Systems medicine approach to model cell signaling activity uncovers disease mechanisms and predicts cancer outcome

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This ultimately involves the knowledge of **disease** and **drug action mechanisms** Requires of a better way of defining diseases by introducing **genomic** technologies in the **diagnostic** procedures and **treatment decisions** 

## Single-gene biomarkers are the result of probabilistic associations

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http://www.fda.gov/drugs/scienceresearch/researchareas/pharmacogenetics/ucm083378.htm

# Most "personalized" therapies are based on this type of biomarkers

### Despite most biomarkers used are single gene variants, most human genetic diseases (and almost all traits) have a modular nature

- Conventional single-gene biomarkers have a demonstrated clinical utility. However, their success is purely probabilistic, often modest and frequently lack any mechanistic anchoring to the fundamental cellular processes responsible for the disease or therapeutic response.
- Modular nature of genetic diseases: Causative genes for the same or phenotypically similar diseases may generally reside in the same biological module, either a protein complex (Lage et al, 2007), a sub-network of protein interactions (Lim et al, 2006), or a pathway (Wood et al, 2007)

Disease genes are close in the interactome





Fernandez, 2013, Orphanet J Rare Dis.

Same disease in different populations is caused by different genes affecting the same functions

#### There are exceptions: MammaPrint, an example of successful breast cancer decision support test based on a multigenic biomarker

#### 1 Finding genes

INSIGHT HEVILO

Karin van der Kooy\*, Matthew J. Marton‡, Anke T. Witteveen\*, George J. Schreiber‡, Ron M. Kerkhoven\*, Chris Roberts‡, Peter S. Linsley‡, René Bernards\* & Stephen H. Friend‡ \* Divisions of Diagnostic Oncology, Radiotherapy and Molecular Carcinogenesis and Center for Biomedical Genetics, The Netherlands Cancer Institute, 121 Plesmanlaan, 1066 CX Amsterdam, The Netherlands

Yudong D. Het, Augustinus A. M. Hart\*, Mao Maot, Hans L. Peterse\*,

Gene expression profiling predicts

Clinical outcome of breast cancer Laura J. van 't Veer't, Hongyue Daitt, Marc J. van de Vijver't,

121 Personanaam, 1000 CA Amsternam, 110 Pernerations ‡ Rosetta Inpharmatics, 12040 115th Avenue NE, Kirkland, Washington 98034, USA † These authors contributed equally to this work



low

risk



Assessing functions

By historic reasons genes were first selected and their functionalities were assessed afterwards.

Biological Function	MammaPrint Gene Count	
Metabolism	7	
Cell cycle and DNA replication	12	
Extracollular matrix adhesion and remodeling	5	
Growth, proliferation, transformation and cell death	12	
General signal transition and intracellular transport	1	
Growth factor	¥6	
MatEty or activ flament related	5	
HitaceRalar hydrofase	1	
Immune response	1	
Wearoprotiste	1	
Predicted transment/brane protein with uninum function	2	
Predicted transcriptional control or DNA binding proteins	5	
Unknown function	4	
Total Gene Count	70-	

Risk is calculated as a function of the 70 gene expression levels

risk= $f(gene_1, gene_2, ... gene_{70})$ 

#### Enabling personalized cancer medicine through analysis of gene-expression patterns

Therapies for patients with cancer have changed gradually over the past decade, moving away from the administration of broadly acting cytotoxic drugs towards the use of more-specific therapies that are targeted to each timesor. To facilitate this shift, tasks meet to be developed to identify those individuals who require therapy and those who are most likely to benefit from certain therapies. In particular, tests that predict the clinical outcome for patients on the basis of the genes expressed by their tumous are likely to increasingly affect patient management, heraiding a new era of personalized medicine.

The strength of this approach is that it is unbiased: there are no assumptions about which genes are likely to be involved in the process of interest. For example, in a **data-driven** study of the prognosis of patients with breast cancer, **little was known about the function** of 15 of the 70 genes that were found to constitute a prognostic gene-expression signature<sup>4</sup>. A drawback of this approach is that the **outcome relies solely on the quality of the data** (and the samples).

By contrast, using the **knowledge-driven** approach, genes that are thought to be relevant to a particular cancer trait are selected on the basis of the scientific literature.



high

# Change in the paradigm



MammaPrint and other multigenic biomarkers: bottom up, from genes to functions that define one (or several) biological modules.



