Assignment#4
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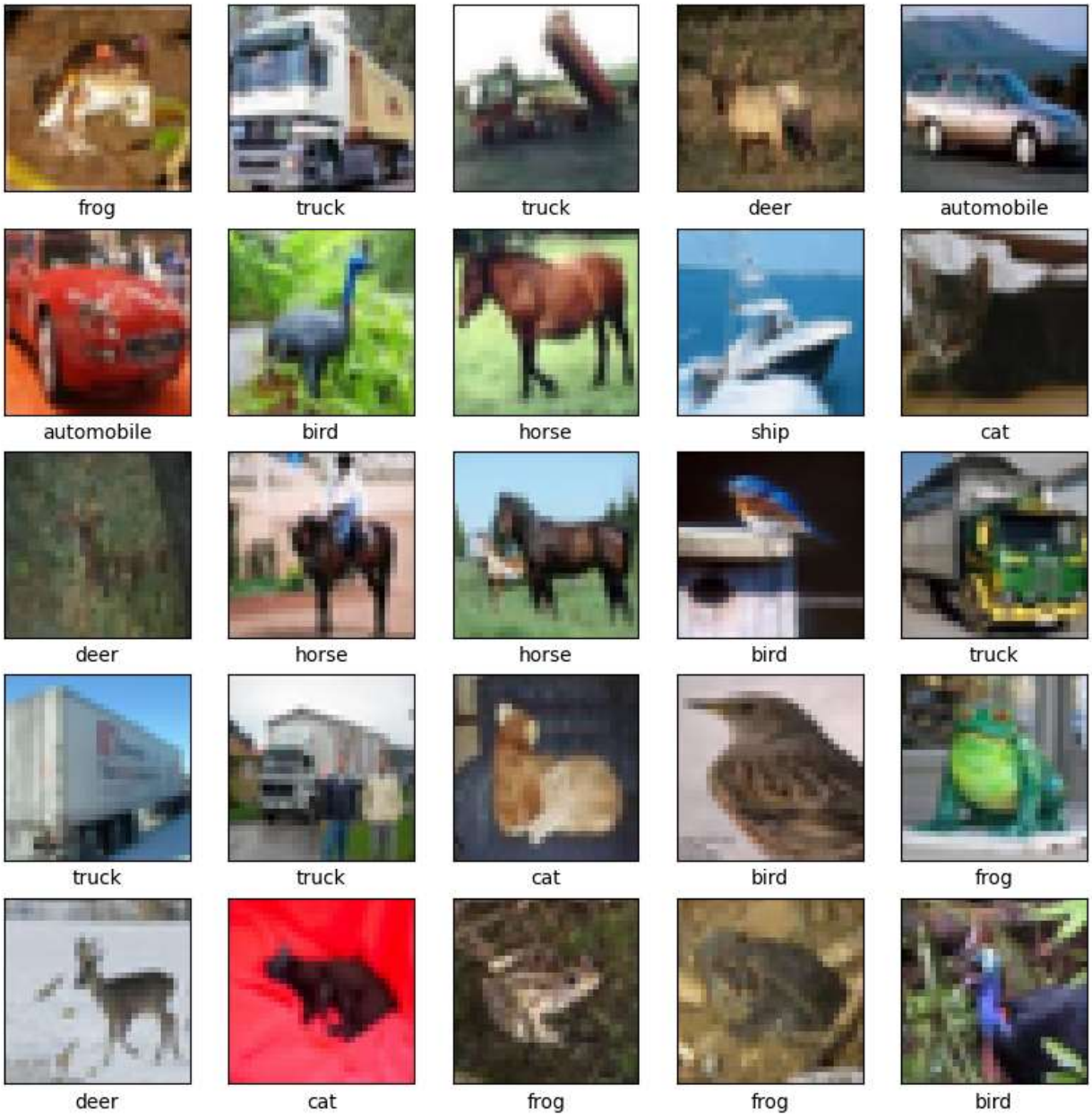
In [1]:
```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt
```

