Train a simple convnet on the Fashion MNIST dataset

In this, we will see how to deal with image data and train a convnet for image classification task.

Load the `fashion_mnist` dataset

** Use keras.datasets to load the dataset **

```
from __future__ import absolute_import, division, print_function
import numpy as np
import keras
from keras.utils import np_utils
from keras.datasets import fashion_mnist
from keras.models import Sequential
from keras.layers import Dense, Activation, Dropout, Flatten, Reshape
from keras.layers import Convolution2D, MaxPooling2D

(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()
```

Find no.of samples are there in training and test datasets

```
print("Number of samples in Training are x_train and y_train ",(x_train.shape,y_train.shape))
```

```
Number of samples in Training are x_train and y_train  ((60000, 28, 28), (60000,))
```

```
print("Number of samples in Test are x_test and y_test",(x_test.shape,y_test.shape))
```

```
Number of samples in Test are x_test and y_test ((10000, 28, 28), (10000,))
```

```
x_train.dtype, x_test.dtype
```

```
(dtype('uint8'), dtype('uint8'))
```

Converting Data type to float 32

```
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')

x_train.dtype, x_test.dtype
```

```
(dtype('float32'), dtype('float32'))
```

Find dimensions of an image in the dataset

```
print('dimensions of an image in the dataset are as ',x_train[0].shape)
```

```
dimensions of an image in the dataset are as  (28, 28)
```

```
set(y_train)
```

```
{0, 1, 2, 3, 4, 5, 6, 7, 8, 9}
```

```
import pandas as pd
pd.value_counts(y_train)
```

```
9    6000
8    6000
7    6000
6    6000
5    6000
4    6000
3    6000
2    6000
1    6000
0    6000
dtype: int64
```

```
pd.value_counts(y_test)
```

```
7    1000
6    1000
5    1000
4    1000
3    1000
2    1000
9    1000
1    1000
8    1000
0    1000
dtype: int64
```

Convert train and test labels to one hot vectors

** check `keras.utils.to_categorical()` **

Since there are 10 unique categorical values in the dataset i.e 10 class labels

```
trainY = np_utils.to_categorical(y_train, num_classes=10)
```

```
testY = np_utils.to_categorical(y_test, num_classes=10)


# Actual value is as follows
y_train[0]
```

```
9
```

```
# one hot encoded value is as follows
trainY[0]
```

```
array([0., 0., 0., 0., 0., 0., 0., 0., 0., 1.], dtype=float32)
```

Normalize both the train and test image data from 0-255 to 0-1

```
x_train /= 255


x_test /= 255
```

Reshape the data from 28x28 to 28x28x1 to match input dimensions in Conv2D l

```
print("Actual x_train shape is ",x_train.shape)
print("Actual x_test shape is ",x_test.shape)
```

```
Actual x_train shape is  (60000, 28, 28)
Actual x_test shape is  (10000, 28, 28)
```

```
x_train = x_train.reshape(x_train.shape[0], 28, 28, 1)
x_test = x_test.reshape(x_test.shape[0], 28, 28, 1)


print("Converted x_train shape is ",x_train.shape)
print("Converted x_test shape is ",x_test.shape)
```

```
Converted x_train shape is  (60000, 28, 28, 1)
Converted x_test shape is  (10000, 28, 28, 1)
```

```
trainY.shape
```

```
(60000, 10)
```

