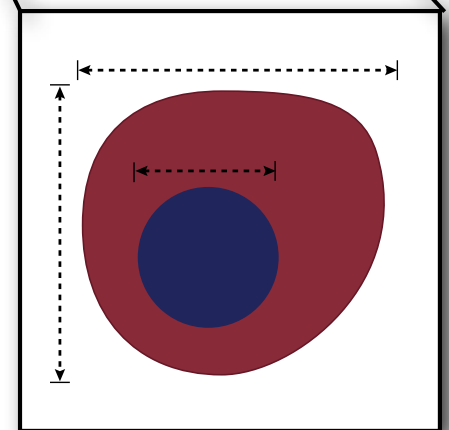


Extracting rich information from biological images

Anne E. Carpenter, Ph.D.



0.4233
54,454
45.777
0.6886
0.0055
6.9994
83.333
14.113
1.5567
0.0954
0.5553

...

Carpenter lab

Broad Institute Imaging Platform

Taking on challenging image analysis and data mining projects



Anne
Carpenter

Image assay development

Apply image analysis methods to biological questions



David
Logan

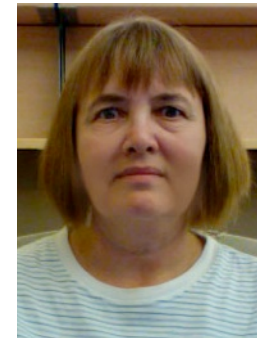


Mark
Bray



Kate
Madden

IT/Administration



Peggy
(Margaret)
Anthony

Algorithm development & software engineering

Develop & test new image analysis and data mining methods
and create open-source software tools



Vebjørn
Ljoså



Adam
Fraser



Lee
Kamentsky



Carolina
Wählby

Students and postdocs

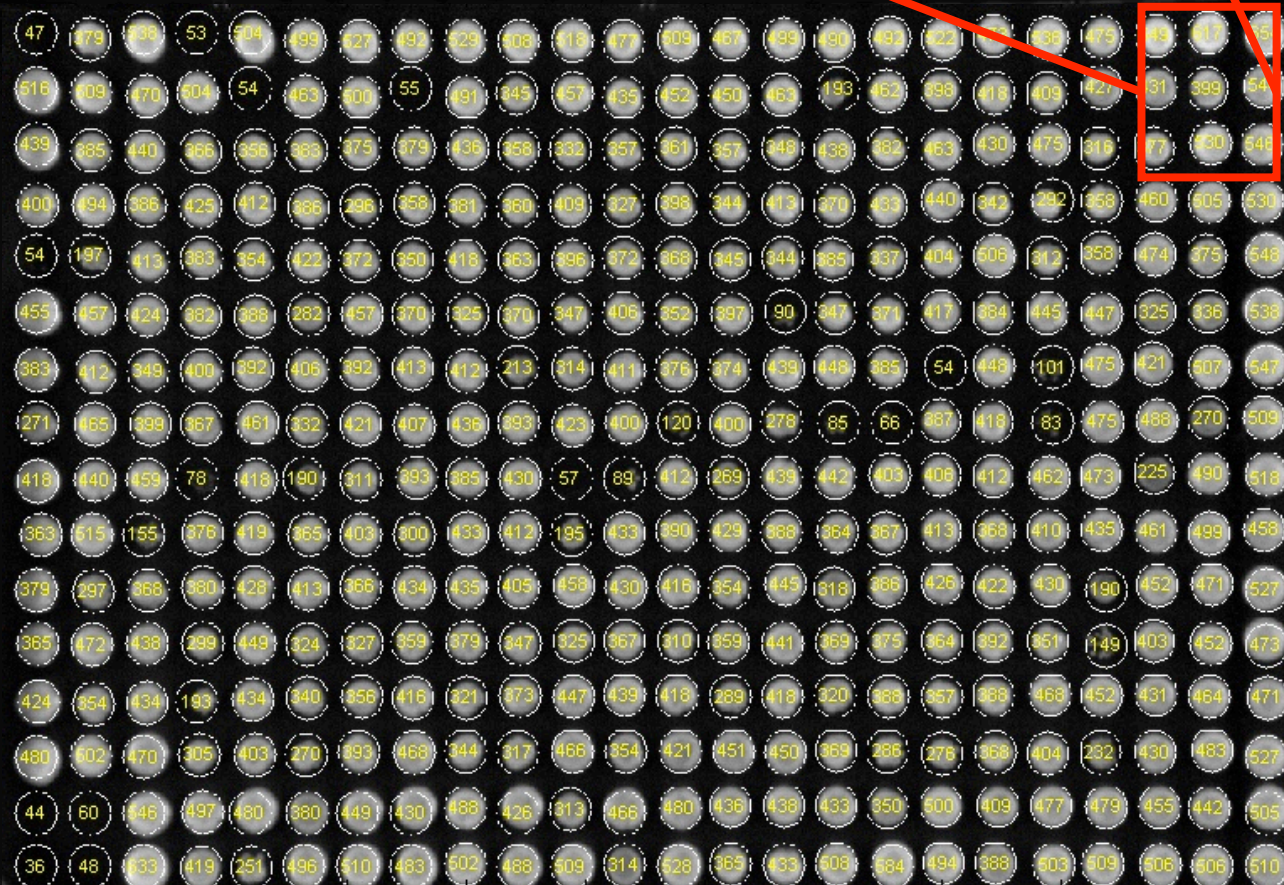


Imtiaz
Khan

Yeast patch growth:

Goal: identify chemicals or genetic knockouts that enhance/suppress growth of a yeast strain

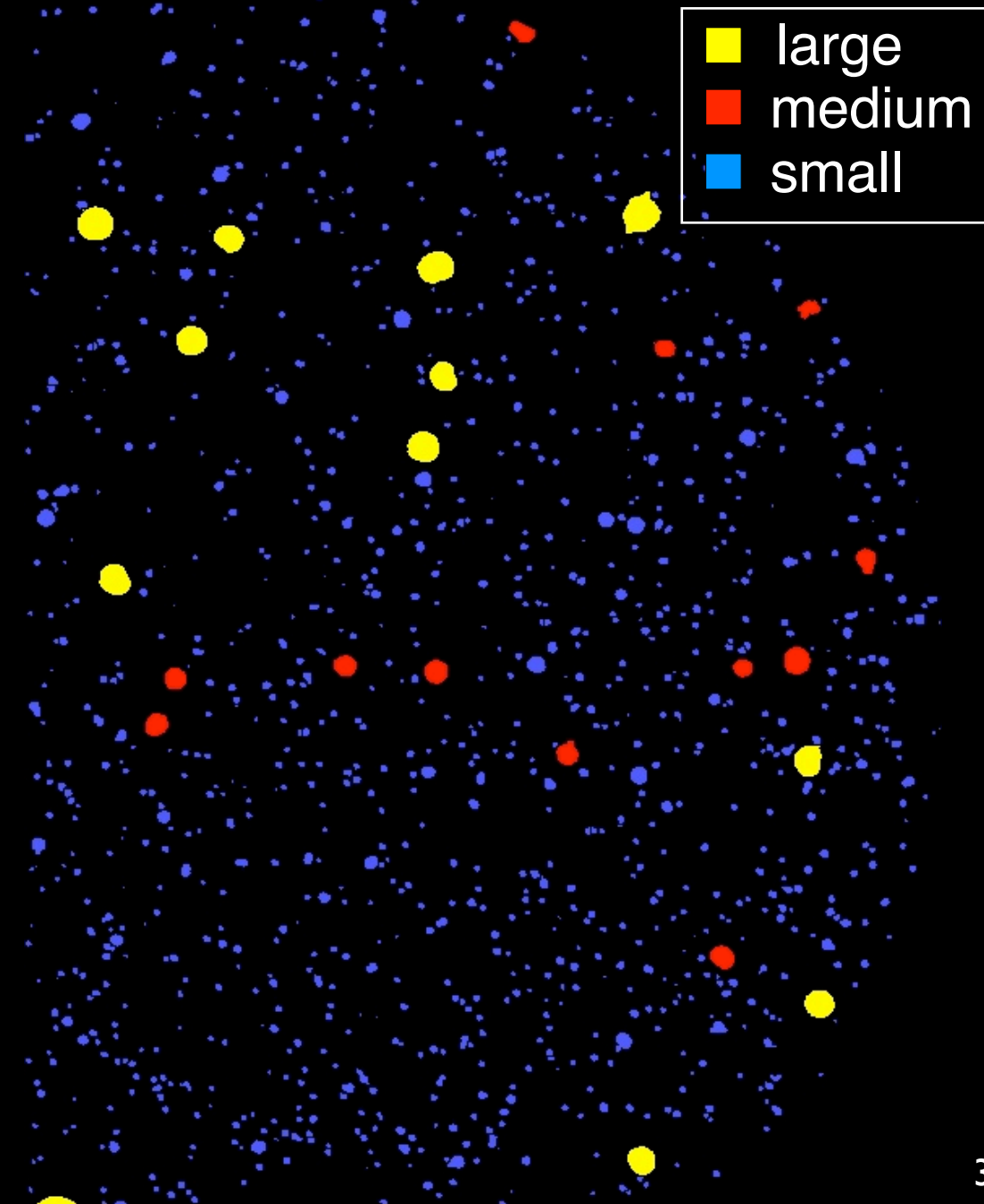
Collaboration with Novartis



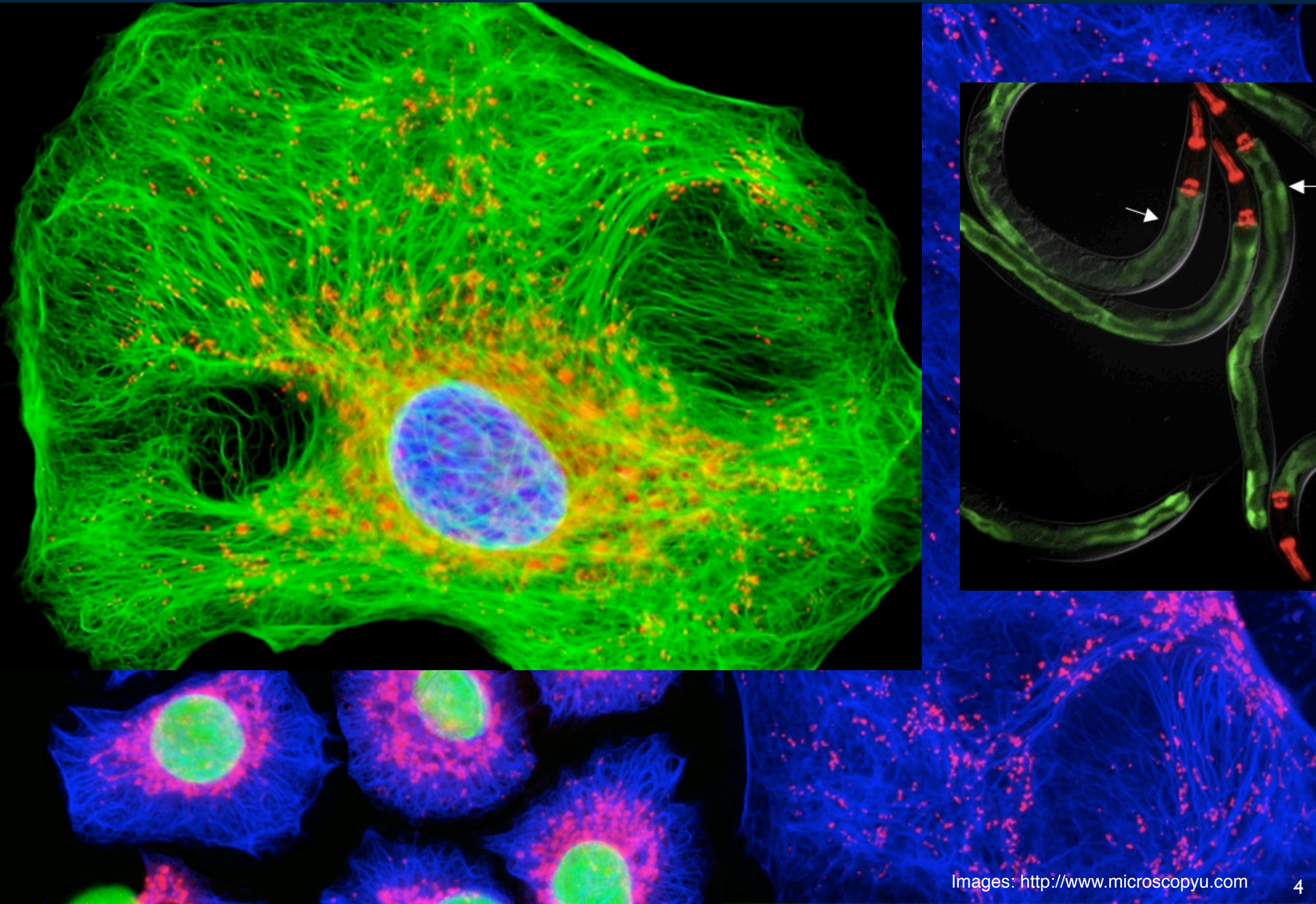
Yeast colony size:

Goal: to understand pathways leading to drug-resistant yeast

Cowen, et al., Eukaryotic Cell, 2006



Images contain a wealth of information

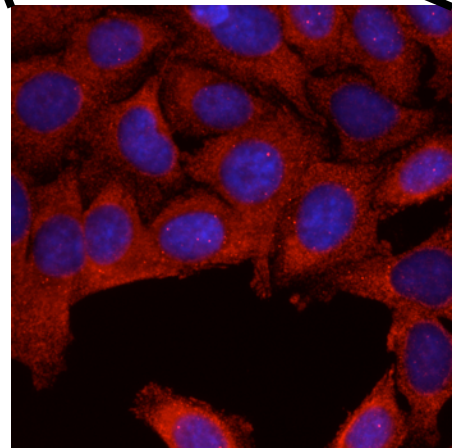
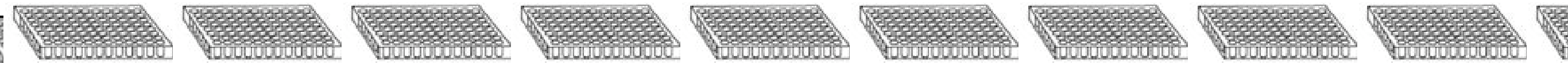


Screening to find genes and chemicals of interest

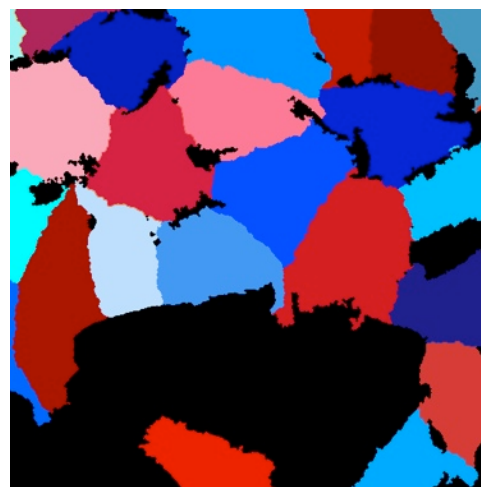
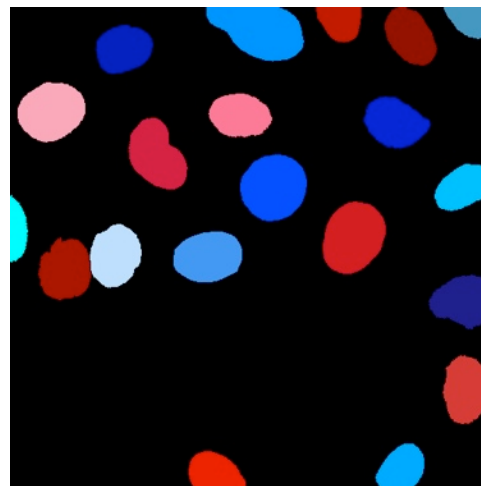
Biology research groups (Harvard, MIT, around the world)

NIH:
MLPCN

Cells in multiwell plates, each well treated with a gene or chemical perturbant

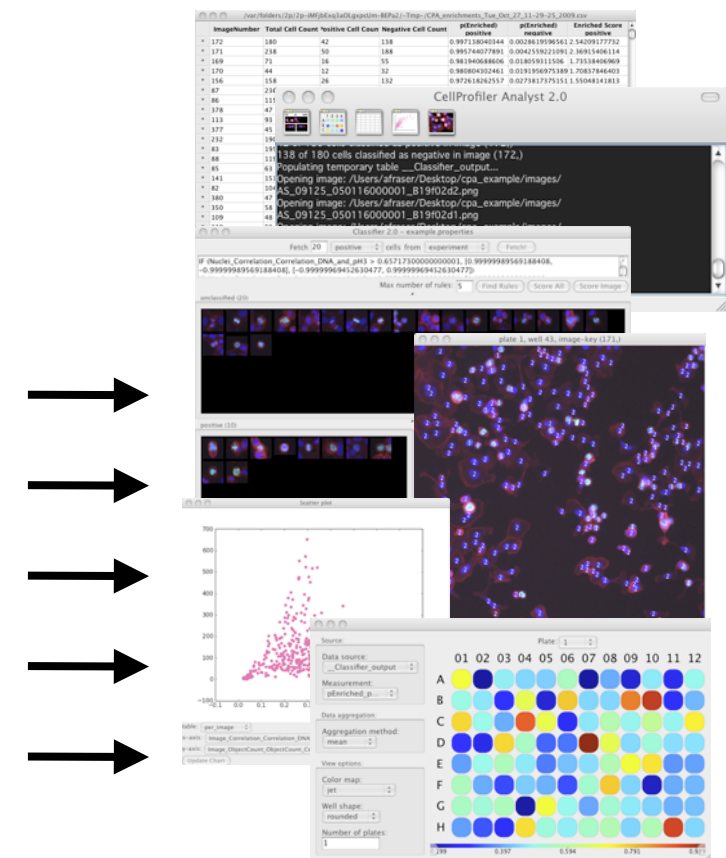


automated
microscopy
(any manufacturer)



→ Cell
→ measurements

→ (size, shape,
→ intensity, texture,
→ etc.)



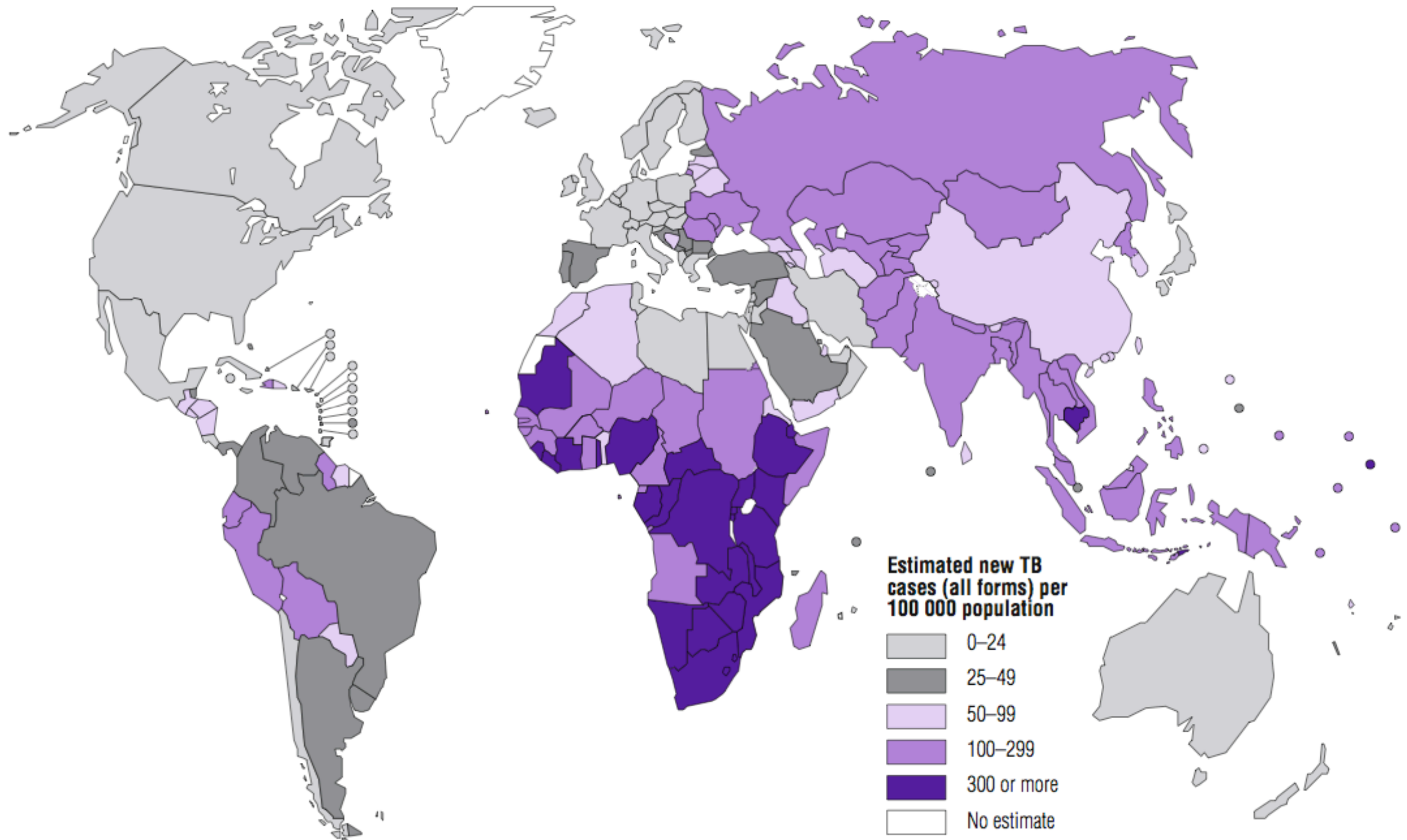
Data exploration
& machine learning



Ray
Jones Anne
Carpenter

Case study: Tuberculosis

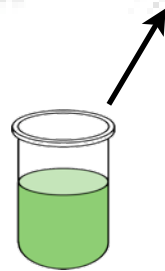
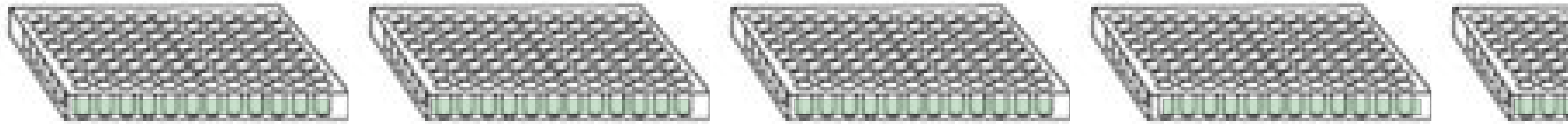
Estimated TB incidence rates, by country, 2006



