

# Studying the subcellular location space with bioimages and other data modalities

Luis Pedro Coelho

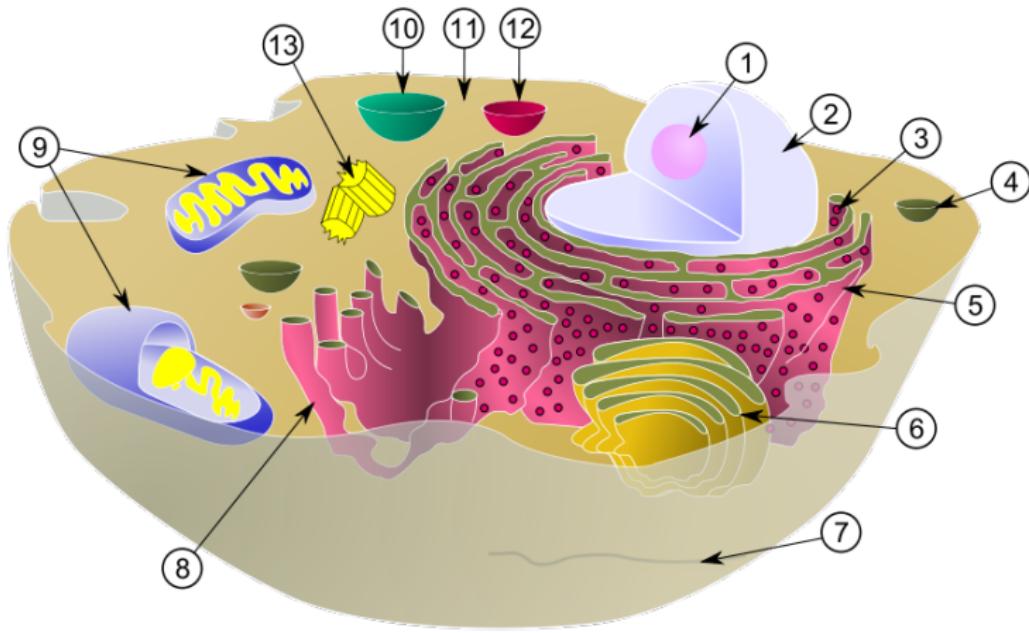
Carnegie Mellon University

September 22 2011

Carnegie Mellon

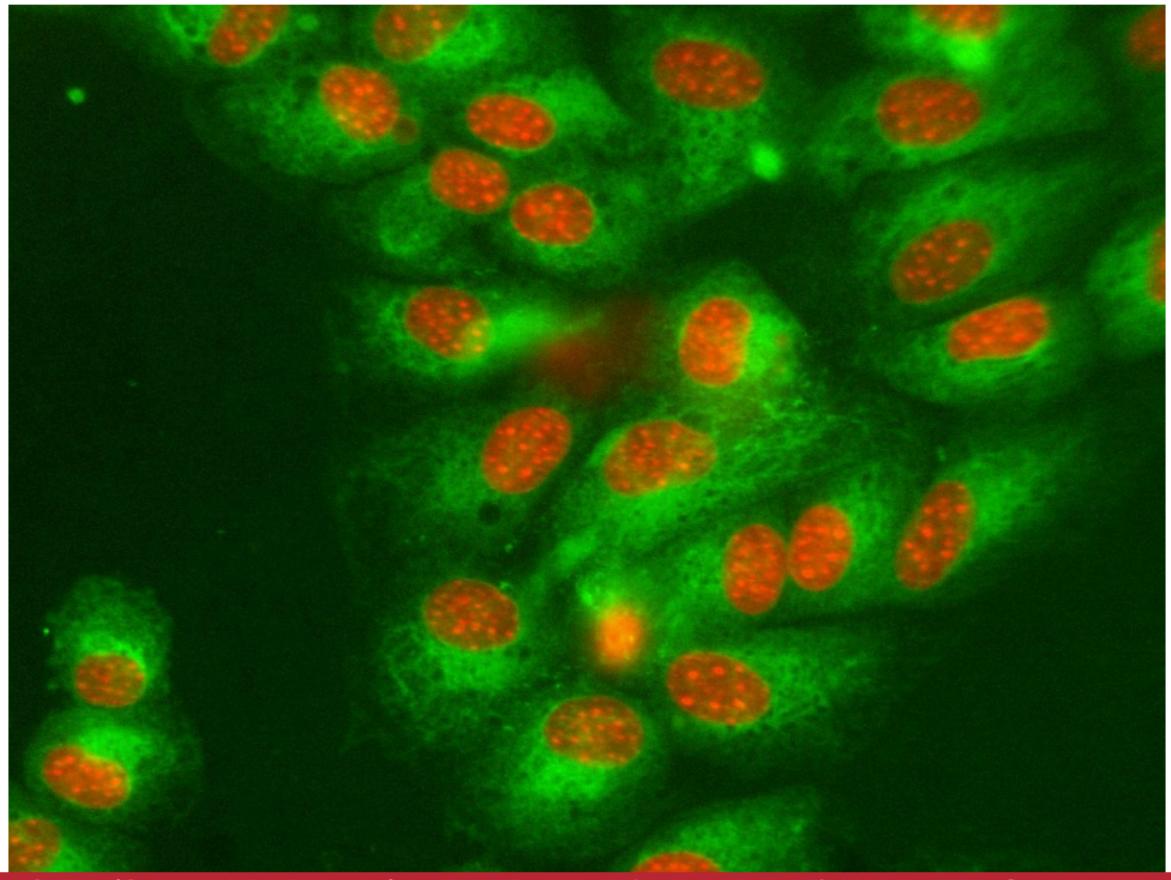
**Note:** All material related to unpublished work has been removed from this online version.

# The Cell

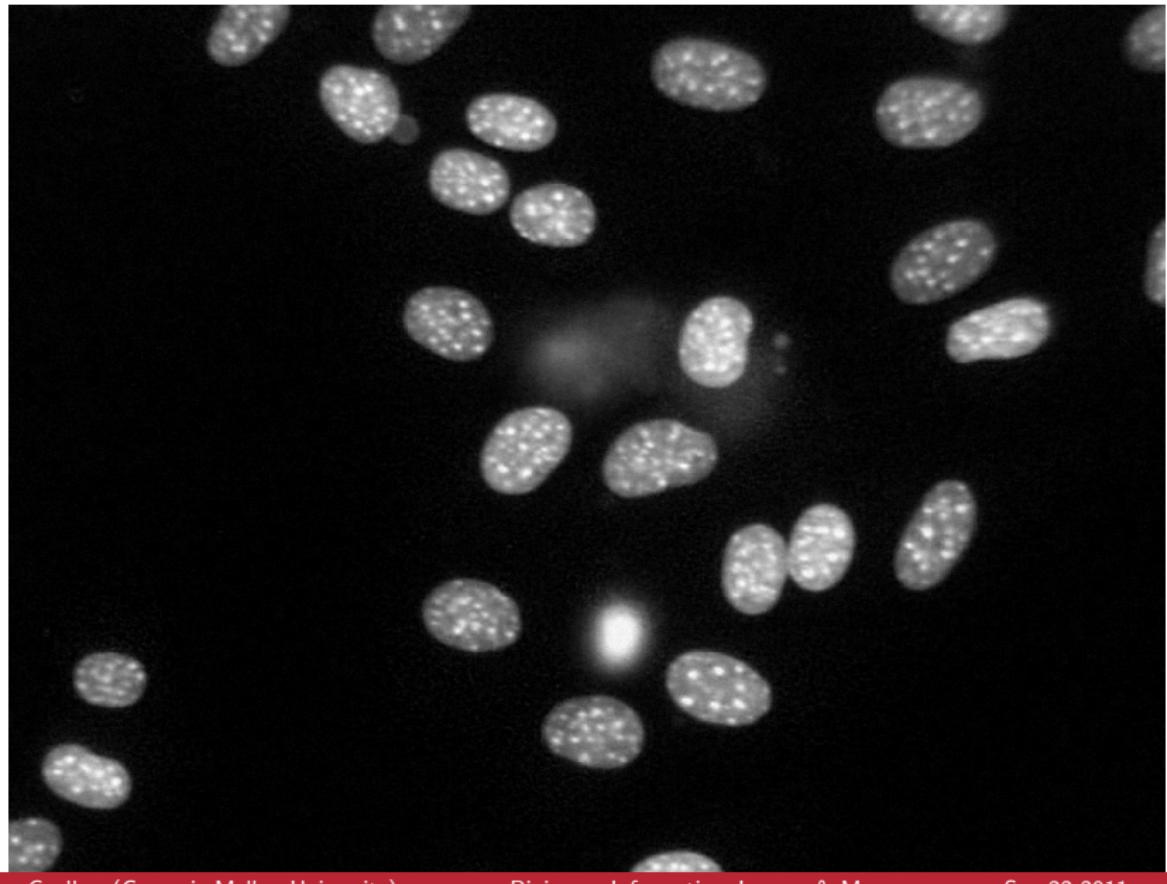


(Wikipedia)

