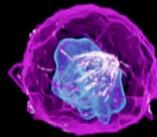




ALLEN INSTITUTE *for*
CELL SCIENCE



Toward a holistic and dynamic stem cell state landscape

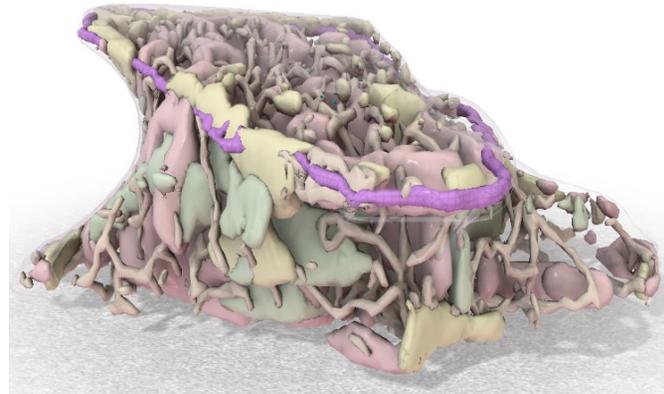
Susanne Rafelski

Developing Regenerative Medicine Therapies with AI
November 2025

Disclosure slide: no disclosures

Our vision: *understand how cells organize, communicate and change*
Look at a cell and know what it is doing

...what it did



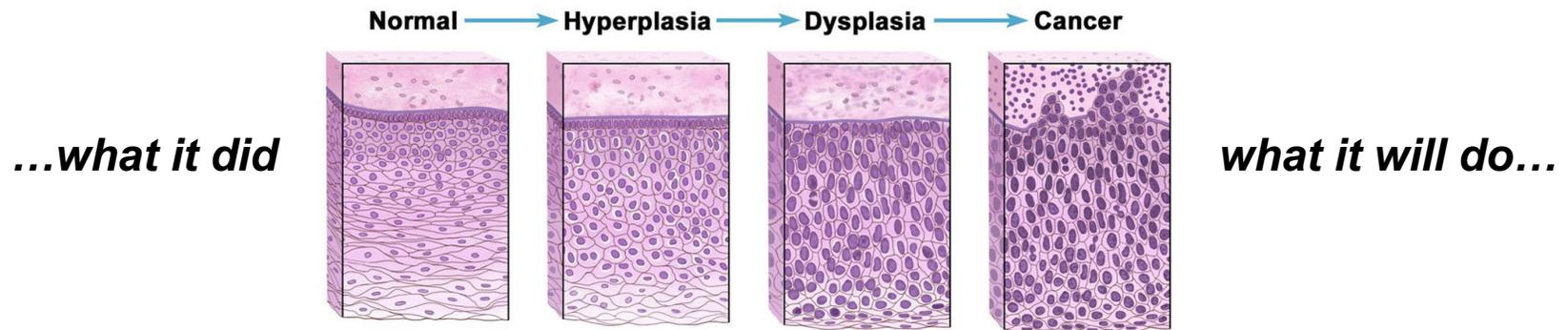
what it will do...

cell → tissue → organ → organ system → organism
“know”

beyond prediction only – we want understanding!

Our vision: *understand how cells organize, communicate and change*

Look at a cell and know what it is doing



© 2014 Terese Winslow LLC
U.S. Govt. has certain rights

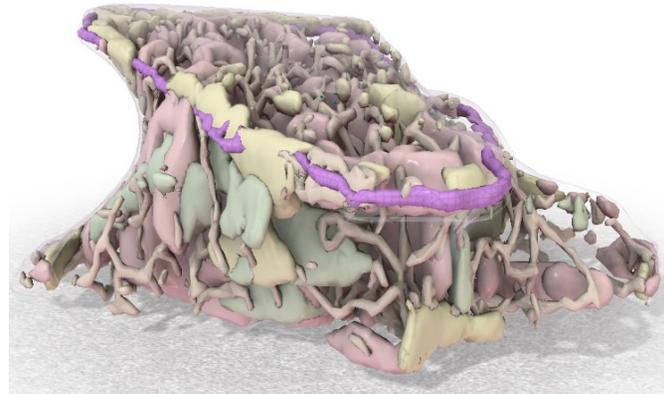
cell → tissue → organ → organ system → organism

normal vs. abnormal cellular basis of damage and disease

variability within cell populations

Our vision: *understand how cells organize, communicate and change*
Look at a cell and know what it is doing

...what it did



what it will do...

How?

images

through time & across scales

Which images?

Talk outline

1: Bringing together spatiotemporal and molecular representations of cell state in the current era of big cell image data and AI

perspective: Establishing a conceptual framework for holistic cell states and state transitions

Rafelski and Theriot, Cell 187, 2633–2651 (2024)

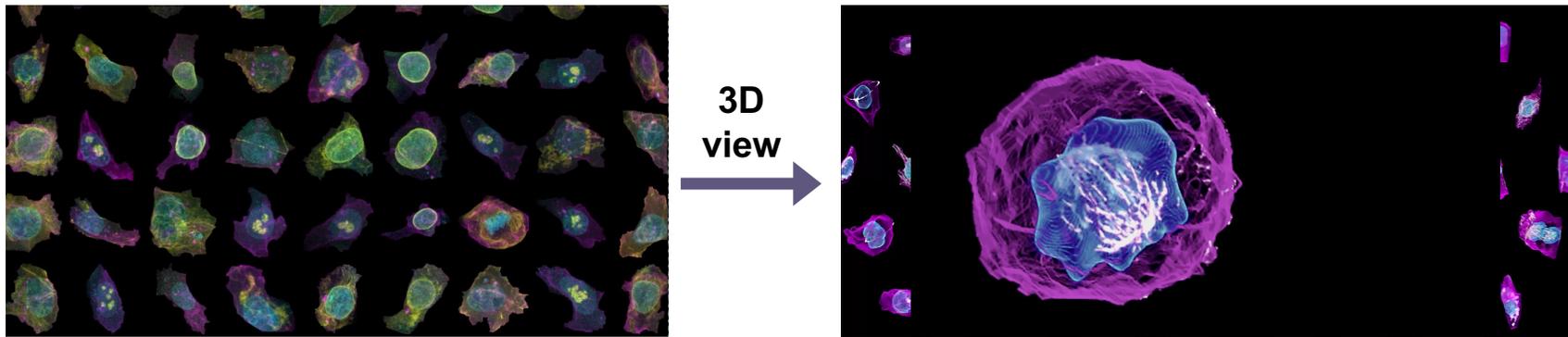


2: Where we have been: 10 years of the Allen Institute for Cell Science

3: Where we are heading: our new initiative – CellScapes + a case study

Single cell imaging and analysis: the next step in the post-genomic era

We are in an era of large-scale cell image datasets
and we want to make sense of them through quantitative (image) data science methods



What do we need to “know” a cell?

what state a cell is in

a range of values for each observable that describes a cell in a relatively stable state

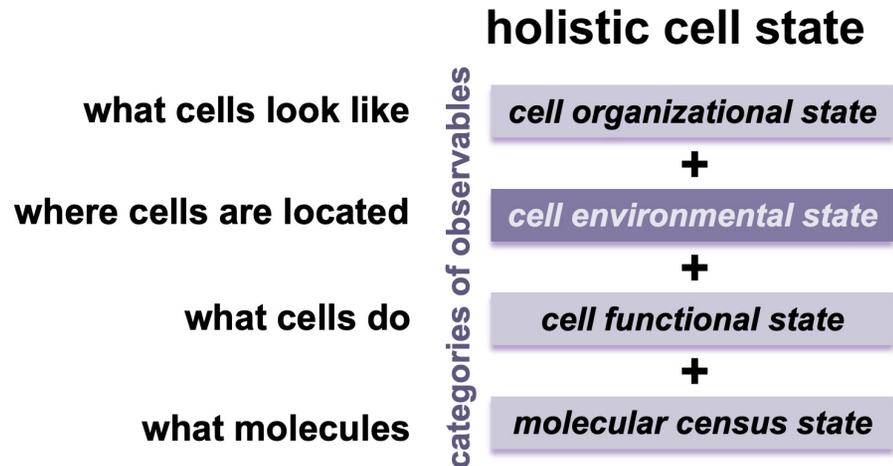
how and why a cell changes state

the dynamics of how these observables change as a cell leaves one state and settles into a new state

cell “observable”: anything we can observe (measure, see) about a cell

What do we need to “know” a cell?

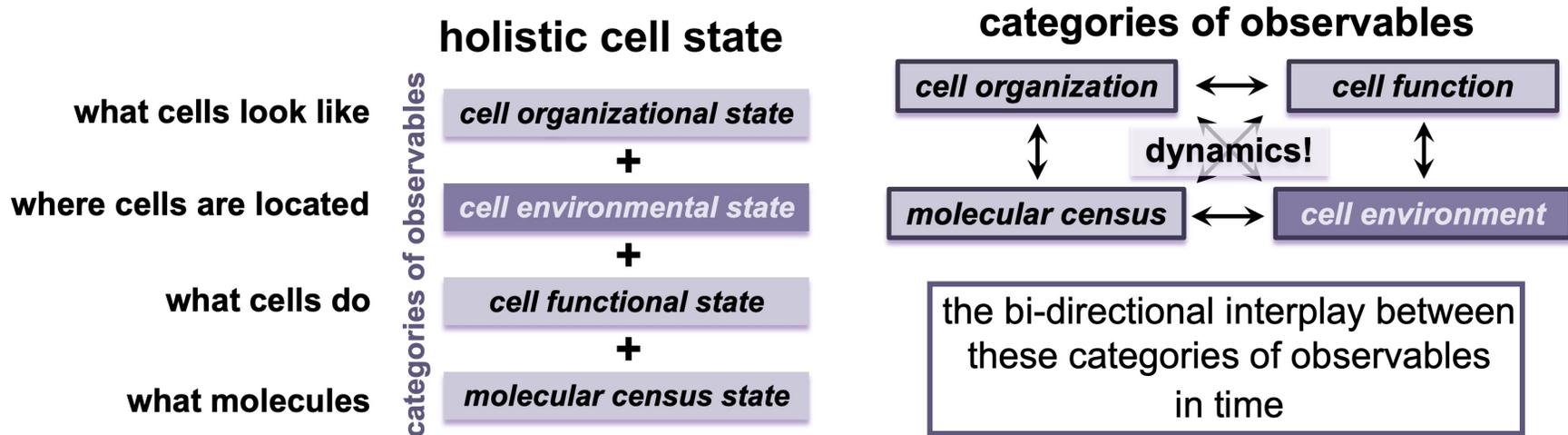
Now is the time to update the concept of a *holistic cell state*
quantitative, spatiotemporal observables + molecular observables



Perspective: Rafelski and Theriot, Cell 187, 2633–2651 (2024)

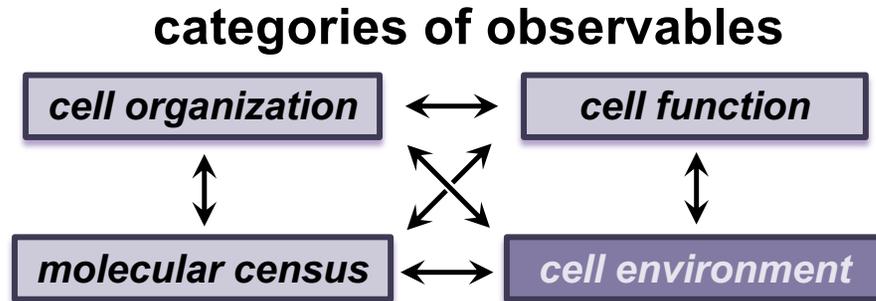
What do we need to “know” a cell?

