

# Scalable Strategies for Image Analysis in Neuroscience

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UNIVERSITY OF  
NOTRE DAME

# Remarkable recent advances in visual recognition

5 o Clock Shadow --  
Arched Eyebrows --  
Attractive --  
Bags Under Eyes --  
Bald --  
Bangs --  
Big Lips --  
Big Nose --  
Black Hair --  
Blond Hair --  
Blurry --  
Brown Hair --  
Bushy Eyebrows --  
Chubby --  
Double Chin --  
Eyeglasses --  
Goatee --  
Gray Hair --  
Heavy Makeup --  
High Cheekbones --  
Male --



Mouth Slightly Open --  
Mustache --  
Narrow Eyes --  
No Beard --  
Oval Face --  
Pale Skin --  
Pointy Nose --  
Receding Hairline --  
Rosy Cheeks --  
Sideburns --  
Smiling --  
Straight Hair --  
Wavy Hair --  
Wearing Earrings --  
Wearing Hat --  
Wearing Lipstick --  
Wearing Necklace --  
Wearing Necktie --  
Young --  
Dominance --  
Trustworthiness --

# Trouble...



I think it's a group of baseball players posing for a photo and they seem 😞😞.

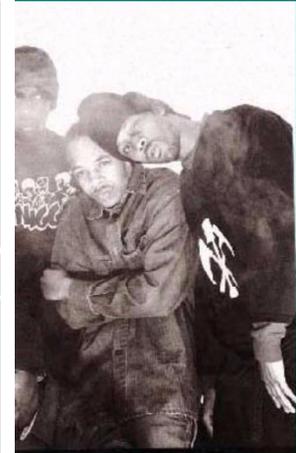
Sorry if we didn't quite get the age and gender right - we...

[Try Another Photo](#)

[Read the story behind this](#)

<https://how-old.net/>

robin	cheetah	armadillo	lesser panda
centipede	peacock	jackfruit	bubble
king penguin	starfish	baseball	electric guitar
freight car	remote control	peacock	African grey

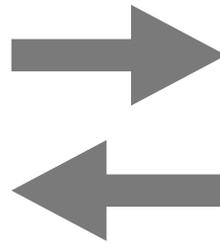


<https://www.captionbot.ai/>

## REVERSE

**Study**  
Natural System

Behavior, fMRI,  
2-photon Imaging,  
Confocal Microscopy,  
Electron Microscopy,  
Electrode Recordings



## FORWARD

**Build**  
Artificial System

Computer Vision  
Machine Learning

# Vision Systems that Work

## Rodents



(brain)

THIS

IS FOUND IN  
HERE



(*rattus norvegicus*)

# Vision Systems that Work: Models



# Neuroscience and Machine Learning Have a Common Problem:

Just because a system works doesn't mean we understand it.

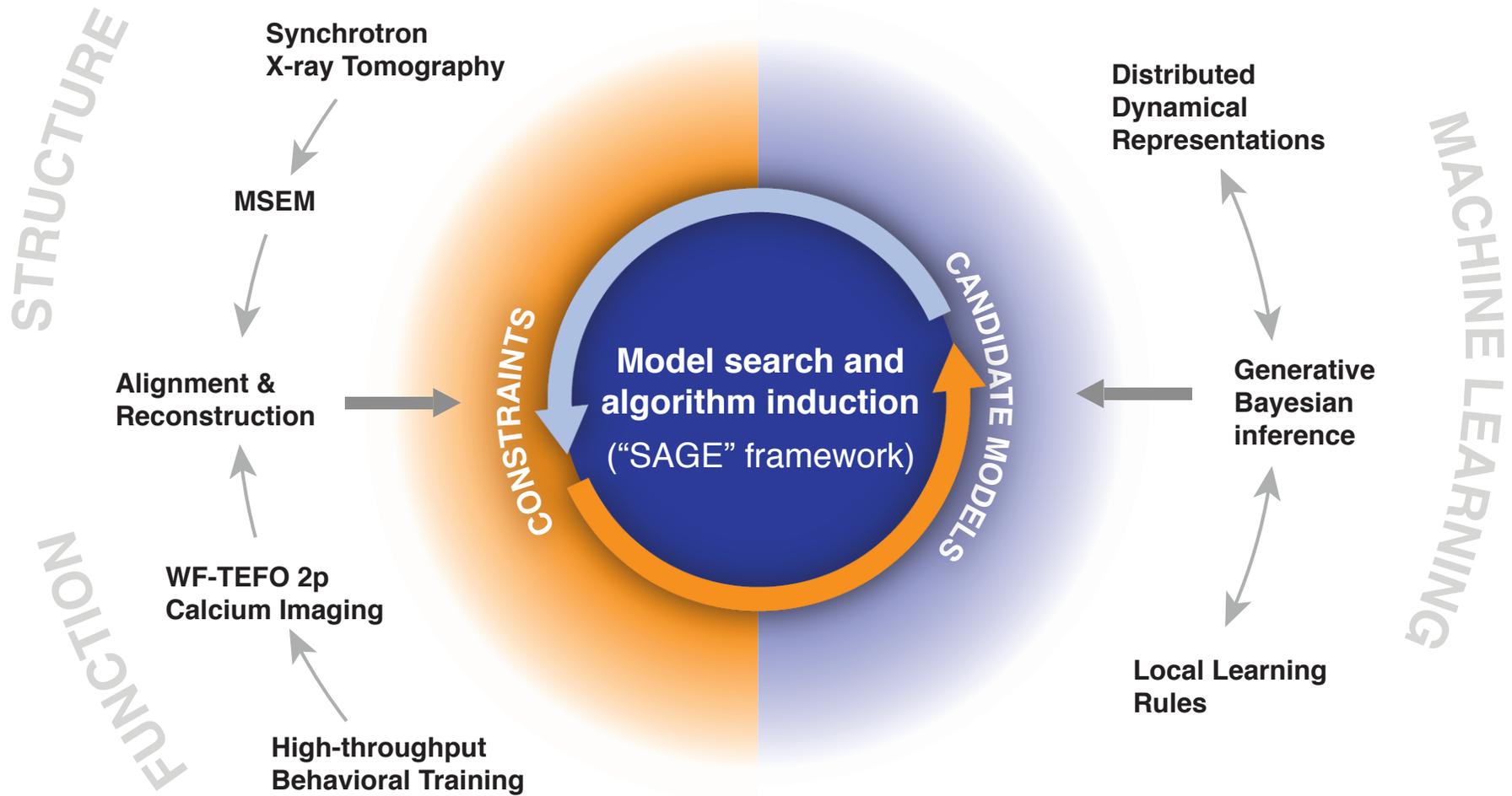
Even when we have considerable access to the system, it's not always easy to answer "why" questions

Maybe we can build tools that help address both issues and learn something in the process

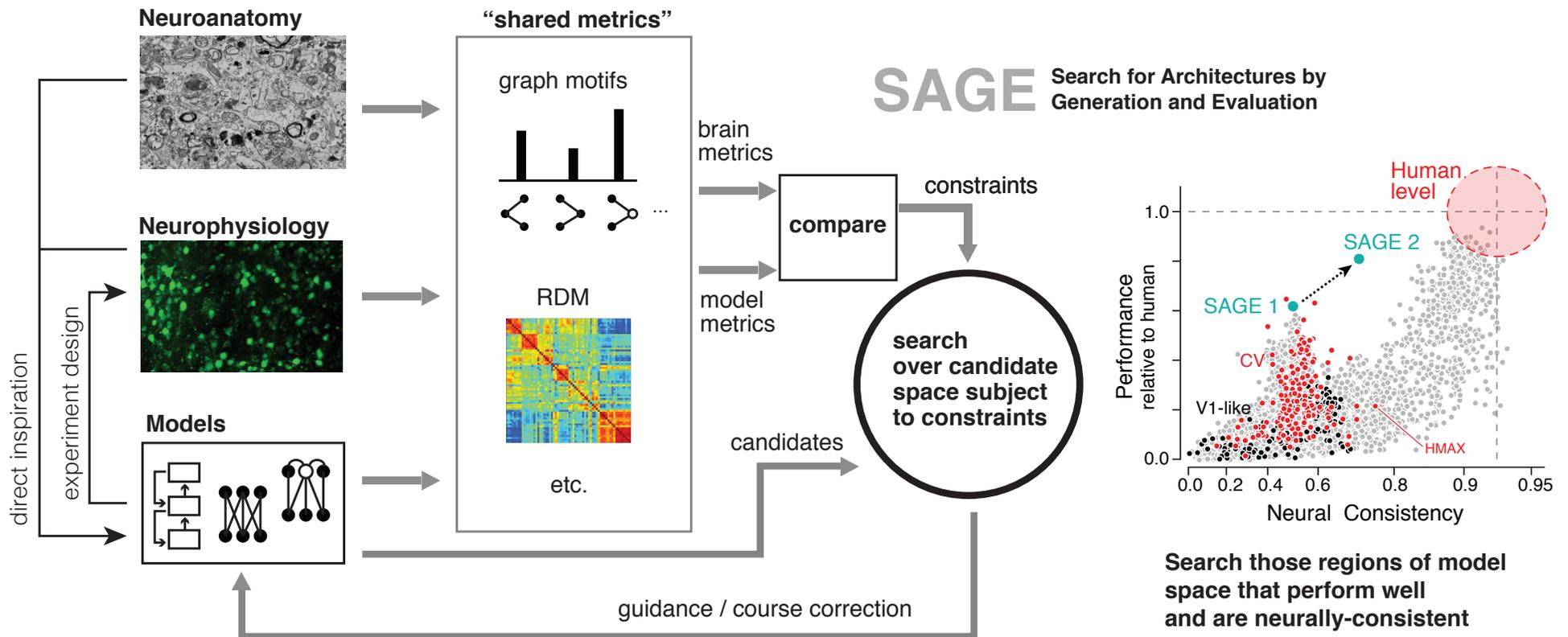


Brain Science at the Notre Dame  
Computer Vision Research Lab

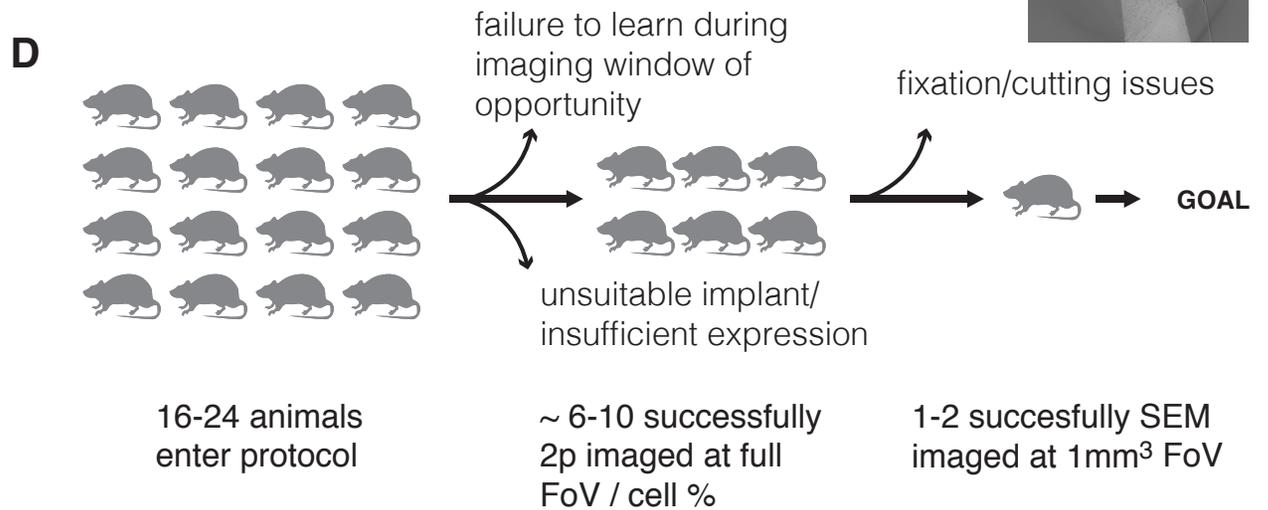
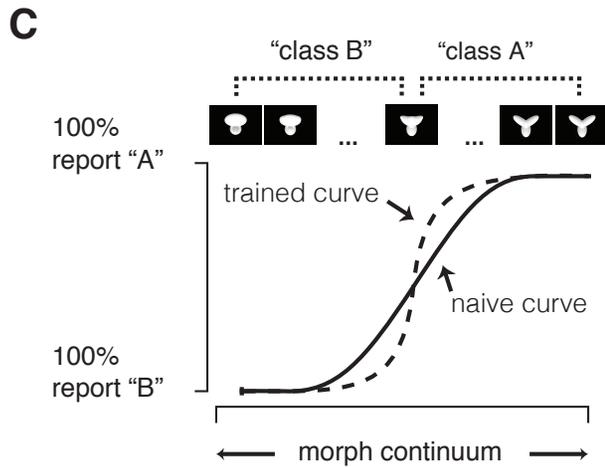
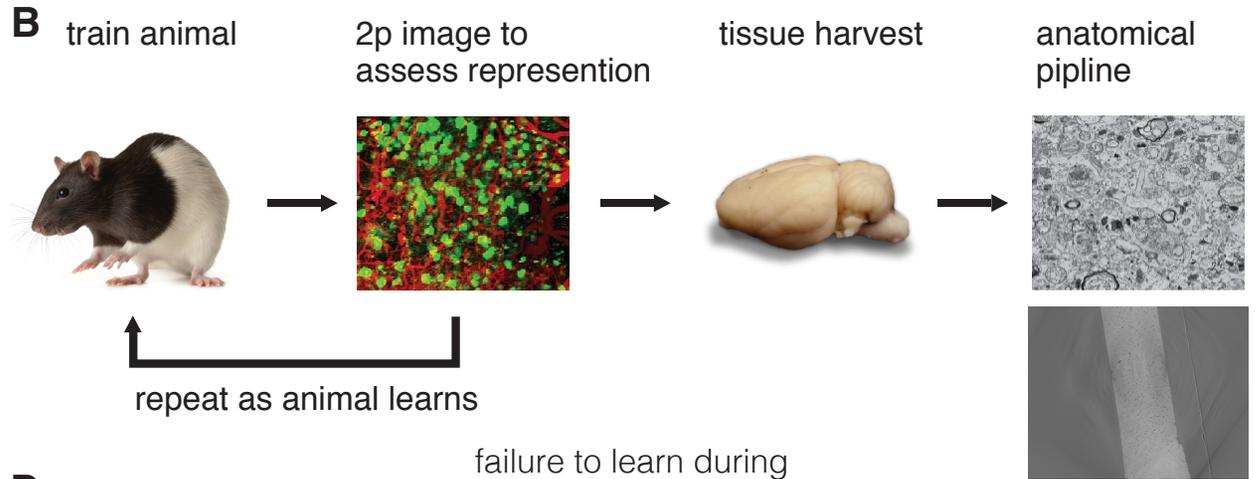
# IARPA MICrONS



# Machine Learning Algorithms from Wet Lab Experimentation



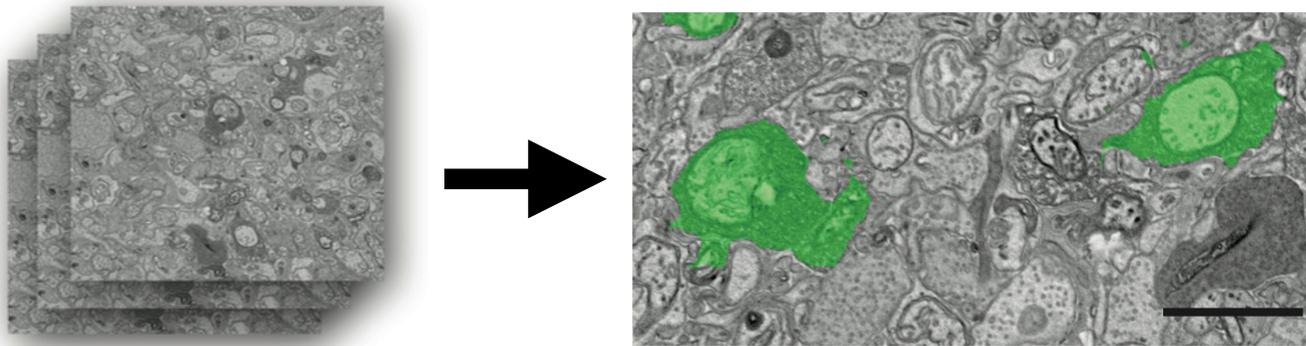
# Experimental workflow



# 2D Segmentation and 3D Reconstruction for EM



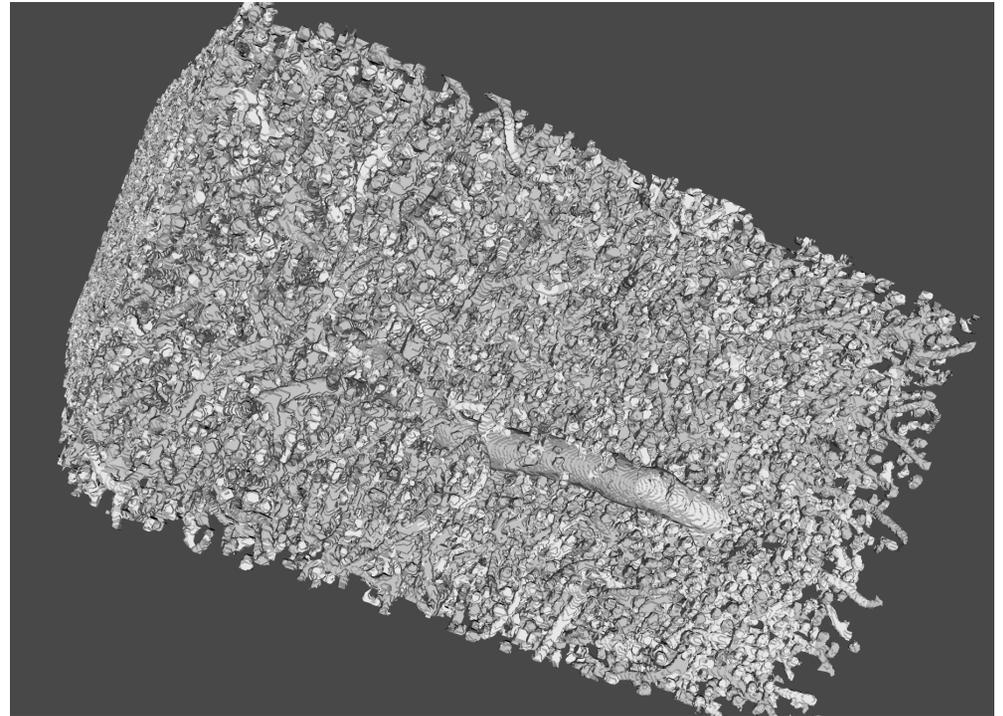
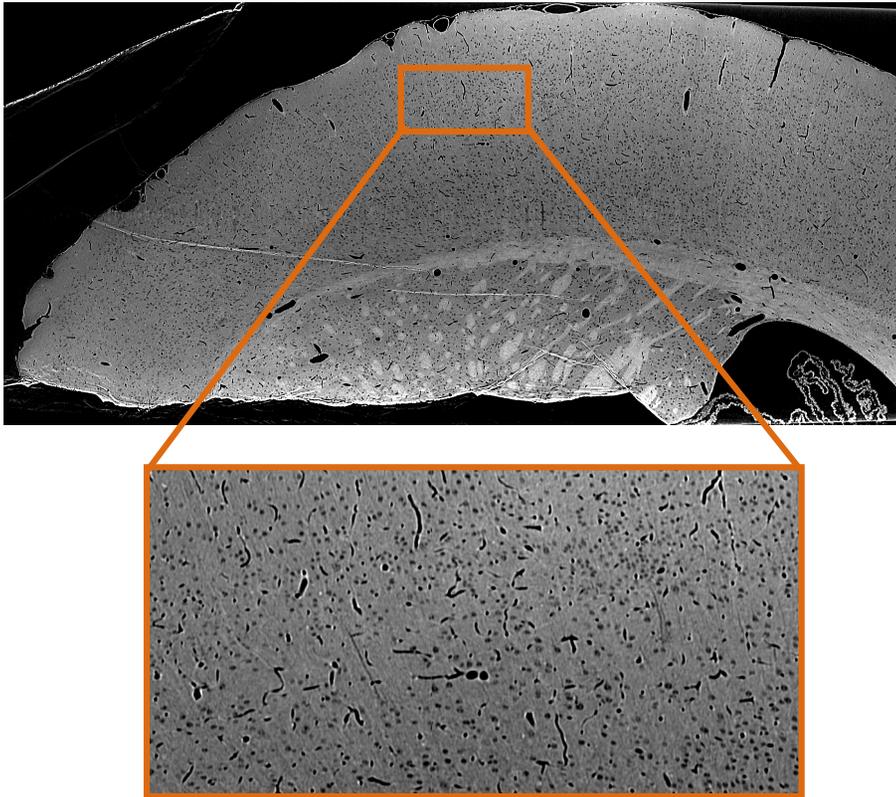
Elia Shabazi



