Efficient inference of interactions from non-equilibrium data and application to multi-electrode neural recordings

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[1]Kavli Institute for Systems Neuroscience, Trondheim (NO)

4th February 2013
NETADIS Politecnico workshop

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Bachelor degree in **physics** (University of Trieste) (ERASMUS PROGRAM: RWTH Aachen)

Master degree in **theoretical physics** (University of Trieste)

Master's Thesis

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Supervisor: Dott. Matteo Marsili

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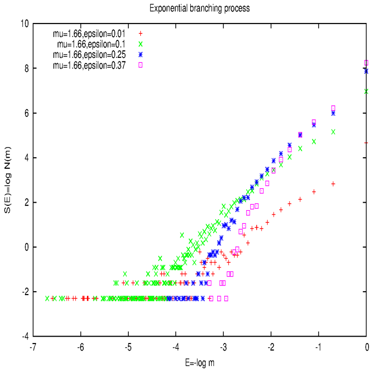

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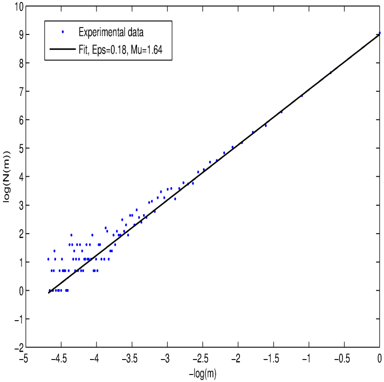
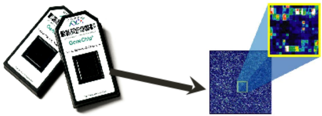
Idea: Modelling protein distribution as a result of a dynamical process (*branching process with mutation*)

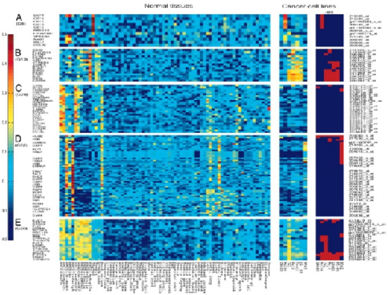
Results:

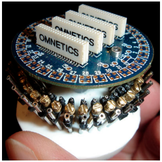
- we have been able to recover Zipf's law both analytically and numerically;
- our model hasn't been completely successful in inferring mutation parameters once applied to real data (protein subsequences);

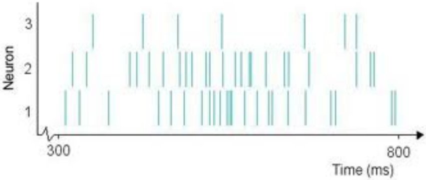


Main goal: modelling point processes









Kinetic Ising Model:

synchronous update

$P(S_i(t+1)|\mathbf{S}(t)) = \frac{e^{S_i(t+1)H_i(t)}}{2\cosh[H_i(t)]}$, $\longrightarrow$ Pareto distribution

where $H_i(t) = \sum_j J_{ij} S_j(t)$

asynchronous update

$\frac{dP(\mathbf{S}(t))}{dt} = \sum_i [P(F_i\mathbf{S}(t))w_i(F_i\mathbf{S};t) - P(\mathbf{S}(t))w_i(\mathbf{S};t)]$, $\longrightarrow$ Equilibrium Ising Model

where $w_i(\mathbf{S};t) = \frac{1}{2}[1 - s_i \tanh[H_i(t)]]$, F_i spin-i flip operator

Inference techniques (maximum likelihood, gradient descendent):

- Exact algorithms;
- Mean field algorithms (nMF,TAP)[1]

[1] Hertz J., Roudi Y., et al.(2013). Ising Models for Inferring Network Structure From Spike Data. *Principles of Neural Coding*, S. Panzeri and R. Q. Quiroga Eds

Mean field approximation

Generating functional

$$Z[\psi, J] \equiv Tr_{\{\mathbf{S}(T),\ldots,\mathbf{S}(0)\}} \left\{ P(\mathbf{S}(T),\ldots,\mathbf{S}(0)) \prod_{i,t} e^{i\psi_i(t) s_i(t)} \right\}$$

Expanding around the saddle point:

$$m_i(t) = \tanh\left[h_i(t-1) + \sum_j J_{ij} m_j(t-1)\right] \qquad \textbf{NAIVE MEAN FIELD}$$

$$m_i(t) = \tanh\left[h_i(t-1) + \sum_j J_{ij} m_j(t-1) + m_i(t) \sum_j J_{ij}^2 \left(1 - m_j(t-1)^2\right)\right] \qquad \textbf{TAP}^{2}$$

[2] Roudi Y., Hertz J. (2011). Dynamical TAP equations for non-equilibrium Ising spin glasses, *J. Stat. Mech.*, P03031

Recently used for learning:

- Error correcting codes
- Image restoration
- Protein residue interaction
- Gene regulatory networks
- Neuronal networks

Kinetic biological networks characteristics:

- Sparse and/or strong connectivity
- partially observable
- time varying external input[3]

[3] Tyrcha J. et al. (2013), Effect of Nonstationarity on Models Inferred from Neural Data, *J. Stat. Mech.*, in press

RESEARCH:

Familiarisation with generating functional and mean field techniques for studying the dynamics of complex systems and applications to reverse engineering partially observed networks.

