Transfer Learning

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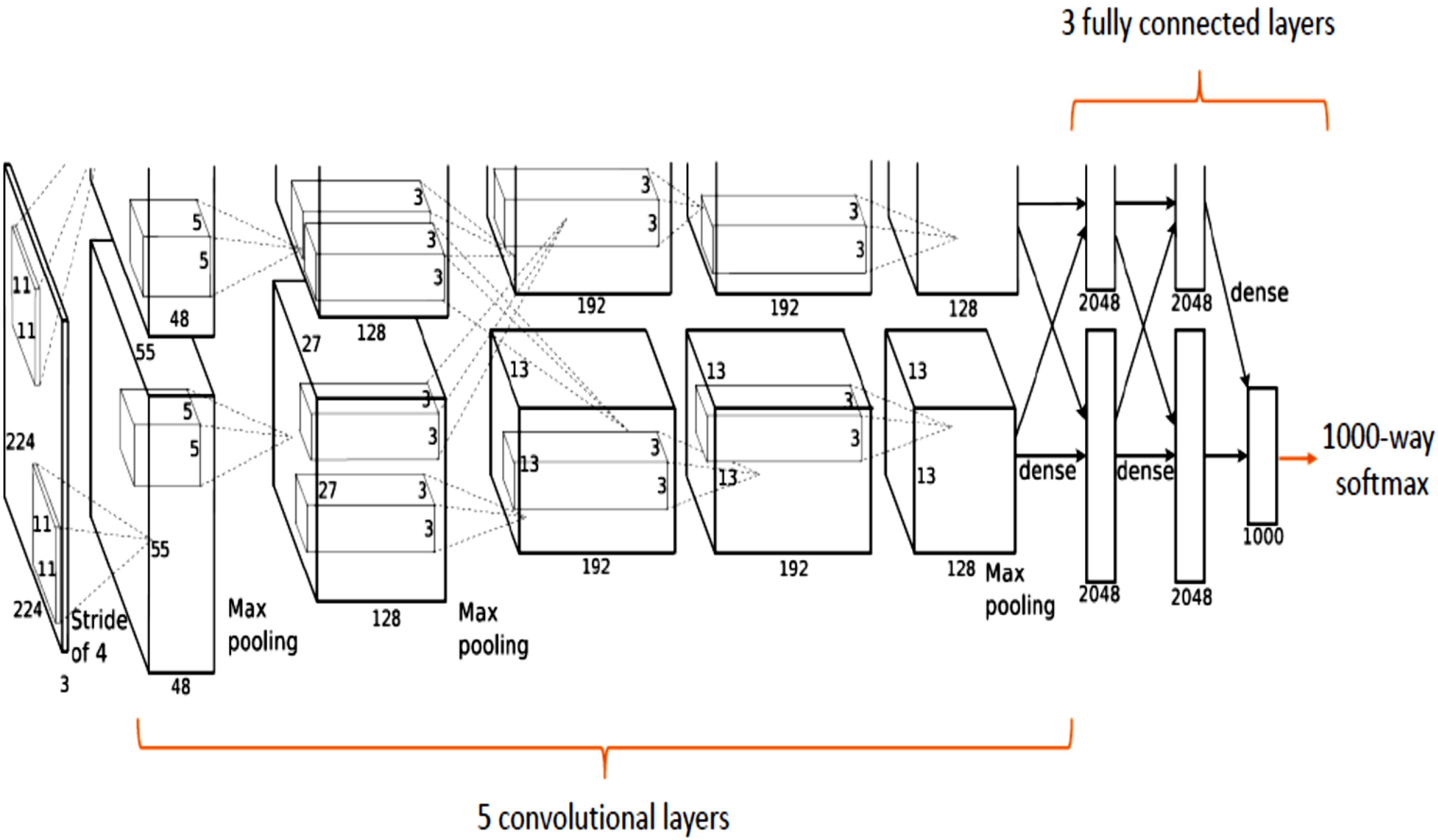
- **In all, there are roughly 1.2 million training images, 50,000 validation images, and 150,000 testing images.**

ImageNet Dataset

- **ILSVRC-2010 is the only version of ILSVRC for which the test set labels are available.**

- On ImageNet, it is customary to report two error rates: **top-1 and top-5**, where the top-5 error rate is the fraction of test images for which the correct label is not among the five labels considered most probable by the model.

