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Generating Tailored Solutions from Big Data: The Future of Health and Environmental Data Interrogation

In Silico Modeling of Biological Networks

Nathan Price

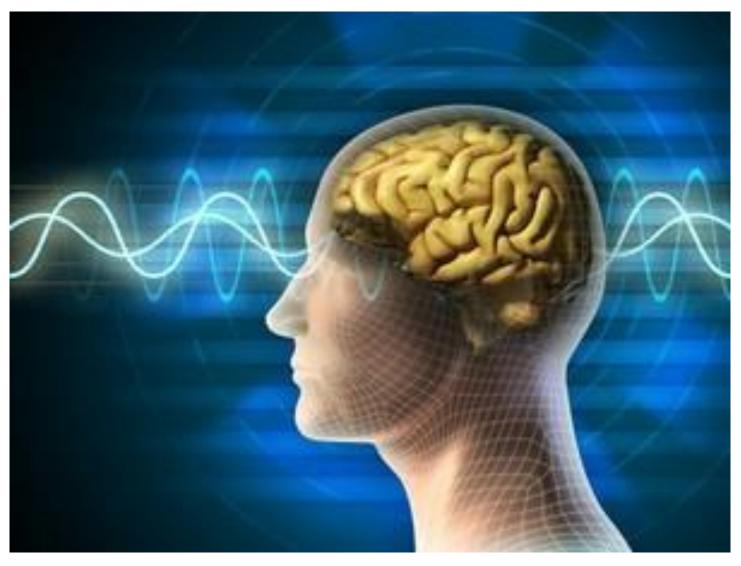


Disclosure

 Dr. Price has a significant financial interest in a commercial entity which partially funds, and which may license discoveries resulting from, the Hundred Person Wellness Project (to be described).

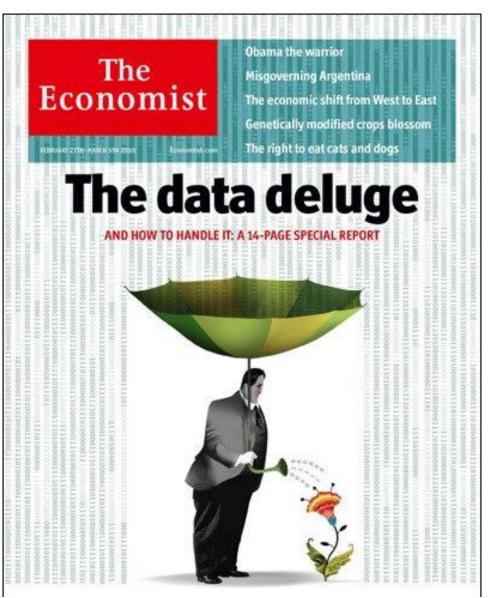


Extracting knowledge from data





We are NOT drowning in data in biology





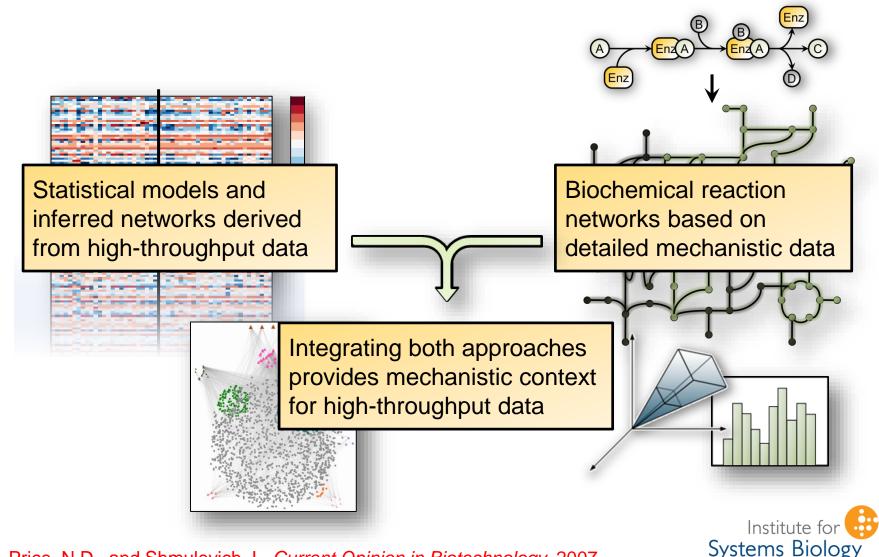




Network models as complex, rigorously structured hypotheses



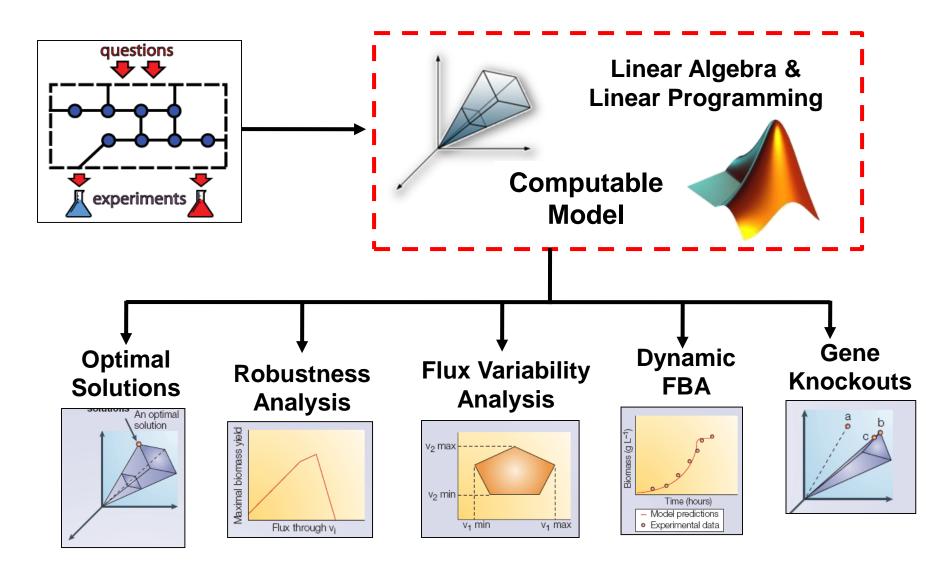
Statistical and mechanistic models provide context for data interpretation



