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Exploring Training Techniques in Reservoir Computing

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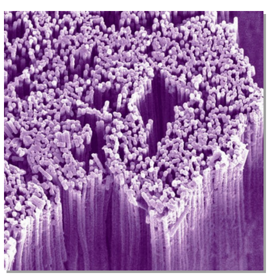
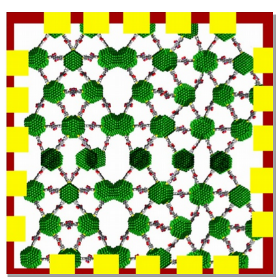
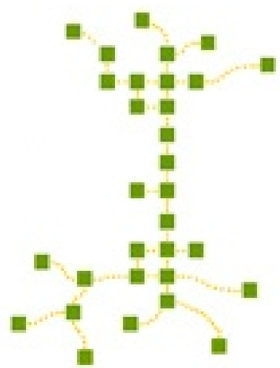

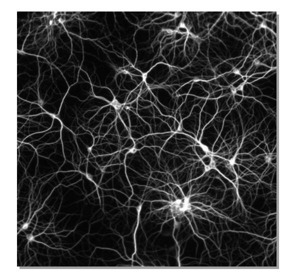

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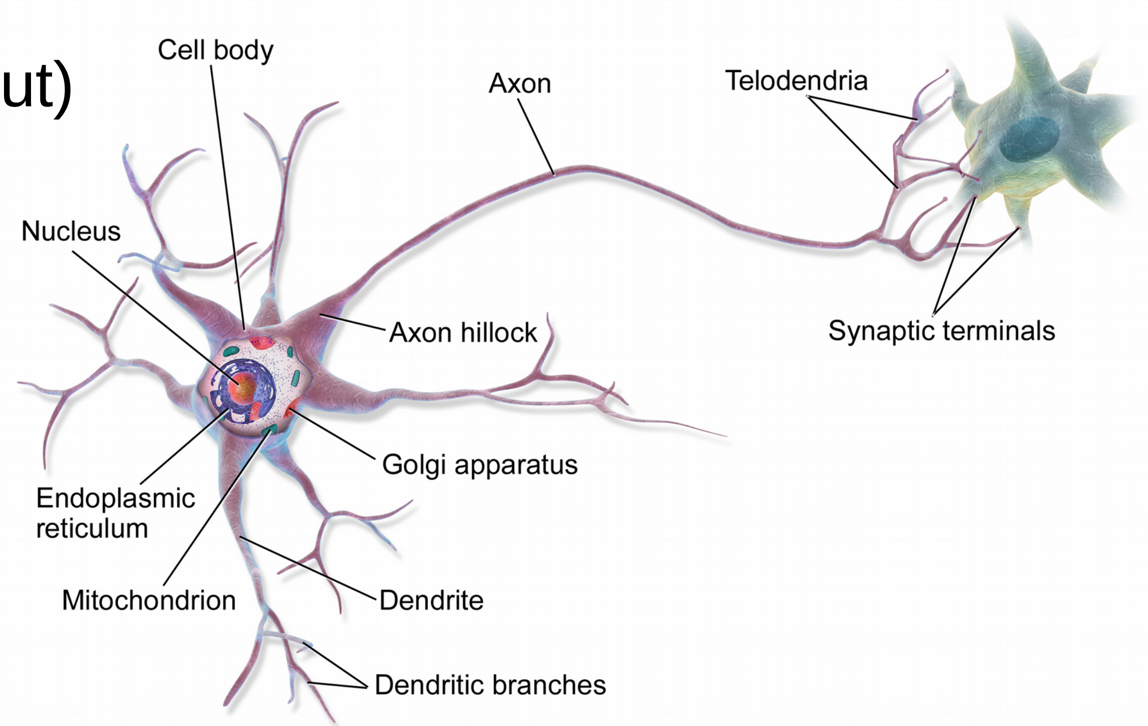
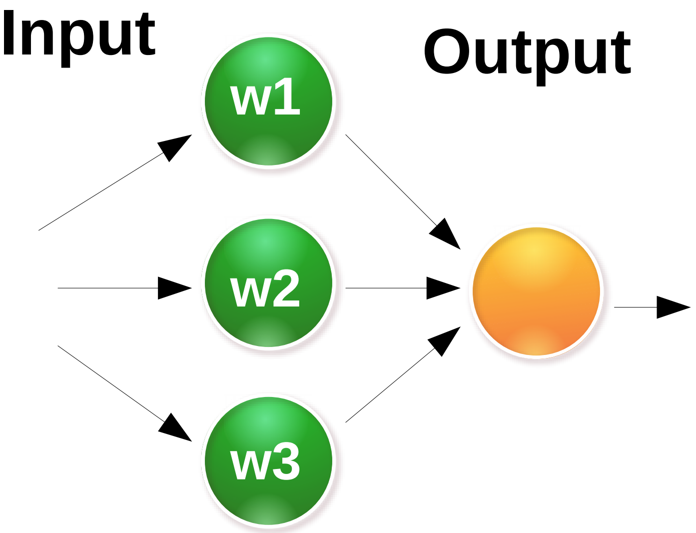
Biological Inspiration for Neural Networks

- Soma/cell body (input)
- Dendrites (inputs)
- Axon (output)
- Information is propagated through activation of neuron and resulting action potential down axon



What Makes Up a Neural Network (NN)?