Import the necessary layers from keras to build the model

Build a model

** with 2 Conv layers having `32 3x3 filters` in both convolutions with `relu activations` and `flatt` fully connected layers (or Dense Layers) having 128 and 10 neurons with `relu` and `softmax` activatio `categorical crossentropy` loss with `adam` optimizer train the model with early stopping `patience=5`

```
TRAIN = False
BATCH_SIZE = 32
EPOCHS = 10


# Define model
    model = Sequential()

    # 1st Conv Layer
    model.add(Convolution2D(32, 3, 3, input_shape=(28, 28, 1)))
    model.add(Activation('relu'))

    # 2nd Conv Layer
    model.add(Convolution2D(32, 3, 3))
    model.add(Activation('relu'))

    # Fully Connected Layer
    model.add(Flatten())
    model.add(Dense(128))
    model.add(Activation('relu'))

    # Prediction Layer
    model.add(Dense(10))
    model.add(Activation('softmax'))

    # Loss and Optimizer
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    # Store Training Results
    early_stopping = keras.callbacks.EarlyStopping(monitor='val_acc', patience=5, verbose=1,
    callback_list = [early_stopping]


    # Train the model2
    model.fit(x_train, trainY, batch_size=BATCH_SIZE, nb_epoch=EPOCHS,
              validation_data=(x_test, testY), callbacks=callback_list)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: UserWarning: Update your
  after removing the cwd from sys.path.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:8: UserWarning: Update your

/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:29: UserWarning: The `nb_ep
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow_core/python/op
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_

Train on 60000 samples, validate on 10000 samples
Epoch 1/10
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_

60000/60000 [==============================] - 28s 472us/step - loss: 0.3733 - acc: 0.86
Epoch 2/10
60000/60000 [==============================] - 20s 337us/step - loss: 0.2332 - acc: 0.91
Epoch 3/10
60000/60000 [==============================] - 20s 328us/step - loss: 0.1709 - acc: 0.93
Epoch 4/10
60000/60000 [==============================] - 20s 329us/step - loss: 0.1203 - acc: 0.95
Epoch 5/10
60000/60000 [==============================] - 20s 330us/step - loss: 0.0793 - acc: 0.97
Epoch 6/10
60000/60000 [==============================] - 20s 331us/step - loss: 0.0531 - acc: 0.98
Epoch 7/10
60000/60000 [==============================] - 20s 329us/step - loss: 0.0383 - acc: 0.98
Epoch 8/10
60000/60000 [==============================] - 20s 328us/step - loss: 0.0283 - acc: 0.99
Epoch 9/10
60000/60000 [==============================] - 20s 328us/step - loss: 0.0232 - acc: 0.99
Epoch 00009: early stopping
<keras.callbacks.History at 0x7f0339055fd0>
```

Now, to the above model add `max` pooling layer of `filter size 2x2` and `dropout` conv layers and run the model

```
# Define model
    model2 = Sequential()
```

```
# 1st Conv Layer
model2.add(Convolution2D(32, 3, 3, input_shape=(28, 28, 1)))
model2.add(Activation('relu'))

# 2nd Conv Layer
model2.add(Convolution2D(32, 3, 3))
model2.add(Activation('relu'))

# Max Pooling
model2.add(MaxPooling2D(pool_size=(2,2)))

# Dropout
model2.add(Dropout(0.25))

# Fully Connected Layer
model2.add(Flatten())
model2.add(Dense(128))
model2.add(Activation('relu'))

# Prediction Layer
model2.add(Dense(10))
model2.add(Activation('softmax'))

# Loss and Optimizer
model2.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
# Store Training Results
early_stopping = keras.callbacks.EarlyStopping(monitor='val_acc', patience=5, verbose=1,
callback_list = [early_stopping]


# Train the model2
model2.fit(x_train, trainY, batch_size=BATCH_SIZE, nb_epoch=EPOCHS,
          validation_data=(x_test, testY), callbacks=callback_list)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: UserWarning: Update your
  after removing the cwd from sys.path.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:8: UserWarning: Update your

/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:35: UserWarning: The `nb_ep
Train on 60000 samples, validate on 10000 samples
Epoch 1/10
60000/60000 [==============================] - 20s 326us/step - loss: 0.3956 - acc: 0.85
Epoch 2/10
60000/60000 [==============================] - 19s 319us/step - loss: 0.2611 - acc: 0.90
Epoch 3/10
60000/60000 [==============================] - 19s 318us/step - loss: 0.2120 - acc: 0.92
Epoch 4/10
60000/60000 [==============================] - 20s 325us/step - loss: 0.1768 - acc: 0.93
Epoch 5/10
60000/60000 [==============================] - 19s 322us/step - loss: 0.1505 - acc: 0.94
Epoch 6/10
60000/60000 [==============================] - 19s 324us/step - loss: 0.1284 - acc: 0.95
Epoch 7/10
60000/60000 [==============================] - 19s 322us/step - loss: 0.1082 - acc: 0.95
Epoch 8/10
60000/60000 [==============================] - 20s 329us/step - loss: 0.0960 - acc: 0.96
Epoch 9/10
60000/60000 [==============================] - 20s 327us/step - loss: 0.0842 - acc: 0.96
Epoch 10/10
60000/60000 [==============================] - 19s 315us/step - loss: 0.0745 - acc: 0.97
<keras.callbacks.History at 0x7f03301aa8d0>
```

