SDSC Summer Institute 2021
Deep Learning

Mai H. Nguyen & Paul Rodriguez

2021-August-05

Deep Learning Agenda

8:00 - 8:45 -- Intro to Neural Networks / CNNs
8:45 - 9:45 -- MNIST & TensorBoard Hands-On
9:45 - 10:00 -- Break
10:00 - 10:45 -- DL Layers & Architectures
10:45 - 11:15 -- Lunch
11:15 - 12:30 -- Transfer Learning Hands-On
12:30 - 12:45 -- Break
12:45 - 1:45 -- Deep Sequence Learning
1:45 - 2:00 -- Wrap-Up

Deep Learning Transfer Learning Hands-On

Mai H. Nguyen, Ph.D.

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

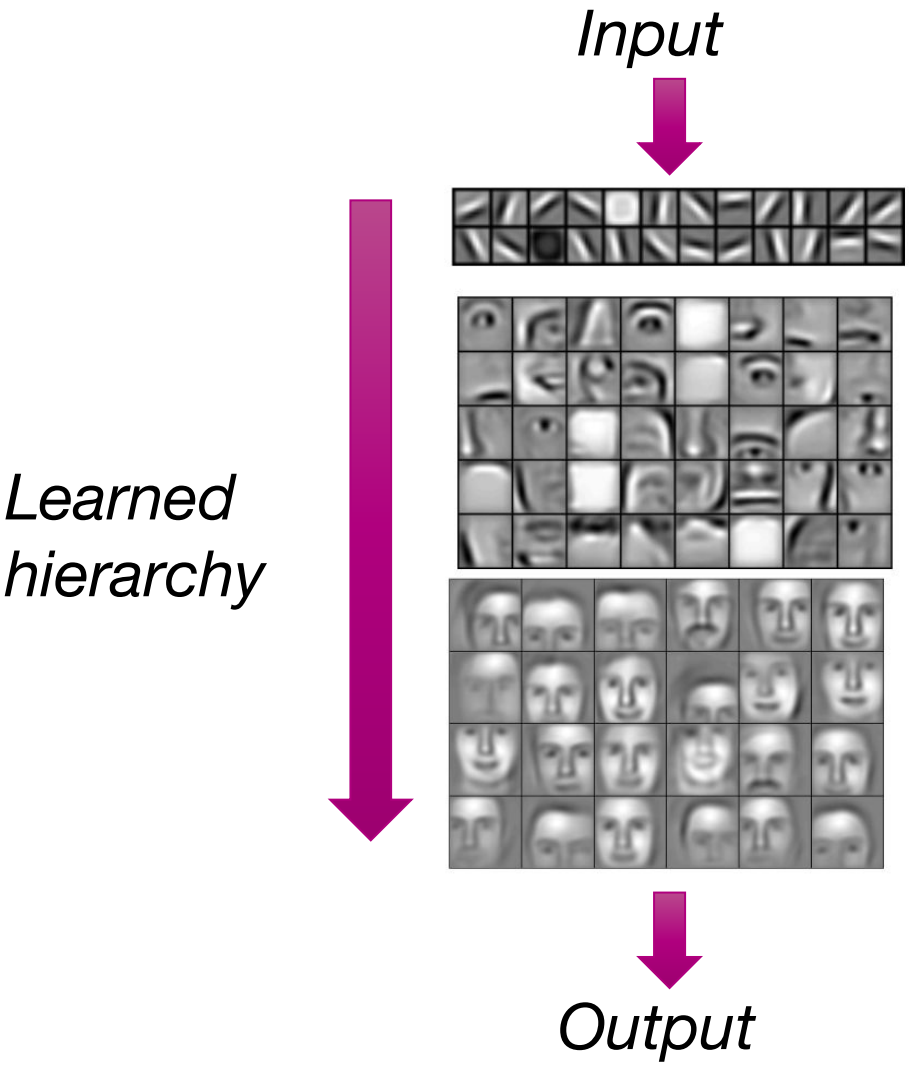
CNNs FOR TRANSFER LEARNING

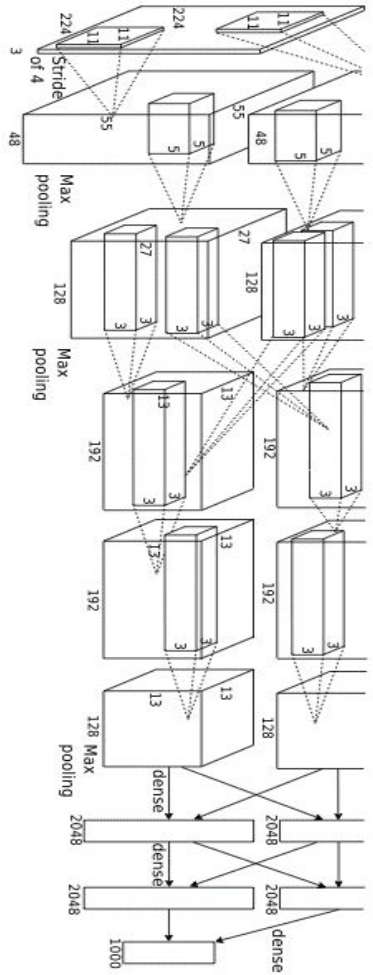
- **Popular architectures**
  - AlexNet
  - GoogLeNet
  - VGGNet
  - ResNet
- **All winners of ILSVRC**
  - ImageNet Large Scale Visual Recognition Challenge
  - Annual competition on vision tasks on ImageNet data

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)

