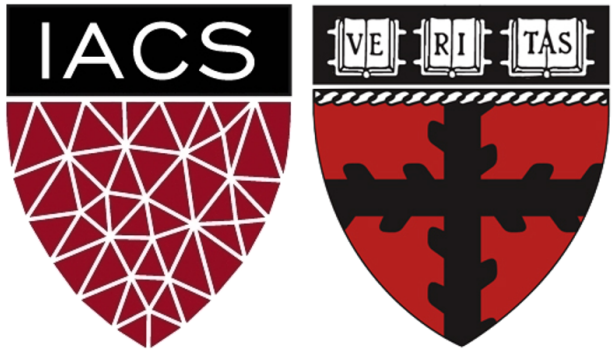
Lecture 5: Intro to Transfer Learning

AC295

Advanced Practical Data Science

Pavlos Protopapas



Outline

1. Communications
2. Motivation
3. The Basics idea for Transfer Learning
4. Formal Definition
5. Transfer Learning Strategies
6. Demo: How Transfer Learning Works in Practice

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1. **Communications**
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Communications

- Practicum submission, please put all your code / memo / video link - within `submissions/practicum_<groupname>.` Anything other than this directory will **not** get graded. We will only be pulling that directory.
- Practicum submissions pulled right after class (due at 10:15 am today).
- Reading question due tomorrow noon (see Ed lessons).
- **Exercise 4** will be released today.

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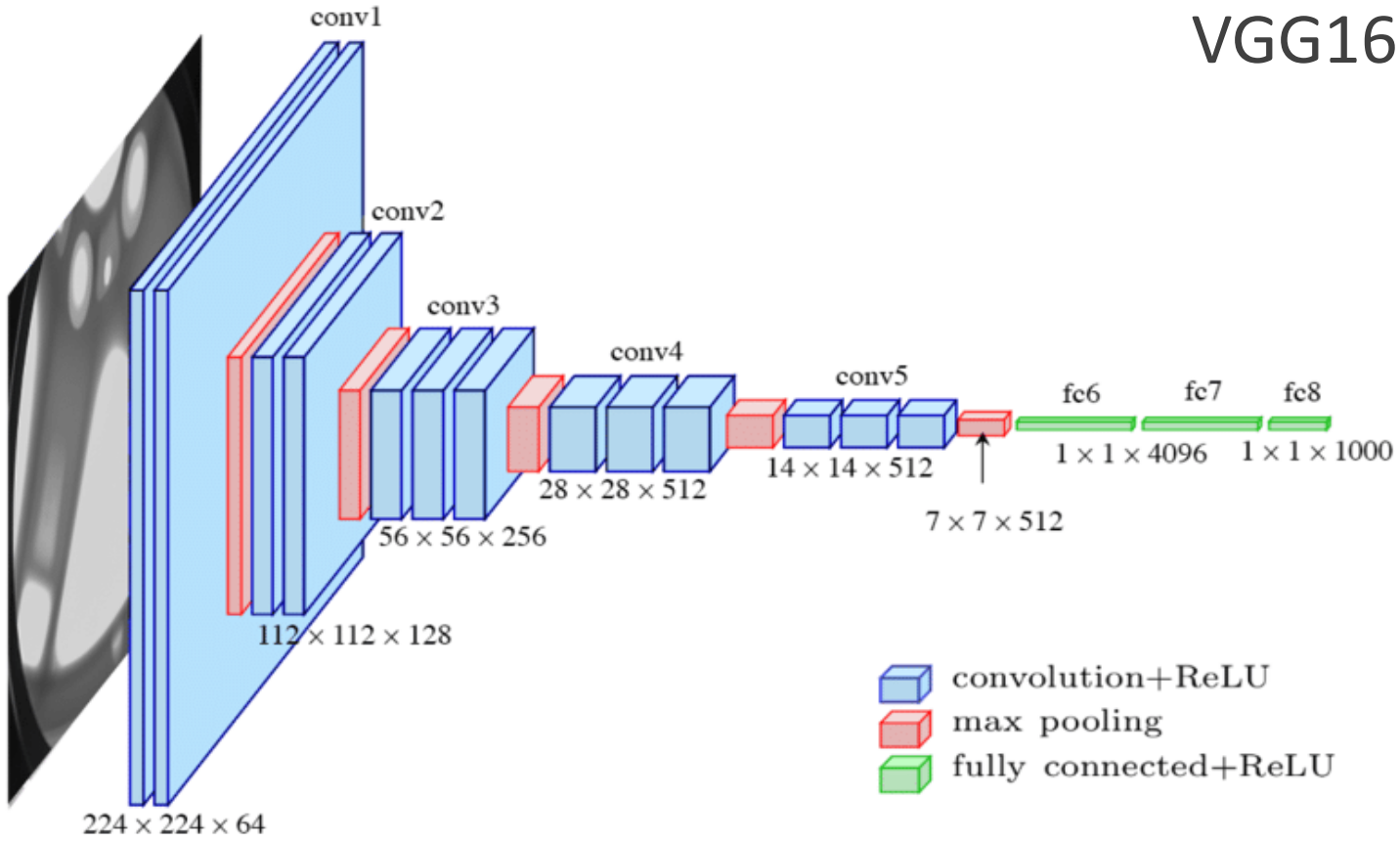
Classify Rarest Animals

