

Imaging Flow Cytometry: Theory and Application

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ISAC SRL Emerging Leader

EMBL: 19/04/2016



The Flow Cytometry Core Facility (FCCF) @ Newcastle University



International Centre for Life



**Newcastle University
Medical School**

**Meeting the cytometry needs
of over 200 users across
several different disciplines/
institutes**

Presentation Overview

- A brief reminder about what Cytometry is all about
- An introduction to Imaging (Flow) Cytometry
- Principles and theory of IFC:
 - Signal generation and image capture
 - Basics of pixel-based image analysis
- Challenges and benefits of Image-based cytometry data
- Two short examples:
 - Measuring Ca^{2+} within organelles sites in activated T cells
 - Label-free analysis of the cell cycle by machine learning
- Conclusions

What is Cytometry?

Cytometry



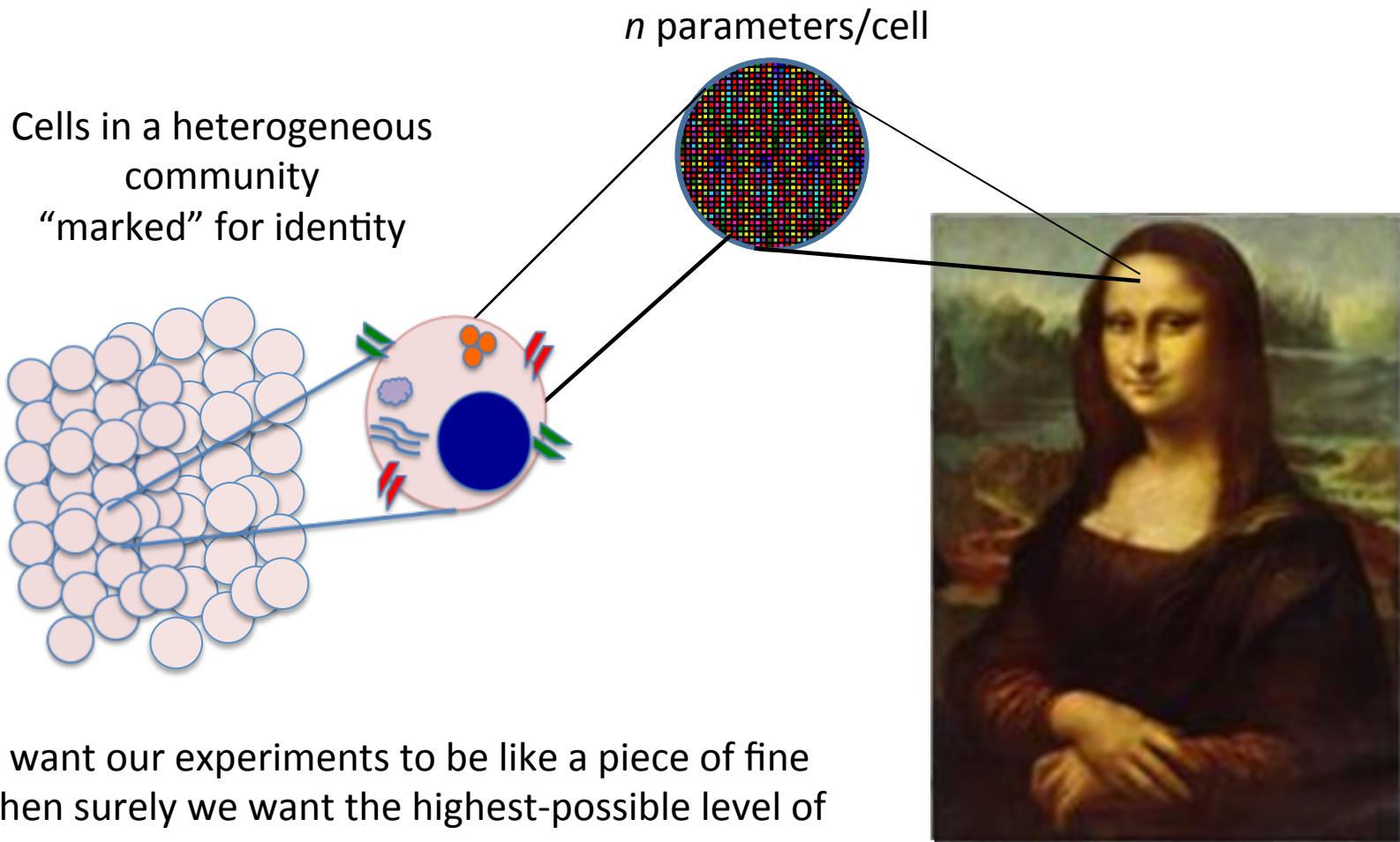
Greek = “Kytos”
“hollow basket”
Relates to CELL



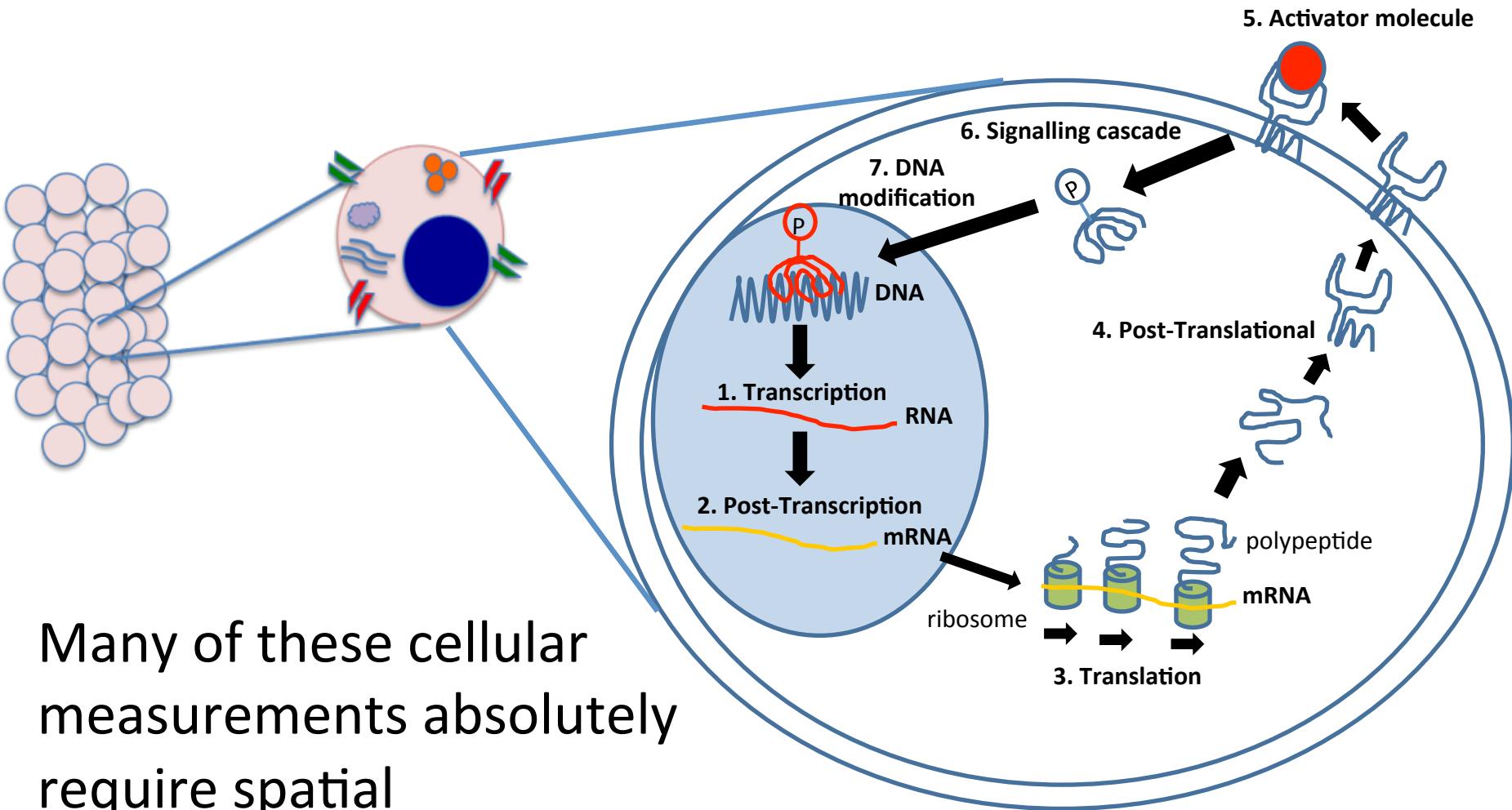
Greek = “Metria”
“Process of Measuring”

“Cytometry is the measurement of cell phenotype, frequency, form and function at the single cell level but conducted on a population-wide basis”

High resolution single cell analysis should provide a high definition picture of the underlying biology



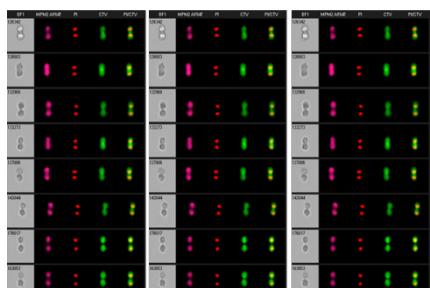
To me, cytometry includes ALL possible single cell-based measurements



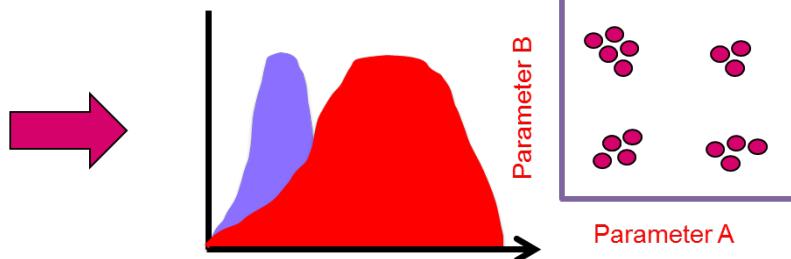
Introduction to Imaging (Flow) Cytometry



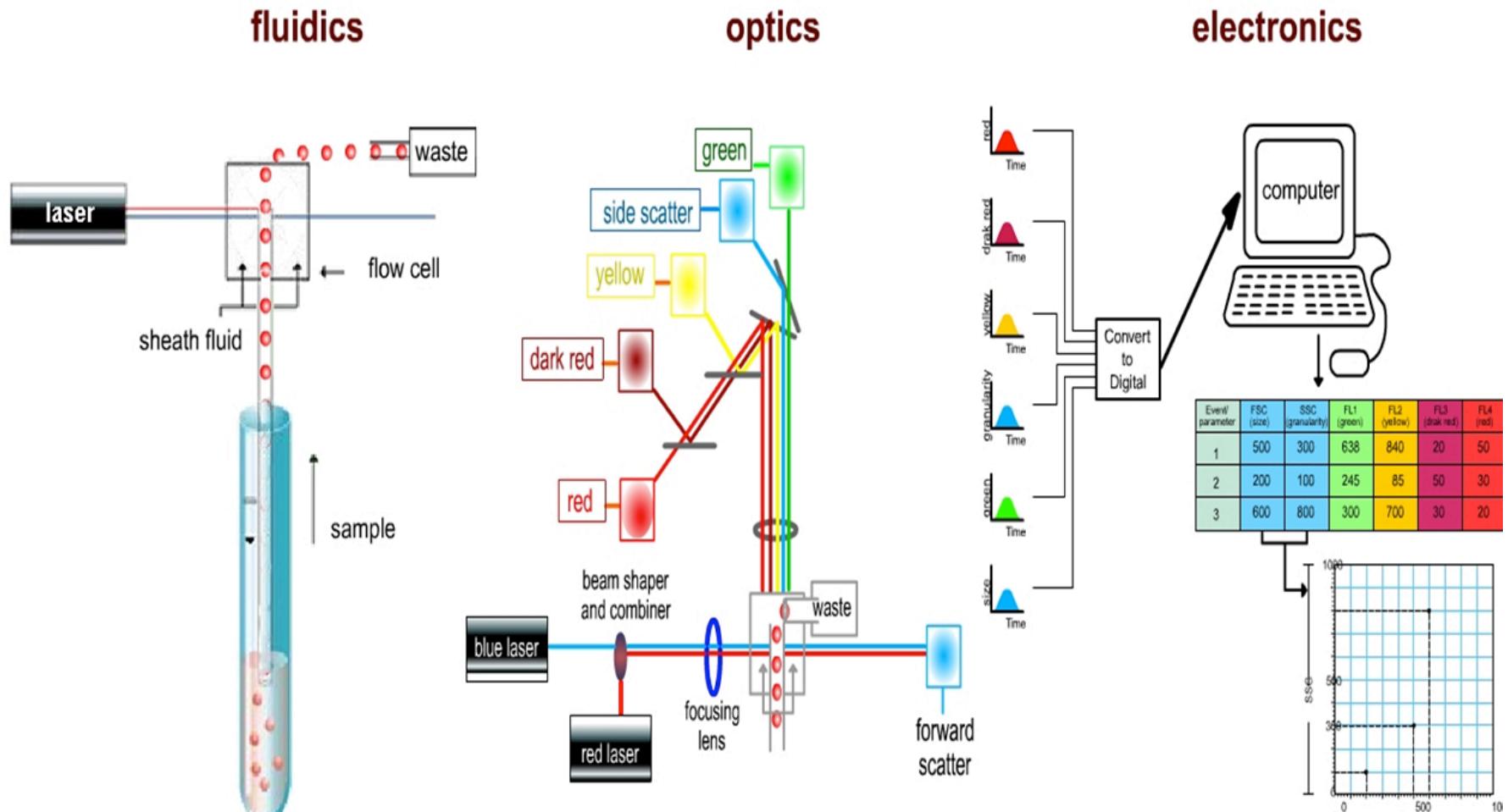
3. Apply to population



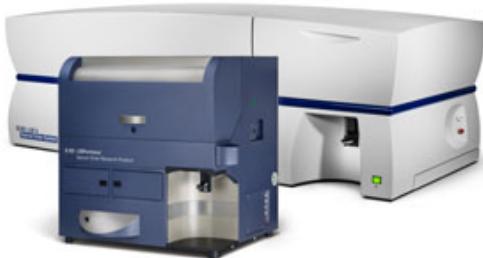
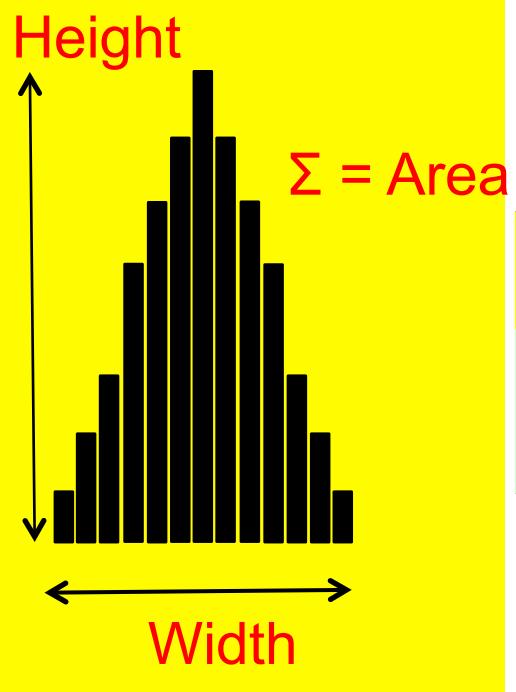
4. Analyse population distributions



How does a Flow Cytometer Work?