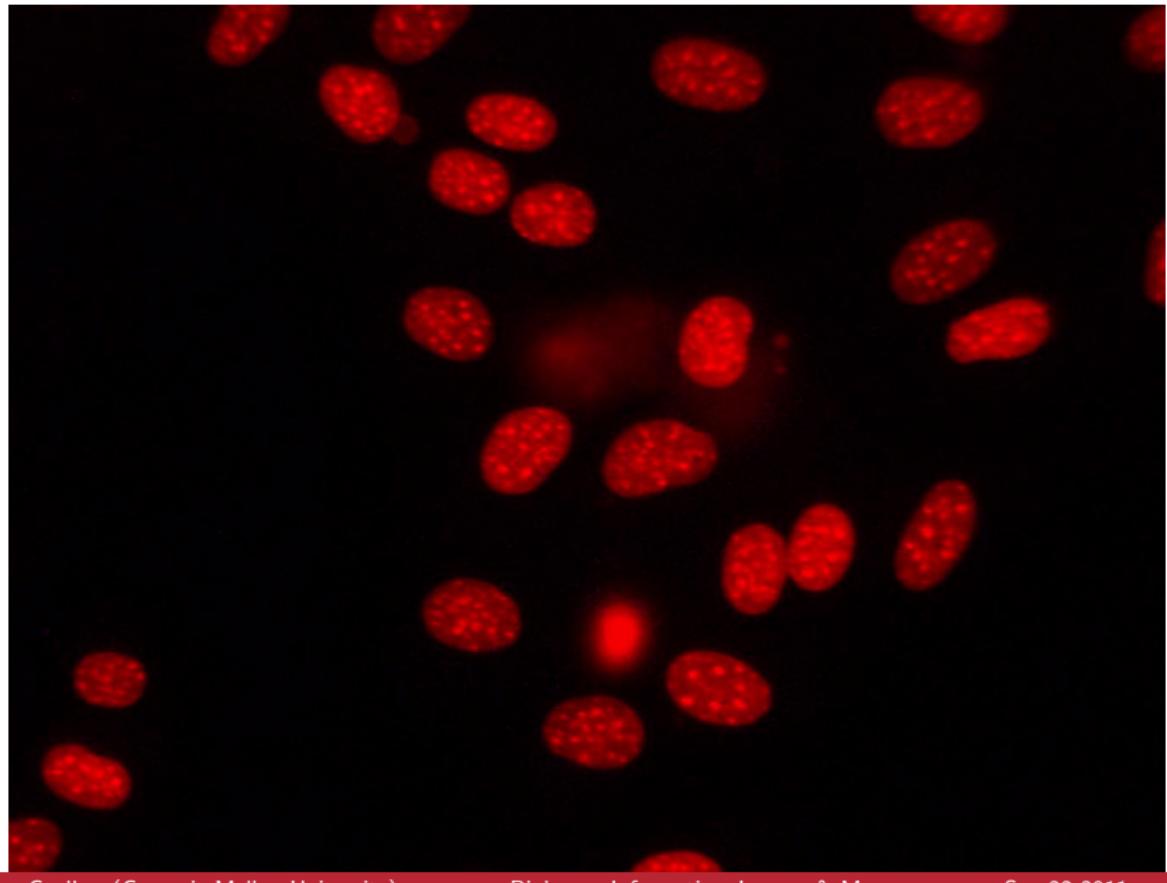
# The Data



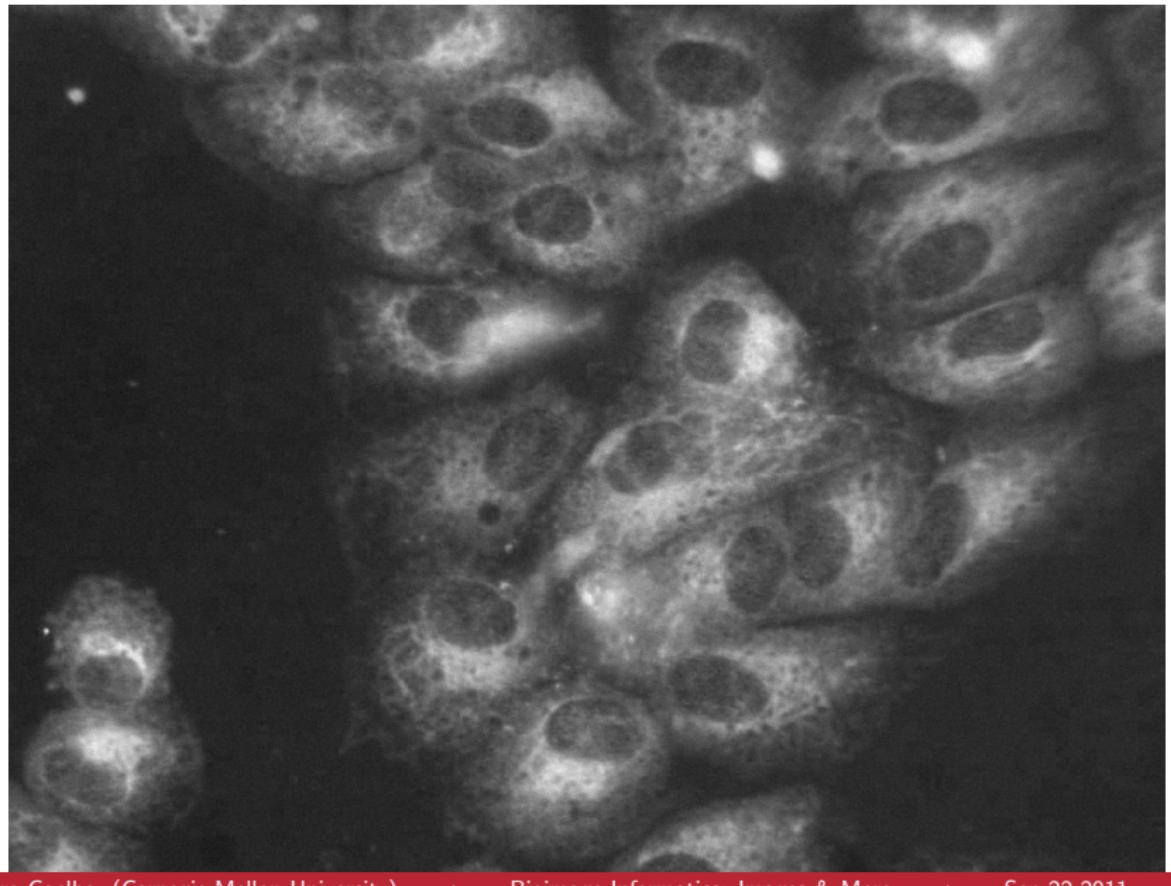
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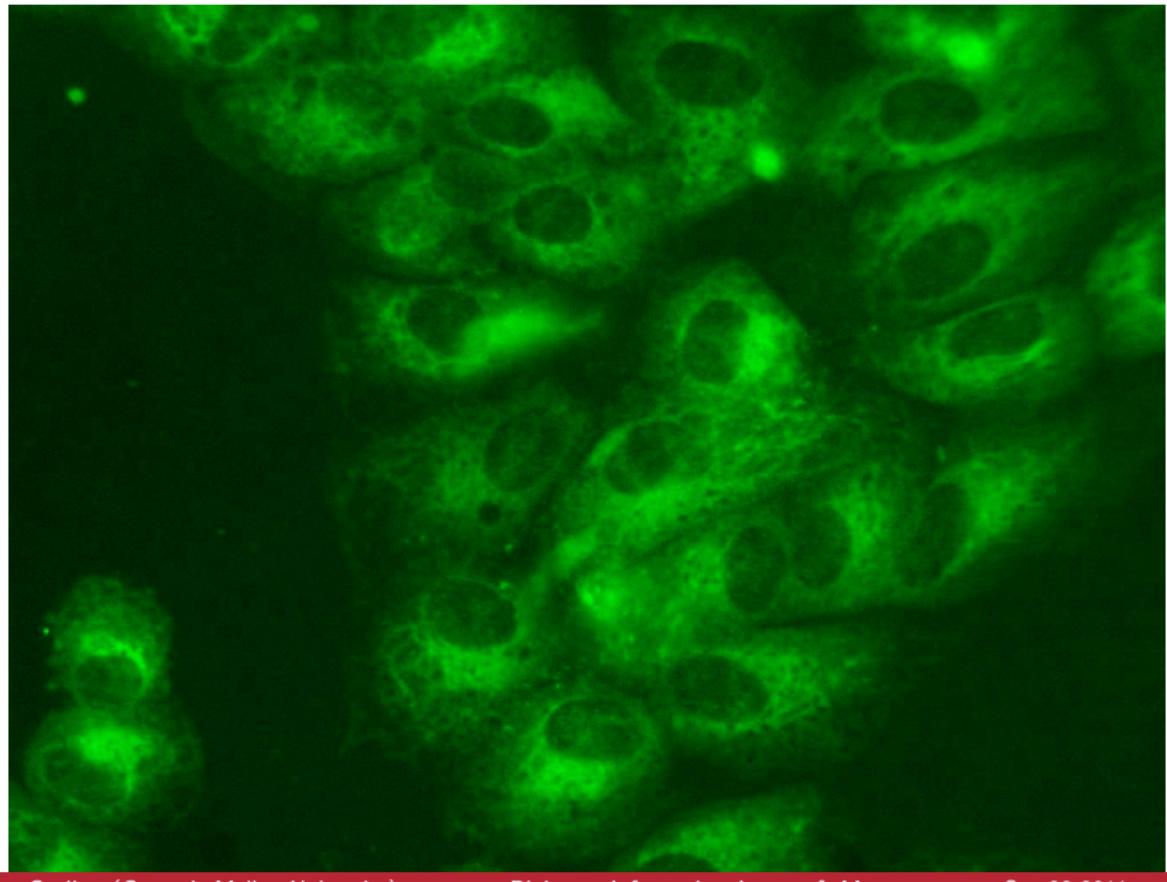
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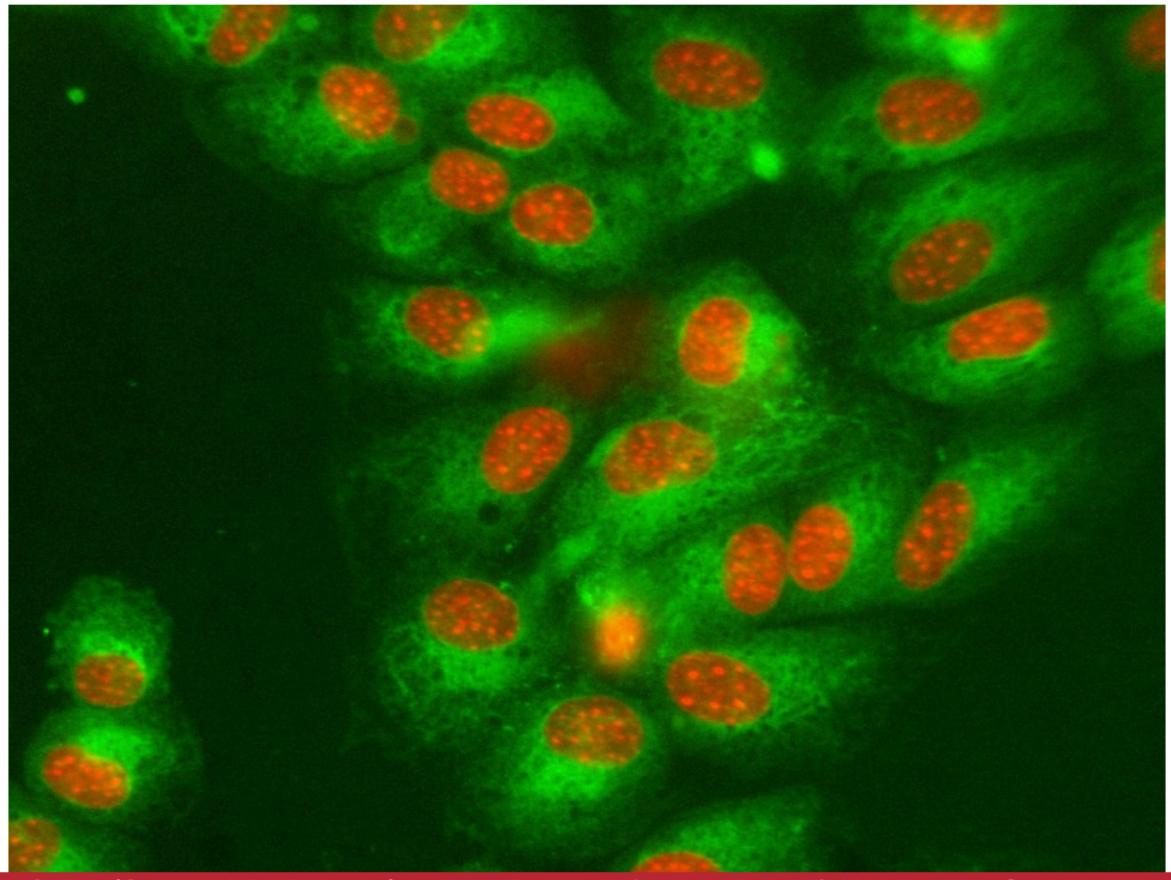
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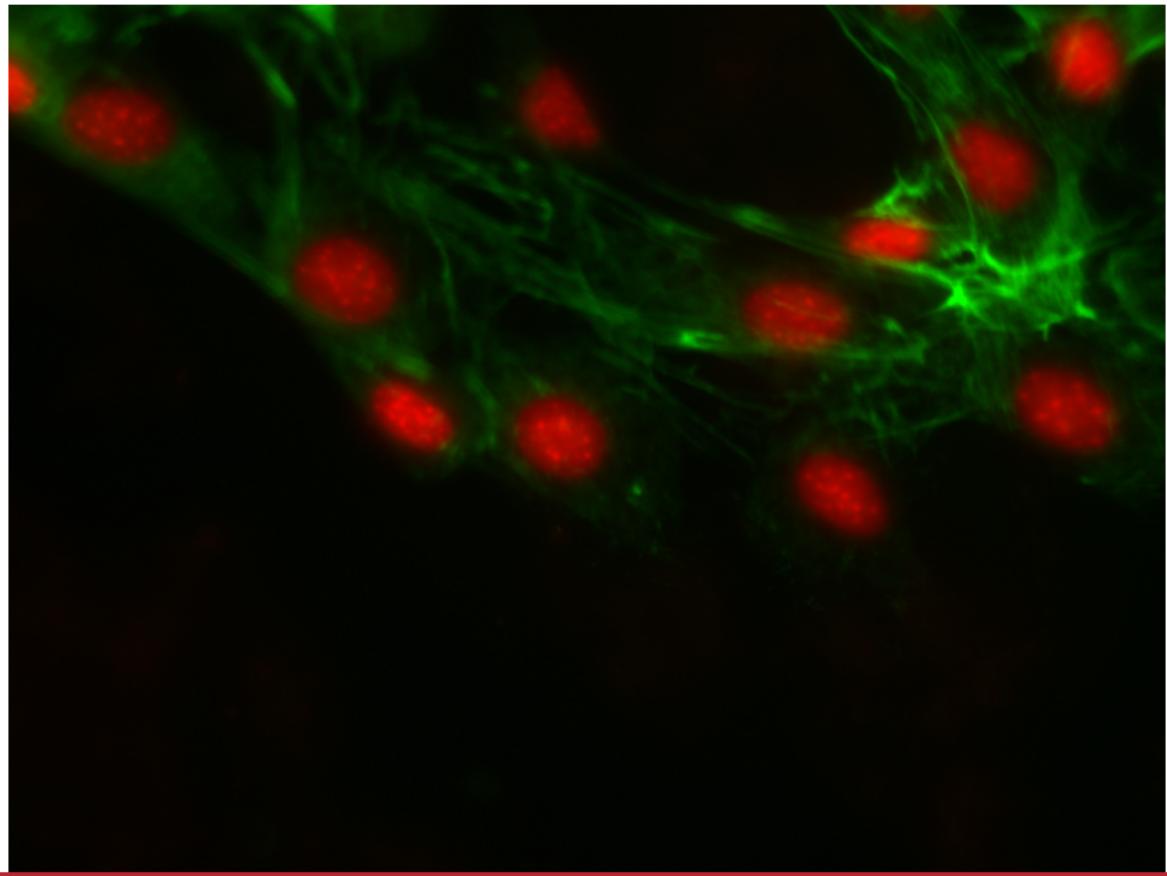
# The Data



