

Principles of systems biology and Dmitri Belyaev's co-selection of traits

UNIVERSITY OF AMSTERDAN VU SUNVERSITY OF SYSTEMS BIOLOGY

Hans V. Westerhoff and friends MCISB, MIB, SCEAS, University of Manchester SysBA, Universities of Amsterdam







Systems Biology

- What is it?
- Principles
 - Lack of dominance (Kacser)
 - Co-selection (Belyaev)
- Progress
 - Make Me My Model
 - The genome wide metabolic maps
 - Epigenetics and noise/cell diversity









Bioinformatics: From biological data to information

Systems Biology: From that information to understanding





From data to understanding: why is this such an issue?

- Because the mapping from genome to function is extremely nonlinear
- E.g.:
 - <u>P.D. Polly</u>. Morphometrics and evolution: the challenge of crossing rugged phenotypic landscapes with straight paths
 - The DNA in all our cells is the same, but:
 a heart cell is essentially different from a brain cell
 - Self organization, bistability: Belousov, Zhabotinsky, Waddington, Ilya Prigogine, Boris Kholodenko







Why systems biology?



2006 Hornberg et al: 'Cancer: a systems biology disease'. Now: 'virtually all disease are Systems Biology diseases.' This causes the 'missing heritability problem (Baranov; Stepanov)'



mcle

L. Alberghina H.V. Westerhoff (Eds.)

Systems Biology Definitions and Perspectives

Topics in Current Genetics

🖄 Springer

Systems Biology=

- The Science that
- aims to understand
- principles governing
- how the biological functions
- arise from the interactions = from the networking

This leads to precision, personalized, 4P medicine, PPP4M And to precision biotechnology







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Henrik Kacser (Student of Waddell)

Henrik Kacser

Recessivity of most lack-of-function mutations Lack of dominance: No loss of function in heterozygote



F1

Lack of dominance: observation



Function= 100% 0% Flux J

Lack of dominance: single molecule explanation fails F0 F0' F1



Lack of dominance: single molecule explanation fails















The systems biology explanation

(Henrik Kacser)





Dependence of pathway flux on the concentration of an enzyme





steady states and all other e_i constant









Example

	4 mM glucose	5 mM gl	5 mM glucose		8 mM glucose	
Reaction	\mathbf{C}_{i}^{J} Γ/\mathbf{K}_{eq}	\mathbf{C}_{i}^{J}	Γ/\mathbf{K}_{eq}	\mathbf{C}_{i}^{J}	Γ/\mathbf{K}_{eq}	
Glucose transport	C is not confined to the single first irreversible step in the pathway			0.63	9.2·10 ⁻³	
НК		0.04	<< 10 ⁻³			
PFK		0.01	<< 10 ⁻³			
ALD				0.10	0.17	
GAPDH				0.09	0.20	
PGK				0.06	3.4.10-3	
РҮК	$C_i^J = \left(\frac{d\ln J }{d\ln e_i}\right)_{steadystate} =$		$=\frac{dJ/J}{de_i/e_i}=\frac{'\% dJ'}{'1\% de_i}$	0.01	<< 10 ⁻³	
Pyruvate transport		dJ/		0.00	<< 10 ⁻³	
GDH		$=\frac{/}{da}$		0.06	9.1·10 ⁻³	
GPO		steadystate $ue_i/$		0.01	<< 10 ⁻³	
ATP utilization		/ 0		0.00		
				1.01		



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L. Alberghina H.V. Westerhoff (Eds.)

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Flux Control Summation Principle

$$C_1^J + C_2^J + C_3^J + \dots + C_n^J \equiv 1$$

- J: steady state flux
- 1, 2, 3, : number of the enzyme (gene product)
- Consequence:

 $C_i^J \approx \frac{\% reduction in function}{for a 50\% reduction in gene dosage} = 1/n$





 $\cong 1/10$,

Flux Control Summation Principle and recessivity



lenrik Kacser Student of Vaddell)

 $\overline{C_i^J} \approx rac{\% reduction in function}{for a 50\% reduction in gene dosage}$ hence 5 % reduction in function for

a pathway of 10 genes





FO FO'

Function= Flux J



Х



F1





Lack of dominance (expectation?)



Flux J





Lack of dominance (network explanation; Kacser)









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Principles

The Novosibirk example of co-selection: Selection for domestication also brings drooping ears







for lack of aggressivity



Function: Aggressivity

Upright ears

Domestified

Drooping ears



Function: Aggressivity

Upright ears

Domesticated



Network explanation VU Stress Siology















N.K. Popova' lecture









Selection during domestication









After selection









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M⁴ @ ISBE.NL team

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Make Me My Model service: Something 4U?





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The human: A jungle of 25 000 genes and gene products and various nutrition, life style and ambition factors This must be impossible to deal with. Where to start.....?









We obtained the consensus genome wide metabolic map (Recon2), i.e. all the human network can make from any nutrition



Data concerning all metabolic genes have hereby been integrated into a predictive format. Predicting how every molecule in our body is made by our body









Does this help?

Could it lead to cures?

Example of map utilization tyrosine metabolism: nature Phenylketonuria (PKU) = IEM



Example of map utilization tyrosine metabolism: Nurture and brain







Now: after hearing Prof Popova: Mapping serotonin (?)







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How can we understand clonal heterogeneity (such as in these glucose transporter activities)?



Yeast uptake of fluorescently labelled glucose analogue







Explanations Phenotypic heterogeneity

- Variations in external conditions (extrinsic noise)
- Genetic diversity
- Epigenetic diversity:
 - Intrinsic Noise
 - Bistability







Explanations Phenotypic heterogeneity

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What is noise?