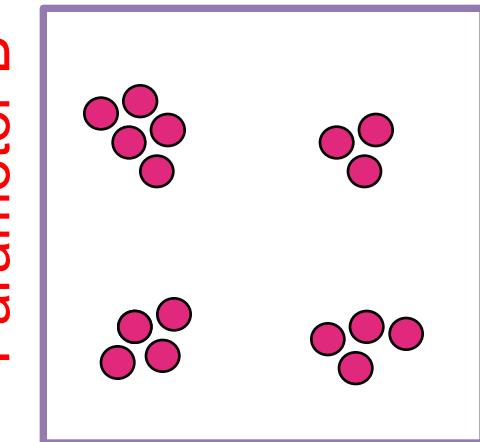


We take all that amazing cellular structure and smash it into single numbers

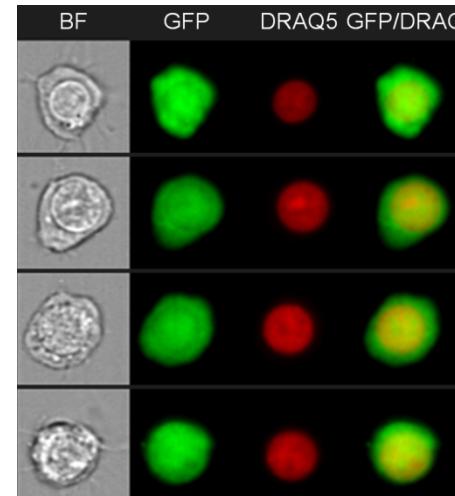
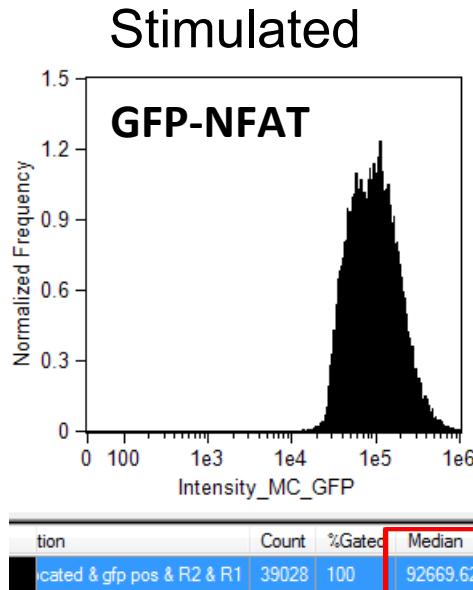
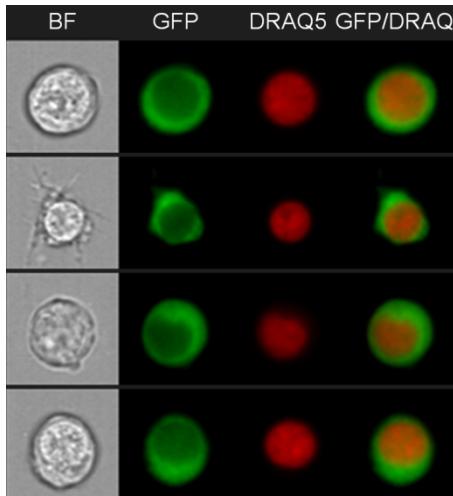
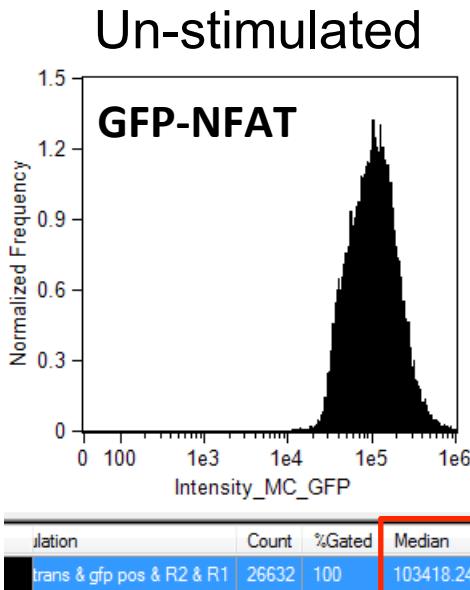


Event Number	FSC	SSC	Blue 530-30-A	Yellow 585-30-A	Violet 450-50-A	Red 670-30-A
1	100	450	10	500	670	780
2	150	443	15	23	1000	456
3	180	250	2000	670	6000	3000
4	167	432	11	50	123	2500

Numbers, numbers, numbers....



But what are we (potentially) missing?



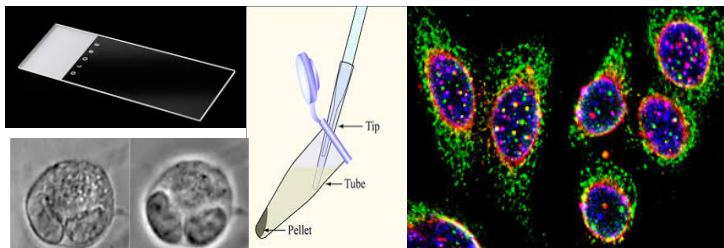
Location and spatial context may be
ESSENTIAL to the biological question.

What makes an Image Cytometer?

- Ability to:
 - Capture images in a spatially registered digitised format (pixels).
 - Capture images in a manner that allows for direct comparisons (relative quantitation) of pixel properties within and between cells.
 - Multi-parameter (highly desirable).
 - Capture images in a high-throughput manner (how many cells do we need for confidence in a measurement?).
- There is overlap with quantitative microscopy BUT we are dealing with population scale.
- IF calibrated correctly, a conventional microscope can be considered an “Image Cytometer”.

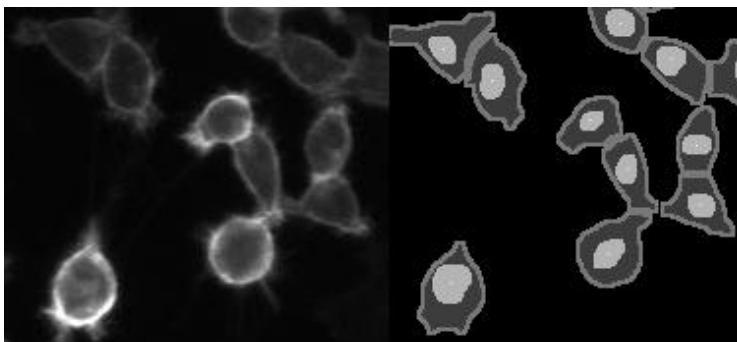
Generic Image Cytometry workflow

1. Sample prep

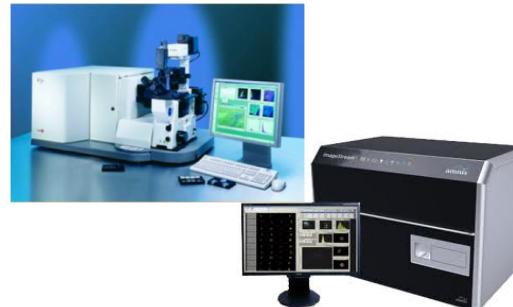


*Not always fluorescence

3. Identification/segmentation of single cells and cellular structures



2. Controlled Image capture



Well Characterized detectors such as CMOS, CCD PMT

4. Feature extraction and “flow-like” data analysis from images

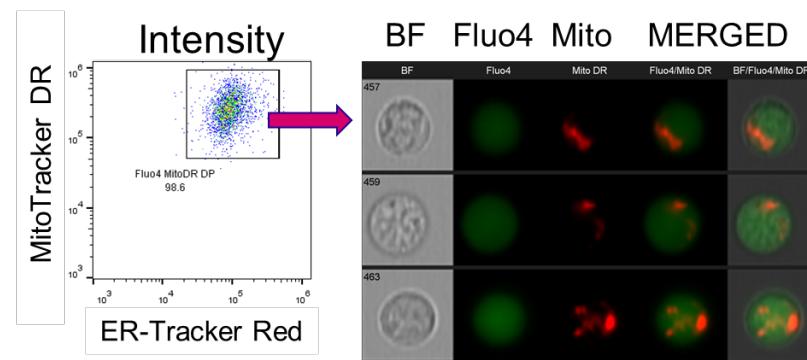


Image Cytometry benefits from dedicated systems/platforms

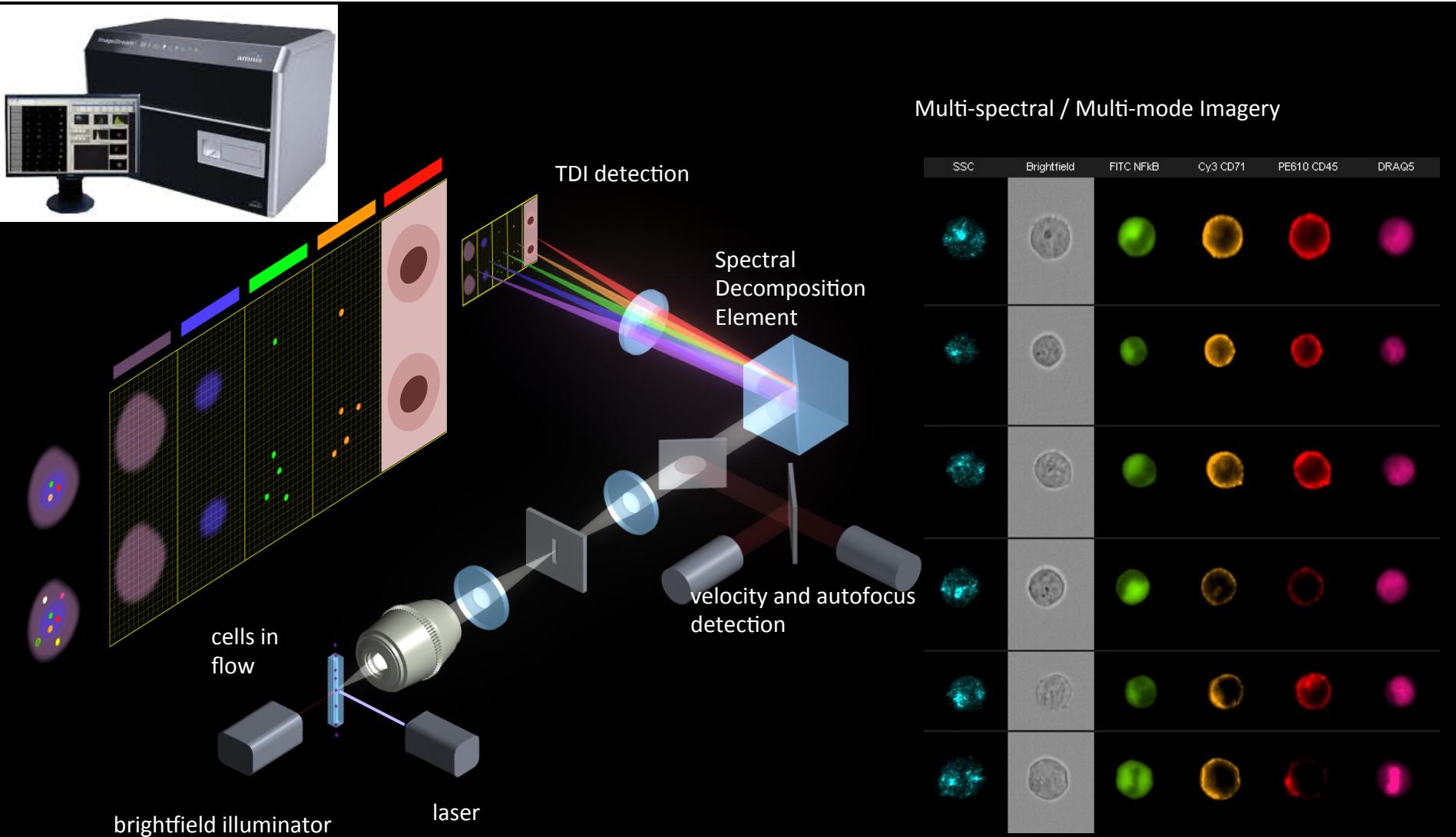
Imaging Cytometry in Flow



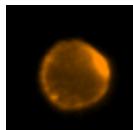
Slide/plate-based Image Cytometry



ImageStream X Optical Configuration (single camera)



It's all about the pixel location and associated values



- 6 or 12 Channel Images are collected using a TDI CCD.
 - Pixel values from a 12 bit detector range from 0 to 4096.
 - Each image is a grey scale two dimensional image of the cell

