

# IBM Machine Learning

## Course 5: Deep Learning

### Topic 1: CIFAR-10 Data

#### 1. Introduction

We will work on the famous CIFAR-10 dataset, which consists of 60000 32x32 color images. The dataset can be split into 50K training images and 10K validation images.

The objective is to classify the images to 10 different classes. The 10 classes are:

- 1. automobile
- 2. bird
- 3. cat
- 4. deer
- 5. dog
- 6. frog
- 7. horse
- 8. ship
- 9. truck

#### 2. Explorative Data Analysis

##### 2.1 CIFAR data

```
In [45]: from keras.datasets import cifar10
import numpy as np

import matplotlib.pyplot as plt
import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten
from tensorflow.keras.optimizers import Adam, SGD, RMSprop
from tensorflow.keras.callbacks import ModelCheckpoint, TensorBoard

warnings.filterwarnings("ignore")

In [46]: # class list
class_list = ('airplane', 'automobile', 'bird', 'cat', 'deer',
            'dog', 'frog', 'horse', 'ship', 'truck')

In [47]: (x_train, y_train), (x_test, y_test) = cifar10.load_data()

In [48]: ## the size of training and test set
print('x_train shape:', x_train.shape)
print('x_test shape:', x_test.shape)
print('y_train shape:', y_train.shape)
print('y_test shape:', y_test.shape)

In [49]: ## randomly select one image from training set
selected = np.random.randint(50000)
print('The image selected is: ', selected)

The image selected is: 8486

In [50]: int(y_train[selected])

Out [50]: 1

In [51]: ## Let's look at one of the images
plt.imshow(x_train[selected])
plt.show(x_train[selected])

Out [51]: automobile
```

Out [51]:



##### 2.2 Data preprocess

```
In [52]: # Let's make everything float and scale
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255

In [53]: # Distribution of class in test set
unique, counts = np.unique(y_test, return_counts=True)
dict(zip(unique, counts))

Out [53]: {0: 1000, 1: 1000, 2: 1000, 3: 1000, 4: 1000, 5: 1000, 6: 1000, 7: 1000, 8: 1000, 9: 1000}
```

##### 3. Build Model

###### 3.1 Get a baseline performance using Random Forest

```
In [54]: ## Flatten our data
x_train_flat = x_train.reshape(len(x_train), -1)
x_test_flat = x_test.reshape(len(x_test), -1)

In [55]: ## the size of training
print('x_train_flat shape:', x_train_flat.shape)
x_train_flat = x_train_flat.reshape((50000, 3072))

In [56]: ## the size of testing
print('x_test_flat shape:', x_test_flat.shape)
x_test_flat = x_test_flat.reshape((10000, 3072))

In [57]: import datetime
Epoch = 100
now = datetime.datetime.now()

In [58]: from sklearn.metrics import confusion_matrix, precision_recall_curve, roc_auc_score, roc_curve, accuracy_score
from sklearn.ensemble import RandomForestClassifier

## Train the RF Model
t = now()
rf_model = RandomForestClassifier(n_estimators=200)
rf_model.fit(x_train_flat, y_train)
Epoch_training_time = (now() - t)

Training time: 0:06:14.270555

In [59]: ## Make predictions on the test set - both "hard" predictions, and the scores (percent of trees voting y)
y_pred_class_rf = rf_model.predict(x_test_flat)
y_prob_prob_rf = rf_model.predict_proba(x_test_flat)

print('Accuracy is (%.3f)' % accuracy_score(y_test, y_pred_class_rf))
accuracy is 0.485

In [60]: Confusion matrix (y_test, y_pred_class_rf)

Out [60]: array([[1570, 38, 52, 21, 36, 18, 26, 22, 160, 57],
       [29, 546, 16, 33, 15, 28, 43, 28, 62, 200],
       [19, 45, 349, 72, 142, 67, 124, 50, 33, 28],
       [15, 43, 68, 289, 71, 183, 144, 57, 22, 73],
       [138, 15, 143, 58, 400, 47, 155, 80, 21, 23],
       [26, 36, 83, 141, 83, 414, 86, 82, 28, 31],
       [11, 38, 70, 73, 92, 54, 597, 21, 5, 39],
       [43, 36, 43, 59, 102, 73, 46, 479, 23, 96],
       [87, 67, 17, 28, 15, 33, 9, 22, 628, 70],
       [39, 153, 20, 33, 18, 24, 24, 36, 78, 575]], dtype=int64)
```

