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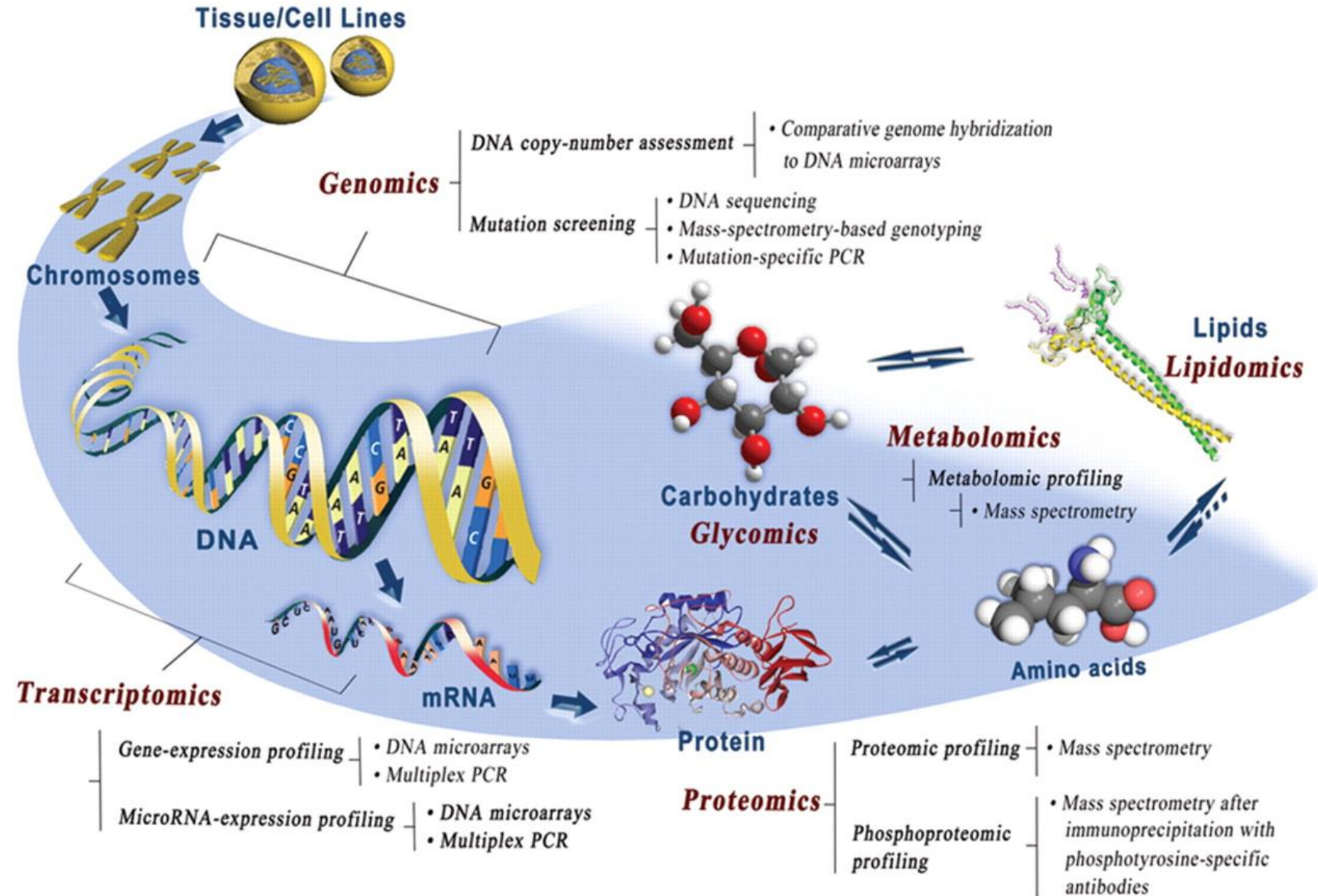
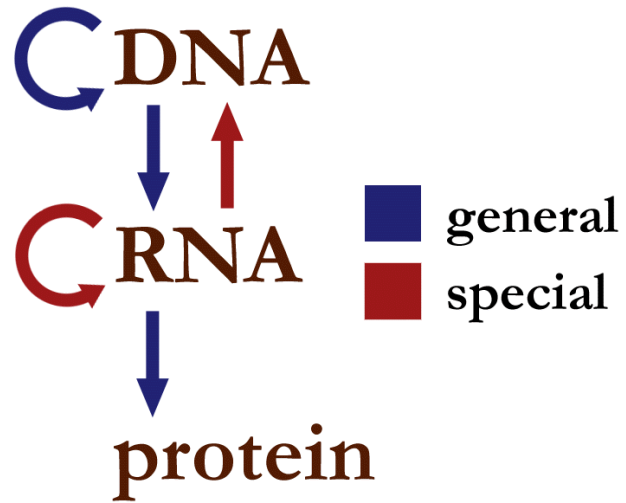
**EXCELENCIA
SEVERO
OCHOA**

Personalised Medicine Centre of Excellence: how can HPC cell- level simulations help us fight against cancer and COVID

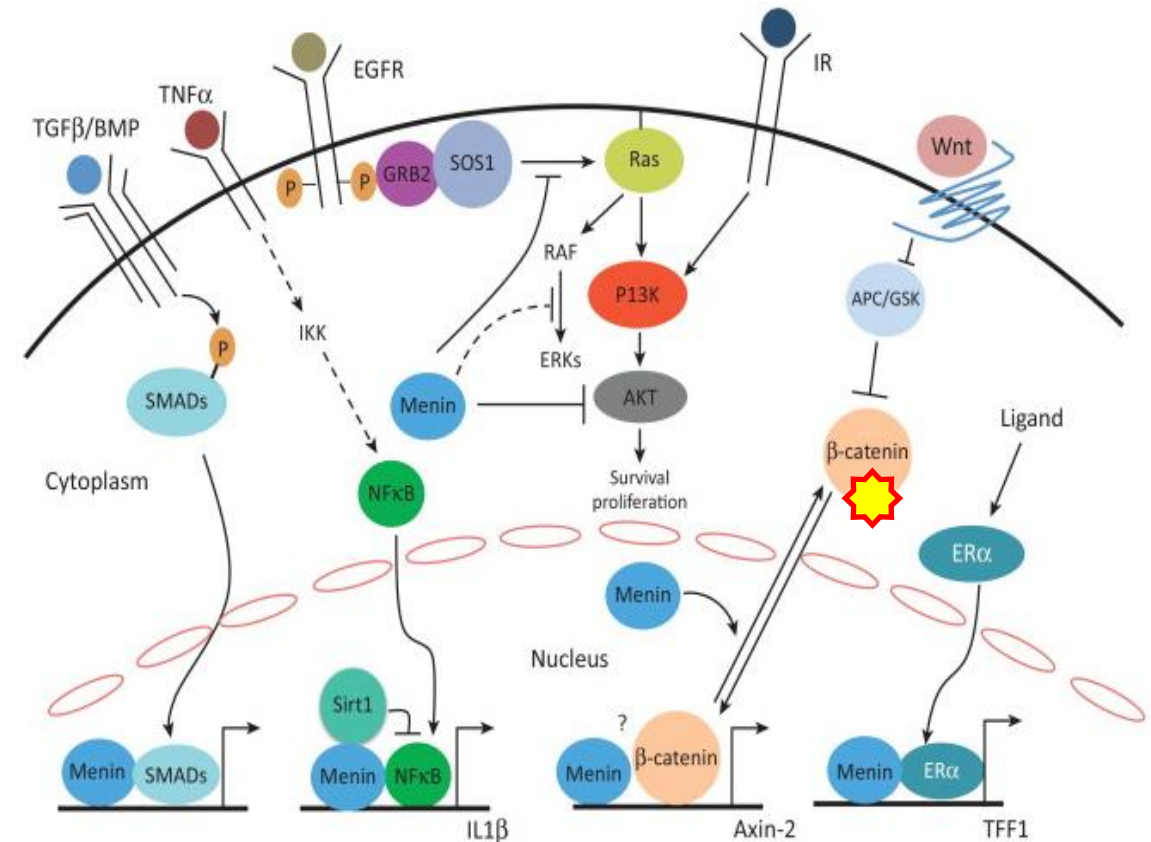
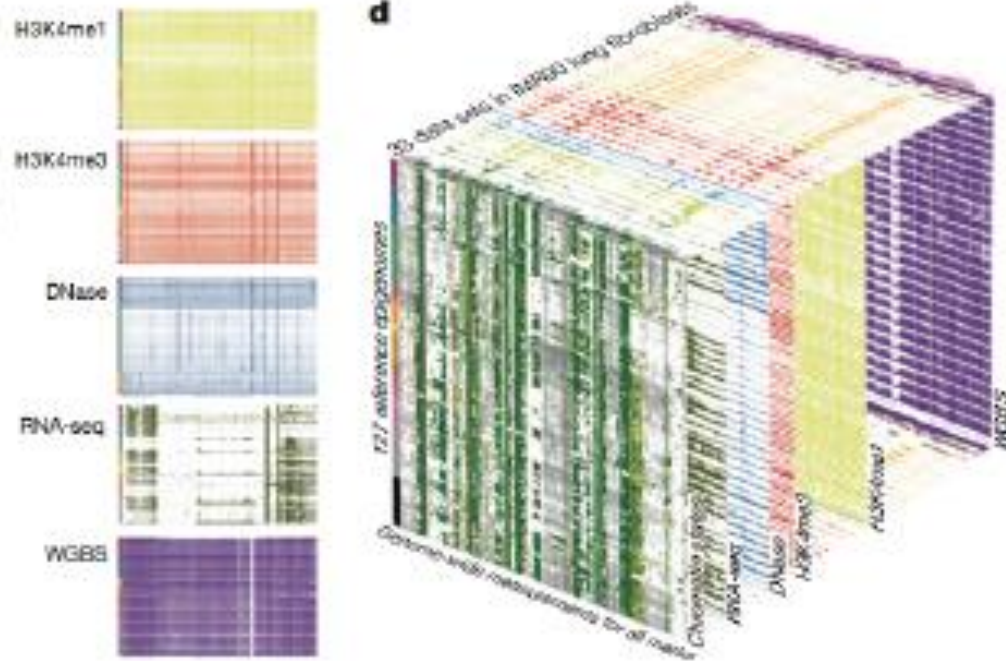
Arnau Montagud
Computational Biology group
Life Science Department

7 October 2019

Central Dogma and the omics data



To infer mechanisms from omics data we need networks and models



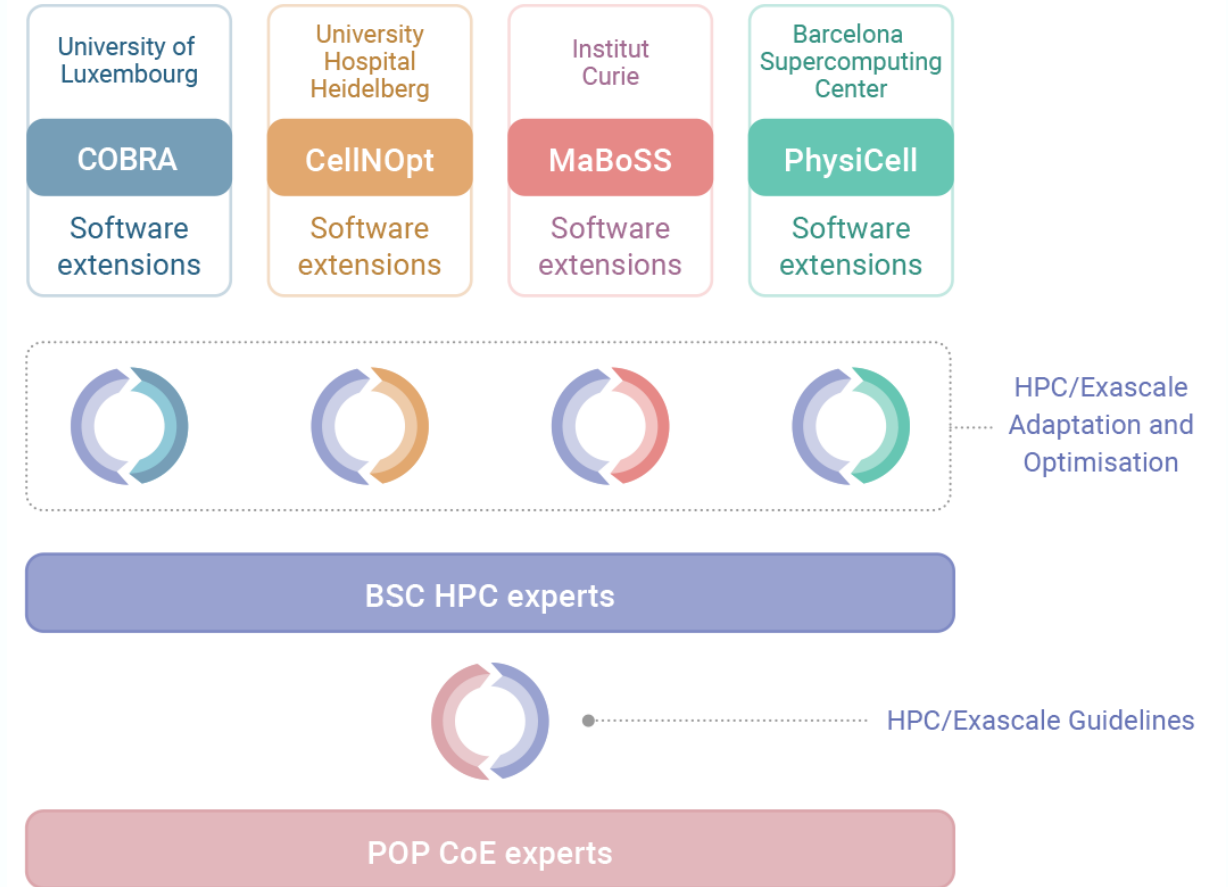
T/BS

CORE APPLICATIONS

PerMedCoE optimises key software for cell-level simulations to the new preexascale platforms

The PerMedCoE four core applications are:

- **COBRA** for the simulation of cellular metabolism at genome-scale
- **CellNOpt** for modelling signal transduction networks
- **MaBoSS** for stochastic simulations of Boolean models
- **PhysiCell** an agent-based modelling framework for simulating cell-cell interactions

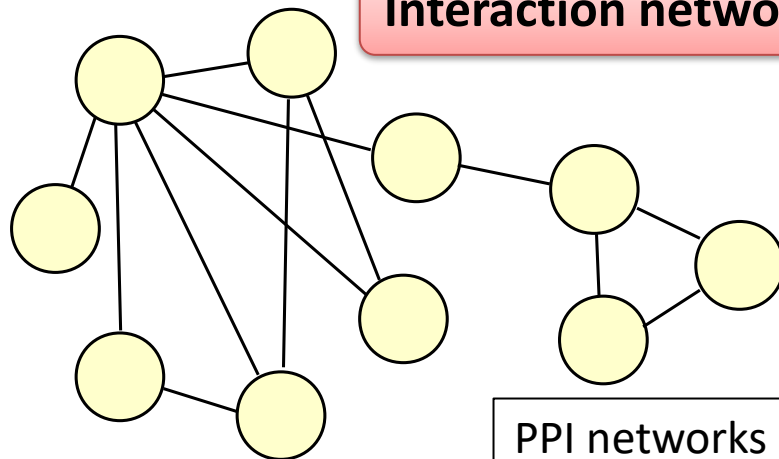


For more information, visit <https://permedcoe.eu/core-applications/>

Data leads to Structure ... and Structure leads to Modelling

Le Novère, Nat Rev Genet. 2015 Mar;16(3):146-58.

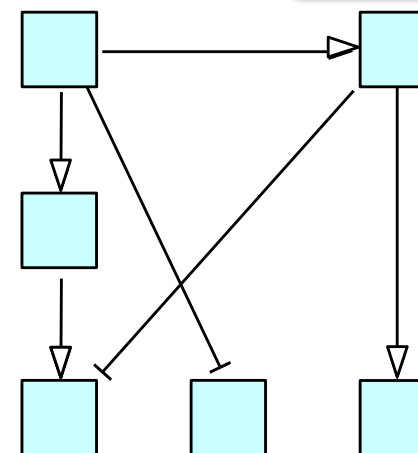
Interaction networks



PPI networks

Statistical modelling

Activity flows



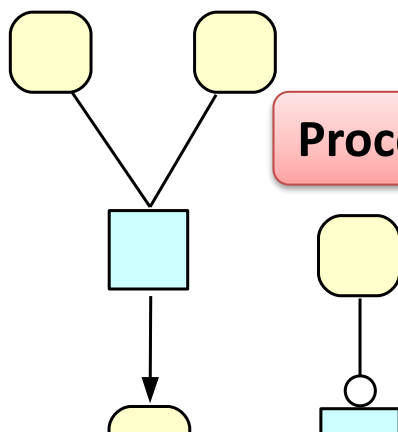
Signalling pathways,
gene regulatory
networks

Logical modelling

MaBoSS

CellNOpt

Process descriptions



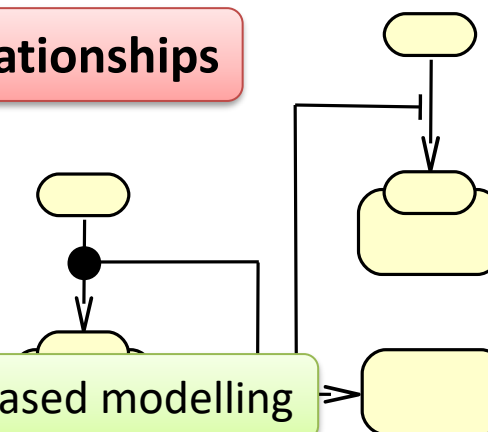
PhysiCell

COBRA

Process modelling (FBA, ODEs, etc.)

Different biological knowledge ↔
different types of networks ↔
different types of modelling

Entity relationships



Rule-based modelling

Metabolic networks, reaction networks

Molecular interactions, reaction networks

Slide from L. Calzone,
Institut Curie

Metabolic modelling

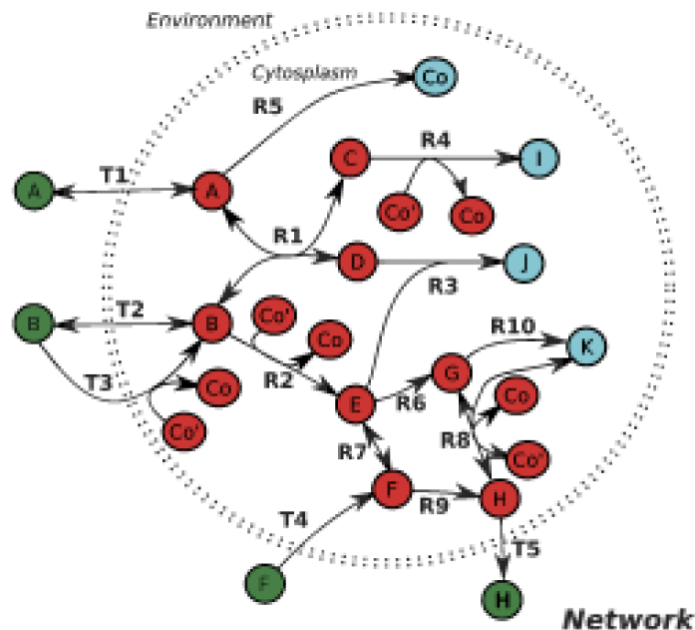


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Omics data are used to build metabolic networks and metabolic models

- ⌘ Network reconstruction
 - From the list of genes in the genome
- ⌘ Flux balance analysis
 - Provides information on **reactions' fluxes**
 - Used to **study cell growth** and **metabolite productivity**
- ⌘ Constraint-based metabolic model



Network

	T1	T2	T3	T4	T5	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	Bio	Ass
A	1	0	0	0	0	-1	0	0	0	-1	0	0	0	0	0	0	0
B	0	1	1	0	0	-1	-1	0	0	0	0	0	0	0	0	0	0
C	0	0	0	0	0	1	0	0	-1	0	0	0	0	0	0	0	0
D	0	0	0	0	0	1	0	-1	0	0	0	0	0	0	0	0	0
E	0	0	0	0	0	0	1	-1	0	0	-2	-1	0	0	0	0	0
F	0	0	0	1	0	0	0	0	0	0	0	1	0	-1	0	0	0
G	0	0	0	0	0	0	0	0	0	0	1	0	-1	0	-1	0	0
H	0	0	0	0	-1	0	0	0	0	0	0	0	1	0	0	0	0
I	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	-2	0
J	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	-2
K	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	-1	0
Co	0	0	1	0	0	0	1	0	1	2	0	0	-1	0	0	-1	0
Co ⁺	0	0	-1	0	0	0	-1	0	-1	0	0	0	1	0	0	0	0
Aext	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bext	0	-1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Fext	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0
Hext	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
Bionass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

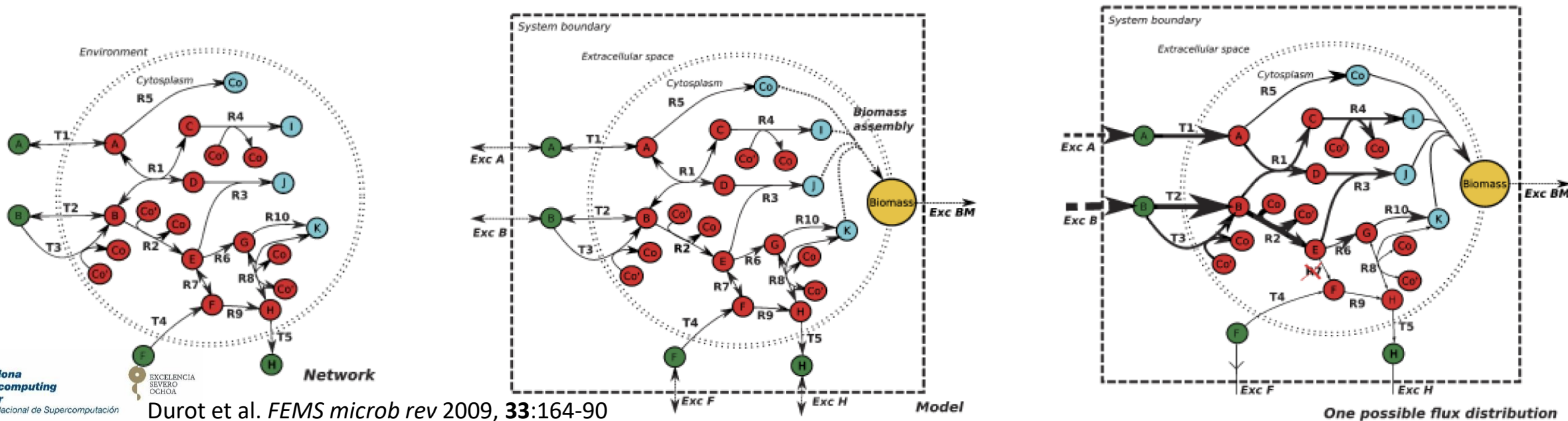
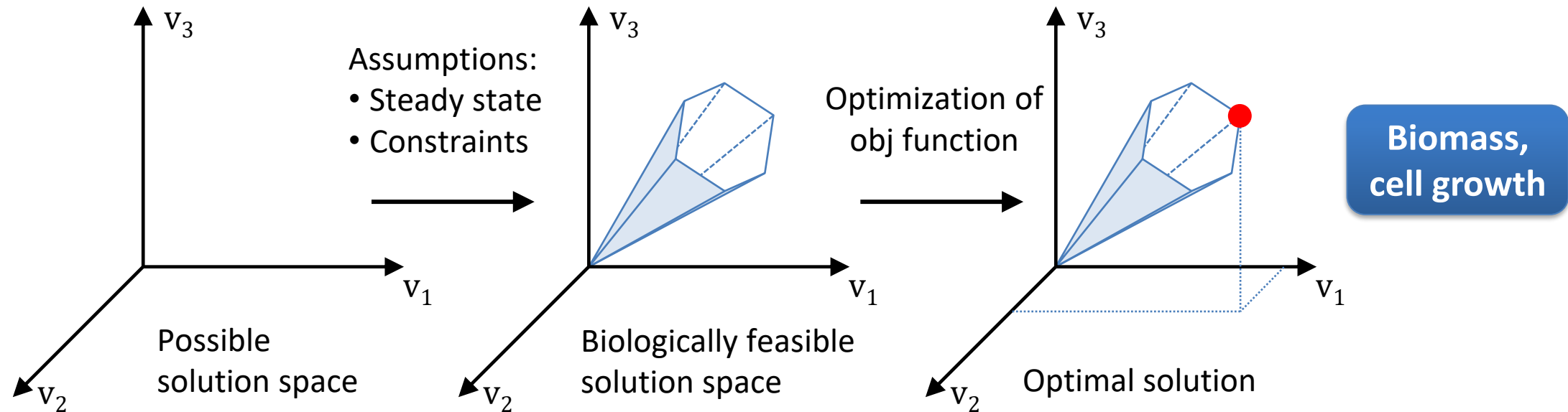
Stoichiometric matrix

$$n > m$$

$$\sum_{i=1}^M \sum_{j=1}^N S_{ij} \cdot v_j = 0$$

1. Consider steady state
Time (cell growth) >> Time (metabolic reactions)
2. Impose constraints

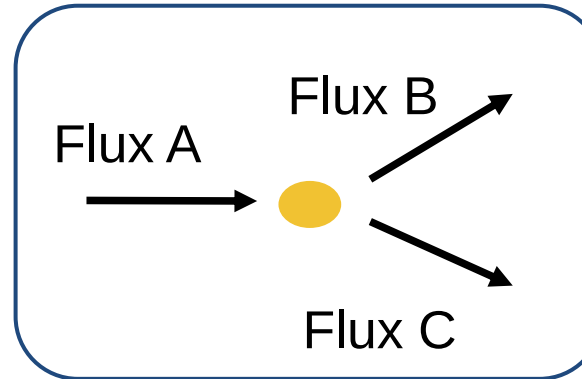
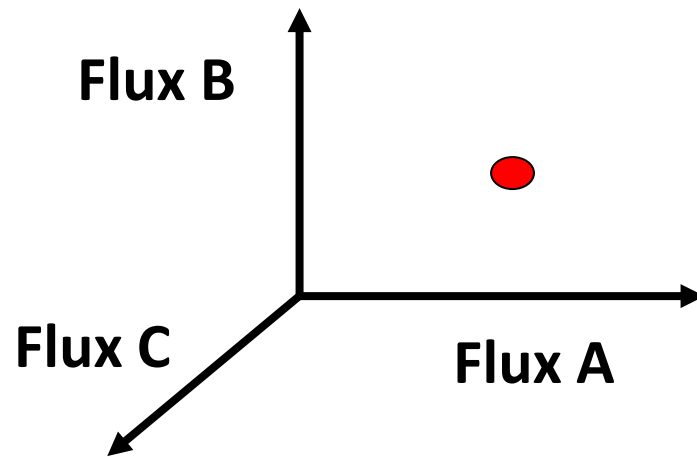
Flux Balance Analysis explained graphically



