Install the dependencies

In [0]:
```
!pip install tensorflow-gpu==2.0.0-rc0
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Flatten, Dense, Conv2D, MaxPool2D, ZeroPadding2D, Dropout, Batch
Normalization
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.optimizers import SGD
import numpy as np
import matplotlib.pyplot as plt
```

```
Collecting tensorflow-gpu==2.0.0-rc0
  Downloading https://files.pythonhosted.org/packages/6a/12/8c64cc62149cc21c70c55018502831bbf4d4
2bd62bed196df7de6830d21b/tensorflow_gpu-2.0.0rc0-cp36-cp36m-manylinux2010_x86_64.whl (380.5MB)
     |████████████████████████████████| 380.5MB 35kB/s
Requirement already satisfied: gast>=0.2.0 in /usr/local/lib/python3.6/dist-packages (from tenso
rflow-gpu==2.0.0-rc0) (0.2.2)
Requirement already satisfied: wrapt>=1.11.1 in /usr/local/lib/python3.6/dist-packages (from ten
sorflow-gpu==2.0.0-rc0) (1.11.2)
Collecting tb-nightly<1.15.0a20190807,>=1.15.0a20190806
  Downloading https://files.pythonhosted.org/packages/bc/88/24b5fb7280e74c7cf65bde47c171547fd02a
fb3840cff41bcbe9270650f5/tb_nightly-1.15.0a20190806-py3-none-any.whl (4.3MB)
     |████████████████████████████████| 4.3MB 46.4MB/s
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.6/dist-packages (from
tensorflow-gpu==2.0.0-rc0) (3.1.0)
Requirement already satisfied: google-pasta>=0.1.6 in /usr/local/lib/python3.6/dist-packages (fr
om tensorflow-gpu==2.0.0-rc0) (0.1.8)
Requirement already satisfied: keras-applications>=1.0.8 in /usr/local/lib/python3.6/dist-packag
es (from tensorflow-gpu==2.0.0-rc0) (1.0.8)
Requirement already satisfied: keras-preprocessing>=1.0.5 in /usr/local/lib/python3.6/dist-packa
ges (from tensorflow-gpu==2.0.0-rc0) (1.1.0)
Collecting tf-estimator-nightly<1.14.0.dev2019080602,>=1.14.0.dev2019080601
  Downloading https://files.pythonhosted.org/packages/21/28/f2a27a62943d5f041e4a6fd404b2d21cb7c5
9b2242a4e73b03d9ba166552/tf_estimator_nightly-1.14.0.dev2019080601-py2.py3-none-any.whl (501kB)
     |████████████████████████████████| 501kB 57.1MB/s
Requirement already satisfied: grpcio>=1.8.6 in /usr/local/lib/python3.6/dist-packages (from ten
sorflow-gpu==2.0.0-rc0) (1.15.0)
Requirement already satisfied: wheel>=0.26 in /usr/local/lib/python3.6/dist-packages (from tenso
rflow-gpu==2.0.0-rc0) (0.33.6)
Requirement already satisfied: absl-py>=0.7.0 in /usr/local/lib/python3.6/dist-packages (from te
nsorflow-gpu==2.0.0-rc0) (0.8.1)
Requirement already satisfied: six>=1.10.0 in /usr/local/lib/python3.6/dist-packages (from tenso
rflow-gpu==2.0.0-rc0) (1.12.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.6/dist-packages (from
tensorflow-gpu==2.0.0-rc0) (1.1.0)
Requirement already satisfied: astor>=0.6.0 in /usr/local/lib/python3.6/dist-packages (from tens
orflow-gpu==2.0.0-rc0) (0.8.0)
Requirement already satisfied: protobuf>=3.6.1 in /usr/local/lib/python3.6/dist-packages (from t
ensorflow-gpu==2.0.0-rc0) (3.10.0)
Requirement already satisfied: numpy<2.0,>=1.16.0 in /usr/local/lib/python3.6/dist-packages (fro
m tensorflow-gpu==2.0.0-rc0) (1.17.4)
Requirement already satisfied: setuptools>=41.0.0 in /usr/local/lib/python3.6/dist-packages (fro
m tb-nightly<1.15.0a20190807,>=1.15.0a20190806->tensorflow-gpu==2.0.0-rc0) (41.6.0)
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python3.6/dist-packages (from
tb-nightly<1.15.0a20190807,>=1.15.0a20190806->tensorflow-gpu==2.0.0-rc0) (0.16.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.6/dist-packages (from t
b-nightly<1.15.0a20190807,>=1.15.0a20190806->tensorflow-gpu==2.0.0-rc0) (3.1.1)
Requirement already satisfied: h5py in /usr/local/lib/python3.6/dist-packages (from keras-applic
ations>=1.0.8->tensorflow-gpu==2.0.0-rc0) (2.8.0)
Installing collected packages: tb-nightly, tf-estimator-nightly, tensorflow-gpu
Successfully installed tb-nightly-1.15.0a20190806 tensorflow-gpu-2.0.0rc0 tf-estimator-nightly-
1.14.0.dev2019080601
```

