

# CS4487 - Machine Learning

## Lecture 10a - Deep Learning 2

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## Outline

- Image Classification and Deep Architectures
- Unsupervised Learning

```
In [1]: # setup
%matplotlib inline
import IPython.core.display          # setup output image forma
t (Chrome works best)
IPython.core.display.set_matplotlib_formats("svg")
import matplotlib.pyplot as plt
import matplotlib
from numpy import *
from sklearn import *
from scipy import stats

rbow = plt.get_cmap('rainbow')
```

```
In [2]: # use TensorFlow backend
%env KERAS_BACKEND=tensorflow
from keras.models import Sequential, Model
from keras.layers import Dense, Activation, Dropout, Conv2D, Flatten,
Input, MaxPooling2D, UpSampling2D, Lambda, Reshape, BatchNormalization,
GlobalAveragePooling2D
import keras
import tensorflow
import logging
logging.basicConfig()
import struct

# use channels first representation for images
from keras import backend as K
K.set_image_data_format('channels_first')

from keras.callbacks import TensorBoard
```

env: KERAS\_BACKEND=tensorflow

Using TensorFlow backend.

```
In [3]: def plot_history(history):
    fig, ax1 = plt.subplots()

    ax1.plot(history.history['loss'], 'r', label="training loss {:.6f}".format(history.history['loss'][-1]))
    ax1.plot(history.history['val_loss'], 'r--', label="validation loss {:.6f}".format(history.history['val_loss'][-1]))
    ax1.grid(True)
    ax1.set_xlabel('iteration')
    ax1.legend(loc="best", fontsize=9)
    ax1.set_ylabel('loss', color='r')
    ax1.tick_params('y', colors='r')

    if 'acc' in history.history:
        ax2 = ax1.twinx()

        ax2.plot(history.history['acc'], 'b', label="training acc {:.4f}".format(history.history['acc'][-1]))
        ax2.plot(history.history['val_acc'], 'b--', label="validation acc {:.4f}".format(history.history['val_acc'][-1]))

        ax2.legend(loc="best", fontsize=9)
        ax2.set_ylabel('acc', color='b')
        ax2.tick_params('y', colors='b')
```

```
In [4]: def show_imgs(W_list, nc=10, highlight_green=None, highlight_red=None, titles=None):
    nfilter = len(W_list)
    nr = (nfilter - 1) // nc + 1
    for i in range(nr):
        for j in range(nc):
            idx = i * nc + j
            if idx == nfilter:
                break
            plt.subplot(nr, nc, idx + 1)
            cur_W = W_list[idx]
            if ndim(cur_W) == 2:
                plt.imshow(cur_W, cmap='gray', interpolation='nearest')
            else:
                plt.imshow(cur_W, interpolation='nearest')

            if titles is not None:
                if isinstance(titles, str):
                    plt.title(titles % idx)
                elif isinstance(titles, list):
                    plt.title(titles[idx])
                else:
                    plt.title(titles)

            if ((highlight_green is not None) and highlight_green[idx]) or \
               ((highlight_red is not None) and highlight_red[idx]):
                ax = plt.gca()
                if highlight_green[idx]:
                    mycol = '#00FF00'
                else:
                    mycol = 'r'
                for S in ['bottom', 'top', 'right', 'left']:
                    ax.spines[S].set_color(mycol)
                    ax.spines[S].set_lw(2.0)
                ax.xaxis.set_ticks_position('none')
                ax.yaxis.set_ticks_position('none')
                ax.set_xticks([])
                ax.set_yticks([])
            else:
                plt.gca().set_axis_off()
```

# Image Classification

- **Goal:** given an image, predict the object class
  - typically only one main object is present
  - If enough classes are considered, then it's a generic high-level vision task



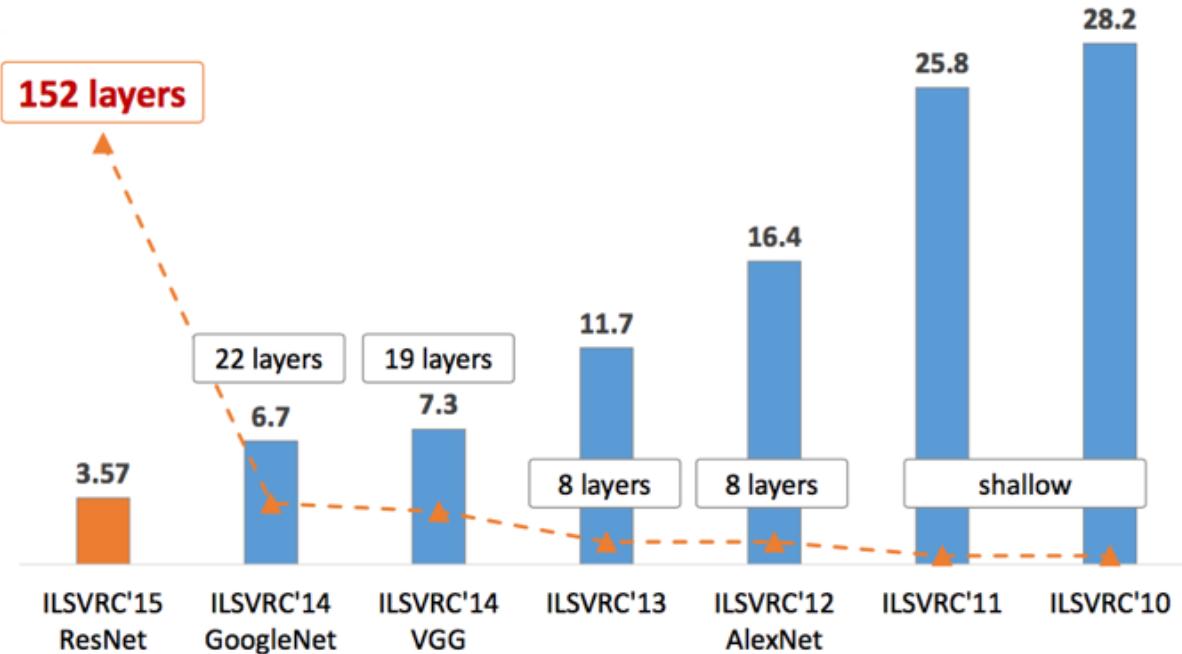
# ImageNet

- ImageNet Large Scale Visual Recognition Challenge (ILSVRC)
  - 1000 image classes
  - 1.2 million images
  - Human performance: ~5.1%



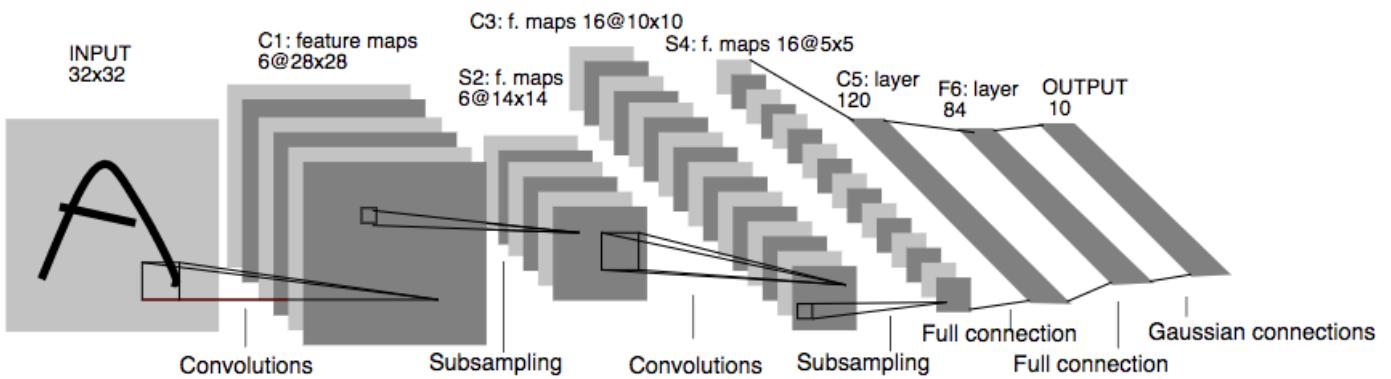
# Performance of Deep Learning

- The introduction of ILSVRC coincided with the emergence of Deep Learning.
- Top-5 error rate decreased as deeper NN were developed
  - Not just deeper, but also the architecture design was smarter



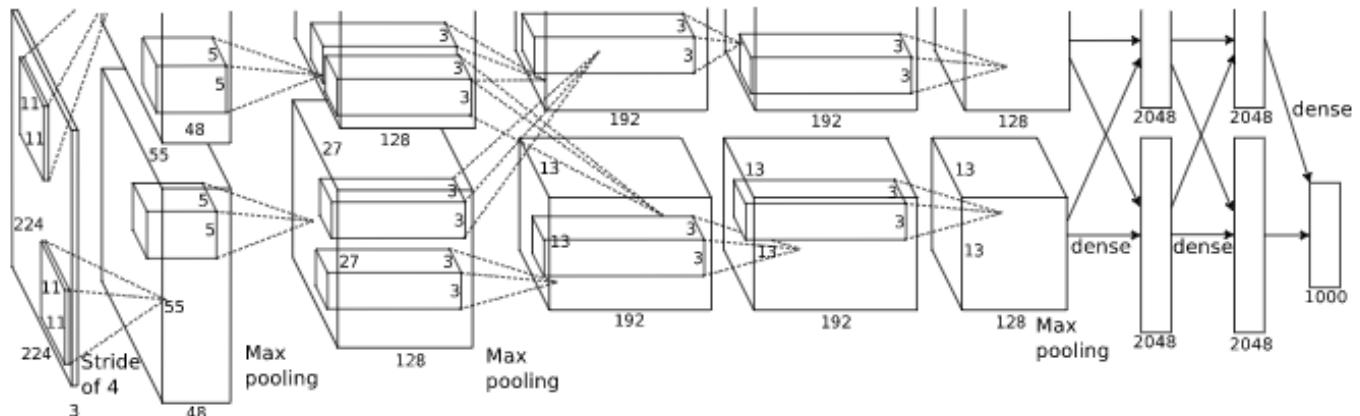
## LeNet-5 (1998)

