

# Processing capacity of recurrent spiking networks

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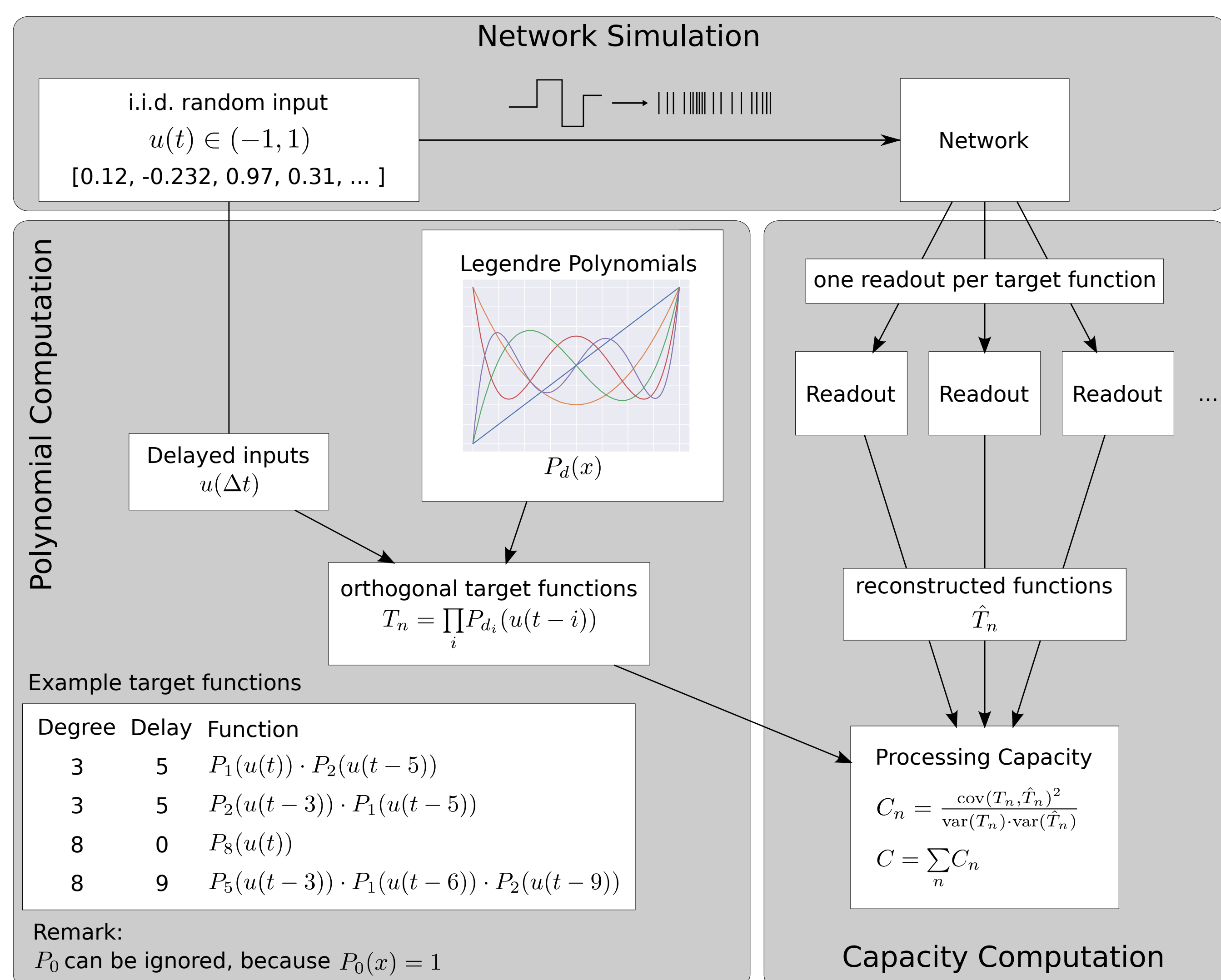


## Introduction

One of the most prevalent characteristics of neurobiological systems is the abundance of recurrent connectivity permeating the micro-, meso- and macroscopic levels. Despite the ubiquity of these observations, it remains unclear whether recurrence and the characteristics of its biophysical properties correspond to important functional specializations and if so, to what extent. Therefore, it would be extremely useful, from both an engineering and a neurobiological perspective, to know to what extent is recurrence necessary for neural computation.

## Methods

In this work, we set out to quantify the extent to which recurrence modulates a circuit's computational capacity, by systematically measuring its ability to perform arbitrary transformations on an input, following [1] and [2]. The diagram below shows how the processing capacity of a network is determined.