Classify Rarest Animals



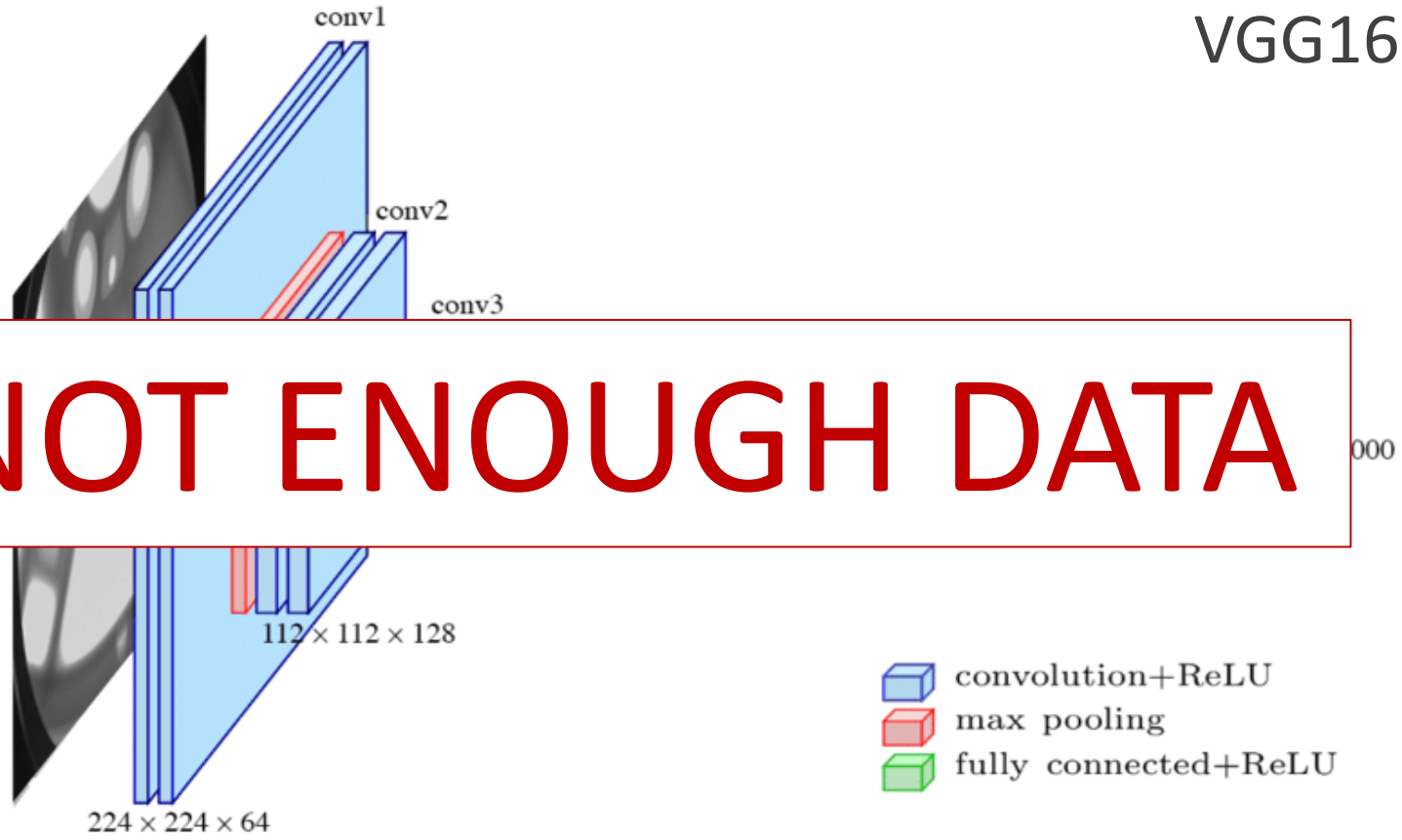
VGG16

Number of parameters: 134,268,737

Data Set: Few hundred images

Classify Rarest Animals

VGG16

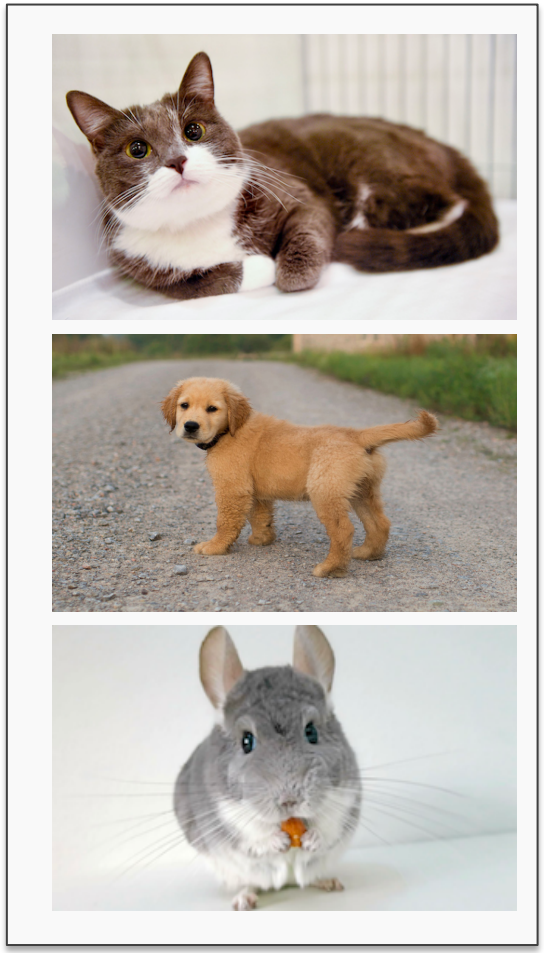


NOT ENOUGH DATA

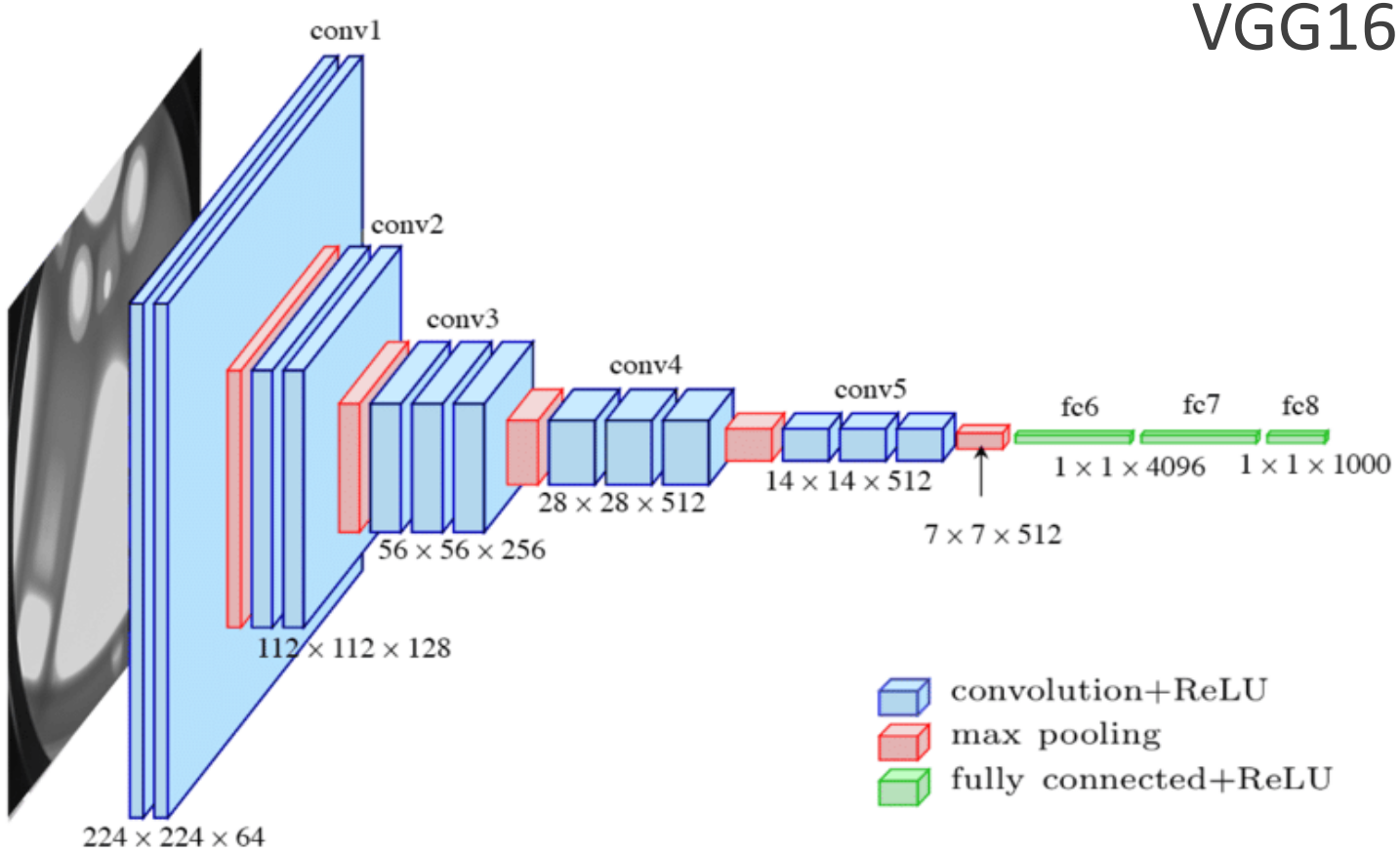
Number of parameters: 134,268,737

Data Set: Few hundred images

Classify Cats, Dogs, Chinchillas etc



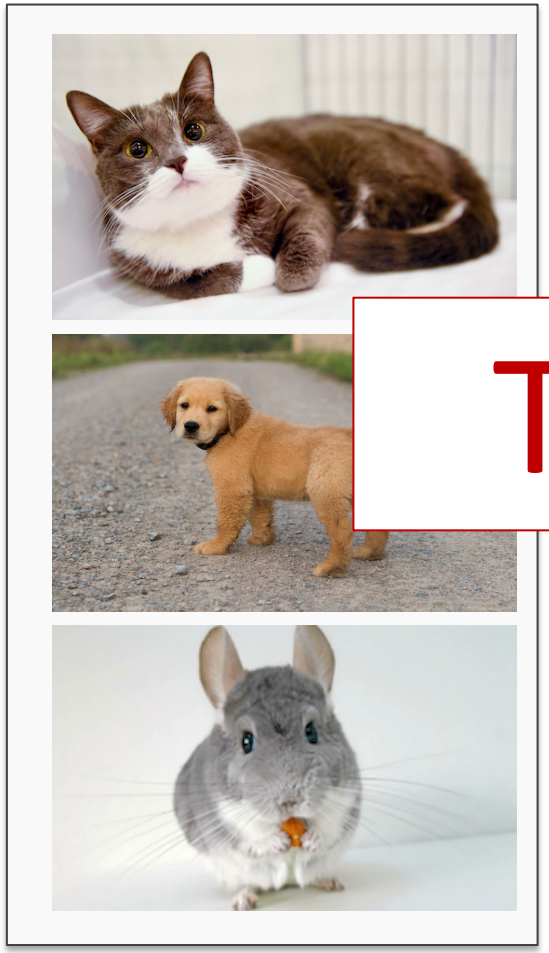
VGG16



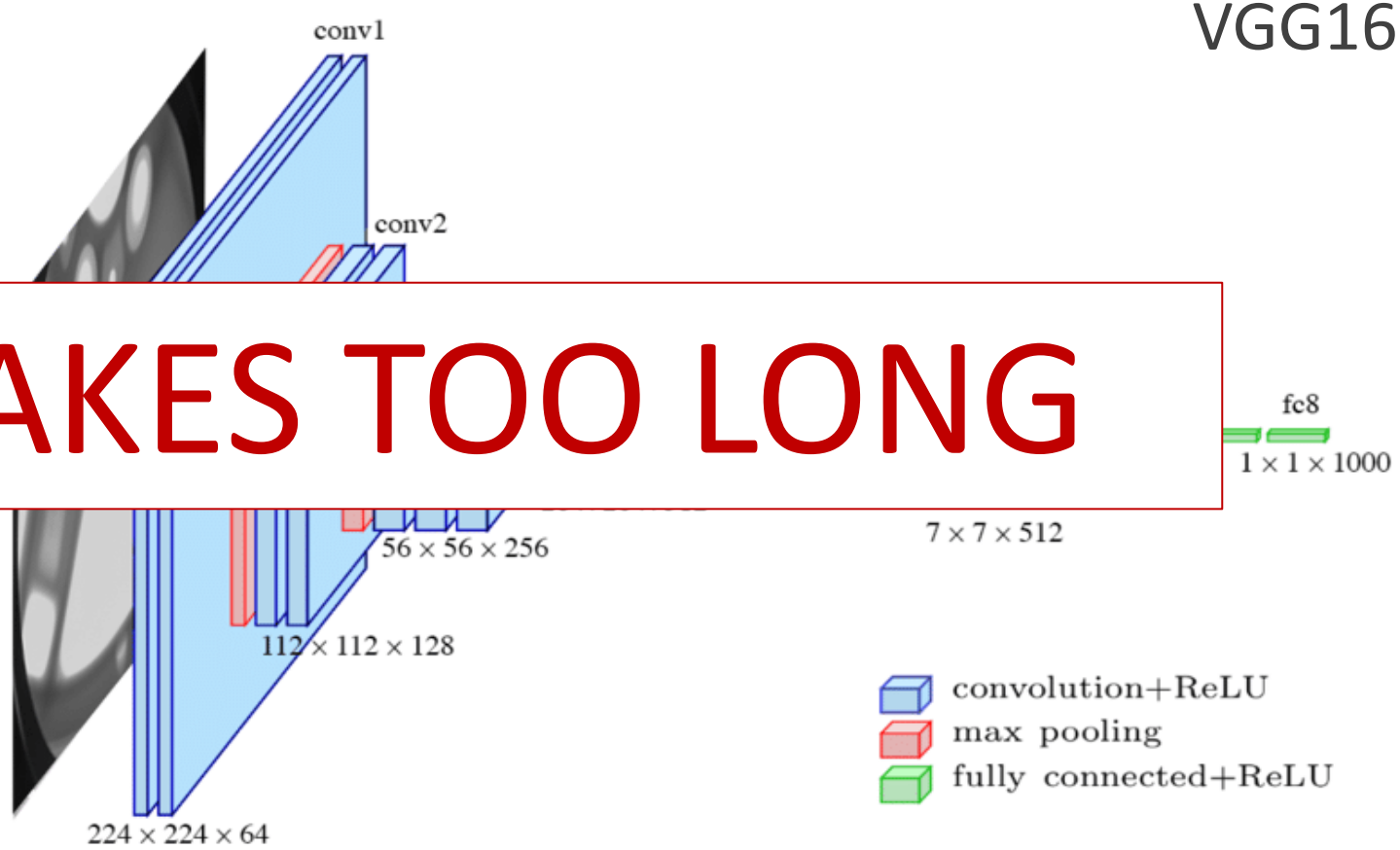
Number of parameters: 134,268,737

Enough training data. ImageNet approximate 1.2M

Classify Cats, Dogs, Chinchillas etc



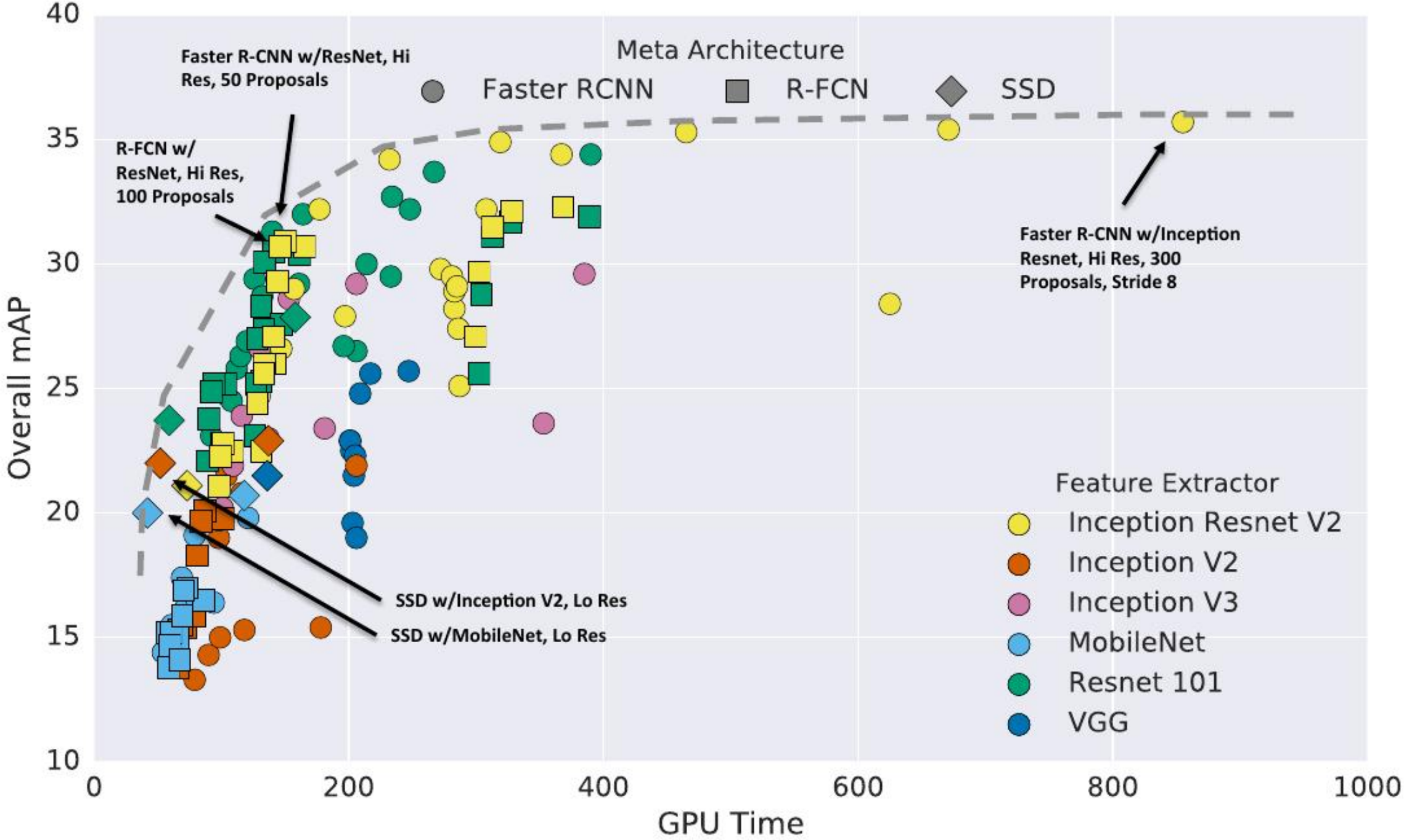
VGG16



TAKES TOO LONG

Number of parameters: 134,268,737

Enough training data. ImageNet approximate 1.2M


Meta Architecture
Faster RCNN
R-FCN
SSD
Faster R-CNN w/ResNet, Hi Res, 50 Proposals
R-FCN w/ ResNet, Hi Res, 100 Proposals
Faster R-CNN w/Inception Resnet, Hi Res, 300 Proposals, Stride 8
SSD w/Inception V2, Lo Res