Alternatives to modelling cellular metabolism

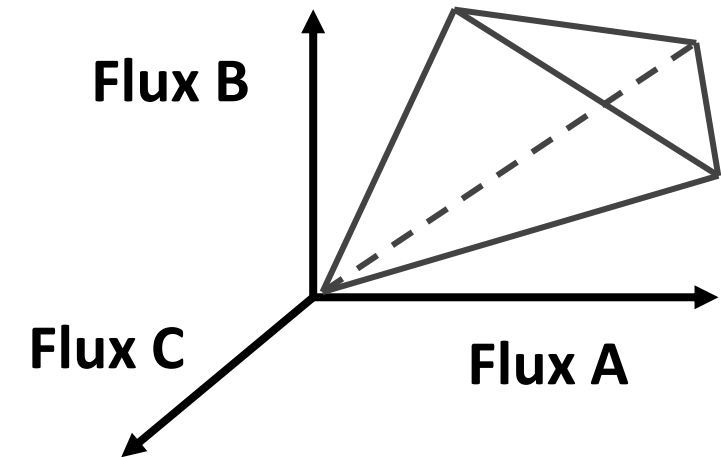
Kinetic modelling

- Complete description
- Solution is a **unique point**



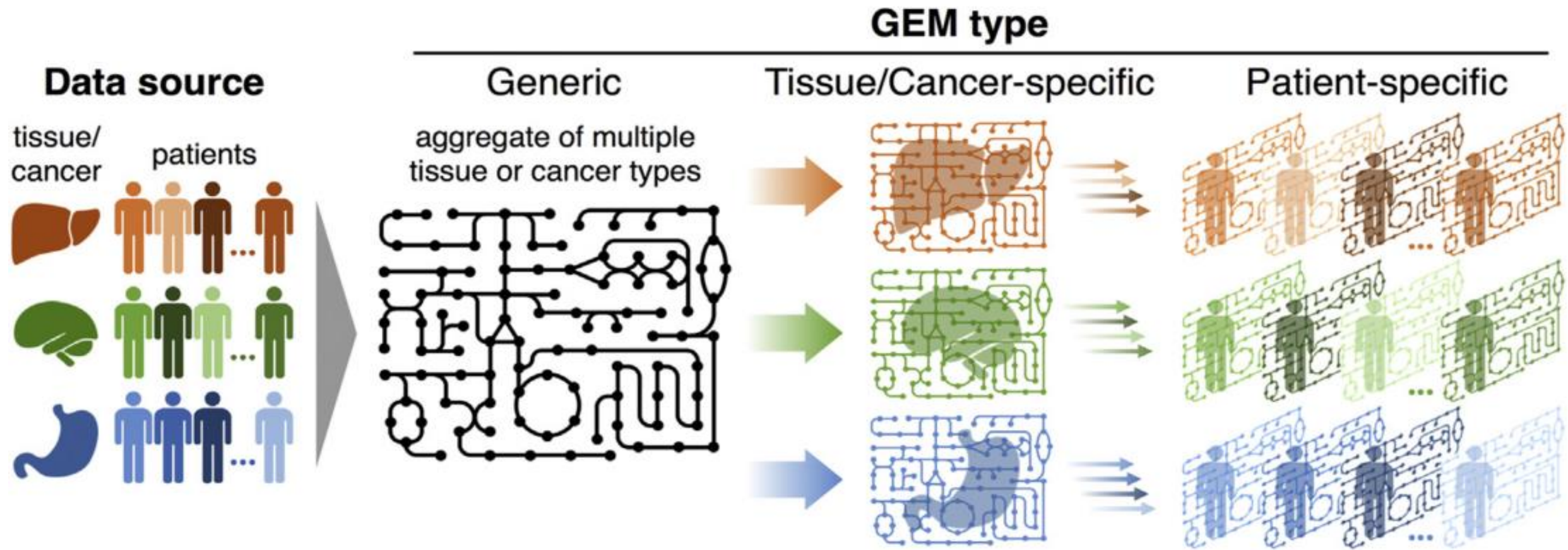
Constraint-based modelling

- Incomplete Information
- **Solution space**



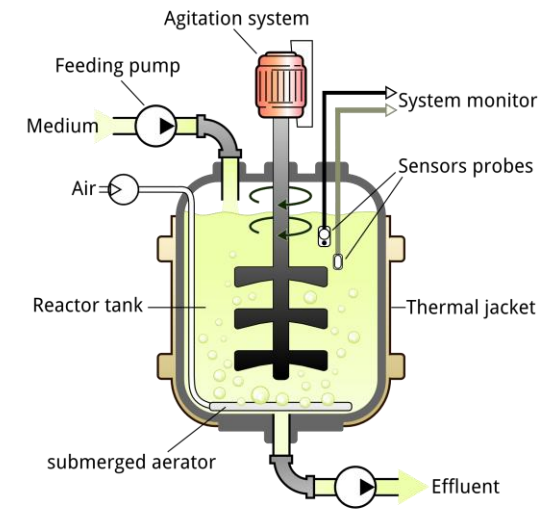
At genome-scale there are no detailed kinetic descriptions → many reactions have unknown mechanisms and parameters!

Context-specific metabolic modelling



Constraint-based modelling applications in biomedicine

- ⌘ Production of by-products
 - Antibiotics
 - Flavoured synthetic milk
- ⌘ Data integration
- ⌘ Cell maximal growth rate
- ⌘ Single gene knockout
- ⌘ Double gene knockout
 - Synthetic lethality
- ⌘ Essential media components
 - Amino acids
 - Vitamins
- ⌘ Biomarkers
- ⌘ Combinatorial therapy
 - Diet restriction + drugs that target a given signalling pathway



If you want more information



models



fluxes



algorithms

Star 263 contributors 42 release v0.21.0

cobrapy is a python package that provides a simple interface to metabolic constraint-based reconstruction and analysis.

```
>>> import cobra
>>> model = cobra.io.read_sbml_model('Ec_core_flux1.xml')
>>> model.metabolites[:3]
[<Metabolite 13dpg_c at 0x112b2d160>,
 <Metabolite 2pg_c at 0x1024eb048>,
 <Metabolite 3pg_c at 0x112b2d748>]
```

<https://opencobra.github.io/cobrapy/>

- COConstraint-Based Reconstruction and Analysis
 - Matlab, Python, Julia
- Practical course "Constraint-based modelling: a primer on basics and examples"
 - https://github.com/ArnauMontagud/cobra_cbm_tutorial
 - Jupyter notebook
 - Adapted from Miguel de Ponce León

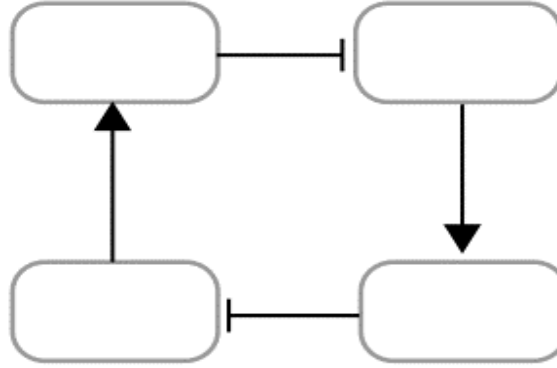
Logical modelling



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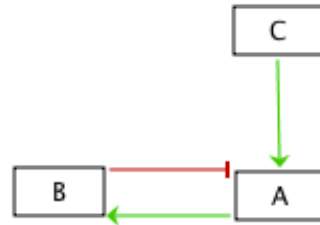
Logical formalism



- ⌈ The questions are **qualitative**
- ⌈ The **data are discrete** (mutations, copy number, etc.)
- ⌈ Expression data are **not absolute values**
- ⌈ **No** information over **time**
- ⌈ **No details** about the precise biochemical reactions

Translation of an influence network into Boolean logic

Regulatory graph



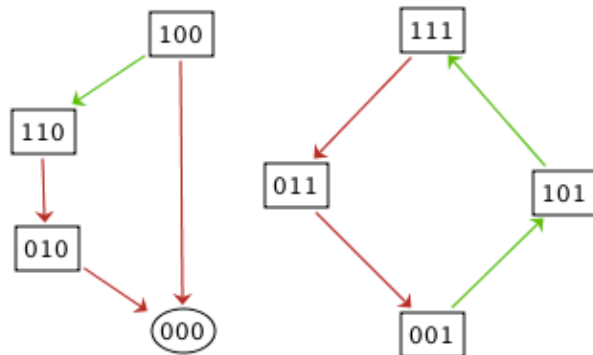
Logical rules

$A = !B \ \& \ C$

$B = A$

$C = \text{input}$

Solutions



Each variable can take **two states**: 0 or 1

Boolean logic:

- Connectors: AND (&), OR (|), NOT (!), XOR (/)
- Logic depends on incoming arrows

Set of discrete variables as **abstractions of activity level** linked by logical rules as **signed interactions**

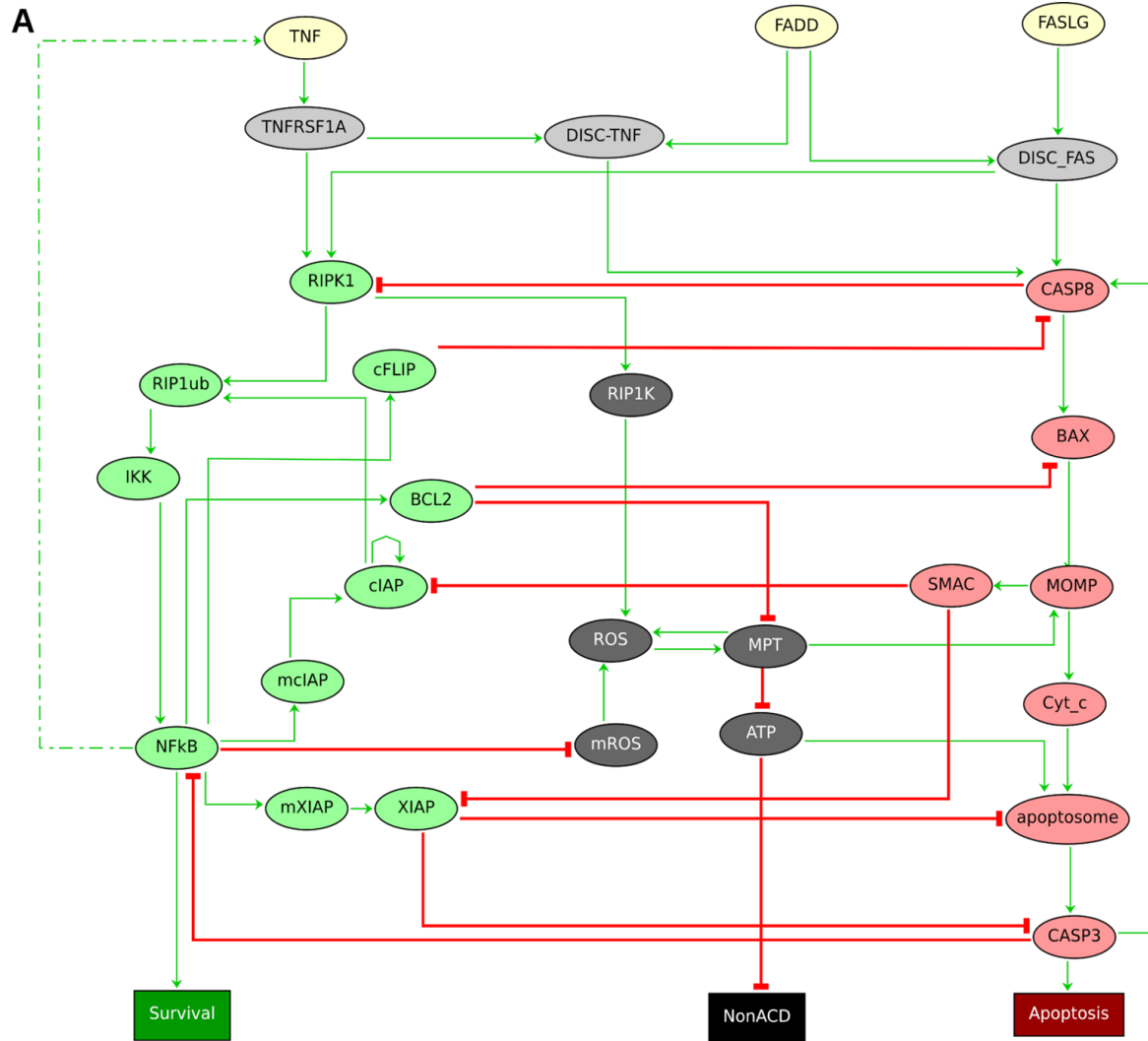
Attractors are subgraphs of the **state transition graph** with no outgoing arrows: can be stable states & cyclic attractors

Stable states = cell fates = phenotypes

Updating dynamics can be

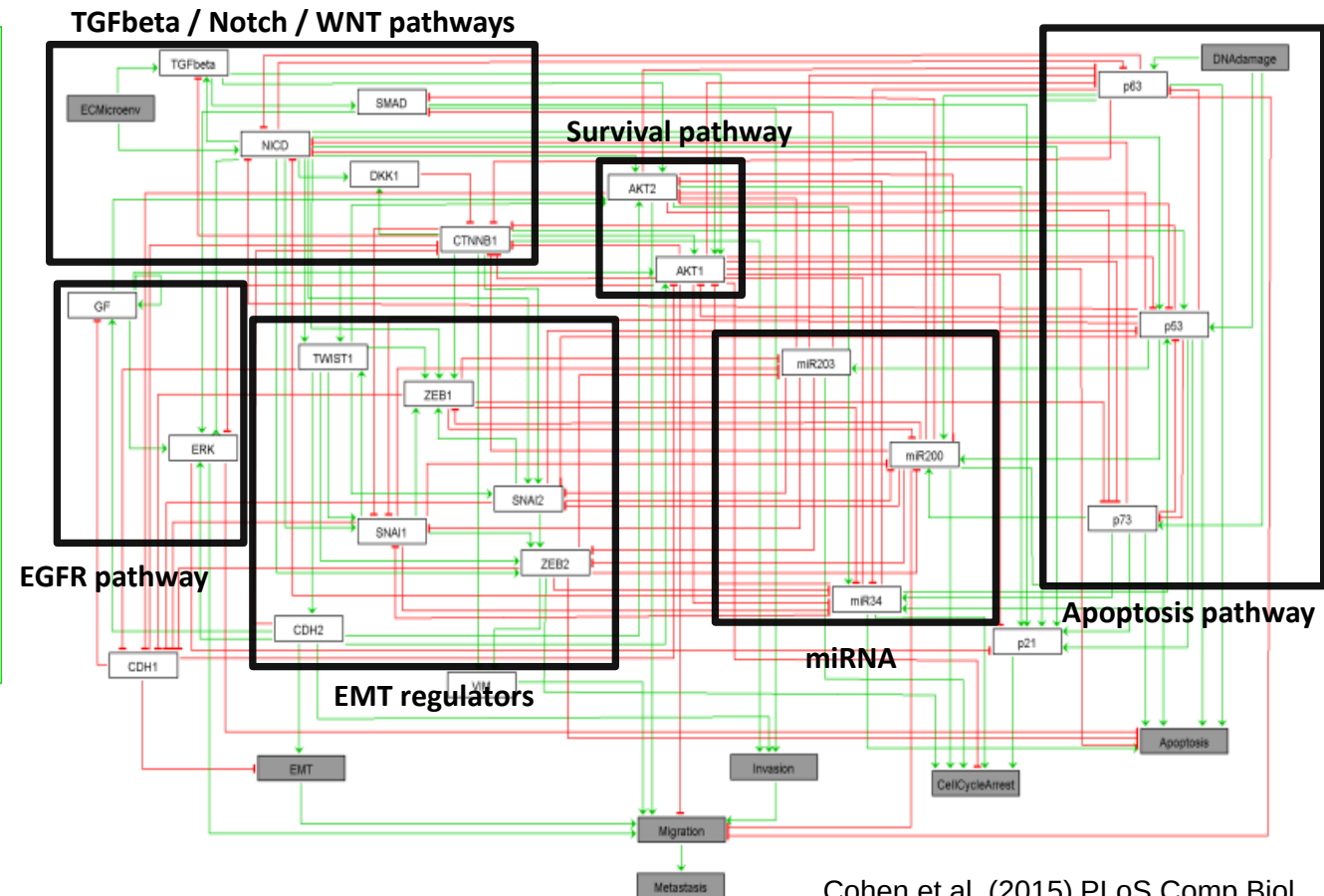
- synchronous: **all variables** that can be updated are updated
- asynchronous**: **only one variable is updated** at a time

Two examples of models: TNF response and cell fates and Metastasis model



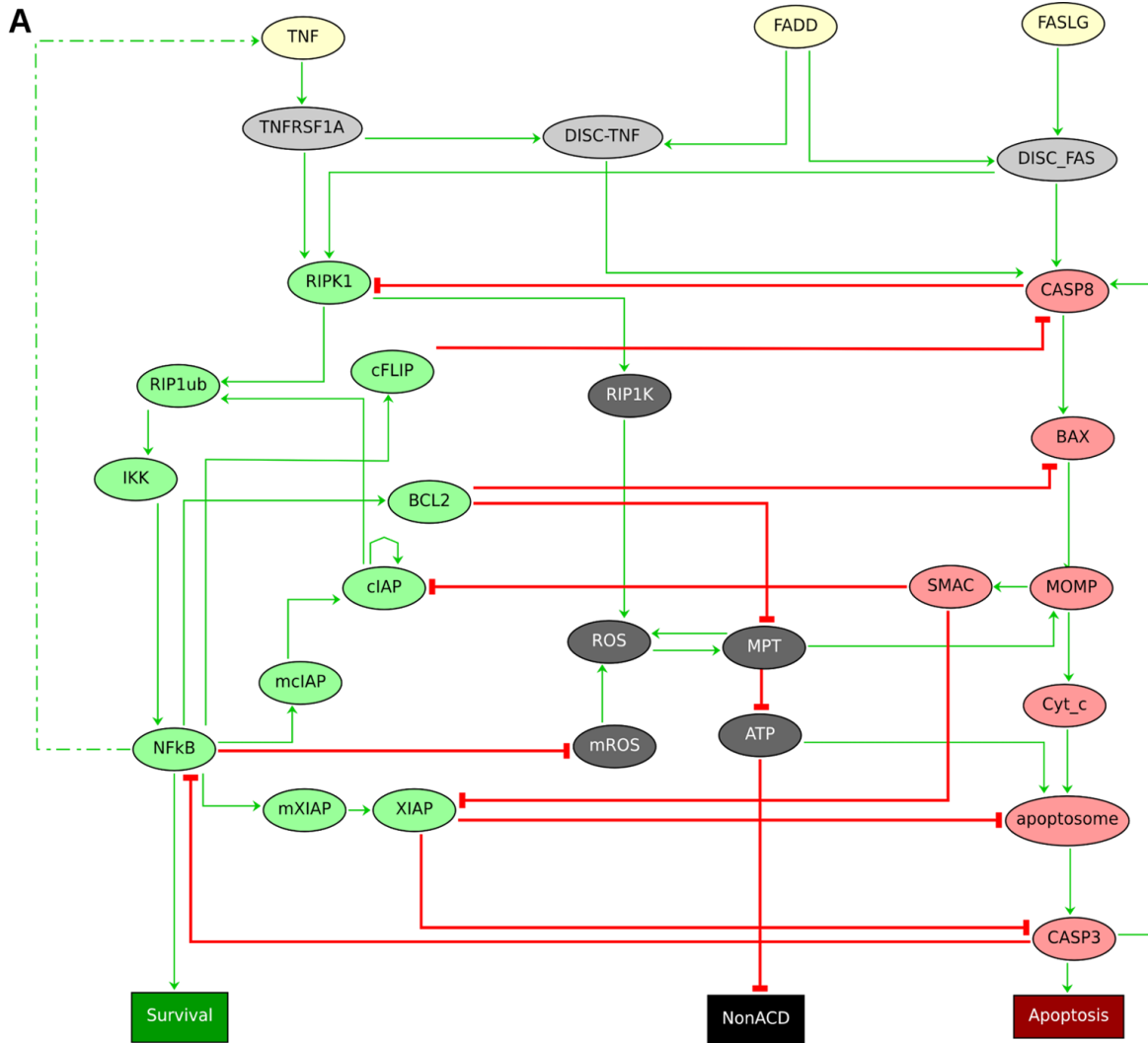
Letort et al., *Bioinformatics*, 2018, bty766

- Convenient way to model regulatory and signalling networks
 - Allows integration of literature & heterogeneous data
 - Provides **qualitative** analysis



Cohen et al. (2015) PLoS Comp Biol

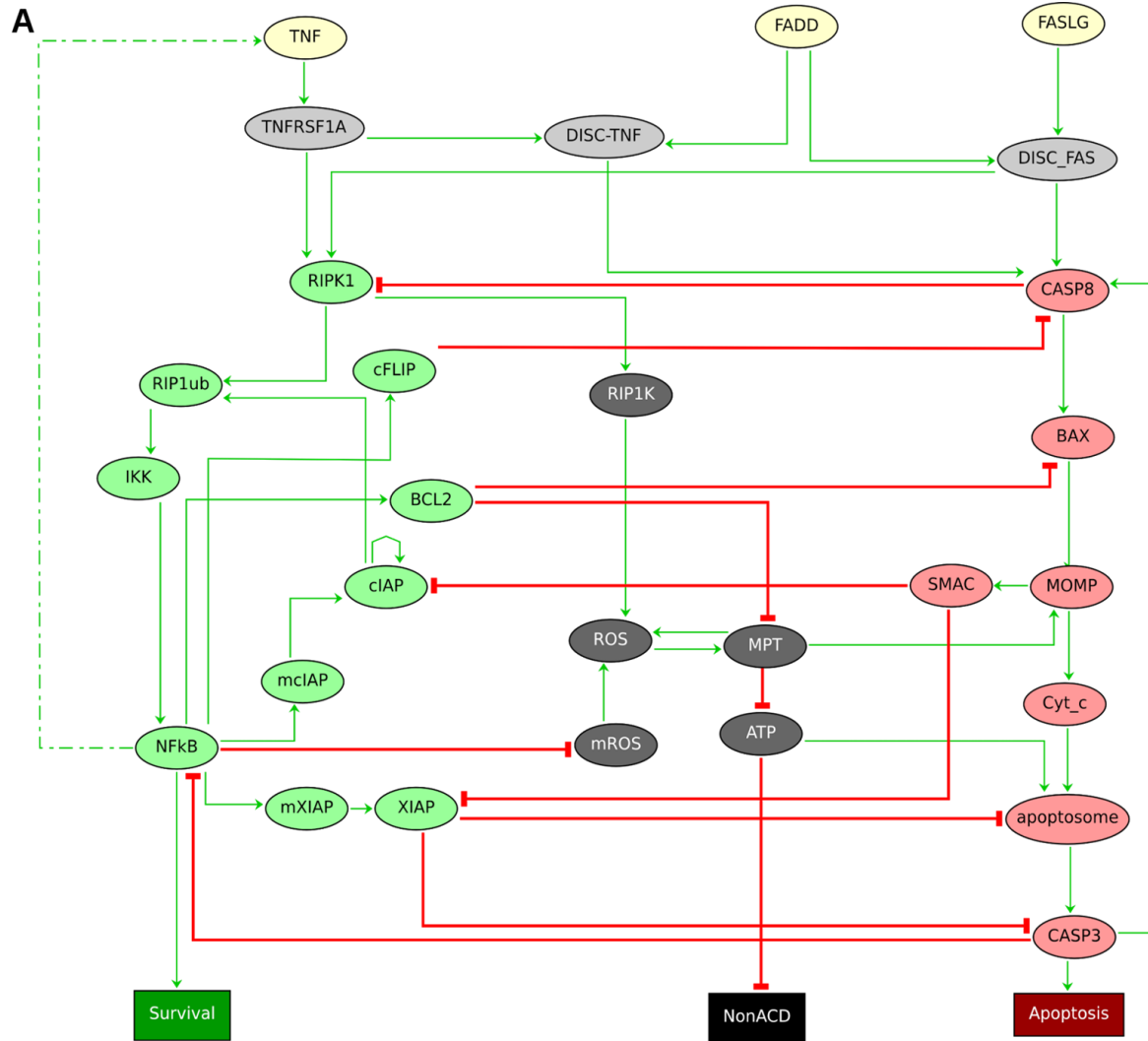
What insights can we get from the mathematical model