# The Data



# The Data



# First Task

## Classification

Given **labeled data**, can we learn a classification model?

# Pre-processing

Preprocessing is denoising, background correction, ...

I am going to ignore that step.

## Feature Based Approach

- Represent the image by a small number of features.
- Proposed by Boland and Murphy, in 1998.
- Very successful.

# Features

- A feature is **any number you can compute from the image.**
- For a good features, you wish to simultaneously
  - ① Capture the important variations.
  - ② Disregard the important variations.
- These are naturally problem dependent,
- but **machine learning helps.**

# Typical Features

- Texture (Haralick, Gabor, ...)
- Edginess, smoothness, ...
- ...

The literature is very vast.

# Example Feature

12	6	5	4	3	5
11	10	4	6	7	4
4	5	3	10	8	9
3	4	12	9	8	14
7	12	10	8	11	13

# Example Feature

12	6	5	4	3	5
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# Algorithm

- For each  $3 \times 3$  region:
- Find the maximum and the minimum.
- Subtract the minimum from the maximum.
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For an **image level feature**, average this number

- ① What is this feature **sensitive** to?
- ② What is this feature **invariant** to?







# Classifiers

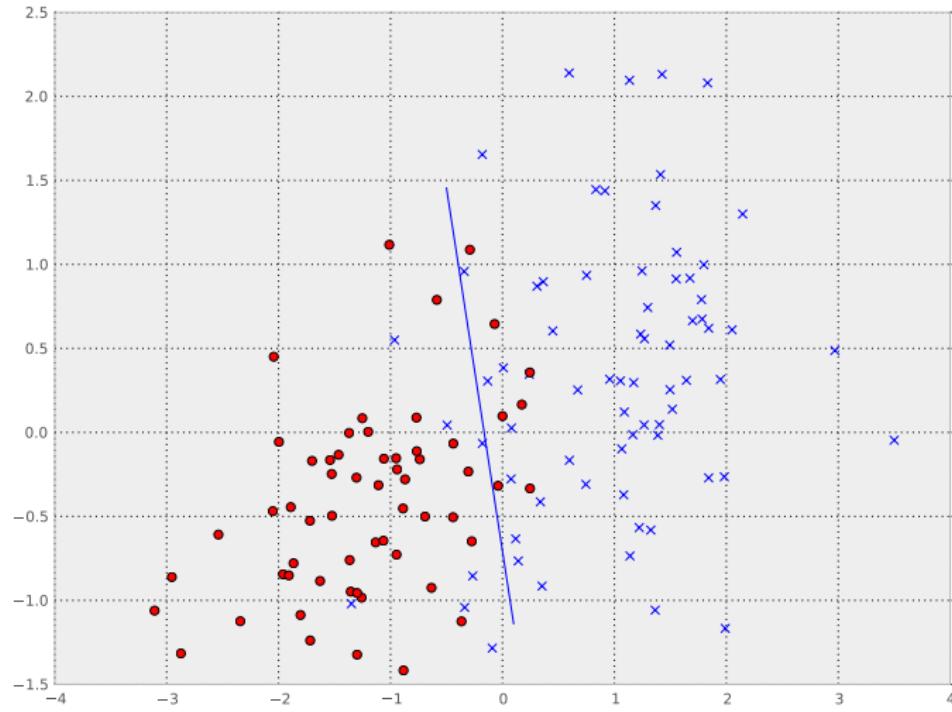
Simple classifier: if average of region is less than 10, call it sky.

# Classifiers

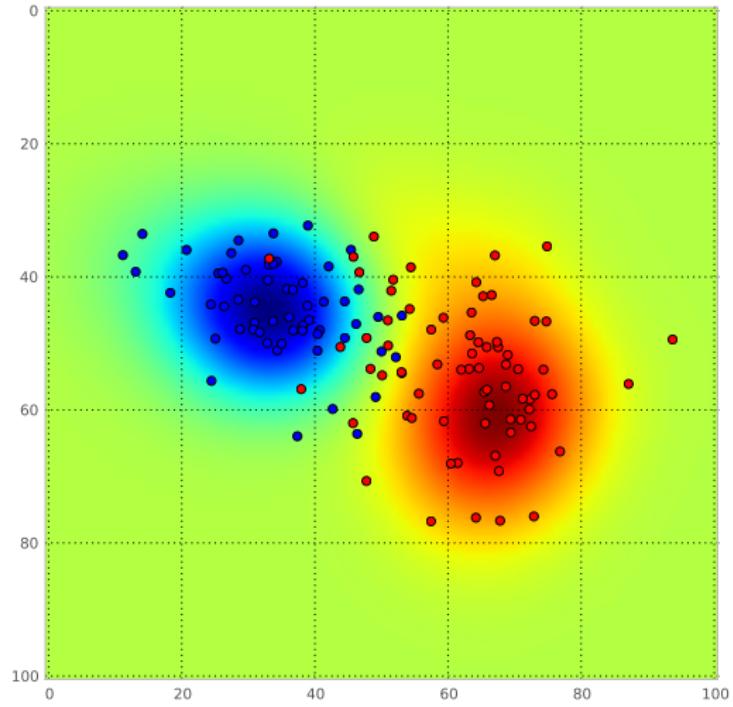
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# Classifiers



# Classifiers



# Results

	Cyto	Cytosk	Lyso	PM	Mito	N	NN
Cyto	115	10	3	15	8	4	0
Cytosk	14	147	3	2	30	1	0
Lyso	3	1	14	0	50	0	1
PM	31	6	2	9	2	1	0
Mito	22	30	15	0	126	6	1
N	25	1	0	1	0	219	9
NN	1	0	0	0	1	16	95

# Other Problems

## Other Typical Classification Problems

- Phenotype in a Genome-wide Screen
- Stem cell differentiation
- ...

# Conclusions

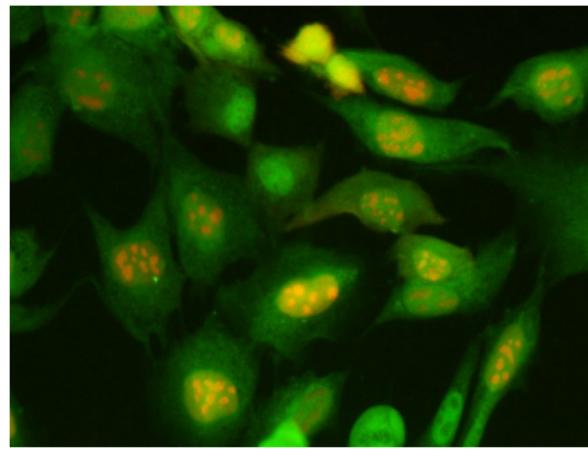
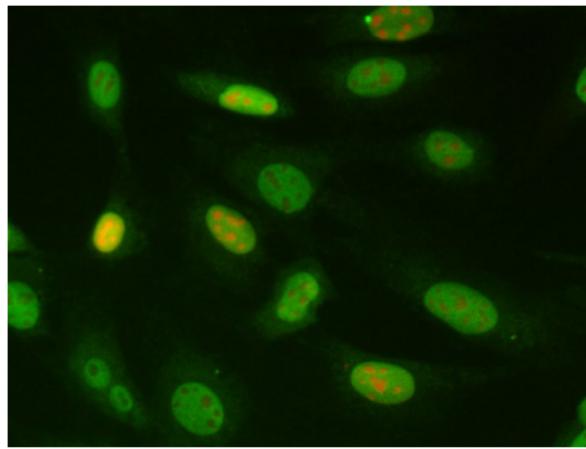
- Computers can do very well at classification.
- Flexible tool if you have the training data.

# Detecting Changes in Pattern

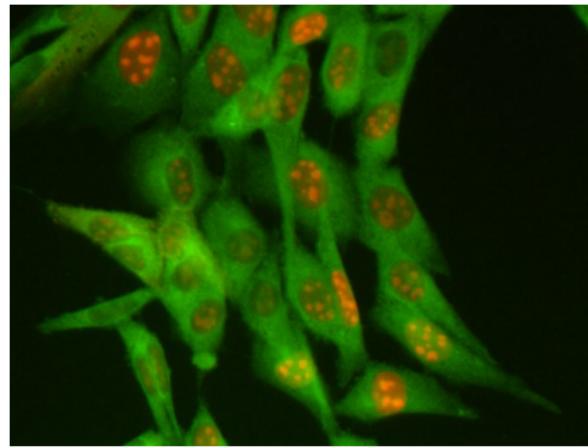
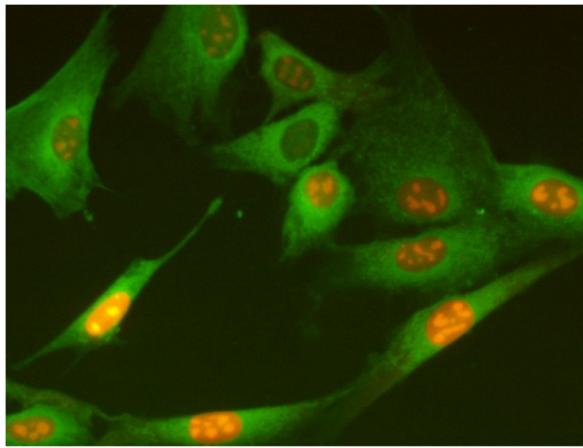
Which proteins change pattern when we stress the cells?