SSD w/MobileNet, Lo Res
Feature Extractor
Inception Resnet V2
Inception V2
Inception V3
MobileNet
Resnet 101
VGG
Overall mAP
GPU Time
40
35
30
25
20
15
10
0
200
400
600
800
1000

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?

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Basic idea of Transfer Learning

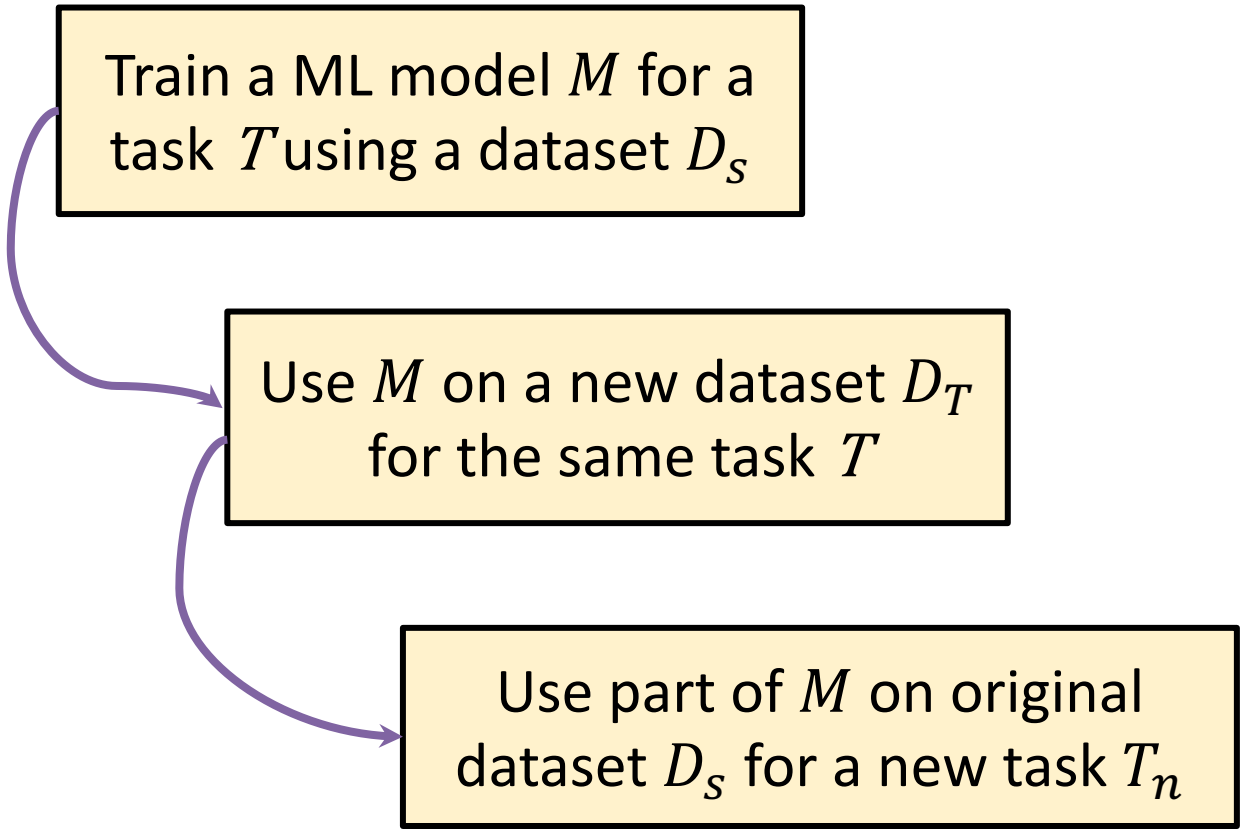
Train a ML model M for a task T using a dataset D_s

Basic idea of Transfer Learning

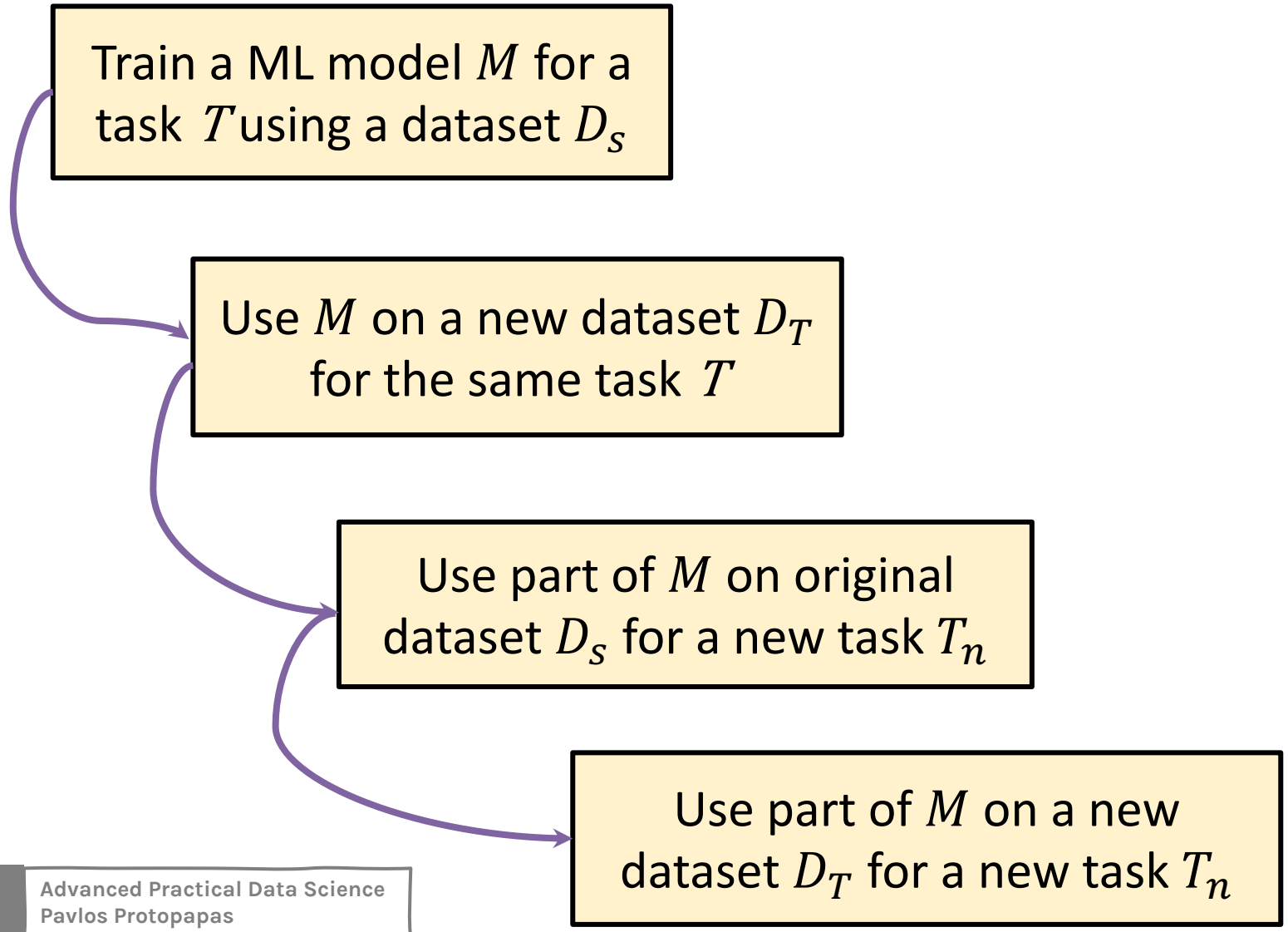
Train a ML model M for a task T using a dataset D_S

Use M on a new dataset D_T for the same task T

Basic idea of Transfer Learning



Basic idea of Transfer Learning



Basic idea of Transfer Learning

Train a ML model M for a task T using a dataset D_s

Use M on a new dataset D_T for the same task T

Use part of M on original dataset D_s for a new task T_n

Use part of M on a new dataset D_T for a new task T_n

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]