- The standard CNN architecture
  - 7 layers
  - convolutions & pooling, final fully-connected layer
- Designed for hand-written digit recognition (MNIST)



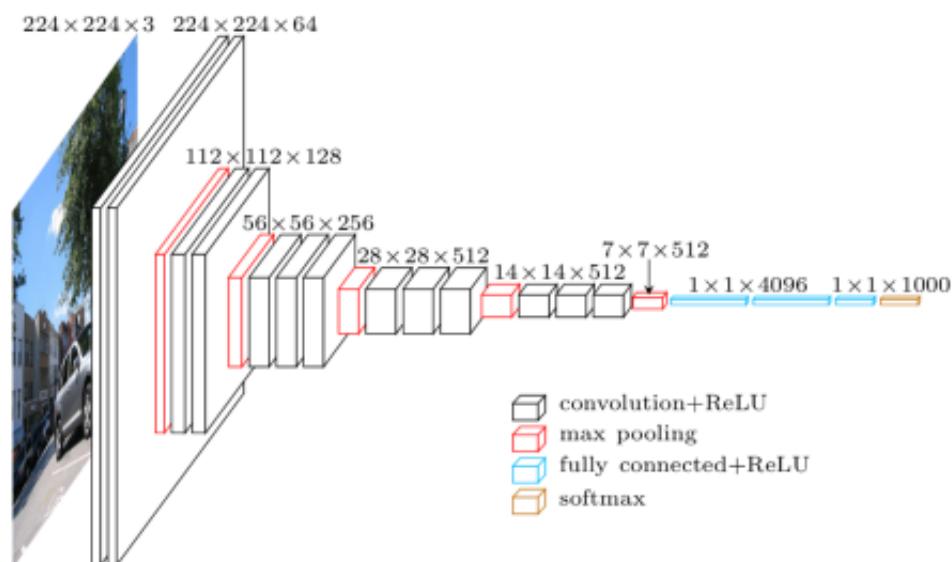
# AlexNet

- Similar architecture to LeNet, but deeper (14 layers)
  - 11x11, 5x5, 3x3 convolutions
- Tricks used: DropOut, ReLU, max pooling, data augmentation, SGD momentum
- One of the first networks trained on GPU
  - (it is split in two pipelines because it was trained on 2 GPUs simultaneously)



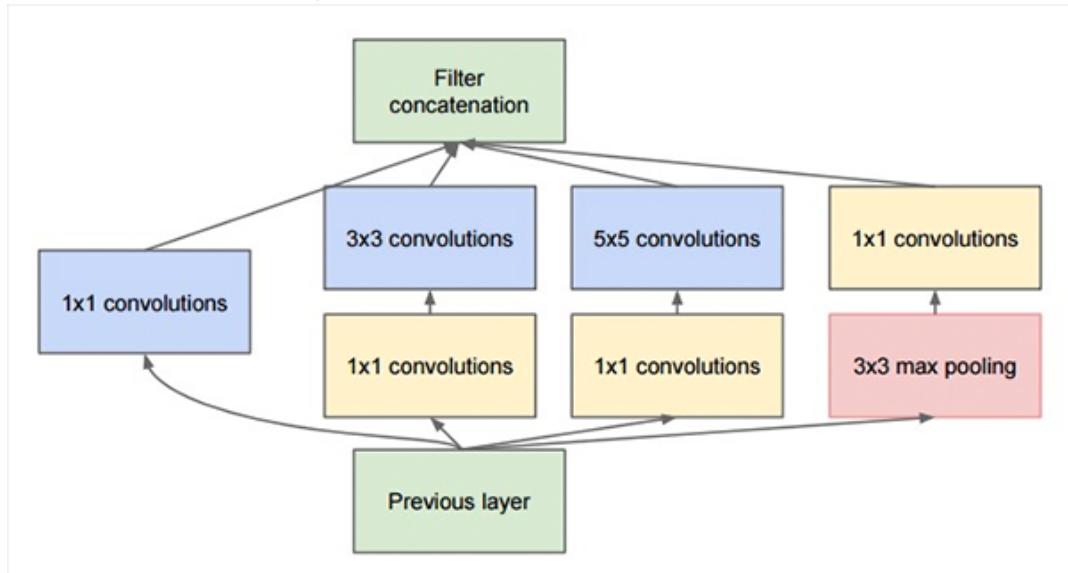
# VGNet

- Same style as LeNet and AlexNet
- Design choices:
  - only use 3x3 convolution filters (less parameters)
  - stack several convolution layers one after another, followed by pooling
    - equivalent to using a larger filter, but with less parameters.
  - number of feature channels doubles after each stage.
    - more higher-level features



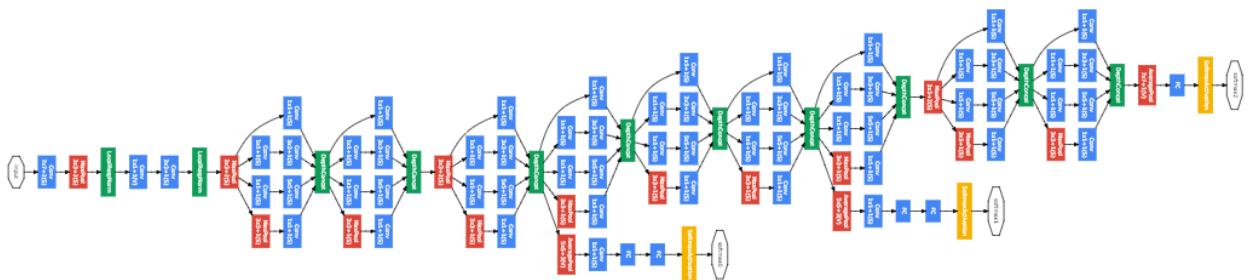
# InceptionNet

- "Network-in-Network" architecture
  - Core building blocks (modules), consisting of several layers, are combined repeatedly.
- Inception Module
  - several convolution filters in parallel
    - extract features at different scales ( $1 \times 1$ ,  $3 \times 3$ ,  $5 \times 5$ )
    - pool features ( $3 \times 3$  max)
  - features are concatenated and passed to next block.



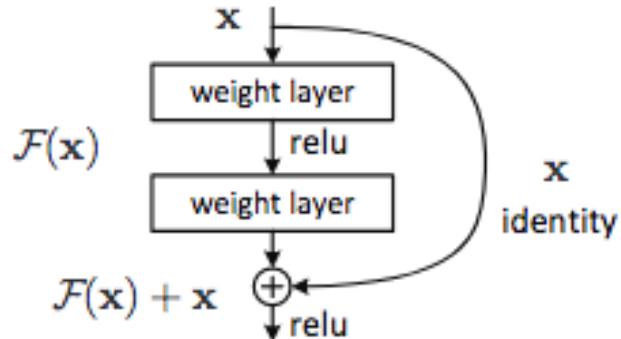
## InceptionNet (V1)

- 9 inception modules, 22 layers
  - 50 convolution blocks
- Auxiliary classification tasks
  - using features in the middle of the network to perform classification
  - strengthen supervisory signals to the middle and earlier layers.



# Residual Learning

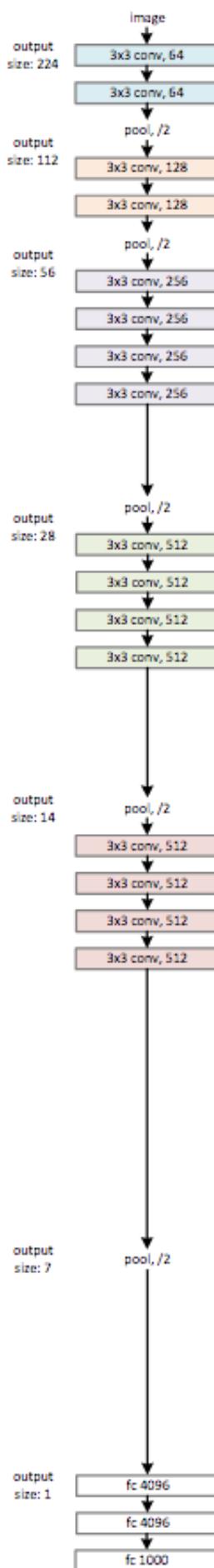
- The network is learning a function (image to class)
  - build the function block-by-block
  - each block learns a residual, which is added to the previous block
    - keep all the previous information and make small changes with the residual



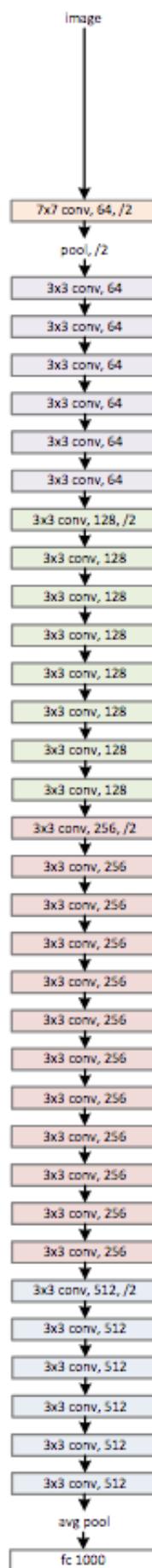
# Residual Network (ResNet)

- 34 layers, 50 layers, 100 layers, 1000 layers
  - 3x3 filters
  - residual connection every two layers.

