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#073374

Deep Learning for Computer Vision (III)

Learning Objectives

- Learn the basic concepts of transfer learning.
- Learn how to use a pretrained network to significantly increase the accuracy of image classification task.

Improve Performance of Your CNN Model

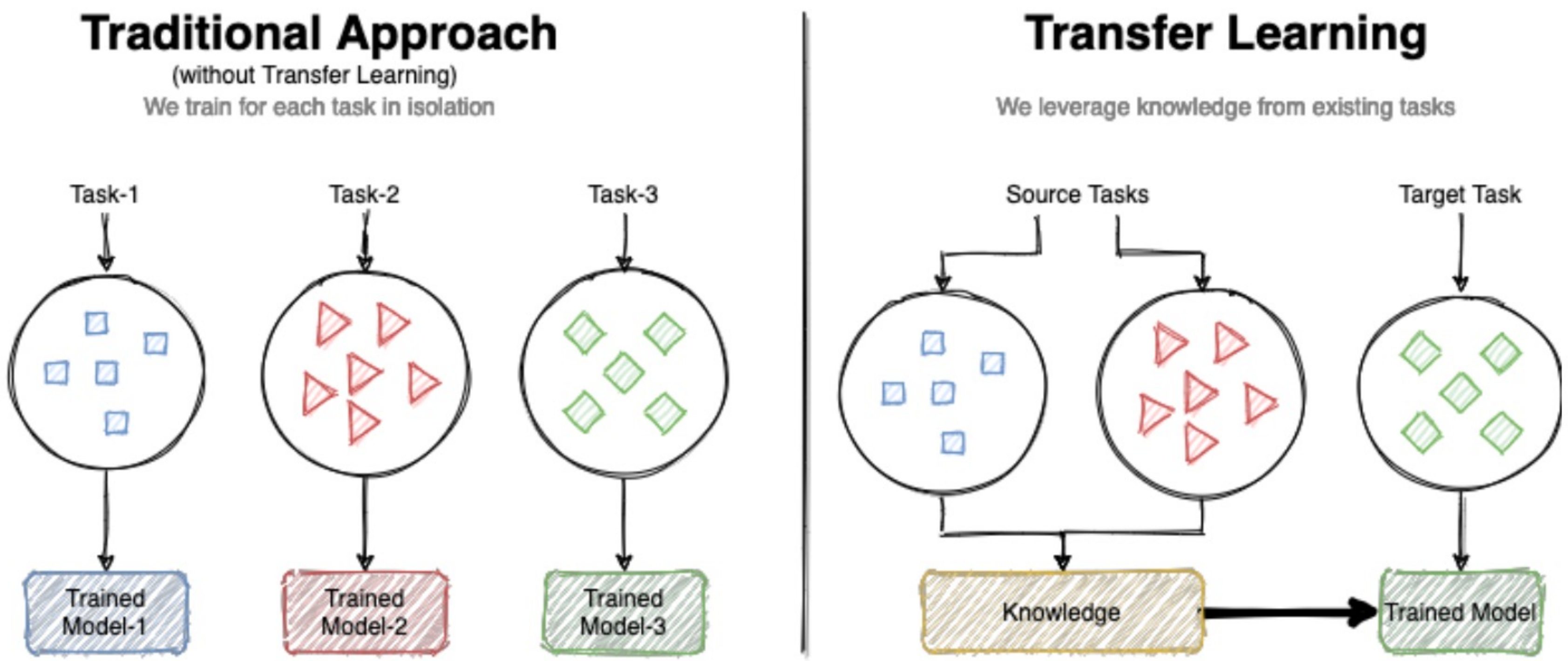
- Network architecture
  - Number of hidden layers (network depth)
  - Number of neurons in each layer (layer width)
  - Activation type
- Learning and optimization
  - Learning rate and decay schedule
  - Mini-batch size
  - Optimization algorithms
  - Number of training iterations or epochs (and early stopping criteria)
- Regularization techniques to avoid overfitting
  - L2 regularization
  - Dropout layers
  - Data augmentation
- Batch normalization
- Transfer learning

