Transfer Learning in Neural Networks

Reuse Knowledge, Save Data, Improve Results

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Roadmap

1. Big Picture and Core Idea
2. Workflow and Strategies
3. Example and Interpretation
4. Takeaways

What Is Transfer Learning and Why Use It?

One-sentence idea

Transfer learning reuses what a model learned before, so a new task can be solved faster and better.

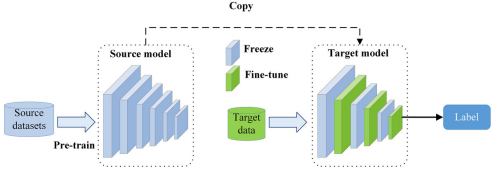
Why it is necessary in practice

- Labeled data is expensive, and annotation quality can vary.
- The dataset may be too small to train a large model from scratch reliably.
- Training from scratch needs much more compute and tuning effort.
- Pretrained weights usually improve optimization stability.

To formalize this setting, we denote source and target data/task pairs as follows:

$$(\mathcal{D}_S, \mathcal{T}_S) \to (\mathcal{D}_T, \mathcal{T}_T), \quad P_S(x, y) \neq P_T(x, y)$$

$\mathcal{D}$: dataset, $\mathcal{T}$: task, S/T: source/target, $P(x, y)$: distribution.



← Source-to-target transfer illustration.

Basic Workflow and the Rationale Behind Each Step

Step 1: Start with a pretrained model

- Use a backbone pretrained on large-scale data (e.g., ImageNet).
- Why: it already learns generic features, so training is faster and more stable.

Step 2: Replace the task head

- Swap the original output layer with a new head for your target labels.
- Why: source and target label spaces are usually different.

Step 3: Adapt on target data

- Train the new head first, then unfreeze upper backbone layers if needed.
- Use data augmentation (e.g., random crop/flip/color jitter) as a training trick to improve generalization.
- Tip: smaller LR for pretrained layers, larger LR for the new head.

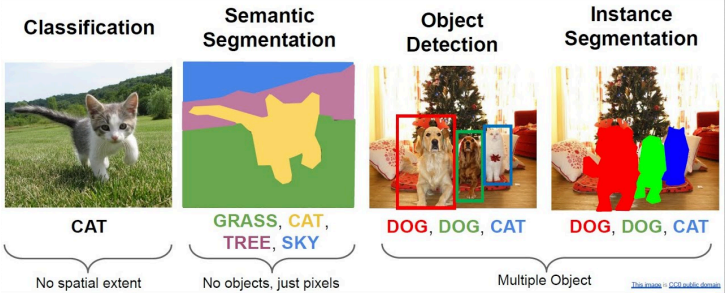
Four Core Vision Tasks and Their Differences

Task definitions

- **Classification**: predict one label for the whole image.
- **Object Detection**: **classification + rough localization** using bounding boxes.
- **Semantic Segmentation**: **per-pixel classification**; same-class objects share one mask.
- **Instance Segmentation**: detection + segmentation; each object instance has its own mask.

Why these tasks matter

- They represent increasing understanding levels: image-level → object-level → pixel-level.
- They support real applications such as autonomous driving, robotics, and medical imaging.



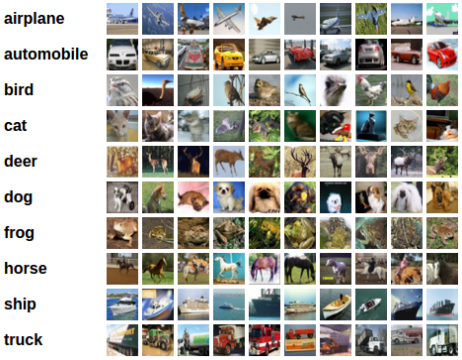
Transfer Learning Example: Classification (CIFAR-10)

This is an example of **image classification** transfer learning.

- Source pretraining: **ImageNet-pretrained** vs **random initialization**.
- Target dataset: **CIFAR-10** (10 classes, 32×32 RGB images).
- Model: ResNet-18.
- Training: same settings and 10 epochs for fair comparison.

Input and output definition

- Input x: one image, $x \in \mathbb{R}^{32\times32\times3}$.
- Output $\hat{y}$: one class label (or a 10-dimensional probability vector).