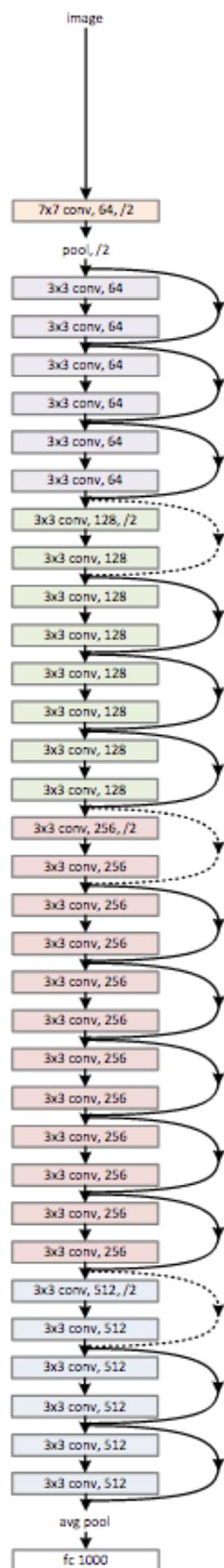
VGG-19



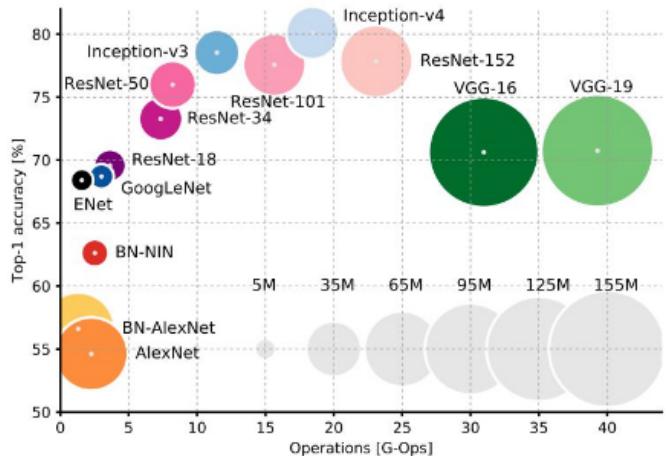
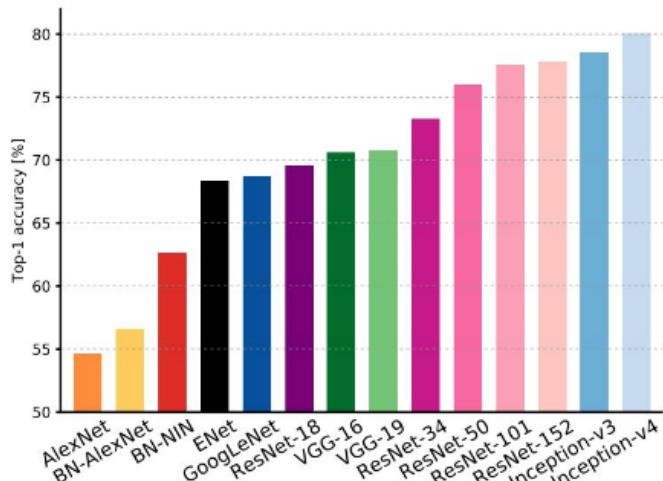
34-layer plain



## 34-layer residual



# Error vs. Computation vs. Number of Parameters



An Analysis of Deep Neural Network Models for Practical Applications, 2017.

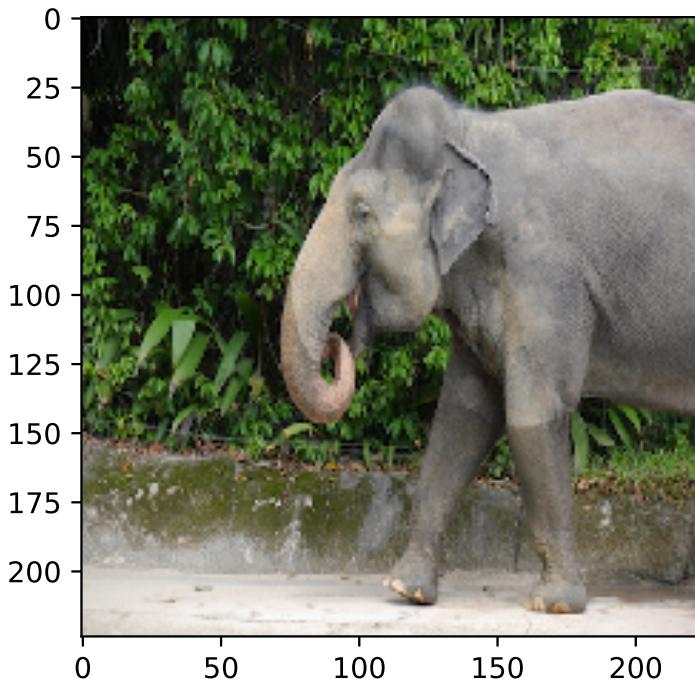
## Image Classifiers in Keras

- Keras includes several pre-trained image classifier networks
  - VGG16, VGG19, ResNet50, InceptionV3, ...
  - already trained on ImageNet
- Can use these networks to:
  - perform image classification (for 1000 classes only)
  - extract image features for our own task
  - transfer learning - modify/adapt a pre-trained network for our own task
- Import the ResNet model class and support functions
- Load and pre-process the image for the network

```
In [59]: # contains the model and support functions for ResNet50
import keras.applications.resnet50 as resnet
from keras.preprocessing import image

# load an image
img_path = 'imgs/elephant1.jpg'
img = image.load_img(img_path, target_size=(224, 224)) # ResNet expects this size
plt.imshow(img)

# process the image for resnet
xi = image.img_to_array(img)
xi = expand_dims(xi, axis=0)
xi = resnet.preprocess_input(xi)
```



- Create an instance of the ResNet50 model
  - trained on ImageNet
  - will download the model if loading for the first time.

```
In [6]: # create an instance of the model
model = resnet.ResNet50(weights='imagenet')
model.summary()
```

---

Layer (type)	Output Shape	Param #
Connected to		
=====	=====	=====
input_1 (InputLayer)	(None, 3, 224, 224)	0
=====	=====	=====
conv1_pad (ZeroPadding2D)	(None, 3, 230, 230)	0

---

input\_1[0][0]

---

conv1 (Conv2D) (None, 64, 112, 112) 9472  
conv1\_pad[0][0]

---

bn\_conv1 (BatchNormalization) (None, 64, 112, 112) 256  
conv1[0][0]

---

activation\_1 (Activation) (None, 64, 112, 112) 0  
bn\_conv1[0][0]

---

pool1\_pad (ZeroPadding2D) (None, 64, 114, 114) 0  
activation\_1[0][0]

---

max\_pooling2d\_1 (MaxPooling2D) (None, 64, 56, 56) 0  
pool1\_pad[0][0]

---

res2a\_branch2a (Conv2D) (None, 64, 56, 56) 4160  
max\_pooling2d\_1[0][0]

---

bn2a\_branch2a (BatchNormalizati (None, 64, 56, 56) 256  
res2a\_branch2a[0][0]

---

activation\_2 (Activation) (None, 64, 56, 56) 0  
bn2a\_branch2a[0][0]

---

res2a\_branch2b (Conv2D) (None, 64, 56, 56) 36928  
activation\_2[0][0]

---

bn2a\_branch2b (BatchNormalizati (None, 64, 56, 56) 256  
res2a\_branch2b[0][0]

---

activation\_3 (Activation) (None, 64, 56, 56) 0  
bn2a\_branch2b[0][0]

---

res2a\_branch2c (Conv2D) (None, 256, 56, 56) 16640  
activation\_3[0][0]

---

res2a\_branch1 (Conv2D) (None, 256, 56, 56) 16640  
max\_pooling2d\_1[0][0]

---

bn2a\_branch2c (BatchNormalizati (None, 256, 56, 56) 1024  
res2a\_branch2c[0][0]

---

bn2a_branch1 (BatchNormalizatio	(None, 256, 56, 56)	1024
res2a_branch1[0][0]		
add_1 (Add)	(None, 256, 56, 56)	0
bn2a_branch2c[0][0]		
bn2a_branch1[0][0]		
activation_4 (Activation)	(None, 256, 56, 56)	0
add_1[0][0]		
res2b_branch2a (Conv2D)	(None, 64, 56, 56)	16448
activation_4[0][0]		
bn2b_branch2a (BatchNormalizati	(None, 64, 56, 56)	256
res2b_branch2a[0][0]		
activation_5 (Activation)	(None, 64, 56, 56)	0
bn2b_branch2a[0][0]		
res2b_branch2b (Conv2D)	(None, 64, 56, 56)	36928
activation_5[0][0]		
bn2b_branch2b (BatchNormalizati	(None, 64, 56, 56)	256
res2b_branch2b[0][0]		
activation_6 (Activation)	(None, 64, 56, 56)	0
bn2b_branch2b[0][0]		
res2b_branch2c (Conv2D)	(None, 256, 56, 56)	16640
activation_6[0][0]		
bn2b_branch2c (BatchNormalizati	(None, 256, 56, 56)	1024
res2b_branch2c[0][0]		
add_2 (Add)	(None, 256, 56, 56)	0
bn2b_branch2c[0][0]		
activation_4[0][0]		
activation_7 (Activation)	(None, 256, 56, 56)	0
add_2[0][0]		

---

res2c_branch2a (Conv2D)	(None, 64, 56, 56)	16448
activation_7[0][0]		
bn2c_branch2a (BatchNormalizati	(None, 64, 56, 56)	256
res2c_branch2a[0][0]		
activation_8 (Activation)	(None, 64, 56, 56)	0
bn2c_branch2a[0][0]		
res2c_branch2b (Conv2D)	(None, 64, 56, 56)	36928
activation_8[0][0]		
bn2c_branch2b (BatchNormalizati	(None, 64, 56, 56)	256
res2c_branch2b[0][0]		
activation_9 (Activation)	(None, 64, 56, 56)	0
bn2c_branch2b[0][0]		
res2c_branch2c (Conv2D)	(None, 256, 56, 56)	16640
activation_9[0][0]		
bn2c_branch2c (BatchNormalizati	(None, 256, 56, 56)	1024
res2c_branch2c[0][0]		
add_3 (Add)	(None, 256, 56, 56)	0
bn2c_branch2c[0][0]		
activation_7[0][0]		
activation_10 (Activation)	(None, 256, 56, 56)	0
add_3[0][0]		
res3a_branch2a (Conv2D)	(None, 128, 28, 28)	32896
activation_10[0][0]		
bn3a_branch2a (BatchNormalizati	(None, 128, 28, 28)	512
res3a_branch2a[0][0]		
activation_11 (Activation)	(None, 128, 28, 28)	0
bn3a_branch2a[0][0]		
res3a_branch2b (Conv2D)	(None, 128, 28, 28)	147584
activation_11[0][0]		