ALEXNET - Architecture



These slides are not original and have been prepared from various sources for teaching purpose.

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Introduction [1]

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- **It is motivated by human learning. People can often transfer knowledge learnt previously to novel situations**
  - **Chess -> Checkers**
  - **Mathematics -> Computer Science**
  - **Table Tennis -> Tennis**

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- In practice, however, we often experience a **deterioration or collapse in performance** as the model has inherited the bias of its training data and does not know how to generalize to the new domain.

- If we want to train a model to perform **a new task, such as detecting bicyclists, we cannot even reuse an existing model, as the labels between the tasks differ.**

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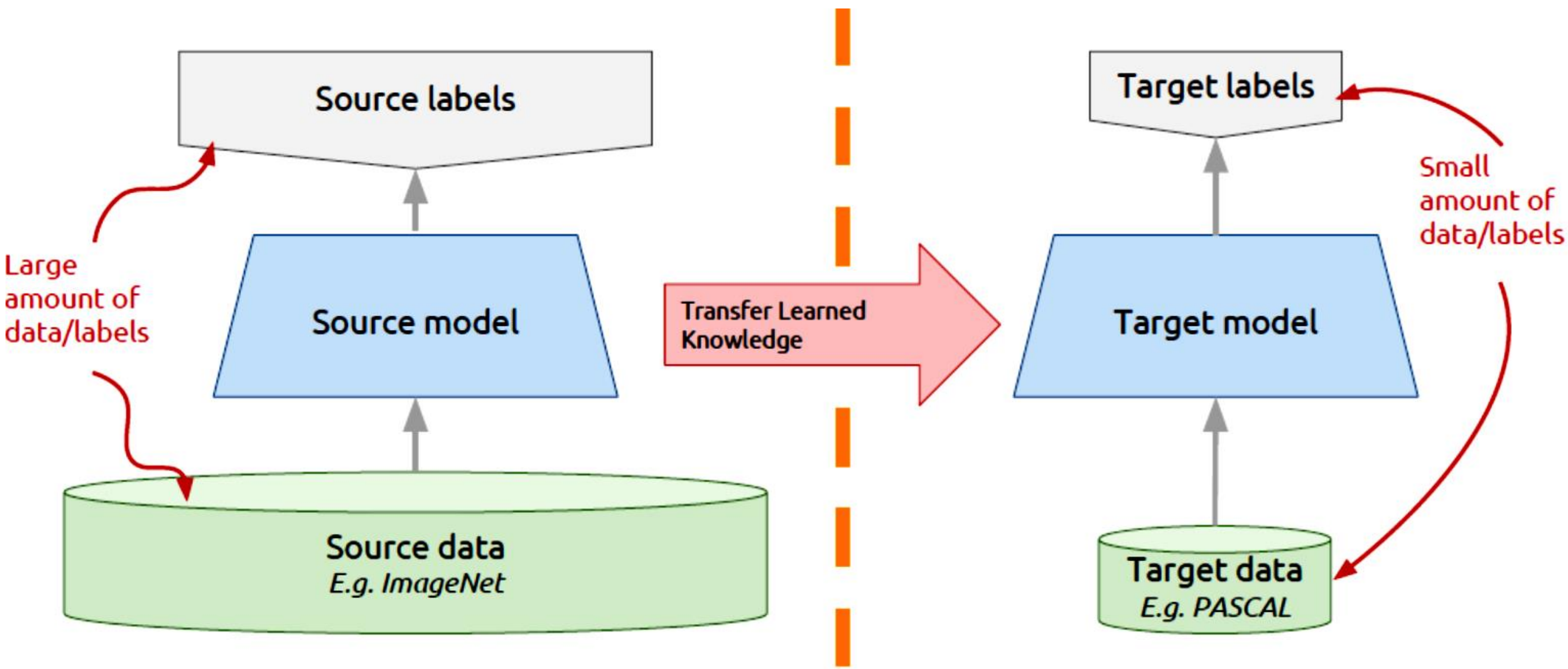
- **We try to store this knowledge gained in solving the source task in the source domain and apply it to our problem of interest.**

