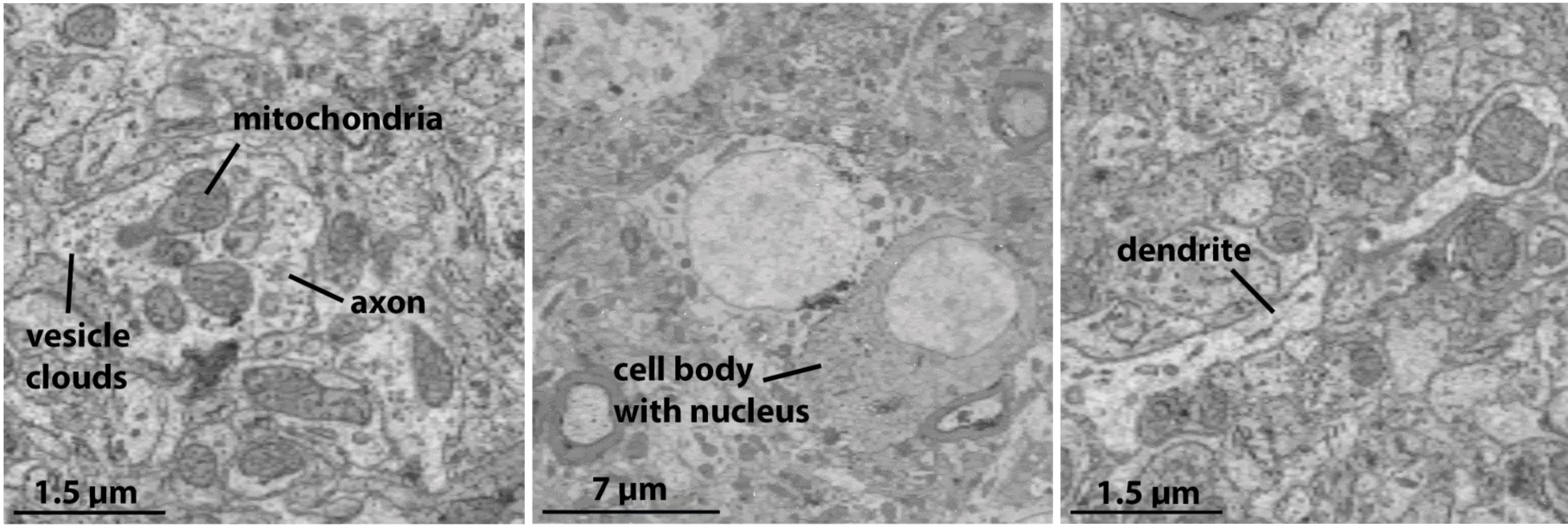
Analysis of Neuronal Morphology Using Semantic Segmentation of Point Clouds

Bachelor thesis in physics

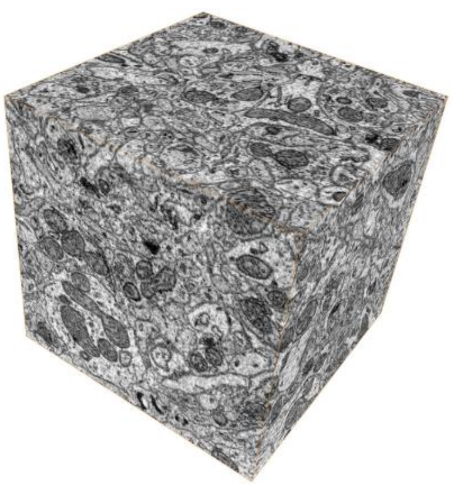
27.07.2020

Jonathan Klimesch

EM dataset

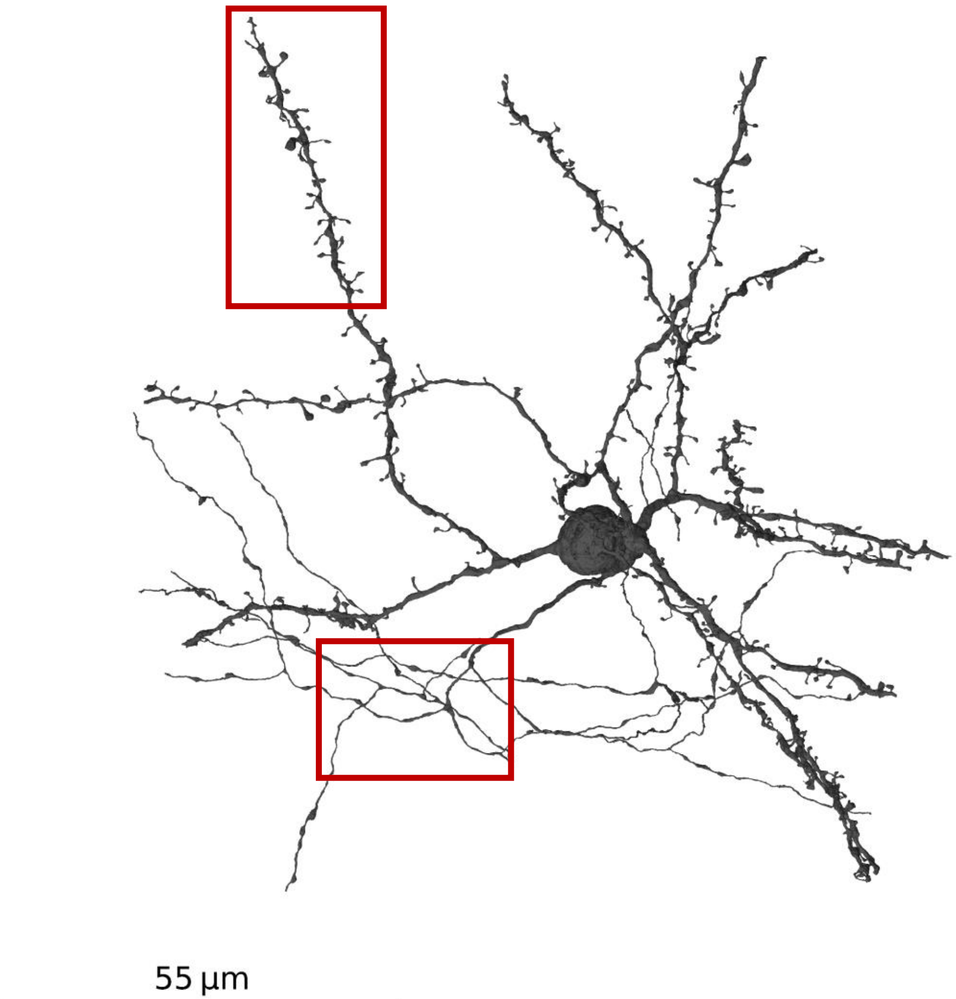


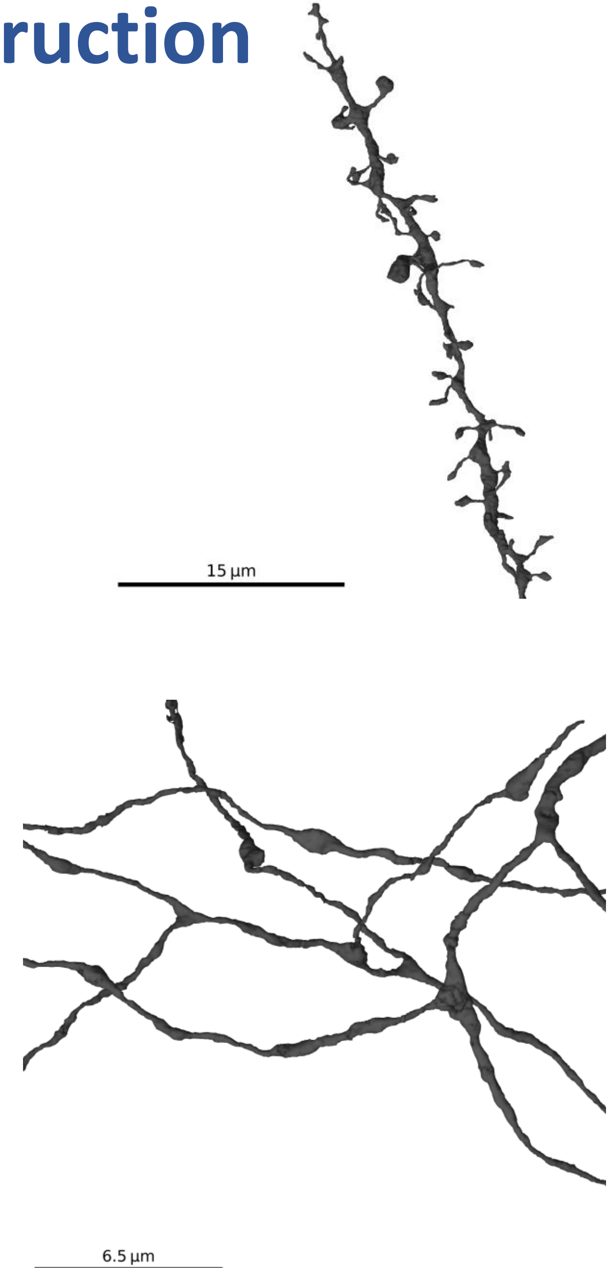
j0126 dataset from Jörgen Kornfeld, Connectomic Analyses in the Zebra Finch Brain, Dissertation, 2017



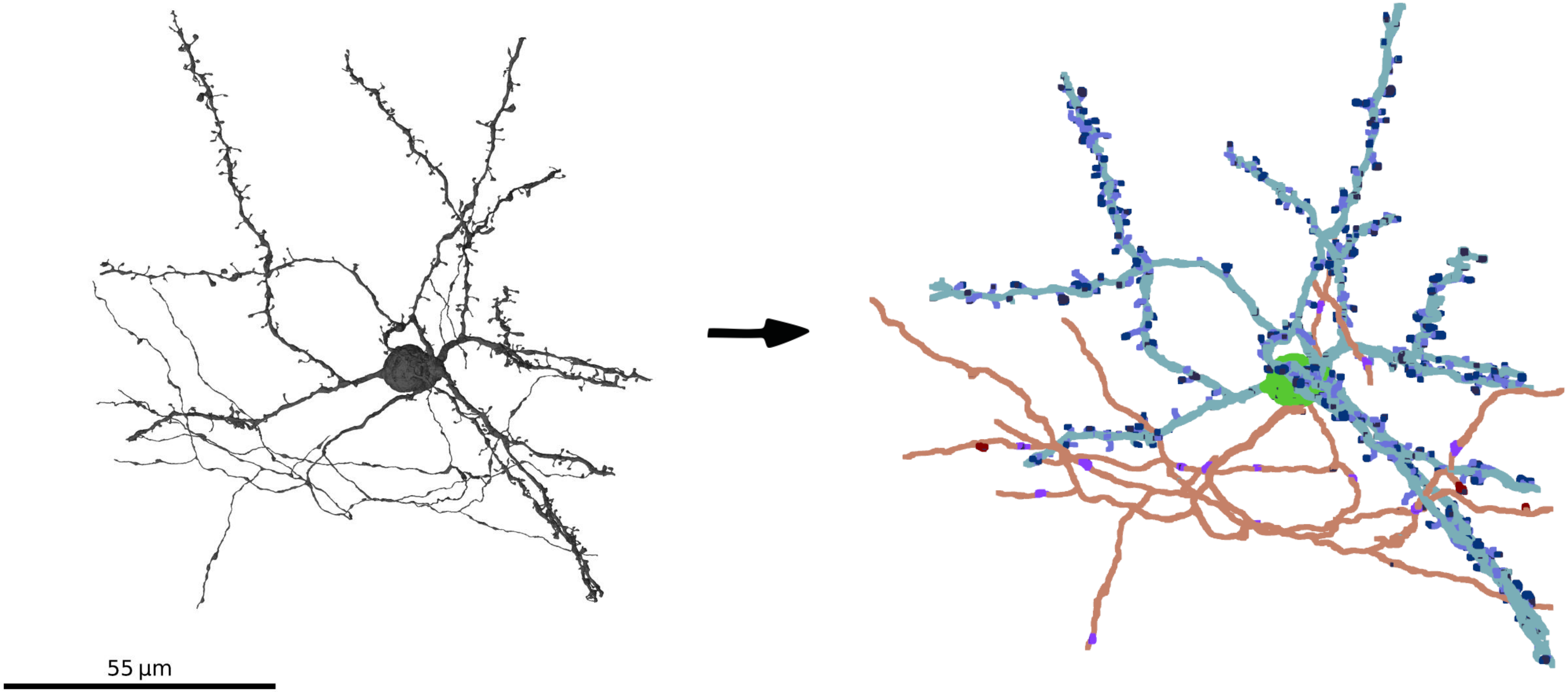
- **Serial block-face electron microscopy (SBEM)**
- **Extent: 96 x 98 x 114 μm^3**
- **xyz-resolution: 9 x 9 x 20 nm^3**

