FORECASTING WITH NEUROSOLVER

Andrzej Bieszczad
Computer Science, California State University Channel Islands, One University Drive, Camarillo, CA 93012, Canada

Keywords: Forecasting, Neural network, Neuromorphic systems, General problem solvers, Predicting future, Behavioral patterns.

Abstract: Neurosolver is a neuromorphic planner and a problem solving system. It was tested on several problem solving and planning tasks such as re-arranging blocks and controlling a software-simulated artificial rat running in a maze. In these tasks, the Neurosolver created models of the problem as temporal patterns in the problem space. These behavioral traces were then used to perform search and generate actions. While exploring general problem capabilities of the Neurosolver, it was observed that the traces of the past in the problem space can also be used for predicting future behavioral patterns. In this paper, we present an analysis of these capabilities in context of the sample data sets made available for the NN5 competition.

1 INTRODUCTION

The goal of the research that led to the original introduction of Neurosolver, as reported in (Bieszczad and Pagurek, 1998), was to design a neuromorphic device that would be able to solve problems in the framework of the state space paradigm (Newell and Simon, 1963). In that paradigm, the states of a system are expressed as points in an n-dimensional space. Trajectories in such spaces formed by state transitions represent behavioral patterns of the system. A problem is presented in this paradigm as a pair of two state: the current state and the desired, or goal, state. A solution to the problem is a trajectory between the two states in the state space. Fundamentally, we are asking how to achieve the goal state of the system given its starting state.

The Neurosolver can solve such problems by traversing the recorded trajectories as described in section 2. In this paper, we demonstrate how the very trajectories can be used for forecasting.

The original research on Neurosolver modelling was inspired by Burnod's monograph on the workings of the human brain (Burnod, 1988). The class of systems that employ state spaces to present and solve problems has its roots in the early stages of AI research that derived many ideas from the studies of human information processing; e.g., on General Problem Solver (GPS) (Newell and Simon, 1963). This pioneering work led to very interesting problem solving (e.g. SOAR (Laird, Newell, and Rosenbloom, 1987)) and planning systems (e.g. STRIPS (Nillson, 1980).

The Neurosolver employs activity spreading techniques that have their root in early work on semantic networks (e.g., (Collins and Loftus, 1975) and (Anderson, 1983)).

2 NEUROSOLVER

2.1 Neurosolver as a GPS

The Neurosolver is a network of interconnected nodes. Each node is associated with a state in a problem space. In its original application, the Neurosolver is presented with a problem by two signals: the goal associated with the desired state and the sensory signal associated with the current state. A sequence of firing nodes that the Neurosolver generates represents a trajectory in the state space. Therefore, a solution to the given problem is a succession of firing nodes starting with the current node and ending with the goal node.

The node used in the Neurosolver is based on a biological cortical column (references to the relevant neurobiological literature can be found in (Bieszczad and Pagurek, 1998)). It consists of two divisions: the upper and the lower, as illustrated in Figure 1. The upper division is a unit integrating internal signals from other upper divisions and from the control

Bieszczad A. (2009).
FORECASTING WITH NEUROSOLVER.
In *Proceedings of the International Joint Conference on Computational Intelligence*, pages 386-393
DOI: 10.5220/0002325303860393

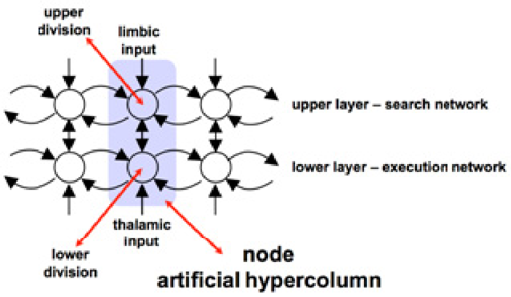


Figure 1: An artificial cortical column.

center providing the limbic input (i.e., a goal or - using more psychological terms - a drive or desire). The activity of the upper division is transmitted to the lower division where it is subsequently integrated with signals from other lower divisions and the thalamic input. The upper divisions constitute a network of units that propagate search activity from the goal, while the lower divisions constitute a network of threshold units that integrate search and sensory signals, and generate sequences of firing nodes. The output of the lower division is the output of the whole node. An inhibition mechanism prevents cycles and similar chaotic behavior. Simply, a node stays desensitized for a certain time after firing.