Transfer Learning: Idea [3]

- Instead of training a deep network from scratch for your task:
  - Take a network trained on a different domain for a different source task
  - Adapt it for your domain and your target task

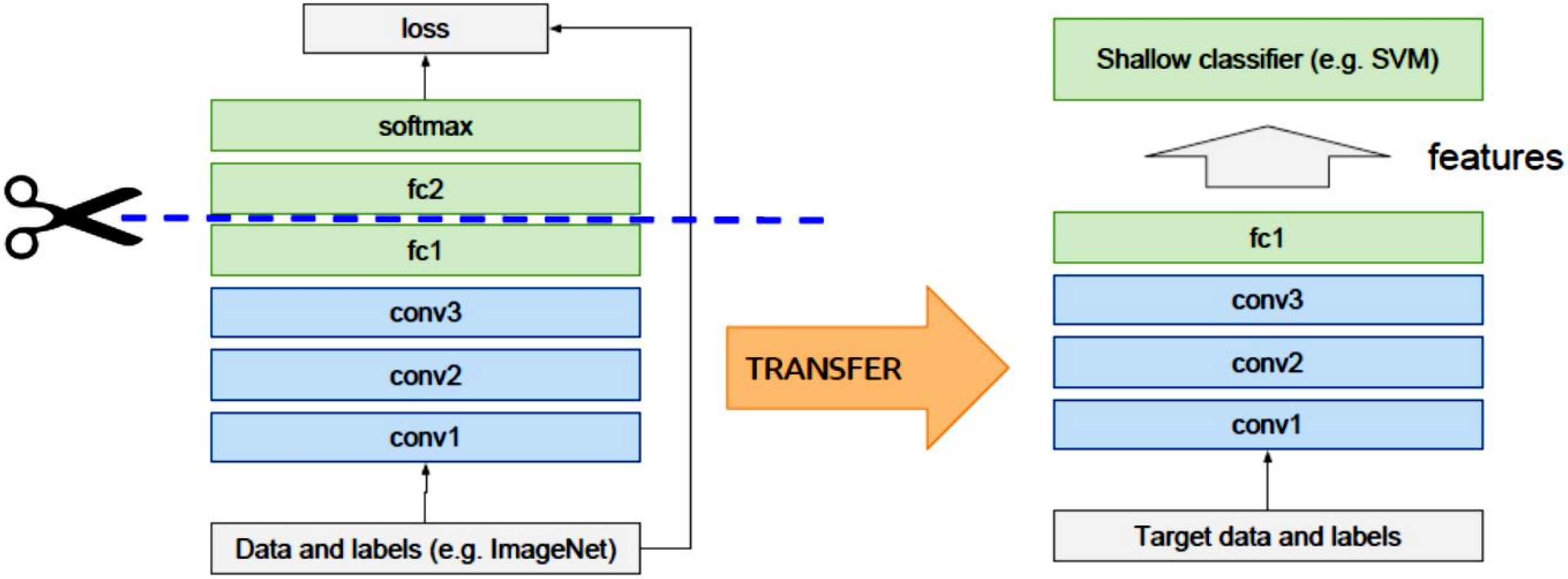


Example: PASCAL VOC 2007 [3]

- Standard classification benchmark, 20 classes, ~10K images, 50% train, 50% test
- Deep networks can have many parameters (e.g. 60M in Alexnet)
- Direct training (from scratch) using only 5K training images can be problematic. Model overfits.
- How can we use deep networks in this setting?

