# STDP driven self-organization of neuronal networks

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# Motivation

- Before  proper understanding of networks, neural models were studied on regular lattice which was clearly unrealistic. To gain proper insight into the phenomena happening in neural networks it is necessary to have a good approximation of the real networks in the brain.

- It is believed that complete information about Neuronal Networks is not genetically stored. Possibly, information about only important neurons and axons is genetically dictated and the rest of the network is dynamically generated.

# Networks

- Past decade has seen enormous activity in the analysis of different networks.
- Various networks arising in nature have been analysed and found to have certain properties like small world, scale free etc.

- As a result, some real brain networks have been studied experimentally with special emphasis on the structure of the neural network.
- Nervous system of a small work C. Elegans in known completely which will be used for comparisons.

# Networks of Neurons and Learning

- Network - neurons are connected with complex network topology. Recent advances in the Network Theory is shading some light on possible structures.
- Synapses - the coupling strength between two neurons at the synapses depends on the edge and it also changes with time on a slower time scale. This is interpreted as learning.
- Hebbian learning - Hebb gave a general argument underlying the learning dynamics which has served as a guiding principle for the most of the learning rules. According to this principle synaptic changes are driven by correlated activity of pre- and postsynaptic neurons.

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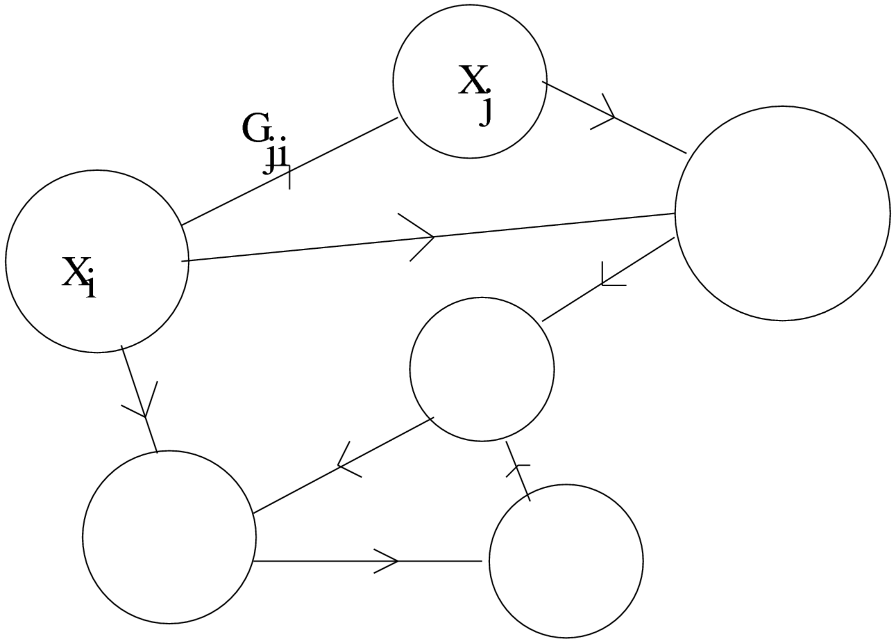

# Models Used

- **Chaotic Logistic Map:** Simple but chaotic discrete dynamics. Has nothing to do with neuronal dynamics.
- **Mirollo-Strogatz with STDP:** This is a crude model of neuron dynamics which gives rise to spikes but the strength of the synapses is made to evolve according to realistic rule.
- **Conductance based leaky Integrate-and-Fire model:** This is a more realistic model. We used a ready made neural simulation tool called NEST (M-O Gewaltig and M. Diesmann (2007), Scholarpedia, 2(4):1430).

# Hebb’s Postulate

When an axon of a cell A is near enough to excite cell B or repeatedly or persistenly takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A’s efficiency, as one of the cells firing B, is increased.

Such a mechanism would help to stabilize specific neuronal activity patterns in the brain. If neuronal activity patterns correspond to behavior, then the stabilization of specific patterns implies the learning of specific types of behaviors.

# Spike timing dependent plasticity

- Last decade has seen a new development in modeling learning. It has been found experimentally that exact timing of the firing of the spikes is important in determining the change in the coupling strength of the synapse.

- If the post-synaptic neuron fires within some time after the pre-synaptic neuron has fired then then the coupling strength increases. On the other hand, if the post-synaptic neuron fires just before the pre-synaptic neuron then it leads to the decrease of the coupling strength.

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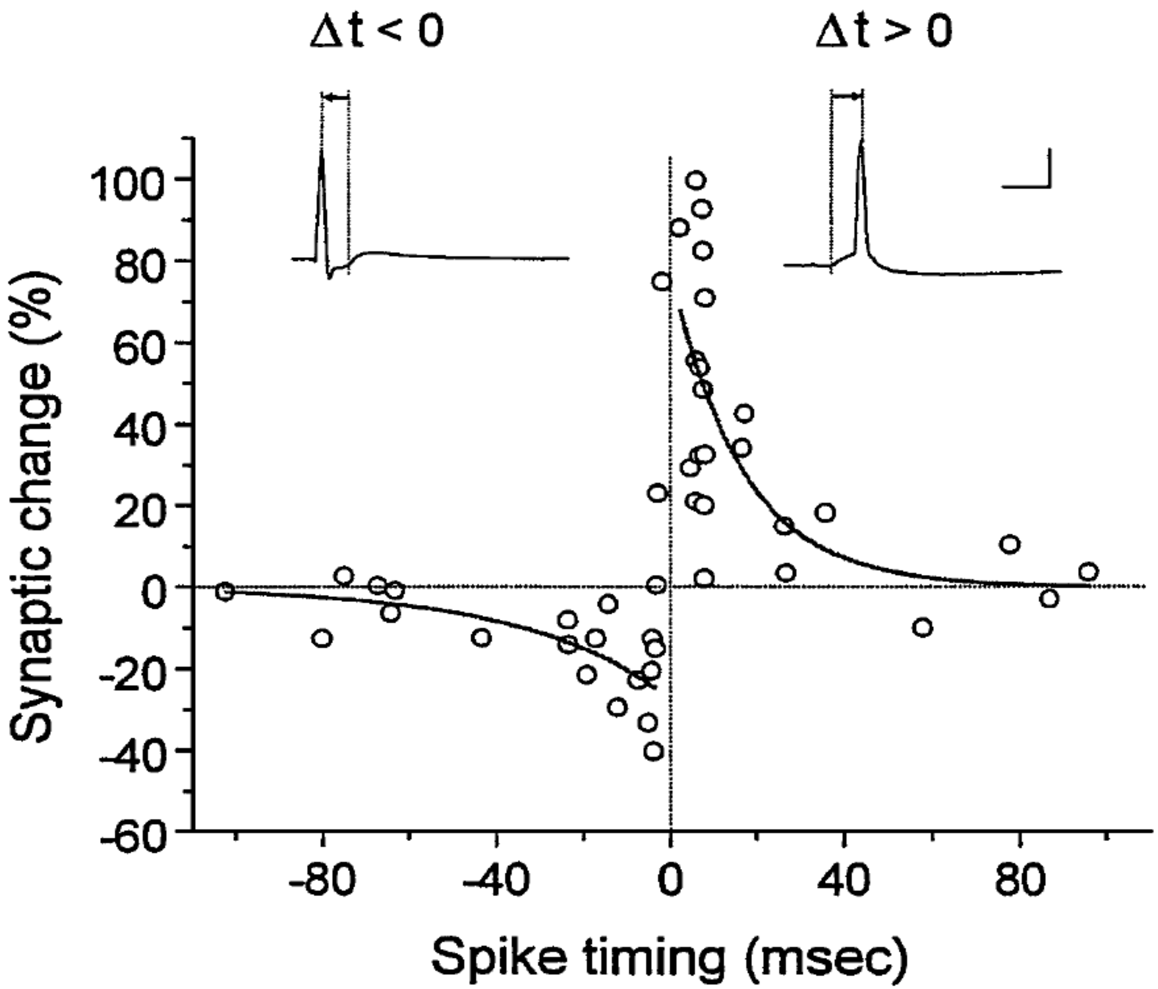


$$\Delta t = t_{post} - t_{pre}$$

$$\Delta W = A_{\pm} e^{-\Delta t / \tau_{\pm}}$$

$$A_{-} \tau_{-} > A_{+} \tau_{+}$$

$$\alpha = \frac{A_{-}}{A_{+}}$$

Bi and Poo, Annu. Rev. Neurosci. (2001) vol 24 pg 139

# Biological Findings

- It has been observed that just after birth the brain has dense network of neurons and in the process of learning some connections are pruned to obtain the final network.
- This indicates that learning is a relevant mechanism in determining the network structure.
- This happens even in a simple organism like C. Elegans which has 306 neurons and around 2400 connections
- It is found that even a simple organism like C. Elegans which has a very simple nervous system produces excess processes which are pruned (see W. G. Wadsworth, Current Biology (2005) vol 15 pg R796).

