BST 261: Data Science II
Lecture 6

Convolutional Neural Networks (CNNs): Pretrained networks (with and without data augmentation)

Santiago Romero-Brufau
Harvard T.H. Chan School of Public Health
Spring 2

Join our team for this summer!!

Opportunity to be a Data Science Intern at Mayo Clinic Department of ENT (ear-nose-throat).

Team: me + another data scientist (HDS graduate) + ENT physicians.

Projects: that directly improve clinical practice for patients. Our main current project uses NLP to improve direct messages to patients after surgery. You’ll also have the opportunity to attend the Mayo Clinic AI summit

Ideal candidate has a data science background, NLP experience preferred but not required.

Interested? email me a cover letter and a CV, title the email “Mayo ENT internship 2023”

Boston Slate Star Codex / Astral Codex Ten

"The AI Safety Problem" - talk by Richard Ngo at Harvard

OpenAI

3

by **delton137** SSC No comments Add to Calendar

Today at 4:30 PM EDT

Harvard Science Center Plaza, Oxford Street, Cambridge, MA, USA

Science Center Hall B

PRESENTATION

See event on Meetup

“

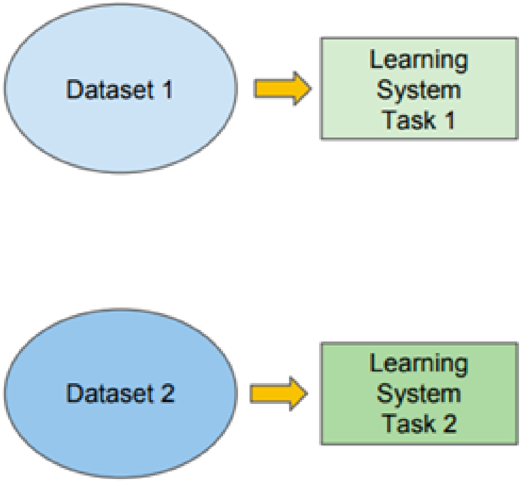
The Pareto principle states that for many outcomes, roughly 80% of consequences come from 20% of causes.

Source: Wikipedia

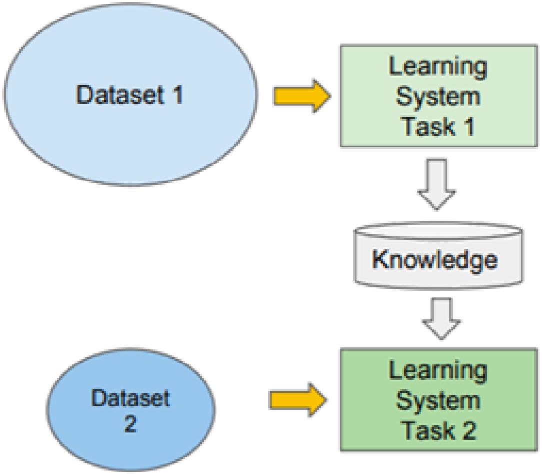
Pretrained Networks

Traditional ML vs Transfer Learning

- Isolated, single task learning:
  - Knowledge is not retained or accumulated. Learning is performed w.o. considering past learned knowledge in other tasks



- Learning of a new tasks relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data



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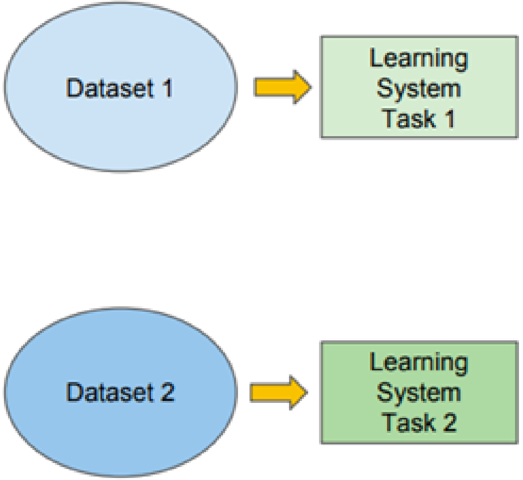

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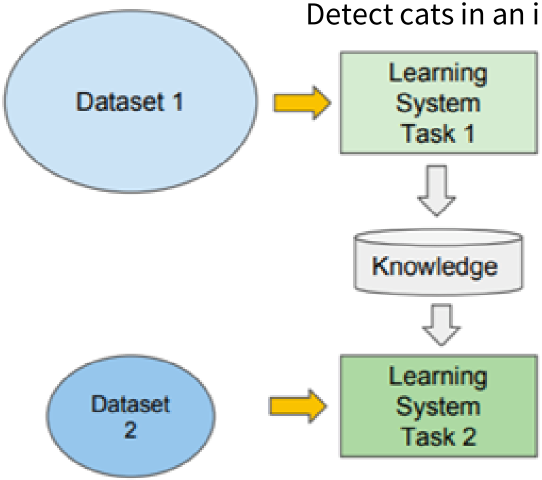
Detect cats in an image



