Performance Analysis of Cost and Accuracy for Whale Swarm and RMSprop Optimizer

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Abstract. The scientific fields’ deals with day to day problems, like economic planning and engineering design, mostly are disconnected, high dimensional, multimodal and oscillated optimization problems. These complex problems cannot be solved well within reasonable time using conventional process based on gradient. The natural phenomenon motivates and animal group behavior characteristics, the investigators have anticipated many efficient natural heuristic algorithms for high-dimensional complex optimization problems in real-world. This manuscript deals with one of the meta-heuristic algorithm, Whale Swarm Optimization algorithm (WSO) and compares the performance with RMS prop optimization techniques.

Keywords: Whale Swarm, Natural Heuristic, optimization, Algorithm

1. Introduction

Optimization algorithms are responsible for reducing the losses and to give the most precise outcomes conceivable. Optimizers are used to change the attributes of neural network, for example, weights and learning rate in order to reduce the losses. Each layer in the neural network holds a bunch of neurons; the input layer contained neurons represent the number of features chosen. The cumulative number of unseen layers depend upon the model, data size and the complication in the problem [1]. The neuron number in the unseen layer does not depend on the number of attributes, and the production of this is given to the logistic functions to observe the probability score of each class at the output layer [2]. By the application of biases or weights in the unseen layer and establishment function gives a nonlinear network.

Genetic Algorithm simulates Darwin’s genetic choice and natural elimination biology evolution process and has opened the prelude of nature-inspired meta-heuristic algorithms [3]. It mainly utilizes selection, crossover, and mutation operations on the individuals (chromosomes) to find the global optimum as far as possible [4]. In [5], authors proposed a swarm intelligence-based algorithm based on particle Swarm Optimization (PSO), which is motivated by social behavior of bird flocking. A complex and real time optimization problem in the world are solved by PSO algorithm [6-8], since it was put ahead.

The numerical experiment results in [9] shows that Whale Optimization Algorithm (WOA) has some advantages in terms of convergence efficiency or precision compared with particle swarm optimization (PSO)[10], gravity search algorithm (GSA)[11], differential evolution (DE)[12],
rapid evolution programming (FTP)[13], and the adaptive covariance matrix evolution strategy (CMA-ES)[14]. Therefore, WOA has been widely applied to solve real-world problems in a wide range of disciplines [15]-[16]. The objective of this paper compares the RMSprop and Whale Swarm Optimization algorithms on optimizing the neural networks applied to analysis of the cardio disease on the cardiovascular disease data.

2. Mathematical Representation of WOA

Whales hunting mechanism involves different steps [17]. They follow a strategic way to get their prey by confusing it. The steps involved are:

1. Searching in each direction.
2. Finding the pray.
3. Communicating with other neighboring whales.
   a. Sending signals through ultrasound in different directions.
   b. When the other whale finds the signal it first checks the distance between the signaling whale and itself.
   c. If the distance is minimal it travels towards it. Else it follows the other direction and finds some other nearest neighbor.
4. After a collection of whales come to the targeted area where they found their food, they begin to form in a circle as shown in figure below.
5. Later, they move in a circular format leaving the air bubbles which will lead no way to their target to escape and confuse them.
6. Later one of the whales reaches the bottom of the circles and moves to top of the water such that it could eat the whole bunch of the food at once.

In this way they confuse and finds have their food in large amounts each time they hunt. On an average a whale has tons of other fishes as its meal in a day.

The step by step mathematical representation of the WOA is shown in Equation,

\[ X(t+1) = X^*(t) - A \cdot |C \cdot X^*(t) - X(t)| \quad \text{if} \quad p < 0.5 \]
\[ X(t+1) = |C \cdot X^*(t) - X(t)| \cdot e^{b \cdot \cos(2\pi t)} + X^*(t) \quad \text{if} \quad p \geq 0.5 \]

Where, \( X \) is a vector of all the whales’ positions
\( t \) is the time or iteration index
\( X^* \) is the best solution found so far
\( A = 2a \cdot (r - a) \), \( c = 2r \), \( a \) is a coefficient vector that linearly decreases from 2 to 0 over the course of iterations
\( b \) is a constant value that defines the shape of the logarithmic spiral depending on the path.