Flood Filling Network reconstruction

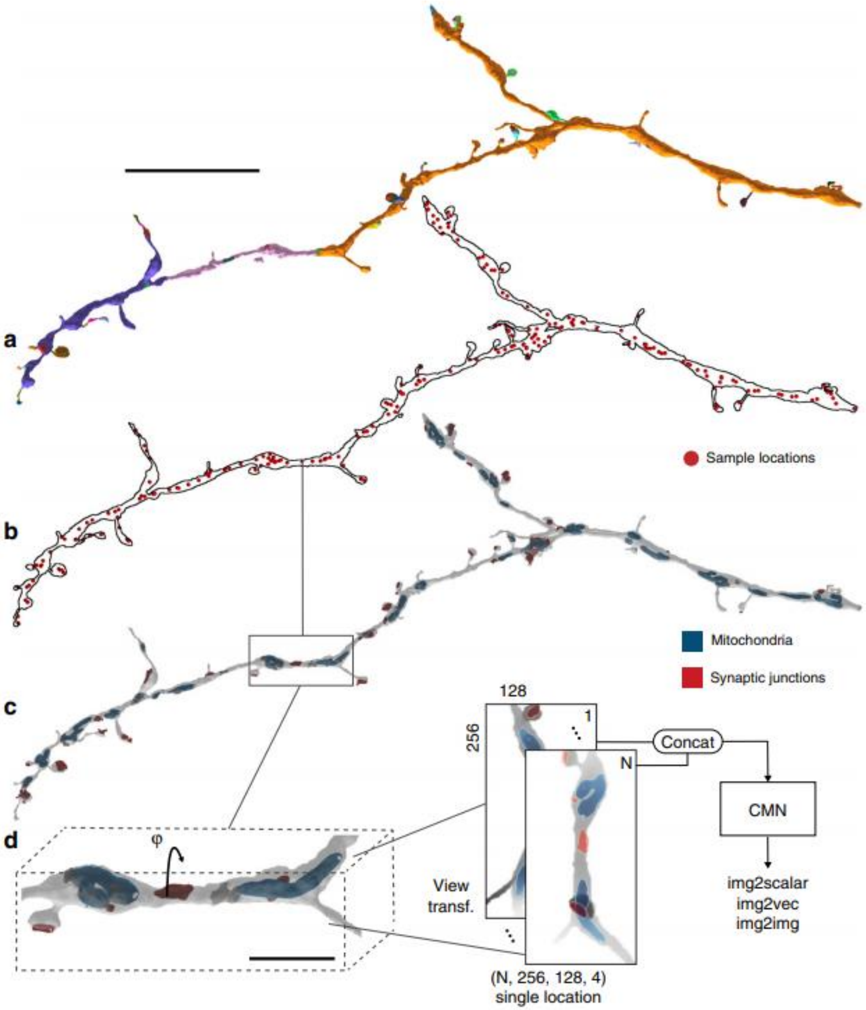




Semantic segmentation of cellular compartments



Cellular Morphology Learning Networks

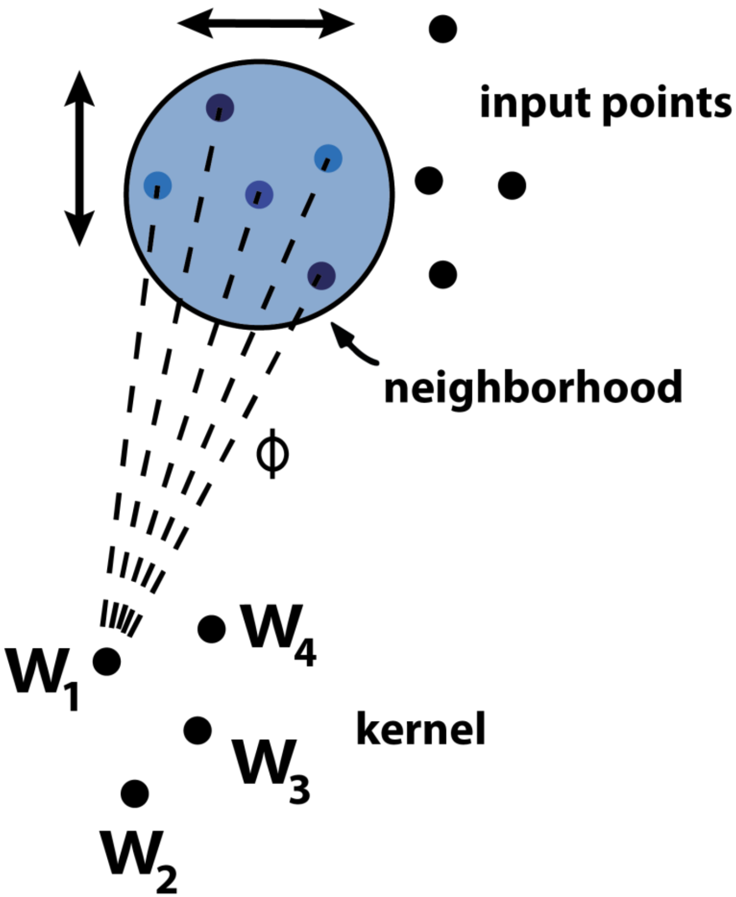


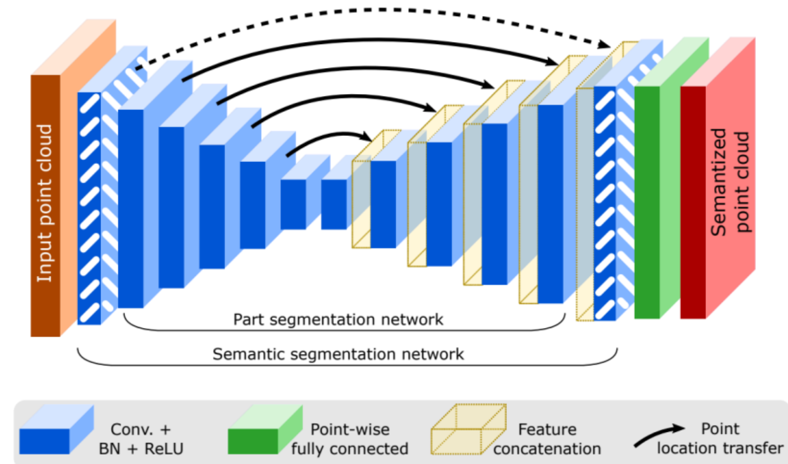
P. J. Schubert, S. Dorkenwald, M. Januszewski, V. Jain, and J. Kornfeld. Learning cellular morphology with neural networks. *Nature Communications*, 10(1):1–12, 2019.

Based on multi-view Convolutional Neural Networks (CNNs)

Goal of thesis:
Try point-based approach

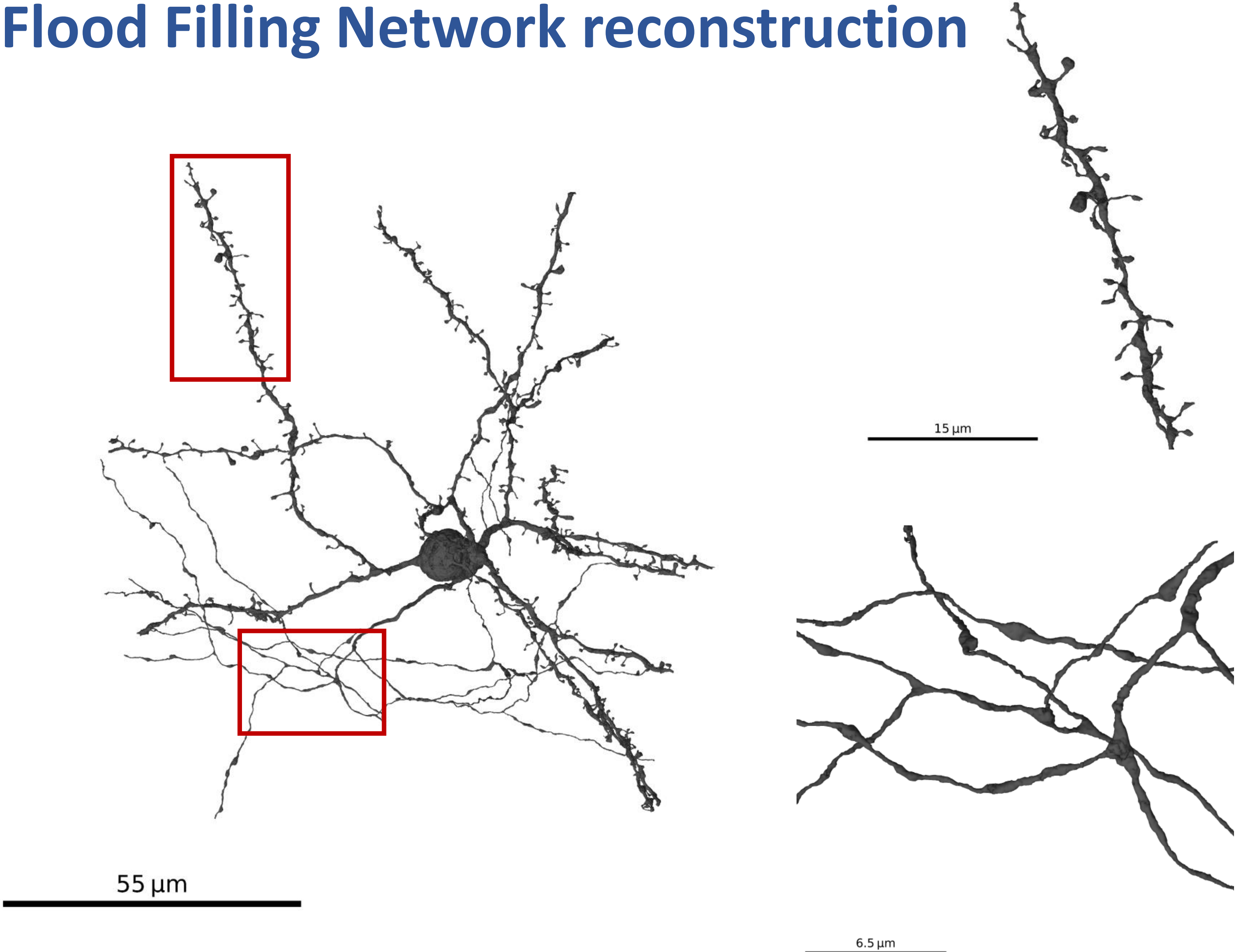
ConvPoint



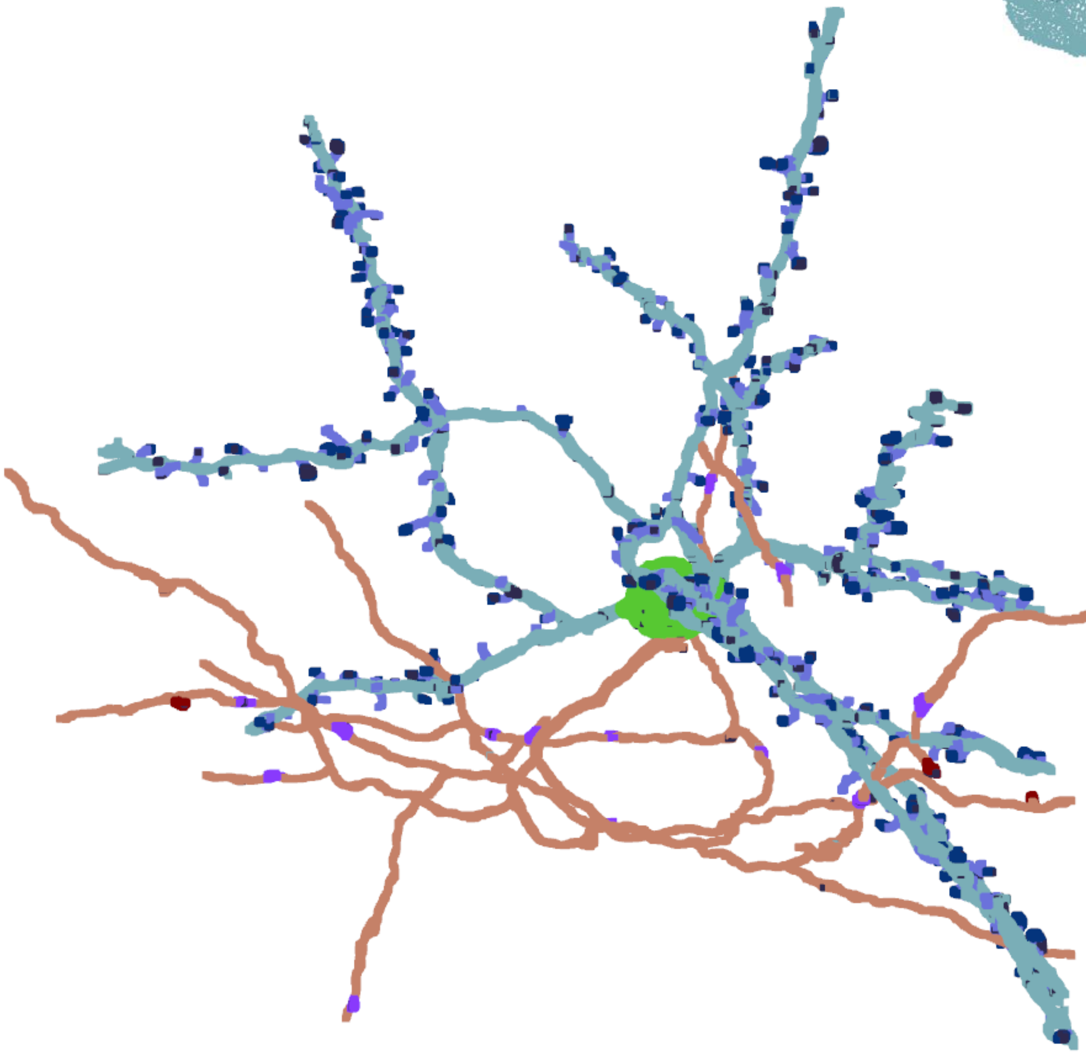


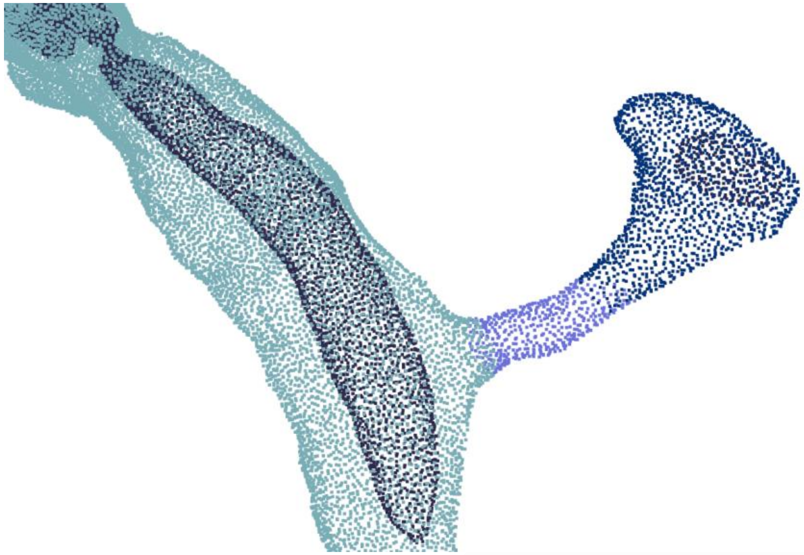
A. Boulch. Convpoint: Continuous convolutions for point cloud processing. arXiv preprint:1904.02375, 2019.

