# ForneyLab: A Toolbox for Biologically Plausible Free Energy Minimization in Dynamic Neural Models *

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The free energy principle (FEP) claims that self-organization in biological agents is driven by variational free energy (FE) minimization in a generative probabilistic model of the agent's environment [6]. Research progress in this field relies substantially on the capability to simulate biologically plausible FE minimization processes in postulated generative neural models.

To this end, we have developed `ForneyLab` as a free and open source toolbox for FE minimization by variational message passing in freely definable probabilistic dynamic models. `ForneyLab` is released as a package for the open source scientific programming language `Julia`, which combines a MATLAB-like syntax and native speed close to that of (compiled) *C* code [1].

`ForneyLab` is based on the formalism of Forney-style factor graphs (FGGs) [5, 9], which facilitates a very modular (plug-in) design approach and automated derivation of biologically plausible message passing-based inference algorithms. FFGs also feature insightful visualizations of both the model and the inference processes. For example, Figure 1 shows an FFG and a variational message passing schedule [3] for online state inference in the *hierarchical Gaussian filter* (HGF) [10, 11]. In an FFG, edges represent variables and nodes capture (probabilistic) relationships among variables.

Here, we introduce the FFG formalism and `ForneyLab` by presenting two example applications that are well-known to FEP researchers. In the first application we perform variational Bayesian inference by message passing in the HGF, which is a biologically plausible structure that enjoys a great reputation for modeling predictive coding systems under the *Bayesian brain* hypothesis [8]. `ForneyLab` can automatically generate a suitable variational message passing algorithm for online state and parameter estimation in this (and freely definable variants of this) structure. Moreover, `ForneyLab` automatically generates an algorithm to compute the variational free energy in the simulated model.

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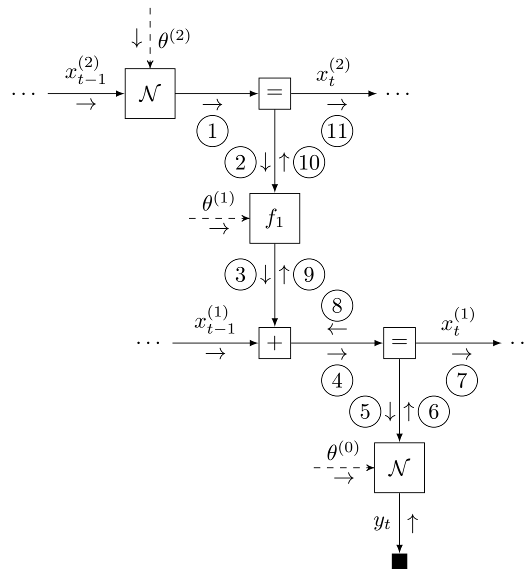


Figure 1: Variational message passing schedule for online state estimation in a Forney-style factor graph (FFG) for the hierarchical Gaussian filter. In an FFG, edges represent variables, and nodes represent factors. In this figure, dashed edges indicate model parameters, and the solid square corresponds to an observation.

The second application is based on a factor graph realization of a *Bayesian thermostat*, which is a well-known simple example of an *active inference* agent [2, 7]; see also [4] for a more general account of active inference in FFGs. The Bayesian thermostat simulates an agent that actively pursues a desired (predicted) temperature by positioning itself relative to a heat source. Again, we present both the factor graph model and the automatically derived message passing schedule for executing variational inference in that model.

With this toolbox we aim to lubricate the execution of research projects on biologically plausible probabilistic modeling. We invite the research community to start experimenting with the toolbox and collaborate on improving `ForneyLab` to a level that truly impacts the productivity and reproducibility of research efforts in the computational neuroscience community.

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