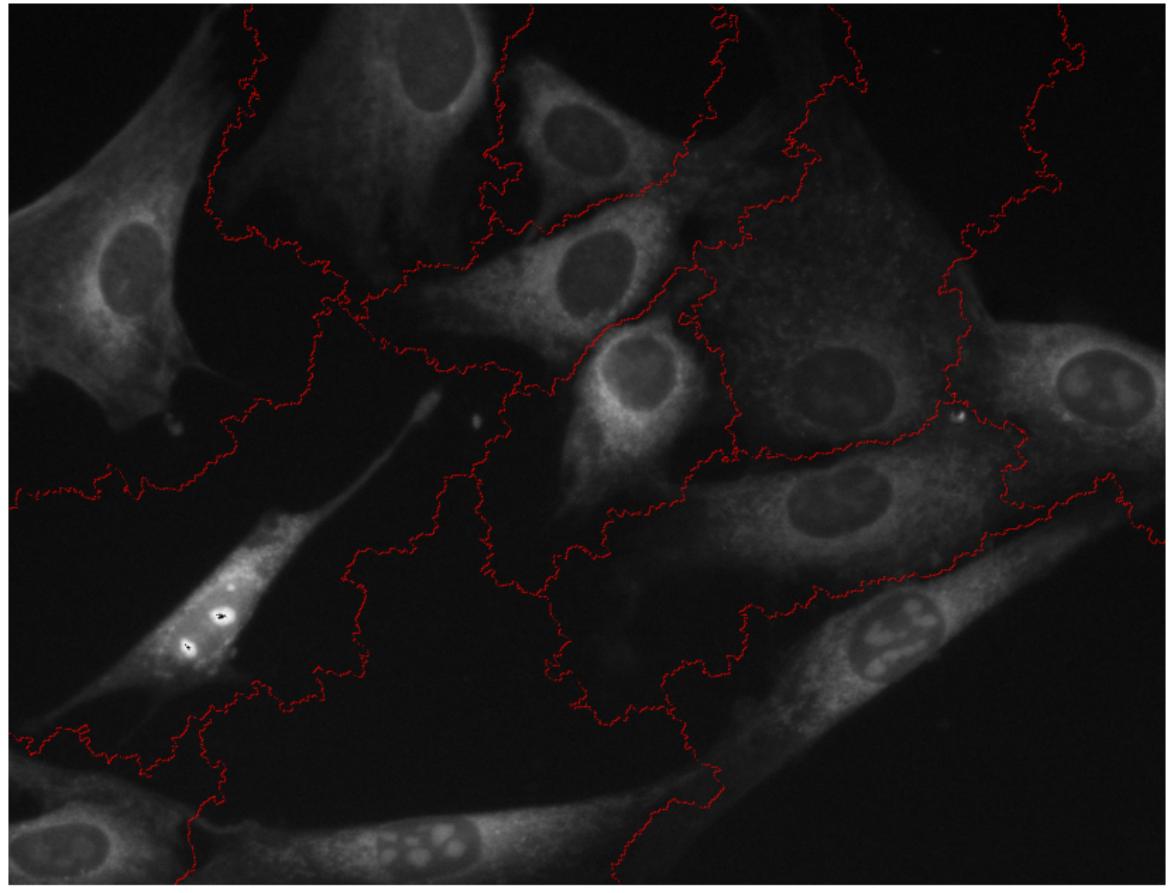
In collaboration with Marc Halterman @ Rochester

## Positive Example

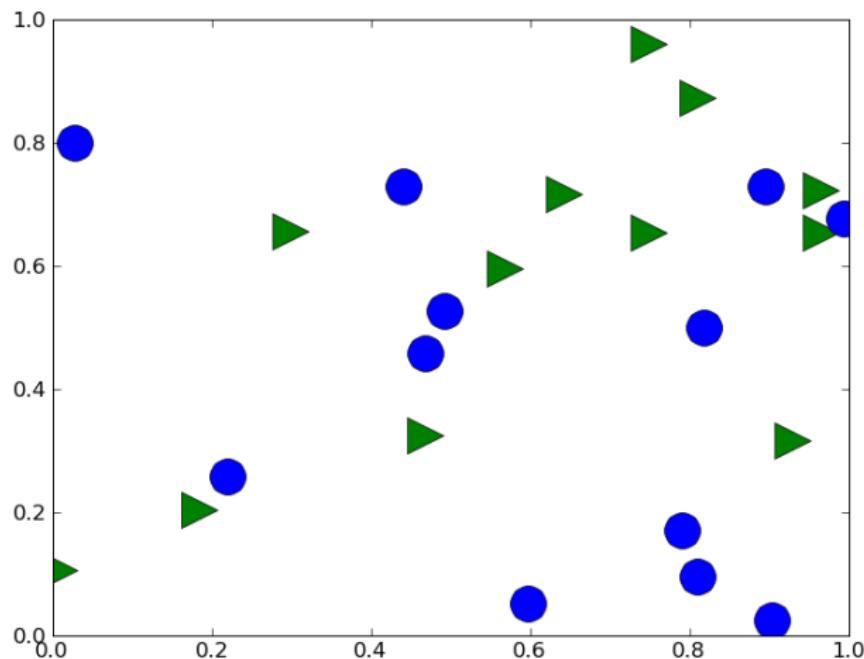


# Negative Example





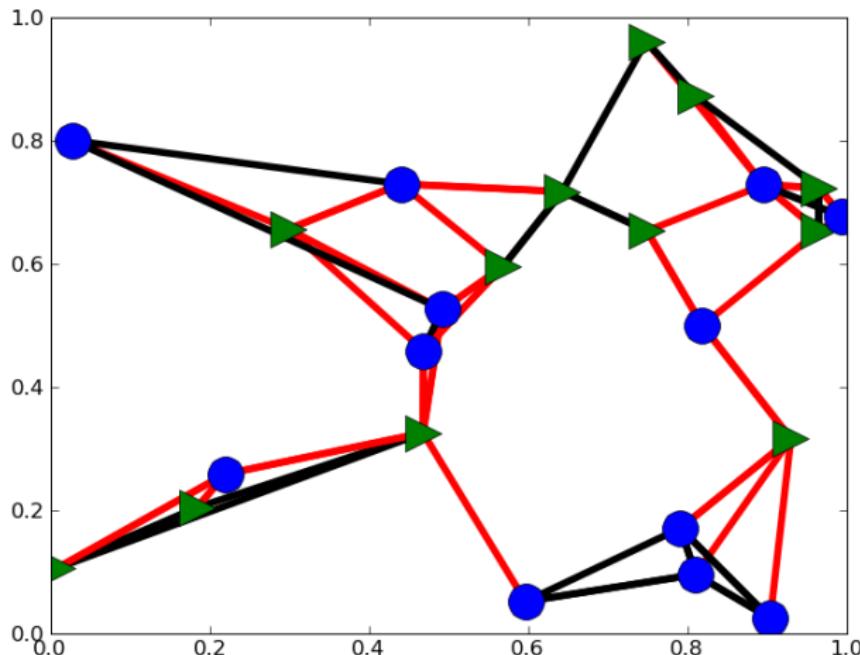
# K-Nearest Neighbour Test



(Henze, 1988)

(T. Zhao et al., 2006)

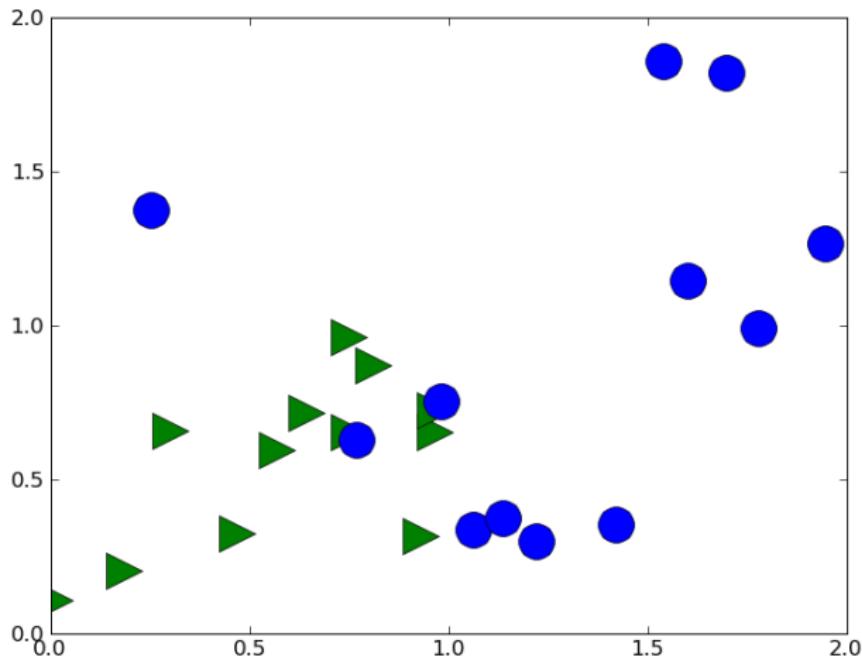
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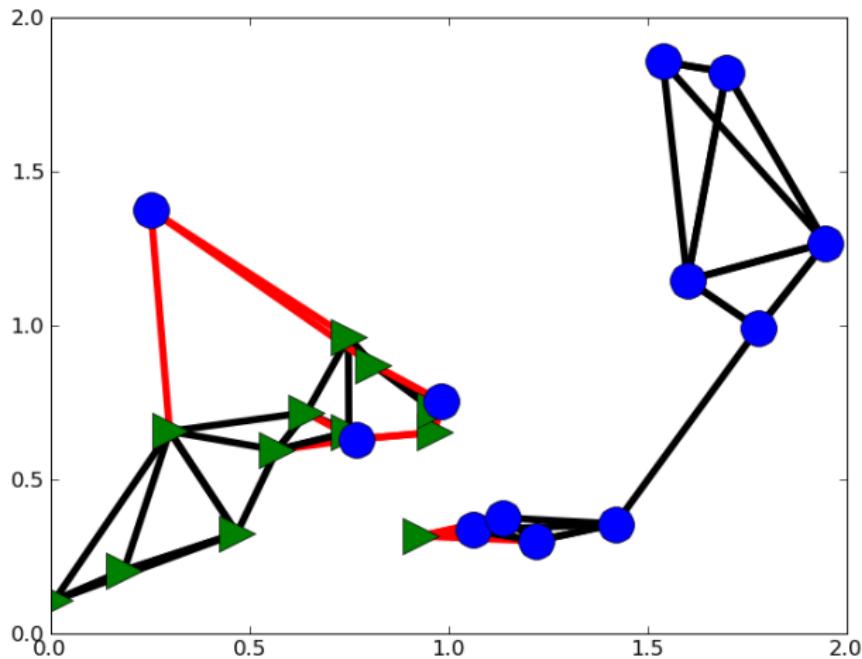
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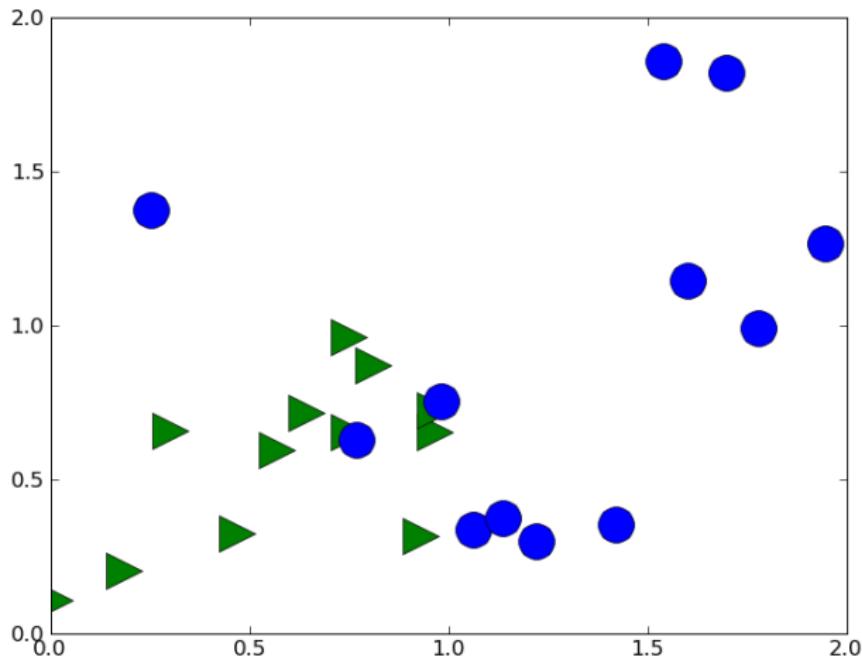
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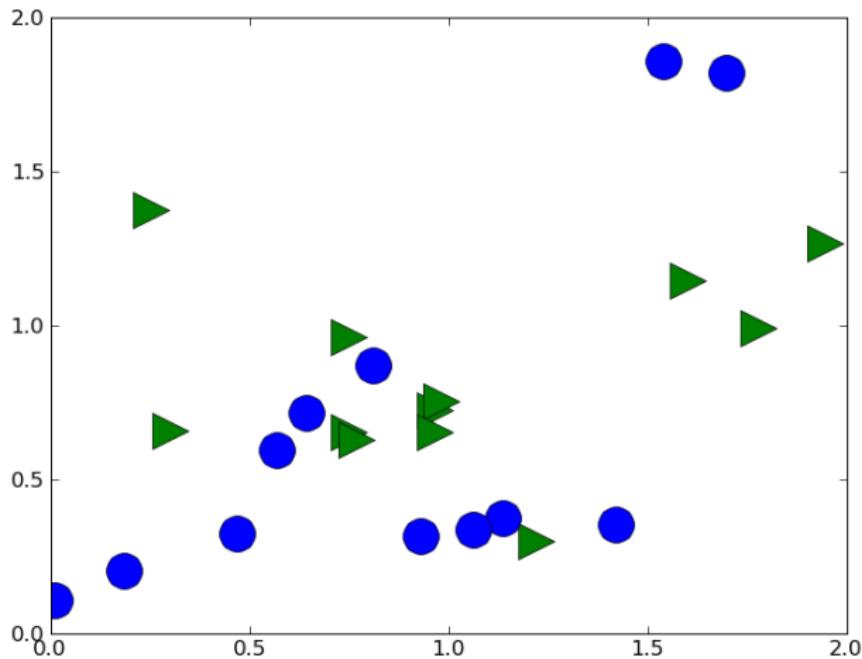
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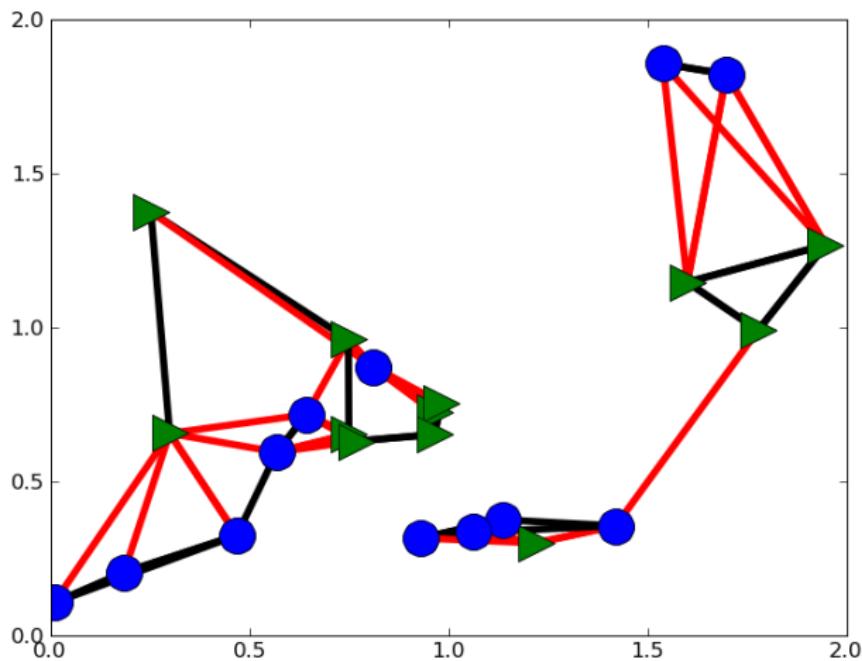
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This is a simple example, but handling **heterogeneity** is an important area of research.