In [2]:
```
(train_images, train_labels), (test_images, test_labels) = datasets.cifar10.load_data()

# Normalize pixel values to be between 0 and 1
train_images, test_images = train_images / 255.0, test_images / 255.0
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 6s 0us/step
```

In [3]:
```
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])
    # 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()
```



1. Using Only Convolution Layers

In [4]:
```
model = models.Sequential()
model.add(layers.Conv2D(8, (3, 3), activation='relu', padding="valid", input_shape=(32,
model.add(layers.Conv2D(24, (3, 3), activation='relu', padding="valid"))
model.add(layers.Conv2D(36, (3, 3), activation='relu'))
#model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(48, (5, 5), activation='relu', padding="valid"))
model.add(layers.Conv2D(36, (7, 7), activation='relu', padding="same"))
#model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(36, (7, 7), activation='relu', padding="same"))
model.add(layers.Conv2D(64, (9, 9), activation='relu'))


model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 30, 30, 8)         224

 conv2d_1 (Conv2D)           (None, 28, 28, 24)        1752

 conv2d_2 (Conv2D)           (None, 26, 26, 36)        7812

 conv2d_3 (Conv2D)           (None, 22, 22, 48)        43248

 conv2d_4 (Conv2D)           (None, 22, 22, 36)        84708

 conv2d_5 (Conv2D)           (None, 22, 22, 36)        63540

 conv2d_6 (Conv2D)           (None, 14, 14, 64)        186688

=================================================================
Total params: 387972 (1.48 MB)
Trainable params: 387972 (1.48 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [5]:

```
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10))

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 30, 30, 8)         224

 conv2d_1 (Conv2D)           (None, 28, 28, 24)        1752

 conv2d_2 (Conv2D)           (None, 26, 26, 36)        7812

 conv2d_3 (Conv2D)           (None, 22, 22, 48)        43248

 conv2d_4 (Conv2D)           (None, 22, 22, 36)        84708

 conv2d_5 (Conv2D)           (None, 22, 22, 36)        63540

 conv2d_6 (Conv2D)           (None, 14, 14, 64)        186688

 flatten (Flatten)           (None, 12544)             0

 dense (Dense)               (None, 64)                802880

 dense_1 (Dense)             (None, 10)                650

=================================================================
Total params: 1191502 (4.55 MB)
Trainable params: 1191502 (4.55 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

