











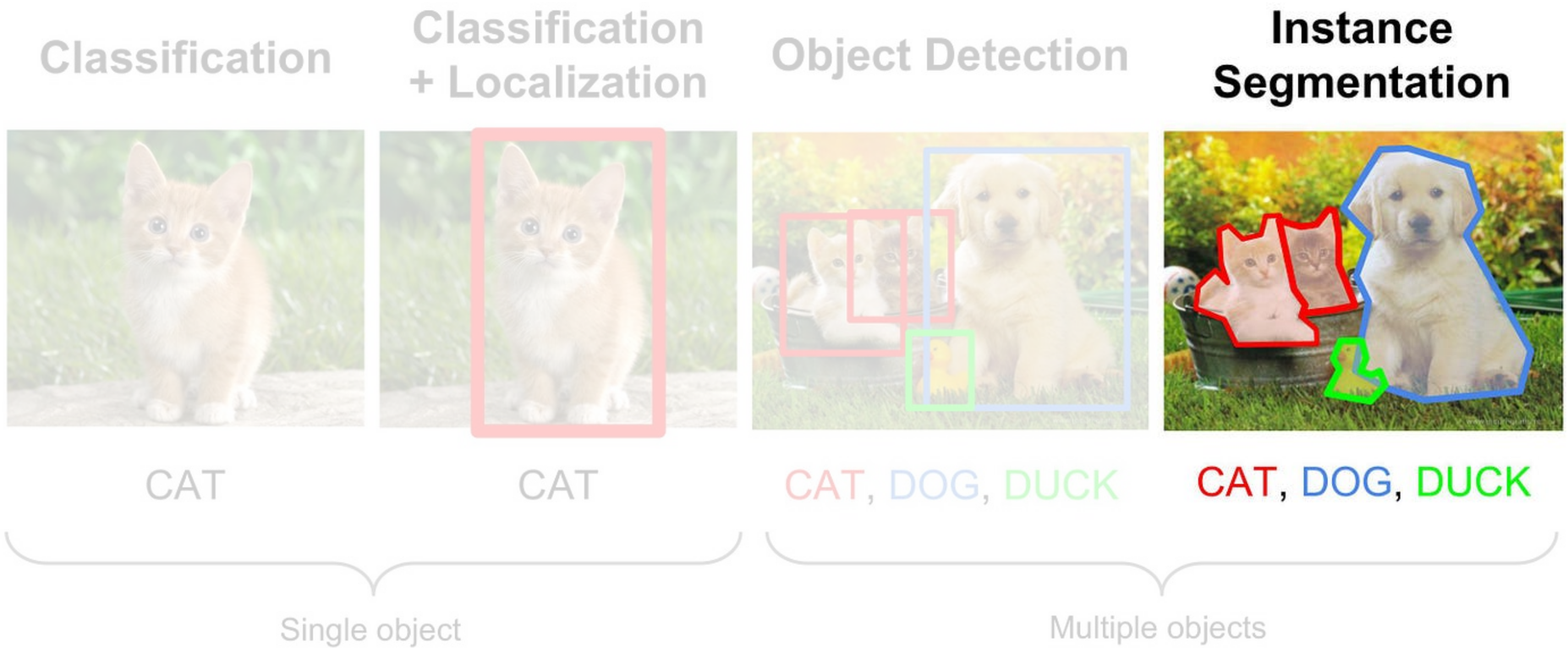


Evolutionary design of explainable algorithms for biomedical image segmentation

Sylvain Cussat-Blanc

Super short introduction

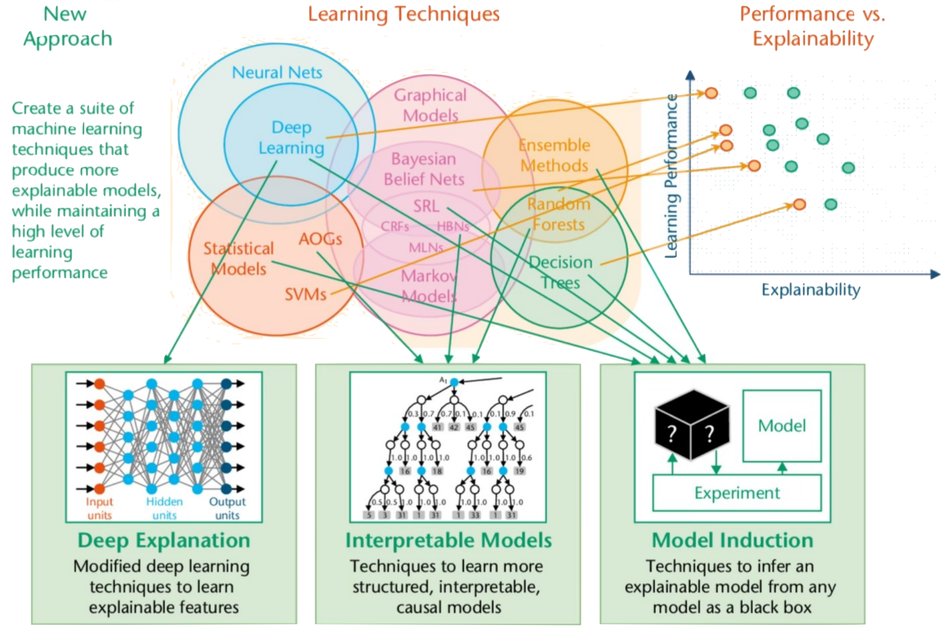
Image processing



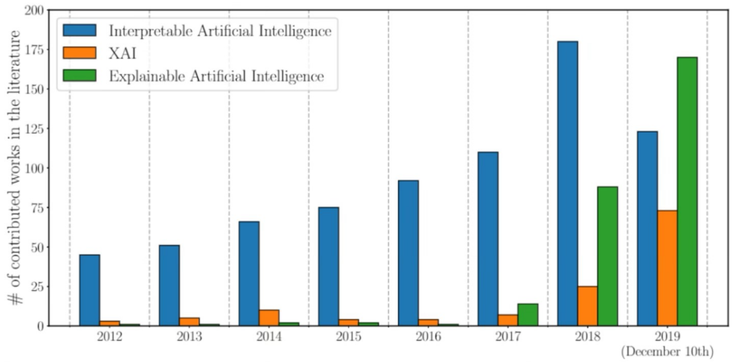
https://www.mdpi.com/2227-7080/9/1/2/htm#

Context - Image processing

- Image processing (IP)
  - is nowadays a highly moving research field
  - recently revolutionised by deep learning
  - attracts the attention of industry