Models of cell functionality: top-down mechanism-based biomarkers, from biological modules to genes

# Two problems: defining functional modules and modeling their behavior







#### Gene ontology:

descriptive; unstructured functional labels Enrichment methods. GO, etc. (simple statistical tests). No information on how components relate among them

**Behavior** 

Interactome: relationships among components but unknown function Connectivity models. Protein-protein, protein-DNA and protein-small molecule interactions (tests on network properties). No information the functional roles of the components



#### Pathways:

relationships among components and their functional roles Mathematical models. Kinetic models including stoichiometry, balancing reactions, etc. Computational models. Models of signalling pathways, metabolic pathways, regulatory pathways, etc. (executable models)

## Defining the module: Pathways: maps of cell activity (in sickness and in health)



# **Defining pathway activity**

We first need a map: pathways are defined in different repositories (KEGG, Reactome, Biocarta, disease maps, etc.)

What pathway level makes a real biological meaning?

Gene sub-pathway pathway

ALE DEC

DRA Date

(Here)

Enrichment methods (pathway-level): Different and often opposite cell behaviors are triggered by the same **pathway**. E.g.: death and survival

Death

Survival

Sub-pathway (elementary circuit) connects stimulus to response

**Gene level:** The same gene can trigger different (and often opposite) responses, depending on the stimulus

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# Decomposition of a pathway into their elementary circuits



## How realistic are models of pathway activity?

#### RESEARCH ARTICLE

#### CANCER

#### Signaling pathway models as biomarkers: Patient-specific simulations of JNK activity predict the survival of neuroblastoma patients

Dirk Fey,<sup>1</sup> Melinda Halasz,<sup>1</sup> Daniel Dreidax,<sup>2</sup> Sean P. Kennedy,<sup>1</sup> Jordan F. Hastings,<sup>2</sup> Nora Rauch,<sup>1</sup> Amaya Garcia Munoz,<sup>1</sup> Ruth Pilkington,<sup>1</sup> Matthias Fischer,<sup>4,5,6</sup> Frank Westermann,<sup>2</sup> Walter Kolch,<sup>1,7,8</sup> Boris N. Kholodenko,<sup>1,7,8</sup>\* David R. Croucher<sup>1,2,9</sup>\*

Signaling pathways control cell fate decisions that ultimately determine the behavior of cancer cells. Therefore, the dynamics of pathway activity may contain prognostically relevant information different from that contained in the static nature of other types of biomarkers. To investigate this hypothesis, we characterized the network that regulated stress signaling by the c-Jun N-terminal kinase (JNK) pathway in neuroblastoma cells. We generated an experimentally calibrated and validated computational model of this network and used the model to extract prognostic information from neuroblastoma patkent-specific simulations of JNK activation. Switch-like JNK activation mediates cell death by apoptosis. An inability to initiate switch-like JNK activation in the simulations was significantly associated with poor overall survival for patients with neuroblastoma with or without *MYCN* amplification, indicating that patients-specific simulations of JNK activation could stratify patients. Furthermore, our analysis demonstrated that extracting information about a signaling pathway to develop a prognostically useful incide requires understanding of not only components and disease-associated changes in the abundance or activity of the components but also how those changes affect pathway dynamics. Beyond static biomarkers—The activity of signalling networks as an alternate biomarker?

Fey et al., Sci. Signal. 8, ra130 (2015).

Inability of JNK activation (that mediates apoptosis) is associated to bad prognostic, irrespective of *MYCN* amplification status



Fig. 1. Using network descriptors of signaling pathway activation potential to predict patient response. After construction of a computational model based on the validated network topology and that reproduces the signaling pathway dynamics, the model can be used to identify network descriptors, such as the Hill coefficient, that are calculated from the dynamic simulation of the activation of a signaling pathway. These in silico biomarkers cannot be directly measured.

Problem: ODE can efficiently solve only small systems

## Signal propagation models of signaling pathways





...to profiles of circuit activity (and functional activity)

### Are scalable

# Gene expression data are transformed into signal activity intensities



A simple transformation of raw data (normalization) and an algorithm for signal propagation results in accurate estimations of circuit activities.