Detect dogs in an image

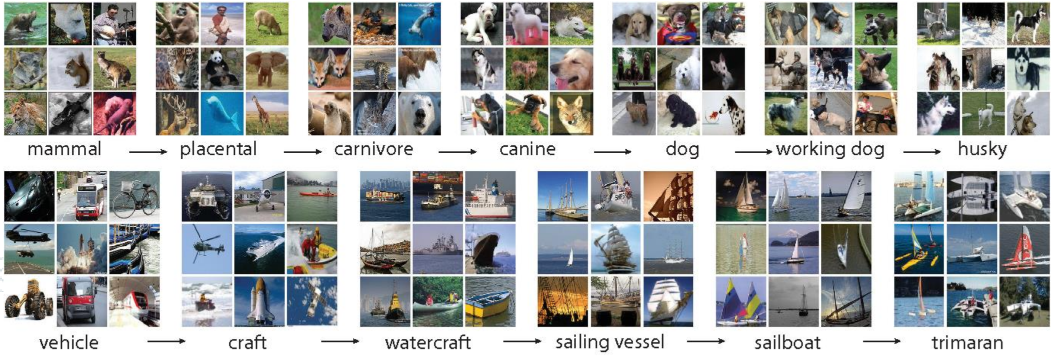
Pretrained Networks

- Another way around having a small number of training examples to learn from is using networks that have been trained on other, bigger datasets similar to the type of data you have
- A **pretrained network** is a saved network that was previously trained on a large dataset
- If the dataset used to train the network is large enough and big enough, the features learned by the pretrained network can act as a generic model to use as a base for your network
- This saves an enormous amount of computing time
- Pretrained networks can be used for **feature extraction** and **fine-tuning**