- Perceptrons
  - Inputs must be linearly separable
  - Linear classifier (binary)
  - Weights are used multiplicatively to modify connections
  - Multilayer perceptrons can form larger networks
    - Are universal function approximators
  - Multi-class perceptrons can handle more categories
- Sigmoid neurons / other models
- Dynamic networks
  - Feedforward / Recurrent
  - Can be made of perceptrons / other models
  - Hopfield networks
  - Boltzmann machines
  - Echo state networks

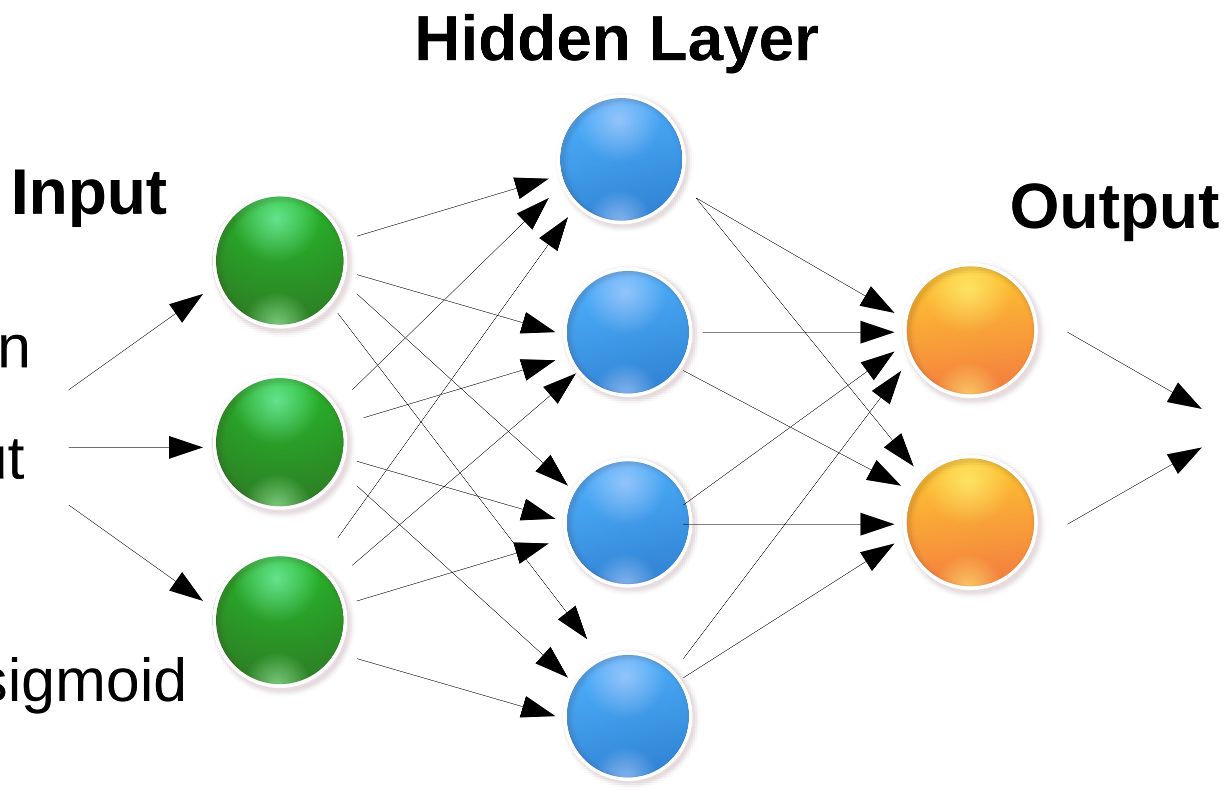


Characteristics of Networks

- **Architecture**
  - Density / sparsity
  - Arrangement of nodes
    - Circular, feedforward
- **System Dynamics**
  - Weights of connections between nodes
- **Learning**
  - How the weights change with time

Composition of a Feed-forward NN (Multi-Layer Perceptron)

- Information moves in one direction (forward)
- Input layer
- Hidden layer
- Output layer
- Activation function determines output of each node, typically tanh or sigmoid



Recurrent NNs

- Can be arranged more “creatively”
- Architecture produces cyclical properties
- Retain memories of past inputs, but have trouble “seeing” long patterns
- RNNs are harder to train

Limitations of Networks

- Calculations of new weights between nodes in hidden layers can be computationally expensive
- No one network is suited to all tasks
- Different training algorithms are needed for different tasks and it can be a challenge to find the optimal algorithm
- Optimizing initial parameters involves guess work

Solutions?