Now is the time to update the concept of a *holistic cell state*
quantitative, spatiotemporal observables + molecular observables



Perspective: Rafelski and Theriot, Cell 187, 2633–2651 (2024)

A conceptual *holistic cell state* framework

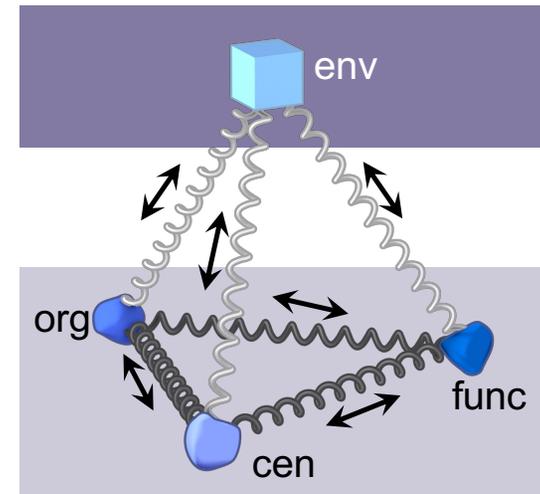


representations:

- **vertices:** the four categories of observables
- **springs:** bi-directional feedback between categories
- **spring-induced movement:** the “push and pull” of the values of one observable category in response to another

conceptual visualization

spring-connected tetrahedron

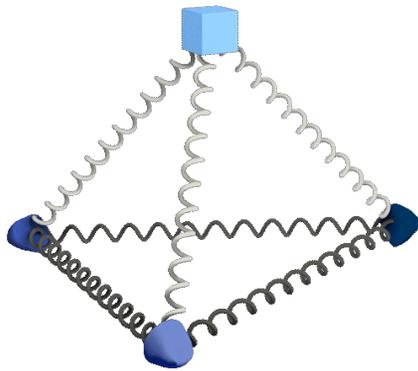


cellular phenotype (*cell-intrinsic*)

cellular environment (cell-extrinsic)

A conceptual *holistic cell state* framework – stable state

In a **stable holistic cell state** the vertices may fluctuate...



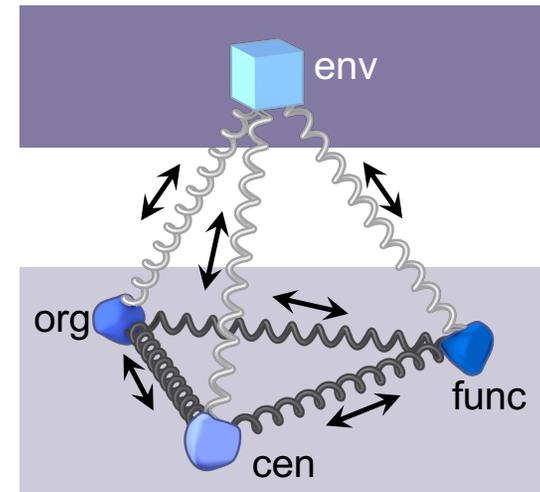
for example:

- *levels of a particular protein*
- *position of a particular organelle*
- *speed of a migrating cell*

can vary

... but ultimately the nature of the relationships between the vertices ***mutually reinforces*** them to maintain a stable holistic cell state

conceptual visualization
spring-connected tetrahedron

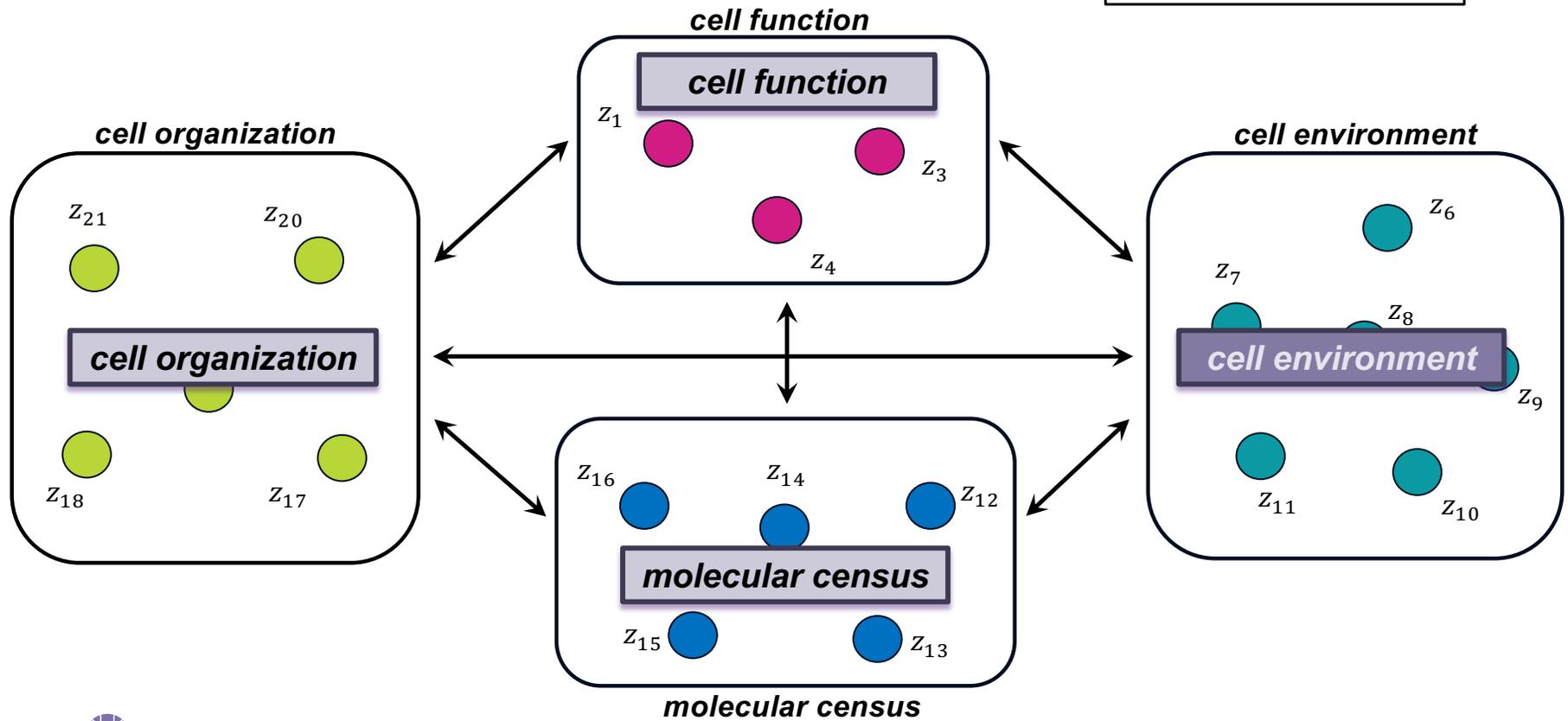


cellular phenotype (*cell-intrinsic*)

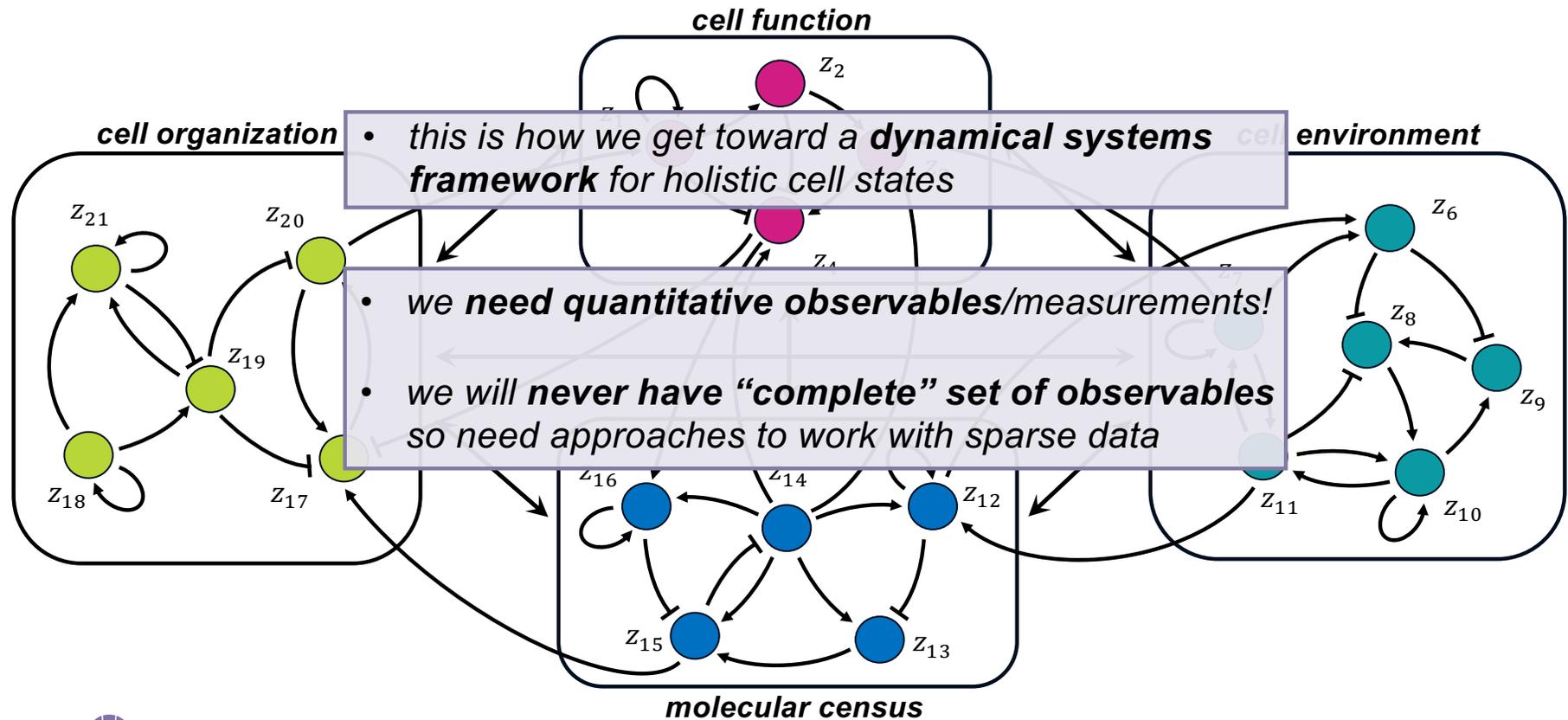
cellular environment (*cell-extrinsic*)

