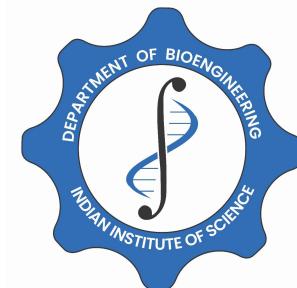


Design principles of complex cellular enabling phenotypic plasticity in cancer



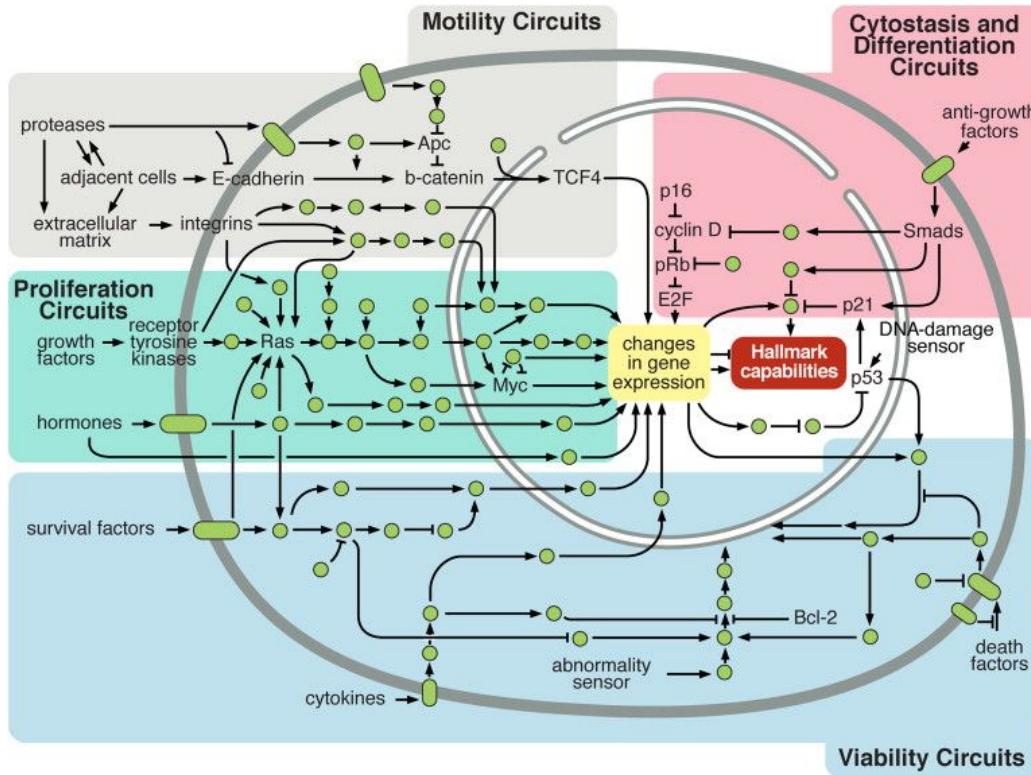
Mohit Kumar Jolly, PhD
Cancer Systems Biology Laboratory
Associate Professor,
Department of Bioengineering,
Indian Institute of Science (IISc), Bangalore, India
mkjolly@iisc.ac.in



Editor-in-Chief, NPJ Systems Biology & Applications

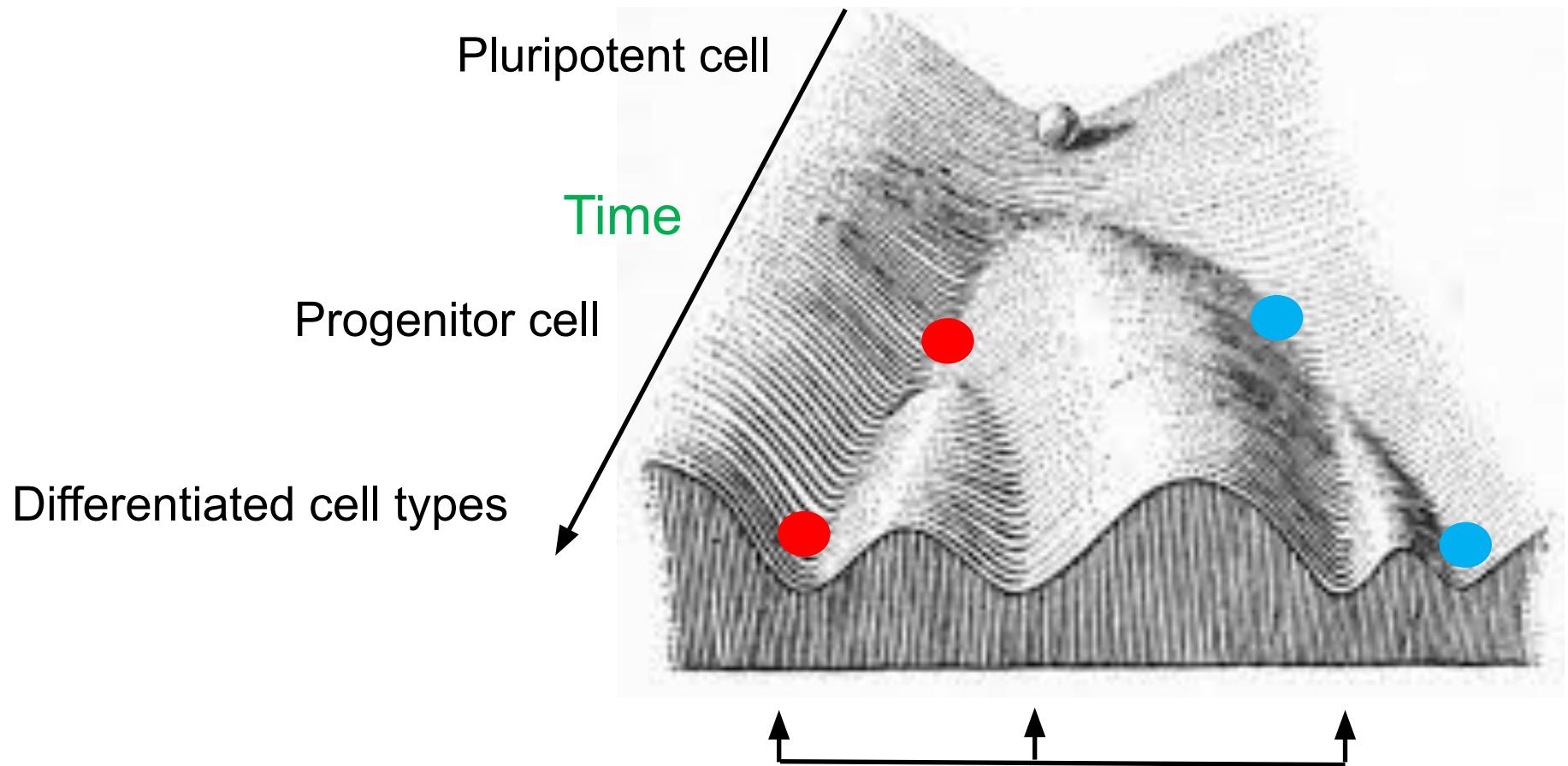
Modularity in Biological Systems Working Group | Feb 2026

Cellular decision-making



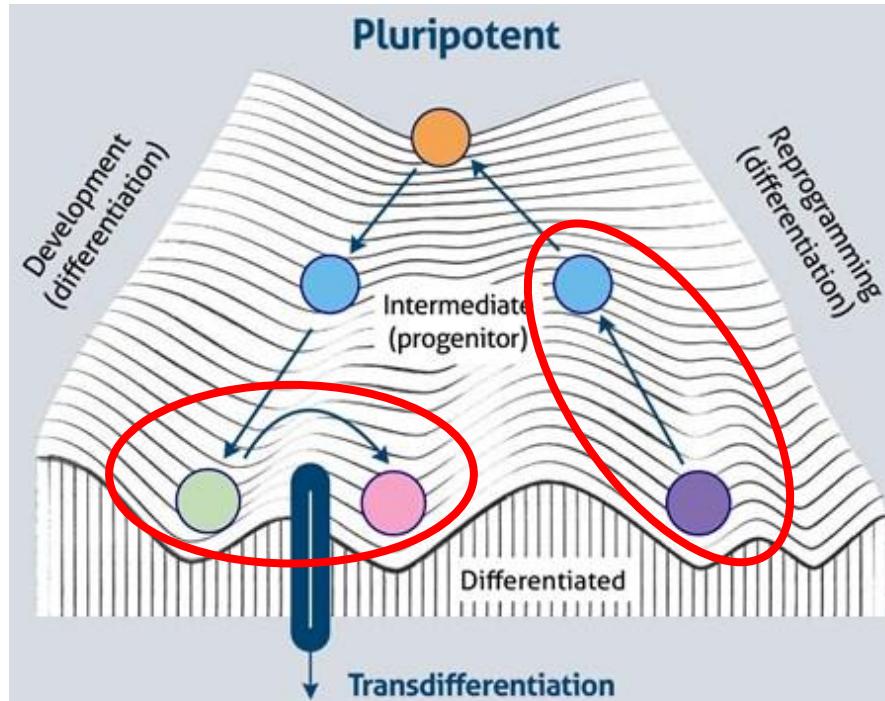
- Cells receive diverse biophysical/chemical signals varying in (x, t).
- Cells in a population can respond differently to the same signals.
- Cellular decision-making is driven by interconnected complex networks.

From 1 cell to 200 cell-types: the developmental trajectory



“Final” or “terminal” cell-fates
(a liver cell is not allowed to become a heart cell)

Cell-state changes: bidirectional, reversible



Granados *et al.* Int J Mol Sci 2020

2012 Nobel Prize in Physiology or Medicine



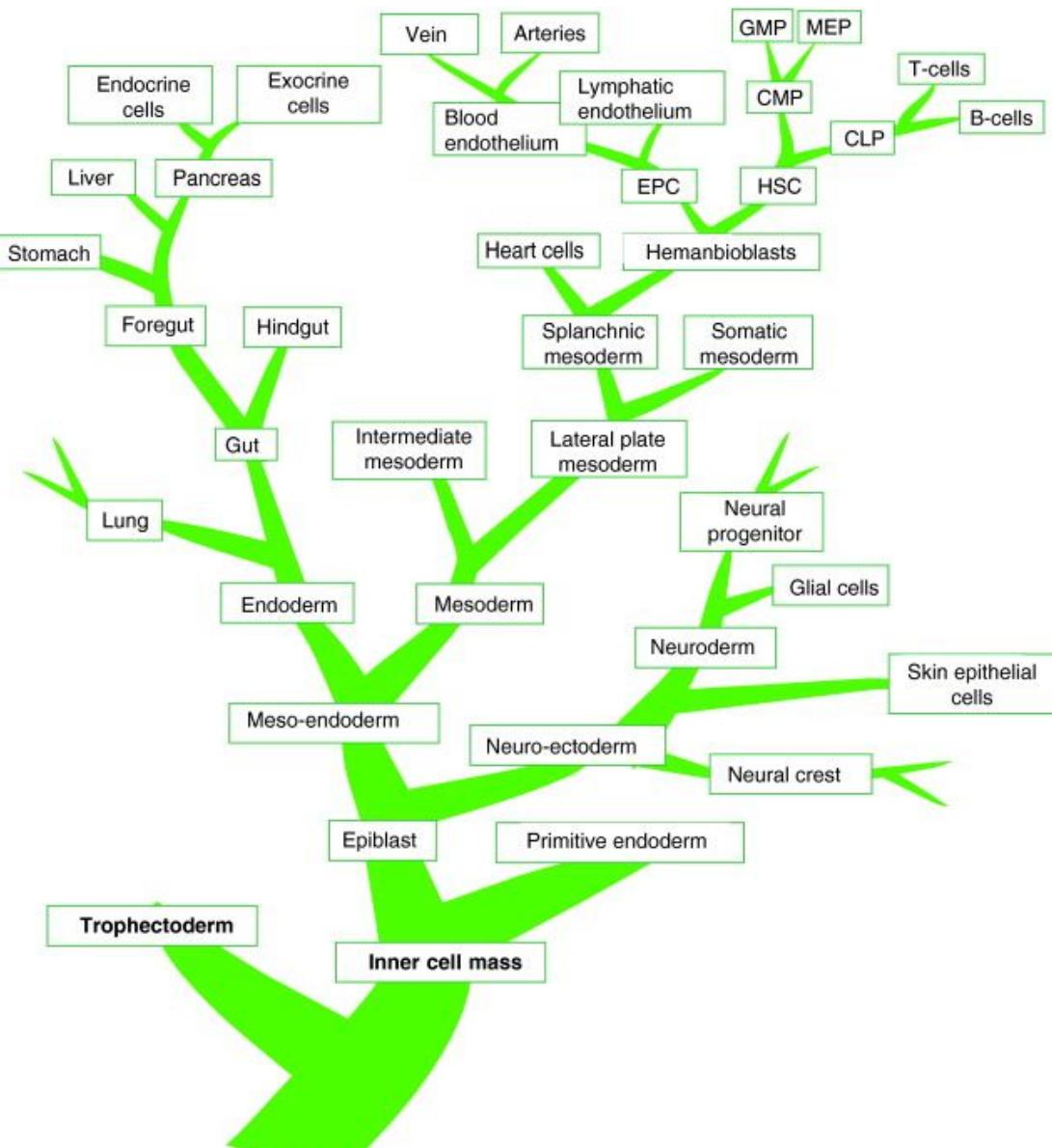
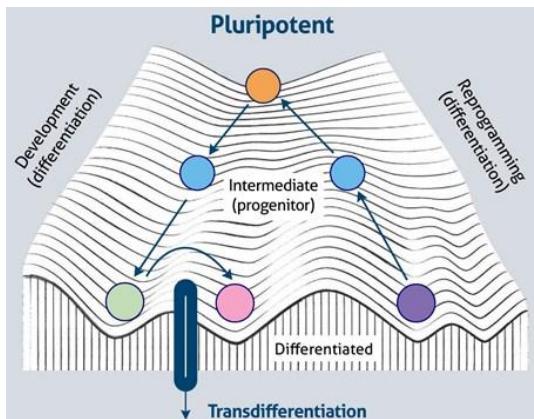
Shinya Yamanaka
University of Kyoto, Japan



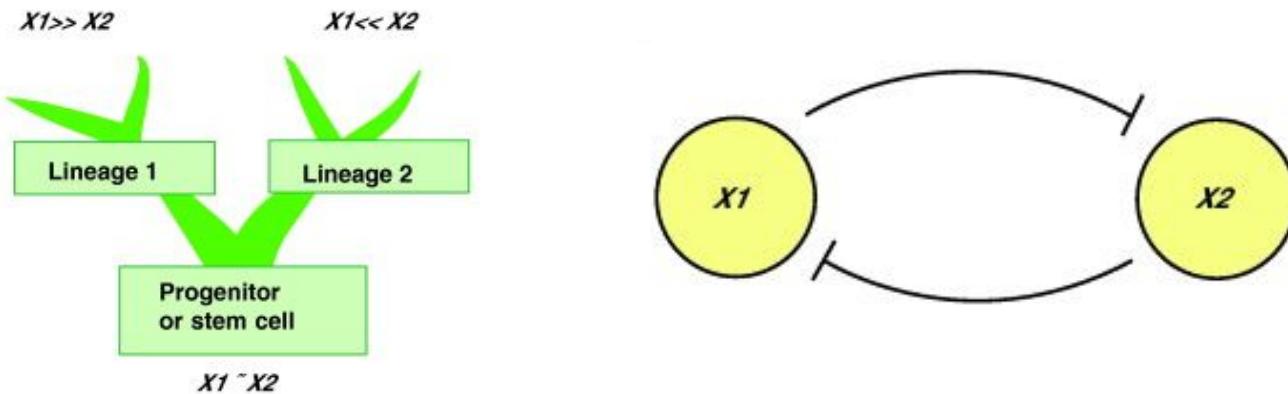
John B. Gurdon
Gurdon Institute in Cambridge, UK

Cells can also reversibly change their identity => “Controlled enthusiasm”

The ‘bifurcating’ cell-state tree



Toggle switch: a motif for bifurcating cell-states



Cells	Transcription factors		Cell fates		
	X1	X2	X1 > X2	X1 ~ X2	X1 < X2
Early embryo	Cdx2	Oct4	Trophectoderm	Totipotent embryo	Inner cell mass
Embryo ICM	GATA6	Nanog	Primitive endoderm	Inner cell mass	Epiblast
Blood	GATA1	PU.1	Erythroid cells	Common myeloid progenitor	Myeloid cells
Pancreas	Ptf1a	Nkx6	Exocrine cells	Pancreatic progenitor	Endocrine cells
Somite	Pax3	Foxc2	Myogenic cells	Dermomyotome progenitor	Vascular cells