---

bn3a_branch2b (BatchNormalizati	(None, 128, 28, 28)	512
res3a_branch2b[0][0]		
activation_12 (Activation)	(None, 128, 28, 28)	0
bn3a_branch2b[0][0]		
res3a_branch2c (Conv2D)	(None, 512, 28, 28)	66048
activation_12[0][0]		
res3a_branch1 (Conv2D)	(None, 512, 28, 28)	131584
activation_10[0][0]		
bn3a_branch2c (BatchNormalizati	(None, 512, 28, 28)	2048
res3a_branch2c[0][0]		
bn3a_branch1 (BatchNormalizatio	(None, 512, 28, 28)	2048
res3a_branch1[0][0]		
add_4 (Add)	(None, 512, 28, 28)	0
bn3a_branch2c[0][0]		
bn3a_branch1[0][0]		
activation_13 (Activation)	(None, 512, 28, 28)	0
add_4[0][0]		
res3b_branch2a (Conv2D)	(None, 128, 28, 28)	65664
activation_13[0][0]		
bn3b_branch2a (BatchNormalizati	(None, 128, 28, 28)	512
res3b_branch2a[0][0]		
activation_14 (Activation)	(None, 128, 28, 28)	0
bn3b_branch2a[0][0]		
res3b_branch2b (Conv2D)	(None, 128, 28, 28)	147584
activation_14[0][0]		
bn3b_branch2b (BatchNormalizati	(None, 128, 28, 28)	512
res3b_branch2b[0][0]		
activation_15 (Activation)	(None, 128, 28, 28)	0

---

bn3b\_branch2b[0][0]

---

res3b\_branch2c (Conv2D) (None, 512, 28, 28) 66048  
activation\_15[0][0]

---

bn3b\_branch2c (BatchNormalizati (None, 512, 28, 28) 2048  
res3b\_branch2c[0][0]

---

add\_5 (Add) (None, 512, 28, 28) 0  
bn3b\_branch2c[0][0]

---

activation\_13[0][0]

---

activation\_16 (Activation) (None, 512, 28, 28) 0  
add\_5[0][0]

---

res3c\_branch2a (Conv2D) (None, 128, 28, 28) 65664  
activation\_16[0][0]

---

bn3c\_branch2a (BatchNormalizati (None, 128, 28, 28) 512  
res3c\_branch2a[0][0]

---

activation\_17 (Activation) (None, 128, 28, 28) 0  
bn3c\_branch2a[0][0]

---

res3c\_branch2b (Conv2D) (None, 128, 28, 28) 147584  
activation\_17[0][0]

---

bn3c\_branch2b (BatchNormalizati (None, 128, 28, 28) 512  
res3c\_branch2b[0][0]

---

activation\_18 (Activation) (None, 128, 28, 28) 0  
bn3c\_branch2b[0][0]

---

res3c\_branch2c (Conv2D) (None, 512, 28, 28) 66048  
activation\_18[0][0]

---

bn3c\_branch2c (BatchNormalizati (None, 512, 28, 28) 2048  
res3c\_branch2c[0][0]

---

add\_6 (Add) (None, 512, 28, 28) 0  
bn3c\_branch2c[0][0]

---

activation\_16[0][0]

---

activation_19 (Activation)	(None, 512, 28, 28)	0
add_6[0][0]		
res3d_branch2a (Conv2D)	(None, 128, 28, 28)	65664
activation_19[0][0]		
bn3d_branch2a (BatchNormalizati	(None, 128, 28, 28)	512
res3d_branch2a[0][0]		
activation_20 (Activation)	(None, 128, 28, 28)	0
bn3d_branch2a[0][0]		
res3d_branch2b (Conv2D)	(None, 128, 28, 28)	147584
activation_20[0][0]		
bn3d_branch2b (BatchNormalizati	(None, 128, 28, 28)	512
res3d_branch2b[0][0]		
activation_21 (Activation)	(None, 128, 28, 28)	0
bn3d_branch2b[0][0]		
res3d_branch2c (Conv2D)	(None, 512, 28, 28)	66048
activation_21[0][0]		
bn3d_branch2c (BatchNormalizati	(None, 512, 28, 28)	2048
res3d_branch2c[0][0]		
add_7 (Add)	(None, 512, 28, 28)	0
bn3d_branch2c[0][0]		
activation_19[0][0]		
activation_22 (Activation)	(None, 512, 28, 28)	0
add_7[0][0]		
res4a_branch2a (Conv2D)	(None, 256, 14, 14)	131328
activation_22[0][0]		
bn4a_branch2a (BatchNormalizati	(None, 256, 14, 14)	1024
res4a_branch2a[0][0]		
activation_23 (Activation)	(None, 256, 14, 14)	0

---

bn4a\_branch2a[0][0]

---

res4a\_branch2b (Conv2D) (None, 256, 14, 14) 590080  
activation\_23[0][0]

---

bn4a\_branch2b (BatchNormalizati (None, 256, 14, 14) 1024  
res4a\_branch2b[0][0]

---

activation\_24 (Activation) (None, 256, 14, 14) 0  
bn4a\_branch2b[0][0]

---

res4a\_branch2c (Conv2D) (None, 1024, 14, 14) 263168  
activation\_24[0][0]

---

res4a\_branch1 (Conv2D) (None, 1024, 14, 14) 525312  
activation\_22[0][0]

---

bn4a\_branch2c (BatchNormalizati (None, 1024, 14, 14) 4096  
res4a\_branch2c[0][0]

---

bn4a\_branch1 (BatchNormalizatio (None, 1024, 14, 14) 4096  
res4a\_branch1[0][0]

---

add\_8 (Add) (None, 1024, 14, 14) 0  
bn4a\_branch2c[0][0]

---

bn4a\_branch1[0][0]

---

activation\_25 (Activation) (None, 1024, 14, 14) 0  
add\_8[0][0]

---

res4b\_branch2a (Conv2D) (None, 256, 14, 14) 262400  
activation\_25[0][0]

---

bn4b\_branch2a (BatchNormalizati (None, 256, 14, 14) 1024  
res4b\_branch2a[0][0]

---

activation\_26 (Activation) (None, 256, 14, 14) 0  
bn4b\_branch2a[0][0]

---

res4b\_branch2b (Conv2D) (None, 256, 14, 14) 590080  
activation\_26[0][0]

---

bn4b\_branch2b (BatchNormalizati (None, 256, 14, 14) 1024  
res4b\_branch2b[0][0]

---

activation\_27 (Activation) (None, 256, 14, 14) 0  
bn4b\_branch2b[0][0]

---

res4b\_branch2c (Conv2D) (None, 1024, 14, 14) 263168  
activation\_27[0][0]

---

bn4b\_branch2c (BatchNormalizati (None, 1024, 14, 14) 4096  
res4b\_branch2c[0][0]

---

add\_9 (Add) (None, 1024, 14, 14) 0  
bn4b\_branch2c[0][0]

---

activation\_25[0][0]

---

activation\_28 (Activation) (None, 1024, 14, 14) 0  
add\_9[0][0]

---

res4c\_branch2a (Conv2D) (None, 256, 14, 14) 262400  
activation\_28[0][0]

---

bn4c\_branch2a (BatchNormalizati (None, 256, 14, 14) 1024  
res4c\_branch2a[0][0]

---

activation\_29 (Activation) (None, 256, 14, 14) 0  
bn4c\_branch2a[0][0]

---

res4c\_branch2b (Conv2D) (None, 256, 14, 14) 590080  
activation\_29[0][0]

---

bn4c\_branch2b (BatchNormalizati (None, 256, 14, 14) 1024  
res4c\_branch2b[0][0]

---

activation\_30 (Activation) (None, 256, 14, 14) 0  
bn4c\_branch2b[0][0]

---

res4c\_branch2c (Conv2D) (None, 1024, 14, 14) 263168  
activation\_30[0][0]

---

bn4c\_branch2c (BatchNormalizati (None, 1024, 14, 14) 4096  
res4c\_branch2c[0][0]

---

add_10 (Add)	(None, 1024, 14, 14) 0
bn4c_branch2c[0][0]	
<hr/>	
activation_28[0][0]	
<hr/>	
activation_31 (Activation)	(None, 1024, 14, 14) 0
add_10[0][0]	
<hr/>	
res4d_branch2a (Conv2D)	(None, 256, 14, 14) 262400
activation_31[0][0]	
<hr/>	
bn4d_branch2a (BatchNormalizati	(None, 256, 14, 14) 1024
res4d_branch2a[0][0]	
<hr/>	
activation_32 (Activation)	(None, 256, 14, 14) 0
bn4d_branch2a[0][0]	
<hr/>	
res4d_branch2b (Conv2D)	(None, 256, 14, 14) 590080
activation_32[0][0]	
<hr/>	
bn4d_branch2b (BatchNormalizati	(None, 256, 14, 14) 1024
res4d_branch2b[0][0]	
<hr/>	
activation_33 (Activation)	(None, 256, 14, 14) 0
bn4d_branch2b[0][0]	
<hr/>	
res4d_branch2c (Conv2D)	(None, 1024, 14, 14) 263168
activation_33[0][0]	
<hr/>	
bn4d_branch2c (BatchNormalizati	(None, 1024, 14, 14) 4096
res4d_branch2c[0][0]	
<hr/>	
add_11 (Add)	(None, 1024, 14, 14) 0
bn4d_branch2c[0][0]	
activation_31[0][0]	
<hr/>	
activation_34 (Activation)	(None, 1024, 14, 14) 0
add_11[0][0]	
<hr/>	
res4e_branch2a (Conv2D)	(None, 256, 14, 14) 262400
activation_34[0][0]	
<hr/>	

bn4e\_branch2a (BatchNormalizati (None, 256, 14, 14) 1024  
res4e\_branch2a[0][0]