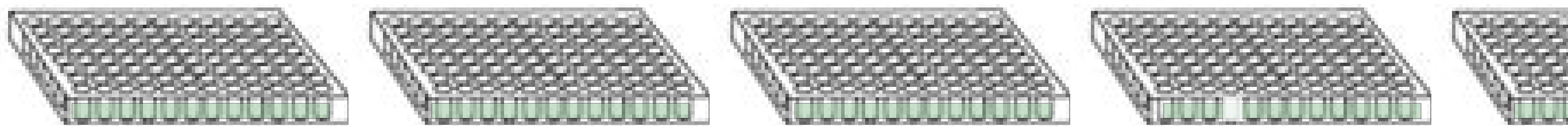
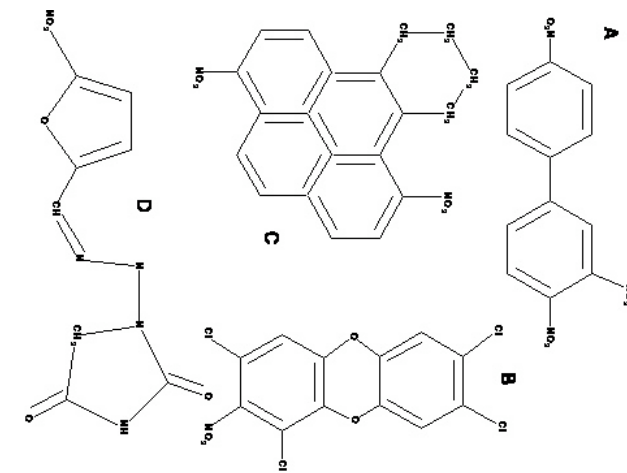
9.2 million new cases of tuberculosis in 2006
1.7 million deaths in 2006

Traditional approach to find antibiotics

Put **bacteria** in individual wells of multi-well plates

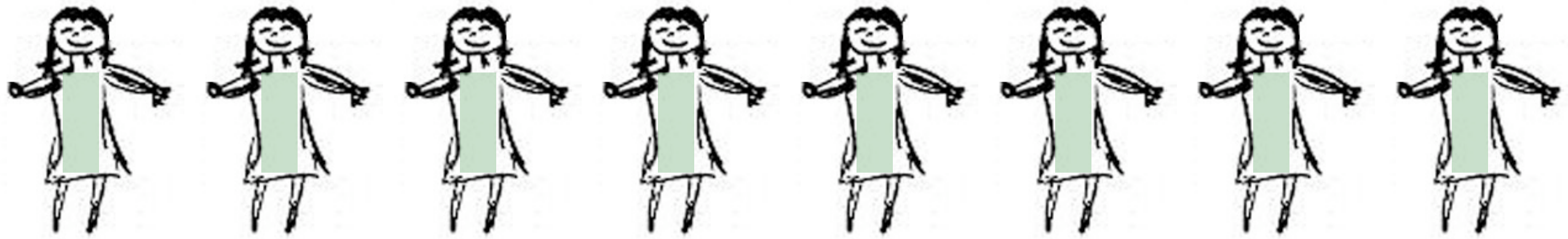


Add 1,000,000 test chemicals, each chemical in a different well

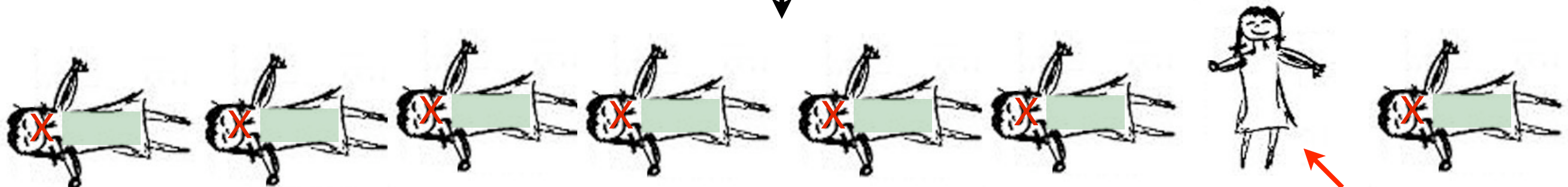
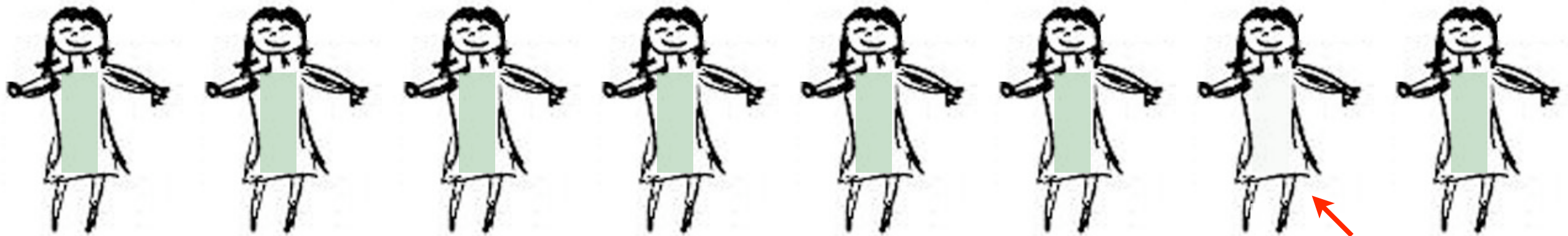
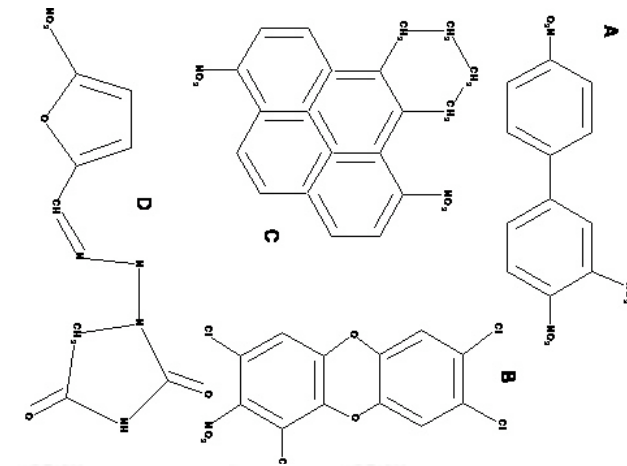


Measure amount of bacteria (fluorescence plate reader) and look for wells where bacteria died

Alternate approach to find antibiotics (effective but non-ideal)



Add 1,000,000 test chemicals, each chemical in a different person



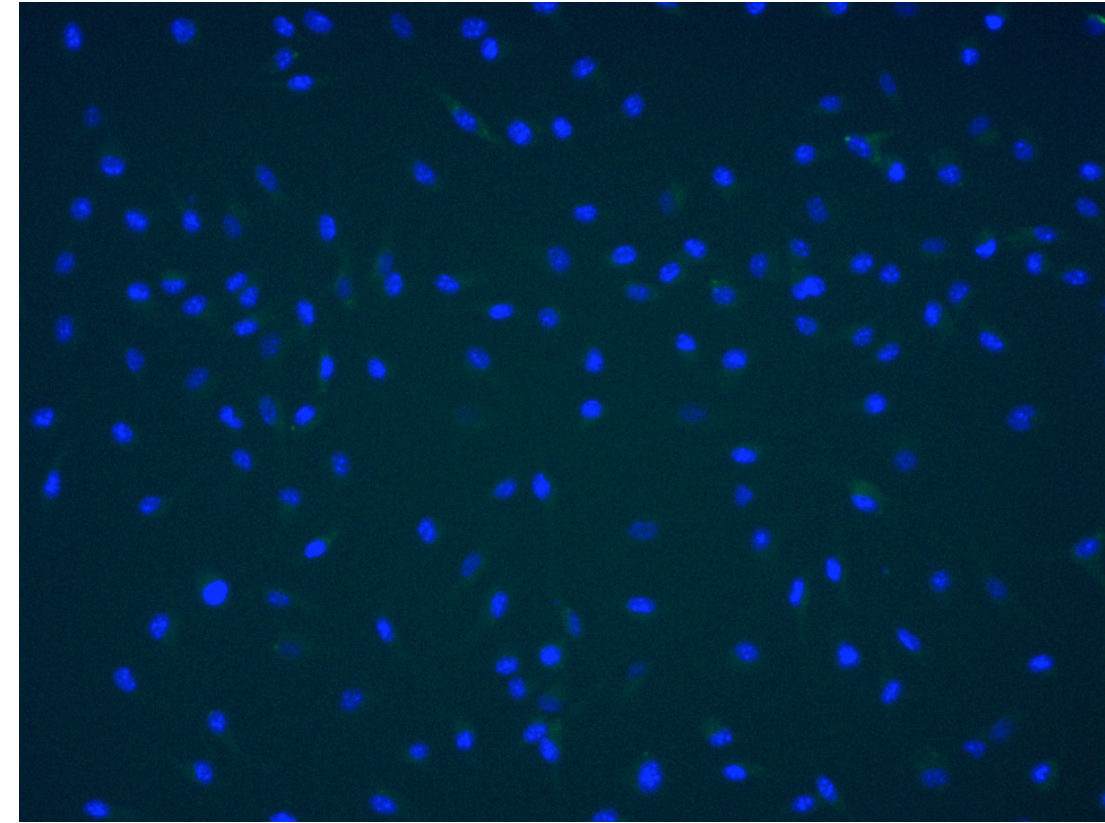
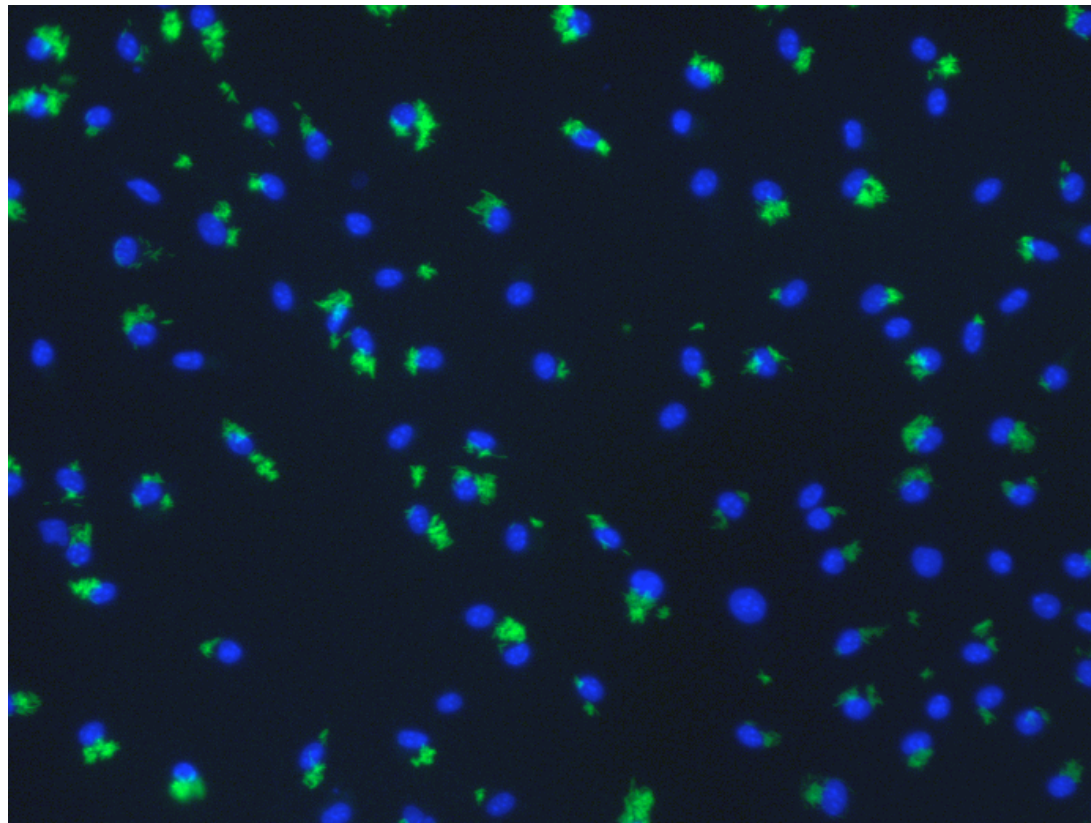
Search for tuberculosis treatments

Without drug

With drug

human
nuclei

tuberculosis
bacteria



Martha
Vokes



Mark
Bray



Deb Hung,
Broad/MGH

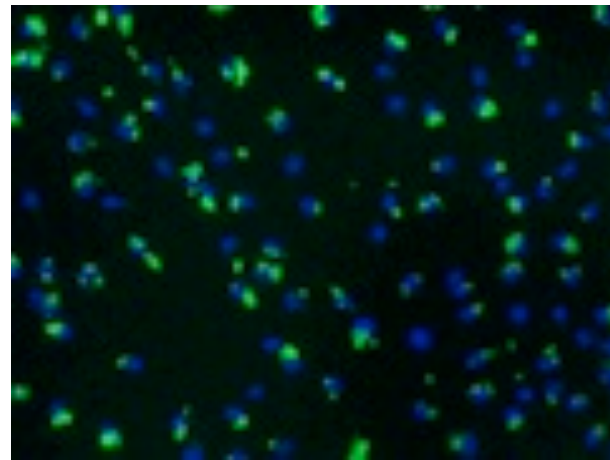
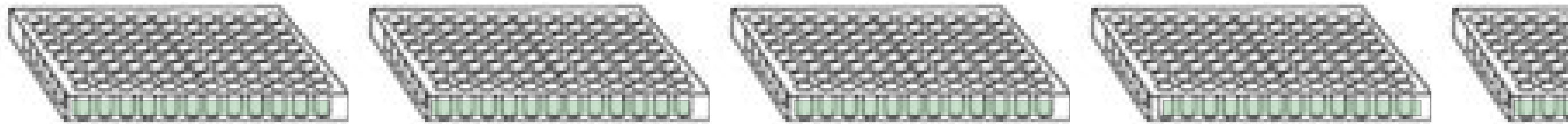


Sarah Stanley,
postdoc

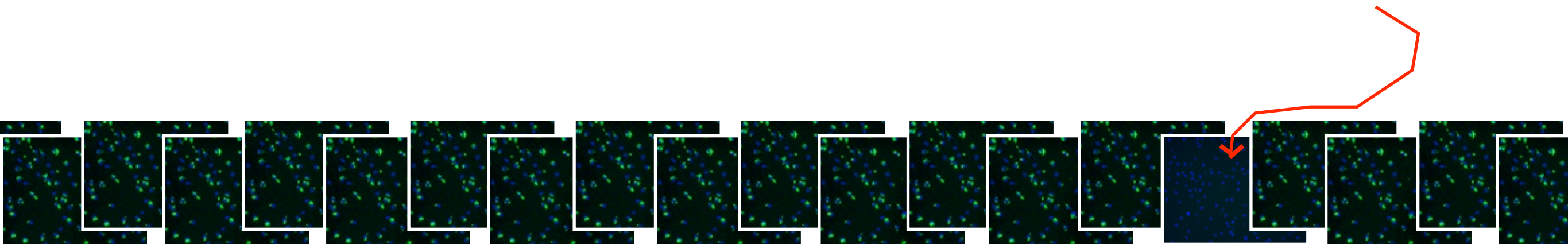
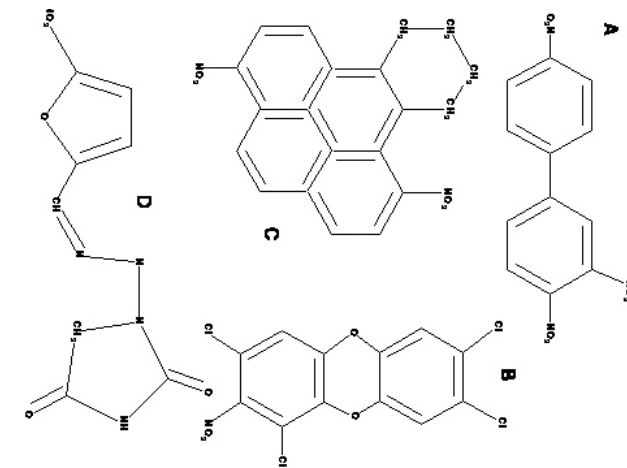
project in progress

Search for tuberculosis treatments

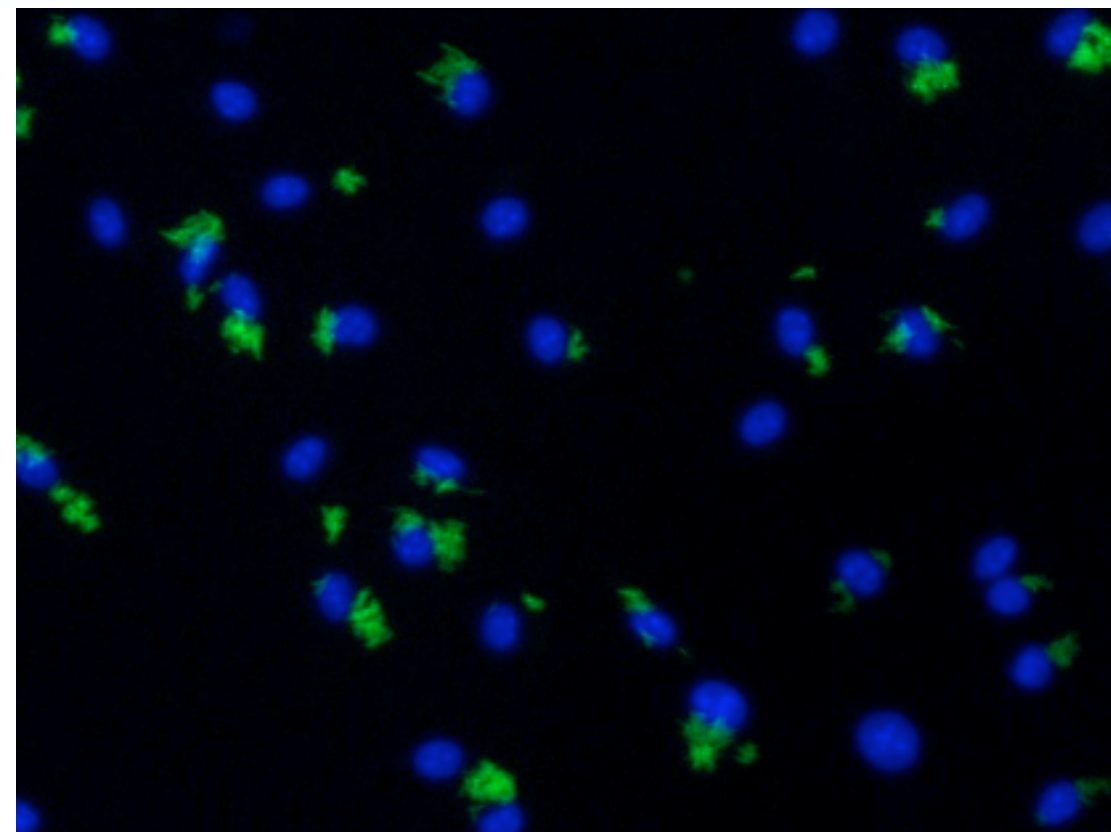
Put **bacteria** and **human cells** in individual wells of multi-well plates



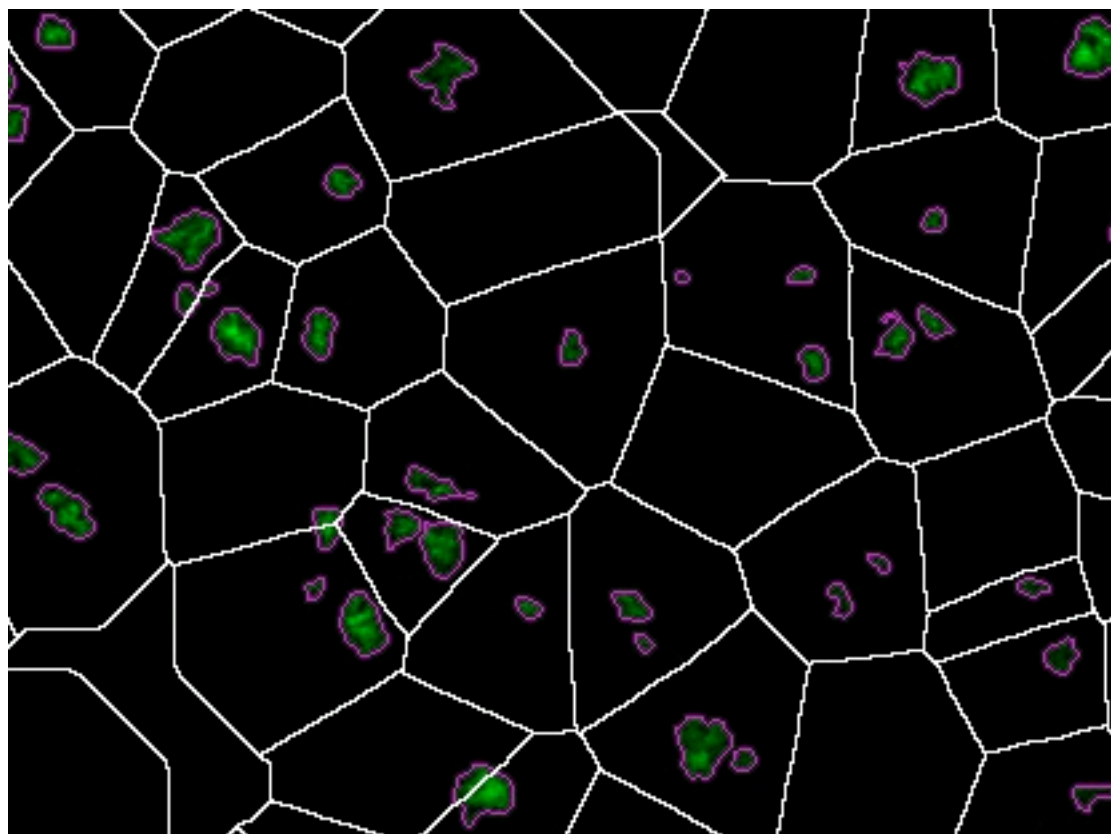
Add 20,000 test chemicals, each chemical in a different well