Bi-stability in toggle switch

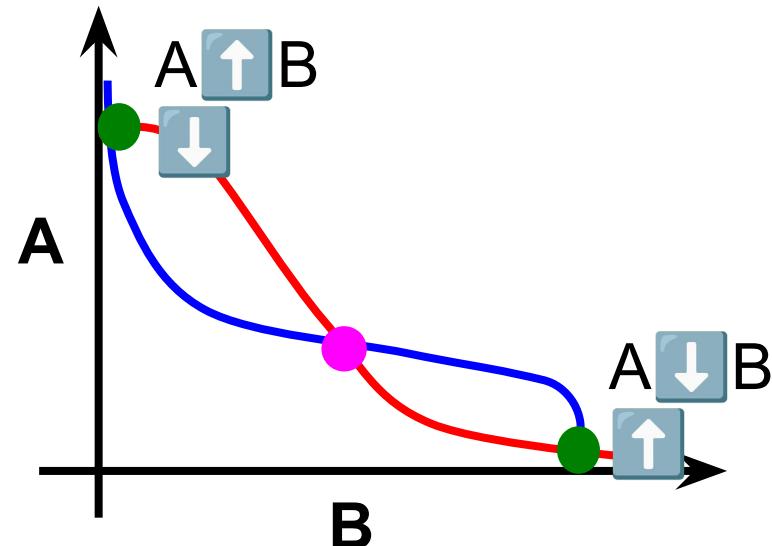


Bistability
 $(A, B) = (\text{high, low})$
 $(A, B) = (\text{low, high})$

Huang, PloS Biology 2013
Gardner et al. Nature 2000

$$\frac{dA}{dt} = g_A \frac{(B_0)^{n_B}}{(B_0)^{n_B} + B^{n_B}} - k_A A$$

$$\frac{dB}{dt} = g_B \frac{(A_0)^{n_A}}{(A_0)^{n_A} + A^{n_A}} - k_B B$$



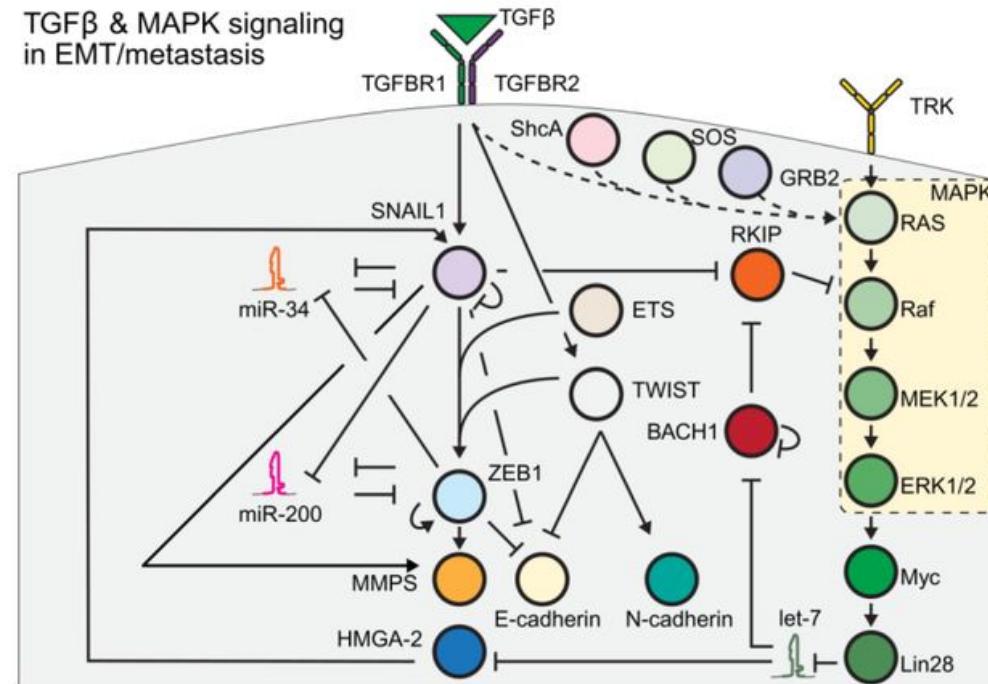
Construction of a genetic toggle switch in *Escherichia coli*

Timothy S. Gardner*,†, Charles R. Cantor*, & James J. Collins*,†

* Department of Biomedical Engineering, † Center for BioDynamics and ‡ Center for Advanced Biotechnology, Boston University, 44 Cummington Street, Boston, Massachusetts 02215, USA

Production Regulation Degradation

Dynamics of decision-making in larger networks



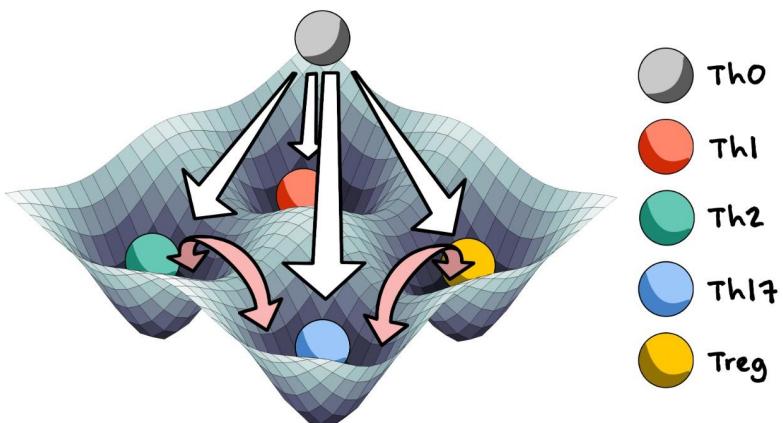
Zanudo et al. Phys Biol 2019

How do regulatory networks govern cellular decision-making?
(Dynamical principles)

Why are regulatory networks designed the way they are?
(Topological hallmarks)

What rules/principles cells follow in decision-making?

CD4+ T-cell differentiation



Atchuta Duddu



Sarthak Sahoo

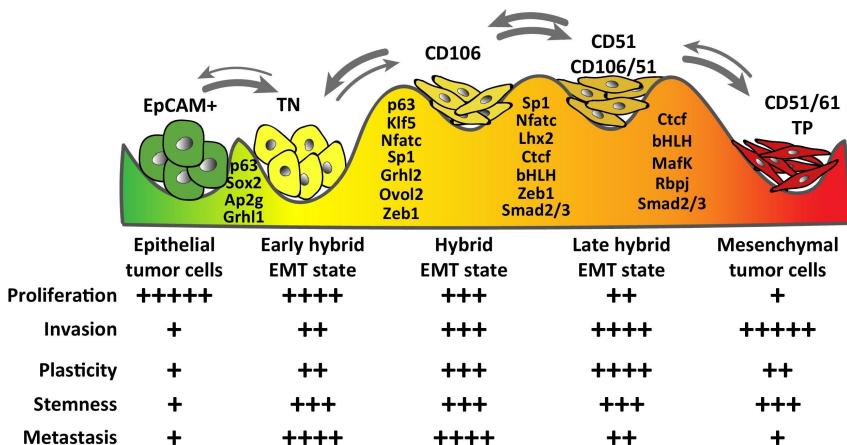


Pradyumna Harlapur



Kishore Hari

Epithelial-Mesenchymal Transition



Hari*, Harlapur* et al. iScience 2025

Duddu et al. NPJ Sys Biol Appl 2024

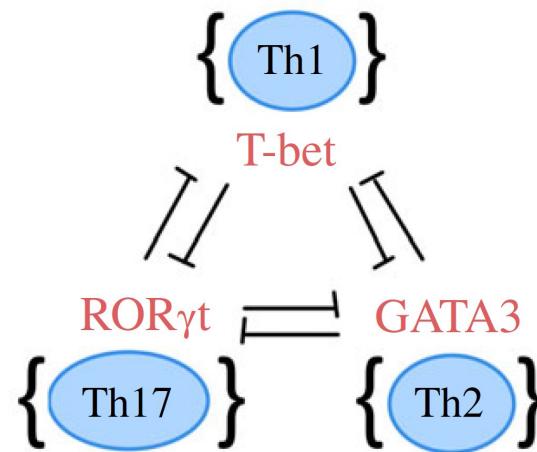
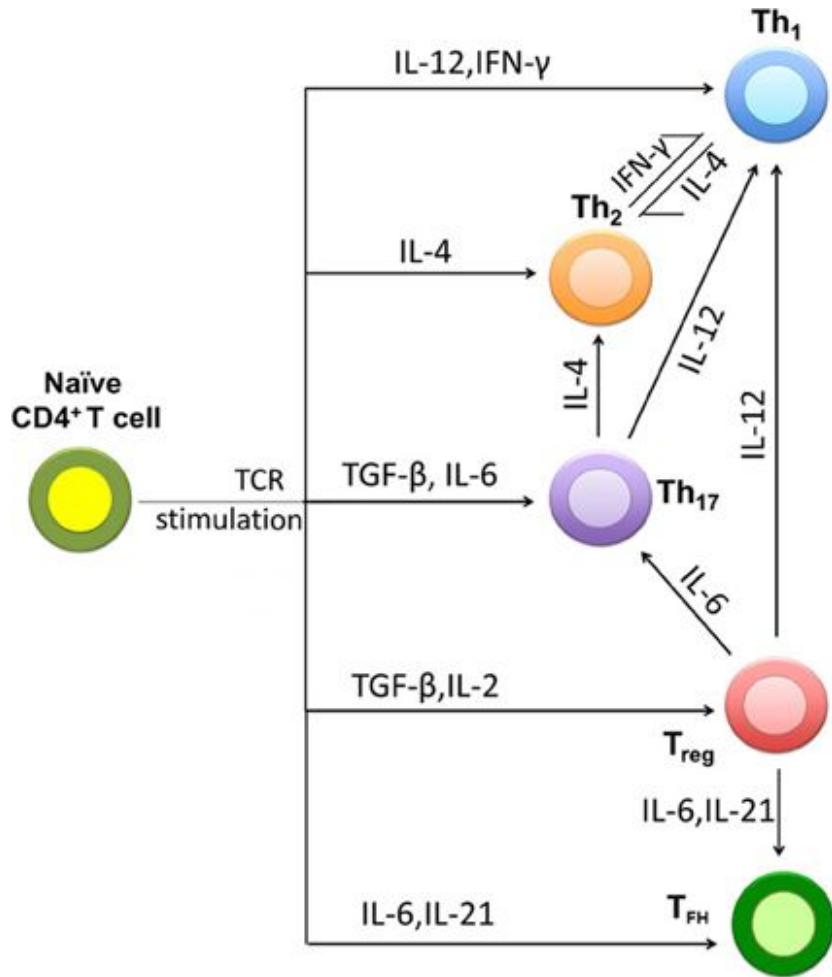
Hari et al. eLife 2022

Harlapur et al. Biomolecules 2022

Sahoo et al. NAR Cancer 2021

Duddu et al. J R Soc Interface 2020

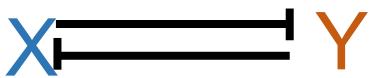
Differentiation of naïve CD4+ T cells into > 2 subsets



- Th₁ | { **T-bet high, GATA3 low, ROR γ T low** }
- Th₂ | { **T-bet low, GATA3 high, ROR γ T low** }
- Th₁₇ | { **T-bet low, GATA3 low, ROR γ T high** }

Can this ‘toggle triad’ explain T-cell differentiation?

ODEs governing the dynamics



$$\frac{d[X]}{dt} = g_X \left(\frac{1 + \lambda_{YX}[Y/T_{YX}]^{n_{YX}}}{1 + [Y/T_{YX}]^{n_{YX}}} \right) - k_X[X]$$

$$\frac{d[Y]}{dt} = g_Y \left(\frac{1 + \lambda_{XY}[X/T_{XY}]^{n_{XY}}}{1 + [X/T_{XY}]^{n_{XY}}} \right) - k_Y[Y]$$

Here,

g_X and g_Y are the production rates of A and B

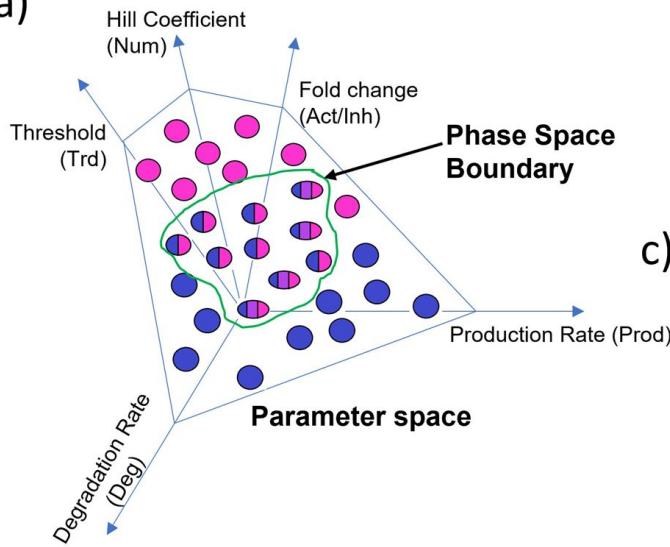
k_X and k_Y are the degradation rates of A and B

λ_{XY} and λ_{YX} is the fold change in interaction

n_{XY} and n_{YX} is the hill's coefficient in interaction

T_{XY} and T_{YX} is threshold value of the interaction

a)



c)

Network topology (say, a toggle triad)

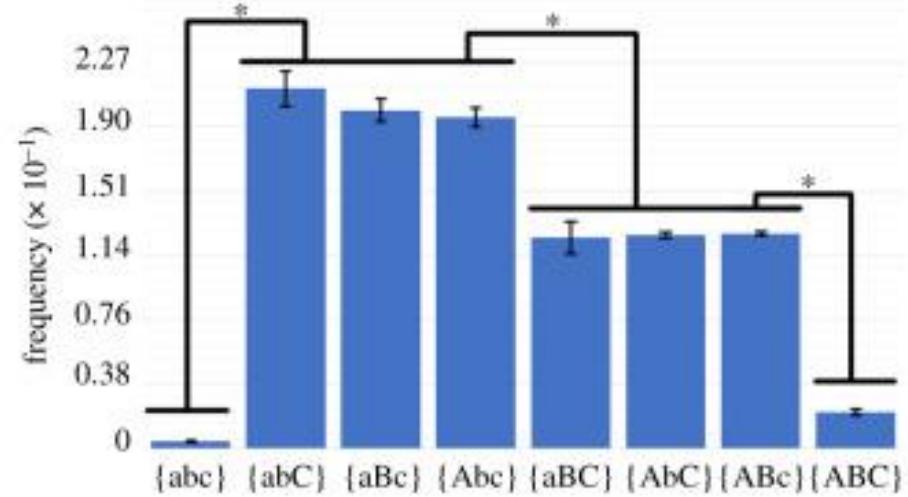
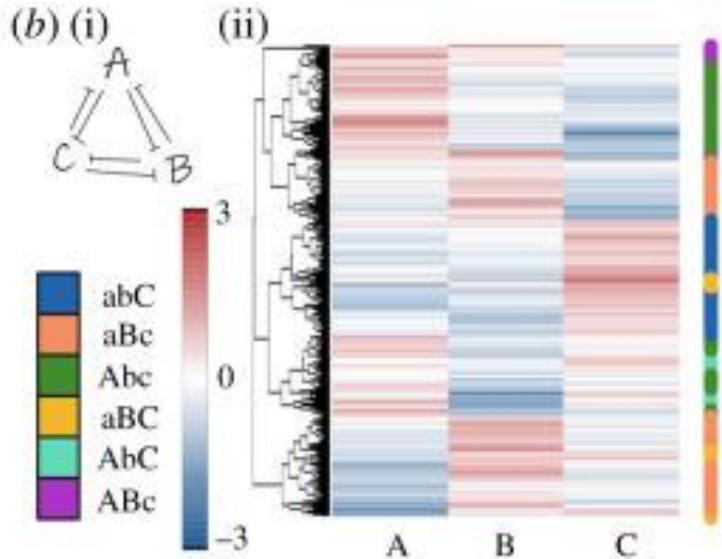
+

Ensemble of kinetic models over a biologically relevant parameter space

=

“Possibility space” of phenotypes

Multistability in toggle triad



Differentiated states:

Abc | { **A high**, B low, C low }
aBc | { A low, **B high**, C low }
ABc | { A low, B low, **C high** }

Hybrid states:

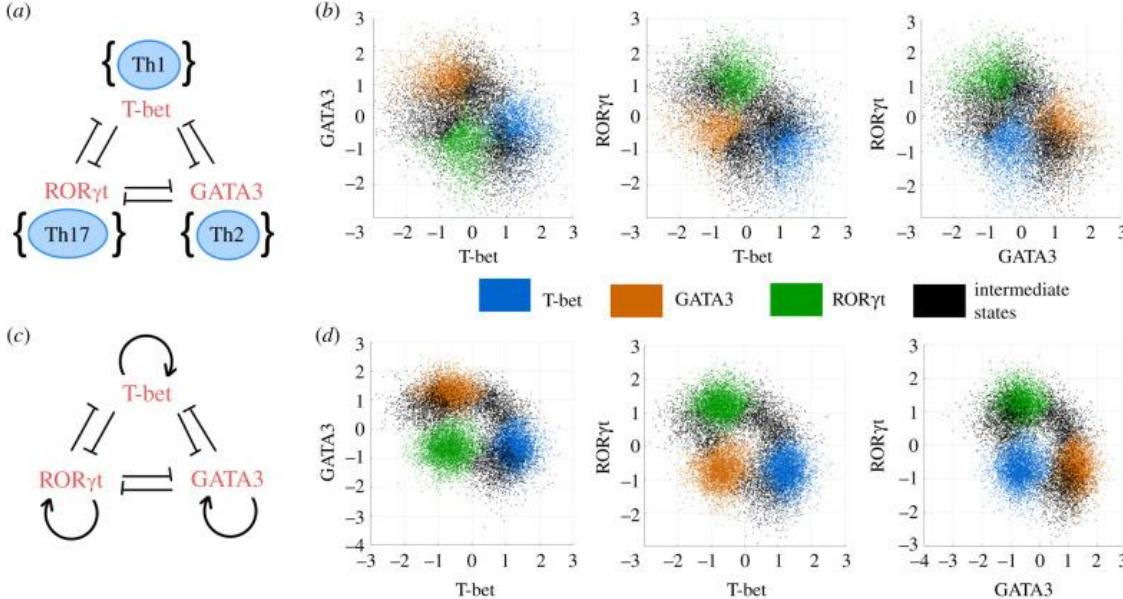
ABc | { **A high**, **B high**, C low }
AbC | { **A high**, B low, **C high** }
aBC | { A low, **B high**, **C high** }

These dynamical traits were unique to this 3-node network topology.