A conceptual *holistic cell state* framework – vector of all observables

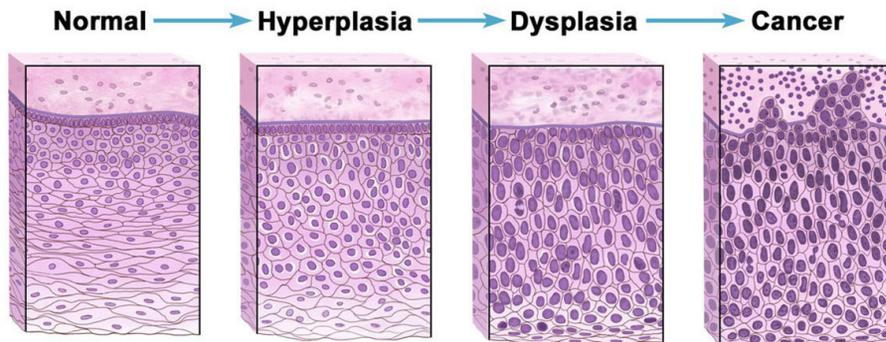
$$\mathbf{z} = (z_1, z_2, \dots, z_N)$$



A conceptual *holistic cell state* framework – bidirectional feedback (network diagram)



To get at the mechanisms underlying normal cell states, cellular damage, and disease we need to integrate across categories of observables...



© 2014 Terese Winslow LLC
U.S. Govt. has certain rights

... via quantitative frameworks

molecular representations:

e.g., bulk or single cell genomics

organizational representations?

holistic cell representations

we will never have **complete** data → **partial** data

all the molecules (and how many) inside a cell

the spatio-temporal, multi-scale arrangement of the molecules inside a cell

How does AI fit in?

- **dimensionality reduction:** detecting/learning patterns in highly complex data and creating *holistic cell representations*, including over time
- **generative AI:** recreating patterns from these representations toward *interpretation and insights*
- **goal: predictive understanding,** not black-box prediction alone

Talk outline

1: Bringing together spatiotemporal and molecular representations of cell state in the current era of big cell image data and AI

2: Where we have been: 10 years of the Allen Institute for Cell Science

Developing quantitative frameworks for cell organization and beyond

- *overview of (some of) our publications and Open Science resources*

3: Where we are heading: our new initiative – CellScapes + a case study

The genome is a giant transformation of the next step in the post-genome data era

Human genome project launched in 1990
30 years of tool and method development
data is very straightforward to analyze

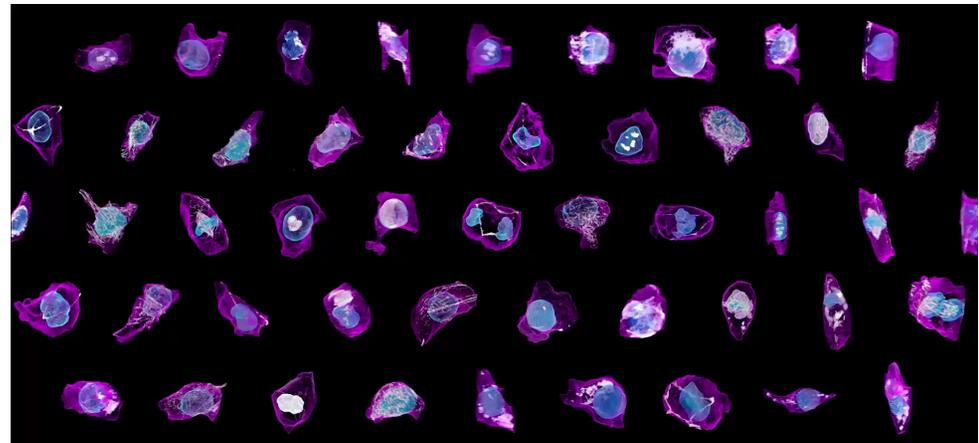
sequence alignment to find mutations

5' ACCTGTCTTGAAACTGTGTC 3'
5' AC**G**TGTCTTG**A**CACTGTGTC 3'

“Cell x Gene” table for RNA expression

| | Cell 1 | Cell 2 |
|--------|--------|--------|
| Gene A | 574 | 581 |
| Gene B | 23 | 15 |
| Gene C | 1068 | 23 |
| Gene D | 75 | 69 |
| Gene E | 1654 | 1702 |

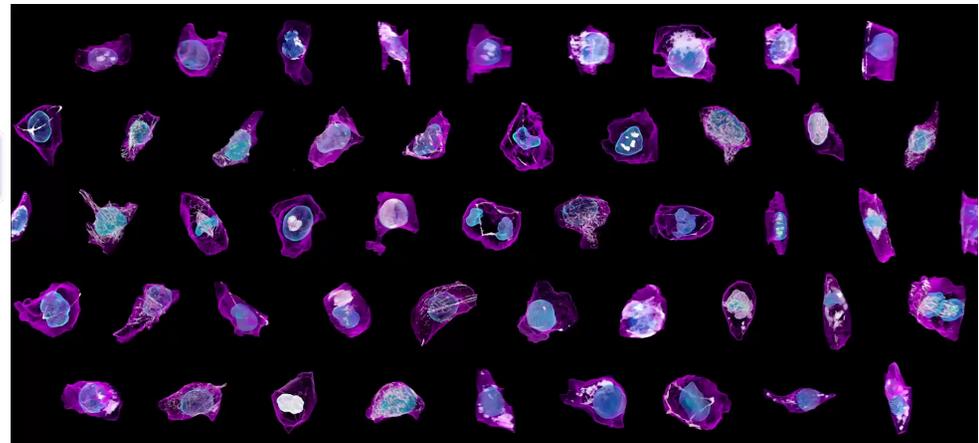
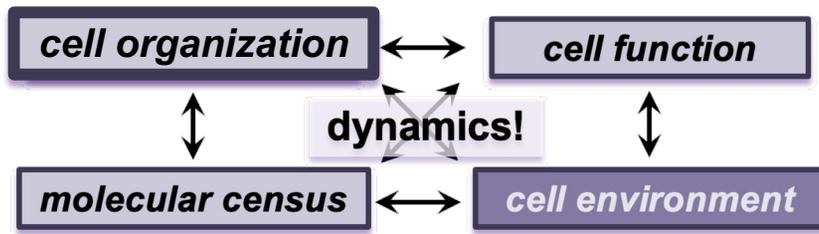
Grand challenge: to establish a quantitative framework to compare the shapes and positions and their changes over time for 3D cellular structures in a comprehensible and generalizable manner



Single cell imaging and analysis: the next step in the post-genomic era

the field needs a quantitative framework for *cell organization*

Grand challenge: to establish a quantitative framework to compare the shapes and positions and their changes over time for 3D cellular structures in a comprehensible and generalizable manner

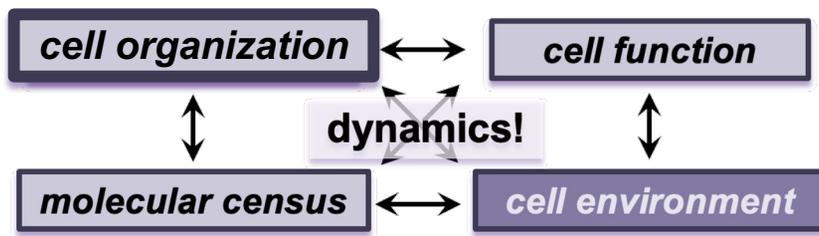


to integrate with other categories of cell observables such as:

- expression signatures
- protein states (signaling)
- chromatin organization

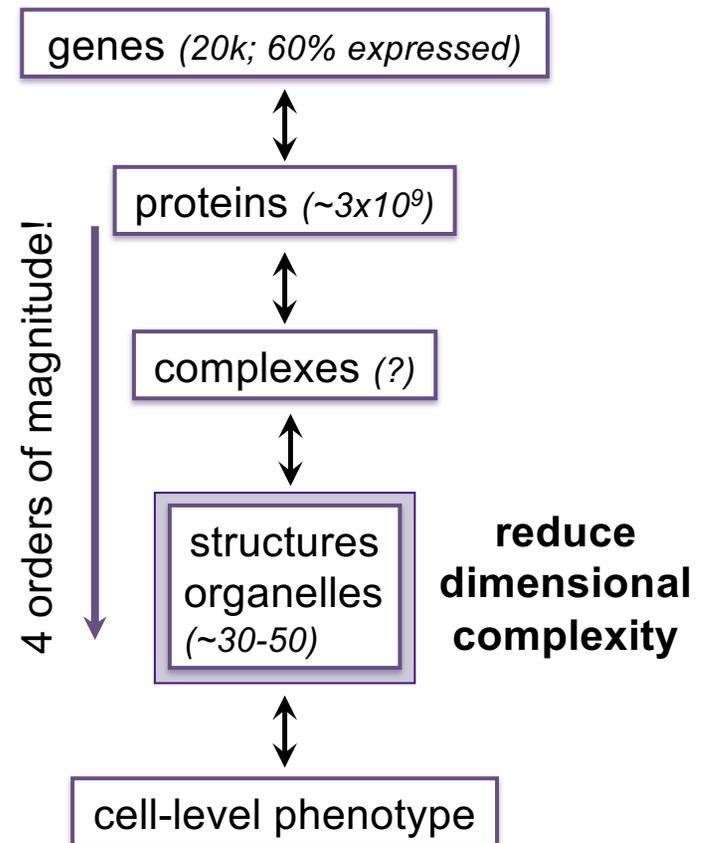
Single cell imaging and analysis: the next step in the post-genomic era

the field needs a quantitative framework for *cell organization*



to integrate with other categories of cell observables such as:

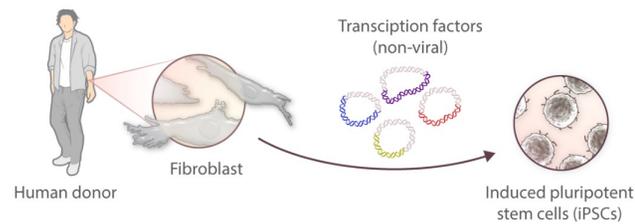
- expression signatures
- protein states (signaling)
- chromatin organization