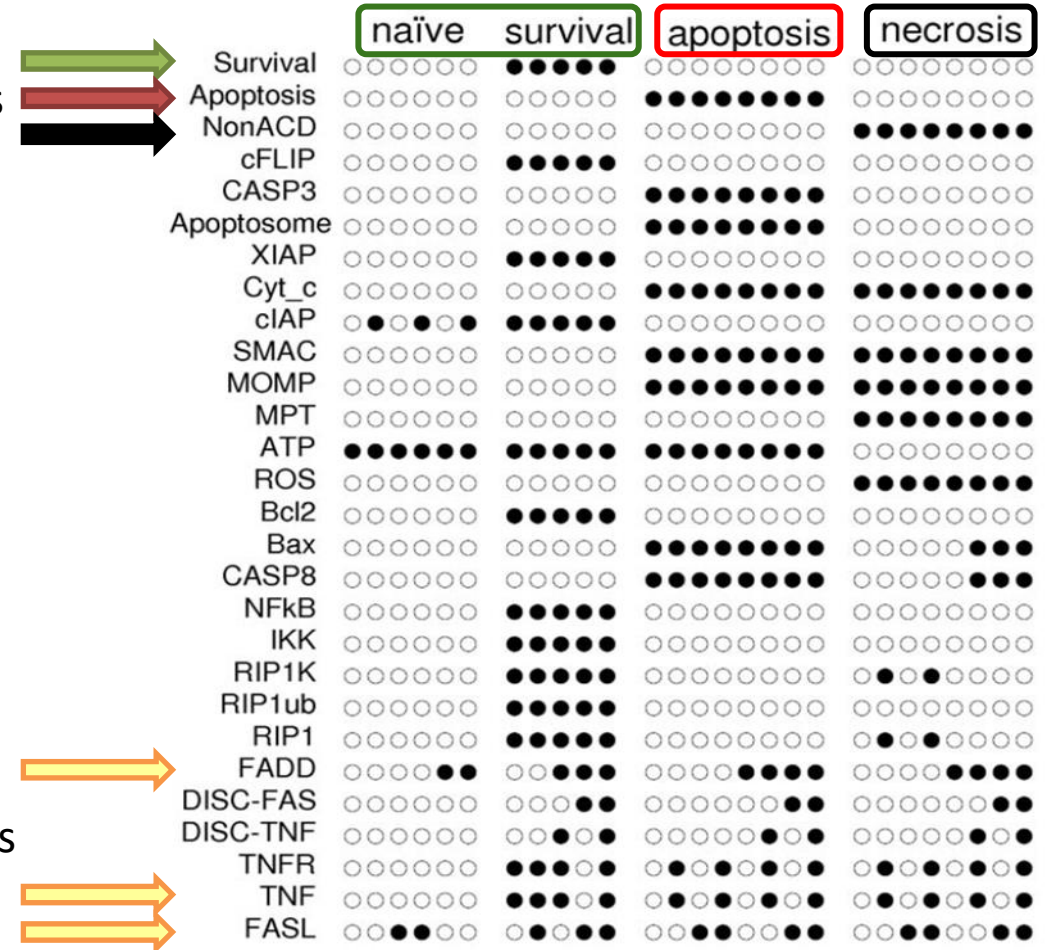
Letort et al., *Bioinformatics*, 2018, bty766

- What are the **solutions of the model** that can be interpreted biologically?
- What are the **important nodes** of the network?
- How **robust/sensitive** is the model?
- Can we **predict genetic interactions** (epistasis, synthetic lethality) from the model?
 - Knock outs & overexpression
- Can we **simplify/reduce the model** to highlight the most important processes?

TNF response and cell fates



Outputs



Inputs

Letort et al., *Bioinformatics*, 2018, bty766

Calzone et al., *PLoS Comput Biol*, 2010, 6(3): e1000702

Analysing stable states probabilistically

Continuous time Markov process on the Boolean transition state space

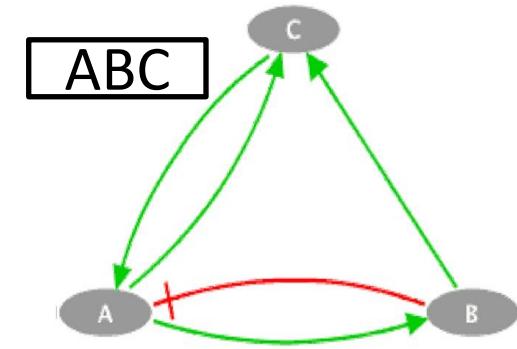
- Each **Boolean state** has an associated **probability**
- **Rate of change** associated to each transition
 - rate up and rate down
- Stochasticity, time, probabilities, ...

Perturbations can be studied in a probabilistic manner

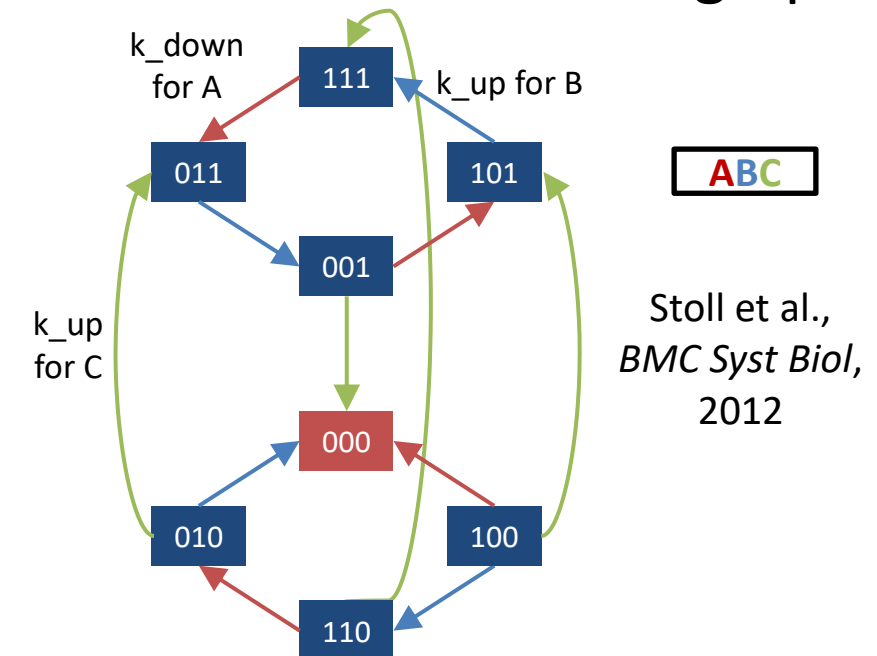
- Transient effects, such as knock downs
- **Dosage** experiments

More information:

- Stoll et al., *BMC Syst Biol*, 2012, DOI: 10.1186/1752-0509-6-116
- Stoll et al., *Bioinformatics*, 2017, DOI: 10.1093/bioinformatics/btx123



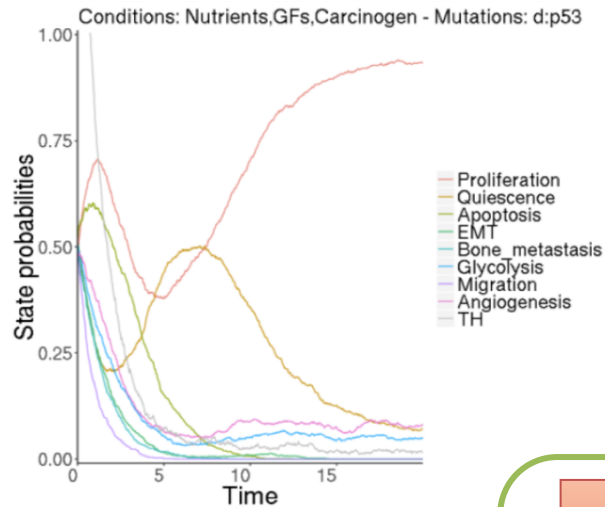
Boolean state transition graph



Stochastic simulations

Conditions

Nutrients	Androgen	GFs	Carcinogen	Hypoxia
50%	50%	50%	10%	10%

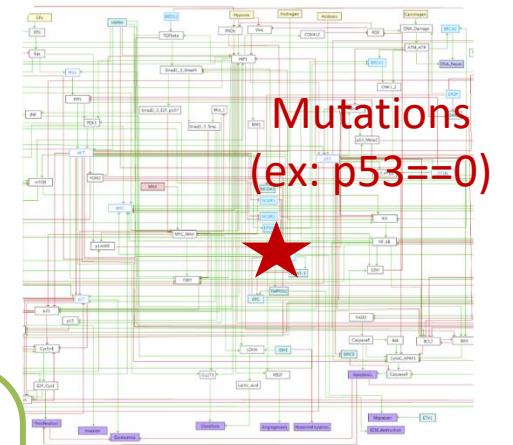


Probabilities
based on 1000
trajectories

Stochastic trajectories

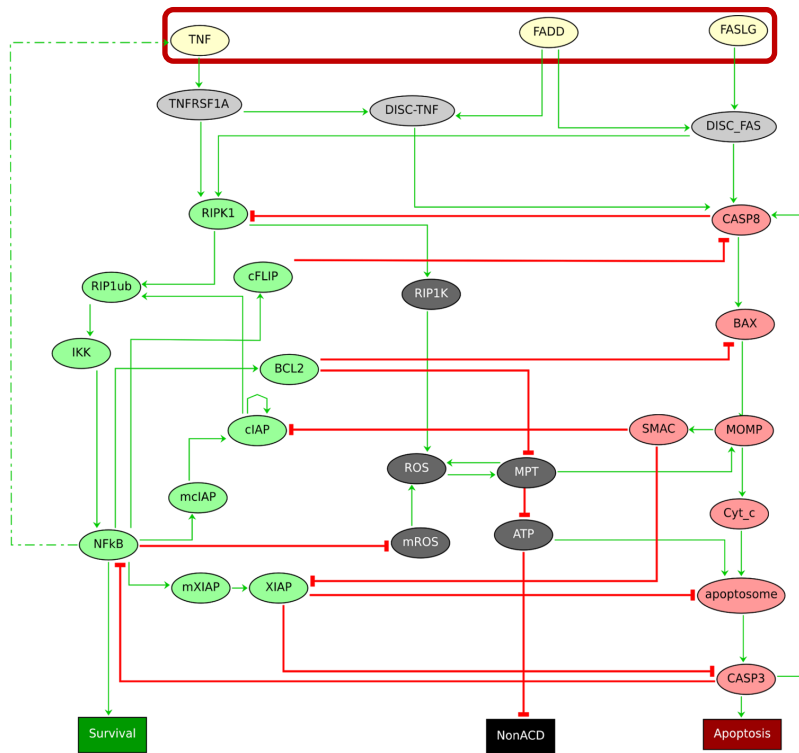
Apoptosis	10%	Proliferation	23%	Quiescence	67%
EMT	0%	Metastasis	0%	Angiogenesis	10%
DNA repair	5%	Migration	0%		

Signalling pathways

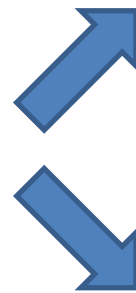


Stoll et al., 2012, 2017

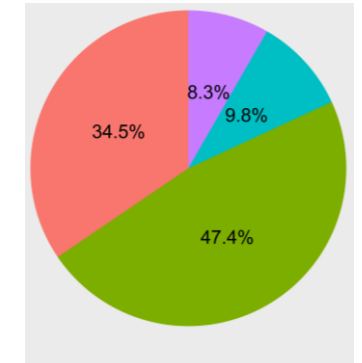
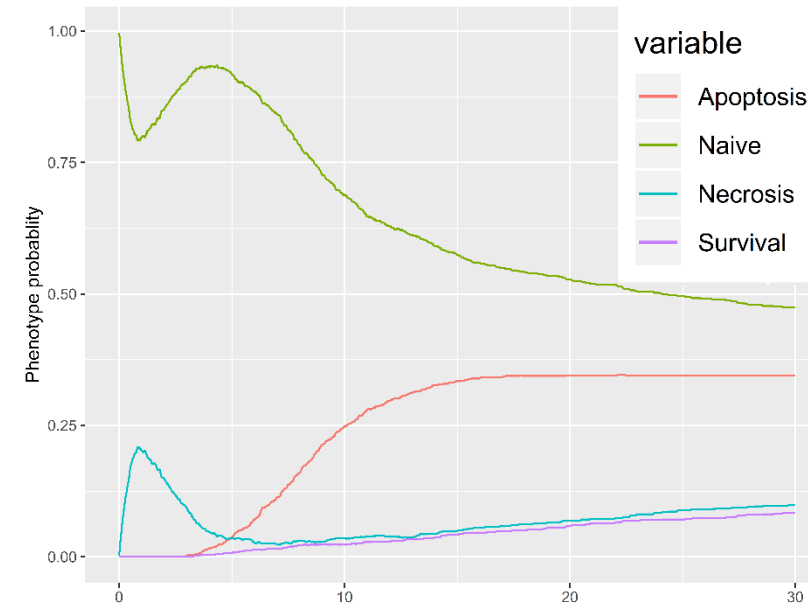
TNF response and cell fates' probabilities



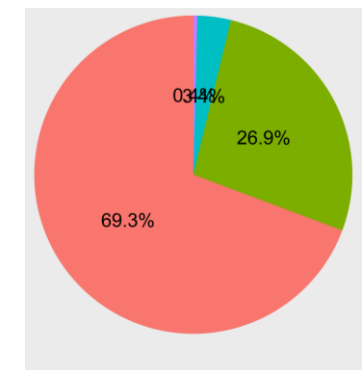
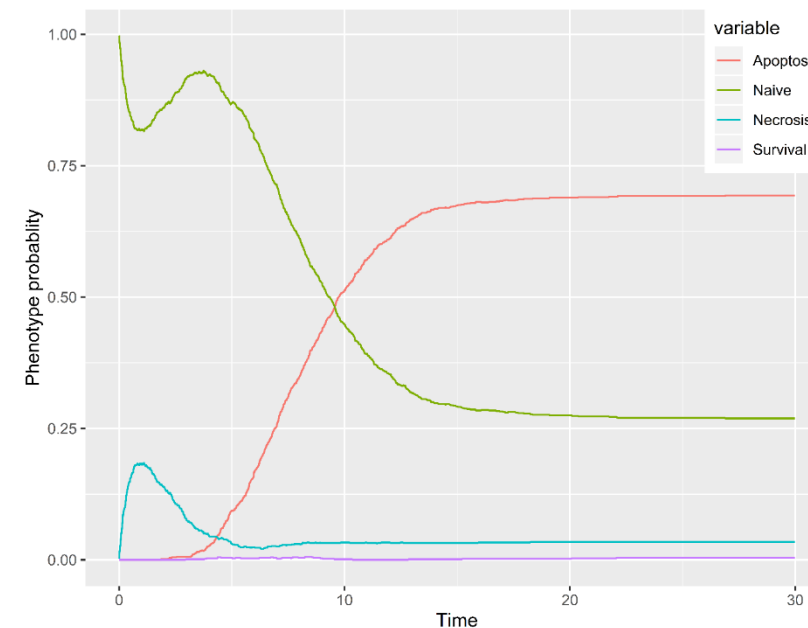
All inputs
random initial
conditions



FADD initial
condition = 1



Apoptosis Naive
Necrosis Survival

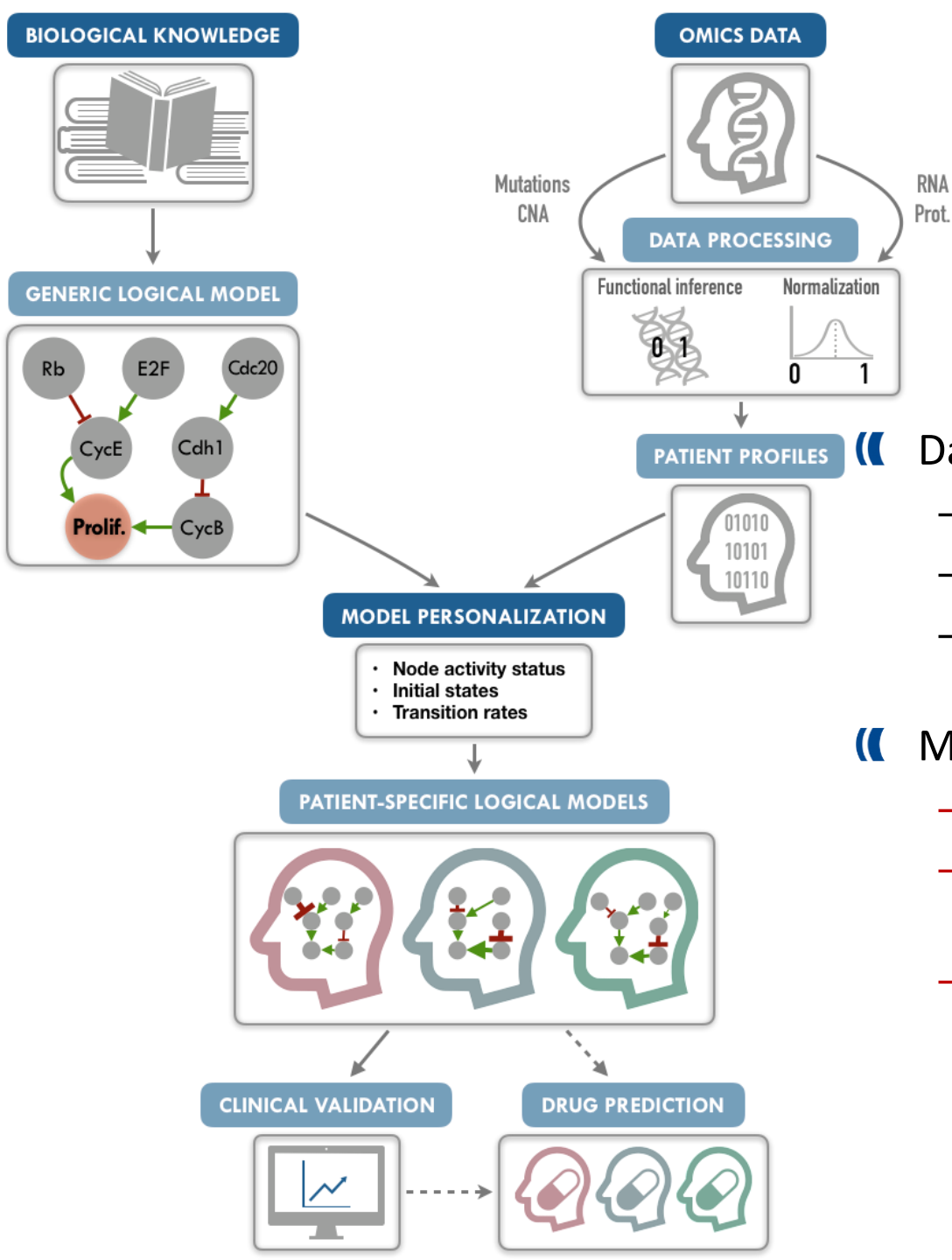


Apoptosis Naive
Necrosis Survival

Modelling patient-specific Boolean networks

MaBoSS

Béal et al., *Frontiers in Physiology*, 2019

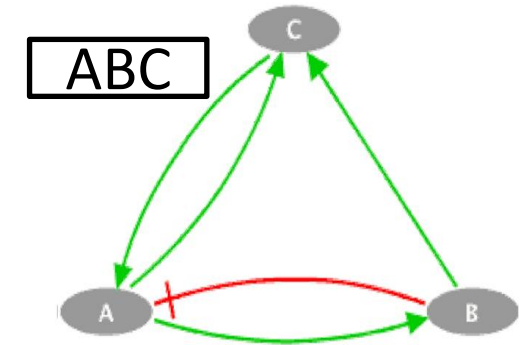


Data types:

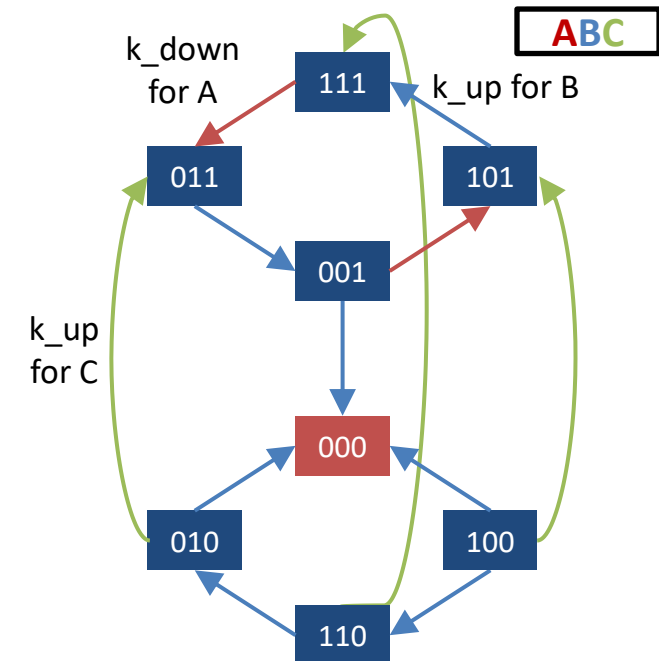
- Copy Number Alterations
- Mutations
- Expression: RNA and/or proteins

Modelling framework's variables:

- **Node states** = mutants
- **Initial conditions** = growth media conditions or experimental setup
- **Transitions rates** = Gene's ability to activate or deactivate



Boolean state transition graph

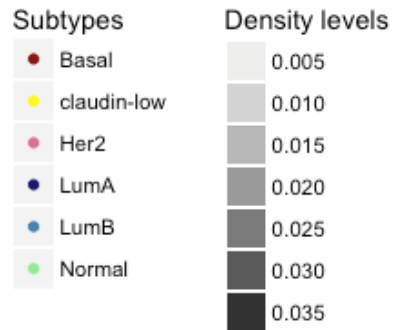
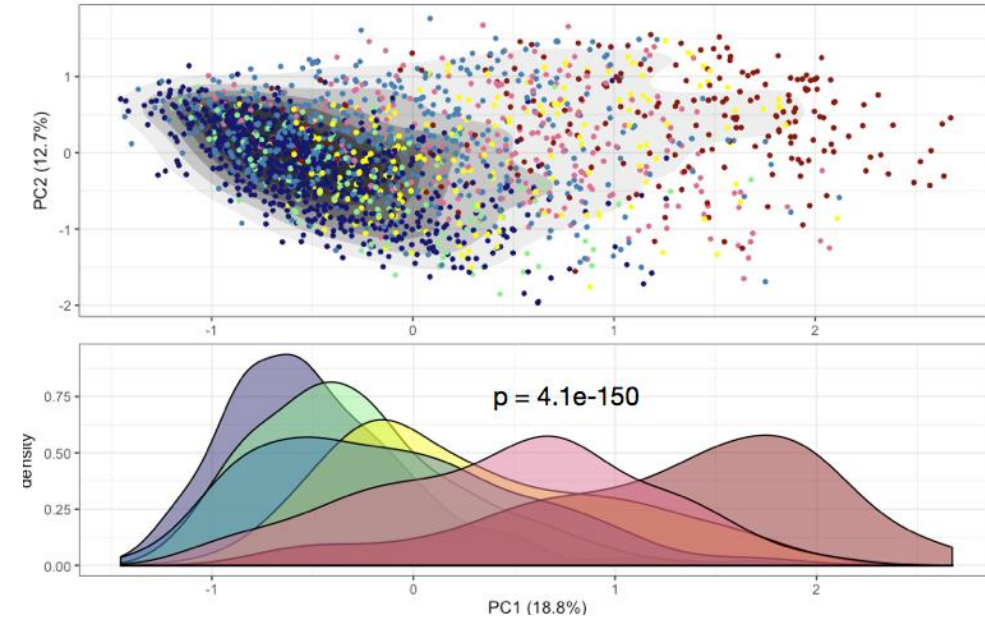


Stoll et al.,
BMC Syst Biol, 2012

Phenotypes correlate with clinical data: METABRIC models vs PAM50 and survival data

