



cuBNM

GPU-accelerated Biophysical Network Modeling of the Brain

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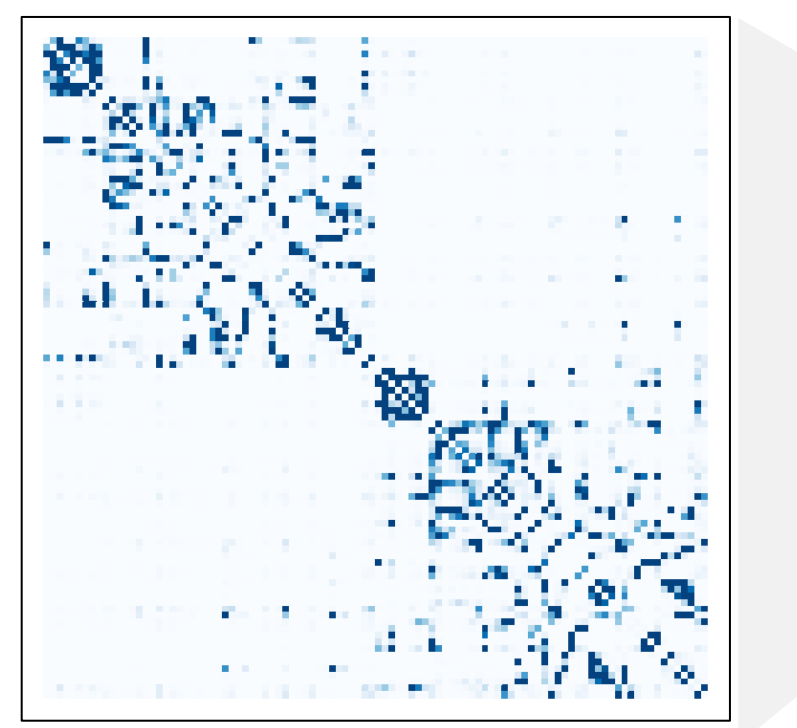
Motivation

Biophysical network modeling (BNM) of the brain is a promising technique to bridge macro- and microscale levels of investigation and enables inferences about latent features of brain activity, such as excitation-inhibition balance. Through this approach, personalized models of the brain can be fitted to the imaging data of individual subjects by parameter optimization^{1, 2}.