As we can see above, the training time is long and the accuracy is quite low (less than 50%)

###### 3.2 Build a full connected neural network

```
In [61]: num_classes = 10

x_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)

In [62]: model = Sequential()
model.add(Dense(100, input_shape=(3072,), activation='sigmoid'))
Epoch_training_time = (now() - t)

In [63]: model.summary()

Model: "sequential_4"
Layer (type)                 Output Shape         Param #
-----
dense_8 (Dense)              (None, 100)          307300
-----
Total params: 308,310
Trainable params: 308,310
Non-trainable params: 0

In [74]: t = now()

# Compile the model with Optimizer, Loss Function and Metrics
opt_1 = keras.optimizers.RMSprop(lr=0.0005)

model.compile(optimizer=opt_1, loss='categorical_crossentropy', metrics=['accuracy'])
run_hist_1 = model_1.fit(x_train_flat, y_train, validation_data=(x_test_flat, y_test), epochs=200)

print('Training time: %s' % (now() - t))

Epoch 1/200
s: 1.8364 - val_accuracy: 0.3399 - 7s 5ms/step - loss: 1.7753 - accuracy: 0.3732 - val_loss: 1.8364 - val_accuracy: 0.3399
Epoch 2/200
s: 1.8374 - val_accuracy: 0.3395 - 6s 4ms/step - loss: 1.7714 - accuracy: 0.3757 - val_loss: 1.8374 - val_accuracy: 0.3395
Epoch 3/200
s: 1.8384 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7708 - accuracy: 0.3762 - val_loss: 1.8384 - val_accuracy: 0.3396
Epoch 4/200
s: 1.8394 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7662 - accuracy: 0.3793 - val_loss: 1.8394 - val_accuracy: 0.3396
Epoch 5/200
s: 1.8404 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7632 - accuracy: 0.3775 - val_loss: 1.8404 - val_accuracy: 0.3396
Epoch 6/200
s: 1.8414 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7604 - accuracy: 0.3805 - val_loss: 1.8414 - val_accuracy: 0.3396
Epoch 7/200
s: 1.8424 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7570 - accuracy: 0.3825 - val_loss: 1.8424 - val_accuracy: 0.3396
Epoch 8/200
s: 1.8434 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7537 - accuracy: 0.3823 - val_loss: 1.8434 - val_accuracy: 0.3396
Epoch 9/200
s: 1.8444 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7509 - accuracy: 0.3845 - val_loss: 1.8444 - val_accuracy: 0.3396
Epoch 10/200
s: 1.8454 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7487 - accuracy: 0.3873 - val_loss: 1.8454 - val_accuracy: 0.3396
Epoch 11/200
s: 1.8464 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7448 - accuracy: 0.3875 - val_loss: 1.8464 - val_accuracy: 0.3396
Epoch 12/200
s: 1.8474 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7406 - accuracy: 0.3887 - val_loss: 1.8474 - val_accuracy: 0.3396
Epoch 13/200
s: 1.8484 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7396 - accuracy: 0.3897 - val_loss: 1.8484 - val_accuracy: 0.3396
Epoch 14/200
s: 1.8494 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7369 - accuracy: 0.3902 - val_loss: 1.8494 - val_accuracy: 0.3396
Epoch 15/200
s: 1.8504 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7315 - accuracy: 0.3928 - val_loss: 1.8504 - val_accuracy: 0.3396
Epoch 16/200
s: 1.8514 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7293 - accuracy: 0.3943 - val_loss: 1.8514 - val_accuracy: 0.3396
Epoch 17/200
s: 1.8524 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7259 - accuracy: 0.3965 - val_loss: 1.8524 - val_accuracy: 0.3396
Epoch 18/200
s: 1.8534 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7230 - accuracy: 0.3946 - val_loss: 1.8534 - val_accuracy: 0.3396
Epoch 19/200
s: 1.8544 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7208 - accuracy: 0.3990 - val_loss: 1.8544 - val_accuracy: 0.3396