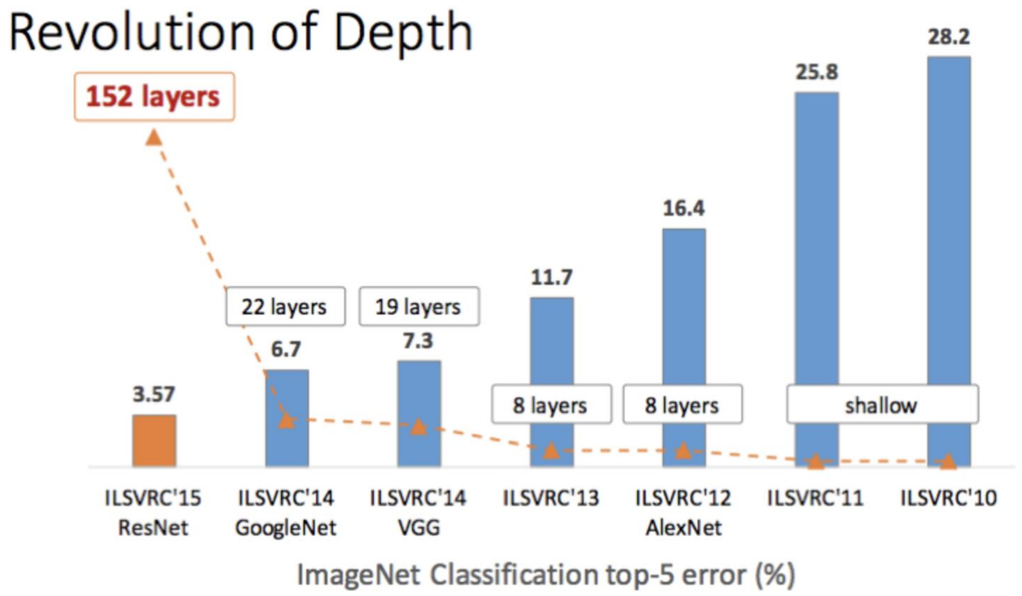
Pretrained Networks

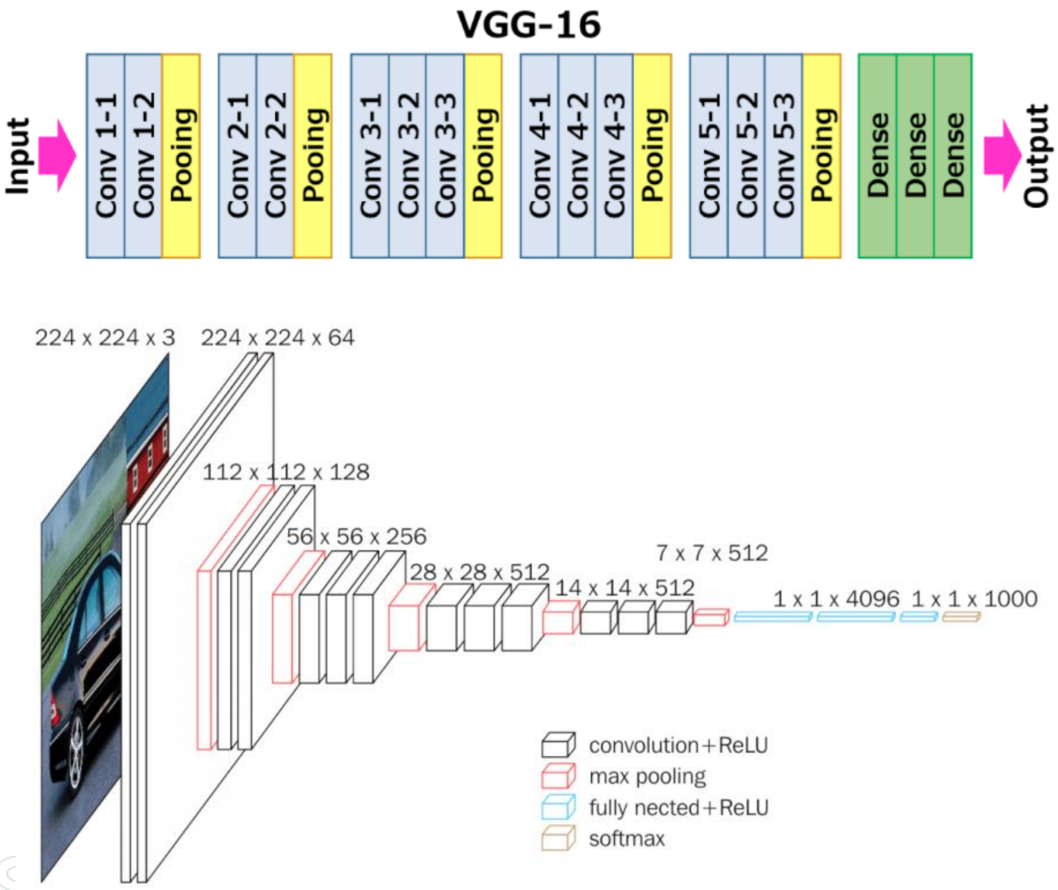
- Commonly used pretrained networks include
  - VGG16
  - ResNet
  - Inception
  - Inception-ResNet
  - Xception

- Commonly used dataset used to train a network is the [ImageNet dataset]
  - 1.4 million labeled images
  - 1,000 different classes
  - Mostly animals and everyday objects

