Validation of Simulated on Experimental Spiking Activity: The Human Brain Project Perspective

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Integrative Loop Workflow

The integrative loop describes an iterative process of comparison and validation of experimental and simulated data. Here we use it to derive a mesocircuit model of the macaque (pre)motor cortex validated in terms of the statistics of neuronal activity as outlined in Gutzen et al. (2018). The workflow will be implemented into the HBP Collaboratory and will have the role of providing an integrated solution for reproducibility.

Senk et al. (2017) have implemented a similar workflow (see collab #507) to compare simulation results of NEST and SpInNaker for the same cortical model, which was continued in T9.1.5 (SGA1). The integrative loop describes an iterative process of comparison and validation of experimental and simulated data. Here we use it to derive a mesocircuit model of the macaque (pre)motor cortex validated in terms of the statistics of neuronal activity as outlined in Gutzen et al. (2018). The workflow will be implemented into the HBP Collaboratory and will have the role of providing an integrated solution for reproducibility.

Validation Workflow

Schematic structure of the validation framework using NetworkUnit. Capabilities, tests, scores and models are defined as classes and allow for a reproducible and modular test design.

Mean-Field Theoretic Approach

Dahmen et al. (2017), arXiv:1711.10930 [cond-mat.dis-nn]

To constrain the parameter space of the model, we make use of a mean-field theory that allows us to infer constraints on the statistics of effective connections from the experimental observations first and second moment of the covariance distribution. Effective connections thereby measure the sensitivity of the postsynaptic firing to a spike of the presynaptic neuron. The figure shows how low mean and large standard deviation (blue dashed horizontal lines) of experimentally observed cross-covariances (blue) are explained by a model network (red) with high variability of connections ($\sigma^2 = 0.5$). The experimental data can thus be used to infer information on the statistical distribution of the underlying structural connectivity and to gain insight into the operational regime of the network.

Analysis of Experimental Data

Data

Data are obtained from (pre)motor cortex of macaque during a resting state experiment in which the monkey is sitting in a chair without task. Spiking activity were measured for 15 min using a Utah array (100 electrodes) and behavior (rest, movement, sleepiness) was identified from video recordings. Spikes were sorted offline resulting in 147 single units.

Preprocessing

To identify putative excitatory and inhibitory neurons, we classify waveforms into broad (bs) and narrow spiking (ns). For a given threshold (30 μs) the percentage consistency of each unit is calculated. Forcing at least 60% consistency we find 95 putative excitatory (bs) and 37 putative inhibitory (ns) units.

Estimation of Covariances and Eigenvalues

Cross-covariances are estimated from binned spike trains $x$ and $y$ with a bin size of 150 ms according to $c_{xy} = \langle x \rangle \cdot \langle y \rangle$. The p.d.f. of cross-covariances are computed for cell-type specific connections (bs-bs, ns-ns) during rest (left panel) and movement (middle panel). As expected from mean-field theory [Dahmen et al., in prep.], inhibitory neurons lead to broader distributions. A singular value decomposition of the covariance matrix (right panel) indicates that the dimensionality is reduced during movement as eigenvalues are larger during movement (green line) than during rest (blue line).

Validation

Gutzen et al. (2018), Front. Neuroinf., submitted

The model is to be cross-validated with respect to the observed network activity within several monkeys using the Python module NetworkUnit [github.com/INM-6/networkunit]. We make use of methods derived in T9.1.5 (collab #2366) for testing simulations on conventional computers against simulations on neuromorphic hardware (i.e. validation of the SpInNaker w.r.t. NEST simulation). For the mesocircuit, the effect sizes of the firing rate distributions (bottom right) show a qualitative fit (effect size < 1) but statistical hypothesis tests for equality of the mean (e.g. Welch’s t-test) still fail, thus demanding a further parameter adaptation of the model.

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Outlook

- Additionally constrain parameter space based on firing rates and coefficient of variation
- Incorporate UNICORE-based computation of mesocircuit on JUELICH clusters
- Add experimental data in Neural Activity Resource NAR (T5.7.2 [SGA2])
- Generate algorithm to automatically update model parameters based on the quantitative results obtained from statistical comparisons