Data Augmentation in SSD (Single Shot Detector)

Over the past few days, I have been investigating how SSD (Single Shot Detector), an object detector introduced in the following paper (Anon. 2016)* in Dec 2016 that claims to achieve a better mAP than Faster R-CNN at a significantly reduced complexity and achieves much faster run time performance. I'll describe the details of SSD in a subsequent blog. The purpose of this blog is to describe the data augmentation scheme used by SSD in detail. According to the paper, the use of data augmentation leads to a 8.8% improvement in the mAP.

	SSD300				
more data augmentation?		✔	✔	✔	✔
include $\{\frac{1}{2}, 2\}$ box?	✔		✔	✔	✔
include $\{\frac{1}{3}, 3\}$ box?	✔			✔	✔
use atrous?	✔	✔	✔		✔
VOC2007 `test` mAP	65.5	71.6	73.7	74.2	**74.3**

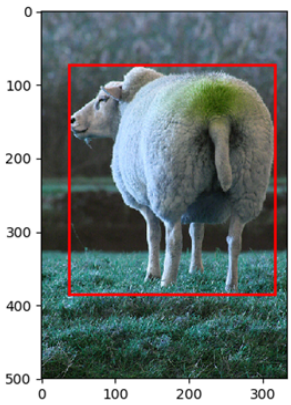
Table 2: **Effects of various design choices and components on SSD performance.**

Data augmentation is particularly important to improve detection accuracy for small objects as it creates zoomed in images where more of the object structure is visible to the classifier. Augmentation is also useful for handling images containing occluded objects by including cropped images in the training data where only part of the object may be visible.

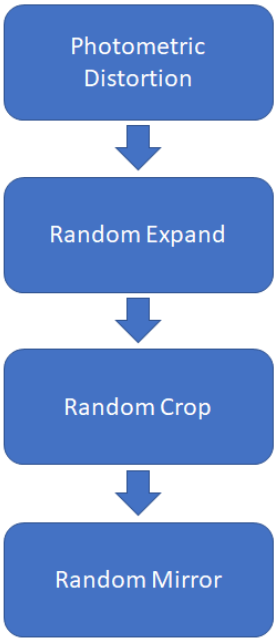
Data Augmentation Steps

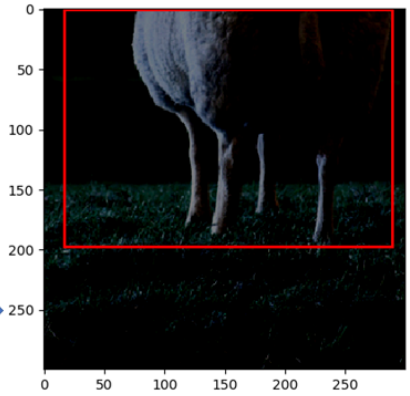
The following data augmentation steps are used and are applied in the order listed.

- Photometric Distortions
- Geometric Distortions
  - ExpandImage
  - RandomCrop
  - RandomMirror



Note: $width \neq height$





Note: $width = height = 300$. Ground truth box is rescaled accordingly.

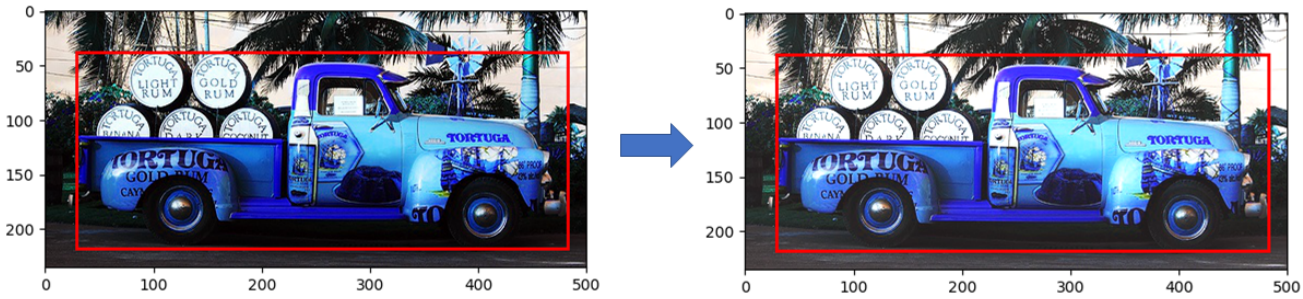
In the sections below, I'll describe these steps in more detail. Note that each distortion is applied probabilistically (usually with probability = 0.5). This means that different training runs will use different image data that results from the augmentation steps applied to the original training data. I will also include the relevant code snippets, making it easier to connect the algorithm with the code that implements it. I've used the following PyTorch code repository in my experiments – https://github.com/amdegroot/ssd.pytorch/

