

NetLand: A comprehensive tool for simulation and visualization of transcriptional network kinetics

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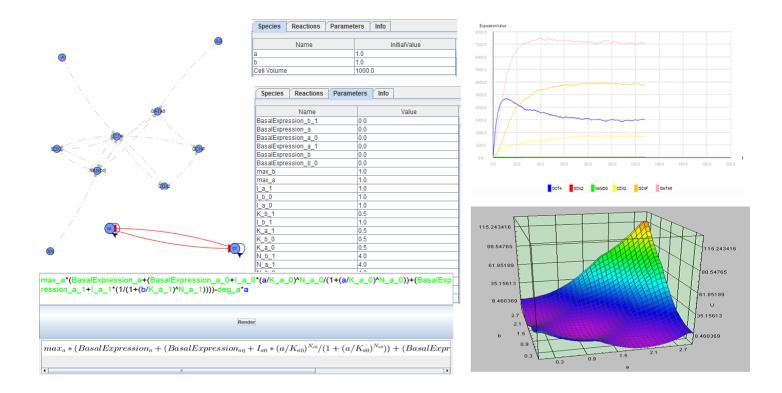
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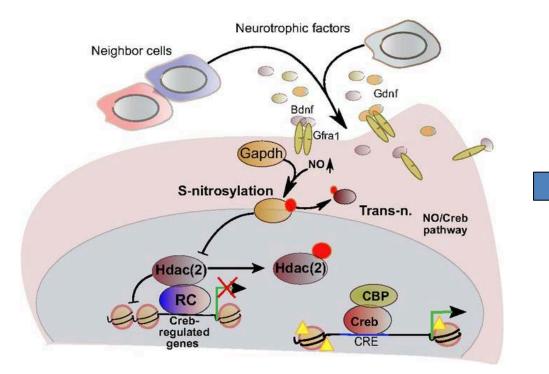
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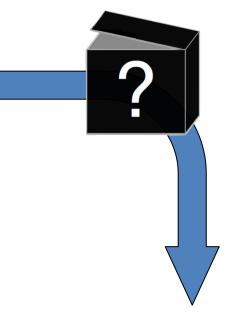
NetLand – A software for global dynamics analysis on genetic system

<u>NetLand</u> is a standalone software too for studying GRN kinetics. It provides comprehensive methods on simulation and visualization of network dynamics.



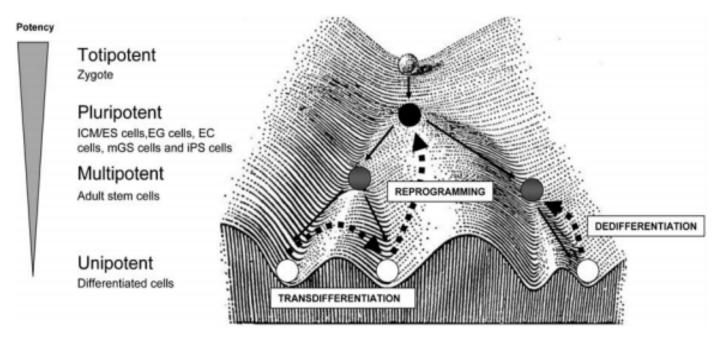
Background





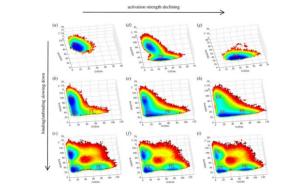
Mechanisms

- Transcriptional network
- Signaling pathway
- Other mechanisms



Differentiation, transdifferentiation and reprogramming on the **Waddington's epigenetic landscape** show trends of cellular dynamics.

The ideas borrowed from **physics** makes the qualitative metaphor a **quantitative model** which is capable of describing the global dynamics of a system.



Mathematical Formulation

Differential Equation Model

 $\frac{d[\text{Gene1}]}{dt} = K^+ \varphi(\text{Gene1}, \text{Gene2}, \text{Gene3} \dots \text{GeneN}) - K^-[\text{Gene1}] + D \cdot \theta(t)$

Where:

- [Gene1] denotes the concentration of Gene 1
- \succ K⁺ is the maximum transcriptional rate
- \succ K⁻ is the degradation rate
- $\succ \phi$ () is kinetics of Gene 1 being regulated by other nodes (e.g. Hill function)
- \succ $\theta(t)$ is the noise term
- D is the strength of noise

Theoretical model mainly follows:

Li C, Wang J (2013). Quantifying Cell Fate Decisions for Differentiation and Reprogramming of a Human Stem Cell Network: Landscape and Biological Paths. *PLoS Comput Biol* 9(8): e1003165.