Subset of Kaggle Cat and Dog Dataset

In [0]:
```
# Subset of Kaggle Cat and Dog Dataset
!git clone https://github.com/ahatamiz/dog-cat-full-dataset.git
test_data_dir = '/content/dog-cat-full-dataset/data/test'
train_data_dir = '/content/dog-cat-full-dataset/data/train'


datagen = ImageDataGenerator(rescale=1./255)
img_width = 32
img_height = 32
batch_size = 20

train_generator = datagen.flow_from_directory(directory=train_data_dir,
                                              target_size = (img_width, img_height),
                                              classes = ['dogs', 'cats'],
                                              class_mode = 'binary',
                                              batch_size=batch_size)


validation_generator = datagen.flow_from_directory(directory=test_data_dir,
                                                   target_size = (32, 32),
                                                   classes = ['dogs', 'cats'],
                                                   class_mode = 'binary',
                                                   batch_size = batch_size)
```

```
Cloning into 'dog-cat-full-dataset'...
remote: Enumerating objects: 25027, done.
remote: Counting objects: 100% (25027/25027), done.
remote: Compressing objects: 100% (25022/25022), done.
remote: Total 25027 (delta 5), reused 25020 (delta 3), pack-reused 0
Receiving objects: 100% (25027/25027), 541.62 MiB | 53.05 MiB/s, done.
Resolving deltas: 100% (5/5), done.
Checking out files: 100% (25001/25001), done.
Found 20000 images belonging to 2 classes.
Found 5000 images belonging to 2 classes.
```

In [0]:
```
def plot_learningCurve(history):
  # Plot training & validation accuracy values
  epoch_range = range(1, 6)
  plt.plot(epoch_range, history.history['accuracy'])
  plt.plot(epoch_range, history.history['val_accuracy'])
  plt.title('Model accuracy')
  plt.ylabel('Accuracy')
  plt.xlabel('Epoch')
  plt.legend(['Train', 'Val'], loc='upper left')
  plt.show()

  # Plot training & validation loss values
  plt.plot(epoch_range, history.history['loss'])
  plt.plot(epoch_range, history.history['val_loss'])
  plt.title('Model loss')
  plt.ylabel('Loss')
  plt.xlabel('Epoch')
  plt.legend(['Train', 'Val'], loc='upper left')
  plt.show()
```

Let's Build a VGG 16 CNN

First implement the first conv block

alt text

In [0]:
```
model = Sequential()
model.add(Conv2D(filters=64, kernel_size=(3,3), activation='relu', padding='same', kernel_initialize
r='he_uniform', input_shape = (img_width, img_height, 3)))
model.add(MaxPool2D(2,2))

model.add(Flatten())
model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'))
model.add(Dense(1, activation='sigmoid'))
```

Let's talk about SGD with Momentum

from tensorflow.keras.optimizers import SGD

What's the gradient descent with momentum ?