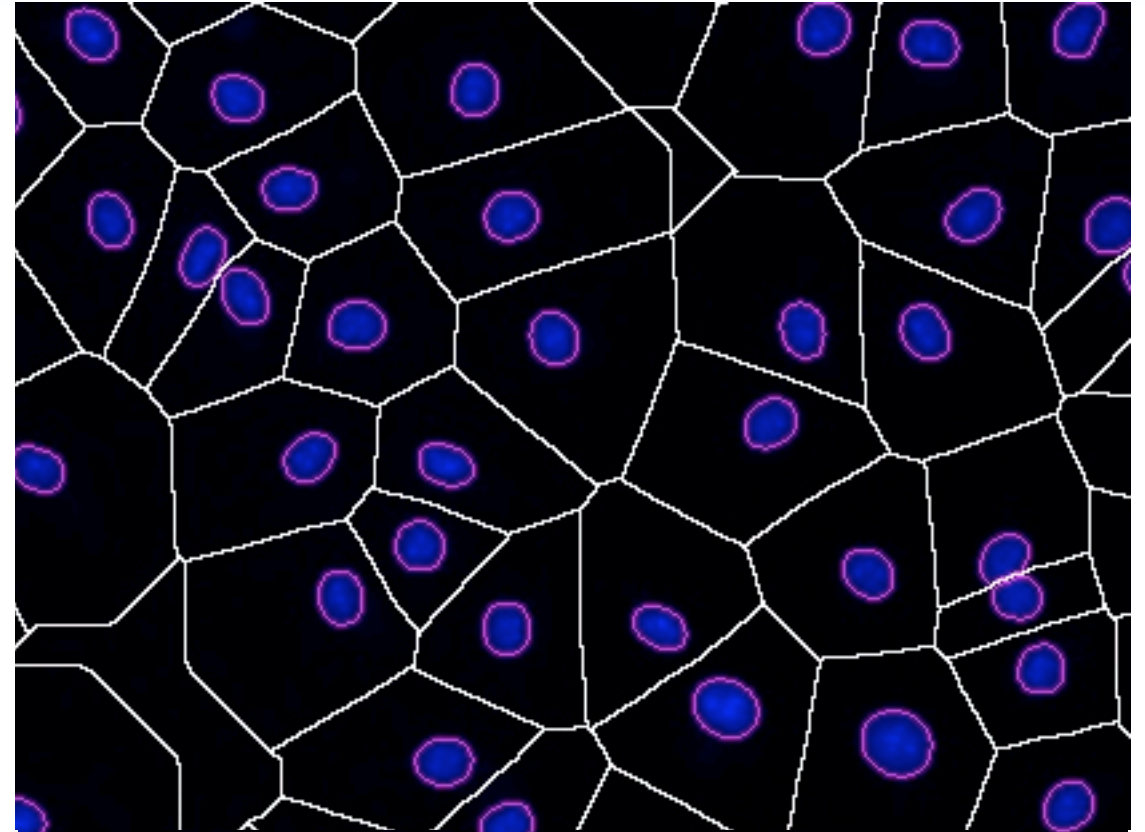
Automated image analysis



↓ Find bacteria



→ Find
human
nuclei



→ Quantify the bacteria
per human nucleus

Status: pursuing hits from
small-scale bioactive
compound screen + scale-up
to 30,000 compounds



Martha
Vokes

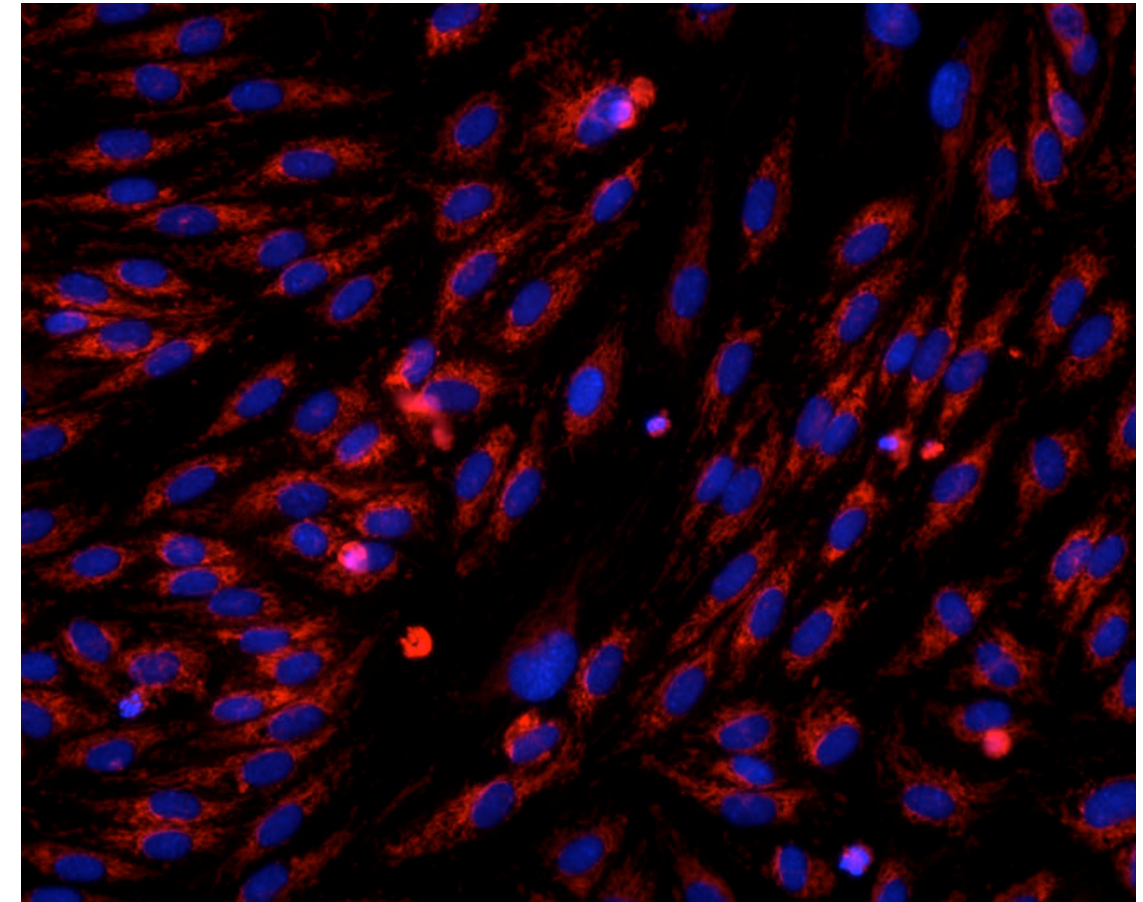
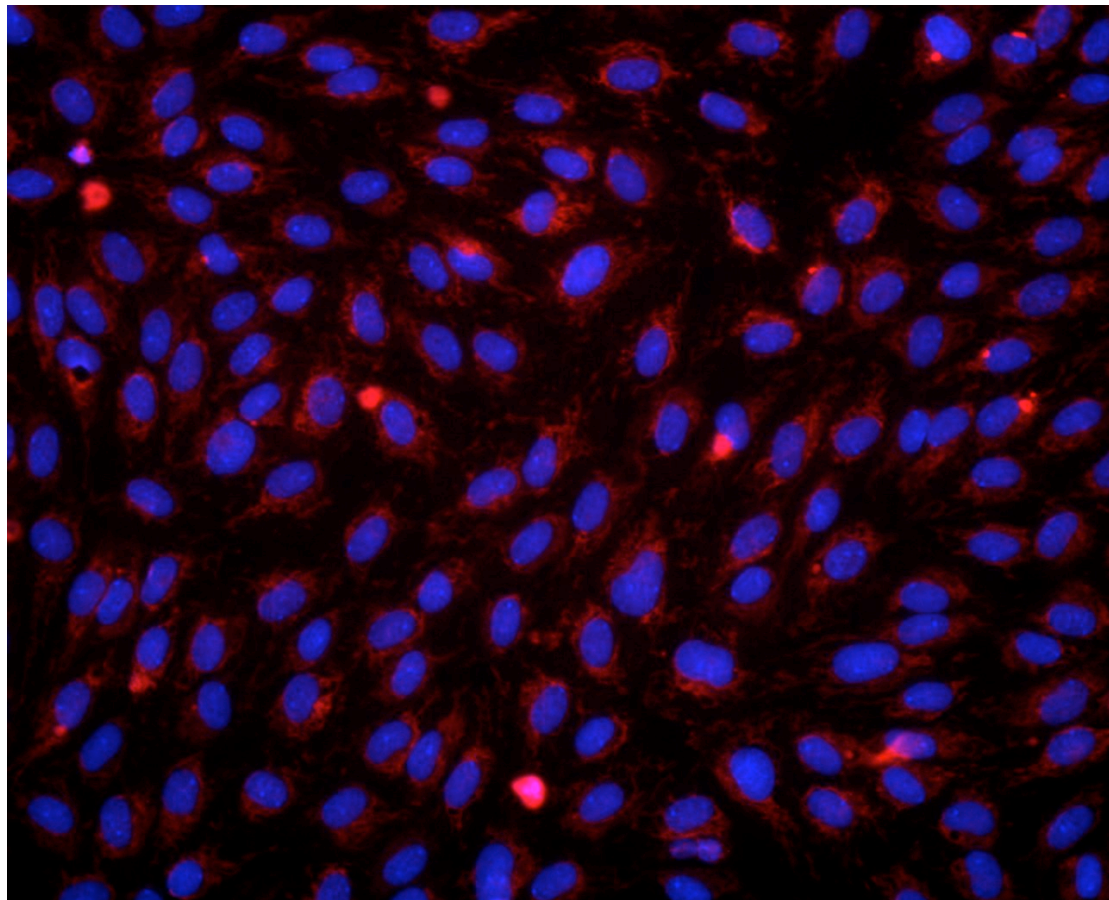
Mitochondrial abundance

Negative control

Positive control

DNA

Mito-
tracker



Ray
Jones



Martha
Vokes



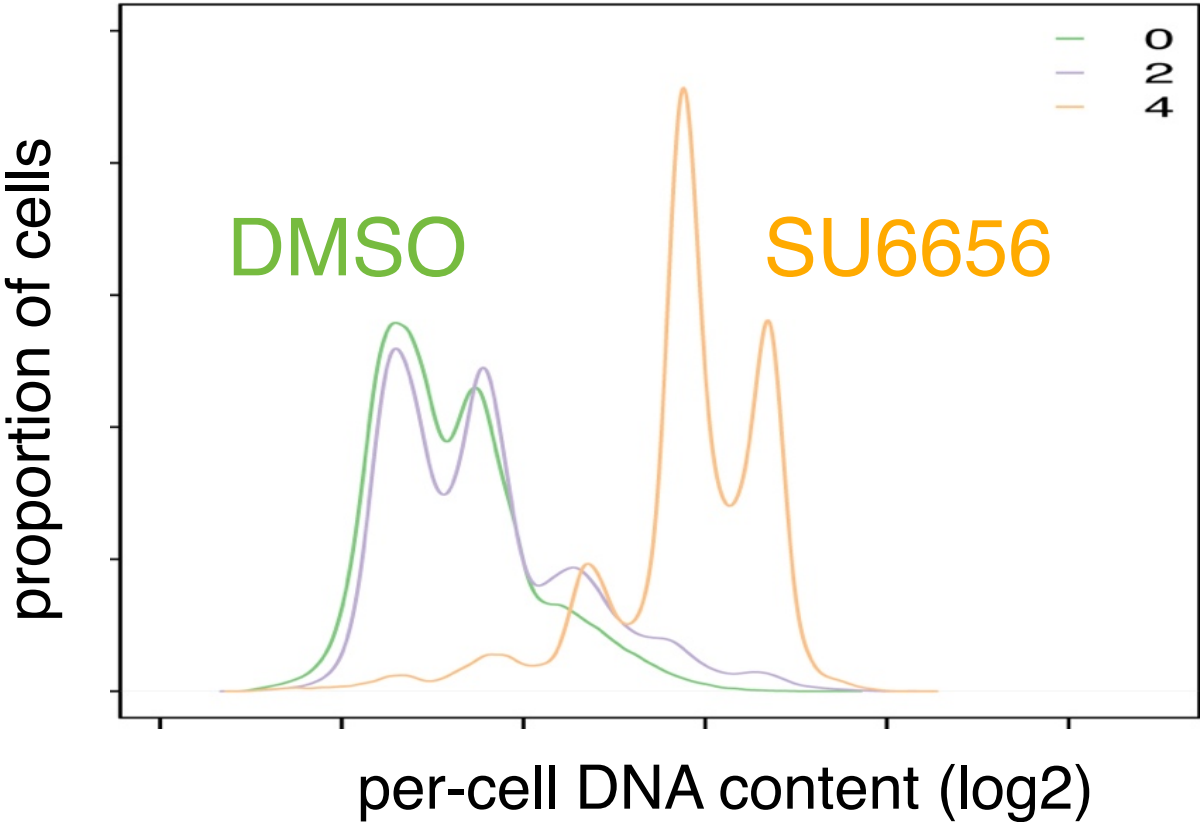
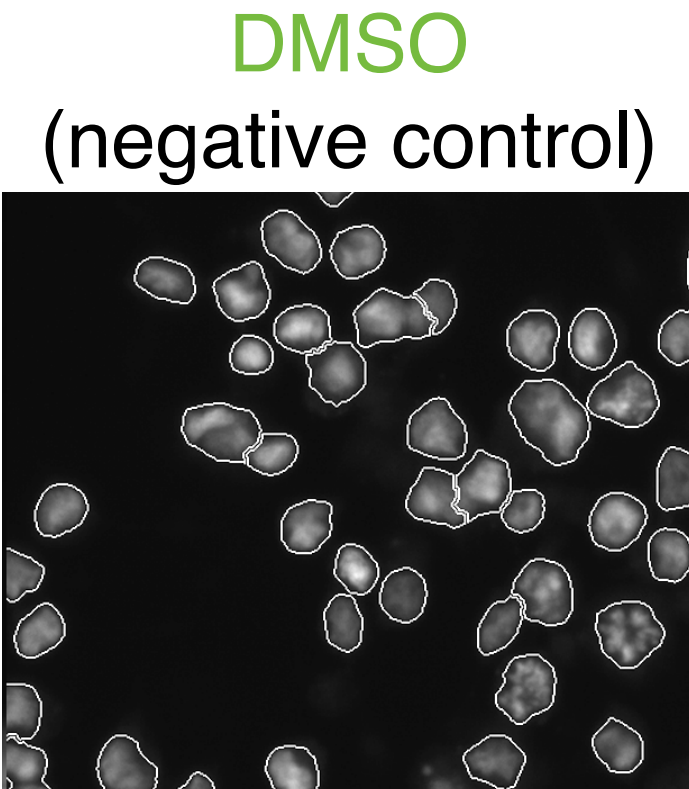
Vamsi Mootha,
Harvard Med/
MGH

Toshi
Kitami,
postdoc

project in progress

Polyploidization of megakaryocytes - AMKL (leukemia)

DNA stain,
with
outlines
identifying
the nuclei



Status: *in vivo* testing of
hits from screen of
10,000 compounds



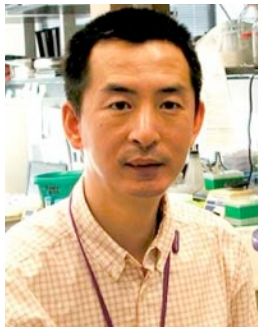
Martha
Vokes



Mark
Bray

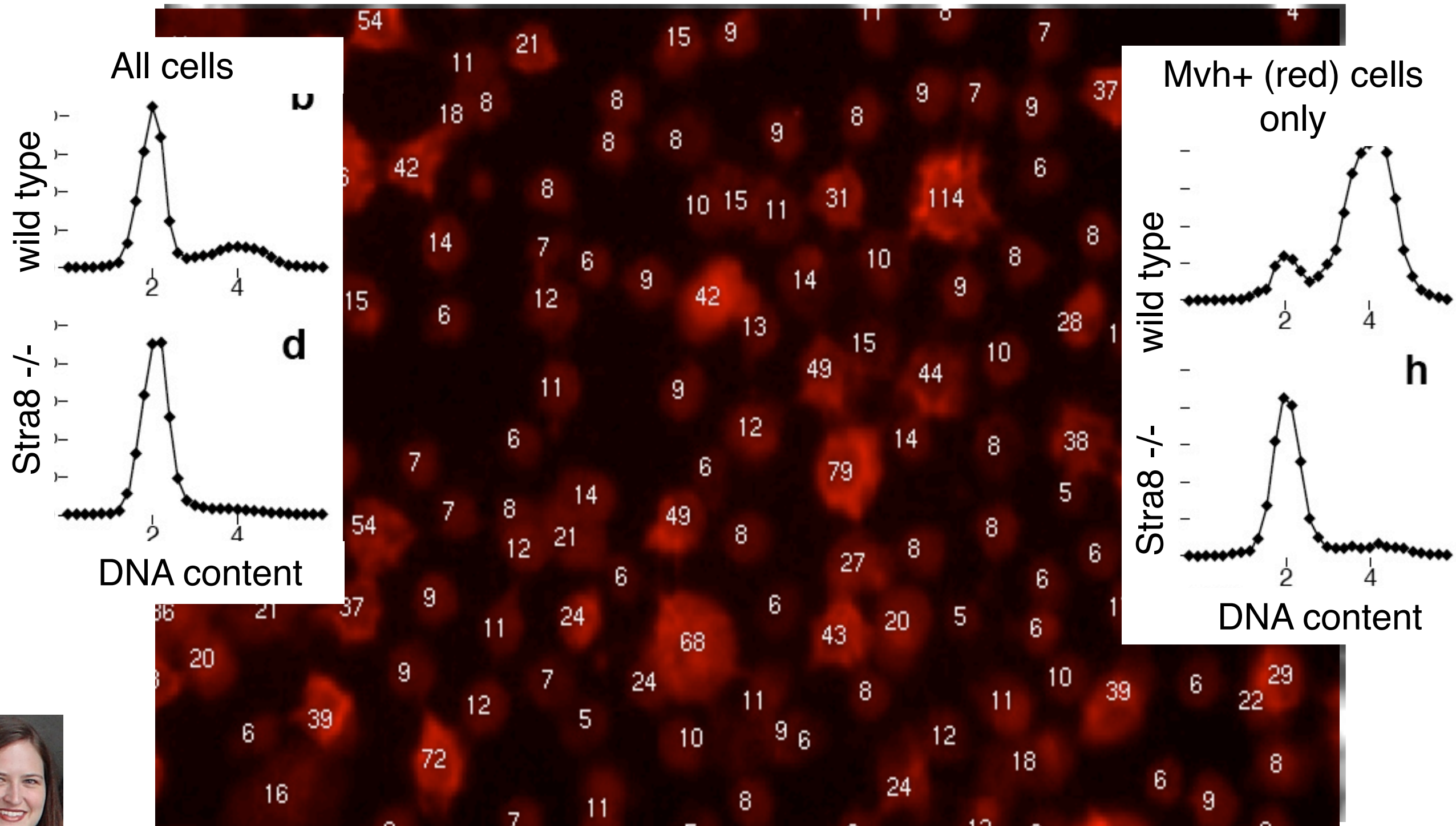


John Crispino,
Northwestern
University



Jeremy
Wen,
postdoc

DNA and antibody staining intensity



Anne
Carpenter

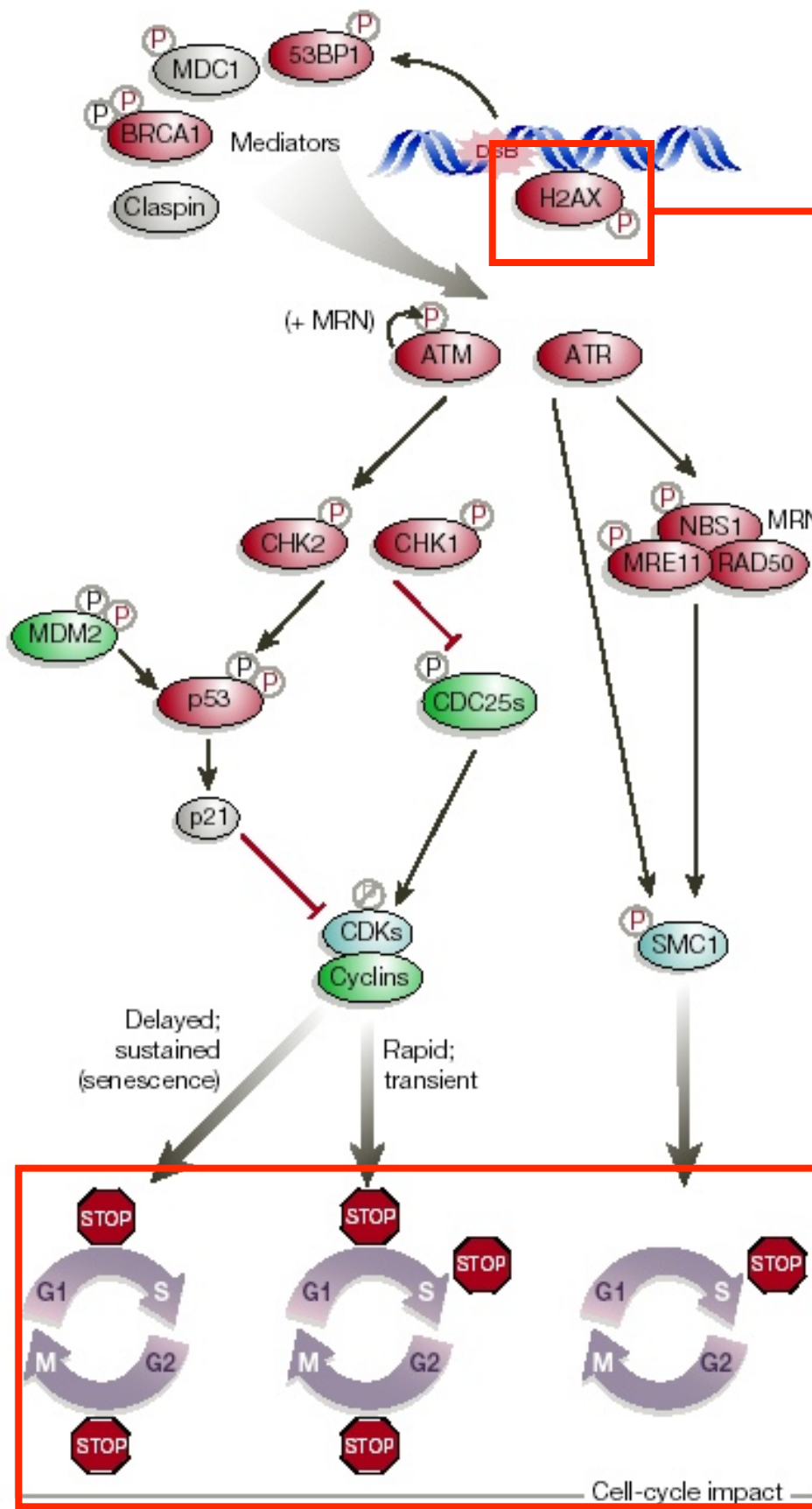
Baltus, ... Carpenter, et al., Nature Genetics, 2006