- Some drawbacks of deep learning
  - requires high volumes of annotated data
  - lacks of interpretability
  - consumes high amounts of energy



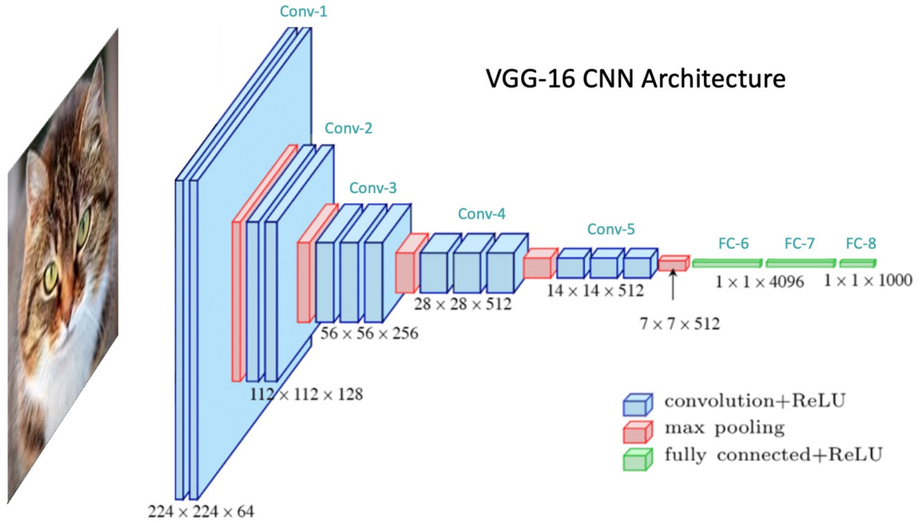
Gunning, D. Explainable artificial intelligence (xai). Defense advanced research projects agency (DARPA), nd Web 2, 1 (2017).



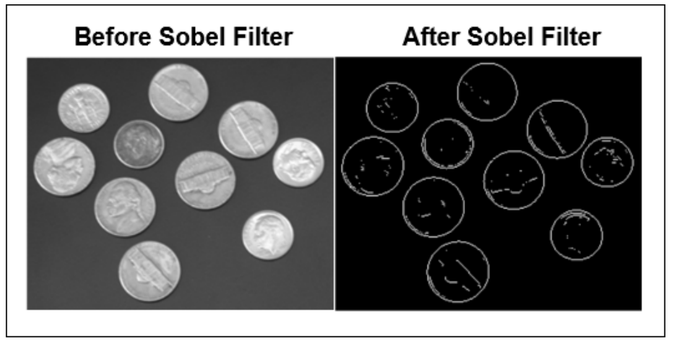
Arrieta, A. B., Diaz-Rodriguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., et al. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information fusion 58, 82–115 (2020).