Epoch 20/200
s: 1.8554 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7182 - accuracy: 0.3979 - val_loss: 1.8554 - val_accuracy: 0.3396
Epoch 21/200
s: 1.8564 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7152 - accuracy: 0.4010 - val_loss: 1.8564 - val_accuracy: 0.3396
Epoch 22/200
s: 1.8574 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7113 - accuracy: 0.4038 - val_loss: 1.8574 - val_accuracy: 0.3396
Epoch 23/200
s: 1.8584 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7079 - accuracy: 0.4007 - val_loss: 1.8584 - val_accuracy: 0.3396
Epoch 24/200
s: 1.8594 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7059 - accuracy: 0.4023 - val_loss: 1.8594 - val_accuracy: 0.3396
Epoch 25/200
s: 1.8604 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.7042 - accuracy: 0.4051 - val_loss: 1.8604 - val_accuracy: 0.3396
Epoch 26/200
s: 1.8614 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6995 - accuracy: 0.4069 - val_loss: 1.8614 - val_accuracy: 0.3396
Epoch 27/200
s: 1.8624 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6978 - accuracy: 0.4072 - val_loss: 1.8624 - val_accuracy: 0.3396
Epoch 28/200
s: 1.8634 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6955 - accuracy: 0.4089 - val_loss: 1.8634 - val_accuracy: 0.3396
Epoch 29/200
s: 1.8644 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6946 - accuracy: 0.4090 - val_loss: 1.8644 - val_accuracy: 0.3396
Epoch 30/200
s: 1.8654 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6905 - accuracy: 0.4104 - val_loss: 1.8654 - val_accuracy: 0.3396
Epoch 31/200
s: 1.8664 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6873 - accuracy: 0.4111 - val_loss: 1.8664 - val_accuracy: 0.3396
Epoch 32/200
s: 1.8674 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6811 - accuracy: 0.4156 - val_loss: 1.8674 - val_accuracy: 0.3396
Epoch 33/200
s: 1.8684 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6765 - accuracy: 0.4174 - val_loss: 1.8684 - val_accuracy: 0.3396
Epoch 34/200
s: 1.8694 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6713 - accuracy: 0.4185 - val_loss: 1.8694 - val_accuracy: 0.3396
Epoch 35/200
s: 1.8704 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6693 - accuracy: 0.4215 - val_loss: 1.8704 - val_accuracy: 0.3396
Epoch 36/200
s: 1.8714 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6695 - accuracy: 0.4213 - val_loss: 1.8714 - val_accuracy: 0.3396
Epoch 37/200
s: 1.8724 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6621 - accuracy: 0.4234 - val_loss: 1.8724 - val_accuracy: 0.3396
Epoch 38/200
s: 1.8734 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6614 - accuracy: 0.4227 - val_loss: 1.8734 - val_accuracy: 0.3396
Epoch 39/200
s: 1.8744 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6592 - accuracy: 0.4263 - val_loss: 1.8744 - val_accuracy: 0.3396
Epoch 40/200
s: 1.8754 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6545 - accuracy: 0.4277 - val_loss: 1.8754 - val_accuracy: 0.3396
Epoch 41/200
s: 1.8764 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6502 - accuracy: 0.4263 - val_loss: 1.8764 - val_accuracy: 0.3396
Epoch 42/200
s: 1.8774 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6516 - accuracy: 0.4284 - val_loss: 1.8774 - val_accuracy: 0.3396
Epoch 43/200
s: 1.8784 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6497 - accuracy: 0.4285 - val_loss: 1.8784 - val_accuracy: 0.3396
Epoch 44/200
s: 1.8794 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6474 - accuracy: 0.4294 - val_loss: 1.8794 - val_accuracy: 0.3396
Epoch 45/200
s: 1.8804 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6449 - accuracy: 0.4309 - val_loss: 1.8804 - val_accuracy: 0.3396
