Global Neuron Shape Reasoning with Point Affinity Transformers

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Abstract

Connectomics is a subfield of neuroscience that aims to map the brain's intricate wiring diagram. Accurate neuron segmentation from microscopy volumes is essential for automating connectome reconstruction. However, current state-of-the-art algorithms use image-based convolutional neural networks that are limited to local neuron shape context. Thus, we introduce a new framework that reasons over global neuron shape with a novel point affinity transformer. Our framework embeds a (multi-)neuron point cloud into a fixed-length feature set from which we can decode any point pair affinities, enabling clustering neuron point clouds for automatic proofreading. We also show that the learned feature set can easily be mapped to a contrastive embedding space that enables neuron type classification using a simple KNN classifier. Our approach excels in two demanding connectomics tasks: proofreading segmentation errors and classifying neuron types. Evaluated on three benchmark datasets derived from state-of-the-art connectomes, our method outperforms point transformers, graph neural networks, and unsupervised clustering baselines. [1]

1. Introduction

The field of connectomics maps the wiring diagrams of biological neural networks using high-resolution 3D microscopy and image segmentation. The recent completion of the connectome of the entire fruit fly brain was a major triumph for neuroscience [8]. Assembling this connectome involved substantial manual proofreading to correct segmentation errors, even with state-of-the-art automatic segmentation algorithms; 622 researchers from 146 laboratories worldwide contributed 33 human-years of manual proofreading effort for just 10^5 neurons in the millimeter-sized fruit fly (Drosophila) brain. Scaling up connectomics to map the $500\times$ larger mouse brain [1] will require orders of magnitude larger human effort with current technology. Therefore, improving the accuracy of automated neuron segmentation algorithms is of vital importance to the field of neuroscience.

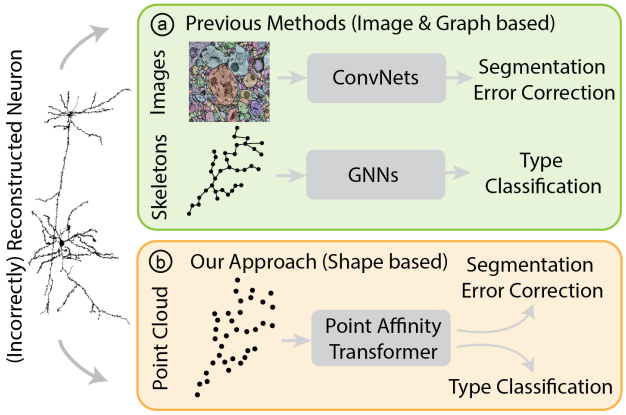

Figure 1. **Overview & Comparison to Previous Work.** ⓐ Previous approaches use 3D ConvNets for improving neuron segmentation accuracy and are thus limited to local fields of view. Additionally, neuron type classification often requires auxiliary skeleton graphs. ⓑ We propose a new point affinity transformer model for neuron segmentation error correction and type classification.

Existing segmentation algorithms [12, 15, 21, 25–27, 37, 41] are largely CNN-based local methods which cannot reason over the shape of an entire neuron. Those algorithms have significantly progressed towards accurately segmenting neurons. Nonetheless, this has led to a mean segmentation-error-free path length of at least 1.1 millimeters of neurite wire [15]. However, a total of 145 meters of cable in a tiny fruit fly brain still necessitates a significant manual effort to proofread and correct machine-generated segmentations [8]. Human proofreaders use 3D renderings of candidate segmentations of entire neurons to detect and correct segmentation errors. These candidate segmentations sparsely span very large volumes with bounding boxes on the order of $10^4 \times 10^4 \times 10^4$ voxels, limiting the ability of image-based CNN to scale to global neuron shape. To address this challenge, we propose a novel type of point cloud transformer, called a point affinity transformer, to reason over global neuron shapes.

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Point clouds can efficiently represent sparse yet expansive neuron shapes. We formulate neuron shape learning as a pairwise affinity prediction problem, where two points have an affinity value of 1 if both belong to the same neuron and 0 otherwise. Critically, our architecture does not require the model to learn explicit spatial parameters (e.g., features over a grid), allowing it to represent sparse spatial neuron shapes flexibly. We apply our approach to automated neuron proofreading, which involves detecting and correcting errors in erroneous neuron point clouds. Additionally, we demonstrate our model's capability to represent global neuron structures by projecting its internal features into a contrastive embedding space, which enables the automatic assignment of type labels to neurons. Both tasks rely on a detailed understanding of global neuron morphology. We empirically evaluate our approach on three state-of-the-art connectome datasets [8, 33, 39]. We benchmark against other learning-based techniques, including graph neural networks (GNNs), alternative point cloud transformer architectures, and unsupervised clustering methods. Our results demonstrate superior performance for both automatic proofreading and neuron-type classification, achieving improvements in terms of common clustering and multi-class classification metrics. In summary, our work makes several contributions:

- We propose a novel neuron shape learning framework centered around pairwise point affinity prediction. Given a (multi-)neuron point cloud, our model's task is to disentangle individual neurons and background fragments by predicting correct affinities between point pairs. Our new transformer-based model, the point affinity transformer, implements this framework and captures complex global neuron morphologies.
- We apply this framework and model to automatic neuron proofreading. We correct reconstruction errors in multi-neuron point clouds using predicted pairwise point affinities and agglomerative clustering. Our approach outperforms baselines, such as graph neural networks (GNNs) and other point cloud transformers.
- Our model's internal neuron representations, trained only for affinity prediction, can easily be projected into a contrastive embedding space for neuron type classification.

