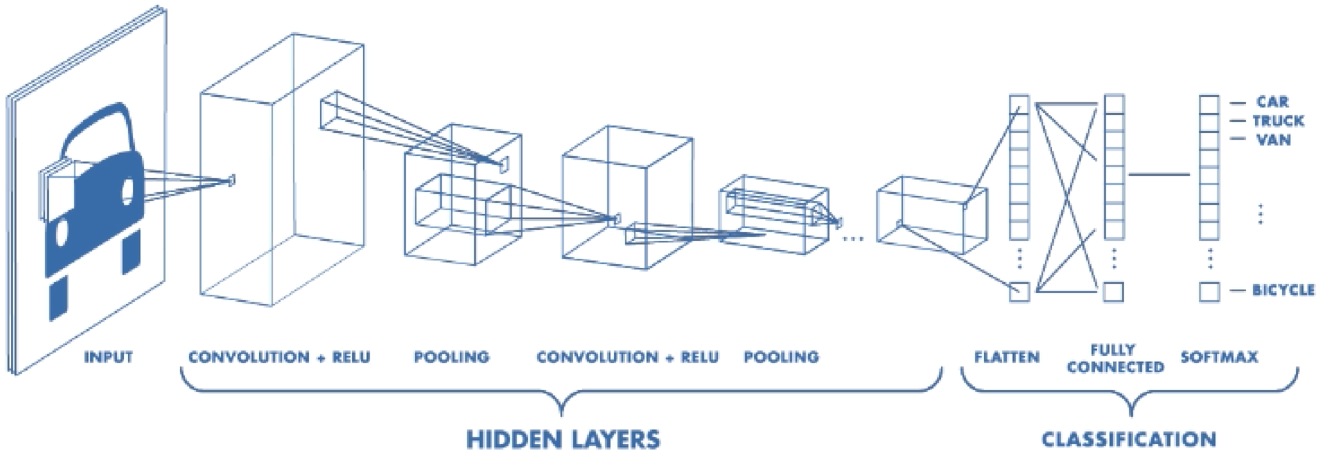
Convolutional Neural Network

make sure you have acces to the keras and tensorflow packages `pip install keras & pip install tensorflow`

A Convolutional neural network is mainly used to categorize images. by copying the behavoir of the brain. the layers are capable of extracting features from images. CNN's have two components:

1. The hidden layers / feature extraction
2. The Classification layers



Sources

https://medium.freecodecamp.org/an-intuitive-guide-to-convolutional-neural-networks-260c2de0a050 (https://medium.freecodecamp.org/an-intuitive-guide-to-convolutional-neural-networks-260c2de0a050)

https://keras.io/layers/convolutional/#conv2d (https://keras.io/layers/convolutional/#conv2d)

In [1]:

```
# Helper libraries
import numpy as np
import matplotlib.pyplot as plt


import keras
from keras.models import Sequential,Input,Model
from keras.layers import Dense, Flatten, Activation
from keras.layers import Conv2D, MaxPooling2D
from keras.layers.normalization import BatchNormalization
from keras.layers.advanced_activations import LeakyReLU
from keras.constraints import maxnorm

batch_size = 64
epochs = 20
num_classes = 10

# Setup the model
model = Sequential()
```

```
D:\Programs\Anaconda\lib\site-packages\h5py\__init__.py:36: FutureWarning: C
onversion of the second argument of issubdtype from `float` to `np.floating`
is deprecated. In future, it will be treated as `np.float64 == np.dtype(floa
t).type`.
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

Enable GPU Acceleration

Software requirements

The following NVIDIA® software must be installed on your system:

1. https://www.nvidia.com/Download/index.aspx?lang=en-us (NVIDIA® GPU drivers) —CUDA 9.0 requires 384.x or higher.
2. https://developer.nvidia.com/cuda-zone (CUDA® Toolkit) —TensorFlow supports CUDA 9.0.
3. https://docs.nvidia.com/cuda/cupti/ (CUPTI) ships with the CUDA Toolkit.
4. https://developer.nvidia.com/cudnn (cuDNN SDK) (>= 7.2)
5. (Optional) https://developer.nvidia.com/nccl (NCCL 2.2) for multiple GPU support.
6. (Optional) https://docs.nvidia.com/deeplearning/sdk/tensorrt-install-guide/index.html (TensorRT 4.0) to improve latency and throughput for inference on some models.

installing gpu support tensorflow

Before we go any further we have to make sure we have libraries for gpu acceleration because this will speed up our processes allot. At this point it is only possible for NVidia GPU's to use this tech because AMD GPU's don't support CUDA

```
pip install tensorflow-gpu
```

Windows setup

See the [https://www.tensorflow.org/install/gpu#hardware_requirements (hardware requirements)] and [https://www.tensorflow.org/install/gpu#software_requirements (software requirements)] listed above. Read the [https://docs.nvidia.com/cuda/cuda-installation-guide-microsoft-windows/ (CUDA® install guide for Windows)].

Make sure the installed NVIDIA software packages match the versions listed above. In particular, TensorFlow will not load without the `cuDNN64_7.dll` file. To use a different version, see the [https://www.tensorflow.org/install/source_windows (Windows build from source)] guide.

Add the CUDA, CUPTI, and cuDNN installation directories to the `%PATH%` environmental variable. For example, if the CUDA Toolkit is installed to `C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\v9.0` and cuDNN to `C:\tools\cuda`, update your `%PATH%` to match:

```
SET PATH=C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\v9.0\bin;%PATH%
SET PATH=C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\v9.0\extras\CUPTI\libx
64;%PATH%
SET PATH=C:\tools\cuda\bin;%PATH%
```

In [2]:

```python
# Verify that tensorflow and keras are running with GPU
from tensorflow.python.client import device_lib
from keras import backend as K

print(device_lib.list_local_devices())
K.tensorflow_backend._get_available_gpus()

import os
os.environ["CUDA_VISIBLE_DEVICES"]="0"
```

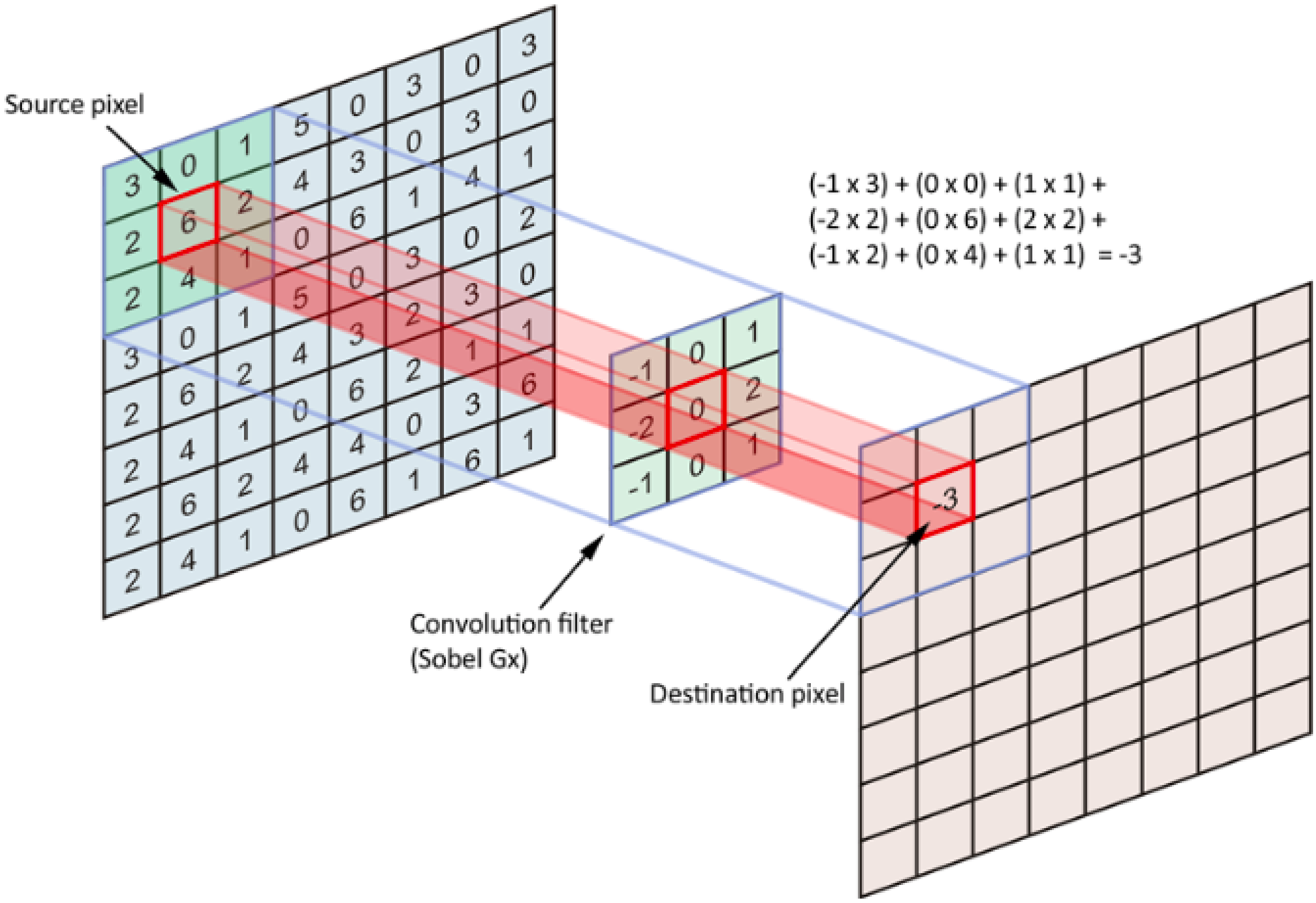
```
[name: "/device:CPU:0"
device_type: "CPU"
memory_limit: 268435456
locality {
}
incarnation: 3765963727577690122
]
```

Hidden layers / Feature extraction

Conv2D Layer

This layer creates a convolution kernel that is convolved with the layer input to produce a tensor of outputs. If `use_bias` is True, a bias vector is created and added to the outputs. Finally, if `activation` is not `None`, it is applied to the outputs as well.

When using this layer as the first layer in a model, provide the keyword argument `input_shape` (tuple of integers, does not include the sample axis), e.g. `input_shape=(128, 128, 3)` for 128x128 RGB pictures in `data_format="channels_last"`.



Arguments

- **filters**: Integer, the dimensionality of the output space (i.e. the number of output filters in the convolution).
- **kernel_size**: An integer or tuple/list of 2 integers, specifying the height and width of the 2D convolution window. Can be a single integer to specify the same value for all spatial dimensions.
- **strides**: An integer or tuple/list of 2 integers, specifying the strides of the convolution along the height and width. Can be a single integer to specify the same value for all spatial dimensions. Specifying any stride value != 1 is incompatible with specifying any `dilation_rate` value != 1.
- **padding**: one of `"valid"` or `"same"` (case-insensitive). Note that `"same"` is slightly inconsistent across backends with strides != 1.
- **data_format**: A string, one of `"channels_last"` or `"channels_first"` . The ordering of the dimensions in the inputs. `"channels_last"` corresponds to inputs with shape `(batch, height, width, channels)` while `"channels_first"` corresponds to inputs with shape `(batch, channels, height, width)` . It defaults to the `image_data_format` value found in your Keras config file at `~/.keras/keras.json.` If you never set it, then it will be "channels_last".
- **dilation_rate**: an integer or tuple/list of 2 integers, specifying the dilation rate to use for dilated convolution. Can be a single integer to specify the same value for all spatial dimensions. Currently, specifying any `dilation_rate value` != 1 is incompatible with specifying any stride value != 1.
- **activation**: Activation function to use. If you don't specify anything, no activation is applied (ie. "linear" activation: `a(x) = x`).
- **use_bias**: Boolean, whether the layer uses a bias vector.
- **kernel_initializer**: Initializer for the `kernel` weights matrix.
- **bias_initializer**: Initializer for the bias vector.
- **kernel_regularizer**: Regularizer function applied to the `kernel` weights matrix.
- **bias_regularizer**: Regularizer function applied to the bias vector.
- **activity_regularizer**: Regularizer function applied to the output of the layer (its "activation").
- **kernel_constraint**: Constraint function applied to the kernel matrix.

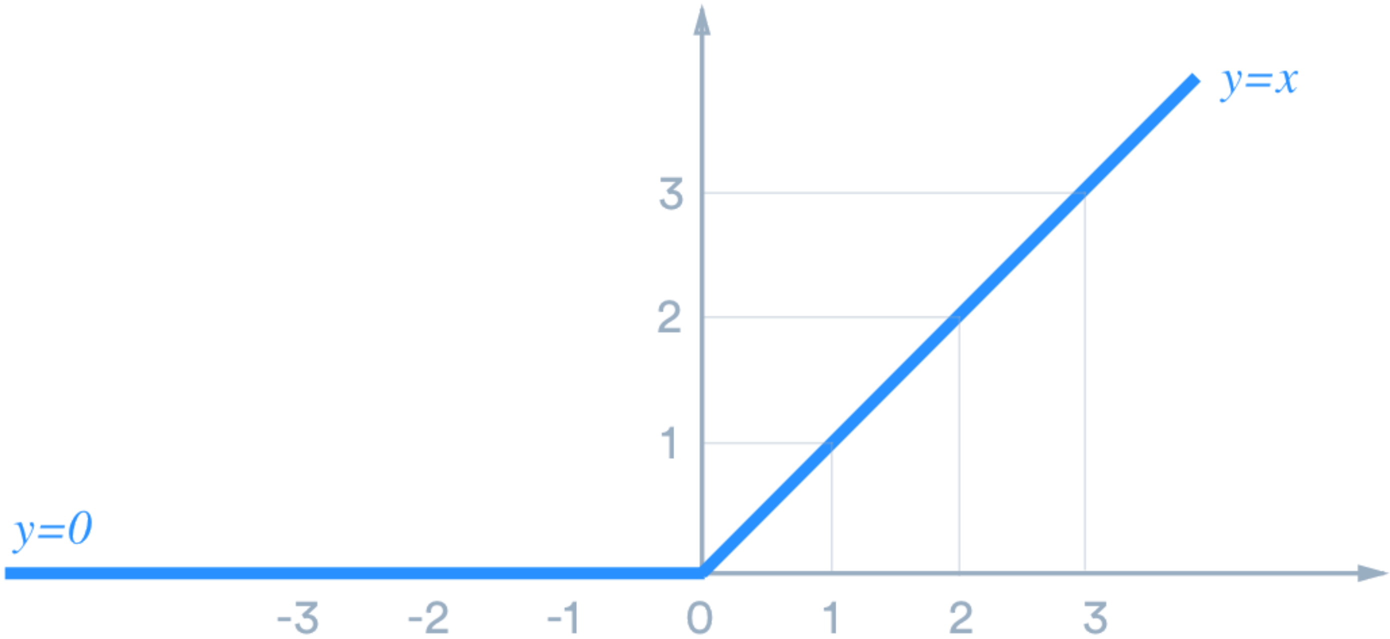
- **bias_constraint**: Constraint function applied to the bias vector.

In [24]:

```
# Images fed into this model are 512x512 pixels with 3 channels (RGB)
image_input_shape  = (512,512,3)

# Add convolutional layer with 3x3x3 filter 32 times and a stride size of 1
model.add(Conv2D(32, kernel_size=(3, 3),activation='linear',input_shape=image_input_shape,p
```

Activation Layer *(ReLU Layer)*

Rectified Linear Unit.



With default values, it returns element-wise `max(x, 0)` .

Otherwise, it follows: `f(x) = max_value` for `x >= max_value` , `f(x) = x` for `threshold <= x < max_value`, `f(x) = alpha * (x - threshold)` otherwise.

Arguments

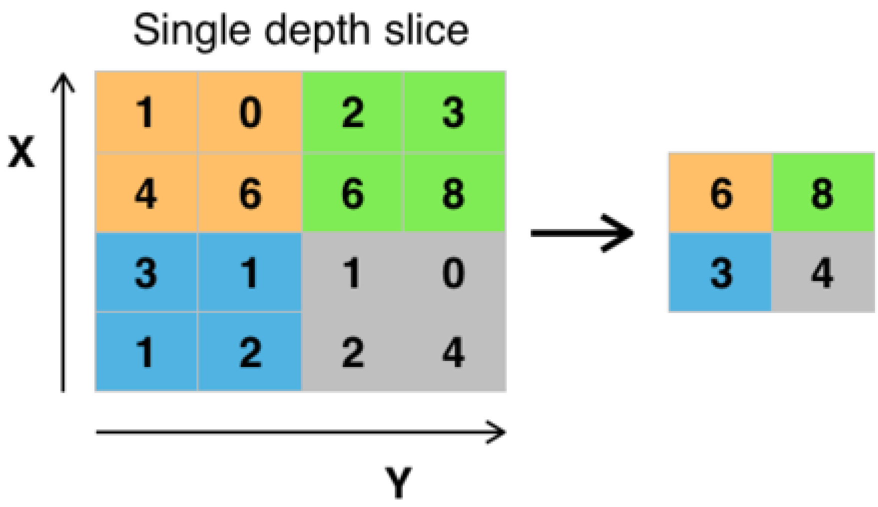
- **activation**: name of activation function to use, or alternatively, a Theano or TensorFlow operation.

In [25]:

```
# Add relu activation to the layer
model.add(Activation('relu'))
```

Pooling Layer

Max pooling operation for spatial data. Pooling is a non linear form of downsizing. Max pooling takes the max value from a certain range and drop all others as seen in de image below.



Arguments

- **pool_size**: integer or tuple of 2 integers, factors by which to downscale (vertical, horizontal). (2, 2) will halve the input in both spatial dimension. If only one integer is specified, the same window length will be used for both dimensions.
- **strides**: Integer, tuple of 2 integers, or None. Strides values. If None, it will default to `pool_size` .
- **padding**: One of `"valid"` or `"same"` (case-insensitive).
- **data_format**: A string, one of `channels_last` (default) or `channels_first` . The ordering of the dimensions in the inputs. `channels_last` corresponds to inputs with shape `(batch, height, width, channels)` while `channels_first` corresponds to inputs with shape `(batch, channels, height, width)` . It defaults to the `image_data_format` value found in your Keras config file at `~/.keras/keras.json` . If you never set it, then it will be "channels_last".

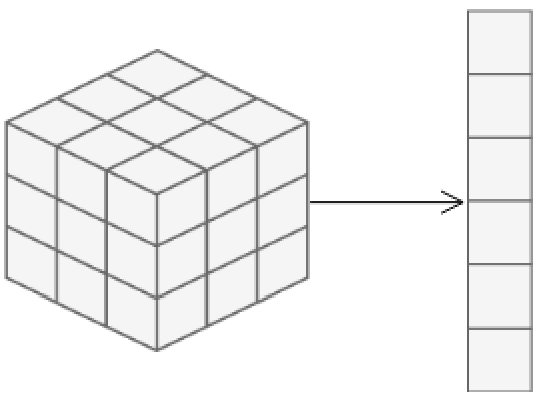
In [26]:

```
#Pooling
model.add(MaxPooling2D(2))
```

Classification Layers

Flatten Layer

Flattens the input. Does not affect the batch size.



Arguments

- **data_format**: A string, one of `channels_last` (default) or `channels_first`. The ordering of the dimensions in the inputs. The purpose of this argument is to preserve weight ordering when switching a model from one data format to another. `channels_last` corresponds to inputs with shape `(batch, ..., channels)` while `channels_first` corresponds to inputs with shape `(batch, channels, ...)`. It defaults to the `image_data_format` value found in your Keras config file at `~/.keras/keras.json`. If you never set it, then it will be "channels_last".

Example

```
model = Sequential()
model.add(Conv2D(64, (3, 3),
                 input_shape=(3, 32, 32), padding='same',))
# now: model.output_shape == (None, 64, 32, 32)

model.add(Flatten())
# now: model.output_shape == (None, 65536)
```

In [27]:

```
# Use Flatten to convert 3D data to 1D
model.add(Flatten())
```

Dense Layers

Just your regular densely-connected NN layer.

`Dense` implements the operation: `output = activation(dot(input, kernel) + bias)` where `activation` is the element-wise activation function passed as the `activation` argument, `kernel` is a weights matrix created by the layer, and `bias` is a bias vector created by the layer (only applicable if `use_bias` is `True`).

`Dense` is the only actual network layer in that model.

`Dense` layer feeds all outputs from the previous layer to all its neurons, each neuron providing one output to the next layer.

It's the most basic layer in neural networks.

`Dense(10)` has ten neurons. A `Dense(512)` has 512 neurons.

Note: if the input to the layer has a rank greater than 2, then it is flattened prior to the initial dot product with `kernel`.

Arguments

- **units**: Positive integer, dimensionality of the output space.
- **activation**: Activation function to use (see activations). If you don't specify anything, no activation is applied (ie. "linear" activation: `a(x) = x`).
- **use_bias**: Boolean, whether the layer uses a bias vector.
- **kernel_initializer**: Initializer for the `kernel` weights matrix.
- **bias_initializer**: Initializer for the bias vector.
- **kernel_regularizer**: Regularizer function applied to the `kernel` weights matrix.

- **bias_regularizer**: Regularizer function applied to the bias vector.
- **activity_regularizer**: Regularizer function applied to the output of the layer (its "activation").
- **kernel_constraint**: Constraint function applied to the `kernel` weights matrix.
- **bias_constraint**: Constraint function applied to the bias vector.

Example

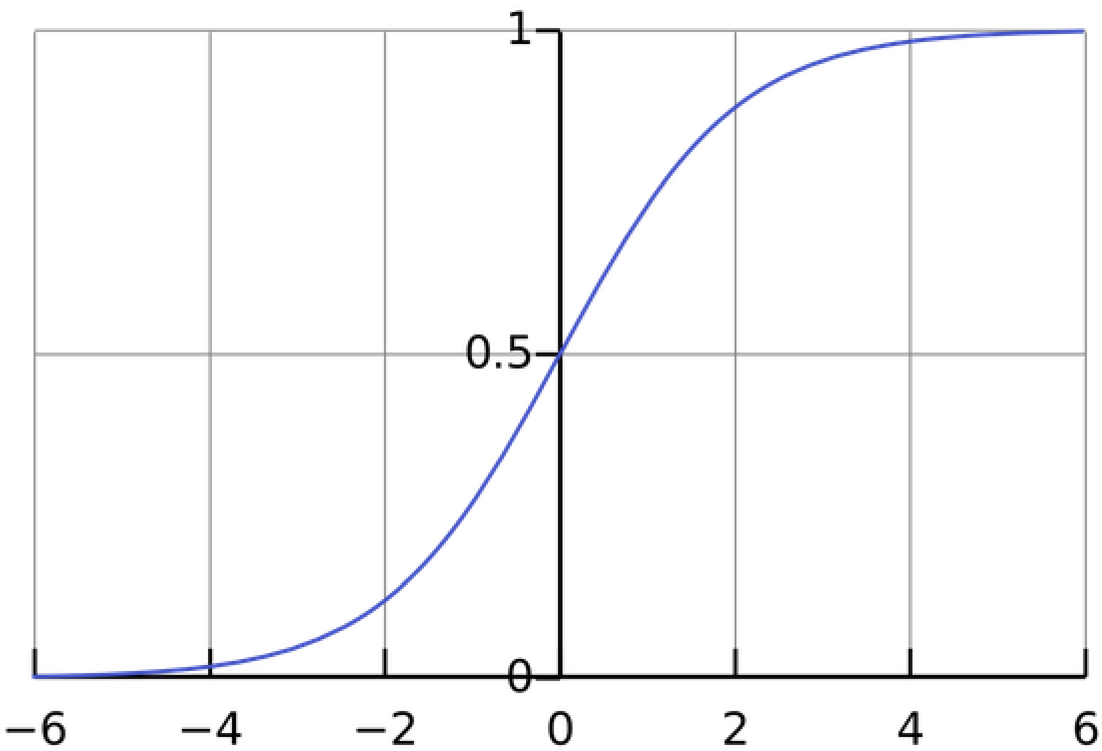
```
# as first layer in a sequential model:
model = Sequential()
model.add(Dense(32, input_shape=(16,)))
# now the model will take as input arrays of shape (*, 16)
# and output arrays of shape (*, 32)

