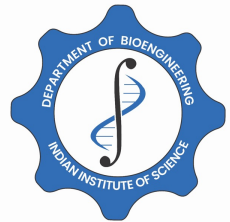


What does not kill cancer can make it stronger: **Dynamical modeling of drug-induced cell-state switching**



Mohit Kumar Jolly, PhD
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Associate Professor,
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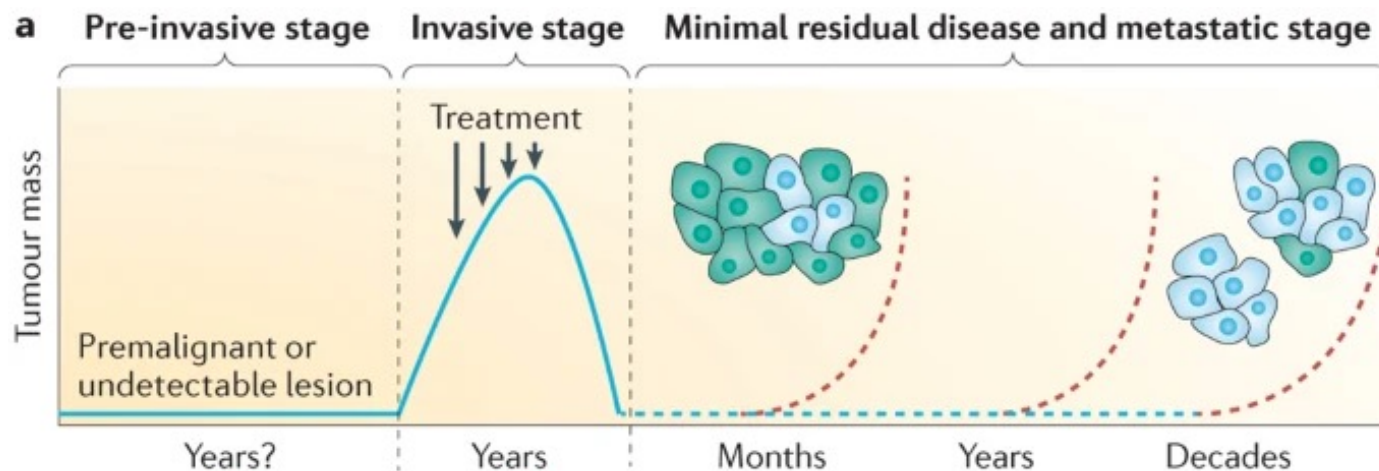
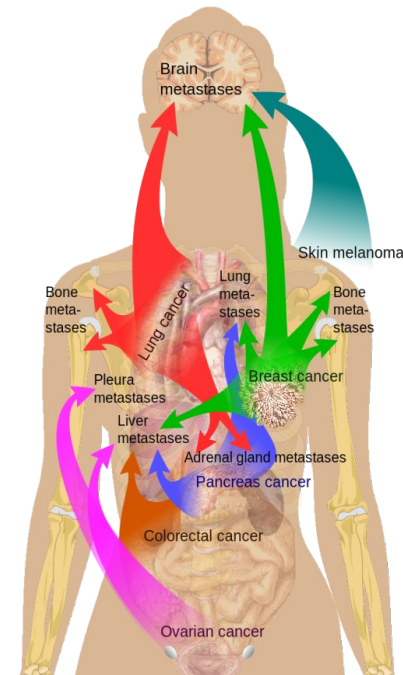
Editor-in-Chief, NPJ Systems Biology & Applications

ICERM workshop on Fostering Cross-Disciplinary Collaboration
in Biology, Medicine, and Computational Science | July 2025

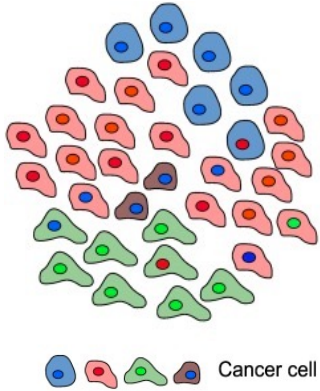
Cancer treatment: current strategies and challenges

- Surgery (1850s)
- Radiation therapy (1900s)
- Chemotherapy (1940s)
- Targeted therapy (1980s)
- Immunotherapy (2010s)

Can we have 'magic bullets'?



Tacit assumptions in current therapeutic strategies



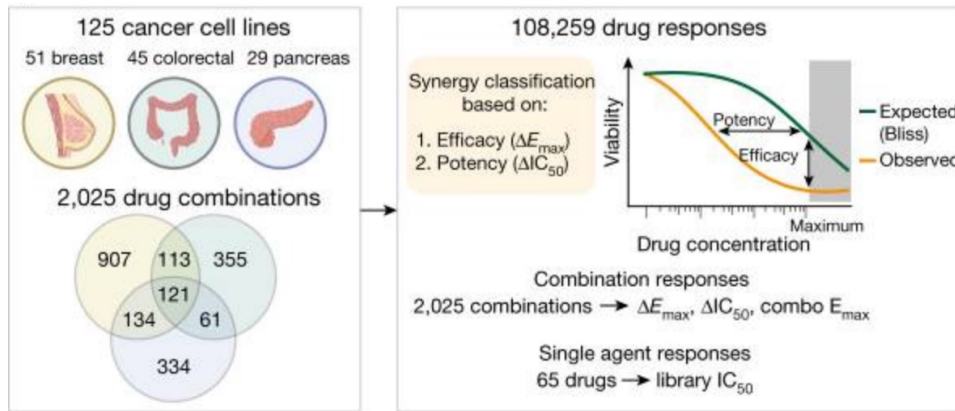
4 types of cancer cells

4 different drugs, each
killing one cell type

- Each red cell will respond identically to concentration X of drug A and die.
(Missing: Phenotypic heterogeneity)
- No drug can induce switch from a red cell to a blue cell.
(Missing: Phenotypic plasticity)
- No cell cooperates with other cells during stress/drug.
(Missing: Cancer as an ecosystem)

Cancer is a dynamic, complex, adaptive system and needs to be understood such.

'Trial-n-error' drug combinations are rarely effective



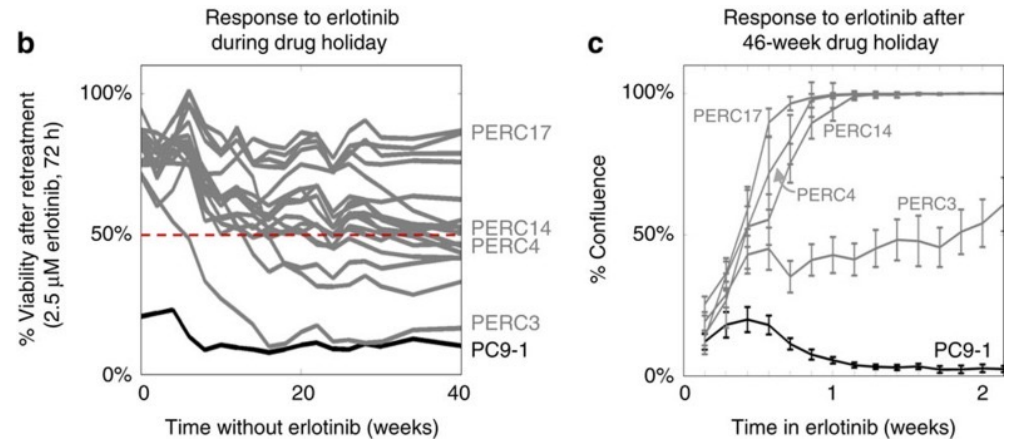
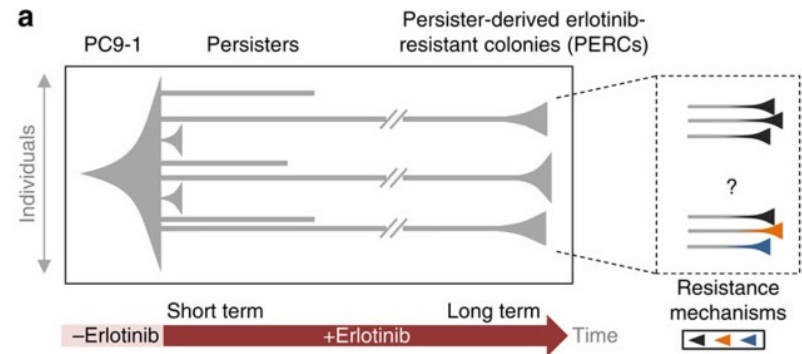
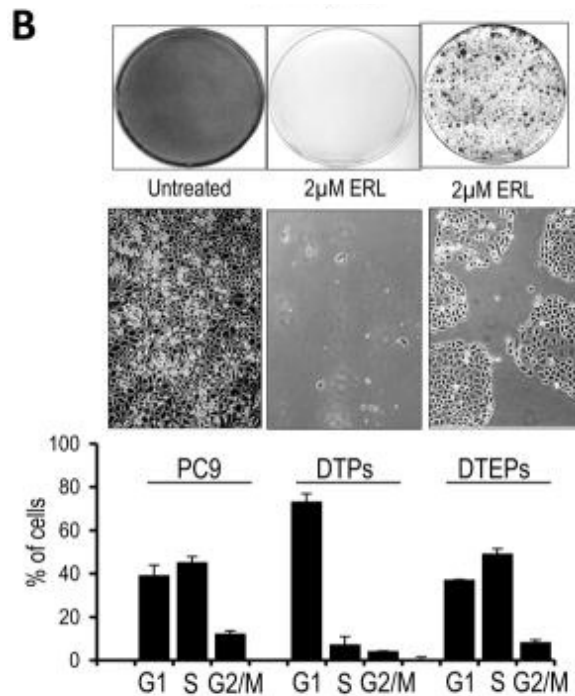
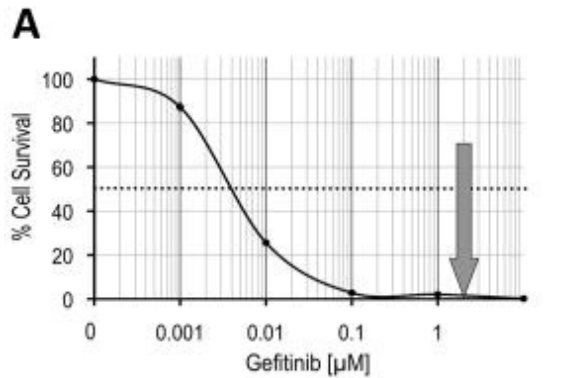
“Overall, 5.2% of the 108,259 combination–cell line pairs showed synergy, with the highest rate in pancreas (7.2%), then colon (5.4%) and breast (4.4%).”



Imagine that your car breaks
“worked” only in 5% cases
and you **did not** know which 5% cases

Can mechanism-based mathematical models help identify
rational drug combinations that are more effective?

What is the fate of cells that are not killed by the drugs?



PC9 (lung cancer) cells not killed undergo :

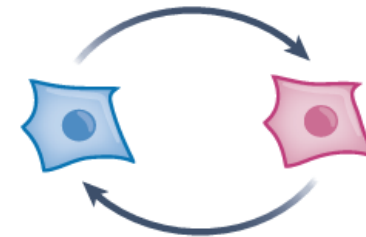
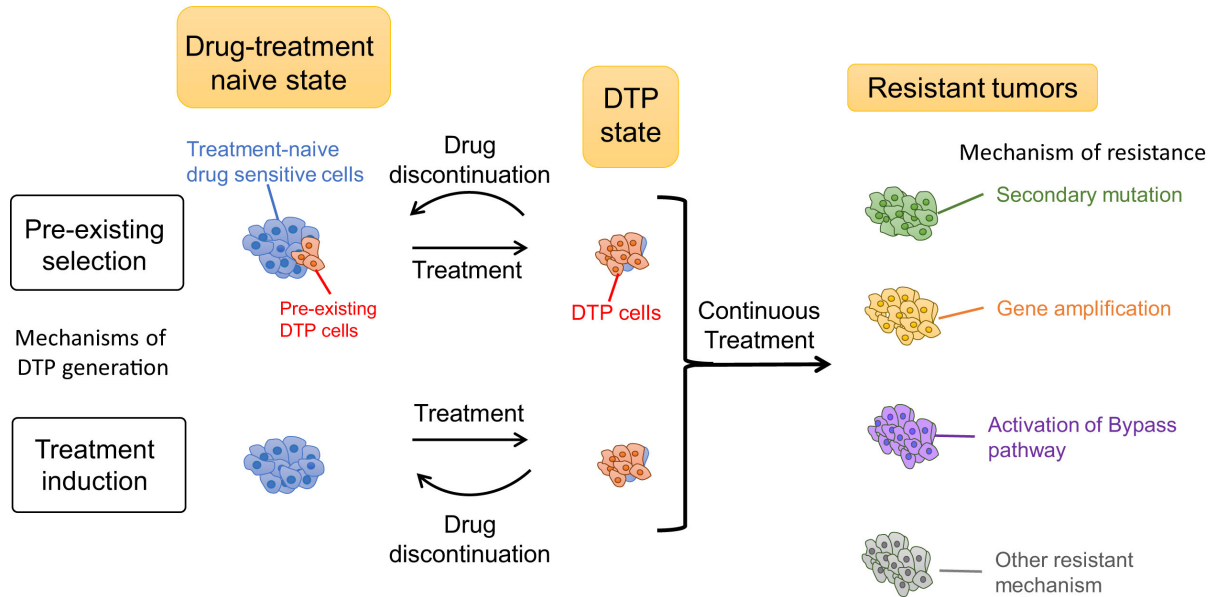
a) rapid non-genetic adaptation

b) slow possible genetic selection/stabilization

DT(E)Ps = Drug-Tolerant
(Expanded) Persisters

Sharma *et al.* Cell 2009; Ramirez *et al.* Nat Comm 2016
Shaffer *et al.* Nature 2017; Shen *et al.* Nat Comm 2019
Rehman *et al.* Cell 2021; Russo *et al.* Nat Genet 2022