# Tracking

- Can you follow the cells in a movie?

# Example

# Example

## Example



## Example



# Techniques

Pipeline Approach:

- (Pre-process)
- Detect/Segment
- Link

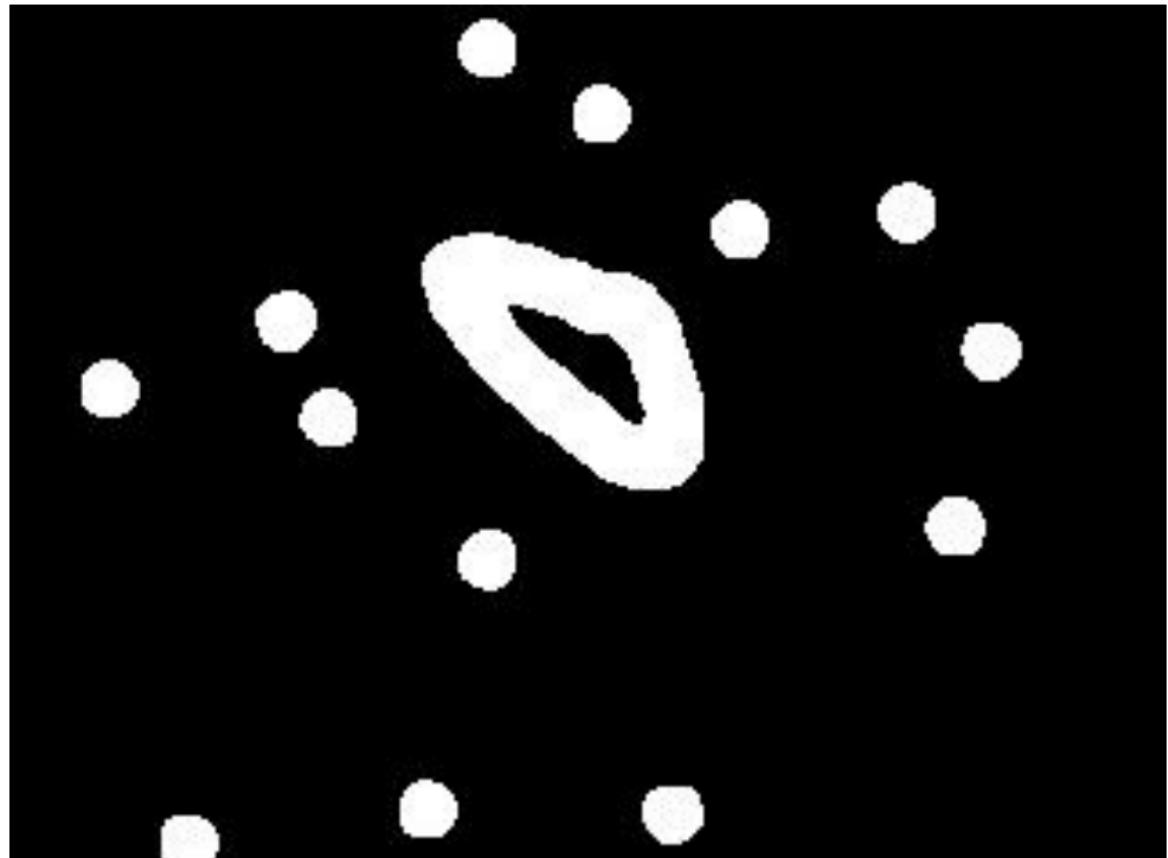
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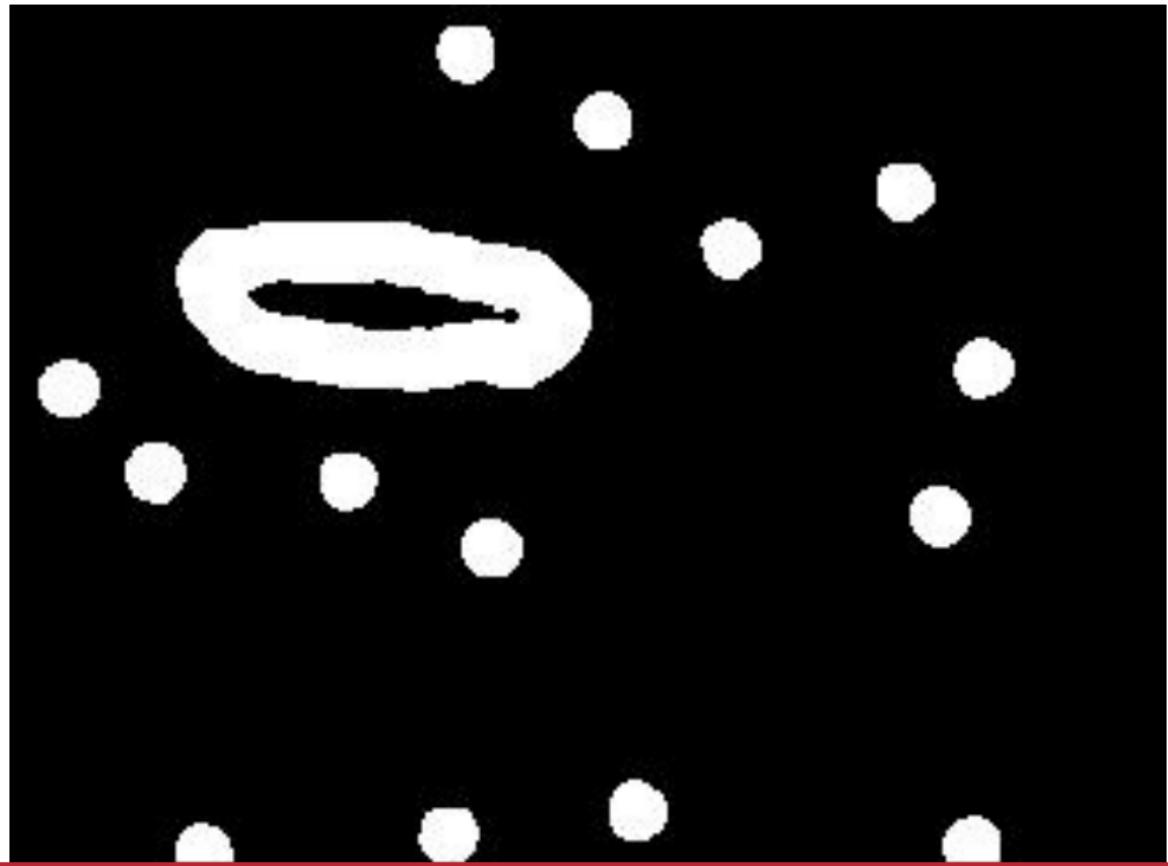
## Example



## Example



## Example



# Greedy Linking Approach

## Linking Problem

Given a set of points in one frame  $\{x_i\}_i$   
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## Marriage Problem

Given a bipartite graph  $M \cup F$  with weights  $w_{mw}$  between the members,  
can we find a matching that maximises  $\sum w_{mf}$ ?

Yes, we can solve this in polynomial time using the Hungarian algorithm.

# Better Approaches

## Hungarian Algorithm

- Simple, off-the-shelf, solution.
  - Computationally efficient
- 
- Not very robust to noisy data

## How to do better

- Take **multiple time-steps** into consideration.
- Active contours approaches combine segmentation and tracking.

# Generative Models

Can we generate fake images that look like real images?