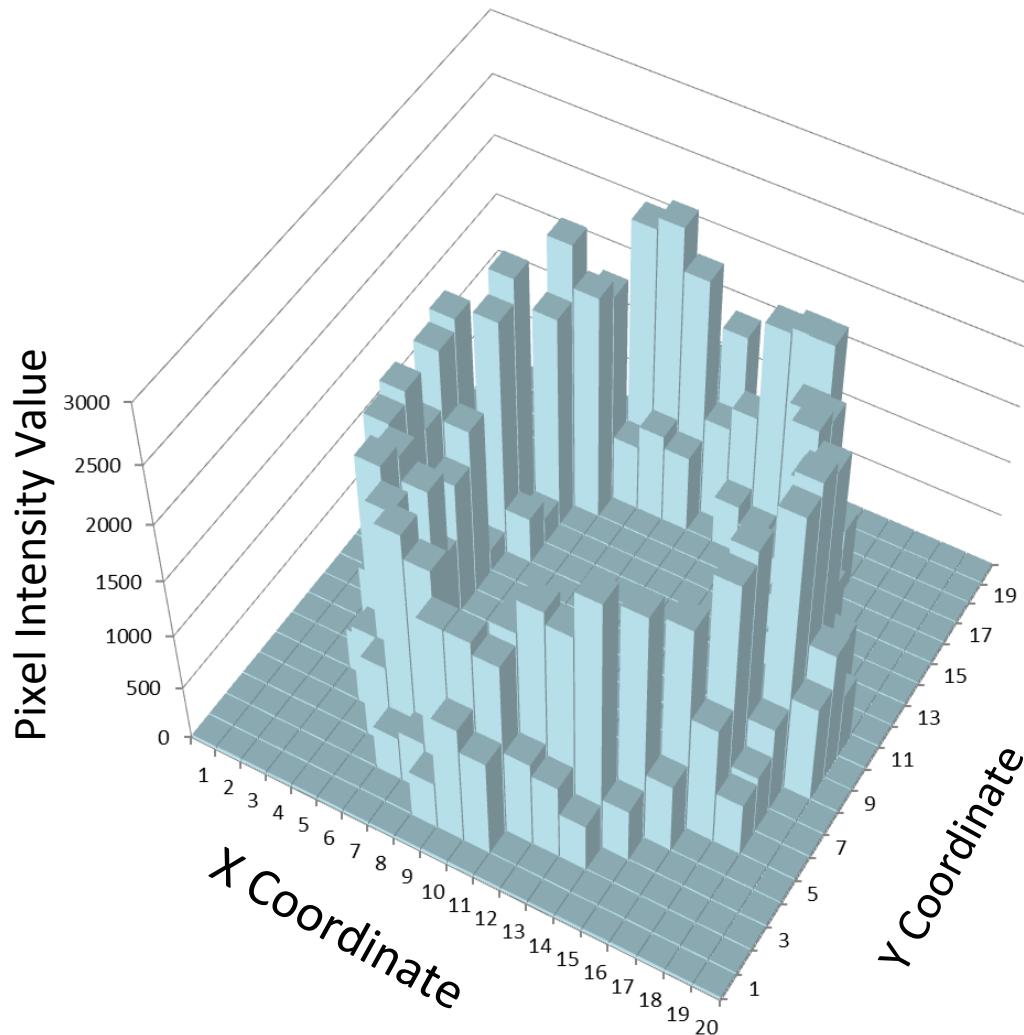
It's all about the pixel location and associated values

31	32	31	30	32	31	32	31	30	32	31	32	31	30	32	31	32	31	30	32
32	32	32	32	32	32	32	450	###	900	32	32	32	32	32	32	32	32	32	32
32	32	30	32	31	32	425	500	###	###	###	800	700	450	31	32	32	30	32	31
32	32	32	31	32	780	###	###	###	980	###	###	###	###	500	32	32	32	31	32
32	31	31	32	750	###	690	31	32	30	32	31	31	500	###	650	31	31	32	30
32	32	32	400	###	700	32	32	32	32	32	32	32	450	###	###	500	32	32	
31	30	32	800	###	###	30	32	32	32	31	30	32	32	32	500	###	550	32	32
32	32	32	###	700	32	32	32	32	31	32	32	32	32	31	32	###	800	32	31
30	32	300	###	700	30	32	30	30	32	30	32	30	30	32	30	700	###	900	32
32	250	###	###	###	32	31	31	32	30	32	31	31	32	30	32	600	###	###	30
32	400	###	###	###	32	32	32	31	32	32	32	32	31	32	32	890	###	600	32
31	32	320	###	210	31	32	30	32	32	31	32	30	32	32	31	###	30	32	32
32	32	230	310	###	430	32	32	32	31	32	32	32	32	31	750	###	600	32	31
32	32	31	420	###	250	32	31	32	32	32	32	31	32	32	###	780	31	32	32
32	31	32	30	320	###	31	32	30	32	32	31	32	30	600	###	31	32	30	32
32	32	32	32	200	###	###	32	32	32	32	32	32	32	###	500	32	32	32	32
32	32	32	31	32	32	###	600	800	700	32	450	300	250	###	650	32	32	31	32
31	32	31	32	32	31	600	###	###	###	900	###	###	###	700	31	32	31	32	32
32	32	32	32	31	32	32	800	###	###	###	32	32	32	31	32	32	32	32	31
30	32	30	32	31	30	32	30	32	31	30	32	30	32	31	30	32	30	32	31

Pixelated Imagery

- Each pixel has an X coordinate, a Y coordinate and an intensity value that corresponds to the amount of light captured at that location.
- The value of these pixels relate to the dynamic range of the detector (12-bit = 0 to 4096)

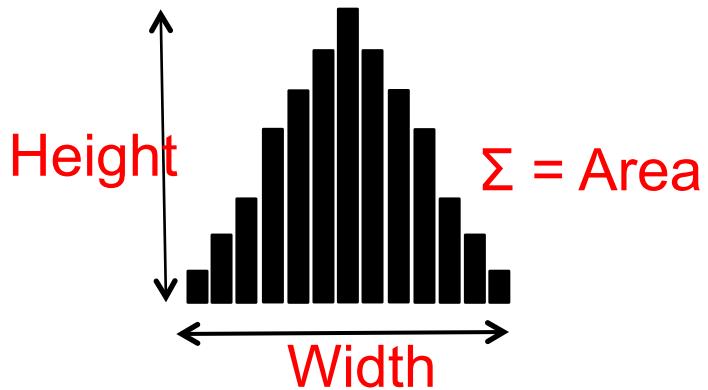
It's all about the pixel location and associated values



Pixelated Imagery

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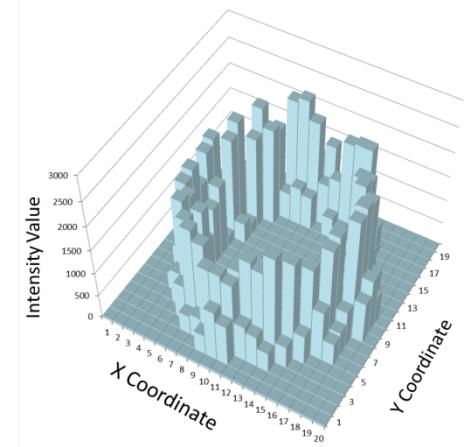
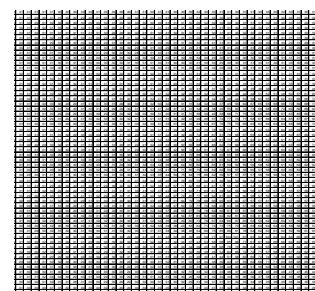
Translating between Flow and Image Cytometry



Maximum Signal = **PULSE HEIGHT**

Total Fluorescence = **PULSE AREA**

Doublet Discrim = **PULSE WIDTH**



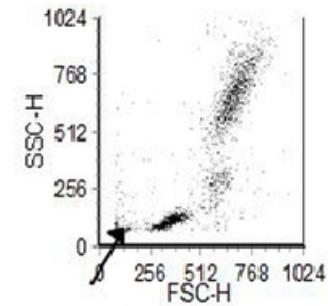
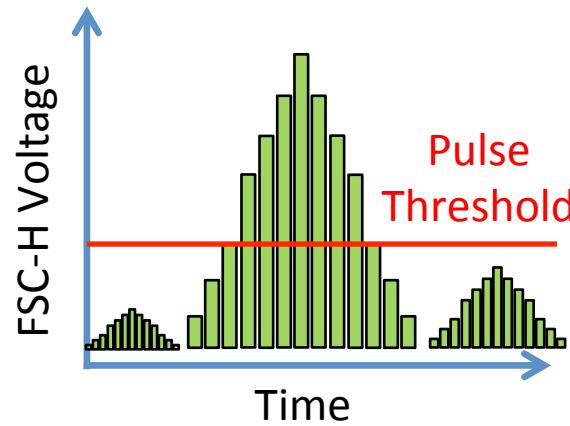
MAX PIXEL

SUM OF ALL PIXEL VALUES

AREA OF PIXELS

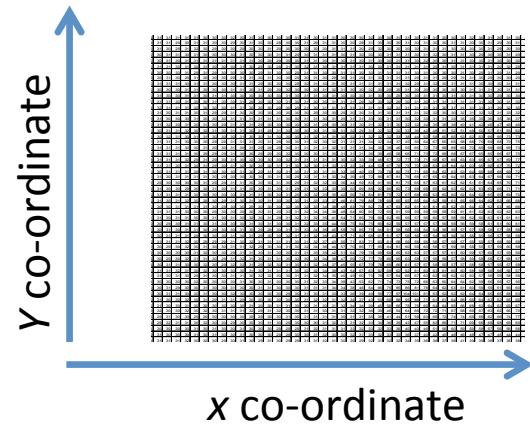
Thresholding a pulse versus thresholding on an image

Conventional Flow Cytometry

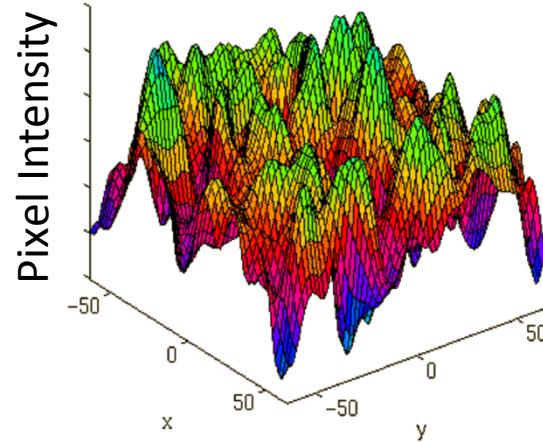
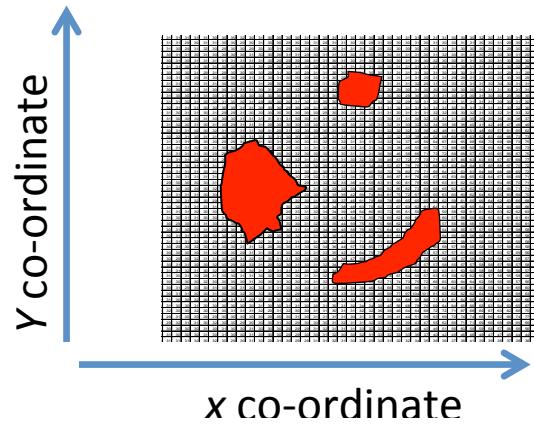


Imaging (Flow) Cytometry

All pixels in frame considered



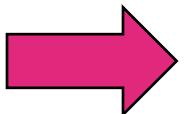
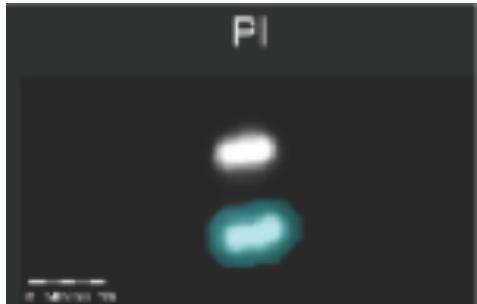
Brightest $x\%$ pixels only considered



THE
Flow Cytometry
Core Facility

Identifying pixels, measuring properties, plotting population-wide measurements

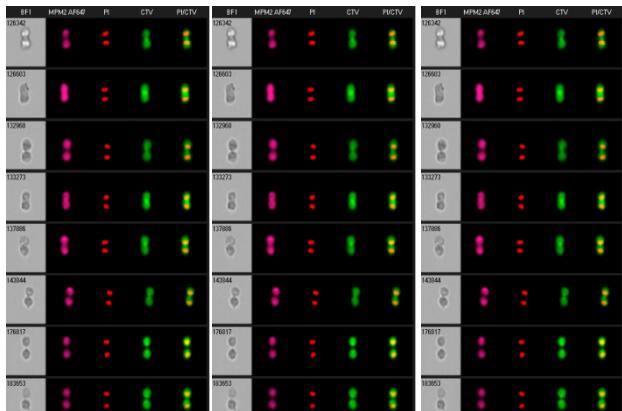
1. Identify (threshold) Pixels



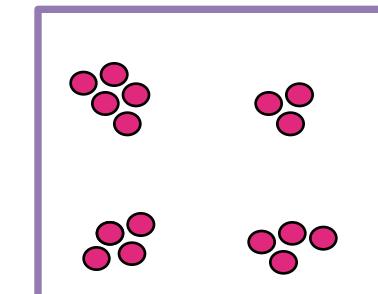
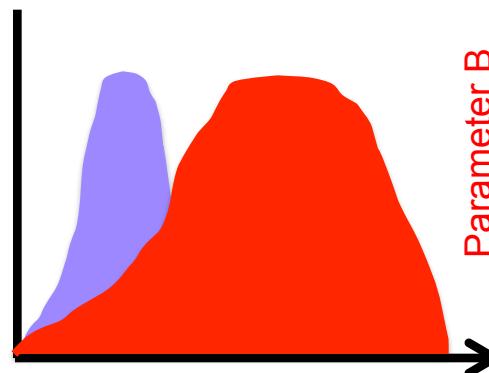
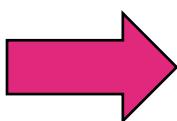
2. Measure Masked Pixels

- Intensity based
 - Sum Intensity
 - Max Pixel
- Texture Based
 - Modulation
 - Standard Dev
- Shape based
 - Circularity
 - Aspect ratio
- Locational
 - Internalisation
 - Translocation