Now, to the above model, lets add Data Augmentation

Import the ImageDataGenrator from keras and fit the training images

```
from keras.preprocessing.image import ImageDataGenerator

# This will do preprocessing and realtime data augmentation:
datagen = ImageDataGenerator(
    featurewise_center=False,  # set input mean to 0 over the dataset
    samplewise_center=False,  # set each sample mean to 0
    featurewise_std_normalization=False,  # divide inputs by std of the dataset
    samplewise_std_normalization=False,  # divide each input by its std
    zca_whitening=False,  # apply ZCA whitening
    rotation_range=50,  # randomly rotate images in the range (degrees, 0 to 180)
    width_shift_range=0.01,  # randomly shift images horizontally (fraction of total width)
```

```
    height_shift_range=0.01,  # randomly shift images vertically (fraction of total height)
    horizontal_flip=False,  # randomly flip images
    vertical_flip=False)  # randomly flip images

# Prepare the generator
datagen.fit(x_train)
```

Showing 5 versions of the first image in training dataset using image datagenerator.flow()

```
from matplotlib import pyplot as plt
gen = datagen.flow(x_train[0:1], batch_size=1)
for i in range(1, 6):
    plt.subplot(1,5,i)
    plt.axis("off")
    plt.imshow(gen.next().squeeze(), cmap='gray')
    plt.plot()
plt.show()
```

Run the above model using fit_generator()

```
model2.fit_generator(datagen.flow(x_train, trainY,batch_size=32),
                     samples_per_epoch=x_train.shape[0],
                     nb_epoch=10,
                     validation_data=(x_test, testY), callbacks=callback_list)
```

```
Epoch 1/10
   7/1875 [..............................] - ETA: 36s - loss: 3.3211 - acc: 0.4732/usr/l
  after removing the cwd from sys.path.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: UserWarning: Update your
  after removing the cwd from sys.path.
1875/1875 [==============================] - 33s 17ms/step - loss: 0.5096 - acc: 0.8179
Epoch 2/10
1875/1875 [==============================] - 33s 18ms/step - loss: 0.3663 - acc: 0.8658
Epoch 3/10
1875/1875 [==============================] - 33s 18ms/step - loss: 0.3319 - acc: 0.8782
Epoch 4/10
1875/1875 [==============================] - 34s 18ms/step - loss: 0.3098 - acc: 0.8851
Epoch 5/10
1875/1875 [==============================] - 34s 18ms/step - loss: 0.2944 - acc: 0.8917
Epoch 6/10
1875/1875 [==============================] - 33s 18ms/step - loss: 0.2836 - acc: 0.8954
Epoch 7/10
1875/1875 [==============================] - 34s 18ms/step - loss: 0.2739 - acc: 0.8997
Epoch 8/10
1875/1875 [==============================] - 34s 18ms/step - loss: 0.2644 - acc: 0.9025
Epoch 9/10
1875/1875 [==============================] - 33s 18ms/step - loss: 0.2591 - acc: 0.9043
Epoch 10/10
1875/1875 [==============================] - 34s 18ms/step - loss: 0.2519 - acc: 0.9071
<keras.callbacks.History at 0x7f0339b5f898>
```