Epoch 46/200
s: 1.8814 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6446 - accuracy: 0.4332 - val_loss: 1.8814 - val_accuracy: 0.3396
Epoch 47/200
s: 1.8824 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6416 - accuracy: 0.4331 - val_loss: 1.8824 - val_accuracy: 0.3396
Epoch 48/200
s: 1.8834 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6391 - accuracy: 0.4324 - val_loss: 1.8834 - val_accuracy: 0.3396
Epoch 49/200
s: 1.8844 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6382 - accuracy: 0.4335 - val_loss: 1.8844 - val_accuracy: 0.3396
Epoch 50/200
s: 1.8854 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6359 - accuracy: 0.4347 - val_loss: 1.8854 - val_accuracy: 0.3396
Epoch 51/200
s: 1.8864 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6332 - accuracy: 0.4353 - val_loss: 1.8864 - val_accuracy: 0.3396
Epoch 52/200
s: 1.8874 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6330 - accuracy: 0.4340 - val_loss: 1.8874 - val_accuracy: 0.3396
Epoch 53/200
s: 1.8884 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6309 - accuracy: 0.4382 - val_loss: 1.8884 - val_accuracy: 0.3396
Epoch 54/200
s: 1.8894 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6302 - accuracy: 0.4368 - val_loss: 1.8894 - val_accuracy: 0.3396
Epoch 55/200
s: 1.8904 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6294 - accuracy: 0.4374 - val_loss: 1.8904 - val_accuracy: 0.3396
Epoch 56/200
s: 1.8914 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6270 - accuracy: 0.4383 - val_loss: 1.8914 - val_accuracy: 0.3396
Epoch 57/200
s: 1.8924 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6270 - accuracy: 0.4379 - val_loss: 1.8924 - val_accuracy: 0.3396
Epoch 58/200
s: 1.8934 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6228 - accuracy: 0.4383 - val_loss: 1.8934 - val_accuracy: 0.3396
Epoch 59/200
s: 1.8944 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6220 - accuracy: 0.4389 - val_loss: 1.8944 - val_accuracy: 0.3396
Epoch 60/200
s: 1.8954 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6183 - accuracy: 0.4392 - val_loss: 1.8954 - val_accuracy: 0.3396
Epoch 61/200
s: 1.8964 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6174 - accuracy: 0.4405 - val_loss: 1.8964 - val_accuracy: 0.3396
Epoch 62/200
s: 1.8974 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6149 - accuracy: 0.4415 - val_loss: 1.8974 - val_accuracy: 0.3396
Epoch 63/200
s: 1.8984 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6119 - accuracy: 0.4418 - val_loss: 1.8984 - val_accuracy: 0.3396
Epoch 64/200
s: 1.8994 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6119 - accuracy: 0.4418 - val_loss: 1.8994 - val_accuracy: 0.3396
Epoch 65/200
s: 1.9004 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6086 - accuracy: 0.4448 - val_loss: 1.9004 - val_accuracy: 0.3396
Epoch 66/200
s: 1.9014 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6061 - accuracy: 0.4421 - val_loss: 1.9014 - val_accuracy: 0.3396
Epoch 67/200
s: 1.9024 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6052 - accuracy: 0.4443 - val_loss: 1.9024 - val_accuracy: 0.3396
Epoch 68/200
s: 1.9034 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6050 - accuracy: 0.4448 - val_loss: 1.9034 - val_accuracy: 0.3396
Epoch 69/200
s: 1.9044 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6037 - accuracy: 0.4448 - val_loss: 1.9044 - val_accuracy: 0.3396
Epoch 70/200
s: 1.9054 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6027 - accuracy: 0.4461 - val_loss: 1.9054 - val_accuracy: 0.3396
Epoch 71/200
