

SYSTEMS BIOLOGY AND DATA SCIENCE FOR BIOLOGICAL DIGITAL TWIN EFFORTS (?)

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WHAT IS A DIGITAL TWIN?

Originally described in 2002 by Michael Grieves:

The digital twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level

The main idea is to predict undesirable or optimal outcome(s) under diverse operating conditions before actual manufacture



AEROSPACE EXAMPLE

FIRST SUCCESSFUL FLIGHT BY WRIGHT BROTHERS IN 1903; TRIAL & ERROR FOR BIPLANE DEVELOPMENT



LASTED 59s COVERING 256M

FORMALISING THEORIES GOVERNING FLUID DYNAMICS

is governed by the three fundamental laws of conservation:

- i) *mass*,
- ii) *energy* &
- iii) *momentum*

Resulting in Navier–Stokes equations

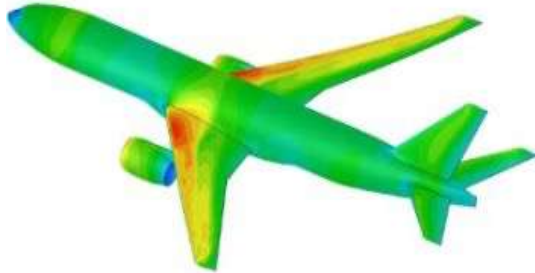
$$\rho \left(\frac{\partial \mathbf{v}}{\partial t} + \mathbf{v} \cdot \nabla \mathbf{v} \right) = -\nabla p + \nabla \cdot \mathbf{T} + \mathbf{f}$$

\mathbf{v} : flow velocity, ρ : fluid density, p : pressure, \mathbf{T} : stress tensor, \mathbf{f} : body forces/volume



CFD DESIGNED BOEING 777

First commercial airline to be modeled and tested *in silico* using computational fluid dynamics (CFD) before production in 1991



**The Impact of CFD on the Airplane Design
Process: Today and Tomorrow**

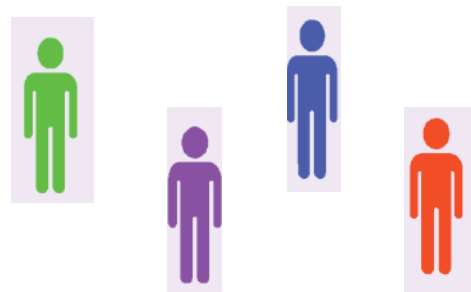
Ronald L. Bengelink and Paul E. Rubbert
Boeing Commercial Airplanes



CAN WE APPLY DIGITAL TWIN CONCEPT FOR BIOLOGY/MEDICINE?

