

In [1]:

```
# Load CIFAR-10 data set
from keras.datasets import cifar10
(X_train, y_train), (X_test, y_test) = cifar10.load_data()
```

Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>
 170500096/170498071 [=====] - 4s 0us/step

In [2]:

```
# Show examples from each class
import numpy as np
import matplotlib.pyplot as plt

num_classes = len(np.unique(y_train))
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
fig = plt.figure(figsize=(8,3))
for i in range(num_classes):
    ax = fig.add_subplot(2, 5, 1 + i, xticks=[], yticks=[])
    ax.set_title(class_names[i])
    idx = np.where(y_train[:,i]==1)[0]
    features_idx = X_train[idx,:]
    rnd_img = np.random.randint(features_idx.shape[0])
    im = np.transpose(features_idx[rnd_img,:], (0, 1, 2))
    plt.imshow(im)
plt.show()
```



In [3]:

```
# Data pre-processing
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train /= 255.0
X_test /= 255.0

from keras.utils import np_utils
Y_train = np_utils.to_categorical(y_train, num_classes)
Y_test = np_utils.to_categorical(y_test, num_classes)
```

In [4]:

```
def plot_model_history(model_history):
    fig, axs = plt.subplots(1,2,figsize=(15,5))
    # Summarize history for accuracy
    axs[0].plot(range(1,len(model_history.history['accuracy'])+1),model_history.history['accuracy'])
    axs[0].plot(range(1,len(model_history.history['val_accuracy'])+1),model_history.history['val_accuracy'])
    axs[0].set_ylim(0, 1)
    axs[0].set_title('Model Accuracy')
    axs[0].set_ylabel('Accuracy')
    axs[0].set_xlabel('Epoch')
```

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    axs[0].set_xticks(np.arange(1,len(model_history.history['accuracy'])+1,step=len(
    axs[0].legend(['train', 'val'], loc='best')
    # summarize history for loss
    axs[1].plot(range(1,len(model_history.history['loss'])+1),model_history.history[
    axs[1].plot(range(1,len(model_history.history['val_loss'])+1),model_history.hist
    axs[1].set_title('Model Loss')
    axs[1].set_ylabel('Loss')
    axs[1].set_xlabel('Epoch')
    axs[1].set_xticks(np.arange(1,len(model_history.history['loss'])+1,step=len(mode
    axs[1].legend(['train', 'val'], loc='best')
    plt.show()

```

```

In [5]: # Tensorboard
        from time import time
        from keras.callbacks import TensorBoard
        tensorboard = TensorBoard(log_dir='logs/{}'.format(time()))

```

```

In [6]: # Data augmentation
        from keras.preprocessing.image import ImageDataGenerator
        datagen = ImageDataGenerator(
            # featurewise_center=True,
            # featurewise_std_normalization=True,
            rotation_range=10.,
            width_shift_range=0.1,
            height_shift_range=0.1,
            horizontal_flip=True,
            zoom_range=0.1,
            shear_range=0.1,
            fill_mode='nearest')

        datagen.fit(X_train)

```

Definición de una red convolucional multicapa

```

In [7]: # Convolutional Neural Network (CNN)
        # Here you are allowed to use convolutional layers
        # You may use also any regularization (see class slides)

        from keras.models import Sequential
        from keras.layers import Dense, Activation, Flatten, Dropout, BatchNormalization
        from keras import optimizers
        from keras.callbacks import EarlyStopping
        from keras.regularizers import l2
        from keras.layers.convolutional import Conv2D, MaxPooling2D
        import keras.backend as K
        from keras.callbacks import ModelCheckpoint

        checkpoint_path = "/gdrive/My Drive/Colab Notebooks/MUIA-ComputerVision/P4/Alberto_C
        checkpoint_callback = ModelCheckpoint(
            checkpoint_path, monitor='val_accuracy', verbose=1, save_weights_only=True,
            # Save weights, every epoch.
            save_freq='epoch', mode='auto', save_best_only=True)

        learning_rate=0.001
        epochs=500
        batch_size=256
        es = EarlyStopping(monitor='val_loss', mode='auto', verbose=1, patience=int(epochs*0
        p_dropou_layert=[0,0.2,0.3,0.5]

```

```

i=0
d_augm=1

model = Sequential()
model.add(Conv2D(filters=32, kernel_size=(3, 3), activation='relu', padding='same', i
model.add(BatchNormalization())
model.add(Conv2D(filters=32, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D( pool_size=(2, 2)))
model.add(Dropout(p_dropou_layert[i]))
i+=1
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(p_dropou_layert[i]))
i+=1
model.add(Conv2D(filters=128, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(filters=128, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(p_dropou_layert[i]))
i+=1
model.add(Conv2D(filters=256, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(filters=256, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
# model.add(BatchNormalization())
model.add(Dropout(p_dropou_layert[i]))
i+=1
model.add(Conv2D(filters=512, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(filters=512, kernel_size=(3, 3), activation='relu', padding='same'))
model.add(BatchNormalization())
model.add(Conv2D(filters=num_classes, kernel_size=(2, 2), padding='valid'))
model.add(Flatten())
model.add(Activation('softmax'))

