Quantum Computing / Machine Learning

Christian Bauer

Why machine learning?

- Much of particle physics and cosmology is about dealing with very large data sets, and ML can help
  - Distinguish BSM(signal) from SM(background)
  - Model independent analyses
  - Simulating the detectors
  - Real time analysis / triggers
- ML learning research ranges from applying state of the art techniques to developing new methods

We have several people involved in machine learning for HEP

Andreasen (Theory), Bhimji (NERSC), Calfiura (CRD), Farrell (NERSC), Gray (ATLAS), Moult (Theory), Nachman (ATLAS), Seljak (Cosmo), Wang (ATLAS)

Why quantum computing?

- HEP is continuously pushing the computing frontier
  - Need to obtaining precise theory predictions
  - Analyzing and reconstructing data
  - Important calculations often lack computing resources
- Scaling up resources by linear factors does not get us where we would like to be
- Hope is that quantum computing could eventually provide exponential increase in computing power

Rapidly growing field, with very strong roots in Berkeley (too many people to list).

Efforts range from building quantum hardware, building quantum sensors and developing quantum algorithms

A few examples…

Machine learning in HEP

K. Datta, A. Larkoski, Nachman, 1902.07180
J. Lin, M. Freytsis, I. Moult, Nachman, JHEP 10 (2018) 101
L. de Oliveira, Nachman, M. Paganini, 1806.05667
Z. Jiang, Nachman, F. Rubbo, ATL-PHYS-PUB-2017-017
L. de Oliveira, M. Kagan, L. Macky, Nachman, A. Schwartzman, JHEP 07 (2016) 069
W. Bhimji, S. Farrell, T. Kurth, M. Paganini, Prabhat, E. Racah, 1711.03573

J. Collins, K. Howe, Nachman, PRD 99 (2019) 014038
J. Collins, K. Howe, Nachman, PRL 121 (2018) 241803
P. Komiske, E. Metodiev, Nachman, M. Schwartz, PRD 98 (2018) 011502
E. Metodiev, Nachman, J. Thaler, JHEP 10 (2017) 51
L. Dery, Nachman, F. Rubbo, A. Schwartzman, JHEP 05 (2017) 145

full supervision / weak supervision

Classification

provide examples for training

arbitrarily many categories

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Generation

Regression

map noise to structure

M. Paganini, L. de Oliveira, Nachman, CSBS 1 (2017) 1
M. Paganini, L. de Oliveira, Nachman, PRD 197 (2018) 014021
M. Paganini, L. de Oliveira, Nachman, PRL 120 (2018) 042003
J. Lin, W. Bhimji, Nachman, 1903.02556