Classification Metrics

Overall accuracy (OA)

$$\mathrm{OA} = \frac{\sum_{c=1}^{C} TP_c}{N}$$

Fraction of all samples predicted correctly.

Average accuracy (AA)

$$\mathrm{AA} = \frac{1}{C} \sum_{c=1}^{C} \frac{TP_c}{TP_c + FN_c}$$

Mean per-class recall; reduces majority-class dominance.

Kappa coefficient

$$\kappa = \frac{p_o - p_e}{1 - p_e}, \quad p_o = \mathrm{OA}, \quad p_e = \sum_{c=1}^{C} \left(\frac{n_{c,\mathrm{true}}}{N} \cdot \frac{n_{c,\mathrm{pred}}}{N} \right)$$

Here $n_{c,\mathrm{true}}$ and $n_{c,\mathrm{pred}}$ are true/predicted counts of class c.

Per-class precision and recall

$$\mathrm{Precision}_c = \frac{TP_c}{TP_c + FP_c}, \qquad \mathrm{Recall}_c = \frac{TP_c}{TP_c + FN_c}$$

Precision: how reliable positive predictions are; recall: how many true samples are found.

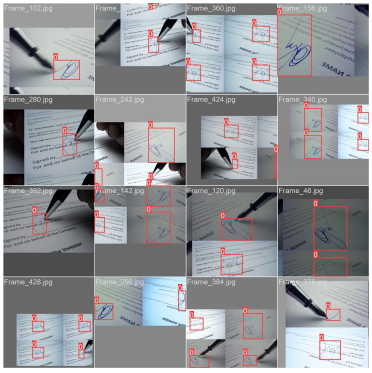
Transfer Learning Example: Object Detection (Signature)

This is an example of **object detection** transfer learning.

- Source pretraining: **COCO-pretrained** vs **random initialization**.
- Target dataset: **Signature** dataset.
- Model: YOLO11n.
- Training: same settings and 10 epochs for fair comparison.

Input and output definition

- Input x: one document image.
- Output $\hat{y}$: bounding boxes + confidence scores for signature regions.



Detection Metrics

IoU for one prediction

$$\mathrm{IoU} = \frac{|B_{pred} \cap B_{gt}|}{|B_{pred} \cup B_{gt}|}$$

A detection is a TP when class is correct and IoU exceeds a threshold.

Single-class AP metrics

TP at threshold t : $\mathrm{IoU}(B_{pred}, B_{gt}) \geq t$ and class is correct, $\quad \mathrm{AP}_t = \int_0^1 P_t(r)\, dr, \quad \mathrm{AP}_{50} = \mathrm{AP}_t\big|_{t=0.50},$

r is recall, $P_t(r)$ is the precision–recall curve built using IoU threshold t; $\mathrm{AP}_{50:95}$ averages stricter IoU thresholds and is more comprehensive.

Multi-class mAP

$$\mathrm{mAP}_{50} = \frac{1}{C}\sum_{c=1}^{C} \mathrm{AP}_{50}^{(c)}, \qquad \mathrm{mAP}_{95} = \frac{1}{C}\sum_{c=1}^{C} \mathrm{AP}_{95}^{(c)}, \qquad \mathrm{mAP}_{50:95} = \frac{1}{C}\sum_{c=1}^{C} \mathrm{AP}_{50:95}^{(c)}$$

Also report precision/recall and F1 at a chosen confidence threshold for deployment.

When It Works, Fails, and What To Do

When transfer works well

- Source and target are semantically related.
- Rationale: shared structure means reusable features.

When it can fail

- Large domain gap or mismatched objectives.
- Rationale: source features may bias learning to wrong cues.

What to do

- Start with feature extractor as baseline.
- Unfreeze gradually from top layers downward.
- Use smaller LR for pretrained layers than for new head.
- For small batch sizes, freeze BatchNorm statistics (or use GroupNorm) to improve stability.
- Track validation curve and early-stop when needed.

Summary + Common Mistakes

Key takeaways

1. Transfer learning is a practical paradigm, not just a trick.
2. Key tradeoff: stability vs adaptability.
3. Backbone + head decomposition enables cross-task reuse.
4. Good engineering (LR, unfreezing, validation) matters.

Common mistakes

- Forgetting to replace the final classification layer.
- Using too large LR for pretrained parameters.
- Evaluating only on training data.
- Reporting one run without variance.

Q&A

Questions?