# Expt: Effect of Sensory Activity

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DEV8570



## Sensory activity affects sensory axon development in *C. elegans*

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### SUMMARY

**The simple nervous system of the nematode *C. elegans* consists of 302 neurons with highly reproducible morphologies, suggesting a hard-wired program of axon guidance. Surprisingly, we show here that sensory activity shapes sensory axon morphology in *C. elegans*. A class of mutants with deformed sensory cilia at their dendrite endings have extra axon branches, suggesting that sensory deprivation disrupts axon outgrowth. Mutations that alter calcium channels or membrane potential cause similar defects. Cell-specific perturbations of sensory activity can cause cell-autonomous changes in axon morphology. Although the sensory axons initially reach their targets in the embryo, the mutations that alter sensory activity cause extra axon growth late in development. Thus, perturbations of activity affect the maintenance of sensory axon morphology after an initial pattern of innervation is established. This system provides a genetically tractable model for identifying molecular mechanisms linking neuronal activity to nervous system structure.**

Key words: *C. elegans*, Sensory neurons, Activity-dependent development, axon outgrowth

# Expt: Scale-Free Networks in Brain

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## Scale-Free Brain Functional Networks

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(Received 13 January 2004; published 6 January 2005)

Functional magnetic resonance imaging is used to extract *functional networks* connecting correlated human brain sites. Analysis of the resulting networks in different tasks shows that (a) the distribution of functional connections, and the probability of finding a link versus distance are both scale-free, (b) the characteristic path length is small and comparable with those of equivalent random networks, and (c) the clustering coefficient is orders of magnitude larger than those of equivalent random networks. All these properties, typical of scale-free small-world networks, reflect important functional information about brain states.

DOI: 10.1103/PhysRevLett.94.018102 PACS numbers: 87.18.Sn, 87.19.La, 89.75.Da, 89.75.Hc

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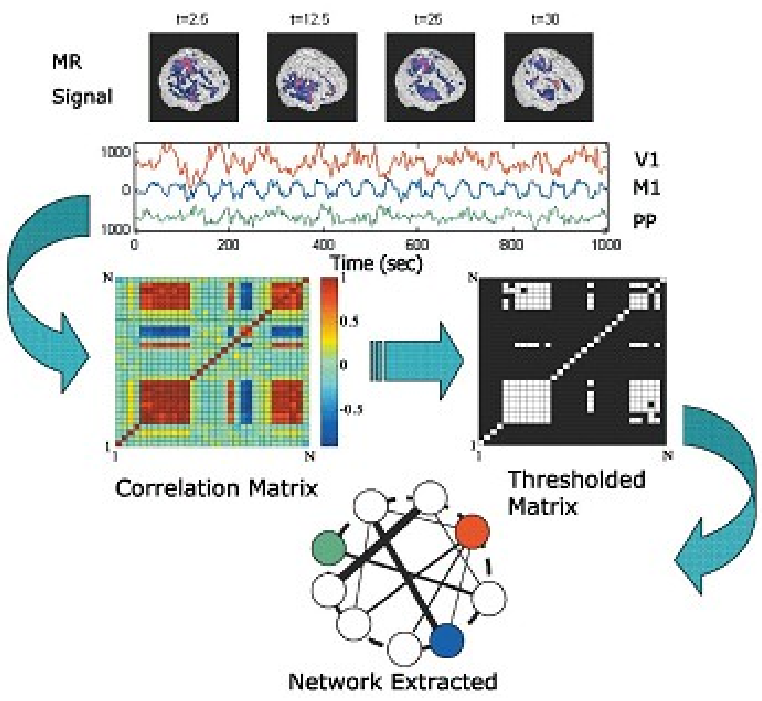
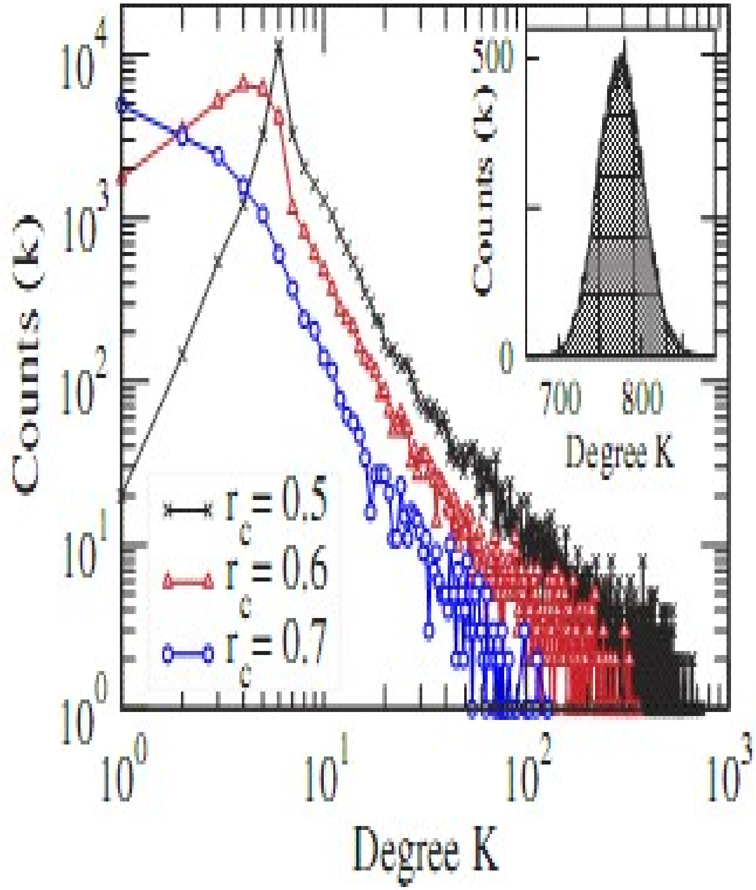


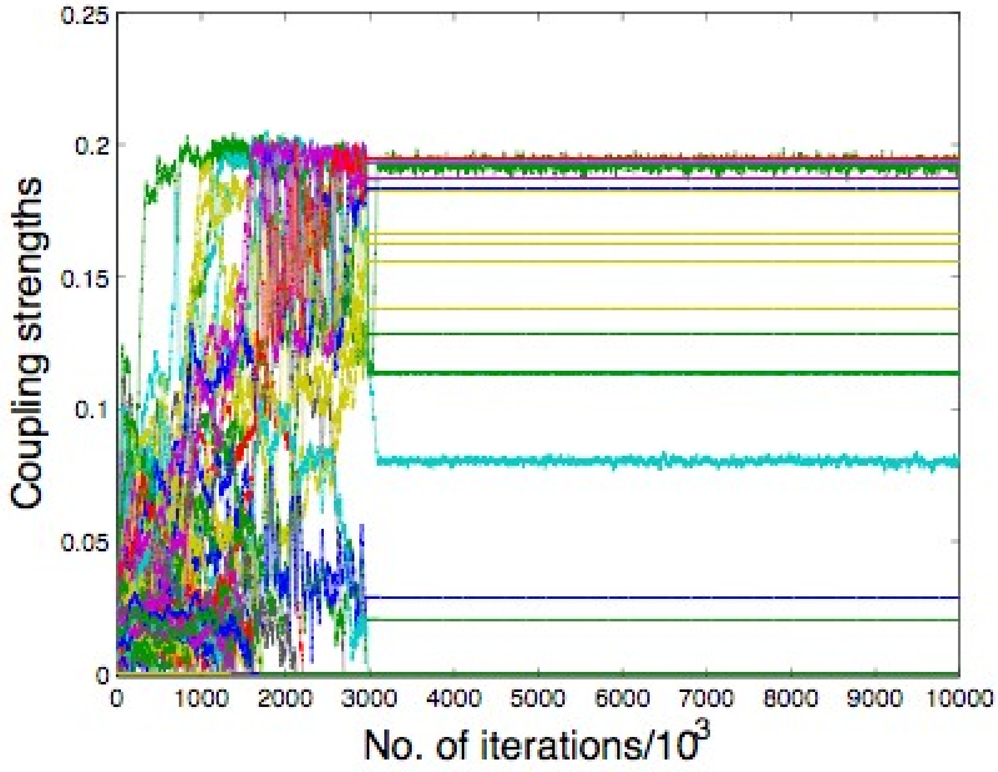
t=2.5
t=12.5
t=25
t=30
MR
Signal
V1
M1
PP
Time (sec)
Correlation Matrix
Thresholded
Matrix
Network Extracted