Model prediction s

Existence of three
'single-positive'
states

Existence of three
'double-positive'



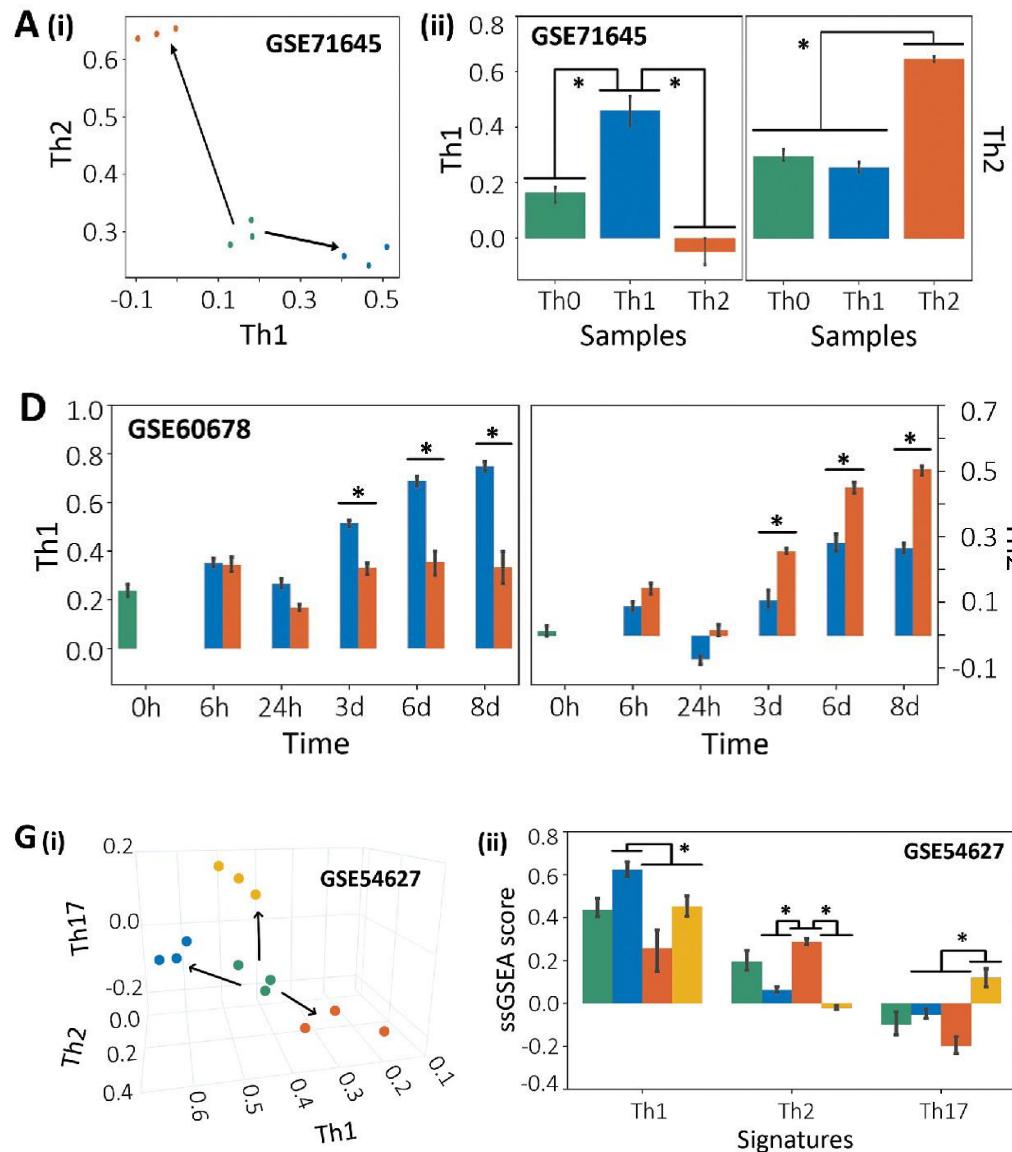
Experimental validations

The three states have been
well established

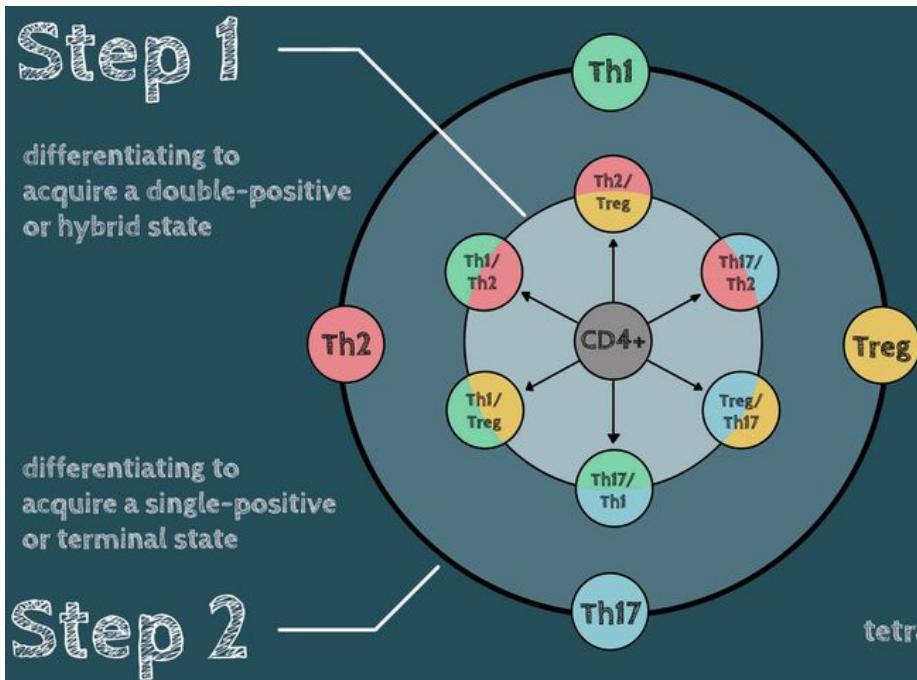
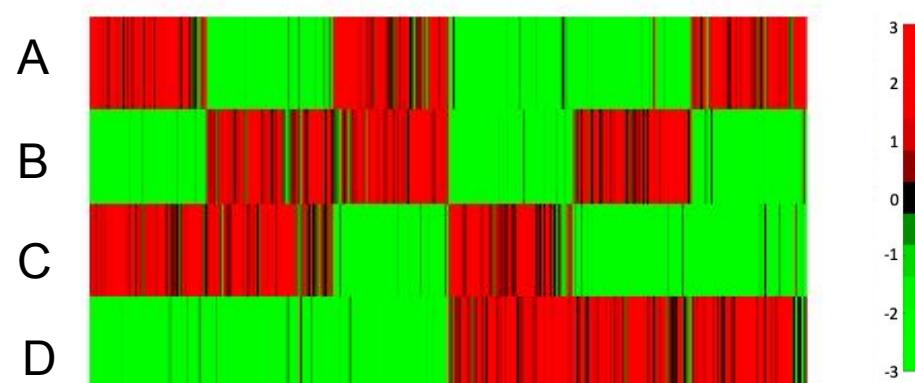
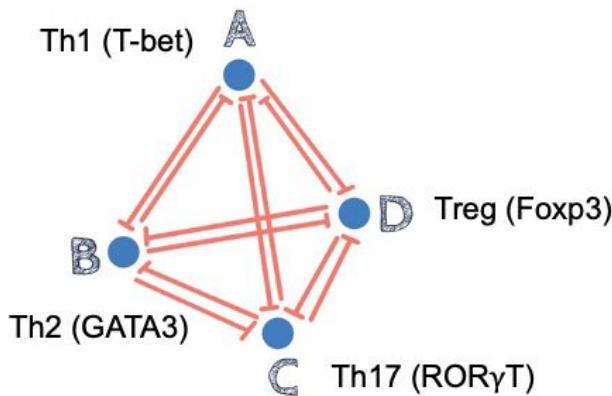
Antebi *et al.*, PLoS Biol.
2013

Chatterjee *et al.*, Cell Metab.

RNA-seq data validates our model predictions

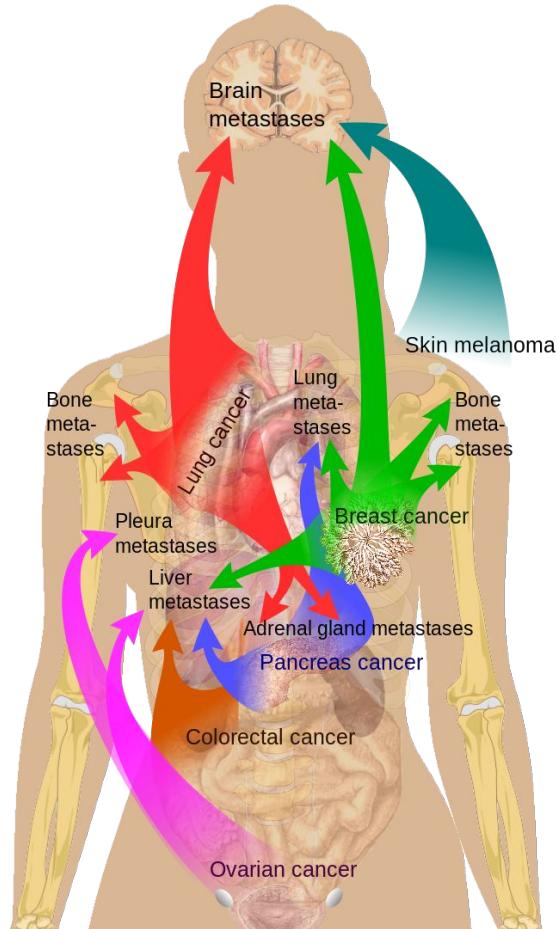


Toggle tetrahedron => Predominant ‘hybrid’ states



- None of the 4-node network topologies allows for ‘single-positive’ (1,0,0,0) states as predominant.
- ‘Single-positive’ states not the predominant ones for toggle-n ($n > 3$) states.

Metastasis : the cause of 90% of all cancer deaths



No unique mutational signatures yet identified for metastasis.

Metastasis is a highly inefficient process (<0.02%)

Challenges in developing anti-metastatic drugs

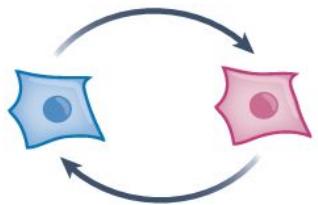


The dynamics of metastasis is poorly understood.

- When and why do cells leave the primary tumor?
- Do they leave as individual cells or as groups? Does it matter?
- Which organs do they stop by, and which organs do they settle in?
- How much time it takes for them to grow a clinically notable metastasis?

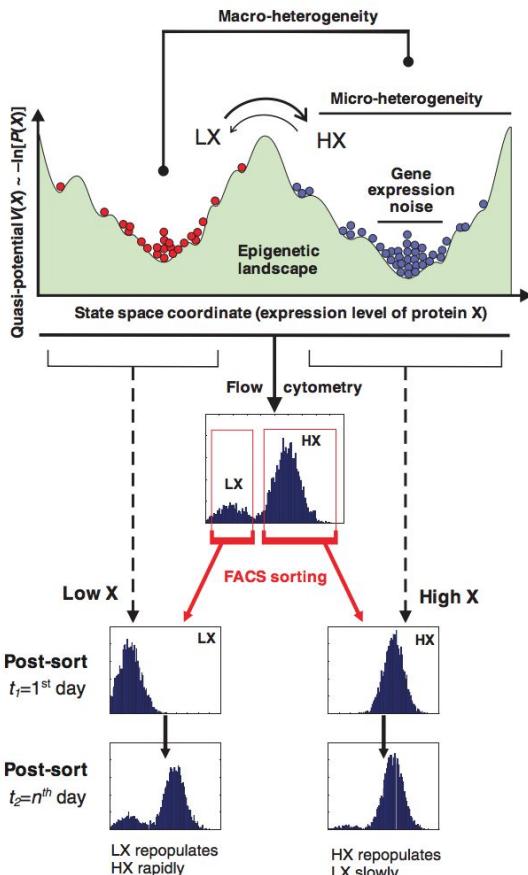
(Harry Potter and the Philosopher's Stone; Harry Potter and the Deathly Hallows)

Phenotypic plasticity : hallmark of cancer metastasis



Phenotypic plasticity:
Ability of cells to switch their 'state'
reversibly in response to environmental conditions

A

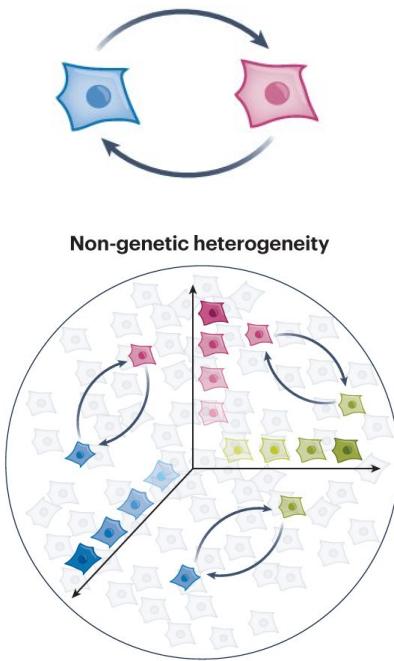


	Genetic mutations	Phenotypic plasticity
Timescale	Slow (months)	Fast (hours)
Reversibility	Irreversible	Reversible (can be transiently heritable too)

No unique mutational signatures have been yet identified for metastasis.

Repopulation studies

Phenotypic plasticity in metastasis and drug resistance



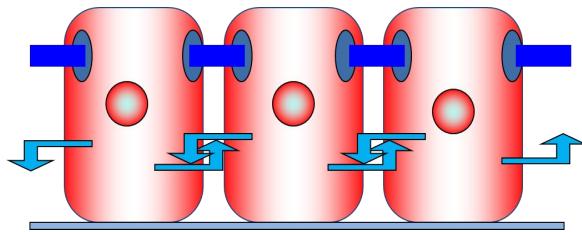
Mathematical models of phenotypic plasticity:

- Intracellular mechanistic biochemical network models
- Population-level models for inferring cell-state transitions
- Agent-based models for the impact of TME on plasticity
- Statistical approaches (infer cell-state trajectories etc.)

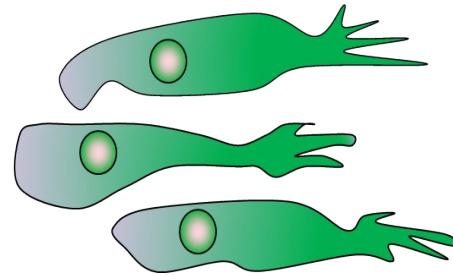
Our focus:

- Develop mechanistic models to understand cancer cell-state transitions
- Analyse single-cell omics data to validate mechanistic dynamical models
- Predict therapeutic strategies based on better dynamical understanding

EMT/MET: The engine of metastasis



Adhere to neighbors
Do NOT migrate or invade
Epithelial (E)

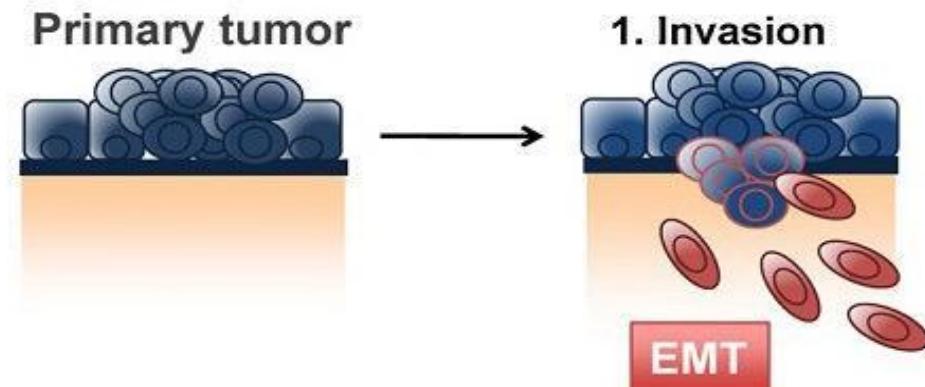
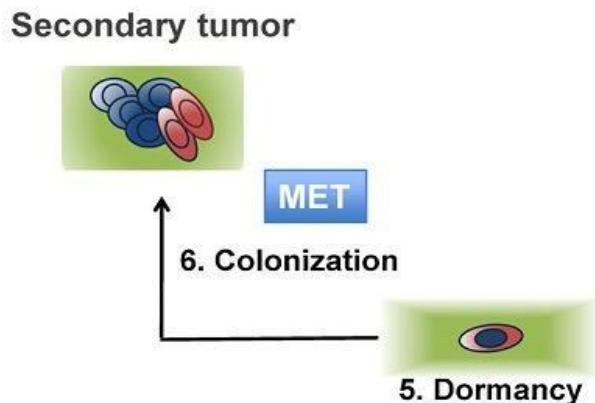


Do NOT adhere to neighbors
Migrate and invade
Mesenchymal (M)

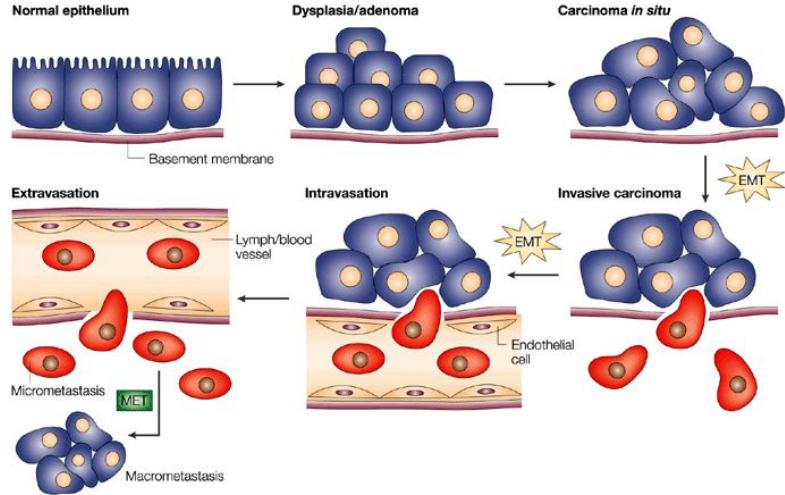


Mesenchymal-to-Epithelial
Transition (MET)

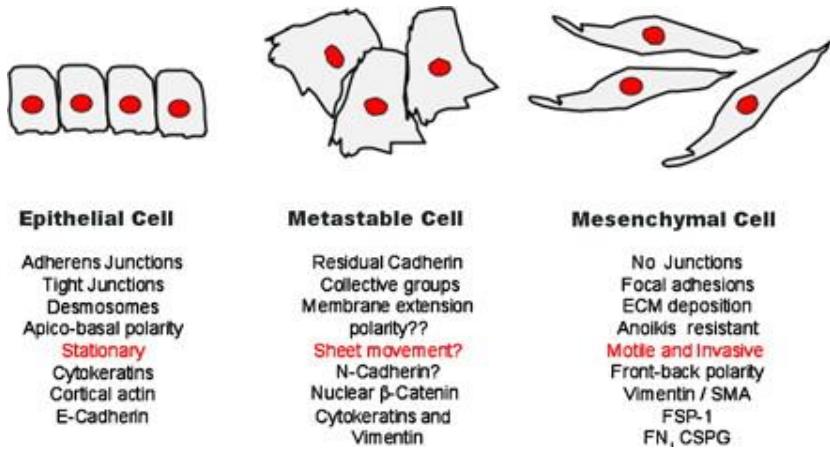
Epithelial-to-Mesenchymal
Transition (EMT)



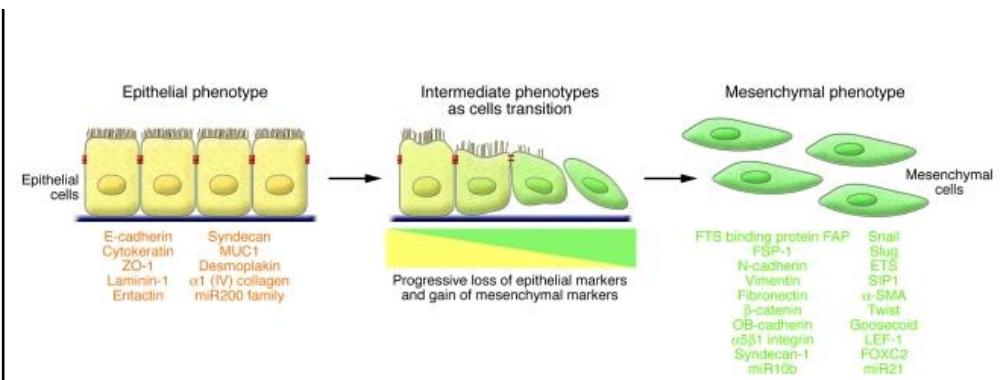
EMT ‘model’ in cancer (2002 – 2012)