A. Cukierman and Nachman, NIMA 858 (2017) 1
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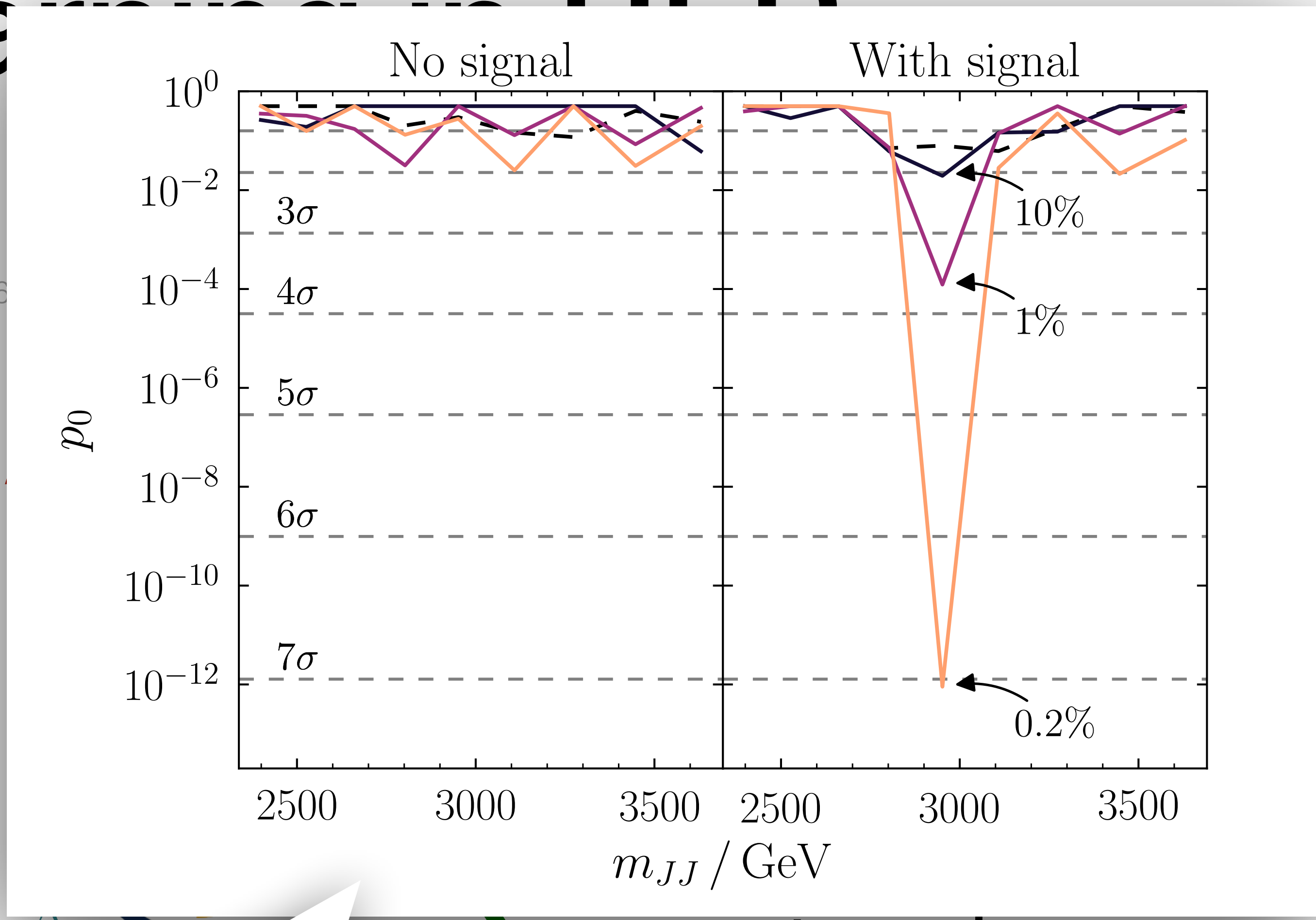
L. de Oliveira, M. Kagan, L. Macky, Nachman, A. Schwartzman, JHEP 07 (2016) 06
W. Bhimji, S. Farrell, T. Kurth, M. Paganini, Prabhat, E. Racah, 1711.03573



full supervision

Class

provide examples for training

categories

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Given that the LHC has found nothing, it is critical that we broaden our search program.

Weak supervision are a set of techniques to train on unlabeled data.

Regression

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Z. Jiang, Nachman, F. Rubbo, ATL-PHYS-PUB-2017-017
L. de Oliveira, M. Kagan, L. Macky, Nachman, A. Schwartzman, JHEP 07
W. Bhimji, S. Farrell, T. Kurth, M. Paganini, Prabhat, E. Racah, 1711.0357

Physics simulation is slow, neural network evaluation is fast.

Generative models use neural network to enhance / extend physics-based models.

