# < Deep Learning - PART2 TF2 CNNs >

# Ch 5. CNNs Workshop 4 - CIFAR10 : Image Classifier on Google Colab & Google Drive ¶

2021/10/01

**[ Reference ] :**

- TensorFlow Core - Tutorials: **Convolutional Neural Network (CNN)** https://www.tensorflow.org/tutorials/images/cnn?hl=zh_tw (https://www.tensorflow.org/tutorials/images/cnn?hl=zh_tw)
- **CIFAR-10 and CIFAR-100 datasets** https://www.cs.toronto.edu/~kriz/cifar.html (https://www.cs.toronto.edu/~kriz/cifar.html)
- 李飛飛教授：Convolutional Neural Networks (教學投影片) (http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture5.pdf (http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture5.pdf))
- 李飛飛教授：Convolutional Neural Networks (CNNs / ConvNets) (https://cs231n.github.io/convolutional-networks/ (https://cs231n.github.io/convolutional-networks/))
- `tf.keras.layers.Conv2D` (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Conv2D (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Conv2D))

---

In [ ]:

```
import tensorflow as tf
print(tf.__version__)

from tensorflow.keras import layers, models
```

```
2.3.0
```

## Download CIFAR-10 Python Version dataset from

- **https://www.cs.toronto.edu/~kriz/cifar.html (https://www.cs.toronto.edu/~kriz/cifar.html)**
- The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

> **[ Reference ] :**

- `Learning Multiple Layers of Features from Tiny Images` , Alex Krizhevsky, 2009. https://www.cs.toronto.edu/~kriz/learning-features-2009-TR.pdf

(https://www.cs.toronto.edu/~kriz/learning-features-2009-TR.pdf)

In [ ]:

```
import numpy as np

class CifarLoader(object):
    def __init__(self, source_files):
        self._source = source_files
        self._i = 0
        self.images = None
        self.labels = None

    def load(self):
        data = [unpickle(f) for f in self._source]
        # print(data)
        images = np.vstack([d[b"data"] for d in data])
        n = len(images)  # 32 x 32 x 3 channels
        self.images = images.reshape(n, 3, 32, 32).transpose(0, 2, 3, 1).as
        self.labels = one_hot(np.hstack([d[b"labels"] for d in data]), 10)
        return self

    def next_batch(self, batch_size):
        x, y = self.images[self._i : self._i+batch_size], self.labels[self.
        self._i = (self._i + batch_size) % len(self.images)
        return x, y
```

## Loading dataset and running this program on the Google's Colab...

In [ ]:

```
# Load the Drive helper and mount
from google.colab import drive

# This will prompt for authorization.
drive.mount('/content/drive')

##  Go to this URL in a browser: https://accounts.google.com/o/oauth2/.....
##  Enter your authorization code:
##   ..........
##  Mounted at /content/drive
```

```
Mounted at /content/drive
```

In [ ]:

```
# After executing the cell above, Drive
# files will be present in "/content/drive/My Drive".
# !ls "/content/drive/My Drive"
!ls "/content/drive/My Drive/Colab Notebooks/cifar-10-batches-py"
##  Loading CIFAR-10 dataset from your Google Drive
DATA_PATH = "/content/drive/My Drive/Colab Notebooks/cifar-10-batches-py"
```

```
batches.meta   data_batch_2   data_batch_4   readme.html
data_batch_1   data_batch_3   data_batch_5   test_batch
```

### Loading dataset from the unzipped files...

In [ ]:

```
import pickle
import os

##  Loading CIFAR-10 dataset from your Google Drive
DATA_PATH = "/content/drive/My Drive/Colab Notebooks/cifar-10-batches-py"

##  < for CIFAR-10 dataset on local host >
##  DATA_PATH = "./cifar-10-batches-py"

def unpickle(file):
    with open(os.path.join(DATA_PATH, file), 'rb') as fo:
        dict = pickle.load(fo, encoding='bytes')    ##  encoding='bytes'
    return dict

def one_hot(vec, vals=10):
    n = len(vec)
    out = np.zeros((n, vals))
    out[range(n), vec] = 1
    return out
```

In [ ]:

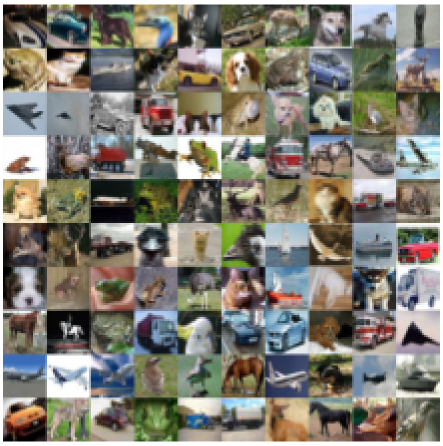
```
class CifarDataManager(object):
    def __init__(self):
        self.train = CifarLoader(["data_batch_{}".format(i)
                                  for i in range(1, 6)]).load()
        self.test = CifarLoader(["test_batch"]).load()
```

In [ ]:

```
import matplotlib.pyplot as plt
%matplotlib inline

def display_cifar(images, size):
    n = len(images)
    plt.figure()
    plt.gca().set_axis_off()
    im = np.vstack([np.hstack([images[np.random.choice(n)] for i in range(s
        for i in range(size)])
    plt.imshow(im)
    plt.show()

cifar = CifarDataManager()  # Loading CIFAR-10 dataset
images = cifar.train.images
display_cifar(images, 10)
```



In [ ]:

```
print("Number of train images: {}".format(len(cifar.train.images)))
print("Number of train labels: {}".format(len(cifar.train.labels)))
print("Number of test images: {}".format(len(cifar.test.images)))
print("Number of test images: {}".format(len(cifar.test.labels)))
```

```
Number of train images: 50000
Number of train labels: 50000
Number of test images: 10000
Number of test images: 10000
```

In [ ]:

```python
print("Train images: {}".format(cifar.train.images.shape))
print("Train labels: {}".format(cifar.train.labels.shape))
print(" Test images: {}".format(cifar.test.images.shape))
print(" Test labels: {}".format(cifar.test.labels.shape))
```

```
Train images: (50000, 32, 32, 3)
Train labels: (50000, 10)
 Test images: (10000, 32, 32, 3)
 Test labels: (10000, 10)
```

---

## < CNN Model > :

---

- **Forward Propagation**

In [200]:

```
model = models.Sequential()

# 1st (Conv Layer + Batch Norm) * 3 + MaxPooling Layer
model.add(layers.Conv2D(32, (3, 3), activation='relu',
            padding='same', input_shape=(32, 32, 3)))
model.add(layers.BatchNormalization())     # Batch Norm
model.add(layers.Conv2D(32, (3, 3), activation='relu', padding='same'))
model.add(layers.BatchNormalization())     # Batch Norm
model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(layers.BatchNormalization())     # Batch Norm
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Dropout(0.25))

# 2nd (Conv Layer + Batch Norm) * 2 + MaxPooling Layer
model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(layers.BatchNormalization())     # Batch Norm
model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(layers.BatchNormalization())     # Batch Norm
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Dropout(0.25))

# 3rd (Conv Layer + Batch Norm) * 2 + MaxPooling Layer
model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
model.add(layers.BatchNormalization())     # Batch Norm
model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
model.add(layers.BatchNormalization())     # Batch Norm
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Dropout(0.5))

# 4th (Conv Layer + Batch Norm) * 2
model.add(layers.Conv2D(256, (3, 3), activation='relu', padding='same'))
model.add(layers.BatchNormalization())     # Batch Norm
model.add(layers.Conv2D(256, (3, 3), activation='relu', padding='same'))
model.add(layers.BatchNormalization())     # Batch Norm
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Dropout(0.5))
```

In [201]:

```
model.add(layers.Flatten())
model.add(layers.Dense(128, activation='relu'))
model.add(layers.BatchNormalization())     # Batch Norm
model.add(layers.Dropout(0.25))
model.add(layers.Dense(10, activation='softmax'))
```