DTPs: an outcome of phenotypic plasticity

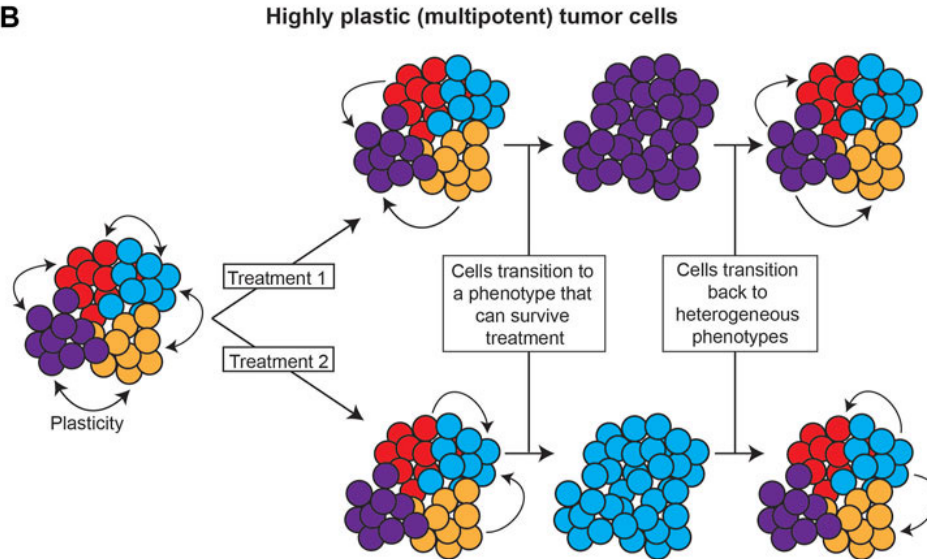


Mikubo *et al.* J Thorac Oncol 2021
Hanahan, Cancer Discov 2022

Pillai, Hojel, Jolly#, Goyal#, Nat Comp Sci 2023

Phenotypic plasticity in drug resistance & metastasis

B

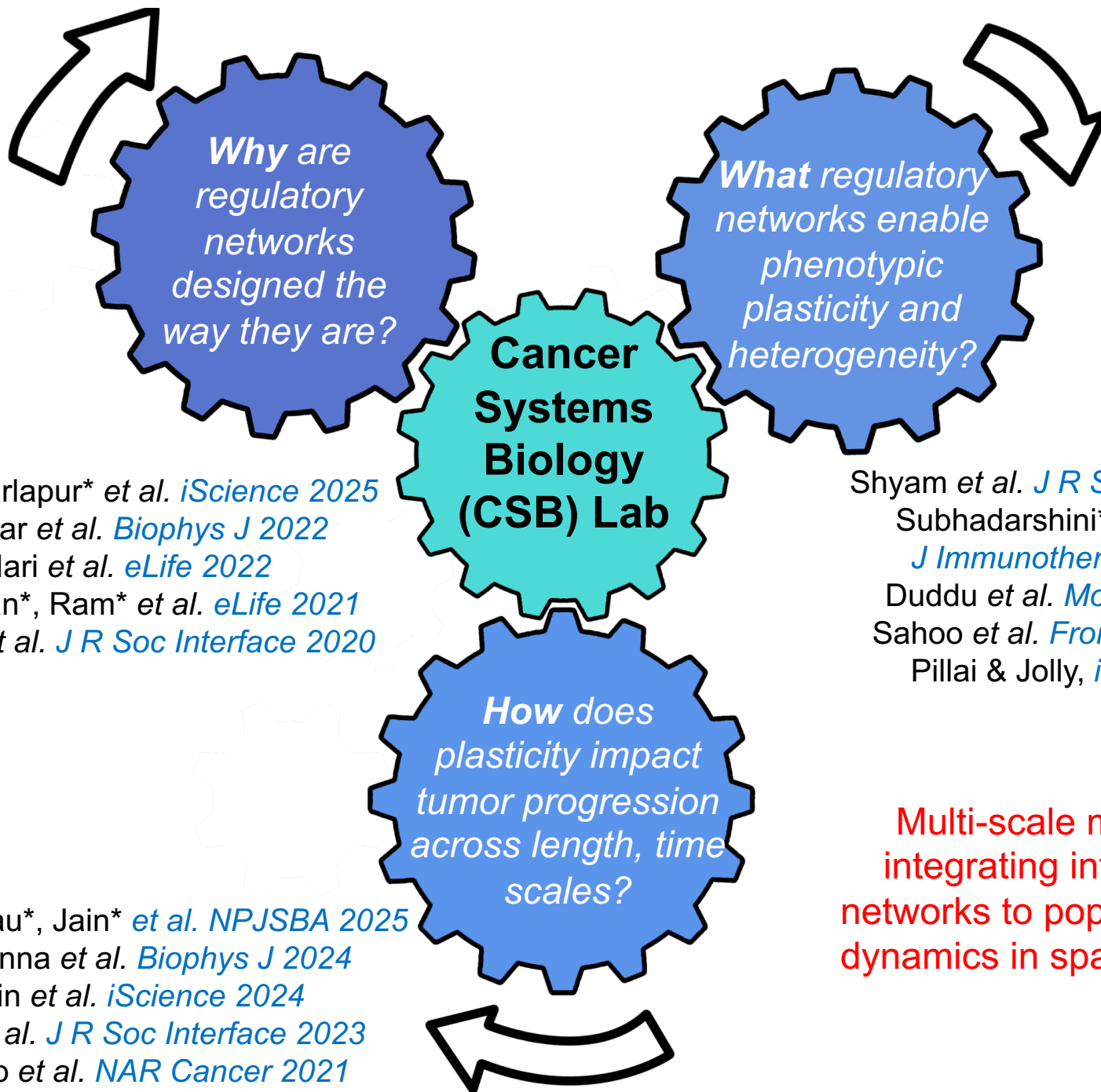


Our focus:

- 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

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

No unique mutational signatures have been yet identified for metastasis.



Hari*, Harlapur* et al. *iScience* 2025
Hebbar et al. *Biophys J* 2022
Hari et al. *eLife* 2022
Chauhan*, Ram* et al. *eLife* 2021
Duddu et al. *J R Soc Interface* 2020

Shyam et al. *J R Soc Interface* 2023
Subhadarshini*, Sahoo* et al. *J Immunother Cancer* 2023
Duddu et al. *Mol Biol Cell* 2022
Sahoo et al. *Front Immunol* 2021
Pillai & Jolly, *iScience* 2021

Guilberteaud*, Jain* et al. *NPJSBA* 2025
Prasanna et al. *Biophys J* 2024
Jain et al. *iScience* 2024
Jain et al. *J R Soc Interface* 2023
Sahoo et al. *NAR Cancer* 2021

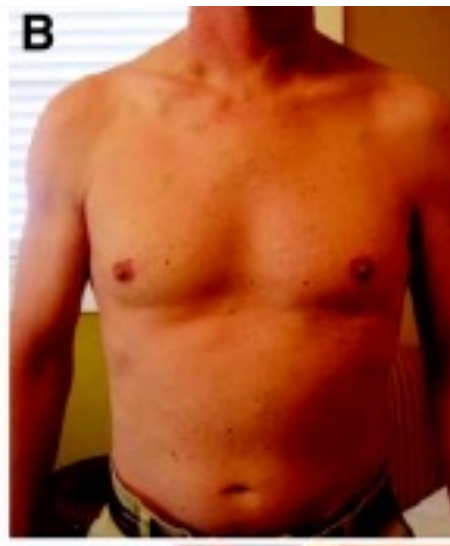
**Multi-scale modeling:
integrating intracellular
networks to population level
dynamics in space and time**

Case study 1: Minimal residual disease in melanoma

- 70% of all melanomas contain mutations in RAS-RAF pathway
- Targeted therapy includes BRAF inhibitors – Vemurafenib
- Only 29% 5-year survival rate post metastasis



Pre-treatment

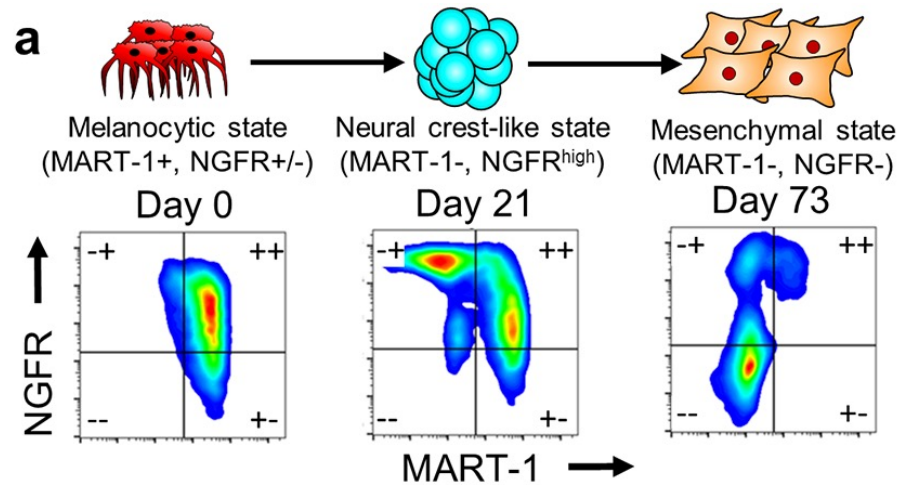


15 weeks after therapy

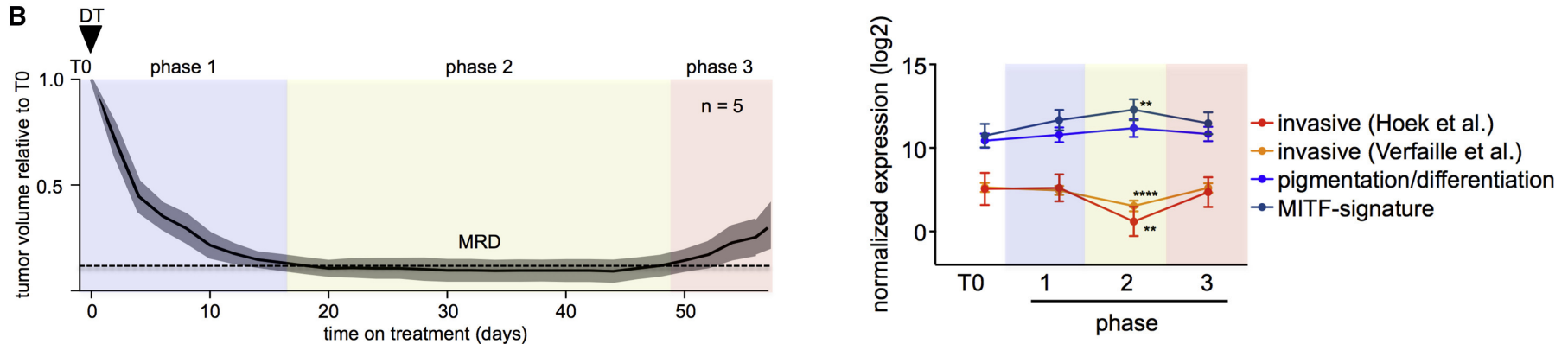


23 weeks after therapy

Drug-induced phenotypic transitions in melanoma

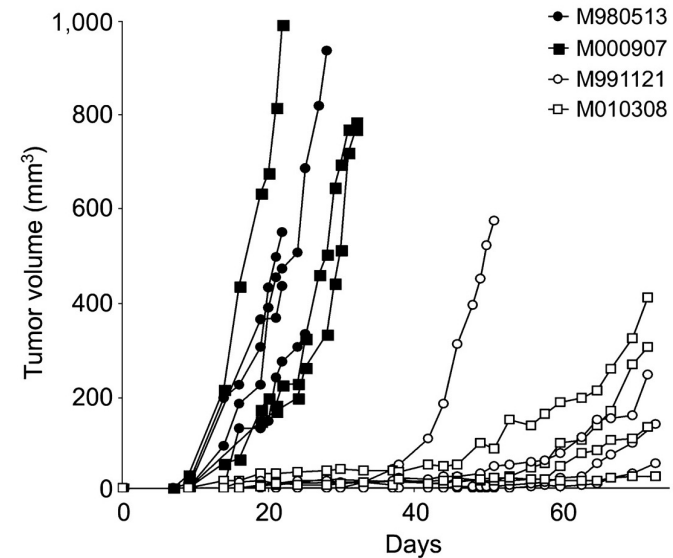
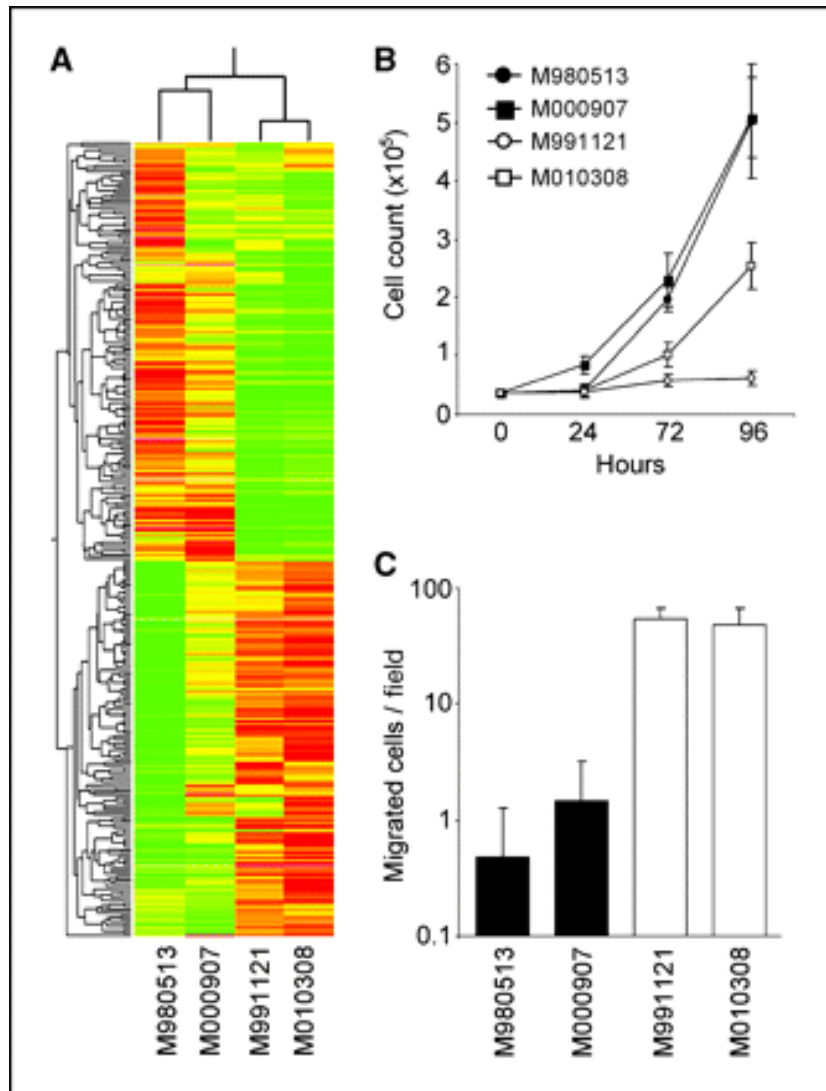


Response of BRAF^{V600E} mutant cell line to BRAF inhibition



Response of BRAF^{V600E} PDX model to BRAF inhibition

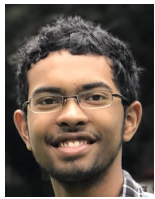
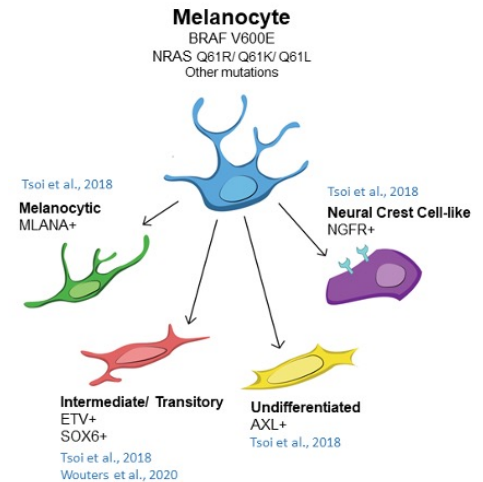
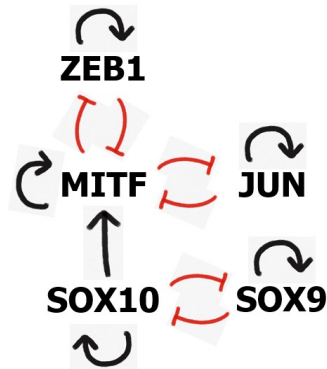
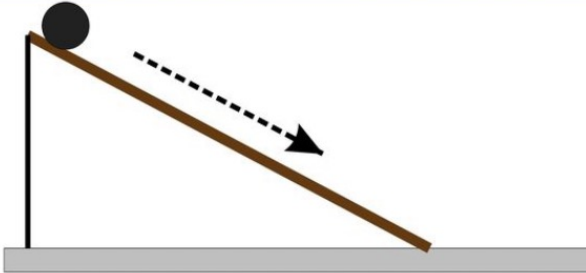
Phenotypic plasticity in melanoma drives heterogeneity



- Both “proliferative” and “invasive” cells grew tumors *in vivo* (PDX).
- Tumors grown *in vivo* from either population contained both “proliferative” and “invasive” cells.