Transfer Learning

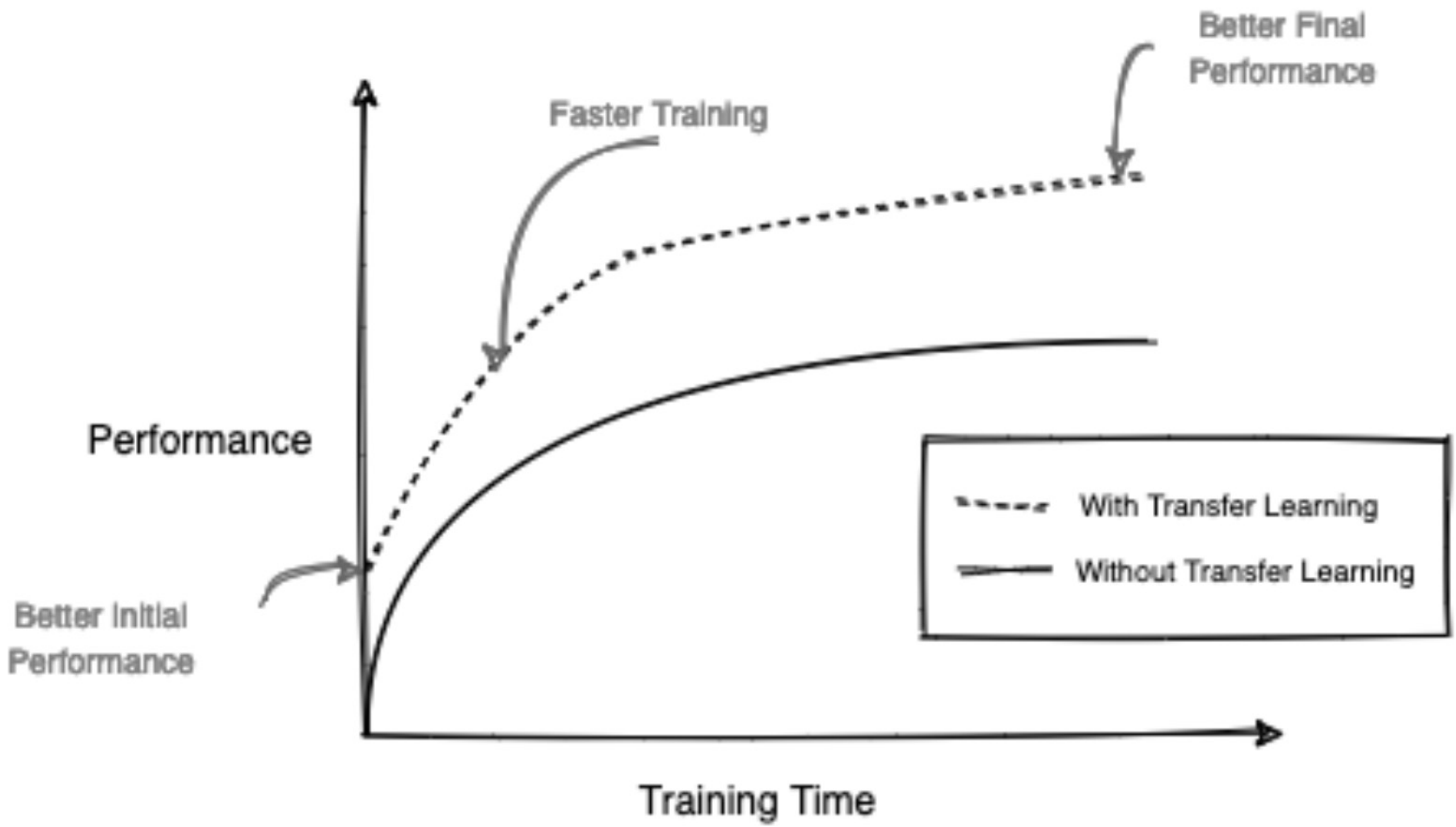
TL will be the next driver of ML commercial success after supervised learning, Andrew Ng (2016 NIPS)

Transfer Learning

- Transfer learning is one of the most important techniques of deep learning.
- Loosely, transfer learning is referred to a situation where what has been learned in one setting is exploited to improve generalization in another setting.



