深度学习框架实战

山东理工大学 数学与统计学院 周世祥

Keras卷积神经网络识别CIFAR图像集

In [1]:

```
import tensorflow as tf
tf.__version__
```

Out[1]:

```
'1.2.1'
```

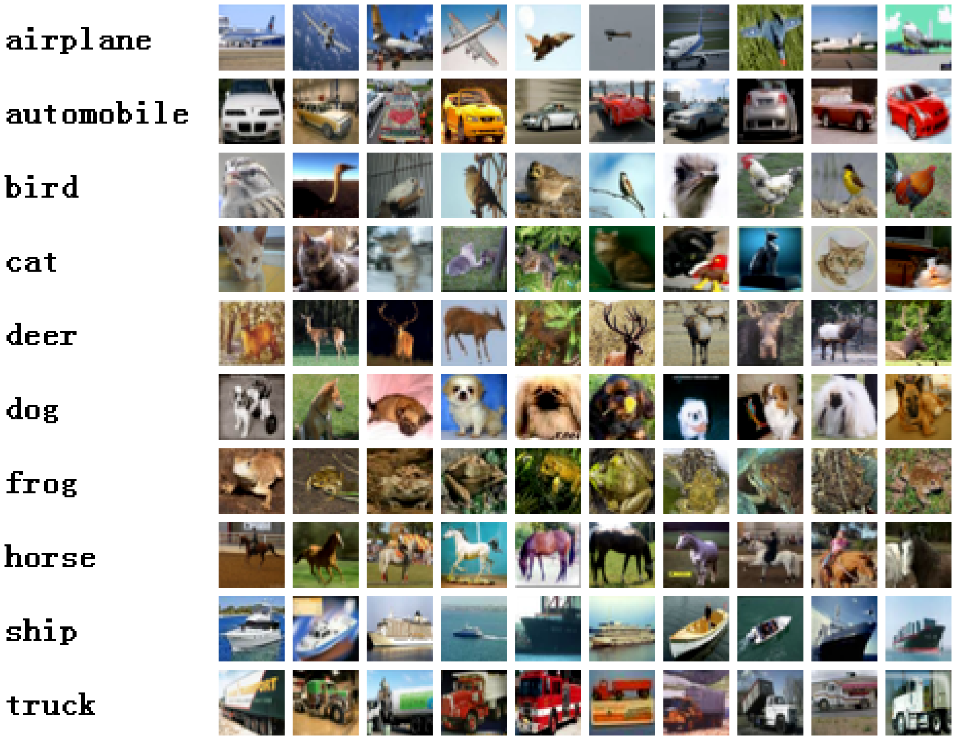
In [2]:

```
import keras
keras.__version__
```

```
Using TensorFlow backend.
```

Out[2]:

```
'2.0.2'
```



共有10类，飞机，汽车，鸟，猫，鹿，狗，青蛙，马，船，卡车。

http://www.cs.toronto.edu/~kriz/cifar.html (http://www.cs.toronto.edu/~kriz/cifar.html)

http://rodrigob.github.io/are_we_there_yet/build/classification_datasets_results.html (http://rodrigob.github.io/are_we_there_yet/build/classification_datasets_results.html)

In [3]:

```
import numpy
from keras.datasets import cifar10
import numpy as np
np.random.seed(10)
#第一次执行cifar10.load_data()方法时，程序会检查是否有cifar-10-batches-py.tar文件
#如果没有会从网络下载，并解压缩文件，运行时间可能有点长。
```

数据准备

In [4]:

```
(x_img_train,y_label_train), \
(x_img_test, y_label_test)=cifar10.load_data()
```

In [5]:

```
print(’train:’,len(x_img_train))
print(’test :’,len(x_img_test))
#查看数据项数
#train训练数据有50000项
#test测试数据有10000项
```

```
train: 50000
test : 10000
```