- Long-Short Term Memory
- Varying architectures (circular, sparsely connected, etc.)
- Hierarchical networks
- Better training algorithms?

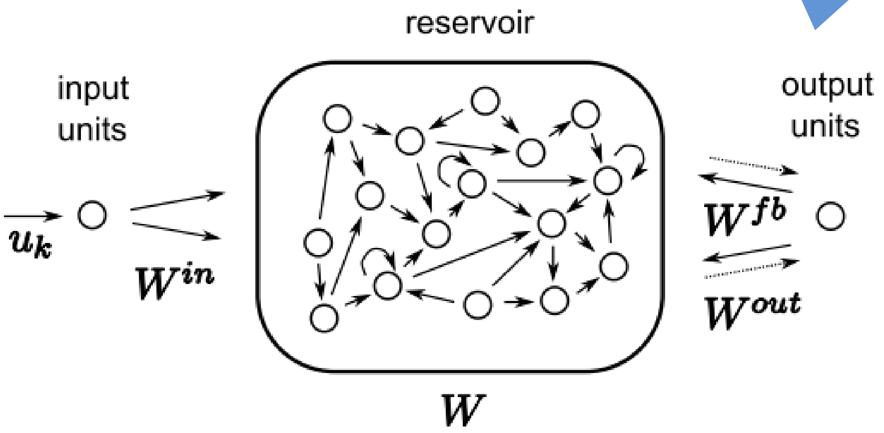
What is a Reservoir Computer?

- Also called an echo state network (ESN)
- Random, sparse architecture of nodes and weights
  - Internal weights are due to dynamical properties of system itself
- We train the output layer, which can produce specific functions based on its adapted weights and the fixed weights of the hidden layers
- Even a bucket of water can be a reservoir computer [3]

[3] Fernando, Chrisantha; Sojakka, Sampsa; Of Series Lecture Notes In Computer Science, ISBN (2005), "Pattern Recognition in a Bucket", In Advances in Artificial Life: 978–3

Training Methods (Simplified)

- Ordinary Linear Regression (OLR)
- Least squares
- Recursive Least Squares (RLS)



[13]

[13] Yildiz, I. B., Jaeger, H., & Kiebel, S. J. (2012). Re-visiting the echo state property. Neural Networks, 35, 1–9. http://doi.org/10.1016/j.neunet.2012.07.005

Benchmarks

- **Nonlinear Autoregressive Moving Average (NARMA-10)**

$$y(t) = 0.3\,y(t-1) + 0.05\,y(t-1)\sum_{i=1}^{10} y(t-i) + 1.5\,u(t-10)\,y(t-1) + 0.1$$ [2]