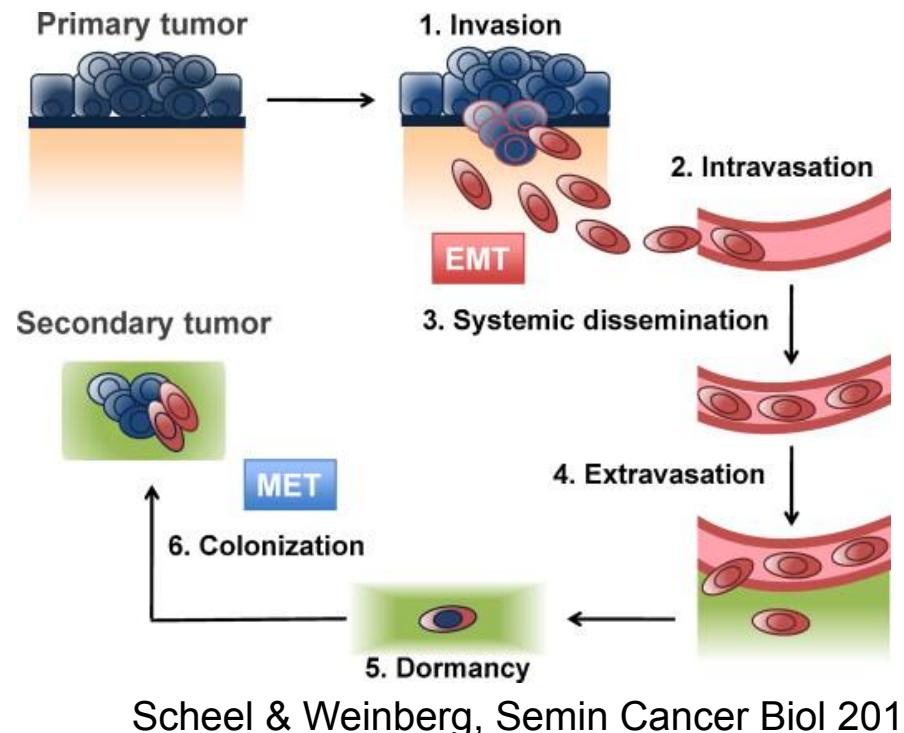
Thiery JP, Nat Rev Cancer 2002



Lee et al. J Cell Biol 2006



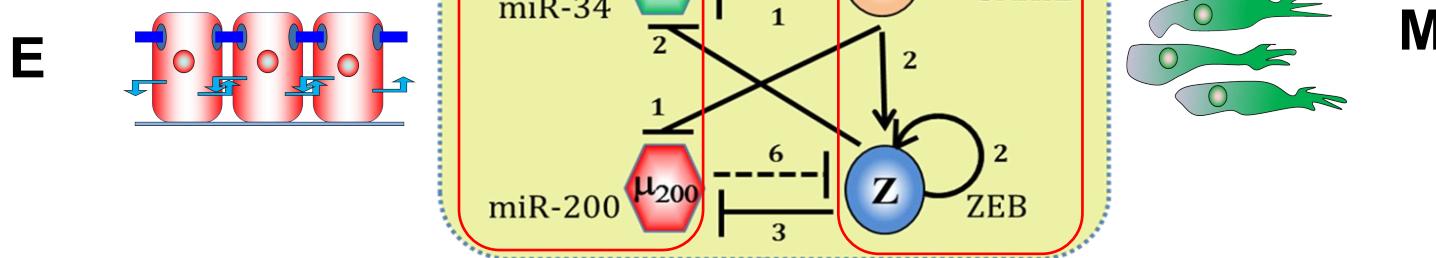
Kalluri & Weinberg, J Clin Invest 2009



Scheel & Weinberg, Semin Cancer Biol 2012

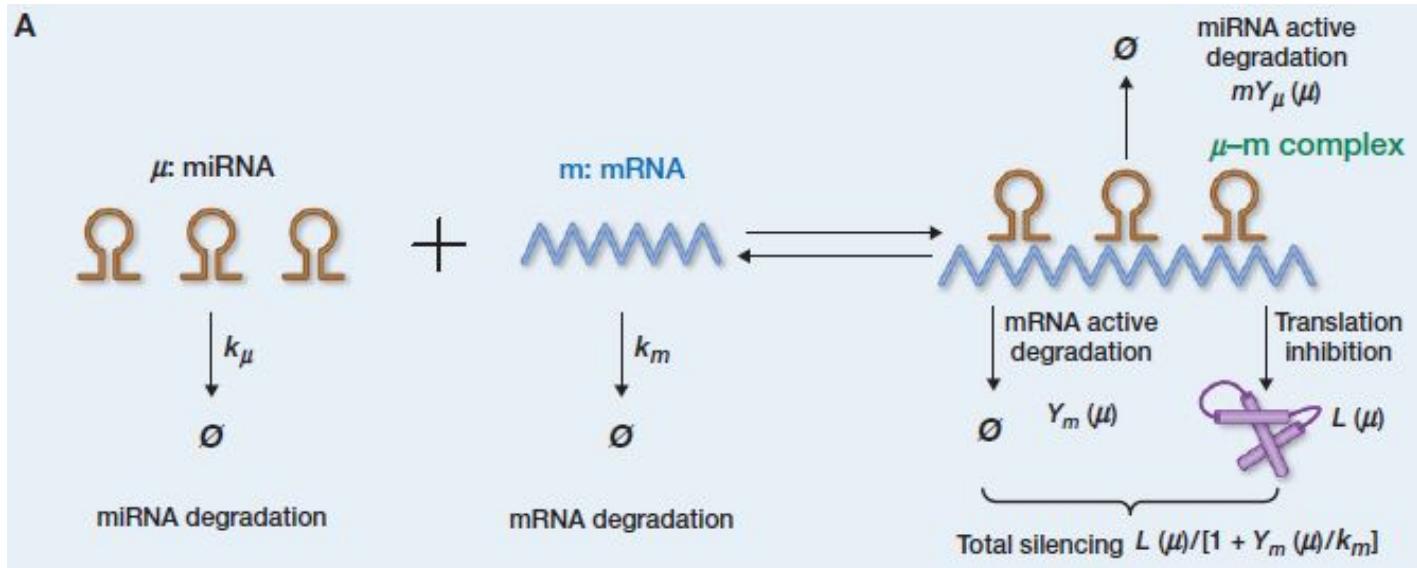
Network that controls EMT/MET

- Transcriptional activation
- | Transcriptional repression
- | miR-mediated repression



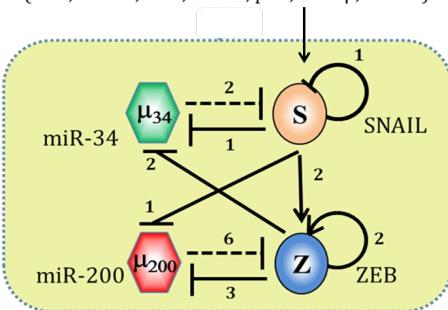
- Each arrow/bar indicates a quantitative input-output relationship.
- Such models have been extensively built for simpler microorganisms.
- Can we decode the emergent properties of these nonlinear interactions?

Mathematical model formulation



Lu*, Jolly* et al. PNAS 2013

I (HGF, NF-κB, Wnt, Notch, p53, TGF-β, HIF1α)



Production

Degradation

miR regulation

TF regulation

$$\frac{d\mu_{200}}{dt} = g_{\mu_{200}} H^S(Z, \lambda_{Z,\mu_{200}}) H^S(S, \lambda_{S,\mu_{200}}) - m_Z Y_\mu(\mu_{200}) - k_{\mu_{200}} \mu_{200}$$

miR-200

$$\frac{dm_Z}{dt} = g_{m_Z} H^S(Z, \lambda_{Z,m_Z}) H^S(S, \lambda_{S,m_Z}) - m_Z Y_m(\mu_{200}) - k_{m_Z} m_Z$$

ZEB mRNA

$$\frac{dZ}{dt} = g_Z m_Z L(\mu_{200}) - k_Z Z$$

ZEB

$$\frac{d\mu_{34}}{dt} = g_{\mu_{34}} H^S(Z, \lambda_{Z,\mu_{34}}) H^S(S, \lambda_{S,\mu_{34}}) - m_S Y_\mu(\mu_{34}) - k_{\mu_{34}} \mu_{34}$$

miR-34

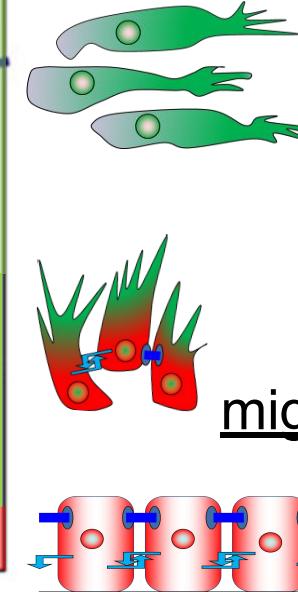
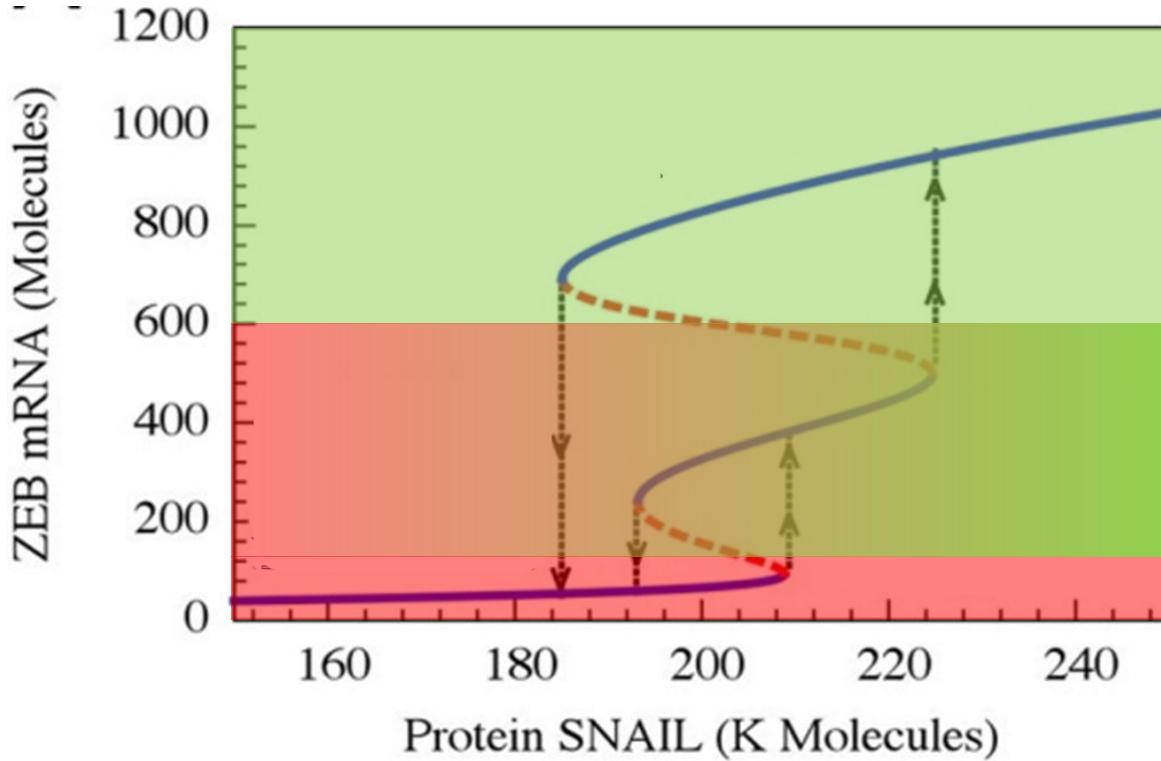
$$\frac{dm_S}{dt} = g_{m_S} H^S(S, \lambda_{S,m_S}) H^S(I, \lambda_{I,m_S}) - m_S Y_m(\mu_{34}) - k_{m_S} m_S$$

SNAIL mRNA

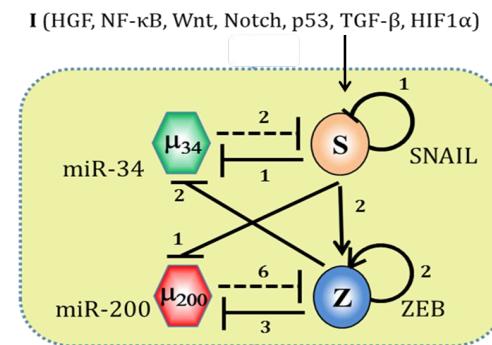
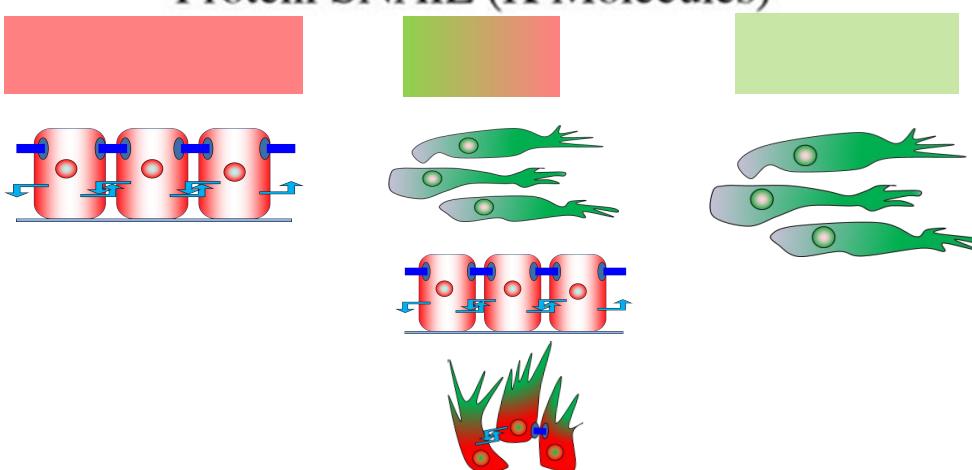
$$\frac{dS}{dt} = g_S m_S L(\mu_{34}) - k_S S$$

SNAIL ₂₃

Model prediction: EMT is NOT binary

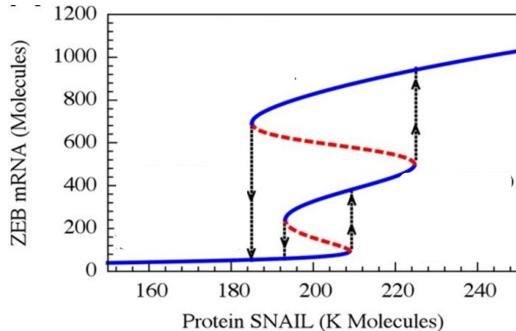


Hybrid E/M
Adhere AND
migrate collectively



Lu*, Jolly* et al. PNAS 2013

Mathematical modeling for EMT dynamics

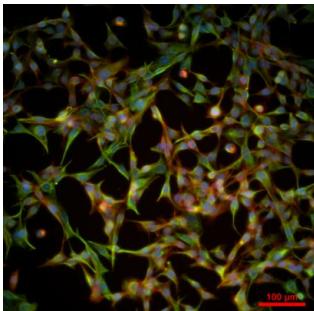


Predictions from mathematical model:

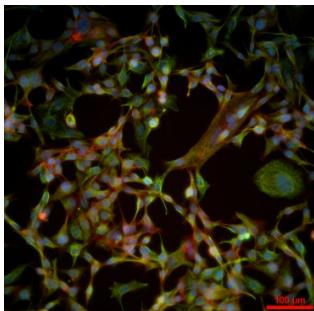
1. Cells can stably exist in hybrid E/M state
2. Isogenic cells can exist in different EMT states
3. Cells can ‘spontaneously’ switch their states

Lu*, Jolly* et al. PNAS 2013

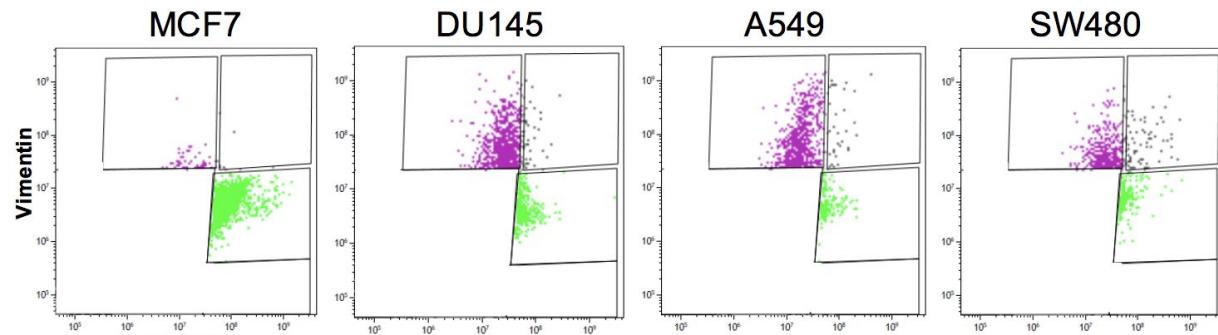
Experimental validation:



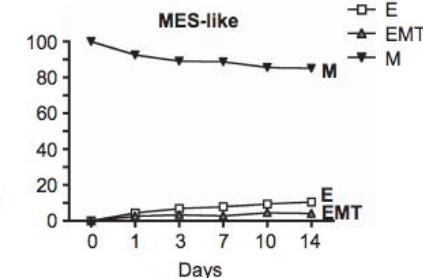
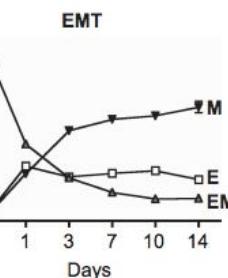
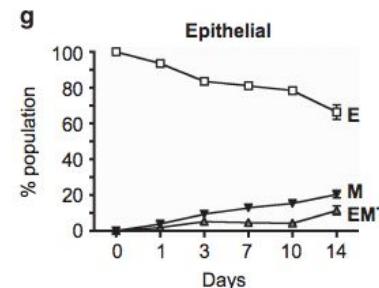
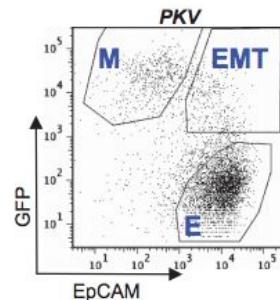
H1975, T=0



