

# Transfer\_Learning\_Lab

April 30, 2020

## 1 Lab: Transfer Learning

Welcome to the lab on Transfer Learning! Here, you'll get a chance to try out training a network with ImageNet pre-trained weights as a base, but with additional network layers of your own added on. You'll also get to see the difference between using frozen weights and training on all layers.

### 1.0.1 GPU usage

In our previous examples in this lesson, we've avoided using GPU, but this time around you'll have the option to enable it. You do not need it on to begin with, but make sure anytime you switch from non-GPU to GPU, or vice versa, that you save your notebook! If not, you'll likely be reverted to the previous checkpoint.

We also suggest only using the GPU when performing the (mostly minor) training below - you'll want to conserve GPU hours for your Behavioral Cloning project coming up next!

```
In [1]: # Set a couple flags for training - you can ignore these for now
        freeze_flag = True # `True` to freeze layers, `False` for full training
        weights_flag = 'imagenet' # 'imagenet' or None
        preprocess_flag = True # Should be true for ImageNet pre-trained typically

        # Loads in InceptionV3
        from keras.applications.inception_v3 import InceptionV3

        # We can use smaller than the default 299x299x3 input for InceptionV3
        # which will speed up training. Keras v2.0.9 supports down to 139x139x3
        input_size = 139

        # Using Inception with ImageNet pre-trained weights
        inception = InceptionV3(weights=weights_flag, include_top=False,
                               input_shape=(input_size,input_size,3))
```

Using TensorFlow backend.

```
Downloading data from https://github.com/fchollet/deep-learning-models/releases/download/v0.5/in
87916544/87910968 [=====] - 1s 0us/step
```

We'll use Inception V3 for this lab, although you can use the same techniques with any of the models in [Keras Applications](#). Do note that certain models are only available in certain versions of Keras; this workspace uses Keras v2.0.9, for which you can see the available models [here](#).

In the above, we've set Inception to use an `input_shape` of 139x139x3 instead of the default 299x299x3. This will help us to speed up our training a bit later (and we'll actually be upsampling from smaller images, so we aren't losing data here). In order to do so, we also must set `include_top` to `False`, which means the final fully-connected layer with 1,000 nodes for each ImageNet class is dropped, as well as a Global Average Pooling layer.

### 1.0.2 Pre-trained with frozen weights

To start, we'll see how an ImageNet pre-trained model with all weights frozen in the InceptionV3 model performs. We will also drop the end layer and append new layers onto it, although you could do this in different ways (not drop the end and add new layers, drop more layers than we will here, etc.).

You can freeze layers by setting `layer.trainable` to `False` for a given layer. Within a model, you can get the list of layers with `model.layers`.

```
In [2]: if freeze_flag == True:
        ## TODO: Iterate through the layers of the Inception model
        ##         loaded above and set all of them to have trainable = False
        for layer in inception.layers:
            layer.trainable = False
```

### 1.0.3 Dropping layers

You can drop layers from a model with `model.layers.pop()`. Before you do this, you should check out what the actual layers of the model are with Keras's `.summary()` function.

```
In [3]: ## TODO: Use the model summary function to see all layers in the
        ##         loaded Inception model
        inception.summary()
```

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 139, 139, 3)	0	
conv2d_1 (Conv2D)	(None, 69, 69, 32)	864	input_1[0][0]
batch_normalization_1 (BatchNor	(None, 69, 69, 32)	96	conv2d_1[0][0]
activation_1 (Activation)	(None, 69, 69, 32)	0	batch_normalization_1[0][0]
conv2d_2 (Conv2D)	(None, 67, 67, 32)	9216	activation_1[0][0]
batch_normalization_2 (BatchNor	(None, 67, 67, 32)	96	conv2d_2[0][0]
activation_2 (Activation)	(None, 67, 67, 32)	0	batch_normalization_2[0][0]

conv2d_3 (Conv2D)	(None, 67, 67, 64)	18432	activation_2[0][0]
batch_normalization_3 (BatchNor	(None, 67, 67, 64)	192	conv2d_3[0][0]
activation_3 (Activation)	(None, 67, 67, 64)	0	batch_normalization_3[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 33, 33, 64)	0	activation_3[0][0]
conv2d_4 (Conv2D)	(None, 33, 33, 80)	5120	max_pooling2d_1[0][0]
batch_normalization_4 (BatchNor	(None, 33, 33, 80)	240	conv2d_4[0][0]
activation_4 (Activation)	(None, 33, 33, 80)	0	batch_normalization_4[0][0]
conv2d_5 (Conv2D)	(None, 31, 31, 192)	138240	activation_4[0][0]
batch_normalization_5 (BatchNor	(None, 31, 31, 192)	576	conv2d_5[0][0]
activation_5 (Activation)	(None, 31, 31, 192)	0	batch_normalization_5[0][0]
max_pooling2d_2 (MaxPooling2D)	(None, 15, 15, 192)	0	activation_5[0][0]
conv2d_9 (Conv2D)	(None, 15, 15, 64)	12288	max_pooling2d_2[0][0]
batch_normalization_9 (BatchNor	(None, 15, 15, 64)	192	conv2d_9[0][0]
activation_9 (Activation)	(None, 15, 15, 64)	0	batch_normalization_9[0][0]
conv2d_7 (Conv2D)	(None, 15, 15, 48)	9216	max_pooling2d_2[0][0]
conv2d_10 (Conv2D)	(None, 15, 15, 96)	55296	activation_9[0][0]
batch_normalization_7 (BatchNor	(None, 15, 15, 48)	144	conv2d_7[0][0]
batch_normalization_10 (BatchNo	(None, 15, 15, 96)	288	conv2d_10[0][0]
activation_7 (Activation)	(None, 15, 15, 48)	0	batch_normalization_7[0][0]
activation_10 (Activation)	(None, 15, 15, 96)	0	batch_normalization_10[0][0]
average_pooling2d_1 (AveragePoo	(None, 15, 15, 192)	0	max_pooling2d_2[0][0]
conv2d_6 (Conv2D)	(None, 15, 15, 64)	12288	max_pooling2d_2[0][0]
conv2d_8 (Conv2D)	(None, 15, 15, 64)	76800	activation_7[0][0]
conv2d_11 (Conv2D)	(None, 15, 15, 96)	82944	activation_10[0][0]