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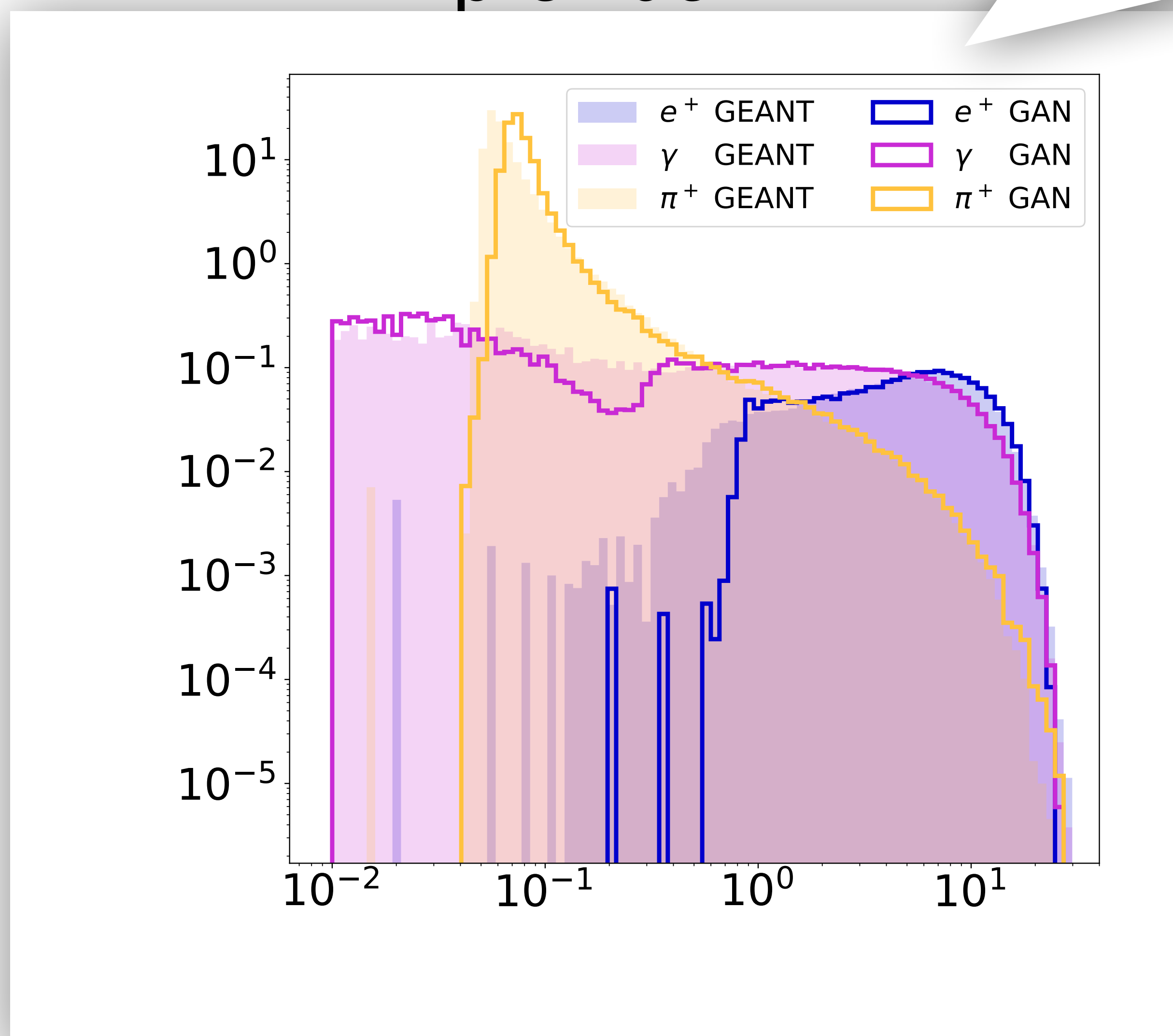

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Investigating advanced deep learning for pattern recognition