2. Related Work

Point Clouds. Our rationale for choosing point clouds over other spatial data representations is two-fold. First, compared to volumetric representations, point clouds fit sparse and thin spatial data well. Second, point clouds are easy to obtain from segmentation volumes and do not require additional processing like surface meshes or skeletons. Approaches for segmentation and classification of point clouds can be broadly categorized into GNNs [38, 43], transformers-based approaches [45, 46, 50–52], and set-based approaches [31, 32]. For the purpose of representing global neuron shapes, we argue that attention-based transformer models are better suited than GNNs. Neurons are thin, long, and sparse, making it hard for traditional message-passing GNNs to update point features based on distant points on the same neuron. In contrast, self-attention overcomes this issue by flexibly allowing node feature updates across long distances on the neuron. Within the space of point cloud transformers, there exist several key limitations for representing neuron shapes. First, several methods [49, 52] rely on spatial references within its internal feature space such as learned features over a grid-like structure, limiting flexibility when fitting to spatially sparse data. Our model's internal feature space has no spatial reference, allowing it to fit flexibly to thin and sparse neuron structures. Second, previous architectures are dependent [52] on *a priori* knowledge about point cloud sizes. Our model easily adapts to variable point cloud input sizes in a single layer through a masked attention mechanism, enabling training on variable-size multi-neuron point clouds.

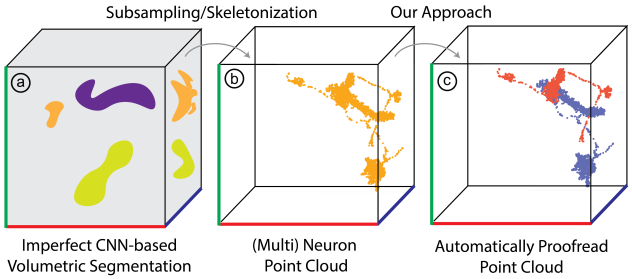

Figure 2. **Automatic Proofreading Workflow.** ⓐ 3D CNN-based volumetric neuron segmentations contain errors. ⓑ We derive a (multi-)neuron point cloud through either skeletonizing or subsampling the segmentation volume. ⓒ Our approach enables automatic proofreading of such (multi-)neuron point clouds.

Neuron Error Correction. Substantial ongoing efforts manually proofread large-scale connectomes [5, 7, 8, 28, 36]. Another common approach is to reduce the number of errors by increasing the robustness and accuracy of image-based segmentation models [12–15, 26, 27, 53]. However, these 3D convolutional networks lack the global context of neuron morphology due to inherently localized convolution operations. Additionally, they must adjust for factors such as image noise and axes-based resolution differences. Instead, we show that point clouds are a robust and expressive shape representation that allows us to take the global neuron shape context into account. Prior work has made progress toward automatically proofreading imperfect connectome reconstructions. However, these approaches either rely on handcrafted heuristics on 3D meshes [17], build on GNNs that require brittle auxiliary skeleton graphs [2], or use agent-based tracing algorithms [34].

Neuron Classification. Approaches for neuron classifica-

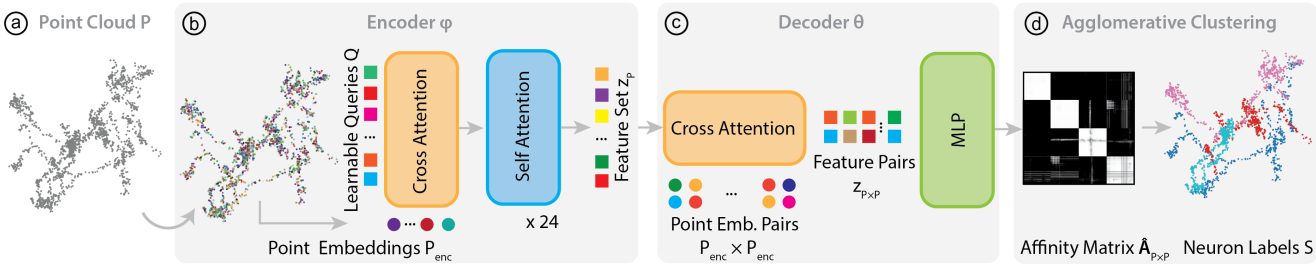

Figure 3. **Automatic Proofreading Pipeline.** ⓐ Our model encodes a point cloud with samples from N neurons ⓑ into a fixed length feature set using a series of cross- and self-attention layers (Sec. 3.2). ⓒ Next, we condition the decoder with this feature set and compute feature pairs of points from the input point cloud using a cross-attention module. These feature pairs are then decoded into affinity values using an MLP (Sec. 3.2). ⓓ We then extract neuron labels by performing feature agglomerative clustering on the affinity matrix (Sec. 3.3).