2.2 Neurosolver as a Forecaster

Normally, in the goal-oriented problem solving the flow of activity from the upper to the lower division is limited. This mode of operation can be described as exploration of possibilities and looking for environmental cues. The cues come as thalamic input from the sensory apparatus. Often though, we operate without far reaching goals forcing our brains to make predictions based on the knowledge of the past and the currently observed facts. In the Neurosolver, similar phenomenon may be observed if the activity in the upper division is gradually increased, and at the same time is allowed to be transmitted in its entirety from the upper to the lower division. Assuming that that activity is allowed to grow above the firing threshold level hosted by the lower division, a node may fire without extra signals from the sensors, or even in absence of the thalamic input whatsoever. In this paper, we explore this capability to predict future outcomes based on the statistical model built in the Neurosolver.

3 DATA SETS

I presented the ideas on using the Neurosolver in the forecasting capacity at ISF'2008 (Bieszczad, 2008). I was encouraged to test the ideas on the data set that was used for the NNx competition. The last published data set is for NN5 that was held in 2008. For this work, I assembled a research group that is acknowledged in the later section this paper.

The NN5 data set is actually a collection of records of daily witdrawals from a number of ATM machines in England over a two-year period. A set from an individual machine is divided into a larger training part collected over two years and smaller test part collected over two months. Each set is a time series that represents a temporal usage pattern of that particular machine. That temporal nature of the patterns was what caught our attention in the context of the Neurosolver.

We started with the use the data in their raw format by assigning each datum to a Neurosolver node. In that sense, each datum is a state of the system in the progression of states as specified by the given time series. The Neurosolver therefore learns the trajectory that corresponds to each training time series, and over time generalizes the trajectories to represent all time series by it adaptation rules.

Due to the large number of data points and the proximity of some of them, we also tried to cluster the data with several cluster sizes. For that, we approximated the k-neighbor algorithm by one that is very straighforward in one dimension. Simply, we decided on an arbitrary number of clusters, and then recursively dividing the data set in two allocating the number of clusters for each of the two division according to the data density. An example of this process is shown in Figure 2.

A simpler approach to clustering is to divide the domain into a number of equal segments and then create clusters based on the data membership in the clusters. However, the problem with this approach is that is does not take into consideration data distribution. Therfore, some clusters might be empty, while others are overcrowded.

After the custering stage, we assigned the centers of the clusters to the Neurosolver's nodes. Subsequently, for each data point we activated the node that represented the cluster to which the point was classified. The predicted sequences were built also out of the numbers that corresponded to the centers of the clusters represented by the firing nodes.

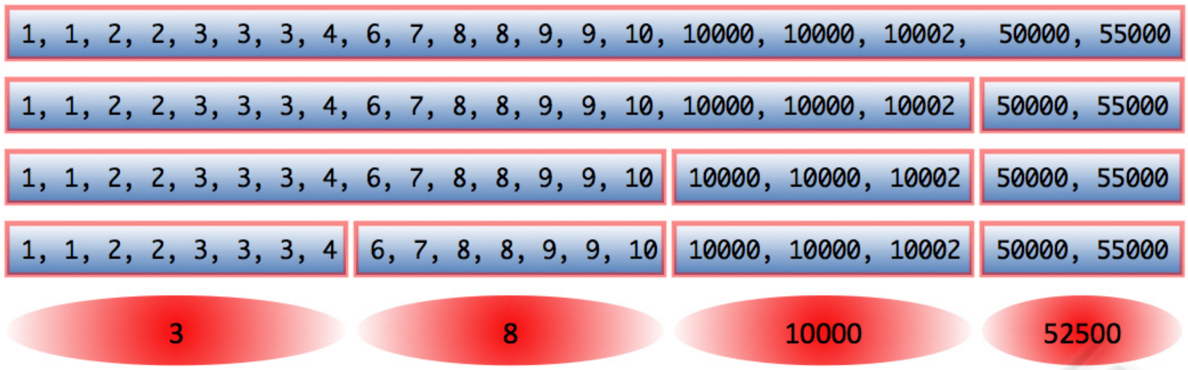


Figure 2: An example of data clustering.