GP - an alternative approach?

- While deep learning optimises filters at the pixel level, GP can be used to automatically assemble image processing functions and to optimise their parameters
  - Re-uses decades of engineering and research on image processing
  - Produces readable programs that can be in turn interpreted



https://learnopencv.com/understanding-convolutional-neural-networks-cnn/



-1	0	+1
-2	0	+2
-1	0	+1

Gx

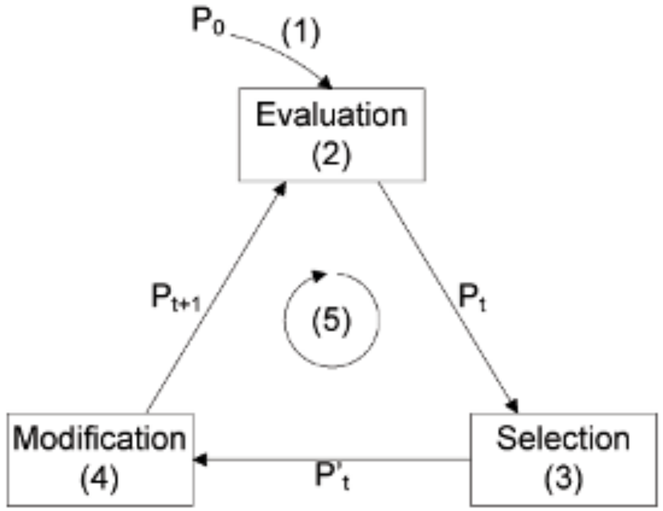
+1	+2	+1
0	0	0
-1	-2	-1

Gy

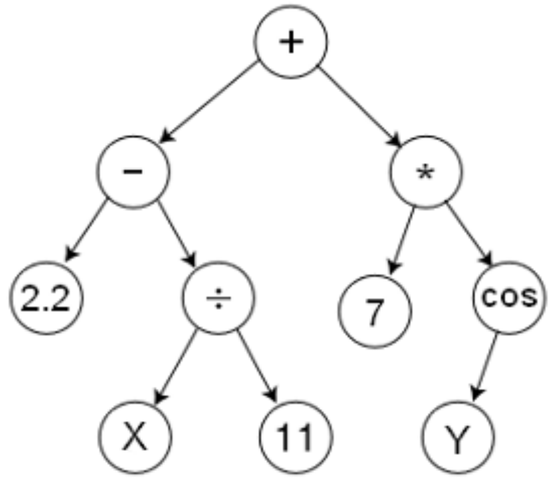
Another super short introduction

Genetic Programming

- Genetic algorithms
  - Stochastic optimisation algorithm
  - Inspired from Darwin's theory of evolution
  - Evolves a population of solutions encoded into genomes



- Genetic programming
  - Based on artificial evolution
  - Evolves functions/programs for a given task



$$\left(2.2 - \left(\frac{X}{11}\right)\right) + \left(7 * \cos(Y)\right)$$

GP to segment images ?

- Requirement for a specific function library
  - Use of computer vision functions
  - What level of abstraction in the functions ?

Function library		
max	median_blur	morph_gradient
min	gaussian_blur	morph_tophat
mean	laplacian	morph_blackhat
add	sobel	fill_holes
subtract	robert_cross	remove_small_objects
bitwise_not	canny	remove_small_holes
bitwise_or	sharpen	threshold
bitwise_and	gabor	threshold_at_1
bitwise_and_mask	abs_diff	distance_transform
bitwise_xor	abs_diff2	dt_and_thresh
sqrt	fluo_tophat	inrange_bin
pow2	rel_diff	inrange
exp	erode	
log	dilate	
	open	
	close	