Basic idea of Transfer Learning (cont)

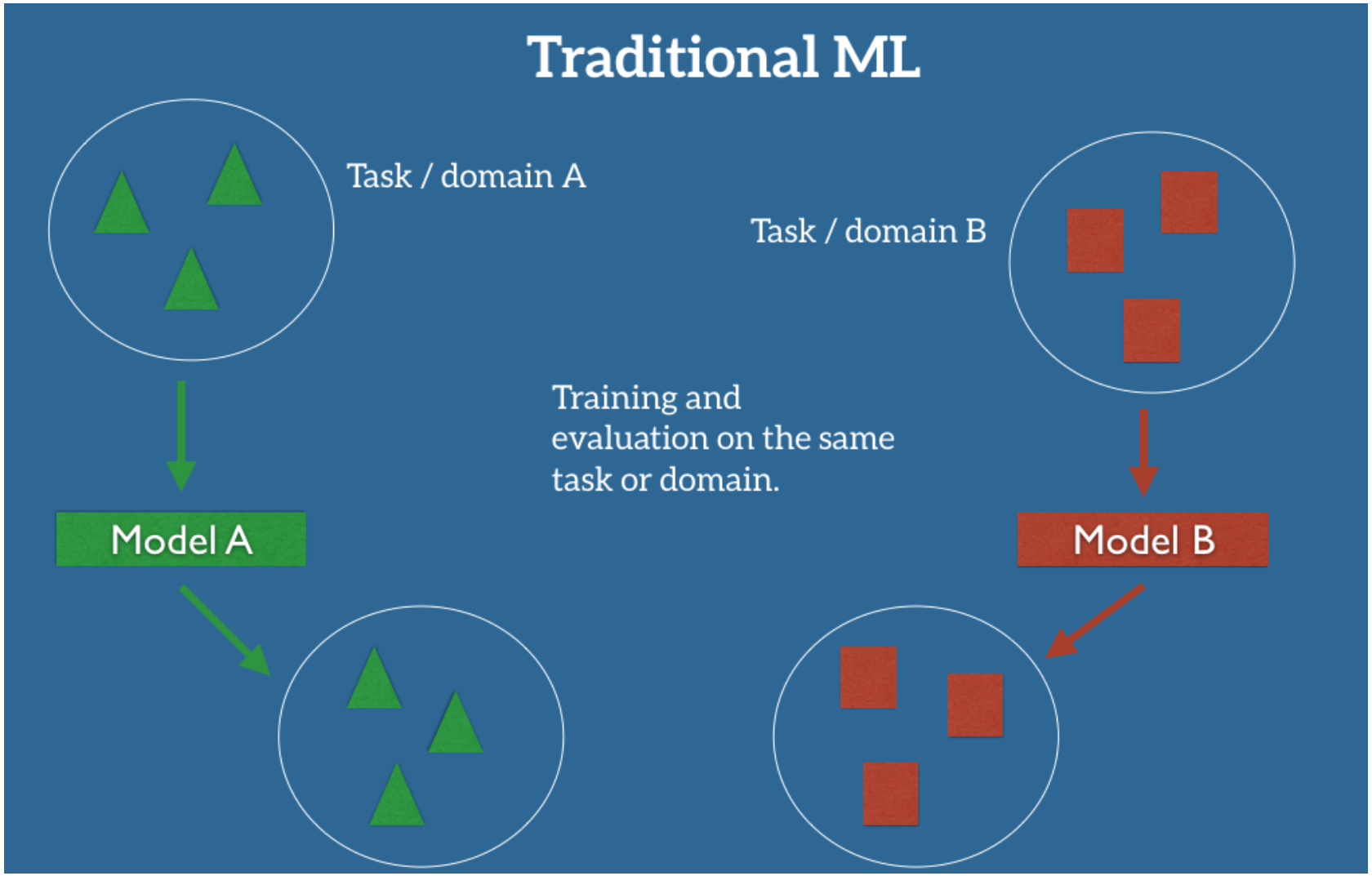
How do you make **an image classifier** that can be **trained in** a few minutes on a CPU with very little data?

Basic idea of Transfer Learning (cont)

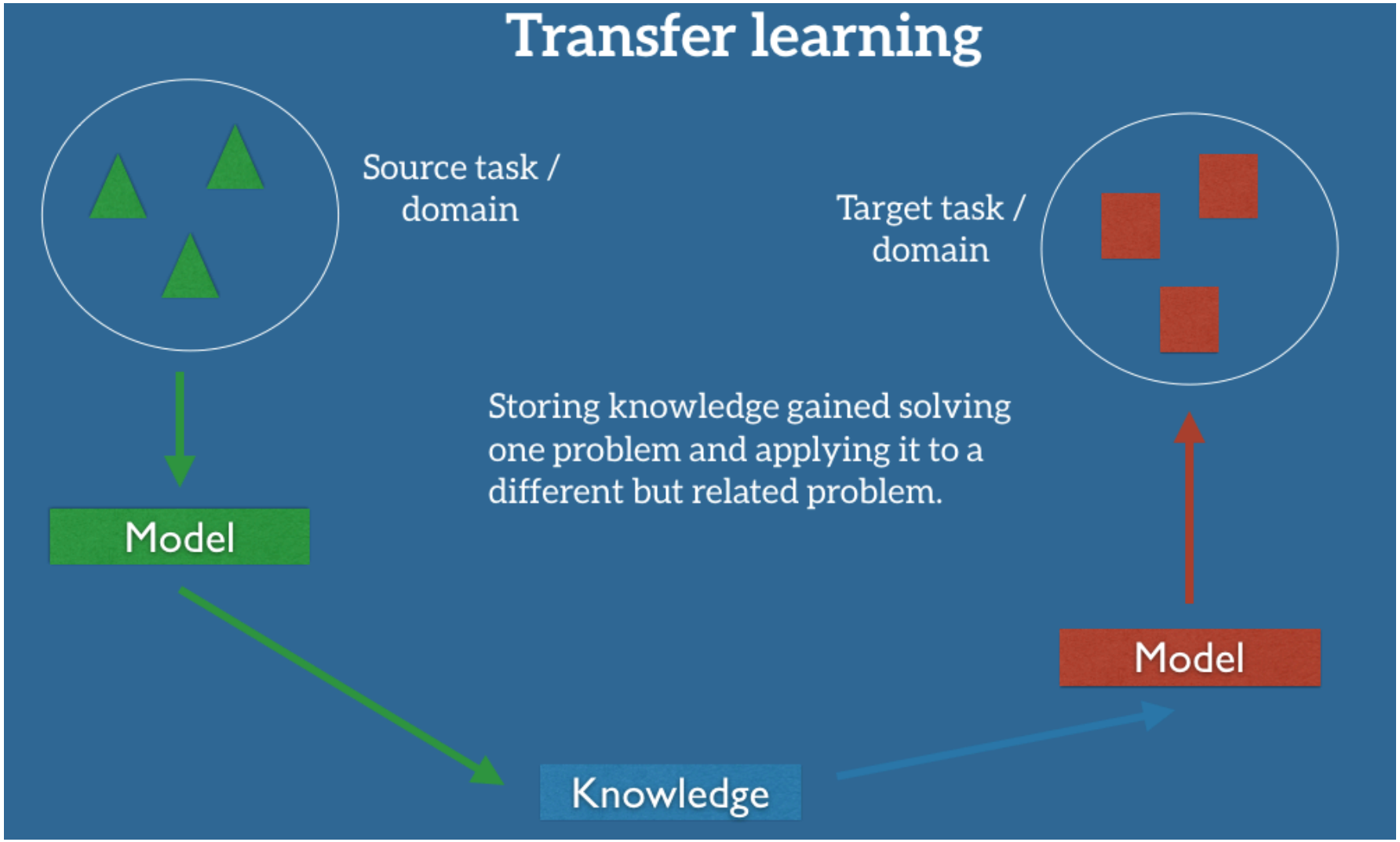
How do you make **an image classifier** that can be **trained in** a few minutes on a CPU with very little data?

Use pre-trained models, i.e., models with known weights.

Basic idea of Transfer Learning (cont.)



Basic idea of Transfer Learning (cont.)



Basic idea of Transfer Learning (cont)

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

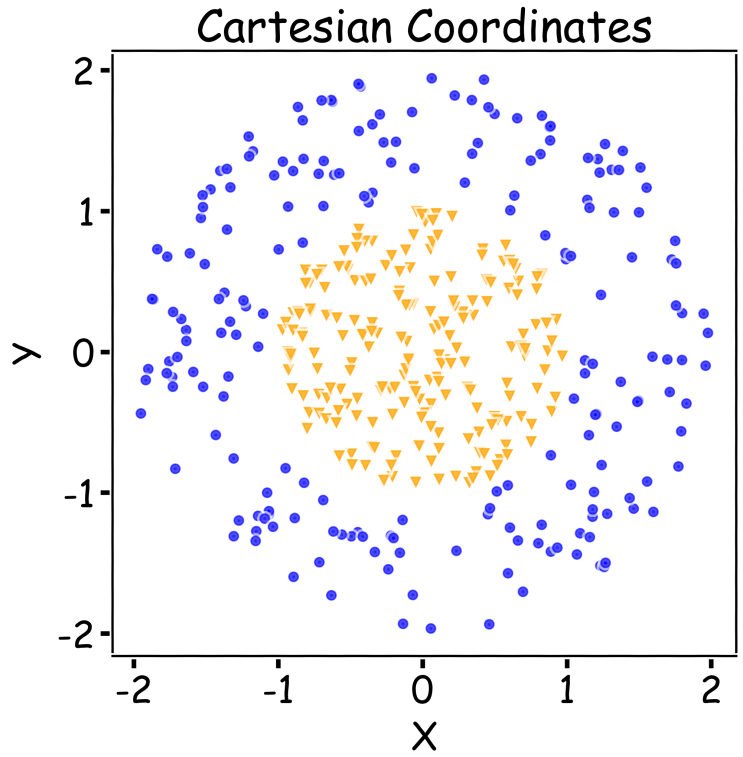
Use pre-trained models, i.e., models with known weights.

Main Idea: Earlier layers of a network learn low level features, which can be adapted to new domains by changing weights at later and fully-connected layers.