Off-the-shelf Features [3]

Idea: use outputs of one or more layers of a network trained on a different task as generic feature detectors. Train a new shallow model on these features.



Off-the-shelf Features [3]

Works surprisingly well in practice!

Surpassed or on par with state-of-the-art in several tasks in 2014

Image classification:

- PASCAL VOC 2007
- Oxford flowers
- CUB Bird dataset
- MIT indoors

Image retrieval:

- Paris 6k
- Holidays
- UKBench

Method	mean Accuracy
HSV [27]	43.0
SIFT internal [27]	55.1
SIFT boundary [27]	32.0
HOG [27]	49.6
HSV+SIFTi+SIFTb+HOG(MKL) [27]	72.8
BOW(4000) [14]	65.5
SPM(4000) [14]	67.4
FLH(100) [14]	72.7
BiCos seg [7]	79.4
Dense HOG+Coding+Pooling[2] w/o seg	76.7
Seg+Dense HOG+Coding+Pooling[2]	80.7
CNN-SVM w/o seg	74.7
CNNaug-SVM w/o seg	**86.8**

Oxford 102 flowers dataset

Razavian et al, **CNN Features off-the-shelf: an Astounding Baseline for Recognition,** CVPRW 2014 http://arxiv.org/abs/1403.6382

Major Transfer Learning Scenarios [5]

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- Instead, it is common to pretrain a ConvNet on a very large dataset (e.g. ImageNet, which contains 1.2 million images with 1000 categories), and then use the ConvNet either as an initialization or a fixed feature extractor for the task of interest.

Major Transfer Learning Scenarios [5]

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  - **ConvNet as fixed feature extractor**
  - **Fine-tuning the ConvNet**

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    - It is important for performance that these codes are ReLUd (i.e. thresholded at zero) if they were also thresholded during the training of the ConvNet on ImageNet (as is usually the case).
    - Once you extract the 4096-D codes for all images, train a linear classifier (e.g. Linear SVM or Softmax classifier) for the new dataset.

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    - **This is motivated by the observation that the earlier features of a ConvNet contain more generic features (e.g. edge detectors or colour blob detectors) that should be useful to many tasks, but later layers of the ConvNet becomes progressively more specific to the details of the classes contained in the original dataset.**

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- **This is a function of several factors, but the two most important ones are the size of the new dataset (small or big), and its similarity to the original dataset** (e.g. ImageNet-like in terms of the content of images and the classes, or very different, such as microscope images).

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- **Keeping in mind that ConvNet features are more generic in early layers and more original-dataset-specific in later layers, here are some common rules of thumb for navigating the 4 major scenarios:**
  - **New dataset is small and similar to original dataset**
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  - Since the data is similar to the original data, we expect higher-level features in the ConvNet to be relevant to this dataset as well.
  - Hence, the best idea might be to train a linear classifier on the CNN codes.

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  - Since we have more data, we can have more confidence that we won't overfit if we were to try to fine-tune through the full network.

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  - Since the data is small, it is likely best to only train a linear classifier.
  - Since the dataset is very different, it might not be best to train the classifier form the top of the network, which contains more dataset-specific features.
  - Instead, it might work better to train the SVM classifier from activations somewhere earlier in the network.

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  - However, in practice it is very often still beneficial to initialize with weights from a pretrained model.
  - In this case, we would have enough data and confidence to fine-tune through the entire network.

Negative Transfer [11]

- **Negative transfer happens when source domain data and task contribute to reduced performance of learning in the target domain.**

- **Causes:**
  - **Domains are too dissimilar.**
  - **Tasks are not well-related**

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