In [202]:

```
1  model.summary()
```

```
Model: "sequential_30"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_245 (Conv2D)          (None, 32, 32, 32)        896
_________________________________________________________________
batch_normalization_280 (Bat (None, 32, 32, 32)        128
_________________________________________________________________
conv2d_246 (Conv2D)          (None, 32, 32, 32)        9248
_________________________________________________________________
batch_normalization_281 (Bat (None, 32, 32, 32)        128
_________________________________________________________________
conv2d_247 (Conv2D)          (None, 32, 32, 64)        18496
_________________________________________________________________
batch_normalization_282 (Bat (None, 32, 32, 64)        256
_________________________________________________________________
max_pooling2d_111 (MaxPoolin (None, 16, 16, 64)        0
_________________________________________________________________
dropout_149 (Dropout)        (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_248 (Conv2D)          (None, 16, 16, 64)        36928
_________________________________________________________________
batch_normalization_283 (Bat (None, 16, 16, 64)        256
_________________________________________________________________
conv2d_249 (Conv2D)          (None, 16, 16, 64)        36928
_________________________________________________________________
batch_normalization_284 (Bat (None, 16, 16, 64)        256
_________________________________________________________________
max_pooling2d_112 (MaxPoolin (None, 8, 8, 64)          0
_________________________________________________________________
dropout_150 (Dropout)        (None, 8, 8, 64)          0
_________________________________________________________________
conv2d_250 (Conv2D)          (None, 8, 8, 128)         73856
_________________________________________________________________
batch_normalization_285 (Bat (None, 8, 8, 128)         512
_________________________________________________________________
conv2d_251 (Conv2D)          (None, 8, 8, 128)         147584
_________________________________________________________________
batch_normalization_286 (Bat (None, 8, 8, 128)         512
_________________________________________________________________
max_pooling2d_113 (MaxPoolin (None, 4, 4, 128)         0
_________________________________________________________________
dropout_151 (Dropout)        (None, 4, 4, 128)         0
_________________________________________________________________
conv2d_252 (Conv2D)          (None, 4, 4, 256)         295168
_________________________________________________________________
batch_normalization_287 (Bat (None, 4, 4, 256)         1024
_________________________________________________________________
conv2d_253 (Conv2D)          (None, 4, 4, 256)         590080
_________________________________________________________________
batch_normalization_288 (Bat (None, 4, 4, 256)         1024
_________________________________________________________________
```

```
max_pooling2d_114 (MaxPoolin (None, 2, 2, 256)         0
_________________________________________________________________
dropout_152 (Dropout)        (None, 2, 2, 256)         0
_________________________________________________________________
flatten_29 (Flatten)         (None, 1024)              0
_________________________________________________________________
dense_64 (Dense)             (None, 128)               131200
_________________________________________________________________
batch_normalization_289 (Bat (None, 128)               512
_________________________________________________________________
dropout_153 (Dropout)        (None, 128)               0
_________________________________________________________________
dense_65 (Dense)             (None, 10)                1290
=================================================================
Total params: 1,346,282
Trainable params: 1,343,978
Non-trainable params: 2,304
_________________________________________________________________
```

- **Back-Propagation**

In [203]:

```
model.compile(optimizer='adam',
       loss='categorical_crossentropy',
       metrics=['accuracy'])
```