During the bubble-net phase, the random value for \( A \) is \([-1, 1]\), but in the searching phase, the random value of vector \( A \) can be greater than 1 or less than 1. The searching mechanism is shown in Eq,

\[ X(t+1) = X_{\text{rand}} - A \cdot |C \cdot X_{\text{rand}} - X(t)| \]

This random search mechanism with the value of \( |A| \) greater than one emphasizes the searching operation and enforces the WOA algorithm to perform a global search. Random solutions are created at the beginning of the WOA searching process. Then, these solutions are updated iteration by iteration using the algorithm. The search will go on until a predefined maximum number of iterations has been arrived.

3. Whale Swarm Optimization (WSO) Algorithm

The proposed WSO framework is summarized based on study performed above:

Whale Swarm Optimization Algorithm Framework

Input: The whale swarm \( \Omega \), a whale \( \Omega_u \).

Output: The good results of whale \( \Omega_u \).

Step 1: begin
Step 2: Variable ‘v’ is initialized as 0 is an integer data type.
Step 3: Variable ‘temp’ is initialized as infinity is a Float data type.
Step 4: for \( i=1 \) to \( |\Omega| \) do
Step 5: if i≠u then
Step 6: if f(Ωi) < f(Ωu) then
Step 7: if dist (Ωi, Ωu) < temp then
Step 8: v=i;
Step 9: temp = dist (Ωi, Ωu);
Step 10: end if
Step 11: end if
Step 12: end if
Step 13: end for
Step 14: return Ωv;
Step 15: end

The integer variable ‘v=o’ is started first. Later we define the float variables. Where |Ω| in Step 4 indicates the count of components in Ω, namely the swarm size. If the location of the whale that produces the signals is not the only whale define, From whale better and nearest whale, where f(Ω) in step 6 is the suitable value of whale Ω and dist (Ωi, Ωu) in Step 7 indicates the space between Ωu and Ωi. If it is good and approximately nearby whale exists, then new whale guide towards the good result.

4. RMSprop Optimizer

The RMSprop optimizer restricts the oscillations in the vertical direction. Therefore, we can increase our learning rate and our algorithm could take larger steps in the horizontal direction converging faster. The RMSprop calculations are shown in the following equations. The value of momentum is denoted by beta and is usually set to 0.9.

\[ v_{dw} = \beta \cdot v_{dw} + (1 - \beta) \cdot dW^2 \]
\[ v_{db} = \beta \cdot v_{db} + (1 - \beta) \cdot db^2 \]
\[ W = W - \alpha \cdot \frac{dW}{\sqrt{v_{dw}} + \epsilon} \]
\[ b = b - \alpha \cdot \frac{db}{\sqrt{v_{db}} + \epsilon} \]

During backward propagation, we use dW and db to update our parameters W and b as follows:

\[ W = W - \text{learning rate} \cdot dW \]
\[ b = b - \text{learning rate} \cdot db \]

In RMSprop, instead of using dW and db independently for each epoch, we take the exponentially weighted averages of the square of dW and db.

\[ S_{dw} = \beta \cdot S_{dw} + (1 - \beta) \cdot dW^2 \]
\[ S_{db} = \beta \cdot S_{db} + (1 - \beta) \cdot db^2 \]

Where beta ‘\beta’ is another hyper parameter and takes values from 0 to 1. The new weighted average is formed using weights, average of previous value and current value square. After calculating exponentially weighted averages, we will update our parameters.

\[ W = W - \text{learning rate} \cdot \frac{dW}{\sqrt{S_{dw}}} \]
\[ b = b - \text{learning rate} \cdot \frac{db}{\sqrt{S_{db}}} \]

\[ S_{dw} \] is comparatively very less so that here we’re dividing it by dW. Whereas \[ S_{db} \] is comparatively large so that here dividing db with a relatively larger number to slow down the updates on a vertical dimension.

5. Results and Discussion

From the information in the cardiovascular dataset [18], the predictions are done regarding the patient’s heart condition. To know such condition, the patient’s bp level and cholesterol levels are more important. These two components help in analysis of the patient’s condition and prediction of cardiac disease may likely be affected or not. The patient’s habits resemble the
treatment to be given. In such a way we can use such data for different analysis.

Figure 1 RMSprop Algorithm

Figure 2 WSO Algorithm

6. Conclusion
As far as cost is concern, Whale swarm algorithm plays a best role between these two optimization algorithms RMSprop and whale swarm. However, WSO is correct match for the Neural Network Optimization for cost optimization and as cost plays a crucial role in neural networks. While analysis of the real world data which gives a future scope for improving this algorithm to perform better.
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