conv2d_12 (Conv2D)	(None, 15, 15, 32)	6144	average_pooling2d_1[0][0]
batch_normalization_6 (BatchNor	(None, 15, 15, 64)	192	conv2d_6[0][0]
batch_normalization_8 (BatchNor	(None, 15, 15, 64)	192	conv2d_8[0][0]
batch_normalization_11 (BatchNo	(None, 15, 15, 96)	288	conv2d_11[0][0]
batch_normalization_12 (BatchNo	(None, 15, 15, 32)	96	conv2d_12[0][0]
activation_6 (Activation)	(None, 15, 15, 64)	0	batch_normalization_6[0][0]
activation_8 (Activation)	(None, 15, 15, 64)	0	batch_normalization_8[0][0]
activation_11 (Activation)	(None, 15, 15, 96)	0	batch_normalization_11[0][0]
activation_12 (Activation)	(None, 15, 15, 32)	0	batch_normalization_12[0][0]
mixed0 (Concatenate)	(None, 15, 15, 256)	0	activation_6[0][0] activation_8[0][0] activation_11[0][0] activation_12[0][0]
conv2d_16 (Conv2D)	(None, 15, 15, 64)	16384	mixed0[0][0]
batch_normalization_16 (BatchNo	(None, 15, 15, 64)	192	conv2d_16[0][0]
activation_16 (Activation)	(None, 15, 15, 64)	0	batch_normalization_16[0][0]
conv2d_14 (Conv2D)	(None, 15, 15, 48)	12288	mixed0[0][0]
conv2d_17 (Conv2D)	(None, 15, 15, 96)	55296	activation_16[0][0]
batch_normalization_14 (BatchNo	(None, 15, 15, 48)	144	conv2d_14[0][0]
batch_normalization_17 (BatchNo	(None, 15, 15, 96)	288	conv2d_17[0][0]
activation_14 (Activation)	(None, 15, 15, 48)	0	batch_normalization_14[0][0]
activation_17 (Activation)	(None, 15, 15, 96)	0	batch_normalization_17[0][0]
average_pooling2d_2 (AveragePoo	(None, 15, 15, 256)	0	mixed0[0][0]
conv2d_13 (Conv2D)	(None, 15, 15, 64)	16384	mixed0[0][0]
conv2d_15 (Conv2D)	(None, 15, 15, 64)	76800	activation_14[0][0]

conv2d_18 (Conv2D)	(None, 15, 15, 96)	82944	activation_17[0][0]
conv2d_19 (Conv2D)	(None, 15, 15, 64)	16384	average_pooling2d_2[0][0]
batch_normalization_13 (BatchNo	(None, 15, 15, 64)	192	conv2d_13[0][0]
batch_normalization_15 (BatchNo	(None, 15, 15, 64)	192	conv2d_15[0][0]
batch_normalization_18 (BatchNo	(None, 15, 15, 96)	288	conv2d_18[0][0]
batch_normalization_19 (BatchNo	(None, 15, 15, 64)	192	conv2d_19[0][0]
activation_13 (Activation)	(None, 15, 15, 64)	0	batch_normalization_13[0][0]
activation_15 (Activation)	(None, 15, 15, 64)	0	batch_normalization_15[0][0]
activation_18 (Activation)	(None, 15, 15, 96)	0	batch_normalization_18[0][0]
activation_19 (Activation)	(None, 15, 15, 64)	0	batch_normalization_19[0][0]
mixed1 (Concatenate)	(None, 15, 15, 288)	0	activation_13[0][0] activation_15[0][0] activation_18[0][0] activation_19[0][0]
conv2d_23 (Conv2D)	(None, 15, 15, 64)	18432	mixed1[0][0]
batch_normalization_23 (BatchNo	(None, 15, 15, 64)	192	conv2d_23[0][0]
activation_23 (Activation)	(None, 15, 15, 64)	0	batch_normalization_23[0][0]
conv2d_21 (Conv2D)	(None, 15, 15, 48)	13824	mixed1[0][0]
conv2d_24 (Conv2D)	(None, 15, 15, 96)	55296	activation_23[0][0]
batch_normalization_21 (BatchNo	(None, 15, 15, 48)	144	conv2d_21[0][0]
batch_normalization_24 (BatchNo	(None, 15, 15, 96)	288	conv2d_24[0][0]
activation_21 (Activation)	(None, 15, 15, 48)	0	batch_normalization_21[0][0]
activation_24 (Activation)	(None, 15, 15, 96)	0	batch_normalization_24[0][0]
average_pooling2d_3 (AveragePoo	(None, 15, 15, 288)	0	mixed1[0][0]
conv2d_20 (Conv2D)	(None, 15, 15, 64)	18432	mixed1[0][0]
conv2d_22 (Conv2D)	(None, 15, 15, 64)	76800	activation_21[0][0]

