Double-click (or enter) to edit

```
!pip install -q keras
import keras
```

```
Using TensorFlow backend.
```

```
import numpy as np
from keras.utils import to_categorical
import matplotlib.pyplot as plt
%matplotlib inline
from tqdm import tqdm
import os
from random import shuffle
import cv2
```

```
from google.colab import drive
drive.mount("/content/drive")
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=9

Enter your authorization code:
··········
Mounted at /content/drive
```

```
train_images=('/file//C:\Users\lenovo\OneDrive\t10k-images-idx3-ubyte.zip')
train_file=('/file//C:\Users\lenovo\OneDrive\t10k-labels-idx1-ubyte.zip')
test_file=('/file//C:\Users\lenovo\OneDrive\train-images-idx3-ubyte.zip')
test_file=('/file//C:\Users\lenovo\OneDrive\train-labels-idx1-ubyte.zip')
```

```
from keras.datasets import fashion_mnist
(train_X,train_Y),(test_X,test_Y)=fashion_mnist.load_data()
```

```
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t
32768/29515 [==================================] - 0s 3us/step
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t
26427392/26421880 [==============================] - 1s 0us/step
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t
8192/5148 [================================================] - 0s 0us/step
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t
4423680/4422102 [==============================] - 1s 0us/step
```

```
import numpy as np
from keras.utils import to_categorical
import matplotlib.pyplot as plt
%matplotlib inline

print('training data shape:',train_X.shape,train_Y.shape)
```

```
print('testing data shape:',test_X.shape,test_Y.shape)
```

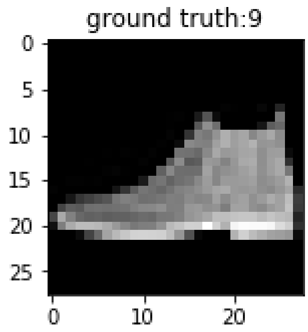
```
training data shape: (60000, 28, 28) (60000,)
testing data shape: (10000, 28, 28) (10000,)
```

```
classes=np.unique(train_Y)
nclasses=len(classes)
print('total number of outputs:',nclasses)
print('output classes:',classes)
```

```
total number of outputs: 10
output classes: [0 1 2 3 4 5 6 7 8 9]
```

```
plt.figure(figsize=[5,5])
plt.subplot(121)
plt.imshow(train_X[0],cmap='gray')
plt.title("ground truth:{}".format(train_Y[0]))

plt.subplot(121)
plt.imshow(test_X[0],cmap='gray')
plt.title("ground truth:{}".format(test_Y[0]))
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/figure.py:98: MatplotlibDeprecat
Adding an axes using the same arguments as a previous axes currently reuses the ea
  "Adding an axes using the same arguments as a previous axes "
Text(0.5, 1.0, 'ground truth:9')
```




```
train_X=train_X.reshape(-1,28,28,1)
test_X=test_X.reshape(-1,28,28,1)
train_X.shape,test_X.shape
```

```
((60000, 28, 28, 1), (10000, 28, 28, 1))
```

```
train_X=train_X.astype('float32')
test_X=test_X.astype('float32')
train_X=train_X/255
test_X=test_X/255
```

```
train_Y_one_hot=to_categorical(train_Y)