In short we use an expotential

alt text

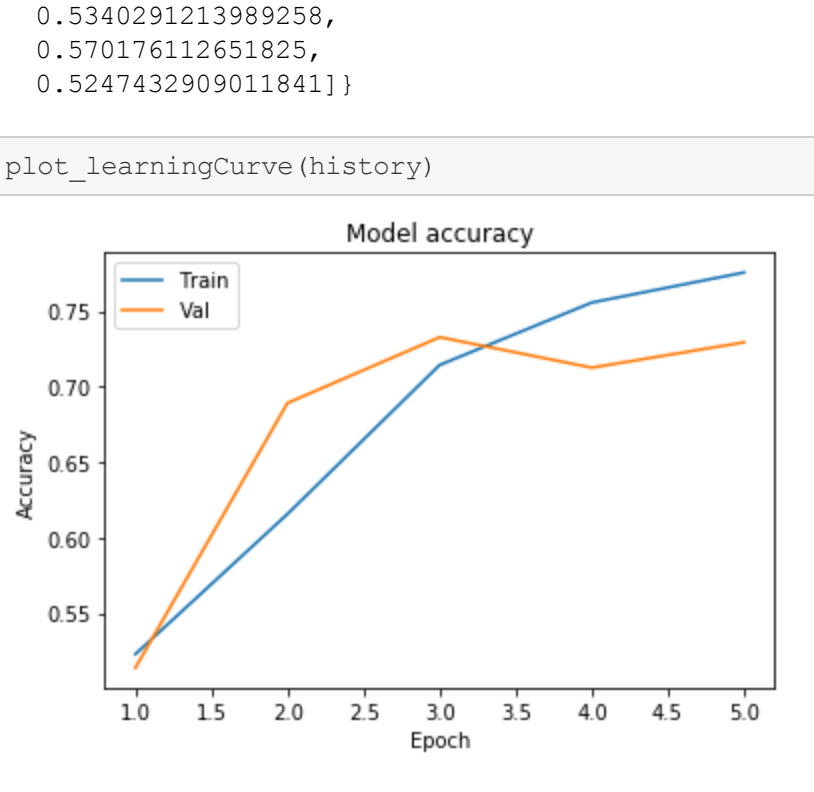
In [0]:
```
from tensorflow.keras.optimizers import SGD

opt = SGD(learning_rate=0.01, momentum=0.9)
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
history = model.fit_generator(generator=train_generator, steps_per_epoch=len(train_generator), epoch
s = 5, validation_data=validation_generator, validation_steps=len(validation_generator), verbose = 1
)
```

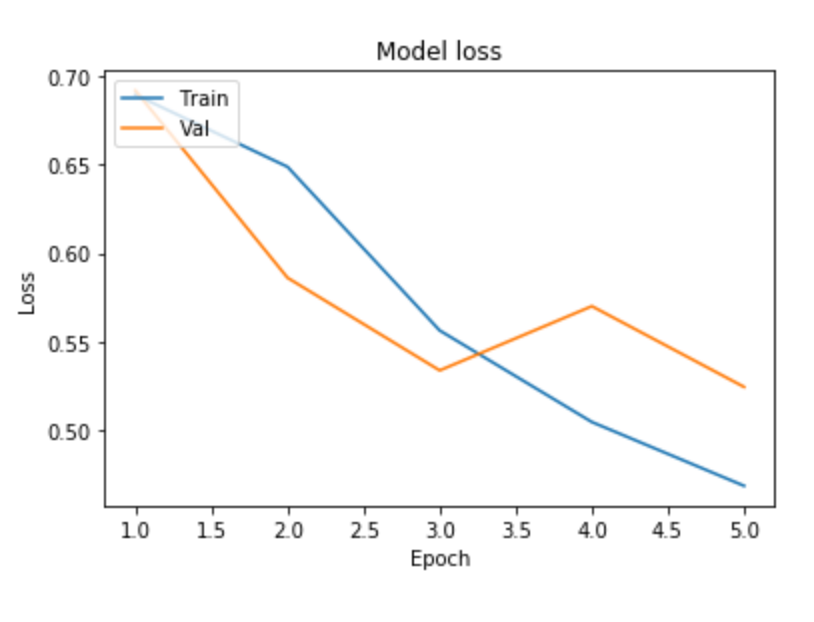
```
Epoch 1/5
1000/1000 [==============================] - 72s 72ms/step - loss: 0.6892 - accuracy: 0.5228 - v
al_loss: 0.6916 - val_accuracy: 0.5138
Epoch 2/5
1000/1000 [==============================] - 72s 72ms/step - loss: 0.6486 - accuracy: 0.6157 - v
al_loss: 0.5862 - val_accuracy: 0.6892
Epoch 3/5
1000/1000 [==============================] - 74s 74ms/step - loss: 0.5565 - accuracy: 0.7144 - v
al_loss: 0.5340 - val_accuracy: 0.7328
Epoch 4/5
1000/1000 [==============================] - 72s 72ms/step - loss: 0.5050 - accuracy: 0.7558 - v
al_loss: 0.5702 - val_accuracy: 0.7126
Epoch 5/5
1000/1000 [==============================] - 72s 72ms/step - loss: 0.4691 - accuracy: 0.7757 - v
al_loss: 0.5247 - val_accuracy: 0.7294
```

