Data Augmentation with Keras and TensorFlow

In this tutorial, we are going to learn how to augment image data using Keras and Tensorflow. Furthermore, you will learn how to use your augmented data to train a simple binary classifier. The code mentioned below is the modified version of TensorFlow's official example.

We recommend following the coding tutorial by practicing on your own. The code source with outputs is available in this DataLab workbook.

Getting Started

We will be using TensorFlow and Keras for data augmentation and matplotlib for displaying the images.

```
%%capture
import matplotlib.pyplot as plt
import numpy as np
import tensorflow as tf
import tensorflow_datasets as tfds

from keras import layers
import keras
```

Explain code POWERED BY datalab

Data Loading

The TensorFlow Dataset collection is huge. You can find text, audio, video, graph, time-series, and image datasets. In this tutorial, we will be using the "cats_vs_dogs" dataset. The dataset size is 786.68 MiB, and we will apply various image augmentation and train the binary classifier.

In the code below, we have loaded 80% training, 10% validation, and a 10% test set with labels and metadata.

```
%%capture
(train_ds, val_ds, test_ds), metadata = tfds.load(
    'cats_vs_dogs',
    split=['train[:80%]', 'train[80%:90%]', 'train[90%:]'],
    with_info=True,
    as_supervised=True,
)
```

Explain code POWERED BY datalab

Data Analysis

There are two classes in the dataset 'cat' and 'dog'.

```
num_classes = metadata.features['label'].num_classes
print(num_classes)
```

Explain code POWERED BY datalab

```
2
```

Explain code POWERED BY datalab

We will use iterators to extract only four random images with labels from the training set and display them using the matplotlib `.imshow()` function.

```
get_label_name = metadata.features['label'].int2str
train_iter = iter(train_ds)
fig = plt.figure(figsize=(7, 8))
for x in range(4):
  image, label = next(train_iter)
  fig.add_subplot(1, 4, x+1)
  plt.imshow(image)
  plt.axis('off')
  plt.title(get_label_name(label));
```

Explain code

POWERED BY datalab

As we can see, we got various dog images and a cat image.

Data Augmentation with Keras Sequential

We usually use keras.Sequential() to build the model, but we can also use it to add augmentation layers.

Resize and rescale

In the example, we are resizing and rescaling the image using Keras Sequential and image augmentation layers. We will first resize the image to 180X180 and then rescale it by 1/255. The small image size will help us save time, memory, and computing.

As we can see, we have successfully passed the image through the augmentation layer, and the final output is resized and rescaled.

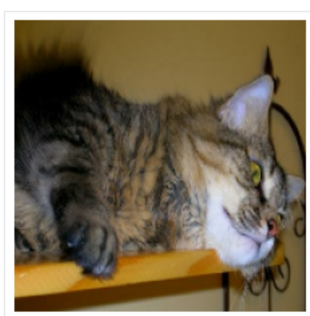
```
IMG_SIZE = 180

resize_and_rescale = keras.Sequential([
  layers.Resizing(IMG_SIZE, IMG_SIZE),
  layers.Rescaling(1./255)
])

result = resize_and_rescale(image)
plt.axis('off')
plt.imshow(result);
```

Explain code

POWERED BY datalab



Random rotate and flip

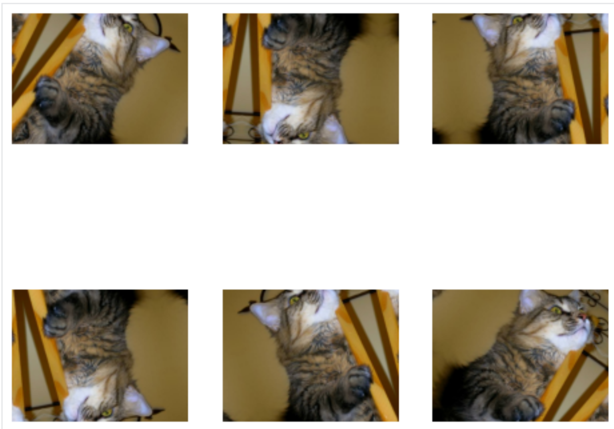
Let's apply random flip and rotation to the same image. We will use loop, subplot, and imshow to display six images with random geometric augmentation.

```
data_augmentation = keras.Sequential([
  layers.RandomFlip("horizontal_and_vertical"),
  layers.RandomRotation(0.4),
])


plt.figure(figsize=(8, 7))
for i in range(6):
  augmented_image = data_augmentation(image)
  ax = plt.subplot(2, 3, i + 1)
  plt.imshow(augmented_image.numpy()/255)
  plt.axis("off")
```

Explain code POWERED BY datalab

Note: if you are experiencing "WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).", try to convert your image to numpy and divide it by 255. It will show you the clear output instead of a washed-out image.



