COMPUTER VISION IN CELL BIOLOGY

Gaudenz Danuser, 2011

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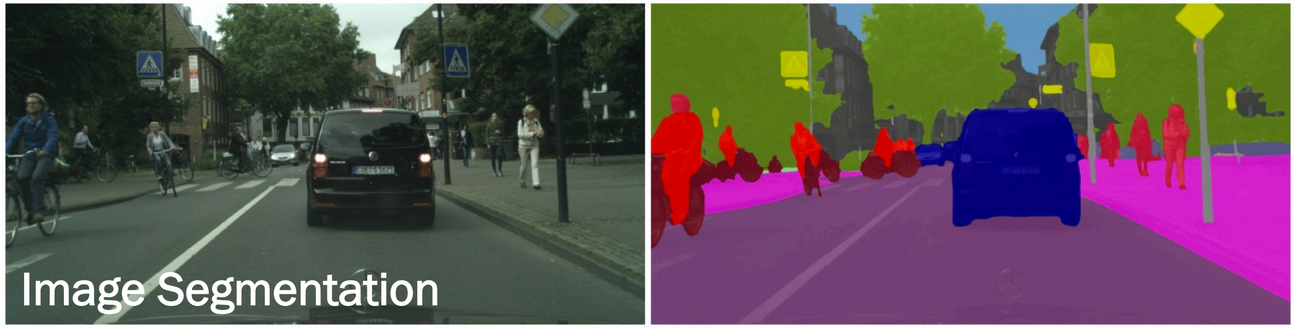

http://vladlen.info/publications/feature-space-optimization-for-semantic-video-segmentation/

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- ***Computer vision***: interdisciplinary field concerned with automatic extraction, analysis, and understanding of useful information from a single image/sequence of images
  - ***Goal of computer vision programs***: to replace the human observer in complex image analysis tasks
  - Earliest application of computer vision program: karyotyping (Gilbert, 1966; Castleman et. al., 1976)

Contributions of Computer Vision Programs in Imaged-Based Cell Biology

1. Automation
2. Completeness
3. Access to Invisible Image Information

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  - Extracted ***145*** relevant features for each individual cell
  - Utilized a set of neural networks to classify single-cell morphologies based on the features extracted
  - Identify local signaling networks that regulate cell shape and migration in a ***robust, cost-effective manner***

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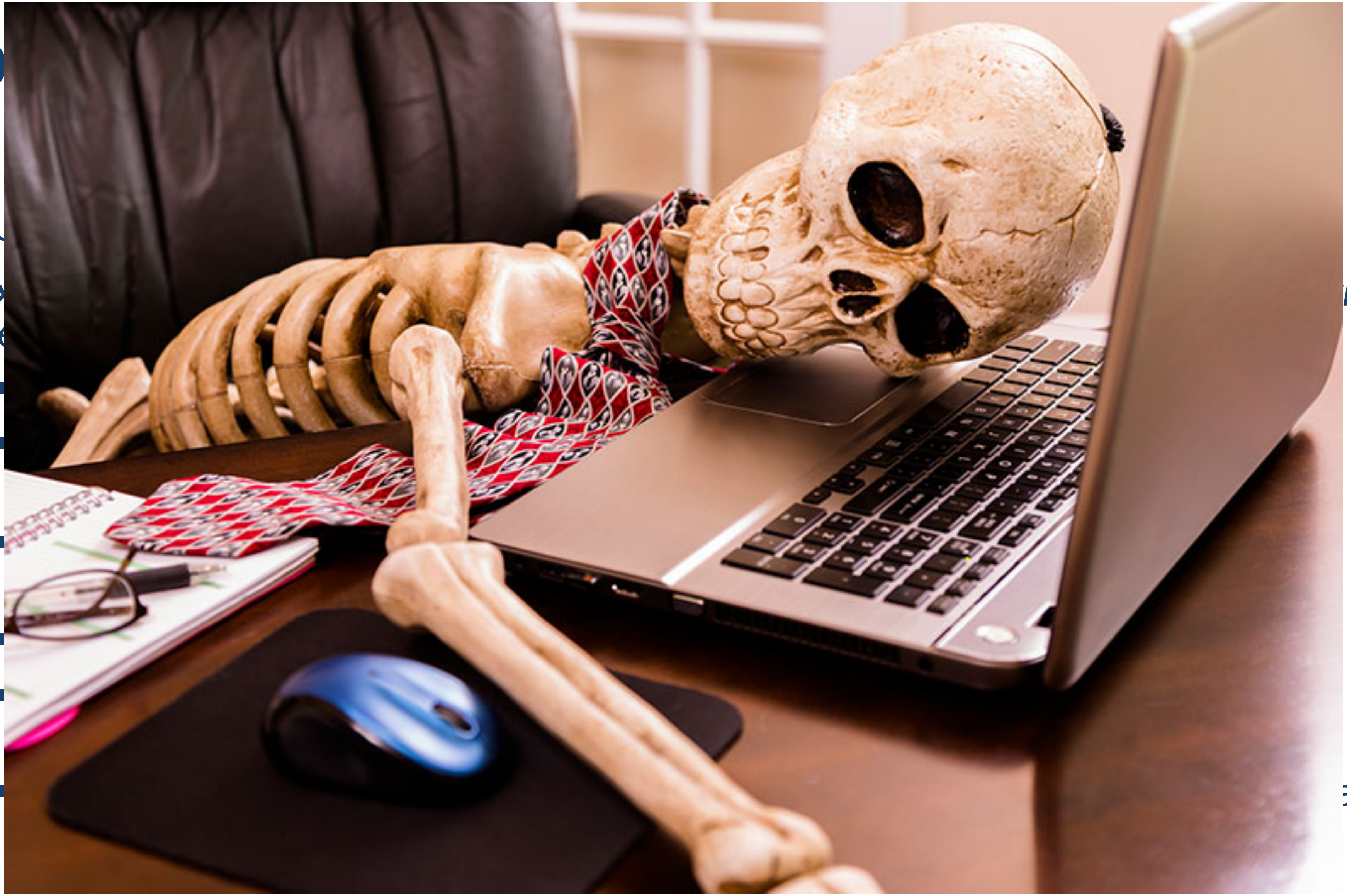