conv2d_25 (Conv2D)	(None, 15, 15, 96)	82944	activation_24[0][0]
conv2d_26 (Conv2D)	(None, 15, 15, 64)	18432	average_pooling2d_3[0][0]
batch_normalization_20 (BatchNo	(None, 15, 15, 64)	192	conv2d_20[0][0]
batch_normalization_22 (BatchNo	(None, 15, 15, 64)	192	conv2d_22[0][0]
batch_normalization_25 (BatchNo	(None, 15, 15, 96)	288	conv2d_25[0][0]
batch_normalization_26 (BatchNo	(None, 15, 15, 64)	192	conv2d_26[0][0]
activation_20 (Activation)	(None, 15, 15, 64)	0	batch_normalization_20[0][0]
activation_22 (Activation)	(None, 15, 15, 64)	0	batch_normalization_22[0][0]
activation_25 (Activation)	(None, 15, 15, 96)	0	batch_normalization_25[0][0]
activation_26 (Activation)	(None, 15, 15, 64)	0	batch_normalization_26[0][0]
mixed2 (Concatenate)	(None, 15, 15, 288)	0	activation_20[0][0] activation_22[0][0] activation_25[0][0] activation_26[0][0]
conv2d_28 (Conv2D)	(None, 15, 15, 64)	18432	mixed2[0][0]
batch_normalization_28 (BatchNo	(None, 15, 15, 64)	192	conv2d_28[0][0]
activation_28 (Activation)	(None, 15, 15, 64)	0	batch_normalization_28[0][0]
conv2d_29 (Conv2D)	(None, 15, 15, 96)	55296	activation_28[0][0]
batch_normalization_29 (BatchNo	(None, 15, 15, 96)	288	conv2d_29[0][0]
activation_29 (Activation)	(None, 15, 15, 96)	0	batch_normalization_29[0][0]
conv2d_27 (Conv2D)	(None, 7, 7, 384)	995328	mixed2[0][0]
conv2d_30 (Conv2D)	(None, 7, 7, 96)	82944	activation_29[0][0]
batch_normalization_27 (BatchNo	(None, 7, 7, 384)	1152	conv2d_27[0][0]
batch_normalization_30 (BatchNo	(None, 7, 7, 96)	288	conv2d_30[0][0]
activation_27 (Activation)	(None, 7, 7, 384)	0	batch_normalization_27[0][0]

activation_30 (Activation)	(None, 7, 7, 96)	0	batch_normalization_30[0][0]
max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 288)	0	mixed2[0][0]
mixed3 (Concatenate)	(None, 7, 7, 768)	0	activation_27[0][0] activation_30[0][0] max_pooling2d_3[0][0]
conv2d_35 (Conv2D)	(None, 7, 7, 128)	98304	mixed3[0][0]
batch_normalization_35 (BatchNo	(None, 7, 7, 128)	384	conv2d_35[0][0]
activation_35 (Activation)	(None, 7, 7, 128)	0	batch_normalization_35[0][0]
conv2d_36 (Conv2D)	(None, 7, 7, 128)	114688	activation_35[0][0]
batch_normalization_36 (BatchNo	(None, 7, 7, 128)	384	conv2d_36[0][0]
activation_36 (Activation)	(None, 7, 7, 128)	0	batch_normalization_36[0][0]
conv2d_32 (Conv2D)	(None, 7, 7, 128)	98304	mixed3[0][0]
conv2d_37 (Conv2D)	(None, 7, 7, 128)	114688	activation_36[0][0]
batch_normalization_32 (BatchNo	(None, 7, 7, 128)	384	conv2d_32[0][0]
batch_normalization_37 (BatchNo	(None, 7, 7, 128)	384	conv2d_37[0][0]
activation_32 (Activation)	(None, 7, 7, 128)	0	batch_normalization_32[0][0]
activation_37 (Activation)	(None, 7, 7, 128)	0	batch_normalization_37[0][0]
conv2d_33 (Conv2D)	(None, 7, 7, 128)	114688	activation_32[0][0]
conv2d_38 (Conv2D)	(None, 7, 7, 128)	114688	activation_37[0][0]
batch_normalization_33 (BatchNo	(None, 7, 7, 128)	384	conv2d_33[0][0]
batch_normalization_38 (BatchNo	(None, 7, 7, 128)	384	conv2d_38[0][0]
activation_33 (Activation)	(None, 7, 7, 128)	0	batch_normalization_33[0][0]
activation_38 (Activation)	(None, 7, 7, 128)	0	batch_normalization_38[0][0]
average_pooling2d_4 (AveragePoo	(None, 7, 7, 768)	0	mixed3[0][0]
conv2d_31 (Conv2D)	(None, 7, 7, 192)	147456	mixed3[0][0]

conv2d_34 (Conv2D)	(None, 7, 7, 192)	172032	activation_33[0][0]
conv2d_39 (Conv2D)	(None, 7, 7, 192)	172032	activation_38[0][0]
conv2d_40 (Conv2D)	(None, 7, 7, 192)	147456	average_pooling2d_4[0][0]
batch_normalization_31 (BatchNo	(None, 7, 7, 192)	576	conv2d_31[0][0]
batch_normalization_34 (BatchNo	(None, 7, 7, 192)	576	conv2d_34[0][0]
batch_normalization_39 (BatchNo	(None, 7, 7, 192)	576	conv2d_39[0][0]
batch_normalization_40 (BatchNo	(None, 7, 7, 192)	576	conv2d_40[0][0]
activation_31 (Activation)	(None, 7, 7, 192)	0	batch_normalization_31[0][0]
activation_34 (Activation)	(None, 7, 7, 192)	0	batch_normalization_34[0][0]
activation_39 (Activation)	(None, 7, 7, 192)	0	batch_normalization_39[0][0]
activation_40 (Activation)	(None, 7, 7, 192)	0	batch_normalization_40[0][0]
mixed4 (Concatenate)	(None, 7, 7, 768)	0	activation_31[0][0] activation_34[0][0] activation_39[0][0] activation_40[0][0]
conv2d_45 (Conv2D)	(None, 7, 7, 160)	122880	mixed4[0][0]
batch_normalization_45 (BatchNo	(None, 7, 7, 160)	480	conv2d_45[0][0]
activation_45 (Activation)	(None, 7, 7, 160)	0	batch_normalization_45[0][0]
conv2d_46 (Conv2D)	(None, 7, 7, 160)	179200	activation_45[0][0]
batch_normalization_46 (BatchNo	(None, 7, 7, 160)	480	conv2d_46[0][0]
activation_46 (Activation)	(None, 7, 7, 160)	0	batch_normalization_46[0][0]
conv2d_42 (Conv2D)	(None, 7, 7, 160)	122880	mixed4[0][0]
conv2d_47 (Conv2D)	(None, 7, 7, 160)	179200	activation_46[0][0]
batch_normalization_42 (BatchNo	(None, 7, 7, 160)	480	conv2d_42[0][0]
batch_normalization_47 (BatchNo	(None, 7, 7, 160)	480	conv2d_47[0][0]
activation_42 (Activation)	(None, 7, 7, 160)	0	batch_normalization_42[0][0]



activation_47 (Activation)	(None, 7, 7, 160)	0	batch_normalization_47[0][0]
conv2d_43 (Conv2D)	(None, 7, 7, 160)	179200	activation_42[0][0]
conv2d_48 (Conv2D)	(None, 7, 7, 160)	179200	activation_47[0][0]
batch_normalization_43 (BatchNo	(None, 7, 7, 160)	480	conv2d_43[0][0]
batch_normalization_48 (BatchNo	(None, 7, 7, 160)	480	conv2d_48[0][0]
activation_43 (Activation)	(None, 7, 7, 160)	0	batch_normalization_43[0][0]
activation_48 (Activation)	(None, 7, 7, 160)	0	batch_normalization_48[0][0]
average_pooling2d_5 (AveragePoo	(None, 7, 7, 768)	0	mixed4[0][0]
conv2d_41 (Conv2D)	(None, 7, 7, 192)	147456	mixed4[0][0]
conv2d_44 (Conv2D)	(None, 7, 7, 192)	215040	activation_43[0][0]
conv2d_49 (Conv2D)	(None, 7, 7, 192)	215040	activation_48[0][0]
conv2d_50 (Conv2D)	(None, 7, 7, 192)	147456	average_pooling2d_5[0][0]
batch_normalization_41 (BatchNo	(None, 7, 7, 192)	576	conv2d_41[0][0]
batch_normalization_44 (BatchNo	(None, 7, 7, 192)	576	conv2d_44[0][0]
batch_normalization_49 (BatchNo	(None, 7, 7, 192)	576	conv2d_49[0][0]
batch_normalization_50 (BatchNo	(None, 7, 7, 192)	576	conv2d_50[0][0]
activation_41 (Activation)	(None, 7, 7, 192)	0	batch_normalization_41[0][0]
activation_44 (Activation)	(None, 7, 7, 192)	0	batch_normalization_44[0][0]
activation_49 (Activation)	(None, 7, 7, 192)	0	batch_normalization_49[0][0]
activation_50 (Activation)	(None, 7, 7, 192)	0	batch_normalization_50[0][0]
mixed5 (Concatenate)	(None, 7, 7, 768)	0	activation_41[0][0] activation_44[0][0] activation_49[0][0] activation_50[0][0]
conv2d_55 (Conv2D)	(None, 7, 7, 160)	122880	mixed5[0][0]

batch_normalization_55 (BatchNo	(None, 7, 7, 160)	480	conv2d_55[0][0]
activation_55 (Activation)	(None, 7, 7, 160)	0	batch_normalization_55[0][0]
conv2d_56 (Conv2D)	(None, 7, 7, 160)	179200	activation_55[0][0]
batch_normalization_56 (BatchNo	(None, 7, 7, 160)	480	conv2d_56[0][0]
activation_56 (Activation)	(None, 7, 7, 160)	0	batch_normalization_56[0][0]
conv2d_52 (Conv2D)	(None, 7, 7, 160)	122880	mixed5[0][0]
conv2d_57 (Conv2D)	(None, 7, 7, 160)	179200	activation_56[0][0]
batch_normalization_52 (BatchNo	(None, 7, 7, 160)	480	conv2d_52[0][0]
batch_normalization_57 (BatchNo	(None, 7, 7, 160)	480	conv2d_57[0][0]
activation_52 (Activation)	(None, 7, 7, 160)	0	batch_normalization_52[0][0]
activation_57 (Activation)	(None, 7, 7, 160)	0	batch_normalization_57[0][0]
conv2d_53 (Conv2D)	(None, 7, 7, 160)	179200	activation_52[0][0]
conv2d_58 (Conv2D)	(None, 7, 7, 160)	179200	activation_57[0][0]
batch_normalization_53 (BatchNo	(None, 7, 7, 160)	480	conv2d_53[0][0]
batch_normalization_58 (BatchNo	(None, 7, 7, 160)	480	conv2d_58[0][0]
activation_53 (Activation)	(None, 7, 7, 160)	0	batch_normalization_53[0][0]
activation_58 (Activation)	(None, 7, 7, 160)	0	batch_normalization_58[0][0]
average_pooling2d_6 (AveragePoo	(None, 7, 7, 768)	0	mixed5[0][0]
conv2d_51 (Conv2D)	(None, 7, 7, 192)	147456	mixed5[0][0]
conv2d_54 (Conv2D)	(None, 7, 7, 192)	215040	activation_53[0][0]
conv2d_59 (Conv2D)	(None, 7, 7, 192)	215040	activation_58[0][0]
conv2d_60 (Conv2D)	(None, 7, 7, 192)	147456	average_pooling2d_6[0][0]
batch_normalization_51 (BatchNo	(None, 7, 7, 192)	576	conv2d_51[0][0]
batch_normalization_54 (BatchNo	(None, 7, 7, 192)	576	conv2d_54[0][0]