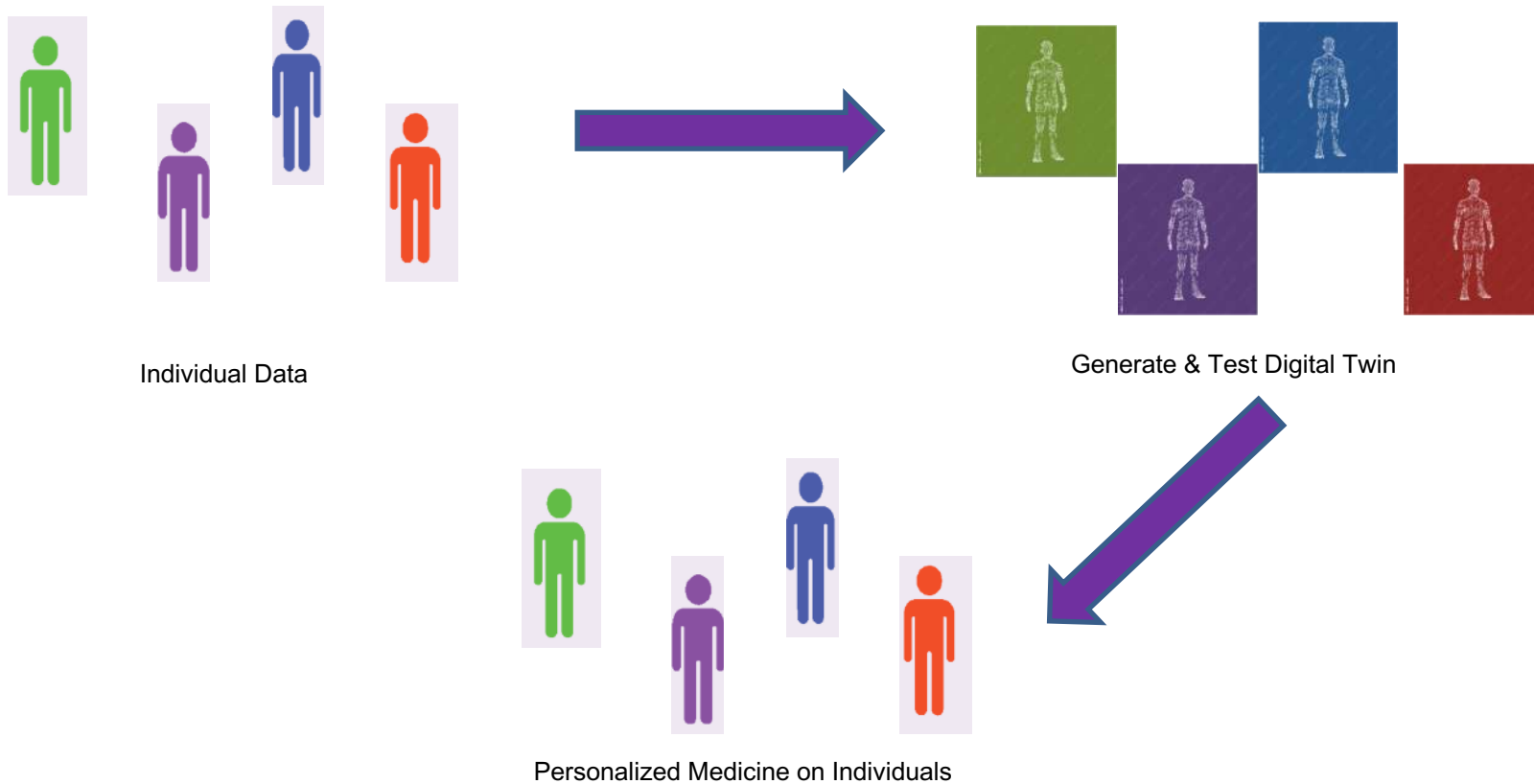


Traditional Medicine on Cohort



Personalized Medicine on Individuals

CAN WE APPLY DIGITAL TWIN CONCEPT FOR BIOLOGY/MEDICINE?

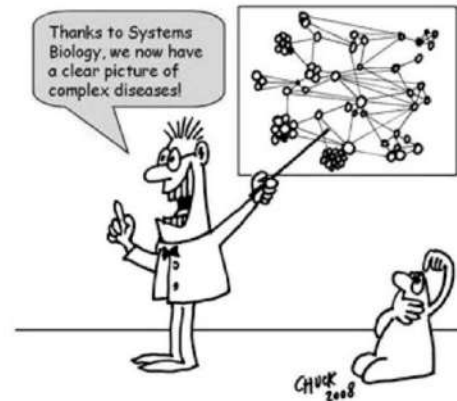




“Systems biology and medicine – not only in the lab but in the everyday lives of people – challenges the imagination and will transform the 21st Century.”

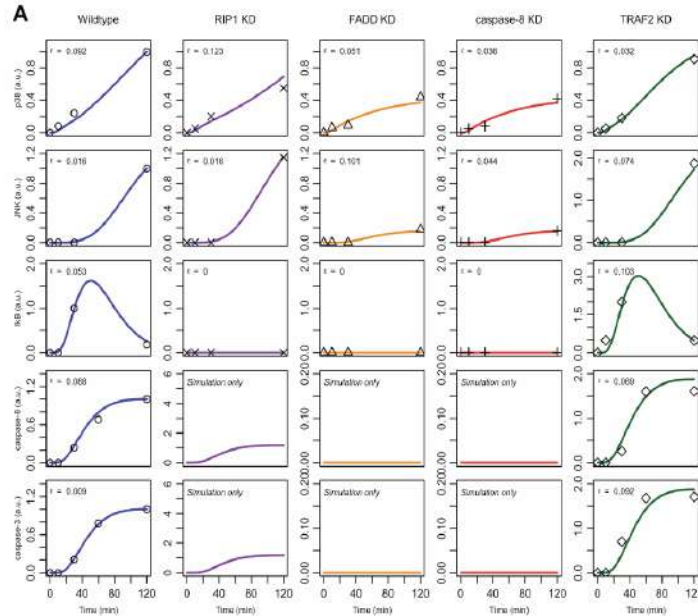
–Lee Hood (pioneer of systems biology & personalised medicine)

WHAT SYSTEMS BIOLOGY AND DATA SCIENCE CAN DO FOR DIGITAL TWINS?