# after the first layer, you don't need to specify
# the size of the input anymore:
model.add(Dense(32))
```

In [28]:

```
# Add dense layer with 10 neurons
model.add(Dense(10))
```

Activation Layer (Softmax Layer)

Softmax activation function.



produces just the result of applying the softmax function to an input tensor. The softmax "squishes" the inputs so that `sum(input) = 1;` it's a way of normalizing. The shape of output of a softmax is the same as the input - it just normalizes the values. The outputs of softmax can be interpreted as probabilities.

Arguments

- **activation**: name of activation function to use, or alternatively, a Theano or TensorFlow operation.

In [29]:

```
# we use the softmax activation function for our last layer
model.add(Activation('softmax'))
```

In [30]:

```
# give an overview of our model
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_2 (Conv2D)            (None, 512, 512, 32)      896       
_________________________________________________________________
activation_3 (Activation)    (None, 512, 512, 32)      0         
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 256, 256, 32)      0         
_________________________________________________________________
flatten_2 (Flatten)          (None, 2097152)           0         
_________________________________________________________________
dense_2 (Dense)              (None, 10)                20971530  
_________________________________________________________________
activation_4 (Activation)    (None, 10)                0         
=================================================================
Total params: 20,972,426
Trainable params: 20,972,426
Non-trainable params: 0
_________________________________________________________________
```

Training

Training a CNN works in the same way as a regular neural network, using backpropagration or gradient descent. However, here this is a bit more mathematically complex because of the convolution operations.

In [12]:

```
# Before the training process, we have to put together a learning process in a particular f
# It consists of 3 elements: an optimiser, a loss function and a metric.

model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam()
```

Testing with sample dataset

In [2]:

```
# TensorFlow and tf.keras
import tensorflow as tf
from tensorflow import keras

# Helper libraries
import numpy as np
from keras.utils import np_utils
import matplotlib.pyplot as plt

print(tf.__version__)
```

```
1.11.0
```

Load Dataset

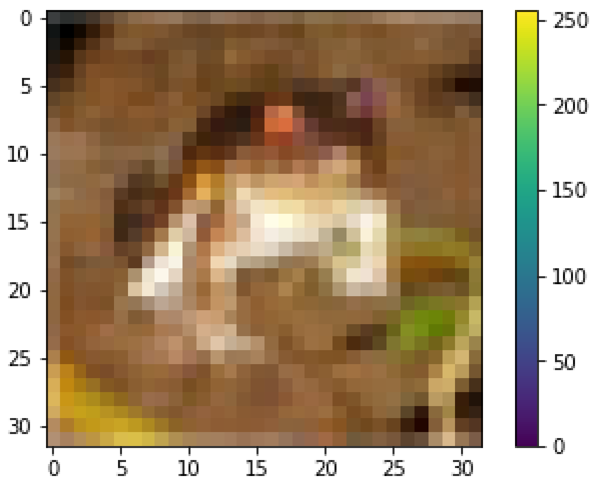
in this instance we will use the fashion dataset from the tensorflow tutorials
https://www.tensorflow.org/tutorials/keras/basic_classification
(https://www.tensorflow.org/tutorials/keras/basic_classification)

In [3]:

```
# dataset import
from keras.datasets import cifar10

(train_imgs, train_lbls), (test_imgs, test_lbls) = cifar10.load_data()

train_data = train_imgs
test_data = test_imgs

train_labels = train_lbls
test_labels = test_lbls

# labels for end results
class_names = ['airplane','automobile','bird','cat','deer','dog','frog','horse','ship','tru

batch_size = 32
# 32 examples in a mini-batch, smaller batch size means more updates in one epoch

num_classes = 10 #
epochs = 20 # repeat 20 times
```

In [4]:

```
plt.figure()
plt.imshow(train_data[0])
plt.colorbar()
plt.grid(False)
```



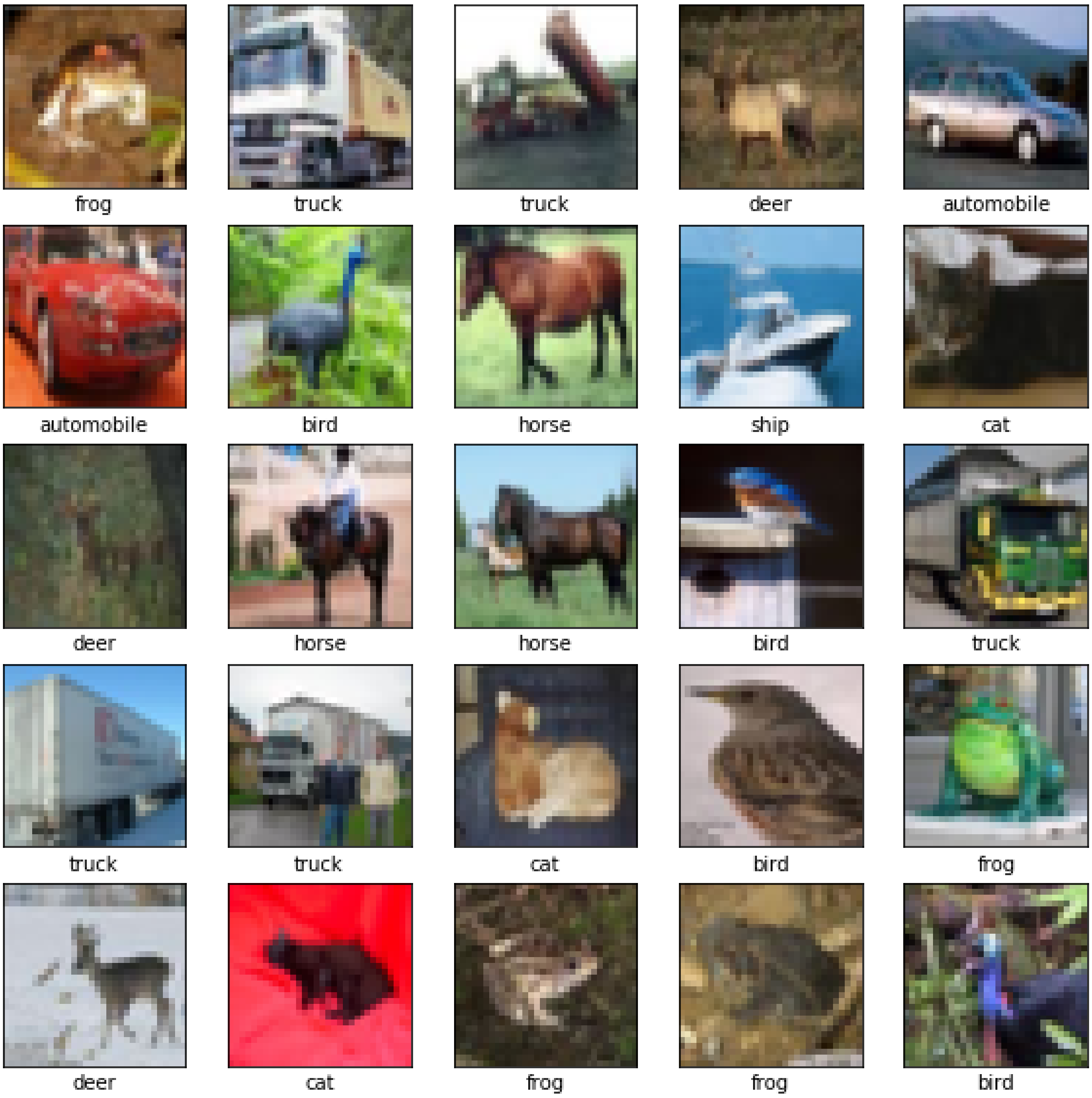
Preproccesing the data

We scale these values to a range of 0 to 1 before feeding to the neural network model. For this, cast the datatype of the image components from an integer to a float, and divide by 255. Here's the function to preprocess the images:

It's important that the training set and the testing set are preprocessed in the same way:

In [5]:

```
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_data[i])
    plt.xlabel(class_names[train_lbls[i][0]])
```



Normalizing the data

In [6]:

```
# Convert and pre-processing

train_lbls = np_utils.to_categorical(train_lbls, num_classes)
test_lbls = np_utils.to_categorical(test_lbls, num_classes)
train_imgs = train_imgs.astype('float32')
test_imgs = test_imgs.astype('float32')
train_imgs  /= 255
test_imgs /= 255
```

In [7]:

```
# exploring the train data
print('Train data')
print(train_imgs.shape)
print(len(train_lbls))
print(train_lbls)

# exploring the test data
print('\nTest data')
print(test_imgs.shape)
print(len(test_lbls))
print(test_lbls)
```

```
Train data
(50000, 32, 32, 3)
50000
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 1.]
 [0. 0. 0. ... 0. 0. 1.]
 ...
 [0. 0. 0. ... 0. 0. 1.]
 [0. 1. 0. ... 0. 0. 0.]
 [0. 1. 0. ... 0. 0. 0.]]

Test data
(10000, 32, 32, 3)
10000
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 1. 0.]
 [0. 0. 0. ... 0. 1. 0.]
 ...
 [0. 0. 0. ... 0. 0. 0.]
 [0. 1. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 1. 0. 0.]]
```

Building test model

In [8]:

```
# Setup the model
model = keras.Sequential([
    # feature extraction layers
    keras.layers.Conv2D(32, kernel_size=(3,3), padding="same", input_shape=train_imgs.shape
    keras.layers.Dropout(0.2),

    keras.layers.Conv2D(32, kernel_size=(3,3), padding="same", activation=tf.nn.relu),
    keras.layers.MaxPool2D(pool_size=(2,2)),

    keras.layers.Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu),
    keras.layers.Dropout(0.2),

    keras.layers.Conv2D(64, kernel_size=(3,3), padding="same", activation=tf.nn.relu),
    keras.layers.MaxPool2D(pool_size=(2,2)),

    keras.layers.Conv2D(128, kernel_size=(3,3), padding="same", activation=tf.nn.relu),
    keras.layers.Dropout(0.2),

    keras.layers.Conv2D(128, kernel_size=(3,3), padding="same", activation=tf.nn.relu),
    keras.layers.MaxPool2D(pool_size=(2,2)),

    # hidden layers
    keras.layers.Flatten(),
    keras.layers.Dense(1024, activation=tf.nn.relu, kernel_constraint=maxnorm(3)),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(10, activation=tf.nn.softmax)
])

# compile the model
model.compile(optimizer=keras.optimizers.Adam(),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

In [9]:

```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 32, 32, 32)        896
_________________________________________________________________
dropout (Dropout)            (None, 32, 32, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 32, 32, 32)        9248
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 16, 16, 64)        18496
_________________________________________________________________
dropout_1 (Dropout)          (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 16, 16, 64)        36928
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 8, 8, 64)          0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 8, 8, 128)         73856
_________________________________________________________________
dropout_2 (Dropout)          (None, 8, 8, 128)         0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 8, 8, 128)         147584
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 4, 4, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 2048)              0
_________________________________________________________________
dense (Dense)                (None, 1024)              2098176
_________________________________________________________________
dropout_3 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 10)                10250
=================================================================
Total params: 2,395,434
Trainable params: 2,395,434
Non-trainable params: 0
_________________________________________________________________
```