batch_normalization_59 (BatchNo	(None, 7, 7, 192)	576	conv2d_59[0][0]
batch_normalization_60 (BatchNo	(None, 7, 7, 192)	576	conv2d_60[0][0]
activation_51 (Activation)	(None, 7, 7, 192)	0	batch_normalization_51[0][0]
activation_54 (Activation)	(None, 7, 7, 192)	0	batch_normalization_54[0][0]
activation_59 (Activation)	(None, 7, 7, 192)	0	batch_normalization_59[0][0]
activation_60 (Activation)	(None, 7, 7, 192)	0	batch_normalization_60[0][0]
mixed6 (Concatenate)	(None, 7, 7, 768)	0	activation_51[0][0] activation_54[0][0] activation_59[0][0] activation_60[0][0]
conv2d_65 (Conv2D)	(None, 7, 7, 192)	147456	mixed6[0][0]
batch_normalization_65 (BatchNo	(None, 7, 7, 192)	576	conv2d_65[0][0]
activation_65 (Activation)	(None, 7, 7, 192)	0	batch_normalization_65[0][0]
conv2d_66 (Conv2D)	(None, 7, 7, 192)	258048	activation_65[0][0]
batch_normalization_66 (BatchNo	(None, 7, 7, 192)	576	conv2d_66[0][0]
activation_66 (Activation)	(None, 7, 7, 192)	0	batch_normalization_66[0][0]
conv2d_62 (Conv2D)	(None, 7, 7, 192)	147456	mixed6[0][0]
conv2d_67 (Conv2D)	(None, 7, 7, 192)	258048	activation_66[0][0]
batch_normalization_62 (BatchNo	(None, 7, 7, 192)	576	conv2d_62[0][0]
batch_normalization_67 (BatchNo	(None, 7, 7, 192)	576	conv2d_67[0][0]
activation_62 (Activation)	(None, 7, 7, 192)	0	batch_normalization_62[0][0]
activation_67 (Activation)	(None, 7, 7, 192)	0	batch_normalization_67[0][0]
conv2d_63 (Conv2D)	(None, 7, 7, 192)	258048	activation_62[0][0]
conv2d_68 (Conv2D)	(None, 7, 7, 192)	258048	activation_67[0][0]
batch_normalization_63 (BatchNo	(None, 7, 7, 192)	576	conv2d_63[0][0]
batch_normalization_68 (BatchNo	(None, 7, 7, 192)	576	conv2d_68[0][0]

activation_63 (Activation)	(None, 7, 7, 192)	0	batch_normalization_63[0][0]
activation_68 (Activation)	(None, 7, 7, 192)	0	batch_normalization_68[0][0]
average_pooling2d_7 (AveragePool)	(None, 7, 7, 768)	0	mixed6[0][0]
conv2d_61 (Conv2D)	(None, 7, 7, 192)	147456	mixed6[0][0]
conv2d_64 (Conv2D)	(None, 7, 7, 192)	258048	activation_63[0][0]
conv2d_69 (Conv2D)	(None, 7, 7, 192)	258048	activation_68[0][0]
conv2d_70 (Conv2D)	(None, 7, 7, 192)	147456	average_pooling2d_7[0][0]
batch_normalization_61 (Batch Normalization)	(None, 7, 7, 192)	576	conv2d_61[0][0]
batch_normalization_64 (Batch Normalization)	(None, 7, 7, 192)	576	conv2d_64[0][0]
batch_normalization_69 (Batch Normalization)	(None, 7, 7, 192)	576	conv2d_69[0][0]
batch_normalization_70 (Batch Normalization)	(None, 7, 7, 192)	576	conv2d_70[0][0]
activation_61 (Activation)	(None, 7, 7, 192)	0	batch_normalization_61[0][0]
activation_64 (Activation)	(None, 7, 7, 192)	0	batch_normalization_64[0][0]
activation_69 (Activation)	(None, 7, 7, 192)	0	batch_normalization_69[0][0]
activation_70 (Activation)	(None, 7, 7, 192)	0	batch_normalization_70[0][0]
mixed7 (Concatenate)	(None, 7, 7, 768)	0	activation_61[0][0] activation_64[0][0] activation_69[0][0] activation_70[0][0]
conv2d_73 (Conv2D)	(None, 7, 7, 192)	147456	mixed7[0][0]
batch_normalization_73 (Batch Normalization)	(None, 7, 7, 192)	576	conv2d_73[0][0]
activation_73 (Activation)	(None, 7, 7, 192)	0	batch_normalization_73[0][0]
conv2d_74 (Conv2D)	(None, 7, 7, 192)	258048	activation_73[0][0]
batch_normalization_74 (Batch Normalization)	(None, 7, 7, 192)	576	conv2d_74[0][0]
activation_74 (Activation)	(None, 7, 7, 192)	0	batch_normalization_74[0][0]

conv2d_71 (Conv2D)	(None, 7, 7, 192)	147456	mixed7[0][0]
conv2d_75 (Conv2D)	(None, 7, 7, 192)	258048	activation_74[0][0]
batch_normalization_71 (BatchNo	(None, 7, 7, 192)	576	conv2d_71[0][0]
batch_normalization_75 (BatchNo	(None, 7, 7, 192)	576	conv2d_75[0][0]
activation_71 (Activation)	(None, 7, 7, 192)	0	batch_normalization_71[0][0]
activation_75 (Activation)	(None, 7, 7, 192)	0	batch_normalization_75[0][0]
conv2d_72 (Conv2D)	(None, 3, 3, 320)	552960	activation_71[0][0]
conv2d_76 (Conv2D)	(None, 3, 3, 192)	331776	activation_75[0][0]
batch_normalization_72 (BatchNo	(None, 3, 3, 320)	960	conv2d_72[0][0]
batch_normalization_76 (BatchNo	(None, 3, 3, 192)	576	conv2d_76[0][0]
activation_72 (Activation)	(None, 3, 3, 320)	0	batch_normalization_72[0][0]
activation_76 (Activation)	(None, 3, 3, 192)	0	batch_normalization_76[0][0]
max_pooling2d_4 (MaxPooling2D)	(None, 3, 3, 768)	0	mixed7[0][0]
mixed8 (Concatenate)	(None, 3, 3, 1280)	0	activation_72[0][0] activation_76[0][0] max_pooling2d_4[0][0]
conv2d_81 (Conv2D)	(None, 3, 3, 448)	573440	mixed8[0][0]
batch_normalization_81 (BatchNo	(None, 3, 3, 448)	1344	conv2d_81[0][0]
activation_81 (Activation)	(None, 3, 3, 448)	0	batch_normalization_81[0][0]
conv2d_78 (Conv2D)	(None, 3, 3, 384)	491520	mixed8[0][0]
conv2d_82 (Conv2D)	(None, 3, 3, 384)	1548288	activation_81[0][0]
batch_normalization_78 (BatchNo	(None, 3, 3, 384)	1152	conv2d_78[0][0]
batch_normalization_82 (BatchNo	(None, 3, 3, 384)	1152	conv2d_82[0][0]
activation_78 (Activation)	(None, 3, 3, 384)	0	batch_normalization_78[0][0]
activation_82 (Activation)	(None, 3, 3, 384)	0	batch_normalization_82[0][0]