查看训练数据

训练数据是由images与label所组成，y_label_train是图像数据真实值，每一个数字代表一种图像类别的名称，共有10个类别。

Images的shape形状：使用shape方法

In [6]:

```
x_img_train.shape
#第四项是3，表示RGB图像
```

Out[6]:

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

In [7]:

```
x_img_test[0]
#第0项images的内容，每一个点是由RGB三原色所组成的
```

Out[7]:

```
array([[[158, 112,  49],
        [159, 111,  47],
        [165, 116,  51],
        ...,
        [137,  95,  36],
        [126,  91,  36],
        [116,  85,  33]],

       [[152, 112,  51],
        [151, 110,  40],
        [159, 114,  45],
        ...,
        [136,  95,  31],
        [125,  91,  32],
        [119,  88,  34]],

       [[151, 110,  47],
        [151, 109,  33],
        [158, 111,  36],
        ...,
        [139,  98,  34],
        [130,  95,  34],
        [120,  89,  33]],


       ...,
       [[ 68, 124, 177],
        [ 42, 100, 148],
        [ 31,  88, 137],
        ...,
        [ 38,  97, 146],
        [ 13,  64, 108],
        [ 40,  85, 127]],

       [[ 61, 116, 168],
        [ 49, 102, 148],
        [ 35,  85, 132],
        ...,
        [ 26,  82, 130],
        [ 29,  82, 126],
        [ 20,  64, 107]],

       [[ 54, 107, 160],
        [ 56, 105, 149],
        [ 45,  89, 132],
        ...,
        [ 24,  77, 124],
        [ 34,  84, 129],
        [ 21,  67, 110]]], dtype=uint8)
```

In [8]:

```
y_label_train.shape
#
```

Out[8]:

```
(50000, 1)
```

In [9]:

```
x_img_test.shape
```

Out[9]:

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

In [10]:

```
x_img_test[0]
```

Out[10]:

```
array([[[158, 112,  49],
        [159, 111,  47],
        [165, 116,  51],
        ...,
        [137,  95,  36],
        [126,  91,  36],
        [116,  85,  33]],

       [[152, 112,  51],
        [151, 110,  40],
        [159, 114,  45],
        ...,
        [136,  95,  31],
        [125,  91,  32],
        [119,  88,  34]],

       [[151, 110,  47],
        [151, 109,  33],
        [158, 111,  36],
        ...,
        [139,  98,  34],
        [130,  95,  34],
        [120,  89,  33]],


       ...,
       [[ 68, 124, 177],
        [ 42, 100, 148],
        [ 31,  88, 137],
        ...,
        [ 38,  97, 146],
        [ 13,  64, 108],
        [ 40,  85, 127]],

       [[ 61, 116, 168],
        [ 49, 102, 148],
        [ 35,  85, 132],
        ...,
        [ 26,  82, 130],
        [ 29,  82, 126],
        [ 20,  64, 107]],

       [[ 54, 107, 160],
        [ 56, 105, 149],
        [ 45,  89, 132],
        ...,
        [ 24,  77, 124],
        [ 34,  84, 129],
        [ 21,  67, 110]]], dtype=uint8)
```

In [11]:

```
y_label_test.shape
```

Out[11]:

```
(10000, 1)
```

In [12]:

```
label_dict={0:"airplane",1:"automobile",2:"bird",3:"cat",4:"deer",
            5:"dog",6:"frog",7:"horse",8:"ship",9:"truck"}
```

用字典定义每一个数字所代表的图形类别的名称

In [13]:

```
import matplotlib.pyplot as plt
def plot_images_labels_prediction(images,labels,prediction,
                                   idx,num=10):
    fig = plt.gcf()
    fig.set_size_inches(12, 14)
    if num>25: num=25
    for i in range(0, num):
        ax=plt.subplot(5,5, 1+i)
        ax.imshow(images[idx],cmap='binary')

        title=str(i)+','+label_dict[labels[i][0]]
        if len(prediction)>0:
            title+='=>'+label_dict[prediction[i]]

        ax.set_title(title,fontsize=10)
        ax.set_xticks([]);ax.set_yticks([])
        idx+=1
    plt.show()
#使用label_dict字典将label与prediction的0到9数字转换为图形类别名称

