

Data science in cell imaging

Lecture 7: deep learning in microscopy



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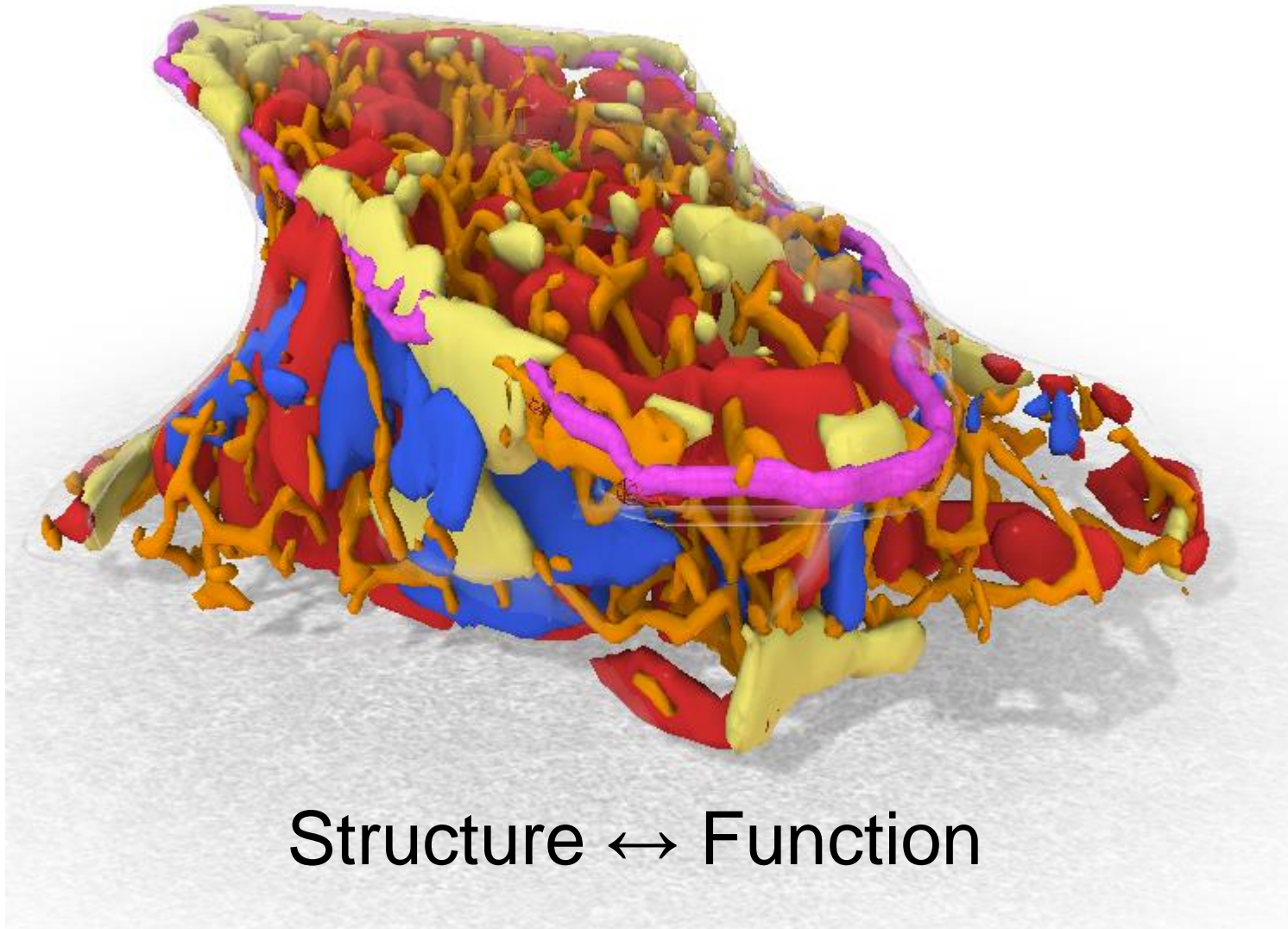


Last week

- Generative models for cell structure with deep learning
- Classifying cell state with deep learning

Look at a cell and know what it is doing

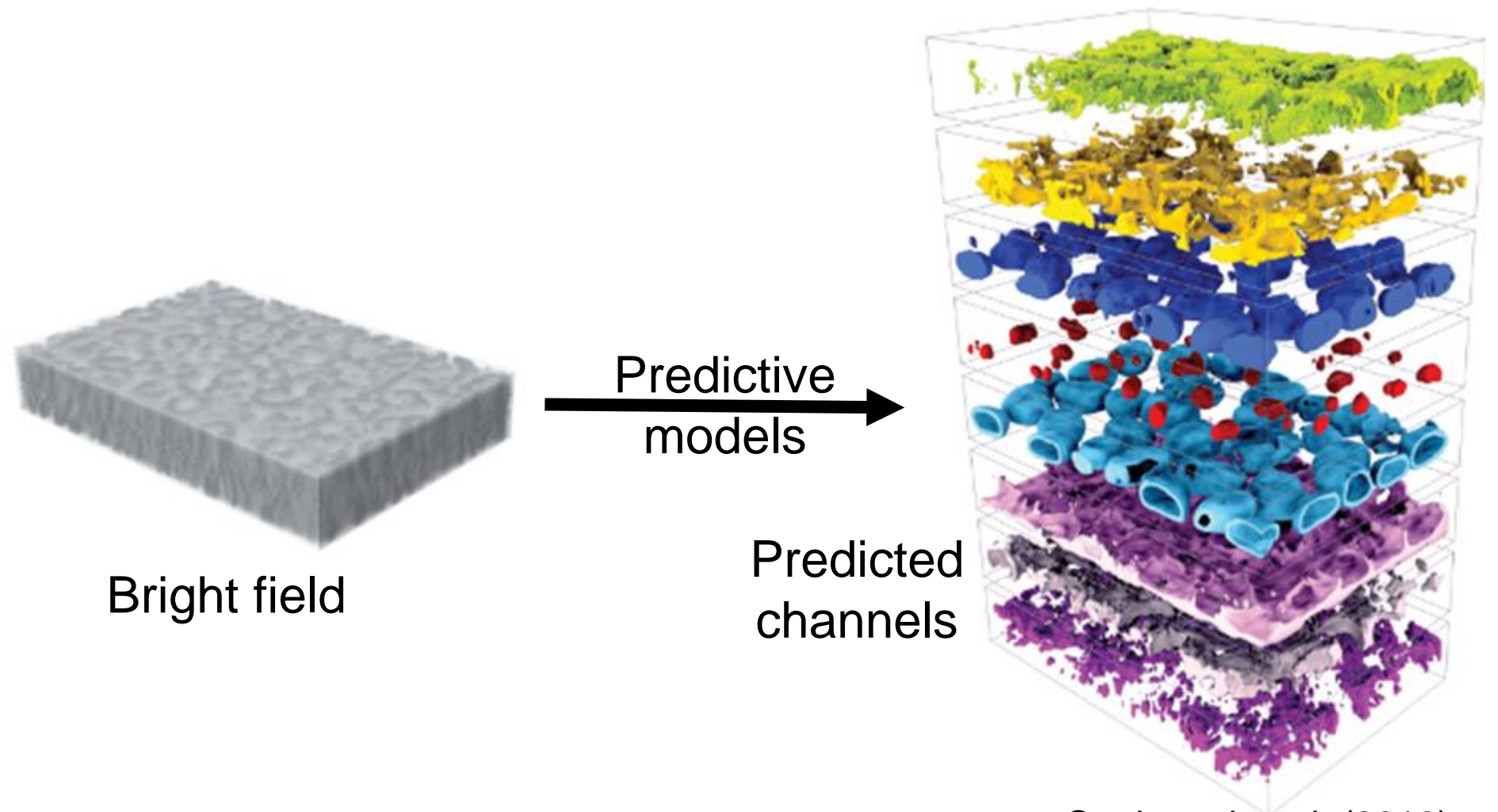
What it did



What it will do

Structure \leftrightarrow Function

Label-free images contain information on the molecular organization of the cell!

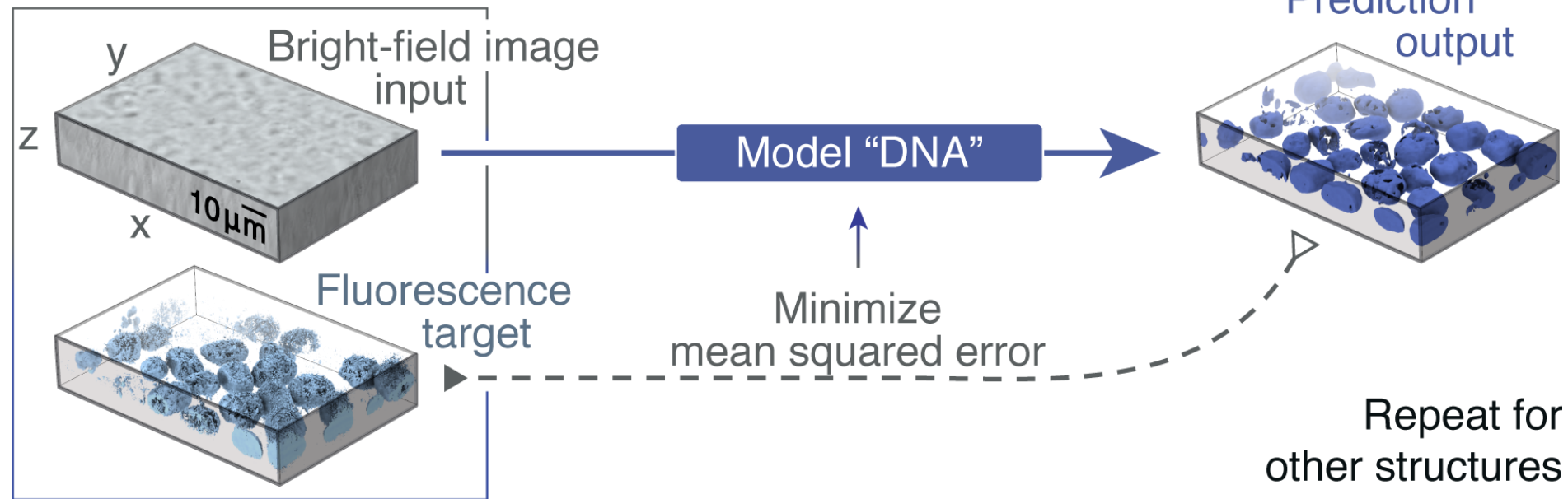


Ounkomol et al. (2018)

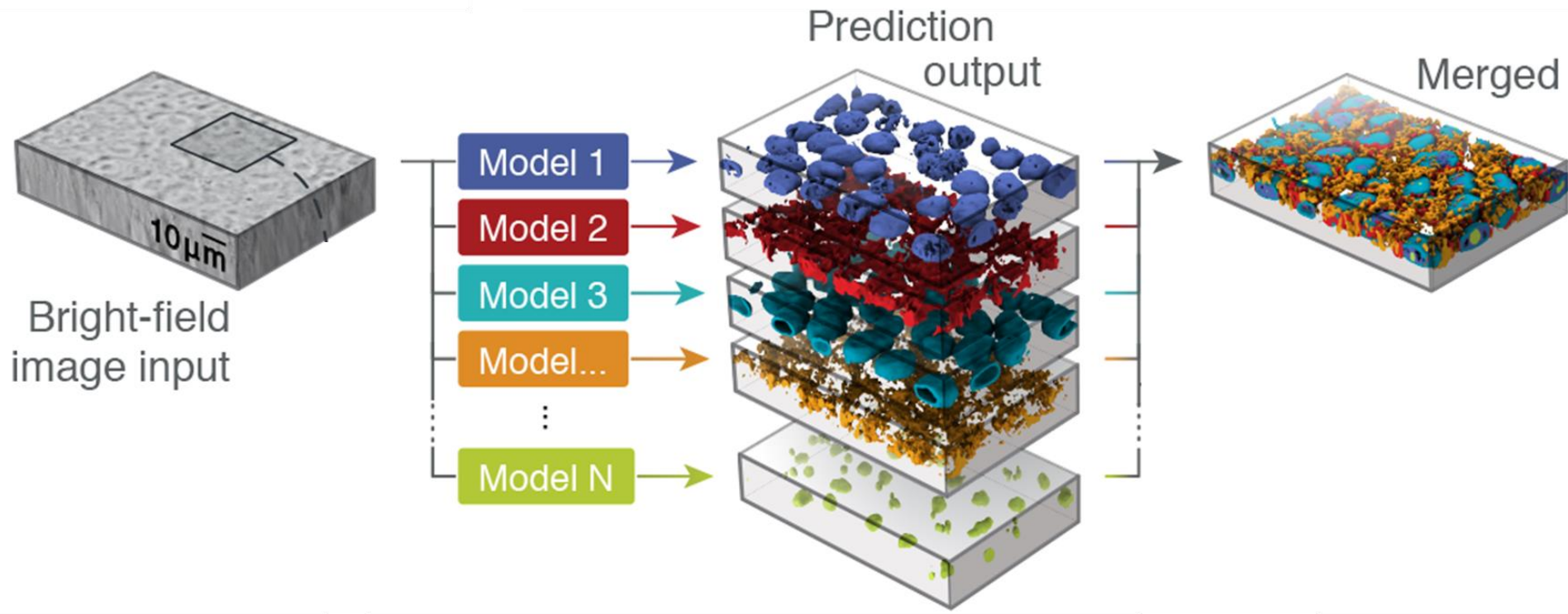
Christiansen et al. (2018)

Unstructured-to-structured information with supervised models

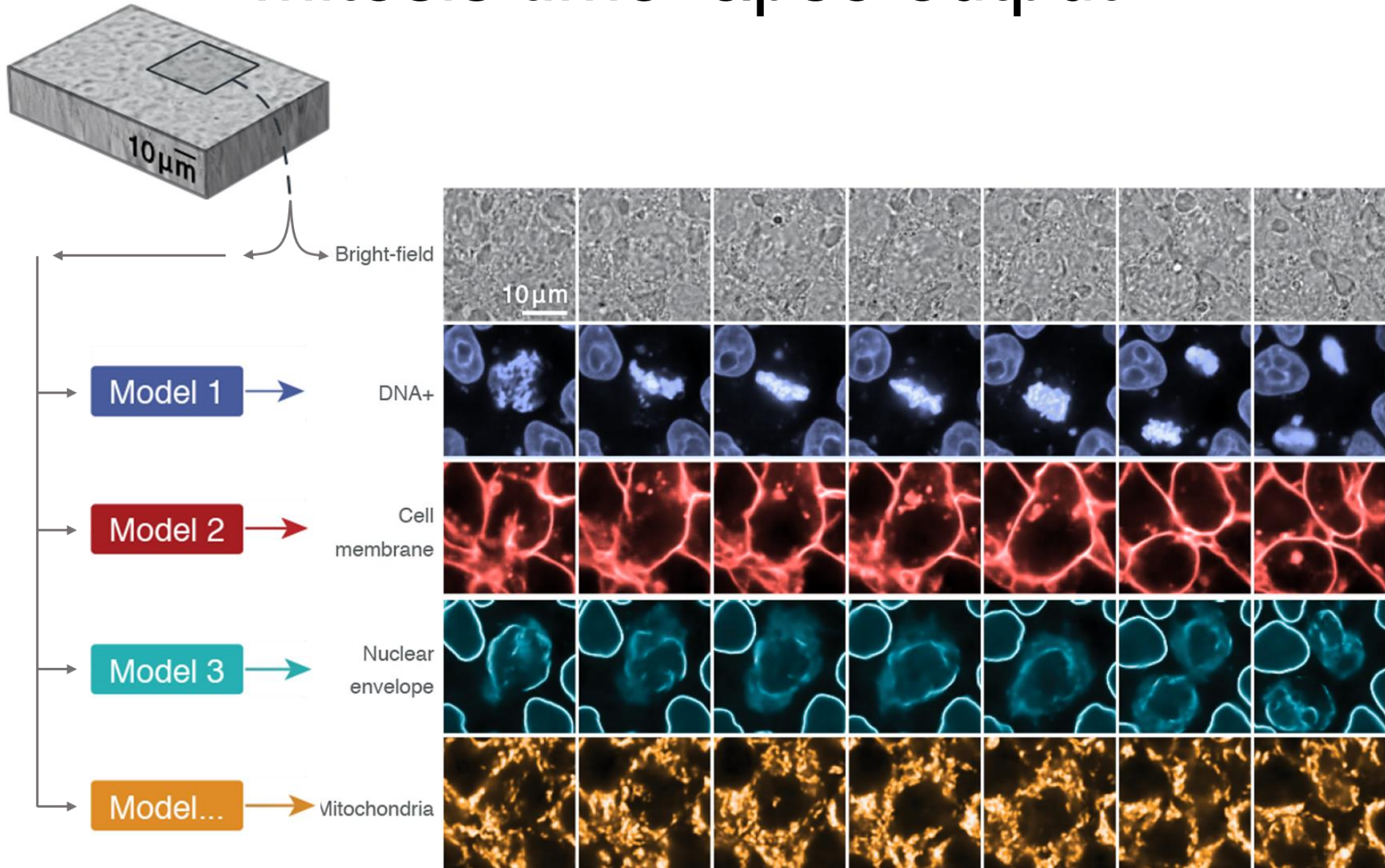
Single model schematic overview



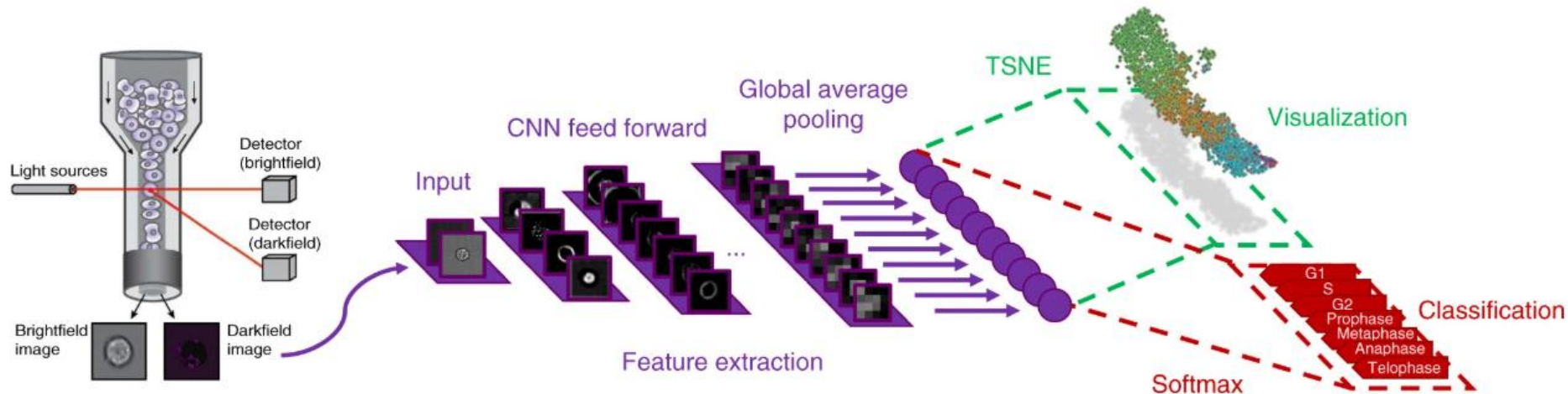
Combining multiple models



Mitosis time-lapse output



Predicting cell cycle / disease progression stage (“pseudo time”) with deep learning



Today

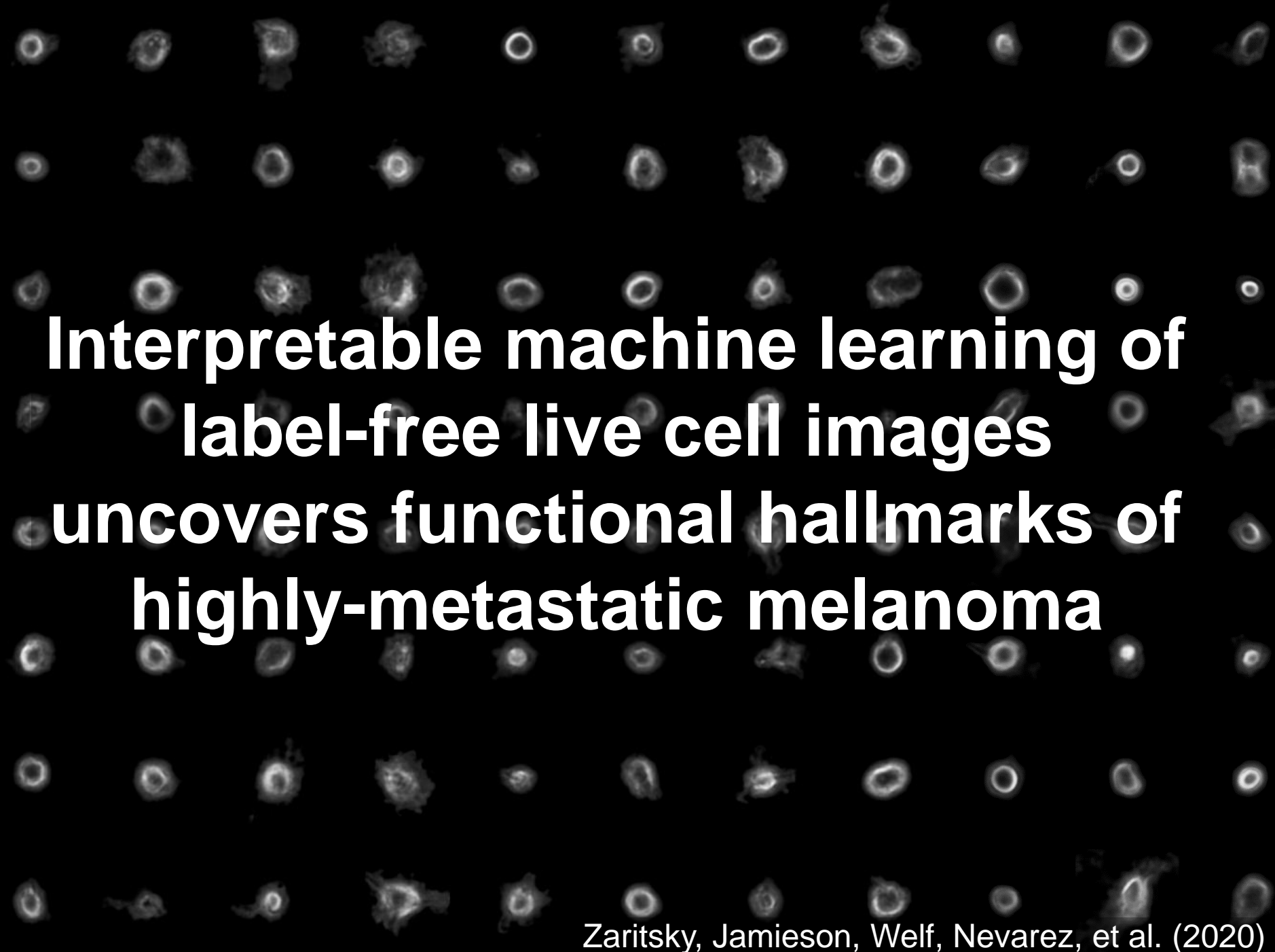
- Guest lecture: Tammy Riklin Raviv, EE, BGU on computer vision in microscopy
- Interpretable deep learning of label-free live cell images uncovers functional hallmarks of highly-metastatic melanoma

Guest lecture

Tammy Riklin-Raviv, EE, BGU

Computer vision in microscopy

(slides not available for public use 😞)



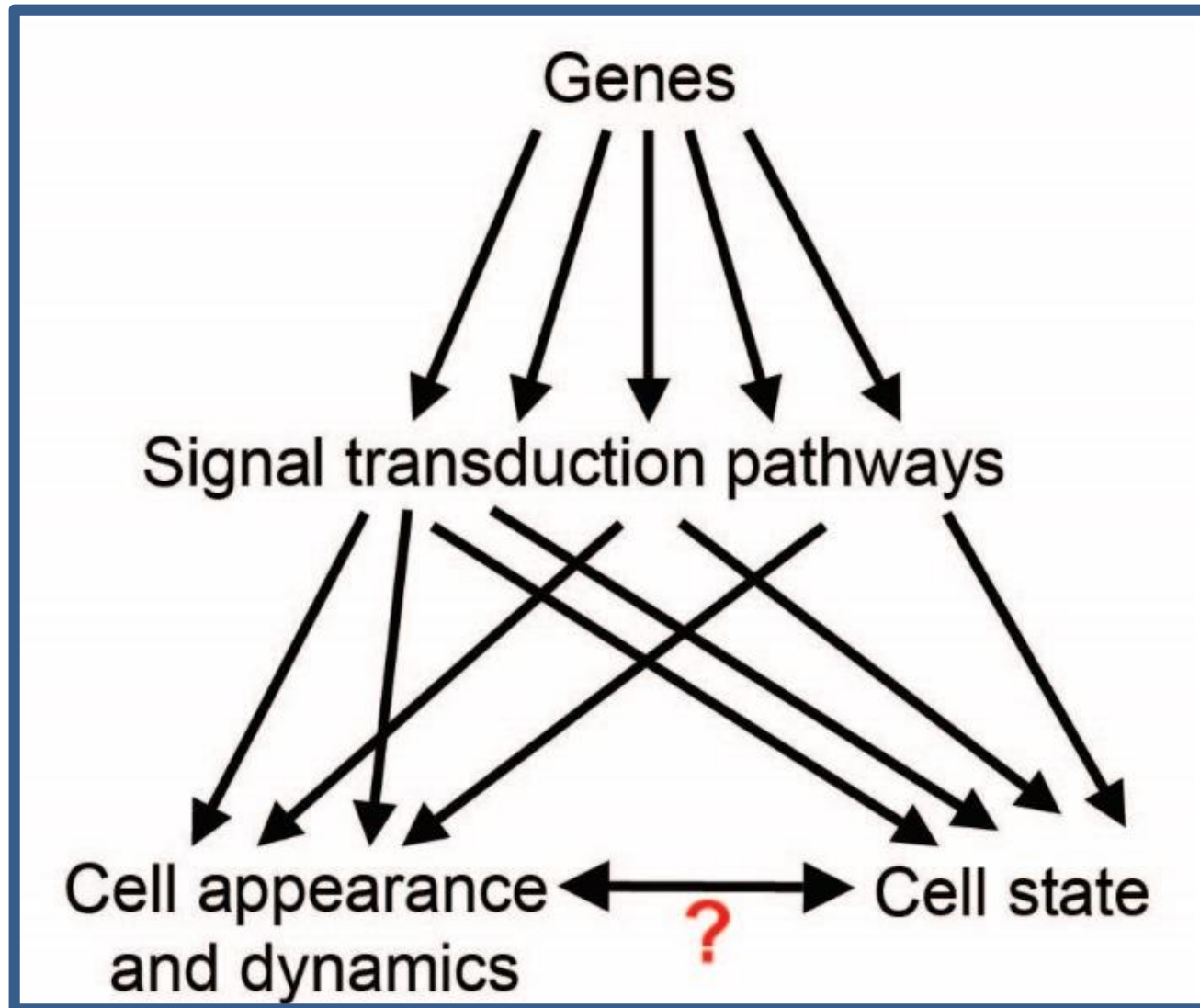
**Interpretable machine learning of
label-free live cell images
uncovers functional hallmarks of
highly-metastatic melanoma**