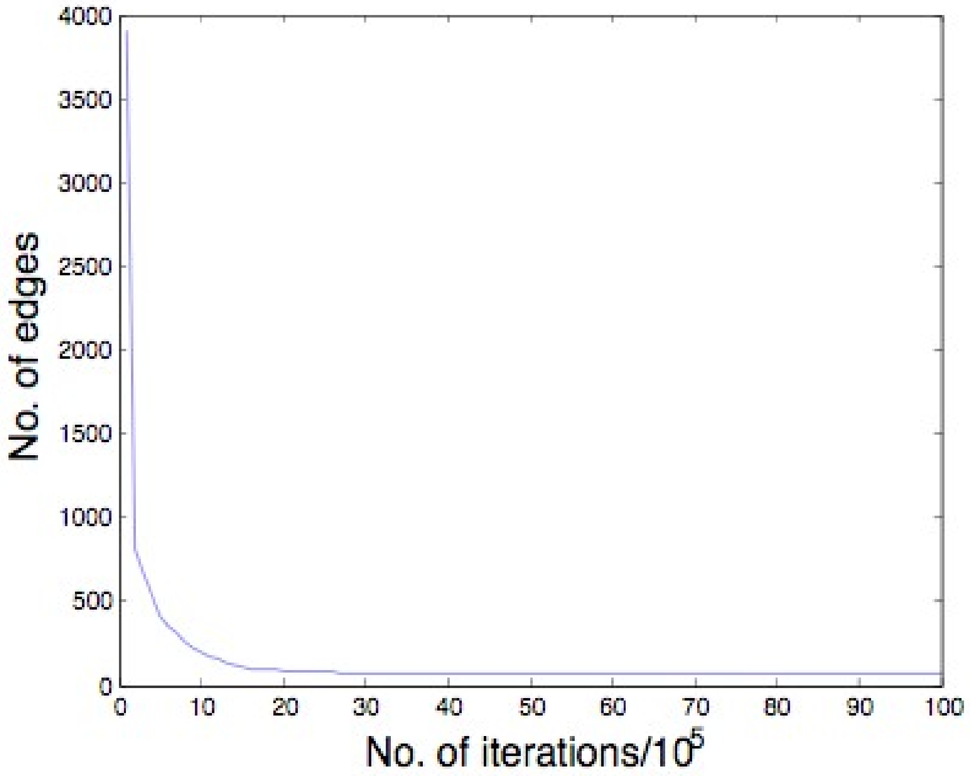



Counts (k)
Degree K
$r_c = 0.5$
$r_c = 0.6$
$r_c = 0.7$

# Evolution of the network

The edges evolve as follows: some of the coupling strengths go to zero and others to a constant value. The total number of edges decrease very



# How to characterize the network

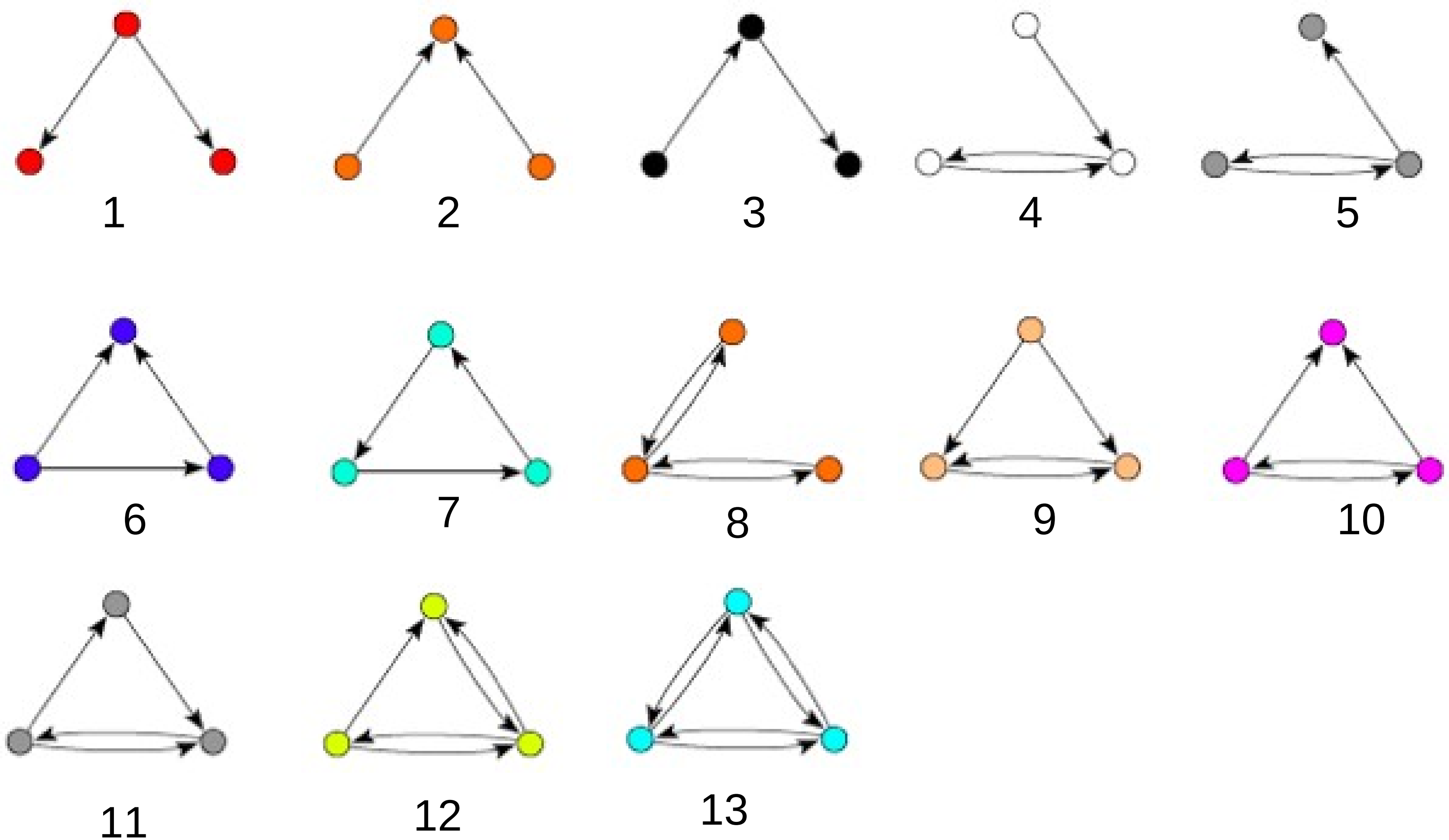
- Eigenvalue spectrum / Spectral Plots

  - global information of network topology
- Motif distribution

  - local information about distribution of subnetworks of given size
- Hierarchical characterization

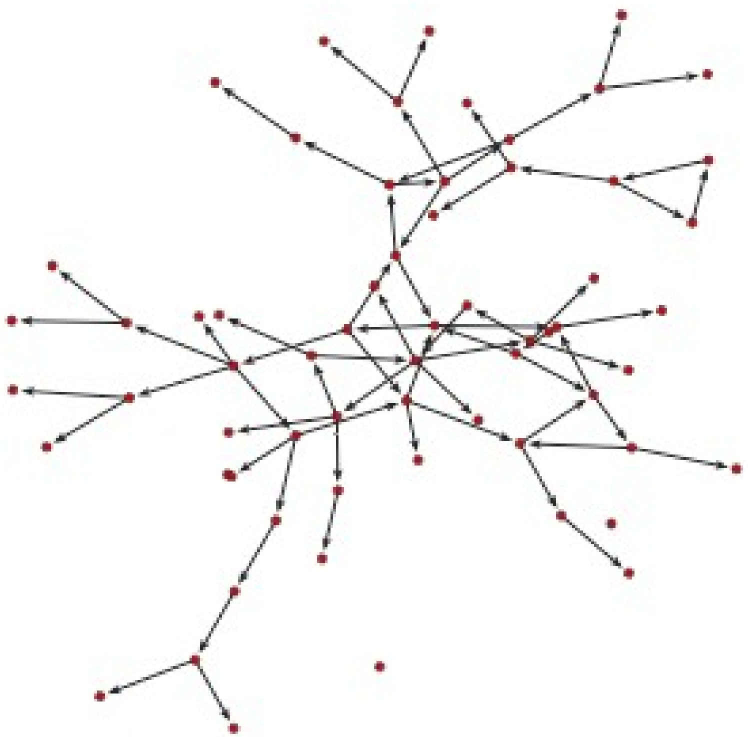
  - studying the distribution of neighbor of neighbors and so on
- Significance profile
- etc...