https://bhtechconnection.com/it-advice-group/skeleton-computer/

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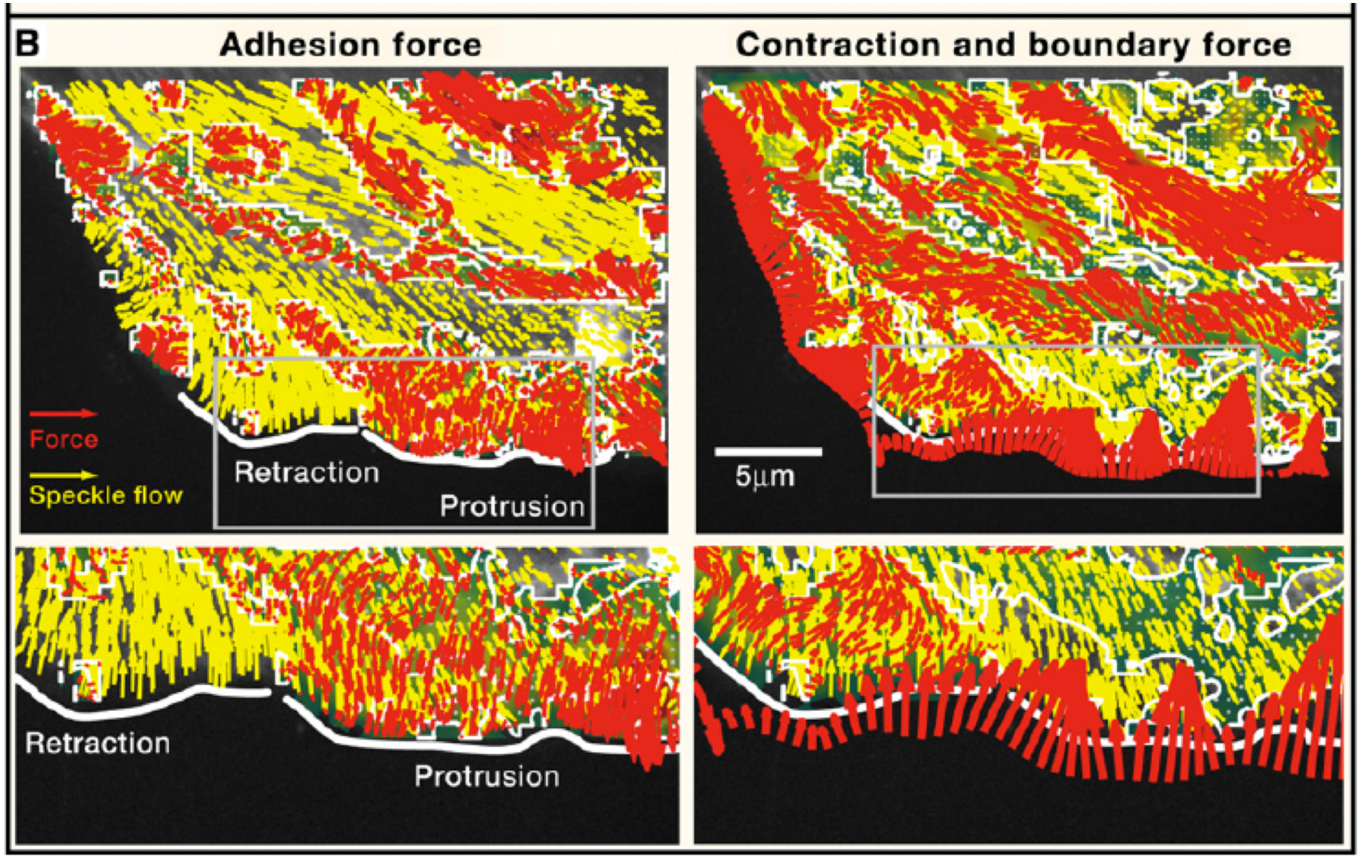
- Computer vision systems provide a better understanding of complex biological pathways and their pleiotropic effects with complete image data extraction

Contribution 3: *Access to Invisible Image Information*



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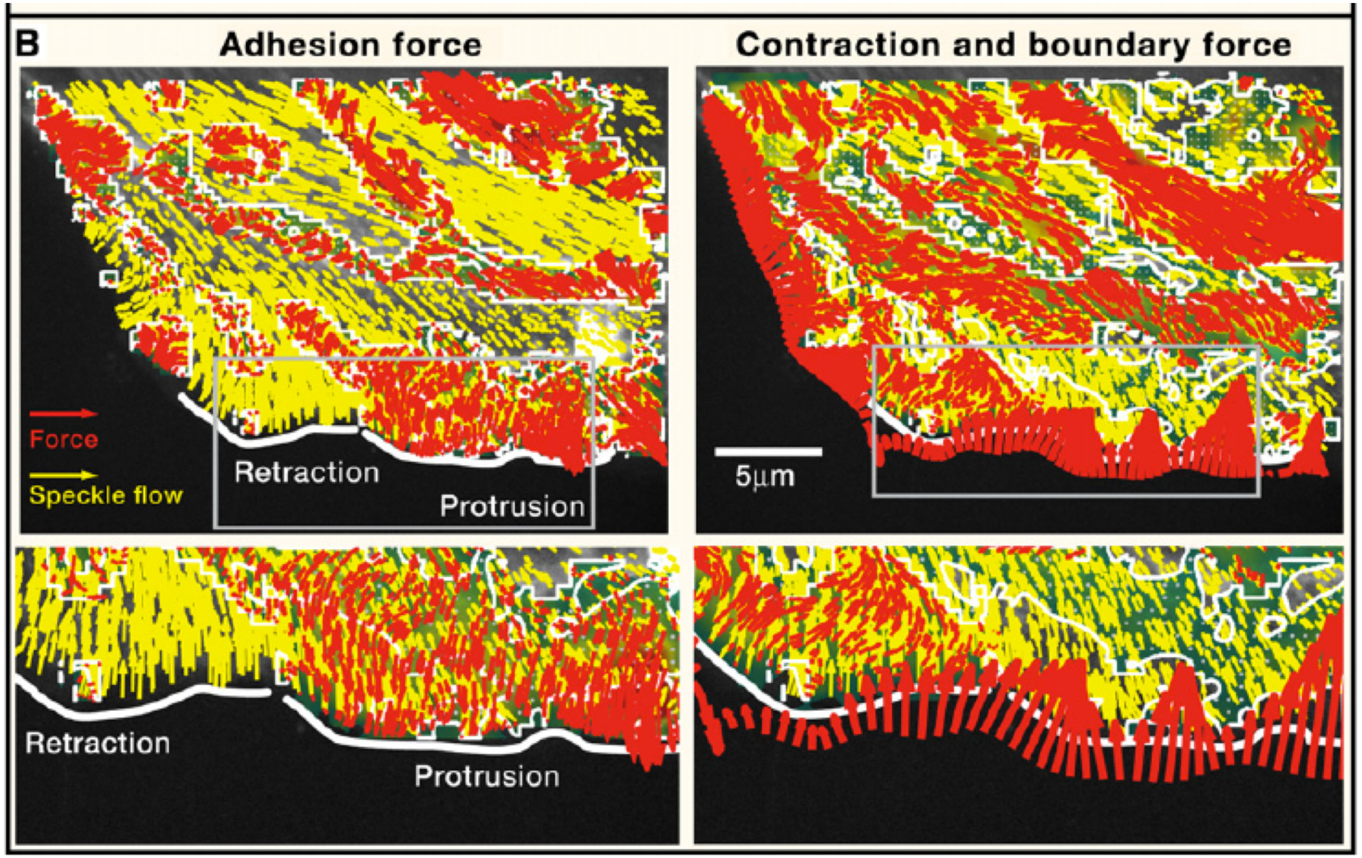

