National Institute of Biomedical Imaging and Bioengineering

Neural Segmentation Algorithm Design for Biomedical Electron Microscopy

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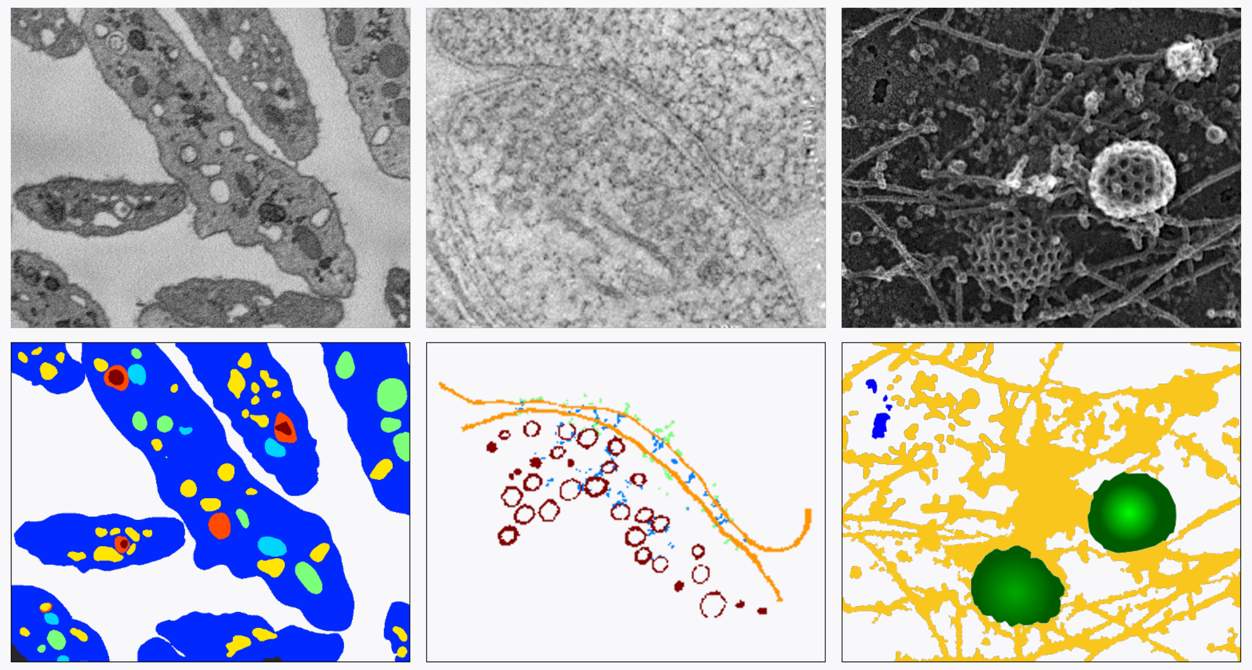
Introduction

- Biomedicine uses electron microscopy (EM) to study biological matter at the nanoscale.
- New electron microscopes can acquire large datasets quickly.
- Serial block-face scanning electron microscopy (SBF-SEM): Image up to $1\,\mathrm{mm}^3$ biological samples at $\sim 5 \times 5 \times 25$ nm resolution by repeated cutting and scanning.
- Systems biology will greatly benefit from high-throughput EM, but data analysis is challenging.
- Major bottleneck is image segmentation: grouping image voxels together according to image content.
- Semantic segmentation: Assign a "class" to each voxel in an image (cell, organelle, etc.). Main focus of this poster.
- Instance segmentation: Assign a unique tag to each object in an image.



