An Analysis of Transfer Learning and its Application in Medicine

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Abstract:

This paper analyses the technique of transfer learning and studies its application in the medical field by implementing transfer learning using the Breast Cancer and Hepatitis datasets, with the Breast Cancer dataset being used to transfer the knowledge to the Hepatitis dataset. The study found that transfer learning did lead to an improvement in the accuracy of the Hepatitis model, particularly when the weights of all the layers in the Breast Cancer model were transferred.

Introduction:

The topic we chose for our CS6375 project was transfer learning, which is a useful machine learning technique that is being used widely in the tech industry.

In brief, transfer learning is where knowledge is stored from one machine learning program and then applied to a related but different problem. Our project will try and implement transfer learning and use it to improve our program and achieve more accurate results. We will see if we can replicate the benefits that transfer learning can provide.

For our project, we will use two datasets from the UCI Machine Learning Repository. The breast cancer dataset and the hepatitis dataset. We want to see if pre-training a program on the breast cancer dataset can help classify the hepatitis dataset.

By extension, this will help dive into the idea that learning information about one disease can potentially help diagnose other diseases. This can have applications in medicine where machine learning and transfer learning can be used to better detect and diagnose diseases using models from other diseases.

Background:

Transfer learning was first proposed by Lorien Pratt in a paper in 1993 titled "Discriminability-Based Transfer Between Neural Networks." Pratt mentions in her thesis on "neural networks are usually trained from scratch" and that they rely "only on their training data". She felt that with the increase in networks being trained for different tasks and problems, it would be "reasonable to seek out methods" that "build on previously trained networks' results".

This is significant because one of the major problems in machine learning is that lack of sufficient training data for every problem. This leads to underperforming programs that do not have the wealth of data needed to yield accurate results.

Using transfer learning, such programs can take advantage of models that have been trained with sufficient data for other problems, allowing the program to circumvent the need for a large amount of data.

Some applications of transfer learning are detecting images, where a model that detects a certain type of image can be used to train a model that detects other types of images, or where a program that can learn how to decipher and understand English can be used to train programs that decipher and understand a different language.

This is something that we are trying to show in our study as well. By training a model on data for breast cancer, we want to exhibit that pre-training the model will lead to a higher accuracy for the hepatitis dataset, than running the program in isolation.

Furthermore, because our hepatitis dataset has fewer records than the breast cancer dataset, we will also try to determine if transfer learning can help overcome the deficiencies of having a lack of sufficient data.

Method:

For our study, we used the breast cancer study as our program to pre-train the model to be used in the hepatitis model. To achieve, we trained the breast cancer model using a neural network with the aid of the Keras framework. We did for the breast cancer dataset so that we could achieve as high an accuracy as possible to have the most impact when transferring the knowledge learned in the model to the hepatitis model.

The knowledge in our project were the weights from the layers in the neural network. These weights were transferred from the breast cancer model to the hepatitis model and the corresponding layer in the hepatitis model was initialized with those weights.

The hepatitis model employed a neural network as well, however this was programmed manually without the use of the Keras framework, in order to demonstrate the implementation of transfer learning clearly.

The model was trained in two distinct cases: one with the transferred weights, and one in isolation, to see whether the model performed better when pre-trained weights were used.

We also had distinct cases for the specific layer the weights were being transferred from, to determine which layer's weights being transferred resulted in the best performance, as well as transferring the weights of all the layers to see what impact it would make.

Implementation and Results:

For the breast cancer model, we tested for various parameters and cases to find the highest performing parameters. We employed the Sequential model in Keras and adjusted parameters such as number of layers, optimizers, activation functions, and more.

We also used a validation set, alongside the training and test set, with an early stopping mechanism to terminate the training if the model started to overfit.

The best set of parameters and their results were as follows:

Layers	5	Train accuracy:	77.2
Neurons (activation):	60 (relu),30 (relu),15 (relu),1 (relu),1 (sigmoid)	Train MSE:	0.1393
Metric:	MSE	Validation accuracy:	71.1
Data split (train/test/validation):	80/20/20	Validation MSE:	0.1671
Optimizer:	rmsprop	Test accuracy:	83.9
Early stopping:	validation loss, patience = 2	Test MSE:	0.1358

To train the Hepatitis Dataset, we first used the same layer structure in the Breast Cancer Dataset which is listed in the table above. This time however, we created the neural without using a library and tested the accuracy as comparison. Then, we transferred all the weights, which were the best parameters for the Breast Cancer dataset, and then tested the accuracy to see if transfer learning was effective for this dataset. In the case that the layer structure for the Breast Cancer dataset was not ideal for the Hepatitis dataset, we decided to set another layer structure to see if it can improve the accuracy.

We tried another set of parameters as 10 (sigmoid), 5 (sigmoid), 5 (sigmoid), 1 (sigmoid) for training and testing the Hepatitis dataset. After using the same parameters to get the weights from the Breast Cancer dataset, we transferred them to the Hepatitis' neural net to test the accuracy and figure out whether transfer learning was effective.