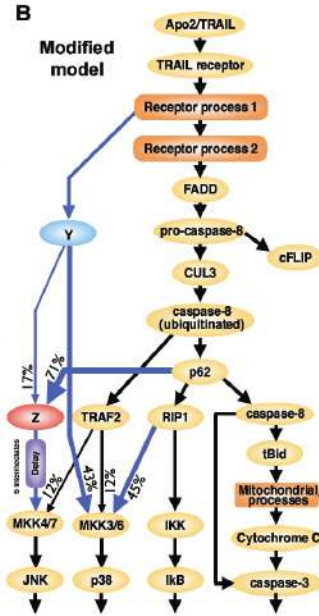


NETWORK MODELING PREDICTS ENHANCEMENT OF APOPTOSIS IN SKIN CANCER BY PKC-Δ TARGET SUPPRESSION

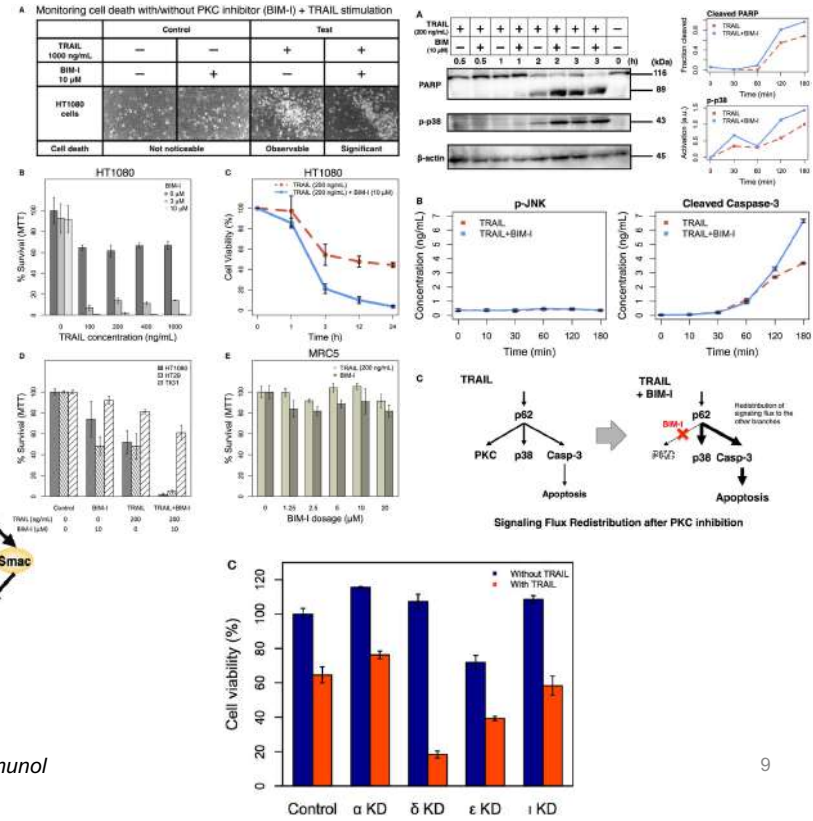
Data & Model Generation



Model Testing & Simulations



Validation of Model Prediction



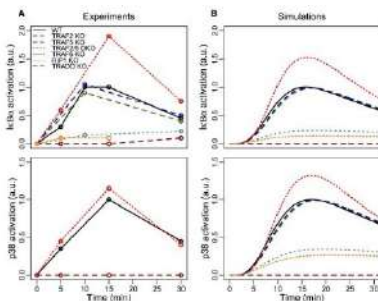
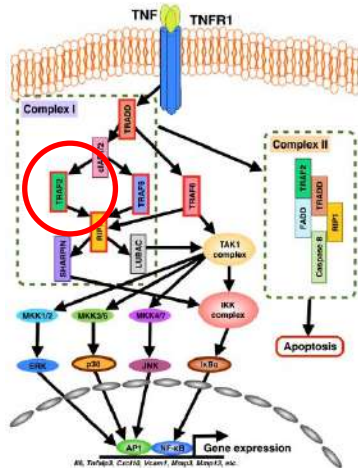
Piras V, ..., Selvarajoo K (2011) *Sci Rep*