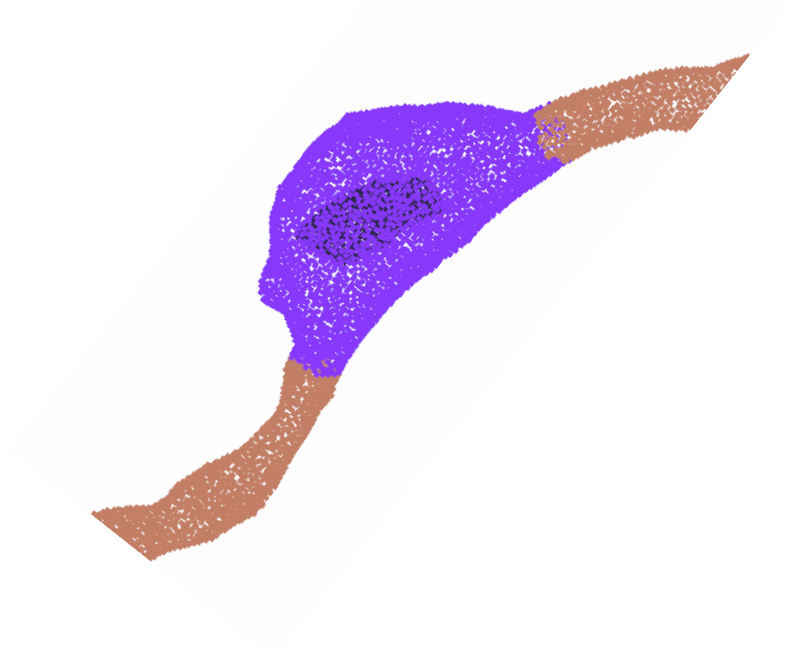
Flood Filling Network reconstruction



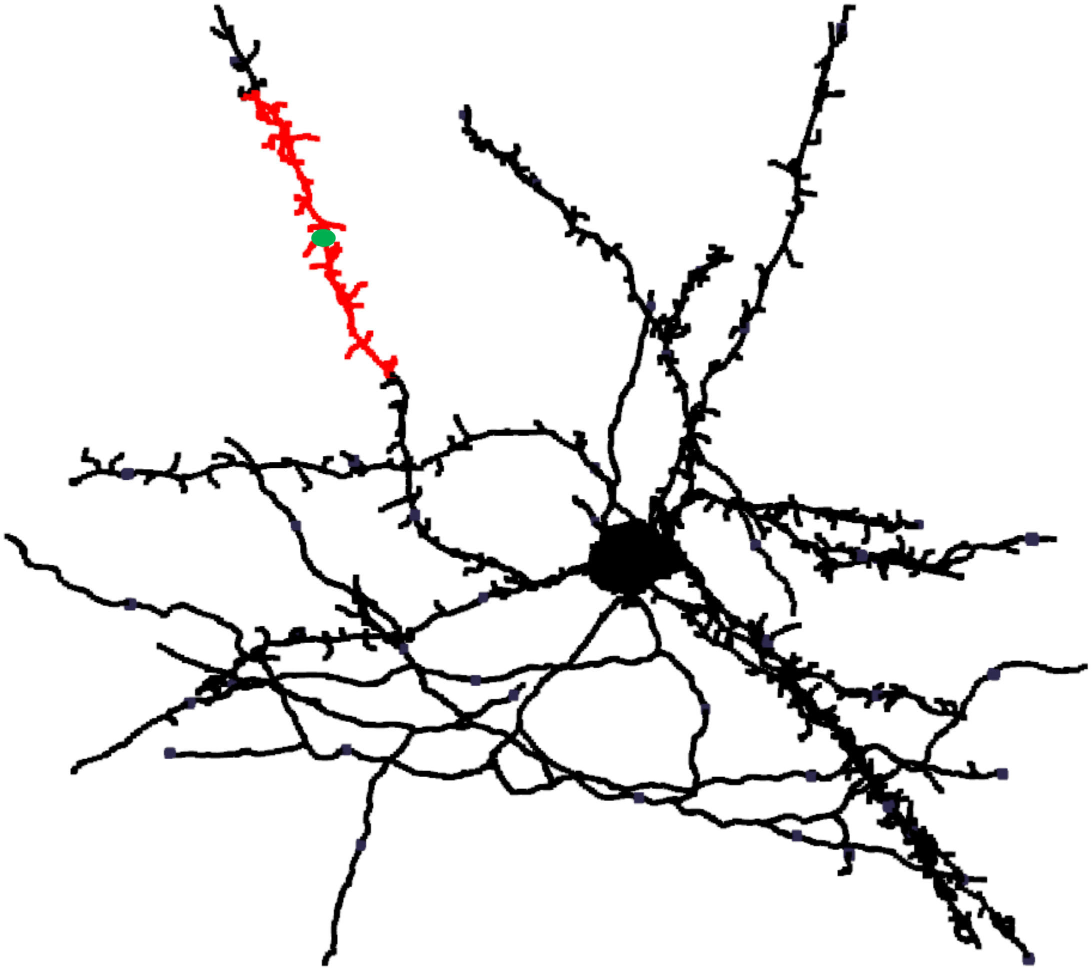
Point representation

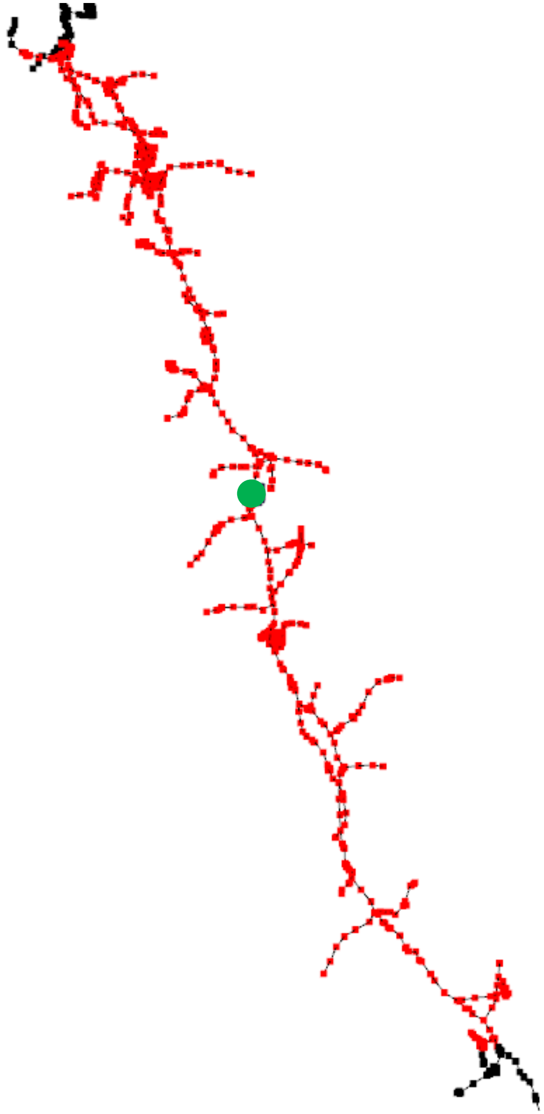




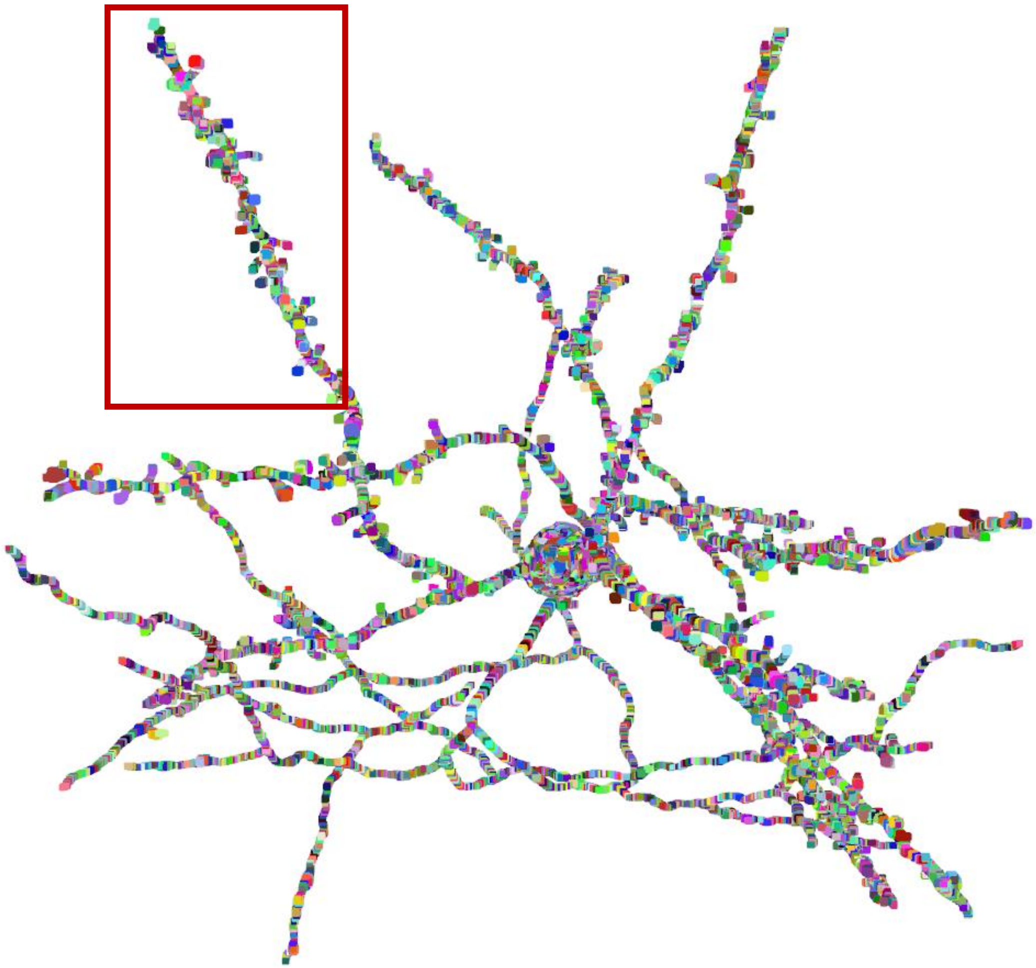


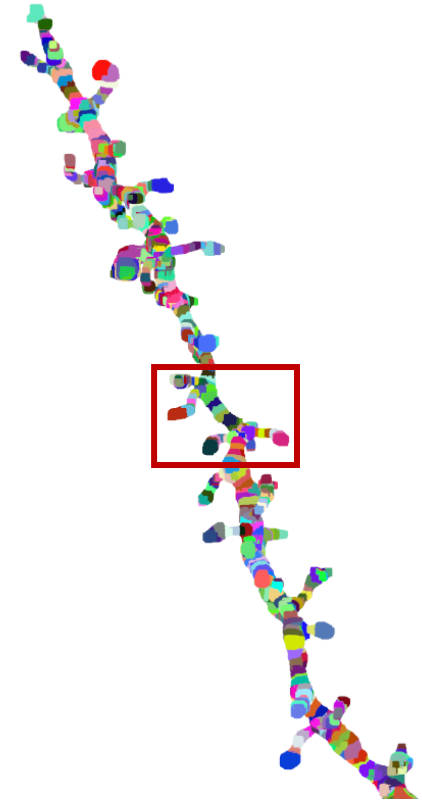
Node-based subgraph extraction

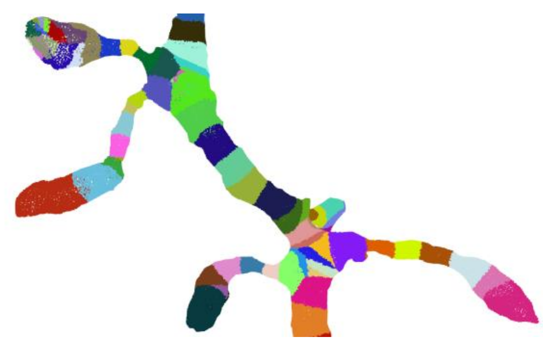




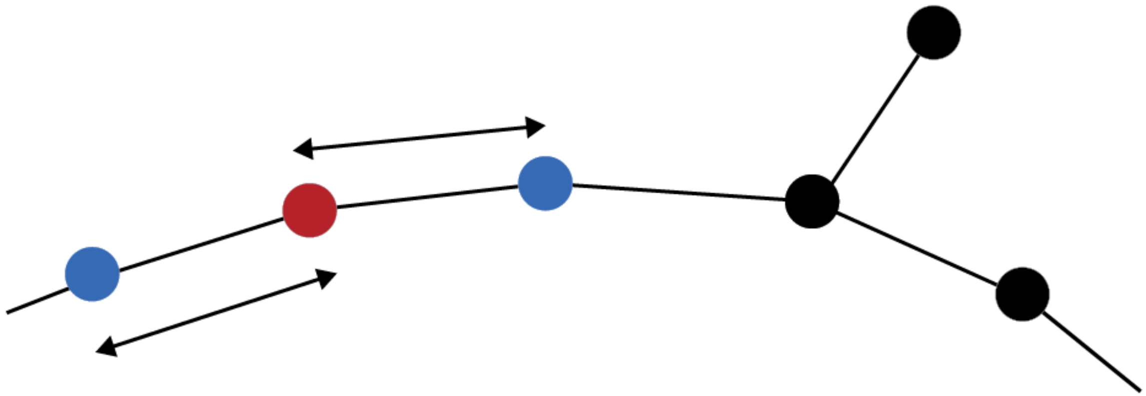
Vertex to node assignment



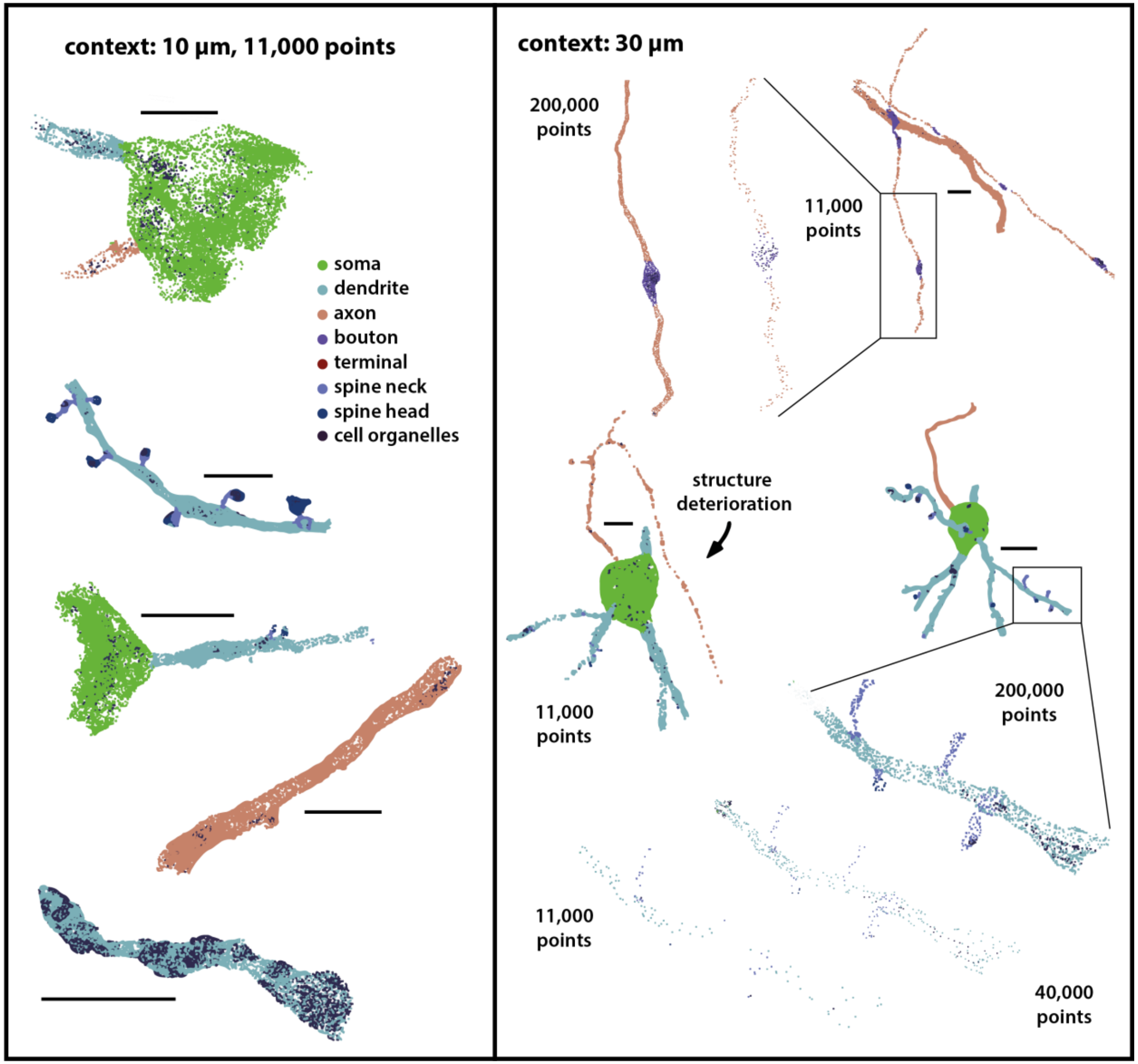




