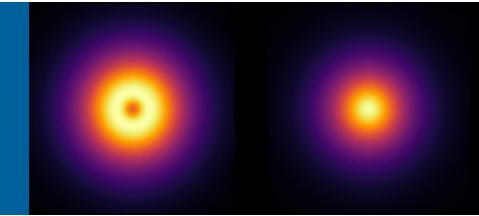




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THE SCIDAC QUANTOM FRAMEWORK: A COMPOSABLE WORKFLOW



DANIEL LERSCH

for the QuantOm Collaboration



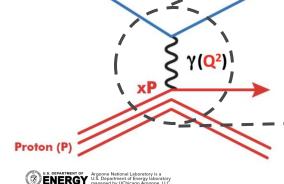
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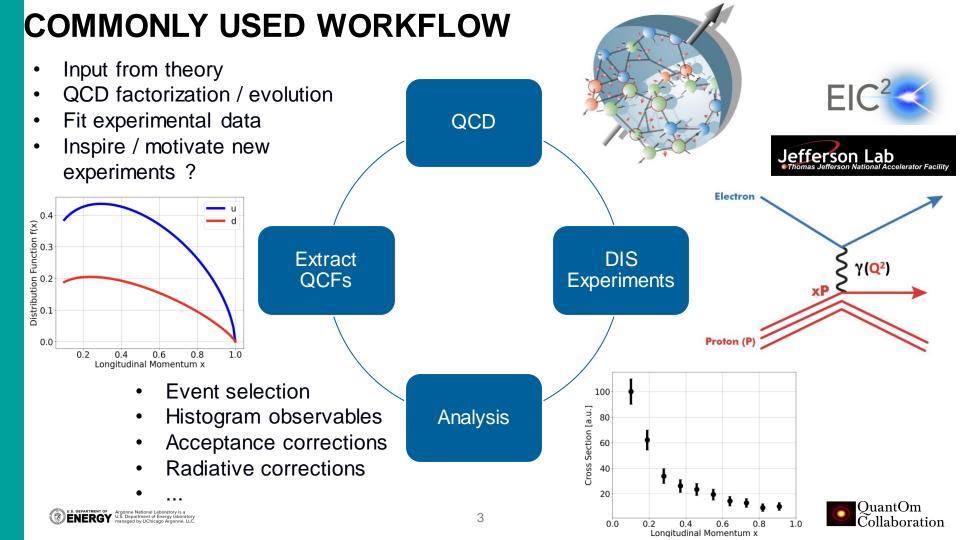
EXPLORING QUARK-GLUON STRUCTURE

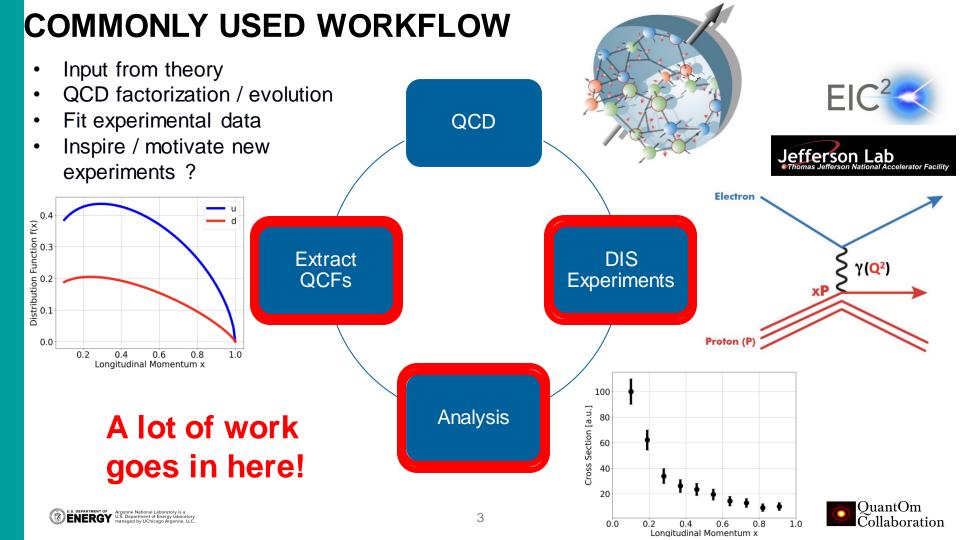
- Want to understand Quark-Gluon system
- Conduct Deep Inelastic Scattering (DIS) experiments
- Extract Quantum Correlation Functions (QCFs) from experiments