David
Page,
Whitehead
Institute

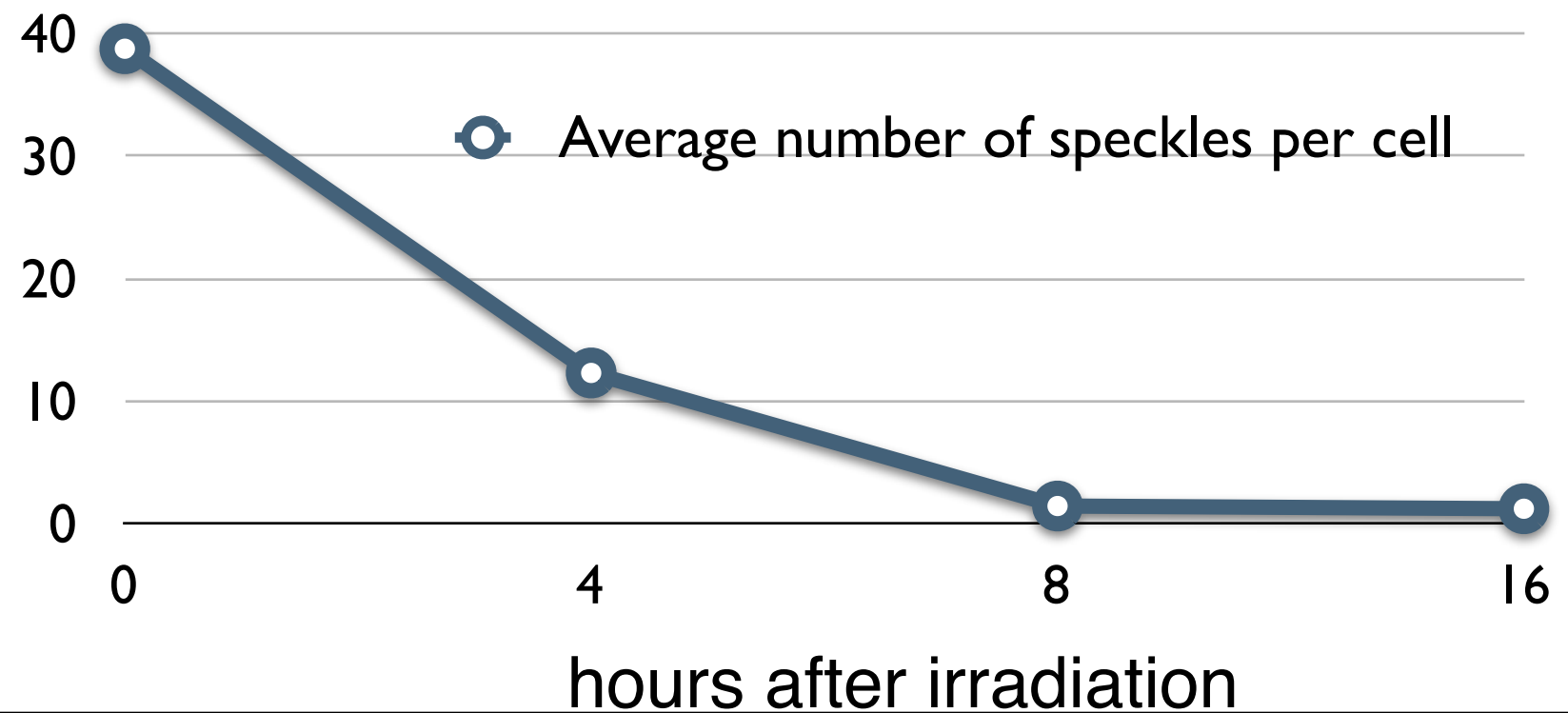
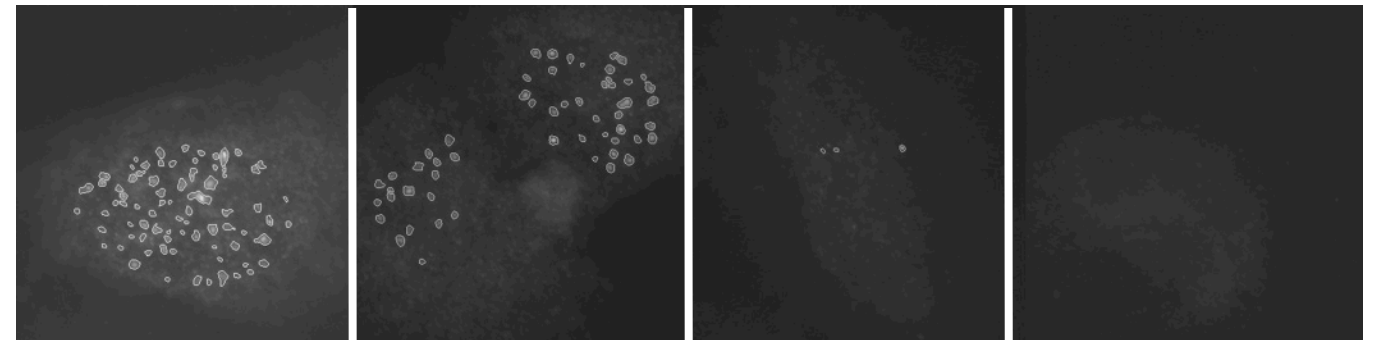
Andrew
Baltus,
postdoc

Screen genes/drugs for DNA damage response

Goal: find new drug targets in the DNA damage response pathway to improve efficacy and reduce side effects of existing treatments.