Implement Waddington's epigenetic landscape

The probabilistic landscape is an implementation of Waddington's epigenetic landscape. It is constructed with the assumption that the noise in gene expression follows Gaussian distribution and the individual probability of each gene is independent. The quasi-potential landscape is based on the notion that the probability of gene expression states determines the stability.

Langevin dynamics that describes the movement of Brownian motion has been applied to studying the stochasticity in gene transcriptional regulation.

In genetic and biochemical circuits, the change rates of species can be formulated as Langevin equations

$$dX(t) = -\nabla U dt + \sqrt{D} dW_t$$

The number of molecules of each gene in the network at time *t* is denoted by vector X(t). *D* is the noise term associated with each reaction. *U* is the particle interaction potential. W_t denotes a Wiener process (Standard Brownian motion). The gradient force *F* is equal to $-\nabla U$. The drift part is composed of the noise term.

The Langevin equation can be reformulated as a **Fokker–Planck** (FP) equation that governs the time evolution of the probability density function of each X(t) under the influence of driving forces and random fluxes. FP equation is a partial differential equation (PDE).

$$\frac{\partial P(X,t)}{\partial t} = -\sum_{i=1}^{N} \frac{\partial [F(x_i)P(x_i,t)]}{\partial x_i} + \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{\partial^2 [\sigma(x_i)P(x_i,t)]}{\partial x_i \partial x_j}$$

The quasi-potential $U = -\ln(P)$.

Numerical solution by **self-consistent mean field approximation** (Li & Wang, *PLoS Comput. Biol.* 2013).

Assumption: probabilities of gene concentrations are independent and follow Gaussian distribution

Gaussian process dynamical model (GPDM) is a probabilistic approach to model high dimensional time series data in a low dimensional latent space with a dynamical model.

In the GPDM framework, the original data consists of N points, $Y = [y_1 \dots y_N]$ with D dimensions are recovered from the latent space with the corresponding two dimensional data $X = [x_1 \dots x_N]$. The relationship between the latent space data and the high dimensional data with Gaussian noise added would be

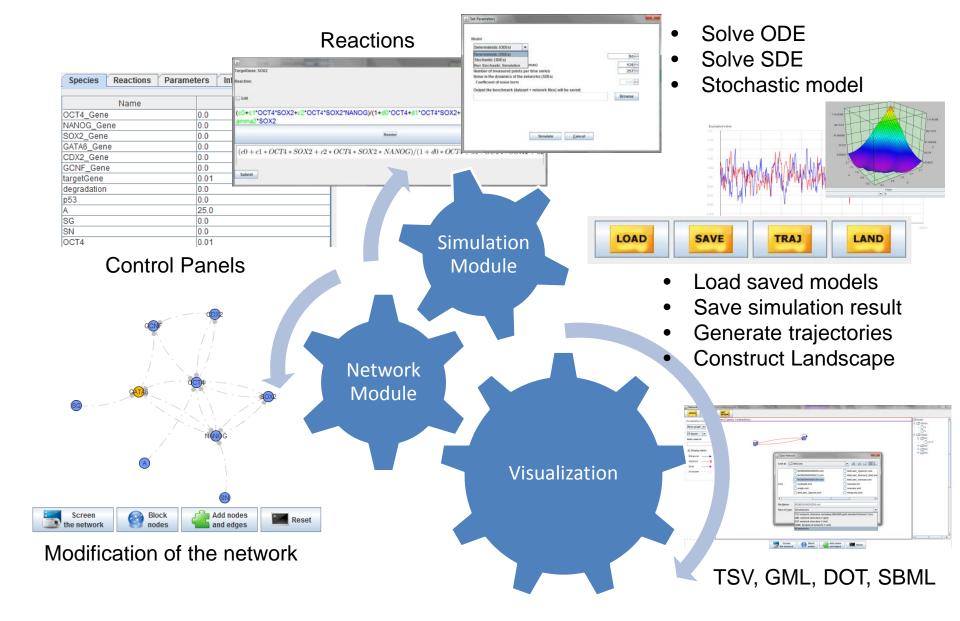
$$y_i = W x_i + \sigma_i$$

where $W \in R^{D*2}$ which has a prior as a spherical Gaussian distribution with zero mean and $\sigma_i \in R^{D*1}$ sampled from a spherical Gaussian distribution with 0 mean and $\beta^{-1}I$ covariance. Thus the likelihood for all data points is

