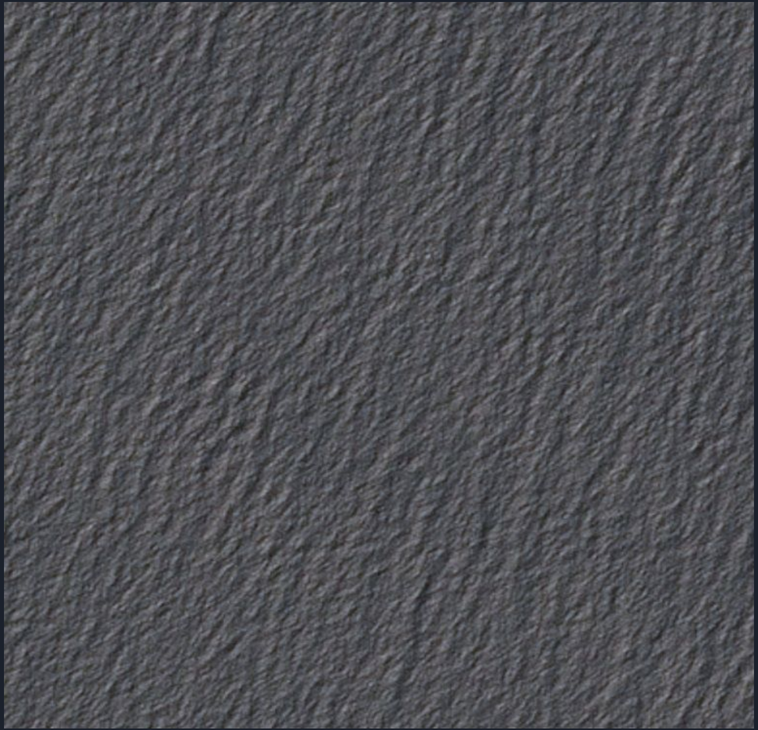
```
img = imread('../input/train/' + ImageId)
img_masks = masks.loc[masks['ImageId'] == ImageId, 'EncodedPixels'].tolist()

# Take the individual ship masks and create a single mask array for all ships
all_masks = np.zeros((768, 768))
for mask in img_masks:
    all_masks += rle_decode(mask)

fig, axarr = plt.subplots(1, 3, figsize=(15, 40))
axarr[0].axis('off')
axarr[1].axis('off')
axarr[2].axis('off')
axarr[0].imshow(img)
axarr[1].imshow(all_masks)
axarr[2].imshow(img)
axarr[2].imshow(all_masks, alpha=0.4)
plt.tight_layout(h_pad=0.1, w_pad=0.1)
plt.show()
```

These are the encoded pixels which shows how many ships are there in an image

- First one is image
- Second one is all masks
- Third one is also another mask

Example Images

source: https://www.kaggle.com/c/airbus-ship-detection/data



Preprocessing for Caffe

- 50000 images for training and 10000 for validation out of 192556
- Split training and validation with subfolders 00000 and 00001 (no ships and ships, respectively)
- Histogram Equalization and image reduction (80 by 80, 32 by 32 and 192 by 192)
- Create Lmdb

```
# Split into training and validation image sets (50,000 and 10,000, respectively)
train_df = pd.DataFrame({"ImageID": X_train2[:50000], "label": y_train2[:50000]})
val_df = pd.DataFrame({"ImageID": X_test2[:10000], "label": y_test2[:10000]})

# Seperate labels for subfolders for Caffe CNN
train_df_lab_1 = train_df[train_df.label==1]
train_df_lab_0 = train_df[train_df.label==0]

val_df_lab_1 = val_df[val_df.label==1]
val_df_lab_0 = val_df[val_df.label==0]
```

```python
# train folder with label 1 (images with ships)
for file in train_df_lab_1.ImageID.tolist():
    try:
        os.rename("../ml2_final/train_v2/" + file, "../ml2_final/train/00001/" + file)
    except:
        print('No')

# train folder with label 0 (images with no ships)
for file in train_df_lab_0.ImageID.tolist():
    try:
        os.rename("../ml2_final/train_v2/" + file, "../ml2_final/train/00000/" + file)
    except:
        print('No')
```

```python
# validation folder with label 1 (images with ships)
for file in val_df_lab_1.ImageID.tolist():
    try:
        os.rename("../ml2_final/train_v2/" + file, "../ml2_final/validation/00001/" + file)
    except:
        print('No')
# validation folder with label 0 (images with no ships)
for file in val_df_lab_0.ImageID.tolist():
    try:
        os.rename("../ml2_final/train_v2/" + file, "../ml2_final/validation/00000/" + file)
    except:
        print("No")
```

