



limhpone / computervision-final-prep

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limhpone

YOLO

fd90b91 · 2 hours ago



914 lines (914 loc) · 117 KB

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```
In [1]: import torch
import torch.nn as nn
```

```
/home/st123439/work/cuda116/.venv/lib/python3.8/site-packages/tqdm/auto.py:21:
TqdmWarning: IPython not found. Please update jupyter and ipywidgets. See ht
tps://ipywidgets.readthedocs.io/en/stable/user_install.html
    from .autonotebook import tqdm as notebook_tqdm
```

YOLO ARCHITECTURE



Image Reference: <https://www.datacamp.com/blog/yolo-object-detection-explained>

The following code is inspired and taken from this repo :

https://github.com/aladdinpersson/Machine-Learning-Collection/blob/master/ML/Pytorch/object_detection/YOLO/

Lets build our model

```
In [2]:
```

```
"""
Information about architecture config:
Tuple is structured by (kernel_size, filters, stride, padding)
"M" is simply maxpooling with stride 2x2 and kernel 2x2
List is structured by tuples and lastly int with number of repeats
"""

architecture_config = [
    (7, 64, 2, 3),
    "M",
    (3, 192, 1, 1),
    "M",
    (1, 128, 1, 0),
    (3, 256, 1, 1),
    (1, 256, 1, 0),
    (3, 512, 1, 1),
    "M",
    [(1, 256, 1, 0), (3, 512, 1, 1), 4], # list architecture
    (1, 512, 1, 0),
    (3, 1024, 1, 1),
    "M",
    [(1, 512, 1, 0), (3, 1024, 1, 1), 2],
    (3, 1024, 1, 1),
    (3, 1024, 2, 1),
    (3, 1024, 1, 1),
    (3, 1024, 1, 1),
]
```

```
In [3]:
```

```
class CNNBlock(nn.Module):
    def __init__(self, in_channels, out_channels, **kwargs):
        super(CNNBlock, self).__init__()
```

```
computervision-final-prep/lab/Lab 08 (YOLO)-20251128/YOLO.ipynb at main · limhphone/computervision-final-prep
    self.conv = nn.Conv2d(in_channels, out_channels, bias=False, **kwargs)
    self.batchnorm = nn.BatchNorm2d(out_channels) # Not used
    self.leakyrelu = nn.LeakyReLU(0.1)

    def forward(self,x):
        return self.leakyrelu(self.batchnorm(self.conv(x)))
```

In [4]:

```
class Yolov1(nn.Module):
    def __init__(self, in_channels=3, **kwargs):
        super(Yolov1, self).__init__()
        self.architecture = architecture_config
        self.in_channels = in_channels
        self.darknet = self._create_conv_layers(self.architecture)
        self.fcs = self._create_fc(**kwargs)

    def forward(self,x):
        x = self.darknet(x)
        return self.fcs(torch.flatten(x, start_dim=1))

    def _create_conv_layers(self, architecture):
        layers = []
        in_channels = self.in_channels

        for x in architecture:
            if type(x) == tuple:
                layers += [
                    CNNBlock(in_channels, out_channels = x[1], kernel_size=x[0])
                ]
                in_channels = x[1]

            if type(x) == str:
                layers += [
                    nn.MaxPool2d(kernel_size=2, stride=2)
                ]

            if type(x) == list:
                conv1 = x[0]
                conv2 = x[1]
                num_repeats = x[2]

                for _ in range(num_repeats):
                    layers += [
                        CNNBlock(in_channels, out_channels = conv1[1], kernel_size=conv1[0])
                    ]
                    layers += [
                        CNNBlock(conv1[1], out_channels = conv2[1], kernel_size=conv2[0])
                    ]
                    in_channels = conv2[1]
        return nn.Sequential(*layers)

    def _create_fc(self, split_size, num_boxes, num_classes):
        S,B,C = split_size, num_boxes, num_classes
        return nn.Sequential(
            nn.Flatten(),
            nn.Linear(1024*S*S , 4096),
            nn.Dropout(0.5), # not implemented in pytorch
            nn.LeakyReLU(0.1),
            nn.Linear(4096, S*S*(C + B*5)), # C+5*B = 30
        )
```

In [5]:

```
# Test our model

model = Yolov1(split_size=7, num_boxes=2, num_classes=20)
print(model)