# Generative Models

## Why?

- Learn biology.
- Serve as input for simulation.
- Communication of image data.
- Test set generation.

# Generative Models

## How?

- ① Define a model
- ② Learn parameters from data
- ③ Generate images

(T. Zhao & Murphy, 2007)

(T. Peng et al., 2009)

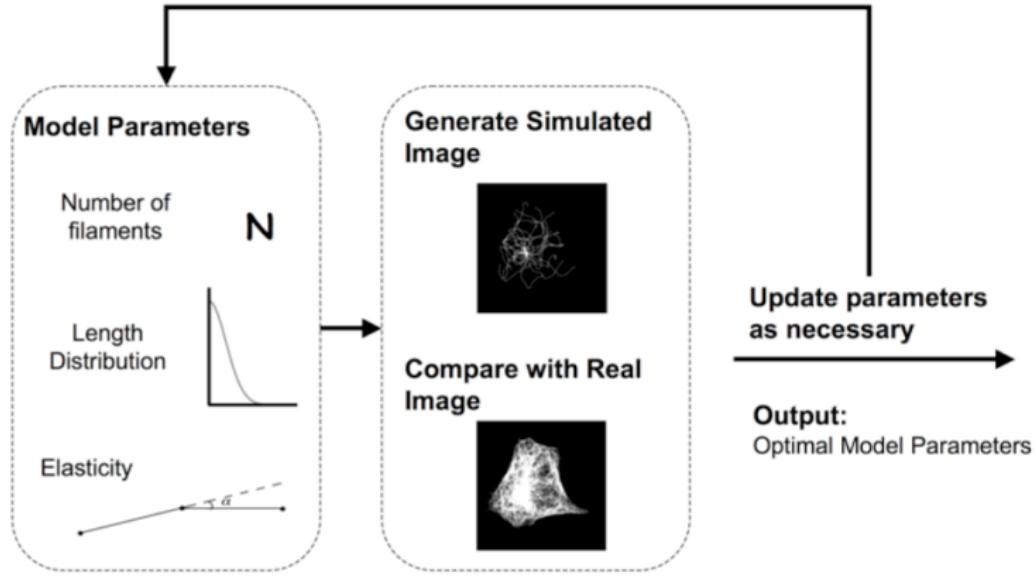
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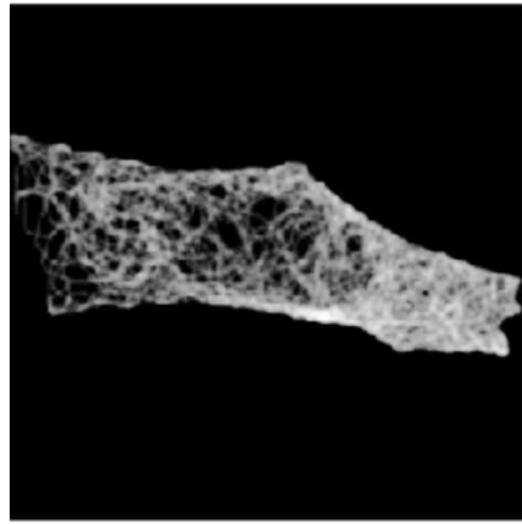
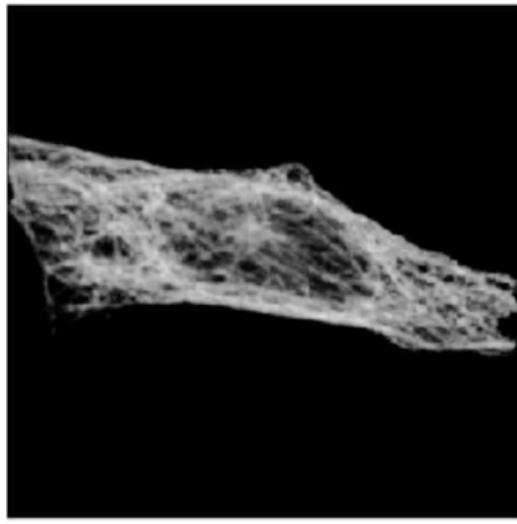
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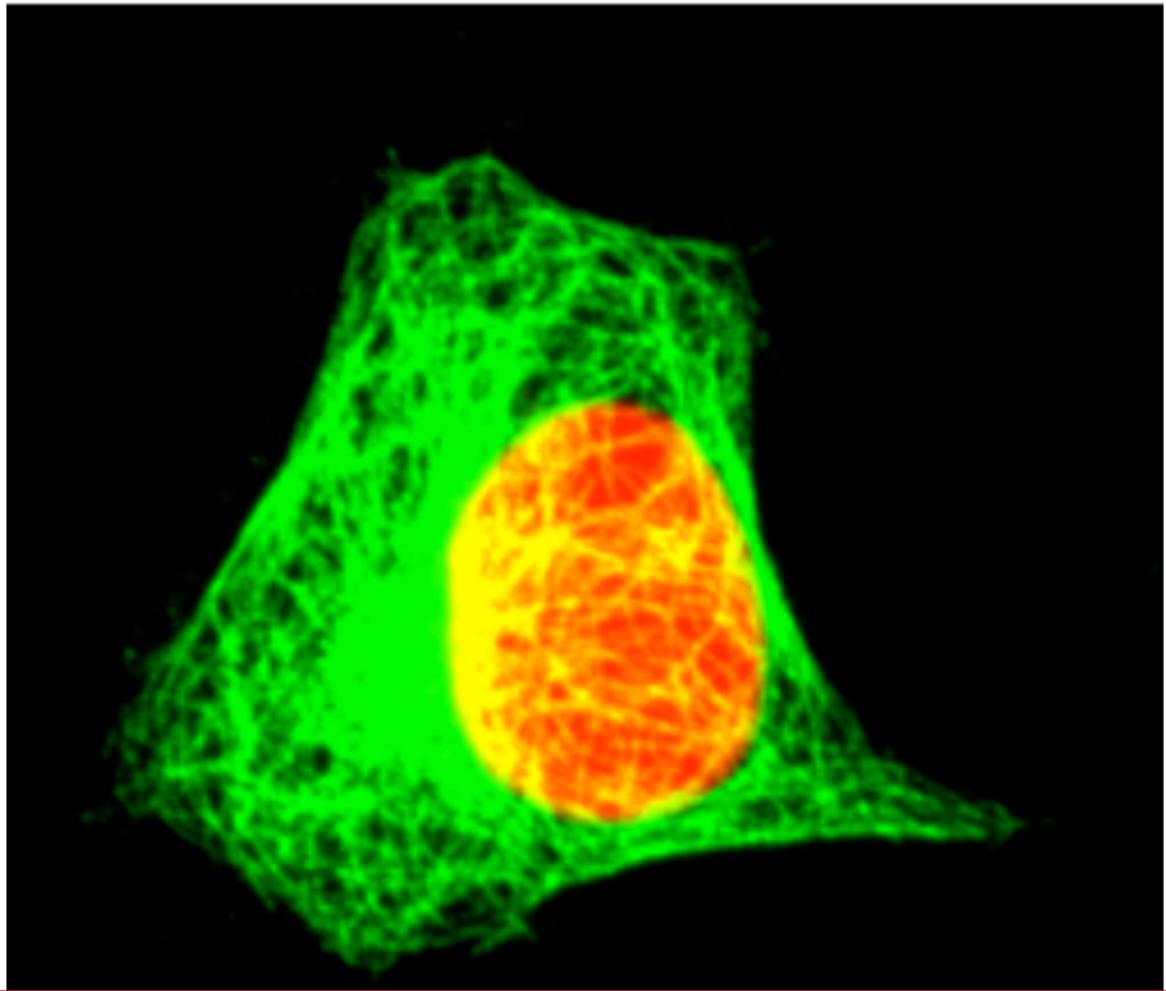


(Shariff et al., 2009, 2010)

## Two Images



(A. Shariff et al., 2009)



# Mixture Patterns Classification

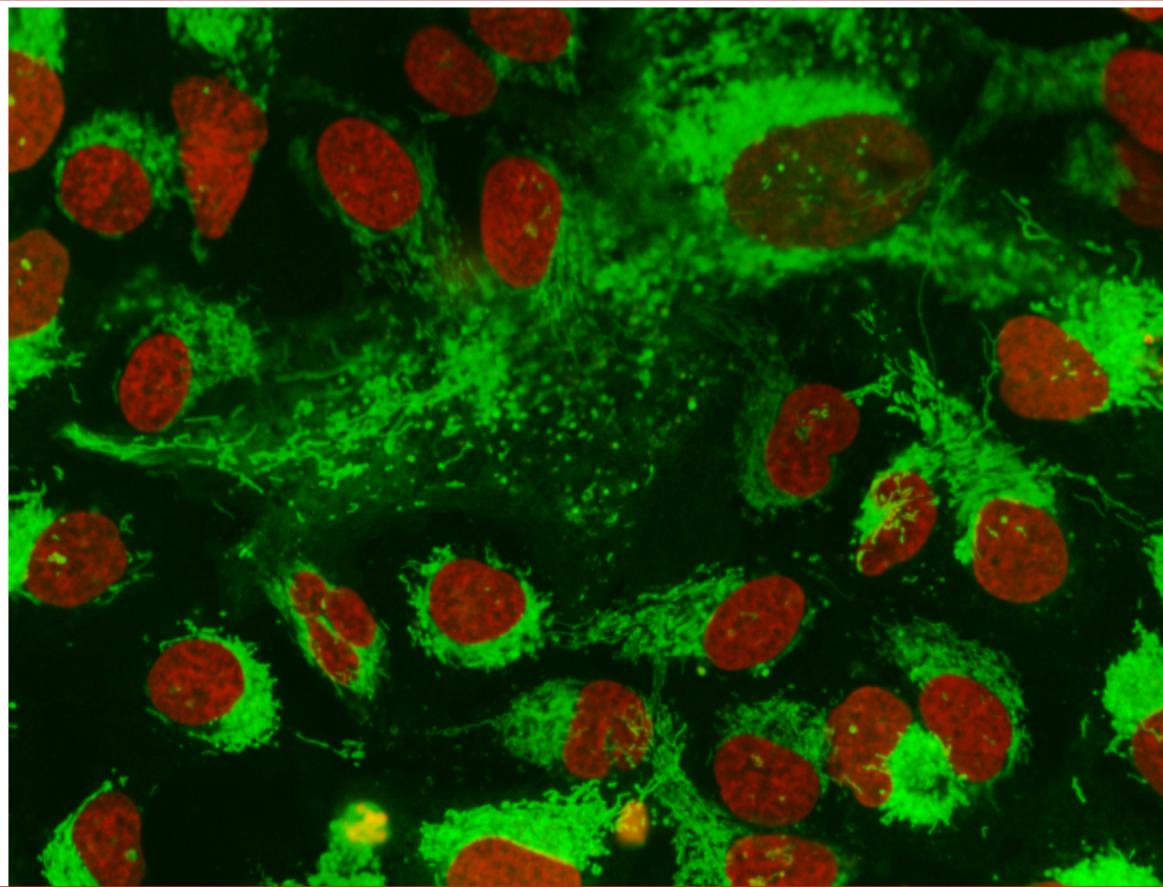
Previously reported methods work well for simple classes, like “endosomes” or “mitochondria.”