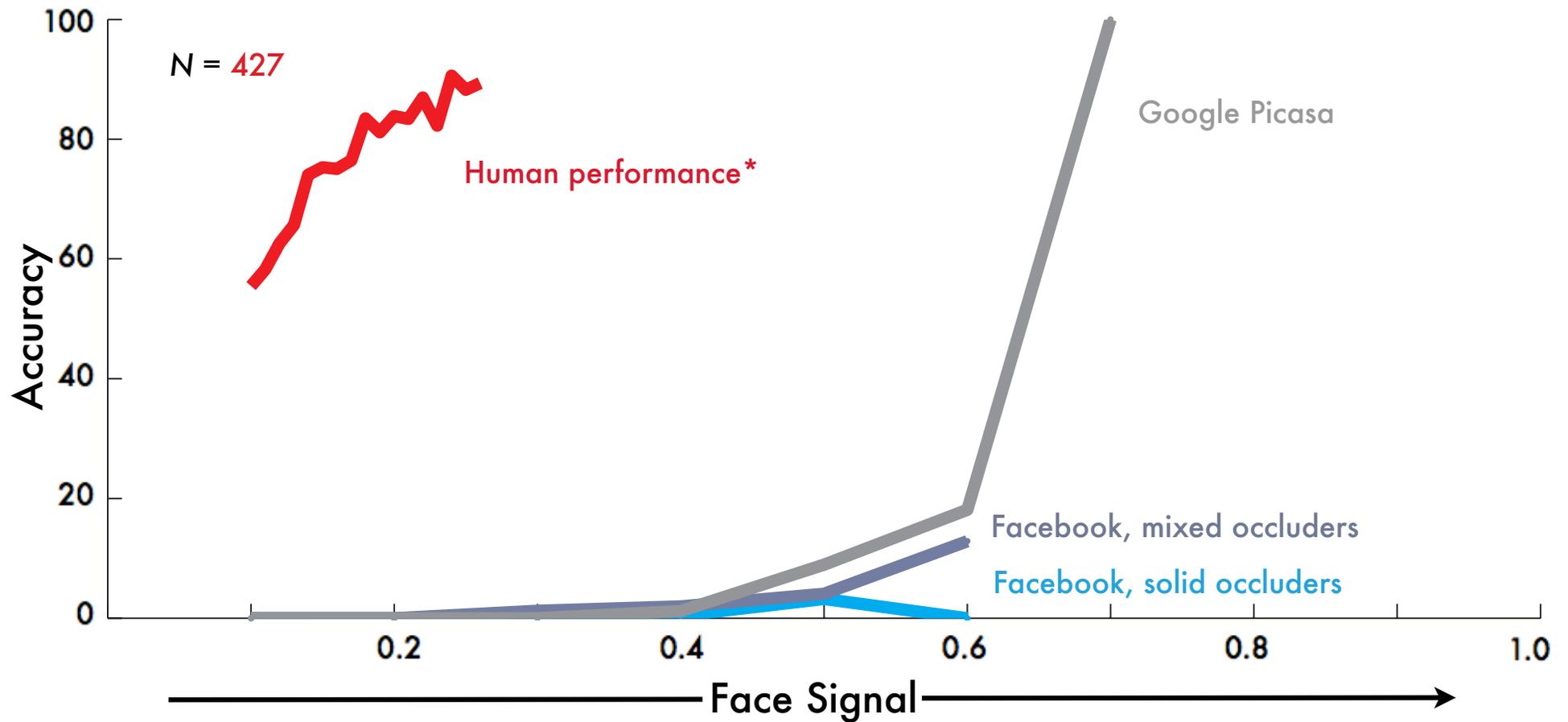
# 2D Segmentation and 3D Reconstruction for X-ray



Elia Shabazi



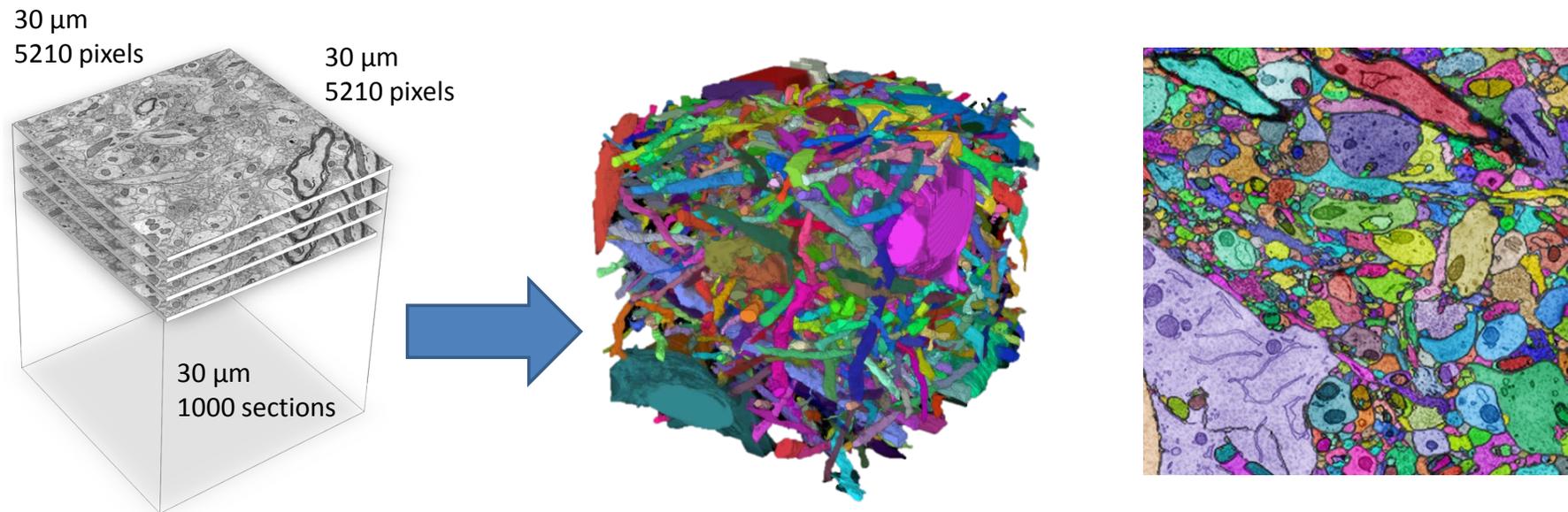
# Psychophysics on the Model



Brandon  
Richard Webster

# Strategies for Image Analysis

# Dense Segmentation and Reconstruction

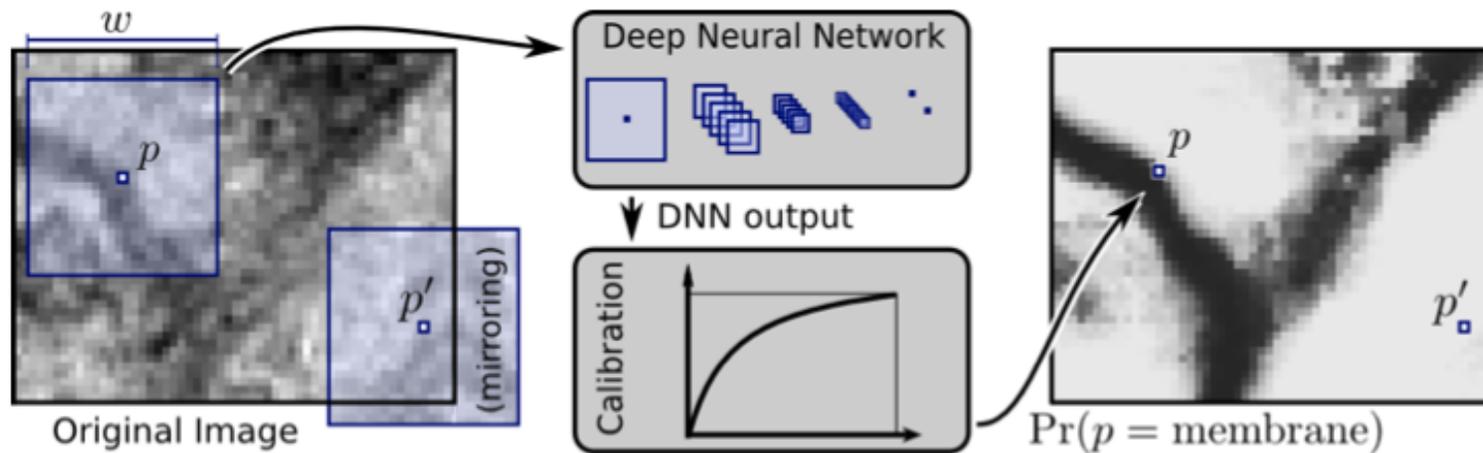


# Software tools for dense reconstruction

<b>Package</b>	<b>Method</b>	<b>Link</b>
Randomer Forests	Decision Forests	<a href="http://ttomita.github.io/RandomerForest">http://ttomita.github.io/RandomerForest</a>
Gala	Active Learning	<a href="https://github.com/janelia-flyem/gala">https://github.com/janelia-flyem/gala</a>
VESICLE	Deep Learning	<a href="http://openconnecto.me/vesicle">http://openconnecto.me/vesicle</a>
Synapse Segmenter	Context Features + Adaboost	<a href="http://cvlab.epfl.ch/software/synapse">http://cvlab.epfl.ch/software/synapse</a>
ATMA	3D Pixel Features + Random Forests	<a href="https://github.com/RWalecki/ATMA">https://github.com/RWalecki/ATMA</a>
ZNN	CNN	<a href="https://github.com/seung-lab/znn-release">https://github.com/seung-lab/znn-release</a>
PRIM	CRF	<a href="http://github.com/funkey/prim">http://github.com/funkey/prim</a>
ilastik	Random Forests	<a href="http://ilastik.org/">http://ilastik.org/</a>
Rhoana	CNN	<a href="https://github.com/Rhoana">https://github.com/Rhoana</a>

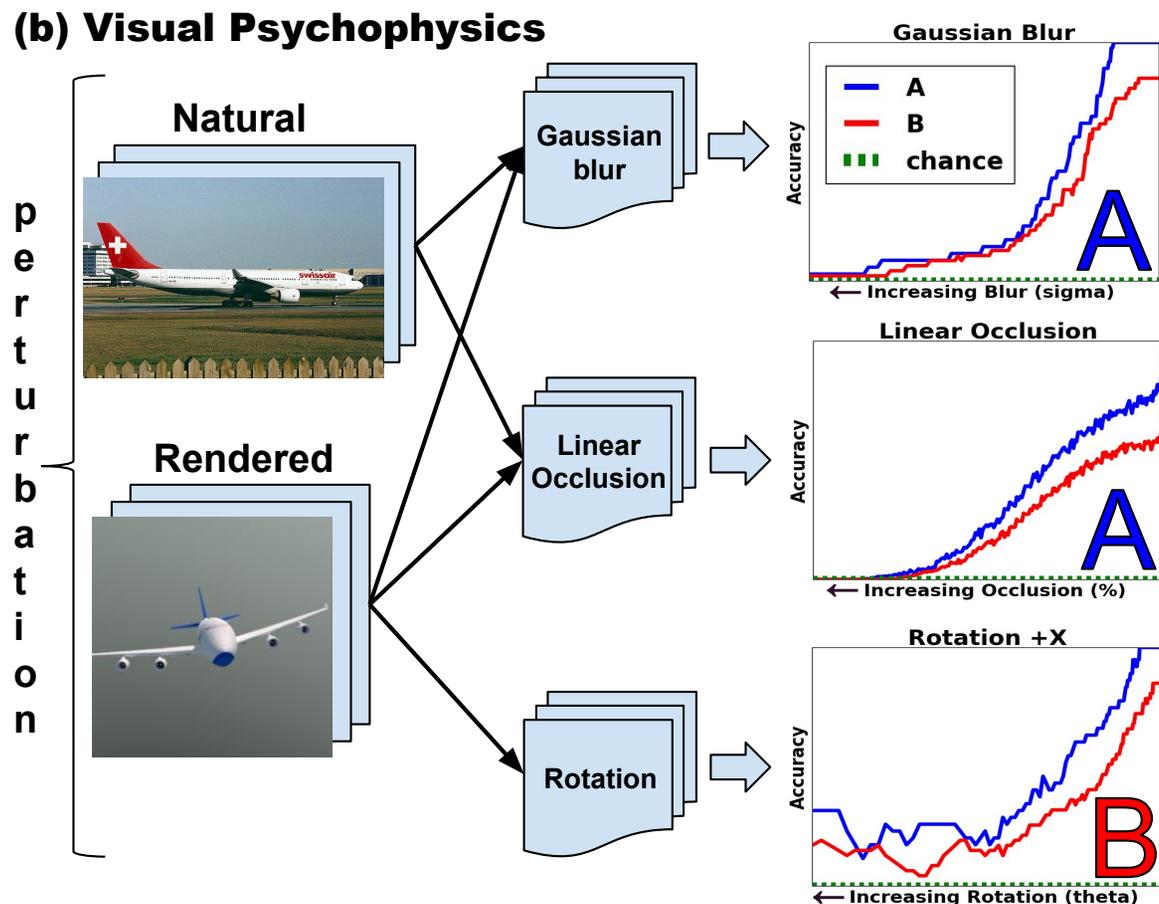
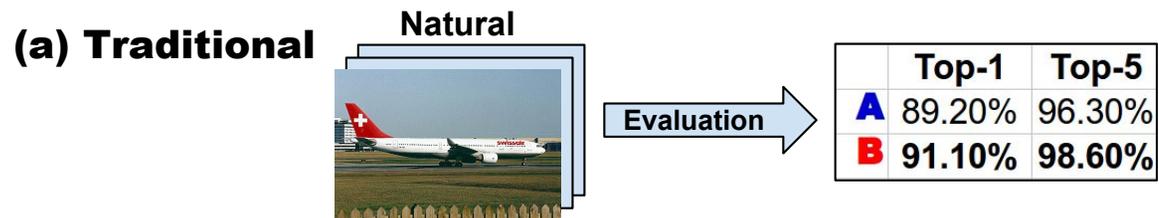
# Preeminent 2D segmentation method: CNN

Feature learning for strongly invariant membrane representations

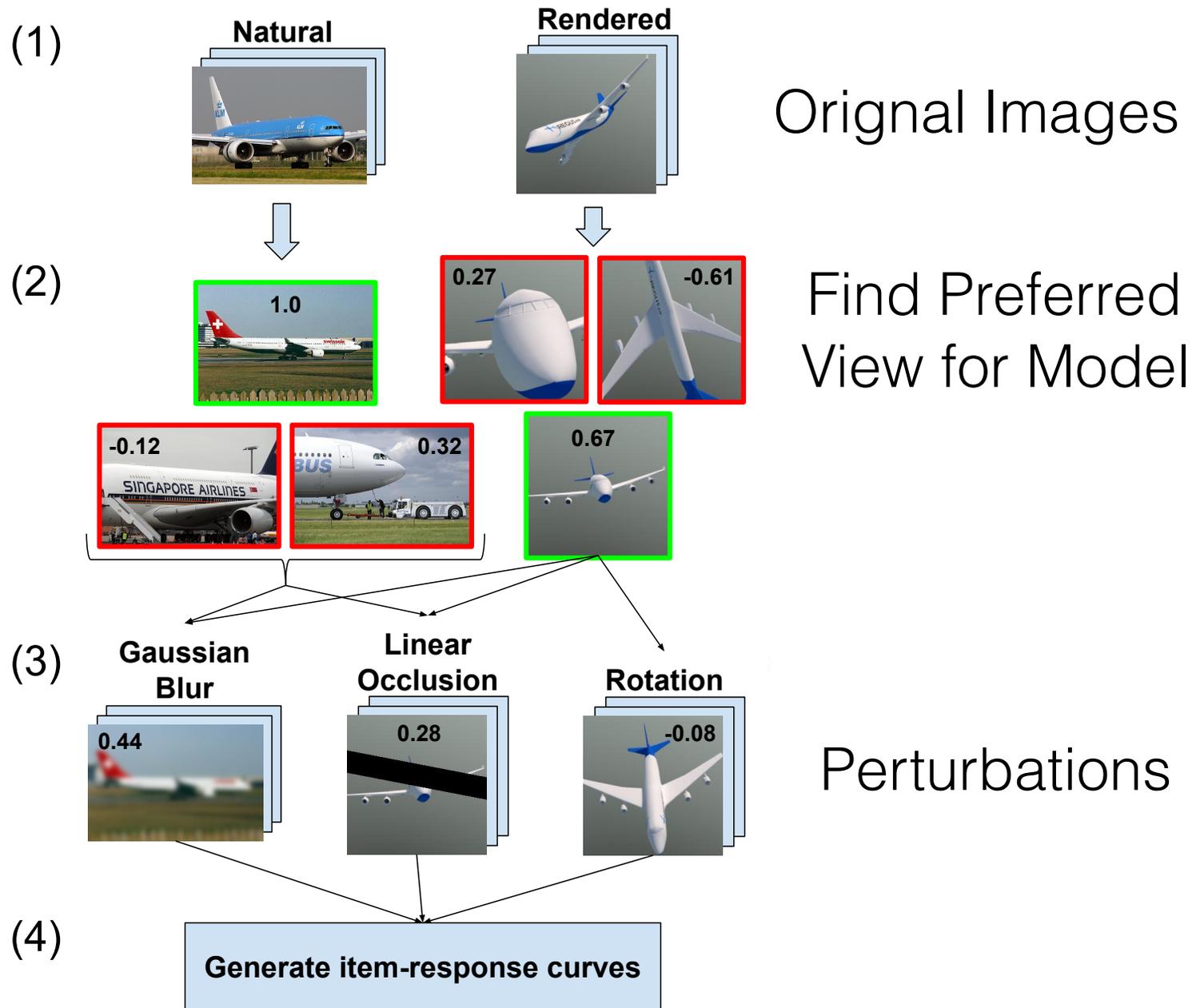


Interlude: is deep learning as  
good as we think it is?