---

activation\_35 (Activation) (None, 256, 14, 14) 0  
bn4e\_branch2a[0][0]

---

res4e\_branch2b (Conv2D) (None, 256, 14, 14) 590080  
activation\_35[0][0]

---

bn4e\_branch2b (BatchNormalizati (None, 256, 14, 14) 1024  
res4e\_branch2b[0][0]

---

activation\_36 (Activation) (None, 256, 14, 14) 0  
bn4e\_branch2b[0][0]

---

res4e\_branch2c (Conv2D) (None, 1024, 14, 14) 263168  
activation\_36[0][0]

---

bn4e\_branch2c (BatchNormalizati (None, 1024, 14, 14) 4096  
res4e\_branch2c[0][0]

---

add\_12 (Add) (None, 1024, 14, 14) 0  
bn4e\_branch2c[0][0]

---

activation\_34[0][0]

---

activation\_37 (Activation) (None, 1024, 14, 14) 0  
add\_12[0][0]

---

res4f\_branch2a (Conv2D) (None, 256, 14, 14) 262400  
activation\_37[0][0]

---

bn4f\_branch2a (BatchNormalizati (None, 256, 14, 14) 1024  
res4f\_branch2a[0][0]

---

activation\_38 (Activation) (None, 256, 14, 14) 0  
bn4f\_branch2a[0][0]

---

res4f\_branch2b (Conv2D) (None, 256, 14, 14) 590080  
activation\_38[0][0]

---

bn4f\_branch2b (BatchNormalizati (None, 256, 14, 14) 1024  
res4f\_branch2b[0][0]

---

activation_39 (Activation)	(None, 256, 14, 14)	0
bn4f_branch2b[0][0]		
res4f_branch2c (Conv2D)	(None, 1024, 14, 14)	263168
activation_39[0][0]		
bn4f_branch2c (BatchNormalizati	(None, 1024, 14, 14)	4096
res4f_branch2c[0][0]		
add_13 (Add)	(None, 1024, 14, 14)	0
bn4f_branch2c[0][0]		
activation_37[0][0]		
activation_40 (Activation)	(None, 1024, 14, 14)	0
add_13[0][0]		
res5a_branch2a (Conv2D)	(None, 512, 7, 7)	524800
activation_40[0][0]		
bn5a_branch2a (BatchNormalizati	(None, 512, 7, 7)	2048
res5a_branch2a[0][0]		
activation_41 (Activation)	(None, 512, 7, 7)	0
bn5a_branch2a[0][0]		
res5a_branch2b (Conv2D)	(None, 512, 7, 7)	2359808
activation_41[0][0]		
bn5a_branch2b (BatchNormalizati	(None, 512, 7, 7)	2048
res5a_branch2b[0][0]		
activation_42 (Activation)	(None, 512, 7, 7)	0
bn5a_branch2b[0][0]		
res5a_branch2c (Conv2D)	(None, 2048, 7, 7)	1050624
activation_42[0][0]		
res5a_branch1 (Conv2D)	(None, 2048, 7, 7)	2099200
activation_40[0][0]		
bn5a_branch2c (BatchNormalizati	(None, 2048, 7, 7)	8192
res5a_branch2c[0][0]		

bn5a_branch1 (BatchNormalizatio	(None, 2048, 7, 7)	8192
res5a_branch1[0][0]		
add_14 (Add)	(None, 2048, 7, 7)	0
bn5a_branch2c[0][0]		
bn5a_branch1[0][0]		
activation_43 (Activation)	(None, 2048, 7, 7)	0
add_14[0][0]		
res5b_branch2a (Conv2D)	(None, 512, 7, 7)	1049088
activation_43[0][0]		
bn5b_branch2a (BatchNormalizati	(None, 512, 7, 7)	2048
res5b_branch2a[0][0]		
activation_44 (Activation)	(None, 512, 7, 7)	0
bn5b_branch2a[0][0]		
res5b_branch2b (Conv2D)	(None, 512, 7, 7)	2359808
activation_44[0][0]		
bn5b_branch2b (BatchNormalizati	(None, 512, 7, 7)	2048
res5b_branch2b[0][0]		
activation_45 (Activation)	(None, 512, 7, 7)	0
bn5b_branch2b[0][0]		
res5b_branch2c (Conv2D)	(None, 2048, 7, 7)	1050624
activation_45[0][0]		
bn5b_branch2c (BatchNormalizati	(None, 2048, 7, 7)	8192
res5b_branch2c[0][0]		
add_15 (Add)	(None, 2048, 7, 7)	0
bn5b_branch2c[0][0]		
activation_43[0][0]		
activation_46 (Activation)	(None, 2048, 7, 7)	0
add_15[0][0]		

res5c_branch2a (Conv2D)	(None, 512, 7, 7)	1049088
activation_46[0][0]		
bn5c_branch2a (BatchNormalizati	(None, 512, 7, 7)	2048
res5c_branch2a[0][0]		
activation_47 (Activation)	(None, 512, 7, 7)	0
bn5c_branch2a[0][0]		
res5c_branch2b (Conv2D)	(None, 512, 7, 7)	2359808
activation_47[0][0]		
bn5c_branch2b (BatchNormalizati	(None, 512, 7, 7)	2048
res5c_branch2b[0][0]		
activation_48 (Activation)	(None, 512, 7, 7)	0
bn5c_branch2b[0][0]		
res5c_branch2c (Conv2D)	(None, 2048, 7, 7)	1050624
activation_48[0][0]		
bn5c_branch2c (BatchNormalizati	(None, 2048, 7, 7)	8192
res5c_branch2c[0][0]		
add_16 (Add)	(None, 2048, 7, 7)	0
bn5c_branch2c[0][0]		
activation_46[0][0]		
activation_49 (Activation)	(None, 2048, 7, 7)	0
add_16[0][0]		
avg_pool (GlobalAveragePooling2	(None, 2048)	0
activation_49[0][0]		
fc1000 (Dense)	(None, 1000)	2049000
avg_pool[0][0]		
=====		
Total params: 25,636,712		
Trainable params: 25,583,592		
Non-trainable params: 53,120		

- Look at the 1000 classes

```
In [54]: tmp = resnet.decode_predictions(eye(1000), top=1) # decode the 1000-dim class vector
tmp2 = [i[0][1] for i in tmp]
tmp2.sort()
print(" ".join(tmp2))
```

Afghan\_hound African\_chameleon African\_crocodile African\_elephant African\_grey African\_hunting\_dog Airedale American\_Staffordshire\_terrier American\_alligator American\_black\_bear American\_chameleon American\_coot American\_egret American\_lobster Angora Appenzeller Arabian.camel Arctic\_fox Australian\_terrier Band\_Aid Bedlington\_terrier Bernese\_mountain\_dog Blenheim\_spaniel Border\_collie Border\_terrier Boston\_bull Bouvier\_des\_Flandres Brabancon\_griffon Brittany\_spaniel CD\_player Cardigan\_Chesapeake\_Bay\_retriever Chihuahua Christmas\_stocking Crock\_Pot Dandie\_Dinmont Doberman Dungeness\_crab Dutch\_oven Egyptian\_cat English\_foxhound English\_setter English\_springer EntleBucher Eskimo\_dog European\_fire\_salamander European\_gallinule French\_bulldog French\_horn French\_loaf German\_shepherd German\_short-haired\_pointer Gila\_monster Gordon\_setter Granny\_Smith Great\_Dane Great\_Pyrenees Greater\_Swiss\_Mountain\_dog Ibizan\_hound Indian\_cobra Indian\_elephant Irish\_setter Irish\_terrier Irish\_water\_spaniel Irish\_wolfhound Italian\_greyhound Japanese\_spaniel Kerry\_blue\_terrier Komodo.dragon Labrador\_retriever Lakeland\_terrier Leonberg Lhasa Loafer Madagascar\_cat Maltese\_dog Mexican\_hairless Model\_T Newfoundland Norfolk\_terrier Norwegian\_elkhound Norwich\_terrier Old\_English\_sheepdog Pekinese Pembroke Persian\_cat Petri\_dish Polaroid\_camera Pomeranian Rhodesian\_ridgeback Rottweiler Saint\_Bernard Saluki Samoyed Scottish\_terrier Scottish\_deerhound Sealyham\_terrier Shetland\_sheepdog Shih-Tzu Siamese\_cat Siberian\_husky Staffordshire\_bull\_terrier Sussex\_spaniel Tibetan\_mastiff Tibetan\_terrier Walker\_hound Weimaraner Welsh\_springer\_spaniel West\_Highland\_white\_terrier Windsor\_tie Yorkshire\_terrier abacus abaya academic\_gown accordion acorn acorn\_squash acoustic\_guitar admiral affenpinscher agama agaric aircraft\_carrier airliner airship albatross alligator\_lizard alp altar ambulance amphibian analog\_clock anemone\_fish ant apiary apron armadillo artichoke ashcan assault\_rifle axolotl baboon backpack badger bagel bakery balance\_beam bald\_eagle balloon ballplayer ballpoint banana bandaged\_gecko banjo bannister barbell barber\_chair barbershop barn\_barn\_spider barometer barracouta barrel barrow baseball basenji basketball basset bassinet bassoon bath\_towel bathing\_cap bathtub beach\_wagon beacon beagle beaker bearskin beaver bee\_bee\_eater beer\_bottle beer\_glass bell\_cote bell\_pepper bib bicyle-built-for-two bighorn bikini binder binoculars birdhouse bison bittern black-and-tan\_coonhound black-footed\_ferret black\_and\_gold\_garden\_spider black\_grouse black\_stork black\_swallow black\_widow bloodhound bluetick boa\_constrictor boathouse bobsled bolete bolo\_tie bonnet book\_jacket bookcase bookshop borzoi bottlecap bow bow\_tie box\_turtle boxer brain\_coral brambling brass brassiere breakwater breastplate briard broccoli

