

Transfer Learning with CNN

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What is Transfer Learning?

- **To overcome challenges of training model from scratch:**
 - Insufficient data
 - Very long training time
- **Use pre-trained model**
 - Trained on another dataset
 - This serves as starting point for model
 - Then train model on current dataset for current task

Transfer Learning Approaches

- **Feature extraction**

- Remove last fully connected layer from pre-trained model
- Treat rest of network as feature extractor
- Use features to train new classifier (“top model”)

- **Fine tuning**

- Tune weights in some layers of original model (along with weights of top model)
- Train model for current task using new dataset

CNNs for Transfer Learning

- **Popular architectures**
 - AlexNet
 - GoogLeNet
 - VGGNet
 - ResNet
- **All winners of ILSVRC**
 - ImageNet Large Scale Visual Recognition Challenge
 - Annual competition on vision tasks on ImageNet data

ImageNet

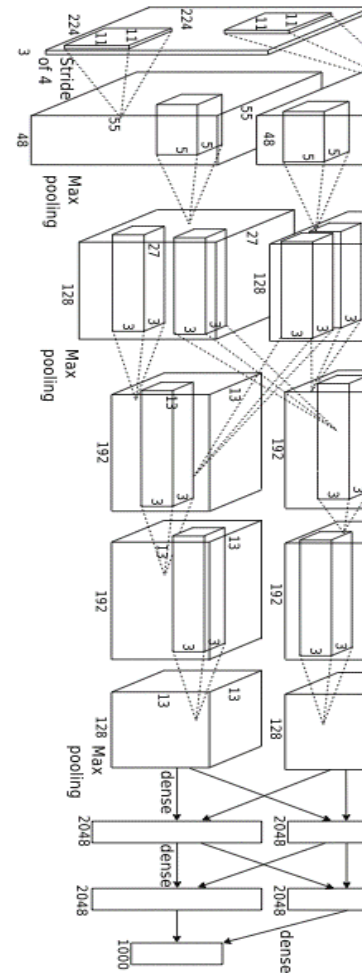
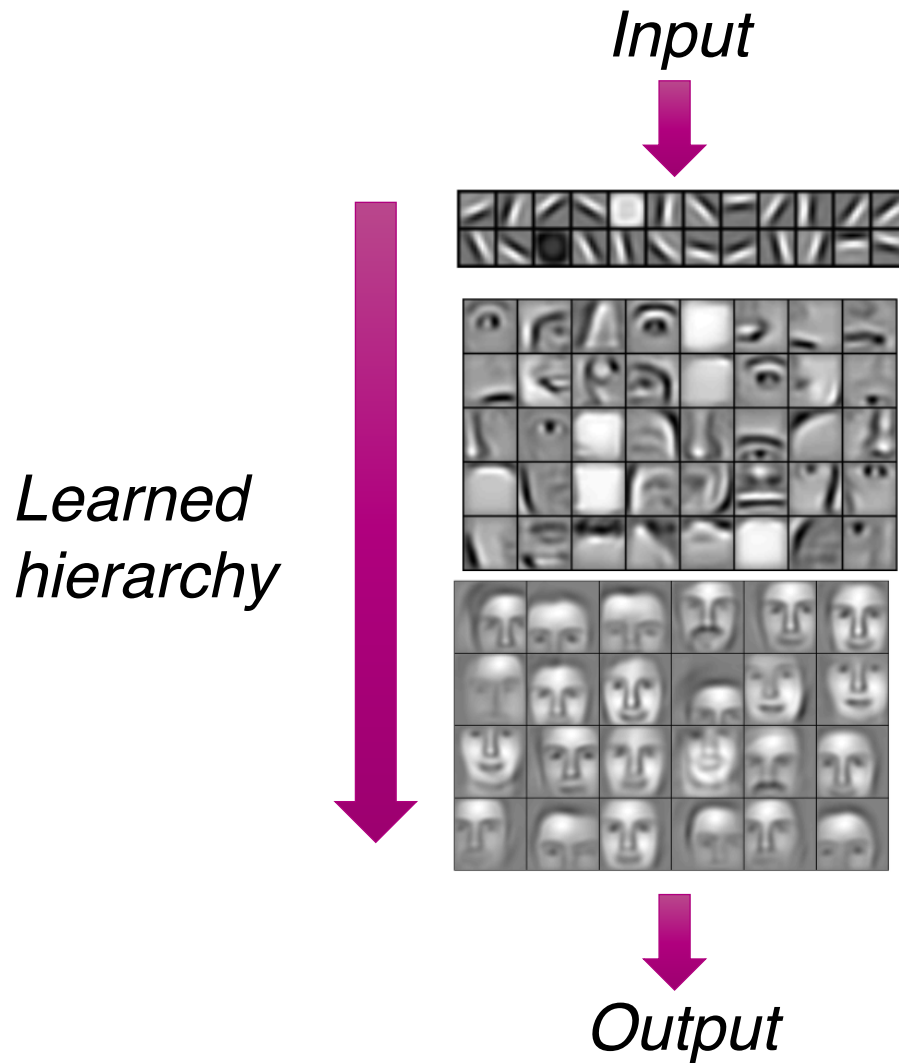
- **Database**

- Developed for computer vision research
- > 14,000,000 images hand-annotated
- > 22,000 categories