tion are separated into two groups. The first group focuses on neuron sub-compartment classification [6, 23], that is, assigning labels to subcellular structures such as dendrites, axons, or cell bodies. Notably, these approaches do not require global shape context to make reliable predictions. The second group focuses on neuron typing [3, 4, 16, 20, 35], which assigns a single label to a neuron that is indicative of its function. This is more challenging than sub-compartment classification since global neuron shape is among the most important factors for assigning a type. In practice, handcrafted feature extractors are still being used to group neurons into types [4, 19]. On the other hand, learning-based methods often operate on auxiliary graph data structures like skeletons [3, 11, 47], a global connectome graph [24], or multiview 2D projections [35] that do not fully capture 3D morphology. We argue that skeletons are brittle, sensitive to hyper-parameters, and accumulated errors in earlier steps. Manual parameter tuning is required to minimize small twigs, and gaps are easily introduced if the underlying image segmentation is discontinuous. Thus, we propose using point clouds for global neuron type classification, which are easy to obtain but also capture the detailed shape of neurons.

3. Method

Our goal is to learn an expressive feature space that can capture global neuron shapes. We demonstrate this capability in two challenging connectomics tasks: automatic neuron proofreading using our point affinity transformer model and neuron type classification.

3.1. Automatic Proofreading Workflow

3D CNNs for neuron segmentation generate voxel-based label volumes, where each label typically represents a "supervoxel" — a small sub-segment of a neuron. Therefore, reconstructing the complete structure of a neuron requires agglomerating numerous supervoxels (Fig.2ⓐ). The specifics of the segmentation technique determine the approach to agglomeration; however, this process is generally susceptible to segmentation errors, resulting in either split or merge errors. The goal of proofreading is to correct these errors by separating incorrectly merged segments and joining incorrectly split ones. In practice, the balance between split and merge errors is influenced by the level of supervoxel agglomeration applied. To address both types of errors, our automated proofreading framework assumes a high degree of supervoxel agglomeration, which biases the segmentation toward merge errors. Consequently, we consider each point cloud as a superset containing all true neuron points (Fig.2ⓑ) alongside background fragments. We sample point clouds from the agglomerated segmentation volume. We either sample points from the vertices of the respective skeleton or directly sample points as a subset of segmentation voxels. Our algorithm then focuses on partitioning this point cloud into individual neurons (Fig. 2ⓒ) while excluding any background fragments that do not correspond to full neurons.

3.2. Point Affinity Transformer

Problem Formulation. The main idea of our approach is to formulate global neuron shape learning as a pair-wise affinity prediction task on multi-neuron point clouds. Given an input point cloud $P = \{p_0, ..., p_n\} \subseteq \mathbb{R}^3$ (Fig. 3ⓐ) sampled from $\{1, ..., K\}$ neurons and a set of background fragments, our model M learns to predict an affinity matrix $\hat{\mathbf{A}}_{P\times P} \in \mathbb{R}^{n\times n}$ between all point pairs $P \times P$ as below:

$$\hat{\mathbf{A}}_{P\times P} = M(P, P \times P) = \{a_{(p_0,p_0)}, ..., a_{(p_n,p_n)}\}, \quad (1)$$

where an affinity value $a_{(p_i,p_j)}$ represents the likelihood that p_i and p_j belong to the same neuron. Given $\hat{\mathbf{A}}_{P\times P}$, we reconstruct segmentation labels $S = \{s_0, ..., s_n\}, s_i \subseteq \mathbb{N}$. Each segmentation label $s_i \in S$ maps to the neuron identity of the respective point $p_i \in P$. Specifically, $s = 0$ denotes a background class, which covers fragments that do not assemble entire neurons. $s > 0$ denotes a label for a specific neuron. We derive S by clustering P using an affinity-based

distance metric $\hat{\mathbf{D}}_{P\times P} = \mathbf{1} - \hat{\mathbf{A}}_{P\times P}$ (Sec. 3.3).

For model training, we use the binary cross entropy (BCE) loss between the predicted matrix $\hat{\mathbf{A}}$ and the binary ground truth matrix $\mathbf{A} \in \{0,1\}^{n\times n}$, which we derived from proofread connectome data:

$$L_{\text{affinity}} = \text{BCE}(\hat{\mathbf{A}}, \mathbf{A}). \tag{2}$$

We reduce computational cost during training by decoding a randomly selected subset of point pairs $(P \times P)' \subset (P \times P)$ and thus also only predict a subset of the entire affinity matrix $\hat{\mathbf{A}}_{(P\times P)'} \subset \hat{\mathbf{A}}_{P\times P}$. At test time, we decode all point pairs $P \times P$ to obtain the segmentation label set S for all points P. Alternatively, we can also condition M using a query point $q \in P$, allowing us to compute affinities for a single neuron or background fragment $\hat{\mathbf{A}}_{P\times q} = M(P, q)$.