test_Y_one_hot=to_categorical(test_Y)

print('original label:',train_Y[0])
print('after conversion to one_hot:',train_Y_one_hot[0])
```

```
original label: 9
after conversion to one_hot: [0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
```

```
from sklearn.model_selection import train_test_split
train_X,valid_X,train_label,valid_label=train_test_split(train_X,train_Y_one_hot,test_si:
```

```
train_X.shape,valid_X.shape,train_label.shape,valid_label.shape
```

```
((48000, 28, 28, 1), (12000, 28, 28, 1), (48000, 10), (12000, 10))
```

```
import keras
from keras.models import Sequential,Input,Model
from keras.layers import Dense,Dropout,Flatten
from keras.layers import Conv2D,MaxPooling2D
from keras.layers.normalization import BatchNormalization
from keras.layers.advanced_activations import LeakyReLU,PReLU
```

```
batch_size=64
epochs=20
num_classes=10
```

```
fashion_model=Sequential()
fashion_model.add(Conv2D(32,kernel_size=(3,3),activation='linear',input_shape=(28,28,1),|
fashion_model.add(MaxPooling2D(pool_size=(2,2),padding='same'))
fashion_model.add(Conv2D(64,(3,3),activation='linear',padding='same'))
fashion_model.add(MaxPooling2D(pool_size=(2,2),padding='same'))
fashion_model.add(Conv2D(128,(3,3),activation='linear',padding='same'))
fashion_model.add(MaxPooling2D(pool_size=(2,2),padding='same'))
fashion_model.add(Flatten())
fashion_model.add(Dense(128,activation='linear'))
fashion_model.add(Dense(num_classes,activation='softmax'))
```

```
fashion_model.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.optimiz
```

```
fashion_model.summary()
```

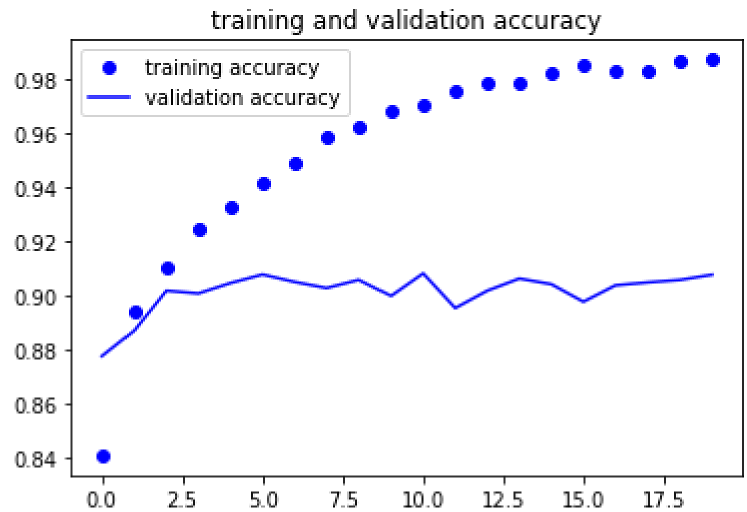
```
fashion_train=fashion_model.fit(train_X,train_label,batch_size=batch_size,epochs=epochs,
```

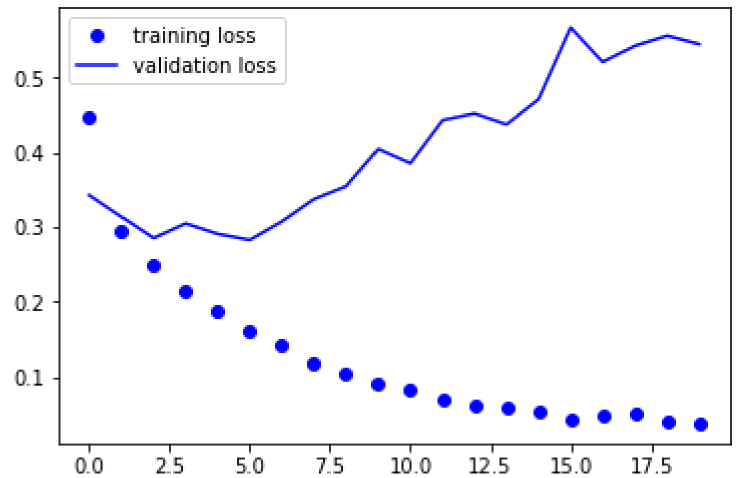
```
W0615 17:29:49.448983 140106155558784 deprecation.py:323] From /usr/local/lib/pyth
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
W0615 17:29:49.529005 140106155558784 deprecation_wrapper.py:119] From /usr/local/

Train on 48000 samples, validate on 12000 samples
Epoch 1/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.4485 - acc:
Epoch 2/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.2936 - acc:
Epoch 3/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.2490 - acc:
Epoch 4/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.2129 - acc:
Epoch 5/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.1881 - acc:
Epoch 6/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.1610 - acc:
Epoch 7/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.1406 - acc:
Epoch 8/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.1185 - acc:
Epoch 9/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.1036 - acc:
Epoch 10/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0896 - acc:
Epoch 11/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0839 - acc:
Epoch 12/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0705 - acc:
Epoch 13/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0622 - acc:
Epoch 14/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0588 - acc:
Epoch 15/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0535 - acc:
Epoch 16/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0430 - acc:
Epoch 17/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0481 - acc:
Epoch 18/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0497 - acc:
Epoch 19/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0391 - acc:
Epoch 20/20
48000/48000 [==============================] - 87s 2ms/step - loss: 0.0375 - acc:
```

```
test_eval=fashion_model.evaluate(test_X,test_Y_one_hot,verbose=0)
```

```
print('test loss:',test_eval[0])
print('test accuracy:',test_eval[1])
```

```
accuracy=fashion_train.history['acc']
val_accuracy=fashion_train.history['val_acc']
loss=fashion_train.history['loss']
val_loss=fashion_train.history['val_loss']
epochs=range(len(accuracy))
plt.plot(epochs,accuracy,'bo',label='training accuracy')
plt.plot(epochs,val_accuracy,'b',label='validation accuracy')
plt.title('training and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochs,loss,'bo',label='training loss')
plt.plot(epochs,val_loss,'b',label='validation loss')
plt.legend()
plt.show()
```






```
batch_size=64
epochs=20
num_classes=10
```

```
fashion_model=Sequential()
fashion_model.add(Conv2D(32,kernel_size=(3,3),activation='linear',input_shape=(28,28,1),
fashion_model.add(MaxPooling2D(pool_size=(2,2),padding='same'))
fashion_model.add(Dropout(0.25))
fashion_model.add(Conv2D(64,(3,3),activation='linear',padding='same'))
fashion_model.add(MaxPooling2D(pool_size=(2,2),padding='same'))
fashion_model.add(Dropout(0.25))
fashion_model.add(Conv2D(128,(3,3),activation='linear',padding='same'))
fashion_model.add(MaxPooling2D(pool_size=(2,2),padding='same'))
fashion_model.add(Dropout(0.4))
fashion_model.add(Flatten())
fashion_model.add(Dense(128,activation='linear'))
fashion_model.add(Dropout(0.3))
```

```
fashion_model.add(Dense(num_classes,activation='softmax'))
```

```
fashion_model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_31 (Conv2D)           (None, 28, 28, 32)        320       
_________________________________________________________________
max_pooling2d_28 (MaxPooling (None, 14, 14, 32)        0         
_________________________________________________________________
dropout_4 (Dropout)          (None, 14, 14, 32)        0         
_________________________________________________________________
conv2d_32 (Conv2D)           (None, 14, 14, 64)        18496     
_________________________________________________________________
max_pooling2d_29 (MaxPooling (None, 7, 7, 64)          0         