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

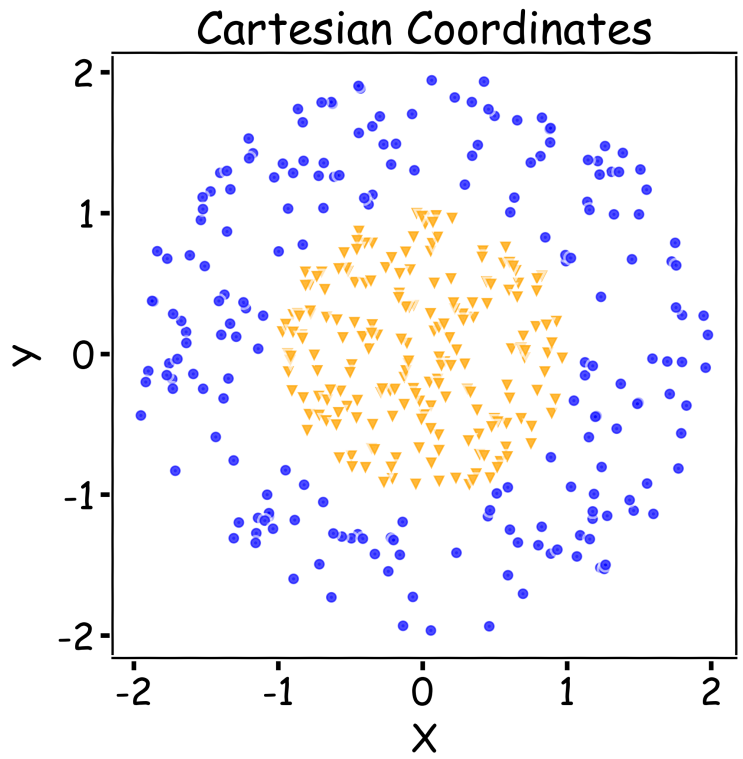
Key Idea: Representation Learning

Relatively difficult task



Key Idea: Representation Learning

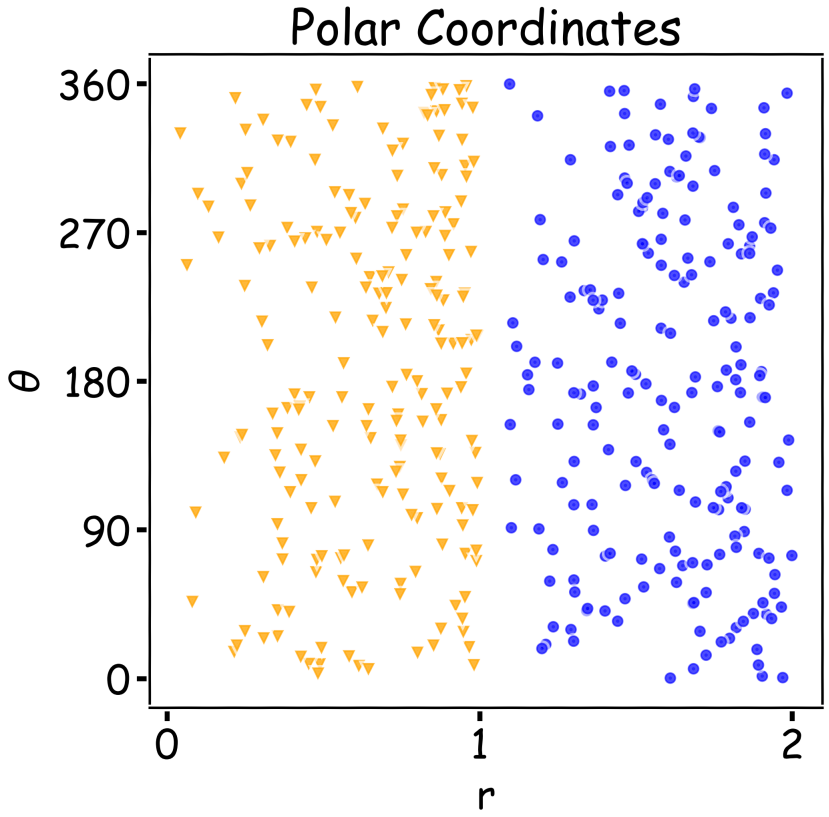
Relatively difficult task



Tranform:

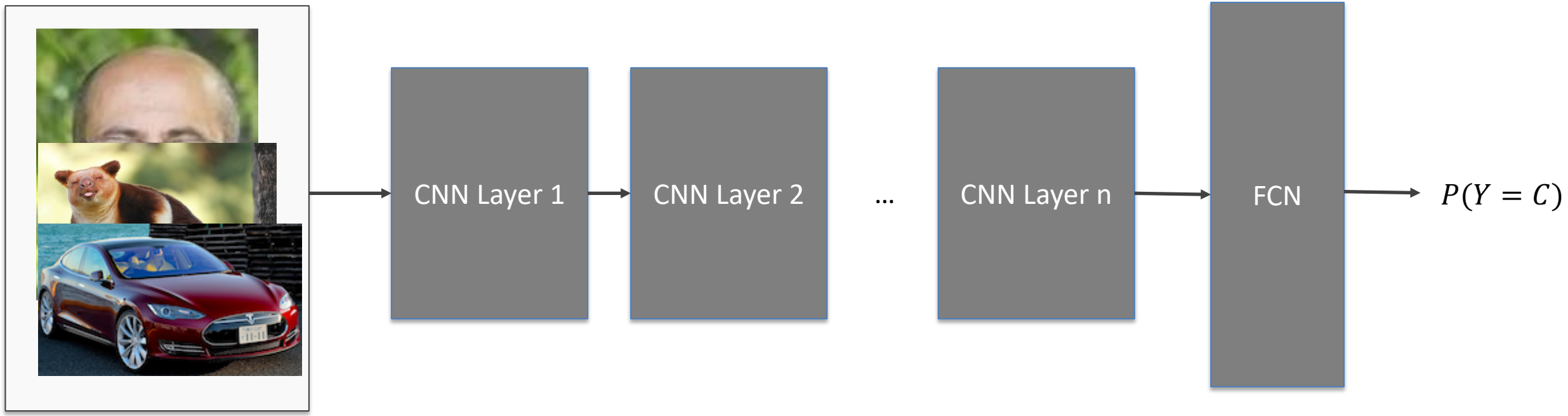
$(X, Y) \rightarrow (r, \theta)$

Easier task



Representation Learning

Task: classify cars, people, animals and objects



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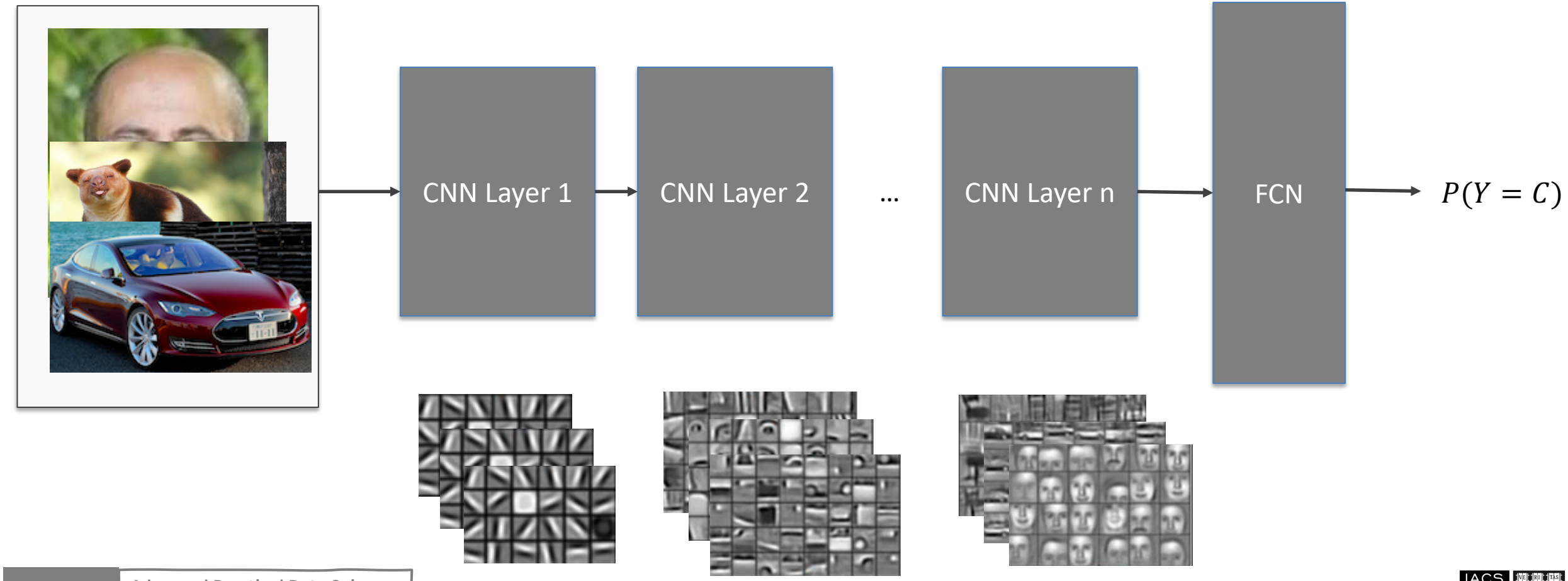

Basic idea of Transfer Learning (cont)

- Train on a big "**source**" data set, with a big model, on one downstream tasks (say classification). Do it once and save the parameters. This is called a **pre-trained model**.
- Use these parameters for other smaller "**target** " datasets, say, for classification on new images (possibly different **domain**, or training distribution), or for image segmentation on old images (new **task**), or new images (new task and new domain).

Basic idea of Transfer Learning (cont)

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- Less helpful if you have a large target dataset with many labels.
- Will fail if source domain (where you trained big model) has nothing in common with target domain (that you want to train on smaller data set).

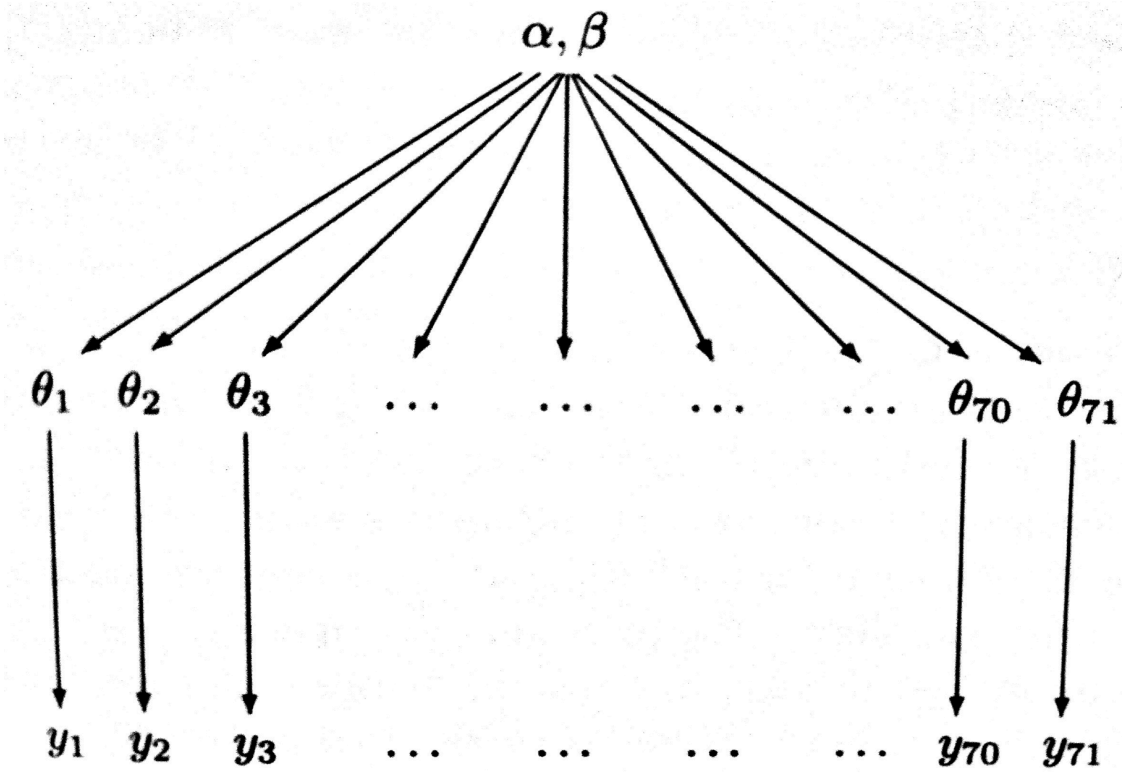
Transfer Learning

Not a new idea!