Hayashi K, ..., Selvarajoo K (2015) *Front Immunol*

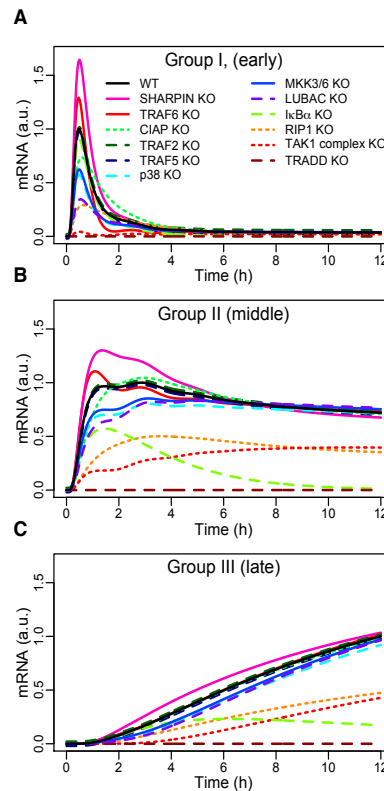


NETWORK MODELING PREDICTS TARGET *IN SILICO* TO SUPPRESS TNF-INDUCED PROINFLAMMATORY GENE EXPRESSIONS VIA RIP1

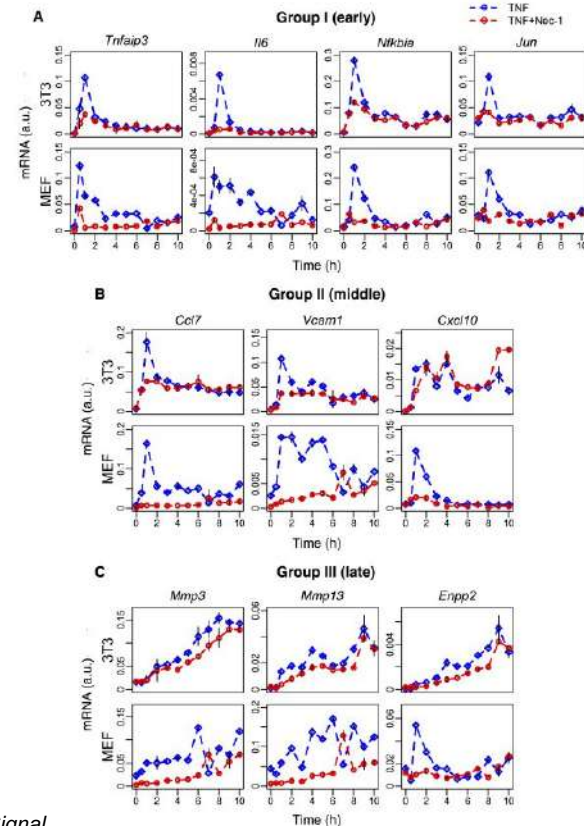
Data & Model Generation



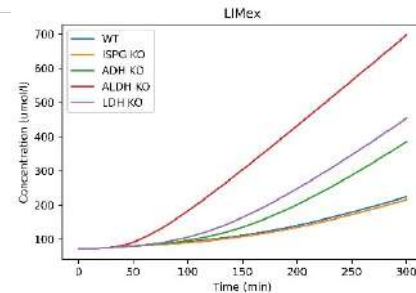
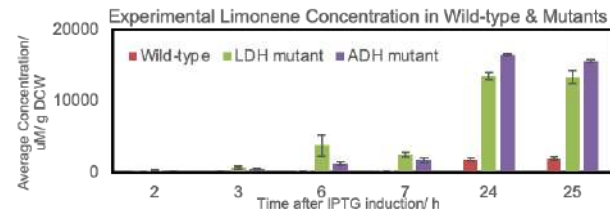
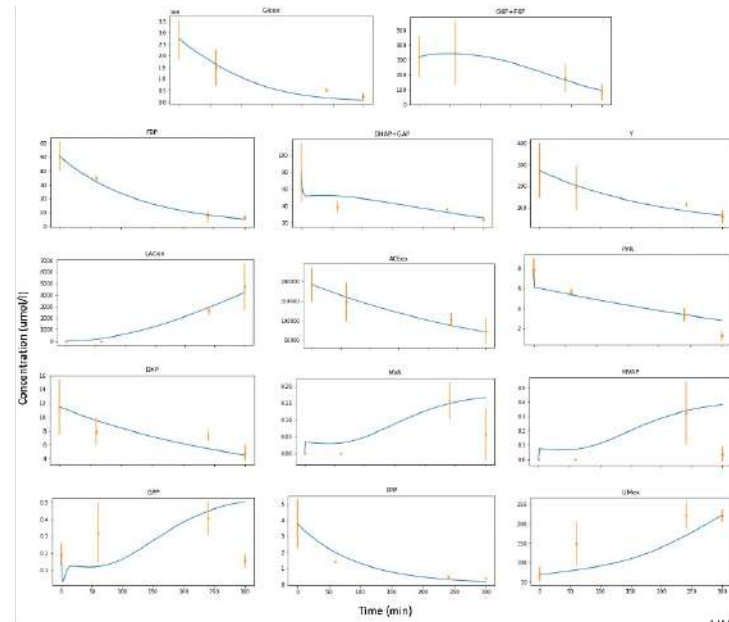
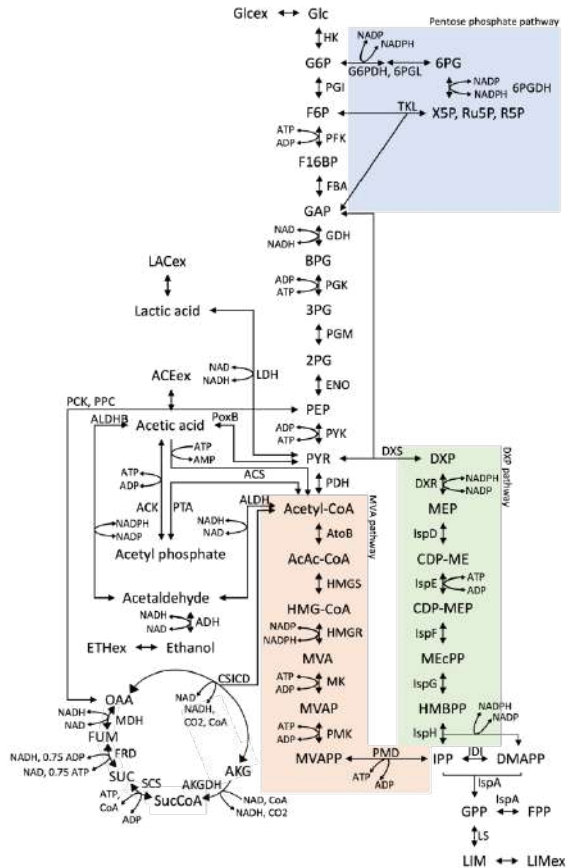
Model Testing & Simulations



Validation of Model Prediction



RE-ENGINEERING CELLS: IDENTIFYING INTRACELLULAR TARGETS FOR LIMONENE YIELD ENHANCEMENT

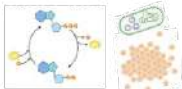


MACHINE LEARNING OF MECHANISTIC SYSTEM MODEL: predicting optimal yield of cell factories

Cell-free production

Yield

-Nil leakage to side reactions & biomass



Design

-simpler system to understand



-feedstock in precise amounts (no cellular interference)