Report the final train and validation accuracy

```
loss_and_metrics = model2.evaluate(x_test, testY)
print(loss_and_metrics)
```

```
10000/10000 [==============================] - 1s 86us/step
[0.27319020503759384, 0.904]
```

DATA AUGMENTATION ON CIFAR10 DATASET

One of the best ways to improve the performance of a Deep Learning model is to add more data to th
instances from the wild that are representative of the distinction task, we want to develop a set of me
have. There are many ways to augment existing datasets and produce more robust models. In the ima
full power of the convolutional neural network, which is able to capture translational invariance. This t
image recognition such a difficult task in the first place. You want the dataset to be representative of t
lightings, and miscellaneous distortions that are of interest to the vision task.

Import neessary libraries for data augmentation

```
from keras.datasets import cifar10
```

Load CIFAR10 dataset

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

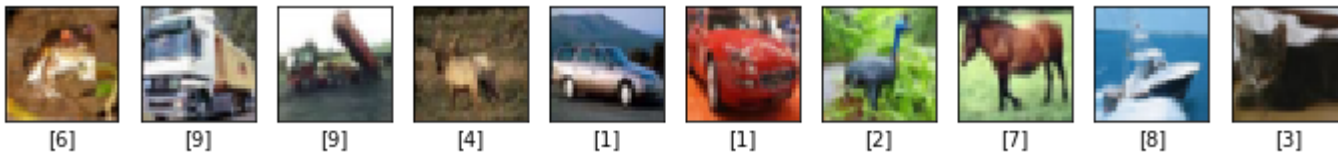
```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170500096/170498071 [==============================] - 11s 0us/step
```

```
print("Number of samples in Training are x_train and y_train ",(x_train.shape,y_train.shape))
```

```
Number of samples in Training are x_train and y_train  ((50000, 32, 32, 3), (50000, 1))
```

```
plt.figure(figsize=(12,12))
for i in range(10):
  plt.subplot(1,10,i+1)
  plt.xticks([])
  plt.yticks([])
  plt.grid(False)
  plt.imshow(x_train[i])
  plt.xlabel(y_train[i])
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/text.py:1150: FutureWarning: elementwi
  if s != self._text:
```



Create a data_gen funtion to genererator with image rotation,shifting image hori random flip horizontally.

```
from keras.preprocessing.image import ImageDataGenerator

# This will do preprocessing and realtime data augmentation:
data_gen = ImageDataGenerator(
    featurewise_center=False,  # set input mean to 0 over the dataset
    samplewise_center=False,  # set each sample mean to 0
```

```
    featurewise_std_normalization=False,  # divide inputs by std of the dataset
    samplewise_std_normalization=False,  # divide each input by its std
    zca_whitening=False,  # apply ZCA whitening
    rotation_range=50,  # randomly rotate images in the range (degrees, 0 to 180)
    width_shift_range=0.01,  # randomly shift images horizontally (fraction of total width)
    height_shift_range=0.01,  # randomly shift images vertically (fraction of total height)
    horizontal_flip=True,  # randomly flip images
    vertical_flip=True)  # randomly flip images
```

Prepare/fit the generator.

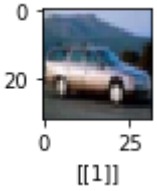
```
# Prepare the generator
data_gen.fit(x_train)
```

```
x_train[4:5].shape
```

```
(1, 32, 32, 3)
```

```
print("Actual Image")
plt.figure(figsize=(1,1))
#plt.plot()
plt.imshow(x_train[4:5][0])
plt.xlabel(y_train[4:5])
plt.show()
```

```
Actual Image
/usr/local/lib/python3.6/dist-packages/matplotlib/text.py:1150: FutureWarning: elementwi
  if s != self._text:
```



Generate 5 images for 1 of the image of CIFAR10 train dataset.

```
generator = data_gen.flow(x_train[4:5],batch_size=1)
for i in range(1,6):
  plt.subplot(1,5,i)
  plt.axis("off")
  plt.imshow(generator.next().squeeze().astype('uint8'))
  plt.plot()
plt.show()
```