Typical Benefit of Transfer Learning



Transfer Learning: A Formal Definition

- The definition of transfer learning is given in terms of **domains** and **tasks**.
- A domain $\mathbb{D}$ consists of a feature space $\mathcal{X}$ and a probability distribution $P(X)$ where $X = \{x_1, x_2 \ldots, x_n\} \in \mathcal{X}$
- A task $\mathbb{T}$ consists of a label space $\mathcal{Y}$ and a predictive function $f: \mathcal{X} \rightarrow \mathcal{Y}$

Given a source domain $\mathbb{D}_s$ and a learning task $\mathbb{T}_s$, a target domain $\mathbb{D}_t$ and a learning task $\mathbb{T}_t$, transfer learning aims to help improve the learning of the target predictive function $f_t(\cdot)$ for the target domain using the knowledge in $\mathbb{D}_s$ and $\mathbb{T}_s$, where $\mathbb{D}_s \neq \mathbb{D}_t$ or $\mathbb{T}_s \neq \mathbb{T}_t$

Domain Adaptation: A Subfield of Transfer Learning

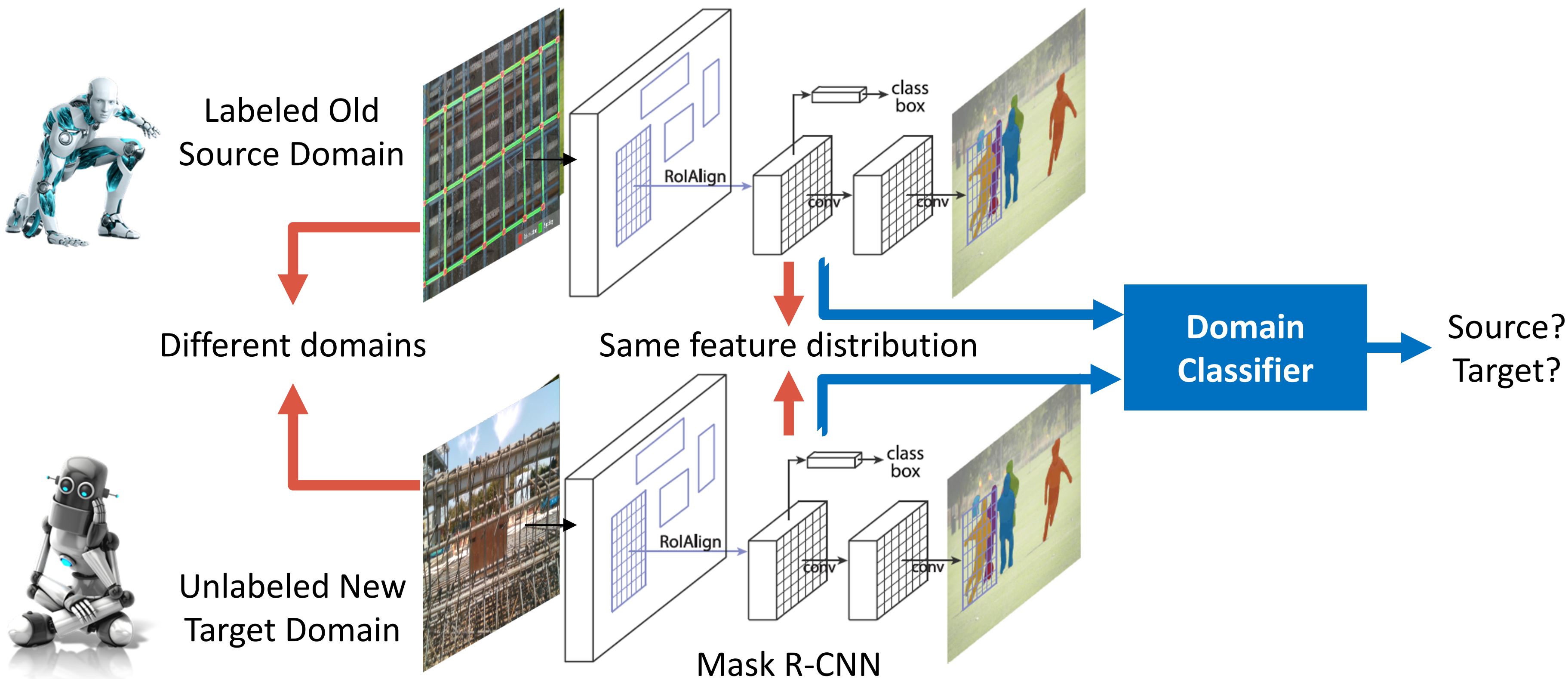
Domain adaptation is a specific scenario where the label space remains same, yet the probabilities between source and target domains change $P(X_s) \neq P(X_t)$