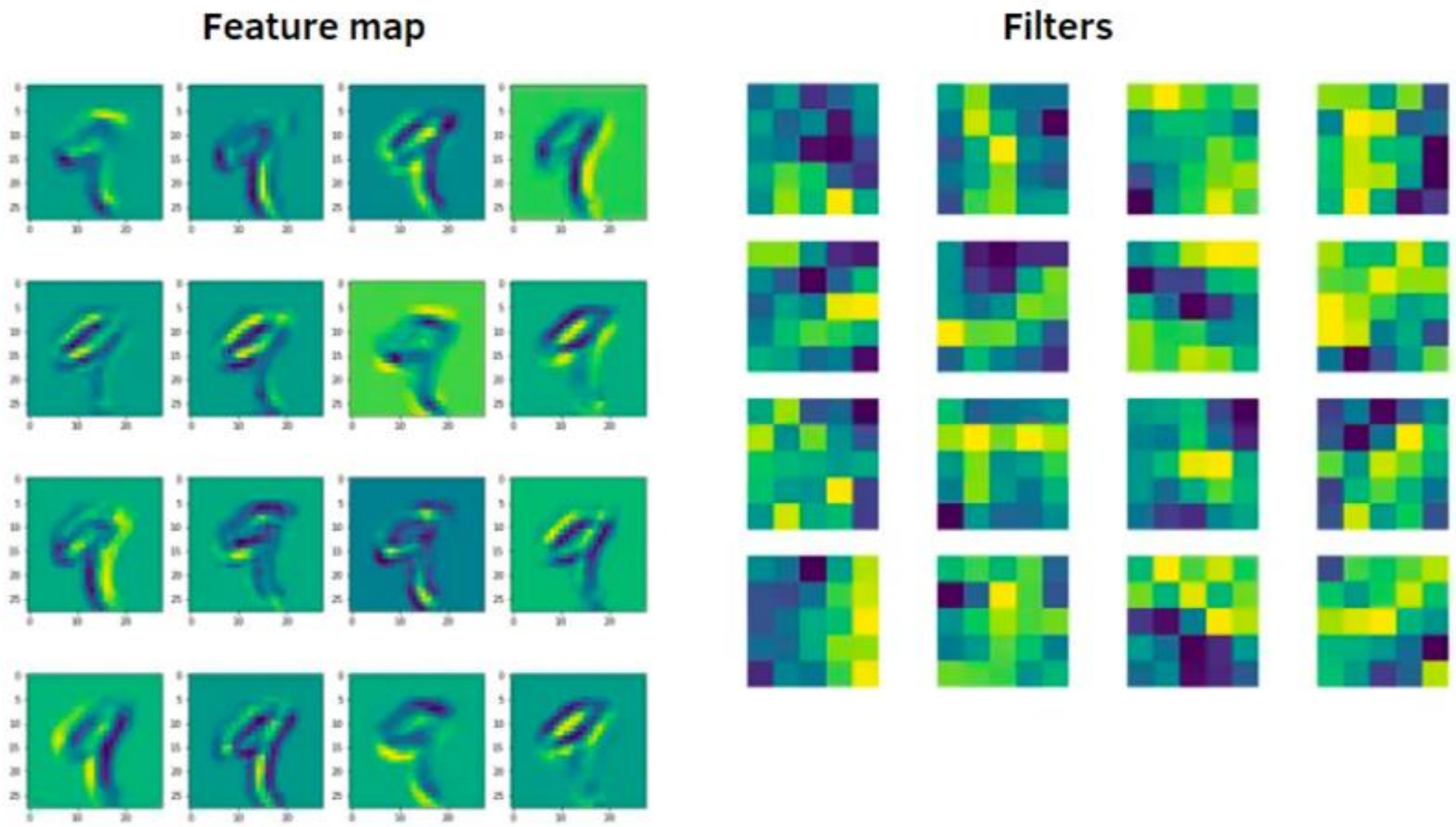


Pretrained Networks



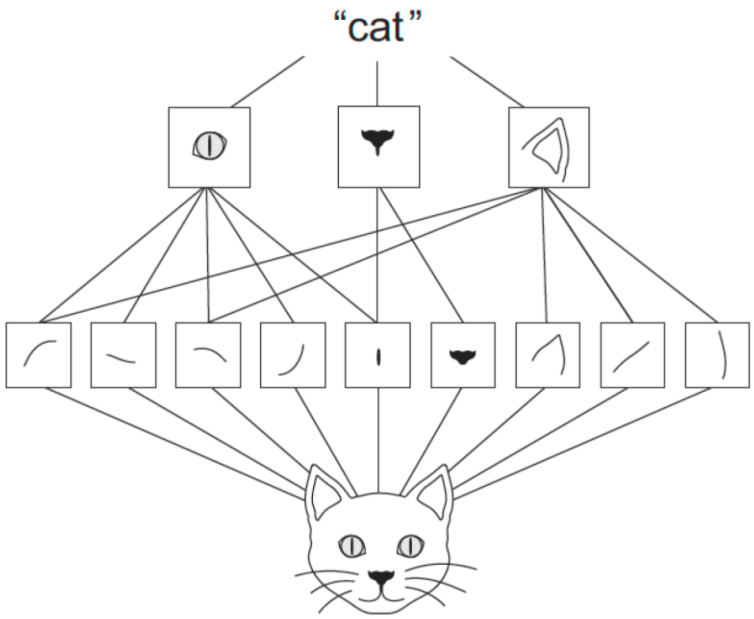


https://neurohive.io/en/popular-networks/vgg16/



Credit: Eugenia Anello. https://medium.com/dataseries/visualizing-the-feature-maps-and-filters-by-convolutional-neural-networks-e1462340518e