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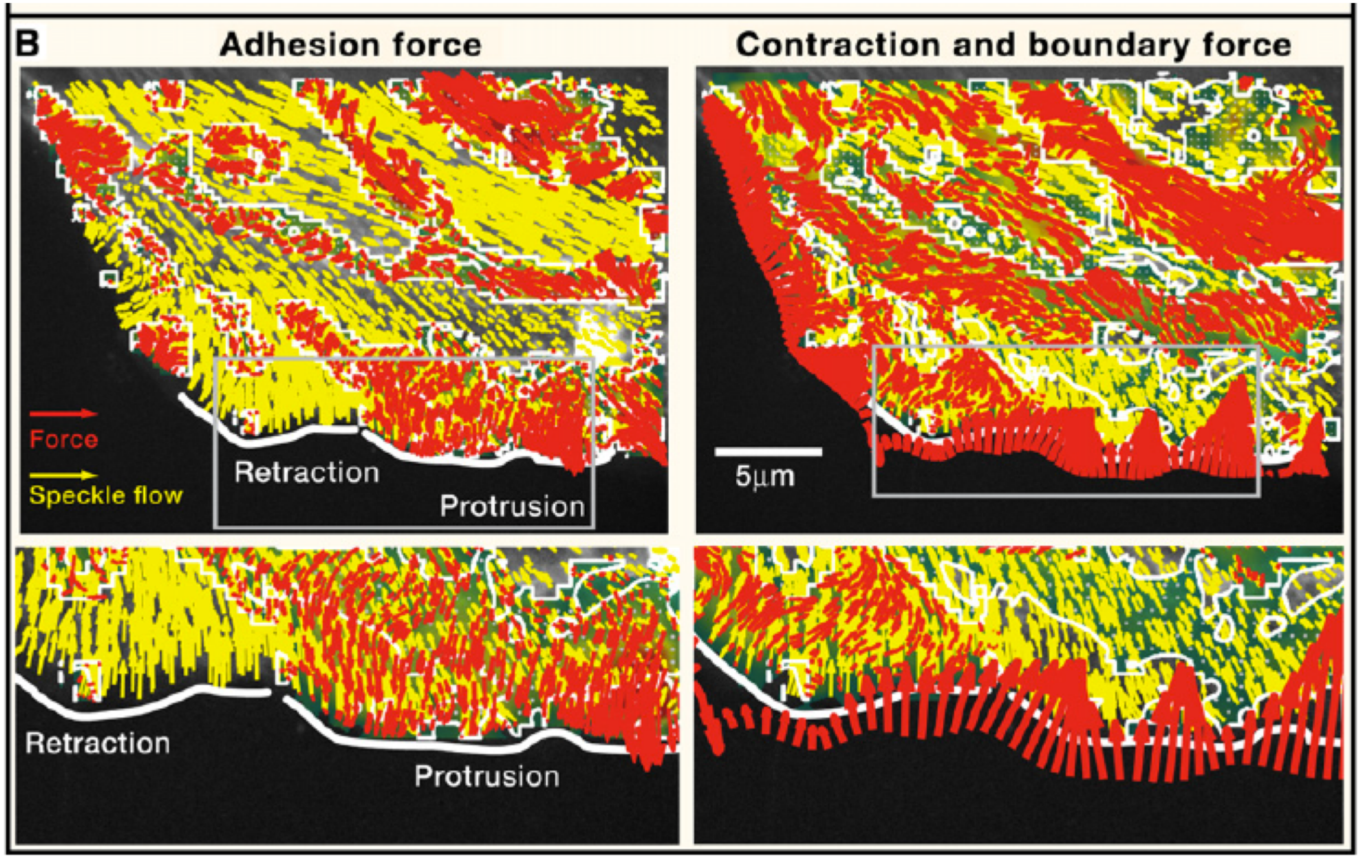

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- *Example*: Ji et. al., 2008
  - Computer tracking program used to extract speckle flows of actin filaments (*yellow*)
  - Mathematical model coupled with program to estimate the forces that must be exerted to explain the speckle flows observed (*red*)

The *Association* Paradigm vs. The *Integrator* Paradigm

The ***Association*** Paradigm

- Humans capable of associating observed images with memory of previous visual experiences and interpret images with relative ease
- Memory bank of previous visual experiences is ***IMMENSE***
- Difficult to train a computer vision system with a full array of visual experiences that may occur within an image

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The *Integrator* Paradigm

- Limitations of the human observer: subjectivity
- Computer vision systems found to outperform humans in ***1.)*** pattern recognition (Murphy et. al. 2003) and ***2.)*** particle tracking (Reid, 1979)
- When decision requires large, integrated analysis, computer vision is superior

MACHINE LEARNING IN CELL BIOLOGY-TEACHING COMPUTERS TO RECOGNIZE PHENOTYPES

Christoph Sommer and Daniel W. Gerlich, 2013

DOI: 10.1242/jcs.123604

Machine Learning in Bioimaging

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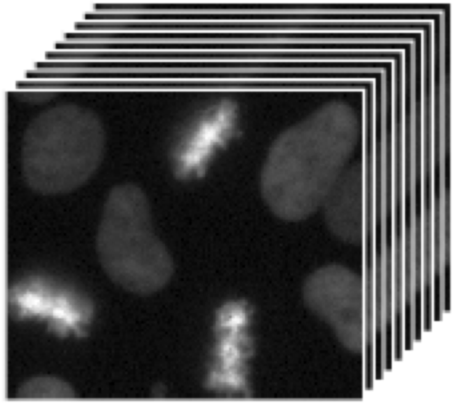
  - Does not rely on manual parameter adjustment
  - More generalizable method
  - Most common use of machine learning in image analysis: image classification

