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Transfer Learning

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A B S T R A C T

Humans are experts at adapting knowledge to different jobs. This means that whenever we encounter a new task or difficulty, we comprehend it, use the pertinent information from our prior learning experiences, and solve it appropriately. Following the same approach, a term was introduced, Transfer Learning in the field of machine learning.

Transfer learning is the application of a machine learning model's previously acquired information to a distinct yet connected issue. The fields of image classification and natural language processing have seen a rise in the popularity of transfer learning. Here knowledge learned in one task is transferred to another related task. It is a potent method by reusing information from previously learned tasks, It can also hasten the creation of machine learning models. Its applications, when to apply Transfer Learning, the various types of Transfer Learning that are available and how it differs from traditional learning are all covered in the article. Transfer learning does have some restrictions, though. In this article, we talk about some of the drawbacks of transfer learning, namely how challenging it is to transfer knowledge between various domains, and How to overcome those problems.

Keywords: Transfer Learning, Machine Learning, Image Classification, Natural Language Processing,

1. Introduction

What is Transfer Learning?

Transfer learning is a technique of instruction that places an emphasis on using the knowledge you've learned to solve one problem to solve another that is unrelated but still exists. Applying a model that has been trained on a lot of labeled training data to a new task that has limited training data is the basic idea. rather than starting the learning process over again.

Transfer learning is a "design methodology" in the field of machine learning , it has become highly popular when used with neural systems, which demand enormous amounts of data and computing power.

Need for transfer learning:

- Better initial model:- Machine learning demands you to build models from scratch. Although you can complete some tasks even without training, transfer training offers the best place to start.
- Higher learning rate: Transfer learning provides a higher learning rate during training because the problem has been trained for similar tasks.
- Higher accuracy after training: With a better starting point and faster learning speed, transfer learning provides a model that can be used to transition to a higher level of proficiency and produce more accurate results.
- Faster training: Training can achieve the expected performance faster than traditional training methods because it uses a previously trained model.
- Less data required:- A model that has already been trained on a task for which labeled training data is plentiful will be able to handle a new but similar task with far less data

Architecture :

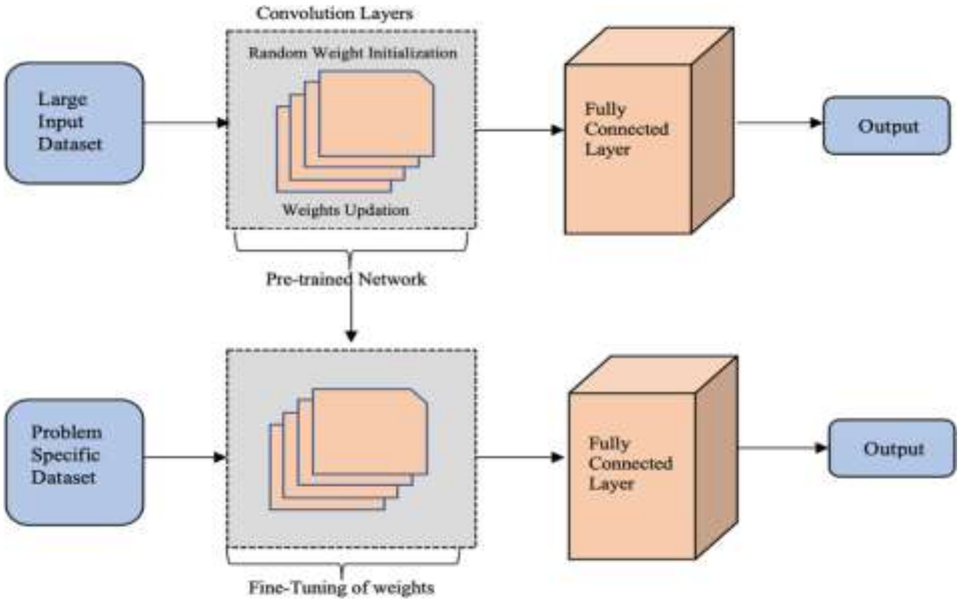

*Figure SEQ Figure * ARABIC 1: Example of transfer learning using convolution model training*