# An alternative to dataset testing



# The framework



# You don't have to use tricky manipulations

## GoogleNet Output

Label: Hammerhead  
Shark



Label: Blow Dryer



Label: Mosque



Label: Syringe



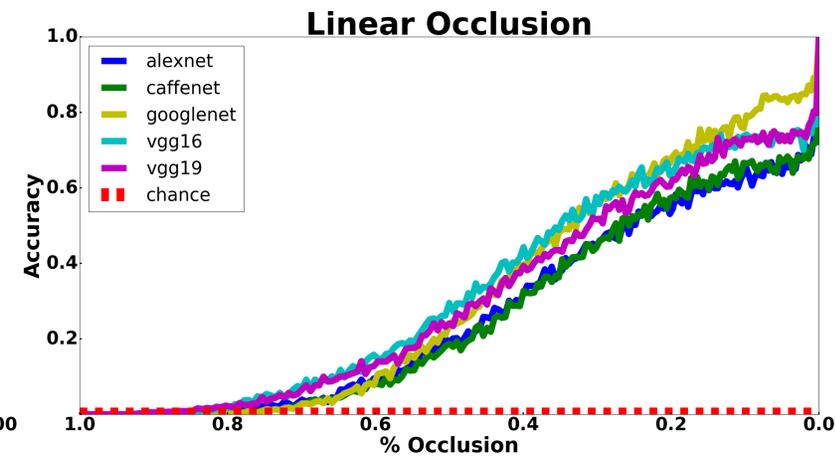
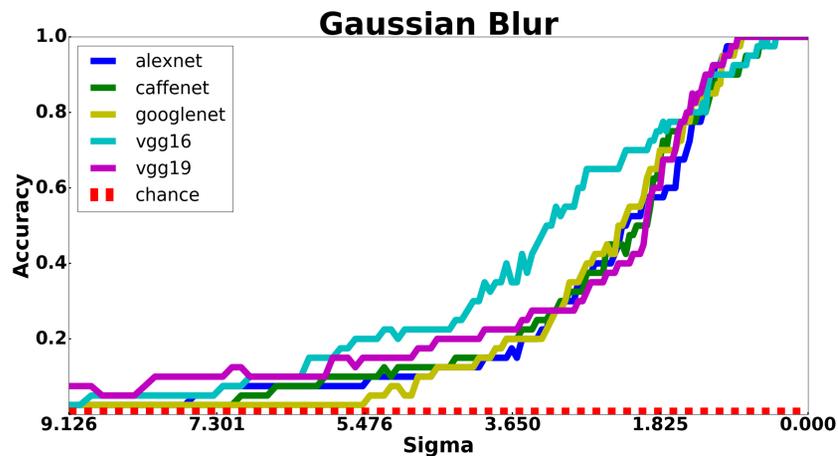
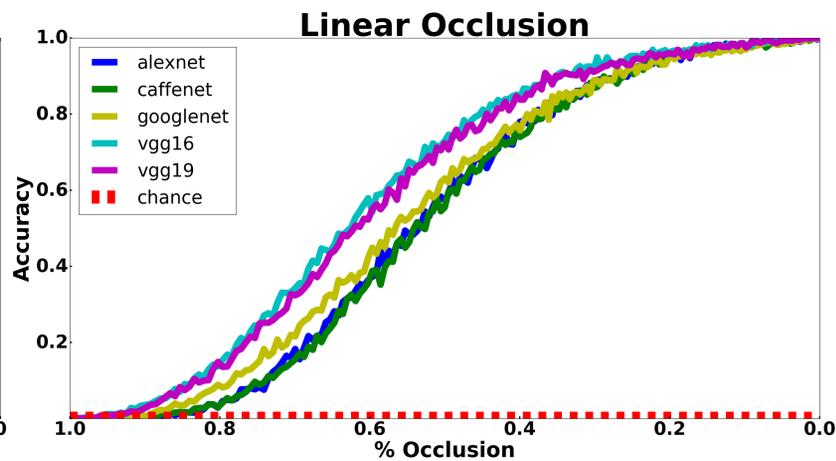
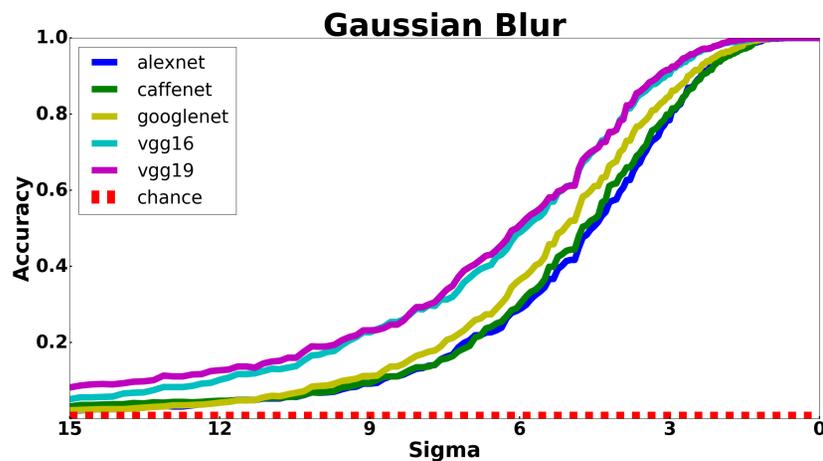
Label: Trimaran



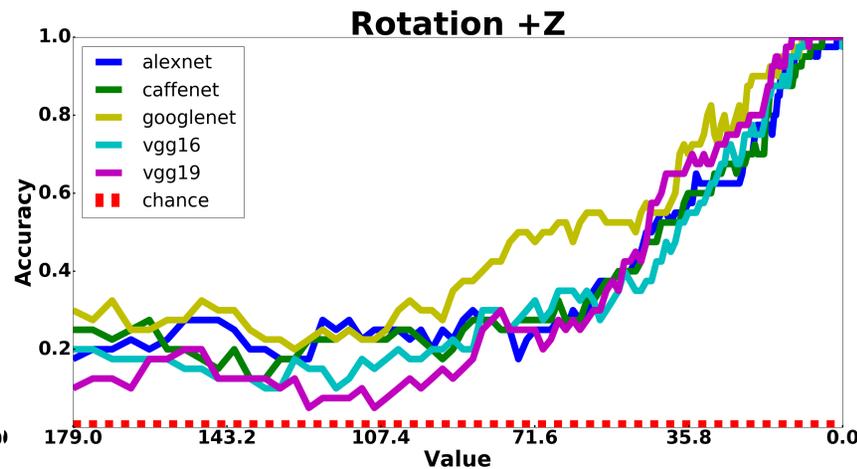
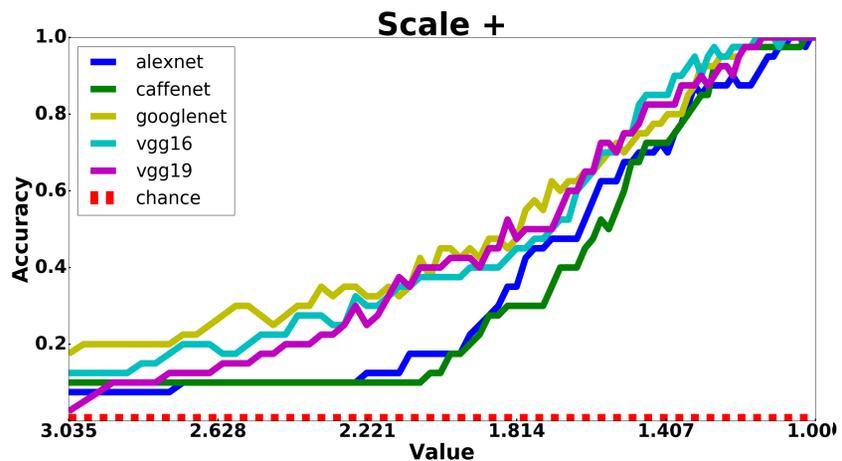
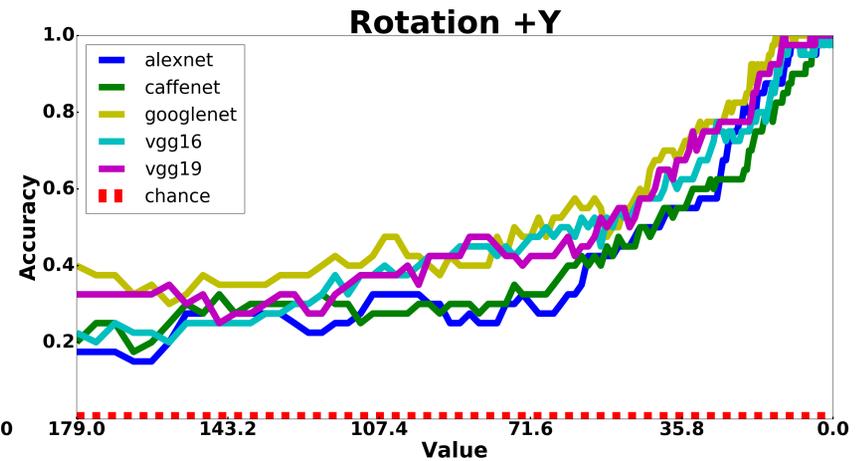
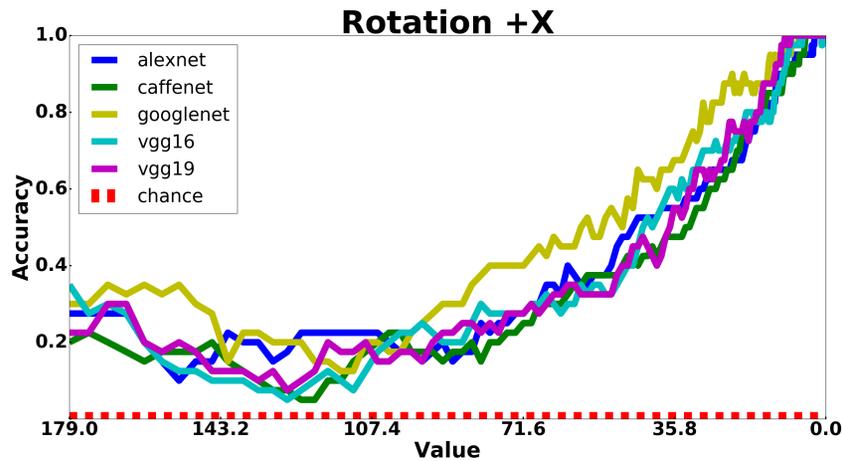
Label: Missile



# Same transformation across 2D and 3D objects



# Various transformations across 3D objects



Back to image analysis...

# Error rates (MICrONS targets)

**100 x 100 x 100  $\mu\text{m}^3$**

Precision:  $\geq 70\%$

Recall:  $\geq 70\%$

NID:  $\leq 0.95$  @ 50th pctl.

$\leq 0.50$  @ 75th pctl.

$\leq 0.20$  @ 95th pctl.

VI  $\leq 1.75$  nats

**1mm x 1mm x 0.1mm**

Precision:  $\geq 85\%$

Recall:  $\geq 85\%$

NID:  $\leq 0.95$  @ 15th pctl.

$\leq 0.35$  @ 50th pctl.

$\leq 0.15$  @ 85th pctl.

VI  $\leq 1.0$  nats

**1mm x 1mm x 1mm**

Precision:  $\geq 97.5\%$

Recall:  $\geq 97.5\%$

NID:  $\leq 0.80$  @ 10th pctl.

$\leq 0.15$  @ 50th pctl.

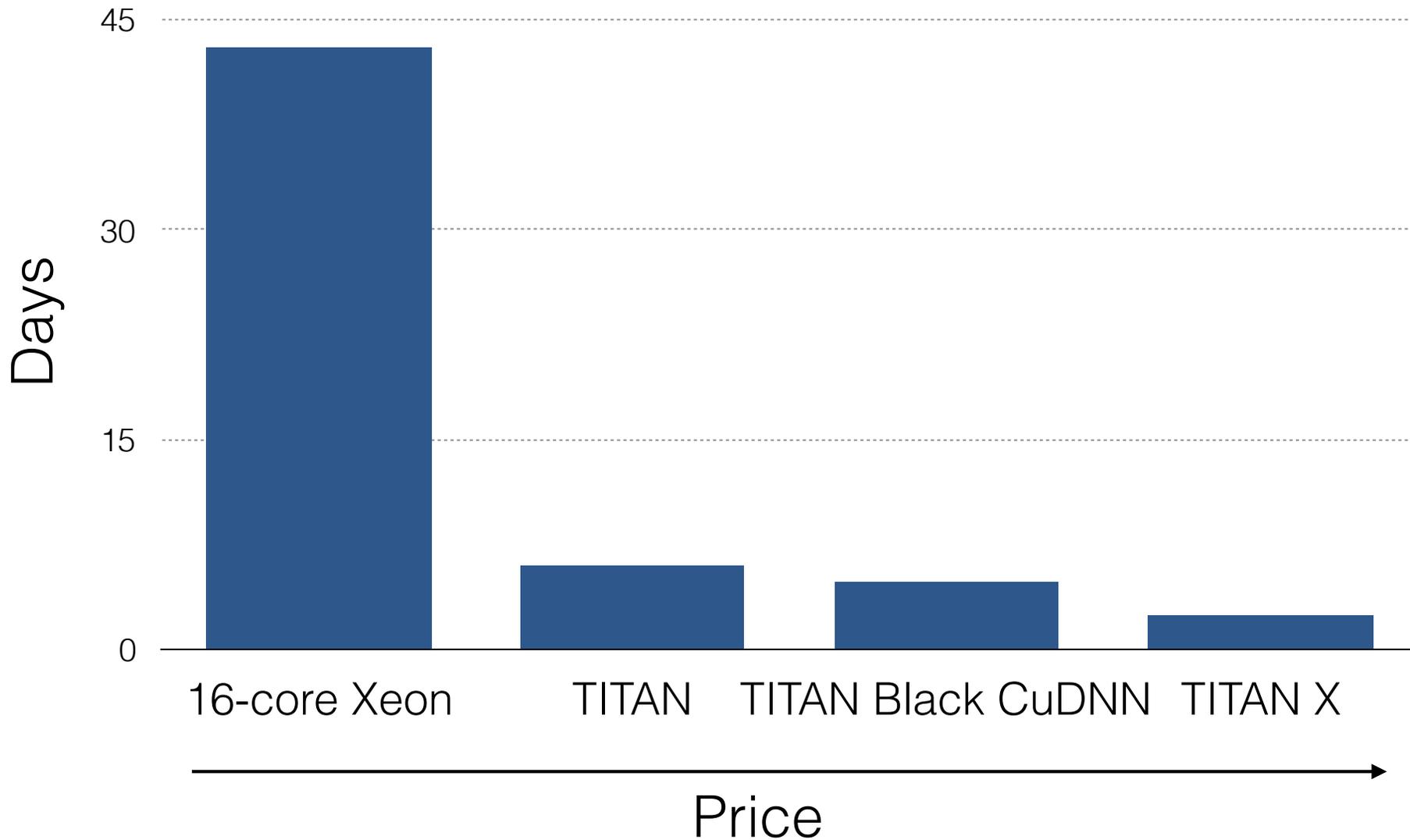
$\leq 0.05$  @ 75th pctl.

VI  $\leq 0.25$  nats

Think about error propagation for even the best of these numbers...

# Training Time

AlexNet:

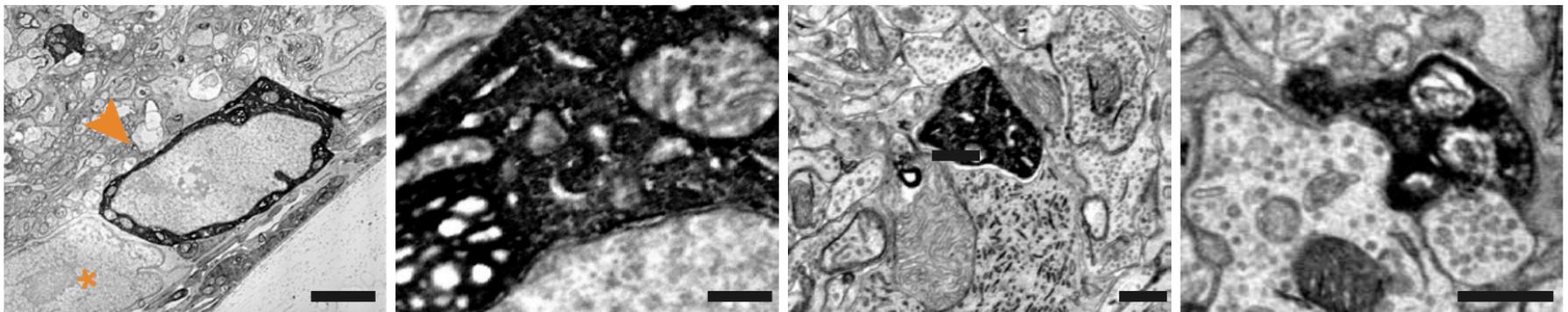


# Rethinking the problem

- Make samples better with high-contrast tissue prep.
- Sparse reconstruction vs. dense reconstruction
- Avoid overfitting with unsupervised methods
- Cell-specific reconstruction strategies
- Solve this problem more like people do

# Assisted Reconstruction Technique for Electron Microscopic Interrogation of Structure (ARTEMIS)

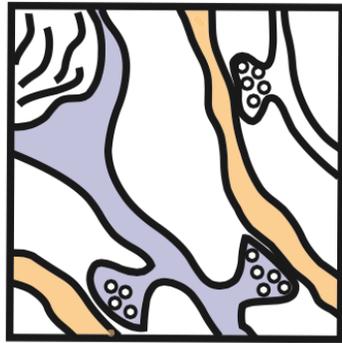
- (a) tagging a genetically identified cell with an electron-dense tracer
- (b) enhancing the electron-dense staining of these tracers
- (c) imaging the cell rapidly at relatively low resolution
- (d) re-imaging small volumes at higher resolution to map connectivity



M. Joesch, D. Mankus, M. Yamagata, A. Shahbazi, R. Schalek, A. Peleg, M. Meister, J. W. Lichtman, W. J. Scheirer, J. R. Sanes, "Reconstruction of Genetically Identified Neurons Imaged by Serial-Section Electron Microscopy," *eLife*, Vol. 5, e15015 2016