In [0]:
```
history.history
```

Out[0]:
```
{'accuracy': [0.52285, 0.6157, 0.7144, 0.75575, 0.77565],
 'loss': [0.6891946232914925,
  0.6486167467236519,
  0.5565113095939159,
  0.5049949596822262,
  0.4690870726406574],
 'val_accuracy': [0.5138, 0.6892, 0.7328, 0.7126, 0.7294],
 'val_loss': [0.6915723826885224,
  0.5861812088489532,
  0.5340291213989258,
  0.570176112651825,
  0.5247432909011841]}
```

In [0]:
```
plot_learningCurve(history)
```





- When the training accuracy is less than the validation accuracy, the model is *underfitting*
- When the training accuracy is higher than the validation accuracy, the model is *overfitting*

Let's Build a VGG 16 CNN

Now, add all the VGG16 Conv blocks

In [0]:
```
![alt text](https://drive.google.com/uc?id=16CUeGt6EIDDGxeMRldoSxVF6IdM1Kujf)
```

```
/bin/bash: -c: line 0: syntax error near unexpected token `('
/bin/bash: -c: line 0: `[alt text](https://drive.google.com/uc?id=16CUeGt6EIDDGxeMRldoSxVF6IdM1K
ujf)'
```

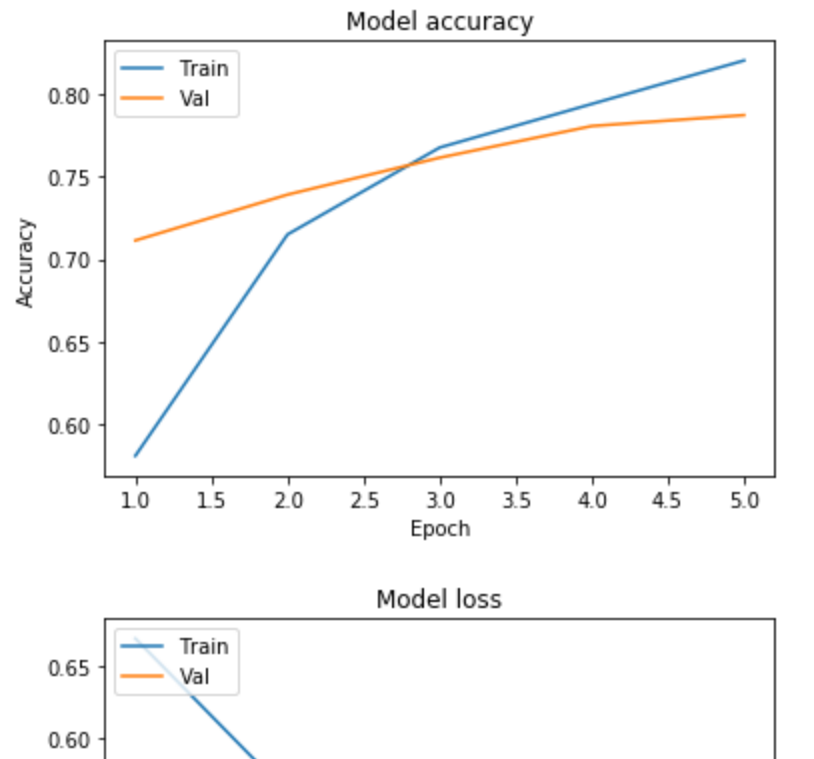
In [0]:
```
model=Sequential()
model.add(Conv2D(filters=64,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(MaxPool2D(2,2))
model.add(Conv2D(filters=128,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(MaxPool2D(2,2))
model.add(Conv2D(filters=256,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(MaxPool2D(2,2))
model.add(Conv2D(filters=512,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(MaxPool2D(2,2))
model.add(Flatten())
model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'))
model.add(Dense(1, activation='sigmoid'))
```