# opt = optimizers.SGD(lr=Learning_rate, momentum=0.9, nesterov=True)
opt = optimizers.Adam(lr=learning_rate, beta_1=0.9, beta_2=0.999)

model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accuracy'])
model.summary()

```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 32, 32, 32)	896
batch_normalization (BatchNo	(None, 32, 32, 32)	128
conv2d_1 (Conv2D)	(None, 32, 32, 32)	9248
batch_normalization_1 (Batch	(None, 32, 32, 32)	128
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
dropout (Dropout)	(None, 16, 16, 32)	0

conv2d_2 (Conv2D)	(None, 16, 16, 64)	18496
batch_normalization_2 (Batch Normalization)	(None, 16, 16, 64)	256
conv2d_3 (Conv2D)	(None, 16, 16, 64)	36928
batch_normalization_3 (Batch Normalization)	(None, 16, 16, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 64)	0
dropout_1 (Dropout)	(None, 8, 8, 64)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	73856
batch_normalization_4 (Batch Normalization)	(None, 8, 8, 128)	512
conv2d_5 (Conv2D)	(None, 8, 8, 128)	147584
batch_normalization_5 (Batch Normalization)	(None, 8, 8, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 128)	0
dropout_2 (Dropout)	(None, 4, 4, 128)	0
conv2d_6 (Conv2D)	(None, 4, 4, 256)	295168
batch_normalization_6 (Batch Normalization)	(None, 4, 4, 256)	1024
conv2d_7 (Conv2D)	(None, 4, 4, 256)	590080
batch_normalization_7 (Batch Normalization)	(None, 4, 4, 256)	1024
max_pooling2d_3 (MaxPooling2D)	(None, 2, 2, 256)	0
dropout_3 (Dropout)	(None, 2, 2, 256)	0
conv2d_8 (Conv2D)	(None, 2, 2, 512)	1180160
batch_normalization_8 (Batch Normalization)	(None, 2, 2, 512)	2048
conv2d_9 (Conv2D)	(None, 2, 2, 512)	2359808
batch_normalization_9 (Batch Normalization)	(None, 2, 2, 512)	2048
conv2d_10 (Conv2D)	(None, 1, 1, 10)	20490
flatten (Flatten)	(None, 10)	0
activation (Activation)	(None, 10)	0
=====		
Total params: 4,740,650		
Trainable params: 4,736,682		
Non-trainable params: 3,968		

In [8]:

```

# Training
if d_augm==1:
    # Fit the model with real time data augmentation
    print("Fitting model with data augmentation")
    start = time()
    history = model.fit(datagen.flow(X_train, Y_train, batch_size=batch_size),
                        epochs=epochs, verbose=2, validation_data=(X_test, Y_test))
    end = time()

```

