Advanced Section #5: Transfer Learning

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CS109B Data Science 2

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TRANSFER LEARNING
WHAT SOCIETY THINKS I DO
WHAT MY FRIENDS THINK I DO
WHAT INVESTORS THINK I DO
WHAT MY MOM THINKS I DO
I'm going to learn jujitsu?
WHAT I THOUGHT I'LL DO
Transfer Learning using Mobilenet and Keras
WHAT I ACTUALLY DO
imgflip.com

Outline

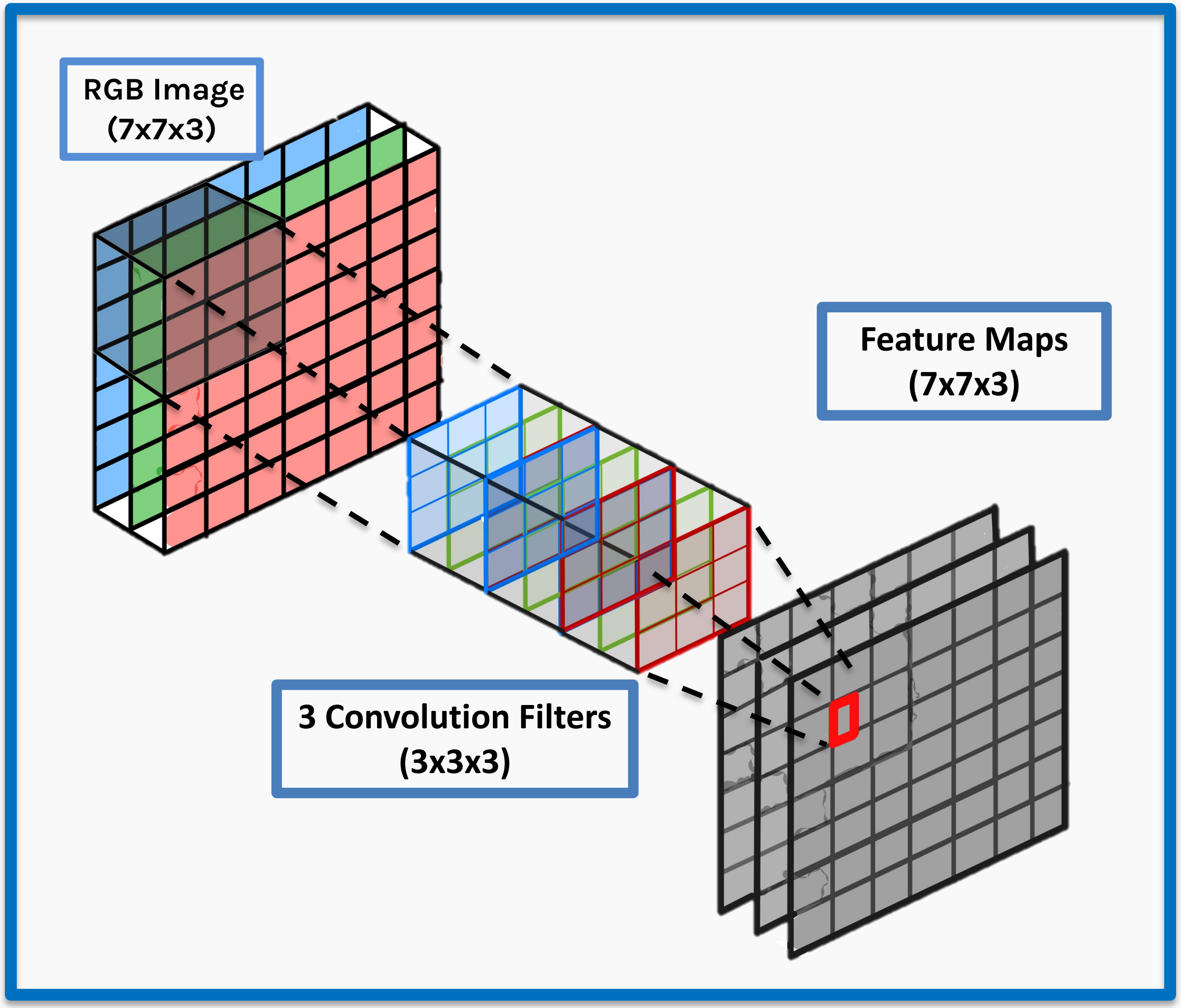
1. Motivation
2. The Basics idea for Transfer Learning
3. Representation Learning
4. Transfer Learning Strategies
5. Transfer Learning for Deep Learning

CNNs: “Convolution” Operation

A convolutional neural network typically consists of feature extracting layers and condensing layers.

The feature extracting layers are called convolutional layers & each node in these layers uses a small fixed set of weights to transform the image in the way below.

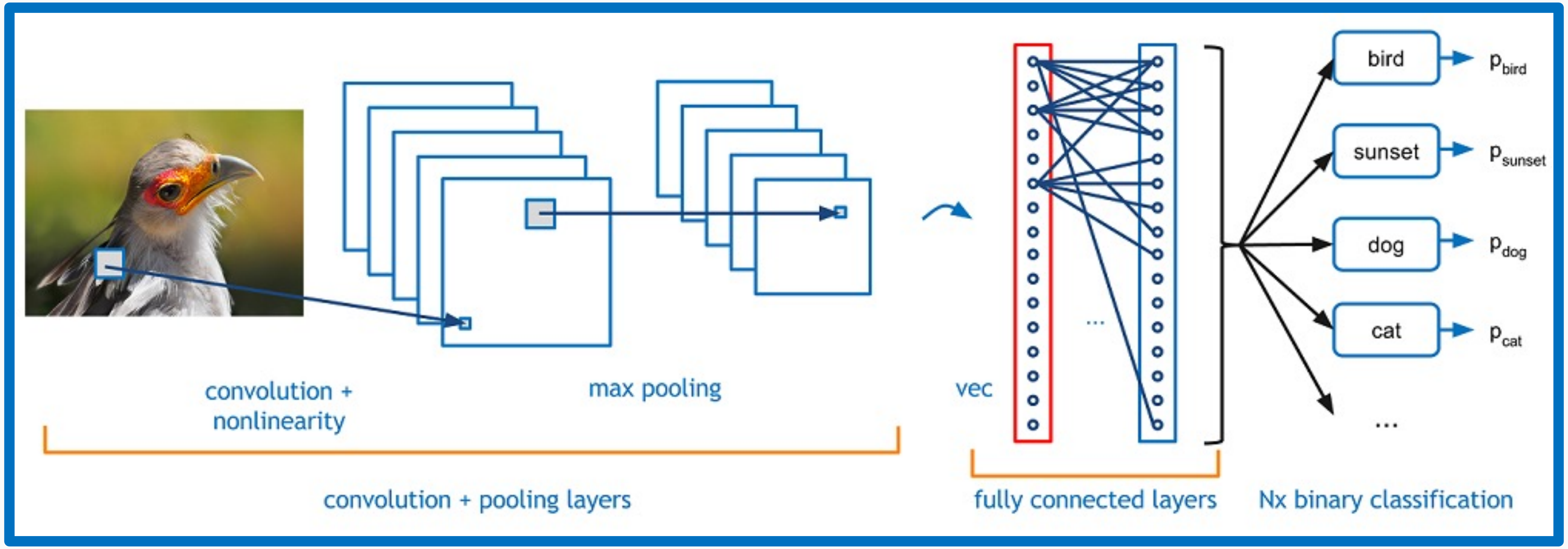
This set of fixed weights for each node in the convolutional layer is often called a filter.



CNNs: Feature Extraction

Rather than processing image data with a pre-determined set of filters, we want to learn the filters of a CNN for feature extraction. Our goal is to extract features that best helps us to perform our downstream task (e.g. classification).

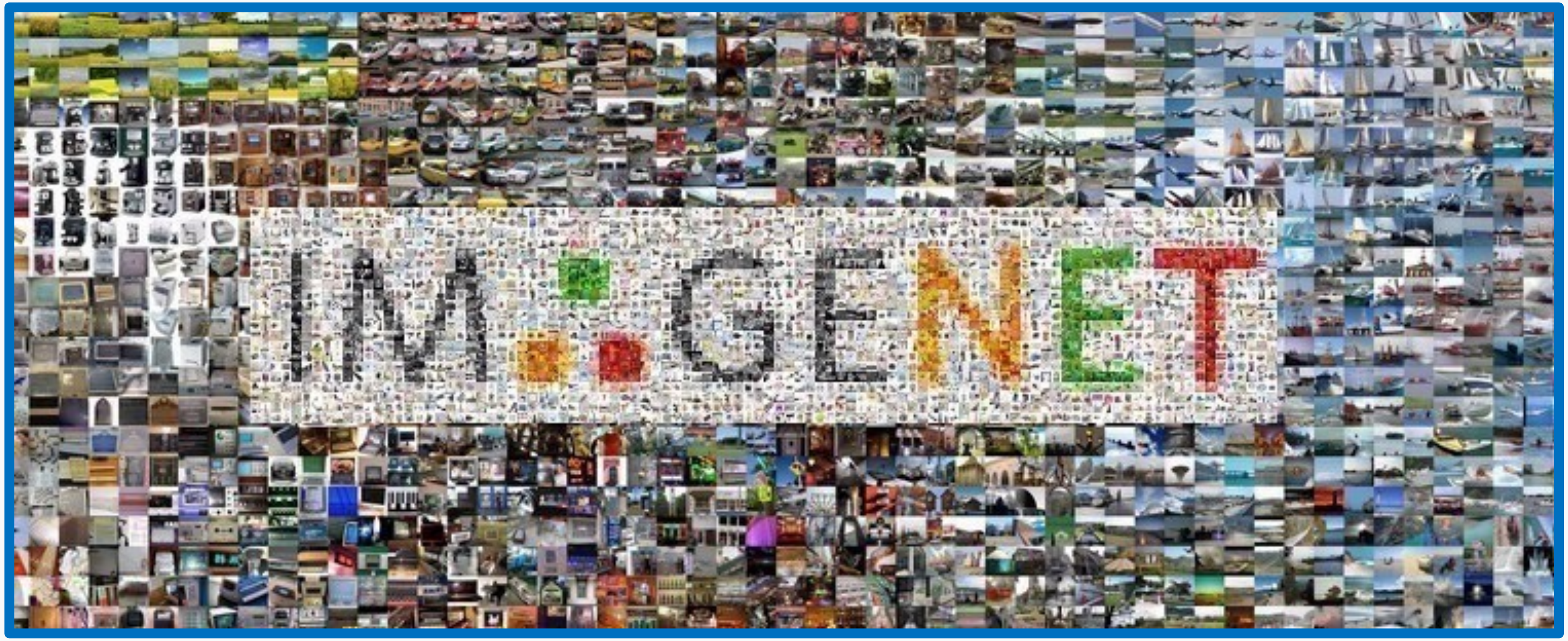
Idea:
We train a CNN for feature extraction and a model (e.g. MLP, decision tree, logistic regression) for classification, simultaneously and end-to-end.