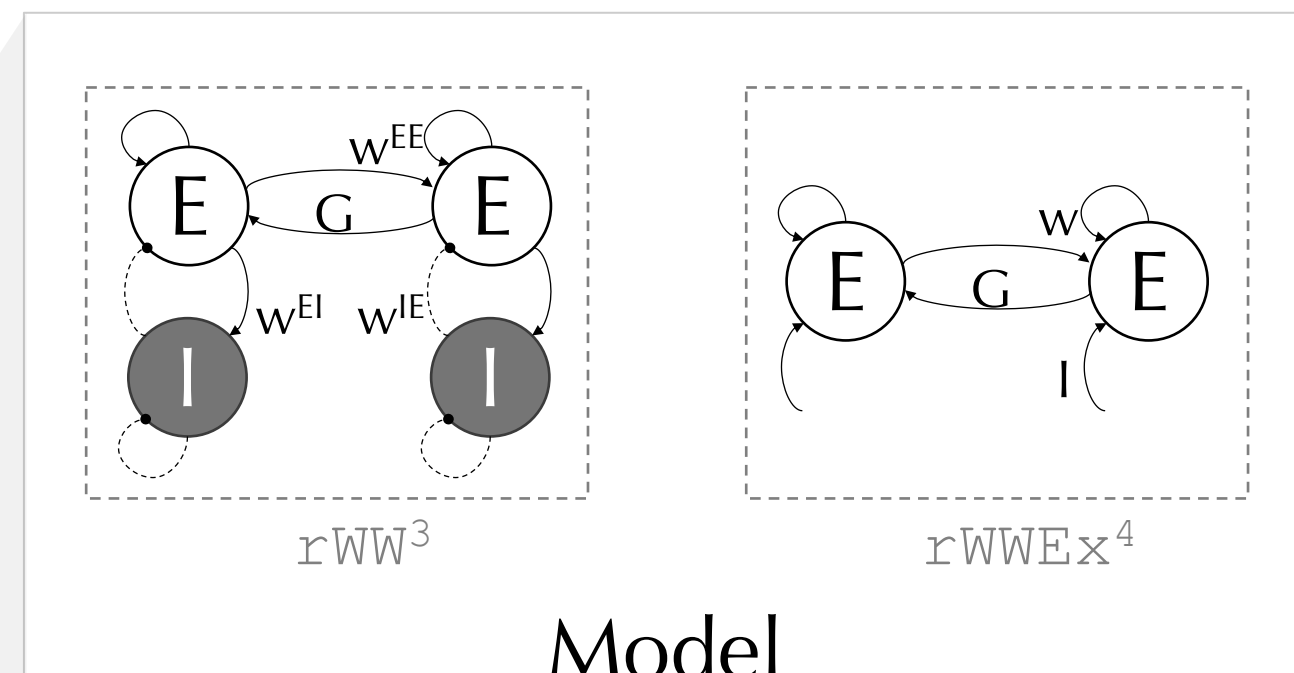
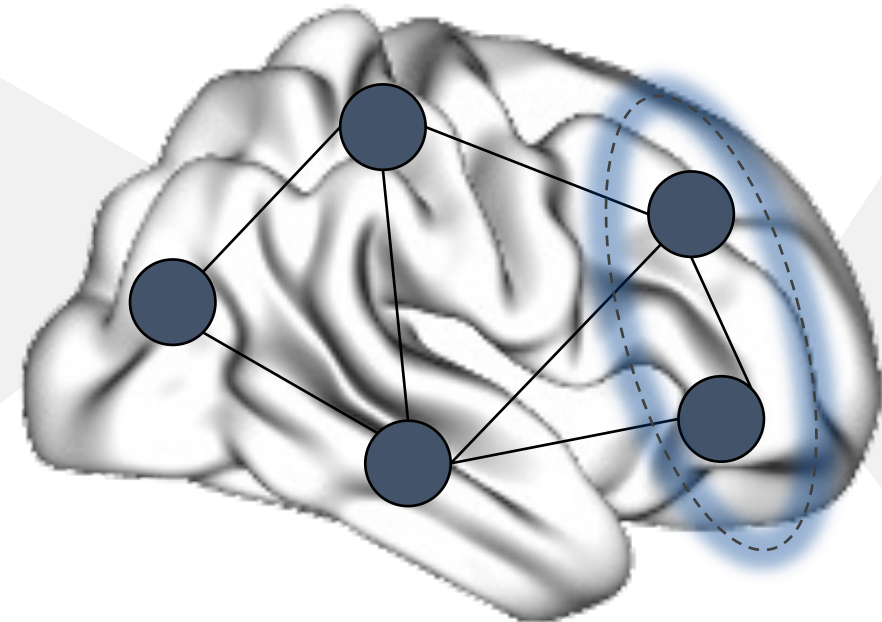
However, this process typically involves running several thousands of simulations for each subject, and therefore is **computationally costly**. This limits its scalability to a higher number of subjects and more complex models.

Here, we present **cuBNM** (<https://cubnm.readthedocs.io>), a toolbox for **efficient** simulation and optimization of BNMs using **GPUs** (but also supports CPUs).

How does BNM work?