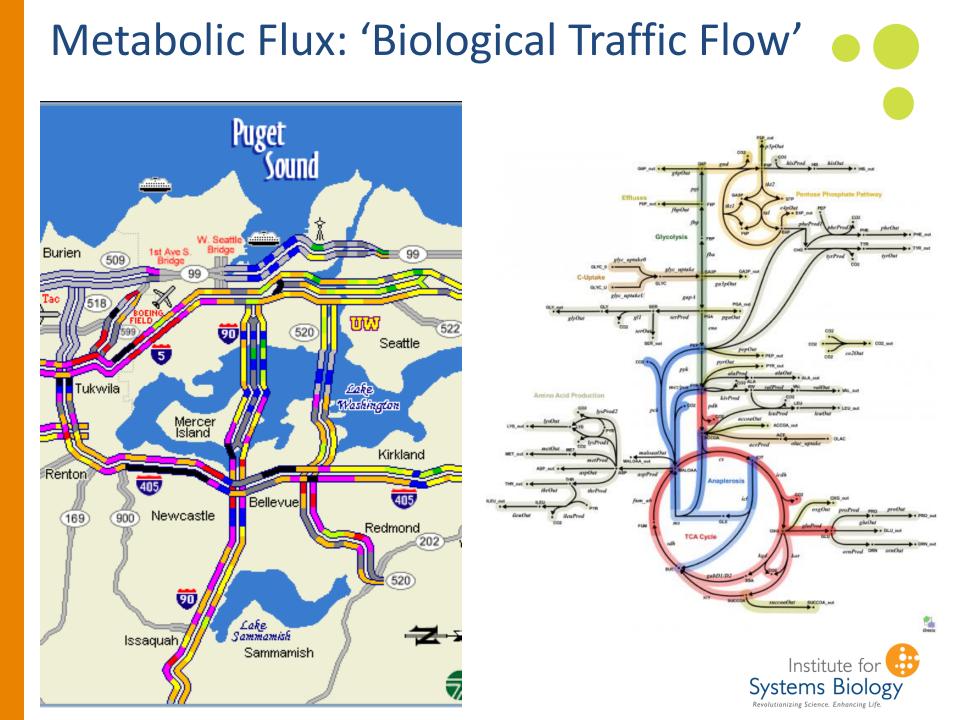
Revolutionizing Science. Enhancing Life

Price, N.D., and Shmulevich, I., Current Opinion in Biotechnology, 2007

Model simulations allow for phenotype prediction



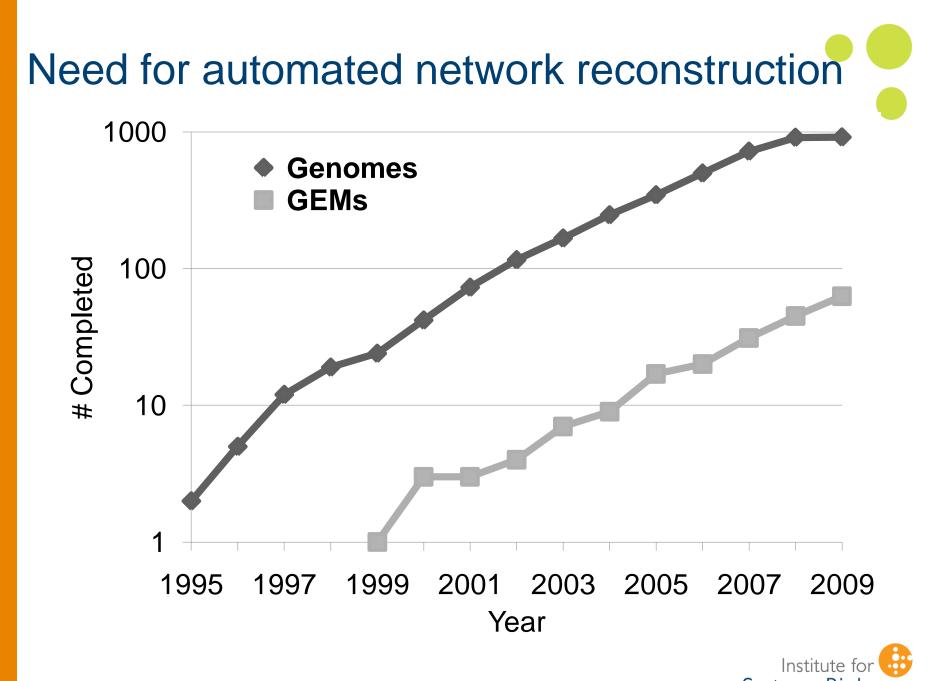
Becker, S. A. F. et al. 2007. Nature Protocols 23: 727-738. Price, N.D. et al.. 2004. Nature Reviews.2: 886



Complex array of regulatory control for metabolic traffic







C Milne, JA Eddy, PJ Kim, ND Price, *Biotechnology*

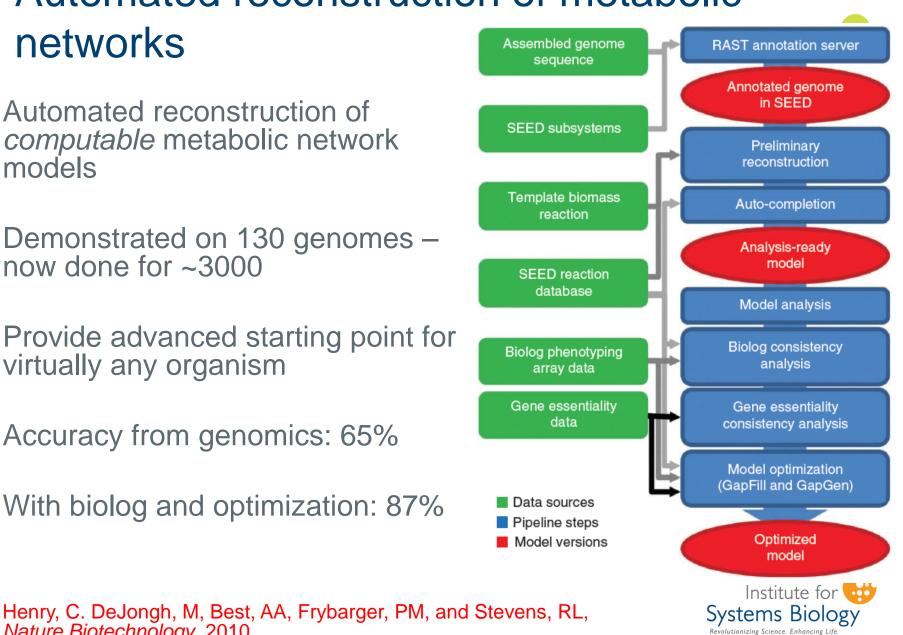
Systems Biology Revolutionizing Science. Enhancing Life.

