Available online at www.sciencedirect.com
ScienceDirect
Neurocomputing 70 (2007) 1897–1901
NEUROCOMPUTING
www.elsevier.com/locate/neucom

Ranking neurons for mining structure-activity relations in biological neural networks: *NeuronRank*

Tayfun Gürel[a,b,*], Luc De Raedt[a,b], Stefan Rotter[a,c]

[a]*Bernstein Center for Computational Neuroscience, Freiburg, Germany*
[b]*Institute for Computer Science, Albert-Ludwigs-University Freiburg, Germany*
[c]*Institute for Frontier Areas of Psychology and Mental Health, Freiburg, Germany*

Available online 6 November 2006

Abstract

It is difficult to relate the structure of a cortical neural network to its dynamic activity analytically. Therefore we employ machine learning and data mining algorithms to learn these relations from sample random recurrent cortical networks and corresponding simulations. Inspired by the *PageRank* and the *Hubs & Authorities* algorithms, we introduce the *NeuronRank* algorithm, which assigns a source value and a sink value to each neuron in the network. We show its usage to extract structural features from a network for the successful prediction of its activity dynamics. Our results show that *NeuronRank* features can successfully predict average firing rates in the network, and the firing rate of output neurons reflecting the network population activity.

Keywords: Structure–function relations; Link mining; Machine learning

1. Introduction

Most functions of our brain are mediated by the operation of complex neuronal networks. The relation between structure and function of the various types of networks has been subject of many theories and intense computational modeling. Fundamental questions, however, remain unanswered: How important is the structure of a network for its function? Is a certain type of structure essential for a particular function? Can one and the same structure support different functions? Can different structures support the same function? How does the repeated usage of a network change its structure and its function, respectively? How does the interaction between networks affect the function of the whole system?

We approach some of these questions by systematically exploring the relation between network structure and activity dynamics in network models of the cortex. The analysis of Brunel [3] and others showed how the complex dynamics of a random-topology cortical network is determined by various structural parameters. In particular, the influence of the relative strength of the inhibitory synaptic couplings in the network and the role of external inputs was elucidated. The question how structural variations contribute to variations in activity dynamics, however, was not tackled in this work. Several recent papers indicate that structural variations indeed influence the network dynamics [1,12].

Neural networks in the brain have, at the structural level, the same format as social networks, food webs, citation networks, the Internet, or networks of biochemical reactions: They can be represented by large graphs, linking many interacting elements to each other. Empirical data of this format are also called 'networked' data. Recently, mining networked data has gained a lot of interest and has resulted in a new subfield called *link mining* [6,7]. Kleinberg [8] proposed the *Hubs & Authorities* algorithm, which is able to detect authoritative sources of information on the web by exploiting its link structure. Page et al. [11] introduced the *PageRank* algorithm underlying the Google search engine, which successfully predicts the relevance of a web page to the user and ranks the page for him, by again exploiting link information.

*Corresponding author. Institute for Computer Science, Albert-Ludwigs-University Freiburg, Germany.
E-mail address: guerel@informatik.uni-freiburg.de (T. Gürel).

0925-2312/$ - see front matter © 2006 Elsevier B.V. All rights reserved.
doi:10.1016/j.neucom.2006.10.064

This note investigates the applicability of link mining techniques to reveal structure–activity relations in biological neural networks. In particular, we are interested in learning a function that maps structural features of neural networks to activity-related features. We introduce the *NeuronRank* algorithm, which yields structural features describing the level to which neurons are *functionally* excitatory and/or inhibitory within a recurrent network. *NeuronRank* is inspired by the *Hubs & Authorities* algorithm, and is shown to yield good predictions of network activity. We proceed by giving an overview of our approach in Section 2. In Section 3, we present our network model. We explain how we analyze the network activity in Section 4. We introduce our key contribution, the *NeuronRank* algorithm, in Section 5. We describe our structural feature extraction methodology in Section 6. In Section 7, we refer to the machine learning algorithms we employ. We finally present our experimental results in Section 8 and our conclusions in Section 9.

2. Overview of the method

Aiming at discovering structure–activity relations in recurrent cortical networks, we focus here on the following specific problem: can we extract meaningful structural features from a random-topology network and use these to predict the characteristics of its activity dynamics? As this problem cannot be solved with current analytical techniques, we tackle it with machine learning and link mining methods. These algorithms learn the desired mappings from a set of examples. In our case, an example consists of a set of values for structural features and the corresponding activity features. Fig. 1a depicts a schematic overview of our approach.

