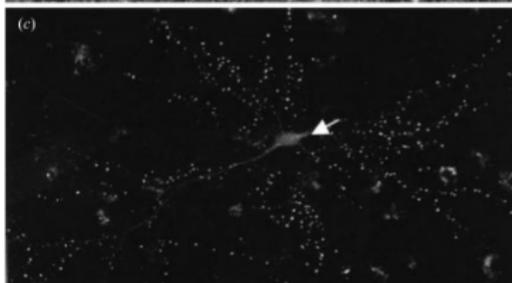
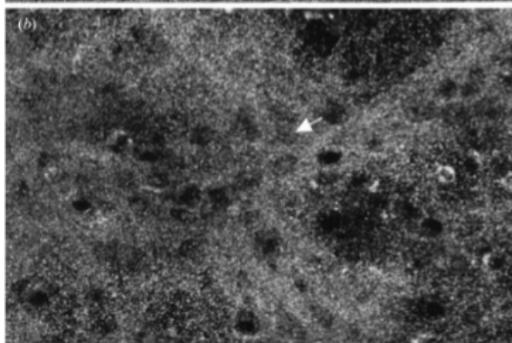
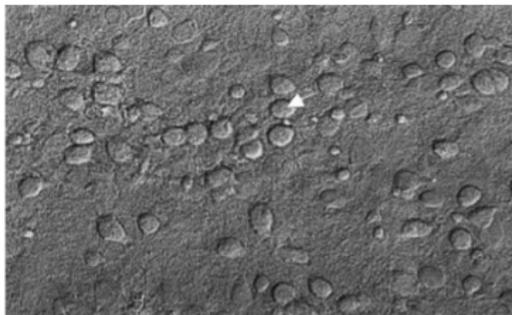


Neuroinformatics

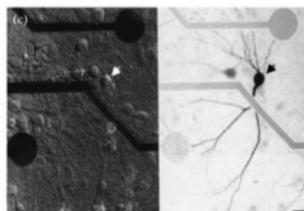
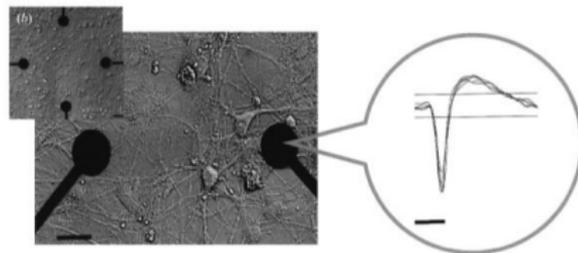
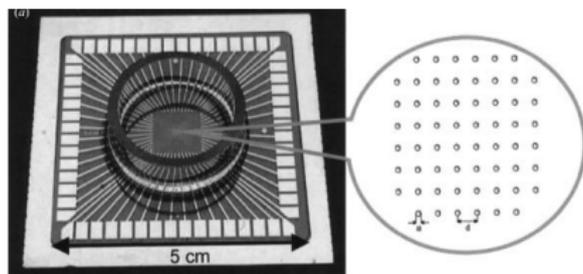
May 16, 2018