- **Mackey-Glass Time Series**

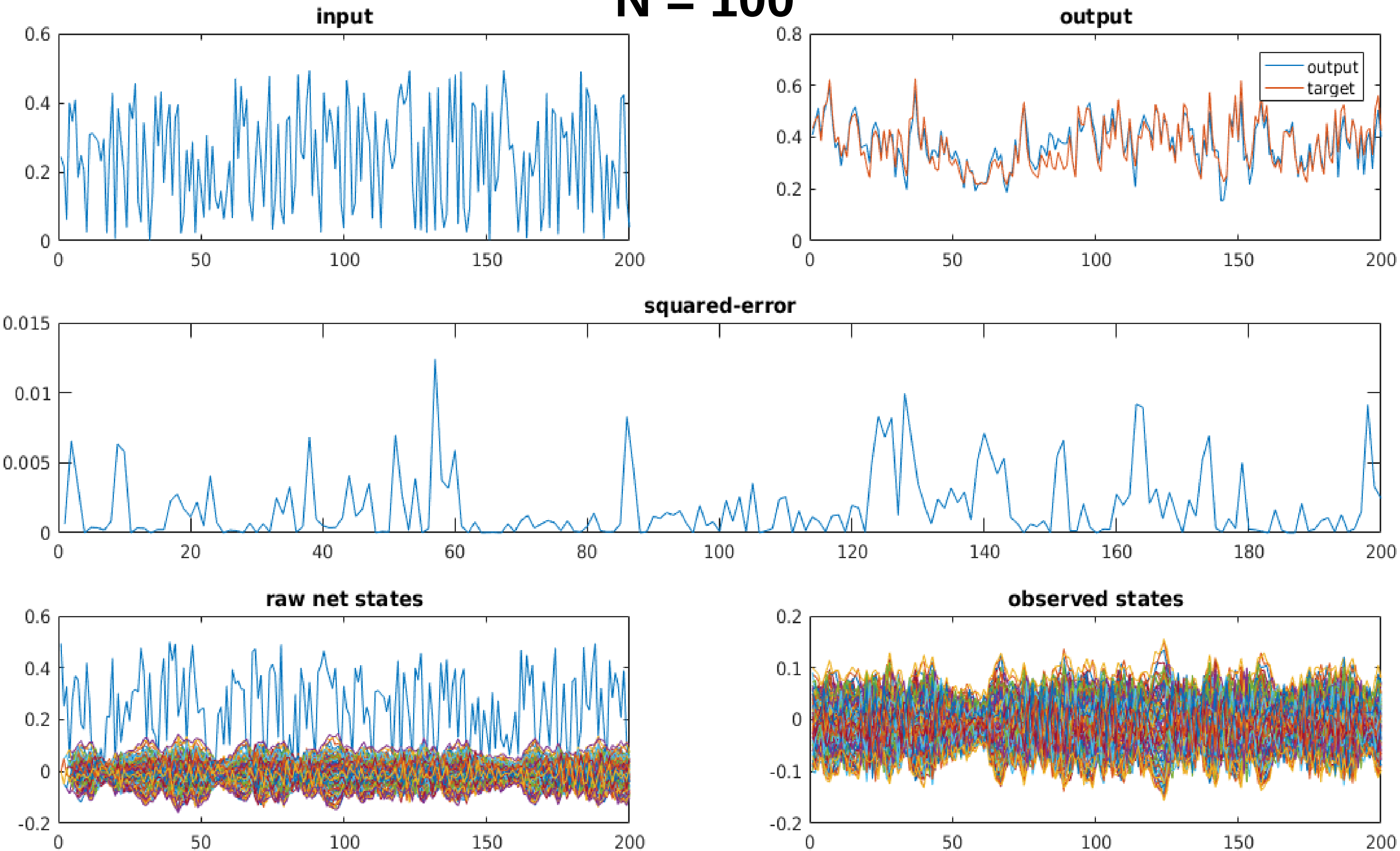
$$\frac{dx(t)}{dt} = \frac{ax(t-\tau)}{1+x(t-\tau)^{10}} - bx(t)$$ [2]

- **Sine wave prediction**

[2] Čerňanský, M., & Tiňo, P. (2008). Predictive Modeling with Echo State Networks. 18th International Conference on Artificial Neural Networks, (1), 778–787.