conv2d_79 (Conv2D)	(None, 3, 3, 384)	442368	activation_78[0][0]
conv2d_80 (Conv2D)	(None, 3, 3, 384)	442368	activation_78[0][0]
conv2d_83 (Conv2D)	(None, 3, 3, 384)	442368	activation_82[0][0]
conv2d_84 (Conv2D)	(None, 3, 3, 384)	442368	activation_82[0][0]
average_pooling2d_8 (AveragePool)	(None, 3, 3, 1280)	0	mixed8[0][0]
conv2d_77 (Conv2D)	(None, 3, 3, 320)	409600	mixed8[0][0]
batch_normalization_79 (Batch Normalization)	(None, 3, 3, 384)	1152	conv2d_79[0][0]
batch_normalization_80 (Batch Normalization)	(None, 3, 3, 384)	1152	conv2d_80[0][0]
batch_normalization_83 (Batch Normalization)	(None, 3, 3, 384)	1152	conv2d_83[0][0]
batch_normalization_84 (Batch Normalization)	(None, 3, 3, 384)	1152	conv2d_84[0][0]
conv2d_85 (Conv2D)	(None, 3, 3, 192)	245760	average_pooling2d_8[0][0]
batch_normalization_77 (Batch Normalization)	(None, 3, 3, 320)	960	conv2d_77[0][0]
activation_79 (Activation)	(None, 3, 3, 384)	0	batch_normalization_79[0][0]
activation_80 (Activation)	(None, 3, 3, 384)	0	batch_normalization_80[0][0]
activation_83 (Activation)	(None, 3, 3, 384)	0	batch_normalization_83[0][0]
activation_84 (Activation)	(None, 3, 3, 384)	0	batch_normalization_84[0][0]
batch_normalization_85 (Batch Normalization)	(None, 3, 3, 192)	576	conv2d_85[0][0]
activation_77 (Activation)	(None, 3, 3, 320)	0	batch_normalization_77[0][0]
mixed9_0 (Concatenate)	(None, 3, 3, 768)	0	activation_79[0][0] activation_80[0][0]
concatenate_1 (Concatenate)	(None, 3, 3, 768)	0	activation_83[0][0] activation_84[0][0]
activation_85 (Activation)	(None, 3, 3, 192)	0	batch_normalization_85[0][0]
mixed9 (Concatenate)	(None, 3, 3, 2048)	0	activation_77[0][0] mixed9_0[0][0] concatenate_1[0][0] activation_85[0][0]

conv2d_90 (Conv2D)	(None, 3, 3, 448)	917504	mixed9[0][0]
batch_normalization_90 (BatchNo	(None, 3, 3, 448)	1344	conv2d_90[0][0]
activation_90 (Activation)	(None, 3, 3, 448)	0	batch_normalization_90[0][0]
conv2d_87 (Conv2D)	(None, 3, 3, 384)	786432	mixed9[0][0]
conv2d_91 (Conv2D)	(None, 3, 3, 384)	1548288	activation_90[0][0]
batch_normalization_87 (BatchNo	(None, 3, 3, 384)	1152	conv2d_87[0][0]
batch_normalization_91 (BatchNo	(None, 3, 3, 384)	1152	conv2d_91[0][0]
activation_87 (Activation)	(None, 3, 3, 384)	0	batch_normalization_87[0][0]
activation_91 (Activation)	(None, 3, 3, 384)	0	batch_normalization_91[0][0]
conv2d_88 (Conv2D)	(None, 3, 3, 384)	442368	activation_87[0][0]
conv2d_89 (Conv2D)	(None, 3, 3, 384)	442368	activation_87[0][0]
conv2d_92 (Conv2D)	(None, 3, 3, 384)	442368	activation_91[0][0]
conv2d_93 (Conv2D)	(None, 3, 3, 384)	442368	activation_91[0][0]
average_pooling2d_9 (AveragePoo	(None, 3, 3, 2048)	0	mixed9[0][0]
conv2d_86 (Conv2D)	(None, 3, 3, 320)	655360	mixed9[0][0]
batch_normalization_88 (BatchNo	(None, 3, 3, 384)	1152	conv2d_88[0][0]
batch_normalization_89 (BatchNo	(None, 3, 3, 384)	1152	conv2d_89[0][0]
batch_normalization_92 (BatchNo	(None, 3, 3, 384)	1152	conv2d_92[0][0]
batch_normalization_93 (BatchNo	(None, 3, 3, 384)	1152	conv2d_93[0][0]
conv2d_94 (Conv2D)	(None, 3, 3, 192)	393216	average_pooling2d_9[0][0]
batch_normalization_86 (BatchNo	(None, 3, 3, 320)	960	conv2d_86[0][0]
activation_88 (Activation)	(None, 3, 3, 384)	0	batch_normalization_88[0][0]
activation_89 (Activation)	(None, 3, 3, 384)	0	batch_normalization_89[0][0]
activation_92 (Activation)	(None, 3, 3, 384)	0	batch_normalization_92[0][0]

activation_93 (Activation)	(None, 3, 3, 384)	0	batch_normalization_93[0][0]
batch_normalization_94 (Batch Normalization)	(None, 3, 3, 192)	576	conv2d_94[0][0]
activation_86 (Activation)	(None, 3, 3, 320)	0	batch_normalization_86[0][0]
mixed9_1 (Concatenate)	(None, 3, 3, 768)	0	activation_88[0][0] activation_89[0][0]
concatenate_2 (Concatenate)	(None, 3, 3, 768)	0	activation_92[0][0] activation_93[0][0]
activation_94 (Activation)	(None, 3, 3, 192)	0	batch_normalization_94[0][0]
mixed10 (Concatenate)	(None, 3, 3, 2048)	0	activation_86[0][0] mixed9_1[0][0] concatenate_2[0][0] activation_94[0][0]