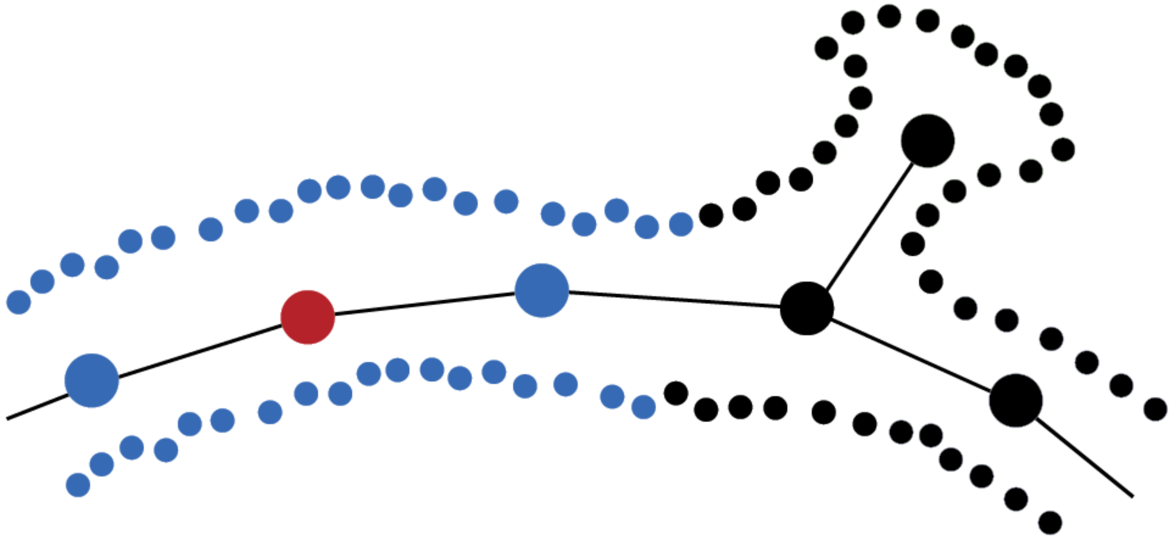
Context-based splitting



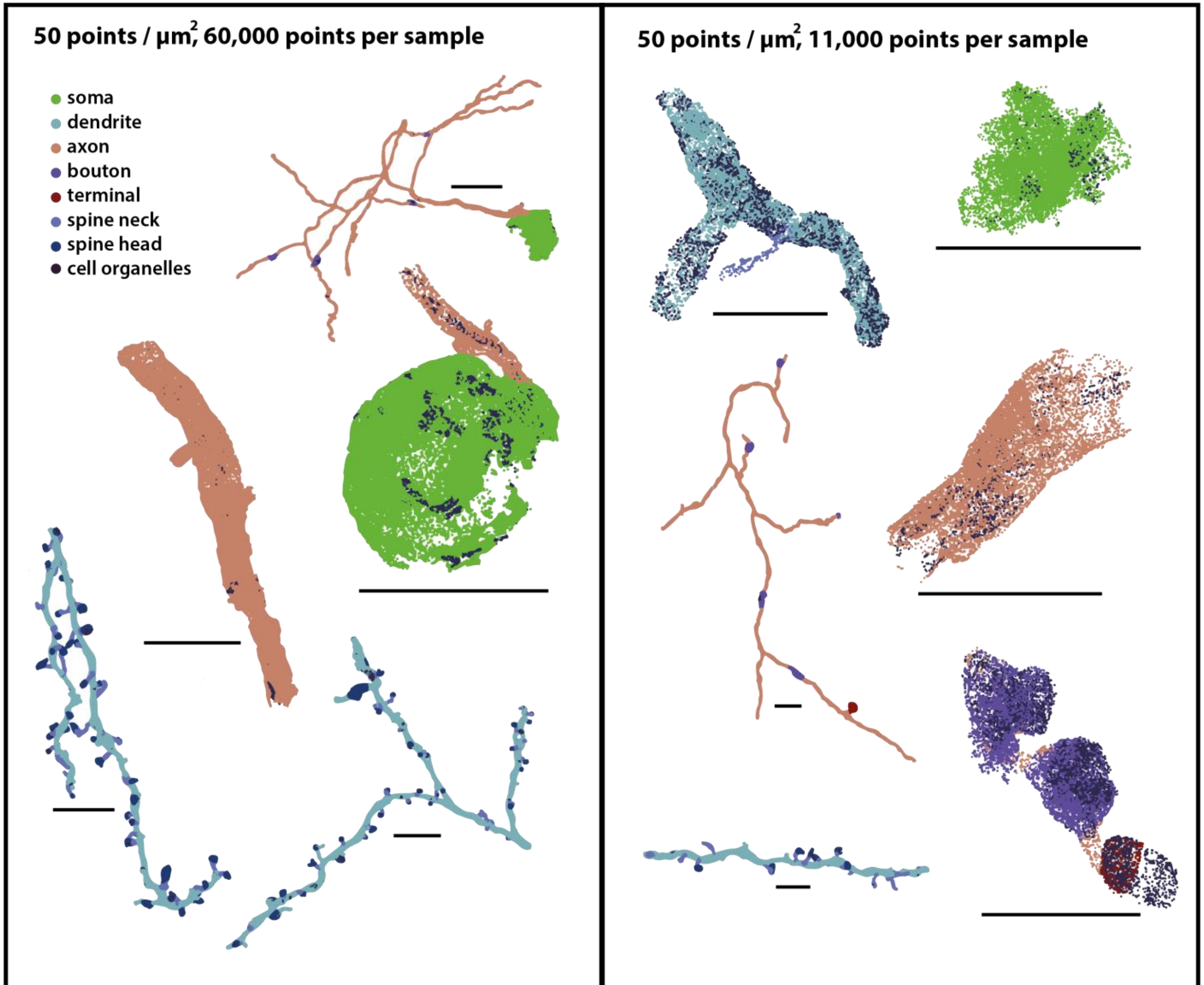
Context-based splitting



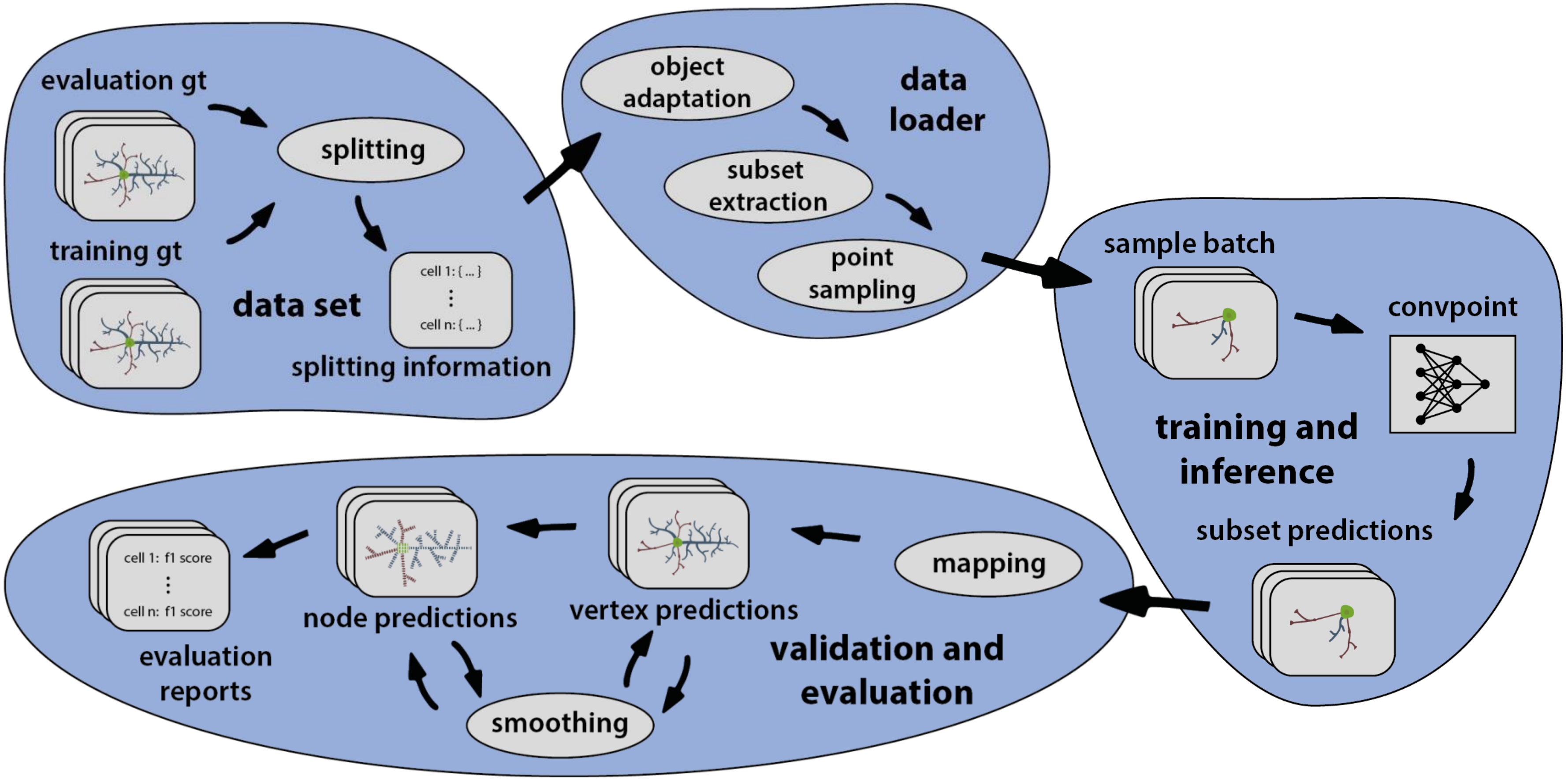
Density-based splitting



Density-based splitting

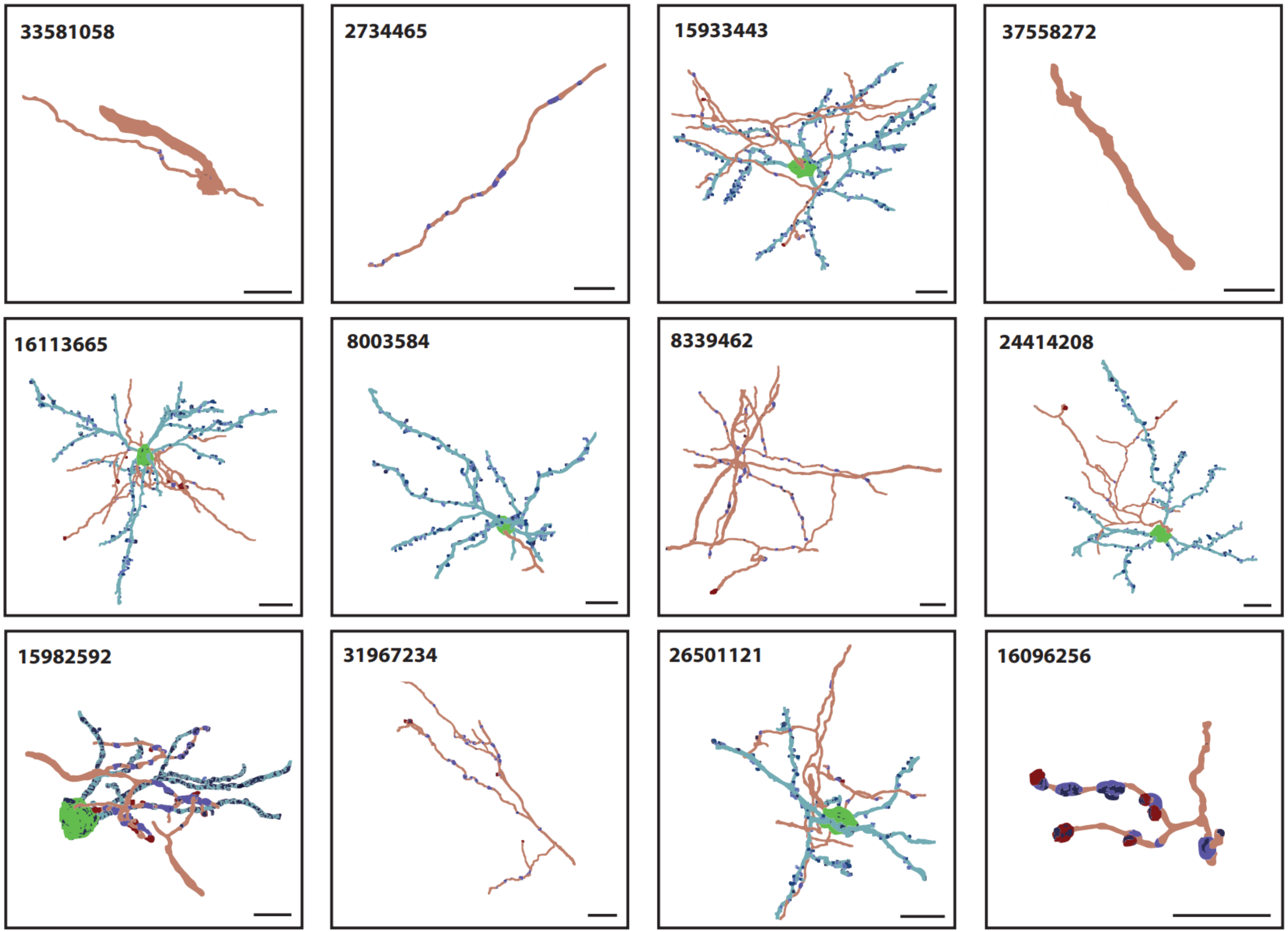


MorphX pipeline



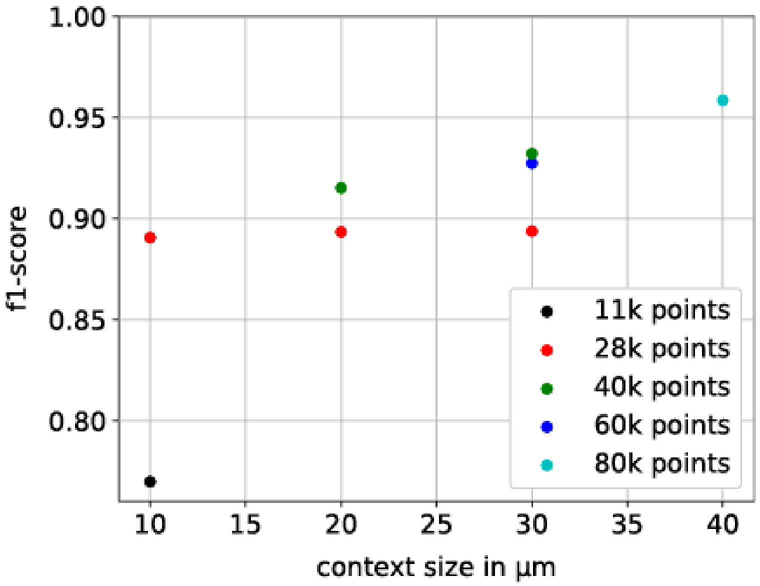
Ground truth

Training set (20 cells), Test set (5 cells)

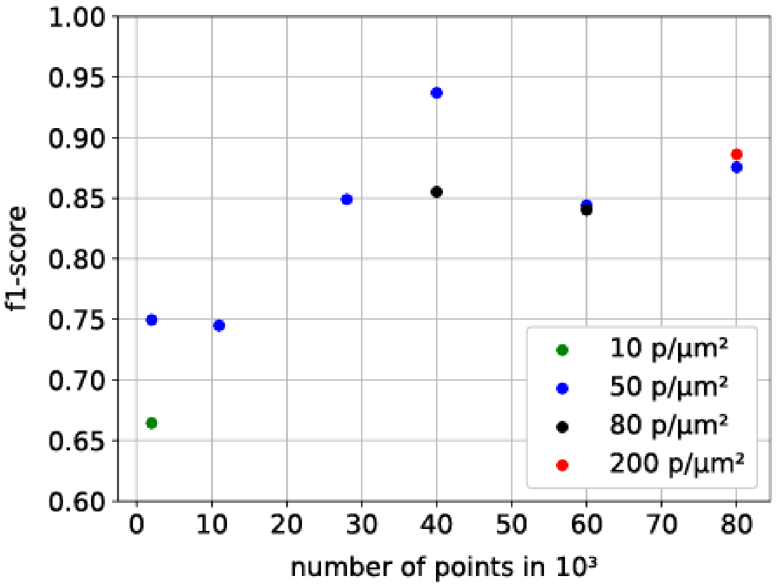