An Occam's razor (minimalistic) approach

Can we identify a *minimal* network that can explain phenotypic switching in melanoma?



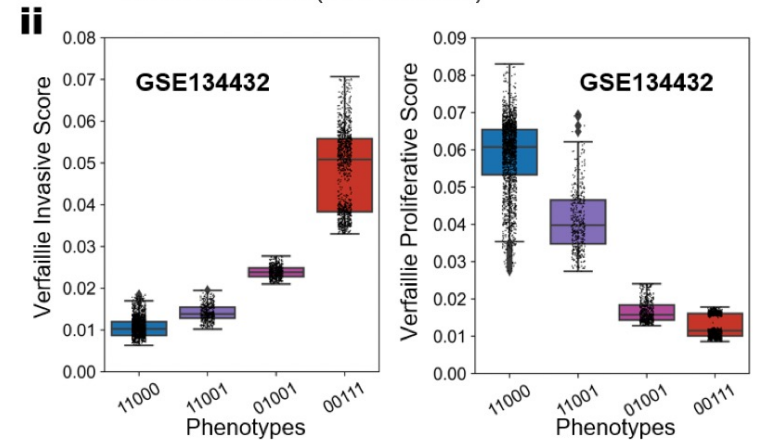
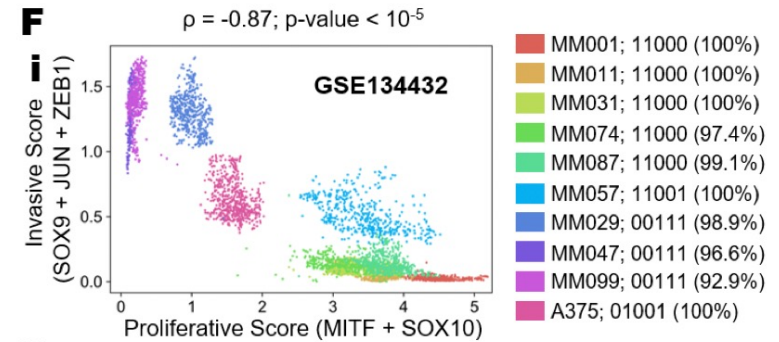
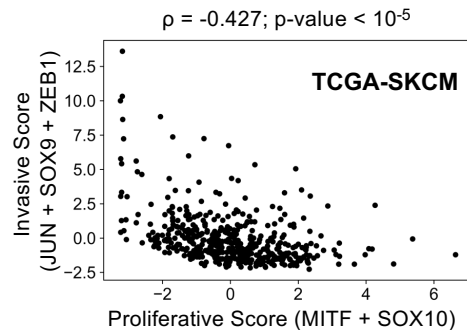
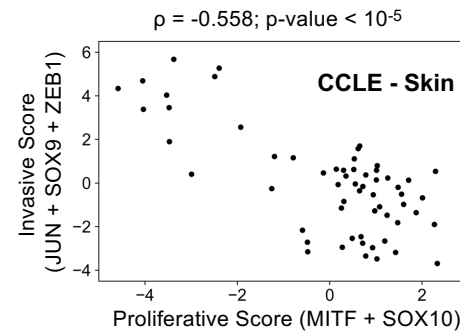
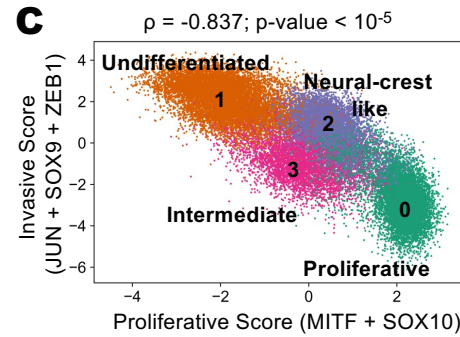
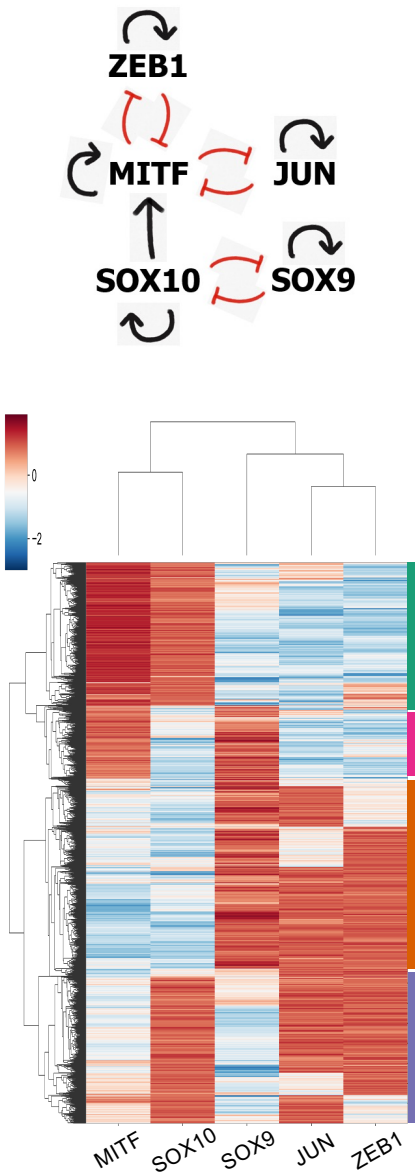
Sarthak Sahoo
(PhD, IISc)



Seemadri Subhadarshini
(PhD, IISc)

(Mechanism-based approach:
from regulatory network to
transcriptomic data)

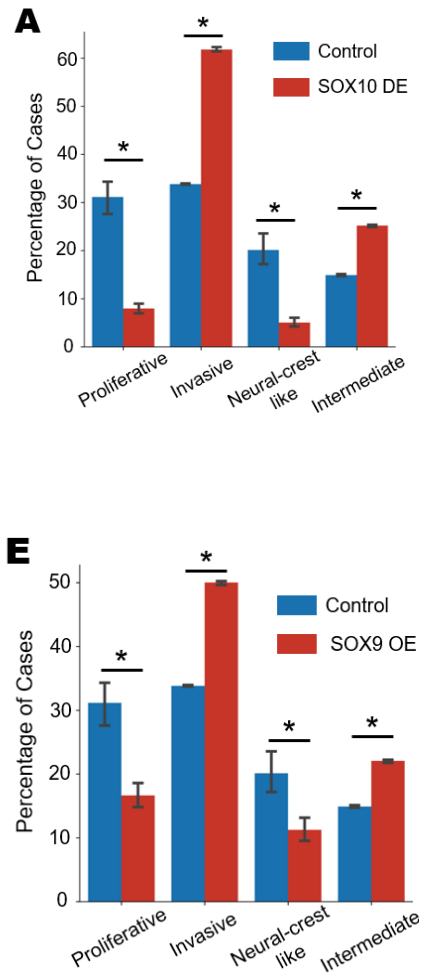
A **minimal** network captures proliferative-invasive transition



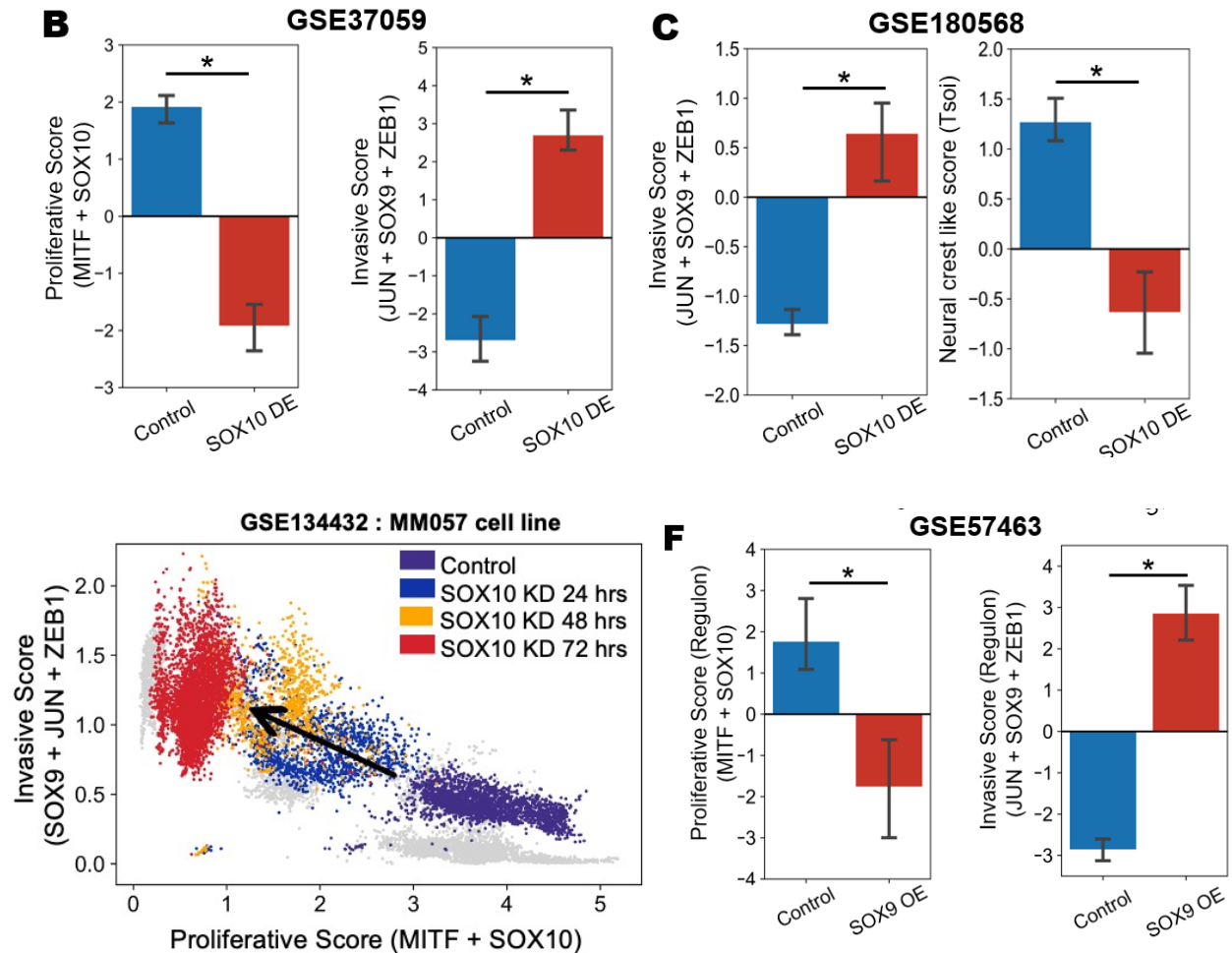
Minimal (5-dimension) network explains patterns observed in ~1000 gene-signature ensemble

In silico recapitulation of SOX10 KD dynamics *in vitro*

In silico
model prediction

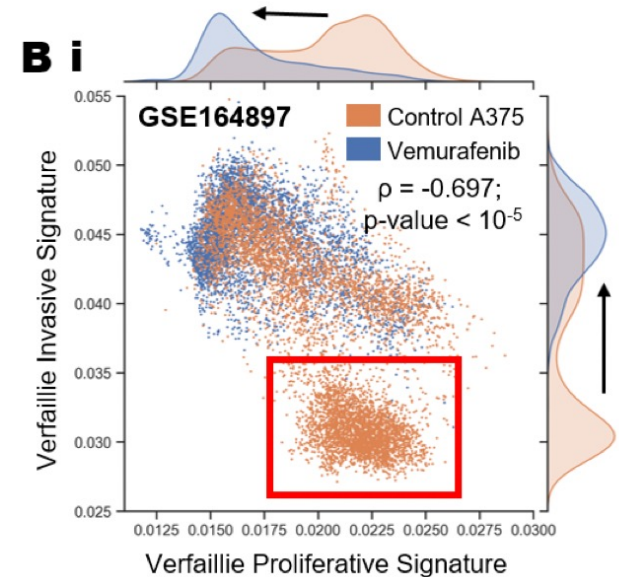
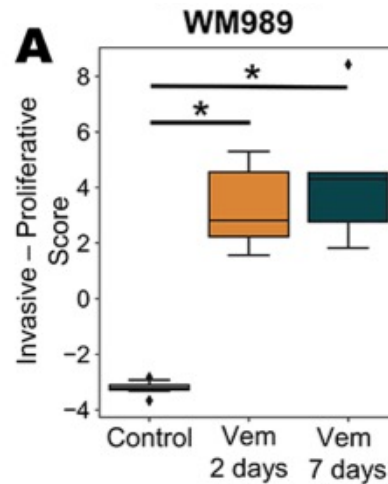


In vitro
experimental validation

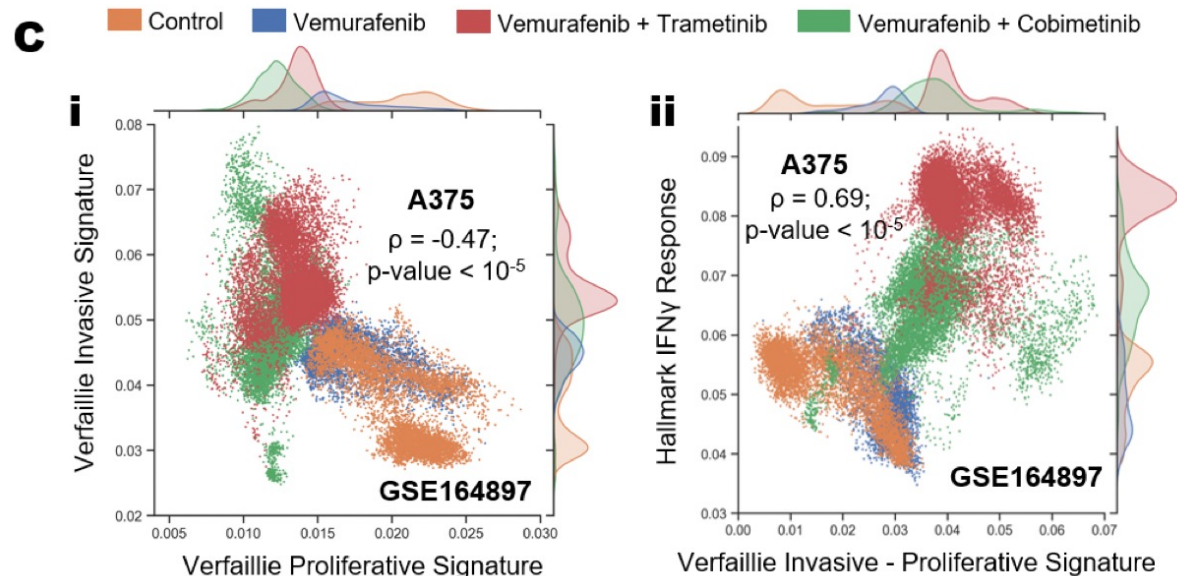


scRNA-seq data analysis reveals drug-induced plasticity

Pre-existing heterogeneity in A375 (scRNA-seq): induction or selection?

