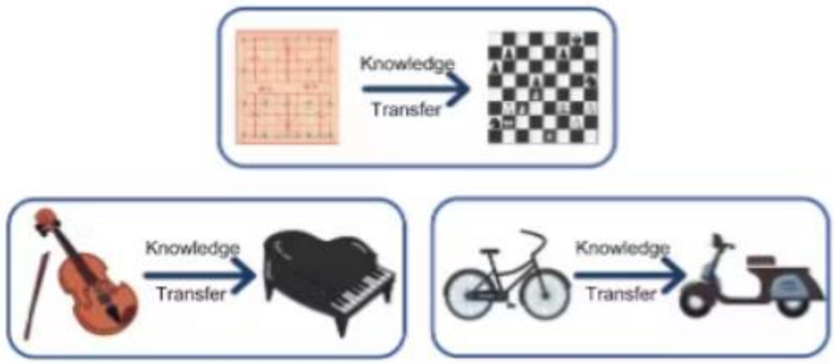
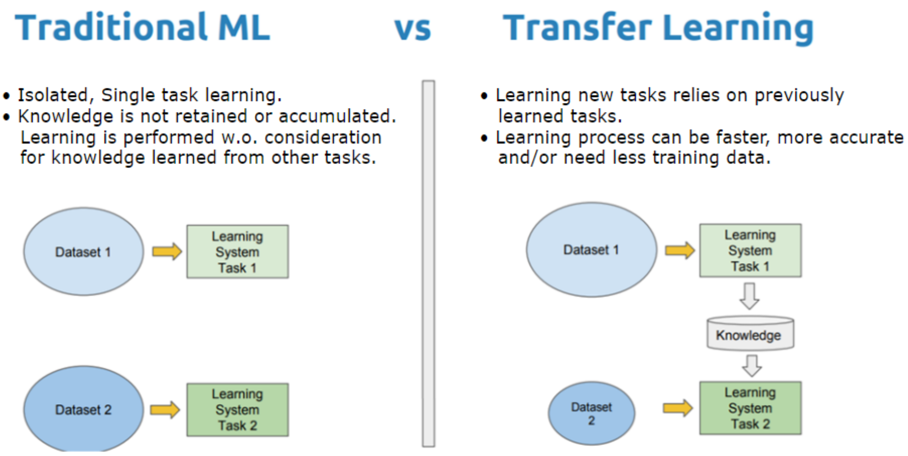
Transfer Learning

- Transfer learning is a technique in machine learning that utilizes knowledge gained from one task (upstream task) to improve performance on another related task (downstream task).
- This approach is particularly beneficial when dealing with limited data for the downstream task.
- Transfer learning involves fine-tuning the weights of a pre-trained upstream model to adapt it to the downstream task.
- Applications include computer vision tasks like object detection and natural language processing tasks like sentiment analysis.
- An example is fine-tuning a cat classifier to recognize dogs, leveraging the shared features between the two animals.



examples:

- If you *know how to ride a motorbike*, then you can *learn how to drive a car*
- If you *know math and statistics*, then you can *learn machine learning*
- If you *know how to play classical piano*, then you can *learn how to play jazz piano*



How Traditional ML differs from Transfer Learning

Transfer learning in vision (image data)

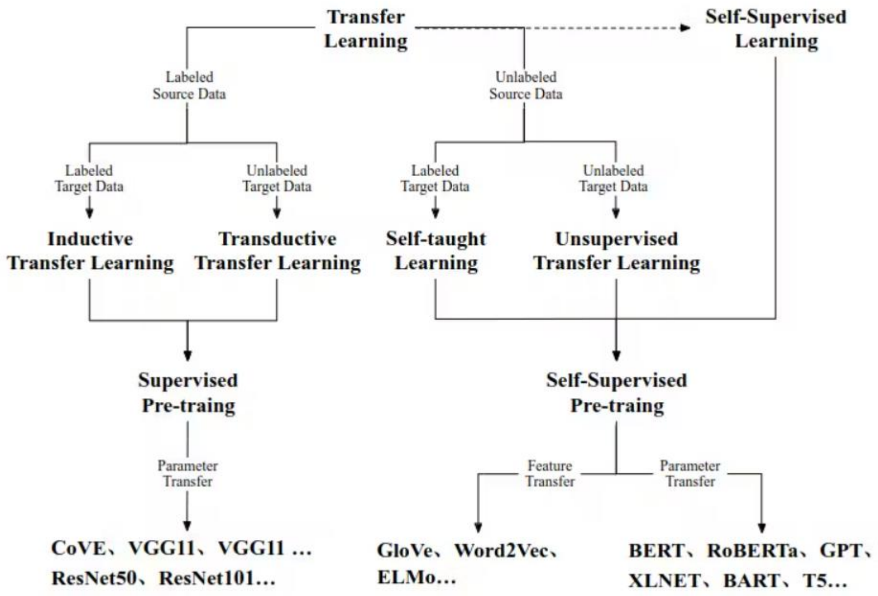
Some of the models are:

- Oxford VGG Model
- Google Inception Model
- Microsoft ResNet Model

Transfer learning in NLP (text data)