H1975, T=2 months



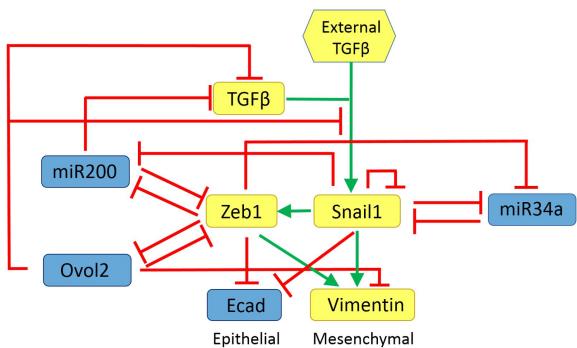
George*, Jolly* et al. Cancer Res 2017



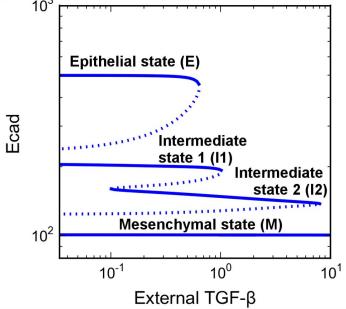
Jolly et al. Oncotarget 2016; Ruscetti et al. Oncogene 2016

Hybrid E/M phenotype(s) seen in other math models too

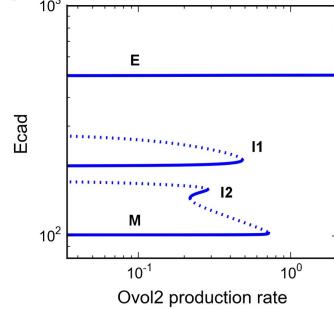
A



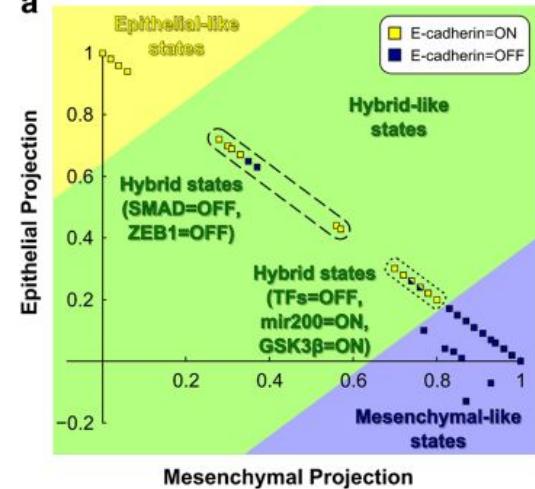
B



C

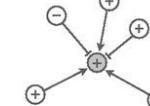


a



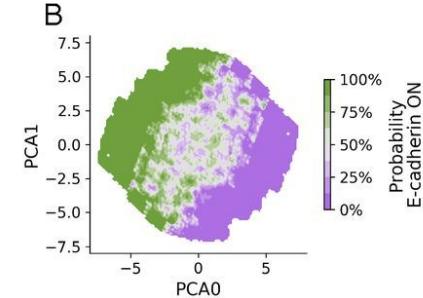
A

Boolean dynamics

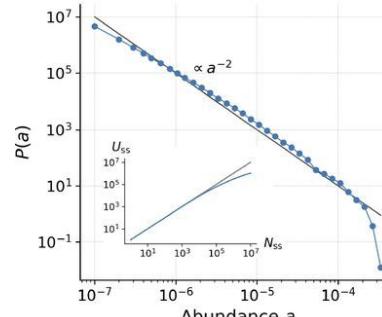


$$s_i = \text{sign}(\sum_j J_{ij} s_j)$$

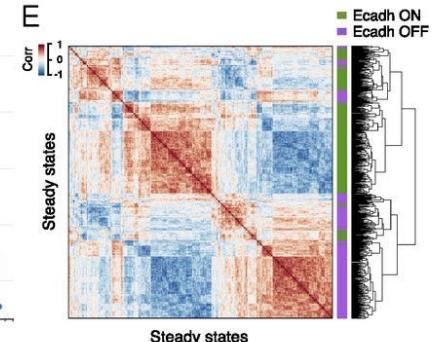
B



D



E



Xing *et al.* Biophys J 2013

Steinway *et al.* Cancer Res 2014, NPJ Sys Biol Appl 2015

Hong *et al.* PLoS Comp Biol 2015

Jolly *et al.* Oncotarget 2016

Huang *et al.* PLoS Comp Biol 2017, BMC Sys Biol 2018

Font-Clos *et al.* PNAS 2018, Cell Systems 2021

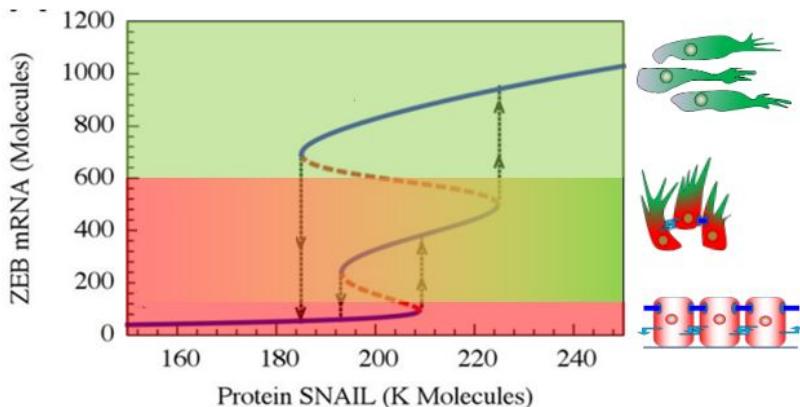
Silveira *et al.* FEBS J 2020, J R Soc Interface 2020

Hari *et al.* NPJ Sys Biol Appl 2020, PLoS Comp Biol 2022

Sullivan *et al.* iScience 2024

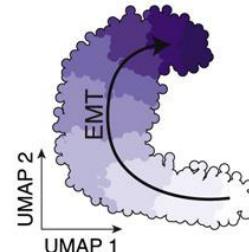
McDermott *et al.* NPJ Sys Biol Appl 2024

From EMT (2002-2012) to EMP (Epi-Mes Plasticity; 2013-now)

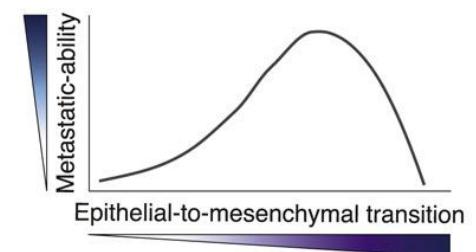


Lu[#], Jolly[#] et al. PNAS 2013

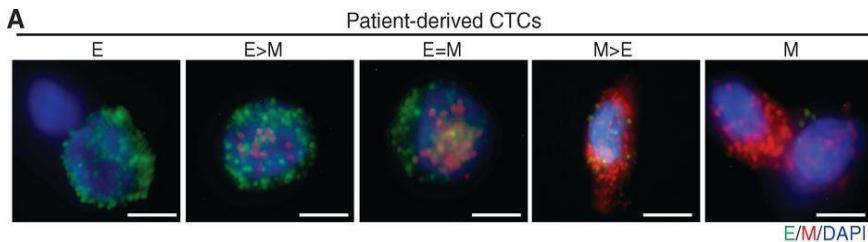
Identify transcriptional features



Relate metastatic phenotypes to transcriptional features



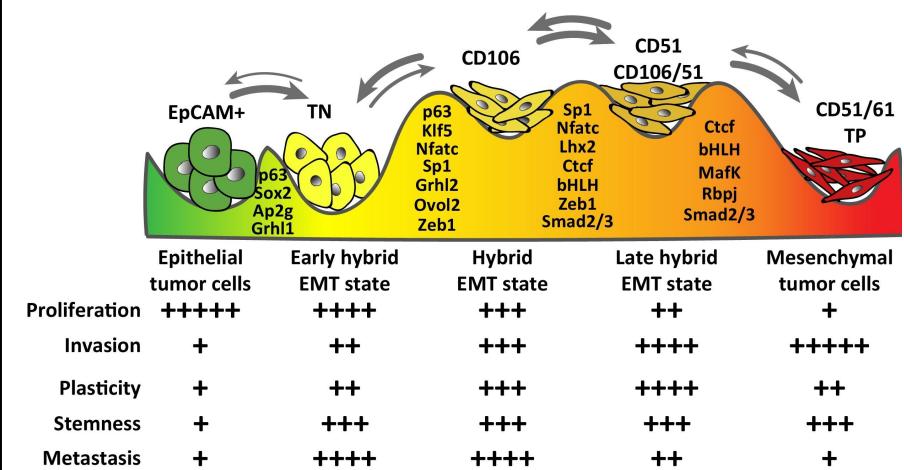
Simeonov et al. Cancer Cell 2021



Acquisition of a hybrid E/M state is essential for tumorigenicity of basal breast cancer cells

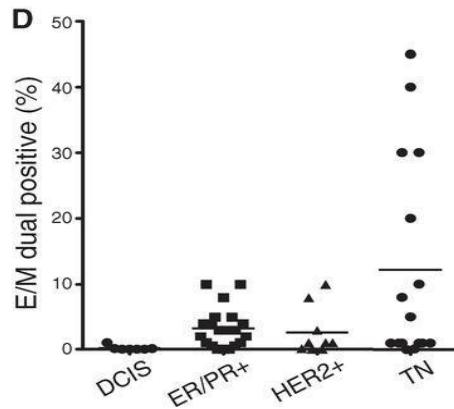
Cornelia Kröger^a, Alexander Afeyan^{a,b}, Jasmin Mraz^{a,c}, Elinor Ng Eaton^a, Ferenc Reinhardt^a, Yevgenia L. Khodor^d, Prathapan Thiru^a, Brian Bierie^e, Xin Ye^{a,e}, Christopher B. Burge^a, and Robert A. Weinberg^{a,f,g,1}

Yu et al. Science 2013
Kroger et al. PNAS 2019

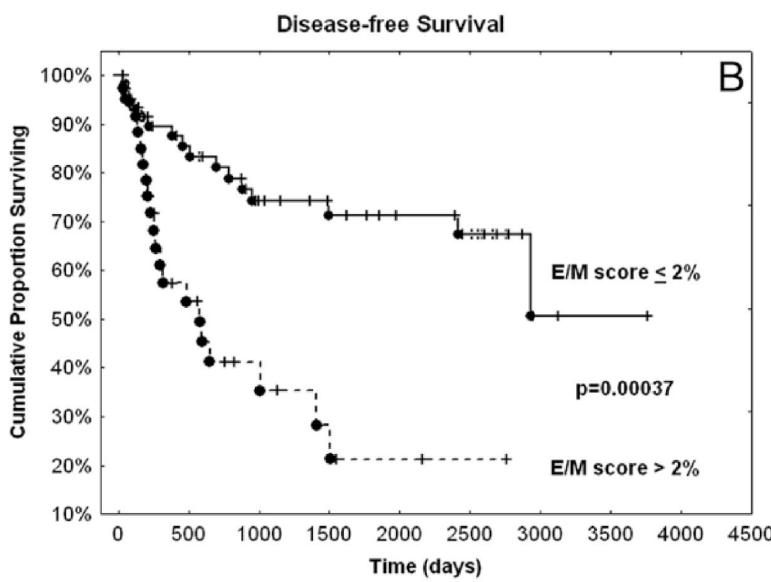
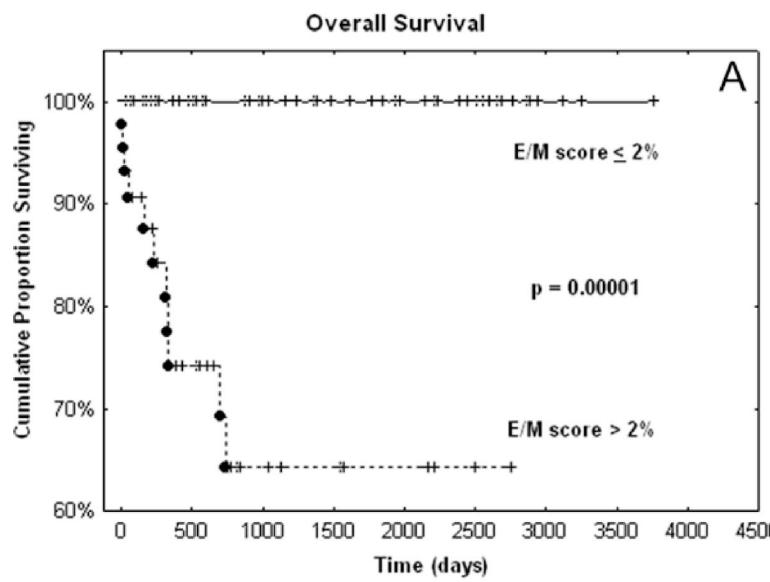


Pastushenko & Blanpain, Trends Cell Biol 2019
Pastushenko et al. Nature 2018

Clinical relevance of hybrid E/M phenotype(s)



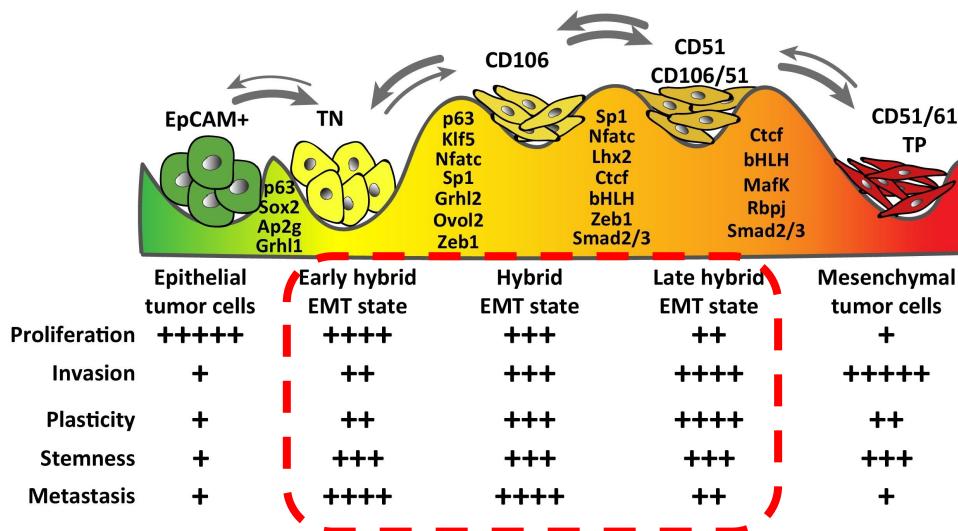
- Single-cell migration is very rare, if any, in cancer
- A small (2-5%) hybrid E/M cells can associate with worse survival



Why are hybrid E/M cells the ‘fittest’?

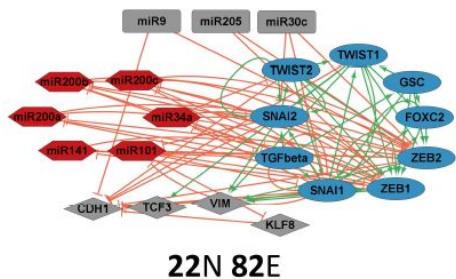


Kishore Hari

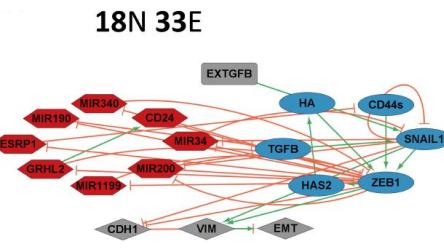


$$s_i(t+1) = \begin{cases} +1, & \sum_j A_{ij} s_j(t) > 0 \\ -1, & \sum_j A_{ij} s_j(t) < 0 \\ s_i(t), & \sum_j A_{ij} s_j(t) = 0 \end{cases}$$

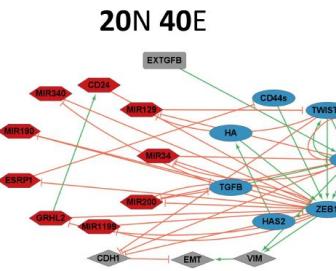
Is the “high plasticity” behavior of hybrid E/M a feature of underlying regulatory networks?



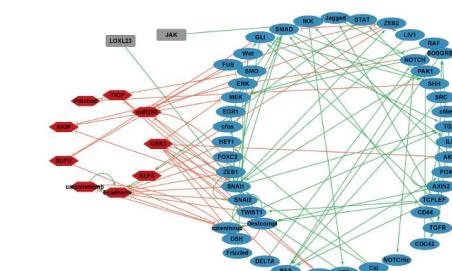
18N 33E



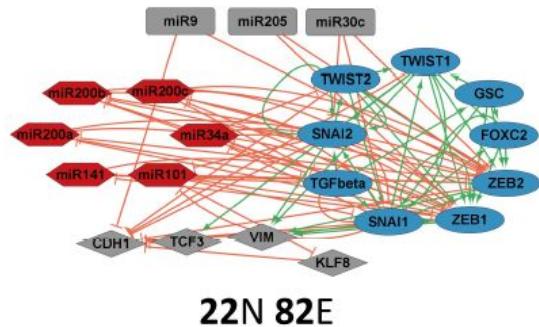
20N 40E



57N 113E



EMT networks consist of two “teams” of players

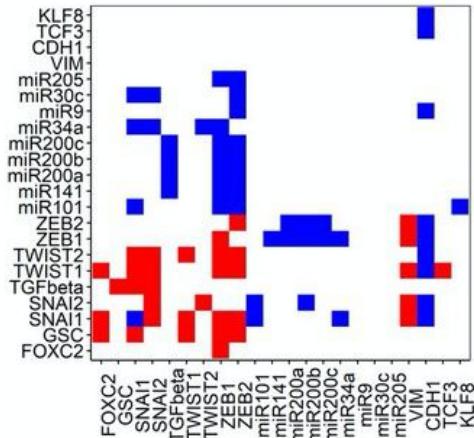


$$Infl = \frac{\sum_{l=1}^{lmax} \frac{Adj^l}{Adj_{max}}}{lmax}$$

$$T_{KL} = \frac{\sum_{i \in T_K} \sum_{j \in T_L} Inf l_{ij}}{n_{KL}}, K, L \in \{1, 2\}$$

$$T_S = \frac{\sum_{K,L \in \{1,2\}} |T_{KL}|}{4}$$

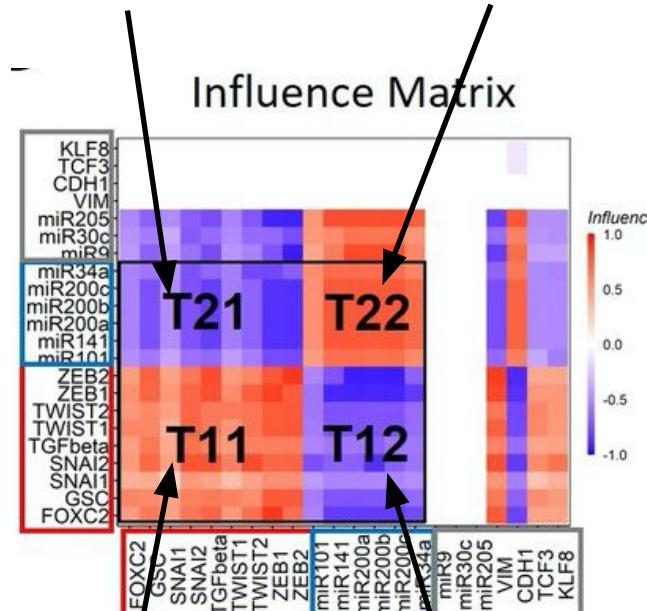
Adjacency Matrix



Row => Source; Column => Target
Red (Activation), Blue (Inhibition)

All Epi nodes
effectively **inhibit**
all Mes nodes.