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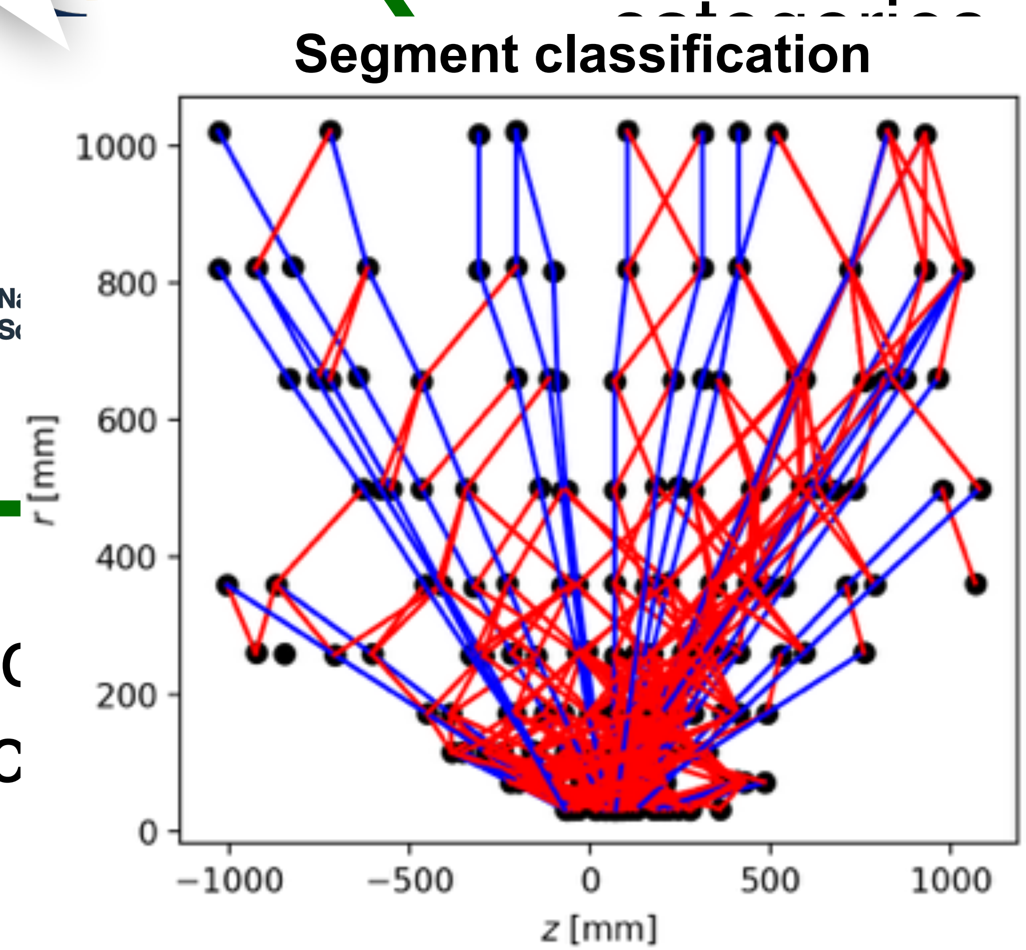

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L. de Oliveira, M. Kagan, L. Macky, Nachman, A. Schwartzman, JHEP 07
W. Bhimji, S. Farrell, T. Kurth, M. Paganini, Prabhat, E. Racah, 1711.03573

These are just a few examples!

We have a broad and deep program, with a close connection to our colleagues at NERSC.

Always looking for students in this endeavor

full supervis

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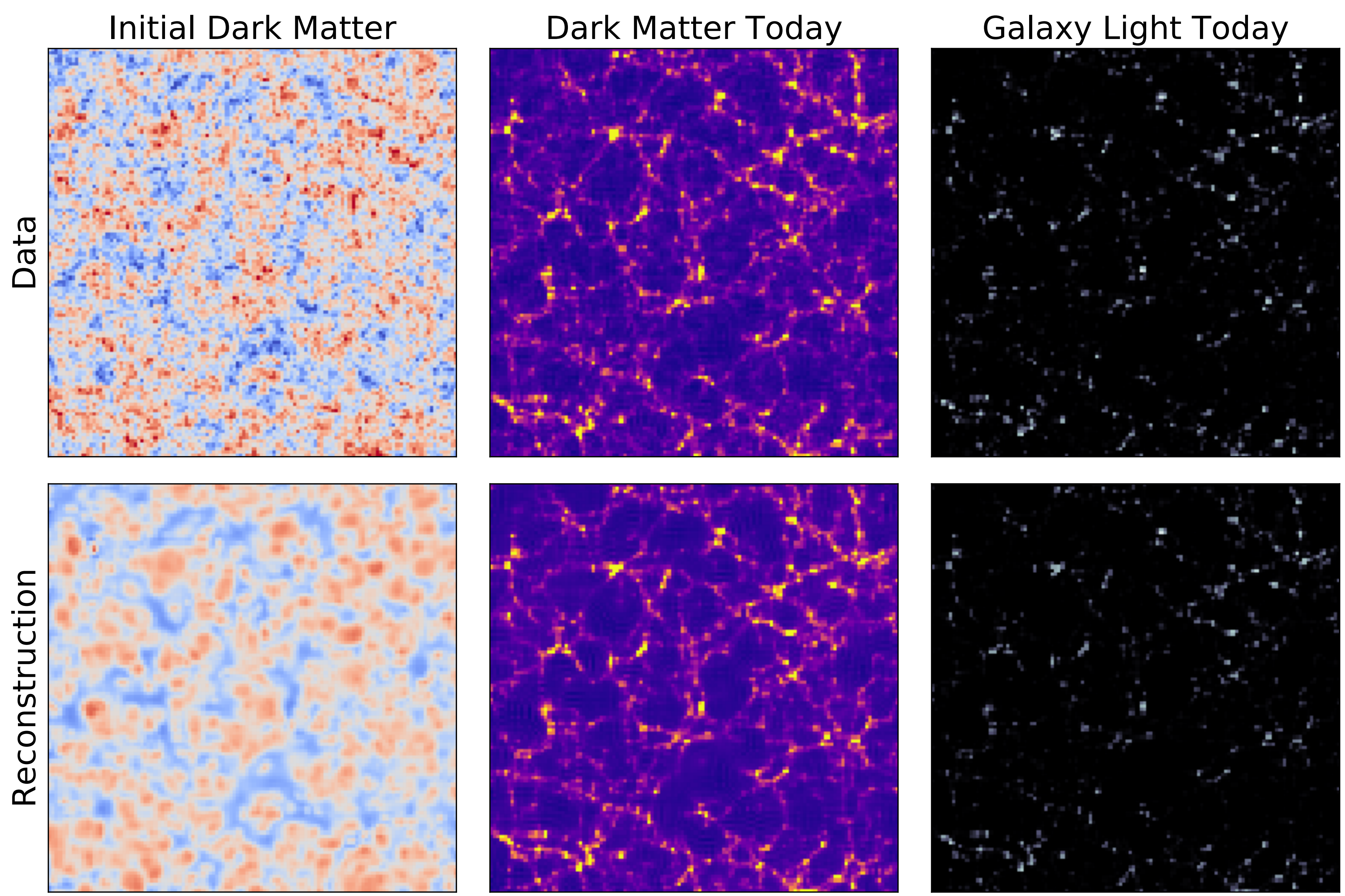
Cosmology initial condition reconstruction