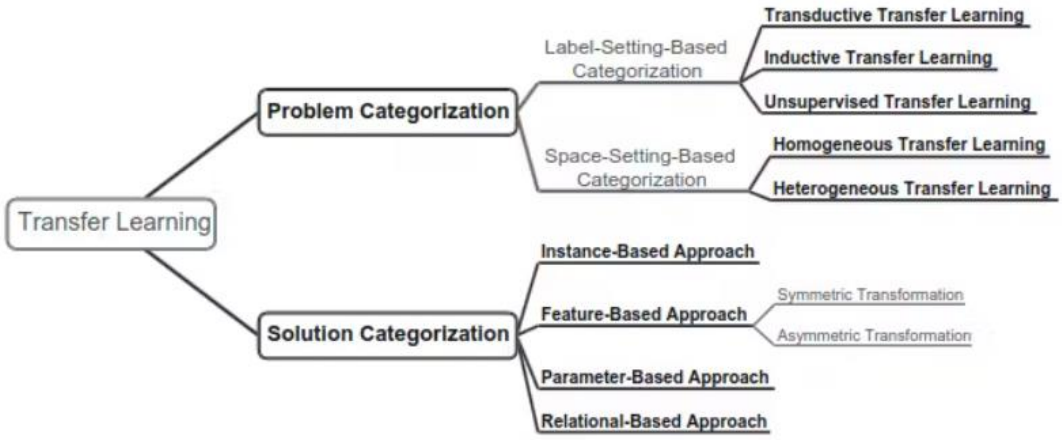
Some popular pre-trained models are:

- Google's word2vec Model
- Stanford's GloVe Model



The Spectrum of Pre-training Methods

Types of Transfer Learning

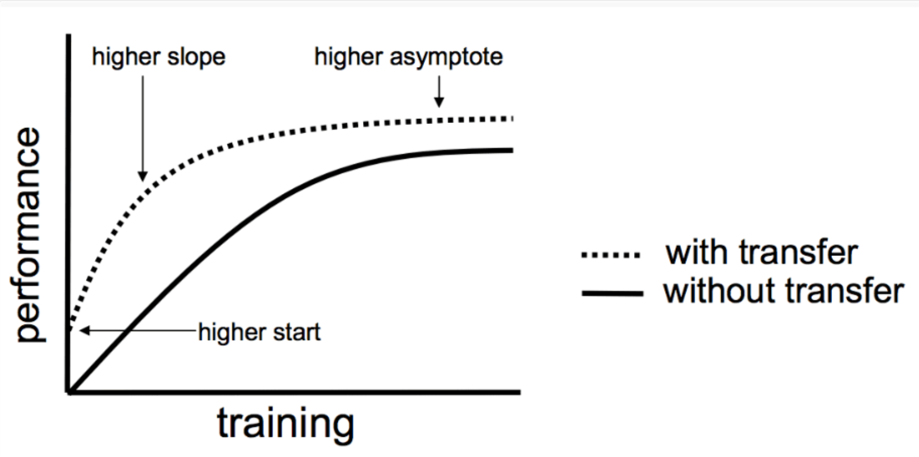


Categorizations of Transfer Learning

When to Use Transfer Learning?

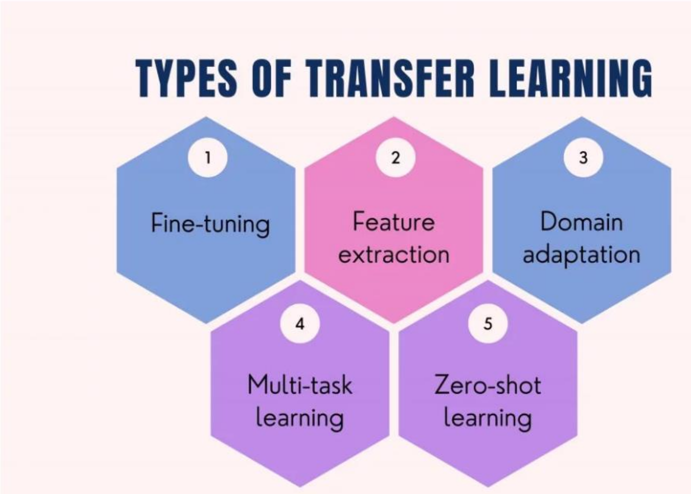
Transfer learning is an optimization, a shortcut to saving time or getting better performance.

1. **Higher start**. The initial skill (before refining the model) on the source model is higher than it otherwise would be.
2. **Higher slope**. The rate of improvement of skill during training of the source model is steeper than it otherwise would be.
3. **Higher asymptote**. The converged skill of the trained model is better than it otherwise would be.



Three ways in which transfer might improve learning.

Types of Transfer Learning in Deep Learning



Fine-tuning: It involves the use of pre-trained models as the underlying framework and then training on a new task with a lower learning rate.

Feature extraction: Here, the developer uses pre-trained models to extract features from new data. Then they use the best features to train a new classifier.

Domain adaptation: It works by adapting a pre-trained model to a new domain by fine-tuning it on the target domain data.

Multi-task learning: Here, the focus is to train a single model on multiple tasks to improve performance on all tasks.

Zero-shot learning: It involves the use of pre-trained models to make predictions on new classes without any training data for those classes.

Transfer Learning	Machine Learning
This technology focuses on reusing pre-trained models for related tasks	It is a wider domain that encompasses different algorithms and techniques for learning from data
It requires fewer labeled examples for training	Here the developer needs large volumes of labeled data to train models
It ensures faster results and enhanced performance.	The process is a bit slower and hence its implementation needs more time.
Limited to tasks that are related to the source task	Can be applied to a wide range of tasks

Applications:

- Image classification
- Object detection
- Sentiment analysis
- Machine translation
- Text summarization
- Speech recognition

Advantages:

- Reduced training time
- Improved performance
- Reduced dataset size
- Ability to handle limited data

Disadvantages:

- Potential for bias transfer
- Overfitting to the source task
- Difficulty in selecting the appropriate pre-trained model
- Increased computational cost