

CS 6384 Computer Vision Homework 5

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Download the [homework5_programming.zip](#) file from eLearning, Course Homepage, Assignments, Homework 5. Finish the following programming problems and submit your scripts to eLearning. You can zip all the data and files for submission. Our TA will run your scripts to verify them.

Install the Python packages needed by

- `pip install -r requirement.txt`

Here are some useful resources:

- Python basics <https://pythonbasics.org/>
- Numpy <https://numpy.org/doc/stable/user/basics.html>
- OpenCV https://docs.opencv.org/4.x/d6/d00/tutorial_py_root.html
- PyTorch <https://pytorch.org/tutorials/>

In this homework, you will implement the YOLO object detector using PyTorch. The code can run on a CPU machine, no GPU is needed.

The implementation is based on the following paper:

- You Only Look Once: Unified, Real-Time Object Detection. Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi. In CVPR, 2016. <https://arxiv.org/abs/1506.02640>.

Problem 1

(2 points) DataLoader in PyTorch for YOLO.

Dataset. We provide a dataset of a cracker box to train the YOLO detector. The images and annotations are stored in [yolo/data/](#). The input images are named as [%06d.jpg](#). The ground truth bounding box locations are stored in [%06d-box.txt](#). The four numbers in a txt file indicate the location of the cracker box in the corresponding image with the format (x1, y1, x2, y2), i.e., top-left and bottom-right corners of the bounding box. The images with names [%06d-gt.jpg](#) are only for visualization. We won't use these images in training and testing. We split the images in this dataset into 100 training images and 100 validation images.

Implement the `__getitem__()` function in `yolo/data.py` for the `CrackerBox` dataset class in PyTorch. The `__getitem__` function loads and returns a sample from the dataset at the given index `idx`. Details about the dataset class in PyTorch can be found here: https://pytorch.org/tutorials/beginner/basics/data_tutorial.html.

In our case, the `__getitem__` function should return a Python dictionary with three items.

- **sample['image']**: this should be a tensor in PyTorch with shape (3, 448, 448) to represent the input image. The original image size in the dataset is 480x640. So you need to resize it to 448x448. After resizing, we need to normalize the pixels by subtracting the `pixel_mean` (defined in the `CrackerBox` class) and then dividing by 255. Finally, tensors in PyTorch are stored with shape (channel, height, width). You need to swap the dimensions of the input image.
- **sample['gt_box']**: this should be a tensor in PyTorch with shape (5, 7, 7) to represent the ground truth bounding box. In this YOLO implementation, an input with size 448x448 are divided into 7x7 grids. If the center of the ground truth bounding box falls into a grid cell, that grid cell is responsible for detecting the object.

In `sample['gt_box']`, each cell stores 5 values. They are $(cx, cy, w, h, confidence)$, where (cx, cy) are the center of the ground truth bounding box and (w, h) are the width and height of the ground truth bounding. For ground truth bounding boxes, the confidence is defined to be 1, i.e., $confidence = 1$.

First of all, you can load the ground truth bounding boxes from the txt annotation files. Note that they are in $(x1, y1, x2, y2)$ format. Since we scaled the input image to 448x448, you need to scale the bounding box as well. After that, we need to normalize (cx, cy, w, h) to $[0, 1]$. To do so, for (cx, cy) , we compute its offset with respect to the top-left corner of the grid cell, and then divide the offset by the size of the cell (64 pixels in our case). In this way, the bounding box center can be normalized to $[0, 1]$. For width and height (w, h) , we divide them by the size of the input image (448 pixels). For cells without objects, we store 0s in `sample['gt_box']`.

- **sample['gt_mask']**: this should be a tensor in PyTorch with shape (7, 7) to represent the location of the ground truth bounding in the grid. This tensor stores 0 and 1, where 1 indicates that the center of the ground truth bounding box falls into the corresponding cell.

After your implementation, run the `yolo/data.py` script in Python to verify it. The main function in this script creates a dataloader of the cracker box dataset and then visualizes the samples generated from the `__getitem__` function. Figure 1 shows an example of running the script. Note that, each call of the `__getitem__` function returns one sample. But PyTorch dataloader automatically groups multiple samples into a mini-batch by adding one more dimension to the tensors in the samples. For example, the image tensor will have size (batch_size, 3, height, width) from the dataloader.