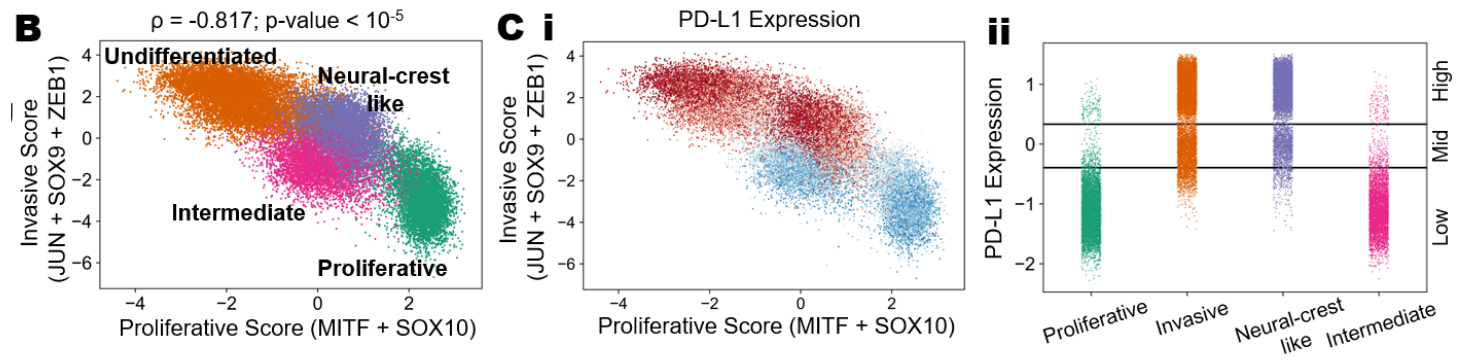


Combinatorial drug treatment leading to new phenotypes: plasticity

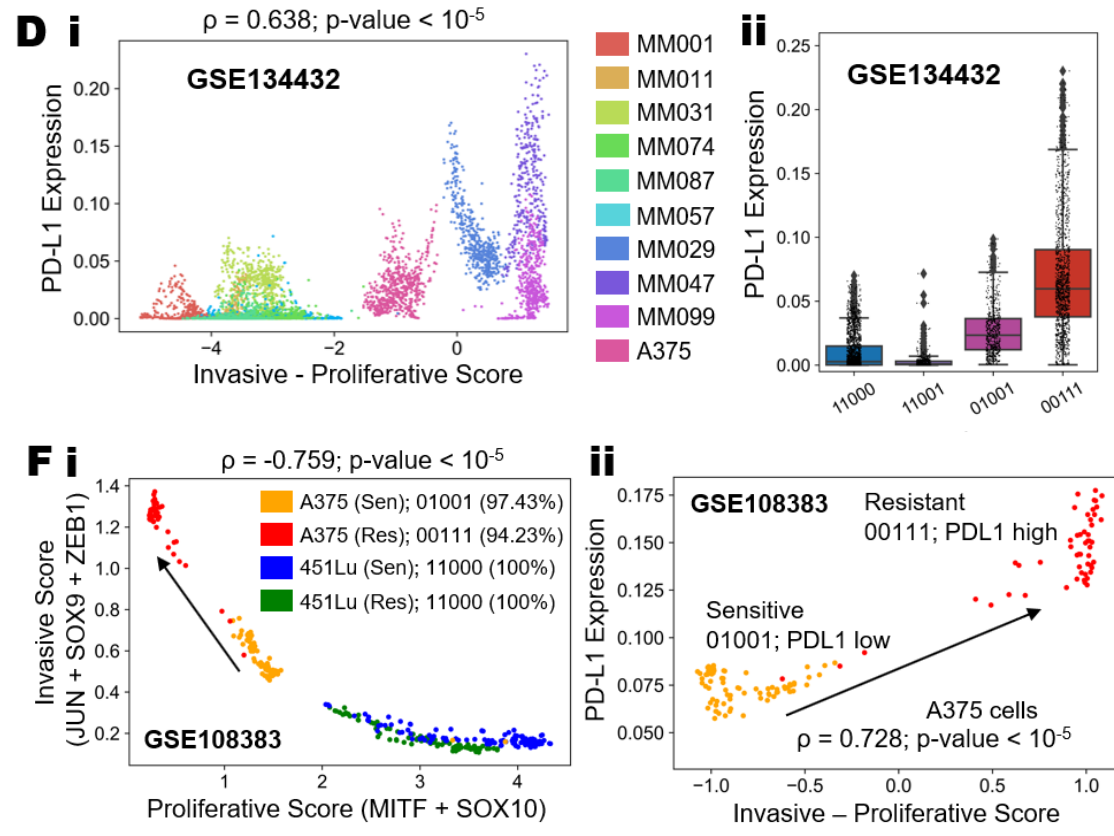


Proliferative-invasive switch associates with increased PD-L1

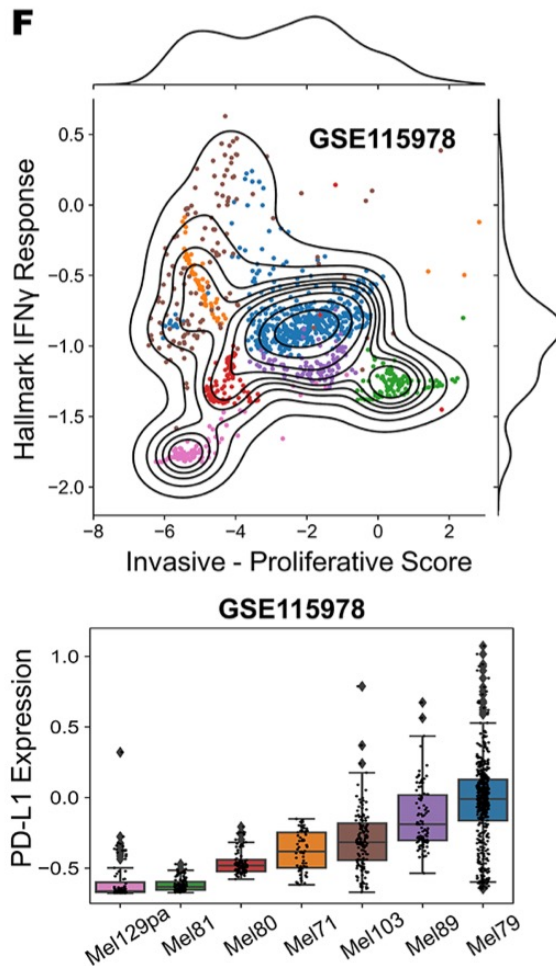
In silico
model prediction



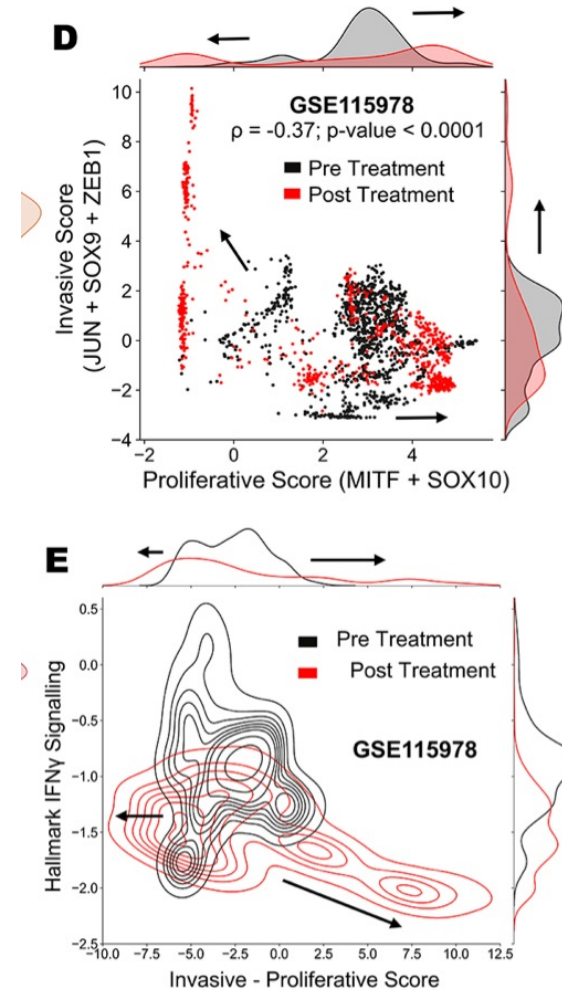
In vitro
experimental validation



Drug-induced plasticity in ICI-treated patient samples



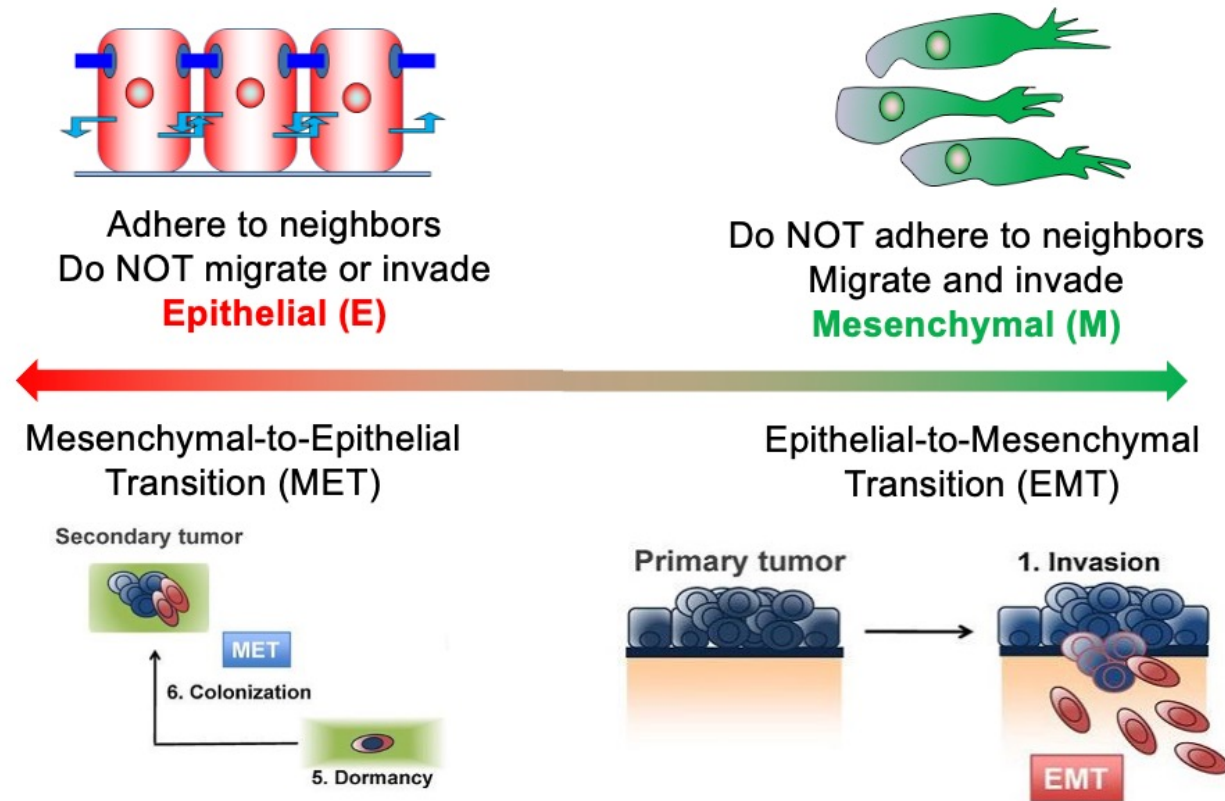
Pre-treatment(immune
checkpoint inhibitor (ICI))
heterogeneity in patient tumors



Post-treatment plasticity &
heterogeneity in patient tumors

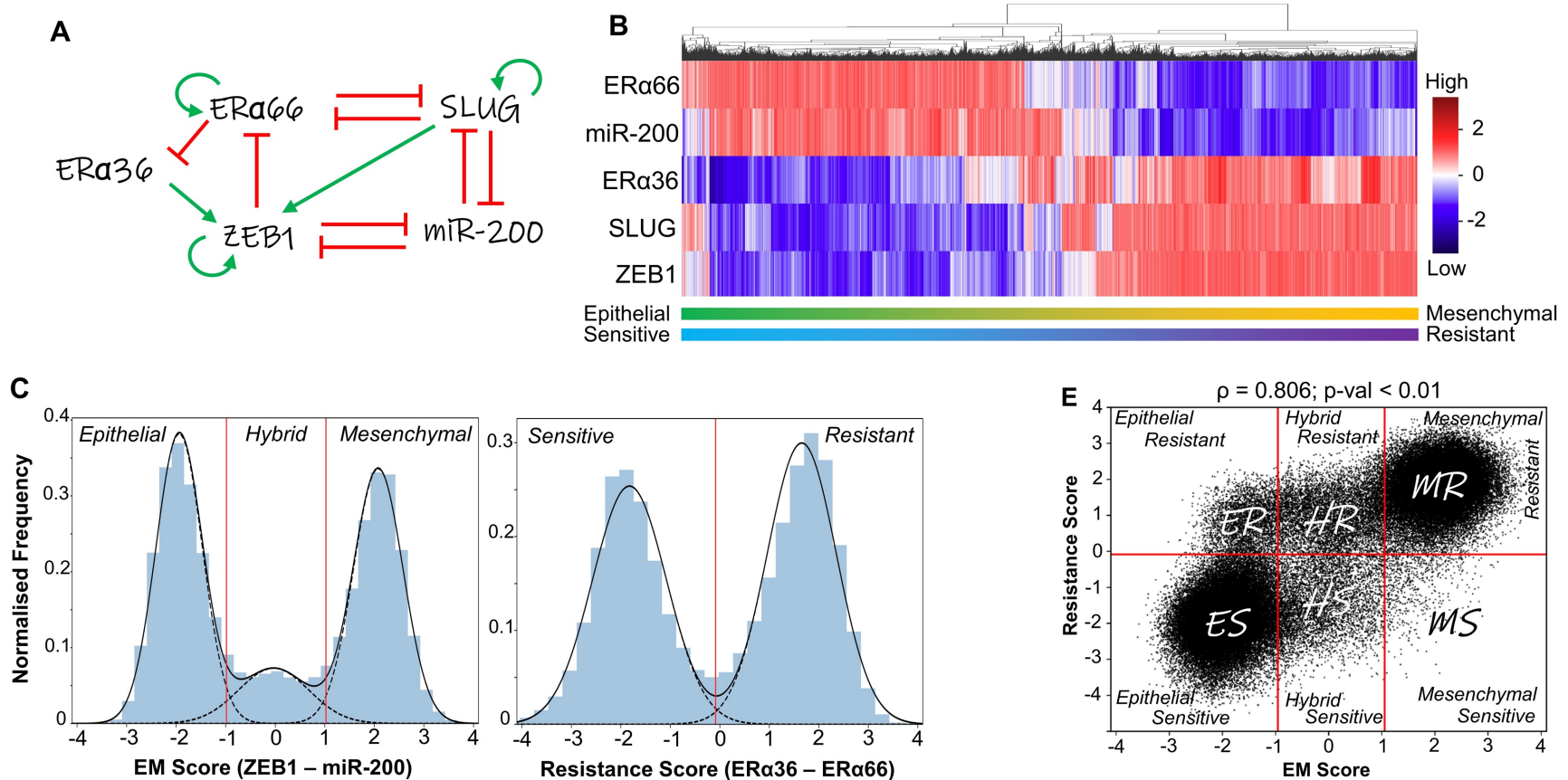
Case study 2: Tamoxifen resistance in ER+ breast cancer

Tamoxifen: 1st targeted therapy; given to ER+ breast cancer patients (75% of BC cases)



- Does EMT drive tamoxifen resistance or *vice versa*?
- Can state-switching enable long-term 'resistance' without genetic changes?