- **ILSVRC History**

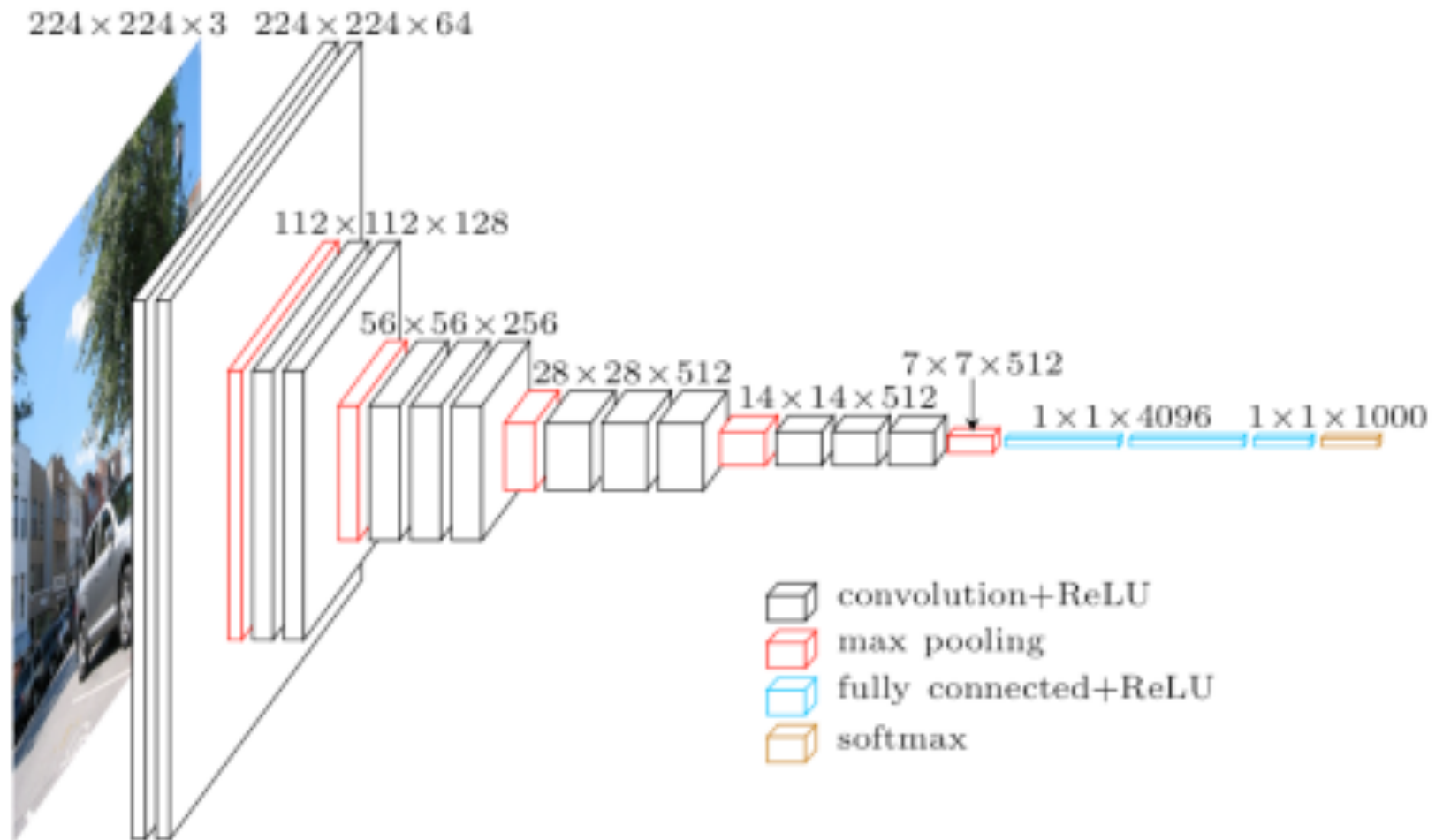
- Started in 2010
- Image classification task: 1,000 object categories
- Image classification error rate
 - 2011: ~25% (conventional image processing techniques)
 - 2012: 15.3% (AlexNet)
 - 2015: 3.57% (ResNet; better than human performance)
 - 2016: 2.99% (16.7% error reduction)
 - 2017: 2.25% (23.3% error reduction)

Why Does Transfer Learning Work?



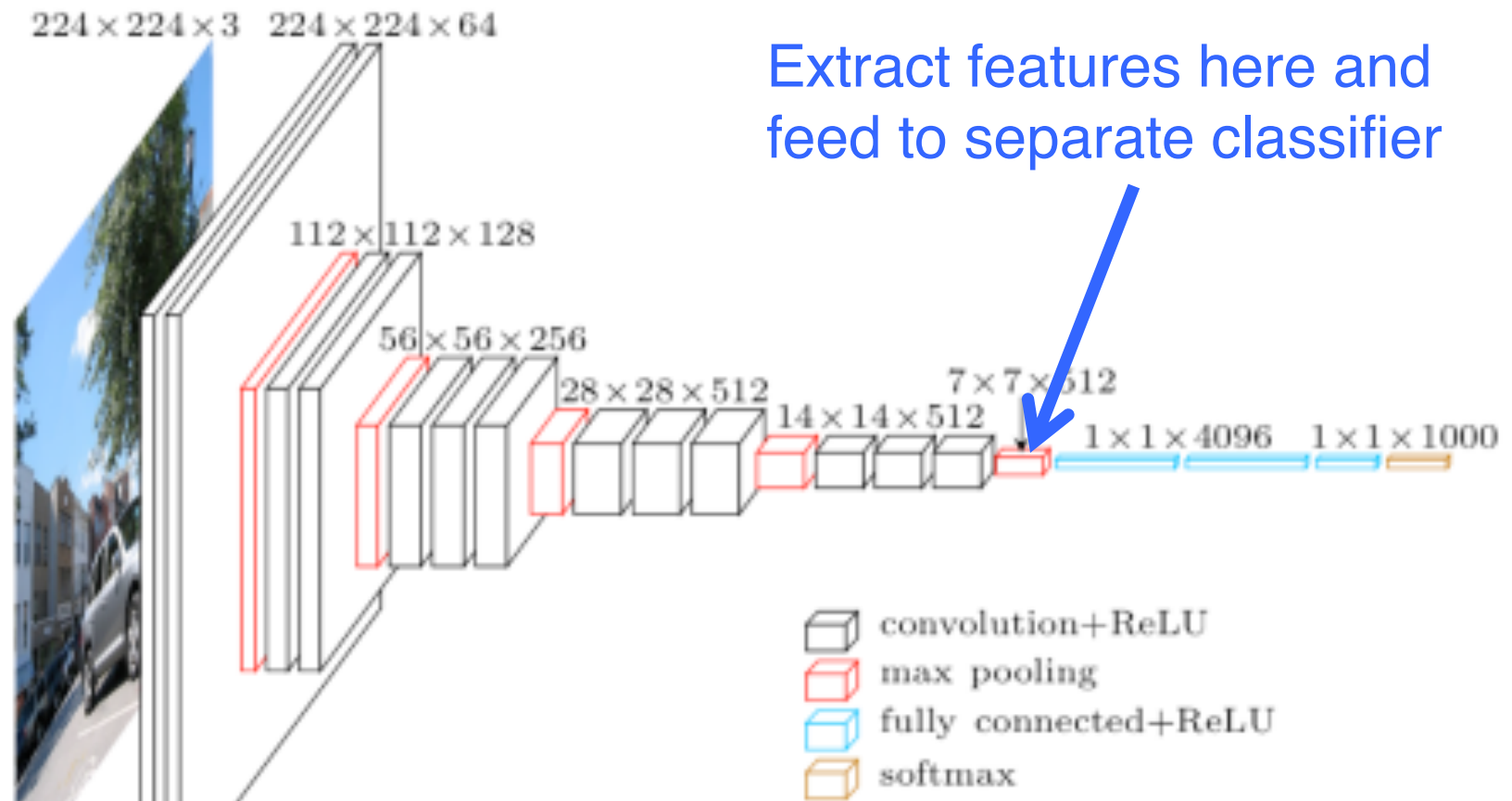
Lee et al. 'Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations' ICML 2009