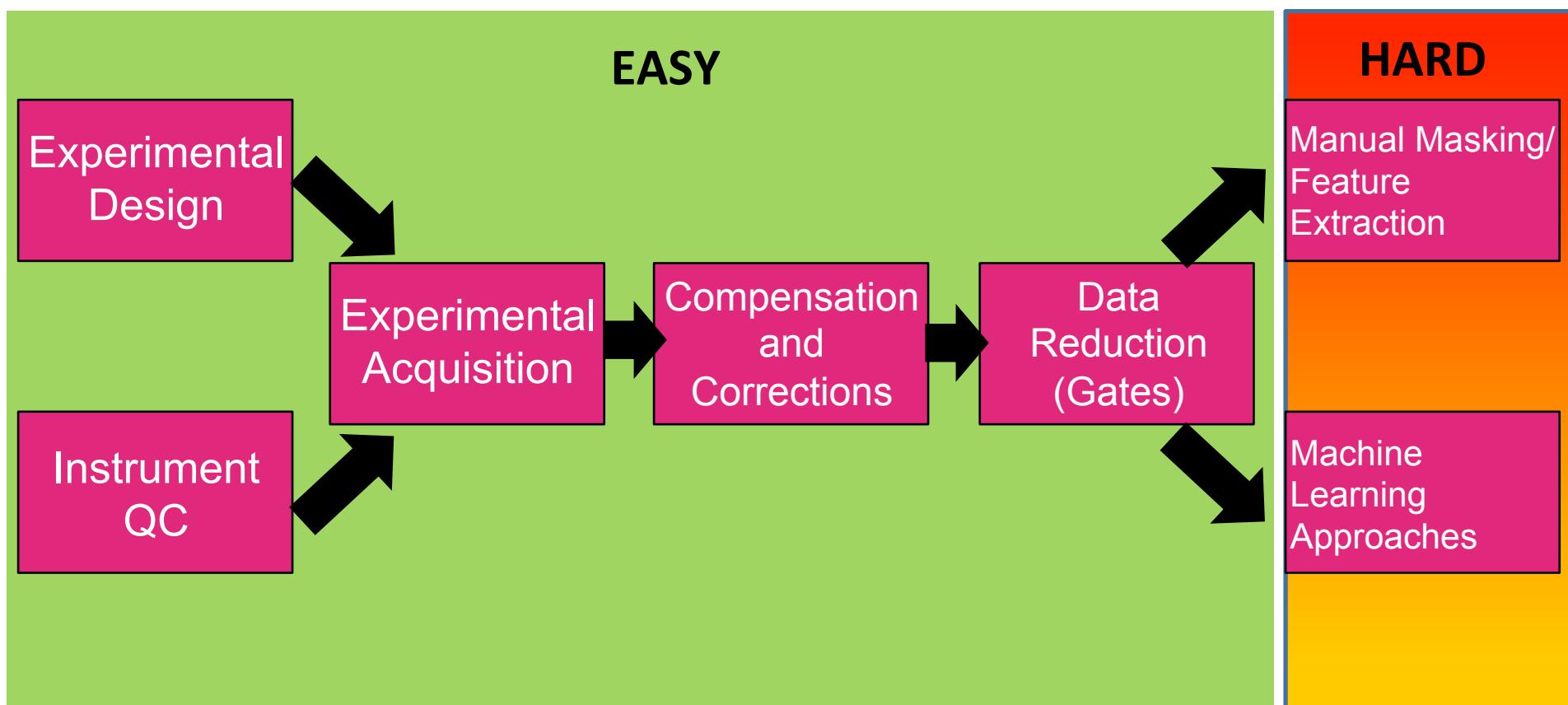
3. Apply to population



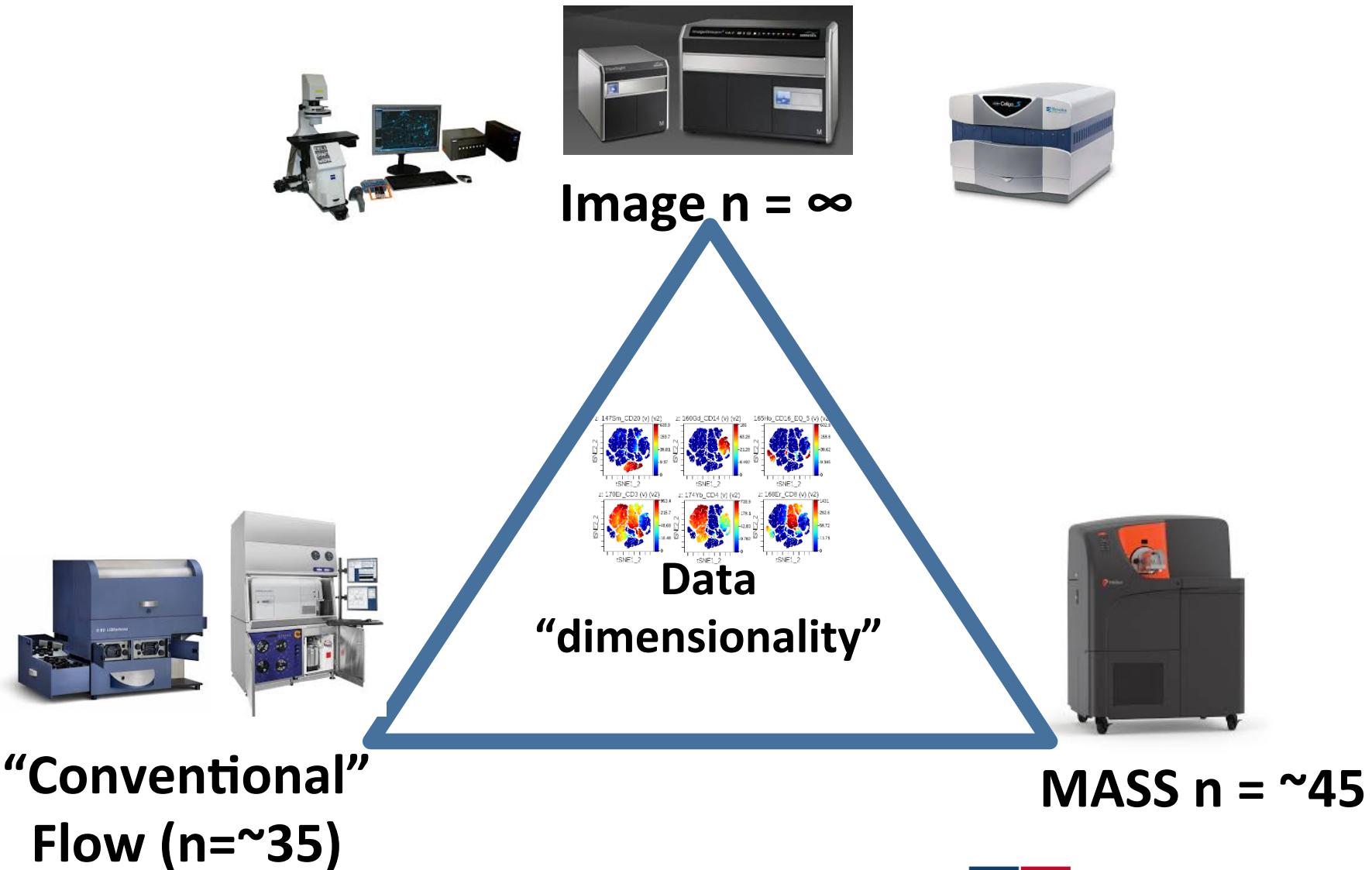
4. Analyse population distributions



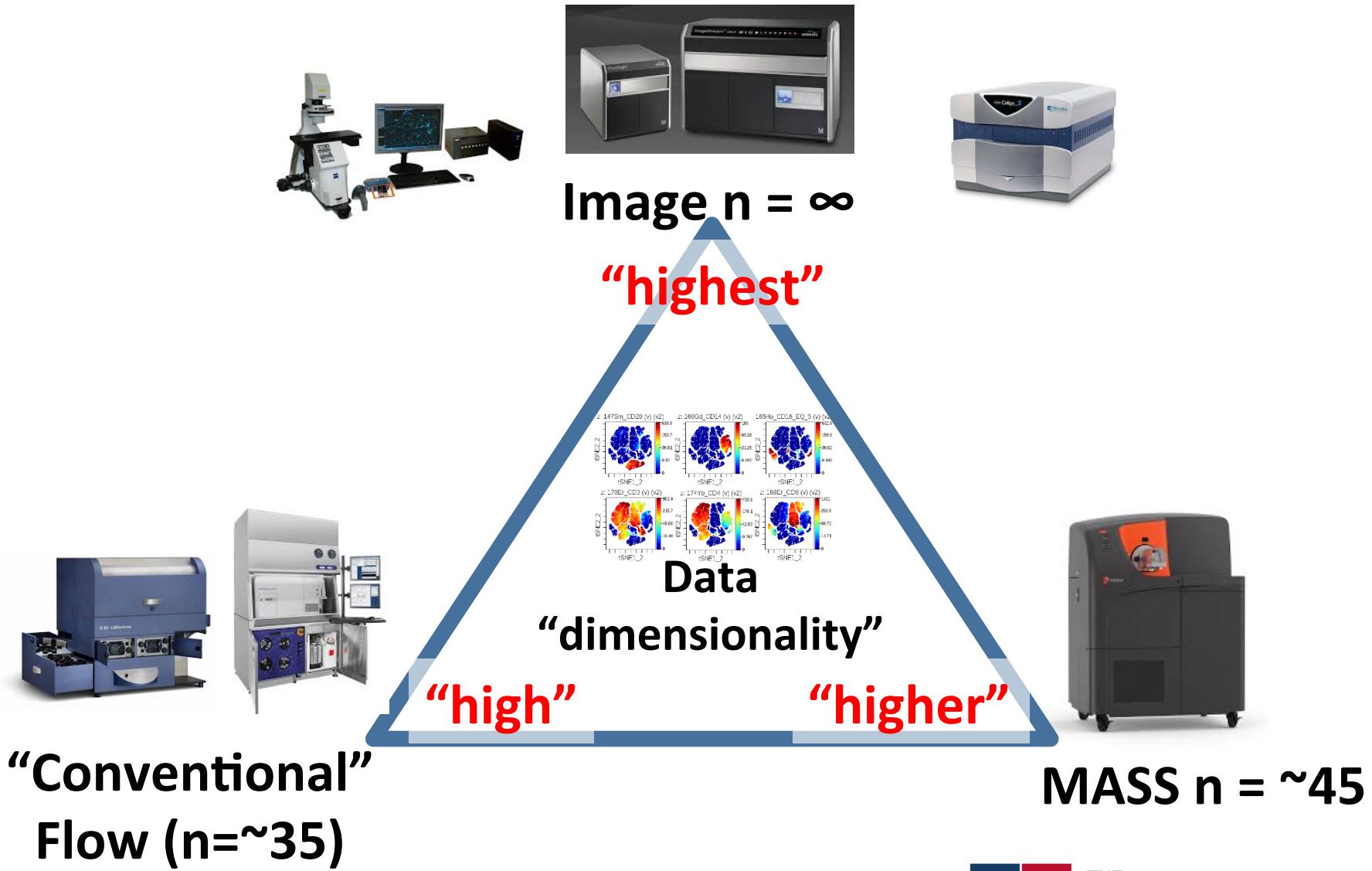
Typical IFC Experimental Work Flow



The Cytometry “Triangle of Data Dimensionality”



The Cytometry “Triangle of Data Dimensionality”



Why do humans find image analysis so hard?



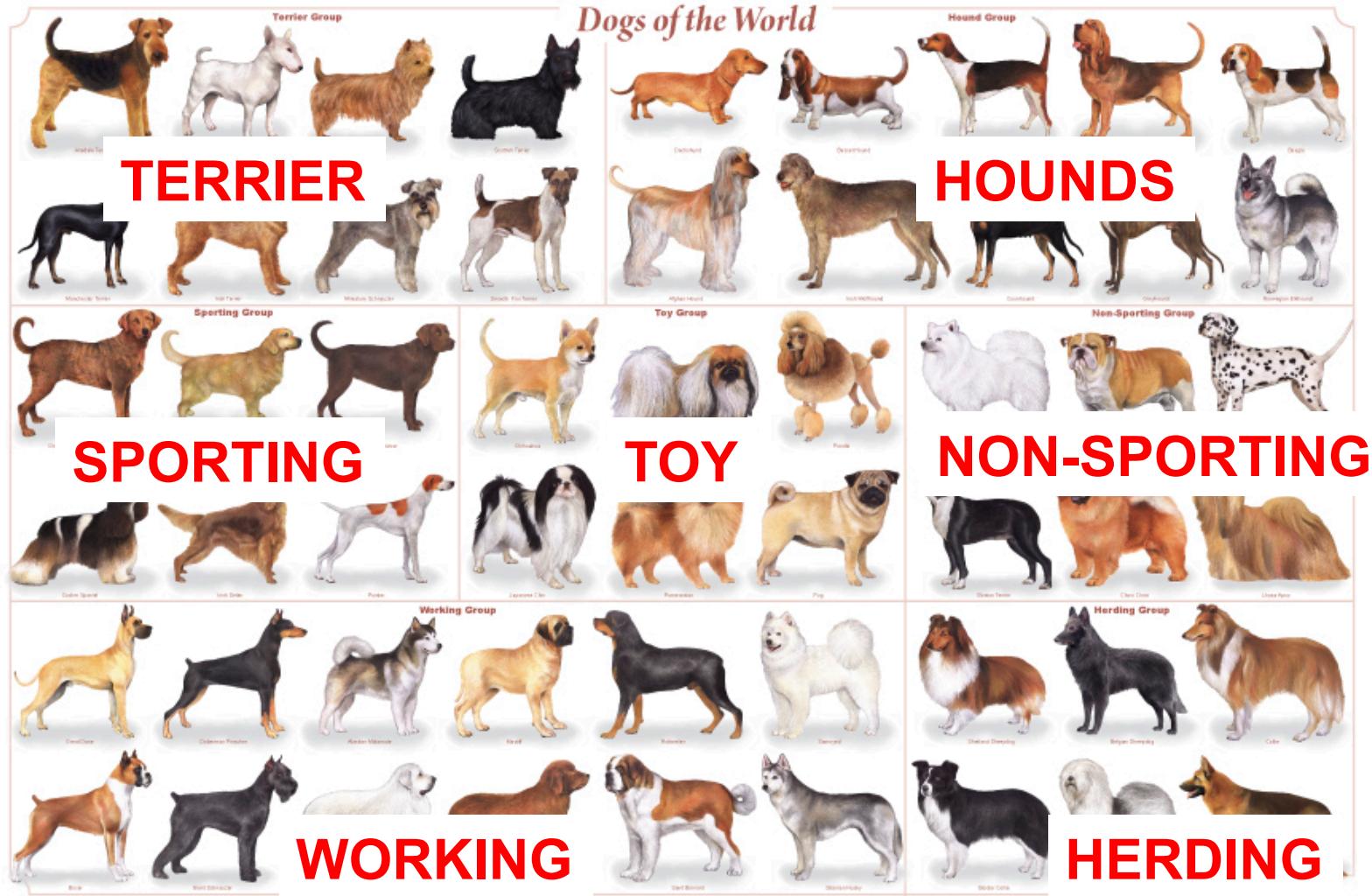
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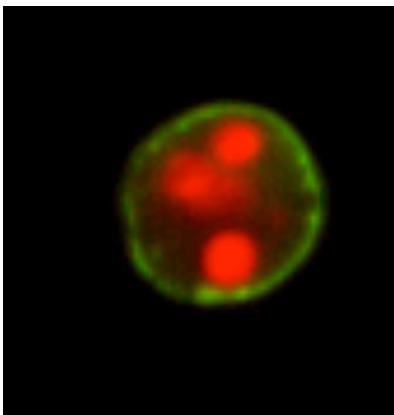
THE
Flow Cytometry
Core Facility

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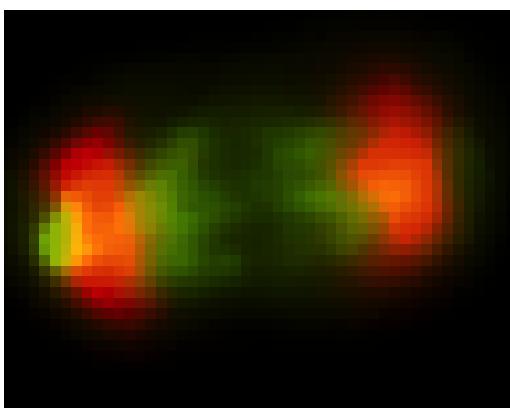


What are we asking and how do we ask it?