Histogram Equalization

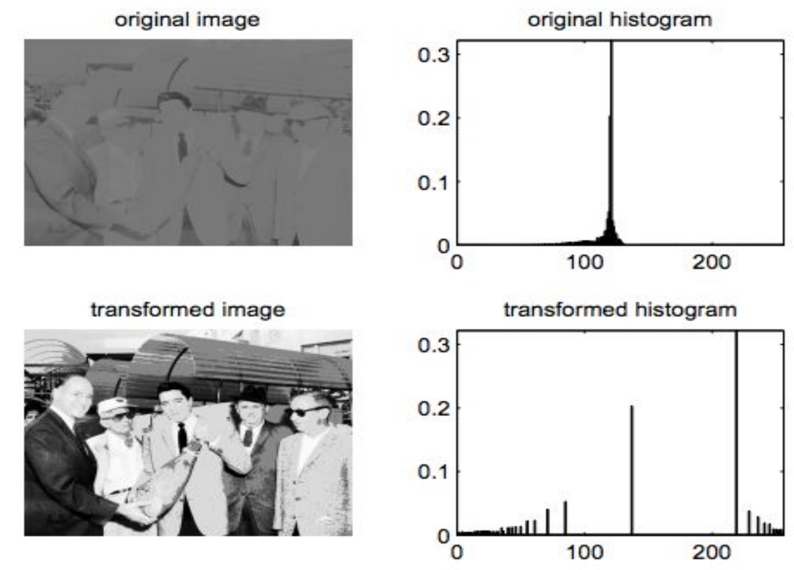


Figure 1: Histogram equalization applied to low contrast image

source :https://www.math.uci.edu/icamp/courses/math77c/demos/hist_eq.pdf

Caffe

- Implement LeNet CNN
  - two convolution layers
  - two pooling layers (max pool)
  - Fully connnected

Architecture file

Airbus_train_test.prototxt

For Convolution 1::

- num_output=60
- kernel_size=5
- stride=1

For Convolution 2:

- num_output=120
- kernel_size=5
- stride=1

For Pooling 1:

- Kernel_size: 5
- Stride=5

For Pooling 2:

- Kernel_size=5
- Stride=5

For inner product

- num_output =1000

Relu

Softmax with loss

Additional Layer for Validation

```
layer {
  name: "accuracy"
  type: "Accuracy"
  bottom: "ip2"
  bottom: "label"
  top: "accuracy"
  include {
    phase: TEST
  }
```

```
layer {
  name: "loss_val"
  type: "SoftmaxWithLoss"
  bottom: "ip2"
  bottom: "label"
  top: "loss_val"
  include {
    phase: TEST
  }
```

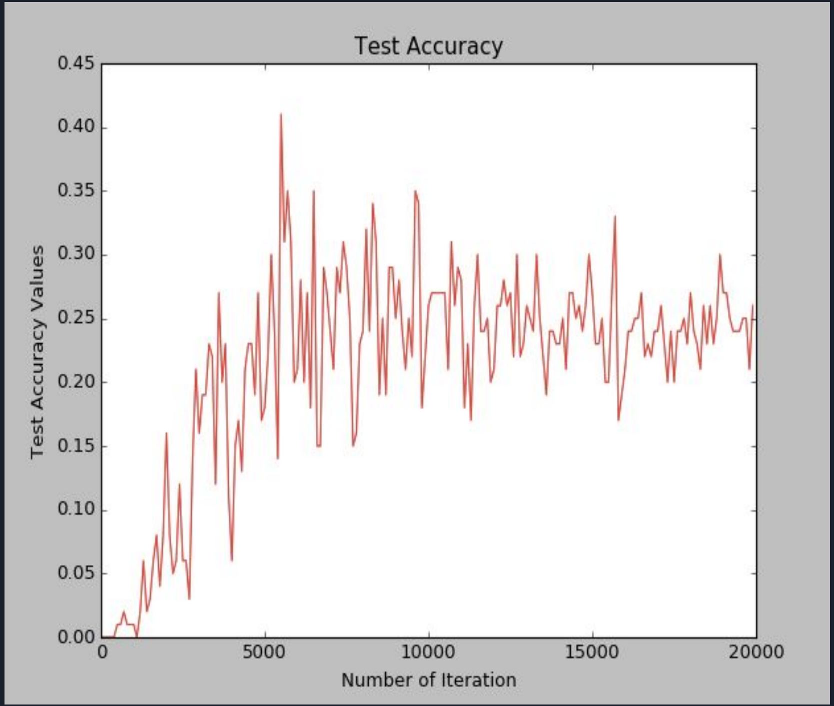
```
layer {
  name: "loss"
  type: "SoftmaxWithLoss"
  bottom: "ip2"
  bottom: "label"
  top: "loss"
}
```

