General AI/ML

Unit 2: Optimization, Fine-tuning, Transfer Learning

2.3.1

Transfer Learning Basics

Introduction to Transfer Learning

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Challenges in Training From Scratch

- High demand for large, labeled datasets
- Extensive computational resources for training complex models
- Long development cycles

Introduction to Transfer Learning

- Definition: A machine learning that involves taking a pre-trained model on a large dataset and repurposing it for a similar but different task

  eg: for image classification, a model trained to recognize cars could be re-applied when trying to recognize trucks

- Unlike traditional machine learning, which starts from scratch, transfer learning leverages learned features (knowledge) from one task to improve learning in another thus saving time and resources

Motivation behind Transfer Learning

- Reduced training time: Pre-trained models provide a starting point, bypassing the need to train from scratch
- Improved performance with limited data: Leverages insights from large datasets, boosting results on smaller datasets
- Tackling complex tasks: Breaks down complex problems using knowledge gained on simpler ones
- Increased accuracy potential: Builds upon strong foundations
- Cost reduction: Lowers the barrier to entry for deploying advanced AI solutions by reducing the need for large-scale data collection and computation

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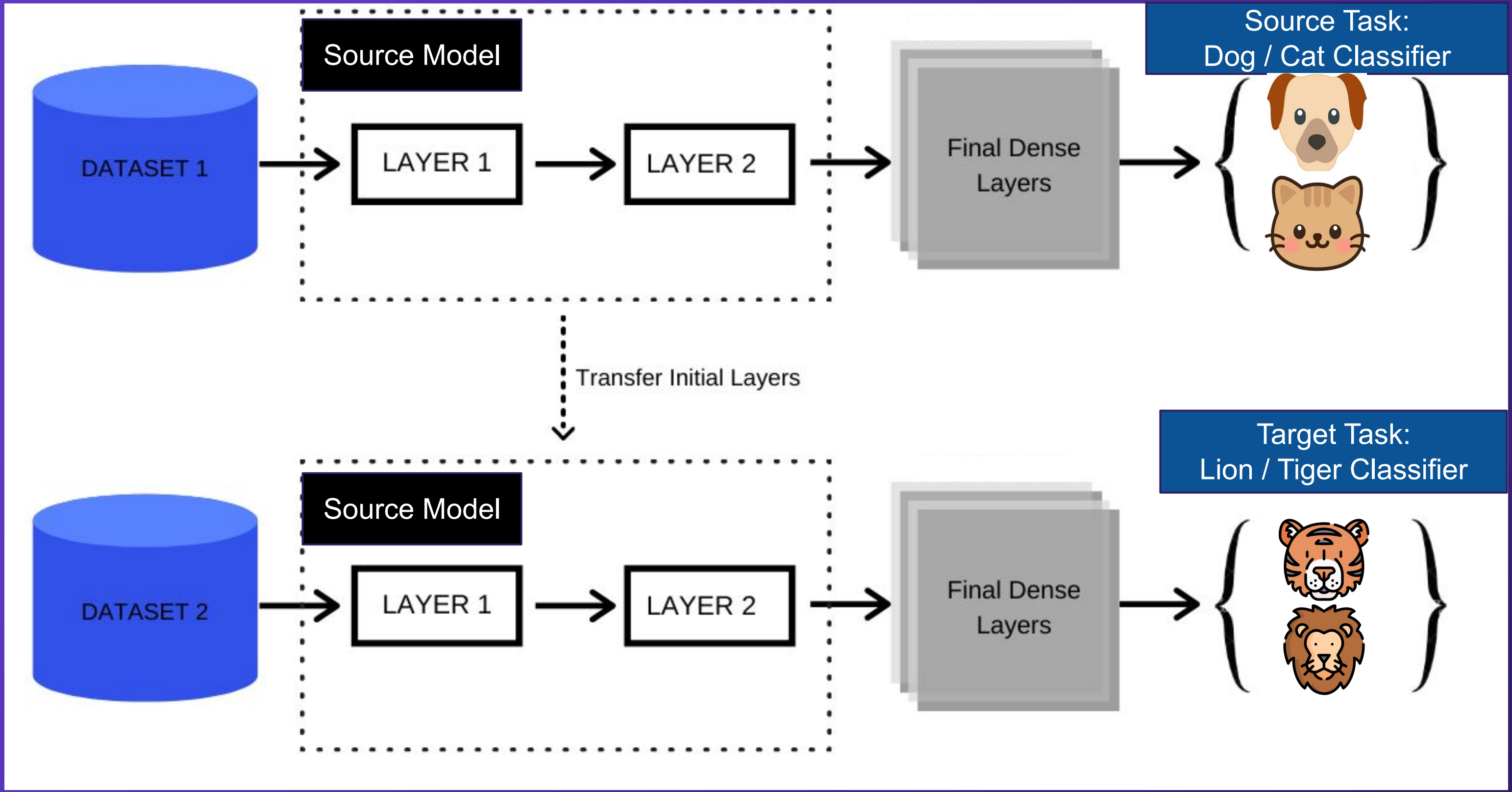
Introduction to Transfer Learning