4 NEUROSOLVER LEARNING

4.1 Learning Rules

We used two types of learning in our experiments. The first follows the traditional incremental learning through gradient ascent (a.k.a gradient descent and hill-climbing) approaches (e.g., Russell, 2003) that are taken by many researchers in the neural networks community. The second, follows the stochastic scheme that was used in the original Neurosolver.

4.1.1 Incremental Learning

The Neurosolver learns by translating teaching samples representing state transitions into sequences of firing nodes corresponding to subsequent states in the samples. For each state transition, two connections are strengthened: one, in the direction of the transition, between the lower divisions of the two nodes, and another, in the opposite direction, between the upper divisions as shown in Figure 3.

In the incremental learning, we simply add a small value to the connection strength.

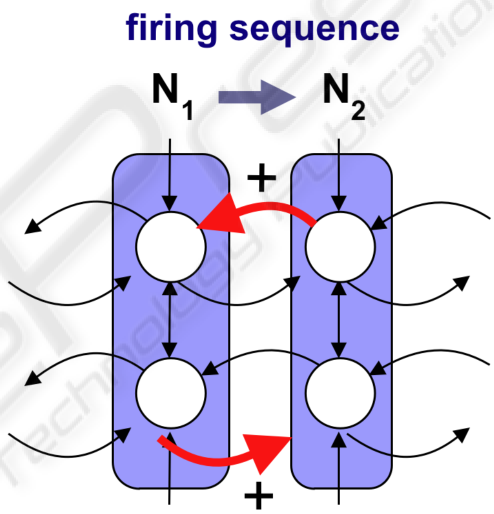


Figure 3: Neurosolver learning rule.

4.1.2 Statistical Learning

In the second approach, the strength of all inter-nodal connections is computed as a function of two probabilities: the probability that a firing source node will generate an action potential in this particular connection and the probability that the target node will fire upon receiving an action potential from the connection.

To compute the probabilities, each division and each connection collects statistics as shown in Figure 4. The number of transmissions of an action potential T_{out} is recorded for each connection. The total number of cases when a division positively influenced other nodes S_{out} is collected for each division. A positive influence means that an action potential sent from a division of a firing node to another node caused that node to fire in the next cycle. In addition, we also collect statistical data that relate to incoming signals. T_{in} is the number of times when an action potential transmitted over the

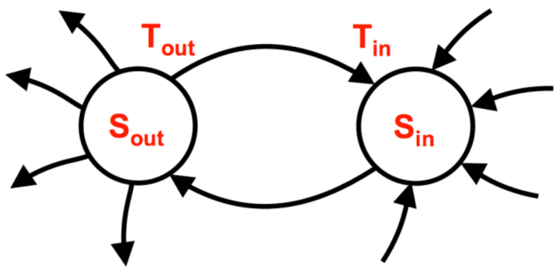


Figure 4: Statistics collected for computation of the connection strength between nodes.