A



B



How does cell A differ from cell B?
Don't describe it, enumerate it...

Limitless combination of masks and measurements available.

Based on pixel information

Example of “Features”

Pixel Intensity: Total, Max, Min

Pixel Texture: SD, Modulation, RMS

Size: Area, Diameter, Height

Shape: Aspect Ratio, Circularity

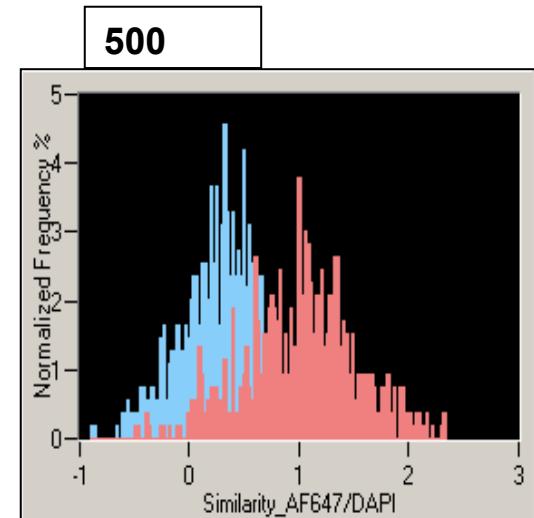
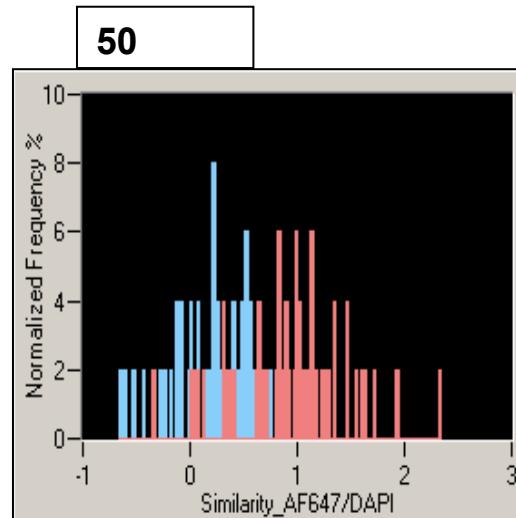
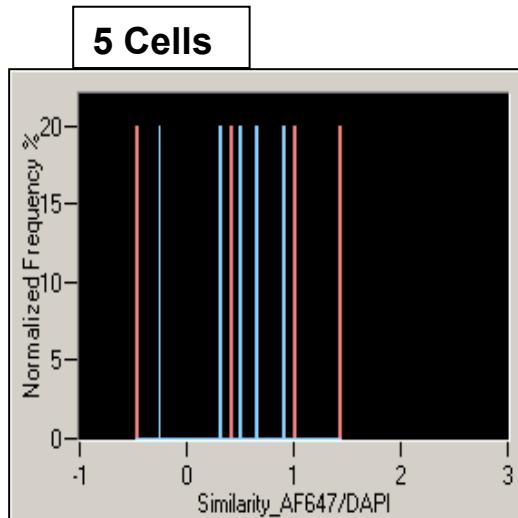
Location: Delta Centroid, Angle

Remember this point and you will not be disappointed by IFC

- Non-image based flow cytometry provides RELATIVE measurements of fluorescence
- Is a cell really GFP positive?
- Must compare to know GFP negative population
- IFC is no different, except measurement is derived from spatial/morphometric parameters.
- STILL RELATIVE measurements (image-based)
- MUST use fluorescent AND spatial controls to provide CONTEXT

How many cells do I need to collect to be confident in my FINAL measurement?

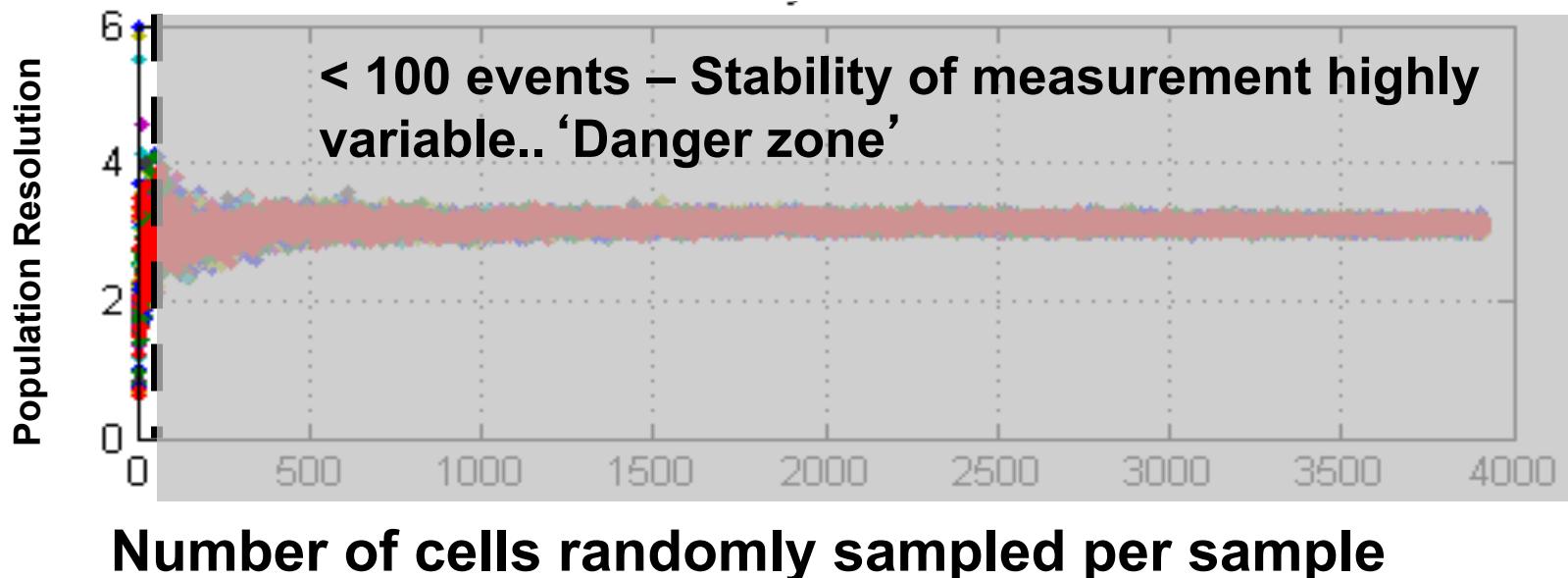
Spatial/Morphometric Measurement



- In other words, how many cells are needed for me to feel confident that the measured difference is representative and **not an artifact of only sampling FEW CELLS?**

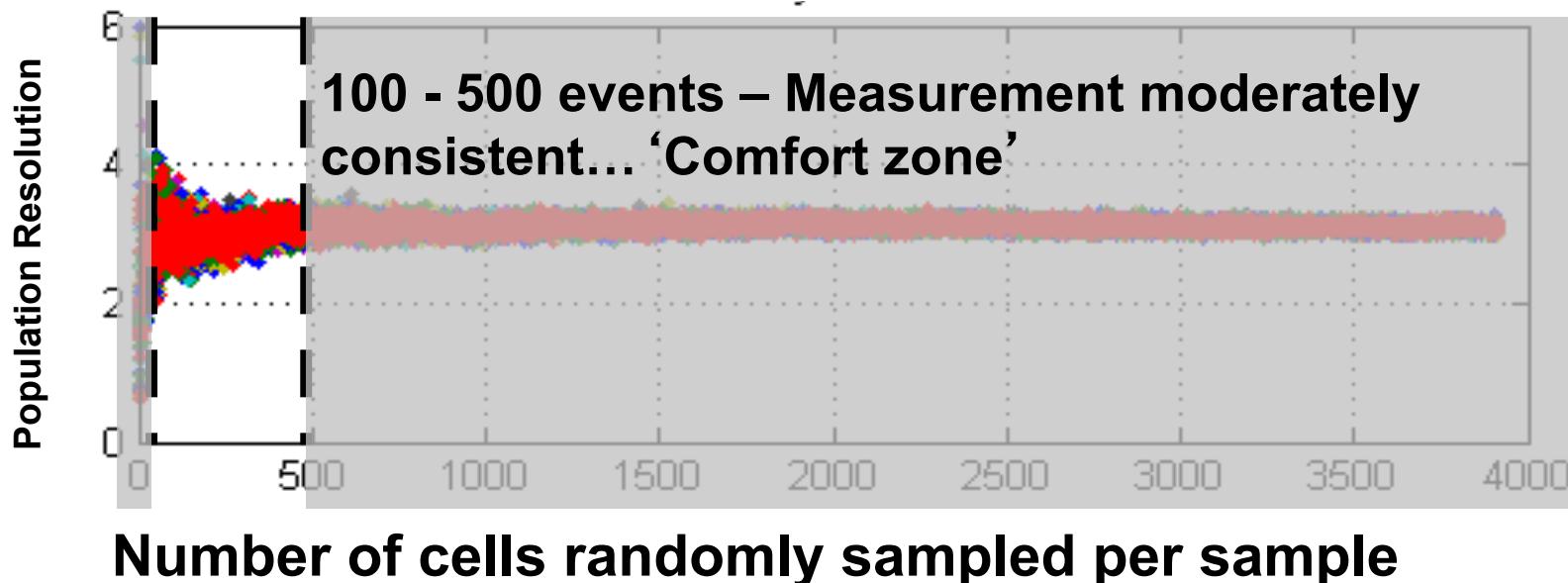
How many cells do I need to collect to be confident in my FINAL measurement?

Repeated random sampling of increasing numbers of cell sets from a larger data set. How many do we need to measure to ensure they represent ENTIRE population?



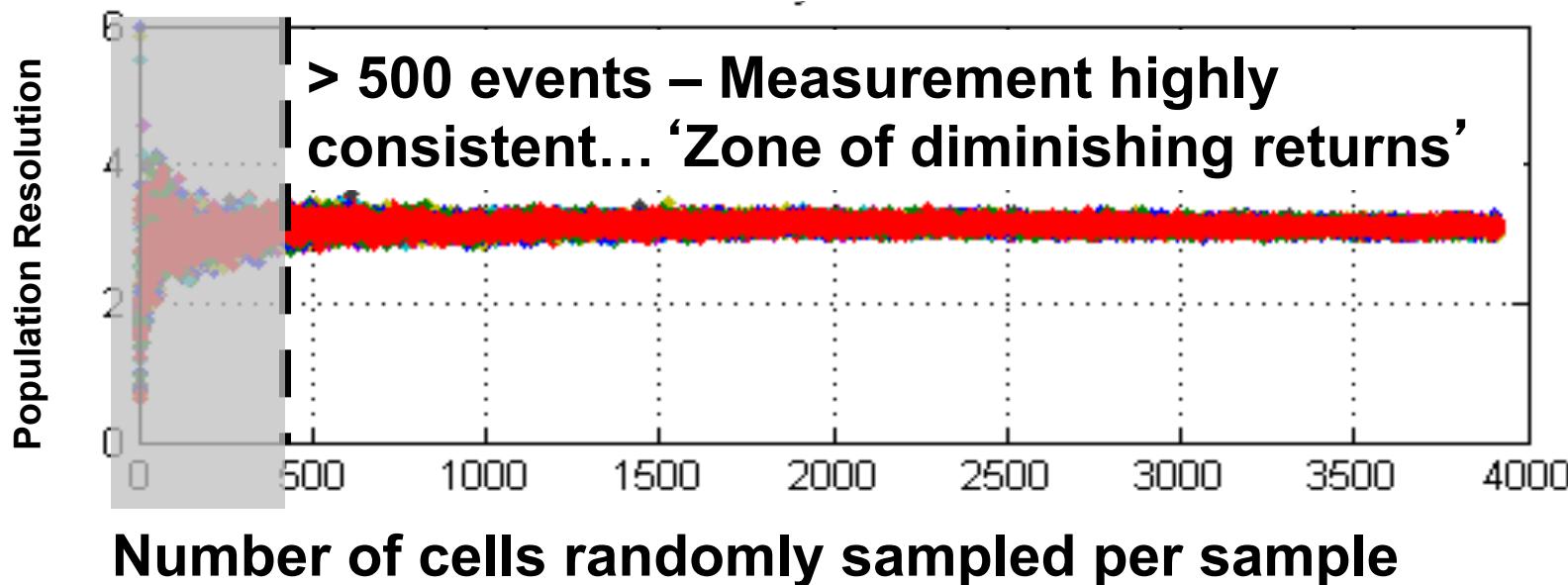
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How many cells do I need to collect to be confident in my FINAL measurement?