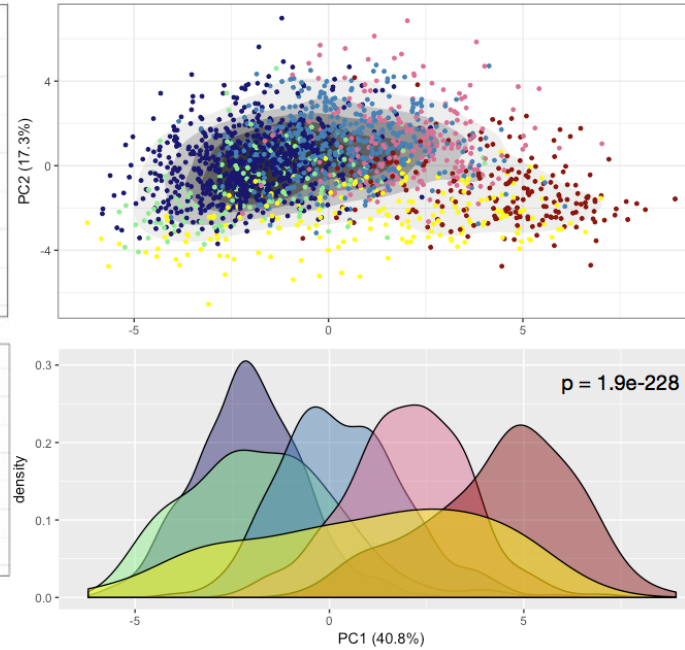
PAM50 Subtypes - PCA with Simulation Outputs from Case #5

With principal components PC1 and PC2 as X and Y axis

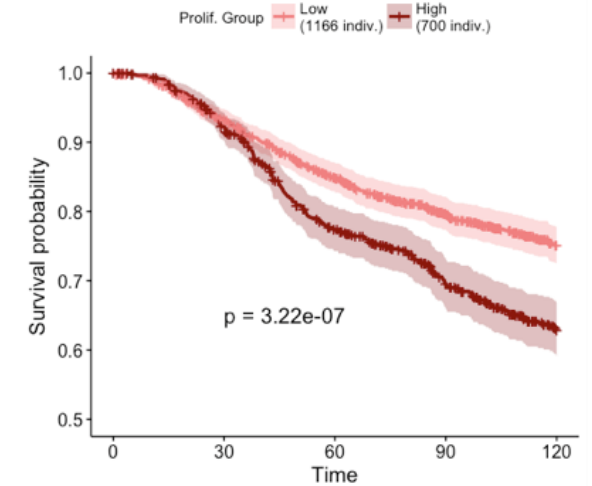


PAM50 Subtypes - Model-related RNA

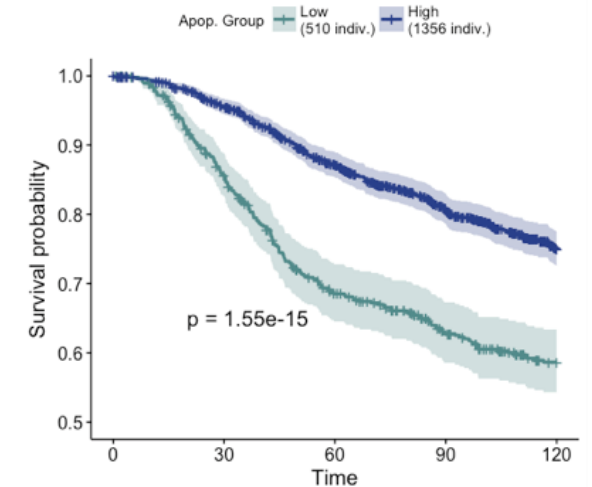
With principal components PC1 and PC2 as X and Y axis



a) Survival Curves Based on Proliferation Scores (0.48 cutoff)

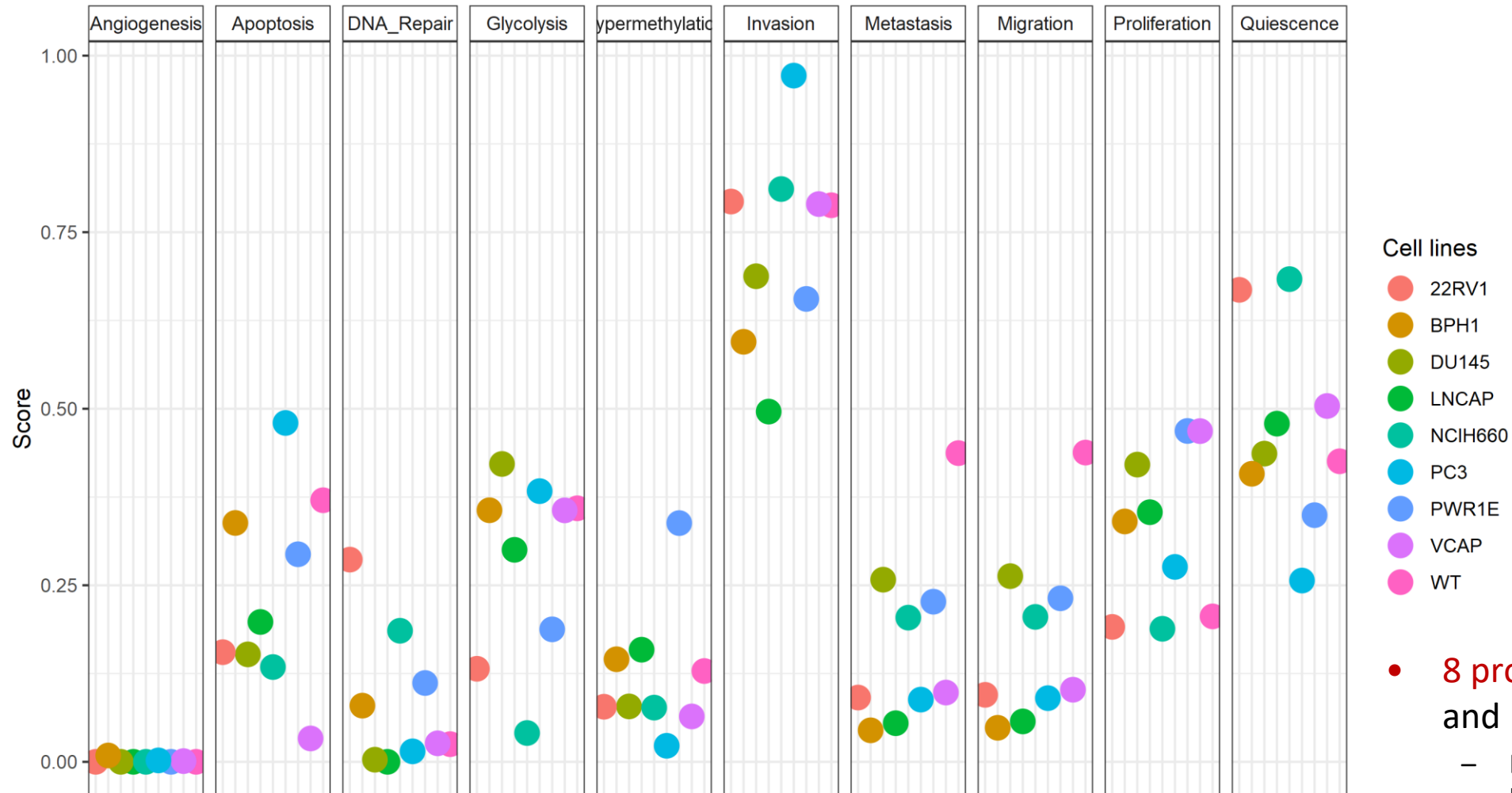


b) Survival Curves Based on Apoptosis Scores (0.67 cutoff)



Cell-line-specific Boolean models

Distribution of phenotypes scores across GDSC prostate cohort,
using Mutations as node states, RNA as transition rates
and random initial conditions



- 8 prostate cell lines have CNA and RNA
 - BPH-1 is a benign prostate hyperplasia
- WT is non-personalised model

If you want more information

Logical modelling pipeline

- ⌈ Extensive and comprehensive studies can be done with a validated model and tools on the field
- ⌈ Experimentally friendly hypotheses can come out of these studies
- ⌈ Available at GitHub

Flexible pipeline of methods

- ⌈ Generates data-tailored models
 - Cell lines
 - Patients
- ⌈ Correlates with clinical data
 - Highly dependent on available clinical data
- ⌈ Available at GitHub

https://github.com/sysbio-curie/Logical_modelling_pipeline



Briefings in Bioinformatics, 2017, 1–12

doi: 10.1093/bib/bbx163
Paper

Conceptual and computational framework for logical modelling of biological networks deregulated in diseases

Arnau Montagud, Pauline Traynard, Loredana Martignetti, Eric Bonnet, Emmanuel Barillot, Andrei Zinovyev and Laurence Calzone

<https://github.com/sysbio-curie/PROFILE>

Personalization of Logical Models With Multi-Omics Data Allows Clinical Stratification of Patients

Jonas Béal, Arnau Montagud, Pauline Traynard, Emmanuel Barillot* and Laurence Calzone*

Institut Curie, PSL Research University, Mines Paris Tech, Inserm, U900, Paris, France

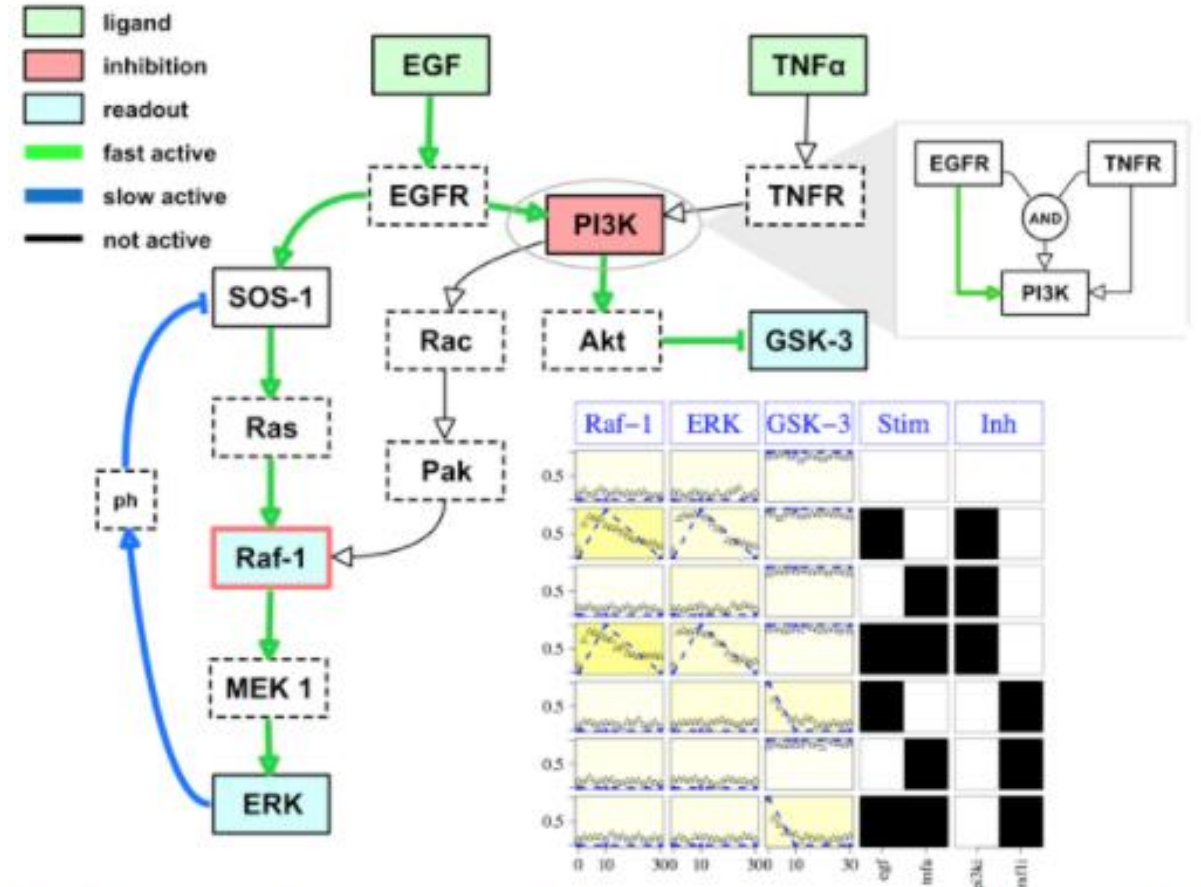
If you want more information – CellNOpt

CellNOpt

Identification of signaling models based on perturbation data and prior knowledge

<https://saezlab.github.io/CellNOptR/>

<https://github.com/saezlab/cellnopt>



An illustration of how we use our logic modeling method CellNOpt to better understand deregulation of signal transduction in disease. Left: simple pathway model; right: experimental data and match between model simulations and data.

Agent-based as multiscale modelling



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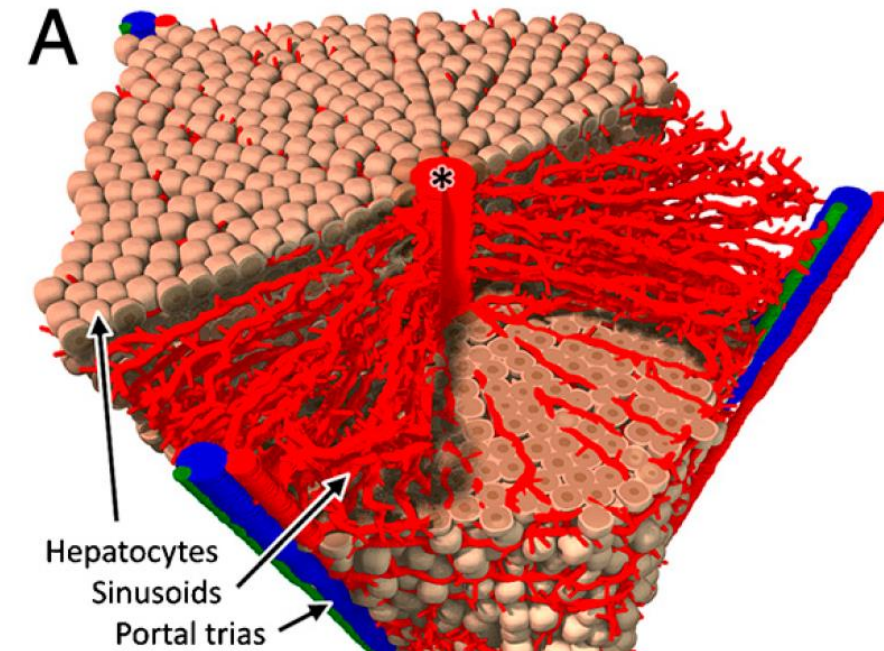
Agent-based modelling

Agent-based models are composed of:

1. numerous agents;
2. decision-making heuristics;
3. an interaction topology; and
4. a description of the environment.

Examples:

- Ecology
- Environmental Science
- Artificial Intelligence
- Tissue Biology

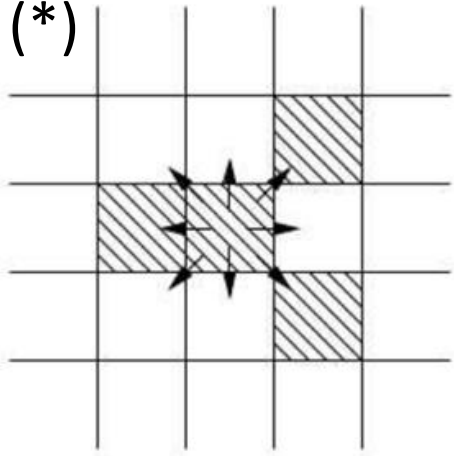


Hoehme et al, PNAS, 2010

Agent-based model for multicellular modelling

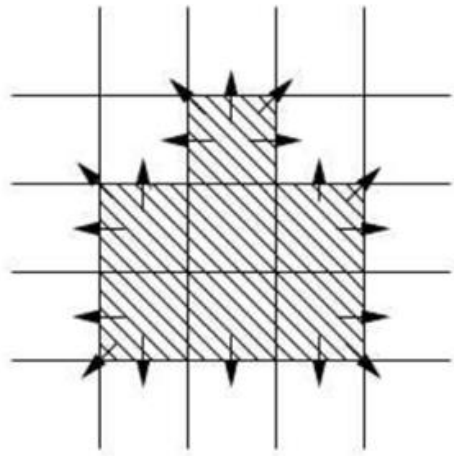
Different ABM approaches for multicellular modelling

(*)



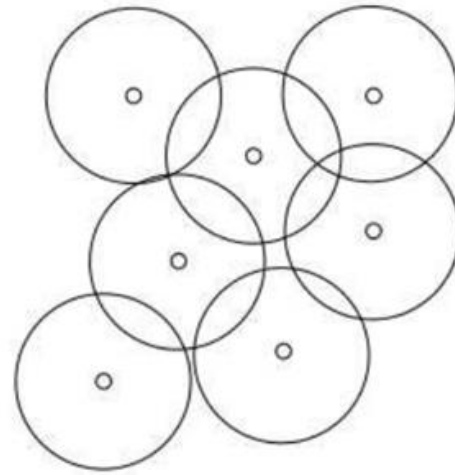
(a)

Cellular automaton



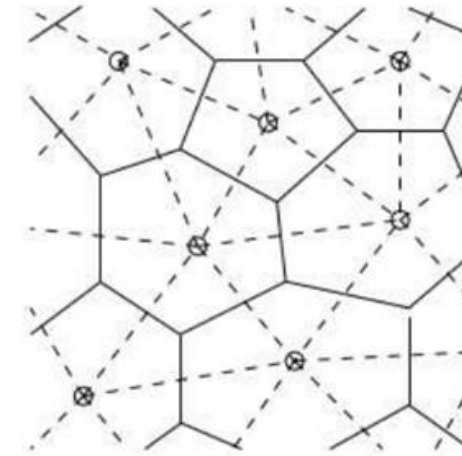
(b)

Cellular Potts

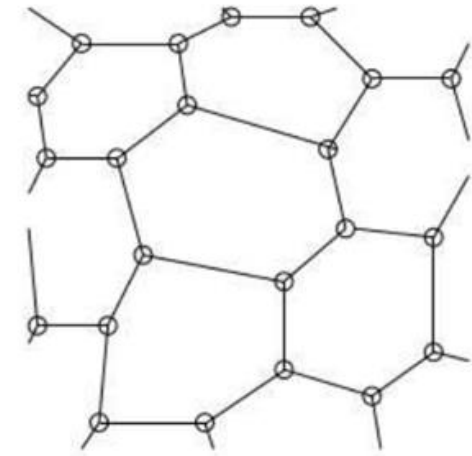


(c)

Overlapping spheres



(d)

Voronoi tessellation
model


(e)

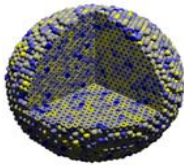
Vertex model

“... An **agent-based model** is a class of *computational models* for *simulating* the actions and interactions of autonomous agents (...) It combines elements of *game theory*, *complex systems*, *emergence*, (...). *Monte Carlo methods* are used to introduce randomness...” (**)

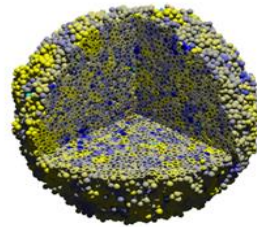
Multi-scale modeling framework: PhysiCell

An open source physics-based cell simulator for 3-D multicellular systems

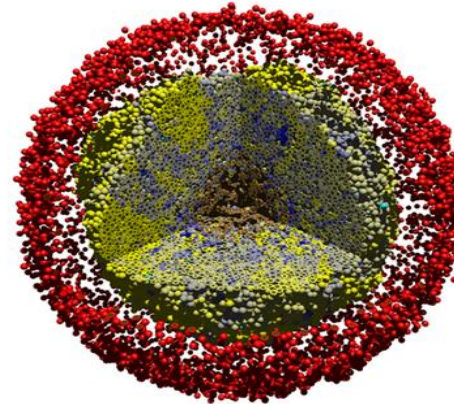
0 days
18,317 cells



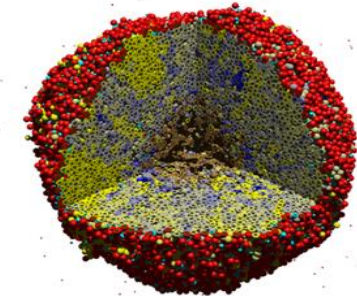
7 days
53,600 cells



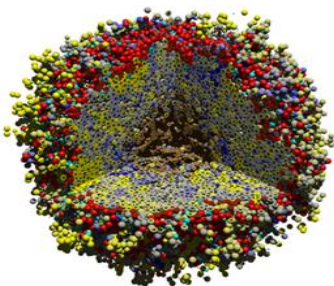
14 days + 3 min
111,479 cells



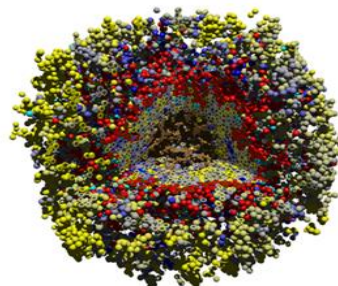
14 days + 6 hours
113,668 cells



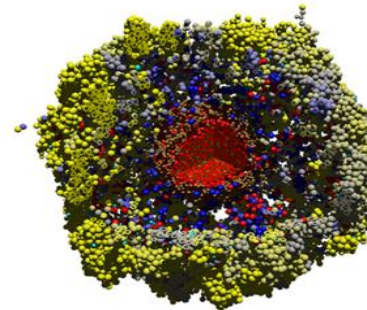
15 days
91,189 cells



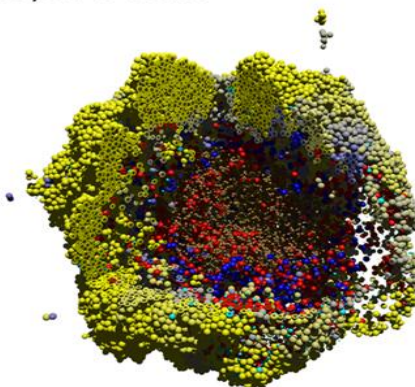
16 days
51,788 cells



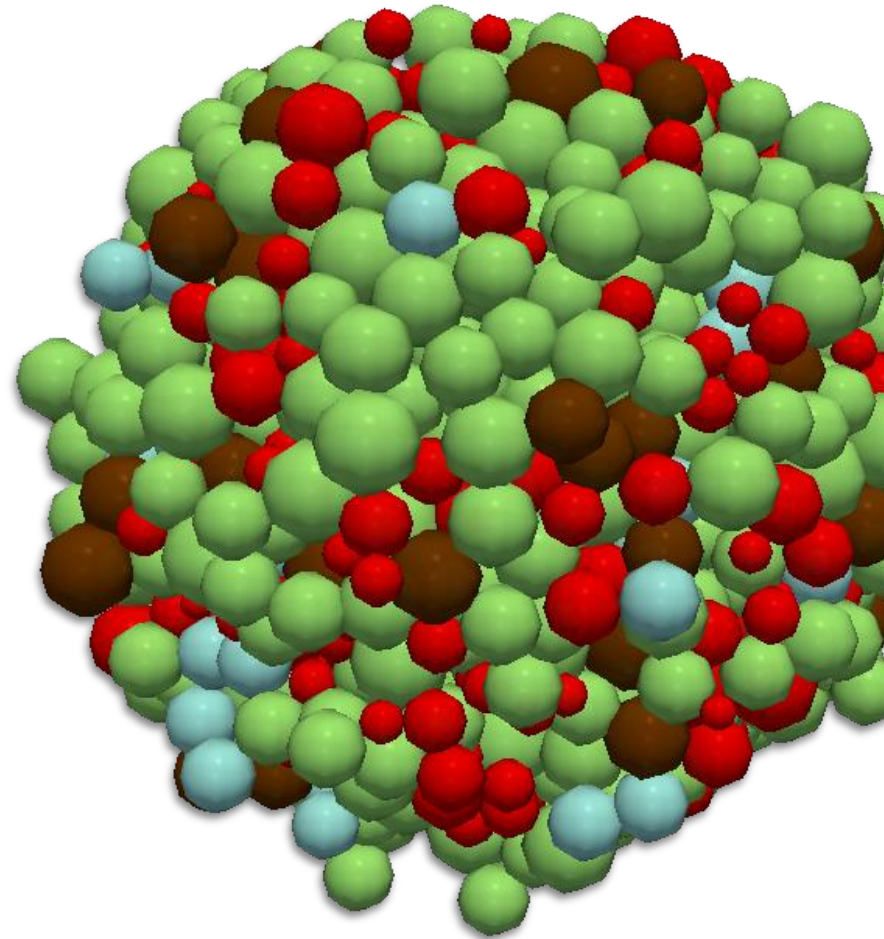
18 days
38,122 cells



21 days
66,978 cells



The basic cell agent has properties



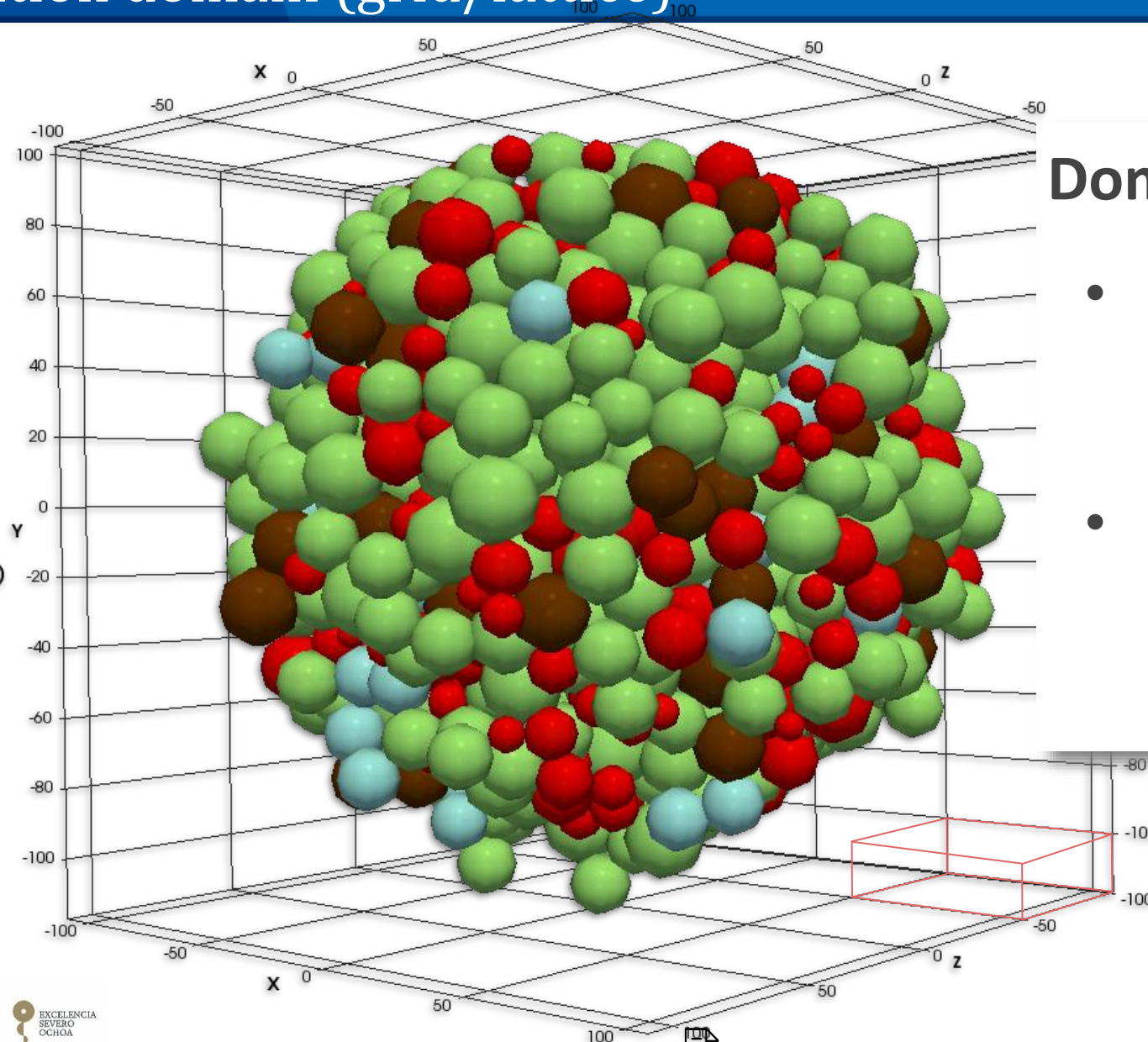
Cell Cycle Phase

- Premitotic
- Postmitotic
- Ki67 negative
- Apoptotic
- Necrotic
- Necrotic (swelling)
- Necrotic (lysis)