Zaritsky, Jamieson, Welf, Nevarez, et al. (2020)

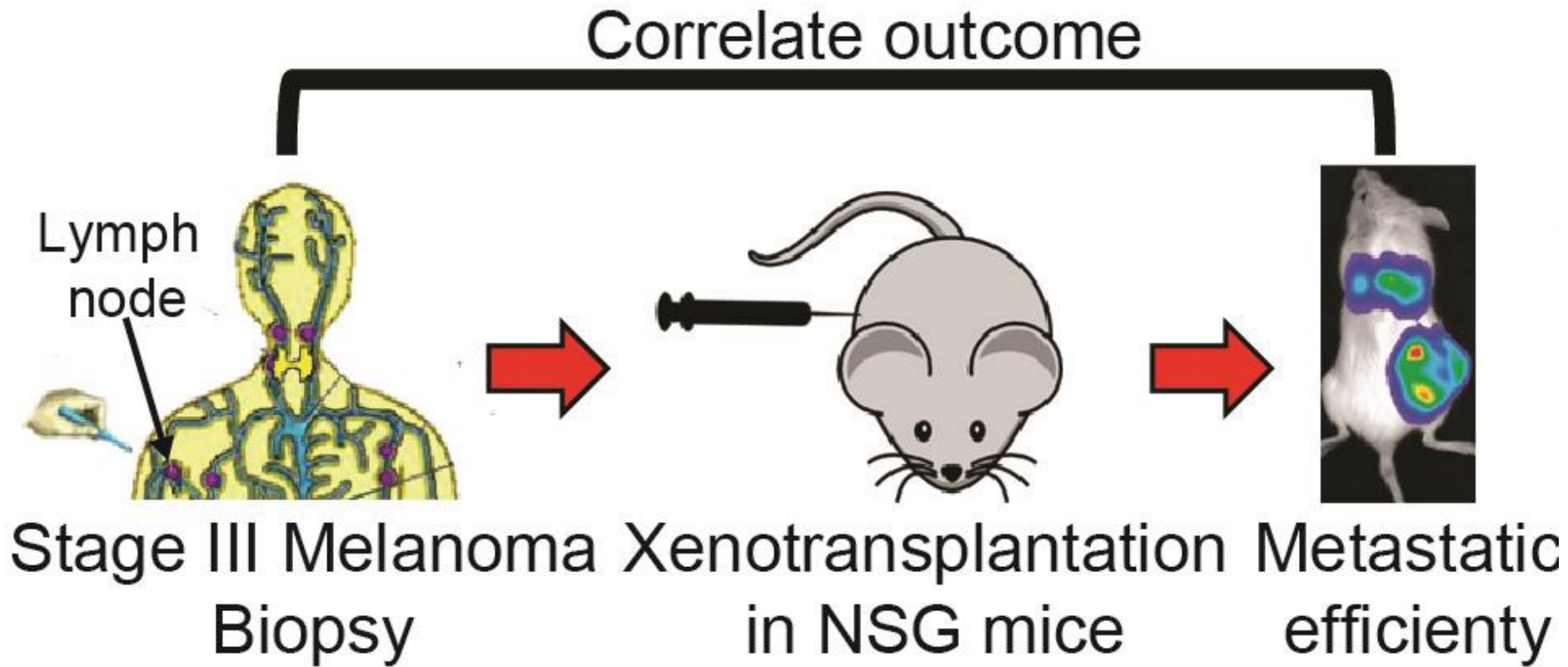
Can we predict cancer cell functional states from live label-free cell images?

Melanoma as model

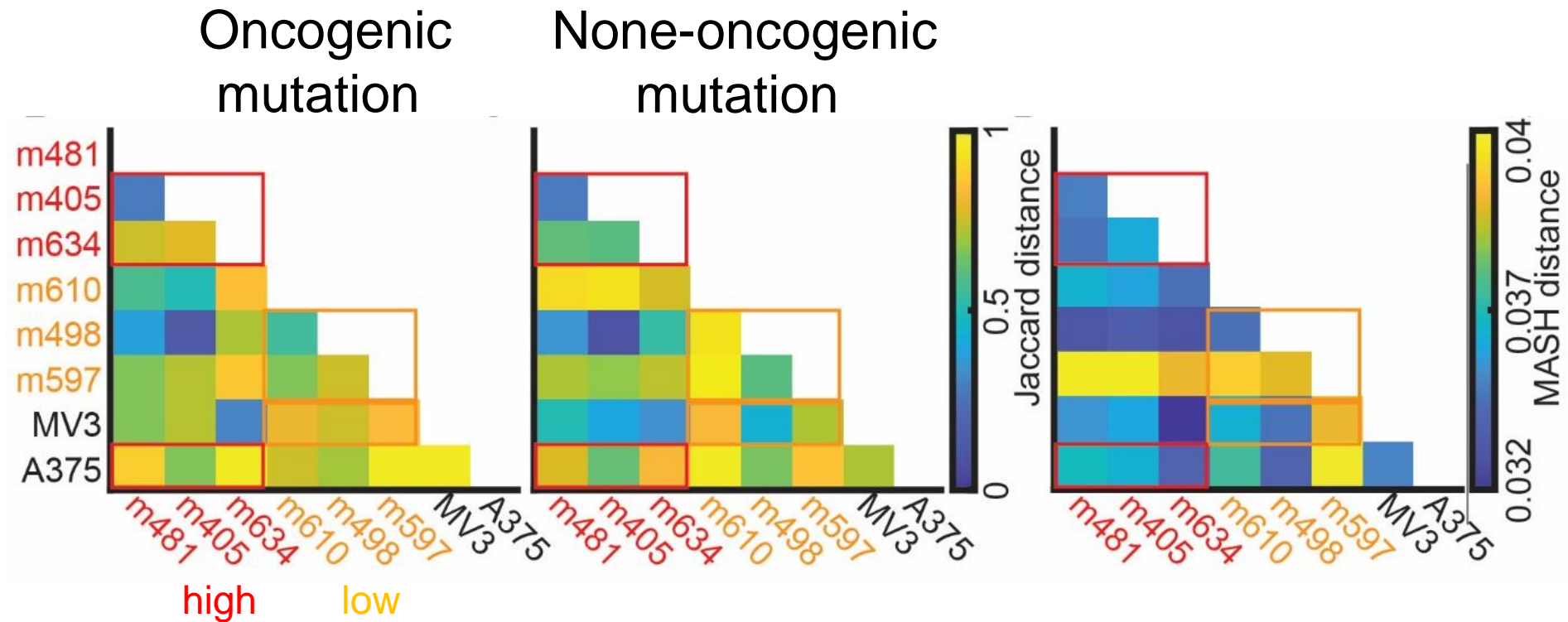
Genetic heterogeneity → functional readout to discriminate cell type



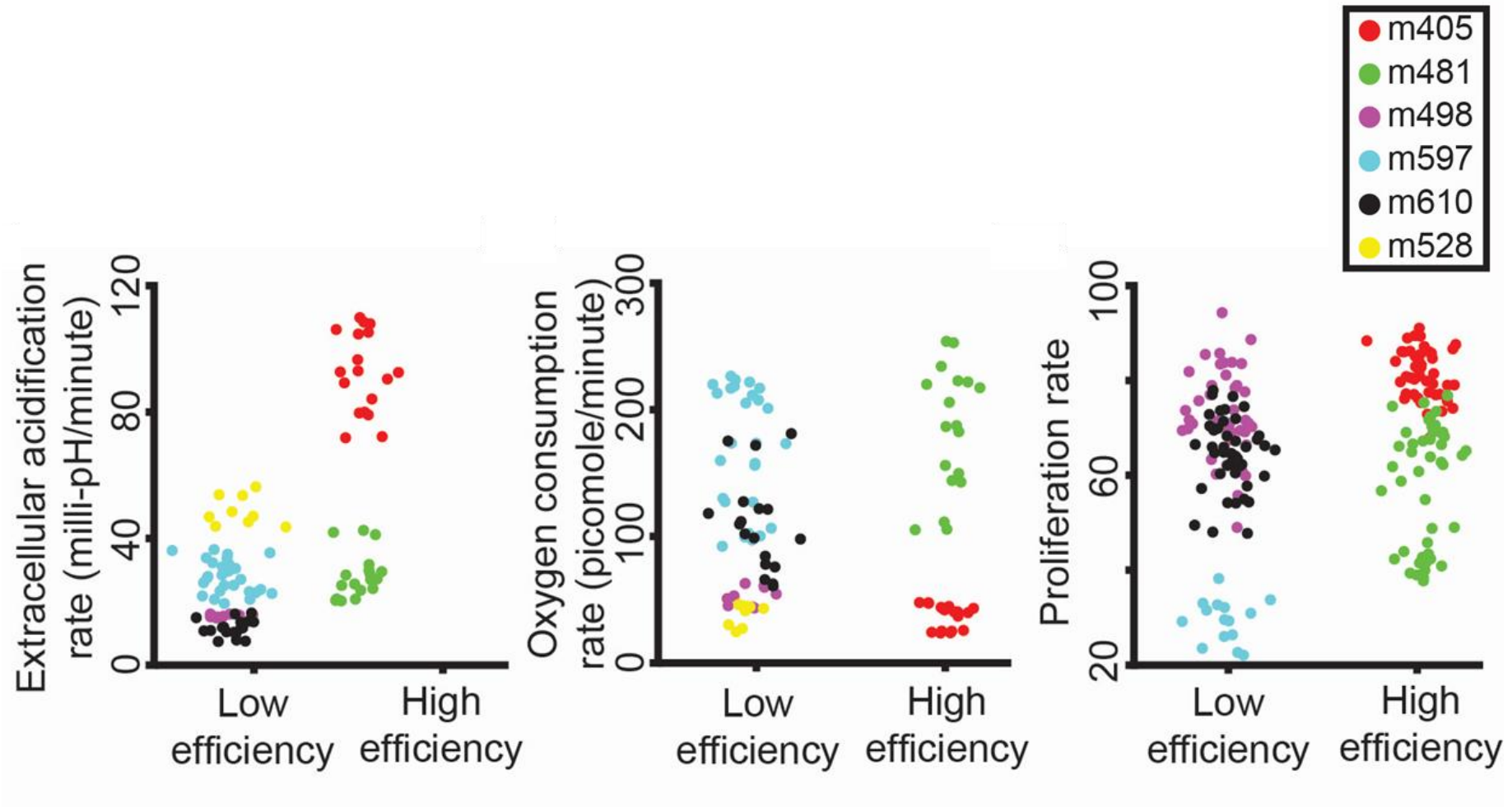
Low versus high metastatic efficiency in patient-derived melanoma



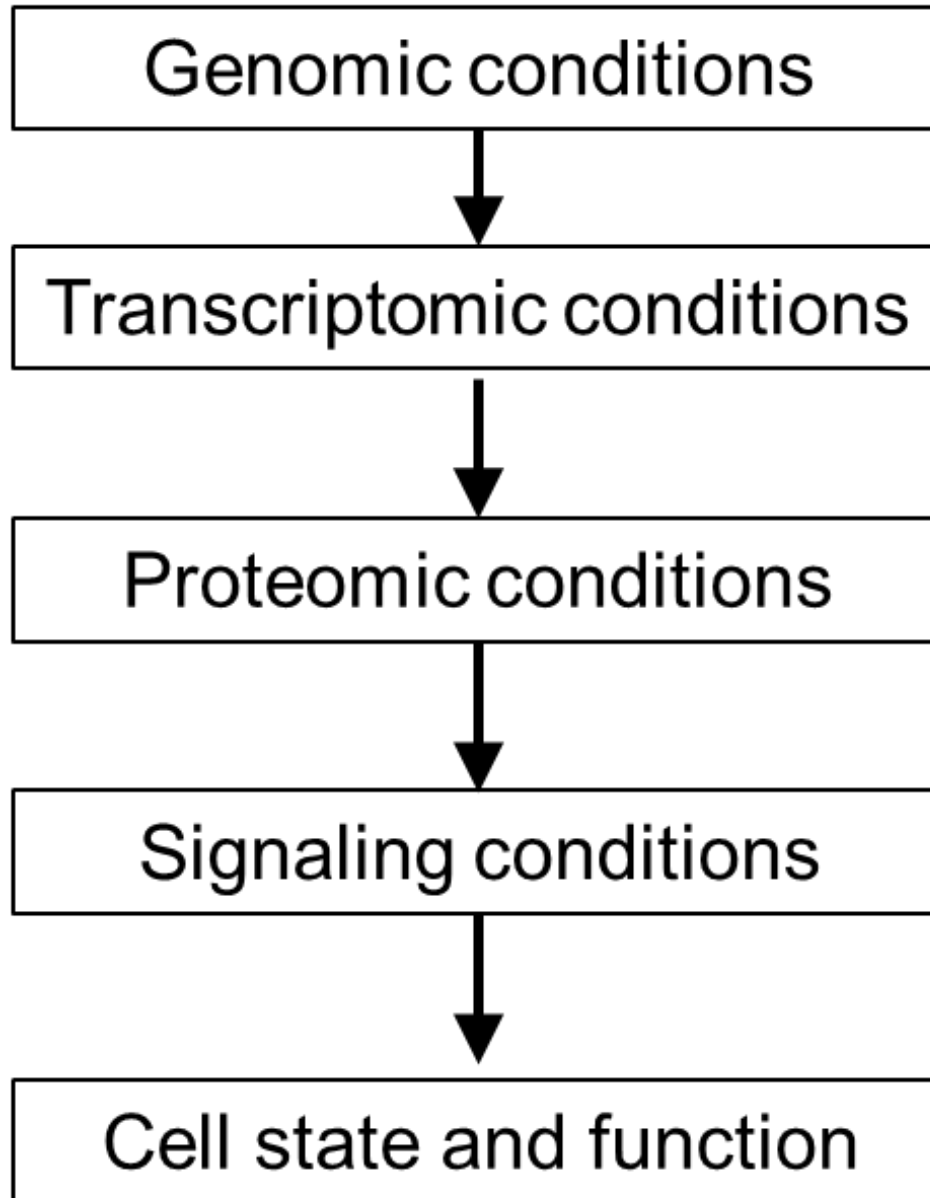
Genomics failed to predict melanoma metastasis efficiency



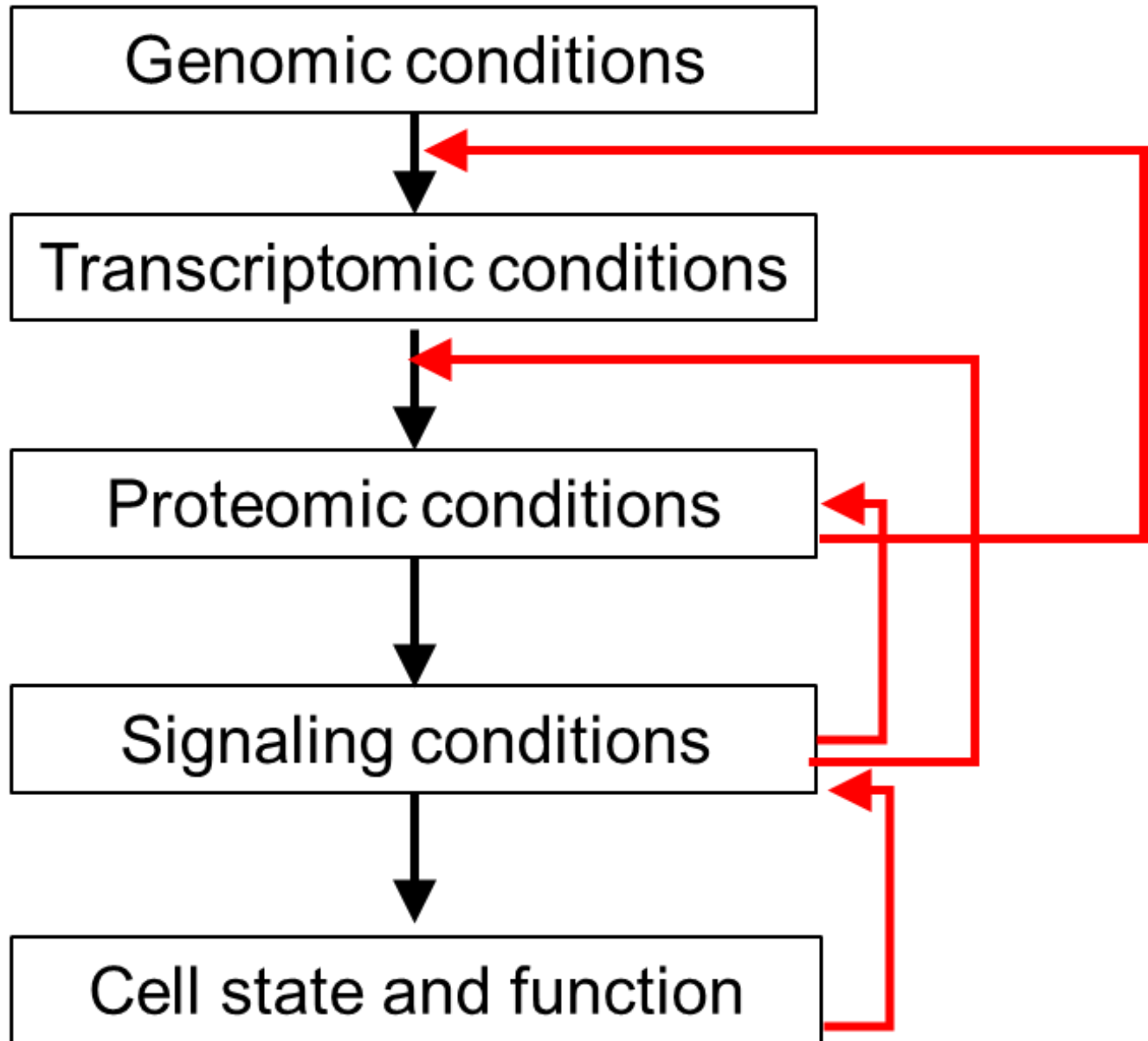
Standard cell biology assays failed to classify melanoma metastasis



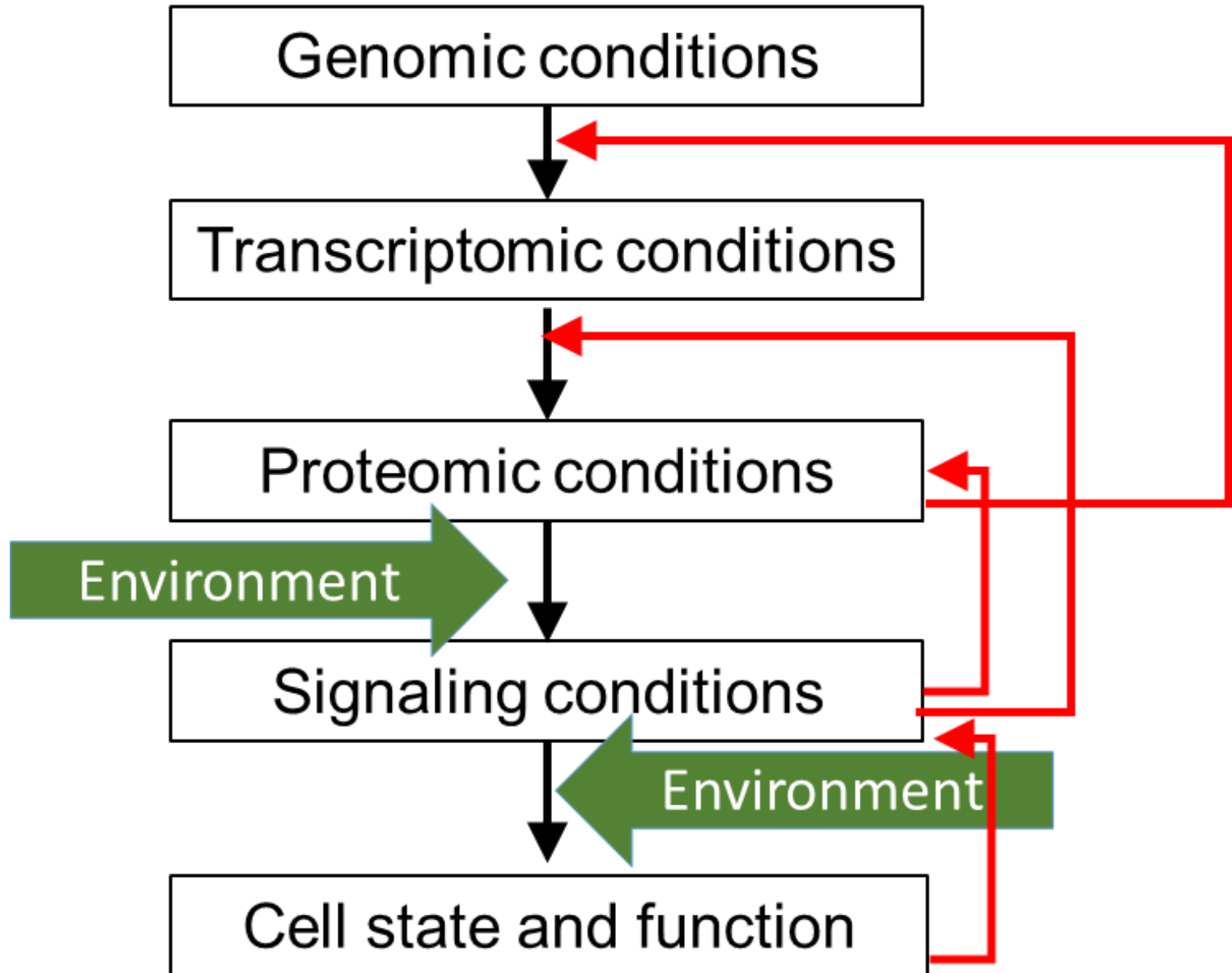
The central dogma of biology



But in reality...



But in reality...



We need functional
readouts to stratify
melanoma!

Experimental settings

Requirement	Implementation
Melanoma cells	Six cell lines, nine stage III patient-derived tumors
Minimal cell intervention	Label-free
Physiologically relevant microenvironment	Cells on top of collagen
Cell dynamics	Live cell imaging
Sufficient N	High-content imaging