VGG as Pre-Trained Network



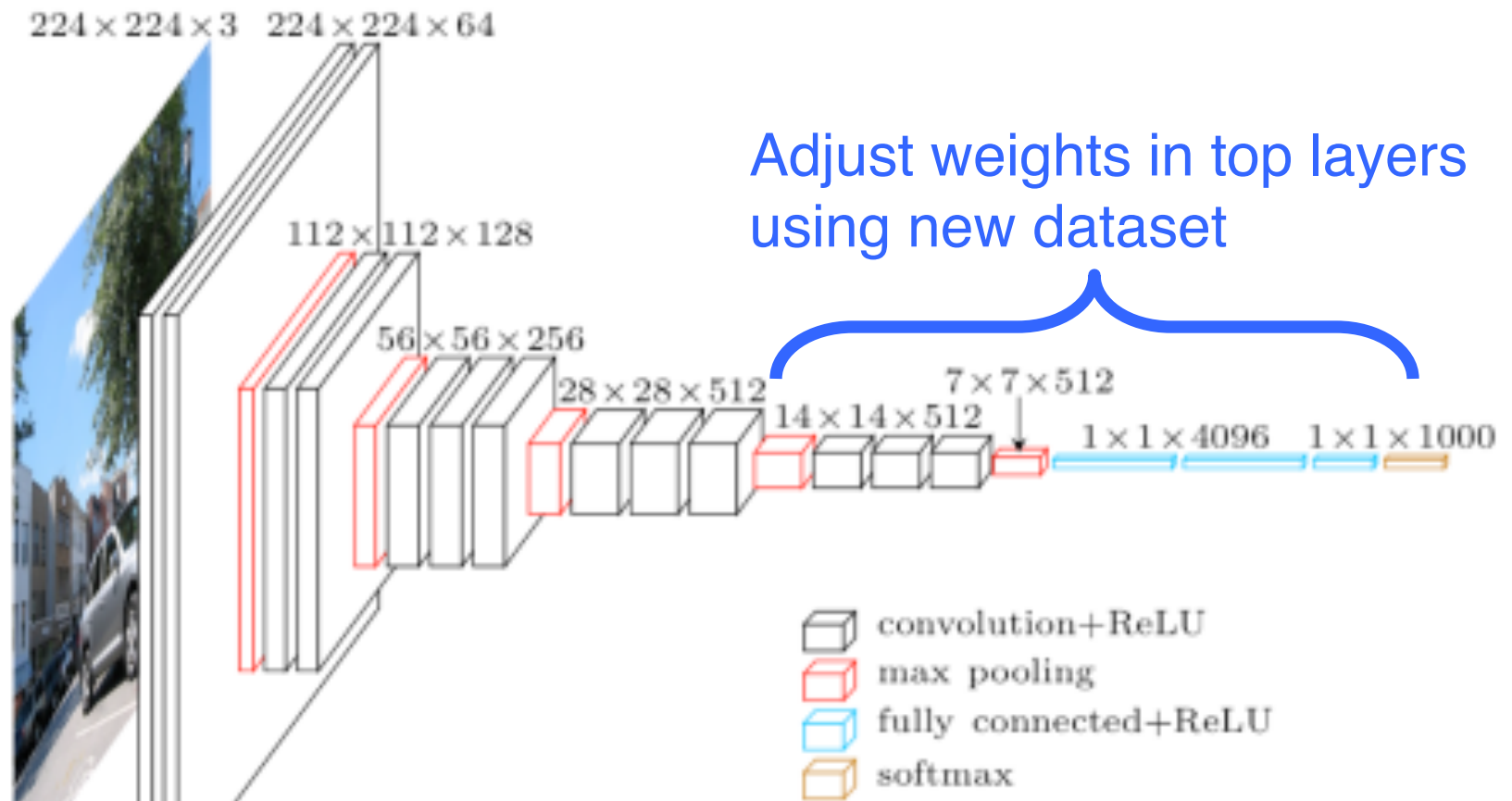
Source: <https://www.cs.toronto.edu/~frossard/post/vgg16/>

Transfer Learning – Feature Extraction



Source: <https://www.cs.toronto.edu/~frossard/post/vgg16/>

Transfer Learning – Fine Tuning



Source: <https://www.cs.toronto.edu/~frossard/post/vgg16/>

When & How to Fine Tune

- **New dataset is small & similar to original dataset**
 - Extract features from higher layer and feed to separate classifier
- **New dataset is large & similar to original dataset**
 - Fine tune top or all layers
- **New dataset is small & different from original dataset**
 - Extract features from lower layer and feed to separate classifier
- **New dataset is large & different from original dataset**
 - Fine tune top or all layers

Other Practical Tips

- **Learning rate**
 - Use very small learning rate for fine tuning. Don't want to destroy what was already learned.
- **Start with properly trained weights**
 - Train top-level classifier first, then fine tune lower layers.
 - Top model with random weights may have negative effects on when fine tuning weights in pre-trained model
- **Data augmentation**
 - Simple ways to slightly alter images
 - Horizontal/vertical flips, random crops, translations, rotations, etc.
 - Use to artificially expand your dataset