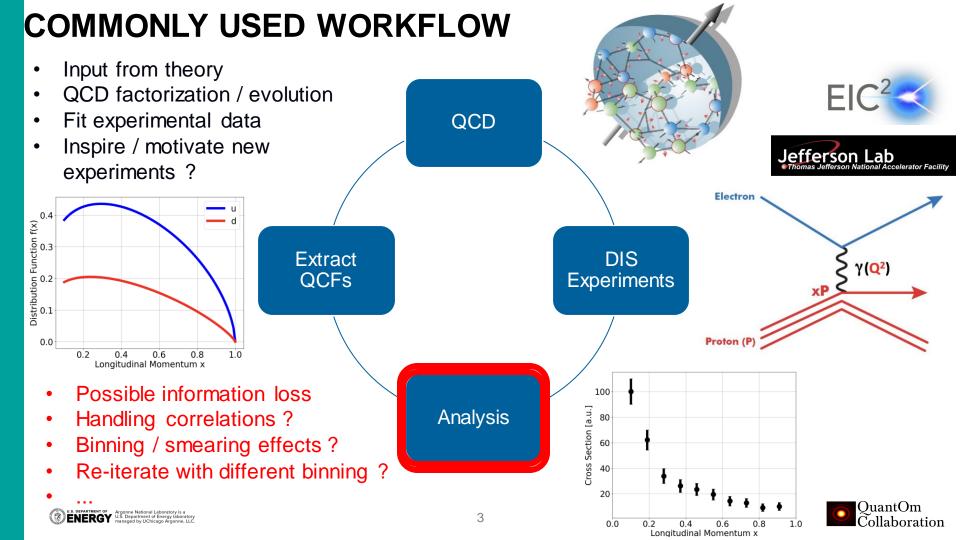
Electron



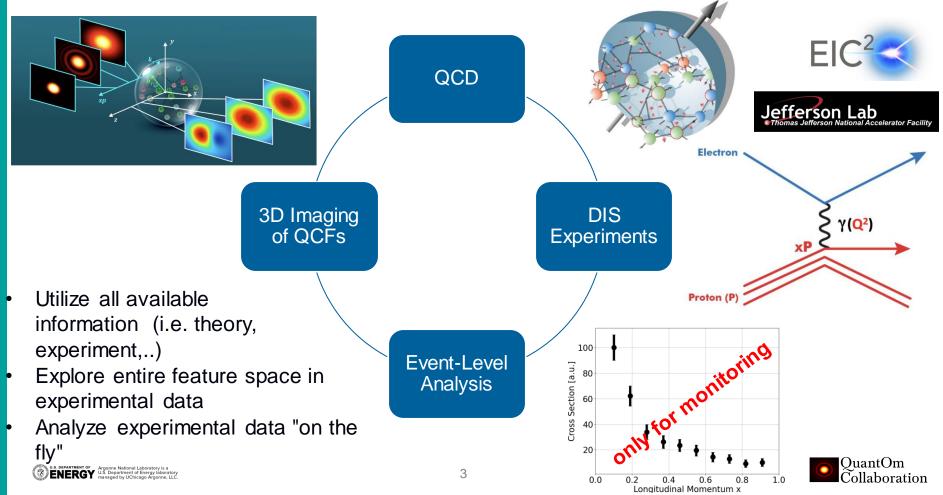








TOWARDS AN EVENT-LEVEL ANALYSIS



THE QUANTUM NUCLEAR TOMOGRAPHY (QUANTOM) COLLABORATION

- Part of Scientific Discovery through Advanced Computing (SciDAC)
- Interdisciplinary research
 - Applied mathematics
 - Computer and data science
 - Theoretical and experimental nuclear physics
 - High performance computing
- Collaboration between multiple national research institutions
 - Jefferson Lab
 - Argonne National Laboratory
 - Old Dominion University
 - Virginia Tech