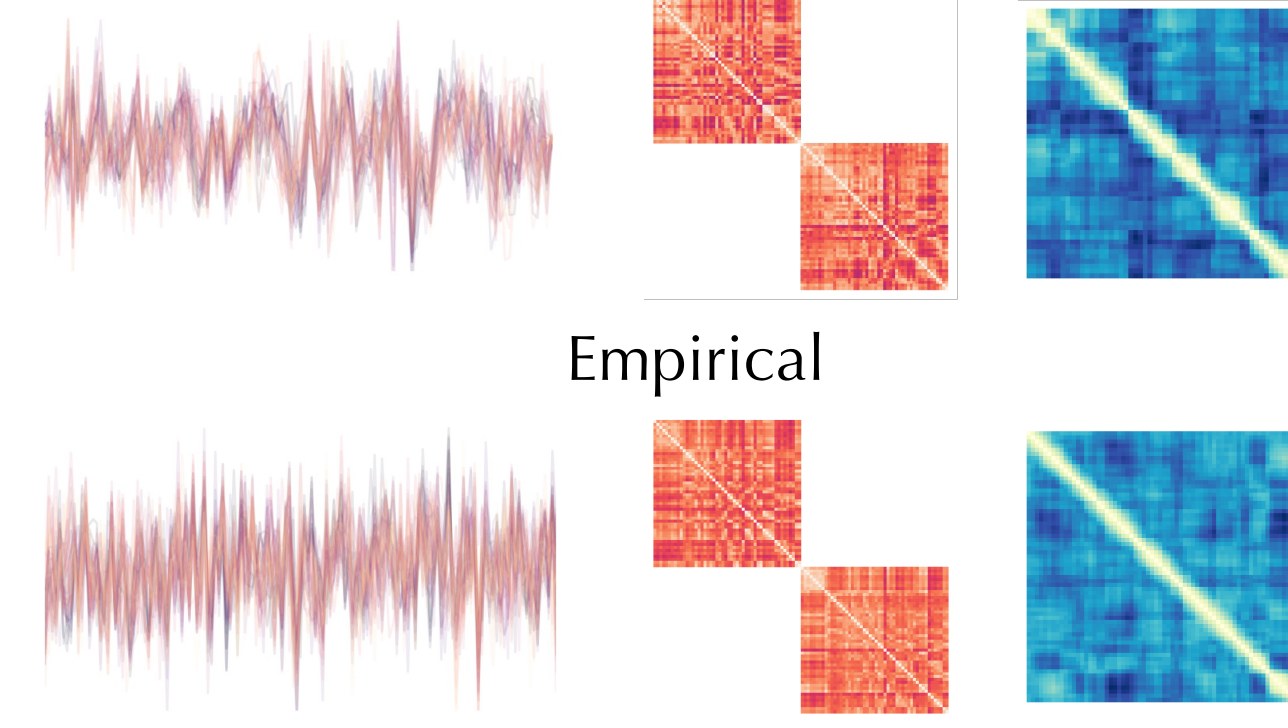


Structural connectome



Model

More models will be added to the toolbox



Empirical

Simulation

AIM

Optimize model parameters for maximal similarity of simulated and empirical signals



Installation

```
pip install cubnm
```

Requirements

Linux, Python ≥ 3.7 , NVIDIA GPU

Two parameter optimization approaches included:

Evolutionary

```
from cubnm import datasets, optimize

problem = optimize.BNMProblem(
    model = 'rWW',
    params = {
        'G': (0.5, 2.5),
        'WEE': (0.05, 0.75),
        'WEI': (0.05, 0.75),
    },
    het_params = ['WEE', 'WEI'],
    maps_path = datasets.load_maps('2maps', 'schaefer-100', return_path=True),
    emp_fcd_tril = datasets.load_functional('FCD', 'schaefer-100'),
    emp_fcd_tril = datasets.load_functional('FCD', 'schaefer-100'),
    duration = 60,
    TR = 1,
    sc_path = datasets.load_sc('strength', 'schaefer-100', return_path=True),
    states_ts = True
)

cmaes = optimize.CMAESOptimizer(popsiz=30, n_iter=10, seed=1)
cmaes.setup_problem(problem)
cmaes.optimize()
cmaes.save()
```