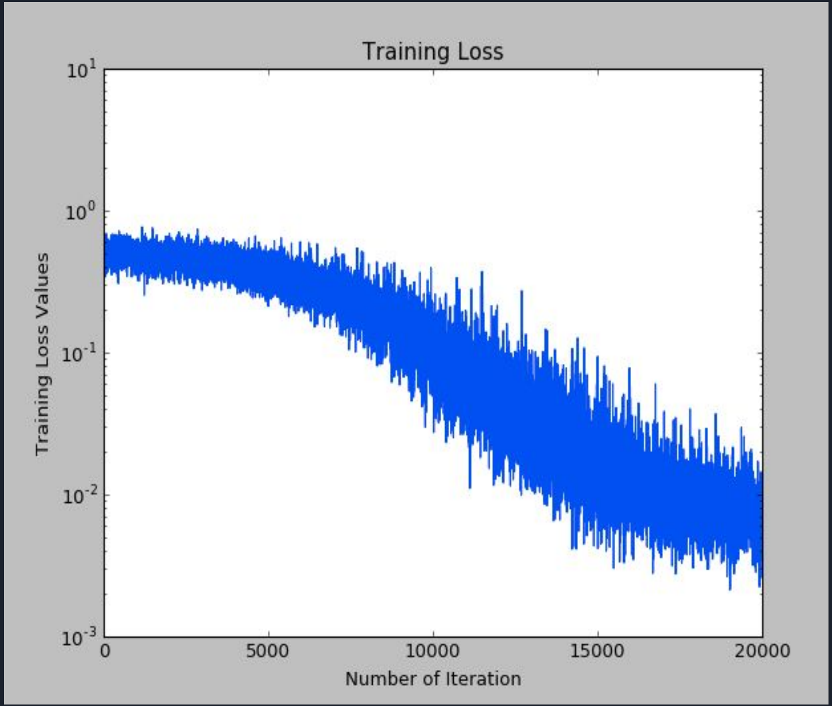
Solver file

```
# File for training and testing
net: "airbus_train_test.prototxt"

# 100 test iteration of a batchsize of 100 for 10,000 testing images
test_iter: 100

# test the network every 500 iterations
test_interval: 500

# The base learning rate, momentum and the weight decay of the network.
base_lr: 0.01
momentum: 0.9
weight_decay: 0.0005
```

```
# The learning rate policy
lr_policy: "inv"
gamma: 0.0001
power: 0.75

# Display every 100 iterations
display: 100

# The maximum number of iterations
max_iter: 100

# Run on GPU (put CPU if not GPU available)
solver_mode: GPU
```

Accuracy and Loss for 80x80 pixels





Accuracy for 32X32 pixels (begin)

```
Iteration 0 testing... accuracy: 0.0
I1209 11:40:14.834834  2359 solver.cpp:239] Iteration 100 (17.509 iter/s, 5.71136s/100 iters), loss = 0.664275
I1209 11:40:14.834915  2359 solver.cpp:258]     Train net output #0: loss = 0.664275 (* 1 = 0.664275 loss)
I1209 11:40:14.834928  2359 sgd_solver.cpp:112] Iteration 100, lr = 0.00992565
Iteration 100 testing... accuracy: 0.0
I1209 11:40:20.498921  2359 solver.cpp:239] Iteration 200 (17.6556 iter/s, 5.66394s/100 iters), loss = 0.498359
I1209 11:40:20.499007  2359 solver.cpp:258]     Train net output #0: loss = 0.498359 (* 1 = 0.498359 loss)
I1209 11:40:20.499032  2359 sgd_solver.cpp:112] Iteration 200, lr = 0.00985258
Iteration 200 testing... accuracy: 0.0
I1209 11:40:26.214808  2359 solver.cpp:239] Iteration 300 (17.4956 iter/s, 5.71573s/100 iters), loss = 0.480157
I1209 11:40:26.214905  2359 solver.cpp:258]     Train net output #0: loss = 0.480157 (* 1 = 0.480157 loss)
I1209 11:40:26.214916  2359 sgd_solver.cpp:112] Iteration 300, lr = 0.00978075
Iteration 300 testing... accuracy: 0.0
I1209 11:40:31.819653  2359 solver.cpp:239] Iteration 400 (17.8423 iter/s, 5.60465s/100 iters), loss = 0.525325
I1209 11:40:31.824090  2359 solver.cpp:258]     Train net output #0: loss = 0.525325 (* 1 = 0.525325 loss)
I1209 11:40:31.824117  2359 sgd_solver.cpp:112] Iteration 400, lr = 0.00971013
Iteration 400 testing... accuracy: 0.0
```