```

In [14]:

```
plot_images_labels_prediction(x_img_train,y_label_train,[],0)
#显示10项数据
#因为还没有预测数据，所用prediction参数输入为空

```

In [15]:

```
print('x_img_test:',x_img_test.shape)
print('y_label_test :',y_label_test.shape)
```

```
x_img_test: (10000, 32, 32, 3)
y_label_test : (10000, 1)
```

Image normalize

照片图像特征features标准化，提高模型预测的准确度，并且收敛更快。

In [16]:

```
x_img_train[0][0][0]
```

Out[16]:

```
array([59, 62, 63], dtype=uint8)
```

In [18]:

```
x_img_train_normalize = x_img_train.astype('float32') / 255.0
x_img_test_normalize = x_img_test.astype('float32') / 255.0
```

In [19]:

```
x_img_train_normalize[0][0][0]
```

Out[19]:

```
array([ 0.23137255,  0.24313726,  0.24705882], dtype=float32)
```

```
#将label照片图像真实的值以一位有效编码进行转换

```

```
将训练数据与测试数据的label都编码，转换label 为OneHot Encoding
```

In [20]:

```
y_label_train.shape
```

Out[20]:

```
(50000, 1)
```

In [21]:

```
y_label_train[:5]
```

Out[21]:

```
array([[6],
       [9],
       [9],
       [4],
       [1]], dtype=uint8)
```

In [22]:

```
from keras.utils import np_utils
y_label_train_OneHot = np_utils.to_categorical(y_label_train)
y_label_test_OneHot = np_utils.to_categorical(y_label_test)
```

In [23]:

```
y_label_train_OneHot.shape
```

Out[23]:

```
(50000, 10)
```

In [24]:

```
y_label_train_OneHot[:5]
```

Out[24]:

```
array([[ 0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.],
       [ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.],
       [ 0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.],
       [ 0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.]])
```

建立模型

In [25]:

```
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Flatten
from keras.layers import Conv2D, MaxPooling2D, ZeroPadding2D
```

In [26]:

```
model = Sequential()
#线性堆叠模型
```

In [27]:

```
#卷积层1
```

In [29]:

```
model.add(Conv2D(filters=32,kernel_size=(3,3),
                 input_shape=(32, 32,3),
                 activation='relu',
                 padding='same'))
#32*32的图像，共产生32个图像
#filters=32：随机产生32个滤镜
#padding='same' 让卷积运算产生的卷积图像大小不变
#input_shape=(32, 32,3)彩色RGB图像
```

In [30]:

```
model.add(Dropout(rate=0.25))
#训练中随机放弃25%的神经元，避免过拟合
```

In [32]:

```
model.add(MaxPooling2D(pool_size=(2, 2)))
#建立池化层1
#将32*32的图形缩减采样成16*16的图形
```

建立卷积层2与池化层2

In [33]:

```
model.add(Conv2D(filters=64, kernel_size=(3, 3),
                 activation='relu', padding='same'))
#执行第二次卷积运算，将原本的32个图像转换为64个图像，卷积运算不会改变图像大小，所以
#图形大小仍然是16*16
```

In [34]:

```
model.add(Dropout(0.25))
```

In [36]:

```
model.add(MaxPooling2D(pool_size=(2, 2)))
#将16*16的图像缩减采样为缩小为8*8的图像
```

建立平坦层

In [37]:

```
model.add(Flatten())
model.add(Dropout(rate=0.25))
```

In [38]:

```
model.add(Dense(1024, activation='relu'))
model.add(Dropout(rate=0.25))
#建立隐藏层，共1024个神经元
```