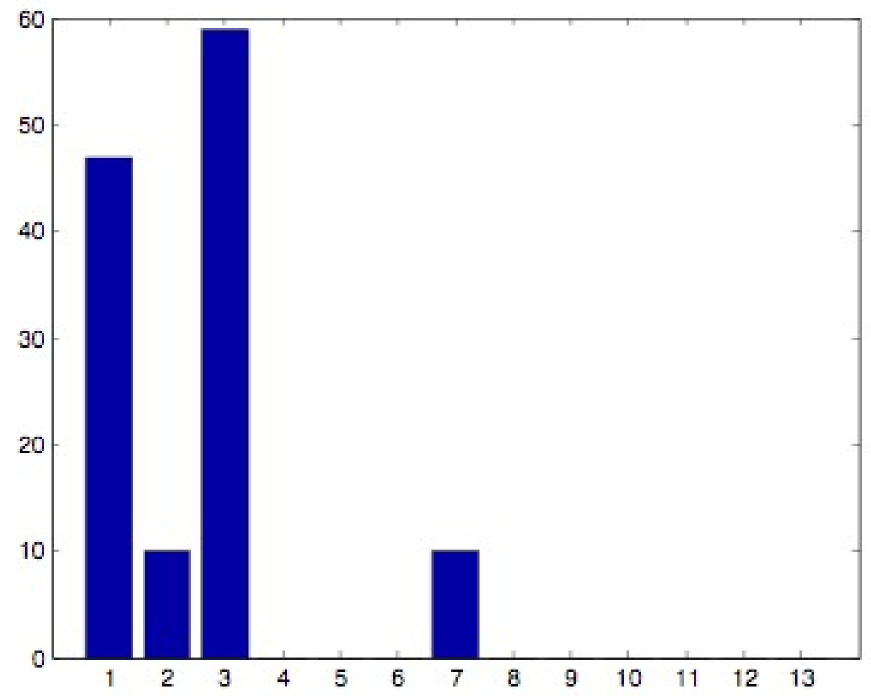
# All possible connected triads



# The final Network

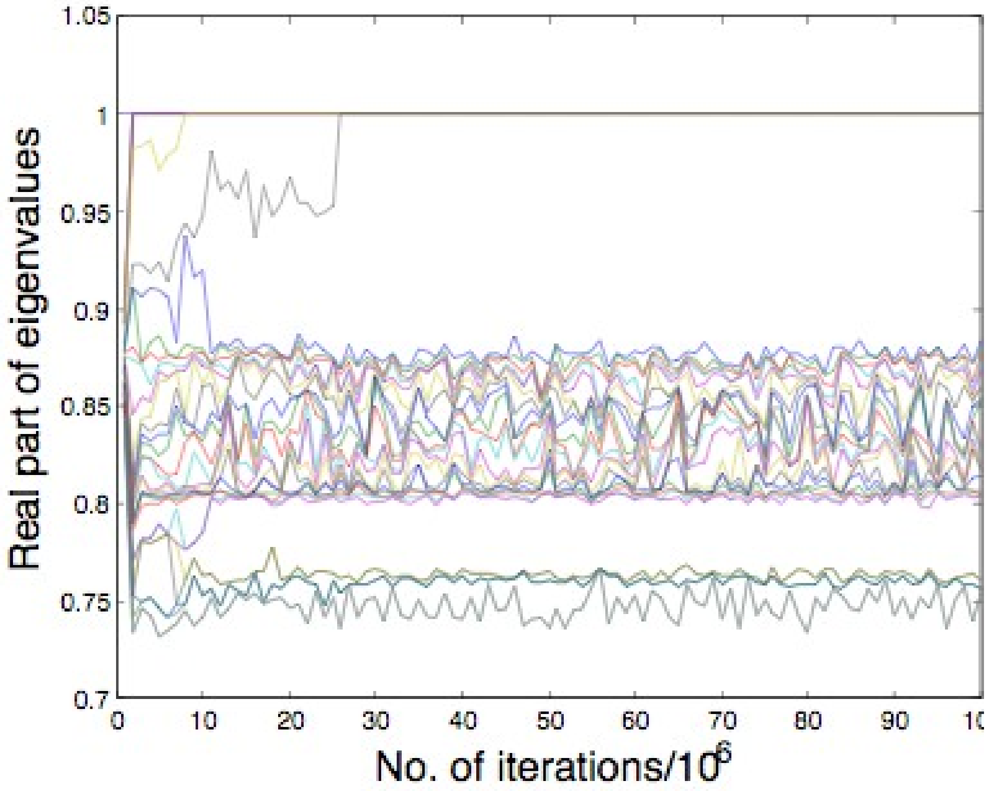
This shows the final network and the histogram of the distribution of triads. This histogram is a robust signature of the final network. We have checked it for networks of different sizes and with addition of noise.