1.1 Limitations of Transfer Learning

When applying transfer learning, there are a few challenges that may arise. The fact that the new data could not be sufficiently comparable to the data the model was first trained on presents one challenge. As a result, the model might not perform well with the new data. If the model is not retrained on the new data, another issue is that it may overfit to the new data. As a result, the model might not perform well with other data sets. Finally, if the original model is poorly described, transfer learning may be challenging to implement.The learned characteristics of the convolutional neural network might not be transferable to other datasets, which is one worry with transfer learning. As a result, when applied to new data, the network may not be able to detect novel properties. Additionally, the network could perform poorly on test data if it is overfit to the training set of data.

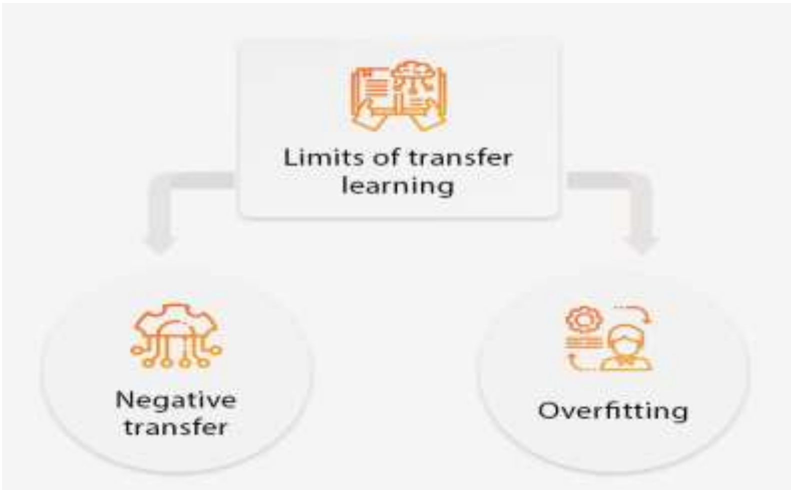

*Figure SEQ Figure * ARABIC 2: Limitations of Transfer Learning*

- NegativeTransfer:
  When utilizing models in machine learning that have been trained on data that is not representative of the data that will be used in the future, there is a risk of negative transfer. This may prevent the model from generalizing to new data, which could result in predictions that are not accurate.
  OverFitting:
  Overfitting occurs in machine learning when a model becomes too closely fitted to the particularities of the training data, and begins to generalize poorly to new data. This problem is often caused by using too many features, or by using a complex model that is not well suited to the data. Overfitting can be avoided by using a simpler model, or by using regularization techniques that penalize the model for becoming too closely fitted to the training data.

There are many potential limitations to transfer learning, as this is still an emerging field of research. One key limitation is the lack of data that is available for training models. This can be a particular issue when trying to transfer learning to new domains or tasks. Another potential limitation is the difficulty in designing effective transfer learning algorithms. This is an active area of research, and there is still much to be learned about how to best design algorithms for transfer learning. Additionally, transfer learning can be limited by the types of features that are available in the source and target data. If the features are not well-suited for transfer learning, then the performance of the transferred model may be poor. Finally, it is important to note that transfer learning is not a silver bullet and will not always result in improved performance. In some cases, it may be better to train a model from scratch on the target data.

2. Literature Survey

Transfer learning is a machine learning method where knowledge learned in one domain can be applied to another domain. It is a powerful technique that has been shown to be effective in a variety of tasks, including natural language processing and computer vision.

There are a few key things that are necessary for successful transfer learning. First, the source and target domains must be similar enough that knowledge learned in the source domain is applicable to the target domain. Second, the model must be able to learn the relevant features for the target domain. And finally, the model must be able to generalize from the limited data in the target domain.