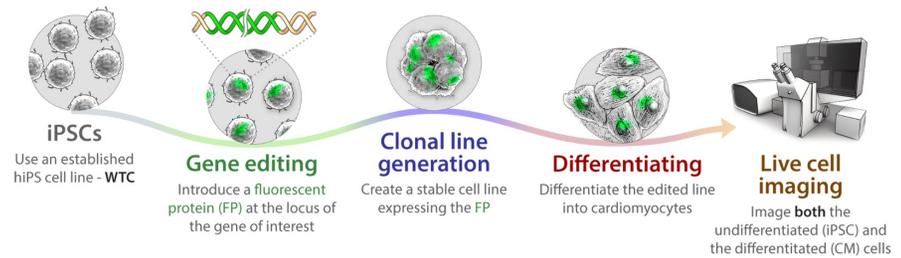
First 10 years – developing frameworks for cell organization and beyond

overview of our approach

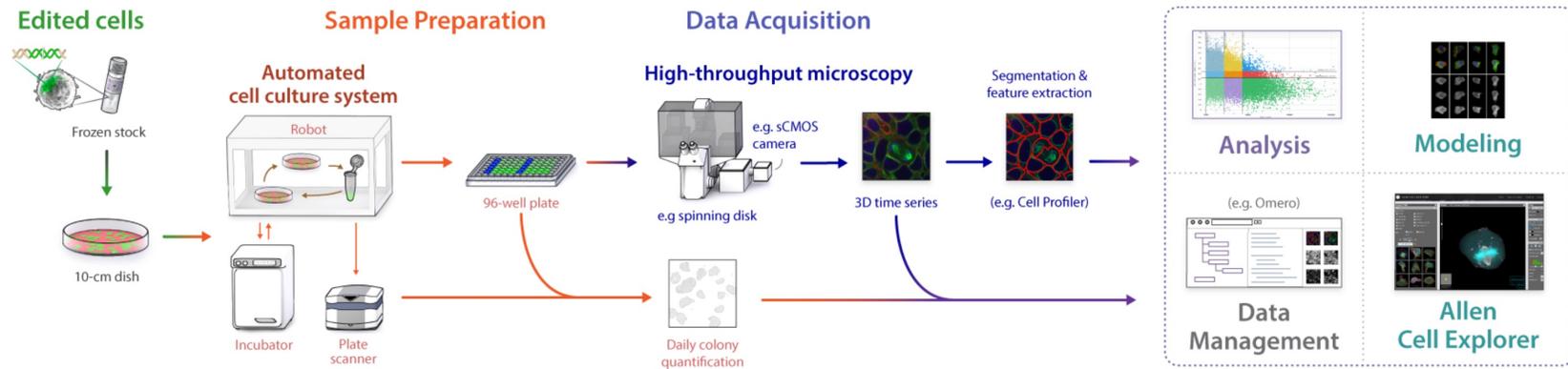
pre-clinical model: hiPS cells (WTC-11)



illuminating cellular structures in hiPS cells



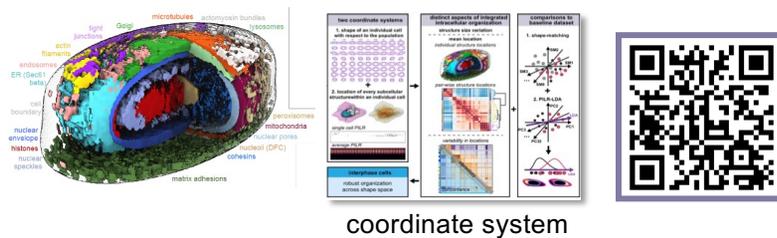
creating and analyzing large 3D image datasets of hiPS cells



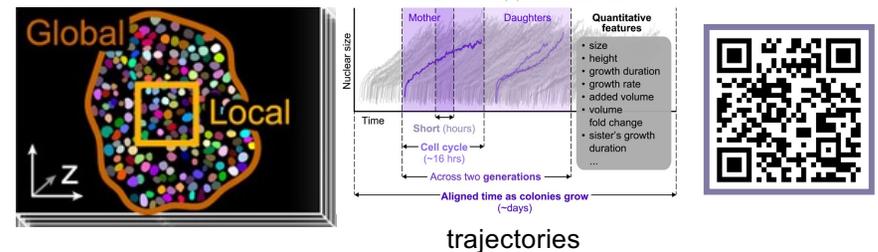
First 10 years – developing frameworks for cell organization and beyond

overview of (some of) our scientific publications

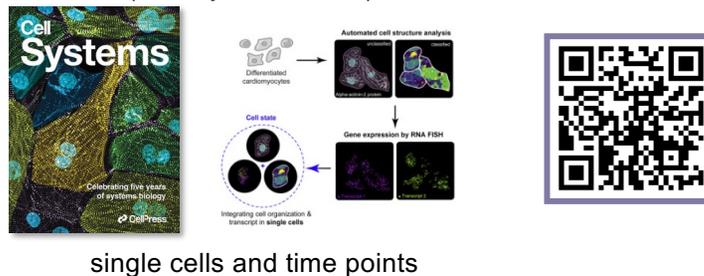
integrated hiPSC organization and variations (Nature 2023)



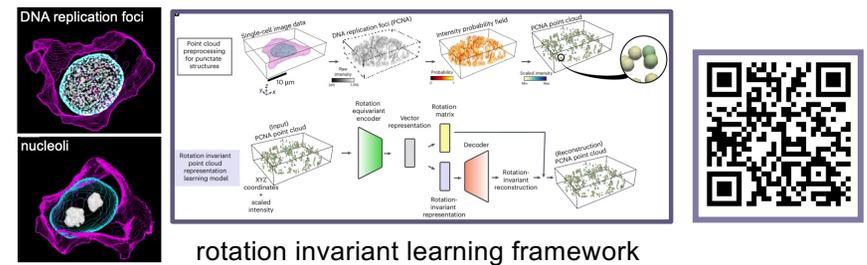
variations in nuclear growth dynamics across space and time (Cell Systems 2025)



correlating organization with gene expression in cardiomyocytes (Cell Systems 2021)



interpretable representations for multipiece cellular structures (Nature Methods 2025)



Tools & resources overview

The Allen Institute is committed to open science, providing researchers, educators, and the public with access to our data, tools, methods, and analyses for reproduction and reuse.

allencell.org

Jump to section [Image analysis & visualization](#) | [Data support](#) | [Code](#) | [Cell lines](#)

Sign up for our [newsletter](#) or join our [forum](#) to stay connected.

Image analysis & visualization



desktop

visualization

AGAVE
Powerful volume viewer with path-trace rendering to display multi-channel TIFF and OME-Zarr images



desktop

analysis visualization

Allen Cell & Structure Segmenter
napari plugin & open-source Python-based toolkit for 3D image segmentation



web

analysis visualization

Timelapse Feature Explorer (TFE)
Online tool to interactively visualize & analyze segmented time-series microscopy data



web

visualization

Vol-E
Online volume viewer to visualize your own volumetric data including OME-Zarr format



web

visualization education

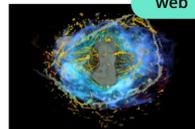
Cell Feature Explorer (CFE)
Online tool composed of a scatterplot & 3D viewer to visualize segmented and processed hiPSC images from our open datasets



web

visualization education

Simularium
Online analysis tool to visualize, share and interrogate biological simulations



web

visualization education

Integrated Mitotic Stem Cell (IMSC)
Online educational tool that uses real-world data to provide a holistic view of human cell division



web

visualization education

Visual Guide to Human Cell
Online educational tool to interact with 3D cell models and learn about individual cell structures and functions

Cell lines



web

cell lines

Allen Cell Catalog
Quality control database of gene-edited hiPSC cell lines



web

cell lines

Disease Cell Collection
Quality control database of gene-edited cell lines that carry mutations in genes known to cause disease



cell lines

Lab Plasmids
Deposited plasmids at Addgene for distribution to the research community



cell lines

Standard operating procedures (SOPs)
Cell culture, differentiation, and microscopy protocols for gene-edited hiPSCs

Data support



python data support

BioIO
Image reading, metadata conversion, and image writing for microscopy images in pure Python



web

data management

BioFile Finder (BFF)
Online tool to curate, interrogate, and share datasets through rich metadata exploration & image viewing



data download

Data Download
Open-access datasets for download

Code



machine learning

CytoDL
Framework to unify and simplify deep learning approaches for analyzing biological data



python analysis

Cell Variance Analysis
Processing of FOVs and cells for the Cell Variance Analysis



analysis

Other Codebases
Open-access code developed at the institute

The Allen Cell Collection – isogenic FP tagged hiPSC’s for live cell imaging

| | Structure | Protein | FP | Status |
|---|------------------|---------------|-------|-----------|
| 1 | Matrix adhesions | Paxillin | EGFP | Available |
| 2 | Microtubules | Alpha-tubulin | mEGFP | Available |
| 3 | Nuclear envelope | Lamin B1 | mEGFP | Available |
| 4 | Mitochondria | Tom20 | mEGFP | Available |
| 5 | Desmosomes | Desmoplakin | mEGFP | Available |
| 6 | Actin filaments | β-actin | mEGFP | Available |

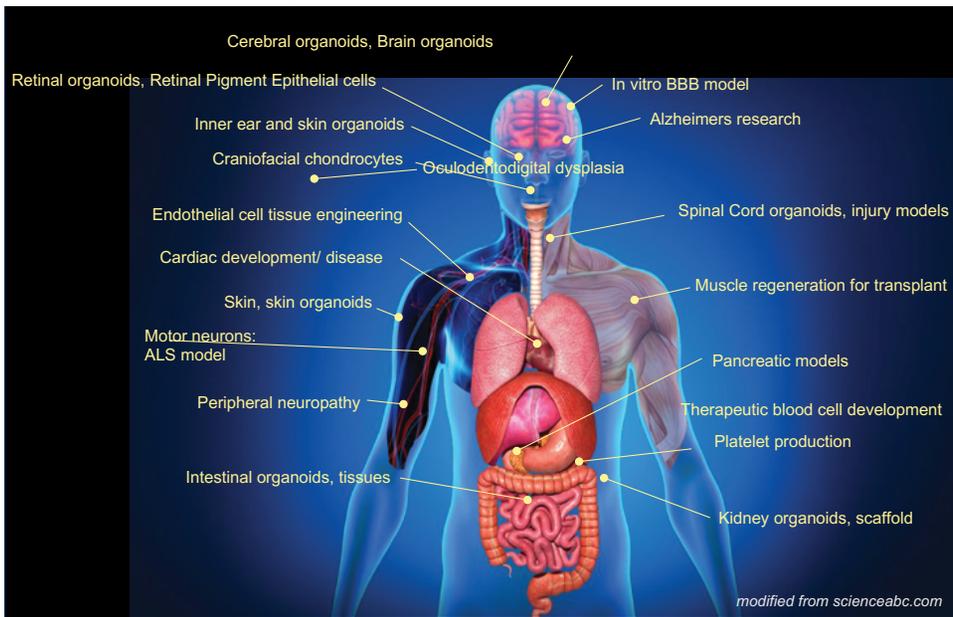
>1600 vials distributed to 25 countries
 established at major universities for basic and applied research