Due to temporarily increased/decreased activities of molecular processes At different moments in different individual cells, Hence noise →cell-cell heterogeneity

From statistical mechanics:

In a flat (bio)chemical network at steady state, noisy molecule numbers should be (approximately) Poisson distributed







Probability distribution: characteristics



N=Number of mRNAs/cell

- $\mu = \overline{x_i}$: the average of x
 - $\sigma^2 = \overline{(x_i \mu)^2} = \overline{(x_i)^2} \mu^2$: Noise:
- $\sigma = standard \ deviation = \sqrt{\sigma^2}$: the width of the distribution
- Relative noise = Coefficient of variation: $cv = \sigma/\mu$
- Fano factor: $F = \frac{\sigma^2}{\mu}$: deviation from trivial noise

The equilibrium case: **Poisson distributed molecule numbers** F=1, i.e. $\sigma^2 = \mu$

BIOLOGY

Relative noise $\left(\frac{\sigma}{\mu}\right)$ **de**creases with

average number of molecules

(μ)

CV=

Absolute noise (σ) **in**creases with average number of molecules (μ)

 $\sigma = \sqrt{\mu}$ 100 0.14 0.12 80 u=10 0.1 60 0.08 m=10 (n/n=x)⊂ (u=x)_{0.06} $\mu = 40$ m=40 40 m=100 20 μ=100 0.02 0 0 0.5 1 1.5 2 50 150 200 100 -20 -0.02 n/μ n



If Poisson, then for 'normal' reactions and 'usual' molecule numbers: relative noise < 3%



E. coli:

1 μ m³, 5 mM ATP: 3 million molecules; 1/ $\sqrt{3000000}=0.1$ % Total protein: 3 million; on average of each type; 1000; **3** % relative noise?

S. cerevisiae: 40 μm³, 5 mM ATP: 120 million molecules; <0.01% Total protein: 100 million; on average of each type; 16 000; **<1 % relative noise?**

Mammalian cell: 2 pL, 5 mM ATP: 6 billion molecules; << 0.01% Total protein: 10 billion; on average of each type; 400 000; **<0.2 % relative noise?**







Therefore: Poisson noise can not explain our (and others') observations.



But what can? And: Is such noise important?

We now study this vis-à-vis oestrogen receptor positive breast cancer



But these outgrow the others

TEMS BIOLOGY







Noise in MCF-7 (clonal) cells; noisy CD44 promotor

 4 MCF-7 sister cells, DAPI stain, GFP that reports CD44 promoter activity(possibly resistance related) and GAPDH FISH mRNA probe.



And as shown by Moshkin this morning it may be important for IVF



Katja N. Rybakova^{1‡¤}, Frank J. Bruggeman^{2‡}, Aleksandra Tomaszewska³, Martijn J. Moné¹, Carsten Carlberg³, Hans V. Westerhoff^{1,4,5}*



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Between 3 and 9 h
precisely b mRNAs
molecules
synthesized:
b = burst size
```







Could such epigenetics lead to transcription bursting and to Non-Poisson distributed mRNA?

The Fano factor =
$$F \stackrel{\text{def}}{=} \frac{\sigma^2}{\overline{n}} = \frac{\left(\frac{\sigma^2}{\overline{n}}\right)}{\left(\frac{\sigma^2}{\overline{n}}\right)_{Poisson}}$$

is a measure of the deviation from Poisson distribution

So, the issue is whether F >>1 due to bursting







Modelling backed up by Statistical Mechanics

Advance in Chemical Physics, Volume XXXIV Edited by I. Prigogine, Stuart A. Rice Copyright © 1976 by John Wiley & Sons, Inc.

THE EXPANSION OF THE MASTER EQUATION

N. G. VAN KAMPEN

Institute of Theoretical Physics of the University, Utrecht, Netherlands



For bursting transcription and linear degradation of mRNAs we derived for the noise in the number of mRNAs: LOGY



Implications:

- For burst size of 1: F=1, distribution is Poisson, variance equals the average
- F is ONLY a function of burst size, not of burst kinetics
- For burst size =100: F=50.5 and distribution far from Poisson, variance 50 times the average, so Yes, bursting can cause high F's









Confirmations by Gillespie modelling





Bursting: indeed a distribution much broader than Poisson









This can even produce a bimodal distribution







Indeed, the Fano factor is independent of k_{burst} and k_{deg}, whereas the other noise factors are not





Hence: one may infer the burst size from the Fano factor precisely because of the non identifiability









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MCF-7 cell, DNA stained with DAPI (blue) and mRNA stained with fluorescent ssDNA probe (red). Green and yellow circles enclose single mRNA molecules.

Distributions of the number of transcripts obtained through smFISH experiments, in MCF-7 cell lines.















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When starting from resting cells F increases as if cells begin to 'exploring'







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Pernette Verschure





Thierry Will Mondeel Beckman

Stefania Astrologo and many other teachers, colleagues and students





Before the tea break

14:40 Plenary lecture: <u>Hans V. Westerhoff</u>. Principles of systems biology and Dmitri Belyaev's co-selection of traits

- 15:10 *N.A. Kolchanov, <u>S.A. Lashin</u>*. Regulatory circuits in gene networks: organization and evolution
- 15:30 N. Sahin, H.V. Westerhoff, <u>A. Kolodkin</u>. Designing the emergence of progressive (PROP) and regressive (REP) preconditioning responses: from intelligent intracellular networks to the domestication of animals
- 15:50 <u>J.G. Koster</u>. Systems forensics: systems biology and the inference of crime
- 16:10 <u>M.V. Sharakhova</u>, A.A. Yurchenko, A.N. Naumenko, G.N. Artemov, V.N. Stegniy, I.V. Sharakhov. Evolutionary history of the malaria mosquitoes from maculipennis group in Eurasia