It has been there in the ML and stats literature for a while.

• An exemplar is hierarchical **glm models** in stats, where information flows from higher data units to lower data units to the lower data.

• Neural networks **learn hierarchical representations** and thus are particularly suited to this kind of learning. Furthermore, since we learn representations, we can deal with domain adaptation/covariate shift.



Applications of Transfer Learning

- Learn from simulations (self-driving cars)
- Domain adaptation: bikes -> bikes with backgrounds, bikes at night, etc
- Speech recognition for immigrants and minorities
- Cross-lingual adaptation for few shot learning of resource-poor languages (English->Nepalis, for example)

Applications of Transfer Learning

- Create a classifier to distinguish dogs and cats.

- Use a convnet previously trained (expensive to learn)
    - e.g. Imagenet (1.4 M images and 1000 classes).

- In NLP, you might use a language model trained on Wikipedia and reddit, and then look at legal documents.

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A Formal Definition

A **Domain** consists of two components: $D = \{\chi, P(X)\}$

- Feature space: χ
- Marginal Distribution: $P(X); X = \{x_1 \ \ldots, x_n\}, x_i \in \chi$

For a given Domain, a **Task** is defined by two components:

$$T = \{\mathcal{Y}, P(Y|X)\} = \{\mathcal{Y}, \eta); Y = \{y_1, \ldots, y_n\}, y_i \in \mathcal{Y}$$

- Label space: $\mathcal{Y}$
- A predictive function η, learned from feature vector/label pairs $(x_i, y_i), x_i \in \chi, y_i \in \mathcal{Y}$.
- For each feature vector in the domain, η predicts its corresponding label $\eta(x_1) = y_1$.

Pan and Yang, A Survey on Transfer Learning

Scenarios

Different features spaces among source and target

$$\chi_{source} \neq \chi_{target}$$

Scenario: document A – the source - is written in one language while document B – the target - is written in a different language

Task: can we use the weights learned training a model that distinguish phonemes on the source to distinguish those in the target written in another language? In NLP this method is called cross lingual adaptation.

Scenarios

Different marginal probabilities among source and target

$$P_s(x) \neq P_t(X)$$

Scenario: Consider two different telescopes, in which one is equipped with a sensor with higher sensitivity than the other.

Task: can we use the weights learned training a model learned training a model on the source data that distinguish topics in another target document?

Scenarios

Different labels among source and target

$$\mathcal{Y}_{source} \neq \mathcal{Y}_{target}$$

Scenario: farm animals versus wild forest animals or different level of classification, e.g. {dogs, cats} different breeds {Retriever, Bulldog, …, Persian, Siamese}.

Scenarios

Different conditional probabilities distribution among source and target task

$$P_s(Y|X) \neq P_t(Y|X)$$

Scenario: source and target are documents are unbalanced regarding their labels. Common scenario in practice, approachable with sampling techniques (e.g. under, over).

Probability Shift: $P_s(Y) \neq P_t(Y)$ not the same class distribution
Conditional Shift: $P_s(X|Y) \neq P_t(X|Y)$

Key Takeaways

During the process of transfer learning, the following three important questions must be answered:

- **What to transfer?** Identify which portion of knowledge is source-specific and what is common between the source and the target.
- **When to transfer?** Aim at utilizing transfer learning to improve target task performance/results and not degrade them. We need to be careful about when to transfer and when not to.
- **How to transfer?** Changes to existing algorithms and different techniques, which we will cover in later sections of this article.

Transfer Learning Strategies

There are different transfer learning strategies and techniques, which can be applied **based on the domain, task** at hand, **and the availability of data:**

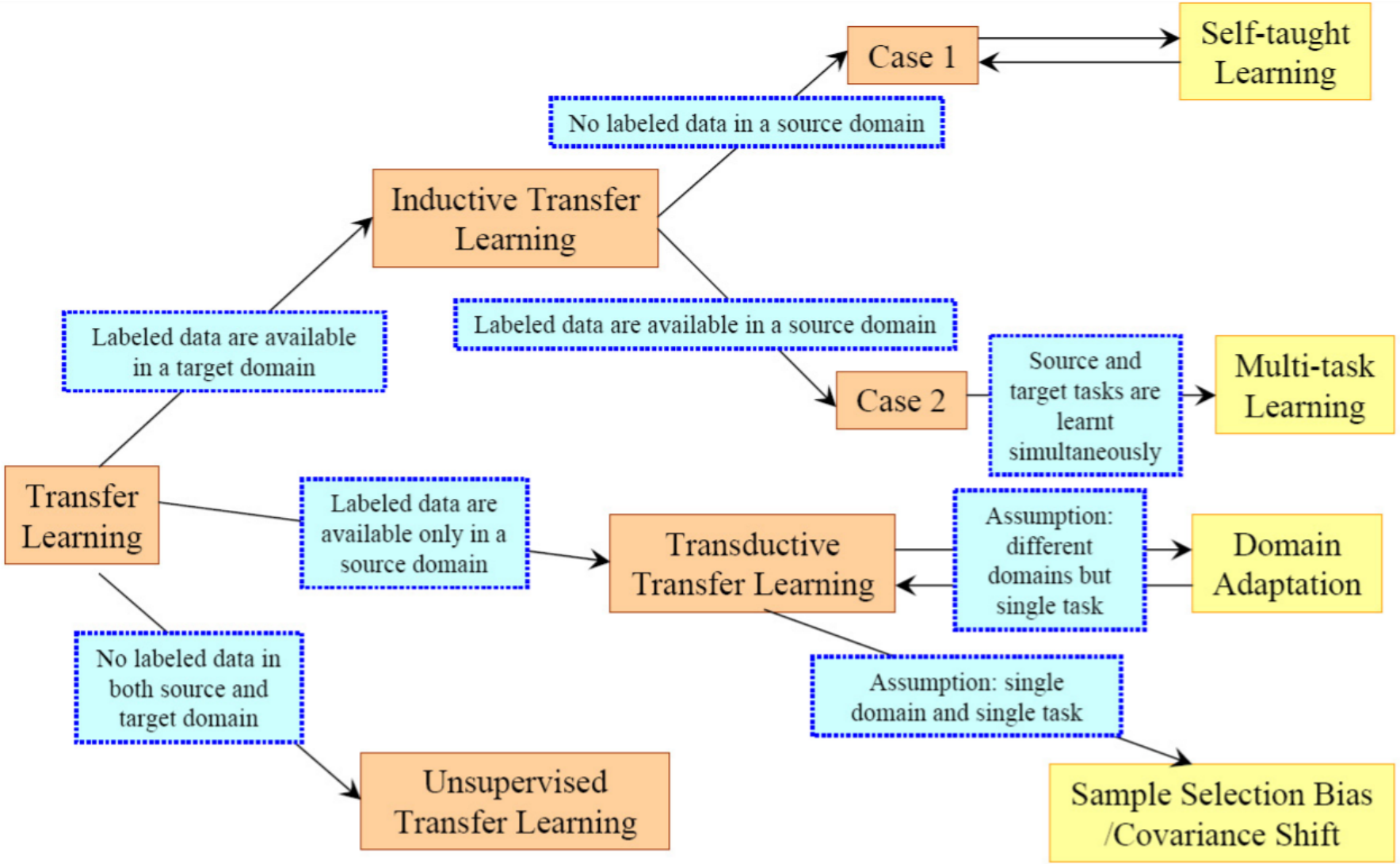
- **Inductive Transfer learning**: the source and target have **same domains**, yet the they have **different tasks**. The algorithms utilize the inductive biases of the source domain to help improve the target task.
- **Unsupervised Transfer Learning:** the source and target have **same domains**, with a focus on **unsupervised tasks in the target** domain. The source and target domains are similar, but the tasks are different. In this scenario, labeled data is unavailable in either of the domains.
- **Transductive Transfer Learning:** In this scenario, there are similarities between the source and target tasks, but the corresponding domains are different. In this setting, the source domain has a lot of labeled data, while the target domain has none.

Transfer Learning Strategies

The approaches for Transfer Learning can be defined in few categories:

- **Instance transfer:** Reusing knowledge from the source domain to the target task (ideal scenario). In most cases, the source domain data cannot be reused directly.
- **Feature-representation transfer:** This approach aims to minimize domain divergence and reduce error rates by identifying good feature representations that can be utilized from the source to target domains.
- **Parameter transfer:** This approach works on the assumption that the models for related tasks share some parameters or prior distribution of hyperparameters.
- **Relational-knowledge transfer** attempts to handle non-IID data, such as data that is not independent and identically distributed.

Transfer Learning Strategies



Pan and Yang, A Survey on Transfer Learning

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Transfer Learning for Deep Learning

What people think

- you can't do deep learning unless you have a million labeled examples.

What people can do, instead

- You can learn representations from unlabeled data
- You can train on a nearby objective for which is easy to generate labels (imageNet).
- You can transfer learned representations from a relate task.