Parameter searches (axon, dendrite, soma)

context-based



density-based

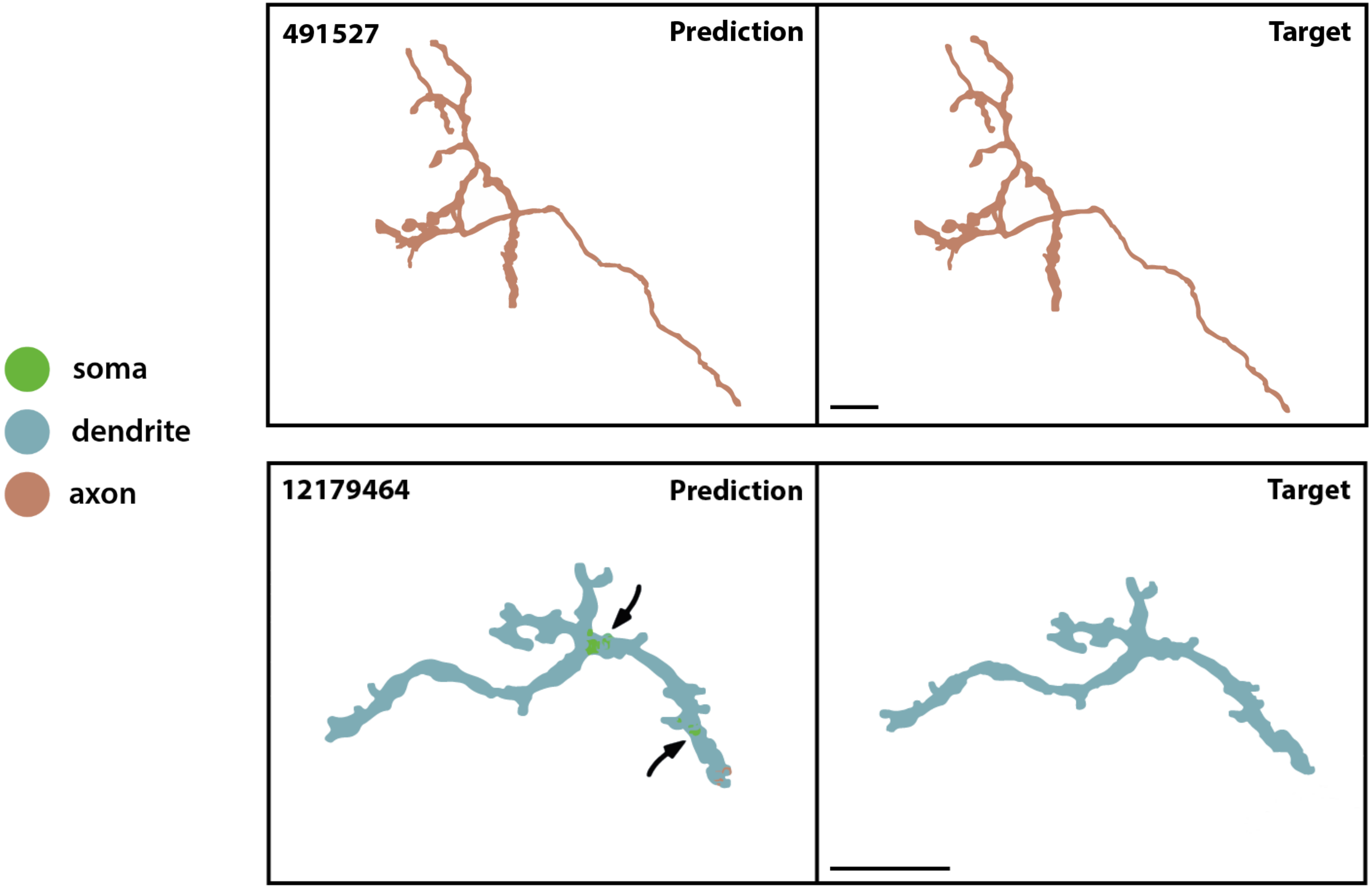


Best 3-class model evaluation

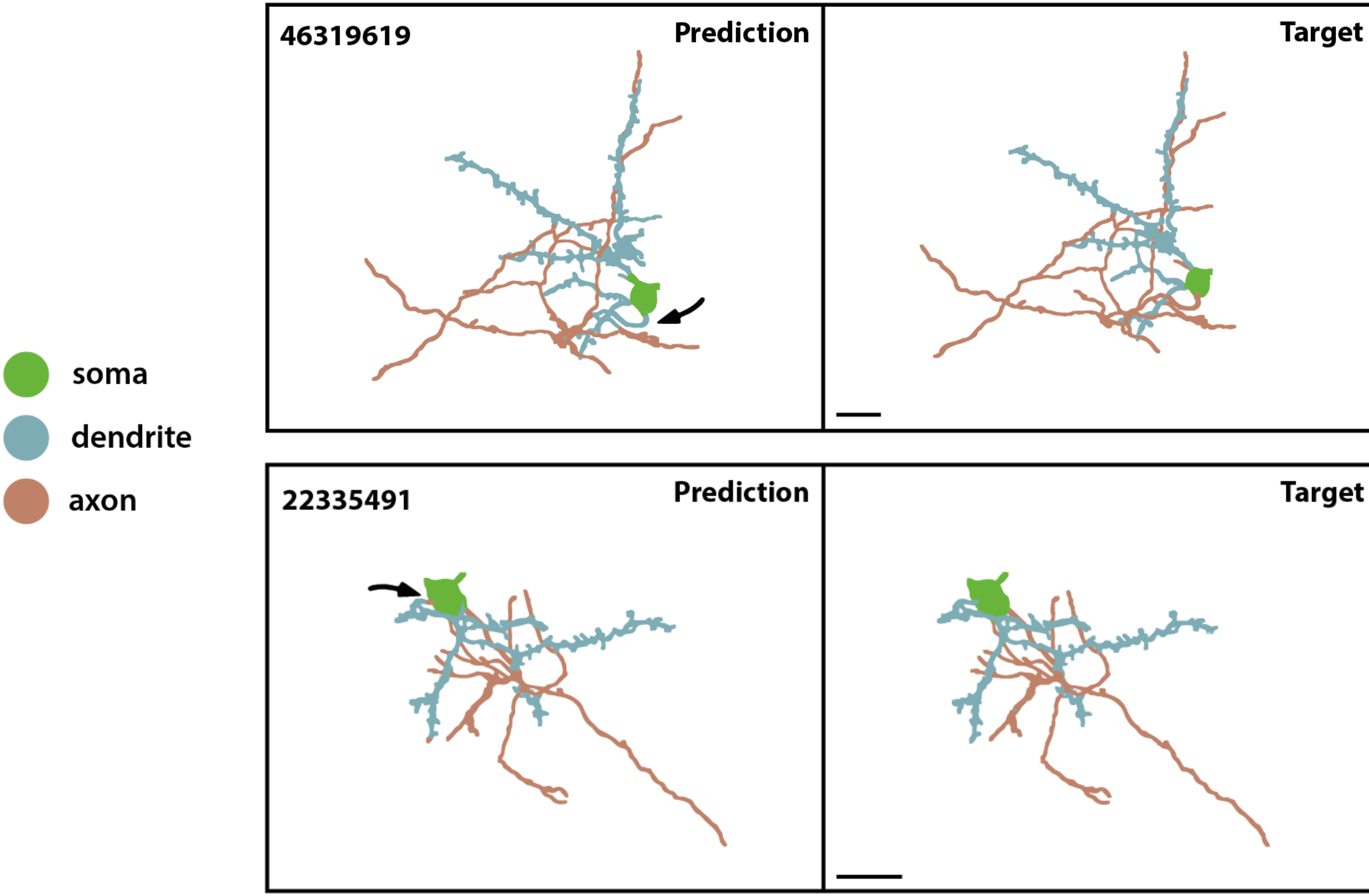
Context-based, 40 um context, 80,000 sample points

type / metric	precision	recall	F_1-score	support
dendrite	0.94	0.98	0.96	12883
axon	0.99	0.97	0.98	26610
soma	0.96	0.96	0.96	9395
accuracy			0.97	48888
macro avg	0.96	0.97	0.97	48888
weighted avg	0.97	0.97	0.97	48888