# ARTEMIS Staining Strategy

Proxidase  
Expressing  
Cell



DAB  
 $H_2O_2$

→

Light  
Microscope

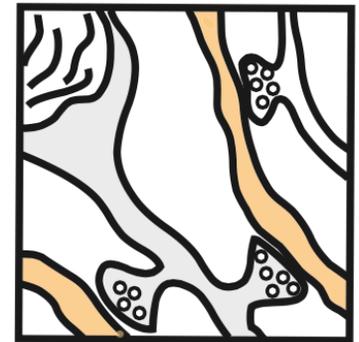


DAB  
reaction

standard

→

Electron  
Microscope



reduction

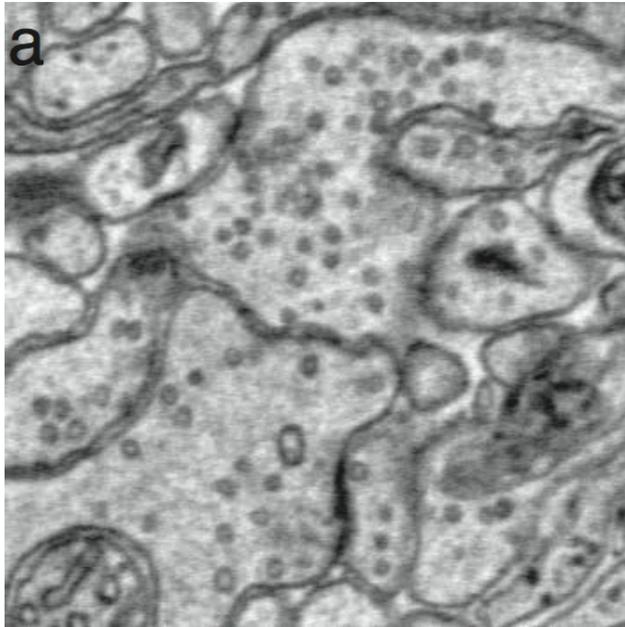
→

EM  
staining

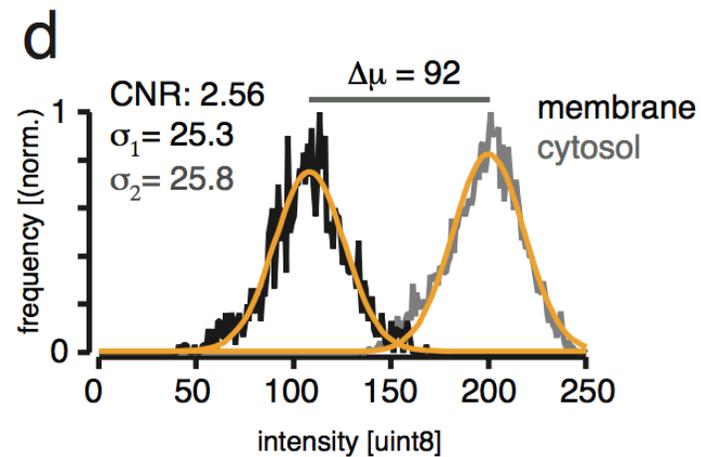
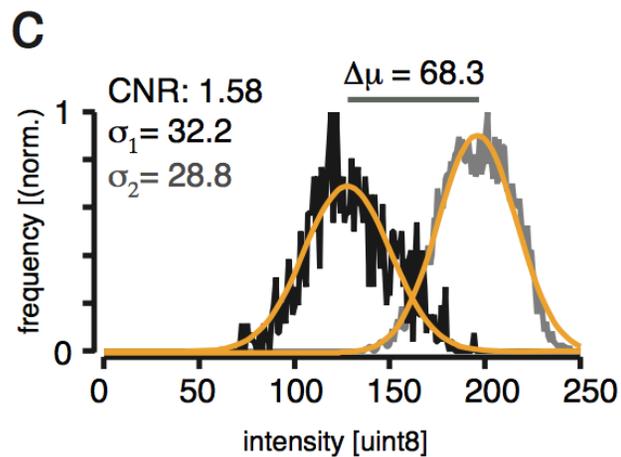
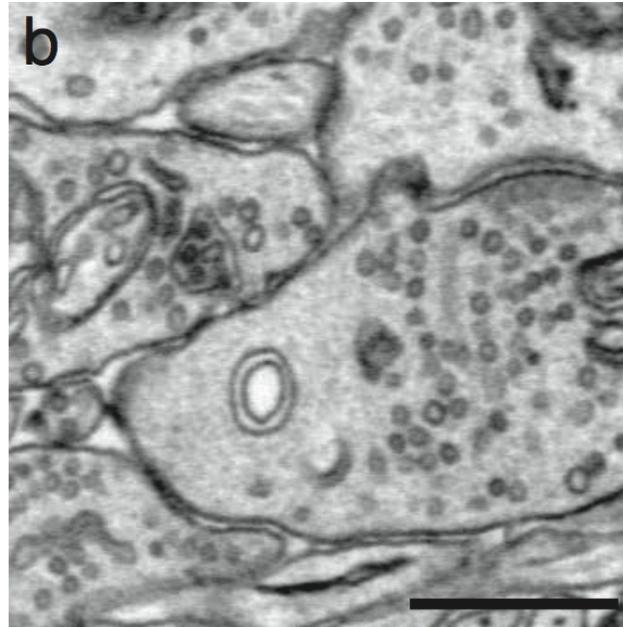


# Improved contrast to noise ratio

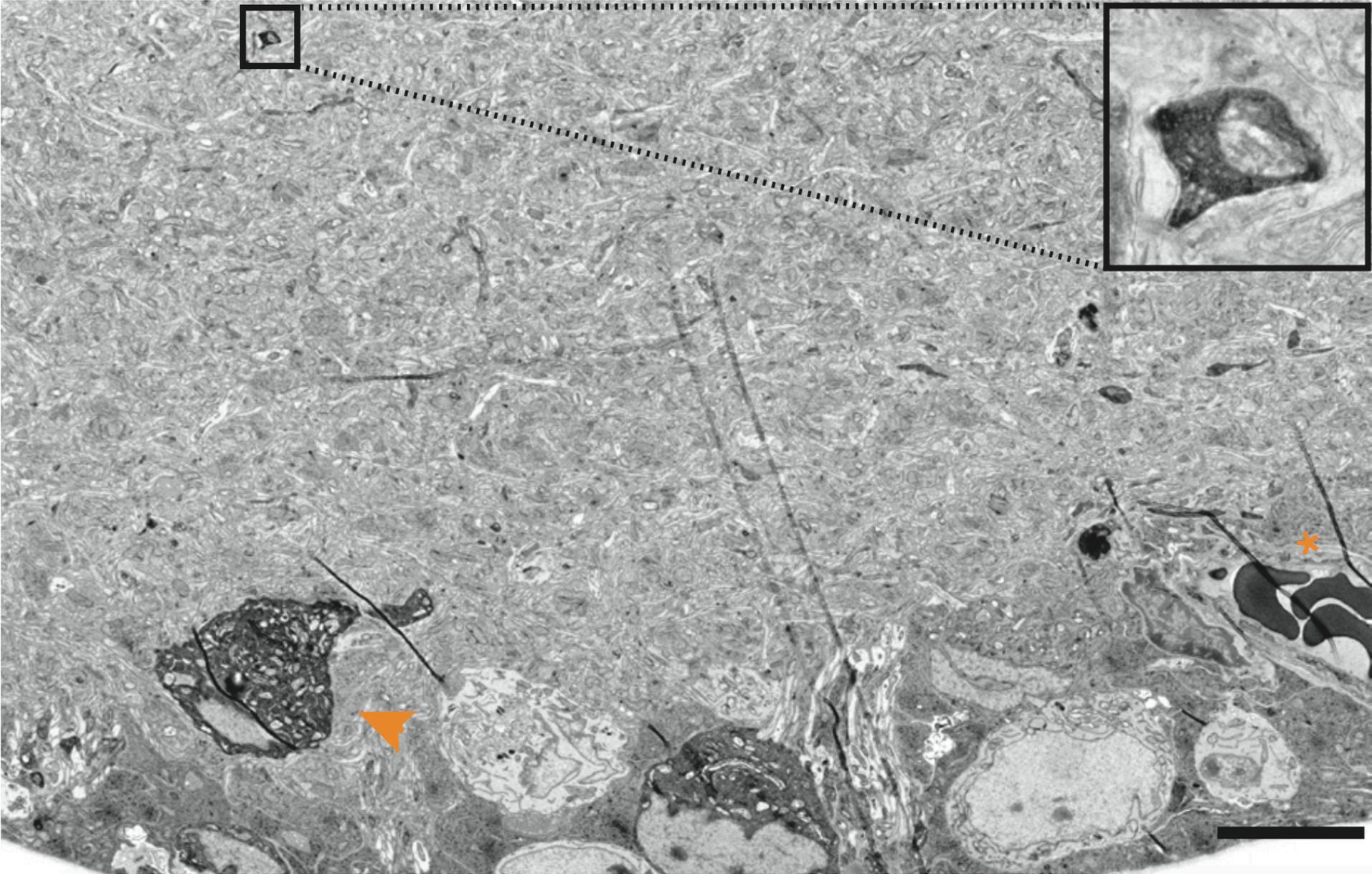
standard



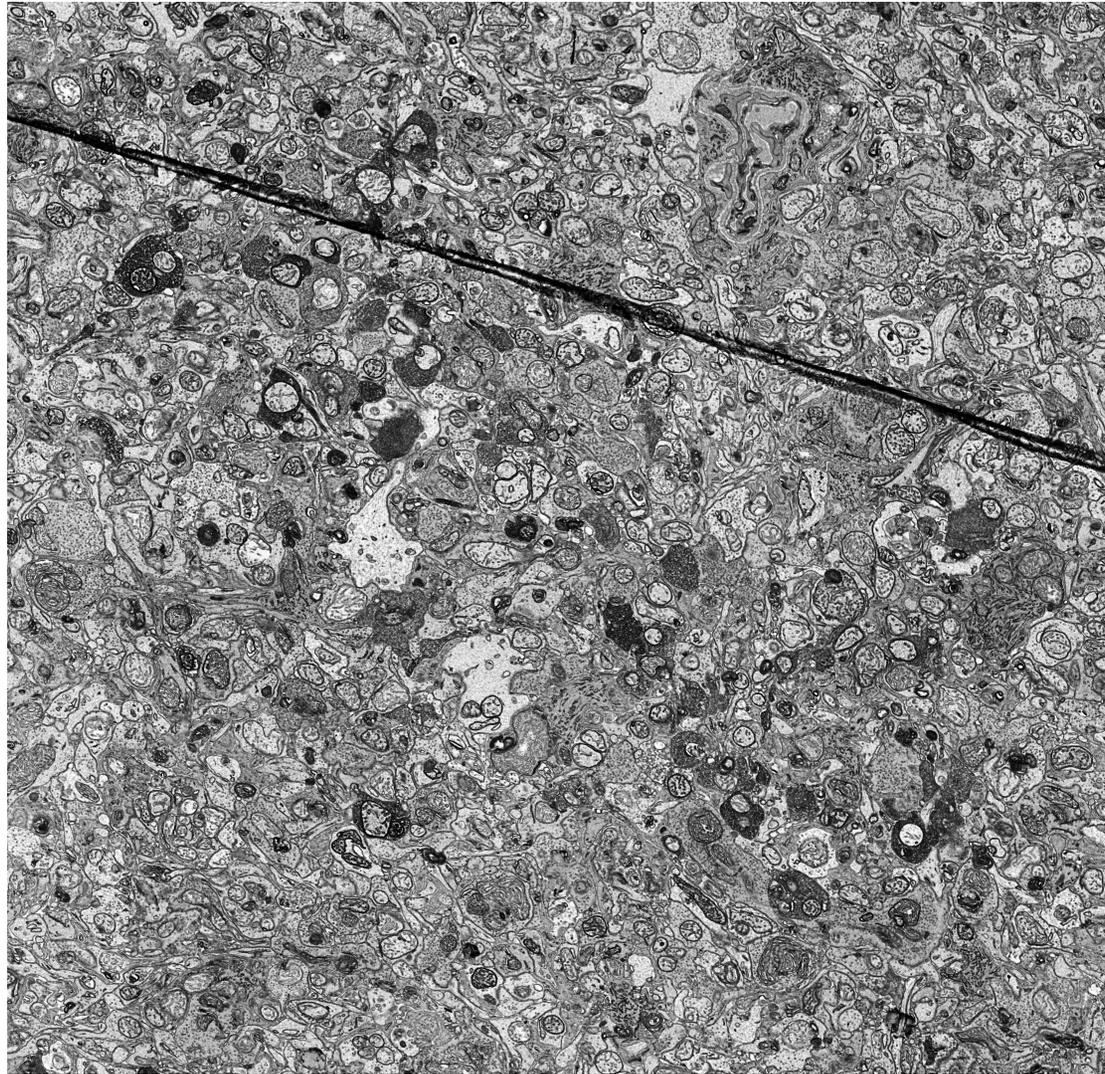
reduced



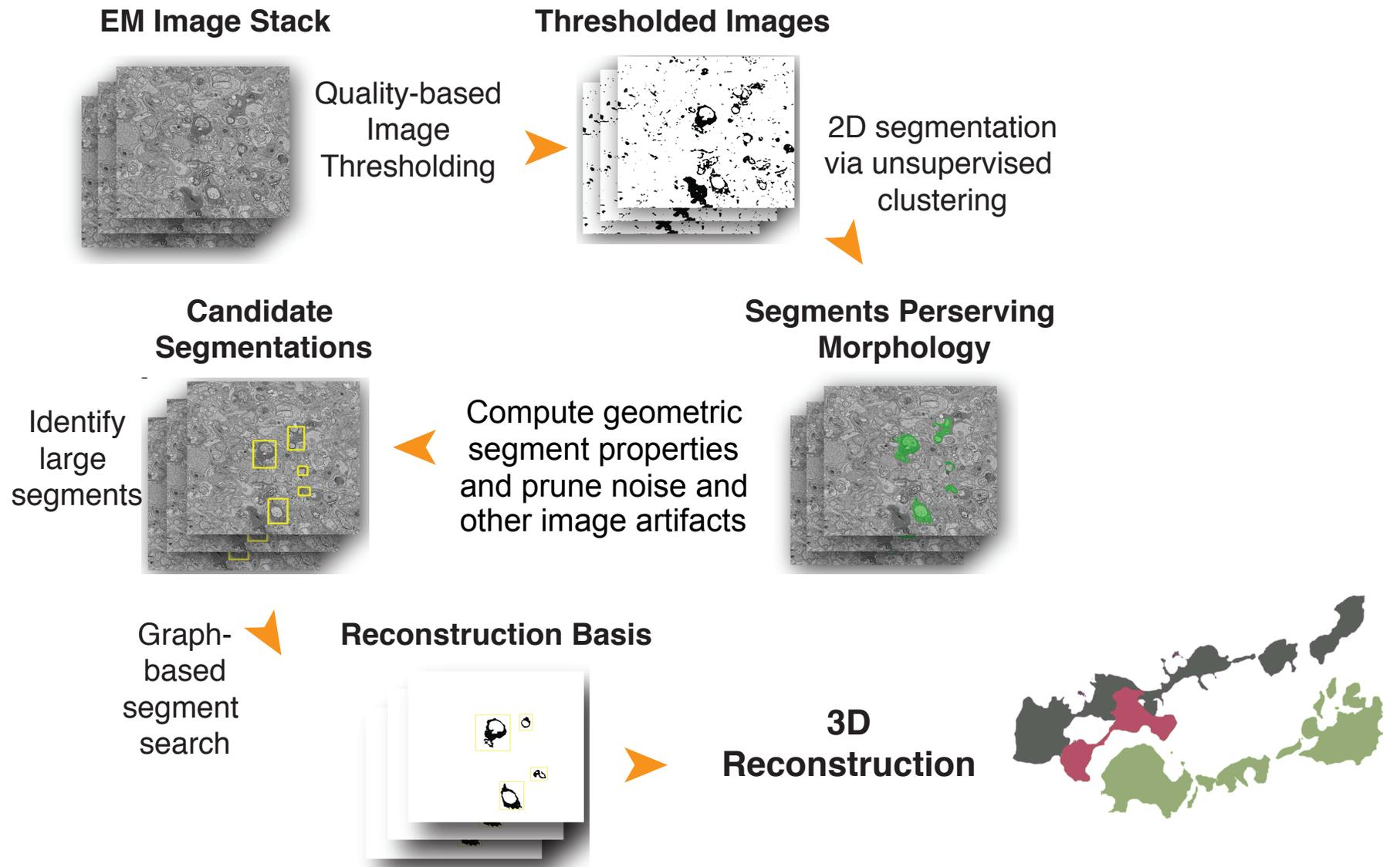
# Cytosolic Apex (enhanced tissue)



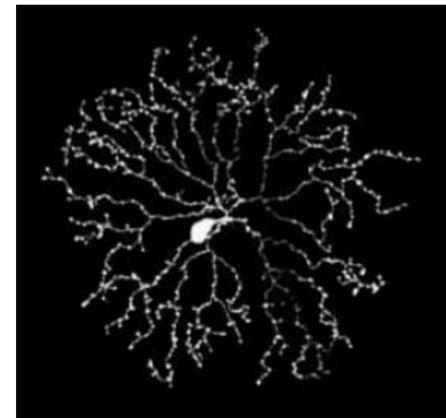
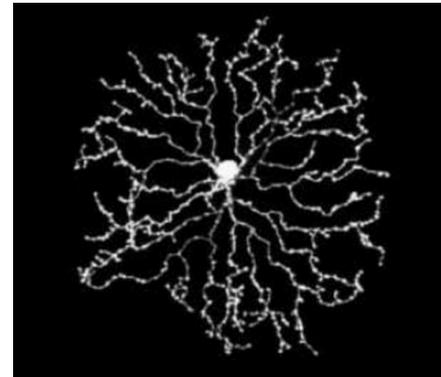
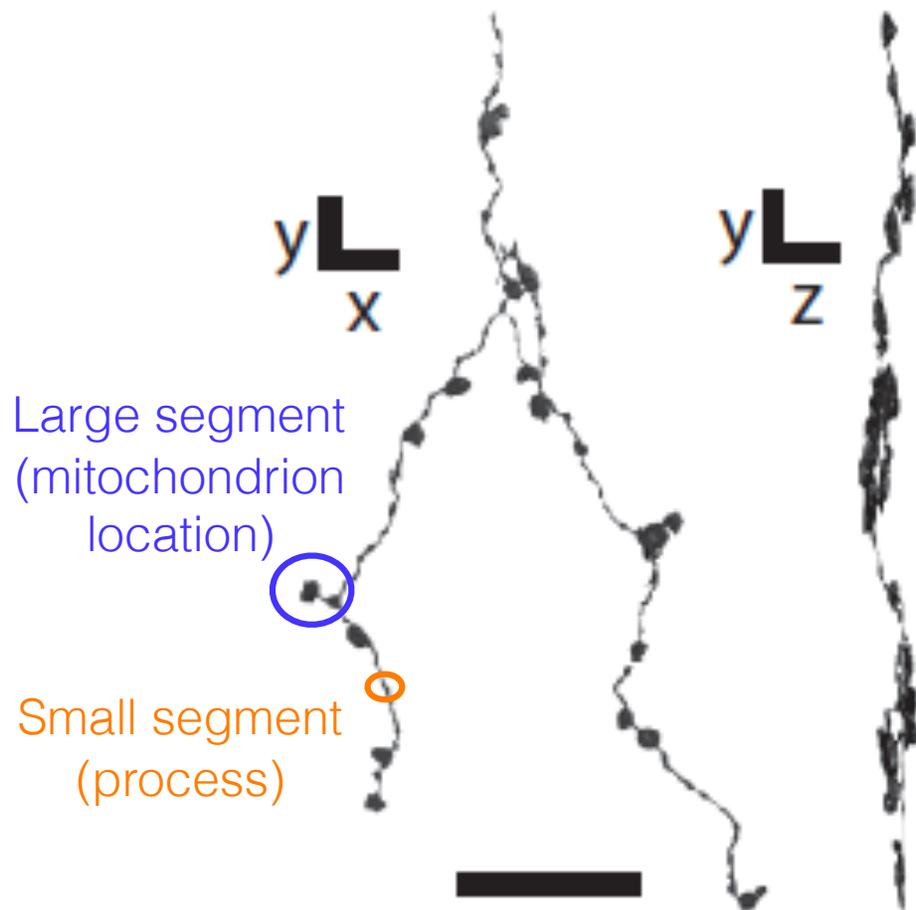
4nm/pixel, detail from 680 $\mu$  x 680 $\mu$   
section