In [10]:

```
# train the model
model.fit(train_imgs, train_lbls, epochs=epochs)
```

```
Epoch 1/20
50000/50000 [==============================] - 298s 6ms/step - loss: 1.5802
- acc: 0.4169
Epoch 2/20
50000/50000 [==============================] - 299s 6ms/step - loss: 1.1050
- acc: 0.6069
Epoch 3/20
50000/50000 [==============================] - 285s 6ms/step - loss: 0.9062
- acc: 0.6794
Epoch 4/20
50000/50000 [==============================] - 282s 6ms/step - loss: 0.7982
- acc: 0.7200 3s - loss: 0
Epoch 5/20
50000/50000 [==============================] - 280s 6ms/step - loss: 0.7196
- acc: 0.7454
Epoch 6/20
50000/50000 [==============================] - 281s 6ms/step - loss: 0.6614
- acc: 0.7684
Epoch 7/20
50000/50000 [==============================] - 281s 6ms/step - loss: 0.6127
- acc: 0.7847
Epoch 8/20
50000/50000 [==============================] - 280s 6ms/step - loss: 0.5701
- acc: 0.7973
Epoch 9/20
50000/50000 [==============================] - 279s 6ms/step - loss: 0.5424
- acc: 0.8093 2s - loss: 0.5415 - acc: 0.8 - ETA: 2s - loss: 0.5415 -
Epoch 10/20
50000/50000 [==============================] - 287s 6ms/step - loss: 0.5162
- acc: 0.8190
Epoch 11/20
50000/50000 [==============================] - 281s 6ms/step - loss: 0.4905
- acc: 0.8272
Epoch 12/20
50000/50000 [==============================] - 279s 6ms/step - loss: 0.4693
- acc: 0.8345 0s - loss: 0.4689 - acc:
Epoch 13/20
50000/50000 [==============================] - 280s 6ms/step - loss: 0.4472
- acc: 0.8437
Epoch 14/20
50000/50000 [==============================] - 279s 6ms/step - loss: 0.4387
- acc: 0.8471 0s - loss: 0.4386 - acc: 0.8
Epoch 15/20
50000/50000 [==============================] - 280s 6ms/step - loss: 0.4232
- acc: 0.8522
Epoch 16/20
50000/50000 [==============================] - 280s 6ms/step - loss: 0.4108
- acc: 0.8581
Epoch 17/20
50000/50000 [==============================] - 280s 6ms/step - loss: 0.4063
- acc: 0.8580
Epoch 18/20
50000/50000 [==============================] - 279s 6ms/step - loss: 0.3954
- acc: 0.8622
Epoch 19/20
50000/50000 [==============================] - 280s 6ms/step - loss: 0.3927
```

```
- acc: 0.8641
Epoch 20/20
50000/50000 [==============================] - 308s 6ms/step - loss: 0.3856
- acc: 0.8661 1s - loss: 0.3850 - a
```

Out[10]:

```
<tensorflow.python.keras.callbacks.History at 0x1a4b4665668>
```

In [11]:

```
# evaluate accuracy
test_loss, test_acc = model.evaluate(test_imgs, test_lbls)

print('Test accuracy:', test_acc)
```

```
10000/10000 [==============================] - 17s 2ms/step
Test accuracy: 0.7692
```

predictions

the prediction score describes the confidence of the model that the image corresponds to each of the 10 different articles of clothing

In [12]:

```
# make predictions
predictions = model.predict(test_imgs)

predictions[0]
```

Out[12]:

```
array([5.3405785e-03, 1.6378282e-03, 4.9716760e-03, 5.9579259e-01,
       2.8712681e-04, 3.6868349e-01, 7.1544969e-03, 3.2069380e-03,
       8.7686814e-03, 4.1566635e-03], dtype=float32)
```

Helper functions

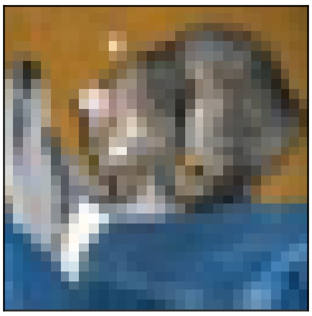
these functions help visualize and check correct predictions

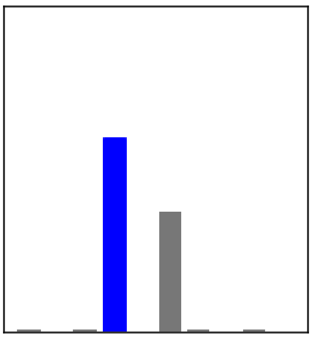
In [13]:

```
def plot_image(i, predictions_array, true_label, img):
  predictions_array, true_label, img = predictions_array[i], true_label[i], img[i]
  plt.grid(False)
  plt.xticks([])
  plt.yticks([])

  plt.imshow(img, cmap=plt.cm.binary)

  predicted_label = np.argmax(predictions_array)
  if predicted_label == true_label:
    color = 'blue'
  else:
    color = 'red'

  plt.xlabel("{} {:2.0f}% ({})".format(class_names[predicted_label],
                                100*np.max(predictions_array),
                                class_names[true_label]),
                                color=color)

def plot_value_array(i, predictions_array, true_label):
  predictions_array, true_label = predictions_array[i], true_label[i]
  plt.grid(False)
  plt.xticks([])
  plt.yticks([])
  thisplot = plt.bar(range(10), predictions_array, color="#777777")
  plt.ylim([0, 1])
  predicted_label = np.argmax(predictions_array)

  thisplot[predicted_label].set_color('red')
  thisplot[true_label].set_color('blue')
```

In [14]:

```
i = 0
plt.figure(figsize=(6,3))
plt.subplot(1,2,1)
plot_image(i, predictions, test_labels[:,0], test_data)
plt.subplot(1,2,2)
plot_value_array(i, predictions,  test_labels[:,0])
```

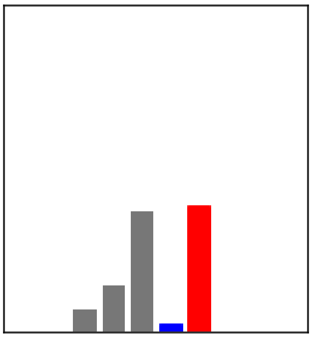

cat 60% (cat)



In [15]:

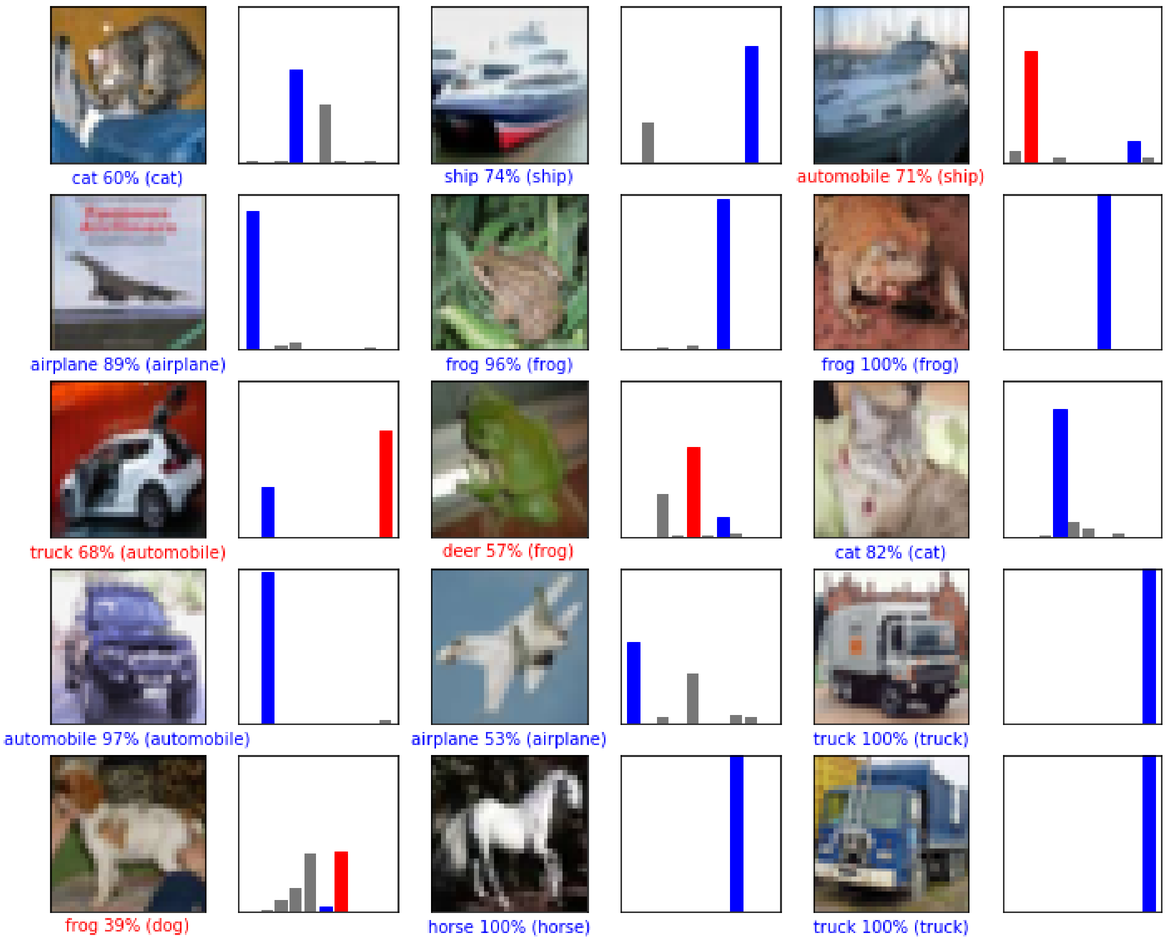
```
i = 12
plt.figure(figsize=(6,3))
plt.subplot(1,2,1)
plot_image(i, predictions, test_labels[:,0], test_imgs)
plt.subplot(1,2,2)
plot_value_array(i, predictions,  test_labels[:,0])
```

frog 39% (dog)



In [16]:

```
num_rows = 5
num_cols = 3
num_images = num_rows*num_cols
plt.figure(figsize=(2*2*num_cols, 2*num_rows))
for i in range(num_images):
  plt.subplot(num_rows, 2*num_cols, 2*i+1)
  plot_image(i, predictions, test_labels[:,0], test_imgs)
  plt.subplot(num_rows, 2*num_cols, 2*i+2)
  plot_value_array(i, predictions, test_labels[:,0])
```



Use of trained model

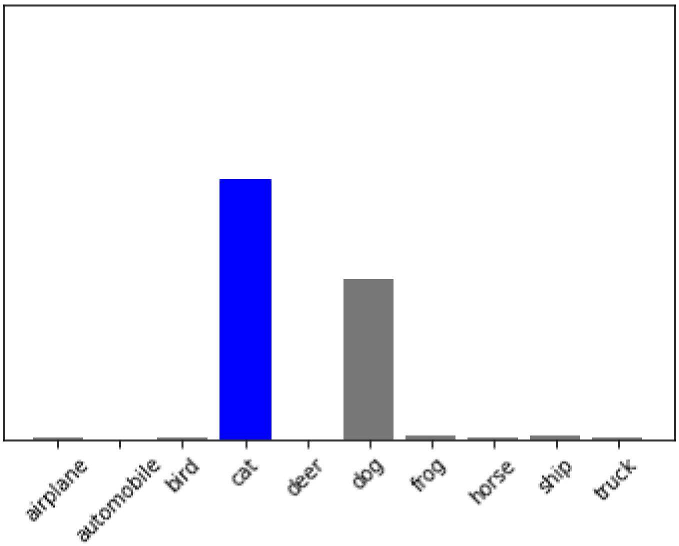
In [17]:

```
# Grab an image from the test dataset
img = test_imgs[0]

print(img.shape)

# Add the image to a batch where it's the only member.
img = (np.expand_dims(img,0))

print(img.shape)

predictions_single = model.predict(img)

print(predictions_single)

plot_value_array(0, predictions_single, test_labels[:,0])
_ = plt.xticks(range(10), class_names, rotation=45)

np.argmax(predictions_single[0])
```

```
(32, 32, 3)
(1, 32, 32, 3)
[[5.3405738e-03 1.6378275e-03 4.9716765e-03 5.9579265e-01 2.8712698e-04
  3.6868337e-01 7.1544903e-03 3.2069352e-03 8.7686786e-03 4.1566617e-03]]
```

Out[17]:

```
3
```



Save the model

In [18]:

```
model.save('./cifar10_model.h5')
```

In [51]:

```
del model
```

In [53]:

```
from keras.models import load_model
model = load_model('cifar10_model.h5')
```

In [ ]:

```

```