_________________________________________________________________
dropout_5 (Dropout)          (None, 7, 7, 64)          0         
_________________________________________________________________
conv2d_33 (Conv2D)           (None, 7, 7, 128)         73856     
_________________________________________________________________
max_pooling2d_30 (MaxPooling (None, 4, 4, 128)         0         
_________________________________________________________________
dropout_6 (Dropout)          (None, 4, 4, 128)         0         
_________________________________________________________________
flatten_9 (Flatten)          (None, 2048)              0         
_________________________________________________________________
dense_10 (Dense)             (None, 128)               262272    
_________________________________________________________________
dropout_7 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_11 (Dense)             (None, 10)                1290      
=================================================================
Total params: 356,234
Trainable params: 356,234
Non-trainable params: 0
_________________________________________________________________
```

```
fashion_model.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.optimiz
```

```
fashion_train_dropout=fashion_model.fit(train_X,train_label,batch_size=batch_size,epochs=
```

```
Train on 48000 samples, validate on 12000 samples
Epoch 1/20
48000/48000 [==============================] - 99s 2ms/step - loss: 0.5484 - acc:
Epoch 2/20
48000/48000 [==============================] - 99s 2ms/step - loss: 0.3833 - acc:
Epoch 3/20
48000/48000 [==============================] - 99s 2ms/step - loss: 0.3475 - acc:
Epoch 4/20
48000/48000 [==============================] - 99s 2ms/step - loss: 0.3257 - acc:
Epoch 5/20
48000/48000 [==============================] - 99s 2ms/step - loss: 0.3117 - acc:
Epoch 6/20
48000/48000 [==============================] - 99s 2ms/step - loss: 0.3012 - acc:
Epoch 7/20
48000/48000 [==============================] - 99s 2ms/step - loss: 0.2924 - acc:
Epoch 8/20
48000/48000 [==============================] - 100s 2ms/step - loss: 0.2833 - acc:
Epoch 9/20
48000/48000 [==============================] - 99s 2ms/step - loss: 0.2759 - acc:
Epoch 10/20
48000/48000 [==============================] - 99s 2ms/step - loss: 0.2726 - acc:
Epoch 11/20
48000/48000 [==============================] - 100s 2ms/step - loss: 0.2678 - acc:
Epoch 12/20
48000/48000 [==============================] - 100s 2ms/step - loss: 0.2634 - acc:
```

```
fashion_model.save("fashion_model_dropout.h5py")
```

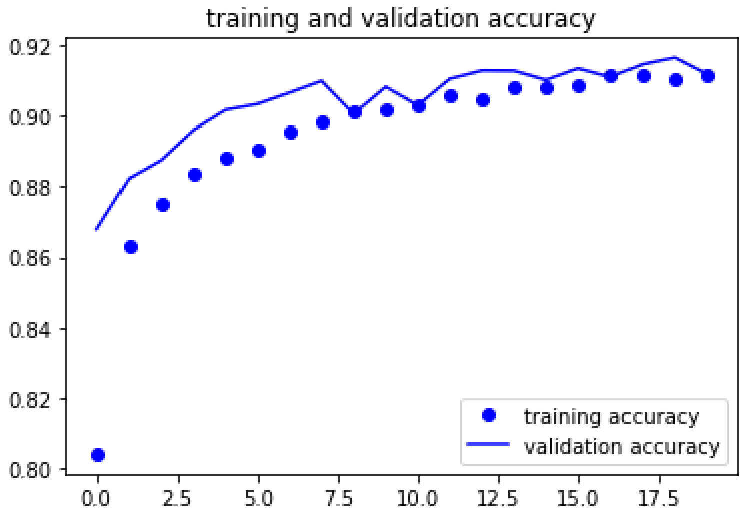
```
test_eval=fashion_model.evaluate(test_X,test_Y_one_hot,verbose=1)
```

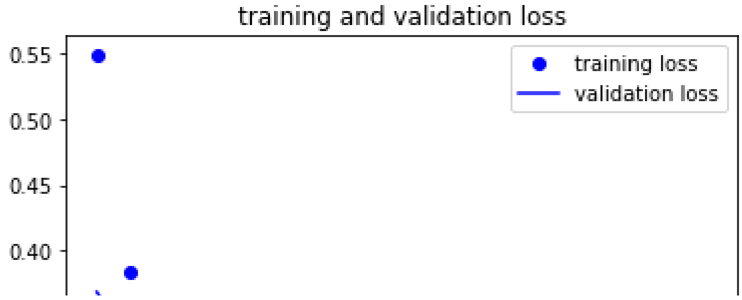
```