Sustainability

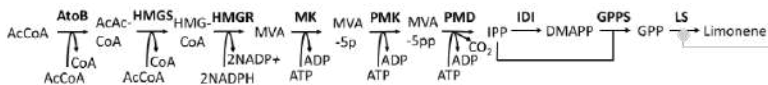
-renewable/waste feedstock

Resilience of supply

-local production on demand
-parts freeze-dried for storage



Joint learning of rate laws & parameters



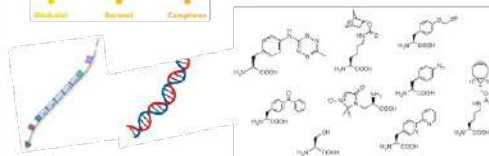
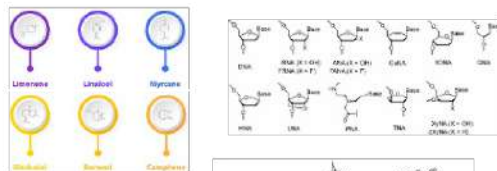
$$R_i = k_1 [LS]^{k_2} [GPP]^{k_3}$$

$$R_{ii} = [LS] (k_1 + k_2 \ln[GPP])$$

$$R_{iii} = k_1 [LS][GPP]/k_2 / (1 + [GPP]/k_2)$$

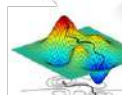
$$R_{iv} = k_1 [LS][GPP]/(k_2 + [GPP])$$

Diverse bioproducts



Systems synthetic biology

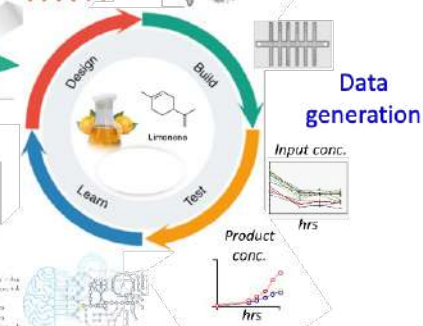
Yield optimization



Digital yield model



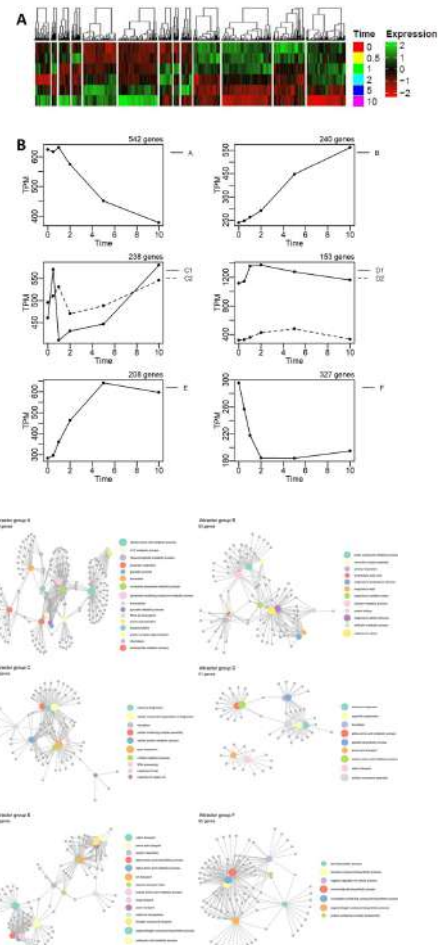
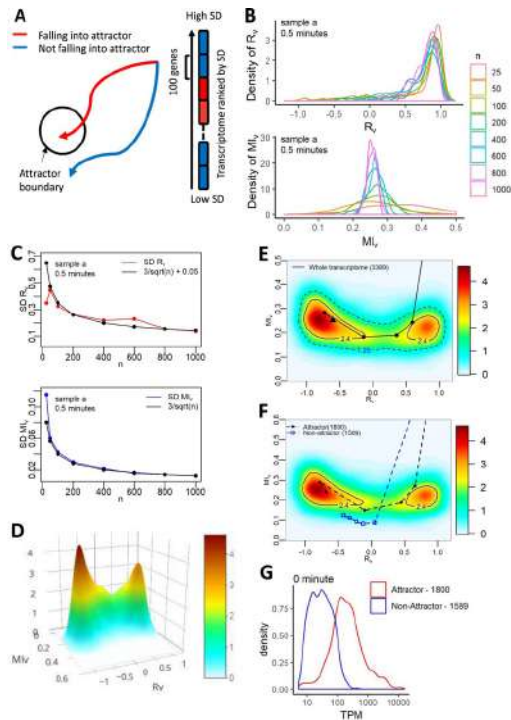
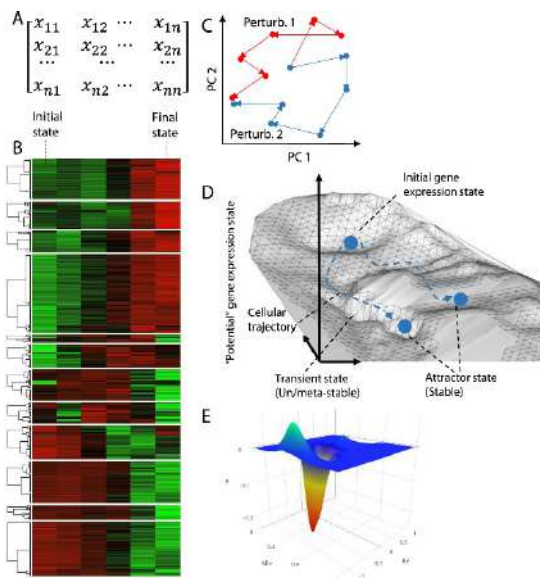
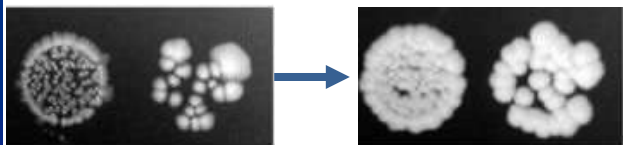
Learning of mechanistic model