Point Cloud Encoding. Inspired by recent progress in neural fields [50], our point cloud encoding procedure consists of three steps. First, we project each point p using a positional frequency encoding γ [40] and a fully connected layer (FC) into D-dimensional embedding space as below:

$$p_{\text{enc}} = \text{FC}(\gamma(p), p),\ \mathbb{R}^3 \rightarrow \mathbb{R}^D. \tag{3}$$

We denote the encoded point cloud as P_{enc}. Second, P_{enc} is transformed into feature set representation $z^{(0)}$ using cross-attention [42] with a learnable queries set $Q \in \mathbb{R}^{D\times C}$ [50] and $P_{\text{enc}} \in \mathbb{R}^{D\times|P|}$ as the key-value pair:

$$z^{(0)} = \text{CrossAttn}(Q, P_{\text{enc}}) \in \mathbb{R}^{D\times C}. \tag{4}$$

Cross-attention is defined as:

$$\text{CrossAttn}(X, X') = \sigma\left(\frac{XW_Q(X'W_K)^T}{\sqrt{D}}\right)XW_V, \tag{5}$$

with X and X' being two input sequences, W_Q, W_K, and W_V denoting three trainable weight matrices, and σ representing the *softmax* function. Here, D is the dimensionality of all C features in the feature set. Q is a randomly initialized trainable parameter in our model. Third, we enable information exchange between all elements z_i in the feature set through a series of $j = 24$ sequential self-attention modules:

$$z^{(j)} = \text{SelfAttn}(z^{(j-1)}) = \text{CrossAttn}(z^{(j-1)}, z^{(j-1)}) \tag{6}$$

Here, $z^{(j)}$ is a feature representation of a (multi-)neuron point cloud after the j self-attention layers. From now on, we use $z^{(24)} = z_P$ for clarity. Note that, unlike other methods [30, 49], z_P has no explicit spatial reference and is thus well suited to fit thin and sparse spatial structures such as neurons flexibly. In summary, the encoder φ uses a series of cross- and self-attention layers to encode P into a feature set z_P (Fig. 3 ⓑ):

$$z_P = \varphi(P)\text{ , with } z_P = \{z_i \in \mathbb{R}^D\}_{i=1}^C. \tag{7}$$

In the following sections, we show how to decode z_P into point pair affinities, which are subsequently used for guiding clustering that leads to the label set S.

Affinity Decoding. Next, we input the feature set z_P and point embedding pairs $P_{\text{enc}} \times P_{\text{enc}}$ into the decoder θ to predict the affinity matrix $\hat{\mathbf{A}}_{P\times P}$ (Fig 3 ⓒ):

$$\hat{\mathbf{A}}_{P\times P} = \theta(z_P, P_{\text{enc}} \times P_{\text{enc}}). \tag{8}$$

We can either use all point pairs $P \times P$ to receive the full affinity matrix $\hat{\mathbf{A}}_{P\times P}$, or only use a subset of point pairs $(P \times P)' \subset (P \times P)$. Next, a cross-attention module maps the feature set $z_P \in \mathbb{R}^{D\times C}$ into a set of feature pairs $z_{P\times P} \in \mathbb{R}^{2D\times|P\times P|}$ given $P_{\text{enc}} \times P_{\text{enc}}$:

$$z_{P\times P} = \text{CrossAttn}(P_{enc} \times P_{\text{enc}}, z_P) \in \mathbb{R}^{2D\times|P\times P|}. \tag{9}$$

Here, $|P \times P|$ represents the number of point pairs. Finally, feature pairs $z_{P\times P}$ are decoded into the affinity matrix $\hat{\mathbf{A}}_{P\times P}$ using a MLP : $\mathbb{R}^{2D} \rightarrow \mathbb{R}$. The MLP has a sigmoid final layer to ensure all affinity values are in $[0, 1]$.

3.3. Affinity-guided Point Clustering

We derive the set of segmentation labels S from the predicted affinity matrix $\hat{\mathbf{A}}_{P\times P}$. Since affinities are computed per point pair, we interpret affinity values as a point proximity metric. Thus, we can cluster the point cloud P according to an affinity-based distance metric $\hat{\mathbf{D}}_{P\times P} = \mathbf{1.0} - \hat{\mathbf{A}}_{P\times P}$.

We use feature agglomerative hierarchical clustering [44] to iteratively merge points into clusters according to $\hat{\mathbf{D}}_{P\times P}$, an average linkage criterion and a termination threshold t (Fig. 3ⓓ). Upon convergence of the agglomerative clustering algorithm, all points in a cluster get the same segmentation label $s \in S$ assigned. This approach allows accurate reconstruction of segmentation labels, even if affinity predictions are imperfect. The background class ($s = 0$) is defined by the union of all clusters with less than 30 points. We find that 30 is a good threshold to summarize background fragments into the background class.