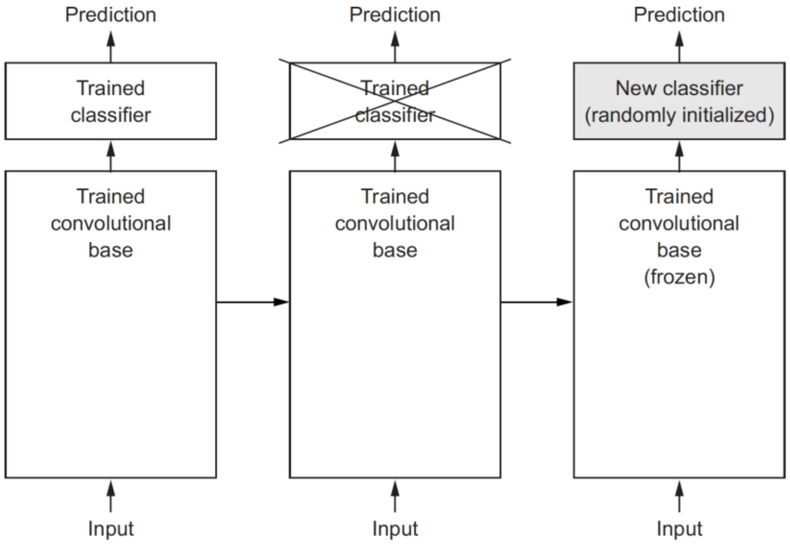
Remember what a convolutional layer does



Feature Extraction

- Consists of using the representations learned by a previous network to extract features from new samples

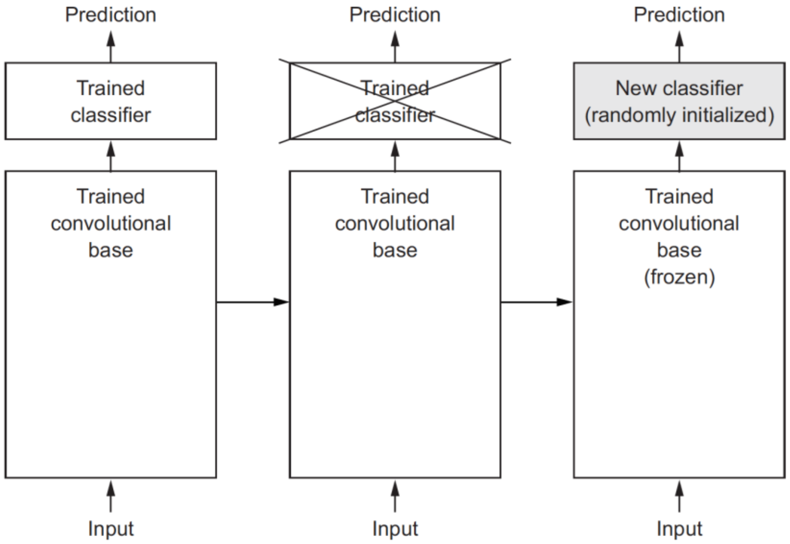
- These features are then run through a new classifier that is trained from scratch, and predictions are made



Feature Extraction

- For CNNs, the part of the pretrained network you use is called the **convolutional base**, which contains a series of convolution and pooling layers

- For feature extraction, you keep the convolutional base of the pretrained network, remove the dense / trained classifier layers, and append new dense and classifier layers to the convolutional base



Feature Extraction

- We could also reuse the densely connected classifier as well, but this is not advised
- Representations learned by the convolutional base are likely to be more generic and thus more reusable
- The representations learned by the classifier will be specific to the set of classes the model was trained on
- They will also no longer contain information about where objects are located in the input image
    - This makes them especially useless when the object's location is important

Feature Extraction

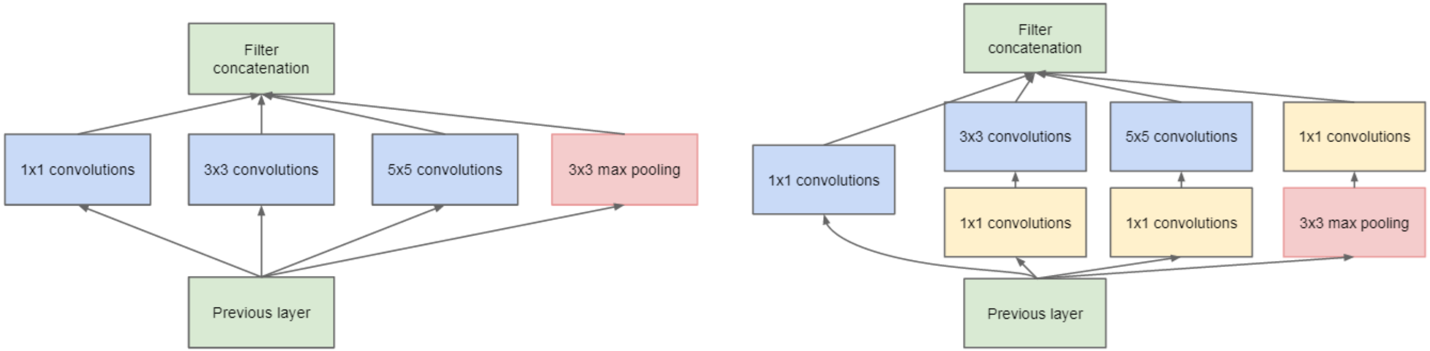
- The level of generality depends on the depth of the layer in the model
  - Early layers extract local, highly generic features, i.e. edges, colors, textures
  - Later layers extract more abstract concepts i.e. “cat ear” or “dog eye”