=====  
 Total params: 21,802,784  
 Trainable params: 0  
 Non-trainable params: 21,802,784  
 =====

In a normal Inception network, you would see from the model summary that the last two layers were a global average pooling layer, and a fully-connected "Dense" layer. However, since we set `include_top` to `False`, both of these get dropped. If you otherwise wanted to drop additional layers, you would use:

```
inception.layers.pop()
```

Note that `pop()` works from the end of the model backwards.

It's important to note two things here: 1. How many layers you drop is up to you, typically. We dropped the final two already by setting `include_top` to `False` in the original loading of the model, but you could instead just run `pop()` twice to achieve similar results. (*Note:* Keras requires us to set `include_top` to `False` in order to change the `input_shape`.) Additional layers could be dropped by additional calls to `pop()`. 2. If you make a mistake with `pop()`, you'll want to reload the model. If you use it multiple times, the model will continue to drop more and more layers, so you may need to check `model.summary()` again to check your work.

#### 1.0.4 Adding new layers

Now, you can start to add your own layers. While we've used Keras's `Sequential` model before for simplicity, we'll actually use the [Model API](#) this time. This functions a little differently, in that instead of using `model.add()`, you explicitly tell the model which previous layer to attach to the current layer. This is useful if you want to use more advanced concepts like [skip layers](#), for instance (which were used heavily in ResNet).



For example, if you had a previous layer named `inp`:

```
x = Dropout(0.2)(inp)
```

is how you would attach a new dropout layer `x`, with its input coming from a layer with the variable name `inp`.

We are going to use the [CIFAR-10 dataset](#), which consists of 60,000 32x32 images of 10 classes. We need to use Keras's Input function to do so, and then we want to re-size the images up to the `input_size` we specified earlier (139x139).

```
In [4]: from keras.layers import Input, Lambda
import tensorflow as tf

# Makes the input placeholder layer 32x32x3 for CIFAR-10
cifar_input = Input(shape=(32,32,3))

# Re-sizes the input with Kera's Lambda layer & attach to cifar_input
resized_input = Lambda(lambda image: tf.image.resize_images(
    image, (input_size, input_size)))(cifar_input)

# Feeds the re-sized input into Inception model
# You will need to update the model name if you changed it earlier!
inp = inception(resized_input)

In [5]: # Imports fully-connected "Dense" layers & Global Average Pooling
from keras.layers import Dense, GlobalAveragePooling2D

## TODO: Setting `include_top` to False earlier also removed the
##         GlobalAveragePooling2D layer, but we still want it.
##         Add it here, and make sure to connect it to the end of Inception
x = GlobalAveragePooling2D()(inp)

## TODO: Create two new fully-connected layers using the Model API
##         format discussed above. The first layer should use `out`
##         as its input, along with ReLU activation. You can choose
##         how many nodes it has, although 512 or less is a good idea.
##         The second layer should take this first layer as input, and
##         be named "predictions", with Softmax activation and
##         10 nodes, as we'll be using the CIFAR10 dataset.
x = Dense(512, activation = 'relu')(x)
predictions = Dense(10, activation = 'softmax')(x)
```

We're almost done with our new model! Now we just need to use the actual Model API to create the full model.

```
In [6]: # Imports the Model API
from keras.models import Model

# Creates the model, assuming your final layer is named "predictions"
```

```

model = Model(inputs=cifar_input, outputs=predictions)

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

# Check the summary of this new model to confirm the architecture
model.summary()

```

```

-----
Layer (type)                 Output Shape              Param #
=====
input_2 (InputLayer)         (None, 32, 32, 3)         0
-----
lambda_1 (Lambda)           (None, 139, 139, 3)       0
-----
inception_v3 (Model)         (None, 3, 3, 2048)        21802784
-----
global_average_pooling2d_1 ( (None, 2048)          0
-----
dense_1 (Dense)              (None, 512)               1049088
-----
dense_2 (Dense)              (None, 10)                 5130
=====
Total params: 22,857,002
Trainable params: 1,054,218
Non-trainable params: 21,802,784
-----

```

Great job creating a new model architecture from Inception! Notice how this method of adding layers before InceptionV3 and appending to the end of it made InceptionV3 condense down into one line in the summary; if you use the Inception model's normal input (which you could gather from `inception.layers.input`), it would instead show all the layers like before.

Most of the rest of the code in the notebook just goes toward loading our data, pre-processing it, and starting our training in Keras, although there's one other good point to make here - Keras callbacks.

### 1.0.5 Keras Callbacks

Keras [callbacks](#) allow you to gather and store additional information during training, such as the best model, or even stop training early if the validation accuracy has stopped improving. These methods can help to avoid overfitting, or avoid other issues.

There's two key callbacks to mention here, `ModelCheckpoint` and `EarlyStopping`. As the names may suggest, model checkpoint saves down the best model so far based on a given metric, while early stopping will end training before the specified number of epochs if the chosen metric no longer improves after a given amount of time.

To set these callbacks, you could do the following:

```
checkpoint = ModelCheckpoint(filepath=save_path, monitor='val_loss', save_best_only=True)
```

This would save a model to a specified `save_path`, based on validation loss, and only save down the best models. If you set `save_best_only` to `False`, every single epoch will save down another version of the model.

```
stopper = EarlyStopping(monitor='val_acc', min_delta=0.0003, patience=5)
```

This will monitor validation accuracy, and if it has not decreased by more than 0.0003 from the previous best validation accuracy for 5 epochs, training will end early.