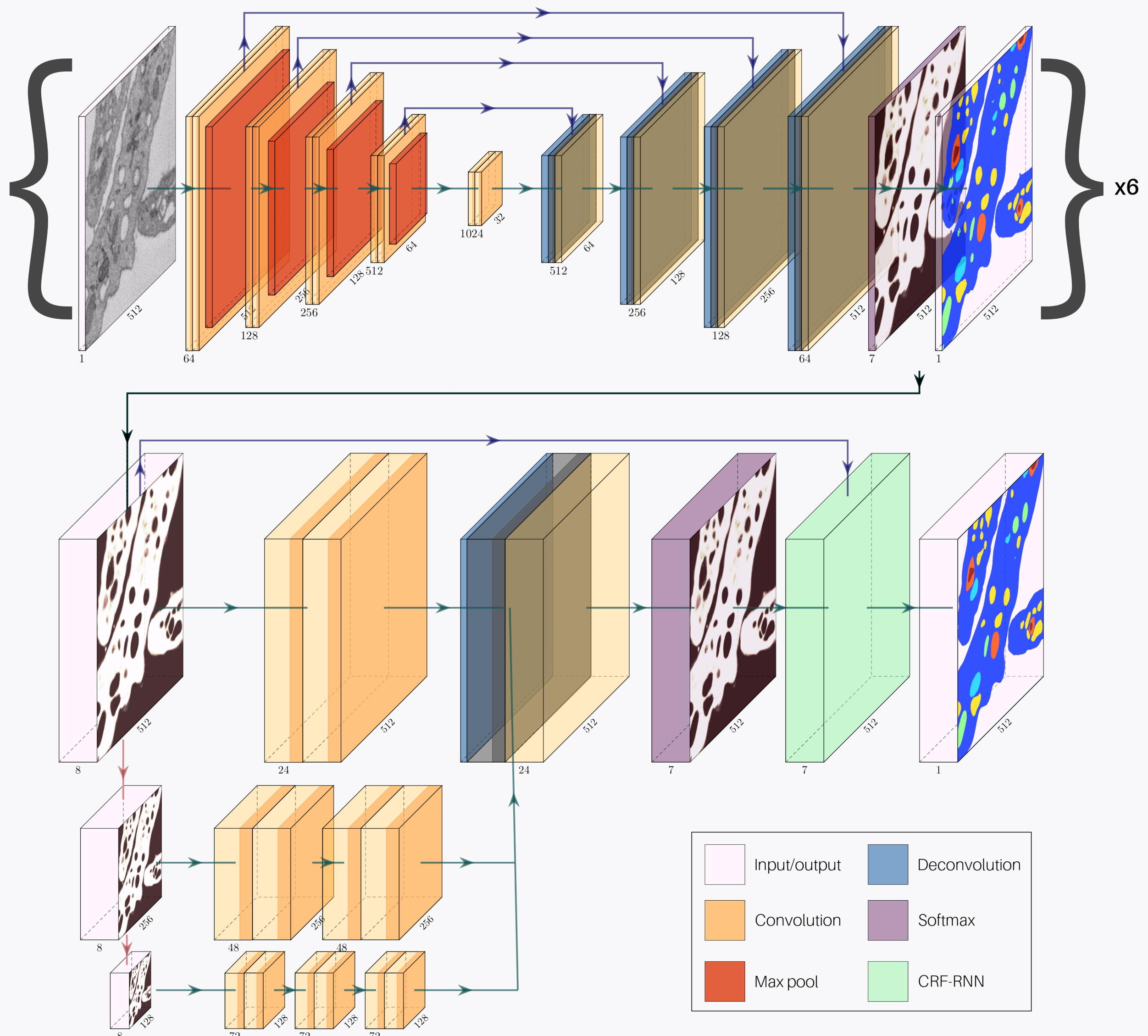
Sample EM images, and their semantic segmentations. **Left**: SBF-SEM image of platelet cells. **Center**: TEM tomographic image of synaptic tissue, courtesy of NINDS Laboratory of Neurobiology. **Right**: Platinum-replica TEM tomographic image of a HeLa cell wall, courtesy of the NHLBI Taraska Lab.

Segmentation Challenges

- Training label generation is tedious, and experts may disagree.
- Different EM hardware + sample combinations create many image types.
- Segmentation automation difficulty is highly problem-dependent.
- **Goal**: A reproducible workflow for effective neural segmentation architecture discovery, training, and usage.
- **Goal**: Use that workflow to design problem-specific segmentation algorithms.

Network Architecture Design

- Segmentation networks use combinations of multi-scale convolutional modules.
- Common modules: pooled convolution blocks, dilated convolution blocks, encoder-decoders, spatial pyramid pooling units, more.
- Architecture design: Construction of a computation graph which contains the variables trained during learning.
- Segmentation network architecture design is a combinatorial search with a large state space and expensive evaluations.