nature communications

Article

https://doi.org/10.1038/s41467-023-42664-x

Evolutionary design of explainable algorithms for biomedical image segmentation

Received: 17 April 2023

Accepted: 18 October 2023

Published online: 06 November 2023

Check for updates

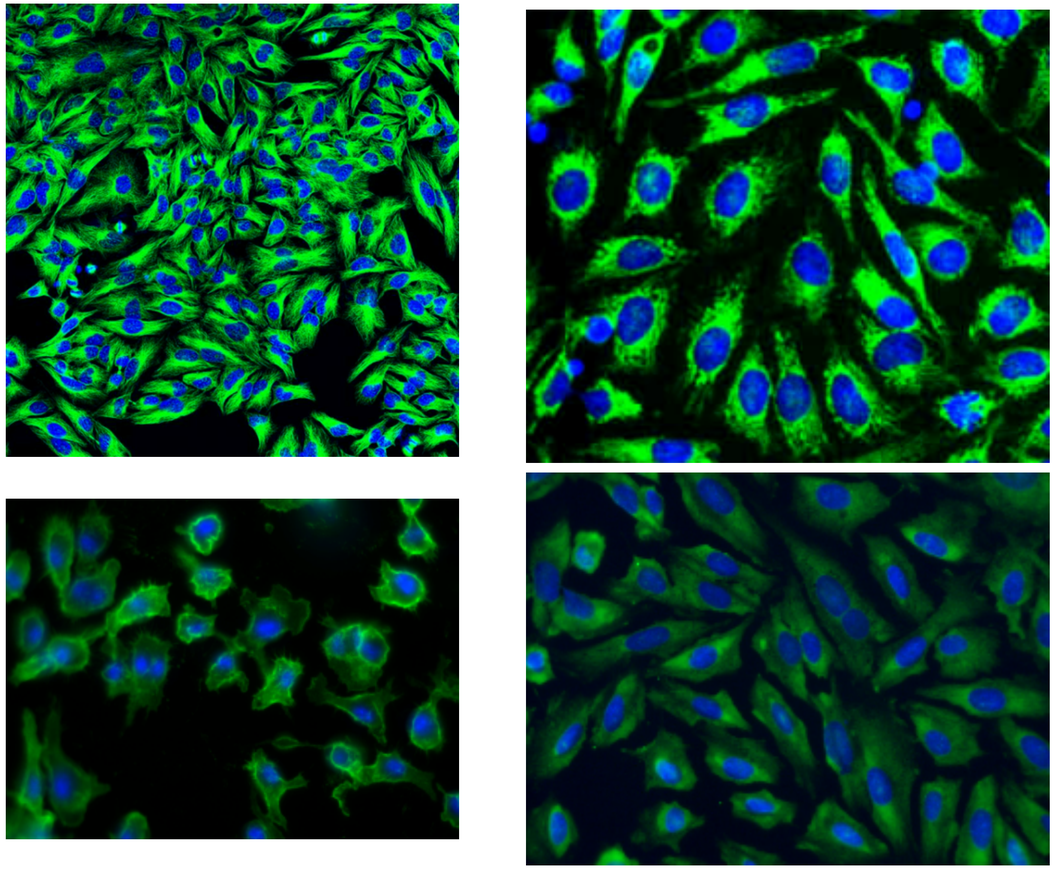
Kévin Cortacero[1,2,3], Brienne McKenzie[1,2,3], Sabina Müller[1,2,3], Roxana Khazen[1,2,3], Fanny Lafouresse[1,2,3], Gaëlle Corsaut[1,2,3], Nathalie Van Acker[4], François-Xavier Frenois[4], Laurence Lamant[4], Nicolas Meyer[5], Béatrice Vergier[6,7], Dennis G. Wilson[8], Hervé Luga[8], Oskar Staufer[9,10], Michael L. Dustin[9], Salvatore Valitutti[1,2,3,4,11] & Sylvain Cussat-Blanc[8,11]

- What part of the pipeline are we considering?
  - Use of non-evolvable nodes for pre- and post- processing
  - Expert knowledge injected depending to the problem

Instance segmentation of cells

CellPose Dataset & approaches

- Dataset - CellPose
  - Instance cell segmentation
  - Train set: 89 images
  - Test set: 11 images
- Deep learning approaches:
  - Mask RCNN
  - Stardist
  - CellPose - transfert learning
- CGP
  - 40 independent runs
  - Trained from scratch
  - End-point: Marker Controlled Watershed
- Evaluation: Average Precision