Accuracy for 32X32 pixels (end)

```
Iteration 19600 testing... accuracy: 0.26
I1209 12:00:26.419978  2359 solver.cpp:239] Iteration 19700 (17.7861 iter/s, 5.62236s/100 iters), loss = 0.00213971
I1209 12:00:26.420035  2359 solver.cpp:258]     Train net output #0: loss = 0.00213971 (* 1 = 0.00213971 loss)
I1209 12:00:26.420044  2359 sgd_solver.cpp:112] Iteration 19700, lr = 0.00442011
Iteration 19700 testing... accuracy: 0.28
I1209 12:00:32.067144  2359 solver.cpp:239] Iteration 19800 (17.7084 iter/s, 5.64703s/100 iters), loss = 0.00301393
I1209 12:00:32.067215  2359 solver.cpp:258]     Train net output #0: loss = 0.00301393 (* 1 = 0.00301393 loss)
I1209 12:00:32.067225  2359 sgd_solver.cpp:112] Iteration 19800, lr = 0.00440898
Iteration 19800 testing... accuracy: 0.32
I1209 12:00:37.713999  2359 solver.cpp:239] Iteration 19900 (17.7093 iter/s, 5.64674s/100 iters), loss = 0.00429516
I1209 12:00:37.714054  2359 solver.cpp:258]     Train net output #0: loss = 0.00429516 (* 1 = 0.00429516 loss)
I1209 12:00:37.714062  2359 sgd_solver.cpp:112] Iteration 19900, lr = 0.00439791
Iteration 19900 testing... accuracy: 0.29
```

Accuracy for 80X80 pixels (begin)

```
Iteration 0 testing... accuracy: 0.0
I1209 14:54:50.121146  3137 solver.cpp:239] Iteration 100 (24.4522 iter/s, 4.08961s/100 iters), loss = 0.655891
I1209 14:54:50.121218  3137 solver.cpp:258]     Train net output #0: loss = 0.655891 (* 1 = 0.655891 loss)
I1209 14:54:50.121229  3137 sgd_solver.cpp:112] Iteration 100, lr = 0.00992565
Iteration 100 testing... accuracy: 0.0
I1209 14:54:54.230852  3137 solver.cpp:239] Iteration 200 (24.3329 iter/s, 4.10966s/100 iters), loss = 0.439718
I1209 14:54:54.230926  3137 solver.cpp:258]     Train net output #0: loss = 0.439718 (* 1 = 0.439718 loss)
I1209 14:54:54.230938  3137 sgd_solver.cpp:112] Iteration 200, lr = 0.00985258
Iteration 200 testing... accuracy: 0.1
I1209 14:54:58.346338  3137 solver.cpp:239] Iteration 300 (24.2987 iter/s, 4.11544s/100 iters), loss = 0.47
I1209 14:54:58.346408  3137 solver.cpp:258]     Train net output #0: loss = 0.47 (* 1 = 0.47 loss)
I1209 14:54:58.346433  3137 sgd_solver.cpp:112] Iteration 300, lr = 0.00978075
```