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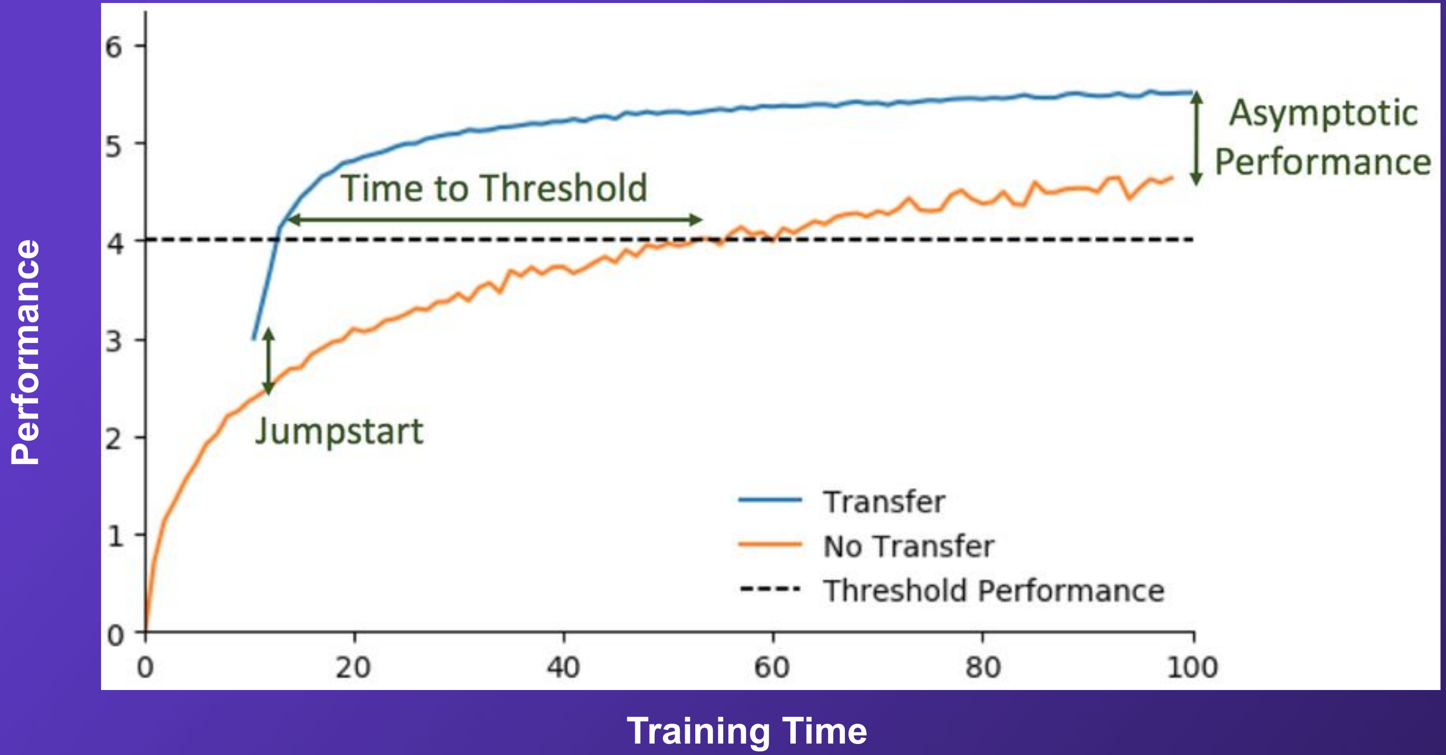
How Does Transfer Learning Work?

- **Source model:** A pre-trained model, typically trained on a large-scale dataset (e.g., ImageNet). These models have learned generalizable features and patterns
- **Target task:** The new task you want to solve, potentially with a smaller dataset
- **Knowledge transfer:** Weights and internal representations learned by the source model are re-used as a starting point for the target task
- **Fine-tuning (optional):** Select which layers to freeze (keep pre-trained weights) and which to retrain on the new data, adapting the model to the target task

The Power of Transfer Learning



Transfer Learning in NLP

- Pre-trained models like BERT and GPT-3 learn complex language patterns and be used for diverse NLP tasks:
  - Sentiment analysis (gauging customer reviews)
  - Text summarization (condense lengthy documents)
  - Machine translation (breaking down language barriers)
  - Chatbot development (creating intelligent virtual assistants)

Transfer Learning in Computer Vision

- Pre-trained models on massive image datasets (e.g., ImageNet) can be adopted for specialized computer vision tasks such as:
  - Object detection (identifying objects in self-driving cars)
  - Image classification (categorizing medical scans)
  - Facial recognition (enhancing security systems)
  - Anomaly detection (spotting irregularities in industrial processes)

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Transfer Learning in ASR

- Pre-trained models on large speech datasets (eg. Common Voice, Librispeech) have been used for improved speech recognition:
  - Voice assistants (understanding spoken commands)
  - Automated captioning (generating captions for videos)
  - Speech-to-text transcription (converting spoken words to text)
  - Language learning applications (providing feedback on pronunciation)

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Key Considerations in Transfer Learning

- Similarity between tasks: Greater overlap leads to better transfer outcomes
- Size and quality of pre-trained model: Larger, high-quality models yield stronger starting points
- Fine-tuning strategies: Careful adaptation of pre-trained model layers is essential

The Future of Transfer Learning

- Continued innovation: Advancements in model architectures and techniques
- Democratizing AI: More accessible pre-trained models enable wider adoption
- Tackling increasing complexity: Enabling solutions for highly complex problems

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