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Transfer Learning: Bridging Domains in Machine Learning

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Abstract

Transfer learning uses pre-trained information from a large-scale dataset (like ImageNet) to a target task with sparsely labeled data. This strategy improves learning performance and generalization by enabling models to draw on the learnt representations and efficiently apply information to new challenges. Transfer learning has been used extensively in many fields, and its use is growing as computer networks, information technology, and related businesses grow quickly. Transfer learning offers excellent growth chances and tremendous development potential. The TL approach has a number of benefits, especially in domains that use images. These benefits include minimizing the scarcity of data, avoiding overfitting, quickening the pace of convergence, enhancing the quality of extracted features and data reuse, facilitating simulation training, cutting down on training time, and enhancing generalization ability.

Keywords: Transfer learning, Information technology, Algorithm, Artificial Neural Networks.

1 Introduction

Transfer learning is a method in machine learning that takes use of prior knowledge to improve performance on similar tasks. Voice recognition, computer vision, and natural language processing are just a few of the many areas that regularly use this technique. An overview of transfer learning and its most recent advancements is the aim of this study. When training on unlabelled data is not readily available, transfer learning becomes invaluable. In these situations, the model may make use of insights

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gained from a similar job that has more labeled data. This allows the model to overcome the overfitting problem and excel at its intended task [1].

Feature-based transfer learning was one of the first forms of transfer learning, which included exploiting features learnt from a source task to improve performance on a target task. In computer vision, for instance, it is possible to enhance performance on a target task like object recognition by using features that have been learnt from a pre-trained model on the ImageNet dataset. Transfer learning also comes in the form of fine-tuning, which comprises training an existing model with a smaller dataset on a specific task. It is possible to fine-tune end-to-end and feature-based models alike. For instance, better performance in natural language processing may be achieved by fine-tuning a transformer model that has already been trained for a particular job like sentiment analysis [2].

Multi-task learning, which entails training a model on many tasks at once, has attracted more attention recently. The model gains the ability to extract common representations during multi-task learning, which may be used to enhance performance across all tasks. In computer vision, for instance, a model trained on many tasks—such as semantic segmentation and object detection—can acquire characteristics that are helpful for both tasks. Instance-based transfer learning involves moving instances from the source job to the target work. One common use of this form of "transfer learning" is domain adaptation, the process of transferring model parameters from one domain to another. A model built on a dataset of vehicle photos, for instance, might be transferred to a dataset of truck images in computer vision by using examples from the car dataset [3].

2 Literature Review

(Zhao et al., 2024) [4] Recently, applications for self-supervised learning and transfer have surfaced in several fields, such as medical image processing, video recognition, and natural language processing. These methods have shown amazing results, leading to advancements in fields like illness detection, item identification, and language comprehension. Though these approaches have many benefits, they are not without restrictions. Transfer learning, for example, could run into domain mismatch issues within "the destination and pre-training domains", in contrast to self-supervised learning that requires meticulous pretext task design to provide relevant representations. The current uses of these pre-training techniques in a variety of sectors during the last three years are examined in this review study. It explores the benefits and drawbacks of each strategy, evaluates the effectiveness of models that use these methods, and suggests possible lines of inquiry for further study. This paper addresses the problem of data scarcity by offering a thorough analysis of existing pre-training techniques and recommendations for choosing the most appropriate approach for certain deep learning applications.

(Wu et al., 2024) [5] Our findings indicate that the Kullback-Leibler (KL) divergence $D(\mu\|\mu')$ is significant in the characterizations, where μ and μ' stand for the distribution of the training and testing data, respectively. This is maybe to be anticipated. We also expand the study to the Gibbs algorithm and the noisy stochastic gradient descent technique to show the utility of the limits. The mutual information constraint is then extended to include various divergences, such as Wasserstein distance and υdivergence, which may result in tighter bounds and allow for the situation where μ is not perfectly continuous with respect to μ′. We provide some numerical results to support our theoretical conclusions. Finally, we develop an algorithm (named InfoBoost) that dynamically modifies the importance weights for both source and target data based on specific information measures, addressing the issue that the bounds are frequently not directly applicable in practice due to the lack of distributional knowledge of the data. The suggested algorithm's efficacy is shown by the empirical findings.

(Baruffa et al., 2024) [6] In order to improve model performance and training, transfer learning (TL), which uses information from related activities, appears as a solution to this issue. This research explores the possibility of combining ANNs with Transfer Learning (TL) to predict the appearance of weld lines in injection-molded components. To transfer information across datasets connected to distinct components, transfer learning (TL) approaches are used. Furthermore, source datasets originating from simulations and experimental testing are used in the study. In order to get insight into the presence of surface defects using process simulations, it was necessary to correlate one of the outcomes with the experimental results. With simulations proving to be a more cost-effective alternative to experimental data, the findings demonstrate how effective TL is in lowering the data required to train predictive models. Even though TL from simulations cuts the target dataset data requirements by 83%, it nevertheless provides the non-pre-trained network with comparable predictive metric values. All things considered, transfer learning seems to have potential for simplifying injection molding optimization and cutting production costs.