Lecture 7: Cortical organization & Random networks

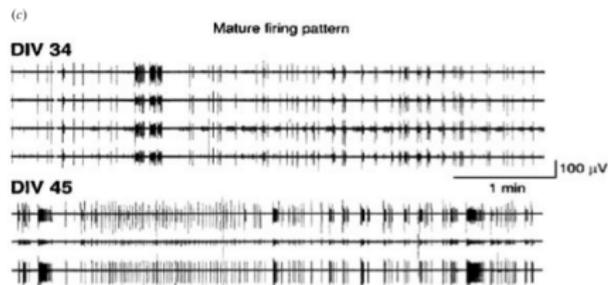
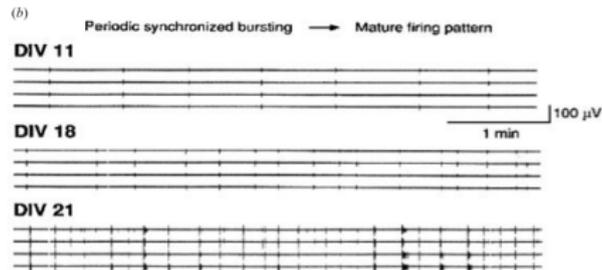
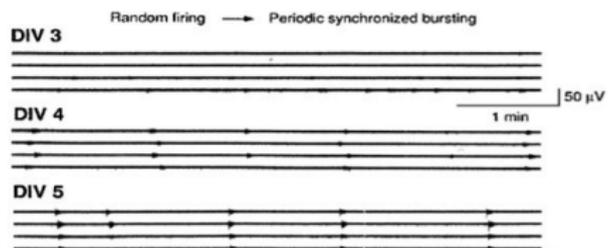
Random networks - ex vivo



Random networks - microelectrode array

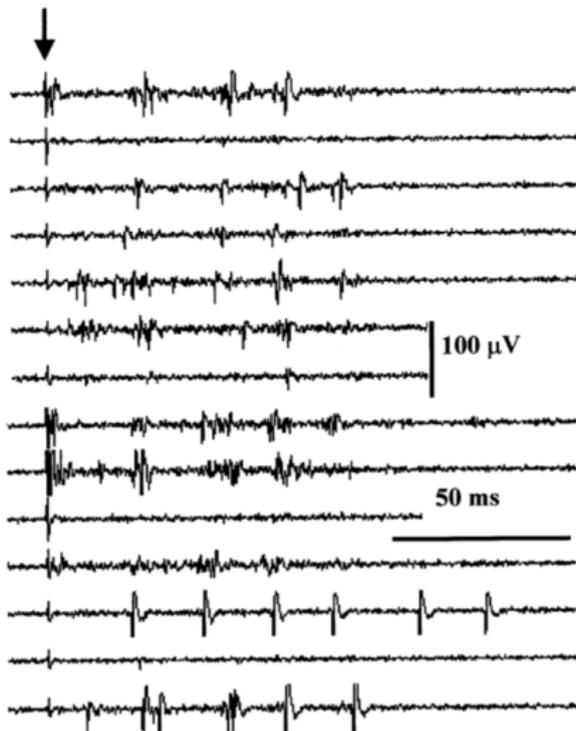


Random networks - Development changes in neocortical activity

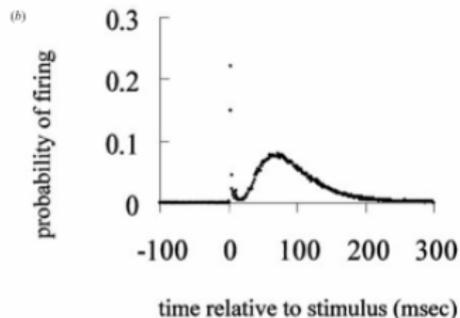
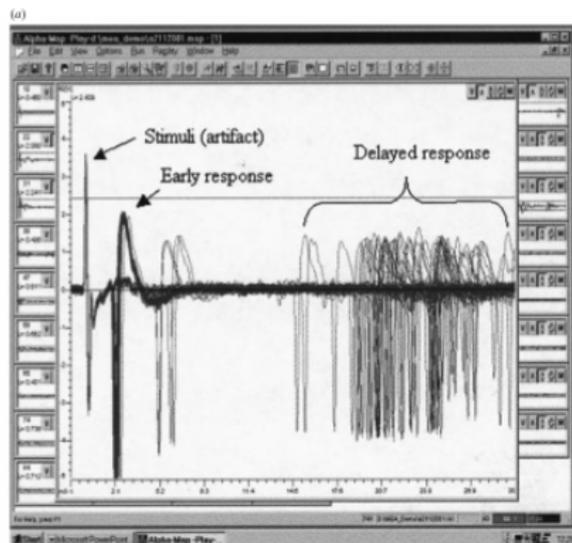