From the above mentioned set of parameters for the layers, we chose the one with the highest test accuracy for further experimentation. We wanted to find out whether transferring only 1 layer can have a better effect on the result. We defined the weights from the first layer to the second layer as w12, and so on as w23, w34. In this case, we transferred each one of layers' weights, and set the others at random to get the accuracy, and compare them to the one with all layers transferred.

In the case of layers with 60 (relu), 30 (relu), 15 (relu), 1 (relu), 1 (sigmoid) with no transferred weights, the test accuracy was 0.5806. However, after transferring all the weights from the Breast Cancer Dataset, the accuracy dropped to 0.322, which is a decrease of 44.54%. It shows that the layer structure for the Breast Cancer Dataset was not suitable for transfer learning.

However, in the case of layers with 10 (sigmoid), 5 (sigmoid), 5 (sigmoid), 1 (sigmoid), the test accuracy is 0.645. Transferring the weights of all the layers from the Breast Cancer Dataset leads to the accuracy becomes 0.7419 which is an increase of 15%. Looking at this improvement, it shows that transfer

learning has a significant impact on the accuracy.

Dataset	Hepatits					
Instance	155					
Attributes	14					
Transfer all the weights from Breats Cancer dataset to Hepatitis dataset and train it with layer 60，30，15，1，1						
Layers	5	Test accuracy	0.322			
Neurons (activation):	60 (relu),30 (relu),15 (relu),1 (tanh),1 (sigmoid)	Data split (train/test/validation):	80/20/0			

Dataset	Hepatits					
Instance	155					
Attributes	14					
Transfer all the weights from Breats Cancer dataset to Hepatitis dataset and train it with layer 10,5,5,1						
Layers	4	Test accuracy	0.741935			
Neurons (activation):	10 (sigmoid),5 (sigmoid),5(sigmoid),1 (sigmoid)	Data split (train/test/validation):	80/20/0			

Some of the results from transferring the weights for different layer structures in the hepatitis dataset

As a result, we found that the best set of parameters for the Breast Cancer dataset was not suitable for transfer learning in the Hepatitis dataset.

Therefore, we chose the layers with 10 (sigmoid), 5 (sigmoid), 5 (sigmoid), 1 (sigmoid) for the next experiment. We transferred one of each layer at a time to test the model. We first transferred w12, setting the weights of the layers as random, which gave us an accuracy of 0.677, which is less than the accuracy of 0.7419 we achieved from transferring all the weights. We then transferred w23 and initialized the other layers with random weights, getting accuracy of 0.7419, which is equal to the accuracy of transferring the weights of all the layers. We then repeated the process with w34, getting a test accuracy of 0.7097, which is less than the accuracy of transferring the weights of all of the layers. However in each case of transfer, improvements were seen.

Conclusion

From the above experiment, we find that not all the parameters are suitable for transfer learning. The best set of parameters for one dataset may not fit well for the second dataset. However, if we find a suitable layer structure for the second dataset, as shown by our study, it will lead to significant improvements in transfer learning with regards to transferring the weights and show that transfer learning can lead to accuracy improvements for the second dataset.

However, while transferring the weights of singular layers did lead to an

improvement in accuracy, we were able to show that transferring the weights from all of the layers provides a marked boost in accuracy.

At the same time, this individual study does not represent all the cases. Since the data is not extensive in either dataset, for other datasets with more exhaustive data, there might be the case that a neural network has a higher boost in accuracy when transferring just one layer than all the layers, as exhibited in our study.

More importantly however, through this study we have not only shown the possible benefits of transfer learning, but also that through transfer learning, the data of one disease can be helpful in diagnosing other diseases, such as breast cancer and hepatitis in our case. While our experiment was relatively simple in comparison, it shows that transfer learning has a place in the medical field.

To make this study more comprehensive, more datasets with larger sample sizes, along with an increased set of varied parameters are needed for further testing.

Resources:

L.Y. Pratt. “Discriminability-Based Transfer Between Neural Networks.” Department of Mathematical and Computer Sciences, Colorado School of Mines. https://papers.nips.cc/paper/641-discriminability-based-transfer-between-neural-networks.pdf

UCI Machine Learning Repository. “Breast Cancer Dataset”. https://archive.ics.uci.edu/ml/datasets/Breast+Cancer

UCI Machine Learning Repository. “Hepatitis Dataset”. https://archive.ics.uci.edu/ml/datasets/hepatitis

Project Data Log:

https://docs.google.com/spreadsheets/d/1CPWzFEdKN73zr8-3ca1LTwX5YJmAxePQ-IfVcrcYiDw/edit?usp=sharing

Source Code Colab Link:

https://colab.research.google.com/drive/1CwXJ9SNm4rZQhvDl4vhlCSk7EaJkTlMP#scrollTo=WJ-gTqqrk3uT