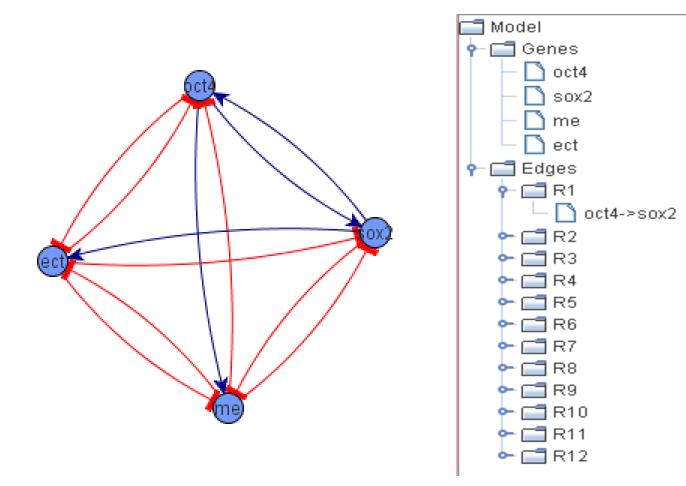
$$p(Y|X,\beta) = \prod_{d=1}^{D} p(y_{:,d}|X,\beta) = \prod_{d=1}^{D} N(y_{:,d}|0,K)$$

The mapping between latent space and original space is through maximization of the above likelihood.

K is the kernel matrix, applied to guarantee the smoothness and nonlinearity of output function.



Example: A 4-gene network of stem cell fate



Species Panel

Species Reactions Paramet	ters Info
Name	InitialValue
oct4	1.0
sox2	1.0
me	0.0
ect	0.0
Cell Volume	1000.0

Reaction Panel

Species	Reactions	Parameters	Info	
	-			
Rxnld	TargetGene	Modifiers	Equation	
R1	oct4	me,ect,oct4	R1	
R2	sox2	me,ect,oct4	R2	
R3	me	oct4,sox2,e	R3	
R4	ect	sox2,oct4,	R4	*8)*(0.4+oct4*sox2/(0.35+oct4*sox2))-sox2)
		Render		
		$) + 1 * 0.7^8 / (0.7^8 + me^8) * 0.7^8 / (0.7^8 + ect^8) * (0.4 + oct4 * sox2 / (0.35 + oct4 * sox2)) - 0.16 + 0$		
Submit				

Parameters Panel

Species Reactions Parameters Info		
Name	Value	
deg_oct4	1.0	
max_oct4	1.0	
BasalExpression_oct4	0.0	
k_oct4_0	0.5	
k_oct4_1	0.5	
k_oct4_2	0.5	
n_oct4_0	4.0	
n_oct4_1	4.0	
n_oct4_2	4.0	
I_oct4_0	1.0	
I_oct4_1	1.0	
I_oct4_2	1.0	
BasalExpression_oct4_0	0.0	
BasalExpression_oct4_1	0.0	
BasalExpression_oct4_2	0.0	
deg_sox2	1.0	
max_sox2	1.0	
BasalExpression sox2	0.0	

Generation of trajectories

🚣 Set Parameters		×
Model		
Deterministic (ODEs)		
Deterministic (ODEs)		10 🗧
Stochastic (SDEs) Run Stochastic Simulation	max)	128
Number of measured points		257
Noise in the dynamics of the		201 -
Coefficient of noise term		0.05 🗧
Output the bonchmark (data	set + network files) will be saved:	
output the benchimark (uata		wse
	Simulate Cancel	
	Zanooi	

Construction of the landscape

\$	×	
Set Up Boundary for GeneExp: 3	3	
Set No of trajectories to generate: 100		
Set MaxTime for trajectories: 1	28	
Set Number of Points for each trajectory: 257		
Set Analysis Genes (seperated by ;): oct4;sox2;me;ect;		
Output landscape will be saved:		
	Browse	
Probabilistic O GPDM O Entropy		
Run		
<u>C</u> ancel		