Photometric Distortions

Random Brightness

With probability 0.5 (see documentation for random.randint for why "2" is passed as an argument), this function adds a number selected randomly from [-delta, delta] to each image pixel. The default value of delta is 32

```
    def __call__(self, image, boxes=None, labels=None):
        if random.randint(2):
            delta = random.uniform(-self.delta, self.delta)
            image += delta
        return image, boxes, labels
```



Random Contrast, Hue, Saturation

After applying brightness, random contrast, hue and saturation are applied. The order in which these are applied is chosen at random. There are two choices – apply contrast first and then apply hue and saturation or apply hue and saturation first and then contrast. Each choice is made with probability 0.5, as shown in the code below

```
self.pd = [
            RandomContrast(),
            ConvertColor(transform='HSV'),
            RandomSaturation(),
            RandomHue(),
            ConvertColor(current='HSV', transform='BGR'),
            RandomContrast()
        ]

 im, boxes, labels = self.rand_brightness(im, boxes, labels)
        if random.randint(2):
            distort = Compose(self.pd[:-1])
        else:
            distort = Compose(self.pd[1:])
        im, boxes, labels = distort(im, boxes, labels)
```

Note that contrast is applied in RGB space while hue and saturation is applied in HSV space. Thus the appropriate color space transformation must be performed before each operation is applied.

Application of contrast, hue and saturation is done in a manner similar to brightness. Each distortion is applied with probability 0.5, by selecting the distortion offset randomly between an upper and lower bound. The code for applying saturation distortion is shown below.

```
def __call__(self, image, boxes=None, labels=None):
        if random.randint(2):
            image[:, :, 1] *= random.uniform(self.lower, self.upper)

        return image, boxes, labels
```

The image below shows the result of applying some of these distortions (I'm not sure which ones were applied since the choice is made randomly)

RandomLightingNoise

The last photometric distortion is “RandomLightingNoise”. This distortion involves a color channel swap and is also applied with probability 0.5. The following color swaps are defined:

```
self.perms = ((0, 1, 2), (0, 2, 1),
                      (1, 0, 2), (1, 2, 0),
                      (2, 0, 1), (2, 1, 0))
```

For a RGB image, the swap (0 2 1) would involve swapping the green and blue channels, keeping the red channel unchanged. The swap that is actually applied is chosen randomly from this array.

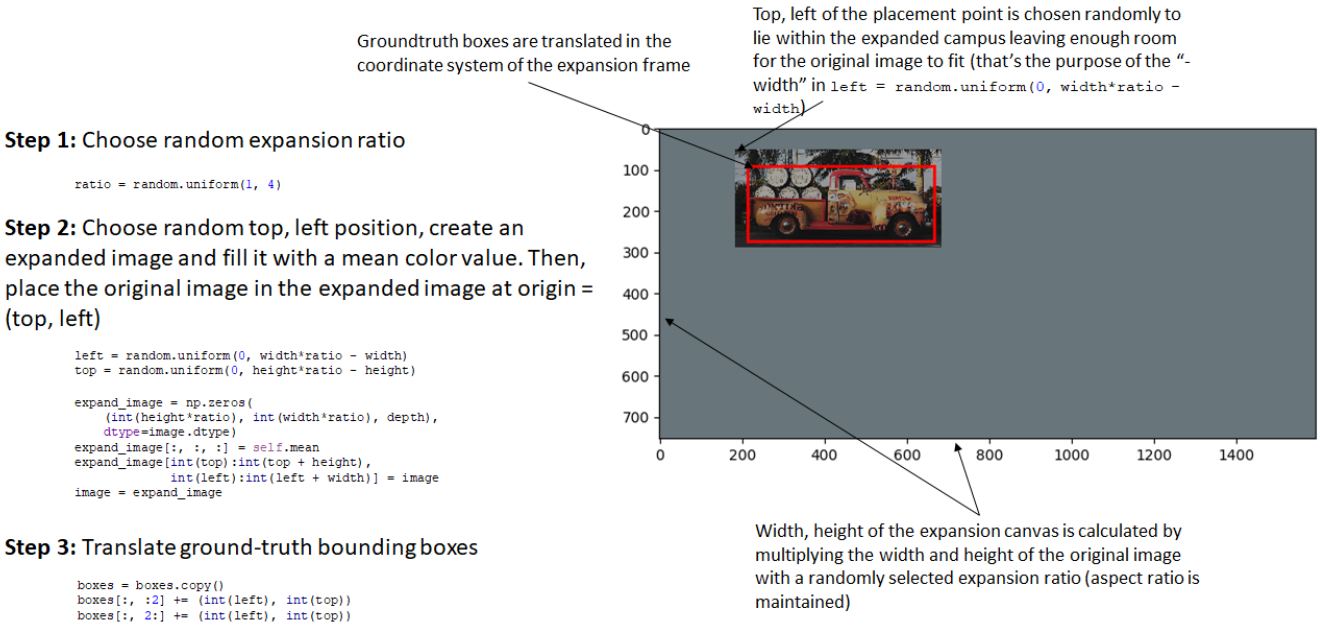
The image produced after applying one of these swaps is shown below:

Geometric Distortions

RandomExpand

Unlike photometric distortion that changes the image pixels but not the image dimensions, the next few augmentation steps are geometric and involve change in the image dimensions. We’ll first consider RandomExpand followed by RandomCrop and RandomMirror. The steps carried out in

RandomExpand are shown in the figure below. As with photometric distortion, RandomExpand is applied with probability 0.5



RandomCrop

The goal of this step is to crop a patch out of the expanded image produced in ExpandImage such that this patch has some overlap with at least one groundtruth box and the centroid of at least one groundtruth box lies within the patch. This requirement makes sense as patches that don't contain significant portion of foreground objects aren't useful for training. At the same time, we do want to train on images where only parts of the foreground object are visible. The steps carried out in RandomCrop are shown in the figure below.

- **Step 1:** Randomly select min, max overlap from a predefined overlap list

```
self.sample_options = (
    # using entire original input image
    None,
    # sample a patch s.t. MIN jaccard w/ obj in
.1,.3,.4,.7,.9
    (0.1, None),
    (0.3, None),
    (0.7, None),
    (0.9, None),
    # randomly sample a patch
    (None, None),
)

mode = random.choice(self.sample_options)
```

- Loop until success or a given number of steps
  - **Step 2:** Randomly select a width, height. This is the width/height of our crop. Ensure that the aspect ratio of the patch is in a given range. Also select a random top, left position

```
w = random.uniform(0.3 * width, width)
h = random.uniform(0.3 * height, height)

if h / w < 0.5 or h / w > 2:

left = random.uniform(width - w)
top = random.uniform(height - h)
```

  - **Step 3:** Now we need to determine if this is a good crop or not. This is done by finding the overlap between between the groundtruth boxes and this crop. The crop is good if the overlap > min in step 1. Makes sense as we don't want crops that don't include significant image regions included in groundtruth boxes. If the overlap < min, we go back and look for another crop

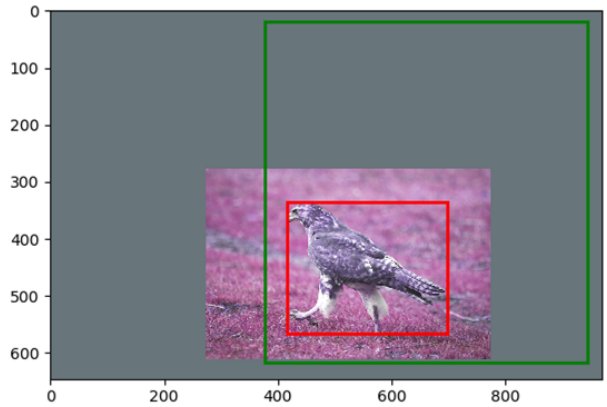
```
# calculate IoU (jaccard overlap) b/t the cropped and gt boxes
overlap = jaccard_numpy(boxes, rect)
# is min and max overlap constraint satisfied? if not try again

if overlap.min() < min_iou and max_iou < overlap.max():
    continue
```