Random networks - stimulation

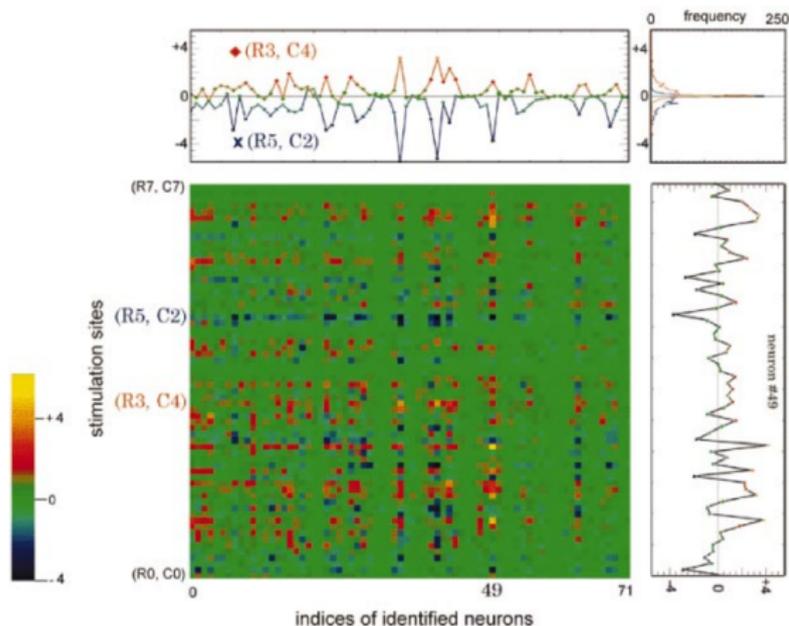
- ▶ $50\mu A$ stimult lasting $420\mu s$
- ▶ three responses: (i) early componet, (ii) refractory period (iii) late component



Random networks - response to stimulation: 3 components

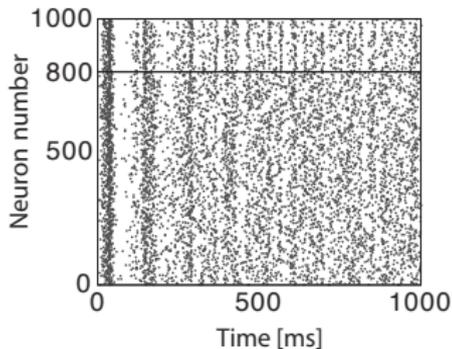


Random networks - response to stimulation: Hebb's rule

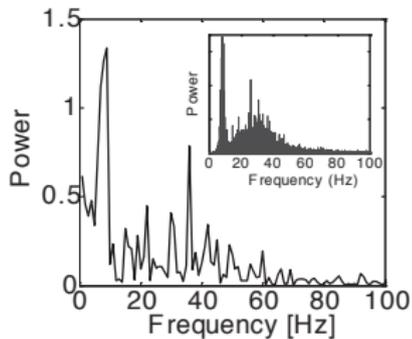


Random networks with axonal delay

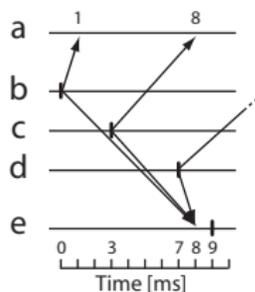
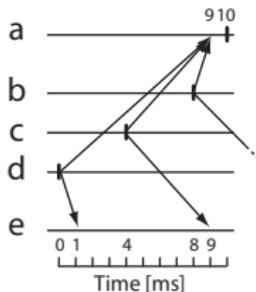
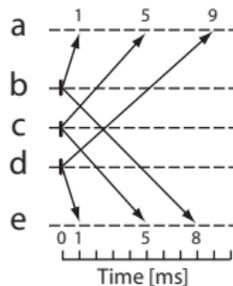
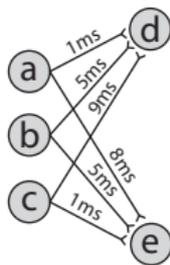
A. Spike trains in random network



