What Is Transfer Learning?

- Transfer learning generally refers to a process where a model trained on one problem is used in some way on a second related problem.

- In deep learning, transfer learning is a technique whereby a neural network model is first trained on a problem similar to the problem that is being solved.
- One or more layers from the trained model are then used in a new model trained on the problem of interest.

- Transfer learning has the benefit of decreasing the training time for a neural network model and can result in lower generalization error.

- The weights in re-used layers may be used as the starting point for the training process and adapted in response to the new problem.
- This usage treats transfer learning as a type of weight initialization scheme.
- This may be useful when the first related problem has a lot more labeled data than the problem of interest and the similarity in the structure of the problem may be useful in both contexts.

How to Use Pre-Trained Models

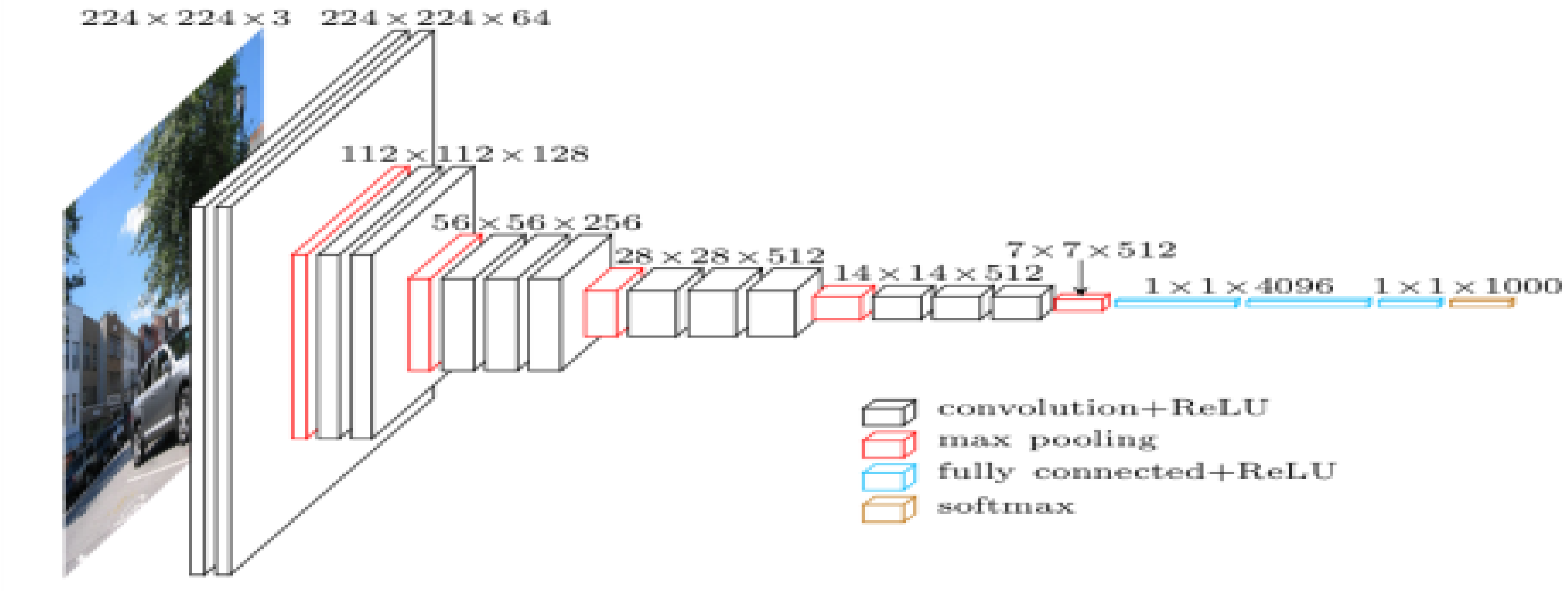
- **Classifier**: The pre-trained model is used directly to classify new images.
- **Standalone Feature Extractor**: The pre-trained model, or some portion of the model, is used to pre-process images and extract relevant features.
- **Integrated Feature Extractor**: The pre-trained model, or some portion of the model, is integrated into a new model, but layers of the pre-trained model are frozen during training.
- **Weight Initialization**: The pre-trained model, or some portion of the model, is integrated into a new model, and the layers of the pre-trained model are trained in concert with the new model.

