

Data Augmentation Programming



Sai Teja P

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Data Augmentation is a technique that can be used for making updated copies of images in the data set to artificially increase the size of a training dataset. This technique is very useful when the training data set is very small.

There are already many good articles published on this concept. We can refer to some of these articles at, learn about when to use data augmentation and concepts of Data augmentation can refer to data augmentation.

Imagine that you are afraid of Thanos and you believe that he is real and will visit Earth one day. As a token of measure you want to build a defence system which has a camera and the system activates when he arrives on Earth by classifying his image from the camera feed. In order to do that we need to train a reliable model for activating the defence system. If we have only 10 pictures of Thanos it's very difficult for us to build a good model that can capture his presence. So in order to have multiple pictures for training set we can consider Data augmentation. A better example and scenarios of when to use augmentation is mentioned at [Let's consider below image for which we want to perform Data augmentation click here.](#)



Image Source : Google

In this article I'm going to solely concentrate on the coding part of Data Augmentation.

At first we will look at , how this can be done using numpy and then we discuss about the image preprocessing Data Augmentation class in keras that brings simplicity for this task.

Using Numpy

Importing required modules

```
1 import numpy as np
2 import scipy
3 import seaborn as sns
4 from scipy.ndimage import rotate
5 import pandas.util.testing as tm
6 import matplotlib.pyplot as plt
7
8
9 sns.set(color_codes=True)
```

Importing_modules.py hosted with ❤ by GitHub

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Loading an image to work on.

```
1 # reading image - modify with the path accordingly
2 image = np.array(plt.imread('thanos.jpg'))
3 # copying the image to a temporary image
4 img = image.copy()
5 print(img.shape)
6 # storing original width and height to use for cropping
7 original_width, original_height, _ = image.shape
```

import.py hosted with ❤ by GitHub

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Cropping : with cropping we can capture the required parts of the images. Here we are cropping at random to capture random windows of the images. Cropping too small images from original image can cause information loss.

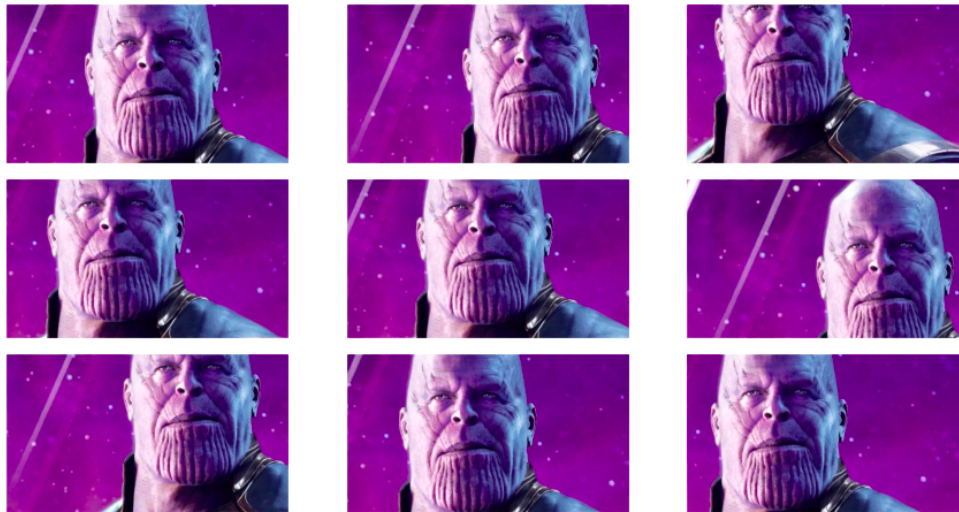
```
1 def image_cropping(img, crop_size=(int(original_width*0.8), int(original_height*0.8))):
2     assert crop_size[0] <= img.shape[0], "Crop width size should be less than image width"
3     assert crop_size[1] <= img.shape[1], "Crop height size should be less than image height"
4     w, h = img.shape[:2]
5     x, y = np.random.randint(w-crop_size[0]), np.random.randint(h-crop_size[1])
6     # print(x,y)
7     img = img[y:y+crop_size[0], x:x+crop_size[1]]
8     # print(img.shape)
9     return img
10
11
12 # define the number of crop ratios that we want to try
13 # not preferred below 70% as we might lose valuable information in the image
14 crop_ratio = [0.7, 0.8, 0.9]
15 # number of iterations for each crop size
16 num_of_iterations = 2
17 # let's define a loop so that we can try out multiple crop ratios and multiple iterations
18 for cr in crop_ratio:
19     # print("cropping window = {0}%".format(cr))
20     for i in range(num_of_iterations):
21         plot_grid([random_cropping(img, crop_size=(crop_width, crop_height)),
22                   random_cropping(img, crop_size=(crop_width, crop_height)),
23                   random_cropping(img, crop_size=(crop_width, crop_height))],
```

```

24         1, 3, figsize=(15, 10))
25         # use below code to save the images instead of displaying them.
26         # matplotlib.image.imsave('thanos_' + str(cr) + '_' + str(i) + '.png', random_cro

