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Article in Mesopotamian Journal of Big Data · February 2023

DOI: 10.58496/MJBD/2023/004

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Mesopotamian journal of Big Data
Vol. **(2023)**, 2023, **pp**. 31–32
DOI: https://doi.org/10.58496/MJBD/2023/004 ISSN: 2958-6453
https://mesopotamian.press/journals/index.php/BigData

Editorial Article

Transfer Learning: A New Promising Techniques

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Transfer Learning[1] is a machine learning technique that involves utilizing knowledge learned from one task to improve performance on another related task. This approach has been widely adopted in various fields such as computer vision, natural language processing, and speech recognition. The goal of this paper is to provide an overview of transfer learning and its recent developments. Transfer learning is particularly useful in situations where there is limited labeled data available for the target task. In these cases, the model can leverage knowledge learned from a related task with a larger amount of labeled data. This allows the model to overcome the problem of overfitting and improve performance on the target task.

One of the earliest forms of transfer learning[2] was feature-based transfer learning, which involved using features learned from a source task to improve performance on a target task. For example, in computer vision, features learned from a pre-trained model on the ImageNet dataset[3] can be used to improve performance on a target task such as object detection. Another form of transfer learning is fine-tuning, which involves training a pre-trained model on a target task with a smaller dataset. Fine-tuning can be applied to both feature-based and end-to-end models[4]. For example, in natural language processing, fine-tuning a pre-trained transformer model on a target task such as sentiment analysis can lead to improved performance.

Recently, there has been a growing interest in multi-task learning[5], which involves training a model on multiple tasks simultaneously. In multi-task learning, the model learns to extract shared representations that can be used to improve performance on all tasks. For example, in computer vision, a model trained on multiple tasks such as object detection and semantic segmentation can learn features that are useful for both tasks. Instance-based transfer learning involves transferring instances from the source task to the target task. This type of transfer learning is often used in the context of domain adaptation, where the goal is to adapt a model trained on a source domain to a target domain. For example, in computer vision, a model trained on a dataset of images of cars could be adapted to a dataset of images of trucks by transferring instances from the car dataset to the truck dataset.

Feature-based transfer learning involves transferring features learned from the source task to the target task. This type of transfer learning is often used in the context of pre-training, where a model is pre-trained on a large dataset and then fine-tuned on a smaller dataset for the target task. For example, in natural language processing, features learned from a pre-trained transformer model on a large dataset of text data could be used to improve performance on a target task such as sentiment analysis. Parameter-based transfer learning involves transferring the parameters of a model trained on the source task to the target task. This type of transfer learning is often used in the context of fine-tuning, where a pre-trained model is further trained on a smaller dataset for the target task. For example, in computer vision, a pre-trained convolutional neural network (CNN) model could be fine-tuned on a dataset of images for the target task of object detection. Another way to categorize transfer learning techniques is based on the number of tasks involved. There are two main types of transfer learning: single-task and multi-task. Single-task transfer learning involves transferring knowledge from a single source task to a single target task. The aforementioned types of transfer learning, instance-based, feature-based, and parameter-based, are all single-task transfer learning techniques. Multi-task transfer learning, on the other hand, involves transferring knowledge from multiple source tasks to a single target task or multiple target tasks. Multi-task transfer learning is often used in the context of multi-task learning, where a model is trained to perform multiple tasks simultaneously. For example, in computer vision, a model trained on multiple tasks such as object detection and semantic segmentation can learn features that are useful for both tasks.

In conclusion, transfer learning is a powerful technique that has been widely adopted in various fields. From feature-based transfer learning to fine-tuning and multi-task learning, it allows models to leverage knowledge learned from related tasks to improve performance on a target task. As the amount of data and computational resources continue to increase, transfer learning will play an increasingly important role in the development of machine learning models.After some time, someone suggested a method that would simplify the kernel matrix. In a similar vein, when the training set is exceptionally

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huge, the kernel matrix likewise grows to be exceptionally enormous. In this scenario, putting all of your storage eggs in the basket of a single workplace is not the best strategy. In this particular scenario, we suggested a whole new distributed method. In this particular approach, the dataset is randomly segmented into multiple sections, each of which is then run on a separate site appropriately. The communication between sites is determined not by the data set itself but rather by the architecture of the network. Using this strategy, you may avoid the issue in which the size of the kernel function grows at an alarming rate as the data set grows larger.

Funding

Non.

Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgment

The authors would like to express their gratitude to the Al-Iraqia University, the Informatics Institute for Postgraduate Studies, and the Al Salam University College for their moral support. Please accept my sincere gratitude for the useful recommendations and constructive remarks provided by the anonymous reviewers.

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