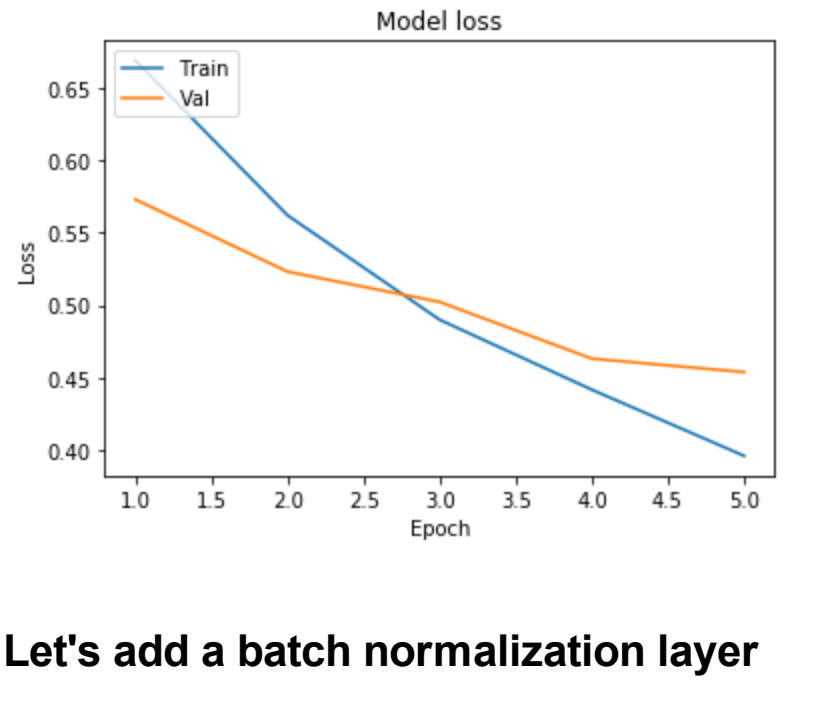
In [0]:
```
opt = SGD(learning_rate=0.01, momentum=0.9)
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
```

In [0]:
```
history = model.fit_generator(generator=train_generator, steps_per_epoch=len(train_generator), epoch
s = 5, validation_data=validation_generator, validation_steps=len(validation_generator), verbose = 1
)
```

```
Epoch 1/5
1000/1000 [==============================] - 87s 87ms/step - loss: 0.6688 - accuracy: 0.5808 - v
al_loss: 0.5729 - val_accuracy: 0.7114
Epoch 2/5
1000/1000 [==============================] - 85s 85ms/step - loss: 0.5620 - accuracy: 0.7150 - v
al_loss: 0.5231 - val_accuracy: 0.7392
Epoch 3/5
1000/1000 [==============================] - 86s 86ms/step - loss: 0.4898 - accuracy: 0.7678 - v
al_loss: 0.5021 - val_accuracy: 0.7616
Epoch 4/5
1000/1000 [==============================] - 86s 86ms/step - loss: 0.4415 - accuracy: 0.7942 - v
al_loss: 0.4630 - val_accuracy: 0.7808
Epoch 5/5
1000/1000 [==============================] - 89s 89ms/step - loss: 0.3959 - accuracy: 0.8206 - v
al_loss: 0.4537 - val_accuracy: 0.7874
```

In [0]:
```
plot_learningCurve(history)
```





Let's add a batch normalization layer

First, normalizing features to have mean zero and variance 1 can spead of learning since input features now take on a similar range of values.

Batch norm disseminates this idea by making the weights in later stages of a neural network to be less susceptible to changes.