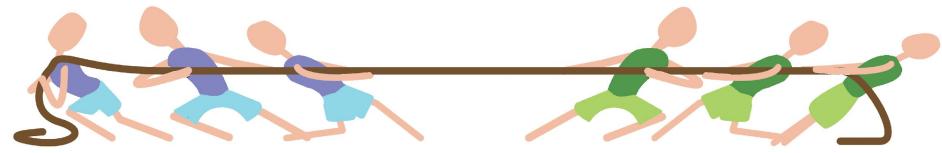
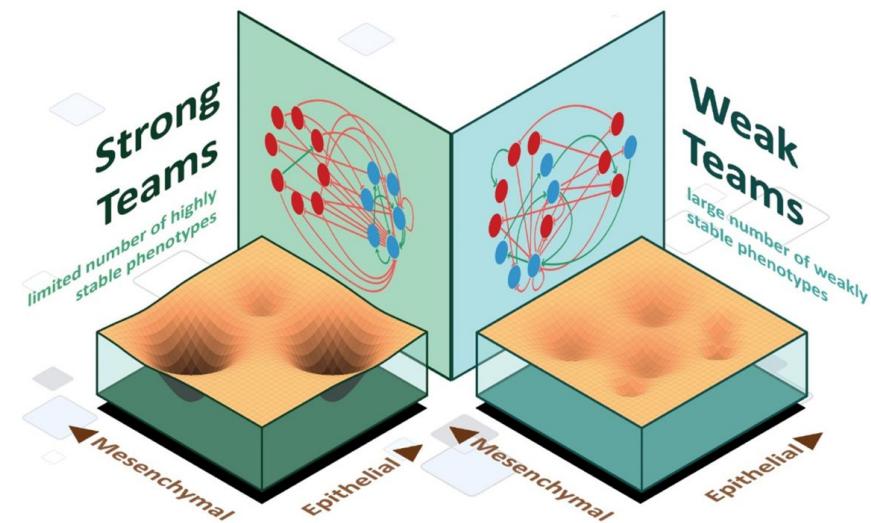
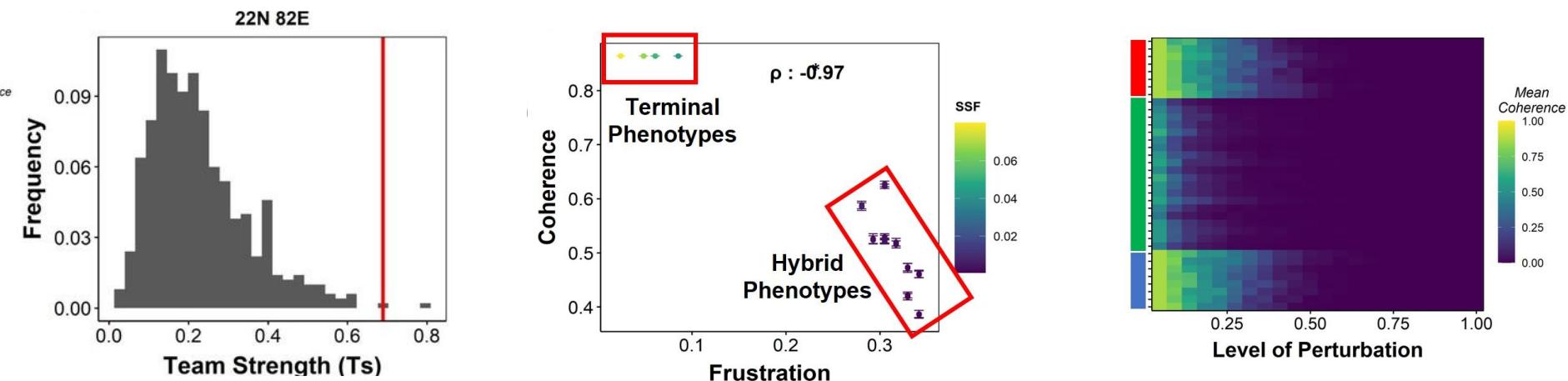
All Epi nodes effectively **activate** all Epi nodes.



All Mes nodes
effectively **activate**
all Mes nodes.

All Mes nodes
effectively **inhibit**
all Epi nodes.

“Teams” offer “resistance” to transition out of E, M

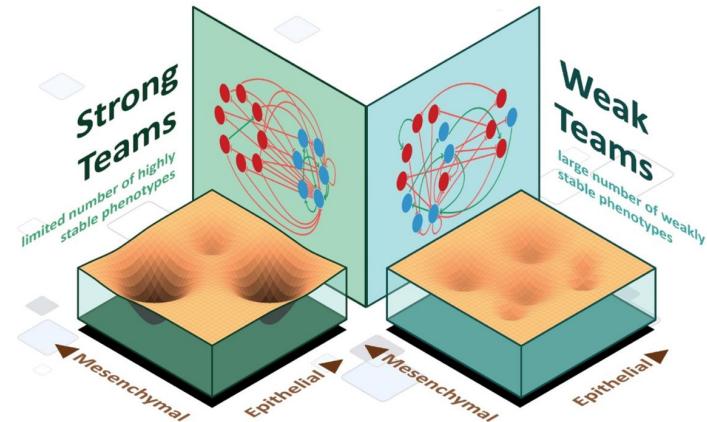


Absence of any “teams” supporting the hybrid E/M phenotypes makes them the ‘fittest’ for metastasis.

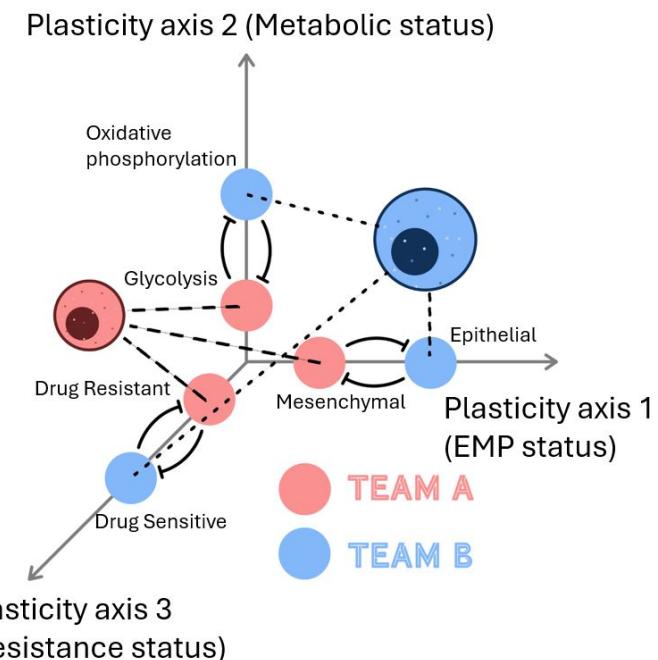
Why do “teams” exist?

To shape the phenotypic plasticity landscape

=> Control the rates of cell-state transitions

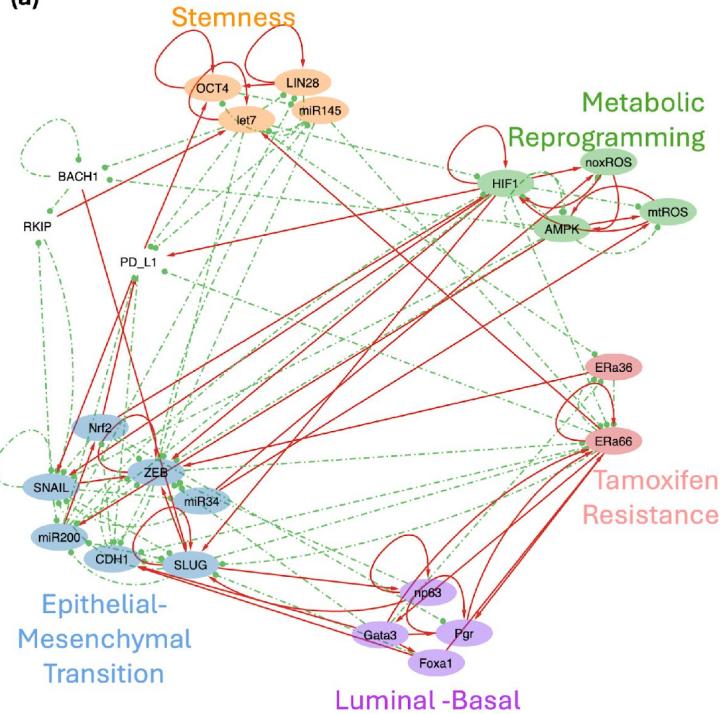


To couple the multiple axes of phenotypic plasticity
=> Increase the ‘fitness’ of metastasizing cells



A gene regulatory network (GRN) for interconnected axes of phenotypic plasticity in ER+ breast cancer

(a)



Ritesh Meena
(BS/MS, IISc)

Prior building blocks:

- EMT-stemness (Jolly *et al.* 2015)
- EMT-metabolism (Galbraith *et al.* 2022)
- EMT-Tamoxifen Res (Sahoo *et al.* 2021)
- EMT-luminal-basal (Sahoo *et al.* 2024)
- EMT-PD-L1 (Sahoo *et al.* 2021; Shyam *et al.* 2023)

Individual axes of plasticity show multi-modal behavior

Definition of scores:

$$\text{EMT} = (\text{ZEB} + \text{SLUG} - \text{CDH1} - \text{miR200}) / 4$$

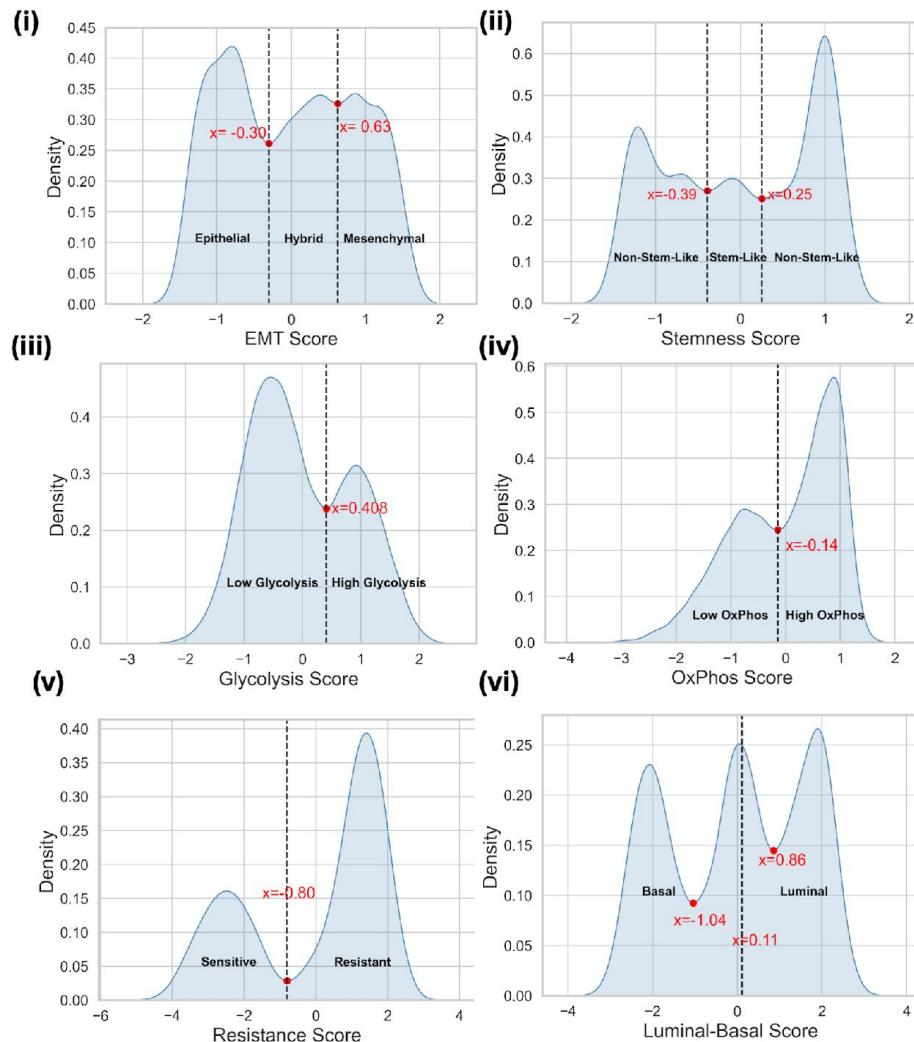
$$\text{SN} = (\text{LIN28} + \text{OCT4} - \text{let-7} - \text{miR145}) / 4$$

$$\text{Glycolysis} = (\text{noxROS} + \text{HIF1}) / 2$$

$$\text{OXPHOS} = (\text{mtROS} + \text{AMPK}) / 2$$

$$\text{Res} = (\text{ERa36} - \text{ERa66}) / 2$$

$$\text{L-B} = (\text{ERa66} + \text{GATA3} + \text{PGR} + \text{FOXA1})/4 - (\text{NP63} + \text{SLUG}) / 2$$



Any topological patterns in this GRN?

(i)

Adjacency Matrix

	Adjacency Matrix																							
	Nrf2	miR34	HIF1	noxROS	SNAIL	let7	CDH1	ZEB	Gata3	PD_L1	BACH1	miR200	SLUG	LIN28	RKIP	miR145	Pgr	mtROS	OCT4	AMPK	ERα66	Foxe1	ERα36	np63
	0	0	1	0	-1	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Nrf2	0	0	1	0	-1	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
miR34	0	0	0	1	-1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0		
HIF1	0	0	1	1	1	0	0	1	0	1	0	-1	1	0	0	0	-1	0	-1	-1	0	0		
noxROS	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0		
SNAIL	0	-1	0	0	-1	0	0	1	0	0	0	-1	-1	0	-1	0	0	0	0	0	0	0		
let7	0	-1	0	0	1	0	-1	0	-1	0	-1	0	0	-1	0	0	0	0	0	0	0	-1		
CDH1	-1	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
ZEB	0	-1	0	0	0	-1	1	0	0	0	-1	0	0	0	-1	0	0	0	0	-1	0	0		
Gata3	0	0	0	0	0	0	1	-1	0	0	0	0	0	0	0	0	1	0	0	0	1	1	-1	
PD_L1	0	0	0	0	1	0	-1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0		
BACH1	0	0	0	0	0	0	0	0	0	-1	0	1	0	-1	0	0	0	0	0	0	0	0		
miR200	1	0	-1	0	0	0	-1	0	-1	0	0	1	1	0	0	0	0	0	0	0	0	0		
SLUG	0	0	0	-1	0	-1	1	0	0	0	-1	1	0	0	0	0	0	0	-1	0	0	1		
LIN28	0	0	0	0	0	-1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0		
RKIP	0	0	0	0	-1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
miR145	0	0	0	0	0	0	-1	0	-1	0	0	0	0	0	0	0	0	-1	0	-1	0	0		
Pgr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0		
mtROS	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0		
OCT4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	1	0	0	0	0		
AMPK	0	0	-1	-1	1	0	0	-1	0	0	-1	1	0	0	0	0	-1	0	-1	0	0	0		
ERα66	0	0	0	0	0	1	-1	0	1	-1	0	0	-1	0	0	0	1	0	0	0	1	-1		
Foxe1	0	0	0	0	0	0	1	0	0	0	-1	0	0	0	0	0	0	1	0	0	0	0		
ERα36	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	-1	0	0	0	0		
np63	0	0	0	0	0	0	-1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1		
	Target																							
Nrf2	miR34	HIF1	noxROS	SNAIL	let7	CDH1	ZEB	Gata3	PD_L1	BACH1	miR200	SLUG	LIN28	RKIP	miR145	Pgr	mtROS	OCT4	AMPK	ERα66	Foxe1	ERα36	np63	

$$Infl = \frac{\sum_{l=1}^{lmax} \frac{Adj^l}{Adj_{max}}}{lmax}$$

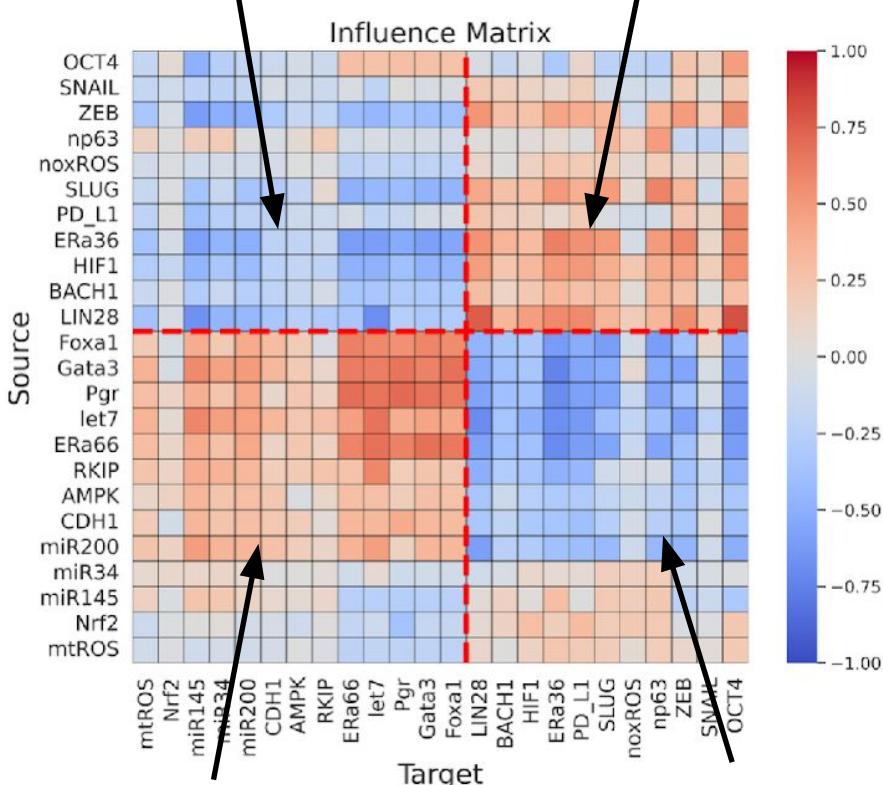
$$T_{KL} = \frac{\sum_{i \in T_K} \sum_{j \in T_L} Inf l_{ij}}{n_{KL}}, K, L \in \{1, 2\}$$

$$T_S = \frac{\sum_{K,L \in \{1,2\}} |T_{KL}|}{4}$$



Team 1 members
effectively **inhibit**
Team 2 members.