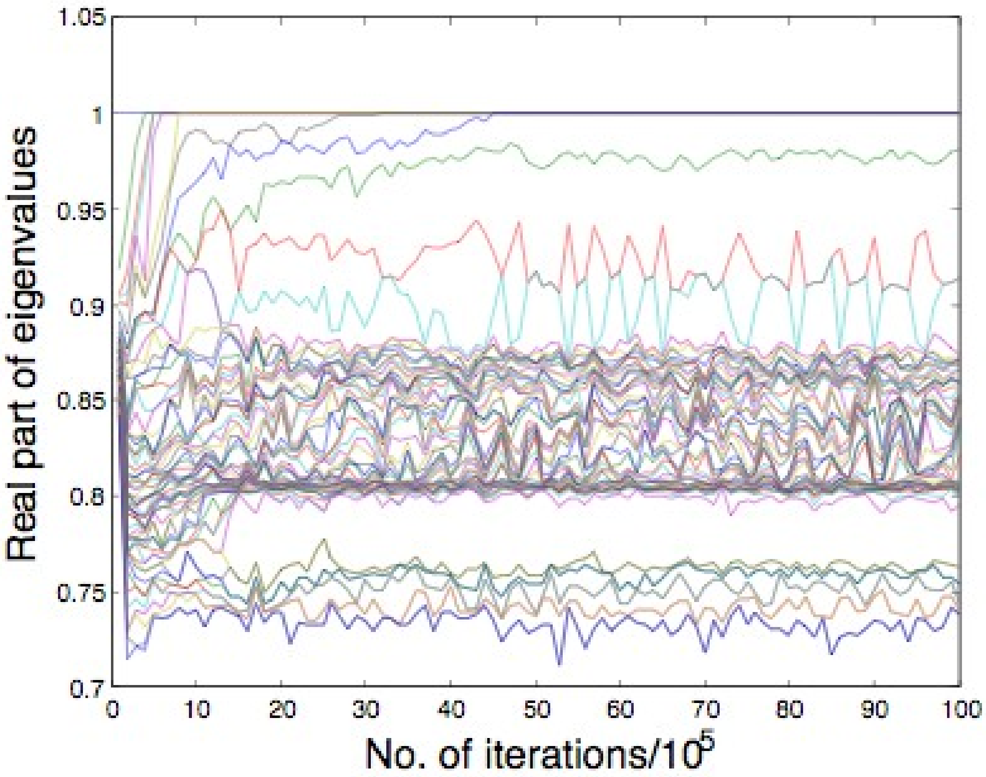


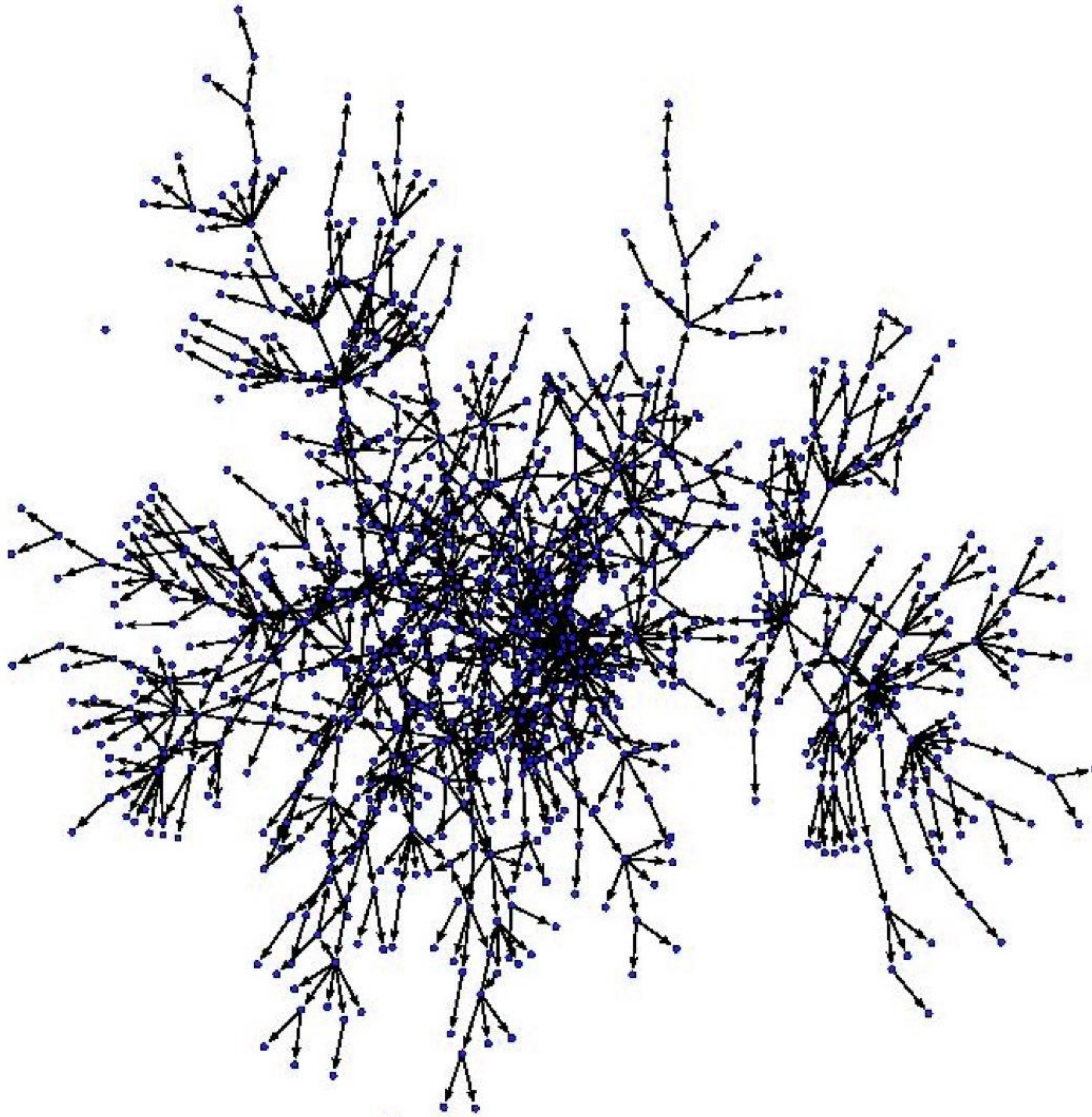
# Evolution of eigenvalues

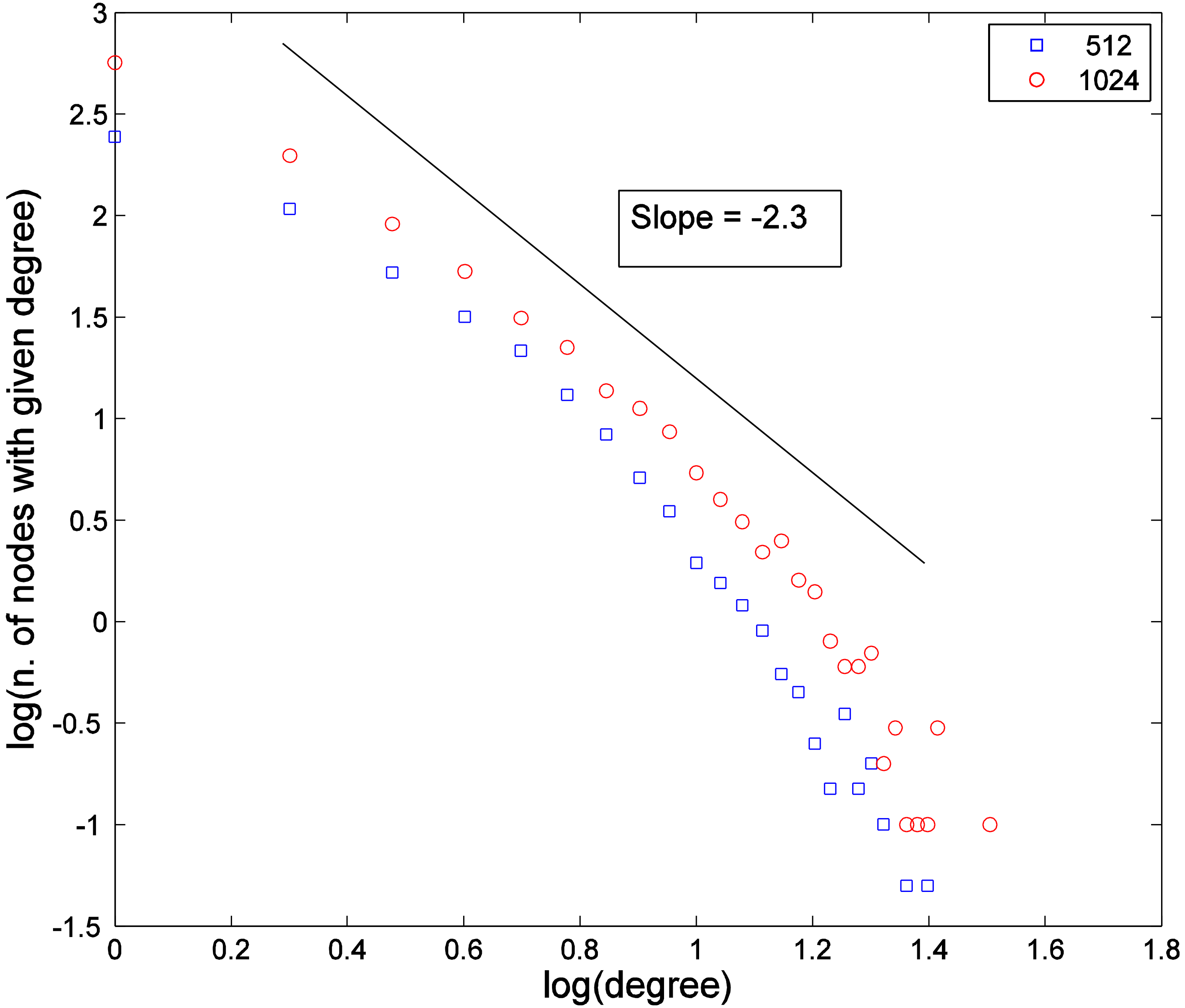
32 nodes




64 nodes