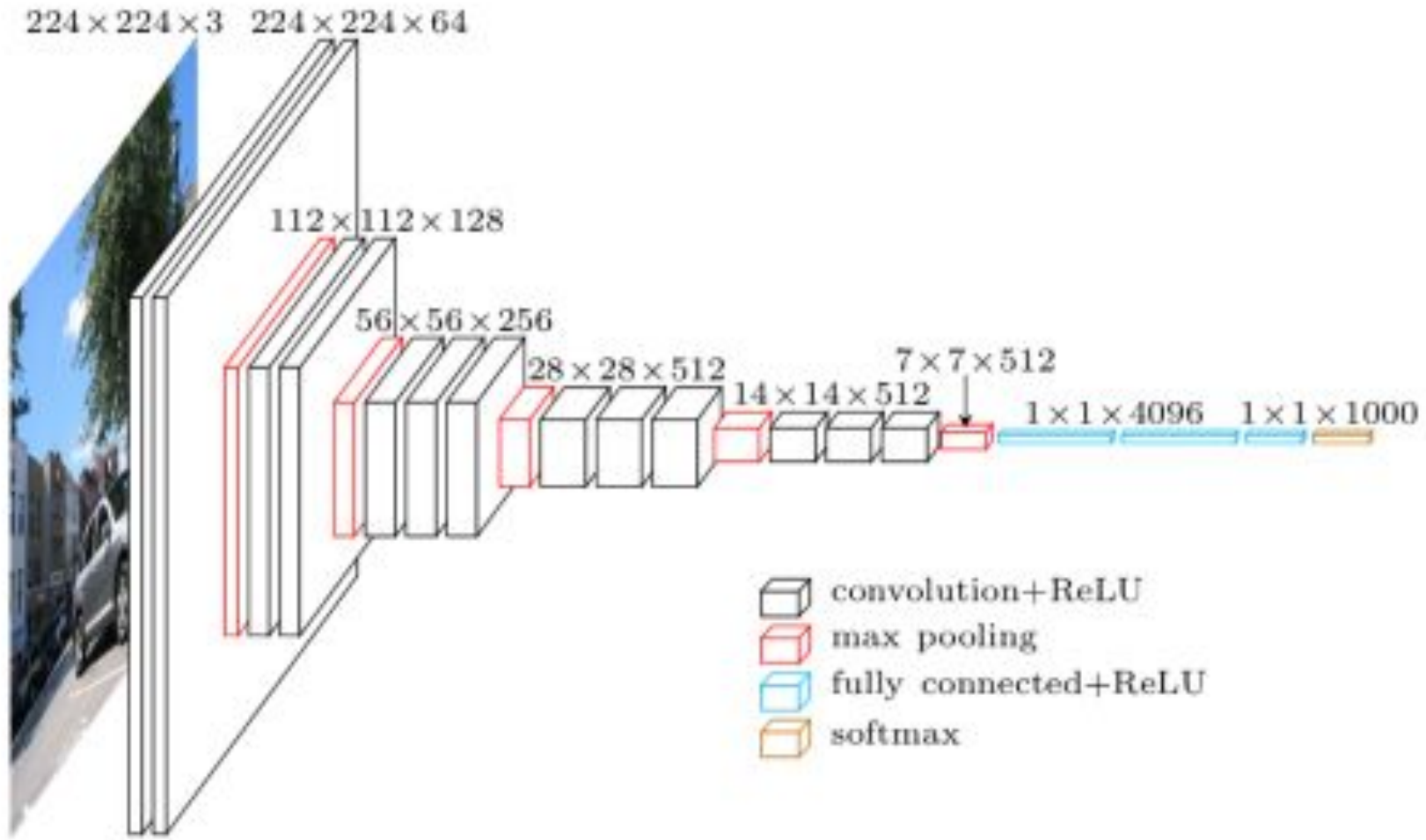
TRANSFER LEARNING





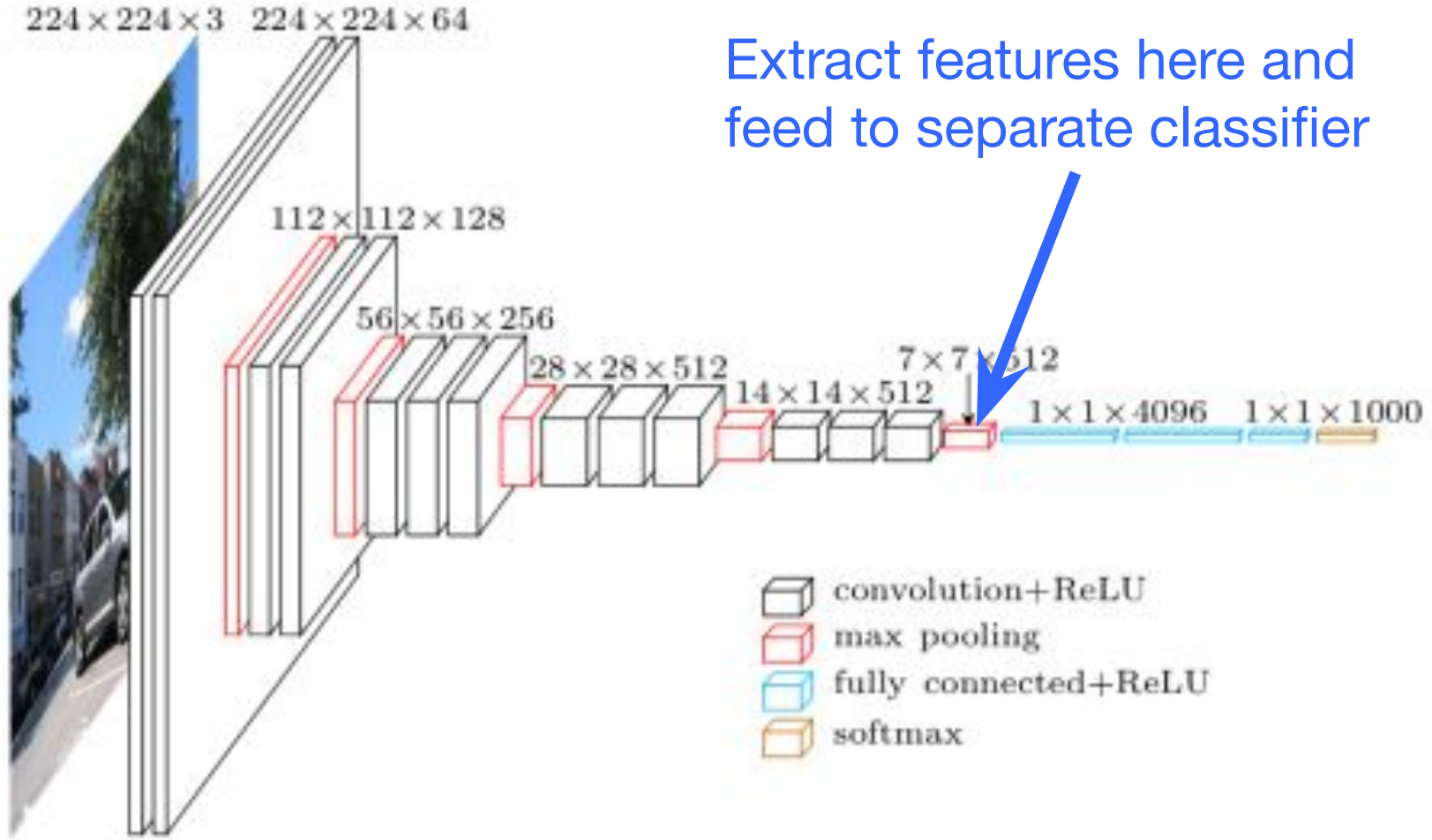
Lee et al. 'Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations' ICML 2009

PRE-TRAINED MODEL



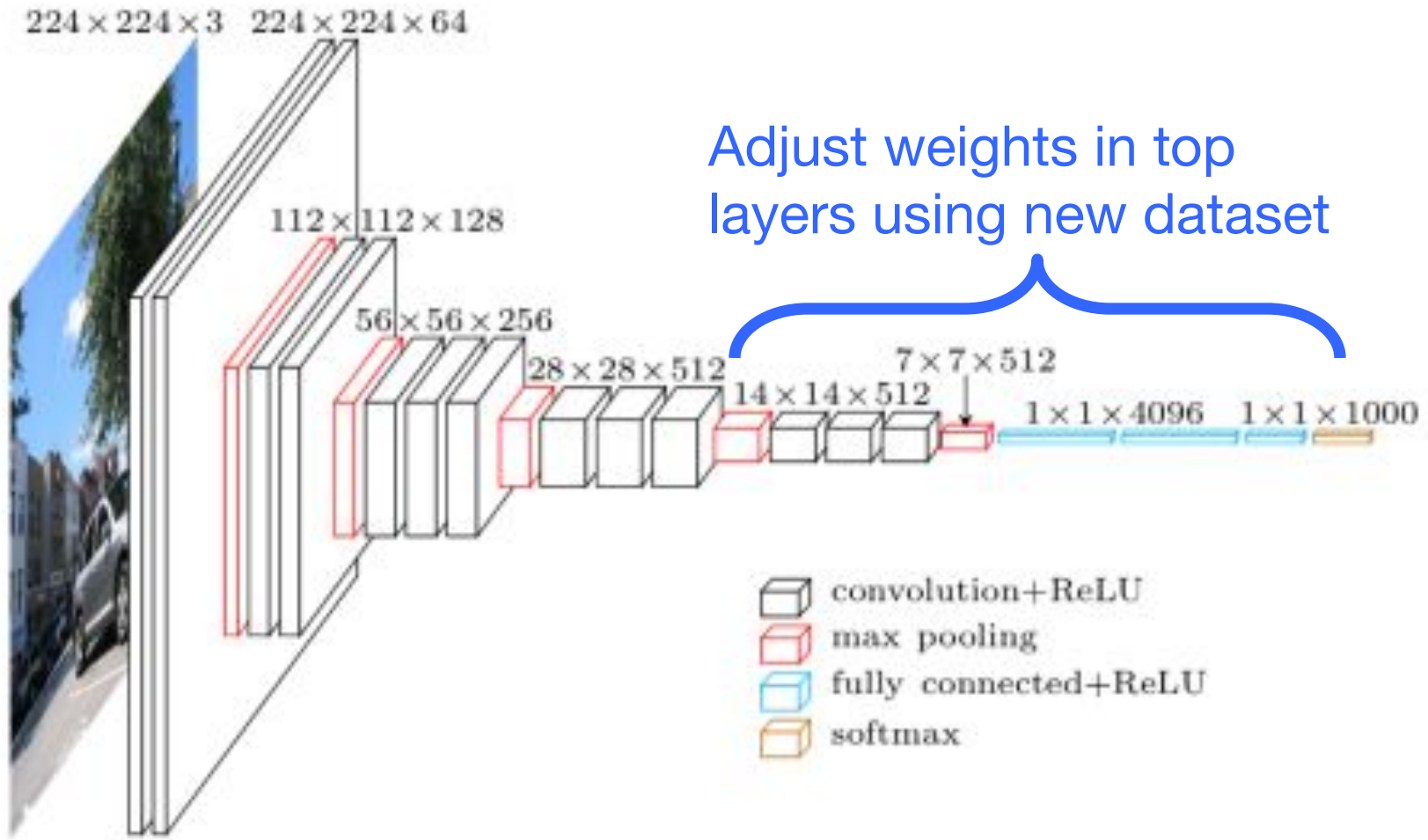
https://www.cs.toronto.edu/~frossard/post/vgg16/