Waymo's Cars Drive 10 Million Miles (A Day in Virtual Space, 10 Years in Real Space)

http://dipakramoliya.com/uncategorized/in-a-perilous-virtual-world-waymos-cars-drive-10-million-miles-a-day/

Domain Adaptation for Rebar Image Segmentation

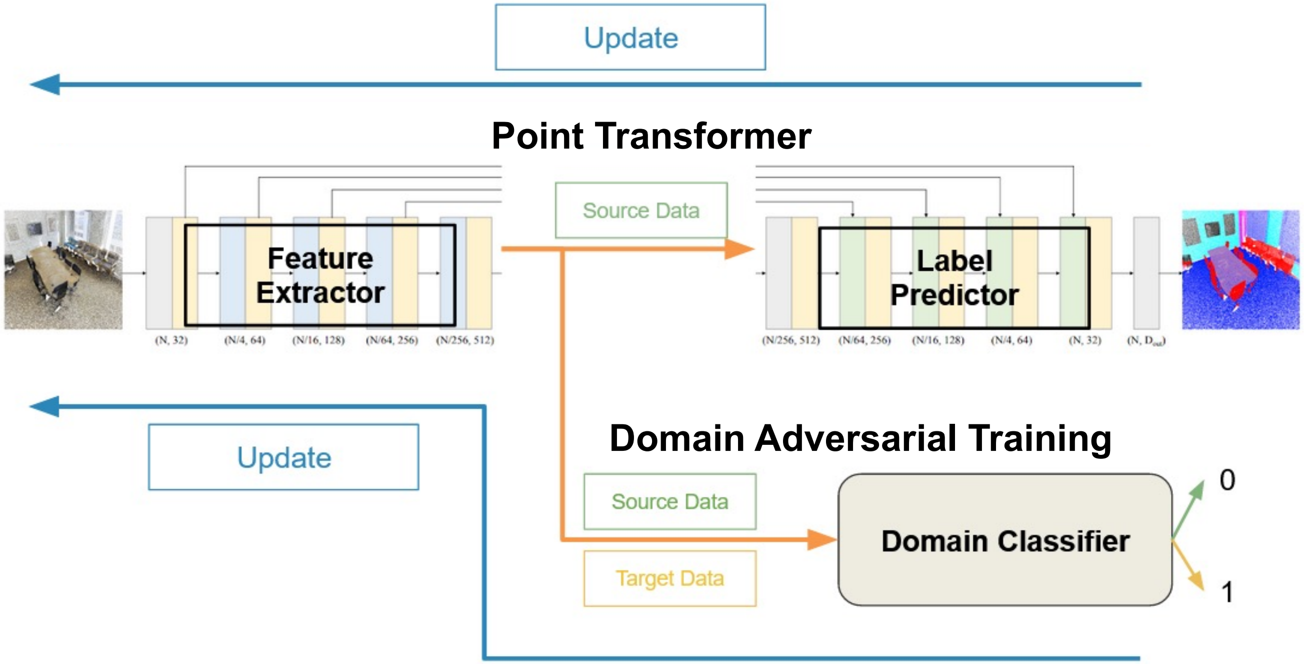
- **Domain variance** in rebar dataset:
  rebar assembly, collecting time, shooting position
- **Domain adversarial training:** reduce discrepancy between domains
  - **Domain classifier:** try to distinguish between source and target domain
  - **Feature extractor:** try to fool domain classifier while training model