The same concept that MammaPrint,  $risk= f(gene_1, gene_2, ... gene_{70})$ but based on biological knowledge, is used here to estimate cell functional activity

### Models of signaling activity provide high-throughput estimations of intensity activation of cell functions from gene expression measurements



Hypothesis: the intensity at which functions are triggered by the signaling system of the cell is more related to phenotypes than the intensity of gene expression

# Signaling activity trigger cell functions directly related to cancer progression



DNA replication= $f(gene_1, gene_2, ... gene_n)$ 

Hidalgo et al., 2017 Oncotarget

DNA replication function is a construct: the activity is inferred not measured

# Actually, signal activity triggers all the cancer hallmarks



generation. Cell 144, 646

### The inferred function activity (mechanistic biomarker) is more correlated to survival than the activity of any gene (conventional biomarker) in the circuit





## Different cancer use different gene expression programs to activate the same functions



## Signal intensity over certain functions increases in the initiation of cancer while on others increases with cancer stage







**Cancer progression** 

## Circuit activation probabilities can be used as features for predictors

## 1. Generation of features: signaling circuit activities



2. Training set



Circuit activation probabilities are mechanism-based biomarkers

#### 3. Prediction



# Prediction of IC<sub>50</sub> values from the activity of signaling circuits





Amadoz et al., Sci. Rep. 2015

# **Actionable models**

The real advantage of models is that, the same way they can be used to convert omics data into measurements of cell functionality that provide information on disease mechanisms and drug MoA, they can be used to test hypothesis such as "*what if I suppress (or over-express) this (these) gen(es)?*" This lead to the concept of **actionable models**.

By **simulating** changes of gene expression/activity it is easy to:

- Directly study of the consequences of induced gene over-expressions or KOs
- Carry out reverse studies of genes that need to be perturbed to change cell functionalities, such as:
  - Reverting the "normal" functional status of a cell
  - Selectively kill diseased cells without affecting normal cells
  - Enhancing or reducing cell functionalities (e.g., apoptosis or proliferation, respectively, to fight cancer)
  - Etc.

# Model validation (1)

#### The activity of some signaling circuits is correlated with cell survival

Survival data from Achilles cell line KOs (Broad Institute) can be compared to the change in circuit activities **predicted** by the model



**Essential circuits**: once found, other ways of deactivating these circuits can be find, opening the door to knowledge-based target discovery

# Model validation (2)

- 1) Prediction of other gene targets, whose inhibition (modeled KO) deactivate these circuits
- 2) Validation of the real KO effects with Achilles II (Tsherniak A, et al. 2017, Defining a cancer dependency map. Cell 170: 564-576)



# Interventions on pathways made easy

Nucleic Acids Research, 2016 1 doi: 10.1093/nar/gkw369

# Actionable pathways: interactive discovery of therapeutic targets using signaling pathway models

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#### Freely available software PathAct http://pathact.babelomics.org/

# **Actionable pathway models**

We can inhibit EGFR (target of Afanatib) by reducing its activity value (0.56 in cancer). Absolute KO value = 0



Estrogen signaling pathway

http://pathact.babelomics.org/

## **Actionable pathway models**



The inhibition of the transcription sought has been attained, but six more pathways have been affected in different ways