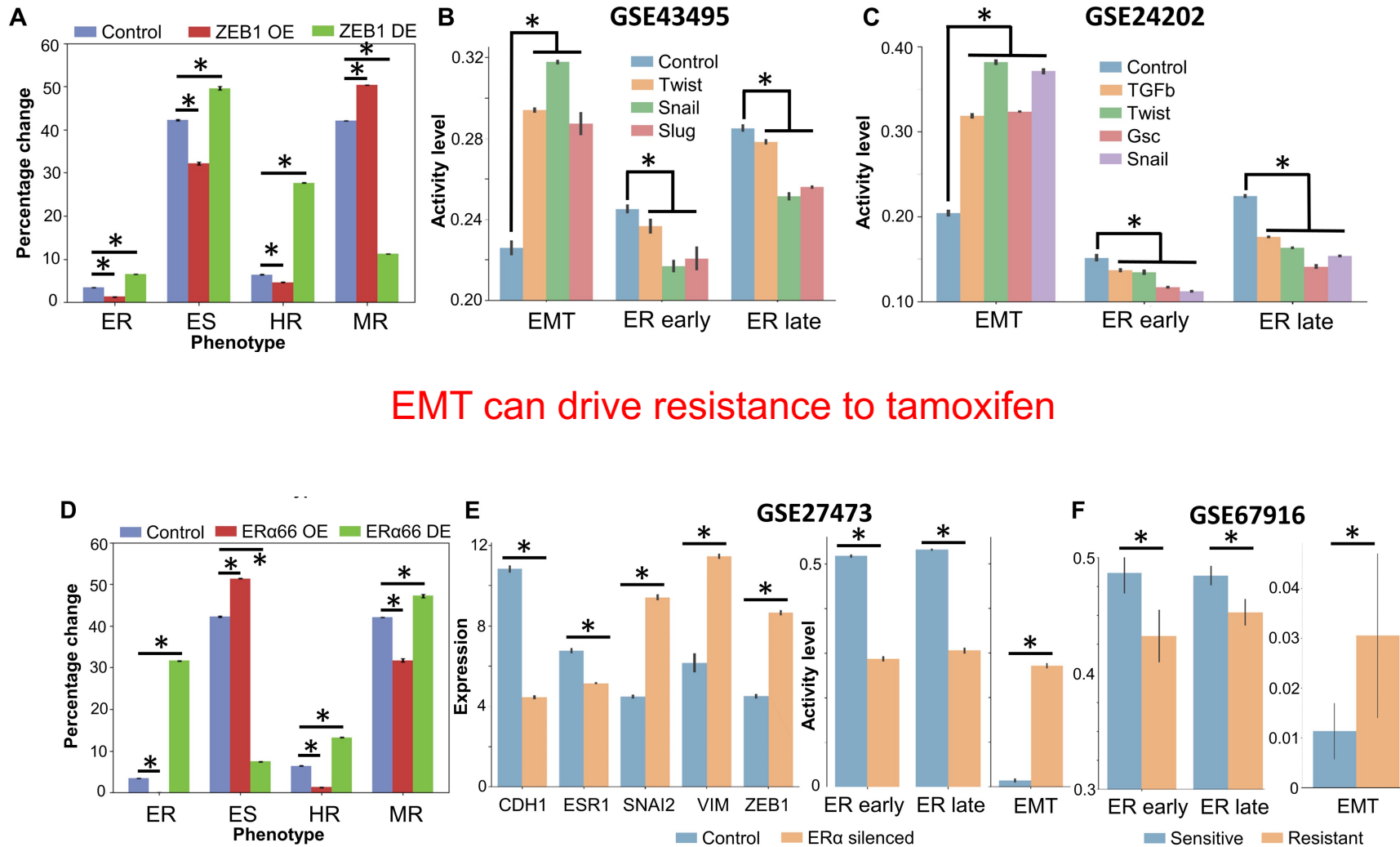
Association between (E, sensitive) and (M, resistant) states



Sarthak Sahoo

- E state usually Tam-Sensitive; M state usually Tam-Resistant
- Hybrid E/M state can be Tam-Resistant too

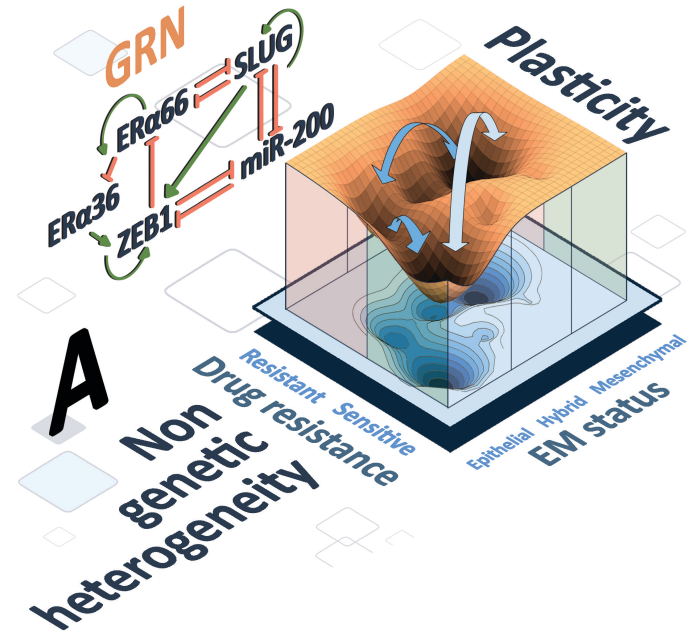
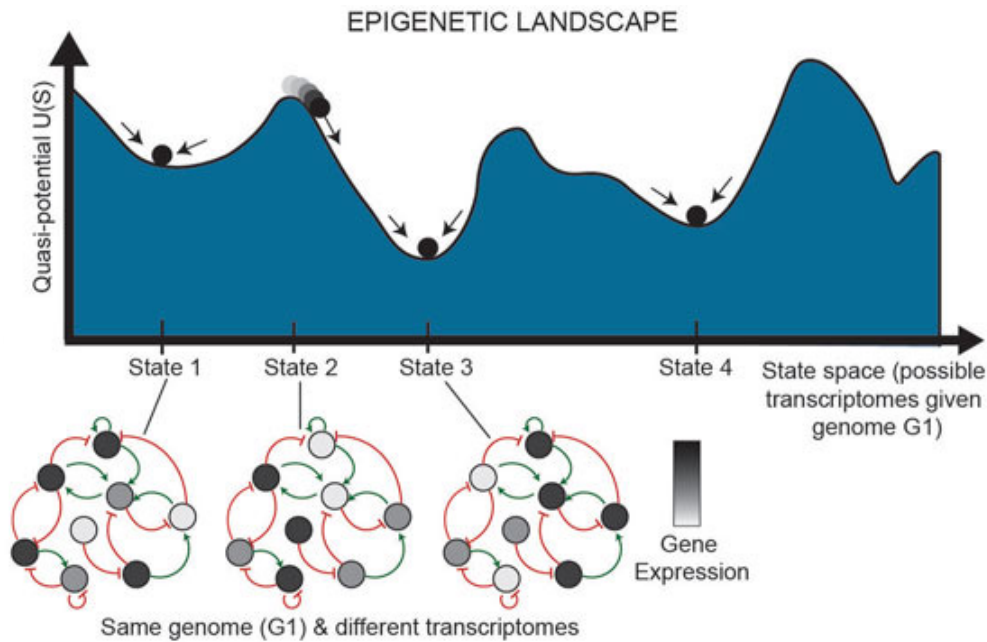
EMT & Tam Res can drive each other



EMT can drive resistance to tamoxifen

Tamoxifen resistance can drive EMT

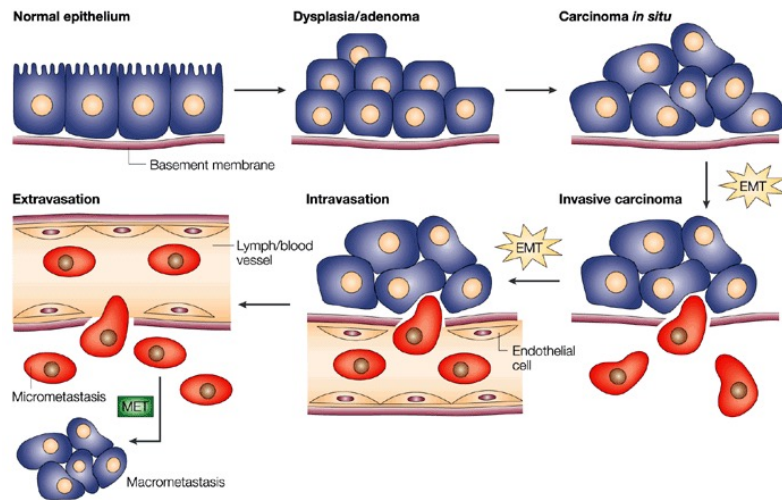
Summary (Part 1)



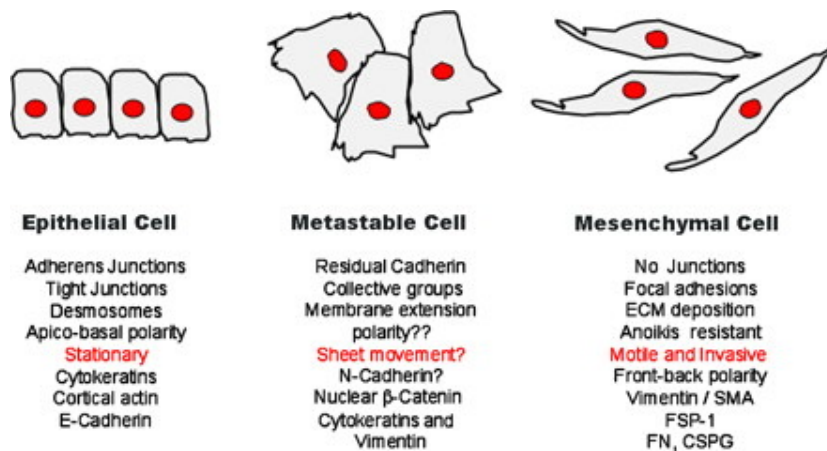
- Regulatory networks underlying melanoma & ER+ breast cancer plasticity are **multi-stable** in nature.
- Multi-stability allows for spontaneous & (drug-) induced **cell-state switching**.

What mechanisms control the rate of cell-state switching and can we measure it quantitatively?

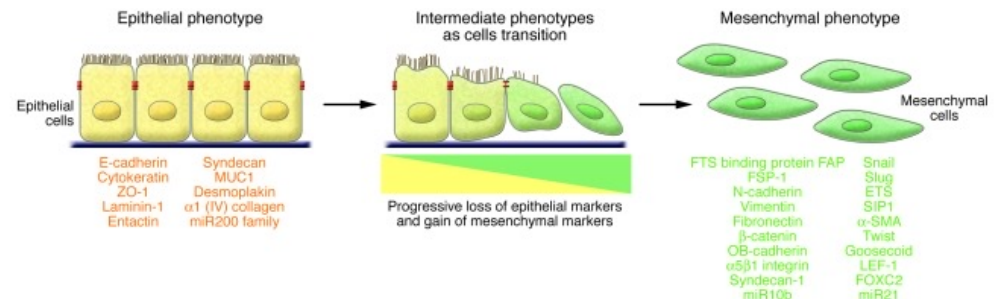
Role of EMT in cancer metastasis (2002 – 2012)