## Training ...

- **BATCH_SIZE = 32 (default value : 32)**

In [204]:

```
history = model.fit(cifar.train.images, cifar.train.labels, epochs=30,
          validation_split=0.1)
```

```
Epoch 1/30
1407/1407 [==============================] - 36s 26ms/step - los
s: 1.6297 - accuracy: 0.4180 - val_loss: 1.1772 - val_accuracy:
0.5842
Epoch 2/30
1407/1407 [==============================] - 36s 26ms/step - los
s: 1.0685 - accuracy: 0.6246 - val_loss: 0.9373 - val_accuracy:
0.6838
Epoch 3/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.8717 - accuracy: 0.6985 - val_loss: 0.7267 - val_accuracy:
0.7464
Epoch 4/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.7530 - accuracy: 0.7415 - val_loss: 0.7063 - val_accuracy:
0.7534
Epoch 5/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.6714 - accuracy: 0.7692 - val_loss: 0.6229 - val_accuracy:
0.7980
Epoch 6/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.6237 - accuracy: 0.7879 - val_loss: 0.6122 - val_accuracy:
0.7910
Epoch 7/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.5640 - accuracy: 0.8100 - val_loss: 0.5447 - val_accuracy:
0.8166
Epoch 8/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.5254 - accuracy: 0.8217 - val_loss: 0.6024 - val_accuracy:
0.7990
Epoch 9/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.4881 - accuracy: 0.8335 - val_loss: 0.5462 - val_accuracy:
0.8170
Epoch 10/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.4608 - accuracy: 0.8414 - val_loss: 0.5271 - val_accuracy:
0.8266
Epoch 11/30
1407/1407 [==============================] - 36s 26ms/step - los
s: 0.4340 - accuracy: 0.8521 - val_loss: 0.4729 - val_accuracy:
0.8408
Epoch 12/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.4074 - accuracy: 0.8621 - val_loss: 0.4527 - val_accuracy:
0.8502
Epoch 13/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.3886 - accuracy: 0.8671 - val_loss: 0.4408 - val_accuracy:
```

```
0.8558
Epoch 14/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.3676 - accuracy: 0.8753 - val_loss: 0.4486 - val_accuracy:
0.8522
Epoch 15/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.3516 - accuracy: 0.8808 - val_loss: 0.4873 - val_accuracy:
0.8440
Epoch 16/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.3299 - accuracy: 0.8876 - val_loss: 0.4335 - val_accuracy:
0.8630
Epoch 17/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.3204 - accuracy: 0.8894 - val_loss: 0.4237 - val_accuracy:
0.8660
Epoch 18/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.3115 - accuracy: 0.8938 - val_loss: 0.4284 - val_accuracy:
0.8658
Epoch 19/30
1407/1407 [==============================] - 36s 26ms/step - los
s: 0.3003 - accuracy: 0.8970 - val_loss: 0.4308 - val_accuracy:
0.8640
Epoch 20/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.2895 - accuracy: 0.8990 - val_loss: 0.4123 - val_accuracy:
0.8666
Epoch 21/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.2723 - accuracy: 0.9065 - val_loss: 0.4504 - val_accuracy:
0.8614
Epoch 22/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.2673 - accuracy: 0.9094 - val_loss: 0.4262 - val_accuracy:
0.8622
Epoch 23/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.2600 - accuracy: 0.9108 - val_loss: 0.4090 - val_accuracy:
0.8734
Epoch 24/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.2544 - accuracy: 0.9116 - val_loss: 0.4136 - val_accuracy:
0.8788
Epoch 25/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.2436 - accuracy: 0.9158 - val_loss: 0.4543 - val_accuracy:
0.8686
Epoch 26/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.2408 - accuracy: 0.9156 - val_loss: 0.3975 - val_accuracy:
0.8820
Epoch 27/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.2309 - accuracy: 0.9218 - val_loss: 0.4165 - val_accuracy:
0.8758
```

```
Epoch 28/30
1407/1407 [==============================] - 36s 26ms/step - los
s: 0.2229 - accuracy: 0.9233 - val_loss: 0.4247 - val_accuracy:
0.8750
Epoch 29/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.2180 - accuracy: 0.9253 - val_loss: 0.4129 - val_accuracy:
0.8808
Epoch 30/30
1407/1407 [==============================] - 36s 25ms/step - los
s: 0.2110 - accuracy: 0.9272 - val_loss: 0.4270 - val_accuracy:
0.8796
```

## Evaluation

In [205]:

```
test_loss, test_acc = model.evaluate(x=cifar.test.images, y=cifar.test.labe
test_loss, test_acc
```

```
313/313 [==============================] - 3s 9ms/step - loss: 0.
4396 - accuracy: 0.8725
```

Out[205]:

```
(0.4396136701107025, 0.8725000023841858)
```

In [206]:

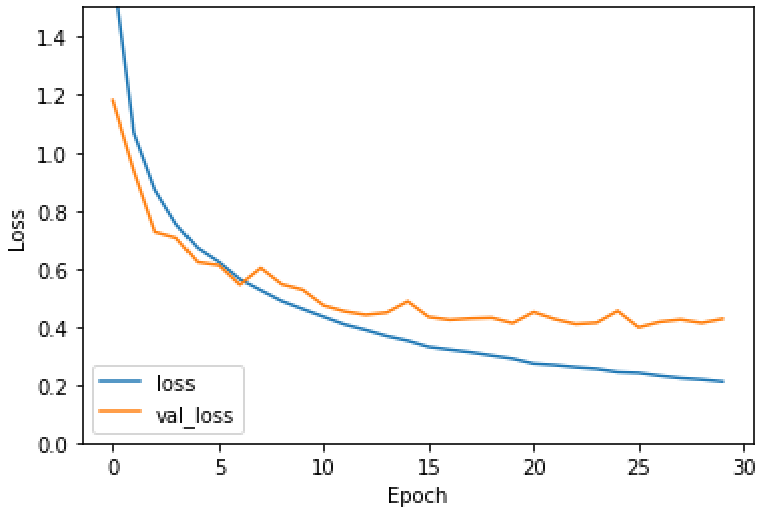
```
history.history.keys()
```

Out[206]:

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

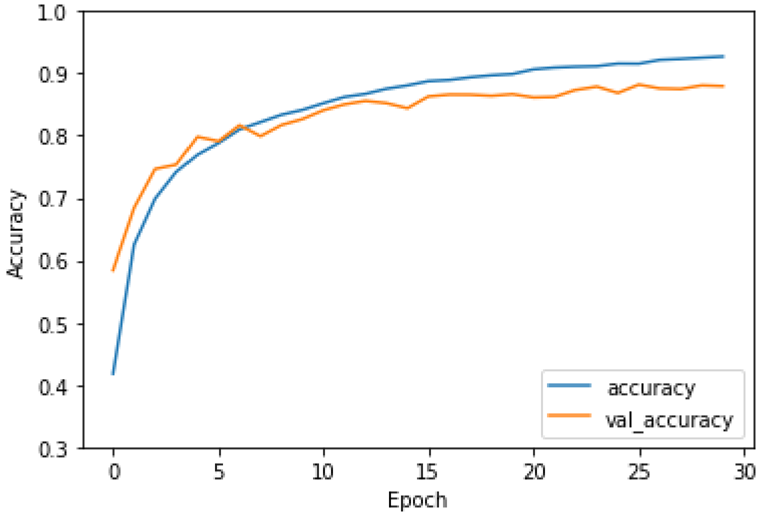
In [211]:

```
plt.plot(history.history['loss'], label='loss')
plt.plot(history.history['val_loss'], label = 'val_loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.ylim([0, 1.5])
plt.legend(loc='lower left')
plt.show()
```




In [212]:

```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.3, 1])
plt.legend(loc='lower right')
plt.show()
```




## Confusion Matrix

In [213]:

```
test_predict = model.predict(cifar.test.images)
test_predict
```

Out[213]:

```
array([[1.4182602e-07, 6.2875465e-08, 1.6014928e-06, ..., 1.25194
69e-07,
        8.0835086e-08, 4.2166075e-08],
       [1.9468818e-05, 1.6829812e-03, 4.2885876e-08, ..., 8.36456
15e-09,
        9.9829668e-01, 1.8060865e-07],
       [2.0425217e-04, 9.9261886e-01, 8.2219703e-06, ..., 1.92755
10e-06,
        7.1251350e-03, 3.2941814e-05],
       ...,
       [1.0717752e-06, 7.5279139e-08, 4.6543805e-06, ..., 1.41682
93e-06,
        3.6145357e-07, 2.2929487e-07],
       [8.8150543e-04, 9.9872953e-01, 1.4206319e-04, ..., 9.55433
55e-06,
        5.1114512e-05, 4.8709891e-05],
       [2.7192047e-07, 1.7739443e-06, 4.2710103e-06, ..., 9.99820
53e-01,
        1.7729168e-07, 1.5285700e-07]], dtype=float32)
```

In [214]:

```
import numpy as np
test_predict_result = np.array([np.argmax(test_predict[i]) for i in range(l
test_predict_result
```