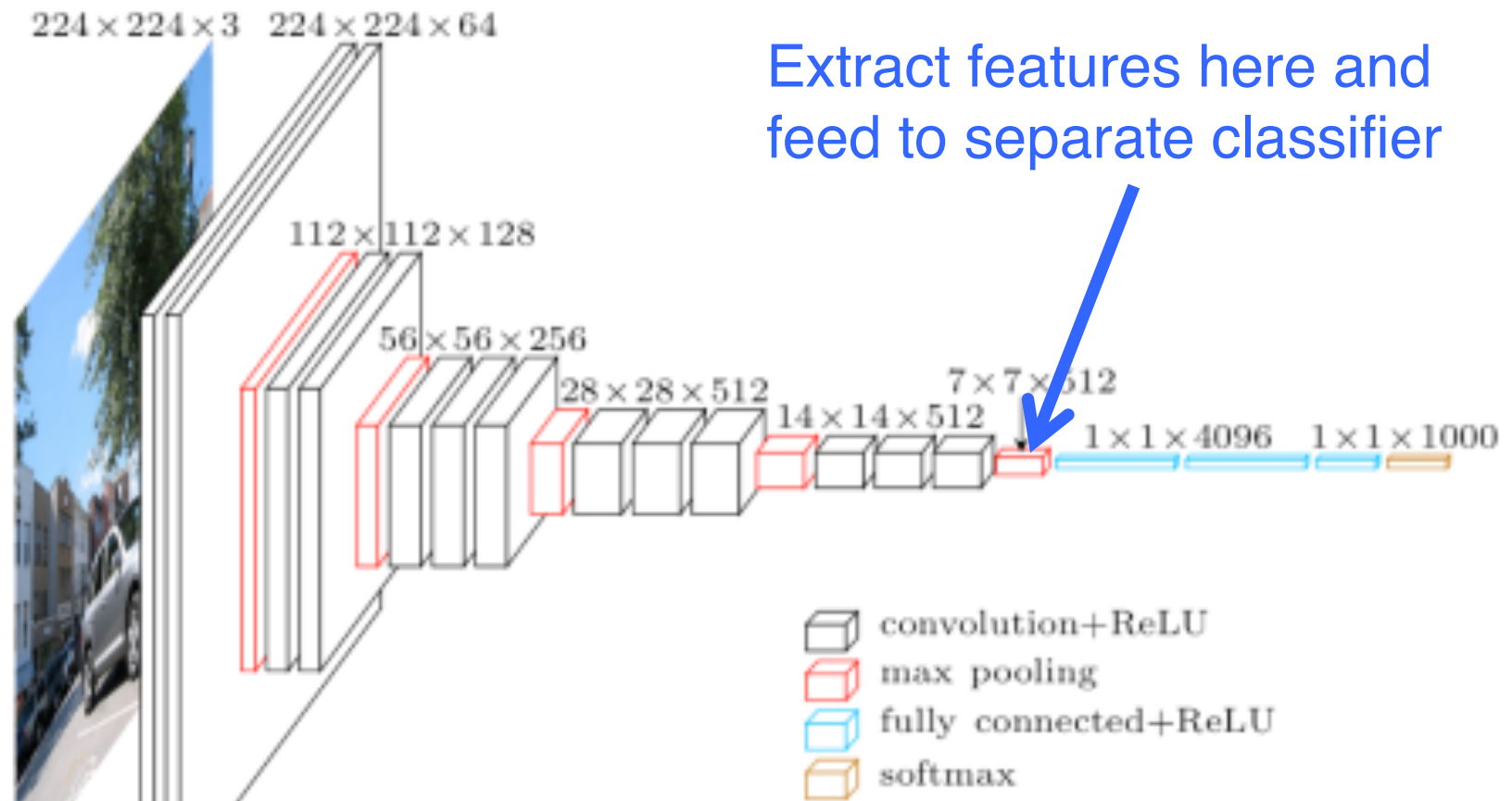
Transfer Learning Hands-On

- **Data**
 - Cats and dogs images from Kaggle
- **Exercises**
 - Feature extraction
 - Use pre-trained CNN to extract features from images
 - Train neural network to classify cats/dogs using extract features
 - Fine tune
 - Adjust weights of last few layers of pre-trained CNN through training

Feature Extraction

- **Data**
 - Cats and dogs images from Kaggle
- **Method**
 - Use VGG16 trained on ImageNet data as pre-trained model. Remove last fully connected layer.
 - Extract features from pre-trained model and save
 - Neural network then trained on extracted features to classify cats vs. dogs

Transfer Learning – Feature Extraction



Source: <https://www.cs.toronto.edu/~frossard/post/vgg16/>

Get Latest from Github Repo

- **If haven't cloned Summer Institute repo**
 - `git clone <URL>`
- **If already cloned Summer Institute repo**
 - `git pull <URL>`
- **<URL>**

<https://github.com/sdsc/sdsc-summer-institute-2020>

Server Setup

- **Set up server**
 - In terminal window: `start_python_gpu`
 - Should get something like this:
Your notebook is here:
<https://unkind-illicitly-mutt.comet-user-content.sdsc.edu?token=6615bbdb1a8e0fbe3ad948fb52678133>
Submitted batch job 35032027
- **Connect to jupyter notebook**
 - In browser, paste URL of notebook from above step
- **Check queue**
 - `squeue -u $USER`

Data Setup

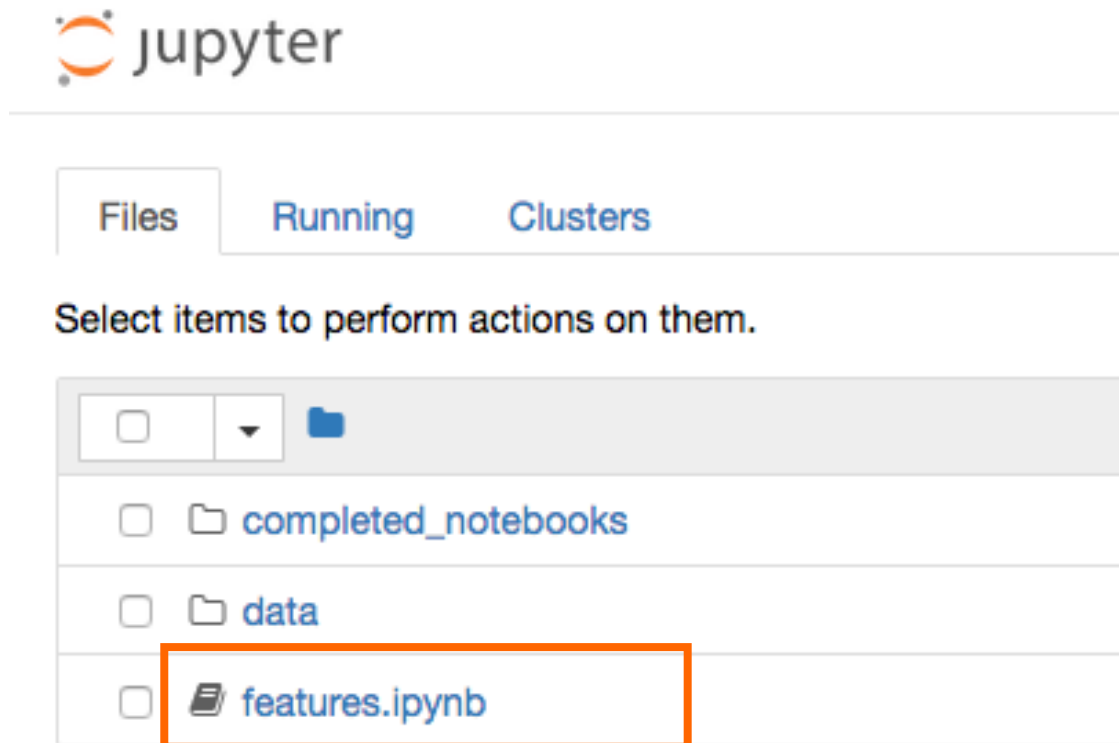
- In terminal window, do the following:
- **Create soft link to data**
 - `ln -s ~/ML-data/data data`
- **Get counts of images**
 - `ls -l data/train/cats/* | wc -l`
 - `ls -l data/train/dogs/* | wc -l`
 - `ls -l data/validation/cats/* | wc -l`
 - `ls -l data/validation/dogs/* | wc -l`