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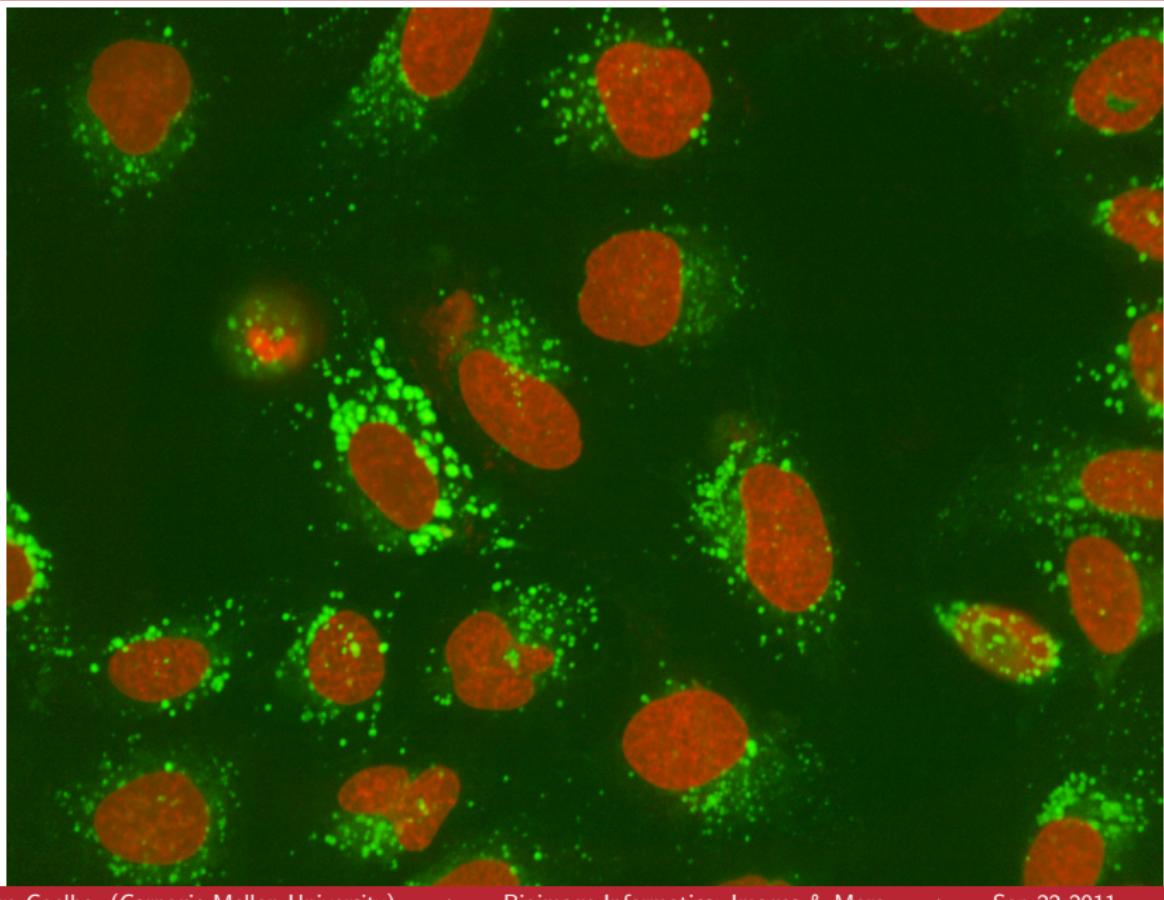
Previously reported methods work well for simple classes, like “endosomes” or “mitochondria.”

What if a protein is present in both endosomes and mitochondria?

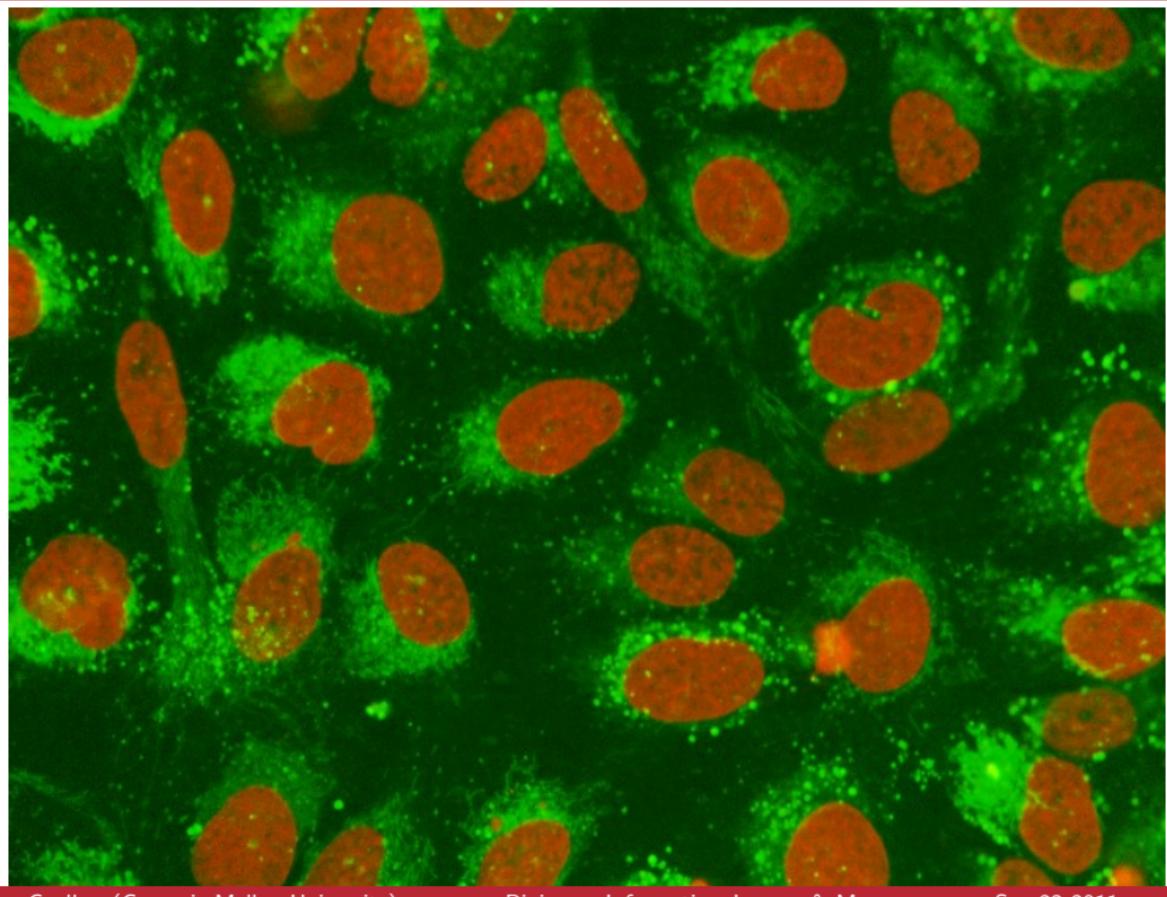
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# Supervised Unmixing Problem

Given examples of **pure patterns** and a mixed pattern,  
can we identify how much each pure pattern contributes to the mixture?

# Supervised Unmixing Problem

Given examples of **pure patterns** and a mixed pattern,  
can we identify how much each pure pattern contributes to the mixture?  
Using an object-based approach, we can solve this.

(T. Zhao et al., 2005)  
(T. Peng, G. Bonami et al., 2010)