TRAINING:

Winter School on Quantitative Systems Biology (ICTP)

Path integral methods course (QFT I, NTNU)

Neural Encoding of Space in Parahippocampal Cortices (Cellular and Molecular Neuroscience, NTNU)

PRESENTATION SKILLS:

Bishop, Machine learning and pattern recognition (NTNU, Roudi's group)

Presentation of my Master's thesis to Roudi's group

Research plan: theory

Advancing the theoretical approaches for modelling point processes using Ising models and Generalized Linear Model:

- developing Bethe approximation[4]
  (for systems with hidden nodes with and without regularizations, e.g. including L-1);
- adaptive approaches[5] useful for systems where the couplings are correlated and/or strong, e.g. neural networks
  (e.g. adaptive TAP for nonequilibrium);
- addressing hidden nodes problem in both equilibrium and nonequilibrium cases;
- extend one-step Markov chain models to processes with memory;

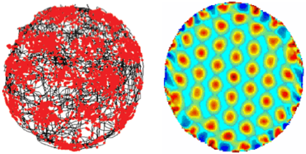
[4] F.R. Tersenghi, The Bethe approximation for solving the inverse Ising problem: a comparison with other inference methods, *Journal of Statistical Mechanics*, 2012

[5] Opper M. and Winther O. (2001) Tractable approximations for probabilistic models: The adaptive TAP mean field approach. *Physical Review Letters*, 86, 3695-3699.

Research plan: application to real data

The inference methods developed from us will have a wide range of application domains (eg. gene regulation, neuronal networks etc.)

Application to Kavli Institute data[6][7]:



- Ethorinal cortex spike trains;
- Ethorinal cortex - Hippocampus joint recordings;

Application to economic time series with prof. Sollich group.

[6] Stensola H et al., The entorhinal grid map is discretized, *Nature* 492: 72-8, 2012

[7] Couey JJ et al.Recurrent inhibitory circuitry as a mechanism for grid formation.*Nat Neurosci*. 2013

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nature neuroscience

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NATURE NEUROSCIENCE | ARTICLE

Recurrent inhibitory circuitry as a mechanism for grid formation

Jonathan J Couey, Aree Witoelar, Sheng-Jia Zhang, Kang Zheng, Jing Ye, Benjamin Dunn, Rafal Czajkowski, May-Britt Moser, Edvard I Moser, Yasser Roudi & Menno P Witter

Affiliations | Contributions | Corresponding authors

Nature Neuroscience (2013) | doi:10.1038/nn.3310
Received 17 August 2012 | Accepted 17 December 2012 | Published online 20 January 2013

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NATURE NEUROSCIENCE | ARTICLE

Grid cells require excitatory drive from the hippocampus

Tora Bonnevie, Benjamin Dunn, Marianne Fyhn, Torkel Hafting, Dori Derdikman, John L Kubie, Yasser Roudi, Edvard I Moser & May-Britt Moser

Affiliations | Contributions | Corresponding authors

Nature Neuroscience (2013) | doi:10.1038/nn.3311
Received 16 August 2012 | Accepted 13 December 2012 | Published online 20 January 2013

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Abstract

Training Plan

Technical skills:

- **Spin Glasses** (NTNU, Fall 2013;SISSA,Spring 2014)
- **Phase Transitions and Critical Phenomena** (NTNU, Fall 2013;SISSA,Spring 2014)
- **Many Body Physics out of Equilibrium** (NORDITA,Spring 2013;SISSA,Spring 2014)
- **NETADIS, NORDITA Schools and Kavli Foundation workshops**

Communication skills:

- **Introduction to research** (NTNU,Spring 2013)
- **Communication of Science** (NTNU,Spring 2014)
- **Neural Networks**, assistant (NTNU,Spring 2013)
- **NETADIS Schools**

October-November 2013
prof. Manfred Opper, Technische Universität Berlin (TUB), Germany

Project:" *Approximate inference for stochastic dynamics in large biochemical networks*"

(application domain: systems biology; tecniques: Bayesian inference)

October-November 2014
prof. Peter Sollich,King's College London (KCL), UK

Project:"*Contagion dynamics across credit networks*"

(application domain: financial networks; tecniques: generating functional methods)

Thanks!