Automated reconstruction of metabolic networks Assembled genome

- Automated reconstruction of *computable* metabolic network models
- Demonstrated on 130 genomes now done for ~3000
- Provide advanced starting point for virtually any organism
- Accuracy from genomics: 65%

Nature Biotechnology, 2010

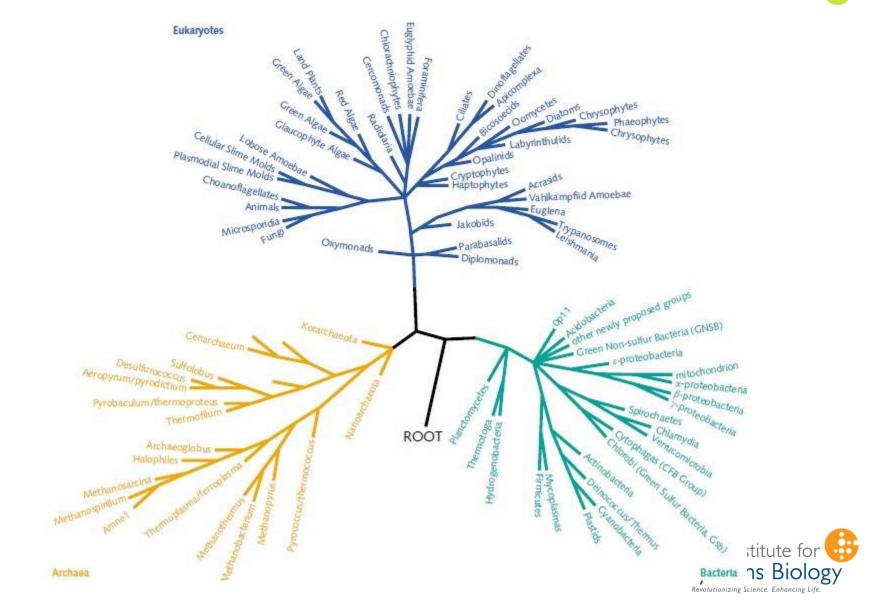
With biolog and optimization: 87%



Enormous scope of microbiomes motivates scalable approaches

Rearth microbiomeproject

Metabolic network expansion around key species in phylogenic tree



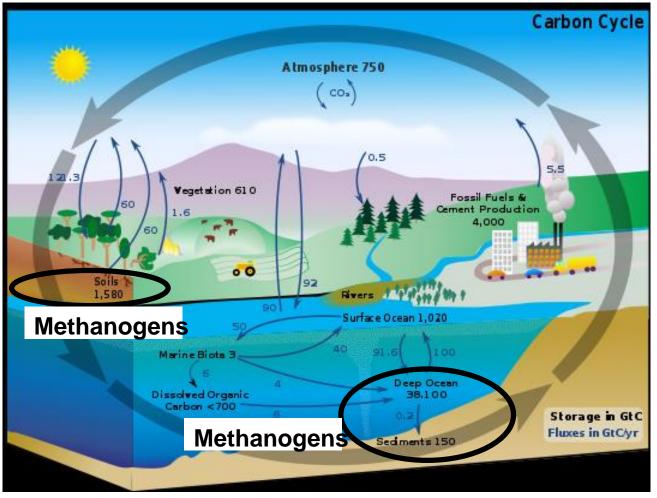
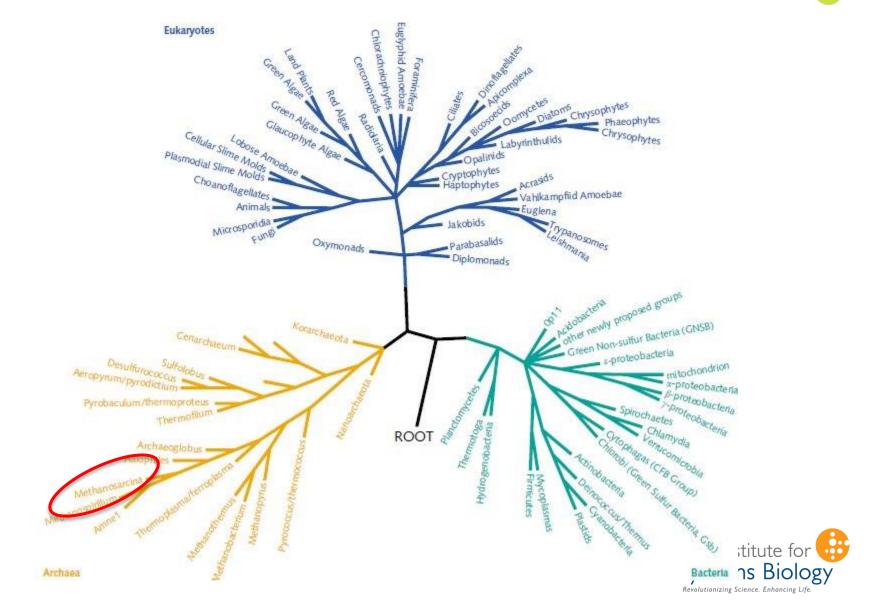




Image Source: NASA

Metabolic network expansion around key species in phylogenic tree



Two keystone manual reconstructions

- Methanosarcina barkeri
 - Gonnerman...Metcalf, Price, BMC Systems Biology, 2012
 - Feist...Palsson, Ideker, Molecular Systems Biology, 2006
- *Methanosarcina acetovorans*
 - Benedict...Metcalf, Price, Journal of Bacteriology, 2011



The *M. acetivorans* metabolic network is highly curated

Number of:					
Metabolic Genes	746				
Annotation Corrections	122 (16%)				
Reactions*	757				
Reactions with Genes	629 (83%)				
Reactions with Literature	289 (38%)				
Supporting Citations	159				

*: Excluding exchanges



Benedict, Gonnerman, Metcalf, Price, J. Bacteriol. (2011)

Validation of the *M. acetivorans* metabolic model

Experimental

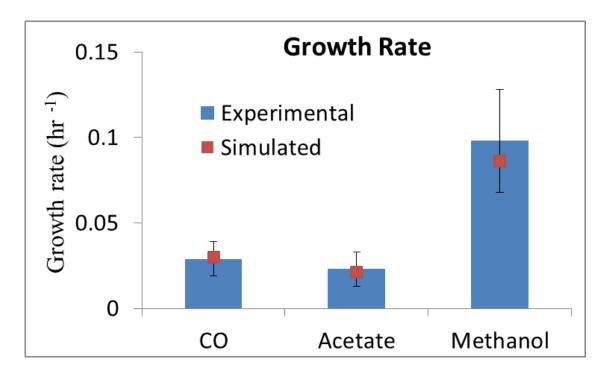
ed		Growth	No Growth			
Simulated	Growth	45/45	3/18			
Sim	No growth	0/45	15/18			
	TOTAL	95% correct				

Gene knockout lethality



Benedict, Gonnerman, Metcalf, Price, J. Bacteriol. (2011)