Data Description

- **Subset of Kaggle cats and dogs dataset**
- **Train**
 - 1000 cats + 1000 dogs
- **Validation**
 - 400 cats + 400 dogs



Open features.ipynb Notebook



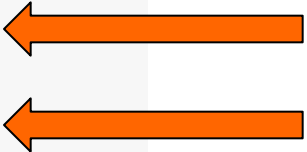
Import Modules

```
import keras
```

```
from keras.models import Sequential  
from keras.preprocessing.image import ImageDataGenerator  
from keras.layers import Dropout, Flatten, Dense  
from keras import backend as K  
from keras import applications  
import numpy as np
```

Print Keras & TensorFlow Versions

```
import tensorflow as tf  
print (tf.__version__)  
print (keras.__version__)
```



Set Data Parameters

- Set image dimensions
 - *img_width, img_height = 150, 150* ←
- Set data location
 - *train_data_dir = 'data/train'* ←
 - *validation_data_dir = 'data/validation'* ←
- Set number of images
 - *nb_train_samples = 2000* ←
 - *nb_validation_samples = 800* ←

(150, 150, 3)

Method to Extract Features from Pre-Trained Network

```
def save_features():
```

```
    ...
```

1. Scale pixel values in each image
2. Load weights for pre-trained network without top classifier
3. Generator reads images from subdir, batch_size number of images at a time.
4. Feed images through pre-trained network and extract features
5. Save features
6. Repeat 3-5 for validation data

Call Method to Extract & Save Features

```
save_features()
```



```
Found 2000 images belonging to 2 classes.
```

```
Found 800 images belonging to 2 classes.
```

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	(None, None, None, 3)	0
block1_conv1 (Conv2D)	(None, None, None, 64)	1792
block1_conv2 (Conv2D)	(None, None, None, 64)	36928
block1_pool (MaxPooling2D)	(None, None, None, 64)	0
block2_conv1 (Conv2D)	(None, None, None, 128)	73856
block2_conv2 (Conv2D)	(None, None, None, 128)	147584
block2_pool (MaxPooling2D)	(None, None, None, 128)	0

Load Saved Features

- Add name of file containing saved features

- For train data

train_data = np.load ('features_train.npy')



- For validation data

validation_data = np.load ('features_validation.npy')



(2000,) (800,)

Create Top Model to Classify Extracted Features

- **Model**

- Fully connected layer from input to hidden
 - 256 nodes in hidden layer
 - Rectified linear activation function
- Fully connected layer from hidden to output
 - 1 node in output layer (cat or dog)
 - Sigmoid activation function

Train Top Model

- Set number of training iterations
 - epochs = 50 
- Train model, keeping track of history

```
from keras.callbacks import History
hist = top_model.fit(train_data, train_labels,
                    epochs=epochs,
                    batch_size=batch_size,
                    validation_data=(validation_data, validation_labels))
```

Train on 2000 samples, validate on 800 samples

Epoch 1/50

2000/2000 [=====] - 1s 451us/step - loss: 0.7173 - acc: 0.7445 - val_loss: 0.2955 - val_acc: 0.8788

Epoch 2/50

2000/2000 [=====] - 1s 262us/step - loss: 0.3366 - acc: 0.8525 - val_loss: 0.2619 - val_acc: 0.8925

Epoch 3/50

2000/2000 [=====] - 1s 262us/step - loss: 0.3366 - acc: 0.8525 - val_loss: 0.2619 - val_acc: 0.8925

Save Model and Weights


- Add name for model files
 - top_model_file = 'features_model' ←
- Save model and weights

```
# Save model & weights to HDF5 file
top_model_file = 'features_model'
top_model.save(top_model_file + '.h5')

# Save model to JSON file & weights to HDF5 file
top_model_json = top_model.to_json()
with open(top_model_file + '.json', 'w') as json_file:
    json_file.write(top_model_json)
top_model.save_weights(top_model_file + '-wts.h5')
```

Test Model on Validation Data

- Get prediction results on validation data

```
# Results on validation set
print (top_model.metrics_names)
results = top_model.evaluate (validation_data, validation_labels)
print (results) 
```

```
['loss', 'acc']
800/800 [=====] - 0s 43us/step
[1.1933523465033795, 0.885]
```

- Load model again and re-test
 - Results should be the same
- Validation accuracy on CNN trained from scratch
 - ~80%