3.4. Contrastive Feature Embeddings

We use neuron type classification to demonstrate that our model learns to represent global neuron shapes, as the shape is among the most important contributing factors for neuron type. Given a pretrained affinity prediction model M (Sec. 3.1) and a single neuron point cloud P_s, we retrieve the respective feature set $z_{P_s} \in \mathbb{R}^{D\times C}$ from M (Sec. 3.2). Next, we train a Deep Set [48] $g : \mathbb{R}^{D\times C} \rightarrow \mathbb{R}^E$, that maps z_{P_s} into a lower dimensional contrastive embedding space with dimensionality E. The Deep Set g consists of a feature embedding MLP ζ, a permutation invariant summation operation $\sum$, and an output MLP ρ that projects into the contrastive embedding space:

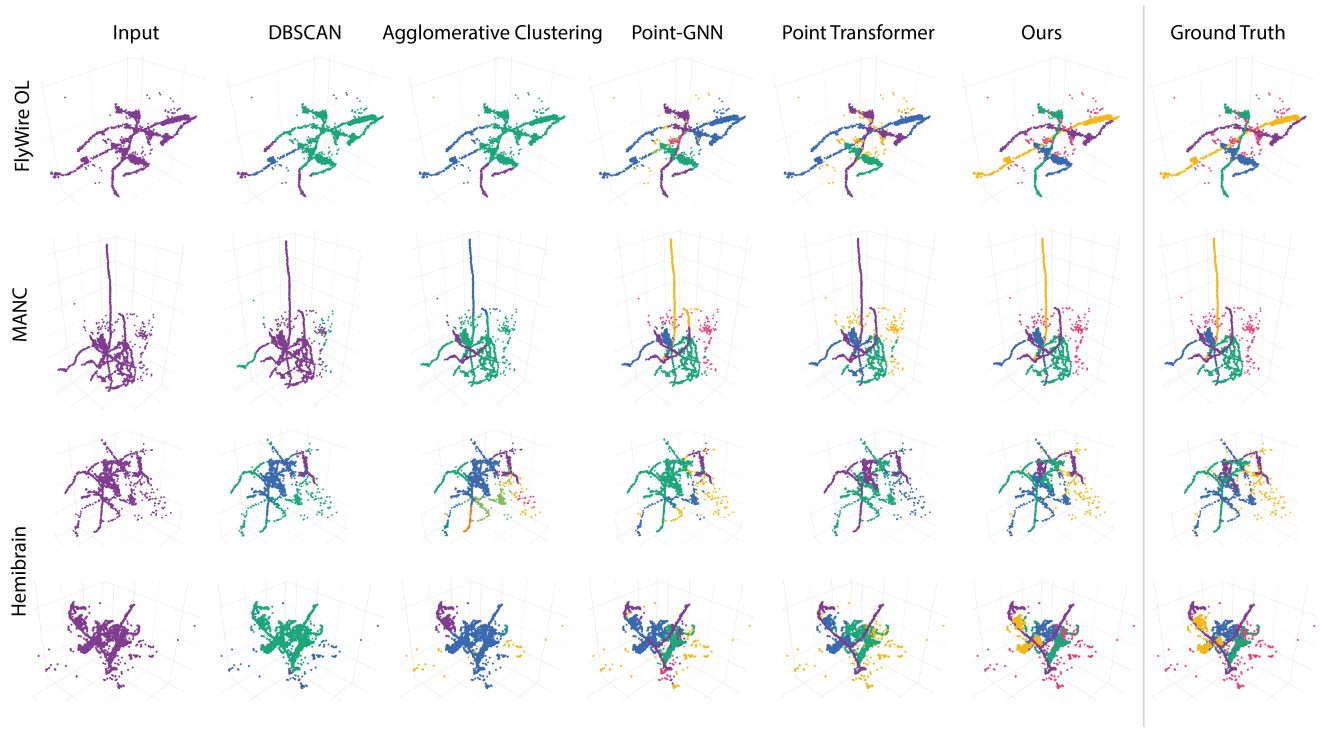

Figure 4. **Automatic Proofreading Examples.** Our approach can reliably correct segmentation errors in (multi-)neuron point clouds. Qualitative results across three datasets demonstrate our model's performance. We compare our approach against unsupervised clustering methods such as DBSCAN and agglomerative clustering, a graph neural network-based approach (Point-GNN), and the commonly used Point-Transformer architecture. The color represents segmentation labels S. The appendix contains a broader set of qualitative examples.

$$g(z_{P_s}) = \rho(\sum_{i}^{C} \zeta(z_i)). \tag{10}$$

Additionally, we normalize contrastive embeddings, such that $|g(z_{P_s})| = 1$. While keeping all parameters of M frozen when retrieving z_{P_s}, we train g with a contrastive loss function :

$$L_{\text{contrastive}} = [d_{\text{pos}} - m_{\text{pos}}]_+ + [m_{\text{neg}} - d_{\text{neg}}]_+. \tag{11}$$

We use neuron type labels to compute Euclidean distances d_{pos} between embeddings derived from point clouds of neurons from the same type. d_{neg} are embedding distances between point clouds from different neuron types. m_{pos} and m_{neg} are the positive and negative margin values, respectively. Finally, an Euclidean k-nearest-neighbors classifier computes neuron-type probabilities for a set of single-neuron contrastive embeddings. We evaluate the performance of our contrastive embeddings in Section 4.5.

4. Experiments

In this section, we evaluate our proposed approach on three benchmark datasets. All three benchmarks are derived from proofread connectomes [7, 33, 39], allowing us to evaluate our model's performance accurately. We report results for the automatic proofreading task and also demonstrate our model's global neuron shape reasoning capability by using its feature representation for neuron type classification.