00:00 HH:MM

50 mm



Live cell histology: label-free live imaging of individual melanoma cells

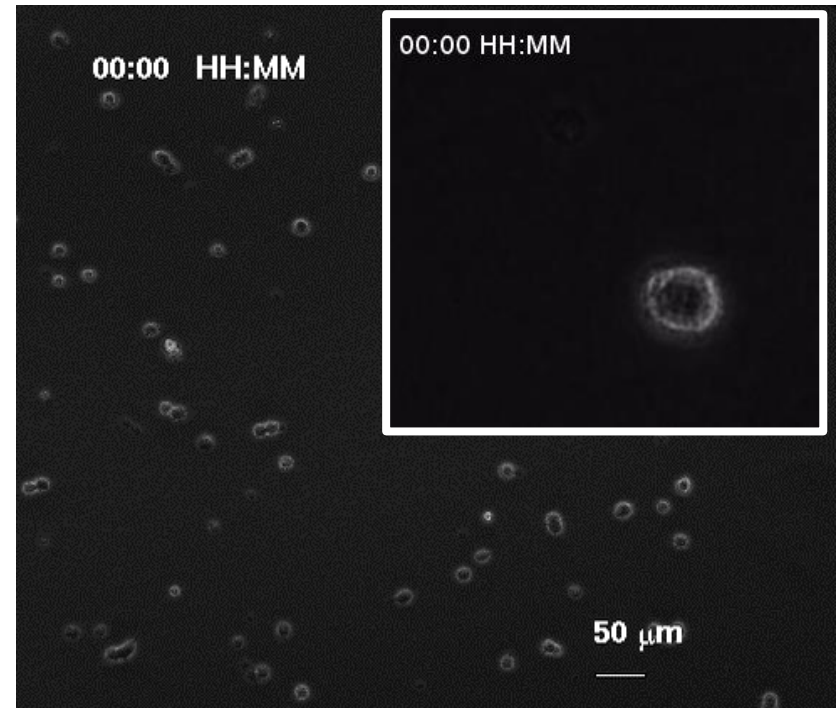
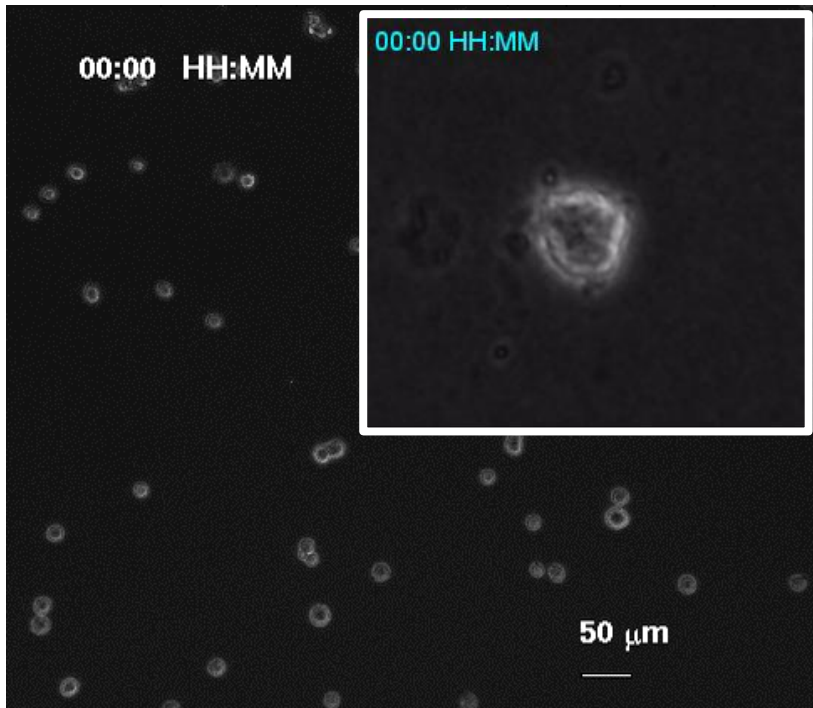
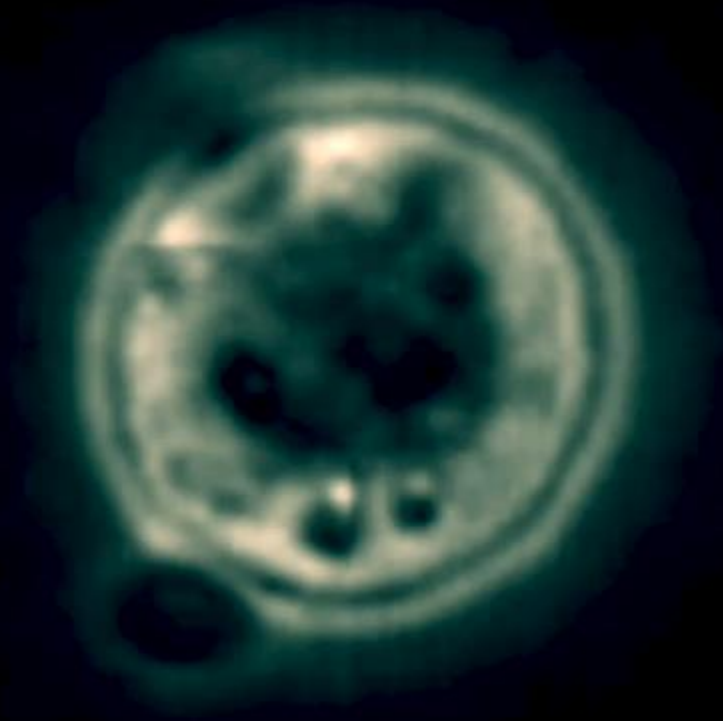
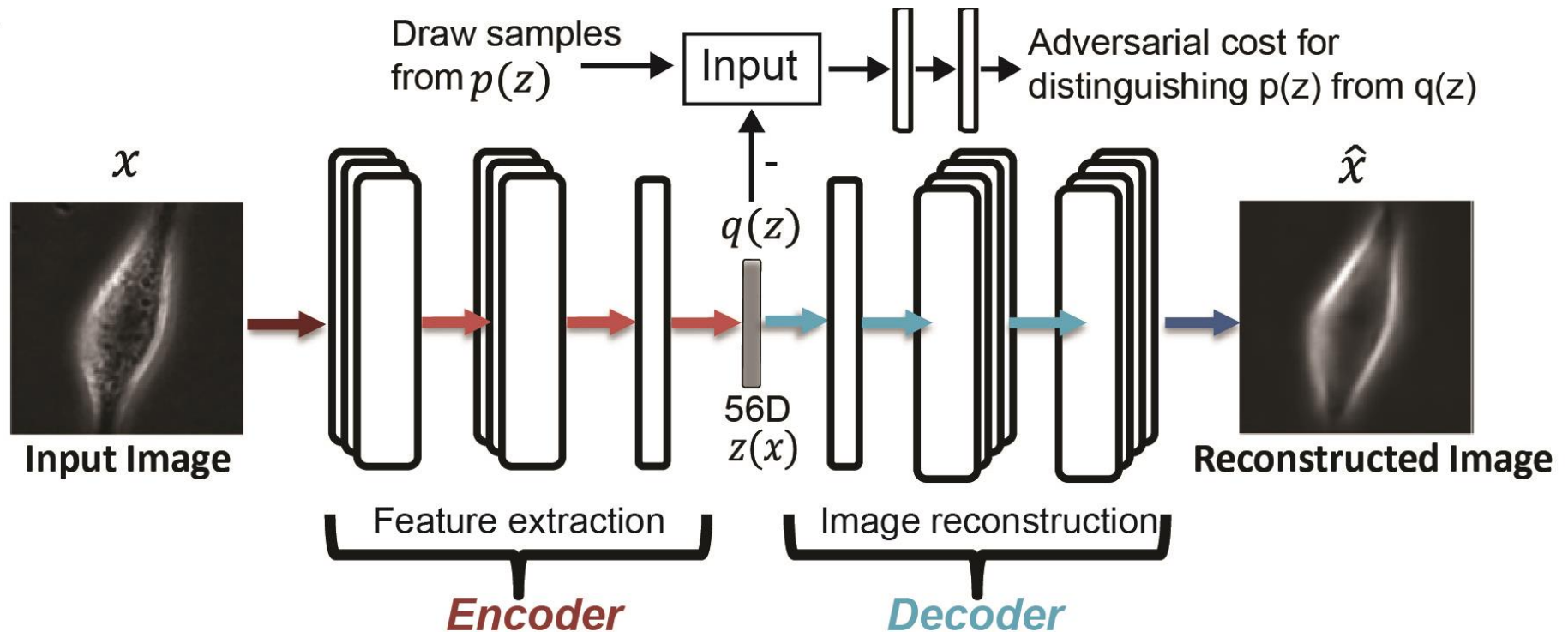


Image analysis pipeline

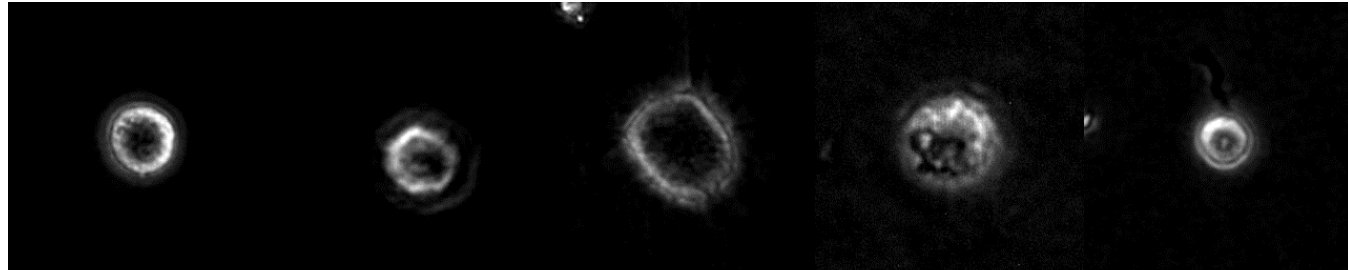


Adversarial autoencoder for unsupervised feature extraction

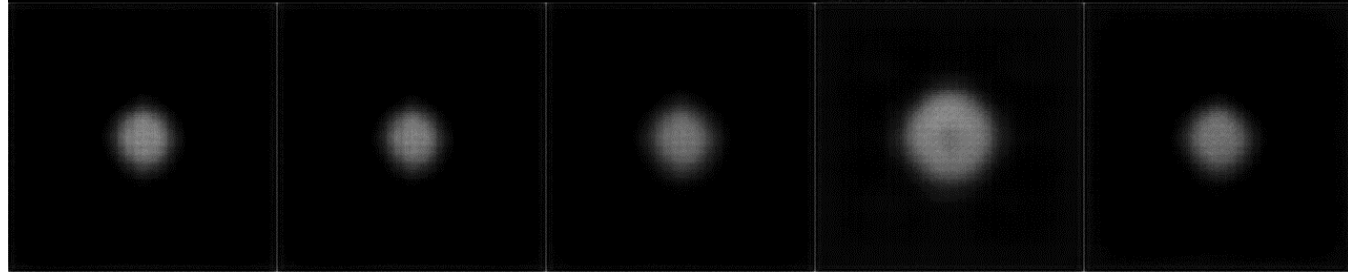


Training to reconstruct a melanoma cell

Input



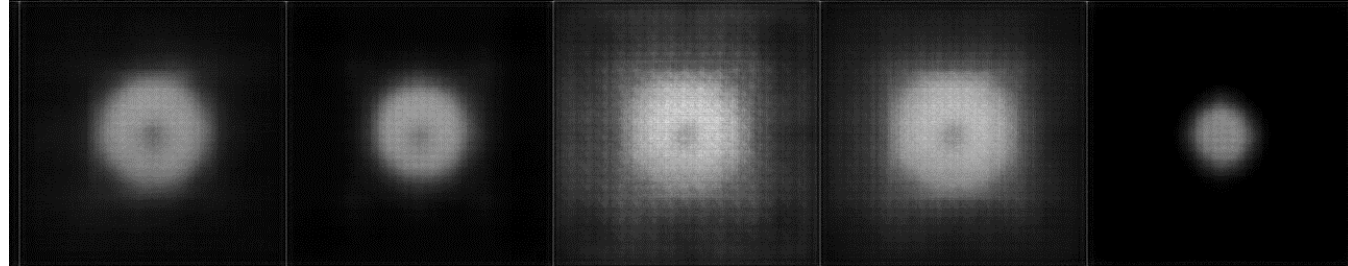
Reconstructed



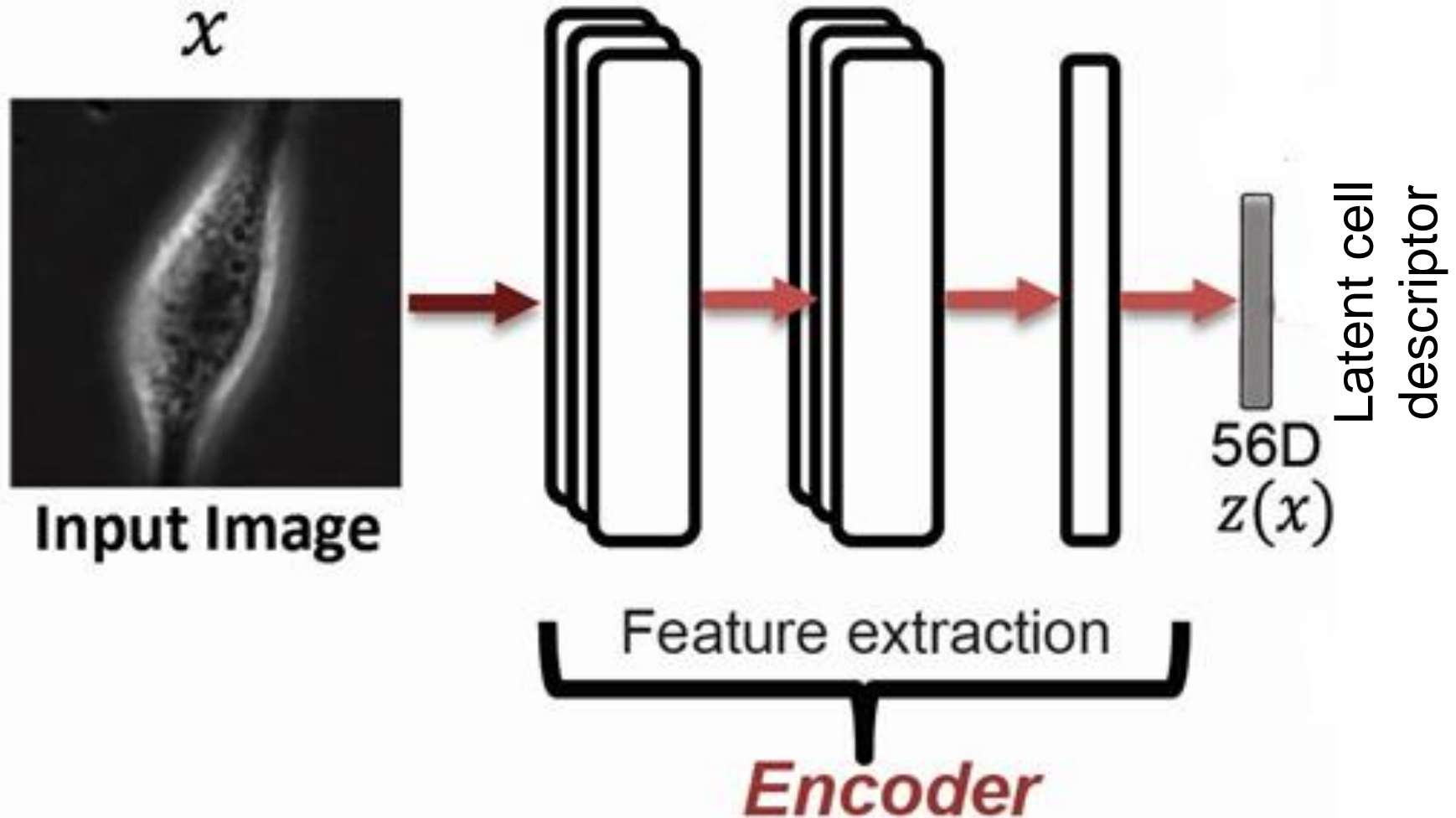
Input



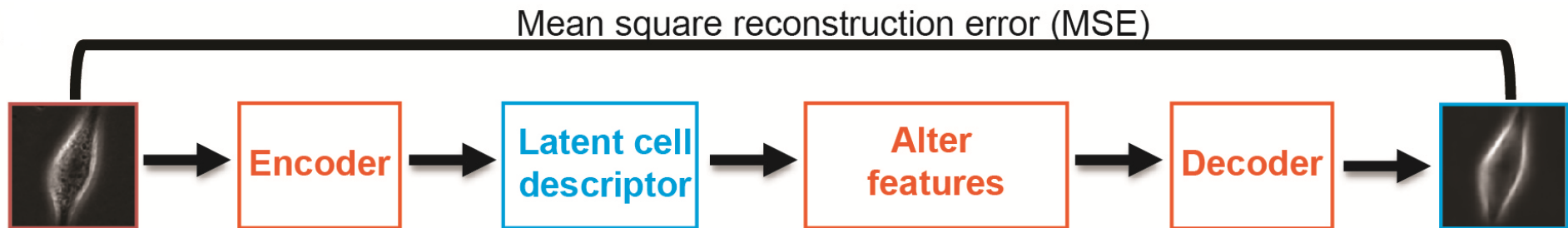
Reconstructed



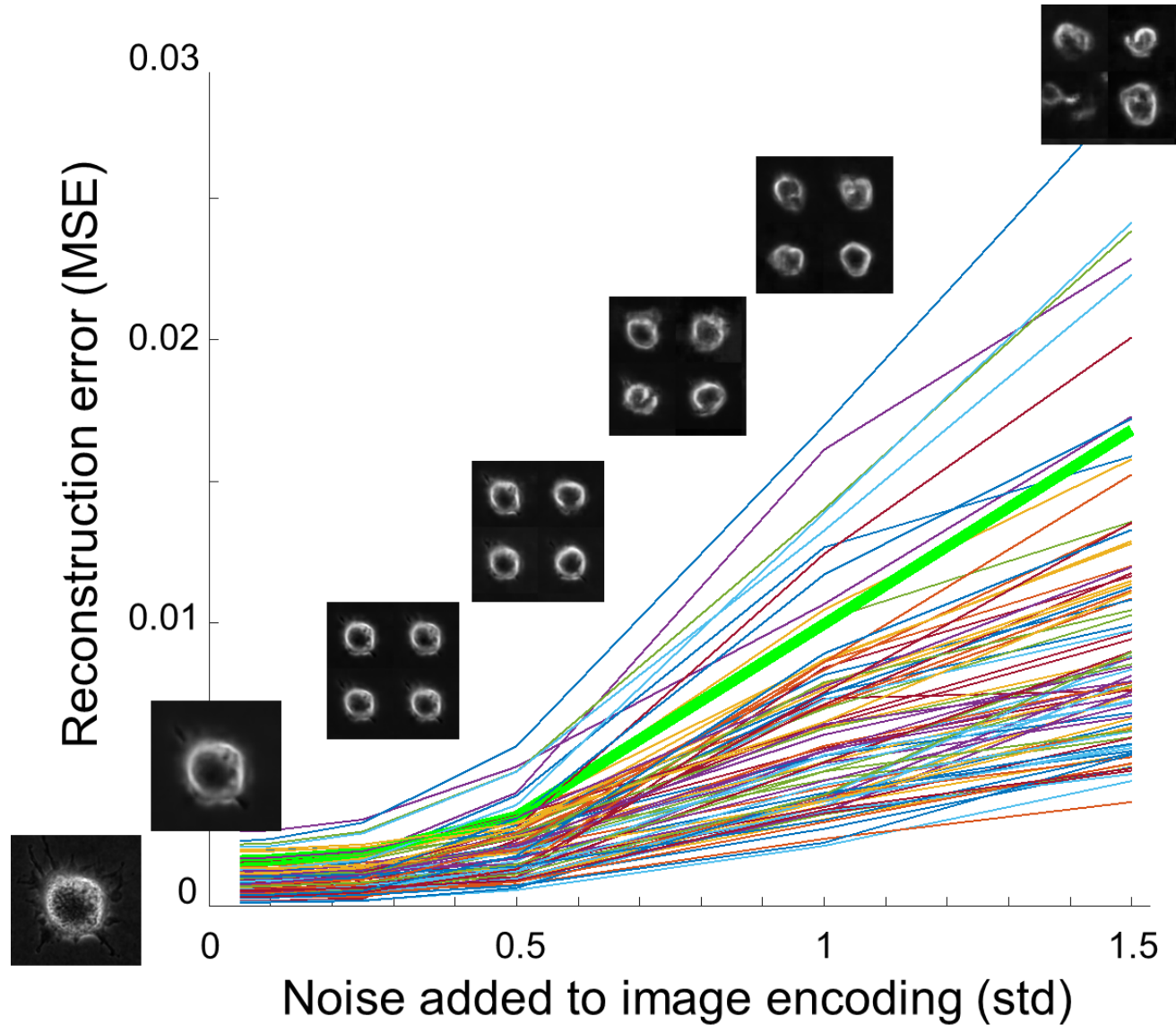
Using adversarial autoencoders for unsupervised feature extraction



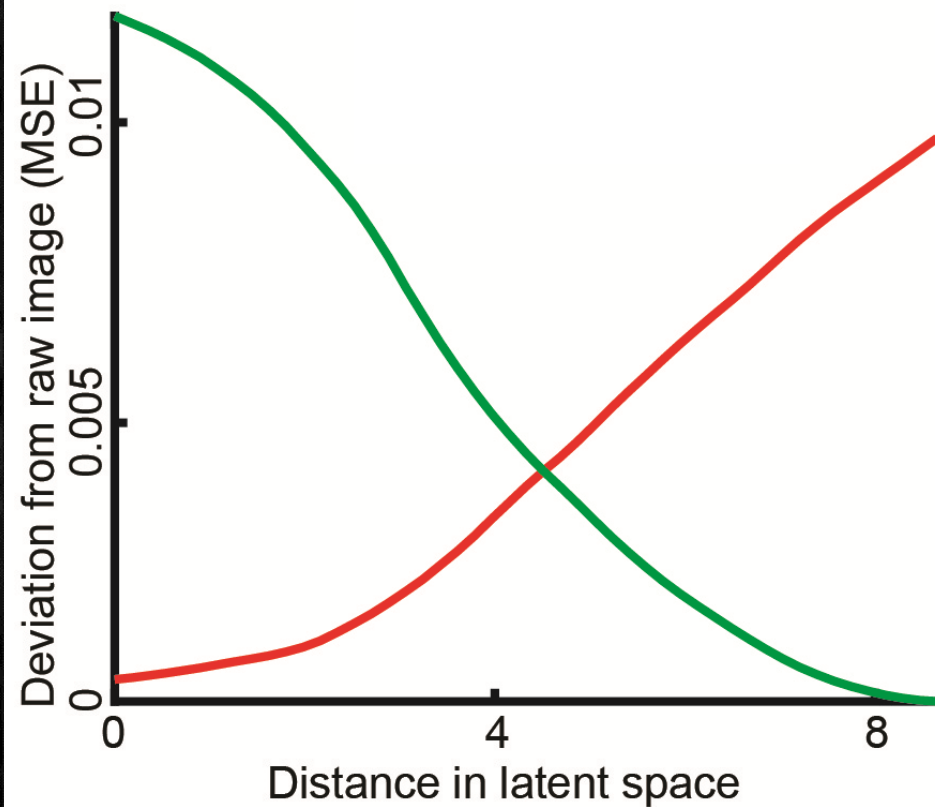
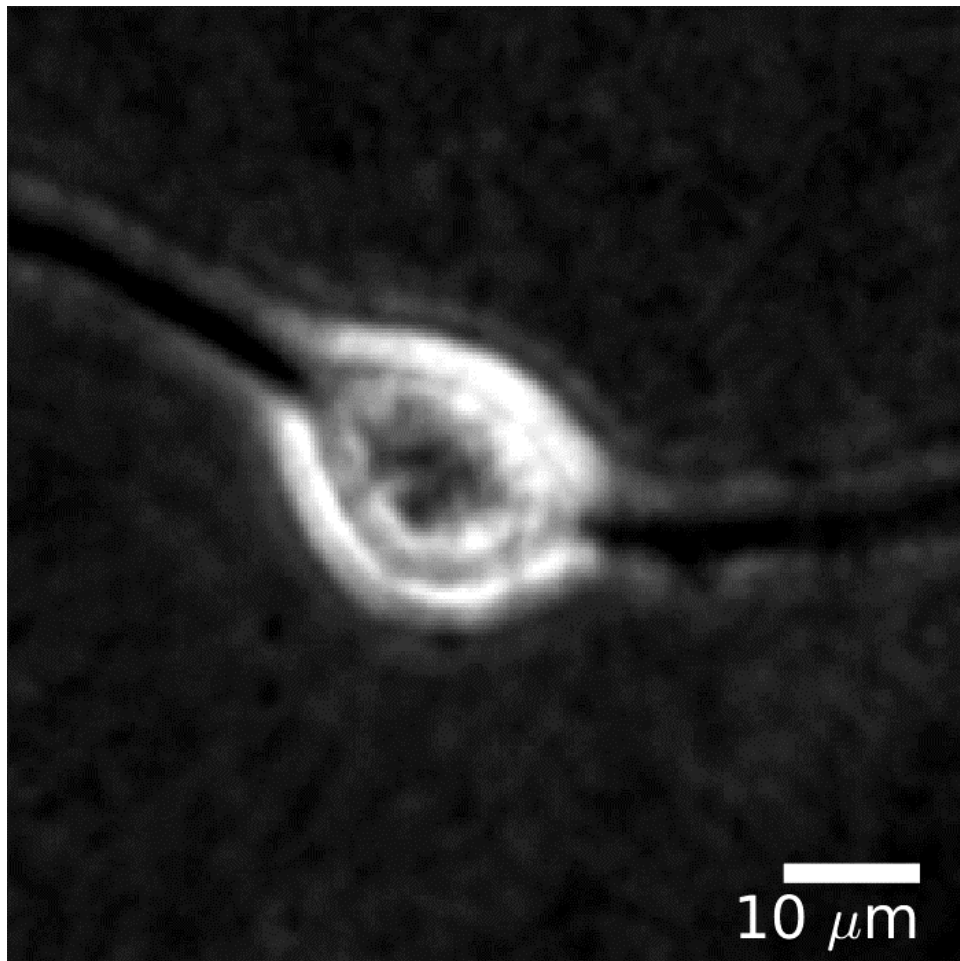
The adversarial autoencoder latent vector is a quantitative measure for cell appearance



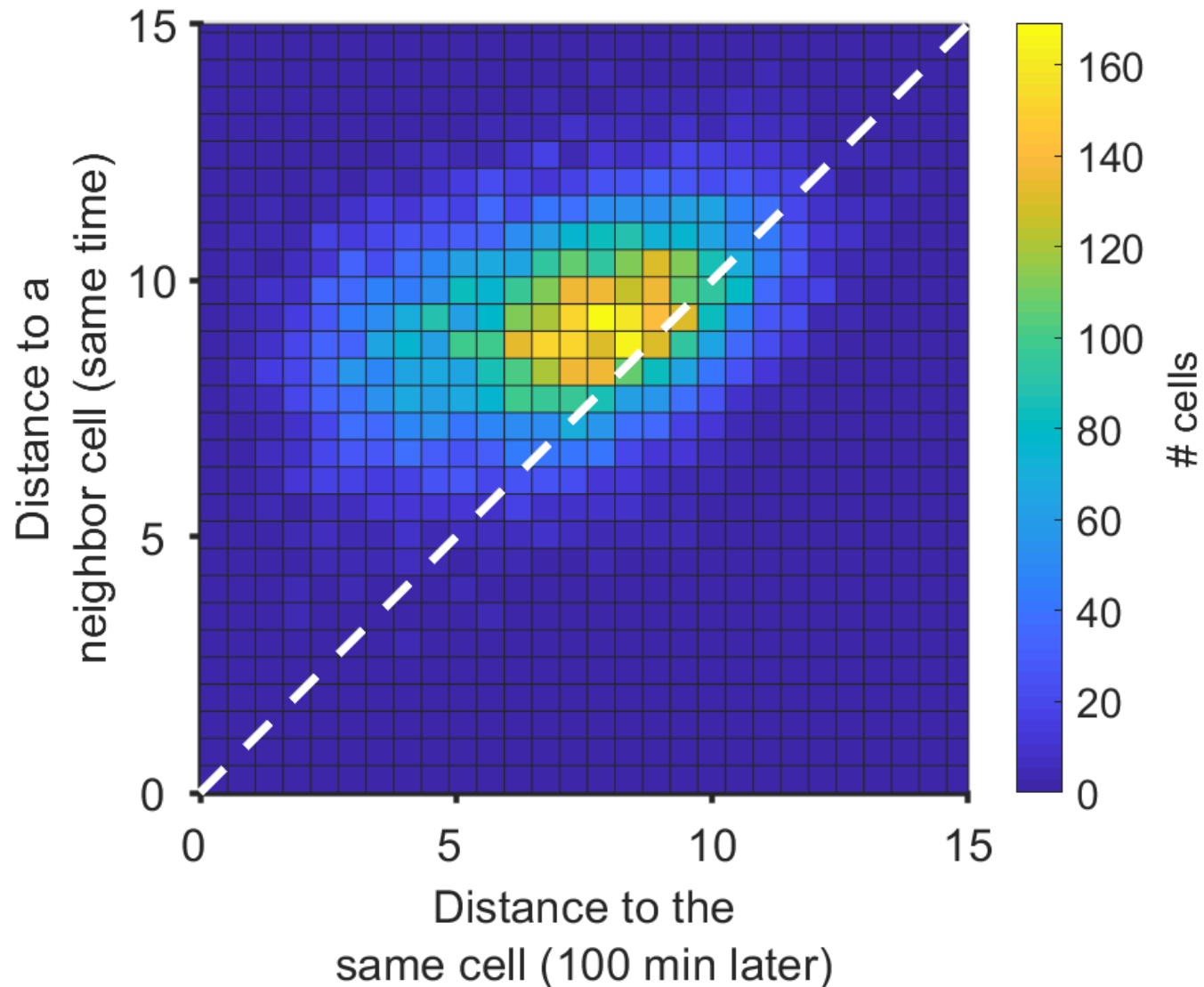
Deviation from encoding associates to deviation from reconstructed image



Cell "morphing": gradually transforming one cell to another



Cells are more self-similar over time than two neighboring cells at the same time