s: 1.9064 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6000 - accuracy: 0.4478 - val_loss: 1.9064 - val_accuracy: 0.3396
Epoch 72/200
s: 1.9074 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.6013 - accuracy: 0.4456 - val_loss: 1.9074 - val_accuracy: 0.3396
Epoch 73/200
s: 1.9084 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5971 - accuracy: 0.4488 - val_loss: 1.9084 - val_accuracy: 0.3396
Epoch 74/200
s: 1.9094 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5967 - accuracy: 0.4472 - val_loss: 1.9094 - val_accuracy: 0.3396
Epoch 75/200
s: 1.9104 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5952 - accuracy: 0.4466 - val_loss: 1.9104 - val_accuracy: 0.3396
Epoch 76/200
s: 1.9114 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5952 - accuracy: 0.4495 - val_loss: 1.9114 - val_accuracy: 0.3396
Epoch 77/200
s: 1.9124 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5934 - accuracy: 0.4489 - val_loss: 1.9124 - val_accuracy: 0.3396
Epoch 78/200
s: 1.9134 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5916 - accuracy: 0.4484 - val_loss: 1.9134 - val_accuracy: 0.3396
Epoch 79/200
s: 1.9144 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5916 - accuracy: 0.4484 - val_loss: 1.9144 - val_accuracy: 0.3396
Epoch 80/200
s: 1.9154 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5911 - accuracy: 0.4486 - val_loss: 1.9154 - val_accuracy: 0.3396
Epoch 81/200
s: 1.9164 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5905 - accuracy: 0.4489 - val_loss: 1.9164 - val_accuracy: 0.3396
Epoch 82/200
s: 1.9174 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5890 - accuracy: 0.4511 - val_loss: 1.9174 - val_accuracy: 0.3396
Epoch 83/200
s: 1.9184 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5866 - accuracy: 0.4519 - val_loss: 1.9184 - val_accuracy: 0.3396
Epoch 84/200
s: 1.9194 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5872 - accuracy: 0.4492 - val_loss: 1.9194 - val_accuracy: 0.3396
Epoch 85/200
s: 1.9204 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5852 - accuracy: 0.4497 - val_loss: 1.9204 - val_accuracy: 0.3396
Epoch 86/200
s: 1.9214 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5850 - accuracy: 0.4511 - val_loss: 1.9214 - val_accuracy: 0.3396
Epoch 87/200
s: 1.9224 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5831 - accuracy: 0.4514 - val_loss: 1.9224 - val_accuracy: 0.3396
Epoch 88/200
s: 1.9234 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5820 - accuracy: 0.4519 - val_loss: 1.9234 - val_accuracy: 0.3396
Epoch 89/200
s: 1.9244 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5810 - accuracy: 0.4492 - val_loss: 1.9244 - val_accuracy: 0.3396
Epoch 90/200
s: 1.9254 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5798 - accuracy: 0.4502 - val_loss: 1.9254 - val_accuracy: 0.3396
Epoch 91/200
s: 1.9264 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5785 - accuracy: 0.4535 - val_loss: 1.9264 - val_accuracy: 0.3396
Epoch 92/200
s: 1.9274 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5783 - accuracy: 0.4513 - val_loss: 1.9274 - val_accuracy: 0.3396
Epoch 93/200
s: 1.9284 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5753 - accuracy: 0.4526 - val_loss: 1.9284 - val_accuracy: 0.3396
Epoch 94/200
s: 1.9294 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5748 - accuracy: 0.4533 - val_loss: 1.9294 - val_accuracy: 0.3396
Epoch 95/200
s: 1.9304 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5748 - accuracy: 0.4533 - val_loss: 1.9304 - val_accuracy: 0.3396
Epoch 96/200
s: 1.9314 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5734 - accuracy: 0.4534 - val_loss: 1.9314 - val_accuracy: 0.3396