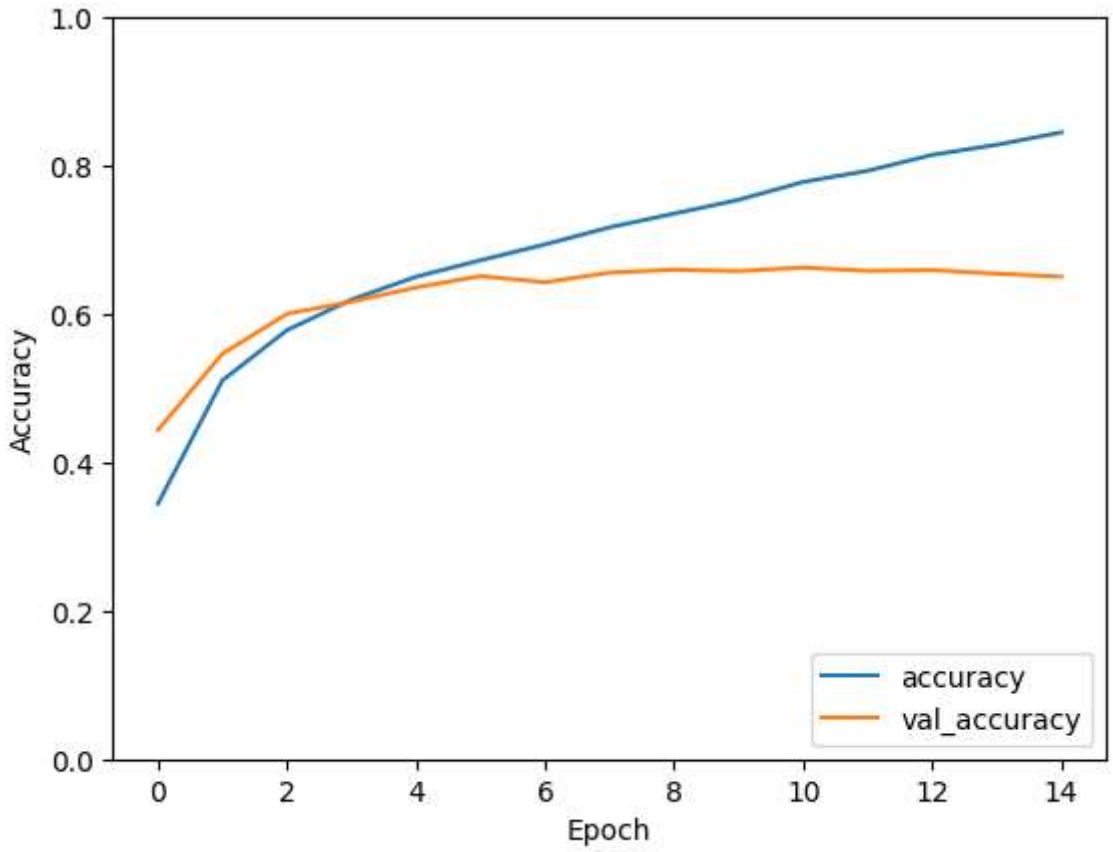
In [6]:
```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

history = model.fit(train_images, train_labels, epochs=15,
                    validation_data=(test_images, test_labels))
```

```
Epoch 1/15
1563/1563 [==============================] - 29s 10ms/step - loss: 1.7485 - accuracy:
0.3443 - val_loss: 1.5231 - val_accuracy: 0.4438
Epoch 2/15
1563/1563 [==============================] - 14s 9ms/step - loss: 1.3580 - accuracy: 0.
5106 - val_loss: 1.2748 - val_accuracy: 0.5465
Epoch 3/15
1563/1563 [==============================] - 14s 9ms/step - loss: 1.1819 - accuracy: 0.
5783 - val_loss: 1.1254 - val_accuracy: 0.6003
Epoch 4/15
1563/1563 [==============================] - 14s 9ms/step - loss: 1.0720 - accuracy: 0.
6195 - val_loss: 1.0908 - val_accuracy: 0.6167
Epoch 5/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.9861 - accuracy: 0.
6503 - val_loss: 1.0437 - val_accuracy: 0.6358
Epoch 6/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.9234 - accuracy: 0.
6725 - val_loss: 1.0149 - val_accuracy: 0.6511
Epoch 7/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.8636 - accuracy: 0.
6939 - val_loss: 1.0350 - val_accuracy: 0.6428
Epoch 8/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.8049 - accuracy: 0.
7169 - val_loss: 0.9983 - val_accuracy: 0.6558
Epoch 9/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.7523 - accuracy: 0.
7354 - val_loss: 1.0271 - val_accuracy: 0.6598
Epoch 10/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.6946 - accuracy: 0.
7540 - val_loss: 1.0405 - val_accuracy: 0.6578
Epoch 11/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.6352 - accuracy: 0.
7780 - val_loss: 1.0625 - val_accuracy: 0.6627
Epoch 12/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.5861 - accuracy: 0.
7932 - val_loss: 1.1349 - val_accuracy: 0.6581
Epoch 13/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.5265 - accuracy: 0.
8146 - val_loss: 1.2415 - val_accuracy: 0.6592
Epoch 14/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.4831 - accuracy: 0.
8282 - val_loss: 1.2006 - val_accuracy: 0.6544
Epoch 15/15
1563/1563 [==============================] - 14s 9ms/step - loss: 0.4398 - accuracy: 0.
8449 - val_loss: 1.4546 - val_accuracy: 0.6504
```

In [7]:
```
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, 1])
plt.legend(loc='lower right')
```