- Balanced networks of 2000 integrate-and-fire neurons are used
- We test networks with varying density of recurrent connections
  - Evaluation of the effect of recurrence on the complexity of the transformations the circuit can carry out and on the memory it is able to sustain
- First, we adjust the minimum and maximum values of the rate-encoded signal to optimize the ability of the networks to reconstruct the input
  - This enhances the comparability of the processing capacities between the networks

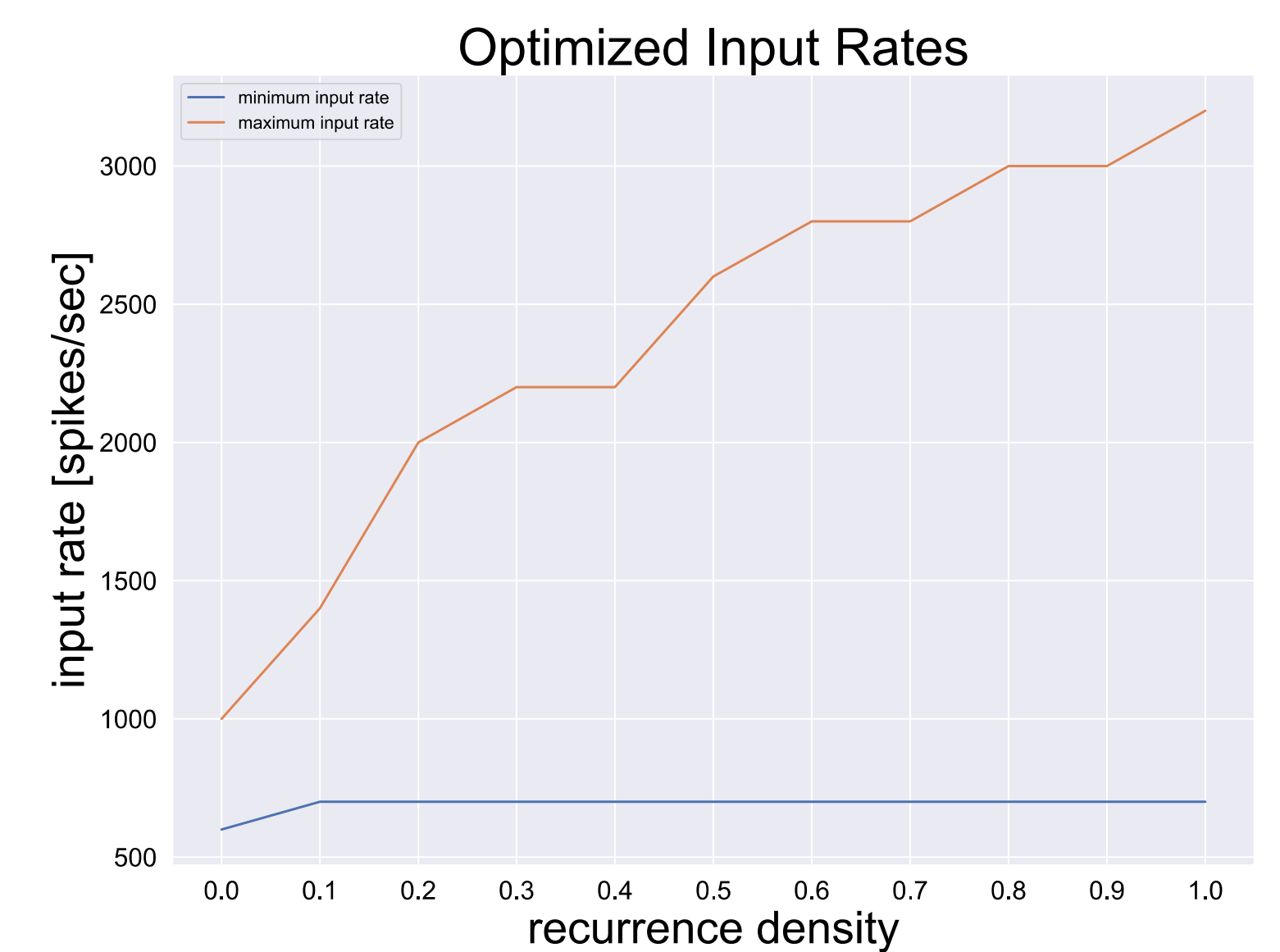
### Parallelization and optimization

- The method is computationally heavy: Thousands of target functions have to be evaluated
- Optimizations:
  - Efficient lookup operation for polynomial functions
  - Caching of functions, which need to be called multiple times with the same inputs
  - The most compute-intense hotspots are optimized with Cython
  - MPI for internode communication