- If your new dataset is very different from the dataset that was used to train the model, you should use only the first few layers for feature extraction rather than the entire base

Pretrained Networks in Keras

- Xception
- Inception V3
- ResNet50
- VGG16
- VGG19
- MobileNet

Inception Models



(a) Inception module, naïve version

(b) Inception module with dimension reductions

https://becominghuman.ai/understanding-and-coding-inception-module-in-keras-eb56e9056b4b

Instantiating the VGG16 Base

```python
#from keras.applications import VGG16

conv_base = tf.keras.applications.VGG16(weights='imagenet',
                                          include_top=False,
                                          input_shape=(150, 150, 3))
```

```python
conv_base.summary()
```

```
_________________________________________________________________
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
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 75, 75, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 75, 75, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 75, 75, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (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
_________________________________________________________________
block3_pool (MaxPooling2D)   (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
_________________________________________________________________
block4_pool (MaxPooling2D)   (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
```

Instantiating the VGG16 Base

```python
#from keras.applications import VGG16

conv_base = tf.keras.applications.VGG16(weights='imagenet',
                                        include_top=False,
                                        input_shape=(150, 150, 3))
```

The final layer is a pooling layer and the final output shape from this base is (4, 4, 512). We need this information when adding layers to the base. This output shape will be the input shape for the densely connected layer we'll add to the base.

```
conv_base.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 150, 150, 3)       0
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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
```

Using a Pretrained Network

- The final output has shape (4, 4, 512)
- You have 2 options:
  1. **Feature extraction without augmented data**: you can run the convolutional base over the dataset, record its output to a numpy array, and then use these values as input to a densely connected classifier
     - This is fast and cheap to run
     - It won't allow you to use augmented data
  2. **Feature extraction with augmented data**: you can extend the convolutional base by adding dense layers on top and running the whole model on the input data
     - This allows data augmentation
     - This is very computationally expensive

Transfer learning without fine-tuning

(Using the convolutional base as a pre-processing step)

```python
import os
import numpy as np
from keras.preprocessing.image import ImageDataGenerator

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

def extract_features(directory, sample_count):
    features = np.zeros(shape=(sample_count, 4, 4, 512))
    labels = np.zeros(shape=(sample_count))
    generator = datagen.flow_from_directory(
        directory,
        target_size=(150, 150),
        batch_size=batch_size,
        class_mode='binary')
    i = 0
    for inputs_batch, labels_batch in generator:
        features_batch = conv_base.predict(inputs_batch)
        features[i * batch_size : (i + 1) * batch_size] = features_batch
        labels[i * batch_size : (i + 1) * batch_size] = labels_batch
        i += 1
        if i * batch_size >= sample_count:
            # Note that since generators yield data indefinitely in a loop,
            # we must `break` after every image has been seen once.
            break
    return features, labels

train_features, train_labels = extract_features(train_dir, 1609)
validation_features, validation_labels = extract_features(validation_dir, 426)
test_features, test_labels = extract_features(test_dir, 392)
```

Colab notebook

We need to reshape the outputs so we can feed them into a dense layer - recall that dense layers take in vectors.

```
train_features = np.reshape(train_features, (1609, 4 * 4 * 512))
validation_features = np.reshape(validation_features, (426, 4 * 4 * 512))
test_features = np.reshape(test_features, (392, 4 * 4 * 512))
```

```
model = keras.Sequential([
  layers.Dense(256, activation='relu', input_dim=4 * 4 * 512),
  layers.Dropout(0.5),
  layers.Dense(1, activation='sigmoid')
])

model.compile(optimizer=tf.keras.optimizers.RMSprop(lr=2e-5),
              loss='binary_crossentropy',
              metrics=['accuracy'])

history = model.fit(train_features, train_labels,
                    epochs=30,
                    batch_size=20,
                    validation_data=(validation_features, validation_labels))
```