broom brown\_bear bubble bucket buckeye buckle bulbul bull\_mas  
tiff bullet\_train bulletproof\_vest bullfrog burrito bustard b  
utcher\_shop butternut\_squash cab cabbage\_butterfly cairn cald  
ron can\_opener candle cannon canoe capuchin car\_mirror car\_wh  
eel carbonara cardigan cardoon carousel carpenter's\_kit carto  
n cash\_machine cassette cassette\_player castle catamaran caul  
iflower cello cellular\_telephone centipede chain chain\_mail c  
hain\_saw chainlink\_fence chambered\_nautilus cheeseburger chee  
tah chest chickadee chiffonier chime chimpanzee china\_cabinet  
chiton chocolate\_sauce chow church cicada cinema cleaver clif  
f cliff\_dwelling cloak clog clumber cock cocker\_spaniel cockr  
oach cocktail\_shaker coffee\_mug coffeepot coho coil collie co  
lobus combination\_lock comic\_book common\_iguana common\_newt c  
omputer\_keyboard conch confectionery consomme container\_ship  
convertible coral\_fungus coral\_reef corkscrew corn cornet cou  
cal cougar cowboy\_boot cowboy\_hat coyote cradle crane crane c  
rash\_helmet crate crayfish crib cricket croquet\_ball crosswor  
d\_puzzle crutch cucumber cuirass cup curly-coated\_retriever c  
ustard\_apple daisy dalmatian dam damselfly desk desktop\_compu  
ter dhole dial\_telephone diamondback diaper digital\_clock dig  
ital\_watch dingo dining\_table dishrag dishwasher disk\_brake d  
ock dogsled dome doormat dough dowitcher dragonfly drake dril  
ling\_platform drum drumstick dugong dumbbell dung\_beetle ear  
earthstar echidna eel eft eggnog electric\_fan electric\_guitar  
electric\_locomotive electric\_ray entertainment\_center envelop  
e espresso espresso\_maker face\_powder feather\_boa fiddler\_cra  
b fig file fire\_engine fire\_screen fireboat flagpole flamingo  
flat-coated\_retriever flatworm flute fly folding\_chair footba  
ll\_helmet forklift fountain fountain\_pen four-poster fox\_squi  
rrel freight\_car frilled\_lizard frying\_pan fur\_coat gar garba  
ge\_truck garden\_spider garter\_snake gas\_pump gasmask gazelle  
geyser giant\_panda giant\_schnauzer gibbon go-kart goblet gold  
en\_retriever goldfinch goldfish golf\_ball golfcart gondola go  
ng goose gorilla gown grand\_piano grasshopper great\_grey\_owl  
great\_white\_shark green\_lizard green\_mamba green\_snake greenh  
ouse grey\_fox grey\_whale grille grocery\_store groenendael gro  
om ground\_beetle guacamole guenon guillotine guinea\_pig gyrom  
itra hair\_slide hair\_spray half\_track hammer hammerhead hampe  
r hamster hand-held\_computer hand\_blower handkerchief hard\_di  
sc hare harmonica harp hartebeest harvester harvestman hatche  
t hay head\_cabbage hen hen-of-the-woods hermit\_crab hip hippo  
potamus hog hognose\_snake holster home\_theater honeycomb hook  
hoopskirt horizontal\_bar hornbill horned\_viper horse\_cart hot  
\_pot hotdog hourglass house Finch howler\_monkey hummingbird h  
yena iPod ibex ice\_bear ice\_cream ice\_lolly impala indigo\_bun  
ting indri iron isopod jacamar jack-o'\_lantern jackfruit jagu  
ar jay jean jeep jellyfish jersey jigsaw\_puzzle jinrikisha jo  
ystick junco keeshond kelpie killer\_whale kimono king\_crab ki  
ng\_penguin king\_snake kit\_fox kite knee\_pad knot koala komond  
or kuvasz lab\_coat lacewing ladle ladybug lakeside lampshade  
langur laptop lawn\_mower leaf\_beetle leafhopper leatherback\_t  
urtle lemon lens\_cap leopard lesser\_panda letter\_opener libra  
ry lifeboat lighter limousine limpkin liner lion lionfish lip  
stick little\_blue\_heron llama loggerhead long-horned\_beetle l  
oriikeet lotion loudspeaker loupe lumbermill lycaenid lynx mac  
aque macaw magnetic\_compass magpie mailbag mailbox maillot ma  
illot malamute malinois manhole\_cover mantis maraca marimba m

armoset marmot mashed\_potato mask matchstick maypole maze mea  
suring\_cup meat\_loaf medicine\_chest meerkat megalith menu mic  
rophone microwave military\_uniform milk\_can miniature\_pinsche  
r miniature\_poodle miniature\_schnauzer minibus miniskirt mini  
van mink missile mitten mixing\_bowl mobile\_home modem monarch  
monastery mongoose monitor moped mortar mortarboard mosque mo  
quito\_net motor\_scooter mountain\_bike mountain\_tent mouse mo  
usetrap moving\_van mud\_turtle mushroom muzzle nail neck\_brace  
necklace nematode night\_snake nipple notebook obelisk oboe oc  
arina odometer oil\_filter orange orangutan organ oscilloscope  
ostrich otter otterhound overskirt ox oxcart oxygen\_mask oyst  
ercatcher packet paddle paddlewheel padlock paintbrush pajama  
palace panpipe paper\_towel papillon parachute parallel\_bars p  
ark\_bench parking\_meter partridge passenger\_car patas patio p  
ay-phone peacock pedestal pelican pencil\_box pencil\_sharpener  
perfume photocopier pick pickelhaube picket\_fence pickup pier  
piggy\_bank pill\_bottle pillow pineapple ping-pong\_ball pinwhe  
el pirate pitcher pizza plane planetarium plastic\_bag plate p  
late\_rack platypus plow plunger pole polecat police\_van pomeg  
ranate poncho pool\_table pop\_bottle porcupine pot potpie pott  
er's\_wheel power\_drill prairie\_chicken prayer\_rug pretzel pri  
nter prison proboscis\_monkey projectile projector promontory  
ptarmigan puck puffer pug punching\_bag purse quail quill quil  
t racer racket radiator radio radio\_telescope rain\_barrel ram  
rapeseed recreational\_vehicle red-backed\_sandpiper red-breast  
ed\_merganser red\_fox red\_wine red\_wolf redbone redshank reel  
reflex\_camera refrigerator remote\_control restaurant revolver  
rhinoceros\_beetle rifle ringlet ringneck\_snake robin rock\_bea  
uty rock\_crab rock\_python rocking\_chair rotisserie rubber\_era  
ser ruddy\_turnstone ruffed\_grouse rugby\_ball rule running\_sho  
e safe safety\_pin saltshaker sandal sandbar sarong sax scabba  
rd scale schipperke school\_bus schooner scoreboard scorpion s  
creen screw screwdriver scuba\_diver sea\_anemone sea\_cucumber  
sea\_lion sea\_slug sea\_snake sea\_urchin seashore seat\_belt sew  
ing\_machine shield shoe\_shop shoji shopping\_basket shopping\_c  
art shovel shower\_cap shower\_curtain siamang sidewinder silky  
\_terrier ski ski\_mask skunk sleeping\_bag slide\_rule sliding\_d  
oor slot sloth\_bear slug snail snorkel snow\_leopard snowmobil  
e snowplow soap\_dispenser soccer\_ball sock soft-coated\_wheate  
n\_terrier solar\_dish sombrero sorrel soup\_bowl space\_bar spac  
e\_heater space\_shuttle spaghetti\_squash spatula speedboat spi  
der\_monkey spider\_web spindle spiny\_lobster spoonbill sports\_  
car spotlight spotted\_salamander squirrel\_monkey stage standa  
rd\_poodle standard\_schnauzer starfish steam\_locomotive steel\_  
arch\_bridge steel\_drum stethoscope stingray stinkhorn stole s  
tone\_wall stopwatch stove strainer strawberry street\_sign str  
eetcar stretcher studio\_couch stupa sturgeon submarine suit s  
ulphur-crested\_cockatoo sulphur\_butterfly sundial sunglass su  
nglasses sunscreen suspension\_bridge swab sweatshirt swimming  
\_trunks swing switch syringe tabby table\_lamp tailed\_frog tan  
k tape\_player tarantula teapot teddy television tench tennis\_  
ball terrapin thatch theater\_curtain thimble three-toed\_sloth  
thresher throne thunder\_snake tick tiger tiger\_beetle tiger\_c  
at tiger\_shark tile\_roof timber\_wolf titi toaster tobacco\_sho  
p toilet\_seat toilet\_tissue torch totem\_pole toucan tow\_truck  
toy\_poodle toy\_terrier toyshop tractor traffic\_light trailer\_  
truck tray tree\_frog trench\_coat triceratops tricycle trifle

```
trilobite trimaran tripod triumphal_arch trolleybus trombone
tub turnstile tusker typewriter_keyboard umbrella unicycle up
right vacuum valley vase vault velvet vending_machine vestmen
t viaduct vine_snake violin vizsla volcano volleyball vulture
waffle_iron walking_stick wall_clock wallaby wallet wardrobe
warplane warthog washbasin washer water_bottle water_buffalo
water_jug water_ouzel water_snake water_tower weasel web_site
weevil whippet whiptail whiskey_jug whistle white_stork white
_wolf wig wild_boar window_screen window_shade wine_bottle wi
ng wire-haired_fox_terrier wok wolf_spider wombat wood_rabbit
wooden_spoon wool worm_fence wreck yawl yellow_lady's_slipper
yurt zebra zucchini
```