TRANSFER LEARNING - FEATURE EXTRACTION



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

TRANSFER LEARNING - FINE TUNING



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

http://cs231n.github.io/transfer-learning/

OTHER PRACTICAL TIPS

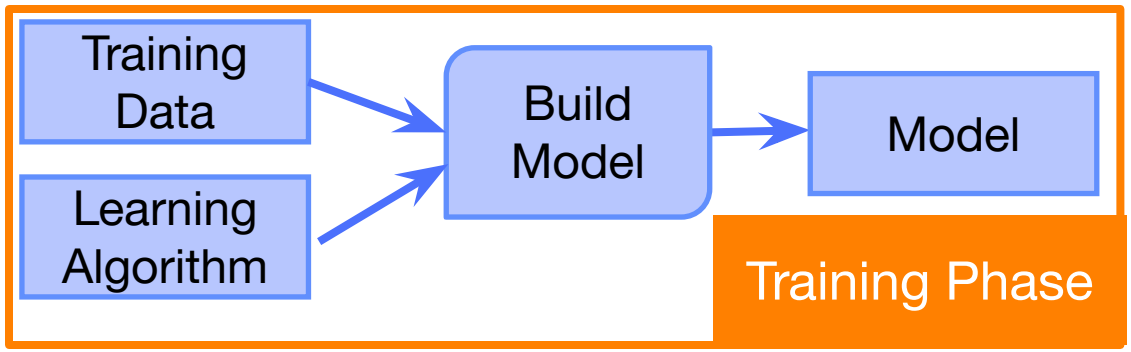
- **Learning rate**
  - Use very small learning rate for fine tuning. Don't want to destroy what was already learned.
- **Start with properly trained weights**
  - Train top-level classifier first, then fine tune lower layers.
  - Top model with random weights may have negative effects on when fine tuning 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 EXERCISES

- **Data**
  - Cats and dogs images from Kaggle

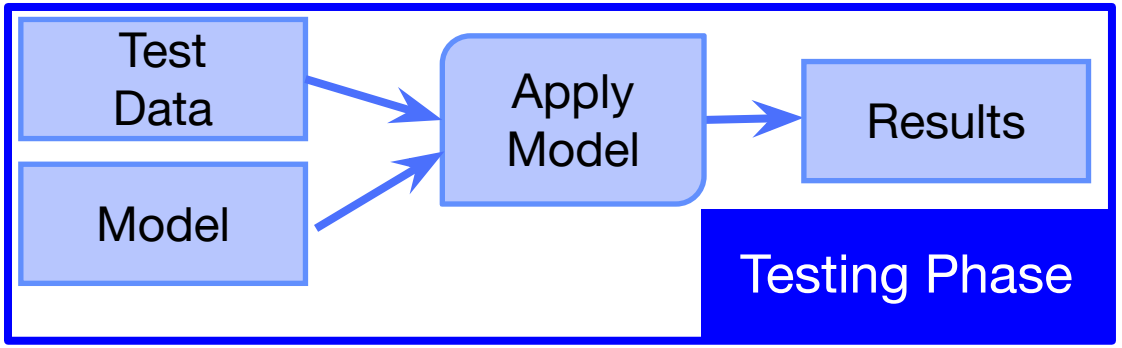
- **Exercises**
  - Feature extraction
    - Use pre-trained CNN to extract features from images
    - Train neural network to classify cats/dogs using extract features
  - Fine tune
    - Adjust weights of last few layers of pre-trained CNN through training