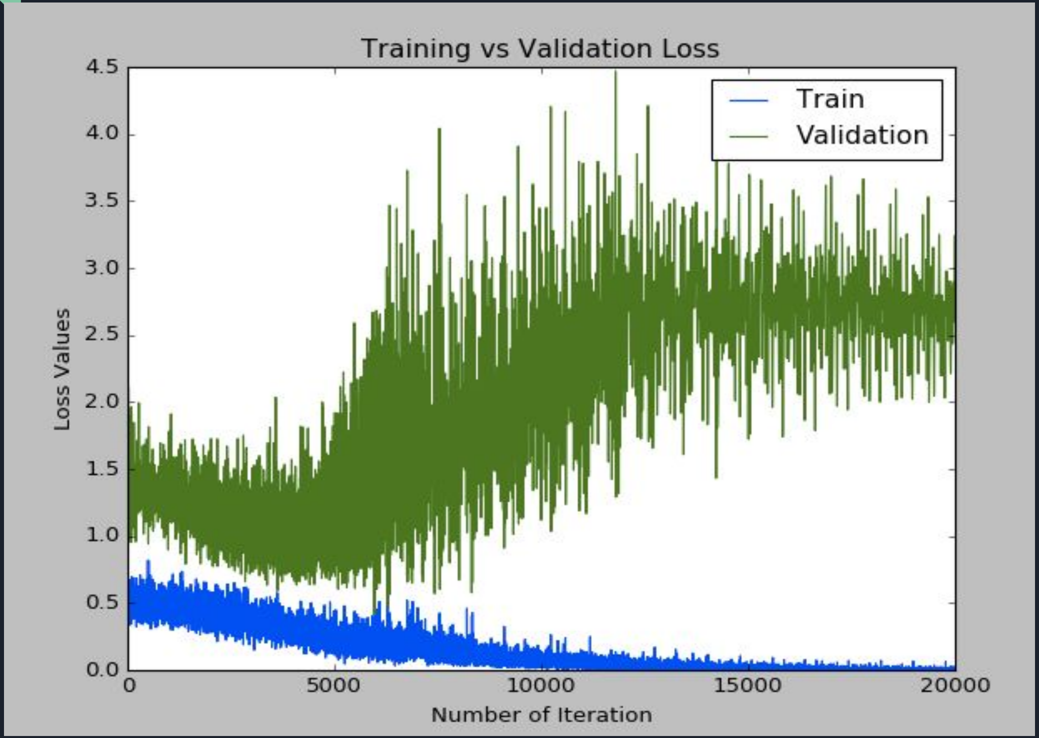
Accuracy for 80X80 pixels (mid)

```
Iteration 10000 testing... accuracy: 0.6
I1209 15:02:17.156886  3137 solver.cpp:239] Iteration 10100 (24.1427 iter/s, 4.14204s/100 iters), loss = 0.0467444
I1209 15:02:17.156965  3137 solver.cpp:258]     Train net output #0: loss = 0.0467444 (* 1 = 0.0467444 loss)
I1209 15:02:17.156975  3137 sgd_solver.cpp:112] Iteration 10100, lr = 0.00592384
Iteration 10100 testing... accuracy: 0.45
I1209 15:02:19.340059  3154 data_layer.cpp:73] Restarting data prefetching from start.
I1209 15:02:21.308784  3137 solver.cpp:239] Iteration 10200 (24.0856 iter/s, 4.15186s/100 iters), loss = 0.0638874
I1209 15:02:21.308858  3137 solver.cpp:258]     Train net output #0: loss = 0.0638874 (* 1 = 0.0638874 loss)
I1209 15:02:21.308887  3137 sgd_solver.cpp:112] Iteration 10200, lr = 0.00590183
Iteration 10200 testing... accuracy: 0.46
I1209 15:02:25.459769  3137 solver.cpp:239] Iteration 10300 (24.0909 iter/s, 4.15094s/100 iters), loss = 0.124397
I1209 15:02:25.459861  3137 solver.cpp:258]     Train net output #0: loss = 0.124397 (* 1 = 0.124397 loss)
I1209 15:02:25.459870  3137 sgd_solver.cpp:112] Iteration 10300, lr = 0.00588001
Iteration 10300 testing... accuracy: 0.64
```

Accuracy for 80X80 pixels (end)