Various structural features of the networks were extracted, based on simple counting statistics and on the new *NeuronRank* algorithm. We also performed numerical simulations of the activity dynamics exhibited by these networks, and then measured the mean firing rates and other characteristic parameters describing the activity dynamics. Eventually, machine learning and data mining algorithms were applied to those data, allowing us to detect any relations between structure and dynamics. Our methods generated statistical models, which were able to predict the dynamics of unseen networks based on their structural features. We assessed the quality of these models by determining their predictive power.

3. The network model

We used the leaky integrate-and-fire neuron model with the following parameters: membrane time constant 20 ms, membrane capacitance 250 pF, spike threshold 20 mV, reset potential 10 mV, refractory period 2 ms. Synaptic currents were modeled as δ-pulses, delayed by 1.5 ms with respect to the inducing action potential, the amplitude of excitatory postsynaptic potentials was 0.1 mV, inhibitory postsynaptic potentials had an amplitude of -0.6 mV.

We created recurrent neural networks of $n = 1000$ integrate-and-fire neurons, according to a simple statistical characterization of the neocortex with respect to neuron types and synaptic connectivity [2]. Each of the $n(n-1)$ potential synapses was established with probability 0.1, independently of all the others. Neurons were inhibitory

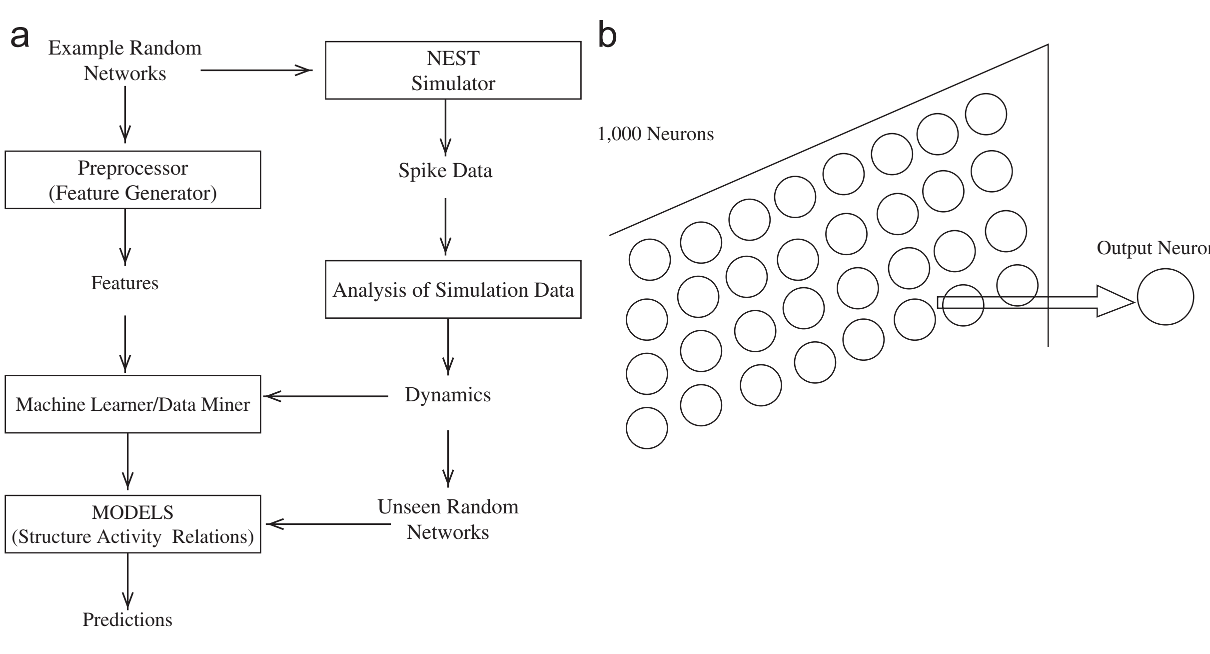

Fig. 1. (a) Mining structure–activity relations in biological neural networks. (b) Setup of the numerical simulations. We simulated recurrent cortical networks of 1000 neurons. Each neuron in the network received external input in the form of a excitatory Poisson spike train with mean rate slightly above the threshold for sustained activity. All neurons in the network projected to a single 'readout' neuron, which did not receive extra external inputs.