~58 FP-tagged isogenic iPSC lines (WTC-11)

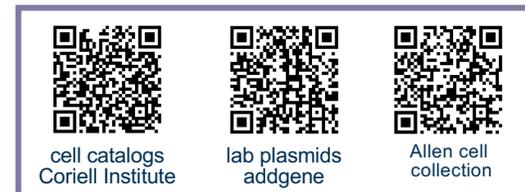
- major structures, nuclear, cardio-specific, multi-edits
- 44 cellular structures
- mostly mono-allelic and single edits
- extensive QC

sharing cell lines, plasmids, and methods

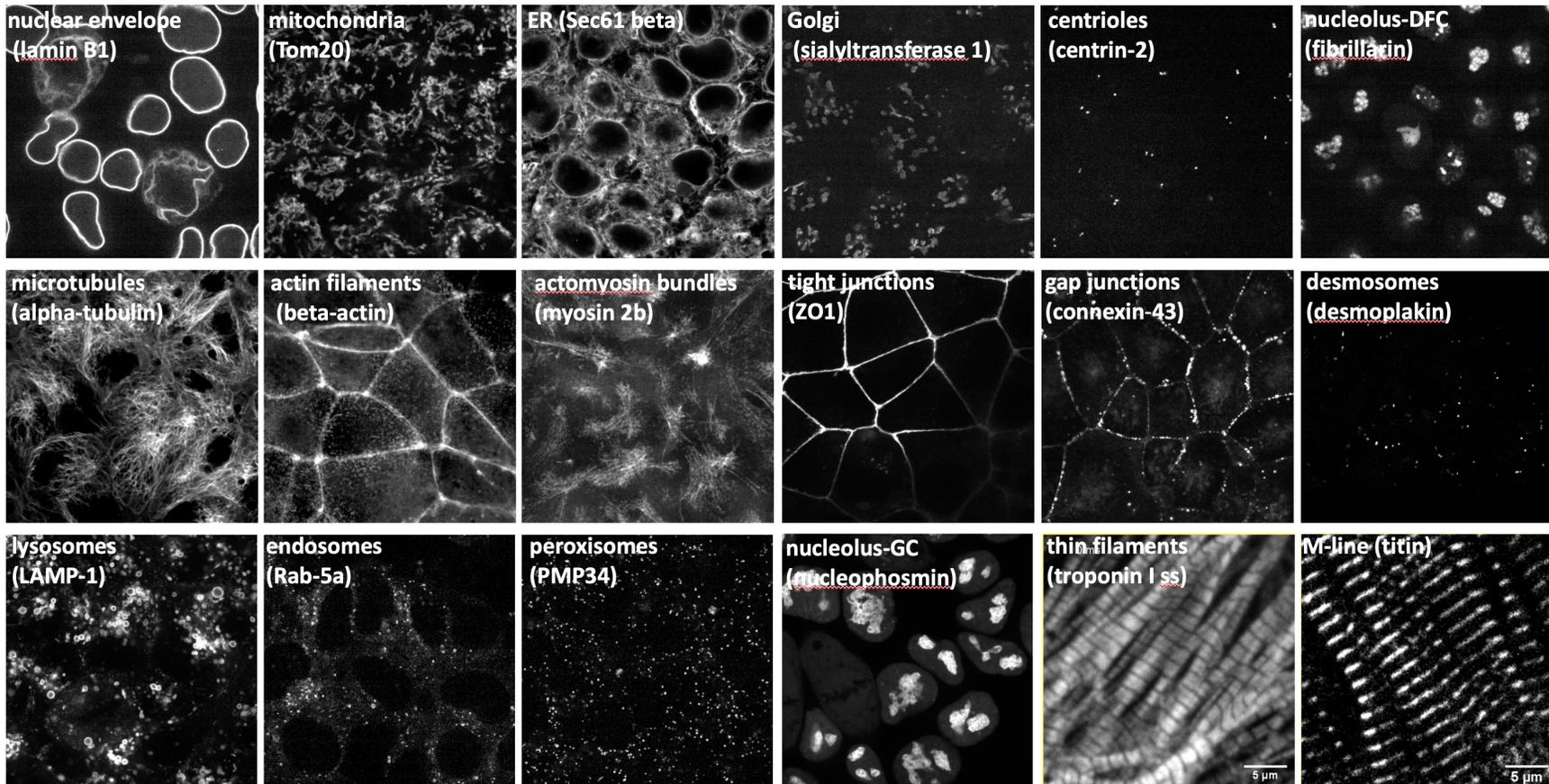
- cell lines – Coriell Institute
- plasmids – Addgene
- distribution to stem cell cores at major institutes
- methods and tutorials - MBoC, Stem Cell Reports, JoVE



| | | | | |
|----|----------------------------|-----------------|-------|-----------|
| 49 | Sarcomeric thick filaments | MLC-2v (late) | mEGFP | Available |
| 50 | Sarcomeric z-discs | Alpha-actinin-2 | mEGFP | Available |
| 51 | Costameres | Dystrophin | mEGFP | Available |



Example cell lines from the Allen Cell Collection



Talk outline

1: Bringing together spatiotemporal and molecular representations of cell state in the current era of big cell image data and AI

2: Where we have been: 10 years of the Allen Institute for Cell Science

3: Where we are heading: our new initiative – CellScapes

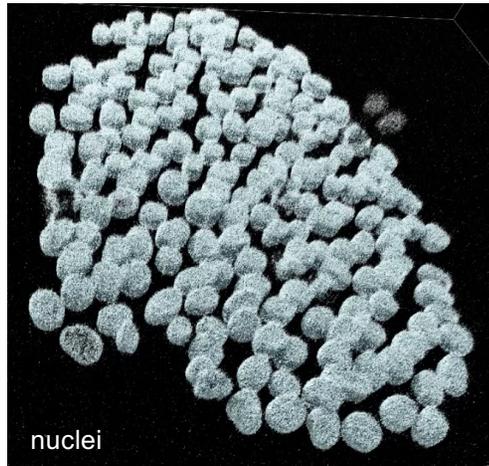
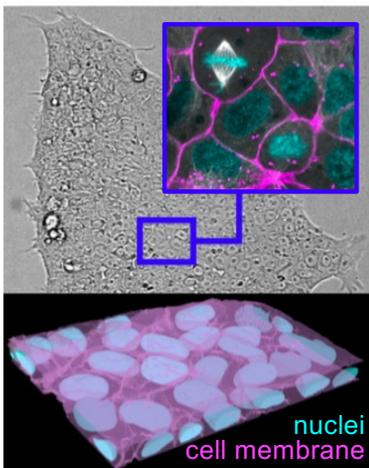
Using hiPSC models and AI toward predictive understanding of multiscale multicellular morphogenesis

Case study: *hiPSC-derived endothelial cells response to shear stress*

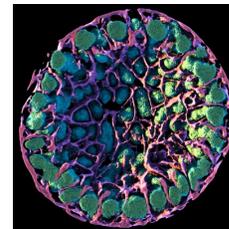
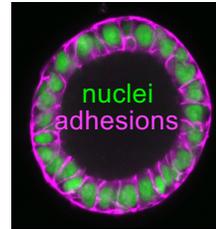
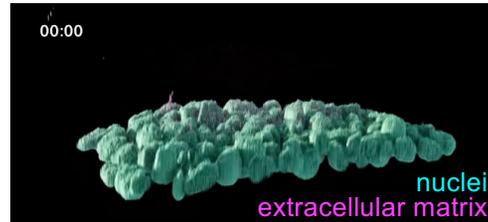
CellScapes: How do cells organize themselves across scales to form complex cell communities and tissues?

nuclei inside of human induced pluripotent stem (hiPS) cells

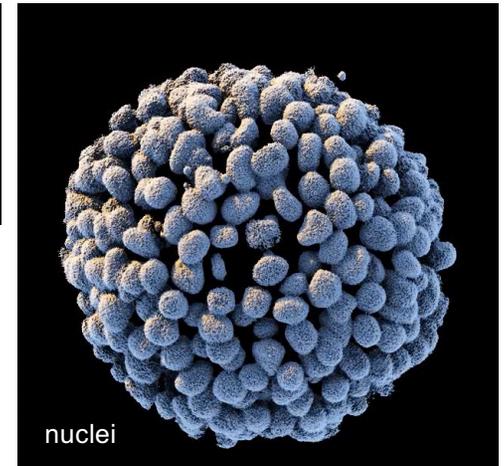
cells grown in 2D sheets



lumenoid formation
from 2D sheet to 3D lumenoid

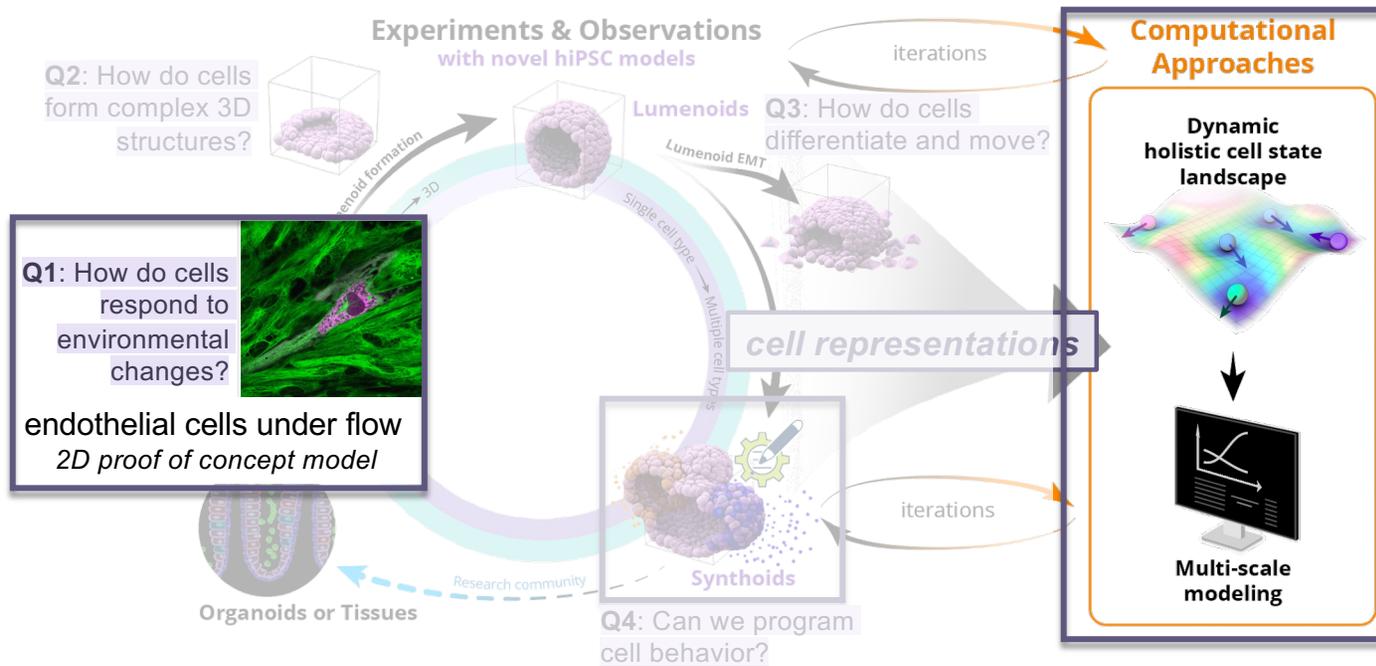


cells grown in 3D lumenoids



Goal: achieve a predictive understanding of cell state transitions during multicellular morphogenesis