Yolov1(
    (darknet): Sequential(
        (0): CNNBlock(
            (conv): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3),
bias=False)
            (batchnorm): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track
_running_stats=True)
            (leakyrelu): LeakyReLU(negative_slope=0.1)
        )
        (1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=F
alse)
        (2): CNNBlock(
            (conv): Conv2d(64, 192, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
            (batchnorm): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, trac
_k_running_stats=True)
            (leakyrelu): LeakyReLU(negative_slope=0.1)
        )
        (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=F
alse)
        (4): CNNBlock(
            (conv): Conv2d(192, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (batchnorm): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, trac
_k_running_stats=True)
            (leakyrelu): LeakyReLU(negative_slope=0.1)
        )
        (5): CNNBlock(
            (conv): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
            (batchnorm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, trac
_k_running_stats=True)
            (leakyrelu): LeakyReLU(negative_slope=0.1)
        )
        (6): CNNBlock(
            (conv): Conv2d(256, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (batchnorm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, trac
_k_running_stats=True)
            (leakyrelu): LeakyReLU(negative_slope=0.1)
        )
        (7): CNNBlock(
            (conv): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
            (batchnorm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, trac
_k_running_stats=True)
            (leakyrelu): LeakyReLU(negative_slope=0.1)
        )
        (8): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=F
alse)
        (9): CNNBlock(
            (conv): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
            (batchnorm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, trac
_k_running_stats=True)
            (leakyrelu): LeakyReLU(negative_slope=0.1)
    )
)
```

```
)  
    (10): CNNBlock(  
        (conv): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,  
1), bias=False)  
        (batchnorm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra  
ck_running_stats=True)  
        (leakyrelu): LeakyReLU(negative_slope=0.1)  
    )  
    (11): CNNBlock(  
        (conv): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)  
        (batchnorm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, tra  
ck_running_stats=True)  
        (leakyrelu): LeakyReLU(negative_slope=0.1)  
    )  
    (12): CNNBlock(  
        (conv): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,  
1), bias=False)  
        (batchnorm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra  
ck_running_stats=True)  
        (leakyrelu): LeakyReLU(negative_slope=0.1)  
    )  
    (13): CNNBlock(  
        (conv): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)  
        (batchnorm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, tra  
ck_running_stats=True)  
        (leakyrelu): LeakyReLU(negative_slope=0.1)  
    )  
    (14): CNNBlock(  
        (conv): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,  
1), bias=False)  
        (batchnorm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra  
ck_running_stats=True)  
        (leakyrelu): LeakyReLU(negative_slope=0.1)  
    )  
    (15): CNNBlock(  
        (conv): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)  
        (batchnorm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, tra  
ck_running_stats=True)  
        (leakyrelu): LeakyReLU(negative_slope=0.1)  
    )  
    (16): CNNBlock(  
        (conv): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,  
1), bias=False)  
        (batchnorm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra  
ck_running_stats=True)  
        (leakyrelu): LeakyReLU(negative_slope=0.1)  
    )  
    (17): CNNBlock(  
        (conv): Conv2d(512, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)  
        (batchnorm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra  
ck_running_stats=True)  
        (leakyrelu): LeakyReLU(negative_slope=0.1)  
    )  
    (18): CNNBlock(  
        (conv): Conv2d(512, 1024, kernel_size=(3, 3), stride=(1, 1), padding=(1,  
1), bias=False)  
        (batchnorm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, tra  
ck_running_stats=True)  
        (leakyrelu): LeakyReLU(negative_slope=0.1)  
    )
```

```

computervision-final-prep/lab/Lab 08 (YOLO)-20251128/YOLO.ipynb at main · limhponer/computervision-final-prep
(19): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
(20): CNNBlock(
    (conv): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (batchnorm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (leakyrelu): LeakyReLU(negative_slope=0.1)
)
(21): CNNBlock(
    (conv): Conv2d(512, 1024, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (batchnorm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (leakyrelu): LeakyReLU(negative_slope=0.1)
)
(22): CNNBlock(
    (conv): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (batchnorm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (leakyrelu): LeakyReLU(negative_slope=0.1)
)
(23): CNNBlock(
    (conv): Conv2d(512, 1024, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (batchnorm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (leakyrelu): LeakyReLU(negative_slope=0.1)
)
(24): CNNBlock(
    (conv): Conv2d(1024, 1024, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (batchnorm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (leakyrelu): LeakyReLU(negative_slope=0.1)
)
(25): CNNBlock(
    (conv): Conv2d(1024, 1024, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (batchnorm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (leakyrelu): LeakyReLU(negative_slope=0.1)
)
(26): CNNBlock(
    (conv): Conv2d(1024, 1024, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (batchnorm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (leakyrelu): LeakyReLU(negative_slope=0.1)
)
(27): CNNBlock(
    (conv): Conv2d(1024, 1024, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (batchnorm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (leakyrelu): LeakyReLU(negative_slope=0.1)
)
)
(fcs): Sequential(
    (0): Flatten(start_dim=1, end_dim=-1)
    (1): Linear(in_features=50176, out_features=4096, bias=True)
    (2): Dropout(p=0.5, inplace=False)
)

```

