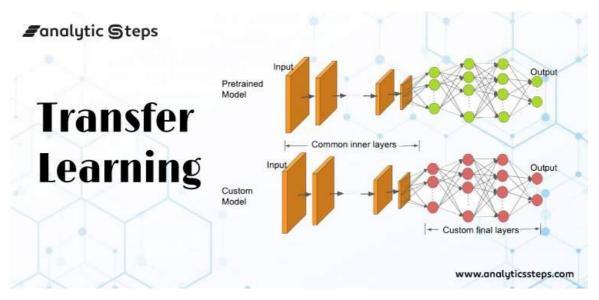
Transfer Learning using Feature Extraction Method -- Without Data Augmentation

Transfer learning is a machine learning technique that allows a model trained on one task to be reused or adapted for a different task. There are two main types of transfer learning:

- **Feature Extraction:** In feature extraction, a pre-trained model is used as a fixed feature extractor. The pre-trained model is typically trained on a large dataset, such as ImageNet, and the final layer(s) that output the class predictions are removed. The remaining layers are then used as a feature extractor for a new dataset. These extracted features can be used as input to train a new model on the new dataset.
- **Fine-tuning:** In fine-tuning, a pre-trained model is used as an initialization for a new model. The pre-trained model is typically trained on a large dataset, such as ImageNet, and the final layer(s) that output the class predictions are replaced with new ones for the new task. The new model is then trained on the new dataset while keeping the weights of the pre-trained layers fixed or with a small learning rate.



```
In [ ]: !mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
```

Downloading & Loading the dataset

```
In [ ]: !kaggle datasets download -d salader/dogs-vs-cats

Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /ro
    ot/.kaggle/kaggle.json'
    Downloading dogs-vs-cats.zip to /content
        99% 1.06G/1.06G [00:07<00:00, 141MB/s]
        100% 1.06G/1.06G [00:07<00:00, 162MB/s]

In [ ]: import zipfile
    zip_ref = zipfile.ZipFile('/content/dogs-vs-cats.zip', 'r')
    zip_ref.extractall('/content')
    zip_ref.close()</pre>
```

Import Necessary Libraries

```
import tensorflow
from tensorflow import keras
from keras import Sequential
from keras.layers import Dense,Flatten
from keras.applications.vgg16 import VGG16
```

Defining the Convolutional Base & Freezing it & discarding the top layer (Dense Layer to train again)

```
In []: conv_base = VGG16(
    weights='imagenet',
    include_top = False,
    input_shape=(150,150,3)
)
```

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5

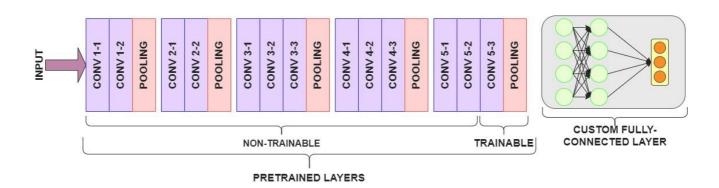
In []: conv_base.summary()

Model: "vgg16"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 150, 150, 3)]	0
block1_conv1 (Conv2D)	(None, 150, 150, 64)	1792
block1_conv2 (Conv2D)	(None, 150, 150, 64)	36928
<pre>block1_pool (MaxPooling2D)</pre>	(None, 75, 75, 64)	0
block2_conv1 (Conv2D)	(None, 75, 75, 128)	73856
block2_conv2 (Conv2D)	(None, 75, 75, 128)	147584
<pre>block2_pool (MaxPooling2D)</pre>	(None, 37, 37, 128)	0
block3_conv1 (Conv2D)	(None, 37, 37, 256)	295168
block3_conv2 (Conv2D)	(None, 37, 37, 256)	590080
block3_conv3 (Conv2D)	(None, 37, 37, 256)	590080
<pre>block3_pool (MaxPooling2D)</pre>	(None, 18, 18, 256)	0
block4_conv1 (Conv2D)	(None, 18, 18, 512)	1180160
block4_conv2 (Conv2D)	(None, 18, 18, 512)	2359808
block4_conv3 (Conv2D)	(None, 18, 18, 512)	2359808
<pre>block4_pool (MaxPooling2D)</pre>	(None, 9, 9, 512)	0
block5_conv1 (Conv2D)	(None, 9, 9, 512)	2359808
block5_conv2 (Conv2D)	(None, 9, 9, 512)	2359808
block5_conv3 (Conv2D)	(None, 9, 9, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0

Total params: 14,714,688 Trainable params: 14,714,688 Non-trainable params: 0

 $From the \ model. summary (), it \ can \ be \ easilty \ insighted \ that \ we're \ only \ proceeding \ with \ the \ convolutional \ layer (conv_base) \ only.$