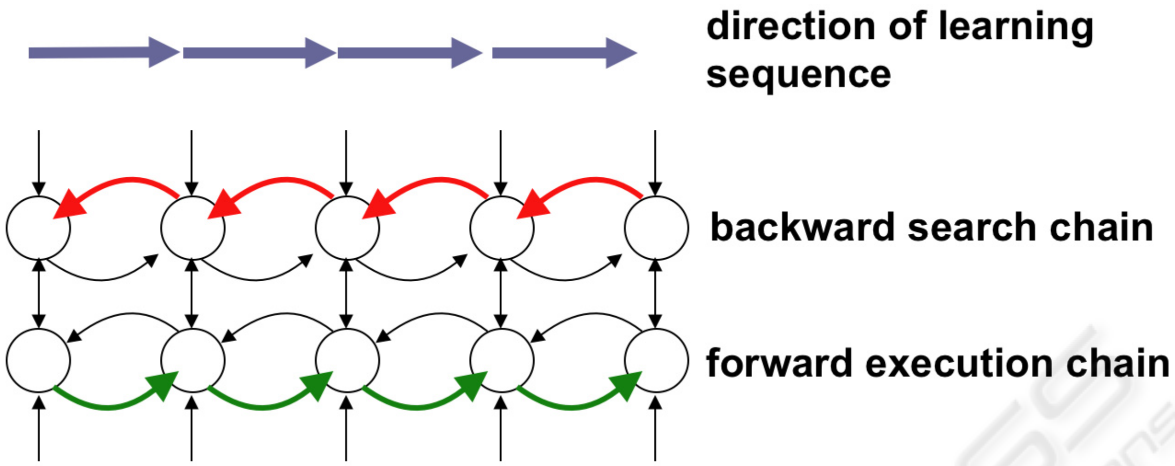


Figure 5: The Neurosolver learn temporal patterns.

connection contributed to the firing of the target node and is collected for each connection. S_{in}, collected for each division, is the total number of times when any node positively influenced the node. With such statistical data, we can calculate the probability that an incoming action potential will indeed cause the target node to fire. The final formula that is used for computing the strength of a connection (shown in Equation 1) is the likelihood that a firing source node will induce an action potential in the outgoing connection, multiplied by the likelihood that the target node will fire due to an incoming signal from the connection:

$$P = P_{out} \cdot P_{in} = (T_{out}/S_{out}) \cdot (T_{in}/S_{in}) \quad (1)$$

4.2 Learning Sequences

As we already indicated, in the goal-oriented problem solving mode the function of the network of upper divisions is to spread the search activity along upper-to-upper connections. In the forecasting mode, this network can be used to provide some guidance in forecasting as we indicate in the notes on the future directions of research. However, in the experiments that we report in this paper, the network of the upper divisions is ignored.

The purpose of the network composed of lower divisions and their connections is to generate a sequence of output signals from firing nodes (along the connections shown in Figure 5). In the goal-oriented search mode, such a sequence corresponds to a path between the current state and the goal state, and—as stated before—can be considered a solution to the problem.

In the forecasting mode, the node corresponding to the current state is activated through the thalamic input and allowed to fire. The activity from the firing node is transmitted to the nodes that are connected to the firing node through the efferent connections with non-zero strengths. Assuming substantial learning sample, it is very likely that there is only one connection that is strongest, so the node that is connected through that connection is the winner of the contest for the highest activation level. The number that is the center of the cluster corresponding to that node is the predicted vale. In non-clustering tests, it is the datum that is associated with the node. Subsequently, the winning node is allowed to fire next, and the process for selecting the winner is repeated until no more predictions can be made.