Best 3-class model evaluation



Best 3-class model evaluation

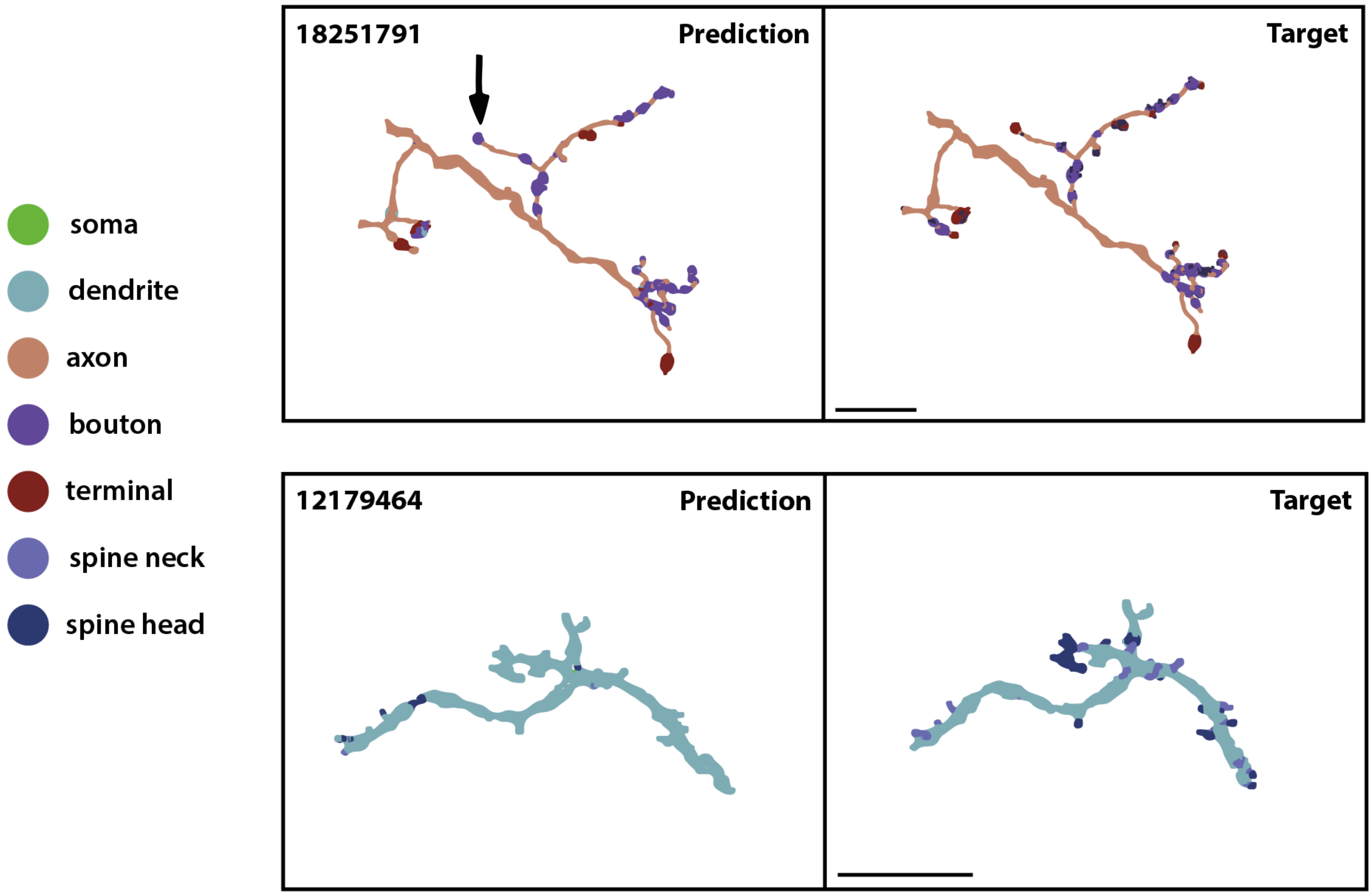


Best 7-class model evaluation

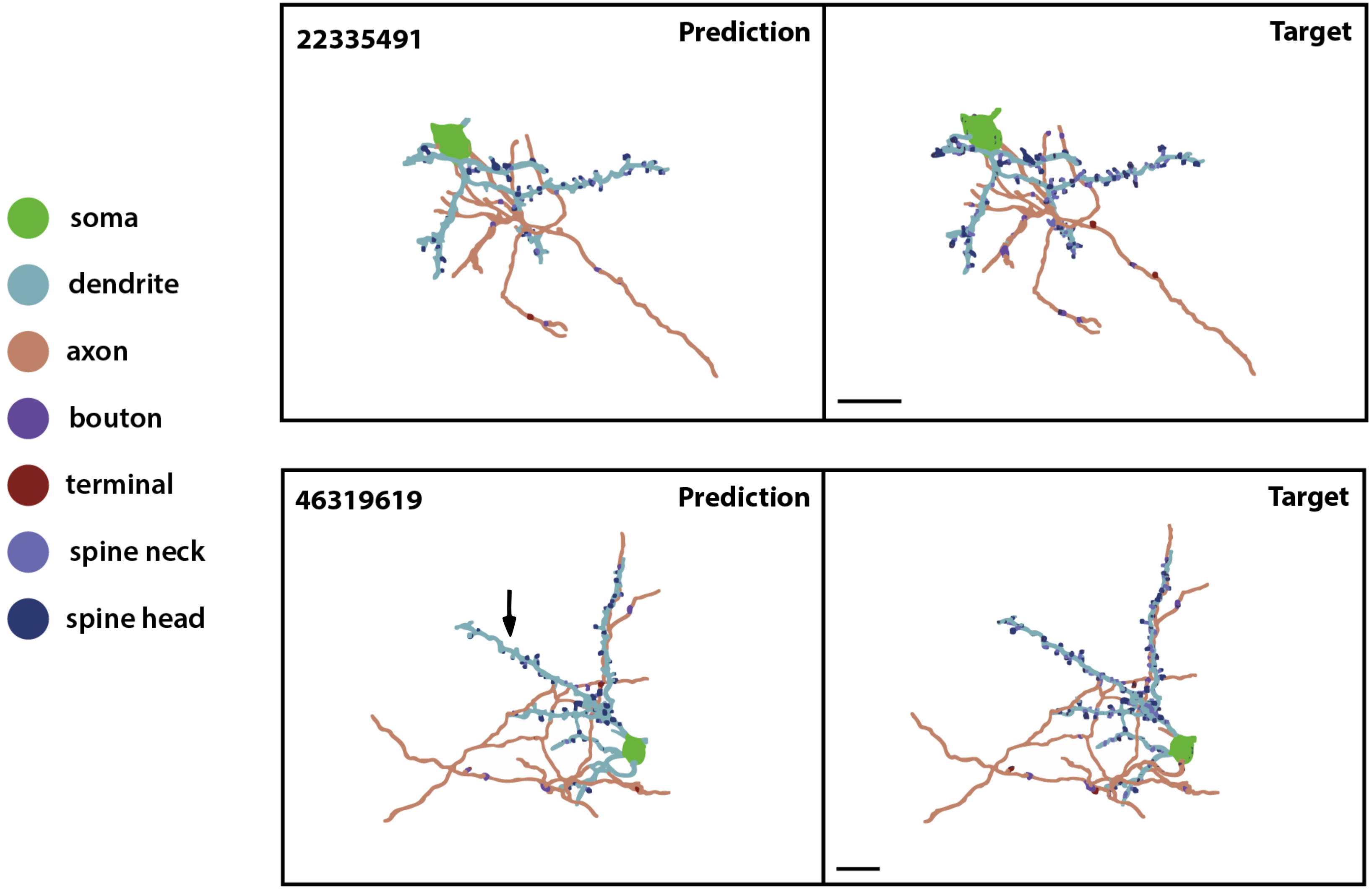
Context-based, 40 um context, 100,000 sample points

type / metric	precision	recall	F_1-score	support
dendrite	0.75	0.98	0.85	9882
axon	0.94	0.90	0.92	20160
soma	0.97	0.95	0.96	9395
bouton	0.71	0.77	0.73	5409
terminal	0.59	0.53	0.56	1041
neck	0.69	0.07	0.13	1782
head	0.70	0.39	0.50	1219
accuracy			0.86	48888
macro avg	0.76	0.65	0.66	48888
weighted avg	0.86	0.86	0.85	48888

Best 7-class model evaluation

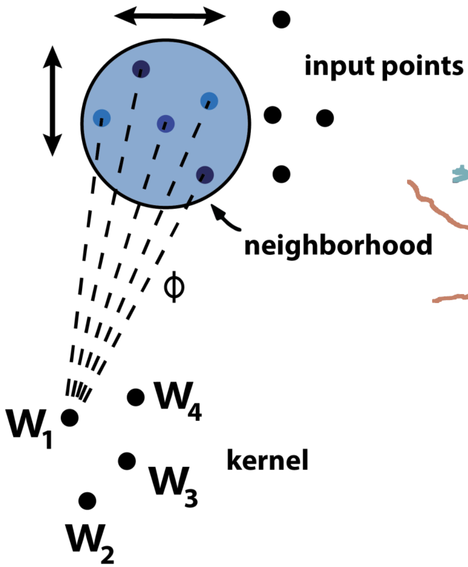


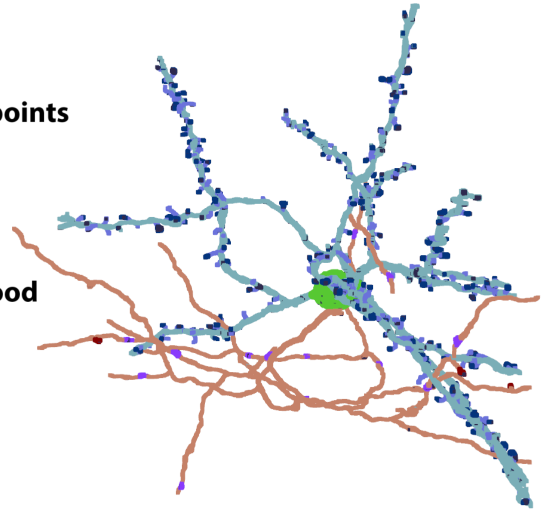
Best 7-class model evaluation

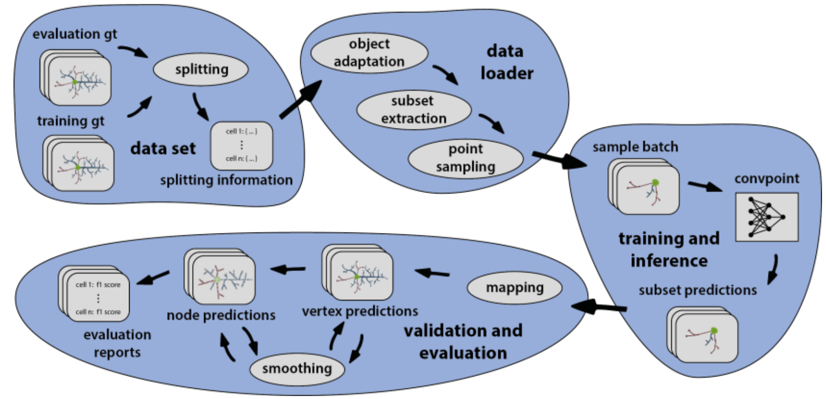


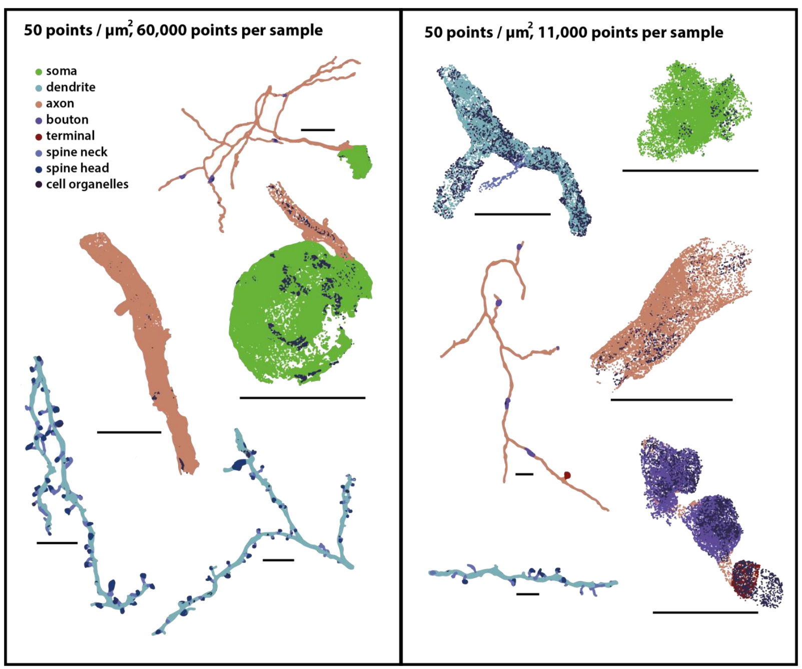
Conclusions

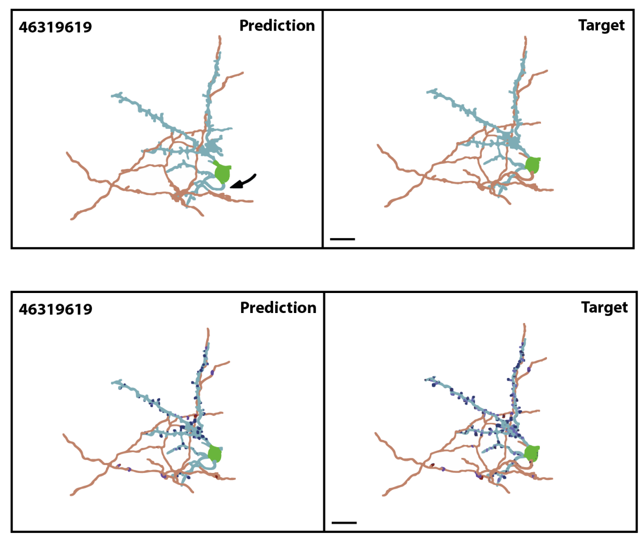
- **Point-based semantic segmentation of reconstructed neurons**
- **ConvPoint architecture shows competitive results for 3-class segmentation**
- **2 different context generation methods were tested, context size and point number did not have significant effects**
- **Spine necks, heads and terminals have major classification problems**
- **Overfitting was solved by further augmentations / larger trainings**