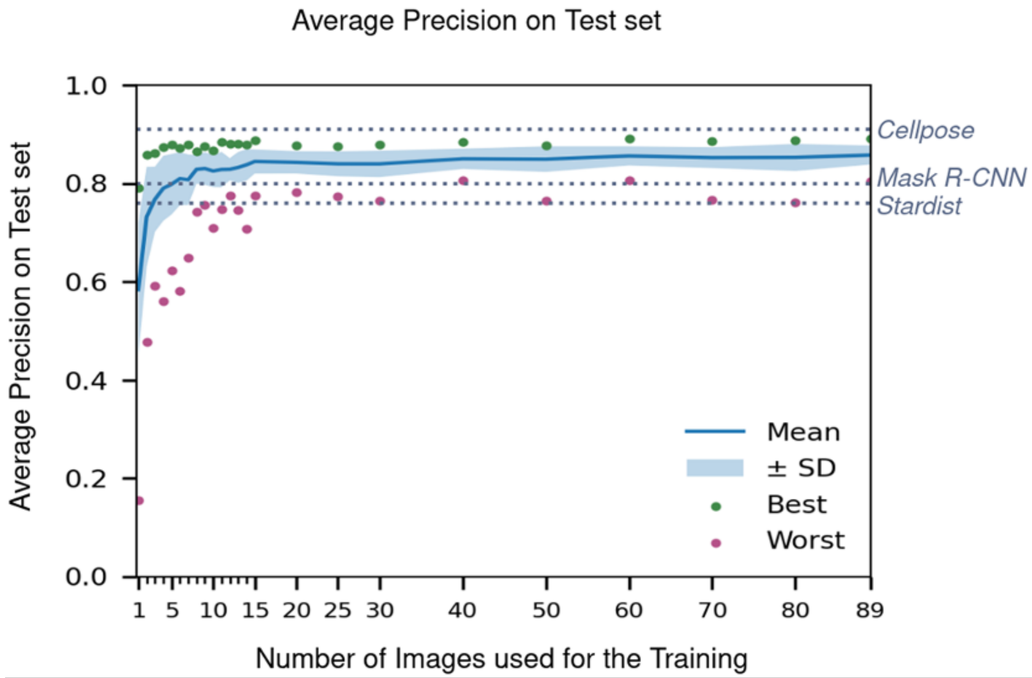


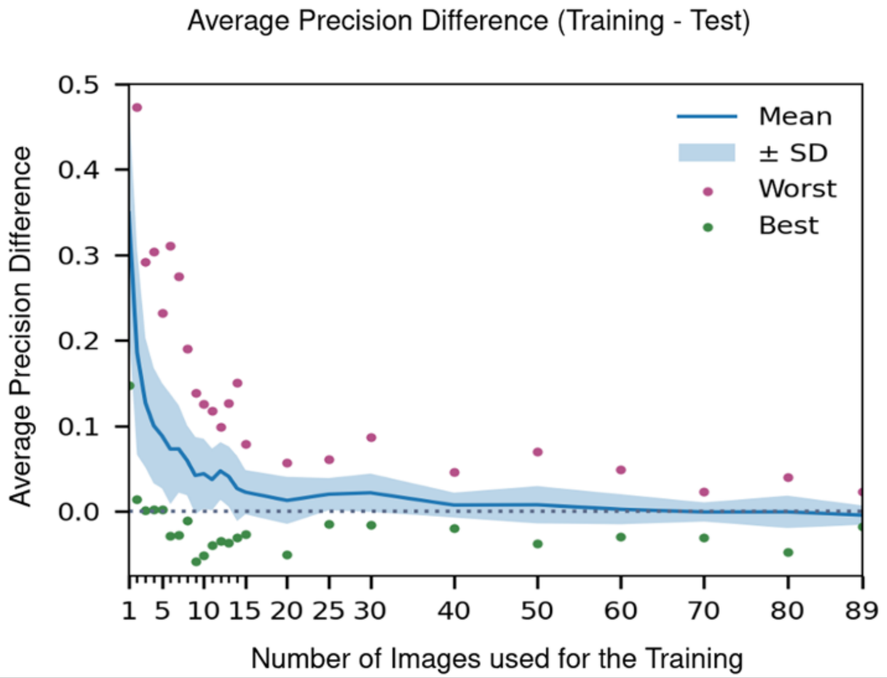
Stringer, C., Wang, T., Michaelos, M. & Pachitariu, M. Cellpose: a generalist algorithm for cellular segmentation. *Nat. Methods* **18**, 100–106 (2021).

Instance segmentation of cells

Results

- CGP can solved this task with
  - Equivalent efficient compared to DL
  - Few images (~10-15)
  - Good generalisation capacities