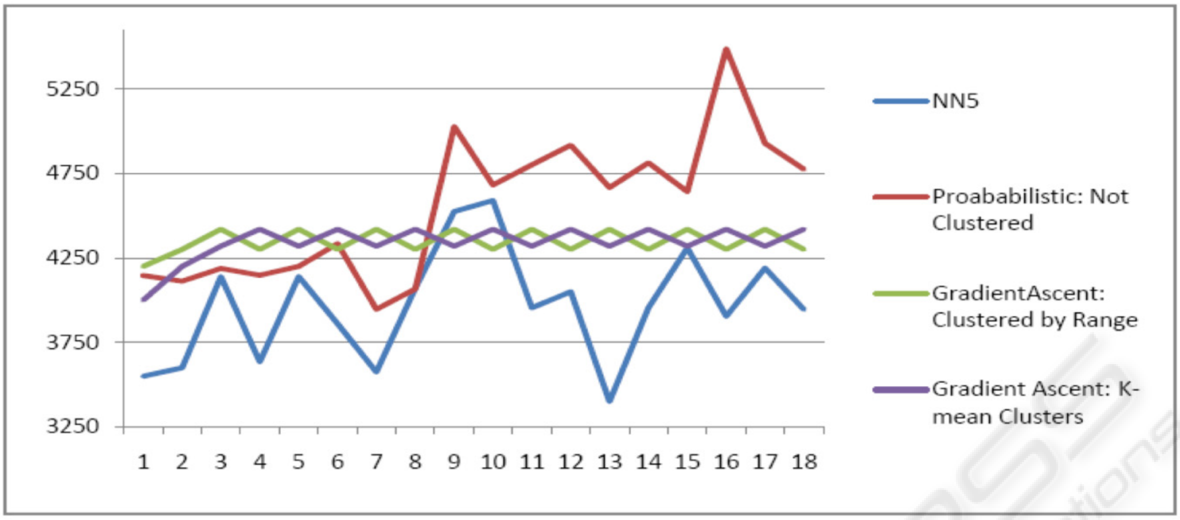
4.3 Implementation Tweaks

4.3.1 Inhibition

As indicated earlier, to avoid oscillations, the firing node is inhibited for a number of computation cycles. The length of the inhibition determines the length of cycles that can be prevented.

4.3.2 Higher-order Connections

Our initial implementation had first degree connections that link only to a direct predecessor of a node. We later enhanced our models with second degree connections, which provided a link to more distant predecessors in the Neurosolver's firing history. Adding connection degrees allows us to take into consideration a number of previously fired



Algorithm (input 4025)	Standard Deviation from NN5
Probabilistic	423.832098 ✓
Gradient Ascent: Not Clustered	913.405457
Gradient Ascent: Clustered	913.405457

Figure 6: Probabilistic vs. Gradient Ascent.

nodes when forecasting the next node to fire. In that respect, this approach is similar to Markov Models (Markov, 2006).

5 EXPERIMENTS

5.1 Quality Measure

To measure the quality of our predictions and to compare them with the benchmarks and submissions to the NN5 competition we used Symmetric Mean Absolute Percent Error (SMAPE) that was recommended by the NN5 organizers. The SMAPE calculates the symmetric absolute error in percent between the actuals X and the forecast F across all observations t of the test set of size n for each time series s with the following formula:

$$SMAPE_s = \frac{1}{n}\sum_{t=1}^{n}\frac{|X_t - F_t|}{(X_t - F_t)/2} * 100 \qquad (2)$$

5.2 Results

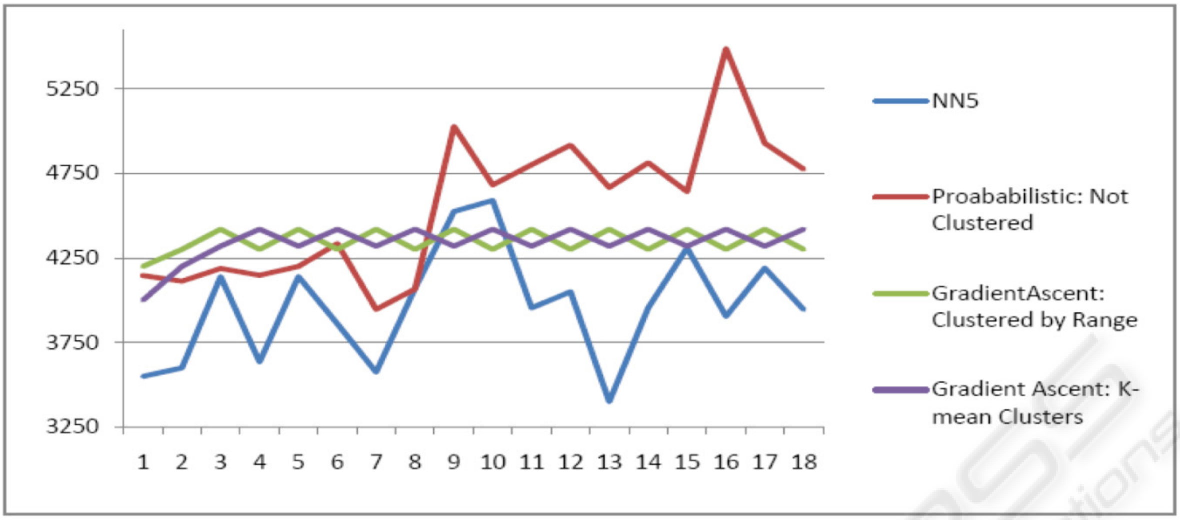
We generated a substantial body of results running the NN5 data sets with numerous incarnations of the Neurosolver. We processed the data in the raw form, as well as pre-processed by clustering techniques as described earlier. We also tested the Nuerosolver with the two learning algorithm: gradient ascent and stochastic.