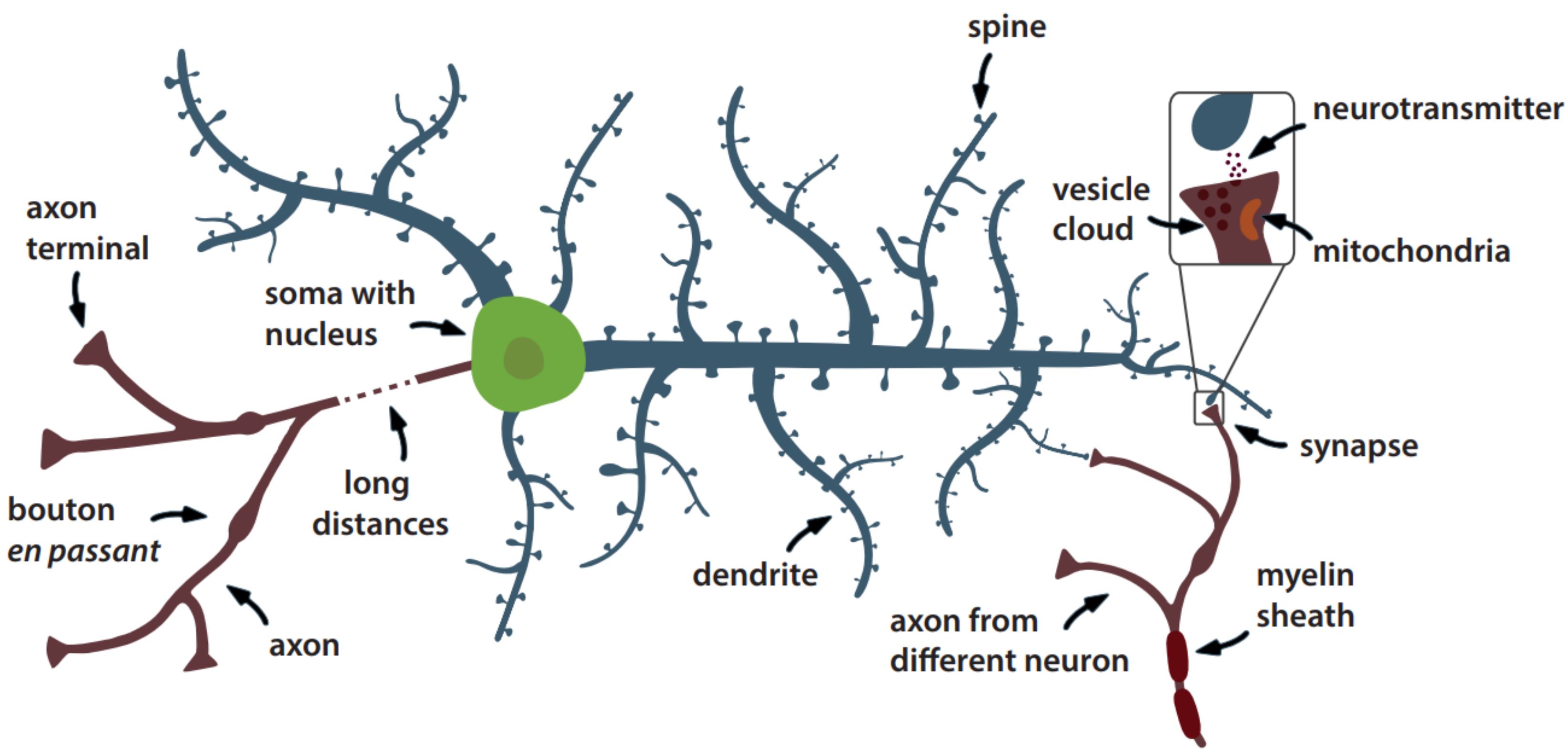


3-class: 0.97

7-class: 0.66

Appendix

Neuron compartments



SyConn pipeline

Detection of ultrastructural objects (mitochondria, vesicles, synapses)

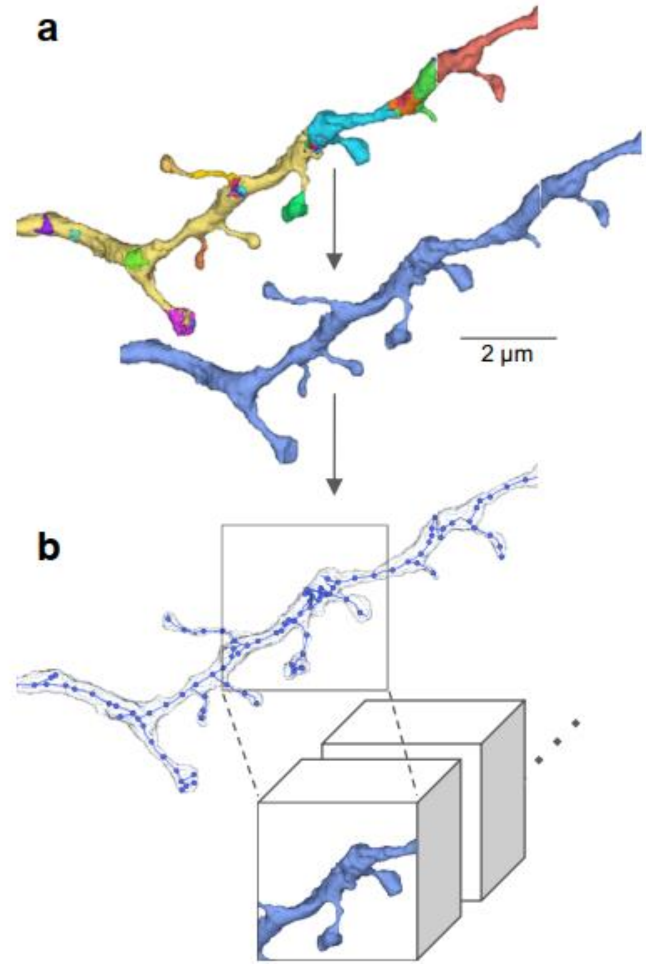
Removal of glia cells

Cell type classification

Semantic segmentation of cellular compartments

Why point-based?

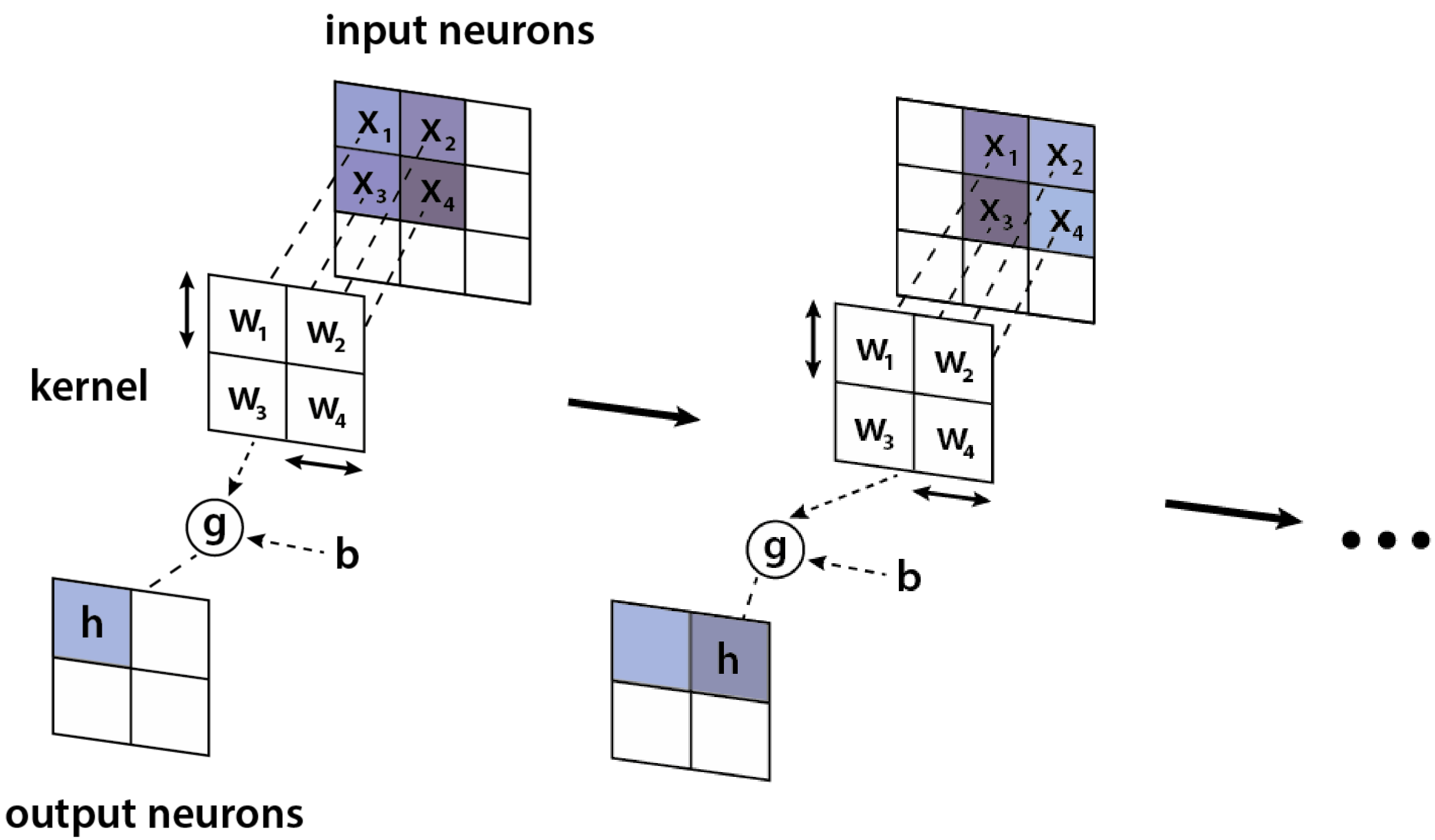
- **No unnecessary computations**
- **Works directly on present data structure**
- **Efficient skeleton-based context extraction**



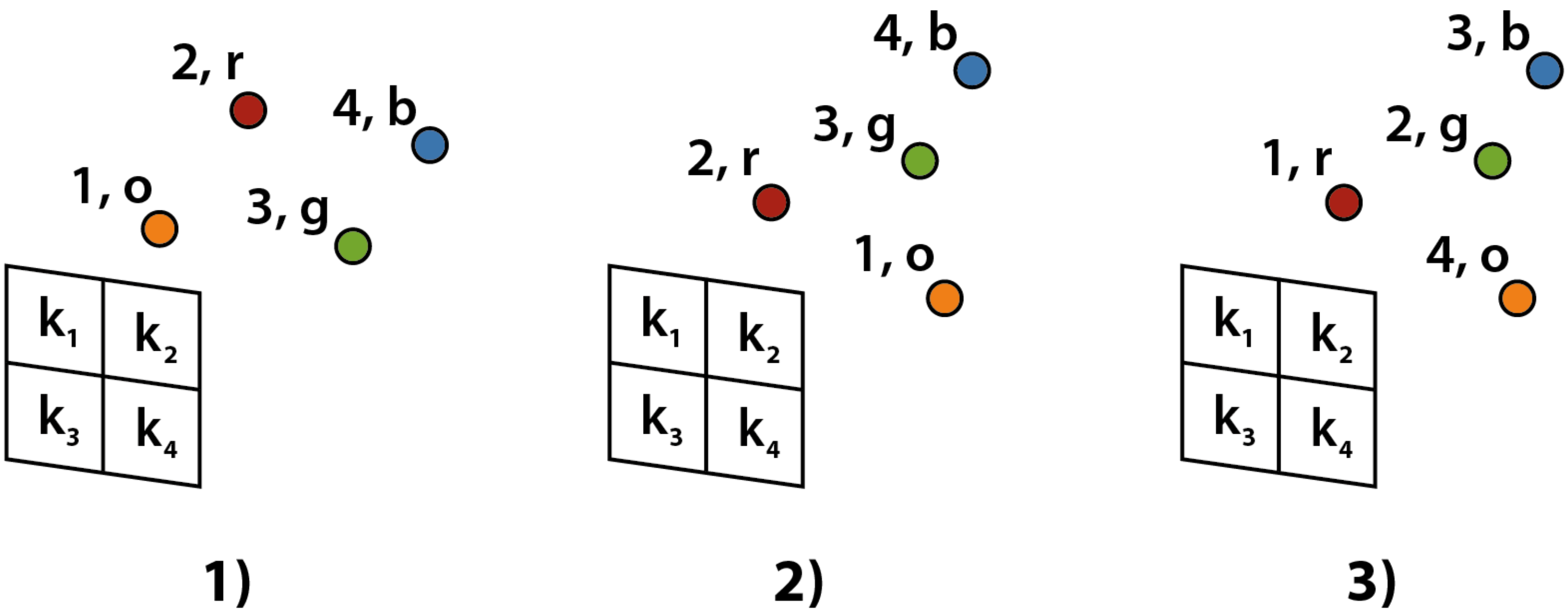
H. Li, M. Januszewski, V. Jain, P. H. Li, Neuronal Subcompartment Classification and Merge Error Correction. bioRxiv preprint: 2020.04.16.043398, 2020

Convolutional Neural Networks (CNNs)