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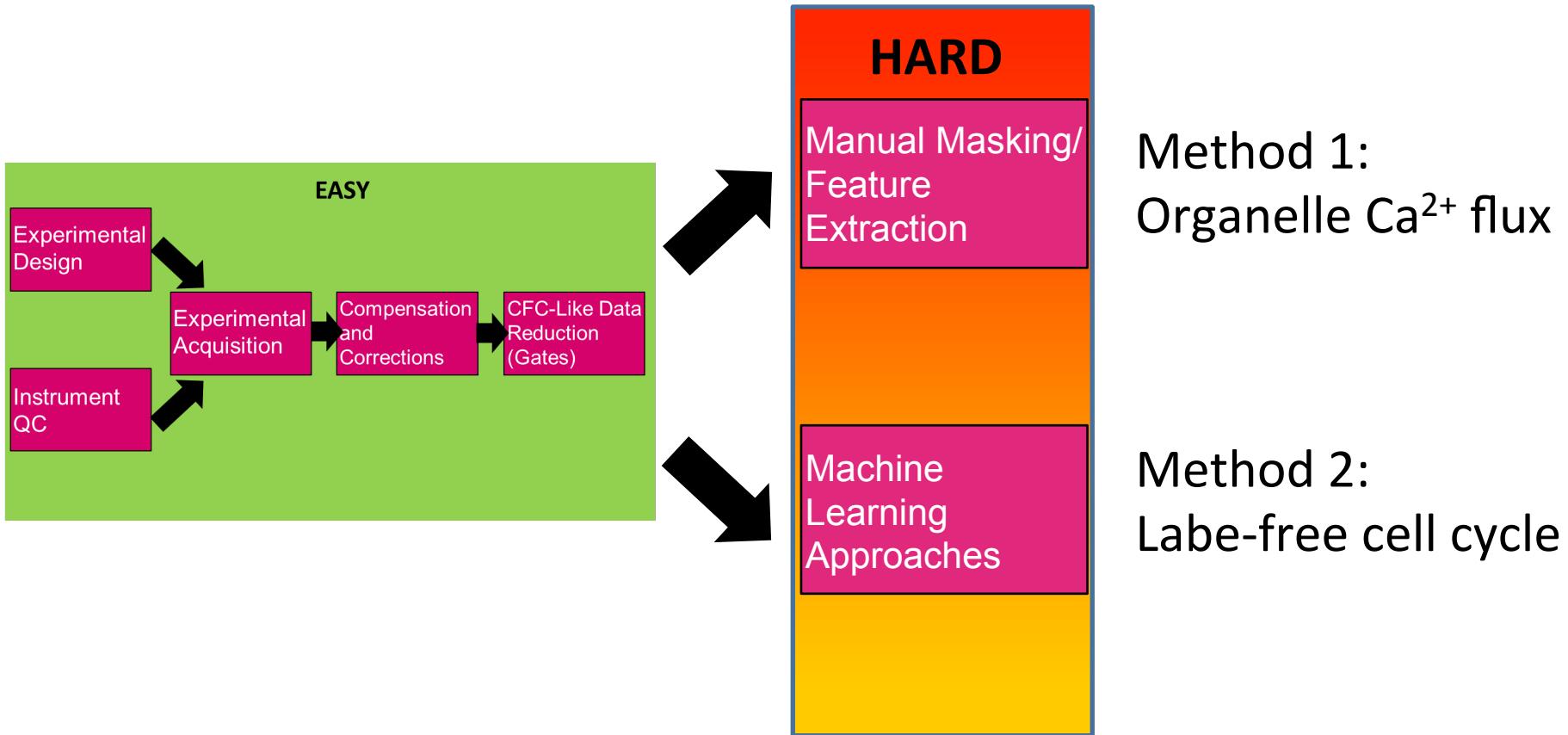


- Therefore collect at least 100 and ideally at least 500 (**FINAL target** events per sample

Summary slide

- Spatial/Morphometric biological questions require imagery
- An Imaging Cytometer MUST:
 - Allow for rapid image collection (100+ FINAL cell number)
 - Be multiparameter in nature to deal with heterogeneity.
 - Must acquire imagery in a fully calibrated, comparable manner
- Analysis must take into consideration:
 - Masking/ROI/Segmentation of single cells and structures
 - Extraction of pixel-based features to then plot as a population measurement.
 - Statistics that describe populations.
- IFC very much TICKS ALL BOXES.
- So what can be done with it?

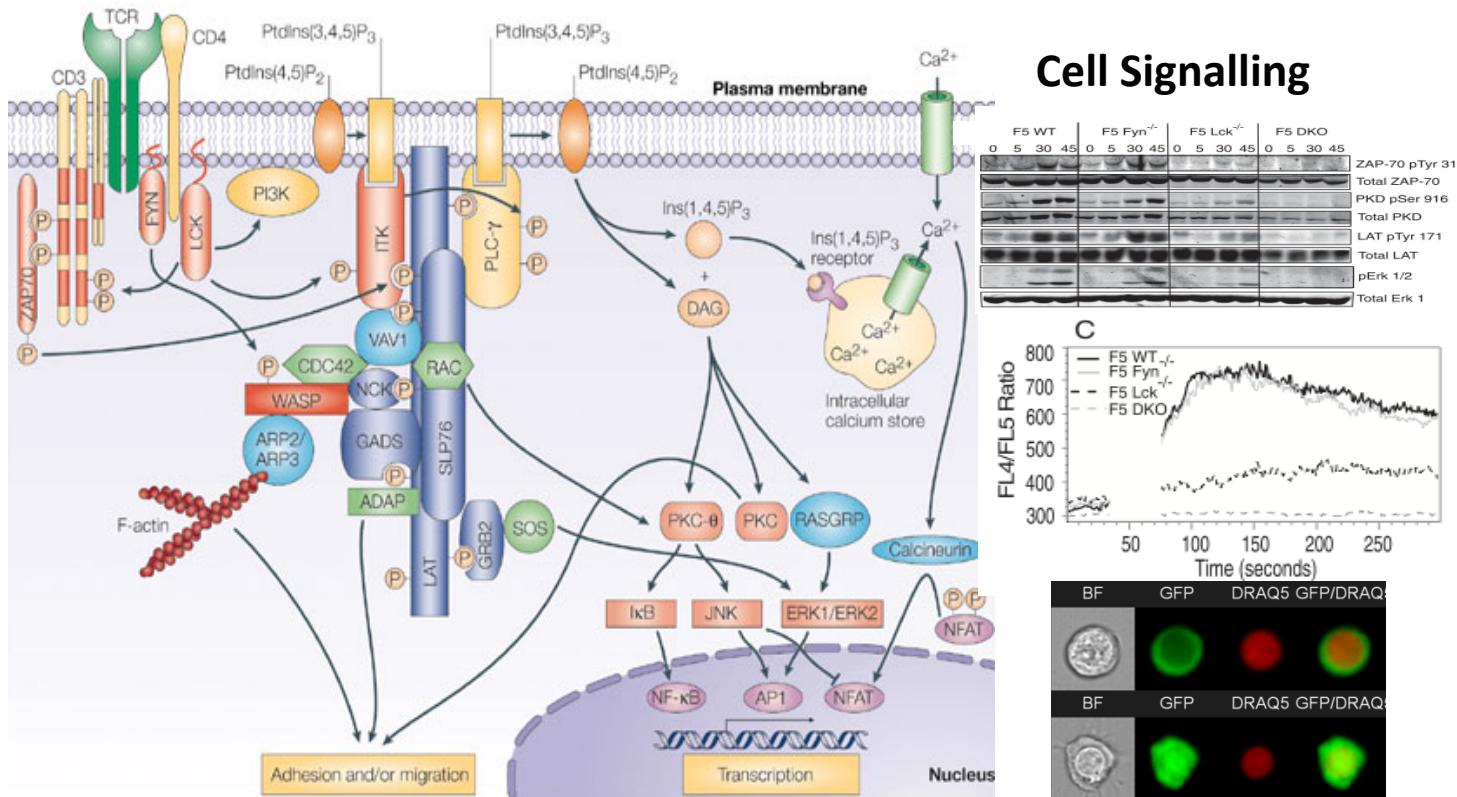
Two examples of very different approaches to IC data analysis



Method 1:
Organelle Ca^{2+} flux

Method 2:
Label-free cell cycle

Application 1: Spatiotemporal Calcium Signalling



Journal of Immunological Methods

Volume 423, August 2015, Pages 120–130

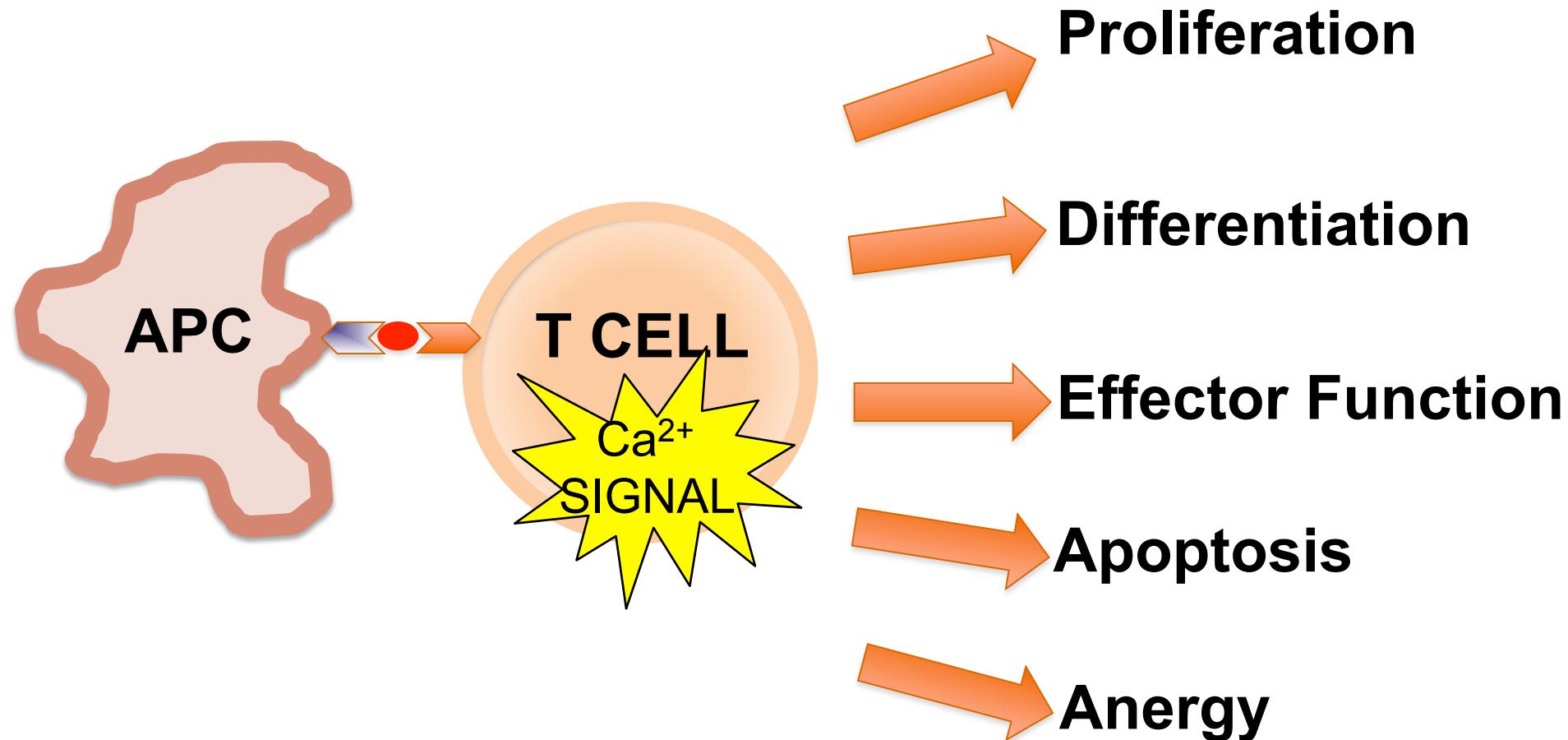


Applications in Imaging Flow Cytometry

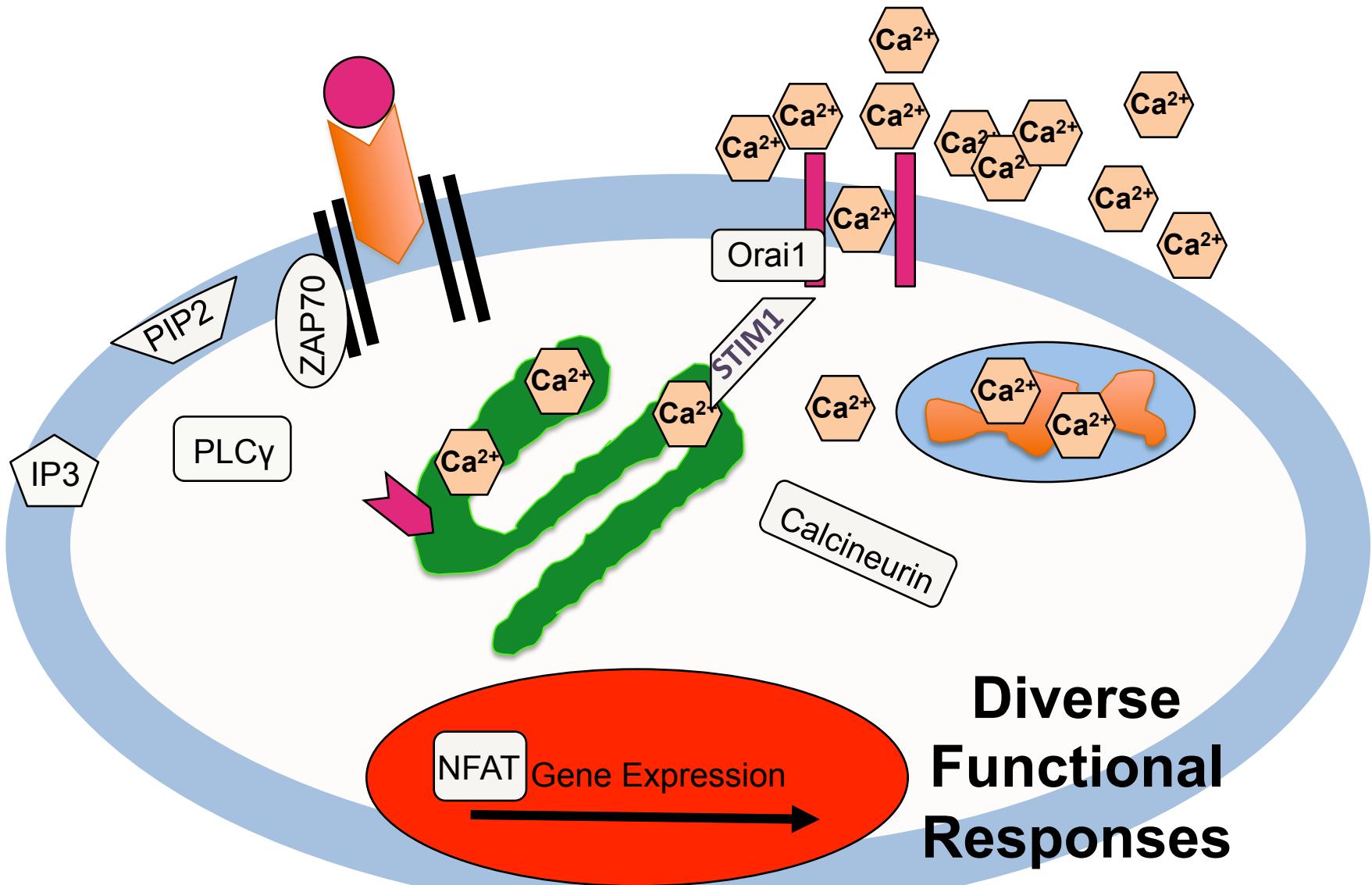
An imaging flow cytometry-based approach to measuring the spatiotemporal calcium mobilisation in activated T cells