IMAGENET challenge

- A large visual database designed for use in visual object recognition software research

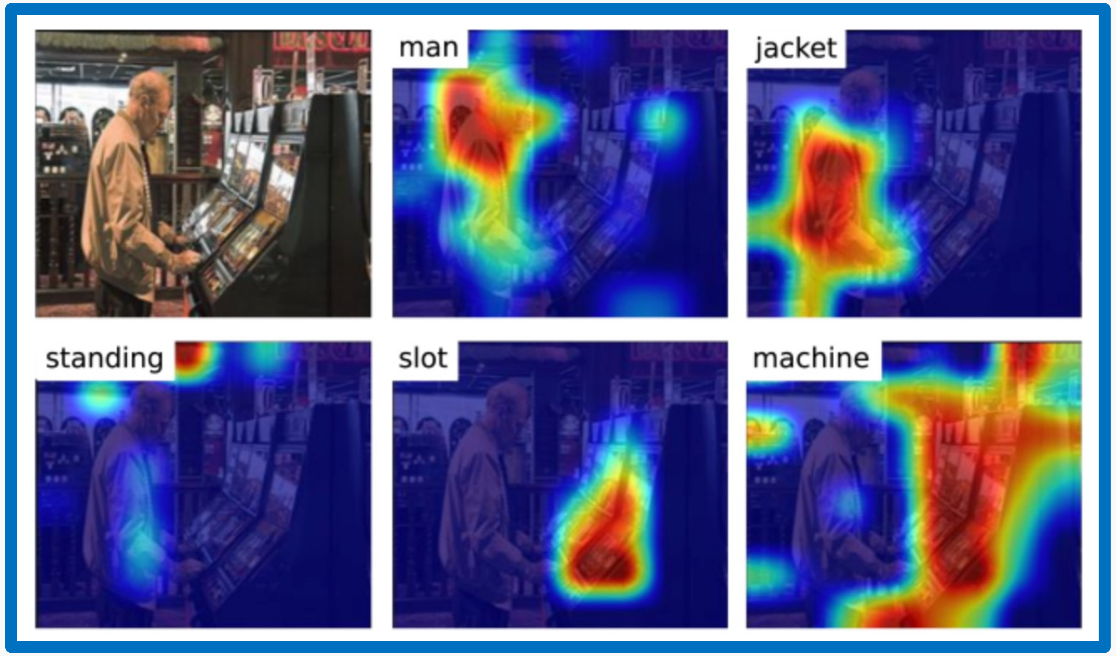
- More than 14 million images have been hand-annotated by the project to indicate what objects are pictured and in at least one million of the images, bounding boxes are also provided

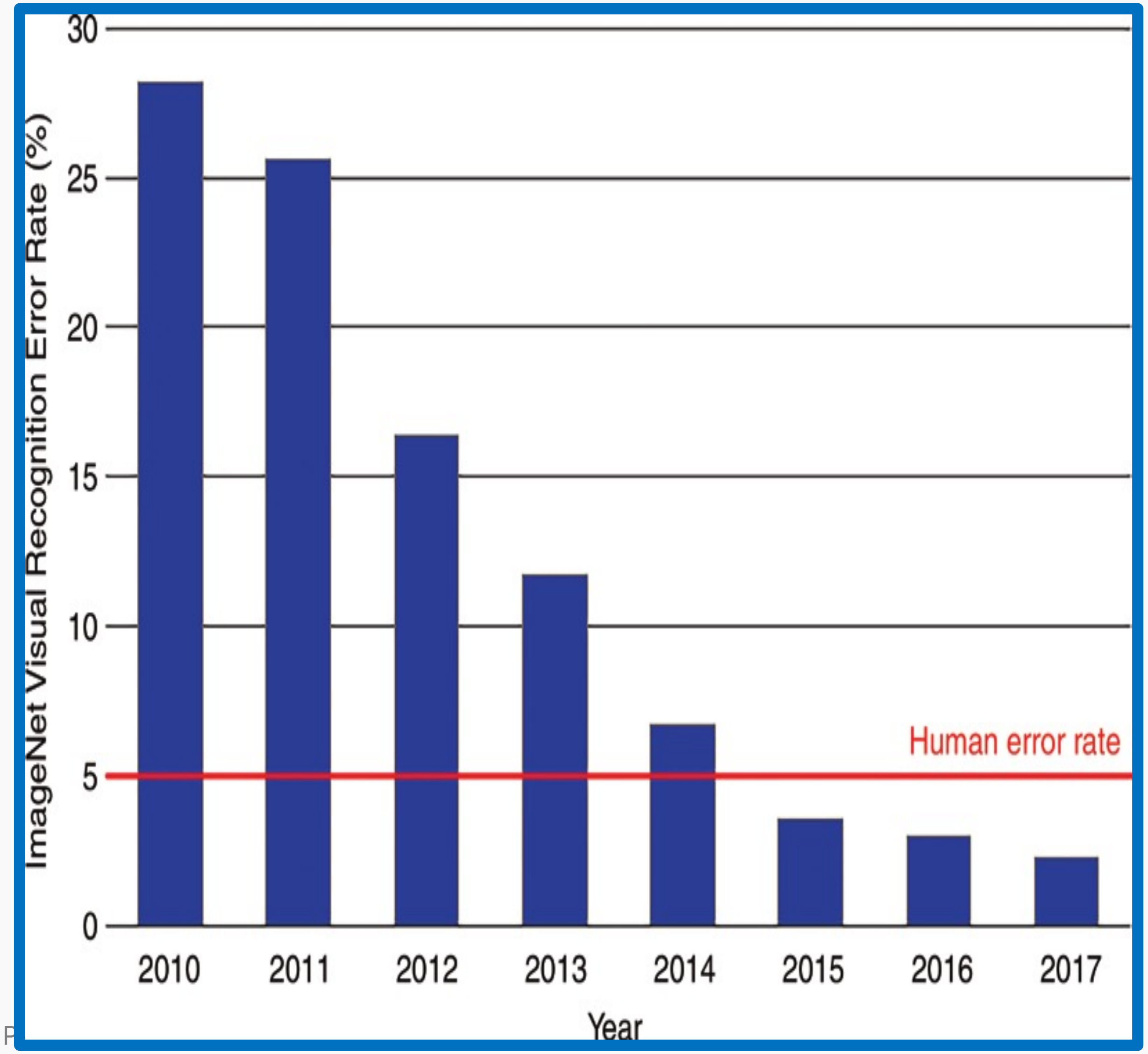


CNNs: Successful object detection

IMAGENET challenge:

- New model architectures consistently outperform even human error rate
- Ablation studies and saliency maps and confirm models are not overfitting





CNNs: So what is the problem?

- IMAGENET has more than a 14 million label images and more than 1000 categories.
- However, the imagenet challenge is only a very tiny subset of all possible categories for which we may not have a lot of training data.
- Eg. Can you guess the animals in the images below?



Classify Rarest Animals

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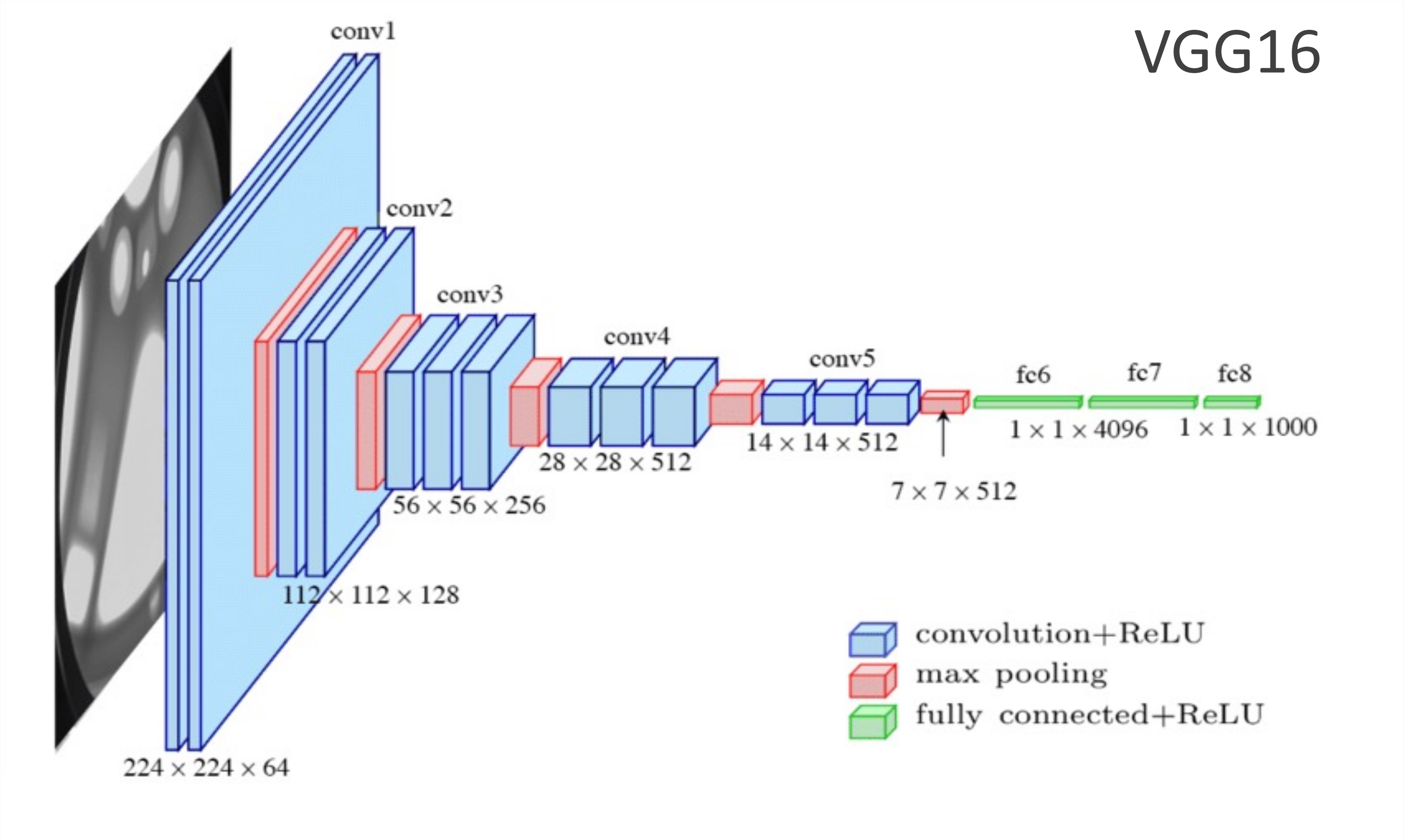

Number of parameters: 134,268,737
Data Set: Few hundred images

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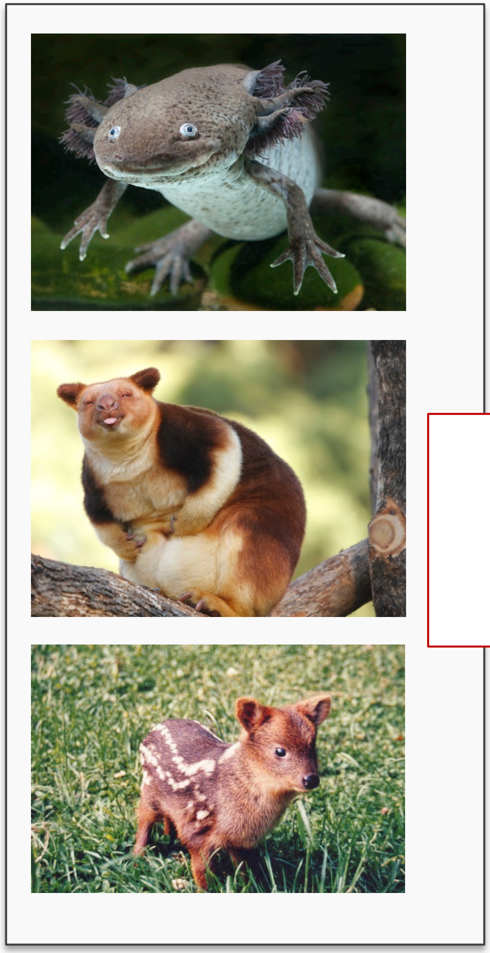