Epoch 97/200
s: 1.9324 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5719 - accuracy: 0.4537 - val_loss: 1.9324 - val_accuracy: 0.3396
Epoch 98/200
s: 1.9334 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5726 - accuracy: 0.4526 - val_loss: 1.9334 - val_accuracy: 0.3396
Epoch 99/200
s: 1.9344 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5698 - accuracy: 0.4552 - val_loss: 1.9344 - val_accuracy: 0.3396
Epoch 100/200
s: 1.9354 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5698 - accuracy: 0.4552 - val_loss: 1.9354 - val_accuracy: 0.3396
Epoch 101/200
s: 1.9364 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5671 - accuracy: 0.4545 - val_loss: 1.9364 - val_accuracy: 0.3396
Epoch 102/200
s: 1.9374 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5679 - accuracy: 0.4536 - val_loss: 1.9374 - val_accuracy: 0.3396
Epoch 103/200
s: 1.9384 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5663 - accuracy: 0.4566 - val_loss: 1.9384 - val_accuracy: 0.3396
Epoch 104/200
s: 1.9394 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5667 - accuracy: 0.4555 - val_loss: 1.9394 - val_accuracy: 0.3396
Epoch 105/200
s: 1.9404 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5651 - accuracy: 0.4543 - val_loss: 1.9404 - val_accuracy: 0.3396
Epoch 106/200
s: 1.9414 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5644 - accuracy: 0.4574 - val_loss: 1.9414 - val_accuracy: 0.3396
Epoch 107/200
s: 1.9424 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5644 - accuracy: 0.4574 - val_loss: 1.9424 - val_accuracy: 0.3396
Epoch 108/200
s: 1.9434 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5639 - accuracy: 0.4563 - val_loss: 1.9434 - val_accuracy: 0.3396
Epoch 109/200
s: 1.9444 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5616 - accuracy: 0.4578 - val_loss: 1.9444 - val_accuracy: 0.3396
Epoch 110/200
s: 1.9454 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5610 - accuracy: 0.4714 - val_loss: 1.9454 - val_accuracy: 0.3396
Epoch 111/200
s: 1.9464 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5610 - accuracy: 0.4714 - val_loss: 1.9464 - val_accuracy: 0.3396
Epoch 112/200
s: 1.9474 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5606 - accuracy: 0.4714 - val_loss: 1.9474 - val_accuracy: 0.3396
Epoch 113/200
s: 1.9484 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5606 - accuracy: 0.4714 - val_loss: 1.9484 - val_accuracy: 0.3396
Epoch 114/200
s: 1.9494 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5606 - accuracy: 0.4714 - val_loss: 1.9494 - val_accuracy: 0.3396
Epoch 115/200
s: 1.9504 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5606 - accuracy: 0.4714 - val_loss: 1.9504 - val_accuracy: 0.3396
Epoch 116/200
s: 1.9514 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5606 - accuracy: 0.4714 - val_loss: 1.9514 - val_accuracy: 0.3396
Epoch 117/200
s: 1.9524 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5606 - accuracy: 0.4714 - val_loss: 1.9524 - val_accuracy: 0.3396
Epoch 118/200
s: 1.9534 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5606 - accuracy: 0.4714 - val_loss: 1.9534 - val_accuracy: 0.3396
Epoch 119/200
s: 1.9544 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5606 - accuracy: 0.4714 - val_loss: 1.9544 - val_accuracy: 0.3396
Epoch 120/200
s: 1.9554 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5606 - accuracy: 0.4714 - val_loss: 1.9554 - val_accuracy: 0.3396
Epoch 121/200
s: 1.9564 - val_accuracy: 0.3396 - 6s 4ms/step - loss: 1.5606 - accuracy: 0.4714 - val_loss: 1.9564 - val_accuracy: 0.3396
Epoch 122/200
s: 1.9574 - val_accuracy: 0.33
```