Models for Transfer Learning

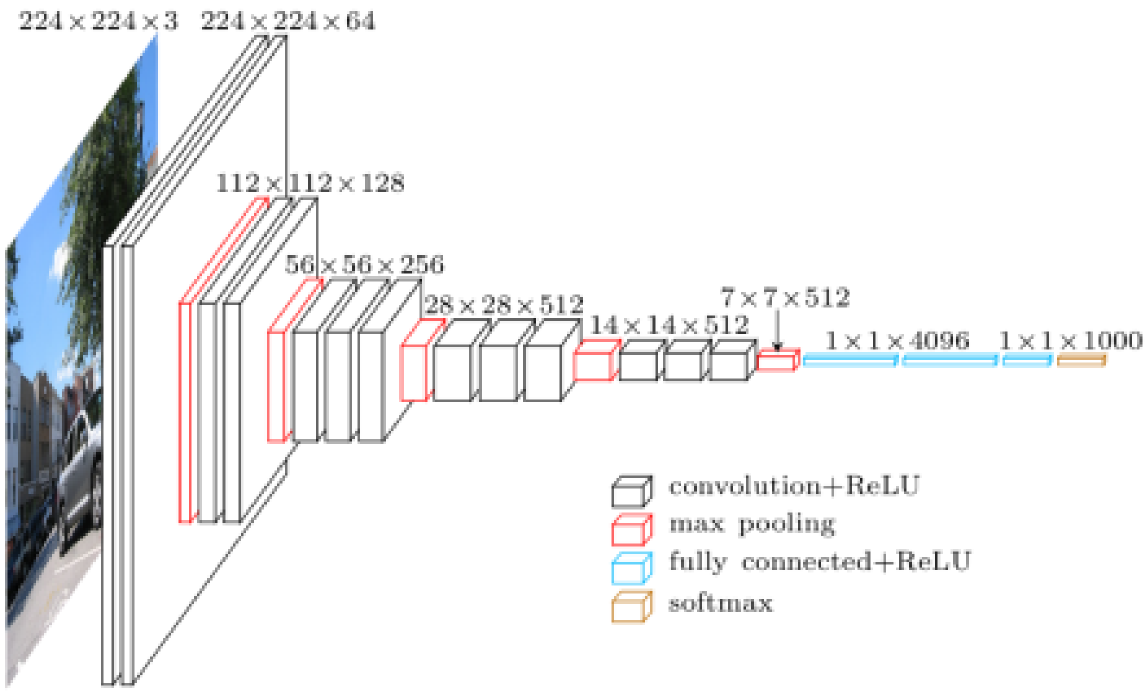
- The three of the more popular models are as follows:

- VGG (e.g. VGG16 or VGG19).
- GoogLeNet (e.g. InceptionV3).
- Residual Network (e.g. ResNet50).

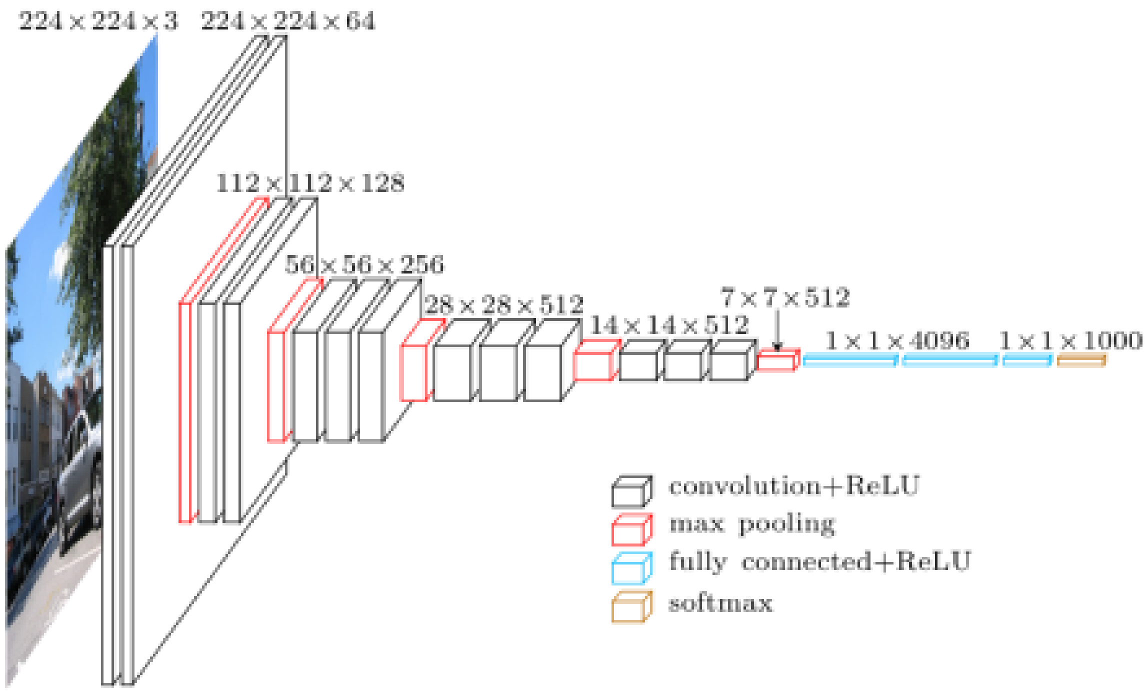
VGG16



convolution layers of 3x3 filter with a stride 1 and always used same padding and maxpool layer of 2x2 filter of stride 2.
The 16 in VGG16 refers to it has 16 layers that have weights. This network is a pretty large network and it has about 138 million (approx) parameters.



Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0



block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
fc1 (Dense)	(None, 4096)	102764544
fc2 (Dense)	(None, 4096)	16781312
predictions (Dense)	(None, 1000)	4097000

Total params: 138,357,544
Trainable params: 138,357,544
Non-trainable params: 0

Pre-Trained Model as Classifier

- A pre-trained model can be used directly to classify new photographs as one of the 1,000 known classes in the image classification task in the ILSVRC.

- We will use the VGG16 model to classify new images.
- vgg16.preprocess_input will convert the input images from RGB to BGR, then will zero-center each color channel with respect to the ImageNet dataset, without scaling.

```
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from keras.applications.vgg16 import preprocess_input
from keras.applications.vgg16 import decode_predictions
from keras.applications.vgg16 import VGG16
# load the model
model = VGG16()
# load an image from file
image = load_img('mug.jpg', target_size=(224, 224))
# convert the image pixels to a numpy array
image = img_to_array(image)
# reshape data for the model
image = image.reshape((1, image.shape[0], image.shape[1], image.shape[2]))
# prepare the image for the VGG model
image = preprocess_input(image)
# predict the probability across all output classes
yhat = model.predict(image)
# convert the probabilities to class labels
label = decode_predictions(yhat)
# retrieve the most likely result, e.g. highest probability
label = label[0][0]
# print the classification
print('%s (%.2f%%)' % (label[1], label[2]*100))
```

Pre-Trained Model as Feature Extractor Preprocessor

- The pre-trained model may be used as a standalone program to extract features from new photographs.
- Specifically, the extracted features of a photograph may be a vector of numbers that the model will use to describe the specific features in a photograph.
- These features can then be used as input in the development of a new model.
- The last few layers of the VGG16 model are fully connected layers prior to the output layer.
- These layers will provide a complex set of features to describe a given input image and may provide useful input when training a new model for image classification or related computer vision task.

- The image can be loaded and prepared for the model.
- We will load the model with the classifier output part of the model, but manually remove the final output layer.
- This means that the second last fully connected layer with 4,096 nodes will be the new output layer.

```
# example of using the vgg16 model as a feature extraction model
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from keras.applications.vgg16 import preprocess_input
from keras.applications.vgg16 import decode_predictions
from keras.applications.vgg16 import VGG16
from keras.models import Model
from pickle import dump
# load an image from file
image = load_img('/content/dog.jpg', target_size=(224, 224))
# convert the image pixels to a numpy array
image = img_to_array(image)
# reshape data for the model
image = image.reshape((1, image.shape[0], image.shape[1], image.shape[2]))
# prepare the image for the VGG model
image = preprocess_input(image)
# load model
model = VGG16()
# remove the output layer
model = Model(inputs=model.inputs, outputs=model.layers[-2].output)
# get extracted features
features = model.predict(image)
print(features.shape)
# save to file
dump(features, open('dog.pkl', 'wb'))
```

```
(1, 4096)
```

Pre-Trained Model as Feature Extractor in Model

- We can use some or all of the layers in a pre-trained model as a feature extraction component of a new model directly.
- This can be achieved by loading the model, then simply adding new layers.
- This may involve adding new convolutional and pooling layers to expand upon the feature extraction capabilities of the model or adding new fully connected classifier type layers to learn how to interpret the extracted features on a new dataset, or some combination.

```python
# load the VGG16 network
print("[INFO loading network...")
model_vgg = VGG16(weights="imagenet", include_top=False, input_shape=train_x.shape[1:])
model_vgg.summary()
```

```python
model_transfer_full = Sequential()
model_transfer_full.add(model_vgg)
model_transfer_full.add(GlobalAveragePooling2D())
model_transfer_full.add(Dropout(0.2))
model_transfer_full.add(Dense(100, activation='relu'))
model_transfer_full.add(Dense(11, activation='softmax'))
model_transfer_full.summary()
```

```python
opt = Adam(lr=0.00001)
model_transfer_full.compile(loss='categorical_crossentropy', optimizer=opt,metrics=['accuracy'])
history = model_transfer_full.fit(train_x, y_train, batch_size=32, epochs=10,
          validation_data=(val_x, y_val), callbacks=[checkpointer],verbose=1, shuffle=True)
```

- Take layers from a previously trained model.
- Freeze them, so as to avoid destroying any of the information they contain during future training rounds.
- Add some new, trainable layers on top of the frozen layers. They will learn to turn the old features into predictions on a new dataset.
- Train the new layers on your dataset.