4.1. Datasets

FlyWire OL [8]. The FlyWire optic lobe (OL) is part of the first-ever full adult Drosophila connectome and includes well-defined cell type families [29].

MANC [39]. The MANC connectome describes the neural wiring architecture of an adult male fruit fly's ventral nerve cord, responsible for signaling motor output to the fly's wings and legs and receiving sensory input.

Hemibrain [33]. The hemibrain dataset is a proofread connectome reconstruction of a fruit fly's central brain, responsible for navigation and integrating visual information, among other tasks.

Data Construction. For each connectome, we randomly sample $15,000$ neurons for model training and $2,000$ for testing. We sample point clouds for each neuron from its respective skeleton. Note that sampling point clouds directly from the segmentation volume is also a valid design choice. We construct artificial reconstruction errors by combining randomly selected neurons and background fragments into

Dataset	Metrics	DBSCAN [10]	Agglomerative [44]	GNN [38]	Point Transformer [52]	Ours
FlyWire OL [8]	VOI ↓	1.19	1.24	0.82	<u>0.32</u>	**0.17**
	VOI_s ↓	<u>0.28</u>	0.37	0.42	**0.07**	**0.07**
	VOI_m ↓	0.91	0.87	0.42	<u>0.26</u>	**0.1**
	ARAND ↓	0.42	0.44	0.24	<u>0.12</u>	**0.04**
MANC [39]	VOI ↓	0.97	0.97	0.51	<u>0.27</u>	**0.2**
	VOI_s ↓	0.21	0.32	0.2	**0.07**	<u>0.08</u>
	VOI_m ↓	0.76	0.65	0.31	<u>0.2</u>	**0.13**
	ARAND ↓	0.33	0.3	0.15	<u>0.09</u>	**0.05**
Hemibrain [33]	VOI ↓	1.12	1.06	0.77	<u>0.39</u>	**0.23**
	VOI_s ↓	0.4	0.48	<u>0.39</u>	**0.09**	**0.09**
	VOI_m ↓	0.72	0.58	0.38	<u>0.3</u>	**0.14**
	ARAND ↓	0.34	0.35	0.23	<u>0.14</u>	**0.05**

Table 1. **Automated Proofreading Evaluation**. Our approach consistently outperforms baseline methods across all three datasets in terms of the VOI, including the split VOI_s and merge VOI_m variants, and the adjusted rand error (ARAND). Overall, the Point Transformer architecture [52] achieves the second best performance. The best scores per row are **bolded**, and the second best scores are <u>underlined</u>.

a single point cloud. Small background fragments (e.g., spine heads or arborizations) are common artifacts in CNN-based image segmentations and must be attached to their respective parent segment. We randomly vary the number of merged neurons in the range of $[1, ..., 4] \in \mathbb{N}$.

Data Augmentation. We apply a series of data augmentations to increase data diversity. Before combining neurons into a single point cloud, we first center each neuron around the origin, which helps the model to learn shapes rather than overfitting on global position. Next, we jitter each point by a random factor of $[0, 1\text{um}] \in \mathbb{R}$ and randomly rotate $[0, 200°]$ and translate individual neurons. Finally, we merge randomly selected neurons and background fragments and apply a global scaling factor to ensure all coordinates are within $[-1, 1]$.

4.2. Evaluation Metrics

Automatic Proofreading. We solve an affinity-guided clustering problem, where points of the same neuron form a cluster. Thus, we use standard clustering metrics such as the *variation of information* (VOI) and the *adjusted rand error* (ARAND). Additionally, the VOI is decomposed into a split (VOI_s) and merge (VOI_m) component, which measures the degree of over- and under-segmentation, respectively. Here, all metrics are better if they are lower.

Neuron Type Classification. For this multi-class classification problem, we report mean average precision (*mAP*), the Top1 Error, and the Top5 Error. The Top1 error indicates the likelihood that the correct type is *not* the top prediction. The Top5 Error measures the likelihood that the correct neuron type is *not* in the top 5 predictions. For *mAP*, higher scores are better, whereas for the error-based metrics, lower values are better.

4.3. Baseline Approaches.

Unsupervised Clustering. We compare our affinity based clustering (Sec. 3.3), to traditional unsupervised approaches such as DBSCAN [10] and agglomerative clustering [44]. We first compute pairwise Euclidean distances between all point pairs $P \times P$ and predict neuron clusters with each respective algorithm. We obtain hyperparameters by performing a grid search on a small training dataset and picking the set of hyperparameters that yields the best VOI score.

GNNs. Graph-based approaches are a set of popular methods for point cloud processing and classification [22]. We compare our approach to Point-GNN [38], a popular message-passing model based on graph convolution. This approach predicts a feature per point, which is decoded to object labels in the original paper. For the purpose of affinity prediction, we add an MLP decoder to the model that decodes point feature pairs to affinity values. We reconstruct a radius graph from the point cloud using radius $= 32$ and a maximum of 64 neighbors per point.

