

## Transfer Learning

Transfer learning is a machine learning technique that allows knowledge gained from one task to be applied to a second, related task. This is particularly useful when the second task has limited data available for training.

There are two main types of transfer learning: **homophilic** and **heterophilic**. Homophilic transfer learning involves transferring knowledge from a source task to a target task where the source and target tasks share similar data distributions. Heterophilic transfer learning involves transferring knowledge from a source task to a target task where the source and target tasks have different data distributions.

Transfer learning is often used in natural language processing (NLP) tasks, such as text classification and sentiment analysis. For example, a model trained on a large dataset of text (the source task) can be used to classify text from a smaller dataset (the target task). This is because the model has learned general features of language that are applicable to both tasks.

Transfer learning is also used in computer vision tasks, such as image classification and object detection. For example, a model trained on a large dataset of images (the source task) can be used to classify images from a smaller dataset (the target task). This is because the model has learned general features of images that are applicable to both tasks.

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