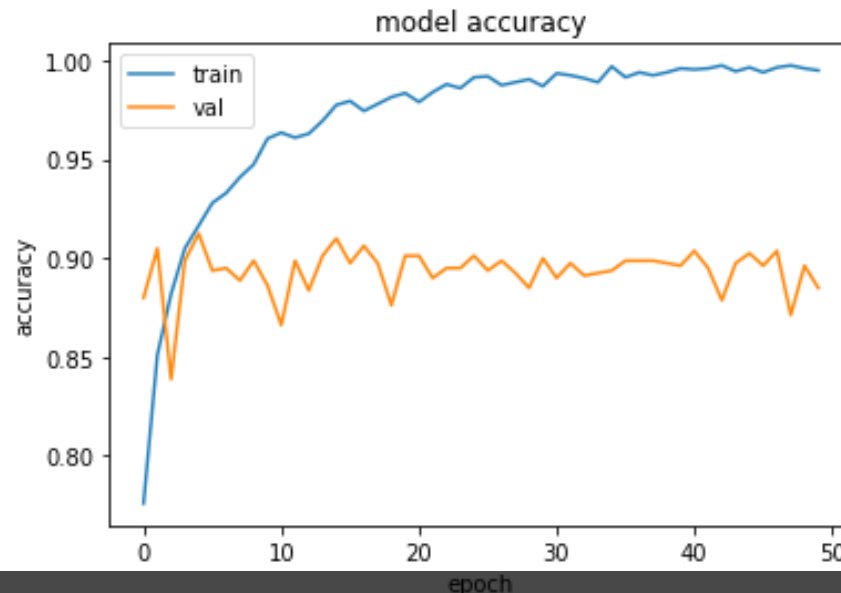
Print History & Plot Performance Measures

- Print training history

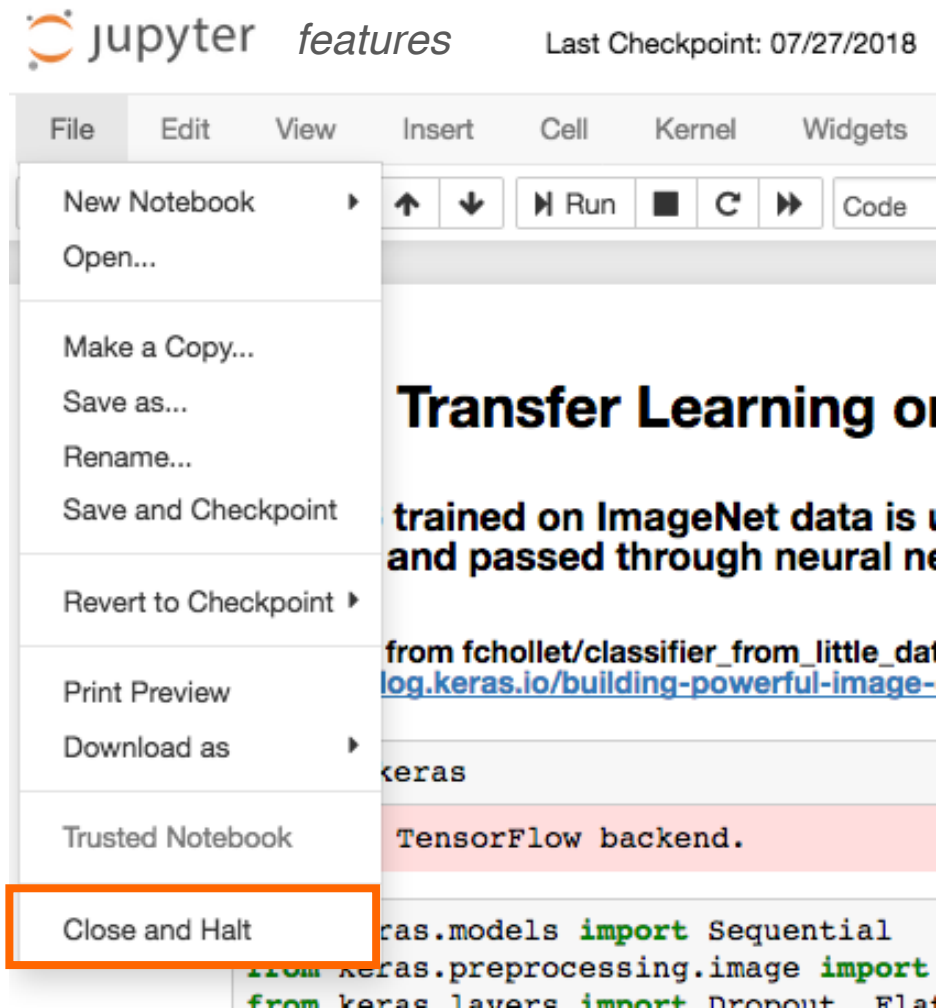
```
print (hist.history)
```

```
{'val_loss': [0.28850417032837866, 0.24813641868531705,  
7, 0.2573309687711298, 0.3192743479809724, 0.3218871263  
5471637994, 0.47818609615555036, 0.5811367122687807, 0.  
5, 0.4588139251829125, 0.45057276758830994, 0.595243040  
.....]
```