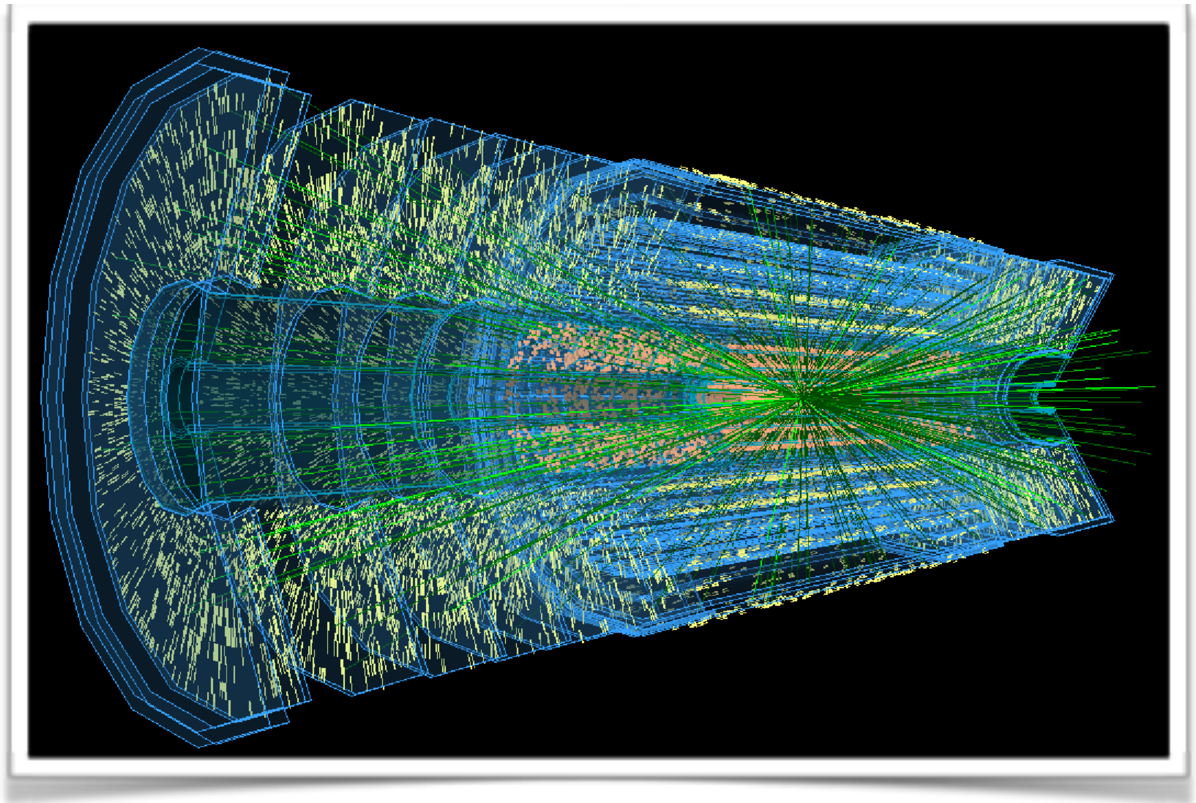
We use optimization that finds the best solution in terms of final data (optimal filter). This 3-d example optimizes in 2 million dimensions. Galaxy are sparse tracers, so we loose small scale info