Toward *predictive understanding* of multiscale multicellular morphogenesis



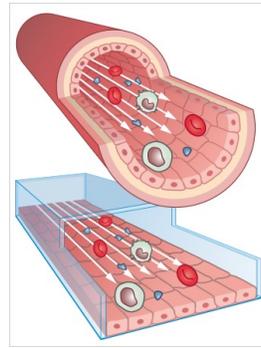
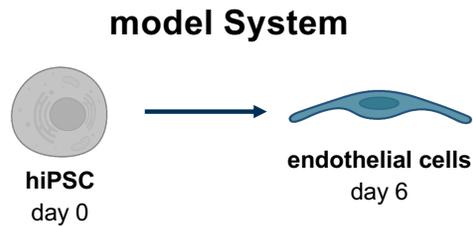
Objectives:

1. Quantify cell state transitions in stem cells
2. Build data-driven and dynamic cell models for discovery
3. Disseminate to amplify impact

testing our “understanding”:

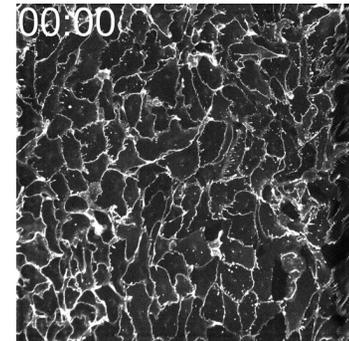
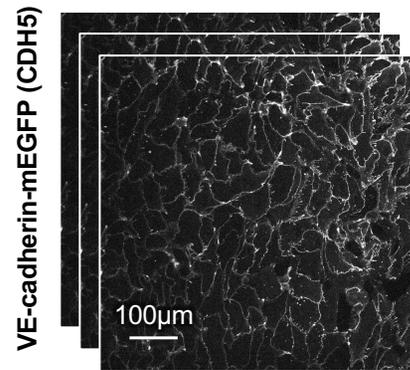
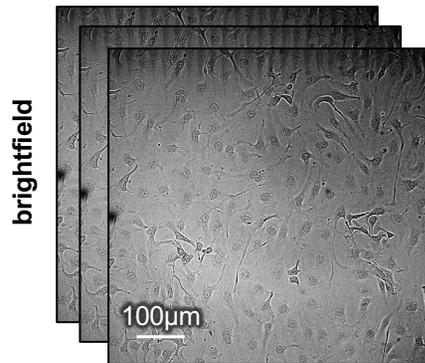
- *explanatory/mechanistic models & theory*
- *“build to understand”* *inspired by Richard Feynman’s “What I cannot build. I do not understand”

hiPSC-derived endothelial cells (hiPSC-ECs) under flow as a model system to study cell state changes

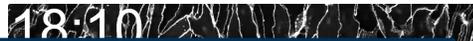
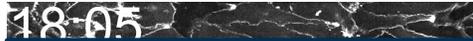


Ibidi.com

imaged in 3D at 20x every 5 minutes on 3i spinning disk confocal



Cells relax into distinct steady at different magnitudes of shear stress



How do we use this microscopy data:

- *to quantitatively define cell states?*
- *to generate a dynamic landscape of cell states?*



VE-cadherin puncta

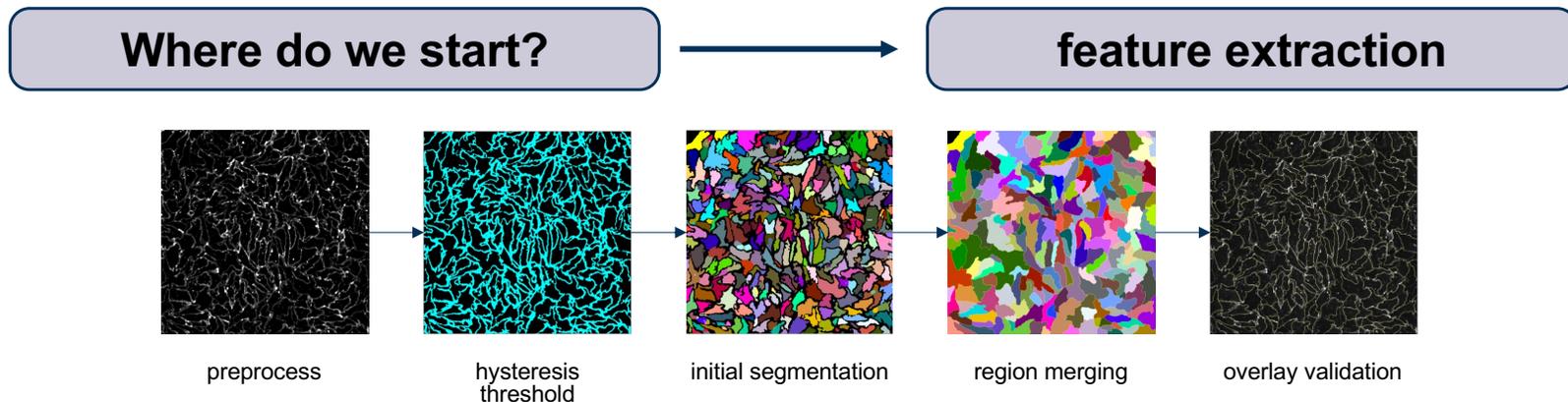


- **Morphology:** elongated & aligned parallel to direction of shear stress
- **Migration:** upstream relative to direction of shear stress
- **VE-cadherin:** puncta between adjacent cells persist

- **Morphology:** elongated & aligned perpendicular to direction of shear stress
- **Migration:** many directions, many perpendicular to the direction of flow
- **VE-cadherin:** puncta rarely observed between adjacent cells



Toward a quantitative framework for studying cell state transitions



Classic image processing workflow:

- single cell segmentation
- tracking + curation
- measurements (orientation, shape, etc.)

Challenges:

- naïve success rate of segmentation is low
- segmentation accuracy not consistent over time
- bias in choice of observables
 - What are the identifiable axes of variation?
- Which features are necessary and sufficient for “useful and interpretable” characterization?

Can we “learn” the features that are important?

Deep learning for unsupervised feature extraction

*machine learning
deep learning / AI*

*unsupervised**

*(*unsupervised \neq naïve, uninformed)*

**Can we “learn” the features
that are important?**

cell representations that are:

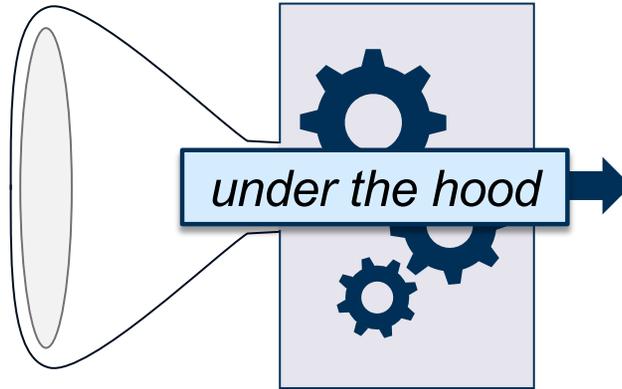
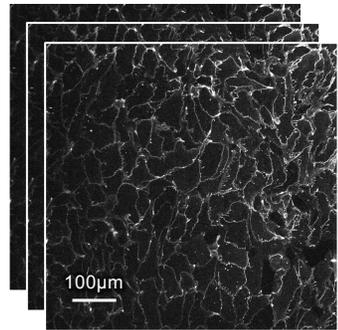
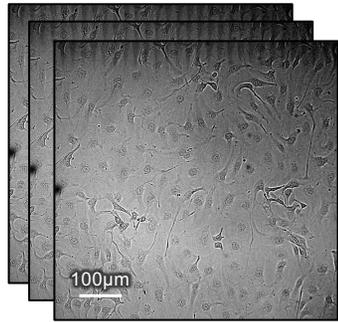
- *complete*
- *compact*
- *interpretable*

*quantitative anchors for
integrating data across
categories of observables*

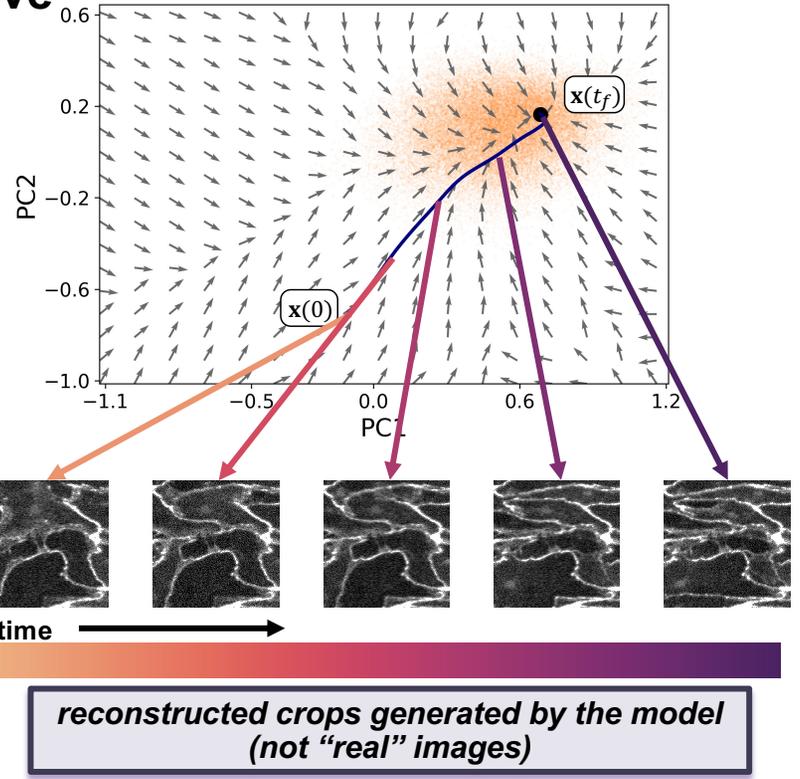
From steady state movies to a dynamic “landscape” at low shear stress

under the hood
precisely predicting for image featurization
interpretable and generative
latent space