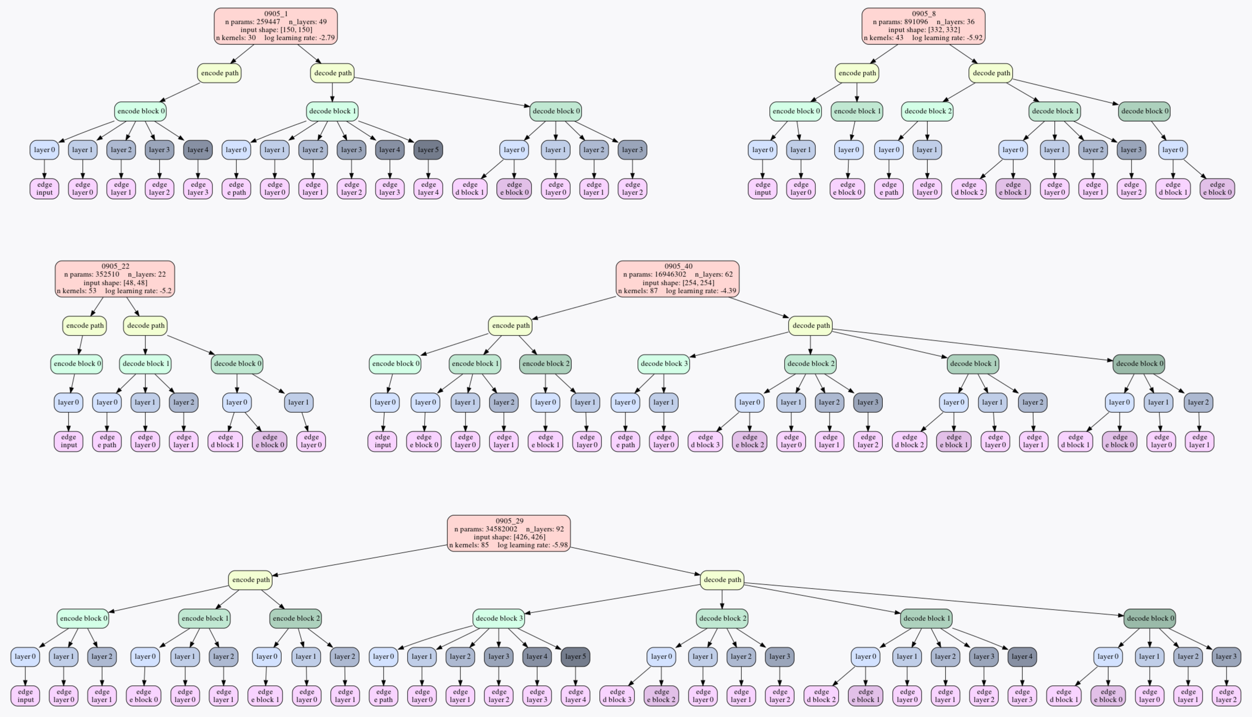
Example of a hybrid-3D + CRF-RNN segmentation network, of the type found most effective on 3D SBF-SEM data so far. More info in the next box.