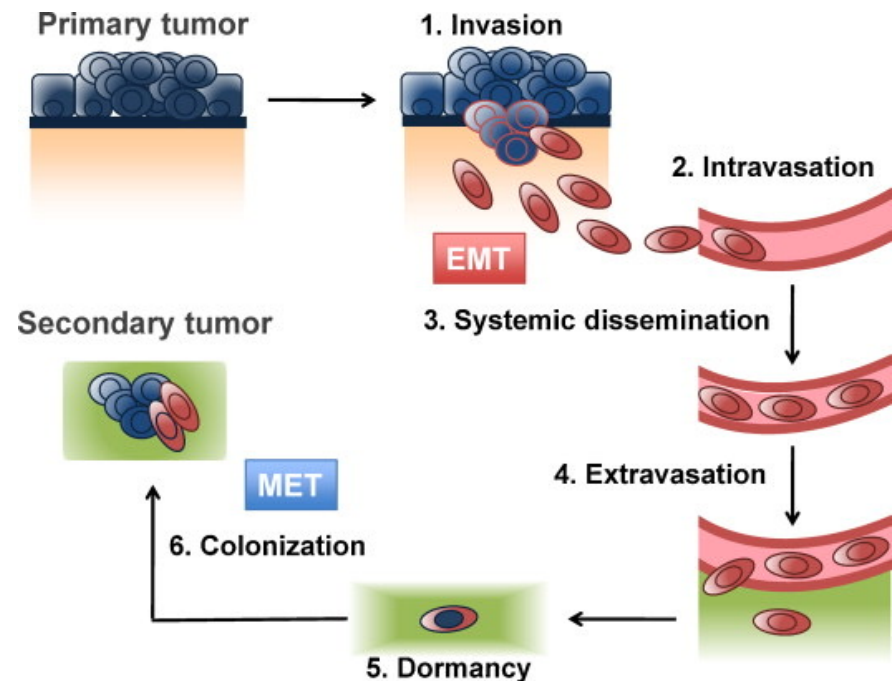
Thiery JP, Nat Rev Cancer 2002



Lee *et al.* J Cell Biol 2006

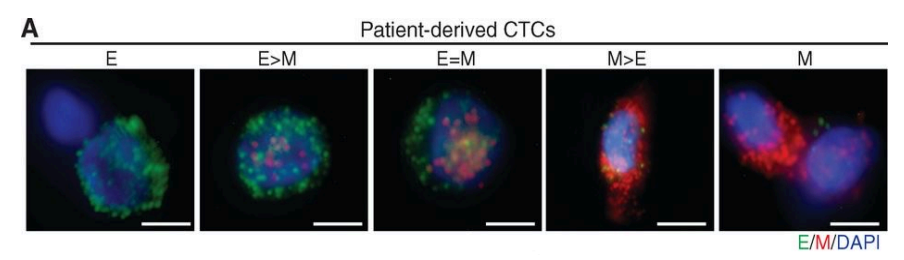
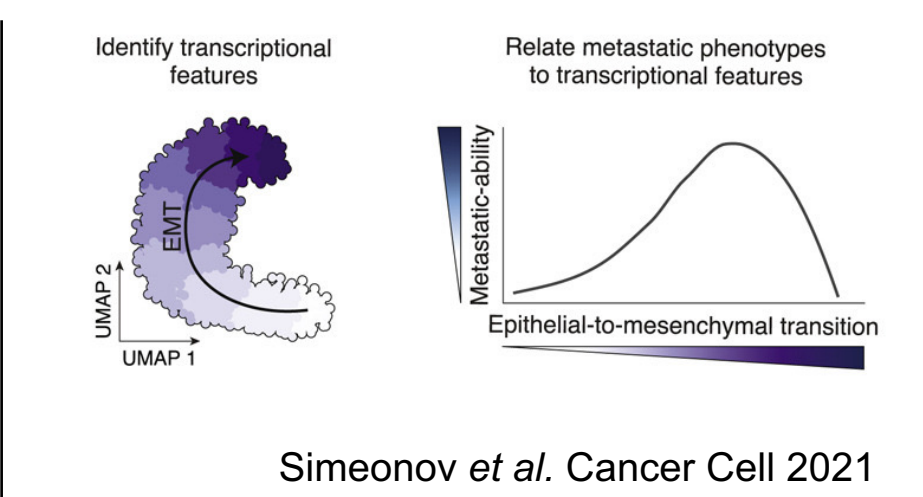
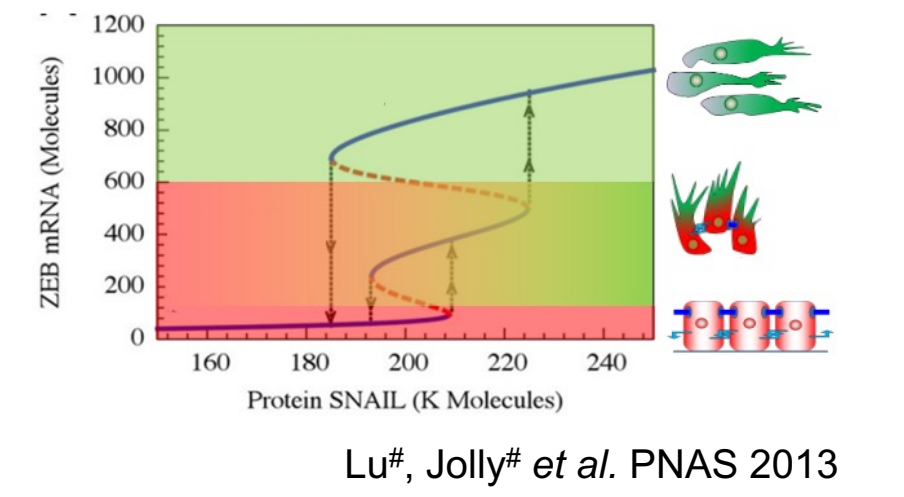


Kalluri & Weinberg, J Clin Invest 2009



Scheel & Weinberg, Semin Cancer Biol 2012

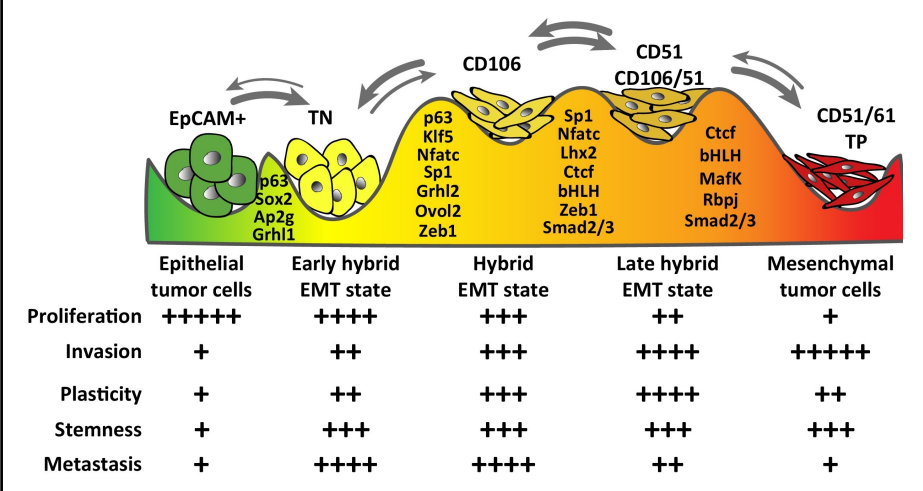
From EMT (2002-2012) to EMP (Epi-Mes Plasticity; 2013-now)



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

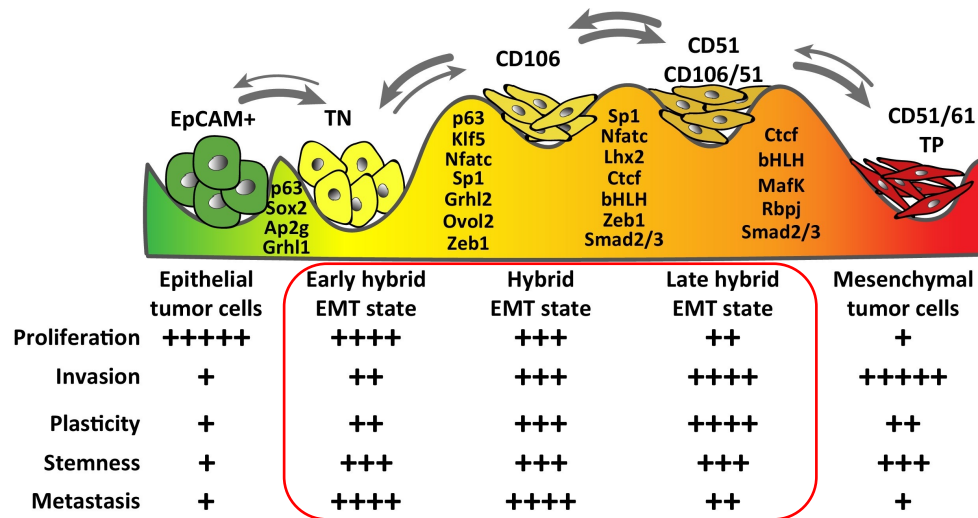
Cornelia Kröger^a, Alexander Afeyan^{a,b}, Jasmin Mraz^{a,c}, Elinor Ng Eaton^a, Ferenc Reinhardt^a, Yevgenia L. Khodor^d, Prathapan Thiruv^a, Brian Bieri^a, Xin Ye^{a,e}, Christopher B. Burge^d, and Robert A. Weinberg^{a,i,9,1}

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



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

Hybrid E/M: the 'fittest' for metastasis?

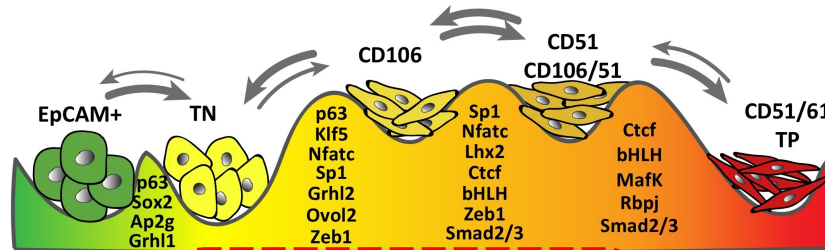


Pastushenko *et al.* 2019
(*Man vs. Wild* TV series – Bear Grylls)

Why are hybrid E/M cells the 'fittest'?



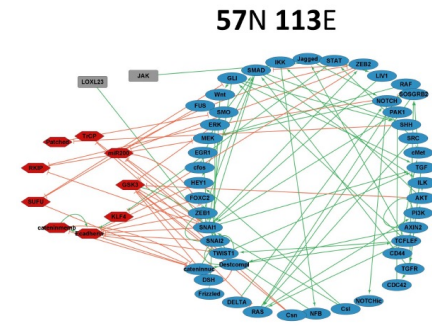
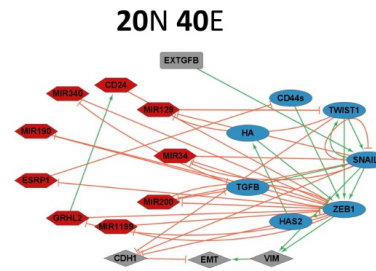
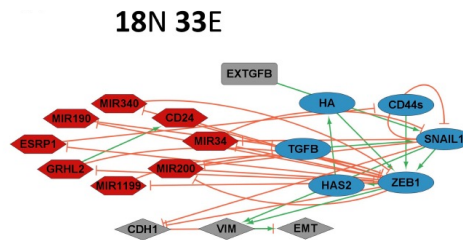
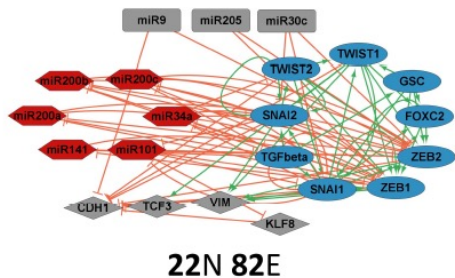
Kishore Hari



	Epithelial tumor cells	Early hybrid EMT state	Hybrid EMT state	Late hybrid EMT state	Mesenchymal tumor cells
Proliferation	+++++	++++	+++	++	+
Invasion	+	++	+++	++++	+++++
Plasticity	+	++	+++	++++	++
Stemness	+	+++	+++	+++	+++
Metastasis	+	++++	++++	++	+

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

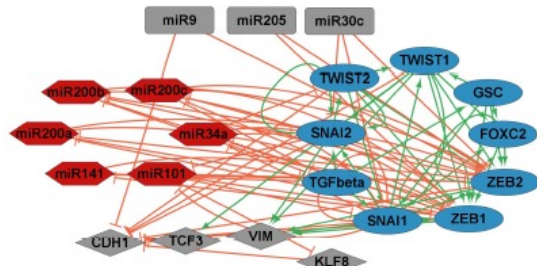
Is the “high plasticity” behavior of hybrid E/M a feature of underlying regulatory networks?



Nodes: Epithelial, Mesenchymal.

Edges: Activation, Inhibition

EMT networks consist of two “teams” of players



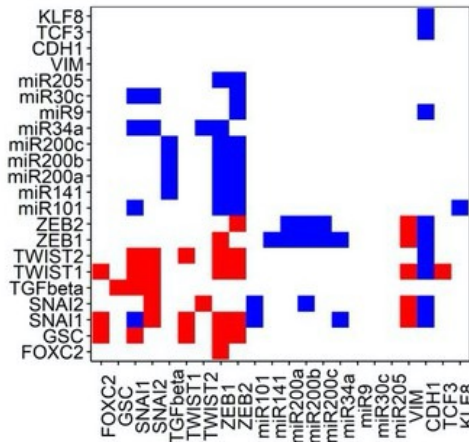
22N 82E

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

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

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

Adjacency Matrix

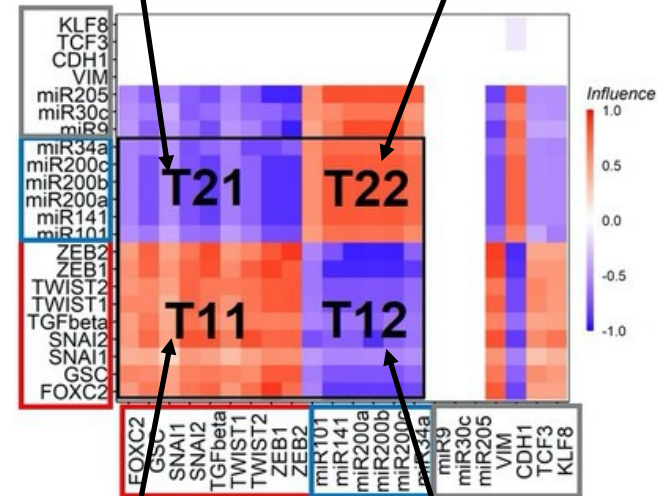


Row => Source; Column => Target
Red (Activation), Blue (Inhibition)

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

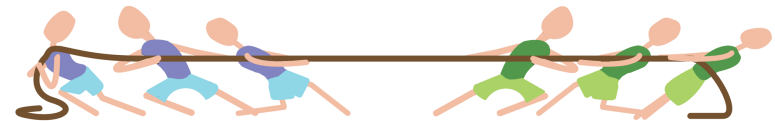
All Epi nodes effectively **activate** all Epi nodes.

Influence Matrix



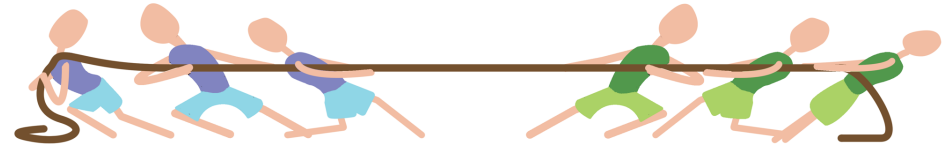
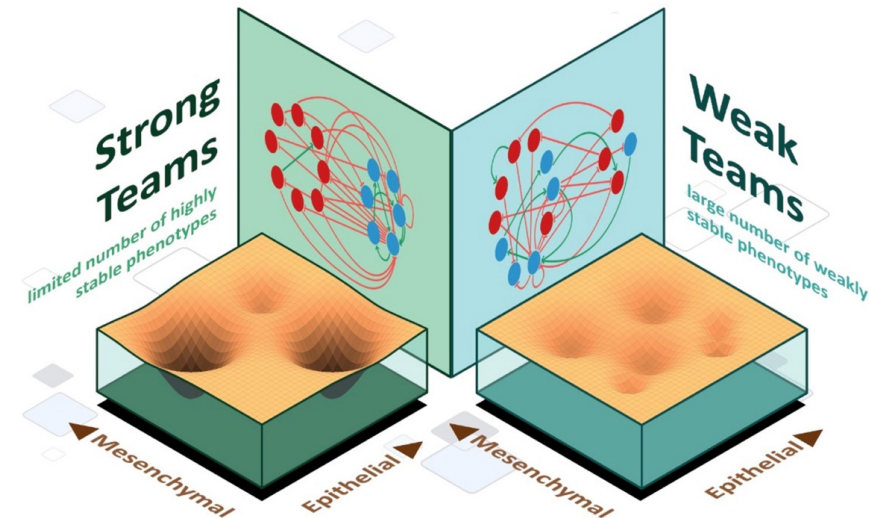
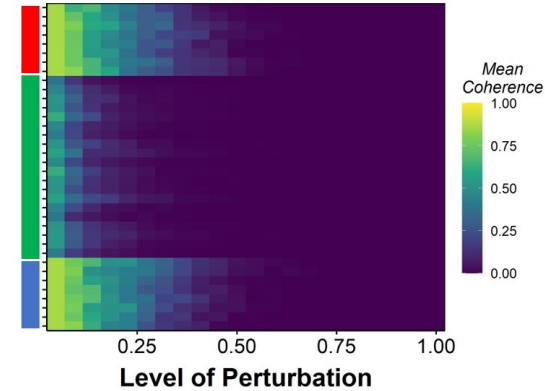
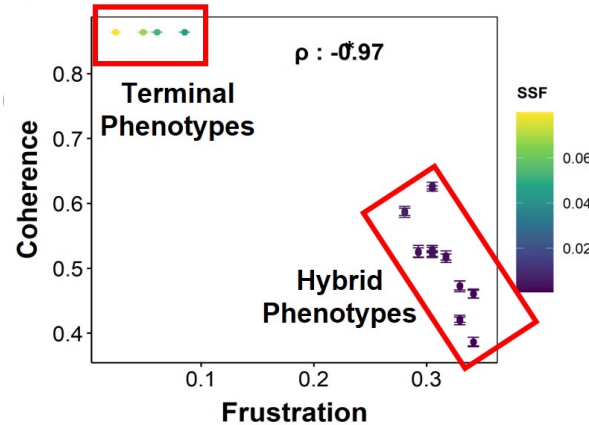
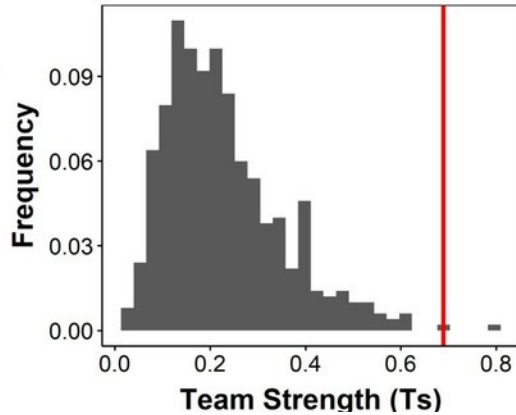
All Mes nodes effectively **activate** all Mes nodes.