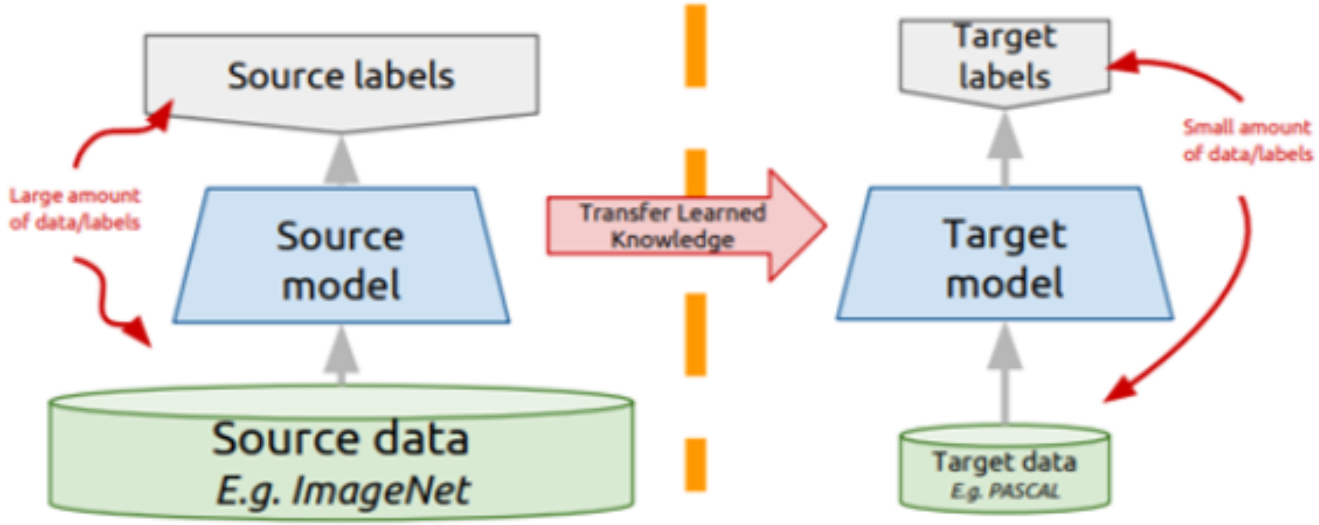
Transfer Learning for Deep Learning

Instead of training a network from scratch:

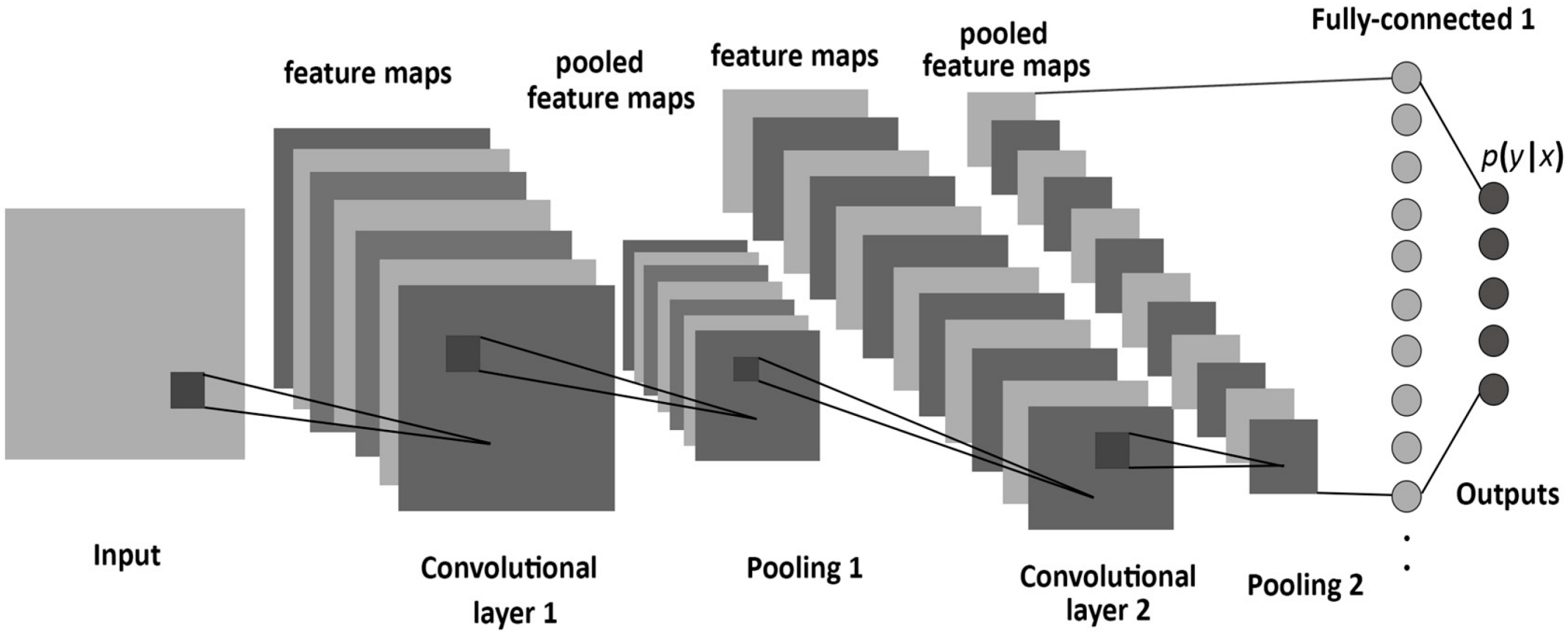
- Take a network trained on a different domain for a different **source task**
- Adapt it for your domain and your **target task**

Variations

- Same domain, different task.
- Different domain, same task.



Extremely short review of CNN

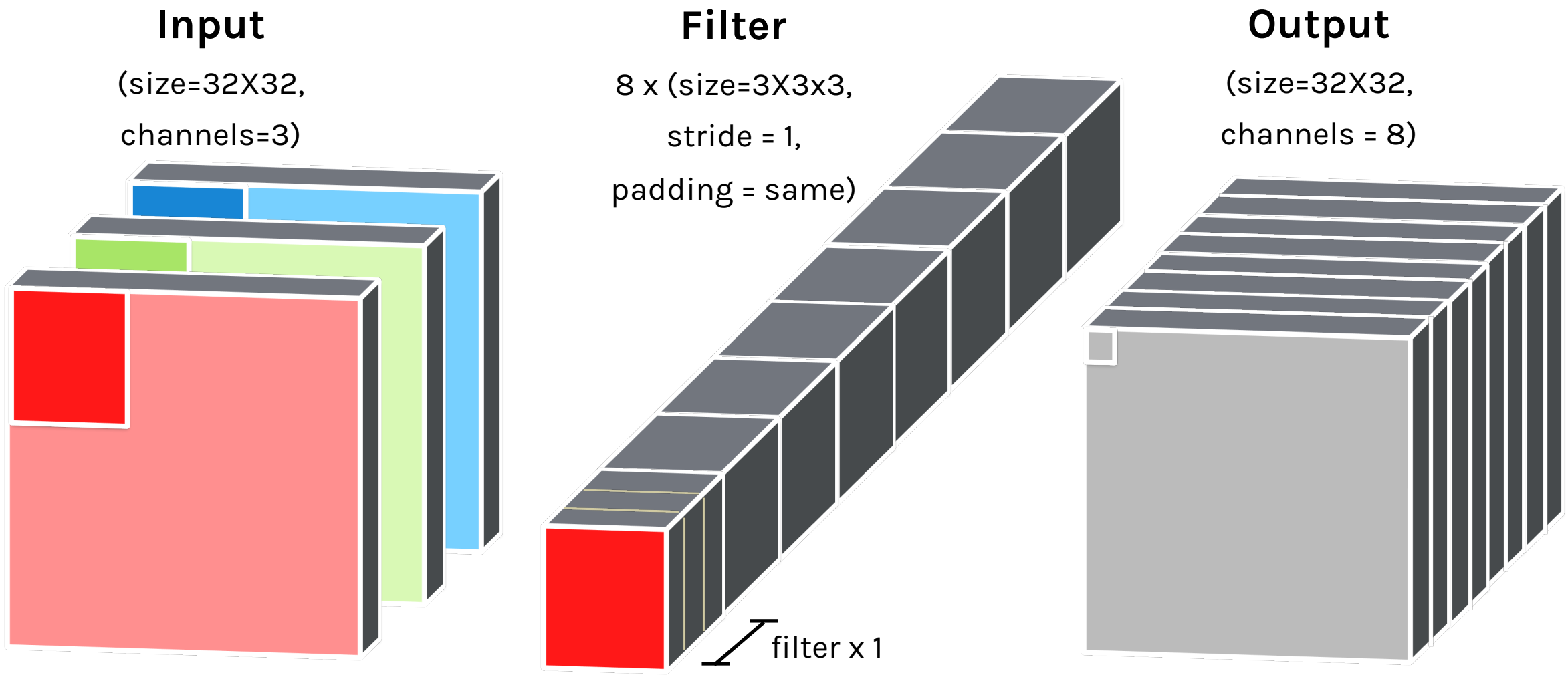


Example

- Let C be a CNN with the following disposition:
  - Input: 32x32x3 images
  - Conv1: 8 3x3 filters, stride 1, padding=same
  - Conv2: 16 5x5 filters, stride 2, padding=same
  - Flatten layer
  - Dense1: 512 nodes
  - Dense2: 4 nodes
- How many parameters does this network have?

$(8 \times 3 \times 3 \times 3 + 8) + (16 \times 5 \times 5 \times 8 + 16) + (16 \times 16 \times 16 \times 512 + 512) + (512 \times 4 + 4)$

Conv1 Conv2 Dense1 Dense2



How many parameters does the layer have if I want to use 8 filters?

n_filters x filter_volume + biases = total number of params

8 x (3 x 3 x 3) + 8 = 224

Input

(size=32X32,

channels=8)

Filter

16 x (size=5X5X8,

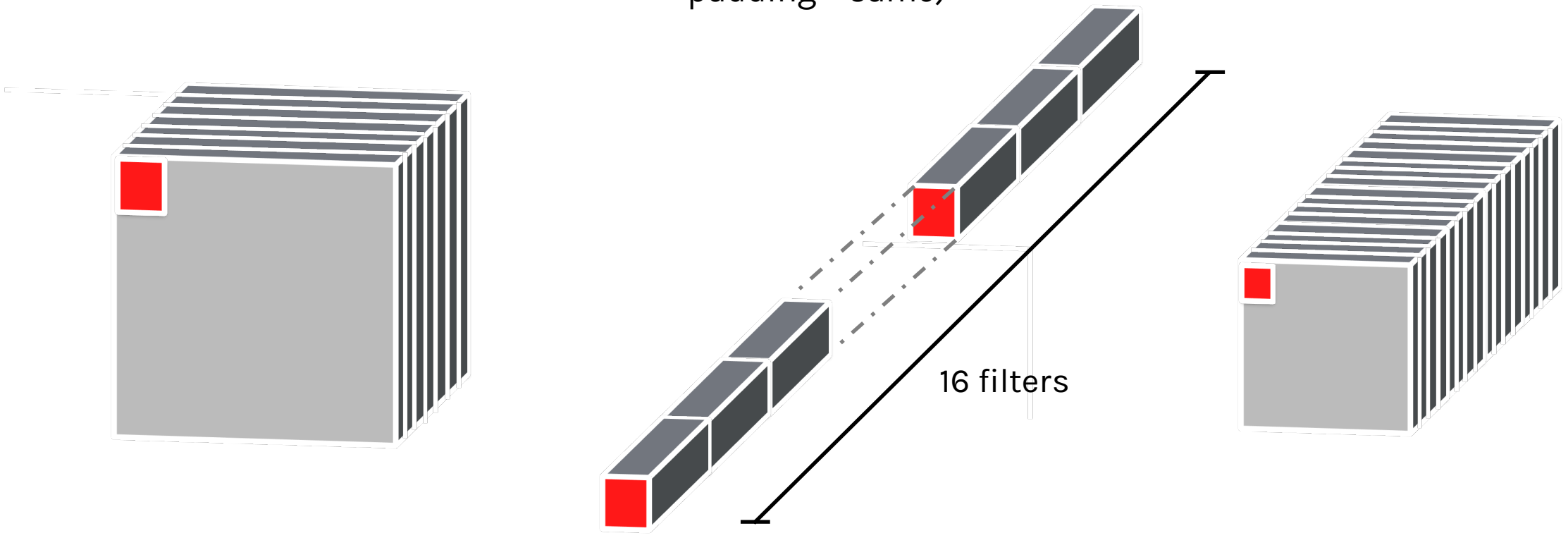
stride = 2,

padding = same)

Output

(size=16X16,

channels=16)



How many parameters does the layer have if I want to use 16 filters?