Cell agent properties

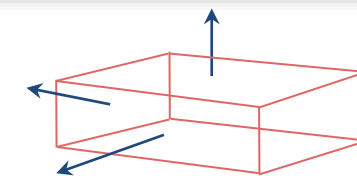
- **Cell Volume**
 - nucleus
 - cytoplasm
- **Position** (x, y, z)
 - Neighborhood
 - Environment
- **Cell internal state**
 - Cell cycle phase (G_0 , M , etc)
 - Growth rate
 - Custom phenotype

The simulation domain (grid/lattice)



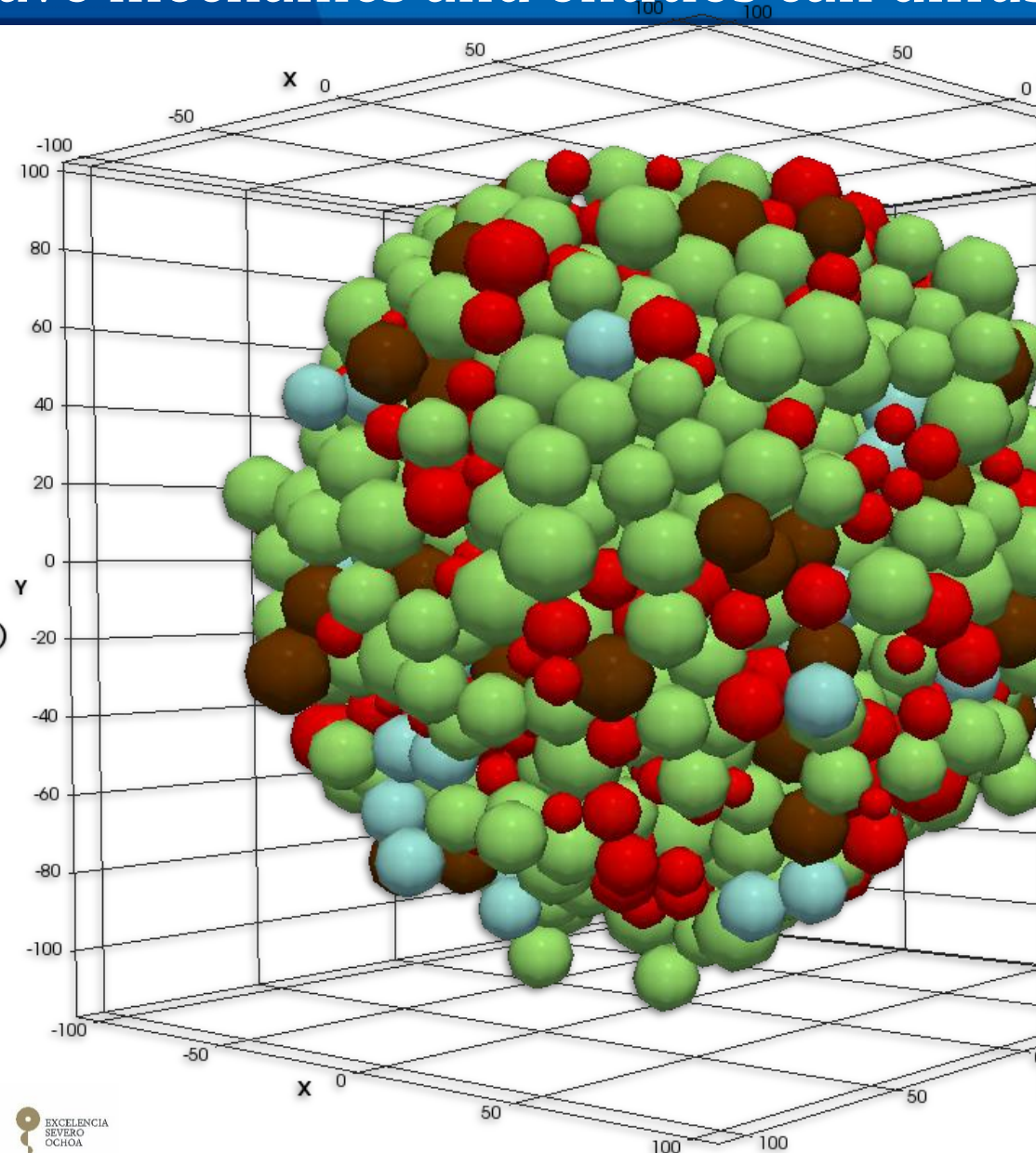
Domain = Voxels' grid

- 2D-Monolayers
 - petri-dish
 - epithelia
 - bio-film
- 3D-Shapes
 - spheroid
 - ductal
 - more complex shapes



Voxel

Cells can have mechanics and entities can diffuse



Diffusion and mechanics are directed by differential equations

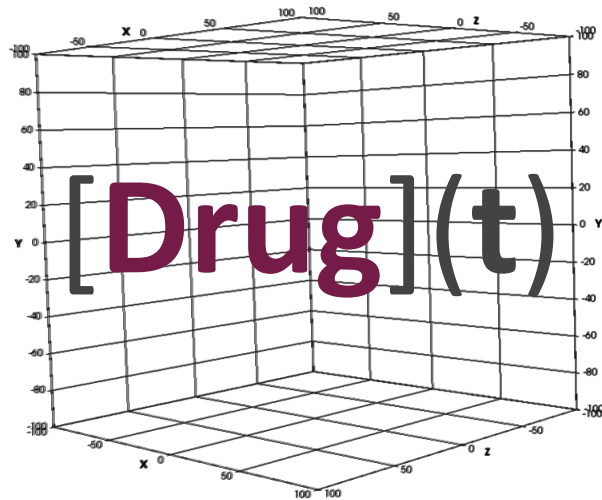
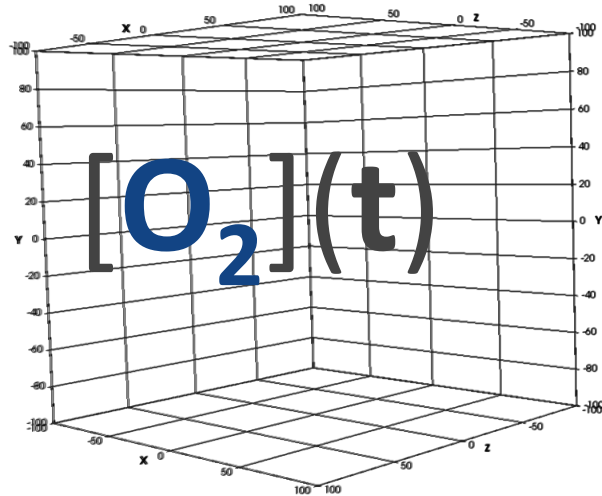
Mechanical equations

$$\mathbf{v}_i = \sum_{j \in \mathcal{N}(i)} \left(\underbrace{-\sqrt{c_{cca}^i c_{cca}^j} \nabla \phi_{1,R_i,A+R_j,A}}_{\text{cell-cell adhesion}} - \underbrace{\sqrt{c_{ccr}^i c_{ccr}^j} \nabla \psi_{1,R_i+R_j}}_{\text{cell-cell repulsion}} \right) - \underbrace{c_{cba}^i \nabla \phi_{1,R_i,A} (-d(\mathbf{x}_i) \mathbf{n}(\mathbf{x}_j))}_{\text{cell-BM adhesion}} - \underbrace{c_{cbr}^i \nabla \psi_{1,R_i} (-d(\mathbf{x}_i) \mathbf{n}(\mathbf{x}_j))}_{\text{cell-BM repulsion}} + \mathbf{v}_{i,\text{mot}}$$

Diffusion equations

$$\frac{\partial \rho}{\partial t} = \underbrace{\mathbf{D} \nabla^2 \rho}_{\text{diffusion}} - \underbrace{\lambda \rho}_{\text{decay}} + \underbrace{\mathbf{S}(\rho^* - \rho)}_{\text{bulk source}} - \underbrace{\mathbf{U} \rho}_{\text{bulk uptake}} + \underbrace{\sum_{\text{cells } k} \delta(\mathbf{x} - \mathbf{x}_k) W_k [\mathbf{S}_k(\rho_k^* - \rho) - \mathbf{U}_k \rho]}_{\text{sources and uptake by cells}} \text{ in } \Omega$$

Environment can be dynamic and reactive



Reaction-Diffusion Equations

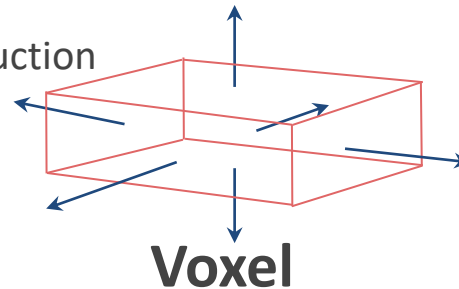
$$\frac{\partial \rho}{\partial t} = \underbrace{D \nabla^2 \rho}_{\text{diffusion}} - \underbrace{\lambda \rho}_{\text{decay}} + \underbrace{S(\rho^* - \rho)}_{\text{bulk source}} - \underbrace{U \rho}_{\text{bulk uptake}}$$

$$+ \sum_{\text{cells } k} \delta(\mathbf{x} - \mathbf{x}_k) W_k [S_k(\rho_k^* - \rho) - U_k \rho] \text{ in } \Omega$$

sources and uptake by cells

System of PDEs for each molecule:

- Diffusion term
- Decay
- Uptake/Production



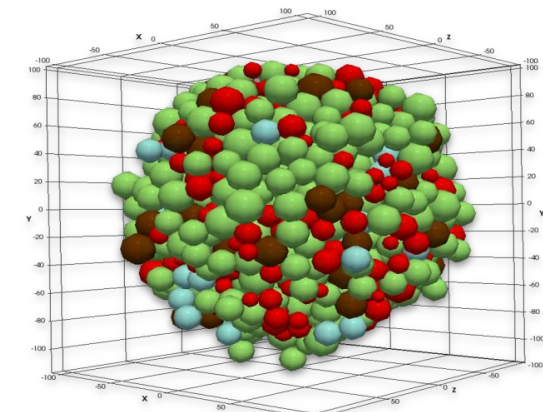
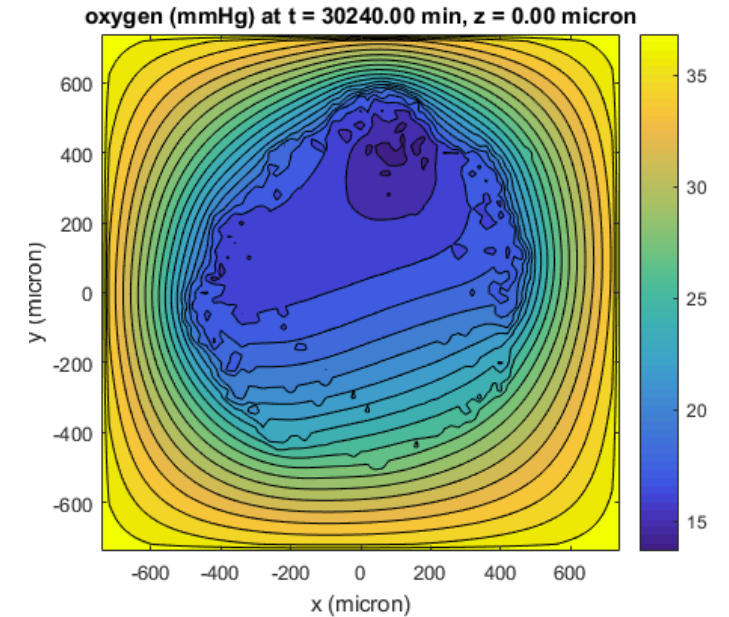
Voxel

Surrounding physical environment

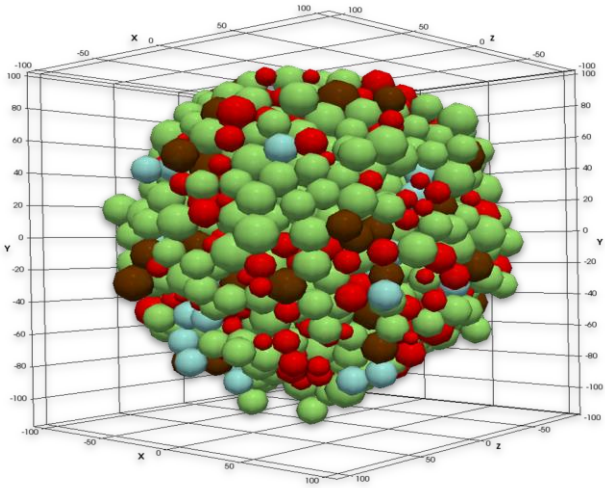
Surrogate for extra-celular matrix

- Field with densities that can be produced & consumed
- Inert agents that can be moved

Gradient of chemical factors (O2)



Simulation workflow

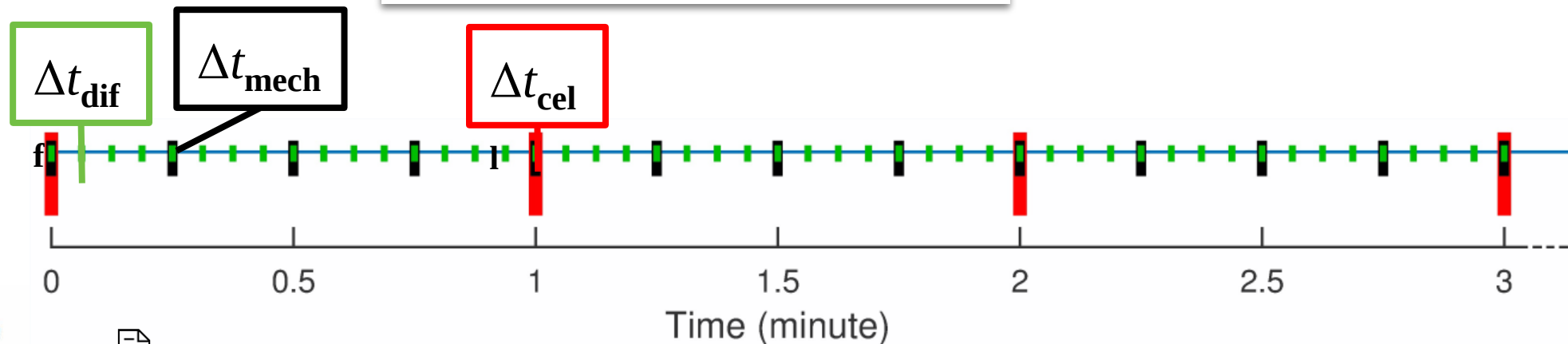


Simulation's main loop

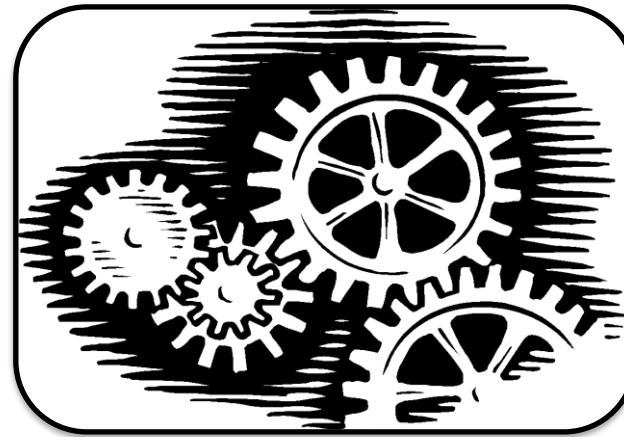
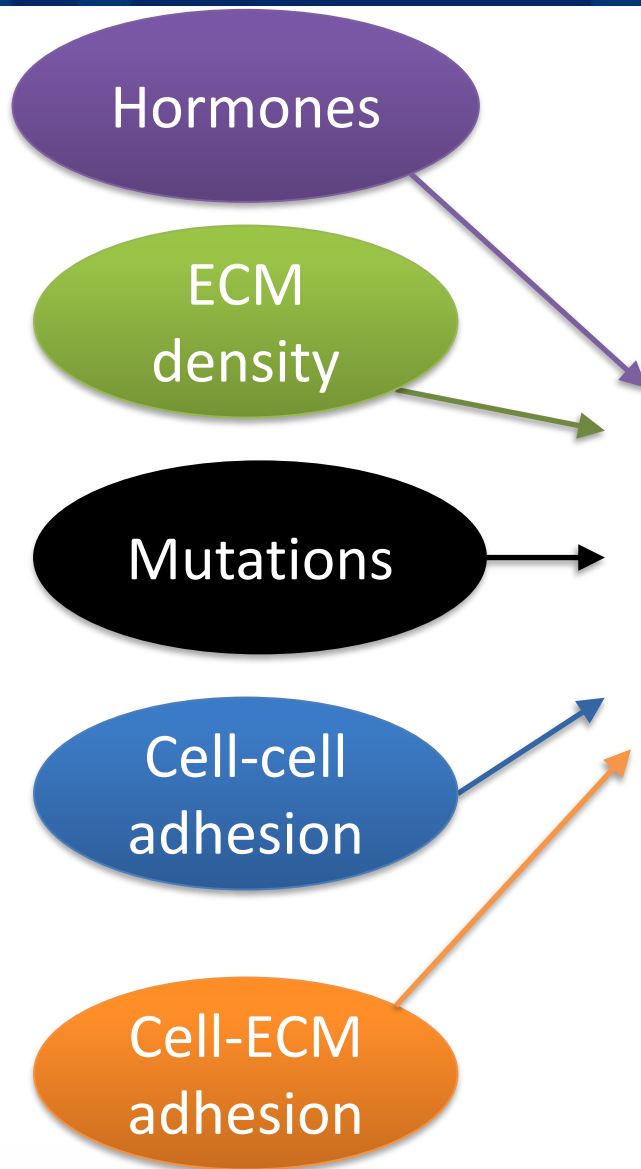
```
while t_current < tend
    update_diffusion()
    if Δt % Δt_mech == 0
        update_cell_mechanics()
    if Δt % Δt_cell == 0
        update_cell_processes()
    Δt = 0
    Δt += t_step
    t_current += t_step
```

Time scales

- Δt_{diff} : (diffusion/transport): 0.01 min
- Δt_{mech} : (cell movement): 0.1 min
- Δt_{cell} : (cell processes): 6 min



Modifying agent-based to have genotype-to-phenotype modelling



Multi-scale modelling

Gene mutations
Signalling pathways
Cell - environment
ECM modification

		Cell-cell junctions	Tumor type
Individual-cell migration	Single-cell migration		
	Amoeboid	-	Leukemia, lymphoma cell subsets (all tumors)
	Mesenchymal	-	Stromal tumors, epithelial tumors after EMT
	Amoeboid (multicellular)	?	All tumors developing amoeboid single-cell dissemination
Multicellular migration	Multicellular streaming	(+)	Tumors with mesenchymal invasion; fibroblasts leading tumor cells
	Cluster	++	Moderately differentiated epithelial tumors
	Solid strand	++	Moderately differentiated epithelial tumors with subregions after EMT; basal and squamous cell carcinoma
	Strand (with lumen)	++	Differentiated epithelial tumors; vascular neoplasia
Growth	Strand (protrusive)	++	Moderately differentiated epithelial tumors lacking EMT
	Outward pushing tumor	++	All solid tumors

From Friedl and Alexander, Cell, 2011

Merging MaBoSS with PhysiCell: PhysiBoSS

Multi-scale ABM framework integrating physical dimension and cell signalling

MaBoSS (Barillot team at Institut Curie)

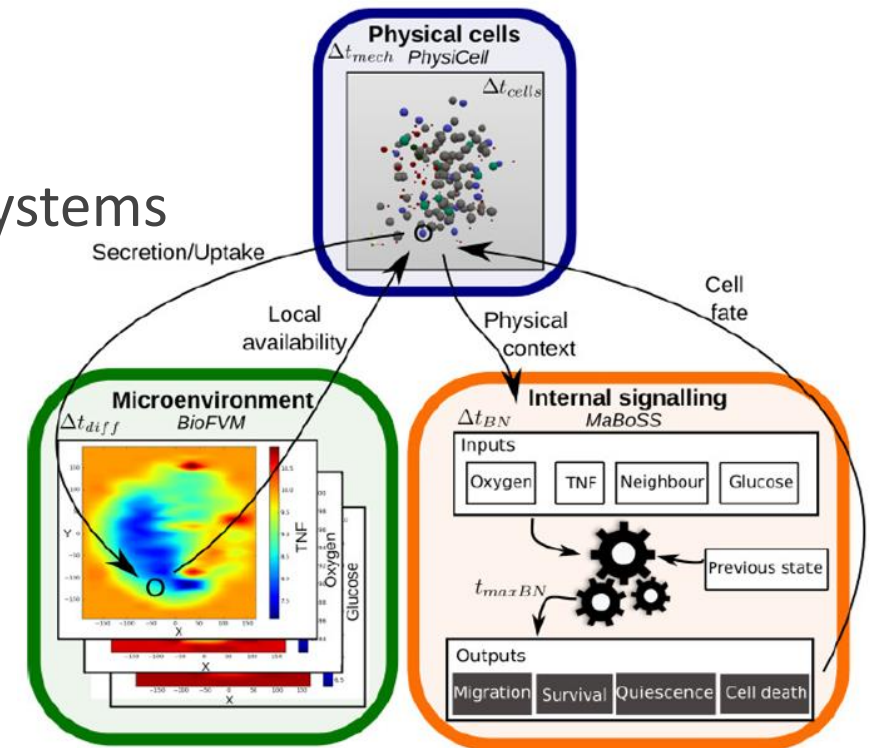
- Boolean model stochastic simulator for cell signalling

PhysiCell (Macklin team at Indiana University)

- Agent-based framework for simulating multicellular systems

PhysiBoSS (Barillot team at Institut Curie)

- A PhysiCell extension to include cellular signalling
- This allows to perform combined studies of:
 - Environmental perturbation
 - Genetic perturbation