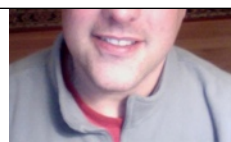
phospho-
Histone
2AX



Mike Yaffe,
MIT



Michael
Pacold,
postdoc



Scott Floyd,
postdoc

project in progress

Novel antibiotics against *E. faecalis*

Control

Rescuing antibiotic

Bright-
field



Ray
Jones



Anne
Carpenter



Fred Ausubel,
Harvard/
Mass. General
Hospital



Terry
Moy

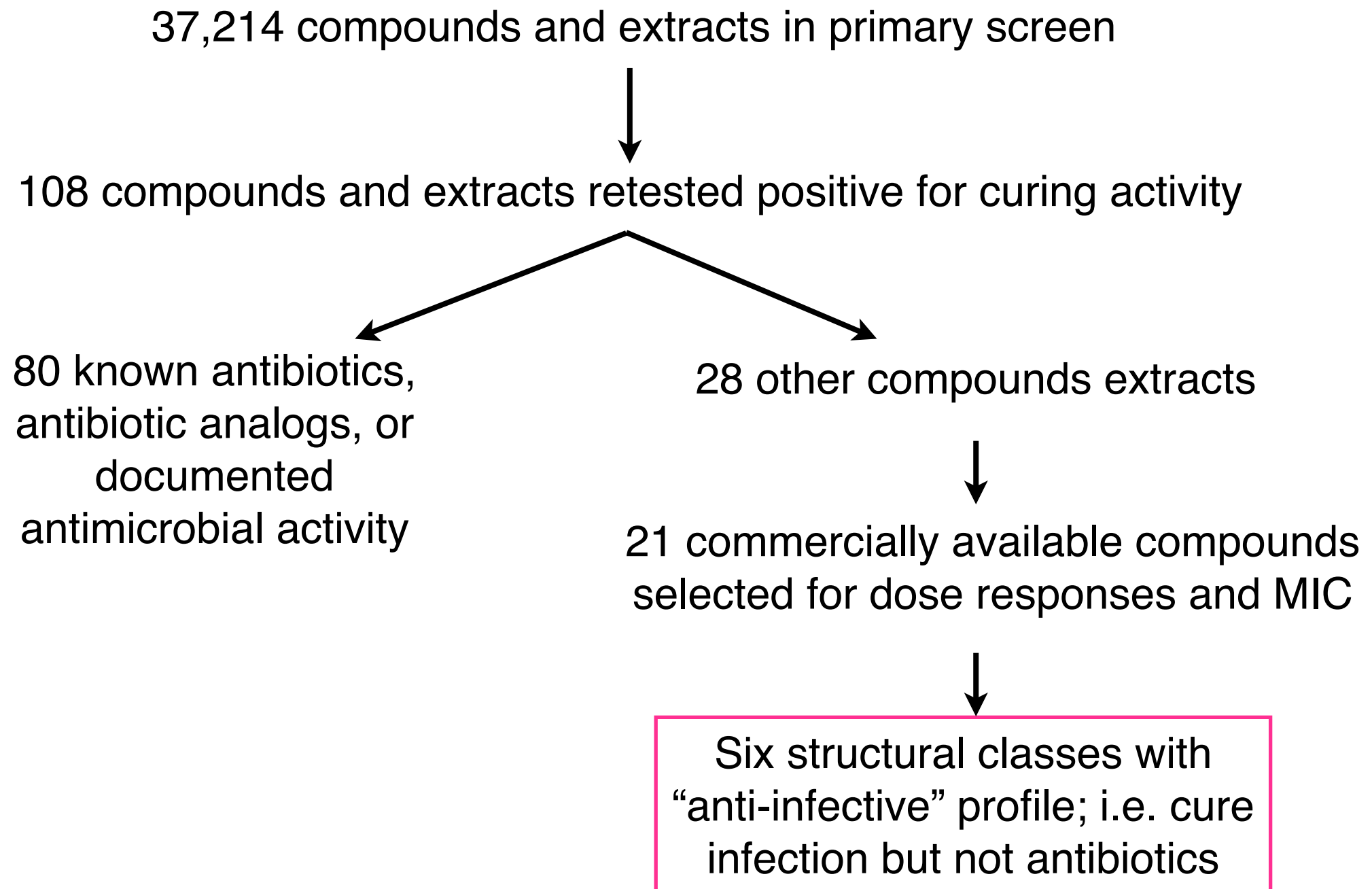


Annie
Lee
Conery

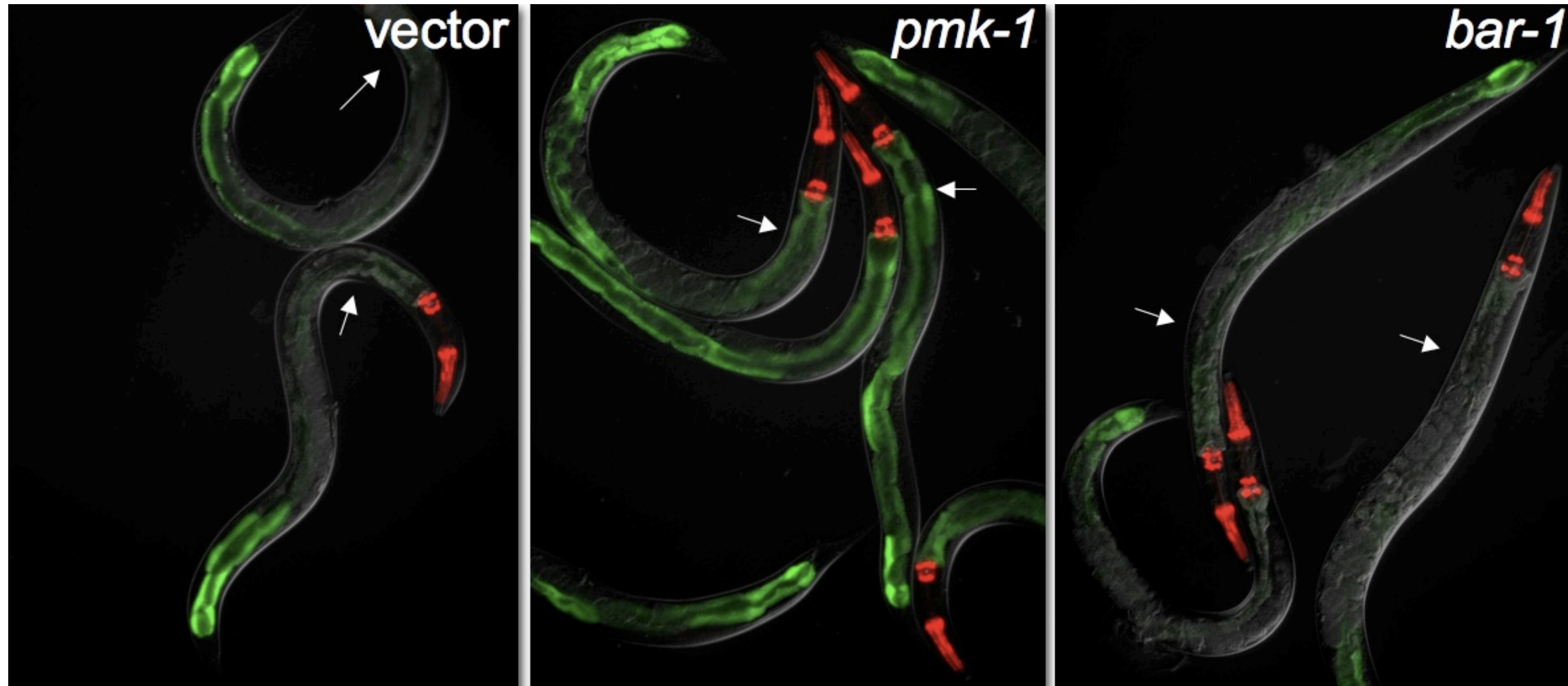


Gang
Wu

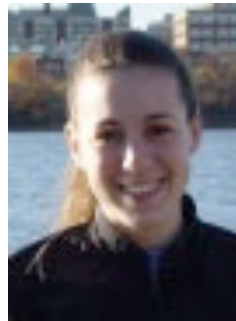
Novel antibiotics against *E. faecalis*



Reporter expression in response to infection



Carolina
Wahlby



Kate
Madden



Zihan
Hans
Liu

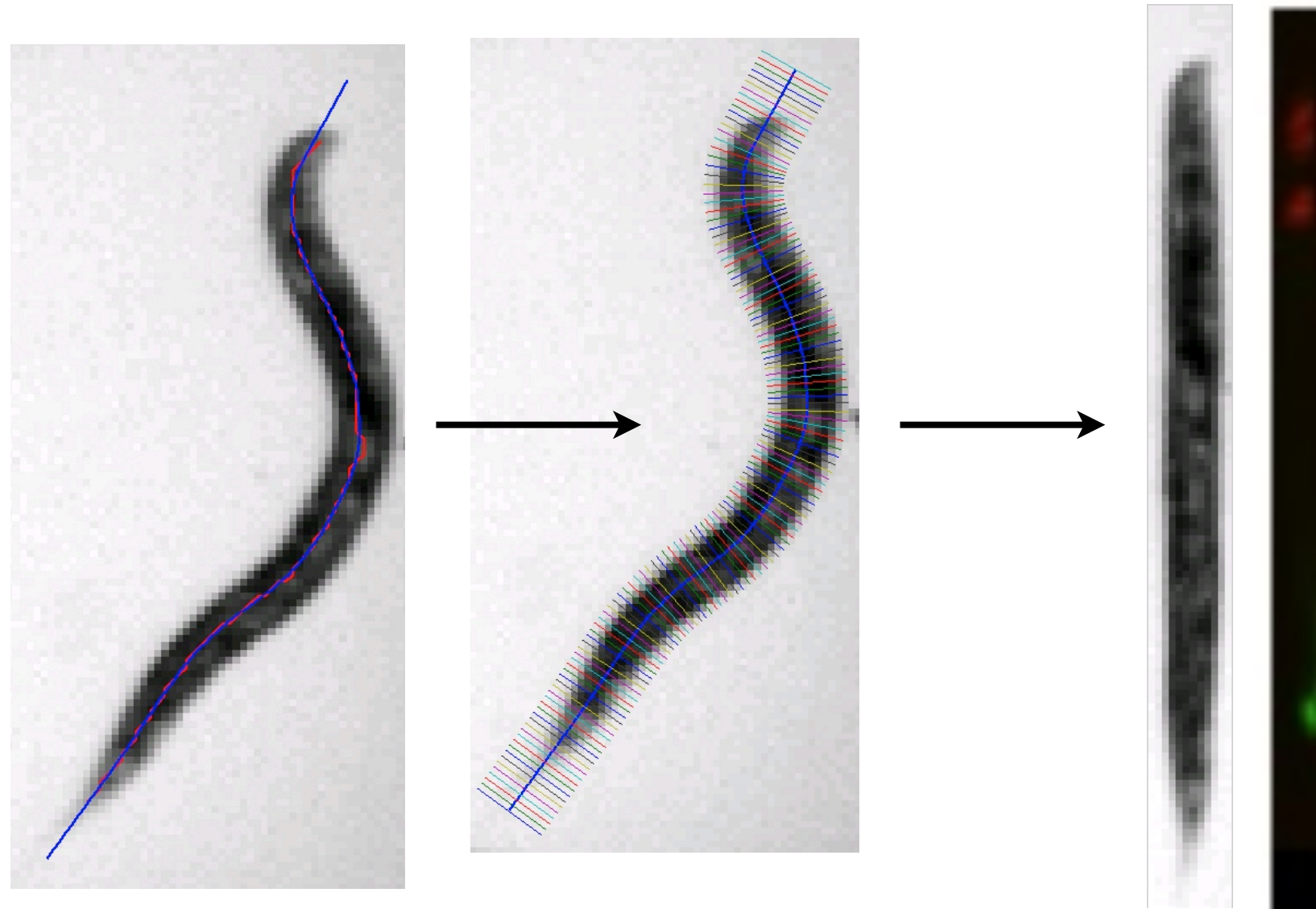


Javier
Irazoqui 18

project in progress

Reporter expression in response to infection

Goal: compare pattern of GFP along the length of the worm



Approach: 'Straighten' worms



Carolina
Wahlby



Kate
Madden



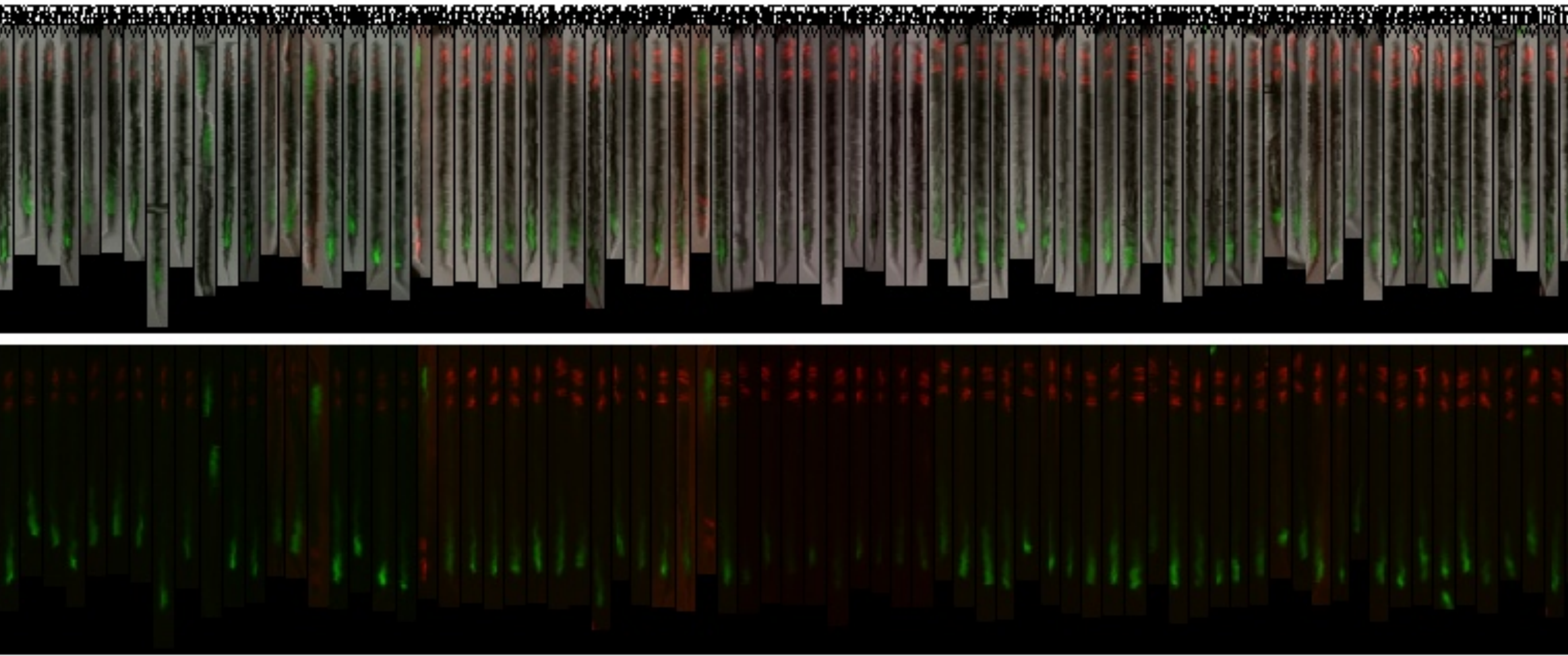
Zihan
Hans
Liu



Javier
Irazoqui 19

project in progress

Reporter expression in response to infection



Carolina
Wahlby



Kate
Madden



Zihan
Hans
Liu



Javier
Irazoqui 20

project in progress

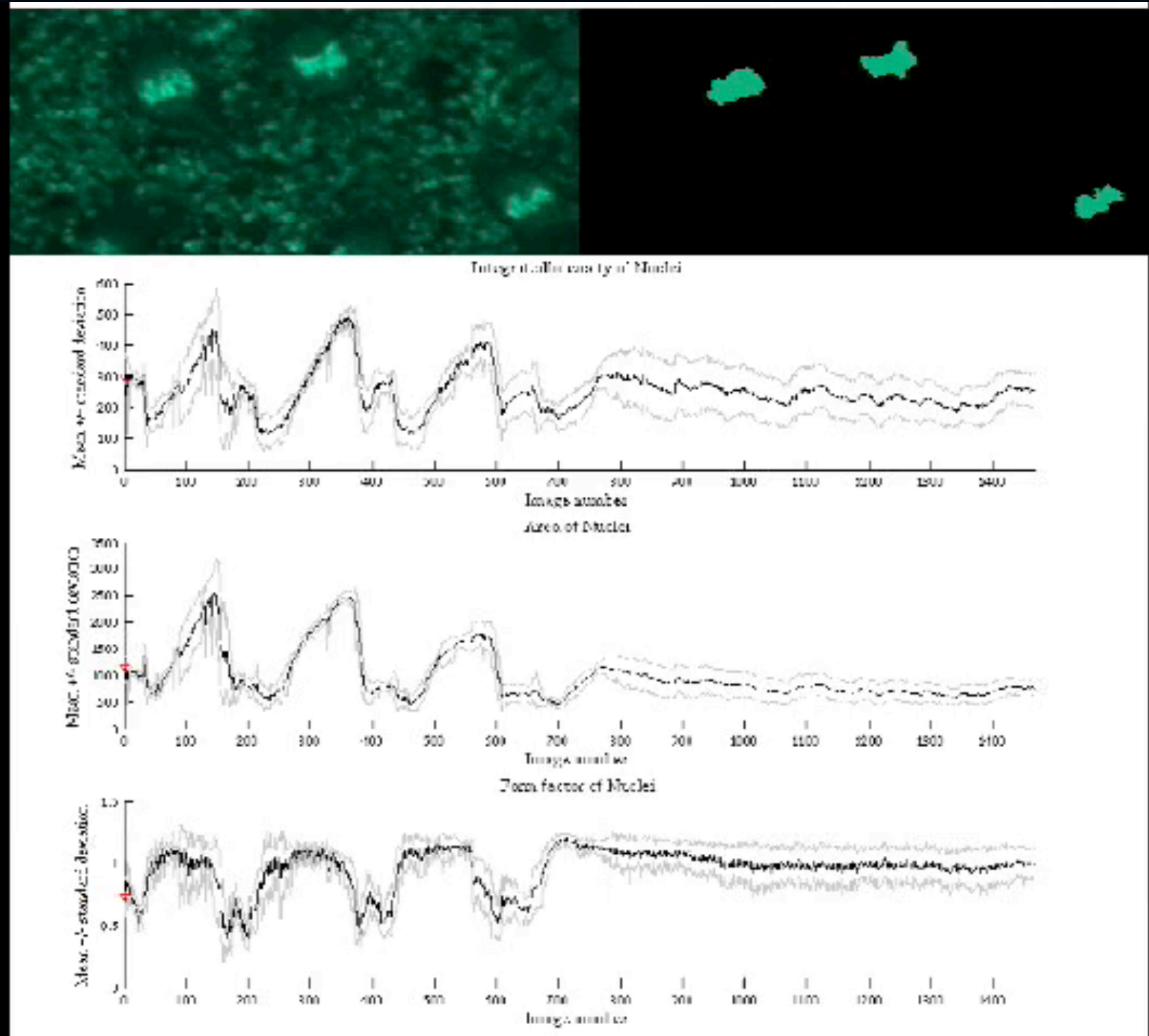
Extracting the wealth of information

movie from Victoria Foe,
Univ. Washington

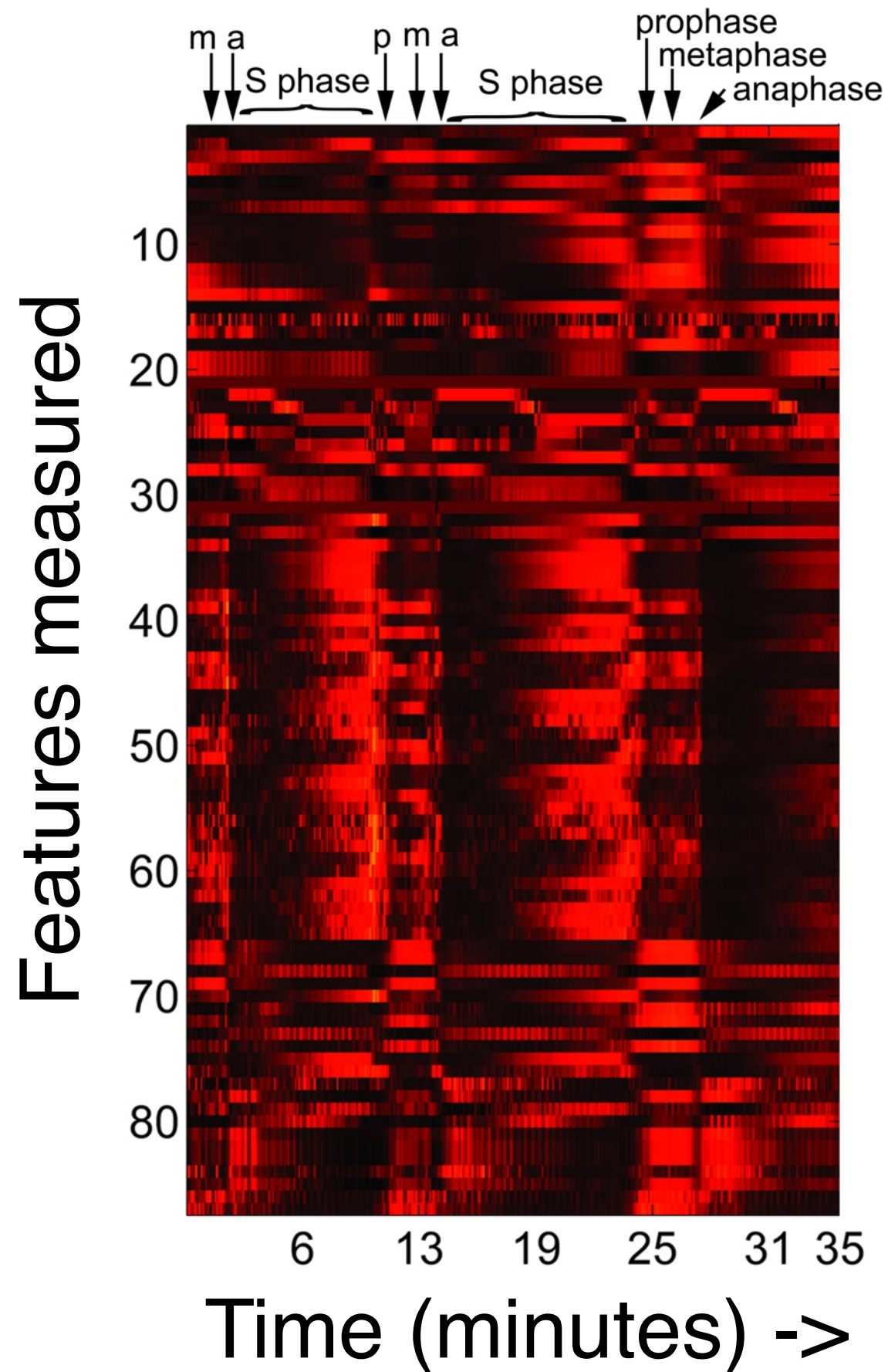
GFP
content

Area

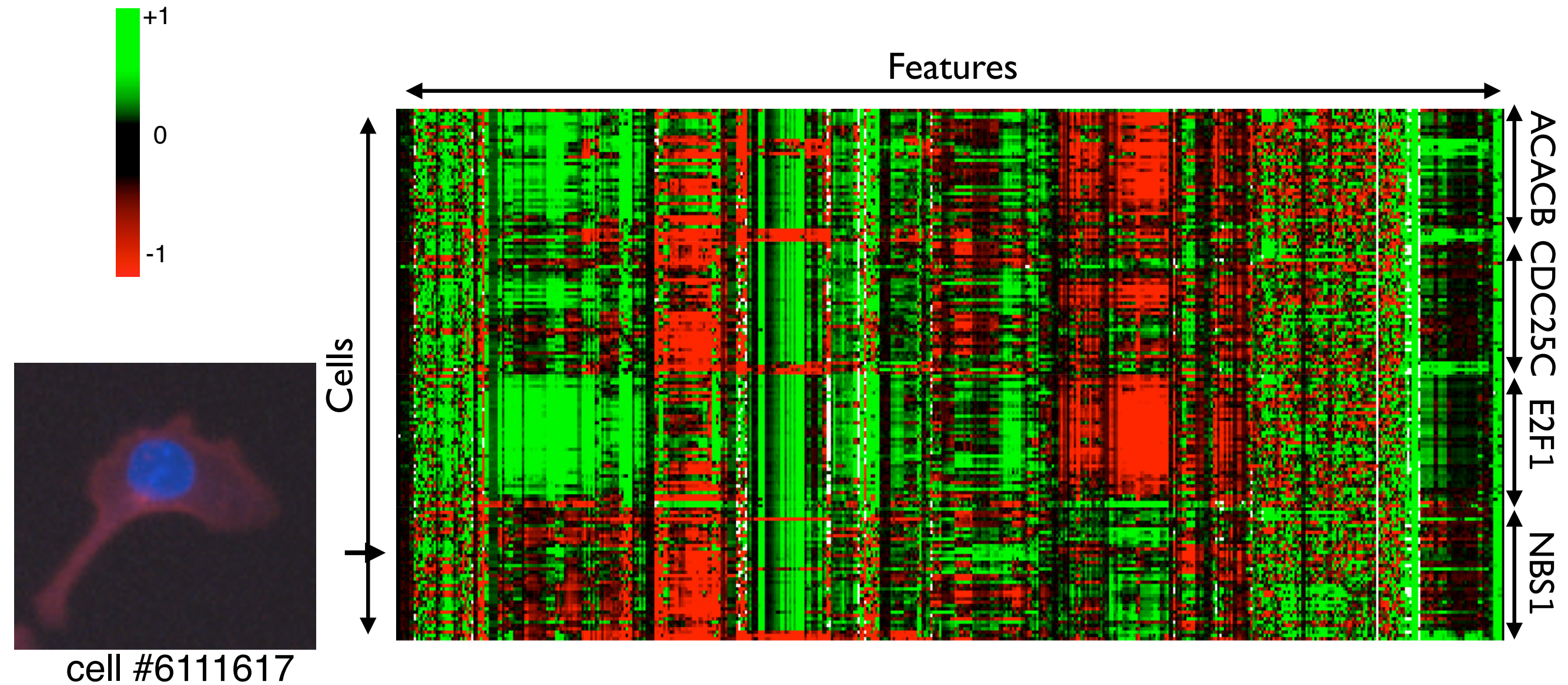
Shape



Extracting the wealth of information



MEASURE EVERYTHING...ASK QUESTIONS LATER.



“Cytological profile”: collection of measurements describing the appearance of a cell
Perlman, et al. Science 2004

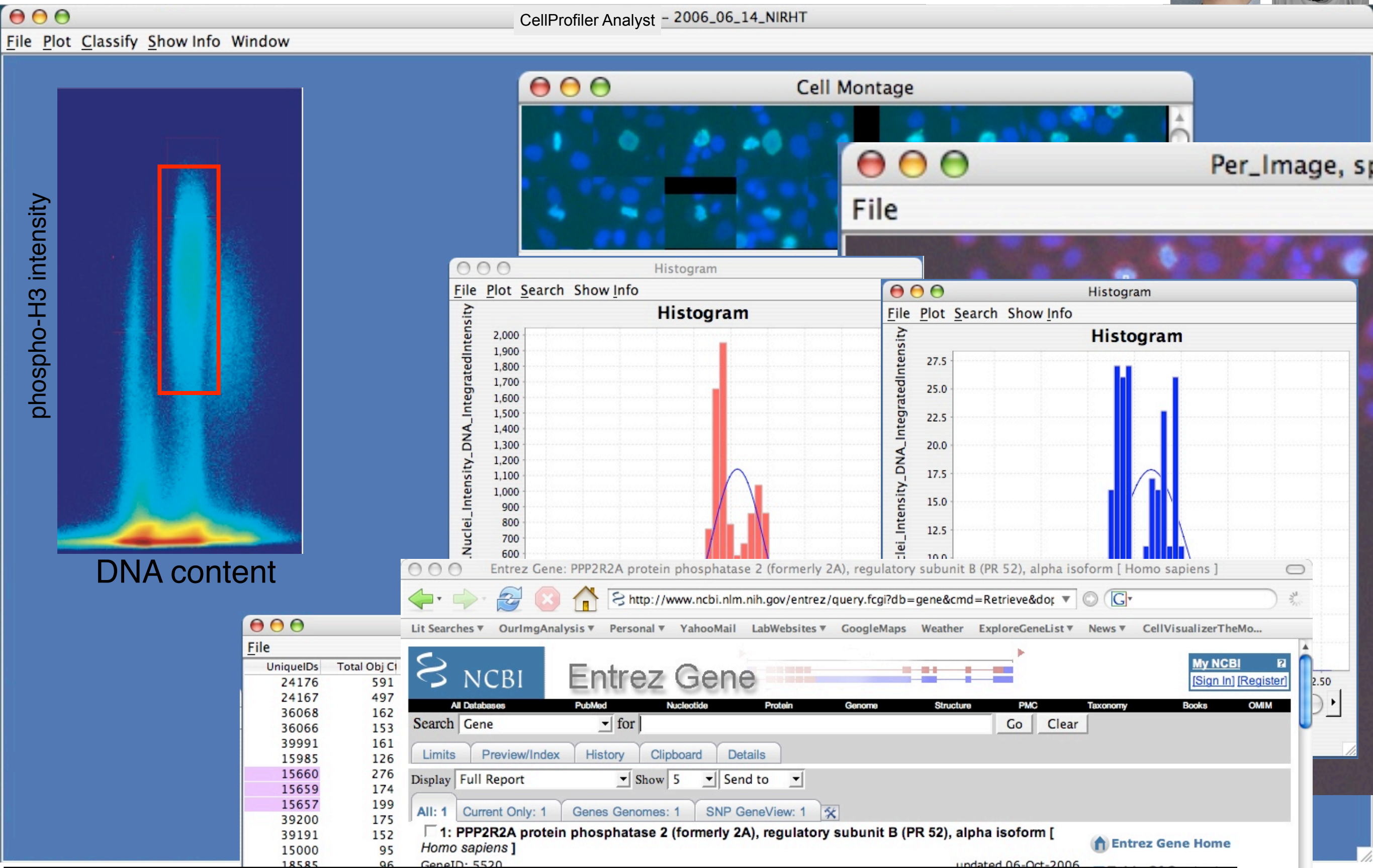
MEASURE EVERYTHING...ASK QUESTIONS LATER.

~500 features per cell: size, shape, staining intensity, texture (smoothness), etc.

Why?

- (a) Several features may be necessary to score the phenotype
- (b) Virtual secondary screens can help characterize hits
- (c) Later re-screening for new phenotypes

Exploring multi-feature cell data



The RNAi Consortium @ Broad, *Moffat, et al. Cell 2006*; CellProfiler Analyst led by In Han Kang, Golland lab, MIT

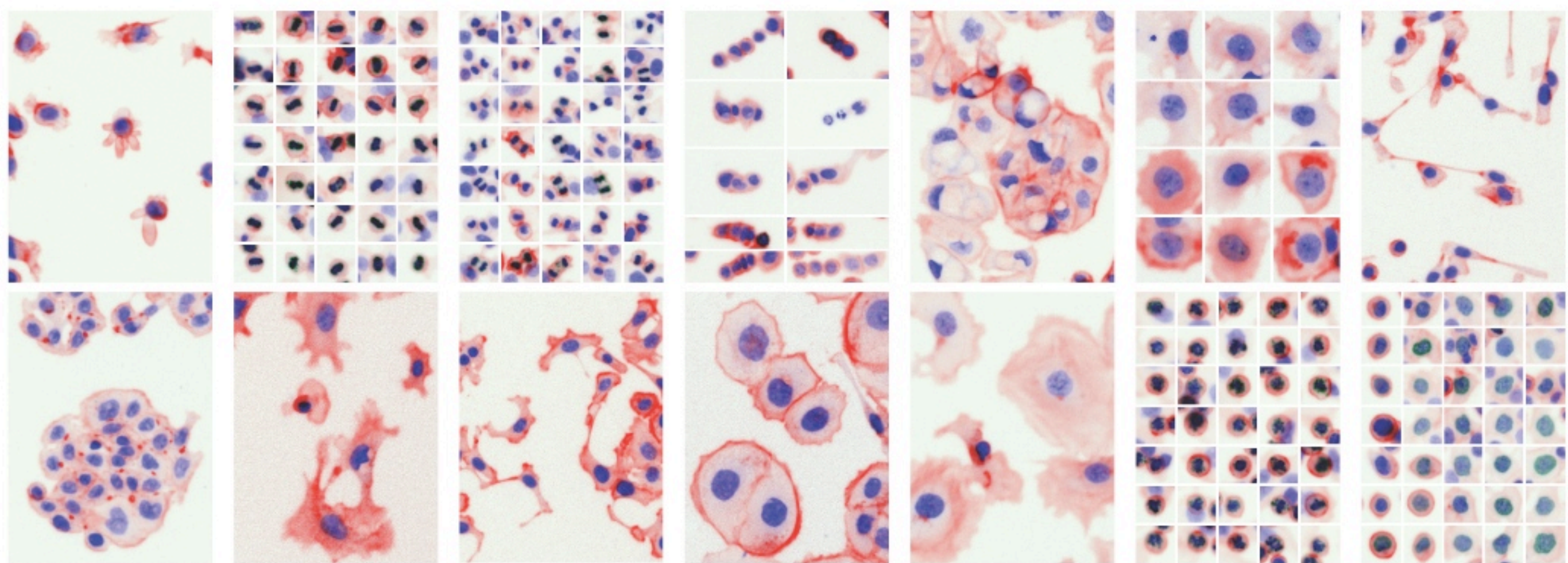
MEASURE EVERYTHING...ASK QUESTIONS LATER.

~500 features per cell: size, shape, staining intensity, texture (smoothness), etc.

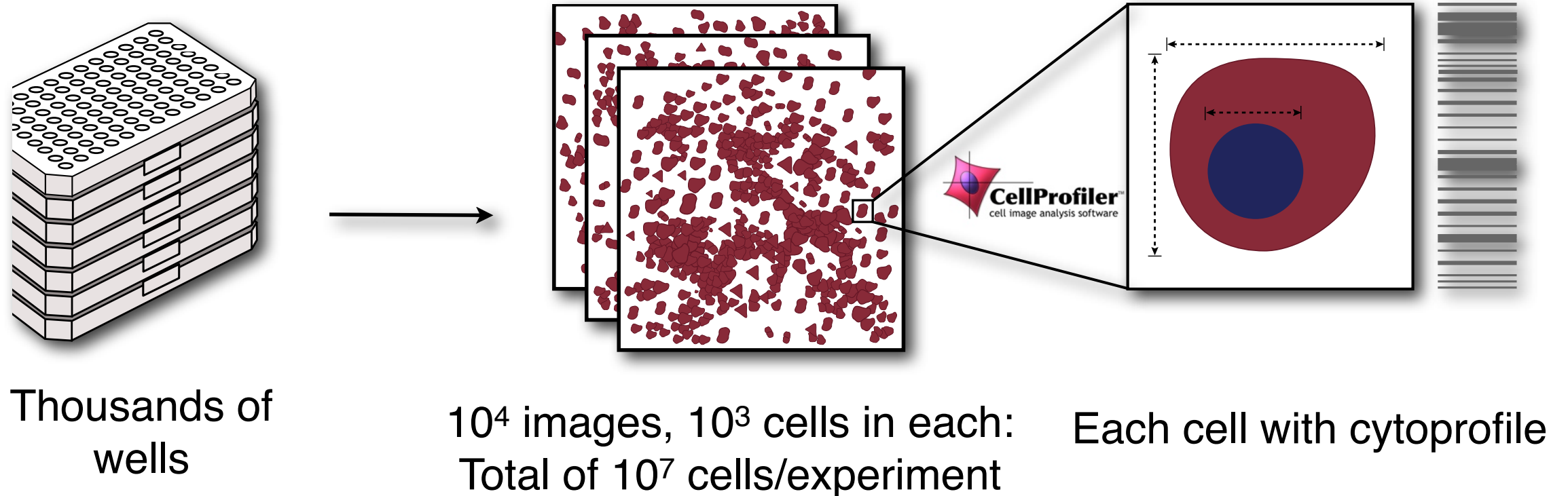
Why?

- (a) Several features may be necessary to score the phenotype
- (b) Virtual secondary screens can help characterize hits
- (c) Later re-screening for new phenotypes
- (d) The measurements required to score the phenotype of interest may not be known a priori

Challenging cellular phenotypes



Automated Cell Image Processing



Cytoprofile of 500+ features measured for each cell



Ray
Jones

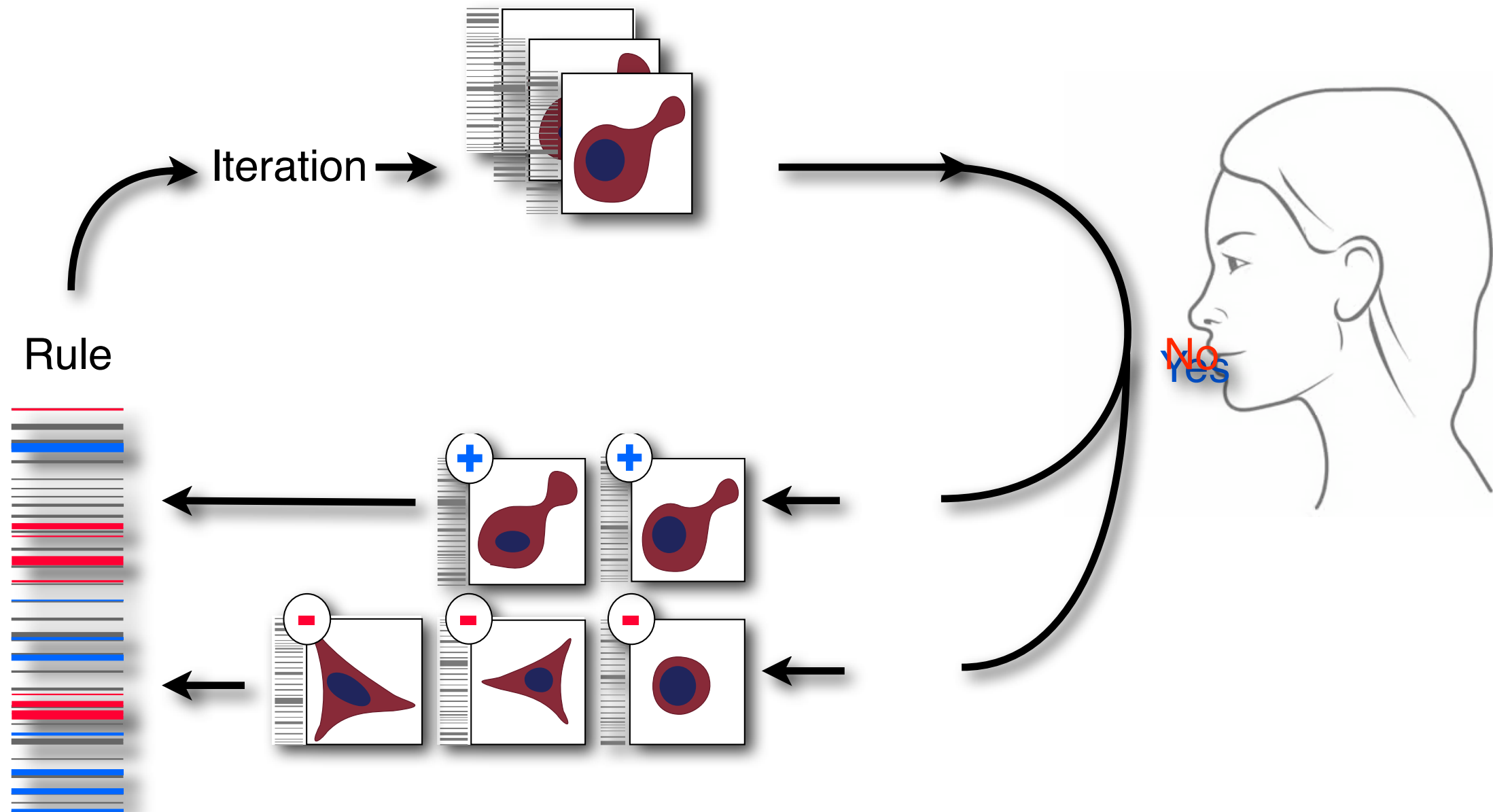
Anne
Carpenter

Illustrations by Bang Wong, Nadav
Kupiec, & Christopher Lewis

Jones, Carpenter ... Sabatini, et al. PNAS 2009

Iterative machine learning

System presents ~500 cells to biologists for scoring



System defines rule based on cytoprofile of scored cells



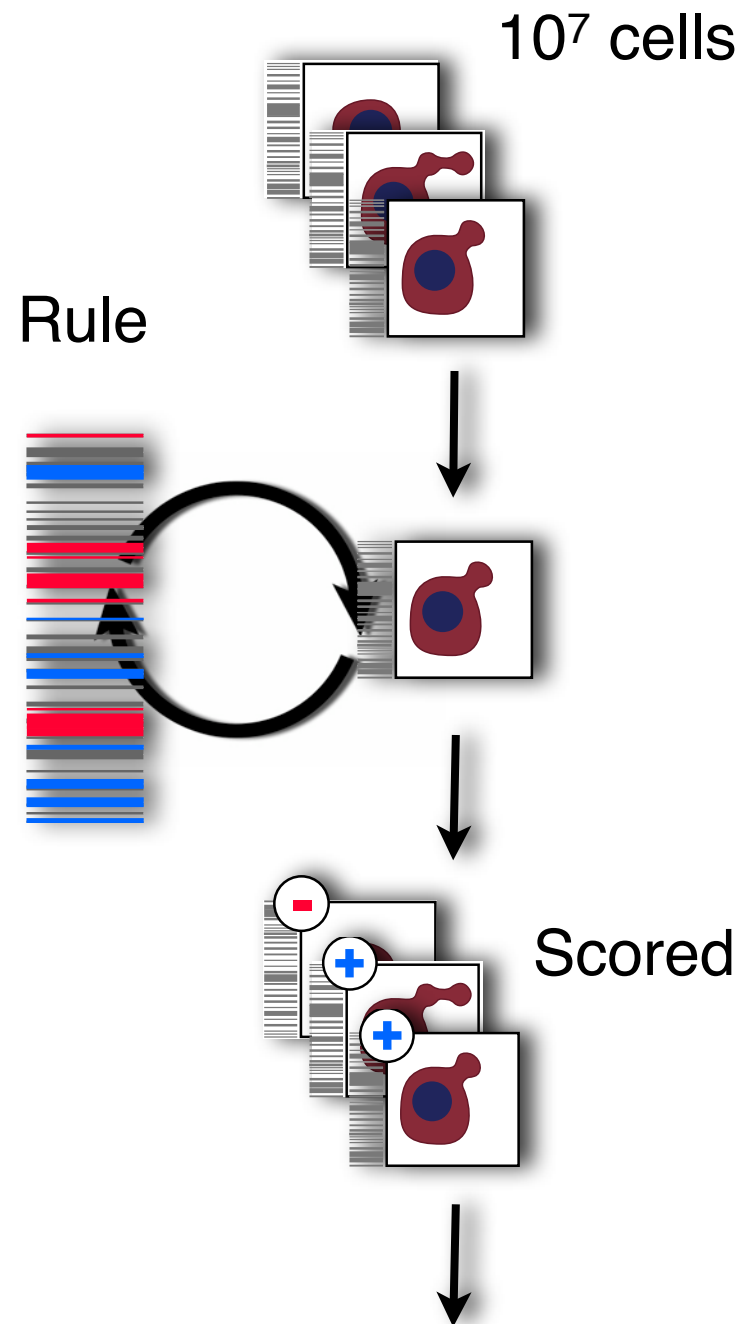
Based on: - Boosting Image Retrieval (Tieu & Viola, 2000)
- GentleBoosting classifier (Friedman, et al. 1998)