B. Power spectrum in random network



C. Spike activation with axonal delay



Polychronization

- ▶ two groups: i) (d,c,b,a) firing spike time pattern (0,4,8,10) ms / ii) (b,c,d,e) firing spike time pattern (0,3,7,9) ms
- ▶ firing is not synchronous but time-locked, poly → many, chronous → time/clock
- ▶ reproducible time locking pattern
- ▶ spike-timing-dependent plasticity (STDP) can spontaneously organize neurons into such groups
- ▶ main result: the number of coexisting polychronous groups could be far greater than the number of neurons in the network, sometimes even greater than the number of synapses
- ▶ Each neuron is part of many groups, firing with one group at one time and with another group at another time.
- ▶ Simulation on 1000 neurons with STDP and conduction delays
- ▶ mammalian cortex → neuron distribution: excitatory (80%) and inhibitory (20%), 0.1 probability of connection between any two neurons

STDP rule

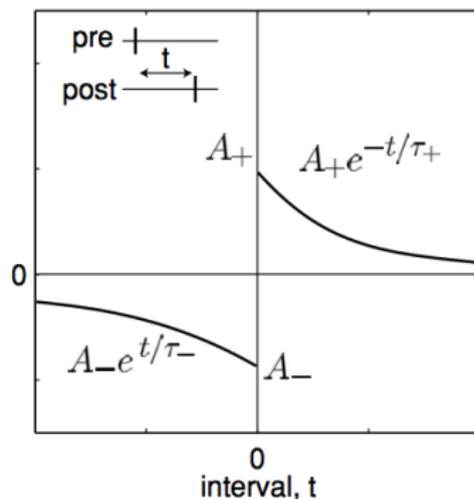
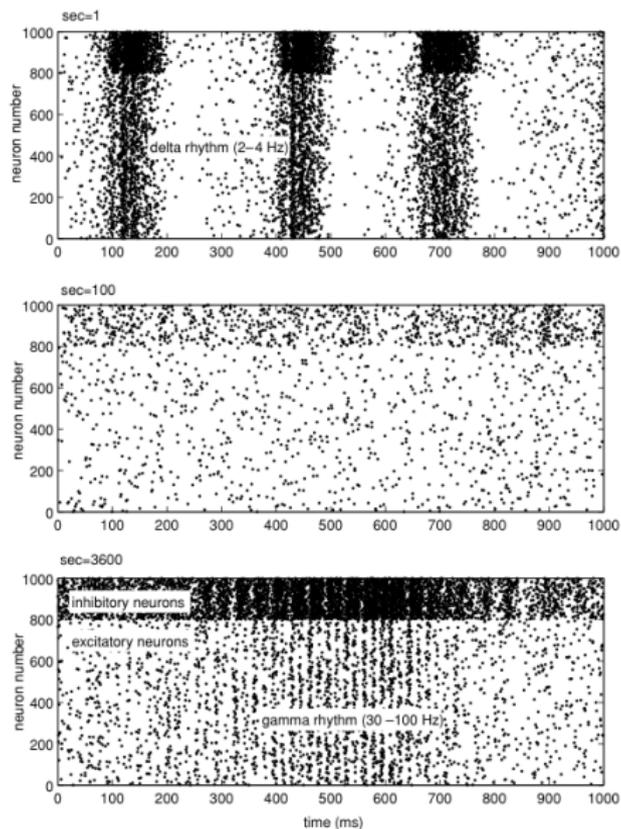
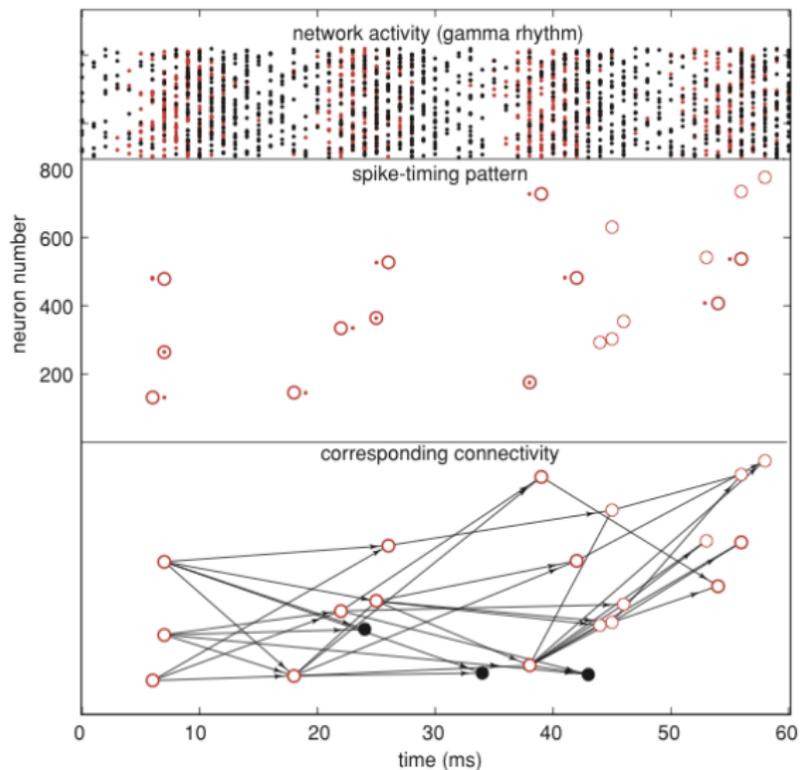