(Iman et al., 2023) [3] The goal of "Deep Transfer Learning (DTL)", a subset of deep learning's transfer learning, is to reduce these overheads and dependencies by recycling trained models from one set of data and tasks into another. The majority of DTL methods that are used are based on networks or models. Famous methods and concepts, including deep transfer learning's notion, definition, and taxonomy, are investigated in this paper. Through an analysis of DTL strategies that have been used in the past five years and a few experimental assessments of DTLs, it seeks to identify the optimum strategy for using DTL in different sets. Along with possible solutions and future prospects in the area, we also take a look at the downsides of DTLs, such as the catastrophic forgetting problem and overly biassed pre-trained models.

(Gupta et al., 2022) [7] Deep learning systems performed better than conventional ones in a variety of trials involving pattern recognition, computer vision, and image processing. In numerous practical applications and hierarchical systems, pattern identification and categorisation tasks have been handled using deep learning and transfer learning algorithms. In practice, however, machine learning settings often defy this assumption due to the difficulty or high cost of acquiring training data and the ongoing need to educate novices to function well while interacting with input from several sources. Aims of this work include elucidating transfer learning, identifying higher-level representational properties, providing current methodologies, and evaluating applications in different fields of "deep learning and transfer learning".

(Yu et al., 2022) [8] Natural language processing, computer vision, text classification, behaviour recognition, and "deep transfer learning (DTL)" have all shown impressive results. DTL blends transfer learning (TL) with new ideas from deep neural networks. DTL, a subfield of machine learning, uses end-to-end learning to address the limitation of conventional machine learning, which treats each dataset separately. While there are several excellent and noteworthy broad surveys on TL, DTL has not received much attention or recent advancements. First, we analyze over 50 sample DTL techniques from the last ten years and comprehensively categorize them in this survey. Specifically, we further subdivide each group based on models, functions, and objects of operations. We also touch on unsupervised TL and new developments in TL in other domains. Lastly, we provide a few intriguing and potential avenues for further investigation.

(Hosna et al., 2022) [9] Machine Learning (ML) approaches are used in many real-world applications to provide perhaps the greatest data possible for consumers. Recently, the academic community has shown a great deal of interest in transfer learning (TL), one of the subdivisions of machine learning. Conventional machine learning technique’s function based on the premise that a model trains and tests samples using a restricted distribution of data. These traditional techniques apply to tiny data distributions and anticipate target activities in an undemanding manner. Still, TL may theoretically overcome this problem. TL is recognized for the connections it makes between the extra training and testing samples, which leads to more rapid production and effective outcomes. By mentioning situational usage depending on their periods and a few of their applications, this work adds to the domain and breadth of TL. The study offers a thorough examination of three methods, including domain adaptation and sample selection: "inductive TL, transductive TL, and unsupervised TL". Contributions and future approaches are then covered.

(Phung et al., 2021) [10] Theoretically sound publications that examine domain adaptation (DA) in depth and cover a range of topics, such as learning domain-invariant representations and associated trade-offs, are beneficial. That does not seem to be the case, however, with the domain generalization (DG) and multiple source DA settings, which are noticeably more intricate and advanced because of the many source domains involved and the possibility of the target domain being unavailable during training. In this article, we establish two types of domain-invariant representations by using our newly developed upper-bounds for the target general loss. We also examine the benefits and drawbacks of requiring the acquisition of every domain-invariant representation, along with the trade-offs. In the end, we carry out experiments to examine the trade-off of different representations in order to provide useful guidance on their practical use and uncover further intriguing aspects of our proposed theory.

(Zhou et al., 2021) [11] The machine learning premise that training and test data must be distributed independently and identically is relaxed by transfer learning. To help the target domain complete the learning work, it teaches it a number of source domains that are similar to the target domain. This helps with the shortage of annotation data, improves the model's resilience and generalisation performance, and more. An overview of transfer learning's development is provided in this article. When it comes to "how to transfer," transfer learning may be divided into four categories: instance-based, feature-based, model-based, and relation-based techniques. This work presents the following: the basic assumptions, main research subjects, standard operating procedures, study of various "transfer learning algorithms", including transfer learning applications. Lastly, we attempt to identify future directions for study.

(ZHUANG et al., 2020) [12] In machine learning, transfer learning has gained popularity and is seen as a promising field because of its vast range of applications. This survey seeks to organize and align the current transfer learning research papers so that readers may have a better grasp of the field's current status and concepts. The methods and approaches of transfer learning are also explained and summarised in it. Additionally, a short introduction to transfer learning's applications is given. More than 20 typical transfer learning models are utilized in the experiments to demonstrate the performance of the various models. Three separate datasets—Office-31, Reuters-21578, and Amazon Reviews—are used to train the models. According to the results of the experiments, choosing the right "transfer learning models" for different practical uses is crucial.

3 Conclusion

The goal of transfer learning is to enhance the performance of target learners on target domains by transferring knowledge from different but related source domains. In this method, building target learners may be done with less reliance on a significant amount of target-domain data. To support process setup with machine learning, new processes and frameworks are required. One such approach might include automatically initiating new (simulated) tests to continuously enhance the learning model. An underlying neural network modifies itself from simulated to actual data during the transfer learning phase. A more thorough examination of this component may aid in understanding and, ideally, in closing the gap between simulation and actual data. To mitigate sparsity issues, TL develops the finest recommendation system by combining collaborative filtering ideas. This approach transfers the information from dense to sparse data sets, increasing the accuracy of recommendations. The new framework that TL creates for e-commerce recommender systems uses information from goal domains and tasks as well as source domains.

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