Point Transformers. Next, we compare to Point Transformer [52], a popular method for point cloud classification and segmentation. This architecture performs step-wise local neighborhood aggregation and predicts features per point. We assemble point feature pairs and decode those into affinity values using an MLP.

Contrastive Embeddings. We compare our contrastive embeddings (Sec. 3.4) against a representative GNN called DGCNN [43]. This approach dynamically builds a graph from a point cloud by connecting nearby points with edges. DGCNN implements graph convolution and predicts a feature per single neuron point cloud P_s. Following the training procedure of our DeepSet g (Sec. 3.4), we optimize DGCNN using the contrastive loss function $L_{\text{contrastive}}$.

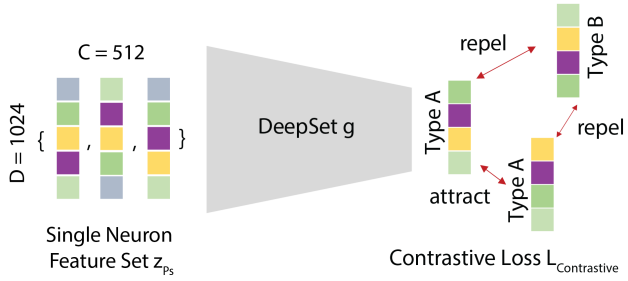

Figure 5. **Neuron Type Contrastive Embeddings.** We project a single neuron feature set z_{P_s} into a lower dimensional embedding space using a DeepSet g, trained using a contrastive loss function $L_{\text{contrastive}}$. In the embedding space, neuron types are predicted with a k-nearest-neighbor classifier using Euclidean distances.

Dataset	Metrics	DGCNN [43]	Ours
FlyWire OL [8]	mAP ↑	0.62	**0.77**
	Top1 Error ↓	0.39	**0.19**
	Top5 Error ↓	0.07	**0.03**
Hemibrain [39]	mAP ↑	0.53	**0.73**
	Top1 Error ↓	0.38	**0.23**
	Top5 Error ↓	0.08	**0.04**

Table 2. **Neuron Type Classification Results.** Our contrastive embeddings significantly outperform DGCNN-based [43] embeddings for neuron type classification. DGCNN is a GNN-based approach. The best scores are **bolded**.

4.4. Implementation

Automated Proofreading. Each point cloud contains 4288 samples, which includes 1024 points per neuron and up to 6 background fragments, with each up to 32 points. We randomly sample $\{1, ..., 4\}$ neurons during affinity prediction training and testing. For cases where the number of neurons is < 4, zero padding is used to get an equal number of points per batch. We also report data ablation for OOD testing with > 4 neurons (Sec. 4.6). Generally, based on manual analysis of segmentation errors and the datasets used, we find ≤ 4 neurons to be a reasonable training distribution. For all reported experiments, the feature set z_P uses $C = 512$ channels, each with a dimensionality of $D = 1024$. The encoder φ includes a series of 24 self-attention modules. The decoder's MLP has two layers, each $2D = 2048$ units. The first layer uses ReLU activations, and the output layer uses a Sigmoid activation function. The convergence threshold for the agglomerative clustering algorithm is $t = 0.8$. All affinity prediction experiments are trained for 946 epochs and a batch size of 230 on 8 NVIDIA H100 GPUs. We use five warmup epochs to linearly increase the learning rate from 0 to $lr_{\text{max}} = 1e^{-4}$ and subsequently use a cosine decay learning rate scheduler with $lr_{\text{min}} = 1e^{-6}$.

Neuron Type Classification. Here, we use single-neuron point clouds without background fragments, resulting in 1024 points. The contrastive Deep Sets are trained for 100 epochs and a batch size of 650 on a single H100 GPU. The k-nearest neighbor classifier uses Euclidean distances and $k = 15$. For both experiments on FlyWire OL and the Hemibrain data (see Table. 4.5), we exclude neurons whose type has fewer than 40 instances in the respective dataset. Due to the imbalance of the neuron type distribution in both datasets, we rebalance the training dataset so that each type is equally represented. With these constraints, the Flywire OL training set has 35 unique types, each with 400 representative neurons. The hemibrain dataset has 41 unique neuron types, each with 300 instances. The DeepSet MLP ζ and ρ consist of two linear layers with ReLU activations. ζ uses 1024 input units and 256 units in the hidden and output layers. ρ has 256 input and 32 output units with no activation function in the last layer. The contrastive embedding space has a dimensionality of $E = 32$.

4.5. Findings

Automated Proofreading. Table 1 shows quantitative comparisons of our approach to four baselines (Sec. 4.3). All learning-based approaches (Point-GNN, Point Transformer & Ours) significantly outperform unsupervised clustering methods such as DBSCAN and Agglomerative Clustering. Among the learning-based methods, transformer architectures are superior to GNNs. In contrast to Point Transformer-based automated proofreading, our method produces significantly fewer neuron merge errors as shown in Table 1 (VOI_m) and in Figure 4. This observation is consistent across all three benchmark datasets. We attribute these performance gains to our model's ability to learn a feature representation without explicit spatial references, allowing flexible fitting to thin and sparse spatial objects, such as neurons. Our method and each baseline depend on a threshold t, which determines the convergence of the agglomerative affinity clustering (Sec. 3.3). We created a small training set for each method and identified t with the highest VOI through a grid search.