Open in Kaggle

Grid search

```
from cubnm import datasets, optimize

gs = optimize.GridSearch(
    model = 'rWW',
    params = {
        'G': (0.5, 2.5, 10),
        'WEE': (0.05, 0.75, 10),
        'WEI': 0.21
    },
    duration = 60,
    TR = 1,
    sc_path = datasets.load_sc('strength', 'schaefer-100', return_path=True),
    states_ts = True
)

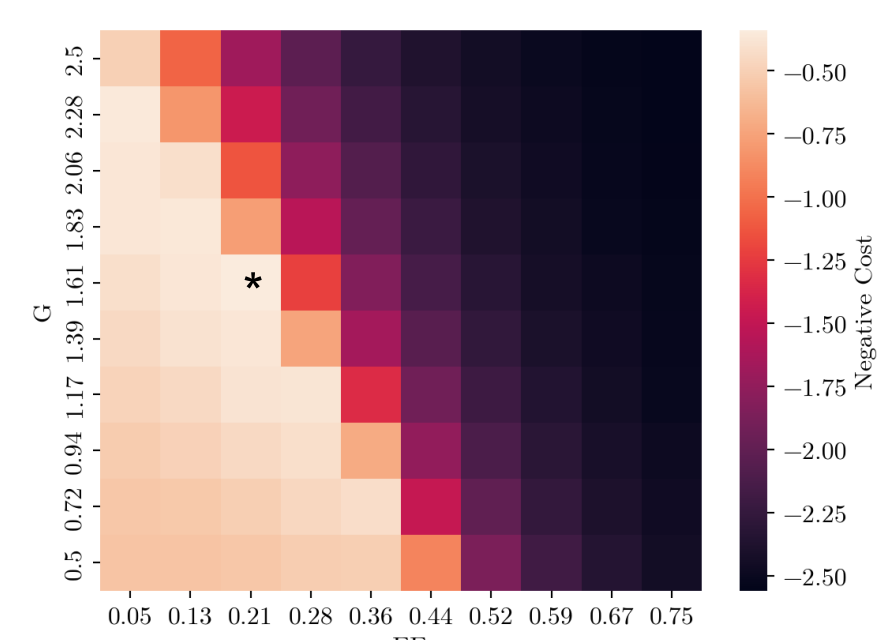
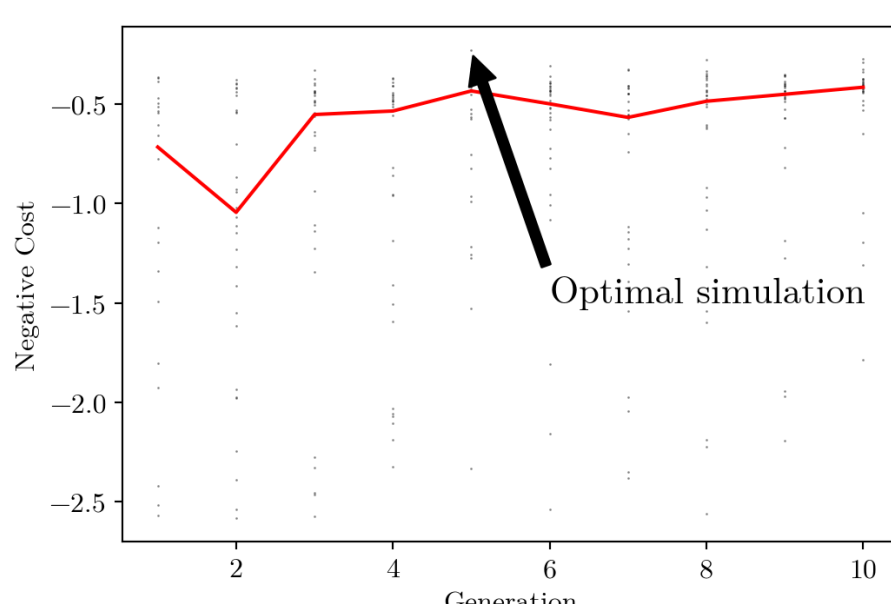
emp_fcd_tril = datasets.load_functional('FCD', 'schaefer-100')
emp_fcd_tril = datasets.load_functional('FCD', 'schaefer-100')
scores = gs.evaluate(emp_fcd_tril, emp_fcd_tril)
scores.to_csv('scores.csv')
gs.save()
```