```

else:
    # Fit the model with plain dataset
    print("Fitting model")
    start = time()
    history = model.fit(X_train, Y_train, batch_size=batch_size, epochs=epochs, verbose=0)
    end = time()

```

Fitting model with data augmentation

Epoch 1/500

196/196 - 33s - loss: 1.7607 - accuracy: 0.4047 - val_loss: 3.6903 - val_accuracy: 0.1000

Epoch 00001: val_accuracy improved from -inf to 0.10000, saving model to /gdrive/My Drive/Colab Notebooks/MUIA-ComputerVision/P4/Alberto_CIFAR10CNN1/best_epoch_val_acc.ckpt

Epoch 2/500

196/196 - 24s - loss: 1.2237 - accuracy: 0.5575 - val_loss: 2.3818 - val_accuracy: 0.3017

Epoch 00002: val_accuracy improved from 0.10000 to 0.30170, saving model to /gdrive/My Drive/Colab Notebooks/MUIA-ComputerVision/P4/Alberto_CIFAR10CNN1/best_epoch_val_acc.ckpt

Epoch 3/500

196/196 - 24s - loss: 1.0069 - accuracy: 0.6440 - val_loss: 1.1037 - val_accuracy: 0.6463

Epoch 00003: val_accuracy improved from 0.30170 to 0.64630, saving model to /gdrive/My Drive/Colab Notebooks/MUIA-ComputerVision/P4/Alberto_CIFAR10CNN1/best_epoch_val_acc.ckpt

Epoch 4/500

196/196 - 23s - loss: 0.8802 - accuracy: 0.6919 - val_loss: 0.8553 - val_accuracy: 0.7177

Epoch 00004: val_accuracy improved from 0.64630 to 0.71770, saving model to /gdrive/My Drive/Colab Notebooks/MUIA-ComputerVision/P4/Alberto_CIFAR10CNN1/best_epoch_val_acc.ckpt

Epoch 5/500

196/196 - 24s - loss: 0.7881 - accuracy: 0.7246 - val_loss: 0.8301 - val_accuracy: 0.7260

Epoch 00005: val_accuracy improved from 0.71770 to 0.72600, saving model to /gdrive/My Drive/Colab Notebooks/MUIA-ComputerVision/P4/Alberto_CIFAR10CNN1/best_epoch_val_acc.ckpt

Epoch 6/500

196/196 - 24s - loss: 0.7349 - accuracy: 0.7439 - val_loss: 0.7803 - val_accuracy: 0.7382

Epoch 00006: val_accuracy improved from 0.72600 to 0.73820, saving model to /gdrive/My Drive/Colab Notebooks/MUIA-ComputerVision/P4/Alberto_CIFAR10CNN1/best_epoch_val_acc.ckpt

Epoch 7/500

196/196 - 24s - loss: 0.6785 - accuracy: 0.7651 - val_loss: 0.7724 - val_accuracy: 0.7504

Epoch 00007: val_accuracy improved from 0.73820 to 0.75040, saving model to /gdrive/My Drive/Colab Notebooks/MUIA-ComputerVision/P4/Alberto_CIFAR10CNN1/best_epoch_val_acc.ckpt

Epoch 8/500

196/196 - 24s - loss: 0.6431 - accuracy: 0.7752 - val_loss: 0.7465 - val_accuracy: 0.7480

Epoch 00008: val_accuracy did not improve from 0.75040

Epoch 9/500

196/196 - 24s - loss: 0.0871 - accuracy: 0.9689 - val_loss: 0.3765 - val_accuracy: 0.9033

Epoch 00246: val_accuracy did not improve from 0.90940

Epoch 247/500

196/196 - 24s - loss: 0.0903 - accuracy: 0.9681 - val_loss: 0.4375 - val_accuracy: 0.8938

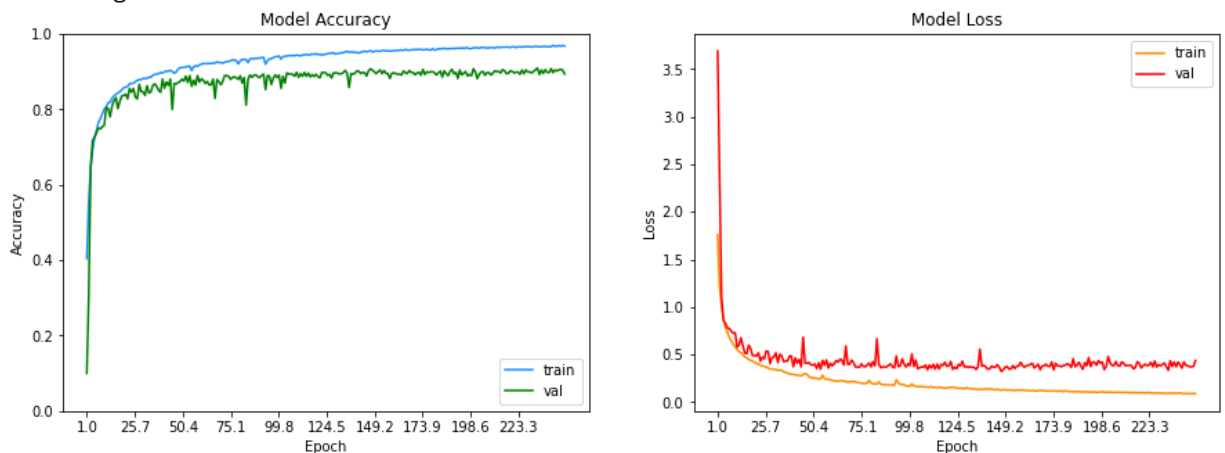
Epoch 00247: val_accuracy did not improve from 0.90940

Epoch 00247: early stopping

In [9]:

```
print("Training CNN took " + str(end - start) + " seconds")
plot_model_history(history)
```

Training CNN took 5831.713987112045 seconds



In [10]:

```
start = time()
loss, acc = model.evaluate(X_test, Y_test, verbose=0)
end = time()
print('CNN took ' + str(end - start) + ' seconds')
print('For final weights configuration:\n\tTest loss: ' + str(loss) + ' - Accuracy:
```

CNN took 1.297666072845459 seconds

For final weights configuration:

Test loss: 0.4375062882900238 - Accuracy: 0.8938000202178955

In [11]:

```
model.load_weights(checkpoint_path)
start = time()
loss, acc = model.evaluate(X_test, Y_test, verbose=0)
end = time()
print('CNN took ' + str(end - start) + ' seconds')
print('For best validation accuracy weights configuration found in training:\n\tTest
```

CNN took 1.2773823738098145 seconds

For best validation accuracy weights configuration found in training:

Test loss: 0.3355124890804291 - Accuracy: 0.9093999862670898