Comparison of Different Machine Learning Algorithms with regards to Task Efficiency

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Abstract

The current issue with the state of machine learning is that there are a plethora of algorithms readily available. This can make choosing the right algorithm a tedious task. Neural networks, random forests, and decision trees are a few of the most common, and they all excel at different tasks. Maximizing efficiency is a common objective in many projects, and if machine learning users are able to choose the algorithm which will be most efficient at their chosen task, achieving this objective will be much easier. The purpose of this project was to run different machine learning algorithms on a variety of tasks and compare the results in terms of efficiency and accuracy. The expected results were that the neural network will outperform the random forest algorithm in most complex scenarios, but the random forest may be more efficient if the task is simple enough for it to complete in a procedural manner. The tasks ranged from a simple solved game (Tic-Tac-Toe), a classification task (Wheat type) and an image classification task (Clothing). In each task, all algorithms were trained for comparable amounts of time with similarly sized training data sets. This allowed for comparisons to be made. The random forest algorithm performed better on a simple solved game, and a simple image classifier; however, the neural network performed better when the dataset was bigger in a classification test. This means that when a task is simple with less data, random forests tend to outperform neural networks; however, as task complexity increases along with data size, neural networks begin to outperform random forests. These results are significant because as researchers go forward in efforts to utilize machine learning in other areas of science, they will be able to better select the algorithms that are best optimized for their chosen task.

Introduction

Machine learning, a developing field of study, is another form of artificial intelligence in which algorithms are able to learn on their own based on training data and then accomplish tasks. There are many different algorithms that are being used currently in the machine learning space. At first, decision trees and reinforcement learning algorithms dominated the field; however, these algorithms got more advanced with the introduction of random forest algorithms and neural networks. Decision trees developed into random forests while reinforcement learning became the basis for deep neural networks. With each of these, the algorithms became more complex and thus more efficient. This created the current problem of determining which algorithm is most efficient for which task.

Efficiency is a challenge which always presents itself, and it is no different with machine learning. With the vast array of algorithms readily available today, choosing the appropriate algorithm could prove quite difficult; therefore, finding out which algorithm is most efficient when it comes to certain tasks would be beneficial for all people working with machine learning algorithms. The question then became that if the two most utilized algorithms — neural networks and random forests — were presented with the same tasks, which algorithm would perform better? Many variables that could influence the results of the tests were considered with data size and task complexity being the most significant of those variables.

It was hypothesized that random forests would outperform neural networks in the most basic and binary tasks, and neural networks would begin to outperform random forests as task complexity grew. This was tested using 3 different tasks of varying complexities that would help limit outside factors from affecting the efficiency and accuracy of the algorithms.

Materials & Methods

The machine learning algorithms were chosen based on popularity. Neural Networks and Random Forests were chosen because they are the two most used algorithms today, and the results for these algorithms would be the most significant. Three tasks were then chosen to be the basis for the comparison. Complexity was the main factor in determining the tasks to be selected. Tasks were chosen with varying complexities to ensure that each algorithm would have the chance to perform optimally. The tasks selected were Tic-Tac-Toe, image classification, and Wheat classification based on a CSV dataset. Tic-Tac-Toe was chosen because of its ability to be done in a procedural manner. Image classification was chosen because of its complexity and the large number of possible outputs. The Wheat classification based on CSV datasets was chosen because of the binary output and the vast data size. The basic machine learning algorithms were acquired from Github repositories and were then trained for comparable amounts of time for the selected task. After the algorithms were trained, the same data was given to each of them. The results were then compared across the algorithms for each task.

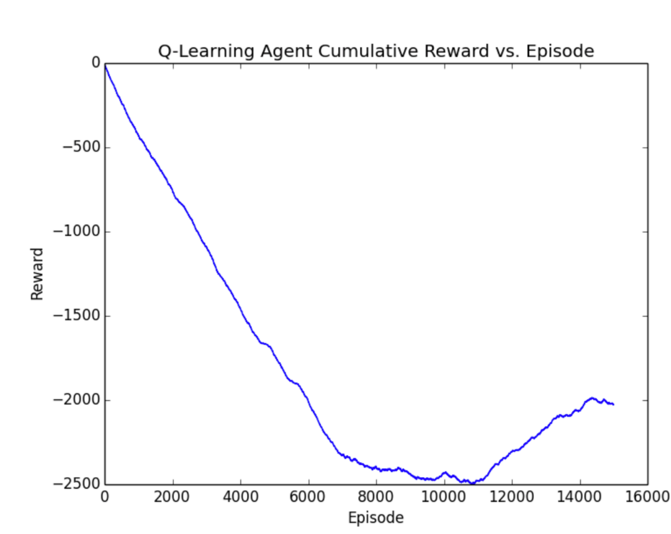
Results

Figure 1: Reinforcement algorithm

Amount of Episodes Trained	Human Wins	Algorithm Wins	Draws
1	17	1	2
10000	13	2	5
15000	17	2	1

Caption: The algorithm is shown to perform better with more training with a max at 10000 training episodes, but never as good as a human.