Ray
Jones

Adam
Fraser

Automated Scoring



Scored cells are sorted by well:
identify samples with a high proportion of positive cells



Ray
Jones

Adam
Fraser

Jones, Carpenter ... Sabatini, et al. PNAS 2009

Classifier 2.0 - /Users/afraser/CPA/properties/nirht_area_test.properties

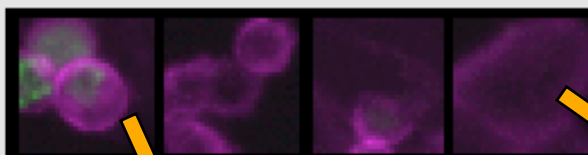
Fetch cells from gene:

Train Classifier

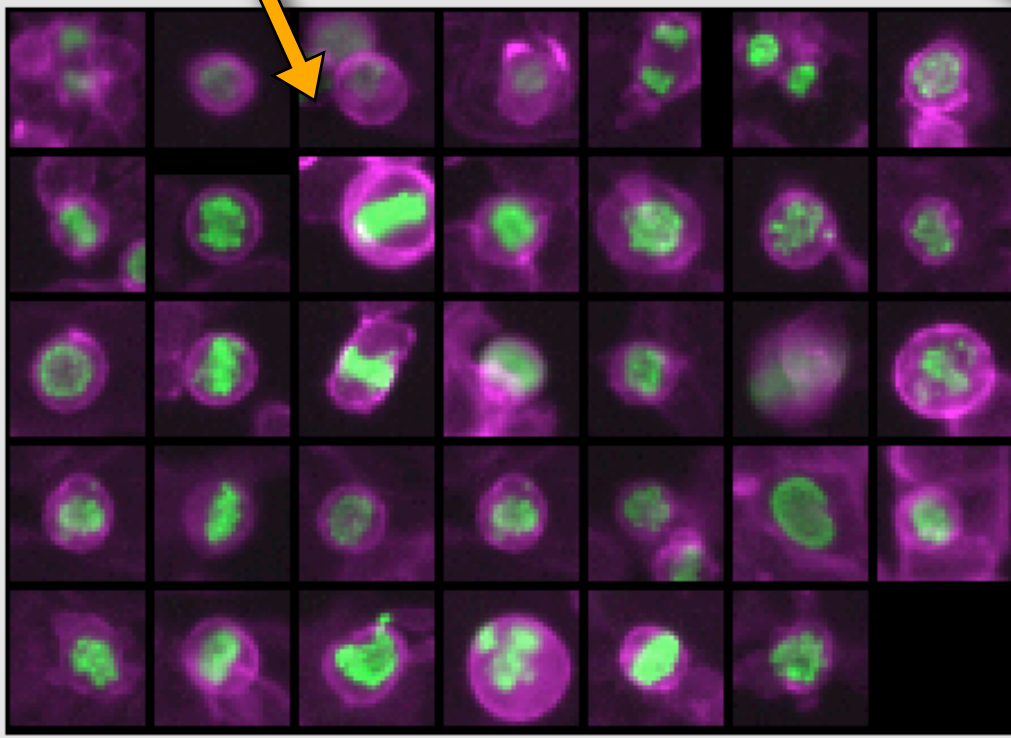
```
IF (Cells_Texture_1_pH3_InformationMeasure1 > -0.37890601, [-1.000001, 1.000001], [0.99999952, -0.99999952])
IF (Cells_Texture_1_pH3_InformationMeasure1 > -0.37890601, [-1.0, 1.0], [1.0, -1.0])
IF (Cells_Texture_1_pH3_Correlation > 0.784787, [0.99999988, -0.99999988], [-1.0000004, 1.0000004])
IF (Nuclei_Intensity_pH3_StdIntensity > 0.021224801, [0.00000088, -0.00000088], [-1.0000001, 1.0000001])
```

Max number of rules:

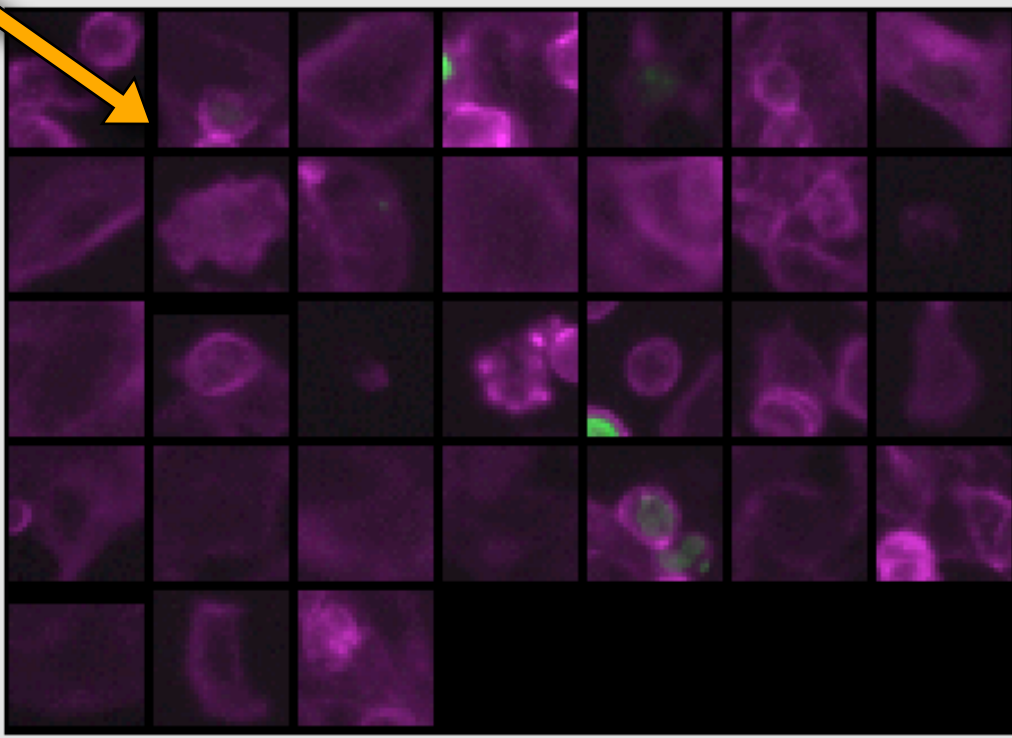
unclassified (25)



mitotic (34)



non_mitotic (31)



fetching 25 mitotic cells from group Gene: gene=NME1



Ray
Jones



Adam
Fraser

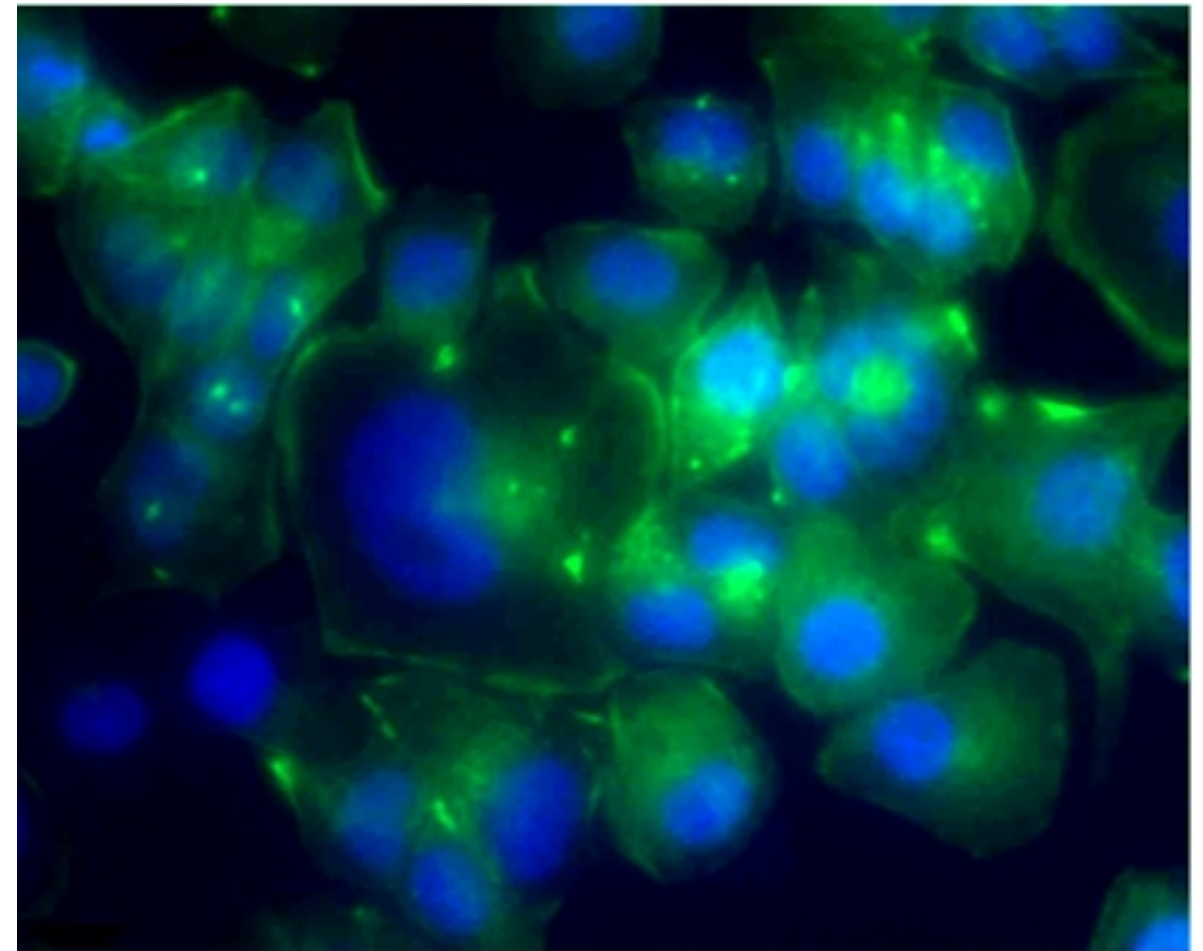
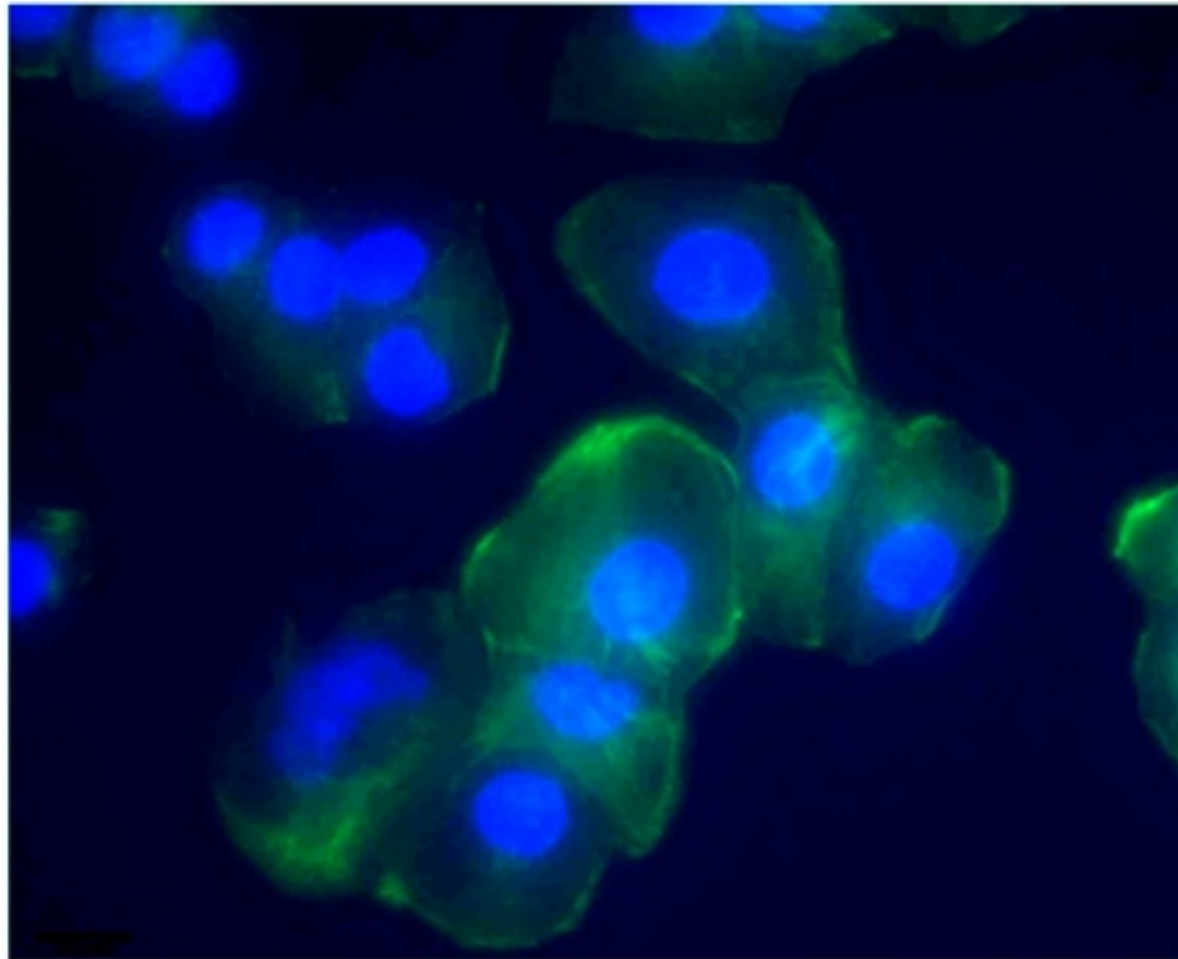
Breast cancer

Control

+ Growth factor

DNA

Actin



Ray
Jones



Anne
Carpenter



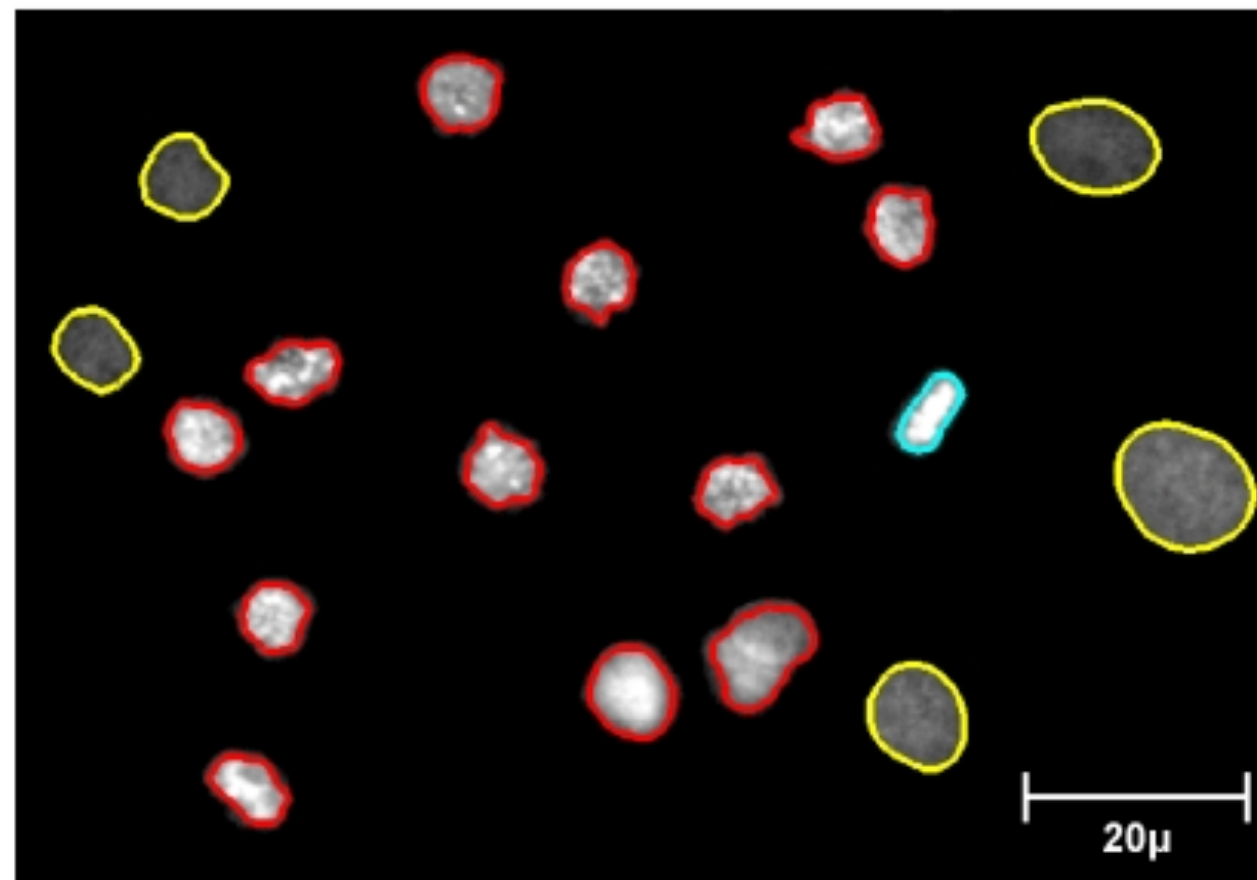
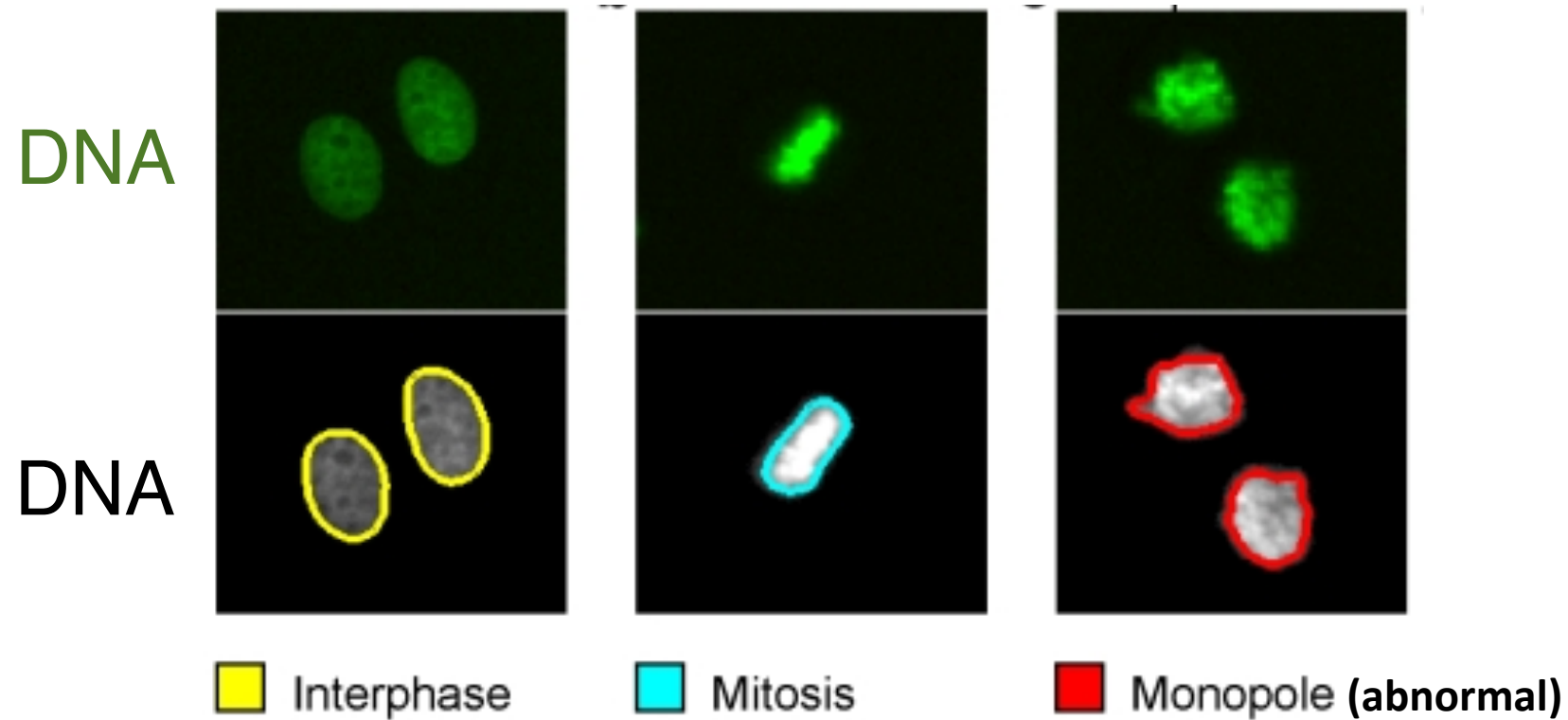
Eric Lander,
Broad
Institute



Piyush Gupta,
postdoc

project in progress

Regulators of cell division



Tim Mitchison,
Harvard Med.