Track Pattern Recognition

- The High-Luminosity LHC (HL-LHC) is expected to pose a challenge for computing
    - Increased luminosity
    - Increased read-out rates (trigger+detector upgrades)
    - Increased pile up
- Currently project to need more CPU time than will be available
    - Dominated by track reconstruction: algorithms to reconstruct the trajectories of charged particles passing through the detector

Vital to explore new algorithms and technologies

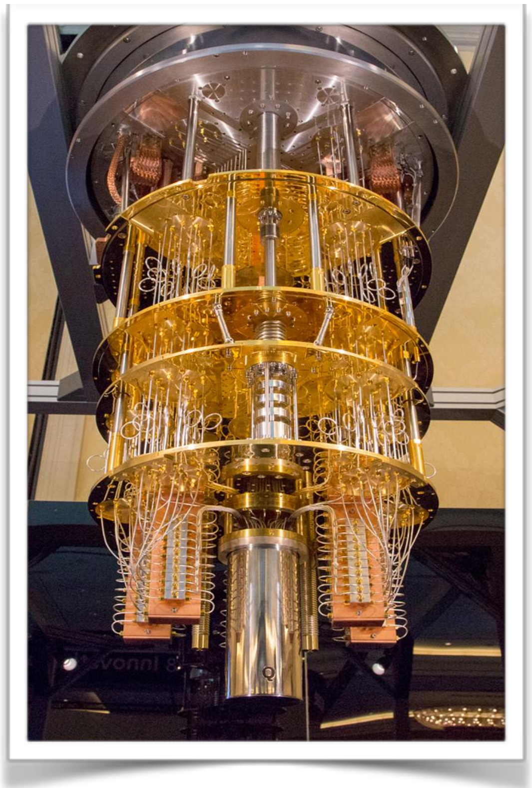
HEP.QPR: can quantum computers play a role



Quantum Pattern Recognition (HEP.QPR)

- Project exploring algorithm for pattern recognition on currently available quantum computers