- Plot accuracy



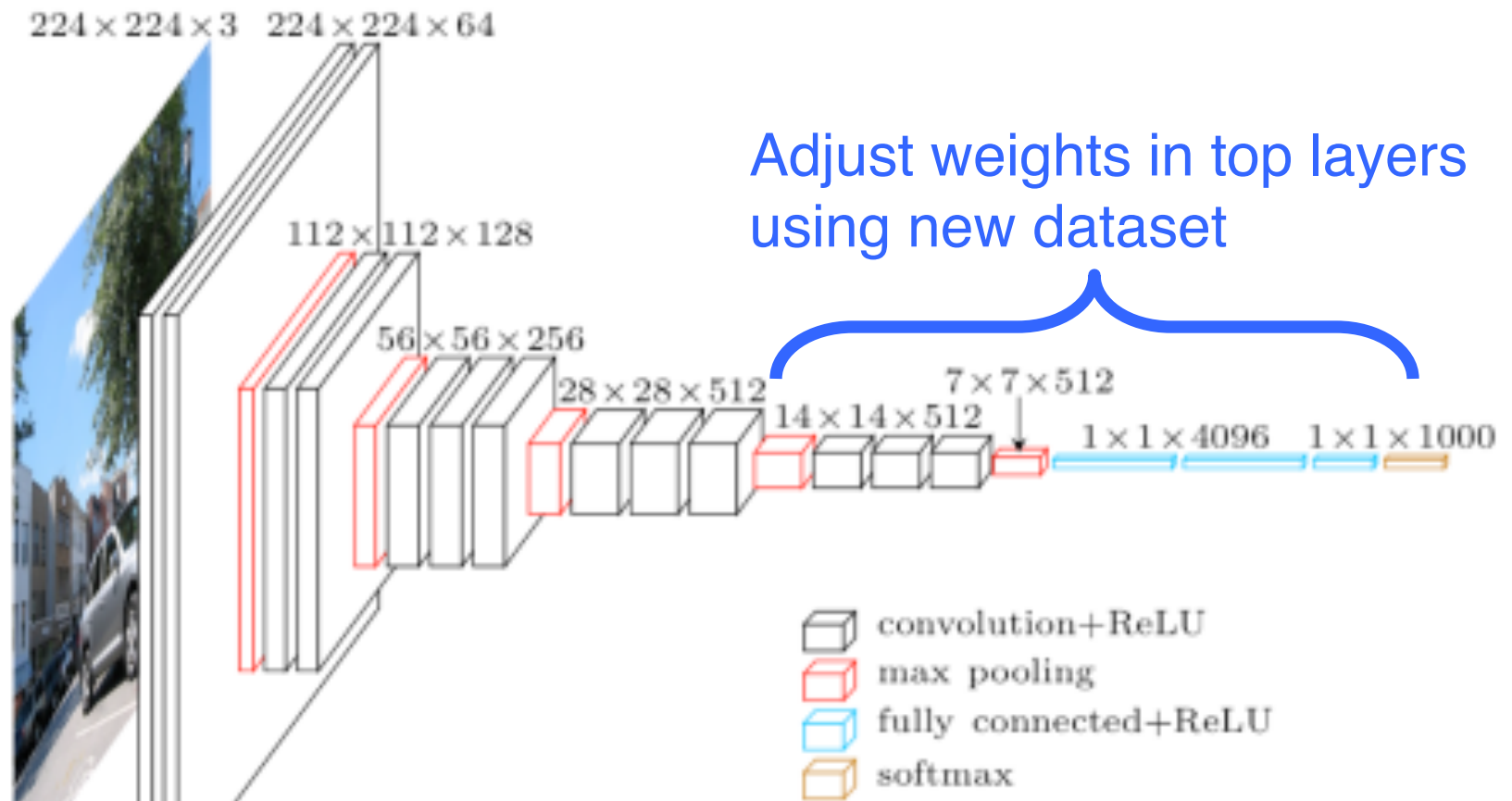
Exit Notebook



Fine Tuning Hands-On

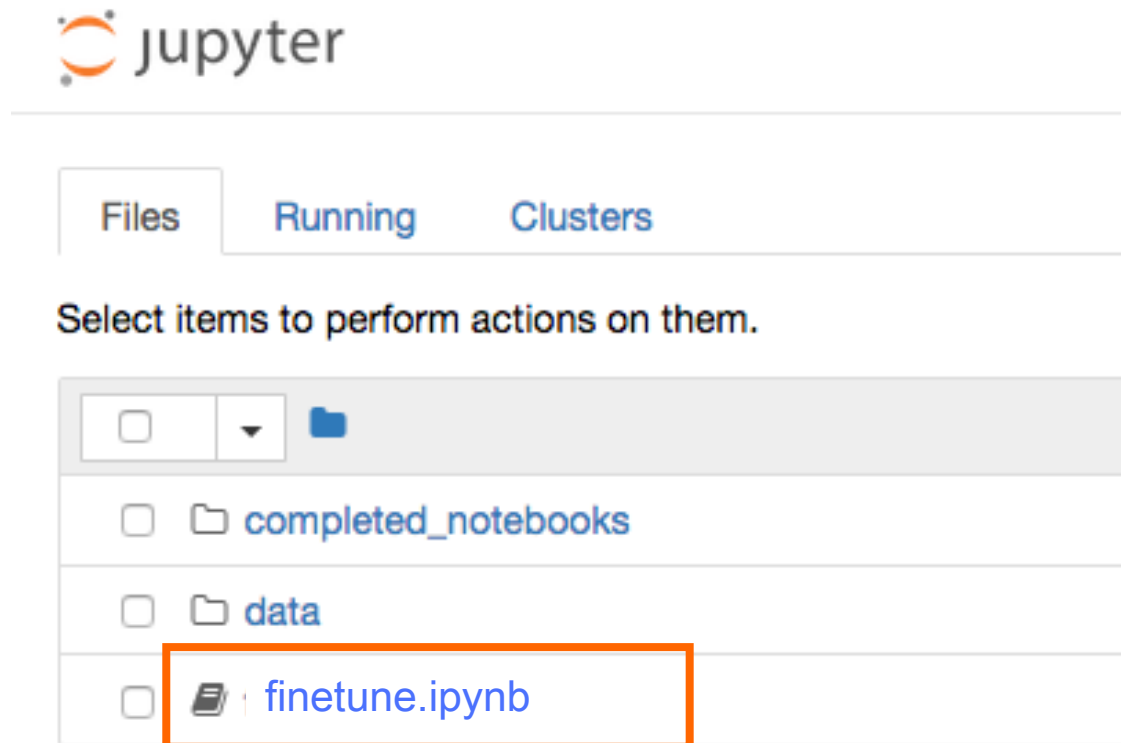
- **Data**
 - Cats and dogs images from Kaggle
- **Method**
 - Use VGG16 trained on ImageNet data as pre-trained model.
 - Replace last fully connected layer with neural network trained from Feature Extraction hands-on.
 - Fine tune last convolution block and fully connected layer.

Transfer Learning – Fine Tuning








Source: <https://www.cs.toronto.edu/~frossard/post/vgg16/>

Open fine-tune.ipynb Notebook



Set Data Parameters

- Set image dimensions
 - *img_width, img_height = 150, 150* 
- Set data location
 - *train_data_dir = 'data/train'* 
 - *validation_data_dir = 'data/validation'* 
- Set number of images
 - *nb_train_samples = 2000* 
 - *nb_validation_samples = 800* 

(150, 150, 3)