Figure 4: STDP rule (spike-timing-dependent plasticity, or Hebbian temporally asymmetric synaptic plasticity): The weight of synaptic connection from pre- to postsynaptic neuron is increased if the postsynaptic neuron fired after the presynaptic spike, that is, the interspike interval $t > 0$. The magnitude of change decreases as A_+e^{-t/τ_+} . Reverse order results in a decrease of the synaptic weight with magnitude A_-e^{t/τ_-} . Parameters used: $\tau_+ = \tau_- = 20$ ms, $A_+ = 0.1$, and $A_- = 0.12$.

Rhythmic activity of the spiking model



Polychronous group activation



Example of polychronous group

- ▶ Although spiking of excitatory neurons looks random and uncorrelated, there are certain persistent spike-timing patterns that emerge and reoccur with millisecond precision
- ▶ Pattern denoted by circles in the middle of the figure repeats itself a few times per hour with 1 ms spike jitter.
- ▶ activation of the group is locked to the gamma oscillation; that is, the first three neurons fire at the first gamma cycle, their spikes travel 10 to 20 ms and arrive at the next four neurons in the next gamma cycle, and so on, resulting in precise stereotypical activity.

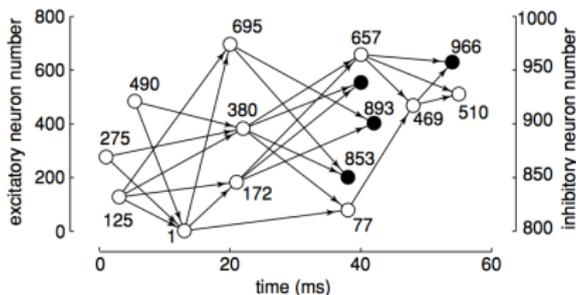
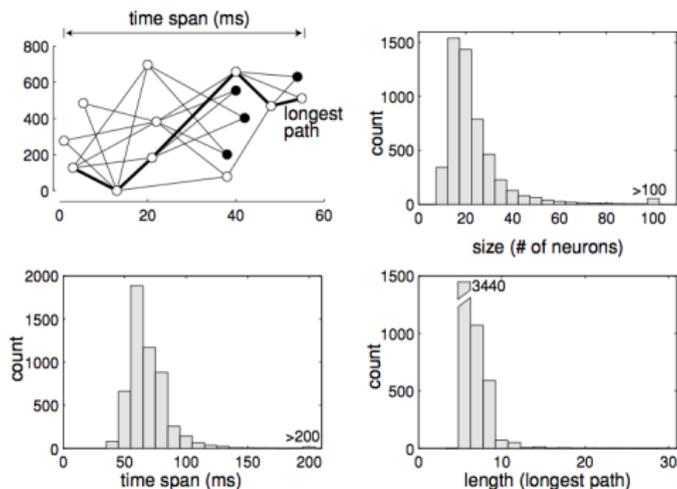