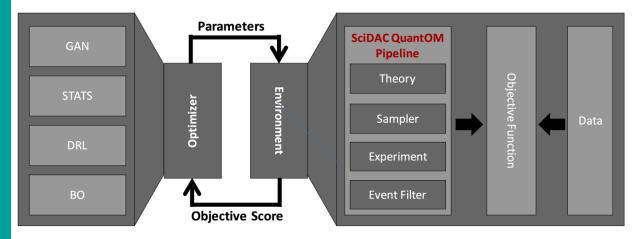


INVERSE PROBLEMS

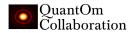
- Measure observable y
- Interested in underlying mechanisms, encoded in x
- x is experimentally not accessible
- Known: y = f(x)
- $f(\cdot)$ can not be trivially inverted
- Theory provides a model: $x \approx \hat{x}(p)$
- Find \tilde{p} that minimizes: $F[y, f(\hat{x}(p))]$
- Use $\hat{x}(\tilde{p})$ as an approximation for unknown x

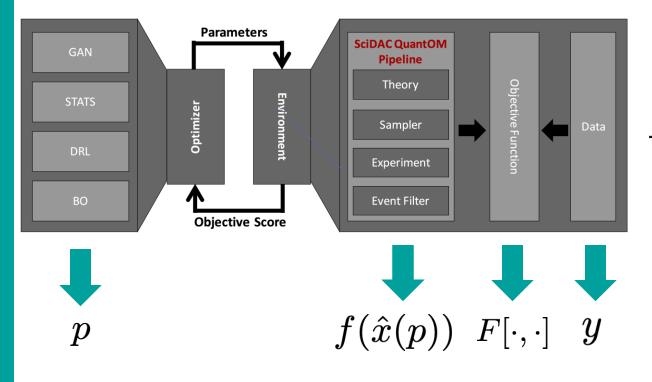
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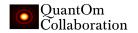