In simpler words, by making sure that the input to all layers have been normalized centered around zero, subsequent layers in a neural networks can be more effectively trained. As a result, it **speeds up training**.

alt text

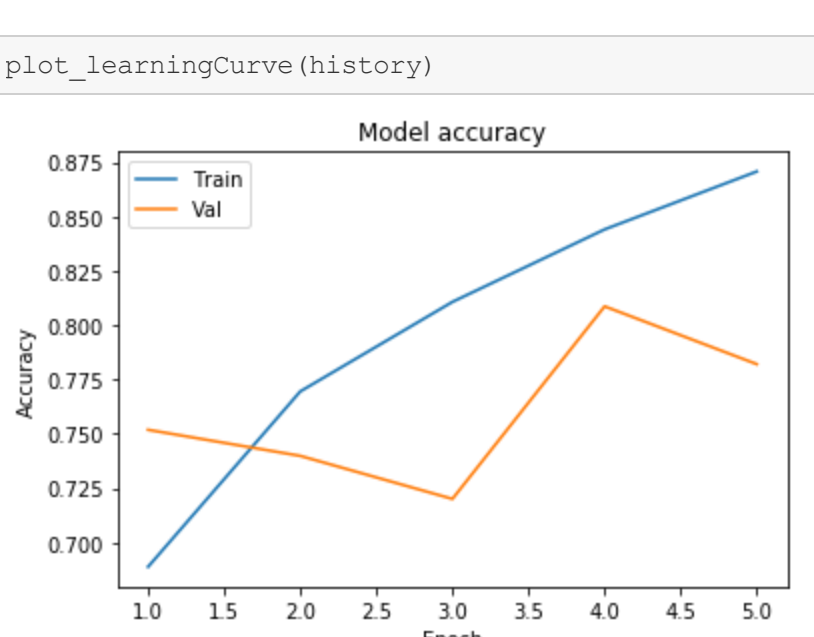
In [0]:
```
model=Sequential()
model.add(Conv2D(filters=64,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Conv2D(filters=128,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Conv2D(filters=256,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Conv2D(filters=512,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Flatten())
model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Dense(1, activation='sigmoid'))
```

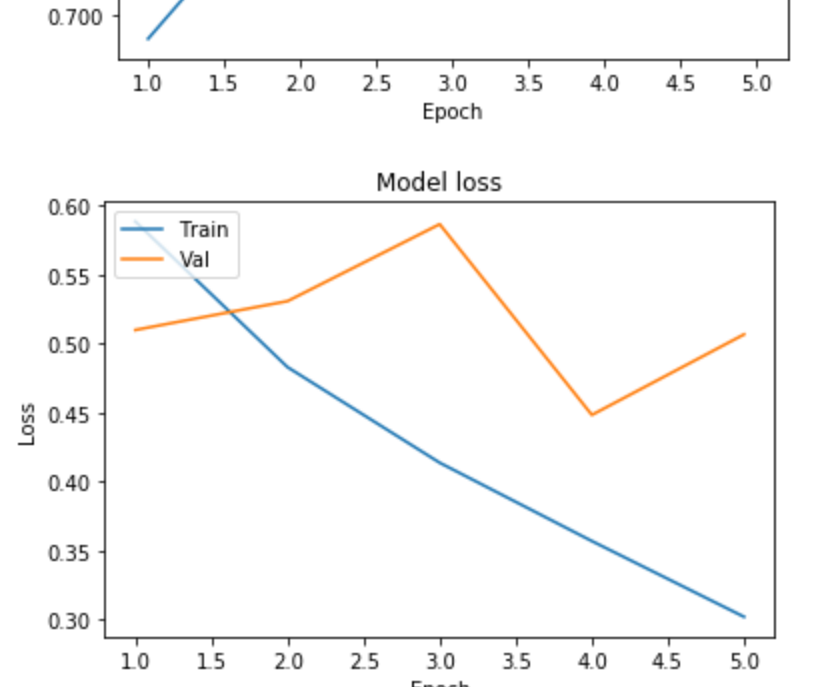
In [0]:
```
opt = SGD(learning_rate=0.01, momentum=0.9)
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
```