BUILDING VS APPLYING MODEL

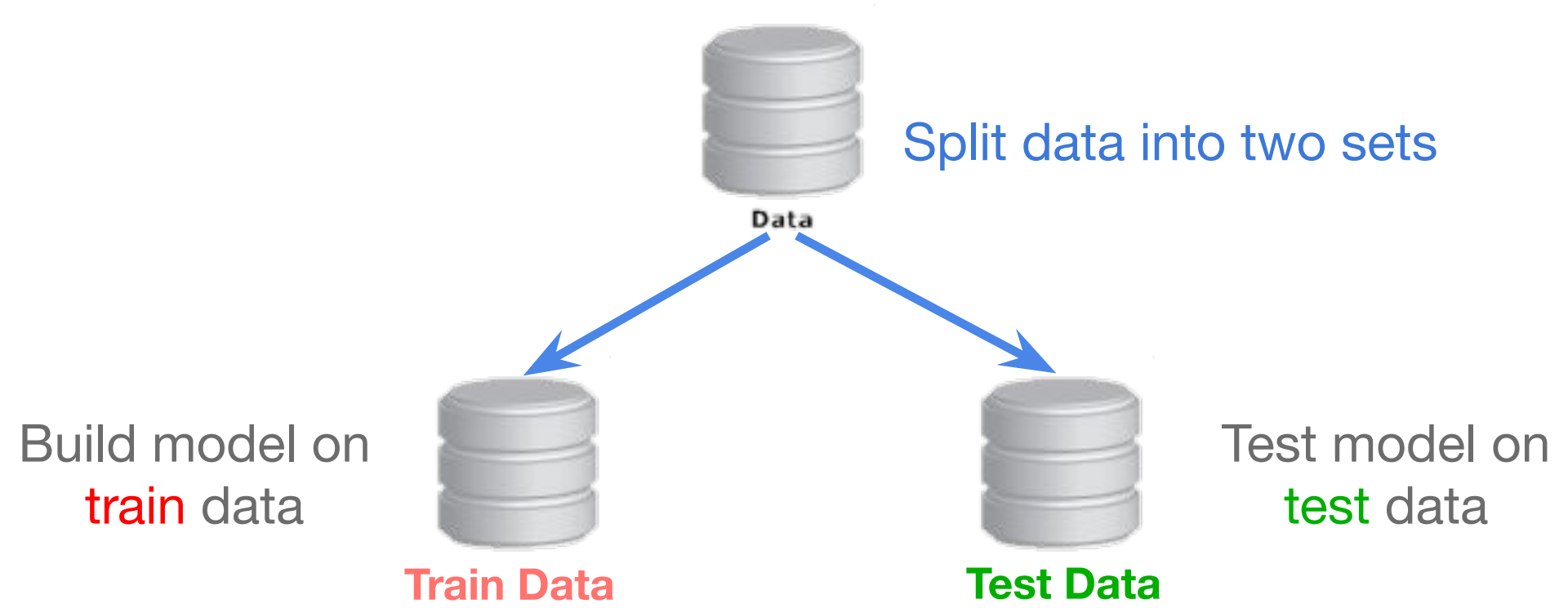


Adjust model parameters
"Train"

Test model on new data
"Inference"



GENERALIZATION

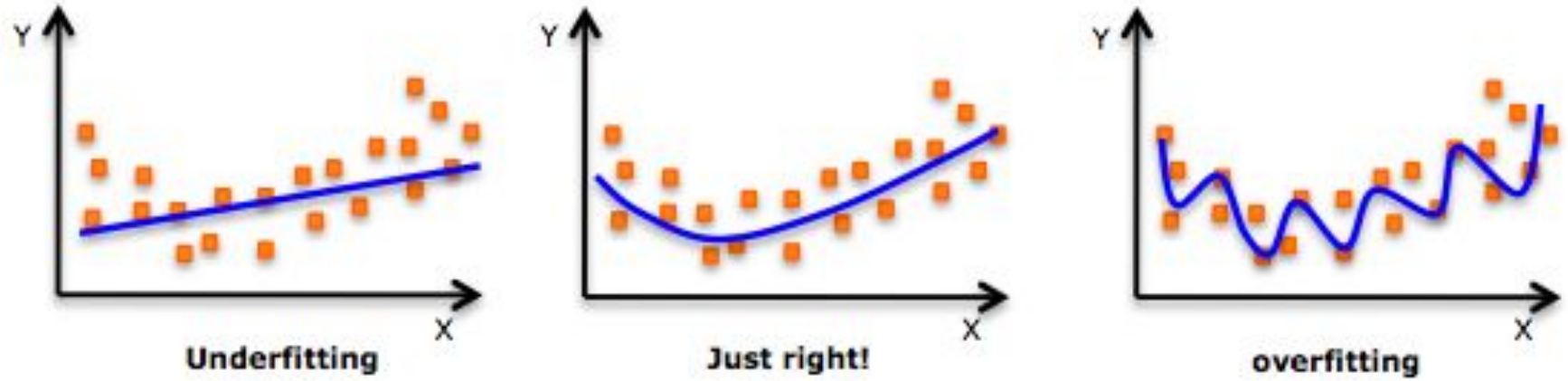


Goal: Want model to perform well on data it was not trained on, i.e., to **generalize** well to unseen data

OVERFITTING & GENERALIZATION

- **Overfitting**
  - Model is fitting to noise in data instead of to underlying distribution of data
- **Reasons for overfitting**
  - Training set is too small
  - Model is too complex, i.e., has too many parameters
- **Overfitting leads to poor generalization**
  - Model that overfits will not generalize well to new data