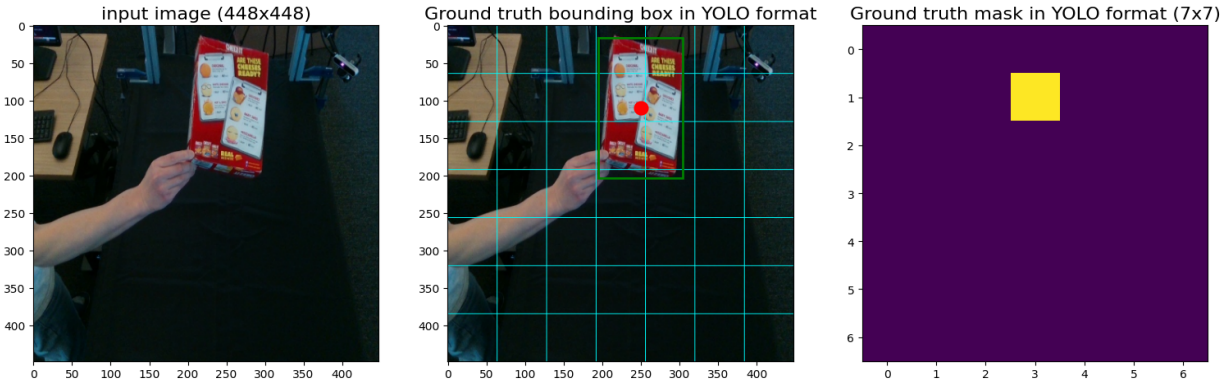


Figure 1: Visualization of data from the CrackerBox dataset class.

Problem 2

(2 points) Implement the YOLO network.

In this problem, you need to implement the YOLO network in `yolo/model.py` using the provided layer functions from PyTorch. Table 1 describes the detailed network architecture of the YOLO network. Follow this architecture and then implement the `create_modules()` function.

In this function, we first define the modules by `modules = nn.Sequential()`. Then you can use `modules.add_module()` to add layers to the modules. Refer to the PyTorch tutorial on building networks: https://pytorch.org/tutorials/beginner/basics/buildmodel_tutorial.html

After your implementation, run the `yolo/model.py` in Python to verify your network. Figure 2 shows a screenshot of running the script.

```
YOLOC
(network): Sequential(
  (conv_1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu_1): ReLU()
  (maxpool_1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv_2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu_2): ReLU()
  (maxpool_2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv_3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu_3): ReLU()
  (maxpool_3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv_4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu_4): ReLU()
  (maxpool_4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv_5): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu_5): ReLU()
  (maxpool_5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv_6): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu_6): ReLU()
  (maxpool_6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv_7): Conv2d(512, 1024, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu_7): ReLU()
  (conv_8): Conv2d(1024, 1024, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu_8): ReLU()
  (conv_9): Conv2d(1024, 1024, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu_9): ReLU()
  (flatten): Flatten(start_dim=1, end_dim=-1)
  (fc1): Linear(in_features=50176, out_features=256, bias=True)
  (fc2): Linear(in_features=256, out_features=256, bias=True)
  (output): Linear(in_features=256, out_features=539, bias=True)
  (sigmoid): Sigmoid()
)
input image: torch.Size([1, 3, 448, 448])
network output: torch.Size([1, 11, 7, 7]) torch.Size([1, 11, 7, 7])
```

Figure 2: Screenshot of running of the `yolo/model.py` script.

Layers	Dimensions (c, h, w)	Parameters
Input	$3 \times 448 \times 448$	
Conv1	$16 \times 448 \times 448$	kernel 3, stride 1, padding 1
ReLU1	$16 \times 448 \times 448$	
MaxPool1	$16 \times 224 \times 224$	kernel 2, stride 2
Conv2	$32 \times 224 \times 224$	kernel 3, stride 1, padding 1
ReLU2	$32 \times 224 \times 224$	
MaxPool2	$32 \times 112 \times 112$	kernel 2, stride 2
Conv3	$64 \times 112 \times 112$	kernel 3, stride 1, padding 1
ReLU3	$64 \times 112 \times 112$	
MaxPool3	$64 \times 56 \times 56$	kernel 2, stride 2
Conv4	$128 \times 56 \times 56$	kernel 3, stride 1, padding 1
ReLU4	$128 \times 56 \times 56$	
MaxPool4	$128 \times 28 \times 28$	kernel 2, stride 2
Conv5	$256 \times 28 \times 28$	kernel 3, stride 1, padding 1
ReLU5	$256 \times 28 \times 28$	
MaxPool5	$256 \times 14 \times 14$	kernel 2, stride 2
Conv6	$512 \times 14 \times 14$	kernel 3, stride 1, padding 1
ReLU6	$512 \times 14 \times 14$	
MaxPool6	$512 \times 7 \times 7$	kernel 2, stride 2
Conv7	$1024 \times 7 \times 7$	kernel 3, stride 1, padding 1
ReLU7	$1024 \times 7 \times 7$	
Conv8	$1024 \times 7 \times 7$	kernel 3, stride 1, padding 1
ReLU8	$1024 \times 7 \times 7$	
Conv9	$1024 \times 7 \times 7$	kernel 3, stride 1, padding 1
ReLU9	$1024 \times 7 \times 7$	
Flatten	50176	
FC1	256	
FC2	256	
FC Output	$7 \times 7 \times (5B + C)$	B : #boxes per cell, C : #classes
Sigmoid	$7 \times 7 \times (5B + C)$	

Table 1: YOLO network architecture.