# Learning-free 2D segmentation and 3D reconstruction



# Starburst Amacrine Cell



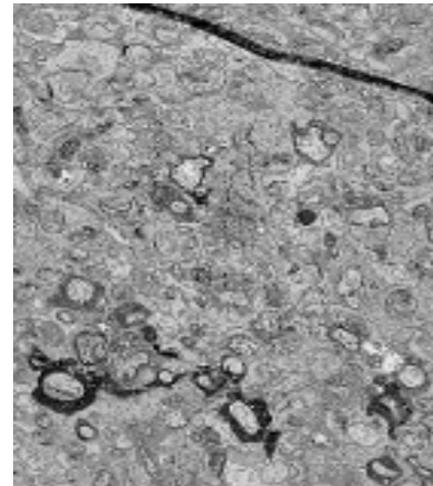
Keeley et al. J. Comp. Neurol. 2007

# Step 1: Pre-processing

Original EM images are of very high resolution (100000 x 50000 pixels)

Process local neighborhoods in 2048 x 2048 tiles

Each tile can be processed separately for 2D segmentation



# Step 2: Adaptive Thresholding on Local Intensity

## Key step enabled by ARTEMIS

Apply a Wiener filter, modulating via known pixel ranges of ARTEMIS markers:



$$\beta(n_1, n_2) = \mu + \frac{\sigma^2 - \nu^2}{\sigma^2} \times (a(n_1, n_2) - \mu)$$

Diagram illustrating the Wiener filter equation with labels:

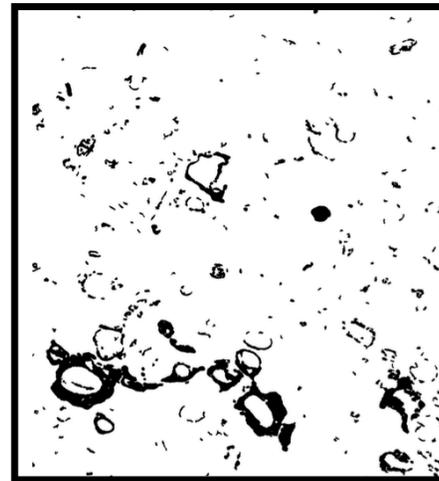
- noise variance (pointing to  $\nu^2$ )
- pixel (pointing to  $a(n_1, n_2)$ )
- pixel mean (pointing to  $\mu$ )
- pixel variance (pointing to  $\sigma^2$ )

# Step 3: Cluster-based Image Segmentation

Choose threshold to minimize the intraclass variance of the black and white pixels

Prune non-ARTEMIS marked segments:  $3 \times n$  matrix to calculate weights based on local pixel neighborhoods

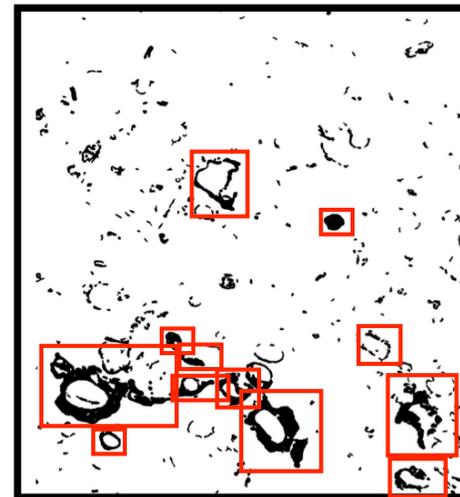
Remove Artifacts



# Step 4: Assess morphology

Catalog the properties of each segment:

- Centroid
- Convex Area
- Area
- Bounding Box
- Extent
- Solidity
- Extrema
- Major Axis Length
- Minor Axis Length
- Equiv. Diameter
- Eccentricity



# Step 5: Database assessment

Analysis moves to abstract representations stored in a MySQL database

Rapid search for large and small segments repeated across layers

storename: 1,659,974 rows total (Approximately), limited to 1,000

id	Layer	gArea	Cent_1	Cent_2	Bbx	Bby	BB	BBB	MagA	MagB	Eccent	ConvArea	ex1	ex2	ex3	ex4	ex5	ex6	ex7	ex8	ex9	ex10
1	207	61	4.21111475409636	4.21111475409636	0.5	0.5	12	12	14.3900344799615	7.42295669191576	0.847236922278112	0.13470513837927	29	0.5	12.5	12.5	1.5	0.5	0.5	0.5	0.5	0.5
2	207	24			0.5	0.5	1	24	27.712812921102	1.13470513837927	0.999111567596817	29	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5	0.5
3	207	140	3.12837637637638	440.155405405405	0.5	0.5	6	33	30.4733727106005	6.79314871891164	0.974836558382174	155	0.5	1.5	6.5	6.5	1.5	0.5	0.5	0.5	0.5	0.5
4	207	750	6.96666666666667	506.796	0.5	0.5	20	86	87.7922813016905	20.1282112999624	0.95486037502018	960	0.5	1.5	20.5	20.5	1.5	0.5	0.5	0.5	0.5	0.5
5	207	73	1.87671222676112	194.689630139186	0.5	0.5	3	29	29.089340837198	3.4381318989661	0.992981296254988	77	0.5	1.5	3.5	3.5	1.5	0.5	0.5	0.5	0.5	0.5
6	207	681	2.5345080761583	707.60792915949	0.5	0.5	6	201	199.911899532927	5.94897695139102	0.999613110620117	901	0.5	1.5	6.5	6.5	1.5	0.5	0.5	0.5	0.5	0.5
7	207	146	2.93839616438396	845.575342465753	0.5	0.5	7	39	33.6680590917887	7.07625879253889	0.977683625091435	176	0.5	1.5	7.5	7.5	1.5	0.5	0.5	0.5	0.5	0.5
8	207	30		886.5	0.5	0.5	1	30	34.641016113775	1.13470513837927	0.99944290037863	30	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5	0.5
9	207	30		1.074.5	0.5	0.5	1	30	34.641016113775	1.13470513837927	0.99944290037863	30	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5	0.5
10	207	409	2.38630806845966	1.10163080684597	0.5	0.5	7	140	36.108790229449	5.4390526120781	0.99939141227616	247	0.5	1.5	7.5	7.5	1.5	0.5	0.5	0.5	0.5	0.5
11	207	238	3.67226890756303	1.209.747891159566	0.5	0.5	10	47	41.5489842101644	9.2247853890946	0.97937911593431	277	0.5	1.5	10.5	10.5	1.5	0.5	0.5	0.5	0.5	0.5
12	207	129	2.798496142311	1.277.3488372095	0.5	0.5	4	35	30.647253182796	6.30762802156757	0.978991297414347	145	0.5	1.5	6.5	6.5	1.5	0.5	0.5	0.5	0.5	0.5
13	207	90	2.06666666666667	1.108.5444444444	0.5	0.5	4	34	31.5706483362757	4.2208620818123	0.99100094051246	103	0.5	1.5	4.5	4.5	1.5	0.5	0.5	0.5	0.5	0.5
14	207	113	1.36283185040708	1.386.54867556637	0.5	0.5	2	72	79.1600514909125	2.22914055363414	0.999603429316087	134	0.5	1.5	2.5	2.5	1.5	0.5	0.5	0.5	0.5	0.5
15	207	368	2.30357142857143	1.461.74404761905	0.5	0.5	6	60	53.1086342893938	5.14529860185817	0.99295823513619	215	0.5	1.5	6.5	6.5	1.5	0.5	0.5	0.5	0.5	0.5
16	207	25		1.556	0.5	0.5	1	25	28.867514594813	1.13470513837927	0.999196797403744	25	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5	0.5
17	207	97	1.23711342306186	1.671.07216494845	0.5	0.5	1.628.5	2	34	83.6322830089977	1.89648485473261	0.99975484011361	122	0.5	1.5	2.5	2.5	1.5	0.5	0.5	0.5	0.5
18	207	267	3.28089887640449	1.753.12657677903	0.5	0.5	1.721.5	8	39	61.1484183207111	8.475489916159945	0.990356934608996	386	0.5	1.5	8.5	8.5	1.5	0.5	0.5	0.5	0.5
19	207	30		1.895.5	0.5	0.5	1.895.5	1	20	23.094010767995	1.13470513837927	0.998746217771809	20	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5
20	207	340	2.42175	1.861.90833333333	0.5	0.5	1.824.5	6	72	88.9779478135766	5.2131023705465	0.9971267588623	283	0.5	1.5	6.5	6.5	1.5	0.5	0.5	0.5	0.5
21	207	128	3.93040928078	1.148.81598933333	0.5	0.5	2.323.5	12	227	233.364868849796	8.81931134884085	0.992614481676323	1.942	0.5	1.5	12.5	12.5	1.5	0.5	0.5	0.5	0.5
22	207	45	1.4	2.326.4	0.5	0.5	2.326.4	2	27	27.652914048814	2.2848716437947	0.996646258472919	49	0.5	1.5	2.5	2.5	1.5	0.5	0.5	0.5	0.5
23	207	26		2.373.5	0.5	0.5	2.360.5	1	26	30.0222139978603	1.13470513837927	0.999300812897327	26	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5
24	207	76	1.72368402105232	2.403.10536315789	0.5	0.5	2.475.5	3	36	34.088094362631	3.2037129190775	0.9952299617187	87	0.5	1.5	3.5	3.5	1.5	0.5	0.5	0.5	0.5
25	207	155	2.90967941835484	2.553.71812903126	0.5	0.5	2.531.5	7	90	38.8838833036803	7.549446396458	0.982029544071866	230	0.5	1.5	7.5	7.5	1.5	0.5	0.5	0.5	0.5
26	207	278	3.66187050289712	2.637.3787894173	0.5	0.5	2.585.5	10	78	64.842284862746	9.46427679739451	0.99126707272960	449	0.5	1.5	10.5	10.5	1.5	0.5	0.5	0.5	0.5
27	207	21		2.737	0.5	0.5	2.726.5	1	21	24.2487113099640	1.13470513837927	0.99880558685858	21	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5
28	207	24		2.762.5	0.5	0.5	2.770.5	1	24	27.712812921102	1.13470513837927	0.999111567596817	24	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5
29	207	29		2.863.5	0.5	0.5	2.846.5	1	28	32.331815074619	1.13470513837927	0.99930041462373	28	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5
30	207	23		2.897	0.5	0.5	2.884.5	1	23	28.867514594813	1.13470513837927	0.999196797403744	23	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5
31	207	62	1.29032258064916	2.938.0864016129	0.5	0.5	2.915.5	2	44	44.3907840371532	2.1457484139901	0.99883147919780	74	0.5	1.5	2.5	2.5	1.5	0.5	0.5	0.5	0.5
32	207	14		2.978.5	0.5	0.5	2.971.5	1	14	16.1638075370095	1.13470513837924	0.997495717412067	14	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5
33	207	188	1.81106382079723	3.041.91489361702	0.5	0.5	3.005.5	4	83	81.4089921524593	3.6658898796829	0.99898967111796	244	0.5	1.5	4.5	4.5	1.5	0.5	0.5	0.5	0.5
34	207	368	4.39402173913043	3.184.94369166322	0.5	0.5	3.153.5	11	61	51.5145140425306	10.7826231381703	0.97767381904871	401	0.5	1.5	11.5	11.5	1.5	0.5	0.5	0.5	0.5
35	207	153	2.281045175183399	3.272.6130868391	0.5	0.5	3.247.5	6	61	54.400681791826	5.4012895741605	0.9959883777879	223	0.5	1.5	6.5	6.5	1.5	0.5	0.5	0.5	0.5
36	207	88	2.9090050509091	3.371.125	0.5	0.5	3.317.5	6	27	21.333172847176	7.89631199027322	0.940133912884654	115	0.5	1.5	6.5	6.5	1.5	0.5	0.5	0.5	0.5
37	207	39	1.15384611384615	3.386.3076328789	0.5	0.5	3.376.5	2	35	35.7925722879662	1.82915271214048	0.99886843296036	52	0.5	1.5	2.5	2.5	1.5	0.5	0.5	0.5	0.5
38	207	96	2.36458123333333	3.428.93823333333	0.5	0.5	3.412.5	4	28	28.101104481473	4.82826366241073	0.98887111108789	88	0.5	1.5	4.5	4.5	1.5	0.5	0.5	0.5	0.5
39	207	22		3.494.5	0.5	0.5	3.483.5	1	22	25.4534118454318	1.13470513837927	0.99886407992041	22	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5
40	207	177	2.90960451877401	3.539.30506447376	0.5	0.5	3.513.5	7	47	41.1329671011	6.8843678213381	0.98889011212893	212	0.5	1.5	7.5	7.5	1.5	0.5	0.5	0.5	0.5
41	207	130	2.68461138461138	3.618.81138461138	0.5	0.5	3.598.5	6	38	33.021165850958	6.20430970121073	0.982121257102869	154	0.5	1.5	6.5	6.5	1.5	0.5	0.5	0.5	0.5
42	207	25		3.668	0.5	0.5	3.655.5	1	25	28.867514594813	1.13470513837927	0.999196797403744	25	0.5	1.5	1.5	1.5	1.5	0.5	0.5	0.5	0.5
43	207	50	1.36	3.709.5	0.5	0.5	3.693.5	2	32	32.083251080406	2.24047813887146	0.997598678004945	56	0.5	1.5	2.5	2.5	1.5	0.5	0.5	0.5	0.5
44	207	144	2.38888888888889	3.794.51388888889	0.5	0.5	3.771.5	5	46	41.8480944147984	5.6483884115128	0.99220891300047	162	0.5	1.5	5.5	5.5	1.5	0.5	0.5	0.5	0.5
45	207	20		3.870.5	0.5	0.5	3.860.5	1	20	23.094010767995	1.13470513837927	0.998746217771809	20	0.5	1.5	1.5	1.5	1.5	0.5			

# Step 6: Graph-based segment search

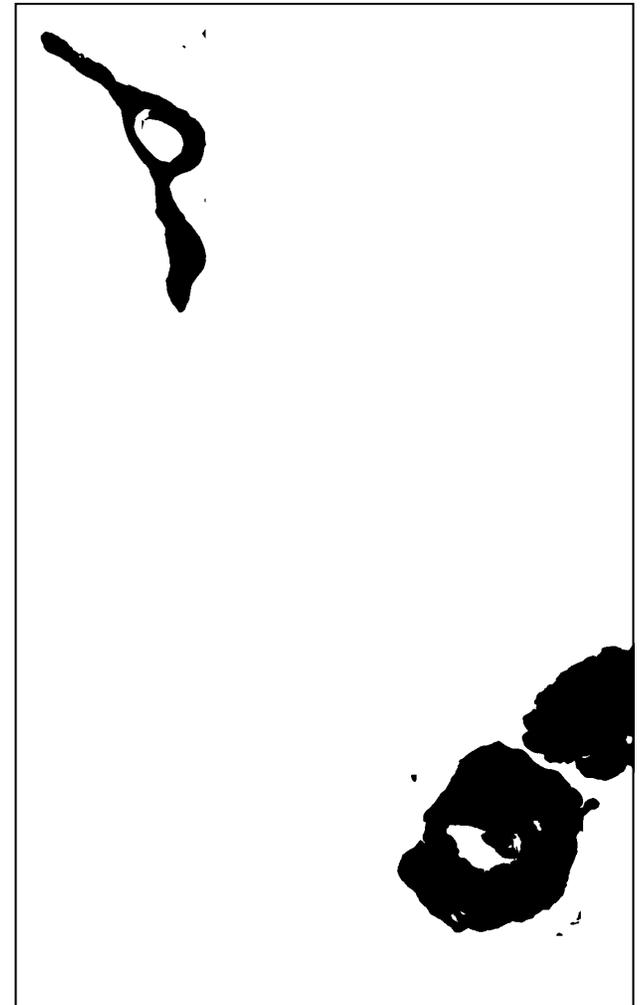
Greedy strategy:

Starting from larger segment, exhaustively reconstruct within a bounding box for a limited number of layers

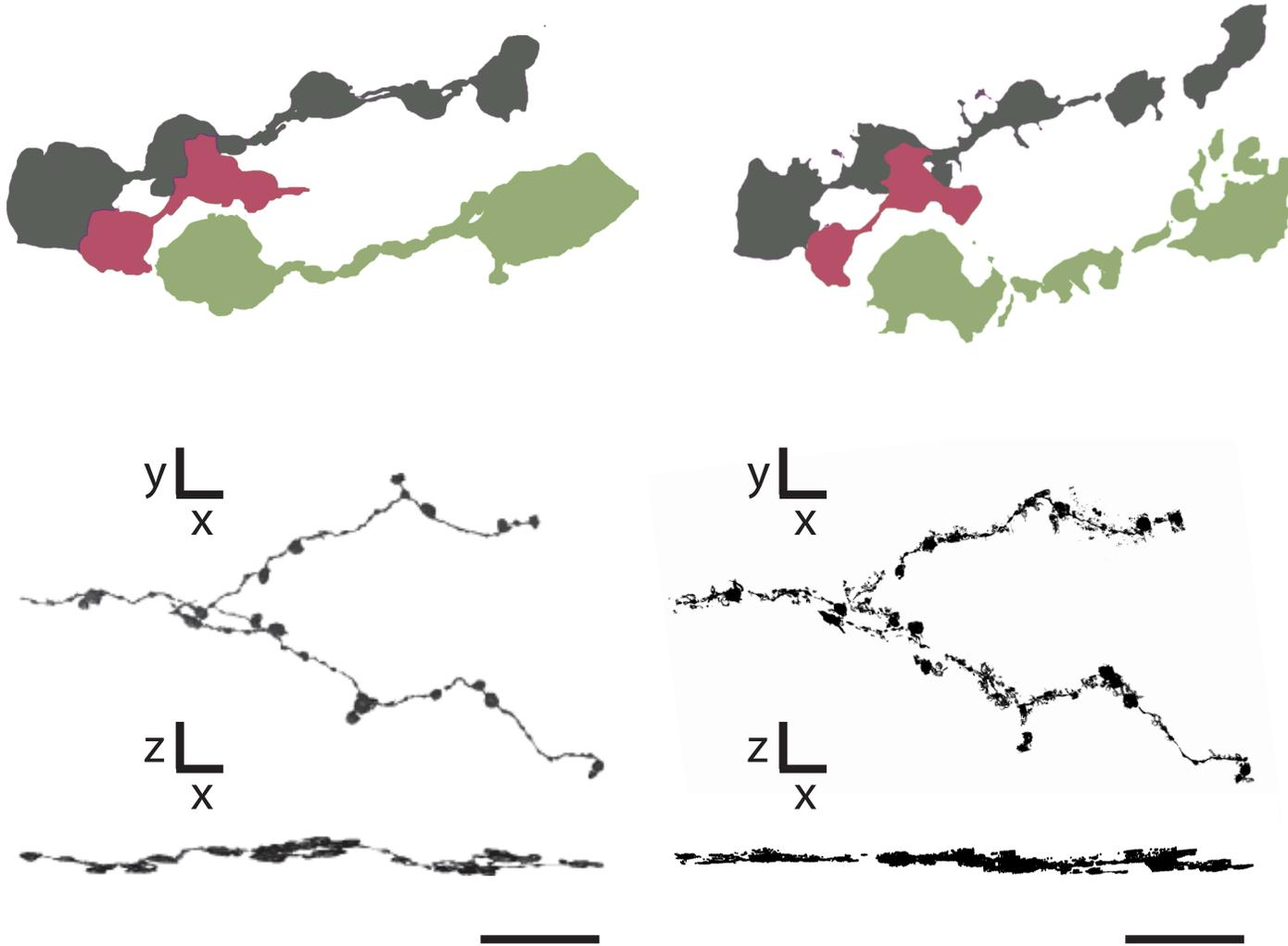
Register all layers into one 2D candidate

Identify direction of the process, and then expand bounding box according to it.