Team 1 members
effectively **activate**
Team 1 members.

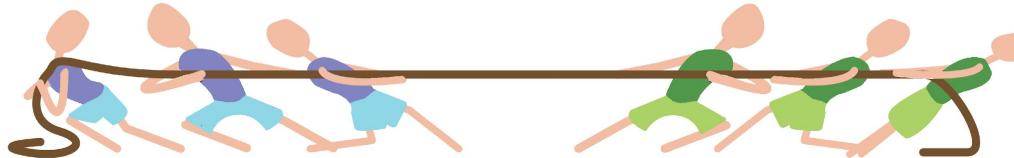


Team 2 members
effectively **activate**
Team 2 members.

Team 2 members
effectively **inhibit**
Team 1 members.

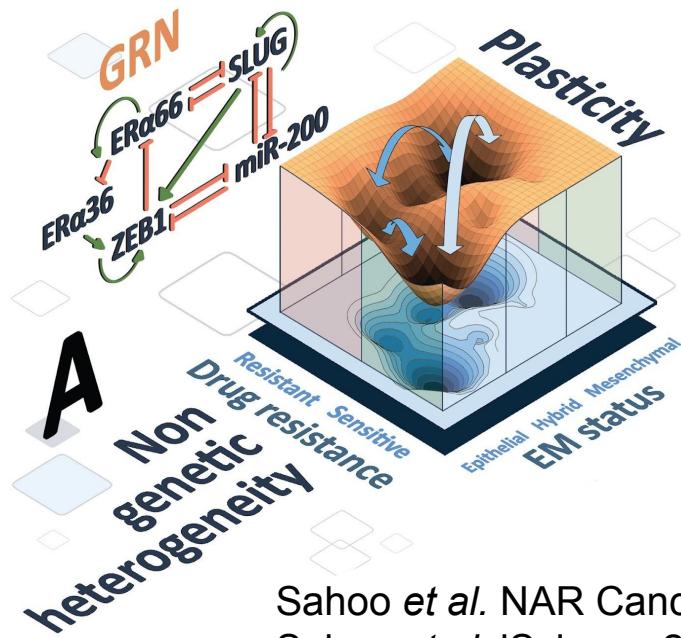
Mutually opposing two-team behavior across plasticity axes

Epithelial
Non-stem like
Tam-Sensitive
Luminal-like
OXPHOS

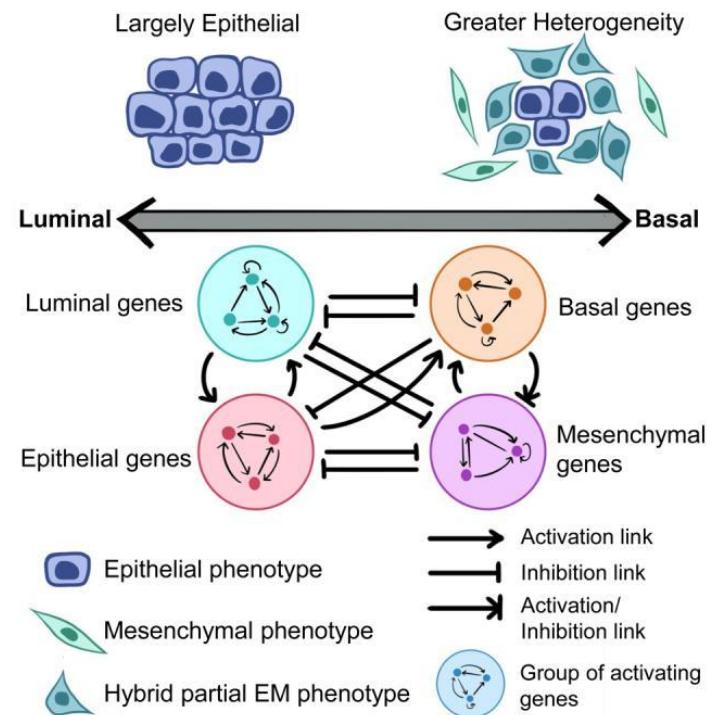


Mesenchymal
Stem-like
Tam-Resistant
Basal-like
Glycolysis

Network topology explains why we had noticed specific patterns in simulation, omics data

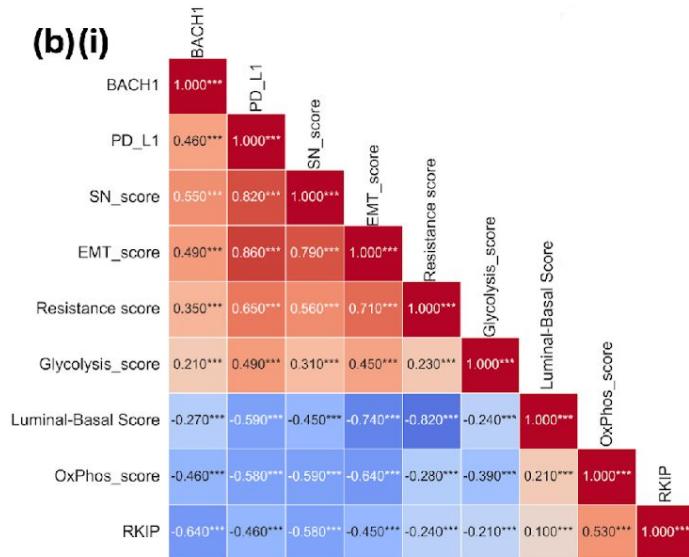


Sahoo et al. NAR Cancer 2021
Sahoo et al. iScience 2024



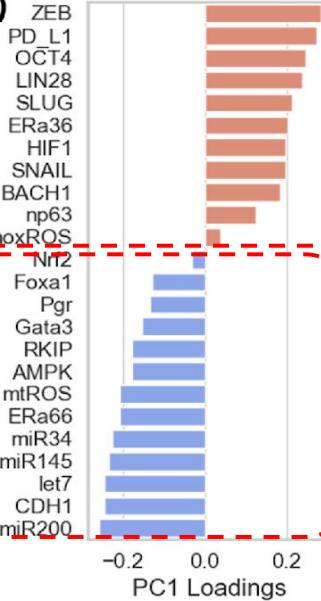
GRN simulations confirm the two-team dynamics across axes

(b)(i)

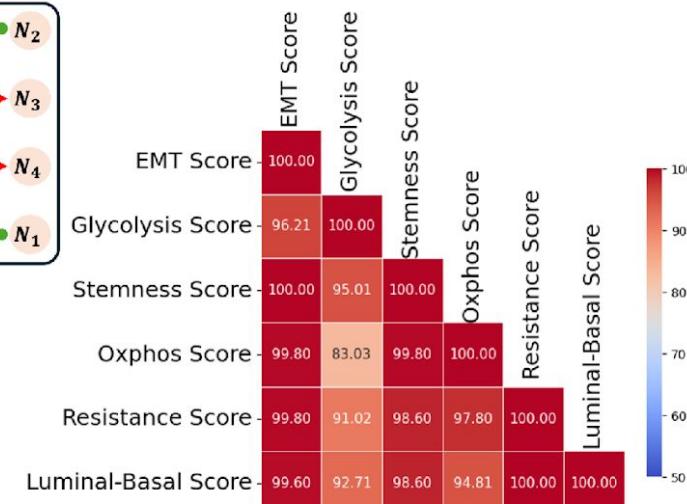
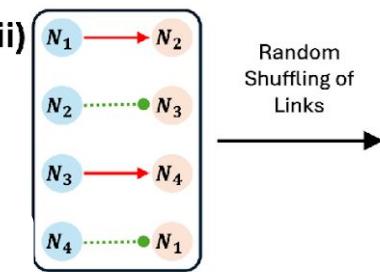


- Phenotypic plasticity is a tightly coordinated multi-axis systems-level process in cancer.
- This coordination is enabled by functional cellular programs forming two opposing ‘teams’.
- ‘Teams’ => evolutionary conserved mechanism?

(i)

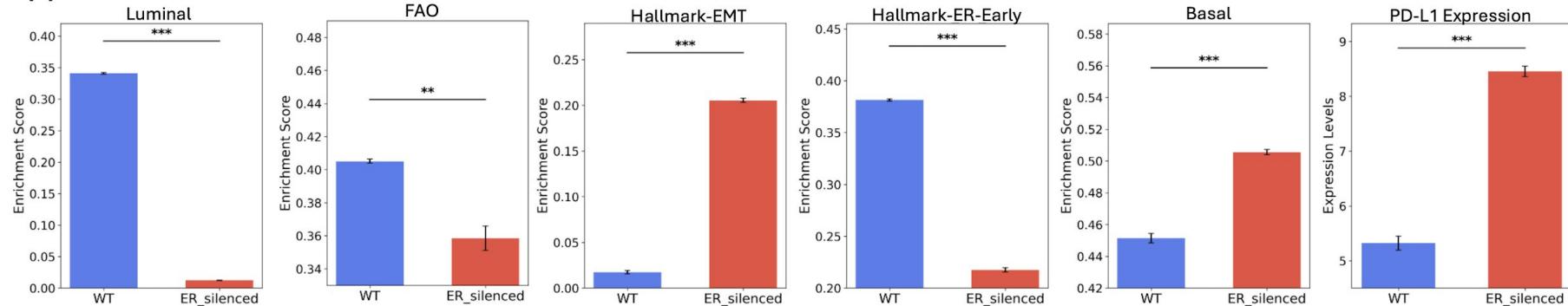


(ii)

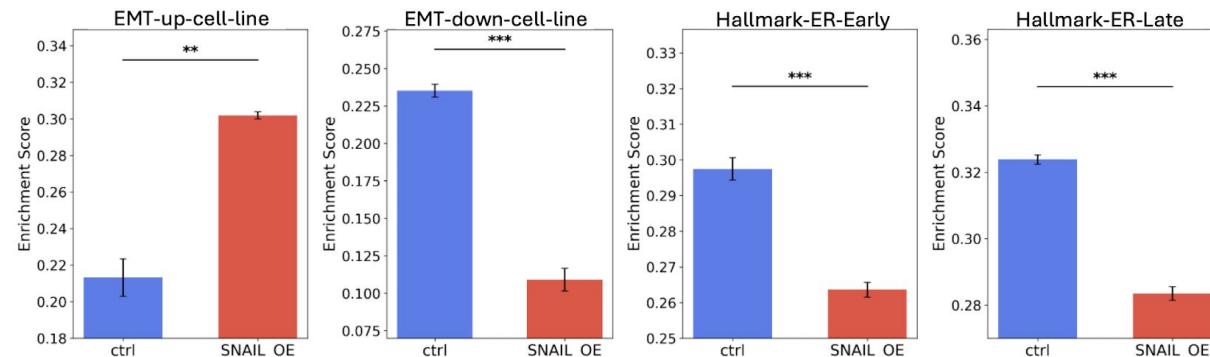


RNA-seq analysis suggests coordinated cell-state transitions

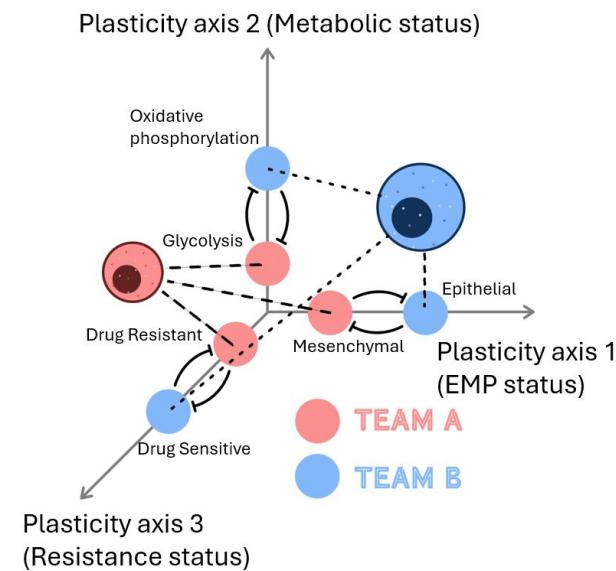
(a) GSE27473



(c) GSE81929

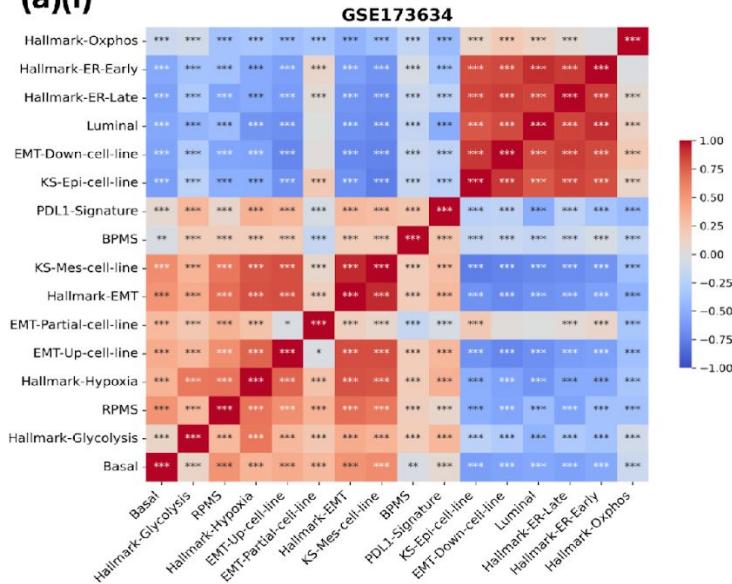


The presence of two opposing ‘teams’ can drive the coordinated cellular responses in specific directions.



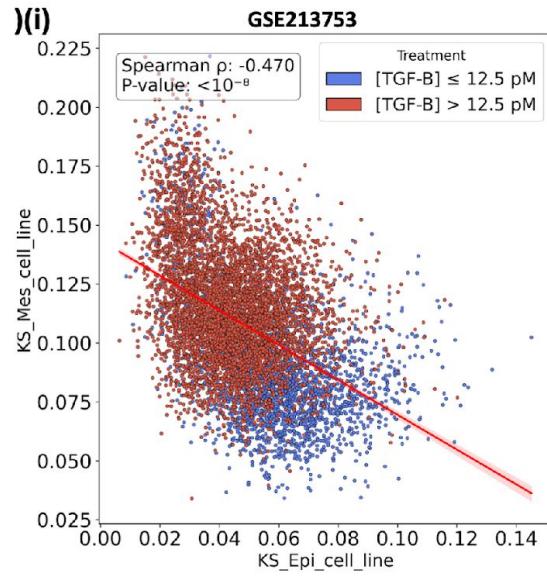
scRNA-seq data recapitulates systemic plasticity patterns

(a)(i)

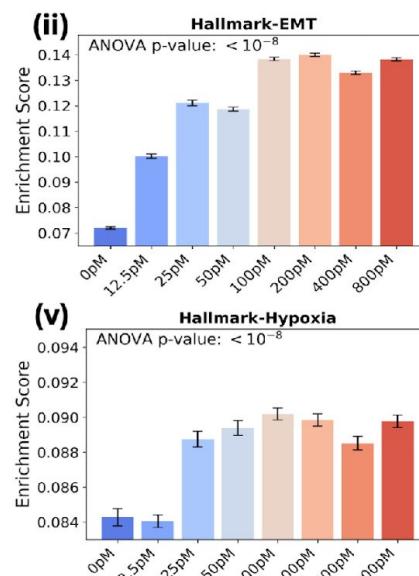


EMT progression usually proceeds with the suppression of ER signaling and increased glycolysis in ER+ breast cancer samples.