```
    (3): LeakyReLU(negative_slope=0.1)
    (4): Linear(in_features=4096, out_features=1470, bias=True)
)
}
```

```
In [6]: x = torch.randn(2, 3, 448, 448)
      print(model(x).shape) # 7*7*30 = 1470

torch.Size([2, 1470])
```

Lets build our Loss Function

loss function:

$$\begin{aligned}
& \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \\
& + \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right] \\
& + \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2 \\
& + \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^B \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2 \\
& + \sum_{i=0}^{S^2} \mathbb{1}_i^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \quad (3)
\end{aligned}$$

```
In [7]: from dataset import VOCDataset  
from utils import intersection over union
```

```
In [8]: class YoloLoss(nn.Module):
    """
        Calculate the loss for yolo (v1) model
    """

    def __init__(self, S=7, B=2, C=20):
        super(YoloLoss, self).__init__()
        self.mse = nn.MSELoss(reduction="sum")

    """
        S is split size of image (in paper 7),
        B is number of boxes (in paper 2),
        C is number of classes (in paper and VOC dataset is 20),
    """
    self.S = S
    self.B = B
    self.C = C
```

```

# These are from Yolo paper, signifying how much we should
# pay loss for no object (noobj) and the box coordinates (coord)
self.lambda_noobj = 0.5
self.lambda_coord = 5

def forward(self, predictions, target):
    # predictions are shaped (BATCH_SIZE, S*S(C+B*5) when inputted
    predictions = predictions.reshape(-1, self.S, self.S, self.C + self.B)

    # Calculate IoU for the two predicted bounding boxes with target bbox
    iou_b1 = intersection_over_union(predictions[..., 21:25], target[...])
    iou_b2 = intersection_over_union(predictions[..., 26:30], target[...])
    ious = torch.cat([iou_b1.unsqueeze(0), iou_b2.unsqueeze(0)], dim=0)

    # Take the box with highest IoU out of the two prediction
    # Note that bestbox will be indices of 0, 1 for which bbox was best
    iou_maxes, bestbox = torch.max(ious, dim=0)
    exists_box = target[..., 20].unsqueeze(3) # in paper this is Iobj_i

    # ===== #
    # FOR BOX COORDINATES #
    # ===== #

    # Set boxes with no object in them to 0. We only take out one of the
    # predictions, which is the one with highest IoU calculated previous
    box_predictions = exists_box * (
        (
            bestbox * predictions[..., 26:30]
            + (1 - bestbox) * predictions[..., 21:25]
        )
    )

    box_targets = exists_box * target[..., 21:25]

    # Take sqrt of width, height of boxes to ensure that
    box_predictions[..., 2:4] = torch.sign(box_predictions[..., 2:4]) *
        torch.abs(box_predictions[..., 2:4] + 1e-6)
    box_targets[..., 2:4] = torch.sqrt(box_targets[..., 2:4])

    box_loss = self.mse(
        torch.flatten(box_predictions, end_dim=-2),
        torch.flatten(box_targets, end_dim=-2),
    )

    # ===== #
    # FOR OBJECT LOSS #
    # ===== #

    # pred_box is the confidence score for the bbox with highest IoU
    pred_box = (
        bestbox * predictions[..., 25:26] + (1 - bestbox) * predictions[...]
    )

    object_loss = self.mse(
        torch.flatten(exists_box * pred_box),
        torch.flatten(exists_box * target[..., 20:21]),
    )

    # ===== #

```

```

#      FOR NO OBJECT LOSS      #
# ===== #

#max_no_obj = torch.max(predictions[..., 20:21], predictions[..., 25
#no_object_loss = self.mse(
#    torch.flatten((1 - exists_box) * max_no_obj, start_dim=1),
#    torch.flatten((1 - exists_box) * target[..., 20:21], start_dim=
#))

no_object_loss = self.mse(
    torch.flatten((1 - exists_box) * predictions[..., 20:21], start_
    torch.flatten((1 - exists_box) * target[..., 20:21], start_dim=1
)

no_object_loss += self.mse(
    torch.flatten((1 - exists_box) * predictions[..., 25:26], start_
    torch.flatten((1 - exists_box) * target[..., 20:21], start_dim=1
)