Neuron Type Classification. Table 2 shows neuron type classification metrics for both our contrastive embeddings (Sec. 3.4) and the embeddings from our GNN-based baseline DGCNN [43] (Sec. 4.3). Our approach outperforms the baselines for both datasets on all reported metrics. Specifically, the Top1 error metric improved, with a -0.2 for FlyWire and a -0.15 for the Hemibrain over the baseline.

4.6. Ablations

We report two ablation studies for the automatic proofreading task to answer the following questions:

- Question 1: Does our approach generalize to out-of-training distributions regarding the maximum number of

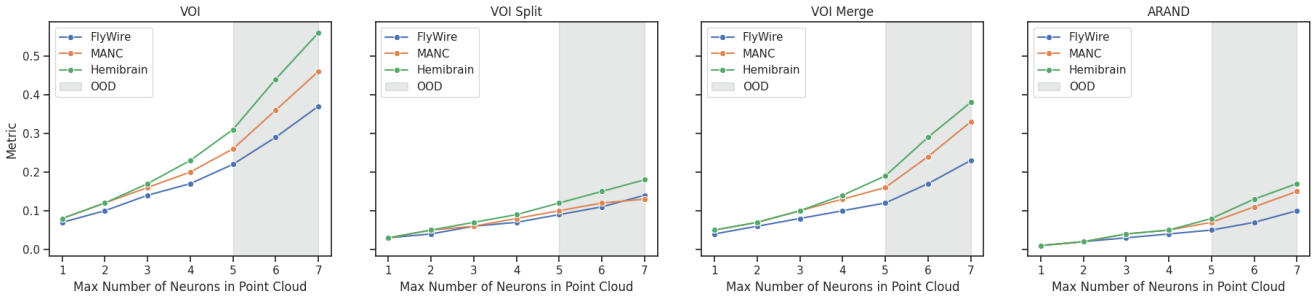

Figure 6. **Input Data Size Ablation.** We train our model with a maximum number of 4 neurons per point cloud. However, our model architecture is agnostic to input size. Hence, we report test set metrics like VOI, VOI_s, VOI_m, and ARAND for individual evaluations with a maximum of 1-7 neurons per point cloud. The grey area indicates out-of-distribution (OOD) performance. While we observe a slow linear decrease in distribution (max 1-4 neurons) and a bias towards under-segmentation for OOD.

Feature Size	$\text{VOI}_s\downarrow$	$\text{VOI}_m\downarrow$	**ARAND**$\downarrow$
$D = 1024, C = 512$	0.07	0.10	0.04
$D = 512, C = 512$	0.09	0.12	0.04
$D = 1024, C = 256$	0.09	0.12	0.04

Table 3. **Feature Size Ablation.** We ablate the size of the feature dimensionality D and the number of elements C in the feature set. Reducing both D or C equally degrades performance metrics.

neurons merged into a single point cloud?

- Question 2a: Does a lower feature dimensionality D reduce performance numbers ?
- Question 2b: Does a lower number of features C reduce performance numbers ?

OOD Data Ablation (Q1). In Figure 6, we show our model performance on various numbers of neurons in a single point cloud for the automatic proofreading task. Note that the model was trained for only a maximum number of four neurons per point cloud. Thus, the grey area indicates OOD performance. As expected, we observe a linear performance decrease within distribution (max. 1-4 neurons per point cloud). For OOD evaluations (max. 5 - 7 neurons per point cloud), identify a bias towards undersegmenting point clouds. In comparison, the VOI_s increases linearly for OOD input data, and VOI_m starts increasing more rapidly. This effect could be mitigated by decreasing the convergence threshold t of the affinity-based agglomerative clustering (Sec. 3.3).

Feature Set Size (Q2a & Q2b). Table 3 shows that reducing either feature dimensionality D or the number of features equally decreases VOI_s and VOI_m. The ARAND error metric does not decrease.

5. Conclusion

The lack of neural network architectures capable of reasoning with the global shapes of neurons has been a major bottleneck for the complete automation of connectome generation. Solving this problem will enable connectome mapping of entire fly brains in mere weeks instead of years, making connectome mapping of entire mouse brains feasible.

Here, we demonstrate a powerful new technique based on point affinity transformers for automating neuron proofreading and neuron type classification, the two challenging tasks still requiring significant human expert annotation efforts. Our results show significant performance gains for both tasks over various baseline methods and datasets.

Our work can be extended in several ways. Point clouds could be augmented with additional feature vectors based on local image information, for instance, based on SegCLR [6] or synapse type [9]. Neuron embeddings generated by our general-purpose encoder based on a small number of annotations in one brain region or animal species could then be used for the unsupervised discovery of new cell types in other brain regions and species. Our method for proofreading can be extended to tracing neurons in light microscopic images by proofreading point clouds segmented with simple binary thresholding. Finally, decoders could be trained to generate skeleton graph representations and computationally efficient renderings (Gaussian splatting [18]) of neuronal shapes from sparsely sampled point clouds.

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