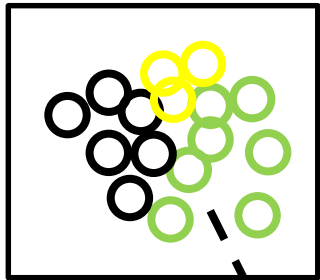


Batch effects (inter-day variability)
mask the functional cell state

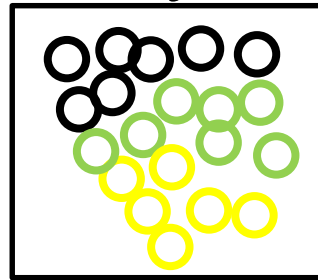
Assessing day-to-day variability in feature representations

○ ○ ○ Different cell origins

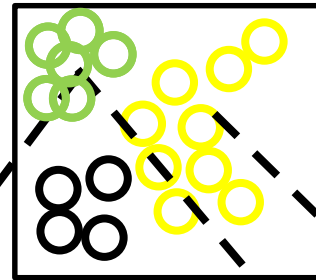
Day 1



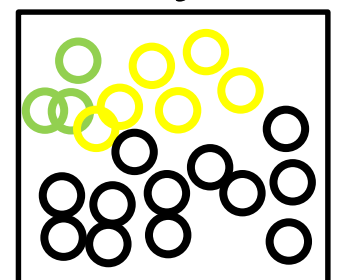
Day 2



Day 3



Day 4



Same cell type,
imaged at different days

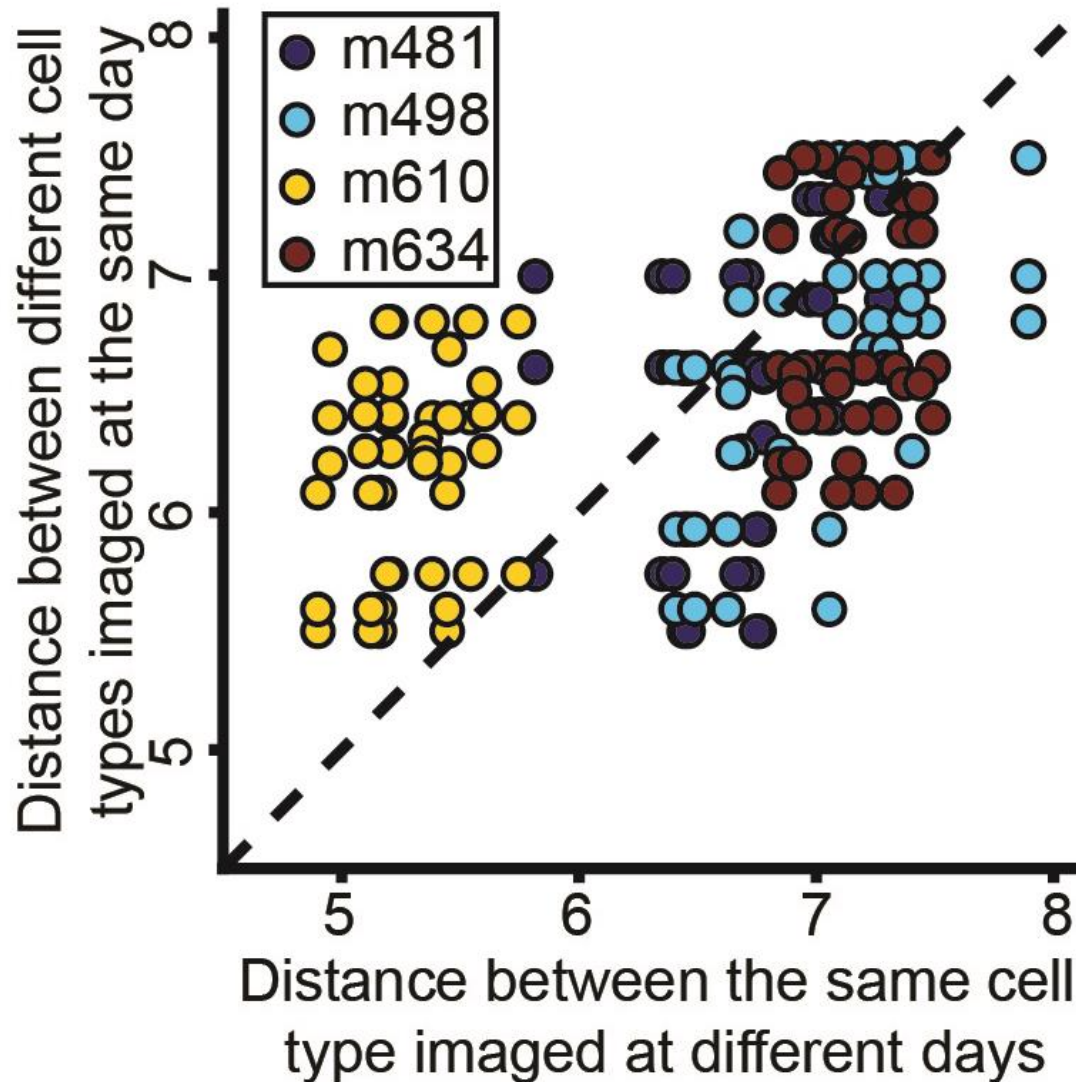
distance(,)

Different cell type,
imaged at same day

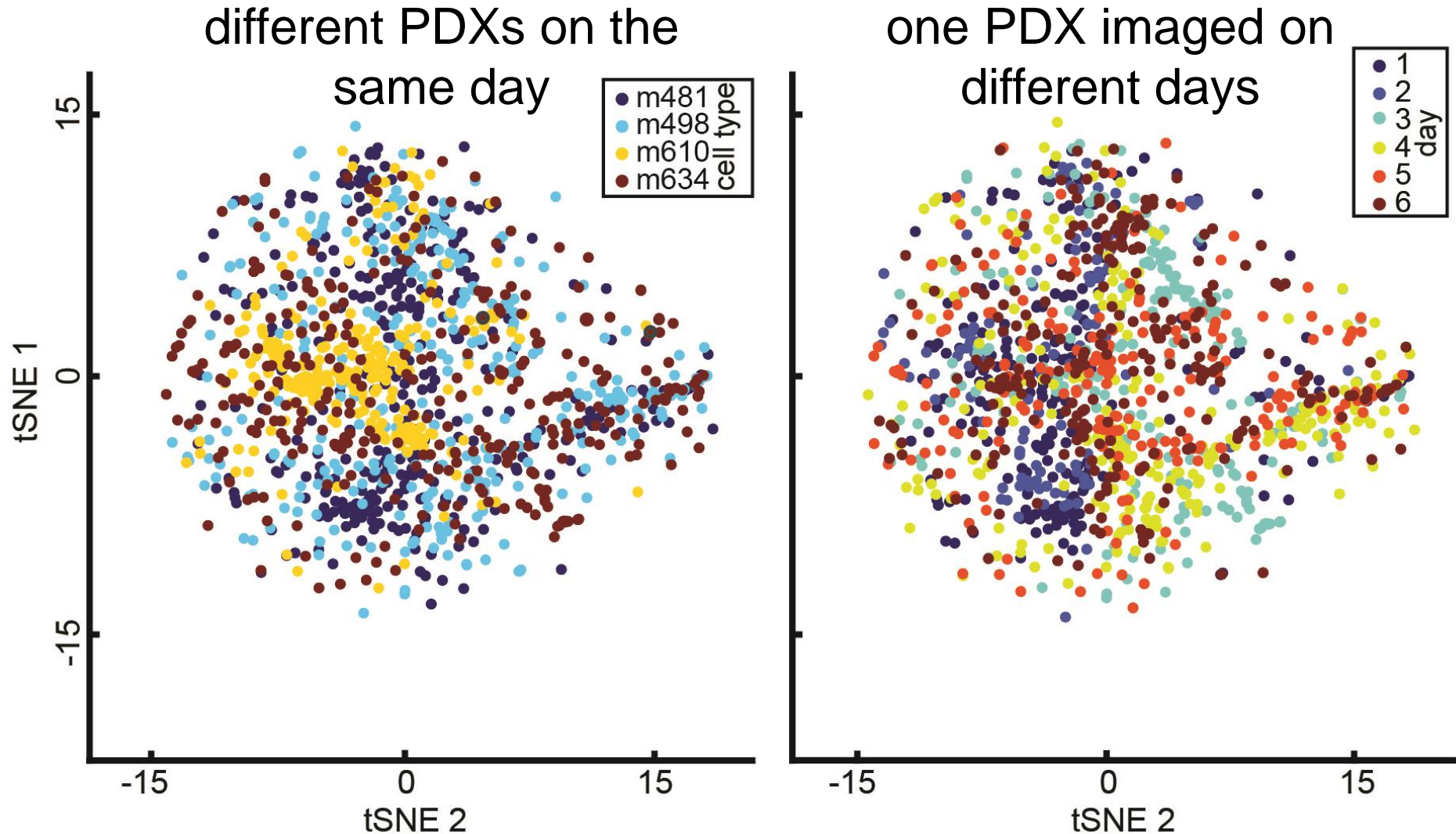
distance(,)

versus

Intra-PDX/inter-day distance (x-axis) versus intra-day/inter-PDX distance



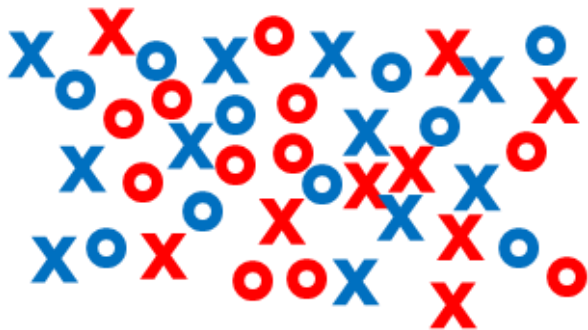
Latent space cell descriptors are significantly distorted by batch effects or lack information on distinct functional states between PDXs



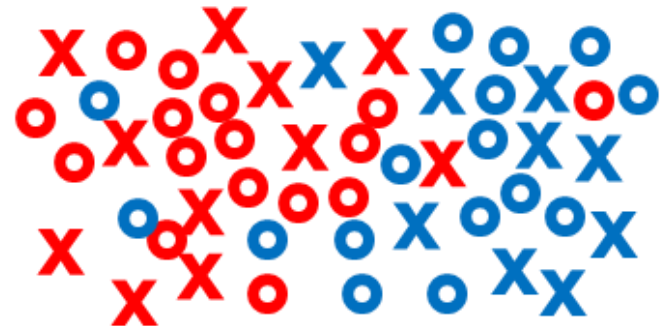
Supervised machine learning for classification

Day 1 ●; Cell type 1 ● x
Day 2 x; Cell type 2 ● x

Unsupervised

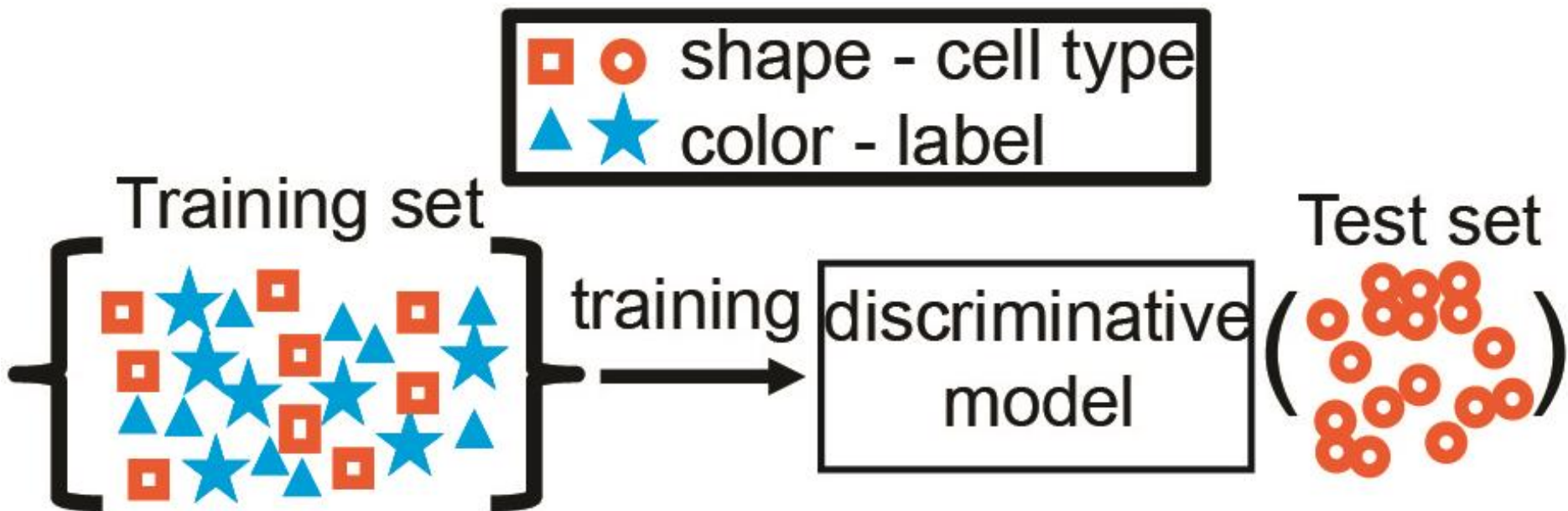


Supervised

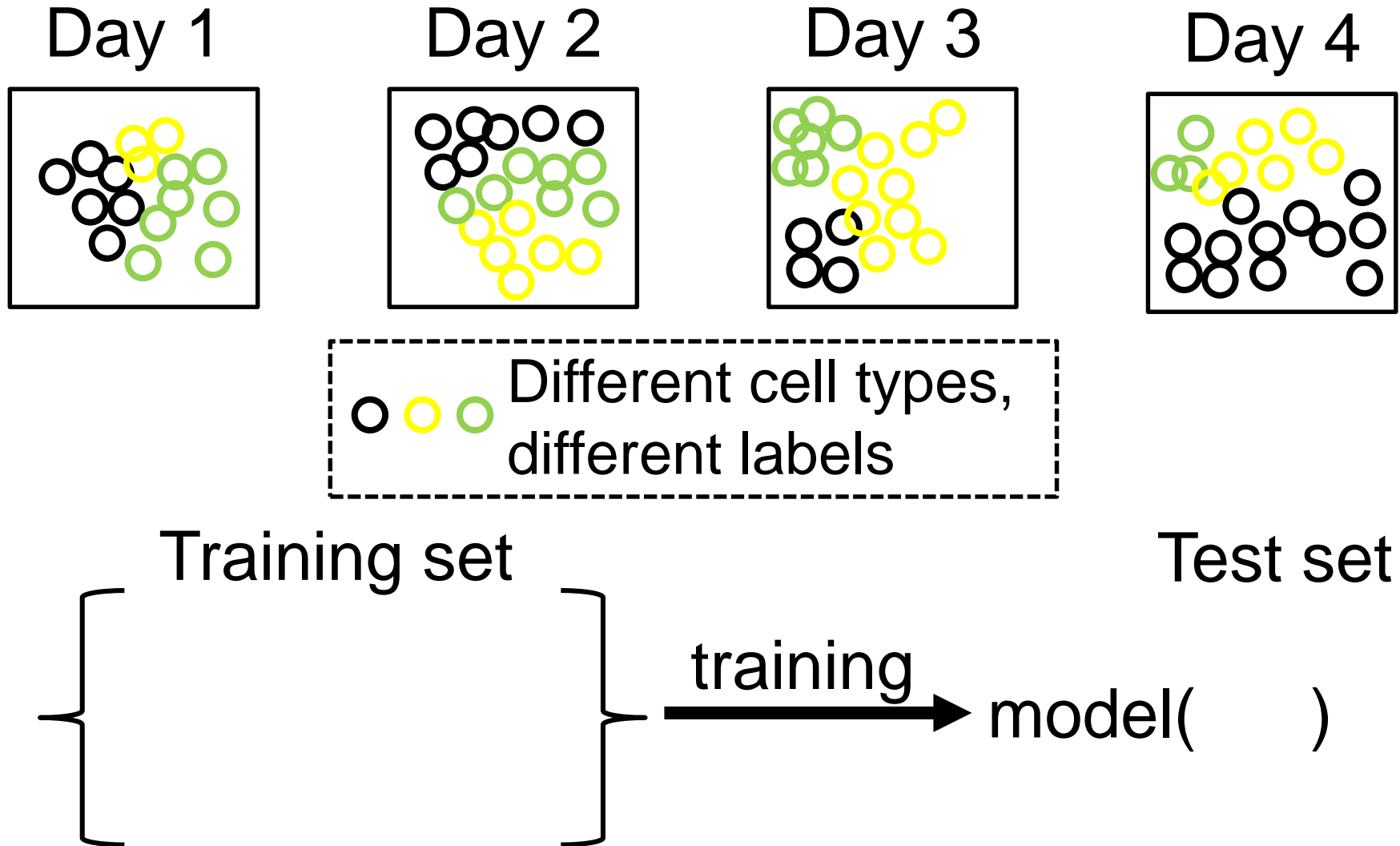


Supervised machine learning for classification

(careful statistical assessment to avoid over-fitting!)

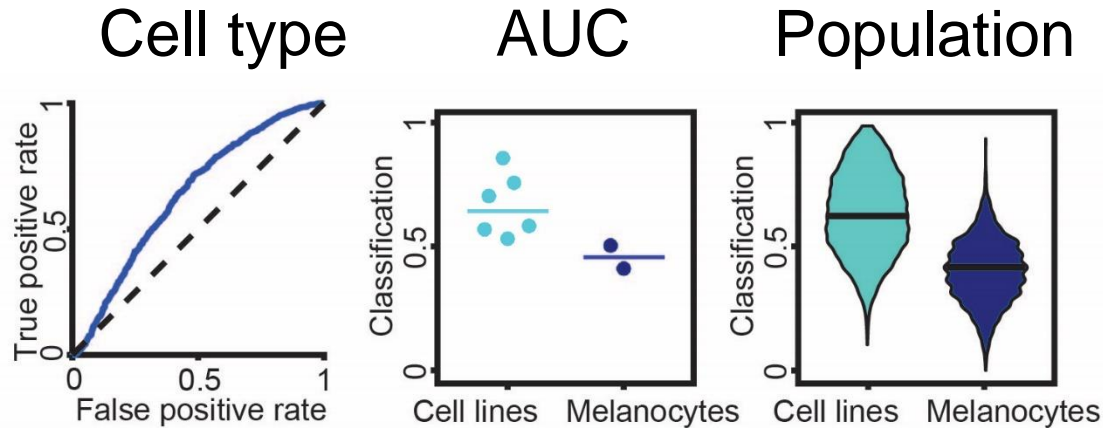


Careful statistical assessment to avoid over-fitting (day + cell type)!

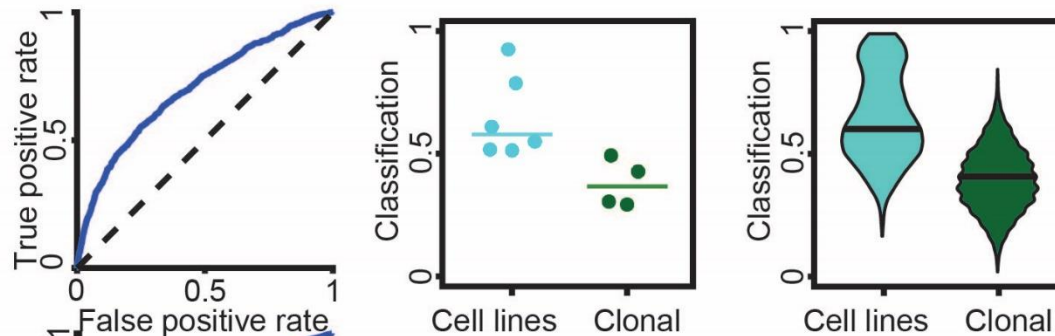


Discrimination of different melanoma cell types (classifier blind to the cell system)

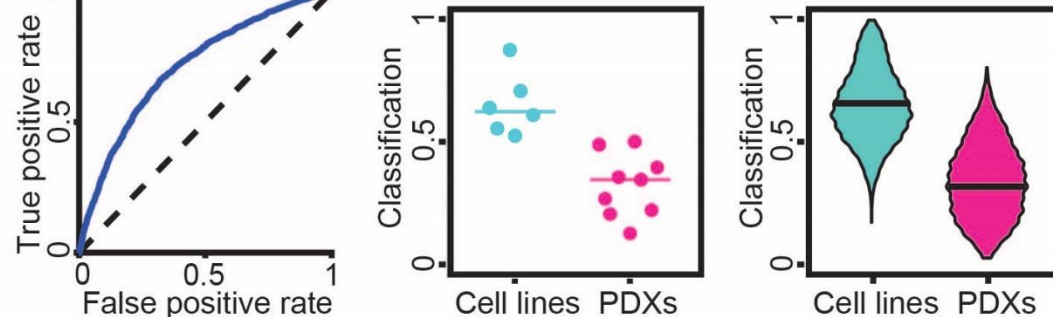
Cell lines vs.
Melanocytes



Cell lines vs.
Clonal

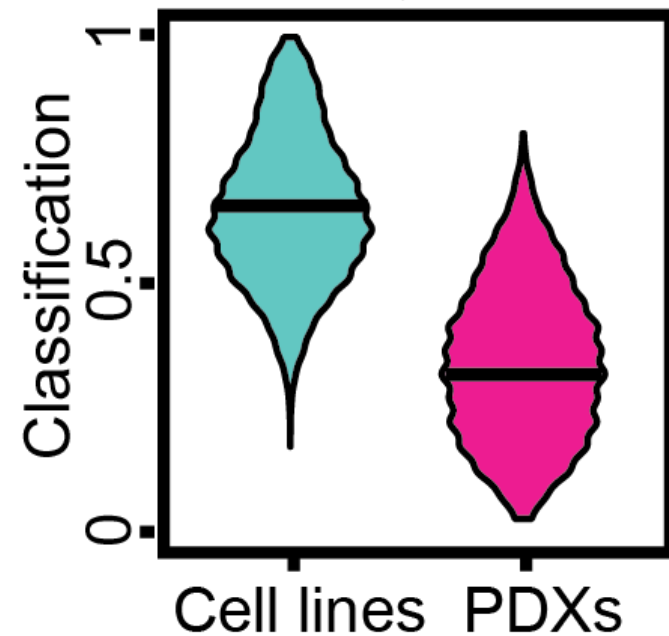
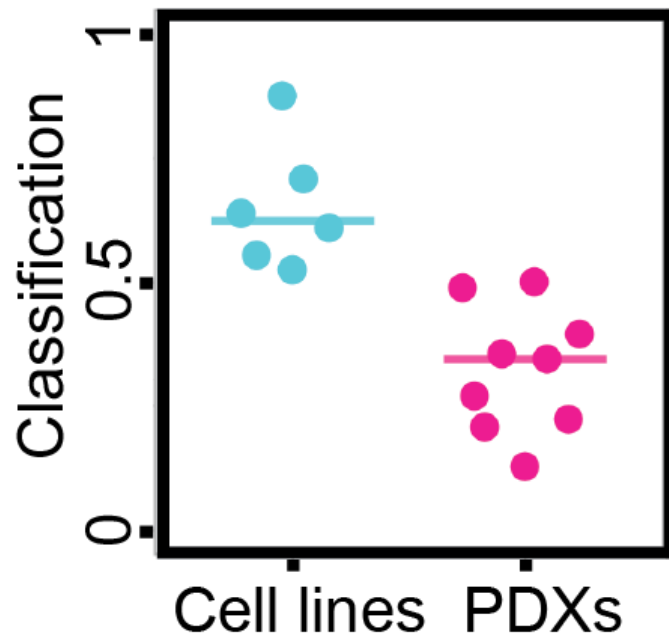


Cell lines vs.
PDXs



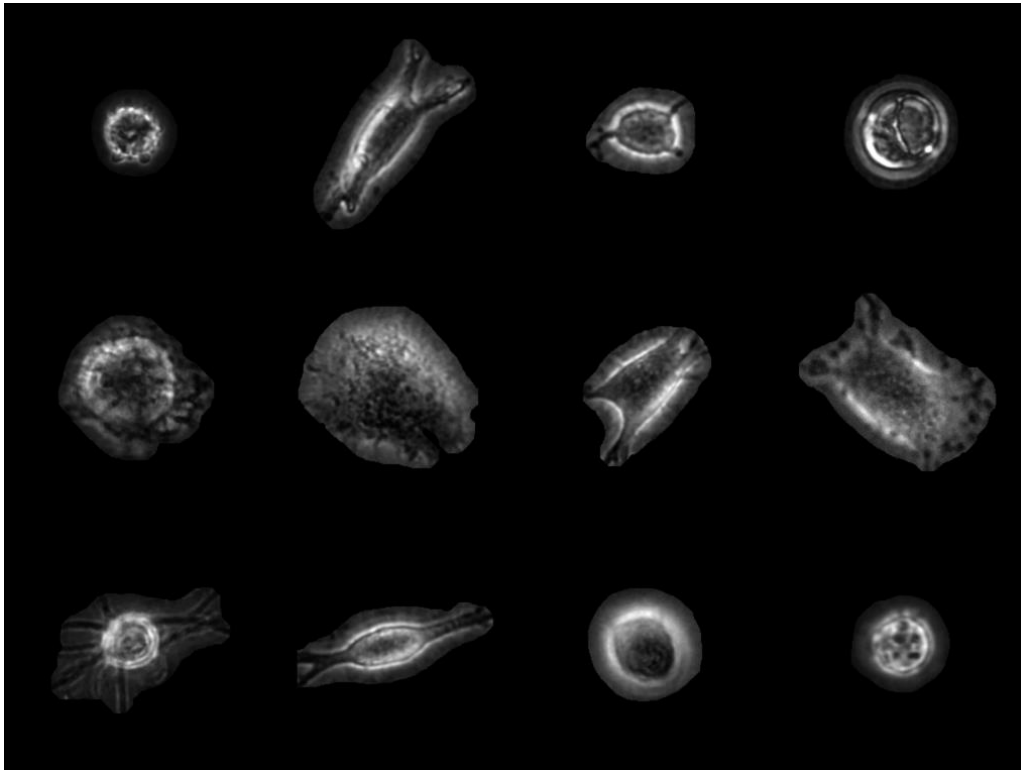
Focus on cell lines versus PDXs...