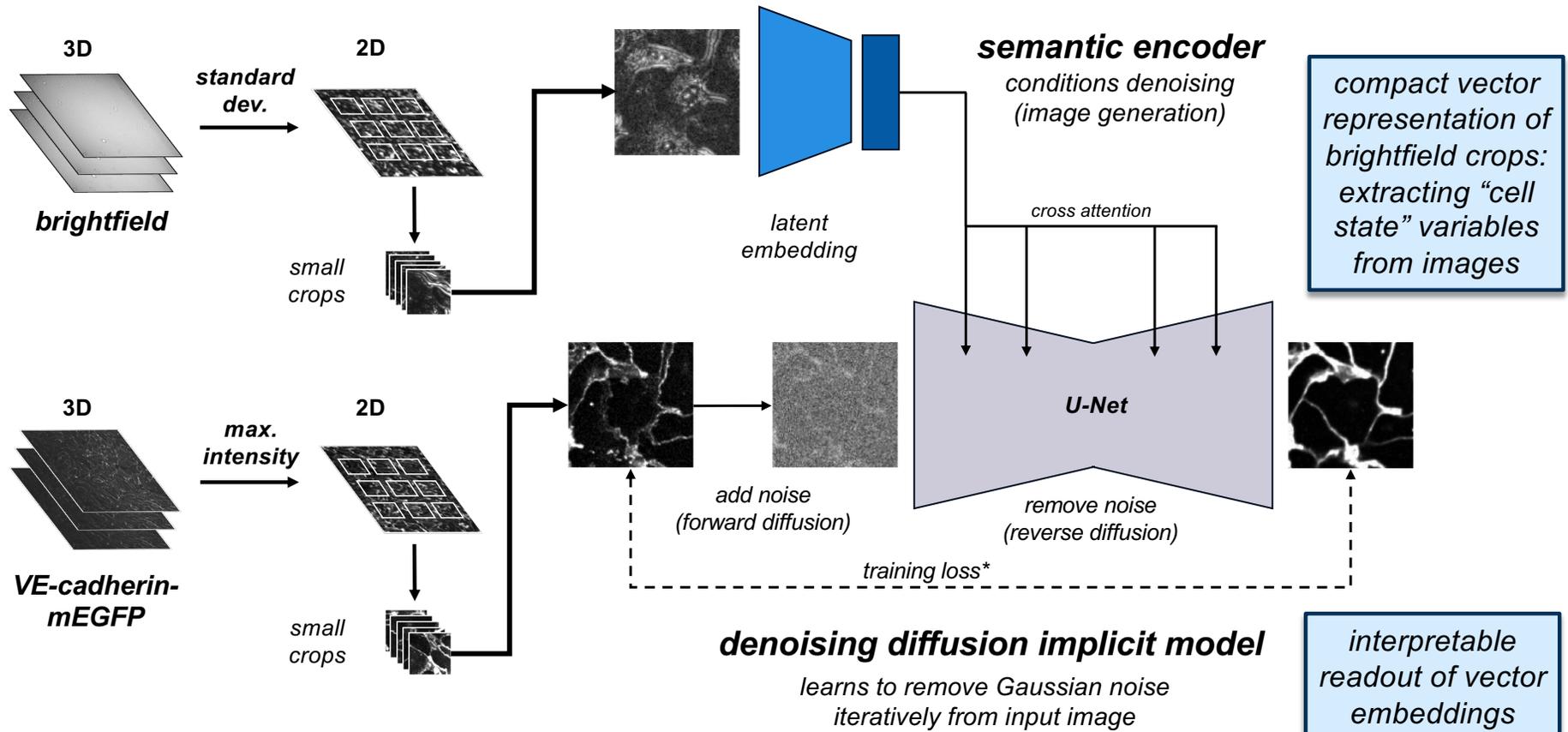
dynamics for low shear stress:



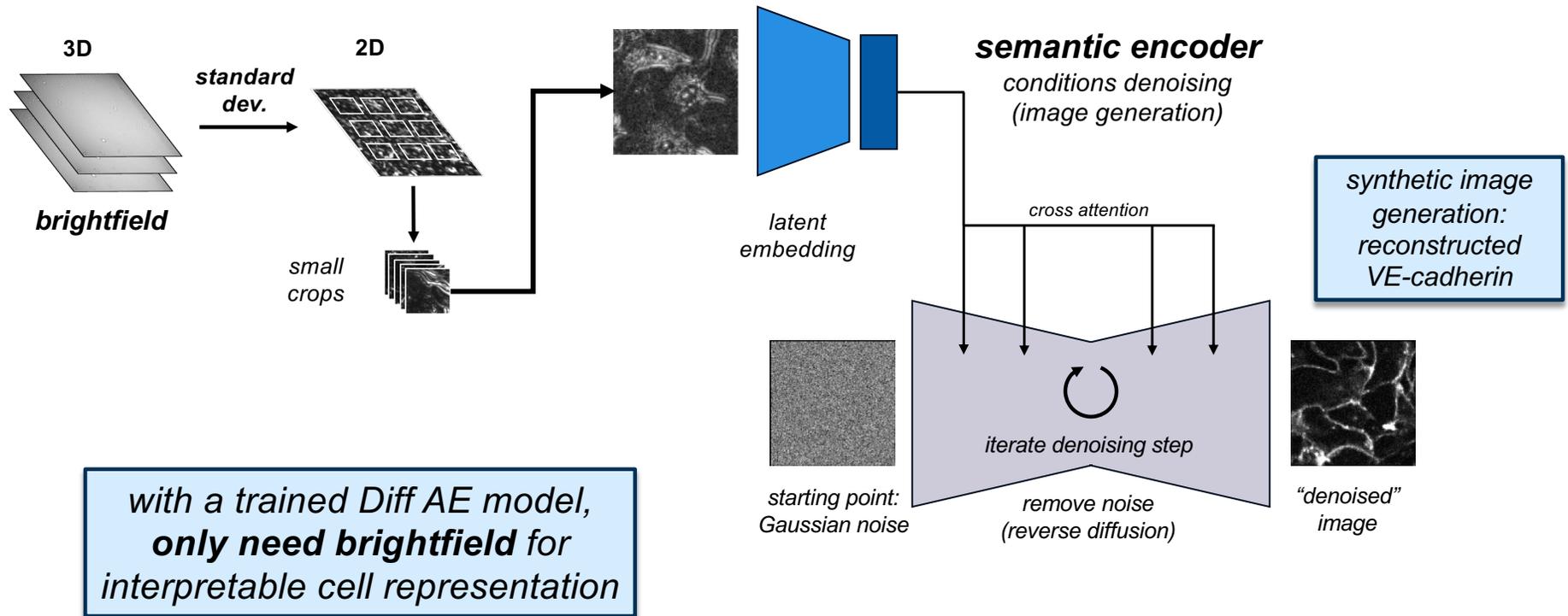
inferring single crop
dynamics from
feature displacements



Diffusion autoencoder: learning high-level features from brightfield



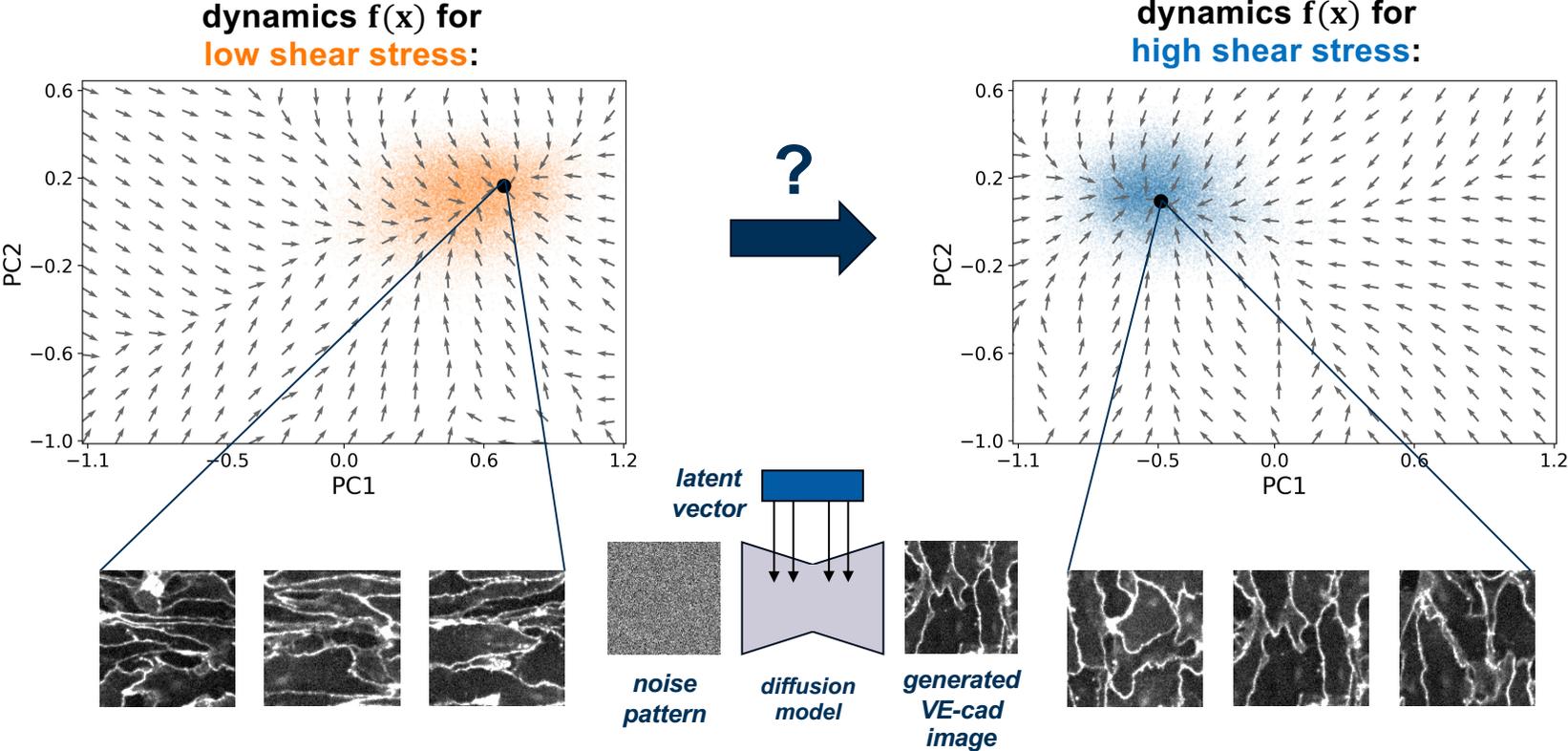
Diffusion autoencoder: extraction and interpretation of latent features



