Comparison of BPA and Neuroevolution for Time Series Prediction

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Objectives

The objective of the project was to compare the optimization techniques: Gradient Descent and Genetic Algorithm, in the context of time series prediction. A neural network was trained with these methods and the performances were compared.

BPA

In BPA, the error is propagated back into the network, based on which, the weights are varied. Gradient Descent is used to determine the optimal weight values. Ideally the gradients would force the network to converge on a minima. The problems: entrapment in local minima, slow to converge.

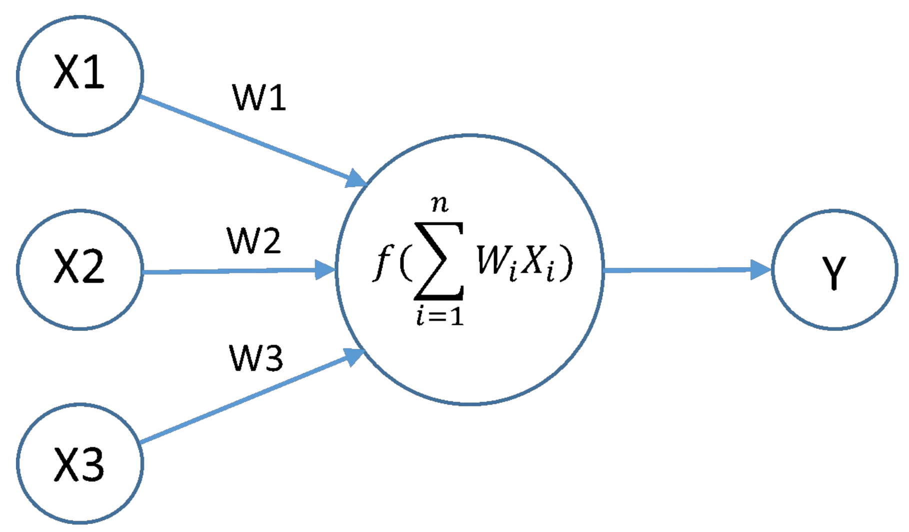

Figure 1: A Neural Network

Neuroevolution

NE is a learning technique that applies Genetic Algorithms to Neural Networks. It seeks to alter not only the weights (like BPA) but the structure of the network (number of hidden layers, nodes, etc) via GA. Though used primarily in Reinforcement Learning applications, it is used here in the context of Time Series Prediction. The problems: computationally intensive and slow.

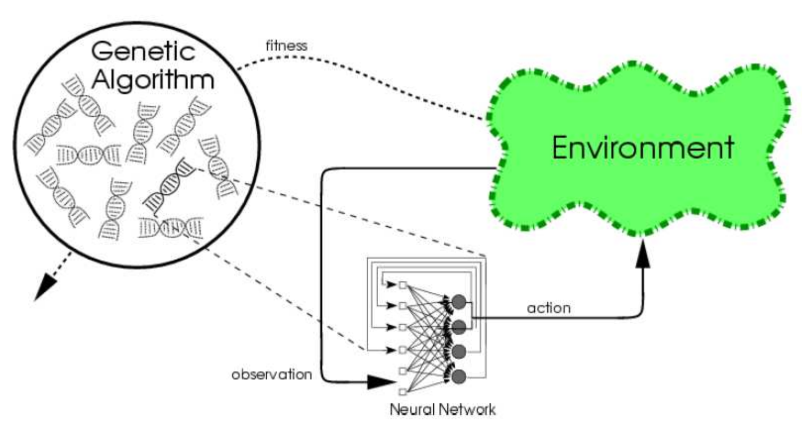

Figure 2: NEAT Algorithm

Algorithmic Description

BPA

- Run through the network.
- Calculate Error.
- Propagate the error back into the network.
- Update the weights accordingly.
- Stop when the error hits a low value.

Neuroevolution

- Generate a population of models.
- Encode the parameters of a model (genotype).
- Generate Neural Network models based on the encoding (phenotype).
- Evolve the population using GA.
- Eliminate the weak.
- Based on performance, perform crossover or mutation.
- Stop when the performance criteria is met.

Time Series Prediction

- Train the network on training data.
- Do a one-step ahead prediction.
- Learn from the error (Update the structure of the network accordingly).
- Test the network on the test data.

Experiments

A batch of 100 data points from each data set was used for training. The remaining for testing. The BPA was run for 20 epochs and the NE algorithm was run for 20 generations. For the genetic algorithm, a population of 100 was initially chosen. The algorithms were compared using three datasets.

- **Astrophysical Data**: Light intensity patterns from a white-dwarf star.
- **Laser Data**: Radiation patterns from an infrared laser operating in a chaotic state.
- **Canadian Lynx Data**: Historical data of Lynx trappings in the North Canadian region from 1821 to 1934.