A number of recent studies have investigated transfer learning in natural language processing tasks. For example, one study found that a model trained on a large corpus of English text could be effectively applied to a smaller dataset of French text. The model was able to learn the relevant features for the target domain and generalize well, despite the limited data.

Another study looked at transfer learning for Named Entity Recognition, a task where the goal is to identify and classify named entities in text. The study found that a model trained on a large English dataset could be applied to a smaller French dataset and achieve similar performance.

These studies demonstrate the effectiveness of transfer learning in natural language processing tasks. However, more research is needed to explore the potential of transfer learning in other tasks, such as computer vision.

3. Methodology

How Transfer Learning works.

Transfer learning entails using skills acquired on one topic to help with a different, related challenge. Transfer learning is typically used for problems where the dataset contains insufficient data to fully train a model from scratch.

The following workflow is the most typical application of transfer learning in the context of deep learning:

1. Take layers from a previously trained model.
2. Freeze them to prevent losing any of the data they contain during upcoming training sessions.
3. On top of the frozen layers, add some fresh, trainable layers. On a new dataset, they will discover how to forecast using the previous features.
4. Train the new layers on your dataset.
5. Fine-tuning is the final, optional step. It entails unfreezing the entire model you received earlier (or a portion of it) and retraining it using the new data at a very slow learning rate. By gradually adjusting the pre-trained features to the fresh data, this has the potential to provide significant improvements.

4. How to Overcome The Limitations of Transfer Learning

There are a number of ways to overcome the limitations of transfer learning:

1. **Use a different dataset** : If the dataset used for training the model is different from the one used for testing, the model will not be able to generalize well and will not perform as well on the test set.
2. **Use a different model** : If the model used for training is not the same as the one used for testing, the model will not be able to generalize well and will not perform as well on the test set.
3. **Use a different optimization algorithm** : If the optimization algorithm used for training is not the same as the one used for testing, the model will not be able to generalize well and will not perform as well on the test set.
4. **Use a different architecture** : If the architecture used for training is not the same as the one used for testing, the model will not be able to generalize well and will not perform as well on the test set.

5. Similar Topic

RANSFER LEARNING AND DOMAIN ADAPTATION

It addresses the problem of transferring some knowledge or some models from a given source task to a related but different target .It works on different sub-problems among which: avoiding negative transfer, scalability, lifelong learning, adaptive online learning.

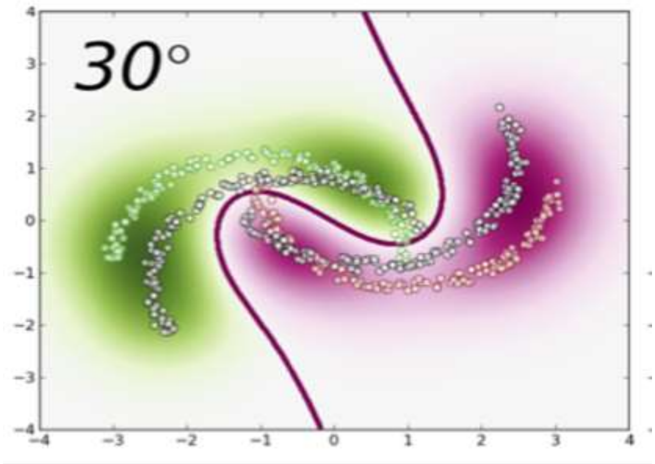

*Figure SEQ Figure * ARABIC 3: Here 2 different domains are converging*

6. Conclusion

In this paper I have tried to cover the most powerful technique called transfer learning .I have also tried to cover what transfer learning is, how to use it, where it can be used and also shared its benefits, limitations and ways to overcome those limitations.

It could be improved further by enhancing the transferring model and choosing appropriate Tr model for our required task .Changing the final output layer and setting it to required target values. If we have a small data set this method still works best and gives desired outputs.

This is still an emerging field, new changes could be seen further with advanced algorithms used to refine these techniques.

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