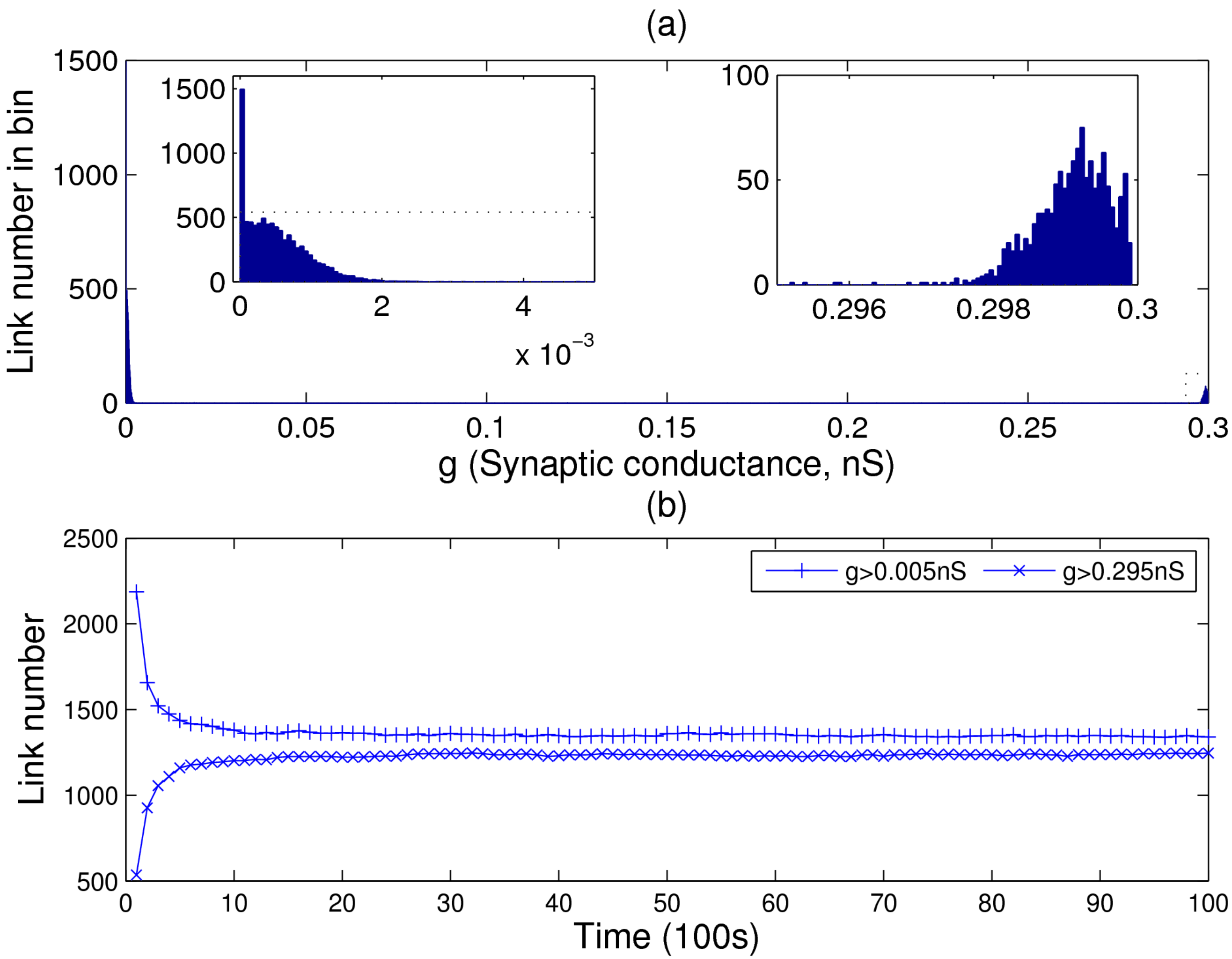




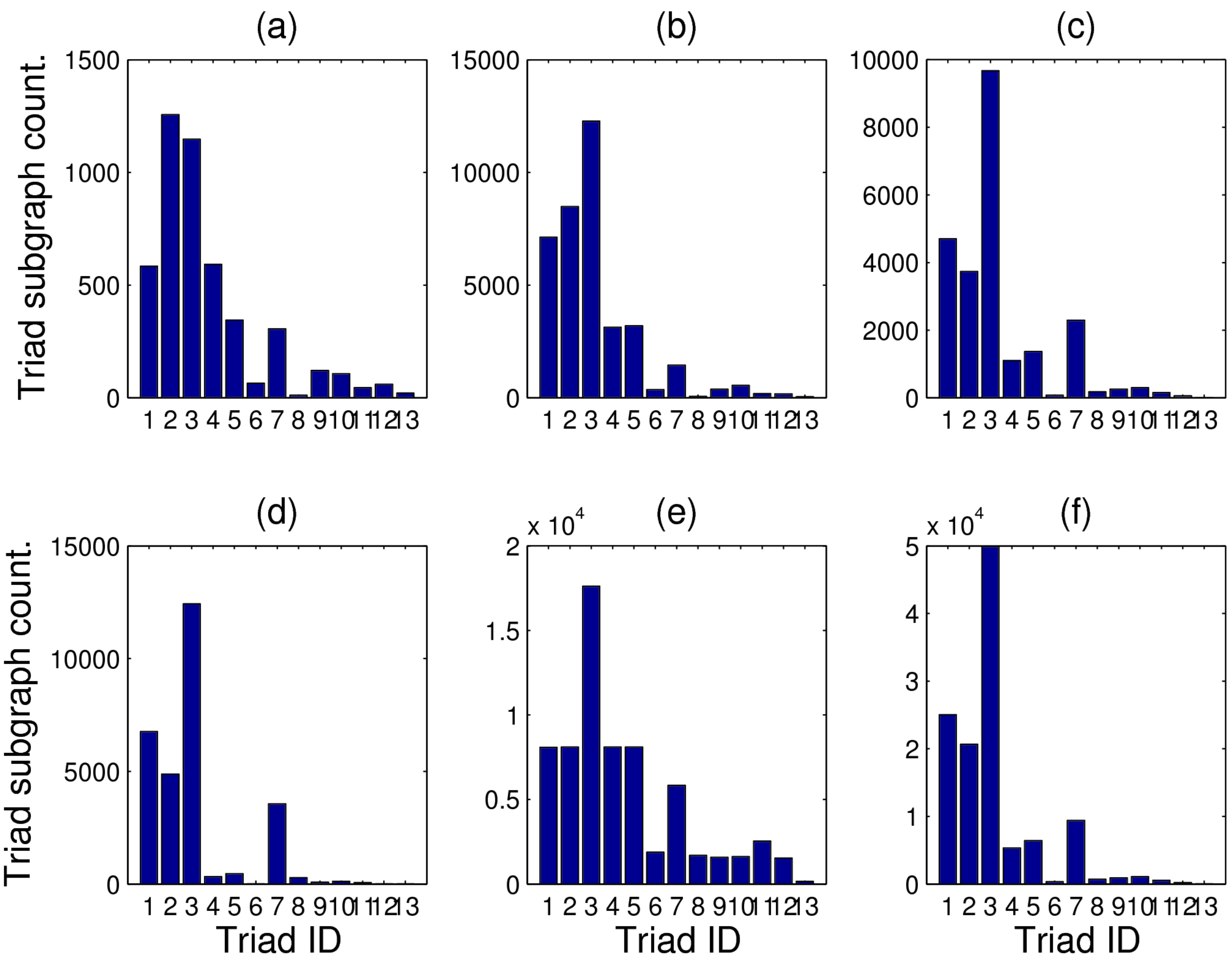


512
1024
Slope = -2.3
log(n. of nodes with given degree)
log(degree)
3
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8