Machine Learning Pipeline

Data preprocessing



Noise reduction,
background correction

(Sommer and Gerlich, 2013)

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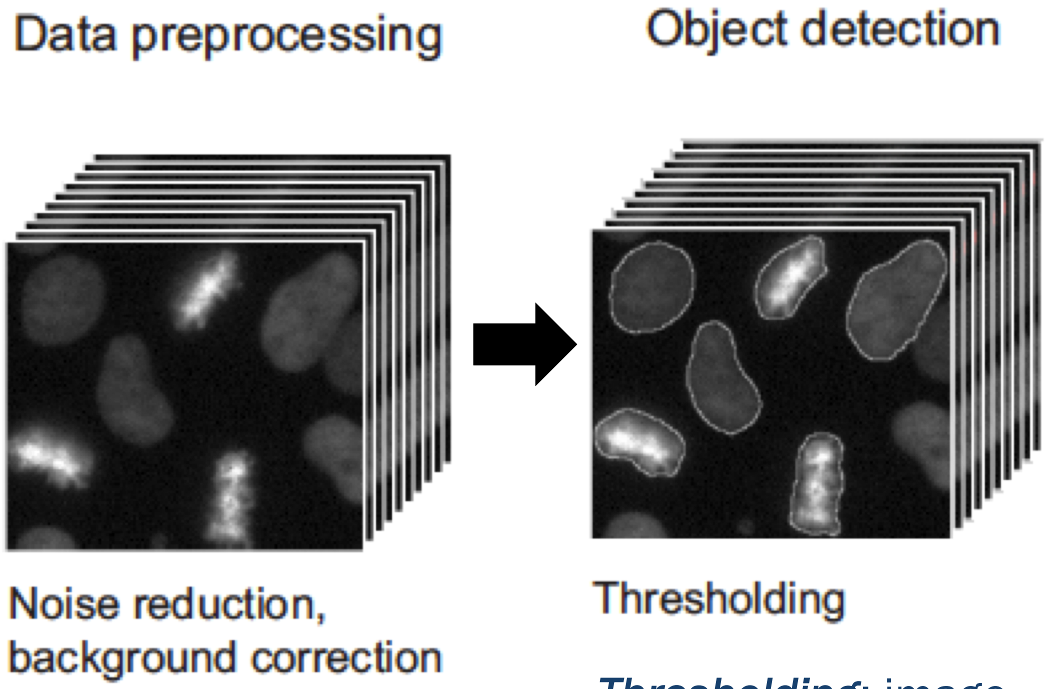

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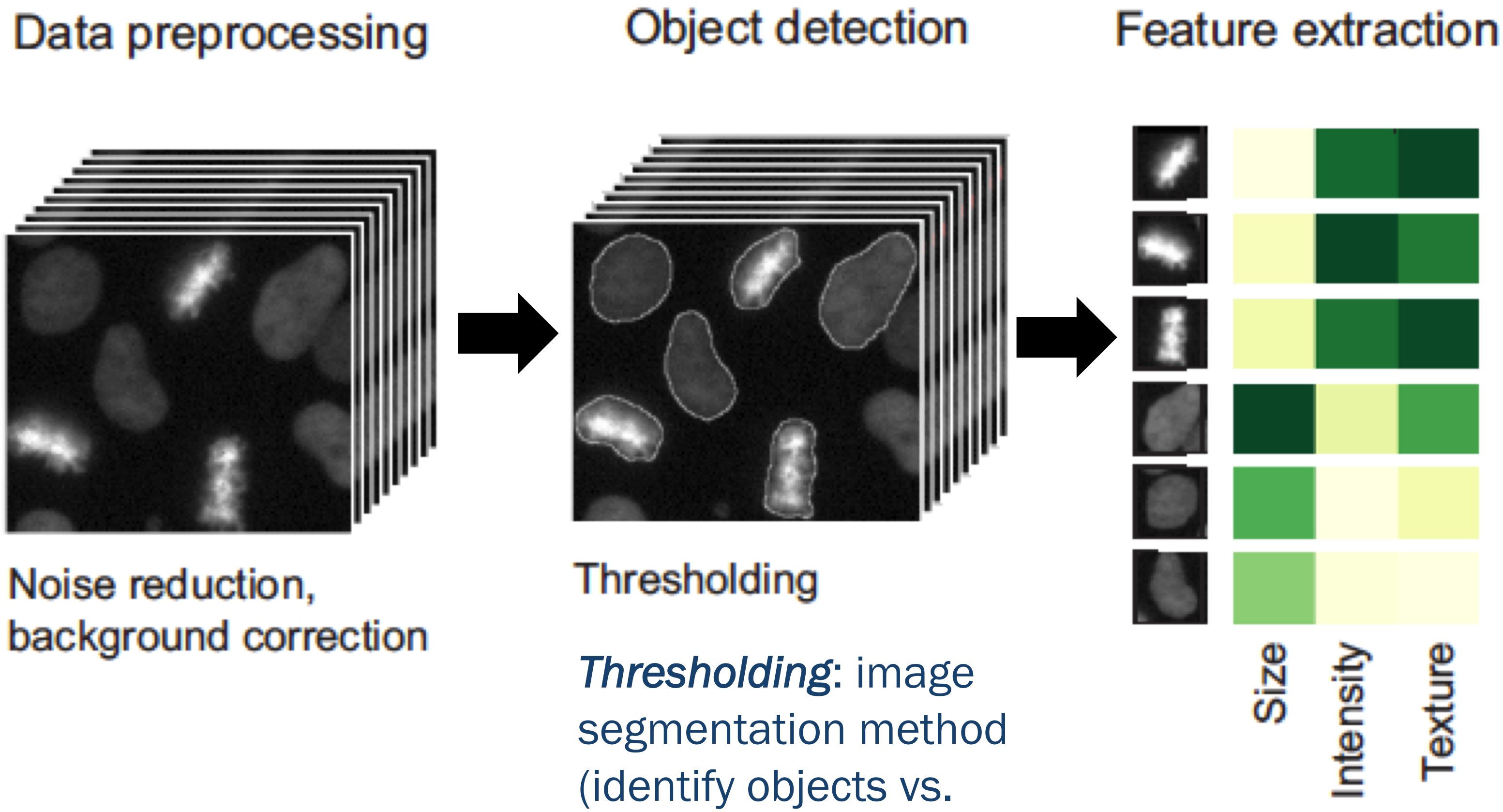