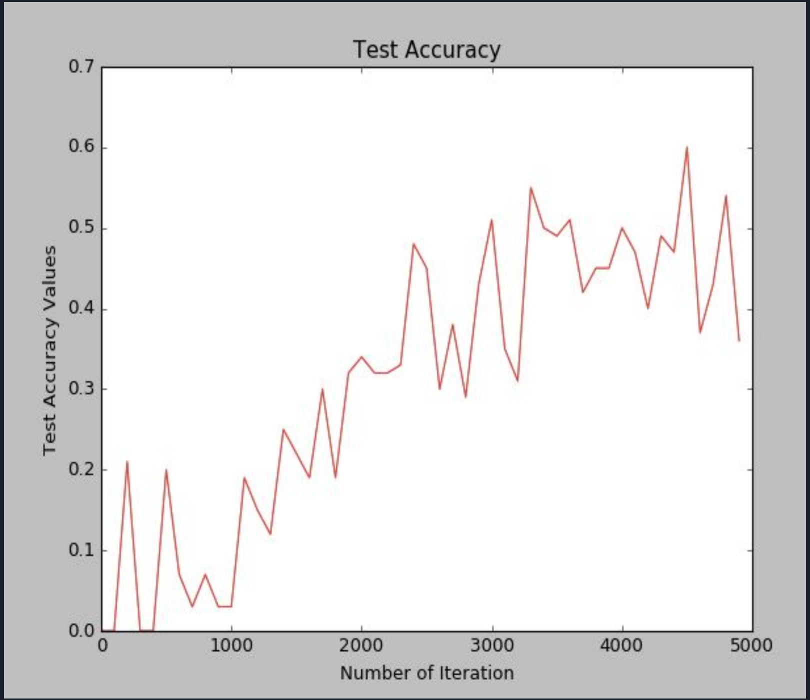
```
Iteration 19600 testing... accuracy: 0.45
I1209 15:09:25.506752  3137 solver.cpp:239] Iteration 19700 (24.0533 iter/s, 4.15743s/100 iters), loss = 0.00296536
I1209 15:09:25.506834  3137 solver.cpp:258]     Train net output #0: loss = 0.00296536 (* 1 = 0.00296536 loss)
I1209 15:09:25.506856  3137 sgd_solver.cpp:112] Iteration 19700, lr = 0.00442011
Iteration 19700 testing... accuracy: 0.51
I1209 15:09:29.656904  3137 solver.cpp:239] Iteration 19800 (24.0957 iter/s, 4.15011s/100 iters), loss = 0.00844194
I1209 15:09:29.656966  3137 solver.cpp:258]     Train net output #0: loss = 0.00844194 (* 1 = 0.00844194 loss)
I1209 15:09:29.656987  3137 sgd_solver.cpp:112] Iteration 19800, lr = 0.00440898
Iteration 19800 testing... accuracy: 0.54
I1209 15:09:33.805871  3137 solver.cpp:239] Iteration 19900 (24.1026 iter/s, 4.14894s/100 iters), loss = 0.024471
I1209 15:09:33.806030  3137 solver.cpp:258]     Train net output #0: loss = 0.024471 (* 1 = 0.024471 loss)
I1209 15:09:33.806040  3137 sgd_solver.cpp:112] Iteration 19900, lr = 0.00439791
Iteration 19900 testing... accuracy: 0.48
```

Checking for Overfitting



- Green line is the validation loss
- Blue line is the testing loss, after 5000 the loss is stagnant.

Early Stopping to Prevent Overfitting



- To prevent overfitting we did early stopping on 5000 iteration

Tuning Hyperparameters

```
// The learning rate decay policy. The currently implemented learning rate
// policies are as follows:
//    - fixed: always return base_lr.
//    - step: return base_lr * gamma ^ (floor(iter / step))
//    - exp: return base_lr * gamma ^ iter
//    - inv: return base_lr * (1 + gamma * iter) ^ (- power)
//    - multistep: similar to step but it allows non uniform steps defined by
//      stepvalue
//    - poly: the effective learning rate follows a polynomial decay, to be
//      zero by the max_iter. return base_lr (1 - iter/max_iter) ^ (power)
//    - sigmoid: the effective learning rate follows a sigmod decay
//      return base_lr ( 1/(1 + exp(-gamma * (iter - stepsize))))
//
// where base_lr, max_iter, gamma, step, stepvalue and power are defined
// in the solver parameter protocol buffer, and iter is the current iteration.
```

```
layer {
  name: "conv1"
  type: "Convolution"
  bottom: "data"
  top: "conv1"
  # learning rate and decay multipliers for the filters
  param { lr_mult: 1 decay_mult: 1 }
  # learning rate and decay multipliers for the biases
  param { lr_mult: 2 decay_mult: 0 }
  convolution_param {
    num_output: 96     # learn 96 filters
    kernel_size: 11    # each filter is 11x11
    stride: 4          # step 4 pixels between each filter application
    weight_filler {
      type: "gaussian" # initialize the filters from a Gaussian
      std: 0.01        # distribution with stdev 0.01 (default mean: 0)
    }
    bias_filler {
      type: "constant" # initialize the biases to zero (0)
      value: 0
    }
  }
}
```

Conclusions

- Our model gives the best accuracy (around 50%) in 80X80 pixels.
- After 5000 iterations, we start to get overfitting.
- The number of convolution layers and parameters has an effect on our result.
- For future action, we can perform trial and error for image resolution, and focus on layer and parameter for better accuracy.
- Using more computational power to train with a larger number of images might help to improve classification.