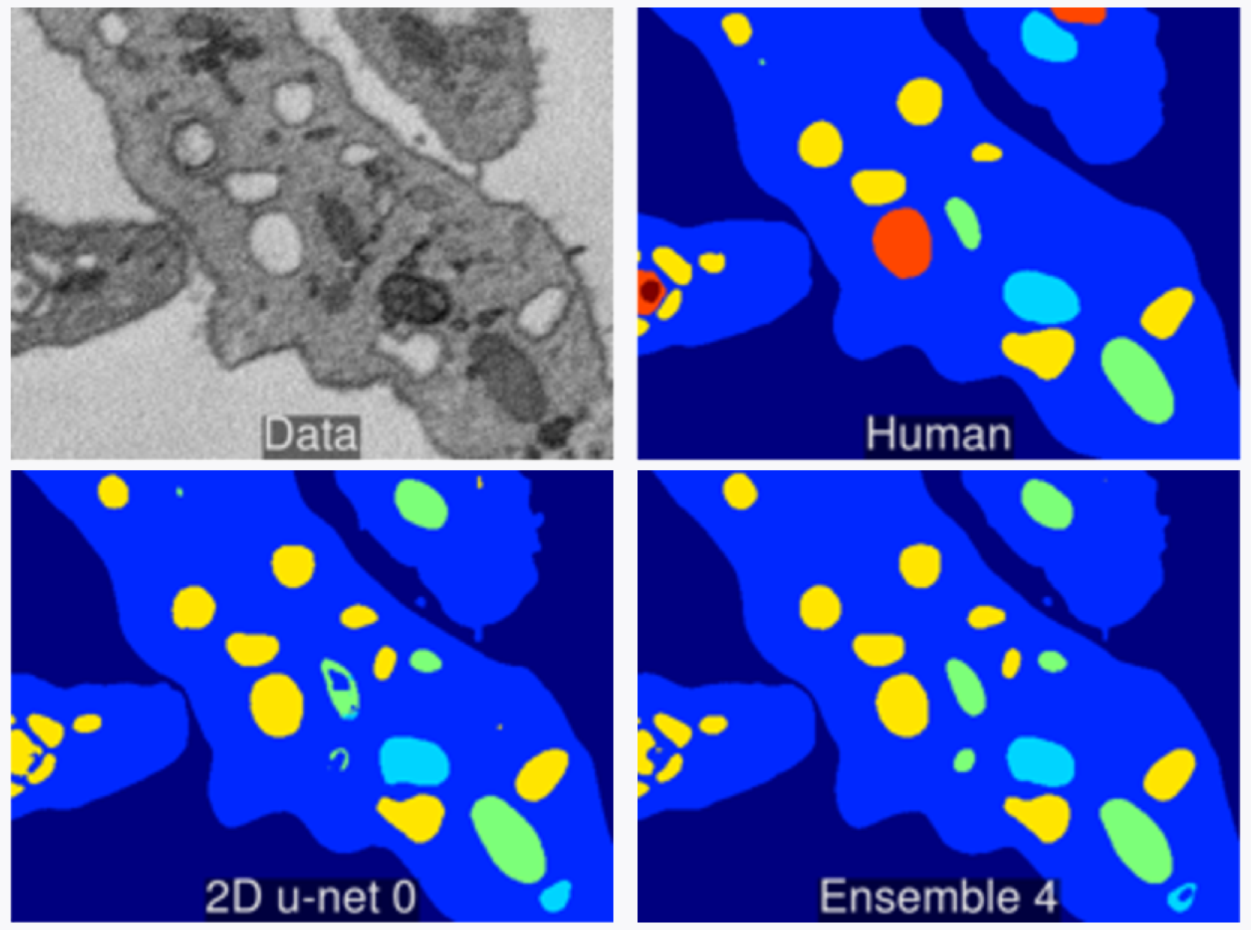
Hybrid-3D Networks

- 2D vs 3D tradeoffs: spatial context vs. memory usage, dealing with anisotropy along z axis.
- Hybrid-3D network: Large 2D convolutional encoder-decoder module forms intermediate predictions. Concatenated 2D predictions form input to a small 3D convolutional spatial pyramid module.
- A 3D CRF-RNN (conditional random field as recurrent neural network) module can be used as well.
- Hybrid-3D + CRF-RNN architecture is currently the best performer.

Architecture Design Algorithms

- Algorithmic architecture design: automatically search the architecture design space.
- Observation: Segmentation networks form hierarchical module trees: A tree of modules built up from repeated, simpler modules.
- Random sampling of module hierarchy trees finds effective segmentation architectures with modest computational resources.
- Combine with other black box optimization tools to improve parameters that do not alter the module hierarchy.
- Run architecture search on NIH's Biowulf using new distributed evaluation tools.
- Diverse high-performing architectures are combined into ensembles for improved prediction.





(**Top**) A collection of randomly-generated module trees for 2D encoder-decoder networks. Each module forms part of a final computation graph. (**Bottom**) Importance of ensembling for segmentation algorithms. Data and human ground-truth labelings are compared with the single best network and the best network ensemble from 100 random 2D encoder-decoder networks.

Conclusion

- We built **high-performing 3D EM segmentation** algorithms with a new architecture which combines 2D and 3D convolutional processing modules.
- Module architecture design made use of random module tree sampling followed by black box optimization.
- Random sampling strategy produces high-performance segmentation networks and requires little machine learning expertise.
- New scripting tools enable efficient, fault-tolerant distributed architecture search on Biowulf.
- Resulting segmentation algorithms accelerate segmentation for lab research workflows.
- Challenges:
  - End-to-end training of large networks with model-parallel multi-GPU.
  - Deal with anomalies in datasets not found in training data.

Future Work

- Robust segmentation: Train a single segmentation model that works across multiple datasets. Requires transfer learning but also more.
- New public dataset: Currently assembling a collection of annotated EM image volumes for release to the machine learning community.
- Use a correction-training feedback loop to produce large amounts of labeled training data.
- Combine instance and semantic segmentation algorithms to increase usefulness of segmentation tools for researchers.
- Work with collaborators to improve segmentation software from preprocessing through data visualization.

Acknowledgements

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- This work made use of the computational resources of the NIH HPC Biowulf cluster. (https://hpc.nih.gov)
- **View this poster online** at (https://leapmanlab.github.io/umd2019.pdf).