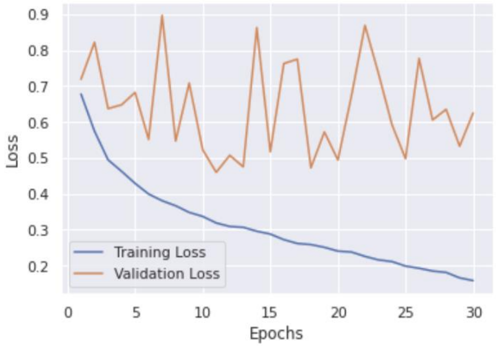
We can add the base just like a layer to our network

```python
model = tf.keras.models.Sequential([
    conv_base(trainable = False)
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])
```

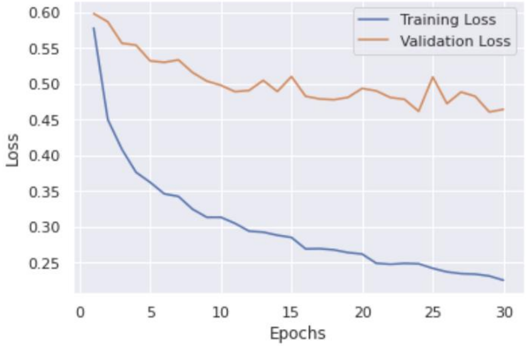
```python
#from keras.applications import VGG16

conv_base = tf.keras.applications.VGG16(weights='imagenet',
                                        include_top=False,
                                        input_shape=(150, 150, 3))
```

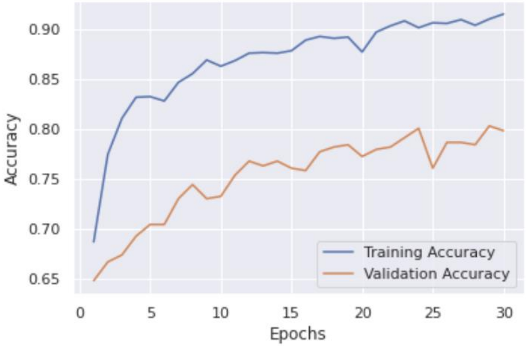
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 4, 4, 512)         14714688
_________________________________________________________________
flatten (Flatten)            (None, 8192)              0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               2097408
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 257
=================================================================
Total params: 16,812,353
Trainable params: 2,097,665
Non-trainable params: 14,714,688
```

Original CNN made from scratch



CNN using pretrained base





Transfer learning with fine-tuning

(allowing to change the weights in the convolutional base)

[Colab notebook]

```
model = tf.keras.models.Sequential([
  conv_base,
  tf.keras.layers.Flatten(),
  tf.keras.layers.Dense(256, activation='relu'),
  tf.keras.layers.Dense(1, activation='sigmoid')
])
```

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
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=================================================================
Total params: 16,812,353
Trainable params: 16,812,353
Non-trainable params: 0
```
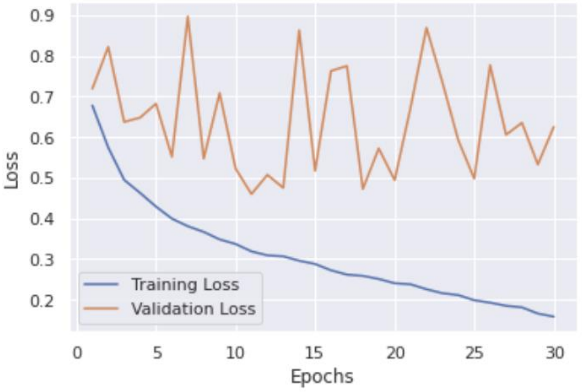

```python
from keras.preprocessing.image import ImageDataGenerator

train_datagen = ImageDataGenerator(
      rescale=1./255,
      rotation_range=40,
      width_shift_range=0.2,
      height_shift_range=0.2,
      shear_range=0.2,
      zoom_range=0.2,
      horizontal_flip=True,
      fill_mode='nearest')

# Note that the validation data should not be augmented!
test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
        # This is the target directory
        train_dir,
        # All images will be resized to 150x150
        target_size=(150, 150),
        batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels
        class_mode='binary')

validation_generator = test_datagen.flow_from_directory(
        validation_dir,
        target_size=(150, 150),
        batch_size=20,
        class_mode='binary')

model.compile(optimizer=tf.keras.optimizers.RMSprop(lr=2e-5),
              loss='binary_crossentropy',
              metrics=['accuracy'])


history = model.fit(
      train_generator,
      steps_per_epoch=81,
      epochs=30,
      validation_data=validation_generator,
      validation_steps=22)
```

