tf-quick-intro

April 19, 2020

1 A Quick Introduction to TensorFlow 2.0 for Deep Learning

1.1 https://towardsdatascience.com/a-quick-introduction-to-tensorflow-2-0-for-deep-learning-e740ca2e974c

1.2 by George Seif, Oct 24, 2019

1.2.1 Google Colab Notebook can be found at: https://colab.research.google.com/drive/1KRi0k5X

1.2.2 YP 200330

[2]:
```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models, optimizers
import matplotlib.pyplot as plt

if tf.__version__ < "2.0.0":
  !pip install --upgrade tensorflow_gpu==2.0
```

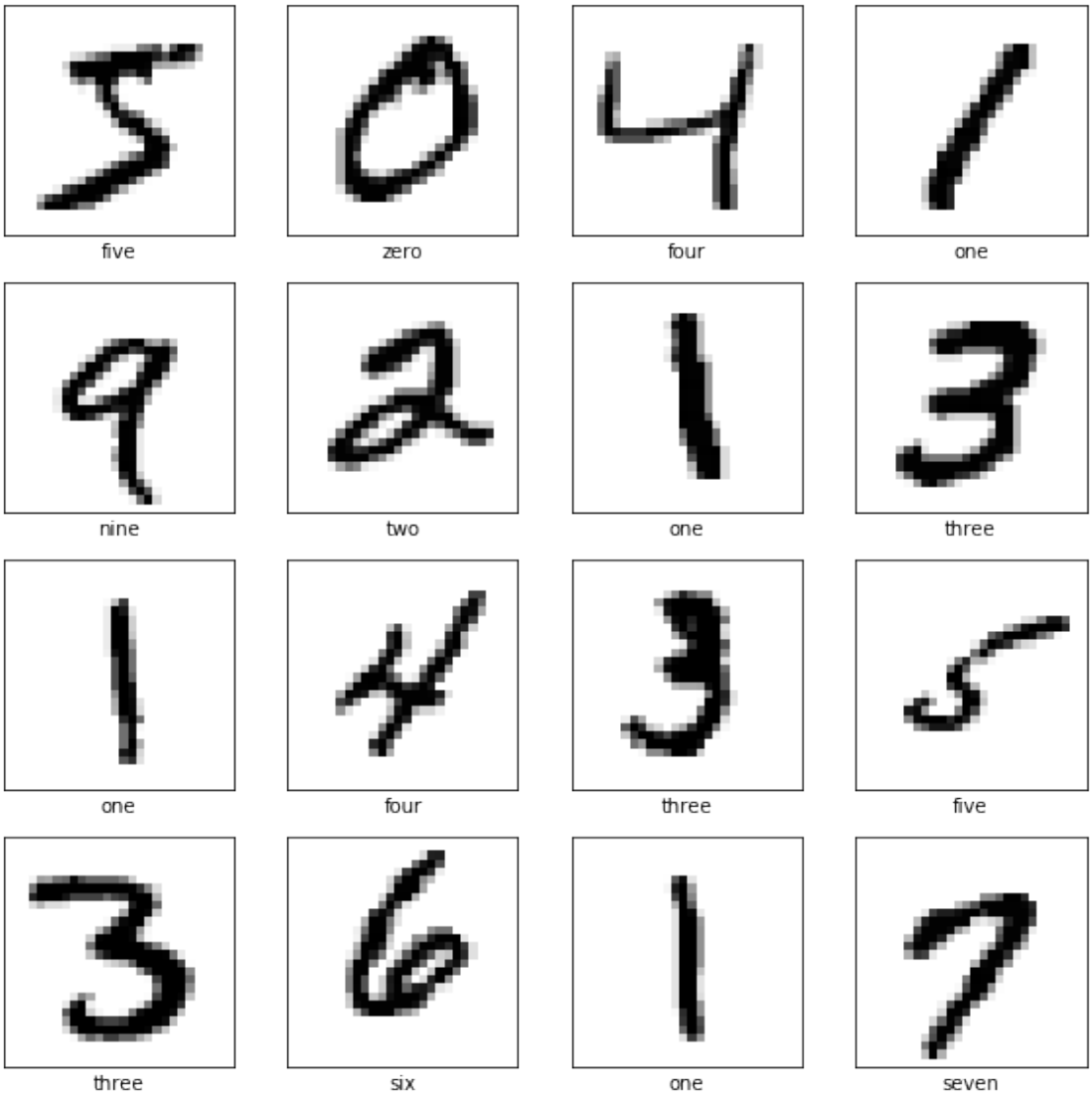
1.3 Loading data and visualisation

1.3.1 MNIST dataset contains

* 60,000 training images
* 10,000 test images
* digits from 0 to 9
* size 28x28

[3]:
```
(train_images, train_labels), (test_images, test_labels) = datasets.mnist.
 ↪load_data()

class_names = ['zero', 'one', 'two', 'three', 'four', 'five',
               'six', 'seven', 'eight', 'nine']

plt.figure(figsize=(10,10))
for i in range(16):
    plt.subplot(4, 4, i+1)
```

```
    plt.xticks([])
    plt.yticks([])
    plt.imshow(train_images[i], cmap=plt.cm.binary)
    plt.xlabel(class_names[train_labels[i]])
plt.show()
```



1.4 Model Definition

[4]:
```
IMG_SIZE = (28, 28, 1)
input_img = layers.Input(shape=IMG_SIZE)

model = layers.Conv2D(32, (3, 3), padding='same')(input_img)
```

```
model = layers.Activation('relu')(model)
model = layers.Conv2D(32, (3, 3), padding='same', strides=(2, 2))(model)
model = layers.Activation('relu')(model)

model = layers.Conv2D(64, (3, 3), padding='same')(model)
model = layers.Activation('relu')(model)
model = layers.Conv2D(64, (3, 3), padding='same', strides=(2, 2))(model)
model = layers.Activation('relu')(model)

model = layers.Conv2D(64, (3, 3), padding='same')(model)
model = layers.Activation('relu')(model)
model = layers.Conv2D(64, (3, 3), padding='same')(model)
model = layers.Activation('relu')(model)

model = layers.GlobalAveragePooling2D()(model)
model = layers.Dense(32)(model)
model = layers.Activation('relu')(model)
model = layers.Dense(10)(model)
output_img = layers.Activation('softmax')(model)

model = models.Model(input_img, output_img)