In [0]:
```
history = model.fit_generator(generator=train_generator, steps_per_epoch=len(train_generator), epoch
s = 5, validation_data=validation_generator, validation_steps=len(validation_generator), verbose = 1
)
```

```
Epoch 1/5
1000/1000 [==============================] - 120s 120ms/step - loss: 0.5887 - accuracy: 0.6888 -
val_loss: 0.5100 - val_accuracy: 0.7518
Epoch 2/5
1000/1000 [==============================] - 121s 121ms/step - loss: 0.4830 - accuracy: 0.7695 -
val_loss: 0.5309 - val_accuracy: 0.7398
Epoch 3/5
1000/1000 [==============================] - 118s 118ms/step - loss: 0.4137 - accuracy: 0.8106 -
val_loss: 0.5867 - val_accuracy: 0.7200
Epoch 4/5
1000/1000 [==============================] - 120s 120ms/step - loss: 0.3569 - accuracy: 0.8440 -
val_loss: 0.4484 - val_accuracy: 0.8086
Epoch 5/5
1000/1000 [==============================] - 118s 118ms/step - loss: 0.3019 - accuracy: 0.8706 -
val_loss: 0.5068 - val_accuracy: 0.7820
```

In [0]:
```
plot_learningCurve(history)
```





Let's add a Dropout layer (overfitting is an issue !)

- Dropout is a regularization technique that prevents overfitting.

> Indented block

- In dropout, at every iteration, some nodes are randomly removed.
- The intuition behind dropout is to not entirely rely on any one feature (it can go away at random).

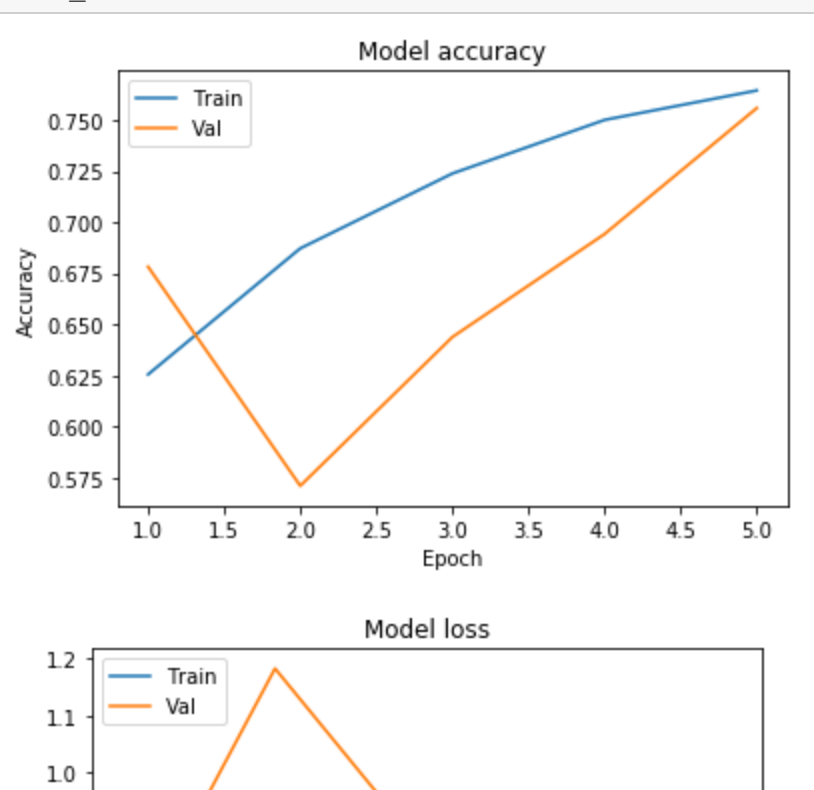
In [0]:
```
model=Sequential()
model.add(Conv2D(filters=64,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Dropout(0.2))
model.add(Conv2D(filters=128,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Dropout(0.3))
model.add(Conv2D(filters=256,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Dropout(0.5))
model.add(Conv2D(filters=512,kernel_size=(3,3),activation='relu', padding='same',kernel_initializer=
'he_uniform',input_shape=(img_width,img_height,3)))
model.add(BatchNormalization())
model.add(MaxPool2D(2,2))
model.add(Flatten())
model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(1, activation='sigmoid'))
```