10000/10000 [==============================] - 5s 525us/step
```

```
print('test loss:',test_eval[0])
print('test accuracy:',test_eval[1])
```

```
test loss: 0.2723303992450237
test accuracy: 0.905
```

```
accuracy=fashion_train_dropout.history['acc']
val_accuracy=fashion_train_dropout.history['val_acc']
loss=fashion_train_dropout.history['loss']
val_loss=fashion_train_dropout.history['val_loss']
epochs=range(len(accuracy))
plt.plot(epochs,accuracy,'bo',label='training accuracy')
plt.plot(epochs,val_accuracy,'b',label='validation accuracy')
plt.title('training and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochs,loss,'bo',label='training loss')
plt.plot(epochs,val_loss,'b',label='validation loss')
plt.title('training and validation loss')
plt.legend()
plt.show()
```






```
predicted_classes=fashion_model.predict(test_X)
```

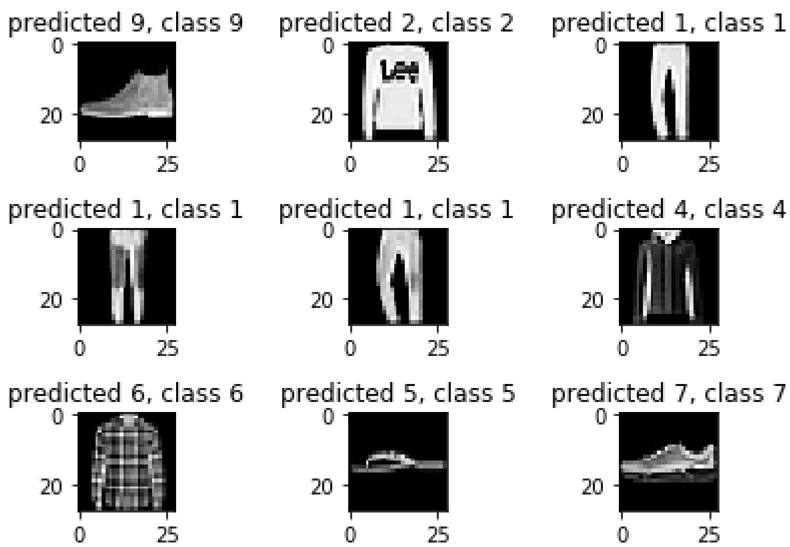
```
predicted_classes=np.argmax(np.round(predicted_classes),axis=1)
```

```
predicted_classes.shape,test_Y.shape
```

```
((10000,), (10000,))
```

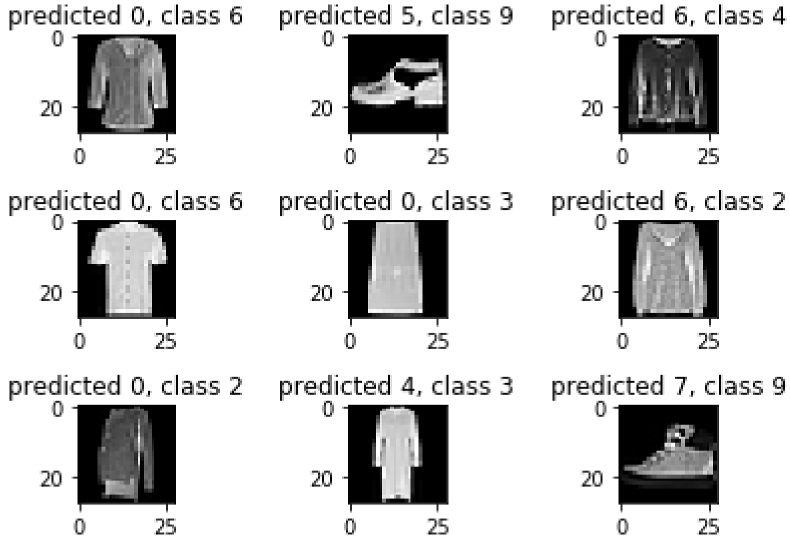
```
correct=np.where(predicted_classes==test_Y)[0]
print("Found %d correct labels" % len(correct))
for i,correct in enumerate(correct[:9]):
  plt.subplot(3,3,i+1)
  plt.imshow(test_X[correct].reshape(28,28),cmap='gray',interpolation='none')
  plt.title("predicted {}, class {}".format(predicted_classes[correct],test_Y[correct]))
  plt.tight_layout()
```

```
Found 8999 correct labels
```



```
incorrect=np.where(predicted_classes!=test_Y)[0]
print("Found %d incorrect labels" % len(incorrect))
for i,incorrect in enumerate(incorrect[:9]):
  plt.subplot(3,3,i+1)
  plt.imshow(test_X[incorrect].reshape(28,28),cmap='gray',interpolation='none')
  plt.title("predicted {}, class {}".format(predicted_classes[incorrect],test_Y[incorrec
  plt.tight_layout()
```

```
Found 1001 incorrect labels
```




```
from sklearn.metrics import classification_report
target_names=["class{}".format(i) for i in range(num_classes)]
print(classification_report(test_Y,predicted_classes,target_names=target_names))
```

```
              precision    recall  f1-score   support

      class0       0.70      0.95      0.81      1000
      class1       0.99      0.98      0.99      1000
      class2       0.83      0.88      0.85      1000
      class3       0.94      0.88      0.91      1000
      class4       0.83      0.86      0.85      1000
      class5       0.99      0.97      0.98      1000
      class6       0.89      0.55      0.68      1000
      class7       0.95      0.98      0.96      1000
      class8       0.99      0.98      0.99      1000
      class9       0.97      0.96      0.97      1000

    accuracy                           0.90     10000
   macro avg       0.91      0.90      0.90     10000
weighted avg       0.91      0.90      0.90     10000
```