Joana Cerveira^{a, 1}, Julfa Begum^{b, 1}, Rafael Di Marco Barros^c, Annemarthe G. van der Veen^d, Andrew Filby^{a, b},

TCR Engagement/signalling leads to diverse outcomes



Calcium signaling: Some of the Key Players

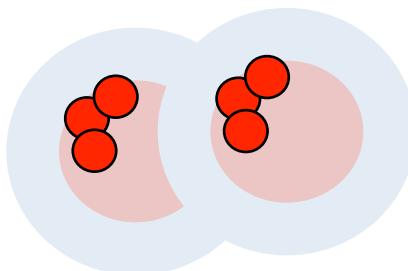


Approaches to Measure Calcium Mobilization in Immune Cells

- Conventional Flow Cytometry
 - Gives a temporal “snap shot” of calcium mobilization
 - High throughput, can analyse populations and subsets.
 - No spatial information
- Microscopy
 - Can provide live cell imaging data on single cells
 - Rapid measurement of calcium dynamics
 - Can use spatial information to localize the calcium signal within the cell
 - Lower throughput (generally)

IFC-protocol overview

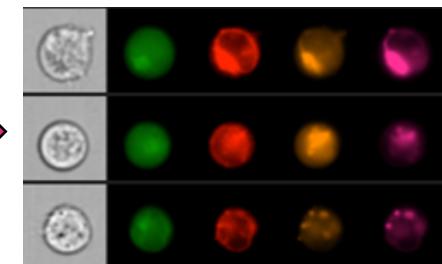
1. Label T cells with vital dyes (Calcium/Organelles) spectrally compatible with IFC systems



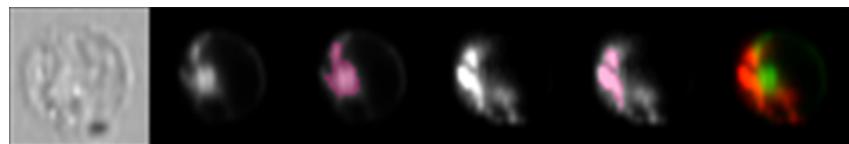
2. Activate with CD3 and acquire on IFC system



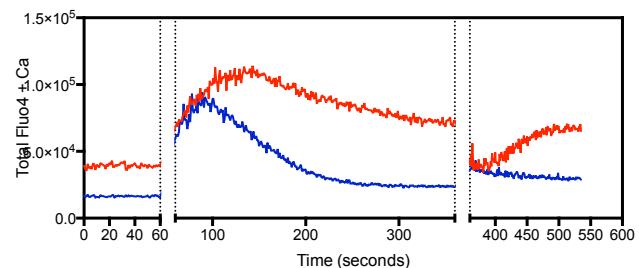
3. Perform compensation on multispectral data



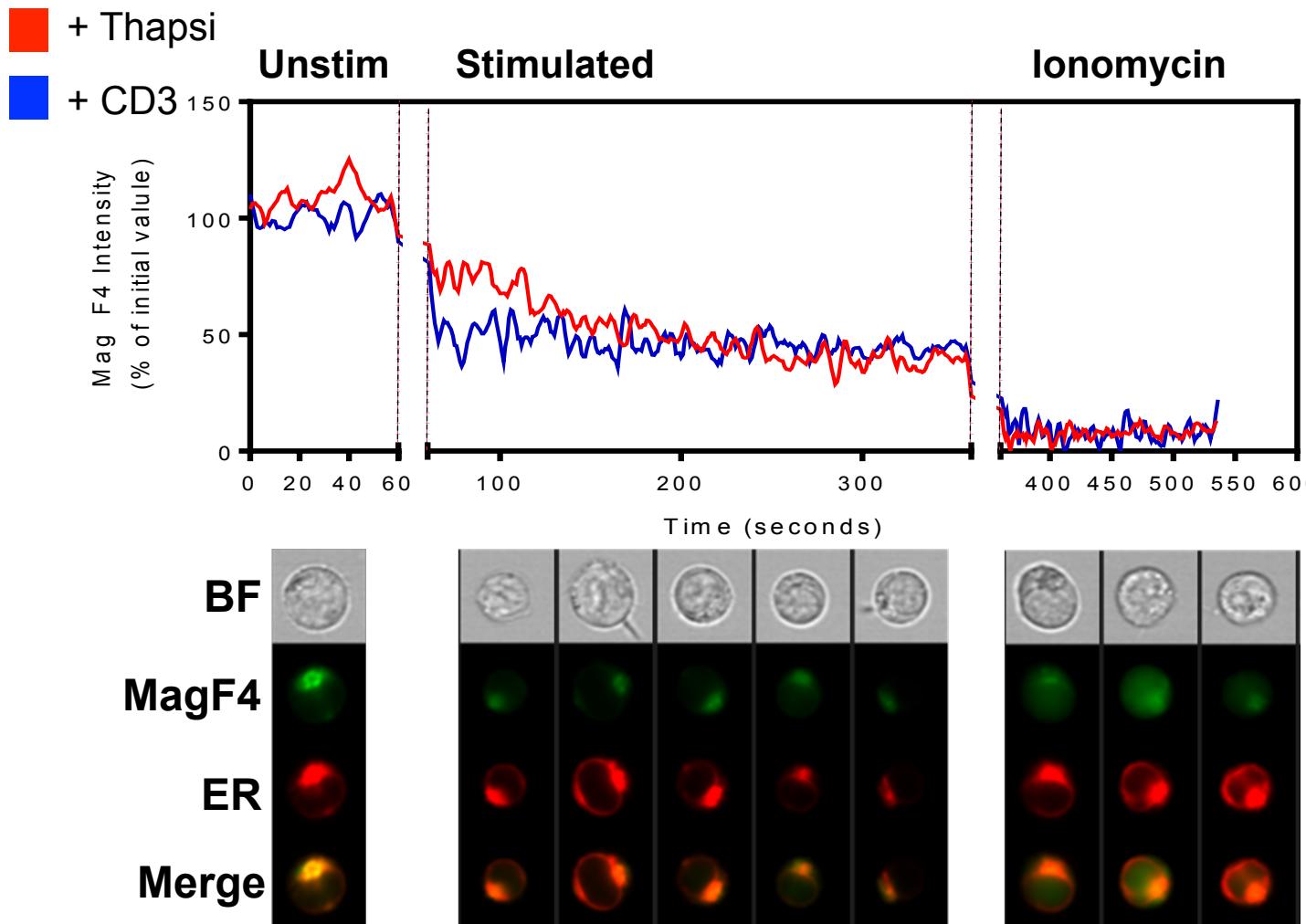
4. Derive masks using organelle signals and measure calcium indicator fluorescence ONLY within that area



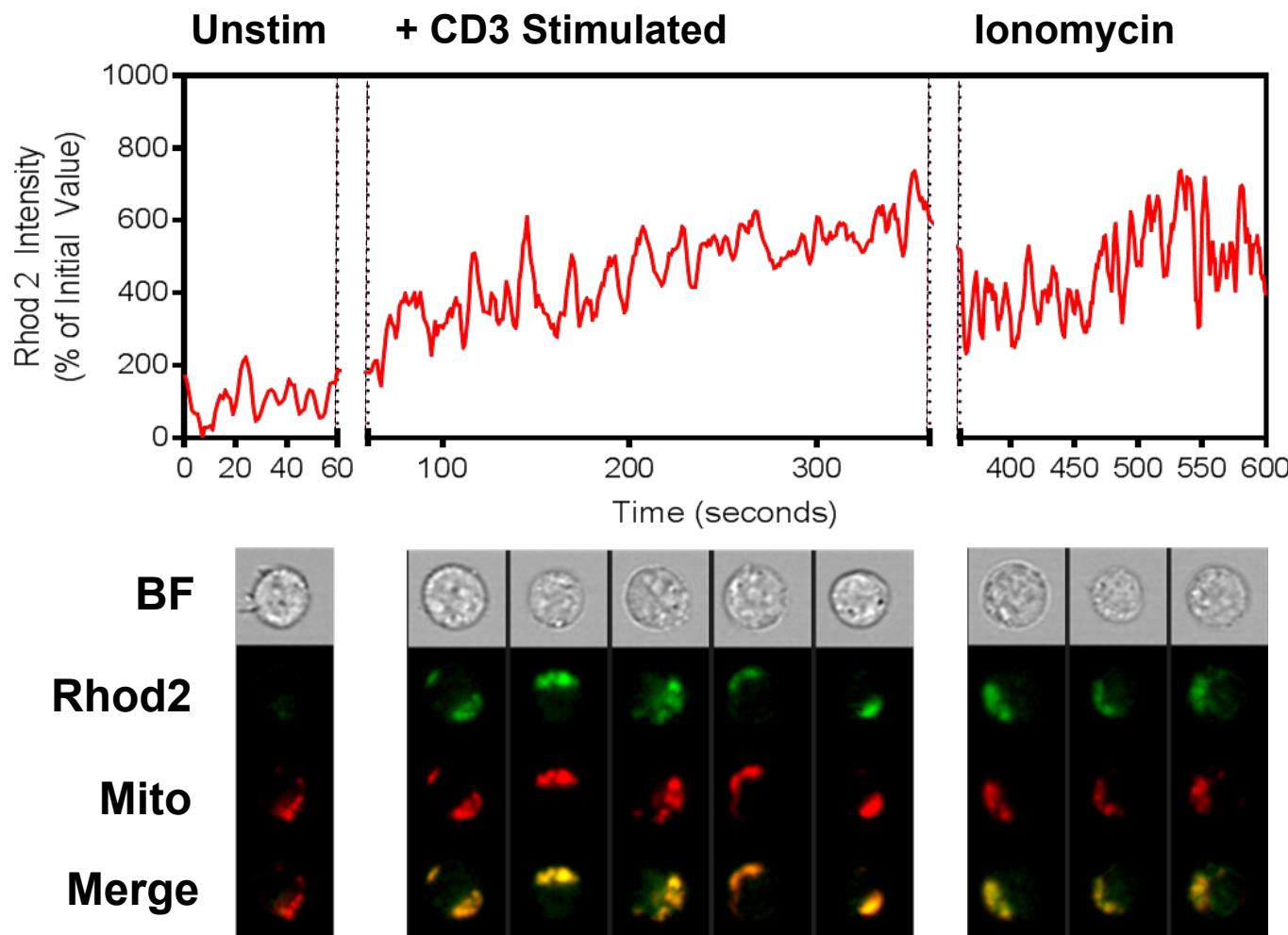
5. Plot organelle-directed intensity as a function of time



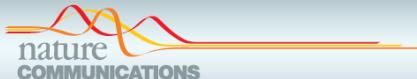
Mag Flou-4 Reports ER store levels of Calcium and decreases with CD3/Thapsigargin Stimulation



Rhod 2 Reports Mitochondrial uptake of Calcium after CD3 Stimulation (even in Ca-free media)



A machine-learning based approach: Remove some of the human element



ARTICLE

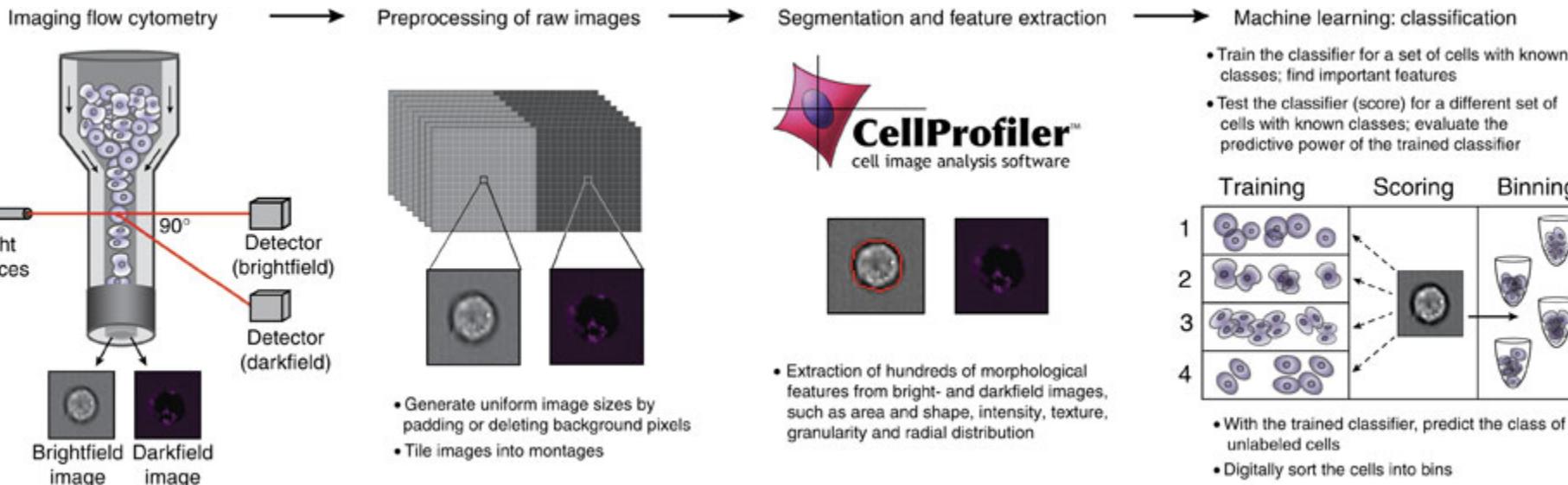
Received 1 Sep 2015 | Accepted 19 Nov 2015 | Published 7 Jan 2016

DOI: 10.1038/ncomms10256

OPEN

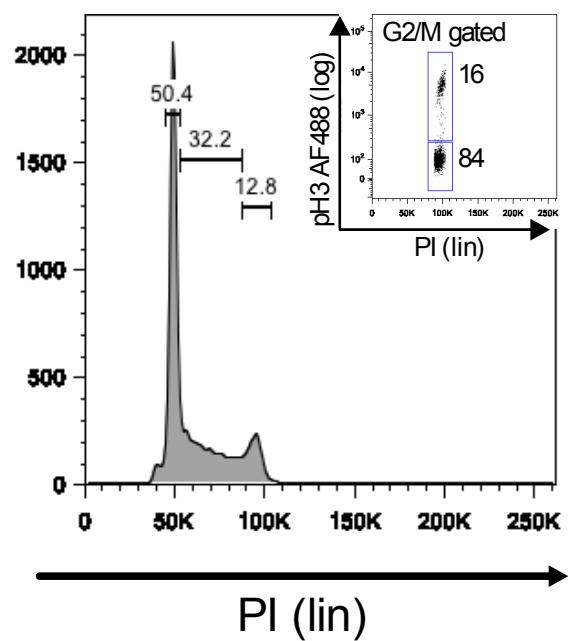
Label-free cell cycle analysis for high-throughput imaging flow cytometry

