Load Cifar10 image dataset and display the first 25 images to verify that loading was successful

```
In [1]: from __future__ import absolute_import, division, print_function, unicode_lite
        rals
        import tensorflow as tf
        from tensorflow.keras import datasets, layers, models
        import matplotlib.pyplot as plt
        (train images, train labels), (test images, test labels) = datasets.cifar10.lo
        ad data()
        # Normalize pixel values to be between 0 and 1
        train_images, test_images = train_images / 255.0, test_images / 255.0
        class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
                        'dog', 'frog', 'horse', 'ship', 'truck']
        plt.figure(figsize=(10,10))
        for i in range(25):
            plt.subplot(5,5,i+1)
            plt.xticks([])
            plt.yticks([])
            plt.grid(False)
            plt.imshow(train images[i], cmap=plt.cm.binary)
            # The CIFAR labels happen to be arrays,
            # which is why you need the extra index
            plt.xlabel(class names[train labels[i][0]])
        plt.show()
```

<Figure size 1000x1000 with 25 Axes>

Create our Convolutional Neural Network. Note that in Tensorflow, we create our network as a static graph and then run our data through it. We cannot change the structure of the network dynamically and the structure of the network does not depend on the data distribution.

```
In [2]: model = models.Sequential()
    model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3
)))
    model.add(layers.MaxPooling2D((2, 2)))
    model.add(layers.Conv2D(64, (3, 3), activation='relu'))
    model.add(layers.MaxPooling2D((2, 2)))
    model.add(layers.Conv2D(64, (3, 3), activation='relu'))
    model.add(layers.Flatten())
    model.add(layers.Dense(64, activation='relu'))
    model.add(layers.Dense(10, activation='relu'))
```

View our Network structure and the number of trainable parameters on each layer.

In [3]: model.summary()

Model: "sequential"

Layer (type)	Output	Shape	Param #
conv2d (Conv2D)	(None,	30, 30, 32)	896
<pre>max_pooling2d (MaxPooling2D)</pre>	(None,	15, 15, 32)	0
conv2d_1 (Conv2D)	(None,	13, 13, 64)	18496
<pre>max_pooling2d_1 (MaxPooling2</pre>	(None,	6, 6, 64)	0
conv2d_2 (Conv2D)	(None,	4, 4, 64)	36928
flatten (Flatten)	(None,	1024)	0
dense (Dense)	(None,	64)	65600
dense_1 (Dense)	(None,	10)	650

Total params: 122,570 Trainable params: 122,570 Non-trainable params: 0

Run the network with our data.

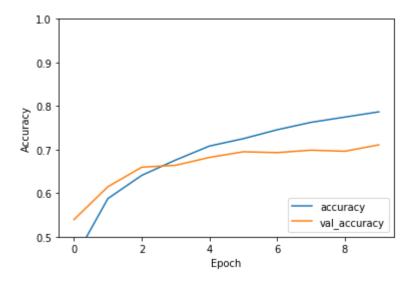
```
In [4]: | model.compile(optimizer='adam',
                    loss='sparse categorical crossentropy',
                    metrics=['accuracy'])
        history = model.fit(train images, train labels, epochs=10,
                          validation_data=(test_images, test_labels))
       Train on 50000 samples, validate on 10000 samples
       Epoch 1/10
       50000/50000 [============== ] - 17s 349us/sample - loss: 1.515
       7 - accuracy: 0.4481 - val_loss: 1.2657 - val_accuracy: 0.5394
       50000/50000 [============== ] - 12s 246us/sample - loss: 1.162
       9 - accuracy: 0.5875 - val loss: 1.0821 - val accuracy: 0.6147
       Epoch 3/10
       50000/50000 [============ ] - 12s 245us/sample - loss: 1.017
       2 - accuracy: 0.6408 - val loss: 0.9818 - val accuracy: 0.6596
       Epoch 4/10
       50000/50000 [============== ] - 12s 238us/sample - loss: 0.916
       9 - accuracy: 0.6760 - val loss: 0.9709 - val accuracy: 0.6640
       Epoch 5/10
       50000/50000 [============== ] - 12s 239us/sample - loss: 0.832
       9 - accuracy: 0.7081 - val_loss: 0.9215 - val_accuracy: 0.6820
       Epoch 6/10
       50000/50000 [============== ] - 12s 240us/sample - loss: 0.776
       8 - accuracy: 0.7251 - val loss: 0.8841 - val accuracy: 0.6950
       Epoch 7/10
       50000/50000 [============ ] - 14s 285us/sample - loss: 0.720
       5 - accuracy: 0.7455 - val loss: 0.8969 - val accuracy: 0.6931
       Epoch 8/10
       50000/50000 [============== ] - 13s 251us/sample - loss: 0.677
       1 - accuracy: 0.7626 - val loss: 0.8878 - val accuracy: 0.6987
       Epoch 9/10
       50000/50000 [============== ] - 12s 243us/sample - loss: 0.639
       0 - accuracy: 0.7746 - val loss: 0.9177 - val accuracy: 0.6962
       Epoch 10/10
       50000/50000 [============== ] - 12s 245us/sample - loss: 0.601
       7 - accuracy: 0.7866 - val loss: 0.8685 - val accuracy: 0.7109
```

Plot the train and validation accuracy

```
In [6]: plt.plot(history.history['accuracy'], label='accuracy')
    plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.ylim([0.5, 1])
    plt.legend(loc='lower right')

test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
```

10000/1 - 1s - loss: 0.8628 - accuracy: 0.7109



Print the final test accuracy

#Class 10 mistaken for class 2 the most

```
In [9]:
        from sklearn.metrics import classification report, confusion matrix
        import numpy as np
        pred=model.predict(train images)
        y pred = np.argmax(pred, axis=1)
        print('Confusion Matrix')
        print(confusion_matrix(train_labels, y_pred))
        #target_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
                         'dog', 'frog', 'horse', 'ship', 'truck']
        Confusion Matrix
        [[4161
                 85
                     260
                            41
                                 54
                                           12
                                                28
                                                    270
                                                           80]
                                       8
                                                 3
                                                    122
                                                           821
            32 4707
                       11
                            10
                                 12
                                           13
           162
                 24 3999
                           138
                                259
                                     103
                                          129
                                                     57
                                                           13]
                                               116
            59
                 34
                     360 3314
                                241
                                     488
                                          215
                                               162
                                                     83
                                                           44]
            82
                 12 342
                           177 3899
                                      72
                                           71
                                               309
                                                     25
                                                           11]
                                168 3195 110
            20
                 23 290 870
                                               267
                                                     33
                                                           24]
            19
                 29 241
                           168
                                188
                                      48 4235
                                                20
                                                     36
                                                           16]
            29
                 15 128
                                 99
                                      88
                            99
                                           17 4481
                                                     17
                                                           27]
           135
                 42
                       35
                            24
                                  6
                                       6
                                           12
                                                 7 4707
                                                           26]
                       42
                                  7
                                       7
            96
                461
                            28
                                           17
                                                32 121 4189]]
In [ ]: #Class 1 mistaken for class 3 the most
        #Class 2 mistaken for class 9 the most
        #Class 3 mistaken for class 5 the most -> Implies Class 3's features aren't di
        stinguishable enough
        #Class 4 mistken for class 6 the most
        #Class 5 mistaken for class 3 the most
        #Class 6 mistaken for class 4 the most
        #Class 7 mistaken for class 3 the most
        #Class 8 mistaken for class 3 the most
        #Class 9 mistaken for class 1 the most
```