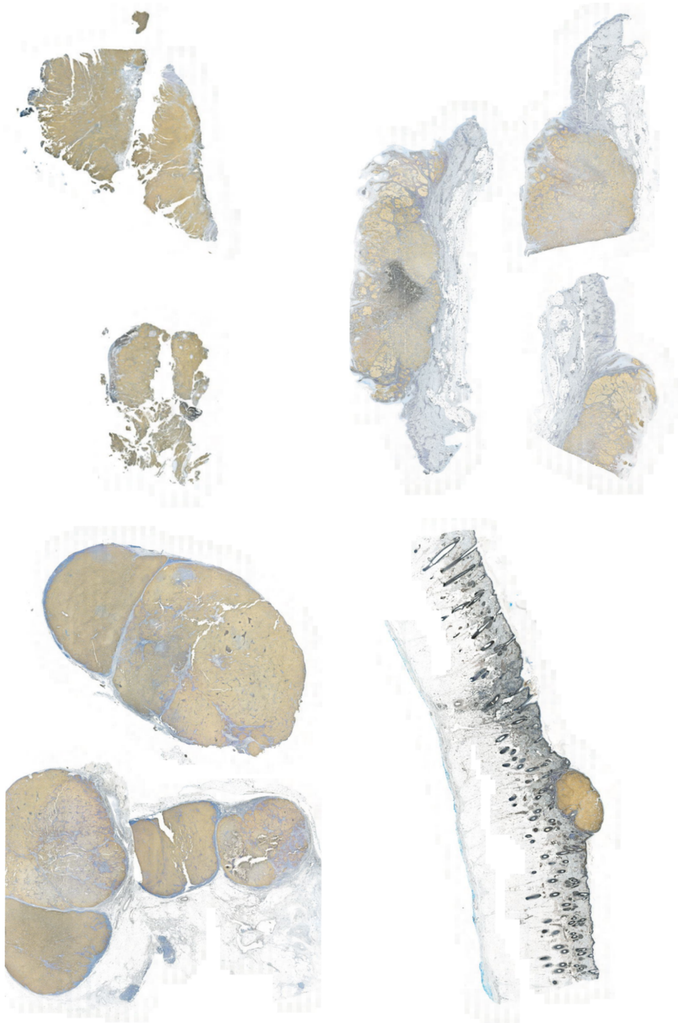




Segmentation of melanoma nodules

Dataset

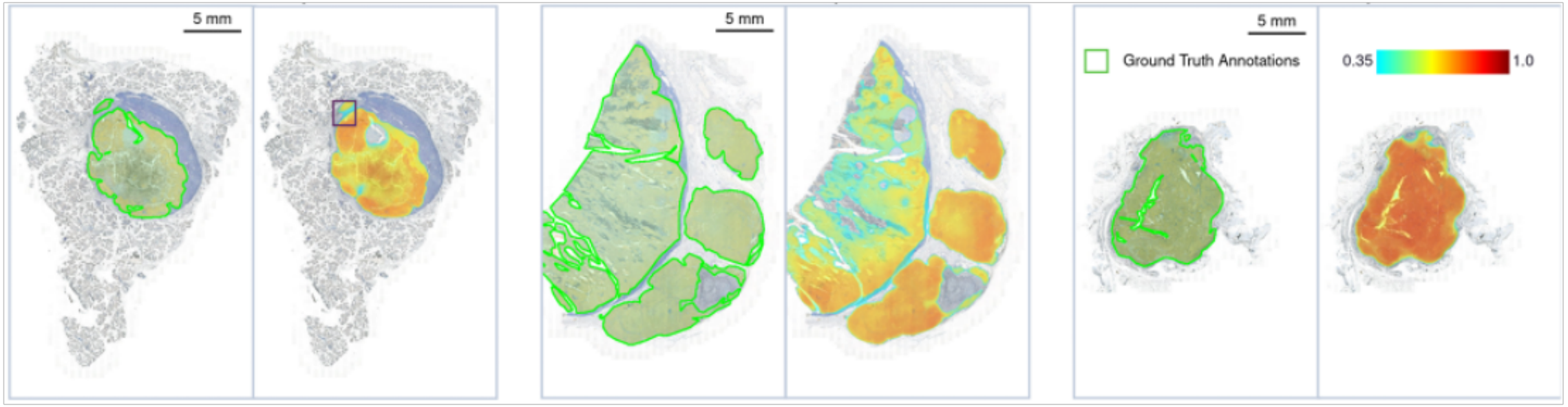
- 12 (train) + 12 (test) stained images of tissues
- Annotation made by an expert
- 100 trained pipelines are aggregated by averaging their output
- Final output: gradient of probabilities of presence of tumoral cells