Ray
Jones



Martha
Vokes



Tiao Xie



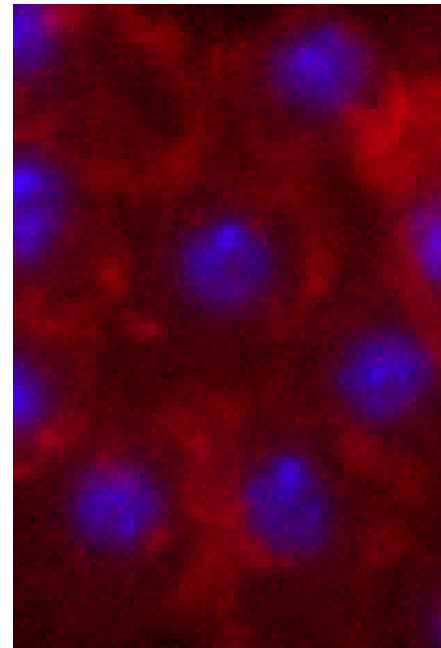
Melody
Tsui

Tsui ... Carpenter ... Mitchison, et al. PLoS ONE, 2009

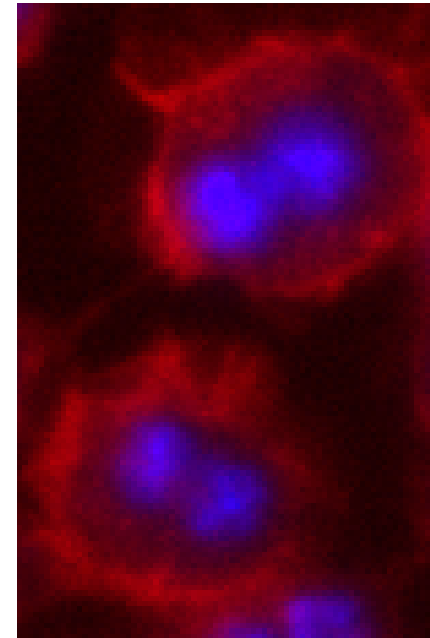
Regulators of cell division

DNA

Actin



Normal:
one **nucleus**
per **cell**



Abnormal:
two **nuclei**
per **cell**



Ray
Jones



Martha
Vokes



Riki Eggert,
Harvard Med.

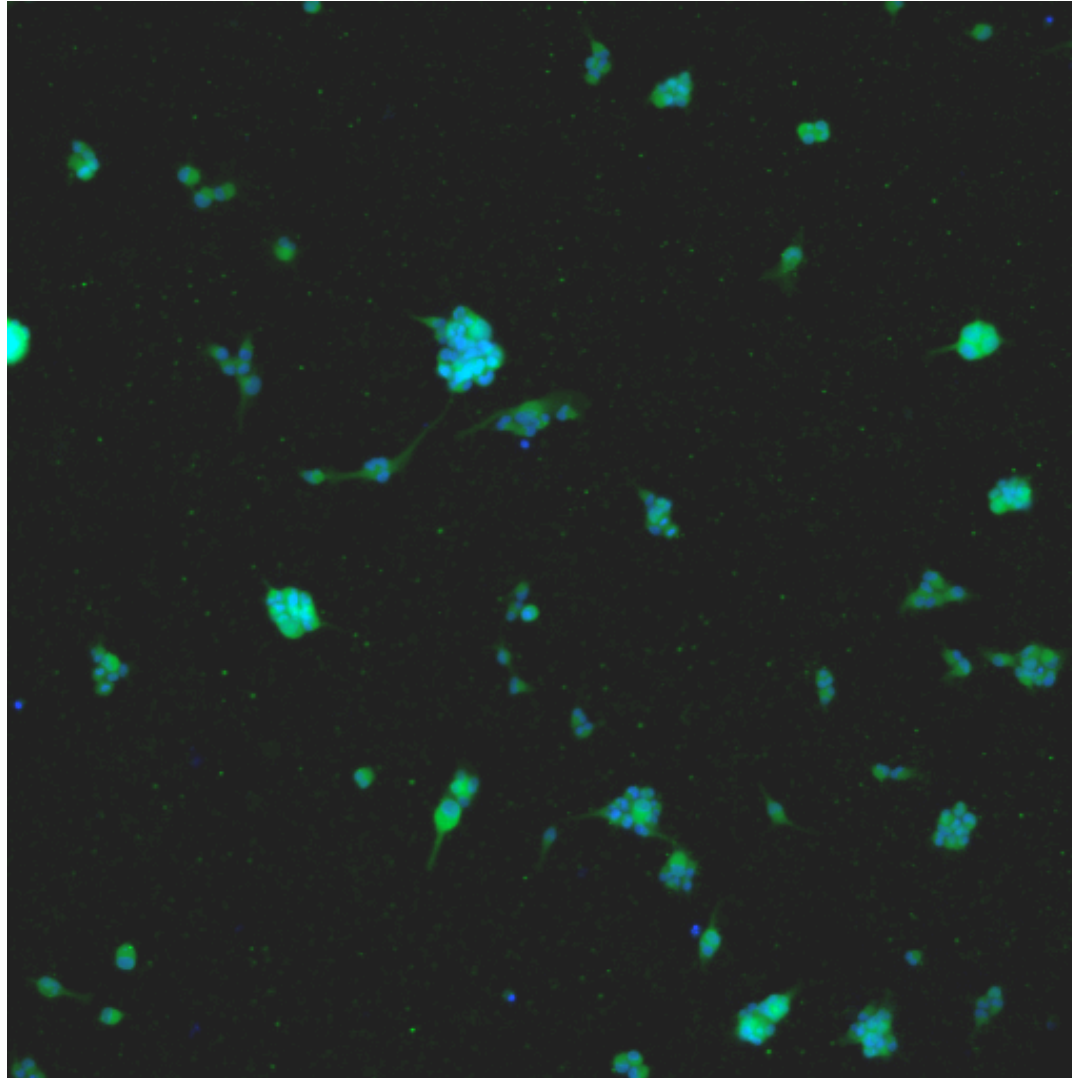


Adam
Castoreno

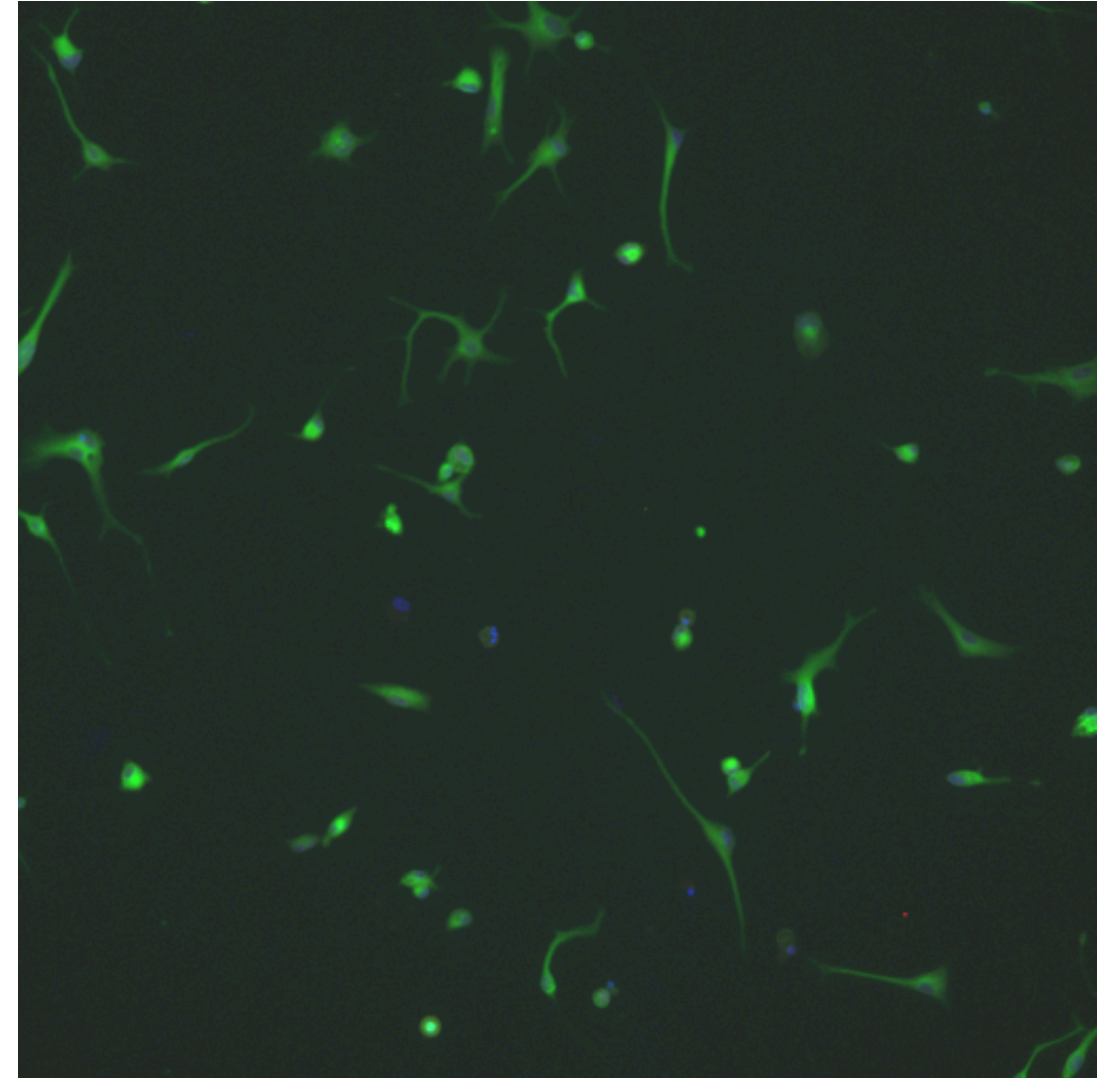
Castoreno... Carpenter ... Eggert, Nature Chem Bio, 2010

RNAi screen: glioblastoma proliferation & differentiation

Neurosphere phenotype



Flat, elongated phenotype



DNA /
Tubulin



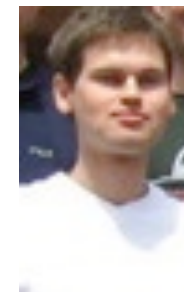
Martha
Vokes



Mark
Bray



David
Sabatini,
Whitehead
Institute



Yakov
Chud-
novsky,
postdoc



William
Hahn,
Broad
Institute



Milan
Chheda,
postdoc



David
Root,
Broad Inst.

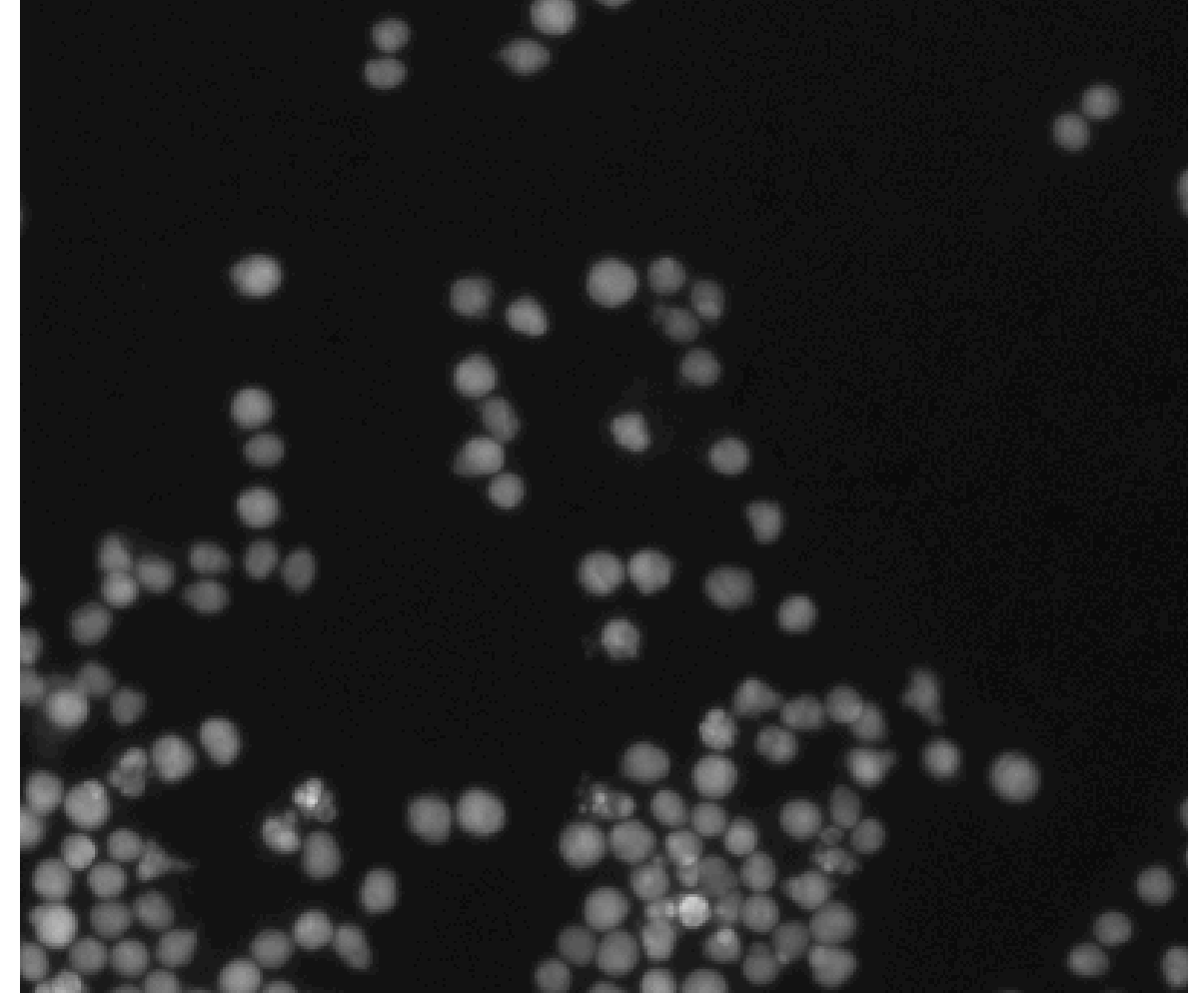
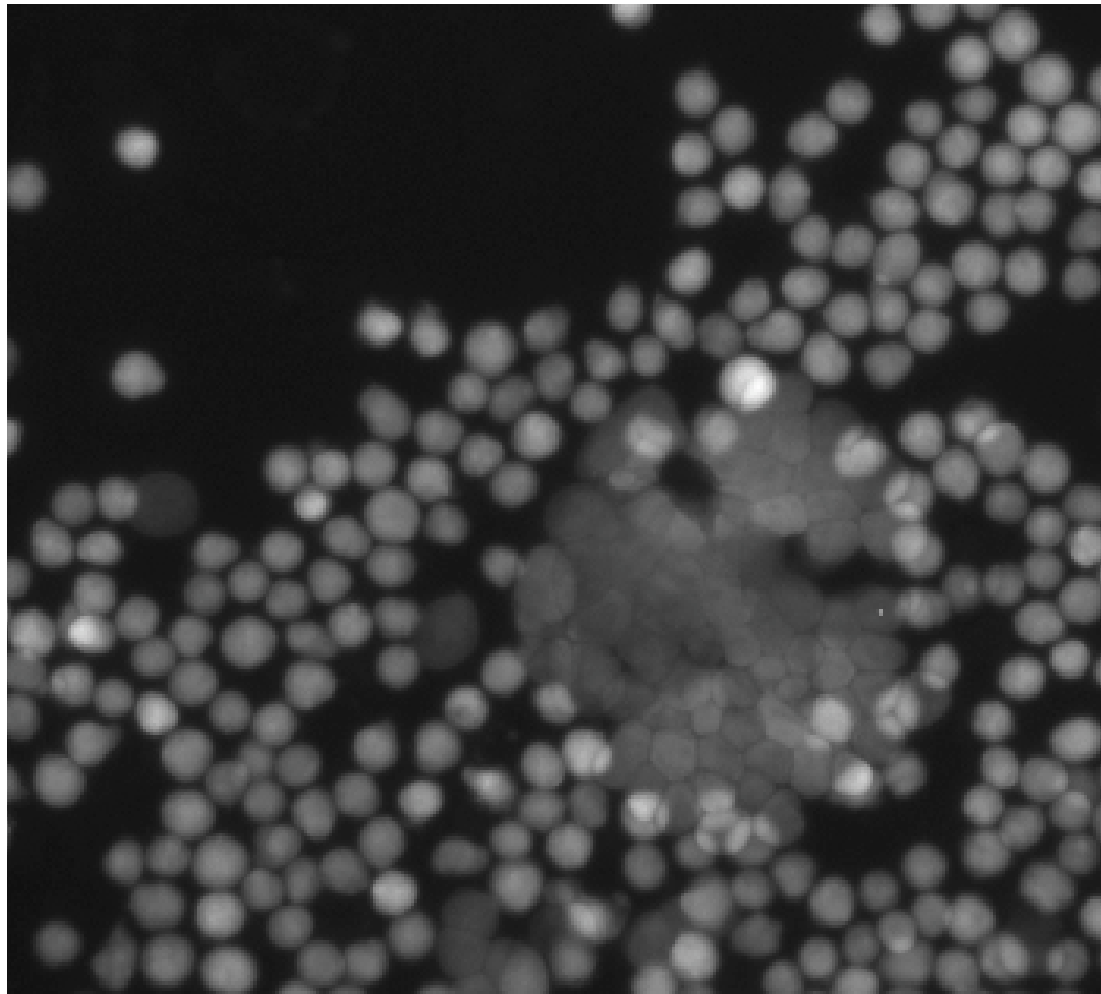
project in progress

Leukemic & hematopoietic stem cells

Cobblestones

Differentiated hematopoietic cells

GFP



David
Logan



Gary
Gilliland,
Brigham &
Women's
Hospital



David
Scadden,
Mass.
General
Hospital



Stuart
Schreiber,
Broad
Institute

postdocs
and
students:
Alison
Stewart,
Kimberly
Hartwell,
Peter
Miller

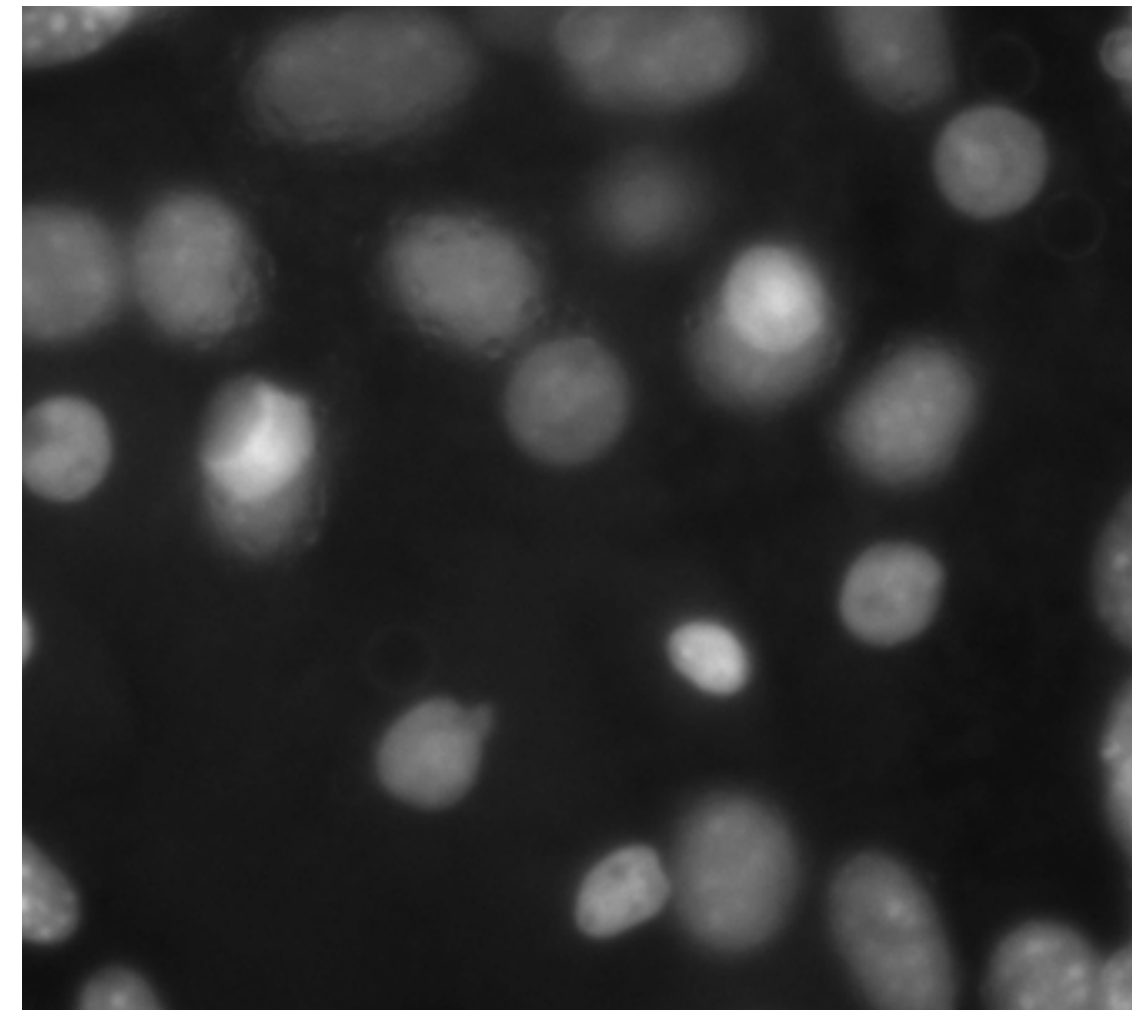
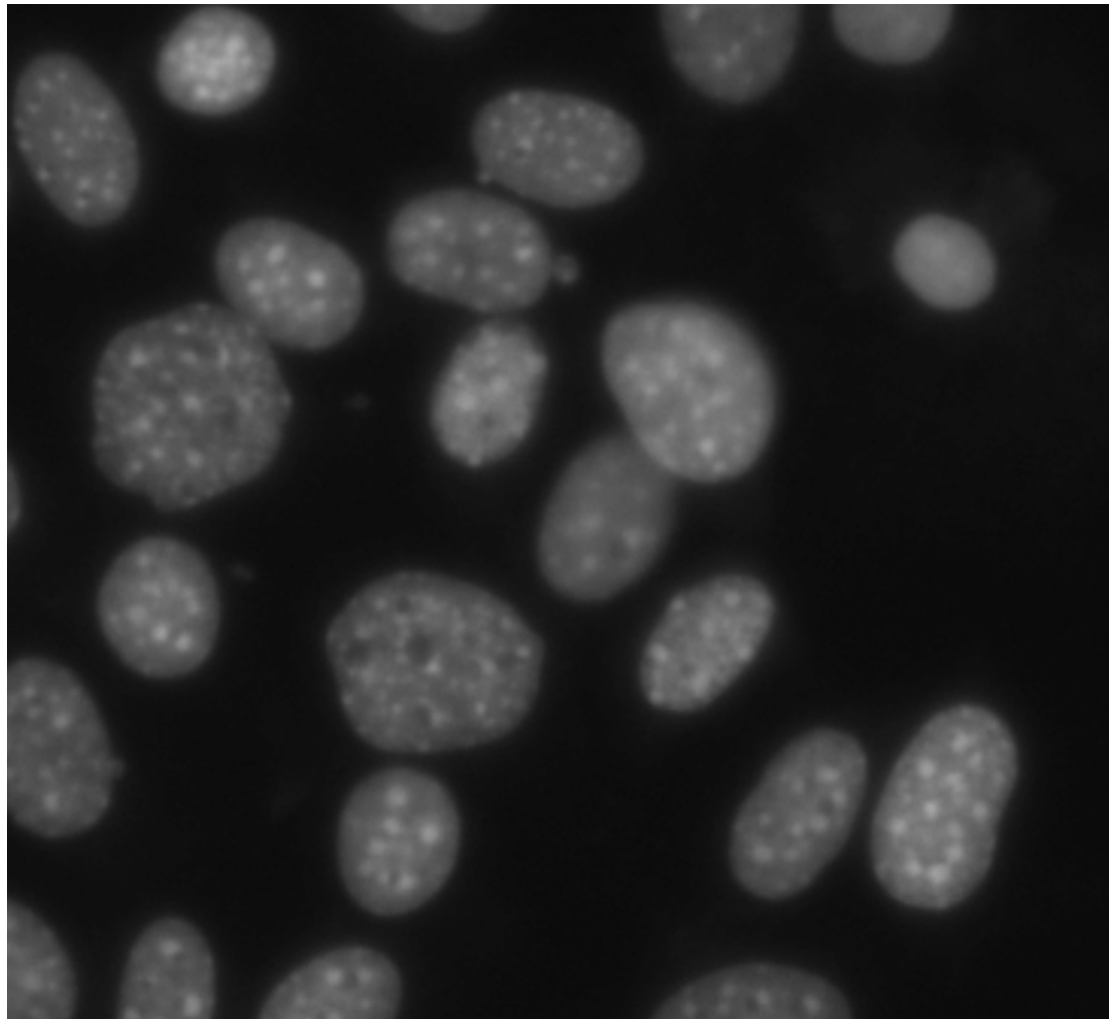
project in progress