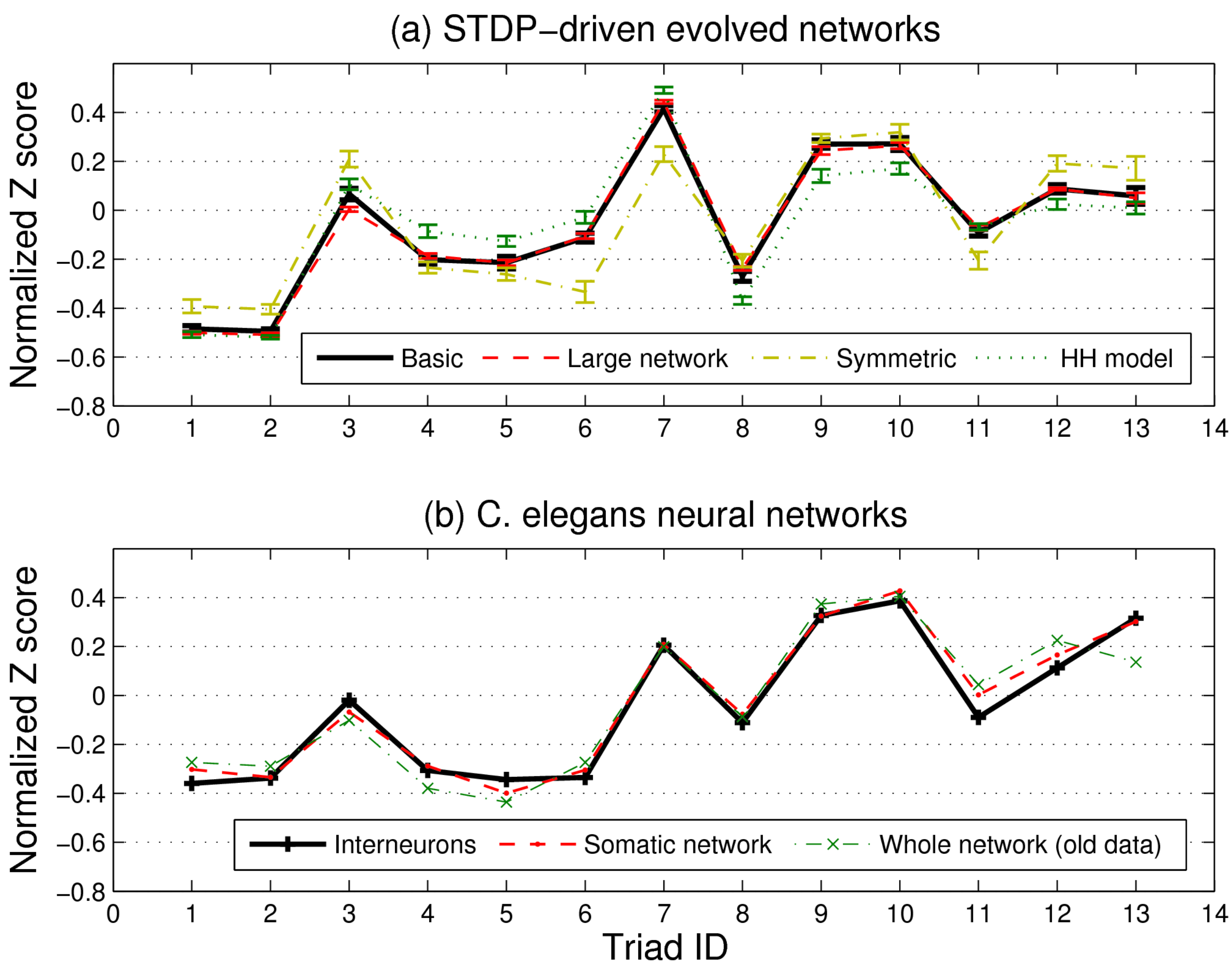
# Evolution of synaptic strengths



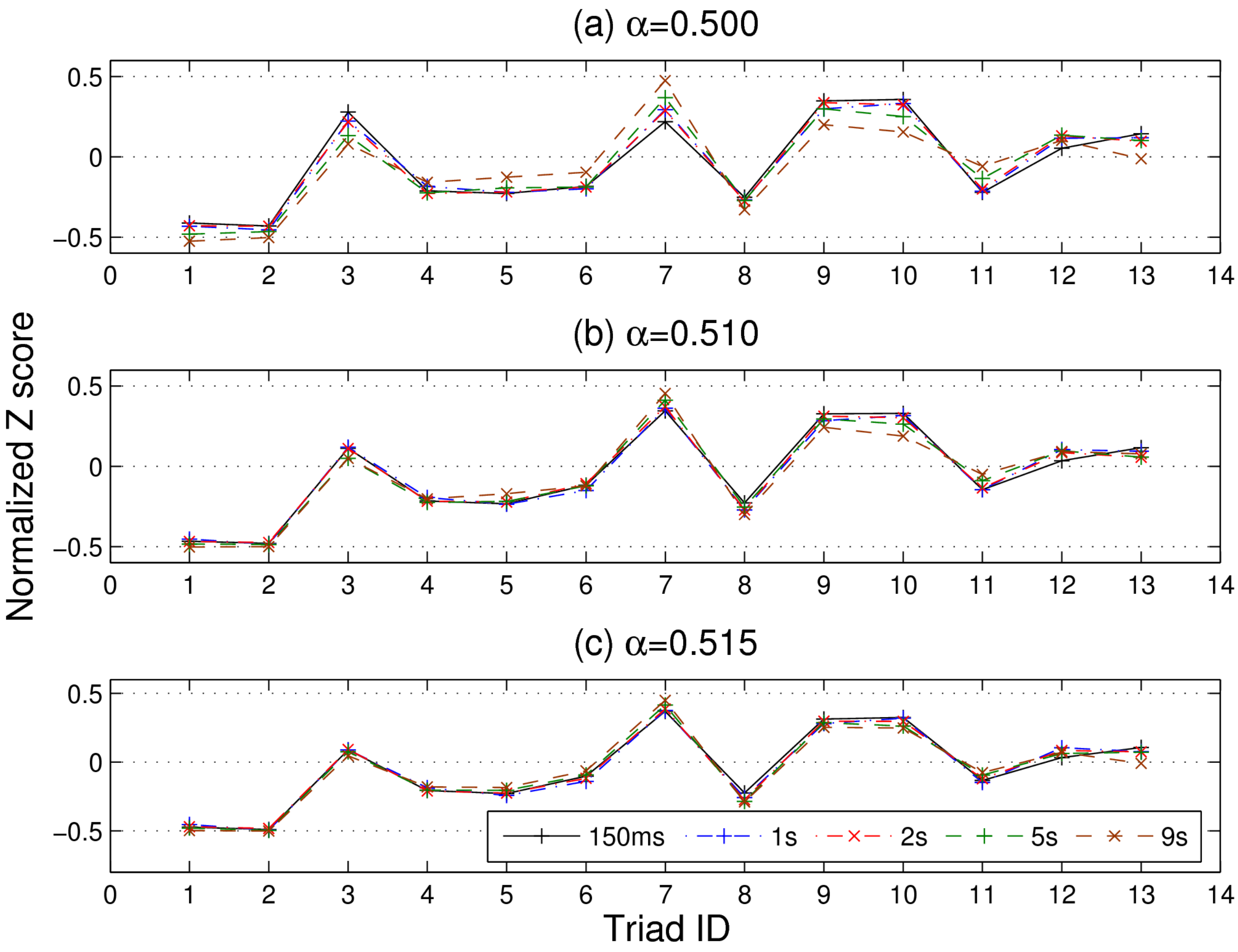
# Final Network: Motif Distribution

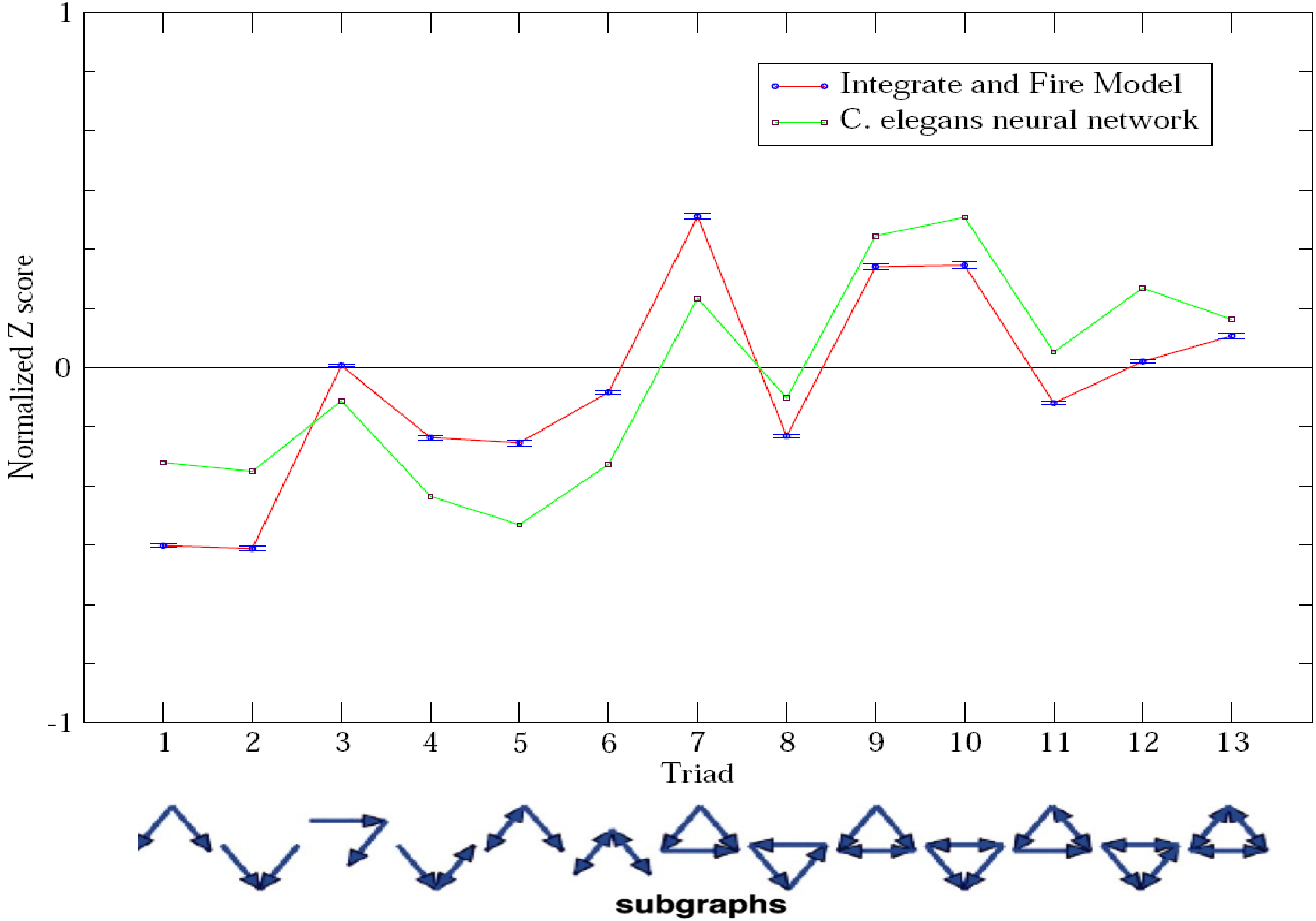


# Final Network: Significance Profile

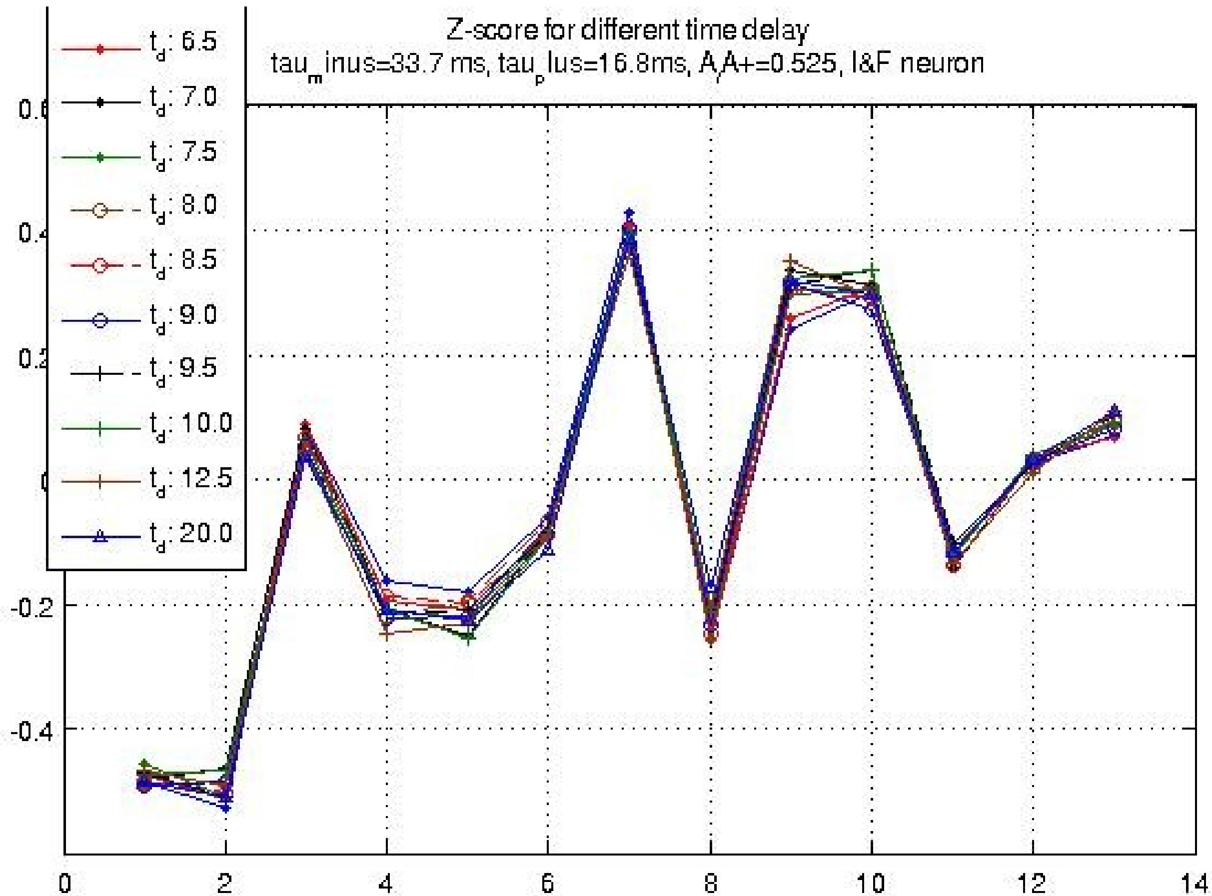


# Effect of Asymmetry

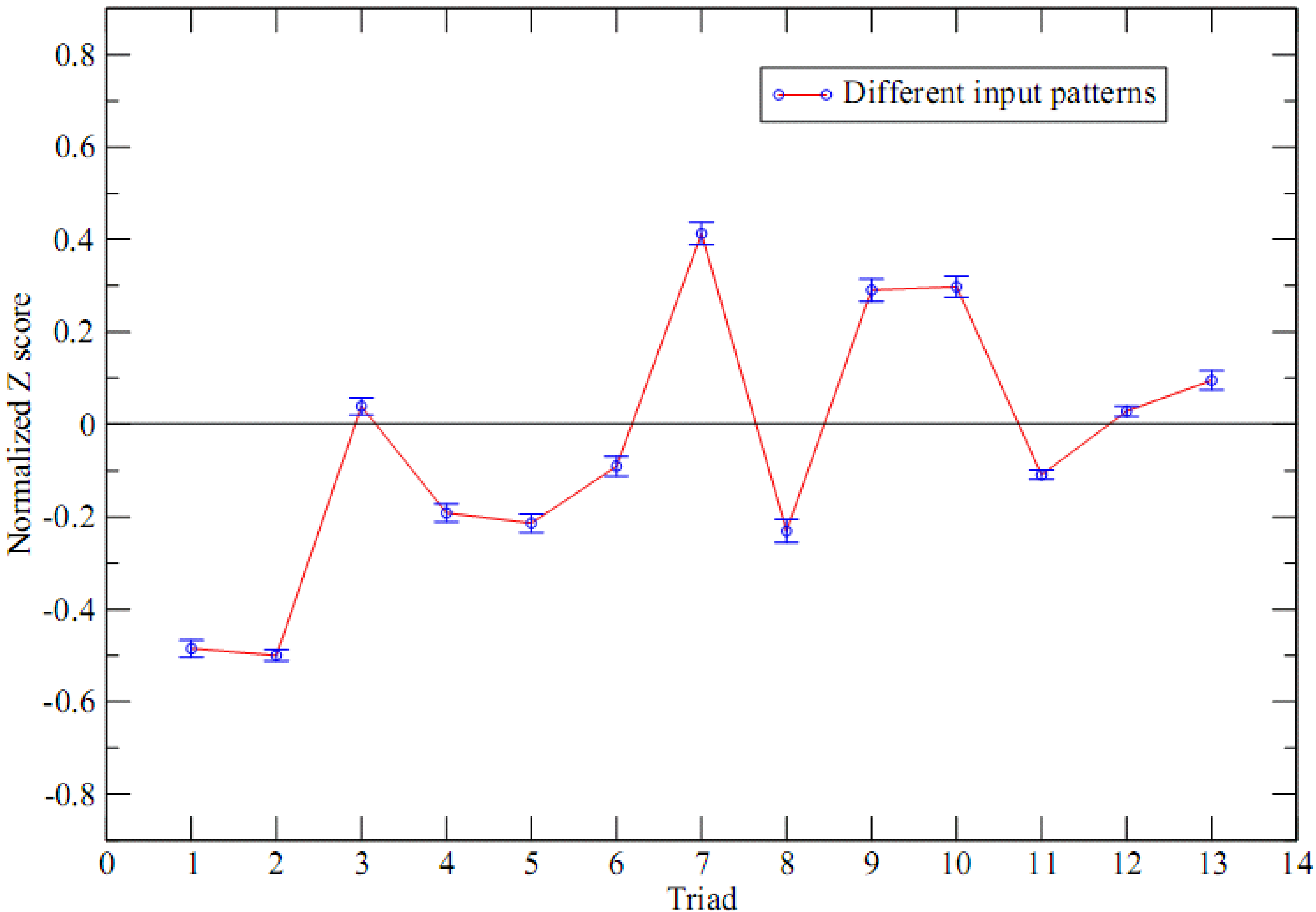


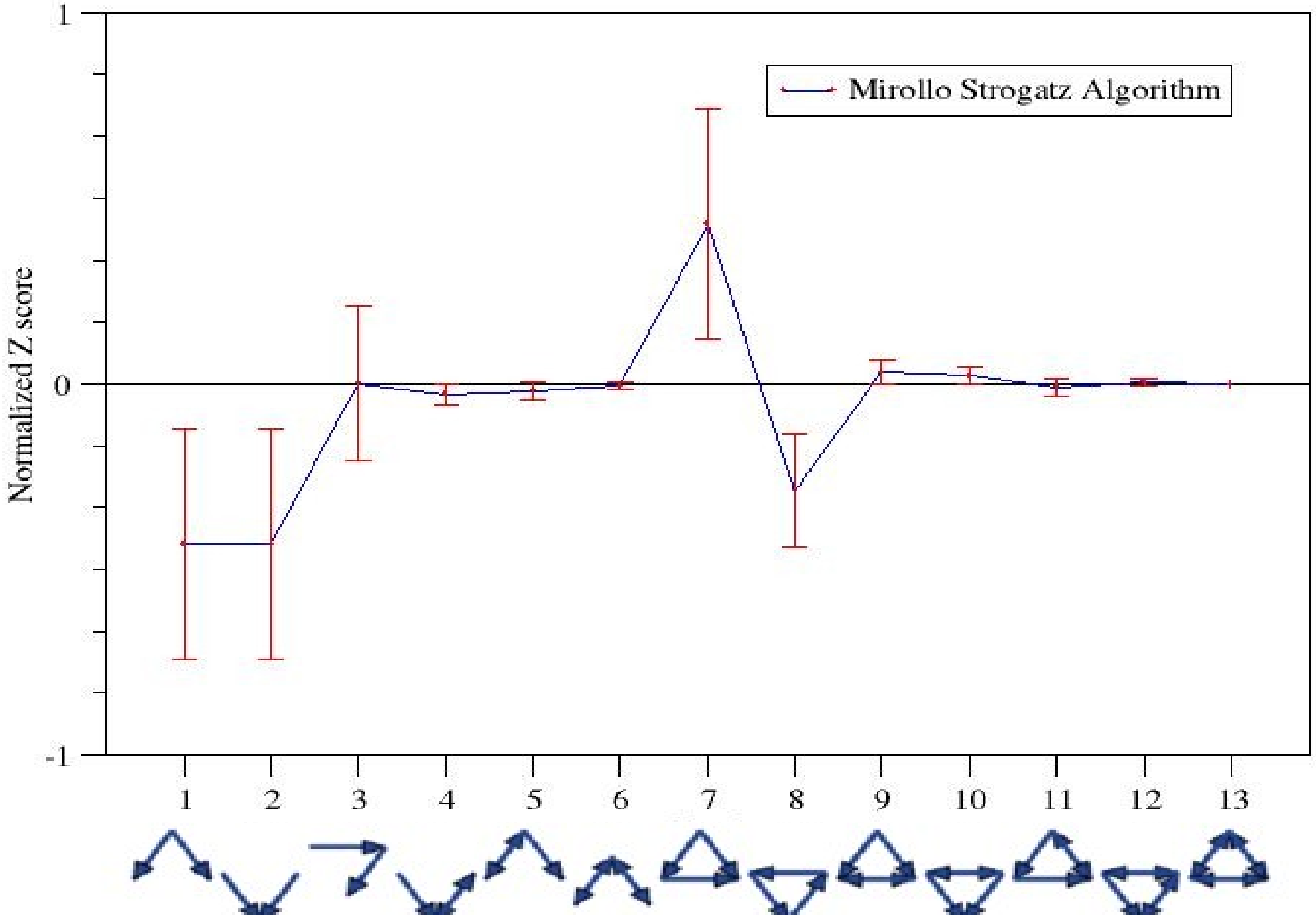


1
0
-1
Normalized Z score
Integrate and Fire Model
C. elegans neural network
1 2 3 4 5 6 7 8 9 10 11 12 13
Triad
subgraphs



Z-score for different time delay
tau_minus=33.7 ms, tau_plus=16.8ms, A_/A+=0.525, I&F neuron
t_d: 6.5
t_d: 7.0
t_d: 7.5
t_d: 8.0
t_d: 8.5
t_d: 9.0
t_d: 9.5
t_d: 10.0
t_d: 12.5
t_d: 20.0
0.4
0.2
0
-0.2
-0.4
0
2
4
6
8
10
12
14


Different input patterns
Normalized Z score
Triad
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14



1
0
-1
Normalized Z score
Mirollo Strogatz Algorithm
1
2
3
4
5
6
7
8
9
10
11
12
13

# Future Directions

- Studying the effect of other factors on network structure.
- Studying information processing capabilities of the STDP driven networks.
- Studying synchronization properties of these networks.