http://pathact.babelomics.org/

# **Actionable pathway models**





Transcription, angiogenesis and other are inhibited in *ErbB signaling pathway* 



Cell cycle inhibited in *Proteoglycans in cancer pathway* 

Cell cycle is inhibited in Oxytocin signaling pathway

#### http://pathact.babelomics.org/

# **Simulating drug inhibition**

Q EGFr	† 1 Adherens junction	Q EGFr	<b>† ↓</b> Adherens junction	
EGFR 0,1 ×	<ul> <li>t ErbB signaling pathway</li> <li>t Estrogen signaling pathway</li> <li>t GnRH signaling pathway</li> </ul>	EGFR 0,1 ×	<ul> <li>t ErbB signaling pathway</li> <li>t Estrogen signaling pathway</li> <li>t Focal adhesion</li> </ul>	
	1 Uxytocin signaling pathway		GnRH signaling pathway	
	† 1 Pathways in cancer		T + HIF-I signaling pathway	
Additional drug targets:	† 1 Proteoglycans in cancer	Additional drug targets:	Oxytocin signaling pathway	
	Adipocytokine signaling pathway Adrenergic signaling in cardiomyocytes AMPK signaling pathway Apoptosis B cell receptor signaling pathway	ERBB2     0,1       Afatinib * inhibitor     0,1       ERBB4     0,1       Afatinib * inhibitor     0,1	Adrenergic signaling pathway Adrenergic signaling pathway Apoptosis	
	Calcium signaling pathway	T. Deleted doublish	B cell receptor signaling pathway	
A Related drug list:	cAMP signaling pathway	A Related drug list:		
Configure target actions	Colloudo	至 Configure target actions		
□ IMC-11F8 ▲		□ IMC-11F8	Real inhibition with	
□ INSM-18	Q EGFr	INSM-18	Afanatib affacts 11	
S-{3-[(4-ANILINOQUINAZOLIN-6-YL)	EGFR 0,1 ×	S-{3-[(4-ANILINOQUINAZOLIN-6-YL)	Alahalib allects 11	
□ N-[4-(3-BROMO-PHENYLAMINO)-Q □ Afatinib ▼	<b>⊿</b> Trastuzumab	N-[4-(3-BROMO-PHENYLAMINO)-Q	pathways	
		1 Adherens junction		
	Additional drug targets:	↑↓ ErbB signaling pathway		
"Ideal" KO of	ERBB2 0,1	↑↓ Estrogen signaling pathway		
ECED offecte 7	Trastuzumab 🕈 antibody	↑↓ Fc gamma R-mediated phagocytosis		
EGER allects /	C1R 0,1	↑↓ Focal adhesion		
pathways	▲ Trastuzumab	↑↓ GnRH signaling pathway		
paamayo		↑↓ HIF-1 signaling pathway	Inhibition with	
	Related drug list: E Configure target actions	↑↓ Natural killer cell mediated cytotoxicity	broader spectrum	
	Cetuximab	1 J Oxytocin signaling pathway	Trastuzumah	
	Trastuzumab	↑↓ Pathways in cancer	παδιαζαπίαυ	
	Lidocaine	↑ ↓ Platelet activation	affects 13 pathways	
	Getitinib	↑ ↓ Proteoglycans in cancer		
		↑ ↓ Transcriptional misregulation in		

## An example with SRC gene. Predicted to be essential in melanoma cell lines



## Prediction of essential genes that were never experimentally tested before



Dasatinib, a specific inhibitor of *SRC*, demonstrates the essentiality of *SRC* predicted because the inhibition of the gene predicts the inhibition of an onco-circuit



# Metabolic pathways can also be modeled

There are 94 modules that recapitulate the main aspects of metabolism of carbohydrates, lipids, amino acids and nucleotides

Metabolic activity:

$$S_n = n_i \cdot \left(1 - \prod_{s_a \in A} (1 - n_a)\right)$$

Where  $n_i$  is the activity of the current node n, A is the total number of edges arriving to the node that account for the flux of metabolites produced in other nodes with activity values  $n_a$ .

hsa\_M00010 Citrate cycle, first carbon oxidation, oxaloacetate => 2-oxoglutarate



**Differential metabolic activity**: two conditions are compared by means of a Wilcoxon test (FDR adjusted across modules)

#### Metabolic modules capture differential metabolic activity



#### Metabolic modules also capture cell functionality associated to cancer prognostic

High activity of *Guanine ribonucleotide biosynthesis* and *Pyrimidine ribonucleotide biosynthesis* modules is associated to **low survival**. These modules are target of *Mercaptopurine* and *Gemcitabine*. The mechanism of action of these drugs involves inhibition of DNA synthesis and that leads to cell death



# Prediction of gene essentiality from metabolic pathway essentiality

Pyrimidine degradation pathway was predicted to be an onco-module in gastric cancer cell lines. Predicted genes that switch the pathway off are *DPYD*, *DPYS* (confirmed in Achilles) and *UPB1* 



UPB1 encodes an enzyme ( $\beta$ -ureidopropionase) that catalyzes the last step in the pyrimidine degradation pathway, required for epithelial-mesenchymal transition

#### Models of cell functional activity bring the dream of precision personalized (even individualized) treatments closer



From: Dopazo, 2014, Genomics and transcriptomics in drug discovery. Drug Discovery Today

## The real transition to precision medicine



The use of new algorithms that enable the transformation of <u>genomic</u> measurements into <u>cell functionality</u> measurements that account for <u>disease mechanisms</u> and for <u>drug mechanisms of action</u> will ultimately allow the real <u>transition</u> from today's empirical medicine to <u>precision</u> <u>medicine</u> and provide an increasingly <u>personalized medicine</u>

#### **Clinical Bioinformatics Area** Fundación Progreso y Salud, Sevilla, Spain, and...

... the INB-ELIXIR-ES, National Institute of Bioinformatics and the BiER (CIBERER Network of Centers for Research in Rare Diseases)



https://www.slideshare.net/xdopazo/

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