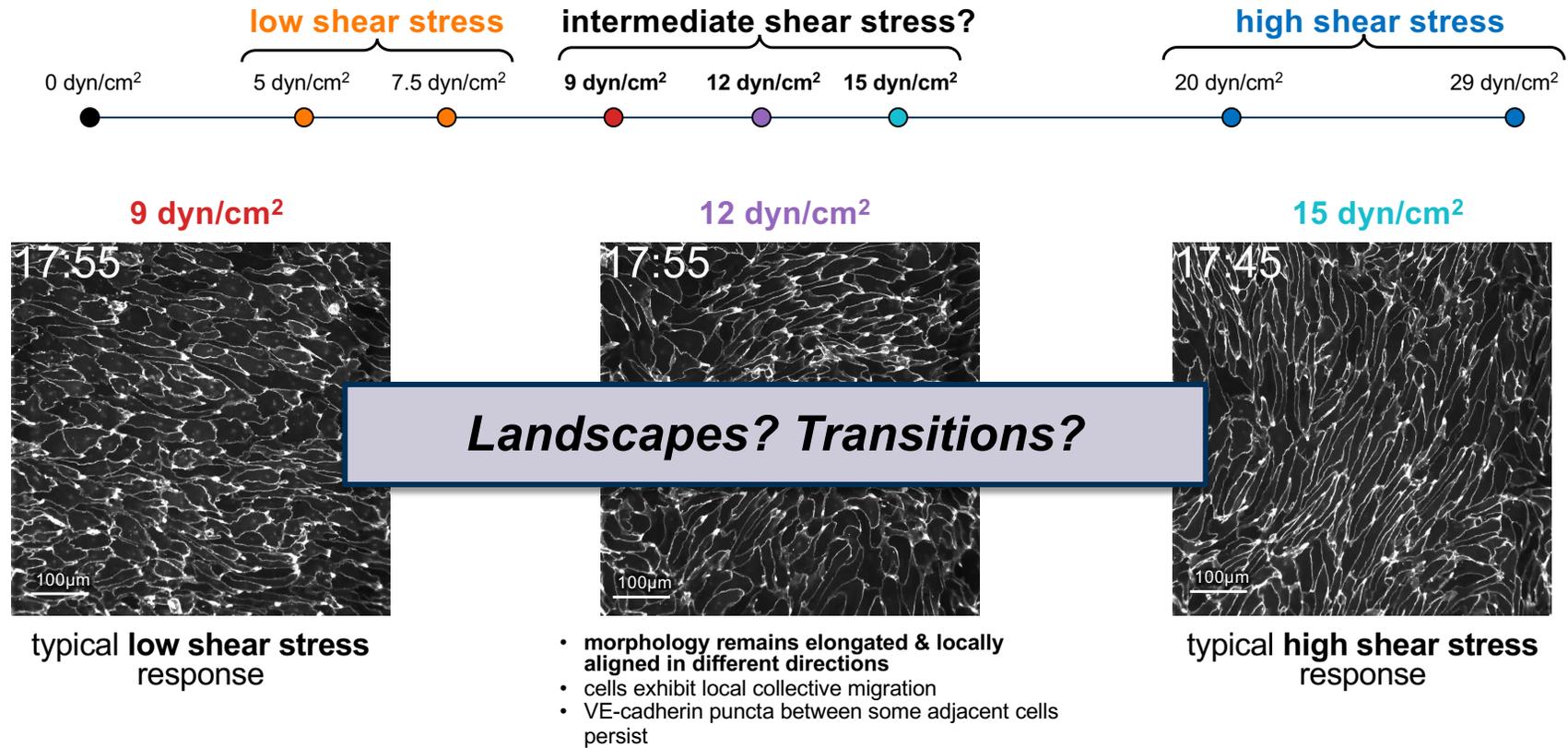
denoising diffusion implicit model

learns to remove Gaussian noise
iteratively from input image

Stable fixed points at low and high shear stress represent distinct endothelial cell morphologies

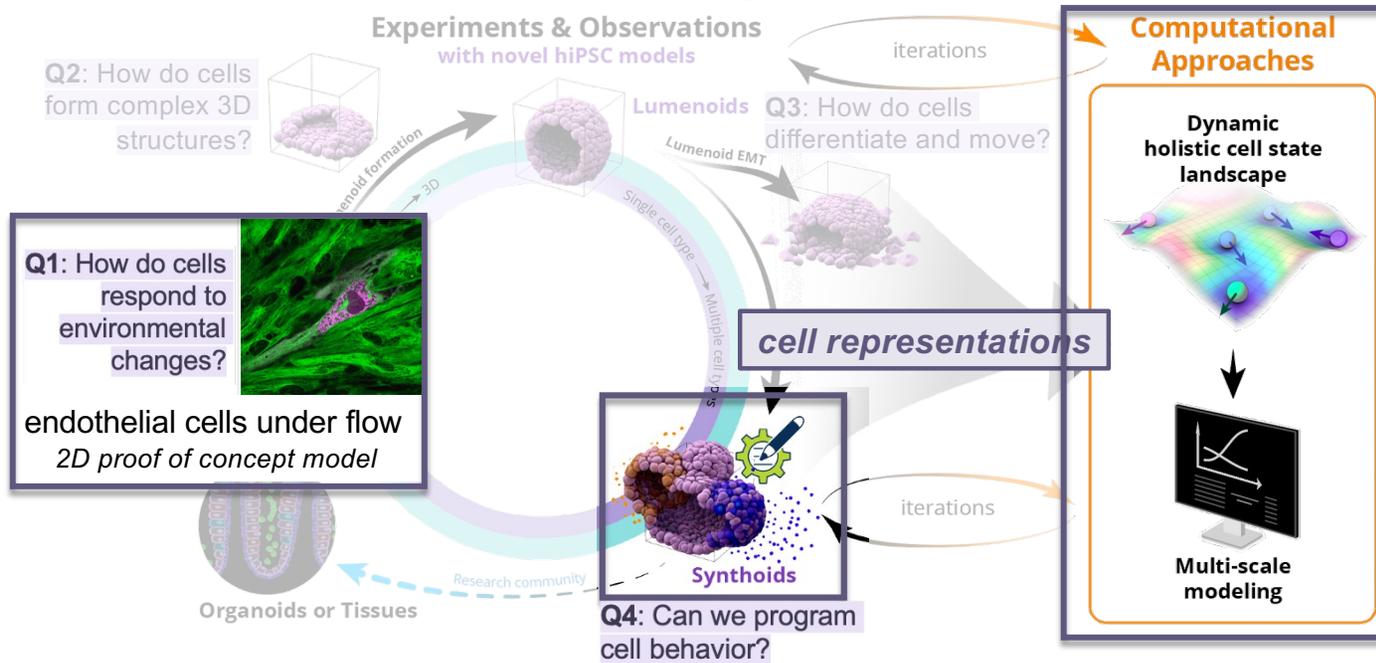


Intermediate shear stress induces mixed cell alignment



CellScapes

Toward *predictive understanding* of multiscale multicellular morphogenesis



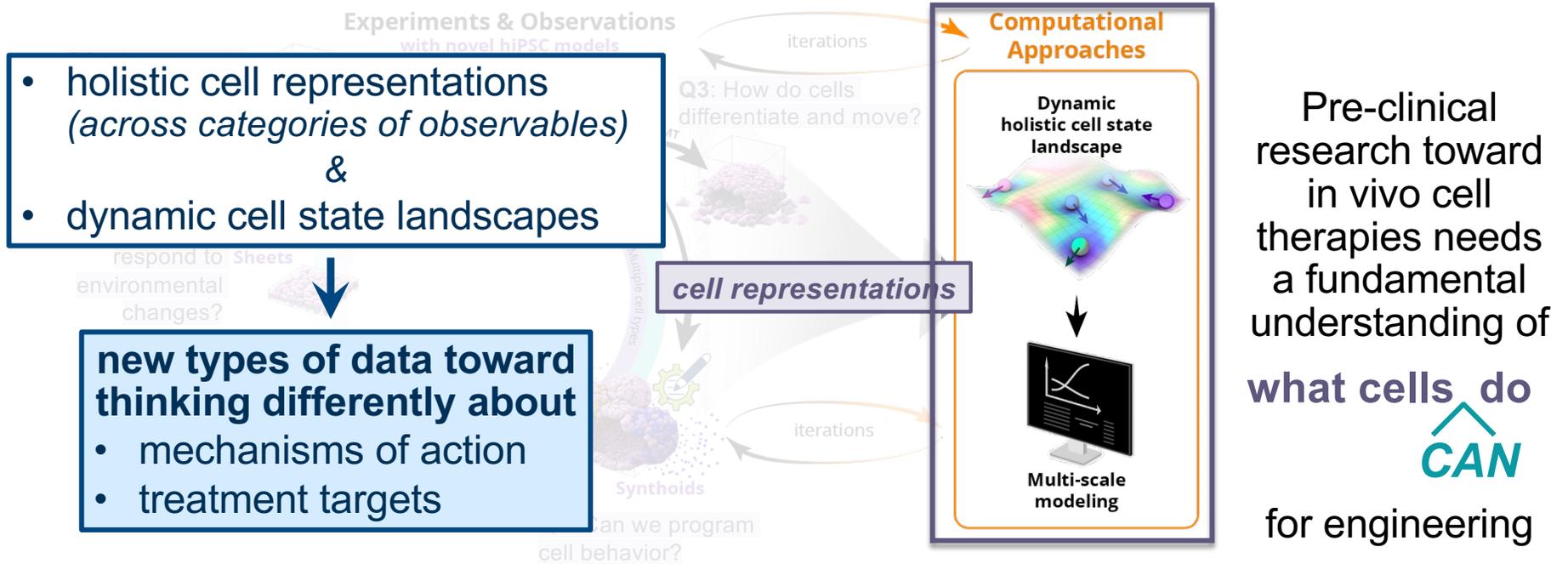
Pre-clinical research toward in vivo cell therapies needs a fundamental understanding of what cells do

CAN

for engineering

CellScapes

Toward *predictive understanding* of multiscale multicellular morphogenesis



THANK YOU

The Allen Institute for Cell Science Team!

Julie Theriot

Department of Biology, University of Washington
and Howard Hughes Medical Institute

Michael Elowitz

Department of Biology and Bioengineering,
Caltech and Howard Hughes Medical Institute

Jin Wang

Department of Chemistry, Stony Brook University

