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.

```
#Make sure we have tensorflow 2.x
#!pip3 install -U tensorflow --quiet
```

Load the `fashion_mnist` dataset

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

```
import tensorflow as tf
```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.
We recommend you upgrade now or ensure your notebook will continue to use TensorFlow 1.x via the %tenso

```
from keras.datasets import fashion_mnist
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()
```

```
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-l
32768/29515 [================================] - 0s 0us/step
Using TensorFlow backend.
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-i
26427392/26421880 [==============================] - 0s 0us/step
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-la
8192/5148 [==============================================] - 0s 0us/step
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-im
4423680/4422102 [==============================] - 0s 0us/step
```

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

```
'Number of samples in the train set -  {}'.format(x_train.shape[0])
```

```
'Number of samples in the train set -  60000'
```

```
'Number of samples in the test set -  {}'.format(x_test.shape[0])
```

```
'Number of samples in the test set -  10000'
```

Find dimensions of an image in the dataset

```
'Dimension of image in the train dataset -  {}'.format(x_train.shape[1:])
```

```
'Dimension of image in the train dataset -  (28, 28)'
```

```
'Dimension of image in the test dataset -  {}'.format(x_test.shape[1:])
```

```
'Dimension of image in the test dataset -  (28, 28)'
```

```
import numpy as np
import pandas as pd
```

```
# Checking the number of classes
```

```
pd.DataFrame(y_train).nunique()
```

```
0    10
dtype: int64
```

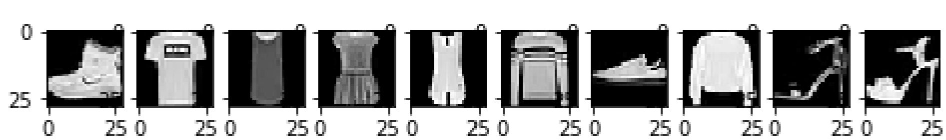
Convert train and test labels to one hot vectors

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

```
y_train = tf.keras.utils.to_categorical(y_train, num_classes=10)
y_test = tf.keras.utils.to_categorical(y_test, num_classes=10)
```

```
## visualize the data
```

```
import numpy as np
import matplotlib.pyplot as plt

w=20
h=20
fig=plt.figure(figsize=(8, 8))
columns = 10
rows = 1
for i in range(1, columns*rows+1):

    img = x_train[i-1]
    fig.add_subplot(rows, columns, i)

    plt.imshow(img,cmap='gray')
plt.show()
```



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

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

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

```
x_train = x_train.reshape(x_train.shape[0], 28, 28, 1).astype('float32')
x_test = x_test.reshape(x_test.shape[0], 28, 28, 1).astype('float32')
x_train /= 255
x_test /= 255

x_train.shape
```

```
(60000, 28, 28, 1)
```

Import the necessary layers from keras to build the model

```
import numpy as np
import keras
from keras.datasets import cifar10, mnist
from keras.models import Sequential
from keras.layers import Dense, Activation, Dropout, Flatten, Reshape
from keras.layers import Convolution2D, MaxPooling2D
from keras.utils import np_utils
import pickle
```

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
    model1 = Sequential()
```

```
# 1st Conv Layer
model1.add(Convolution2D(32, 3, 3, input_shape=(28, 28, 1)))
model1.add(Activation('relu'))

# 2nd Conv Layer
model1.add(Convolution2D(32, 3, 3))
model1.add(Activation('relu'))

# Fully Connected Layer
model1.add(Flatten())
model1.add(Dense(128))
model1.add(Activation('relu'))

# Prediction Layer
model1.add(Dense(10))
model1.add(Activation('softmax'))

# Loss and Optimizer
model1.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])


# Store Training Results
early_stopping = keras.callbacks.EarlyStopping(monitor='val_acc', patience=10, verbose=1,
callback_list = [early_stopping]

# Train the model2
model1.fit(x_train, y_train, batch_size=BATCH_SIZE, nb_epoch=EPOCHS,
          validation_data=(x_test, y_test), 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_

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:793:

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

/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:30: 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 [==============================] - 26s 440us/step - loss: 0.3780 - acc: 0.86
Epoch 2/10
60000/60000 [==============================] - 19s 319us/step - loss: 0.2297 - acc: 0.91
Epoch 3/10
60000/60000 [==============================] - 19s 317us/step - loss: 0.1657 - acc: 0.93
Epoch 4/10
60000/60000 [==============================] - 19s 316us/step - loss: 0.1146 - acc: 0.95
Epoch 5/10
60000/60000 [==============================] - 19s 315us/step - loss: 0.0759 - acc: 0.97
Epoch 6/10
60000/60000 [==============================] - 19s 318us/step - loss: 0.0508 - acc: 0.98
Epoch 7/10
60000/60000 [==============================] - 19s 316us/step - loss: 0.0351 - acc: 0.98
Epoch 8/10
60000/60000 [==============================] - 19s 313us/step - loss: 0.0275 - acc: 0.99
Epoch 9/10
60000/60000 [==============================] - 19s 321us/step - loss: 0.0210 - acc: 0.99
Epoch 10/10
60000/60000 [==============================] - 19s 313us/step - loss: 0.0197 - acc: 0.99
<keras.callbacks.History at 0x7f0491ef9a90>
```

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=10, verbose=1,
callback_list = [early_stopping]

# Train the model2
model2.fit(x_train, y_train, batch_size=BATCH_SIZE, nb_epoch=EPOCHS,
          validation_data=(x_test, y_test), 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:36: UserWarning: The `nb_ep
Train on 60000 samples, validate on 10000 samples
Epoch 1/10
60000/60000 [==============================] - 19s 311us/step - loss: 0.3904 - acc: 0.85
Epoch 2/10
60000/60000 [==============================] - 18s 303us/step - loss: 0.2563 - acc: 0.90
Epoch 3/10
60000/60000 [==============================] - 18s 302us/step - loss: 0.2116 - acc: 0.92
Epoch 4/10
60000/60000 [==============================] - 18s 302us/step - loss: 0.1758 - acc: 0.93
Epoch 5/10
60000/60000 [==============================] - 19s 309us/step - loss: 0.1489 - acc: 0.94
Epoch 6/10
60000/60000 [==============================] - 18s 306us/step - loss: 0.1253 - acc: 0.95
Epoch 7/10
60000/60000 [==============================] - 18s 303us/step - loss: 0.1083 - acc: 0.95
Epoch 8/10
60000/60000 [==============================] - 18s 301us/step - loss: 0.0911 - acc: 0.96
Epoch 9/10
60000/60000 [==============================] - 18s 300us/step - loss: 0.0793 - acc: 0.97
Epoch 10/10
60000/60000 [==============================] - 18s 301us/step - loss: 0.0691 - acc: 0.97
<keras.callbacks.History at 0x7f043a5420b8>
```

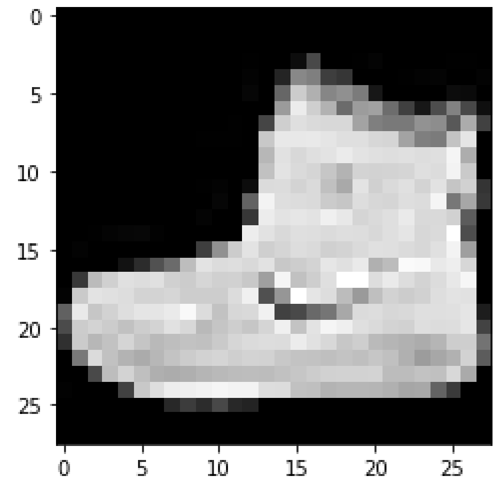
Now, to the above model, lets add Data Augmentation

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
```

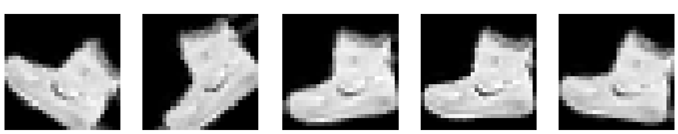
```
datagen.fit(x_train)


plt.imshow(x_train[0].squeeze(), cmap='gray')
plt.plot()
```

```
[]
```



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()

```
    # Define Model
    model3 = Sequential()

    # 1st Conv Layer
    model3.add(Convolution2D(32, 3, 3, input_shape=(28, 28, 1)))
    model3.add(Activation('relu'))

    # 2nd Conv Layer
    model3.add(Convolution2D(32, 3, 3))
```

```
    model3.add(Activation('relu'))

    # Max Pooling
    model3.add(MaxPooling2D(pool_size=(2,2)))

    # Dropout
    model3.add(Dropout(0.15))

    # Fully Connected Layer
    model3.add(Flatten())
    model3.add(Dense(128))
    model3.add(Activation('relu'))

    # More Dropout
    model3.add(Dropout(0.2))

    # Prediction Layer
    model3.add(Dense(10))
    model3.add(Activation('softmax'))

    # Loss and Optimizer
    model3.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

    # Store Training Results
    early_stopping = keras.callbacks.EarlyStopping(monitor='val_acc', patience=7, verbose=1,
    callback_list = [early_stopping]
```

