

Investigating Transfer Learning Techniques for Neural Networks in Limited Data Scenarios

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Description

Transfer learning has emerged as a powerful approach for leveraging pre-trained neural networks in various domains. In limited data scenarios, where obtaining large labeled datasets is challenging, transfer learning offers a promising solution to overcome data scarcity. This research article aims to investigate the effectiveness of transfer learning techniques for neural networks in limited data scenarios. We explore different transfer learning strategies, including fine-tuning, feature extraction, and domain adaptation, and evaluate their performance on limited datasets. The experimental results demonstrate the potential of transfer learning to enhance the generalization and performance of neural networks when training data is scarce. The findings of this research contribute to the understanding of transfer learning techniques and provide insights into their practical applications in real-world scenarios with limited data. Limited data scenarios pose a significant challenge for training neural networks, as they often require a substantial amount of labeled data to achieve satisfactory performance. However, in many practical applications, acquiring large labeled datasets is impractical or costly [1-3].

Transfer learning, a technique that transfers knowledge from a pre-trained model to a new task, has shown promise in mitigating the limitations of limited data scenarios. The main objective of this research is to investigate the efficacy of transfer learning techniques in limited data scenarios. We aim to evaluate different transfer learning strategies and assess their performance in enhancing the generalization capabilities of neural networks when training data is limited.

Fine-tuning

Fine-tuning involves taking a pre-trained model and further training it on a target task with limited data. This technique enables the network to adapt its learned representations to the specific characteristics of the new dataset.

Feature extraction

Feature extraction utilizes the pre-trained model as a fixed feature extractor, where only the top layers of the network are retrained on the target task. By extracting high-level features from the pre-trained model, this technique allows for better utilization of limited data.

Domain adaptation

Domain adaptation focuses on addressing the domain shift between the source and target datasets. It aims to adapt the pre-trained model to the target domain by aligning the distributions of the two datasets, enabling effective knowledge transfer.

Experimental setup

We conducted experiments on several benchmark datasets in various

domains, including computer vision and natural language processing, to assess the performance of transfer learning techniques in limited data scenarios. We used limited subsets of the original datasets to simulate realistic scenarios where labeled data is scarce. Our experimental results demonstrate that transfer learning techniques significantly improve the performance of neural networks in limited data scenarios. Fine-tuning consistently outperformed other transfer learning strategies, indicating its effectiveness in adapting the pre-trained model to the target task. Feature extraction also yielded competitive results, showcasing the value of leveraging pre-trained representations. Domain adaptation techniques proved beneficial in mitigating the domain shift problem, enabling better generalization in limited data scenarios [4,5].

This research investigated the application of transfer learning techniques for neural networks in limited data scenarios. The findings highlight the efficacy of transfer learning in enhancing the performance and generalization capabilities of neural networks when training data is scarce. Fine-tuning, feature extraction, and domain adaptation techniques have shown promise in tackling the limitations of limited data scenarios. Further exploration and refinement of transfer learning approaches can potentially unlock their full potential in real-world applications with limited data.

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Conflict of Interest

Authors declare no conflict of interest.

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