Cells have different phenotypes depending on their genes' activation

Cell Cycle Phase

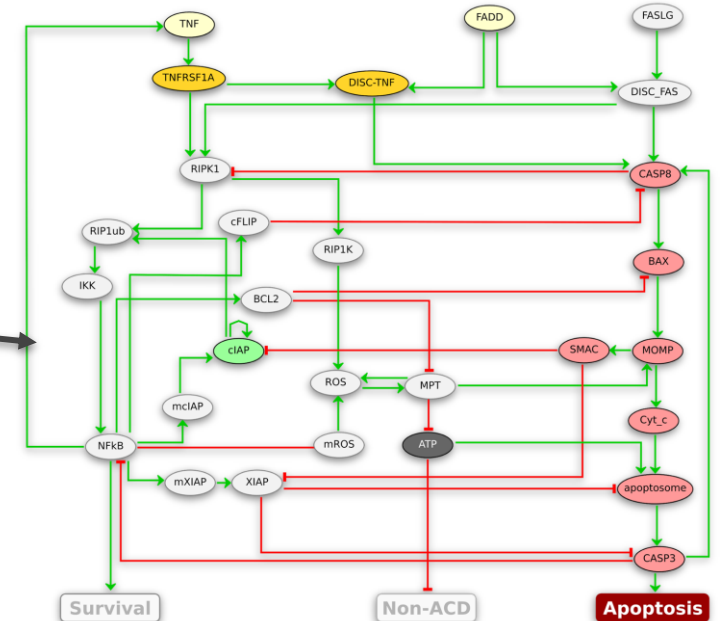
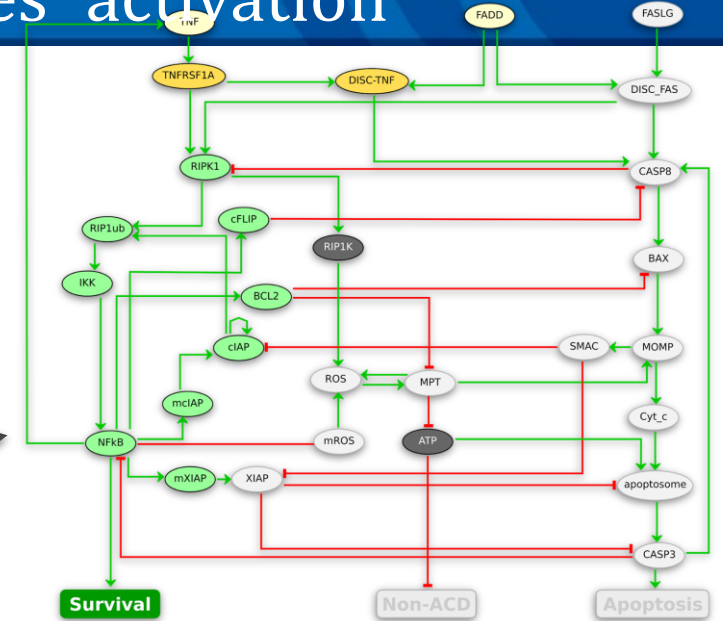
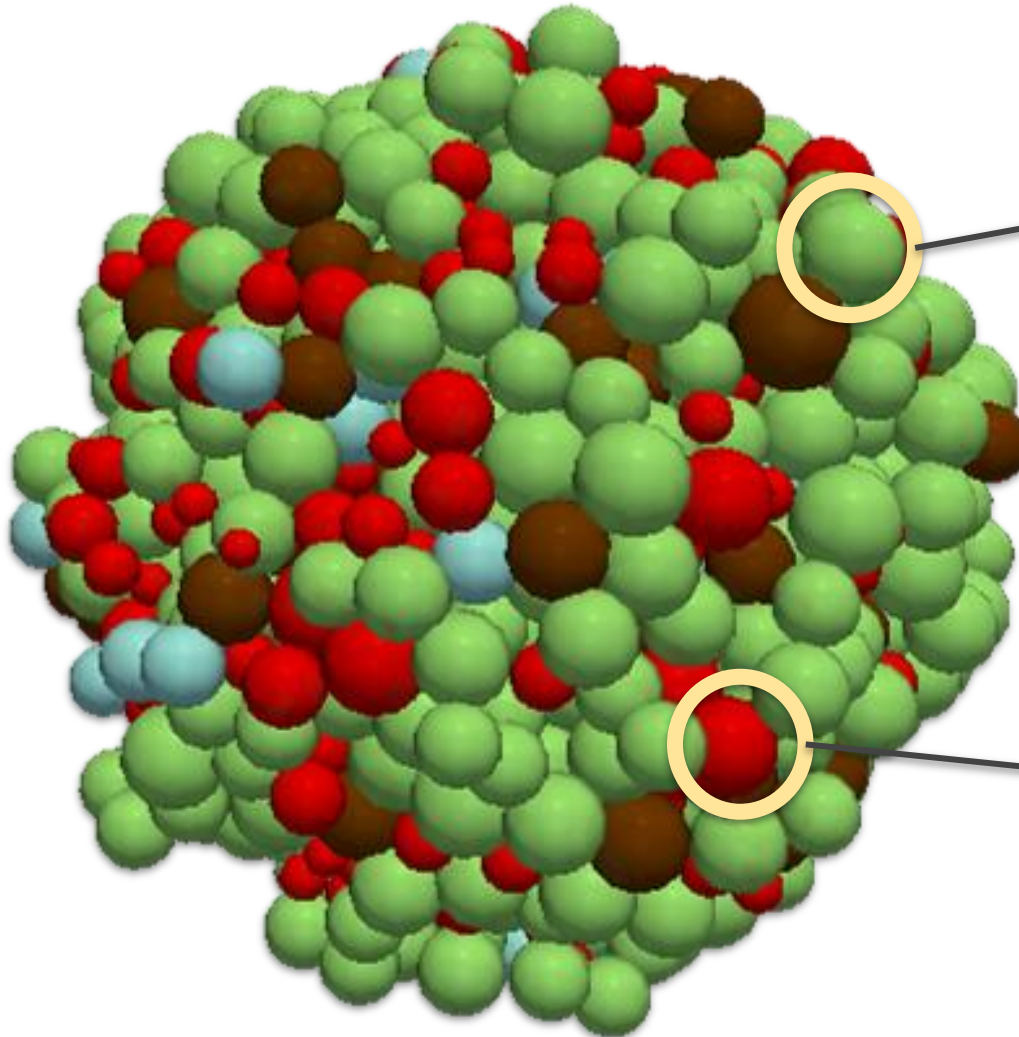
- Premitotic
- Postmitotic
- Ki67 negative
- Apoptotic
- Necrotic
- Necrotic (swelling)
- Necrotic (lysis)

Time scales

$$- \Delta t_{\text{diff}} / \Delta t_{\text{mech}} / \Delta t_{\text{cell}}$$

$$- \Delta t_{\text{signaling}}$$

Different cell signaling states



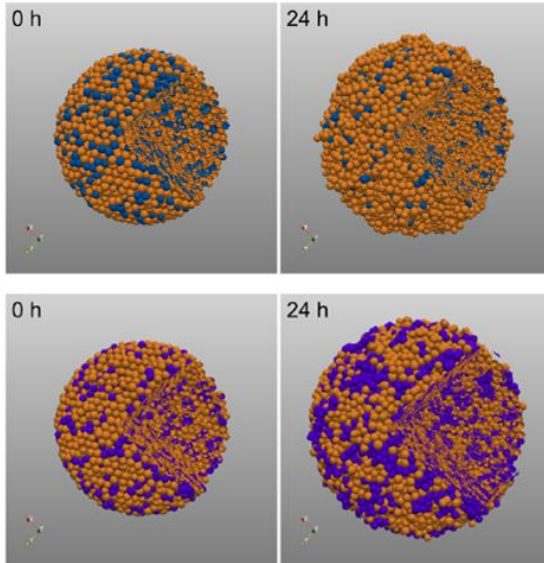
The framework allows for genetic and environmental heterogeneities

Agents can represent different cell strains

- With different biology
 - WT and mutants
 - Patient-specific networks
- With different physical properties
 - Cell-cell adhesion
 - Cell-matrix adhesion

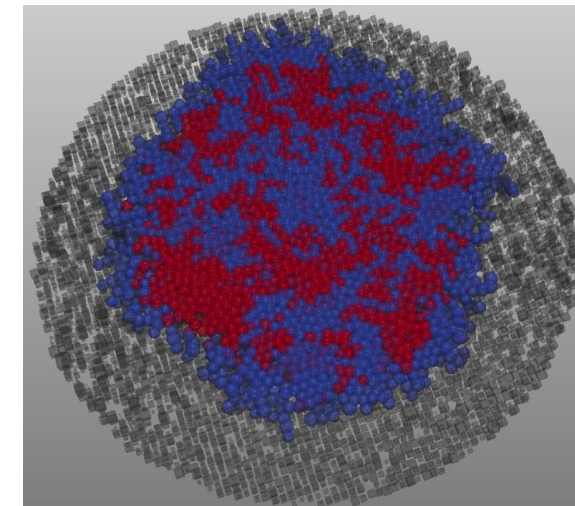
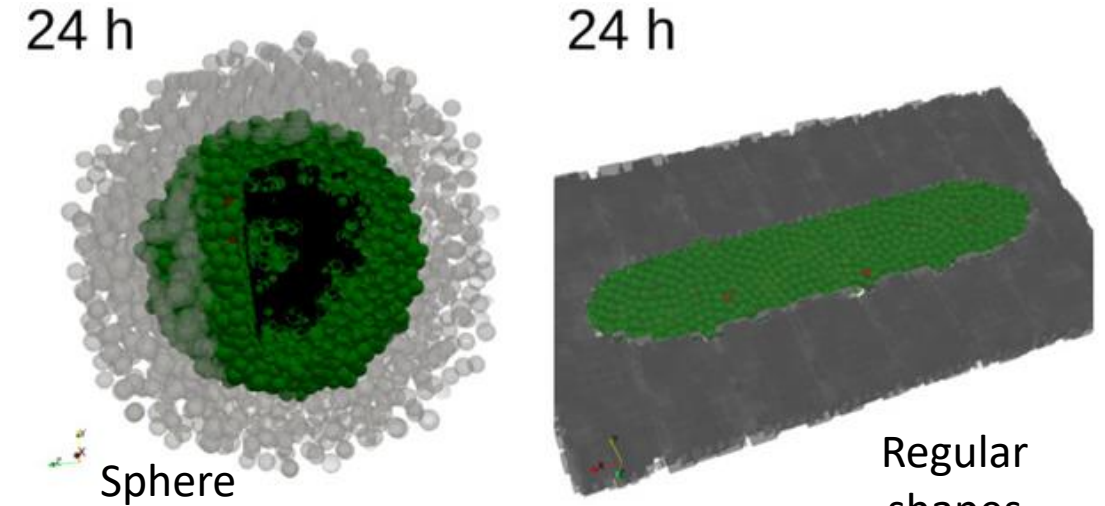
TNF: 0.5 ng/mL, cont.

Orange circle	WT	Blue circle	mROS+ cIAP-
Light blue circle	CASP3+ CytC+	Purple circle	IKK+ cFLIP+



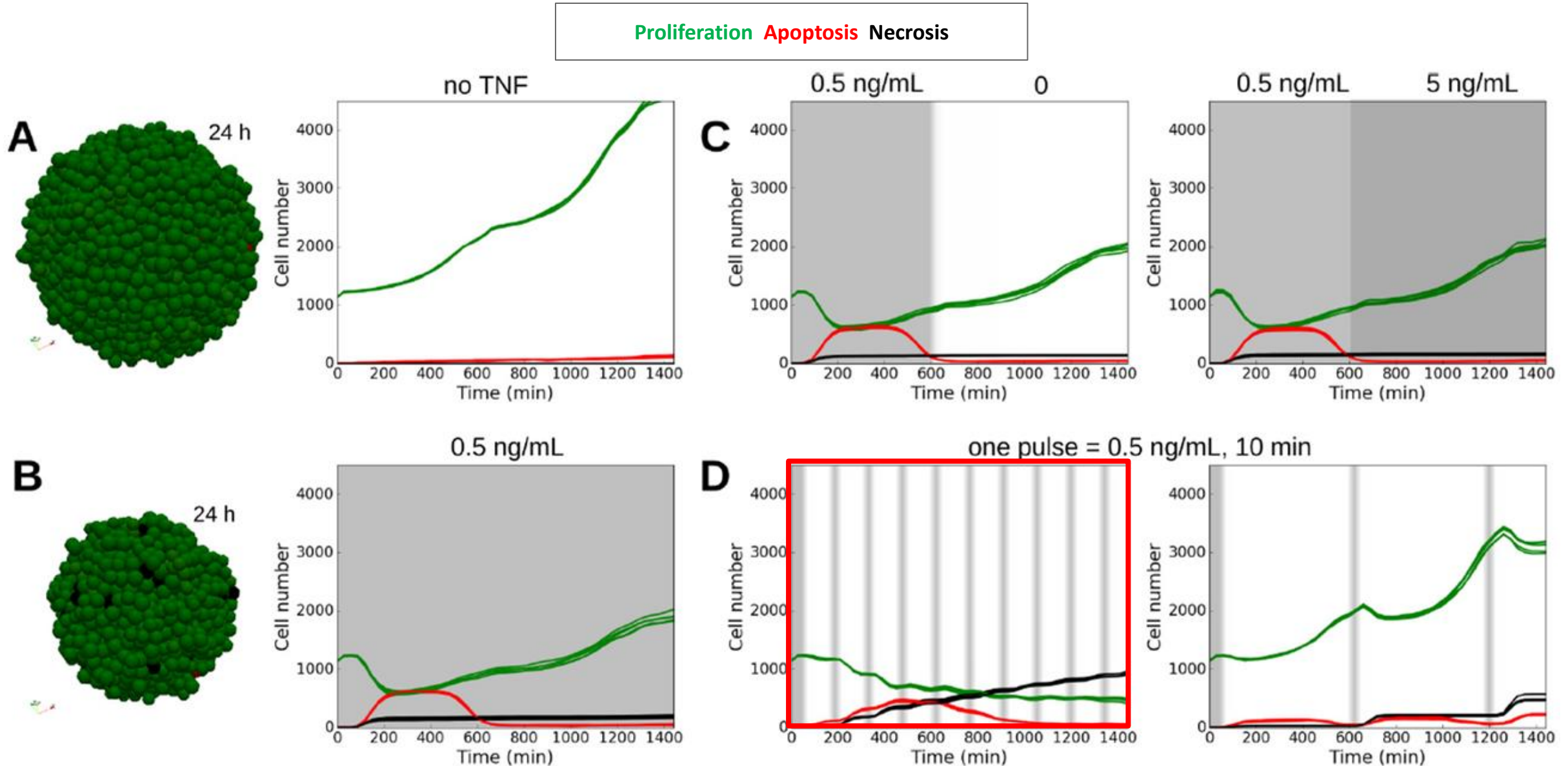
Letort et al.,
Bioinformatics, 2018,
bty766

Different tumour architectures

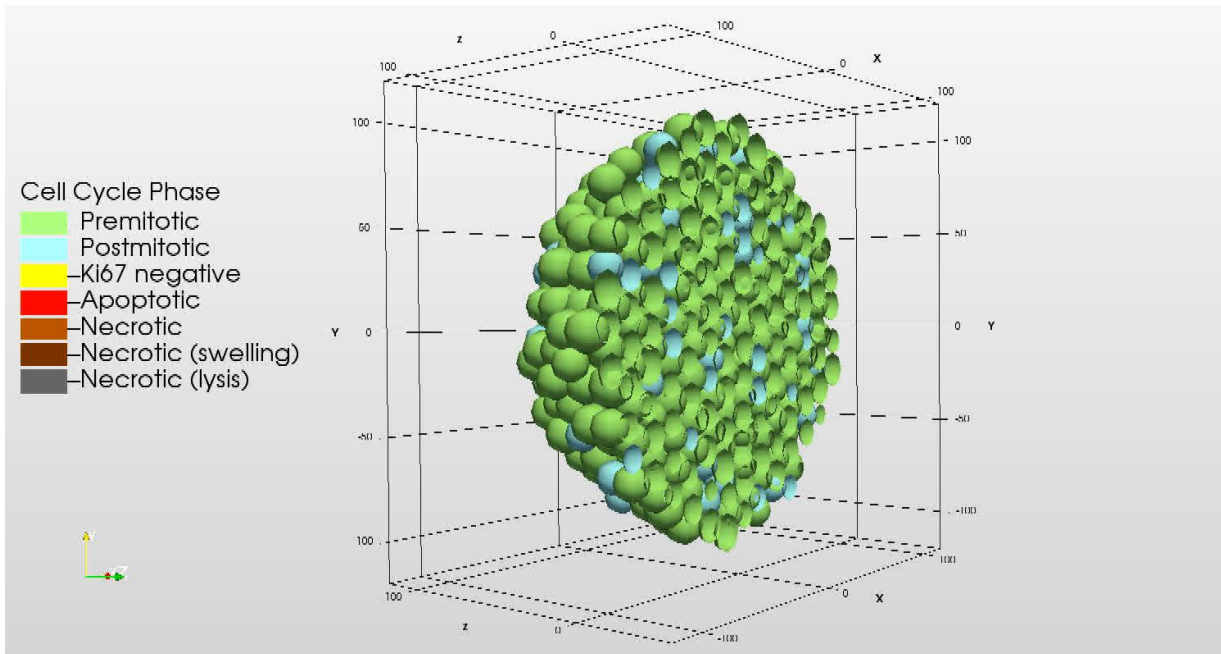


One-cell-thick
monolayer

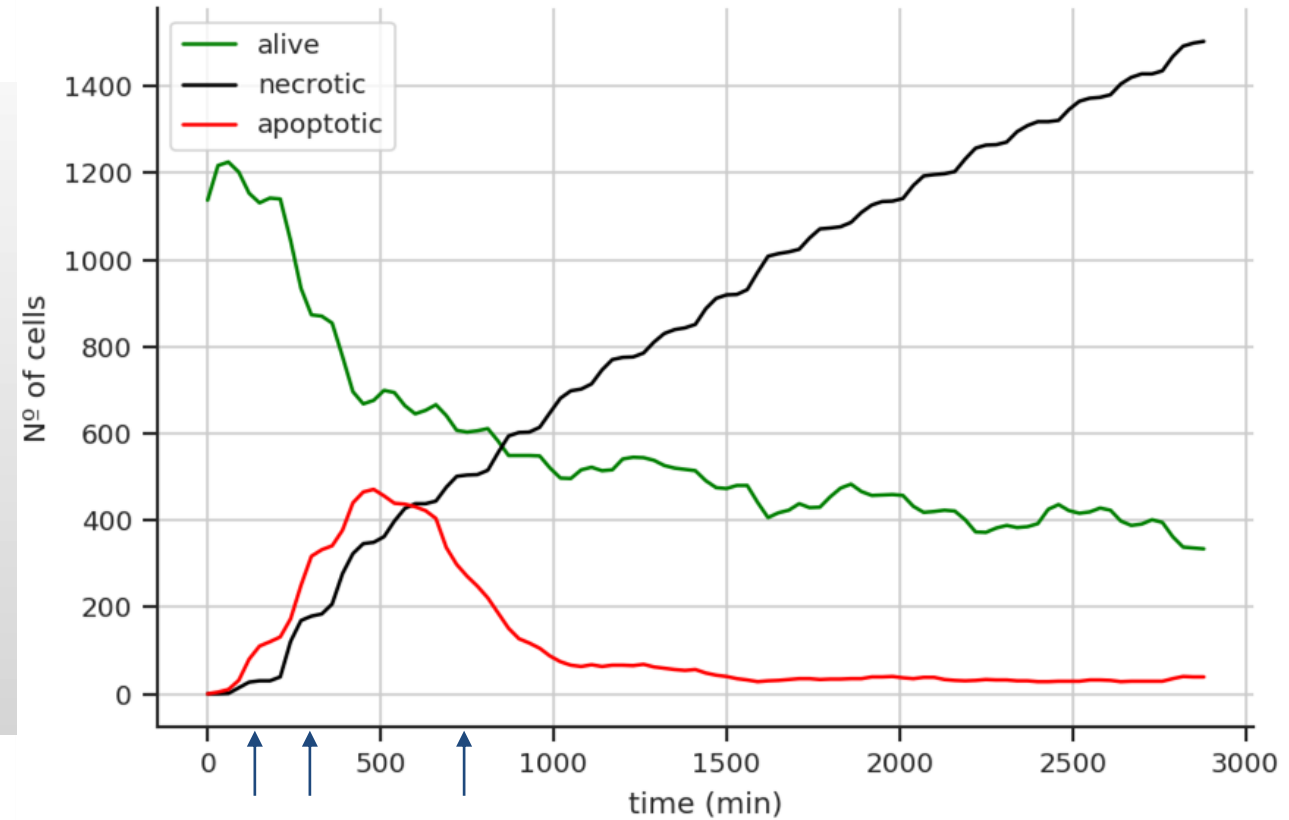
The framework allows for finding optimal drug regimes