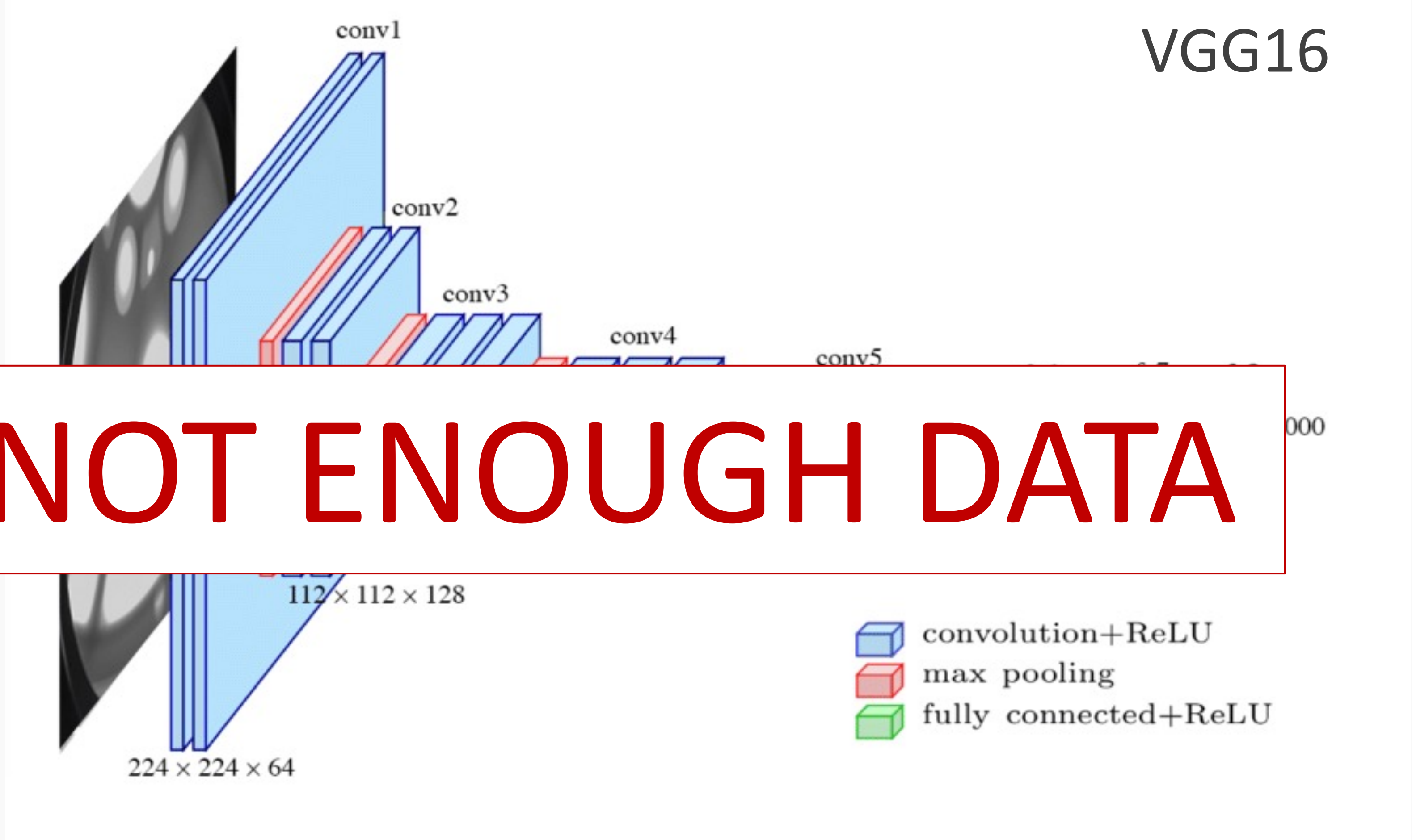

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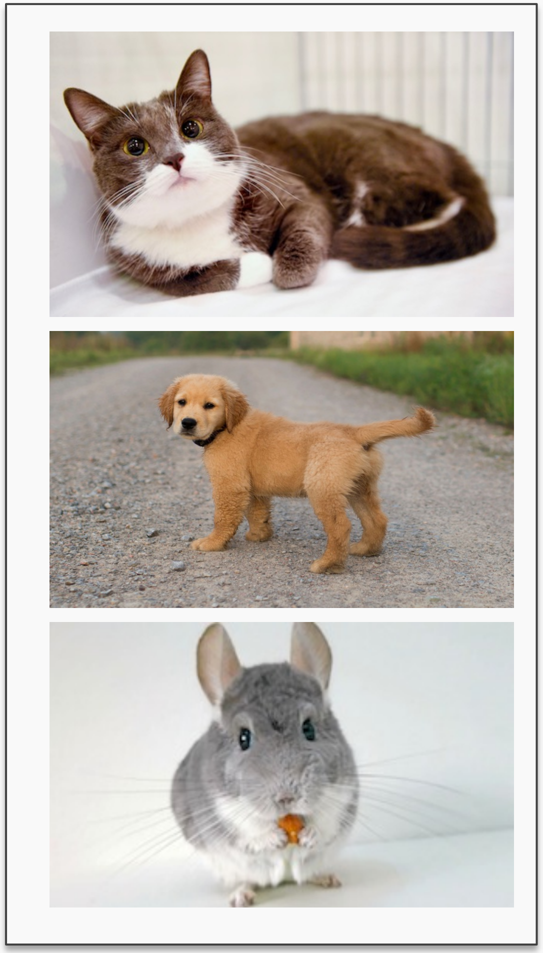
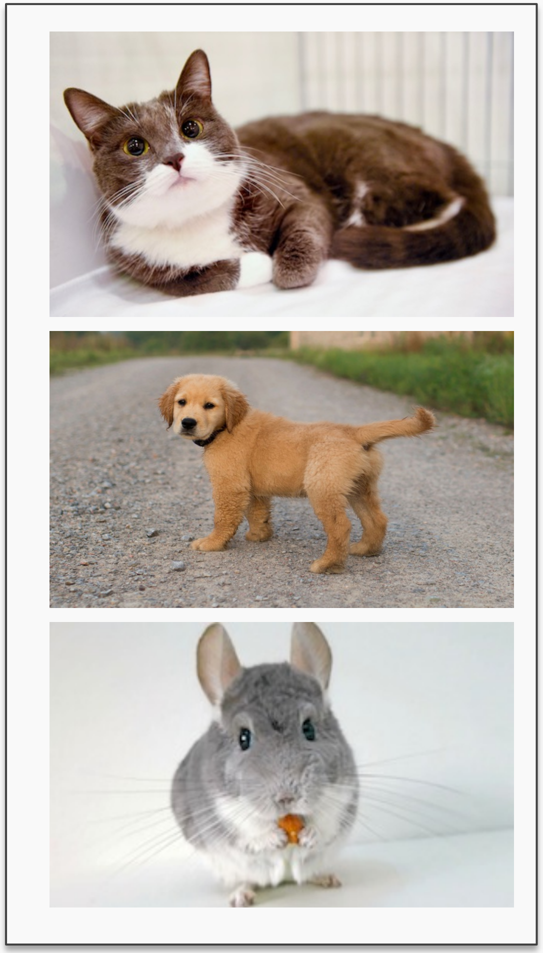
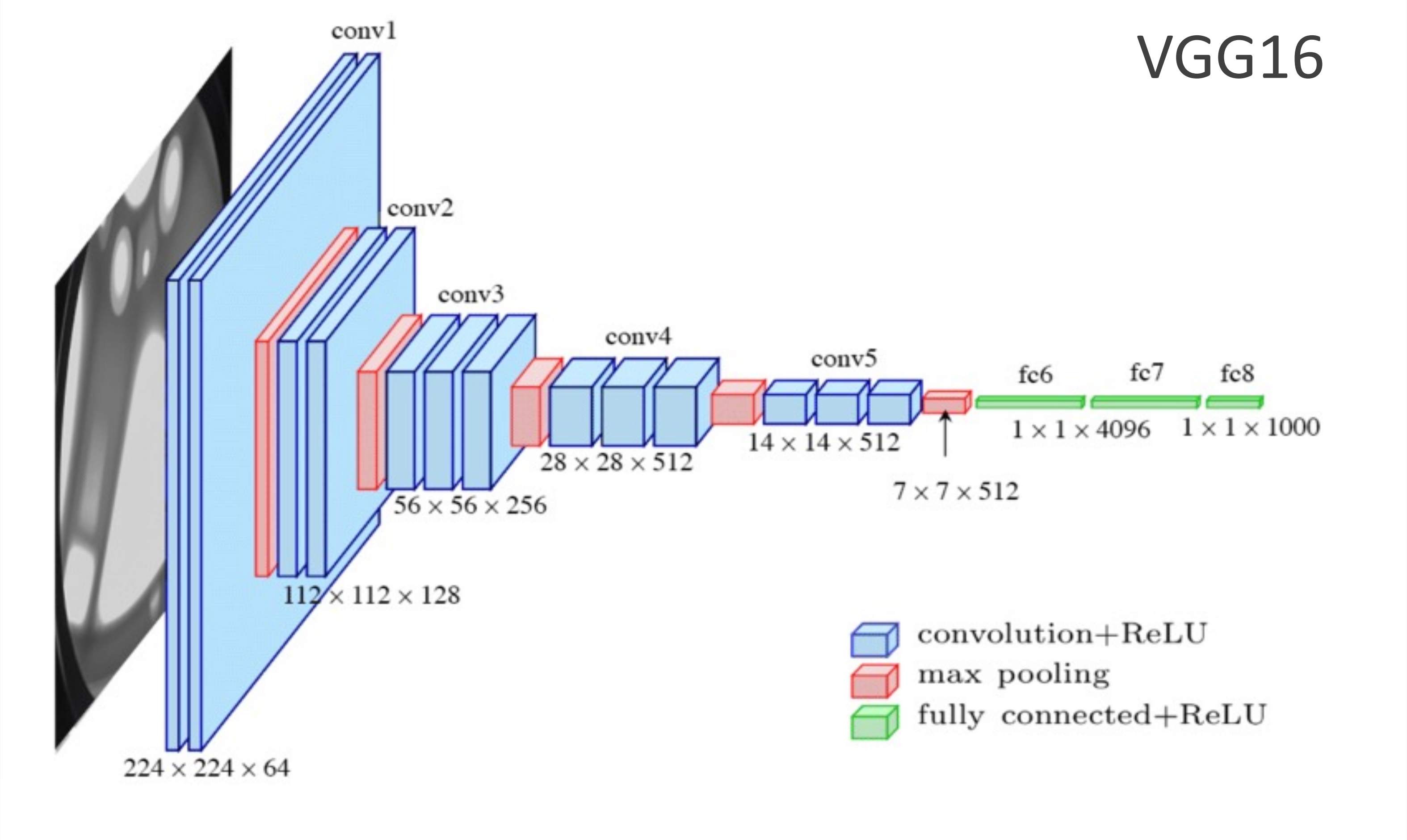
Classify Cats, Dogs, Chinchillas etc



VGG16

Classify Cats, Dogs, Chinchillas etc





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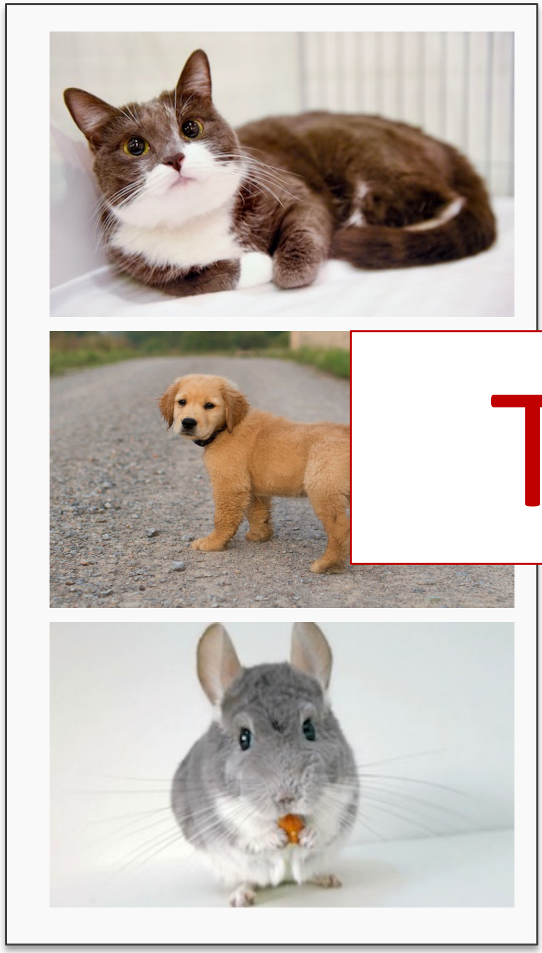
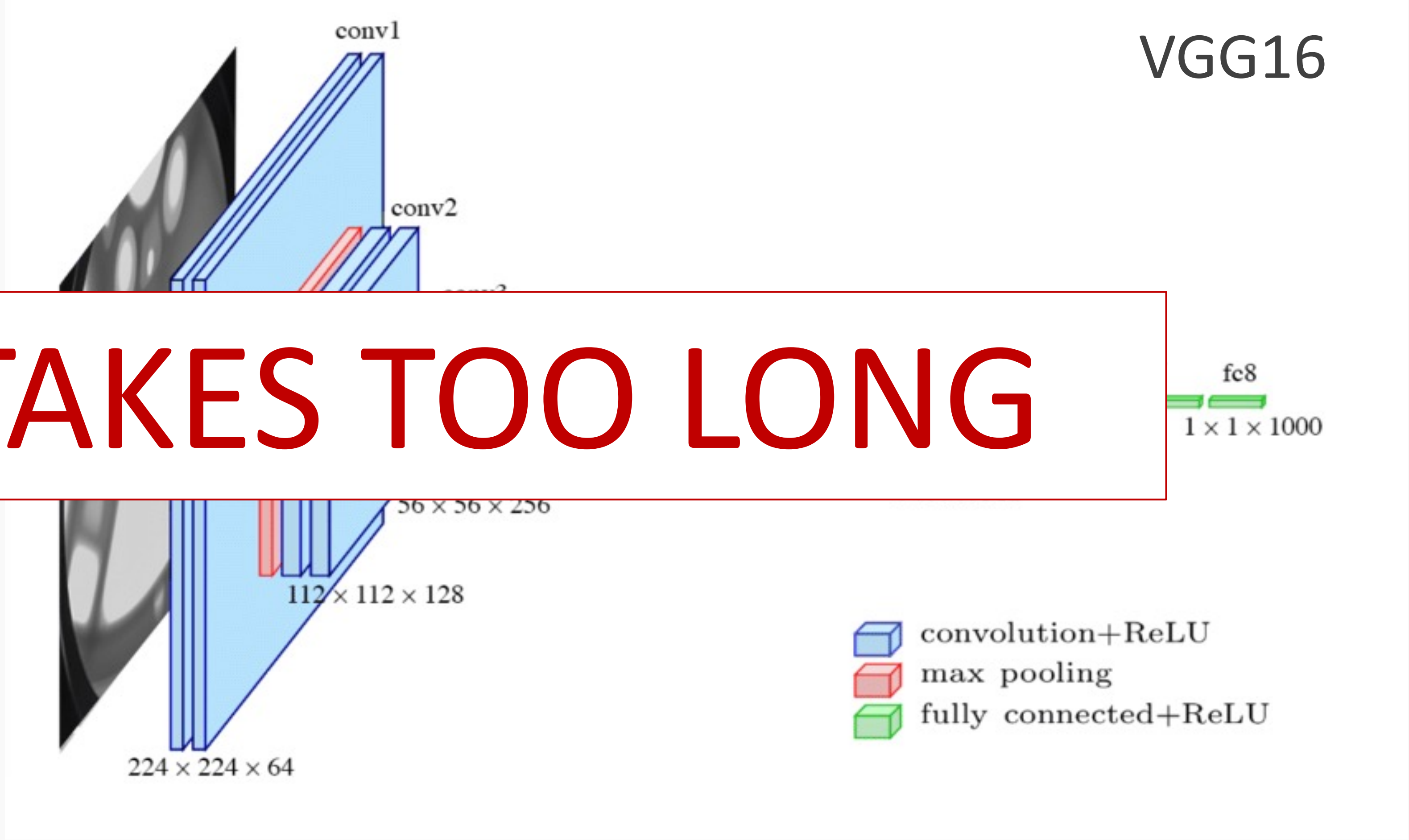


