Deterministic neural networks as sources of uncorrelated noise for probabilistic computations

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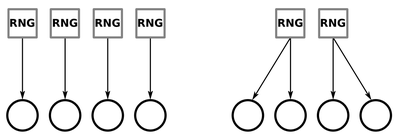
Motivation

Noise in functional networks

- neural implementations of probabilistic computing rely on presence of some form of stochasticity/noise [1,2] → input from (pseudo) random-number generators
- requirements for RNGs:
  1. (quasi) chaotic dynamics (seed sensitivity) with long (ideally infinite) cycle length
  2. high throughput (rate of random-number production)
  3. vanishing serial (temporal) correlations
  4. vanishing spatial correlations
  5. modulation of noise amplitude



- space/bandwidth constraints in hardware → limited number → **shared-noise correlations**

- Suitable sources of stochasticity in biological neural networks and hardware implementations?
- Do shared-noise correlations impair performance of networks implementing prob. computations?
- How can a limited number of noise sources provide uncorrelated input?

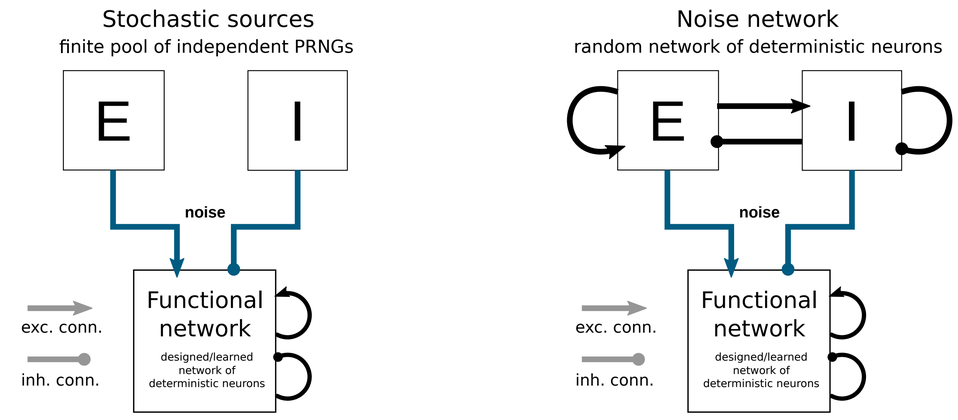
Recurrent neural networks as RNGs

Stochastic sources

- finite number N of exc./inh. independent stochastic units (e.g., Ginzburg)
- mutually unconnected

Noise network

- recurrent network of N exc./inh. deterministic neurons (e.g., McCulloch-Pitts)
- sparse, random connectivity

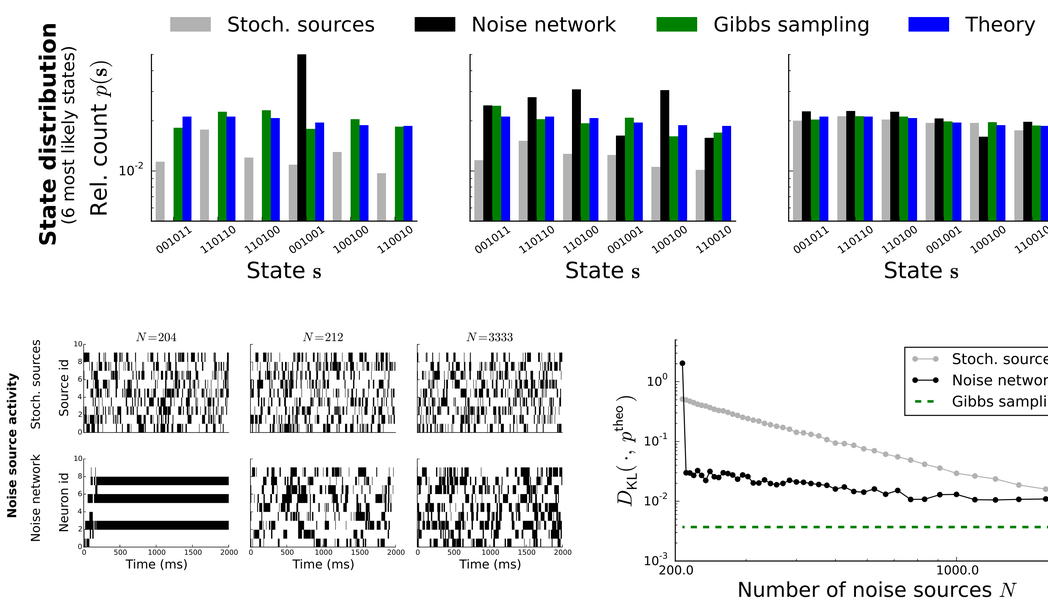


Why recurrent neural networks?

- chaotic dynamics (for sufficiently strong excitation) [3] (req. 1. & 3.)
- easy/flexible to implement on neuromorphic hardware (req. 2.)
- irregular activity (CV ~ 1) [3,4] (req. 3.)
- active suppression of shared-input correlations through inhibitory feedback [6,7] (req. 2. & 4.)
- rate modulation via change of, e.g., external input (req. 5.)

