

(Shallow) Deep Learning for **Cellular Tomogram Segmentation** (and other things)

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Chen, M., Dai, W., Sun, S.Y., Jonasch, D., He, C.Y., Schmid, M.F., Chiu, W. & Ludtke, S.J., 2017, Convolutional neural networks for automated annotation of cellular cryo-electron tomograms, *Nature methods*.



James (Michael) Bell

Cyanobacteria Wei Dai (Rutgers)

Trypanosome Stella Sun (SLAC) **Cynthia He (NUS)**

PC12 Neurite Wei Dai (Rutgers)

Mouse Neurite Patrick Mitchell (SLAC) Gong-her Wu (SLAC)

Wah Chiu, Mike Schmid (SLAC)



Movie of Tomogram Excluded





hidden layer 1 hidden layer 2 hidden layer 3

http://neuralnetworksanddeeplearning.com/chap5.html











... and it's extremely inefficient (no translational equivalence)



- <u>Many</u> different concepts
 - Deep networks
 - Convolutional networks
 - Modules

. . .

- Autoencoders
- Recursive Neural Networks
- Long Short-Term Memory

Deep Learning

Convolutional Neural Network (CNN)





Deep or Shallow?

- Deep:
 - Extremely flexible, one network could handle many different features and cell types
 - Extremely expensive to train, may not converge
- Shallow:
 - Easy to train. Fixed network structure possible
 - Limited Scope, Focused on one user and one feature

- Mimic a human annotator
- One network = 1 feature x 1 annotator
- Easily trained with a small number of regions

Convolutional Neural Networks





Competitive Merging

Movie showing usage deleted



Microtubule PC12,JEM2100, Apix=14.3

Trypanosoma Brucei

Ribosome

EMDB-2239 (filtered)

Trypanosome Subtomogram Average

Ribosome

Note: EMAN2.2 can do per-particle/per-tilt CTF corrected subtomogram averaging.

Wedge-aware 3-D alignment: 6000, 300x300x300 particles <12 hours on a multicore workstation without GPU avg ~7 sec/alignment

EMDB-2239 (filtered)

Trypanosome Subtomogram Average

Cultured Mouse Neuron, 6.6 Å/pix

Cyanobacteria, late stage phage infection

Thylakoid membrane cyanobacteria, phase plate, Apix=10.4

Using the Tools

- For each Feature of Interest (FOI):
 - Select ~10 tiles (64x64) with FOI
 - Select ~100 tiles without FOI
 - Draw the FOI manually on the ~10 tiles
 - Train the network (~3m on GPU)
- Apply all networks to each tomogram
 - 2k x 2k x 512 tomogram ~1hr/FOI on CPU (good) workstation)
- Competitive merging for each tomogram

layer

Che, C., Lin, R., Zeng, X., Elmaaroufi, K., Galeotti, J., Xu, M. Improved deep learning based macromolecules structure classification from electron cryo tomograms. arXiv:1707.04885.

Particle Picking Using CNNs

- Why is this is a good idea?
 - Gold standard for particle picking is the human brain
 - Neural networks do a good job at mimicking humans
 - Particles look similar, but things that are NOT particles are diverse

Particle Picking Using CNNs

Positive examples

2D patches from tomogram

Corresponding manual annotation

Tomogram Segmentation

Negative examples

Particle Picking Using CNNs

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Reference-based autopicker using 20 hand-picked references

Reference-based autopicker using autogenerated projection references from a good 3-D map

CNN Autopicker using the same 20 manual references and 60 "bad" references.

Training = 37s on 1 GPU

Autopicking (4k) =10 s/image on 1 CPU

CNN Autopicker (red) vs. manual selection (blue)

Problems Ice Contamination

(B-gal, empiar 10012)

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Problems with aggregated particles

(B-gal, empiar 10012)

CNN Particle Picking v2

- 3 sets of references:
 - Good particles, preferably isolated
 - Empty ice/background
 - Contamination, or anything else which isn't a particle
- images (different defocus)

About 10-15 boxes in each category, preferably drawn from several

-> 2 Networks, particles vs. background and particles vs. contamination

Background **Bad Refs Good Refs**

(B-gal, empiar 10012)

2D Classification																			
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256 Classes 8 minutes **1** Workstation (28 cores, no GPU)

~2-3 hours same machine

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Warning

- EMAN2.2 uses Theano for GPU accelerated neural networks. Much slower on CPU
- After installing, you need to enable GPU support in Theano tied to your own CUDA installation. This is explained in the EMAN2.2 install instructions.
- Mac support is CPU only

- Gaussian Mixture Model with Autoencoder for 3-D Dynamics from 2-D particles
- Missing Wedge Compensated Subtomogram Classification
- Dimension Reduction and Manifold Generation for Flexibility Analysis

Other Neural Net Applications

The End