Microscopic Advances with Large-Scale Learning: Stochastic Optimization for Cryo-EM

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Structure Determination

- Macromolecules
- Protein structure determines function

- Traditional approaches:
 X-ray Crystallography
 - NMR Spectroscopy



Electron Cryo-Microscopy (Cryo-EM)



No crystals needed, large molecules and complexes

Cryo-EM Image Formation Low dose electron beam 2D Particle Images Corruption by CTF Particles in unknown 3D pose Ice **Transfer** Function Film/CCD Frequency Corrupted Noisy Integral Projections

- Challenges for reconstruction:
 - Destructive CTF
 - Low SNR
 - Unknown pose

Cryo-EM Image Formation



$p(\mathcal{I}|\theta, \mathbf{R}, \mathbf{t}, \mathcal{V}) = \mathcal{N}(\mathcal{I}|\mathbf{S}_{\mathbf{t}}\mathbf{C}_{\theta}\mathbf{P}_{\mathbf{R}}\mathcal{V}, \sigma^{2}\mathbf{I})$

Cryo-EM Image Formation



Cryo-EM Image Formation



Marginalization for Latent Variables



$$p(\tilde{\mathcal{I}}|\theta, \tilde{\mathcal{V}}) = \int_{\mathbb{R}^2} \int_{\mathcal{SO}(3)} p(\tilde{\mathcal{I}}|\theta, \mathbf{R}, \mathbf{t}, \tilde{\mathcal{V}}) p(\mathbf{R}) p(\mathbf{t}) d\mathbf{R} d\mathbf{t}$$

Marginalization for Latent Variables



$$p(\tilde{\mathcal{I}}|\theta, \tilde{\mathcal{V}}) = \int_{\mathbb{R}^2} \int_{\mathcal{SO}(3)} p(\tilde{\mathcal{I}}|\theta, \mathbf{R}, \mathbf{t}, \tilde{\mathcal{V}}) p(\mathbf{R}) p(\mathbf{t}) d\mathbf{R} d\mathbf{t}$$
$$\approx \sum_{j=1}^M w_j p(\tilde{\mathcal{I}}|\theta, \mathbf{R}_j, \mathbf{t}_j, \tilde{\mathcal{V}})$$

Numerical Quadrature

Maximum-a-Posteriori Estimation



K $p(\mathcal{V}|\mathfrak{D}) \propto p(\mathcal{V}) \prod p(\tilde{\mathcal{I}}_i|\theta_i, \tilde{\mathcal{V}})$ i=1

Optimization Problem



$$p(\mathcal{V}|\mathfrak{D}) \propto p(\mathcal{V}) \prod_{i=1}^{K} p(\tilde{\mathcal{I}}_i|\theta_i, \tilde{\mathcal{V}})$$

$$\arg\min_{\mathcal{V}} - \sum_{i=1}^{K} \left(\log p(\tilde{\mathcal{I}}|\theta, \tilde{\mathcal{V}}) + K^{-1} \log p(\mathcal{V}) \right)$$

Stochastic Optimization for Cryo-EM

$$\arg\min_{\mathcal{V}} - \sum_{i=1}^{K} \left(\log p(\tilde{\mathcal{I}}|\theta, \tilde{\mathcal{V}}) + K^{-1} \log p(\mathcal{V}) \right)$$

- Expensive to compute objective with large K
- Stochastic Optimization:
 - Approximate objective with subset of images
 - Update based on approximate gradient
- Various Algorithms (vary by update rule)
- Advantages: speed, random initialization

Experiments: Datasets

Real Dataset:

- ▶ 46K Images of ATP Synthase from *Thermus Thermophilius*
- Low SNR and known CTF parameters





Experiments: Datasets

Synthetic Dataset:

- ▶ 50,000 Projections of known artificial density
- Low SNR and realistic CTF parameters





Experiments: Seven Methods

- Vanilla Stochastic Gradient Descent (SGD)
- Momentum Methods:
 - Classical Momentum
 - Nesterov's Accelerated Gradient
- Adaptive Methods:
 - AdaGrad
 - TONGA
- Quasi-Second Order Methods:
 - Online L-BFGS
 - Hessian Free

 Identical random initialization in all experiments





Simplest Method



Momentum Method



Adaptive Step-size



Quasi-second order



- Qualitatively Similar
- Reasonable in one pass through data







Projection Matching

RELION (E-M)

Proposed Approach

3 Hours – 1 Epochs



Projection Matching

24 Hours – 5 Epochs

RELION (E-M) 24 Hours – 5 Epochs Proposed Approach

3 Hours – 1 Epochs



Projection Matching

24 Hours – 5 Epochs



RELION (E-M) 24 Hours – 5 Epochs



Proposed Approach 3 Hours – 1 Epochs







Projection Matching 24 Hours – 5 Epochs

RELION (E-M) 24 Hours – 5 Epochs

Proposed Approach 3 Hours – 1 Epochs

 Random Initialization is difficult for other methods

Conclusions

- Introduced Cryo-EM Structure Determination
- Stochastic Optimization solution
- Simple methods are best
- State of the art speed and robustness

Recent Progress

- Higher resolution reconstructions
- Importance Sampling: 100,000x speedup



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- Higher resolution reconstructions
- Importance Sampling: 100,000x speedup



• Forward:

- Heterogeneous mixtures of particles
- Better priors
- Video exposure