```

image_cropping.py hosted with ♥ by GitHub [view raw](#)



Randomly cropped images from original image

Rotating Images : rotating the images to capture the real time effect of capturing pictures at different angles.

```

1  def image_rotation(img, angle, bg_patch=(5,5)):
2      assert len(img.shape) <= 3, "image shape dimensions are incorrect"
3      rgb = len(img.shape) == 3
4      if not rgb:
5          bg_color = np.mean(img[:bg_patch[0], :bg_patch[1]])
6      else:
7          bg_color = np.mean(img[:bg_patch[0], :bg_patch[1], :], axis=(0,1))
8      img = rotate(img, angle, reshape=False)
9      mask = [img <= 0, np.any(img <= 0, axis=-1)][rgb]
10     img[mask] = bg_color
11     return img
12
13     # specify the angle required to rotate the image
14     # for random selection of angle use np.rand
15     for ang in [15,30]:
16         plot_grid([rotate_img(img, angle=-ang), rotate_img(img, angle=ang)], 1, 2, figsize=(15

```

image_rrotation.py hosted with ♥ by GitHub [view raw](#)





Sample output after rotating images

Image Shifting or otherwise called Image translation : this is nothing but shifting pixels of a picture in some direction and adding back the shifted pixels back to the opposite direction.

```

1  def image_shifting(img, shift=100, direction='right', roll=True):
2      assert direction in ['right', 'left', 'down', 'up'], 'Directions should be top|up|le
3      img = img.copy()
4      if direction == 'right':
5          right_slice = img[:, -shift:].copy()
6          img[:, shift:] = img[:, :-shift]
7          if roll:
8              img[:, :shift] = np.fliplr(right_slice)
9      if direction == 'left':
10         left_slice = img[:, :shift].copy()
11         img[:, :-shift] = img[:, shift:]
12         if roll:
13             img[:, -shift:] = left_slice
14     if direction == 'down':
15         down_slice = img[-shift:, :].copy()
16         img[shift:, :] = img[: -shift, :]
17         if roll:
18             img[:, shift, :] = down_slice
19     if direction == 'up':
20         upper_slice = img[:, shift, :].copy()
21         img[:, -shift, :] = img[shift:, :]
22         if roll:
23             img[-shift:, :] = upper_slice
24     return img
25
26 plot_grid([image_shifting(img, direction='up', shift=100), image_shifting(img, direction=
27             image_shifting(img, direction='left', shift=100), image_shifting(img, directio
28             1, 4, figsize=(20, 10))

```

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Sample output after shifting images

For more better results we can combine some of these techniques , as we will get augmented pictures of different styles.

We have seen that using numpy makes us to manually change the values of the image array which is both computationally expensive and requires lot of code as mentioned above.

Now, we can try augmentation using Keras Neural Network framework, which makes our job lot easier.

Using Tensor flow and Keras

TensorFlow has a separate class which deals with data augmentation with a lot of different options rather than just flipping, zooming and cropping the images.

By using Keras, there is no need for manual adjustment of pixels. Keras will automatically take care of these things. So the code required for augmentation with keras is way less along with multiple options.

Lets look at keras's image preprocessing ImageDataGenerator class:

```
1  tf.keras.preprocessing.image.ImageDataGenerator(  
2      featurewise_center=False,  
3      samplewise_center=False,  
4      featurewise_std_normalization=False,  
5      samplewise_std_normalization=False,  
6      zca_whitening=False,  
7      zca_epsilon=1e-06,  
8      rotation_range=0,  
9      width_shift_range=0.0,  
10     height_shift_range=0.0,  
11     brightness_range=None,  
12     shear_range=0.0,  
13     zoom_range=0.0,  
14     channel_shift_range=0.0,  
15     fill_mode="nearest",  
16     cval=0.0,  
17     horizontal_flip=False,  
18     vertical_flip=False,  
19     rescale=None,  
20     preprocessing_function=None,  
21     data_format=None,  
22     validation_split=0.0,  
23     dtype=None,  
24 )
```

keras.py hosted with ❤ by GitHub

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Lets look at important arguments that are used for common data argumentation techniques:

- **rotation_range:** Int. Degree range for random rotations.
- **width_shift_range:** Float, 1-D array-like or int — fraction of total width
- **height_shift_range:** Float, 1-D array-like or int — fraction of total height
- **brightness_range:** Tuple or list of two floats. Range for picking a brightness shift value from.
- **shear_range:** Float. Shear Intensity (Shear angle in counter-clockwise direction in degrees)
- **zoom_range:** Float or [lower, upper]. Range for random zoom. If a float, [lower, upper] = [1-zoom_range, 1+zoom_range]. Fraction of

total image to be zoomed.

- **horizontal_flip**: Boolean. Randomly flip inputs horizontally.
- **vertical_flip**: Boolean. Randomly flip inputs vertically.
- **rescale**: rescaling factor. Defaults to None. If None or 0, no rescaling is applied, otherwise we multiply the data by the value provided (after applying all other transformations).
- **preprocessing_function**: function that will be applied on each input. The function will run after the image is resized and augmented. The function should take one argument: one image (Numpy tensor with rank 3), and should output a Numpy tensor with the same shape.
- **data_format**: Image data format, either “channels_first” or “channels_last”.
- **validation_split**: Float. Fraction of images reserved for validation (strictly between 0 and 1).
- **dtype**: Dtype to use for the generated arrays.

For more details and arguments please check out **tf documentation**.

Lets augment our images with some of the most common techniques like flipping, rotation, width and height shifting, varying brightness of the image, zooming and re-scaling the images.

```
1  from keras.preprocessing.image import *
2
3  # lets define a ImageDataGenerator object
4  # change the arguments below as per the requirment
5  idg = ImageDataGenerator(rescale = 1/255,
6
7                          horizontal_flip = True,
8                          rotation_range = 30,
9                          width_shift_range = 0.3,
10                         height_shift_range = 0.3,
11                         brightness_range=[0.2,1.0],
12                         zoom_range=[0.5,1.0]
13
14
15  # sample code to check if our agumentation is working for a single image
16  # lets read our image to be processed - change the directory as needed
17  image = load_img("thanos.jpg")
18  input_arr = img_to_array(image)
19  # reshaping the image to a 4D array to be used with keras flow function.
20  input_arr = input_arr.reshape((1,) + input_arr.shape)
21
22  i = 0
23  # keras flow function usually work for batches
24  # chnage the directory and number of iterations as required
25  for batch in idg.flow(input_arr, batch_size=1,
26
27                        save_to_dir='/content/cat', save_prefix='cat', save_format='jp
28
29                        i += 1
30                        if i > 6:
31                            break # need to break the loop otherwise it will run infinite times
```




Sample output after using Keras agumentation

Now lets look at how to augment a complete data set. We will consider cifar10 data set.

```

1  from keras.datasets import cifar10
2  import numpy as np
3  from keras.utils.np_utils import to_categorical
4
5  # loading the data into train and test sets
6  (x_train, y_train), (x_test, y_test) = cifar10.load_data()
7
8  num_classes = 10
9  #converting the output labels to one hot encoding
10 y_train = to_categorical(y_train, num_classes)
11 y_test = to_categorical(y_test, num_classes)
12
13 # creating data augmentation object with required arguments
14 data_gen = ImageDataGenerator(
15     rotation_range=20,
16     width_shift_range=0.2,
17     height_shift_range=0.2,
18     horizontal_flip=True,
19     brightness_range=[0.2,1.0],
20     zoom_range=[0.5,1.0],
21     featurewise_center=True,
22     featurewise_std_normalization=True,
23 )
24
25 # fitting training data to our datagen object
26 data_gen.fit(x_train)
27
28 #build your model here and assume its name is "model"
29 # model = .....
30
31 # fits the model on batches with real-time data augmentation:
32 # fitting the model with augmented train data
33 model.fit(data_gen.flow(x_train, y_train, batch_size=32),
34         steps_per_epoch=len(x_train) / 32, epochs=epochs)
35 #do something with the model you developed

```

We can notice from the above examples, its better to use keras for data augmentation that using numpy.

Hope these large set of augmented images can help you to activate your defence system and save our planet.

The complete Jupiter notebook can be found at my ***git hub*** .

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