- Predict on the loaded image

```
In [61]: # make a prediction on the image
preds = model.predict(xi)

# decode the results into a list of tuples (class, description
, probability)
predsc = resnet.decode_predictions(preds, top=3)[0]

for i in predsc:
    print(i)

('n02504013', 'Indian_elephant', 0.8574033)
('n01871265', 'tusker', 0.13916093)
('n02504458', 'African_elephant', 0.003434056)
```

## Pre-trained Image Features

- The network is trained on ImageNet, which contains many classes and images.
- The learned features generalize well to other tasks
  - capture high-level discriminative information about objects

```
In [8]: # load dessert dataset
import glob

imglist = glob.glob('imgs/dessert/*/*.jpg')
Xraw = []
Xim = zeros((len(imglist), 3, 224, 224))
Ylab = []
for i,img_path in enumerate(imglist):
    img = image.load_img(img_path, target_size=(224, 224))
    Xraw.append(img)
    x = image.img_to_array(img)
    x = expand_dims(x, axis=0)
    x = resnet.preprocess_input(x)
    Xim[i,:] = x
    Ylab.append(img_path.split('/')[-2])
```

```
In [9]: print(Xim.shape)
        print(len(Ylab))
```

(200, 3, 224, 224)  
200

```
In [67]: # convert class strings into integers
print("class labels (strings):", unique(Ylab))
le = preprocessing.LabelEncoder()
Y = le.fit_transform(Ylab)
print("Converted labels:")
print(Y)
```

- Show a few examples of "ice cream" and "frozen yogurt"

```
In [69]: inds = [0, 1, 2, 3, 4, -1, -2, -3, -4, -5]
            tmp = [Xraw[i] for i in inds]
            t = [Ylab[i] for i in inds]
            plt.figure(figsize=(9,4))
            show_imgs(tmp, nc=5, titles=t)
```



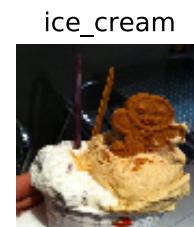
frozen yogurt



frozen yogurt



frozen yogurt



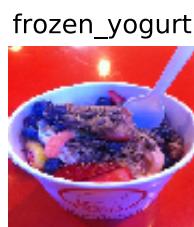
frozen yogurt



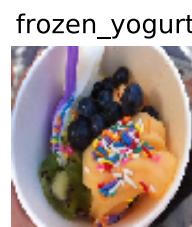
frozen yogurt



frozen yogurt



frozen yogurt



frozen yogurt



frozen yogurt



frozen yogurt

# Computing Image Features

- Use the pre-trained network as a feature extractor
  - remove the last layer (the classifier)
  - apply average pooling on the feature map
    - $7 \times 7 \times 2048 \rightarrow 1 \times 2048$

```
In [12]: # create an instance of the model w/o the last layer
model_f = resnet.ResNet50(weights='imagenet', include_top=False,
                           pooling='avg')

# compute the features
Xf = model_f.predict(Xim)
print(Xf.shape)

(200, 2048)
```

- Now use the features to train a binary classifier
- First setup the dataset

```
In [80]: # convert class labels to binary indicators
Yb = keras.utils.np_utils.to_categorical(Y)

# randomly split data into train and test set
( trainXf, testXf,          # features
  trainY, testY,            # class labels
  trainXim, testXim,        # pre-processed images
  trainYb, testYb,          # binary class vector (for Keras)
  trainXraw, testXraw      # original images
) = \
    model_selection.train_test_split(Xf, Y, Xim, Yb, Xraw,
    train_size=0.8, test_size=0.2, random_state=4487)

trainX = trainXim.reshape((trainXim.shape[0], -1))
testX = testXim.reshape((testXim.shape[0], -1))

print(trainXf.shape)
print(testXf.shape)
print(trainXim.shape)
print(trainX.shape)

(160, 2048)
(40, 2048)
(160, 3, 224, 224)
(160, 150528)
```

- Setup validation set for later

```
In [14]: # generate a fixed validation set using 10% of the training set
vtrainXim, validXim, vtrainYb, validYb = \
    model_selection.train_test_split(trainXim, trainYb,
        train_size=0.9, test_size=0.1, random_state=6487)

# validation data
validset = (validXim, validYb)
```

- Use the image features to train a standard SVM classifier

```
In [70]: # setup the list of parameters to try
paramgrid = {'C': logspace(-3,3,13)}
print(paramgrid)

# setup cross-validation
svmcv = model_selection.GridSearchCV(svm.SVC(kernel='linear'),
paramgrid, cv=5,
n_jobs=-1, verbose=True)

# run cross-validation (train for each split)
svmcv.fit(trainXf, trainY);

{'C': array([1.0000000e-03, 3.16227766e-03, 1.0000000e-02,
3.16227766e-02,
           1.0000000e-01, 3.16227766e-01, 1.0000000e+00, 3.1622
7766e+00,
           1.0000000e+01, 3.16227766e+01, 1.0000000e+02, 3.1622
7766e+02,
           1.0000000e+03])}
Fitting 5 folds for each of 13 candidates, totalling 65 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done   26 tasks      | elapsed:    2.7s
[Parallel(n_jobs=-1)]: Done   65 out of  65 | elapsed:    3.1s
finished
```

- Predict with the classifier
- The accuracy is great!

```
In [16]: # predict
predY = svmcv.predict(testXf)

acc = metrics.accuracy_score(testY, predY)
print("test accuracy = " + str(acc))

test accuracy = 0.925
```

- For comparison, also train an SVM on the raw images
- The accuracy is really bad (almost chance level)

```
In [17]: svmcv_im = model_selection.GridSearchCV(svm.SVC(kernel='linear'),
                                              paramgrid, cv=5,
                                              n_jobs=-1, verbose=True)

# run cross-validation (train for each split)
svmcv_im.fit(trainX, trainY);

# Directly use svmcv to make predictions
predY = svmcv_im.predict(testX)

acc = metrics.accuracy_score(testY, predY)
print("test accuracy = " + str(acc))
```

[Parallel(n\_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.

Fitting 5 folds for each of 13 candidates, totalling 65 fits

```
/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/process_executor.py:700: UserWarning: A worker stopped while some jobs were given to the executor. This can be caused by a too short worker timeout or by a memory leak.
    "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done  65 out of  65 | elapsed:  2.7min
finished
```

test accuracy = 0.525

## Transfer learning and fine-tuning

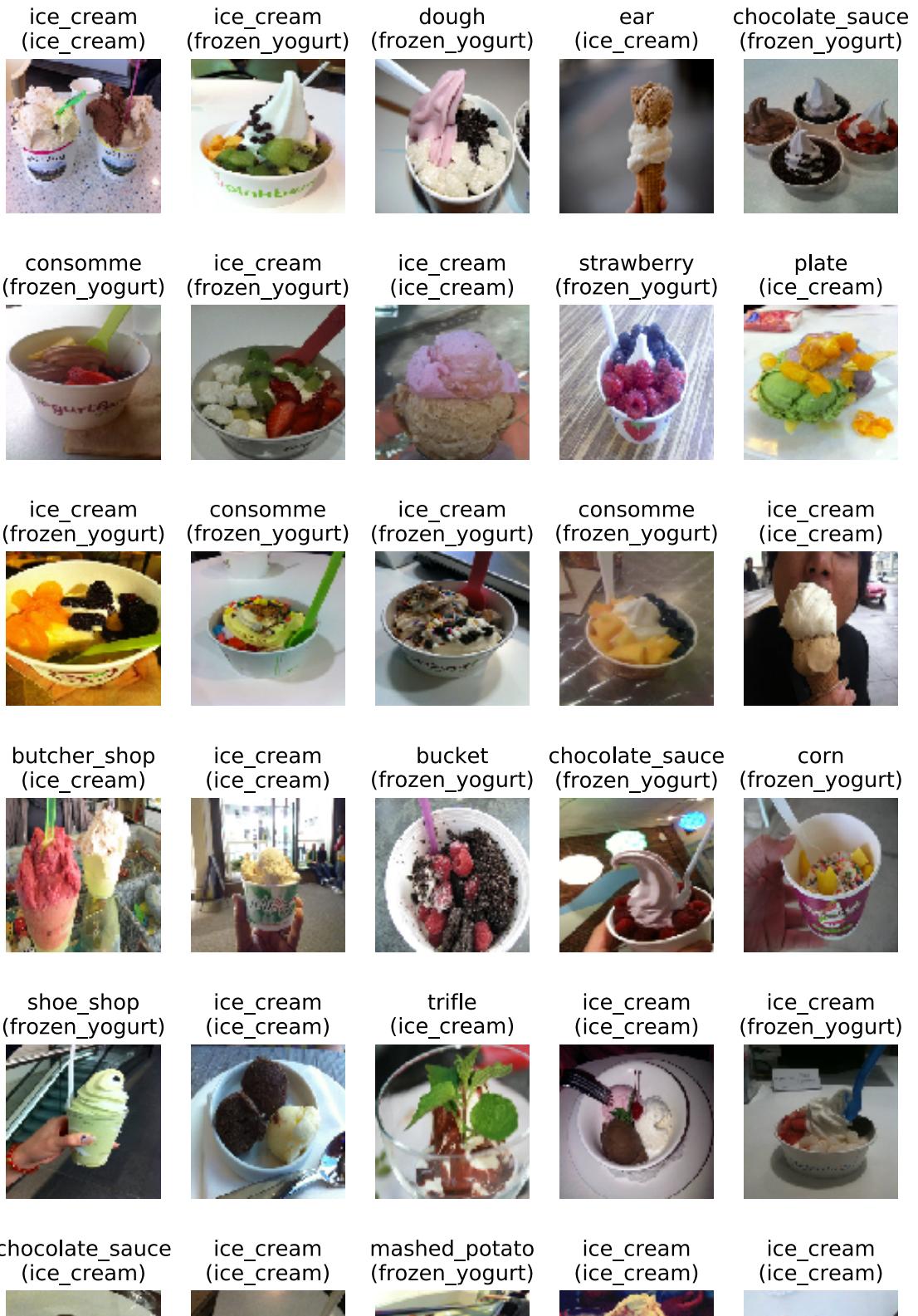
- The network can also be "fine-tuned" for a new image classification task.
  - This is called transfer learning.
- Rather than retrain the whole network,
  - fix the lower layers that extract features (no need to train them since they are good features)
  - train the last few layers to perform the new task
- Does not need as much data, compared to the original ImageNet.
  