Figure 7: Example of a polychronous group: Firing of neurons (125, 275, 490) with the timing pattern (0, 3, 7) ms results in spikes arriving simultaneously at neuron 1, then at neurons 172, 695, and 380. This multitiming (polychronous) activity propagates farther along the network and terminates at neuron 510.

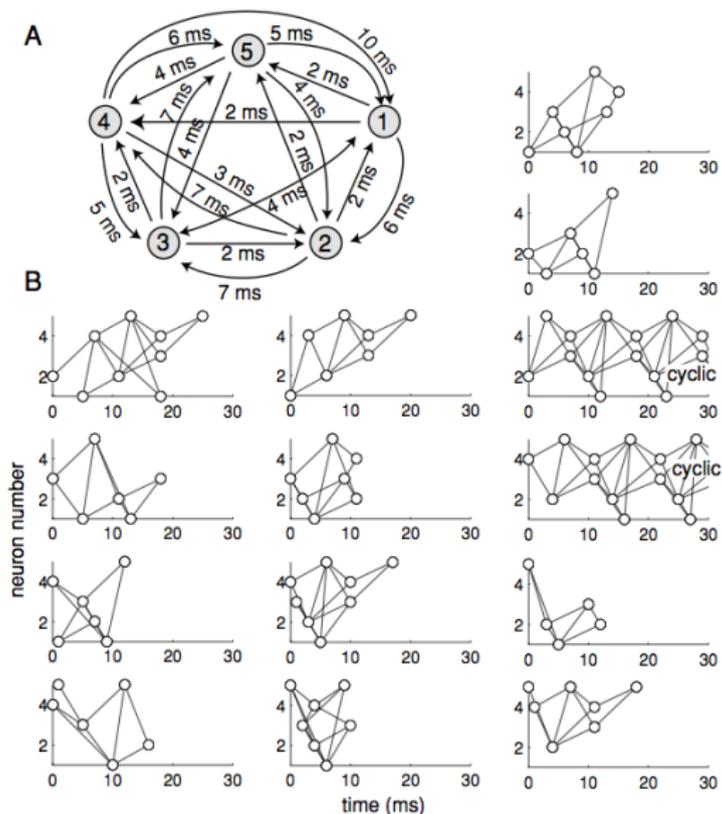
Group emergence

- ▶ 1000 neurons: 5000 groups, The groups did not exist at the beginning of simulation but appear as a result of STDP acting on random spiking
- ▶ groups constantly appear and disappear; their total number fluctuates between 5000 and 6000
- ▶ a core of 471 groups that appeared and survived the entire duration of 24 hour simulation