model.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 28, 28, 1)]       0
_________________________________________________________________
conv2d (Conv2D)              (None, 28, 28, 32)        320
_________________________________________________________________
activation (Activation)      (None, 28, 28, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 14, 14, 32)        9248
_________________________________________________________________
activation_1 (Activation)    (None, 14, 14, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 14, 14, 64)        18496
_________________________________________________________________
activation_2 (Activation)    (None, 14, 14, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 7, 7, 64)          36928
_________________________________________________________________
activation_3 (Activation)    (None, 7, 7, 64)          0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 7, 7, 64)          36928
```

```
_________________________________________________________________
activation_4 (Activation)    (None, 7, 7, 64)          0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 7, 7, 64)          36928
_________________________________________________________________
activation_5 (Activation)    (None, 7, 7, 64)          0
_________________________________________________________________
global_average_pooling2d (Gl (None, 64)                0
_________________________________________________________________
dense (Dense)                (None, 32)                2080
_________________________________________________________________
activation_6 (Activation)    (None, 32)                0
_________________________________________________________________
dense_1 (Dense)              (None, 10)                330
_________________________________________________________________
activation_7 (Activation)    (None, 10)                0
=================================================================
Total params: 141,258
Trainable params: 141,258
Non-trainable params: 0
_________________________________________________________________
```