$$h(\vec{x}) = g(\sum_j w_j x_j + b)$$



CNNs for unstructured data



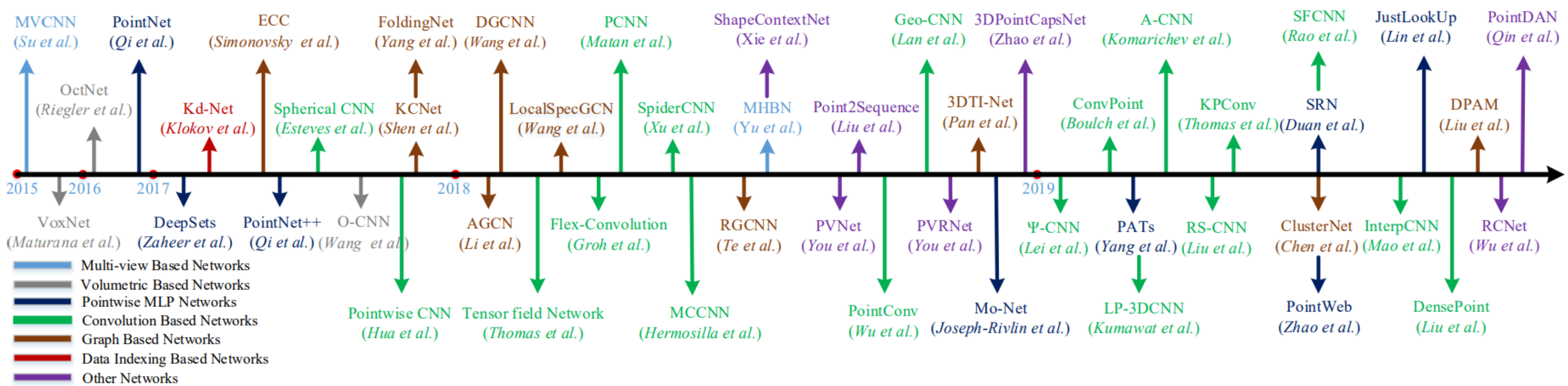
$$f_1 = k_1 o + k_2 r + k_3 g + k_4 b$$

$$f_3 = k_1 r + k_2 g + k_3 b + k_4 o$$

$$f_2 = k_1 o + k_2 r + k_3 g + k_4 b$$

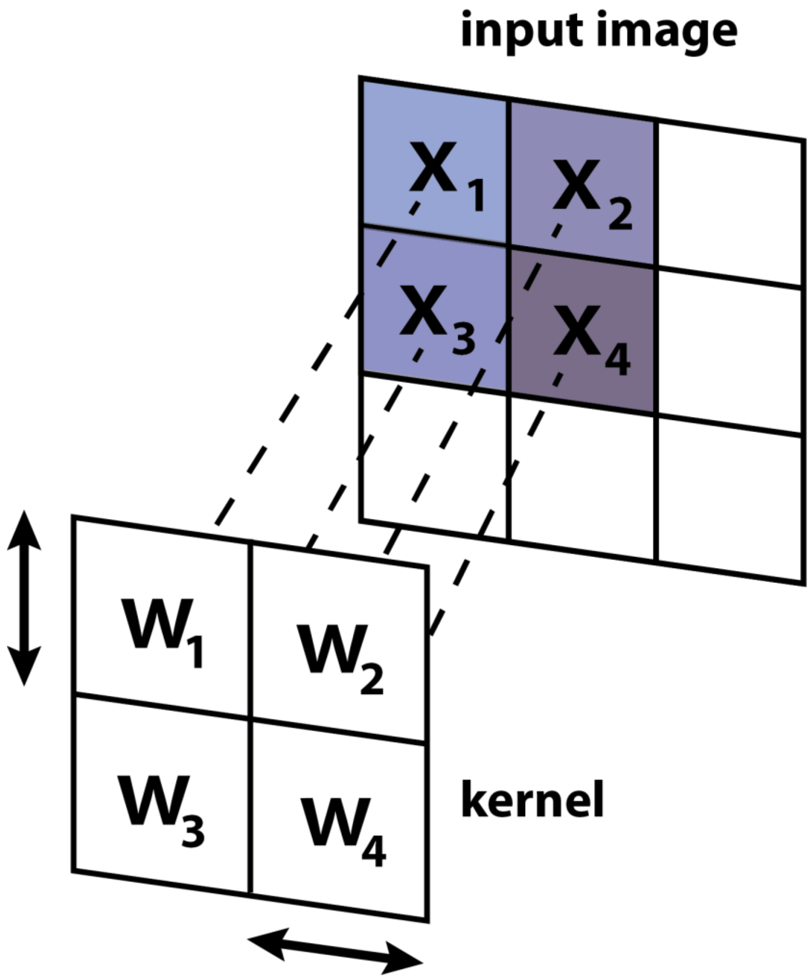
Invariance to point permutations is necessary

CNNs for unstructured data



Y. Guo, H. Wang, Q. Hu, H. Liu, L. Liu, and M. Bennamoun. Deep learning for 3d point clouds: A survey. 2019.

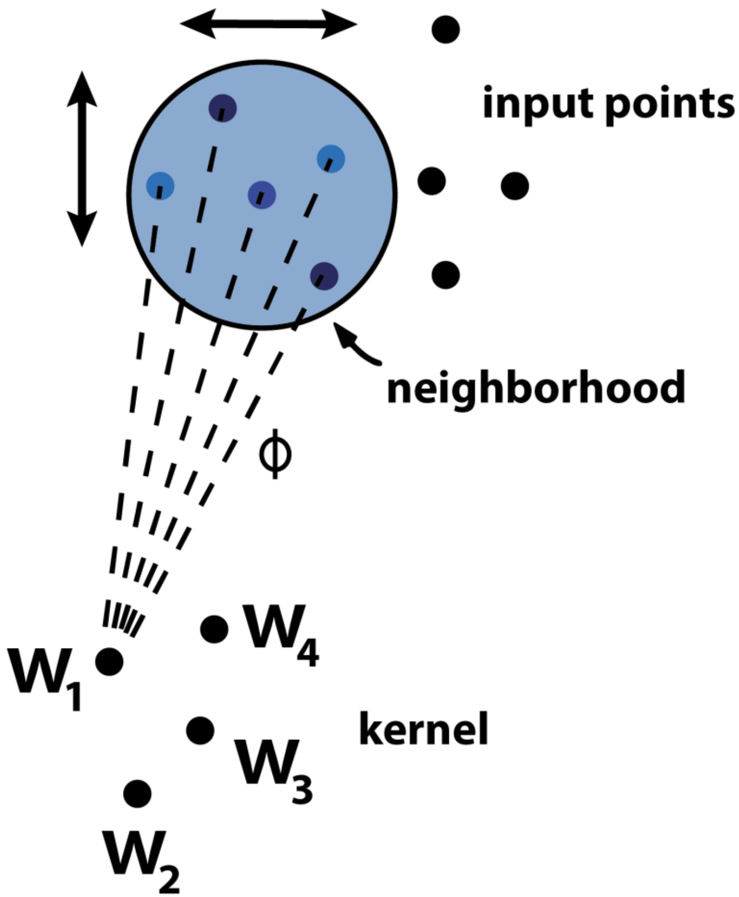
Discrete convolution



$$o = \sum_j w_j x_j$$

$$o = \sum_i \sum_j w_i x_j 1(k_i, p_j)$$

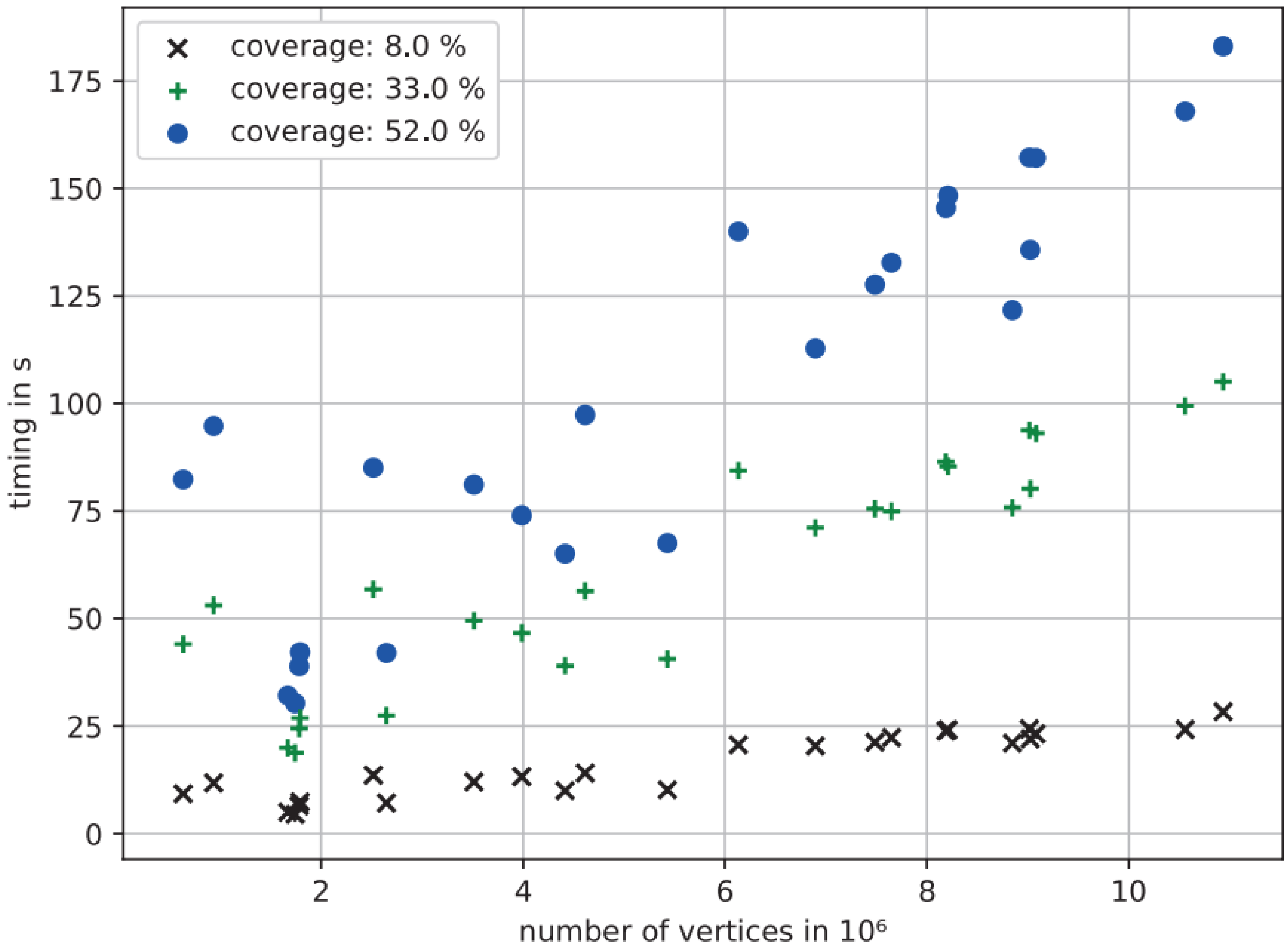
ConvPoint



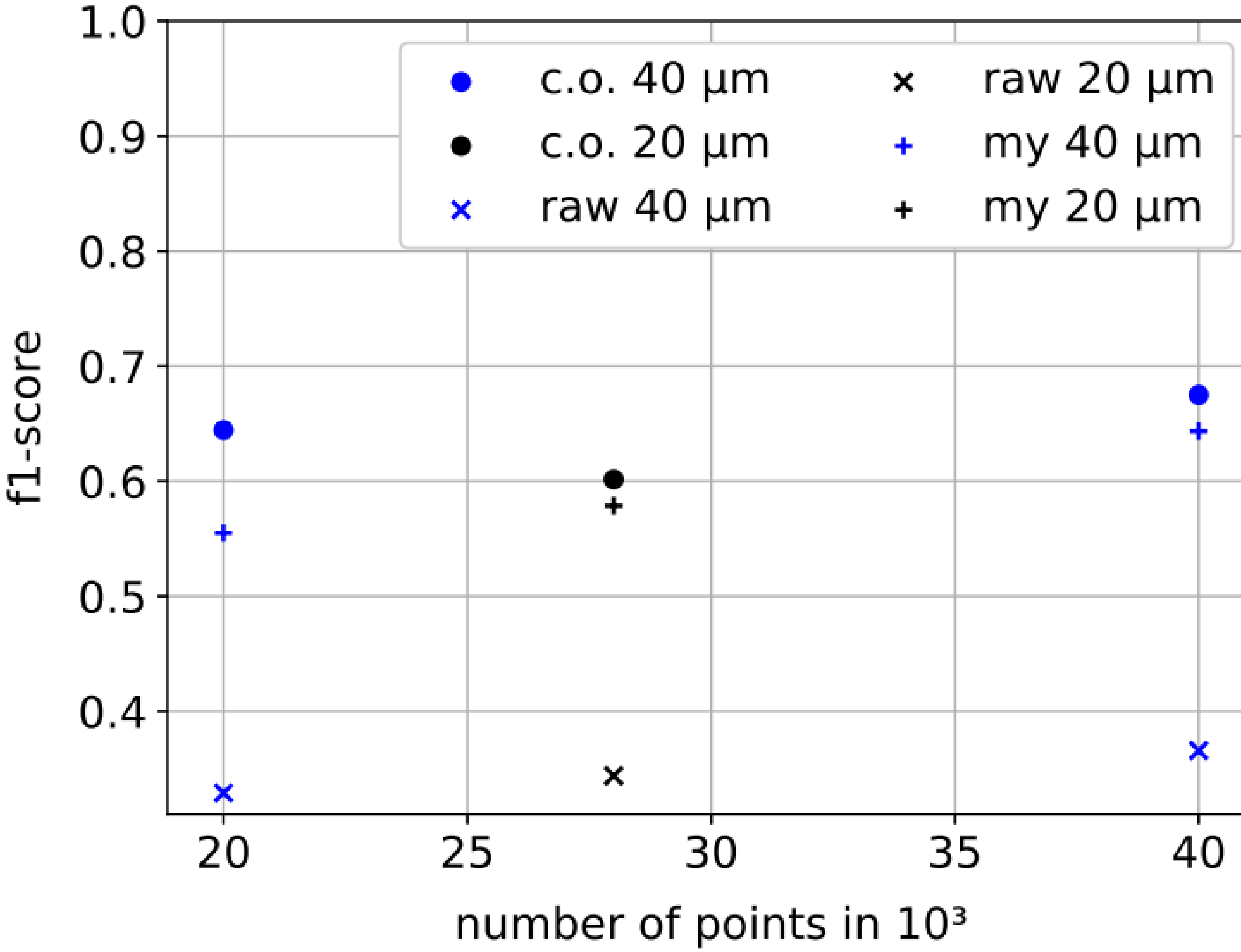
$$o = \sum_i \sum_j w_i x_j 1(k_i, p_j)$$

$$o = \sum_i \sum_j w_i x_j \phi(p_j - k_i)$$

Timing


coverage: 8.0 %
coverage: 33.0 %
coverage: 52.0 %
timing in s
0
25
50
75
100
125
150
175
2
4
6
8
10
number of vertices in 10^6

Effects of cell organelles



Evaluation metrics

$$P = \frac{tp}{tp + fp}$$

Precision: What percentage of predicted dendrite points are actually on a dendrite?

$$R = \frac{tp}{tp + fn}$$

Recall: How many of the dendrite points have been predicted as dendrite?

$$F_1 = 2\frac{P \cdot R}{P + R}$$

F1-score: Harmonic mean of precision and recall?

$$a(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{n_{samples}} 1(\hat{y}_i = y_i)$$

Accuracy: What percentage of total points is labelled as the right class?

Model specifications

layer	output channels C	output points Q	neighborhood size k
0 conv	64	input size	16
1 conv	64	2048	16
2 conv	64	1024	16
3 conv	64	256	16
4 conv	128	64	8
5 conv	128	16	8
6 deconv	128	8	4
7 deconv	128	16	4
8 deconv	128	64	4
9 deconv	64	256	4
10 deconv	64	1024	4
11 deconv	64	2048	8
12 deconv	64	input size	8
13 linear			

Table 2.1: Layer specifications of the ConvPoint based architecture which was used for the segmentation tasks.

- **Adam optimizer**
- **StepLR learning rate scheduler**
- **Random rotations as augmentations**