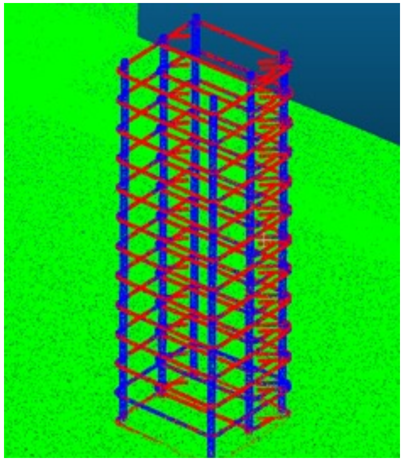
Domain Adaptation for Rebar Point Cloud Segmentation

Task: 3D semantic segmentation
Classes:

1. **Background**
2. **Main rebars (主筋)**
3. **Ties (箍筋)**

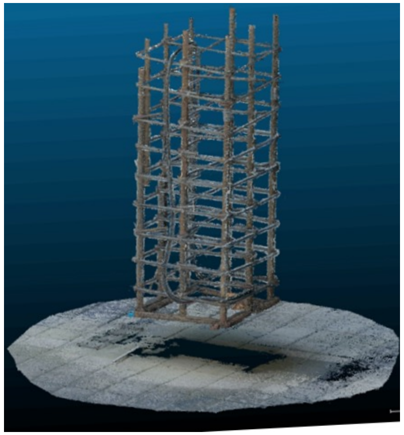


Model Architecture



Source Data