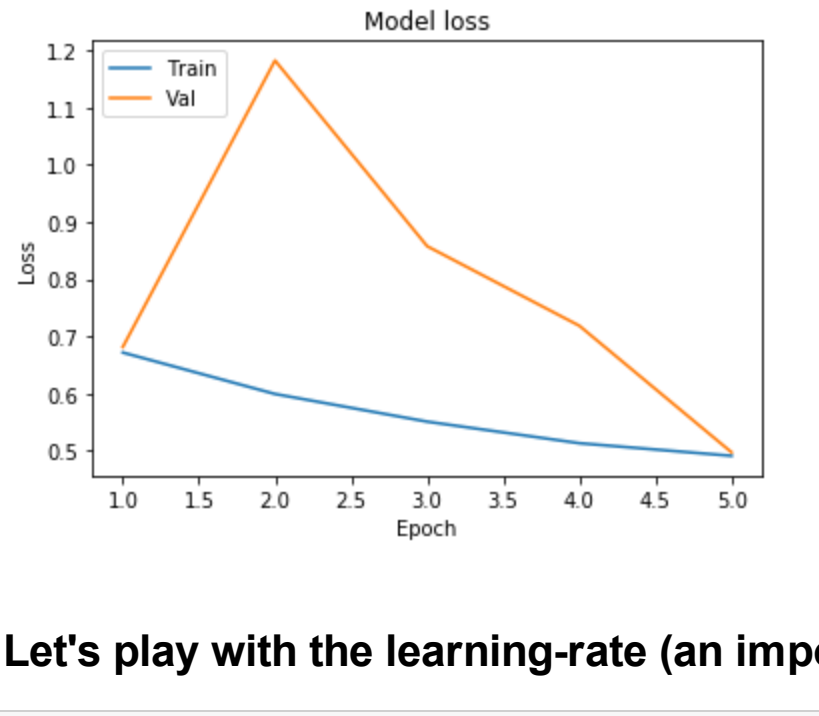
In [0]:
```
opt = SGD(learning_rate=0.01, momentum=0.9)
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
```

In [0]:
```
history = model.fit_generator(generator=train_generator, steps_per_epoch=len(train_generator), epoch
s = 5, validation_data=validation_generator, validation_steps=len(validation_generator), verbose = 1
)
```

```
Epoch 1/5
1000/1000 [==============================] - 131s 131ms/step - loss: 0.6716 - accuracy: 0.6255 -
val_loss: 0.6813 - val_accuracy: 0.6782
Epoch 2/5
1000/1000 [==============================] - 131s 131ms/step - loss: 0.5991 - accuracy: 0.6872 -
val_loss: 1.1827 - val_accuracy: 0.5710
Epoch 3/5
1000/1000 [==============================] - 129s 129ms/step - loss: 0.5507 - accuracy: 0.7238 -
val_loss: 0.8577 - val_accuracy: 0.6438
Epoch 4/5
1000/1000 [==============================] - 129s 129ms/step - loss: 0.5129 - accuracy: 0.7500 -
val_loss: 0.7185 - val_accuracy: 0.6942
Epoch 5/5
1000/1000 [==============================] - 129s 129ms/step - loss: 0.4909 - accuracy: 0.7644 -
val_loss: 0.4970 - val_accuracy: 0.7558
```

In [0]:
```
plot_learningCurve(history)
```





Let's play with the learning-rate (an important hyper-parameter)

In [0]:
```
opt = SGD(learning_rate=0.001, momentum=0.9)
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
```

In [0]:
```
history = model.fit_generator(generator=train_generator, steps_per_epoch=len(train_generator), epoch
s = 5, validation_data=validation_generator, validation_steps=len(validation_generator), verbose = 1
)
```

```
Epoch 1/5
1000/1000 [==============================] - 129s 129ms/step - loss: 0.4517 - accuracy: 0.7868 -
val_loss: 0.4806 - val_accuracy: 0.7840
Epoch 2/5
1000/1000 [==============================] - 129s 129ms/step - loss: 0.4375 - accuracy: 0.7948 -
val_loss: 0.4723 - val_accuracy: 0.7882
Epoch 3/5
1000/1000 [==============================] - 128s 128ms/step - loss: 0.4269 - accuracy: 0.8054 -
val_loss: 0.4812 - val_accuracy: 0.7846
Epoch 4/5
1000/1000 [==============================] - 128s 128ms/step - loss: 0.4300 - accuracy: 0.8025 -
val_loss: 0.4393 - val_accuracy: 0.8070
Epoch 5/5
1000/1000 [==============================] - 130s 130ms/step - loss: 0.4248 - accuracy: 0.8064 -
val_loss: 0.4784 - val_accuracy: 0.7888
```

In [0]:
```
plot_learningCurve(history)
```