Results of OLR on NARMA-10 Task

N = 100

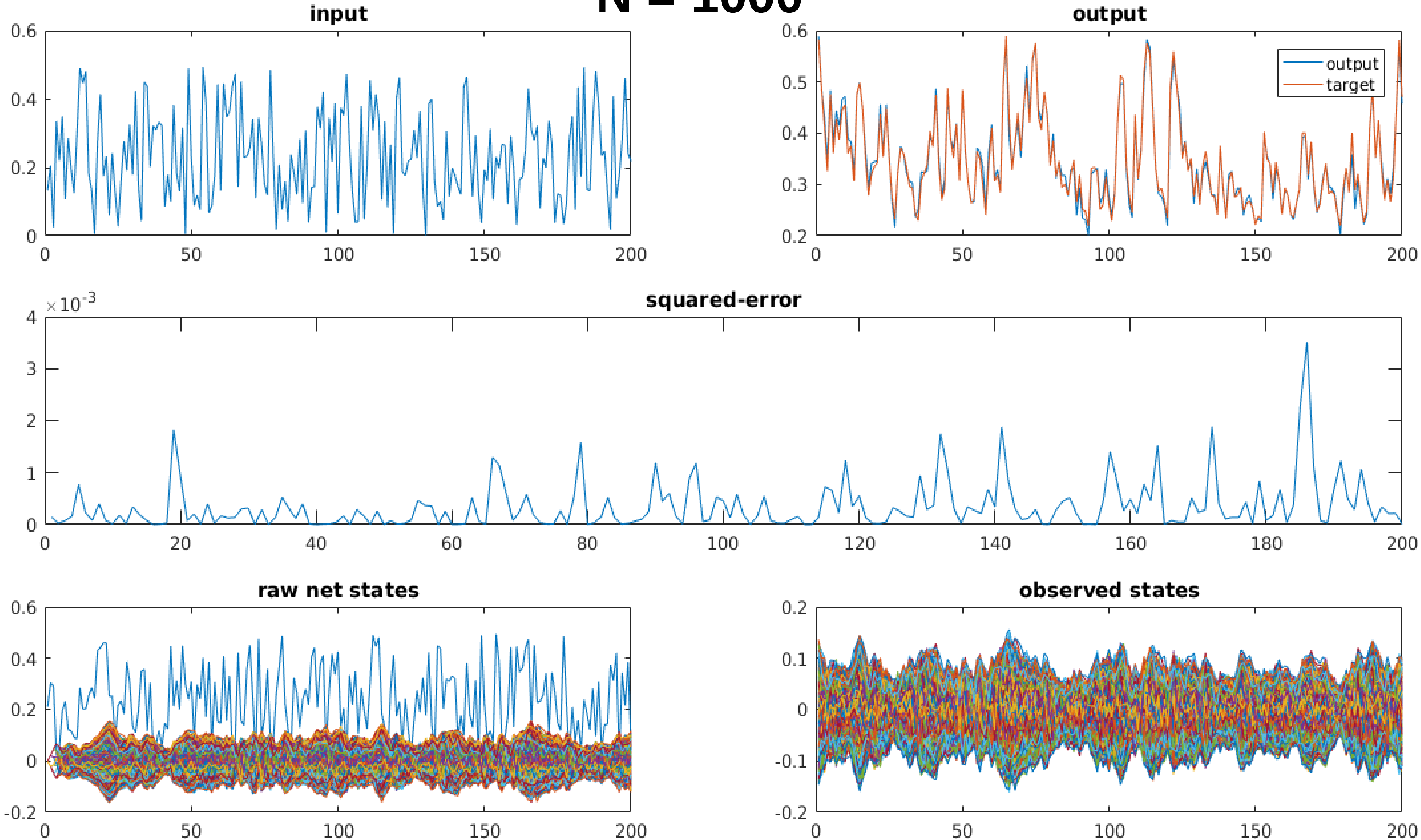


ESN framework by A. Goudarzi

NMSE = 0.1283

Results of OLR on NARMA-10 Task

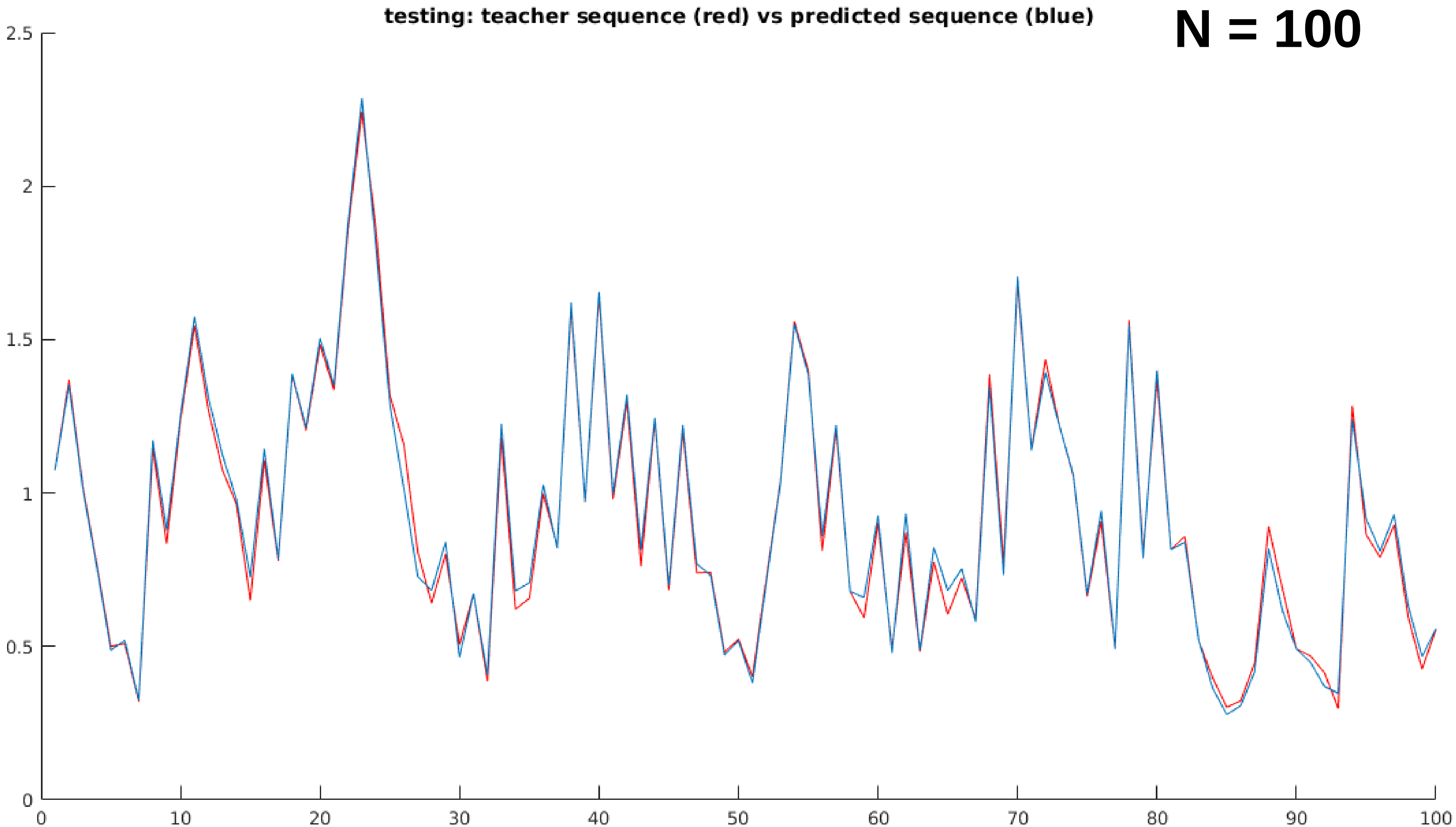
N = 1000



ESN framework by A. Goudarzi

NMSE = 0.0274

Results of OLR (batch) NARMA-10