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

```
313/313 - 1s - loss: 1.4546 - accuracy: 0.6504 - 1s/epoch - 4ms/step
```



In [8]:
```
print(test_acc)
```

```
0.6503999829292297
```

2. Conv2d+Maxpooling

Variation no. 1

In [9]:
```
model_2 = models.Sequential()
model_2.add(layers.Conv2D(8, (3, 3), activation='relu', padding="same", input_shape=(32,
model_2.add(layers.Conv2D(24, (3, 3), activation='relu', padding="same"))
model_2.add(layers.MaxPooling2D((2, 2), padding="valid", strides=(1,1)))
model_2.add(layers.Conv2D(36, (3, 3), activation='relu', padding="same"))
model_2.add(layers.Conv2D(48, (5, 5), activation='relu', padding="same"))
model_2.add(layers.MaxPooling2D((2, 2), padding="valid", strides=(1,1)))
model_2.add(layers.Conv2D(36, (7, 7), activation='relu', padding="same"))
model_2.add(layers.Conv2D(36, (7, 7), activation='relu', padding="same"))
model_2.add(layers.MaxPooling2D((2, 2), padding="valid"))
model_2.add(layers.Conv2D(64, (9, 9), activation='relu'))
model_2.add(layers.Flatten())
model_2.add(layers.Dense(64, activation='relu'))
model_2.add(layers.Dense(10))

model_2.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_7 (Conv2D)           (None, 32, 32, 8)         224

 conv2d_8 (Conv2D)           (None, 32, 32, 24)        1752

 max_pooling2d (MaxPooling2  (None, 31, 31, 24)        0
 D)

 conv2d_9 (Conv2D)           (None, 31, 31, 36)        7812

 conv2d_10 (Conv2D)          (None, 31, 31, 48)        43248

 max_pooling2d_1 (MaxPoolin  (None, 30, 30, 48)        0
 g2D)

 conv2d_11 (Conv2D)          (None, 30, 30, 36)        84708

 conv2d_12 (Conv2D)          (None, 30, 30, 36)        63540

 max_pooling2d_2 (MaxPoolin  (None, 15, 15, 36)        0
 g2D)

 conv2d_13 (Conv2D)          (None, 7, 7, 64)          186688

 flatten_1 (Flatten)         (None, 3136)              0

 dense_2 (Dense)             (None, 64)                200768

 dense_3 (Dense)             (None, 10)                650

=================================================================
Total params: 589390 (2.25 MB)
Trainable params: 589390 (2.25 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [10]:

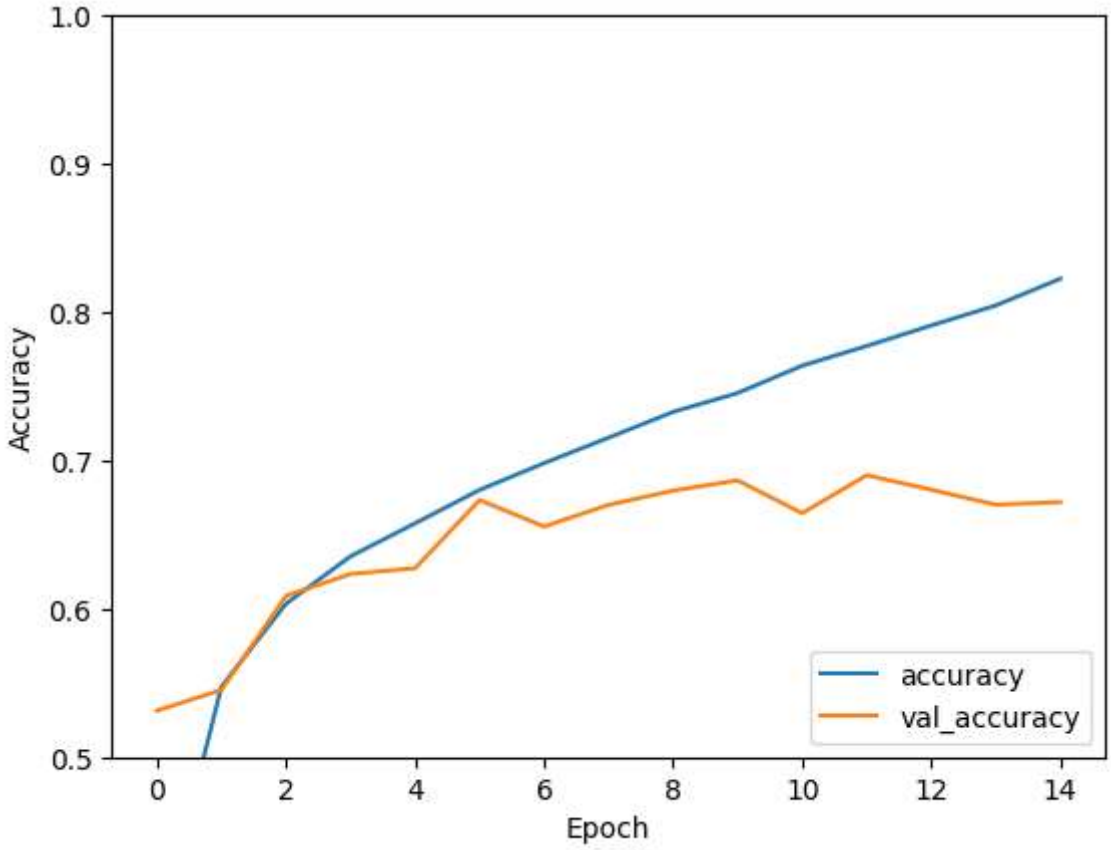
```
model_2.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