IBM 20Q Tokyo



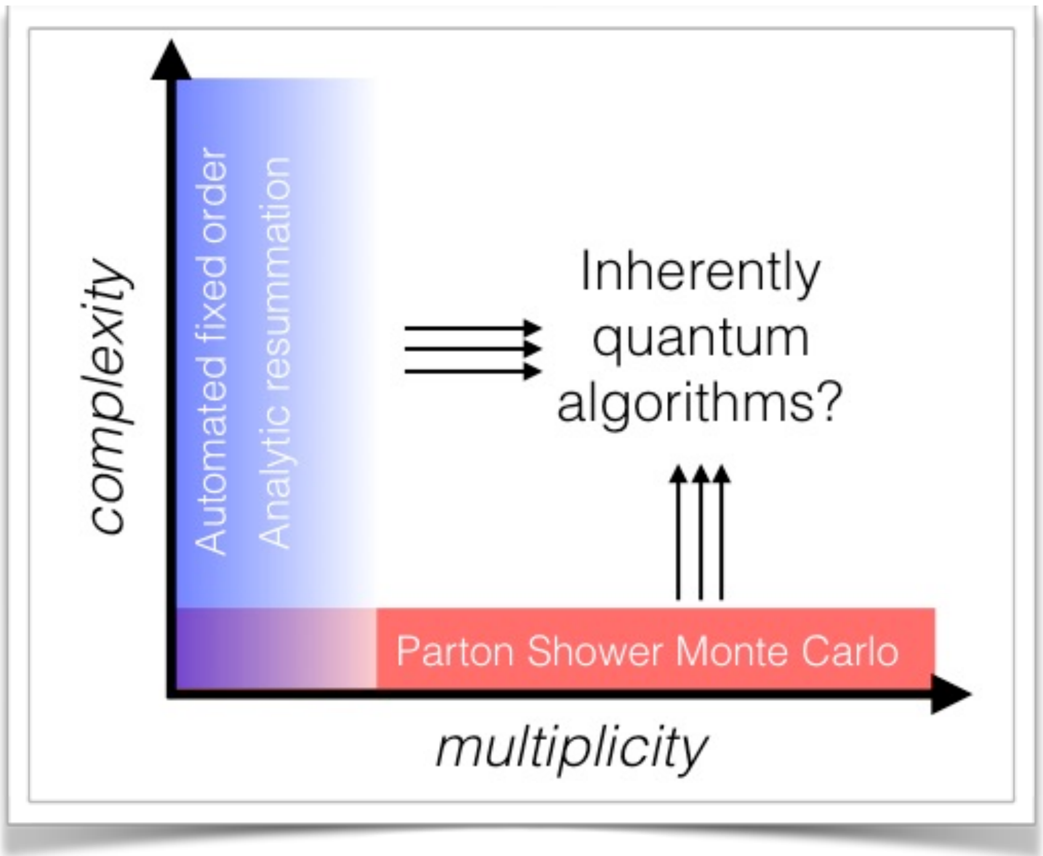
D Wave

- Recent publications on quantum annealing (D-Wave) and quantum associative memory
- Berkeley/LBL Team: Heather Gray (PI), Paolo Calafiura, Wim Lavrijsen, Wahid Bhimji, Alex Smith and collaborators in Switzerland, Canada and Japan
- More details: https://sites.google.com/lbl.gov/hep-qpr/
- Openings for graduate students (including this summer!)

Quantum computing for simulations

Bauer, Nachman, Provasoli, deJong

Can quantum algorithms allow more precise calculations?



Simulations for scattering can not be performed with high accuracy for high multiplicity final states

Main limitation is that quantum interference effects can not be included for high multiplicity

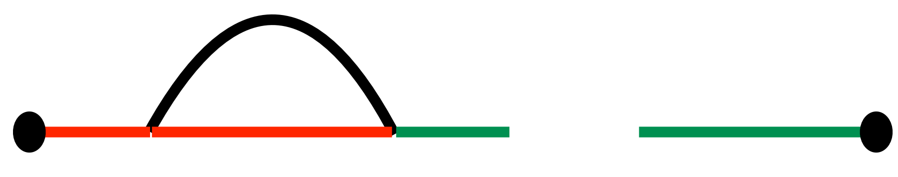
Goal to develop quantum algorithms that can do high multiplicity simulations including quantum interference effects