1.5 Training and Testing

[5]:
```
train_images = train_images.reshape(60000, 28, 28, 1).astype('float32') / 255.0
test_images = test_images.reshape(10000, 28, 28, 1).astype('float32') / 255.0

train_labels = tf.keras.utils.to_categorical(train_labels, 10)
test_labels = tf.keras.utils.to_categorical(test_labels, 10)
```

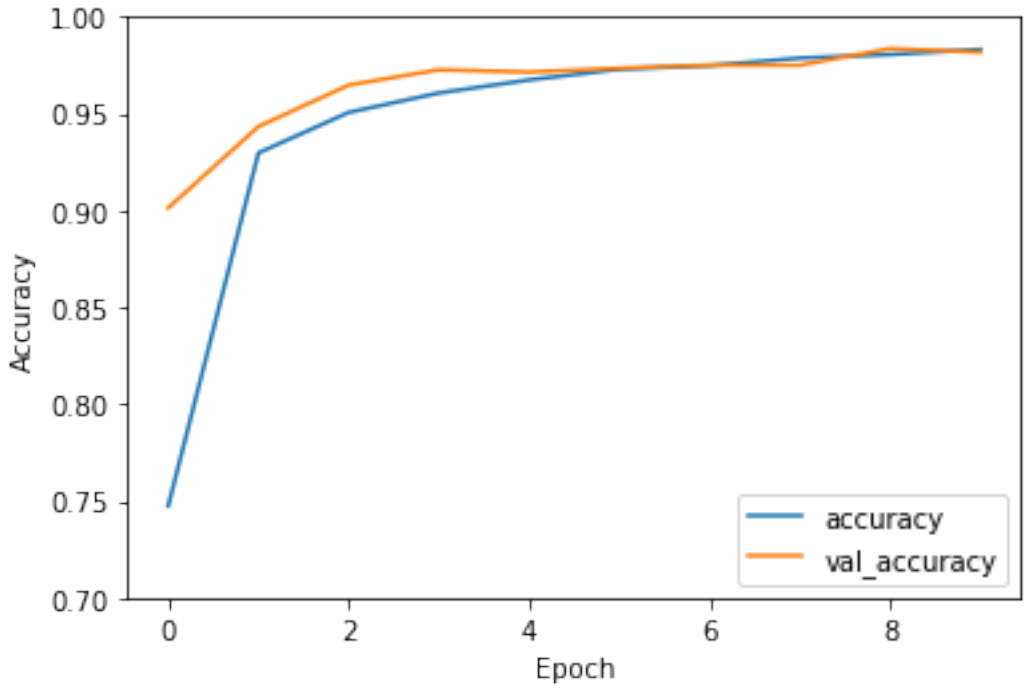
[6]:
```
adam = optimizers.Adam(lr=0.0001)
model.compile(adam, loss='categorical_crossentropy', metrics=["accuracy"])

history = model.fit(train_images, train_labels, epochs=10,
                    validation_data=(test_images, test_labels))
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/10
60000/60000 [==============================] - 7s 124us/sample - loss: 0.7584 -
accuracy: 0.7474 - val_loss: 0.3452 - val_accuracy: 0.9013
Epoch 2/10
60000/60000 [==============================] - 6s 103us/sample - loss: 0.2451 -
accuracy: 0.9297 - val_loss: 0.1927 - val_accuracy: 0.9433
Epoch 3/10
60000/60000 [==============================] - 6s 106us/sample - loss: 0.1698 -
accuracy: 0.9506 - val_loss: 0.1262 - val_accuracy: 0.9647
Epoch 4/10
```

```
60000/60000 [==============================] - 6s 104us/sample - loss: 0.1330 -
accuracy: 0.9606 - val_loss: 0.0880 - val_accuracy: 0.9726
Epoch 5/10
60000/60000 [==============================] - 6s 105us/sample - loss: 0.1091 -
accuracy: 0.9674 - val_loss: 0.0942 - val_accuracy: 0.9714
Epoch 6/10
60000/60000 [==============================] - 7s 109us/sample - loss: 0.0923 -
accuracy: 0.9729 - val_loss: 0.0848 - val_accuracy: 0.9734
Epoch 7/10
60000/60000 [==============================] - 6s 108us/sample - loss: 0.0824 -
accuracy: 0.9747 - val_loss: 0.0760 - val_accuracy: 0.9750
Epoch 8/10
60000/60000 [==============================] - 6s 105us/sample - loss: 0.0715 -
accuracy: 0.9786 - val_loss: 0.0763 - val_accuracy: 0.9750
Epoch 9/10
60000/60000 [==============================] - 6s 105us/sample - loss: 0.0637 -
accuracy: 0.9805 - val_loss: 0.0503 - val_accuracy: 0.9835
Epoch 10/10
60000/60000 [==============================] - 6s 105us/sample - loss: 0.0564 -
accuracy: 0.9831 - val_loss: 0.0584 - val_accuracy: 0.9817
```