The full connection neural network perform slightly better than random forest. The accuracy is similar to random forest. We can increase the hidden layers and number of epochs, however the time will increase too.

### 3.3 Convolutional Neural Network

```
In [65]: model_2 = Sequential()

model_2.add(Conv2D(32, (3, 3), padding='same',
                  input_shape=x_train.shape[1:]))
model_2.add(Activation('relu'))
model_2.add(Conv2D(32, (3, 3)))
model_2.add(Activation('relu'))
model_2.add(MaxPooling2D(pool_size=(2, 2)))
model_2.add(Dropout(0.25))

model_2.add(Conv2D(64, (3, 3), padding='same'))
model_2.add(Activation('relu'))
model_2.add(Conv2D(64, (3, 3)))
model_2.add(Activation('relu'))
model_2.add(MaxPooling2D(pool_size=(2, 2)))
model_2.add(Dropout(0.25))

model_2.add(Flatten())
model_2.add(Dense(512))
model_2.add(Activation('relu'))
model_2.add(Dropout(0.5))
model_2.add(Dense(num_classes))
model_2.add(Activation('softmax'))

In [66]: model_2.summary()

Model: "sequential_5"

Layer (type)                 Output Shape              Param #
-----
conv2d_4 (Conv2D)            (None, 32, 32, 32)       896
activation_6 (Activation)     (None, 32, 32, 32)       0
conv2d_5 (Conv2D)            (None, 30, 30, 32)       9248
activation_7 (Activation)     (None, 30, 30, 32)       0
max_pooling2d_2 (MaxPooling2 (None, 15, 15, 32)       0
dropout_3 (Dropout)          (None, 15, 15, 32)       0
conv2d_6 (Conv2D)            (None, 15, 15, 64)       18496
activation_9 (Activation)     (None, 15, 15, 64)       0
conv2d_7 (Conv2D)            (None, 13, 13, 64)       36928
activation_10 (Activation)    (None, 13, 13, 64)       0
max_pooling2d_3 (MaxPooling2 (None, 6, 6, 64)        0
dropout_4 (Dropout)          (None, 6, 6, 64)         0
flatten_1 (Flatten)          (None, 2304)             0
dense_10 (Dense)              (None, 512)              1180160
activation_10 (Activation)    (None, 512)              0
dropout_5 (Dropout)          (None, 512)              0
dense_11 (Dense)              (None, 10)               5130
activation_11 (Activation)    (None, 10)               0
-----
Total params: 1,250,858
Trainable params: 1,250,858
Non-trainable params: 0

In [67]: batch_size = 32

# initiate RMSprop optimizer
opt_2 = keras.optimizers.RMSprop(lr=0.0005)

# Let's train the model using RMSprop
model_2.compile(loss='categorical_crossentropy',
               optimizer=opt_2,
               metrics=['accuracy'])

In [68]: t = now()
model_2.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=10,
          validation_data=(x_test, y_test),
          shuffle=True)

print('Training time: %s' % (now() - t))

Epoch 1/10
1563/1563 [=====] - 121s 77ms/step - loss: 1.5786 - accuracy: 0.4241 - val_l
oss: 1.2191 - val_accuracy: 0.5587
Epoch 2/10
1563/1563 [=====] - 121s 77ms/step - loss: 1.1826 - accuracy: 0.5803 - val_l
oss: 1.1232 - val_accuracy: 0.6035
Epoch 3/10
1563/1563 [=====] - 122s 78ms/step - loss: 1.0084 - accuracy: 0.6490 - val_l
oss: 0.8676 - val_accuracy: 0.6975
Epoch 4/10
1563/1563 [=====] - 121s 78ms/step - loss: 0.9088 - accuracy: 0.6838 - val_l
oss: 0.8688 - val_accuracy: 0.7032
Epoch 5/10
1563/1563 [=====] - 121s 78ms/step - loss: 0.8552 - accuracy: 0.7069 - val_l
oss: 0.8810 - val_accuracy: 0.6986
Epoch 6/10
1563/1563 [=====] - 121s 78ms/step - loss: 0.8237 - accuracy: 0.7176 - val_l
oss: 0.8932 - val_accuracy: 0.7008
Epoch 7/10
1563/1563 [=====] - 122s 78ms/step - loss: 0.8139 - accuracy: 0.7250 - val_l
oss: 0.8127 - val_accuracy: 0.7383
Epoch 8/10
1563/1563 [=====] - 123s 79ms/step - loss: 0.8150 - accuracy: 0.7280 - val_l
oss: 0.8685 - val_accuracy: 0.7352
Epoch 9/10
1563/1563 [=====] - 123s 79ms/step - loss: 0.8285 - accuracy: 0.7278 - val_l
oss: 0.8039 - val_accuracy: 0.7467
Epoch 10/10
1563/1563 [=====] - 122s 78ms/step - loss: 0.8387 - accuracy: 0.7237 - val_l
oss: 0.9243 - val_accuracy: 0.7309
Training time: 0:20:19.926330

In [78]: score = model_2.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])

Test score: 0.9243311285972595
Test accuracy: 0.73089989860495
```

### 4. Conclusion

In this course, we learn different deep learning architecture. They are suitable for different task. Convolutional Neural network is very good in image classification tasks. Each pixel can be treated as one feature. The relative location and value of each pixel is very important for image.