TRANSCRIPTOME-WIDE ATTRACTOR DATA ANALYTICS OF *E. COLI* STATE TRANSITION

Understanding high-throughput gene expression response of *E. Coli* under aerobiosis

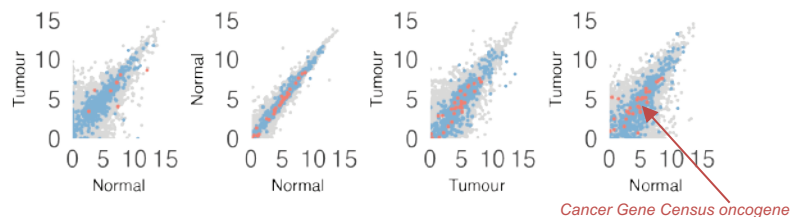
ANAEROBIC TO AEROBIC TRANSITION



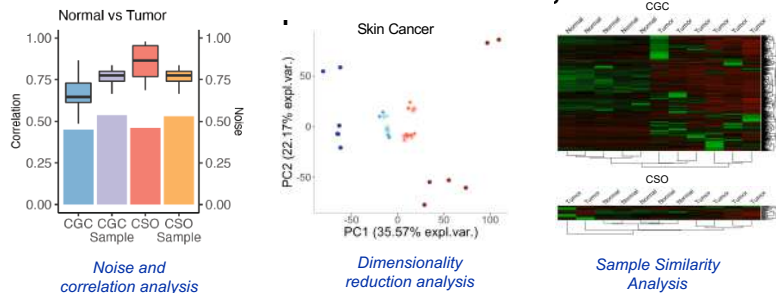
CANCER TRANSCRIPTOMIC ANALYSIS:

BULK (INVARIANT) VS SINGLE CELLS (VARIANT) ONCOGENES

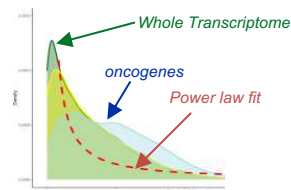
- 1 Using Cancer Gene Census (CGC) database to identify oncogenes for analysis



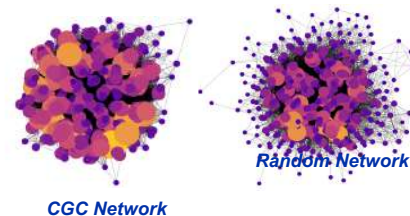
- 2 Various statistical/ML tools applied on bulk RNA-seq data reveal invariance of oncogene expression



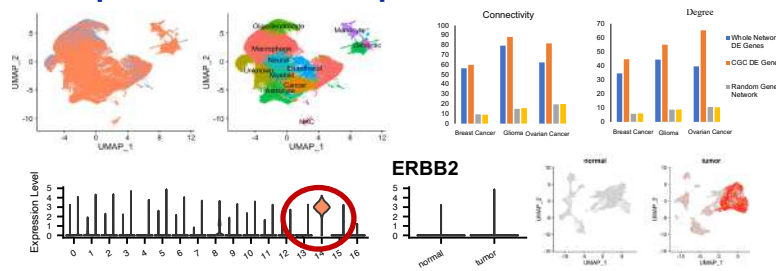
- 3 PPI Connectivity of oncogenes does not follow Power Law