Repeat steps until the connectivity path reaches another large segment or another smaller path



# Reconstruction Results



# Reconstruction Results

Ground  
Truth



Our  
Method



Ground  
Truth



Our  
Method



# Quantitative Performance

Ground-truth: 444 APEX positive segments

Recall statistic: 91.8% for the 2D segmentation portion of the algorithm

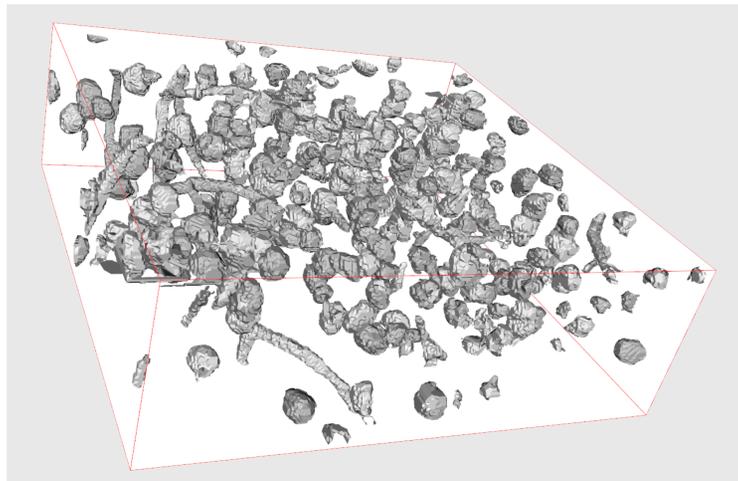
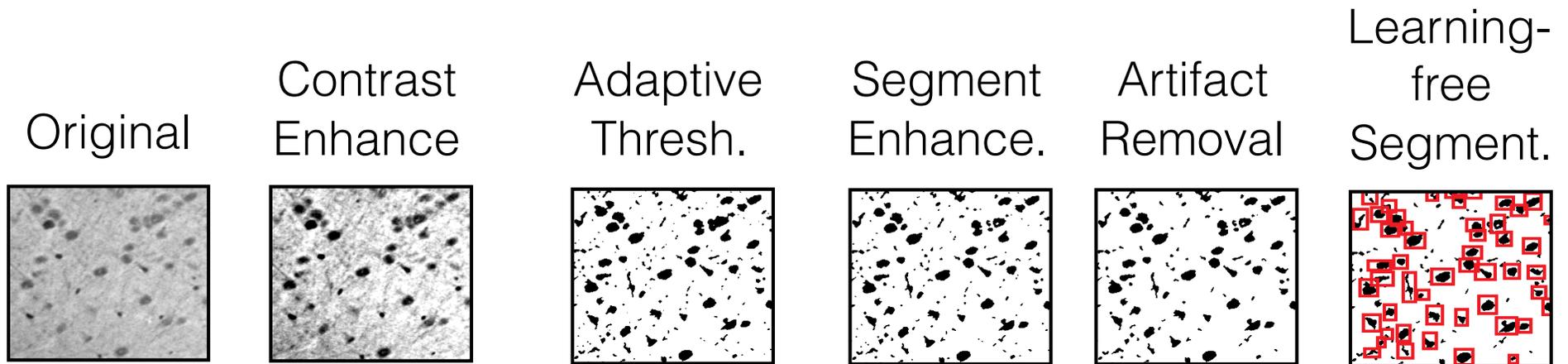
Two orders of magnitude faster compared to Random Forests\* (supervised machine learning)

Not perfectly accurate, but **much** faster

# Quantitative Performance

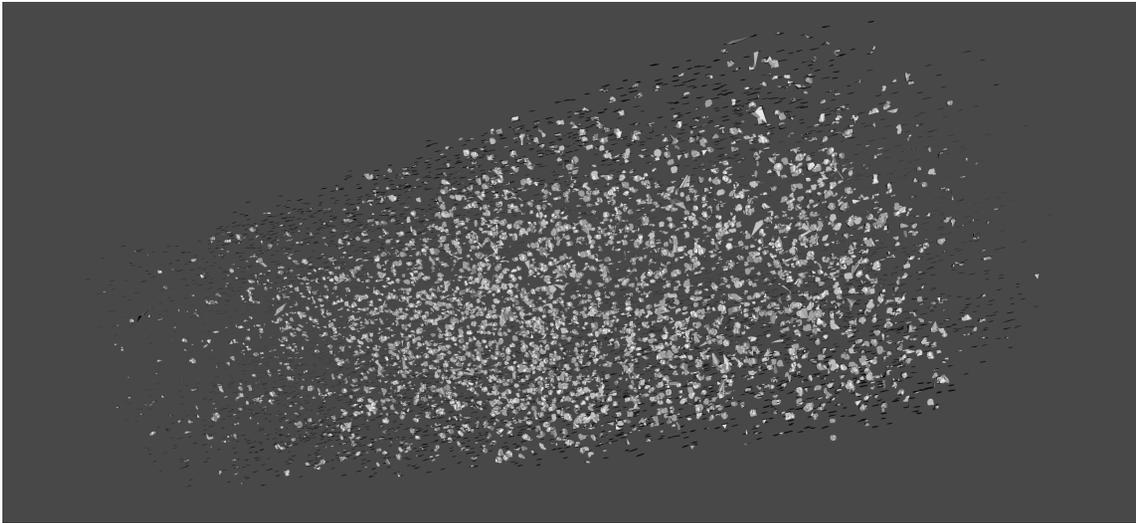
	<b>3D U-Net</b>	<b>Ours (Cluster Based Thresh.)</b>	<b>Ours (Adaptive Thresh.)</b>
<b>Manual Annotation</b>	40 Hr.	-	-
<b>Training</b>	926 Min.	-	-
<b>Segmentation</b>	233 Min.	8 Min.	8 Min.
<b>Reconstruction</b>	-	128.8 Min.	16.82 Min.

# Also works for X-ray

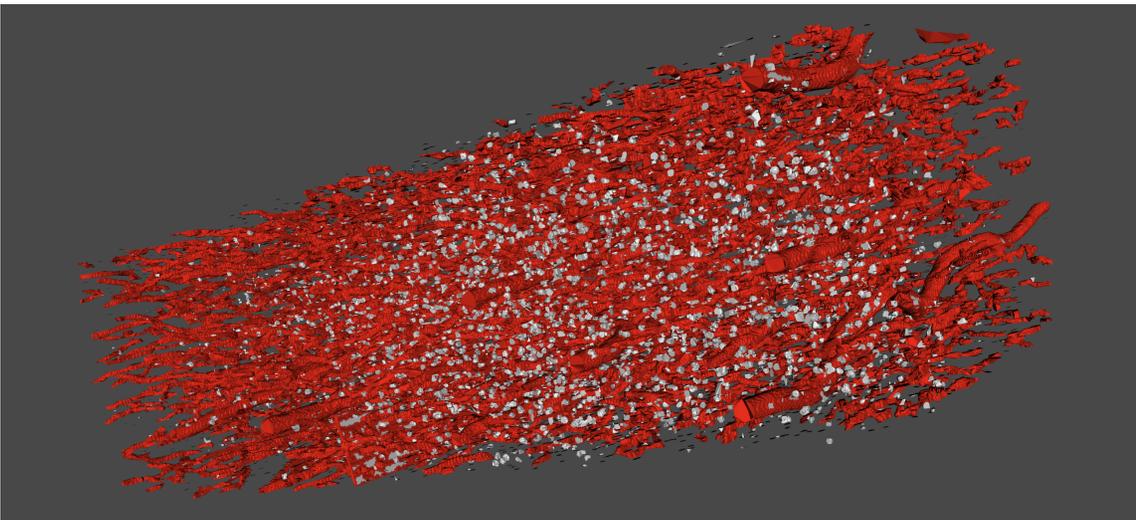


Reconstruction

# Reconstruction Results

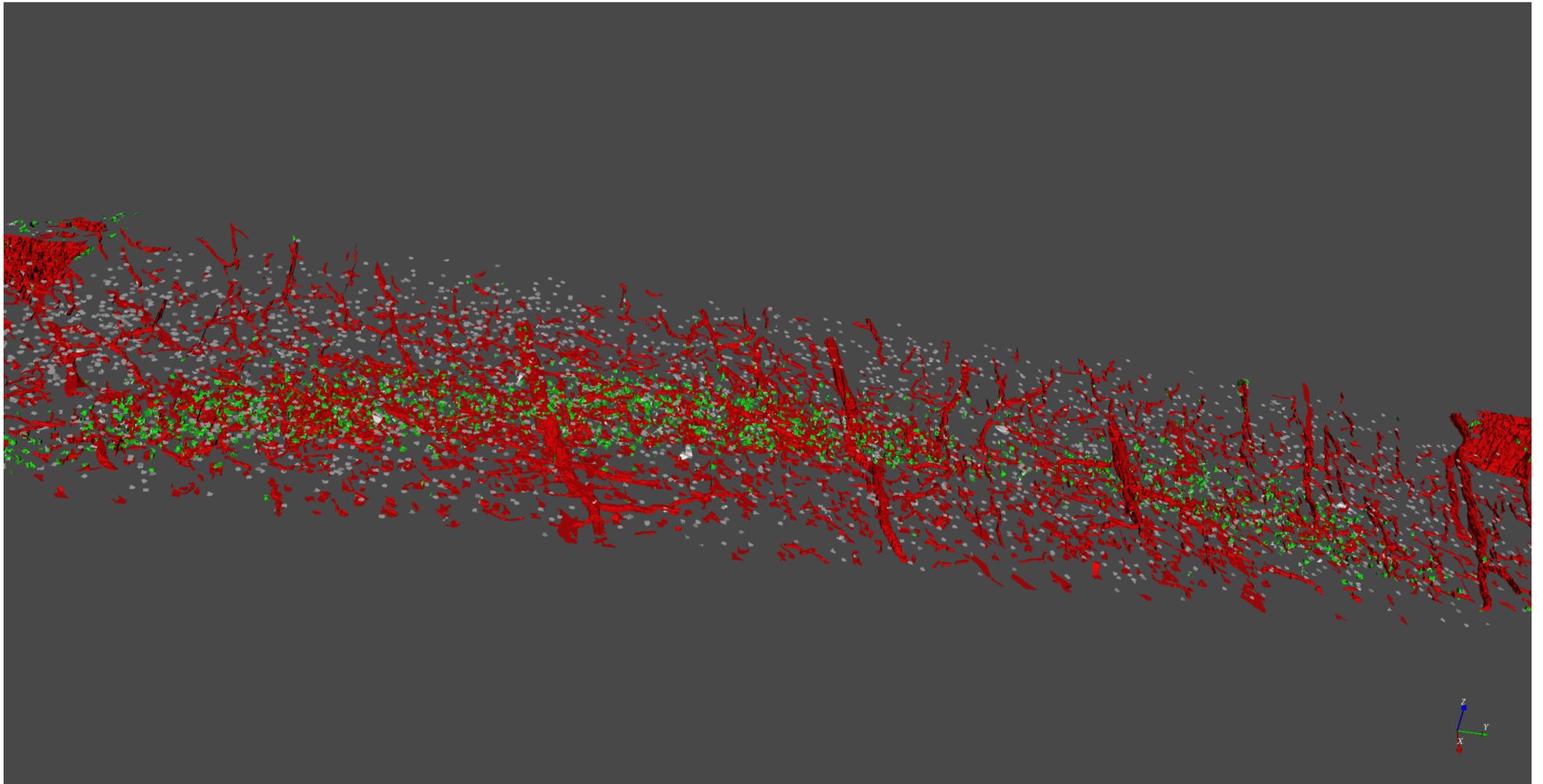


Cells

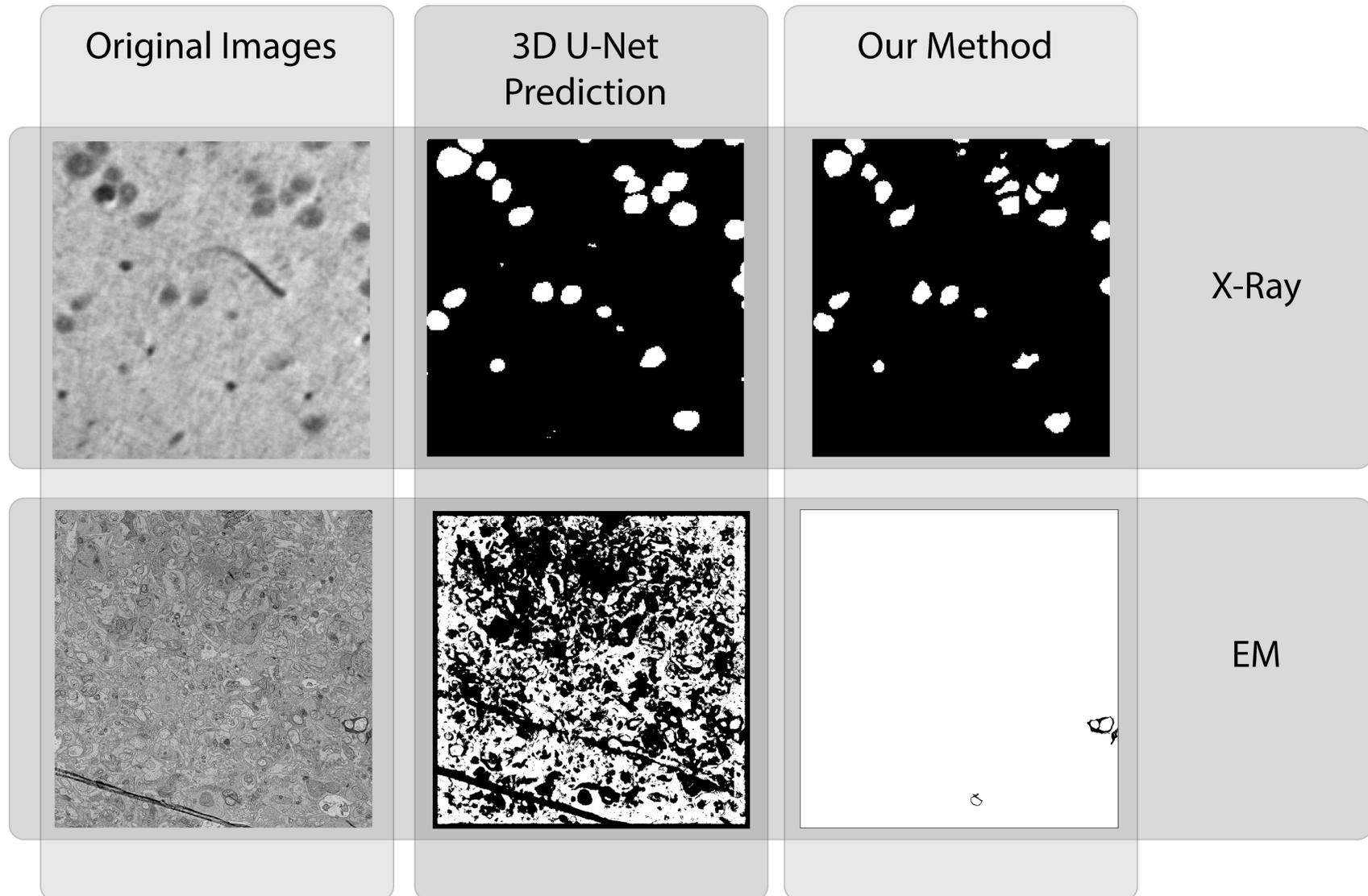


Vasculature + Cells

# Apex Cells Imaged with X-ray



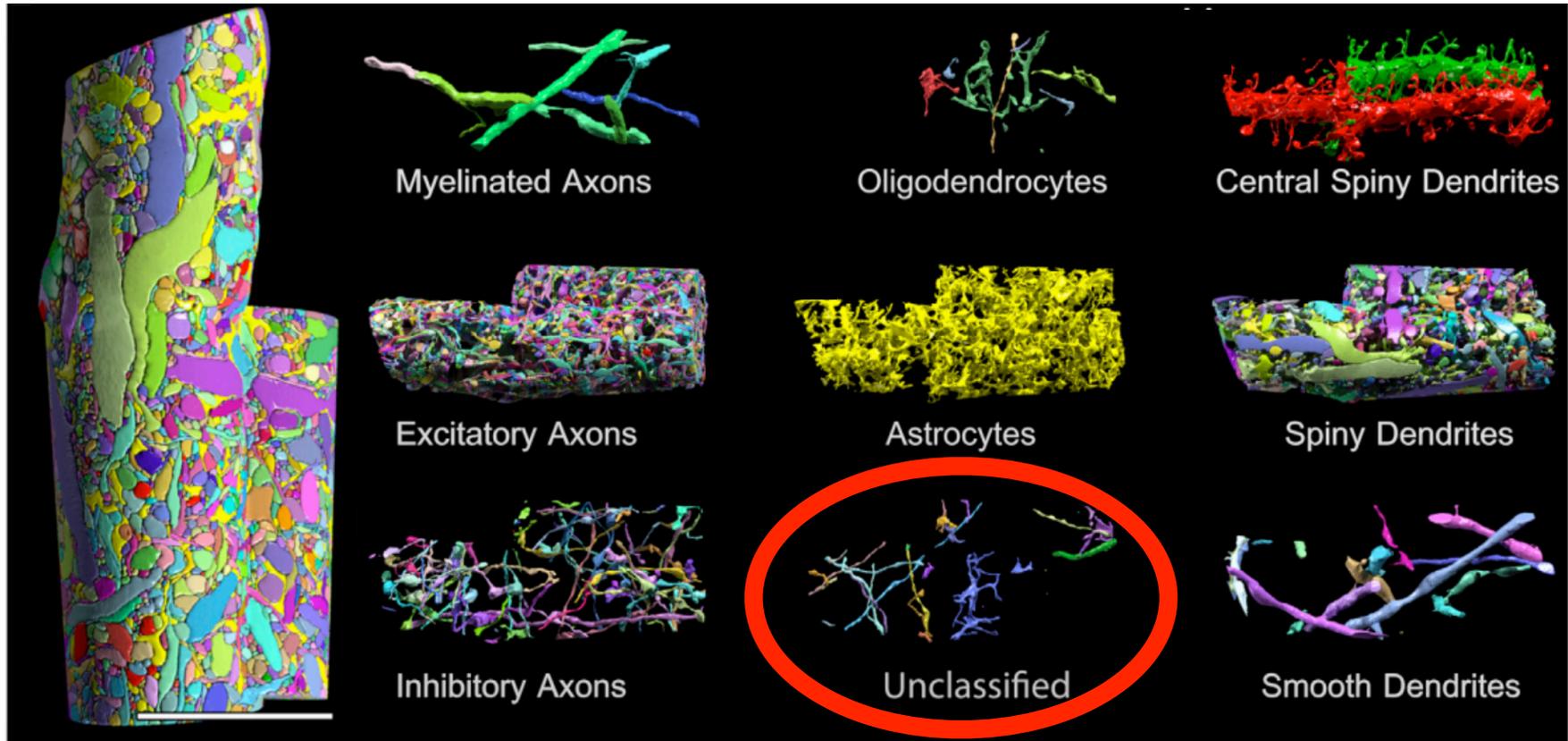
# Comparison to deep learning



Bringing learning back in

# Open Set Machine Learning

Can we bring supervised machine learning back into the picture to handle unknown data?