In the following sections, we present an analysis of the Neurosolver's performance on some selected data. In the analysis, we compare several models and approaches that we used, and relate the results to the test data provided with the NN5 data sets. We conclude with a comparison with the benchmark predictions generated by non-neural methods provided by the organisers of the NN5 competition for reference [NN5].

5.2.1 Comparing Learning Models

The graph in Figure 6 illustrates Neurosolver's predictions following presentation of one of the data points (4025) from the NN5 data sets. The four lines in the graph represent:

- the actual data provided by the NN5 competition (drawn in blue),
- our forecasted values for the stochastic model (in red), and
- forecasting made with two hill-climbing models (in green and purple).



Algorithm (input 4025)	Standard Deviation from NN5
Probabilistic: Not Clustered	423.832098
Gradient Ascent: Clustered by Range (50)	254.011766 ✓
Gradient Ascent: K-mean Clusters (input/50)	257.527038

Figure 7: Clustered vs. Unclustered.

The data in the table below the graph show the standard deviation between our results and the test data from the NN5 data sets.

The graph in Figure 6, illustrates how the Neurosolver behaves when the data is not shaped by clustering algorithms. We used a cluster size of one in the shown clustered gradient ascent, so a node is used per each value, making it virtually the same as an un-clustered model. Therefore, the Neurosolver generated the same forecasts for both the clustered and un-clustered gradient ascent models. The lines corresponding to the two gradient ascent models—drawn in purple and green—are collapsed and displayed as a single purple line.

From the graph and the standard deviation between the forecasted values and the NN5 data (given in the table below the graph), we observe that the probabilistic model provides forecasts that are closer to the actual data (as provided with the NN5 sets) in terms of the standard deviation from the measured data.

5.2.2 The Clustering Factor

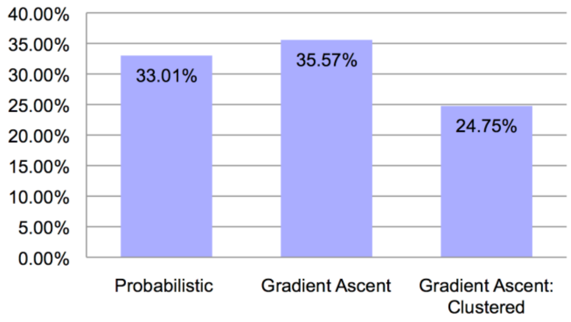
The graph in Figure 7 illustrates how the clustering algorithms affect the forecasting. The value used as the input to our forecaster is the same as before (4025). The cluster-by-range gradient ascent model divides the input into 50 clusters. The k-means clustering algorithm divides the size of the input by 50, giving us 173 clusters for this particular data set. The significance of the clustering process can be seen in the change in our standard deviation for the gradient ascent model. The forecasted values from the gradient ascent models are now much closer to the actual data provided with the NN5 data sets.

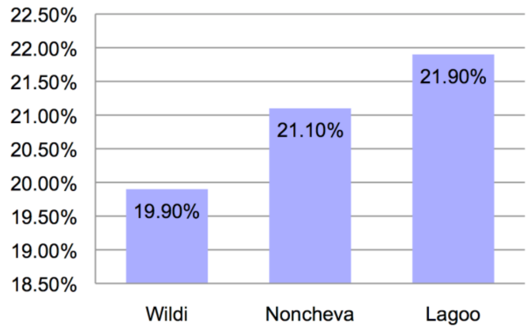
The clustering algorithms provide an overall improvement in our results; however, we have encountered some cases in which the clustering algorithm increased our deviation from the actual values.