Apart from simple augmentation, you can also apply RandomContrast, RandomCrop, HeightCrop, WidthCrop, and RandomZoom to the images.

Directly adding to the model layer

There are two ways to apply augmentation to the images. The first method is by directly adding the augmentation layers to the model.

```
model = keras.Sequential([
  # Add the preprocessing layers you created earlier.
  resize_and_rescale,
  data_augmentation,
  # Add the model layers
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(64, activation='relu'),
  layers.Dense(1,activation='sigmoid')
])
```

Explain code POWERED BY datalab

Note: the data augmentation is inactive during the testing phase. It will only work for Model.fit, not for Model.evaluate or Model.predict.

Applying the augmentation function using .map

The second method is to apply the data augmentation to the entire train set using Dataset.map.

```
aug_ds = train_ds.map(lambda x, y: (data_augmentation(x, training=True), y))
```

Explain code

POWERED BY datalab

Data pre-processing

We will create a data preprocessing function to process train, valid, and test sets.

The function will:

1. Apply resize and rescale to the entire dataset.
2. If shuffle is True, it will shuffle the dataset.
3. Convert the data into batches using 32 batch size.
4. If the augment is True, it will apply the data argumentation function on all datasets.
5. Finally, use Dataset.prefetch to overlap the training of your model on the GPU with data processing.

```
batch_size = 32
AUTOTUNE = tf.data.AUTOTUNE

def prepare(ds, shuffle=False, augment=False):
  # Resize and rescale all datasets.
  ds = ds.map(lambda x, y: (resize_and_rescale(x), y),
              num_parallel_calls=AUTOTUNE)

  if shuffle:
    ds = ds.shuffle(1000)

  # Batch all datasets.
  ds = ds.batch(batch_size)

  # Use data augmentation only on the training set.
  if augment:
    ds = ds.map(lambda x, y: (data_augmentation(x, training=True), y),
                num_parallel_calls=AUTOTUNE)

  # Use buffered prefetching on all datasets.
  return ds.prefetch(buffer_size=AUTOTUNE)


train_ds = prepare(train_ds, shuffle=True, augment=True)
val_ds = prepare(val_ds)
test_ds = prepare(test_ds)
```

Explain code

POWERED BY datalab

Model building

We will create a simple model with convolution and dense layers. Make sure the input shape is similar to the image shape.

```
model = keras.Sequential([
    layers.Conv2D(32, (3, 3), input_shape=(180,180,3), padding='same', activation
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Flatten(),
```

```
    layers.Dense(32, activation='relu'),
    layers.Dense(1,activation='softmax')
])
```

Explain code

POWERED BY datalab

Training and evaluation

We will now compile the model and train it for one epoch. The optimizer is Adam, the loss function is Binary Cross Entropy, and the metric is accuracy.

As we can observe, we got 51% validation accuracy on the single run. You can train it for multiple epochs and optimize hyper-parameters to get even better results.

The model building and training part is just to give you an idea of how you can augment the images and train the model.

```
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
epochs=1
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

Explain code

POWERED BY datalab

```
582/582 [==============================] - 98s 147ms/step - loss: 0.6993 - a ra
```

Explain code

POWERED BY datalab

```
loss, acc = model.evaluate(test_ds)
```

Explain code

POWERED BY datalab

```
73/73 [==============================] - 4s 48ms/step - loss: 0.6932 - accur :
```

Explain code

POWERED BY datalab

Learn to conduct image analysis, and construct, train, and evaluate convolution networks by taking the Image Processing with Keras course.

Data Augmentation using tf.image

In this section, we will learn to augment images using TensorFlow to have finer control of data augmentation.

Data Loading

We will load the cats_vs_dogs dataset again with labels and metadata.

```
%%capture
(train_ds, val_ds, test_ds), metadata = tfds.load(
    'cats_vs_dogs',
    split=['train[:80%]', 'train[80%:90%]', 'train[90%:]'],
    with_info=True,
```

```
    as_supervised=True,
)
```

Explain code

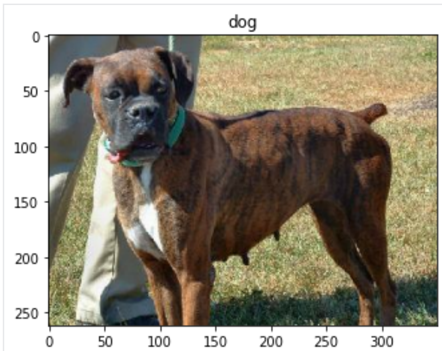
POWERED BY datalab

Instead of a cat image, we will be using the dog image and applying various augmentation techniques.