Quantitative Predictions of Growth Rates

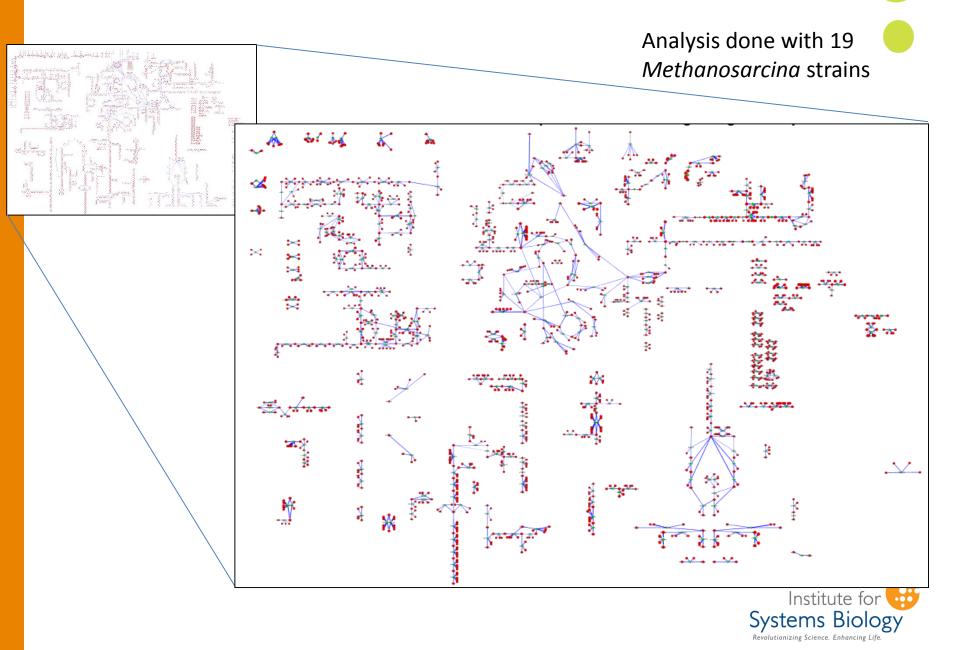


Growth rate predictions within experimental error

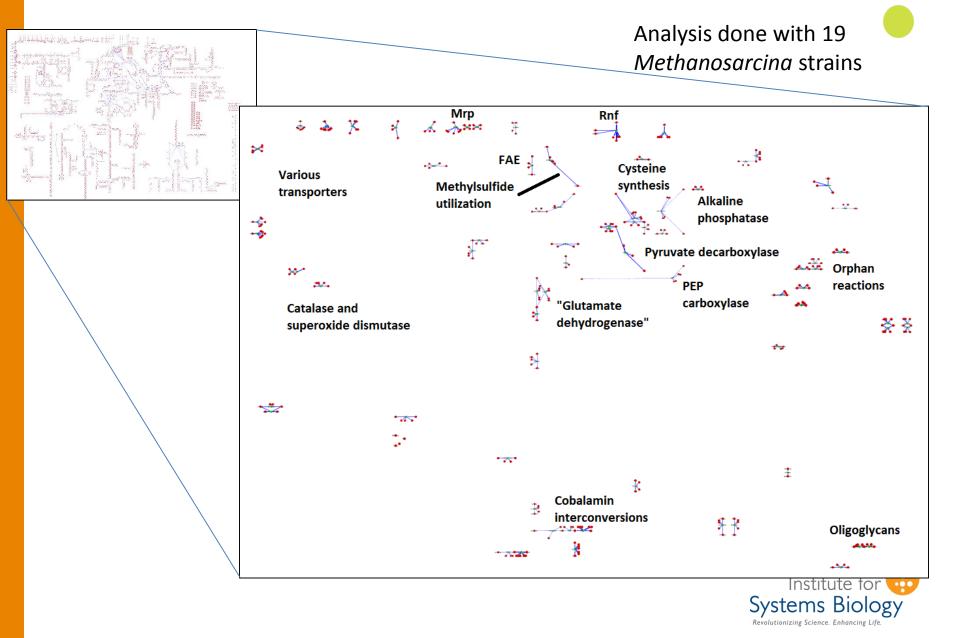


Benedict, Gonnerman, Metcalf, Price, J. Bacteriol. (2011)

Conserved Methanosarcina metabolism –



Variable *Methanosarcina* metabolism



		MrpABCDEF B	RnfABCDEF0	EchABCDEF EchC'	EhrABCDEF	VhtGACD (Vht) VhtACD VhtCD	VhtGAC(vhx\vho) VhtCCCD VhtCCCD	FrhADGB (Frh) FrhA' FrhADG (Fre)	HdrACB (ACB1) HdrCBA HdrCBA+Mvh	HdrA+Fd (A2) HdrCB (C2B2) HdrB' HdrB'	HdrED (D1) HdrD (D2)	
	Methanocorpusculum labreanum Z Methanospirillum hungatei JF 1 Methanosphaerula palustris E1 9c Methanoregula boonei 6A8 Methanoculleus marisnigri JR1 -Methanoplanus petrolearius DSM11571 Methanocella arvoryzae RC1	- - - - -						Ŀ				
	Methanocella paludicola SANAE Methanosaeta harundinacea 6Ac Methanosaeta thermophila PT Methanosaeta concilii GP6 Methanohalobium evestigatum Z 7303 Methanosalsum zhilinae DSM 4017 Methanomethylovorans hollandica WWM590 Methanohalophilus mahii DSM 5219 Methanococcoides burtonii DSM 6242 Methanococcoides methylutens MM1						1			F		
	Methanosarcina calensis cali Methanosarcina baltica type strain Methanosarcina sp. MTP4 Methanosarcina thermophila CHTI55 Methanosarcina thermophila TM1 DSM1825 Methanosarcina thermophila MST A1 Methanosarcina barkeri 3 Methanosarcina sp. Kolksee Methanosarcina barkeri 4 Methanosarcina barkeri Weismoor Methanosarcina barkeri Fusaro Methanosarcina barkeri 227 Methanosarcina barkeri MS											
0.1 Legend: Dataset Number of operons 0 1 2 3 4 5 6	Methanosarcina mazei LYC Methanosarcina mazei GO1 Methanosarcina mazei SG Methanosarcina mazei Sar pi Methanosarcina mazei WWM610 Methanosarcina mazei TMA Methanosarcina lacustris Z-7289 Methanosarcina lacustris ZS Methanosarcina thermophila TM1? Methanosarcina acetivorans C2A Methanosarcina naples 100 Methanosarcina siciliae C2J Methanosarcina siciliae T4M						ŀ			į		
	Methanosarcina siciliae HI350			 						Insti	tute to	or 👶

Tree visualized using iTOL (<u>http://itol.embl.de/</u>).