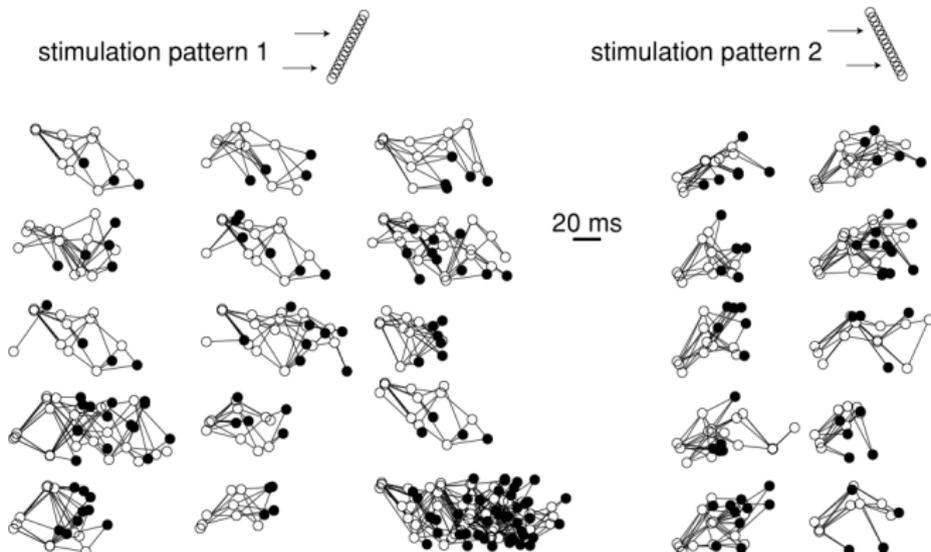
More groups than synapses

- ▶ 5 neurons: 14 groups, 6 neurons, 42 groups > synapses !



Representation: Significance of polychronous group?

- ▶ Representation of memories and experience
- ▶ no coherent external input to the system was present, random groups emerge; that is, the network generates random memories not related to any previous experience
- ▶ Stimulation Every second during a 20-minute period, we stimulate 40 neurons, 1, 21, 41, 61, . . . , 781, either with the pattern (1,2,...,40) ms or with the inverse pattern (40,...,2,1) ms
- ▶ after 20 minutes of simulation 25 new groups emerged



Conclusion

- ▶ minimal model: spiking neurons, axonal conduction delays, and STDP: well-established properties of the real brain
- ▶ Polychronous groups are representations of possible inputs to the network, so that each input selects groups from the repertoire.
- ▶ Learning of a new input consists of selecting and reinforcing an appropriate group (or groups) that resonates with the input, persistent stimuli may create new groups
- ▶ FeedForward: The anatomy of the spiking networks that we consider is not feedforward but reentrant. Thus, the network does not wait for stimulus to come but exhibits an autonomous activity.
- ▶ Spiking networks with delays have more groups than neurons. The system has potentially enormous memory capacity and will never run out of groups, which could explain how networks of mere 10^{11} *neurons* (the size of the human neocortex) could have such a diversity of behavior.

```

1  % Created by Eugene M. Izhikevich, February 25, 2003
2  % Excitatory neurons      Inhibitory neurons
3  Ne=800;                   Ni=200;
4  re=rand(Ne,1);           ri=rand(Ni,1);
5  a=[0.02*ones(Ne,1);      0.02+0.08*ri];
6  b=[0.2*ones(Ne,1);       0.25-0.05*ri];
7  c=[-65+15*re.^2;         -65*ones(Ni,1)];
8  d=[8-6*re.^2;           2*ones(Ni,1)];
9  S=[0.5*rand(Ne+Ni,Ne), -rand(Ne+Ni,Ni)];
10
11 v=-65*ones(Ne+Ni,1);    % Initial values of v
12 u=b.*v;                 % Initial values of u
13 firings=[];             % spike timings
14
15 for t=1:1000             % simulation of 1000 ms
16     I=[5*randn(Ne,1);2*randn(Ni,1)]; % thalamic input
17     fired=find(v>=30); % indices of spikes
18     if ~isempty(fired)
19         firings=[firings; t+0*fired, fired];
20         v(fired)=c(fired);
21         u(fired)=u(fired)+d(fired);
22         I=I+sum(S(:,fired),2);
23     end;
24     v=v+0.5*(0.04*v.^2+5*v+140-u+I);
25     v=v+0.5*(0.04*v.^2+5*v+140-u+I);
26     u=u+a.*(b.*v-u);
27 end;
28 plot(firings(:,1),firings(:,2),'.');

```

Further Readings

Edward L. White (1989) **Cortical circuits**, Birkhäuser

Moshe Abeles (1991) **Corticonics: Neural circuits of the cerebral cortex**, Cambridge University Press