Classifier blind to the cell system

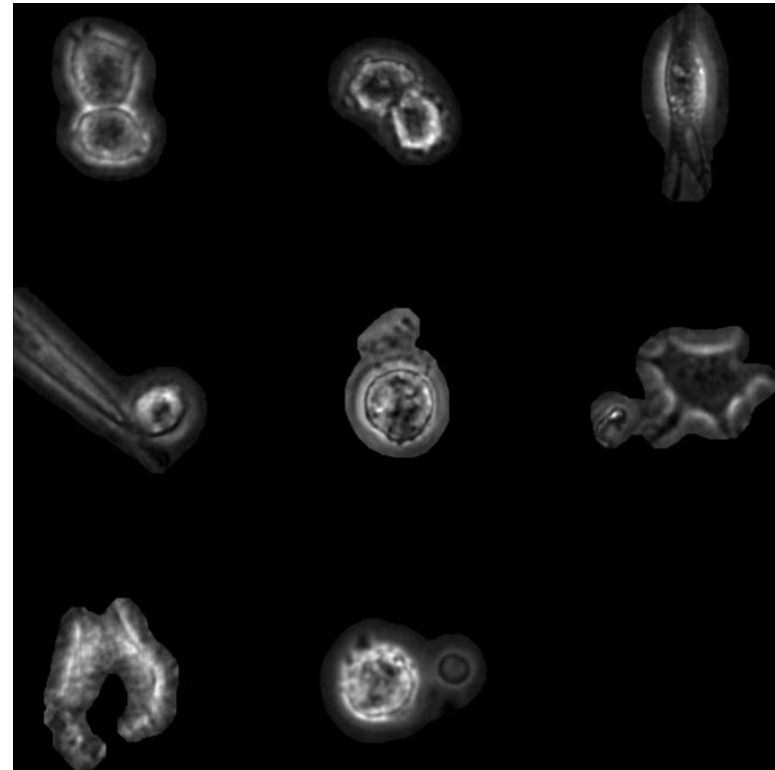


Alternative descriptors - shape: single cell segmentation in phase-contrast images by LEVER

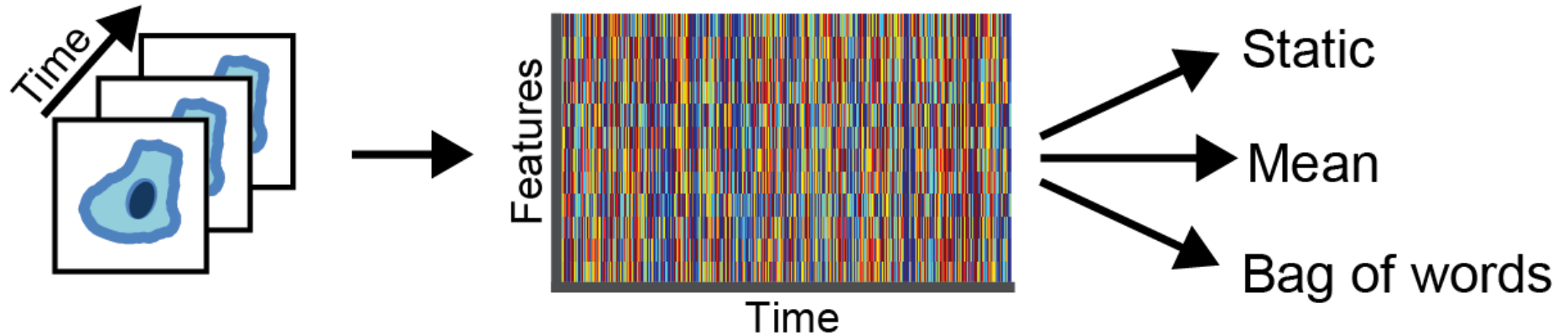
Successful



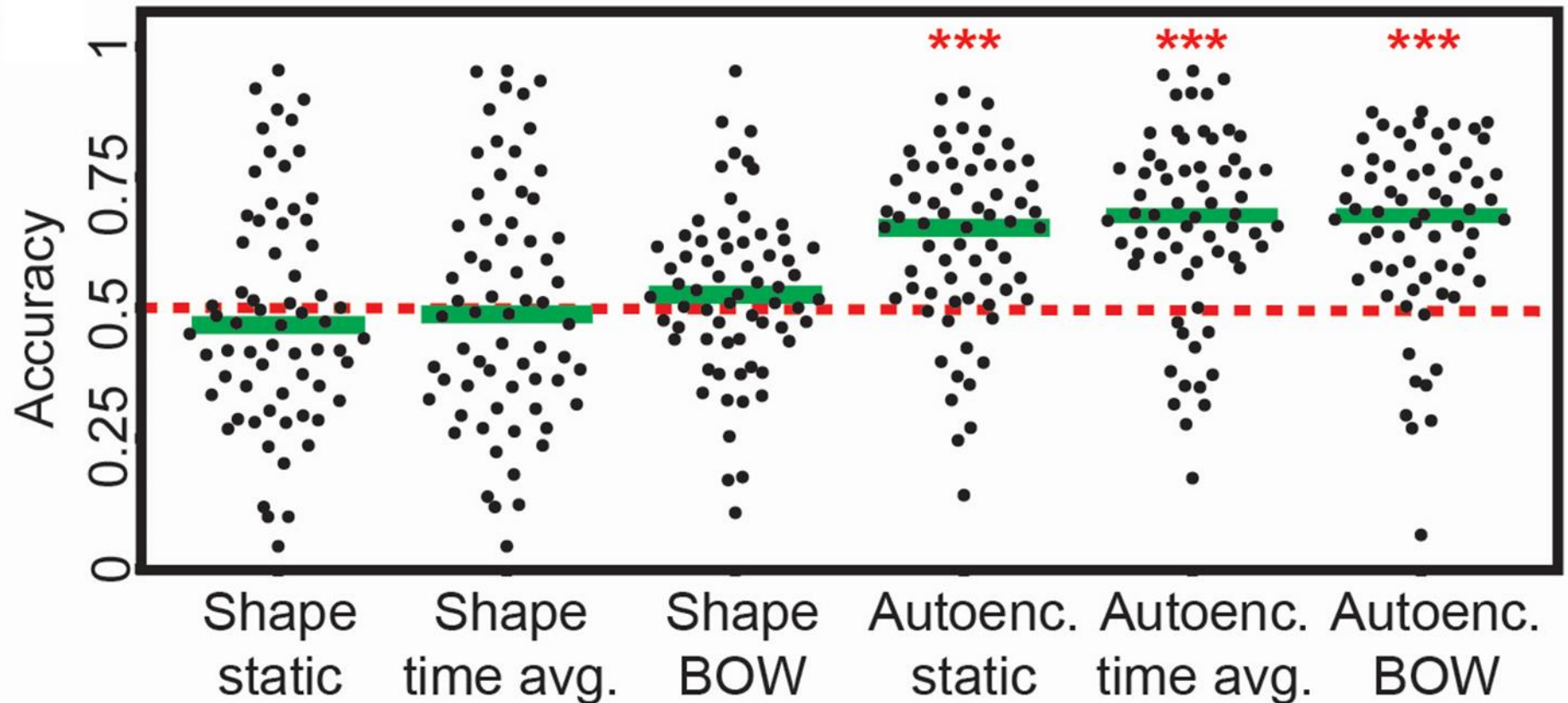
Failed



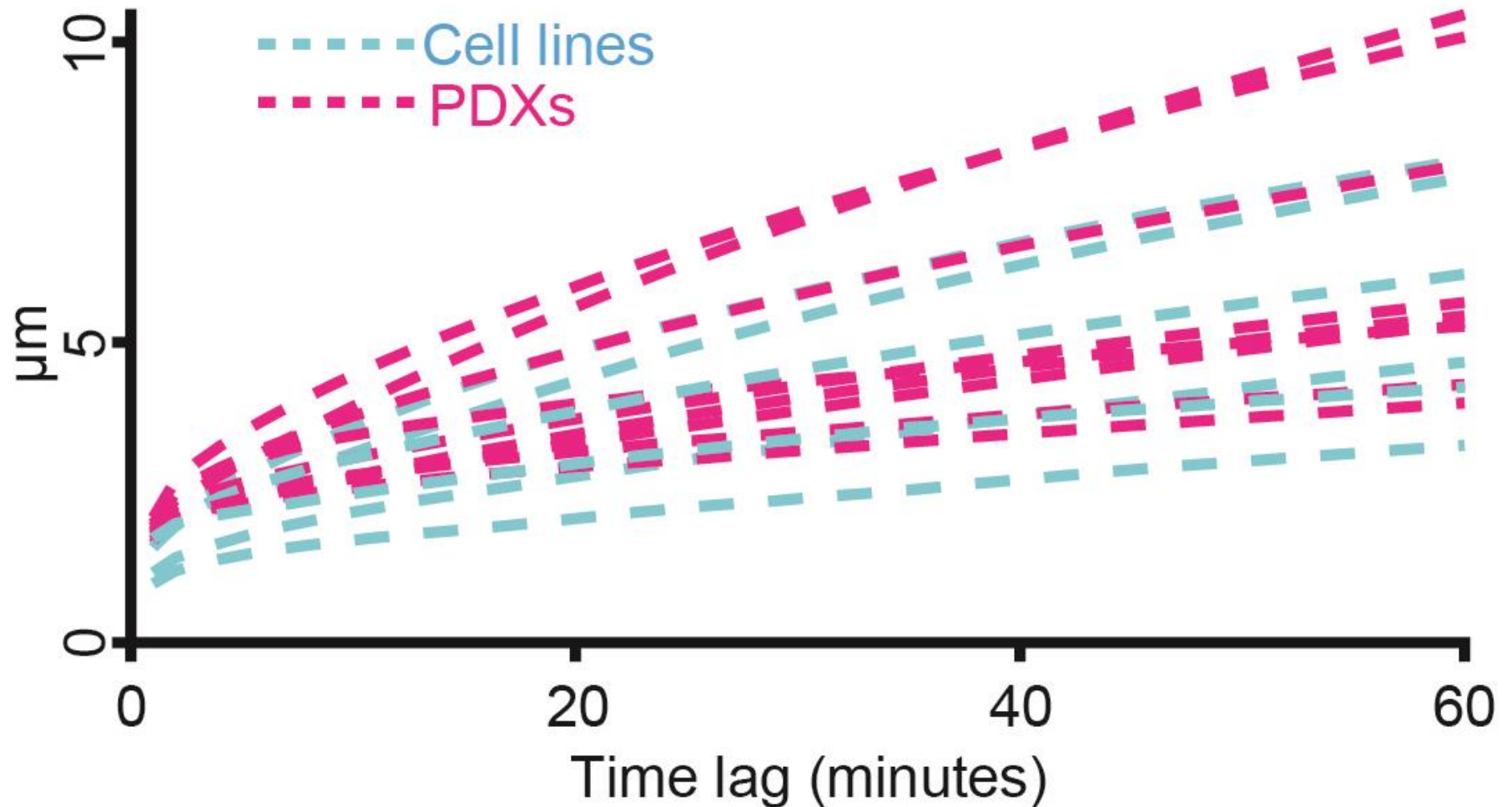
Alternative descriptors



Classification comparison using cell shape and temporal information to distinguish cell lines from PDXs

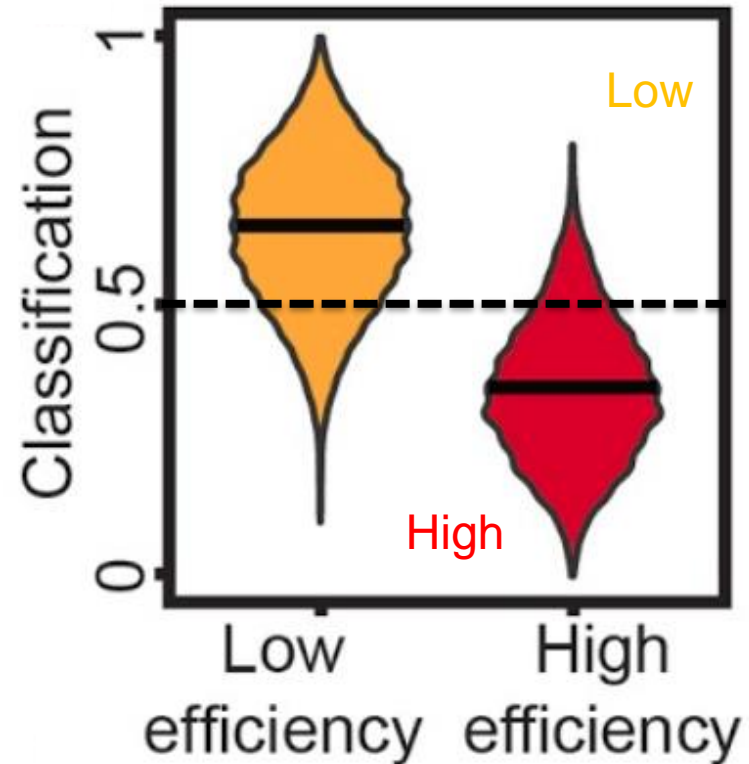
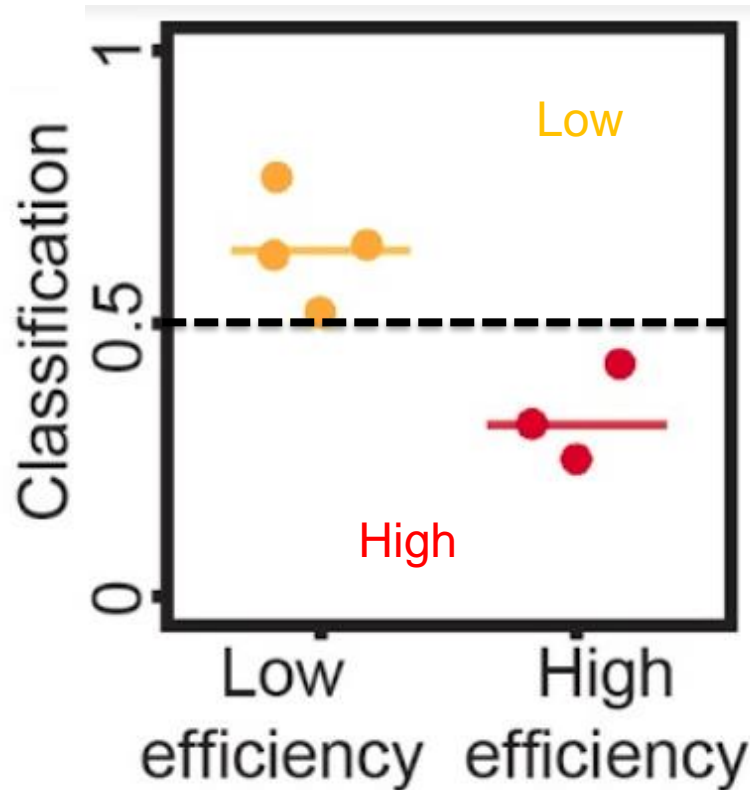


Mean squared displacement analysis of single cell trajectories



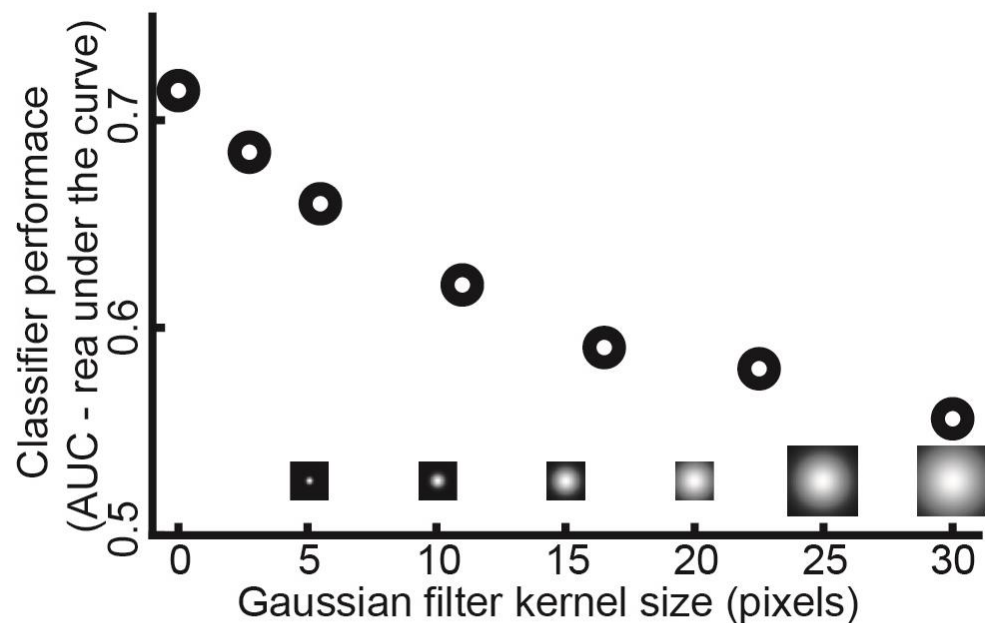
Live cell histology for classification of melanoma metastatic efficiency

Classifier blind to the patient

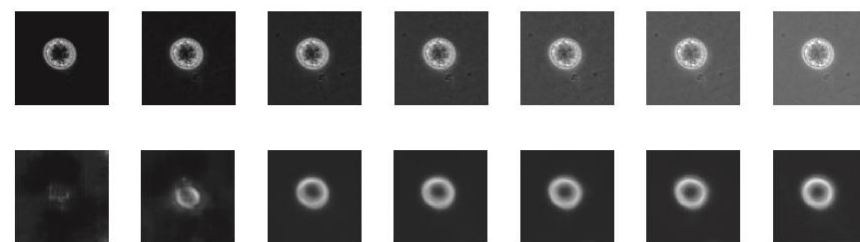
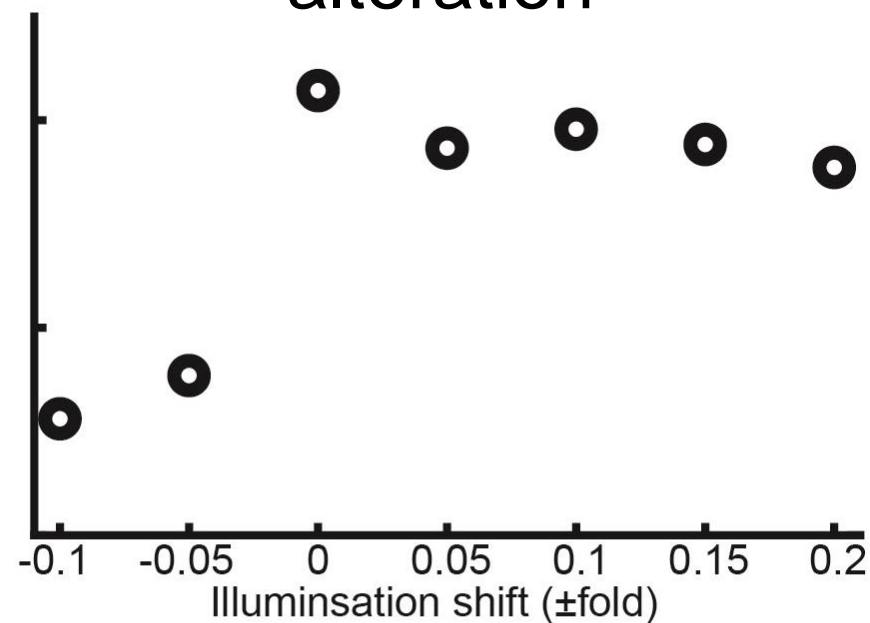


Robustness analysis

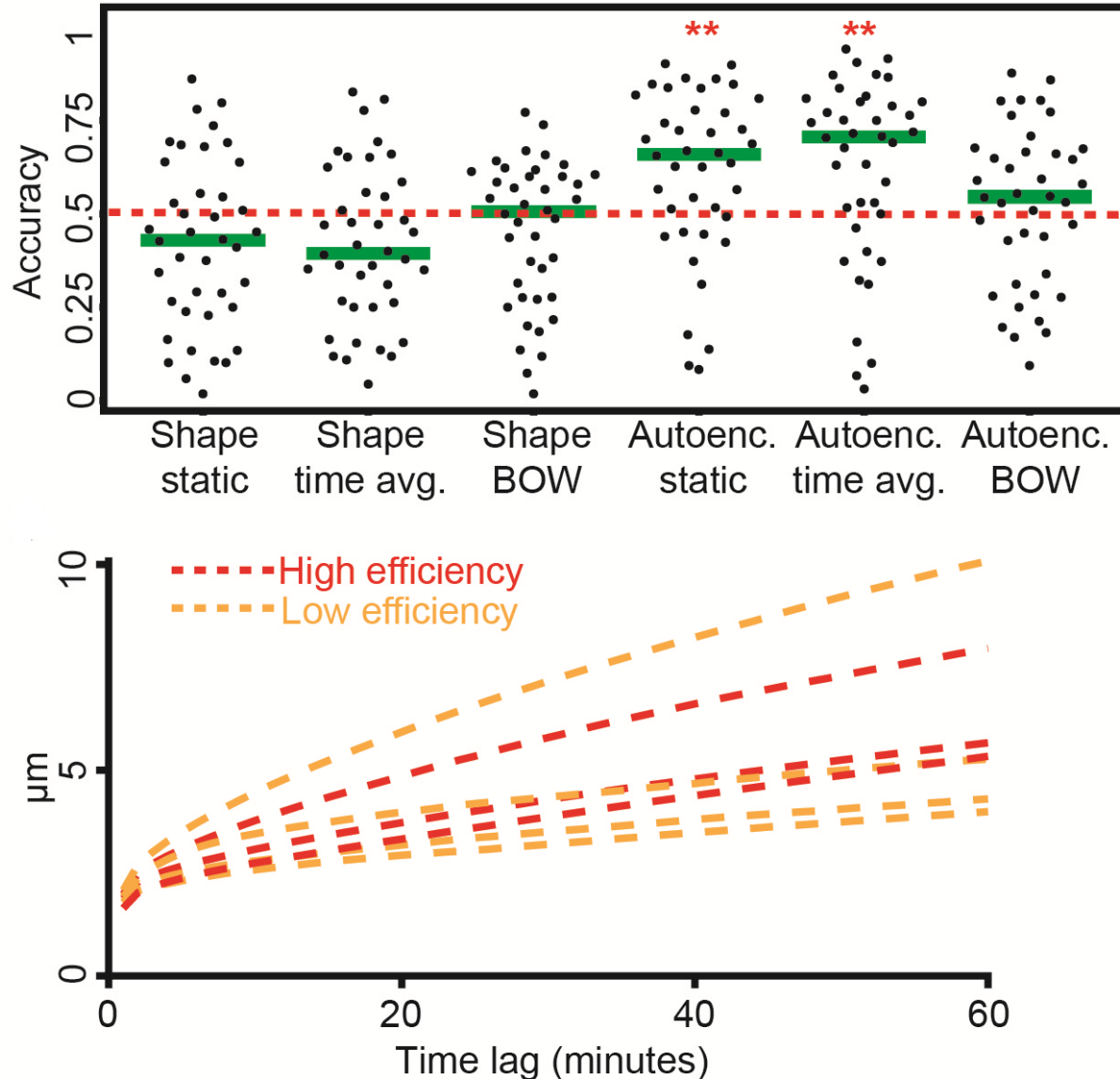
Gaussian blur



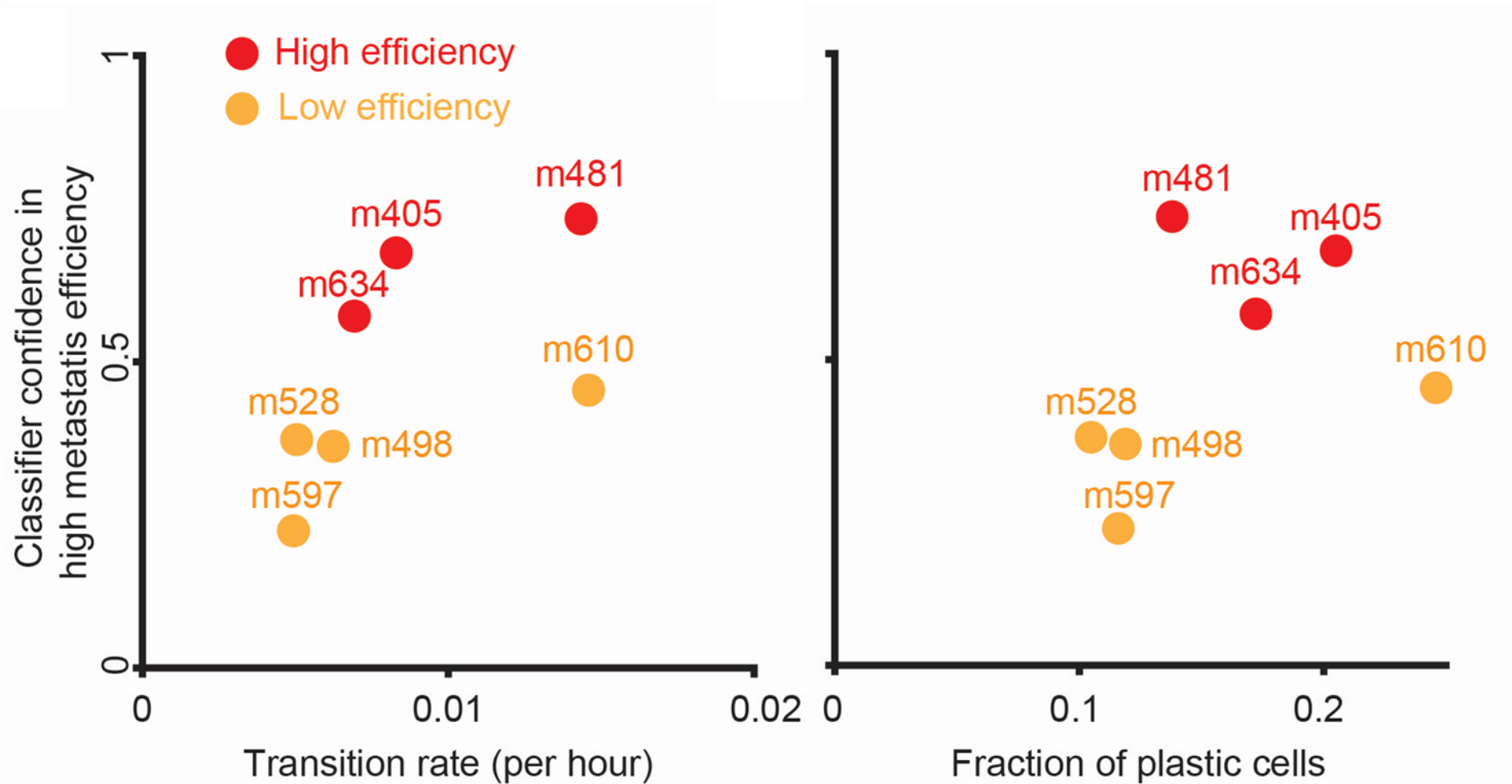
Simulated illumination alteration



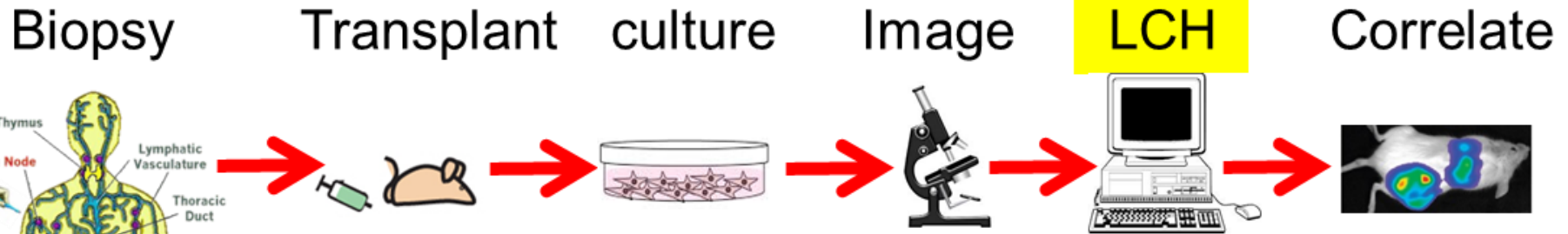
Shape and motility can not distinguish metastatic efficiency