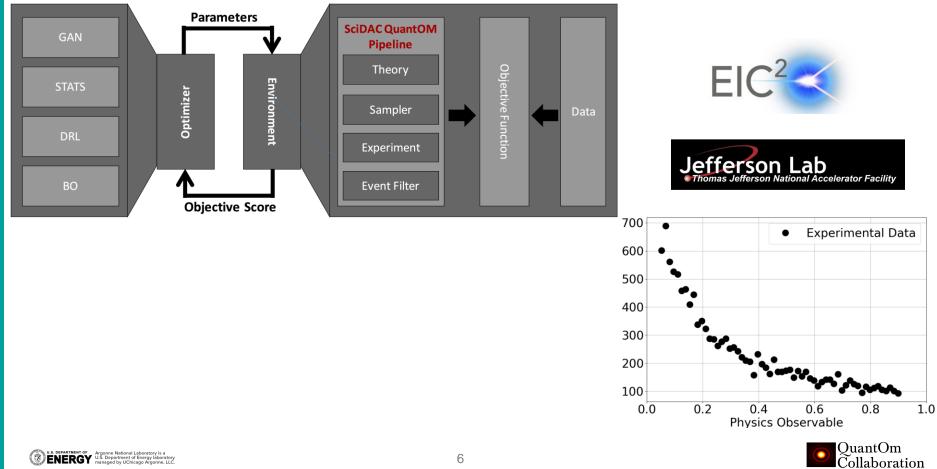


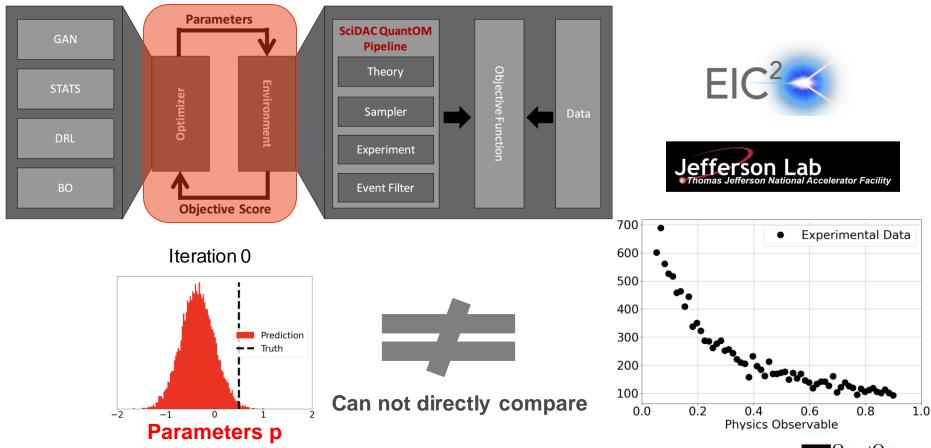


 $F[y, f(\hat{x}(p))]$



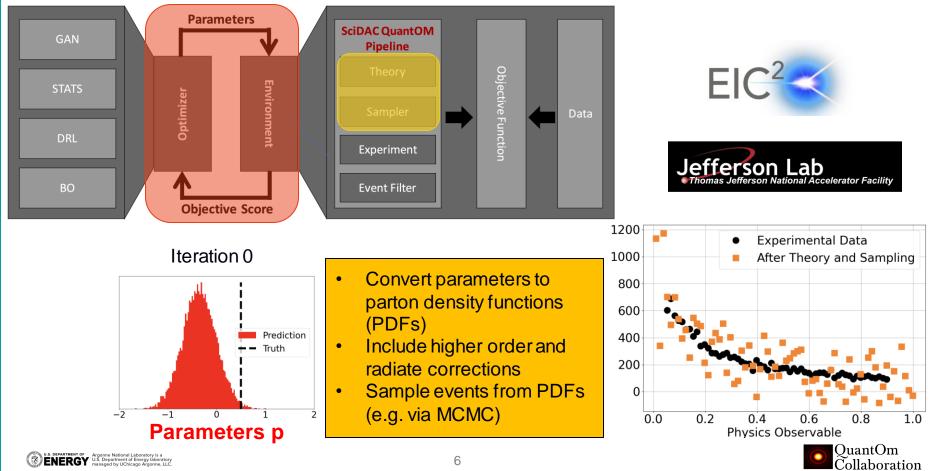


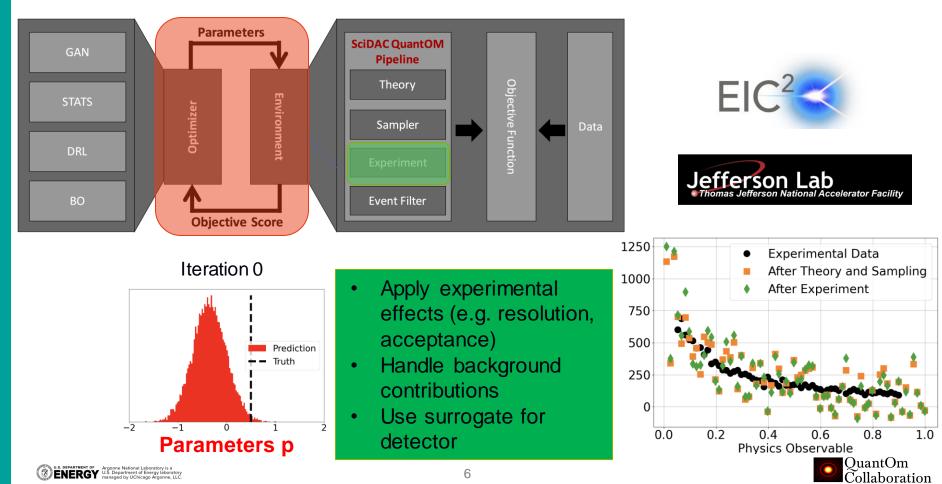


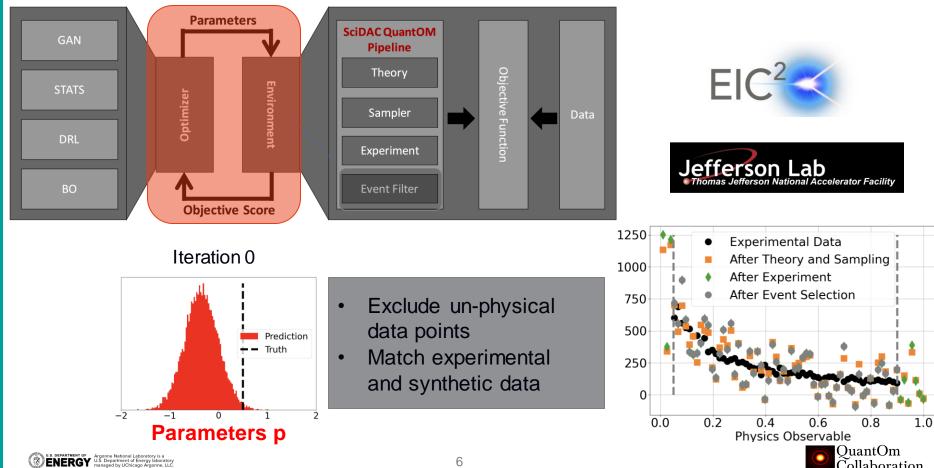




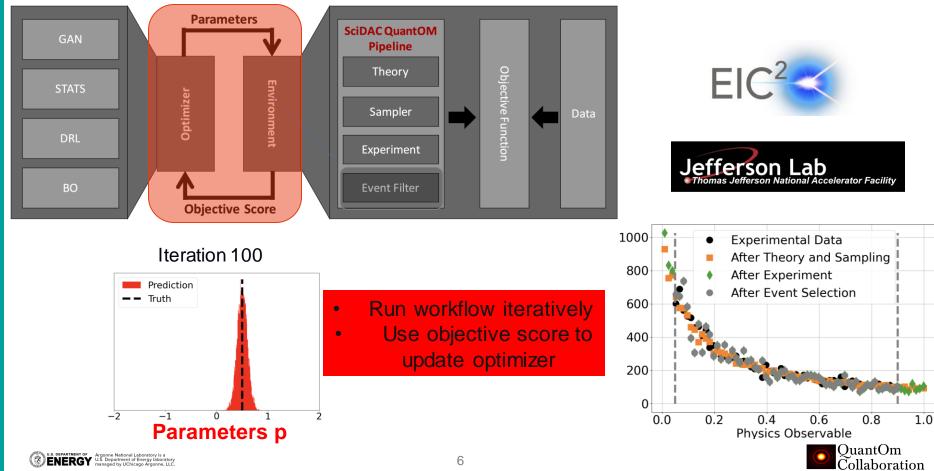


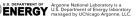






Ollaboration





WORKFLOW SPECS

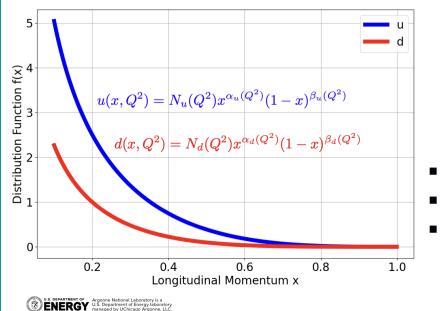
- Written in python
- Supports Tensorflow, Keras, PyTorch,...
- Runs on CPU / GPU
- Modular
 - Change / update / add individual modules
 - Customize entire pipeline