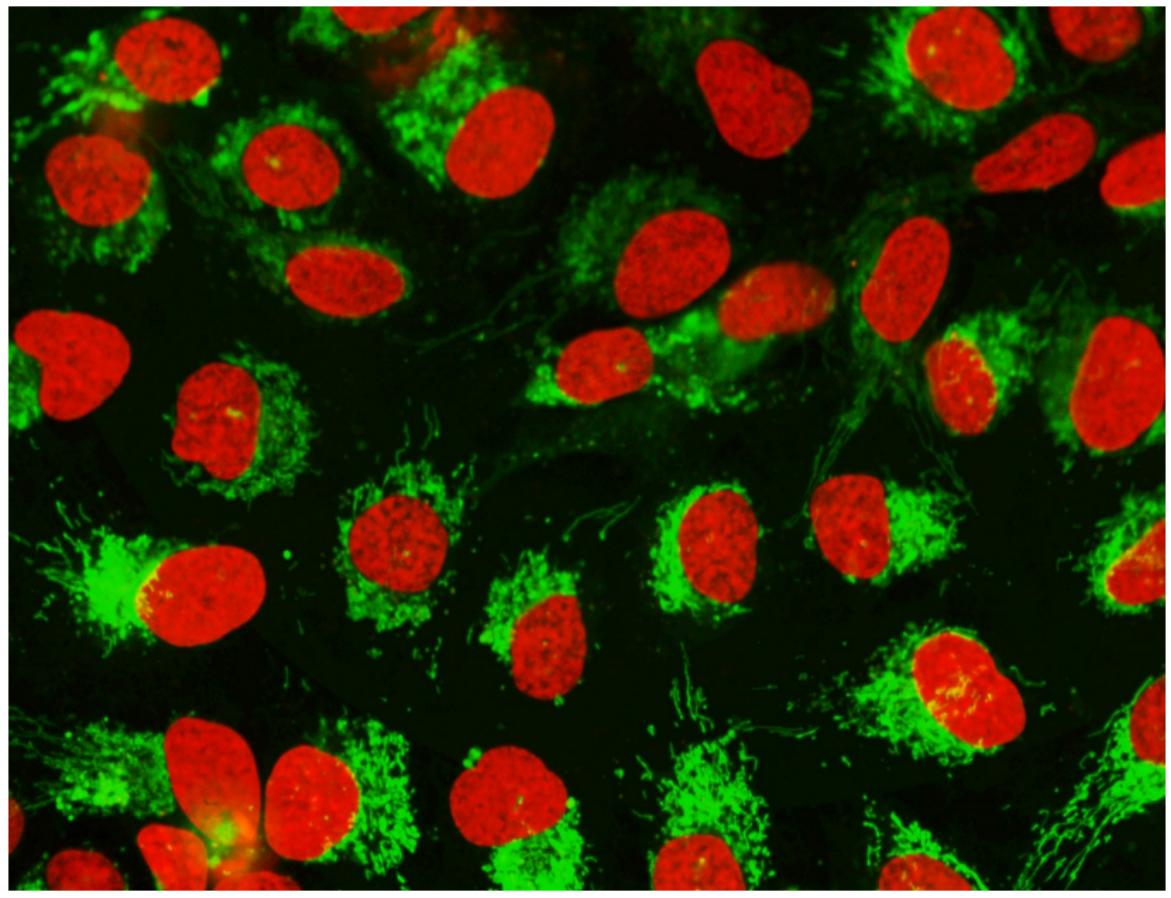
# Unsupervised Unmixing Problem

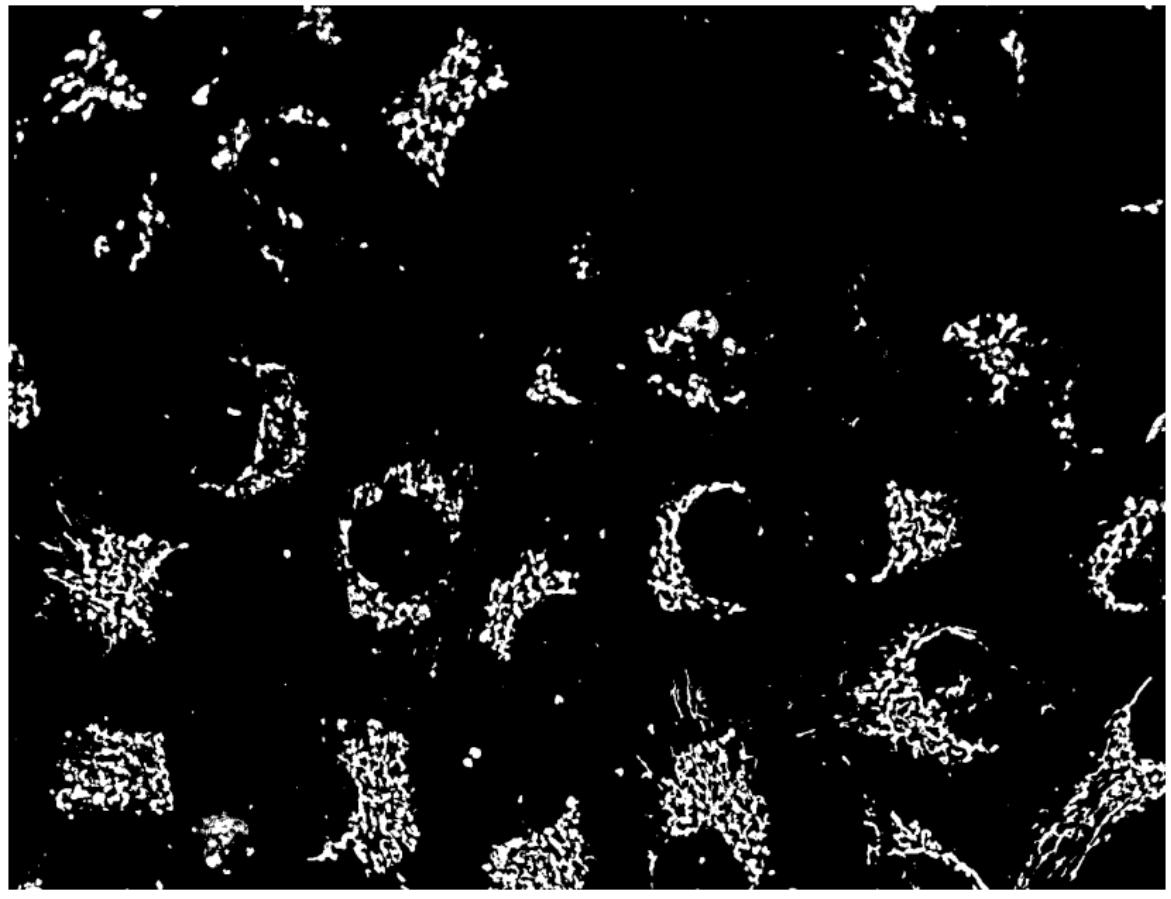
What if we don't know the pure patterns?

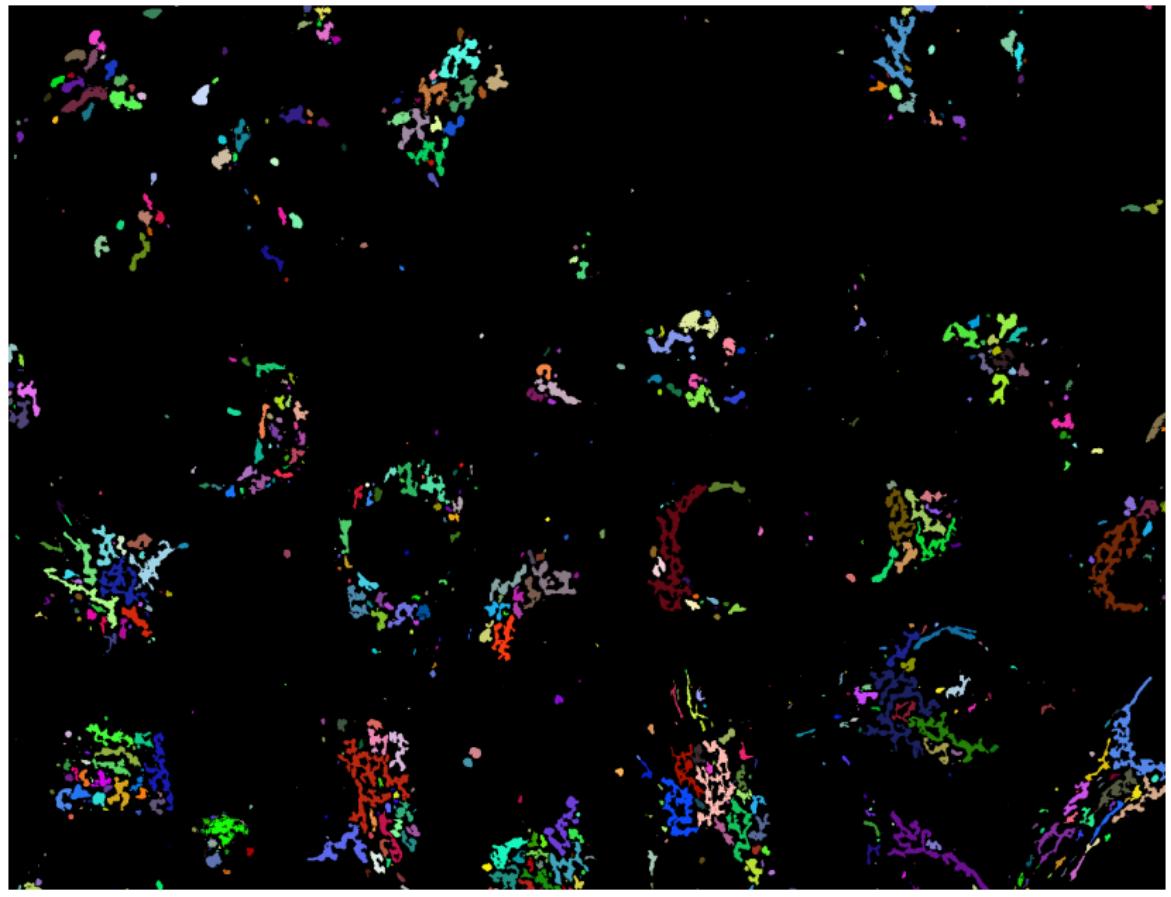
# Unsupervised Unmixing Problem

What if we don't know the pure patterns?

Given a collection of **untagged** images,  
can we **identify** the pure and mixed patterns?



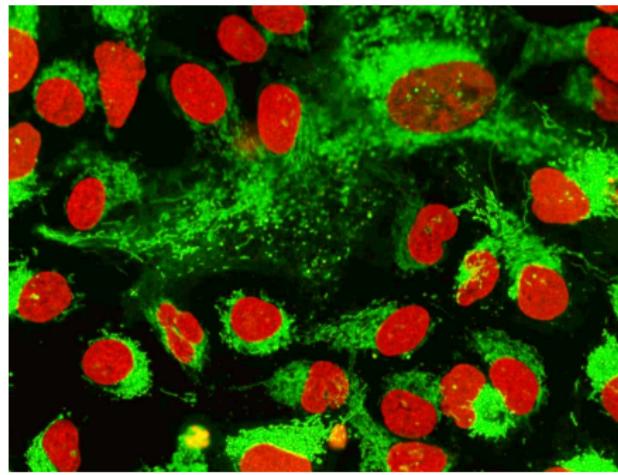
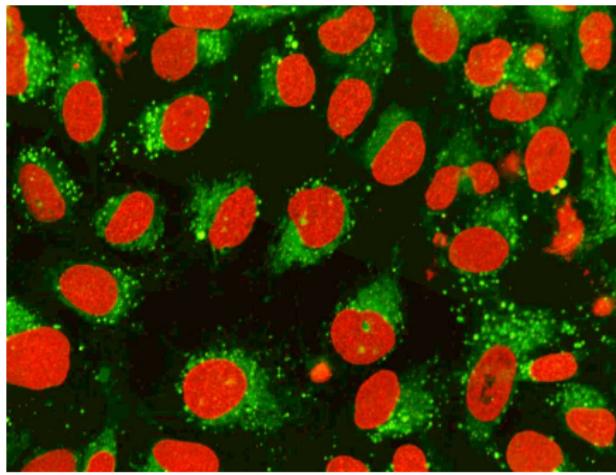




$$\min \sum_i \|X_i - Bc\|$$

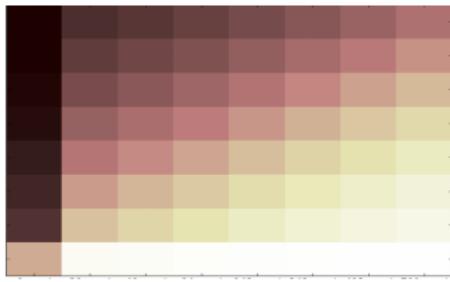
where  $B$  is the basis,  
 $c$  are the coefficients,  
and the problem subject to the constraint that the elements come from  
the dataset.

## Results: Mixing Bases

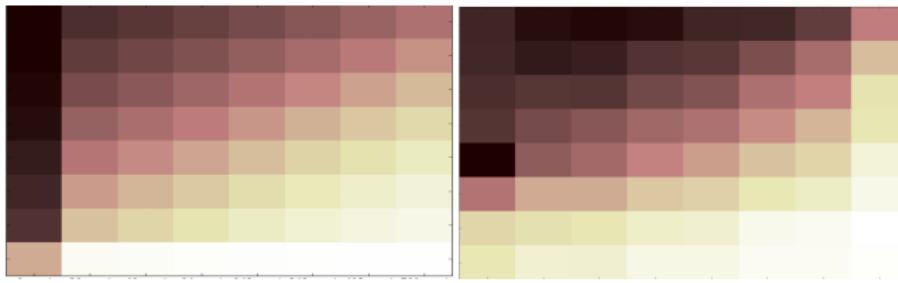


(Coelho et al., 2010)

# Results: Mixing Fractions

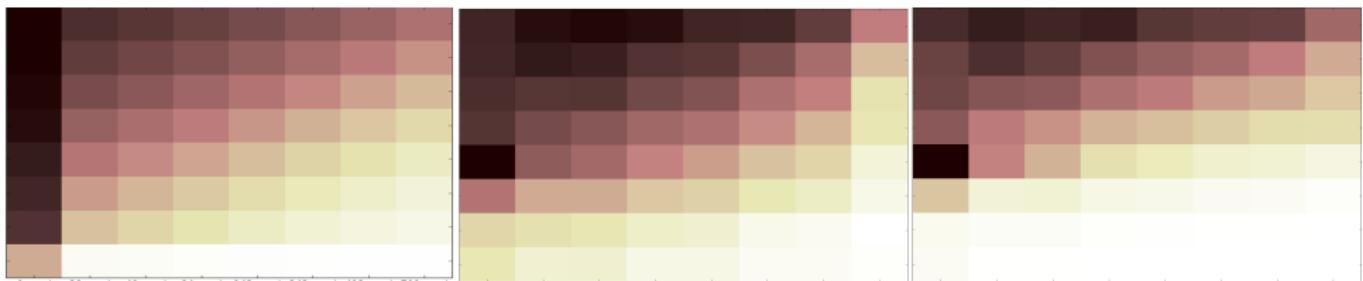


# Results: Mixing Fractions



Correlation:  
88%

# Results: Mixing Fractions



Correlation:  
88%

Correlation:  
91%

(Coelho et al., 2010)

- Pattern Unmixing works both in supervised and unsupervised modes.

# Conclusions

- ① Intersection between computer vision and biology.
- ② Basic problems are solved with machine learning.
- ③ Problems from image processing
- ④ Specific problems to this area:
  - generative (or indirect) modeling
  - pattern unmixing

# Areas of Active and Future Research

- ① New modalities.
- ② Computational efficiency.
- ③ Robust algorithms (less parameter tuning).
- ④ Post-pipeline algorithms.
- ⑤ Integrating human and computer computation.
- ⑥ Integrating different data modalities.
- ⑦ Finding needles in haystacks.
- ⑧ Machine learning with very noisy data, but lots of it  
(web community is going similar things, what can we borrow?)
- ⑨ Active learning.
- ⑩ Unsupervised or semi-unsupervised methods.

# Acknowledgements

- Robert F. Murphy
- Tao Peng
- Aabid Shariff
- Ting Zhao
- Estelle Glory-Afshar
- Murphy Lab

Thank you.