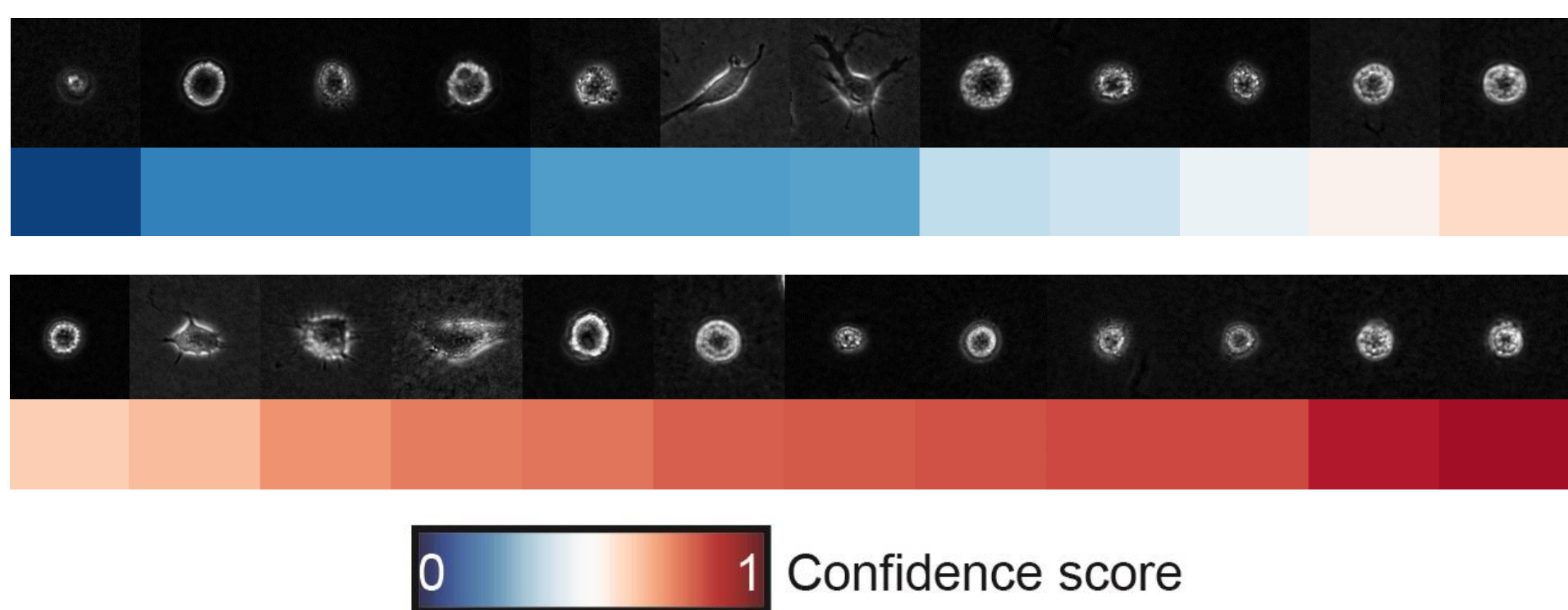
Cell plasticity



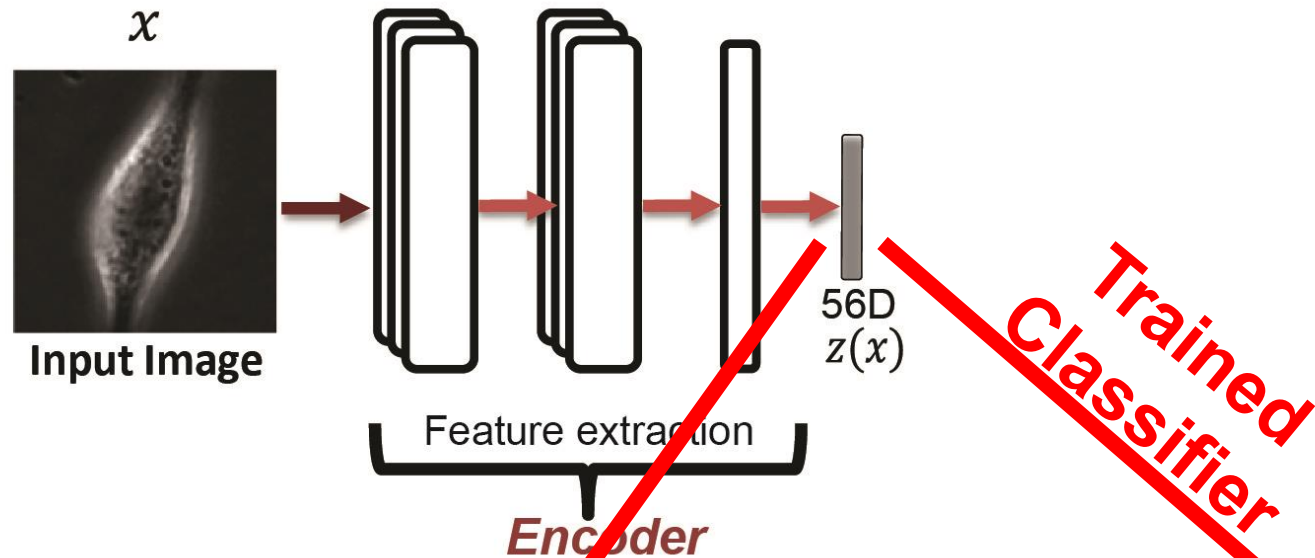
The dream: live cell histology (LCH) of fresh biopsies to predict metastatic potential



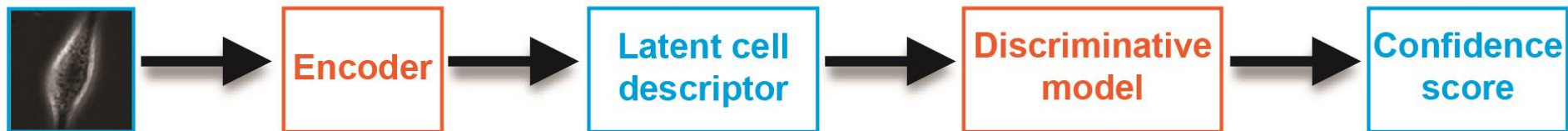
What are the physical attributes that discriminate high from low metastatic efficient cells?



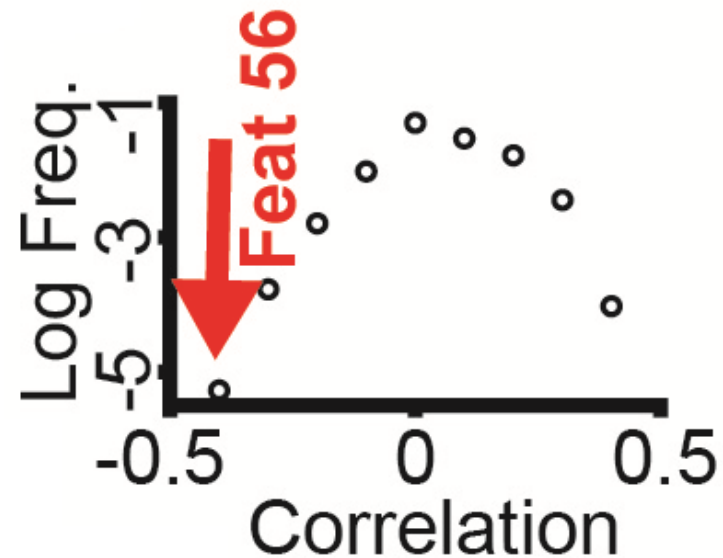
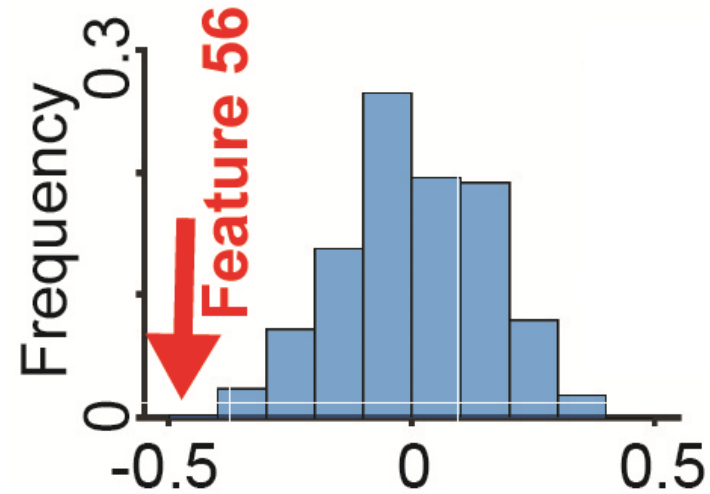
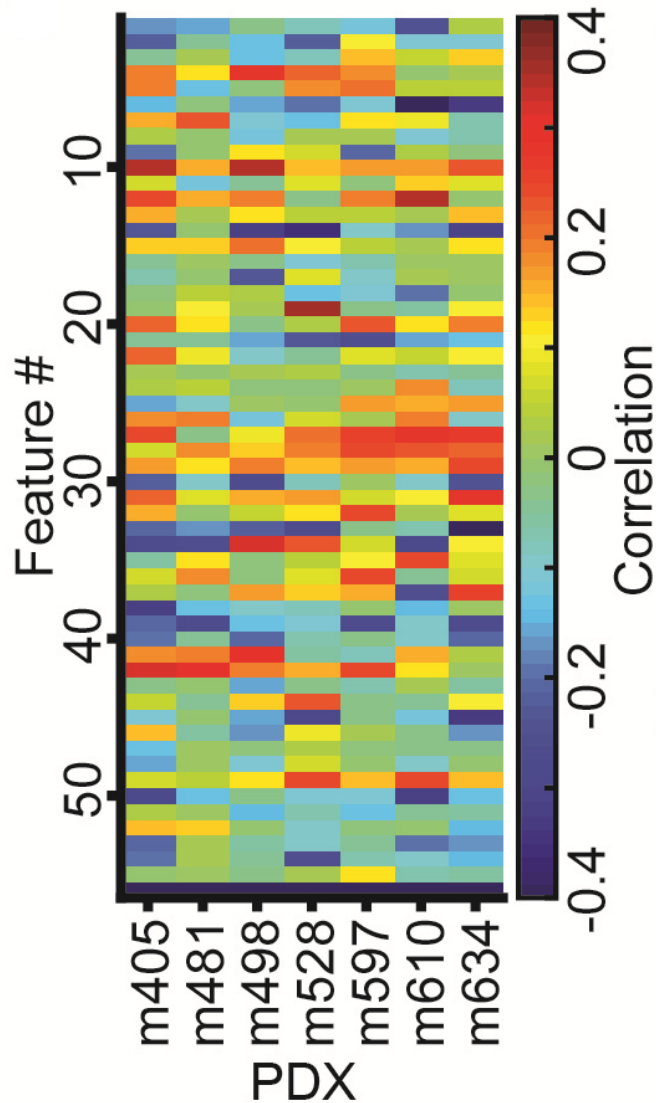
Using the variability within the data to identify key features for the classification



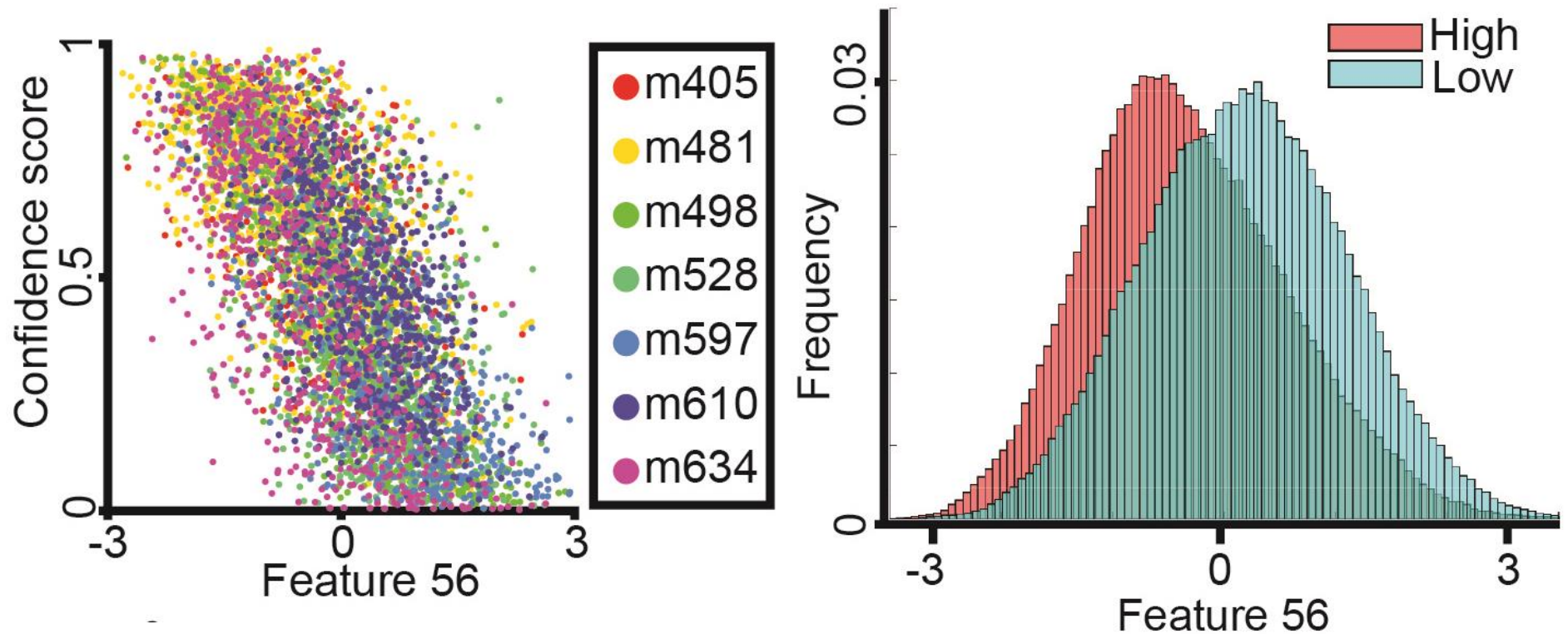
Correlate confidence score with each feature



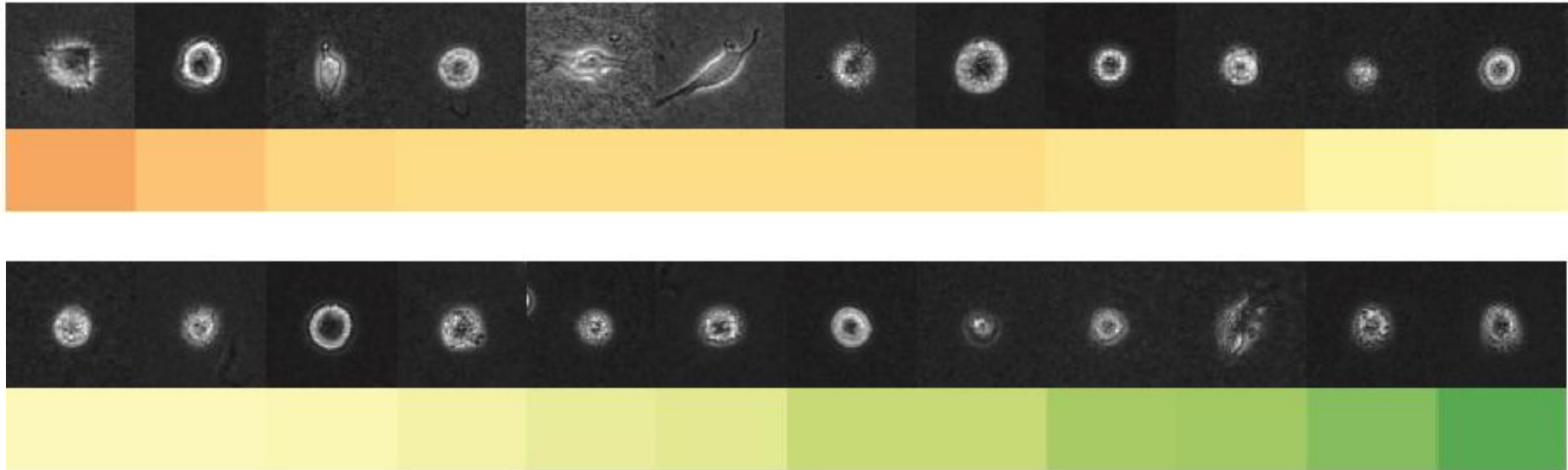
Correlating all features and classifier scores for all PDXs



Feature #56 is negatively correlated with the classifiers' predictions!



Second try: what physical properties are encoded by feature #56?



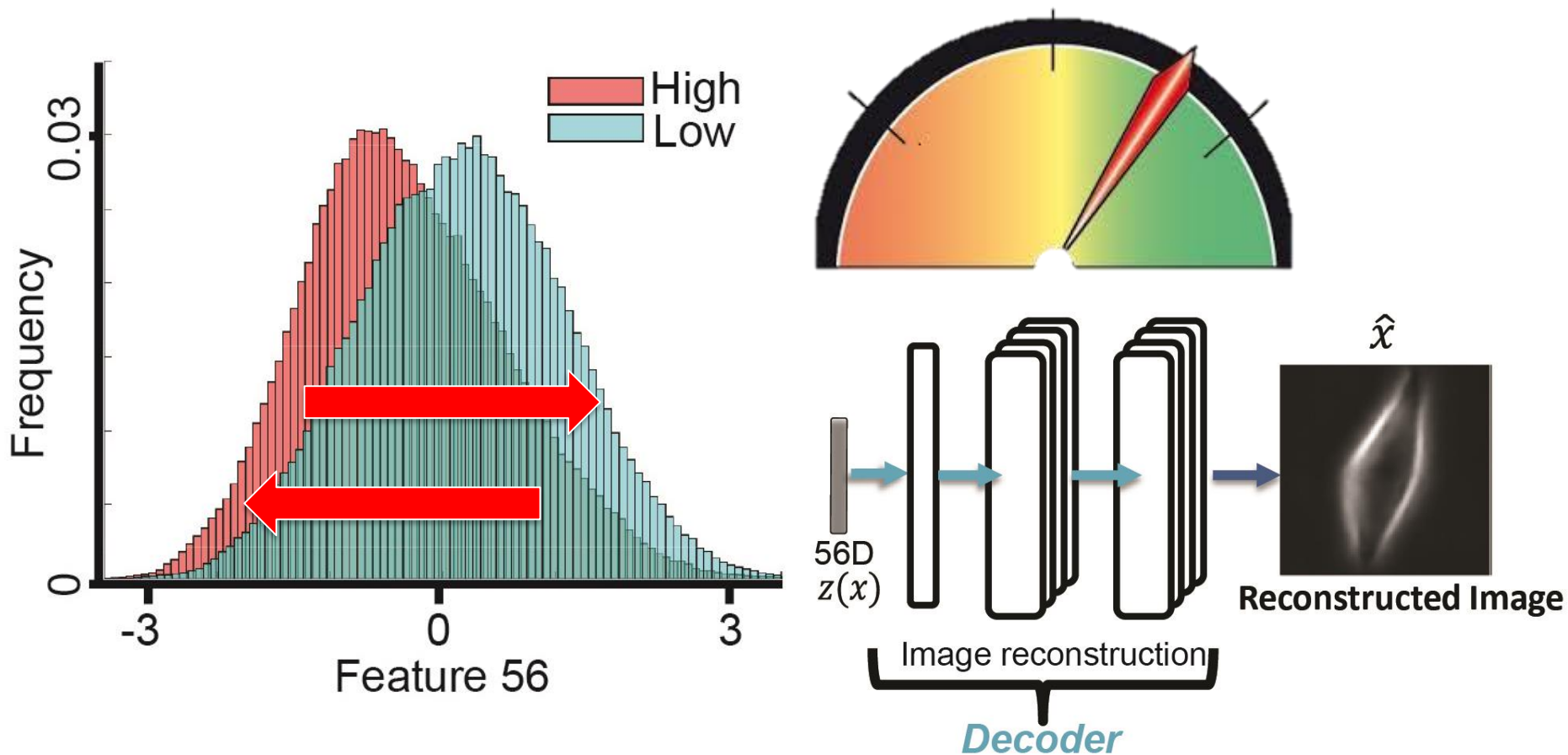


Morphing (celebrity) faces

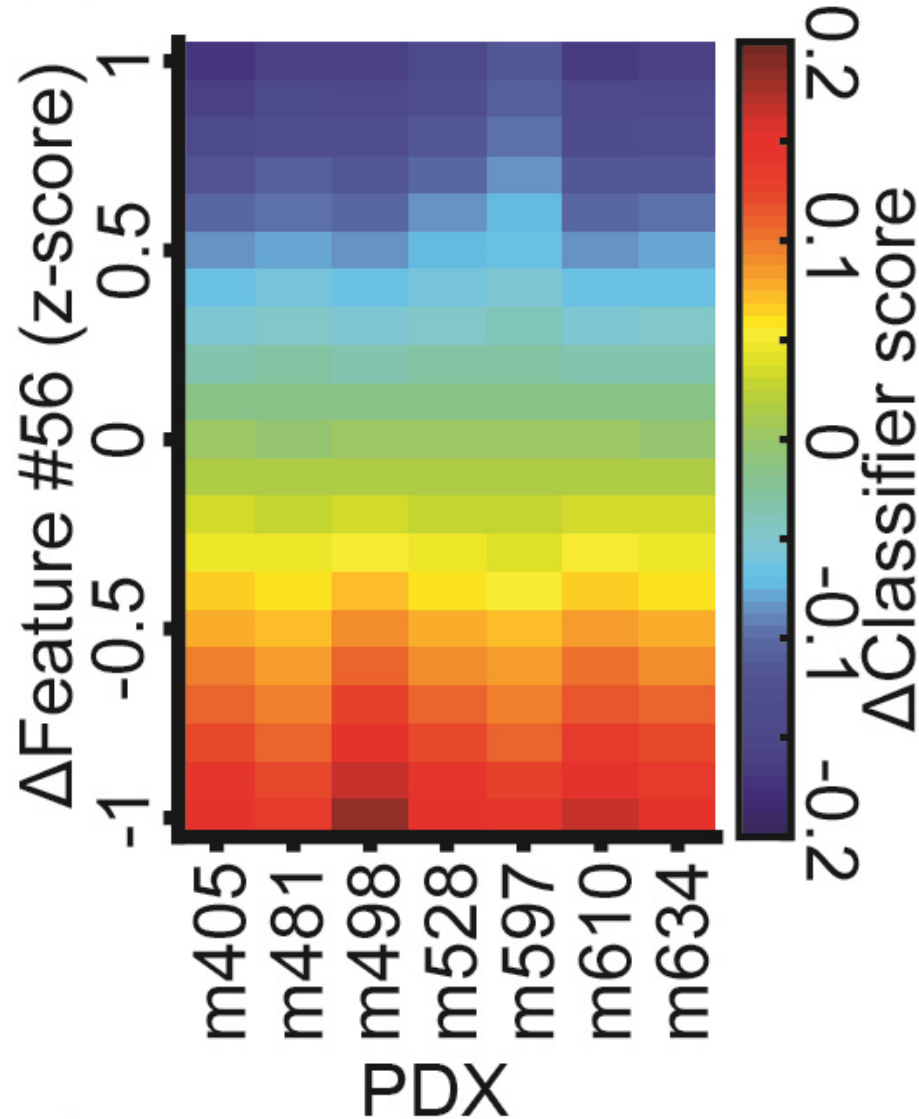


Source: <http://picchore.com/animated-gif-2/rather-mesmerizing-face-morphing-gif-of-assorted-celebrities/>

Transforming cells “in silico”

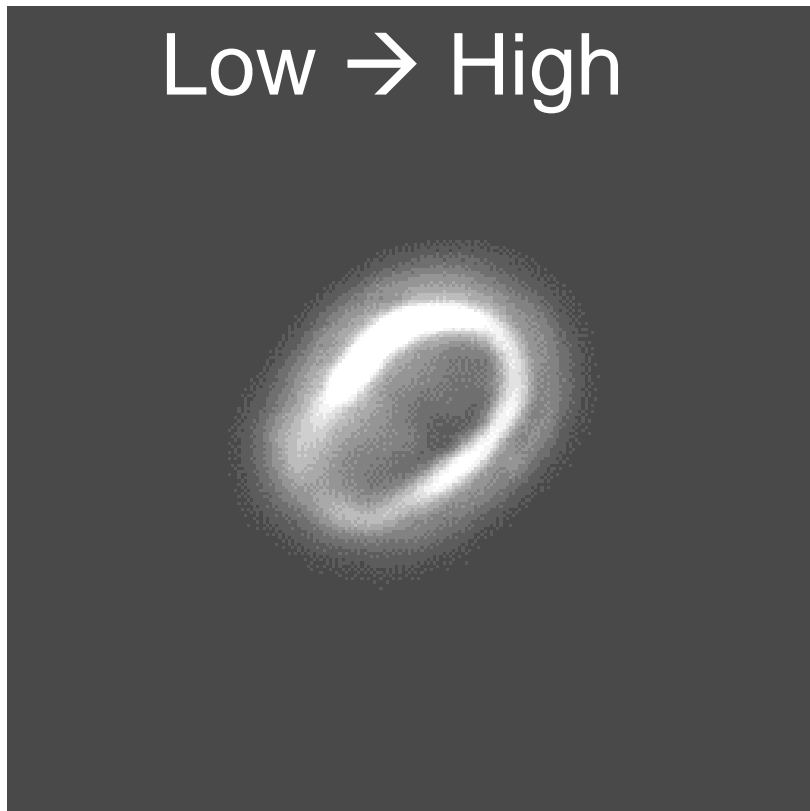


Shifts in feature #56 negatively correlated with variation in the classifier scores