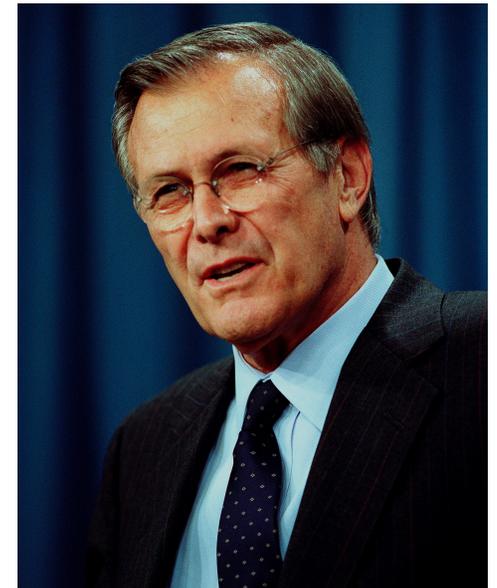


# “There are known knowns...”

**known classes:** the classes with distinctly labeled positive training examples (also serving as negative examples for other known classes)

**known unknown classes:** labeled negative examples, not necessarily grouped into meaningful categories

**unknown unknown classes:** classes unseen in training



# Learning Objective

Minimize open set risk:

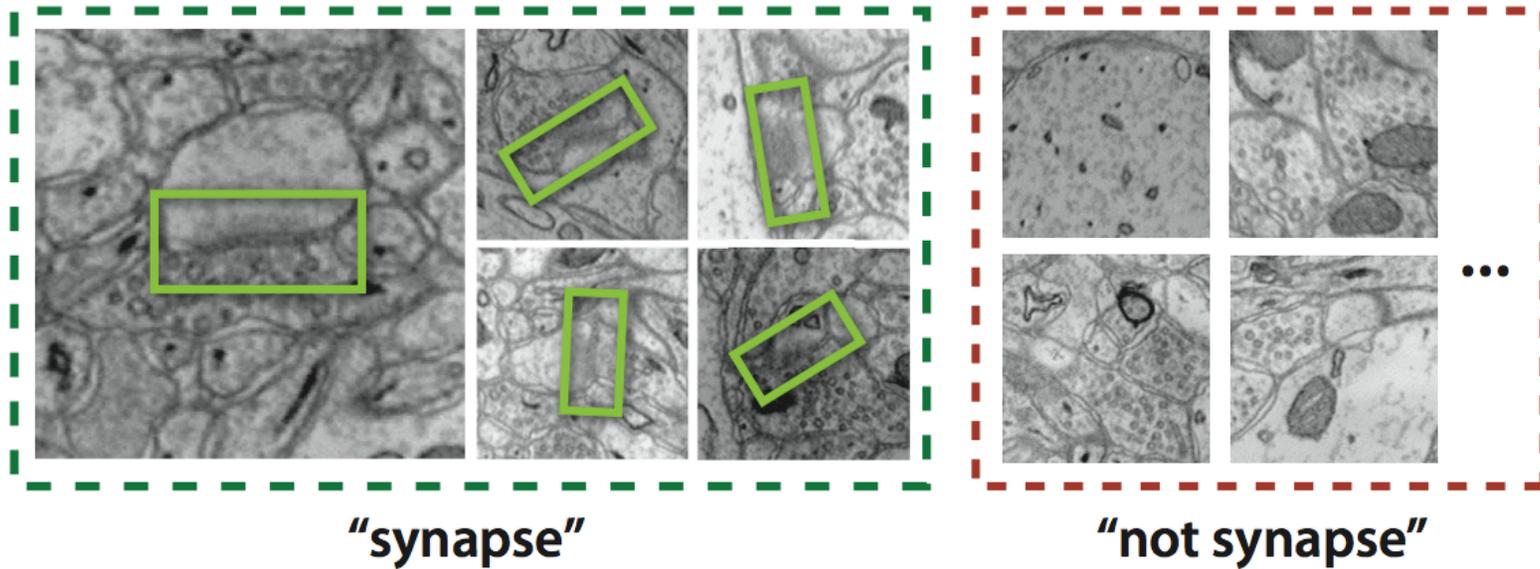
$$\operatorname{argmin}_{f \in \mathcal{H}} \left\{ R_{\mathcal{O}}(f) + \lambda_r R_{\mathcal{E}}(f(\hat{V} \cup \hat{K})) \right\}$$

The diagram illustrates the components of the learning objective equation. It features three text labels at the bottom with arrows pointing to specific parts of the equation above:

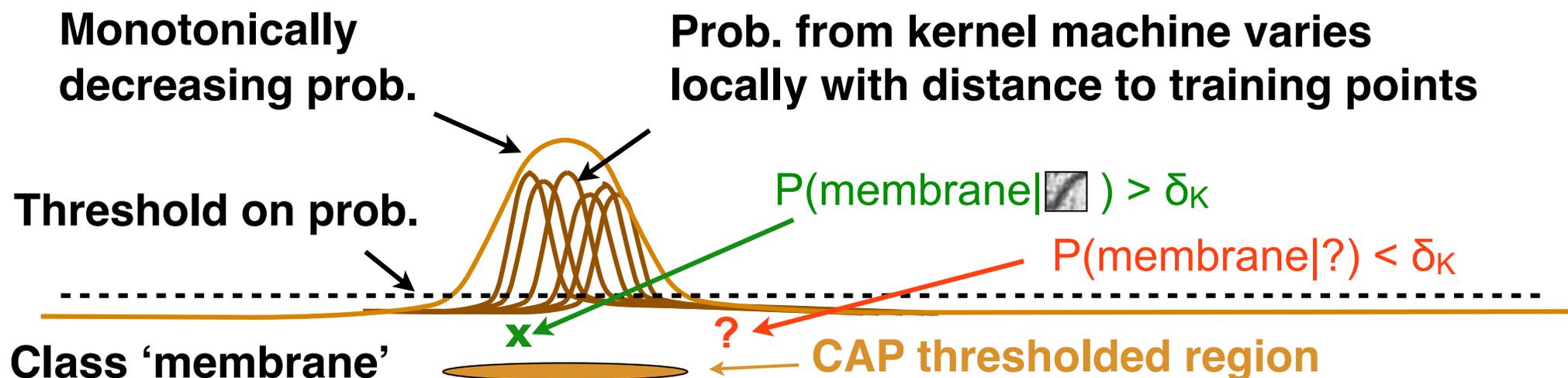
- Open Space Risk Associated with  $\mathcal{U}$** : An arrow points from this label to the  $R_{\mathcal{O}}(f)$  term in the equation.
- Regularization Constant**: An arrow points from this label to the  $\lambda_r$  term in the equation.
- Empirical Risk Function**: An arrow points from this label to the  $R_{\mathcal{E}}(f(\hat{V} \cup \hat{K}))$  term in the equation.

Additionally, the text **Training Data** is located at the top right, with an arrow pointing to the  $\hat{K}$  term within the empirical risk function.

# MICrONS use case: “synaptomics”



# Model: Compact Abating Probability



# Binary RBF SVM incorporating a CAP model: W-SVM

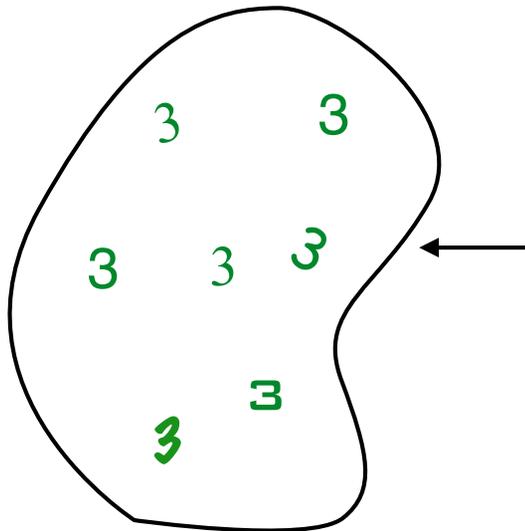
Combine probabilities computed for both 1-class and binary RBF SVMs

1-class SVM CAP model is a conditioner

if  $P_O(y|x) > \delta_\tau$ , then  could be very small  
    consider  $P_O(y|x)$   
else  
    reject

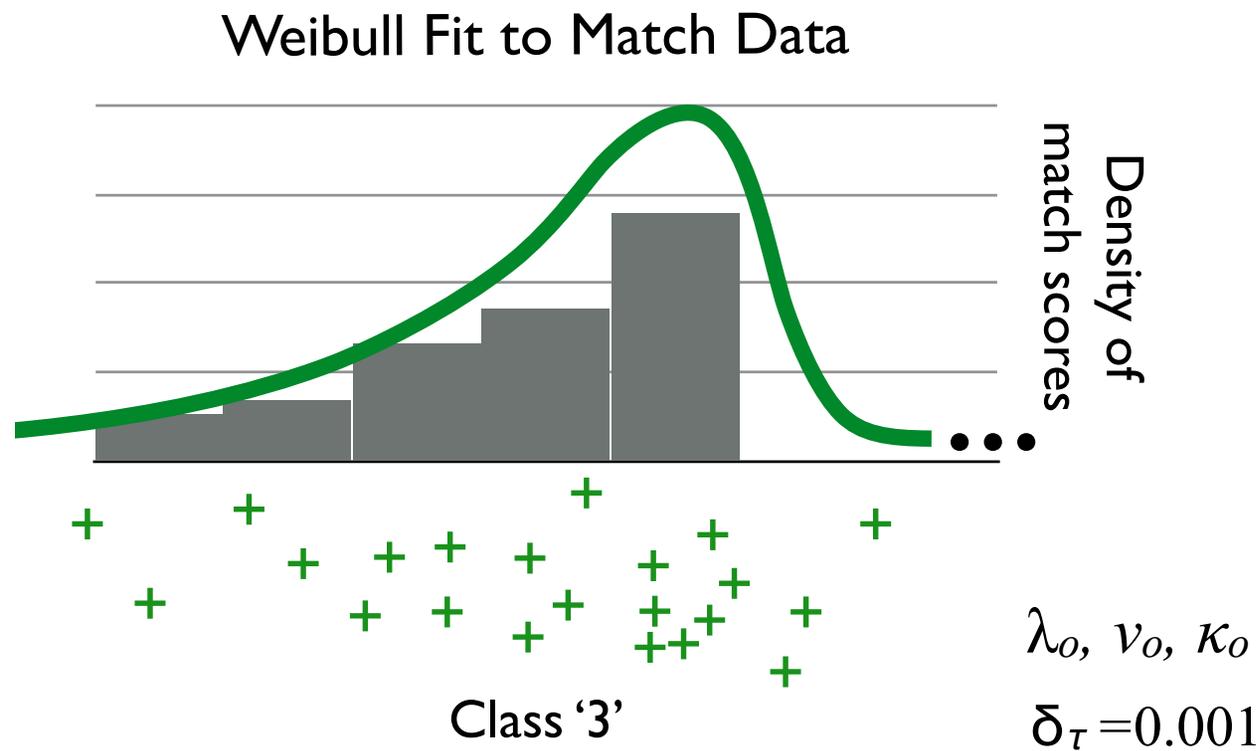
# Step 1: Train a 1-class SVM $f^0$

Class Label = '3'

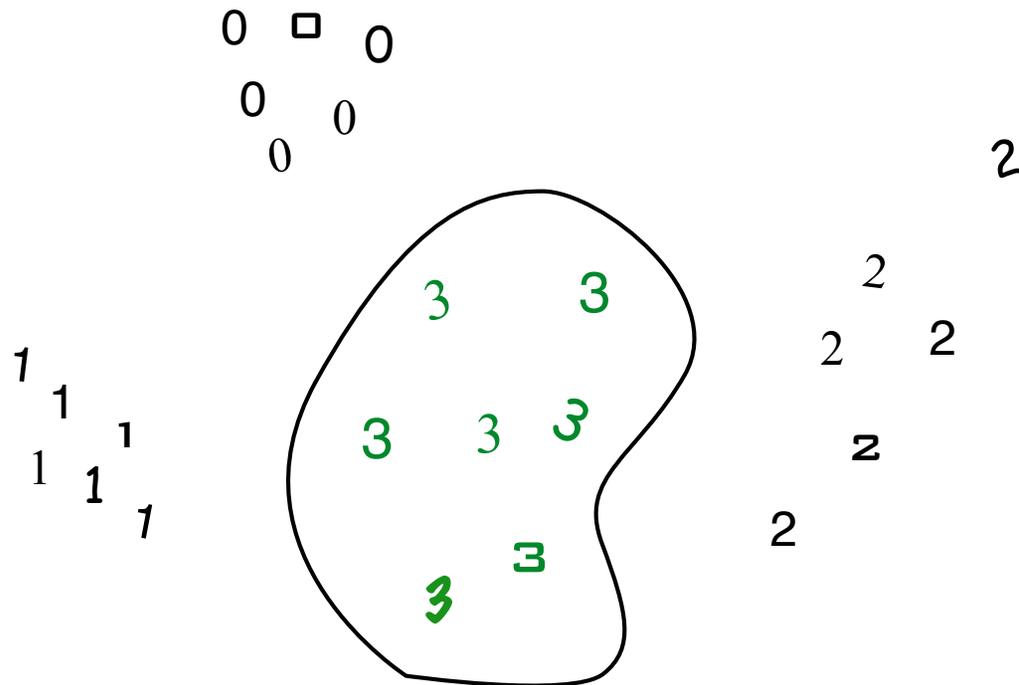


← RBF one-class SVM  
yields a CAP model

# Step 2: Fit Weibull over tail of scores from $f^o$



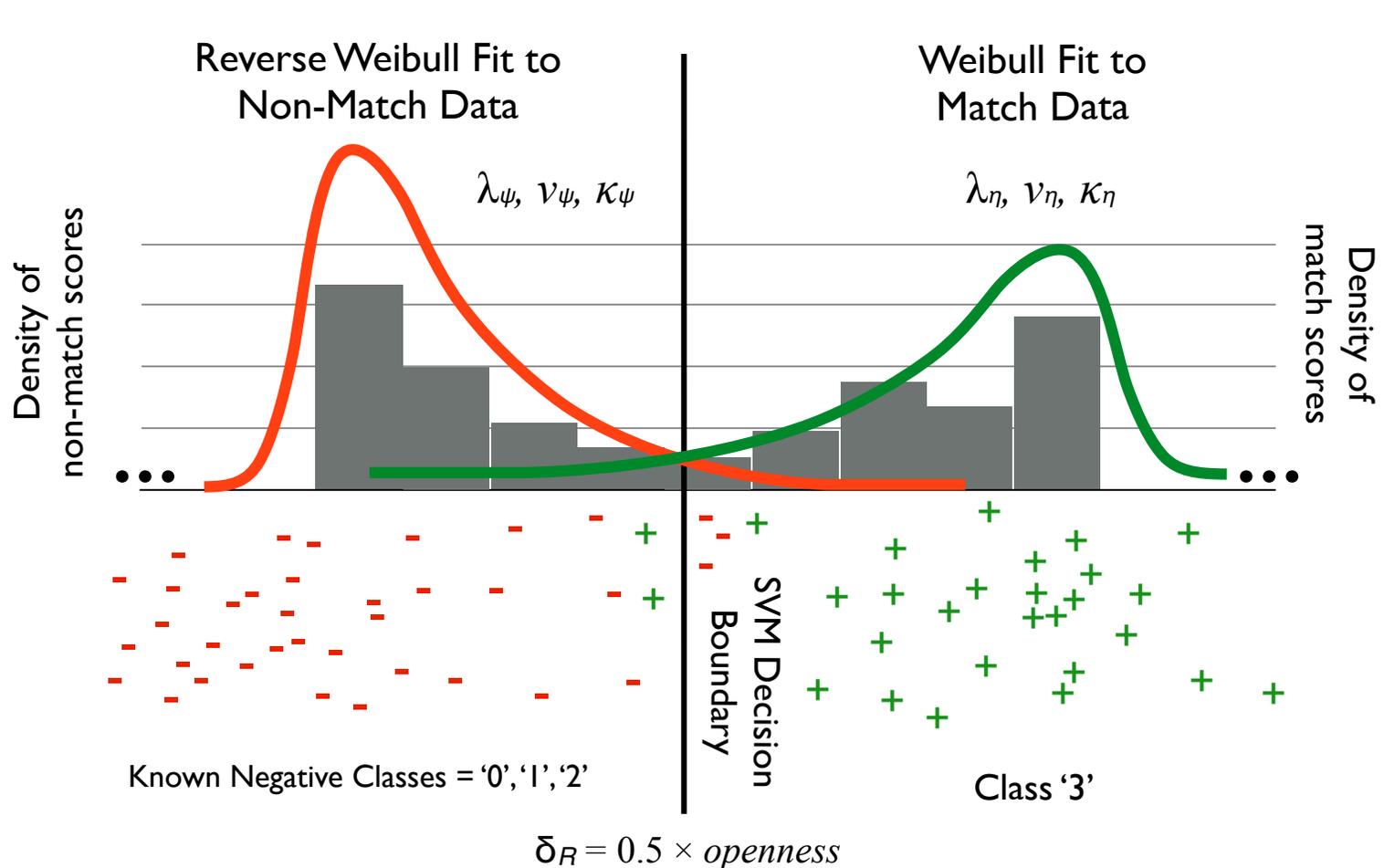
# Step 3: Train a binary SVM $f$



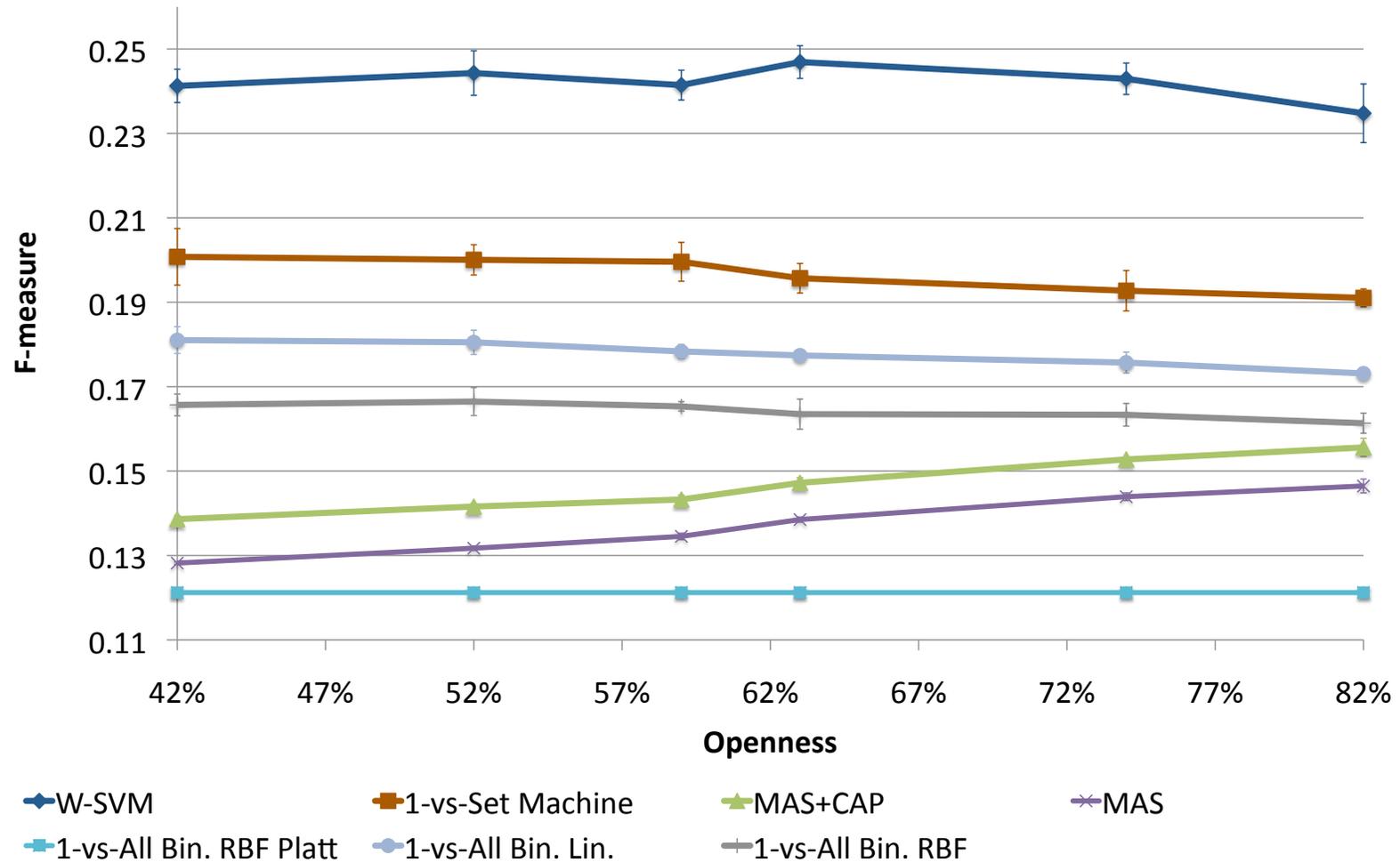
Class Label = '3'