OVERFITTING



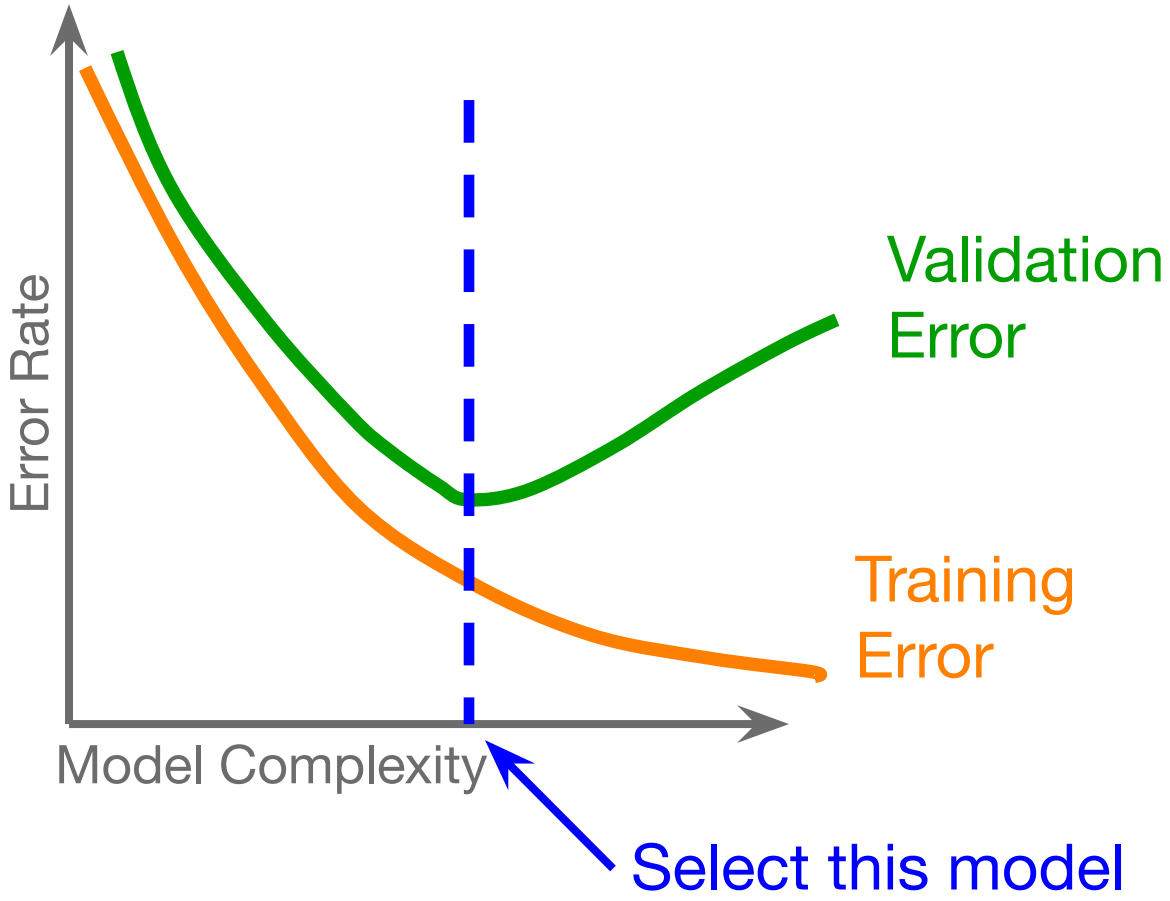
http://stats.stackexchange.com/questions/192007/what-measures-you-look-at-the-determine-over-fitting-in-linear-regression

Underfitting	Just Right	Overfitting
Model has not learned structure of data	Model has learned distribution of data	Model is fitting to noise in data
High training error High test error	Low training error Low test error	Low training error High test error

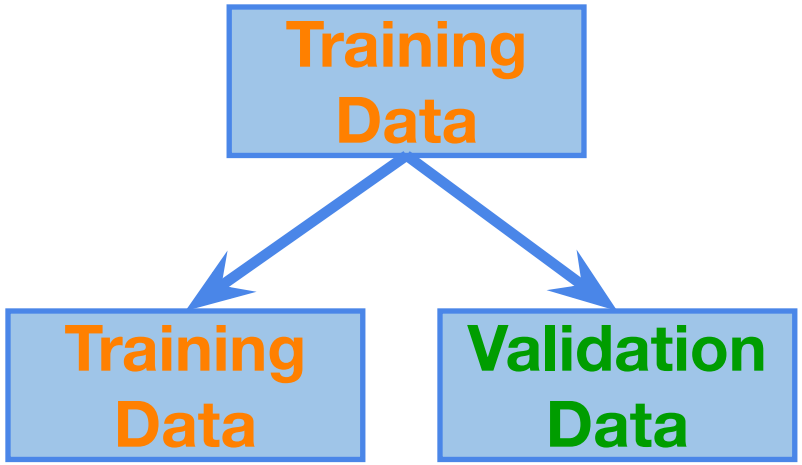
ADDRESSING OVERFITTING

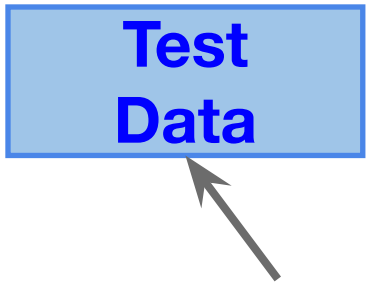
- **Model complexity**
  - Number of parameters in model
  - Chance of overfitting increases with model complexity
- **Validation set**
  - Monitor error on training and validation data
  - To determine when to stop training
- **Regularization**
  - Constrain or shrink (“regularize”) model parameters
  - Add penalty term to error function used to train model
    - e.g., Add L1-norm and/or L2-norm regularization to linear regression model

VALIDATION SET



ADDRESSING OVERFITTING USING VALIDATION SET





Cannot be used in <u>any</u> way in model fitting!

Model Fitting:
Adjust model parameters

Model Selection:
Select model to avoid overfitting
Estimate generalization performance