- 4 Oncogenes have higher connectivity



- 5 scRNA-seq data reveals variance of oncogene expression at tissue-specific level




MULTI-OMICS ML INTEGRATION FOR PREDICTING INDIVIDUAL DRUG RESPONSE




CREATING GROWTH, ENHANCING LIVES

Data acquisition

WES	Somatic mutations TP53 ...
RNA-seq	DEG ESR1 ...
	Molecular markers Swanton. Paclitaxel Score ...
	Microenv Mast cell ...

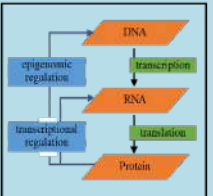




Tumour	Primary tumour bed area Fraction of invasive cancer
lymph node	Diameter of largest metastasis Number of positive lymph nodes

pCR	RCB-I	RCB-II	RCB-III
Not tumour	Increasing residual disease		

Feature Selection & Multi-Omics integration



BMSCCA: Biologically structured Multi-class SCCA) Learning with Feature Selection

Objective function:

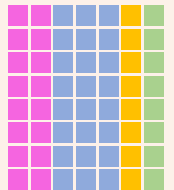
$$\min_{W, V} \sum_{k=1}^K \sum_{m=1}^M -u_k^T X_k^T V_{kmm} v_{kmm} + R(W) + R(V_m),$$

s. t. $\|X_k u_k\|_2 = \|V_k v_k\|_2 = 1, \forall k$

regularizations:
 $R(W) = \alpha_1 \|W\|_{1,1} + \alpha_2 \|W\|_{2,1}$
 $R(V_m) = \beta_1 \|V_m\|_{1,1} + \beta_2 \|V_m\|_{2,1}$
 $k(1 \dots K)$: disease subtypes
 $m(1 \dots M)$: different omics modality

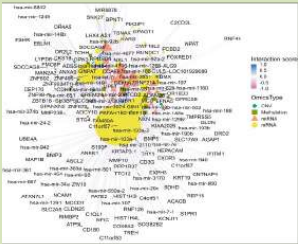
- Omics relationships
- Central dogma
- Additional relationships

Machine learning



Logistic regression	Ensemble
Support vector machine	
Random forest	

Disease and Patient Specific Results

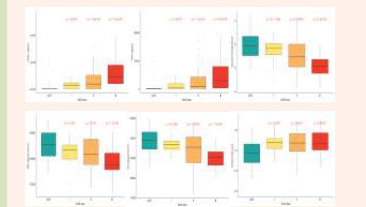
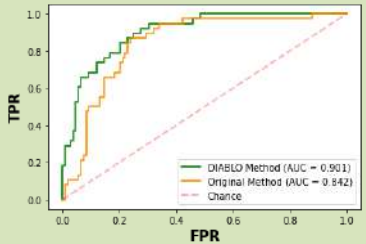


Normal-like

Identification novel interactions

ZNF496/ADSS

hsa-mir-92b



SUMMARY

- Various *in silico* tools/methods (based on physical laws, rules and machine learning) have shown predictive results that are experimentally tested, verified or validated
- These, however, are at cellular levels, and mostly at single layer levels (e.g. transcriptomics, proteomics, metabolomics)
- Digital Twins approach requires a more holistic understanding of the interaction at many levels and layers (e.g. organ level, tumor microenvironment, multi-omics dynamic interactions)
- Big challenges ahead, thus, closer interaction between physicists, mathematicians, biologists, chemists and medical doctors are imminent with **clearly defined objectives**



Current Members

Dr Hock Chuan Yeo (BII)
Dr Mamun Rashid (BII)
Olga Sirbu (BII)
Yan Ting Hee (BII)
Dr Jasmeet Kaur (SIFBI)
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THANK YOU

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Vincent Piras (Toulouse)
Florian Bellvert (Toulouse)
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CNRS (Toulouse) members

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<https://www.cbio-kumar.org>