5.2.3 Comparing with the NN5 Submissions

The NN5 website provides a list of contest submissions and benchmark results. They use the SMAPE formula to calculate the quality of predictions generated by the competing and benchmark models. The best predictions that come from benchmark models are shown on the right side of Figure 8. No competing submission exceeded the performance of the benchmark models.

The left side of Figure 8 shows the performance of several models of the Neurosolver.





Algorithm	SMAPE
Probabilistic	33.01%
Gradient Ascent	35.57%
Gradient Ascent: Clustered	24.75%

Algorithm	SMAPE
Wildi	19.90%
Noncheva	21.10%
Lagoo	21.90%

Figure 8: Neurosolver vs. Benchmarks.

6 CONCLUSIONS

Currently our results are below the benchmarks on the NN5 website. However, we are not that much apart. We have found our current findings to be promising and plan to amply a number of improvements that we believe will improve the performance of the Neurosolver significantly.

We plan to further investigate and compare our results with other data sets. We are also looking forward toward participating in the future NNx competitions. As of this writing, a new competition has not been announced.

We have concluded that a potential source for our deviation in forecasted values could be due to incomplete data in our learning set. In such cases the Neurosolver gets stuck. We will be looking into providing some means to boost Neurosolver's activity to address such problems.

As we indicated, we use node inhibition to solve the problem with cycles that can lead to looping. At the same time, however, we may prevent generation of genuine cycles that may be present in the data. We believe that this is the main cause of the Neurosolver's inability to generate predictions at some points. We are planning to look into developing a mechanism that would accommodate generating genuine cycles while preventing endless loops.

The improvement to our predictions after adding second order connections was significant; therefore, we expect that even higher-degree connections will improve the results even further. However, higher-degree connections are also computationally expensive, so we will need to strike a balance between the improvement to the prediction capabilities and the efficiency of computations.

ACKNOWLEDGEMENTS

The author would like to express gratitude to several students that were members of the research group operating in Spring 2009 semester under the umbrella of Faculty-Undergraduate Student Research Initiative supported by California State University Channel Islands. The following students provided great help with programming, testing, analyzing data and charting the results: Fahimeh Fakour, Douglas Holmes, Maximillian Kaufmann, and Nicholas Peters.

REFERENCES

Bieszczad, A. and Pagurek, B., 1998. *Neurosolver: Neuromorphic General Problem Solver*, Information Sciences: An International Journal 105, pp. 239-277, Elsevier North-Holland, New York, NY..

Bieszczad, A., 2008. *Exploring Neurosolver's Forecasting Capabilities*, Proceedings of the 28th International Symposium on Forecasting, Nice, France, June 22-25.

Newell, A. and Simon, H. A., 1963. *GPS: A program that simulates human thought*, in Feigenbaum, E. A. and Feldman, J. (Eds.), Computer and Thought. New York, NJ: McGrawHill.

Burnod, Y., 1988. *An Adaptive Neural Network: The Cerebral Cortex*, Paris, France: Masson.

Laird, J. E., Newell, A. and Rosenbloom, P. S., 1987. *SOAR: An architecture for General Intelligence*, Artificial Intelligence, 33: 1--64.

Nillson, N. J., 1980. *Principles of Artificial Intelligence*, Palo Alto, CA: Tioga Publishing Company.

Collins, Allan M.; Loftus, Elizabeth F., 1975. *A spreading-activation theory of semantic processing*, Psychological Review. Vol 82(6) 407-428.

Anderson, J. R., 1983. *A spreading activation theory of memory*. Journal of Verbal Learning and Verbal Behavior, 22, 261-295.

Markov, A. A., 2006. *An Example of Statistical Investigation of the Text Eugene Onegin Concerning the Connection of Samples in Chains*, translation. by David Link. Science in Context 19.4: 591-600.

Russell, Stuart J.; Norvig, Peter (2003), *Artificial Intelligence: A Modern Approach* (2nd ed.), Upper Saddle River, NJ: Prentice Hall, pp. 111-114

NN5: http://www.neural-forecasting-competition.com/