Load Pre-Trained CNN

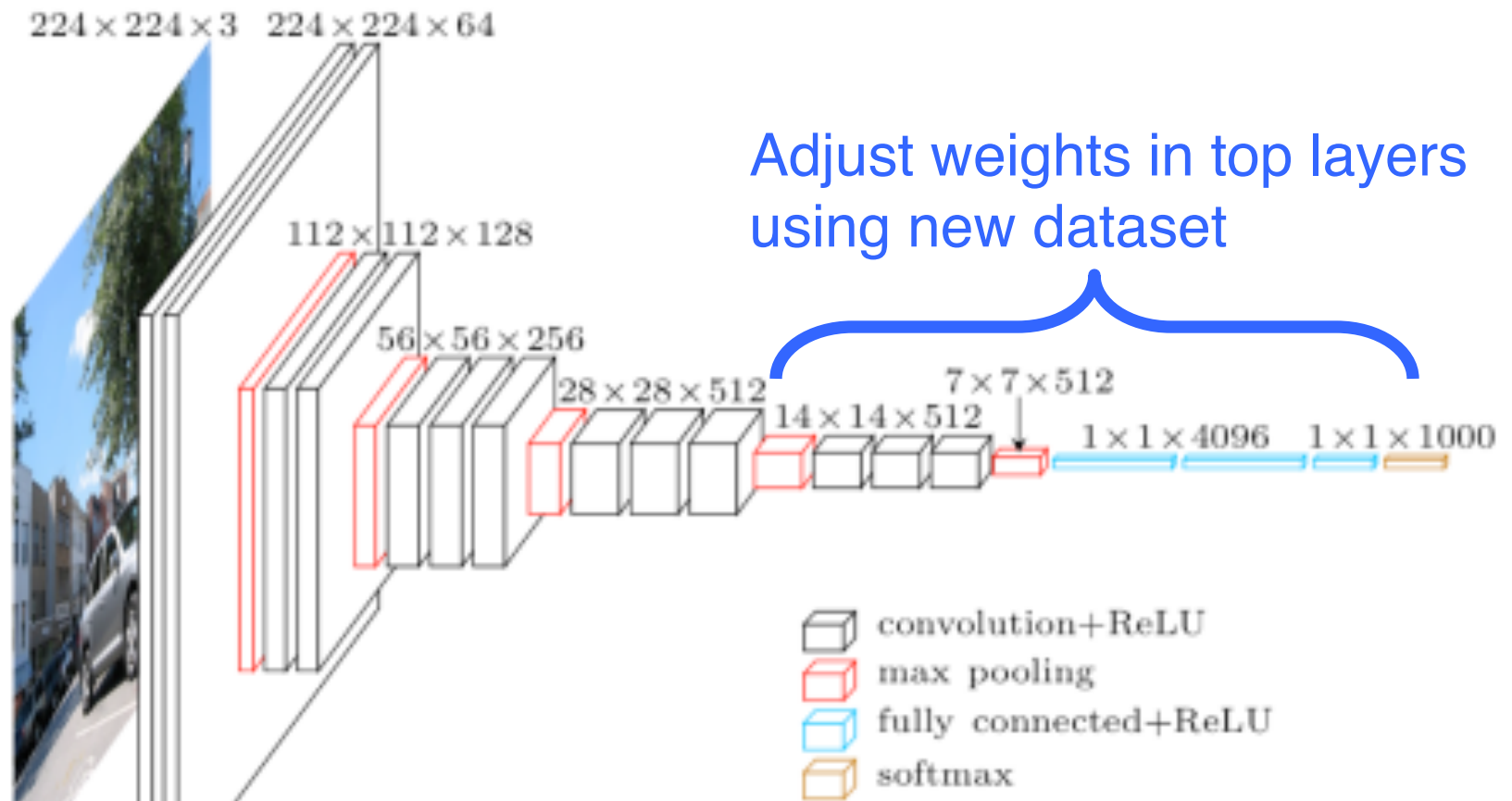
- Load pre-trained model without last fully connected layer

```
base_model = applications.VGG16  
    (weights='imagenet',  
     include_top=False,  
     input_shape=(img_width,img_height,3))  
print ('Model loaded')
```

- Print out base model summary

```
base_model.summary() 
```

Transfer Learning – Fine Tuning



Source: <https://www.cs.toronto.edu/~frossard/post/vgg16/>

Create Top Model

- Create top model
 - Create fully connected layer as top model and connect to pre-trained base model
- Load top model's weights
 - Weights are in 'features_model_wts.h5'
- Add top model to base CNN to create model
- Freeze weights

for layer in model.layers[:15]

layer.trainable = False 

- Compile model
- Print out model summary

model.summary() 

Model

- **Original Model**

Total params: 14,714,688

Trainable params: 14,714,688

Non-trainable params: 0

- **Freeze some weights**

```
# Freeze weights in CNN up to last Conv block  
for layer in model.layers[:15]:  
    layer.trainable = False
```

Total params: 16,812,353

Trainable params: 9,177,089


Non-trainable params: 7,635,264

Prepare Data

- Set batch size

batch_size = 16 

- Set batch size for train_generator

```
train_generator = train_datagen.flow_from_directory(  
    train_data_dir,  
    target_size=(img_width, img_height),  
    batch_size=batch_size,   
    class_mode='binary',  
    seed=seed)
```


Fine Tune Model

- Set number of training epochs

epochs = 5 

- Set batch size for train_generator

from keras.callbacks import History

hist = model.fit_generator(

train_generator,

steps_per_epoch = nb_train_samples // batch_size,

epochs = epochs, 

validation_data = validation_generator,


validation_steps = nb_validation_samples // batch_size,


initial_epoch=0,

verbose = 2)

Get Classification Results

- Get classification results after fine tuning

```
results = model.evaluate_generator(  
    train_generator,   
    steps=nb_train_samples // batch_size)  
print (results)
```

```
results = model.evaluate_generator(  
    validation_generator,   
    steps=nb_validation_samples // batch_size)  
print (results)
```

Save Model and Weights

- Save model & weights

```
model_file = 'finetune' ←
```

- Get results on validation set

```
print (model.metrics_names)  
results = model.evaluate_generator( ←  
    validation_generator,  
    steps = nb_validationsamples // batch_size)  
print (results)
```

Print Training History

- Print history

print (hist.history) 

Predict Class of Image

- Use model to predict class of image

result = model.predict(x) ←

print ("Prediction probability: ", result) ←

Clean Up

- **Exit notebook**
 - File -> Close and Halt
- **Exit Jupyter Notebook**
 - Click on 'Logout'

References

- **F. Chollet. The Keras Blog.**
 - <https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html>
- **ImageNet**
 - <http://www.image-net.org/>
- **Transfer Learning**
 - <http://cs231n.github.io/transfer-learning/>
- **Satellite Image Analysis Use Case**
 - https://ieeexplore.ieee.org/abstract/document/8109118?casa_token=TCdQ0aSgBjgAAAAA:fQUwcByPhSuByj_8u2iTII_kLh9BPKISq6akqSK04SwBKKV1Yp rcVoezhcjpWcpIDxIXdtlF