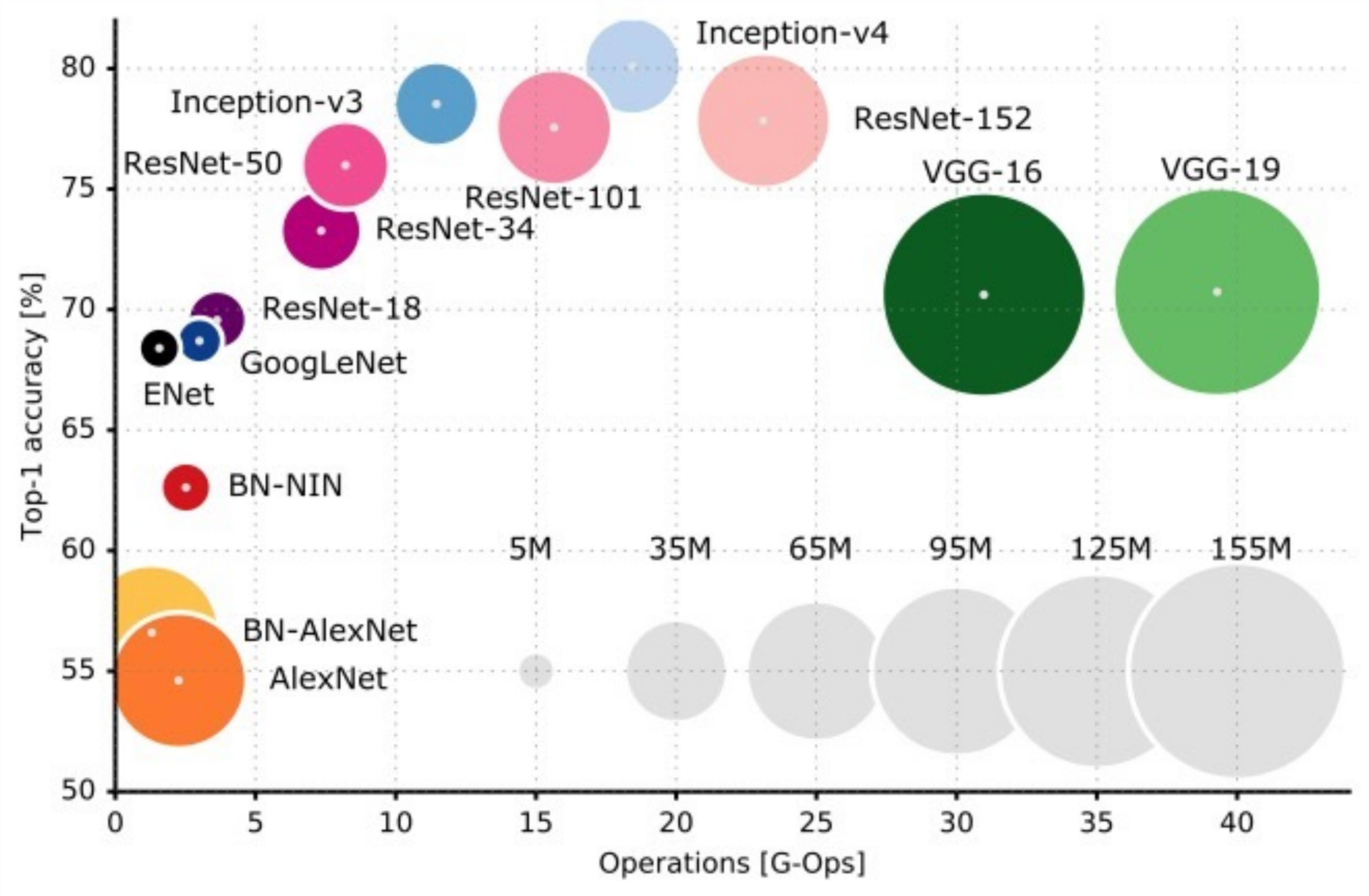


TAKES TOO LONG

Number of parameters: 134,268,737

Enough training data. ImageNet approximate 1.2M

Training time for SOTAs



Transfer Learning To The Rescue

How do you build an image classifier that can be trained in a few minutes on a CPU with very little data?

?

Basic idea of Transfer Learning

Wikipedia:

Transfer learning (TL) is a research problem in machine learning (ML) that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem.[1]

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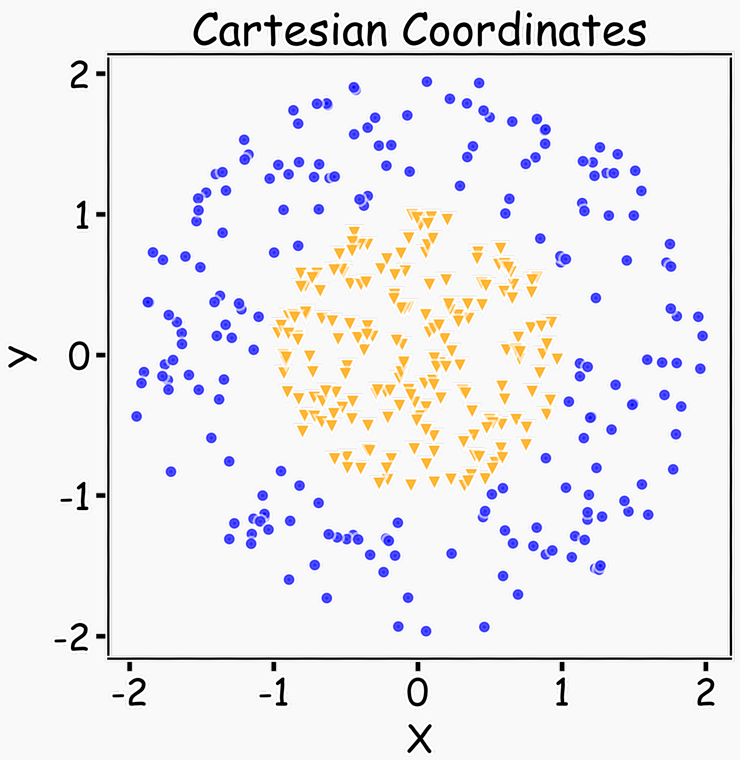
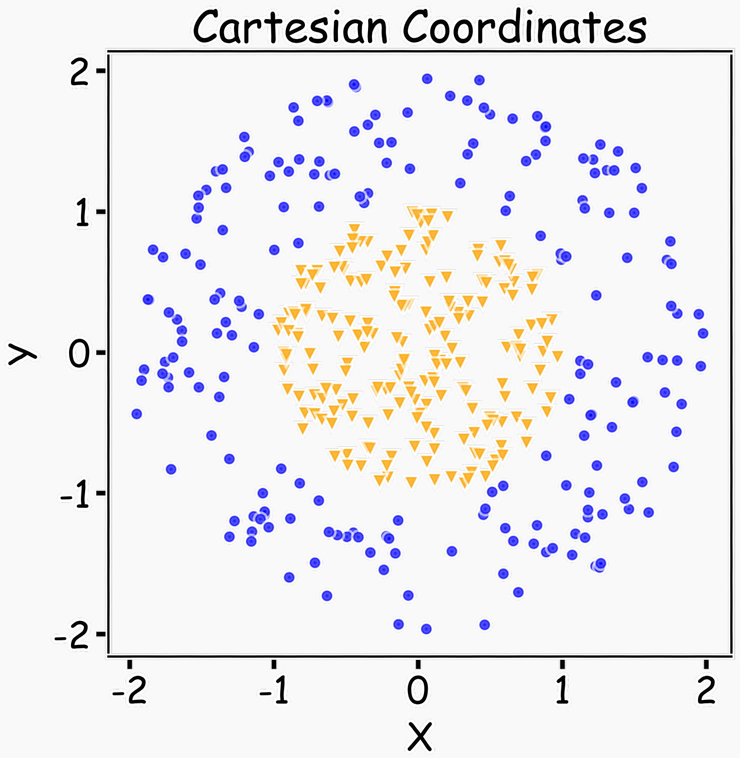


Key Idea: Representation Learning

Relatively difficult task



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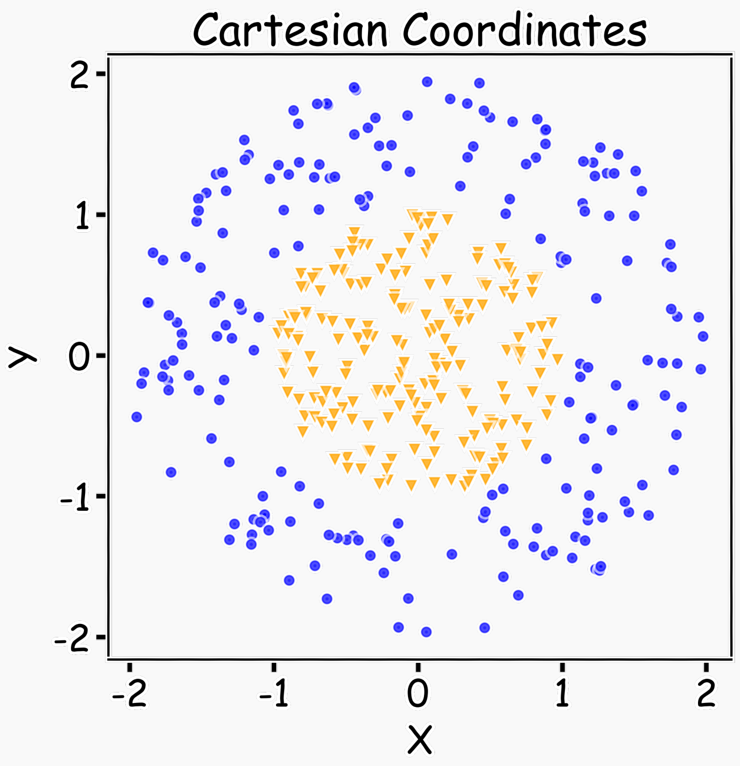
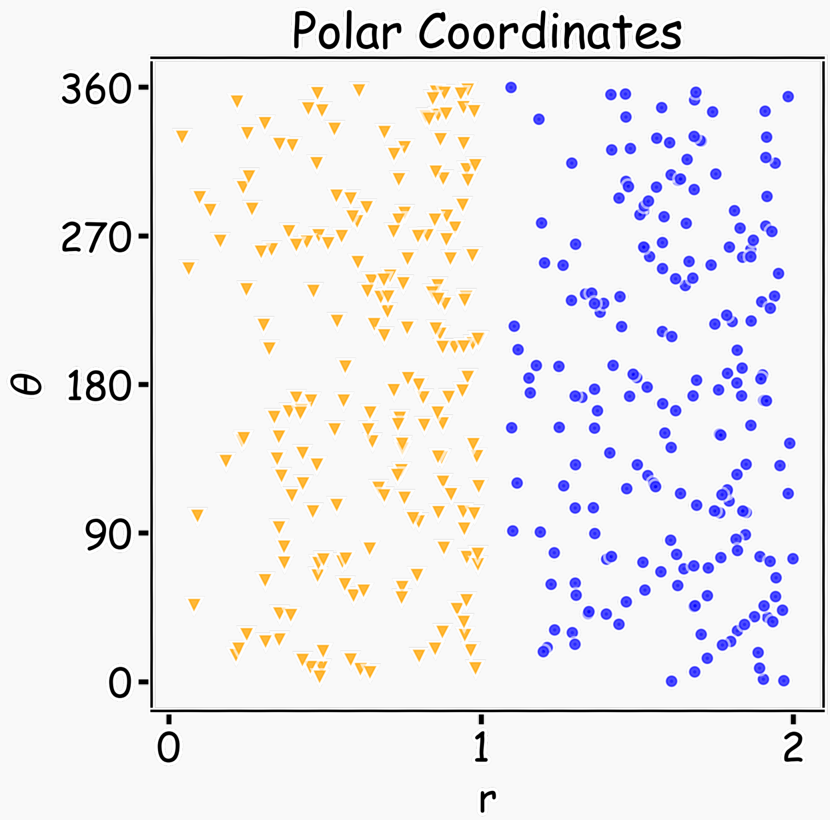