- **Virtual (parametric modeling by Revit)**
- **Labeled (automatic)**



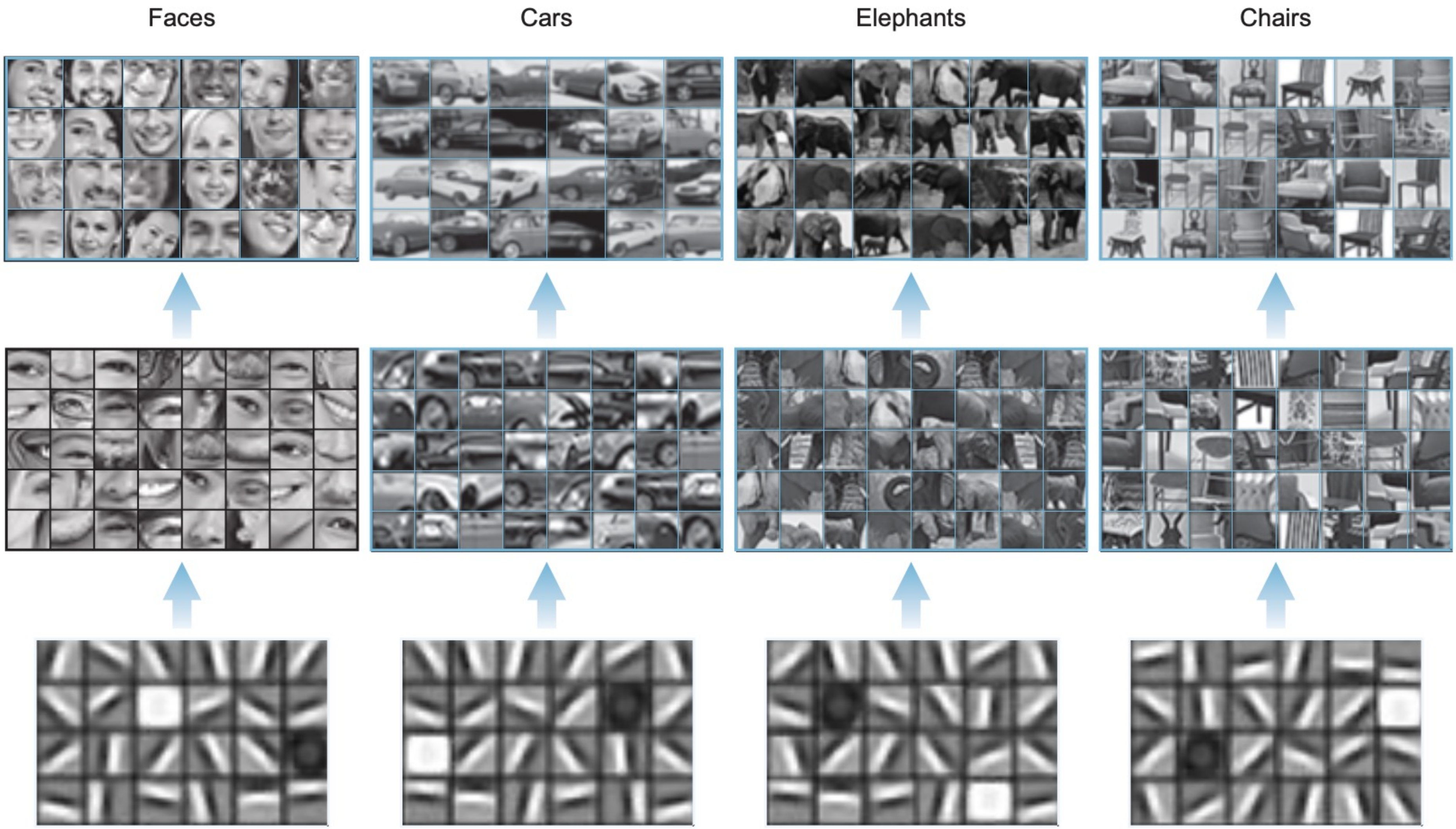
Target Data

- **Real (SfM + MVS)**
- **Unlabeled**

Transfer Learning for Image Classification

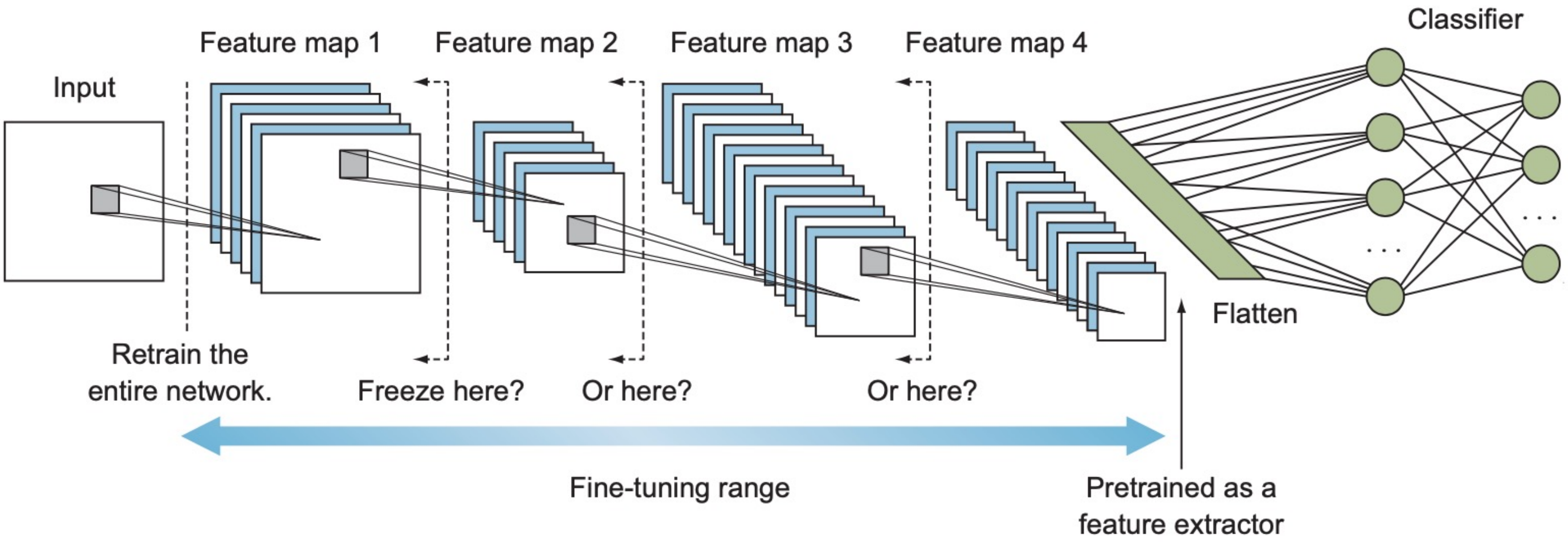
Transfer Learning for Image Classification: Rationale