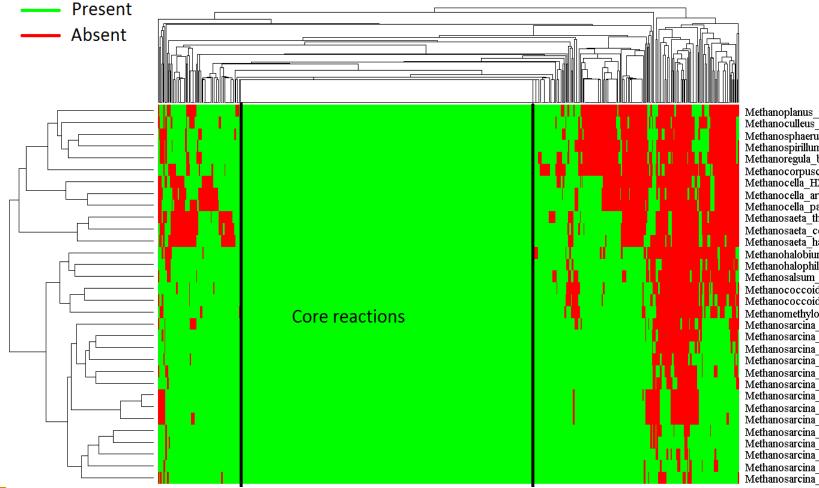
Systems Biology Revolutionizing Science. Enhancing Life.

Methanocorpusculum labrea Methanospirillum hungatei J Methanosphaerula palustris Methanoregula boonei 6A8	F1	RnfABCDEFGH EchABCDEF EchABCDEF	EhrABCDEF VhtGACD (Vht) VhtACD VhtCD	VhtGCD VhtGAC(vhx\who) VhtCCCD VhtD	FrhAUGB (Frh) FrhA' FrhADG (Fre) HdrACB (ACB1)	HdrCBA+Mvh HdrA+Fd (A2) HdrB (C2B2) HdrB HdrB	HdrD (D2)
Methanoculleus marisnigri Jl	DSM11571						
Methanocella arvoryzae RC Methanocella paludicola SAI Methanocella HZ254	1 ··· NAE ···						
Methanosaeta harundinacea Methanosaeta thermophila F							
Methanosaeta concilii GP6 Methanohalobium evestigatu	um Z 7303					1.1	
Methanosalsum zhilinae ĎSI Methanomethylovorans holla Methanohalophilus mahii DS	andica WWM590				- 6		
Methanococcoides methylut	DSM 6242				- E.		
Methanosarcina calensis cal Methanosarcina baltica type							
Methanosarcina sp. MTP4 Methanosarcina thermophila Methanosarcina thermophila	CHTI55						
Methanosarcina thermophila	MST A1						
Methanosarcina sp. Kolksee	-761						
Methanosarcina barkeri Weis Methanosarcina barkeri Fusi Methanosarcina barkeri 227							
0.1 Methanosarcina barkeri MS				-1 I			
Legend: Dataset Number of operons Dataset Number of operons							
Dataset Number of operons Methanosarcina mazei Sar p Methanosarcina mazei WWM			1.7				
¹ Methanosarcina mazei TMA ² Methanosarcina lacustris Z-7							
A Methanosarcina lacustris ZS							
⁵ Methanosarcina sp WH1 ⁶ Methanosarcina acetivorans ⁶ Methanosarcina naples 100						- 10 E	
Methanosarcina siciliae C2J Methanosarcina siciliae T4M	1 I I I						
Methanosarcina siciliae HI35	50						
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Tree visualized using iTOL (<u>http://itol.embl.de/</u>). Systems Biology							Biology

Tree visualized using iTOL (<u>http://itol.embl.de/</u>).

Revolutionizing Science. Enhancing Life.

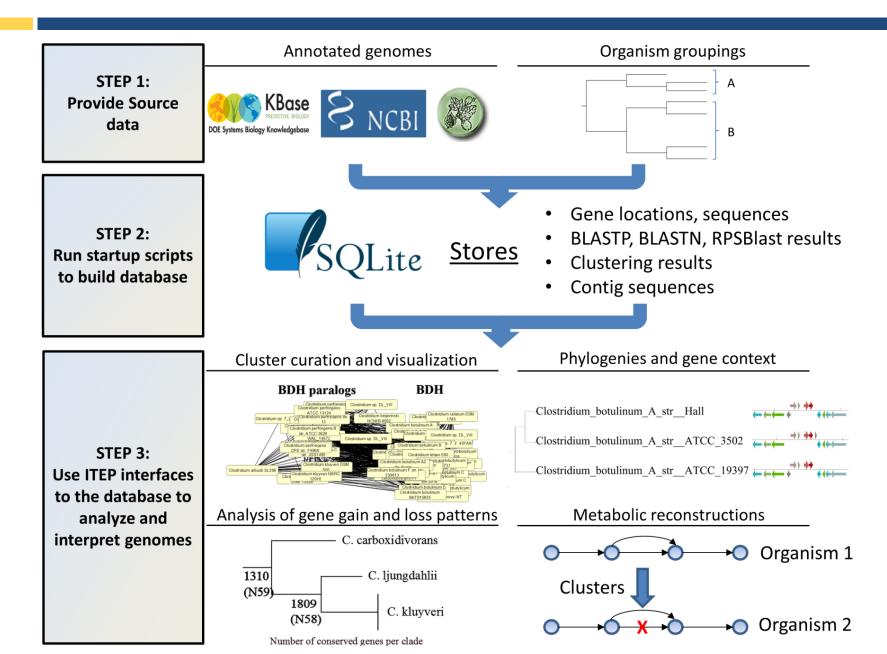
Comparison of curated Methanosarcina



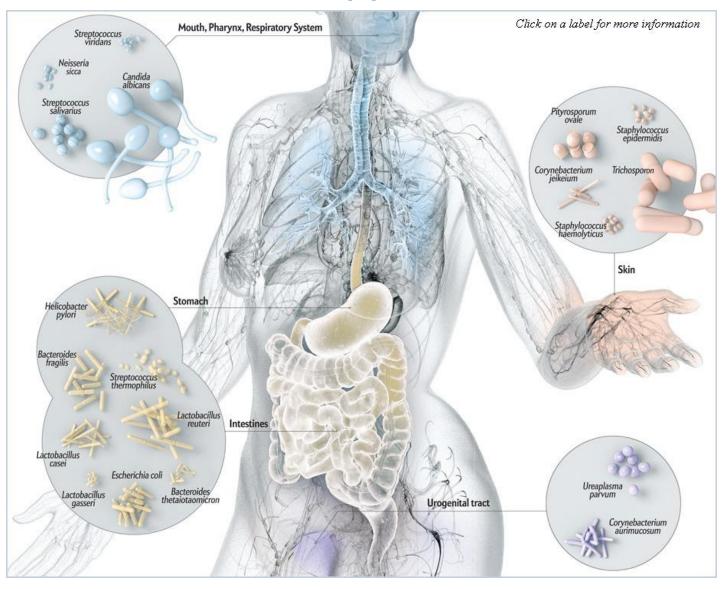
Methanoplanus petrolearius DSM1157 Methanoculleus marisnigri JR1 Methanosphaerula palustris E1_9c Methanospirillum_hungatei_JF_1 Methanoregula boonei 6A8 Methanocorpusculum labreanum Z Methanocella HZ254 Methanocella arvoryzae RC 1 Methanocella paludicola SANAE Methanosaeta thermophila PT Methanosaeta concilii GP6 Methanosaeta harundinacea 6Ac Methanohalobium evestigatum Z 7303 Methanohalophilus mahii DSM 5219 Methanosalsum zhilinae DSM 4017 Methanococcoides burtonii DSM 624 Methanococcoides methylutens MM1 Methanomethylovorans_hollandica_WV Methanosarcina baltica type strain Methanosarcina calensis cali Methanosarcina sp. MTP4 Methanosarcina mazei Sar pi Methanosarcina lacustris \vec{Z} -7289 Methanosarcina sp WHI Methanosarcina thermophila TM1 DS Methanosarcina thermophila CHTI55 Methanosarcina thermophila MST A1 Methanosarcina naples 100 Methanosarcina acetivorans C2A Methanosarcina siciliae T4M Methanosarcina barkeri Fusaro Methanosarcina vacuolata Z-761