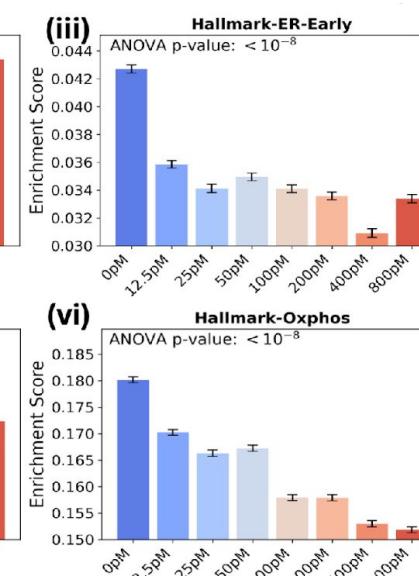
(i)



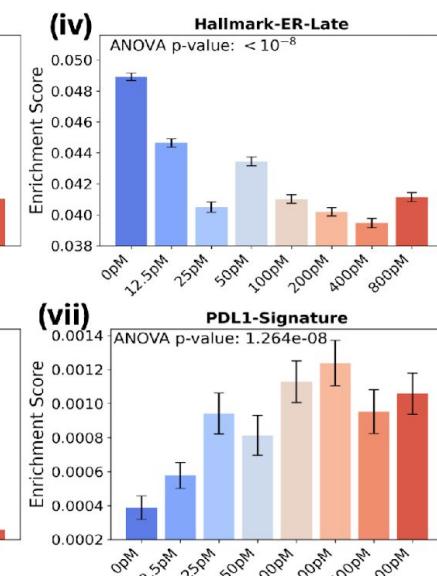
(ii)



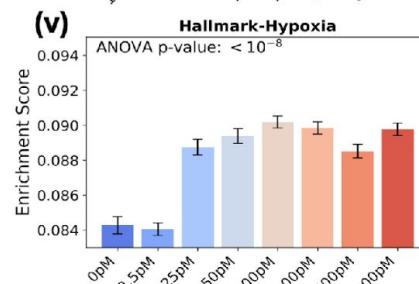
(iii)



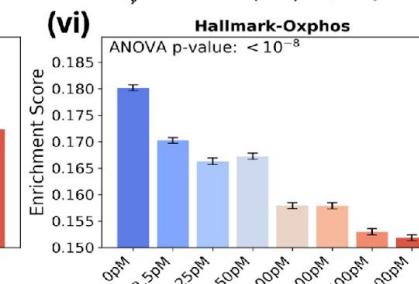
(iv)



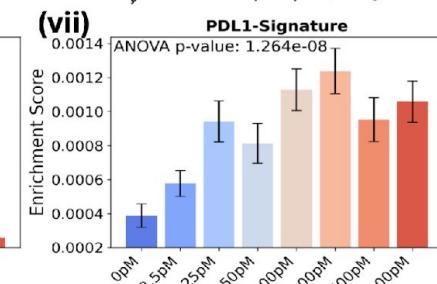
(v)



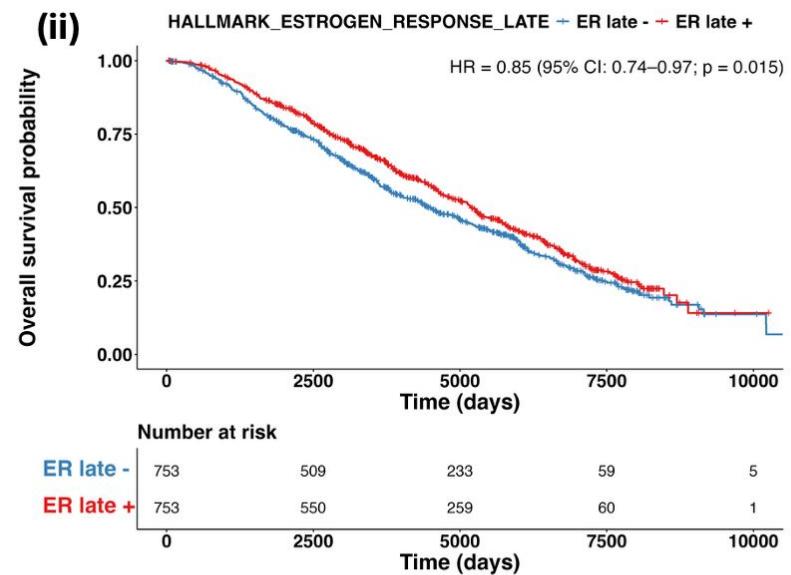
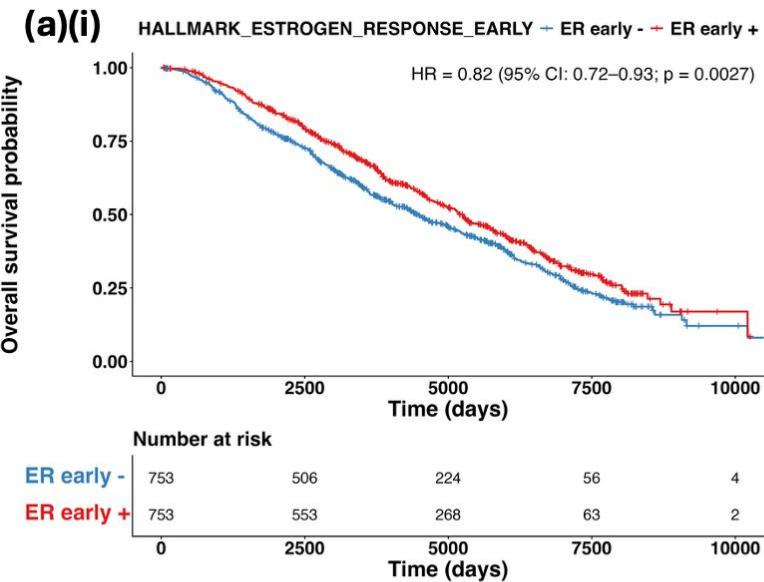
(vi)



(vii)



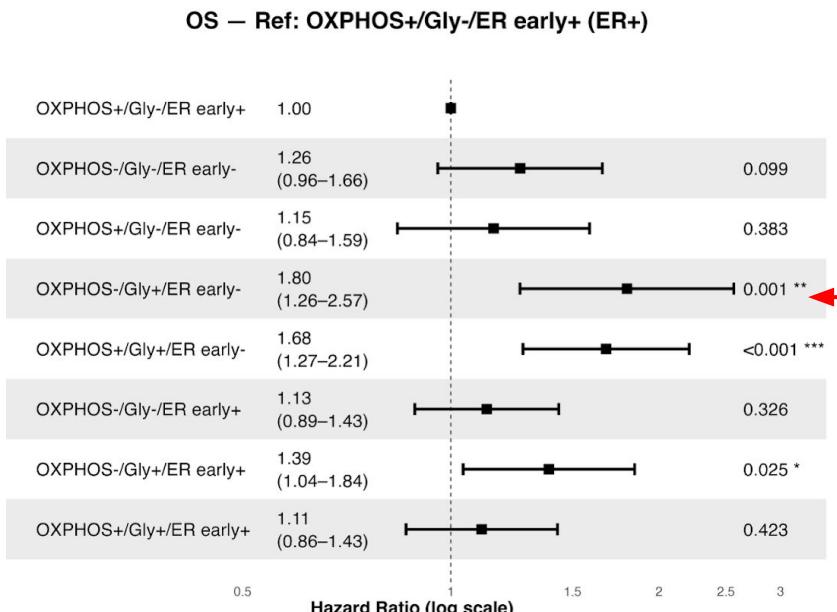
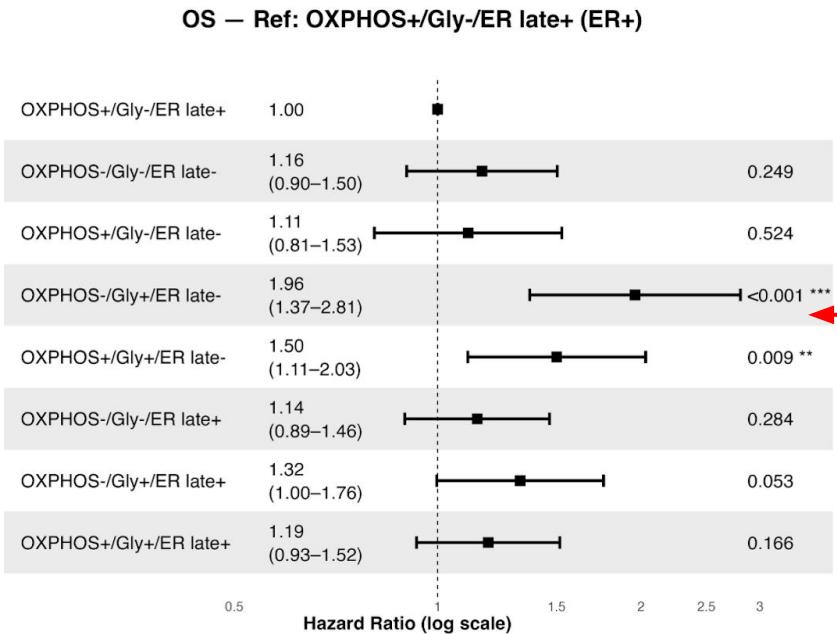
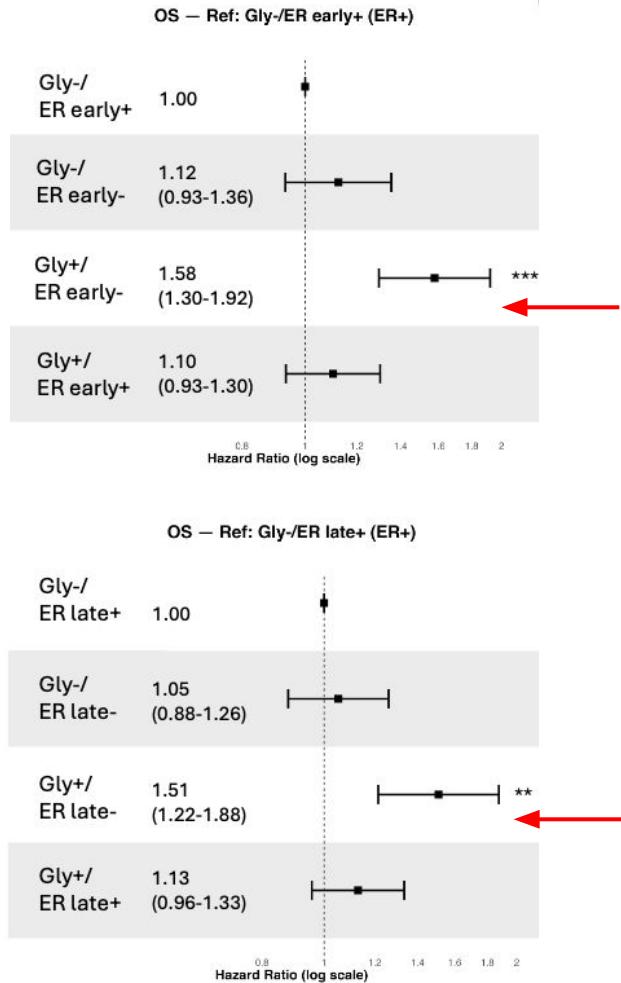
Any clinical relevance of coordinated cell-state transitions?



Suppression of ER signaling associated with worse clinical outcomes in ER+ BCa (TCGA, METABRIC cohorts).

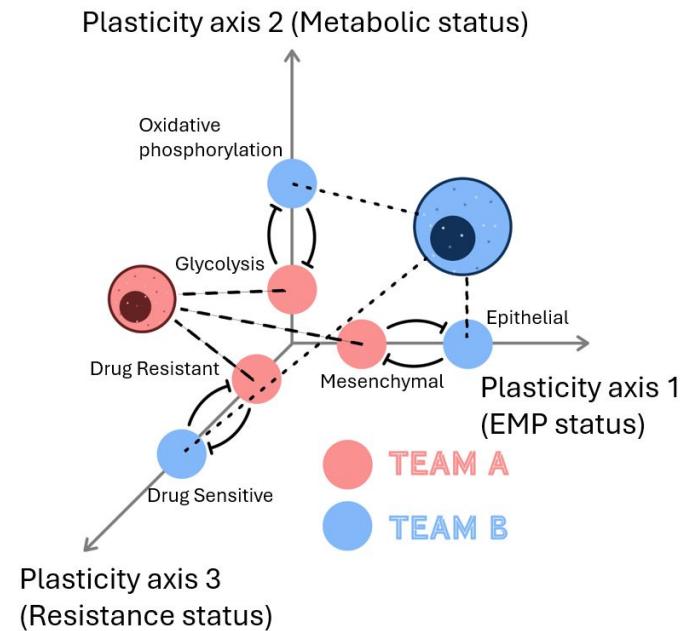
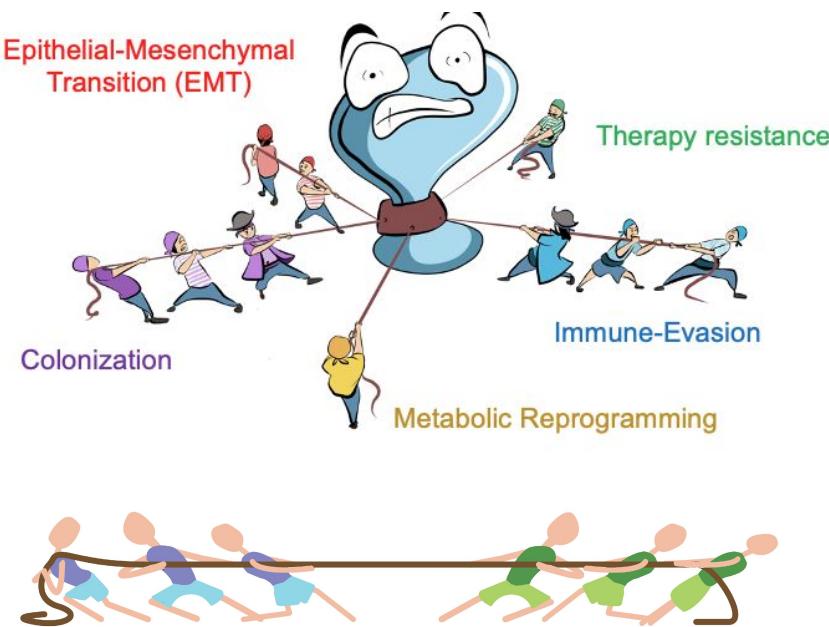
Does suppression of ER AND increased glycolysis or PD-L1 makes it even worse?

Coordinated plasticity leads to worse clinical outcomes in TCGA, METABRIC cohorts

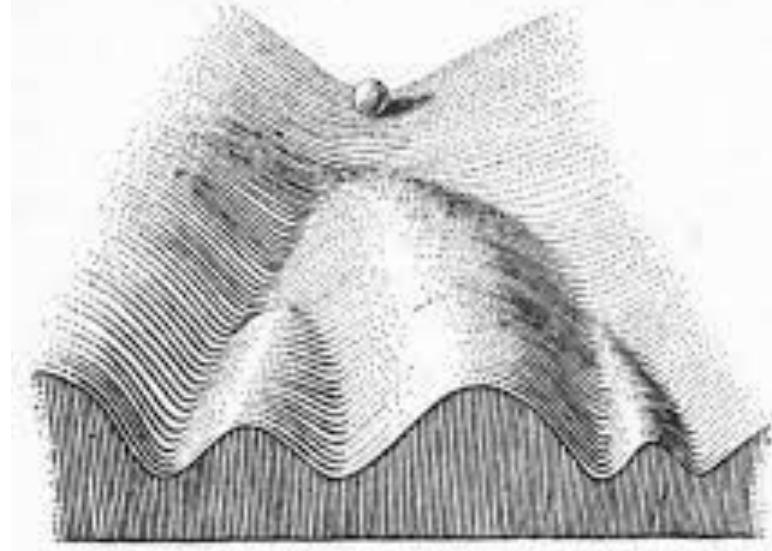
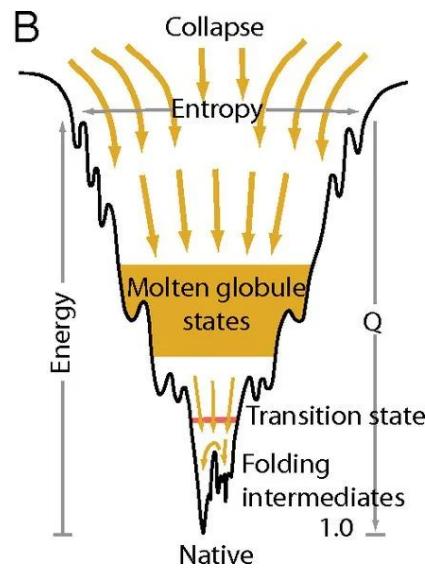


Summary

- ‘Design principles’ of regulatory networks driving cell-state switching:
 1. **Multistable** dynamics => Phenotypic plasticity & heterogeneity
 2. Existence of “**teams**” enables coordination across axes of plasticity
- Coordinated cell-state transitions increase cancer cell fitness and associate with **worse patient survival**



“Teams” ~ a driving principle of cell-fate canalization?

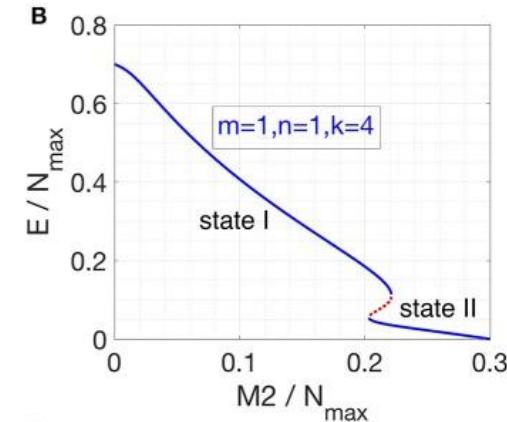
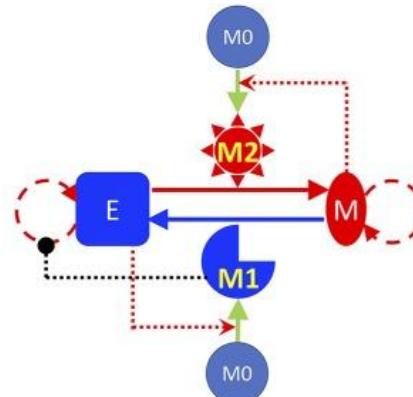


Englander & Mayne, PNAS 2014; Waddington, 1942

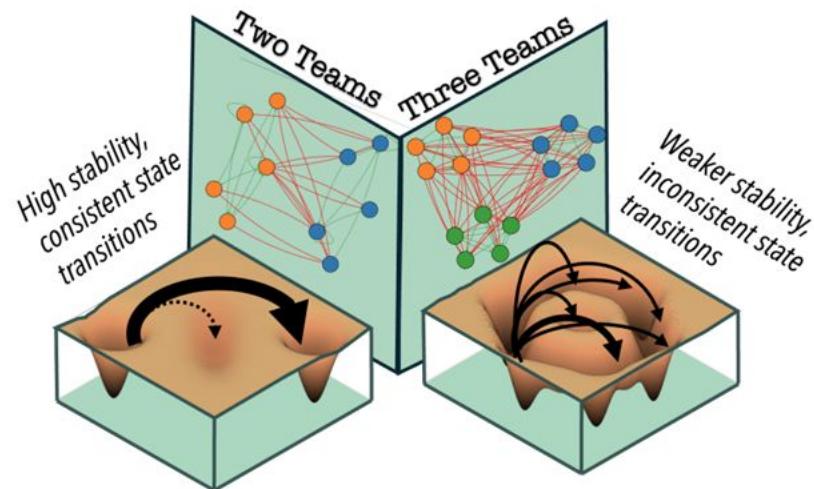
“Teams” can minimize “frustration” in EMT networks,
allowing only a limited number of trajectories and cell-states.

Open questions

- Can ‘teams’ be defined for cell types in a tissue, similar to our definition of ‘teams’ within a cell?
- How does spatial interplay impact team formation?
- Is the composition of ‘teams’ similar in other epithelial cancers as well?
- How is the behavior of 3 team networks different than 2 team ones?
- Can we predict the number and the composition of teams in a network without calculating influence matrix?
- How to build multi-scale models for ‘teams’ within cells and in a tissue?



Li*, Jolly* *et al.* Front Oncol 2019



Haldar*, Anand* *et al.* bioRxiv 2025: 679762

Acknowledgements: Our “team”



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