- A CNN learns the features in a dataset step by step in increasing levels of complexity. These are called feature maps. The deeper you go through the network layers, the more **image-specific** features are learned.



Transfer Learning for Image Classification: How

- Instead of starting from scratch, we can leverage a pretrained neural network (often a complex NN such as ResNet) and use their optimized parameters (weights) trained on a large dataset as a starting point to train our model on a smaller dataset for a given task.
- See CNN_Transfer_Learning_Part1.pdf

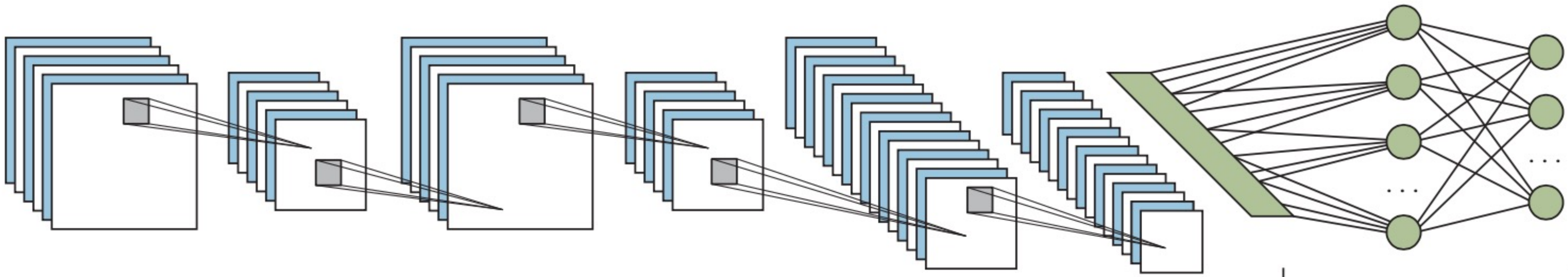


Transfer Learning Scenarios

Scenario	Size of the target data	Similarity of the original and new datasets	Approach
1	Small	Similar	Pretrained network as a feature extractor
2	Large	Similar	Fine-tune through the full network
3	Small	Very different	Fine-tune from activations earlier in the network
4	Large	Very different	Fine-tune through the entire network

- Scenario 3: see CNN_Transfer_Learning_Part2.pdf

Summary: Transfer Learning Scenarios and Strategies



Scenario #1: You have a small dataset that is similar to the source dataset.

Scenario #2: You have a large dataset that is similar to the source dataset.

Scenario #3: You have a small dataset that is different from the source dataset.

Scenario #4: You have a large dataset that is different from the source dataset.

Summary: Transfer Learning

- Given a source domain $\mathbb{D}_s$ and a learning task $\mathbb{T}_s$, a target domain $\mathbb{D}_t$ and a learning task $\mathbb{T}_t$, transfer learning aims to help improve the learning of the target predictive function $f_t(\cdot)$ for the target domain using the knowledge in $\mathbb{D}_s$ and $\mathbb{T}_s$, where $\mathbb{D}_s \neq \mathbb{D}_t$ or $\mathbb{T}_s \neq \mathbb{T}_t$
- Domain adaptation is a subfield of transfer learning where the label space remains same, yet the probabilities between source and target domains change $P(X_s) \neq P(X_t)$
- Transfer learning migrates the knowledge learned from the source dataset to the target dataset, to save training time and computational cost and to improve generalization in target.
- The two main transfer learning approaches for image classification are using a pretrained network as a feature extractor, and fine-tuning.