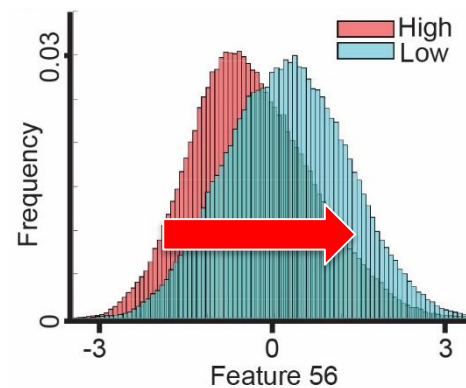
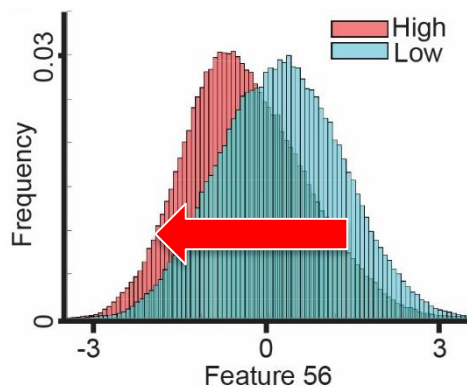
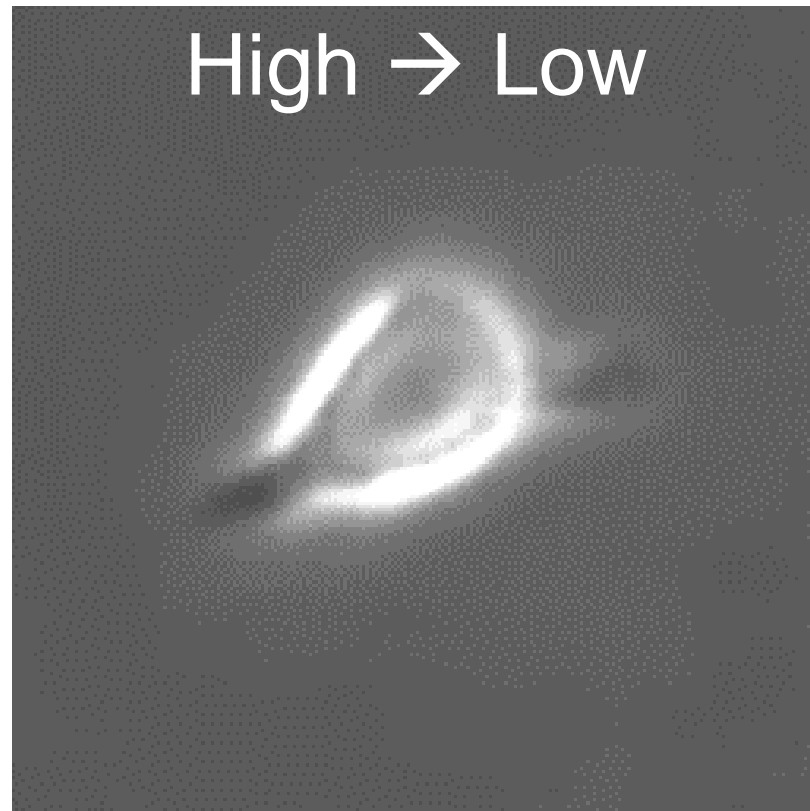


Morphing melanoma *in silico*

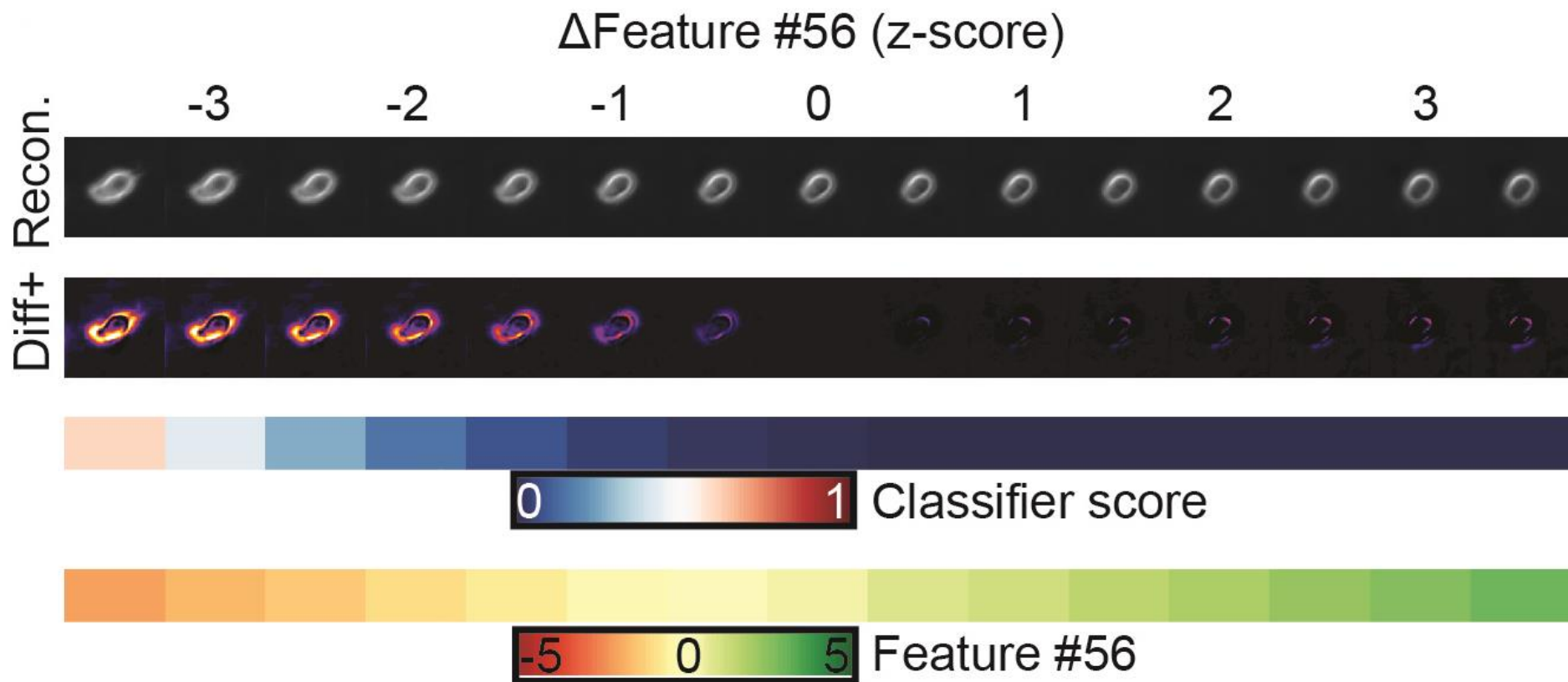
Low \rightarrow High



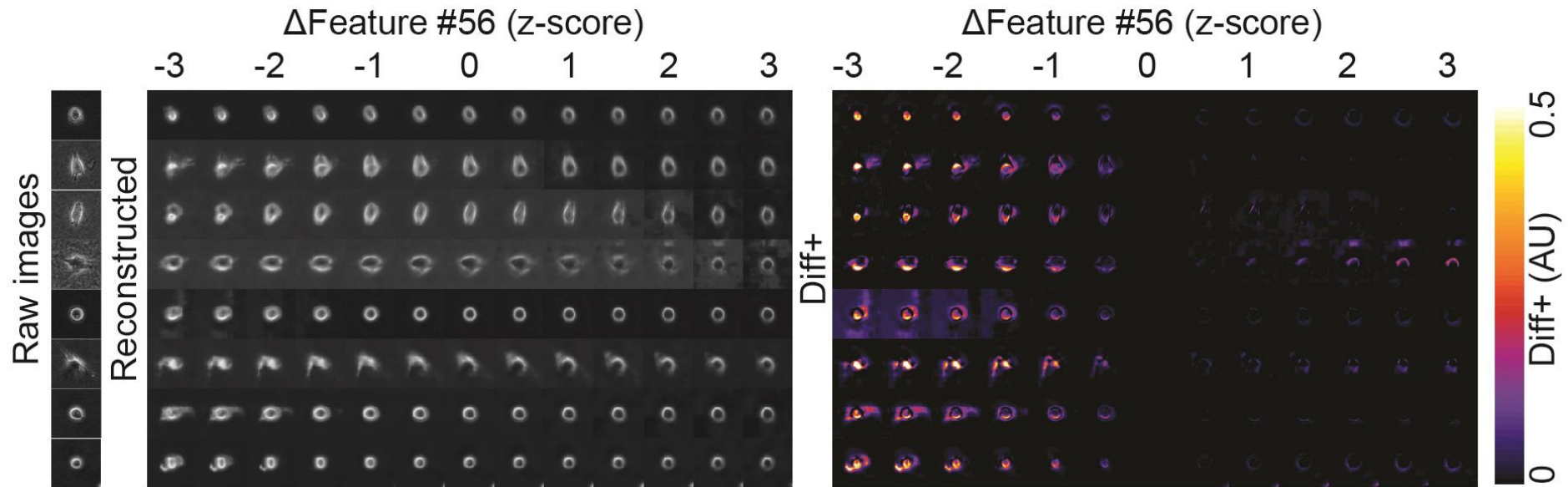
High \rightarrow Low



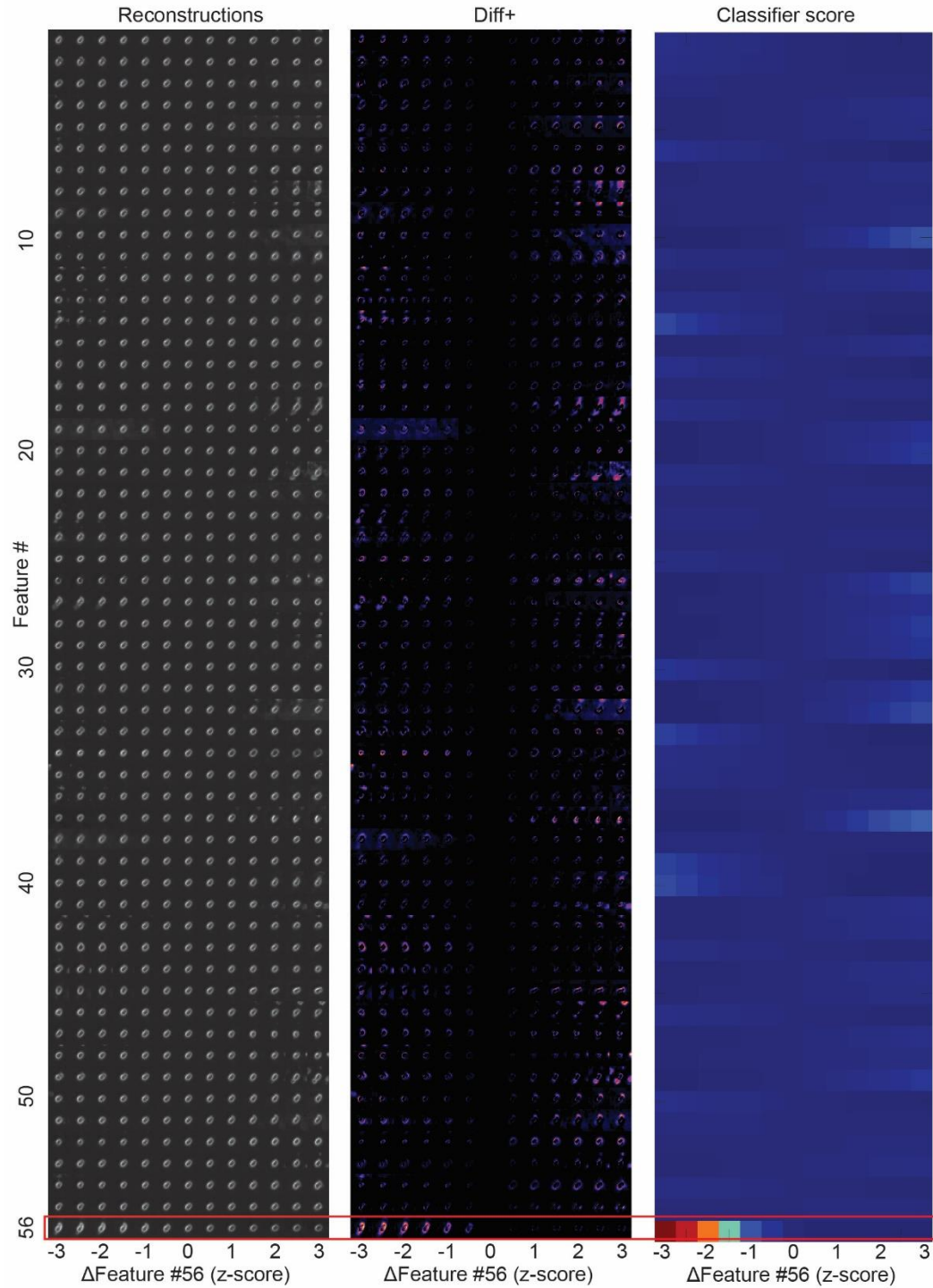
What can we see?



Is it replicated?



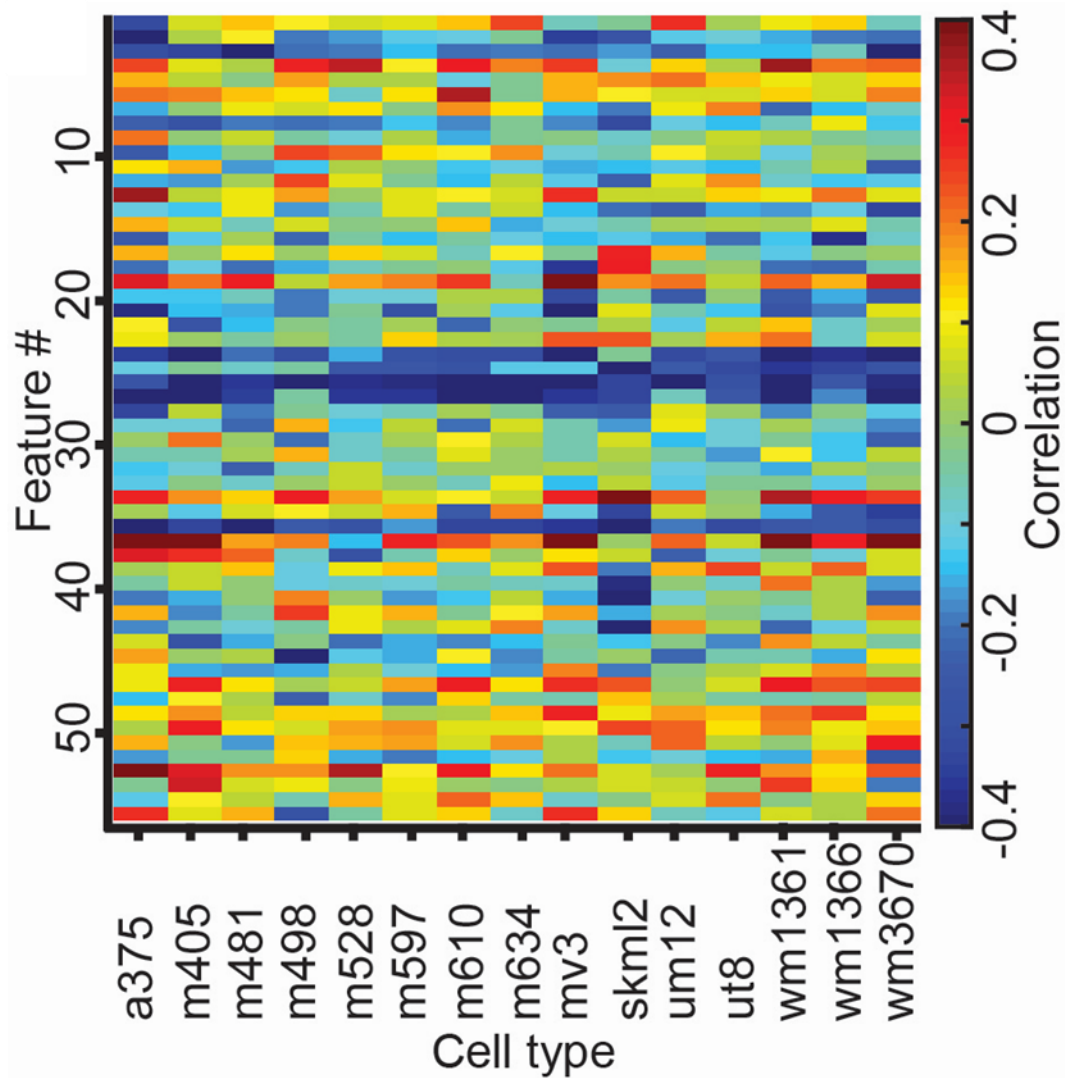
Is it specific?



Hypothesis: feature #56 is associated
with a combination of
enhanced protrusive activity, and
increased light scattering

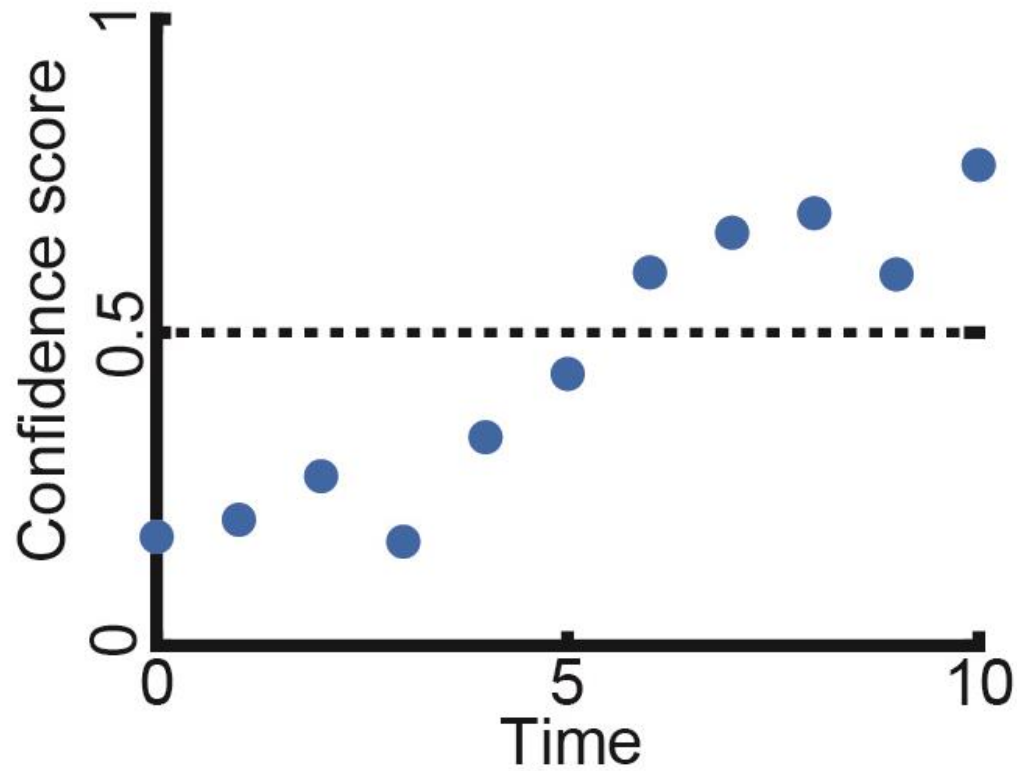
Just one feature? We were lucky!

Multiple features are classification-driving for discriminating cell lines from PDXs

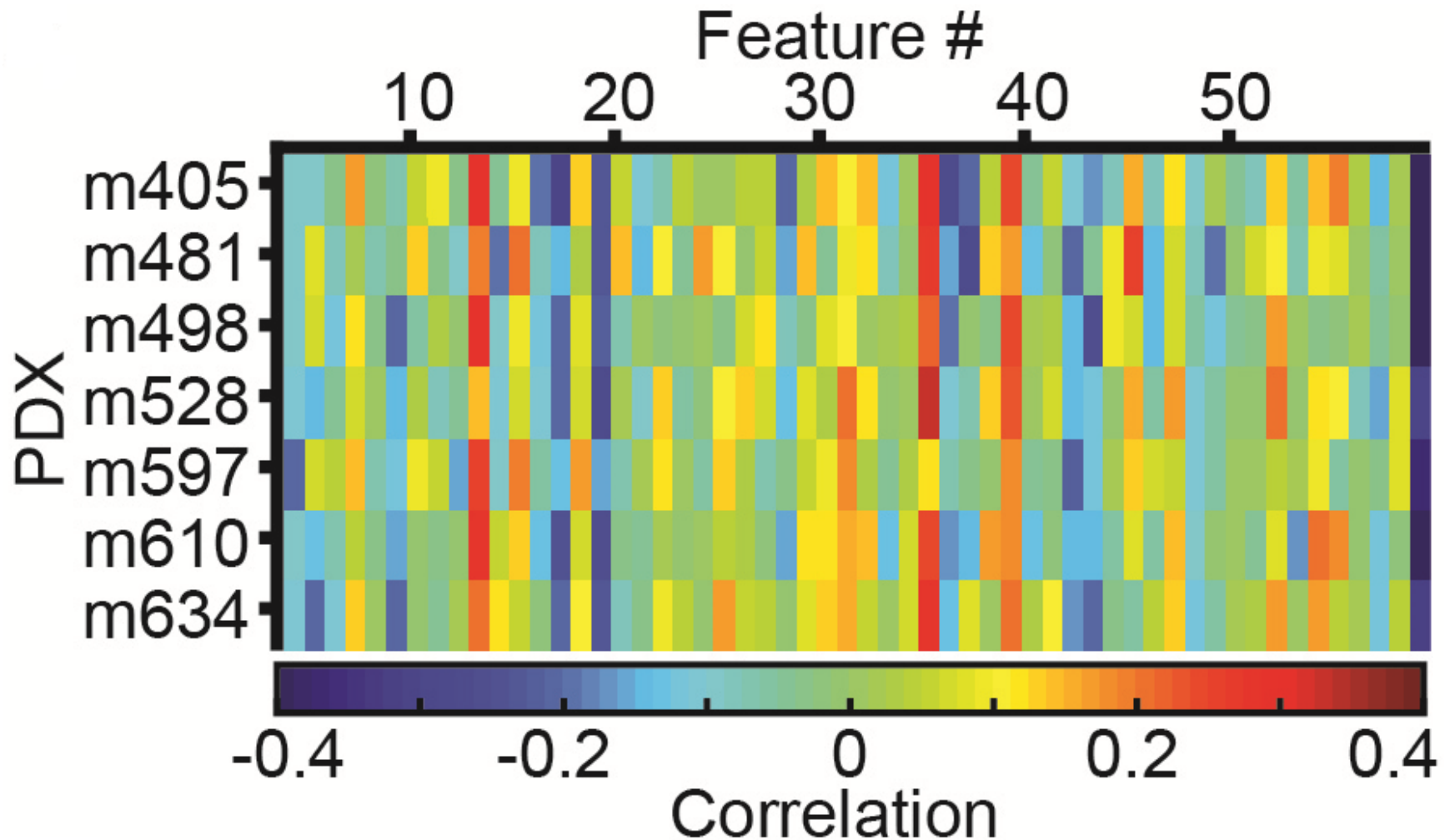


Validation with live cell imaging!