In [39]:

```
model.add(Dense(10, activation='softmax'))
#建立输出层
```

In [40]:

```
print(model.summary())
#模型摘要
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_1 (Conv2D)            (None, 32, 32, 32)        896       
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 32, 32, 32)        9248      
_________________________________________________________________
dropout_1 (Dropout)          (None, 32, 32, 32)        0         
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 16, 16, 32)        0         
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 8, 8, 32)          0         
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 8, 8, 64)          18496     
_________________________________________________________________
dropout_2 (Dropout)          (None, 8, 8, 64)          0         
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 4, 4, 64)          0         
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 2, 2, 64)          0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 256)               0         
_________________________________________________________________
dropout_3 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 1024)              263168    
_________________________________________________________________
dropout_4 (Dropout)          (None, 1024)              0         
_________________________________________________________________
dense_2 (Dense)              (None, 10)                10250     
=================================================================
Total params: 302,058.0
Trainable params: 302,058.0
Non-trainable params: 0.0
_________________________________________________________________
None
```

加载之前训练的模型，

In [41]:

```
try:
    model.load_weights("SaveModel/cifarCnnModelnew1.h5")
    print("加载模型成功!继续训练模型")
except :
    print("加载模型失败!开始训练一个新模型")
```

加载模型失败!开始训练一个新模型

训练模型

In [42]:

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

In [43]:

```
train_history=model.fit(x_img_train_normalize, y_label_train_OneHot,
                        validation_split=0.2,
                        epochs=10, batch_size=128, verbose=1)
#开始训练，训练过程会存储在train_history变量中
#verbose=2显示训练过程
```

```
Train on 40000 samples, validate on 10000 samples
Epoch 1/10
40000/40000 [==============================] - 189s - loss: 1.6941 - acc: 0.3739 -
 val_loss: 1.5088 - val_acc: 0.4760
Epoch 2/10
40000/40000 [==============================] - 192s - loss: 1.3632 - acc: 0.5062 -
 val_loss: 1.3045 - val_acc: 0.5794
Epoch 3/10
40000/40000 [==============================] - 204s - loss: 1.1903 - acc: 0.5725 -
 val_loss: 1.1796 - val_acc: 0.5976
Epoch 4/10
40000/40000 [==============================] - 204s - loss: 1.0961 - acc: 0.6075 -
 val_loss: 1.1266 - val_acc: 0.6188
Epoch 5/10
40000/40000 [==============================] - 199s - loss: 1.0240 - acc: 0.6325 -
 val_loss: 1.0397 - val_acc: 0.6598
Epoch 6/10
40000/40000 [==============================] - 202s - loss: 0.9578 - acc: 0.6613 -
 val_loss: 0.9773 - val_acc: 0.6772
Epoch 7/10
40000/40000 [==============================] - 203s - loss: 0.9284 - acc: 0.6710 -
 val_loss: 0.9499 - val_acc: 0.6732
Epoch 8/10
40000/40000 [==============================] - 205s - loss: 0.8951 - acc: 0.6836 -
 val_loss: 0.9464 - val_acc: 0.6844
Epoch 9/10
40000/40000 [==============================] - 204s - loss: 0.8528 - acc: 0.6965 -
 val_loss: 0.9426 - val_acc: 0.6774
Epoch 10/10
40000/40000 [==============================] - 204s - loss: 0.8301 - acc: 0.7030 -
 val_loss: 0.9365 - val_acc: 0.6924
```

50000*0.8=40000项作为训练数据，10000项作为验证数据。40000项数据分为每一批128项，所以大约分为160批次(40000/128=313)进行训练。