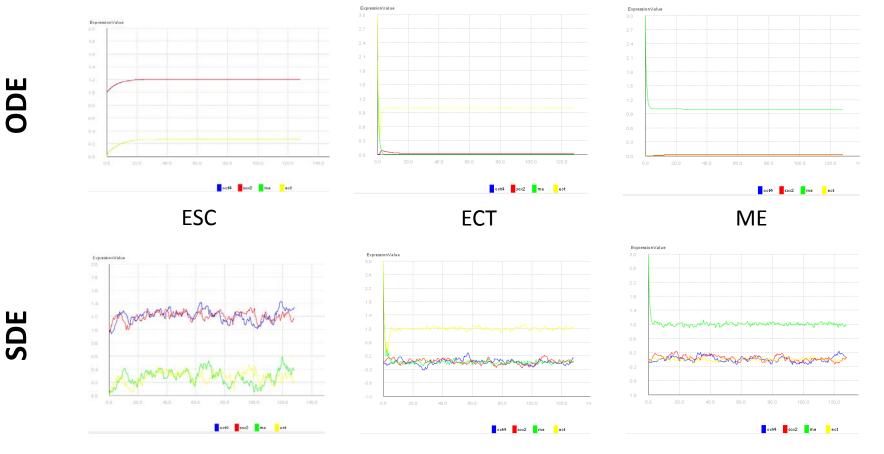
- Solving ODEs
- Solving SDEs
- Stochastic model

- Probabilistic Landscape
- Scaled Landscape

Deterministic model

Runge-Kutta method to solve the ODE model

Euler-Maruyama method to get the approximate numerical solution of SDEs



ESC

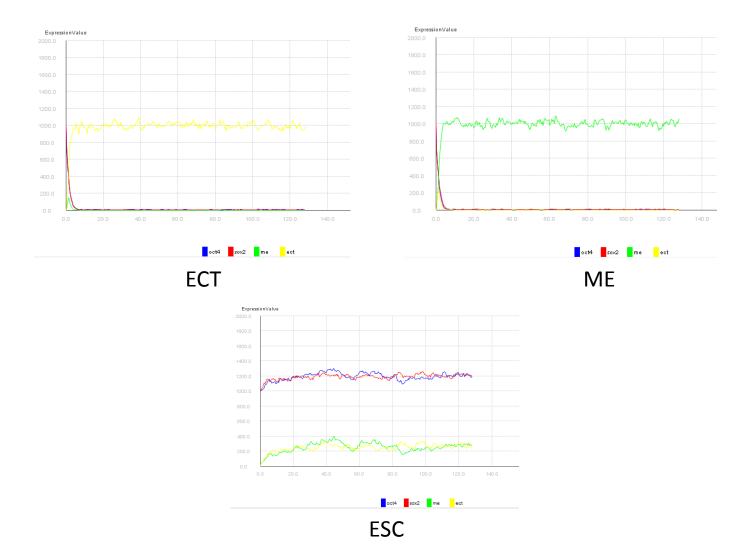
ECT

ME

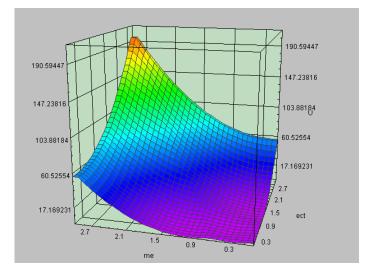
T=128, D=0.03

Stochastic model

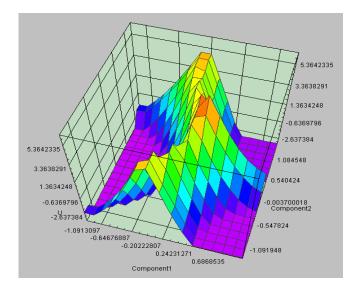
Gillespie algorithm is used for simulation



Visualization result



Visualization of global dynamics in a landscape. The high dimensional data is reduced to two dimensions as x-axis and yaxis. It shows the landscape of the 10-gene network with expression values of Sox1 and Gata6 as x-axis and y-axis. Three attractors were located at (0,0), (2.5,0) and (0,2.5) representing stem cell state, ectoderm and mesoderm respectively.



Summary

- NetLand is a software tool for simulation and visualization of kinetics of transcriptional regulatory networks (GRN).
- Both deterministic (ODE) and stochastic (SDE) models are supported.
- Plot the Waddington's epigenetic landscape for GRNs of more than 3 genes.
- Future work:
 - Scalability of bigger networks (> 30 genes)
 - Validation with real data
 - Add discrete version (Boolean network)

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