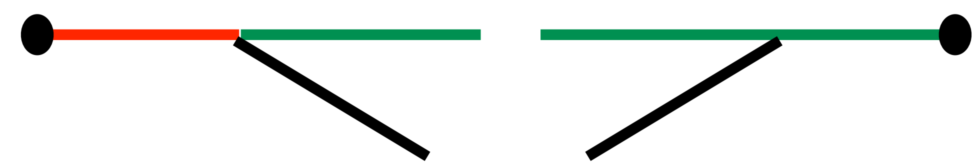
Quantum computing for simulations

Bauer, Nachman, Provasoli, deJong

Consider simple toy model which exhibits quantum interference

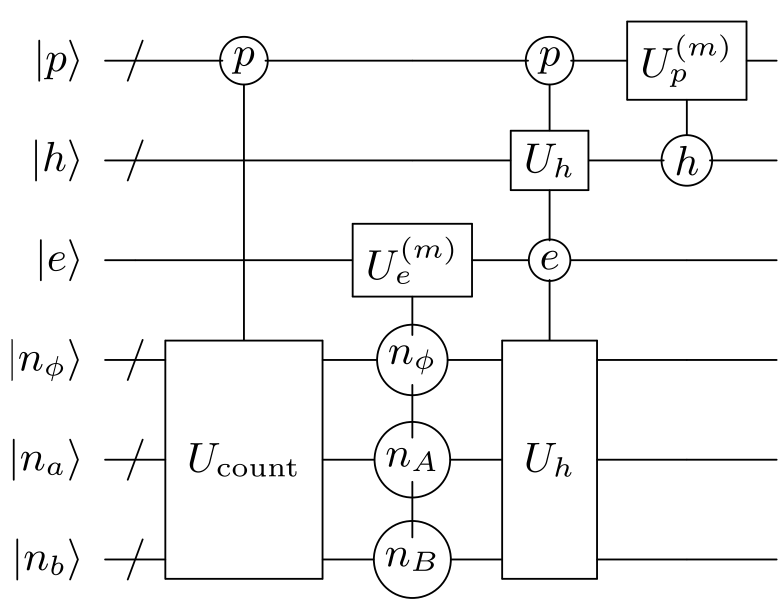
$$\mathcal{L} = \bar{f}_1 i(\not{\partial} + m_1) f_1 + \bar{f}_2(i\not{\partial} + m_2) f_2 + (\partial_\mu \phi)^2 + g_1 \bar{f}_1 f_1 \phi + g_2 \bar{f}_2 f_2 \phi + g_{12}\left[\bar{f}_1 f_2 + \bar{f}_2 f_1\right]\phi$$

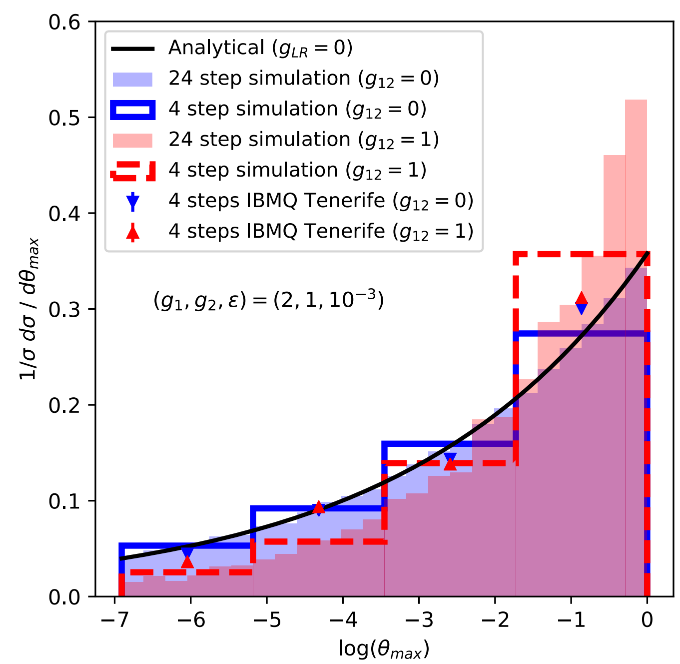


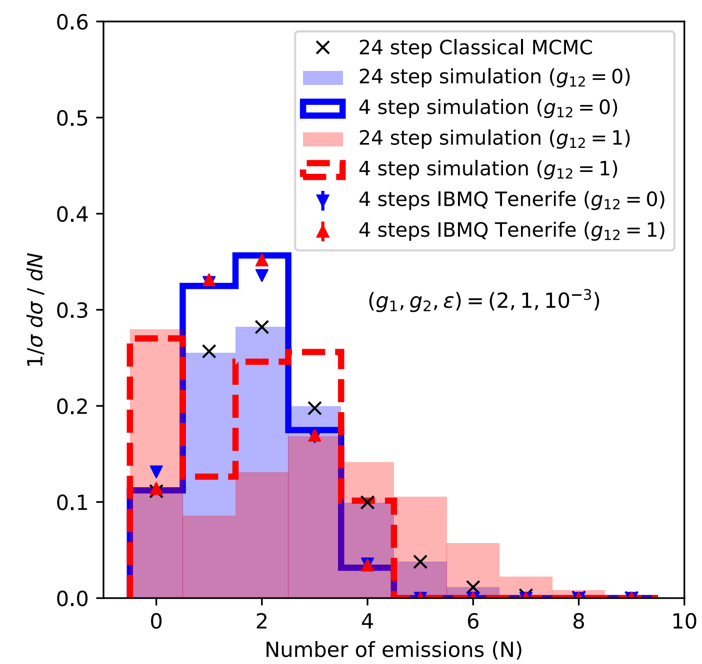


Simulation on classical computer takes 2^N computations

Can be simulated on quantum computer with N^4 scaling







Exciting cutting edge research with opening for graduate students

If you have any more questions, you can talk to a few of us in a little bit during the “lab tour”