# ===== #
#      FOR CLASS LOSS      #
# ===== #

class_loss = self.mse(
    torch.flatten(exists_box * predictions[..., :20], end_dim=-2),
    torch.flatten(exists_box * target[..., :20], end_dim=-2),
)

loss = (
    self.lambda_coord * box_loss # first two rows in paper
    + object_loss # third row in paper
    + self.lambda_noobj * no_object_loss # forth row
    + class_loss # fifth row
)

return loss

```



In [9]:

```

import torchvision.transforms as transforms
import torch.optim as optim
import torchvision.transforms.functional as FT
from tqdm import tqdm
from torch.utils.data import DataLoader
from utils import (
    non_max_suppression,
    mean_average_precision,
    intersection_over_union,
    cellboxes_to_boxes,
    get_bboxes,
    plot_image,
    save_checkpoint,
    load_checkpoint,
)

```

In [10]:

```

seed = 123
torch.manual_seed(seed)

```

Out[10]: <torch._C.Generator at 0x7f2ae000d650>

```
In [11]: # Hyperparameters etc.
LEARNING_RATE = 2e-5
DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
BATCH_SIZE = 16 # 64 in original paper but I don't have that much vram, grad
WEIGHT_DECAY = 0
EPOCHS = 1000
NUM_WORKERS = 2
PIN_MEMORY = True
LOAD_MODEL = False
LOAD_MODEL_FILE = "overfit.pth.tar"
IMG_DIR = "data/images"
LABEL_DIR = "data/labels"
```



```
In [12]: class Compose(object):
    def __init__(self, transforms):
        self.transforms = transforms

    def __call__(self, img, bboxes):
        for t in self.transforms:
            img, bboxes = t(img), bboxes

        return img, bboxes

transform = Compose([transforms.Resize((448, 448)), transforms.ToTensor(),])
```



```
In [13]: def train_fn(train_loader, model, optimizer, loss_fn):
    loop = tqdm(train_loader, leave=True)
    mean_loss = []

    for batch_idx, (x, y) in enumerate(loop):
        x, y = x.to(DEVICE), y.to(DEVICE)
        out = model(x)
        loss = loss_fn(out, y)
        mean_loss.append(loss.item())
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        # update progress bar
        loop.set_postfix(loss=loss.item())

    print(f"Mean loss was {sum(mean_loss)/len(mean_loss)}")
```

```
In [14]: def main():
    model = Yolov1(split_size=7, num_boxes=2, num_classes=20).to(DEVICE)
    optimizer = optim.Adam(
        model.parameters(), lr=LEARNING_RATE, weight_decay=WEIGHT_DECAY
    )
```

```
loss_fn = YoloLoss()

if LOAD_MODEL:
    load_checkpoint(torch.load(LOAD_MODEL_FILE), model, optimizer)

train_dataset = VOCDataset(
    "data/100examples.csv",
    transform=transform,
    img_dir=IMG_DIR,
    label_dir=LABEL_DIR,
)

test_dataset = VOCDataset(
    "data/test.csv", transform=transform, img_dir=IMG_DIR, label_dir=LAB
)

train_loader = DataLoader(
    dataset=train_dataset,
    batch_size=BATCH_SIZE,
    num_workers=NUM_WORKERS,
    pin_memory=PIN_MEMORY,
    shuffle=True,
    drop_last=True,
)

test_loader = DataLoader(
    dataset=test_dataset,
    batch_size=BATCH_SIZE,
    num_workers=NUM_WORKERS,
    pin_memory=PIN_MEMORY,
    shuffle=True,
    drop_last=True,
)

for epoch in range(EPOCHS):
    pred_boxes, target_boxes = get_bboxes(
        train_loader, model, iou_threshold=0.5, threshold=0.4
    )

    mean_avg_prec = mean_average_precision(
        pred_boxes, target_boxes, iou_threshold=0.5, box_format="midpoint"
    )
    print(f"Train mAP: {mean_avg_prec}")

    #if mean_avg_prec > 0.9:
    #    checkpoint = {
    #        "state_dict": model.state_dict(),
    #        "optimizer": optimizer.state_dict(),
    #    }
```