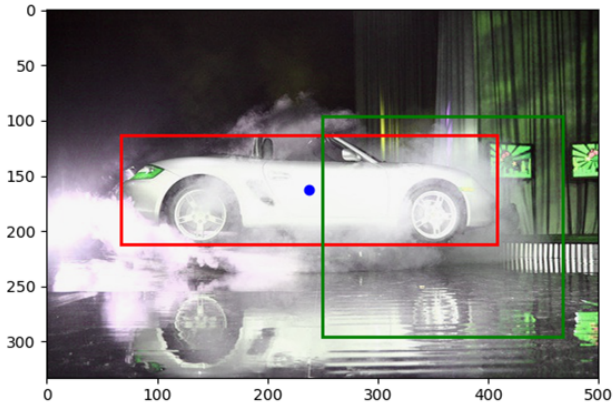
  - **Step 4:** Cut out the region if overlap criteria is satisfied
  - **Step 5:** Find the centers of the ground truth boxes and remove the boxes whose centers don't lie in the crop. If no boxes are left, start over
  - **Step 6:** Finally, adjust the coordinates of the ground truth box corners that cross the boundary

Let's now look at a few examples to further illustrate these ideas. Ground truth boxes are shown in red while the cropped patch is shown in green in the images below. Recall that the RandomCrop step follows the ExpandImage step, which is applied with probability 0.5. So some of these images have an expansion canvas around them, while others don't.

Example 1: ExpandImage was not used and only one of the ground truth boxes will be part of the final crop



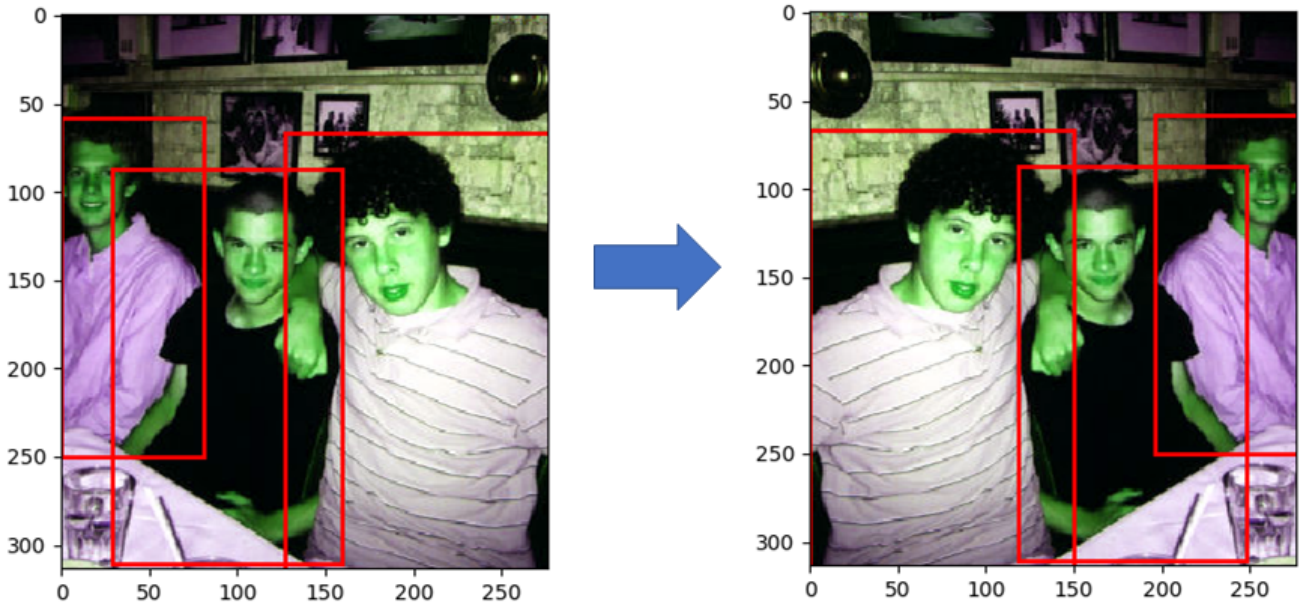
Example 2: ExpandImage was used and the final crop will contain part of the original image and part of the canvas



Example 3: This shows a crop that will not pass the ground truth centroid test. The blue dot is the centroid of the groundtruth box and lies outside the crop region. Thus another crop region will have to be sampled

RandomMirror

The last augmentation step is RandomMirror. This one simply involves a left-right flip and is a common augmentation step used in other object detection and image classification systems also.



Finally, as in other object detection and image classification systems, the image is resized to 300, 300, ground truth coordinates are adjusted accordingly and normalized and mean is subtracted from the image.