Tranform:
$(X, Y) \rightarrow (r, \theta)$



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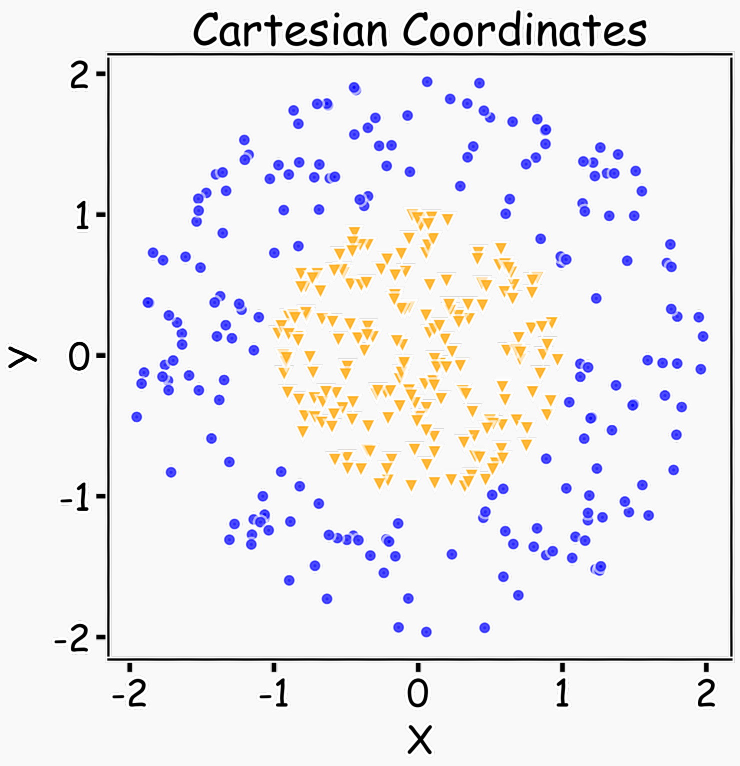

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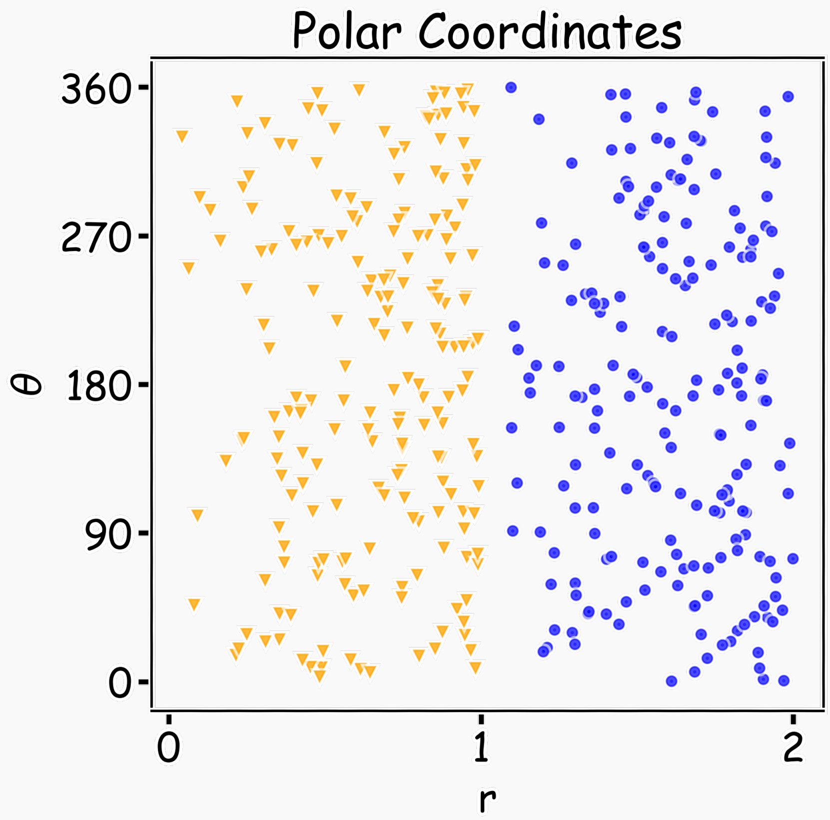
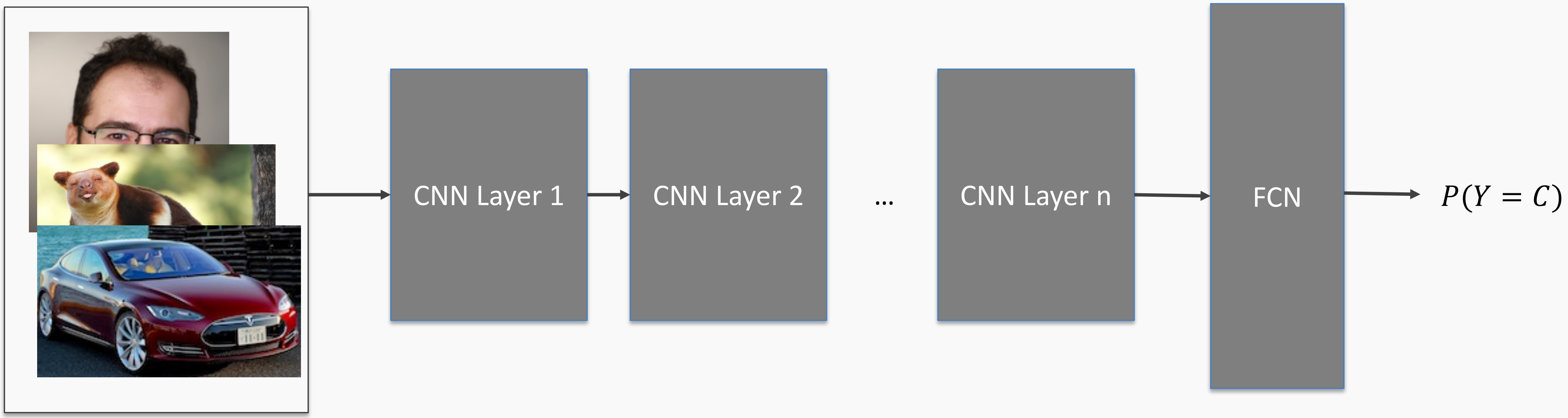
Easier task



Representation Learning

Task: classify cars, people, animals and objects



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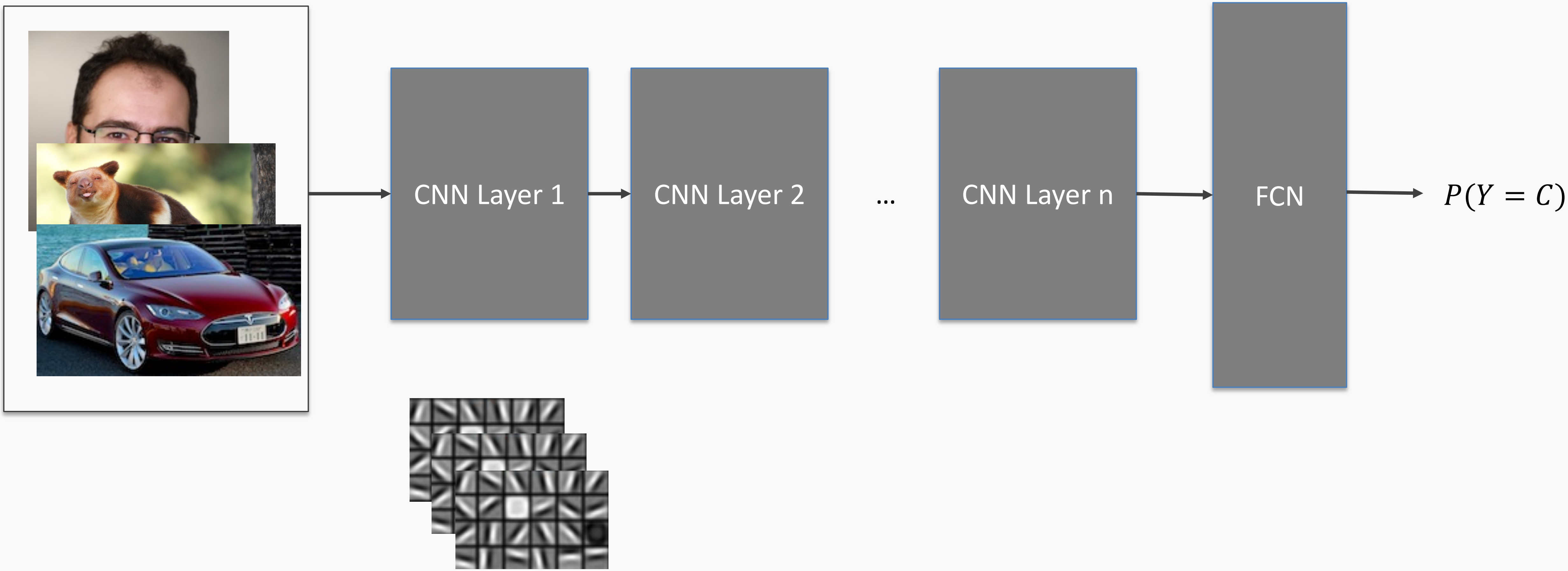

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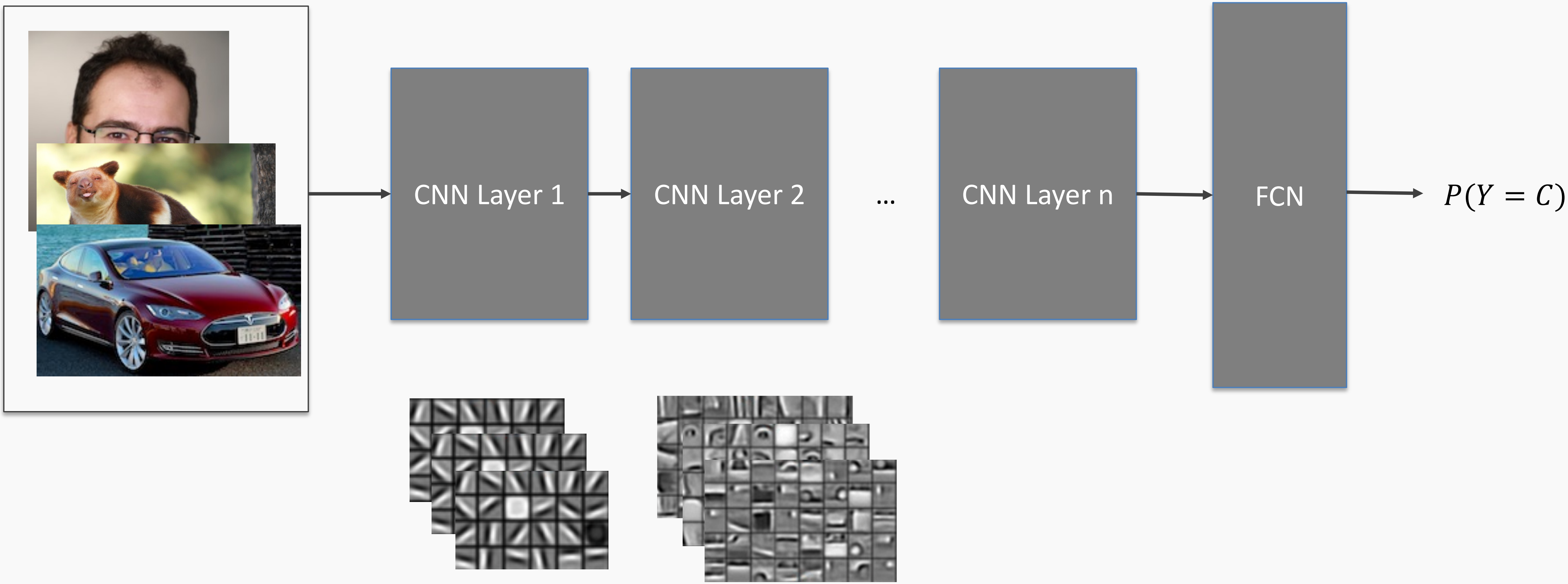