Known Negative Classes = '0', '1', '2'

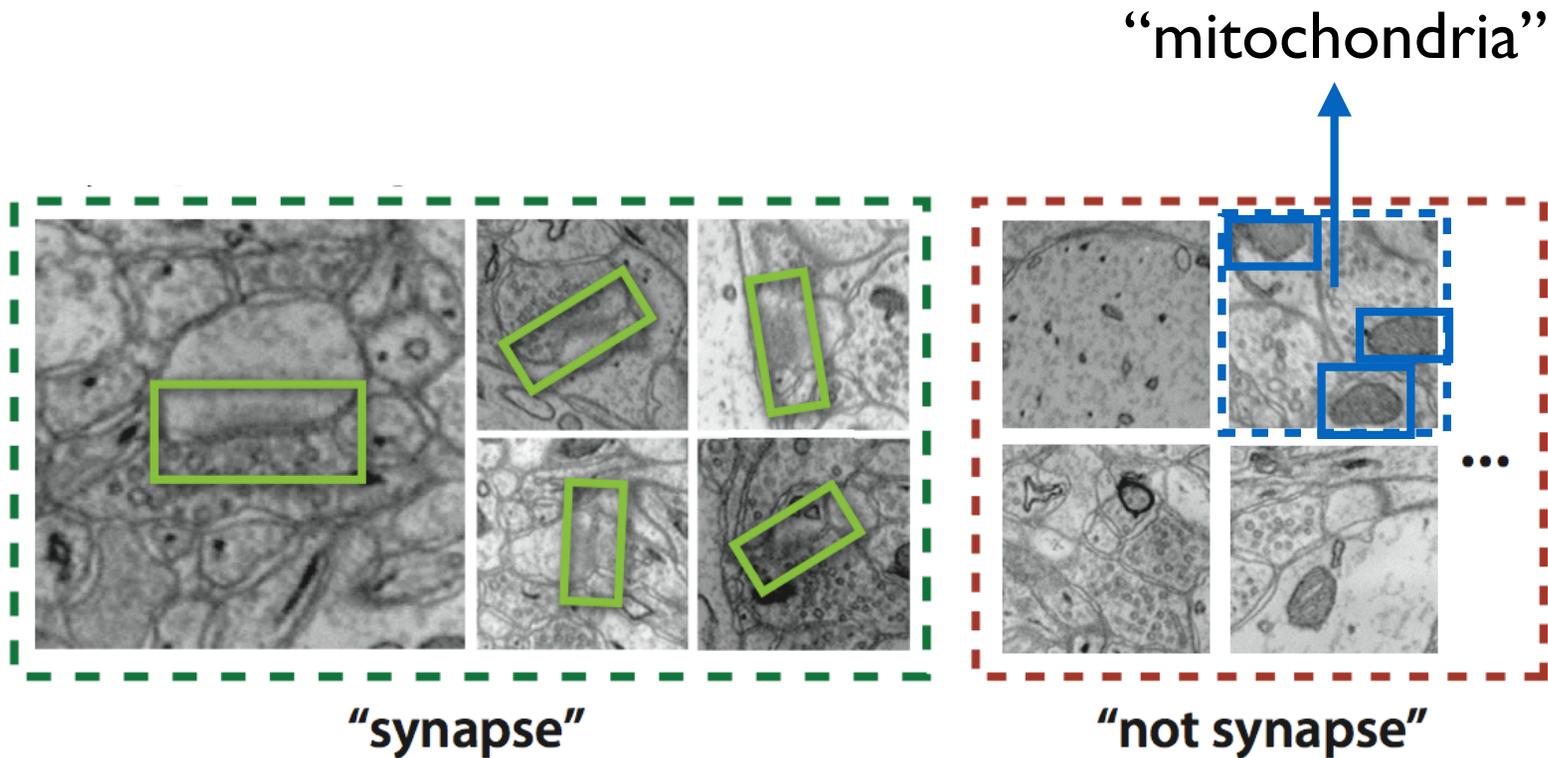
# Step 4: Fit EVT distributions over tails of scores from $f$



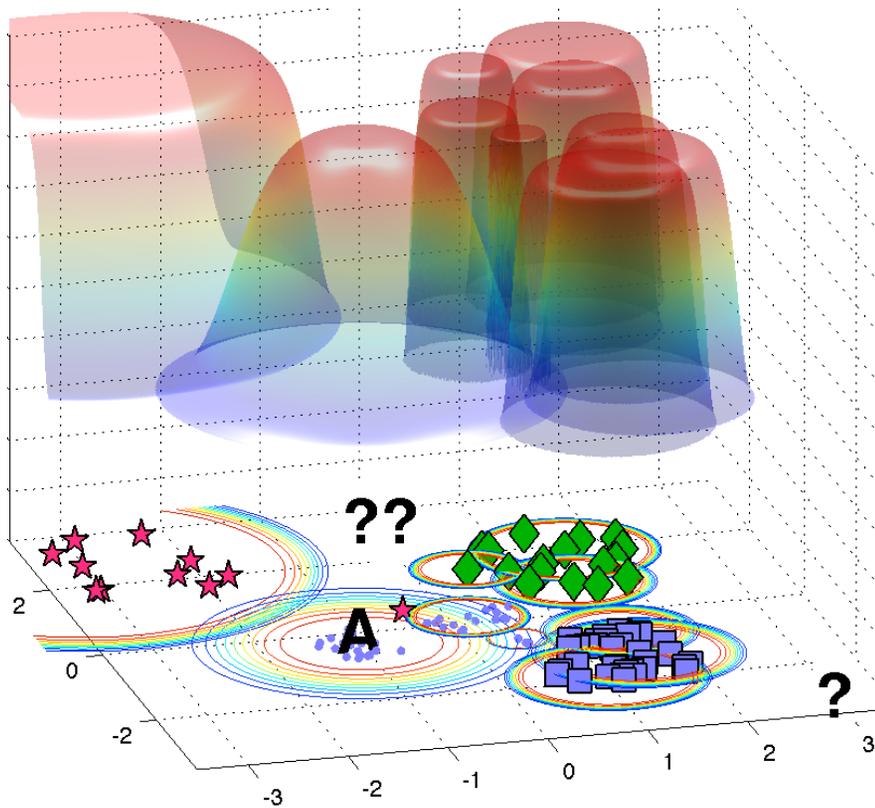
# W-SVM Object Recognition



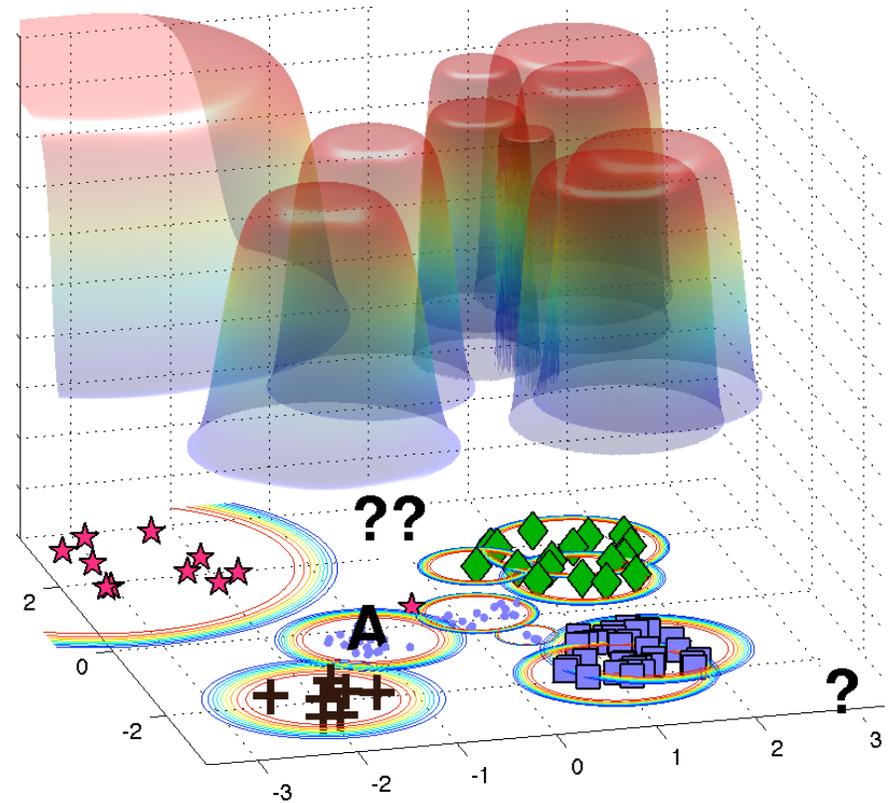
# Incremental learning



# Extreme Value Machine (EVM)



EVM Model for four known classes



Addition of a new class

# EVM Learning Objective:

Number of Extreme Vectors Retained

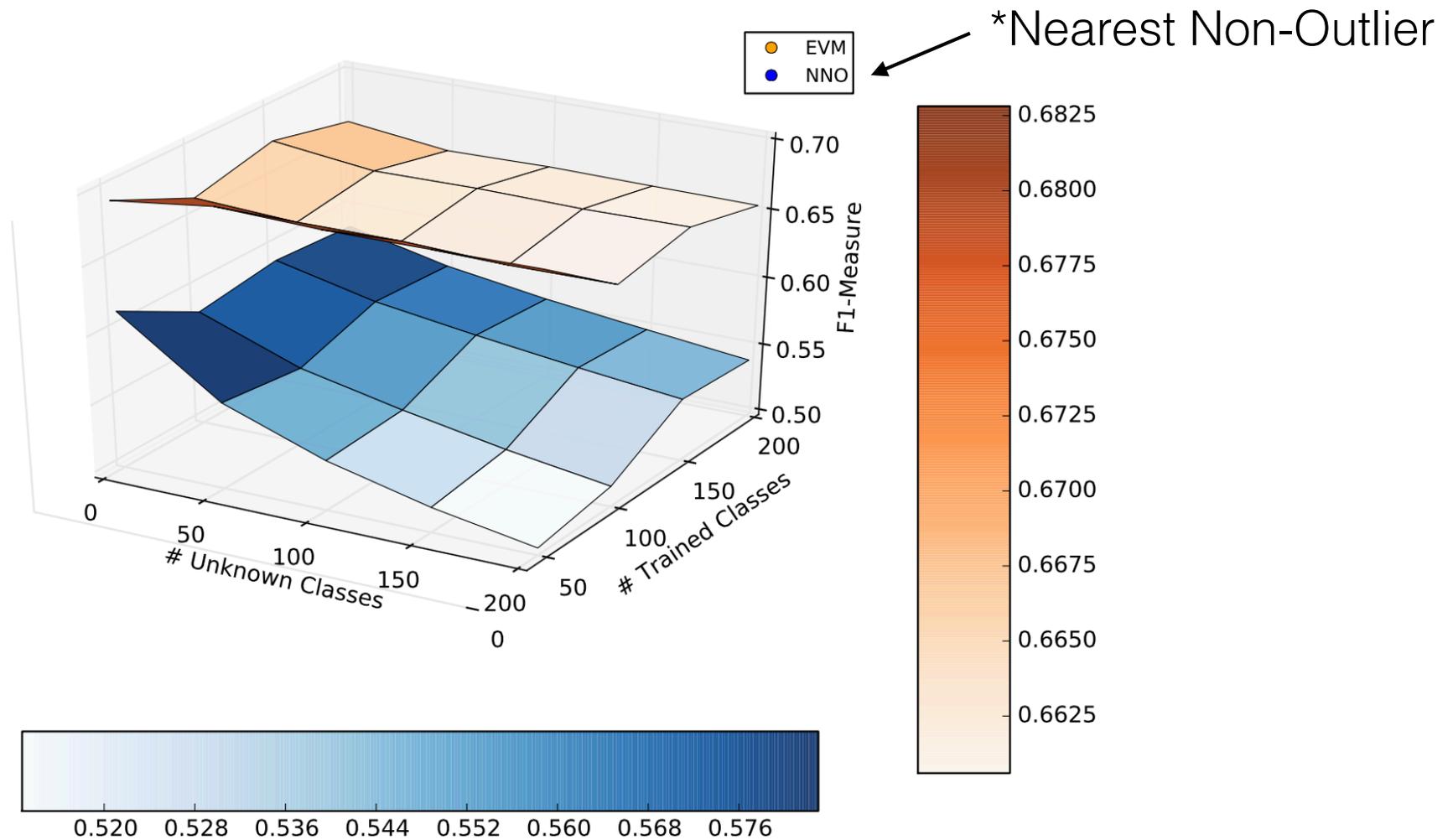
minimize  $\sum_{i=1}^{N_l} I(x_i)$  subject to

$$N_l = \sum_{i=1}^{N_l} \left[ \left( \sum_{j=1}^{N_l} I(x_j) \hat{\Psi}(x_i, x_j, \hat{\kappa}_i, \hat{\lambda}_i) \right) \geq \varsigma \right]$$

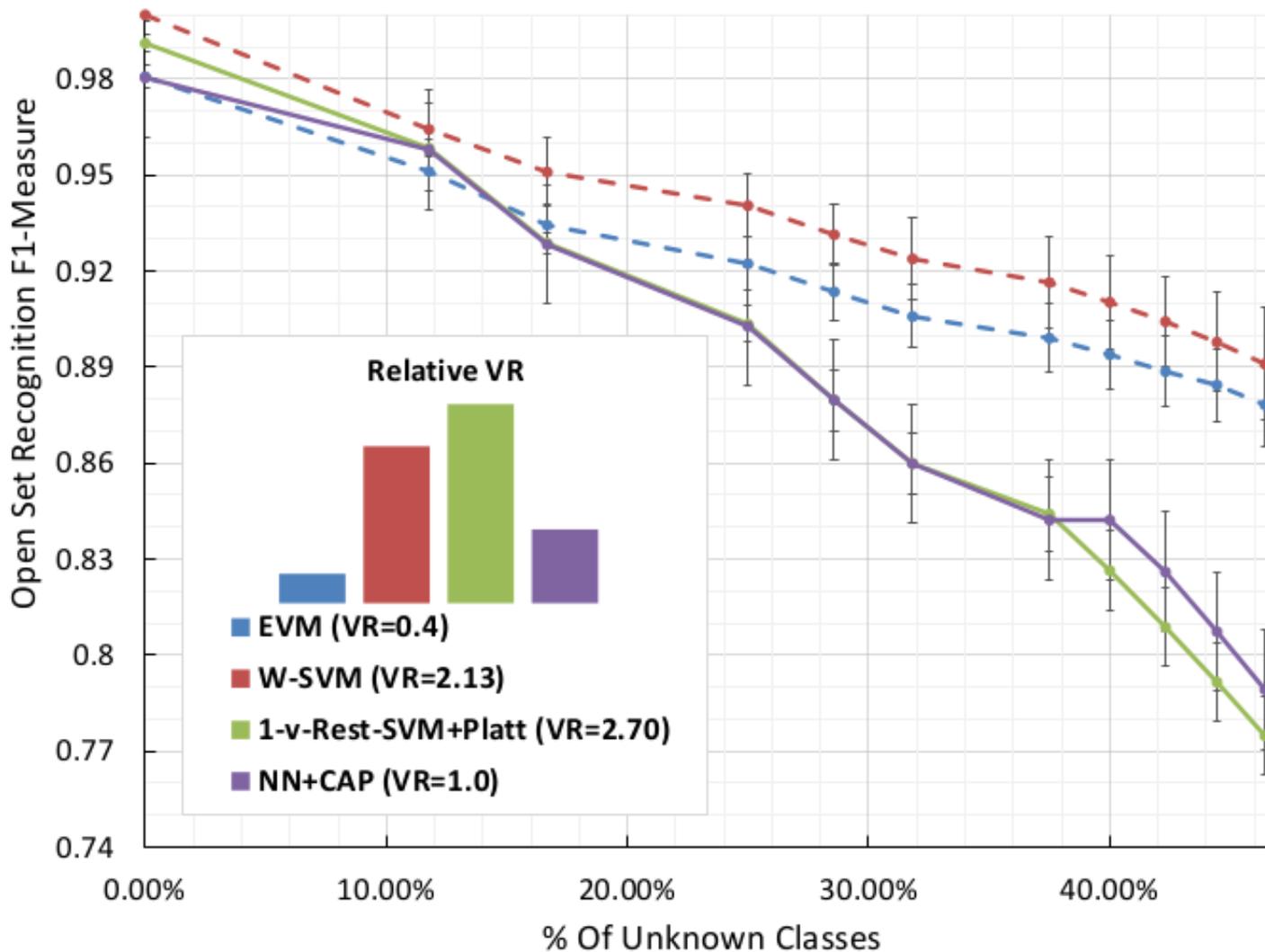
Vector Pair and  
EVT Model for  $x_i$

Probability Threshold  
for Redundancy

# Incremental learning: ImageNet



# Basic Machine Learning Benchmark: LETTER



Thank you!

(web) [www.wjscheirer.com](http://www.wjscheirer.com)  
(code coming soon) <https://github.com/CVRL>