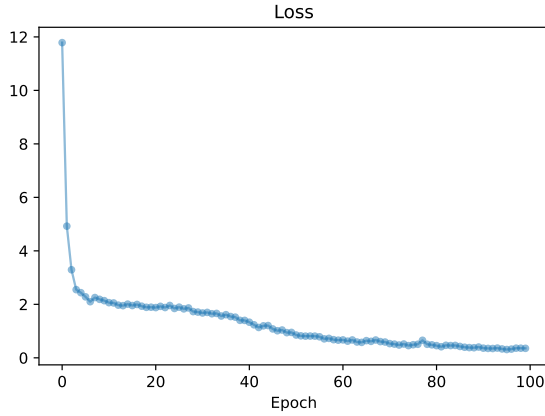
Problem 3

(2 points) Training and testing the YOLO network.

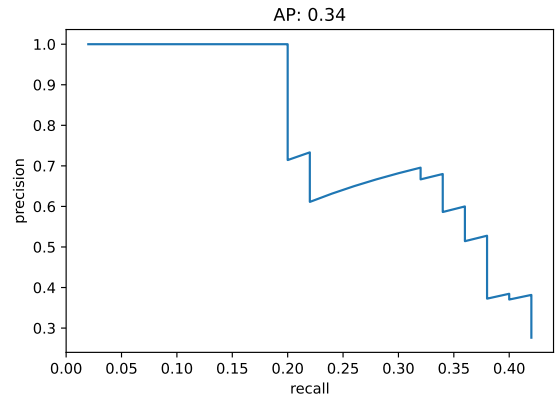
(3.1) Loss function. In order to train the YOLO network, we need to implement the loss function first. Figure 3 shows the loss function defined in the YOLO paper. Finish the `compute_loss()` function in `yolo/loss.py` to implement this loss function.

$$\begin{aligned}
 & \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{I}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \\
 & + \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{I}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right] \\
 & + \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{I}_{ij}^{\text{obj}} (C_i - \hat{C}_i)^2 \\
 & + \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{I}_{ij}^{\text{noobj}} (C_i - \hat{C}_i)^2 \\
 & + \sum_{i=0}^{S^2} \mathbb{I}_i^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2
 \end{aligned}$$

Figure 3: YOLO loss function.



(a) Training losses for 100 epochs.



(b) Precision-recall curve and Average Precision on the validation set.

Figure 4: Training and testing of the YOLO network for object detection.

In YOLO, each grid cell predicts multiple bounding boxes. In our case, each cell predicts 2 bounding boxes. In this `compute_loss()` function, we first find out which predicted bounding box is responsible for the ground truth bounding box. This is done by computing the Intersection over

Union (IoU) between the prediction and the ground truth. This assignment is stored in the `box_mask` tensor for future use, which corresponds to $\mathbb{1}_{ij}^{\text{obj}}$ in the loss function in Figure 3. Meanwhile, the IoUs are stored in the `box_confidence` tensor, which is treated as the target confidence scores the YOLO network should predict, i.e., C_i in the loss function.

(3.2) Training. After implementing the loss function, run the `yolo/train.py` script to train the network. You can tune the hyper-parameters defined in the beginning of the main function in this training script. Figure 4a shows the training loss over 100 epochs in our run. After training, the weights of the network will be saved to `yolo/checkpoints/yolo_final.checkpoint.pth`. The plot of the training losses will be saved to `train_loss.pdf`. You need to include this training loss plot in your homework submission.

(3.2) Testing. Test your trained model by running the `yolo/test.py` script. This script will create a dataloader for the validation set and run detection over all the validation images. In the end, it will compute recall, precision and average precision (AP), and plot the PR-curve as shown in Figure 4b. Include this plot in your submission. **You need to achieve at least 30% AP for your trained model on the validation set, and the higher AP the better. You can tune these hyper-parameters for training if needed.** The test script also has a `visualize()` function to show the detection on the validation images. You can use it to visualize the detection results.