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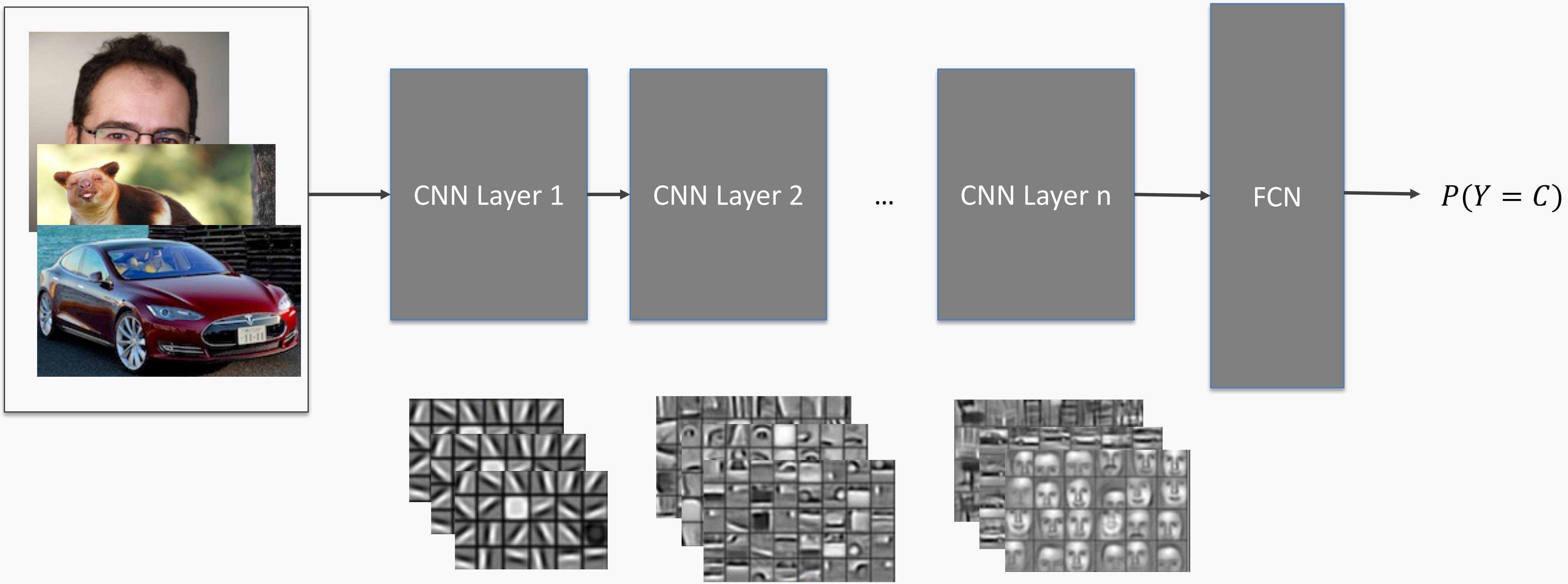

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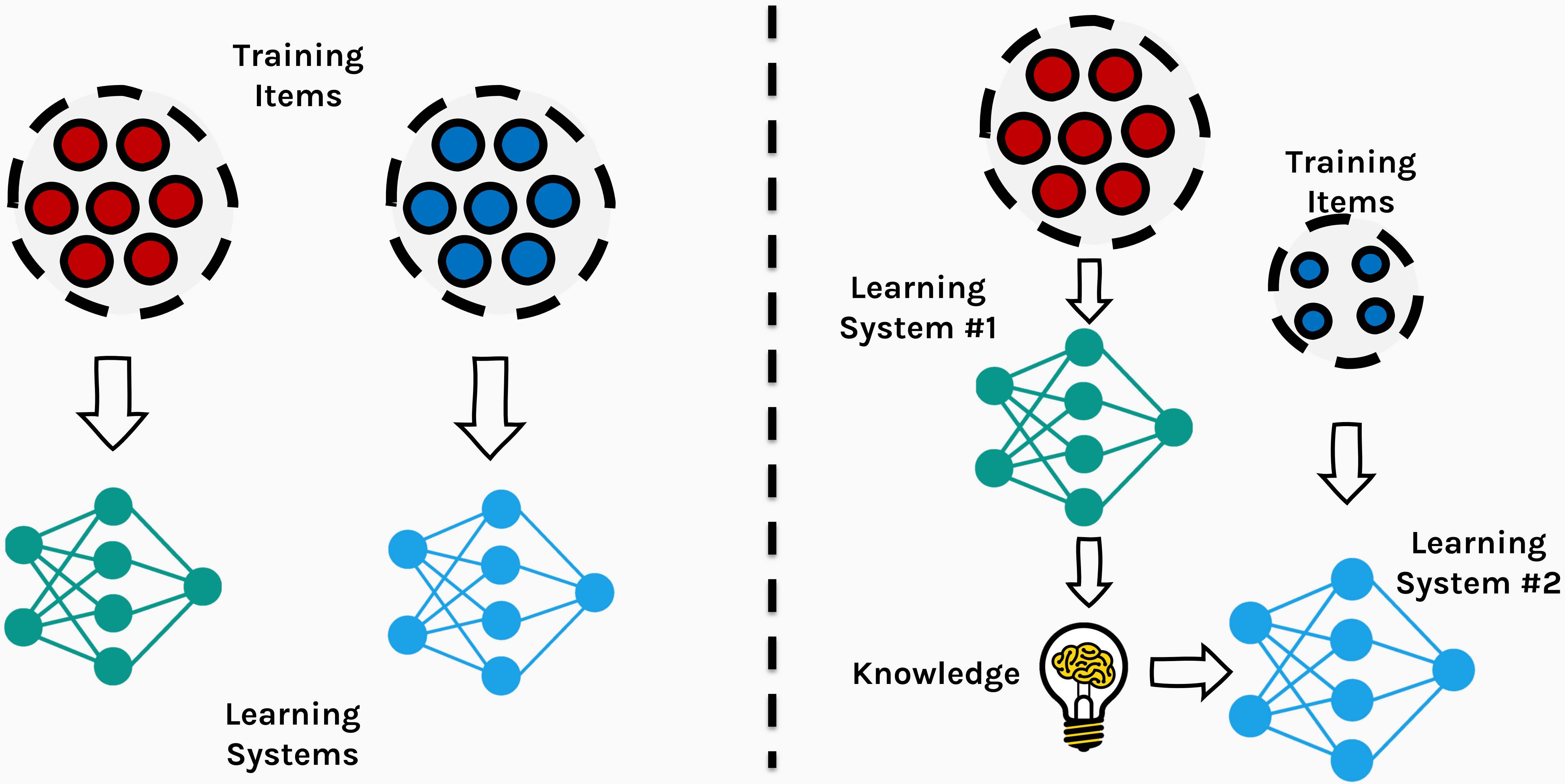
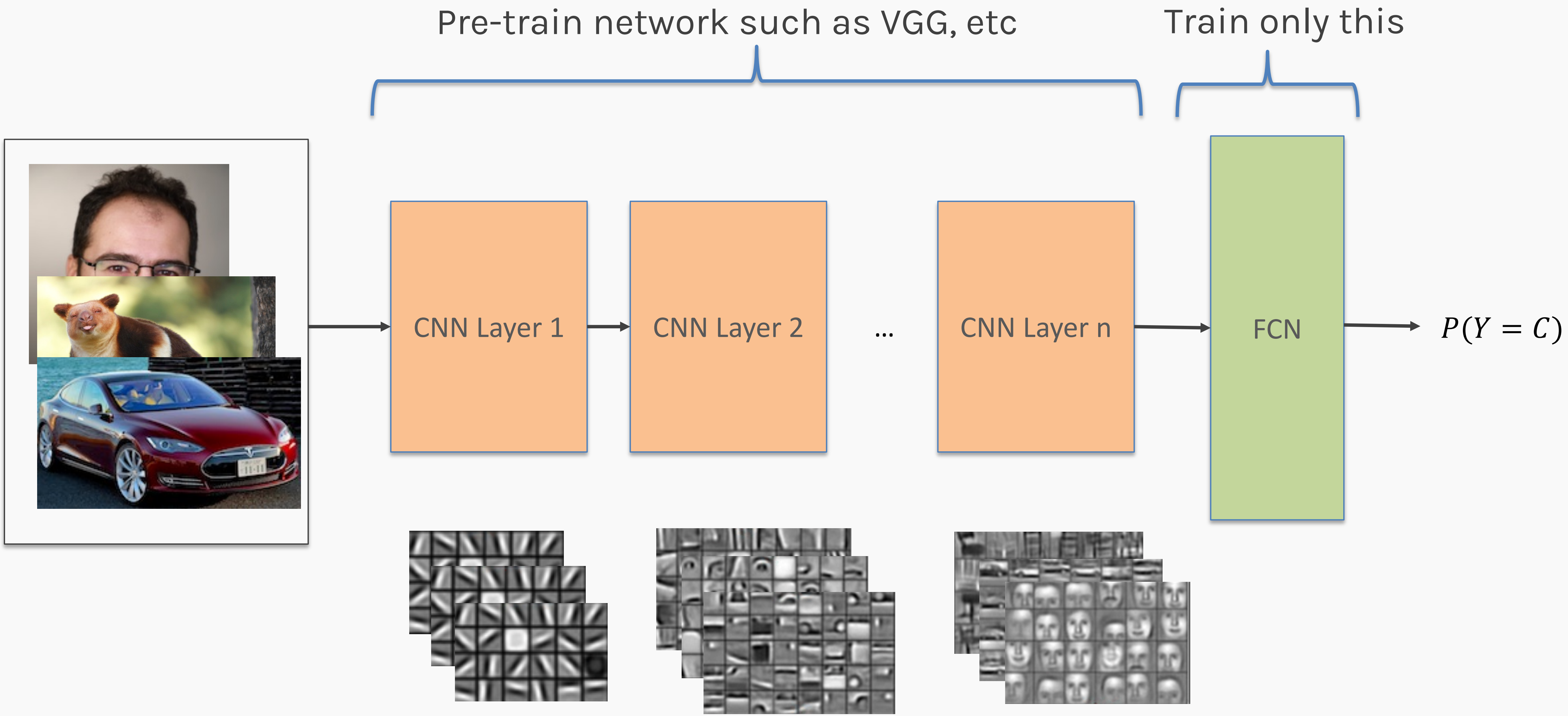
Example: use ImageNet trained with any sophisticated huge network. Then retrain it on a few images.