Thomas Blasj^{1,2,3}, Holger Hennig¹, Huw D. Summers⁴, Fabian J. Theis^{2,3}, Joana Cerveira⁵, James O. Patterson⁶, Derek Davies⁵, Andrew Filby⁷, Anne E. Carpenter¹ & Paul Rees^{1,4}



A machine-learning based approach to cell cycle analysis

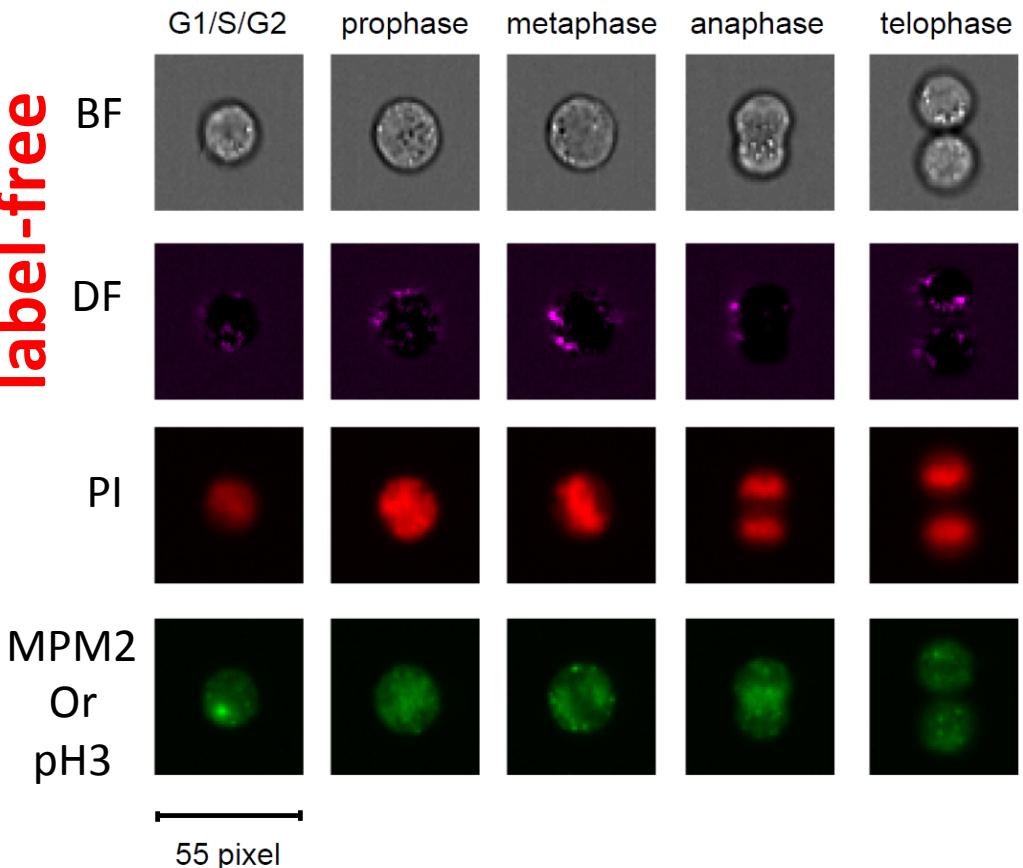
Traditional flow-based analysis



label-free

Imaging-flow based cell cycle analysis

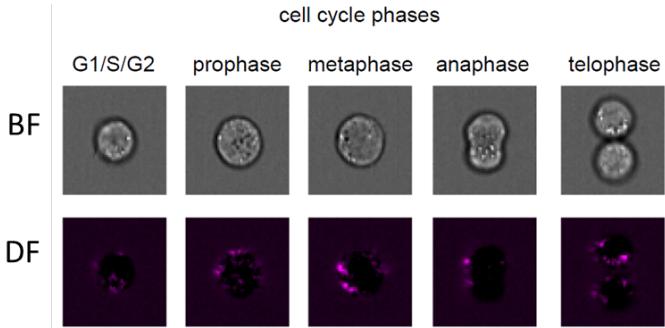
cell cycle phases



We start with cell-cycle fluorescent stains then throw them away to be “label-free”

1. Collect lots of images

label-free



Throw away
fluorescent labels

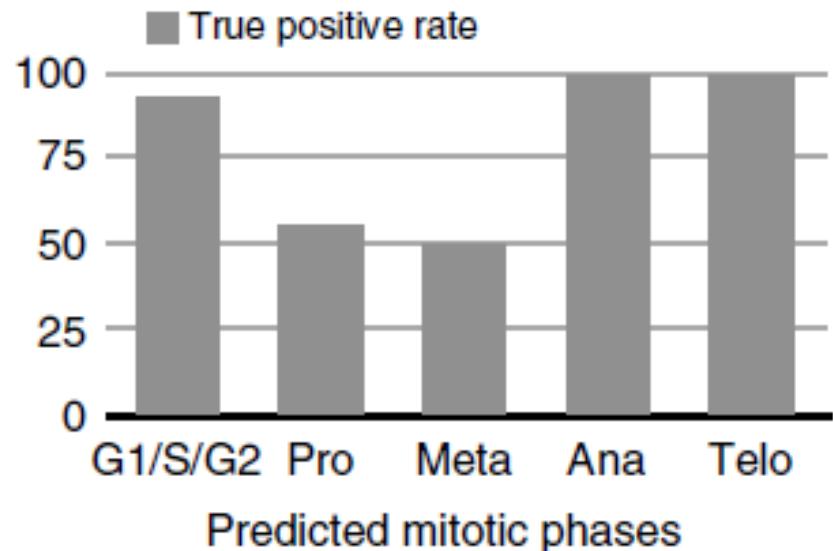
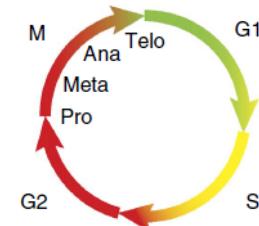
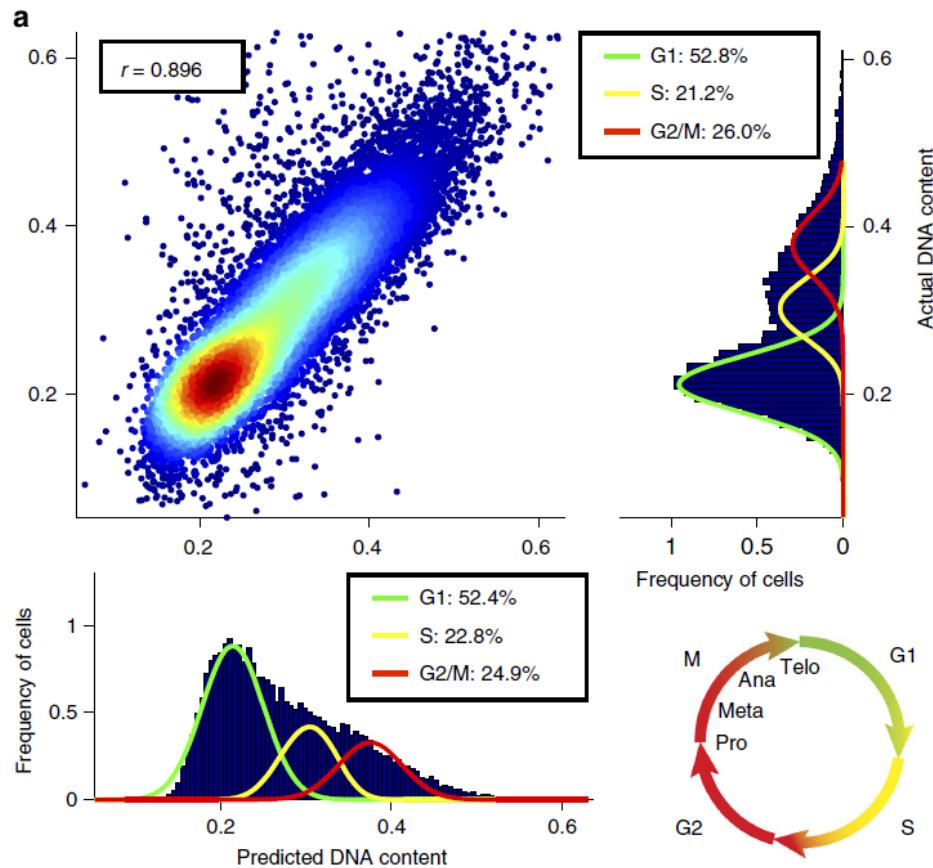
2. Ask computer to make 100s of pixel based measurements on BF and DF images and find the best correlates of cell cycle phase

Feature class	Feature number	Feature name	Brightfield	Darkfield	Texture	
Area and shape	1	AreaShape_Area	x	o		77 Texture_AngularSecondMoment_3_135
	2	AreaShape_Compactness	x	o		78 Texture_AngularSecondMoment_3_45
	3	AreaShape_Eccentricity	x	o		79 Texture_AngularSecondMoment_3_90
	4	AreaShape_Excentricity	x	o		80 Texture_Contrast_3_0
	5	AreaShape_Factor	x	o		81 Texture_Contrast_3_135
	6	AreaShape_MajorAxisLength	x	o		82 Texture_Contrast_3_45
	7	AreaShape_MajFeretDiameter	x	o		83 Texture_Contrast_3_90
	8	AreaShape_MaximumRadius	x	o		84 Texture_Correlation_3_0
	9	AreaShape_MeanRadius	x	o		85 Texture_Correlation_3_135
	10	AreaShape_MedianRadius	x	o		86 Texture_Correlation_3_45
	11	AreaShape_MinFeretDiameter	x	o		87 Texture_Correlation_3_90
	12	AreaShape_MinorAxisLength	x	o		88 Texture_DifferenceEntropy_3_0
	13	AreaShape_Perimeter	x	o		89 Texture_DifferenceEntropy_3_135
Zernike polynomials	14	AreaShape_Zernike_0_0	x	o		90 Texture_DifferenceEntropy_3_45
	43	AreaShape_Zernike_9_9	x	o		91 Texture_DifferenceEntropy_3_90
Granularity	44	Granularity_1	x	x		92 Texture_DifferenceVariance_3_0
	48	Granularity_5	x	x		93 Texture_DifferenceVariance_3_135
Intensity	49	Intensity_IntegratedIntensityEdge	x	x		94 Texture_DifferenceVariance_3_45
	50	Intensity_IntegratedIntensity	x	x		95 Texture_DifferenceVariance_3_90
	51	Intensity_LowerQuartileIntensity	x	x		96 Texture_Entropy_3_0
	52	Intensity_MADIntensity	x	x		97 Texture_Entropy_3_135
	53	Intensity_MassDisplacement	x	x		98 Texture_Entropy_3_45
	54	Intensity_MaxIntensityEdge	x	x		99 Texture_Entropy_3_90
	55	Intensity_MaxIntensity	x	x		100 Texture_Gabor
	56	Intensity_MeanIntensityEdge	x	x		101 Texture_InfoMeas1_3_0
	57	Intensity_MeanIntensity	x	x		102 Texture_InfoMeas1_3_135
	58	Intensity_MedianIntensity	x	x		103 Texture_InfoMeas1_3_45
	59	Intensity_MinIntensityEdge	x	x		104 Texture_InfoMeas2_3_0
	60	Intensity_MinIntensity	x	x		105 Texture_InfoMeas2_3_0
Radial distribution	61	Intensity_SdIntensityEdge	x	x		106 Texture_InfoMeas2_3_135
	62	Intensity_SdIntensity	x	x		107 Texture_InfoMeas2_3_45
	63	Intensity_UpperQuartileIntensity	x	x		108 Texture_InfoMeas2_3_90
	64	RadialDistribution_FracAD_1	x	x		109 Texture_InverseDifferenceMoment_3_0
	65	RadialDistribution_FracAD_2	x	x		110 Texture_InverseDifferenceMoment_3_135
	66	RadialDistribution_FracAD_3	x	x		111 Texture_InverseDifferenceMoment_3_45
	67	RadialDistribution_FracAD_4	x	x		112 Texture_InverseDifferenceMoment_3_90
	68	RadialDistribution_MeanFrac_1	x	x		113 Texture_SumAverage_3_0
	69	RadialDistribution_MeanFrac_2	x	x		114 Texture_SumAverage_3_135
	70	RadialDistribution_MeanFrac_3	x	x		115 Texture_SumAverage_3_45
	71	RadialDistribution_MeanFrac_4	x	x		116 Texture_SumAverage_3_90
	72	RadialDistribution_RadialCV_1	x	x		117 Texture_SumEntropy_3_0
	73	RadialDistribution_RadialCV_2	x	x		118 Texture_SumEntropy_3_135
	74	RadialDistribution_RadialCV_3	x	x		119 Texture_SumEntropy_3_45
	75	RadialDistribution_RadialCV_4	x	x		120 Texture_SumEntropy_3_90
	76	Texture_AngularSecondMoment_3_0	x	x		121 Texture_SumVariance_3_0
						122 Texture_SumVariance_3_135
						123 Texture_SumVariance_3_45
						124 Texture_SumVariance_3_90
						125 Texture_Variance_3_0
						126 Texture_Variance_3_135
						127 Texture_Variance_3_45
						128 Texture_Variance_3_90



THE
Flow Cytometry
Core Facility

A machine-learning based approach to cell cycle analysis



- Good label-free predictive rate for G1/S/G2
- Challenge with Pro/Meta (expected)
- Very accurate for Ana/Telophase

Summary and conclusions

- Preserves high-throughput capabilities of flow
- Provides spatial information to ask where the Ca^{2+} mobilisation localises to in the T cell
- Provides a kinetic measurement on high numbers of cells.
- Number of cells analysed and quality of label free imagery (BF and SSC) allows for bold machine-learning approaches.

Acknowledgements

David McDonald



Andrew Filby

Carly Foster

Jack Wigham

Andrew Fuller

Gillian Hulme

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The ISAC SRL Emerging Leaders Programme

Organelle Ca²⁺ Story:

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Joana Cerveira

Julfa Begum

Label-free Cell Cycle Story:

Swansea University, UK

Paul Rees

Broad Institute, USA

Anne Carpenter

Holger Hennig

Helmholtz Zentrum, Germany

Fabian Theis

Thomas Blasi



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