Segmentation of melanoma nodules

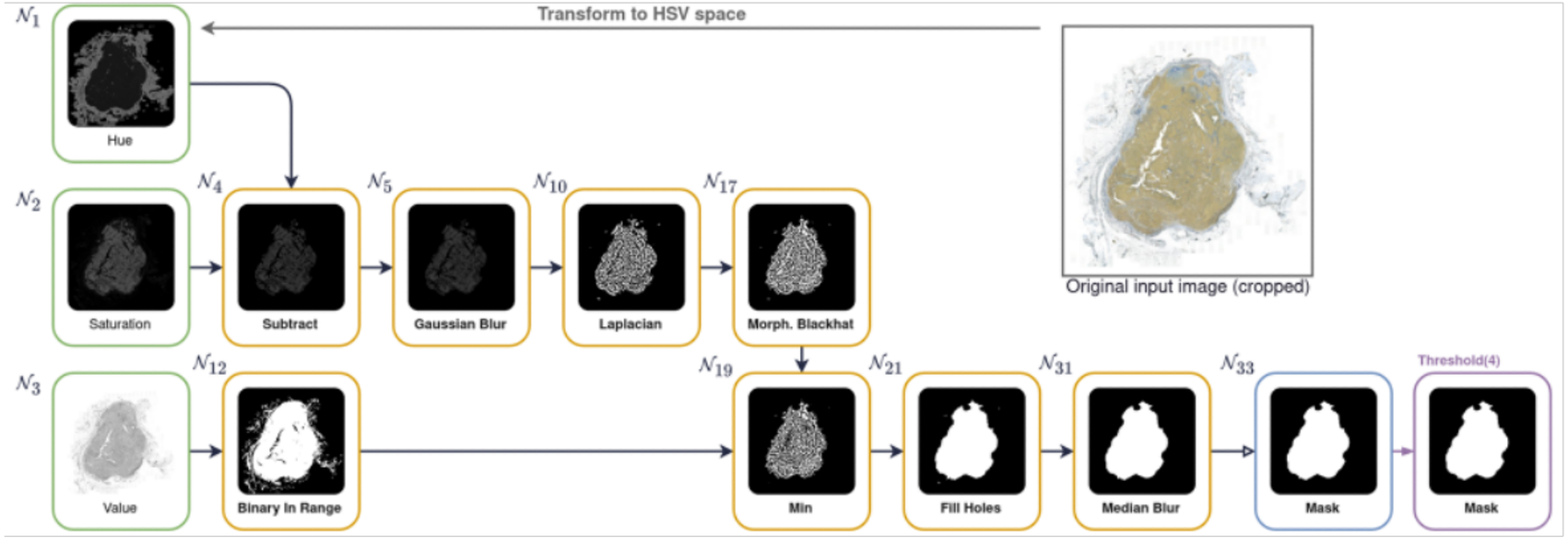
CGP can generate accurate masks

- Examples of 3 images from the test set



Segmentation of melanoma nodules

Generated pipelines can be interpreted



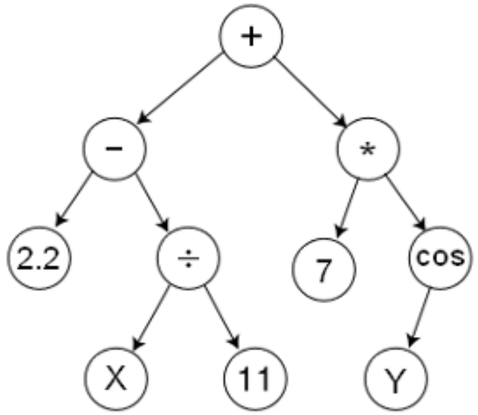
The first step (node 3) of this pipeline consisted of subtracting the Hue channel (node 0) from the Saturation channel (node 1), **allowing for the exclusion of pixels corresponding to CD8+ T cells and to other cells belonging to the tumor microenvironment.** Then Kartezio used a Gaussian Blur filter (node 4) in order to smooth the previously obtained area. Next, Kartezio chose a Laplacian filter (node 10) to detect the variations in the image obtained in node 4, thus **delimiting the tumor borders**. Interestingly, the sequence Gaussian Blur/Laplacian filters is frequently used by image analysts for image segmentation tasks. To highlight the segmented areas, Kartezio used Morphological Black Hat (node 17) which **reveals small objects that are darker than their surroundings**. Altogether, these initial calculations provided an accurate estimation of tumor area.

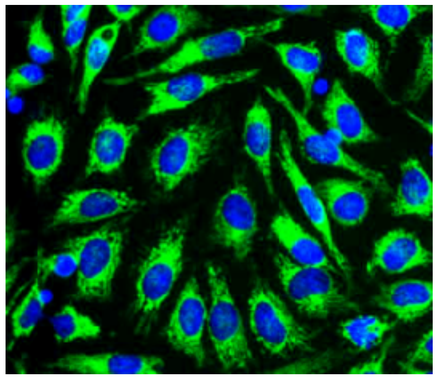
In parallel, node 12 created a binary mask of the Value channel (brightness) allowing for **the establishment of a global map of the area of interest**. The next step selected by Kartezio consisted of **merging the two maps with the min operator** (node 19). This allowed for **the elimination of all pixels detected by the first calculation (results of node 17) that fell outside the area of interest**. Kartezio next selected a Fill Hole filter in order to transform the selected area limits into a solid binary mask. A final step consisted of removing the noise from the edges of the mask using a Median Blur filter (node 31)

