

Supplementary information

Supplementary Video I . This supplementary video illustrates an interactive model exploration using our tools, as described in the example Jupyter notebook (which is distributed with the sources code). Video available here:

<https://www.dropbox.com/s/o0wszm7xdsnc7ri/paper1.mp4?dl=0>

Parameter sweep design of test GRN model Table 1 outlines the parameter bounds used in the exploration of the oscillator and the robust parameter points for the validation points used in Results phase 3 and 4.

Parameter	lower bound	upper bound	robust
θ_A	0.5	5000	50
θ_R	1.0	10000	100
α_A	0.5	5000	50
α'_A	5.0	50000	500
α_R	0.0001	1.0	0.01
α'_R	0.5	5000	50
β_A	0.5	5000	50
β_R	0.05	500	5.0
δ_A	0.01	100	1.0
δ_{MA}	0.1	1000	10
δ_{MR}	0.005	50	0.5
δ_R	0.002	20	0.2
γ_A	0.01	100	1.0
γ_C	0.02	200	2.0
γ_R	0.01	100	1.0

Table 1: Parameter Sweep design and robust settings for oscillations (24 h period).

Summary statistics Summary statistics (time series features from TSFRESH) used apart from the extreme values, mean, median, standard deviation, variance and sum.

- Absolute sum of changes:

$$\sum_{i=1}^{n-1} |x_{i+1} - x_i|$$

- Autocorrelation:

$$\frac{1}{(n-l)\sigma^2} \sum_{t=1}^{n-l} (X_t - \mu)(X_{t+l} - \mu)$$

where n is the length of the time series X_i , σ^2 its variance and μ its mean. l denotes the lag.

Toggle switch example Here we demonstrate our method on separate problem involving a smaller stochastic biochemical network of a genetic toggle switch (Gardner et al. 2000). The model is a bistable toggle network consisting of two repressor and two promoter regions where the opposing repressors inhibit transcription of each other. Here we assume no knowledge of the bistability inherent in the model, and naively begin exploring the simulation outputs by randomly sample the parameter space using our workflow. The range of parameter space is presented in table 2. The summary statistics used for this example were extreme values, mean, median, standard deviation, variance and sum for both repressors and an additional summary being the Pearson correlation coefficient between repressors expression levels. Figure 1 A shows a reduced 2D TNSE plot of this feature space containing an initial batch of 500 uniformly sampled points. The principal behavior of the model becomes apparent while exploring the data, showing both bistability and monostable behaviors. While most points produces low

copy number noise, the interesting points can be separated by human-in-the-loop labeling and semi-supervised modelling. Here we have used the full set of summary statistics as input to label propagation using the RBF kernel as the similarity measure to construct the graph Laplacian. The hyper-parameter optimization was then performed in the same manner as in our main example. Figure 2 B show the potential benefits of a downstream process using the learned model as a predictor. By continuously sample a total of 34000 points the label propagation model filtered out 5166 as belonging to interesting classes. Mapping these points back to their associated parameters we can get an initial qualitative understanding of which parameters give rise to these behaviors (Figure 1 B).

Parameter	lower bound	upper bound
α_1	0.01	100
α_2	0.01	100
β	0.02	200
γ	0.02	200
μ	0.01	100

Table 2: Parameter Sweep design of genetic toggle switch.

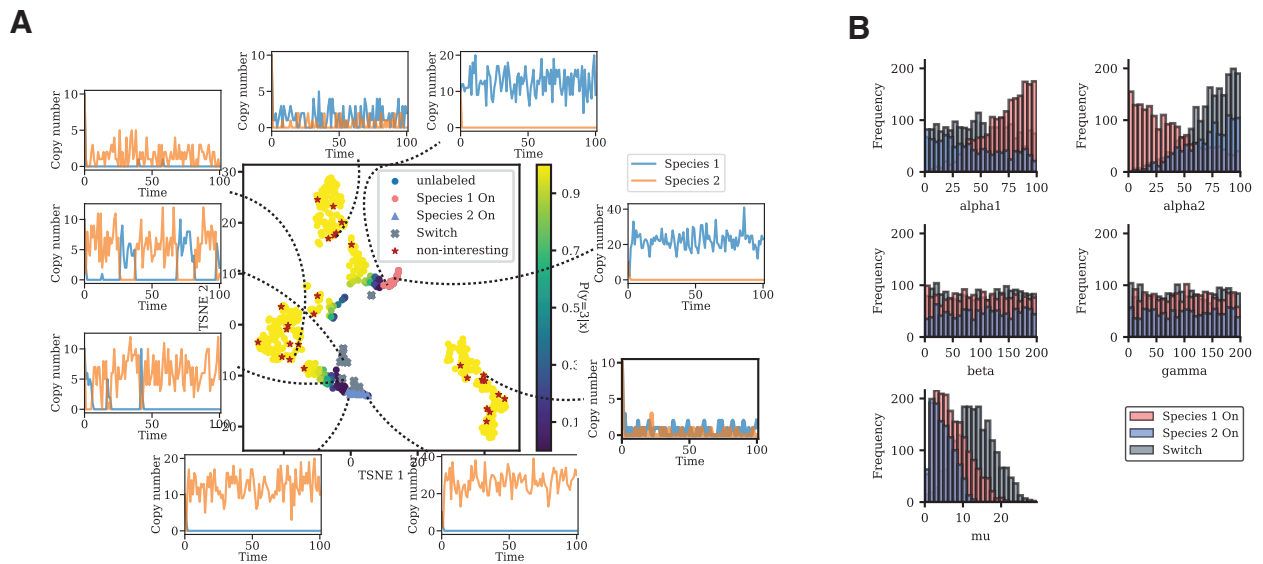


Figure 1: (A) Model exploration of genetic toggle switch. (B) Mapping of parameters after downstream prediction