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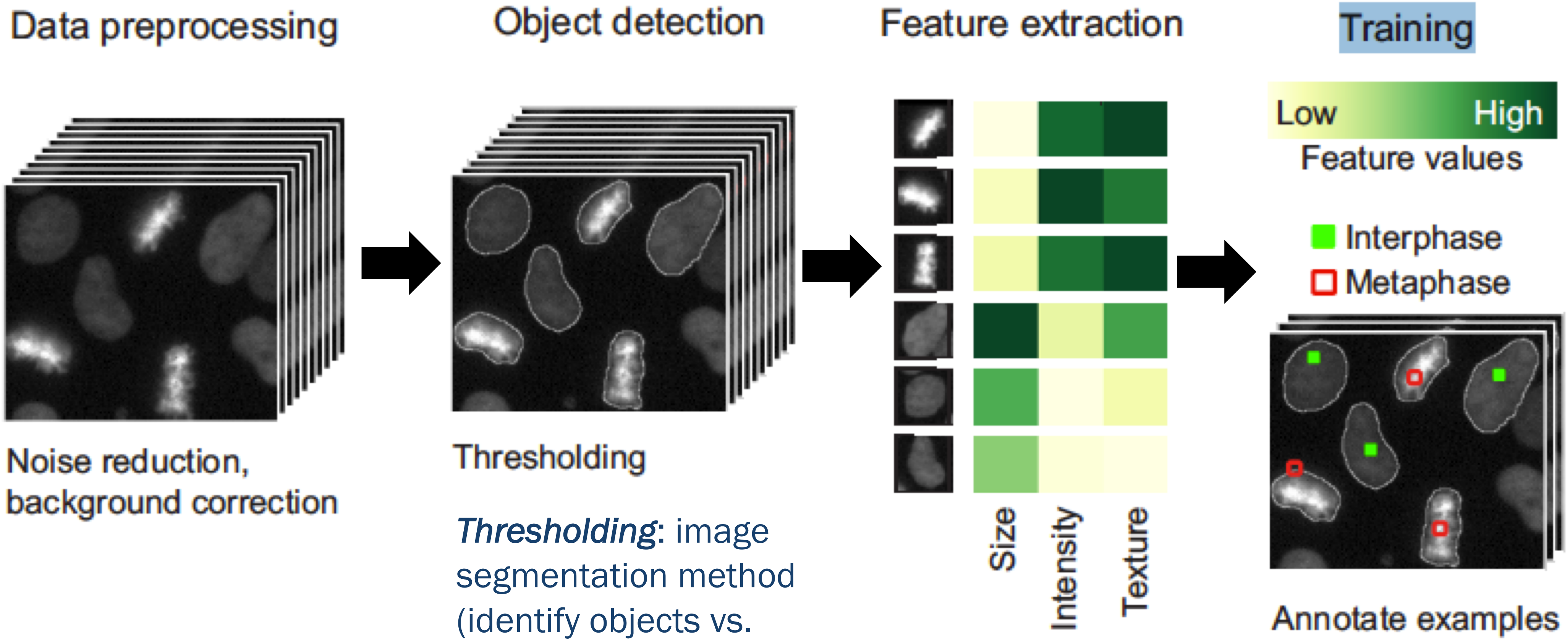

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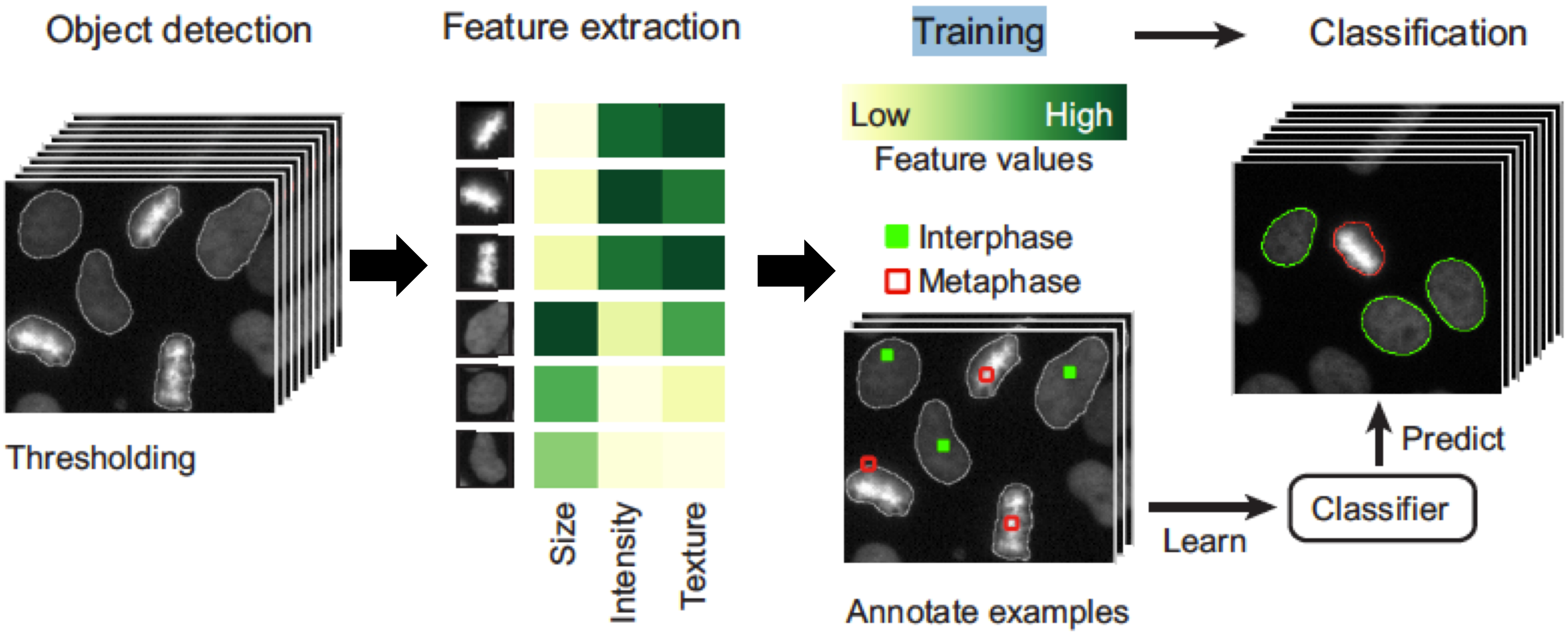