Model Evaluation:
Evaluate performance on new data

TRANSFER LEARNING HANDS-ON DATA

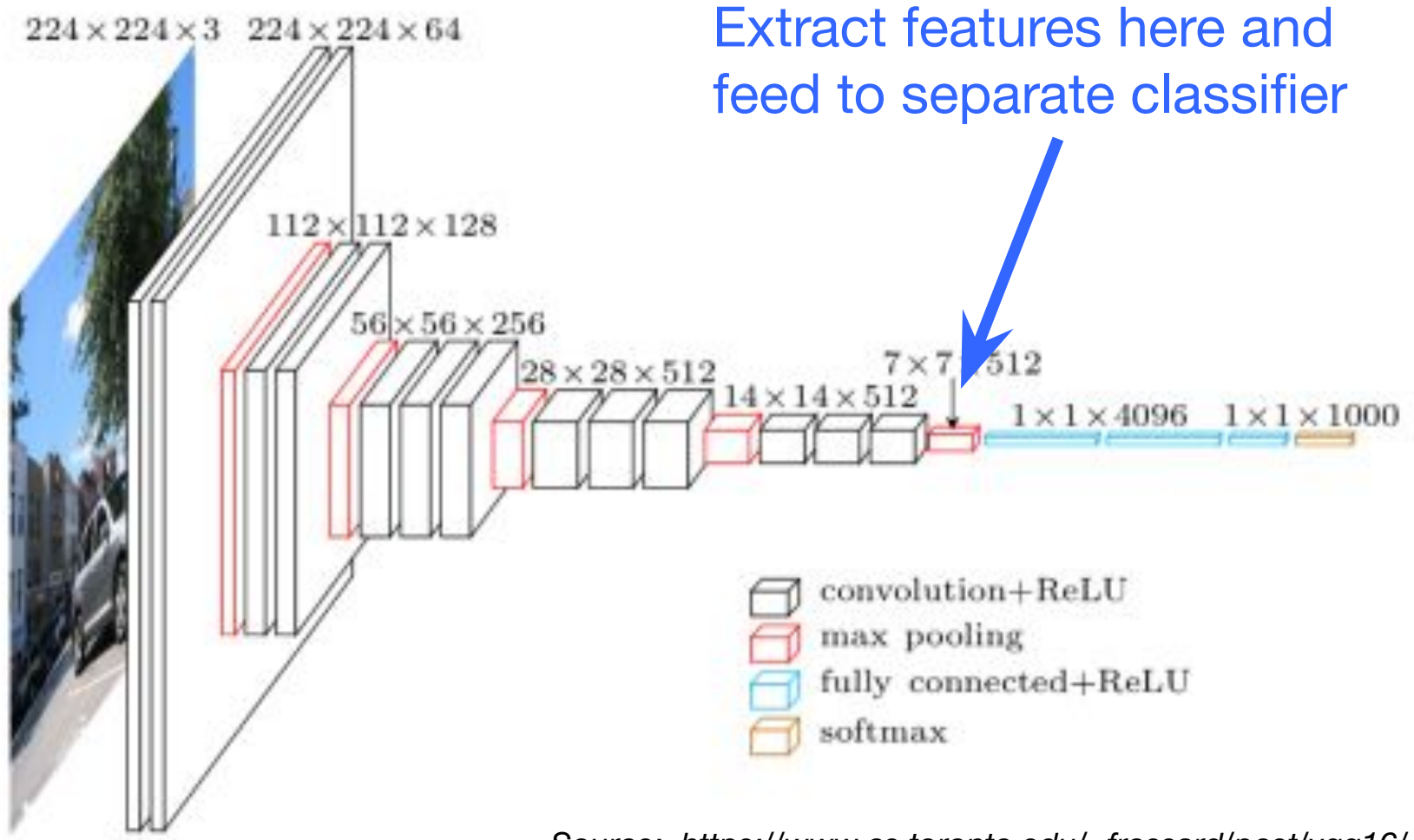
- **Subset of Kaggle cats and dogs dataset**
- **Train**
  - 1000 cats + 1000 dogs
- **Validation**
  - 200 cats + 200 dogs
- **Test**
  - 200 cats + 200 dogs

TRANSFER LEARNING - 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/

Feature Extraction Overview

- **Data**
  - Set image dimensions & location
  - Use ImageDataGenerator to read images from folder
- **Model**
  - Load model pre-trained on ImageNet data
  - Freeze weights in pre-trained model to use as feature extractor
  - Add top model to classify cats vs dogs
  - Model = Pre-trained base model + top model classifier
- **Train model**
  - Use training data to adjust model weights
  - Use validation data to determine when to stop training
- **Evaluate model**
  - Calculate accuracy, etc.
  - Perform inference on test images

Code

- **features_extract_tf.ipynb**
  - Transfer learning with feature extraction using TensorFlow

Setup

- **Login to Expanse**
  - Open terminal window on local machine
  - ssh xdtrXXX@login.expanse.sdsc.edu
- **Pull latest from repo**
  - cd <your-SI-repo>
  - git pull
  - URL: https://github.com/ciml-org/ciml-summer-institute-2021

Server Setup for TensorFlow - Portal

- **Expanse Portal**
  - https://portal.expanse.sdsc.edu
  - Use trainXXX account
  - Interactive Apps -> Jupyter
- **Parameters**
  - Account: crl155
  - Partition: gpu-shared
  - Time limit (min): 180
  - Number of cores: 10
  - Memory required per node: 90 GB
  - GPUs: 1
  - Singularity image: /cm/shared/apps/containers/singularity/tensorflow/tensorflow-latest.sif
  - Environment module: singularitypro
  - Reservation: SI2021RES
  - QoS: gpu-shared-si2021

Server Setup for TensorFlow - Command Line

- **In terminal window**
  - cd 4.2b_Deep_Learning_part_2
  - start-tf-gpu
    - Alias for:
    - export PATH="/cm/shared/apps/sdsc/galyleo:${PATH}";
    - galyleo launch --account crl155 --reservation SI2021RES --partition gpu-shared --qos gpu-shared-si2021 --cpus-per-task 10 --memory-per-node 90 --gpus 1 --time-limit 03:00:00 --env-modules singularitypro --sif /cm/shared/apps/containers/singularity/tensorflow/tensorflow-latest.sif --bind /expanse,/scratch --nv --quiet
  - Copy & paste URL in web browser
- **To check queue**
  - squeue -u $USER