- Each module has its dedicated working group (e.g. theory, experiment,...)
- Fit multiple experiments simultaneously <--> Each experiment has its dedicated module

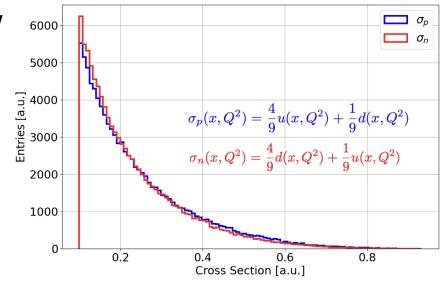


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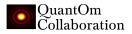
THE 1D PROXY APP

- Test, debug and benchmark workflow
- Given: Toy data set consisting of cross section "measurements"
- Goal: Extract the underlying PDFs that determine the cross sections

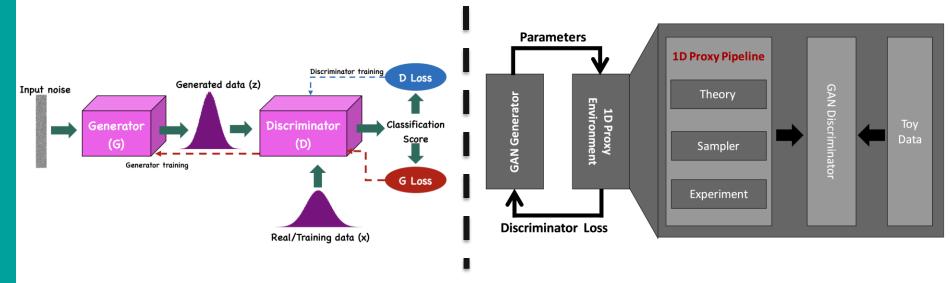




- Approach: Use workflow to find PDFs
- Truth, i.e. inputs, is known here
- Perform loop closure tests