If we notice that the last block is the block5 ending with the maxpooling layer for block5:

block5_conv1 (Conv2D) (None, 9, 9, 512) 2359808

block5_conv2 (Conv2D) (None, 9, 9, 512) 2359808

block5_conv3 (Conv2D) (None, 9, 9, 512) 2359808

block5_pool (MaxPooling2D) (None, 4, 4, 512) 0

```
In [ ]: model = Sequential()

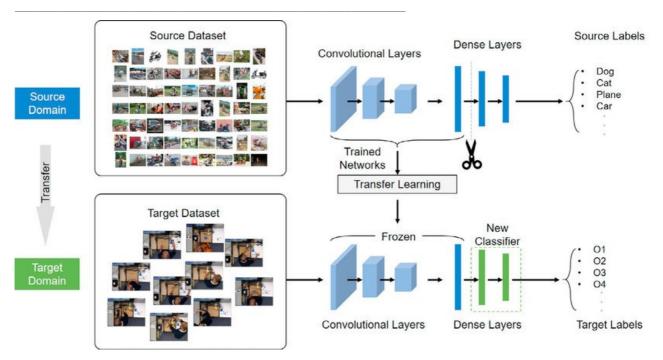
model.add(conv_base)
model.add(Flatten())
model.add(Dense(256,activation='relu'))
model.add(Dense(1,activation='sigmoid'))
```

In []: model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 4, 4, 512)	14714688
flatten (Flatten)	(None, 8192)	0
dense (Dense)	(None, 256)	2097408
dense_1 (Dense)	(None, 1)	257

Total params: 16,812,353 Trainable params: 2,097,665 Non-trainable params: 14,714,688



Here it can be noticed that the Trainable Parameters have been reduced to 2,097,665 from 16,812,353 (After adding the dense layer (2,097,665) to the conv base (14,714,688)).

So, this in turn prevents the training of basic features again rather to focus on the classification part to focus on, to give proper output.

```
In [ ]: conv_base.trainable = False
```

Defining Training & Validation set for model training

Found 20000 files belonging to 2 classes. Found 5000 files belonging to 2 classes.

Normalizing the dataset for smooth training

```
In []: # Normalize
def process(image,label):
    image = tensorflow.cast(image/255. ,tensorflow.float32)
    return image,label

train_ds = train_ds.map(process)
validation_ds = validation_ds.map(process)
```

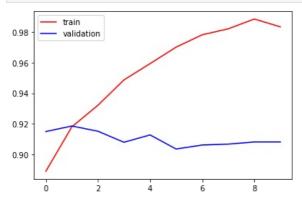
Model Training

```
In [ ]: model.compile(optimizer='adam',loss='binary crossentropy',metrics=['accuracy'])
In [ ]: history = model.fit(train_ds,epochs=10,validation_data=validation_ds)
     Epoch 1/10
     625/625 [=
                          :======] - 78s 105ms/step - loss: 0.2631 - accuracy: 0.8891 - val loss: 0.2011
     - val_accuracy: 0.9150
     Epoch 2/10
     625/625 [===
                        ========] - 66s 106ms/step - loss: 0.1949 - accuracy: 0.9181 - val loss: 0.1935
      val_accuracy: 0.9186
     Epoch 3/10
     625/625 [========= ] - 66s 106ms/step - loss: 0.1594 - accuracy: 0.9322 - val loss: 0.2044
      - val_accuracy: 0.9152
     Epoch 4/10
     - val_accuracy: 0.9080
     Epoch 5/10
     val accuracy: 0.9128
     Epoch 6/10
     625/625 [============ ] - 67s 107ms/step - loss: 0.0798 - accuracy: 0.9700 - val_loss: 0.2662
      val accuracy: 0.9036
     Epoch 7/10
     val_accuracy: 0.9062
     Epoch 8/10
     625/625 [========= ] - 75s 119ms/step - loss: 0.0506 - accuracy: 0.9820 - val loss: 0.3019
     - val_accuracy: 0.9068
     Epoch 9/10
     625/625 [==
                         :=======] - 67s 107ms/step - loss: 0.0338 - accuracy: 0.9884 - val loss: 0.3378
     - val accuracy: 0.9082
     Epoch 10/10
                  625/625 [===
     - val_accuracy: 0.9082
```

Loss curve for Accuracy

```
import matplotlib.pyplot as plt

plt.plot(history.history['accuracy'],color='red',label='train')
plt.plot(history.history['val_accuracy'],color='blue',label='validation')
plt.legend()
plt.show()
```



We can see that there is a huge gap between the train & validation curve, indicating the model overfitting.

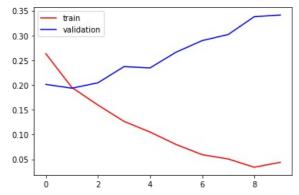
```
Epoch 10/10
```

Just check the accuracy & val_accuracy change, which can be easily be seen in the loss graph as well.

This can be improved by optimizing the parameters or by increasing the no. of epochs or most importantly by using Data Augmentation.

Loss curve for training loss

```
In [ ]: plt.plot(history.history['loss'],color='red',label='train')
    plt.plot(history.history['val_loss'],color='blue',label='validation')
    plt.legend()
    plt.show()
```



Epoch 10/10

val_accuracy: 0.9082

Check the val_loss & the loss values, the gap shows how the model is overfitted.

Name: Shobhandeb Paul

Linkedin: https://www.linkedin.com/in/shobhandeb-paul/

Github: https://github.com/herbert0419

In []:

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