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



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

22N 82E

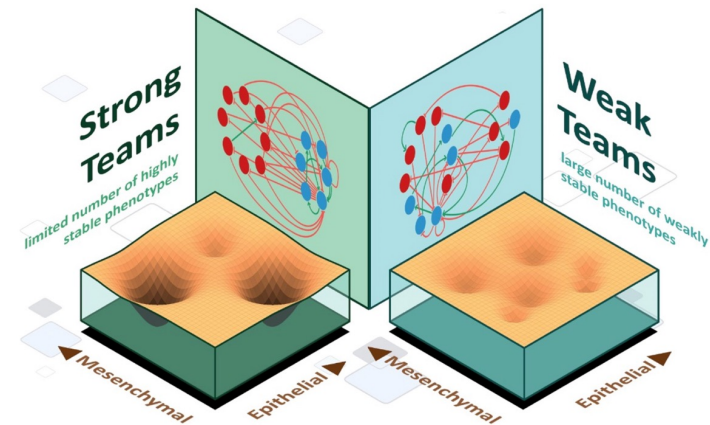


Absence of any “teams” supporting the hybrid E/M phenotypes makes them the ‘fittest’ for metastasis.

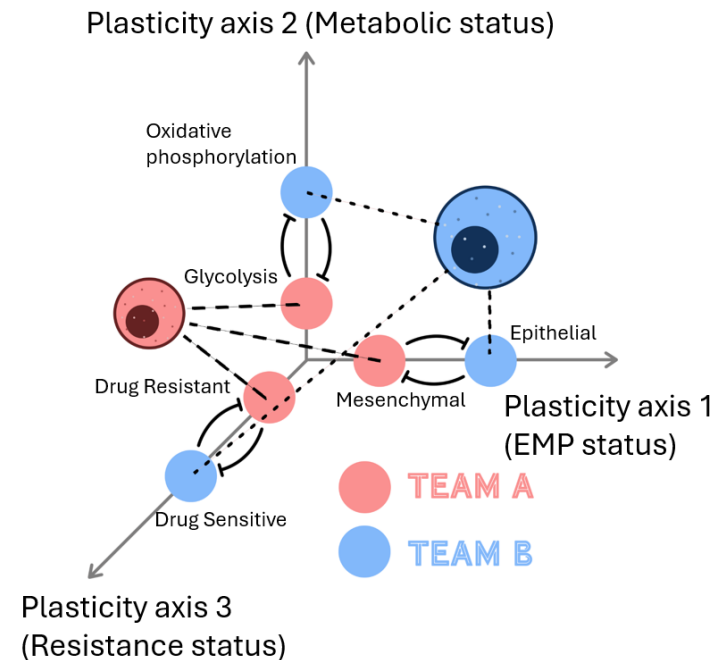
Why do “teams” exist?

To shape the phenotypic plasticity landscape

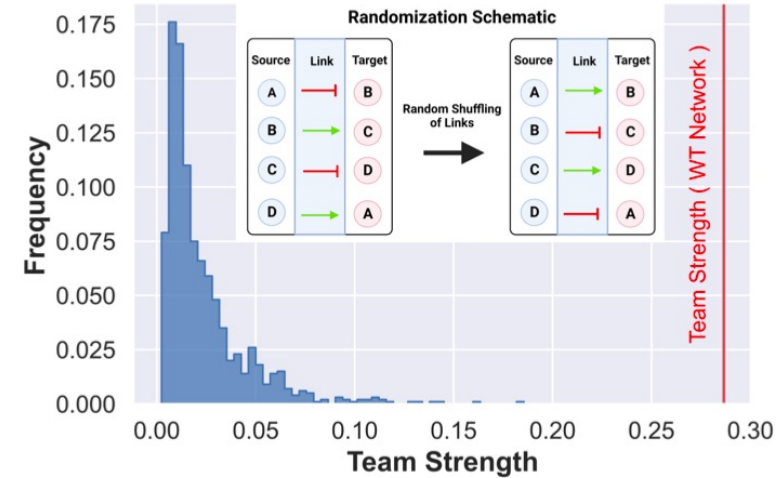
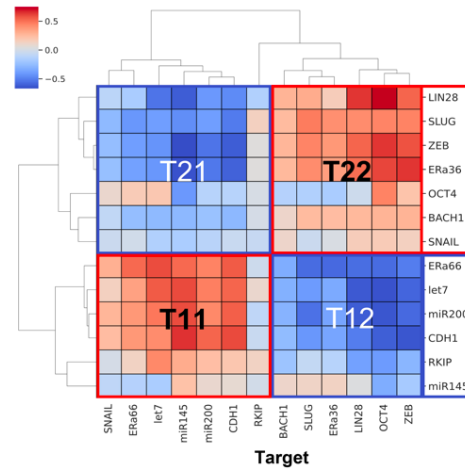
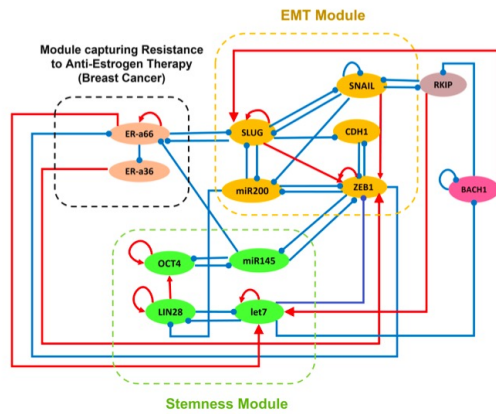
=> Control the rates of cell-state transitions



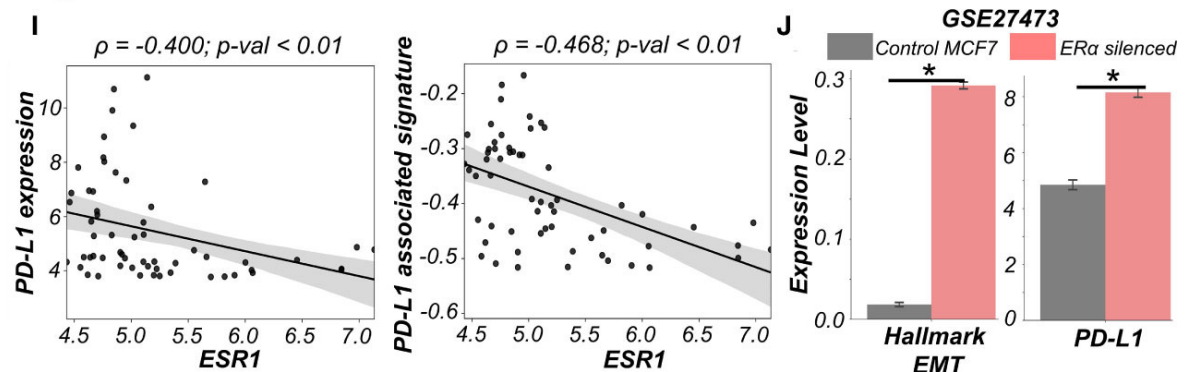
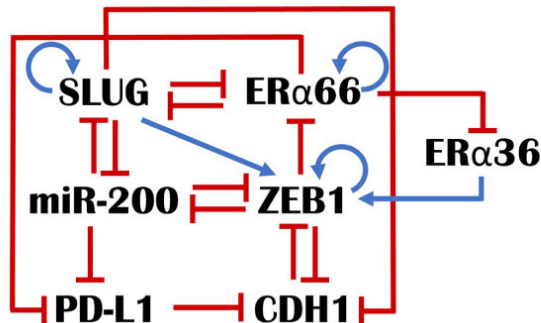
To couple the multiple axes of phenotypic plasticity
=> Increase the ‘fitness’ of metastasizing cells



“Teams” enabling coupling between more than 2 axes



“Teams” connecting EMT, Tam-Res and stemness phenotypes



“Teams” connecting EMT, Tam-Res and PD-L1 (+ve) phenotypes

Data deluge era: Mapping different trajectories of EMP

- Multiple trajectories during EMT induction; varying molecular profiles/functions
- Different possible trajectory(ies) of MET compared to EMT
- Different rates/extents of MET depending on intrinsic EMT state

PNAS

RESEARCH ARTICLE

BIOPHYSICS AND COMPUTATIONAL BIOLOGY

Reconstruction of single-cell lineage trajectories and identification of diversity in fates during the epithelial-to-mesenchymal transition

Yu-Chen Cheng^{a,b,c,d}, Yun Zhang^e, Shubham Tripathi^f, B. V. Harshavardhan^g, Mohit Kumar Jolly^h, Geoffrey Schiebingerⁱ, Herbert Levine^{id j,k,1}, Thomas O. McDonald^{a,b,c,d}, and Franziska Michor^{a,b,c,d,l,m,1}

communications biology

ARTICLE

<https://doi.org/10.1038/s42003-023-05668-3>

OPEN

 Check for updates

Transcriptional state dynamics lead to heterogeneity and adaptive tumor evolution in urothelial bladder carcinoma

Antara Biswas^{1✉}, Sarthak Sahoo², Gregory M. Riedlinger¹, Saum Ghodoussipour¹, Mohit K. Jolly² & Subhajyoti De^{1✉}

“Teams” (meaningful dimension-reduction metric) at transcriptional, epigenetic, metabolic levels can help see “mechanistic patterns” in this high-dimensional data.

From ‘data’ to ‘information’: what ‘trajectory’ do we take?

Cell

Leading Edge

Perspective

Establishing a conceptual framework for holistic cell states and state transitions

Susanne M. Rafelski^{1,*} and Julie A. Theriot^{2,*}

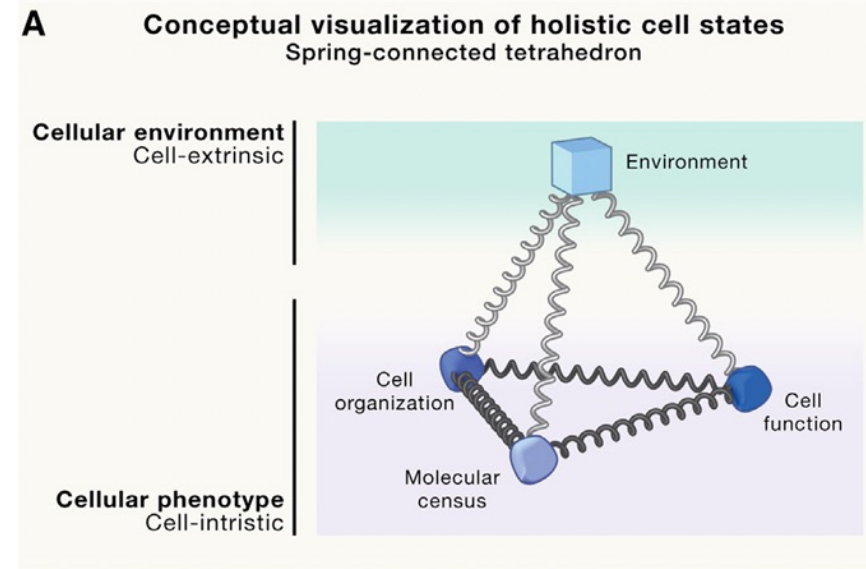
¹Allen Institute for Cell Science, 615 Westlake Avenue N, Seattle, WA 98125, USA

²Department of Biology and Howard Hughes Medical Institute, University of Washington, Seattle, WA 98195, USA

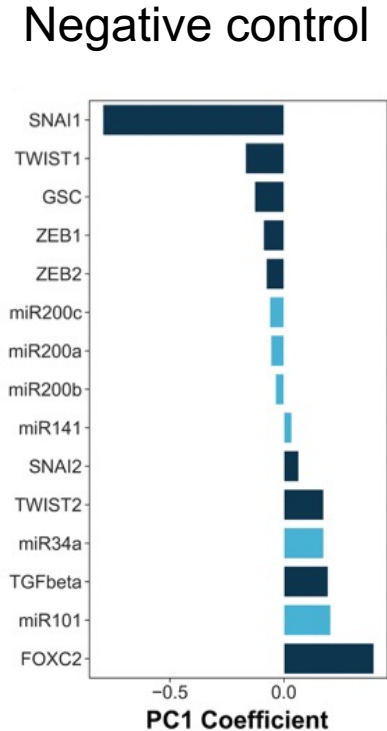
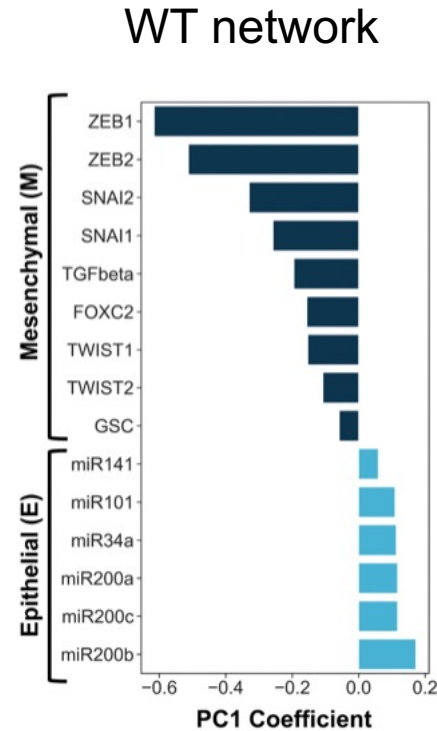
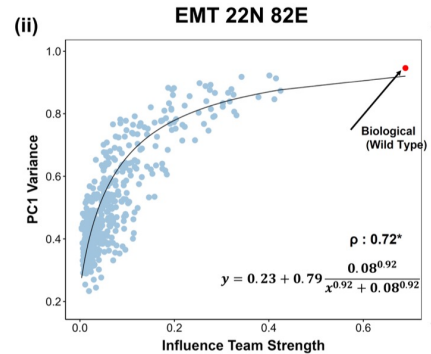
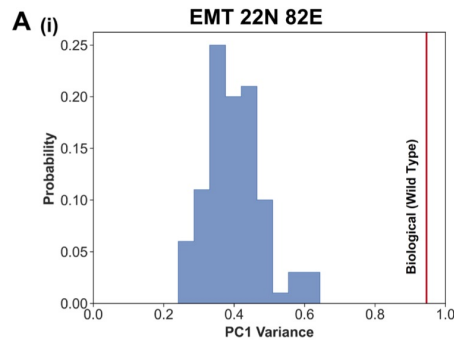
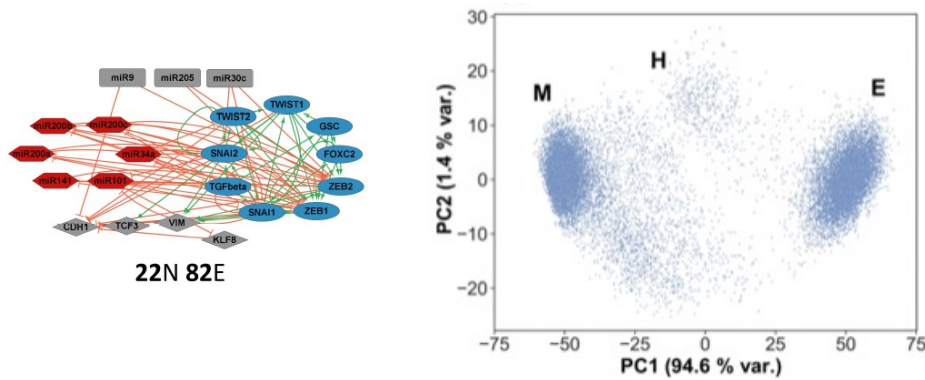
*Correspondence: susanner@alleninstitute.org (S.M.R.), jtheriot@uw.edu (J.A.T.)