- First, let's see ResNet50 predicts on our images

```
In [27]: # try the original ResNet50
testYscore = model.predict(testXim)
```

```
In [84]: # get the class labels
predY = resnet.decode_predictions(testYscore, top=1)
testYcl = le.inverse_transform(testY)

# make titles
titles = []
for i in range(len(predY)):
    titles.append(predY[i][0][1] + "\n(" + testYcl[i] + ")")

# make a plot: predicted (true)
plt.figure(figsize=(9,20))
show_imgs(testXraw, nc=5, titles=titles)
```





ice\_cream  
(ice\_cream)



ice\_cream  
(ice\_cream)



ice\_cream  
(frozen\_yogurt)



burrito  
(ice\_cream)



ice\_cream  
(frozen\_yogurt)



chocolate\_sauce  
(ice\_cream)



ice\_cream  
(ice\_cream)



consomme  
(frozen\_yogurt)



ice\_cream  
(frozen\_yogurt)



comic\_book  
(ice\_cream)



- We will use the `Model` class
  - allows for more complex layer interactions than "Sequential"
- Connect layers one-by-one
  - instantiate the layer (with hyperparameters)
  - then pass the previous layer to it.

```
In [20]: #random.seed(4487); tensorflow.set_random_seed(4487)
```

```
# create the base pre-trained model with-out the classifier
base_model = resnet.ResNet50(weights='imagenet', include_top=False)

# start with the output of the ResNet50 (7x7x2048)
x = base_model.output

# for each channel, average all the features (1x2048)
x = GlobalAveragePooling2D()(x)

# fully-connected layer (1 x32)
# (only two classes so don't need so many)
x = Dense(32, activation='relu')(x)

# finally, the softmax for the classifier (2 classes)
predictions = Dense(2, activation='softmax')(x)
```

- Create the Model
  - specify the input and output layers
  - the network is everything in between
- Fix the weights of the layers of ResNet so they will not change during training

```
In [ ]: # build the model for training
# - need to specify the input layer and the output layer
model_ft = Model(inputs=base_model.input, outputs=predictions)

# fix the layers of the ResNet50.
for layer in base_model.layers:
    layer.trainable = False

# compile the model - only the layers that we added will be trained
model_ft.compile(optimizer='rmsprop',
                  loss='categorical_crossentropy', metrics=[ 'accuracy' ])
```

- Setup the data augmentation generator

```
In [21]: from keras.preprocessing.image import ImageDataGenerator

def add_gauss_noise(X, sigma2=0.05):
    # add Gaussian noise with zero mean, and variance sigma2
    return X + random.normal(0, sigma2, X.shape)

# build the data augmenter
datagen = ImageDataGenerator(
    rotation_range=10,           # image rotation
    width_shift_range=0.2,        # image shifting
    height_shift_range=0.2,       # image shifting
    shear_range=0.1,             # shear transformation
    zoom_range=0.1,              # zooming
    horizontal_flip=True,
    preprocessing_function=add_gauss_noise,
)

# fit (required for some normalization augmentations)
datagen.fit(vtrainXim)
```

- Train the model
  - only the last layers that we added are updated

```
In [22]: # train the model on the new data for a few epochs
bsize = 32
callbacks_list = []
history = model_ft.fit_generator(
            datagen.flow(vtrainXim, vtrainYb, batch_size=bsize
), # data from generator
            steps_per_epoch=len(vtrainXim)/bsize, # should
be number of batches per epoch
            epochs=20,
            callbacks=callbacks_list,
            validation_data=validset, verbose=True)
```

Epoch 1/20  
5/4 [=====] - 102s 20s/step - loss  
s: 1.4617 - acc: 0.4925 - val\_loss: 0.5829 - val\_acc: 0.6250  
Epoch 2/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.4334 - acc: 0.8252 - val\_loss: 0.7617 - val\_acc: 0.7500  
Epoch 3/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.3738 - acc: 0.8200 - val\_loss: 0.4603 - val\_acc: 0.9375  
Epoch 4/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.3278 - acc: 0.8559 - val\_loss: 0.5222 - val\_acc: 0.6875  
Epoch 5/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.2908 - acc: 0.8571 - val\_loss: 0.5414 - val\_acc: 0.9375  
Epoch 6/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.3211 - acc: 0.8160 - val\_loss: 1.1114 - val\_acc: 0.5625  
Epoch 7/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.1661 - acc: 0.9375 - val\_loss: 0.6020 - val\_acc: 0.8125  
Epoch 8/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.1656 - acc: 0.9554 - val\_loss: 0.5891 - val\_acc: 0.8750  
Epoch 9/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.1315 - acc: 0.9745 - val\_loss: 0.6747 - val\_acc: 0.7500  
Epoch 10/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.1815 - acc: 0.9323 - val\_loss: 1.5723 - val\_acc: 0.6250  
Epoch 11/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.1607 - acc: 0.9184 - val\_loss: 0.8087 - val\_acc: 0.7500  
Epoch 12/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.0803 - acc: 0.9809 - val\_loss: 0.7585 - val\_acc: 0.8125  
Epoch 13/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.2739 - acc: 0.8791 - val\_loss: 0.6258 - val\_acc: 0.8125  
Epoch 14/20  
5/4 [=====] - 87s 17s/step - loss  
: 0.0477 - acc: 1.0000 - val\_loss: 0.7634 - val\_acc: 0.7500  
Epoch 15/20  
5/4 [=====] - 87s 17s/step - loss

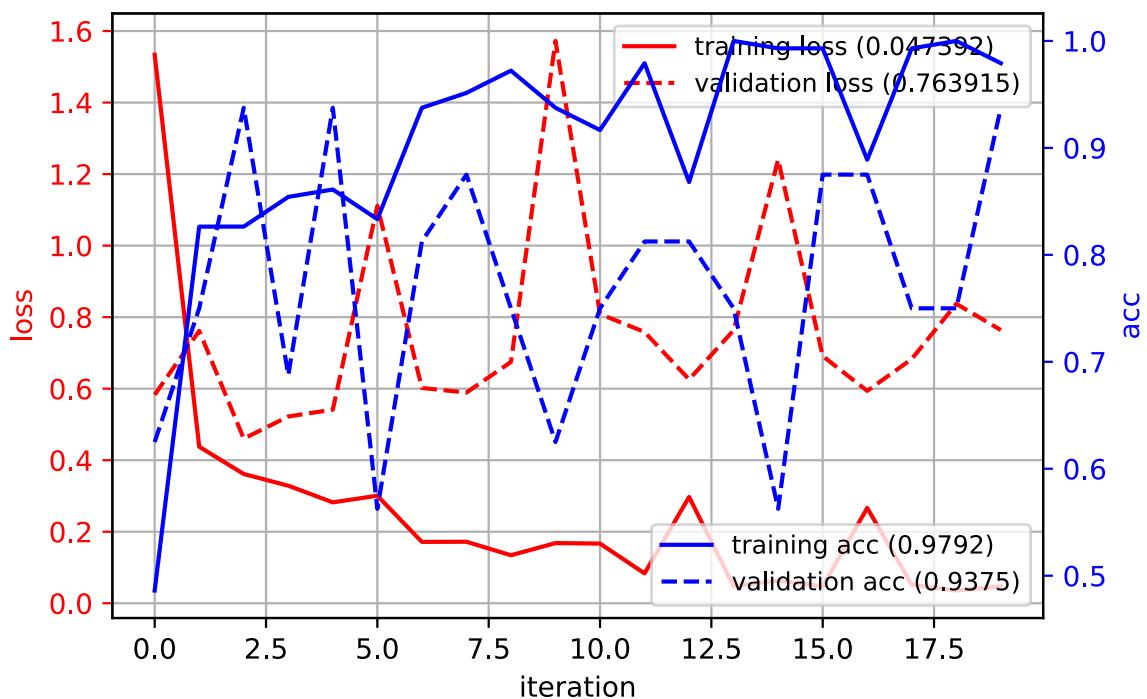
```

: 0.0636 - acc: 0.9936 - val_loss: 1.2406 - val_acc: 0.5625
Epoch 16/20
5/4 [=====] - 87s 17s/step - loss
: 0.0503 - acc: 0.9884 - val_loss: 0.6912 - val_acc: 0.8750
Epoch 17/20
5/4 [=====] - 87s 17s/step - loss
: 0.3316 - acc: 0.8617 - val_loss: 0.5938 - val_acc: 0.8750
Epoch 18/20
5/4 [=====] - 87s 17s/step - loss
: 0.0509 - acc: 0.9936 - val_loss: 0.6830 - val_acc: 0.7500
Epoch 19/20
5/4 [=====] - 87s 17s/step - loss
: 0.0335 - acc: 1.0000 - val_loss: 0.8373 - val_acc: 0.7500
Epoch 20/20
5/4 [=====] - 88s 18s/step - loss
: 0.0570 - acc: 0.9705 - val_loss: 0.7639 - val_acc: 0.9375

```

- Training/validation curves

In [23]: `plot_history(history)`



- Compute test accuracy

In [89]: `predYscore = model_ft.predict(testXim, verbose=False)  
predY = argmax(predYscore, axis=1)  
acc = metrics.accuracy_score(testY, predY)  
print("test accuracy:", acc)`

test accuracy: 0.9

- Visualize the predictions

```
In [98]: # get the class labels
predYcl = le.inverse_transform(predY)
# make titles
titles = []
for i in range(len(predYcl)):
    titles.append(predYcl[i] + "\n(" + testYcl[i] + ")")

# make a plot: predicted (true)
plt.figure(figsize=(9,20))
show_imgs(testXraw, nc=5, titles=titles)
```