## Experimental results

### Sensitivity to changes in the input

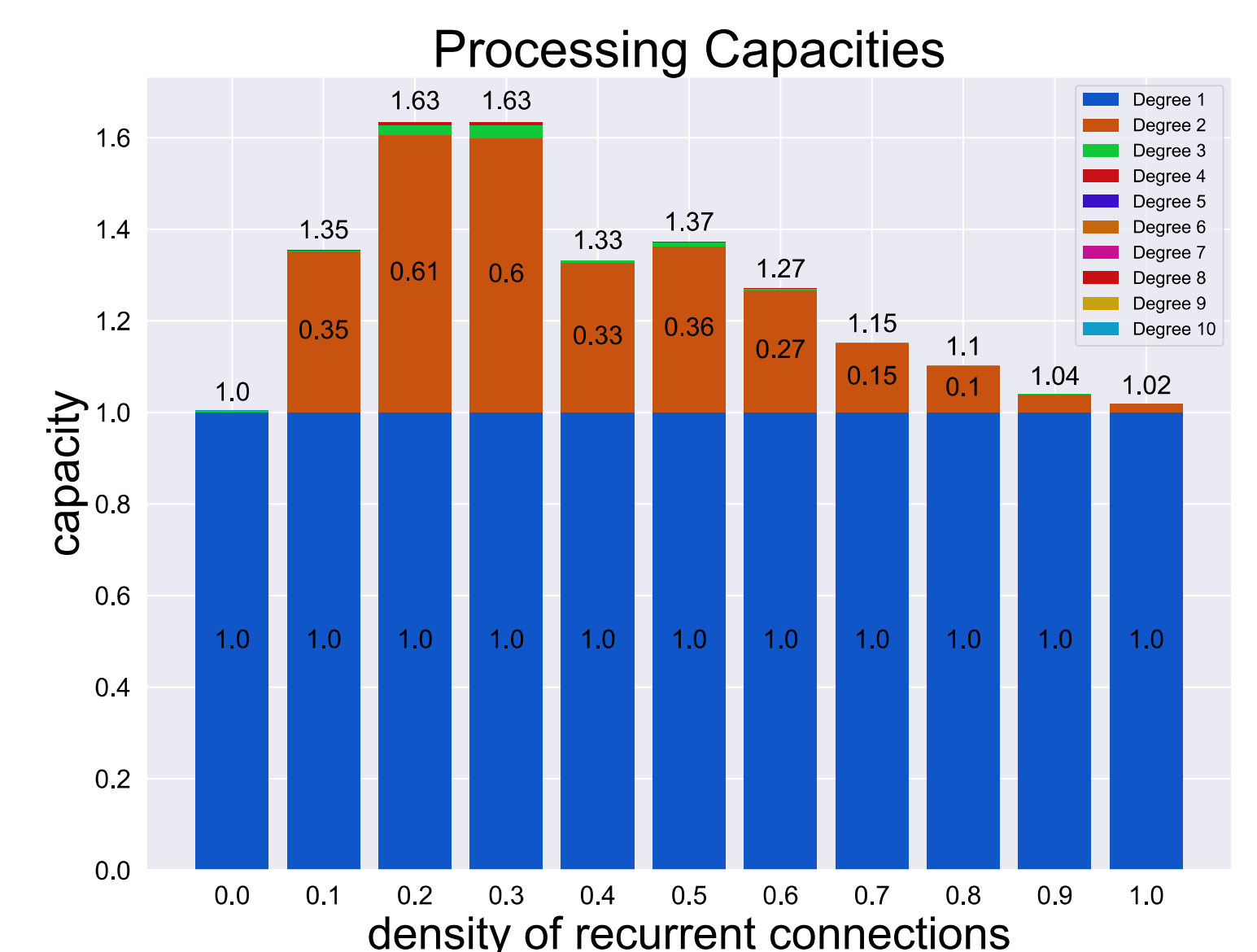
- A strong correlation between amount of recurrent connections and the width of the the range of input rates the newtork needs to reconstruct the signal is observed
  - Systems with higher recurrence densities need a broader range of rates encoding the input than systems with a low amount of recurrent connectivity



**Figure 2** Minimum and maximum input rates that optimize the reconstruction of the signal for networks with different recurrence densities

### Processing Capacity

- Shown are networks with different connections densities
- Averaged over 3 trials
- None of the networks showed a linear memory (greater than the step size of 50 ms)
- The density of recurrent conectivity plays an important role in the network's processing capabilities for mappings that involve varying degrees of nonlinearity
- In our set up connection densities of 0.2 and 0.3 lead to the best performance
- Without recurrent connections, the network was not able to compute any target function of higher degree



**Figure 3** Processing capacities for networks with different recurrence densities, separated by the degree of the reconstructed target functions.

## Conclusion

- We developed a highly scalable version of the processing capacity method introduced in [1].
- With increased density of recurrent connections the network's sensitivity to changes in the input rate decreases
- Recurrent connectivity endows balanced spiking networks with the ability to perform non-linear transformations of their input.
- There is a sweet spot of recurrence density for the ability to perform these transformations.

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