THE 1D PROXY APP WITH GIPS

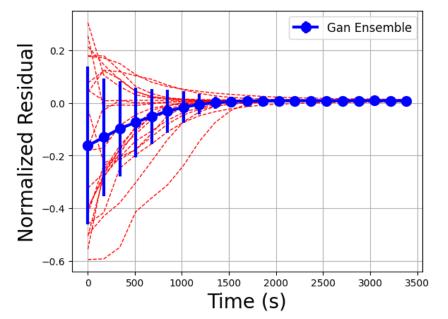


- 1. Generator predicts 6 parameters
- 2. Parameters are translated to synthetic events by environment
- 3. Discriminator (part of environment) is trained on synthetic and toy data
- 4. Use discriminator loss on synthetic data to update generator
- 5. Repeat steps 1 4 until convergence



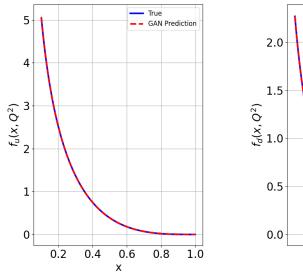


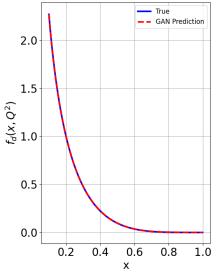
ENSEMBLE ANALYSIS ON 1D PROXY APP



- Ran loop closure tests with / without resolution effects
- Reproduced input PDFs
- Need to include uncertainty quantification

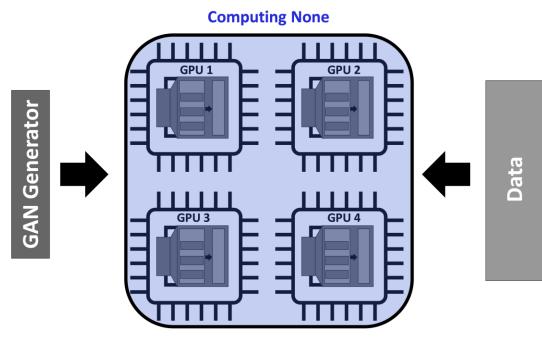
- Used ensemble with 20 GANs
- Benefit from individual parameter initialization
- Ensemble converges earlier to expected solution than individual GAN







SCALING GIPS WITH THE 1D PROXY APP



- Handle data volume --> run GIPS across multiple nodes
- Tricky due to stochastic nature of sampling process
- Each GPU has its own environment
- Use asynchronous data parallel training to update GAN generator
- Ran tests on Polaris --> See poster: "Scaling the SciDAC QuantOm Workflow"

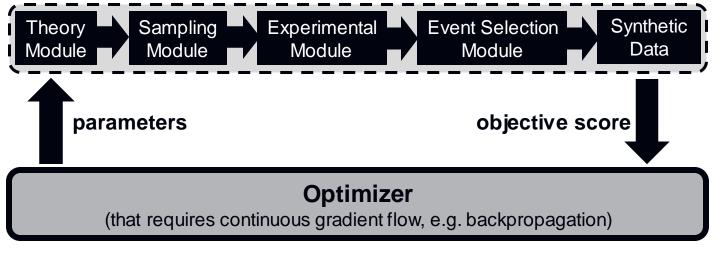


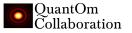


MANAGING THE GRADIENT FLOW

Forward pass

- Optimizer predicts parameters
- Parameters are translated to synthetic data
- Synthetic data defines, together with experimental data, an objective score

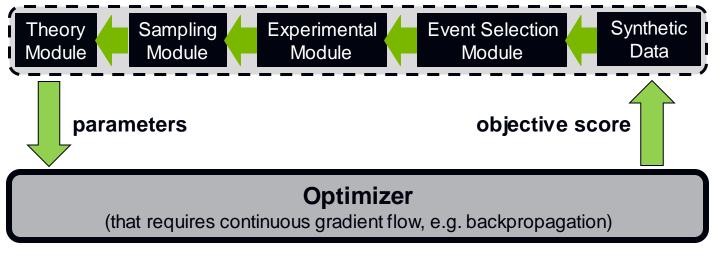


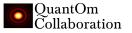


MANAGING THE GRADIENT FLOW

Backward pass

- Rely on chain rule to update optimizer state
- Propagate gradients back through entire pipeline
- Every module needs to be differentiable