Open in Kaggle

FEATURES

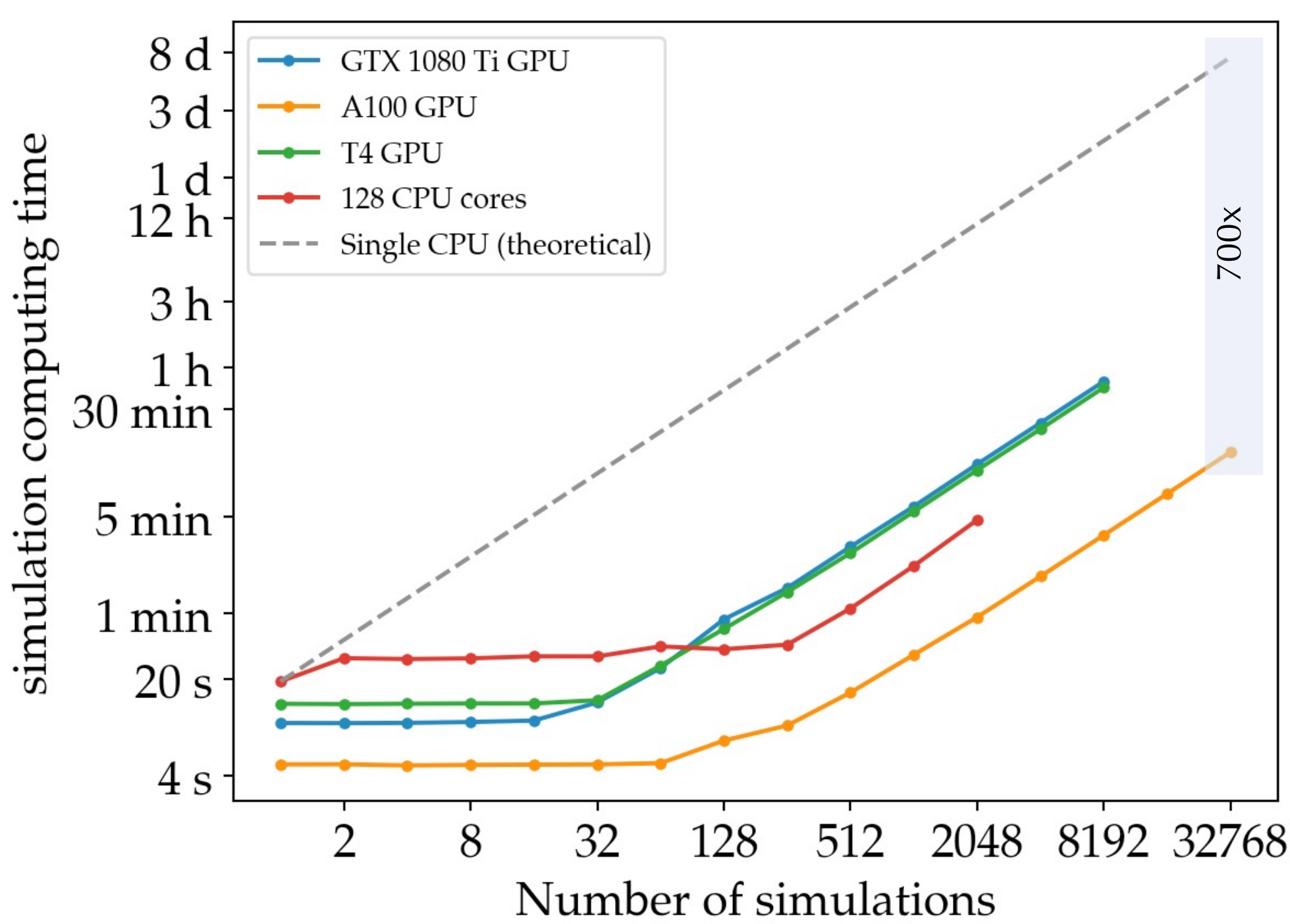
- ✓ Modular design
- ✓ Simulation + FC and FCD on GPU
- ✓ Extensive options for simulations
- ✓ Regional parameter heterogeneity
- ✓ Supports *pymoo* optimizers