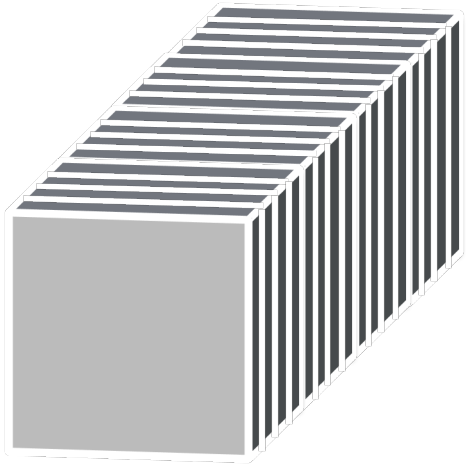
n_filters x filter_volume + biases = total number of params

16 x (5 x 5 x 8) + 16 = 3216

Input

(size=16X16,

channels=16)



Flatten

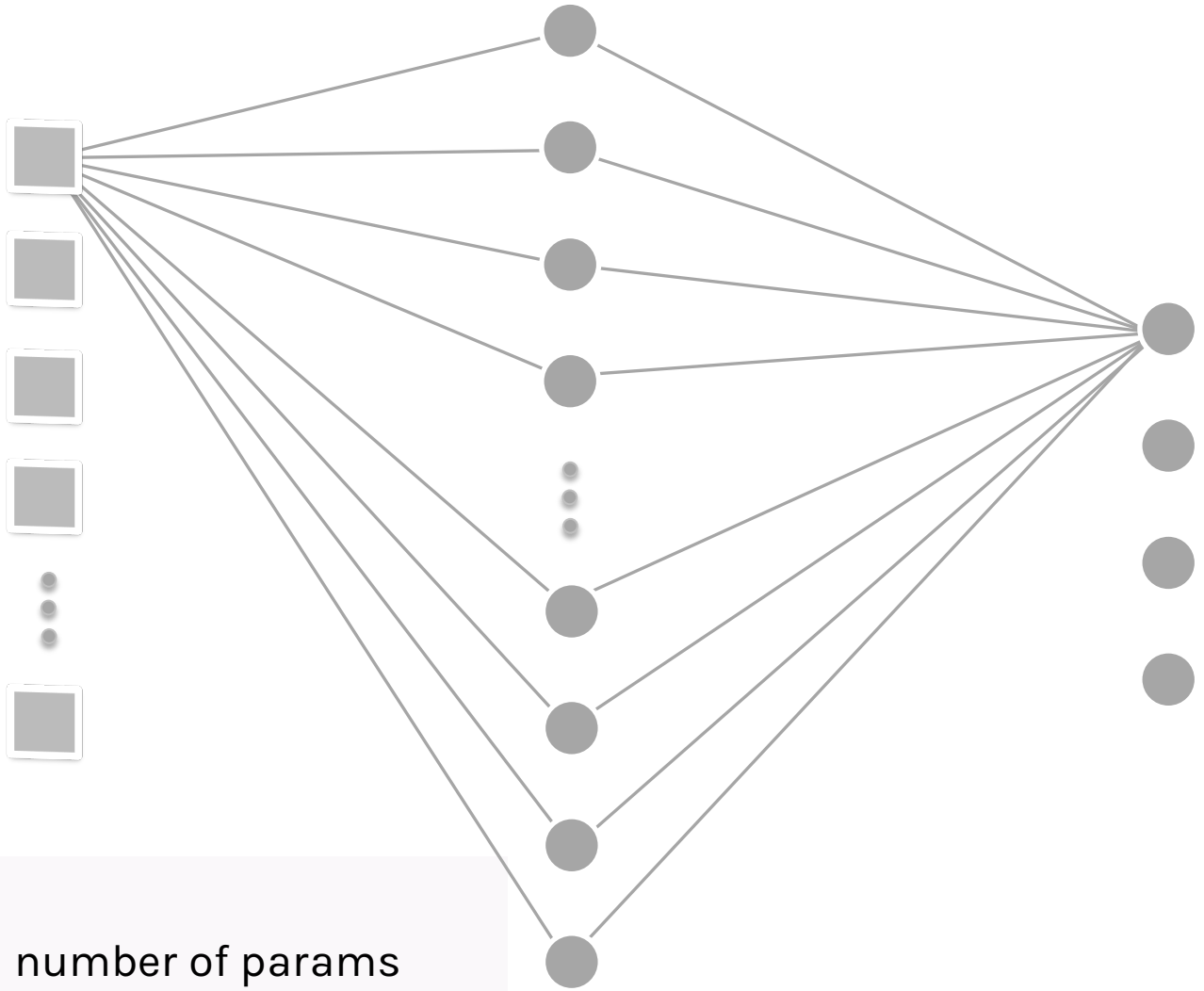
(size= 16X16X16)

Fully Connected

(n_nodes=512)

Fully Connected

(n_nodes=4)



How many parameters ... ?

input x FC1_nodes + FC2_nodes = total number of params

(16x16x16) x 512 + 512 + 512 x 4 + 4 = 2,099,716

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Representation Extraction

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

- 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.
- Since there are both dogs and cats in *ImageNet* you could get **away** with using the head FC layers as well. But by throwing it away you can learn more from other dog/cat images.

$$P_s(Y|X) \neq P_t(Y|X)$$

Fine-tuning

• Up to now we have frozen the entire convolutional base.

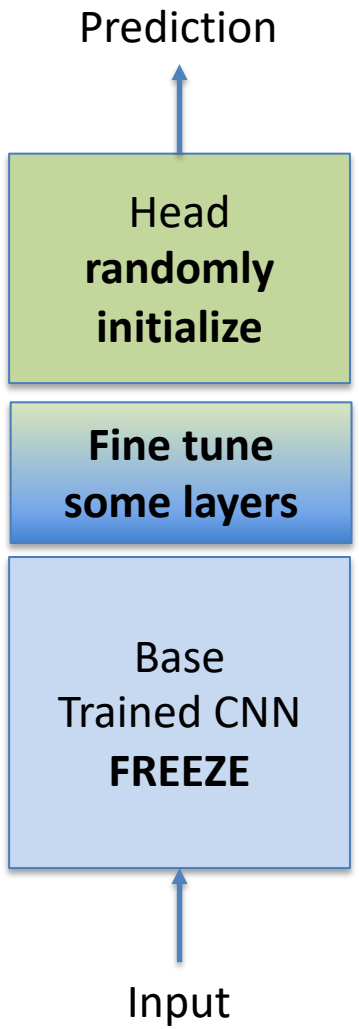
• Remember that earlier layers learn highly generic feature maps (edges, colors, textures).

• Later layers learn abstract concepts (dog's ear).

• 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.

$$P_s(x) \neq P_t(X)$$



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**.

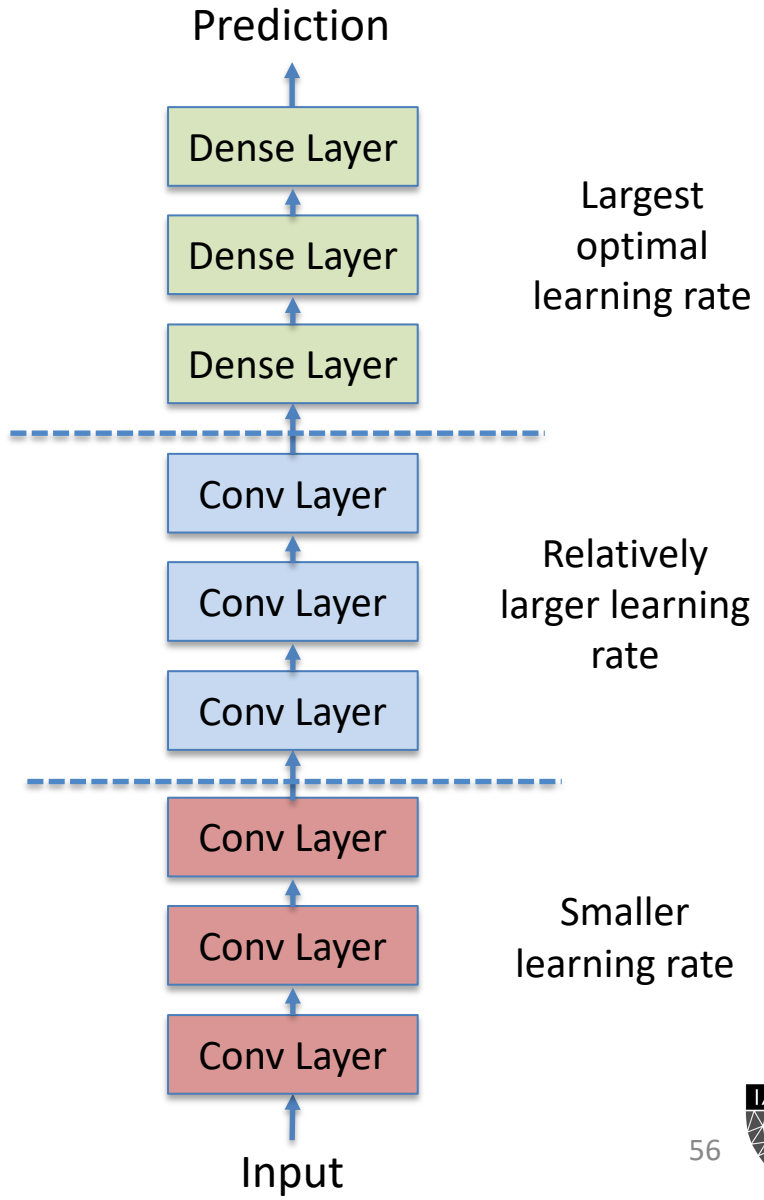
Transfer Learning for Deep Learning: Differential Learning Rates

• 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.

• General Idea: **Train different layers at different rates**.

• Each "earlier" layer or layer group (the color-coded layers in the image) can be trained at 3x-10x smaller learning rate than the next "later" one.

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



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TF Classification

THANK YOU

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