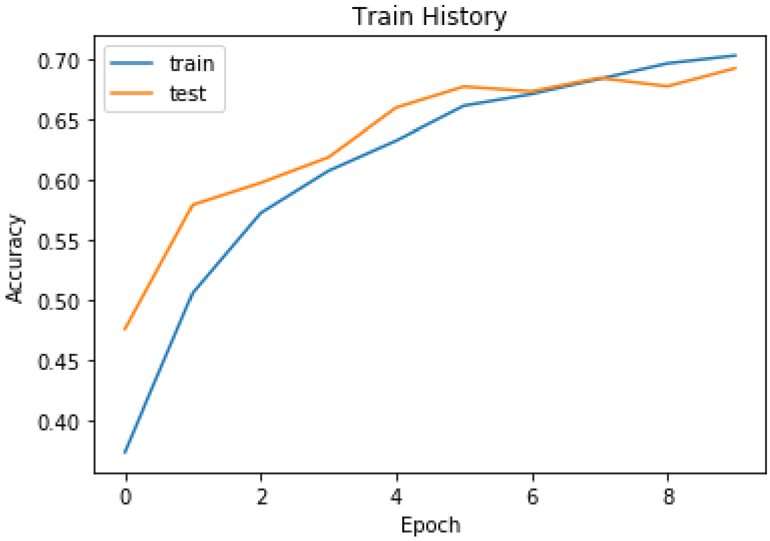
Epoch训练周期训练完成后，会计算这个训练周期的准确率与误差，并且在train_history中新增一项数据记录。

In [45]:

```
import matplotlib.pyplot as plt
def show_train_history(train_acc,test_acc):
    plt.plot(train_history.history[train_acc])
    plt.plot(train_history.history[test_acc])
    plt.title('Train History')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()
#画出准确率执行结果
```

In [46]:

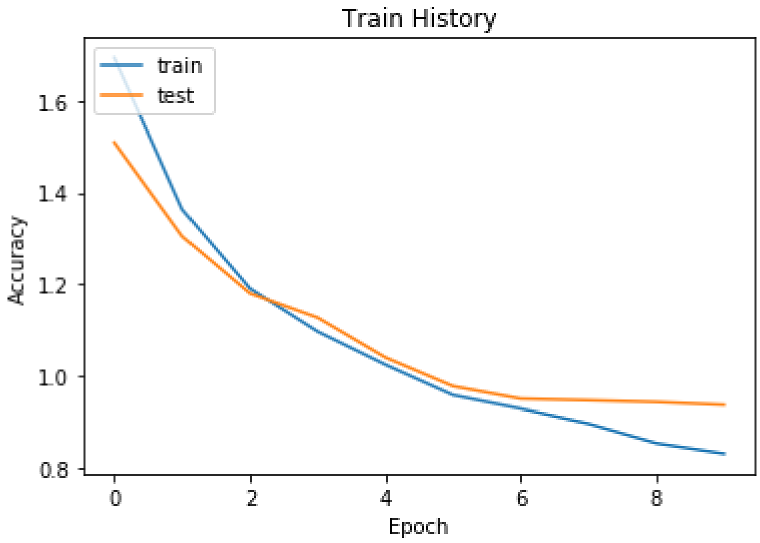
```
show_train_history('acc','val_acc')
```



In [47]:

```
show_train_history(’loss’,’val_loss’)
#误差执行结果

```



评估模型的准确率

In [48]:

```
scores = model.evaluate(x_img_test_normalize,
                        y_label_test_OneHot, verbose=0)
scores[1]
#模型评价的准确率
```

Out[48]:

```
0.68559999999999999
```

In [ ]:

```

```

进行预测

In [49]:

```
prediction=model.predict_classes(x_img_test_normalize)
```

```
 9984/10000 [============================>.] - ETA: 0s
```

In [50]:

```
prediction[:10]
#查看前十项预测结果

```

Out[50]:

```
array([3, 8, 8, 8, 6, 6, 1, 4, 3, 1], dtype=int64)
```

查看预测结果

In [51]:

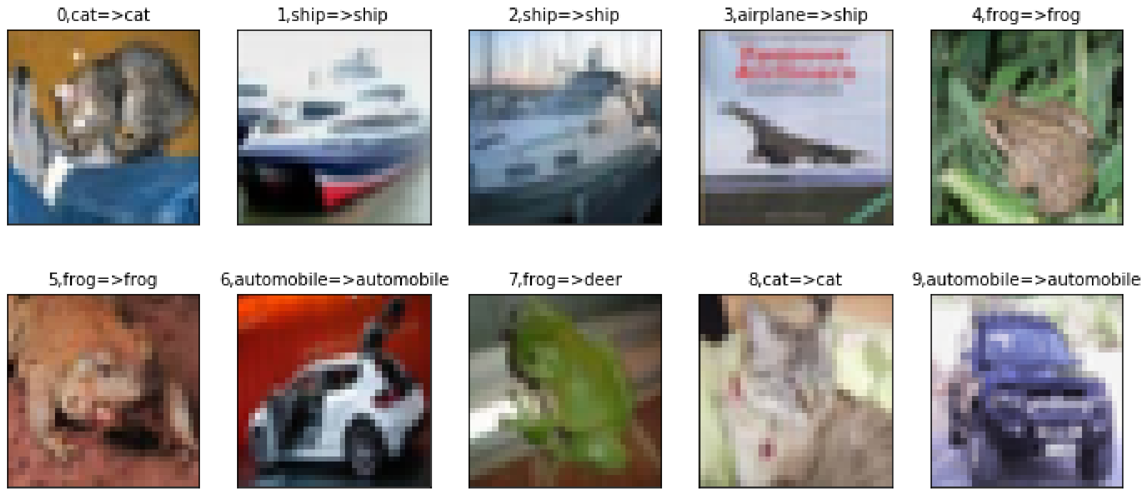
```
import matplotlib.pyplot as plt
def plot_images_labels_prediction(images,labels,prediction,
                                 idx,num=10):
    fig = plt.gcf()
    fig.set_size_inches(12, 14)
    if num>25: num=25
    for i in range(0, num):
        ax=plt.subplot(5,5, 1+i)
        ax.imshow(images[idx],cmap='binary')

        title=str(i)+','+label_dict[labels[i][0]]
        if len(prediction)>0:
            title+='=>'+label_dict[prediction[i]]

        ax.set_title(title,fontsize=10)
        ax.set_xticks([]);ax.set_yticks([])
        idx+=1
    plt.show()
```

In [52]:

```
plot_images_labels_prediction(x_img_test,y_label_test,
                             prediction,0,10)
```



第3号图预测错误：真实值是airplain，但是预测值是ship；

查看预测概率

In [53]:

```
Predicted_Probability=model.predict(x_img_test_normalize)
```

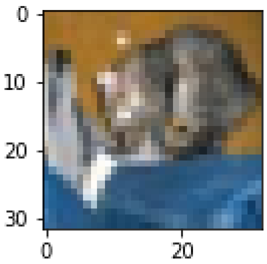
In [54]:

```
def show_Predicted_Probability(y,prediction,
                               x_img,Predicted_Probability,i):
    print('label:',label_dict[y[i][0]],
          'predict:',label_dict[prediction[i]])
    plt.figure(figsize=(2,2))#设置图像大小
    plt.imshow(np.reshape(x_img_test[i],(32, 32,3)))
    plt.show()
    for j in range(10):
        print(label_dict[j]+
              ' Probability:%1.9f'%(Predicted_Probability[i][j]))
#建立显示概率函数，y为真实值，predict为预测结果，x_img预测的图像，
#Predicted_Probability预测概率，i指开始显示的数据index
```

In [55]:

```
show_Predicted_Probability(y_label_test,prediction,
                           x_img_test,Predicted_Probability,0)
```

```
label: cat predict: cat
```



```
airplane Probability:0.000801388
automobile Probability:0.001107088
bird Probability:0.012050506
cat Probability:0.619248748
deer Probability:0.009993414
dog Probability:0.285810739
frog Probability:0.063496605
horse Probability:0.001948276
ship Probability:0.005124065
truck Probability:0.000419154
```

显示第0项数据项预测的概率，预测为“猫”的概率最大，其次为“狗”。