Results

It can be observed from the results that NE performs slightly better than BPA. Though mostly their values are comparable, NE is more time-consuming and computationally intensive than BPA.

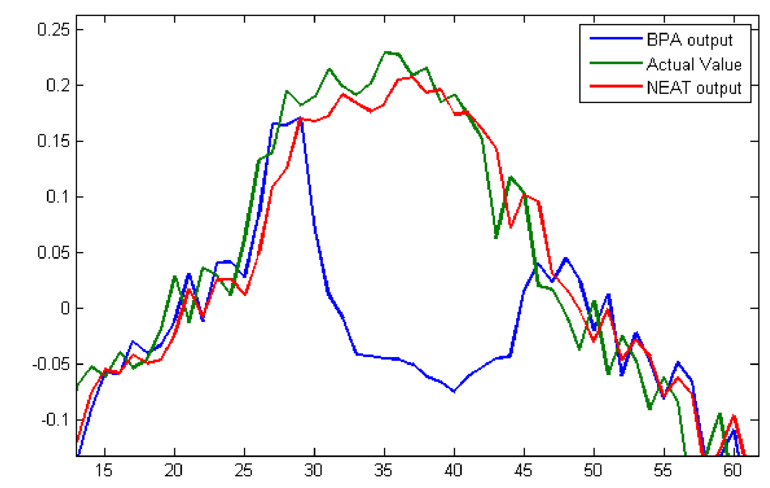

Figure 3: Comparison of Estimates for Astrophysical Data

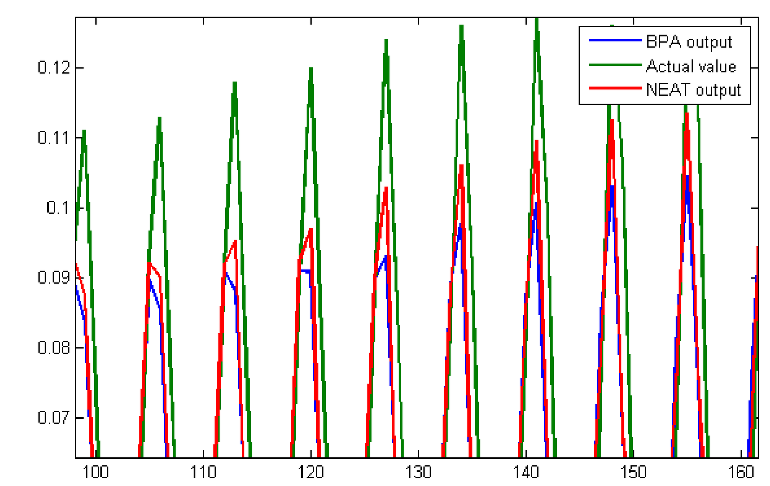

Figure 4: Comparison of Estimates for Laser Data

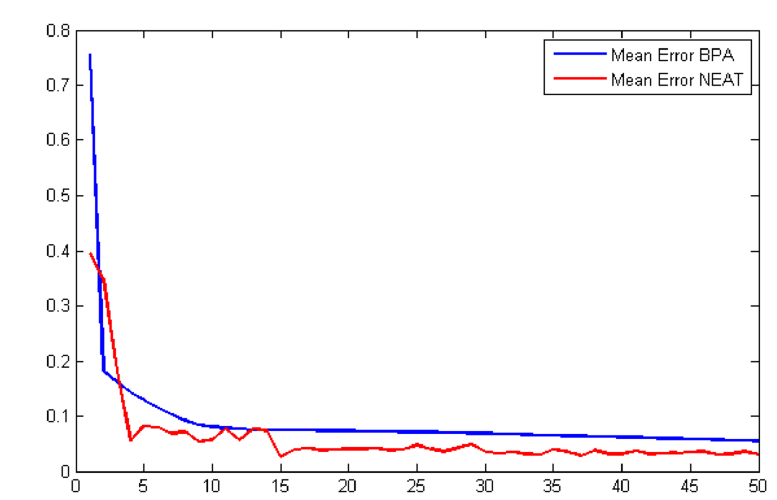

Figure 5: Error Comparison for Lynx Data

Algorithm	Time
BPA	0.0003262
NEAT	0.0015681

Table 1: Computation Time

Conclusion

We can observe from the graphs that NE performs better at modeling the data than BPA. It has been my experience that the NE algorithm performs badly on sparse datasets. And also NE is computationally intensive, requiring enormous time and processing memory.

Future Plan

NE is an potentially powerful algorithm. It has shown exceptional promise in the field of reinforcement learning. It has to be improvised a little for the purposes of function approximation. By introducing the concept of plasticity and memory, the processing time can be reduced significantly. My future plan will entail exploring the biological plausibility of the NE.

References

[1] Stanley, K and Miikkulainen,R: Evolving Neural Networks through Augmenting Topologies, The MIT Press Journals.

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