<https://doi.org/10.1016/j.cell.2024.04.035>

“we must aim to Keplerize the cell, to discover general patterns and concepts that can lead to a better fundamental understanding of how cells work and what it means for a cell to be alive.”

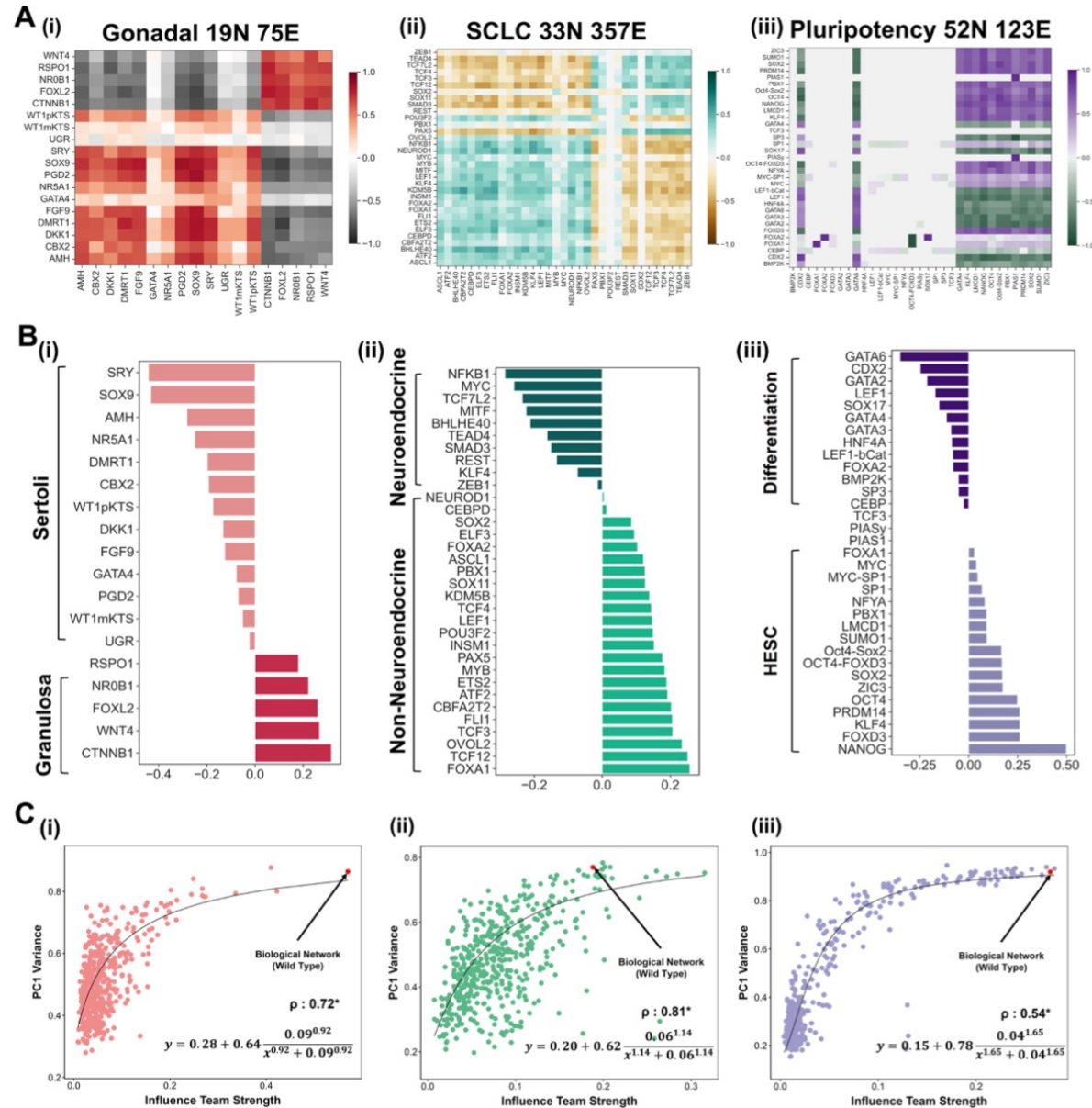


“Teams” – a meaningful dimension-reduction metric?

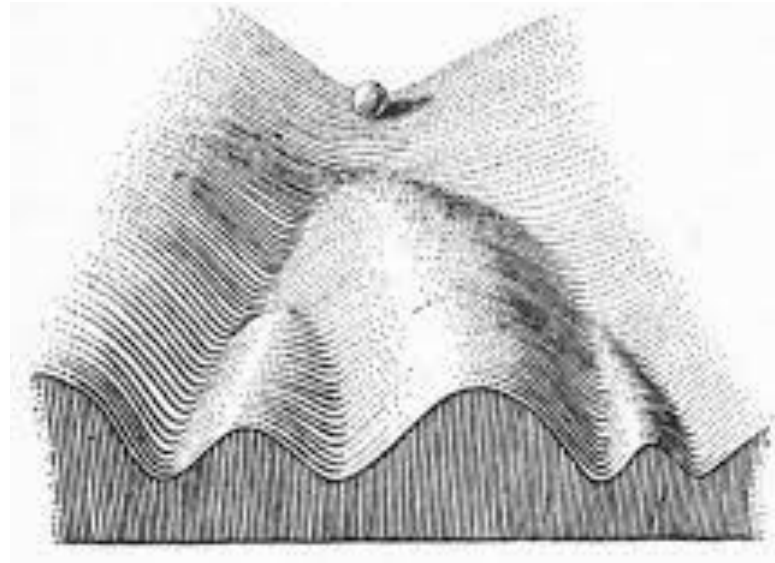
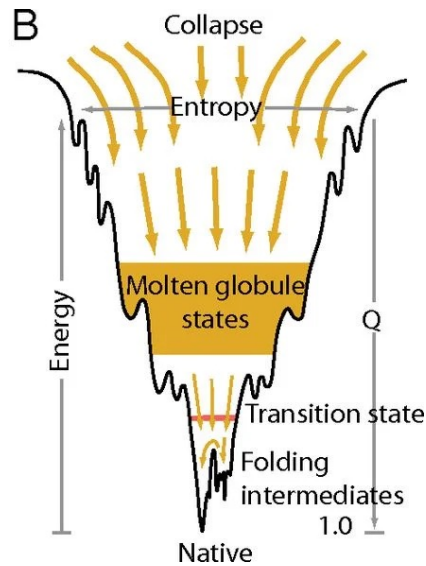


- EMT networks or transcriptomic data can be explained mostly by PC1.

Low-dimensionality of phenotypic space : other examples



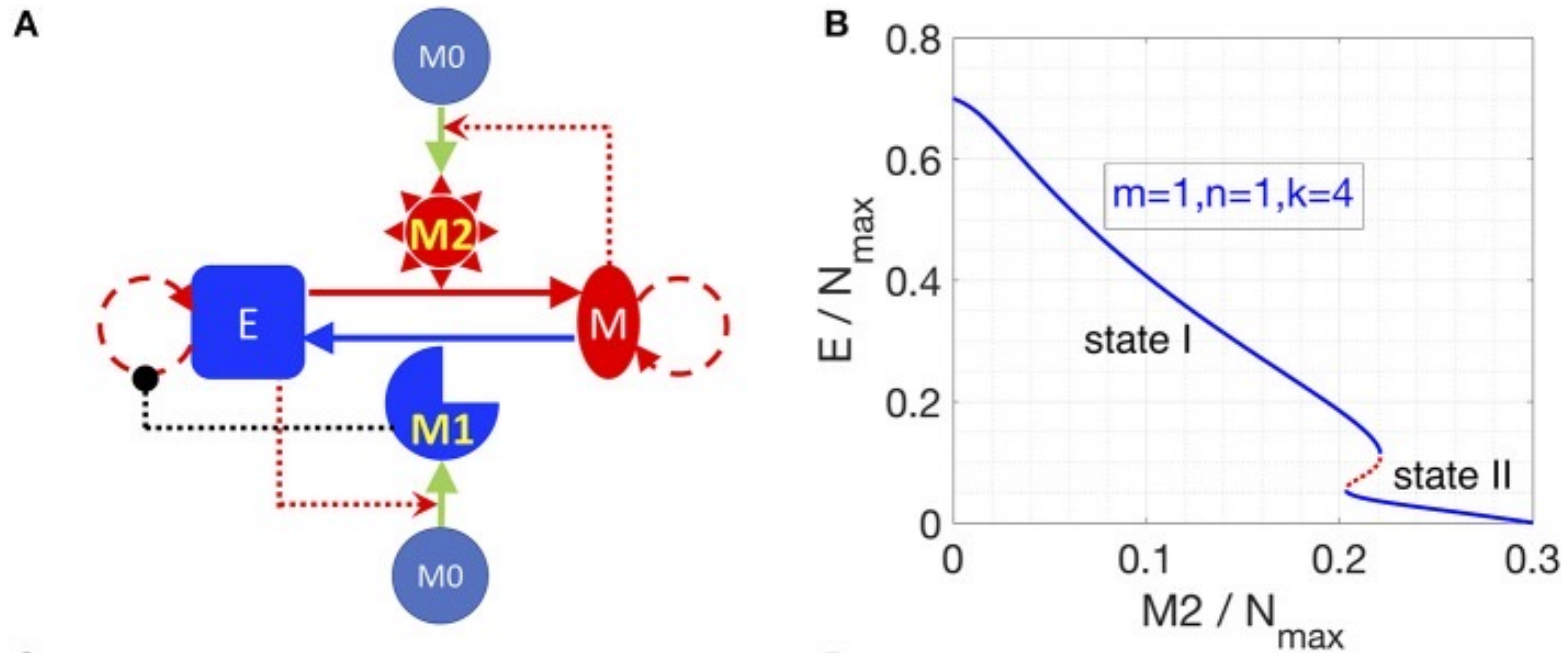
“Teams” ~ a driving principle of cell-fate canalization?



Englander & Mayne, PNAS 2014; Waddington, 1942

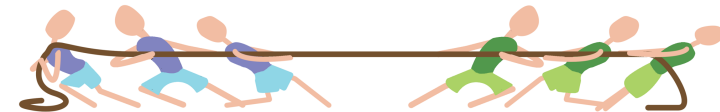
“Teams” can minimize “frustration” in EMT networks, allowing only a limited number of trajectories and cell-states.

From “teams” of nodes in a cell to “teams” of cells in a tissue



Two states of the cell population model:

1. Epithelial cancer cells, M1 macrophages
2. Mesenchymal cancer cells, M2 macrophages



More recent reports on M1/M2 mixed macrophages - that may stabilize hybrid E/M?

Summary (Part 2): Why do “teams” exist?

- “Teams” can coordinate many axes of plasticity (EMT, TamRes *et al.*) that can facilitate therapy-driven adaptive responses, aggravating outcomes.
- “Teams” can explain why cancer cells that are not killed become stronger.
- Math models can help in identifying better therapeutic strategies (rational combinations of drugs).



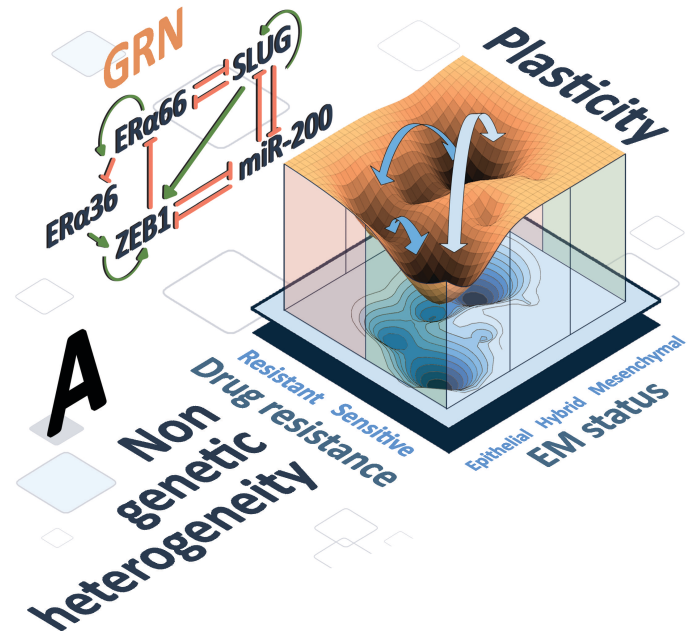
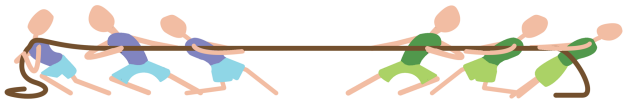
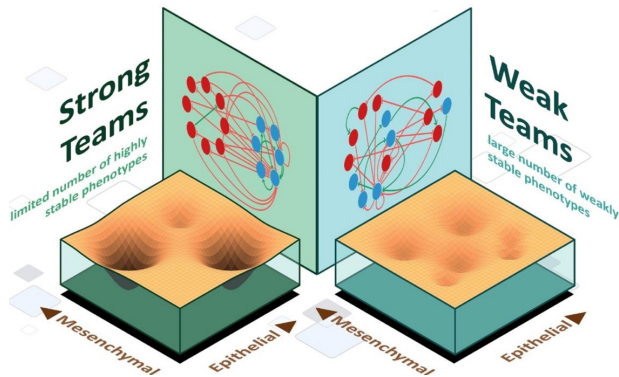
Avada Kedavra
(Targeted therapy)



Cells that adapt & survive:
Hail the “Team” Potter!

Summary

- ‘Design principles’ of regulatory networks driving cell-state switching:
 1. **Multistable** dynamics => Phenotypic plasticity & heterogeneity
 2. Existence of “**teams**” exist in multiple such networks
- **Drug-induced cell-state transitions** can aggravate tumor progression
- Math models can help identify **rational combinatorial strategies**



Acknowledgements

∫

Oncologists
Clinicians
Mathematicians
Physicists
Chemists
Engineers



∫

Biotechnology
Electrical Engineering
Bioinformatics
Physics
Mathematics
Cancer Biology



Funding agencies



Open for new collaborations : mkjolly@iisc.ac.in