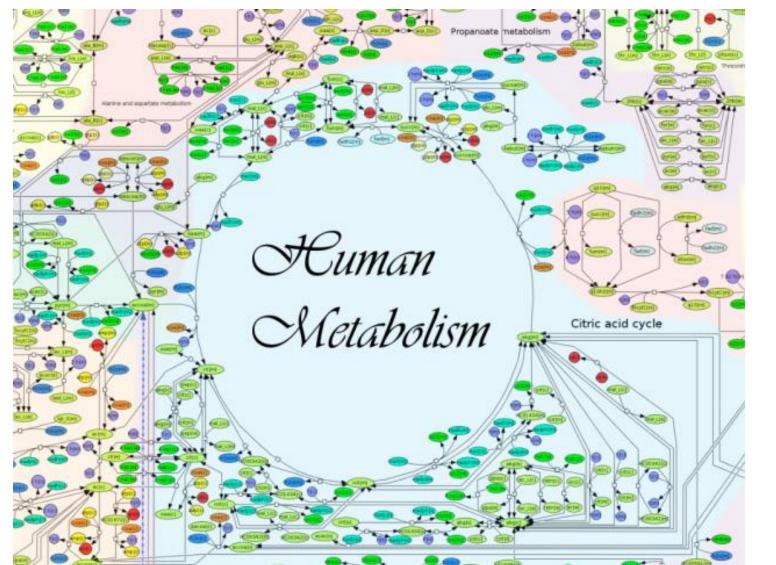
ITEP: A toolkit for comparative genomics and curation



Enormous scope of microbiomes motivates scalable approaches



A "Google Map" of Human Metabolism



PROM: Chandrasekaran and Price, PNAS, 2010 mCADRE: Wang, Eddy, Price, BMC Systems Biology, 2012 GEMINI: Chandrasekaran and Price, PLOS Computational Biology, 2013 RECON2: Thiele et al, Nature Biotechnology, 2013

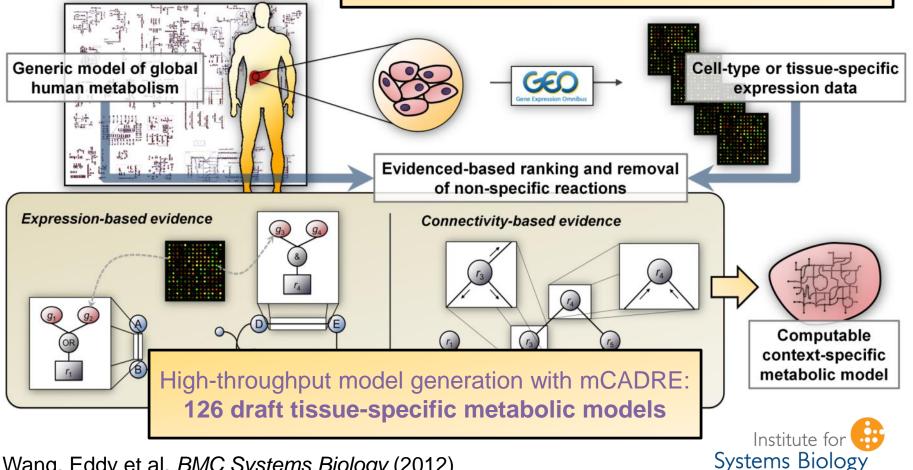


mCADRE

Semi-automated tissue-specific model generation

Metabolic Context-specificity Assessed by **Determinisitic Reaction Evaluation (mCADRE)**

Revolutionizing Science. Enhancing Life



Wang, Eddy et al. BMC Systems Biology (2012)

Early success: prediction and validation of synthetic lethal targets for combination

LETTER

doi:10.1038/nature10363

Haem oxygenase is synthetically lethal with the tumour suppressor fumarate hydratase

Christian Frezza¹, Liang Zheng¹, Ori Folger², Kartik N. Rajagopalan³, Elaine D. MacKenzie¹, Livnat Jerby², Massimo Micaroni⁴, Barbara Chaneton¹, Julie Adam⁵, Ann Hedley¹, Gabriela Kalna¹, Ian P. M. Tomlinson⁶, Patrick J. Pollard⁵, Dave G. Watson⁷, Ralph J. Deberardinis³, Tomer Shlomi⁸*, Eytan Ruppin^{2,9}* & Eyal Gottlieb¹

- Germline mutations of FH are responsible for hereditary leiomyomatosis and renal-cell cancer
- Use genome-scale metabolic model to explain how these cells survive without a complete TCA cycle
- Then identify specific target that is lethal in the new metabolism, and NOT to normal human metabolism
- Cell experiments then validated the finding *Nature* 2011



Take home points 1

- One critical factor in understanding the environment is mapping out the functions of microbes
- Genome-scale metabolic models and community interaction network models can aid in this task
- Similar approaches can be employed in humans, providing a platform for studying symbiotic and pathogenic relationships
- Initial success for human metabolic network modeling in predicting new candidate cancer therapy that has been initially experimentally validated



Bringing P4 Medicine to Practice





The convergence of three revolutions leads to proactive P4 medicine

Digital Revolution--Big Data Sets And Analysis

> P4 Medicine

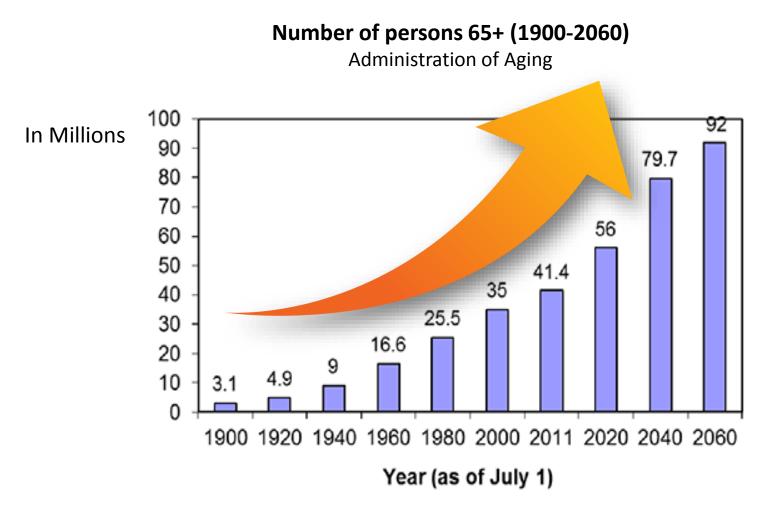
Patient-driven Social Networks Personalized Predictive Preventive Participatory