You still need to actually feed these callbacks into `fit()` when you train the model (along with all other relevant data to feed into `fit`):

```
model.fit(callbacks=[checkpoint, stopper])
```

## 1.1 GPU time

The rest of the notebook will give you the code for training, so you can turn on the GPU at this point - but first, **make sure to save your jupyter notebook**. Once the GPU is turned on, it will load whatever your last notebook checkpoint is.

While we suggest reading through the code below to make sure you understand it, you can otherwise go ahead and select *Cell > Run All* (or *Kernel > Restart & Run All* if already using GPU) to run through all cells in the notebook.

```
In [7]: from sklearn.utils import shuffle
        from sklearn.preprocessing import LabelBinarizer
        from keras.datasets import cifar10

        (X_train, y_train), (X_val, y_val) = cifar10.load_data()

        # One-hot encode the labels
        label_binarizer = LabelBinarizer()
        y_one_hot_train = label_binarizer.fit_transform(y_train)
        y_one_hot_val = label_binarizer.fit_transform(y_val)

        # Shuffle the training & test data
        X_train, y_one_hot_train = shuffle(X_train, y_one_hot_train)
        X_val, y_one_hot_val = shuffle(X_val, y_one_hot_val)

        # We are only going to use the first 10,000 images for speed reasons
        # And only the first 2,000 images from the test set
        X_train = X_train[:10000]
        y_one_hot_train = y_one_hot_train[:10000]
        X_val = X_val[:2000]
        y_one_hot_val = y_one_hot_val[:2000]
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170500096/170498071 [=====] - 2s 0us/step
```

You can check out Keras's [ImageDataGenerator documentation](#) for more information on the below - you can also add additional image augmentation through this function, although we are skipping that step here so you can potentially explore it in the upcoming project.

```
In [8]: # Use a generator to pre-process our images for ImageNet
        from keras.preprocessing.image import ImageDataGenerator
        from keras.applications.inception_v3 import preprocess_input

        if preprocess_flag == True:
            datagen = ImageDataGenerator(preprocessing_function=preprocess_input)
            val_datagen = ImageDataGenerator(preprocessing_function=preprocess_input)
        else:
            datagen = ImageDataGenerator()
            val_datagen = ImageDataGenerator()

In [9]: # Train the model
        batch_size = 32
        epochs = 5
        # Note: we aren't using callbacks here since we only are using 5 epochs to conserve GPU
        model.fit_generator(datagen.flow(X_train, y_one_hot_train, batch_size=batch_size),
                            steps_per_epoch=len(X_train)/batch_size, epochs=epochs, verbose=1,
                            validation_data=val_datagen.flow(X_val, y_one_hot_val, batch_size=batch_size),
                            validation_steps=len(X_val)/batch_size)
```

```
Epoch 1/5
313/312 [=====] - 49s 156ms/step - loss: 1.2783 - acc: 0.5731 - val_loss: 1.2783
Epoch 2/5
313/312 [=====] - 45s 145ms/step - loss: 0.9639 - acc: 0.6675 - val_loss: 0.9639
Epoch 3/5
313/312 [=====] - 46s 148ms/step - loss: 0.9008 - acc: 0.6885 - val_loss: 0.9008
Epoch 4/5
313/312 [=====] - 46s 148ms/step - loss: 0.8352 - acc: 0.7122 - val_loss: 0.8352
Epoch 5/5
313/312 [=====] - 46s 148ms/step - loss: 0.7896 - acc: 0.7287 - val_loss: 0.7896
```

```
Out[9]: <keras.callbacks.History at 0x7f916dc36cf8>
```

As you may have noticed, CIFAR-10 is a fairly tough dataset. However, given that we are only training on a small subset of the data, only training for five epochs, and not using any image augmentation, the results are still fairly impressive!

We achieved ~70% validation accuracy here, although your results may vary.

## 1.2 [Optional] Test without frozen weights, or by training from scratch.

Since the majority of the model was frozen above, training speed is pretty quick. You may also want to check out the training speed, as well as final accuracy, if you don't freeze the weights. Note that this can be fairly slow, so we're marking this as optional in order to conserve GPU time.

If you do want to see the results from doing so, go back to the first code cell and set `freeze_flag` to `False`. If you want to completely train from scratch without ImageNet pre-trained weights, follow the previous step as well as setting `weights_flag` to `None`. Then, go to *Kernel > Restart & Run All*.

### 1.3 Comparison

So that you don't use up your GPU time, we've tried out these results ourselves as well.

Training Mode	Val Acc @ 1 epoch	Val Acc @ 5 epoch	Time per epoch
Frozen weights	65.5%	70.3%	50 seconds
Unfrozen weights	50.6%	71.6%	142 seconds
No pre-trained weights	19.2%	39.2%	142 seconds

From the above, we can see that the pre-trained model with frozen weights actually began converging the fastest (already at 65.5% after 1 epoch), while the model re-training from the pre-trained weights slightly edged it out after 5 epochs.

However, this does not tell the whole story - the training accuracy was substantially higher, nearing 87% for the unfrozen weights model. It actually began overfit the data much more under this method. We would likely be able to counteract some of this issue by using data augmentation. On the flip side, the model using frozen weights could also have been improved by actually only freezing a portion of the weights; some of these are likely more specific to ImageNet classes as it gets later in the network, as opposed to the simpler features extracted early in the network.

#### 1.3.1 The Power of Transfer Learning

Comparing the last line to the other two really shows the power of transfer learning. After five epochs, a model without ImageNet pre-training had only achieved 39.2% accuracy, compared to over 70% for the other two. As such, pre-training the network has saved substantial time, especially given the additional training time needed when the weights are not frozen.

There is also evidence found in various research that pre-training on ImageNet weights will result in a higher overall accuracy than completely training from scratch, even when using a substantially different dataset.