```
/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
```

```
model3.fit_generator(datagen.flow(x_train, y_train,batch_size=32),
                    samples_per_epoch=x_train.shape[0],
                    nb_epoch=10,
                    validation_data=(x_test, y_test), callbacks=callback_list)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: UserWarning: The semanti
  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.
Epoch 1/10
1875/1875 [==============================] - 33s 18ms/step - loss: 0.6431 - acc: 0.7644
Epoch 2/10
1875/1875 [==============================] - 32s 17ms/step - loss: 0.4634 - acc: 0.8298
Epoch 3/10
1875/1875 [==============================] - 32s 17ms/step - loss: 0.4088 - acc: 0.8485
Epoch 4/10
1875/1875 [==============================] - 33s 17ms/step - loss: 0.3766 - acc: 0.8618
Epoch 5/10
1875/1875 [==============================] - 33s 17ms/step - loss: 0.3607 - acc: 0.8676
Epoch 6/10
1875/1875 [==============================] - 32s 17ms/step - loss: 0.3444 - acc: 0.8721
Epoch 7/10
1875/1875 [==============================] - 32s 17ms/step - loss: 0.3304 - acc: 0.8792
Epoch 8/10
1875/1875 [==============================] - 32s 17ms/step - loss: 0.3246 - acc: 0.8798
Epoch 9/10
1875/1875 [==============================] - 32s 17ms/step - loss: 0.3138 - acc: 0.8839
Epoch 10/10
1875/1875 [==============================] - 32s 17ms/step - loss: 0.3059 - acc: 0.8878
<keras.callbacks.History at 0x7f043a6a3b70>
```

Report the final train and validation accuracy

```
loss_and_metrics = model3.evaluate(x_train, y_train)
print(loss_and_metrics)
```

```
60000/60000 [==============================] - 5s 87us/step
[0.2502768676221371, 0.9073333333333333]
```

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
lightings, and miscellaneous distortions that are of interest to the vision task.

Import neessary libraries for data augmentation

```
from keras.preprocessing.image import ImageDataGenerator
```

Load CIFAR10 dataset

```
from keras.datasets import cifar10
(x_train1, y_train1), (x_test1, y_test1) = cifar10.load_data()
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170500096/170498071 [==============================] - 6s 0us/step
```

```
x_train1.shape
```

```
(50000, 32, 32, 3)
```

```
x_test1.shape
```

```
(10000, 32, 32, 3)
```

```
'Number of samples in the train set -  {}'.format(x_train1.shape[0])
```

```
'Number of samples in the train set -  50000'
```

```
'Number of samples in the test set -  {}'.format(x_test1.shape[0])
```

```
'Number of samples in the test set -  10000'
```

```
'Dimension of image in the train dataset -  {}'.format(x_train1.shape[1:])
```

```
'Dimension of image in the train dataset -  (32, 32, 3)'
```

```
'Dimension of image in the test dataset -  {}'.format(x_test1.shape[1:])
```

```
'Dimension of image in the test dataset -  (32, 32, 3)'
```

```
import numpy as np
import pandas as pd
```

```
# Checking the number of classes
```

```
pd.DataFrame(y_train1).nunique()
```

```
pd.DataFrame(y_train1).nunique()
```

```
0    10
dtype: int64
```

Convert train and test labels to one hot vectors

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

```
y_train1 = tf.keras.utils.to_categorical(y_train1, num_classes=10)
y_test1 = tf.keras.utils.to_categorical(y_test1, num_classes=10)
```

```
## visualize the data
```

```
import numpy as np
import matplotlib.pyplot as plt

w=20
h=20
fig=plt.figure(figsize=(8, 8))
columns = 10
rows = 1
for i in range(1, columns*rows+1):

    img = x_train1[i-1]
    fig.add_subplot(rows, columns, i)

    plt.imshow(img,cmap='gray')
plt.show()
```

```
x_train1 = x_train1.astype('float32')
x_test1 = x_test1.astype('float32')
y_train1 = y_train1.astype('float32')
y_test1 = y_test1.astype('float32')
```

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

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

```
x_train1 /= 255
x_test1 /= 255

x_train.shape
```

```
(60000, 28, 28, 1)
```

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

```
# This will do preprocessing and realtime data augmentation:
datagen1 = 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
datagen1.fit(x_train1)
```

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

```
from matplotlib import pyplot as plt
gen = datagen1.flow(x_train1[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()
```