PLANS

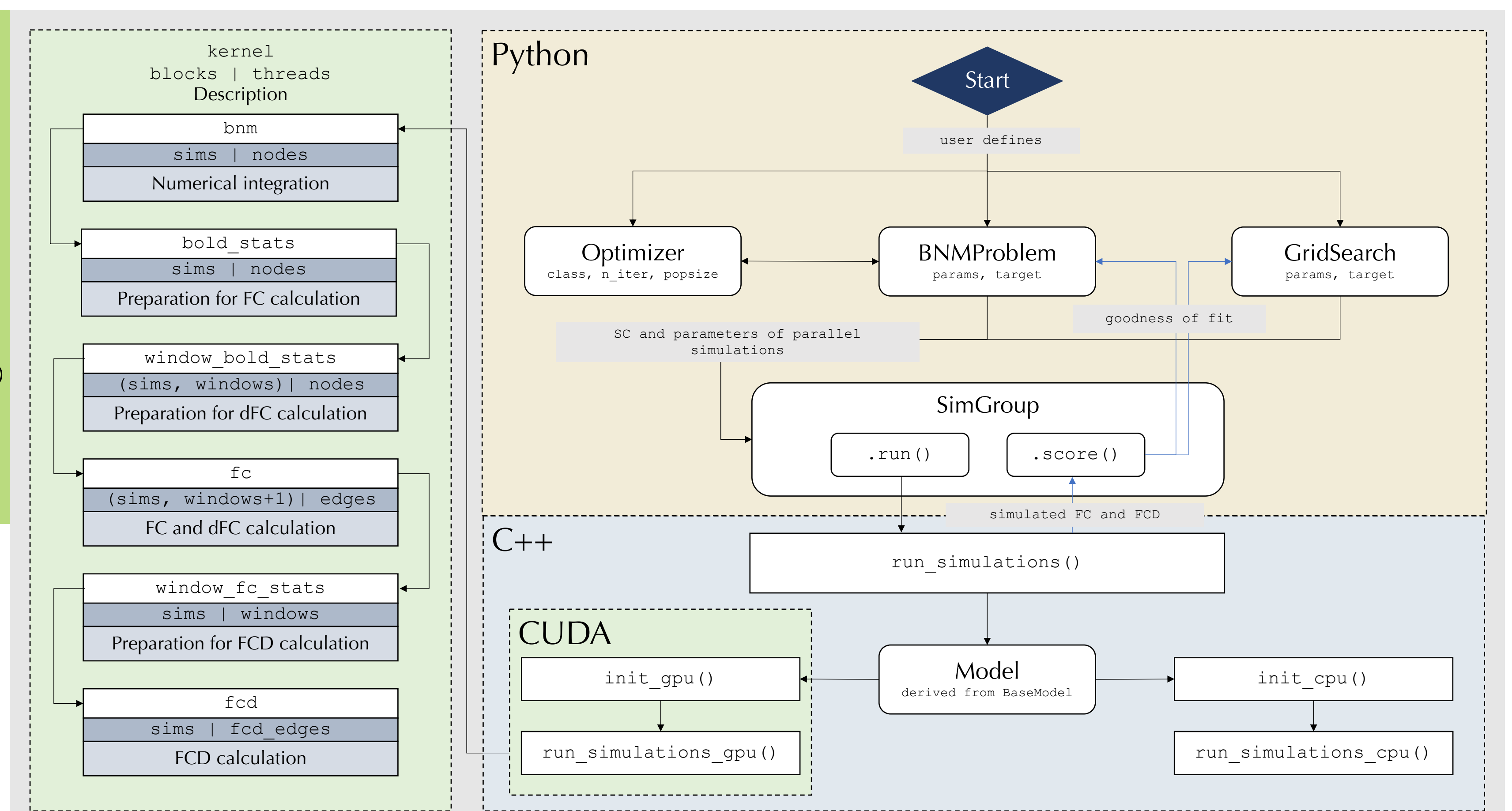
- ✓ New models
- ✓ Improve documentations and add tutorials
- ✓ Command-line interface
- ✓ Docker container

Contact us if you're interested to contribute :)



A100 GPU up to 700x faster than a CPU

Program flowchart



References:

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2. Ritter P, Schirner M, McIntosh AR, Jirsa VK. The Virtual Brain Integrates Computational Modeling and Multimodal Neuroimaging. *Brain Connectivity*. 2013;3:121-145.
3. Deco G, Ponce-Alvarez A, Hagmann P, Romani GL, Mantini D, Corbetta M. How local excitation-inhibition ratio impacts the whole brain dynamics. *J Neurosci*. 2014;34:7886-7898. 4. 1.
4. Deco G, Ponce-Alvarez A, Mantini D, Romani GL, Hagmann P, Corbetta M. Resting-State Functional Connectivity Emerges from Structurally and Dynamically Shaped Slow Linear Fluctuations. *J Neurosci*. 2013 Jul 3;33(27):11239-52.

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