```
image, label = next(iter(train_ds))
plt.imshow(image)
plt.title(get_label_name(label));
```

Explain code

POWERED BY datalab



Flip left to right

We will create the **visualize** function to display the difference between the original and augmented image.

The function is pretty straightforward. It takes the original image and the augmentation function as input and displays the difference using matplotlib.

```
def visualize(original, augmented):
    fig = plt.figure()
    plt.subplot(1,2,1)
    plt.title('Original image')
    plt.imshow(original)
    plt.axis("off")

    plt.subplot(1,2,2)
    plt.title('Augmented image')
    plt.imshow(augmented)
    plt.axis("off")
```

Explain code

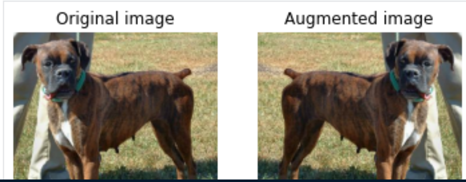
POWERED BY datalab

As we can see, we have flipped the image from left to right using the tf.image function. It is much simpler than keras.Sequential.

```
flipped = tf.image.flip_left_right(image)
visualize(image, flipped)
```

Explain code

POWERED BY datalab



Grayscale

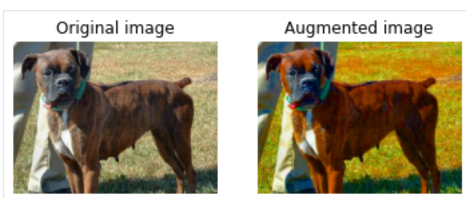
Let's convert the image to grayscale using `tf.image.rgb_to_grayscale`.

```
grayscaled = tf.image.rgb_to_grayscale(image)
visualize(image,  tf.squeeze(grayscaled))
```


Adjusting the saturation

You can also adjust saturation by a factor of 3.

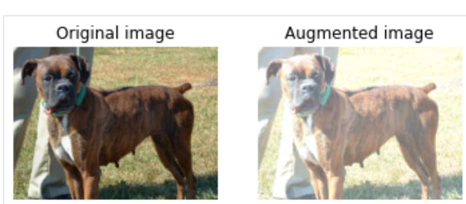
```
saturated = tf.image.adjust_saturation(image, 3)
visualize(image, saturated)
```

Adjusting the brightness

Adjust the brightness by providing a brightness factor.

```
bright = tf.image.adjust_brightness(image, 0.4)
visualize(image, bright)
```

Central Crop

Crop the image from the center using a central fraction of 0.5.

```
cropped = tf.image.central_crop(image, central_fraction=0.5)
visualize(image, cropped)
```

Explain code

POWERED BY datalab

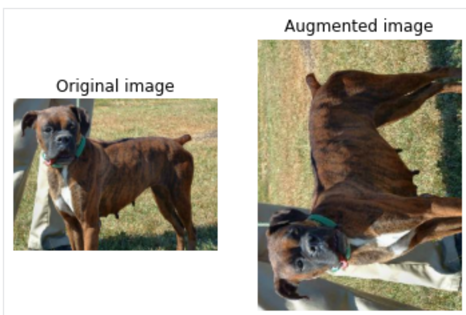
90-degree rotation

Rotate the image to 90 degrees using the `tf.image.rot90` function.

```
rotated = tf.image.rot90(image)
visualize(image, rotated)
```

Explain code

POWERED BY datalab



Applying random brightness

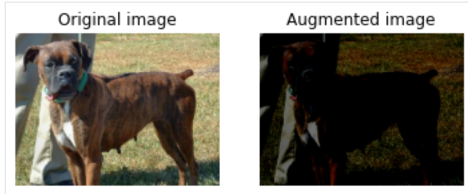
Just like Keras layers, tf.image also has random augmentation functions. In the example below, we will apply the random brightness to the image and display multiple results.

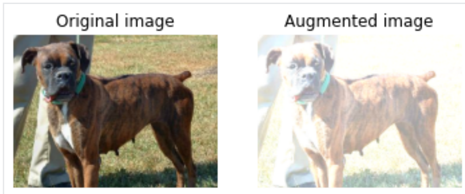
As we can see, the first image is a bit darker, and the next two images are brighter.

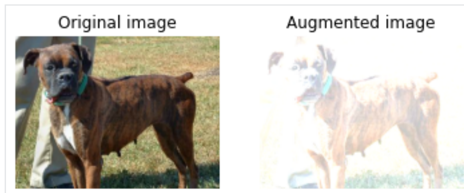
```
for i in range(3):
  seed = (i, 0)  # tuple of size (2,)
  stateless_random_brightness = tf.image.stateless_random_brightness(
      image, max_delta=0.95, seed=seed)
  visualize(image, stateless_random_brightness)
```

Explain code

POWERED BY datalab







Applying the augmentation function

Just like keras, we can apply a data augmentation function to the entire dataset using Dataset.map.