Systems Medicine



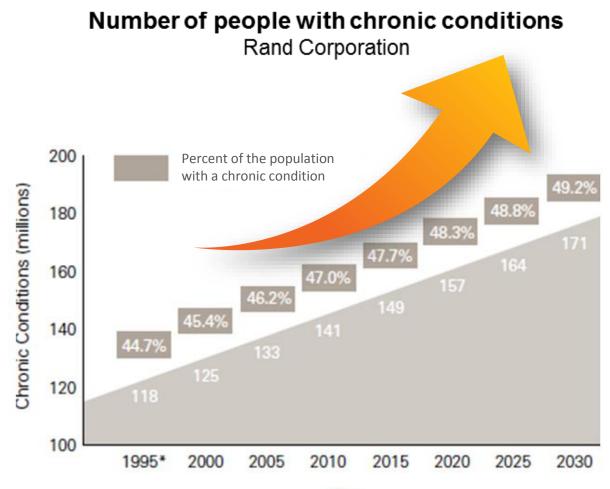


Aging Populations: Skyrocketing





Chronic Disease: Skyrocketing



Year



The Problem

 Current medical field focused entirely on care after illness

 Data is based on What if this were different?

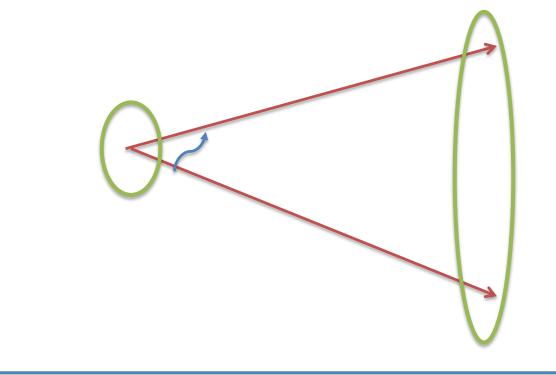
chronically ill





Health: What do we really want to understand?

Health



- Bigger effect size
- Larger likelihood for paper
- Smaller sample size required
- Less \$

Time

- Longitudinal
- More complex study
- Larger sample size required
- More \$\$\$





- 100 participants
- 9-month study started in March
- IRB approved

- Whole genome sequence
- Detailed blood, urine, saliva measurements 3x
- Gut microbiome 3x
- Continual activity and lifestyle monitoring
- Discovery research on samples
- Data integration
- Coaching, events, education