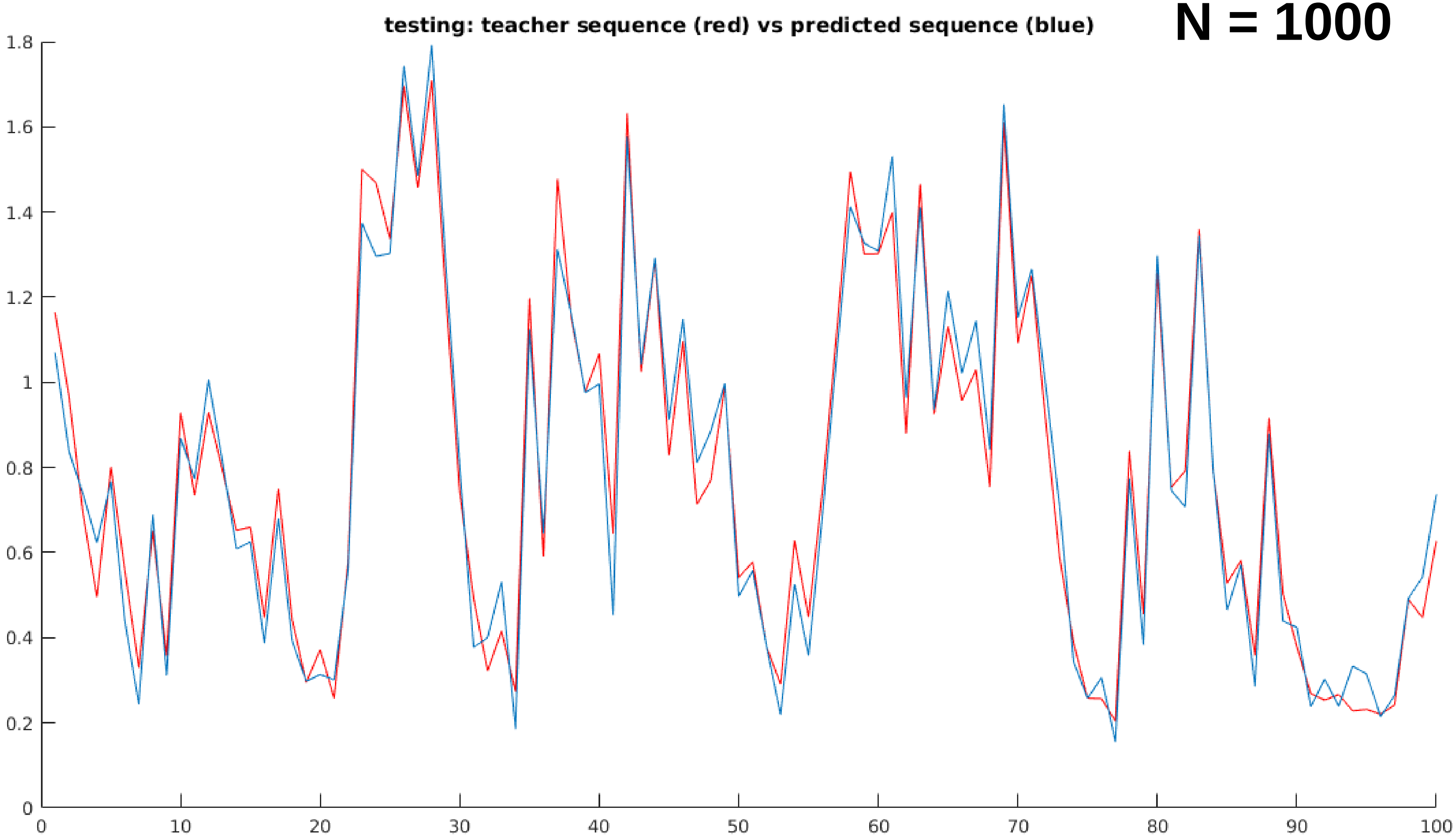
N = 100

ESN toolbox by H. Jaeger

NRMSE = 0.11899

Results of OLR (batch) NARMA-10

N = 1000

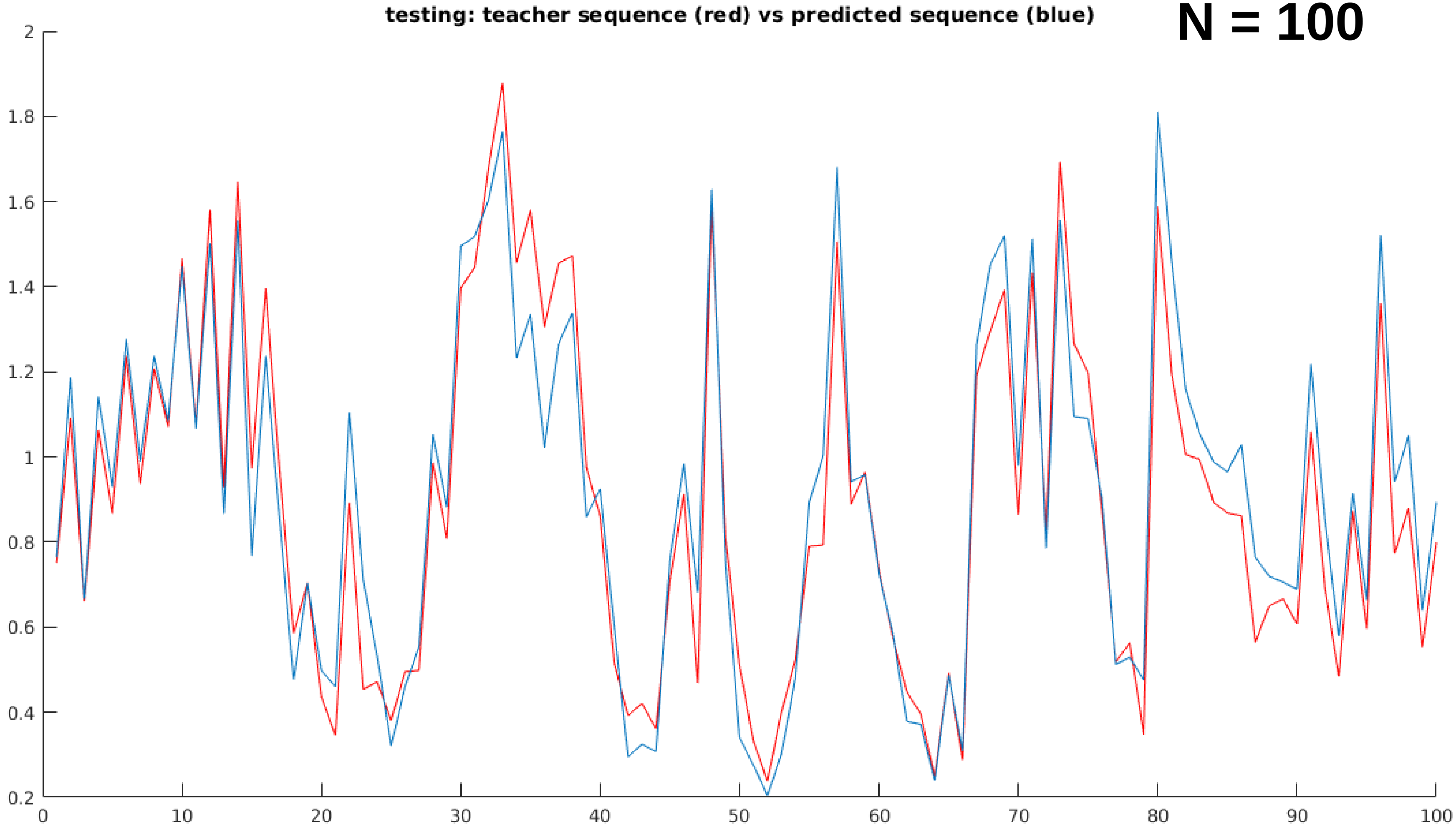


ESN toolbox by H. Jaeger

NRMSE = 0.16854

Results of RLS (online) NARMA-10

N = 100