Figure 2: Q-Learning



Caption: Figure shows that the reinforcement algorithm performed better and better until 10000 training episodes where it then became worse.

Figure 5: Random Forest Wheat Classification

Amount of Trees	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Average
1	92.86%	90.48%	85.71%	78.57%	85.71%	86.67%
5	95.24%	90.48%	85.71%	85.71%	90.48%	89.52%
10	88.10%	92.86%	90.48%	92.86%	90.48%	90.95%
1000	92.86%	99.9%	92.85%	85.71%	95.24%	93.33%

Caption: The random forest was able to classify wheat at a high accuracy and performed better with an increase of trees.

Figure 3: Decision Tree Algorithm

	Human Wins	Algorithm Wins	Draws
Min/Max Decision Tree	0	2	18

Caption: The decision tree was shown to be able to keep up with humans at tic-tac-toe.

Figure 4: Neural Network Wheat Classification

Trials	Train Accuracy	Test Accuracy
1	94.94%	96.15%
2	95.57%	98.08%
3	98.73%	92.13%
4	96.84%	96.15%
Average	96.52%	95.67%

Caption: The Neural Network was able to train and test at a very high accuracy on wheat classification.

Figure 6: Neural Network Clothing image classifier Compared to a Random Forest image Classifier

	Accuracy of Neural Network	Accuracy of Random Forest
T-Shirt	94%	76%
Trouser	43%	98%
Pullover	76%	73%
Dress	55%	86%
Coat	70%	73%
Sandal	80%	94%
Buttoned up-Shirt	55%	70%
Sneaker	78%	92%
Bag	59%	96%
Ankle Boot	46%	94%
Average	65.6%	85.2%

Caption: The Random Forest on average had a higher accuracy than the Neural Network classifier

Discussion

Tic-Tac-Toe was thought of as a simple game that was very binary and easy to comprehend. However, as shown in Figure 1, it is very difficult for machines to learn the game through reinforcement learning. This shows that neural networks, which tend to use reinforcement learning in their processes, are inefficient with simple, binary tasks as the neural networks could not keep up with a human even after being trained for an extended period of time. Even with extensive training, as shown in Figure 2, the reinforcement learning algorithm still performed inefficiently. However, the decision tree algorithm, which is the basis for random forests, as shown in Figure 3 was able to keep up with a human quickly after it was trained on a dataset showing that supervised learning is more efficient when it comes to a binary tasks. This proved the hypothesis — the basis for random forests (decision trees) outperform the basis for neural networks (reinforcement learning algorithms) — correct.
An image classification task was used to demonstrate a more complex, non-binary task.

It was shown that a random forest outperformed the neural network as seen in Figure 6. However, the neural network was trained using transfer learning, which is similar to the reinforcement learning, where it uses its own knowledge to transfer knowledge to another subject. This may be why the neural network was very poor at classifying some types of images while being better at other types of images because it was able to transfer some knowledge over better. However, when a random forest used supervised learning, once again it was able to outperform the neural network. This shows the inefficiencies within transfer learning and neural networks as it was outperformed by a random forest. However, neural networks with the right training could potentially outperform a random forest as it showed better accuracy than the random forest in some subsets of the images dataset.

Lastly, a classification using a large dataset was used. The algorithms were tasked to classify the type of wheat seed using a large dataset. This time both the neural network and random forest were trained the exact same way using supervised learning; however, a neural network was much faster in learning while a random forest took an extended amount of time to build 1000 trees to make classifications with. The neural network was able to perform at a high level as shown in Figure 4. The random forest was able to perform at a high level as well which is shown in Figure 5; however, the random forest was outperformed by the neural network even at 1000 trees. The neural network performed more efficiently and more accurately than the random forest. This showed that with a large dataset, a neural network could outperform a random forest with all other variables held constant.

Overall, it was shown that with the simplest tasks, supervised learning and random forests perform best. However, as the datasets and complexity of the tasks grew, reinforcement learning and neural networks gradually became more efficient and more accurate than random forests. The hypothesis was supported by the data, but further research is required to look at increased number of tasks and algorithms to find the most efficient and accurate algorithms for each task. Many other variables could be changed as well such as noise, training time, other machine learning algorithms, tasks, complexity, and data size. However, at the moment, the best conclusion that can be drawn is that neural networks seem to be the most efficient when it comes to complex tasks whereas random forests and supervised learning will outperform neural networks when tasks are binary and procedural. There were possible sources of error and other variables that could be tested in the future to eventually prove the most efficient algorithm in any case. These errors could include inefficiencies in code and processing power of the laptops available which may have limited the success of the algorithms.

Acknowledgements

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