Hepatocyte proliferation

Control

Hepatocyte-enriched

DNA



Z' factor for
doubled
hepatocyte
count: 0.29



David
Logan



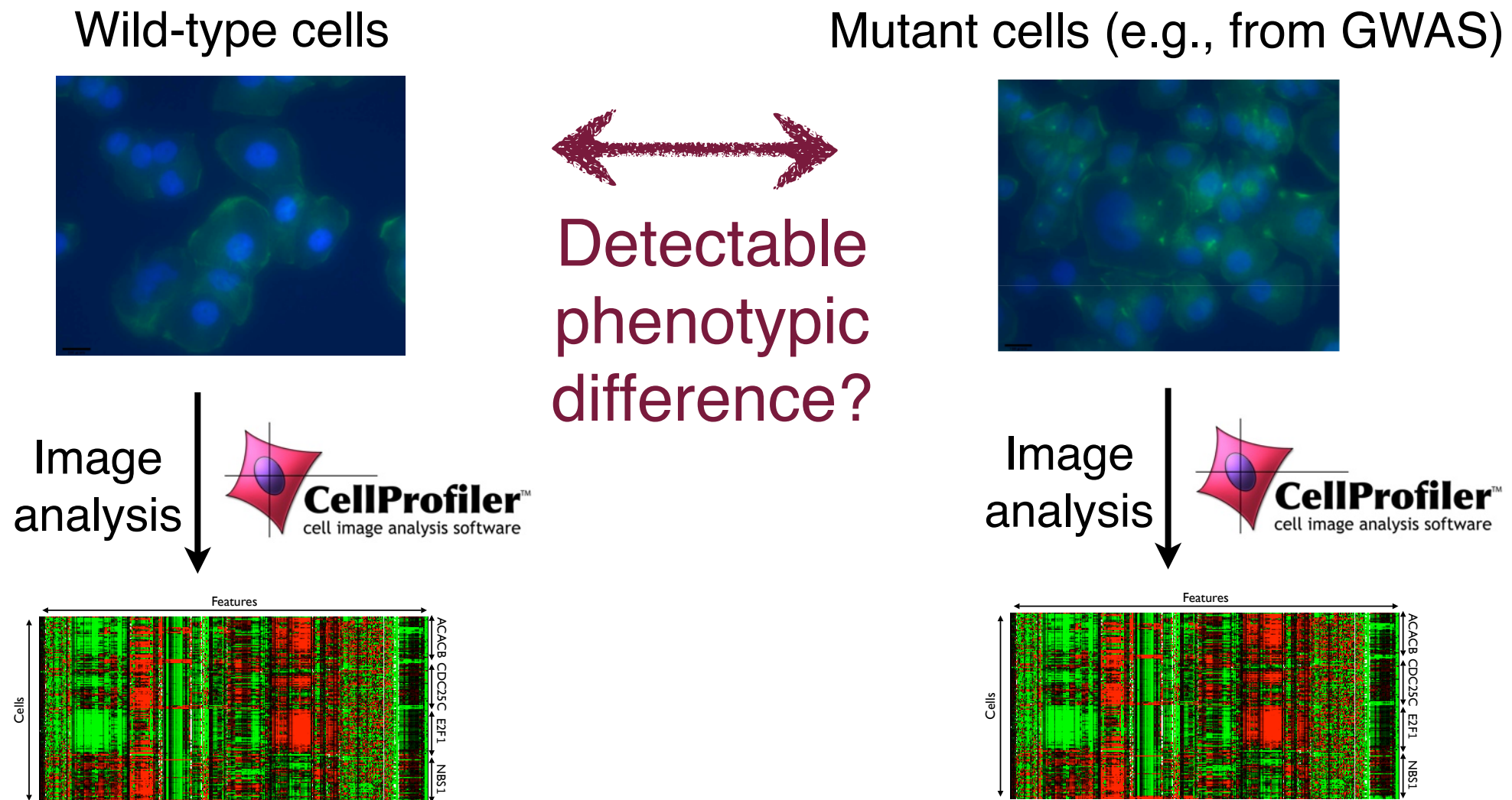
Sangeeta
Bhatia,
MIT



Meghan
Shan,
student

project in progress

Automatically extracting image-based phenotypes



Identify mutant phenotype from image features
even if “invisible” to the human eye

Screen for chemicals that can revert
mutant phenotype -> wild type



Ray
Jones

Vebjorn
Ljosa

Kate
Madden

MEASURE EVERYTHING...ASK QUESTIONS LATER.

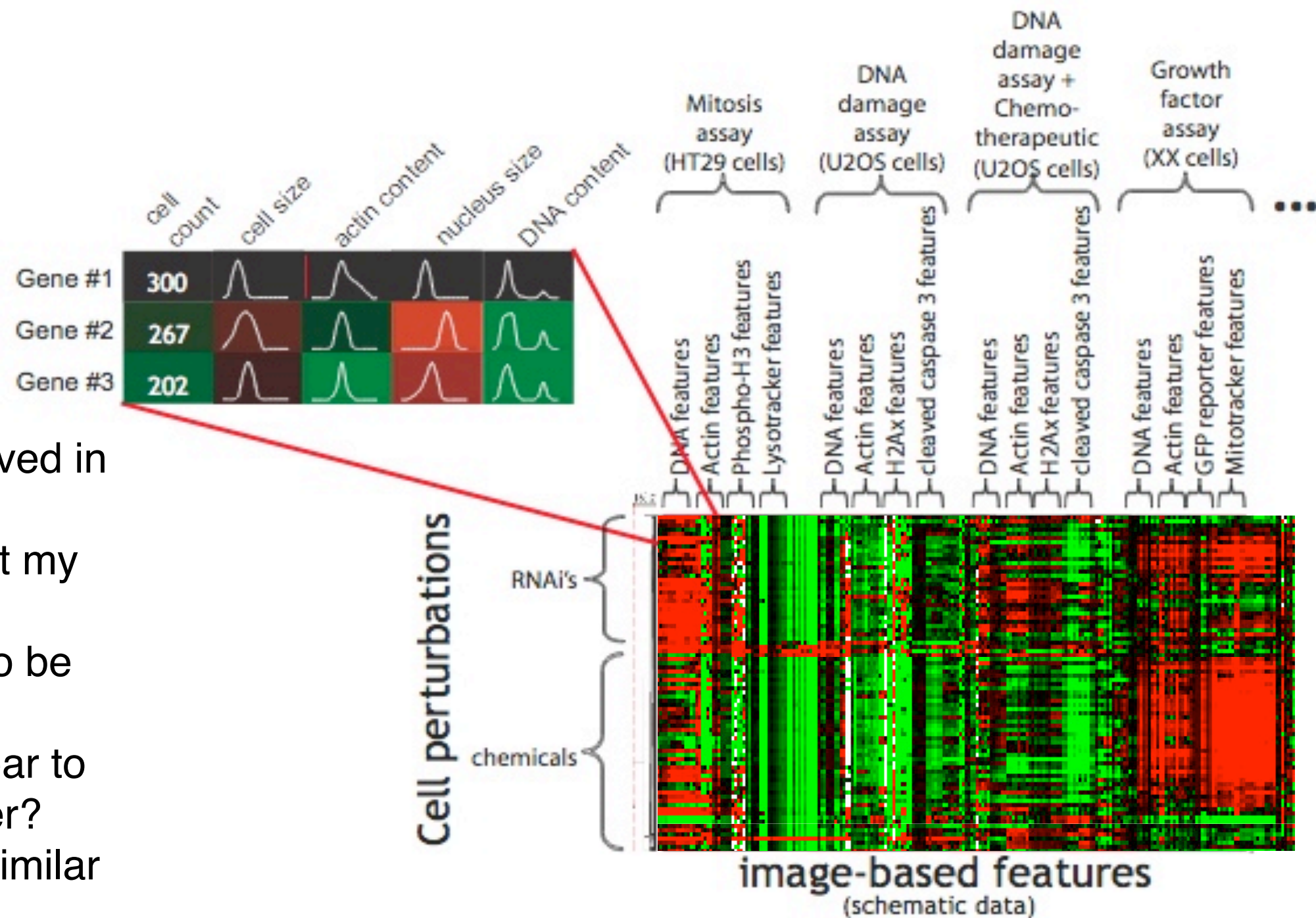
~500 features per cell: size, shape, staining intensity, texture (smoothness), etc.

Why?

- (a) Several features may be necessary to score the phenotype
- (b) Virtual secondary screens can help characterize hits
- (c) Later re-screening for new phenotypes
- (d) The measurements required to score the phenotype of interest may not be known a priori
- (e) The full spectrum of cellular responses to each treatment (even those not visible by eye) may be useful for data mining/machine learning/clustering...systems biology

Look for patterns/similarities/relationships among samples, phenotypes, and external data sources

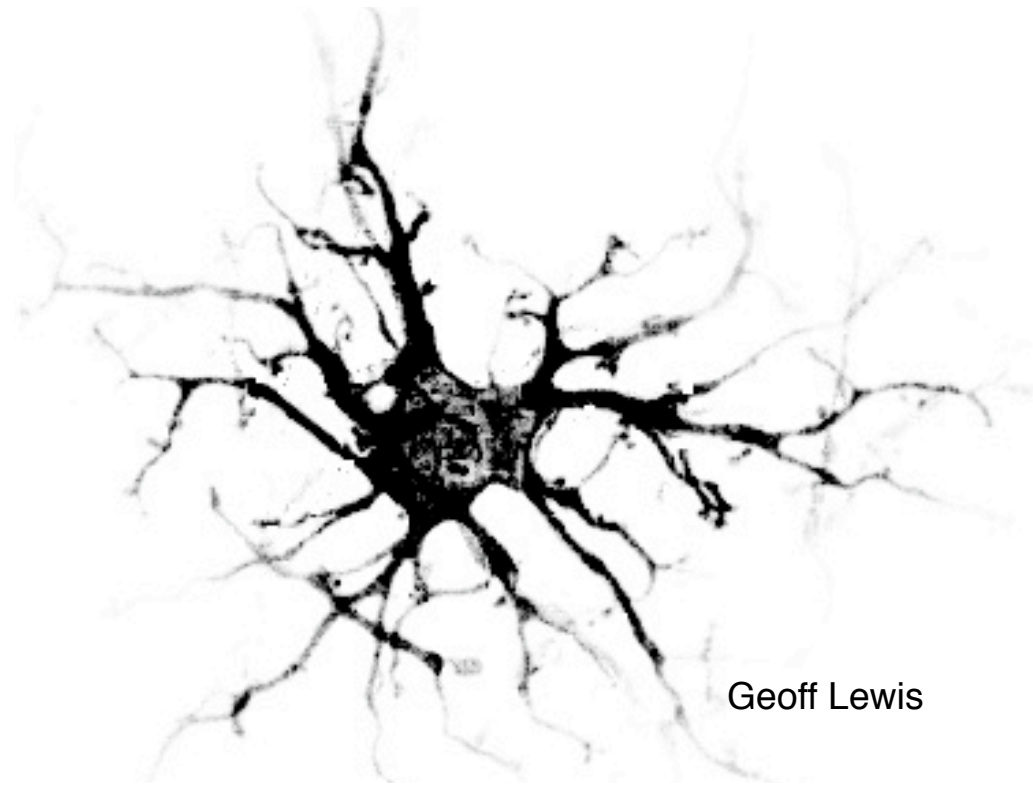
- What genes are involved in my phenotype?
- What chemicals affect my phenotype?
- What genes appear to be similar to each other?
- What chemicals appear to be similar to each other?
- What genes appear similar to a chemical?
- What phenotypes are coordinated?



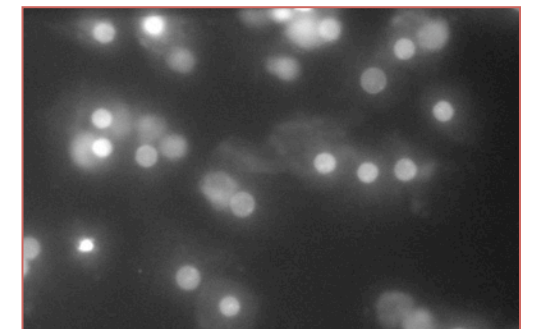
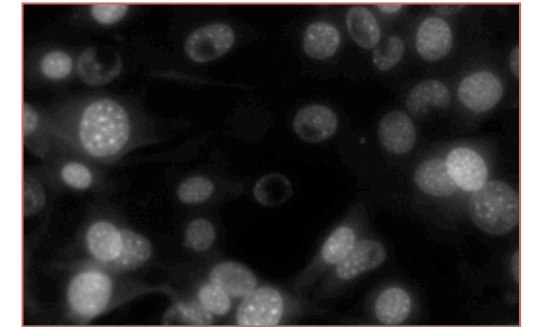
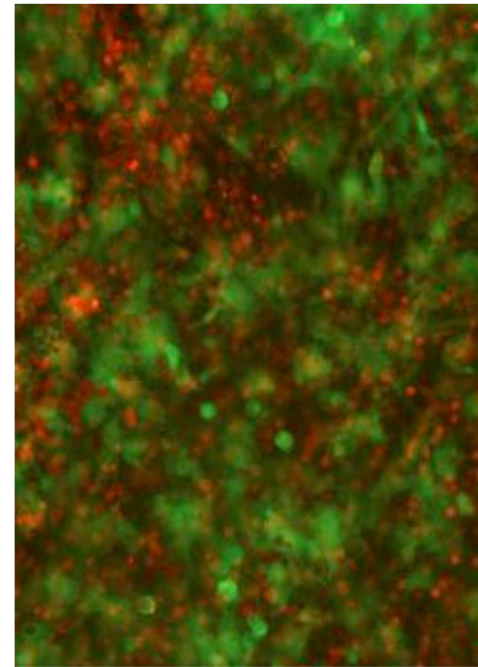
- What relationships exist between my phenotype and known information about the samples (proteomics, transcriptional microarrays)?

In progress

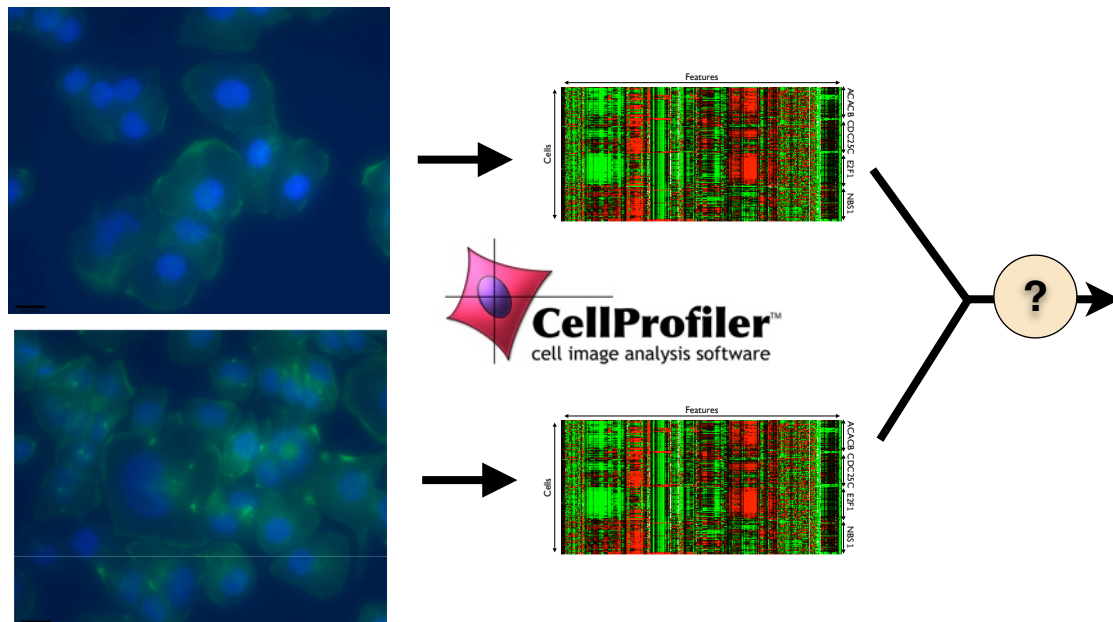
Neurons...



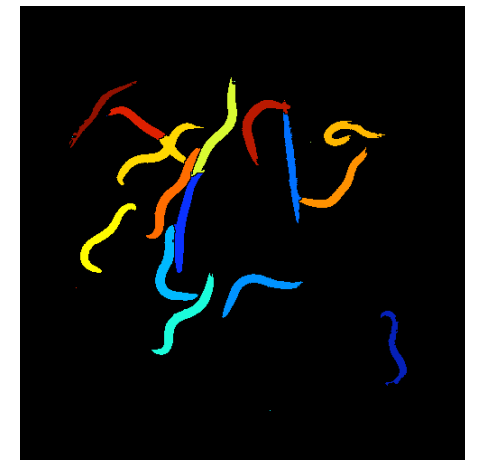
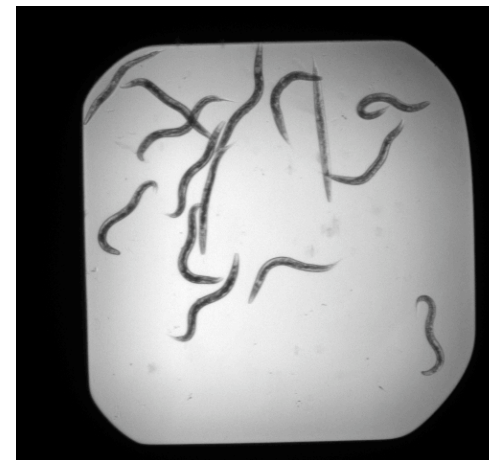
Co-cultured cell types...



Unexpected phenotypes...



Organisms...

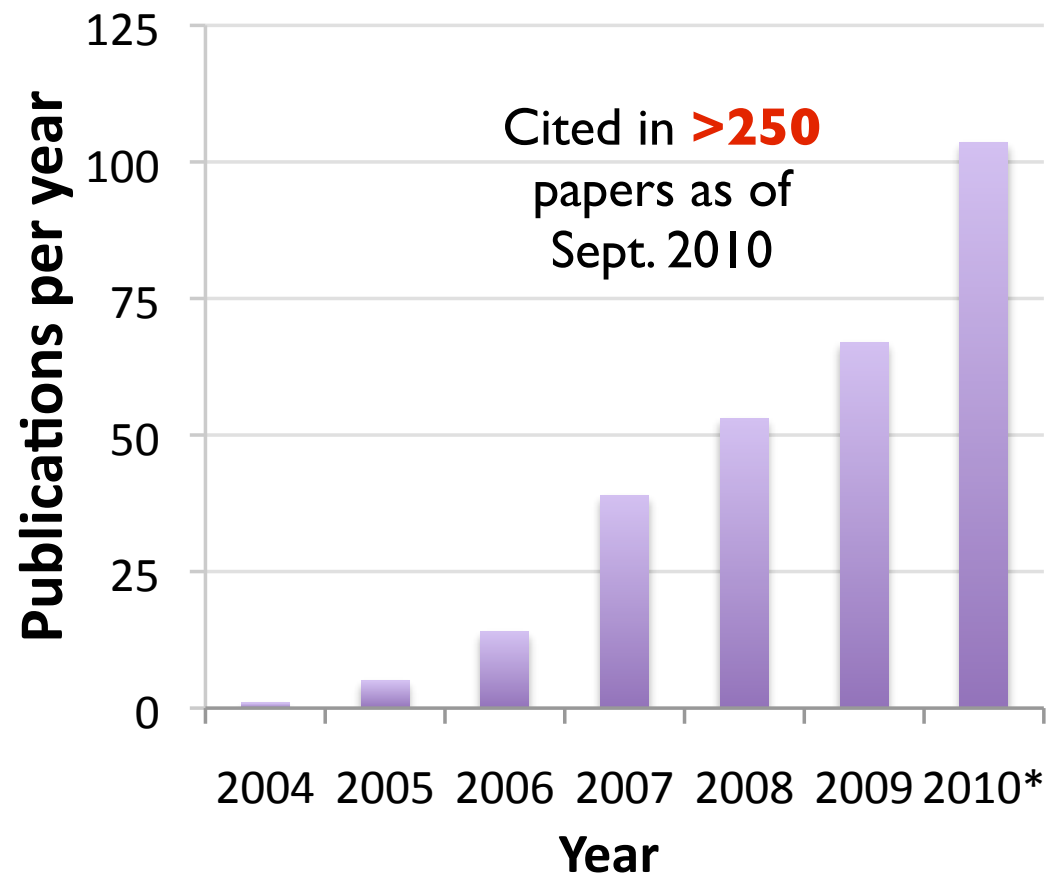


Time-lapse, 3D...

The CellProfiler project

free, at www.CellProfiler.org

Publications citing CellProfiler



Selected high-throughput screens using CellProfiler

| | |
|--|--|
| Root lab, Cell, 2006 | Screen for cell cycle regulators |
| Alon lab, Nature Methods, 2006 | High-throughput analysis of protein dynamics |
| Neefjes lab, Nature, 2007 | Screen for levels of Salmonella typhimurium infection |
| Raff lab, PLoS Biology, 2008 | Screen for centriole duplication and mitotic PCM recruitment |
| Carpenter lab, PNAS 2009 & BMC Bioinformatics 2008 | Screens for > 15 diverse phenotypes in human and <i>Drosophila</i> cells |
| Shokat lab, Cancer Cell, 2008 | Screen for PI3K inhibitor resistance mutations in <i>S. cerevisiae</i> |
| Pelkmans lab, Nature, 2009 | High-throughput infection assay |
| Ausubel lab, ACS Chem Bio, 2009 | Screen for inhibitors of infection by <i>E. faecalis</i> |

CellProfiler's is the 5th most-accessed Genome Biology paper of all time

Gratitude



Anne E. Carpenter

Peggy Anthony
Mark Bray
Adam Fraser

Lee Kamentsky
Imtiaz Khan
Vebjørn Ljoså

David Logan
Kate Madden
Carolina Wählby

free, at www.cellprofiler.org :



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