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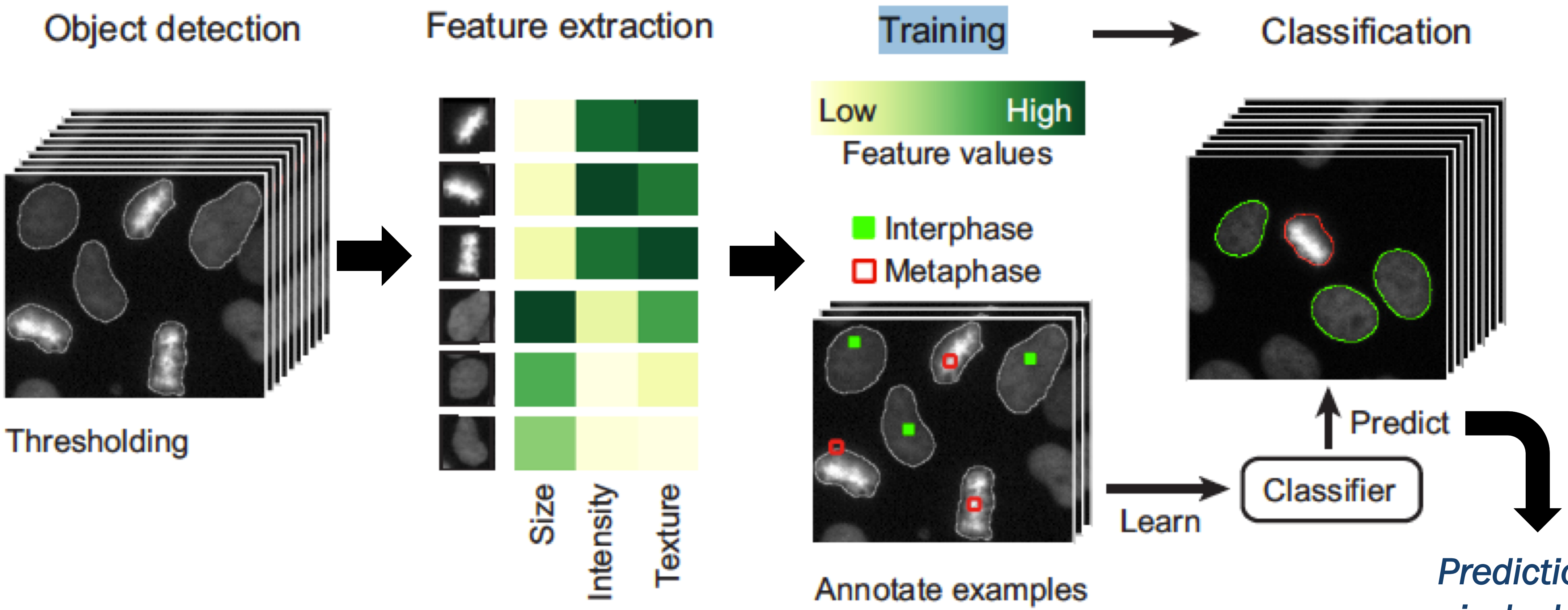

Prediction of pixel, object, or image classes

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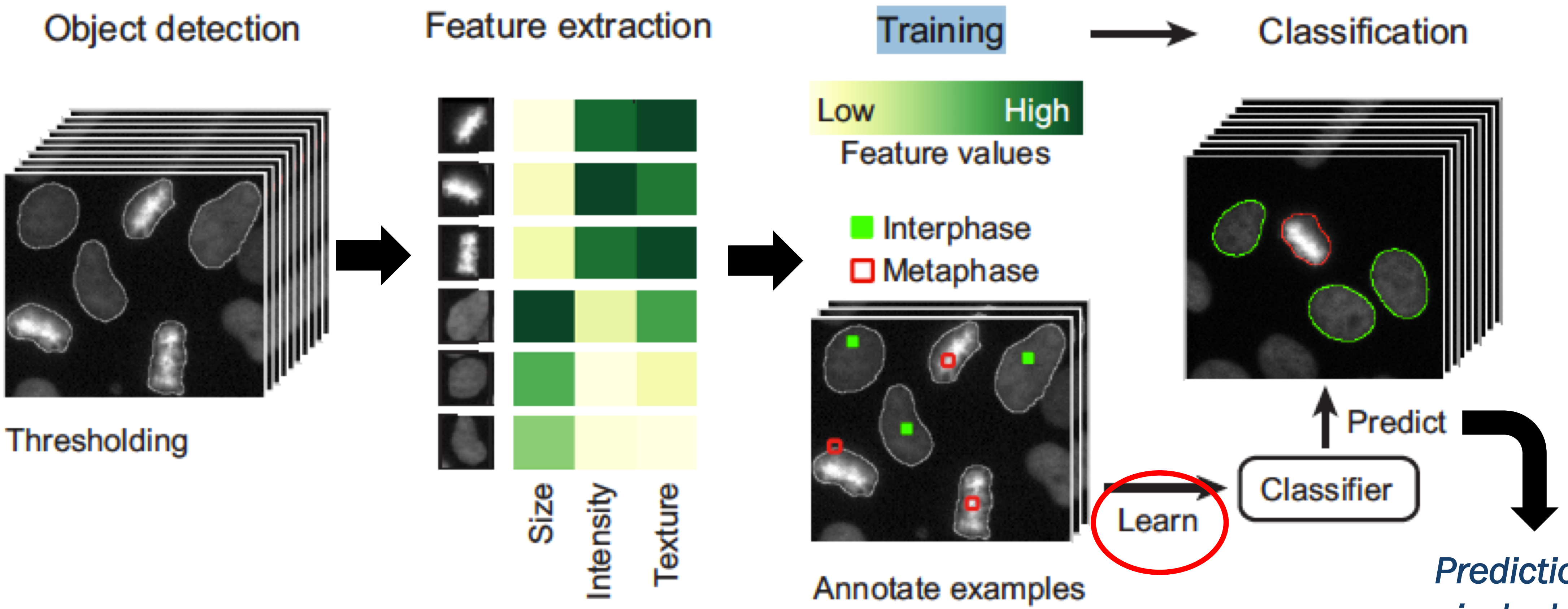

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  - ***Training set***: used for initial learning
  - ***Validation set***: used for parameter tuning
  - ***Testing set***: used for evaluation of learner performance