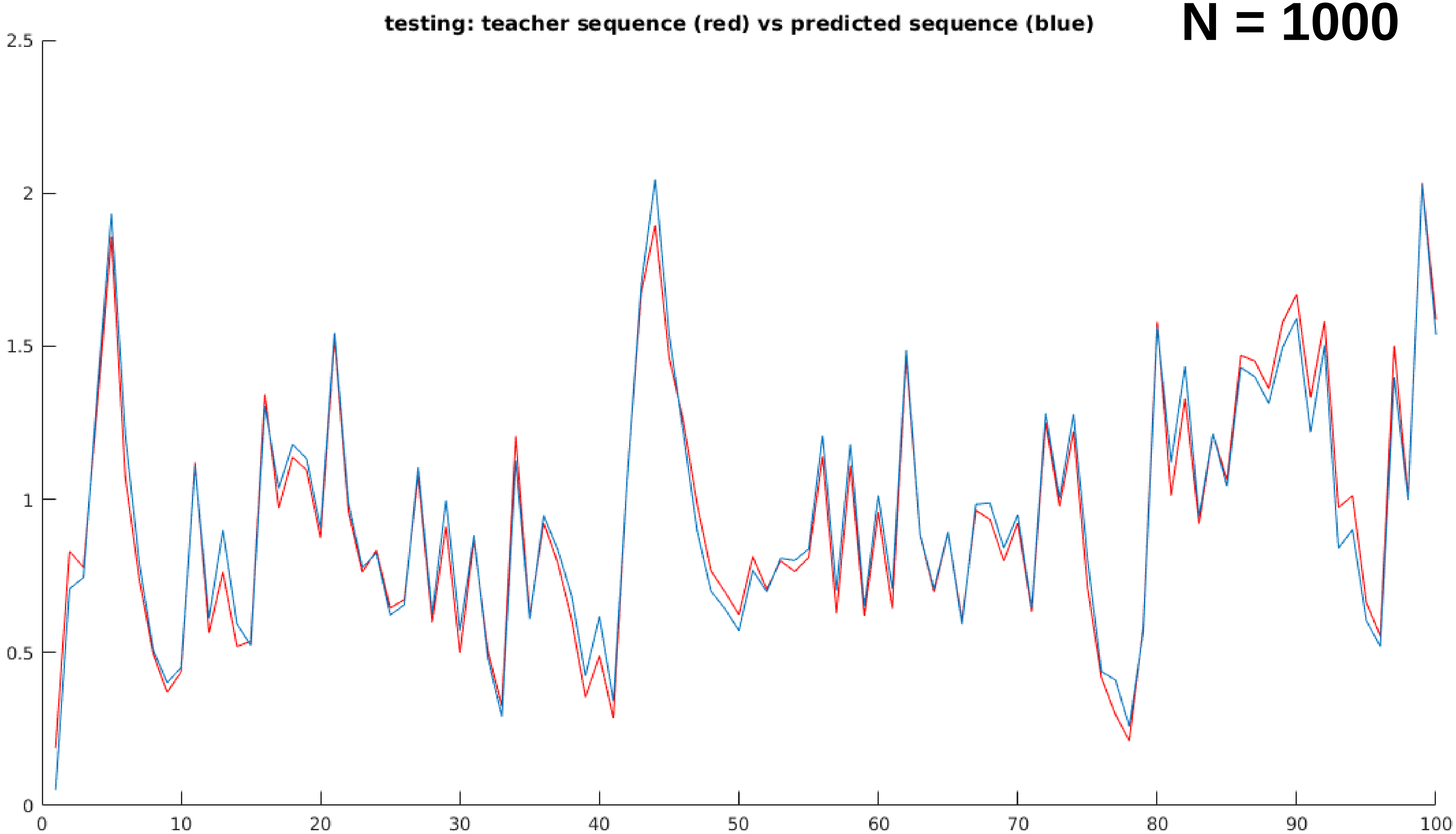


ESN toolbox by H. Jaeger

NRMSE = 0.29867

Results of RLS (online) NARMA-10

N = 1000



NRMSE = 0.16362

ESN toolbox by H. Jaeger

Conclusions

- RLS performs well for implementation in online learning schemes
- More benchmarks need to be tested to evaluate strengths and limitations of RLS
- Initial parameters may be further optimized to improve performance
- Next steps:
  - NARMA-30
  - Mackey-Glass time-series
  - Need to compare RLS to OLR in online contexts

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