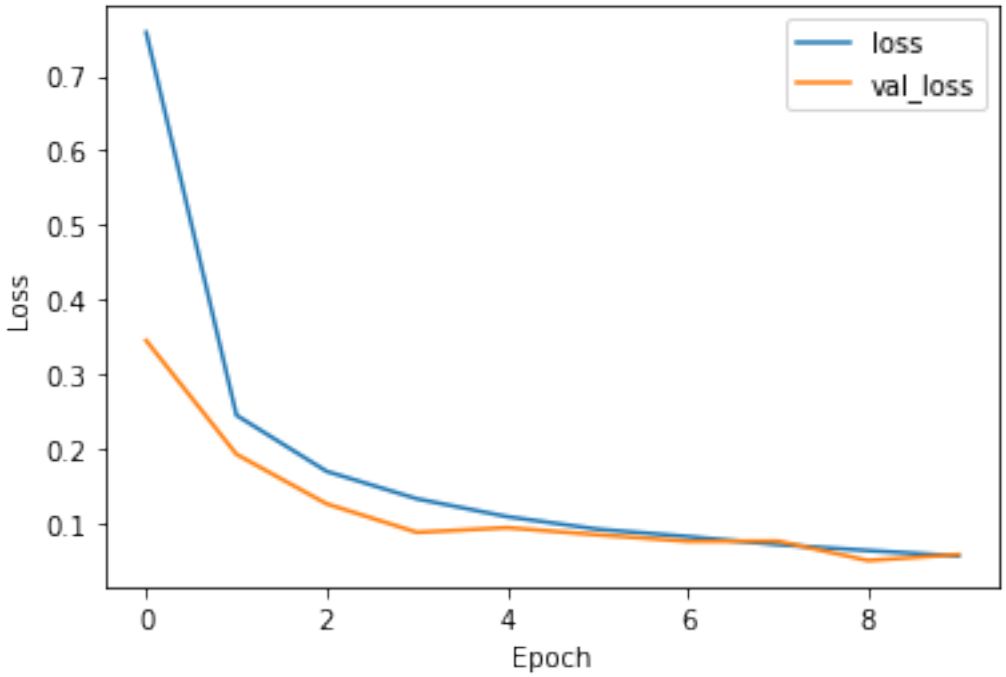
[7]:
```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.7, 1])
plt.legend(loc='best')
```

[7]:
```
<matplotlib.legend.Legend at 0x7f77504c8e90>
```



[8]:
```
plt.plot(history.history['loss'], label='loss')
plt.plot(history.history['val_loss'], label='val_loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(loc='best')
```

[8]: <matplotlib.legend.Legend at 0x7f775049f110>



[9]:
```
test_loss, test_accuracy = model.evaluate(test_images,  test_labels, verbose=2)

print('\nTest accuracy = {0:.2f}%'.format(test_accuracy*100.0))
```

```
10000/1 - 0s - loss: 0.0293 - accuracy: 0.9817

Test accuracy = 98.17%
```