PhysiBoSS experiment: TNF pulse studies

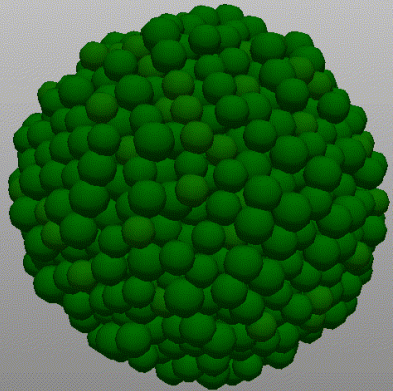


~48 h simulation time, 30 min wall time
~2500 cells

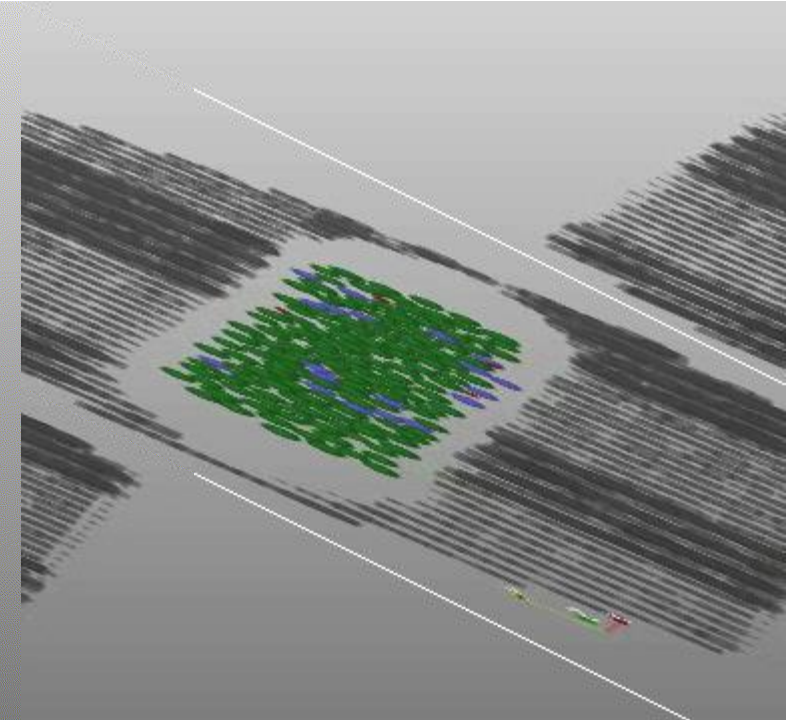
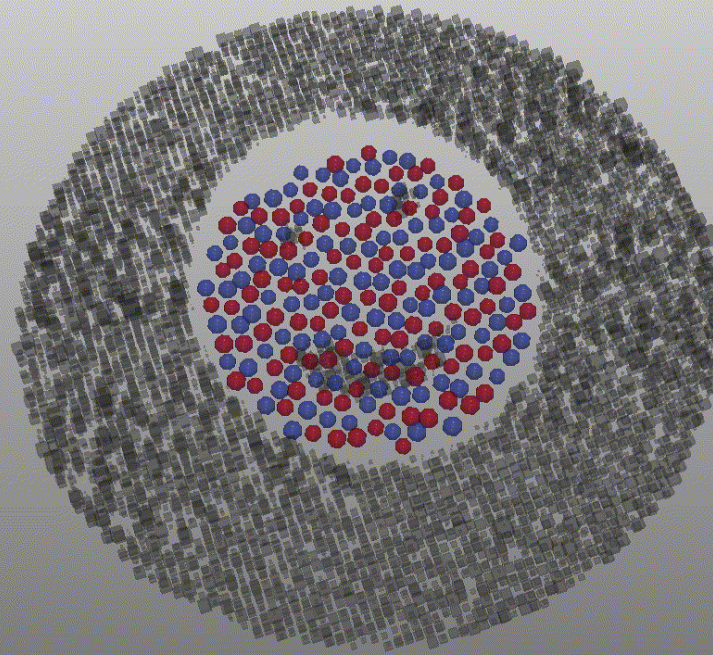
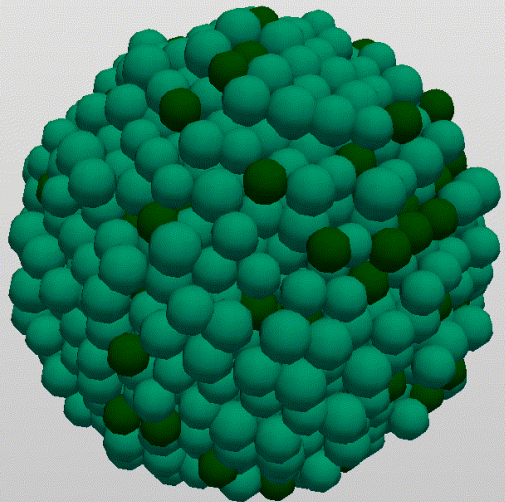
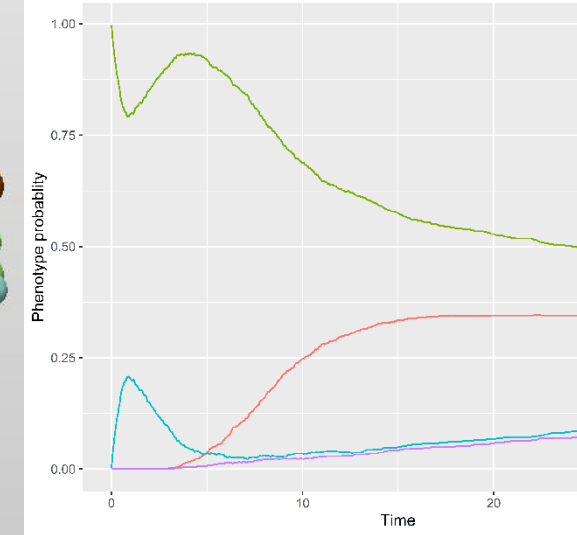
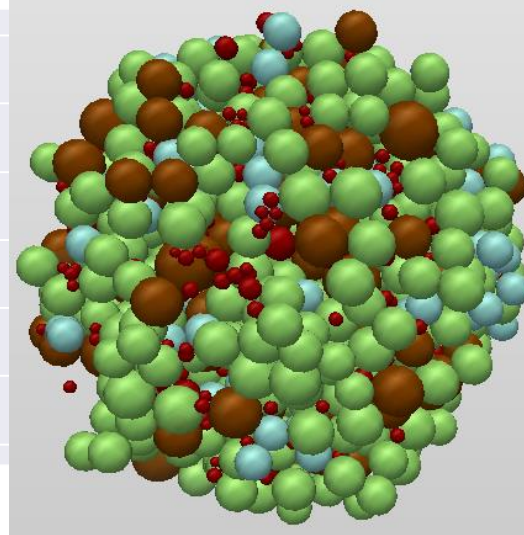
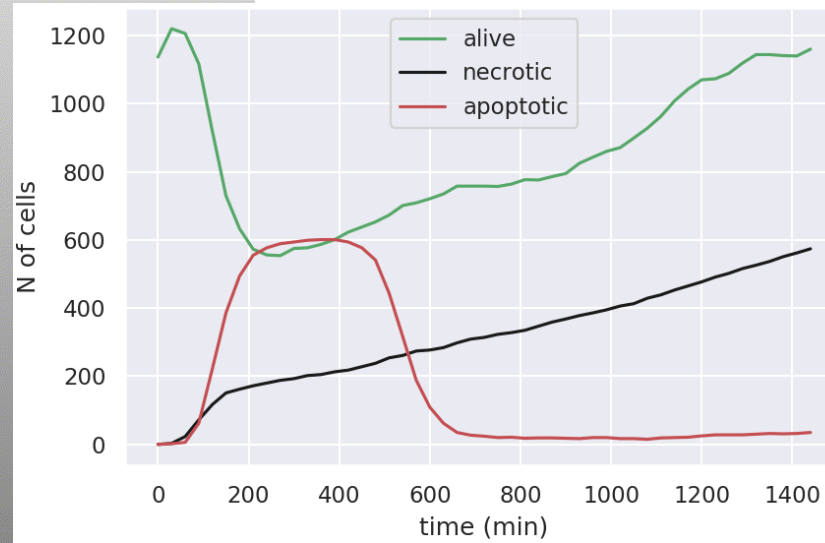


TNF pulses every 150 min

Examples of use of PhysiBoSS



premitotic-
postmitotic-
Ki67 negative-
apoptotic-
necrotic-
necrotic_swelling-
necrotic_lysis-



Ongoing work: Migrating PhysiBoSS to use MPI

Currently:

- Intra-node shared memory
- OpenMP is possible: 1 node
- max 48 cores in MN4
- 1B cells in **several simulations**

Ideal:

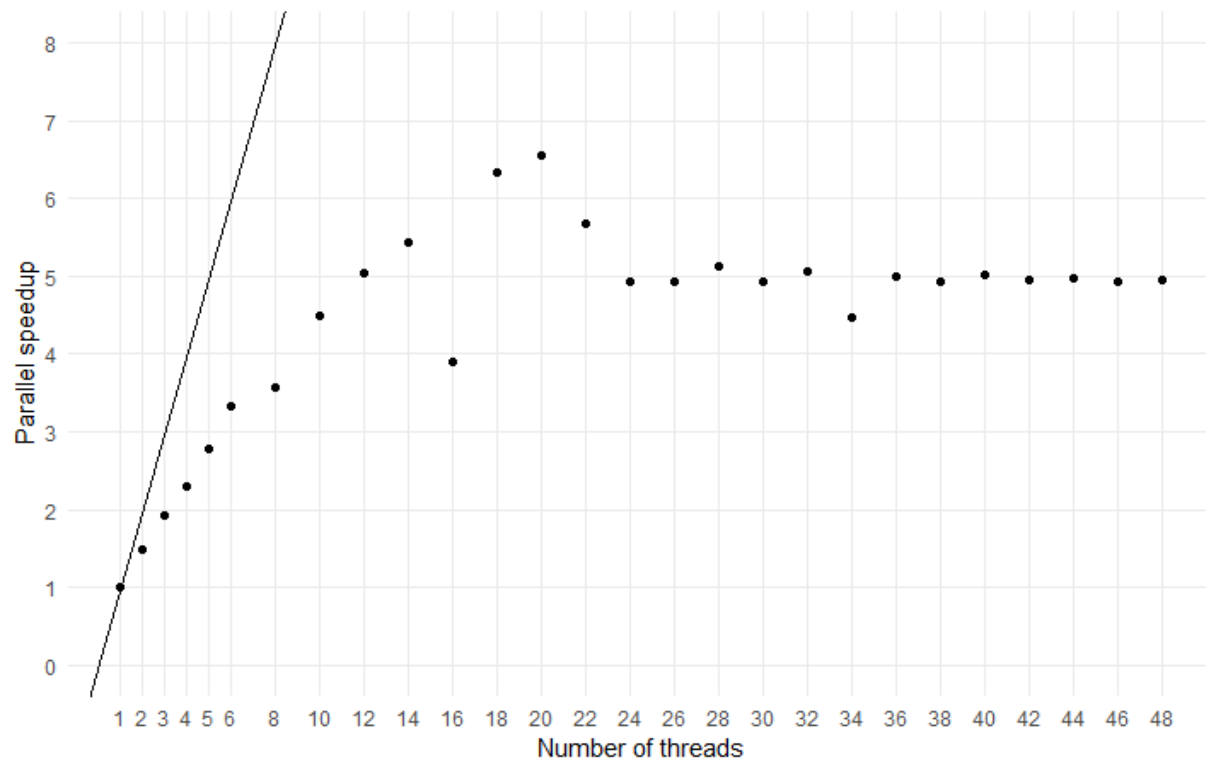
- Inter-node shared memory
- Combine OpenMP + MPI
- 1B cells in one **single simulation**

Lead by Gaurav Saxena, BSC

Goals:

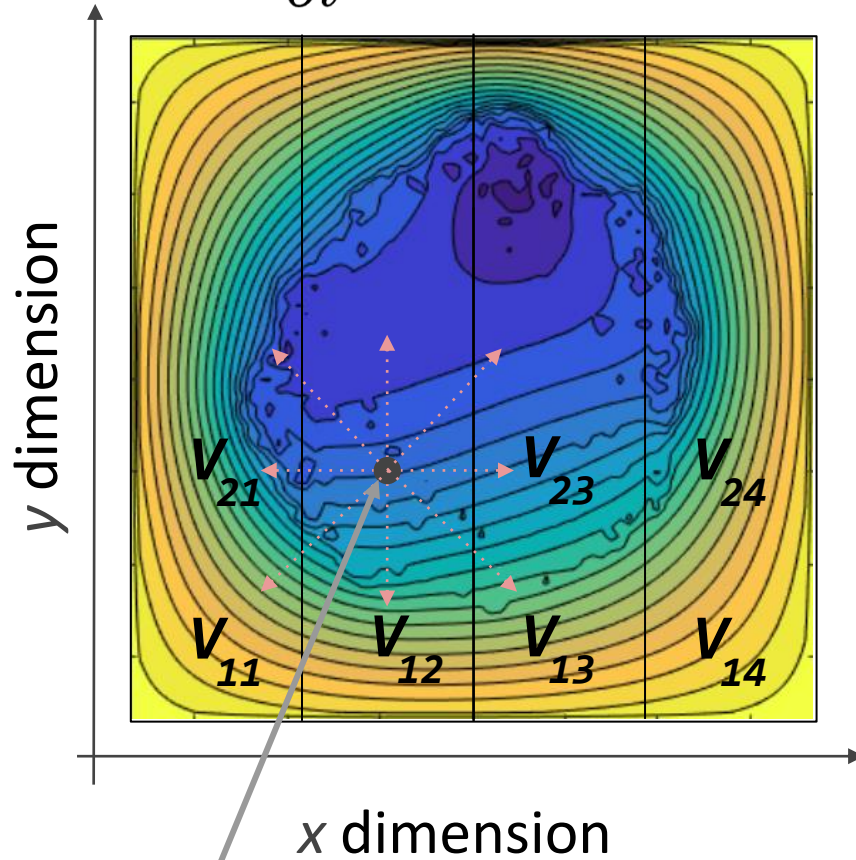
- Expand the **scope** of the simulations by several orders of magnitude
- Enable the simulation of **complex behaviours**

PhysiCell parallel performance in MareNostrum4



Domain decomposition: 2D example

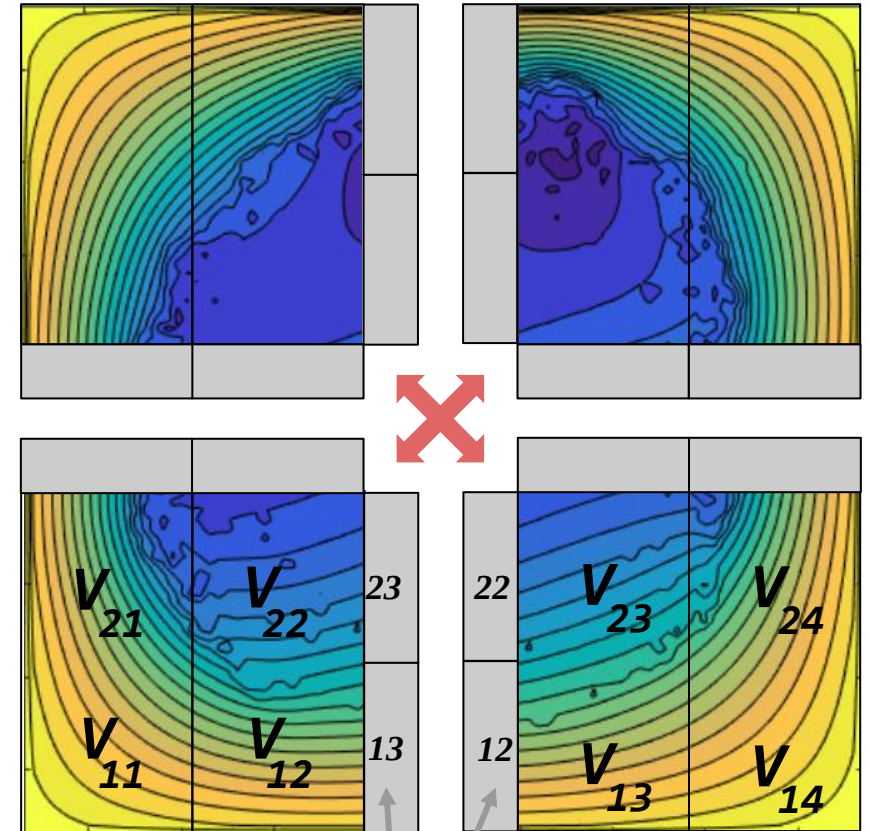
Full Domain ($\frac{\partial \rho}{\partial t} = D \nabla^2 \rho - \lambda \rho \dots$)



Domain
Decomposition



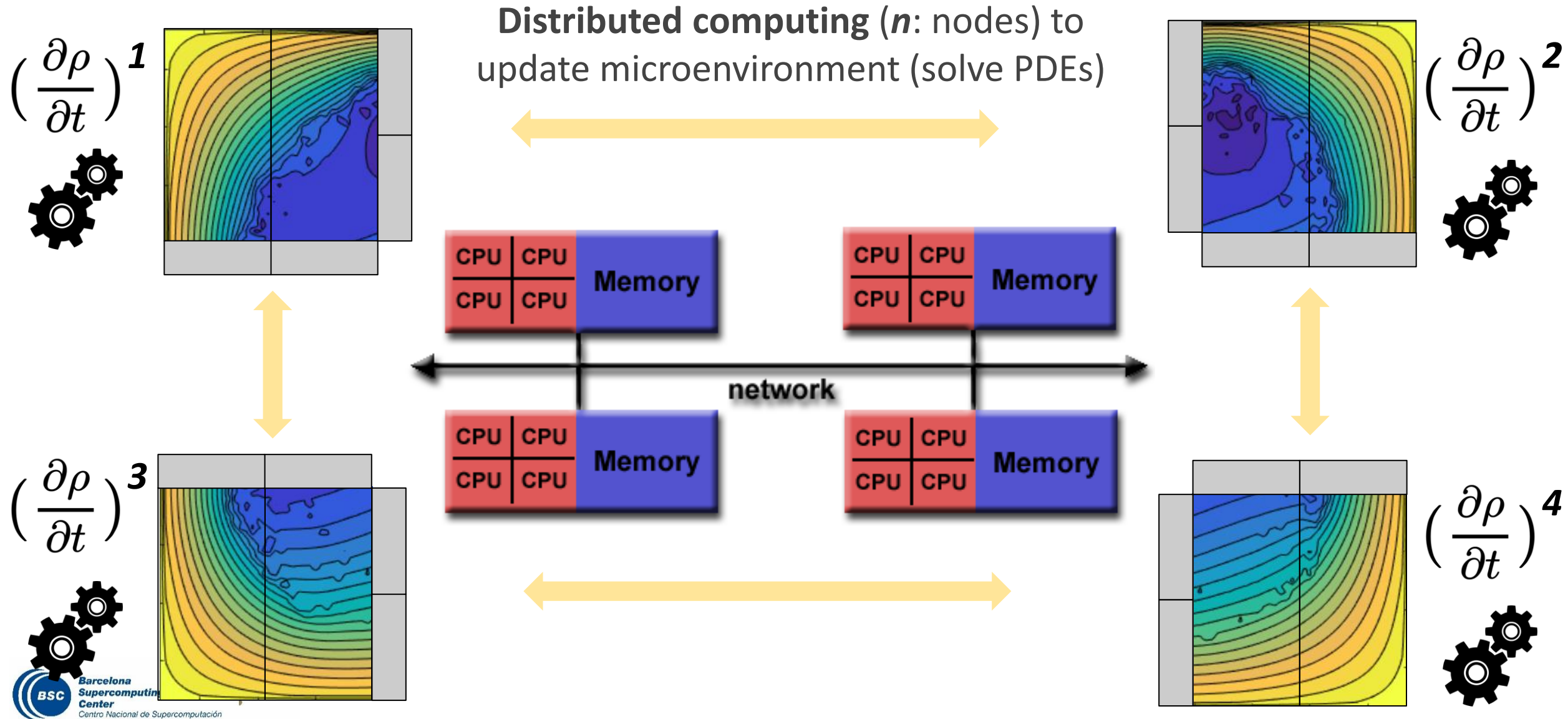
Sub-Domains i ($i = 1 \dots 4$)



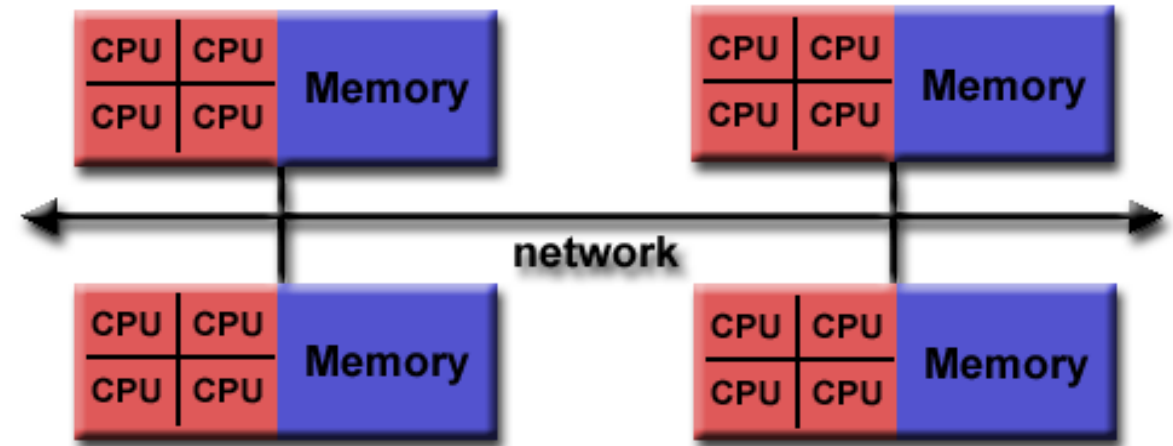
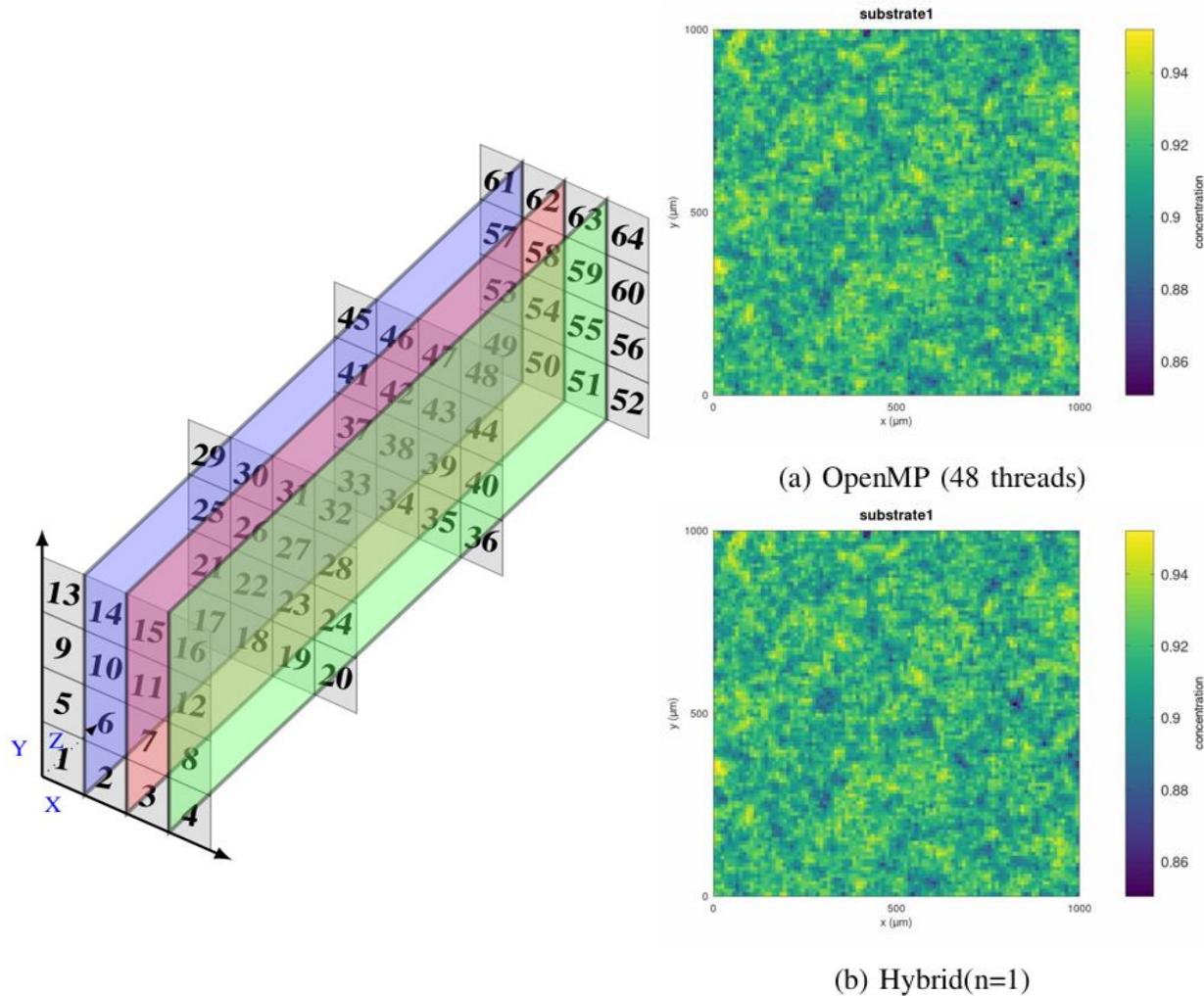
Individual Voxel: stores the values of each molecule concentration. Connected to other voxels through Moore neighborhood (PDE solver)

Ghost (Halo) Cells: needed to update boundary voxels in a transparent way. Needed to exchange information between neighbour voxels

Domain decomposition: 2D example



Ongoing work: Migrating PhysiBoSS to use MPI



Collaboration with Gaurav Saxena & David Vicente, HLST, BSC

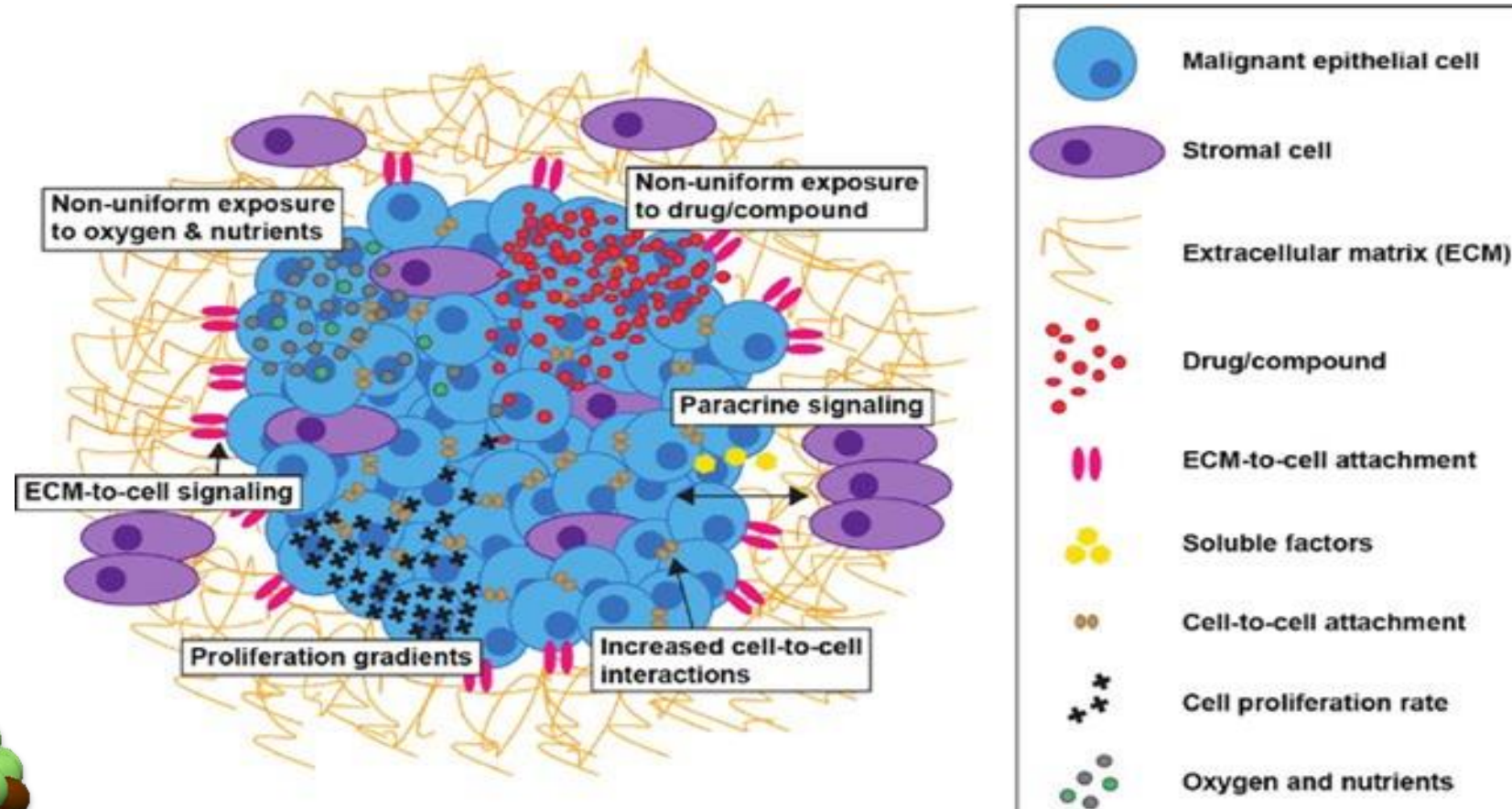
- Refactoring parts of the code to implement MPI
- Environmental data has to be shared among different nodes