history = model_2.fit(train_images, train_labels, epochs=15,
                    validation_data=(test_images, test_labels))
```

```
Epoch 1/15
1563/1563 [==============================] - 27s 15ms/step - loss: 1.6893 - accuracy:
0.3743 - val_loss: 1.3107 - val_accuracy: 0.5313
Epoch 2/15
1563/1563 [==============================] - 24s 15ms/step - loss: 1.2528 - accuracy:
0.5475 - val_loss: 1.2781 - val_accuracy: 0.5453
Epoch 3/15
1563/1563 [==============================] - 23s 15ms/step - loss: 1.1161 - accuracy:
0.6034 - val_loss: 1.1016 - val_accuracy: 0.6087
Epoch 4/15
1563/1563 [==============================] - 24s 15ms/step - loss: 1.0206 - accuracy:
0.6353 - val_loss: 1.0489 - val_accuracy: 0.6234
Epoch 5/15
1563/1563 [==============================] - 23s 15ms/step - loss: 0.9544 - accuracy:
0.6576 - val_loss: 1.0661 - val_accuracy: 0.6273
Epoch 6/15
1563/1563 [==============================] - 24s 15ms/step - loss: 0.9002 - accuracy:
0.6801 - val_loss: 0.9558 - val_accuracy: 0.6733
Epoch 7/15
1563/1563 [==============================] - 23s 15ms/step - loss: 0.8450 - accuracy:
0.6981 - val_loss: 0.9819 - val_accuracy: 0.6554
Epoch 8/15
1563/1563 [==============================] - 23s 15ms/step - loss: 0.8011 - accuracy:
0.7153 - val_loss: 0.9460 - val_accuracy: 0.6700
Epoch 9/15
1563/1563 [==============================] - 23s 15ms/step - loss: 0.7524 - accuracy:
0.7327 - val_loss: 0.9406 - val_accuracy: 0.6796
Epoch 10/15
1563/1563 [==============================] - 22s 14ms/step - loss: 0.7139 - accuracy:
0.7454 - val_loss: 0.9511 - val_accuracy: 0.6865
Epoch 11/15
1563/1563 [==============================] - 24s 15ms/step - loss: 0.6690 - accuracy:
0.7639 - val_loss: 1.0512 - val_accuracy: 0.6644
Epoch 12/15
1563/1563 [==============================] - 22s 14ms/step - loss: 0.6293 - accuracy:
0.7771 - val_loss: 0.9683 - val_accuracy: 0.6900
Epoch 13/15
1563/1563 [==============================] - 23s 14ms/step - loss: 0.5856 - accuracy:
0.7910 - val_loss: 1.0173 - val_accuracy: 0.6802
Epoch 14/15
1563/1563 [==============================] - 23s 15ms/step - loss: 0.5457 - accuracy:
0.8044 - val_loss: 1.0353 - val_accuracy: 0.6701
Epoch 15/15
1563/1563 [==============================] - 23s 15ms/step - loss: 0.4959 - accuracy:
0.8224 - val_loss: 1.1521 - val_accuracy: 0.6719
```

In [11]:

```
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_2.evaluate(test_images,  test_labels, verbose=2)
```

```
313/313 - 2s - loss: 1.1521 - accuracy: 0.6719 - 2s/epoch - 6ms/step
```



Alexnet Computation Memory & Time

AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Input: 227x227x3 Memory: 154,587 Parameters: 0
Conv1: 55x55x96 Memory: 290,400 Parameters: 11,616
Maxpool: 27x27x96 Memory: 69,984 Parameters: 0
Norm Layer: 27x27x96 Memory: 69,984 Parameters: 0
Conv2: 27x27x256 Memory: 186,624 Parameters: 6400
Maxpool: 13x13x256 Memory: 43,264 Parameters: 0
Norm Layer: 13x13x256 Memory: 43,264 Parameters: 0
Conv3: 13x13x384 Memory: 64,896 Parameters: 3,456
Conv4: 13x13x384 Memory: 64,896 Parameters: 3,456
Conv5: 13x13x256 Memory: 43,264 Parameters: 2,304
Maxpool: 6x6x256 Memory: 9,216 Parameters: 0
FC6: 6x6x256x4096 Memory: 4096 Parameters: 37,748,736

FC7: 4096x4096 Memory: 4096 Parameters: 16,777,216
FC6: 1000x4096 Memory: 1000 Parameters: 4,096,000
Total Parameters: 58,649,184
Total Memory: 1,049,751 x 4 bytes = 4.2 MB

Computing Time for i3 1st gen system with 4GB RAM.

Method 1

The peak clock speed of an i3 is 3.06 GHz and it has 2 cores. Let us assume different processes are consuming around half of the RAM and the available clock speed is 2.5 GHz.

The total memory for one forward/back pass is 4.2 MB for AlexNet. Let's say that our model runs for 15 epochs. That would be a total of 30 passes (forward & backward). The total memory consumption comes out to be 126 MB.

For first case, let us assume that each instruction is processed sequentially. Given that there are 1,049,751 instructions for one pass, the total number of instructions amounts to 31,492,530. It takes 1/2,500,000,000 of a sec to process a single instruction, thus the total time would come up to 0.012597s to process a single image.

Lets assume that AlexNet is applied on a dataset of 10,000 images. Given that we now have the time needed to process one image, the total time for learning of this instance of AlexNet would be 126s or 2 mins approximately.

Now lets assume we are using all cores (2 in this case). That effectively means its running 2 instructions at the same time. If all the threads are engaged as well (4 threads), that would enable the system to execute 4 commands at the same time, while still processing 2 at the same time. This would roughly bring down the time to less than half, approximately between 40-60s.

Method 2

The second and more traditional method is to run the program directly and measure the time taken for a single epoch. This would allow us to extrapolate the approximate time taken for the entire operation. However, as the system mentioned for this

calculation is not present on hand, it is not feasible to find the actual time.

In [16]:
```
%%shell
jupyter nbconvert --to html /content/drive/MyDrive/ColabNotebooks/Assignment#4
```

```
[NbConvertApp] Converting notebook /content/drive/MyDrive/ColabNotebooks/Assignment#4 t
o html
[NbConvertApp] Writing 1071605 bytes to /content/drive/MyDrive/ColabNotebooks/Assignmen
t#.html
```

Out[16]:

In [ ]:
```

```