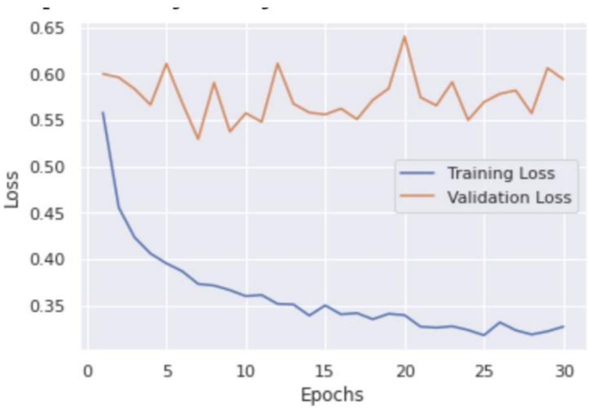
Note: do not run this code without access to a GPU.

Back to Colab notebook

Original CNN made from scratch with data augmentation



CNN using pretrained base with data augmentation

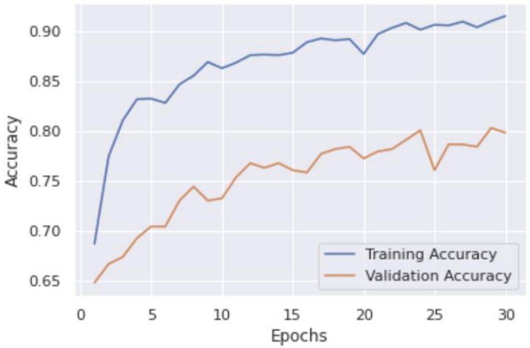


Let’s compare the two approaches

First approach:

Freezing the convolutional base
Training only the fully connected layers

Trainable parameters = 2M
Accuracy: ~0.78



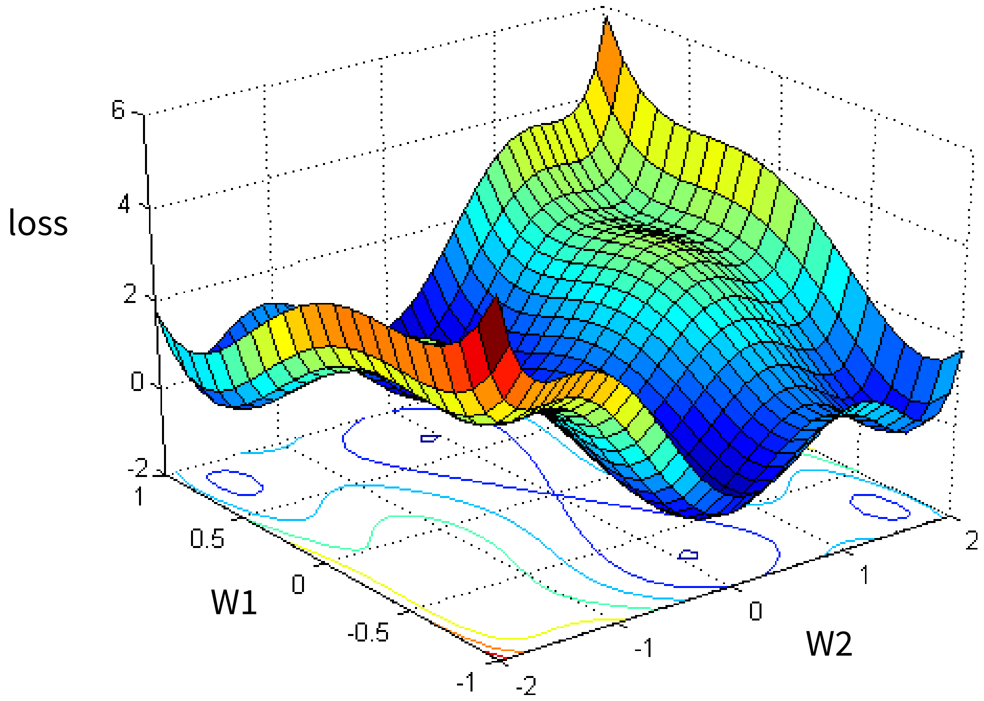
Second approach:

Conv_base and dense layers both trainable
(we still initialize conv_base with VGG weights)

Trainable parameters = 16M
Accuracy: ~0.69

With these results, can you think of a third approach that may work better?

Some intuition about why the first approach worked better



When starting to train, it is less likely that we will fall into a local minimum if we are only training few parameters (as opposed to trying to simultaneously train the parameters from the dense layer AND fine-tune the convolutional layers)

Additional questions

How do we unfreeze some of the convolutional layers?

https://medium.com/@timsennett/unfreezing-the-layers-you-want-to-fine-tune-using-transfer-learning-1bad8cb72e5d