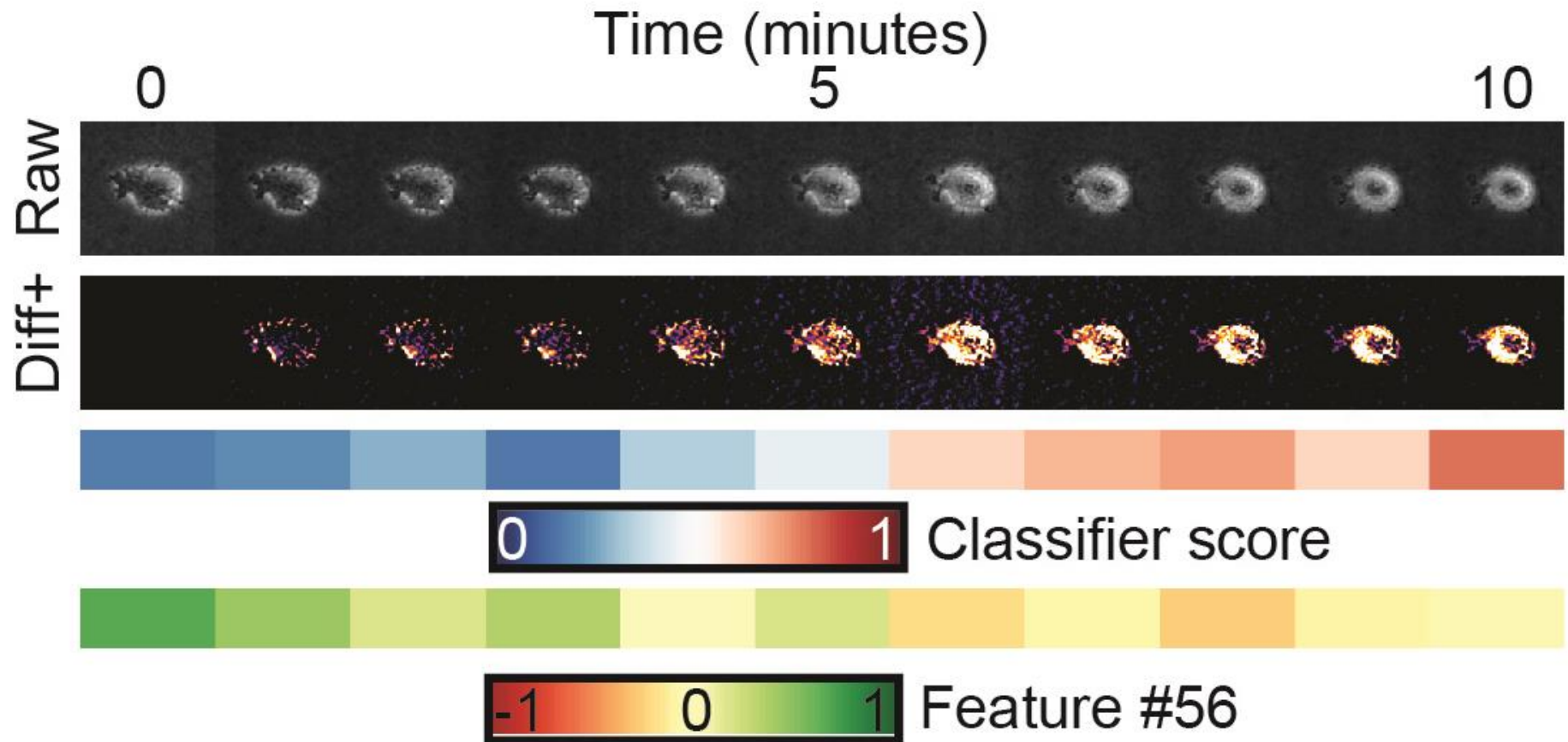
Cell transitioning “in the wild”



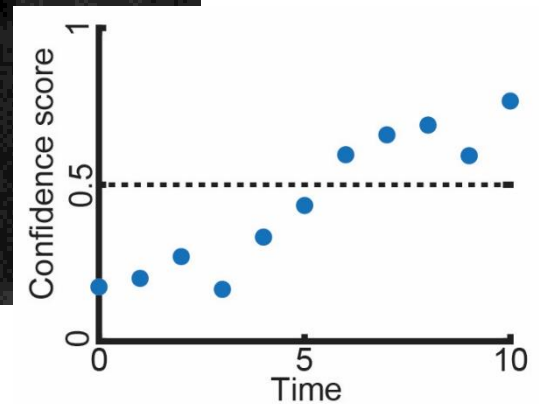
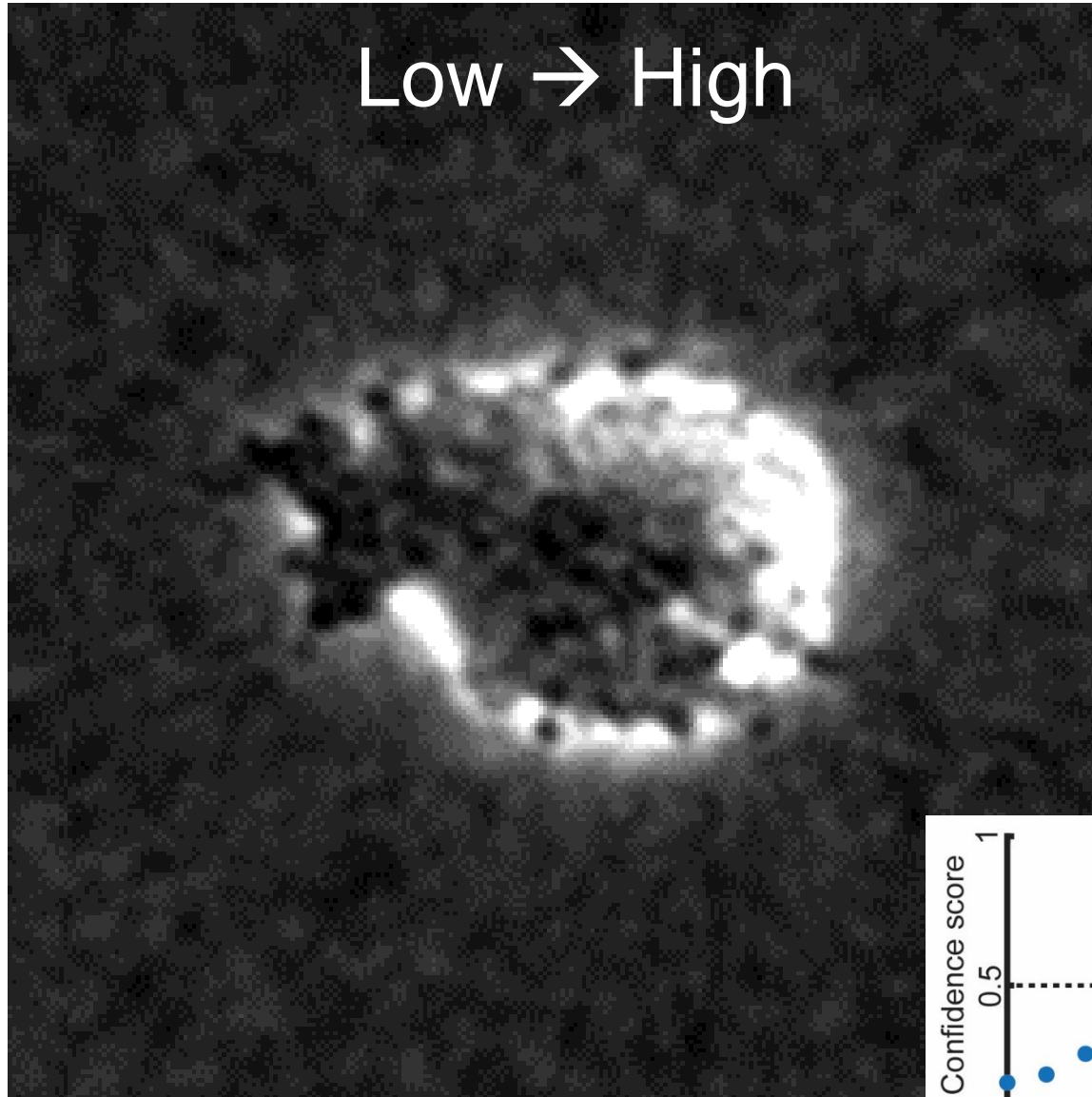
Temporal fluctuations in feature #56
negatively correlated with the temporal
fluctuations in the classifier scores



Spontaneously transitioning from a predicted low to high met. efficiency

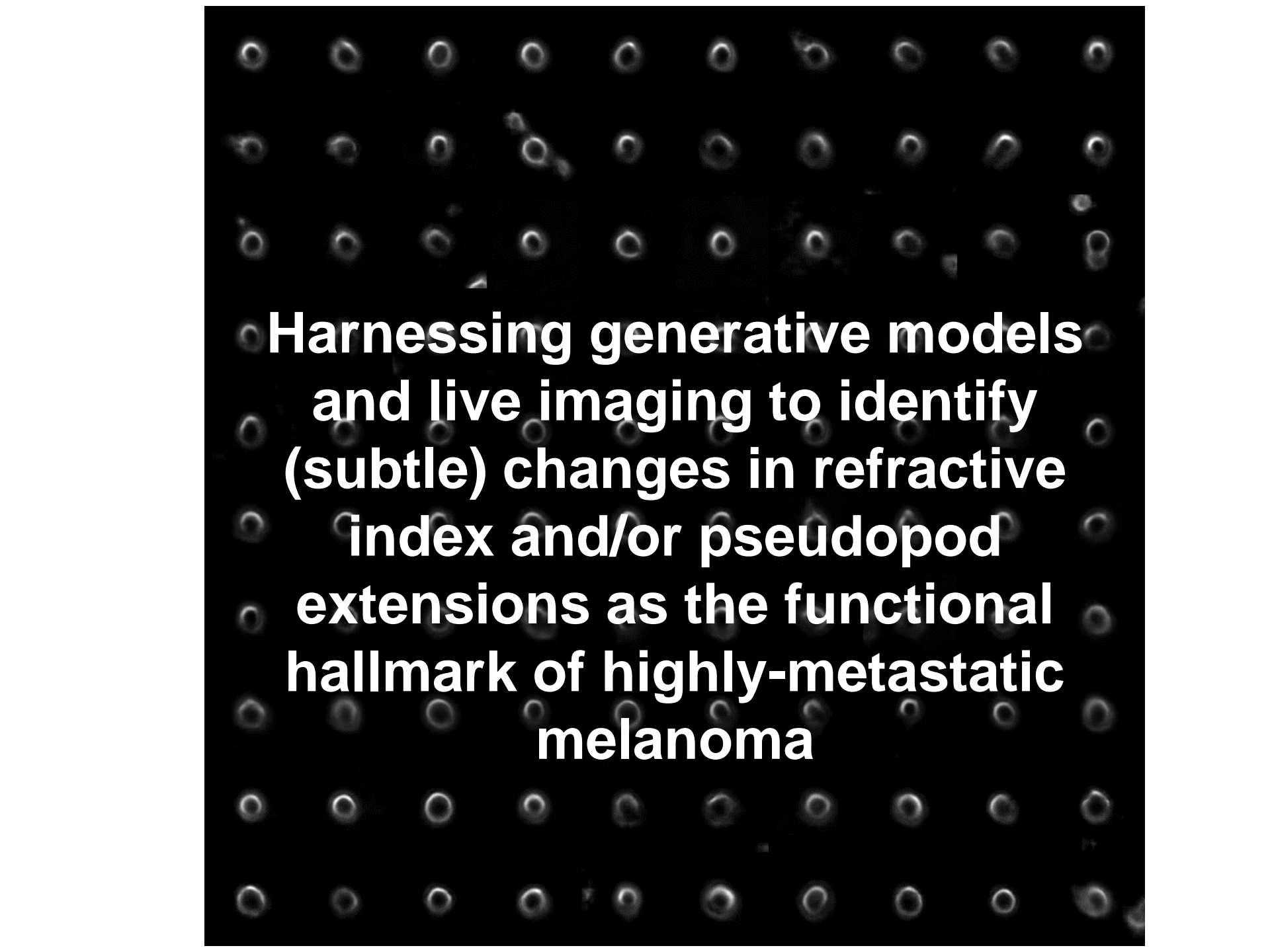


Cell transitionning “in the wild”



Hypothesis: feature #56 is associated
with a combination of
enhanced protrusive activity and
increased light scattering

Increased light scattering must be caused by
alteration in the refractive index: fluctuations in
organelle/cytoplasm composition? cell stiffness?

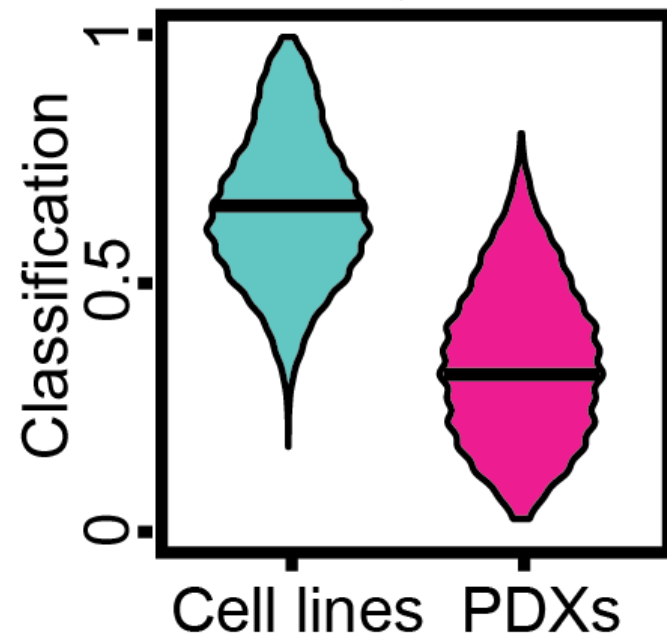
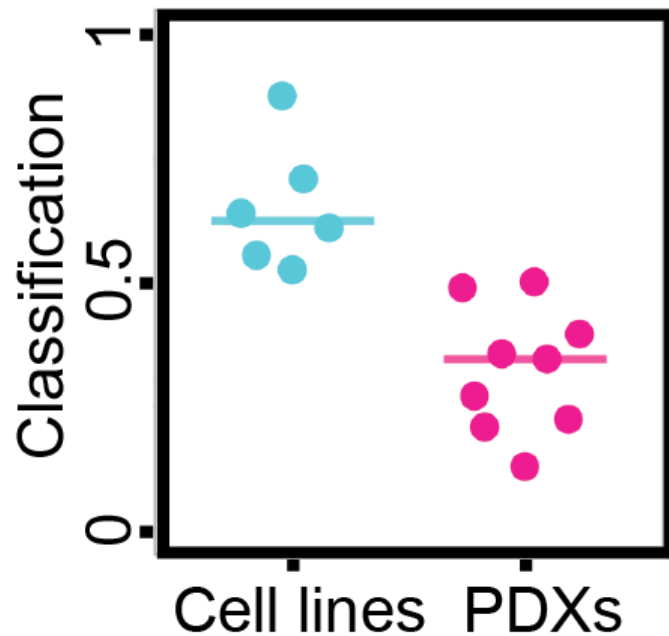


**Harnessing generative models
and live imaging to identify
(subtle) changes in refractive
index and/or pseudopod
extensions as the functional
hallmark of highly-metastatic
melanoma**

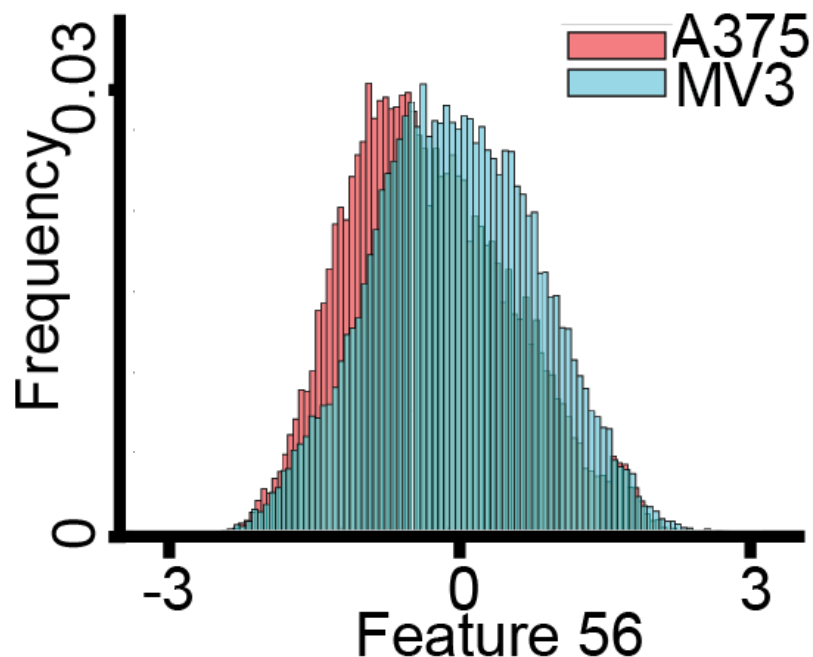
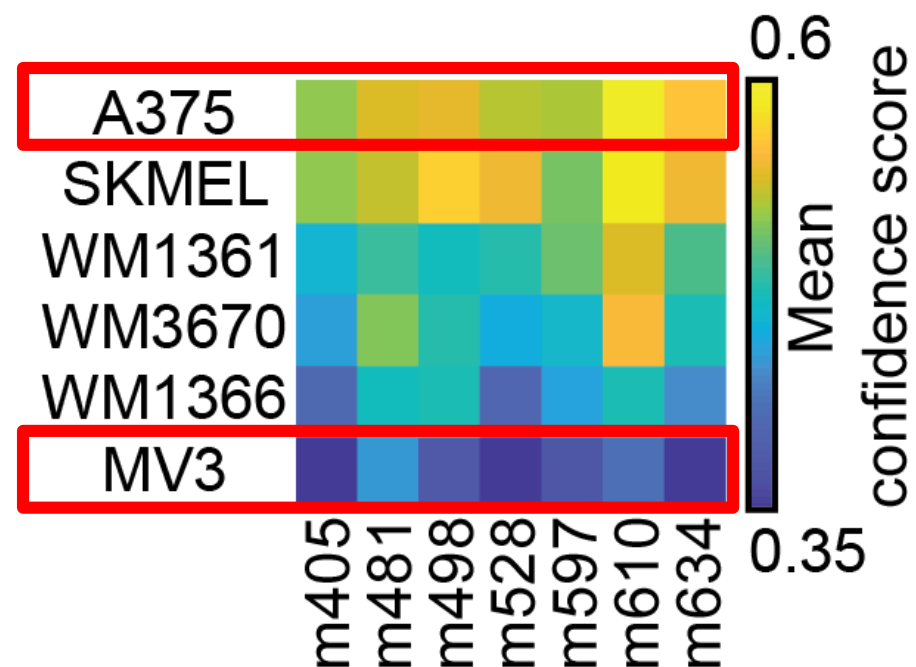
What about melanoma cell lines?

Definitely different than PDXs...

Classifier blind to the cell system

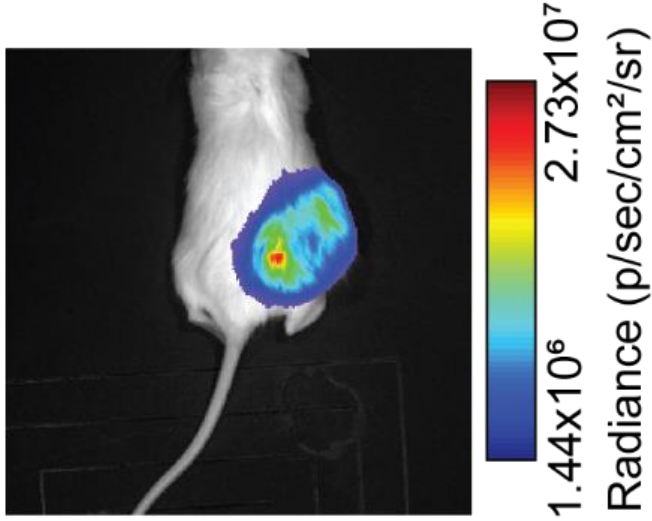


A375 has the highest and MV3 the lowest **predicted** metastatic efficiency

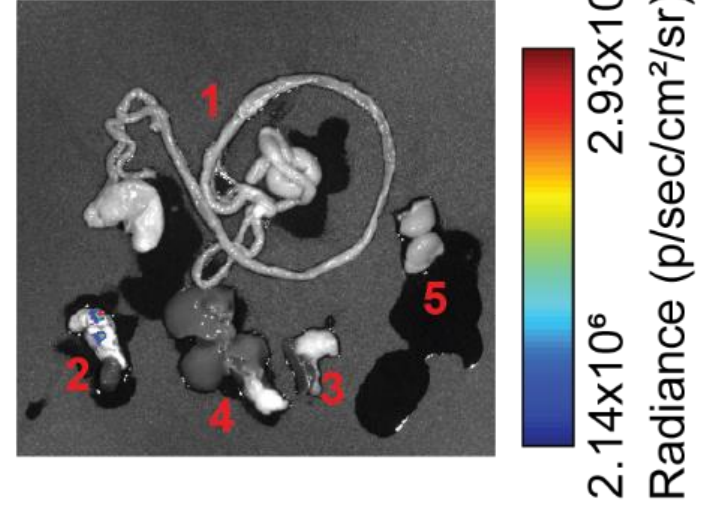
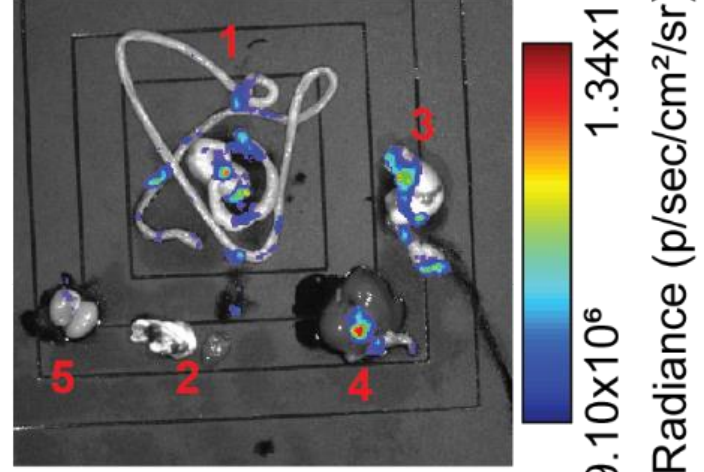
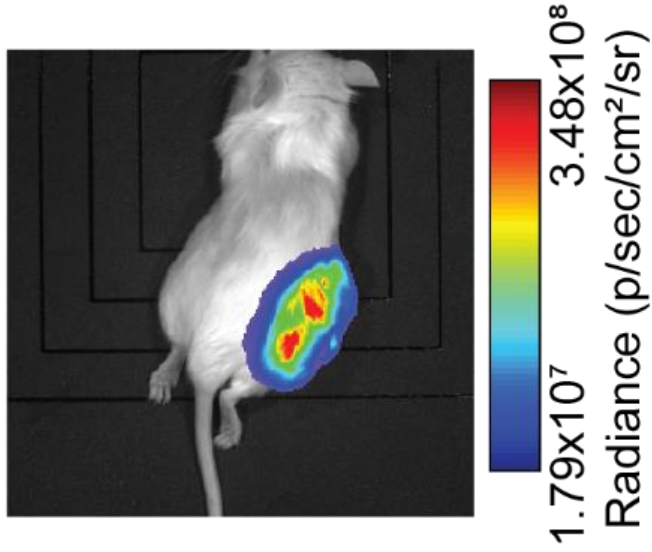


Xenografting A375 and MV3 cells into NSG mice

A375



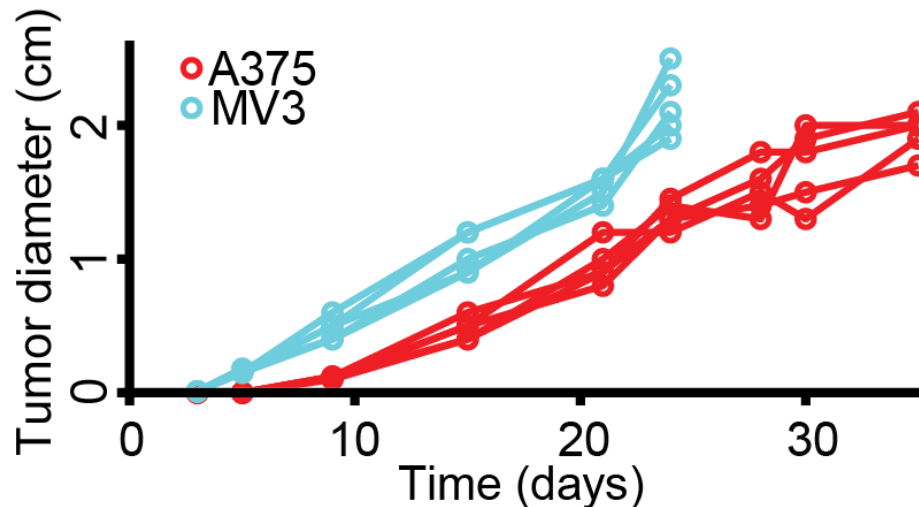
MV3



A375 is more aggressive than MV3

Cell line	BLI Lungs	BLI other organs	Remote macro mets
A375	(4/5)	(4/5)	(5/5)
MV3	(5/5)	(2/5)	(1/5)

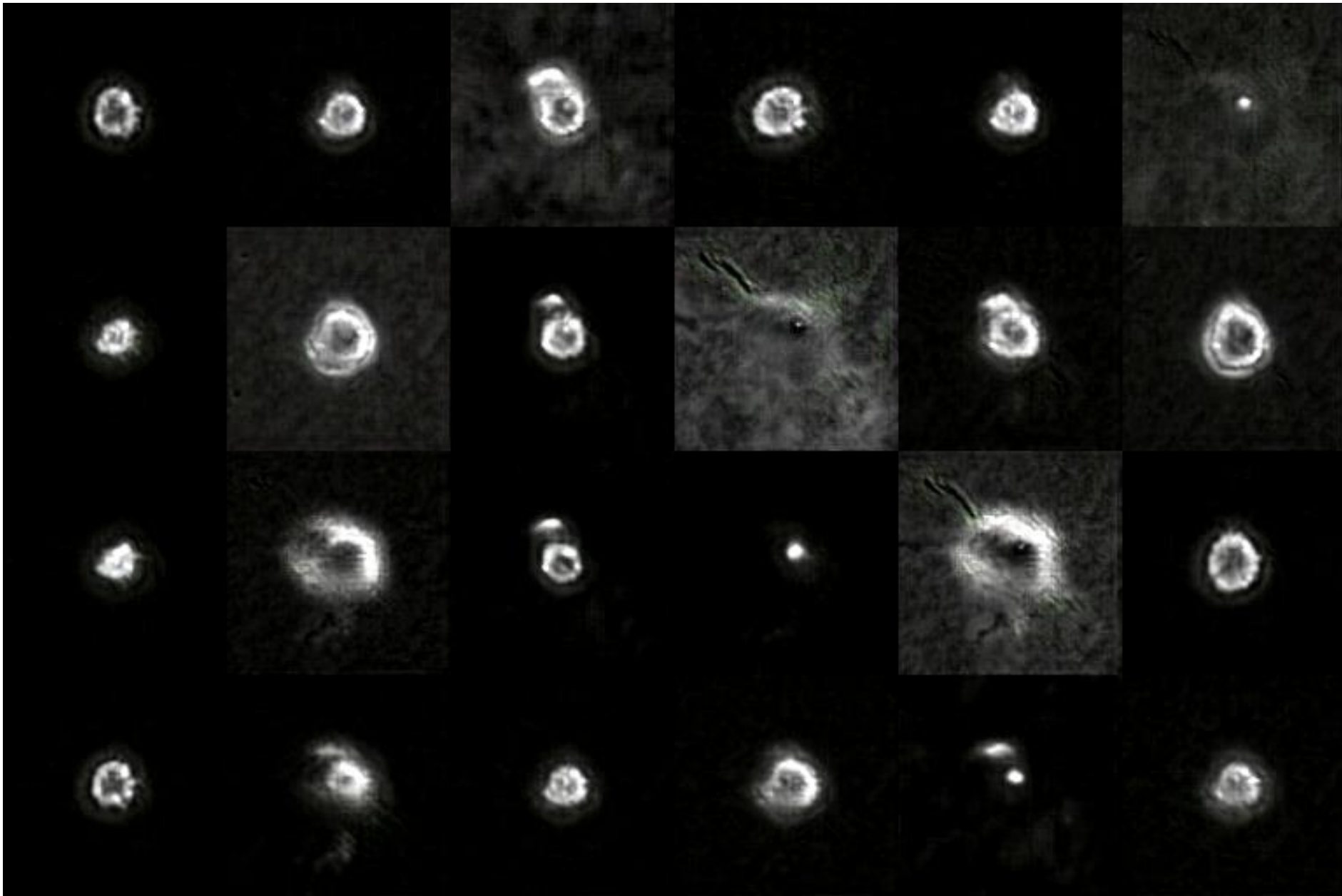
Uncoupled from tumor growth



PDX-trained classifier can predict
metastatic potential of melanoma cell
lines in mouse xenografts

Capturing a generic predictive property
for the metastatic potential of
melanoma

Summary



Acknowledgments



Andrew Jamieson



Andres Nevarez



Erik Welf



Justin Cillay



Gaudenz Danuser



Available soon

(next week?) @

bioRxiv

THE PREPRINT SERVER FOR BIOLOGY

Next week 20.5

- Kota Miura, NEUBIAS, on bioimage analysis (English), 17:10!
- Students lectures:
 - Oron Barazani - DL in microscopy
 - Deep learning enables cross-modality super-resolution in fluorescence microscopy. Hongda Wang, Yair Rivenson,..., Aydogan Ozcan (2019)
 - Shani Kleiman - medical imaging
 - Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. Poplin, Varadarajan,..., Peng, Webster (2018)