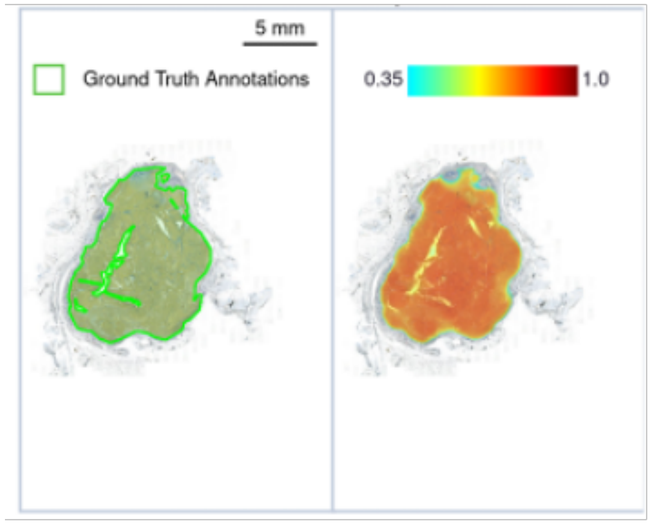
Conclusion

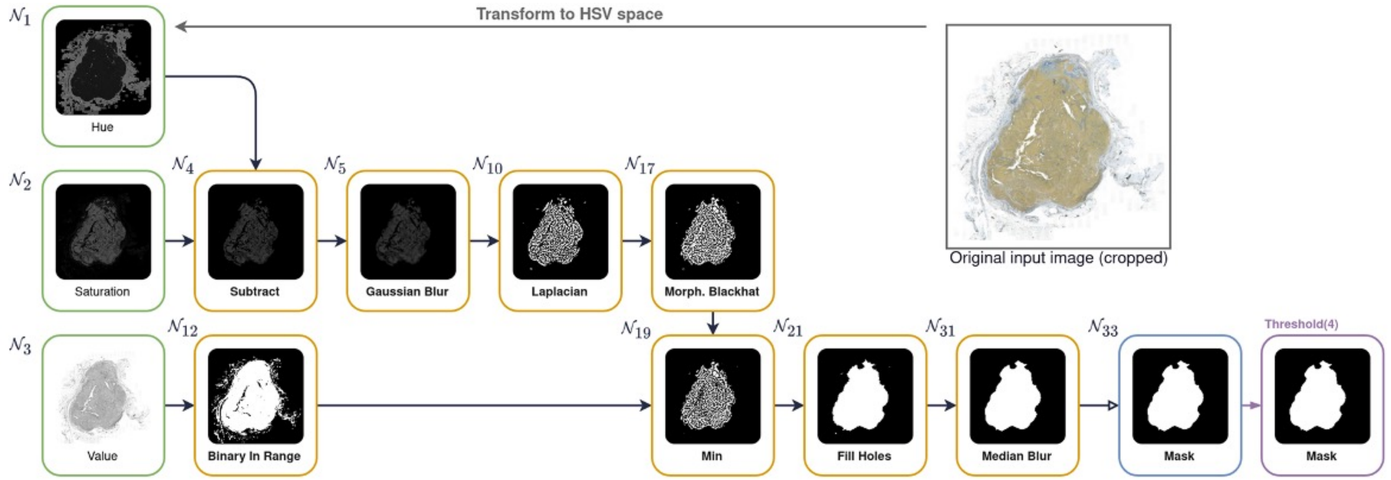
- We showed that:
  - CGP is a viable alternative to deep learning for image processing tasks
  - CGP produces interpretable and, in some cases, explainable pipelines
  - Multi-objective optimization can be used to produce a variety of solutions balancing task efficient and computational cost
- Perspectives:
  - Include the expert in the training loop using (Inter)active learning
  - Consider new objectives such as divergence search, explainability, etc.
  - Handle various types of data within the pipeline
  - Consider other evolutionary approaches for the evolution of CGP

Thank you!


+
−
*
2.2
÷
7
cos
X
11
Y
$\left(2.2-\left(\frac{X}{11}\right)\right)+\left(7*\cos(Y)\right)$




5 mm
Ground Truth Annotations
0.35
1.0


Transform to HSV space
$\mathcal{N}_1$
Hue
$\mathcal{N}_2$
Saturation
$\mathcal{N}_4$
Subtract
$\mathcal{N}_5$
Gaussian Blur
$\mathcal{N}_{10}$
Laplacian
$\mathcal{N}_{17}$
Morph. Blackhat
$\mathcal{N}_3$
Value
$\mathcal{N}_{12}$
Binary In Range
$\mathcal{N}_{19}$
Min
$\mathcal{N}_{21}$
Fill Holes
$\mathcal{N}_{31}$
Median Blur
$\mathcal{N}_{33}$
Mask
Threshold(4)
Mask
Original input image (cropped)