Traditional Machine Learning vs Transfer Learning



Transfer Learning



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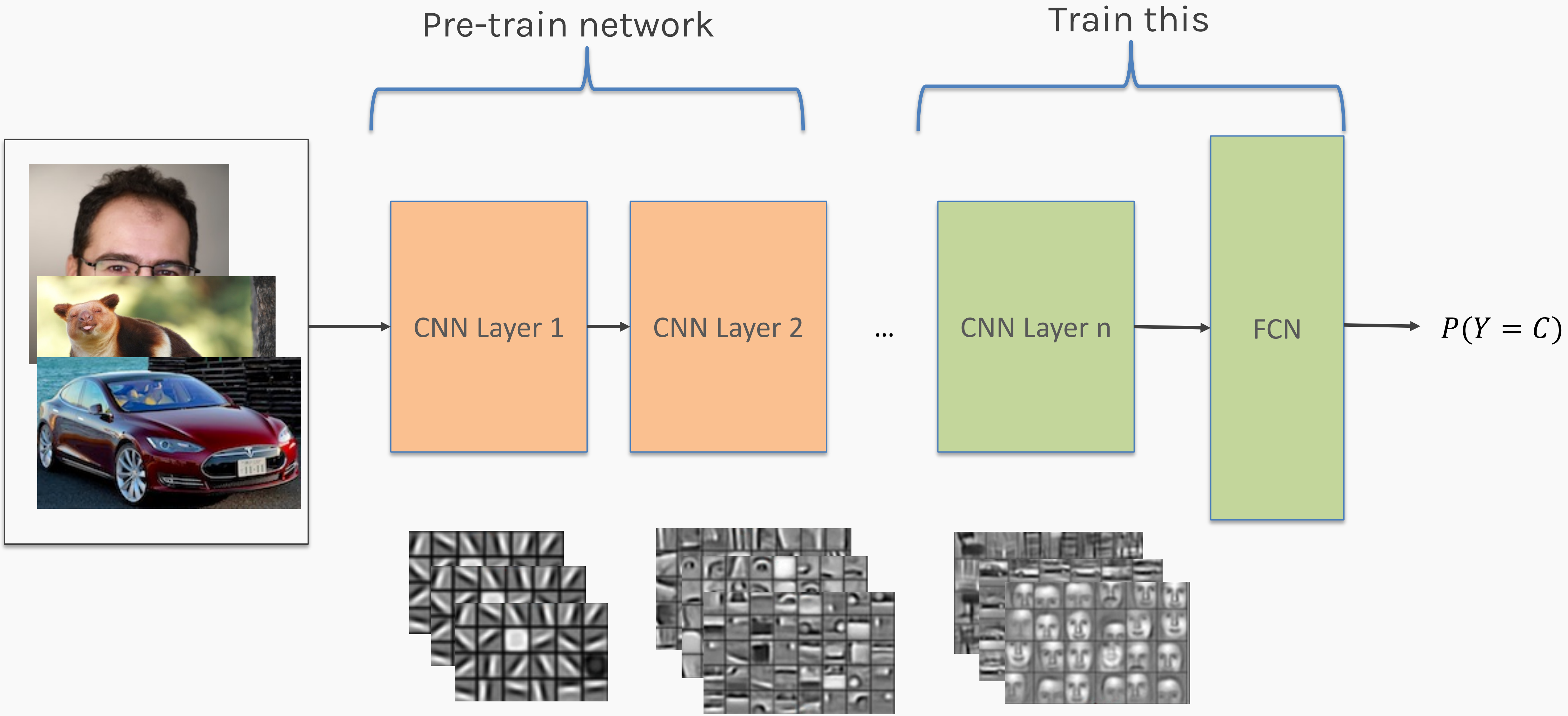
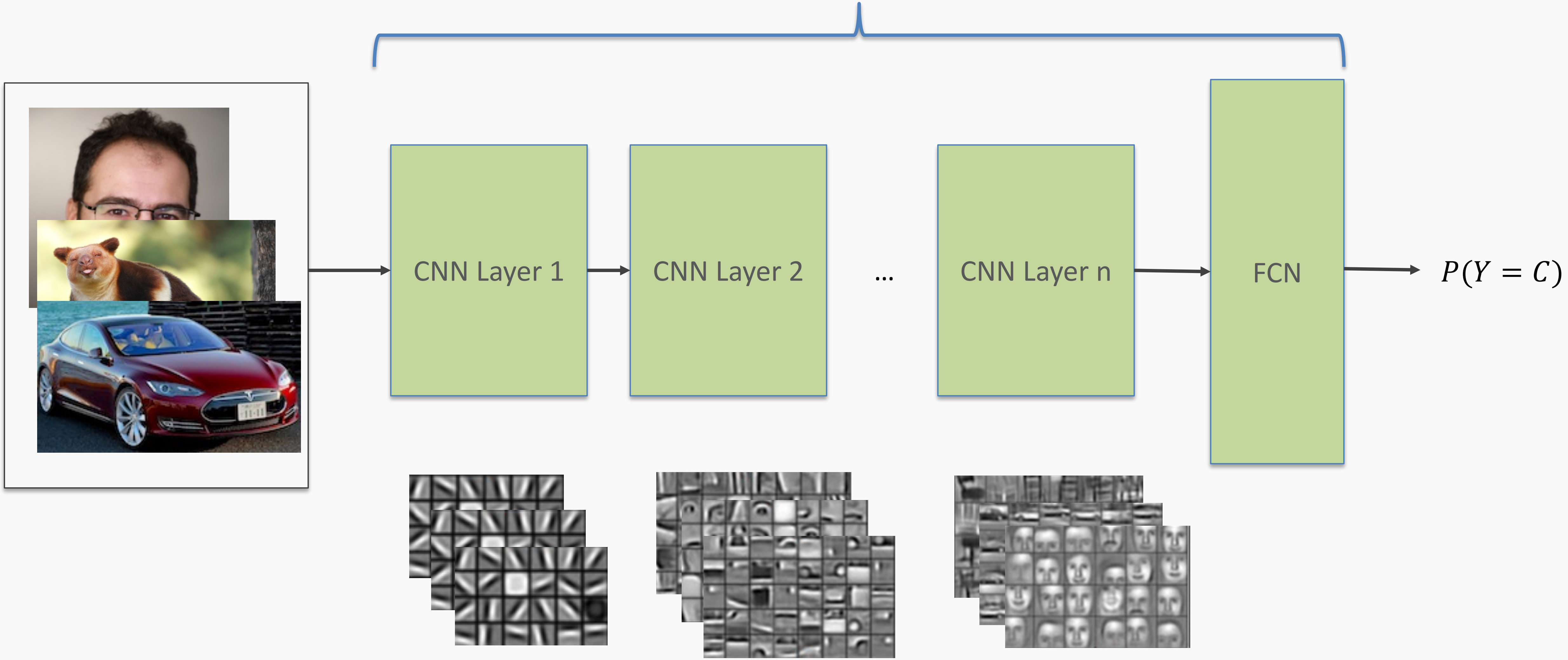


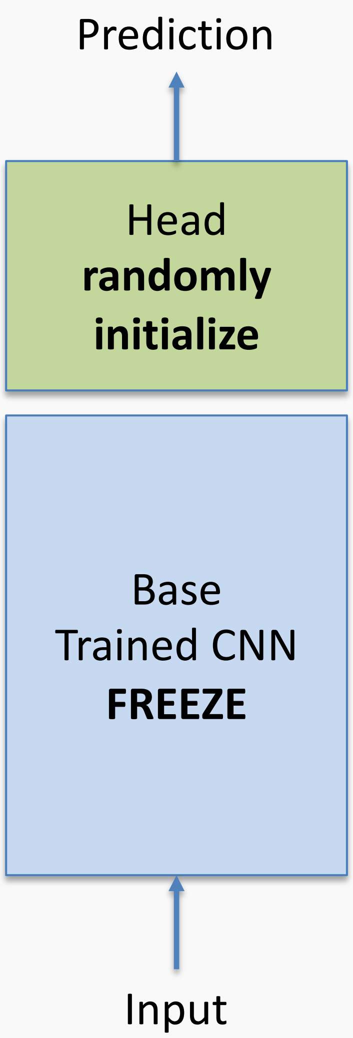
Transfer Learning – fine tuning

Train everything but start with weights that are trained already



Feature-Representation Extraction

Use representations learned by big net to extract features from new samples, which are then fed to a new classifier:



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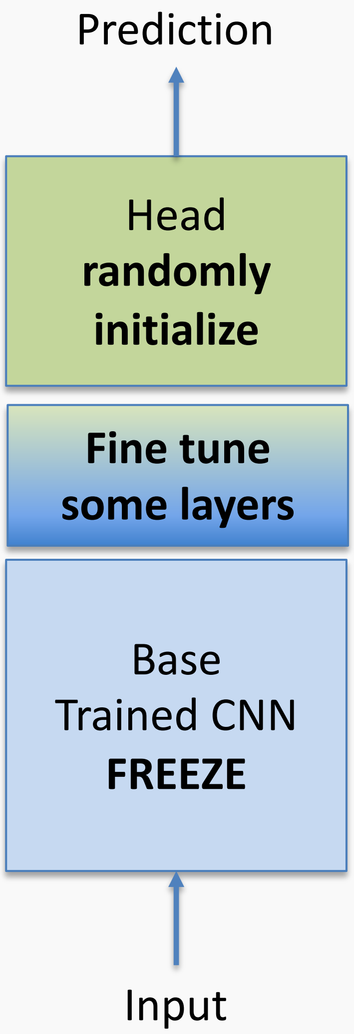
- Keep (frozen) convolutional **base** from big model.
- Generally, throw away **head** FC layers since these have no notion of space, and convolutional base is more generic.
- If the tasks includes the same classes, you could get **away** with using the head FC layers as well (instance TL) since there are both datasets include dogs and cats. But by throwing it away you can learn more from other dog/cat images.

Fine-tuning

Up to now we have frozen the entire convolutional base.



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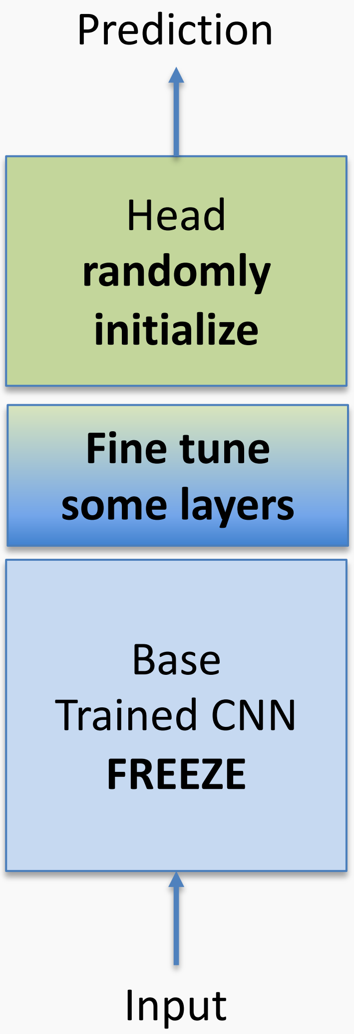

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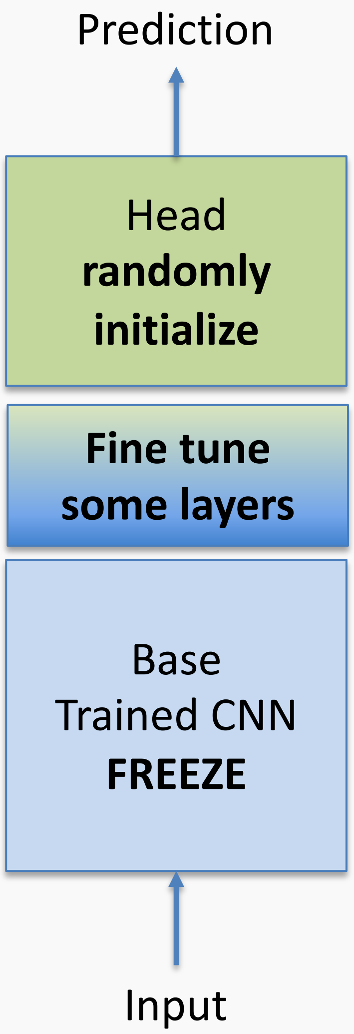
- Later layers learn abstract concepts (dog's ear).
- To particularize the model to our task, its often worth tuning the later layers as well.



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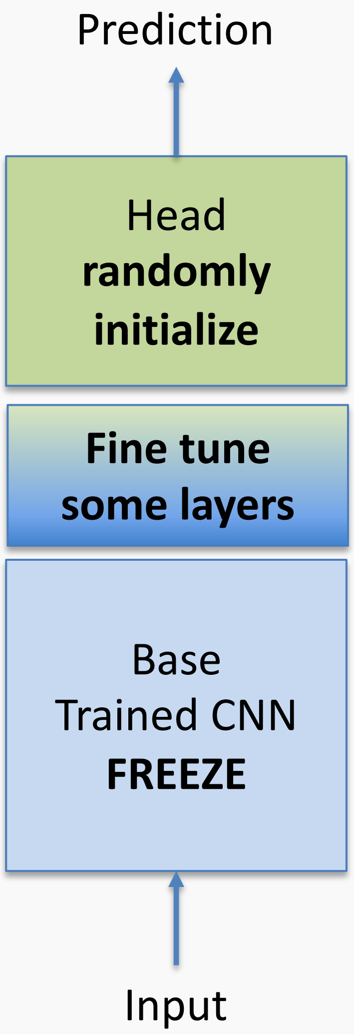
- To particularize the model to our task, its often worth tuning the later layers as well.
- But we must be very careful not to have big gradient updates.



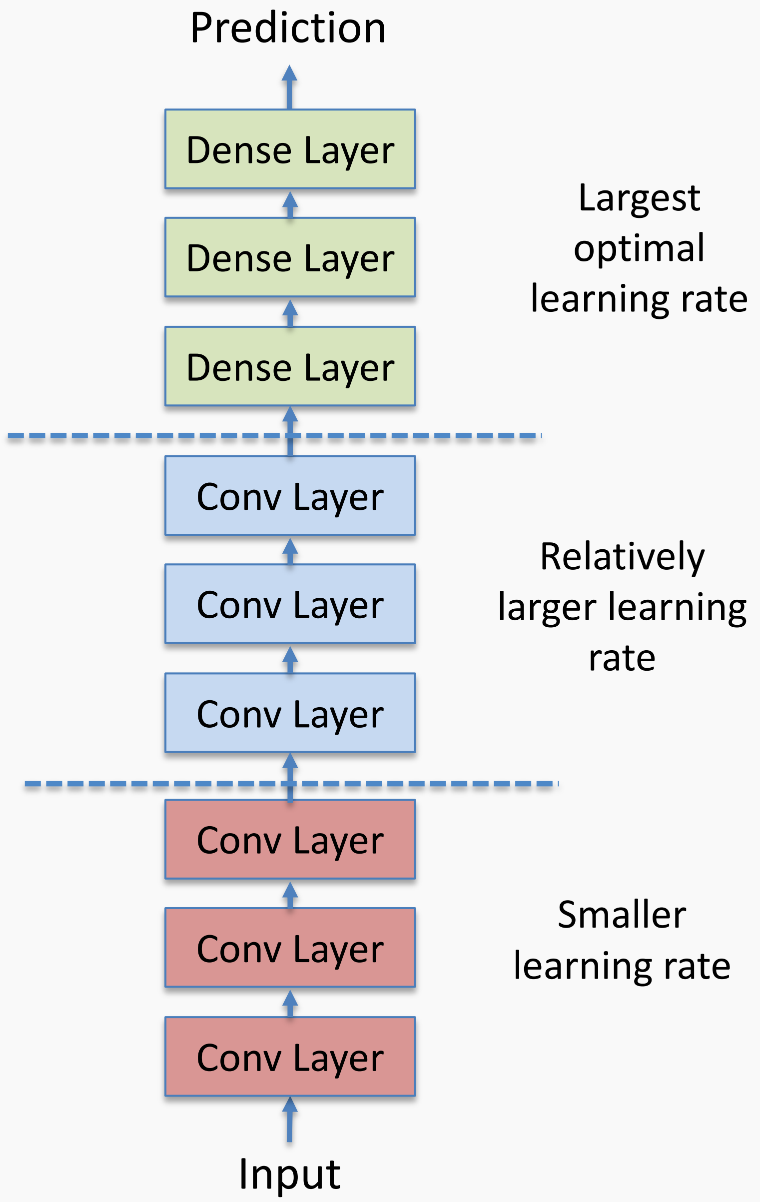
Procedure for Fine-tuning

1. Freeze the convolutional base.
2. First train the fully connected head you added, keeping the convolutional base fixed.
3. Unfreeze some "later" layers in the base net and now train the base net and FC net together.