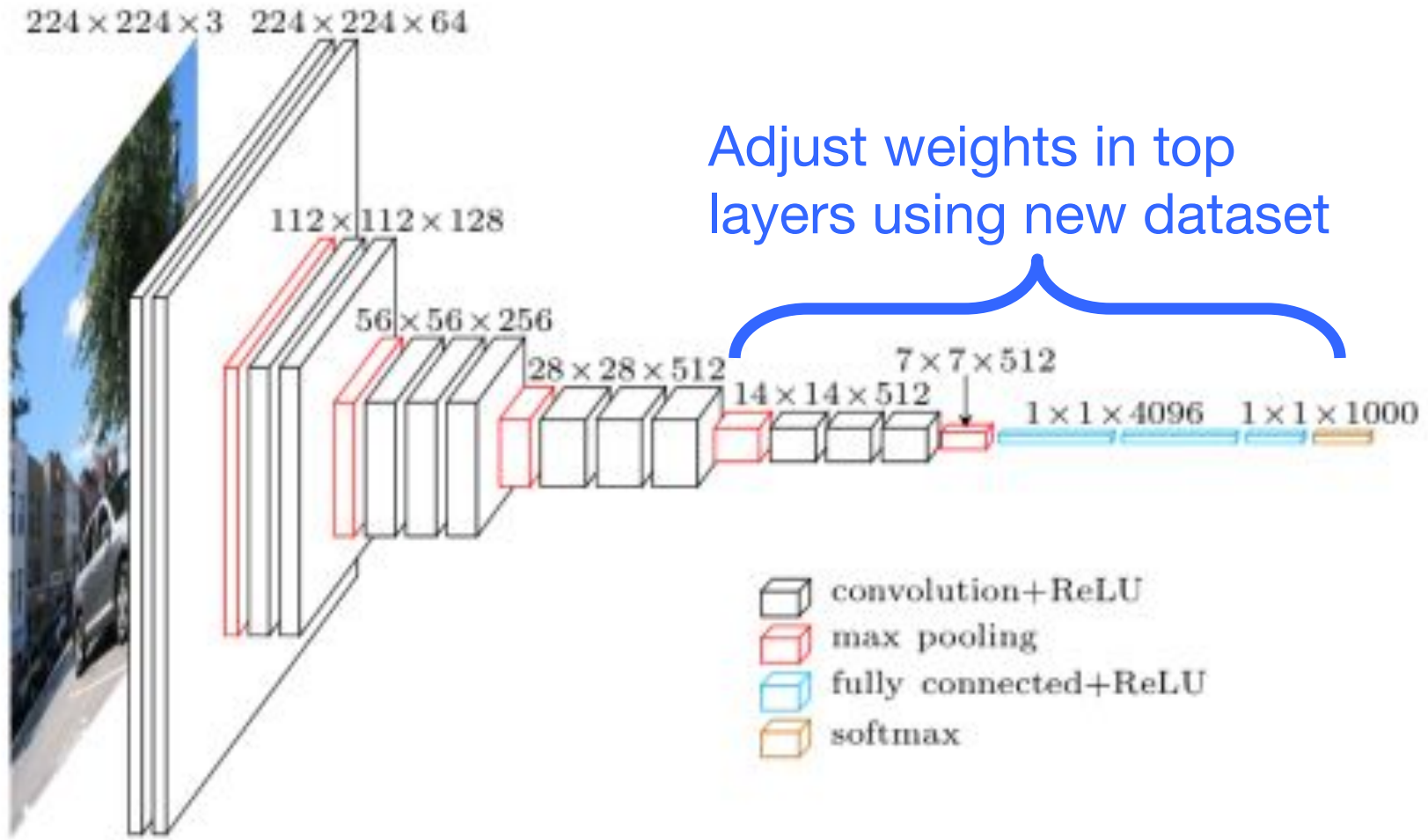
Data

- **In terminal window in Jupyter Lab, do the following**
- **Get counts of images**
  - ls –l ~data/ml/train/cats/* | wc -l
  - ls –l ~data/ml/train/dogs/* | wc -l
  - ls –l ~data/ml/validation/cats/* | wc -l
  - ls –l ~data/ml/validation/dogs/* | wc -l
  - ls –l ~data/ml/test/cats/* | wc -l
  - ls –l ~data/ml/test/dogs/* | wc -l

TRANSFER LEARNING - FINE TUNING

- **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/

Fine Tune Overview

- **Data**
  - Set image dimensions & location
  - Use ImageDataGenerator to read images from folder
- **Model**
  - Load trained model from feature extraction code
  - Freeze weights up to last convolutional block
  - Weights in last convolutional block and top classifier will be adjusted during training
- **Train model**
  - Use training data to adjust model weights
  - Use validation data to determine when to stop training
- **Evaluate model**
  - Calculate accuracy, etc.
  - Perform inference on test images

Code

- **finetune_tf.ipynb**
  - Transfer learning with fine tuning using TensorFlow

- **Note**
  - To avoid out-of-memory errors, before running finetune_tf.ipynb
    - Restart kernel in features_extract_tf.ipynb OR
    - Exit out of features_extract_tf.ipynb

REFERENCES

- **TensorFlow tutorial**
  - https://github.com/tensorflow/docs/blob/master/site/en/tutorials/images/transfer_learning.ipynb
- **TensorFlow/Keras API**
  - https://www.tensorflow.org/api_docs/python/tf/keras/Model
- **Transfer Learning**
  - http://cs231n.github.io/transfer-learning/