```
def augment(image, label):
  image = tf.cast(image, tf.float32)
  image = tf.image.resize(image, [IMG_SIZE, IMG_SIZE])
  image = (image / 255.0)
  image = tf.image.random_crop(image, size=[IMG_SIZE, IMG_SIZE, 3])
  image = tf.image.random_brightness(image, max_delta=0.5)
  return image, label


train_ds = (
    train_ds
    .shuffle(1000)
    .map(augment, num_parallel_calls=AUTOTUNE)
    .batch(batch_size)
    .prefetch(AUTOTUNE)
)
```


Data Augmentation with ImageDataGenerator

The Keras ImageDataGenerator is even simpler. It works best when you are loading data from a local directory or CSV.

In the example, we will download and load a small CIFAR10 dataset from Keras default dataset library.

After that, we will apply augmentation using `keras.preprocessing.image.ImageDataGenerator`. The function will randomly rotate, change the height and width, and horizontally flip the images.

Finally, we will fit ImageDataGenerator to the training dataset and display six images with random augmentation.

Note: the image size is 32×32, so we have a low-resolution display.

```
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()
```

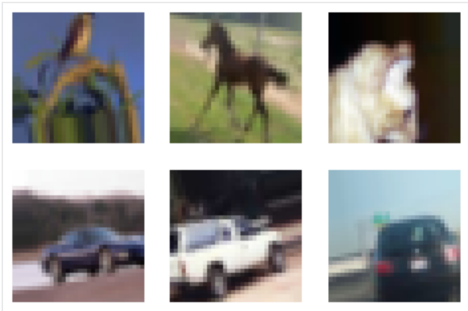
```python
datagen = keras.preprocessing.image.ImageDataGenerator(rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    horizontal_flip=True,
    validation_split=0.2)

datagen.fit(x_train)

for X_batch, y_batch in datagen.flow(x_train,y_train, batch_size=6):
    for i in range(0, 6):
        plt.subplot(2,3,i+1)
        plt.imshow(X_batch[i]/255)
        plt.axis('off')
    break
```

Explain code

POWERED BY datalab



Data Augmentation Tools

In this section, we will learn about other open-source tools that you can use to perform various data augmentation techniques and improve the model performance.

Pytorch

Image transformation is available in the torchvision.transforms module. Similar to Keras, you can add transform layers within torch.nn.Sequential or apply an augmentation function separately on the dataset.

Augmentor

Augmentor is a Python package for image augmentation and artificial image generation. You can perform Perspective Skewing, Elastic Distortions, Rotating, Shearing, Cropping, and Mirroring. Augmentor also comes with basic image pre-processing functionality.

Albumentations

Albumentations is a fast and flexible Python tool for image augmentation. It is widely used in machine learning competitions, industry, and research to improve the performance of deep convolutional neural networks.

Imgaug

Imgaug is an open-source tool for image augmentation. It supports a wide variety of augmentation techniques, such as Gaussian noise, contrast, sharpness, crop, affine, and flip. It has a simple yet powerful stochastic interface, and it comes with keypoints, bounding boxes, heatmaps, and segmentation maps.

OpenCV

OpenCV is a massive open-source library for computer vision, machine learning, and image processing. It is generally used in building real-time applications. You can use OpenCV to augment images and videos hassle-free.

Conclusion

Image augmentation functions provided by Tensorflow and Keras are convenient. You just have to add an augmentation layer, tf.image, or ImageDataGenerator to perform augmentation. Apart from deep learning frameworks, you can use standalone tools such as Augmentor, Albumentations, OpenCV, and Imgaug to perform data augmentation.

In this tutorial, we have learned about data augmentation advantages, limitations, applications, and techniques. Furthermore, we have learned to apply image augmentation on the cats vs. dog dataset using Keras and Tensorflow. If you are interested in learning more about image processing, check out the Image Processing with Python skill track. It will teach you the basics of image transformation and manipulation, medical image analysis, and advanced image processing using Keras.

Data Augmentation FAQs

What does data augmentation mean?

It is a set of techniques to artificially increase the dataset by modifying the copies of existing data or synthetically generating new copies of the dataset by using the existing dataset. While training the machine learning model, it acts as regularization and reduces overfitting.

Does data augmentation improve accuracy?

What is the disadvantage of data augmentation?

What is an example of data augmentation?

What are a few data augmentation techniques?

What is data augmentation in CNN?

TOPICS

Machine Learning Python