Since you are now in a better part of the loss surface already, gradients won't be terribly high, but we still need to be careful. Thus, often we use a **very low learning rate**.

Transfer Learning for Deep Learning: Differential Learning Rates

- A low learning rate can take a lot of time to train on the "later" layers. Since we trained the FC head earlier, we could probably retrain them at a higher learning rate.



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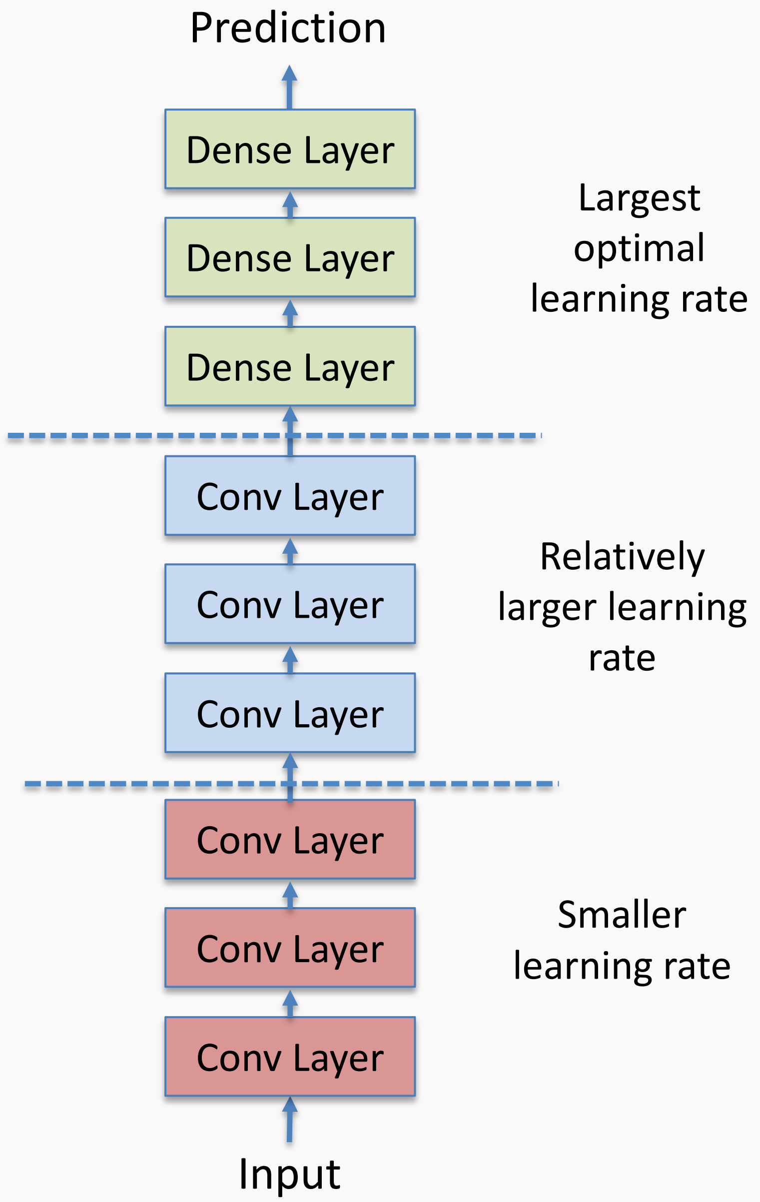

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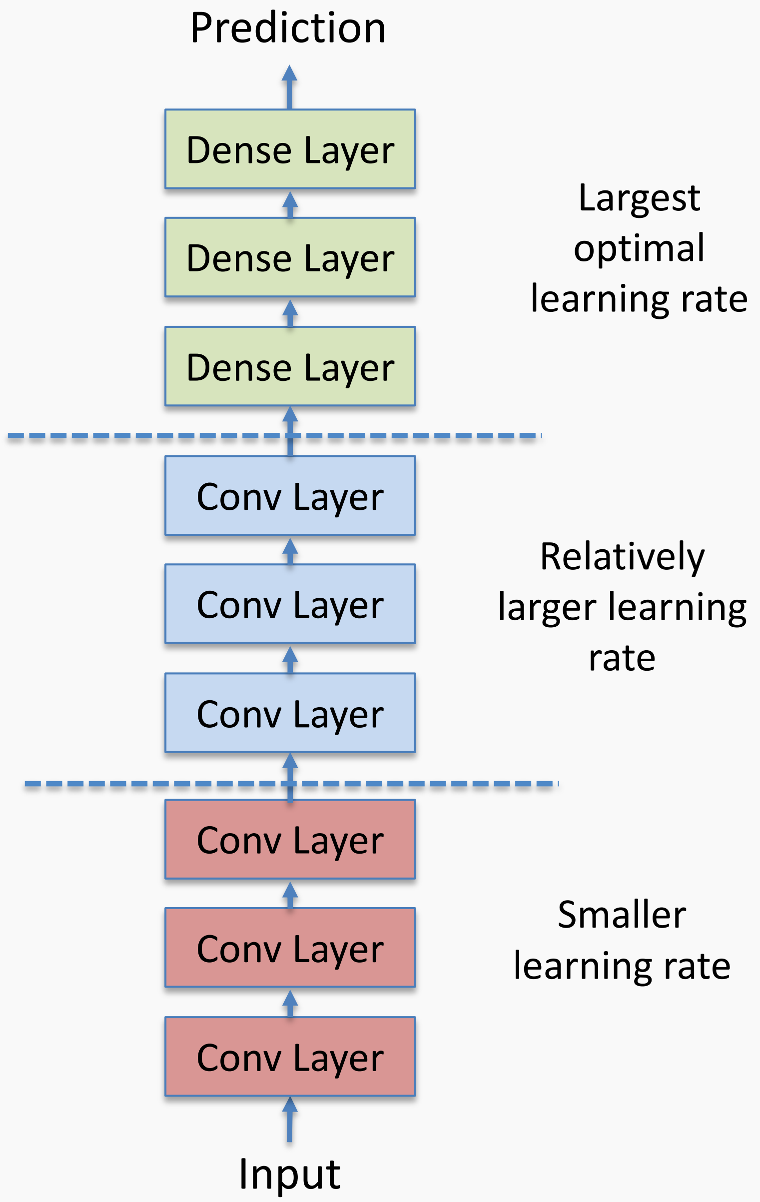

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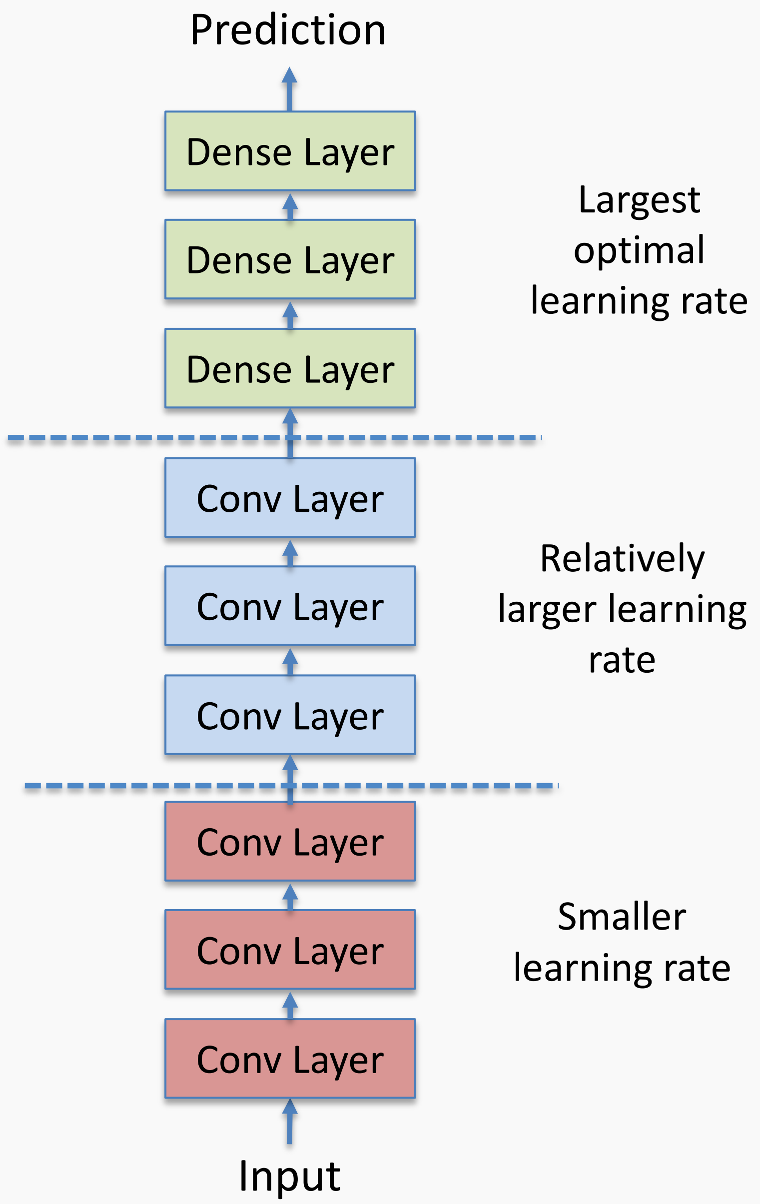
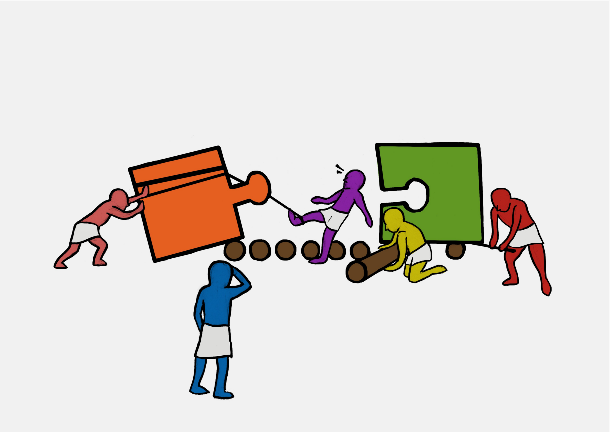
- One could even train the entire network again this way until we overfit and then step back some epochs.



Exercise: Transfer Learning



The goal of this exercise is to use Transfer Learning to achieve near-perfect accuracy for a highly customized task. The task at hand is to distinguish images of people with Sunglasses or Hat.

Prediction: people_with_sunglasses
(with confidence: 0.99)

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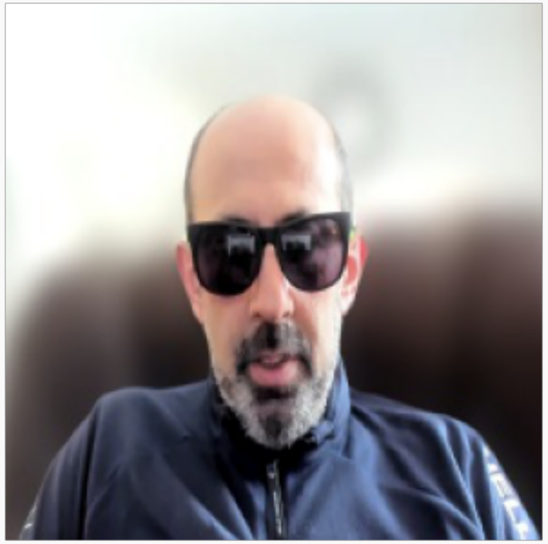

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