Out[214]:

```
array([3, 8, 1, ..., 5, 1, 7])
```

In [215]:

```
test_labels = np.array([np.argmax(cifar.test.labels[i])
                        for i in range(len(cifar.test.labels))])
test_labels
```

Out[215]:

```
array([3, 8, 8, ..., 5, 1, 7])
```

In [217]:

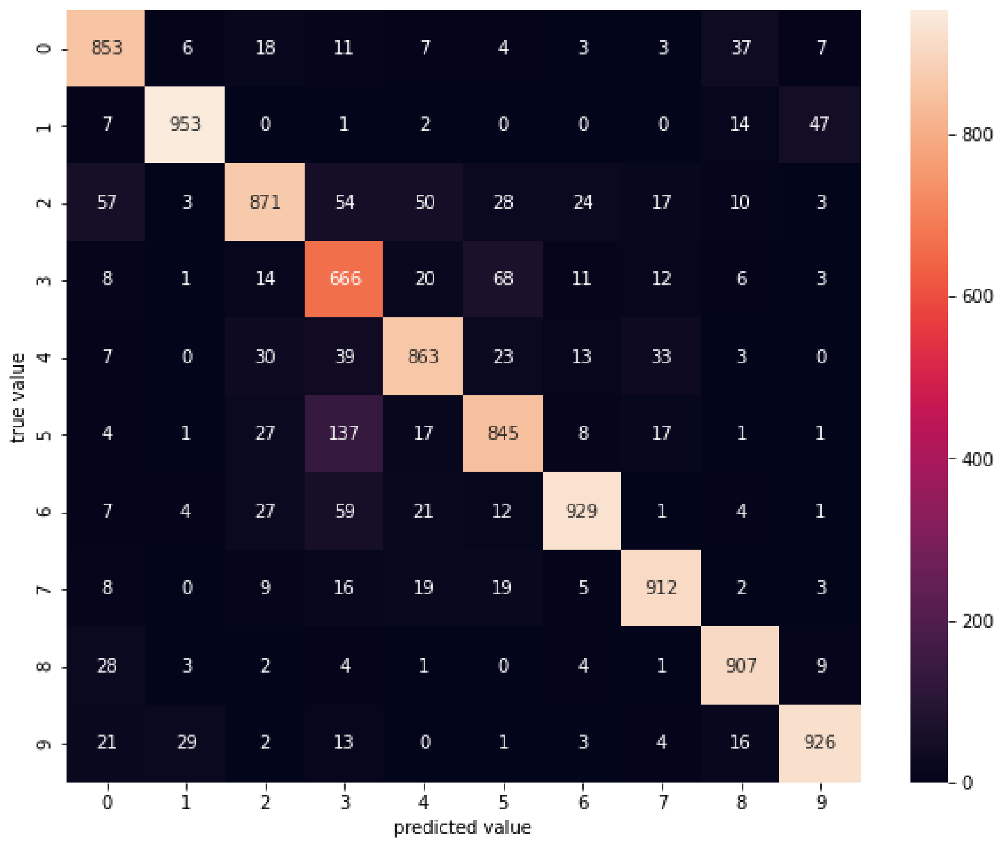
```python
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from sklearn.metrics import confusion_matrix

mat = confusion_matrix(test_predict_result, test_labels)

plt.figure(figsize=(10,8))
sns.heatmap(mat, square=False, annot=True, fmt ='d', cbar=True)
plt.xlim((0, 10))
plt.ylim((10, 0))
plt.xlabel('predicted value')
plt.ylabel('true value')
plt.show()

print(mat)
```




```
[[853   6  18  11   7   4   3   3  37   7]
```

```
[   7 953   0   1   2   0   0   0  14  47]
[  57   3 871  54  50  28  24  17  10   3]
[   8   1  14 666  20  68  11  12   6   3]
[   7   0  30  39 863  23  13  33   3   0]
[   4   1  27 137  17 845   8  17   1   1]
[   7   4  27  59  21  12 929   1   4   1]
[   8   0   9  16  19  19   5 912   2   3]
[  28   3   2   4   1   0   4   1 907   9]
[  21  29   2  13   0   1   3   4  16 926]]
```