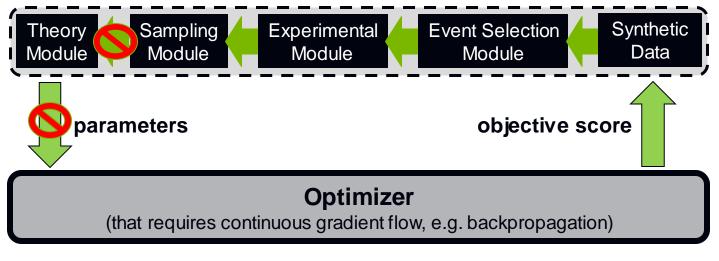


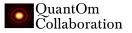


MANAGING THE GRADIENT FLOW

Trouble

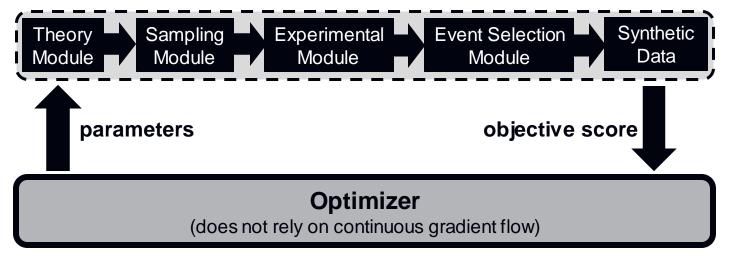
- Rely on chain rule to update optimizer state
- Gradient flow is disturbed
- At least one module is not differentiable (e.g. sampler)

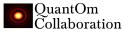




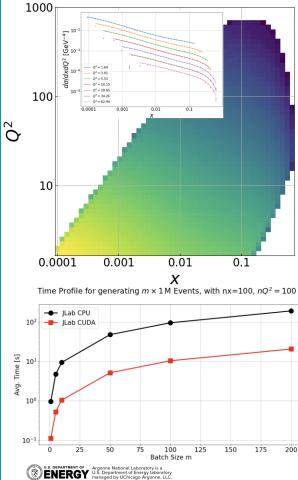
ALTERNATIVE: AVOID GRADIENT FLOW

- Do not care about differentiability
- Minimize / Maximize objective score w.r.t predicted parameters
- Currently exploring: Reinforcement Learning, Genetic Algorithms, Simulated Annealing,...

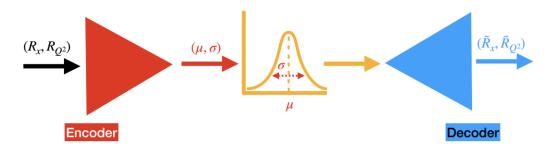




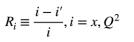
TOWARDS A 2D PROXY APP AND DIS ANALYSIS



- DIS Theory following Duke & Owens
- Generate DIS events in x and Q
- Differentiable sampler with GPU capability
- Use VAE as a detector surrogate ==> Model residuals in x and Q
- Enable analysis of real measured DIS data
- Workflow already set up for 2D proxy analysis
- Currently in testing and debugging phase



 $\mathbf{Loss} \sim \|(R_{\mathbf{x}}, R_{Q^2}) - (\tilde{R}_{\mathbf{x}}, \tilde{R}_{Q^2})\| + \mathbf{KL}\text{-Divergence}$





SUMMARY AND OUTLOOK

- Generative Inverse Problem Solver GIPS
 - Composable workflow
 - Successful loop-closure tests on 1D proxy app
 - Enable faster convergence with ensemble analysis
 - Need to formulate proper uncertainty quantification (UQ)
 - Define proper convergence metric (truth is unknown in "real" measurement)
- Currently summarizing scaling efforts in paper
- Explore non-gradient based optimizers
- 2D proxy analysis in the pipeline
- Extend experimental module ==> Include effects other than detector resolution / acceptance (e.g. background)
- Deploy workflow to HPC machines, e.g. Aurora, Sunspot,...





THE END



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