Ongoing: to have different kind of cells in the microenvironment

Cells could be:

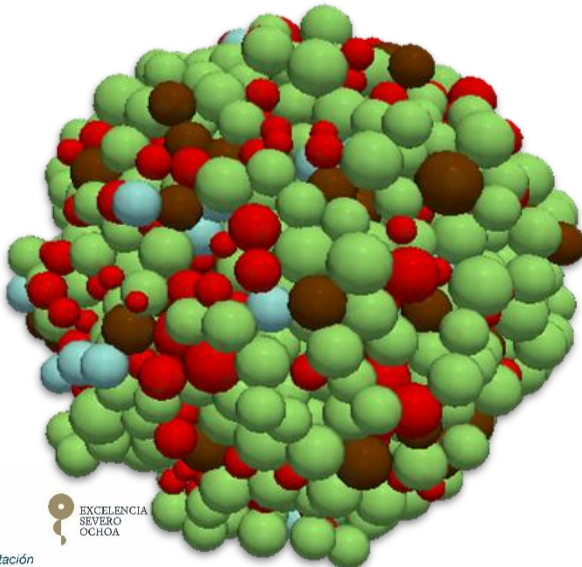
- Stromal cells
- Immune cells
- Cancer-associated cells

We want to model cancer-immune system interaction

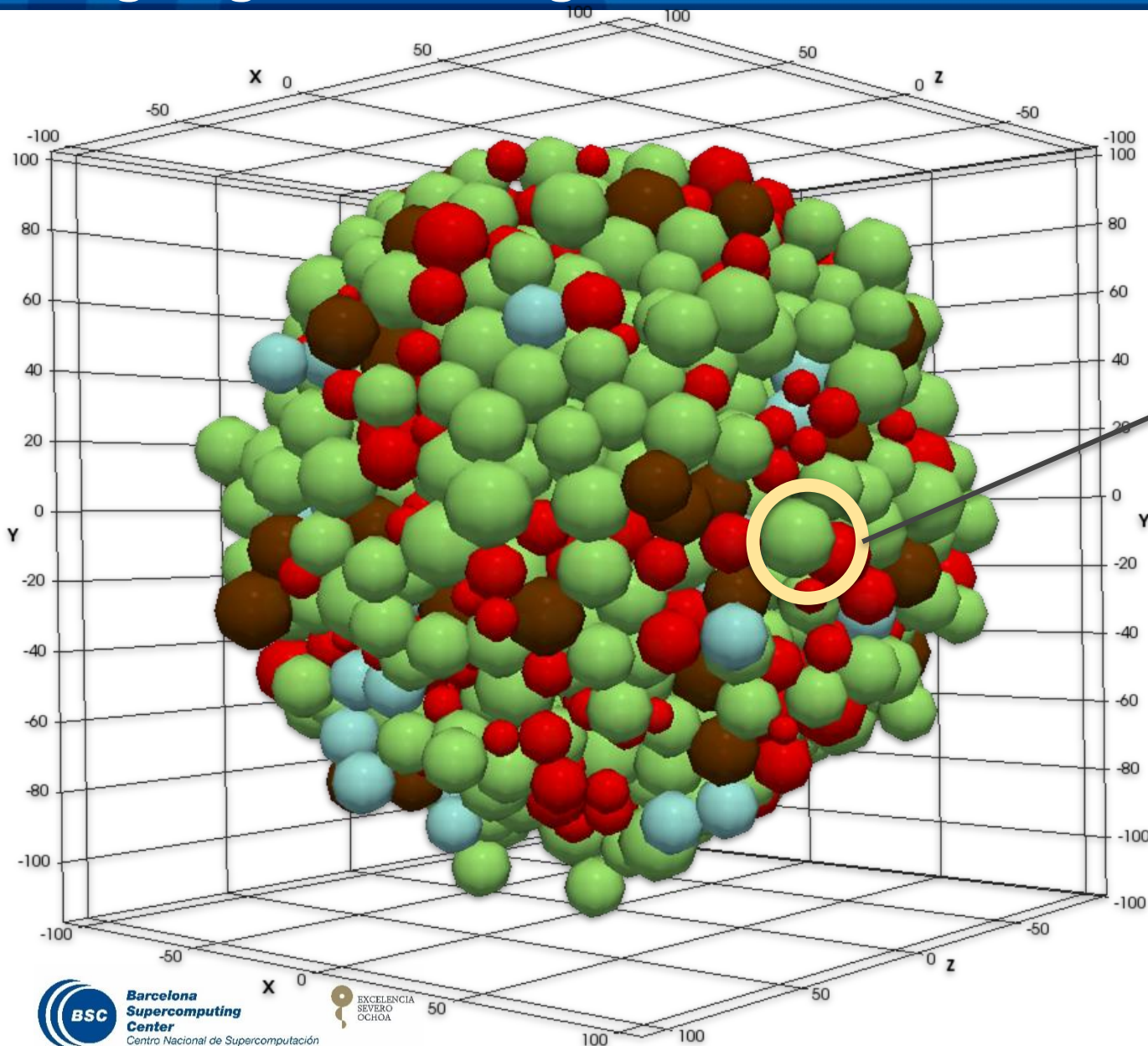


Cell Cycle Phase

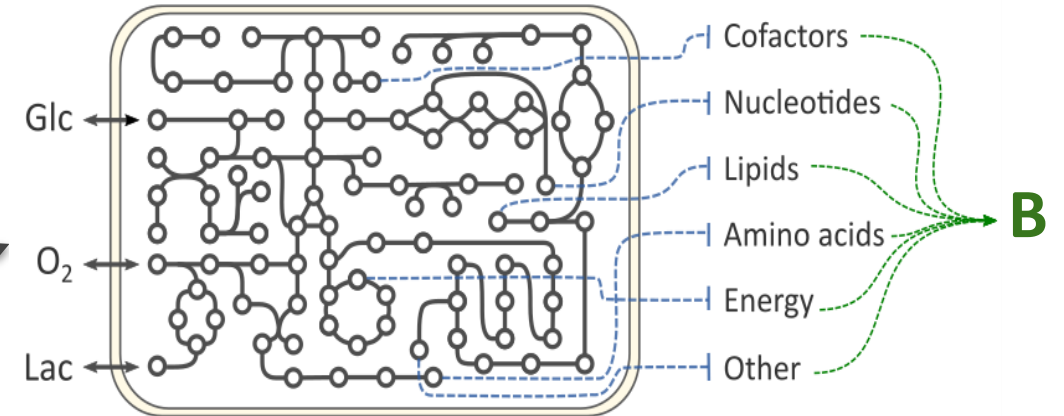
- Premitotic
- Postmitotic
- Ki67 negative
- Apoptotic
- Necrotic
- Necrotic (swelling)
- Necrotic (lysis)



Ongoing: Connecting metabolic models to PhysiCell



Genome-Scale Metabolic Model



Constraint-Based Modelling → metabolic phenotype

- Import fluxes
- Excretion fluxes
- Growth rate μ

If you want more information

- “ Open source code for multi-scale modelling
 - Available at GitHub
- “ Uses agent-based modelling for physical phenomena
- “ PhysiBoSS uses Boolean modelling for biological phenomena
 - Adapted from MaBoSS

<https://github.com/MathCancer/PhysiCell>

<http://physicell.org/tutorials/>

RESEARCH ARTICLE

PhysiCell: An open source physics-based cell simulator for 3-D multicellular systems

Ahmadreza Ghaffarizadeh¹, Randy Heiland², Samuel H. Friedman^{1,3}, Shannon M. Mumenthaler¹, Paul Macklin^{1,2*}

¹ Lawrence J. Ellison Institute for Transformative Medicine, University of Southern California, Los Angeles, California, United States of America, ² Intelligent Systems Engineering, Indiana University, Bloomington, Indiana, United States of America, ³ Opto-Knowledge Systems, Inc., Torrance, California, United States of America

* macklinp@iu.edu

<https://github.com/bsc-life/PhysiBoSSv2>

Systems biology

PhysiBoSS: a multi-scale agent based modelling framework integrating physical dimension and cell signalling

Gaelle Letort^{1,2,3*}, Arnau Montagud^{1,2,3}, Gautier Stoll⁴, Randy Heiland⁵, Emmanuel Barillot^{1,2,3}, Paul Macklin⁵, Andrei Zinovyev^{1,2,3} and Laurence Calzone^{1,2,3,*}

USE CASES

PerMedCoE works on five use cases to drive the development of cell-level simulations



**Cancer Diagnosis
Based on Omics
Information**



**Drug Synergies for
Cancer Treatment**



**Tumour Evolution
Based on Single-
Cell Omics and
Imaging**



**Personalised
Modelling of
Groups of Rare-
Disease Related
Patients**



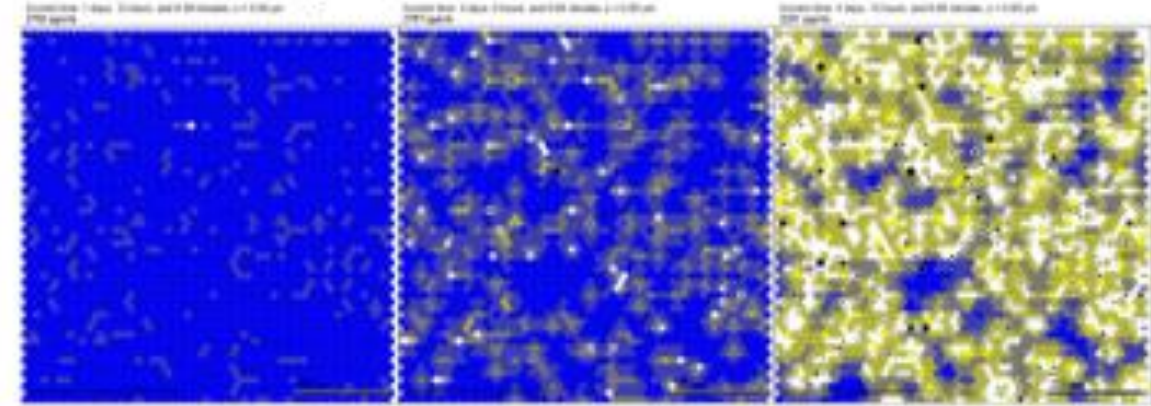
**COVID-19
Multiscale
Modelling of the
Virus and Patients'
Tissue**

Multiscale modelling for COVID-19 infection

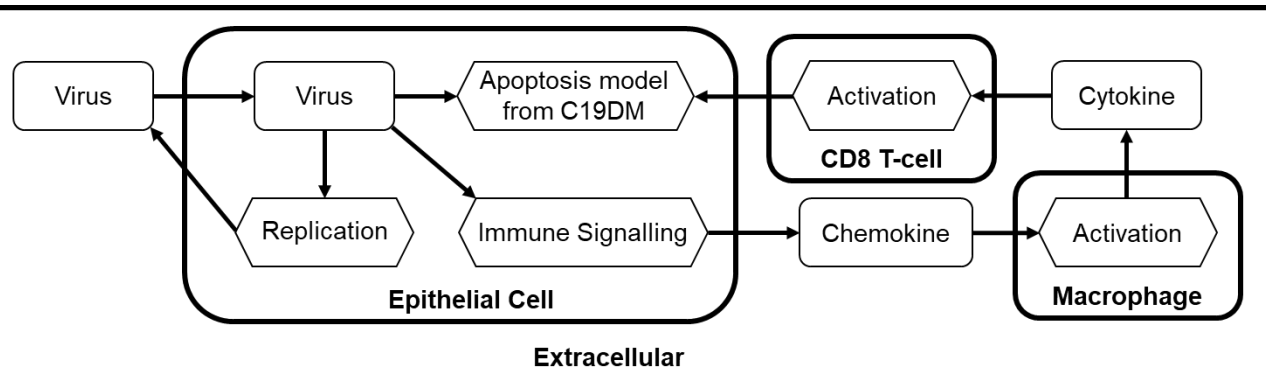
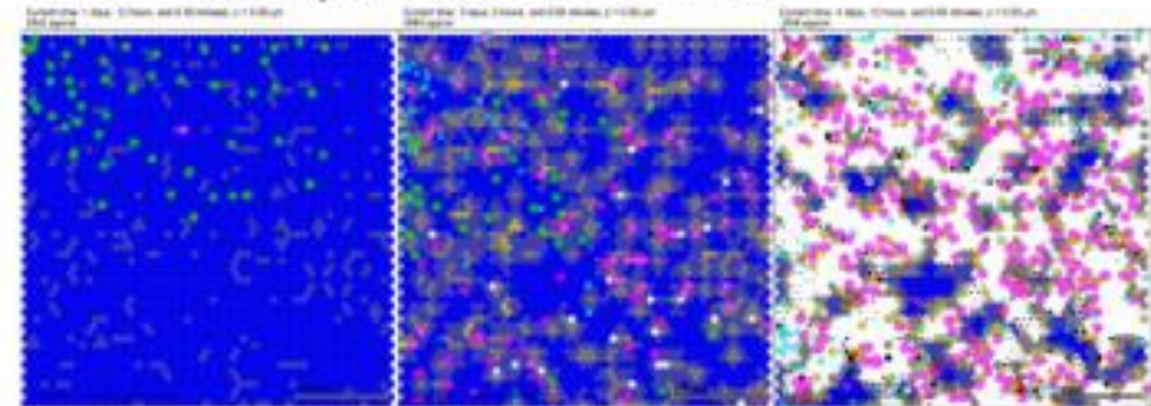
- Our work builds upon the **PhysiCell for COVID initiative**, a **multiscale model of SARS-CoV-2 dynamics in lung tissue** that can integrate
 - virus infection
 - epithelial host cell demise
 - different immune cells' response
- We incorporate PhysiBoSS so we can **integrate Boolean models**
 - offers **mechanistic insights** of SARS-CoV-2 infection and dissemination among human host cells

MOI: multiplicity of infection

MOI = 0.10, no immune



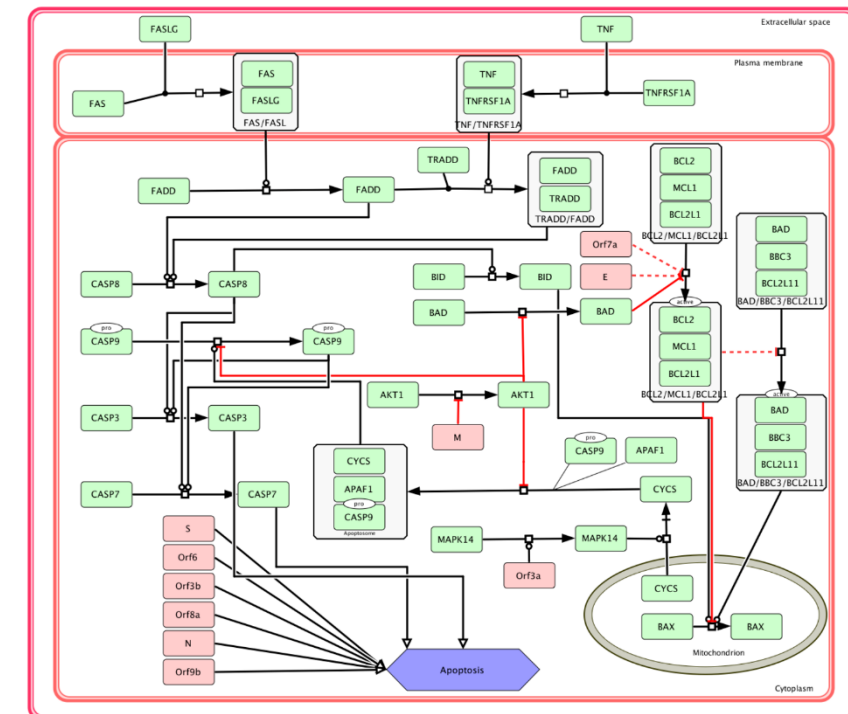
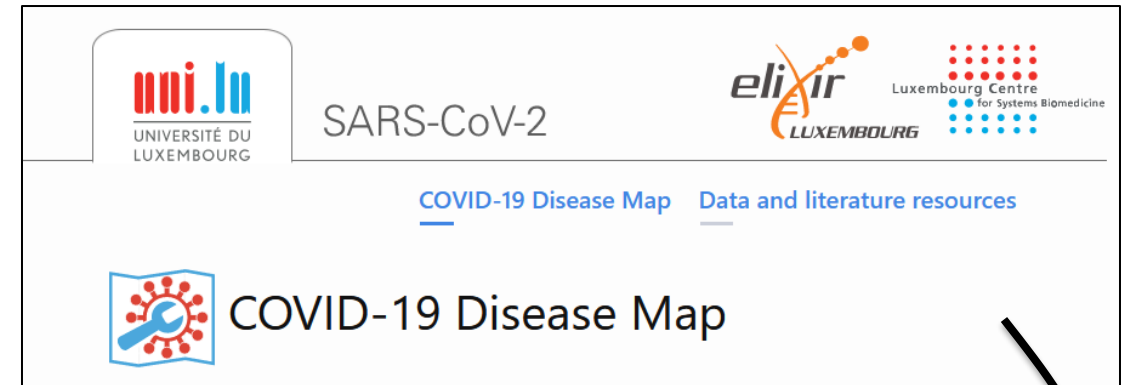
MOI = 0.10, default immune



PhysiBoSS-COVID can integrate cell-specific Boolean models

- ❧ We incorporate **cell- and pathway-specific Boolean models** to detail the interactions of virus and human cells.
- ❧ These models come from the **COVID-19 Disease Map initiative**
 - Integrates and formalises **mechanistic knowledge of COVID-19 infection**
 - Map to model converted by **CaSQ**
- ❧ These Boolean models can then be simulated using MaBoSS allowing for the **study of the cells' mechanisms and their perturbations**

<https://covid.pages.uni.lu/>

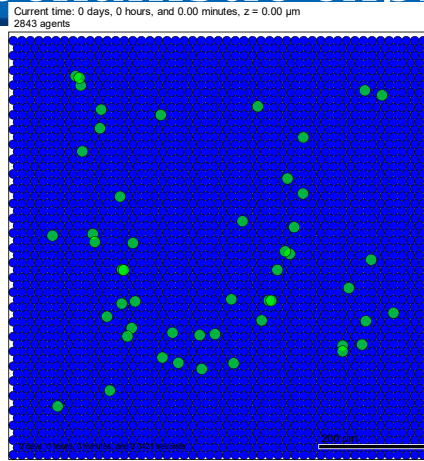


PhysiBoSS allows for the mechanistic exploration of COVID-19 infection

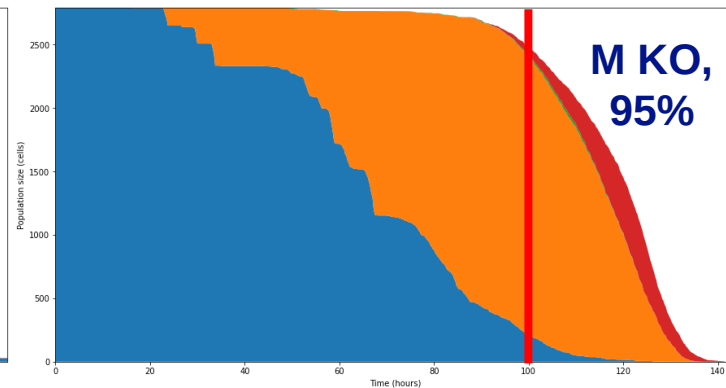
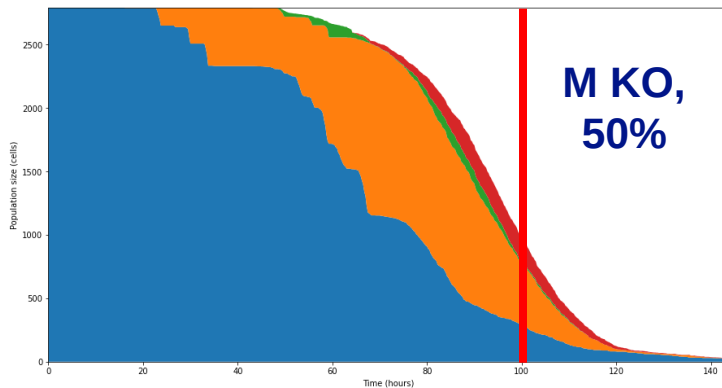
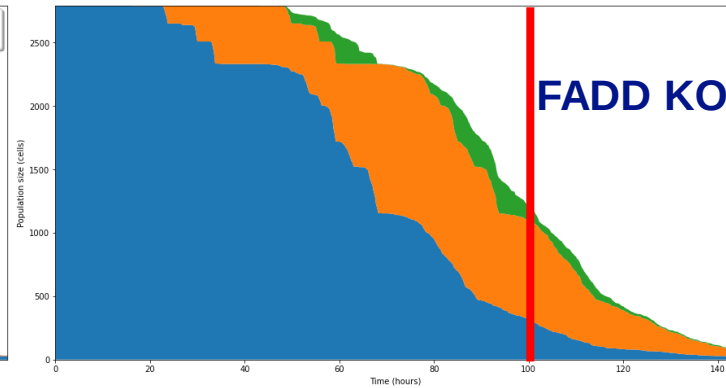
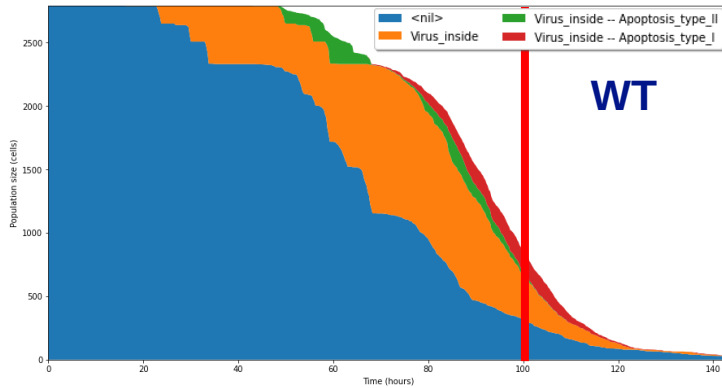
- With PhysiBoSS we can now inspect

- mutants that affect epithelial cells' apoptosis
- heterogeneous cell populations

t=0

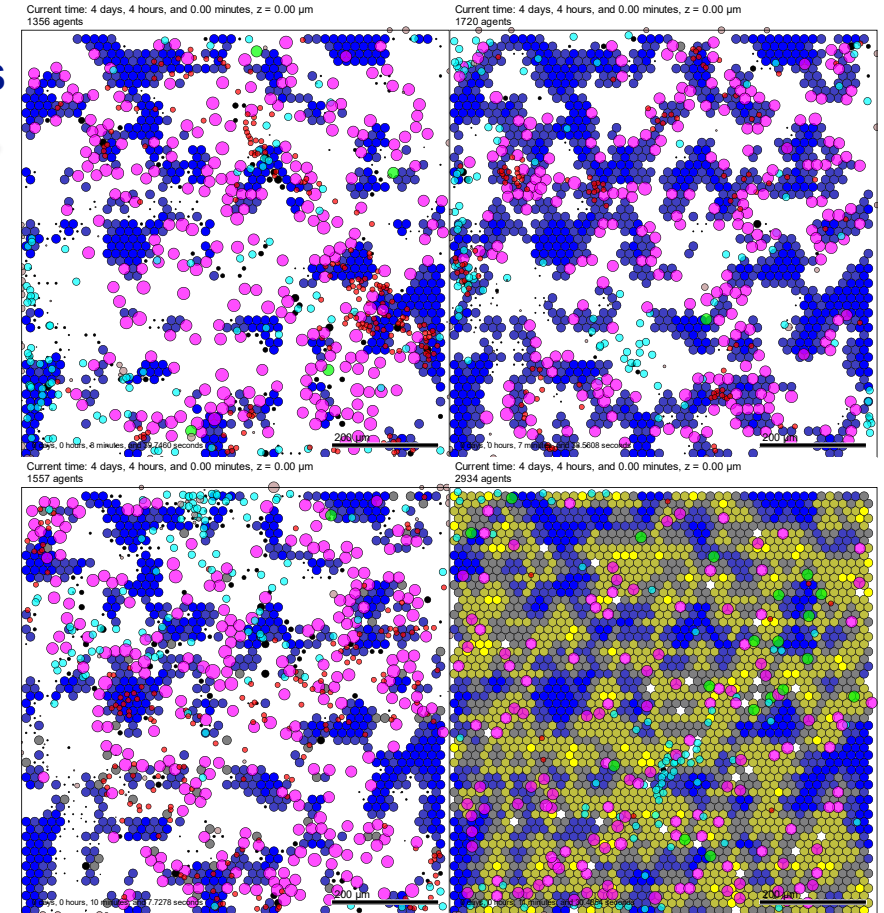


t=100 hours



WT

FADD KO



M KO, 50%

M KO, 95%

PARTNERS



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