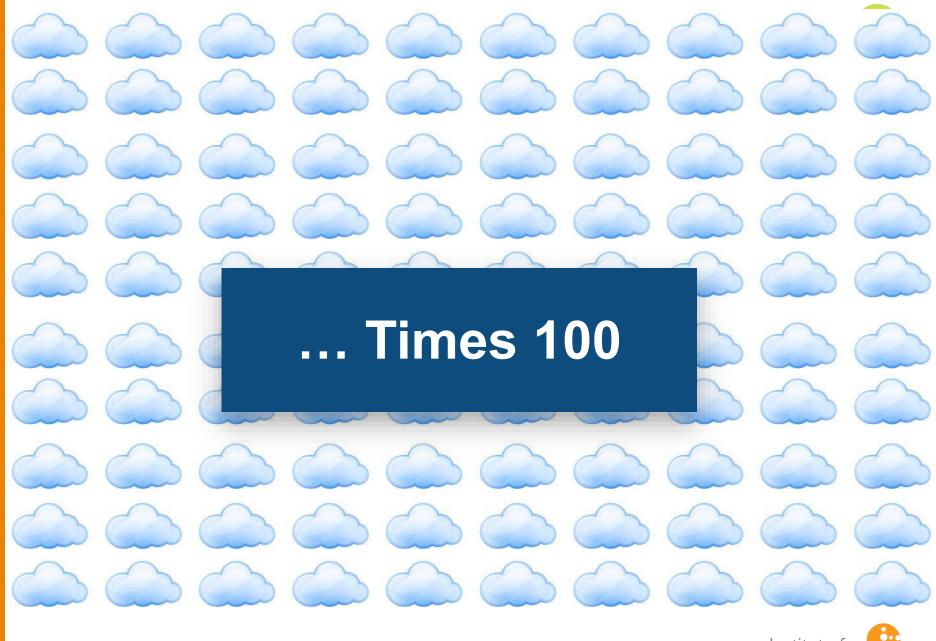
A Systems Medicine Approach to Wellness



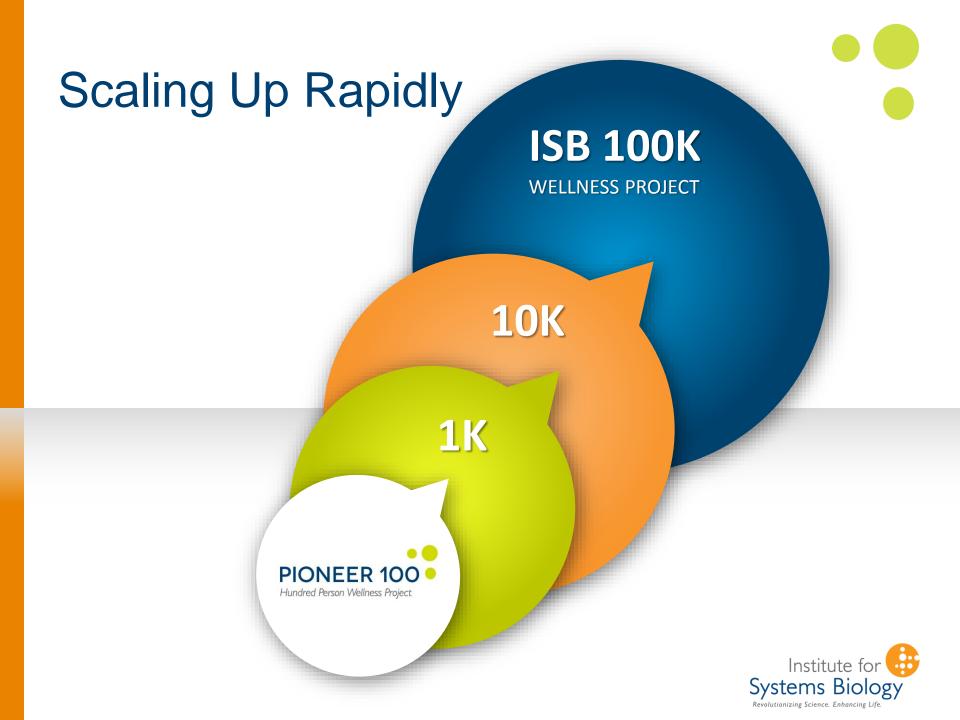
A Unique, N=1 Data Cloud

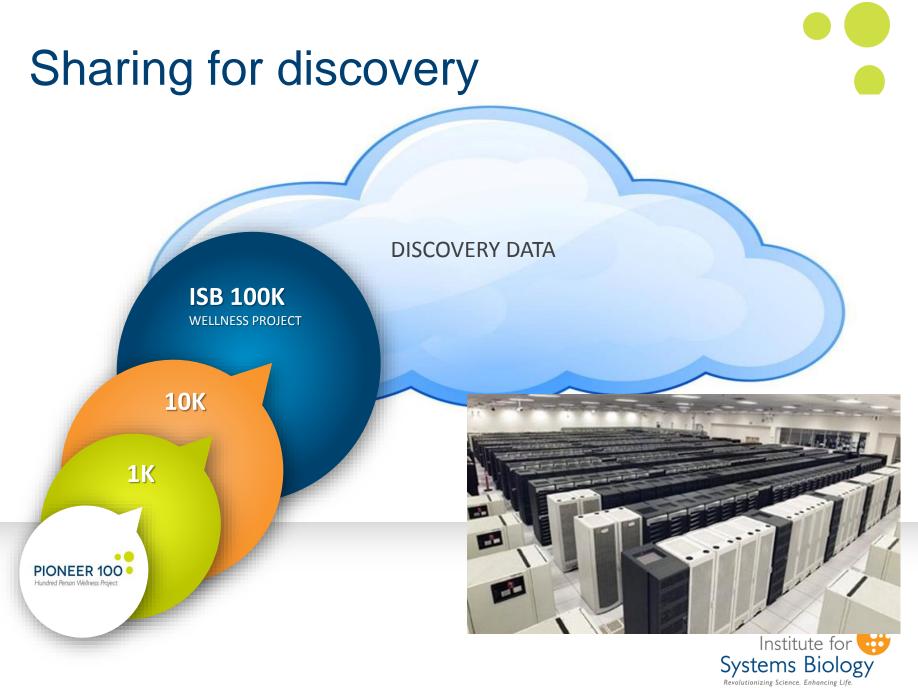












Three scales of analysis

- Short term—optimize wellness and reduce disease for each individual patient and reduce the costs
- Intermediate term—longitudinal assessments of individuals over time and what brings about change
- Long term—generate a data base from individuals that will allow us to follow transitions from wellness to disease for major diseases



N = 1

N <= 100K



From complexity, simplicity

5 I would not give a fig for the simplicity on this side of complexity; but I would give my right arm for the simplicity on the far side of complexity

Oliver Wendell Holmes



Goals



- 1. Establish scientifically validated metrics for wellness
- 2. Determine "actionable items" to present to individuals participating in 100-person pilot project
- 3. Identify transitions between disease and wellness
- 4. Identify what benefits are compelling for individuals



Conclusion and Further Reading

Clinical OMICs INNOVATOR

Promoting Wellness & Demystifying Disease: The 100K Project

Leroy Hood, M.D., Ph.D., and Nathan D. Price, Ph.D.

EDITORIAL



Demystifying Disease, Democratizing Health Care

SYSTEMS BIOLOGY

UNSUSTAINABLE COST INCREASES THREATEN THE GLOBAL HEALTH CARE SYSTEM, and further progress is stymied more by societal than technological factors. Only by engaging health care consumers (that is, patients) as pioneers who provide both health-related data and insights into pathophysiology can we meet these societal challenges and thus accelerate the pace of biomedical innovation.

In March 2014, the Institute for Systems Biology will launch a longitudinal, Framingham-

Leroy Hood is President of the Institute for Systems Biology, Seattle, WA 98109, USA E-mail Ihood@ like study (www.framinghamheartstudy.org) of 100,000 (100K) healthy individuals that we systemsbiology.org believe will be instrumental in bringing predictive, preventive, personalized, and participatory (P4) medicine to patients. Participatory medicine means that patients, researchers,



Nathan D. Price is Associate Director of the Institute for Systems Biology, Seattle, WA 98109, USA. E-mail: nprice@ systemsbiology.org

Citation

L Hood, N. D. Price, Demystifying disease, democratizing health care. Sci. Transl. Med. 6, 225ed5 (2014)

medicine to make it more proactive than reactive-and, in turn, less expensive and more effective (1). **PEOPLE POWER** A systems approach is necessary for the effective management of complex diseases (1). This fundamental component of P4 medicine is built on two central features. The first is a conviction that, in 5 to 10 years, each patient will have a dynamic data cloud consisting of billions of diverse types of data points and that medicine will be informed by computational analy-

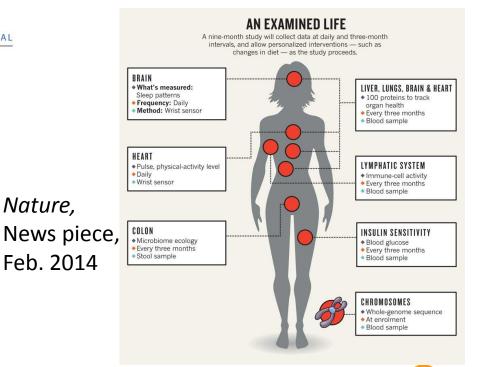
physicians, and the entire health care community join forces to transform the practice of

ses that reduce high-dimensional data to actionable hypotheses designed with the intent of optimizing wellness and minimizing disease in individual patients. The second feature is that integration of patient data will reveal biological networks that specify health and are altered in disease, and that through an understanding of these differences, one can gain fundamental insights into disease mechanisms. Such insights are essential for developing more effective diagnostic and therapeutic approaches. Indeed, such an approach has already provided powerful new technologies and strategies (2) that have brought us to the brink of P4 medicine (3).

At its foundation, P4 medicine is about quantifying wellness and demystifying disease. Individual data clouds will let us predict future wellness and disease. The preventive element focuses on how well we can improve individual wellness and take actions to stop or de-

Hood and Price, Science Translational Medicine (2014)

Hood and Price, Clinical Omics, May. 2014





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<u>Scientific Project Manager</u> Julie Bletz

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Collaborators

Lee Hood (ISB) Bill Metcalf (Illinois)



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- Department of Defense
- Energy Biosciences Institute (BP)
- Roy J. Carver Young Investigator Award
- Camille Dreyfus Teacher-Scholar Award



Roy J. Carver

Energy Biosciences