Models Underlying Machine Learning

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  - Models the decision boundary between classes

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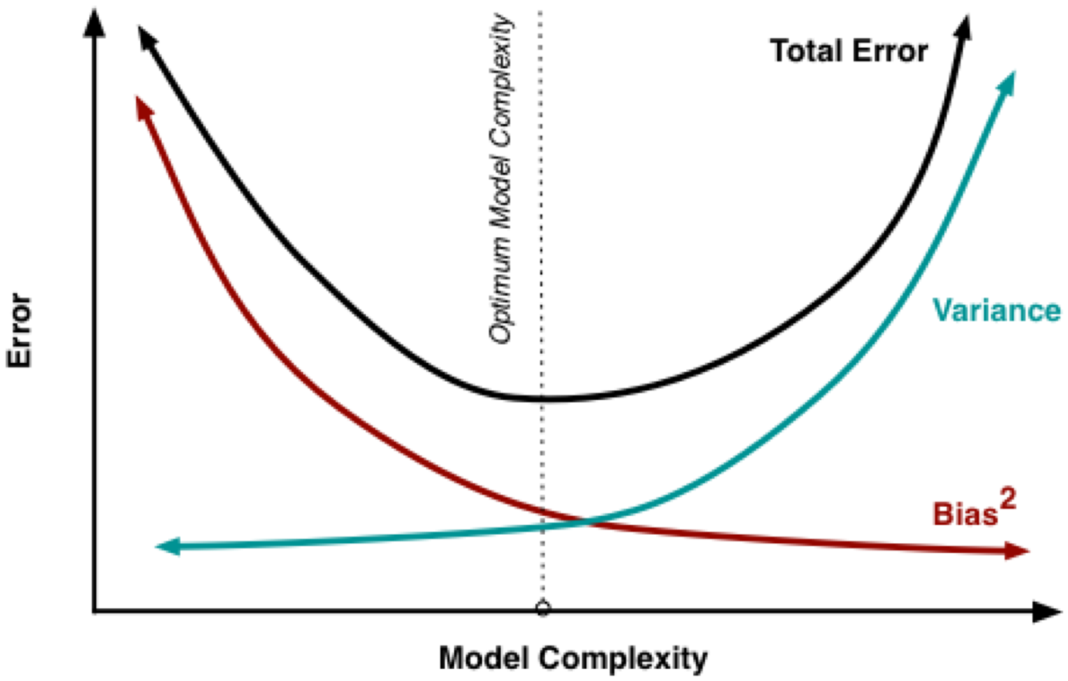

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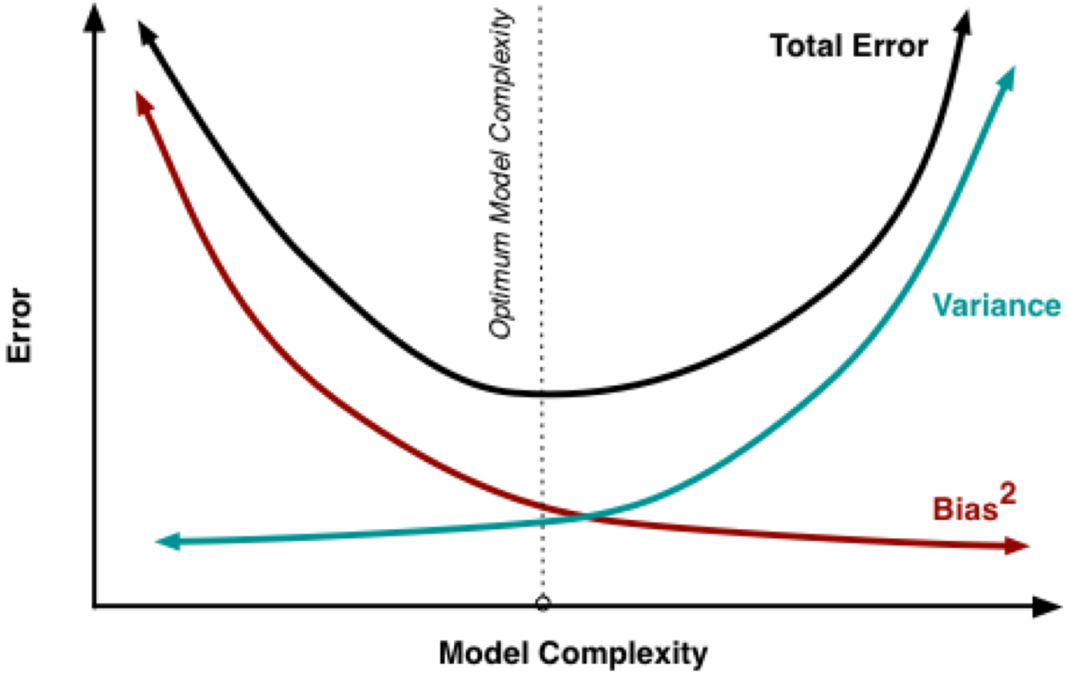

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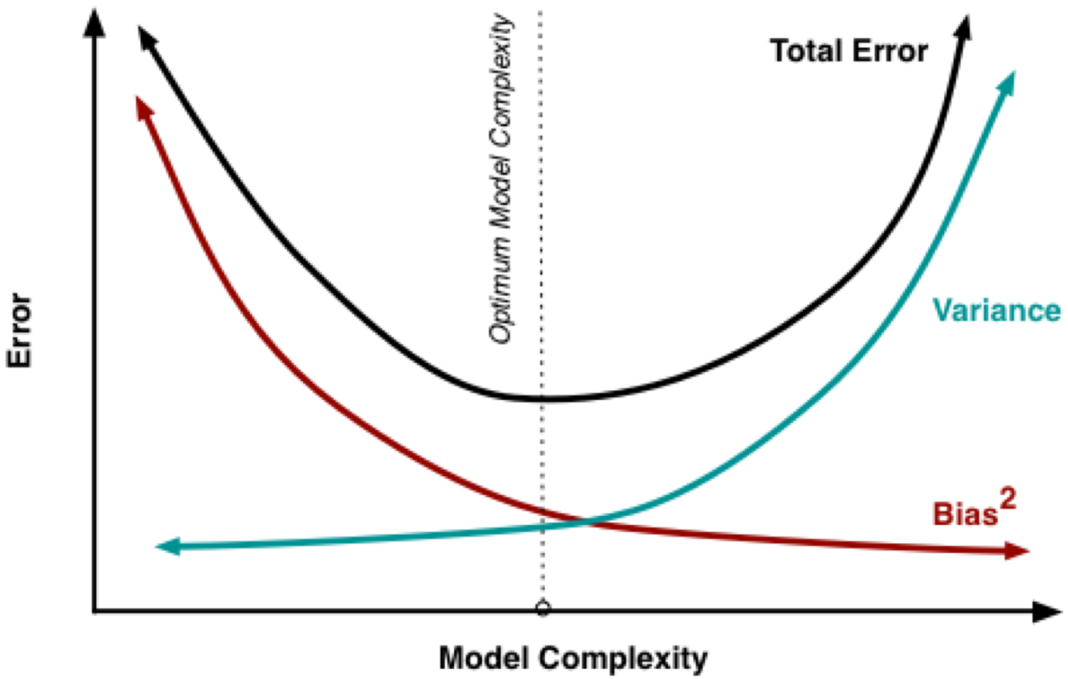