Sampling performance in presence of network-generated noise

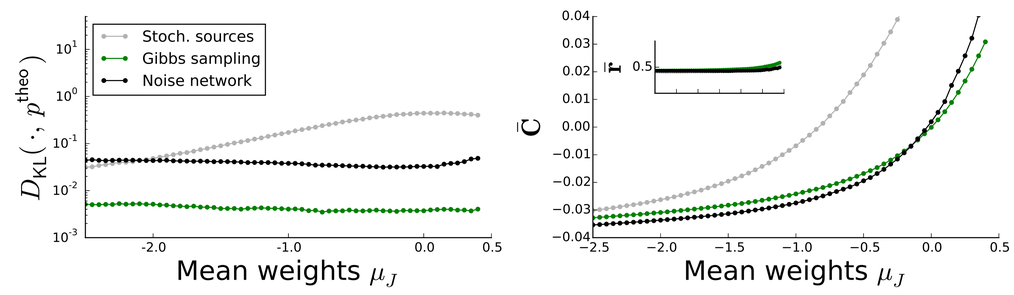
- sampling network: symmetric network with random weights
- fixed number K of background inputs to functional network
- modulation of shared-input correlations via number of noise sources N



- **increased sampling error due to shared-input correlations**
- **recovery of sampling performance for network-generated noise**

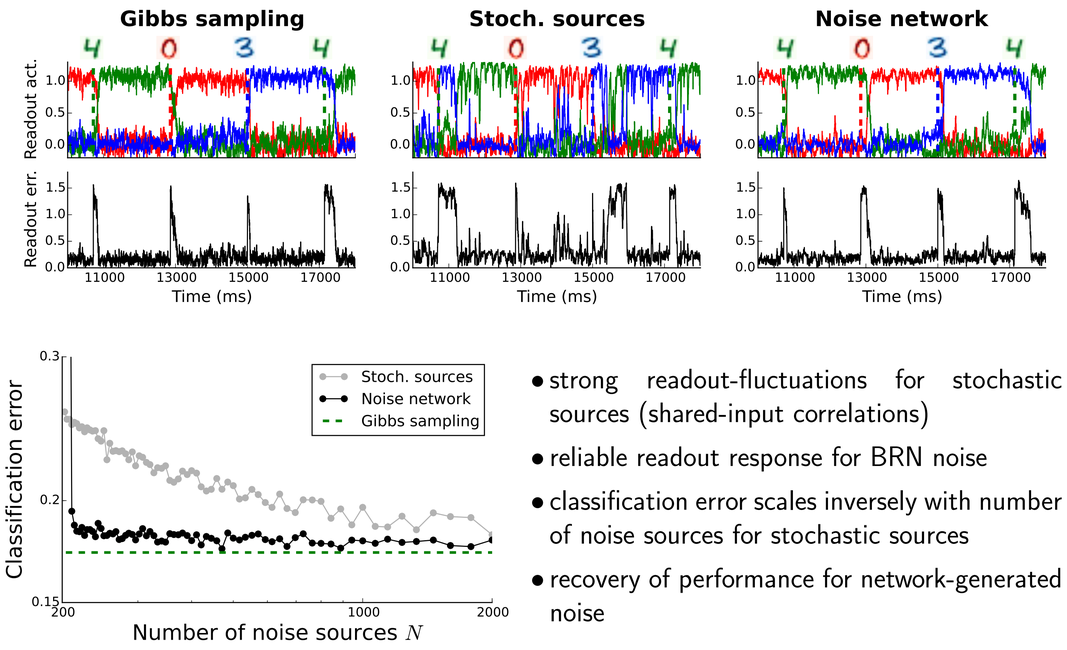
Decorrelation within functional networks

- active suppression of external correlations in recurrent networks with sufficient inh. feedback [5]



- **for stochastic sources: significant decrease of sampling error for increasingly negative average coupling in Boltzmann machine (holds also for increasing the size)**
- **for BRN noise: sampling error approx. independent of average coupling**

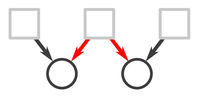
Pattern recognition



- strong readout-fluctuations for stochastic sources (shared-input correlations)
- reliable readout response for BRN noise
- classification error scales inversely with number of noise sources for stochastic sources
- recovery of performance for network-generated noise

Decorrelation by inhibitory feedback [6,7]

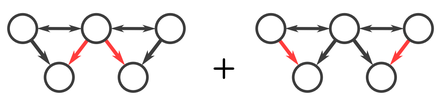
- finite stochastic sources



$$c^{in} = c^{in}_{shared} > 0$$

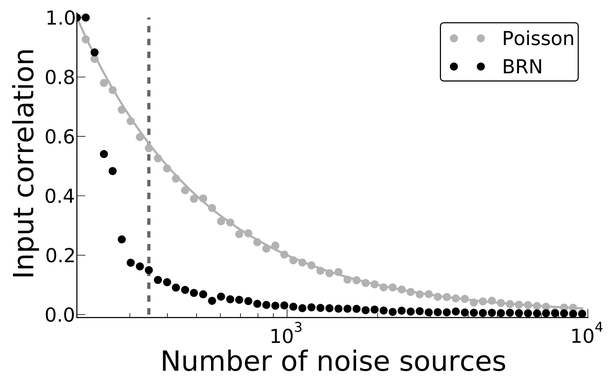
(if Dale's law is respected)

- BRN



$$c^{in} = \underbrace{c^{in}_{shared}}_{>0} + \underbrace{c^{in}_{corr}}_{<0} \approx 0$$

(if connectivity is sparse)



- shared noise sources lead to input correlations
- due to feedback, activity in noise network is correlated

→ **suppression of shared-input correlations by spike-train correlations (consequence of inhibitory feedback)**

Conclusion

- **shared-input correlations impair performance of functional networks**
- **recovery of network performance in presence of network-generated noise, due to active supression of shared-input correlations**
- **active decorrelation in functional networks with negative feedback**
- **results generalize: sampling with LIF neurons (current-based / conductance-based synapses), attractor networks**

→ **recurrent neural networks can serve as noise sources both in biological and in synthetic neuromorphic substrates**

References

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