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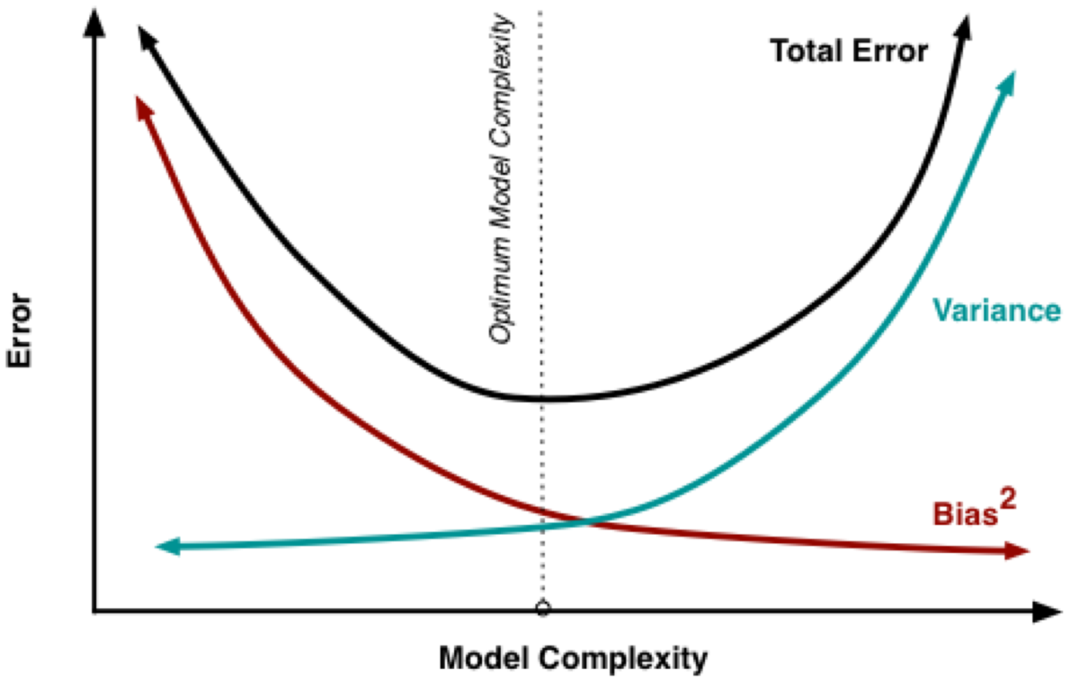

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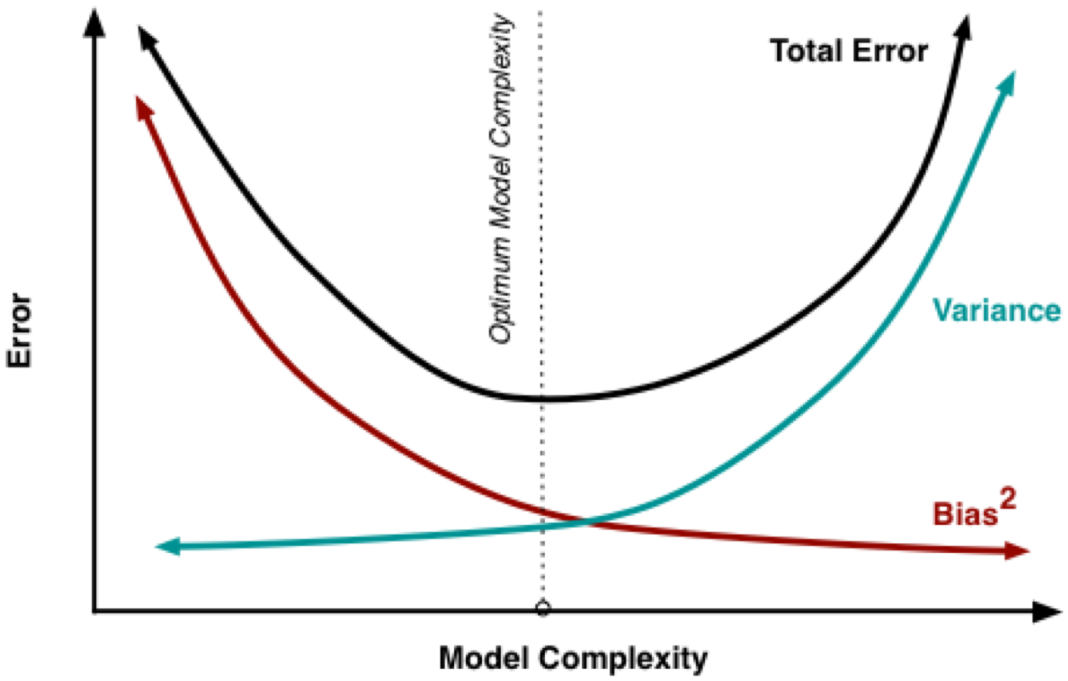

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- *Goal*: optimize the bias-variance tradeoff and minimize total error

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- Becomes more difficult to define objective function
  - Objective function developed using clustering techniques that aim to minimize the distance between objects within clusters and maximize distances between objects in different clusters

Examples of Supervised and Unsupervised Machine Learning Algorithms

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- Unsupervised machine learning algorithms
  - *K*-means clustering ⟶ iterative process
  - Gaussian mixture modeling ⟶ extends *k*-means clustering to account for more complex distributions of the data
  - Hierarchical clustering ⟶ based solely on the distance between data points
  - Dimensionality reduction ⟶ PCA, ICA, MDS, feature selection